Multiple AI Competition in Self Developed Game
Term 2 Report
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Abstract

(some abstract)

1 Background

1.1 Previous Progress

In the last semester, we have implemented the preliminary version of the game environment and Q-Learning agent. In this section, we will briefly reiterate our previous progress before introducing new progress and our opinions.

1.1.1 Environment

When we started to draft our proposal, original considerations for designing our environment included complexity, scalability and implemental difficulty. We hoped to design an environment which is easy to implement, complex enough to distinguish the power of different algorithms and can be reused for different game modes, including 1 player, 1 versus 1, and multi-players against multi-players.

Therefore, we designed a game similar to football, and the graph user interface for 1 versus 1 version can be found in figure 1. In this environment, each agent controls one player which is represented as a blue(team 0) or an orange(team 1) rounded rectangle. And the purpose of players is to shoot the ball, which is represented as a white ball, to goal of opponent team, which is represent as white rectangle in the left border(for team 0) and right border(for team 1).

The environment can output a list to represent the game state. For 1 versus 1 mode, the list will contain the position of the current player, the position of the opponent player and the position of the ball.

The environment can receive a list with size equal 2 from a player as input, the first element represents the direction and the second element represents the action, shoot or not.

After receiving an action, we can call the reward function to calculate the reward of the given action, and return the reward as a scalar number to that agent.

1.1.2 Agent

In the last semester, we have finished the design of Q-Learning agent by following the algorithm provided in the background theory section. Moreover, our conclusion of the last term is that our game is too complicated to be trained by Q-Learning even for 1 vs 1 mode, even if we simplified input states.

The reason to simplify states is that the number of raw game states is an enormous figure even without considering the action space. The simplify function will replace the positions of opponent player and ball by logarithms of relative positions(distances) with base 10, which will compress the range of these 4 parameters from several hundred to 7. This will significantly reduce the size of Q-Table and make some simpler situations trainable, and we will discuss this later.

2 Implementation

2.1 Single Player Mode

In the beginning stage of our project in this term, we found that it's hard to train AI to play our game with DQN. So to simplify the issue and solve our prolem better, we first implement a single player mode. Then with the experience from single player mode, we are finally able to train DQN AI that

could play 1v1 mode with logic.

In this mode, we randomize the initialization of our player and ball. They will be put on the soccer field randomly when each episode begins. And once the player shoot the ball in a door, no matter right door or not, the current episode would end and a new episode of game would start.

```python
def reset_random(ball, player):
    ball.rect.centerx = screen_rect.centerx + (np_random.rand() - 0.5) * conf.width * 0.65
    ball.rect.centery = screen_rect.centery + (np_random.rand() - 0.5) * conf.height * 0.65
    ball.if_caught = False
    ball.catcher = -1
    ball.v.x = 0
    ball.v.y = 0
    player.rect.centerx = screen_rect.centerx + (np_random.rand() - 0.5) * conf.width * 0.65
    player.rect.centery = screen_rect.centery + (np_random.rand() - 0.5) * conf.height * 0.65
    player.v.x = 0
    player.v.y = 0
```

Figure 1: implementation of reset_random

2.2   Agent State

The state of agent represent the features sent to neural network. We add one more item into the agent state, which shows if the player is catching the ball or not. In the soccer game, there is cool down time for each player to prevent it to get the ball back as soon as it just shoots the ball. Therefore the coincidence of positions of player and ball doesn't mean that player could catch and shoot the ball. So one more item in agent state could help AI better understand its situation.

2.3   Reward Function

Reward function is crucial in reinforcement learning. As a soccer game, when a team get a goal, it will get huge reward. Besides, when a player catch a ball, it will also recive reward. Besides, to encourage player to keep the ball

longer, once the player shoot the ball, it will get punishment.

However, only these basic rewards are not enough for training. Below are our modification for other part of reward function.

2.3.1 Original Reward Function

In our original reward function, we give reward to the agent if it's closer to the ball than other player. Otherwise, the agent would get punishment. Besides, if the ball get closer to one door, the team attacking this door would get reward, and other team would get punishment.

Algorithm 1 Original Reward($Agent1, Agent2, Ball$)

Closer_Agent(Agent1, Agent2, Ball).reward $+=200$
Further_Agent(Agent1, Agent2, Ball).reward $-=200$
if Ball Moves right **then**
    Agent1.reward $+=600$
    Agent2.reward $-=600$
if Ball Moves left **then**
    Agent2.reward $+=600$
    Agent1.reward $-=600$
if Ball goes into right door **then**
    Agent1.reward $+=100000$
    Agent2.reward $-=10000$
if Ball goes into left door **then**
    Agent2.reward $+=100000$
    Agent1.reward $-=10000$
if Agent shoot the ball **then**
    Agent-shoot-ball.reward $-=1000$

2.3.2 Reward Function For Single Mode

With Single Player Mode, we need a new reward function. This one is simple. If the player is moving closer to the ball, it will get reward, otherwise it will

get punishment. Also, if the player shoot the ball to the direction to the right door, it will get reward. But if it shoots to wrong direction, it will get punishment. Then to encourage the player to keep the ball, it will also have reward when it keeps the ball.

Algorithm 2 Single Mode Reward($Agent, Ball$)

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    if Closer(Agent, Ball) or Keep(Agent, Ball) **then**
        Agent.reward $+ = 200$
    else
        Agent.reward $- = 200$
    if Ball goes into right door **then**
        Agent.reward $+ = 100000$
    if Ball goes into left door **then**
        Agent.reward $- = 10000$
    if Agent shoot the ball **then**
        team-of-the-agent.reward $- = 1000$

2.3.3 New Reward Function

Then, with experience from single player mode, we modify our original reward function. We cancel the comparison of distance to ball between two agents, instead we only care if the agent is closer to the ball. Also, we cancel some punishment to avoid agent playing to negatively. And we adjust the amount of reward during our test.

Algorithm 3 Original Reward(*Agent*1, *Agent*2, *Ball*)

---

if Closer(Agent1, Ball) **then**

    Agent1.reward $+ = 100$

else

    Agent1.reward $- = 100$

if Closer(Agent2, Ball) **then**

    Agent2.reward $+ = 100$

else

    Agent2.reward $- = 100$

if Ball Moves right **then**

    Agent1.reward $+ = 100$

if Ball Moves left **then**

    Agent2.reward $+ = 100$

if Ball goes into right door **then**

    Agent1.reward $+ = 100000$

    Agent2.reward $- = 10000$

if Ball goes into left door **then**

    Agent2.reward $+ = 100000$

    Agent1.reward $- = 10000$

if Agent shoot the ball **then**

    Agent-shoot-ball.reward $- = 1000$

2.4 Neural Network

In the implementation of our DQN, we look through a good tutorial of MorvanZhou(Zhou), which help us a lot. And we use two DQN implementation in our project, one offered in the tutorial, and another one implemented by us with keras, inspired by previous version, referenced from tutorial. Below we will use the second implementation, to briefly introduce our neural network.

2.4.1 Structrue of Nerual Network

There are two layers in our nerual network. In the first layer, we add a relu activation layer in the end. All variables are initialized with random normal initializers.

```python
n_l1 = 50
model = models.Sequential()
model.add(layers.Dense(n_l1, activation='relu',
                       kernel_initializer=tf.keras.initializers.RandomNormal(
                           stddev=0.01),
                       bias_initializer=tf.keras.initializers.Constant(0.01)))
model.add(layers.Dense(self.actions,
                       kernel_initializer=tf.keras.initializers.RandomNormal(
                           stddev=0.01),
                       bias_initializer=tf.keras.initializers.Constant(0.01)))
model.compile(loss=tf.keras.losses.MeanSquaredError(reduction='auto'),
              optimizer=tf.keras.optimizers.Adagrad(learning_rate=self.greedy))
```

Figure 2: structure of nerual network

2.4.2 Update

We randomly pick batch of memory, and calculate their actions from previous state to target network, and after state to eval network. Then we calculate relative q values of target model, and update the parameters in eval network. Also, the parameters in target network will be updated every R rounds of update.(R=300 in our project).

```python
def update(self, lr=1):
    if self.step_counter % self.replace_target_iter == 0:
        self.replace_target_params()
    if self.step_counter > self.memory_size:
        sample_index = np.random.choice(self.memory_size, size=self.batch_size)
    else:
        sample_index = np.random.choice(self.memory_counter, size=self.batch_size)
    batch_memory = self.memory[sample_index, :]
    q_eval = self.model.predict(batch_memory[:, :self.features])
    q_next = self.target_model.predict(batch_memory[:, -self.features:])
    q_target = q_eval.copy()
    for i, replay in enumerate(batch_memory):
        a = replay[self.features]
        r = replay[self.features+1]
        q_target[i][a] = (1-lr) * q_target[i][a] + lr * \
            (r + self.gamma * np.max(q_next, axis=1))
    history = self.model.fit(batch_memory[:, :self.features], q_target, verbose=0)
    self.cost_history.append(history.history['loss'])
    self.epsilon = self.epsilon + \
        self.epsilon_increment if self.epsilon < self.epsilon_max else self.epsilon_max
    self.step_counter += 1
```

Figure 3: update

2.5   Measurement of Performance

In the reference tutorial of reinforcement learning, the cost was used to measure the performance of DQN, which is quite a bad measurement in fact. Therefore, in our project, we use the q-values and average reward as measurements of our performances. We record the value of action we choose to form the history of q-values. And for every 100 steps, we sum up the rewards of 100 steps and calculate the average reward.

3   Result

In this section, we will show our result in two different modes.

3.1   Single Player Mode

In the single player mode, we use both Q-learning and DQN to train our agent. Although according to our previous conclusion, Q-learning can not play very complicated game, however with one less player, the relative complexity of Q-table also reduce a lot. Therefore we decide to also use Q-learning in the single player mode.
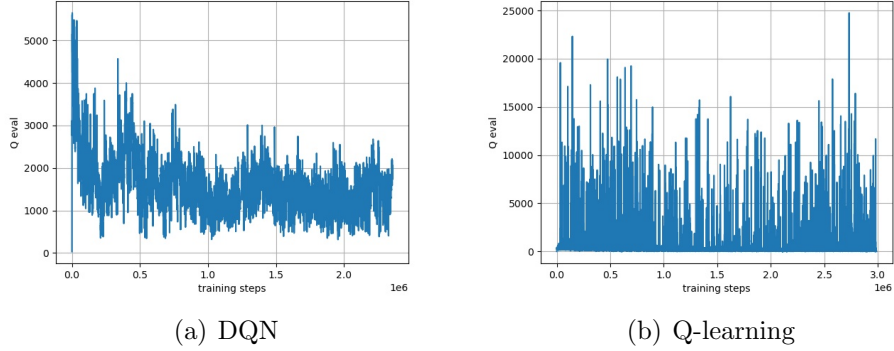

| (a) DQN | (b) Q-learning |

Figure 4: Q-values in single mode
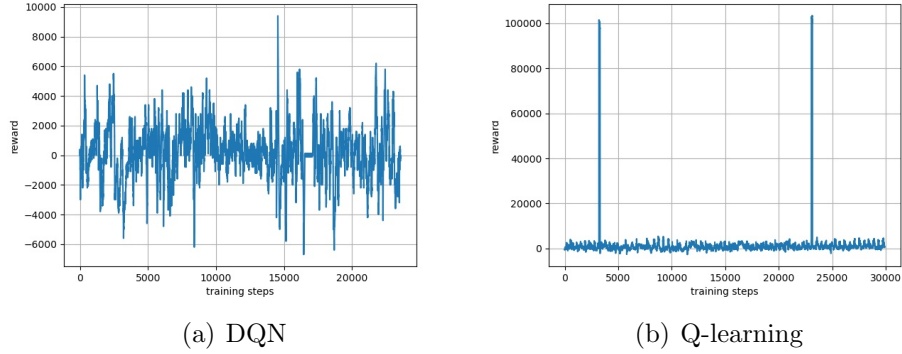

| (a) DQN | (b) Q-learning |

Figure 5: rewards in single mode

Comparing two Q-values figures, we can find thay there is an appearent decline in DQN, but for Q-learning, the distribution of Q-values seems more

random. And for average rewards, the waves in DQN is much more significant compared with Q-learning.

However, these 2 measurement are not that accurate for measuring performance. So, we use make a test on the DQN and Q-learning agent. We test how many how many score they can get in 100 episodes of game.

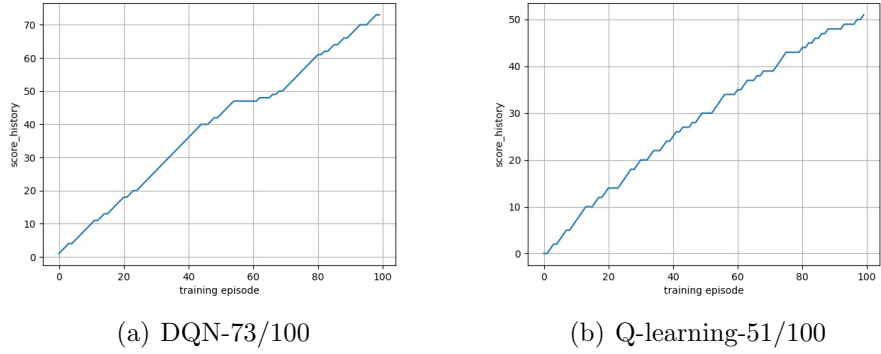(a) DQN-73/100   (b) Q-learning-51/100

Figure 6: total score for 100 round

The result shows that both DQN and Q-learning can play the game with logic, since the score they get are appearntly higher than a random player. And the performance of DQN (73 in 100 scores) is higher than Q-learning(51 in 100 scores), which could prove that DQN is more powerful than Q-learning.

3.2 1v1 Mode

compare 0-0/1000-1000/2000-2000/4000-4000/0-1000/1000-2000/2000-4000

4 Discussion

References

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[5] Mnih, Volodymyr, et al. "Human-level control through deep reinforcement learning." nature 518.7540 (2015): 529-533.

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