Improving the Performance of Deep Q Network in Decision Making Environment: Applying Multi-Head Attention into DQN

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Keywords: Deep Q-Network(DQN), Multi-Head Attention, Deep Learning, Reinforcement Learning, Mahjong.

Abstract: Deep q-network (DQN) is a deep reinforcement learning algorithm. It has been used to solve value function-based reinforcement learning problems, and with deep neural networks, it can solve complex decision-making tasks. Multi-Head Attention is a mechanism that can capture various aspects of the input data in parallel, improving the model's capacity to recognize complex patterns in the data. Mahjong, being a traditional multi-player imperfect information card game, fits well in training and testing a decision-making model. This study introduces an application of combination of DQN and Multi-Head Attention mechanism, seeking to enhance the performance of DQN models by leveraging the benefits of multi-head attention. Through RL Card platform, which provides a variant of mahjong model that can be used for training, the paper applies the Multi-Head Attention with its original DQN agent for mahjong. The trained model shows a higher winning rate in the battle against the baseline model, demonstrating the promotion the combination brings to the mahjong agent model.

1 INTRODUCTION

In the domain of games, especially in the area towards decision-making, deep learning(LeCun et al., 2015) has been pivotal in achieving milestones that were previously thought to be decades away. In the perfect information game, AlphaGo utilized deep learning and tree search to outperform human masters for the first time, which subsequently caused a research boom in deep learning in computer gaming. In incomplete information games, AI using deep learning has been used in Texas Hold'em(Bowling, et al., 2015), Doudizhu(Zha et al., 2021) and even DOTA(Berner et al., 2019).

A notable application of deep learning in gaming is Deep Q-Network (DQN)(Mnih et al., 2013). It has been applied to seven Atari games and proved outstanding performance on six of the games.

Multi-Head Attention(Vaswani et al., 2017) is a pivotal feature in modern neural network architectures that allows for concurrent processing of information across multiple subspaces and positions. This capability leads to a richer understanding of the input data, enhancing the model's performance on complex tasks involving significant contextual interpretation.

Originating in China in the late 1800s, Mahjong, a popular game involving tiles, has since captivated hundreds of millions of enthusiasts worldwide. It's a multi-player game that unfolds over several rounds, characterized by its element of incomplete information. Players must employ strategy, skill, and calculation, though luck also plays a role in the game's outcome.

In the environment of mahjong, the agent continuously assesses the present condition of the game to maximize some form of cumulative reward. This is akin to decision-making processes in real-world applications, making games an excellent platform for developing and testing AI algorithms.

Many methods based on the DQN algorithm have been attempted to be used in mahjong games. In 2021, DQN has been applied to mahjong with search algorithm(Sun, 2021). In the case, DRL makes game trees work better in complex states. However, due to the influence of the sparse mahjong rewards, the model meets a lot of draw situations in the game. In the same year, an improved DQN model towards mahjong is proposed. It promotes the model with Double DQN and improved valuation function for search algorithms(Lei et al., 2021).

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In this paper, the author tries to promote the performance of the DQN agent for mahjong by integrating the multi-head attention mechanism into it. The RL Card platform(Zha et al., 2021) will be used to test the model.

2 BASIC KNOWLEDGE OF THE ALGORITHMS

2.1 Double DQN

With advancements in reinforcement learning, researchers developed the DQN, which enhances the traditional Q-learning algorithm by integrating deep learning. DQN computes the Q-value for each action to inform decision-making, similar to its predecessor. And it has been proved to be able to master the difficult control strategies of the Atari 2600 computer game.

However, like traditional Q-learning, DQN still suffers from the problem of overestimating Q-values, which can lead to sub-optimal policy decisions. To mitigate this issue, the Double DQN was introduced, building upon DQN by employing a dual network architecture to reduce Q-value overestimation by decoupling the selection from the evaluation of the action.

The DQN algorithm has two neural networks, the original network and the target network, and although they have the same structure, the weight updates are not synchronized. The loss function of the DQN algorithm's weight updates is defined using the mean squared error with the following expression:

$$L(\theta) = E[(Y - Q(S_t, a; \theta_t))^2] \tag{1}$$

$$Y_t^{\text{DQN}} = R_{t+1} + \gamma \max Q(S_{t+1}, a; \theta_t) \tag{2}$$

where a is the execution action, R_{t+1} is the reward score, S_t is the current game state information, S_{t+1} is the next game state information, θ is the network weight, γ is the discount factor, and Q(S, a) represents the valuation of executing action a in state S. The use of the max operation in the DQN algorithm for both selecting and evaluating actions introduces an overestimation bias. This occurs because the algorithm might frequently choose actions with exaggerated value estimations, which can adversely affect the learning of optimal strategies. This issue highlights a fundamental challenge in reinforcement learning that needs to be addressed to enhance the accuracy and reliability of value-based learning algorithms like DQN. For this reason, the Double DQN(Van et al., 2016) algorithm decouples the selection and measurement of actions and rewrites equation (2) in the following form:

$$Y_t^{\text{Double DQN}} = R_{t+1} + \gamma Q(S_{t+1}, \operatorname{argmax} Q(S_{t+1}, a; \theta_t), \theta_t') \tag{3}$$

2.2 Attention

2.2.1 Scaled Dot-Product Attention

Multi-head attention is a feature that plays a crucial role in the Transformer model, enhancing its capability to handle diverse data representations simultaneously. Introduced in 2017, it utilizes parallel processing heads to capture various data aspects, significantly enriching the input's representation. This mechanism underpins the Transformer's advanced performance across many complex tasks, particularly in natural language processing.

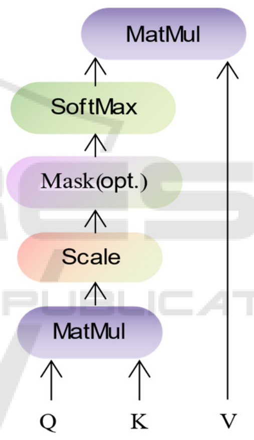


Figure 1: Scaled Dot-Product Attention.

In actuality, the output matrix is computed from the attention function, which is simultaneously calculated on a set of queries organized into a matrix Q.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

The dimension of queries and keys is represented by d_k, d_k and d_v refers to values of dimension in the equation. The weights on the values are obtained using a softmax function.

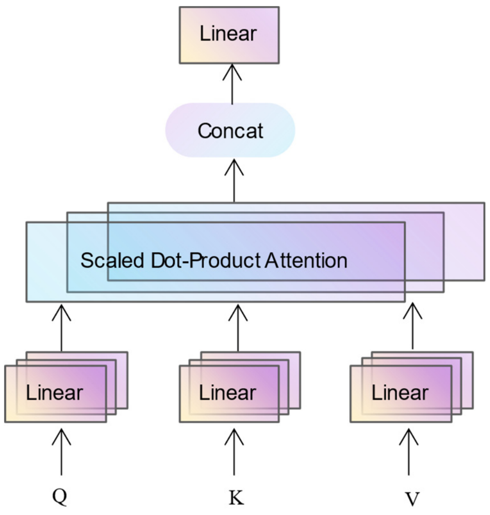


Figure 2: Multi-Head Attention.

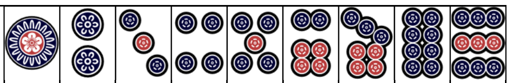
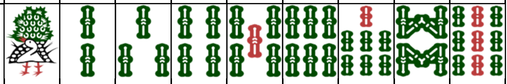
This enhanced method utilizes multiple linear projections to repeatedly alter the dimensions of keys, queries, and values, boosting the model's capacity to simultaneously process information across various subspaces. The subsequent execution of attention functions on these transformed sets and the aggregation of their outputs enable a more nuanced and effective synthesis of information, leading to superior performance in tasks requiring complex relational understanding and data integration. The method is depicted schematically in Figure 2.

3 FEATURES AND MODEL STRUCTURES

3.1 Features of RL Mahjong

According to the mahjong environment provided in the RL Card platform, there are 136 tiles, divided into 34 different types, with four tiles of each type. The 34 tile types include three suits−Manzu, Pinzu, and Souzu, each ranging from 1 to 9, along with 7 different Honor tiles. A game, comprising multiple rounds, ends upon meeting the winning condition(Ron).

Table 1: Mahjong Tiles.

	Numbers								
Manzu									
Pinzu									
Souzu									

Honors	Winds				Dragons		
	Ton	Nan	Shaa	Pei	Haku	Hatsu	Chun

3.2 Actions of the Agent

The actions of the agent are as follows:

● *Chow*: an agent has the option to take a tile that has just been discarded by opponent on the left to create a meld. After performing a Chow, the agent must discard another tile.

● *Pong/Kong*: an agent has the option to take a tile that has just been discarded by another player to create a triplet/quad. This move might result in the skipping of another player's turn. After performing a Pong, the agent must discard another tile. After performing a Kong, the agent will draw another tile and discard one.

● *Discard*: Discard is the main action the agent would do in a mahjong game. The discard problem in Mahjong can be modeled in this ways: as a 34-class classification problem, where each class corresponds to one of the 34 unique tile types in the game.

● *Ron*: In RL mahjong, Ron or not is judged by whether a player has got 4 sets of tiles or more.

3.3 Encoding of Actions

Table 2: Encoding of Actions.

Indices	Corresponding Tiles
0~8	Souzu, i.e., 1~9s
9~17	Manzu, i.e., 1~9m
18~26	Pinzu, i.e., 1~9p
27~29	Hatsu, Chun, Haku
30~33	Ton, Nan, Shaa, Pei
34~36	Pong, Chow, Kong

Encoding the tiles of a player into four distinct channels makes it easier to transfer mahjong data, which helps to process the deep learning algorithms.

4 EXPERIMENTS

4.1 Framework

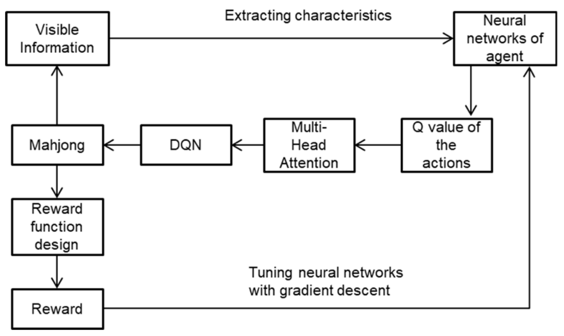


Figure 3: Training procedure of Multi-Head Attention combined DQN mahjong model.

Figure 3 shows the training process of combining MultiHeadAttention and Double DQN network model, the specific steps are as follows:

●*Extract Visible Information*: Gather every visible game information, including the agent's hand, the discards of all players, the count of remaining cards in the deck, and the count of game rounds.

●*Making Decision*: Based on the a priori knowledge of Mahjong, encode the visible information into feature data. Make decisions by analyzing the available data currently.

● *Estimate*: Evaluate the Action's Q Value.

● *Get result*: By training the Double DQN neural network with the gradient descent algorithm based on the execution actions, reward scores, current game state information and next game state information, get the mahjong learning model.

● *Circulate*: Loop through this process until the total number of training steps is reached.

4.2 Setting of the Algorithm

Table 3. Experimental parameter.

Parameter	Value
Batch size	512
Replay memory size	20000
ε-greedy start	1.0
ε-greedy end	0.1
Learning rate	0.00005
Discount factor γ	0.9

The settings of the parameters of DQN are the same for both models. The relevant parameter settings are shown in Table 3.

4.3 Results

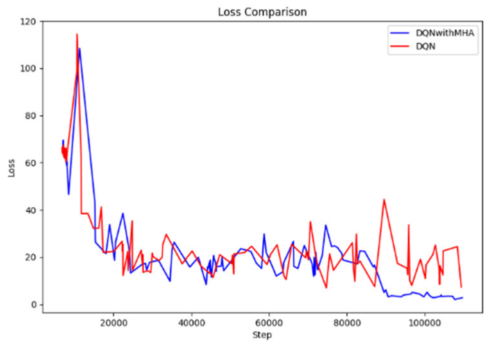


Figure 4: Loss comparison.

The paper pre-trained the original DQN model and the DQN with Multi-Head Attention agent.

Loss is computed as follows:

●*Sample Data*: Sample the data such as states, actions, rewards, next states from the experience replay buffer.

●*Compute Best next Actions using Q-Network*: The Q-network predicts Q-values for next states.

●*Loss Computation and Gradient Descent*: The Q-network is updated by training on the present state batch, the decision made, and the target Q-values computed. The calculation of loss in reinforcement learning models employing Q-learning is essential for refining the predictions of Q-values. This loss, typically determined by mean squared error, serves to adjust the predictive model towards greater accuracy in estimating the expected rewards from actions taken, thus directly influencing the learning progress and performance of the agent. This step updates the Q-network parameters through backpropagation.

Figure 4 shows the loss at each step for both models.It shows that comparing to the DQN model, DQN with Multi-Head Attention's loss curve is lower in the later stage.

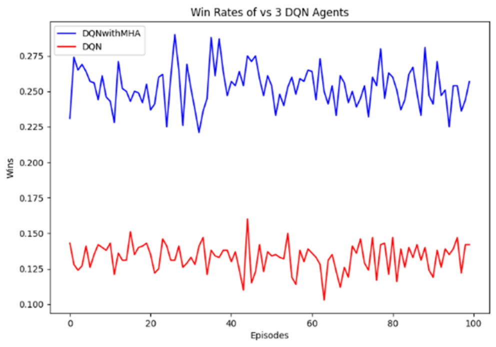


Figure 5: Win rate of vs 3 DQN Agents.

The paper tested four agents in total: one DQN agent enhanced with multi-head attention and three standard DQN agents. Let them play 1,000 games per episode, with win rates calculated over a total of 100 episodes. Figure 5 outlines that the win rate of the Multi-Head Attention-enhanced DQN agent is significantly higher compared to the baseline DQN agents. This enhancement demonstrates a substantial improvement in model performance.

5 CONCLUSION

In this article, a mahjong based on Deep Q Network is chosen as the baseline. By combining DQN with multi-head attention mechanism, the paper promote the model's performance. The outcomes of the experiments show that the algorithm improves the win rate on RL mahjong by 12 percentage points compared to the original implemented DQN algorithm. The superior performance shows that multi-head attention mechanism can significantly improve the decision making ability of DQN models in adversarial environments.

It is acknowledged that various of problems in reality have a lot of traits in common. For example, imperfect information, intricate rules for operation and complex distribution of incentives. Therefore, the paper gives a new way of optimising decision making models in real life problems.

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