Multiple AI Competition in Self Developed Game
Term 2 Report
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Abstract

(some abstract)

1 Background

1.1 Basic Theory

In our last report, we have provided theories of reinforcement learning, Q-learning and Deep Q-learning and pseudo codes for them. In this part, in order to make the report easier to understand, we will provide pseudo codes and intuitive descriptions for these algorithms, and the advantages and disadvantages will not be discussed this time.

1.1.1 Q-Learning

The pseudo code of Q-learning is shown as Algorithm 1:

Algorithm 1 Reinforcement Learning (Zoph et al, 31)

Require: γ, α

Initialize Q (e.g. $Q(s,a) = 0 \ for \ \forall s \in S, \forall a \in A$)
for each episode **do**
    Modify α and γ
    $s \in S$ is initialized as the starting state
    repeat
        choose a random action or the best action $a \in A(s)$ based on the exploration strategy.
        perform action a
        observe the new state s' and received reward r
        $Q_{k+1}(s,a) = Q_k(s,a) + \alpha(r + \gamma \cdot max_{a' \in A(s')} Q_k(s,a') - Q_k(s,a))$
        using the experience $\langle s, a, r, s' \rangle$
        $s := s'$
    until s' is a goal state or t reaches the limitation

The core of Q-learning is that we use a table, Q-table, as the memory to identify states of environment and remember the performance of every action in every state. The procedure of training the agent is the procedure to adjust its memory.

The performance of an action is the expected reward if we choose this action. Therefore, the term $max_{a' \in A(s')} Q_k(s, a')$ is the optimal expected reward of the next state, which represents the future reward. γ, as the discount factor, represents the magnitude of the 'future'. Larger γ will make an agent consider in longer-range because the importance of the future will be higher. α is the learning rate, an agent will change the memory faster with higher learning rate, but it may not be great if the learning rate is too high or too low, because we may 'discard' too much previous memory or cannot learning almost anything.

1.1.2 Deep Q-Learning

The algorithm of DQN is:

Algorithm 2 Deep Q-Network(Mnih et al)

Setup replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ with weights θ'
for each episode **do**
    Initialize sequence $s_1 = x_1$ and preprocessed sequence $\phi_1 = \phi(s_1)$
    $t := 1$
    repeat
        Choose a random action or the best action $a_t \in A(s)$ based on the exploration strategy.
        Perform action a_t
        Observe the new input x_{t+1} and received reward r_t
        Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
        Store the experience $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
        Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ in D
        Set $y_j = r_j + \gamma max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta')$
        Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ with respect to the network parameters θ
        Every C steps reset $\hat{Q} = Q$
    until s' is a goal state or t reaches the limitation

The core of DQN is similar to Q-learning, which is to train a estimator to judge the performance of actions. The difference is that the estimator in Q-learning is a memory table but the estimator in DQN is a function with game states as input.

According to previous research, a neural net can approximate any computable function(Wang, 2003), so we can use neural network to approximate the estimate function. In this way, we can train the model in deep learning algorithm to obtain the function without any knowledge about the function itself.

1.2 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.

1.2.1 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.

1.2.2 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 3 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 4 Single Mode Reward($Agent$, $Ball$)

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 try to 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 5 New Reward($Agent1, Agent2, Ball$)

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. However for our experiment, since the training of keras is appearently slower than tensorflow, so we use first implementation to collect the data.

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.

```
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

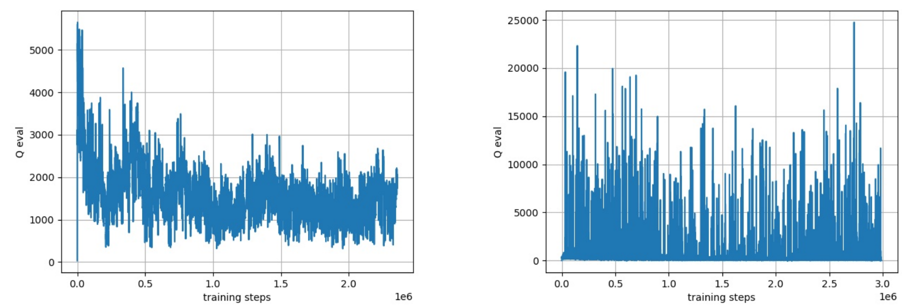
In the reference tutorial of reinforcement learning, the cost was used to measure the performance of DQN, which is quite a bad measurement in fact. Therefore, in our project, we use the q-values and average reward as measurements of our performances. We record the value of action we choose to form the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

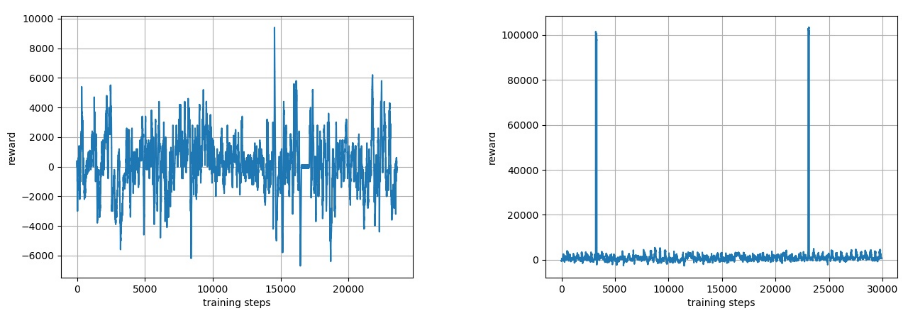
3.1 Single Player Mode

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

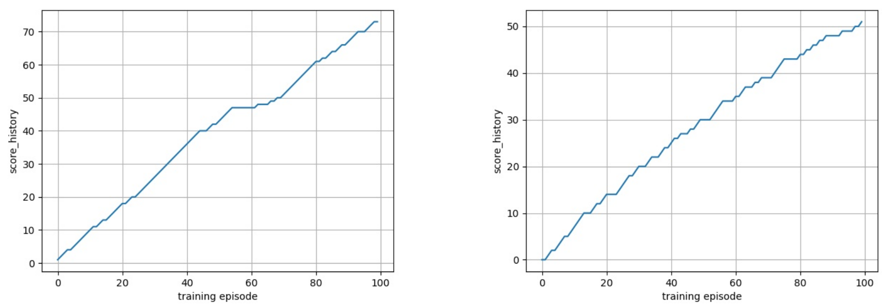


(a) DQN (b) Q-learning

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 in single mode

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

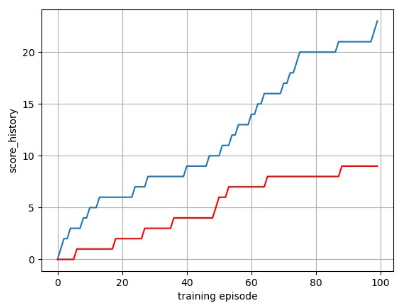
With the success and experience from single mode, we could better adjust the configure of DQN for the 1v1 mode.

Basically, the agent trained with DQN can play the game with some logic. There are able to chase for the ball and disturb its opponent at most of the time.

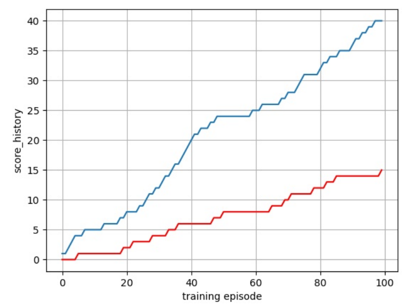
However, we found that there are quite many own goals while testing. Therefore, we add own goals of each team for helping our discussion. And further discussion about our result would be introduced in our next part.

3.2.1 Different Training Episode

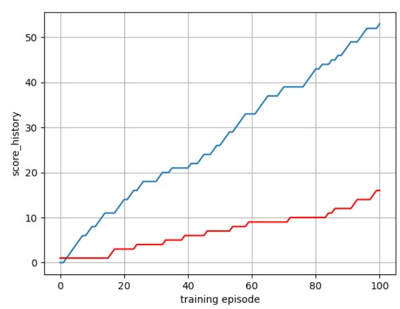
First of all, we train a pair of agents with 4000 episodes of game.



(a) 1000 episodes



(b) 2000 episodes



(c) 4000 episodes

Figure 7: total final scores for 100 round with different training episodes

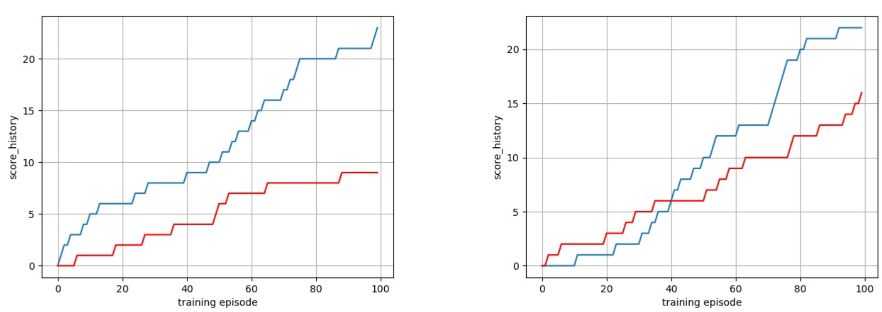
episodes	blue score	red score	blue own goal	red own goal
0	0	0	0	0
1000	23	9	21	0
2000	40	15	23	3
4000	53	16	22	8

Table 1: Statistics of scores and own goal

From the result, we can see that with more training, the agent becomes more powerful, since both agent could get more scores (no matter if they get the goal by themselves). However, there are too many own goals, especially from the red team. And the diatance of scores are becoming larger and larger. These two phenomenons both show the imbalance of two players during training.

3.2.2 Different Reward Function

Then we'd like to find out the difference between our old and new reward function. And the result is below. In each case, the agent is trained with 1000 episodes.



(a) original reward function

(b) new reward function

Figure 8: total final scores for 100 round with different reward function

reward	blue score	red score	blue own goal	red own goal
original	23	9	21	0
new	22	16	22	5

Table 2: Statistics of scores and own goal

From the comparison we could see that, although no significant difference, but the imbalance between two agents do reduce to a certain extent, approximately 15%.

4 Discussion

We have to admit that we are far behind our plan in the proposal. We encountered many unexpected difficulty, and we try to solve some of them and try to figure out the reason behind some problem cannot be solved now. In this part, we will discuss these problems we met, and give our opinion and lesson we learnt from them.

4.1 Slow training speed

Before we started to train our models, we never reckoned with the slow training speed. The maximum frames we can run per second is about 1000 in a computer with an average CPU, and we train 1 times in 10 frames. This number, 100 times of train in one second, is not a small number at the first look, but it is much slower than what it should have been.

The limitation of the training speed is not the training process itself. The interaction between agents and environment is the limitation. The evidence is that when we use the GPU to do the neural network training, the GPU occupancy is always lower than 2%, even for a entry level GPU MX350, which really shocks us. Therefore, the game process occupies most of the running time.

Before we found this problem, we through we can use GPU servers provided by CSE Department to accelerate our training, but now we know that the design of our project make it impossible. The lesson we learnt from this problem is that it's better to choose an simple environment, at least a high-performance environment, otherwise the environment may become the barrier to accelerate the training process.

4.2 Reinforcement Learning is training inefficient

The part of slow training speed has been discussed in the last section, and the other part of the problem is because of the property of Reinforcement learning. During our training process, we found that the model usually needs thousands of trains to get a perceptible improvement, even in the single player mode, which is a simple environment for even Q-learning.

We think this is a universal problem in deep reinforcement learning. Atari games is a standard benchmark for performance of different algorithms, and the exist data show that the the training times for even the best algorithm is in the order of magnitude of 10 million, and those classic algorithms like native-DQN and Double DQN need more rounds(Hessel et al.).

However, CNN is also a popular deep learning algorithm, which is widely used in image recognition. The MNIST is a well-known dataset which is used to train for recognizing handwriting numbers. If we train a CNN model in this dataset, we may not need more than 100 rounds to get 90% of accuracy, which is much more efficient than deep reinforcement learning.

4.3 Random seed matters

Every time we initialize a new agent, we will initialize the parameter of the network, because we will use the gradient decline to get optimal parameters and different initial values may result in different local optima. In most cases, this will not have a huge negative impact as long as we try several times. However, in our experiments, randomization will have a huge impact. Agents with the same hyper-parameters can have a huge difference in training speed and performance after training. This also affects AI versus AI mode, because the power of agents with different initial estimators will be unbalanced during and after training. The most depressing impact is that it is hard to know if a bad result is caused by incorrect structure or parameters, or caused by bad luck. From previous research, we found that a model set correctly still has a 25% fail probability(Houthooft et al.). Therefore, we need to train more models with the same parameters to ensure that we can make a fair judgement on our setting. However, slow and ineffective training makes repetition become a time-consuming process. We guess we can reduce the effect of randomization by giving some prior knowledge, which means we can initialize the network by a user defined function instead of randomizing function. This may help agents to converge in the way we expect.

4.4 Difficulty in reward functions

In the result section, we conclude that different reward functions will affect the quality of training. Therefore, the quality of reward function is important for a good training result. However, it is hard to predict the quality of a reward function, since we do not know whether a reward has some side effects.

For example, in one version of our reward function, we calculate the distance between the ball and current or opponent players. If the difference in these two distances decreases, we will give a reward to the current player, otherwise, a punishment will be given. We thought that this may help player to keep the ball away from the opponent. However, we found that the player may move the ball toward his half and wrongly kick a own goal.

Therefore, we cannot predict how the agent will respond to our reward function, the only things we can do in our project is to try different functions.

4.5 Overfitting

In deep reinforcement learning, overfitting may not be a thing we have to avoid, since we will not use the model in other environments. Therefore, overfitting in a specific environment may not affect the accuracy of a model in that environment. However, the problem we met is that the other player is seen as a part of the environment, and an agent will adjust itself according to the other agent.

This overfitting causes 2 problems. First, if there is difference in the performance between the 2 agents, the better one will become better and better as training. The stronger agent will get higher reward because it can always defeat the opponent, so it will become an expert against the other. However, the weaker one cannot get enough positive feedback because the reward is not satisfactory no matter what it does.

The second problem is that a well-trained agent may not perform well when it faces a stranger. The overfitting makes the performance of an agent in a testing environment worse than the training environment. However, our goal is to train an agent to play the game, instead of beating a specific agent.

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