Chapter 1
Introduction

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You have just started reading a book about Procedural Content Generation in Games. This book will contain quite a lot of algorithms and other technical content, and plenty of discussion of game design. But before we get to the meat of the book, let us start with something a bit more dry: definitions. In particular, let us define Procedural Content Generation, which we will frequently abbreviate as PCG. The definition we will use is that *PCG as the algorithmical creation of game content with limited or indirect user input* [33]. In other words, PCG refers to computer software that can create game content on its own, or together with one or many human players or designers.

A key term here is "content". In our definition, content is most of what is contained in a game: levels, maps, game rules, textures, stories, items, quests, music, weapons, vehicles, characters, etc. The game engine itself is not considered to be content in our definition. Further, non-player character behaviour – NPC AI – is not considered to be content either. The reason for this narrowing of the definition of content is that within the field of artificial and computational intelligence in games, there is much more research done in applying CI and AI methods to character behaviour than there is on procedural content generation. While the field of PCG is mostly based on AI methods, we want to set it apart from the more "mainstream" use of game-based tasks to test AI algorithms, where AI is most often used to learn to play a game. Like all definitions (except perhaps those in mathematics), our definition of PCG is somewhat arbitrary and rather fuzzy around the edges. We will treat it as such, and are mindful that other people define the term differently. In particular, some would rather use the term "generative methods" for a superset of what we call PCG [8].

Another important term is "games". Games are famously hard to define (see Wittgenstein's discussion of the matter [37]), and we will not attempt this here. Suffice to say that with games we mean such things as video games, computer games, board games, card games, puzzles, etc. It is important that the content generation system takes the design, affordances and constraints of the game that it is being generated for into account. This sets PCG apart from such endeavours as generative art and many types of computer graphics, which do not take the particular constraints and affordances of game design into account. In particular, a key requirement of generated content is that it must be playable – it should be possible to finish a generated level, ascend a generated staircase, use a generated weapon or win a generated game.

The terms "procedural" and "generation" imply that we are dealing with computer procedures, or algorithms, that create something. A PCG method can be run by a computer (perhaps with human help), and will output something. A PCG *system* refers to a system that incorporates a PCG method as one of its part, for example an adaptive game or an AI-assisted game design tool. This book will contain plenty of discussion of algorithms and quite a lot of pseudocode, and most of the exercises that accompany the chapters will involve programming.

To make this discussion more concrete, we will list a few things we consider to be PCG:

- A software tool that creates dungeons for an action adventure game like *The Legend of Zelda* without any human input – each time the tool is run, a new level is created;
- a system that creates new weapons in a space shooter game in response to what the collective of players do, so that the weapons that a player is presented with are evolved versions of weapons other players found fun to use;
- a program that generates complete, playable and balanced board games on its own, perhaps using some existing board games as starting points;
- a game engine middleware that rapidly populates a game world with vegetation;
- a graphical design tool that lets a user design maps for a strategy game, while continuously evaluating the designed map for its gameplay properties and suggesting improvements to the map to make it better balanced and more interesting.

In the upcoming chapters, you will find descriptions of all of those things described above. Let us now list a few things that we do not consider to be PCG:

- A map editor for a strategy game that simply lets the user place and remove items, without taking any initiative or doing any generation on its own;
- an artificial player for a board game;
- a game engine capable of integrating automatically generated vegetation.

Several other authors have tackled the issue of surveying PCG or part of the field we call PCG, though the overlap is far from complete [12, 26].

1.1 Why use procedural content generation?

Now that we know what PCG is, let us discuss the reasons for using and developing such methods. It turns out there are a number of different reasons.

Perhaps the most obvious reason for generating content is that it removes the need for having a human designer or artist generate that content. Humans are expensive and slow, and it seems we need more and more of them all the time. Ever since computer games were invented, the number of man-months that go into the development of a successful commercial game have increased more or less constantly [1]. It is now common for a game to be developed by hundreds of people over a period of a year or more. This leads to a situation where fewer games are profitable, and fewer developers can afford to develop a game, leading in turn to less risk-taking and less diversity in the games marketplace. Many of the costly employees necessary in this process are designers and artists rather than programmers. The game development company that could replace some of the artists and designers by algorithms would have a competitive advantage, as games could be produced faster and cheaper while preserving quality. (This argument was made forcefully by legendary game designer Will Wright in his talk "The Future of Content" at the 2005 Game Developers Conference, a talk which helped reinvigorate interest in procedural content generation.)

Of course, threatening to put them out their jobs is no way to sell PCG to designers and artists. We could therefore turn the argument around: content generation, especially embedded in intelligent design tools, can augment the creativity of individual human creators. This could make it possible for small teams without the resources of large companies, and even for hobbyists, to create content-rich games by freeing them from worrying about details and drudge work while retaining overall directorship of the games.

Both of these arguments assume that what we want to make is something like the games we have today. But PCG methods could also enable completely new types of games. To begin with, if we have software that can generate game content at the speed it is being "consumed" (played), there is in principle no reason why games would need to end. For everyone who has ever been disappointed by their favourite game not having any more levels to clear, characters to meet, areas to explore, etc., this would be an exciting prospect.

Even more excitingly, the newly generated content could be tailored to the tastes and needs of the player playing the game. By combining PCG with player modelling, for example through measuring and using neural networks to model the response of players to individual game elements, we can create player-adaptive games that seek to maximise the enjoyment of players. The same techniques could be used to maximise the learning effects of a serious game, or perhaps the addictiveness of a "casual" game.

Another reason for using PCG is that it might help us be more creative. Humans, even those of the "creative" vein, tend to imitate each other and themselves. Algorithmic approaches might come up with radically different content than a human would create, through offering an unexpected but valid solution to a given content generation problem. Outside of games, this is a well-known phenomenon in e.g. evolutionary design.

Finally, a completely different but no less important reason for developing PCG methods is to understand design. Computer scientists are fond of saying that you

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[1] At least, this is true for "AAA" games, which are boxed games sold at full price worldwide. The recent rise of mobile games seems to have made single-person development feasible again, though average development costs seem to be rising on that front too.

don't really understand a process until you have implemented it in code (and the program runs). Creating software that can competently generate game content could help us understand process by which we can "manually" generate the content, and clarify the affordances and constraints of the design problem we are addressing. This is an iterative process, whereby better PCG methods can lead to better understanding of the design process, which in turn can lead to better PCG algorithms.

1.2 Games that use PCG

Overcoming the storage limitations of computers was one of the main driving forces behind the development of PCG techniques. The limited capabilities of home computers in the early eighties constrained the space available to store game content forcing designers to pursue other methods for generating and saving content. *Elite* [4] is one of the early games that solved this problem by storing the seed numbers used to procedurally generate eight galaxies each with 256 planets each with unique properties. Another classical example of the early use of PCG is the early eighties' game *Rogue*, a dungeon-crawling game in which levels are randomly generated every time a new game starts. Automatic generation of game content, however, often comes with tradeoffs; Rogue-like games can automatically generate compelling experiences, but most of them (such as Dwarf Fortress [1]) lack visual appeal.

Recently, procedural content generation has witnessed increasing attention in commercial games. *Diablo* [2] is an action role-playing hack and slash video game featuring procedural generation for creating the maps, the type, number and placement of items and monsters. PCG is a central feature in *Spore* [15] where the designs the players create is animated using procedural animation techniques [22]. These personalized creatures are then used to populate a procedurally generated galaxy. *Civilization IV* [10] is a turn based strategy game that allows unique gameplay experience by generating random maps. *Minecraft* [19] is one of the recent popular indie games featuring extensive use of PCG techniques to generate the whole world and it's content. *Spelunky* [39] is another notable 2D platform rogue-like indie game that utilizes PCG to automatically generate variations of game levels (Figure 3.12). *Tiny Wings* [13] is yet another example of a mobile 2D game featuring a procedural terrain and texture generation system giving the game a different look with each replay.

1.3 Visions for PCG

As we can see in the previous section, procedural content generation has been a part of some published games for three decades. In the past few years, there has also been a surge in academic research on PCG, where researchers from very different academic backgrounds have brought their perspectives and methods to bear on the

Fig. 1.1: Snapshot from Spelunky.

problems of game content generation. This has resulted in a number of new methods, and variations and combinations of old methods, some of which are in need of further research and development before being useful in actual games. The chapters of this book will present many of the most significant contributions of recent years' research.

To guide the research being done, it is useful to have some visions of where we might be going; this is analogous to lists of "unsolved problems" in some research fields such as mathematics and physics. The authors of a recent survey paper defined three such visions for procedural content generation [32]. These are things that we cannot do with current technology, and might never be possible to achieve exactly as stated, but serve to point out limitations of the state of the art and by extension interesting problems to work on.

1. *Multi-level, multi-content PCG* refers to a content generator that, for a given game engine and set of game rules, would be able to generate all of the content for the game such that the content is of high quality and fits perfectly together with each other. For example, given the engine and ruleset for the popular computer role-playing game *Skyrim*, this imaginary software would generate backstory, quests, characters, items, weapons, vegetation, terrain, graphics, etc. in such a fashion that it all becomes a coherent, believable new world and an enjoyable game to play.
2. *PCG-based game design* refers to creating games that do not only rely on procedural content generation, but for which PCG is an absolutely central part of the gameplay, so that if you took the content generation part away there would not be anything recognisable left of the game. Some progress have been made towards this, notably in games such as *Galactic Arms Race* [11] or *Endless Web* [29],

but these games are still based on established game genres and core parts of the games could function without PCG.

3. *Generating complete games* refers to a generator capable of generating not only content for a given game, but the game itself. This means the rules, reward structures and graphical representation as well as the levels, characters, etc. Some work has been done in this direction, mainly to generate rules for different kinds of games [34, 7, 20, 9], but the rules generated are so far rather simplistic.

Much of the work described in the upcoming chapters can be seen as making progress towards one or several of these visions, but as you will see, there is much work to be done. At the same time, it is important to keep in mind that it is equally worthwhile to develop generators for more narrowly defined tasks.

1.4 Desirable properties of a PCG solution

We can think of implementations of PCG methods as *solutions* to *content generation problems*. A content generation problem might be to generate new grass with a low level of detail which does not look completely weird within 50 milliseconds. It might also be to generate a truly original idea for a game mechanic after days of computing time, or it might be to polish up in-game items to a perfect sheen in a background thread as they are being edited by a designer. The desirable – or required – properties of a solution are different for each application. The only constant is that there are usually tradeoffs involved, e.g. between speed and quality, and expressivity/diversity and reliability. Here is a list of common desirable properties of PCG solutions:

- *Speed:* Requirements for speed vary wildly, from a maximum generation time of milliseconds to months, depending on (amongst other things) whether the content generation is done during gameplay or during development of the game.
- *Reliability:* Some generators shoot from the hip, whereas others are capable or guaranteeing the content they generate indeed satisfy some given quality criteria. This is more important for some types of content than others, for example a dungeon with no exit or entrance is a catastrophic failure, whereas a flower that looks a bit weird just looks a bit weird without this necessarily breaking the game.
- *Controllability:* There is frequently a need for content generators to be controllable in some sense, so that a human user, or an algorithm (such as a player-adaptive mechanism), can specify some aspects of the content to be generated. There are many possible dimensions of control, e.g. one might ask for a smooth oblong rock, a car that can take sharp bends and has multiple colours, a level that induces a sense of mystery and rewards perfectionists, or a small rulesets where chance plays no part.
- *Expressivity and diversity:* There is often a need for being able to generate a diverse set of content, to avoid the content looking like it's all minor variations on a tired theme. At an extreme of non-expressivity, consider a level "generator" that

always outputs the same level but randomly changes the colour of a single stone in the middle of the level; at the other extreme, consider a "level" generator that assembles components completely randomly, yielding senseless and unplayable levels. Measuring expressivity is a non-trivial topic in its own right, and designing level generators that generate diverse content without compromising with quality is even less trivial.
- *Creativity and believability:* In most cases, we would like our content not to look like it has been designed by a procedural content generator. There is a number of ways in which generated content can look generated as opposed to human-created.

1.5 A taxonomy of PCG

With the variety of content generation problems and methods that are now available, it helps to have a structure that can highlight the differences and similarities between approaches. In the following, we introduce a revised version of the taxonomy of PCG that was originally presented by Togelius et al. [35]. It consists of a number of dimensions, where an individual method or solution should usually be thought of as lying somewhere on a continuum between the ends of that dimension.

1.5.1 Online versus offline

PCG techniques can be used to generate content online, as the player is playing the game, allowing the generation of endless variations, making the game infinitely replayable and opening the possibility of generating player-adapted content, or offline during the development of the game or before the start of a game session. The use of PCG for offline content generation is particularly useful when generating complex content such as environments and maps. An example of the use of online content generation can be found in the game *Left 4 Dead* [36], a recently released first-person shooter game that provides dynamic experience for each player by analysing player behaviour on the fly and altering the game state accordingly using PCG techniques [3].

NERO [31] is an example of the use of AI techniques to allow the players to evolve real-time tactics for a squad of virtual soldiers. *Forza Motorsport* [17] is a car racing game where the Non-Player Characters (NPCs) can be trained offline to imitate the player driving style and can later be used to drive on behalf of the player. Another important use of the offline content generation is the creation and sharing of content. Some games such as *LittleBigPlanet* [16] and *Spore* [15] provide a content editor (level editor in the case of *LittleBigPlant* and *creature editor* for *Spore*) that allows the players to edit and upload complete creatures or levels to a central online server where they can be downloaded and used by other players.

1.5.2 Necessary versus optional

PCG can be used to generate necessary game content that are required for the completion of a level, or it can be used to generate auxiliary content that can be discarded or exchanged for other content. The main distinctive feature between necessary and optional content is that necessary content should always be correct while this condition does not hold for optional content. An example of optional content is the generation of different types of weapons in first-person shooter games or the auxiliary rewarding items in Super Mario Bros [21]. Necessary content can be the main structure of the levels in Super Mario Bros, or the collection of certain items required to pass to the next level.

1.5.3 Degree and dimensions of control

The generation of content by PCG can be controlled in different ways. The use of random seed is one way to gain control over the generation space, another way is to use a set of parameters that control the content generation along a number of dimensions. Random seeds were used when generating the world in *Minecraft* [19] which allow regenerating the same world if the same seed is used [18]. A vector of content features was used in [25] to generate levels for *Infinite Mario Bros* [23] that satisfy a set of feature specifications.

1.5.4 Generic versus adaptive

Generic content generation refers to the paradigm of PCG where content is generated without taking player behaviour into account as opposite to adaptive, personalised or player-centered content generation where player interaction with the game is analysed and content is created based on player's previous behaviour. Most of the attempts that can be found in commercial games tackle PCG in a generic way, while adaptive PCG has been receiving increasing attention in academia recently. A recent extensive review of PCG for player-adaptive games can be found in [38].

Left 4 Dead [36] is an example of the use of adaptive PCG in a commercial game where an algorithm is used to adjust the pacing of the game on the fly based on player's *emotional intensity*. In this case, adaptive PCG is used to adjust the difficulty of the game in order to keep the player engaged [3]. Adaptive content generation can also be used with another motive such as the generation of more content of those the player seems to like. This approach was followed in the *Galactic Arms Race* [11] game where the weapons presented to the player are evolved based on her previous weapon use and preferences. Figure 1.2 presents examples of evolved weapons for different players.

Fig. 1.2: Three example weapons created in the Galactic Arms Race game for different players. Adapted from [11].

1.5.5 Stochastic versus deterministic

Deterministic PCG allows the regeneration of the same content given the same starting point and method parameters as opposite to stochastic PCG where recreating the same content is usually not possible. The regeneration of the galaxies in *Elite* [4] is an example of the deterministic use of PCG.

1.5.6 Constructive versus Generate-and-test

In constructive PCG, the content is generated once and modifications are not permitted, e.g. rogue-like games. Generate-and-test PCG techniques, on the other hand, go through the loop of generate-test for a number of times until a satisfactory solution is generated. *Yavalath* [5] is a two players board game generated completely by a computer program using the generate-and-test paradigm [7].

1.5.7 Automatic generation versus mixed authorship

Up until recently, PCG has allowed limited input from game designers who usually tweak the algorithm parameters to control and guide content generation while the main purpose of PCG remains the generation of infinite variations of playable content [39, 7, 1, 2]. A new interesting paradigm, however, has emerged recently focusing on incorporating designer and/or player input through the design process. In the mixed-initiative paradigm, a human (designer or player) cooperates with the algorithm to generate the desired content.

Tanagra [30] is an example of a system where the designer draws part of a 2D level and a constraint satisfaction algorithm is used to generate the missing parts while retaining playability. Another example is *SketchaWorld* framework [27] which is an interactive procedural sketching system for creating landscapes and cityscapes where designers can manually edit and tune the generated results while the virtual world model is kept consistent. *Ropossum* [24] is yet another recent example of the use of PCG for completing unfinished designs, suggesting modifications, handling constraints and testing for playability for the 2D physics-based game *Cut the Rope* [40].

1.6 Metaphors for PCG

In the phrase "procedural content generation system", we discussed what the words "procedural", "content", and "generation" mean. But what about the word *system*? A *PCG system* is a generic term for any piece of software that does PCG. But these systems do different things, are used in different ways, and have quite different relationships to the overall game-design process. Some PCG systems try to help a designer out with a small part of the design process. Others try to provide a new way of working with game content. Some are interactive; others aren't. Some aim to do fully autonomous, creative game design; others aim to automate routine or common aspects of design.

To break this broad term, *PCG system*, into more specific kinds of systems, Khaled *et al.* [14] proposed four metaphors for thinking of how PCG systems relate to the game-design process. Some PCG systems are *tools*: instruments that give designers enhanced capabilities, in the way that a programmer's development environment or an architect's CAD system do. Others define new kinds of *materials*, allowing a designer to work in a new medium, the way stone, clay, and laser installations are different materials for an artist. Some PCG systems are intended to be *designers* themselves, carrying out fully autonomous design of parts or even entire games, rather than assisting game designers. And some systems are primarily *domain experts*, carrying with them extensive knowledge of game-design that can be used to critique or improve designs. Many systems can be viewed through more than one of these lenses, though few will exhibit all of them equally.

PCG *tools*, like non-PCG design tools, aim to improve a designer's workflow, but PCG tools do it by adding a generative component. A common example is a PCG-enhanced level editor. The level-editing tools included with many game engines already improve the level-design process by providing specialized ways of editing and laying out levels, rather than the designer having to do level design in a more generic tool, or entirely in code. A PCG-enhanced level editor adds a generative component to the passive traditional level editor. The *Tanagra* [30] level editor generates levels that fit a theory of rhythmic patterns in platformer games, which the designer can modify and add more constraints to, followed by re-generation of the relevant portions. This back-and-forth pattern, alternating procedural content generation and human editing, is called *mixed-initiative* generation, and is covered in Chapter 11. Among the visions for PCG discussed earlier in this chapter, "multi-level multi-content PCG" can be seen as using a tool metaphor.

PCG systems can also create new, generative, *materials* that a game designer manipulates and sculpts to produce content. A popular commercial example is *SpeedTree*. In one sense it's a tool for designing trees to place as scenery in videogames. But the way it does this is by turning trees into an interactive generative material: the designer can click and drag them around, add and remove branches, etc., and they always look like a tree, because the trees are procedurally generated in real time as the designer manipulates them. The fractal landscapes discussed in Chapter 4 are also a kind of procedurally generative material, which a designer manipulates to produce their desired landscapes. For the PCG vision of "PCG-based game design", the appropriate metaphor is material.

A procedural content *designer* has less interaction with the human designer, and instead has ambitions of designing content all on its own. In the limit case, a PCG designer turns into a fully autonomous game generator that creates new games, usually in a specific genre. Work on automatic game design is still at an exploratory stage, but promising prototype systems exist [20, 34, 7, 9]. A key challenge for a lead designer is that it must design not only the content *in* a game, but the rules of the game itself. Chapter 6 looks at these systems that generate rules and game mechanics. The PCG vision of "generating complete games" relies on a designer metaphor.

A procedural *domain expert* is a slightly different kind of system, full of knowledge about games or players, and able to apply it to critique and modify content. Often it will apply that expertise by being part of a system that also serves as a tool or a designer. A domain expert may have purely formal knowledge of games, such as what makes a particular set of rules elegant [6]. Or it may have extensive knowledge of human players, being able to predict what people will do in a game, and what they will find challenging, fun, or boring. For a PCG-based educational game, the domain expert may have pedagogical knowledge. For example, the procedural level generation in the fraction-teaching game *Refraction* is constrained so that generated levels meet the system's pedagogical goals [28]. Chapter 10 discusses the experience-driven PCG approach, which builds PCG systems that are experts in player behaviour and reactions.

1.7 Outline of the book

This book is structured as a series of chapters, co-written by the main authors of the book and the leading experts on the topic of each chapter. Most chapters are organised so that they introduce both a family of methods (e.g. fractals or grammars) and an application domain (e.g. plants or dungeons). The method is typically introduced through an example in the application domain, and the chapter then also discusses how the same method could be used for other domains or how different methods could be used for that domain. This structure is partly motivated by the interdisciplinary nature of PCG research and practice, where the algorithms used come from numerous different fields (and thus rarely build on each other) and game design knowledge is vital in all cases. Each chapter ends with a summary and typically also with a proposed lab exercise.

In Chapter 2 we present the search-based approach to procedural content generation, which is very versatile and which has recently been used in a large number of academic research projects as well as some released games. In the search-based approach, evolutionary algorithms are used to search for good game content using principles from Darwinian evolution. The two main challenges when building a search-based content generator is the evaluation function, which evaluates candidate content artefacts, and the content representation, which defines the search space for the algorithm. While this chapter contains several examples of content generators based on artificial evolution, there are further such examples scattered in the upcoming chapters.

Chapter 3 discusses the specific example of creating dungeons for roguelike games, and similar levels based on navigating a mostly two-dimensional space – for example, levels for platform games or first-person shooters. A number of fast and constructive algorithms for generating such levels are described. Some of these algorithms come from the game development community and are widely used in roguelikes such as Diablo. Others, such as cellular automata, have their origin in physics. We also describe the Mario AI framework, a common testbed for level generation algorithms based on a clone of Super Mario Bros.

Chapter 4 describes several algorithms with a background in computer graphics research, namely simple fractal algorithms and other noise algorithms. These are commonly used to produce terrains and complete landscapes, as well as textures and features such as clouds. While these algorithms are fast and reliable, they lack some forms of controllability. Therefore two other approaches to generating landscapes are presented, one search-based and one based on collections of agents.

Chapter 5 is about grammars. Grammars, common to computer science and linguistics, prove to be very useful for creating many types of game content. The chapter starts with the example of creating lifelike plants, which is a very common form of PCG; in fact, hundreds of AAA games from recent years feature procedurally generated vegetation based on grammars. But grammars can also be used for e.g. level generation; the rest of the chapter details how to use grammars for generating levels and missions for Zelda-style action-adventure games, and how to evolve grammars that generate Super Mario Bros levels.

While some of the application domains of the previous chapters may be seen as somewhat peripheral, Chapter 6 addresses the problems of generating the absolutely most central part of any game: its rules. We describe a number of different attempts at generating rules for games, from board games to card games and arcade games. Some of these attempts are constructive, but most of them are search-based in one way or another. The chapter also describes the Video Game Description Language, a way of encoding game rules for simple arcade games of the kind you would find in the early eighties – one of the purposes of this language is to enable automatic generation of complete games.

Most games feature stories of some kind, either backstories or interactive stories that the player can affect; stories can be seen as content, so Chapter 7 is devoted to the generation of game stories. It turns out that almost all methods for story generation are based on planning algorithms; planning is a classic AI method originally developed for robot control and now widely used in various domains. The chapter also discusses how story generation can be combined with map generation, so that game maps are generated that fit with the generated story.

Chapter 8 is focused on a single method, namely Answer Set Programming (ASP). This is a form of logic programming based on constraint satisfaction: conditions are specified in a language called AnsProlog, and a solver produces all configurations of certain variables that are compatible with the specified conditions. While this might seem abstract and unrelated to PCG, it has recently been demonstrated that certain PCG problems can be easily stated in AnsProlog form, and the results of the solver interpreted as game content. This yields a highly efficient method for creating some form of game content, for example levels for puzzle-like games.

Chapter 9 returns to the topic of Chapter 2, search-based PCG, and dwells on the question of how to represent the game content. Representation is important as it defines the shape of the search space and the ways in which it can be explored. This chapter demonstrates how a wise choice of representation can alter the style of the generated content as well as enable more effective search for content that better satisfies the evaluation function. Examples include flowers represented as neural networks and level generators represented as collections of agents.

One of the motivations for PCG is that it can enable player-adaptive games. Chapter 10 describes a framework for adapting games to the player, namely that of experience-driven PCG. We describe different methods for creating models of player experience based on data collected from players.

A theme throughout much of the book is that the relationship between procedural content generation and human game designers can be quite varied. PCG can be used in a highly automated way, but it can also be used in close coupling with the designer's own design choices. Chapter 11 looks at this close coupling explicitly, considering mixed-initiative systems, in which a human designer and a procedural-content system collaborate to produce content.

Finally, Chapter 12 discusses how the quality of a PCG solution can be evaluated once it has been implemented.

1.8 Summary

Procedural content generation (PCG) in games is the algorithmical creation of game content with limited or indirect user input. PCG methods are developed and used for a number of different reasons, including saving development time and costs, increasing replayability, allowing for adaptive games, assisting designers and studying creativity and game design. While PCG algorithms have been used in some commercial games since the early eighties, they are typically either used in a peripheral role or their scope is highly limited; current research in academia is trying to push the boundaries of what can be generated and with what quality it can be generated. Ideally, a PCG solution should be fast, reliable, controllable, expressive and creative, but in practice there are certain tradeoffs that need to be made between these properties. PCG solutions can be classified according to a relatively extensive taxonomy, which might help identify their strengths and weaknesses. Another lens through which to understand a PCG system is the metaphor according to which it is used; here we can differentiate between using a system as tool, material, designer or domain expert. PCG algorithms are drawn from a variety of different fields, and this methodological diversity is evident from the table of contents of this book.

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Chapter 2
The search-based approach (DRAFT)

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2.1 What is the search-based approach to procedural content generation?

There are many different approaches to generating content for games. In this chapter, we will introduce the *search-based approach*, which has been intensely investigated in academic PCG research in recent years. In search-based procedural content generation, an evolutionary algorithm or some other stochastic search/optimisation algorithm is used to search for content with the desired qualities. The basic metaphor is that of design as a search process: a good enough solution to the design problem exists within some space of solutions, and if we keep iterating and tweaking on one or many possible solutions, keeping those changes which make the solution(s) better and discarding those that are harmful, we will eventually arrive at the desired solution. This metaphor has been used to describe the design process in many different disciplines: for example, Will Wright (designer of *SimCity* and *The Sims*) described the game design process as search in his talk at the 2005 Game Developers Conference **??**. Others have previously described the design process in general, and in other specialised domains such as architecture, the design process could be conceptualised as search and implemented as a computer program [29, 2].

The core components of the search-based approach to solving a content generation problem are the following:

- A *search algorithm*. This is the "engine" of a search-based method. As we will see, often relatively simple evolutionary algorithms work well enough, though sometimes there are substantial benefits to using more sophisticated algorithms that take e.g. constraints into account, or that are specialised for a particular content representation.
- A *content representation*. This is the representation of the artefacts you want to generate, e.g. levels, quests or winged kittens. The content representation could be anything from an array of real numbers to a graph to a string. The content

representation defines (and thus also limits) what content can be generated, and determines whether effective search is possible.
- One or more *evaluation functions*. An evaluation function is a function from an artefact (an individual piece of content) to a number indicating the quality of the artefact. The output of an evaluation function could indicate e.g. the playability of a level, the intricacy of a quest or the aesthetic appeal of a winged kitten. Crafting an evaluation function that reliably measures the aspect of game quality that it is meant to measure is often among the hardest tasks in developing a search-based PCG method.

This chapter will describe each of these components in turn. It will also discuss several examples of search-based methods for generating different types of content for different types of games.

2.2 Evolutionary search algorithms

An evolutionary algorithm is a stochastic search algorithm loosely inspired by Darwinian evolution through natural selection. The core idea is to keep a *population* of *individuals* (also called chromosomes or candidate solutions), which in each *generation* are evaluated, and the *fittest* (highest evaluated) individuals get the chance to *reproduce* and the least fit are removed from the population. A generation can thus be seen as divided into *selection* and reproduction phases. In your backyard, a generation of newly born rabbits may be subject to selection by the hungry wolf who eats the slowest of the litter, with the surviving rabbits being allowed to reproduce. The next generation of rabbits is likely to, on average, be better at running from the wolf. Similarly, in your search-based PCG implementation, a generation of strategy game units might be subject to selection by an evaluation function that grades them based on how complementary they are, and then mixed with each other (*recombination* or *crossover*) or copied with small random changes (*mutation*). The next generation of strategy game units is likely to, on average, be more complementary. It is important to note that this process works even when the initial generation consists of randomly generated individuals which are all very unfit for the purpose; some individuals will be less worthless than others, and a well-designed evaluation function will reflect these differences.

To make matters more concrete, let us describe a simple but fully usable evolutionary algorithm, the $\mu + \lambda$ *evolution strategy* (ES). The parameter μ represents the size of the part of the population that is kept between generations, the *elite*; the parameter λ represents the size of the part of the population that is generated through reproduction in each generation. For simplicity, imagine that $\mu = \lambda = 50$ while reading the following description.

1. Initialise the population of $\mu + \lambda$ individuals. The individuals could be randomly generated, or include some individuals that were hand-designed or the result of previous evolutionary runs.

2. Shuffle the population (permute it randomly). This phase is optional but helps escaping loss-of-gradient situations.
3. Evaluate all individuals with the evaluation function, or some combination of several evaluation functions, so that each individual is assigned a single numeric value indicating its fitness.
4. Sort the population in order of ascending fitness.
5. Remove the λ worst individuals.
6. Replace the λ removed individuals with copies of the μ remaining individuals. The newly made copies are called the *offspring*. If $\mu = \lambda$, each individual in the elite is copied once; otherwise, it could be copied fewer or more times.
7. Mutate the λ offspring, i.e. perturb them randomly. The most suitable mutation operator depends on the representation and to some extent on the fitness landscape. If the representation is a vector of real numbers, an effective mutation operator is *Gaussian mutation*: add random numbers drawn from a Gaussian distribution with a small standard deviation to all numbers in the vector.
8. If the population contains an individual of sufficient quality, or the maximum numbers of generations is reached, stop. Otherwise, go to step 2 (i.e. start the next generation).

Despite the simplicity of this algorithm (it could be implemented in 10-20 lines of code), the $\mu + \lambda$ ES can be remarkably effective; even degenerate versions such as the $1+1$ ES can work well. However, the evolution strategy is just one of several types of evolutionary algorithms; another commonly used type is the genetic algorithm, which relies more on recombination and less on mutation, and which uses different selection mechanisms. There are also several types of stochastic search/optimisation algorithms that are not strictly speaking evolutionary algorithms but can be used for the same purpose, e.g. swarm intelligence algorithms such as particle swarm optimisation and ant colony optimisation. A good overview of evolutionary algorithms and some related approaches can be found in Eiben and Smith's book [8].

Some evolutionary algorithms are especially well suited to particular types of representation. For example, numerous variations on evolutionary algorithms have been developed especially for evolving runnable computer programs, often represented as expression trees [18]. If the artefacts are represented as vectors of real numbers of relatively short length (low dimensionality), a particularly effective algorithm is the Covariance Matrix Adaptation Evolution Strategy (CMA-ES), for which there are several open source implementations available [9].

In many cases we want to use more than one evaluation function, as it is hard to capture all aspects of an artefact's quality in one number. For using a standard single-objective evolutionary algorithm such as the evolution strategy, the evaluation functions could be combined as a weighted sum. However, this comes with its own set of problems, particularly that some functions tend to be optimised at the expense of others. Instead, one could use a *multiobjective* evolutionary algorithm, that optimises for several objectives at the same time and finds the set of *nondominated* individuals which have unique combinations of strengths. The perhaps most popular multiobjective evolutionary algorithm is the NSGA-II [7].

2.2.1 Other types of search algorithms

It could be argued that an evolutionary algorithm is "overkill" for some content generation problem. If your search space is very small and/or you have lots of time at hand to produce your content, you could try an exhaustive search algorithm that simply iterates through all possible configurations. In other cases, when it is easy to find good solutions and it is more important to maintain high diversity in the generated content, random search – simply sampling random points in the search space – could work well. Even when using exhaustive or random search the content needs to be represented in such a way that the space can be effectively searched/sampled and an evaluation function is necessary to tell the bad content from the good.

Another approach to content generation which can also be seen as search in content space is the solver-based approach, where e.g. Answer Set Programming is used to specify the logical conditions on game content. That approach will be discussed in Chapter 8.

2.3 Content representation

Content representation is a very important issue when evolving game content. The representation chosen plays an important role in the efficiency of the generation algorithm and the space of content the method will be able to cover. In evolutionary algorithms, the solutions in the generation space are usually encoded as *genotypes* which are used for efficient searching and evaluation. Genotypes are later converted to *phenotypes*; the actual entities being evolved. In a game content generation scenario, the genotype might be the instructions for creating a game level, and the phenotype is the actual game level.

Examples of content representation in the game domain include the work done by Togelius et al. [26] who used an indirect representation for evolving maps for the real-time strategy game *StarCraft* [1]. In this experiment, the genotypes of maps were simply arrays of real numbers, whereas the phenotypes were complete StarCraft maps including passable/impassable areas, positions of bases and resources, etc. This experiment will be discussed in more detail in section 2.5.

In another game genre, Cardamone et al. [4] conducted a study for evolving tracks for a car racing game. The tracks were represented as a set of control points the track has to cover and Bezier curves were employed to connect these points and ensure smoothness, a method inspired by the work done by Togelius et al. [24] on the same game genre. An example track evolved following this method is presented in Figure 2.1. This work will be discussed further in section 2.6

As a concrete example of different representations, a level in Super Mario Bros might be represented:

1. directly as a level map, where each variable in the genotype corresponds to one "block" in the phenotype (e.g. bricks, question mark blocks, etc.);

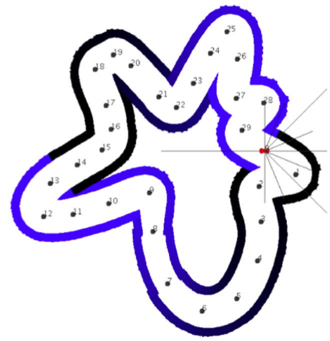

Fig. 2.1: A track evolved based on sequences of Bezier curves. Adapted from [24]

2. more indirectly as a list of the positions and properties of the different game entities such as enemies, platforms, gaps and hills (an example of this can be found in [19]);
3. even more indirectly as a repository of different reusable patterns (such as collections of coins or hills), and a list of how they are distributed (with various transforms such as rotation and scaling) across the level map (an example of this can be found in [23]);
4. very indirectly as a list of desirable properties such as number of gaps, enemies, coins, width of gaps (an example of this can be found in [20]); or
5. most indirectly as a random number seed.

These representations yield very different search spaces. It's easy to think that the best representation would be the most direct one, which gives the evolutionary process most control over the phenotype. One should be aware, however, of the "curse of dimensionality" associated with representations that yield large search spaces: the larger the search space, the harder it is (in general) to find a certain solution. Another useful principle is that the representation should have a high *locality*, meaning that a small change to the genotype should on average result in a small change to the phenotype and a small change to the fitness value. In that sense, the last representation is unsuitable for search-based PCG because there is no locality and in this case, all search methods perform as badly (or as well) as random search.

The choice of proper representation depends on the type of problem one is trying to solve. In the work done by Shaker et al. [20], the levels of *Infinite Mario Bros* [17], a public clone of the popular game *Super Mario Bros* [14], are represented according to option 4 as a vector of integers; each level is parametrized by four selected content features with the intension of finding the best combination of these features that can be used to generate content that optimises specific experience for a particular player. In a latter study by the same authors [19], a more expressive representation is used following option 2, in which the structure of the levels of the same game was described in a Design Grammar, written in Backus-Naur Form which specifies the type, position and properties of each item to be placed in the level map. The design grammar is later employed by Grammatical Evolution [15] to evolve level design. A set of design elements, following option 3, was proposed in [23], also on the same game, where levels were described as a list of design elements placed in 2D maps, and in this study a standard genetic algorithm was used to evolve content.

An issue closely related to the representation on the direct-indirect continuum is the expressive range of the chosen representation. The expressive range is relative to a particular measure of it: one could measure the expressivity of a platform game level generator in terms of how many different configurations of blocks it could produce, but it would make more sense to measure some quality that is more relevant to the experience of playing the game as a human. For example, the four-feature vector representation used to represent Infinite Mario Bros levels allows control of the generation over only the four dimensions chosen, and consequently the search space is bounded by the range of these four features. On the other hand, a generator with a wider expressive range was built when representing the possible level designs in a design grammar which imposes fewer constraints on the structures evolved.

Chapter 9 discusses the issue of representation in search-based PCG further, and gives additional examples of representations tailored to particular content generation needs.

2.4 Evaluation functions

Candidate solutions, represented in the proper representation, are evaluated by an evaluation function that assigns a score (a fitness value or evaluation value) to each candidate. This is essential for the search process; if we do not have a good evaluation function, the evolutionary process will not work as intended and will not find good content. In general, the evaluation function should be designed to model some desirable quality of the artefact, e.g. it's playability, regularity, entertainment value, etc. The design of an evaluation function depends to a great extend on the designer and what she thinks are the important aspects that should be optimised and how to formulate that.

For example, there are many studies on evolving game content that is "fun" [25, 24, 20, 4]. This term, however, is not well defined and hard to measure and formalise. This problem has been approached by many authors from different perspectives. In some studies, fun is considered a function of player behaviour and it is measured accordingly. An example of such method can be found in the work done by Togelius et al. [25] for evolving entertaining car racing tracks. In this study, indicators of player performance, such as the average speed achieved, were used as a measure of suitability of each evolved track for individual players. In another study by Shaker et al. [20], fun is measured through self reports by directly asking the players about their experience. In other studies [22], a game is considered fun if the content presented follows predefined patterns that specify regions in the game and alternate between segments of varying challenge. In this case, challenge is considered the primary cause of a fun experience.

In search-based PCG, one commonly distinguishes between three classes of evaluation functions:

2.4.1 Direct evaluation functions

Direct evaluation functions map features extracted from the content generated to a content quality value and in that sense, they base their fitness calculations directly on the phenotype representation of the content. Direct evaluation functions are fast to compute and often relatively easy to implement, but it is sometimes hard to devise a direct evaluation function for some aspects of game content. Example features include the placement of bases and resources in real-time strategy games [26] or the size of the ruleset in strategy games [12]. The mapping between features and fitness might be contingent on a model of the playing style, preferences or affective state of players. An example of this form of fitness is the study done by Shaker et al. [20, 21] for personalising player experience using models of players as a measures of content quality.

Within direct evaluation functions, one distinguishes between *theory-driven* and *data-driven* functions. Theory-driven functions are guided by intuition and/or qualitative theories of player experience. Togelius et al. [24] used this method to evaluate the tracks in a car racing game. The evaluation function derived is based on several theoretical studies on fun in games [6, 11] and the authors' intuition of what makes an intertraining track. Data-driven functions, on the other hand, are based on quantitative measures of player experience that approximate the mapping between the content presented and players' affective or cognitive states collected via questionnaires or physiological measurements [21, 30].

2.4.2 Simulation-based evaluation functions

Simulation-based evaluation functions use AI agents that play through the content generated and estimate its quality. Statistics are usually calculated about the agents behaviour and playing style and used to score game content. The type of the evaluation task determines the area of proficiency of the AI agent; if content is evaluated on the basis of playability, that is the existence of a path from the start to the end in a maze or a level in a 2D platform game, then AI agents should be designed that are excel in reaching the end of the game. On the other hand, if content is optimised to maximise particular player experience, then an AI agent that imitates human behaviour is usually adopted. An example study that implements a human-like agent for assessing content quality is presented in [24] where neural network-based controllers are trained to drive like human players in a car racing game and then used to evaluate the generated tracks. Each track generated is given a fitness value according to playing behaviour statistics calculated while the AI controller is playing. Another example of a simulation-based evaluation function is measuring the average fighting time of bots in a first-person shooter game [5].

An important distinction within simulation-based evaluation functions is between *static* and *dynamic* functions. Static evaluation functions assume that the agent behaviour is maintained during gameplay. A dynamic evaluation function, on the other hand, uses an agent that adapts during gameplay. In such agents, the fitness value can be dependent on learnability: how well and/or fast the agent learns to play the content that is being evaluated.

2.4.3 Interactive evaluation functions

Interactive functions evaluate content based on interaction with a human, so they requires a human “in the loop”. Examples of this method can be found in the work done by Hastings et al. [10] who implemented this approach by evaluating the quality of the personalised weapons evolved implicitly based on how often and how long the player chooses to use these weapons. Cardamone et al. [4] also used this form of evaluation to score racing tracks according to the users’ reported preferences. The first case is an example of an *implicit* collection of data while players’ preferences were collected *explicitly* in the second. The problem with explicit data collection is that it usually requires interrupting the gameplay session if not well integrated. This method however provides a reliable and accurate estimator of player experience as opposite to implicit data collection which is usually noisy and based on assumptions. Hybrid approaches are sometimes employed to accommodate for the drawbacks of these two methods by collecting information across multiple modalities such as combining player behaviour with eye gaze and/or skin conductance. Example studies that use this approach can be found in [13, 21, 30].

2.5 Example: StarCraft maps

In two recent papers, Togelius et al. presented a search-based approach to generating maps for the classic real-time strategy game (RTS) *StarCraft* [26, 27]. Despite being released in the previous millennium, this game is still widely played and was until very recently the focus of large tournaments broadcast on national TV in countries such as South Korea. The focus of the game is on building bases, collecting resources, and waging war with armies of units built using these bases. The maps of the game play a crucial role, as they constrain what strategies are possible through their distribution of paths, obstacles, resources, etc. Given the competitive nature of the game, it is very important that the maps are fair. Therefore, evaluation functions were designed to measure the fairness of the maps as well as their affordances for interesting and diverse strategies.

Representation: The maps are represented as vectors of real numbers (of around 100 dimensions). In the genotype-to-phenotype process, some of these numbers are interpreted directly as the positions of resources or base starting locations. Other numbers are interpreted as starting positions and parameters for a turtle-graphics-like procedure that "draws" impassable regions (walls, rocks, etc.) on the initially empty map. The result of the transformation is a two-dimensional array where each cell corresponds to a block in the StarCraft map format; this can then automatically be converted to a valid StarCraft map.

Evaluation: Eight different evaluation functions were developed that address base placement, resource placement and paths between bases. These evaluation functions are based mostly on calculations of free space in different areas of the map and on the shortest paths between different points as calculated by the A* algorithm, and the functions are thus direct (though, if you see the path calculations as abstract simulations of unit behaviour in the game, the functions can be seen as simulation-based). There are functions for evaluating that bases are sufficiently fair from each other, that there is enough space to grow a base, and that there is equal access to nearby resources. One particularly complicated function is the choke point function, which returns a higher value if the shortest path between two bases has a so called choke point, where a tactically skilled player can defend against a superior attacking forces through using the level geometry.

Algorithm: Given the number of evaluation functions, it seemed very complicated to combine all of them into a single objective. The SMS-EMOA, a state-of-the-art multiobjective evolutionary algorithms, was therefore used to evolve combinations of two or three objectives (some additional objectives were also converted to constraints). It was found that there are partial conflicts between several objectives, meaning that it is impossible to find a map that maximises all of them, but certain combinations of objectives yield interesting and reasonably fair maps.

2.6 Example: Racing tracks

In an early and influential paper, Togelius et al. evolved racing tracks to fit particular players' playing style in a simple two-dimensional racing game [24]. This particular game had already been used for a series of experiments investigating how evolutionary algorithms could best be used to create neural networks that could play the game well, when the authors decided to see whether the same technique could be applied to evolve the tracks the car was racing on. The reasoning was that creating challenging opponent drivers for commercial racing games is actually quite easy, especially if you are allowed to "cheat" by giving the computer-controlled cars superior performance (and who would stop you?) – on the other hand, creating an interesting racing track is not trivial at all.

Representation: The tracks are represented as vectors of real numbers, which are interpreted as control points for b-splines, i.e. sequences of Bezier curves.

Evaluation: The tracks are meant to be personalised for individual players. Therefore, the first stage in evolving a track for a given player is to model the playing style of that player. This is done by teaching a neural network (via another evolutionary process) to drive like that player. Then a candidate track is evaluated in a simulation-based manner by letting the neural network driver drive on that track in lieu of the human player and investigate its performance. This information is used by three different evaluation functions, that measure whether the track has appropriate challenge and diversity for the player.

Algorithm: Given that there are three different evaluation functions, there remains the problem of combining them. The algorithm used, *cascading elitism*, is similar to $\mu + \lambda$ ES but has several stages of selection to ensure appropriate selection pressure on all objectives.

2.7 Example: Board game rules

In an influential paper, Browne and Maire demonstrated that it is possible to automatically generate complete board games of such quality that they can be sold as commercial products [3]. The system described, *Ludi*, is restricted to simple board games similar to Go, Othello and Connect Four, but does a remarkable job of exploring this search space. This example will be discussed further in Chapter 6.

Representation: The board games, including board layouts and rules, are represented as strings (which can be interpreted as expression trees) in a special purpose game description language. This is a relatively high-level language, describing entire games in just a few lines.

Evaluation: The games were evaluated by playing them with a version of the MiniMax algorithm, with an evaluation function that had been automatically tuned for each game. A number of values are extracted from investigating the performance of the algorithm on the game, e.g. how long time it took to finish the game, how often the game ends in a draw, how many of the rules were used etc. These values were combined using a weighted sum based on empirical investigations of the properties of successful board games.

Algorithm: A relatively standard genetic algorithm was used.

2.8 Example: Galactic Arms Race

Galactic Arms Race (GAR) is a space shooter video game where the player traverses the space in a space ship, shoots enemies, collects items and upgrades her ship. The game was first released in 2010 as a free research game and a commercial version of the game was recently released in 2012. The game is interesting from a research perspective because it is one of very few games, if any, that incorporate online automatic personalised content generation in a highly and very well-chosen playable context. The main innovation of the game is in personalising the weapons used by the player through evolution. As the game is played, new particle weapons are automatically generated based on player behaviour.

Representation: Particle system weapons are controlled by Artificial Neural Networks (ANNs) evolved by a method called NeuroEvolution of Augmenting Topologies (NEAT) [10] which evolves neural network through complexification; a term refers to starting the evolution with a population of simple, small networks and increasingly complexity the network topologies over generations. Each weapon in the game is represented as a single ANN that controls the motion (velocity) and appearance (colour) of the particles given the particle's current position in the space. The evolution starts with a set of simple weapons that shoot only in a straight line.

Evaluation: During the game, a fitness is assigned for each weapon based on how much this particular weapon is used by the player. Not picking up a weapon causes its ineligibility for reproduction. The weapons used by the user are assigned higher fitness values and thus have higher probability of being evolved. The newly evolved content are then spawned in the space for the player to pick up.

Algorithm: The whole game thus represents a collective, distributed evolutionary algorithm. This process allows the generation of unique weapons for each player and by playing the game, more novel and personalised weapons based on those preferred could be found.

2.9 Lab exercise: Evolve a dungeon

Roguelike games are a type of games that use PCG for level generation; in fact, the runtime generation and thereafter the infinite supply of levels is a key feature of this genre. As in the original game *Rogue* from 1980, a roguelike typically lets you control an agent in a labyrinthine dungeon, collecting treasures, fighting monsters and levelling up. A level in such game thus consists of rooms of different sizes containing monsters and items and connected by corridors. There are a number of standard constructive algorithms for generating roguelike dungeons [16], such as:

- Create the rooms first and then connect them by corridors or,
- use maze generation methods to create the corridors and then connect adjacent sections to create rooms.

The purpose of this exercise is to allow you to understand the search-based approach through implementing a search-based dungeon generator. Your generator should evolve playable dungeons for an imaginary roguelike. The phenotype of the dungeons should be 2D matrices (e.g. size 50x50) where each cell could be one of the following: free space, wall, starting point, exit, monster, treasure. It is up to you whether to add other possible types of cell content, such as traps, teleporters, doors, keys, or different types of treasures and monsters. One of your tasks is to explore different content representations and quality measures in the context of dungeon generation. Possible content representations include [28]:

- A grid of cells that can contain one of the different items including: walls, items, monsters, free spaces and doors;
- a list of walls with their properties including their position, length and orientation;
- a list of different reusable patterns of walls and free space, and a list of how they are distributed across the grid;
- a list of desirable properties (number of rooms, doors, monsters, length of paths and branching factor); or
- a random number seed.

There are a number of advantages and disadvantages for each of these representations. In the first representation, for example, a grid of size 100×100 would need to be encoded as a vector of length 10,000, which is more than many search algorithms can effectively approach. The last option, on the other hand, explores one-dimensional space but it has no locality.

Content quality can be measured directly by counting the number of unreachable rooms or undesired properties such as a corridor connected to a corner in a room or a room connected to too many corridors.

2.10 Summary

In search-based PCG, evolutionary computation or other stochastic search/optimisation algorithms are used to create game content. The content creation can be seen as a search for the content that best satisfies an evaluation function in a content space. When designing a search-based PCG solution, the two main issues are the content representation and the evaluation function. The same space of content phenotypes can be represented in several different ways in genotype space; in general, we can talk about the continuum from direct representations (where genotypes are similar to phenotypes) to indirect representations (where genotypes are much smaller than phenotypes). Indirect representations yield less control and potentially sparser coverage of content space, but often cope better with the curse of dimensionality. There are three types of evaluation functions: direct, simulation-based and interactive. Direct evaluation functions are fast, simulation-based evaluation functions require an AI to play through part of the game and interactive evaluation functions require a human in the loop. Search-based PCG is currently very popular in academia and there are multiple published studies; a few complete games have been released incorporating this approach to PCG.

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Chapter 3
Constructive generation methods for dungeons and levels (DRAFT)

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A dungeon, in the real world, is a cold, dark and dreadful place where prisoners are kept. A dungeon, in a computer game, is a labyrinthine environment where adventurers enter at one point, collect treasures, evade or slay monsters, rescue noble people, fall into traps and ultimately exit at another point. This conception of dungeons probably originated with the roleplaying board game *Dungeons and Dragons*, and has been a key feature of almost every computer role playing game (RPG), including genre-defining games such as the *Legend of Zelda* series and the *Final Fantasy* series, and recent megahits such as *The Elder Scrolls V: Skyrim*. Of particular note is the "roguelike" genre of games which, following the original *Rogue* from 1980, features procedural runtime dungeon generation; the *Diablo* series is a high-profile series of games in this tradition. Because of this close relationship with such successful games, and also due to the unique control challenges in their design, dungeons are a particularly active and attractive PCG subject.

For the purposes of this chapter, we define adventure and RPG dungeon levels as labyrinthic environments, consisting mostly of inter-related challenges, rewards and puzzles, tightly paced in time and space to offer highly structured gameplay progressions [13]. An aspect which sets dungeons apart from other types of levels is a sophisticated notion of gameplay pacing and progression: although dungeon levels are open for free player exploration (more than *e.g.* platform levels), this exploration has a tight bond with the progression of challenges, rewards and puzzles, as intended by game designers. In contrast with *e.g.* platform levels or race tracks, dungeon levels encourage free exploration while keeping strict control over gameplay experience, progression and pacing (unlike open worlds, where the player is more independent). For example, players may freely choose their own dungeon path among different possible ones, but never encounter challenges that are impossible for their current skill level (since the space to back track is not as open as, for example, a sandbox city). Designing dungeons is thus a sophisticated exercise of emerging a complex game space from predetermined desired gameplay, rather than the other way around.

In most adventure games and RPGs, dungeons structurally consist of several rooms connected by hallways. While originally the term 'dungeon' refers to a labyrinth of prison cells, in games it may also refer to caves, caverns, or human-made structures. Beyond geometry and topology, dungeons include non-player-characters (*e.g.* monsters to slay, princesses to save), decorations (typically fantasy-based) and objects (*e.g.* treasures to loot).

Procedural generation of dungeons refers to the generation of the topology, geometry and gameplay-related objects of this type of levels. A typical dungeon generation method consists of three elements:

1. A representational model: an abstract, simplified representation of a dungeon, providing a simple overview of the final dungeon structure.
2. A method for constructing that representational model.
3. A method for creating the actual geometry of a dungeon from its representational model.

Above, we distinguished dungeons from platform levels. However, there are also clear similarities between these two types of game level. Platform game levels were made famous by classic games such as *Super Mario Bros*, *Sonic, the Hedgehog*, and their countless clones and near-clones, as well as by other games that have drawn inspiration from them; a modern-day example of a game in this tradition that features procedural level generation is *Spelunky*, discussed in the first chapter. Like dungeons, platform game levels typically feature free space, walls, treasures or other collectables, enemies and traps. However, in the game mechanics of platformers, the player agent is typically constrained by gravity: the agent can move left or right and fall down, but can typically only jump a small distance upwards. As a result, the interplay of platforms and gaps is an essential element in the vocabulary of platform game levels.

In this chapter, we will study a variety of methods for procedurally creating dungeons and platform game levels. Although these methods may be very disparate, they have one feature in common: they are all constructive, producing only one output instance per run, in contrast with *e.g.* search-based methods. They also have in common that they are fast; some were even successful in creating levels at runtime. In general, these methods provide (rather) limited control over the output and its properties.The degree of control provided is nowadays a very important characteristic of any procedural method. With 'control' we mean the set of options that a designer (or programmer) has in order to purposefully steer the level generation process, as well as the amount of effort that steering takes. Control also determines to which extent editing those options and parameters causes sensible output changes, *i.e.* the intuitive responsiveness of a generator. Proper control assures that a generator creates consistent results (*e.g.* playable levels), while maintaining both the set of desired properties and variability.

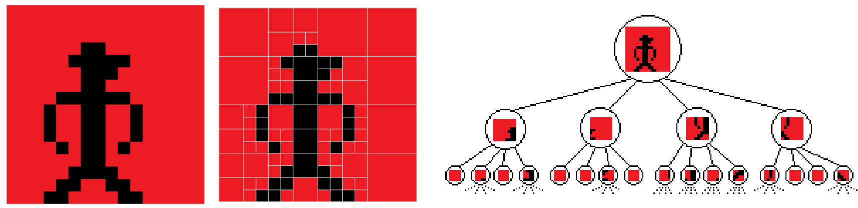
As PCG methods grow in complexity, and different PCG methods are combined to form more complex generation processes, meaningful parameters have been developed to help generate content towards a specific output. As a result, PCG control is evolving towards more natural and high-level interaction between designer and machine, with the use of techniques like declarative modeling [29, 10], controllable agents [5] and gameplay-based control [14].

We will discuss several families of procedural techniques. For simplicity, each of these technique will be presented in the context of a single content type, either dungeons or platform game levels. The first family of algorithms to be discussed in this chapter is space partitioning. Two different examples of how dungeons can be generated by space partitioning are given; the core idea is to recursively divide the available space in pieces and then connect them to form the dungeon. This is followed by a discussion on agent-based methods for generating dungeons, with the core idea that agents dig paths into a primeval mass of matter. The next family of algorithms to be introduced is cellular automata, which turn out to be a simple and fast means of generating structures such as cave-like dungeons. Generative grammars, yet another family of procedural methods, are discussed next, as they can naturally capture higher-level dungeon design aspects. We then turn our attention into several methods that were developed for generating platform levels, some of which are applicable to dungeons as well. The chapter ends with a discussion of the platform level generation methods implemented in the commercial game Spelunky and the open-source framework Infinite Mario Bros, and its recent offshoot InfiTux. The lab exercise will have you implementing at least one method from the chapter using the InfiTux API.

3.1 Space partitioning for dungeon generation

True to its name, a space partitioning algorithm yields a *space partition*, *i.e.* a subdivision of a 2D or 3D space into disjoint subsets, so that any point in the space lies in exactly one of these subsets (also called *cells*). Space partitioning algorithms often operate hierarchically: each cell in a space partition is further subdivided by applying the same algorithm recursively. This allows space partitions to be arranged in a so-called *space partitioning tree*. Furthermore, such a tree data structure allows for fast geometric queries regarding any point within the space; this makes space partitioning trees particularly important for computer graphics, enabling, for example, efficient raycasting, frustum culling and collision detection.

The most popular method for space partitioning is *binary space partitioning* (BSP), which recursively divides a space into two subsets. Through binary space partitioning, the space can be represented as a binary tree, called a *BSP tree*. Different variants of BSP choose different splitting hyperplanes based on some specific rules. Such algorithms include quadtrees and octrees: a quadtree partitions a two-dimensional space into four quadrants and an octree partitions a three-dimensional space into eight octants. We will be using quadtrees on two-dimensional images as the simplest example, although the same principles apply for octrees, on 3D space, and for other types of stored data. While a quadtree's quadrants can have any rectangular shape, they are usually equal-sized squares. A quadtree with a depth of n can represent any binary image of 2^n by 2^n pixels, although the total number of tree



(a) Image and partition

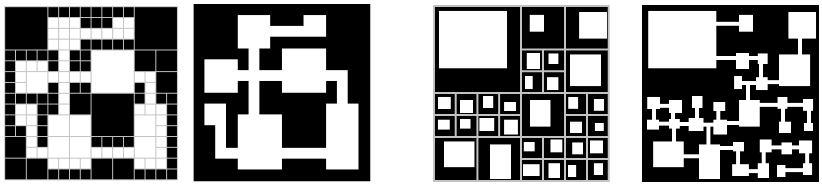
(b) Quadtree

Fig. 3.1: An example quadtree partition of a binary image (0 shown as red, 1 as black). Large areas of a single colour, such as those on the right edge of the image, are not further partitioned. The image is 16 by 16 pixels, so the quadtree has a depth of 4. While a fully expanded quadtree (with leaf nodes containing information about a single pixel) would have 256 leaf nodes, the large areas of a single colour result in a quadtree with 94 leaf nodes. The first layers of the tree are shown in (b): the root node contains the entire image, with the four children ordered as: top left quadrant, top right quadrant, bottom left quadrant, bottom right quadrant (although other orderings are possible).

nodes (and its depth) depend on the structure of the image. The root node represents the entire image, and its four children represent the top left, top right, bottom left and bottom right quadrants of the image. If the pixels within any quadrant have different colors, that quadrant is subdivided; the process is applied recursively until each leaf quadrant (regardless of size) contains only pixels of the same color (see Figure 3.1).

When space partitioning algorithms are used in 2D or 3D graphics, their purpose is typically to represent existing elements such as polygons or pixels rather than create new ones. However, the principle that space partitioning results in disjoint subsets with no overlapping areas is particularly suitable for creating rooms in a dungeon or, in general, distinct areas in a game level. Dungeon generation via BSP follows a *macro* approach, where the algorithm acts as an all-seeing dungeon architect rather than a 'blind' digger as is often the case with agent-based approaches presented in Section 3.2. The entire dungeon area is represented by the root node of the BSP tree and is partitioned recursively until a terminating condition is met (such as a minimum size for rooms). The BSP algorithm guarantees that no two rooms will be overlapping, and allows for a very 'structured' appearance of the dungeon.

How closely the generative algorithms follow the principles of 'traditional' partitioning algorithms affects the appearance of the dungeon created. For instance, a dungeon can be created from a quadtree by selecting quadrants at random and splitting them; once complete, each quadrant can be assigned a value of 0 (empty) or 1 (room), taking care that all rooms are connected. This creates very symmetric, 'square' dungeons such as those seen in Figure 3.2a. Furthermore, the principle that a leaf quadrant must consist of a uniform element (or of same colour pixels, in the case of images) can be relaxed for the purposes of dungeon generation; if each leaf quadrant contains a single room but can also have empty areas allows for rooms of



(a) (b)

Fig. 3.2: In (a) is a dungeon created using a quadtree, with each cell consisting entirely of empty space (black) or rooms (white). In (b), a dungeon created using a quadtree, but with each quadrant containing a single room (placed stochastically) as well as empty space; corridors are added after the partitioning process is complete.

different sizes, as long as their dimensions are smaller than the quadrant's bounds. These rooms can then be connected with each other, using random or rule-based processes, without taking the quadtree into account at all. Even with this added stochasticity, dungeons are still likely to be very neatly ordered (see Figure 3.2b).

We now describe an even more stochastic approach loosely based on BSP techniques. We consider an area for our dungeon, of width w and height h, stored in the root node of a BSP tree. Space can be partitioned along vertical or horizontal lines, and the resulting partition cells do not need to be of equal size. While generating the tree, in every iteration a leaf node is chosen at random and split along a randomly chosen vertical or horizontal line. A leaf node is not split any further if it is below a minimum size (we will consider a minimal width of $w/4$ and minimal height of $h/4$ for this example). In the end, each partition cell contains a single room; the corners of each room are chosen stochastically so that the room lies within the partition and has an acceptable size (i.e. is not too small). Once the tree is generated, corridors are generated by connecting children of the same parent with each other. Below is the high-level pseudo-code of the generative algorithm, and Figure 3.3 and 3.4 shows the process of generating a sample dungeon.

```
1: start with the entire dungeon area (root node of the BSP tree)
2: divide the area along a horizontal or vertical line
3: select one of the two new partition cells
4: if this cell is bigger than the minimal acceptable size:
5:   go to step 2 (using this cell as the area to be divided)
6: select the other partition cell, and go to step 4
7: for every partition cell:
8:   create a room within the cell by randomly
     choosing two points (top left and bottom right)
     within its boundaries
9: starting from the lowest layers, draw corridors to connect
   rooms in the nodes of the BSP tree with children of the same
   parent
10:repeat 9 until the children of the root node are connected
```

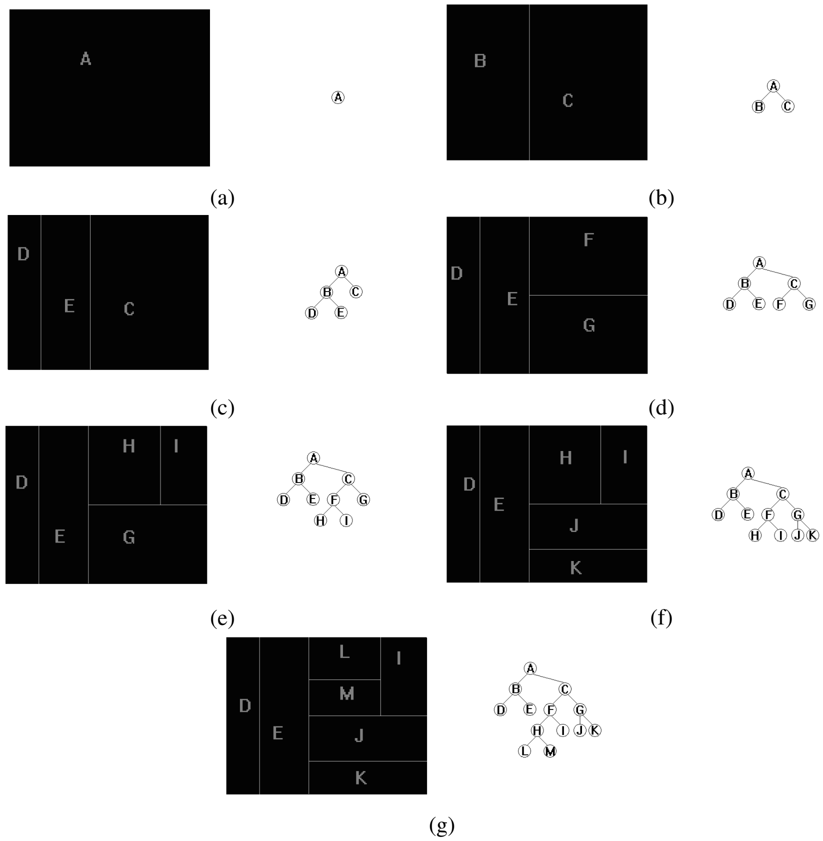


Fig. 3.3: Stochastically partitioning the dungeon area A, which is contained in the root node of the BSP tree. Initially the space is split into B and C via a vertical line (its x-coordinate is determined randomly). The smaller area B is split further with a vertical line into D and E; both D and E are too small to be split (in terms of width) so they remain leaf nodes. The larger area C is split along a horizontal line into F and G, and areas F and G (which have sufficient size to be split) are split along a vertical and a horizontal line respectively. At this point, the partition cells of G (J and K) are too small to be split further, and so is partition cell I of F. Cell H is still large enough to be split, and is split along a horizontal line into L and M. At this point all partitions are too small to be split further and dungeon partitioning is terminated with 7 leaf nodes on the BSP tree. Figure 3.4 demonstrates room and corridor placement for this dungeon.

While binary space partitioning was here primarily used to create non-overlapping rooms, it should be noted that the hierarchy of the BSP tree can be used for other aspects of dungeon generation as well. The previous example of Figure 3.4 has demonstrated how room connectivity can be determined by the BSP tree: using corridors

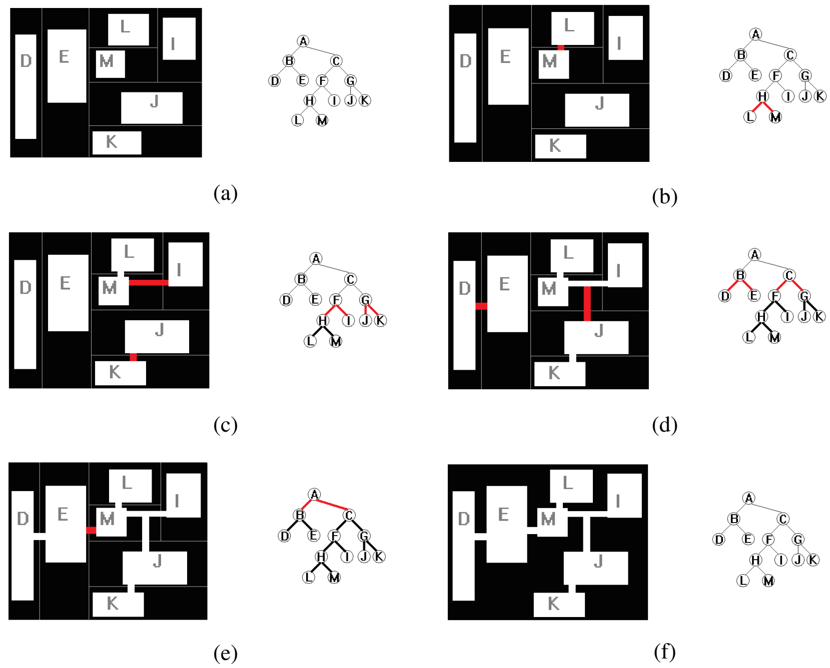


Fig. 3.4: Room and corridor placement in the partitioned dungeon of Figure 3.3. For each leaf node in the BSP tree, a room is placed by randomly choosing coordinates for top left and bottom right corners, within the boundaries of the partition cell (1st image). Then a corridor is added to connect the leaf nodes of the lowest layer of the tree (L and M); for all purposes, the algorithm will now consider rooms L and M as joined, grouping them together as their parent H. Moving up on the tree, H (the grouping of rooms L and M) is joined via a corridor with room I and rooms J and K ar joined via a corridor into their parent G. Further up, rooms D and E of the same parent are joined together via a corridor, and the grouping of rooms L, M and I are joined with the grouping of rooms J and K. Finally, the two subtrees of the root node are joined together and the dungeon is fully connected.

to connect rooms belonging to the same parent reduces the chances of overlapping or intersecting corridors. Moreover, non-leaf partition cells can be used to define groups of rooms following the same theme; for instance, a section of the dungeon may contain higher-level monsters, or monsters that are more vulnerable to magic. Coupled with corridor connectivity based on BSP tree hierarchy, these groups of rooms may have a single entrance from the rest of the dungeon; this allows such a room to be decorated as a prison or as an area with dimmer light, favoring players who excel at stealthy gameplay. Some examples of themed dungeon partitions are shown in Figure 3.5.

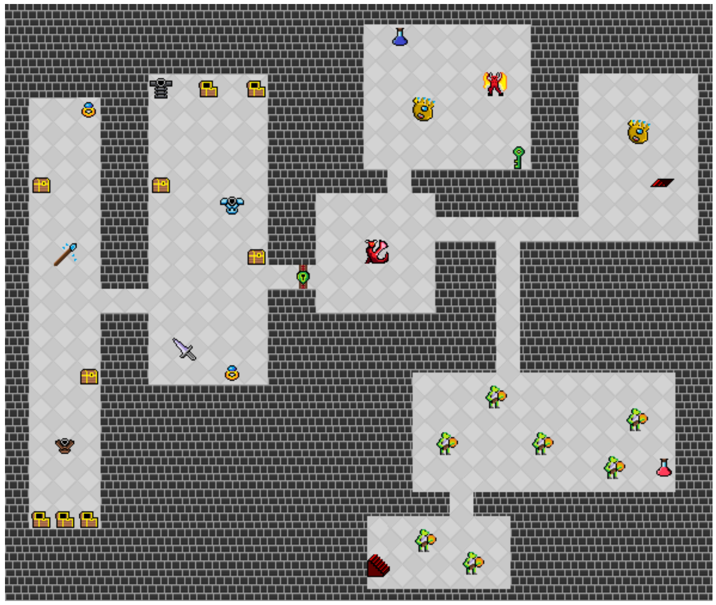


Fig. 3.5: The example dungeon from Figure 3.4, using the partitions to 'theme' the room contents. Partition cells B and C are only connected by a single corridor; this allows the rooms of partition B to be locked away (green lock), requiring a key from cell C in order to be accessed (room L). Similarly, rooms of cell B contain only treasures and rewards, while rooms of partition C contain predominantly monsters. Moreover, the challenge rating of monsters in cell C is split between its child nodes: partition G contains weak goblins while cell F contains challenging monsters with magical powers. Further enhancements could increase the challenge of cell G by making it darker (placing fewer light sources), using different textures for the floor and walls of cell B, or changing the shape of rooms in cell C to circular.

3.2 Agent-based dungeon growing

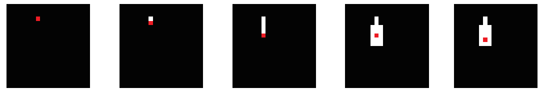
Agent-based approaches for dungeon generation usually amount to using a single agent to dig tunnels and create rooms in a sequence. Contrary to the space partitioning approaches of Section 3.1, an agent-based approach such as this follows a *micro* approach and is more likely to create an organic and perhaps chaotic dungeon instead of the neatly organised dungeons of Section 3.1. The appearance of the dungeon largely depends on the behaviour of the agent: an agent with a high degree of stochasticity will result in very chaotic dungeons while an agent with some "look-ahead" may avoid intersecting corridors or rooms. It should be noted that the impact of the AI behaviour's parameters on the generated dungeons' appearance is difficult to guess without extensive trial-and-error; as such, agent-based approaches are much more unpredictable than space partitioning methods. Moreover, there is no guarantee that an agent-based approach will create a dungeon without rooms overlapping with each other or a dungeon which spans only a corner of the dungeon area rather than its entirety. The following paragraphs will demonstrate two agent-based approaches for generating dungeons.

There is an infinite amount of AI behaviours for digger agents when creating dungeons, and they can result in vastly different results. As an example, we will first consider a highly stochastic, 'blind' method. The agent is considered to start at some point of the dungeon, and a random direction is chosen (up, down, left or right). The agent starts digging in that direction, and every dungeon tile dug is replaced with a 'corridor' tile. After making the first 'dig', there is a 5% chance that the agent will change direction (choosing a new, random direction) and another 5% chance that the agent will place a room of random size (in this example, between 3 and 7 tiles wide and long). For every tile that the agent moves in the same direction as the previous one, the chance of changing direction increases by 5%. For every tile that the agent moves without a room being added, the chance of adding a room increases by 5%. When the agent changes direction, the chance of changing direction again is reduced to 0%. When the agent adds a room, the chance of adding a room again is reduced to 0%. Figure 3.6 shows an example run of the algorithm, and below is the pseudo-code for running this algorithm.

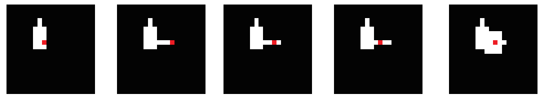
```
initialize chance of changing direction Pc=5
initialize chance of adding room Pr=5
place the digger at a dungeon tile and randomize its direction
dig along that direction
roll a random number Nc between 0 and 100
if Nc below Pc:
  randomize the agent's direction
  set Pc=0
else:
  set Pc=Pc+5
roll a random number Nr between 0 and 100
if Nr below Pr:
  randomize room width and room height between 3 and 7
  place room around current agent position
  set Pr=0
else:
  set Pr=Pr+5
if the dungeon is not large enough:
  go to step 4
```

In order to avoid the lack of control of the previous stochastic approach, which can result in overlapping rooms and dead-end corridors, the agent can be a bit more informed about the overall appearance of the dungeon and 'look ahead' whether the addition of a room would result in room-room or room-corridor intersections. Moreover, the change of direction does not need to be rolled in every step, to avoid winding pathways.

We will consider a less stochastic agent with 'look ahead' as a second example. Like above, the agent starts at a random point in the dungeon. The agent checks whether adding a room in the current position will cause it to intersect existing



(a)



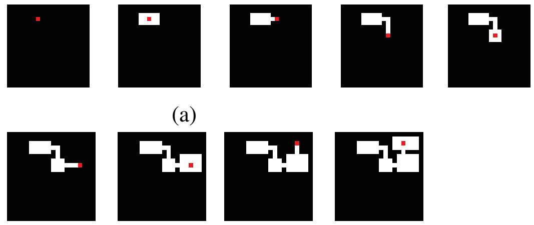
(b)

Fig. 3.6: A short run of the stochastic, 'blind' digger. The digger starts at a random tile on the map (1st image), and starts digging downwards. After digging 5 tiles (3rd image), the chance of adding a room is 25%, and it is rolled, resulting in the 4th image. The agent continues moving downwards (4th image) with the chance of adding a room at 5% and the chance of changing direction at 30%: it is rolled, and the new direction is right (6th image). After moving another 5 tiles (7th image), the chance of adding a room is at 30% and the chance of changing direction is at 25%. A change of direction is rolled, and the agent starts moving left (8th image). After another tile dug (9th image), the chance of adding a room is 40% and it is rolled, causing a new room to be added (10th image). Already from this very short run, the agent has created a dead-end corridor and two overlapping rooms.

rooms. If all possible rooms result in intersections, the agent picks a direction and a digging distance that will not result in the potential corridor intersecting with existing rooms or corridors. The algorithm stops if the agent stops at a location where no room and no corridor can be added without causing intersections. Figure 3.7 shows an example run of the algorithm, and below is the pseudo-code for running this algorithm.

```
place the digger at a dungeon tile
set helper variables Fr=0 and Fc=0
for all possible room sizes:
  if a potential room will not intersect existing rooms:
    place the room
    Fr=1
    break from for loop
for all possible corridors of any direction and length 3 to 7:
  if a potential corridor will not intersect existing rooms:
    place the corridor
    Fc=1
    break from for loop
if Fr=1 or Fc=1:
  go to 2
```

It should be noted that the examples provided with the 'blind' and 'look ahead' digger agents show naive, simple approaches; Figures 3.6 and 3.7 show to a large degree 'worst-case scenarios' of the algorithm being run, with resulting dungeons



(a)

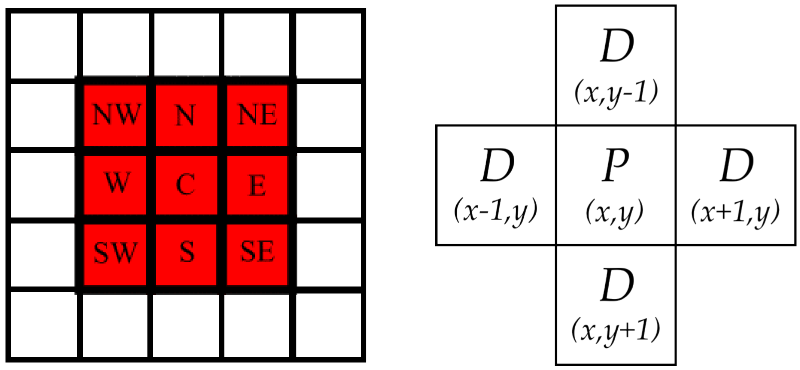
(b)

Fig. 3.7: A short run of the informed, “look ahead” digger. The digger starts at a random tile on the map (1st image), and places a room (2nd image) and a corridor (3rd image) since there can’t be any overlaps in the empty dungeon. After placing the first corridor, there is no space for a room (provided rooms must be at least 3 by 3 tiles) which doesn’t overlap with the previous room, so the digger makes another corridor going down (4th image). At this point, there is space for a small room which doesn’t overlap (5th image) and the digger carries on placing corridors (6th image and 8th image) and rooms (7th image and 9th image) in succession. After the 9th image, the digger can’t add a room or a corridor that doesn’t intersect with existing rooms and corridors, so generation is halted despite a large part of the dungeon area being empty.

being either overlapping or prematurely terminated. While simpler or more complex code additions to the provided digger behaviour can avert many of these problems, the fact still remains that it is difficult to anticipate such problems without running the agent’s algorithm on extensive trials. This may be a desirable attribute, as the uncontrollability of the algorithm may result in organic, realistic caves (simulating human miners trying to tunnel their way towards a gold vein) and reduce the dungeon’s predictability to a player, but may also result in maps that are unplayable or unentertaining. Moreso than most approaches presented in this chapter, the digger agent’s parameters can have a very strong impact on the playability and entertainment value of the generated artefact and tweaking such parameters to best effect is not a straightforward or easy task.

3.3 Cellular automata

A cellular automaton (plural: cellular automata) is a discrete computational model. Cellular automata are widely studied in computer science, physics and even some branches of biology, as models of computation, growth, development, physical phenomena, etc. While cellular automata have been the subject of many publications, the basic concepts are actually very simple and can be explained in a few paragraphs and a picture or two.



(a) Moore neighborhood

(b) von Neumann neighbourhood

Fig. 3.8: Two types of neighbourhoods for cellular automata. Adapted from wikipedia

A cellular automaton consists of an n-dimensional grid, a set of states and a set of transition rule. Most cellular automata are either 1-dimensional (vectors) or 2-dimensional (matrices). Each cell can be in one of several states; in the simplest case, cells can be *on* or *off*. The distribution of cell states at the beginning of an experiment (at time t_0) is the initial state of the cellular automaton. From then on, the automaton evolves in discrete steps based on the rules of that particular automaton. At each time t, each cell decides its new state based on the state of itself and all of the cells in its *neighbourhood* at time $t-1$.

The neighbourhood defines which cells around a particular cell c affects c's future state. For one-dimensional cellular automata, the neighbourhood is defined by its size, i.e. how many cells to the left or right the neighbourhood stretches. For two-dimensional automata, the two most common types of neighbourhoods are *Moore neighbourhoods* and *von Neumann neighbourhoods*. Both neighbourhoods can have a size of any whole number, one or greater. A Moore neighbourhood is a square: a Moore neighbourhood of size 1 consists of the eight cells immediately surrounding c, including those surrounding it diagonally. A von Neumann neighbourhood is like a cross centred on c: a von Neumann neighbourhood of size 1 consists of the four cells surrounding c above, below, to the left and to the right (see Figure 3.8).

The number of possible configurations of the neighbourhood equals the number of states for a cell to the power of the number of cells in the neighbourhood. These numbers can quickly become huge, for example a two-state automaton with a Moore neighbourhood of size two has $2^{25} = 33554432$ configurations. For small neighbourhoods, it is common to define the transition rules as a table, where each possible configuration of the neighbourhood is associated with one future state, but for large neighbourhoods the transition rules are usually based on the proportion of cells that are in each state.

Cellular automata are very versatile, and several types have been shown to be Turing complete. It has even been argued that they could form the basis for a new way of understanding nature through bottom-up modelling [35]. However, in this chapter we will mostly concern ourselves with how they can be used for procedural content generation.

In a paper from 2010, Johnson *et al.* describe a system for generating infinite cave-like dungeons using cellular automata [7]. The motivation was to create an infinite cave crawling game, with environments stretching out endlessly and seamlessly in every direction. An additional design constraint is that the caves are supposed to look organic or eroded, rather than having straight edges and angles. No storage medium is large enough to store a truly endless cave, so the content must be generated at runtime, as players choose to explore new areas. The game does not scroll but instead presents the environment one screen at a time, which offers a time window of a few hundred milliseconds to create a new room every time the player exits a room.

This method uses the following four parameters to control the map generation process:

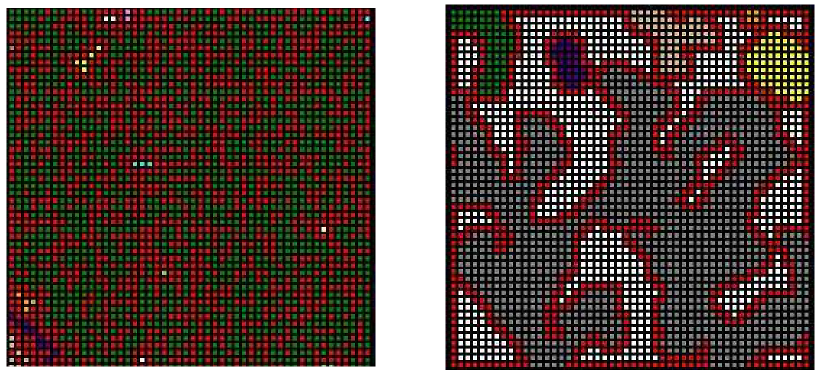
- A percentage of rock cells (inaccessible area);
- The number of cellular automata generations;
- A neighbourhood threshold value that defines a rock (T=5);
- The number of neighbourhood cells.

Each room is a 50*x*50 grid, where each cell can be in one of two states: *empty* or *rock*. Initially, the grid is empty. The generation of a single room works as follows.

- The grid is “sprinkled” with rocks: for each cell, there is probability r (*e.g.* 0.5) that it is turned into rock. This results in a relatively uniform distribution of rock cells.
- A cellular automaton is applied to the grid for n (*e.g.* 2) steps. The single rule of this cellular automaton is that a cell turns into rock in the next time step if at least T (*e.g.* 5) of its neighbours are rock, otherwise it will turn into free space.
- For aesthetic reasons the rock cells that border on empty space are designated as “wall” cells, which are functionally rock cells but look different.

This simple procedure generates a surprisingly lifelike cave-room. Figure 3.9 shows a comparison between a random map (sprinkled with rocks) and the results of a few iterations of the cellular automaton.

But while this generates a single room, the game requires a number of connected rooms. A generated room might not have any openings in the confining rocks at all, and there is certainly no guarantee that any exits align with entrances to the adjacent rooms at all. Therefore, whenever a room is generated, its immediate neighbours are also generated. If there is no connection between the largest empty spaces in the two rooms, a tunnel is drilled between those areas at the point where they are least separated. Two more iterations of the cellular automaton are then run on all nine neighbouring rooms together, to smooth out any sharp edges. Figure 3.10 shows the result of this process, in the form of nine rooms that seamlessly connect. This



(a) Random map

(b) CA map

Fig. 3.9: Cave generation: Comparison between a CA and a randomly generated map ($r = 0.5$ in both maps); CA parameters: $n = 4$, $M = 1$, $T = 5$. Rock and wall cells are represented by red and white colour respectively. Coloured areas represent different tunnels (floor clusters). Adapted from [7]

generation process is extremely fast, and can generate all nine rooms in less than a millisecond on a modern computer.

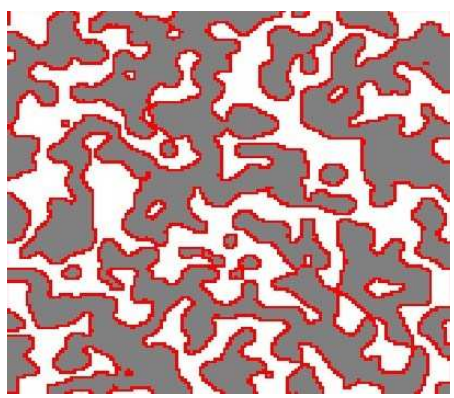


Fig. 3.10: Cave generation: a 3×3 base grid map generated with CA. Rock and wall cells are represented by red and white colour respectively. Grey areas represent floor. ($M = 2; T = 13; n = 4; r = 50\%$). Adapted from [7]

We can conclude that the small number of parameters, and the fact that they are relatively intuitive, is an asset of cellular automata approaches like Johnson *et al.*'s. However, this is also one of the downsides of the method: for both designers and programmers, it is not easy to fully understand the impact that a single parameter has on the generation process, since each parameter affects multiple features of the generated maps. It is not possible to create a map that has specific requirements, like a given number of rooms with a certain connectivity. Therefore, gameplay features are somewhat disjoint from these control parameters. Any link between this generation method and gameplay features would have to be carried out through a process of trial and error.

3.4 Grammar-based dungeon generation

Generative grammars were originally developed to formally describe structures in natural language. These structures—phrases, sentences, etc.—are modeled by a finite set of recursive rules that describe how larger-scale structures are built from smaller-scale ones, grounding out in individual words as the terminal symbols. They are *generative* because they describe linguistic structures in a way that also describes how to generate them: we can sample from a generative grammar to produce new sentences featuring the structures it describes. Similar techniques can be applied to other domains. For example, graph grammars [20] model the structure of graphs using a similar set of recursive rules, with individual graph nodes as the terminal symbols.

Back to our topic of dungeon generation, Adams [1] uses graph grammars to generate first-person shooter (FPS) levels. FPS levels may not obviously be the same as dungeons, but for our purposes his levels qualify as dungeons, because they share the same structure, a maze of interconnected rooms. He uses the rules of a graph grammar to generate a graph that describes a level's topology: nodes represent rooms, and an edge between two rooms means that they are adjacent. The method doesn't itself generate any further geometric details, such as room sizes. An advantage of this high-level, topological representation of a level is that graph generation can be controlled through parameters such as difficulty, fun, and global size. A search algorithm looks for levels that match input parameters by analyzing all results of a production rule at a given moment, and selecting the rule that best matches the specified targets.

One limit of Adams' work is the *ad-hoc* and hard-coded nature of its grammar rules, and especially the parameters. It is a sound approach for generating the topological description of a dungeon, but generalizing it to a broader set of games and goals would require creating new input parameters and rules each time. Regardless, Adams' results showcase the motivation and importance of controlling dungeon generation through gameplay.

Dormans' work [6] is more extensively covered in Chapter 5, so we will only briefly refer here to his use of generative grammars to generate dungeon spaces for adventure games. Through a graph grammar, missions are first generated in the form of a directed graph, as a model of the sequential tasks that a player needs to perform. Subsequently, each mission is abstracted to a network of nodes and edges, which is then used by a shape grammar to generate a corresponding game space.

This was the first method to succesfully introduce gameplay-based control, most notably with the concept of a mission grammar. Still, the method does not offer real control parameters, since control is actually exerted by the different rules in the graph and shape grammars, which are far from intuitive for most designers.

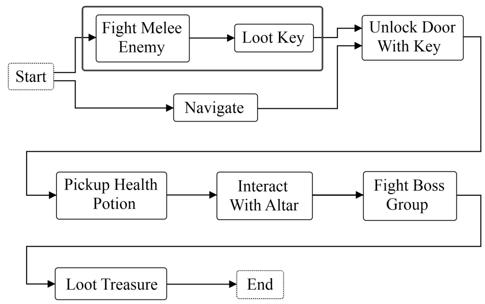
Explicitly inspired by the work of Dormans, van der Linden *et al.* [12] recently proposed the use of gameplay grammars to generate dungeon levels. Game designers specify, *a priori*, design constraints expressed in a gameplay-oriented vocabulary, consisting of player actions to perform in-game, their sequencing and composition, inter-relationships and associated content. These designer-authored constraints directly result in a generative graph grammar, a so-called *gameplay grammar*, and multiple grammars can be expressed through different sets of constraints. A grammar generates graphs of player actions, which subsequently determine layouts for dungeon levels. For each generated graph, specific content is synthesized by following the graph's constraints. Several proposed algorithms map the graph into the required game space and a second procedural method generates geometry for the rooms and hallways, as required by the graph.

This approach aims at improving gameplay-based control on a generic basis, as it provides designers with the tools to effectively create, from scratch, grammar-based generators of graphs of player actions. The approach is generic, in the sense that such tools are not connected to any domain, and player actions and related design constraints can be created and manipulated across different games. However, integration of graphs of player actions in an actual game requires a specialized generator, able to transform such a graph into a specific dungeon level for that game. van der Linden *et al.* demonstrated such a specialized generator for only one case study, yielding fully-playable 3D dungeon levels for the game Dwarf Quest [34]. Figure 3.11 show (a) a gameplay graph and (b) a dungeon generated from this method.

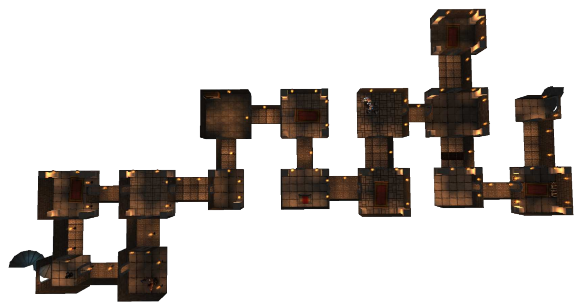
As for gameplay-based control, this approach empowers designers to specify and control dungeon generation with a more natural design-oriented vocabulary. Designers can create their own player actions and use them as the vocabulary to control and author the dungeon generator. For this, they specify the desired gameplay which then constrains game-space creation. Furthermore, designers can express their own parameters (*e.g.* difficulty) which control rule rewriting in the gameplay grammar. Setting such gameplay-based parameters allows for an even more fine-grained control over generated dungeons.

3.5 Advanced platform generation methods

In this section, we turn our attention to platform generation methods, by discussing two recent methods that were originally proposed for generating platform levels. Unlike the previous sections, there is no single category or family to characterize these methods. Interestingly, as we will point out, the central concepts of each of them could very well contribute to improve the generation of dungeons as well.



(a)



(b)

Fig. 3.11: (a) A gameplay graph created by van der Linden *et al.* [11] and (b) a corresponding dungeon layout generated for it.

The first method, proposed by Smith *et al.* [30], is *rhythm-base platform generation*. It proposes level generation based on the notion of rhythm, linked to the timing and repetition of user actions. They first generate small pieces of a level, called rhythm groups, using a two-layered grammar-based approach. In the first layer, a set of player actions is created, after which this set of actions is converted into corresponding geometry. Many levels are created by connecting rhythm groups, and a set of implemented critics selects the best level.

Smith *et al.* propose a set of 'knobs' that a designer can manipulate to control the generation process, including (i) a general path through the level (i.e. start, end, and intermediate line segments), (ii) the kinds of rhythms to be generated, (iii) the types and frequencies of geometry components, and (iv) the way collectables (coins) are divided over the level (*e.g.* coins per group, probability for coins above gaps, etc.). There are also some parameters per created rhythm group, such as the frequency of jumps per rhythm group, and how often specific geometry (springs) should occur for a jump. Anorher set of parameters provides control over the rhythm length, density, beat type, and beat pattern.

Overall, the large amount of parameters at different levels of abstraction provides many control options, and allows for the versatile generation of very disparate levels.

Furthermore, they relate quite seamlessly to gameplay, specially in the platformer genre. However, this approach could nicely tie in with dungeon generation as well. As with Dormans, a two-layered grammar is used, where the first layer considers gameplay (in this case, player actions) and the second game space (geometry). The notion of 'rhythm' as defined by Smith *et al.* is not exactly applicable to dungeons, but the pacing or tempo of going through rooms and hallways could be of similar value in dungeon-based games. The decomposition of a level into rhythm groups also connects very well with the possible division of a dungeon into dungeon-groups with distinct gameplay features, *e.g.* pacing.

Our second method, proposed by Mawhorter *et al.* [16] is called Occupancy-Regulated Extension (ORE), and it directly aims at procedurally generating 2D platform levels. ORE is a general geometry assembly algorithm that supports human-design-based level authoring at arbitrary scales. This approach relies on pre-authored 'chunks' of level as a basis, and then assembles a level using these chunks from a library. A chunk is referred to as level geometry, such as a single ground element, a combination of ground elements and objects, interact-able objects, etc. This differs from the rhythm groups introduced by Smith *et al.* [30], because rhythm groups are separately generated by a PCG method whilst the ORE chunks are pieces of manually-created content in a library. The algorithm takes the following steps: (i) a random potential player location (occupancy) is chosen to position a chunk; (ii) a chunk needs to be selected from a list of context-based compatible chunks; (iii) the new chunk is integrated with the existing geometry. This process continues until there are no potential player locations left, after which post-processing takes care of placing objects such as power-ups.

This framework is meant for general 2D platform games, so specific game elements and mechanics need to be filled in, and chunks need to be designed and added to a library. Versatile levels can only be generated given that a minimally interesting chunk library is used.

Mawhorter *et al.* do not mention specific control parameters for their ORE algorithm, but a designer still has some control. Firstly, the chunks in the library and their probability of occurrence are implicit parameters, *i.e.* they actually determine the level geometry and versatility, and possible player actions need to be defined and incorporated in the design of chunks. And above all, their mixed-initiative approach provides the largest amount of control one can offer, even from a gameplay-based perspective. However, taken too far, this approach could come too close to manually constructing a level, decreasing the benefits of PCG. In summary, much control can be provided by this method, but the generation process may still be not very efficient, as a lot of manual work seems to still be required for specific levels to be generated.

This ORE method proposes a mixed-initiative approach, where a designer has the option to place content before the algorithm takes over and generates the rest of the level. This approach seems very interesting also for dungeon generation, where an algorithm that can fill in partially designed levels would be of great value. Imagine a designer placing special event rooms and then have an algorithm add the other parts of the level that are more generic in nature. This mixed-initiative approach

Fig. 3.12: Snapshot from Spelunky [4].

would increase both level versatility, and control for designers, while still taking work out of their hands. Additionally, it would fit to the principles of dungeon design, where special rooms are connected via more generic hallways. Also, using a chunk library fits well in the context of dungeon-level generation (*e.g.* combining sets of template rooms, junctions and hallways). However, 3D dungeon levels would typically require a much larger and more complex chunk library than 2D platform levels, which share a lot of similar ground geometry.

3.6 Example applications to platform generation

3.6.1 Spelunky

Spelunky is a 2D platform indie game originally created by Derek Yu in 2008 [4]. The PC version of the game is available for free. An update version of the game was later released in 2012 for the Xbox Live Arcade with better graphics and more content. An enhanced edition was also released on PC in 2013. The gameplay in Spelunky consists of traversing the 2D levels, collecting items, killing enemies and finding your way to the end. To win the game, the player needs to have good skills in managing different types of resources such as ropes, bumps and money. Losing the game at any level requires restarting the game from the beginning.

The game consists of four groups of maps of increasing level of difficulty. Each set of levels has a distinguished layout and introduces new challenges and new types of enemies. An example level from the second set is presented in Figure 3.12.

The standout feature of Spelunky is the procedural generation of game content. The use of PCG allowed the generation of endless variations of content that are unique in every playthrough.

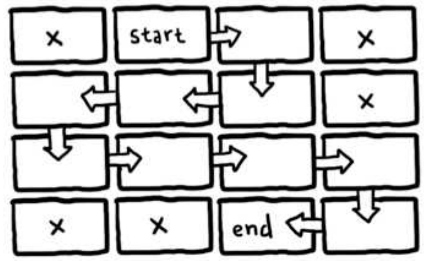


Fig. 3.13: Level generation in Spelunky. Adapted from [15]

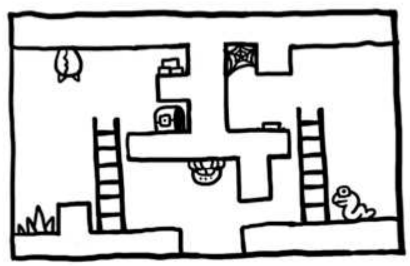


Fig. 3.14: An example design of a room in Spelunky. Adapted from [15]

Each level in Spelunky is divided into a 4×4 grid of 16 rooms with two rooms marking the start and the end of the level (see Figure 3.13) and corridors connecting adjacent rooms. Not all the rooms are necessarily connected; in Figure 3.13 there are some isolated rooms such as the ones at the top left and down left corners. In order to reach these rooms, the player needs to use bombs, which are a limited resource, to destroy the walls.

The layout of each room is selected from a set of predefined templates. An example template for one of the rooms presented in Figure 3.13 can be seen in Figure 3.14. In each template, a number of chunks are marked in which randomisation can occur. Whenever a level is being generated, these chunks are replaced by different types of obstacle according to a set of randomised number generators [15]. Following this method, a new variation of the level can be generated with each run of the algorithm.

More specifically, each room in Spelunky consists of 80 tiles arranged in a 8×10 metrics [3]. An example room template can be:

```
0000000011
0060000L11
0000000L11
0000000L11
0000000L11
0000000011
```

```
0000000011
1111111111
```

Where 0 represents an empty cell, 1 stands for walls or bricks, L for ladders. The 6 in this example can be replaced by random obstacles permitting the generation of different variations. The obstacles, or traps, are usually of 5×3 blocks of tiles that overwrite the original tiles. Examples traps included in the game can be spikes, webs or arrow traps, to name some.

While the basic layout of the level is partially random, with the presence of opportunities for variations, the placement of monsters and traps is 100% random. After generating the physical layout, the level map is scanned for potential places where monsters can be generated. These include for example, a brick with empty tiles behind that offer enough space for generating a spider. There are another set of random numbers that control the generation of monsters. These numbers control the type and the frequency of the generation. For example, there is a 20% chance of creating a giant spider and once a spider is generated, this probability is set to 0 preventing the existence of more than one giant spider in a level.

In this sense, level generation in Spelunky can be seen as a composition of three main phases: in the first phase, the main layout of the level is generated by choosing the rooms from the templates available and defining the entrance and exit points. The second phase is obstacle generation which can be thought of as an agent going through the level and placing obstacles in predefined spaces according to a set of heuristics. The final phase is the monsters generation phase where another agent search the level and place a monster when proper space is found and a set of conditions is satisfied.

3.6.2 Infinite Mario Bros

Super Mario Bros is a very popular 2D platform game developed by Nintendo and released in the mid eighties [17]. A public domain clone of the game, named *Infinite Mario Bros.* (IMB) [19] was later published by Markus Persson. IMB features the art assets and general game mechanics of Super Mario Bros. but differs in level construction. Infinite Mario Bros is playable on the web, where the Java source code is also available[1]. While implementing most features of Super Mario Bros, the standout feature of Infinite Mario Bros is the automatic generation of levels. Every time a new game is started, levels are randomly generated by traversing the level map and adding features according to certain heuristics.

The internal representation of the levels in Infinite Mario Bros is a two-dimensional array of game elements. In "small" state, Mario is one block wide and one block high. Each position in the array can be filled with a brick block, a coin, an enemy or nothing. The levels are generated by placing the game elements in the two-dimensional level map.

[1] http://www.mojang.com/notch/mario/

Different approaches can be followed to generate the levels for this game [27, 25, 21, 31]. In the following we describe one possible approach.

The Probabilistic Multi-pass Generator (PMPG) was created by Ben Weber [27] as an entry for the level generation track of the Mario AI Championship [22]. The generator is an agent-based and works by first creating the base level and then performing a number of passes through it. Level generation consists of six passes from left to right and adding one of the different types of game elements. Each pass is associated with a number of events (14 in total) that may occur according to predefined uniform probability distributions. These distributions are manually weighted and by tweaking these weights one can gain control over the frequency of different elements such as gaps, hills and enemies.

The six passes considered are:

1. An initial pass that changes the basic structure of the level by changing the hight of the ground and starting or ending a gap;
2. the second pass adds the hills in the background;
3. the third pass adds the static enemies such as pipes and cannons based on the basic platform generated;
4. moving enemies such as koopas and goombas are added in the fourth pass;
5. the fifth pass adds the unconnected horizontal blocks, and finally,
6. the sixth pass places coins throughout the level.

Playability, or the existence of a path from the starting to the ending point, is guaranteed by imposing constraints of the different items created or places. For example, the width of generated gaps is limited by the maximum number of blocks that the player can jump over and the hight of pipes is limited to ensure that the player can pass through.

3.7 Lab session: Level generator for InfiTux (and Infinite Mario)

InfiTux, short for Infinite Tux, is a 2D platform game built by combining the underlying software used to generate the levels for Infinite Mario Bros (IMB) with the art and sound assets of *Super Tux* [33]. The game was created to replace IMB which is the platform extensively used in research [18, 28, 32, 9, 2] and the software for the Mario AI Championship [26, 24, 8]. Since the level generator for InfiTux is the same as the one used for IMB, the game features infinite variations of levels by the use of a random seed. The level of difficulty can also be tuned using different difficulty values which control the number, frequency and types of the obstacles and monsters.

The purpose of this exercise is to use one or more of the methods presented in this chapter to implement your own generator that creates content for the game. The software you will be using is the one used for the Level Generation Track of the Platformer AI Competition [23]; a successor to the Mario AI Championship that is based on InfiTux. The software provides an interface that eases the interaction with the system and is a good starting point. You can either modify the original level generator, or use it as an inspiration. In order to help you to start with the software, we will in the following describe the main components of the interface provided and how it can be used.

As the software is developed for the Level Generation track of the competition, which invites participants to submit level generator that are fun for specific players, the interface incorporates information about player behaviour that you could use while building your generator. This information is collected while the player is playing a test level and stored in a gameplay metrics that contains statistical features extracted from a gameplay session. The features include, for example, the number of jumps, the time spent running, the number of items collected and the number of enemies killed.

For your generator to work properly, your level should implement the *LevelInterface* which specifies how the level is constructed and how different types of elements are scattered around the level:

```
public byte[][] getMap();
public SpriteTemplate[][] getSpriteTemplates()
```

The size of the level map is 320×15 and you should implement a method of your choice to fill in the map. Note that the basic structure of the level is saved in a different map than the one used to store the placement of enemies.

The level generator, which passes the gameplay metrics to your level and communicates with the simulator, should implement the *LevelGenerator* interface:

```
public LevelInterface generateLevel(GamePlay playerMet);
```

There are quite a few examples reported in the literature that use this software for content creation, some of them are part of the Mario AI Championship and their implementation is open source and freely available at the competition website [22].

3.8 Summary

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Chapter 4
Fractals, noise and agents with applications to landscapes (DRAFT)

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4.1 Terraforming and making noise

This chapter is about terrains (or landscapes – we will use the words interchangeably) and noise, two types of content which have more in common than might be expected. We will discuss three very different types of methods for generating such content, but first we will discuss where and why terrains and noise are used, so as to characterise the general case of their content generation problems.

Terrains are ubiquitous. Almost any three-dimensional game will feature some ground to stand or drive on, and in most of them there will be some variety such as different types of vegetation, differences in elevation etc. What changes is how much you can interact directly with the terrains, and thus how they affect the game mechanics.

At one extreme of the spectrum are flight simulators. In many cases, the terrains has no game-mechanical consequence – you crash if your altitude is zero, but in most cases the minor variations in the terrain are not enough to affect your performance in the game. Instead, the role of the terrain is to provide a pretty backdrop and help the player to orientate. Key demands on the terrain is therefore that it is visually pleasing and believable, but also that it is huge: airplanes fly fast, are not hemmed in by walls, and can thus cover huge areas. From 30.000 feet one might not be able to see much detail and a low-resolution map might therefore be seen as a solution, but preferably it should be possible to swoop down close to the ground and see hills, houses, creeks and cars. Therefore, a map where the larger features were generated in advances but where details could be generated on demand would be useful. Also, from a high altitude it is easy to see the kind of regularities that results from essentially copying and pasting the same chunks of landscape, so reusing material is not trivial.

In open-world games such as *Skyrim* or the those in the *Grand Theft Auto* terrains sometimes have mechanical and sometimes aesthetic roles. This poses additional demands on the design. When driving through a landscape in Grand Theft Auto, it needs to believable and visually pleasing, but it also needs to support the stretch of road you are driving on. The mountains in Skyrim look pretty in the distance, but also function as boundaries of traversable space and to break line of sight. To make sure that these demands are satisfied, the generation algorithms need a higher degree of controllability.

At the other end of the spectrum are those games where the terrain severely restricts and guides the player's possible course of actions. Here we find first person shooters such as those in the *Halo* and *Call of Duty* series. In these cases, terrain generation has more in common with the level generation problems we discussed int the previous chapter.

Like terrains, noise is a very common type of game content. Essentially, noise is useful wherever small variations need to be added to a surface (or something that can be seen as a surface). One example of noise is in skyboxes, where cloud cover can be implemented as white noise on blue background. Other examples where noise is used are dust that settles on the ground or walls, certain aspects of water (though water simulation is a complex topic in its own right), fire, plasma, skin and fur coloration etc. You can also see minor topological variations of the ground as noise, which brings us to the similarity between terrains and noise.

4.1.1 Heightmaps and intensity maps

Both noise and most aspects of terrains can fruitfully be represented as two-dimensional matrices of real numbers. The width and height of the matrix maps to the x and y dimensions of a rectangular surface. In the case of noise, this is called an *intensity map*, and the values of cells correspond directly to the brightness of associated pixels. In the case of terrains, the value of each cell corresponds to height of the terrain (over some baseline) at that point. This is called a *height map*. If the resolution with which the terrain is rendered is greater than the resolution of the height map, intermediate points on the ground could simply be interpolated between points that do have specified height values. Thus, using this common representation, any technique used to generate noise could also be used to generate terrains, and vice versa – though they might not be equally suitable.

It should be noted that in the case of terrains, other representations are possible and occasionally suitable or even necessary. For example, one could represent the terrain in three dimension, by dividing the space up into *voxels* (cubes) and compute the three-dimensional *voxel grid*. An example is the popular open-world game *Minecraft*, which uses unusually large voxels. Voxel grids allow structures that cannot be represented with height maps, such as caves and overhanging cliffs, but they require much larger amount of storage.

4.2 Random terrain

Let's say we want to generate completely random terrain. We won't worry for the moment about the questions in the previous chapter, such as whether the terrain we generate would make a fair, balanced, and playable RTS map. All we want for now is random terrain, with no constraints except that it looks like terrain.

If we encode terrain as a heightmap, then it's represented by a two-dimensional array of values, which indicate the height at each point. Can generating random terrain be as simple as just calling a random-number generator to fill each cell of the array? Alas, no. While this technically works—a randomly initialized heightmap is indeed a heightmap that can be rendered as terrain—the result is not very useful. It doesn't look anything like random terrain, and isn't very useful as terrain, even if we're being generous. A random heightmap generated this way looks like random *spikes*, not random terrain: there are no flat portions, mountain ranges, hills, or other features typically identifiable on a landscape.

The key problem with just filling a heightmap with random values is is that every random number is generated independently. In real terrain, heights at different points on the terrain are not independent of each other: The elevation at a specific point on the earth's surface is statistically related to the elevation at nearby points. If you pick a random point within 100 km of Mount Everest, it will almost certainly have a high elevation. If you pick a random point within 100 km of Copenhagen, you are very unlikely to find a high elevation.

There are several alternative ways of generating random heightmaps to address this problem. These methods were originally invented, not for landscapes, but for textures in computer graphics [3]. Like when we randomly generated a heightmap's values by randomly generating each element of the array, we could randomly generate graphical textures by randomly generating each pixel of the texture. But this produces something that looks like television static, which isn't appropriate for textures that are going to represent the surfaces of "organic" patterns found in nature, such as the texture of rocks. We can think of landscapes heightmaps as a kind of natural pattern, but a pattern that's interpreted as 3d elevation rather than a 2d texture. So it's not a surprise that similar problems and solutions apply.

4.2.1 Interpolated random terrain

One way of avoiding unrealistically spiky landscapes is to require that the landscapes we generate are smooth. That change does exclude some realistic kinds of landscapes, since discontinuities like cliffs exist in real landscapes. But it's a change that will provide us with something much more landscape-like than the random heightmap method did.

How do we generate smooth landscapes? We might start by coming up with a formal definition of *smoothness* and then develop a method to optimize for that criterion. A simpler way is to make landscapes smooth by construction: fill in the values in such a way that the result is less spiky than the fully random generator. *Interpolated noise* is one such method, in which we generate fewer random values, and then interpolate between them.

Instead of generating a random value at *every* point in the heightmap, we generate random values on a courser *lattice*. The heights in between the generated lattice points are interpolated in a way that makes them smoothly connect the random heights. Put differently, we randomly generate elevations for peaks and valleys with a certain spacing, and then fill in the slopes between them.

That leaves one question: how do we do the interpolation, i.e. how do we connect the slopes between the peaks and valleys? There are a number of standard interpolation methods for doing so, which we'll discuss in turn.

4.2.1.1 Bilinear interpolation

A simple method of interpolating is to calculate a weighted average in first the horizontal, and then the vertical direction (or vice-versa, which gives the same result). If we choose a lattice that's one-tenth as finely detailed as our heightmap's resolution, then $height[0,0]$ and $height[0,10]$ will be two of the randomly generated values. To fill in what should go in $height[0,1]$, then, we notice it's 10% of the way from $height[0,0]$ to $height[0,10]$. Therefore, we use the weighted average, $height[0,1] = 0.9 \times height[0,0] + 0.1 \times height[0,10]$. Once we've finished this interpolation in the x direction, then we do it in the y direction. This is called *bilinear interpolation*, because it does linear interpolation along two axes, and is both easy and efficient to implement.

While it's a simple procedure, coarse random generation on a lattice followed by bilinear interpolation does have drawbacks. The most obvious one is that mountain slopes become perfectly straight lines, and peaks and valleys are all perfectly sharp points. This is to be expected, since a geometric interpretation of the process just described is that we're randomly generating some peaks and valleys, and then filling in the mountain slopes by drawing straight lines connecting peaks and valleys to their neighbors. This produces a characteristically stylized terrain, like a child's drawing of mountains—perhaps what we want, but often not. For games in particular, we often don't want these sharp discontinuities at peaks and valleys, where collision detection can become wonky and characters can get stuck.

4.2.1.2 Bicubic interpolation

Rather than having sharp peaks and valleys connected by straight slopes, we can generate a different kind of stylized mountain profile. When a mountain rises from a valley, a common way it does so is in an S-curve shape. First, the slope starts rising slowly. It grows steeper as we move up the mountain; and finally it levels off at the top in a round peak. To produce this profile, we don't want to interpolate linearly:

when we're 10% of the way between lattice points, we don't want to be 10% of the way up the slope's vertical distance yet.

Therefore we don't want to do a weighted average between the neighboring lattice points according to their distance, but according to a nonlinear function of their distance. We introduce a slope function, $s(x)$, specifying how far up the slope (vertically) we should be when we're x of the way between the lattice points, in the direction we're interpolating. In the bilinear interpolation case, $s(x) = x$. But now we want an $s(x)$ whose graph looks like an S-curve. There are many mathematical functions with that shape, but a common one used in computer graphics, because it's simple and fast to evaluate, is $s(x) = -2x^3 + 3x^2$. Now, when we are 10% of the way along, i.e. $x = 0.1$, $s(0.1) = 0.028$, so we should be only 2.8% up the slope's vertical height, still in the gradual portion at the bottom. We use this as the weight for the interpolation, and this time $height[0,1] = 0.972 \times height[0,0] + 0.028 \times height[0,10]$.

Since the $s(x)$ we chose is a cubic (third-power) function of x, and we again apply the interpolation in both directions along the 2d grid, this is called *bicubic interpolation*.

4.2.2 Gradient-based random terrain

In the examples so far, we've generated random values to put into the heightmap. Initially, we tried generating all the heightmap values directly, but when that proved too noisy. Instead, we generated values for a coarse lattice, and interpolated the slopes in between the generated values. When done with bicubic interpolation, this produced a smooth slope.

An alternate idea is to generate the slopes directly, and infer height values from that, rather than generate height values and interpolate slopes. The random numbers we're going to generate will be interpreted as random *gradients*, i.e., the steepness and direction of the slopes. This kind of random initialization of an array is called *gradient noise*, rather than the *value noise* discussed in the previous section. It was first done by Ken Perlin in his work on the 1982 film *Tron*, so is sometimes called *Perlin noise*.

Generating gradients instead of height values has several advantages. Since we're interpolating gradients, i.e. rates of change in value, we have an extra level of smoothness: rather than smoothing the change in heights with an interpolation method, we smooth the *rate of change* in heights, so slopes grow shallower or steeper smoothly. Gradient noise also allows us to use lattice-based generation (which is computationally and memory efficient) while avoiding the rectangular grid effects produced by the interpolation-based methods. Since peaks and valleys are not directly generated on the lattice points, but rather emerge from the rises and falls of the slopes, they are arranged in a way that looks more organic.

As with interpolated value-based terrain, we generate numbers on a coarsely spaced lattice, and interpolate between the lattice points. However, we now generate a 2d vector, (d_x, d_y), at each lattice point, rather than a single value. This is the random gradient, and d_x and d_y can be thought of as the slope's steepness in the x and y directions. These gradient values can be positive or negative, for rising or falling slopes.

Now we need a way of recovering the height values from the gradients. First, we set the height to 0 at each lattice point. This might seem like it would produce noticeable grid artifacts, but unlike with value noise, it doesn't in practice. Since peaks and valleys rise and fall to different heights and with different slopes away from the $h = 0$ lattice points, the zero value is sometimes midway up a slope, sometimes near the bottom, and sometimes near the top, rather than in any visually regular position.

To find the height values at non-lattice points, we look at the four neighboring lattice points. Consider first only the gradient to the top-left. What would the height value be at the current point if terrain rose or fell from $h = 0$ only according to that one of the four gradients? It would be simply that gradient's value multiplied by the distance we've traveled along it: the x-axis slope, d_x, times the distance we are to the right of the lattice point, added to the y-axis slope, d_y, times the distance we are down from the lattice point. In terms of vector math, this is the *dot product* between the gradient vector and a vector drawn from the lattice point to our current point.

Repeat this what-if process for each of the four surrounding lattice points. Now we have four height values, each indicating the height of the terrain if only one of the four neighboring lattice points had influence on its height. Now to combine them, we simply interpolate these values, as we did with the value-noise terrain. We have four surrounding lattice points that now have four height values, and we have already covered, in the previous section, how to interpolate height values, using bilinear or bicubic interpolation.

4.3 Fractal terrain

While gradient noise looks more organic, there is still a rather unnatural aspect to it when treated as terrain: terrain undulates at a constant frequency, the frequency chosen for the lattice point spacing. Real terrain has variation at multiple scales. At the largest scale (i.e., lowest frequency), plains rise into mountain ranges. But at smaller scales, mountain ranges have peaks and valleys, and valleys have hills and ravines. In fact, as you zoom in to many natural phenomena you see the same kind of variation that was seen at the larger scale, but reproduced at a new, smaller scale. This self-similarity is the basis of *fractals*, and generated terrain with this property is called *fractal terrain*.

Fractal terrain can be produced through a number of methods, some of them based directly on fractal mathematics, and others producing a similar effect via simpler means.

A very easy way to produce fractal terrain is to take the single-scale random terrain methods from the previous section and simply run them several times, at multiple scales. We first generate random terrain with very large-scale features, then with smaller-scale features, then even smaller, and add all the scales together. The larger-scale features are added in at a larger magnitude than the smaller ones: mountains rise from plains a larger distance than boulders rise from mountain slopes. A classic way of producing multi-scale terrain in this way is to scale the generated noise layers by the inverse of their frequency, which is called $1/f$ noise. If we have a single-scale noise-generation function, like those in the previous section, we can give it a parameter specifying the frequency; let's call this function $noise(f)$. Then starting from a base for our lowest-frequency (largest-scale) features, f, we can define $1/f$ noise as:

$$noise(f) + \frac{1}{2}noise(2f) + \frac{1}{4}noise(4f) + \ldots$$

4.4 Agent-based landscape creation

In Chapter 1, we discussed the desired properties of a PCG algorithm. The previously discussed methods satisfy most of these properties, however they suffer from uncontrollability. The results delivered by these methods are fairly random and they offer very limited interaction with designers who can only provide inputs on the global level through modifying a set of unintuitive parameters. [13]. Several variations of these methods have been introduced that grant more control over the output [7, 1, 12, 15].

The main advantage of software agents approaches for terrain generation over fractal-based methods is that they offer a greater degree of control while maintaining the other desirable properties of PCG methods. Similar to the discussion of agent-based approaches for dungeon growing (Section 3.2), agent-based approaches for landscape creation constitute the set of techniques that employ a single or multiple software agents. According to Russell et al. [11] a software agent passes through the environment, senses it and changes it by performing an agent's specific task. The desired agent properties according to Russell et al. include accessibility, deterministic in the results of their effectors, non-episodicality and the ability to work in a dynamic and in a discrete environment.

When multiple agents are employed in a system, they usually interact directly with the environment (through sending and acting) and indirectly with each other (through observing the changes in the environment performed by the other agents). This allows a simpler implementation of the system, and therefore more control and possibility of extension. A complex output with the desired properties can be developed as the result of the interaction between several relatively simple agents, each following a simple behavioural rules [9].

Agent-based approaches was first introduced for procedural city generation by Lechner et al. [9]. In this work, cities are divided into areas (such as squares, industrial, commercial, residential, etc...) and agents are implemented to construct the road networks. Differenty types of agents were identified such as *extenders* who search for unconnected areas in the city and *connectors* who add highways or direct connections between roads with long travel time. The authors further introduced different agents for constructing main roads and small streets [8].

In the following, we discuss work on agent-based terrain generation by Doran et al. [2], which focuses primarily on the issue of controllability. Previous attempts for terrain generation reported in the literature are mostly based on fractal techniques and offer limited, if any, control for designers as discussed in Section **??**. Because of the lack of input and interaction with designers, fractal-based methods are usually evaluated in term of efficiency rather than the aesthetic features of the terrains generated [2]. Agent-based approaches on the hand, offer the possibility of defining more fine-grained measures of the *goodness* of the terrains according to the behaviour of the agents. And by controlling how and how much the agent changes the environment, one can vary the quality of the generated terrains.

4.4.1 Doran and Parberry's terrain generation

The main objective of the work done by Doran et al. [2] is to provide a greater degree of control for designers. The authors defined five different types of agents that work concurrently in an environment simulating natural phenomena. The agents are allowed to sense the environment and change it at will. Designers are provided with a number of ways to influence terrain generation: controlling the number of agents of each type is one way to gain control, another is by limiting the agent lifetime using a predefined number of actions that the agent can perform. After the number of steps is consumed, the agent becomes inactive.

The agents can modify the environment by performing three main tasks:

- Coastline: in this phase, the outline or shape of the terrain is generated using multiple agents.
- Landform: the detailed features of the land are defined in this phase employing larger number of agents than the one used in the previous phase. The agents work simultaneously on the environment to set the details of the mountains, create beaches and shape the lowlands.
- Erosion: this is the last phase of the generation and it constitutes the creation of rivers through eroding the previously generated terrain. The number of river to create is determined by the number of agents defined in this phase.

According to these phases, several types of agents can be identified to achieve the several tasks defined in each phase. The authors focused their work on five different types:

1. Coastline agents: these agents work in the coastline phase to draw the outline of the landscape before any other agents. The map is initially placed under sea level and the agents work by raising points above sea level. The process starts with a single agent working on the entire map. According to the size of the map, this agent multiplies by creating many other coastline agents which subdivide themselves in turn until each agent is assigned with a small part of the map. The process undertaken by each agent to generate the coastline can be described as follows:

- Each agent is assigned a single seed point at the edge of the map, a direction to follow and a number of token to consume.
- The agent checks its surrounding and if it is already a land (this might happens since all the agents are working simultaneously on the map) the agent starts searching in the assigned direction for another appropriate starting point.
- Once the starting point is located, the agent stats working on the environment by changing the hight of the points. This is done by:
  a. generating two points at random in different directions: one works as an attractor and another as a repulser.
  b. identifying the set of points for elevation above the sea level.
  c. scoring the points according to their distance from the attractor and the repulser points. The ones closer to the attractor are scored higher.
  d. the point with the heighst score is then elevated above sea level and it becomes part of the coastline.
  e. the agent then continue by moving to another point in the map.

   This method allows multiple agent to work concurrently on the map while reserving localisation since each agent moves in its surrounding and has a predefined number of token to consume. The number of token given to each agent and the number of agents working on the map are directly related. The smaller the number of tokens, the larger the number of agents since more agents will be required to cover the whole map. These parameters also affect the level of details of the coastline. A map generated with a small number of token will feature more fine details than a one with a hight number since in the first case more agents will be created, each of which influencing a small region.

2. Smoothing agents: after the shape of the landscape has been defined by the coastline agents, smoothing agents operate on the map to eliminate rapid elevation changes. This is done by creating a number of agents each assigned with a single parameter specifying the number of times that agent has to revisit its starting point. The more the revisits, the smoother the area around this point.
   The agents are scattered around the map, they move randomly and while wandering they change the heights of arbitrary points according to the heights of their neighbours. For each point chosen, a new height value is assigned taking the weighted averages of the heights of its four orthogonal surrounding points and the four points beyond these.
3. Beach agents: after the smoothing phase, the landscape is ready for creating sandy beaches. This is the work assigned to beach agents. These agents traverse the shoreline in random directions creating sandy areas close to water. Beach generation is controlled by the adjusting the agents' parameters. These include the depth of the area the agent is allowed to flatten, the total number of steps the agents can move, the altitude under which the agents are permitted to work and the range of height values they can assign to the points they effect.
   The agents are initially placed in a coastline area where they work on adjusting the height of their surrounding points by lowering them as long as their height is below the predefined altitude. This prevent elevation mountain areas located

close to the sea. The new values assigned to the points are randomly chosen from the designer specified range. This allows the creation of flat beaches if the range is narrow and more bumpy beaches when the range is high.

4. Mountain agents: The coastline agents elevate areas of the map above sea level. These areas are then smoothed by the smoothing agents and beaches along the shoreline are then flattened via the beach agents. Regions above a certain threshold are kept untouched by the beach agents, and these are then modified by mountain agents.
   The agents are placed at random positions in the maps and are allowed to move in random directions. While moving, if a V shaped wedge of points is encountered, the wedge is elevated creating a ridge. Frequently, the agents might decide to turn randomly within 45 degree from their initial course resulting in zig-zag paths. Mountain agents also produces foothills periodically perpendicular to their movement direction.
   The shape of the mountains can be controlled by designers via specifying the range of the rate at which the slops can be dropped, the maximum mountain altitude and the width and slop of the mountain. Designers can also determine the number of agents, the number of steps each one can perform, the length of foothills and their frequency.
   After mountain generation, a smoothing step is followed to blend nearby points. This step is further followed up by an addition of noise to retain some of the details lost while smoothing.
5. Hill agents: these agents work in a similar way to the mountain agents but they have three distinctive characteristics: they work on a lower altitude, the are assigned smaller ranges and they are not allowed to generate foothills.
6. River agents: in the final phase of terrain generation, river agents walk through the environment digging rivers near mountains and the ocean. To resemble nature rivers, a river agent works in the following steps:

   a. initiate two random points one on the coastline and another on the mountain ridge line.
   b. starting at the coastline, the agent moves towards to mountain guided by the elevation gradient uphill. This determined the general path of the river.
   c. as the agent reaches the mountain, it starts moving downwards while digging the river. This is done by lowering a wedge of a terrain following a similar method to the one implemented by mountain agents.
   d. increase the width of the wedge as the agent is moving closer to the ocean.

   Designers specify the initial width of the river, the frequency of widening and the downhill slop. Designers also determine the shortest length possible for a river. A river agent might make several attempts for placing its starting and ending positions before it satisfies the shortest length threshold. If this condition is not met after several attempts, the river will not be created.

The method followed for defining the agents and their set of parameters allows the generation of endless variations of terrains through the use of different random seed numbers. The technique can be used to generate landscapes on-the-fly or it can be employed by designers who can investigate different setups and tweak the system's parameters as desired.

4.5 Search-based landscape generation

We have seen two families of methods for terrain and noise generation, which both have several benefits. However, at least in the form presented here, these methods suffer from a certain lack of controllability. It is not easy to specify constraints or desirable properties, such that there must be an area with no more than a certain maximum variation in altitude, or that two points on a terrain should be easily reachable from each other. This form of controllability is one of the strengths of search-based methods. Unsurprisingly, there have been several attempts to apply search-based methods to terrain generation.

4.5.1 Genetic Terrain Programming

In a series of papers, Frade et al. developed the concept of Genetic Terrain Programming (GTP). This is a search-based method with an indirect encoding, where the phenotype representation is a height map but the genotype representation is an *expression tree* evolved with genetic programming [5, 6, 4].

Genetic programming is a method for creating runnable programs using evolutionary computation [10]. The standard program representation in genetic programming is an expression tree, which in its simplest case is nothing more than an algebraic expression in prefix form such as $(+3(*52))$ (written in infix form as $3+5*2$). This can be visualised as a tree with the $+$ sign as the root node, and the 3 and $*$ in separate branches from the root. The plus and multiplier are arithmetical functions, and the constants are called *terminals*. In genetic programming, a number of additional functions are commonly employed, including if-then-else, trigonometric functions, max, min etc. Additional types of terminals might include external inputs to the program, random number generators etc. The evolutionary search proceeds through adding and exchanging functions and terminals, and by recombining parts of different trees.

In GTP, the function set typically includes arithmetical and trigonometric functions, as well as functions for exponentiation and logarithms. The terminal set includes x and y location, standard noise functions (such as Perlin noise) and functions that are dependent on the distance from the centre of the map.

The core idea of GTP is that in the genotype-to-phenotype mapping, the algorithm iterates over cells in the (initially empty) height map and queries the evolved terrain program with the x and y parameters of that cells as input to the program. This is therefore a highly indirect and compact representation of the map. The representation also allows for infinite scalability (or zooming), as increasing the resolution or expanding the map simply means querying the program using new coordinates as inputs.

Several different evaluation functions were tried. In initial experiments, interactive evaluation was used: users selected which of several presented maps should be used for generating the next generation. Later experiments explored various direct evaluation functions. One of these functions, accessibility, was motivated by game design: the objective was to maximise the area which is smooth enough to support vehicle movement. To avoid that completely flat surfaces are evolved, the accessibility metric had to be counterbalanced by other metrics, such as the sum of the edge length of all obstacles in the terrain. See figure 4.1 for some examples of landscapes evolved with GTP.

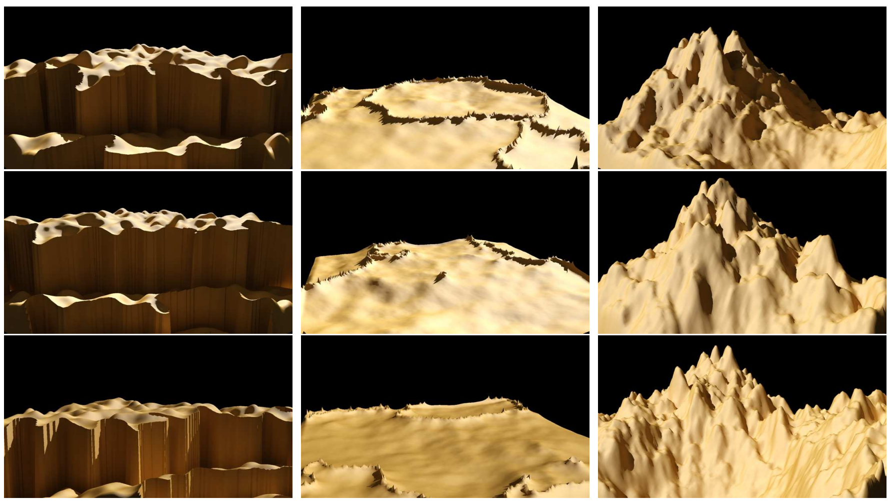

Fig. 4.1: Landscapes generated by Genetic Terrain Programming. From left to right: cliffs, corals and mountains. Adapted from [4]

4.5.2 Simple RTS map generation

Another search-based landscape generation method was described by Togelius et al. [14], in the context of map generation for an imaginary real-time strategy game with smoothly varying height. The phenotype in this problem consists of a height map and the locations of resources and base starting locations.

The representation is rather direct. Base and resource locations are represented directly as polar coordinates (ϕ and θ coordinates for each location). The height map is initially flat, and then a number of hills is added. These hills are modelled

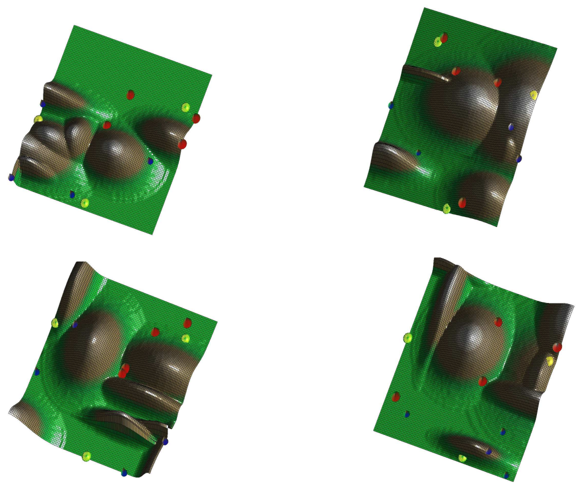

Fig. 4.2: Four maps generated using a search based methods with the height map determined by hills represented by Gaussians. The coloured dots represent locations of resources and bases in an imaginary RTS game. Adapted from [14]

as simple Gaussian distributions, and encoded in the phenotype with their x and y positions, their heights z, and their standard distributions σ_x and σ_y (i.e. their widths). Ten mountains were used in each run.

Three different evaluation functions were defined. Two of them relate to the placements of bases and resources to create a fair game, whereas the third is the topological asymmetry of the map. This is because the simplest way of satisfying the first two evaluation functions is to create a completely symmetric map, but this would be visually uninteresting for players. Given that the three fitness functions are in partial conflict, a multiobjective evolutionary algorithm was used to optimise all three evaluation functions simultaneously. Figure 4.2 show three different terrains that resulted from the same evolutionary run.

4.6 Lab session: Generate a terrain with Diamond-square

The purpose of this exercise is to use the diamond-square method to generate the hight map of a terrain. The method has already been presented in Section **??** and your job is to implement it. Basically, you have to implement an interface that contains the following method:

```
public int[][] buildMap(int iteration, int seed,
                        int variation, double roughness);
```

Fig. 4.3: Three hight maps generated the diamond-square method. The parameters used are: iteration = 9 for all maps, seed = 12, 128, 128 and roughness = 256, 256, 128 for the first, second and third map, respectively.

For simplicity purposes, you can visualise your map by converting it to an RGB image. To do this, you can use the *Frame* class included in the software package provided in the lab sessions. You can simply instantiate your own generator in the *main* method of the *Frame* class, then a call for your map generation method will be made and the corresponding hight map will be drawn. Areas in the map with high values are drawn in light colours while darker areas in the image represent low values of the hight map. Fig. 4.3 presents three example hight maps generated using different initialisation setups.

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Chapter 5
Grammars and L-systems with applications to vegetation and levels (DRAFT)

Julian Togelius, Noor Shaker and Joris Dormans

5.1 Plants are everywhere

Just like most games that feature physical movement include some form of terrains, very many games feature some vegetation in some form. Grass, trees, bushes and a myriad other forms. Vegetation seems like the perfect case for PCG: we need to create a huge number of artefacts (there are many trees in the forest and many straws of grass in the lawn) that are similar to each other, recognisable, but also slightly different from each other. Just copy-pasting trees won't cut it[1] as players will spot it quickly. Further, in most roles vegetation is of little functional significance, meaning that a botched plant will not make the game unplayable, just look a bit weird.

And in fact, vegetation is one of the success stories of PCG. Very many games use procedural vegetation generation, and there are many software frameworks available. For example, the *SpeedTree* middleware has been used in dozens of AAA games.

It turns out that one of the simplest and best ways to generate a tree or bush is to use a particular form of *formal grammar* called an *L-system*, and interpret its results as drawing instructions. This fact is intimately connected to the "self-similar" nature of plants, i.e. that the same structures can be found on both micro- and macro-levels. For an example of this, take a look at a branch of a fern, and see how the shape of the branch repeats in each sub-branch, and then in each branch of the sub-branch. Or look at a romanesco broccoli, which consists of cones on top of cones of top of cones... (see figure 5.1). As we will see, L-systems are naturally suited to reproducing such self-similarity.

In this chapter, we will introduce formal grammars in general, L-systems in particular and how to use a graphical interpretation of L-systems to generate plants. We will also give examples of how L-systems can be used as a representation in search-based PCG, allowing you to evolve plants. However, it turns out that plants

[1] In William Gibson's *Neuromancer*, portal novel of the cyberpunk movement, one of the main characters is busy copy-pasting trees in one of the early chapters.

Fig. 5.1: Romanesco broccoli. Note the self-similarity.

are not the only thing for which formal grammars are useful. In the rest of the chapter, we will explain how grammar-based systems can be used to generate quests and dungeon-like environments for adventure games such as Zelda, and levels for platform games such as Super Mario Bros.

5.2 Grammars

A (formal) *grammar* is a set of *production rules* for rewriting strings, i.e. turning one string into another. Each rule is of the form (symbol(s)) $\rightarrow$ (other symbol(s)). Here are some example production rules:

1. $A \rightarrow AB$
2. $B \rightarrow b$

Using a grammar is as simple as going through a string, and each time a symbol or sequence of symbols that occurs in the left hand side (LHS) of a rule is found, those symbols are replaced by the right hand side (RHS) of that rule. For example, if the initial string is “A”, in the first rewriting step the A would be replaced by B by rule 1, and the resulting string will be “AB”. In the second rewriting step, the A would again be transformed to AB and the B would transformed to Bb using rule 2, resulting in the string “ABb”. The third step yields the string “ABbb” and so on. A convention in grammars is that upper-case characters are nonterminal symbols, which are on the LHS of rules and therefore rewritten further, whereas lower-case characters are terminal symbols which are not rewritten further.

Formal grammars were originally introduced in the 1950’s by the linguist Noam Chomsky as a way of modelling natural languages [3]. However, they have since found widespread application in computer science, as basically any computer science problem can be cast in terms of generating and understanding strings in a given language. Many results in theoretical computer science and complexity theory are therefore expressed using grammar formalisms. There is a rich taxonomy of grammars which we can only hint at here. Two key distinctions that are relevant for the application of grammars in procedural content generation are whether the grammars are deterministic, and the order in which they are expanded.

Deterministic grammars have exactly one rule that applies to each symbol or sequence of symbols, so that for a given string, it is completely unambiguous which rules to use to rewrite it. In nondeterministic grammars, several rules could apply to a given string, yielding different possible results of given rewriting step. So, how would you decide which rule to use? One way is to simply choose randomly. In such cases, the grammar might even include probabilities for choosing each rule. Another way is to use some parameters for deciding which way to expand the grammar — we will see an example of this in the section on grammatical evolution towards the end of the chapter.

5.3 L-systems

The other distinction of interest here is in which order the rewriting is done. *Sequential* rewriting goes through the string from left to right and rewrites the string as it is reading it; if a production rule is applied to a symbol, the result of that rule is written into the very same string before the next symbol is considered. In *parallel* rewriting, on the other hand, all the rewriting is done at the same time. Practically, this is implemented as new string being implemented at a separate memory location containing only the effects of applying the rules, and the original string is left unchanged. Sometimes, the difference between parallel and sequential rewriting can be major.

L-systems are a class of grammars whose defining feature is parallel rewriting, and which was introduced by the biologist Aristid Lindenmayer in 1968 explicitly to model the growth of organic systems such as plants and algae [9]. The following is a simple L-system defined by Lindenmayer to model yeast growth:

1. $A \rightarrow AB$
2. $B \rightarrow A$

Starting with the axiom A (in L-systems the seed strings are called axioms) the first few expansions look as follows:

1. A
2. AB
3. ABA
4. ABAAB
5. ABAABABA
6. ABAABABAABAAB
7. ABAABABAABAABABAABABA
8. ABAABABAABAABABAABABAABAABABAABAAB

There are several interesting things about this sequence. For one thing, the obvious regularity, which is more complex than simply repeating the same string over and over, and certainly seems more complex than is warranted by the apparent simplicity of the system that generates it. But also note that the rate of growth of the strings in each iteration is increasing. In fact, the length of the strings is a Fibonacci sequence: 1 2 3 5 8 13 21 34 55 89... This can be explained by the fact that the string of step n is a concatenation of the string of step $n-1$ and the string of step $n-2$.

Clearly, even simple L-systems have the capacity to give rise to highly complex yet regular results. This seems like an ideal fit for PCG. But how can we move beyond simple strings?

5.3.1 Graphic interpretation of L-systems

One way of using the power of L-systems to generate 2D (and 3D) artefacts is to interpret the generated strings as instructions for a turtle in *turtle graphics*. Think of the turtle as moving across a plane holding a pencil, and simply drawing a line that traces its path. We can give commands to the turtle to move forwards, and to turn left or right. For example we could use the following key to interpret the generated strings:

- F: move forward a certain length (e.g. 10 pixels)
- +: turn left 90 degrees
- -: turn right 90 degrees

Such an interpretation can be used in conjunction with a simple L-system to give some rather remarkable results. Consider the following system, consisting only of one rule:

1. $F \rightarrow F+F-F-F+F$

Starting this system with the axiom F, it would expand into $F+F-F-F+F$ and then into $F+F-F-F+F+F+F-F-F+F-F+F-F-F+F-F+F-F-F+F+F+F-F-F+F$ etc. Interpreting these strings as turtle graphics instructions, we get the sequence of rapidly complexifying pyramid-like structures shown in figure 5.2, known as the Koch curve.

Fig. 5.2: Koch curve generated by the L-system $F \to F+F-F-F+F$ after 0, 1, 2 and 3 expansions.

5.3.2 Bracketed L-systems

While interpreting L-system-generated strings as turtle instructions allows us to draw complex fractal shapes, we are fundamentally limited by the constraint that the figures must be drawable in one contiguous line – the whole shape must be drawn "without lifting the pencil". However, many interesting shapes cannot be drawn this way. For example, plants are branching and requires you to finish drawing a branch before returning to the stem to draw the next line. For this purpose, *bracketed* L-systems were invented. These L-systems have two extra symbols, [and], which behave like any other symbols when rewriting the strings but act as "push" and "pop" commands to a stack when interpreting the string graphically. (The stack is simply a first-in, last-out list.) Specifically, [saves the current position and orientation of the turtle onto the stack, and and] retrieves the last saved position from the stack and resets the turtle to that position – in effect, the turtle "jumps back" to a position it has previously been at.

Bracketed L-systems can be used to generate surprisingly plant-like structures. Consider the L-system defined by the single rule $F \to F[-F]F[+F][F]$. This is interpreted as above, except that the turning angles are only 30 degrees rather than 90 degrees as in the previous example. Figure 5.3 shows the graphical interpretation of the L-system after 1, 2, 3 and 4 rewrites starting from the single symbol F. Minor variations of the rule in this system generate different but still plant-like structures, and the general principle can easily be extended to three dimensions by introducing symbols that represent rotation along the axis of drawing. For a multitude of beautiful examples of plants generated by L-systems see the book "The Algorithmic Beauty of Plants" by Prusinkiewicz and Lindenmayer [15].

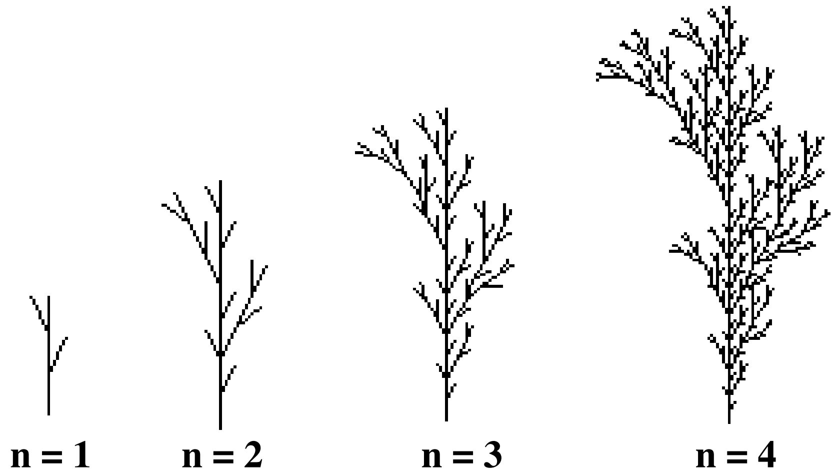

Fig. 5.3: Four rewrites of the bracketed L-system $F \to F[-F]F[+F][F]$.

5.4 Evolving L-systems

Like any parametrisable PCG method, L-system expansions can be used as genotype-to-phenotype mapping in search-based PCG. An early paper by Ochoa presents a method for evolving L-systems to attain particular 2D shapes [10]. She restricts herself to L-systems with the simple alphabet used above ($F+-[]$), the axiom F and a single rule with the LHS F. The genotype is the RHS of the single rule. Ochoa used a canonical genetic algorithm with crossover and mutation together with a combination of several evaluation functions. The fitness functions all relate to the shape of the phenotype, namely the height ("phototropism"), bilateral symmetry, exposed surface area ("light gathering ability"), structural stability and proportion of branching points. By varying the contributions of each fitness function, she showed that it is possible to control the type of the plants generated with some precision. Fig. 5.4 shows some examples of plants evolved with a combination of fitness functions, and Fig. 5.5 shows some examples of organism-like structures evolved with the same representation but a fitness function favouring bilateral symmetry.

5.5 Generating missions and spaces with grammars

A game level is not a singular construction, but rather a combination of two interacting structures: a mission and a space [4]. A mission describes the things a player can or need to do to complete a level, while the space describes the geometric layout of the environment. Both mission and space have their own structural quali-

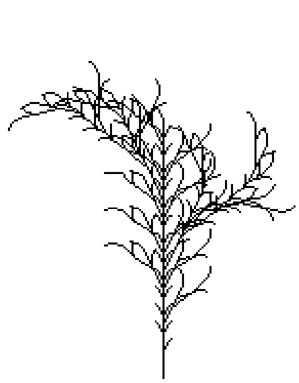

Fig. 5.4: Some evolved L-system plants.

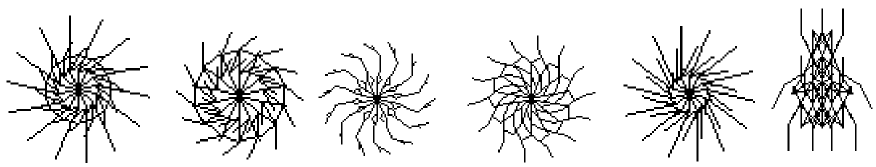

Fig. 5.5: Some L-system structures evolved for bilateral symmetry.

ties. For missions it is important to keep track of flow, pacing and causality, while for the space connectedness, distance and sign posting are critical dimensions. To successfully generate levels that feel consistent and coherent it is important to use techniques that can generate each structure in such way that strengthens their individual qualities while making sure that the two structures are interrelated and work together. This section discusses how different types of generative or transformative grammars can be used to achieve this.

5.5.1 Graph grammars

Generative grammars typically operate on strings, but they are not restricted to that type of representation. Grammars can be used to generate many different types of structures: graphs, tile maps, two or three dimensional shapes, and so on. In this section and the following section, we will explore how grammars can be used to generate graphs and tile maps. These structures are useful ways to represent game missions and game spaces that combine into game levels.

Graph are more useful than strings to represent missions and spaces for games, especially when these missions and spaces need to have a certain level of sophistication. For example, a completely linear mission (which might be represented by a

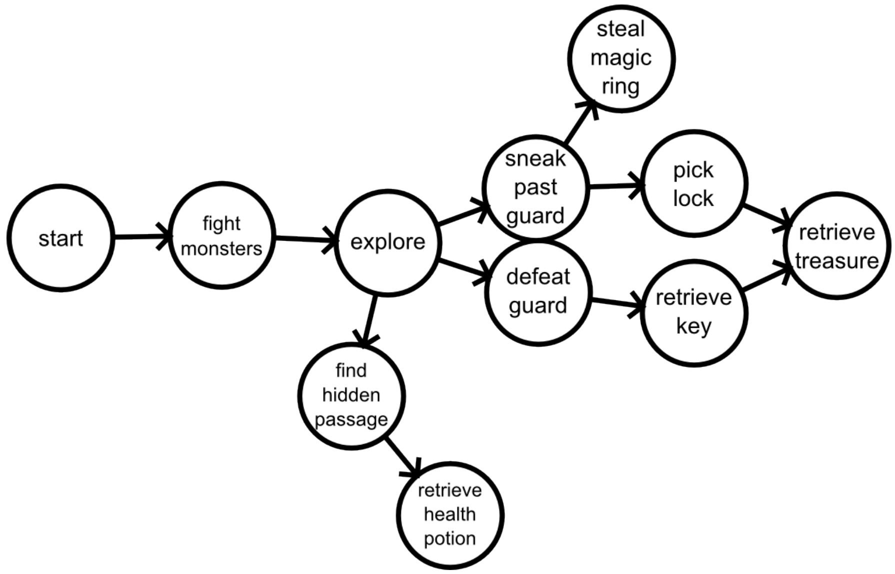

Fig. 5.6: A mission structure with two paths.

string) might be suitable for simple and linear games, but for explorative adventure games such as RPG dungeons you will want missions to contain lock and key puzzles, bonus objectives, and possibly multiple paths to lead to the level goal. Graphs can express this type of structures more easily. For example, Fig. 5.6 contains a mission that can be solved in two different ways.

Graph grammars work quite similar to string grammars; graph grammar rules also have a left hand part that identifies a particular graph construction that can be replaced by one of the constructions in the right hand part of the rule. However, to make the transformation, it is important to identify each node in the left hand individually and to match them with individual nodes in each right hand part. Fig. 5.7 represents a graph grammar rule and uses numbers to identify each individual node. When using this rule to transform a graph, follow 5 steps (as illustrated by Fig. 5.8)[2]:

1. Find a subgraph in the target graph that matches the left hand of the rule and mark that subgraph by coping the identifiers of the nodes.
2. Remove all edges between the marked nodes.
3. Transform the graph by transforming marked nodes into their corresponding nodes on the right hand side, adding a node for each node in the right hand

[2] in simple graph transformations there is no need to identify and transform individual edges in the same way as nodes are identified and transformed. However, a more sophisticated implementation that requires edges to be transformed rather than removed and added for each transformation can be realised by identifying and replacing edges in the same way as nodes.

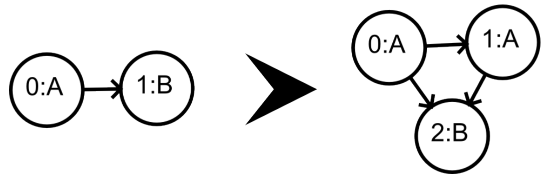

Fig. 5.7: A graph grammar rule.

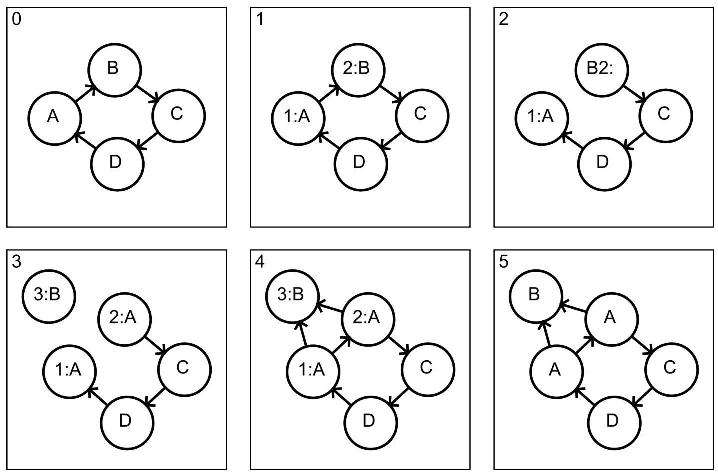

Fig. 5.8: Graph grammar transformation.

that has no match in the target graph, and removing any nodes that have no corresponding node in the right hand side[3].

4. Copy the edges as specified by the right hand side.
5. Remove all marks [16].

5.5.2 *Using graph grammars to generate missions*

To generate a simple mission using graph grammars, it is best to start defining the alphabet the grammar is designed to work with. In this case the alphabet consists of the following nodes and edges:

- Start (node marked S): the start symbol from which the grammar generates a mission (the axiom).

[3] Take into account that the removal of nodes only works when the node to be removed is only connected to nodes that have been marked. This is something to take into account when designing graph grammar rules.

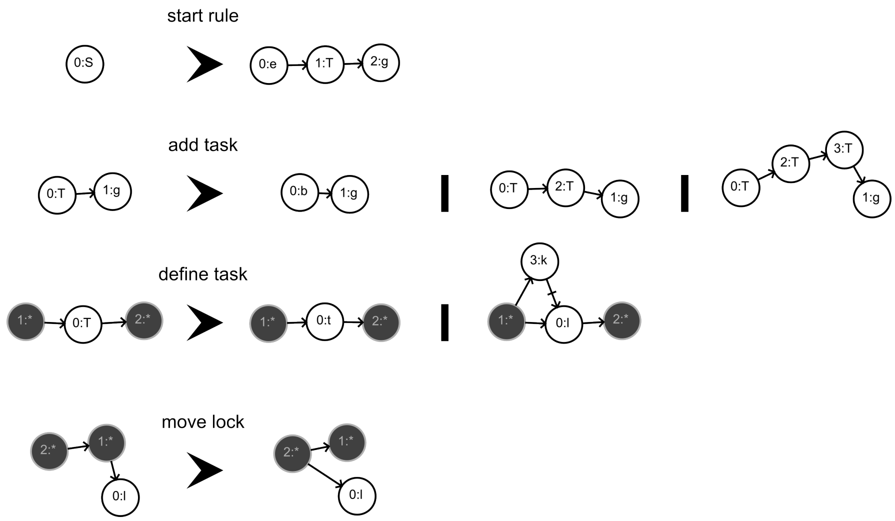

Fig. 5.9: Mission rules.

- Entrance (nodes marked e): the starting place of the player.
- Tasks (nodes marked t): arbitrary, unspecified tasks (here be monsters!).
- Goals (nodes marked g): an task that finishes the level when successfully completed.
- Locks (nodes marked l): a tasks that requires a key to perform successfully.
- Keys (nodes marked k).
- Nonterminal task nodes (nodes marked T)
- Normal edges (represented as solid arrows) connecting nodes and identifying which task follows which.
- Unlock edges (represented as solid arrows marked with a dash) connecting keys to locks.

With this alphabet we can construct rules that generate missions. For example, the rules in Fig. 5.12 were used to generate the sample missions in Fig. 5.10[4].

One thing you might notice from studying these rules is that graph grammars can be hard to control. In the case of the rule set represented in Fig 5.12, the number of task generated (by the application of the "add task" rule) can be as low as one and has no upper limit. As soon as the Start node is removed from the graph, the number of tasks no longer grows. One way to get a better grip on the generated structures is not to apply rules indiscriminately, but to specify a sequence of rules so that each rule in the sequence is applied once to one possible location in the graph. For example, if we split up the "add task" rule from Fig. 5.12 into two rules (see

[4] The rules use a special wildcard node (marked with a*) to indicate a match with any node. Wildcards in the right hand side of a rule never change the corresponding node in the graph being transformed. An alternative to these wildcards is to allow rules to have edges without origin or target node.

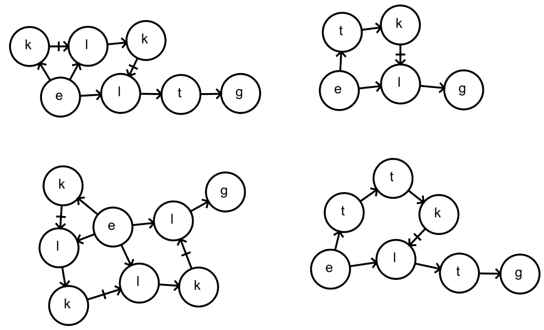

Fig. 5.10: Generated Missions.

Fig. 5.11: Two new rules to replace the old “add task”.

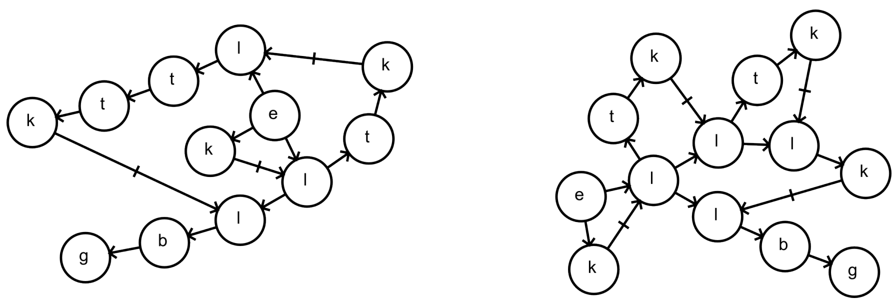

Fig. 5.12: Missions generated from the same sequence of rules.

Fig. 5.11), the missions in Fig. 5.12 are generated by apply the following sequence of rules[5]:

- start rule (x1),
- add task (x6),
- add boss (x1),
- define task (x6),
- move lock (x5).

[5] Obviously, the sequence of rules might be generated by a string grammar.

5.5.3 Breaking the process down into multiple generation steps

So far, the graph grammars are relatively simple. However, to generate anything resembling the complexity of the mission in Fig. 5.6, many more rules are required. Designing the grammars to achieve such results takes practice and patience. A key strategy to design successful grammars is to break down the process into multiple steps. Trying to generate everything at once using only one grammar is a daunting task, and next to impossible to debug and maintain[6].

When breaking down the generation process into multiple steps, it useful to think of each step as a simulation of the design process. One step might generate the overall specifications of the mission, while the next might flesh out those specifications. In game design, a successful design strategy is to start from a set of random set of requirements and use your creativity to shape that random collection into a coherent whole. Following a similar approach for breaking down the generation procedure and designing individual grammars yields good results. In particular, designing one simple step to create a highly randomised graph and use a second step the restructure that graph into something that makes sense from the game's perspective, is a very effective strategy to create very expressive generation procedures [6].

For example, we can use a single step to generate a mission of a specified length and randomly choose between locks, keys and other tasks to fill in the spaces between the entrance and the goal. Although in this case we also make sure that the first task is always a key and the last task is always a lock. Fig. 5.13 and Fig. 5.14 represent the rules and a sample mission built using those rules. Note that although locks and keys are placed, no relationship between them is established.

The next step is to extract lock and key relationships. Based on the spread of the locks and keys over the tasks, multiple keys can be assigned to a single lock, and vice versa. This would represent multiple levers that need to be activated to open a single door, or a special weapon that can be used multiple times to get past a special type of barrier. Fig. 5.15 represents the rules to add these relationships, and Fig. 5.16 is a sample configuration created from the sample set in Fig. 5.14.

Next steps could include the movement of locks through the graph (as we have seen in the example above), generating more details of the nature of the locks and keys, or adding tasks of a different type. One of the advantages of using these two steps is that two relatively simple grammars can create a large variety of different relationships (two keys to a single lock, or keys that are reused). Getting the same level of variation using explicit rules that create an X number of keys to a single lock would require many more rules which are much harder to maintain. In addition, the second step can also be executed on graphs that have been built to different specifications. For example, the same rules can be used to create lock and key relationships for a dungeon that has two separate paths (see Fig. 5.17).

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[6] Breaking down the generation into multiple steps is in line with the approach to software engineering and code generation suggested by model driven engineering. When done right, this approach leads to a flexible generation processes that allow you to generate spaces from missions or vice versa, and creates opportunities to design generic, reusable generation steps [1, 5].

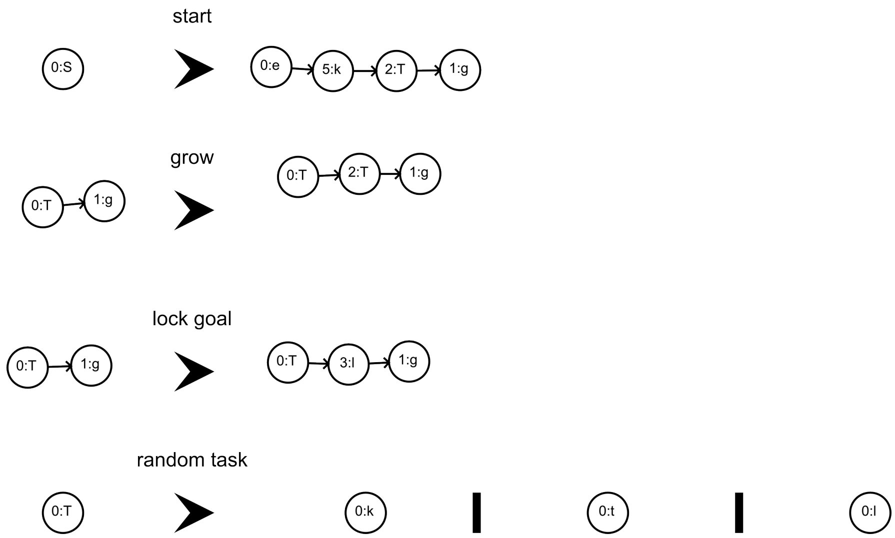

Fig. 5.13: Rules to create random set.

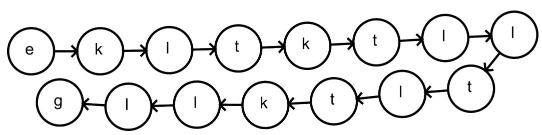

Fig. 5.14: Sample random set.

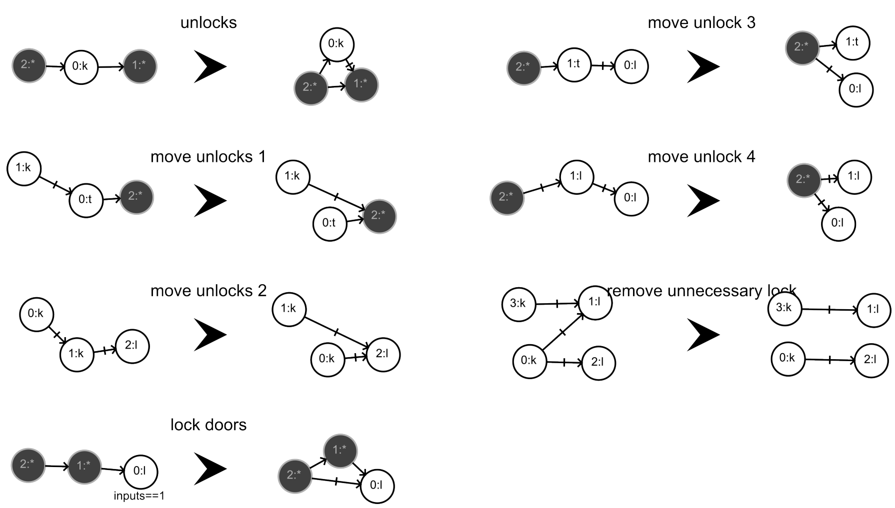

Fig. 5.15: Rules to add lock and key relationships.

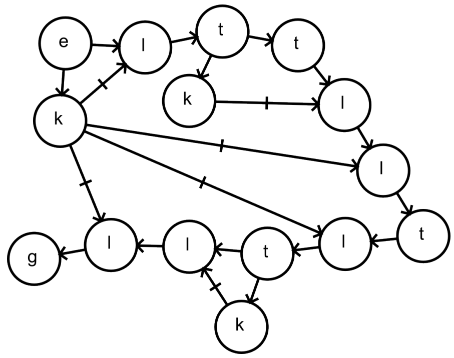

Fig. 5.16: Generated lock and key relationships.

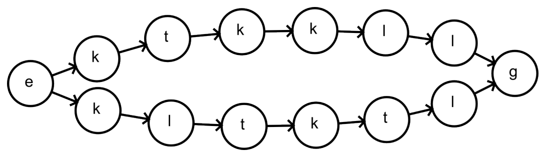

Fig. 5.17: Two paths to a single goal.

5.5.4 Generating spaces to accommodate a mission

Having a representation of a mission itself is only one step towards the generation of levels for a game. Missions need to be transformed into spaces that the player can actually traverse. Transforming from mission to space is one of the hardest steps in this process. The problem comes down to generating two different, independent but linked structures: an abstract mission that details the things a player needs to do, and a concrete space that creates the world where the player can do these things. Below you find three strategies to deal with the problem of generating the two structures:

1. Transform from mission to space. The transition from Fig. 5.14 to Fig. 5.16 reflects the gradual transition from abstract missions to a more concrete representation of a game space. Although in this case, the game space is still highly abstract. However by using automatic graph layout algorithms and sampling the results into a tile map, you are able to generate usable level geometry. This approach works well for games such as action adventure games or games with a strong narratives, where mission coherence and pacing is important. The disadvantage of this approach is that the difficulty of going from mission to space is most pronounced.
2. Transform a mission to a set of instructions to build a space. Instead of transforming a mission structure into a space directly you can transform the mission into a set of building instructions that can be used to build a space to match the requirements. This approach has the advantage that the transition from graphs

to tiles or shapes is much easier, it also comes at a cost: it is very difficult to generate spaces that have multiple paths leading to the same goal or location. So this approach works best for very linear games like platformers or certain story driven games.

3. Build level geometry and distill a more abstract representation of the game space to generate the missions from. This approach reverts the problem by generating level geometry first and set up missions for that geometry. You can do this by generating a geometry using cellular automata, grammars, evolution, or any other technique, then analysing the geometry to create an abstract graph representation of that same space which you can transform into suitable mission structures. This approach works well for strategic games, levels that take place in locations that require some consistent architecture (such as castles, dwarf fortresses, police stations, or space ships), and for levels that the player is going to visit multiple times. The downside of this approach is that it is critical that the geometry is generated with enough mission potential (are there doors to be locked, bottleneck to set up traps, and so on) and that you have far less control over the mission than with the other two approaches.

When choosing between these strategies, or when trying to come up with another strategy, it is important to think like a designer. The most effective way of generating levels using a multistep process and different representations of missions and spaces is to model the real design process. Ask yourself, how would you go about designing a level by hand? Would you start by listing mission goals, or by sketching out a map? What sort of changes do you make and can those changes be captured by transformational grammars?

5.5.5 Extended Example: ‘Dules

An extended example following the third strategy concludes this section. The example details the part of the PCG for the game ‘Dules, which is currently in development. In this game, players control futuristic combat vehicles (tanks, hovercraft, and so on) in a post-apocalyptic, alien-infested world. The players can choose missions from a world map, after which the game generates an environment to match the location on the map and sets up a mission based on the affordances of the environment and specifications dictated by the current game state (who controls the environment, is the player trying to take over, or defending from alien incursion, and so on).

The content generation of ‘Dules makes use of transformation grammars that operate on strings, graphs, and tiles. Tile grammars are very simple. They also consist of rules with one left and one or more right hands where the left hand can be replaced by one of the right hand constructions. Like graph grammars, the tile grammars used in ‘Dules can work with wildcards to indicate that certain tiles can be ignored. In contrast to string and graph grammars, tile grammars cannot change the number of tiles. In addition, tile grammars can be made to stack tiles onto each other instead of replacing them.

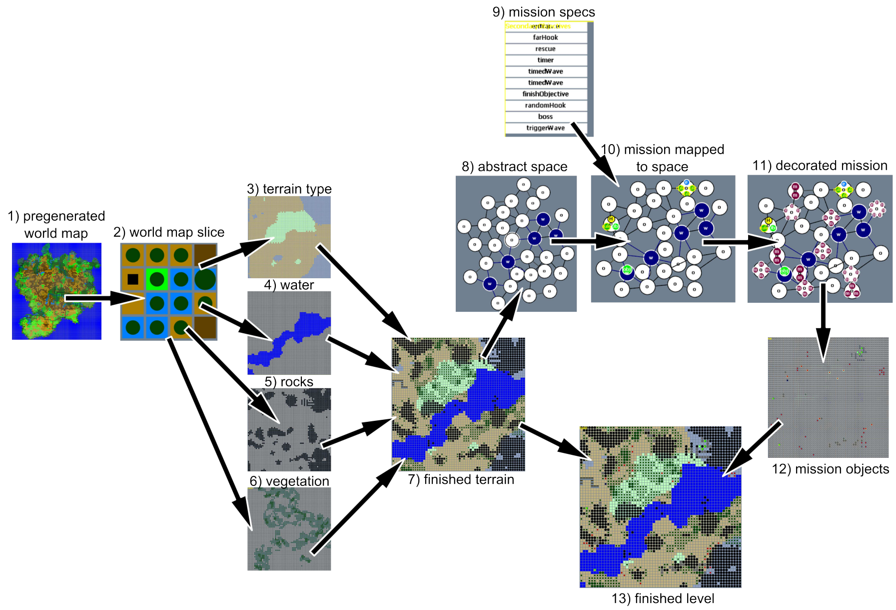

Fig. 5.18: The generation steps to create a level for ‘Dules.

The procedural content generation procedure roughly follows the steps as outlined Fig. 5.18. In this case taking the tile-based world map as an input (1), the particular location is selected (2). Based on the presence of particular tiles indicating vegetation, elevation, buildings, and such, a combination of tile grammars and cellular automata are used to create the terrain (3-7). The terrain is analysed and transformed into an abstract representation (8). At the same time, mission specifications are generated using a string grammar (9), which are used as building instructions to plot a mission onto the space graph (10)[7]. Finally, some extra enemies are added to the mission (11), all the mission specific game objects are placed onto the same tile map (12) and combined with the terrain to create the complete mission (13).

Almost all steps in the process are handled by grammars. Tile grammars are used to generate the terrain, tile grammars are even used to specify different cellular automata. String grammars are used to create the mission specification and graph grammars are used to create the mission itself. The translation of the terrain into the space graph is done using a specialised algorithm that distinguishes between walkable terrain, impassible terrain, and bodies of water. Each node in (8) represents around 100 tiles, and a reference between the node and the tiles is kept to be able to place the game objects in the right area during (12).

[7] In this case certain graph nodes are represented to contain other nodes. This is just a representation, for the implementation and the grammars, such a containment is nothing but a special type of edge, that is rendered differently.

5.6 Grammatical evolution for Infinite Mario Bros level generation

Grammatical Evolution (GE) is an evolutionary algorithm based on Grammatical Programming (GP) [13]. The main difference between GE and GP is the genome representation; while a tree-based structure is used in GP, GE relies on a linear genome representation. Similar to general Genetic Algorithms (GAs), GE applies fitness calculations for every individual and it applies genetic operators to produce the next generation.

The population of the evolutionary algorithm is initialised randomly consisting of variable-length integer vectors; the syntax of possible solution is specified through a context-free grammar. GE uses the grammar to guide the construction of the phenotype output. The context-free grammar employed by GE is usually written in Backus Naur Form (BNF). Because of the use of a grammar, GE is capable of generating anything that can be described as a set of rules such as mathematical formulas [18], programming code, game levels [17] and physical and architectural designs [2, 14]. GE has been used intensively for automatic design [8, 2, 14, 7, 11], a domain where it has been shown to have a number of strengths over more traditional optimisation methods.

5.6.1 Backus Naur Form

Backus Naur Form (BNF) is a set of production rules usually used to express a grammar. A BNF grammar $G = \{N, T, P, S\}$ consists of terminals, T, non-terminals, N, production rules, P and a start symbol, S. Such as in any grammar, non-terminals can be expanded into one or more terminals and non-terminals through applying the production rules. An example BNF to generate valid mathematical expressions is given in Fig. 5.19.

```
(1) <exp> ::= <exp> <op> <exp>
            | ( <exp> <op> <exp> )
            |  <var>
(2) <op> :: = + | - | * | /
(3) <var> ::= X
```

Fig. 5.19: Illustrative grammar for generating mathematical expressions.

Each chromosome in GE is a vector of codons. Each codon is an integer number used to select a production rule from the BNF grammar in the genotype-to-phenotype mapping. A complete program is generated by selecting production rules from the grammar until all non-terminal rules are mapped. The resulted string is evaluated according to a fitness function to give a score to the genome. To better understand the genotype-to-phenotype mapping, we will give a brief example.

Consider the grammar in Fig. 5.19 and the individual genotype integer string $(4,5,8,11)$. We begin the processing of the mapping from the start symbol $< exp >$. In this case there are three possible productions, to decide which production to choose, we use the first value in the input genome and apply the mapping function $4\%3 = 1$, where 3 is the number of possible productions, the result from this operation indicates that the second production should be chosen, and $< exp >$ is replaced with $(< exp >< op >< exp >)$. The mapping continues by using the next integer with the first unmapped symbol in the mapping string, the mapping string then becomes $(< var >< op >< exp >)$ through the formula $5\%3 = 2$. At this step $< var >$ has only one possible outcome and there is no choice to be made, hence, X is inserted without reading any number from the genome. The expression becomes $(X < op >< exp >)$. Continuing to read the codon values from the example, individual's genome $< op >$ is mapped to $+$ and $< exp >$ is mapped to X through the two formulas, $8\%4 = 0$ and $11\%3 = 2$, respectively. This results in the expansion $(X+X)$.

During the mapping process, it is possible for individuals to run out of genes, in this case GE either declares the individual as invalid by assigning it with a penalty fitness value or it wraps around and reuses the genes.

5.6.2 Grammatical evolution level generator

In the work done by Shaker et al. [17] grammatical evolution was adopted to generate content for Infinite Mario Bros (IMB) motivated by the number of advantages it provides over more traditional optimization methods [12]: it maintains a simple way of describing the structure of the levels; it enables an open-ended structure where the design and model size are not known a priori; it enables the design of aesthetically pleasing levels by exploring a wide space of possibilities since the exploratory process is not constrained or biased by imagination or known solutions; it allows an easy incorporation of domain knowledge through its underlying grammatical representation permitting level designers to maintain greater control of the output and it makes possible to easily generalize to different types of games.

The following section summarises the work done by Shaker et al. [17]. We start by presenting the design grammar used by GE to specify the structure of IMB levels, after that we present how GE was employed to evolve playable levels for the game.

5.6.2.1 Design grammar for content representation

As mentioned earlier, GE uses a Design Grammar (DG), written in BNF, to specify the representation of solutions (in our case a level design). Several methods can be followed to specify the structure of the levels in a design grammar, but since the

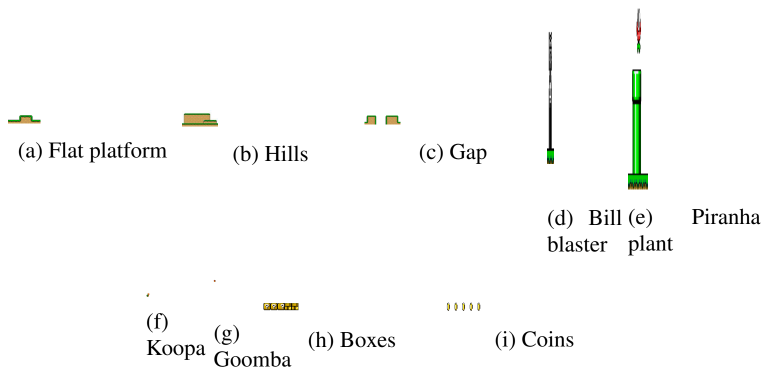

Fig. 5.20: The geometric representation of the different chunks used for constructing Infinite Mario Bros levels.

grammar employed by GE is of context-free nature, this limits the possible solutions available. To accommodate for this constraint, and to keep the grammar as simple as possible; the implementation proposed is to add a game elements to the 2D level array regardless of the positioning of the other elements. With this solution, however, arises a number of conflicts in level design that should be resolved. Section 5.6.2.2 discusses this issue and the proposed solution in details.

The internal representation of the levels in IMB is a two-dimensional array of objects, such as brick blocks, coins and enemies. The levels are generated by placing a number of chunks in the two-dimensional level map. The list of chunks that was considered includes platforms, gaps, stairs, piranha plants, bill blasters, boxes (blocks and brick blocks), coins, goombas and koopas. Each of these chunks has a distinguishable geometry and properties. Fig. 5.20 presents the different chunks that collectively constitute a level. The level initially contains a flat platform that spans the whole x-axis, this explains the need of defining gaps as one of the chunks.

A design grammar was specified that takes into account the different chunks. In order to allow more variations in the design, platforms and hills of different types were considered such as a blank platform/hill, a platform/hill with a bill blaster, and a platform/hill with a piranha plant.

Variations in enemy placements were achieved by (1) constructing the physical structure of the level, (2) calculating the possible positions on which an enemy can be placed (this includes all positions where a platform was generated) and (3) placing each generated enemy in one of the possible positions.

The design grammar constructed can be seen in Figure 5.21. A level is constructed by placing a number of chunks each assigned with two or more properties, the x and y parameters specify the coordinates of the chunk starting point position in the 2D level array and are limited to the ranges [5,95] and [3,5], respectively. These ranges are constrained by the dimension of the level map. The first and last five blocks in the x dimension are reserved for the starting platform and the ending gate, while the y values have been constrained in a way that insures playability (the existence of a path from the start to the end position) by placing all items in areas reachable by *Mario* by performing jumps. The w_g parameter specifies the width of gaps that insures the ability to reach the other edge, w stands for the width of a platform or a hill, w_c defines the number of coins, and h indicates the height of a tube of the piranha plant or the height of a bill blaster. This height is also constrained to the range [3,4] assuring the possibility of jumping over tubes and bill blasters.

```
<level> ::= <chunks>  <enemy>
<chunks> ::= <chunk> |<chunk> <chunks>
<chunk> ::= gap(<x>,<y>, <w_g>,<w_before>,<w_after>)
  | platform(<x>,<y>,<w>)
  | hill(<x>,<y>,<w>)
  | blaster_hill(<x>,<y>,<h>,<w_before>,<w_after>)
  | tube_hill(<x>,<y>,<h>,<w_before>,<w_after>)
  | coin(<x>,<y>,<w_c>)
  | blaster(<x>,<y>,<h>,<w_before>,<w_after>)
  | tube(<x>,<y>,<h>,<w_before>,<w_after>)
  | <boxes>

<boxes> ::=  <box_type> (<x>,<y>)^2 | ...
  | <box_type> (<x>,<y>)^6

<box_type> ::= block_coin | block_powerup
  | brick_coin   | brick_empty

<enemy> ::= (koopa | goomba)(<pos>) ^2 | ...
  | (koopa | goomba)(<pos>) ^10
<x> ::= [5..95]
<y> ::= [3..5]
<w_g> ::= [2..5]
<w_before> ::= [2..5]
<w_after> ::= [2..5]
<w> ::= [2..6]
<w_c> ::= [2..6]
<h> ::= [3..4]
<pos> ::= [0..100000]
```

Fig. 5.21: The design grammar employed to specify the design of the level. The superscripts (2, 6 and 10) are shortcuts specifying the number of repetition.

5.6.2.2 Conflict resolution and content quality

There are a number of conflicts inherent within the design grammar. According to the design approach, each chunk generated can be assigned any x and y values from the ranges [5,95] and [3,5], respectively, depending on the genotype without any restrictions. This means that it is very likely that there will be an overlap between the coordinates of the generated chunks. For example: $hill(65,4,5)$ $hill(25,4,4)$ $blaster\_hill(67,4,4,4,3)$ $coin(22,4,6)$ $platform(61,4,4)$ is a phenotype that has been generated by the grammar and contains a number of conflicts: e.g., $hill(65,4,5)$ and $blaster\_hill(67,4,4,4,3)$ were assigned the same y value, and overlapping x values; another conflict occurs between $hill(25,4,4)$ and $coin(22,4,6)$; as the two chunks also overlap on the $x-axes$.

To resolve these conflicts, a priority value was manually defined and assigned to each of the chunks. Hills with bill blasters or piranha plants are given the highest priority followed by blank hills, platforms with enemies (bill blasters or piranha plants) come next then blank platforms and finally come coins and blocks with the lowest priority. After generating a genotype (with possible conflicts), a post-processing step is applied in which the chunks are arranged in a descending order according to their priorities, coordinates and type. The resulted ordered phenotype is then scanned and whenever two overlapping chunks are detected, the one with the higher priority value is maintained and the other is removed. Nevertheless, to allow more diversity, some of the chunks are allowed to overlap such as hills of different height (Figure 5.20. b), and coins or boxes with hills (hills here refer to all types of hills; blaster-hills, tube-hills and flat hills). Without this refinement, most levels would look rather flat and uninteresting.

To measure content quality, a relatively simple fitness function was implemented. The main objective of the fitness function is to allow for exploring the design space by creating levels with an acceptable number of chunks permitting for rich design and variability. Thus, the fitness function used is a weighted sum of two normalised measures; the first one, f_p, is the difference between the number of chunks placed in the level and a predefined threshold that specifies the maximum number of chunks that can be placed. The second, f_c, is the number of different conflicting chunks found in the design. Apparently, the two fitness functions partially conflict since optimising f_p by placing more chunks implicitly increases the chance of creating conflicting chunks (f_c). Some example levels generated are presented in Fig. 5.22.

5.7 Lab exercise: create plants with L-systems

At this point, you should be able to implement a bracketed simple L-system to generate plants, which is what you will be doing for this lab exercise. Use an L-system to generate your plants and a turtle graphics program to draw them. You will be given a software package that contains three main classes: *LSystem*, *State* and *Canvas*. Your main work will be to implement the two main methods in the *LSystem* class:

```
public void expand(int depth)
public void interpret(String expression)
```

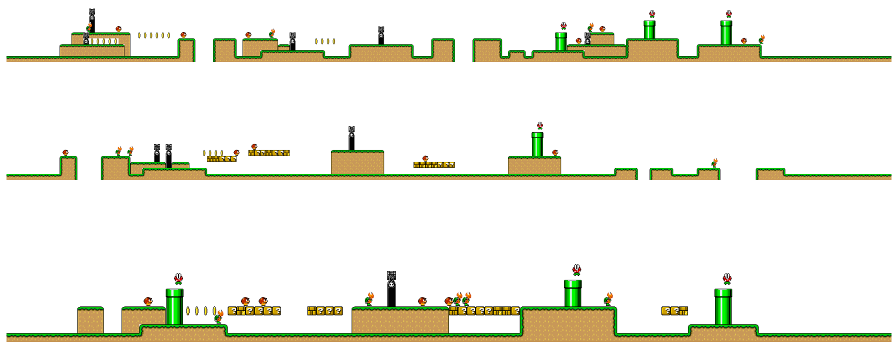

Fig. 5.22: Example levels generated by the GE-generator using the design grammar in Fig. 5.21.

Fig. 5.23: Example trees generated with an L-system using different instantiation parameters.

The L-system has an alphabet, axioms, production rules, a starting point, a starting angle, a turning angle and a length for each step. The expand method is used to expand the axiom of the L-system a number of times specified in the *depth* parameter. After expansion, the system processes the expansion and visualises it through the *interpret* method. The result of each step is drawn on the canvas. Since the L-system will be in a different number of states during expansion, a *State* class is defined to represent each state. An instance of this class is made for each state of the L-system and the variables required for defining the state are passed on from the L-system to the state; these include the x and y coordinates, the starting and turing angels and the length of the step. The L-system is visualised by gradually drawing each of its states.

The *State* and the *Canvas* classes are helpers, and therefore there is no need to do any modifications to them. The *Canvas* class has the methods required for simple drawing on the canvas and it contains the main method to run your program. In the *main* method, you can instantiate your L-system, define your axiom, your production rules and the number of expansions. Fig. 5.23 presents example L-systems generated using the following rules: $(F, F, F \rightarrow [-F]F[+F][F])$ (Fig. 5.23.**??**) and $(F, f, (F \rightarrow FF, f \rightarrow F - [[f] + f] + F[+Ff] - f))$ (Fig. 5.23.**??**). (Note that the rules are written in the form $G = (A, S, P)$, where A is your alphabet, S is the axiom or the starting point and P is the set of production rules).

You can of course use the same software to draw fractal-like forms such as the ones presented in Fig. 5.24. Some example simple rules that you can use to create

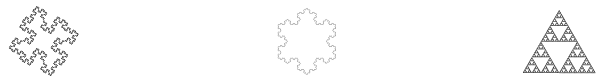

Fig. 5.24: Example fractals generated with an L-system using different production rules.

relatively complex shapes are the followings: $(F, F+F+F+F, (F+F+F+F \rightarrow F+F+F+F, F \rightarrow F+F-F-FF+F+F-F))$ (Fig. 5.24.**??**), $(F, F++F++F, F \rightarrow F-F++F-F)$ (Fig. 5.24.**??**) and $(F, f, (f \rightarrow F-f-F, F \rightarrow f+F+f))$ (Fig. 5.24.**??**).

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Chapter 6
Rules and mechanics (DRAFT)

Mark J. Nelson, Julian Togelius, Cameron Browne, and Michael Cook

So far in this book, we have seen a large number of methods for generating content for existing games. So, if you have a game already, you could now generate many things for it: maps, levels, terrain, vegetation, weapons, dungeons, racing tracks. But what if you don't already have a game, and want to generate the game itself? What would you generate, and how? At the heart of any game are its rules. This chapter will discuss representations for game rules of different kinds, along with methods to generate them, and evaluation functions and constraints that help us judge complete games rather than just isolated content artefacts.

Our main focus here will be on methods for generating interesting, fun, and/or balanced game rules. However, an important perspective that will permeate the chapter is that game rule encodings and evaluation functions can encode game design expertise and style, and thus help us understand game design. By formalising aspects of the game rules, we define a space of possible rules more precisely than could be done through writing about rules in qualitative terms; and by choosing which aspects of the rules to formalise, we define what aspects of the game are interesting to explore and introduce variation in. In this way, each game generator can be thought of an executable micro-theory of game design, though often a simplified, and sometimes even a caricatured one [22].

6.1 Encoding game rules

To generate game rules, we need some way of *representing* or *encoding* them in a machine-readable format that some software system can work with.[1] An ambitious starting point for a game encoding might be one that can encode game rules *in general*: an open-ended way to represent any possible game. The game generator

[1] There are many other uses for machine-readable game rules, such as for use in game-playing AI competitions [**?**, **?**] and in game-design assistants targeted at human game designers [16, 7]. This chapter focuses on encodings for *generating* rules, but multi-use encodings are often desirable.

would then work on games in this encoding, looking for variants or entirely new games in this space. But such a fully general encoding provides a quite unhelpful starting point. A completely general representation for games cannot say very much specific about games at all. Some kinds of games have turns, but some don't. Some games are primarily about graphics and movement, while others take place in an abstract mathematical space. The only fully general encoding of a computer game would be simply a general encoding for all software. Something like "C source code" would suffice, but it produces an extremely *sparse* search space. Although all computer games could in principle be represented in the C programming language, almost all things that can be represented in C's syntax are not in fact games, and indeed many of them are not even working programs, making a generator's job quite difficult.[2]

Instead of having a generator search through the extremely sparse space of all computer programs to find interesting games, a more fruitful starting point is to pick an encoding where the space includes a more dense distribution of things that are games and meet some basic criteria of playability. That way, our generator can spend most of its time attempting to design interesting game variants. Furthermore, it's helpful for game encodings to start with a specific genre. Once we restrict focus to a particular genre, it's possible to abstract meaningful elements common to games in the genre, which the generator can take as given. For example, an encoding for turn-based board games can assume that the game's time advances in alternating discrete turns, that there are pieces on spaces arranged in some configuration, and that play is largely based on moving pieces around. This means the game generator does not have to invent the concept of a "turn", but instead can focus on finding interesting rules for turn-based board games. An encoding for a side-scrolling space shooter would be very different: here the encoding would include continuous time; entities such as terrain, enemies, physics, lives, and spawn points; and events such as shooting, object collision, and scrolling. Of course, the encoding cannot be *too* narrow: at the limit, an encoding that specifies exactly one game (or only a few) is not very interesting for a game-generation system. The most productive point on the spectrum between complete generality and complete specificity is one of the key tradeoffs in designing an encoding for game generators to use: smaller spaces typically are more dense in playable, interesting candidates, but larger spaces may allow for more interesting variation [19].[3]

In addition to being a more fruitful space for game generators to work in, genre-specific encodings also make it easier to produce *playable* games. Whereas a computer could generate purely abstract rule systems, making interesting games that are

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[2] This is not to say generating games encoded as raw programs would be *impossible*: genetic-programming techniques evolve programs encoded in fairly general representations [20], and applying genetic programming to videogame design could produce interesting results. But the techniques in this chapter focus on higher-level representations, which allow the generators to work on more familiar game-design elements rather than on low-level source code.

[3] Some interesting future work lies in modular encodings: instead of choosing a specific genre, a generator might pick and choose a generative space consisting of a combat system, 2d grid movement, an inventory system, etc. [15].

playable by humans requires connecting those abstract rules to concrete audiovisual representations [14]. For example, the abstract notion of a "capture" in board games is often represented by physically removing a piece from the board. The idea of "hidden information" in card games is represented by how players hold their cards, and which cards on the table are face-up versus face down. Concepts such as "health" can be represented in any number of ways, ranging from numerical display of hitpoints or health percentage on the screen, to more indirect methods such as changing a character's color, or even varying the music when a player's health drops below a threshold. Matching generated rules to these concrete representations can be a challenging research problem in itself [17], but working with encodings of specific genres allows us to sidestep the issue, by having a standard concrete representation for the genre being considered.

Finally, using a genre-specific encoding provides a first step towards answering a key question: how do we evaluate what constitutes a good set of game rules? Rather than the extremely general question of what makes a good game, we can take ask what makes a good *two-player board game*, a good *real-time strategy game*, or a good *first-person shooter*. That lets us take advantage of existing genre-specific design knowledge, which is usually better-developed and more amenable to being formalized. Design of new board games may focus on properties such as balance, availability of multiple nontrivial strategies, etc. Criteria for designing a good sidescrolling shooter, meanwhile, may instead focus on the pace of the action, patterns of enemy waves, and the difficulty progression—very different kinds of criteria. When we generate the rules for games using encodings of these well-defined genres, we can use a wide variety of existing design knowledge to made our playability and quality judgments. This allows rule-generating PCG systems to start from the basis of being *domain experts* in a specific genre, to use Khaled *et al.*'s terms for PCG system roles [10].

The two sections that follow describe game-generator experiments that a number of researchers have undertaken in those two domains that have seen the most study: board games, and 2d graphical-logic games.

6.2 Board games

Board games were the first domain in which systems were built to procedurally generate game rules. They have several features that make them a natural place to start. For one, there is a discrete, finite structure to the games that simplifies encoding; unlike computer games, which are defined by an often complex body of code, games like chess are defined by simple sets of rules. Secondly, there is already a culture of inventing board-game variants, so automatic invention of game variants can draw from existing investigations into *manual* generation of game variants, and the design books that have been written about those investigations [6, 2].

6.2.1 Symmetric, chess-like games

The earliest rule-generating system, predating the more recent resurgence in PCG research, was METAGAME [19], which generated "symmetric, chess-like games". The *chess-like* part means that the games take place on a grid, and are structured around two players taking turns moving pieces according to certain rules; these pieces can also be removed from the board in certain circumstances. The *symmetric* part means that the two players start on opposite ends of the board with symmetric starting configurations, and all game rules are identical for each player, just flipped to the other side of the board. For example, if METAGAME invented a chess variant in which pawns could capture sideways, this would always be true for both the black and white player; the space of games METAGAME represents doesn't include asymmetric games where players start with different pieces, or make moves according to differing rules.

The symmetric aspect of the game rules is enforced by construction: only one set of rules is encoded in the generator, and those rules are applied to both players, so any change to an encoded rule automatically changes the rules for both sides. The space of possible rules is encoded in a hierarchical *game grammar* that specifies options for the board layout, how pieces can move, how they can capture, win conditions, and so on. Specific games are generated by simply stochastically sampling from that grammar, and then imposing some checks for basic game playability. Note that this is a constructive rather than a search-based approach; the system does not test the quality of generated games as part of the generation process, and does not search the space of games it can express as much as it randomly samples it. The generator also has a few parameter knobs available, allowing the user to tweak some aspects of what's likely to be generated, such as the average complexity of movement rules.

Pell's motivation for building METAGAME was not game generation itself, but testing AI systems on the problem of general game playing. By the early 1990s, there was a worry that computer chess competitions were causing researchers to produce systems *so* specifically engineered to play chess and only chess, that they might no longer be advancing artificial intelligence in general. Pell proposed that more fundamental advances in AI would be better served by forcing game-playing AI systems to play a wider space of games, where they wouldn't know all the rules in advance, and couldn't hard-code as many details of each specific game [18]. To actually set up such a competition, he needed a way to define a larger space of games, and a generator that could produce specific games from that space, to send to the competing systems. METAGAME was created to provide that more general space of test games, and as a result, also became the first PCG system for game rules.

6.2.2 Balanced board games

While METAGAME generated a fairly wide range of games, the end result was controllable only implicitly: games were not selected for specific properties, but chosen randomly from the game grammar.

One property that is frequently desired in symmetric games is game balance: there shouldn't be a large advantage for one side or the other, such that the outcome is too strongly determined by who starts with the white pieces versus the black pieces. METAGAME produces games that are *often* balanced by virtue of having symmetric rule-sets, which tend to produce balanced gameplay. But a symmetric rule-set does not automatically mean a game will be balanced: moving first can often be a large advantage, or it might even in some cases be a disadvantage. Hom and Marks [9] decided to address the goal of balance directly. They first took a much smaller space of chess variants, to allow the space to be more exhaustively searched. Then, they evaluated candidate games for balance by having computer players play against each other a number of times, and rejected games with simulated win-rates that deviated too far from 50/50.

This process ends up feeding the original motivating application of METAGAME back into the generation of game rules. METAGAME had been designed to test general game-playing agents, which were new at the time. Over the years, a number of research and commercial systems were developed, which could take an arbitrary game encoded in a description language, and attempt to play it. Hom and Marks took one such general game-playing system, Zillions of Games, and set it to play their generated games as a way of evaluating them.

The changes from METAGAME introduced here are fairly general ones which are seen in other PCG systems: the idea of an *evaluation function* to decide what constitutes a good example, and *simulation* as a way of specifying an evaluation function in a complex domain, where it's difficult to specify one directly. Here, simulation is done by the computer playing the game against itself, and the evaluation function is how close its win rate comes to being 50/50 from each side of the board.

6.2.3 Evolutionary game design

The obvious next step is to use this ability to simulate and evaluate general games to guide the automated search for new games. For example, the evaluation function (also known as *fitness function*) can be used to direct the evolution of rule sets, to search for new combinations of mechanics that produce fit, interesting games. This section describes an experiment in evolutionary board game design called LUDI, which produced the first fully computer-invented games to be commercially published [3].

6.2.3.1 Representation

Games are described in the LUDI system as symbolic expressions in simple *ludemic* form (a *ludeme* is a unit of game information). For example, Tic-Tac-Toe is described as follows:

```
(game Tic-Tac-Toe
  (players White Black)
  (board (tiling square i-nbors) (shape square) (size 3 3))
  (end (All win (in-a-row 3)))
)
```

This game is played by two players, White and Black, on a square 3×3 board including diagonals (*i-nbors*), and is won by the first player to form 3-in-a-row of their colour. By default, players take turns placing a piece of their colour on an empty board cell per turn.

The LUDI language is *procedural* rather than *declarative* in nature, being composed of high-level rule concepts rather than low-level machine instructions or logic operations, as per the Stanford GDL. This makes the language less general as every rule must be predefined by the programmer, but has the advantages of simplicity and clarity; most readers should be able to recognise the game described above despite having no prior knowledge of the system. Further, it allows rule sets to be described and manipulated as high-level conceptual units, much as humans conceptualise games when playing and designing them.

6.2.3.2 Evaluation

The LUDI system evaluates a rule set by playing the game against itself over a number of self-play trials. A rule set is deemed to be “fit” in this context if it produces an a non-trivial and interesting contest for the players. The basic approach is similar to that used by Althöfer [1] and Hom and Marks [9], but in this case a much broader range of 57 aesthetic measurements are made, divided into:

- *Intrinsic* criteria based directly on the rule set.
- *Playability* criteria based on the outcomes of the self-play trials.
- *Quality* criteria based on trends in play play.

The intrinsic criteria measure the game at rest directly from its rule set. However, the true nature of a game does not emerge until the game is actually played, so it was not surprising that no intrinsic criteria ultimately proved useful when these criteria were correlated with human player rankings for a suite of test games.

It was found that the playability criteria, based on the game outcomes, provided a useful and robust estimate of the basic playability of a game. Four of these criteria proved particularly good at identifying unfit rule sets, constituting a *playability filter* that formed the first line of defense to quickly weed out games that:

- result in draws more often than not,
- are too unbalanced towards either player,
- have a serious first or second move advantage, or
- are too short or too long on average.

Games that pass the playability filter are then subject to a number of more subtle and time-intensive quality measurements, based on the *lead histories* of the simulated games. The lead history of a game is a record of the difference between the estimated strength of the board position of the eventual winner and the eventual loser at each turn. Such quality measurements are more subtle and less reliable than the playability measurements, but offer the potential to capture a richer snapshot of the player experience.

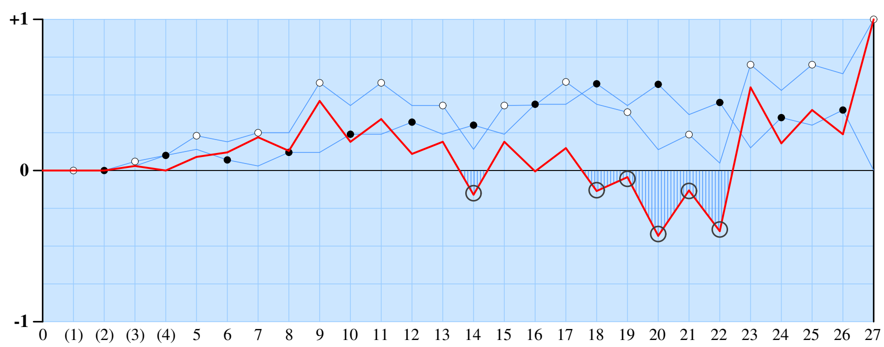

Fig. 6.1: Lead history showing drama in a game.

For example, Figure 6.1 shows the lead history of a game lasting 27 moves. The white and black dots show the players' estimated fortunes, respectively, while the bold line shows the difference between them at each move. This example demonstrates a dramatic game, in which the ultimate winner (White) spends several moves in a relatively negative (losing) position before recovering to win the game. Such *drama* is a key indicator of interesting play that human designers typically strive to achieve when designing board games.

6.2.3.3 Generation

Rule sets are evolved using a *genetic programming* (GP) approach, summarised in Figure 6.2. A population of games is maintained, ordered by fitness, then for each generation a pair of relatively fit parents are selected and mated using standard *crossover* and *mutation* operations to produce a child rule set. The symbolic expressions used to describe games constitute rule trees that are ideal for this purpose.

Each child rule set is checked for correctness according to the LUDI language, playability, performance and similarity to other rule sets in the population. Rule sets

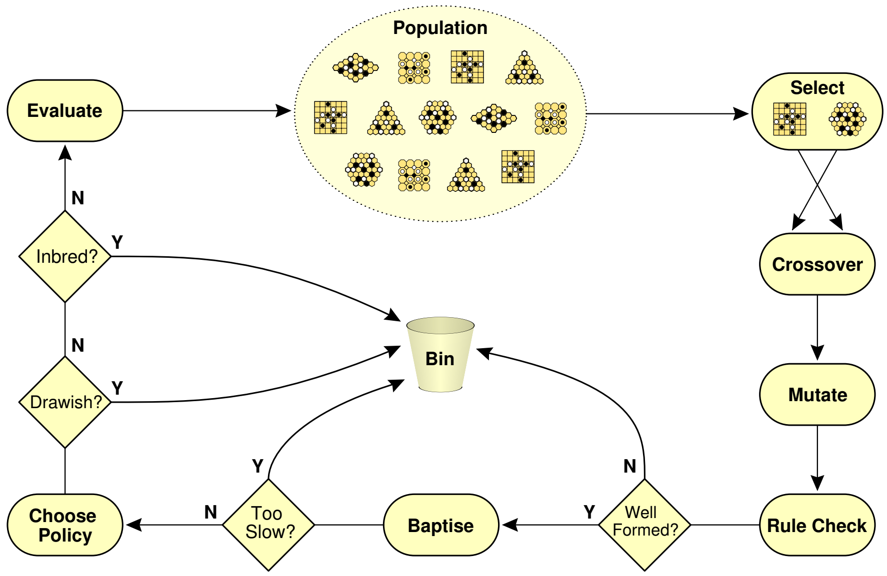

Fig. 6.2: Evolutionary game design process.

that pass these checks are given a unique name, officially making them a game, and are then measured for fitness and added to the population. The name for each game is also generated by the system, based on letter frequencies in a list of Tolkien-style names.

6.2.3.4 Evolved Games

LUDI evolved 1,389 new games over a week, of which 19 where deemed "playable" and two have proven to be of exceptional quality. The best of these, Yavalath, is described below:

```
(game Yavalath
  (players White Black)
  (board (tiling hex) (shape hex) (size 5))
  (end (All win (in-a-row 4)) (All lose (in-a-row 3)))
)
```

Yavalath is similar to Tic-Tac-Toe played on a hexagonal board, except that players win by making 4-in-a-row (or more) of their colour but lose by making 3-in-a-row beforehand. This additional condition may at first seem a redundant afterthought, but players soon discover that it allows some interesting tactical developments in play.

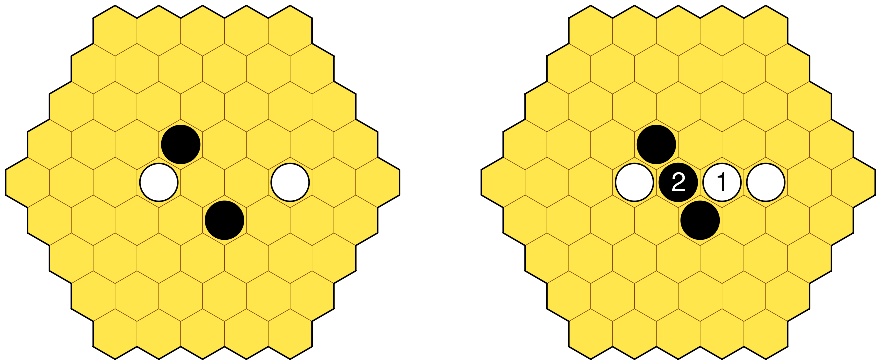

Fig. 6.3: White forces a win in Yavalath.

For example, Figure 6.3 shows a position in which White move **1** forces Black to lose with blocking move **2**. Such forcing moves allow players to dictate their opponent's moves to some extent and set up clever forced sequences. This *emergence* of complex behaviour from such simple rules provides an "aha!" moment that players find quite compelling, and is exactly what is hoped for from an evolutionary search.

The other interesting game evolved by LUDI is called Ndengrod:

```
(game Ndengrod
  (players White Black)
  (board (tiling hex) (shape trapezium) (size 7 7))
  (pieces (Piece All (moves (move
    (pre (empty to)) (action (push)) (post (capture surround))
  ))))
  (end (All win (in-a-row 5)))
)
```

This is also an *n*-in-a-row game—this rule dominated the rule sets of evolved games—but in this case players capture enemy groups that are surrounded to have no freedom, as per Go. This rule set also demonstrates the emergence of interesting and unexpected behaviour, due to an inherent conflict between the "capture surround" and "5-in-a-row" rules, as shown in Figure 6.4.

White squeezes Black against the edge to force a ladder (left), which Black must extent each turn to keep their group alive (middle). However, once the ladder reaches four pieces long after move **5**, then White cannot continue the attack at point *a* but must instead block the line at point *b*, allowing White to escape with move **7**, and the game continues with White piece **6** now under threat.

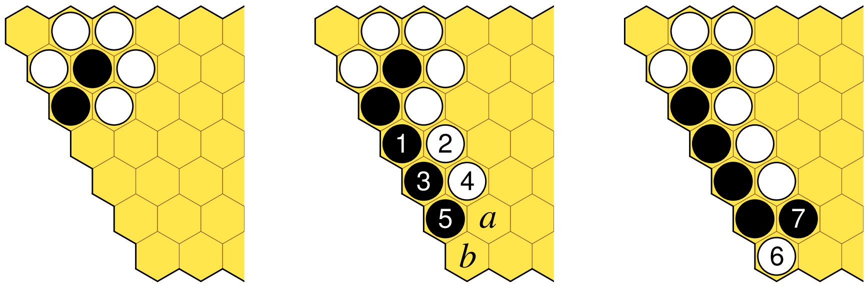

Fig. 6.4: Ladders don't work as planned in Ndengrod.

6.2.3.5 Legacy

Yavalath and Ndengrod (renamed Pentalath) were the first fully computer-invented games to be commercially published. Yavalath was the first game released by Spanish publisher Nestorgames, and continues to be the flagship product in its catalogue of over 100 games.

Ndengrod is actually the better game of the two; it is deeper, involving a complex underlying friction between enclosure and connectivity, and is definitely more of a brain-burner. However, the more complex rules create a higher barrier to entry for beginners, hence it is destined to remain second choice. Conversely, the rules of Yavalath are intuitively obvious to any new player, and it has since been ranked in the top #100 abstract board games ever invented [4].[4]

The successful invention of board games by computer did not cause a backlash from players and designers as expected. The most common response from players is simply that they're surprised that a computer-designed game could be this simple and fun to play, while designers have so far dismissed this automated incursion into the very human art of game design as not much of a threat, as long as it produces such lightweight games. However, this attitude may change as PCG techniques—and their output—becomes increasingly sophisticated and challenges human experts in the field of design as well as play.

One near-miss produced by LUDI, called Lammothm, is worth mentioning to highlight a pitfall of the evolutionary approach. Lammothm is played as per Go (i.e. surround capture on a square grid) except that the aim is to connect opposite sides of the board with a chain of your pieces. Unfortunately, the evolved rule set contained the *i-nbors* attribute, meaning that pieces connect diagonally which all but ruins the game, but if this attribute is removed then the rule set suddenly becomes equivalent to that of Gonnect, one of the very best connection games [2]. LUDI was one mutation away from rediscovering a great game, but the very nature of the evolutionary process means that this mutation is not guaranteed to ever be tried for this rule set. It is possible alternative approaches with stronger inherent local search, including *Monte Carlo tree search* (MCTS), can help address this issue.

[4] BoardGameGeek database, October 2010 (http://www.boardgamegeek.com).

6.2.4 Card games

Traditional card games – Poker, Uno, Blackjack, Canasta, Bridge etc. – have many features in common with board games. In particular, they are turn-based and and deal in discrete units (cards) which are in limited supply and can exist at any of a limited number of positions (player hands, piles etc). They have also some features that distinguish them from most board games, including not typically relying on a board and the often central importance of imperfect information (a player does not know which cards their opponents have). The limited ontology and relative easy of automated playing (due to limited branching factor) make the domain of card games appealing for research in game generation.

Font et al developed a description language for card games and attempted to generate card games using evolutionary search in the space defined by this language [8]. The language was defined so as to include thee well-known card games – Texas Hold'em Poker, Uno and Blackjack – and implicitly games positioned between these in game space. Initial attempts to evolve new card games in this language were made, but it was discovered that unexpectedly many of the generated games were unplayable. Efforts continue to refine the language and evaluation functions to direct the search towards playable games.

6.3 Graphical games

In the last few years, a small number of researchers have worked on representing and generating simple 2d graphical-logic games. By *2d graphical-logic games* we mean those games in which gameplay is based on 2d elements moving around, colliding with each other, appearing and disappearing, and the like.[5] While 2d elements moving around and colliding with each other constitutes a rather simple set of primitives out of which to build game rules, a quite large range of games can be built out of them, including such classics as *Pong*, *Pac-Man*, *Space Invaders*, *Missile Command*, and *Tetris*. These games have a different set of properties from those typically seen in board games. They are usually characterised by featuring more complex game-agent or agent-agent interaction that could easily be handled by human calculation in a board game, including semi-continuous positioning, timesteps that advance much faster than board-game turns, multiple moving NPCs, hidden state, and physics-based movement that continues even without player input. Many such games feature an avatar which the player assumes the role of and controls more or less directly, rather than selecting pieces from a board: the player "is" the Pac-Man in *Pac-Man*, which adds a new layer of interpretation [**?**] and experiential feeling to such games, and in turn a new axis of opportunity and challenge for rule generators.

[5] We borrow the term from Wardrip-Fruin [**?**].

6.3.1 "Automatic Game Design": Pac-Man-like grid-world games

In a 2008 paper, Togelius and Schmidhuber describe a search-based method for generating simple two-dimensional computer games [23]. The design principles of this system was that it should be able to represent a simplified discrete version of Pac-Man, that other games should be easy to find through simple mutations, and that the descriptions should be compact and human-readable.

The games that this system can represent all take place on a grid with dimensions 15×15 (see figure **??**). The grid has free space and walls, and never changes; see figure [**?**]. On the grid, there is a player agent (represented in cyan in the screenshot) and *things* of three different colours (red, blue and green). Whether the things are enemies, food, helpers etc is up to the rules to define. The player agent and the things can move in discrete steps of one grid cell up, down, left or right. Each game runs for a certain number of time steps, and is won if the player reaches a score equal to or above a score threshold.

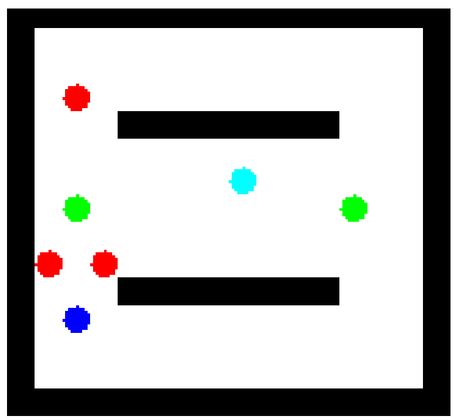

Fig. 6.5: The Automatic Game Design system by Togelius and Schmidhuger.

Representation: The game representation consists of a few variables and two matrices. The variables define the length of the game, the score limit, and the number of things of each colour. They also define the movement pattern of each colour. All things of a particular colour move in the same way, and the available movement patterns are standing still, moving randomly with frequent direction changes, moving randomly with infrequent direction changes, moving clockwise along walls and moving counterclockwise along walls. The first of the the two matrices determines the collision effects of collisions between things, and between things and the agent. There is a cell for each combination of thing colours, and a cell for the combination of each colour with the player agent. The possible effects are that nothing happens, one or both things die, or one or both things teleport to a random location. For example, the matrix could specify that when a blue and a red thing collide, the blue thing dies and the red thing teleports. The other matrix is the score effects matrix. It has the same structure as the collision effects matrix, but the cells instead contain negative or positive changes to the score; for example, the player agent colliding with a blue thing might mean a score increment.

Evaluation: In the experiments described in the paper, the aim was to make games that were *learnable*. The motivation for this is the theory, introduced in various forms by psychologists such as Piaget and game designers such as Koster, that playing is learning and that a large part of the fun in games comes from learning to play them better [**?**, 11]. Translated to an evaluation function for game rules, the evaluation should reward games that are hard initially, but which are possible to rapidly learn to play better. Under the assumption that learnability for a machine somehow reflects learnability for a human, the evaluation function uses an evolutionary learning mechanism to learn to play games. Games that are possible to win for random players receive low fitness, whereas games that can be learnt (where the agent increases score as much as possible) to play receive high fitness.

6.3.2 Sculpting rule spaces: **Variations Forever**

All of the possible games that can be specified in a particular rule encoding make up a *generative space* of games. We've just looked at one way to explore a generative space of games and pick out interesting games from the large sea of uninteresting or even unplayable games. If we define an evaluation function to rate games from the space, we can use evolutionary computation to find games that rate highly. A different approach is to carve out interesting subsets of the space, not by rating each individual game, but by specifying properties that we want games to have, or want games to avoid. This leaves a smaller generative space with only games that satisfy the desired properties; iterative refinement can then let us zoom in on interesting areas of the generative space.

Variations Forever [21] is a game-generator turned into a game, built with Answer Set Programming (ASP, see Chapter 8). In this game, the player explores different variations of game rules through playing games. The ontology and rule space is similar to but expanded compared to the rule space used in the Togelius and Schmidhuber experiment above. The games all contain things moving in a two-dimensional space, and the bulk of rules are defined by the graphical-logic effects of various types of interactions between the moving and stationary elements. However, the search mechanic is radically different. Instead of searching for rulesets that score highly on certain evaluation functions, the constraint solver finds rulesets where certain constraints are satisfied. Examples of constraints on the ruleset include: it should be possible to win the game by pushing a red thing onto a yellow thing, or it should not be possible to lose all blue things in the game while there are still green things. These constraints are specified by the game designer, and different choices of constraints will produce larger or smaller sets of games, with different properties. The player then gets a specific game randomly chosen from that constrained space (and then another one, and then another one), and part of the game is for them to try to figure out how the rules work, and what's in common between each successive game.

The aim of *Variations Forever* is not to produce a specific game deemed to be good, but to provide a way for game designers to define and "sculpt" generative spaces of games, where games can be included in or excluded from the space based on specific criteria. Players then in turn explore these designer-carved generative spaces, seeing a series of games that differ in specifics but all share the specified properties.

6.3.3 Angelina

Angelina is an ongoing project by Cook and Colton to create a complete system for automatically generating novel videogames. The system has gone through several iterations, each focusing on developing a different kind of game. In the first iteration, the focus was on discrete arcade-style 2D games, and the encoding system was along the lines of the Togelius and Schmidhuber experiment above [5]. The main change is that rather than keeping the map fixed and placing the agent randomly, Angelina sees the ruleset, the map, and the initial placement as three separate entities, and evolves all three of them using a form of cooperative coevolution. This means that each different design element is evaluated partly in isolation, according to objectives which are independent of the rest of the game. However, these individual elements are also combined into full games, which are then evaluated through automated playouts to assess how well the different elements cooperate with one another. For example, a level design might be individually fit by exhibiting a certain amount of branching or dead-ends, but be a bad fit for an object layout because it places walls over the start point for the player.

Representation: The representation of rules and mechanics in Angelina has changed through the different iterations of the software, in an attempt to increase the expressivity of the system and remove constraints on its exploration of the design space. In the first iteration of Angelina rules are composed out of a grammar-like representation of rule chunks, which produces good sets of rules, but is very dependent on the grammar it starts with. This is in turn dependent on the human that wrote the grammar. For Angelina, this is important because the research is partly motivated by questions of computational creativity. It's a good idea to think about issues like this when building a procedural content generator, however—if we want our systems to create things that are surprising and new, things that we could not have thought of ourselves, then it helps to consider whether our representation is constraining our systems with too many of our own preconceptions. Deciding how general or how specific your representation needs to be is a very important step in designing a generator of this kind.

To provide Angelina with more responsibility in designing the game's mechanics and rules, the second iteration of the software provided a less discrete domain for Angelina to explore. This version was focused on the design of simple Metroidvania-style platform games, where players incrementally gain powers that allow them to explore new areas of the world. Powerups are scattered through the game which change the value of one of a few hand-chosen variables in the game engine—such as the player's jump height, or the state of locked doors. The precise value associated with a given powerup was evolved as a design element in the co-evolutionary system of this version of Angelina. This meant that Angelina could make fine-grained distinctions between the player's jump height being 120 pixels or 121 pixels, which in some cases was the difference between making the player suddenly able to access the entire game world, or carefully allowing access to a small part that would provide a more natural game progression.

This notion of game mechanics as data modifiers was carried through to the next iteration of Angelina, which took the idea a step further and opened up the codebase of the underlying game engine to Angelina. This time, instead of being given a fixed set of obvious variables to choose from, Angelina was responsible for choosing both the target value *and* the target variable, out of all the variables hidden away in the entire game's code. Below is an example 'mechanic' designed by the system. It finds the `acceleration` variable in the `player` object, and inverts the sign on its `y` component.

```
player.acceleration.y *= -1
```

In the Java-based game engine Flixel-GDX[6], which Angelina uses, this is equivalent to inverting the gravitational pull on an object, similar to the gravity-flipping mechanic in Terry Cavanagh's *VVVVVV* [**?**]. To generate this, Angelina searched through available data fields within a sample game, and generated a type-specific modifier for it (in this case, multiplying by a negative number). This exploration of a codebase was made possible by using Java's Reflection API—a metaprogramming library that allows for the inspection, modification and execution of code at runtime. Code generation and modification is a risky business, in general—the state space can very quickly become too large to explore in any reasonable timeframe, and modifying code at runtime is similarly perilous, particularly when done in using something so potentially destructive as evolutionary computation.

The approach used in Angelina tries to mitigate these problems in two ways: firstly, using Java as a basis for the system means that it has robust error handling. Generating and executing arbitrary code is liable to throw every kind of error imaginable. A typical run of Angelina will throw `OutOfMemoryExceptions` (by modifying data which triggers an infinite loop), `ArrayIndexExceptions` (by modifying variables which act as indexes into data structures) and `ArithmeticExceptions` (by modifying variables used in calculations, causing problems like division by zero). However, none of these errors cause the top-level execution of Angelina to fail. Instead, they can be caught as runtime errors, and suppressed. The mechanic which caused these errors is given a low or zero fitness score, and the system then proceeds to test the next mechanic.

[6] http://www.flixel-gdx.com

The next and most important way that Angelina's design overcomes issues with code generation is the evaluation criteria used to assess whether a mechanic is good or not. Figure 6.6 shows the outline for a simple level from a Mario-like platform game. The player starts the level in the red square on the left, and can run and jump. The aim is to reach the blue square on the right. We can verify that this level is unsolvable for a given jump height—the player is simply unable to scale the wall in the center of the level. This is the game configuration that Angelina begins with when evaluating a new game mechanic. The system can then add this new game mechanic to the game's codebase, and try to solve the level by reaching the exit. If Angelina is able to make progress and get to the exit, since we know the level was previously unsolvable and only the mechanic has been added we can conclude that the mechanic adds some affordance which we did not previously have. In other words, it provides some *utility* for the player.

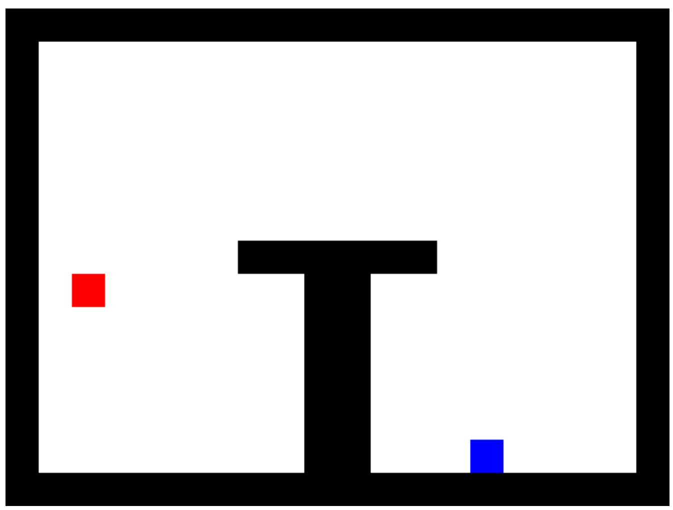

Fig. 6.6: A test level used by Angelina to evaluate generated game mechanics. The player starts in the red square on the left-hand side. They must reach the blue square on the right.

This constraint-like evaluation approach (either the simulation reaches the exit, or it does not) is helpful in directing search through this kind of unpredictable state space. There are a few things to note about this kind of evaluation, however. Firstly, because we are generating arbitrary code modifiers, we can't give Angelina any heuristics to help it test the mechanic out. We have no idea whether a given mechanic will affect the player, enemies, the level geometry, the physics system, or whether it will outright crash the game. This means that Angelina's approach to simulating gameplay with the new mechanic is to attempt a breadth-first exhaustive simulation of gameplay. While this is almost tenable for a small example level and a restrictive move set (left, right, jump and 'special mechanic'), it's hard to imagine expanding this to a game with the complexity and scale of *Skyrim*, for example, or even *Spelunky*.

The other thing to bear in mind is that how useful a mechanic is does not necessarily relate to whether it is a good idea or not. We could imagine a very useful mechanic which automatically teleports the player to the exit, but which trivialises the rest of the game's systems entirely. Similarly, many game mechanics are specifically designed to balance utility with risk (enchanting items in *Torchlight* might result in the item being destroyed, for example) or simply exist to entertain the player. This last category is very important—mechanics such as the infinite parachute in *Just Cause 2* certainly add utility to the player's mechanical toolkit, but is clearly designed to be enjoyable to interact with. Feelings like flow, tactility or immersion are difficult quantify at the best of times, and are certainly not captured by the extremely utilitarian approach taken by Angelina.

Despite these shortcomings, the use of code as a domain for procedural content generation is exciting, and holds much promise. Angelina was able to rediscover many popular game mechanics, such as gravity inversion (as seen in *VVVVVV*), and bouncing (as seen in *NightSky* [**?**]). The purely simulation-based approach also enabled Angelina to discover obscure and nuanced emergent effects in the generated code. In one case, Angelina developed a mechanic for simple teleportation, in which the player is moved a fixed amount in a particular direction when a button is pressed. This mechanic can be used for bypassing walls, but Angelina's breadth-first simulation of gameplay also discovered that by teleporting inside a wall, it was possible to jump up out of the wall, teleport back inside, and repeat the process. This technique could be used to wall-climb—even though the game had no code relating to this feature—all made possible by a single line of code modified by Angelina.

Evaluating Angelina as an autonomous game designer has proven difficult for a number of reasons. During the development of Angelina many of the games features are still static and coded by hand, such as the control schemes or (in earlier versions of the software) the game's artwork. Focusing player surveys on the aspects of games which change is difficult. Comparative testing is also difficult when the expressive range of the software is as low as it has been in some versions of Angelina. The output of the system varies within a small subgenre which means it is difficult to make strong value judgements on whether one game is better than another, particularly mechanically. However, survey-based studies might still be the best way of getting meaningful information about the system's performance.

6.3.4 The Video Game Description Language

The Video Game Description Language (VGDL) is an effort to create a generic and flexible but compact description language for video games of the types that were seen on early home game consoles such as the Atari 2600. In this sense, it is a direct follow-up to the efforts described above (in particular Togelius and Schmidhuber), and its conceptual structure is similar. However, it is intended to be more general in that can encode a larger range of games, and more flexible in that it decouples the description language from the game engine, the game evaluation metrics, and the generation method.

The basic design of VGDL was outlined in [**?**], and a first implementation of a working game engine for the language (together with several improvements to the design) was published in [**?**]. One of the design goals for VGDL is to be usable for "general video game playing" competitions, where learning artificial intelligence agents are tested on their capacity to play a number of games which neither the agent or the designer of the agent has seen before [**?**]. These games could be manually or automatically generated, and for the idea to be viable in the long run automatic game generation will need to be implemented at some point. The language is thus designed with ease of automatic generation in mind, though the initial stages of development have rather focused on re-implementing a range of classic games in VGDL to show the viability of doing this and test the limits of the game engine. A first iteration of the General Video Game Playing Competition **??** was run in 2014. This competition tests submitted agents against several unseen games defined in VGDL, and uses a Java-based implementation of VGDL game engine. For future iterations, there are plans to use generated games to test agents, and to include competition tracks focused on game generation and on level generation.

A VGDL game is written in a syntax derived from Python, and is therefore relatively readable. There are four parts to a VGDL game: level mapping, sprite set, interaction set and termination set. In addition, there are level descriptions for an arbitrary positive number of levels. A level description describes a level for the game as two-dimensional matrix of standard ASCII characters, where the level mapping defines which character maps to which type of sprite. The sprite set defines what types of sprites there are in the game and their movement behaviour, for example wall (stands still), guard robot (moves around the walls) and missile (chases the avatar). A special case is the player avatar, which the player controls directly. All sprites can obey different types of physics, such as grid-based movement or continuous movement with or without gravity. The interaction set defines most of what we call operational rules in the game, as it describes what happens when two sprites collide—similarly to the previous graphical game description efforts above, the list of possible interaction effects include death, teleportation, score increase or decrease and several others. The termination set describes various ways of ending the game, such as all sprites of a particular type disappearing, a particular sprite colliding with another etc.

6.3.5 Rulearn: Mixed-initiative game level creation

All the game generators described above have been non-interactive content generators, in that they generate a complete ruleset without human contribution. The Rulearn system by Togelius instead tries to realise interactive generation of game rules [**?**]. The system starts with the player controlling an agent obeying simple car physics in a 2D space containing agents of three other colours, moving randomly. Collisions will happen, but have no consequences. The player is also given an array of buttons which will effect consequences, such as “kill red”, “increase score”, “chase blue” and “split green”. Every time the player presses a button, that consequence will happen. However, the system will also try to figure out why the player pressed that button. Using machine learning methods on the whole history of past actions, the system will try to figure out which game the player is playing, and induce the rules behind it. The result is a mixed-initiative system for game rules, which in early test has proved far from easy to use.

6.3.6 Strategy games

In a series of papers, Mahlmann et al. have described the evolution a system for generating key parts of strategy games. Strategy games are games, typically adversarial and themed on military conflict, where the player manages resources and moves units (representing e.g tanks, soldiers and planes) around on a board. Examples include the *Civilization* series, *Advance Wars* and *Europa Universalis*; this genre of games is closely related to real-time strategy games such as *Dune II* and *StarCraft*, except for being turn-based. They share characteristics with both traditional board games, such as typically being turn-based and playing out on a discrete board/map, and with graphical games in the relatively complex interactions between units and in the world, more complex than would be comfortably simulated in a non-digital games.

In order to be able to generate strategy games, Mahlmann et al. developed a description language for such games, aptly called the Strategy Game Description Language (SGDL). They also developed a game engine that allows a human or a computer player to play any game described in this language. In a series of experiments, different parts of strategy games represented in this language were evolved using genetic programming. In initial experiments, the focus was on evolving how much damage each type of unit could inflict on the others in a simple strategy game with the aim of creating balanced sets of units [12]. In a later set of experiments, the complete logics for the strategy game units were evolved, with the goal of finding sets of units of balanced strengths but which were functionally different between players [13]. In these experiments several new strategy game mechanics (previously unseen to the experimenters) emerged from the experiments, including units that modified the shooting range of other units based on their proximity.

6.3.7 The future: Better languages? Better games? 3D games?

As we can see, all existing work on generating graphical game has targeted games in the style of classic arcade games and home console games from the early 80's, or simple arcade games. There is still considerable work to be done here, and nobody has yet constructed a system that could generate novel graphical games of high quality, comparable to the novel high-quality board games produced by Cameron Browne's Ludi system. One of the really important open questions is how to best balance expressivity of the game description language with locality of search and density of good games; we want a representation which can represent truly novel games, but we also want that representation to be searchable. However, there is also considerable opportunities in developing game description languages that can effectively and economically describe other types of games, and game generators that take into account the specific game design affordances and challenges that come with such games. For example, what would it take to generate playable, interesting and original FPS games?

6.4 Exercise: VGDL

The main theme of this chapter has been that generating rules heavily depends on how we encode rules for a particular kind of game, since these encodings define a space of games. The Video Game Description Language (VGDL) provides a fairly straightforward encoding for a set of graphical-logic games, allowing for some variation in gameplay styles, without going all the way to the intractable complexity of trying to encode every possible kind of game. In addition, it includes an interpreter and simulator in Python (pyVGDL) and another in Java (jVGDL), so that games produced in the encoding can easily be played.

This exercise is in two parts, with an open research question suggested as an optional third.

Part 1: Understanding a VGDL game. Download pyVGDL[7] or jVGDL[8]. Both packages come with a number of example games in the *examples* directory. Choose a game, and understand its encoding. You may do this by first playing it, and trying to figure out what its rules are. Then look at the rules as they're encoded in its definition file: are they the rules you figured out? Were there other rules you didn't notice? Play it again, this time with the rules in mind. Go back and forth between the written rules and the gameplay experience until you're confident you understand what happens in the game, and how that relates to what's written in the VGDL definition.

Part 2: Write a new game in VGDL. Choose a graphical-logic game suitable for representation using VGDL's vocabulary. (Many traditional arcade games of the

[7] https://github.com/schaul/py-vgdl

[8] https://github.com/EssexUniversityMCTS/gvgai

Atari 2600 era or early Nintendo or Commodore 64 era are in their essence implementable in VGDL.) Which are the objects in the game, and which rules specify the game's mechanics? You may want to start by first listing these on paper in natural language, and then figuring out how to encode them in VGDL. You may make up your own game, or choose an existing arcade-style game to translate to VGDL.

Part 3 (optional): Write a generator for VGDL games. As of this writing, no generator that produces VGDL games as output exists. How would one work?

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Chapter 7
Planning with applications to quests and story (DRAFT)

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Games often have storylines. In some games, they are short backstories, serving to set up the action. The first-person shooter game *Doom*'s storyline, about a military science experiment that accidentally opens a portal to hell, is perhaps the canonical example of this kind of story: its main purpose is to set the mood and general theme of the game, and motivate why the player is navigating levels and shooting demons. The level progression and game mechanics have very little to do with the storyline after the game starts. In other games, the storyline structures the progression of the game more pervasively, providing a narrative arc within which the gameplay takes place. The *Final Fantasy* games are a prominent representative of this style of game storyline.

Since the theme of this book is to procedurally generate anything that goes into a game, it will not surprise the reader that we will now look at procedurally generating game storylines. As with procedural generation of game rules, discussed in the previous chapter, procedural generation of storylines is somewhat different from generation of other kinds of procedural *content*, because storylines are an unusual kind of content. They often intertwine pervasively with gameplay, and their role in a game can depend heavily on a game's genre and mechanics.

A common way of integrating a game's storyline with its gameplay, especially in adventure games and role-playing games, is the *quest* [24, 1]. In a quest, a player is given something to do in the game world, which is usually both motivated by the current state of the storyline, and upon completion will advance it in some way. For example, the player may be tasked with retrieving an item, helping an NPC, defeating a monster, or transporting some goods to another town. Some games (especially RPGs) may be structured as one large quest, broken down into smaller sub-quests that interleave gameplay and story progression.

There are several reasons a game designer might want to procedurally generate game stories, beyond the general arguments for procedural content generation discussed in Chapter 1. One reason is that procedurally generated game worlds can lack meaning or motivation to the player, unless they are tied into the game story by procedurally generating relevant parts of story along with the worlds. As Ashmore and Nitsche [2] argue, "without context and goals, the generated behaviors, graphics, and game spaces run the danger of becoming insubstantial and tedious". A second reason is that proceduralizing quests can make them truly *playable*. Sullivan *et al.* [22] note that computer RPGs often have a particularly degenerate form of quest, "generally structured as a list of tasks or milestones", rather than open-ended goals the player can creatively satisfy. Table-top RPGs have more complex and open-ended quests, since in those games, quests can be dynamically generated and adapted during gameplay by the human game-master, rather than being prewritten. Procedural quest generation gives a way to bring that flexibility back into videogame quests.

7.1 Procedural story generation via planning

One way to think about procedurally generating stories is to consider them to be a *planning* problem. In artificial intelligence, planning algorithms search for sequences of actions that satisfy a goal. A robot, for example, plans out the series of actuator movements necessary to pick up an object and carry it somewhere.

What are the sequences of actions for a story, and what is the goal? There are a number of ways to answer those questions, and researchers on procedural story generation started looking at them in the 1970s—at the time, generating purely text-based short stories, not game stories.

We could answer that a story is a sequence of events in a story world (in our case, a game world)—a sequence that eventually leads, through the chain of events, to the story's ending. Therefore we generate stories by simulating a fictional work: to tell a story, we first simulate what happens as characters move around and take actions in the story world, and then the story is comprised of simply recounting the events that happened. One of the first influential story-generation systems, *Tale-Spin* [14], takes this approach.

Generating stories by simulating a story world does have some shortcomings. It does not take into account what makes a *story*—particularly an interesting story—different from simply a log of events. Stories are carefully crafted by authors to have a certain pace, dramatic tension, foreshadowing, a narrative arc, etc., whereas a simulation of a day in the life of a virtual character does not necessarily have any of these features of a good story, except by accident. To solve that problem, we can look at the story-planning problem from the perspective of an author writing the story, rather than from the perspective of a protagonist taking actions in the story world. Story planning then becomes a problem of putting together a narrative sequence that fits the *author's* goals [6]. *Universe* [12] and *Minstrel* [26] are two well-known story generators that take this author-oriented approach.

For videogame stories, planning from the perspective of an author can become a more problematic concept, because players act in the game's story world, rather than in the author's head. Procedurally generating stories using an approach more like *Tale-Spin*, that takes place within the story world, can be more straightforward, since it has the advantage of talking about the same place and events that the player will be interacting with. On the other hand, we may still want a narrative arc and other author-level goals, which may lead to hybrid systems that plan author-level goals on top of story-world events [13, 19]. Many questions remain open, so procedural story generation in games is an active area of research.

In the rest of this chapter, we'll introduce the concepts and algorithms behind story planning, and walk through examples of using planning to generate interactive stories.

7.2 Planning as search through plan space

Planning can be viewed a process that searches through a space of potential solutions to find a solution to a given problem, when knowledge about the problem domain is given. The problem is called a *planning problem* and consists of the *goal state* and the *initial state*. A solution in planning is called a plan which contains a sequence of actions. A plan is *sound* if it reaches the goal state starting from the initial state when executed. The *domain knowledge* is represented as a library of *plan operators* where each operator consists of a set of *preconditions* and a set of *effects*. Preconditions are just those conditions that must be established for the operator to be executed and effects are just those conditions that are updated by the execution of the plan operator.

A space of potential solutions can be represented in two different ways: either as a state space or as a plan space. A *state space* can in turn be represented as a tree that consists of nodes and arcs where a node represents a state and an arc represents a state transition by the application of an operator. The root node of the space represents the initial state when the algorithm is forward progression search while the root node represents the goal state when the algorithm is backward regression search.

Here is the pseudo-code description of a state space algorithm:

```
1: construct the root node as the initial state
2: select a non-terminal node
    if non-terminal nodes are not found, return failure and exit
    if the goal state is true, return the path from the initial state
        up to the current node as a solution and exit
3: select an operator applicable
(its preconditions are true in forward progression search and
its effects are true in backward regression search)
    if no such operators are found, mark the node as terminal
        and go to step 2
4: construct child nodes by applying the operator
    if the number nodes in the graph exceeds a predefined
       maximum search nodes, return failure and exit
5. go to step 2
```

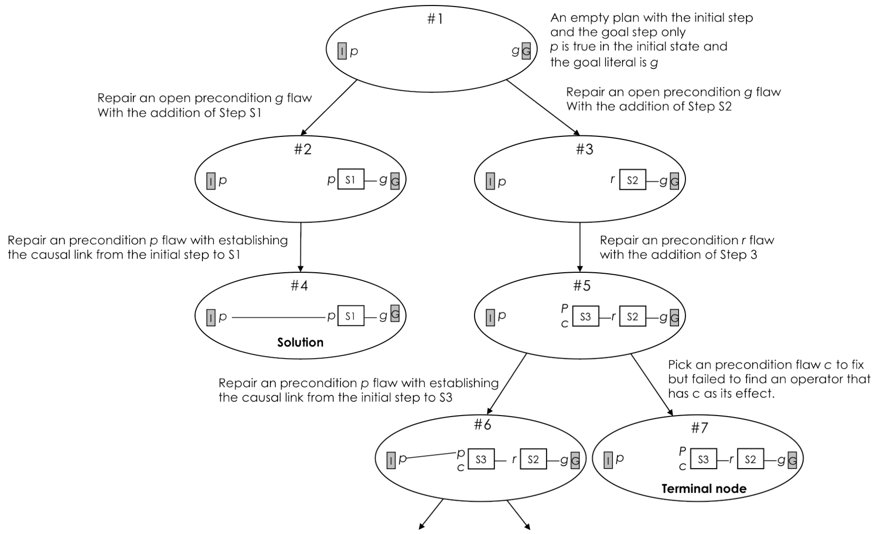

Fig. 7.1: A plan space graph. A box represents an event. A literal on the left side of the box denotes a precondition and a literal on the right side denotes an effect. An effect is omitted if it establishes a causal relationship to a precondition of another event. The root node #1 represents an empty plan that contains the initial and the goal step only. The initial state contains p as an effect and the goal step contains g as its precondition. Each arc between two nodes indicates a refinement of the parent node into a child node. The nodes #2 and #3 are partial plans that repairs the open precondition g by adding two different plan steps $S1$ and $S2$. The node #4 is a complete plan repairing an open precondition p by establishing a causal link from the initial step. The planning algorithm can return the node as a solution and exit. To find all the solutions, the refinement search process continues to generate more children (#5, #6, #7). Although the node #7 is not a complete plan, the algorithm mark this as terminal since no operators that are applicable to repair the open precondition c are found. The further search process to refine the node #6 is omitted due to space limit.

A *plan space* can be represented as a tree which consists of nodes and arcs. Unlike a state space, however, the root node of the tree specifies the planning problem, the initial state and the goal state. Each leaf node represents a *complete plan* (i.e., solution) which can achieve the goal state from a given initial state when being executed or a partial plan that cannot be refined any more due to inconsistencies in the plan. Internal nodes represent *partial plans* that contain flaws. The search process can be viewed as refining the parent node into a plan that fixes a flaw of the parent node [10]. A *flaw* in the plan can be an *open precondition* that has not been established by a prior plan step or a *threat* that can undone an established causal relationship in the plan.

Here is the pseudo-code description of a partial-order planning algorithm.

```
1: construct the root node as the planning problem
2: select a non-terminal node (based on its heuristic value)
3: select a flaw in the node
    if no flaw is found, return the node as a solution and exit
4: construct children nodes by repairing the flaw
   if the flaw is an open precondition, either
       a) establishes a causal link from an existing plan step, or
       b) adds a new plan step whose effects establish the precondition
   if the flaw is a threat, either
       a) add a temporal ordering constraint
          so that the threatened causal link is not intervened, or
      b) add a binding constraint to separate the threatening step
          from the steps involved in the threatened causal link.
   if the flaw is not repairable, mark the node as terminal
        and go to 2
   if the number nodes in the graph exceeds a predefined
       maximum search nodes, return failure and exit
5. go to step 2
```

The complete plans generated by state-space search algorithm are *total-order plans*. A *total-order plan* structure specifies the temporal ordering constraint of every step in the plan while a *partial-order plan* specifies only those temporal orderings that must be established to resolve threats. For instance, imagine that you are given the goal of purchasing milk and bread in a grocery store. The goal can be successfully fulfilled without being worried about which one should be purchased first. And yet, a total-order plan specifies the order of these two purchasing actions and generates two plans: a) to purchase milk first and to purchase bread, and b) to purchase bread first and to purchase milk. On the other hand, a partial-order plan does not specify the ordering constraint and defers the decision until when it is necessary.

In a plan-space search, the search process can be guided by a *heuristic function* which estimates the length of the optimal complete plan, based on the number of the plan steps and the number of the flaws that the current plan contains.

While both state-space search and plan-space search algorithms have advantages, plan-space search planners have been favored in creating stories, because their representations are similar to the mental structure that humans construct when reading a story [25] and their search processes resemble the way humans reason to find a solution [17]. Furthermore, the causal relationships encoded in the plan structure allow further investigation of computational models of narrative, such as story summarization and affect creation [3, 5]. However, Partial-Order Planning (POP) is computationally expensive because its space exponentially grows as the length of the plan increases. Therefore, it has not been used in practical applications.

Hierarchical Task Network (HTN) [21, 23] is a simple plan-space search that recursively replaces non-primitive actions into primitive actions. Figure 7.2 shows HTN *action schemas* that decompose abstract tasks into primitive tasks.

A simple HTN algorithm is described below. HTN is relevant to generate a story via generating character behaviors.

```
1: construct the root node with an abstract operator
2: select an abstract operator to expand
```

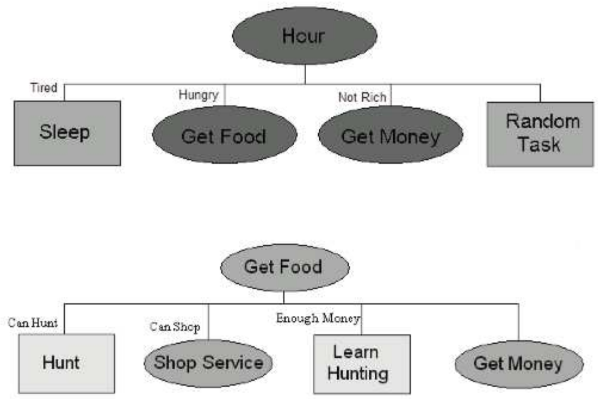

Fig. 7.2: The diagram shows an HTN action schema example where an oval denotes an abstract operator and a rectangle denotes a primitive operator. The method encodes an NPC's activity which can be done for the duration of an hour in the game world. The NPC can sleep if tired or perform a random task. He may want to *get food* if he is hungry. *Get Food* is an abstract task that needs to be decomposed into primitive tasks such as *Hunt* and *Learning Hunting*. [11]

```
    if no abstract operators are found and
       all the preconditions are satisfied,
       return the network as a solution and exit
3: select an action schema whose preconditions are true
    if no such methods are found, return failure
4: decompose the abstract operator into sub-tasks
     as encoded in the action schema
5. go to step 2
```

7.3 Domain Model

A *domain model* is the library of plan operator templates that encode knowledge in a particular domain (in this chapter, a story world). Various formal languages have been proposed to describe planning problems in terms of states, actions, and goals. This section focuses on two planning languages, STRIPS and ADL, which have been widely used for classical planners.

Before we get to the formalism, let us take an example. Imagine that a character in a story, named Alex, is on the rooftop of a building. His goal is to be on the ground level of the building without being injured. Alex can think of several plans immediately. For instance, Alex can take a lift (Plan 1), can walk the stairs (Plan 2), or can jump from the roof (Plan 3). Making the decision will consider a variety of constraints such as his capability (e.g., Alex could be an old man having some mobility problems), the building's facility (e.g., lift), his preference (e.g., Alex always prefers walking down the stairs for exercise), etc. If the building has a lift and Alex wants to go to the ground level quickly, Plan 1 would be suitable. Alex may choose Plan 2 if there is no lift in the building. Alex may take Plan 3 if he has a parachute with him and a serial killer with knife is running toward him. As explained above, the goal of planning, often provided with limited resources, is to find a possibly optimal solution that minimizes the cost of executing the plan considering various conditions and preference. Thus, it is important to select a formal language that best expresses the problem domain.

7.3.1 STRIPS-style planning representation

STRIPS, introduced by Fikes and Nilson in 1971 [7], is in many ways a forefather of modern formal languages in planning. In STRIPS-style, a state is represented by either a *propositional literal* or *first-order literal* where literals are ground (i.e., variable-free) and function-free. A propositional literal states a proposition which can be true or false (e.g., p, q, $PoorButler$). A first-order logic literal consists of a relation and objects (e.g., $At(Butler, House)$, $Lord(Higginbotham)$). In STRIPS-style representation, we make a *closed-world assumption* — any conditions that are not explicitly specified are considered as false. Thus only positive literals are used for the description of initial states, goal states, and preconditions. The effects of actions may include negative literals to assure the negativity of particular conditions. An exemplary planning representation of the previous example using STRIPS-style formalization is as below:

- Initial state representation
  $At(Alex, Rooftop)$ $\wedge$ *Alive(Alex)* $\wedge$ *Walkable (Rooftop, Ground)* $\wedge$ *Person(Alex)* $\wedge$ *Place(Rooftop)* $\wedge$ *Place(Ground)*
- Goal State representation
  At(Alex, Ground) $\wedge$ *Alive(Alex)*
- Action representation
  Action (WalkStairs (p, from, to))
  PRECONDITION: *At (p, from)* $\wedge$ *Walkable (from, to)* $\wedge$ *Person(p)* $\wedge$ *Place (from)* $\wedge$ *Place (to)*
  EFFECT: $\neg$*At(p, from)* $\wedge$ *At (p, to)*

In the above example, the initial state is represented by the conjunction of six first-order logic predicates. The goal state is represented by the conjunction of the two predicates in the same manner. In the action representation, the action named *WalkStairs* has three variable parameters $(p, from, to)$; the action's preconditions are represented by the conjunction of five predicates; and the action's effects are denoted by the conjunction of two predicates including a negative literal. The action *WalkStairs* will be applicable and executed only when its two preconditions are satisfied. And then after execution, the condition of $At(p, from)$ will be deleted from the current state of the world and the condition of $At(p,to)$ will be added to the current state of the world.

7.3.2 ADL (Action Description Language)

STRIPS is an efficient representation language for modeling states of the world. It can convert, using relatively simple logic description (e.g., a conjunction of positive and function-free literals), the states and actions of a particular domain in the real world into corresponding abstract planning problems. This simplicity, however, can be clear limitations to representing complicated planning problems. Therefore, as an effort to extend the expressiveness of STRIPS, ADL has been introduced as an advanced modification of STRIPS. [16]. Compared to original STRIPS representation, ADL can represent actions and states in a less restrictive way [20, 16]:

- Both positive and negative literals are allowed for the description of states, assuming open-world (that is, any unspecified conditions are considered as unknown).
- Quantified variables and the combination of conjunction and disjunction are allowed in the goal state description.
- Conditional effects are allowed.
- Equality and non-equality predicates (e.g., (from $\neq$ to)) and type in variable (e.g, (p: Person), (from: Location)) are supported.

An ADL-style planning representation of the previous example is shown below:

- Initial state representation
  At(Alex, Rooftop) $\wedge$ *¬Dead(Alex)* $\wedge$ *Walkable (Rooftop, Ground)* $\wedge$ *Person(Alex)* $\wedge$ *Place(Rooftop)* $\wedge$ *Place(Ground)* $\wedge$ *Wearing(Alex, Parachute)* $\wedge$ *¬Injured(Alex)* $\wedge$ *Thing(Parachute)*
- Goal State representation
  At(Alex, Ground) $\wedge$ *(¬Dead(Alex)* $\vee$ *¬Injured(Alex))*
- Action representation
  Action (WalkStairs (p: Person, from: Place, to: Place))
  PRECONDITION:*At (p, from)* $\wedge$ *(from* $\neq$ *to)* $\wedge$ *(Walkable (from, to))*
  EFFECT: *¬At(p, from)* $\wedge$ *At (p, to)*
  Action (JumpFromRooftop (p: Person, from: Place, to: Place, sth:Thing))
  PRECONDITION: *At (p, from)* $\wedge$ *(from* $\neq$ *to)* $\wedge$ *Emergent(p)*
  EFFECT: *¬At(p, from)* $\wedge$ *At (p, to)* $\wedge$ *(when Wearing(p, Parachute): ¬Dead(p))*

7.4 Planning a Story

A story can be represented as a partial-order plan, a tuple $< S, O, C >$ where

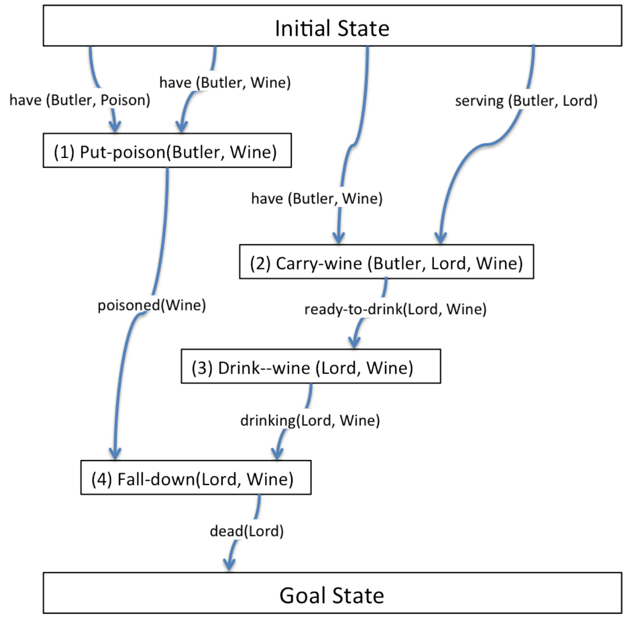

Fig. 7.3: The Butler story. A rectangle denotes an event and an arrow denotes a causal link where the event in the source establishes a condition for the event in the destination. The temporal ordering proceed from the top to the bottom. (The original story is from [4])

- S is a series of events (i.e., instantiated plan operators),
- O is temporal ordering information represented as ($s1$ ¡ $s2$) where $s1$ precedes $s2$,
- C is a list of causal links where a causal link is represented by (s, t; c) notating a plan step s establishes c, a precondition of a step t

Figure 7.3 illustrates a story that consists of four events that fulfills the goal of $dead(Lord)$ starting from the initial state of $have(Butler,Wine) \wedge have(Butler,Poison)$ $\wedge$ $serving(Butler,Lord)$. The textual description of the plan can be read as: (1) Butler puts poison in wine. (2) Butler carries wine to Lord Higginbotham. (3) Lord Higginbotham drinks wine. (4) Lord Higginbotham falls down. (The original story is from [4])

The plan seems to be reasonable as a story. But, is it an optimal plan that has the minimum plan steps? What if the butler gives the poison to the Lord instead? Then, the plan would consist of three steps: 1) The butler carries the poison. 2) The lord drinks the poison. 3) The lord falls down.

As you may have sensed already, the new plan is logically sound but does not make a good story since the lord would not cooperate with the plan if he intends to be alive. This addresses the problem of the *author-centric story generation approach* which may ignore individual character's intention. The alternative approach, *character-centric story generation*, lets every character plan his/her own actions, expecting that some stories emerge from the character interaction. As one can easily imagine, however, a tellable situation rarely arises without the help of authorial goals. To tackle this issue, Riedl and Young have proposed an intent-driven planning algorithm to balance the author-centric approach and character-centric approach to story generation [19].

7.5 Generating Game Worlds and Stories Together

Many computer games engage players through interleaved periods of *story play* and *open-ended play*. Story play encompasses the activities of the players that promote the progression of the game world through a narrative sequence toward a desired conclusion. As laid out in this chapter, a story can be represented as a partially-ordered plan of actions that, when executed, transform the world progressively closer to a desired conclusion, represented by the goal situation. Open-ended play encompasses player activities that do not progress (nor inhibit) the story plan. Examples of open-ended include exploring the spatial environment, encountering random enemies, and finding treasure or items.

This section concerns itself with the generation of playable game experiences including both story play and open-ended play. Players expect to be immersed in a *game world*, a spatial environment encompassing all locations relevant to story play and open-ended play, and inhabited by the player character and all other non-player characters. Both story play and open-ended play are often tied to the spatial environment. Unfortunately, the generation of a story plan generator does not necessarily result in a playable experience without being tied to a spatial environment. In the case that a game world does not exist that suits the purposes of an automatically generated story plan, the game world may be automatically generated.

Table 7.1: Example plan with event locations.

1.	*Take* (paladin, water-bucket, palace)
2.	*Kill* (paladin, baba-yaga, water-bucket, graveyard1)
3.	*Drop* (baba-yaga, ruby-slippers, graveyard1)
4.	*Take* (paladin, shoes, graveyard1)
5.	*Gain-Trust* (paladin, king-alfred, shoes, palace)
6.	*Tell-About* (king-alfred, treasure, treasure-cave, paladin)
7.	*Take* (paladin, treasure, treasure-cave)
8.	*Trap-Closes* (paladin, treasure-cave)
9.	*Solve-Puzzle* (paladin, treasure-cave)
10.	*Trap-Opens* (paladin, treasure-cave)

To motivate the need for game world generation, consider the fully-ordered plan in Table 7.1. The plan involves a player character, the Paladin, performing a series of tasks to gain the King's trust, learn about a treasure cave, and escape a trap. Each action in the plan establishes a number of world conditions necessary for subsequent actions to occur. For example, the Witch will drop her shoes only once dead, and the King will trust the Paladin once he is presented with the shoes of the Witch. A story plan only provides the essential steps to progress toward a goal situation, but does not reason about player activities that do not otherwise impact the progression of the story.

The domain model abstracts away much of the moment to moment activity of the player and NPCs in order to focus on the aspects of the world that are most crucial for story progression. Game play, however, is not always a sequence of discrete operations. For example, solving a puzzle may require many levers to be triggered in the right sequence. For the purposes of this chapter, we will refer to operations in a story plan as *events* to highlight their abstract nature. Events are *temporally extended*; each event can take a continuous duration of time, and there may be large durations of time that take place between events. The plan also does not account for opportunities for open-ended play between events. For example, where is the graveyard relative to the castle, how long does it take to travel that distance, and what might the player see or experience along the way that is not directly relevant to the story plan?

If the game world is a given—i.e., there is a fixed world with a number of locations and NPCs—then there is a mapping of story events in the plan to virtual locations in the game world. For example, the game world for Table 7.1 requires a graveyard, a castle, and a treasure cave. However, due to the nature of automatically generated story plans, it is not always feasible to have a single fixed game world that meets the requirements of a story plan: Locations may be missing, there may be too many irrelevant locations, or locations may need to be reordered to make a more coherent and sensible flow. In the next section, we describe a technique to automatically generate a playable game world based on a story plan.

7.5.1 From Story to Space: Game World Generation

Recalling that games often interleave plot points and open-ended game play, the game world to be generated must ensure a coherent sequence of events are encountered in the world. The problem can be specified as follows: given a list of events that reference locations of known types, generate a game world that allows a linear progression through the events. To map from story to space, we will utilize a metaphor of *islands* and *bridges*. Islands are areas in the spatial environment where events occur. Bridges are areas of the world between islands where open-ended game play occurs. Bridges can branch, meaning there can be areas that the player does not necessarily need to visit in the course of the story. The length of bridges and the branching factor of bridges are parameters that can be set by the designer or dictated by a player model. A game world is generated in a 3-stage pipeline in which (1) a story plan is parsed for location information referenced by events, (2) an intermediate, abstract representation of the navigable space is generated, and (3) the graphical visualization of the navigable space is realized.

Table 7.2: A portion of the initial state declaration for a planning domain.

Hero (paladin)	Thing (water-bucket)	Type (palace, castle)
NPC (baba-yaga)	Thing (treasure)	Type (graveyard1, graveyard)
NPC (king-alfred)	Thing (ruby-slippers)	Type (treasure-cave, cave)
Place (palace)	Evil (baba-yaga)	Type (water-bucket, bucket)
Place (graveyard1)	Type (baba-yaga, witch)	Type (ruby-slippers, shoes)
Place (treasure-cave)	Type (king-alfred, king)	Type (treasure, gold)

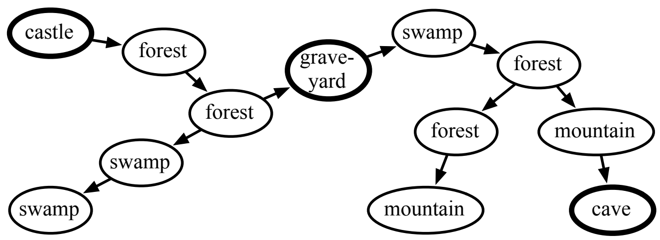

Fig. 7.4: An example space tree. Islands are marked with bold lines.

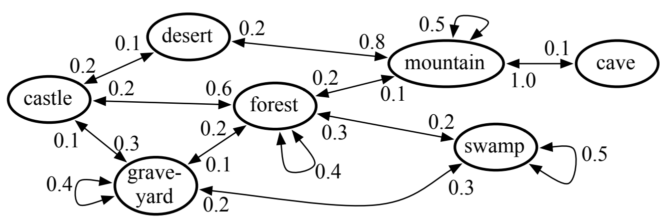

Fig. 7.5: An environment transition graph.

First, the generated story plan is parsed to extract a sequence of locations, each of which becomes an island. The story plan must be fully ordered to generate such a sequence (any partially ordered plan can be converted into a full-ordered plan). Each event in the story plan must be associated with a location. For example, in the story plan in Table 7.1, events occur at places referenced by the symbols *palace*, *graveyard1*, and *treasure-cave*. Each referenced location must have a type. This information is often found in the initial state declaration of the planning domain. Table 7.2 shows a portion of the initial state for the domain used to generate the example story plan. Thus the example story plan plays out in three locations: a castle (events 1, 5 and 6), a graveyard (events 2 through 4), and a cave (events 7 through 10).

The next stage is to generate an intermediate representation of the game world as a graph of location types called a *space tree*. A space tree is a discrete data structure that indicates how big the game world will be, how many unique locations, and which locations are adjacent to each other. Figure 7.4 shows an example of a space tree in which the nodes corresponding to island locations—where story plan events are to occur—are highlighted in bold and the rest of the nodes comprise the bridges.

The planning domain does not provide enough information to tell us what types of locations should be used for the bridges. We require an addition knowledge structure, called an *environment transition graph*. An environment transition graph is a data structure that captures the game designer's beliefs about good environment type transitions. Each node in an environment transition graph is a possible location type and edges indicate non-zero probability of transitioning from one location type to another. Figure 7.5 shows an example of an environment transition graph.

Space Tree generation can utilize any optimization search algorithm to find a space tree that meets the evaluation criteria. See Chapter 2 for the general search-based approach to procedural content generation, and see [8] for specific implementation details. The evaluation criteria are:

- Degree to which the number of bridges nodes in the space tree between islands have the preferred length.
- Whether the bridges have the preferred branching factor.
- Degree to which the length of side paths—branch nodes that are not directly between two islands—matches the preferred side path length.
- How closely environment type transitions between adjacent nodes match the environment transition graph probabilities.

These evaluation criteria make use of parameters set by the designer. Other evaluation criteria may be used as well.

Once the space tree has been generated via a search-based optimization process, the third stage is to *realize* the game world graphically. The space tree gives us an abstract representation of this game world but doesn't tell us what each locations should look like. Where should art assets be placed spatially to create the appearance of a forest, town, or graveyard, etc.?

We describe a graphical realization process that creates a 2-D, top-down, tile-based, graphical visualization of a game world described by a space tree. Starting with a grid of empty tiles, we will first map the space tree to the 2D grid and the choose tiles for each cell in the grid. If the grid is $m_{\text{world}} \times n_{\text{world}}$ tiles, then each $m_{\text{screen}} \times n_{\text{screen}}$ tiles is the number of tiles that can be displayed on the screen at any one time. Each node in the space tree will be mapped to a $m_{\text{location}} \times n_{\text{location}}$ grid of screens. In Figure 7.6, the world is 340×160 tiles, each screen is 34×16 tiles, and each location encompasses a 3×3 grid of screens (only a portion is shown). The mapping of space tree to grid is as follows. Use a depth-first traversal of the space tree, placing each child adjacent to its parent on a grid. In order to prevent an algorithmic bias toward growing the world in a certain direction (e.g. from left to right), one can randomize the order of cardinal directions it attempts to place each child. To minimize the likelihood that nodes will be mapped to the same portion of the grid, one can constrain the space tree such that nodes have no more than two children, for a total of three adjacent nodes. Backtrack if necessary. If there is no mapping solution, discard the space tree and return to the optimization search to generate the next best space tree.

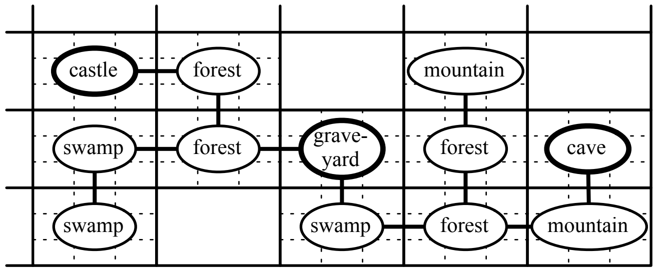

Fig. 7.6: A space tree mapped to a grid.

Once each node in the space tree has been assigned a region on the grid, the module begins graphical instantiation of the world. Each node from the space tree has an environment type, which determines what *decorations* will be placed. Decorations are graphical assets that overlay tiles and visually depict the environment type. For a 2D tile-based realization of a game world, decorations are sprites that depict scenery found in different environment types. A forest environment has decorations consisting of grass, trees, and bushes, while a town has decorations that look like buildings, castle walls, and street paving stones.

But how does the system know where to place each decoration? This knowledge is also not present in the domain model, and a third type of external knowledge is necessary. Each environment type is associated with a function that maps decorations to a probability distribution over XY tile coordinates. We have identified two types of mapping functions.

A *Gaussian distribution* defines the dispersement of decorations around the center point of a location such that decorations are placed more densely around the center point of each location. The advantage of a Gaussian distribution is that decorations can be placed in adjacent locations, creating the appearance that one location blends into the next, as in Fig 7.7.

A *custom distribution* is an arbitrary, designer-specified function that returns the probability of placing a decoration at any XY coordinate. Fig 7.8 shows the custom distribution for a town location type such that buildings are likely arranged in a grid-like city blocks, paving stones make up streets between city blocks, and guard towers are arranged in a ring around the town perimeter.

Fig 7.9 shows an example of a complete game world with three islands extracted from Table 7.1.

7.5.2 From Story to Time: Story Plan Execution

Once the space in which the story will unfold has been generated, there are two additional issues that must be addressed: (a) the world must be populated with NPCs, and (b) the NPCs must act out the story, which was not known prior to execution.

Fig. 7.7: A forest adjacent to a swamp, both with Gaussian distributions resulting in a blended transition.

Population of the world by NPCs is a simple process of parsing the story plan for references to NPCs and instantiating sprites (based on NPC type) in the location in which they are first required to participate in an event. Because of the temporal extension of events, NPCs must elaborate on events, including engaging in combat, engaging in dialogue, setting up and triggering traps (the world itself can be an NPC), etc. Because the story and world geometry are *a priori* unknown, the NPCs must be flexible enough to elaborate on an event under a wide range of conditions based on what events preceded the current time point and how the world is laid out.

One solution is to pair each event with a *reactive script* that decomposes the event into a number of primitive NPC behaviors. Roughly, a reactive script is an AND-OR tree structure in which internal nodes represent abstract behaviors—possibly joint between a number of characters—and leaf nodes represent primitive, executable behaviors such as animations. Reactive script execution is a walk of the tree implementing an event such that AND-nodes create sequences of sub-behaviors and OR-nodes express alternative means of decomposing achieving a behavior, implementing *if-then-else* decision-making logic. Internal nodes may implement applicability criteria (similar to preconditions) that are used to prune sub-trees that are not supported by the state of the virtual world at execution time. Examples of reactive script technologies include behavior trees [9], hierarchical finite state machines, hierarchical task networks [21] such as *SHOP 2* [15], and the ABL reactive behavior planner [13].

There are two types of reactive scripts necessary to execute an automatically generated story in an open-ended game world [18]: narrative directive behaviors and local autonomous behaviors. *Narrative directive behaviors* are reactive scripts associated with event templates in the domain model. They operate as above, decomposing events into primitive behaviors. Narrative directive behaviors enact an event as if it were a stage manager in a play; they are not associated directly with

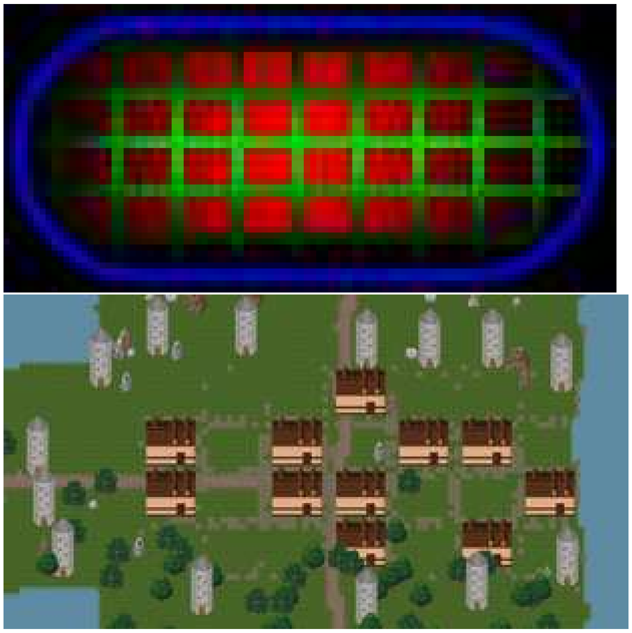

Fig. 7.8: A custom distribution for a town (left) and an example of the result (right). Brighter color indicates greater probability of a decoration, where red indicates buildings, green indicates paving stones, and blue indicates towers.

Fig. 7.9: Example game world generated from the islands in the plan in Table 7.1.

any one character, but may control many characters at once. *Local autonomous behaviors* are associated with NPC types and execute whenever an NPC is instantiated in the world but not otherwise playing a role in an event. Local autonomous behaviors create the appearance that NPCs have rich internal lives if they are encountered by the player during open-ended play.

7.6 Summary

Most games have stories, be they backstories as in a typical shooter or stories that structure the game experience as in a role-playing game. Stories can be seen as content and generated. The most common approach to generating stories is to use some kind of planning algorithm. A planning algorithm finds a path from an initial state to a goal state; the sequence of actions that constitute this path can then be interpreted as a story. Among planning algorithms, there is a distinction between plan space search, where the algorithm searches in the space of possible plans, and state space search, where a plan is built up through adding new parts sequentially. A domain model is a collection of facts about the (game) world and possible actions that can be taken in it, which is then used by the planner to create a plan. There are several ways of representing a domain model, such as the STRIPS and ADL languages. For stories which have an impact on gameplay, there are ways of generating the map at the same time as the story, or the map to follow the story. Search and optimisation techniques can be used to map out plot points to physical locations.

7.7 Lab exercise: Write a story domain model

The purpose of this exercise is to let you be able to write a story domain model and characterize different planning algorithms.

1. Get familiarized with JSHOP2 - an off-shelf JAVA implementation of SHOP2 HTN planner (originally written in LISP).
   - Download and install JSHOP 2.0 (http://www.cs.umd.edu/projects/shop/)
   - Check out and test the sample examples included in the package.
2. Write a planning problem in terms of initial state, goal state, and actions by defining two story domains (Little Red Riding Hood and The Gift of the Magi) using either STRIPS-style or ADL-style representation. Discuss which representation is more suitable to describe the two storyworld domains and explain why.
3. Convert the above planning problems into HTN representation that is applicable in JSHOP2 planner, and execute them. Discuss the strength and weakness of HTN planning (or SHOP2 planner) as a story generation method/tool.
4. In the Butler story described in Section 1.4, suppose that the lord knows that the wine is poisoned and he just pretends to be dead, but the butler does not know that the lord knows. The new authorial goal is now reprensented as $\neg dead(Lord) \wedge Arrested(Butler)$. Make a complete story plan by adding additional actions

(e.g., $Call-911(Lord)$, $Arrest(Police, Butler)$), states, and causal links. Do you think that it will make the story more interesting? Why or why not?
5. Discuss the overall advantages and limitations of planning-based story generation.
6. Discuss how planning-based story generation techniques can be effectively used in interactive storytelling systems and games.

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Chapter 8
ASP with applications to mazes and levels (DRAFT)

Mark J. Nelson and Adam M. Smith

A common theme underlying procedural content generation is that we need to be able to specify both *what* we want our generated content to be like, and *how* to generate it. Sometimes these two parts are tightly intertwined. In the constructive methods of Chapter 3 and the fractal and noise methods of Chapter 4, we can produce different kinds of output by tweaking the algorithms until we're satisfied with their output. But if we know what properties we'd like generated content to have, it's more convenient to be able to directly specify what we want, and then have a more general algorithm find content meeting our criteria.

The search-based framework introduced in Chapter 2 is one common way of making a content-generation algorithm general, so we can tell it what kind of content we want, and have it search for content meeting our request. An *evaluation function* specifies the properties we'd like the content to have, by numerically rating the quality of generated content according to whatever criteria we choose. A *search algorithm* then searches a space of *content encodings* to find highly rated content.

Evaluation functions summarize a large range of possible content qualities into a single numerical rating. Then the search process, such as an evolutionary algorithm, finds content that rates highly on that scale. Elements of an evaluation function may include both *hard constraints*—things that the content absolutely must have, such as a level being passable—and softer preferences. Evaluation of content quality may also depend on the game's mechanics. For example, whether a level is passable can depend on how a player can move, what items are available for the player's use, how enemies move, and so on; in search-based PCG this is often addressed by simulating gameplay when compute the rating.

In this chapter we look at another way of dealing with the *what* and *how* of PCG. We specify what we want our generated content to be like by writing programs in answer-set programming (ASP), a language for writing logic and constraints. We then do the actual generation by passing the program to an ASP *solver*, which outputs content that meets the specifications of our program.

8.1 Game logic and content constraints

Instead of using a content encoding and a numerical evaluation function, here we define the *logic* of a content domain, along with *constraints* on the properties that we want the generated content to exhibit [9].

The logic of a game content domain is its structure and game mechanics. A grid-based map has a structure in which tiles are arrayed horizontally and vertically, with walls, items, structures, or other entities placed on tiles. Mechanics specify how gameplay takes place on this grid. Common mechanics include: a player starts somewhere, can move to any unoccupied adjacent square, can pick up certain kinds of items, can break certain kinds of barriers (this might require an item), etc. In short, how a game *works* makes up its logic. This logic can be encoded in computational logic [7], which means we will be able to use it to guide PCG. We don't encode how the *entire* game works, to be clear: just how the game works to the extent that it's relevant to generating the content we want.

Once we have the logic of a domain, we can write down properties that we want all generated content to have, by writing constraints that refer to the game's logic. For example: a level must have a valid path through it. What is a valid path? A sequence of moves that a player can legally make. The sequence of moves the player can legally make in turn depends on the logic of the particular game's world and rules, discussed in the previous paragraph. Some other possible constraints: all valid paths should be at least a certain minimum length, the exit and entrance must be at opposite edges of the map, and so on. We can add and remove from these properties, as we think of them: perhaps the player shouldn't be able to get through a level without using at least one item (if our game has items). Maybe at least one jump should be required, or there should be a boss placed somewhere that can't be avoided. Specifying these constraints will often be done iteratively. Once we generate a few example levels, we may see things we didn't expect, and modify the set of desired properties accordingly.

The logic and constraints together serve the role that the encoding and evaluation function in search-based PCG, but in a more explicit, symbolic form, where we've written out the logic of a game world and the properties we'd like in the generated content. The logic and constraints are then passed to a tool, called a *solver*, which solves the logic problem: it finds content that conforms to the logic of the game world and satisfies all the constraints we've specified. This approach is particularly useful when many of our desired properties are hard constraints, and may depend (perhaps in complex ways) on the game's mechanics.

8.2 Answer set programming

To apply the approach we just described in practice, we need a specific language in which to encode the game logic and constraints, and a solver for that language. In this chapter, we use *answer-set programming* (ASP), a logic programming language. While there are other possible ways to do PCG with constraint solving [6], answer-set programming is a well-developed programming language with reliable existing tools, and which can be used to specify both game logic and constraints within the same language. Therefore it serves as good general-purpose choice for programming logic- and constraint-based PCG systems.[1]

Before we jump into using ASP for a content generation task, we will first introduce some basic syntax. Answer set programs are expressed in a language called AnsProlog [1, 4], a language that visually resembles Prolog while having semantics that are more directly relatable to SAT and MAX-SAT problems.

The simplest ASP construct is a *fact*. A fact is something we declare to be true. It can be an atomic fact, which is simply a symbol that is declared true:

```
game_over.
gravity_enabled.
```

Or, a fact can be specified using *predicates*, which take parameters. A predicate can be declared true for specific choices of parameters:

```
max_jump(3).
contains((2,2),wall).
```

So far, this is just a bare list of facts. We could encode a whole level this way, specifying the locations of walls, items, etc. But the interesting part comes when we add rules in addition to lists of facts. Rules specify that we can infer certain facts from others. This encodes dependencies between game elements, and also lets us start specifying dynamic elements of the game, like game mechanics. For example, let's say a tile is impassable if it contains a wall:

```
impassable(Tile) :- contains(Tile,wall).
```

We could have specified a list of facts listing explicitly which tiles are impassable, but this rule captures in one line that *every* tile with a wall is impassable. Here, `Tile` is a logic variable. In AnsProlog, variables start with a capital letter, while predicates and atoms start with a lowercase letter. These rules can be thought of as a reversed version of the implication formulas in first-order logic. Written in conventional mathematical notation, it would be:

$$\forall Tile, item\_at(Tile, wall) \implies impassable(Tile)$$

Read left to right, this says: for all tiles, if the tile contains a wall, then the tile is impassable. The symbol `:-` in AnsProlog is a leftward-pointing version of this implication arrow, following the programming-language convention that assignments go from right to left. Variables in AnsProlog are implicitly universally quantified, so the "for-all" ($\forall$) in the mathematical version doesn't appear in the AnsProlog code.

Once we have facts and rules, that would in principle be enough to constructively generate content. However, it is typically difficult to write a set of facts and rules so that *only* content we want is derived by the implications, placing everything in exactly the right combination of places and never generating broken or undesirable output. Instead, we usually generate content in two steps. First, we constructively

[1] ASP has also been used for content generation outside of games, notably to generate music [2].

define a *design space*. Then we specify constraints that exclude unwanted parts of the design space.

The initial, larger design space is created by using the AnsProlog construct of *choice rules*. A choice rule specifies that the solver has an arbitrary choice in how to assign certain facts—as long as they meet some numerical constraints, and any other constraints that we might add later. The following choice rule specifies that there are between 5 and 10 walls in the level, but it doesn't specify exactly how many, or on which tiles they're located:

```
5 { item_at(T,wall) : tile(T) } 10.
```

More precisely, this syntax says that, if we construct a big collection of candidate `item_at(T,wall)` facts, for every possible `T` that is a `tile`, then the size of this set is at least 5, but no greater than 10. If we have no desire to constrain the set size, we can leave off one or both of these numbers. The following choice rule simply says that a level has any number of walls:

```
{ item_at(T,wall) : tile(T) }.
```

A program consisting of only the above rule produces a generative space of levels that contains any possible arrangement of walls on a grid. Of course, interesting levels require more than this. Besides adding numerical constraints on how the ASP solver makes it choices, we can exclude unwanted choices by adding different constraints that the solver must take into account. A standalone constraint is written like a rule, but has nothing on the left hand side of the `:-` syntax. A solution that matches the right-hand side of the rule will be *rejected* as an invalid choice. The following example rule excludes any generated map that has a wall at $(1,1)$:

```
:- item_at((1,1),wall).
```

If we read this again as a logical implication written backwards, this translates to:

$$item_at((1,1),wall) \implies \text{[reject]}$$

By intermixing rules that create generative spaces, and others that prune them back down to interesting subsets, we can achieve strong control over the kinds of content that is generated.

AnsProlog code is put into files with the conventional extension `.lp` (for "logic program"), and then passed to the solver. In this chapter we use the solver `clingo` from the University of Potsdam, a free and actively maintained AnsProlog solver that's part of the Potassco project of answer-set programming tools [5].

Now that we have the basic machinery of AnsProlog, we can define facts and implications, specify design spaces as free choices, and specify constraints rejecting some of those choices. We'll walk through some complete examples to show how to build and modify procedural level generators using this method.

8.3 Perfect mazes

Using our new found ability to reason over all possible logical worlds, we will start with a simple maze generation problem. In particular, we will look at generating *perfect* mazes. A perfect maze (which may or may not actually be a desirable maze) is one in which every location is reachable while not having any closed loops. In effect, perfect mazes are trees that have been embedded into a fixed space, usually a grid.

One way to represent a tree embedded in a grid is to assign each tile in the grid a parent pointer that points to one of its adjacent cells. If the choice of parent pointers actually forms a tree, then it will be possible to traverse these pointers back to the root of the tree no matter where we start.

Let's begin by establishing a representational vocabulary for our mazes. Figure 8.1 is a self contained AnsProlog program that uses a choice rule to assign each X/Y location a unique parent direction. This choice rule can produce facts like `parent(5,7,0,-1)` which might read that the tile at location $(5,7)$ has a parent of $(5,6)$. The location $(1,1)$ will later function as the root of our tree, so we don't assign it a parent direction.

```
#const width = 5.
dim(1..width).

1 { parent(X,Y, 0,-1),
   parent(X,Y, 1, 0),
   parent(X,Y,-1, 0),
   parent(X,Y, 0, 1) } 1 :-
   dim(X), dim(Y), (X,Y) != (1,1).
```

Fig. 8.1: maze-core.lp

With just a single interesting rule, we can already begin visualizing the output of the design space we are representing so far. Using a command like the following, which uses the answer set solving system from the Potassco project (discussed in the previous section), we can generate ASCII-art previews of possible mazes. Examples from our program so far can be seen in Figure 8.2.

```
clingo maze-core.lp --rand-freq=1
```

To make sure we only see valid trees, we should enforce the property that the root is reachable from every tile on the grid. Figure 8.3 uses a fact, a recursive rule, and an integrity constraint to accomplish this. The `linked(X,Y)` property holds for the root of the tree trivially. Any tile that has a parent that is linked is linked as well. Finally, if there is some tile which does not have the linked property, something is wrong with the current assignent of parent directions and this possible world should be rejected.

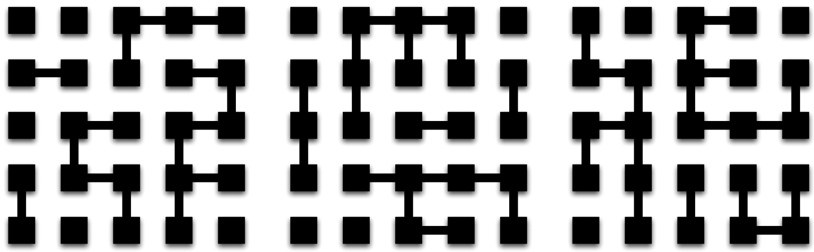

Fig. 8.2: When each tile in the maze is assigned a random parent, typical outputs show several disconnected components. Some tiles on the edges of the maze even point to a parent cell outside of the maze.

```
linked(1,1).
linked(X,Y) :- parent(X,Y,DX,DY), linked(X+DX,Y+DY).

:- dim(X;Y), not linked(X,Y).
```

Fig. 8.3: maze-reach.lp

After adding these rules, we can sample examples of all and only those perfect mazes by running a command like the following. Example outputs are showin in Figure 8.4

```
clingo maze-core.lp maze-reach.lp
```

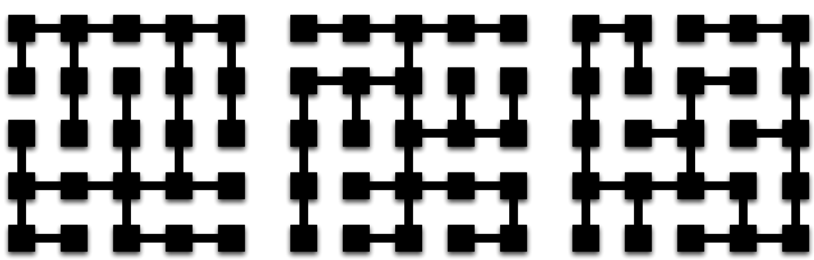

Fig. 8.4: After adding reachability constraint for each tile, the desired tree network appears. This program captures exactly the set of all perfect mazes of a given width.

So far, we have used only hard constraints: tiles have exactly one parent, and every tile must be linked to the root. We can express soft constraints in AnsProlog as well by defining optimization criteria. As an example of this for the primitive domain of mazes, let us suppose that vertical links in the maze are undesirable and that their use should be minimized. To accomplish this, the rules in Figure 8.5 define two ways of detecting a vertical link (an upward or downward parent), and the `minimize` statement tells the solver that solutions which use the least-possible count of vertical links are those that interest us. Although such statements are typically read as implying an *optimality constraint* (that only globally optimal solutions should be emitted, most answer set solvers will emit a series of answer sets they find along the way to finding one such optimal solution. By stopping the solver once it gets close enough or runs for enough time, we can implement approximate optimization within this framework as well.

```
% soft style preferences: minimize vertical links
vertical(X,Y) :- parent(X,Y,0, 1).
vertical(X,Y) :- parent(X,Y,0,-1).
#minimize { vertical(X,Y) }.
```

Fig. 8.5: maze-bias.lp

Including the rules defining our bias against vertical links, a command like the following will allow us to sample maze designs that optimize our working evaluation criterion. Example outputs are show in Figure 8.6.

```
clingo maze-core.lp maze-reach.lp maze-bias.lp
```

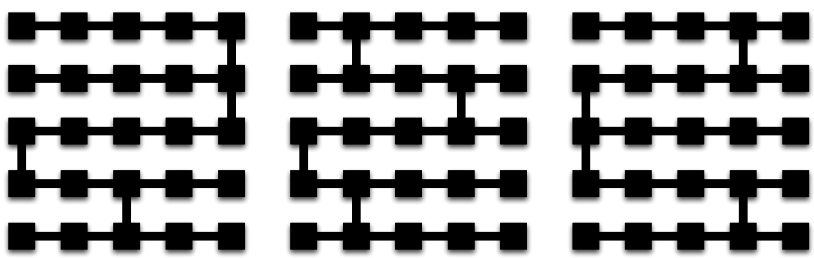

Fig. 8.6: Using the count of horizontal connections as an evaluation function, we can sample several alternative designs with a globally optimal score.

8.4 Playable dungeons

Mazes are an overly simplistic example of how to carry out content generation using ASP because they can be represented with only a single kind of choice. As a slightly richer example, this section looks at generating simple dungeon maps in which a few different types of sprites are stamped down onto the familiar two-dimensional grid.

Our task will be to design a level in which the player character starts in the top-left of the grid, finds a gem in the wall of the dungeon, carries it to a central altar when it is used to magically unlock the exit, and then walks out of that exit in the bottom right. We would like every generated level to be guaranteed to be solvable as well as have some basic control over the pacing of the level.

To begin, examine Figure 8.7. This program establishes a vocabulary of dimension values, tiles as value pairs, and adjacency between pairs of tiles. In the character movement model we intend to capture, tiles that are one step up/down/left/right of each other are considered adjacent. A mathematical statement of this is that tile pairs with a coordinate distance of one are considered adjacent. The key part of this program is the choice rule that states that every tile has between zero and one sprites from the set of walls, the gem, and the altar. Because we know we only want to see maps with one gem and one altar, we immediate add integrity constraints that reject those maps for which there isn't exactly one of each.

```
#const width=10.

param("width",width).

dim(1..width).

tile((X,Y)) :- dim(X), dim(Y).

adj((X1,Y1),(X2,Y2)) :-
  tile((X1,Y1)),
  tile((X2,Y2)),
  #abs(X1-X2)+#abs(Y1-Y2) == 1.

start((1,1)).
finish((width,width)).

% tiles have at most one named sprite
0 { sprite(T,wall;gem;altar) } 1 :- tile(T).

% there is exactly one altar and one gem in the whole level
:- not 1 { sprite(T,altar) } 1.
:- not 1 { sprite(T,gem) } 1.
```

Fig. 8.7: level-core.lp

Starting with these core rules, commands like the following will generate outputs like those seen in Figure 8.8.

```
clingo level-core.lp --rand-freq=1
```

Our preliminary outputs hardly resemble interesting dungeon maps. There are many interesting maps lurking in the space we have defined, but they are hard to spot amongst the multitude of other combinations in the space. To zoom in on those maps of stylistic interest, we'll use a mixture of rules and integrity constraints to carve undesirable alteratives. A dungeon with only a sparse set of walls doesn't feel like a dungeon. A single wall sprite takes on the character of a wall when it is placed contiguously with other wall sprites. An altar should be surrounded by a few tiles of blank space, and gems should be well-attached to surrounding walls. Examine Figure 8.9 for a one-line encoding of each of these concerns.

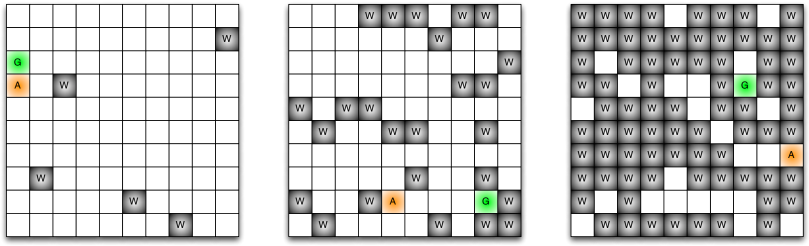

Fig. 8.8: A random result given rules that capture the basic representational vocabulary for the dungeon generation problem. A few walls (W, gray) are present, along with exactly one gem (G, green) and one altar (A, orange).

```
% style: at least half of the map has wall sprites
:- not (width*width)/2 { sprite(T,wall) }.

% style: altars have no surrounding walls for two steps
0 { sprite(T3,wall):adj(T1,T2):adj(T2,T3) } 0 :- sprite(T1,altar).

% style: altars have four adjacent tiles (not up against edge of map)
:- sprite(T1,altar), not 4 { adj(T1,T2) }.

% style: every wall has at least two neighboring walls (no isolated rocks and spurs)
2 { sprite(T2,wall):adj(T1,T2) } :- sprite(T1,wall).

% style: gems have at least three surrounding walls (they are stuck in a larger wall)
3 { sprite(T2,wall):adj(T1,T2) } :- sprite(T1,gem).
```

Fig. 8.9: level-style.lp

With this addition, commands like the following can be used to sample stylistically valid maps such as those in Figure 8.10. Note that while the levels look reasonable locally, they are still completely undesirable on the basis of them not supporting the kind of play we want—there's often not even a path from the gem to the altar, let alone from the entrance to the exit.

```
clingo level-core.lp level-style.lp
```

The general strategy for ensuring we only generate playable maps is conceptually simple: generate a reference solution along with the level design. If a map contains a valid reference solution, we have a proof (by existence) that it is solvable. Even though we won't be representing the reference solution in our final output involving sprites on tiles, we can use the same language constructs as before to describe and constrain the space of possible solutions for a working map design.

Examine the rules in Figure 8.11. The key predicate is `touch(Tile,State)` which describes which tiles we expect the player character to touch in which gameplay state on the path to solving the level. To capture the sequence of picking up the gem, bringing it to the altar, and then exiting the level, we define three numbered states. The first rule tells us that the player will touch the start tile in state 1. From

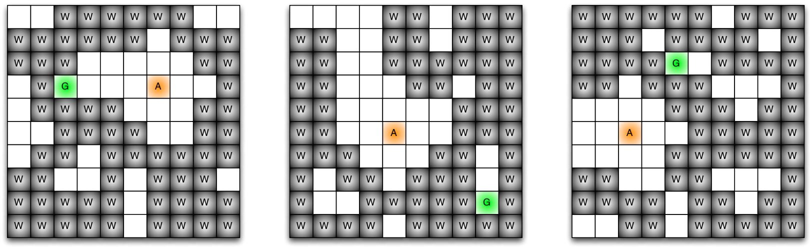

Fig. 8.10: After adding style constraints, there are many walls, the altar is surrounded by open space, and the gem is surrounded by walls on three sides. The fact that the gem is walled-off is a clue that we have not yet modeled a key contraint: the level must be playable.

here, a series of choice rules say that touching one tile allows the player character to potentially touch any adjacent tile while retaining the same gameplay state. If the character is touching a tile containing the gem or the altar, they can transition to the next state in the sequence. The `completed` predicate holds (is true) if the player character touches the finish tile in final state (after placing the gem in the altar). By rejecting every logical world where `completed` is not true, we zoom in on the space of different ways of solving the level. No algorithm is needed to solve a level, only a definition of what it means for a set of touched tiles to constitute a valid solution.

```
% states:
% 1 --> initial
% 2 --> after picking up gem
% 3 --> after putting gem in altar

% you start in state 1
touch(T,1) :- start(T).

% possible navigation paths
{ touch(T2,2):adj(T1,T2) } :- touch(T1,1), sprite(T1,gem).
{ touch(T2,3):adj(T1,T2) } :- touch(T1,2), sprite(T1,altar).
{ touch(T2,S):adj(T1,T2) } :- touch(T1,S).

% you can't touch a wall in any state
:- sprite(T,wall), touch(T,S).

% the finish tile must be touched in state 3
completed :- finish(T), touch(T,3).
:- not completed.
```

Fig. 8.11: level-sim.lp

Although we could use the contents of Figure 8.11 as a stand-alone playability checker for human-designed dungeon maps, it is easy enough to simply use it as the same time as our previous map generator to construct a representation of the space of maps-with-valid-solutions. A command like the following yields guaranteed-playable, styled dungeon maps like those in Figure 8.12.

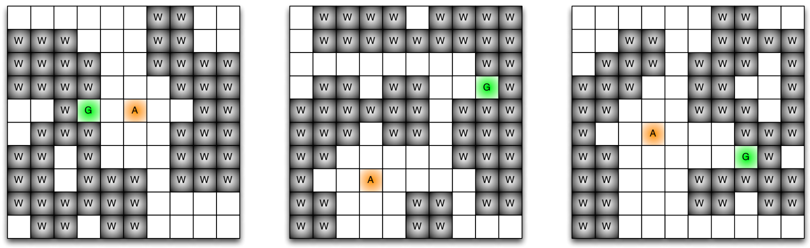

Fig. 8.12: After adding a simulation of player activity and placing constraints on the outcome, we now only see dungeon maps that have valid solution.

8.5 Constraining the entire space of play

The dungeon maps emerging from the previous section look about as good as sprite-on-grid maps containing two special objects and some walls can get. However, if we imagine playing through these maps, perhaps with simple arrow-key controls, there are still problems to resolve. In many of these maps, the task of placing the gem in the altar represents only a minor deviation from the more basic task of walking from the entrance to the exit of the dungeon. If the gem and the altar are to have any meaning for the gameplay of these maps, their placement and the arrangment of walls should conspire to make us explore the map, take detours from a start-to-finish speed-run, and backtrack through familiar areas. Although each of these concerns *could* be boiled down to a set of overlapping evaluation criteria in the form of statements about the relative distances between sprites, there is a better strategy.

If our goal is to get the player to work to progress through the sequence of gameplay states, we can state a much higher-level goal. The low-level design details of the map should somehow work to make sure the player character spends at least some amount of time walking around the map in each state. How this is accomplished (with with a network of rooms connected by indirect passages perhaps) is not immediately important to us. Our high-level design goal is most directly cast as a statement about the player's experience, not the form of any particular level. We'd like to demand that, across all possible solutions to a given level design, spending a minimum amount of time in each state is unavoidable. Interpreted logically, this is a statement that is quantified over the entire space of play.

Recent advances in the use of ASP for representing design spaces now allow the direct expression of this kind of design goal. Smith et al. [8] offer a small metaprogramming library that extends normal ASP with two special predicates.

Their `__level_design(Atom)` and `__concept` predicates allow the expression of a query like this: starting with a given level design and reference solution, does the design space model allow another possibility in which identical choices are made for every predicated tagged with `__level_design(Atom)` and in which `__concept` is *not* true? If so, the tagged `__concept` condition must not be true for the entire space of play for the given level design, and it should be rejected. The end result is a design space of level design with reference solutions in which `__concept` is an *unavoidable* condition across all alternative solutions to the level. As `__concept` could be any quantifier-free logical formula, this language extension allows the class of extended answer set programs to express any problem in the complexity class Σ_2^P (conventionally assumed to be much larger than the class *NP*).

Returning to the dungon map generation scenario, the rules in Figure 8.13 tag the `sprite(Tile,Name)` predicate as uniquely defining a level and the condition of touching at least `width`-many tiles in each of the three states as the desired unavoidable condition. A command like the following, which makes use of a special *disjunctive* answer set solver capable of solving the broader class of high-complexity problems, yields outputs like those shown in Figure 8.14.

```
clingo level-core.lp \
     level-style.lp \
     level-sim.lp \
     level-shortcuts.lp \
     --reify \
    | clingo - meta{,D,O,C}.lp -l \
    | clasp
```

```
% holding sprites constant, ensure every solution touches at least "width" many tiles in each state
__level_design(sprite(T,Name)) :- sprite(T,Name).
__concept :-
  width { touch(T,1) },
  width { touch(T,2) },
  width { touch(T,3) }.
```

Fig. 8.13: level-shortcuts.lp

Before we close this section, it is instructive to ask why the following simple rule doesn't achieve the same outcome. It would seem to prune away all those solutions in which the player doesn't spend enough time in each state.

```
:- width { touch(T,1) }, width { touch(T,2) }, width { touch(T,3) }.
```

This integrity constraint works like the "`:- not completed.`" rule from before. It works to make sure we only observe solutions (choices for `touch(Tile,State)`) that demonstrate an interesting property. Zooming in on solutions which complete the level doesn't preclude the player from choosing *not* to complete the level by simply wasting time before quitting. Likewise, zooming in on solutions in which the player wanders for a while doesn't imply that the wandering was inescapable. If we were to use this rule instead of the `__level_design`/`__concept` construction, we would most likely see many more examples like those from the previous section

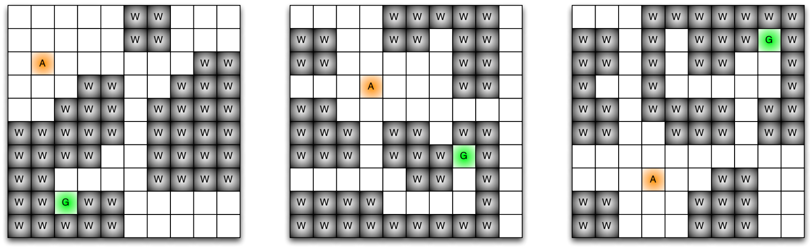

Fig. 8.14: Ensuring that the player cannot avoid spending a certain amount of time in each state has interesting emergent effects. Certain patterns that we might expect in human-crafted designs, such as the presence of hidden rooms of the main path through the level, occur naturally as the solver searches for the form of a level that gives rise to our requested function at a higher level.

(Figure 8.12). In every example, it would be *possible* to wander and backtrack, but it would be unlikely to be actually required.

The idea of casting the most important properties of a level design as statements *quantified over the entire space of play* was first developed in the context of the educational puzzle game *Refraction*. What makes a given *Refraction* level desirable and relevant to its location in a larger level progression is strongly tied to which spatial and mathematical problem solving skills *must* be exercised to solve the level, even if the level admits many possible solutions. The idea of defining a level progression primarily on the basis of which concepts were required in which levels was the basis for one of the direct-manuipulation controls in the mixed-initiative progression design tool for *Refraction* [3].

Answer-set programming is not the only way to write down constraints over which kinds of gameplay must be possible (e.g. a level should be solvable) and which properties of gameplay are required (e.g. that a certain skill is exercised). The key strategy to follow is to generate not just a minimal description of the content of interest, but also a description of how the content can be used towards its desired function (such as a reference solution). Many interesting properties of a piece of game content are most naturally expressed as criteria that refer to how the content is used, as opposed to any direct properties of the content itself: a good level is one that produces desired gameplay when used together with a particular game's mechanics. Despite the fact that generating content under universally-quantified constraints maps to extremely high-complexity search and optimization problems, many of these problems can be solved, in practice, in short enough times to power interactive design tools and responsive online content generators embedded into games. The use of ASP as a generation technique provides a declarative modeling language that separates the designer of a content generator from the design of the search algorithms that will be applied to these complex problems.

8.6 Exercises: Elaborations on dungeon generation

1. Run each of the examples from the text on your own machine.
2. Add a new style constraint. Make sure you understand how it changes the maps that are generated.
3. Add a new type of tile sprite, call it `lava`, that can only be traversed after the player character has touched the special `boots` tiles.
4. Change the generator so that it can be initialized with a partial map, and the generator only fills in unconstrained tiles, in a way that fits style constraints.
5. Separate the playability checker from the rest of the dungeon generation program. Now apply it as a "machine playtester" [10] to point out playability flaws in levels you create yourself.
6. Design question: In the previous exercise, you took a playability checker whose initial job was to say "I wouldn't let a PCG system generate this level", and adapted it to say, "you, human designer, might have some flaws in this level you showed me". Are these really answering the same question? If you were writing a playability checker specifically to comment on human designers' levels, would you have written it differently? (See also Chapter 11.)

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Chapter 9
Representations for search-based methods

Dan Ashlock, Sebastian Risi, Julian Togelius

9.1 No generation without representation

As discussed in Chapter 2, representation is one of the two main problems in search-based PCG, and one of the two concerns when developing a search-based solution to a content generation problem. In that chapter, we also discussed the tradeoff between direct and indirect representations (the former are simpler and usually result in higher locality, whereas the latter yield smaller search spaces) and presented a few examples of how different kinds of game content can be represented. Obviously, the discussion in Chapter 2 has only scratched the surface with regards to the rather complex question of representation. This chapter will dig deeper, partly relying on the substantial volume of research that has beed done on the topic of representation in evolutionary computation [**?**].

In the first section of this chapter, we will return to the topic of dungeons, and shows how the choice of representation substantially affects the appearance of the generated the dungeon. The next section discusses the generation of maps for paper-and-pen role-playing games in particular. After that, we discuss a particular kind of representation that has seen some success recently, namely Compositional Pattern-Producing Networks, or CPPNs. As we will see, this representation can be used for both flowers and weapons, and many things in between. Finally, we will discuss how we can represent not only the game content but the content generator itself, and search for good level generators in a search-based procedural procedural level generator generator.

9.2 Representing dungeons: a maze of choices

Dungeons or mazes (we mostly use the words interchangeably) is a topic that we have returned to several times during the book; the topic of most of Chapter **??**

was dungeons, as well as the programming exercise in Chapter 2 and some of the examples in Chapter 8. The reasons for this is both the very widespread use of this type of content (including but certainly not limited to roguelike games) and the simplicity of mazes, allowing us to discuss and compare the various vastly different ways of generating mazes without getting lost in implementation details. It turns out that when searching for good mazes, the choice of representation matters in several different ways.

Often when the issue of representation arises, the goal is enhanced performance. Enhanced performance could be improved speed in the search algorithm, creation of game features with desirable secondary properties that smooth ease-of-use, or simply fitting in with the existing computational infrastructure. In procedural content generation, there is another substantial impact of changing representation: appearance.

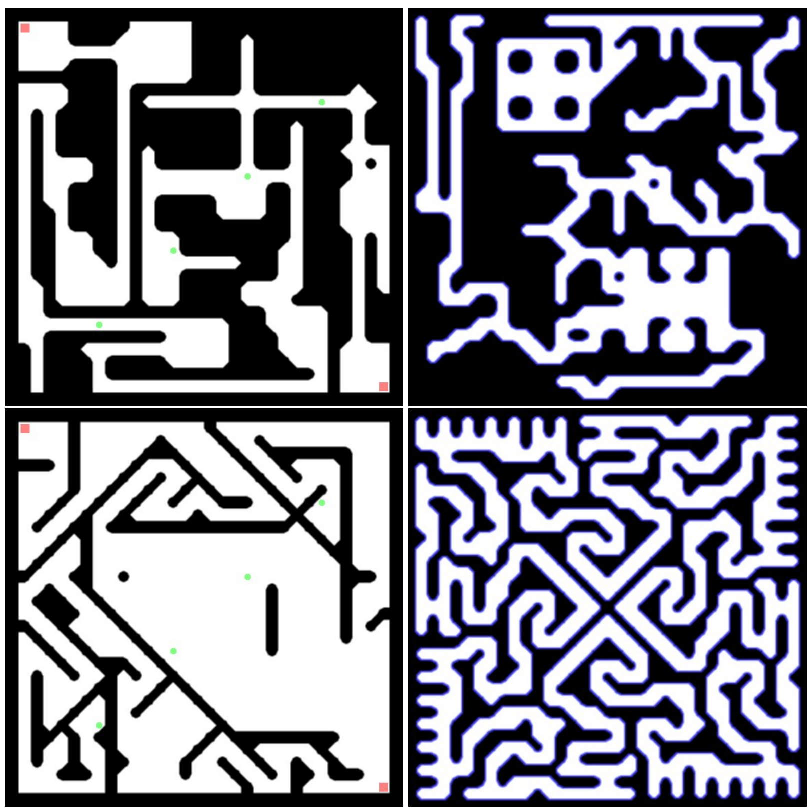


Fig. 9.1: Maps generated using four different representations that all generate 1=full 0=empty common currency maps. In reading order the representations are negative, binary with required content, positive, and binary with rotational symmetry.

The pictures shown in Figure 9.1 are all level maps procedurally generated by similar evolutionary algorithms. Notice that they have very different appearances. The difference lies in the representation. All representations specify full and empty squares, but in different manners. The fitness function can be varied depending on the designer's goals and so is left deliberately vague.

Negative

The upper left level map in Figure 9.1 starts with a matrix filled with ones. Individual loci in the gene specify where the upper left corner of a room goes and its length and height. The corridors are rooms with one dimension of length one. The red dots represent the position of a character's entrance and exit from the level. There is a potential problem with a random level having no connection from the entrance to the exit. If there is a large enough population and the representation length (number of rooms in each chromosome) is sufficient then the population contains many connected levels and selection can use these to optimise the level. This representation creates maps that look like mines.

Binary with Content

The upper right map in Figure 9.1 is created used a simple binary representation, but with *required content*. The large room with four pillars and the symmetric room with a closet opening north and south of it are the required content. They are specified in a configuration file. The first few loci of the chromosome specify the position of the required content elements. The remainder specify bits 1=full 0=empty. The fitness function controls relative distances of required content elements and entrances and exists. The required content represents elements the designer wants placed in an otherwise procedurally generated level. This representation generates maps that look like cave systems.

Positive

The lower left map in Figure 9.1 uses a representation in which the loci specify walls. The starting position, direction, and maximum length of a wall are given as well as a behavioural control. The behavioural control is 0 or 1. If it is zero it stops when it hits another wall, if it is one it grows through the other wall. This representation generates maps that look like floor plans of buildings. The example shown uses eight directions - eliminating the diagonal directions yields even more building-like appearances.

Binary with Symmetry

This representation specifies directly, as full and empty, the squares of one quarter of the level with a binary gene. Each bit specifies the full/empty status of four squares in rotationally symmetric positions. There are a large number of possible symmetries that could be imposed. The imposition of symmetry yields a very different appearance.

9.2.1 Notes on Usage

Other than the negative representation, there is an important additional factor needed when implementing the search algorithm. In the plain binary representation, if the probability of filling a square is 0.5 then it is incredibly unlikely that there is any path between entrance and exit. Similarly, if the length of walls in the positive representation is close to the diameter of the level, connected levels are an unlikely outcome. In both cases a trick called *sparse initialisation* is used. Setting the probability of a filled square to 0.2 or the maximum length of a wall to 5 make almost all random levels connected. They are also, on average, very highly connected and so not very good. This leaves the problem of locating good levels to whatever technique the search algorithm uses to improve levels. In the examples shown, the crossover and mutation operators of the evolutionary algorithm found this to be quite easy.

The representations shown to illustrate the impact of changing representation are relatively simple. Figure 9.2 shows a more complex version of the positive representation. It has three types of walls. Operating under the presumption that there are two types of players, one of which can move through water and the other of which can move through fire, this representation permits the simultaneous generation of two mazes, stone-fire and stone-water that can be optimised for particular tactical properties. In this case the stone-water maze is easier to navigate than the stone-fire maze.

9.3 Automatically Generating Levels for a Fantasy Role-Playing Game

An under-explored application of procedural content generation is the automatic creation of pen-and-paper (i.e. played without a computer) fantasy role-playing (FRP) modules. Popular examples of fantasy roleplaying games include *Dungeons and Dragons* and the associated open gaming licence D20 system which are used for heroic fantasy settings, *Paranoia* set in a dystopian, Orwellian future, *Champions* which is used for comic-book style environments, or *Deadlands*, set in a haunted version of the old west. These are typically pencil and paper games in which players run characters and a *referee* (also known as *game master*) interprets their actions

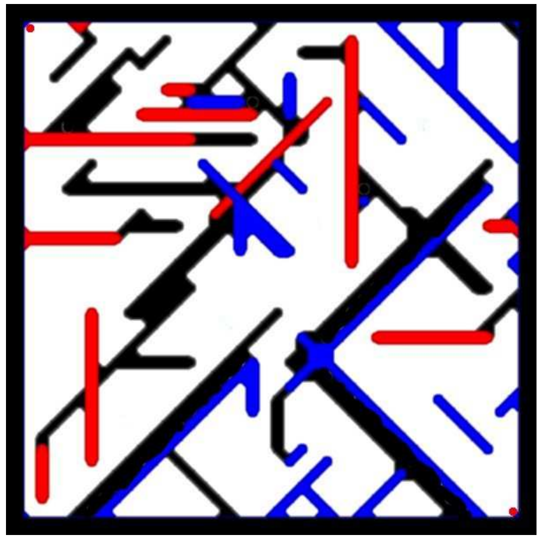


Fig. 9.2: An example of a maze, using a positive representation, with three sorts of walls: stone, fire, and water.

with the help of dice, though some of these games have also been adapted into computer role-playing games. The system described here is intended to generate small adventure modules for a heroic fantasy setting.

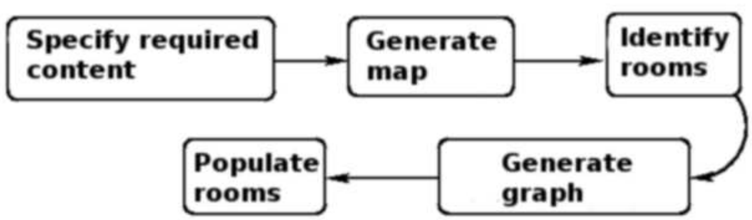


Fig. 9.3: Flowchart of the FRP level generator.

There are a number of ways to structure generation of this type of content. The one presented here starts with required-content generation of a level. This means that the designer specifies blocks of the map, such as groups of rooms, that are forced into the level. The rest of the level is generated by filling in area to match a relative distance between objects specified by the designer. This technique permits us to used search based content generation to create many different levels all of which have basic properties specified by the designer. An example of a level generated in this fashion appears in Figure 9.4. Room 14 is an example of required content as is the block represented by rooms 7, 8, 11, and 12. These four rooms are a single required content object.

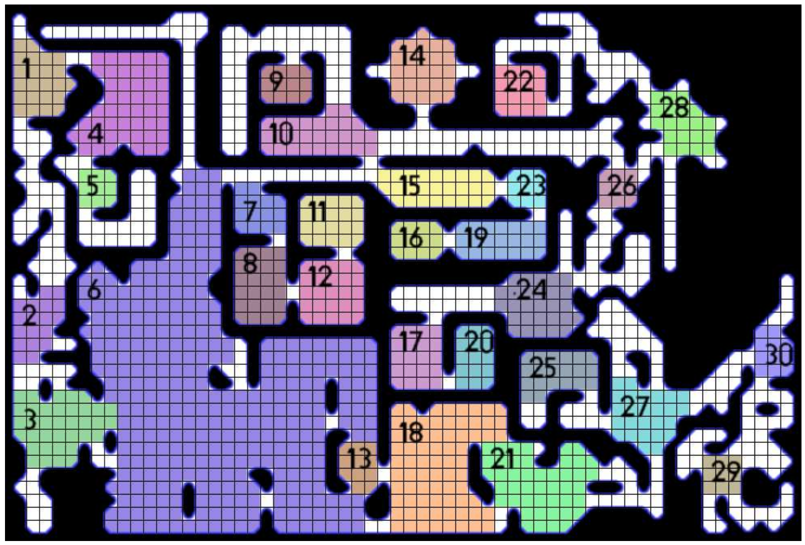


Fig. 9.4: A example of a level with automatically detected and numbered rooms.

Once the level map has been generated, the ACG system then automatically identifies room-sized open spaces on the map - this includes the rooms in the required content but also other spaces generated by the search algorithm optimising the level. The rooms are numbered and a combinatorial graph is abstracted from the map with rooms as vertices. The adjacency relation on the rooms is the existence of a path between the rooms that does not contain a square in any other room. The graph for the map in Figure 9.4 is shown in Figure 9.5. The rooms are coloured to show their grid-by-grid membership. The map with the numbered rooms, probably *sans* colours is saved for use by the referee. The graph is handed off to the room population engine.

We now look at the details of the level generator. Each of these modules is exemplary and can be transparently swapped for alternate methods with other capabilities.

9.3.1 Required Content

The underlying representation for creating the levels is a simple binary one in which 1=full and 0=empty. It is modified with specifications of *required content*. An entry in the required content configuration file looks like this.

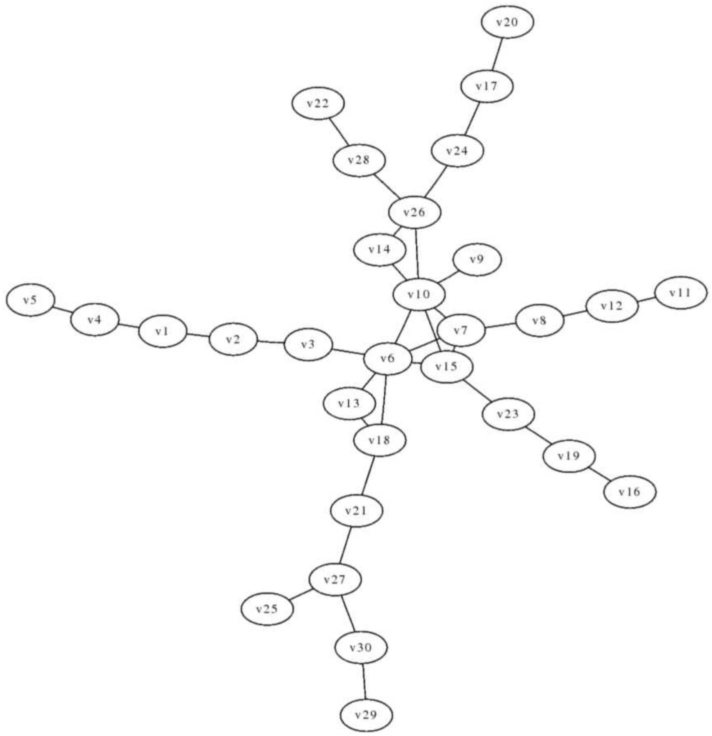


Fig. 9.5: This is the room adjacency graph abstraction for the level shown in Figure 9.4. Vertex v**n** represents room **n**.

```
12 12
111111111111
100100000001
100000000001
100111011001
100100001001
100100001001
100130001001
100111111001
100100000002
100100000002
100100000002
111111111111
```

The object specified is a 12×12 area. The representation specifies the position in the level of the upper left hand corner of the room, which is part of the optimisation performed by the search algorithm. The values 0,1 are mapped directly into the level, forcing values. The value 2 means that those squares are specified by the binary gene used to evolve the level. This means that some of the squares in the required content are seconded to the search algorithm. The 3 is the same as a zero - empty space - but it marks the check point in the required content object from which distances are measured. Distances are computed by dynamic programming and the fitness function uses distances between checkpoints as part of the information needed to compute fitness.

9.3.2 Map Generation

The map is generated by an evolutionary algorithm. The chromosome has $2N$ integer loci for N required content objects that are reduced modulo side length to find potentially valid places to put required content objects. If required content objects overlap, the chromosome is awarded a maximally bad fitness. The remainder of the position in the map, including 2's in required content, are specified by a binary gene. This gene is initialized to 20% ones, 80% zeros to make the probability the map is connected high. This is *sparse initialization*, described earlier. The fraction of ones in popualtion members is increased during evolution by the algorithm's crossover and mutation operators.

9.3.3 Room Identification

The room identification algorithm contains an implicit definition of what a room is. The rooms appearing in the required content must satisfy this implicit definition, if not they will not be identified as rooms. For that reason a relatively simple algorithm is used to identify rooms.

Room identification algorithm

```
N=0
Scan the room in reading order.
    If a 3x3 block is empty
      mark the block as in room N
      iteratively add to the room all squares with three neighbors
        already in the room
      N=N+1
    End If
End Scan
```

Once a square is marked as being part of a room, it is not longer empty, forcing rooms to have disjoint sets of squares as members. The implementation reports the squares that are members of each room and the number of squares in each room.

9.3.4 Graph Generation

The rooms form the vertices of the graph of the dungeon. Earlier, a painting algorithm was used to partition space. The adjacency of rooms is computed in a very similar fashion. For each room, a painting algorithm is used to extend the room into all adjacent empty spaces until no such spaces are left. The rooms that the paint algorithm reaches are those adjacent to the room that was its focus. Each room is extended individually by painting and the paint added is erased before treating the next room. While the painting could be done simultaneously for all rooms, this might cause problems in empty spaces adjacent to more than two rooms.

The adjacency relationship has the form of a list of neighbours for each room but can be re-formatted in any convenient fashion. The graph in Figure 9.5 was generate with the *GraphVis* package from an edge list - a list of all adjacent pairs of rooms.

9.3.5 Room Population

The adjacency graph for the rooms is the simplest object to pass to a room population engine. The designer knows which room(s) and entrances and typically supplies this information to the population engine. The engine then does a breadth-first traversal of the graph placing lesser challenges, like traps and smaller monsters in the first layer, tougher monsters in the next layer, treasure (other than that carried by monsters) in the next layer. Exits to the next level are typically in the last layer.

The required content is tagged if there is a special population engine connected with it. An evil temple, a crypt, a dragon's den or other boss can be placed with required content to make sure they always appear in the automatically generated level. Correct design of the fitness function ensures that the encounters appear in an acceptable sequence, even in a branching level, and so enable replayability.

The population engine needs a database of classified opponents, traps, and treasures scaled by difficulty. It can select randomly or in a fashion constrained by "mood" variables. A dungeon level in a volcano, for example, might be long on fire elementals and salamanders and short on wraith, vampires, and other flammable undead. A crypt, on the other hand, would be long on ghouls or skeletons and short on officious tax collectors. The creation of the encounter database, especially a careful typing system to permit enforcement of mood and style, if a critical portion of the level creation. The database needs substantially more encounters not associated with required content that it will use in a particular instance of the output of the level generator.

9.3.6 Final Remarks

The FRP level generator described here is an outline. Many details can only be filled in when it is united with a particular rules system. The level generator has the potential to create multiple version of a level and so make it more nearly replayable even when one or more of the players in a group has encountered the dungeon before. While fully automatic, the system leaves substantial scope for the designer in creating the required content and populating the encounter database.

9.4 Generating Game Content with Compositional Pattern Producing Networks

In Chapter **??** we saw how grammars such as L-systems can create natural-looking plants and we learned that they are well suited to reproduce self-similar structures. In this chapter we will look at a different representation that also allows the creation of life-like patterns called *Compositional Pattern Producing Networks* (CPPNs) [7]. Instead of formal grammars, CPPNs are based on artificial neural networks. In this chapter, we will first take a look at the standard CPPN model and then see how that representation can be successfully adapted to produce content as diverse as weapons in the game Galactic Arms Race [2] (also mentioned in Chapter 1) or flowers in the social video game Petalz [4]. In Petalz, a special CPPN encoding enables the player literally to breed an unlimited amount of naturally looking flowers that are symmetric, contain repeating patterns and have distinct petals.

9.4.1 Compositional Pattern Producing Networks (CPPNs)

Because CPPNs are a variation of artificial neural networks (ANNs), we will first formally introduce ANNs and then see we can modify them to produce a variety of different content. ANNs are computational models inspired by real brains that are capable of solving a variety of different tasks, from handwriting recognition and computer vision to robot control problems. ANNs are also applied to control NPCs in games and can even serve as PCG evaluation functions. For example, neural network-based controllers can be trained to drive like human players in a car racing game to rate the quality of a procedurally generated track ([**?**]; Chapter 1).

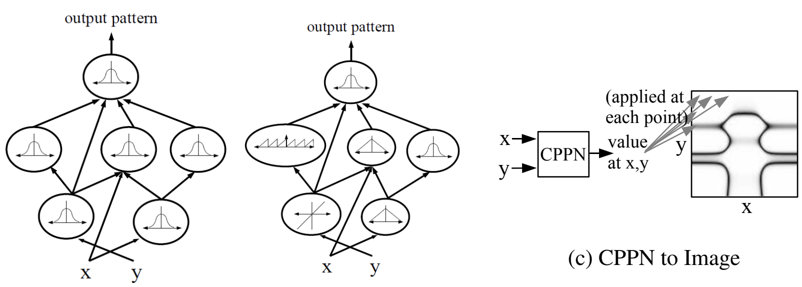
An ANN (Figure 9.6a) is an interconnected group of nodes (also called neurons) that can compute values based on external signals (e.g. infrared sensors of a robot) by feeding information through the network from its input to its output neurons. Neurons that are neither input nor output neurons are also called hidden neurons. Each neuron i has an activation level y_i that is calculated based on all its incoming signals x_j scaled by connection weights w_{ij} between them:

$$y_i = \sigma\left(\sum_j^N w_{ij}x_j\right), \tag{9.1}$$

where σ is called the activation function that determines the response profile of the neuron. In traditional ANNs the activation function is often the sigmoid function:

$$\sigma(x) = \frac{1}{1+e^{-kx}}, \tag{9.2}$$

where the constant k determines the slope of the sigmoid function. The behaviour of an ANN is mainly determined by its architecture (i.e. which neurons are connected to which other neurons) and the strength of the connection weights between the neurons.



(a) Neural Network (b) CPPN (c) CPPN to Image

Fig. 9.6: While traditional ANNs typically only have Gaussian or sigmoid activation functions (a), CPPNs can use a variety of different function like sigmoids, Gaussian, sine and many others (b). The CPPN example in this figure takes two arguments x and y as input, which can be interpreted as coordinates in two-dimensional space. Applying the CPPN to all the coordinates and drawing them with an ink intensity determined by its output results in a two-dimensional image (c). Taken from [2]

While ANNs are usually used for control or classification problems, they can also be adapted to produce content for games. CPPNs are such a variation of ANN that function similarly but can have a different set of activation functions [7]. Later we will see how special kinds of CPPNs can produce flowers in the Petalz video game and weapons in GAR. While CPPNs are similar to ANNs, they have a different terminology because CPPNs are mainly used as pattern-generators instead of as controllers. Let us now take a deeper look at the differences in implementation and applications between CPPNs and ANNs.

Instead of only sigmoid or Gaussian activation functions, which we can also find in ANNs (Figure 9.6a), CPPNs can include a variety of different functions (Figure 9.6b). The type of functions that we include has a strong influence on the type of patterns and regularities that the CPPN produces. Typically the set of CPPN activation functions includes a periodic function such as sine that produces segmented patterns with repetition. Another important activation function is the Gaussian, which produces symmetric patterns. Both repeating and symmetric patterns are common in nature and including them in the set of activation functions allows the CPPNs to produce similar patterns artificially. Finally, linear functions can also be added to produce patterns with straight lines. The activation of a CPPN follows the ANN activation we saw in Equation 9.1, except that we now have a variety of different activation functions.

Additionally, instead of applying a CPPN to a particular input only (e.g. the position of an enemy, etc.) as is typical for ANNs, CPPNs are usually applied across a broader range of possible inputs like coordinates of a two-dimensional space (figure 9.6c). This way the CPPN can represent a complete image or as we shall see shortly also other patterns like flowers. Another advantage of CPPNs is that they can be sampled at whatever resolution is desired because they are compositions of functions. Successful CPPN-based applications include Picbreeder [6], in which users from around the Internet collaborate to evolve pictures, EndlessForms [1] that allows users to evolve three-dimensional objects and MaestroGenesis [3], a program that enables users to generate musical accompaniments to existing songs. Figure 9.7 shows some of the images that were evolved by users in Picbreeder, which demonstrate the great variety of patterns CPPNs can represent. The CPPNs encoding these images and the other procedurally generated content in this chapter are evolved by the NEAT algorithm, which we will now take a closer look at.

Fig. 9.7: Examples of collaboratively evolved images on Picbreeder.

9.4.2 *Neuroevolution of Augmenting Topologies (NEAT)*

This section will only give a very short introduction to NEAT but the interested reader is refereed to [8] for a complete overview. NEAT [8] is an algorithm to evolve neural networks and since CPPNs and ANNs are very similar the same algorithm can also evolve CPPNs. The idea behind NEAT is that it begins with a population of simple neural networks or CPPNs that have no initial hidden nodes and over generations new nodes and connections are added through mutations. The advantage of NEAT is that the user does not need to decide on the number of neurons and how they are connected. NEAT determines the network topology automatically and creates more and more complex networks as evolution proceeds. This is especially

Fig. 9.8: Screenshot from a Petalz balcony that a player has decorated with various available flower pots and player-bred flowers (apps.facebook.com/petalzgame/).

important for encoding content with CPPNs because it allows the content to become more elaborate and intricate over generations. While there are other methods to also evolve ANNs, NEAT is a good choice to evolve CPPNs because is worked well in the past in a variety of different domains [6, 3, 8, 2], and it is also fast enough to work in real time environments like interactive games.

9.4.3 CPPN-generated Flowers in the Petalz Video Game

Petalz [4] is a recently developed social video game on Facebook in which procedurally generated content plays a significant role. In Petalz the player can breed a collection of unique flowers and arrange them on their balconies (figure 9.8). A flower context menu allows the player, among other things, to create new offspring through pollination of a single flower or combine two flower genomes together through cross-pollination. In addition to interacting with the flower evolution, the player can also post their flowers on Facebook, sell them in a virtual marketplace, or send them as gifts to other people. An important aspect of the game is that once a player purchases a flower, he can now breed new flowers from the purchased seed, and create a whole new lineage. Recently, Petalz was also extended with a collection game mechanics, which encourages the players to discover 80 unique flower species [5].

The flowers in Petalz are generated through a special kind of CPPN that is described next. Because the CPPN representation can generate patterns with symmetries and repetition, it is especially suited to generate naturally looking flowers with distinct petals. The basic idea behind the flower encoding is to first deform a circle to generate the shape of the flower and then to color that resulting shape based on the CPPN generated pattern. In contrast to the example we saw in Figure 9.6c, we now input polar coordinates $\{\theta, r\}$ into the CPPN (Figure 9.9) to generate radial flower patterns. Then we query the CPPN for each value of θ by inputting $\{\theta, 0\}$. However, instead of inputting θ into the CPPN directly, we input $sin(P\theta)$, which makes it easier for the CPPN to produce flower-like images with radial symmetry in the form of their petals. Parameter P can also be adjusted to create flowers with a different maximum numbers of petals. After the first step of the flower generating algorithm we determined the outline of our flower, i.e. we calculated a radius value r_{max} for each θ value. In the next step, we determine the RGB color pattern of the flower's surface by querying each polar coordinate between 0 and r_{max} with the same CPPN. Finally, the CPPN also allows us to create flowers with different layers, which reflects the fact that flowers in nature often have internal and external portions. This feature is implemented through an additional CPPN input L that determines the current layer that is being drawn. The algorithm starts by drawing the outermost layer and then each successive layer is drawn on top of the previous layers, scaled based on its depth. Because the same CPPN is determining all the layers, the different patterns can share regularities just like the different layers in real flowers.

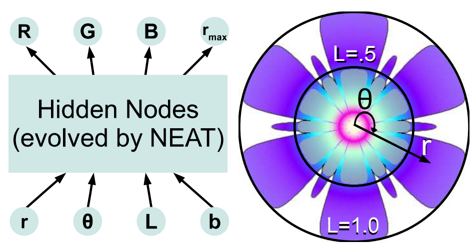


Fig. 9.9: The flower-encoding CPPN in Petalz has four inputs: polar coordinates r and θ, current layer L and bias b. The first three outputs determine the RGB color values for that coordinate. In the first step of the algorithm the maximum radius for a given θ is determined through output r_{max}. In the next step RGB values of the flower's surface are determined by querying each polar coordinate between 0 and r_{max} with the same CPPN. The number and topology of hidden nodes is evolved by NEAT, which means that flowers can get more complex over time. Taken from [4].

Figure 9.10 shows examples of flowers evolved by players in Petalz. The CPPN-based encoding allows the discovery of a great variety of aesthetically-pleasing flowers, which show varying degrees of complexity.

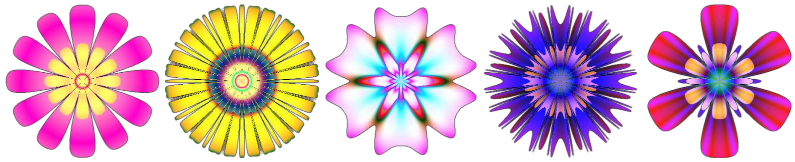


Fig. 9.10: Examples of flowers collaboratively evolved by players in the Petalz video game.

9.4.4 CPPN-generated Weapons in Galactic Arms Race

Galactic Arms Race [2] is another successful example of a game that uses procedurally generated content and interactive evolution. The procedurally generated weapon projectiles, which are the main focus of this space shooter game, are evolved interactively based on gameplay data. The idea behind the interactive evolution in GAR, which was briefly discussed in Chapter 1, is that the number of times a weapon is fired is considered an indication of how much the player enjoys that particular weapon. As the game is played, new particle weapons are automatically generated based on player behaviour. We will now take a closer look at the underlying CPPN encoding that can generate these weapon projectiles.

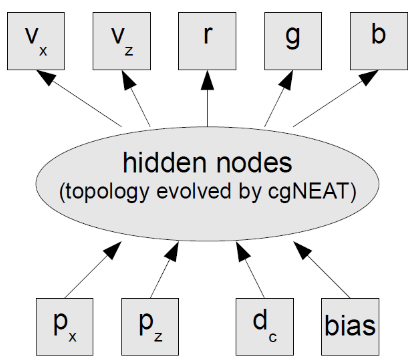
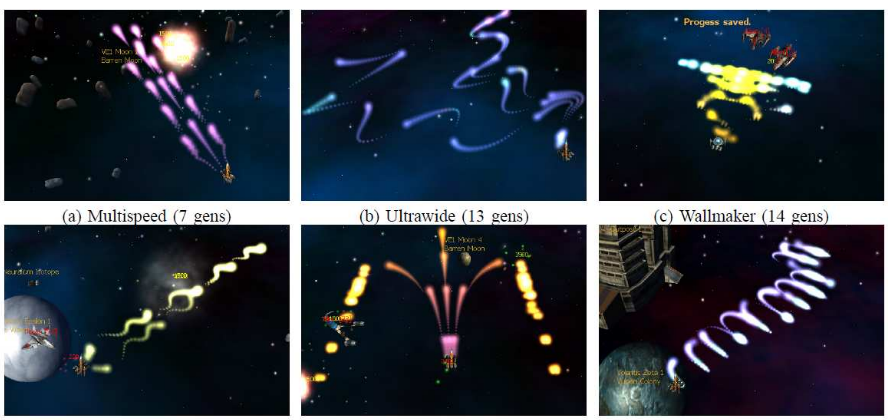


Fig. 9.11: CPPN representation of weapon projectiles in GAR. The movement of each particle is controlled by the same CPPN, which has four inputs and five outputs. The first three inputs described the current position of the particle (p_x, p_y) and the distance d_c from the location that it was fired from. After the CPPN activation, the outputs determine the particle's velocity (v_x, v_y) and RGB color value. Taken from [2].

Each weapon in the game is represented as a single CPPN (Figure 9.11) with four inputs and five outputs. Instead of creating a static image (Figure 9.7) or flower

(Figure 9.9) the CPPNs in GAR determine the behavior of each weapon particle over time. Each animation frame the CPPN is queried for the movement (velocity in the x and z direction) and appearance (RGB color values) of the particles given the particles current position in the space relative to the ship (p_x, p_y) and distance d_c to its starting position. After activating the CPPN the particles are moved to their newly determined position and the CPPN is queried again in the next frame of animation. Evolution starts with a set of simple weapons that shoot only in a straight line and then more and more complex weapons are evolved based on the NEAT method. By adding new nodes with different activation functions like Gaussian and sine very interesting particle movements can evolve and the player can discover an unlimited variety of different weapons.

Figure 9.12 shows a variety of interesting weapons with vivid patterns that were evolved by players during the game. Interestingly, different weapons do not just have a different look but also tactical implications. For example, the wallmaker weapon (Figure 9.12c) can create a wall of particles in front of the player, which allows for a more defense-oriented play. Other guns like the multispeed weapon (Figure 9.12a) can be used in tactical situations in which a more offense-oriented approach is needed.



(a) Multispeed (7 gens) (b) Ultrawide (13 gens) (c) Wallmaker (14 gens)

(d) Corkscrew (3 gens) (e) Tunnelmaker (2 gens) (f) Blue Ladder (42 gens)

Fig. 9.12: Examples of CPPN-encoded weapon evolved in the Galactic Arms Race video game. Take from [2].

9.5 Generating level generators

Our final example of an advanced representation is not a representation of a particular type of game content, but rather of a level generator itself. This example, due to Kerssemakers et al., takes as its starting point the question what would happen if we chose to view the content generator itself as a form of content, and create a generator for it; a procedural procedural content generator generator (PPLGG) **??**. The answer was to create a search-based generator which searches a space of generators that generate levels for Super Mario Bros in the Mario AI Framework.

As usual, we can understand a search-based generator in terms of representation and evaluation. The evaluation in this case is interactive: a human user looks at the various content generators, and chooses which of them (one or several) that will get to survive and form the basis of the next generation. In order to be able to assess these content generators, the user can look at a sample of ten different levels generated by each content generator, and play any one of them; the tool also gives an estimate of how many of these levels are playable using simulation-based evaluation. Complementarily, the user can see a "cloud view" of each generator, where a number of levels generated by that generator are superimposed so that patterns shared between the levels can be seen 9.13. Figure 9.14 shows a single level in condensed view, and part of the same level in game view, where the user can actually play the level.

More interesting from the vantage point of the current chapter is the question of representation. How could you represent a content generator so as to create a searchable space of generators? In this case, the answer is that the generator is based on agents (each generator contains between 14 and 24 agents), and the generator genome consists of the parameters that define how the agents will behave. During generation, the agents move concurrently and independently, though they affect each other indirectly through the content they generate.

The genome consists of specifications for a number of agents. An agent is defined by a number of parameters, that specify how it moves, for how long, where and when it starts, how it changes the level and in response to what. The agent's behaviour is not deterministic, meaning that any collection of agents (or even any single agent) is a level generator that can produce a vast number of different levels rather than just a generative recipe for a single level.

The first five parameters below are simple numeric parameters that consist in an integer value in the range specified below. The last five parameters are categorical parameters specifying the logic of the agent, which might be associated with further parameters depending on the choice of logic. The following is a list of all parameters:

- **Spawn time [0-200]**: The step number on which this agent is put into the level. This is an interesting value as it allows the sequencing of agents, but still allows for overlap.
- **Period [1-5]**: An agent only performs movement if its lifetime in steps is divisible by the period.
- **Tokens [10-80]**: The amount of resources available to the agent. One token roughly equals a change to one tile.
- **Position [Anywhere within the level]**: The center of the spawning circle in which the agent spawns.

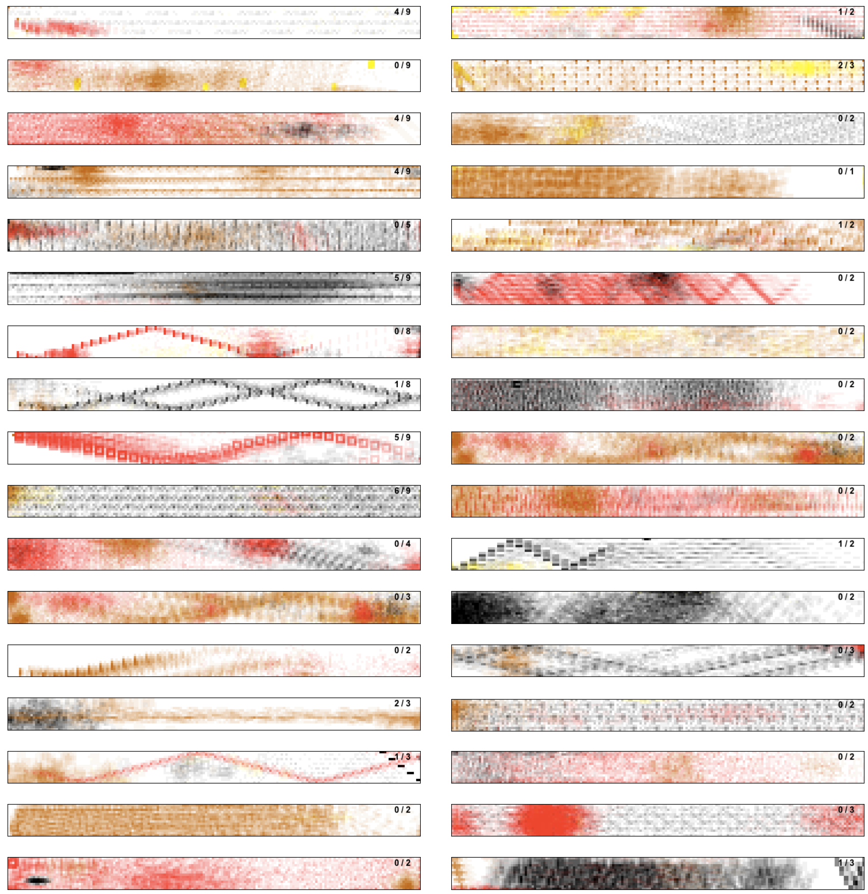


Fig. 9.13: A cloud view of several content generators. Each content generator is represented by a "cloud" consisting of multiple levels generated by that generator, overlaid on top of each other with low opacity.

- **Spawn radius [0-60]**: The radius of the spawning circle in which the agent spawns.
- **Move style**: the way the agent moves every step.
  - follow a line in a specified direction (of 8 possible directions) with a specified step size.
  - take a step in a random direction
- **Trigger state**: The condition for triggering an action, checked after each movement step.
- always

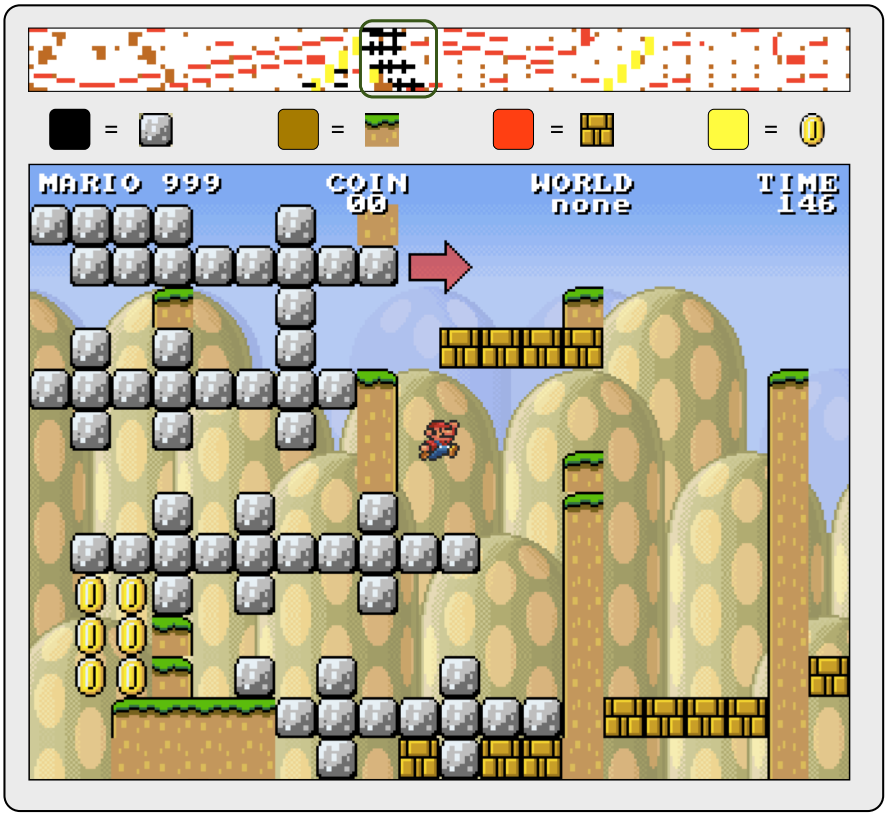


Fig. 9.14: A single generated level, and a small part of the same level in the game view.

- when the agent hits a specified type of terrain.
- when a specified rectangular area is full of a specified tile type.
- when a specified area does not contain a specified tile type.
- with a specified probability

• **Boundary movement**: The way the agent handles hitting a boundary.

- bounce away
- go back to start position
- go back to within a specified rectangular area around the start position

• **Action type**: The type of action performed if it is triggered.

- place a specified tile at position
- place a rectangular outline of specified tiles and size around position
- place a filled rectangle of specified tiles and size around position
- place a circle of specified tiles and size around position

– place a platform/line of specified tiles and size at position
– place a cross of specified tiles and size at position

Given that the starting position of agents imply a large amount of randomness, and a number of other behaviours imply some randomness, the same set of agents will produce different levels each time the generator is run. This is what makes this particular system a content generator generator rather than "just" a content generator.

9.6 Summary

This chapter has addressed the issue of content representation within search-based PCG. How content is represented affects not only how effectively the space can be searched, but also biases the search process to different parts of the search space. This can be illustrated by how different ways of representing a dungeon or maze yields end products that look very differently, even though they are evolved to satisfy the same evaluation function and reach similar fitness. Representations can be tailored to extend the search-based paradigm in various ways, for example by providing "required content" that cannot be altered by the variation operators of the search/optimisation algorithm. More complicated representations might require a multi-step genotype-to-phenotype mapping that can be seen as a PCG algorithm in its own right. For example, compositional pattern-producing networks (CPPNs) are a form of neural network that map position in some space onto intensity, colour, direction or some other property of pixels or particles at that direction. This is an interesting content generation algorithm in itself, but can also be seen as an evolvable content representation. Taking this perspective to its extreme, we can set out to evolve actual content generators, and judge them not on any single content artefact they produce but on samples of their almost infinitely variable output. The last example in this chapter explains one this can be done, by representing Mario AI level generators as parameters of agent-based systems and evolving those.

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Chapter 10
The experience-driven perspective (DRAFT)

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10.1 Nice to get to know you

As you play a game, you get to know it better and better. You understand how to use its core mechanics and how to combine them; you get to know the levels of the game, or, if the levels are procedurally generated, the components of the levels and typical ways in which they can be combined. You learn to predict the behaviour of other creatures, characters and systems in the game. All this you learn from your interaction from the game. While playing, you also adapt to the game: you change your behaviour so as to achieve more success in the game, or so as to entertain yourself better.

However, both you and your game take part in this interaction, and all of your interaction data is available to the game as well. In principle, the game should be able to get to know you as much as you get to know it. After all, it has seen you succeed at overtaking that other car, fail that sequence of long jumps, give up and shut down the game after crashing your plane for the seventh time or finally resort to buying extra moves after almost clearing a particular puzzle. A truly intelligent game should know how you play better than you know it yourself. And then, it should be able to adapt itself so as to entertain you better, or let you achieve more or less success in the game, or perhaps to give you some other kind of experience you would not otherwise have had.

The idea of *game adaptation*, the game adapting itself in response to how you play (or some other information if might have about you), is an old one. In its simplest form it is called “dynamic difficulty adjustment” (DDA), and simply means that the difficulty of the game is increased if the player does well and decreased if the player plays poorly. This can be seen in many car racing games, where the opponent cars always seem to be just ahead of you or just behind you, regardless of how well you play (also known as “rubber banding”). The game design rationale for rubber banding is that if the player is much in front of the opponents he/she will not perceive a challenge, and if the player is far behind the opponents he/she will lose hope of ever catching up; in either case, the player will likely lose interest in the game. This is sometimes rationalised as a way of keeping the player in the "flow channel". *Flow* is a concept which was invented by the psychologist Czikszentmihalyi to signify the "optimal experience", where someone is completely absorbed in the activity they are performing; one condition for this is constant but not unassailable challenge [5]. The flow concept has inspired several theories of challenge and engagement in games, such as GameFlow [**?**] it is, however, rather limited to challenge which is only one of the the multiple concurring dimensions of player experience [3].

DDA mechanisms in racing games are often implemented simply by letting the opponent cars drive faster or slower. There are interesting exceptions, such as the Mario Kart series, which gives more powerful power-ups to players who lag behind, some of which allow them to attack players who lead the pack. Other games might lower the difficulty of a particular section of the game after a player has failed numerous times; *Grand Theft Auto V* allows the player to simply skip any action sequence which the player has failed three times already. There are several proposals for how this could be done more automatically, using AI techniques [12]. A key realisation is that adaptation is about more than just difficulty: to begin with, difficulty is multi-dimensional, as a game could be difficult in many different ways, and people have unbalanced skill sets. The same game could be different for player A because of its requirement for quick reactions, for player B because of how difficult the spatial navigation is and for player C because of the nuances of the story that needs to be understood in order to solve its puzzles. Also, just having the right difficulty is in general not enough for a game to be perfectly tailored for a particular player. Different players might prefer different balances of game elements or atmospheres, such as scary, intense or contemplative parts of the game. Adaptation could in principle happen among any of multiple axes, many of which are not properly formalised or even described. There are also many possible methods for adaptation, many of which would include modifying the content of the game or even generating new content.

In this chapter, we will focus on the use of PCG methods to adapt games to the experience of the player. The perspective we adopt is called *experience-driven procedural content generation* [39]. In experience-driven PCG, a model of player experience is learnt, that can predict some aspect of the player's experience (e.g. challenge, frustration, engagement, spatial involvement, etc.) based on some aspect of game content. This model can then used as a base for an evaluation function in search-based or mixed-initiative PCG. For example, a model might be learned that predicts how engaging some players think individual building puzzles are in a physics-based puzzle game. This model can then be used for evolving new puzzles, where the evaluation function rewards such puzzles that are predicted to be most engaging for the target player(s).

The chapter is structured as follows. First we describe the various ways we can elicit player experience through a game and collect information about player experience. The next section discusses algorithms for creating models of player experience, such as neuroevolutionary preference learning, based on data collected during the game interaction (model's input) and annotated player experience (model's output). A short section discusses how these models can be used in content generation, followed by a prolonged example describing experience-driven level generation in Super Mario Bros in detail.

10.2 Eliciting Player Experience

Games can elicit rich and complex patterns of user experience as they combine unique properties such as rich interactivity and potential for a multifaceted player immersion [3]. User experience in games can be elicited primarily through the long or short term interaction with various core game elements. Arguably social interaction (or else *shared involvement* [3]) may have a clear impact on a player's experience; however, it offers a rather challenging problem for artificial intelligence and signal processing and experience-driven PCG techniques. While a valid research question for further study social interaction is not included in the list of player experience stimuli considered in this chapter.

Experience-driven PCG views game content as potential *building blocks of player experience* [39]. That is precisely the fundamental link between game content and player experience. In that regard, all potential content types can elicit player experience . Game content refers to the game environment and its impact on player experience can be directly linked to *spatial involvement* and *affective involvement*. But it also refers to fundamental game design building blocks such as game mechanics (linked to *ludic involvement*), narrative (linked to *narrative involvement*), and reward systems [3].

Beyond the game environment itself — such as a game level/map [31, 15] — game content includes audiovisual settings such as lighting [7], saturation, and music [8] and sound effects [25] but also virtual camera profiles and effects [**?**, 36, 2] and game rules [32]. The environment usually provides the representation format of stories and narratives and it is also linked to NPCs (if existent in the game) as it forms their context, living habitats and surroundings. In a broader sense, both agents and narratives can be viewed as game content that can be parameterized and altered [39]. Whether games can tell stories or whether they are more properly understood as a form of narrative has been extensively debated within game studies [16, **?**]. In any case, stories play an essential part in creating the ambiance, style, climax and feelings of a game. In interactive storytelling, the story is used as an adaptive mechanism that adjusts according to the actions of the players, offering variant player experiences [**?**]. By breaking the game narrative into further subareas of game content we can find core game content elements such as the game's plotline [9], but also the ways this story-plot is represented in the game environment.

In summary, all game content surrounding NPCs (whether those are existent in the game or not) including game mechanics, rules, story-nodes and reward systems may have an effect on the experience of the player [39]. In addition complex, social and emotional non-player characters can be used as triggers of desired player experience. In order for agents to elicit meaningful experience and immerse the player they need to engage players in rich and emotional interaction. Towards that purpose they may embed computational models of cognition, behaviour and emotion which is e.g. based upon the OCC model [23].

10.3 Modeling Player Experience

The detection and computational modelling of a user's affective state are core problems in user experience and affective computing research. Detecting and modelling affective state in games can be seen as a special case of this, though an unusually complex special case. Given the complexity and richness of game-player interaction and the multifaceted nature of player experience, methods that manage to overcome the above challenges and model player experience successfully advance our understanding of human behaviour and emotive reaction with human computer interaction. Player experience modelling (PEM) can thus be viewed as a form of user modelling within games incorporating aspects of behaviour, cognition and affect. PEM involves all three key phases for computational model construction. These are signal processing, feature extraction and feature selection for the model's input;, experience annotation for the model's output; and various machine learning and computational intelligence techniques that learn the mapping between the two. Within Experience-driven PCG, game content is also represented in the underlying function that characterises player experience.

We can distinguish between *model-based* and *model-free* approaches to player experience modelling[39] as well as potential hybrids between them. The difference is whether the computational model is based on or structured by a theoretical framework. A completely model-based approach relies solely on a theoretical framework that maps game context and player responses to experience. In contrast, a completely model-free approach assumes there is an unknown function between modalities of user input, game content and experience that a machine learner (or a statistical model) may discover which does not assume anything about the structure of this function. The space between a completely model-based and a completely model-free approach can be viewed as a continuum along which any PEM approach might be placed. The rest of this section presents the key elements of both model-based and model-free approaches and discusses the core components of a learned computational model (i.e. model input, model output and common modeling methods).

10.3.1 Model Input and Feature Extraction

The PEM's input can be of three main types: a) player behavioral responses to game content as gathered from **gameplay** data (i.e. behavioural data); b) **objective** data collected as player experience manifestations to game content stimuli such as physiology and body movements; and c) the **game context** which comprises of any type of game content viewed, played through, and/or created [39, 37, 38].

Given the multifaceted nature of player experience the input of a PEM usually consists of complex spatio-temporal patterns found in user inputs, sometimes sampled from multiple modalities. These signals need to be processed and relevant data features need to be extracted to feed the model. Relevant features, however, are hard to find within such signals and the ad-hoc design of statistical features is often undermining the performance of PEM. There are several available methods within feature extraction (such as principal component analysis and fisher projection) and feature selection (such as sequential forward selection and genetic search based selection) that are applicable to the problem. Recently techniques such as *sequence mining* [19] for feature extraction and *deep learning* [17] for feature combination have shown potential to construct meaningful features for PEM. These methods have been able to fuse data from multiple sources across several player inputs and between player input and game content. In particular, deep learning is a powerful pattern recognition method that manages to detect the most distinct patterns across multiple signals and provides complex spatio-temporal data attributes that complement standard ad-hoc feature extraction [17]. Sequence mining, on the other hand, identifies the most frequent sequences of events across user input modalities and game context which could be relevant as features for any PEM attempt [19].

The three above-mentioned input types for a PEM are detailed in the remaining of this section.

10.3.1.1 Gameplay input

The key motivation behind the use of behavioural (gameplay-based) player input is that player actions and real-time preferences are linked to player experience as games affect the player's cognitive processing patterns, cognitive focus and emotional state. Essentially, you express the contents of your mind through gameplay. Arguably it is possible to infer a player's current experience state by analyzing patterns of the interaction and associating player experience with game context variables [4, 10]. The models built on this user input type rely on detailed attributes from the player's behavior which are extracted from player behavioural responses during the interaction with game content stimuli. Such attributes, also named *game metrics*, are statistical spatio-temporal features of game interaction [6] which are usually mapped to levels of cognitive states such as attention, challenge and engagement [28]. In general, both generic measures — such as the level of player performance and the time spent on a task — as well as game-specific measures — such as the items picked and used — are relevant for the gameplay-based PEM.

10.3.1.2 Objective input

The variety of available content types within a game can act as elicitators for complex and multifaceted player experience patterns. As expected such patterns of experience may affect changes in the player's physiology, reflect on the player's facial expression, posture and speech, and alter the player's attention and focus level. Monitoring such bodily alterations can assist in recognising and synthesising predictors of player experience. The objective approach to PEM assumes access to multiple modalities of player input which manifest aspects of player experience.Thus, the impact of game content to a number of real-time recordings of the player may be investigated. Physiology offers the primary medium for detecting a player's experience via objective measures: signals obtained from electrocardiography (ECG) [36], photoplethysmography [36, 33], galvanic skin response (GSR) [11], respiration [33], electroencephalography (EEG) [21] and electromyography (among others) are commonly used for the detection of player experience given the recent advancements on sensor technology and physiology-based game interfacing. In addition to physiology the player's bodily expressions may be tracked at different levels of detail and the real-time cognitive or affective responses to game content may be inferred. The core assumption of such input modalities is that particular bodily expressions are linked to basic emotions and cognitive processes. Motion tracking may include body posture [26], facial expression and head pose [28].

Beyond the non-verbal cues discussed above there is also room for verbal cue investigation within games. In general, social signals derived from human verbal communication can potentially be used within social games that allow player-to-player interaction (direct or indirect). Such signals challenge the principles of individual player experience modelling but are expected to open the horizon and augment the potential of the EDPCG framework.

10.3.1.3 Game context input

In addition to gameplay and objective data, the context of the game — e.g. the game content experienced, played or created — defines a necessary input for PEM. Game context refers to the real-time parameterised state of the game which could extend beyond the game content. Without the game context input, player experience models run into the risk of inferring erroneous experience states for the player. For example, an increase in galvanic skin response (GSR) can be linked to a set of dissimilar high-arousal affective states such as frustration and excitement. Thus, the cause of GSR increase (e.g. due to a player's death in a gap between platforms, or alternatively, due to a game level completion) needs to be fused within the GSR signal and embedded in the model. Context-free modelling (while important and desired) has not been investigated to the degree we could identify generic and context-independent content patterns, features and attributes across games and players. A few recent studies, however, such as that of Martinez et al. [18] attempt to investigate context-independent physiological features that can capture player experience across variant game genres.

10.3.2 Model Output: Experience Annotation

The output of the player experience model is provided through an experience annotation process which can either be based on first person reports (self-reports) or on reports expressed indirectly by experts or external observers [39]. The model's output is, therefore, linked to a fundamental research question within player experience and affective computing: what is the ground truth of player experience and how to annotate it? To address this challenge a number of approaches have been proposed; each having benefits and pitfalls. The most direct way to annotate player experience is to ask the players themselves about their experience and build a model based on these annotations. Subjective annotation can be based on either players free-response during play or on forced data retrieved through questionnaires. Alternatively, experts or external observers may annotate the playing experience in a similar fashion. Third-person player experience annotation entails the identification of particular user (cognitive, affective, behavioral) states by user experience and game design experts.

Annotations (either forced self-reports or third-person) can be classified as *rating* (scalar), *class* and *preference* (or ranking). In rating, annotators are asked to answer questionnaire items given in a rating/scaling form — such as the Game Experience Questionnaire [13] or the Geneva Emotion Wheel [1] — which labels user states with a scalar value (or a vector of values). In a class-based format subjects are asked to pick a user state from a particular representation which is usually a simple boolean question (Was that game level frustrating or not? Is this a sad facial expression?). Using the preference annotation format [34], annotators are asked to compare a playing experience in two or more variants/sessions of the game (Was that level more engaging that this level? Which facial expression looks happier?). Recent comparative studies have exposed the limitations of rating approaches over ranking questionnaire schemes which include increased order of play and inconsistency effects [35] and lower inter-rater agreement [20].

10.3.3 Modelling approaches

The approach for constructing models of player experience heavily relies on the modelling approach followed (model-based vs. model-free) and the annotation scheme adopted. For the model-based approach components of the model and any parameters that describe them are constructed in an ad-hoc manner and, sometimes, tested for validity in a trial and error basis. No machine learning or sophisticated computational tools are required for these approaches even though one could envisage the optimisation of the parameter space to yield more accurate models; that, however, would require empirical studies which brings the approach closer to a model-free perspective.

Model-free approaches, on the other hand, are dependent on the annotation scheme and, in turn, the type of model output available. If data recorded includes either a scalar representation (e.g. via ratings) or classes of annotated labels of user states any of a large number of machine learning (regression and classification) algorithms can be used to build affective models. Available methods include artificial neural networks, Bayesian networks, decision trees, support vector machines and standard linear regression. Alternatively, if experience is annotated in a ranked format standard supervised learning techniques are inapplicable, as the problem becomes one of preference learning [34]. Neuro-evolutionary preference learning [34] and rank-based support vector machines [14] but also simpler methods such as linear discriminant analysis [33] are some of the available approaches for learning preferences.

10.4 Content generation through player experience models

The ultimate goal of constructing models of player experience is to use these models as measures of content quality and consequently, realize affective, cognitive and behavioral interaction in games and generate personalized or player-adapted content. Quantitative models of player experience can be used to capture player-game interaction and the impact of game content on player experience. According to Yannakakis and Togelius [**?**] models of player experience can be used to assess content quality and achieve game adaptation.

10.5 Example: Super Mario Bros

A successful complete implementation of the EDPCG framework suggested by Yannakakis and Togelius [**?**] is the work done by Shaker et al. [30, 28, 29] to model and personalize player experience in Infinite Mario Bros (IMB) [24] — a public domain clone of Super Mario Bros [22]. In this work, models of player experience are built based on information collected from the interaction between the player and the game. Different types of features capturing different aspects of player behavior are considered: *subjective* self-reports of player experience; *objective* measures of player experience are collected by video recording gameplay sessions and later extracting information about head movement behavior in reaction to game events [27, 28] (Figures 10.1, 10.2 and 10.3 present example instances of players' reaction when losing, winning and when encountering hard situations, respectively); players' actions while playing the game are also registered and used as *gameplay* features [30].

Fig. 10.1: Typical player responses to losing in IMB

Fig. 10.2: Typical player responses to winning in IMB

Fig. 10.3: Typical player responses to hard situations in IMB

The choice of feature representation is vitally important since it allows capturing different dimensions of player experience and game content. Furthermore, the choice of content representation defines the search space that can be explored and it affects the efficiency of the content creation method. To accommodate for this, the different sets of features collected are represented as frequencies describing the number of occurrences of various events or the accumulated time spent doing a certain activity (such as the number of killings of a certain type of enemies or the total amount of time spent jumping). Features are also represented as sequences capturing the spatial and temporal order of events and allowing the discovery of temporal patterns [30]. Table 10.1 presents representative example features from each representation from.

Based on the features collected, a modelling approach is followed in an attempt to approximate the unknown function between game content, players' behaviour and how players experience the game. The player experience models are developed

Table 10.1: The different types of representations of content and gameplay features.

Feature	Description
	Flat platform
( )(,)	A sequence of three coins
$(R^{\blacktriangleright}, R^{\blacktriangleright\Uparrow})$( )	Moving then jumping in the right direction when encountering an enemy
(,)( )	A gap followed by a decrease in platform height
$(\Uparrow^{\blacktriangleright})(S)(\blacktriangleright)$	Jumping to the right followed by standing still then moving right
t_{right}	Time spent moving right
n_{jump}	Total number of jumps
n_{coin}	Total number of coins
k_{stomp}	Number of enemies killed by stomping
N_e	Total number of enemies
B	Total number of blocks

on different types and representations of features allowing a thorough analysis of the player-content relationship.

The following sections describe the approach followed to model player experience and the methodology proposed to tailor content generation for particular players using the constructed models as measures of content quality.

10.5.1 Player experience modeling

When constructing player experience models, one should identify relevant features from game content and player behavior that affect player experience. This could be done by recording gameplay sessions and extracting several features as indicators of players' affect, performance and playing characteristics. Given the large size of the feature set that could be extracted, feature selection becomes a critical step for efficient knowledge discovery. The selection of the relevant subset of features not only helps us reduce the dimension of the input space resulting in more accurate models that are easier to analyse, but it also eliminates noisy features that are irrelevant for the player experience modelling as well as improving the model's generalisation capabilities.

Feature selection was applied as a first step when modelling players' experience. The input space constitutes of the different features extracted from the gameplay sessions. The models are trained to predict reported player experience from a subset of selected features. There are many approaches that could be followed to select the relevant subset of features, the feature selection method followed in this example is Sequential Forward Selection (SFS) combined with neuroevolutionary preference learning (using Single Layer Perceptrons (SLP) and simple Multi-Layer Perceptrons (MLPs) consisting of one layer of two hidden neurons) to measure the performance of each subset of features selected. Applying this approach yields different subsets of selected features for predicting each reported emotional states.

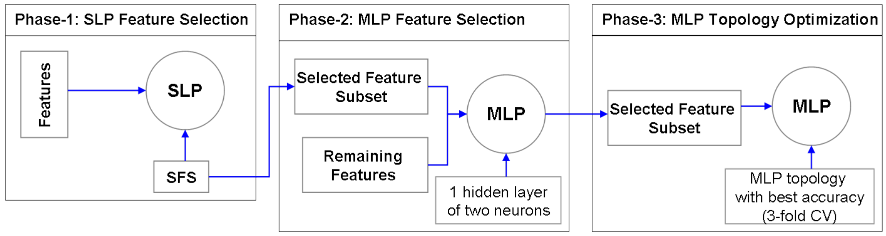

Fig. 10.4: The three-phase player experience modeling approach followed.

The underlying function between gameplay, content features and reported player experience is considered to be complex and cannot be easily captured using SLPs and simple MLPs and robust estimators are required if we are to accurately model the features-experience relationship. Therefore, once all features that contribute to accurate simple MLP models are found, an optimisation step is followed to build more powerful MLPs with more sophisticated structures. This is achieved by gradually increasing the complexity of the MLPs through adding hidden nodes and layers while monitoring the models' performance. Figure 10.4 presents an overview of the process followed to construct the PEMs.

Following this approach, models with high accuracies were constructed for predicting players' reports of engagement, frustration and challenge from different subsets of features from different modalities. The models constructed were also of varying topologies and prediction accuracies.

10.5.2 Grammatical based personalised level generator

In Chapter **??**, we described how Grammatical Evolution (GE) can be used to evolve content for IMB. As discussed earlier, GE employs a design grammar to specify the structure of possible level designs. The grammar is used by GE to transform the phenotype into a level structure by specifying the types and properties of the different game elements that will be presented in the final level design. The fitness function defined in our earlier description was a purely aesthetics-based measure that score designs based on the number of elements presented and their placement properties.

In this section, we present a method for using the GE-based content generator to evolve personalised content for IMB. This is achieved by employing an adaptation mechanism as a fitness function to optimise player experience. The content is ranked according to the experience it evokes for a specific player and the content generator searches the resulting space for content that maximises particular aspects of player experience. To facilitate this, the player experience models constructed are used as fitness functions scoring each design evolved according to its appeal for a particular player. The fitness value assigned for each individual in the population

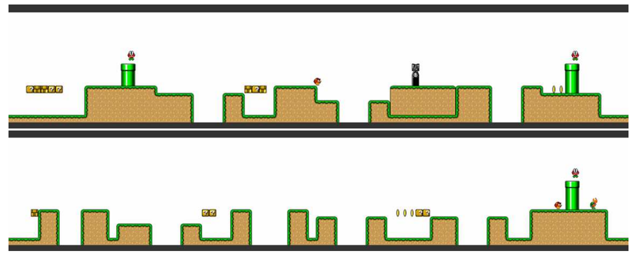

Fig. 10.5: The best levels evolved to maximise predicted challenge for two AI agents.

(a level design) in the evolutionary process is the output of the player experience model which is the predicted value of an emotional state. The PEMs output is calculated by computing the values of the models's inputs; this includes the values of the content features which are directly calculated for each level design generated by GE and the values of the gameplay features estimated from the player's behavioural style while playing a test level.

The search for the best content features that optimise a particular state is guided by the model's prediction of the player experience states, with a higher fitness given to the individuals that are predicted to be more engaging, frustrating or challenging for a particular player.

10.5.2.1 On-line personalised content generation

While the level is being played, the playing style is recorded and then used by GE to evaluate each individual design generated. Each individual is given a fitness according to the recorded player behaviour and the values of its content features. The best individual found by GE is then visualised for the player to play.

It is assumed that the player's playing style is largely maintained during consecutive game sessions and thus his playing characteristics in a previous level provide a reliable estimator of his gameplay behaviour in the next level. To compensate for the effect of learning while playing a series of levels, the adaptation mechanism only considers the recent playing style, i.e. the one which the player exhibited in the most recent level. Thus, in order to effectively study the behaviour of the adaptation mechanism, it is important to monitor this behaviour over time. For this purpose, AI agents with varying playing characteristics have been employed to test the adaptation mechanism since this requires the player to play-test a large number of levels. Figure 10.5 presents the best levels evolved to optimise player experience of challenge for two AI agents with different playing styles. The levels clearly exhibit different structures; a slightly more challenging level with more gaps was evolved for the second agent with more gaps and enemies than the one generated for the first agent.

10.6 Lab exercise: Generate personalised level for Super Mario Bors

In this lab session, you will generate personalised levels for a specific player using the InfiTux benchmark. The same software interface illustrated in Chapter 3 **??** will be used but this time you should focus on customisation of content for specific playing style so that the output of your *generateLevel* method should be player-driven content.

In order to facilitate meaningful detection of player experience and to allow you to develop player experience models, you will be given a dataset of 597 instances containing several statistical gameplay and content features collected from hundreds of players playing the game. The data contains information about several aspects of players' behaviour captured through features representing the frequencies of performing specific actions such as killing an enemy of jumping and the time spent doing certain behaviour such as moving right or jumping. Your task is to use this data to build PEM using a machine learning or a dataminig technique of your choice. The models you build can then be used to recognise the playing style of a new player.

After you build the models and successfully detect player experience, you should implement a method to adjust game content to change how player experience the game. You can adopt well-known concepts of player experience such as *fun*, *challenge*, *difficulty* or *frustration* and adjust the game content according to the aspect you would like your player to experience.

10.7 Summary

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Chapter 11
Mixed-initiative Content Creation (DRAFT)

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Many kinds of PCG discussed so far in this book have focused on fully automated content generation. *Mixed-initiative* Mixed-initiative procedural content generation covers a very broad range of generators, algorithms and tools which share one common trait: they require human input in order to be of any use. While most generators arguably require a human to press "generate" or to provide some rudimentary arguments (such as the map size or map type in Civilization maps), mixed-initiative PCG automates only part of the process, requiring significantly more human input than other forms of PCG.

As its name suggests, both a human creator and a computational creator "take the initiative" in mixed-initiative PCG systems. However, there is a sliding scale on the type and impact of each of these creators' initiative. For instance, one can argue that a human novelist using a text editor on their computer is a mixed-initiative process, with the human user providing most of the initiative but the text editor facilitating their process (spell-checking, word counting or choosing when to end a line); on the other extreme, the map generator in *Civilization V* (Firaxis 2014) is a mixed-initiative process, since the user provides a number of desired properties of the map. This chapter will focus on less extreme cases, however, where both human and computer have some significant impact on the sort of content generated.

It is naive to expect that the human creator and the computational creator always have equal say in the creative process:

- In some cases, the human creator has an idea for a design, requiring the computer to allow for an easy and intuitive way to realize this idea. Closer to a word editor or to *Photoshop*, such content generators facilitate the human in his creative task, often providing an elaborate user interface; the computer's initiative is realized as it evaluates the human design, testing if it breaks any design constraints and presents alternatives to the human designer. Generators where the creativity stems from human initiative, as seen in Figure 11.1, and will be discussed in Section 11.1.
- In other cases, the computer is able to autonomously generate content but lacks the ability to judge whether what it has created is sufficiently good. In cases where evaluating generated artifacts is subjective, unknown in advance, or too daunting to formulate mathematically, such generators request human users to act as the judge and guide their generative processes towards content that these users deem better. The most common method for accomplishing this task is interactive evolution, as seen in Figure 11.2, and will be discussed in Section 11.2. In interactive evolution the computer has the creative initiative while the human acts as an advisor, trying to steer the generator towards their own goals. In most

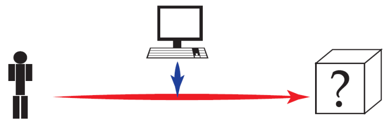

Fig. 11.1: Computer-Aided Design: humans have the idea, the computer supports their creative process.

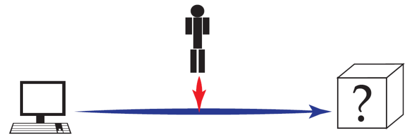

Fig. 11.2: Interactive Evolution: the computer creates content, humans guide it to create content they prefer.

cases, human users don't have direct control over the generated artifacts; selecting their favorites does not guarantee in which way the computer will interpret and accommodate their choice.

11.1 Computer Aided Design tools

To understand how mixed-initiative PCG systems are designed today, as well as to attain future inspiration for such systems, it is important to also understand several older systems from which current work draws inspiration. There are three main threads of work that we'll look at in this section: mixed-initiative interaction, computer-assisted design, and creativity support tools. Each of these areas of work have inspired different aspects of the systems we'll talk about in the chapter.

11.1.1 Mixed-Initiative Interaction

In 1960, J.C.R. Licklider [22] laid out his dream of the future of computing: man-computer symbiosis. Licklider was the first to suggest that the operator of a computer take on any role other than that of the puppetmaster — he envisioned that one day the computer would have a more symbiotic relationship with the human operator. Licklider described a flaw of existing interactive computer systems as: "In the man-machine systems of the past, the human operator supplied the initiative, the direction, the integration, and the criterion."

Notice the use of the term "initiative" to refer to how the human interacts with the computer, and the implication that the future of man-computer symbiosis therefore involves the computer being able to share initiative with its human user.

The term "mixed-initiative" was first used by Jaime Carbonell to describe his computer-aided instruction system, called SCHOLAR [2]. SCHOLAR is a text-based instructional system that largely consisted of the computer asking quiz-style questions of the student using the system; the mixed-initiative component of the system allows the student to ask questions of the computer as well. Carbonell argued that there were two particularly important and related aspects of a mixed-initiative system: context and relevancy. Maintaining context involved ensuring that the computer would only be able to ask questions that were contextually relevant to the discussion thus far, so that large sways in conversation did not occur. Relevancy involves only answering questions with relevant information, rather than all of the information known about the topic.

Mixed-initiative interaction describes a form of interaction between computer and human in which initiative is shared. It can be helpful to think about this style of interaction as a conversation-imagine, for example, two human colleagues having a conversation in the workplace:

Kevin: "Do you have time to chat about the tutorial levels for the game?"
Sarah: "Yes, let's do that now! I think we need to work together to re-design the first level. Do you—."
Kevin: "Yeah, I agree, players aren't understanding how to use the powerups. I was thinking we should make the tutorial text bigger and have it linger on the screen for longer."
Sarah: "Well, information I got from the user study session two days ago implied that players weren't reading the text at all. I'm not sure if making the text bigger will help."
Kevin: "I think it will help."
pause
Kevin: "It's easy to implement, at least."
Sarah: "Okay, how about you try that, and I'll work on a new idea I have for having the companion character show you how to use them."
Kevin: "Great! Let's meet again next week to see how it worked."

There are several ways in which Kevin and Sarah are sharing initiative in this conversation. Novick and Sutton [27] describe several components of initiative:

1. Task initiative: deciding what the topic of the conversation will be, and what problem needs to be solved. In our example, Kevin takes the task initiative, by bringing up the topic of altering the tutorial levels, and by introducing the problem that, specifically, players don't understand how to use the powerups.
2. Speaker initiative: determining when each actor will speak. Mixed-initiative is often characterized as a form of turn-taking interaction, where one actor speaks while the other waits, and vice versa. Our example conversation mostly follows a turn-taking model, but deviates in two major areas: a) Kevin interrupts Sarah's comments because he thinks he already knows what she will say, and b) Kevin later speaks twice in a row, in an effort to move the conversation along.
3. Outcome initiative: deciding how the problem introduced should be solved, sometimes involving allocating tasks to participants in the conversation. For this example, Sarah takes the outcome initiative, determining which tasks she and Kevin should perform as a result of the conversation.

The majority of mixed-initiative PCG systems focus entirely on the second kind of initiative: speaker initiative. They involve the computer being able to provide support during the design process, an activity that design researcher Donald Schön has described as a reflective conversation with the medium [29] (more on this in the next section). However, they all explicitly give the human designer sole responsibility for determining what the topic of the design conversation will be and how to solve the problem; all mixed-initiative PCG systems made thus far have prioritized human control over the generated content.

11.1.2 Computer-Assisted Design and Creativity Support

Doug Engelbart, an early pioneer of computing, posed that computers stand to augment human intellect. He envisioned a future in which computers were capable of "increasing the capability of a man to approach a complex problem situation, to gain comprehension to suit his particular needs, and to derive solutions to problems" [8]. Engelbart argued that all technology can serve this purpose. His de-augmentation experiment, in which he wrote the same text using a typewriter, a normal pen, and a pen with a brick attached to it, showed the influence that the technology (in this case, the way we write) has on the ways that we write and communicate.

A peer of Engelbart, Ivan Sutherland's created the Sketchpad system in 1963 [40]. This was the first system to offer computational support for designers; it was also the first example of an object-oriented system (though it did not involve programming). Sketchpad allowed designers to specify constraints on the designs they were drawing; for example, it was possible to draw the general topology of an item such as a bolt. The user could then place constraints on the edges of the bolt to force them to be perpendicular to each other. The system was object-oriented in that individual sketches could be imported into others to produce entire diagrams and drawings; if the original sketch was altered, that change would propagate to all diagrams that imported the sketch. The idea of letting users create through adding and removing constraints has carried forward into mixed-initiative tools such as Tanagra and Sketchaworld, described later in this chapter.

A decade after Engelbart and Sutherland's work, Nicholas Negroponte proposed the creation of design amplifiers. Negroponte was particularly interested in how to support non-expert designers, as he was concerned that experts often push their own agendas without regard for the need of the occupant [25]. However, home-owners do not have the domain expertise required to design their own home. His vision was for tools that could help the general population in creating their own homes using the computer to support their designs and ensure validity of the design. The idea that human creators should take the forefront and have the majority of control over a design situation is reflected in all mixed-initiative design tools; in general, the computer is never allowed to override a decision made by the human. However, all tools must push an agenda to some extent, though it may not be intentional: the choices that go into how the content generator operates and what kind of content it is capable of creating vastly influences the work that the human designer can create with the system.

More recently, Chaim Gingold has pushed the idea of "magic crayons": software that supports a novice's creativity while also being intuitive, powerful, and expressive [10]. Gingold argues that using design support tools should be as simple and obvious as using a crayon, and allow for instant creativity. Any child who picks up a crayon can quickly and easily grasp how to use it and go on to create several drawings quite rapidly. The "magic" part of the magic crayon comes in the crayon's computational power and expressive potential: the crayons are imbued with computational support that allows a user to create something better than what they would normally create themselves, while still echoing their original design intent.

11.1.3 Requirements, Caveats, and Open Problems for Mixed Initiative Systems

When designing a mixed-initiative system, there are several main questions to consider. These points are based on the authors' experiences creating their own prototype mixed-initiative tools:

- *Who is your target audience?*

How to design both the underlying technology and the interface for a mixed-initiative system depends wildly upon who the target audience is. A tool for professional designers might look considerably different than a tool intended for game players who have no design experience.

- *What novel and useful editing operations can be incorporated?*

A mixed-initiative environment offers the opportunity for more sophisticated level editing operations than merely altering content as one could do in a non-AI supported tool. The way the generation algorithm works might prioritize certain aspects of the design. For example, Tanagra's underlying generator used rhythm as a driver for creating levels; thus, it was relatively straightforward to permit users to interact with that underlying structure to be able to directly manipulate level pacing.

- *How can the method for control over content be balanced?*

Mixed-initiative content generators can involve both direct and indirect manipulation of the content being created. For example, the tool will typically support a user directly drawing in aspects of the content (e.g. level geometry), but also allow the computer to take over and make new suggestions for the generator. How to balance these forms of control can be challenging (especially when the human and computer conflict, see next point). Should the computer be allowed to make new suggestions whenever it wants, or only when specifically requested? How much of the content should be directly manipulable?

- *How to resolve conflicts that arise due to the human stating conflicting desires?*

In situations where both human and computer are editing content simultaneously, editing conflict inevitably arises. The majority of mixed-initiative tools follow the principle that the human has final say over what is produced by the tool. However, when the human user states contradictory desires, the system must decide how to handle the situation. Should it simply provide an error message? Should it randomly choose which desire is more important for the human? Should it generate several plausible answers and then ask the human to choose which solution is most reasonable?

More generally, the issue is: how can the computer infer human design intent via an interface where the human simply interacts with the content itself.

- *How expressive is the system?*

All content that a human can produce using a mixed-initiative PCG system must be possible for the computer to generate on its own. Thus it is vital for the system to be expressive enough to offer a meaningful set of choices to the human user. More information about expressivity evaluation is in Chapter 12.

- *Can the computer explain itself?*

It is difficult for a human and computer to engage in a design collaboration if neither is able to explain itself to the other. In particular, a human designer may become frustrated or confused if the computer consistently acts as though it is not following the model that the human designer has in her head for how the system should work. The computer should appear intelligent (even if the choices it is making do not involve a sophisticated AI system), and ideally should be able to explain its actions to the human. Being able to communicate at a meta-level about the design tasks and outcomes has not been well-explored in mixed-initiative PCG work thus far.

11.1.4 Examples of CAD tools for Games

Although not comprehensive, the following Computer-Aided Design tools do not only afford interaction and feedback for the human designer, but also introduce some initiative (in varying degrees and in different forms) to the computational designer.

11.1.4.1 Tanagra

Tanagra is a mixed-initiative tool for level design, allowing a human and a computer to work together to produce a level for a 2D platformer [9]. An underlying, reactive level generator ensures that all levels created in the environment are playable, and provides the ability for a human designer to rapidly view many different levels that meet their specifications. The human designer can iteratively refine the level by placing and moving level geometry, as well as through directly manipulating the pacing

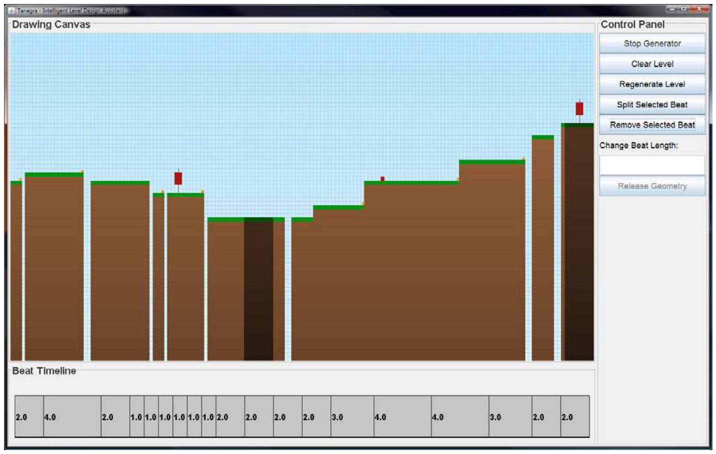

Fig. 11.3: The Tanagra intelligent level design tool. The large area in the upper left is where the level is created. Below that is a beat timeline, allowing manipulation of the pacing of the level. On the right are buttons for editing the level.

of the level. Tanagra's underlying level generator is capable of producing many different variations on a level more rapidly than human designers, whose strengths instead lie in creativity and the ability to judge the quality of the generated content. The generator is able to guarantee that all the levels it creates are playable, thus refocusing early playtesting effort from checking that all sections of the level are reachable to exploring how to create fun levels.

A combination of reactive planning and constraint programming allows Tanagra to respond to designer changes in real-time. A Behavior Language (ABL) [23] is used for reactive planning, and Choco [43] for numerical constraint solving. Reactive planning allows for the expression of generator behaviors, such as placing patterns of geometry or altering the pacing of the level, which can be interleaved with a human designer's actions.

The version of Tanagra displayed in Fig. 11.3 incorporates (1) the concept of a user "pinning" geometry in place by adding numerical positioning constraints, (2) the system attempting to minimize the number of required positioning changes (including never being allowed to move pinned geometry), and (3) direct changes to level pacing by adding, removing, and altering the length of beats. Later versions of Tanagra altered the UI to make it clearer what geometry was "pinned" and what was not. The latest version of Tanagra also added the idea of geometry preference toggles, allowing designers an additional layer of control over the system by letting them state whether or not particular geometry patterns are preferred or disliked on a per-beat basis. More information about the Tanagra tool, including a full description of its system architecture and an evaluation of its expressivity, has been published [9].

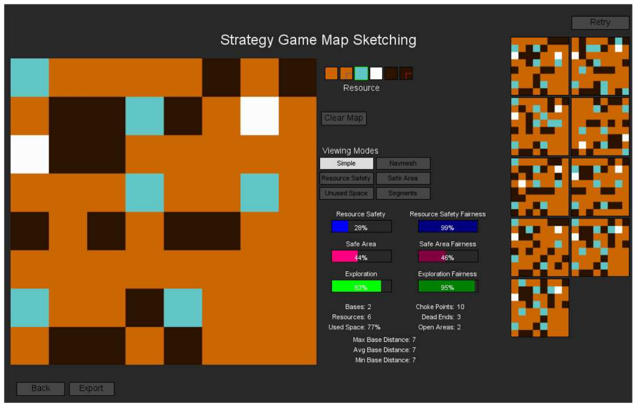

Fig. 11.4: The user interface of Sentient Sketchbook as a human designer edits their sketch (left) and a generator, acting as the artificial designer, creates map suggestions to the users sketch (far right).

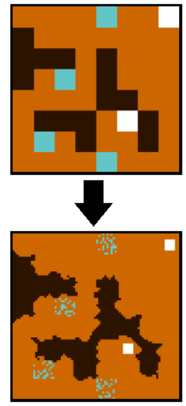

Fig. 11.5: The map sketch can be transformed into a high-resolution map.

11.1.4.2 Sentient Sketchbook

Sentient Sketchbook is a computer-aided design tool which assists a human designer in creating game levels, such as maps for strategy games [20] (shown in Fig. 11.4) or dungeons for roguelike games [21]. Sentient Sketchbook uses the notion of map sketch as a minimal abstraction of a full game level (see Fig. 11.5); this abstraction limits user fatigue while creating new levels and reduces the computational effort of automatically evaluating such sketches. Like popular CAD tools, Sentient Sketchbook supports the human creator by automatically testing maps for playability constraints, by calculating and displaying navigable paths, by evaluating the map on gameplay properties and by converting the coarse map sketch into a playable level.

The innovation of Sentient Sketchbook is the real-time generation and presentation of alternatives to the user's sketch. These alternatives are evolved from an initial population seeded by the user's sketch, and thus a certain degree of map integrity is maintained with the user's designs. The shown suggestions are guaranteed to be playable (i.e. have all vital components such as bases and resources for strategy games connected with passable paths) via the use of constrained evolutionary optimization with two populations [15]. The suggestions are either evolved to maximize one of the predefined objective functions inspired by popular game design patterns such as balance and exploration [21], or towards divergence from the user's current sketch through feasible-infeasible novelty search [19].

Fig. 11.6: A screenshot from one of the interfaces in Ropossum. The components highlighted are the ones constrained by the designer and therefore will not be changed when evolving complete playable levels.

11.1.4.3 Ropposum

Ropossum is an authoring tool for the generation and testing of levels of the physics-based puzzle game, *Cut the Rope* [33]. Ropossum integrates many features: (1) automatic design of complete solvable content, (2) incorporation of designer's input through the creation of complete or partial designs, (3) automatic check for playability and (4) optimization of a given design based on playability.

Ropossum consists of two main modules: an evolutionary framework for procedural content generation [31] and a physics-based playability module to solve given designs [32]. The second module is used both for evolving playable content and for play testing levels designed by humans. The parameters of the evolutionary system and the AI agent were optimized so that the system can respond to the user's inputs within a reasonable amount of time. Grammatical Evolution (GE) is used to evolve the content. The level structure is defined in a Design Grammar (DG) which defines the positions and properties of different game components and permits an easy to read and manipulate format by game designers [31]. First-order logic is used to encode the game state as facts specifying the game components and their properties (such as position, speed, and moving direction) [32]. The relationships between the components are represented as rules used to infer the possible next actions.

The two methods for evolving game design and assessing whether the design is playable are combined in a framework to evolve playable content. An initial level design, according to the design grammar, is generated or created by the designer (see Fig. 11.6) and encoded as facts that can be used by the AI reasoning agent. Given the game state, the agent infers the next best action(s) to perform. The actions are then sent to the physics simulator that performs the actions according to a given priority and updates the game state accordingly. The new game state is sent to the agent to infer the next action. If the sequence of actions does not lead to winning the

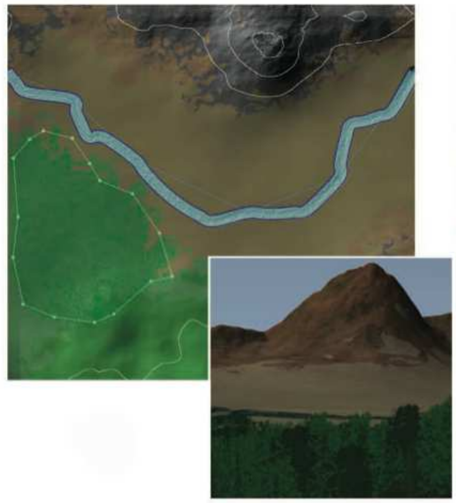

Fig. 11.7: A screenshot from Sketchaworld showing the user input consisting of a sketch of a mountain, river and forest and the corresponding 3D terrain generated.

level, the system backtracks. A state tree is generated that represents the actions and states explored. For each action performed, a node in the tree is generated and the tree is explored in a depth-first approach. The size of the explored branches in the solution tree was drastically reduced through the use of different priorities for the actions and the employment of domain knowledge encoded by the rules followed by the reasoning agent when inferring the best action to perform.

11.1.4.4 Sketchaworld

Sketchaworld is an interactive tool created to enable a non-specialist user to easily and efficiently create a complete 3D virtual world by integrating different procedural techniques [36]. Sketchaworld integrates many features: (1) it facilitates easy interaction with designers who can specify procedural modeling operations and directly visualize their effects, (2) it builds 3D worlds by fitting all features with their surroundings and (3) it supports iterative modeling.

The tool allows user interactions in two main modes: *landscape mode* and *feature mode*. The first mode consists of the user input which is a 2D layout map of the virtual world formatted in a coloring grid that includes information about elevations and soil materials painted with a brush. In the feature mode, users add more specific land features such as cities and rivers (see Fig. 11.7).

While users sketch on the 2D grid, the effects of their modification is directly visualized in the 3D virtual world. This requires blending the features added with its surroundings. To this end, whenever a new feature is created, an automatic local adaptation step is performed to ensure smoothness and correctness. This includes for example removing trees on a generated road's path or adding a road to connect a generated bridge.

11.2 Interactive Evolution

As its name suggests, Interactive Evolutionary Computation (IEC) is a variant of evolutionary computation where human input is used to evaluate content. As artificial evolution hinges on the notion of survival of the fittest, in interactive evolution a human user essentially selects which individuals create offspring and which individuals die. According to Takagi [42], interactive evolution allows human users to evaluate individuals based on their subjective preferences (their own *psychological space*) while the computer searches for this human-specified global optimum in the genotypical space (*feature parameter space*); as such, the collaboration between human and computer makes IEC a mixed-initiative approach. In interactive evolution a human user can evaluate artifacts by assigning to each a numerical value (proportionate to their preference for this artifact), by ordering artifacts in order of preference, or by simply selecting one or more artifacts that they would like to see more of. With more control to the human user, the artifacts in the next generation may match users' desires better; the user's cognitive effort may also increase, however, which results in *user fatigue*, which is covered in Section 11.2.1

Interactive evolution is often used in domains where designing a fitness function is a difficult task; for instance, the criteria for selection could be a subjective measure of beauty as in evolutionary art, a deceptive problem where a naive quantifiable measure may be more harmful than helpful, or in cases where mathematically defining a measure of optimality is as challenging as the optimization task itself. Since it allows for a subjective evaluation of beauty, IEC has often been used to create 2D visual artifacts based on L-systems [24], mathematical expressions [34], neural networks [30] or other methods. Using interactive evolution in art was often motivated by a general interest in Artificial Life, as is the case with Dawkin's Biomorph [6]. In evolutionary art, human users may often evaluate not the phenotypes but situational system outputs specified by the phenotypes, in cases where the phenotypes are image filters or shaders [7]. Apart from 2D visual artifacts, IEC has also been used in generating 3D art [5], graphic movies [35], typographies [28] and graphic design [39]. Evolutionary music has also used IEC to generate the rhythm of percussion parts [44], jazz melodies [1] or accompaniments to human-authored music scores [13], among others. Outside evolutionary art and music, IEC has been used for industrial design [11], image database retrieval [4], human-like robot motion [26] and many others. The survey by Takagi [42] provides a thorough, if somewhat dated, overview of IEC applications.

11.2.1 User Fatigue and Methods of Combating it

Since interactive evolution is entirely reliant on human input to drive its search processes, its largest weakness is the effect of human fatigue in human-computer interaction. Human fatigue becomes an issue when the users are required to perform a large number of content selections, when feedback from the system is slow, when the users are simultaneously presented with a large number of content on-screen, or when users are required to provide very specific input. All of these factors contribute to the *cognitive overload* of the user, and several solutions have been proposed to counteract each of these factors.

As human users are often overburdened by the simultaneous presentation of information on-screen, user fatigue can be limited by an interactive evolutionary system that shows only a subset of the entire population. There are a number of techniques for selecting which individuals to show, although they all introduce biases from the part of the tool's designers. An intuitive criterion is to avoid showing individuals which all users would consider unwanted. Deciding which individuals are unwanted is sometimes straightforward; for instance, musical tracks containing only silence or 3D meshes with disconnected triangles. However, such methods often only prune the edges of the search space and are still not guaranteed to show wanted content. Another technique is to show only individuals with the highest fitness; since fitness in interactive evolution is largely derived from user choices, this is likely to result in individuals which are very similar - if not identical - to individuals shown previously, which is more likely to increase fatigue due to perceived stagnation.

User fatigue is often induced when the requirement of a large number of selections becomes time-consuming and cumbersome. As already mentioned, fewer individuals than the entire population can be shown to the user; in a similar vein, not every generation of individuals needs to be shown to the user, instead showing individuals every 5 or 10 generations. In order to accomplish such a behavior, the fitness of unseen content must be somehow predicted based on users' choices among seen content. One way to accomplish such a prediction is via distance-based approaches, i.e. by comparing an individual that hasn't been presented to the user with those individuals which were presented to the user: the fitness of this unseen individual can be proportional to the user-specified fitness of the closest seen individual while inversely proportional to their distance [14]. Such a technique essentially clusters all individuals in the population around the few presented individuals; this permits the use of a population larger than the number of shown individuals as well as an offline evolutionary sprint with no human input. Depending on the number of seen individuals and the expressiveness of the algorithm's representation, however, a number of strong assumptions are made - the most important of which pertains to the measure of distance used. In order to avoid extraneous bias of the search from these assumptions, most evolutionary sprints are only for a few generations before new human feedback is required.

Another solution to the extraneous choices required of IEC systems' users is to crowdsource the selection process among a large group of individuals. Some form of online database is likely necessary towards that end, allowing users to start evolving content previously evolved by another user. A good example of this method is PicBreeder [30], which evolves images created by compositional pattern-producing networks (CPPNs). Since evolution progressively increases the size of CPPNs due to the Neuroevolution of Augmenting Topologies algorithm [38], the patterns of the images they create become more complex and inspiring with large networks. This, however, requires extensive evolution via manual labor, which is expected to induce significant fatigue on a single user. For that reason, the PicBreeder website allows users to start evolution "from scratch", with a small CPPN able to create simple patterns such as circles or gradients, or instead load images evolved by previous users and evolve them further. Since such images are explicitly saved by past users because they are visually interesting, the user starts from a "good" area of the genotypical space and is more likely to have meaningful variations rather than if they were starting from scratch and had to explore a large area of the search space which contains non-interesting images.

Another factor of user fatigue is the slow feedback of evolutionary systems; since artificial evolution is rarely a fast process, especially with large populations, the user may have to sit through long periods of inaction before the next set of content is presented. In order to alleviate that, interactive evolution addresses it by several shortcuts to speed up convergence of the algorithm. This is often accomplished by limiting the population size to 10 or 20 individuals, or by allowing the user to actively interfere directly on the search process by designating an estimated global optimum on a visualization of the search space [41].

To reduce the cognitive load of evaluating individuals, the most common solution is to limit the number of rating levels. In the simplest of cases, the rating levels can be two, i.e. selected and unselected, limiting the user's effort; they either like the content or they don't. Since taste is rarely a boolean value, however, usually more rating levels are included - often using existing scales such as that of "5 stars" which is popular in restaurant and cinema reviews. Another solution which is expected to limit the cognitive load and subjectivity of ratings is to use rankings [16], i.e. stating preference of A over B without explicitly specifying that A is 3 of 5 stars and B is 1 of 5 stars.

11.2.2 Examples of Interactive Evolution for Games

Recent trends have shown an increase in the use of IEC for evolving game content. As highly interactive experiences themselves, games are ideal for interactive evolution as the user's preference can be inferred based on gameplay traces. In this fashion, the selection of favored content is masqueraded into in-game activities such as shooting, trading or staying alive. Done properly, interactive evolution in games can bypass to a large extent the issue of user fatigue. However, the mapping between player actions and player preference is often not straightforward; for instance, do humans prefer to survive in a game level for a long time, or do they like to be challenged and be constantly firing their weapons? Depending on the choice of metric

Fig. 11.8: Galactic Arms Race with multiple players using different weapons.

(in this example, survival time or shots fired), different content may be favored. Therefore, gameplay-based evaluations may include more biases on the part of the programmer than traditional interactive evolution, which tries to make no assumptions.

11.2.2.1 Galactic Arms Race

Galactic Arms Race [12] is one of the more successful examples of games using interactive evolution. The procedurally generated weapon projectiles, which are the main focus of this space shooter game, are evolved interactively based on gameplay data. In Galactic Arms Race, the number of times a weapon is fired is considered an indication of preference; Hastings et al. assume that players who don't like a weapon will not use it as much as others. Weapon projectiles, represented as particles, are evolved via neuroevolution of augmenting topologies [38]; the velocity and color of each particle is defined as the output of a CPPN [37], with the input being the current position and distance from the firing spaceship. Newly evolved weapons are dropped as rewards for destroying enemy bases; the player can pick them up, and use them or switch among three weapons at any given time. Galactic Arms Race can be also played by many players; in the case of multiplayer, the algorithm uses the firing rates of all players when determining which weapons to evolve. The weapons evolved in Galactic Arms Race, and details of its framework have been presented in Chapter **??**.

Fig. 11.9: The user interface used to visualise and collect the ranking of tracks.

11.2.2.2 TORCS track generation

A more "traditional" form of interactive evolution — with a user directly stating preference of game content — was applied to generate tracks for a car racing game [3]. The system uses the Open Racing Car Simulator[1] (TORCS) and allows user interaction through a web browser where users can view populations of racing tracks and evaluate them (see Fig. 11.9). The other component of the system is an evolutionary backend which handles all evolutionary-based operations. Racing tracks are represented in the engine as a list of segments which can be either straight or turning. In the evolution process, a set of control points and Bezier curves were employed to connect these points and ensure smoothness.

Different variations of the interactive evolution method are implemented to evaluate the generated tracks. In the *single-user mode*, human subjects were asked to play 10 generations of 20 evolved tracks each and evaluate them using two scoring interfaces: like/dislike and rating from 1 to 5 stars. The feedback provided by users about each track is used as a fitness in the evolution process. In the *multi-user mode*, the same population of 20 individuals is played and evaluated by five human subjects. The fitness given to each track in the population is the average score received

[1] http://torcs.sourceforge.net/

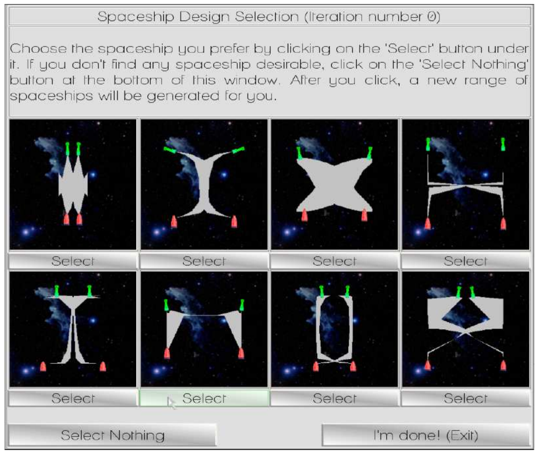

Fig. 11.10: The user interface of the spaceship generator, where the user can select their favorite among a subset of the population of feasible spaceships.

by all users. The feedback provided by users showed improvements in the quality of the tracks and an increase in their interestingness.

11.2.2.3 Spaceship Generation

The work of Liapis et al. [18] is an example of fitness prediction applied for the purpose of speeding up and enhancing the convergence of interactive evolution. This work generates spaceship hulls and their weapon and thruster topologies in order to match a user's visual taste as well as conform to a number of constraints aimed for playability and game balance [17]. The 2D shapes representing the spaceship hulls are encoded as pattern-producing networks (CPPNs) and evolved in two populations using the feasible-infeasible 2-population approach (FI-2pop) [15]. One population contains spaceships which fail ad-hoc constraints pertaining to rendering, physics simulation and game balance, and individuals in this population are optimized towards minimizing their distance to feasibility. Removing such spaceships from the population shown to the user reduces the chances of unwanted content and reduces user fatigue.

The second population contains feasible spaceships, which are optimized according to ten fitness dimensions pertaining to common attributes of visual taste such as symmetry, weight distribution, simplicity and size. These fitness dimensions are aggregated into a weighted sum which is used as the feasible population's fitness function. The weights in this quality approximation are adjusted according to a user's selection among a set of presented spaceships (see Fig. 11.10). This adaptive aesthetic model aims to enhance the visual patterns behind the user's selection and minimize visual patterns of unselected content, thus generating a completely new set of spaceships which more accurately match the user's tastes. A small number of user selections allows the system to recognize the users' preference, reducing fatigue.

The proposed two-step adaptation system, where (1) the user implicitly adjusts their preference model through content selection and (2) the preference model affects the patterns of generated content, should demonstrate the potential of a flexible tool both for personalizing game content to an end-user's visual taste but also for inspiring a designer's creative task with content guaranteed to be playable, novel and yet conforming to the intended visual style.

11.3 Class Exercise

1. Choose one of the tools described in this chapter. Perform a design task similar to that which is supported by the tool without any computational support. Reflect upon this process what was easy and what was hard? What did you wish the computer could do to help? What do you feel the computer would not be able to assist with? If the tool is available for download, try to perform the same design task using the AI-supported tool. What were some of the key differences in your experience as a designer?
2. Create a requirements analysis document and mock-up architecture diagram for a mixed-initiative design tool that operates in a domain of your choice. Make sure to consider: (a) Who is your audience? (b) What, specifically, is your domain? (c) What is the PCG system capable of creating? (d) What is the mixed-initiative conversational model the system will follow?
3. Create a paper prototype of the tool you designed in exercise two. Test the prototype with someone else in the class, with you acting as the "AI system" and your partner acting as the designer. Be careful to only act according to how the AI system itself would be able to act.

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Chapter 12
Evaluating content generators (DRAFT)

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12.1 Motivation: I created a generator, now what?

The entirety of this book thus far has been focused on how to create procedural content generators, using a variety of techniques and for many different purposes. We hope that, by now, you've gained an appreciation for the strengths and weaknesses of different approaches to PCG, and also the surprises that can come from writing a generative system. We imagine that you also have experienced some of the frustration that can come from debugging a generative system: "is the interesting level I created a fluke, a result of a bug, or a genuine result?"

Creating a generator is one thing; evaluating it is another. Regardless of the method followed all generators shall be evaluated on their ability to achieve the desired goals of the designer (or the computational designer). This chapter reviews methods for achieving that. Arguably, the generation of any content is trivial; the generation of *valuable* content for the task at hand, on the other hand, is a rather challenging procedure.

What makes the evaluation of content (such as stories, levels, maps etc.) difficult is the subjective nature of players, their large diversity and, on the other end of the design process, the designer's variant intents, styles and goals [1]. Most importantly, content quality is affected by algorithmic stochasticity (such as metaheuristic search algorithms) and human stochasticity (such as unpredictable playing behavior, style and emotive responses) that affect content quality at large. All these factors are obviously hard to control in an empirical fashion.

In addition to factors that affect content quality there are hard (or softer) constraints put forward by the designers or the other game content elements that might be in conflict with the content generated (e.g. a proposed puzzle is not compatible with the level generated). A PCG algorithm needs to be able to satisfy designer constraints as part of its quality evaluation. Constrained satisfaction algorithms such as the feasible-infeasible two-population evolutionary algorithm used broadly by Liapis et al.[2] for mixed-initiative content creation and constrained solvers such as answer set programming (see Chapter 8 of this book and [7]) are able to handle this.The generated results is within constraints, thereby valuable for the designer. *Value* however has variant degrees of success (depending on all the aforementioned factors) and this is where alternative methods or heuristics discussed in this chapter can help.

PGC can be viewed as a computational creator (either assisted or autonomous). One important aspect that has not been investigated in depth is the aesthetics and creativity of PCG within game design. How creative can an algorithm be? Is it deemed to have appreciation, skill, and imagination (Colton, 2008)? Evaluating creativity of current PCG algorithms a case can be made that most of them possess only skill. Does the creator manage to explore novel combinations within a constrained space thereby resulting in *exploratory* game design creativity (Boden); or, is on the other hand trying to break existing boundaries and constraints within game design to come up with entirely new designs, demonstrating *transformational* creativity (Boden)? If used in a mixed-initiative fashion, does it enhance the designer's creativity by boosting the possibility space for her? Arguably, the appropriateness of variant evaluation methods for autonomous PCG creation or mixed-initiative co-creation remains largely unexplored within both human and computational creativity research.

Content generators exhibit highly emergent behavior, making it difficult to understand what the results of a particular generation algorithm might be when designing the system. When making a PCG system, we are also creating a large amount of content for players to experience, thus it's important to be able to evaluate how successful the generator according to players who interact with the content.

The next section highlights a number of factors that make evaluating content generator important.

12.1.1 Why is evaluation important?

There are several main reasons that we want to be able to evaluate procedural content generation systems:

1. To better understand their capabilities. It is very hard to understand what the capabilities are of a content generator based solely on seeing individual instances of their output.
2. To confirm that we can make guarantees about generated content. If there are particular qualities of generated content that we want to be able to produce, it is important to be able to evaluate that those qualities are indeed present.
3. To more easily iterate upon the generator by seeing if what it is capable of creating matches the programmer's intent. As with any creative endeavor, creating a procedural content generator involves reflection, iteration, and evaluation.
4. To be able to compare content generators to each other, despite different approaches. As the community of people creating procedural content generators continues to grow, it's important to be able to understand how we are making progress in relationship to other people.

This chapter describes strategies for evaluating content generators, both in terms of their capabilities as generative systems and in performing evaluations of the content that they create. The most important concept to remember when thinking of how to evaluate a generator is the following: make sure that the method you use to evaluate your generator is relevant to what it is you want to investigate and evaluate. If you want to be able to make the claim that your generator produces a wide variety of content, choose a method that explicitly examines qualities of the generator rather than individual pieces of content. If you want to be able to make the claim that players of a game that incorporates your generator find the experience more engaging, then it is more appropriate to evaluate the generator using a method that includes the player.

12.2 Matching outcomes to design goals

One of the ultimate goal of evaluating content generators is to check their ability to meet the goals they are intended to achieve while being designed. Looking at individual samples gives a very high level overview of the capabilities of the generators but one would like for example to examine the frequency in which specific content is generated or the amount of variations in the designs produced by the system. It is therefore important to visualise the space of content covered by a generator. The effects of modifications made to the system can then be easily identified in the visualised content space as long as the dimensions according to which the content is plotted are carefully defined to reflect the goals intended when designing the system.

12.3 Expressivity measures

A tempting way to evaluate the quality of a content generator is to simply view the content it creates and evaluate the artifacts subjectively and informally. But if a content generator is capable of creating thousands, even millions, of unique levels, it is not feasible to view all of the output to judge whether or not the generator is performing as desired. If you see five levels that are impressive, among 50 that you choose to ignore or re-generate, what does that say about the qualities of the content generator?

To solve this problem, it is possible to evaluate the expressive range of the level generator. *Expressive range* refers to the space of potential levels that the generator is capable of creating, including how biased it is towards creating particular kinds of content in that space [8]. This evaluation is performed by choosing metrics along which the content can be evaluated, and using those metrics as axes to define the space of possible content. A large number of pieces of content are then generated and evaluated according to the defined metrics and plotted in a heatmap. This heat map can reveal biases in the generator, and comparisons of the heatmap across different sets of input parameters can show how controllable the generator is.

- Being able to understand how controllable your generator is by seeing how expressive range shifts according to input changes.

12.3.1 Visualising expressive range

The expressive range of a content generator can be visualized as an N-dimensional space, where each dimension is a different quality of the generator that can be quantified. This allows us to imagine authoring level generators as creating these spaces of potential levels as a result of the emergent qualities of the system. By adding and removing rules from a rule-based generator, the shape of the generator's expressive range (also referred to as a generative space) can be altered.

For only two dimensions, the generative space can be visualized using a two-dimensional histogram. Higher dimensionality requires more sophisticated visualizations, which has not been deeply explored in the procedural content generation communities. This requires generating a representative sample of the content and ranking them according to the metrics; determining the amount of content to generate can be tricky. While it is simple for some systems to compute the total number of variations that can be generated, others may be able to create infinite variety. One method to ensure an acceptable sample size in the case of infinite content is to generate increasingly large amounts of content and visualizing expressive range, stopping when the graphs begin to look the same as the previous, smaller amount of content. Expressive range charts are not intended to be perfect, mathematical proofs of variety; rather, it is a visualization that can help the creator of a generative system to understand its behavior, and potential users of that system to understand its abilities.

Figure 12.1 shows the expressive range of the Launchpad level generator [9]. Notice that there is one large hot-spot for creating medium leniency, low linearity levels, and another bias towards creating medium leniency, high linearity levels (more on these metrics in the next section). Understanding that the system is biased towards these areas forces the designer of the system to ask why such biases exist.

Figure 12.2 presents another alternative method for visualising the expressive range of one of the content generators for Infinite Mario Bros [4]. The figure shows different distributions of the levels according to three expressive measures defined: linearity, leniency and density.

12.3.2 Choosing appropriate metrics

The metrics used for any content generator are bound to vary based on the domain that content is being generated for. The "linearity" and "leniency" metrics used in

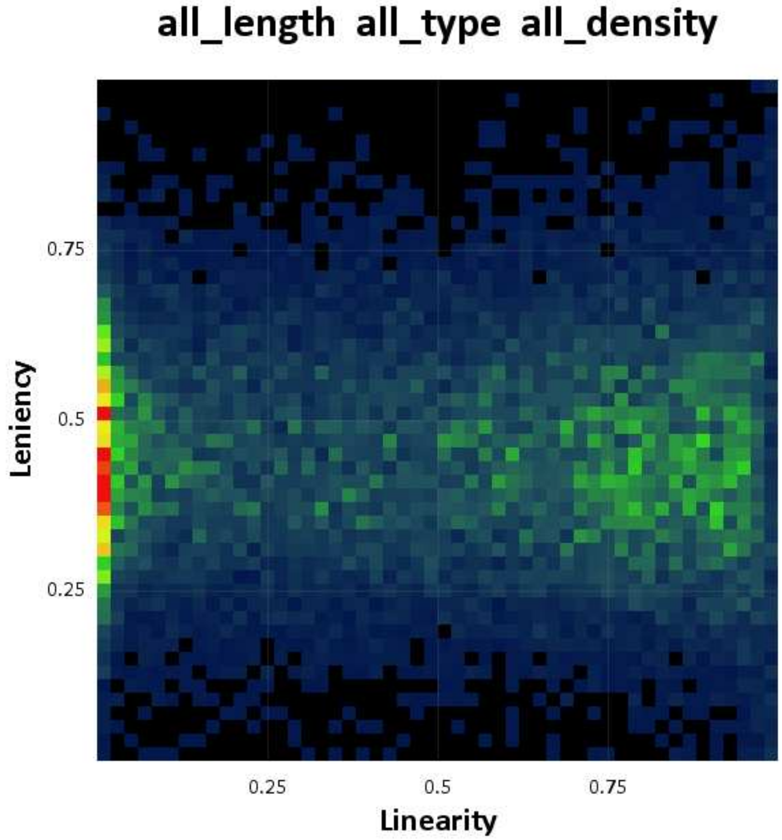

Fig. 12.1: The expressive range of the Launchpad level generator [9].

the Launchpad generator mentioned above make sense in the context of 2D platforming levels, but perhaps not in the context of weapons for a space shooting game.

The important rule of thumb to remember when choosing metrics for your content generator is this:

Strive to choose metrics that are as far as possible from the input parameters to the system. The goal of performing an expressive range evaluation is to understand the emergent properties of the generative system. Choosing a metric that is highly correlated to one that is used as an input parameter (e.g. if your generator accepts "difficulty" as an input and has "difficulty" as an expressive range metric) can only ever provide confirmatory results. If the system is specifically designed to create a particular kind of output, measuring for that output can only show that the algorithm operates as expected; it cannot deliver insight into unexpected behaviour or surprising output.

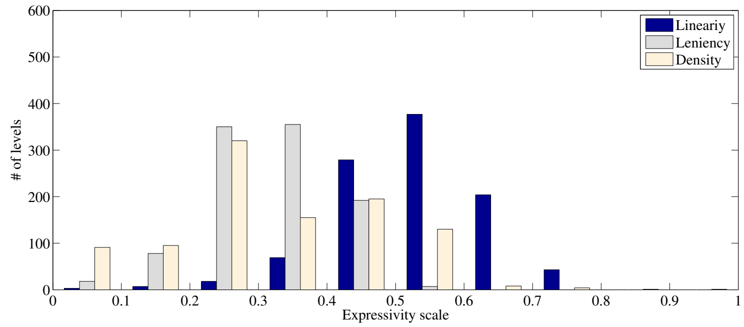

Fig. 12.2: The histograms of the linearity, leniency and density measures for one of the Infinite Mario Bros generator [4].

12.3.3 Understanding controllability

An important consideration in procedural content generation is understanding how well the generator can be controlled to produce different kinds of output, and especially how small changes in rule systems or priorities alters the expressivity of the system. If a designer requests that the system create shorter levels, will it still be capable of producing a broad range of content? Will adding a new rule to the grammar fundamentally alter the qualities of levels that can be produced?

Insight into these issues can be visualised by comparing expressive range graphs for different configurations of input parameters, either through visual comparison shows the expressive range of the Launchpad level generator when varying its rhythm input parameters (length of segment, pacing of segment, and type of rhythm) (see Figure 12.3). Notice that, while several graphs look quite similar to each other, there are notable parameter configurations that lead to drastically different resulting spaces. Gaining insight into the problem is helpful not only after creating a system and wanting to evaluate it, but also during the development process itself as a debugging tool.

12.4 User studies

Complementary to qualitative approaches to the evaluation of content generation, quantitative user studies can be of immense benefit for content quality assurance. The most obvious approach to evaluate the content experience by players (or designers) is to directly ask them about it. Within the subjective evaluation there are several schemes and questionnaires one can adopt. The general guidelines for self-report (or expert/designer-report) suggest that questionnaires should ask subjects to *rank* (and not rate) amongst various content experienced [10] as rating-based

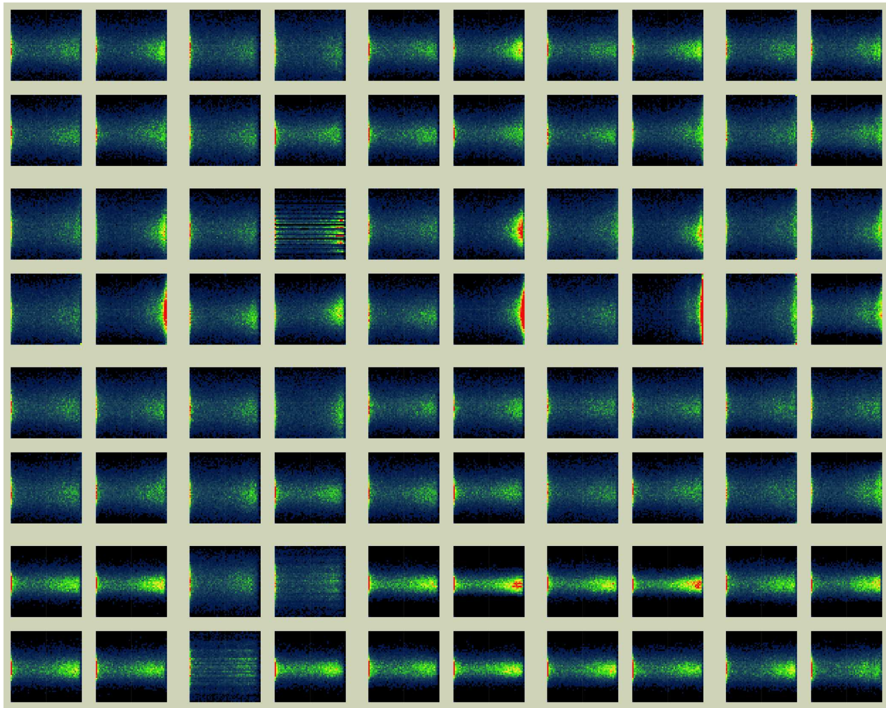

Fig. 12.3: The expressive range corresponding to different input parameters.

questionnaires — such as the game experience questionnaire [?] — generate higher levels of inconsistency and order effects, lower inter-rater agreement, and are dominated by a number of critical biases that make any post analysis questionable (to say the least) [11, ?]. The rank-based game survey approach has been successfully used in the Super Mario AI competition: level generation track [5]. The study can involve anything from a small number of dedicated players that will play through variant amounts of content to a crowd-sourced approach (see [6, ?, ?] among others. The numerous limitations of self-reporting can be eliminated via the use of rank-based questionnaires; however, not all issues of self-reporting can be surpassed this way. Self-reports can be replaced by or fused with alternate measures of player experience such as physiological manifestations (of e.g. arousal, interest and attention) and/or behavioral playing patterns that may map to particular a player state directly (e.g. a player which is stuck at the same map point for several rounds might be an indication of frustration). More details about objective measurement of player experience can be found in Chapter 9.

The data-driven (crowd-sourcing approach) has a number of limitations. The core objection against this method is the potential treatment of subjects as random content evaluators. Thus, ideally, the generator should be coupled with selection mechanisms that will prune the available content (which arguably can be generated in massive amounts automatically) prior to it be presented to the players. On that basis, content can be evaluated (up to a good degree) via a sequence of logic operations without the need of player behavioral metrics or other input from players [3]. Further, the satisfaction of constraints or logical operators can be coupled with rapid simulations of AI agents that evaluate the quality of generated content (i.e.offline generate and test PCG).

12.5 Summary

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