CIS 519: Project Proposal

BroadMind: A Better Platformer AI

Yesha Ouyang, David Kotfis, Zhi Li

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Many scholarly works in reinforcement learning have focused on building generalist video game agents, as opposed to focusing on a particular type, or genre of games. One prominent example is a Deep Q Learning method applied by researchers at DeepMind, which demonstrated that a single agent could be trained to play 7 different games, achieving better-than-human performance on 2/7, and acceptable performance on 6/7. However, many of these games were very similar in structure and less challenging for a machine to perceive. We aim to build a more specialized high-performance agent focused on the more challenging genre of platform games, which has received less attention in the literature.

Platform games, also known as platformers, are video games in which players guide a free-running avatar to jump between suspended platforms and avoid obstacles to advance through levels in the game. As a result of the array of environments to parse and the huge decision space for strategies, these games are very difficult for machines to play well. Instead of intuiting all levels of gameplay from first principles, we aim to build an agent that breaks down the problem as a human player would. Humans decompose games into perceiving the environment state, determining optimal paths, and controlling the avatar. We will investigate the effectiveness of decomposing platformers in a similar fashion, using reinforcement learning to handle environment perception and controller timing, while mapping out avatar trajectories using higher-level search algorithms. This approach is inspired by the Observe-Orient-Decide-Act cycle often found in robotics and autonomous systems.

We will be leveraging the Arcade Learning Environment, an open-source framework built on top of an Atari 2600 emulator. It provides an API for interfacing with the raw pixels, the current score, and the controller input of the game. This will enable us to use original Atari games as training and testing data. Initially, we plan to train an agent on a single Atari 2600 platformer. If our research proves timely and successful, we will train an agent on multiple different platformers simultaneously. These games will feature distinct physics, obstacles, and environments, which will help us test our agent's capacity for learning generalized pathfinding techniques, action-strategy mapping, and environment perception.

Our solution aims to create a more realistic platformer AI. Unlike those in other genres, platformer AI derives no benefit from omniscience and is insufficient for competitive or cooperative gameplay. Furthermore, our solution may generalize to perform well in other genres. We intend to measure the capability of the agent to finish different platform levels, as well as track in-game performance, including the time taken to complete a stage, the number of points earned, and the amount of progress made from start to goal before failing. We will also measure the agent's detection of environmental conditions, accuracy of avatar control, optimality of path searching.