Abstract

Procedural content generation (PCG) has arisen as one major research field in games. PCG aims to provide content that meets specific criteria of quality, such as playability, difficulty, and entertainment. In addition, the generated game content should be different from those currently offered. Therefore, achieving quality and diversity becomes one of PCG's most important objectives.

Machine learning is a representative algorithm for PCG and is called procedural content generation via machine learning (PCGML). PCGML usually requires data for learning. However, collecting sufficient and good data can be costly. Another typical method is search-based PCG, where content is generated by evolutionary and other metaheuristic search algorithms. The search-based PCG does not require training data. Instead, it tries to optimize the given evaluation functions. The optimization process is time-consuming, making search-based PCG challenging to generate content immediately on demand.

To solve these problems, we apply reinforcement learning (RL), which does not require training data but learns from interactions with the environment. Another advantage of RL is that once the training is done, it can generate content quickly when required. In this dissertation, we target two kinds of games with distinct characteristics, turn-based role playing games (turn-based RPG) and Super Mario Bros. (Super Mario).

For turn-based RPG, we train RL agents to generate stages, where a stage is a series of events such as battles and recovery. For Super Mario, we train RL agents to generate levels, where a level consists of tiles such as walls and enemies. The generation is a challenging task since components in the stages and levels, such as the events and tiles, are highly correlated.

In order to address this challenge using RL, it is necessary to formulate the problem by a Markov decision process (MDP). Thus, we formulate the stage/level generation into MDPs, where the ideas can be generalized to other PCG problems. For the rewards in MDP, hand-crafted evaluation functions which reflect players' enjoyment are used to evaluate generated content.

For the stage generation problem, two classical RL algorithms are adopted. One is a deep Q-network (DQN) for discrete action spaces, and the other is a deep deterministic policy gradient (DDPG) for continuous action spaces. Experiments show that both DQN and DDPG can generate good stages, where those by DDPG generally receive higher scores from the evaluation function.

Next, we try to apply similar approaches to the level generation for Super Mario. However, Super Mario's level generation has several distinct challenges that do not exist in the stage generation. One is related to how to represent the levels. Unlike events in turn-based RPG that can be straightforwardly represented by a small number of parameters, tiles in Super Mario levels need to be represented by a large number of parameters. For this challenge, we employ conditional generative adversarial networks (CGAN), which have succeeded in generating images. Another challenge is related to how to evaluate the levels' difficulty. For this challenge, we employ a human-like AI agent and have it play the generated levels. We use twin delayed DDPG (TD3) for the level generation problem. As a result, the generated levels receive high evaluation values indicating good quality.

Finally, virtual simulations that give rewards to intermediate actions are employed to obtain content with even higher quality. In addition, we introduce noise to avoid generating similar stages/levels while trying to keep the quality high. The experimental results highlight that the proposed methods successfully generate good and diverse stages/levels for turn-based RPG and Super Mario.

Keywords: Reinforcement learning, Procedural content generation, Turn-based RPG, Super Mario, Quality-Diversity