

Ena igra za vse: Generiranje personalizirane vsebine v mobilnih igrah

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Izvleček

Proceduralno generiranje vsebine uporablja razne algoritme za ustvarjanje velikih količin novih vsebin v video igrah in s tem znižuje stroške produkcije. Tako generirana vsebina pa je navadno enaka za vse igralce – ni prilagojena in optimizirana za posameznega igralca. Jedro našega raziskovanja je zato usmerjeno v izboljšanje proceduralnega generiranja vsebine, tako da to upošteva karakteristike igralca. Izboljšavo nameravamo doseči z uporabo sodobnih tehnik strojnega učenja, s pomočjo katerih lahko izluščimo karakteristike posameznega igralca. Te karakteristike bodo potem uporabljene kot vhodni parametri algoritma za produkcijo personalizirane vsebine. Pričakujemo, da bo tovrstna personalizacija proceduralnega generiranja vsebine imela pozitiven vpliv na igralčevo izkušnjo.

Ključne besede: mobilne igre, proceduralno generiranje vsebine, personalizacija

ONE GAME FITS ALL: PERSONALIZED CONTENT GENERATION IN MOBILE GAMES

Abstract

Procedural content generation uses algorithmic techniques to create large amounts of new content for games and thus reduces the cost of production. However, this content generation is typically the same for all players and is not used to personalize and optimize the game for players' characteristics. Thus, the core of our research is the improvement of procedural content generation through personalization. We plan to achieve personalization by using modern machine learning algorithms to learn the characteristics of the player. These characteristics will be then used as input parameters for procedural content generation algorithms to produce personalized content. We expect that personalized procedural content generation will have a positive effect on the user's gameplay experience.

Keywords: Mobile gaming, Procedural content generation, Personalization

1 INTRODUCTION

To succeed in a highly saturated mobile game market just creating a good game is not enough. You usually also need a sizeable advertising investment. Because of this, the cost per install can be high, and retaining players is very important. We can keep the player in the game by providing new and engaging content, which can, again, be expensive, as it requires a lot of

time from developers, artists, and game designers. A popular way to address this is the procedural content generation (PCG).

PCG uses algorithmic techniques to create content for games. It is employed to increase replay value, reduce production costs and effort, or save storage space. Apart from accounting for difficulty, it is usually not personalized – content is not generated

to match the preferences of a specific player. In other words, procedurally generated content is the same for all players, regardless of their play style.

Our idea is to improve PCG algorithms by empowering them with modern ML (machine learning) algorithms. Some interesting work has already been done in the area, like the proposal of the Play Data Profiling (PDP) framework [1], which included psychophysiological measurements and eye tracking for the purpose of adjusting the game to the given player's current state. There has also been some industry-driven research, mostly done by game studios [2], whose data science teams aim to improve the KPIs (key performance indicators) of their games. Only a limited amount of their research appears to be published and even in those cases, implementation details are very scarce.

To address this challenge, we plan to develop a proof-of-concept framework for personalized PCG in mobile games. The framework will be an end-to-end solution for personalized PCG. To offer a consistent experience for all players we want our approach to be able to generate decent personalized levels from the beginning. For this, we need to address the cold start problem. Alongside we plan to develop a prototype that we will also use to compare our approach to existing game design approaches to validate the benefits it brings to players.

2 RELATED WORK

A recent article on the state of AI research on personalized games confirms the market need for our proposed solution. Zhu and Ontañón [3] argue that the research can benefit from more player-centred perspectives. Authors argue that computer games represent an ideal research domain for the next generation of personalized digital applications and that to reach the full potential of personalized games, a player-centred approach is necessary.

Personalization. A personalized approach aimed at player retention was utilized by Milošević et al. [4]. They focused on retaining players in a mobile game by utilizing early churn prediction and personalized player targeting. They first predicted which players are likely to churn and sent each one of them a personalized notification. They determined that such a personalized approach can retain players that would have otherwise left the game.

An interesting model for personalization was proposed by researchers Rajanen and Rajanen [1]. Their

idea is that a gaming system should be built in a way that it collects real-time play data which is used for player profiling even after the system has been developed. They introduce a PDP model which proposes that gamification elements are adapted based on the data derived from the interaction and the personal data of the player. A periodic reassessment of the player may determine that a player is moved from one profile cluster to another.

Procedural content generation. Content generation is currently a very active field for ML research. There generated content can vary from visual to audio and narrative aspects of the game, according to Karpouzis and Tsatiris [5]. Especially popular are fully automated PCG techniques, which are usually matched with a generation algorithm and relevant constraints in order for the game to make sense.

Researchers at Electronic Arts [2] tackled dynamic difficulty adjustment as an optimization problem. The match 3 game generated random levels with varying difficulty. The goal of ML-based optimization in their case was to maximize player engagement over the entire game. Their solution resulted in an increase in core engagement metrics such as rounds played and gameplay duration, however, it only focused on adjusting the difficulty, while our research aims to facilitate broader personalization.

Synthetic player data. A different area where ML can improve in mobile games is testing the game's playability. Gudmundsson et al. [6], researchers from game developer King, tested human-like playtesting in computer games based on ML trained on player data. The model was used to predict the difficulty of newly designed levels without requiring real players, which drastically reduced test times. Another solution was proposed by Shin et al. [7]. To automate playtesting in a match 3 type game, they used an approach based on reinforcement learning, which produced performance within a 5 per cent margin of human performance.

3 METHODOLOGY

For the purpose of our research, we developed and published a basic match 3 mobile game. The game is developed in C# programming language using the Unity game engine and will interact with Google Cloud using Google's Firebase platform. Products from the Google Cloud such as Firebase, BigQuery and Cloud Functions were used for data collection

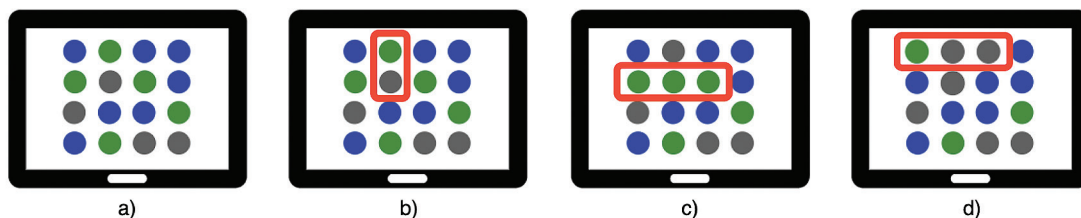


Figure 1: (a) A basic illustration of game mechanics in our match 3 puzzle game. (b) The player's objective is to find and match three board elements of the same colour. He can do that by swapping neighbouring pieces. (c) Once three or more elements of the same colour form a line, the player is awarded a certain amount of points, while the matching elements are removed from the board. (d) To fill the void, elements above the removed line are moved down and replaced by newly assigned elements.

and processing as well as ML training and inference. To train the agents, we plan to develop an algorithm based on Proximal Policy Optimization (PPO) [8] which belongs to the family of deep reinforcement learning algorithms.

Our game uses match 3 mechanics. The basic gameplay is visualized in Figure 1. For simplicity, our game consists of a sequence of levels without a hub that connects them. Before starting, the user is shown a pop-up with objectives and limitations for the level. An example of an objective is a score that the player has to reach combined with the number of elements of specific colour he needs to connect and consequently remove from the board. The player is constrained by the number of moves. The time limit can also be used to create additional pressure.

The popularity of Unity, the game engine used for development, as well as the popularity of the match 3 genre help with development as multiple useful templates, are readily available. Our game will be based on one such template.

4 RESULTS

Before we could evaluate our approach, we had to prepare a prototype mobile game and connect it to a backend system which collected the data. Initial tests, therefore, do not test our fully developed solution but serve as an approximation by comparing a personalized and static solution. The design of our game allows for concurrent testing with any number of players. However, for the initial test, where we also wanted to make sure everything works as expected, we decided on a smaller group of fifteen testers personally asked to play.

The basic personalization utilized assigned the user to be either in a control group that is served normal levels or is in the test group that is, based on the player's performance in the diagnostic level, served easy, normal, tactical or dynamic levels. Seven users

out of fifteen were randomly assigned to a group that got served levels using the basic personalization. Two of those were assigned tactical, one was assigned easy, and four were assigned normal types of levels. We asked the users to rate levels. Scores ranged from 1 to 5, the latter representing the highest level of satisfaction. To the experimental group, we served the levels for the user based on how they played the first, diagnostic level. To the control group, levels were served the same for all users.

Initial results, as shown in Table 1, tell us that basic personalization will not necessarily outperform conventional game design. A more advanced approach is required to improve performance. In our initial testing, the average rating of levels by groups that were served either static or personalized levels was almost identical. The personalization in the test did not rely on ML, but on simple, hardcoded conditions. The results are about in line with expectations, as personalization that would improve the results is likely to require more sophistication.

5 CONCLUSION

In this paper, we presented a proof-of-concept framework for personalized PCG in mobile games. The framework will be an end-to-end solution for personalized PCG. To offer a consistent experience for all players we want our approach to be able to gene-

Tabela 1: Average scores assigned to individual levels by the two user groups were very similar. The p-value calculated using an independent two-tailed t-test was 0.87, way above the commonly used 0.05 mark. Based on the results of the test we can conclude that there is no statistically significant evidence of a difference between the two groups.

	Players	Average level score	Standard deviation
Static levels	8	3,89	1,12
Personalized levels	7	3,85	0,98

rate decent personalized levels from the beginning. A direct result of the approach is also that players are provided with an unlimited, personalized game experience. While there have been developments in real-time content generation using ML, procedurally generated content is typically the same for all players, regardless of their play style.

The weakness of our approach is that, as the initial results show, the benefits are not guaranteed and a lot of experimentation is likely to be required to realize an improvement. Our approach also required a complex software solution before we could focus our work on the algorithms.

Our framework will make it easier for game developers to switch from conventional game design to a design that – by leveraging modern ML approaches – increases their chance of creating a game that the players will enjoy. Our research aims to bridge the gap between purely academic research, which is often not directly usable by industry, and industry research, which has practical goals but is not easily reproducible by studios with fewer resources.

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