CIS 510: Competitive Super Mario Kart

Deep Q Reinforcement Learning for Multiplayer Super Mario Kart

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1 Project Description

In this project we will be creating two competitive agents that will be able to play Super Mario Kart against one another and the game's agents. An extra goal is to be able to play against these agents in a match. A full description of Super Mario Kart can be found in the official documentation.

2 Short Background

In this section we will discuss the various tools and break down how we will formulate the project. In the next section we will discuss our proposition of how to achieve these goals.
For this project we will be using a Deep Q Learner. A simple Q learner and explanation can be found in this gist that I wrote. A link is also provided to explain how a deep Q learner works.
For this problem we will be using OpenAI's retro gym. Similar to gym, retro gym creates and environment that allows us to play "retro" video games. It handles all the emulation and provides us with bindings to the buttons that would be pressed on an actual controller. Retro also provides some states and actions for common games, though not Super Mario Kart (more on this later). Using this module a user can focus on just creating a reinforcement learner to learn to play the game and they do not have to think much about the environment or action states, that is: they do not need to formulate the quality matrix to create a basic learner.

3 Proposed Solution

Completing this project will require several tasks. First it will require importing the game into retro's engine. Next it requires defining the reward function, which means that the state and action set needs to be well defined. Lastly, the agents need to be trained to complete the tasks.

3.1 Integration into Retro

Currently we have completed the task of integrating the Super Mario Kart package into retro's engine, but this is not enough to play the game. Retro relies on different "states", which can be defined as different starting states. This is placed in quotes because the state will continuously be changing as the agent progresses through the level, more on this later. For this project we are starting with the scenario where there is a single agent playing the 50cc Mushroom Cup. Essentially we set a place in the game where we want our agent to start. Retro provides a UI where we can interactively play the game and save specific states. For this example our initial state looks like this:

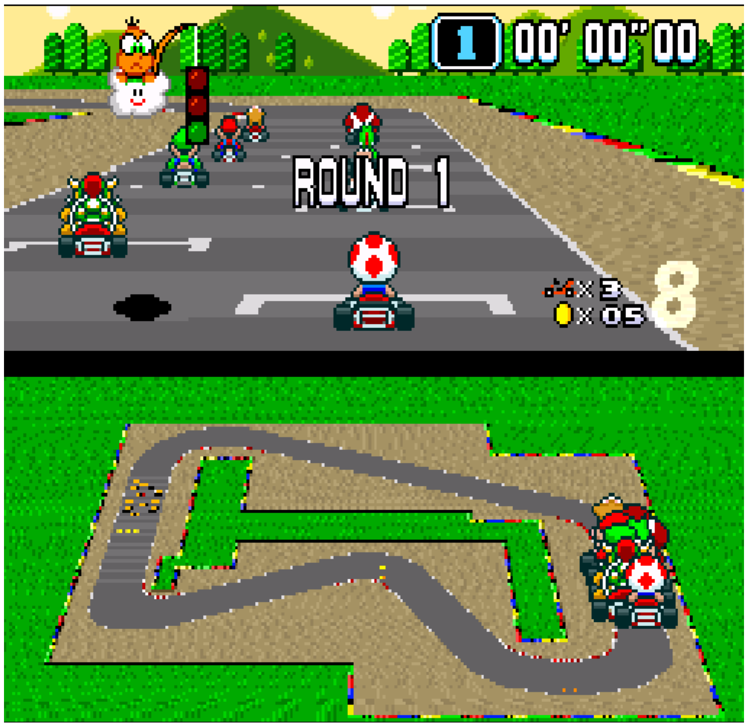


Figure 1: Initial state for 1P_GrandPrix_50cc_MushroomCup.state

From this we can see that in the upper half we see our player and the world around us. In the bottom half we see the entire map and can actually identify certain features like coins and items. We will be focusing on the top half.
Now that we have where we want to start, we need to define everything else. Retro uses json files to define many different parts to the game. There are two important files for each game: data.json and scenario.json. Data defines information about the level, lives, and score. Scenario defines the ending condition and the reward structure. An example with the Nintendo Entertainment System's (NES) Mario Brothers are shown below.

Additionally, scenario.json can contain information about the action set. We can either restrict our action set to a specific set of buttons, and button combinations, or we can expose all possible set of actions to the agent. Initially we will be limiting our agent, since certain actions like ["DOWN","UP"] are not likely to be useful, excluding glitches. Super Mario Kart has the following set of actions: Steering with the D-Pad, B for Accelerate, A to use an item, Y for Brakes, X for the rear-view, L or R for Hop/Power-side (same action), Start to pause the game, and select for Rear-View. We will limit the agent so that it may not look behind itself, cannot pause the game, and we will select R for hop/power-slide (because that is what I use when playing). So our new full action set for the steering will be {{UP},{DOWN},{LEFT},{RIGHT}, {UP,LEFT}, {UP, RIGHT}, {DOWN,RIGHT}, {DOWN,LEFT}}. This represents the left side of the controller. For the right side of the controller we will assume that the agent can play like a human does (this will also limit glitches that the agent might be able to exploit). The controls action set will be defined as {{B},{A},{Y}, {R},{A,B},{B,R},{A,R}}. The full action set is the combination of actions from the steering set and the control set.
To summarize the integration: we need to fully define how our agent will receive rewards, when the

Listing 1: data.json

```
{
    "info": {
        "level": {
            "address": 65,
            "type": "|d1"
        },
        "lives": {
            "address": 72,
            "type": "|u1"
        },
        "score": {
            "address": 148,
            "type": ">d4"
        }
    }
}
```

Listing 2: scenario.json

```
{
    "done": {
        "variables": {
            "lives": {
                "op": "equal",
                "reference": 0
            }
        }
    },
    "reward": {
        "variables": {
            "score": {
                "reward": 1
            }
        }
    }
}
```

Figure 2: data.json and scenario.json for NES Mario Brothers

agent ends, and our action set.

3.2 Rewards

Defining rewards is always a challenging problem in any machine learning task. There are many fantastic examples where a well thought out reward function leads to outcomes not expected by the machine learning engineer. For this game there are several criteria that will help us create different reward functions to test out.
First off, we need to have a clear goal. Since Super Mario Kart is a competitive racing game, each player is given a ranking when they finish the race. This gives us a well defined goal: be first. Since we will be training over a cup, multiple tracks, we do not need to place first in every race to win the cup, but placing first in every race will always result in placing first in the cup. The position can be seen in the bottom right of the screen, in our picture we start in 8th place (starting position changes depending on finishing position of the previous race).
The second factor that is key is that we have a clock, seen in the upper right of the screen. While we want to place first every time, setting a reward function purely based on position will only train the agent to beat the game's AI. Instead we want the agent to finish the race as fast as possible.
There are other factors to include that we will not consider until combinations of the first two are tested. Such factors include that the number of coins, with maximum of 10, determine how fast one can go. So having more coins helps optimize the first two, but may be harder to incorporate. Additionally, there are pieces on the may that boost the player. We hope that the agent will recognize these features on its own and that we do not need to assign a reward for using these. Including features like these have a higher potential to create an undesirable reward function. So first we will keep the reward system simple and iterate as needed.

3.3 Determining Finish

As mentioned previously, by incorporating a game that is not already defined by retro we need to tell retro when we are done. To accomplish this we will actually need to play this game in an emulator and record the state when finishing a race as well as when we finish a cup. This task is not yet accomplished but is not expected to be exceedingly difficult.

3.4 Seeing the Environment

We have mentioned that we will only be using the top half of the screen, the reason being is that this is where the agent gains the most information about their environment. Additionally, when playing in 2 player mode, the bottom half will be used for that agent's view. Therefore to train properly we need to only rely on the top half.
Retro does not create a way for the agent to "see" its current state. To accomplish this we need to turn this Q learner into a Deep Q learner. To do that we first create a Convolutional Neural Network (CNN) that will determine our state. Using this we will have a simple network which will then determine the action that needs to be taken at any given state, position on the track.
A simple way to think about this flow is with the following image. Using the position of Mario and

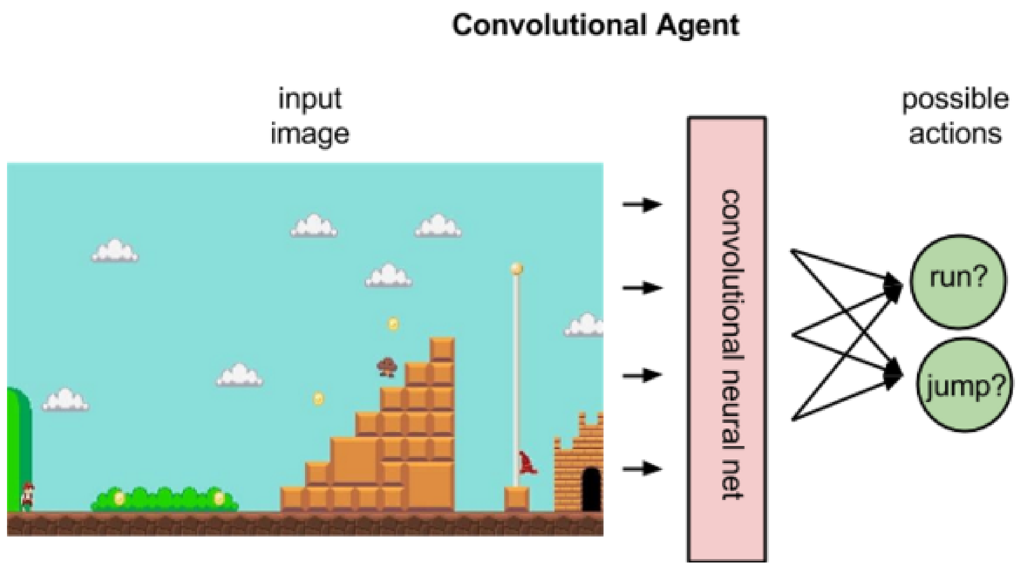


Figure 3: Example flow of network with Mario Brothers

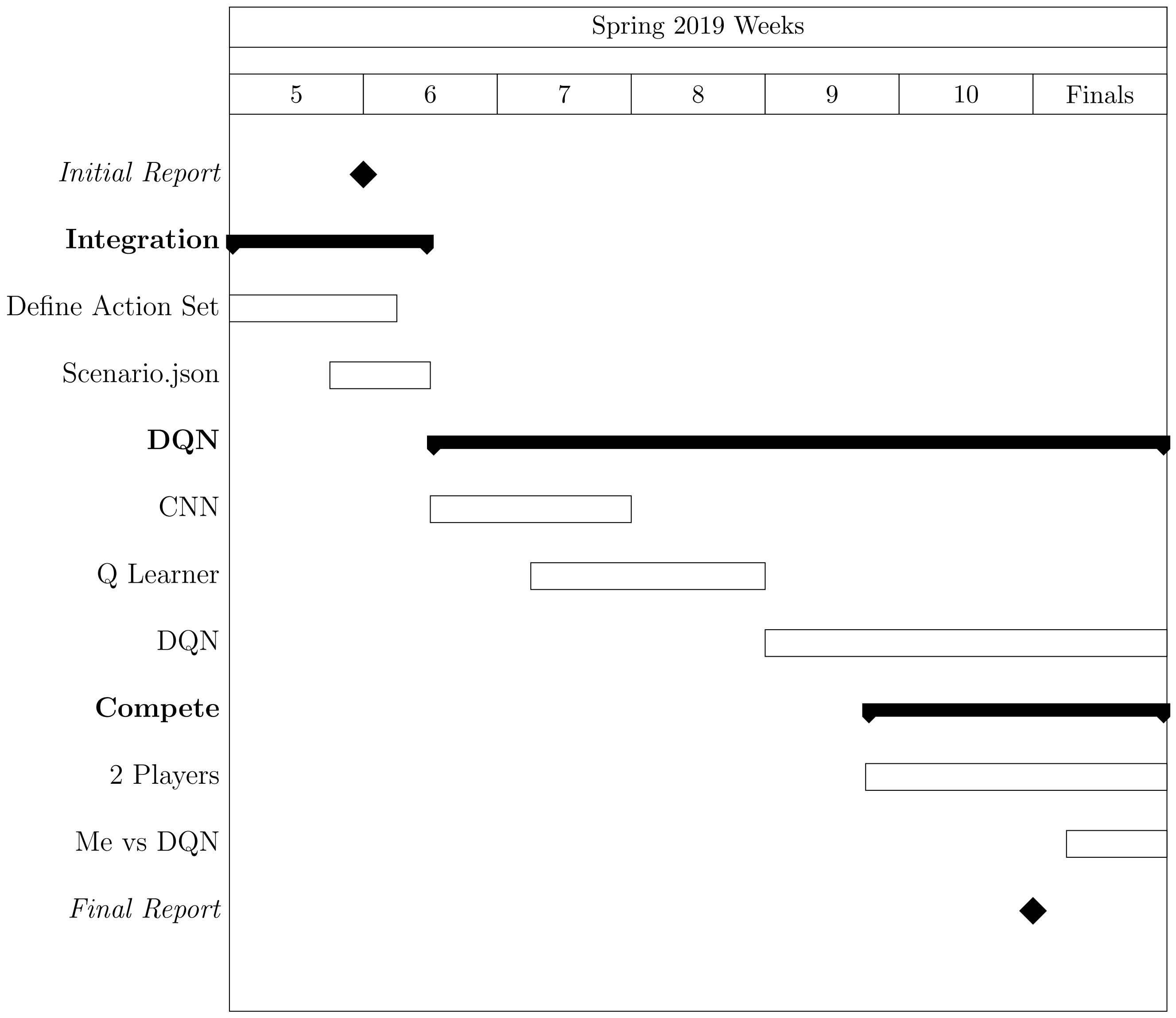
other objects on the screen, the agent needs to determine if it will run or jump. Our action set will be slightly more complicated.

3.5 Policy Gradient

Since we do not have labeled solutions to perform an error with back propagation, our reinforcement learner uses a policy gradient. Having defined our reward structure we can teach the network that certain actions are better than others. Essentially we are teaching the learner a set of actions that will beat the game. In a solved game we would expect this set of actions to converge on the solved action sequence, but in a game like this we do not have such a solution so can only base it upon how well it ranks.

4 Timeline

A proposed timeline is given below.


Spring 2019 Weeks
Finals
Initial Report
Integration
Define Action Set
Scenario.json
DQN
CNN
Q Learner
DQN
Compete
2 Players
Me vs DQN
Final Report