Generative spaces: assisting the level designer in creating world maps

Abstract

Creating two-dimensional tile maps by hand is a long and tedious process. Tile maps contain an inherent structure and repetition that we should be able to exploit. We provide a way of generating these maps automatically using machine learning techniques while still allowing the level designer to specify the high level spatial structure of the world. With these set of tools level designers will be able to create worlds that are much larger in scope.

1 Introduction

The development of a video game requires a great variety of assets. A typical game combines music, art and code to form a coherent whole.

This need for resources is one of the reasons why games are so costly to develop. Procedural content generation—the automatic creation of content—has emerged as an answer to this problem and is currently widely used, particularly in studios with few resources. For example, *No Man's Sky (2016)* is a space exploration game that uses procedural generation to generate a whole universe of over 18 quintillion planets $1.8 \cdot 10^{19}$, suffice to say that you would need many lifetimes to explore them all.

Most approaches to procedural generation are rule based, meaning that they rely on the definition of explicit rules. L-systems are an example of such a rule based system. they allow the creation of tree-like structures. TODO: Reference to an image of an L-system. The limitations of rule based systems lies on the fact that they cannot learn from already existing examples and reproduce them. We would not be able to show an L-system images of oaks for example and expect it to reproduce trees in the same style. We would need to define exactly the rules that represent "oakness", the attributes that make an oak an oak. TODO: citation L-systems

Data-driven techniques for procedural generation are still relatively rare; in this paper we try to see whether it is possible to reproduce the spatial style of a given game using data-driven techniques.

- We show how 2d Markov chains can be applied to the generation of 2d tile-maps that are non-linear in nature. As opposed to past litterature Snodgrass and Ontañón (2013) we use maps with a larger number of tile types. Section 2 provides a few background information on what tile-maps are and their current uses while Section 4.1 describes the technical side of their implementation.
- We argue that the generated maps keep the spatial style of the originals by comparing compare how different input maps influence the generated maps in Section 4.2.
- We come up with a backoff smoothing method appropriate for 2d chains. First we explain why it can be useful in Section 3 and then we give the technical details of its implementation in Section 4.3.
- We provide a C# implementation of a text based 2d Markov chain which is accessible at the following link[1].

2 Background

First of all let us define more precisely what a tile-map is. Tile-maps are a staple of many genres of games, they are formed by individual tiles of predefined size and assembled into a grid.

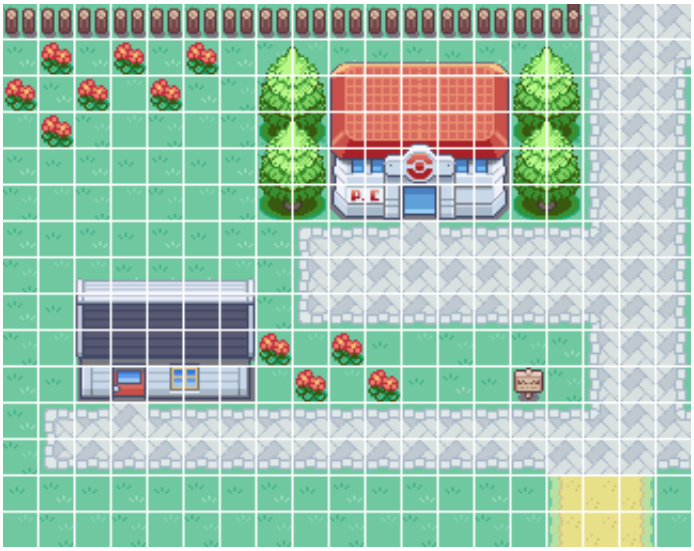

Figure 1: An example of a tile-map with the grid structure visible. *Pokemon FireRed (2004)*

[1] https://github.com/stonecauldron/markov2d

(a) sub-figure 1 caption (b) sub-figure 2 caption

Figure 2: Caption of figure

Game developers make use of tile-maps for various reasons:

- They reduce the number of art assets that need to be created for the game since the same tile can be reused in multiple places.
- Levels created with tile-maps can be easily represented in a digital format; we can simply represent them as a matrix where each entry identifies a tile uniquely.
- They allow the level designer to create new levels without having to worry about creating new art assets. In some cases this can be extended into fully-fledged level editors where the players themselves can create new levels[2]
- They permit the separation of gameplay and visual appearance. Tiles can for example represent non-traversable space independently from their visual appearance.

Traditionally tile-maps are built manually: the level designer chooses one tile for each cell of the grid. Given that the grids can be very large, we can easily imagine that this is a time-consuming process. It puts a human limit into the size of the maps that can be used in a game. Being able to generate these maps procedurally would lift a burden off the shoulders of the level designers and allow the generation of much larger worlds.

The use of tile-maps might seem like an outdated method but they are still used in many independent games, some of which have been quite successful.

TODO: example of games with tile-maps

3 The idea

Let us remind you of our objective; we want to be able to generate tile-maps from a set of representative examples. Our process has the following steps:

1. We choose the set of maps whose spatial style we want to reproduce.

[2] A striking example is the game *Super Mario Maker* which is built entirely around the concept of players creating *Mario Bros.* levels.

2. We represent the maps as matrices where each entry contains a tile type identifier. This will be our input dataset.
3. We generate a Markov chain whose probability distributions reflect those of the original dataset. This is the learning phase of the model.
4. We then sample this Markov chain to generate a map of any given dimension. TODO: explain sampling better?

This is comparable to the case where Markov chains are used for automatic essay writing TODO: reference to Murphy book. These automatically written essays use similar idioms and vocabulary to the ones present in the learning dataset; in a certain sense they emulate the style of a given text. For the same reasons we expect our Markov chains to reproduce the spatial style of its learning examples.

One of the problems that appears when sampling Markov chains is that is likely for a chain to generate a sequence of elements that do not exist in the training dataset. As an example take the word predictors that are present in most mobile phones today; Imagine you have just typed the words "Colorless green ideas sleep"[^This sentence is an example of a grammatically correct sentence with no meaning which we can assume does not occur in a standard English text. Taken from Chomsky 1956], since this sentence is not present in the training corpus, the Markov chain will not be able to infer what the next most probable word is and will simply have to stop generating text.

A way of solving this problem is to use what is called backoff smoothing TODO: Murphy citation in which we consider less elements of the chain when faced with unknown data. To take our above example again, instead of considering the whole chain to infer the next most likely word we can restrict ourselves to the previous word only, which in this case is "sleep". By reducing the number of elements we consider in the chain, we increase the chances of finding equivalent sequences in the training data, thus improving the robustness of the model.

While the definition of backoff smoothing is simple with linear chains, it becomes more complicated in the case of 2d chains. Our approach is detailed in the next section.

4 Technical details

4.1 2D Markov chains

- explain Markov chains very briefly
- say that probabilities are computed with the frequencies
- kernel explanation
- show how different kernels affect the results

4.2 Spatial style conservation

- show how different inputs give rise to different styles
- input of pokemon red for example and link to the past
- show space versions and full versions

4.3 Backoff smoothing in 2d

- explain in detail how the smaller matrix is computed
- show how it improves the results

5 Results

- show a few examples of maps generated with the method pokemon red, pokemon firered and link to the past
- evaluate them qualitatively

6 Related work

Game companies generally do not publish their procedural content generation methods so it is hard to evaluate what is common in the industry. In academia, researchers have looked into various approaches for automatic level generation. The game *Super Mario Bros.* in particular has received much attention.

Shaker et al. (2012) uses generative grammars combined with an evolutionary algorithm to create *Mario* levels that adapt themselves to the player's experience. In another insightful paper, Sorenson and Pasquier (2010) also uses an evolutionary algorithm to create a generic framework for level creation. Their approach allows the level designer to enforce multiple constraints on the generated levels making it adaptable to multiple genres of games.

Rather than being evolutionary, our method draws from machine learning techniques. The designers do not have to explicitly articulate rules about their designs but simply need to provide the system with examples of what they want to create.

Papers using machine learning methods to generate content are still a minority, bu the trend seems to be on the rise. Our use of Markov chains is directly inspired by the work of Snodgrass and Ontañón (2013) and Dahlskog, Togelius, and Nelson (2014). They both use Markov chains to create *Mario* levels with very convincing results. The difference with our approach lies in the fact that *Mario* levels have a linear nature. The maps we focus on are non-linear; the player can move through both dimensions.

Adam J Summerville and Mateas (2015) explore non-linear level generation in the context of dungeons for the game *The Legend of Zelda*. Their use of a graph to represent the game space comes from Dormans (2010). Both papers gave us the idea of using a graph to define the high level structure of the world. Our focus is more on world maps rather than dungeons. Dungeons have a clear compartmentalization of individual rooms while world maps have a more organic unfolding of space. Furthermore, dungeons have elements such as locked doors that restrict the order in which the player can traverse the rooms. World typically do not have these types of constraints.

Finally, the video game level corpus provided by Adam James Summerville et al. (2016) encouraged us to contribute to the corpus with our own extracted data and gave us a set of guidelines to follow when formatting the data.

7 Conclusion and further work

- metrics to evaluate the maps quantitatively
- conditional random fields as in TODO: Snodgrass2016
- limits of procedural generation with markov models

Can we automate the holistic feel of a level? How does one recreate themes in design works successfully? Can machine learning capture the essence of something?

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