Predicting MBTI Personality Type Based on Social Media Record

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Abstract

Board Games always push the player not only consider how to do the local optimal decision at current state, but also ask the plaer to guess how will his opponent will perform in the next state. MiniMax tree is one of the basic idea to consider the states in the future. However, MiniMax tree has high time complexity and hard to define the reward and its parameters, only use MiniMax tree in an agent is hard to perform well.

1. Introduction

In the general board games, it has initial states s_0, and other states s_t at *t* time. Two players denoted as p_1 and p_2. its next action set depends on the current state $action\,(s_t, p_i) = \{PointPosition\}$. With specific rules, update function, *Update*$(s_t, p_i, action)$ to update the chess board. s_t = *Update*$(s_{t-1}, p_i, action)$

2. Related Works

In our project, we decide to utilize the Reversi, which has a different way of attacking, scrambling the opponent in the other chess games, , to implement an agent that could learn the specific strategy to try to beat other agents online or even people.

3. Feature Extraction

3.1. Dataset

3.2. Word2vec

Players in the Reversi aim to get more positions in the limited 8×8 space chess board, so the basic strategy for the beginer of this game is to flip more opponent's chess in each transaction t.

3.2.1 One-hot Coding

However, the most important thing is that the space is limited for the player, the weight of position can be strongly different from one to another.

3.3. CBOW Model

What's more, when one player is trying to flip his opponent's chess, the opponent is also trying to flip his.

3.4. N-gram Model

The players have to design a strategy to help them to occupy more edges and corners in the game, also to defend themselves from being flipped.

4. Model for Prediction

5. Experiments and Results

6. Discussion

7. Conclusion

After several algorithm updates, MiniMax Dueling DQN is the most powerful algorithm at present, and the interval time of each drop is very short, so there is almost no waiting time for people. This algorithm not only effectively approximates the q-value through Dueling DQN, but also can consider the advantages of MiniMax in the future step, while avoiding the disadvantages of long calculation time of MiniMax algorithm. There is no battle with the MCTS algorithm in chess, but it is certain that MiniMax Dueling DQN is superior to MCTS in time. The MCTS algorithm will be completed later and the two will be compared.

8. Contribution

References

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