Intelligent Non-Player Character with Deep Learning

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1. Introduction

1.1. Motivation

Artificial Intelligence (AI), especially machine learning has been experiencing a burst of evolution in recent years, as the computing capability of computers has increased a lot so that the computations required by machine learning approaches are achievable using much shorter time. Among all, Google's AlphaGo is a good example. AlphaGo is a game AI that plays GO, and it beat Lee Sedol, one of the top-class professional players, in a five-game match with the score of 4-1 in March 2016. It's a surprising but expected result, which shows the powerfulness of AlphaGo, and more importantly, the great potential of machine learning. It uses a method called deep learning, which uses Neural Network (NN) to search for the best option for current situation.

Figure 1.1. AlphaGo Playing against Lee Sedol

Currently, many people are trying to use deep learning to solve different kinds of problems, including building game AI for different games. While most of them focus on Go or chess, none has ever applied the approach of deep learning to Chinese chess. Chinese chess is one traditional strategy game, which is still very popular nowadays. Nowadays, the existing game engines of Chinese chess are all based on searching approach without using machine learning and primarily rely on hard-coded libraries of the initial phases and the final phases of games to make move choice. As the approach of deep learning has been used on many fields, like GO and chess, however, the field of Chinese chess remains blank. Therefore, we tried to build a game AI for Chinese chess, using deep learning.

1.2. Background

1.2.1. Development of AI in Go

In Go, the size of game board is 19*19=361, which is much larger than other games. For example, there are 8*8=64 available positions in chess, and there are 9*10=90 available positions in Chinese chess. In a recent research, the number of legal positions on a game board of Go is $2.801682*10^{170}$. [18] The number is 1090 times larger than the number of atoms in the universe. It means the complexity is much larger than other chess games, like chess and Chinese chess. So, direct searching approach is not applicable for Go because searching is slow and limited in global area where the depth of searching may be too large.

In the beginning process of development history of AI, however, there were no better algorithms to search and evaluate the game board. All they could do was to modify the evaluation function and pruning condition. As Go uses a really big game board, players are required to have the ability to judge the current situation (the difference of areas controlled by players). But in a game, the ownership of one place may be fuzzy and hard to decide even for human players, and for computer program at that time, it made lots of mistakes and couldn't be used for a high-level AI. So, for the scientist that time, building an AI to overcome top-class human players seems impossible.

To solve the problem, Monte Carlo Tree Search (MCTS) was introduced in this field. To explain what MCTS is, imagine that a person who is absolutely a beginner and knows nothing about Go, and let him choose a place randomly. Then repeat the process and calculate the winning rate of every possible move. However, simple randomization is not suitable for complex board games. For instance, in Go, there exist situations where there may exist many legal moves but only few among them are reasonable.

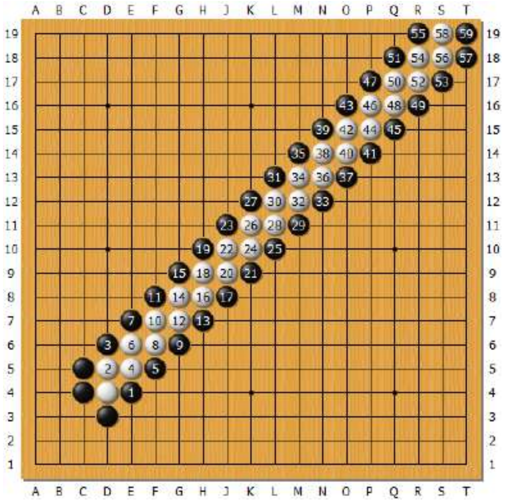


Figure 1.2. An Example of "Ladder" In Go

As shown in Figure 1.2. above, what the black side does is called “ladder”. The black side forces those white stones to move like zigzag, and finally can capture them all. During this period, the black side must put its stones in correct points as indicated in Figure 1.2., or the white side can escape, which is a common sense for Go players. This is easy for human players but not for a computer program.

In 2006, the invention of UCT (Upper Confidence Bound 1 applied to trees), an improved version of MCTS, changed this status. UCT would prefer a known better move with higher winning rate other than select them completely randomly. By this improvement, the efficiency of searching had been growing fast. In 2006, the level of the best AI that time had only k level, below the average level of amateurs. But in 2012, Zen, a Go engine using MCTS, beat top-class professional player at four stones handicap, which means it could win against nearly half of amateurs.

However, MCTS also has its own limit in global view though it is good at local battle. The level of program hardly improved until 27 January 2016, the day when the paper about AlphaGo was published on Nature. AlphaGo had beat Fan Hui, a 2-dan pro, in 5-0 complete victory, which is the first victory between Go program and professional Go players in equal condition. This revolutionary improvement could attribute to the use of neural network. The detail of the algorithm of AlphaGo can be found in the literature review. To be brief, neural network provides a faster way to evaluate the situation on board and to generate a quick predicted move, like what human players will do. Combining with the accurate calculation, distributed AlphaGo running on Google's cloud service wins all 500 games against "old" AI. And In March 2016, AlphaGo beat Lee Sedol, one of the top class professional players, in a five-game match with the score of 4-1 in March 2016. In an ELO-ranking website GoRatings, it is the second-best player in the world.

The success of AlphaGo has proved that it is possible for computer programs to beat human players in Go.

1.2.2. Development of AI in Chess

In chess, Deep Blue has done it long before. In May 1997, it beat Garry Kasparov with 3½–2½. Nowadays, even top-level professional players have little possibility to win against AI running on normal computers as current personal computers have higher computation ability than Deep Blue.

But the AI of Deep Blue is different from AlphaGo. In fact, the hardware of Deep Blue consists of 30 paralleled CPUs and 480 specially made VLSI chips, meaning that the computer could only run chess program. But nowadays, the newest chess engine, Stockfish, can run on Windows machines, and beat any other players or AIs on personal computer with 4-cores CPU.

Nowadays, a normal game engine of chess or Chinese chess will contain searching part and libraries for opening and ending. In fact, though usage of these libraries is not necessary, it can improve the performance of AI greatly. This is because that the number of branches in searching will increase greatly as the number of available moves increases. So, using hard-coding libraries will be a good choice. But if we use Neural Network, this should not be a problem. The best neural network AI, Giraffe, can reach the level of an FIDE International Master though Stockfish is still stronger.

1.2.3. Development of AI in Chinese Chess

However, those game engines in Chinese chess are still using traditional methods. In National Computer Games Tournament of 2016, Chess Nade ("象棋名手" in Chinese) won its fifth consecutive champion. And it is recognized as the best Chinese engine in China. The detail algorithm of it remains secret as it is commercial software. But we can infer that it still uses traditional method, including searching and pruning. Now, there is no any software using Neural Network in Chinese Chess. So, it is a blank field for us.

1.3. Difference among Chinese Chess, Chess and Go

The main difference between Chinese chess and Go is the way to make a move. In Go, players should put one stone into an empty position every turn, while in chess and Chinese chess, players should move a piece on the board following a set of rules depending on the type of the piece selected. And in chess and Chinese chess, pieces can be captured so that the number of pieces on the board will become less and less, leaving the possible moves of those remaining pieces become more and more. While in Go, the number of stones on the board will generally become more and more and the available positions to place a stone become less and less.

Besides, compared with chess, there are mainly two different points in Chinese chess. First, there are two fortresses and one river on the chessboard, restricting the move of certain types of pieces, like King, Bishop and Advisor. Second, there is a special type of pieces, called Cannon, which can capture only with exactly one piece in the middle but move like Rock. Therefore, certain considerations are necessary for these difference, compared with the methodologies used in previous researches about GO and chess.

1.4. Objective

Our objective is to implement a game AI which can play Chinese chess with human users, and the whole game system should have following components.

a) A user interface lets human players to play Chinese chess against our AI. It should be able to communicate with our AI, like sending information describing the chessboard status to the server and receiving move choice of our AI from the server. It should be able to judge whether every move is legal or not and decide if a player is checkmated.

b) A game AI makes moves against the opposite player based on the output of pre-trained NN model. It should be able to receive the message sent from frontend, preprocess it, then feed it into NN model to get a move choice, and at last send the choice back to frontend. It would be better if it is able to play Chinese chess with multiple users simultaneously and record game histories for further training usage.

c) A program trains NN model ahead to be used in our AI and saves the trained model. For our AI, it only restores the previously saved model to do calculation.

1.5. Definition of Terms

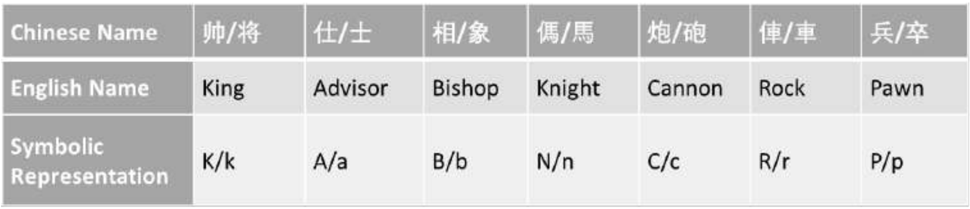
1.5.1. PGN

PGN is short for Portable Game Notation, which is one popular string format to record the game history for chess games. [1] The basic format for recording moves is simple: [one character to represent the type of selected piece] [the coordinates of the destination of this move]. Obviously, only a complete sequence of PGN starting from an initial chessboard status will make sense, as the original position of the selected piece in each move is not recorded.

Besides, there is a Chinese version of PGN to record Chinese chess games. The basic rationale is quite similar, with little difference. There are also other formats in English or Chinese to record games. The common problem of them, however, is as the same as stated above, which is that only the whole sequence together will make sense.

1.5.2. FEN

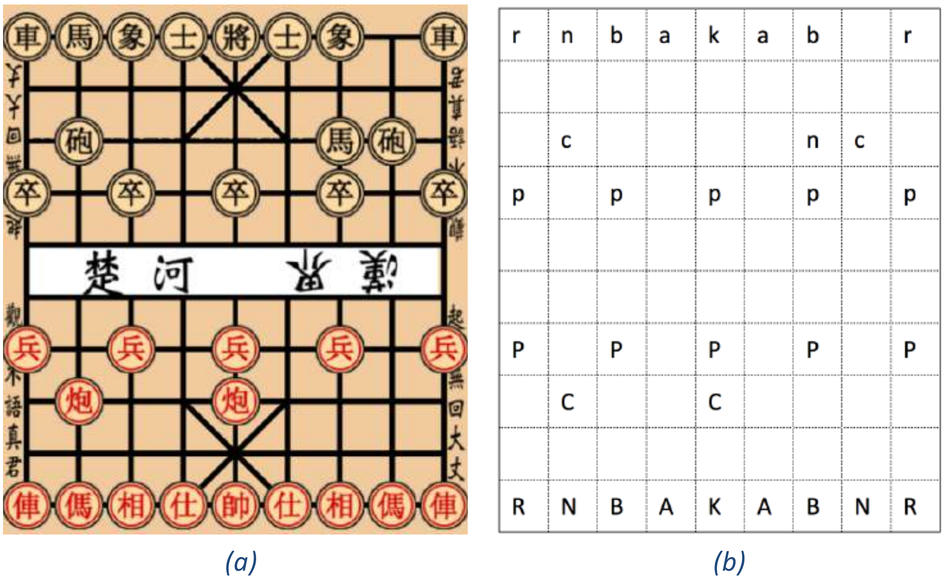
FEN is short for Forsyth–Edwards Notation. Similarly, it is one standard string format representation of the chessboard status, using one letter to represent each type of chess pieces as shown in Figure 1.3. below.



Chinese Name	帅/将	仕/士	相/象	傌/馬	炮/砲	俥/車	兵/卒
English Name	King	Advisor	Bishop	Knight	Cannon	Rock	Pawn
Symbolic Representation	K/k	A/a	B/b	N/n	C/c	R/r	P/p

Figure 1.3. Symbolic Representation for Different Pieces

We also made certain modifications for simplicity, like using ‘1’ to denote an empty position. Lowercase letters are to represent the pieces of upper-side player while uppercase letters are to represent the pieces of lower-side player. FEN represents the whole chessboard row by row, with ‘/’ as delimiter. At last, the player to make the next move is also declared in FEN, with ‘b’ for black side and ‘r’ for red side. The move is recorded using four digits, by combining the coordinates of both the original position and the new position of that piece. Clearly, FEN is much better then PGN for our NN training usage, as it contains complete information for every intermediate game status.



r	n	b	a	k	a	b		r
	c					n	c	
p		p		p		p		p
P		P		P		P		P
	C			C				
R	N	B	A	K	A	B	N	R

(a) *(b)*

Figure 1.4. An Example of FEN Format

Here is an example of FEN. Picture (a) in Figure 1.4. is a chessboard status and Picture (b) is the chessboard after replacing real pieces with symbols. And the next move is the turn of the red side. The corresponding FEN representation of this chessboard status is:

“rnbakab1r/111111111/1c1111nc1/p1p1p1p1p/111111111/111111111/P1P1P1P1P/1C11C1111/111111111/RNBAKABNR, r”

2. Literature Review

2.1. AlphaGo

AlphaGo mainly contains four Neural Networks.

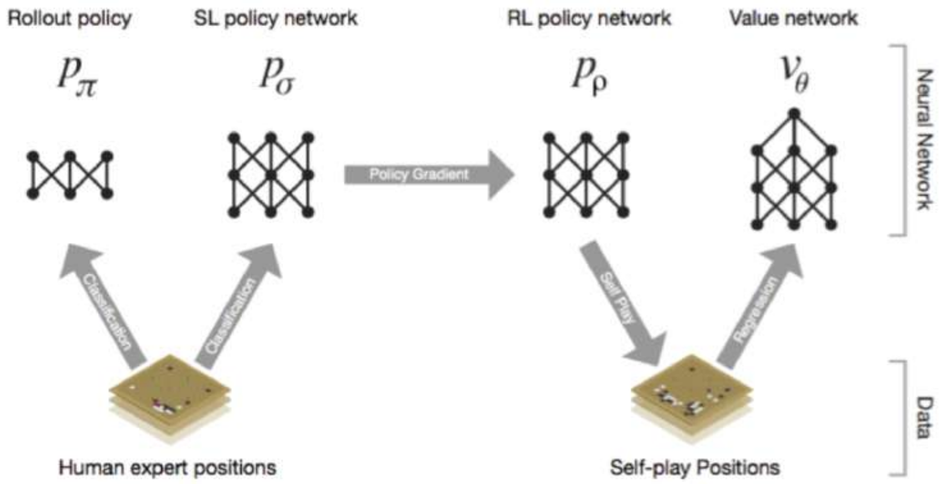


Figure 2.1. Neural Network of AlphaGo

In Figure 2.1., the left two networks learned from human experts, which use supervised learning to train.

Rollout policy network is a simple network that can deal with chessboard. It is similar as first impression of human players. It has relatively low accuracy about 24.2% in predicting human players' moves, mainly used for reducing the nearly impossible moves of searching tree. The mainly advantage of this neural network is that it can run faster which needs only 2 nanoseconds to select a move while SL policy network needs 3 ms to do that.

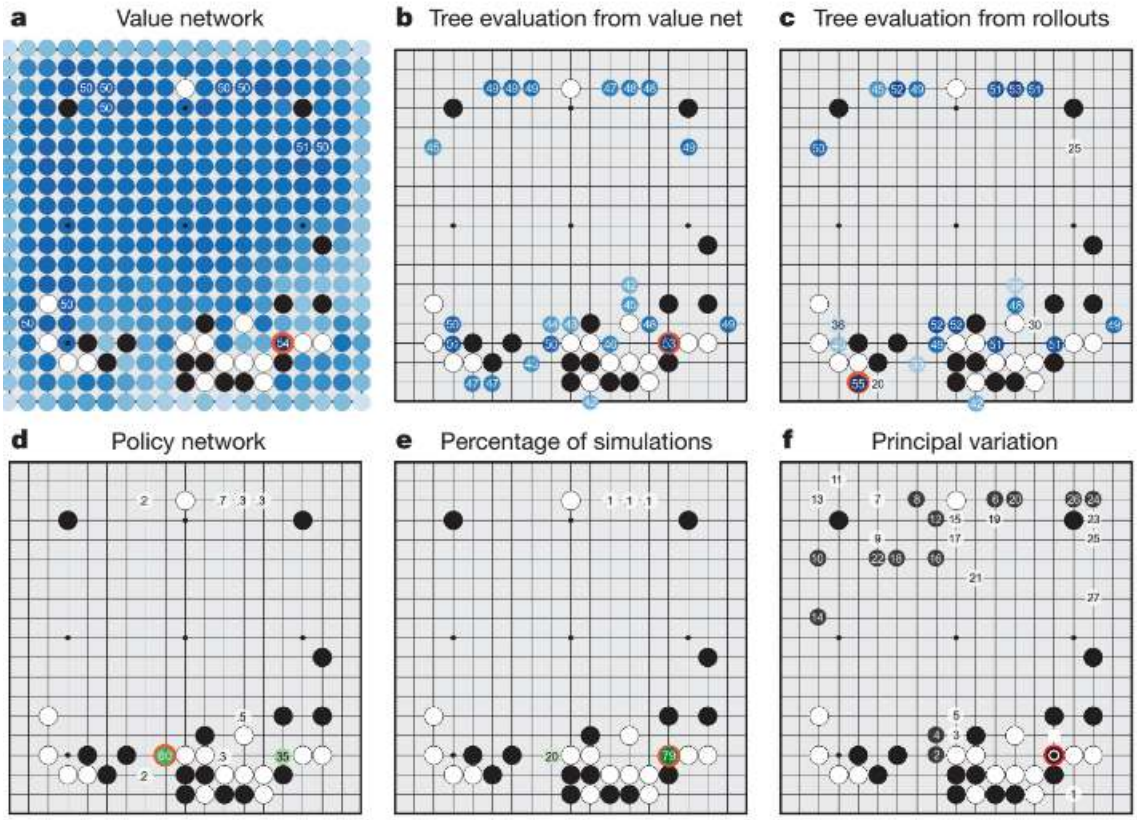
SL policy network also is used to predict the human player's move.

However, as it is more complex in structure which have 13 layer and well-trained which uses 30 million positions to train, it has higher correct rate. For normal chessboard, the accuracy can reach 57.0%. However, it is not enough as it has only approximately 10% winning rate again traditional AI using MCTS.

The two networks on the right side are using reinforcement learning. RL policy network has same structure as SL policy network, but it continuously plays with itself, and makes improvement based on the result. After reinforcement learning, it has 80% winning ratio against previous version using supervised learning. Even if it does nothing search at all, it performs better than any other AI.

The last part is value network. Though the structure of this network is not very different from policy network, it only output a value representing the prediction of winning rate for one side. It uses the positions sampling from the self-playing game from RL policy network in order to prevent overfitting. Because if it uses normal games as training dataset, it would trace every move in a specific game and then record the result of the game instead of the stone distribution.

Besides Neural Networks, it also uses MCTS. Different from normal AI, with the help of Neural Networks, the single searching used by AlphaGo will start with using SL policy network predicting a chain of moves, and using the result from value network and rollout to improve it. The result will be the score of next move. After repeating this procedure for enough time, it will have a map of score for all possible next move and put next move according to it.



Value network

Tree evaluation from value net

Tree evaluation from rollouts

Policy network

Percentage of simulations

Principal variation

Figure 2.2. An Example of AlphaGo Making a Move

Figure 2.2. shows an example for how AlphaGo makes next move. The position is taken from the game with Fan Hui, and AlphaGo is on black side. In all of these subgraphs, the point with red circle is the best move according to the method it uses.

Figure a is representing the evaluation after next move using valuation network. Figure b is representing the result from searching where it uses only value network without rollout network. Figure c is representing the result from searching where it uses only rollout network without value network. We can notice that the result form MCTS would be different if the ratio between them are changed. In their practice, they discovered that a mixed version would have best level. Figure d is the result from SL policy network directly. The first move chose by it is a move of middle level. Figure e shows the results from its search tree, and it will choose the move with the highest value. Figure f shows AlphaGo's principal variation from search tree. The number of sequence number means a most possible prediction about process of the game. Though Fan Hui's move is not the same as AlphaGo's thought, he admitted that AlphaGo's suggested move would be better.

Due to the improvement above, AlphaGo has become the strongest AI in the world. Consisting of 1,202 CPUs and 176 GPUs, the distributed version of AlphaGo beat any other while a normal version using 48 CPUs, and 8 GPUs only lose one game in 495 games in total. Even with handicaps, it still had high winning rate against others.

Though the rules of Go and Chinese Chess are different, we can still learn from the method and ideas of building AlphaGo.

2.2. Predicting Moves in Chess using Convolutional Neural Networks

The work from Oshri, B., & Khandwala, N also uses convolutional neural network. As it is design for chess, we think it more helpful for our project because chess is a lot more similar from Chinese chess compared with paper about AlphaGo.

In their work, they mainly build policy neural network. And in predicting next move from human players, it reached the accuracy of 44.4%, which is pretty high. The success of their work proves that it is possible to use CNN to train an AI for playing chess.

In their thesis, the recognize reasoning of chess as kind of pattern recognition while traditional method only consists of searching and evaluation. And the way for the neural network to select a move is to separate a move into two parts: select a piece and move it to other places. And use piece selector and move selectors to solve the part respectively. This is different from AlphaGo, because of the difference between moving a piece in chess and putting a stone in Go.

However, the high accuracy in predicting next move doesn't mean that the program has high level of playing chess. In the 100 games with Sunfish, a famous chess engine, it loses 74 games and draws in the rest of game. In those draw games, this program play well in the middle game, and force opponents to make a draw. However, in the sparse ending game, it faces many troubles because patterns can't be found in that kind of position.

2.3. Giraffe: Using Deep Reinforcement Learning to Play Chess

In Matthew Lai's work, he implemented evaluation function of game engine based on neural network. We use his paper as reference on our evaluation network.

The feature of the inputs of neural network has following features.

a) Side to Move – It is turn for black or for white.

b) Castling Rights - Presence or absence of castling rights. Castling is a special rule for chess. In Chinese Chess, we don't need to consider it

c) Material Configuration – Amount of each kind of pieces

d) Piece Lists – for every piece, note their position coordinate, existence

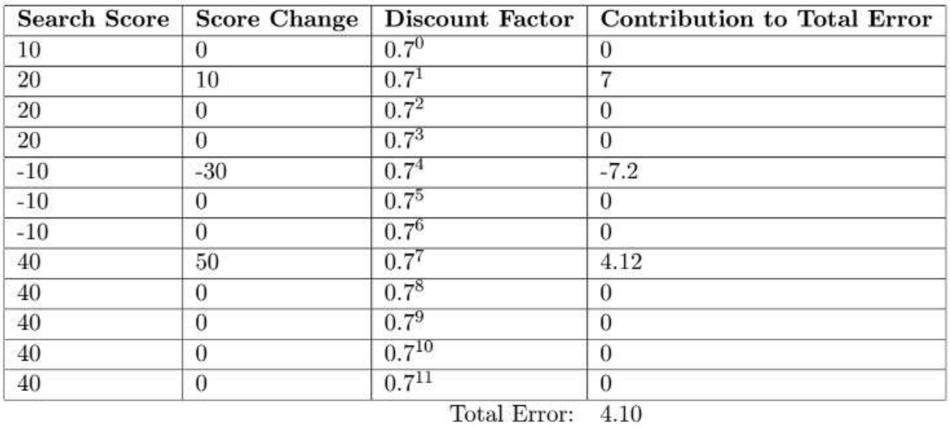
e) Sliding Pieces Mobility – for sliding piece, note how far they can move along a direction, and liberty of them.

f) Attack and Defend Maps – for each square, note the attacker and defender with lowest value.

After determining these features, the author did not mix them directly because the connection between two features with long distance logically would have no benefits to the results. As a result, the last 2 layers are fully connected, while the prior one was trained separately.

For their training dataset, instead of using that collected on Internet. They added a random legal move to the board and used the processed one as training data. The reason of this process is to increase the variety of dataset, in order to help the neural network to evaluate the unseen situation.

Then the author used reinforcement learning to the neural network, and use TD-leaf algorithm. In each time of iteration, they use the network to move 12 moves, and trace on the move to see when the score of board will change, weighted by the distance from the beginning position.



Search Score	Score Change	Discount Factor	Contribution to Total Error
10	0	0.7^0	0
20	10	0.7^1	7
20	0	0.7^2	0
20	0	0.7^3	0
-10	-30	0.7^4	-7.2
-10	0	0.7^5	0
-10	0	0.7^6	0
40	50	0.7^7	4.12
40	0	0.7^8	0
40	0	0.7^9	0
40	0	0.7^{10}	0
40	0	0.7^{11}	0
		Total Error:	4.10

Figure 2.3. An Example of TD-leaf Searching Results

In the sample graph as shown in Figure 2.3., the network used a discount parameter 0.7. The second move changed the score by 10, then its effect on Total Error is 10 * 0.7 ^ 1 = 7. We can see that in this algorithm, if a move which will change the board is far away from now, it would have lower contribution. The algorithm is consistent with our common senses about chess.

The result of their Neural Network is remarkable. Their program, named Giraffe, have an evaluation function comparable to those of best chess engines worldwide, though evaluation functions of those engines are all designed and tuned by human over many years.

3. Methodology

3.1. Supervised Learning

Supervised learning is one of deep learning approaches, through which the NN model is trained by dataset with target labels. In supervised learning, examples in the training dataset are composed of inputs, usually representing features of objects to be learned, and target outputs. Generally speaking, the goal of supervised learning is to learn a function, classifying objects into different labels depending on the values of certain features, out of the training data. An acceptable function should be able to deal with unseen instances correctly, which requires the function to classify the data in a learned reasonable way. In supervised learning, there are several tradeoff issues, which would affect the training results, as stated hereinafter. [2]

Bias-variance Tradeoff: The tradeoff between bias and variance is the first issue to be considered. [3] An algorithm with high bias will ignore the relevant relations between features and expected outputs and give incorrect answers. And an algorithm with high variance will record the random noise rather than expected labels and perform bad in unseen inputs, which is also called overfitting. An algorithm should have flexibility to retain low bias. If we try to increase its flexibility, the variance of the algorithm would increase as well. Also, the similar tradeoff issue happens between the complexity of regression function and the size of training data. [4] A complex function will require a large amount of data for the model to learn correctly and the function may have low bias and high variance. On the opposite, a simple function only needs a small size of data, but it may become inflexible, and have high bias and low variance. To handle the tradeoff issues, a good model should adjust between bias and variance and make a balance.

Dimensionality of Input Space: If there are lots of features in inputs, it will be difficult for the model to learn, because redundant unrelated features will confuse the model. To solve this problem and increase the accuracy, a reduction of features should be done.

Noise in Output Values: In reality, the desired outputs in a dataset may not be always correct or optimal due to many reasons, such as human errors. For instance, in our project, human players may make faults and choose a bad move sometime. It’s also possible that different players may apply different strategies based on personal reasoning, and choose different moves in one same situation. If the learning algorithm wants to make perfect matches, it will overly fit into a specific training dataset and perform quite bad for other datasets.

3.2. Convolutional Neural Network

In machine learning, a Convolutional Neural Network (CNN) is a special type of NN and its connection pattern between neurons imitates the structure of cat's visual system. The main difference of CNN and normal Neural Network is that CNN makes assumption that inputs are pictures. And it has following features. [5]

Local Receptive Fields： In a fully-connected Neural Network, the input is connected to every hidden neuron. In CNN, however, neurons in the first hidden layer will only be connected to small region of inputs. The values of the first layer will be the results of a convolution between the input layer and filters. [5]

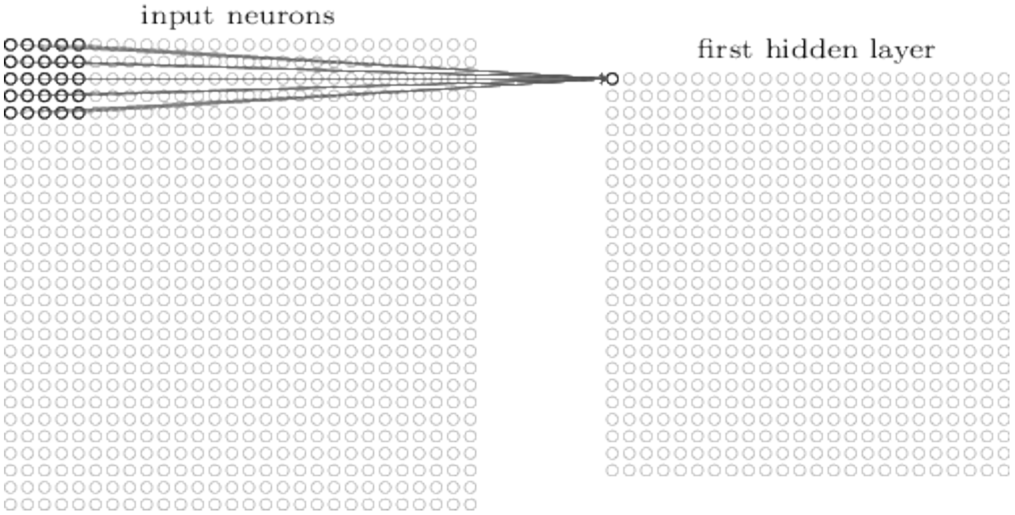


Figure 3.1. Local Receptive Fields

As shown in Figure 3.1., it applies a 5*5 filter to a 28*28 input image, and will get a 24*24 hidden layer. Usually the filter is moved for one pixel at a time, but sometime a larger stride will be used. For instance, sometime we may use a stride of 2, which means that each time we move the filter by 2 pixels to the right or down.

Shared Weights and Biases: For a given feature, the weight and bias of every neuron are same, resulting in the identical feature being detected by all neurons. The advantage of using this method is that it can reduce the total number of parameters and computations in the network. [5]

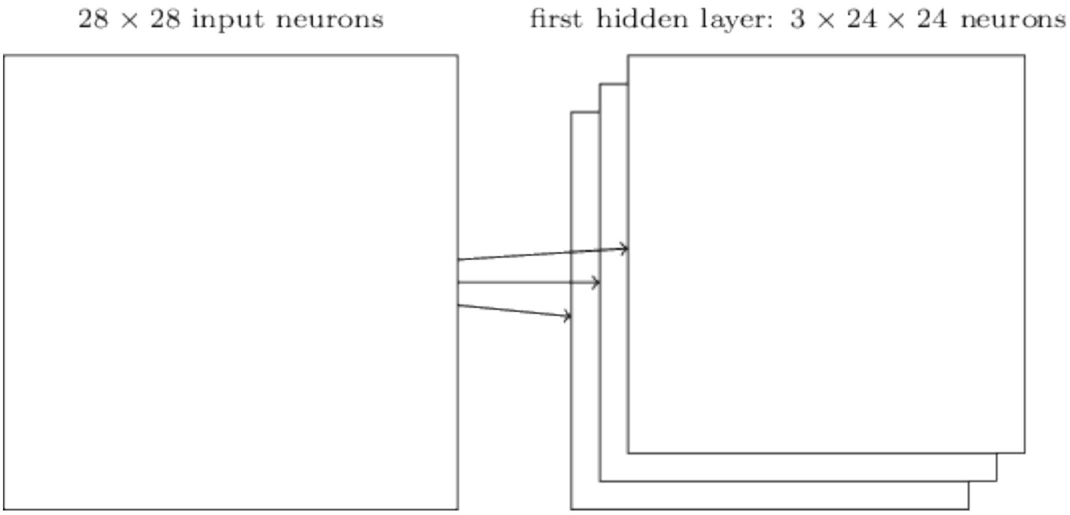


Figure 3.2. Shared Weights and Biases

In Figure 3.2., there exist 3 feature maps in the network. In every feature map, a 5*5 filter is used, and the whole image shares the identical weights and bias. This network can detect 3 different kinds of features across the whole image.

Pooling Layers: Pooling layers are used to condense the output from convolutional layers and simplify the information. For example, max-pooling, a most-used method for pooling will pick the maximum value in a region of specific size, and then the number of neurons in the output of pooling layer will decrease greatly. [5]

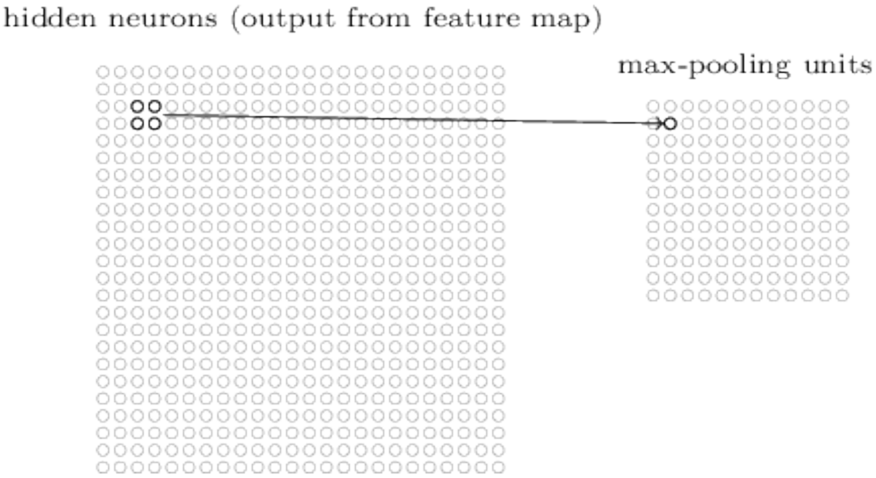


Figure 3.3. Pooling Layer

In Figure 3.3., a 2*2 max-pooling is used. In every 2*2 region, the pooling unit will find the maximum value in the region and use it as the output. After the pooling process, the size of the output layer will become half of the hidden layer.

The final layer of CNN is usually a fully connected layer, connecting every neuron in its previous layer to every neuron in this layer, and uses a logistic function to output result.

With all these features, CNN will have better performance in some appropriate problems than traditional NN. The reason that we choose CNN will be mentioned afterwards.

In our project, we choose the rectifier as the activation function used in CNN.

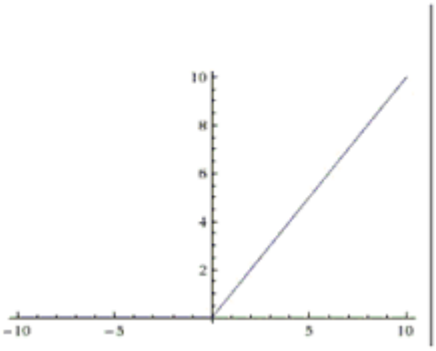


Figure 3.4. Plot of ReLU Function

The graph above is the plot of the rectifier function. In NN, any unit employing the rectifier is called a rectified linear unit (ReLU). Compared with normal logistic functions like sigmoid function, it has higher efficiency in computation because it only contains comparison and addition, and avoids the problem of vanishing or exploding gradient. [6]

3.3. Softmax

The softmax function is a generalization of logistic regression when we need to classify among multiple classes. [7] After softmax, the highest input value will have highest probability and other values will be depressed. Every element in the output vector has a value in [0,1] represents the probability of the label is correct. For a K-dimension vector z, the softmax function can be represented as:

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \qquad \text{for } j = 1, \cdots, K$$

σ is the output vector with sum equal to 1.

3.4. TensorFlow

As an open-source project, TensorFlow is a software library designed to do numerical computation. It can support different platforms, including desktop, server and mobile platform, and can run on both CPU and GPU. TensorFlow provides developers using deep learning with an easy way to handle underlying layer computation. They just need to define the architecture of their own Neural Network model, select the objective function they want to use, and then feed the training data into the model. TensorFlow makes their work much easier and clearer. As TensorFlow is built to support threads, queues, and asynchronous computation, it can make the best of the computation ability of hardware including both CPU and GPU. [8]

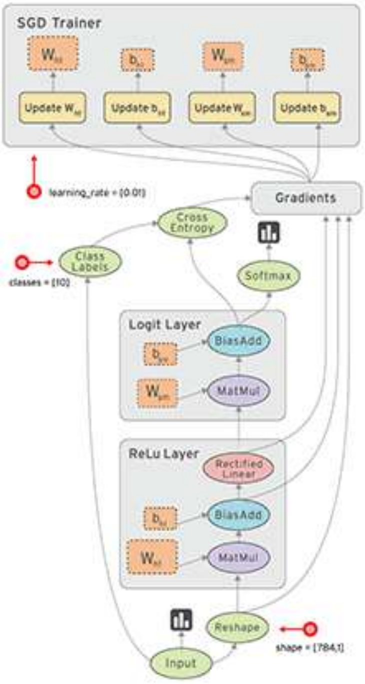


Figure 3.5. Data Flow Graph

4. Implementation

4.1. Project Workflow

Our project development process could be roughly divided into the following four steps: Model Design, Model Building, Model Training and Model Testing. These four steps were repeated until we found that the final performance of the game AI was reasonable, or satisfying to certain extent.

First, based on previous works of other game engines in Chinese chess, chess and Go, our own model was designed, like the structure of NN, the component of our AI, the algorithms to make move choices, and so on, considering the special aspects of Chinese chess. Secondly, an AI model was built based on our previous design, and functions were implemented accordingly. Next, the AI model was to be trained, using training datasets collected previously, by certain training strategies.

At last, the trained AI model was to be tested so that its performance could be quantified or directly demonstrated. Here, it was firstly tested by a testing dataset, which was in the same format with the training dataset, and its prediction accuracy was calculated, which was a quantitative measurement of the AI model. Besides that, the AI model was also tested against real human players, to see whether its performance appeared to be reasonable in actual games. Basically, only after a satisfying accuracy was achieved in that simple Accuracy Testing, the AI model would be tested in real games.

After testing, the results were analyzed to find the reasons behind, and then certain modifications would be made. If the design was determined to be ineffective, a new model would be designed, after more researches, and analysis and reasoning. But if errors were found in the procedures of Model Building or Model Training, or those steps could be changed to improve the training results, according modifications would also be made and the re-trained AI would be tested again.

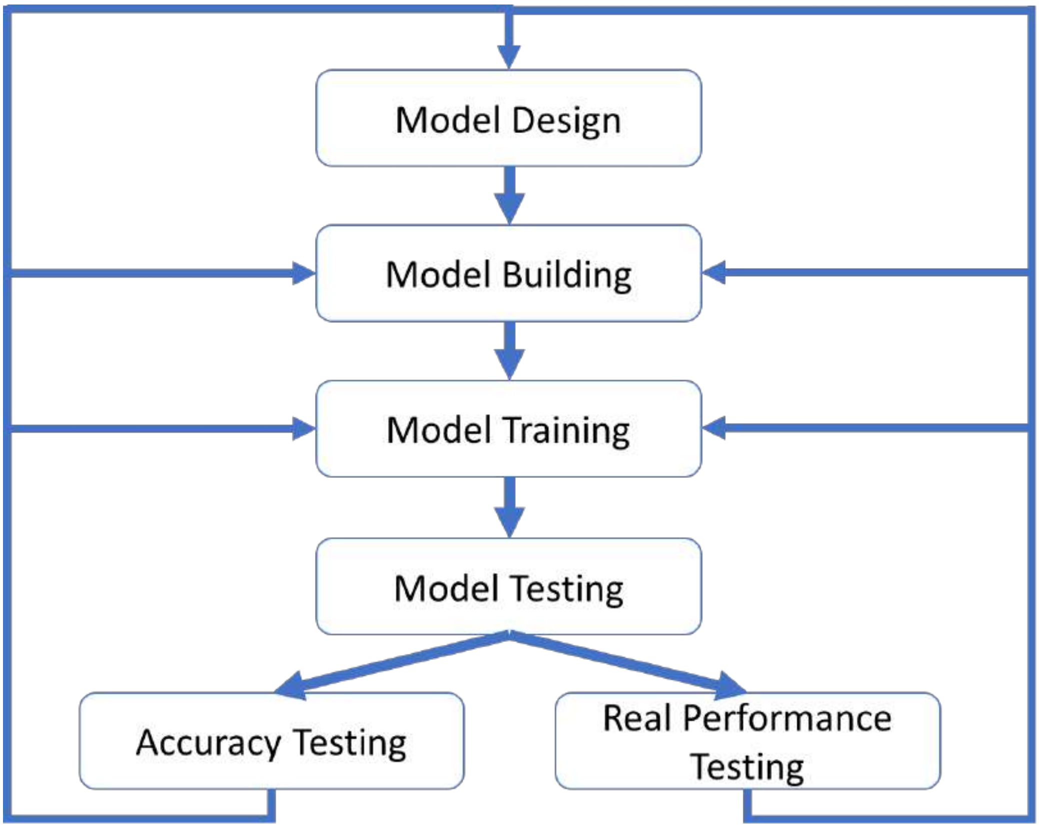


Figure 4.1. Project Workflow

4.2. Structure Overview

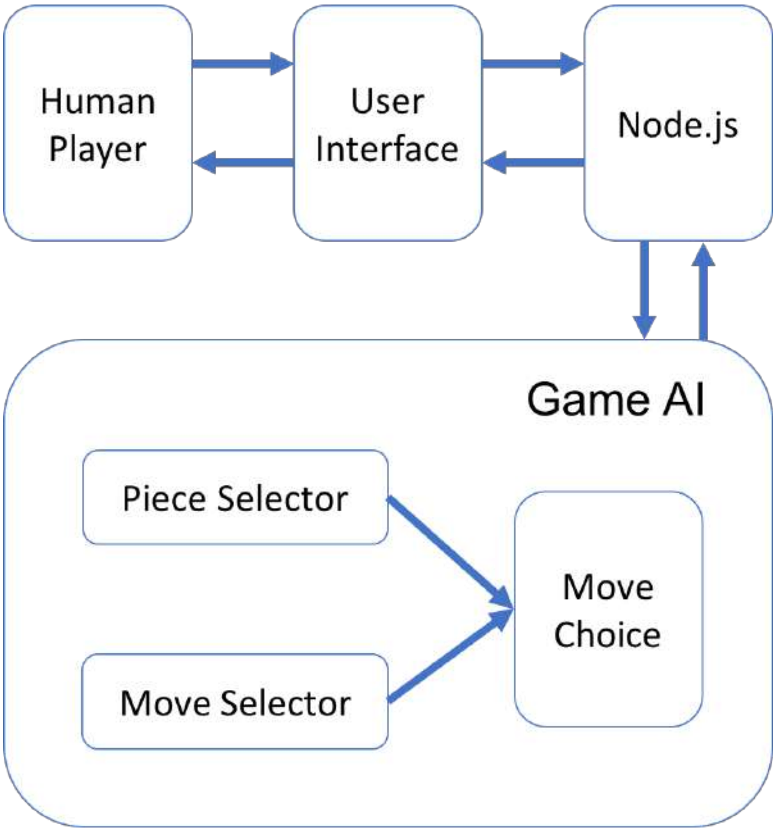


Figure 4.2. Structure Overview

Our game engine mainly consists of three parts: frontend, backend and the connection between them. The frontend is the User Interface, which self-evidently serves as the interface for players to play Chinese chess against our game AI. The backend is basically the AI model, with several minor functions. This is the most important and difficult part of our whole project.

At last, a connection between frontend and backend is necessary, considering the fact that our model cannot directly run on the browser, as the library provided by TensorFlow is required but may not be supported by the frontend. This is also a tricky part, as our frontend is written in JavaScript while our backend is written in Python. Conventionally, JavaScript programs and work well together with PHP programs. TensorFlow, however, does not provide libraries for PHP. Therefore, this connection needs to be established by special techniques.

4.3. User Interface

Our game User Interface (UI) was written in JavaScript, using the cocos2d-html5 engine, so that it can support different types of platforms, like PC, iOS and Android. This UI was primarily based on an open-source project in GitHub [9], and certain modifications were made per the special requirements of our project.

Self-evidently, the main function of UI is to convey messages between human players and backend programs. But it also needs to ensure the rules of the game, i.e. Chinese chess, to be obeyed and the game can continue smoothly. Therefore, our UI can be divided roughly into two parts: Game-Related Functions and Communication Functions.

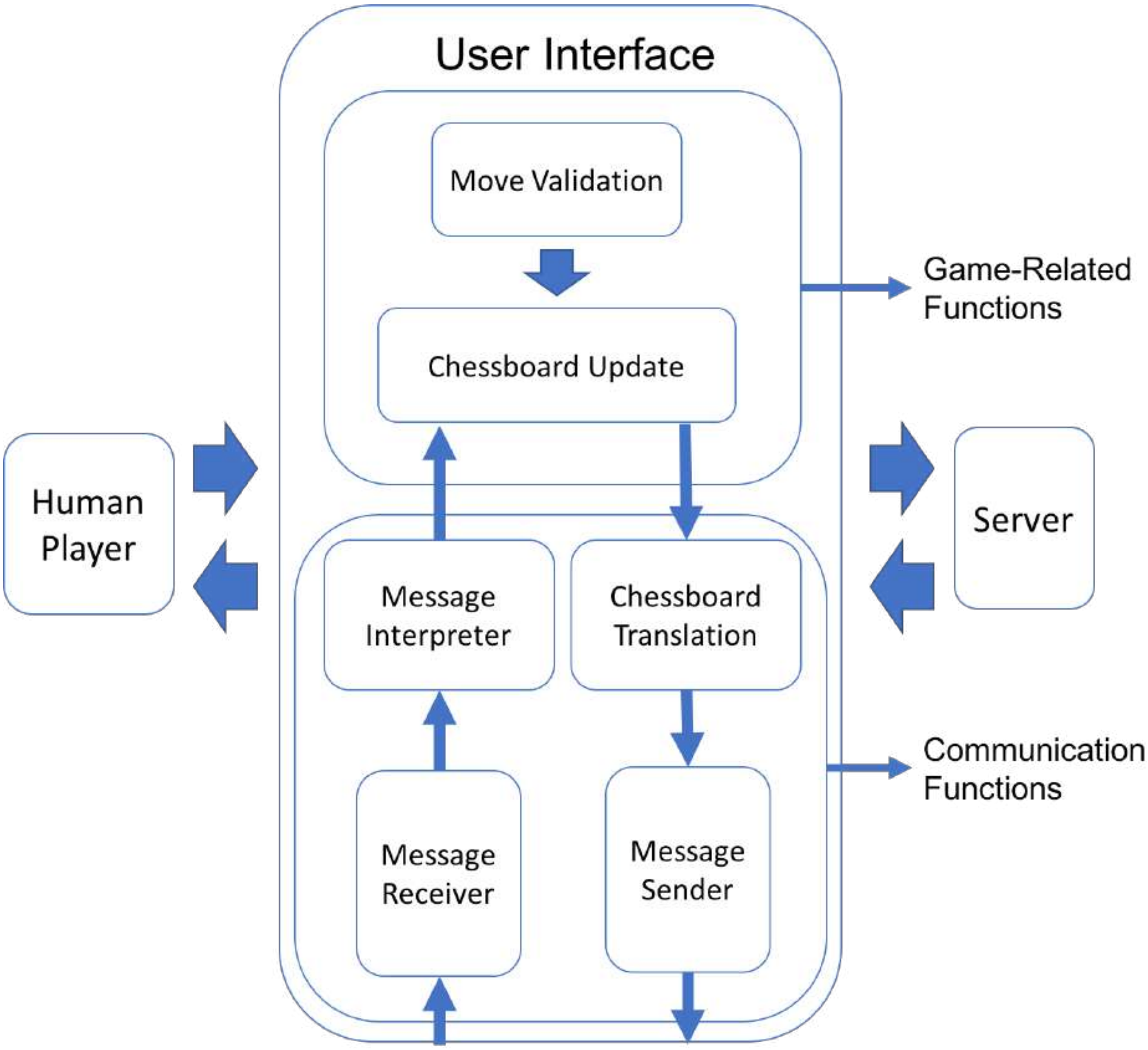


Figure 4.3. User Interface Structure

4.3.1. Game-Related Functions

Following basic game-related functions were implemented:

a) Move Choosing – to let players make moves alternately

b) Move Validation – to ensure only valid moves per rules of Chinese chess can be made

c) Move Execution – to make the move per players' choice and update the chess board status accordingly

d) Checkmate Checking – to check whether one of the players is in check and whether one side is wining

These basic functions ensured our game engine could function correctly and legally.

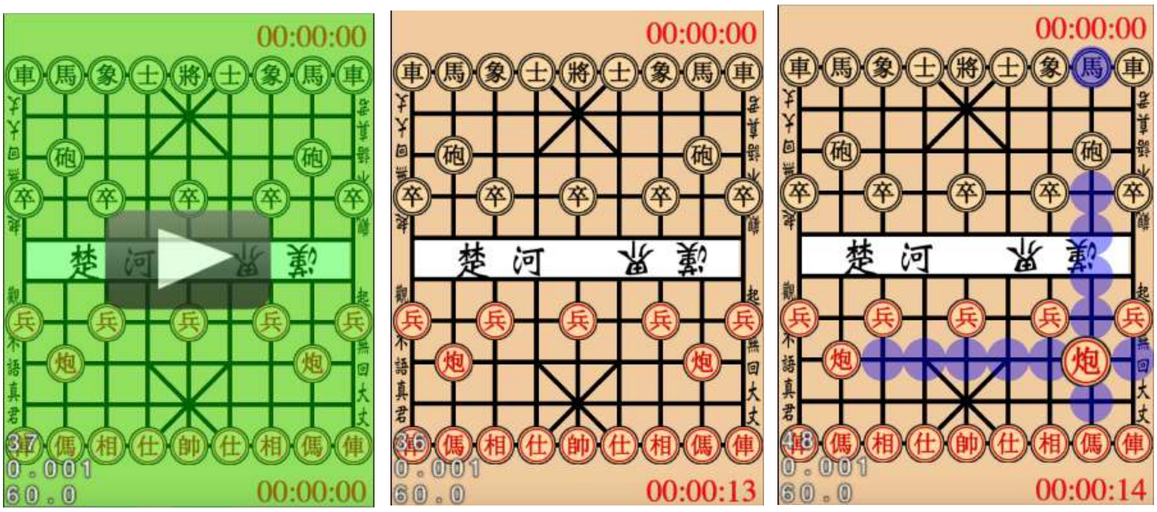


Figure 4.4. Examples of User Interface

In Figure 4.4., the left picture is the beginning of UI and users need to click the button to start the game. The middle picture shows the initial chessboard. The right picture shows when the user is trying to make a move for the red Cannon and the purple cycles indicates the legal moves for it.

4.3.2. Communication Functions

Apart from the basic functions mentioned above, several more functions were implemented as well, allowing our UI to communicate with our AI.

a) Chessboard Translation - to represent the chessboard status in FEN format

b) Message Sender - to send the FEN of chessboard status to the server via socket

c) Message Receiver - to receive the message of move choice of our AI from the server via socket

d) Message Interpreter - to interpret the received message and allow our UI to update the chessboard correctly

4.4. Game AI

Our game AI consists of several Neural Network (NN) models, written in Python, with some other minor functions. Theoretically, there should be mainly two NN modules, Policy Network, to predict the most possible next move and Evaluation Network, to evaluate the winning rate, given certain chessboard status. Combine the results of these two modules and do some searching, the AI will make a move choice.

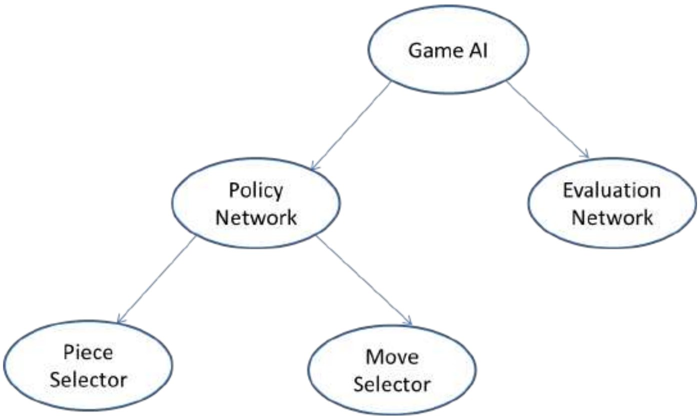


Figure 4.5. Design of AI Structure

For Policy Network, it can be further divided into two NN models, Piece Selector and Move Selector, which will be explained in detail later. Simply speaking, Piece Selector decides which piece to be moved and Move Selector decides where that piece to be moved to. For both the two NN models, a probability distribution over the all 90 positions of a chessboard will be output, indicating the possibility to choose each position.

This term, we mainly focus this module, and basically our current AI will make move choices only based on the results of Policy Network. Next term, the Evaluation Network will also be implemented and a new move selection strategy will be designed.

As shown in Figure 4.6., the detail structure of our current game AI, it mainly consists of these components: Message Receiver, Format Converter, Feature Exactor, Decision Maker, Message Sender, and most importantly, Piece Selector and Move Selector. The overall flow is: Message Receiver receives the FEN information from frontend via socket, and Format Converter preprocesses the information so that Feature Exactor can identify it and extract according features out. After that, Piece Selector and Move Selector together outputs the probability distributions of possible moves. At last, Decision Maker makes a move choice and Message Sender sends the choice back to frontend.

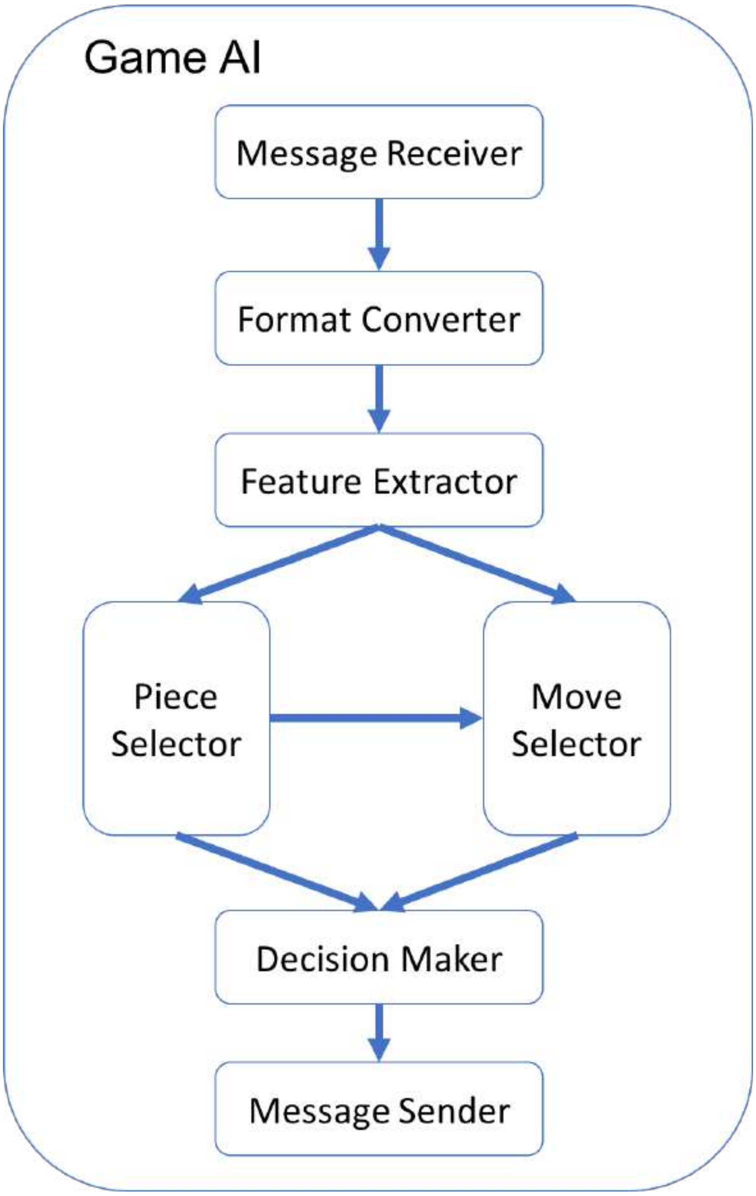


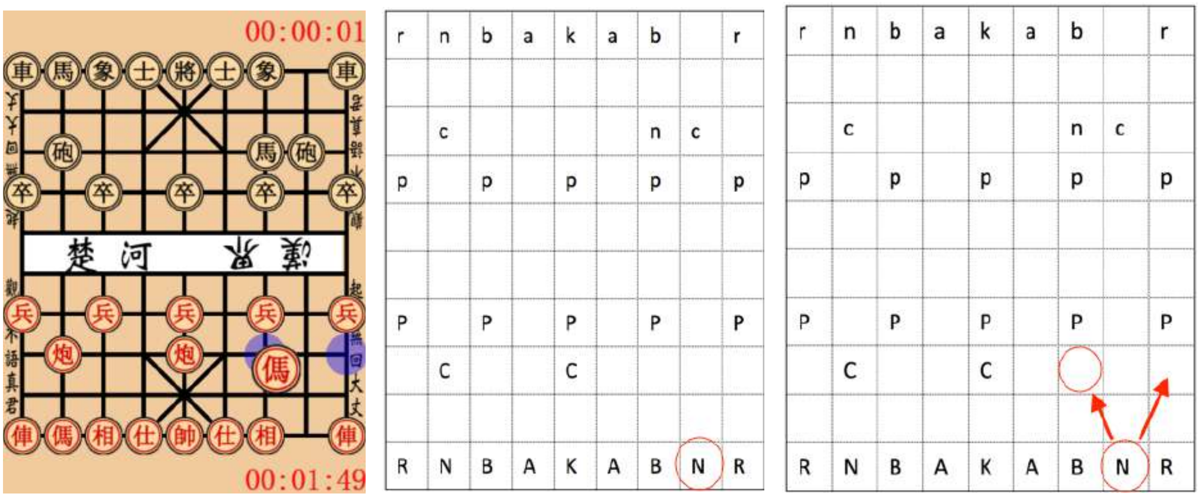
Figure 4.6. Structure of Game AI

4.4.1. Piece Selector and Move Selector

To make a move, the player needs to choose a self-side piece first and then choose a destination for that piece. Accordingly, our AI consists of two parts, Piece Selector and Move Selector, either of which is a NN model itself. [10]

Evidently, Piece Selector is to choose a piece per the chessboard information and Move Selector is to choose a destination for that piece chosen by Piece Selector. So, firstly Piece Selector will decide which piece to move and pass this information to Move Selector as well. Next, Move Selector will decide where that piece to be moved to. Combining the outputs of two NN models together, our game AI would output a four-element array to denote the move choice, decided by certain selection strategy, and send it back to frontend.

As different kinds of pieces should obey different rules when making moves, different Move Selectors were trained and used for each kind of pieces. So, Move Selector itself actually consists of 7 different NN models, and will use different ones to generate output accordingly, while Piece Selector consists of only one NN model.



r	n	b	a	k	a	b		r
	c					n	c	
p		p		p		p		p
P		P		P		P		P
	C			C				
R	N	B	A	K	A	B	N	R

r	n	b	a	k	a	b		r
	c					n	c	
p		p		p		p		p
P		P		P		P		P
	C			C				
R	N	B	A	K	A	B	N	R

Figure 4.7. An example of Piece Selector and Move Selector

As shown in Figure 4.7. above, the first picture is a real screen capture of our UI. The second and third ones represent the digital information that our AI receives. In the second one, the Knight piece in the red cycle indicates that our Piece Selector decides to choose this piece to move by certain selection strategy, like choosing the one with the highest probability. Then with the chessboard information and the output of Piece Selector, Move Selector uses the NN model for Knight pieces, and decides a destination for that piece, i.e. the other red cycle in the third picture. And the two red arrows indicate the legal moves for that Knight piece.

4.4.2. Neural Network Structure

The general structure of Piece Selector and Move Selector is basically the same, as shown in Figure 4.8.. Both them accepts several same features of the chessboard status as input while Move Selector needs one more feature indicating valid moves for the piece selected by Piece Selector. Several convolutional layers were used first to do convolution among different feature channels. At last, one softmax layer would process the results of convolutional layers and output a probability distribution over all the 90 positions in a chessboard.

The first and second convolutional layers were designed to have 32 and 128 feature channels respectively. And the size of filters was set as 3*3*depth. The reason for us to choose CNN is that there exist many common patterns in realistic Chinese chess games, similar with joseki in Go. Given a certain pattern, players will have relatively fixed solutions based on previous experience, which are usually considered as optimal. Undoubtedly, CNN works well in recognizing patterns seen from previous research results. Also, CNN can greatly reduce the number of parameters and accelerate training speed, compared with fully connected NN. That is why CNN is chosen to build our model, instead of fully connected NN.

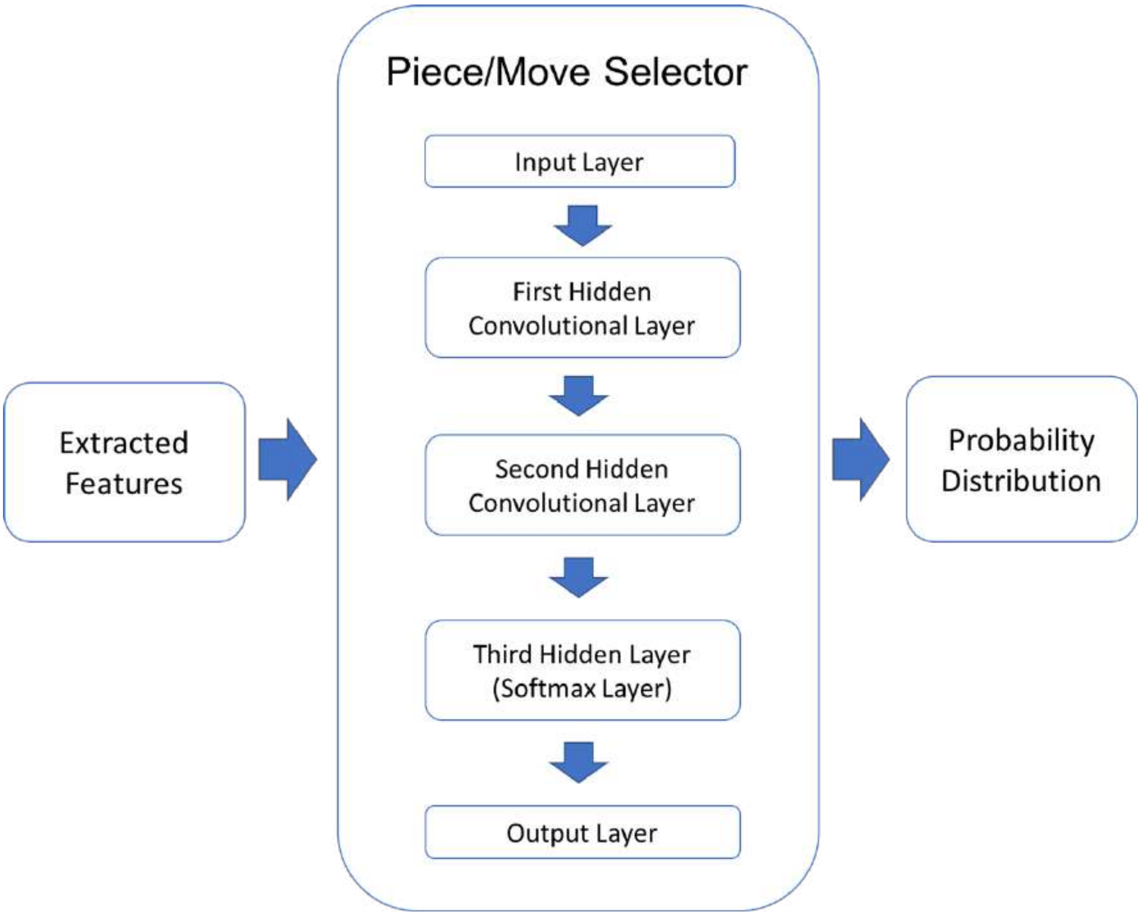
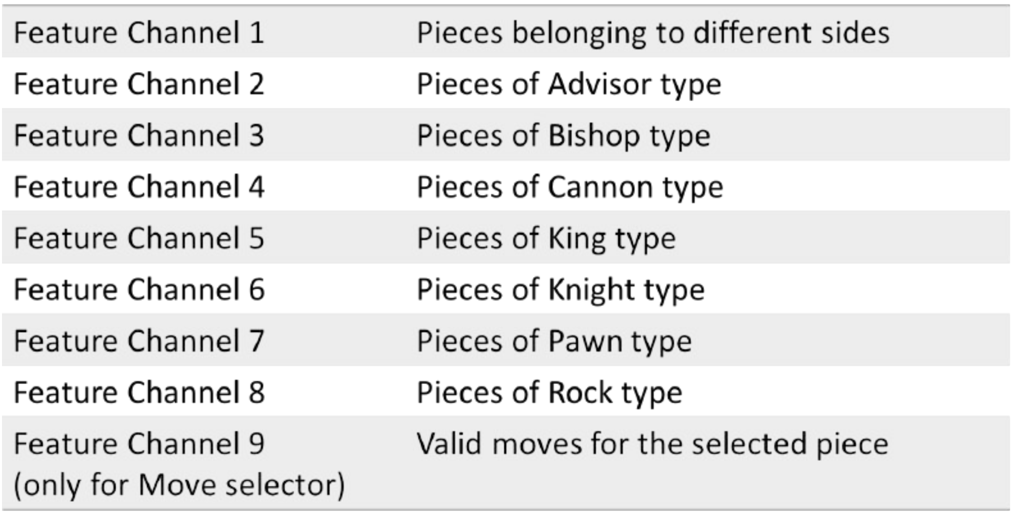

Piece/Move Selector
Input Layer
First Hidden Convolutional Layer
Second Hidden Convolutional Layer
Third Hidden Layer (Softmax Layer)
Output Layer
Extracted Features
Probability Distribution

Figure 4.8. Structure of Piece/Move Selector

In our final model, pooling layer was not used because the information in the chessboard was already quite sparse and it would be better for all information to be preserved. Since the size of input is small and every value in the input represent a piece, a pooling layer may greatly influence the result. For the same reason, dropout was not used as well.

4.4.3. Features Extractor

As mentioned above, several feature channels would be extracted as input feeding into the NN models, after converting the FEN string format into a 10*9 matrix representing the chessboard and getting the current player.

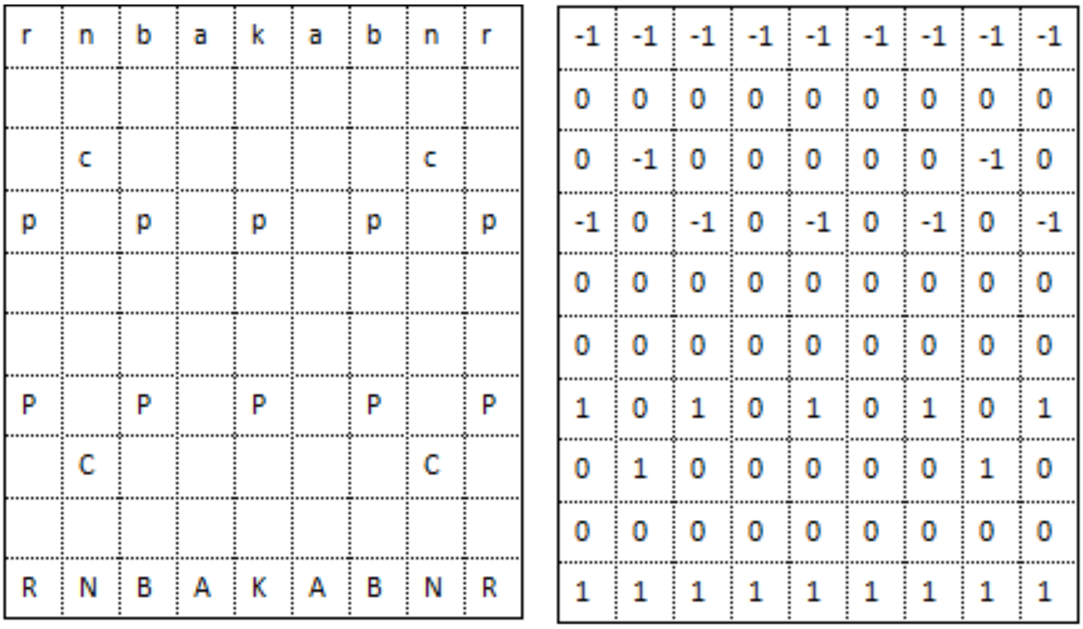


Feature Channel 1	Pieces belonging to different sides
Feature Channel 2	Pieces of Advisor type
Feature Channel 3	Pieces of Bishop type
Feature Channel 4	Pieces of Cannon type
Feature Channel 5	Pieces of King type
Feature Channel 6	Pieces of Knight type
Feature Channel 7	Pieces of Pawn type
Feature Channel 8	Pieces of Rock type
Feature Channel 9 (only for Move selector)	Valid moves for the selected piece

Figure 4.9. Feature Channels

First channel was to use ‘1’ and ‘-1’ to respectively denote the positions of self-side pieces and opponent-side pieces, and ‘0’ to denote empty positions.

For example, as shown in Figure 4.10. below, for the red side, all pieces represented by lowercase letters are of the opponent, so they are represented by ‘-1’ in this feature channel, while the other pieces, which belongs to the red side, are represented by ‘1’.

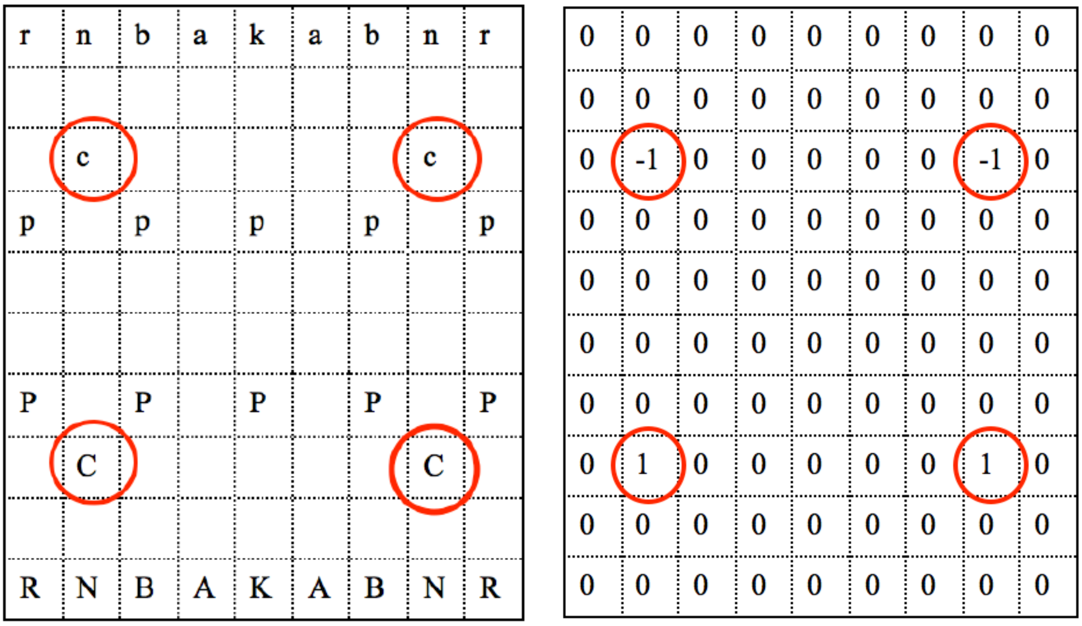


r	n	b	a	k	a	b	n	r
	c						c	
p		p		p		p		p
P		P		P		P		P
	C						C	
R	N	B	A	K	A	B	N	R

-1	-1	-1	-1	-1	-1	-1	-1	-1
0	0	0	0	0	0	0	0	0
0	-1	0	0	0	0	0	-1	0
-1	0	-1	0	-1	0	-1	0	-1
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
1	0	1	0	1	0	1	0	1
0	1	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1

Figure 4.10. An Example of First Feature Channel

For each type of pieces, there was a feature channel to denote the positions of pieces of that type. Still, use '1' and '-1' to respectively denote self-side pieces and opponent-side pieces, and '0' to denote empty positions. The reason for separating them into seven channels is that the values of different kinds of pieces are difficult to assign and they may vary in different situations, but we still need to find a way to tell our model that they belong to different categories, which is neither ordinal nor cardinal. Therefore, using 7 channels, one for each type, would be a good choice to distinguish different types of pieces.



r	n	b	a	k	a	b	n	r
	c						c	
p		p		p		p		p
P		P		P		P		P
	C						C	
R	N	B	A	K	A	B	N	R

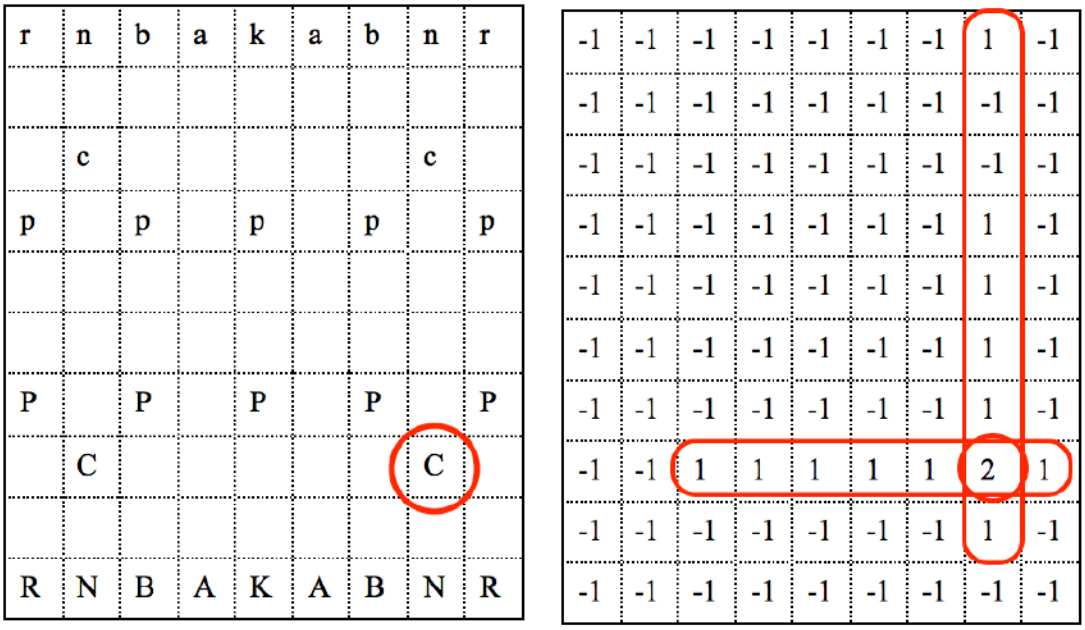
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	-1	0	0	0	0	0	-1	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0

Figure 4.11. An Example of Feature Channels 2 ~ 8

For example, as shown in Figure 4.11. above, for the feature channel to represent pieces of Cannon type, we can find ‘1’ and ‘-1’ for Cannon pieces of two sides respectively in corresponding positions.

For Move Selector, there was one more feature channel. In that feature channel, the position of chosen piece was denoted by ‘1’, and all possible valid destinations for that piece were denoted by ‘2’ while all possible invalid destinations were denoted by ‘-1’.

For example, as shown in Figure 4.12. below, assuming that the Cannon piece in red cycle is chosen, all the possible valid moves for it are represented by ‘1’, while the invalid moves are represented by ‘-1’ and its own position is indicated by’2’.



r	n	b	a	k	a	b	n	r
	c						c	
p		p		p		p		p
P		P		P		P		P
	C						C	
R	N	B	A	K	A	B	N	R

-1	-1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	1	1	1	1	2	1
-1	-1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Figure 4.12. An Example of Ninth Feature Channel

In total, 8 feature channels for Piece Selector and 9 feature channels for Move Selector would be extracted accordingly.

4.4.4. Decision Maker

After getting outputs from Piece Selector and Move Selector, an algorithm is needed to make the final decision about move choice. After all, they only output probability distributions over all 90 positions. We designed several selection strategies and tested them respectively.

The simplest way to select a move is to select the piece with highest possibility given by Piece Selector and then select the destination of that piece with highest possibility given by Move Selector.

Considering the fact that the probabilities given by Move Selector are essentially conditional probabilities, we designed another selection strategy, maybe appearing to be more reasonable. Here, we don't separately consider the probabilities given by Piece Selector and Move Selector, but we multiply them respectively, i.e. the probability of moving a piece * the probability of a destination of that piece, and then select the combination with highest probability. In cases where there is one piece with relatively much higher probability given by Piece Selector, this strategy will much likely give the same result as the previous one. In other cases, however, where there are several pieces with all high but quite close probabilities given by Piece Selector, this strategy may perform better, as there is no clearly better piece to move and this strategy will consider more options.

At last, these two selection strategies both can be modified by increasing the randomness. Previously, the decision is made by picking the one with the highest value, and every time met with the same situation, the AI model will make the same decision. To encourage exploration, a random number between 0 and 1 will be generated, and the move will be chosen treating the outputs of Piece Selector and Move Selector in statistical way.

4.5. Connection between Frontend and Backend

We used Node.js to build the connection between server and frontend, and used socket.io to support the communication between our UI in JavaScript and our AI in Python.

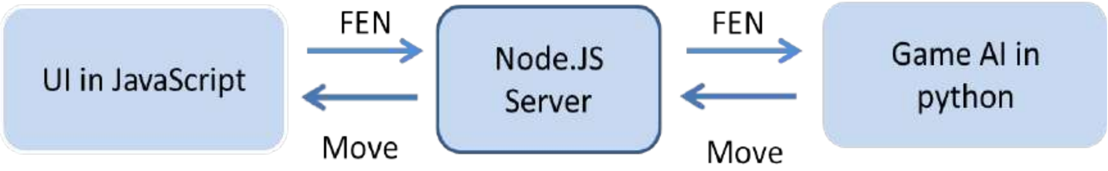


Figure 4.13. The Connection between Frontend and Backend

The game AI, running on the server and connecting to Node.js as a user, waits for the message from the frontend and sends move choice back, via socket supported by Node.js. To be more precise, after the server starts, every time a user opens the UI, it will connect to Node.js on the server through socket.io. After the player makes a move, the UI will generate the current FEN and send it to server via socket. The server receives FEN and transfers the message to the game AI. For the AI in python, we used the library socketIO-client to read the message because the socket in python cannot read message. After the AI generates the next move, it will send the coordinates in the form of four numbers back to frontend. And then UI will make a move to update the chessboard after receiving the coordinates.

The reason we choose socket.io is that the JavaScript program cannot invoke our python program directly. So, socket is our solution because it can communicate between server and client in real-time and support programs written in different programming language.

5. Training Process

5.1. Training Dataset

We collected records of over 30000 Chinese chess games and about 2,000,000 moves in total, including games in professional competitions, classical ancient games, and online games between high-ELO players. As it was unable to determine an optimal or good enough move given certain chessboard status, the moves in collected were recognized as reasonable good moves and used as the supervised labels in training process. The objective of our supervised learning process was to train the model to predict the choice of professional experts given certain chessboard status.

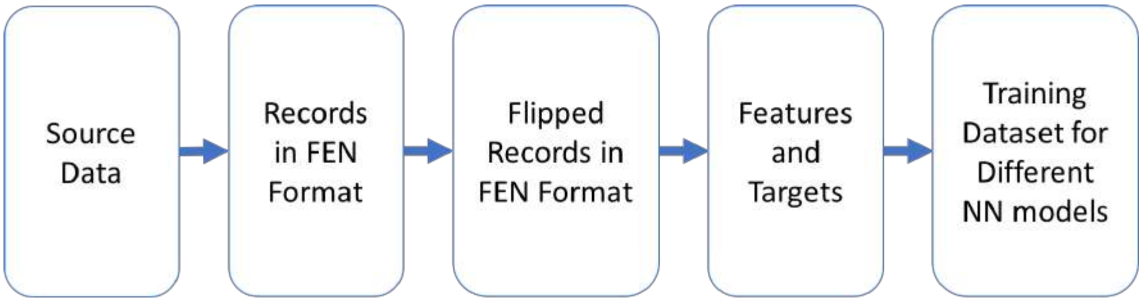

Source Data
Records in FEN Format
Flipped Records in FEN Format
Features and Targets
Training Dataset for Different NN models

Figure 5.1. Generation of Training Data

The source records downloaded from online libraries are in PGN format, which cannot be directly read by program. The PGN source data were firstly preprocessed and converted into FEN format. Then, the training dataset was generated by extracting the features of chessboard from FEN representation. The position from which a piece is moved is used as supervised label for Piece Selector and the position to which a piece is moved is used as supervised label for Move Selector. And for Move Selector, we need to classify the moves by the types of pieces moved. Though the total number of moves with chariot, cannon and horse is obviously greater than the moves with other types, the possible moves of these pieces are also greater than king and advisor, so training samples are enough for Move Selector of different types of pieces.

5.2. Preprocessing

After collecting source data of game records of Chinese chess, they cannot be directly used for training NN models, without being preprocessed.

For chess, we can find game records in PGN format which is easy to read and interpret for computers, and every move is represented by the type of the moved piece and the position where it is moved to. However, for Chinese chess, the game records are stored in Chinese version of PGN format, like “炮二平五”, and the place the piece will move to is only represented by its X coordinate while the coordinates of black and white are adverse, which is much harder for computer to directly process. Besides, PGN is not preferred for training usage, as only the whole PGN records sequence recording a game from start to end can make sense, each of which records only one move but not the status of the whole chessboard. However, our model is designed to be trained by each move, not each game.

Considering this, FEN is a much better record format, as one FEN record contains quite complete information, of both the move and the chessboard status, for training usage.

To solve this problem, certain preprocessing is necessary to generate the training dataset. Firstly, we wrote a program to convert the records in Chinese into symbolic representations using only English letters and numbers, avoiding potential problems in coding. And then, we created an initial chessboard, followed the PGN records to make moves step by step and recorded every chessboard status in FEN format, which could be conveniently used for future NN model training.

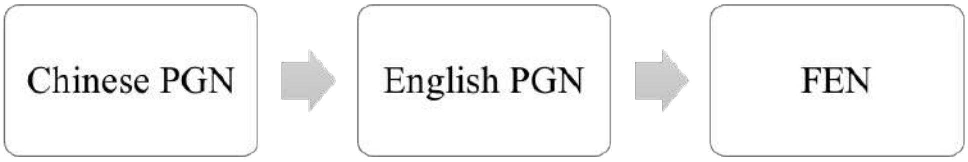


Figure 5.2. Format Conversion

There are many special cases to be considered. For example, the phase “进五” will have different meaning for different types of piece. For chariot and cannon, it represents move to five blocks forward. But for other pieces like knight or bishop, it will mean move to a block with X-coordinate 5. Another situation to be dealt with is when moving a piece with multiple this kind of piece in a row, for normal piece, the character “前” (front) or “后” (back) should be used. But for bishops and advisors, it won’t do that because the available blocks for them are limited.

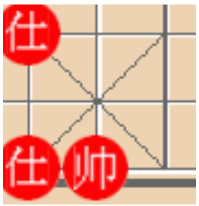
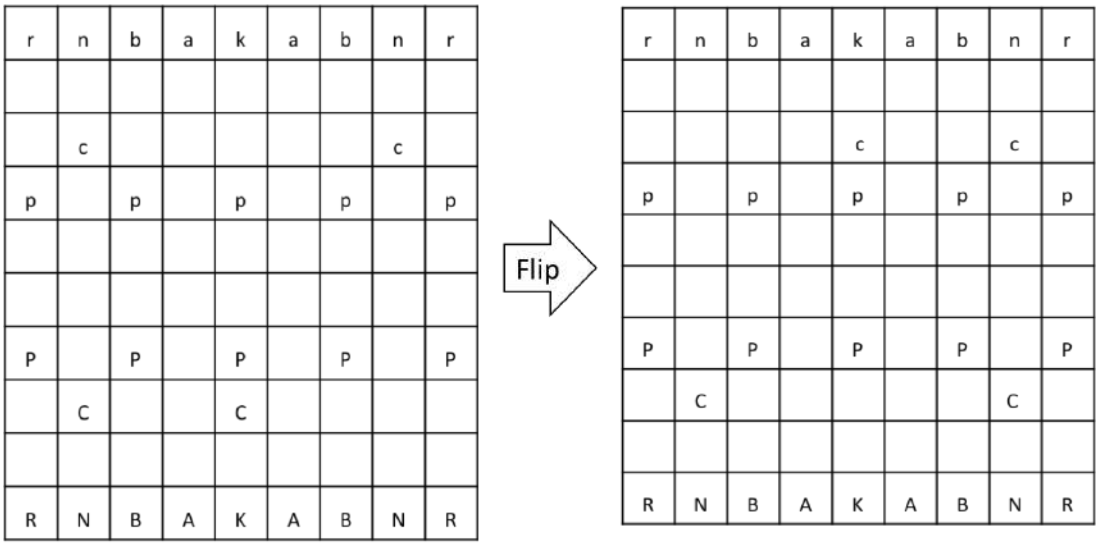


Figure 5.3. A Special Case in PGN

In Figure 5.3. above, two advisors are all in row 6, but if the next move is “仕六退五”, only the upper advisor can move backward. So, the upper advisor will be moved.

5.3. Chessboard Flipping

When preprocessing the source game records, a small trick was used, called flipping. Since there are two players in the game, to diminish the effect of different sides and accelerate the training speed, the chessboard would be flipped when generating the FEN information to ensure that the player to make next move is always the lower side.



r	n	b	a	k	a	b	n	r
	c						c	
p		p		p		p		p
P		P		P		P		P
	C			C				
R	N	B	A	K	A	B	N	R

r	n	b	a	k	a	b	n	r
				c			c	
p		p		p		p		p
P		P		P		P		P
	C						C	
R	N	B	A	K	A	B	N	R

Figure 5.4. An Example of Chessboard Flipping

For example, as shown in Figure 5.4., now it is the turn for the black side, i.e. the upper side to make next move, then the chessboard will be flipped so that our model can treat it as a turn of the red side.

5.4. Training Strategy

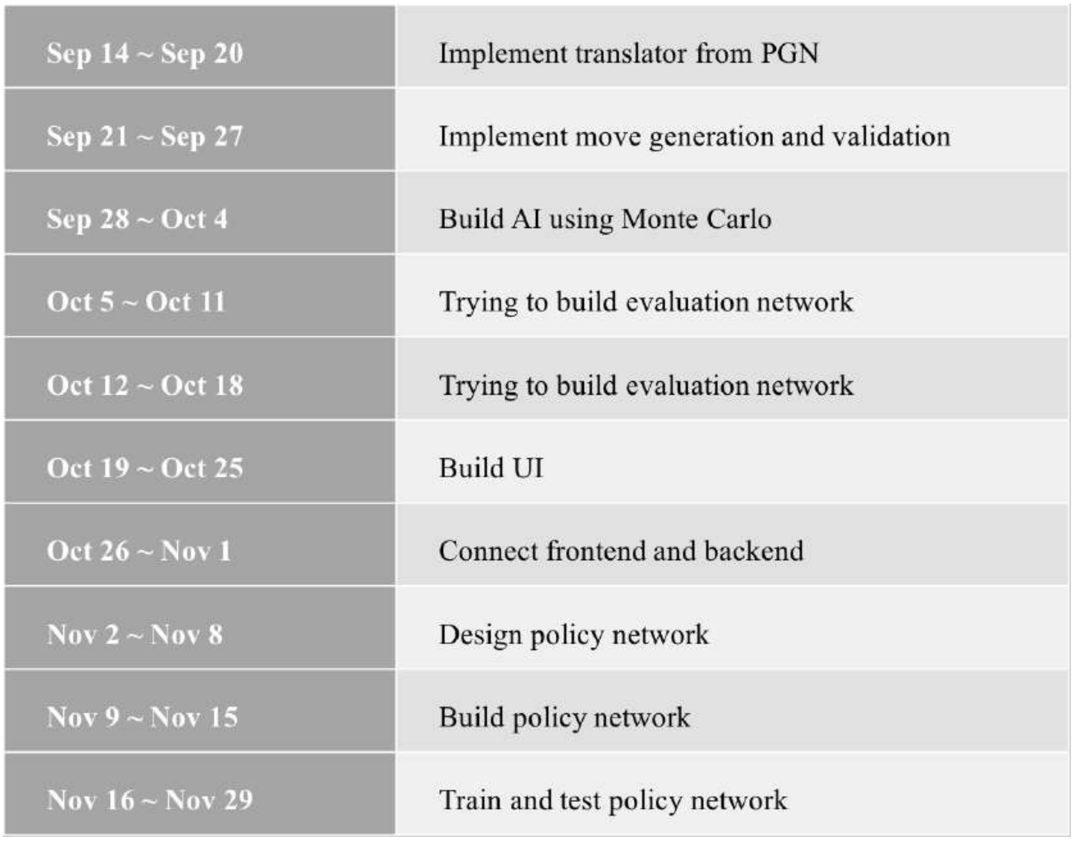
Piece Selector and Move Selector were trained separately. Piece Selector was trained first, and after the accuracy of Piece Selector was over 40%, we started to train Move Selector. For Piece Selector, the training target was the position of the piece selected by the expert players under each chessboard status. For Move Selector, as mentioned above, seven different NN models were trained separately, one for each type of pieces. The training dataset only contained the moves where the expert players selected pieces of that particular type, and the training target was the destination of that move.

The training dataset was divided into batches of size 1000. The models were trained batch by batch, and every 50 batches they would be tested based on the next batch to be trained and the accuracy would be records. Also, a testing dataset was prepared containing about 1,000 games, near 100,000 moves and the trained models would be tested using this dataset at last. If the models also perform well in these unseen situations, we can safely conclude that the models are not overfitted.

The collected source data were game-based, i.e. the records were ordered game by game. If such an order is kept, however, the training results may not be good, as the chessboard statuses in first several turns or last several turns could be very similar in different games, making the whole dataset too regular and not random enough. To increase the randomness, the records were shuffled first, to break the order, before being used to train the NN models.

6. Project Progress

6.1. Project Schedule



Sep 14 ~ Sep 20	Implement translator from PGN
Sep 21 ~ Sep 27	Implement move generation and validation
Sep 28 ~ Oct 4	Build AI using Monte Carlo
Oct 5 ~ Oct 11	Trying to build evaluation network
Oct 12 ~ Oct 18	Trying to build evaluation network
Oct 19 ~ Oct 25	Build UI
Oct 26 ~ Nov 1	Connect frontend and backend
Nov 2 ~ Nov 8	Design policy network
Nov 9 ~ Nov 15	Build policy network
Nov 16 ~ Nov 29	Train and test policy network

Figure 6.1. Project Schedule

At first, we planned to build evaluation network first. However, we faced a trouble in setting the label for training dataset. So, we changed our plan and built policy network first.

6.2. Simple AI with Monte Carlo

First of all, we planned to build a simple AI use MCTS. There two main reason for us to build these simple AI as stated following.

One reason is that, after we finish the AI model by using Neural Network method, we can compare the performance between two kinds of AI. If our AI based on Neural Network has better performance, our AI has obtained good capability. The other reason is that in our evaluation network, we may need to calculate the winning rate of a chessboard using our AI.

To build these simple AI, first we shall build chess board that can move the piece per our input instructions. However, we must make sure that the input is legal. So, we have implemented move generator and validator to examine the inputs.

The move generator and validator works similarly in some aspects. First, we should define what kind of movement is allowed. Among all kinds of pieces, cannons are hardest to implement. For cannons, they are only allowed to capture an enemy by jumping over exactly one piece in a straight line no matter how many empty blocks exist among the line. Also, the knights of Chinese chess are slightly different from them on chess. If there exists a piece adjacent to it, it can’t move to that direction. After that, the move generator will apply these move patterns to the piece and use validator to determine whether the move is legal.

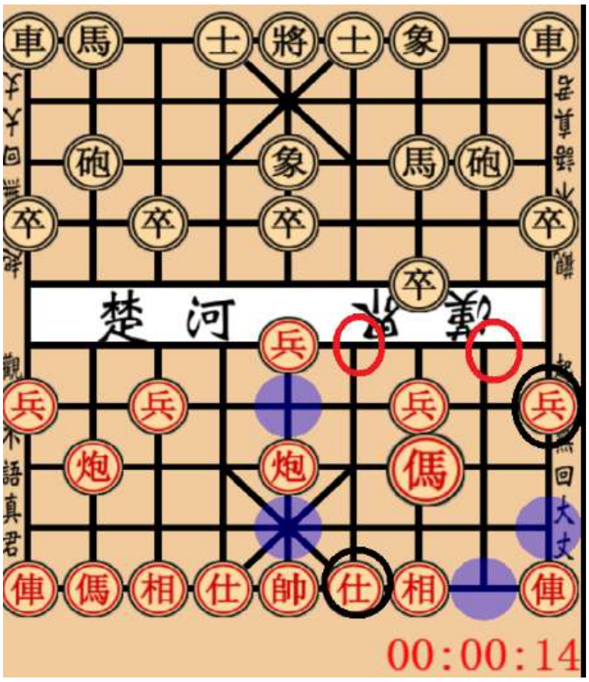
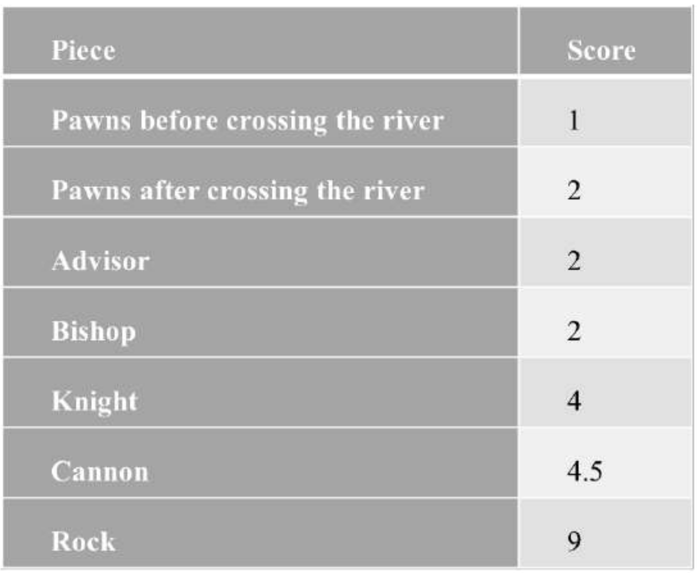


Figure 6.2. An Example of Move Generator and Validator

In Figure 6.2., all the circles are generated by move generator. And the validator will examine all these eight moves. The blue circles represent legal move of the knight. Black circles represent that there is piece of red side on the point. And red circles represent that a pawn blocks the way for the knight to move upside.

After we have these components, we should apply MCTS to Chinese chess by following steps below. For a given situation, first we find all the possible valid moves use our move generator. Then we shall traverse all of those moves. For every possible move, move forward and randomly select possible move until an end condition, usually when it reaches the maximum iteration depth and return the evaluation about the status. The evaluation of the chessboard mainly bases on the number of pieces exist, and different kinds of pieces have different scores, as shown in Figure 6.3..



Piece	Score
Pawns before crossing the river	1
Pawns after crossing the river	2
Advisor	2
Bishop	2
Knight	4
Cannon	4.5
Rock	9

Figure 6.3. Values of Different Pieces

Repeat the search for 10 times and use their average as the score of the move and choose the move with highest score. After this move, check if the current side is being checked. If the side to move will still be checked after the move, try to select a new move. Or we use this move as final output.

By this method, we have a basic AI which responses to easy game board. However, since the basic AI is very simple, it has some major disadvantages.

First, as the evaluation function of it is completely based on the value of weight. The highest priority of the AI is always trying to capture enemy's piece. For example, most probably, the first step of red side will be shown as Figure 6.4.. The red side uses its cannon to capture black knight.

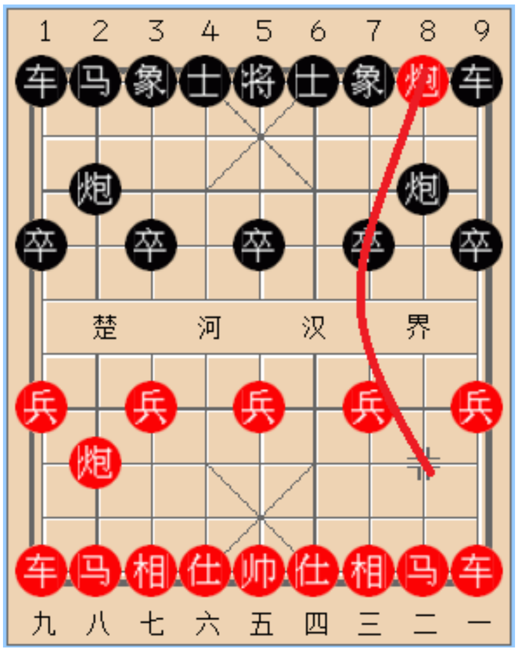


Figure 6.4. Choice of the Simple AI

And the response of black will be like in Figure 6.5., using its rock to capture red cannon.

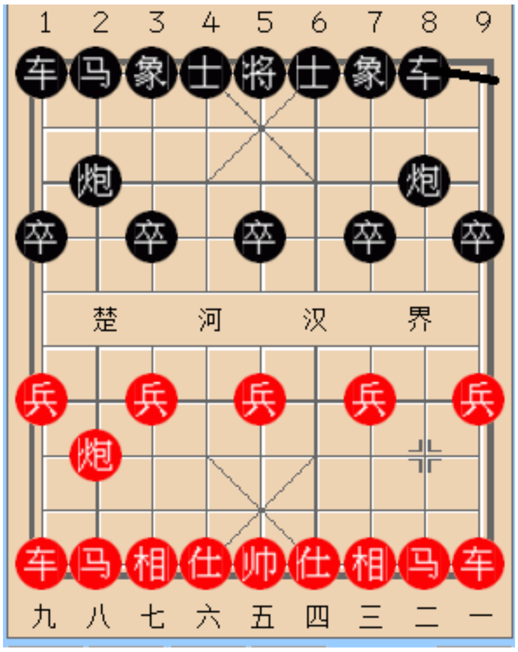


Figure 6.5. Choice of the Simple AI

The reason for this phenomenon is very simple. The algorithm only searches for one layer, and finds that it can capture enemy's piece. If it uses red cannon to capture the black knight and stay live, this move will have higher score. It doesn't see that the rock can capture red cannon as response because it is out of search boundary.

To solve this problem, we must add the amounts of layers of search tree before starting random search and use minimax to reduce possible search time. But this will reduce the speed of the program greatly.

6.3. Evaluation Network

Between evaluation network and policy network, what we chose first is evaluation network rather than policy network. In evaluation network, for training dataset, we decide to use the feature below:

a) Side to Move – Red or black. Indicating the current side to move next.

b) Number of each type of pieces 7*2=14. Indicating the number of each type of piece. Different color of pieces should be counted separately.

c) The existence and the current position of pieces 16*2*2=64 The features consist of pairs. One is the existence of the special kind of piece. If a kind of pieces may exist more than one on the board, for example pawns, we will note them from p1 to p5 accord to the relative position. As we didn't track every piece on the board, the piece searched first (has lowest x-coordinate value) would be p1, the other one is the position of piece.

d) The number of possible moves of each piece 16*2 = 32. Normally if a piece has more liberty or more possible moves, its effect will be larger. Oppositely, if the piece has no legal move, it means it has nearly no effect on the chessboard. So, we decided to add it as a feature.

e) Whether the block is under attack or protection 90. This feature represents if there exist some pieces can reach the specific block. If the amount of our pieces can move to the block is greater than the amount of enemy's pieces can move to the block, then we can say the block is under attack, otherwise the block is under protection which means our piece will be captured if move to the block.

In total, there are 1 + 14 + 64 + 32 + 90 =201 features. And we can separate them into three groups.

The first group is global feature including some feature directing to the overall situation including Side to Move and Number of each type of pieces. The second group is piece-centric feature including information about pieces. The existence, the current position of pieces and the number of possible moves of each piece would be needed. The last group is square-centric features about the status of each block. In our project, that would be attack or protection map.

For each group, we'll arrange a hidden layer for them and conclude them to the second hidden layer like the figure below because the information of each group is distinct and the connections between each group are usually useless. By this separation, the efficiency of training will increase.

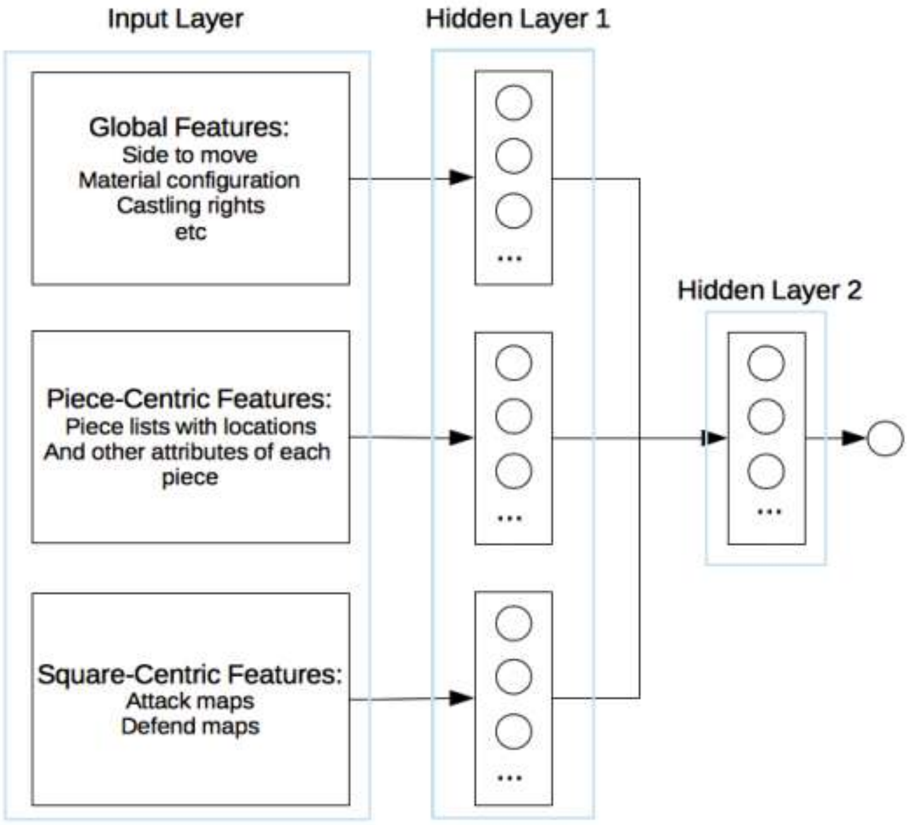


Figure 6.6. Structure of Evaluation Network

Besides training dataset, we need to give them a label representing the current winning rate or the advantage. If we look at the status and score them one by one, that would be inaccurate and inefficient. So, we want to use MCTS to calculate the winning accuracy of the chessboard.

However, in our practice, the random game was really slow and nearly impossible to end. It is very obvious that a complete stochastic game has little chance to end. So, we tried different ending condition.

First, we tried to end the search by the time a check happened and calculate the amount of which side suffered a check. However, even if the number of pieces between two sizes was extremely large, the result was still neutral. Tracing the exactly branches of the search, we found that the side who had less piece would have less possible move, meaning the possibility of a suicide check would increase which never happened in a game between humans, but would cheat the evaluation progress. On the other hand, for the dominant side, as his piece was more than the opposite, a random choosing may select invariant bad move.

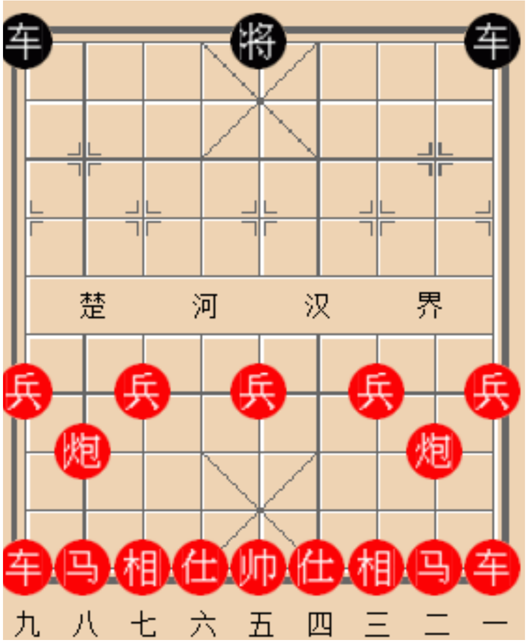


Figure 6.7. An Example of Extreme Cases

As shown in Figure 6.7., the black side has only two rocks remained. In this situation, the winning rate for red is nearly 100%. But in this method, the liberty of rocks means that they have freedom to move everywhere， where equally random selection make the move of red side awakward. In this case, the times of both sides are checked first are nearly equal. That’s not good obviously.

Another way is not to use random selection, and use our MCTS AI instead. Though it may have good result, the speed of it is a disaster because the depth is too high and need too much instruction for next move. Dealing with a chessboard need more than 5 minutes. If we want to give the label to all data in the dataset, this may cost more than a year. So, this is also not a good way.

The last method is to regulate a maximum depth and return the final status after counting the live pieces of each side. However, besides problem from the first method, this evaluation method overemphasizes the importance of capturing enemy’s pieces. The policy trained would be like simply calculating the live pieces with weight.

As long as the three methods are all unworkable, we decide to use result from policy network to replace random selection. As a result, the implementation of value network will be postponed until we finish policy network.

6.4. Previous Design

At first, we did not come up with the idea to use Piece Selector and Move Selectors separately. Instead, we had some different designs.

One of the ideas is to use a vector to map all possible move for pieces. For example, a rock will have maximum of 17 moves in total (9 horizontal and 8 vertical) and a knight will have 8. And then serialize them according the order of relative moves. For example, for a knight, the move to front left would be k1, and the move to front right would be k2. Using this method, we would have 122 possible moves in total. And use it as the label. As the relative order of all moves would not change, we can restore the move from the vector. If the 75th label is correct, we can find the corresponding move. This method transforms the high-dimension move into a one-dimension vector suitable for neural network training.

However, this method is not very intuitive. The corresponding relations are hard to find even for humans. And for neural network, the training efficiency would be low for the same reasons. Another disadvantage is that the same relative move will have different value in distinct situation. Usually moving a pawn upside is a good move. However, moving it into the top line is not a good idea because it cannot return backward.

Because we had a better model later, this method has not been implemented.

Another model we used to implement is adding high-level information into the neural network. For example, the liberty of a piece would be considerable information for human chess player because a piece that has higher liberty would affect more space on the chessboard. We think that this kind of information can speed up the training process and make it faster to converge.

However, the result was not satisfying from our expect. The accuracy even dropped compared to the version without high-level information. The reason may be the meaning of this map is different from other channel, which confuses the neural network to make false prediction.

In fact, Neural Network can extract information internally and interferes of human are not always necessary. In our project, the feature channel of valid moves helped in training Piece Selector, because the meaning of the channel is clear and consistence with other channels. But a bad channel will cause overfitting or sheer drop in accuracy. So, we should take care of this kind of additional information.

7. Results

7.1. Accuracy Testing

In Accuracy Testing, the AI model was simply tested based one a testing dataset in the same format with the training dataset, recording the moves made by professional expert players in realistic top-class competitions. This testing is to test the accuracy of our trained NN models predicting the choice of an expert player given a chessboard status. And this testing was done separately for Piece Selector and Move selector.

7.1.1. Piece Selector

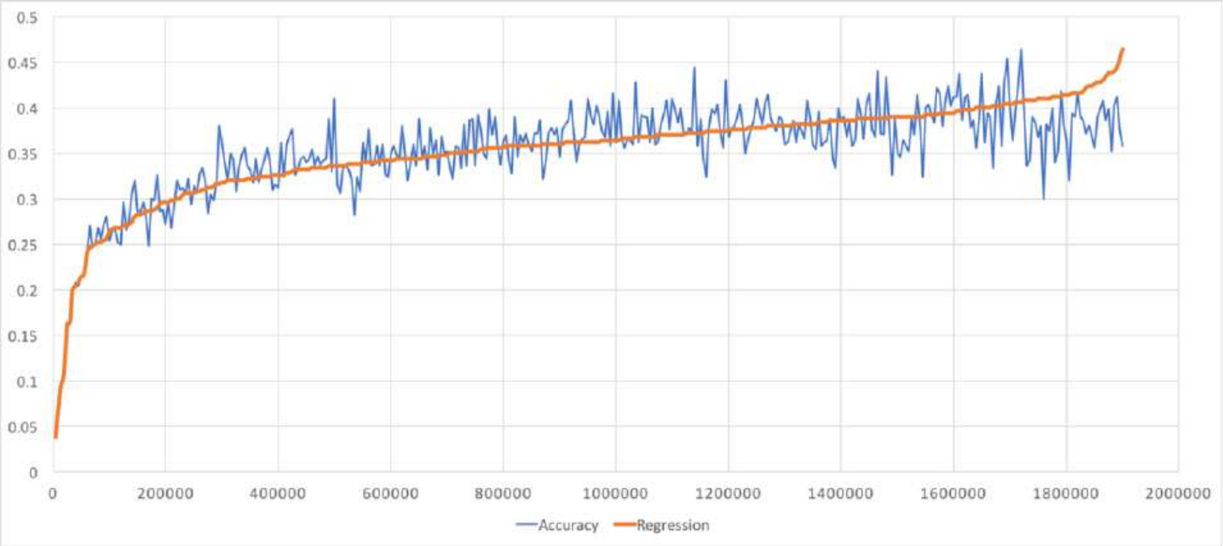


Figure 7.1. Piece Selector Accuracy

The accuracy of Piece Selector was recorded along the training process, as shown in Figure 7.1.. Evidently, the accuracy is generally increasing over the process, with reasonable oscillations. At last, for our testing dataset, Piece Selector has achieved an accuracy of 44.7%, which is quite high.

For the initial chessboard status, the output from our Piece Selector when the AI plays the red side is as shown below. Figure 7.2. (a) shows the real chessboard, and Figure 7.2. (b) shown the corresponding output of Piece Selector with eliminating values less than 0.1% while Figure 7.2. (c) shows the source output from Piece Selector. The most suggested piece is the right red cannon in the blue cycle with 57.8% probability in the red cycle, which is a popular opening way. The second highest suggested piece is the middle red pawn with 22.1% probability, which is also a good choice. Note that at positions with probability larger than 0.1% there always exists a red piece, indicating that our Piece Selector has learned to select pieces of its own side.

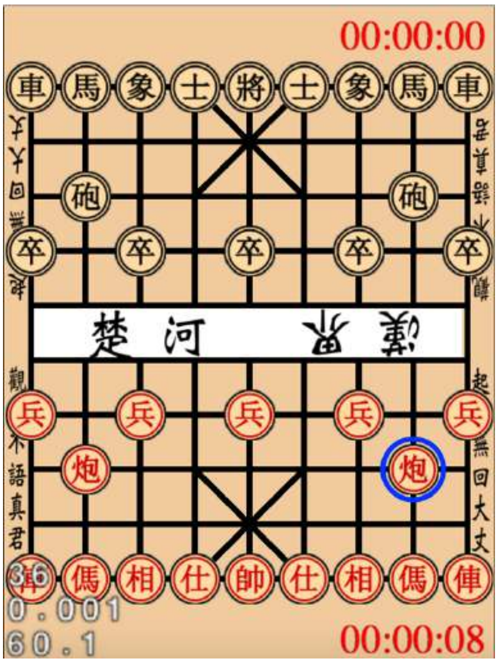
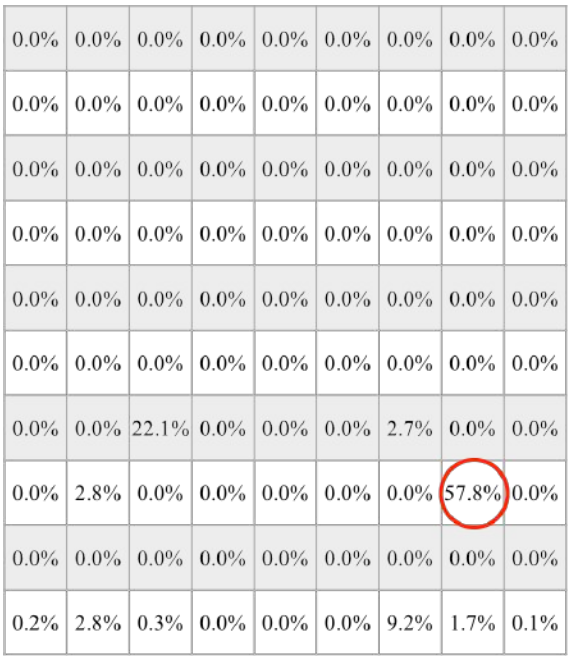
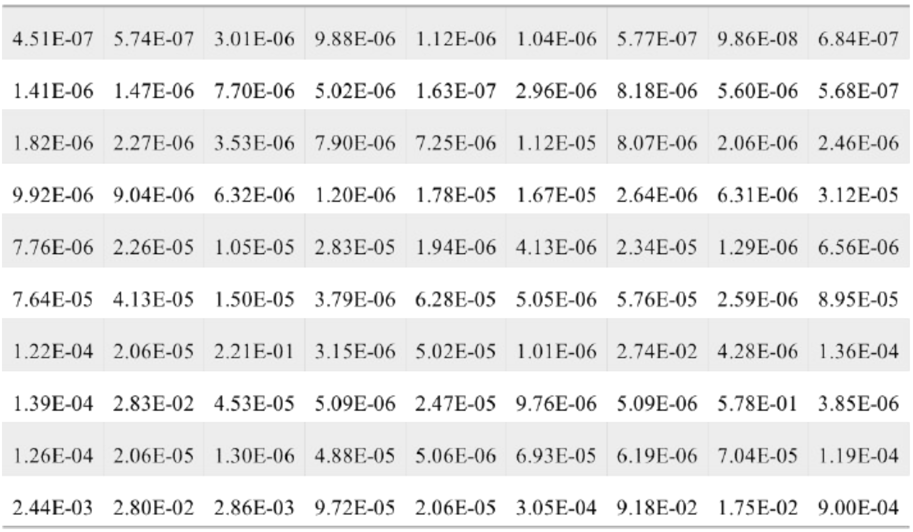


Figure 7.2. (a)



0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	22.1%	0.0%	0.0%	0.0%	2.7%	0.0%	0.0%
0.0%	2.8%	0.0%	0.0%	0.0%	0.0%	0.0%	57.8%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.2%	2.8%	0.3%	0.0%	0.0%	0.0%	9.2%	1.7%	0.1%

Figure 7.2. (b)



4.51E-07	5.74E-07	3.01E-06	9.88E-06	1.12E-06	1.04E-06	5.77E-07	9.86E-08	6.84E-07
1.41E-06	1.47E-06	7.70E-06	5.02E-06	1.63E-07	2.96E-06	8.18E-06	5.60E-06	5.68E-07
1.82E-06	2.27E-06	3.53E-06	7.90E-06	7.25E-06	1.12E-05	8.07E-06	2.06E-06	2.46E-06
9.92E-06	9.04E-06	6.32E-06	1.20E-06	1.78E-05	1.67E-05	2.64E-06	6.31E-06	3.12E-05
7.76E-06	2.26E-05	1.05E-05	2.83E-05	1.94E-06	4.13E-06	2.34E-05	1.29E-06	6.56E-06
7.64E-05	4.13E-05	1.50E-05	3.79E-06	6.28E-05	5.05E-06	5.76E-05	2.59E-06	8.95E-05
1.22E-04	2.06E-05	2.21E-01	3.15E-06	5.02E-05	1.01E-06	2.74E-02	4.28E-06	1.36E-04
1.39E-04	2.83E-02	4.53E-05	5.09E-06	2.47E-05	9.76E-06	5.09E-06	5.78E-01	3.85E-06
1.26E-04	2.06E-05	1.30E-06	4.88E-05	5.06E-06	6.93E-05	6.19E-06	7.04E-05	1.19E-04
2.44E-03	2.80E-02	2.86E-03	9.72E-05	2.06E-05	3.05E-04	9.18E-02	1.75E-02	9.00E-04

Figure 7.2. (c)

The testing dataset used here were collected independently from training dataset. The opening turns of different games, however, are quite similar because players tend to follow some fixed opening move sequences, which is considered to be optimal or at least good enough according to previous experiences, also called joseki in Go. In other word, there may hardly exist two same games, but they may very probably exist several same opening moves between games. Similarly, for middlegame moves and ending moves, there also exists such a phenomenon, more or less. This phenomenon would probably alter the testing accuracy because there may exist many duplicate testing examples, if comparing those records move by move but not game by game. If those duplicate moves were removed, the testing accuracy of Piece Selector was 40.2%, 4.5% less than before. However, we cannot certainly say which accuracy is correct.

On the one hand, it is consistent with reality because the frequency of every board may not be equal, not only in our collected records but also in realistic games. In fact, the frequency of every situation in the dataset may reflect the realistic frequency of the situation. In this sense, the duplicate items do not need to be removed, as the accuracy can better measure the performance of Piece Selector in reality.

On the other hand, it is expected to have ability to deal with any situation, not only those very frequent situations but also the less frequent situations. In fact, the accuracy of predicting more frequent moves is higher than less seen moves because they are trained with more times, as they may also appear more frequently in our training dataset, indicating that the learning process would be better with larger dataset. Even worse, it can be treated as our model being overfitted into the training data.

Above all, we prefer to think that it’s both OK whether to eliminate the duplicate records in testing dataset or not, but it’s necessary to keep those duplicates in training dataset. More frequent moves in real games represent that more professional players think they are better moves, which is necessary in current phase.

Except for the issue discussed above, Piece Selector still needs to be further improved in other aspects. For example, in a case that a player is checked, the Piece Selector sometimes selects piece far away, which mean no matter how the selected piece moves, it can't save the king. The problem may attribute to lack of negative feedback. In the beginning phase of our training, we planned to set the moves of winner a positive weight and that of losers a negative way. But there are two reasons for us to abandon this idea. One is that many records are not complete, precisely not including the final result. The other reason is that it's hard to judge which move is the bad move. As most of our records were played by professional players, only one small mistake would lead to failure despite other moves were good. If we set them all negative, lots of good moves will be depressed.

7.1.2. Move Selector

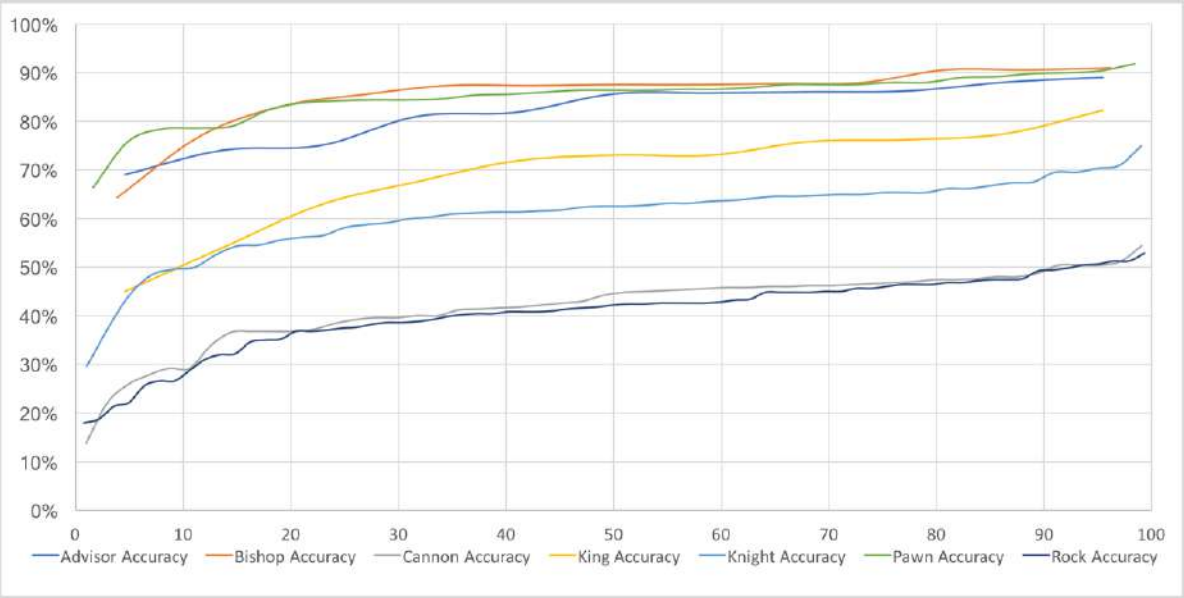


Figure 7.3. Move Selector Accuracy

Similar with Piece Selector, the accuracy of Move Selector was records along the training process, as shown above. After training, Move Selector was also tested busing the testing dataset and the results are as shown below.

For Move Selector, the models of some types of pieces have achieved clearly better performance. For example, the Move Selectors of Advisor, Bishop and Pawn have achieved accuracies of near 90%, while the Move Selectors of Cannon and Rock have achieved accuracies of only around 50%. One possible reason may be that the possible moves of former pieces are relatively limited. Bishops have at most two legal moves in general, Advisors usually have only one possible move, and Pawns also only have few choices before they cross the river. So, Move Selectors of them are easier to train. But for Cannons and Rocks, the number of move choices is usually more than 10, and every move can be reasonable in some view, which means no absolute best move, and Move Selectors of them are more difficult to train.

Move Selector	Accuracy	Accuracy After Eliminating Duplicates
Advisor	89.8%	89.0%
Bishop	91.2%	89.8%
Cannon	54.1%	48.5%
King	79.8%	79.2%
Knight	70.1%	63.8%
Pawn	90.4%	88.5%
Rock	53.6%	48.1%

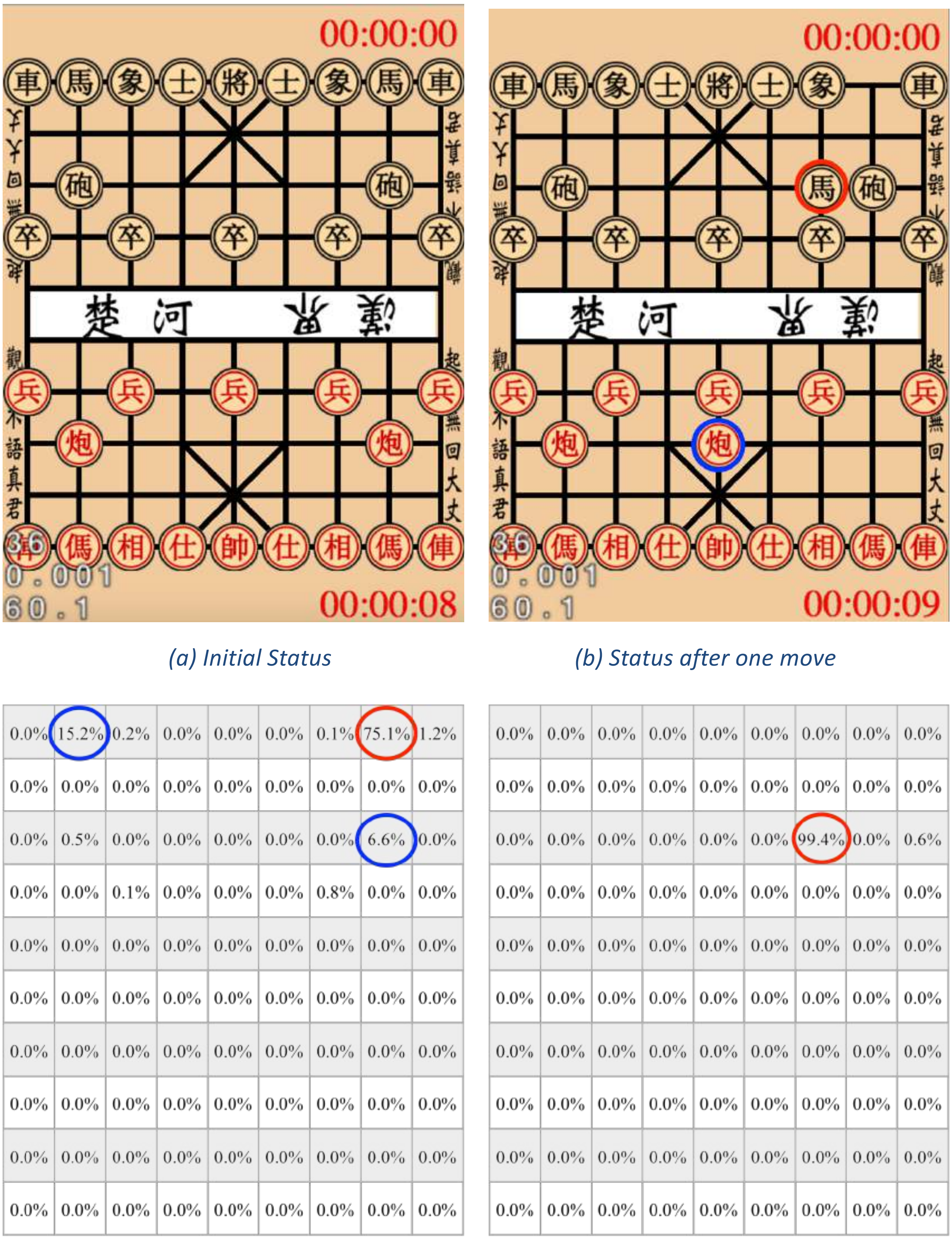
Figure 7.4. Move Selector Accuracy for Different Piece Types

The duplicates issue also exists for Move Selector. As shown in the table below, the accuracies of Move Selector models for different types all decreased, more or less, as expected. The discuss and conclusion is also similar, that we think it is fine, or even necessary, to keep those duplicates.

7.2. Real Performance Testing

As mentioned before, except for Accuracy Testing, the AI model was also tested in real games, playing against human players. In this section, several real game-playing samples are analyzed in detail and the performance of our AI is judged by some evident criteria, such as the responsiveness to being checked, the responsiveness when one piece is to be attacked and so on.

7.2.1. Game-Playing Case 1



(a) Initial Status

(b) Status after one move

0.0%	15.2%	0.2%	0.0%	0.0%	0.0%	0.1%	75.1%	1.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	6.6%	0.0%
0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.8%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Piece Selector

0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	99.4%	0.0%	0.6%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(d) Output of Move Selector

Figure 7.5.

This started from the initial game chessboard status, as shown in Figure 7.5.

(a). AI played black side, and we played red side. In first turn, we moved the right cannon to the middle. This is one of the most popular opening moves, and after this step, the black pawn in the middle was under attack. The black side, i.e. our AI, chose to move the knight forward, as shown in Figure 7.5. (b), with 75.1% possibility given by Piece Selector and 99.4% possibility given by Move Selector, which is quite high, as shown in Figure 7.5. (c) & (d). This is also one of the most popular opening moves, and after that, the middle black pawn was protected by this knight.

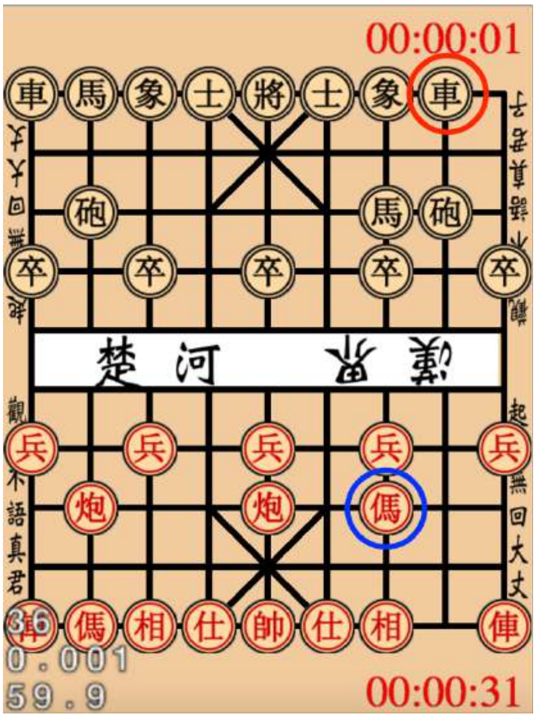


Figure 7.6. (a) Status after two moves

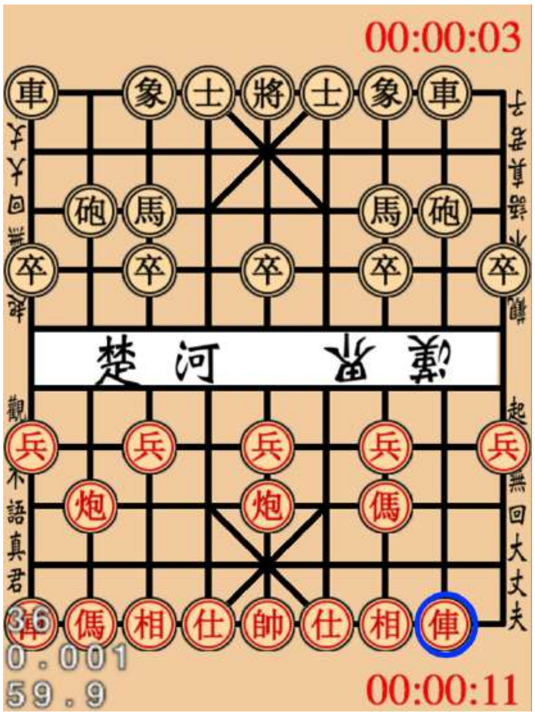
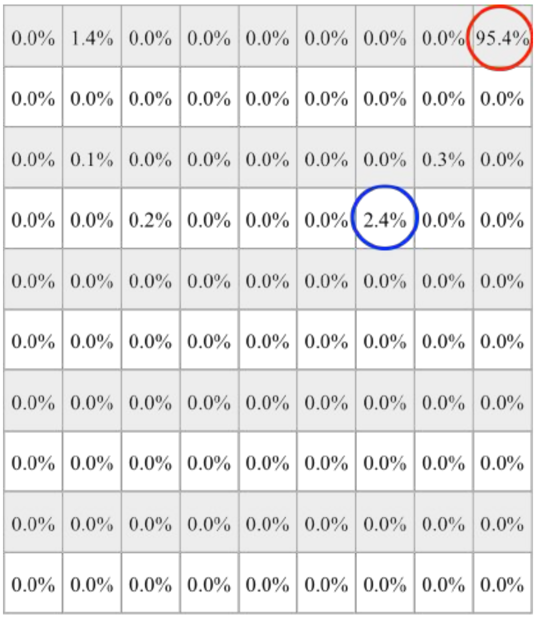
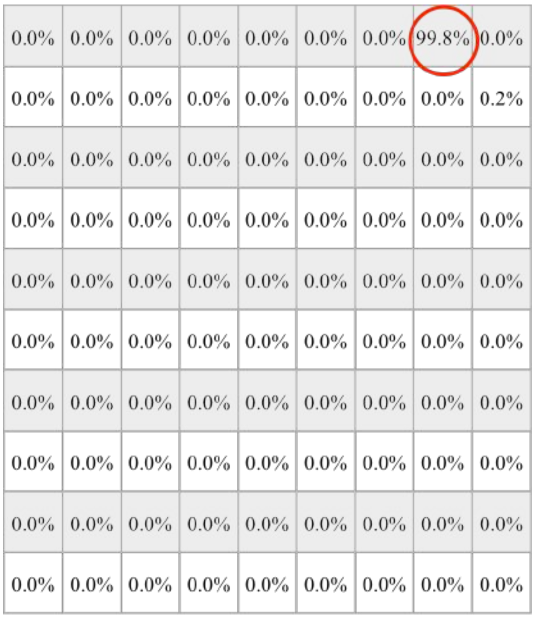


Figure 7.6. (b) Status after three moves



0.0%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	95.4%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%
0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	2.4%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 7.6. (c) Output of Piece Selector

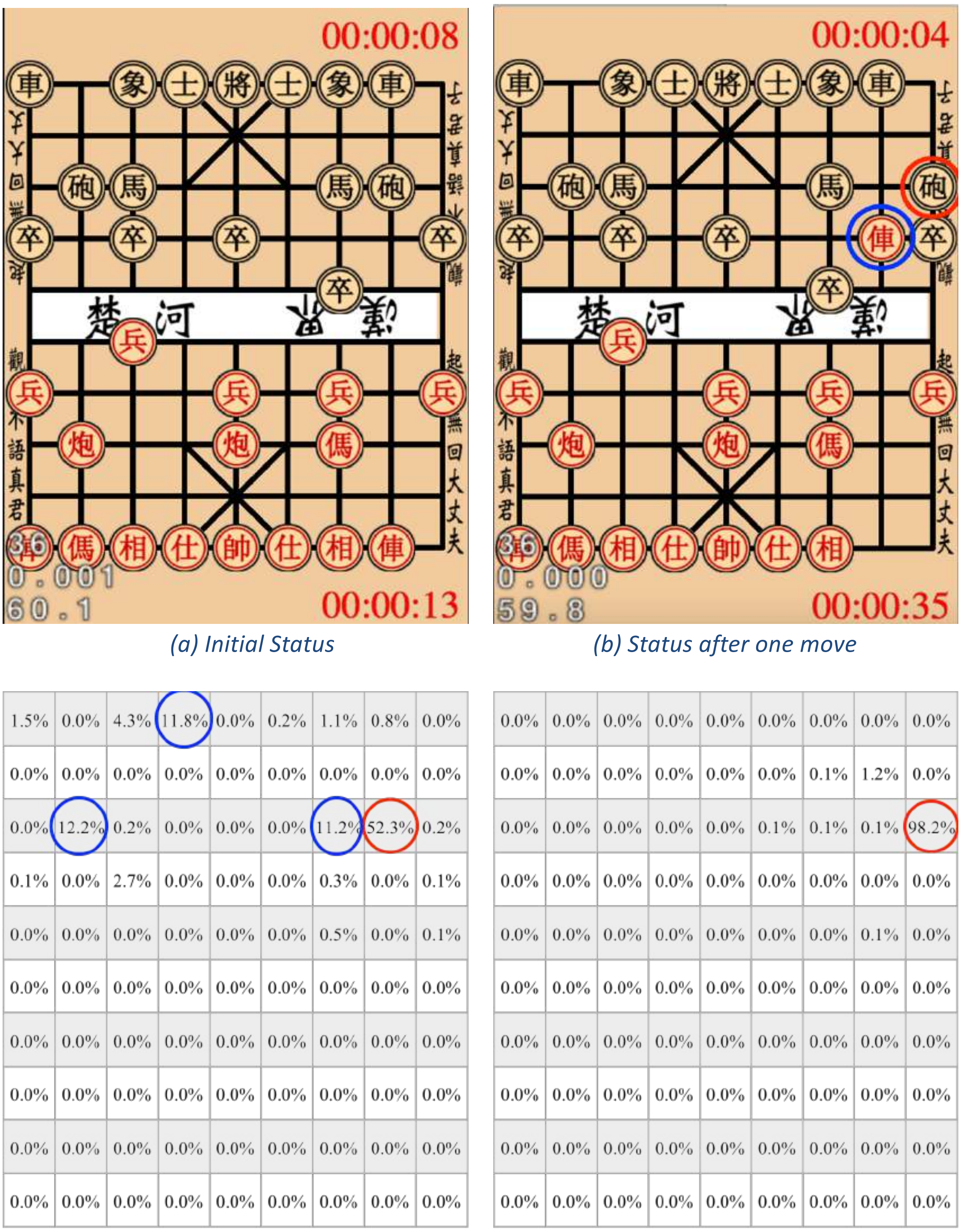


0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	99.8%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 7.6. (d) Output of Move Selector

In second turn, we chose to move the right red knight forward and our AI chose to move the right black rock left, as shown in Figure 7.6. (a), with 95.4% possibility given by Piece Selector and 99.8% possibility given by Move Selector, which is even higher, as shown in Figure 7.6. (c) & (d). Actually, it's a good move, as our next move was to move the right red rock out so that the right black cannon would be under attack, as shown in Figure 7.6. (b). In this step, our AI predicted what the opponent would do and reacted effectively. As shown in these steps, our AI learned well in opening moves and reacted responsively. Generally speaking, the result is satisfying.

7.2.2. Game-Playing Case 2



(a) Initial Status

(b) Status after one move

1.5%	0.0%	4.3%	11.8%	0.0%	0.2%	1.1%	0.8%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	12.2%	0.2%	0.0%	0.0%	0.0%	11.2%	52.3%	0.2%
0.1%	0.0%	2.7%	0.0%	0.0%	0.0%	0.3%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

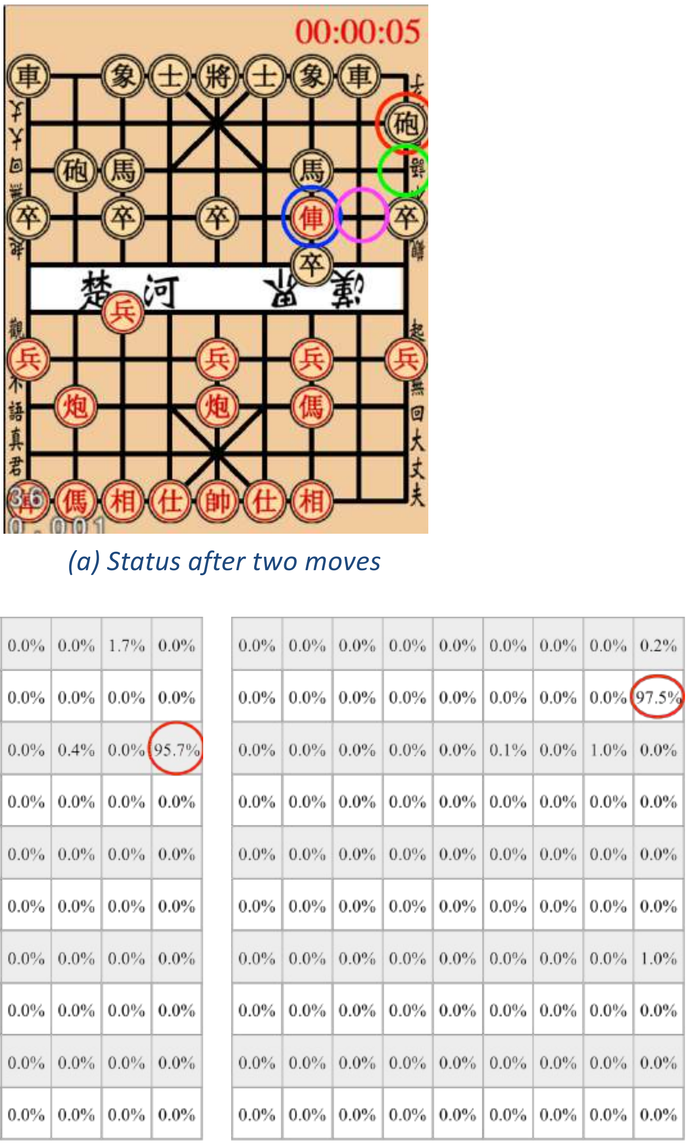
(c) Output of Piece Selector

0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	1.2%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	98.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(d) Output of Move Selector

Figure 7.7.

This is an interesting turn where AI again plays the black side. The initial status is as shown in Figure 7.7. (a). We moved the right rock forward, and our AI chose to move the cannon to the right, which is a good move, as shown in Figure 7.7. (b). First, it left our rock to be attacked by the black rock. Secondly, it left the right pawn to be protected by the black knight, as before this move, that knight can’t protect that pawn because that will be an illegal move. Third, the middle black pawn is still protected by two knights. Actually, this move left us few choices to save our rock.



(a) Status after two moves

0.1%	0.0%	0.3%	1.3%	0.0%	0.0%	0.0%	1.7%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	95.7%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	97.5%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	1.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

Figure 7.8.

So, we chose to move rock one block left. And our AI chose to move the cannon downward, as shown in Figure 7.8. (a), which turned out to be a good move but we did not realize that in the first place due to our limited skill in Chinese chess.

Two turns later, the AI chose to move the right black cannon from the position of green cycle to the position of the red cycle, as shown in Figure 7.9. (a), leaving the red rock under attack, with 84.6% possibility given by Piece Selector and 99.0% possibility given by Move Selector, as shown in Figure 7.9. (b) & (c).

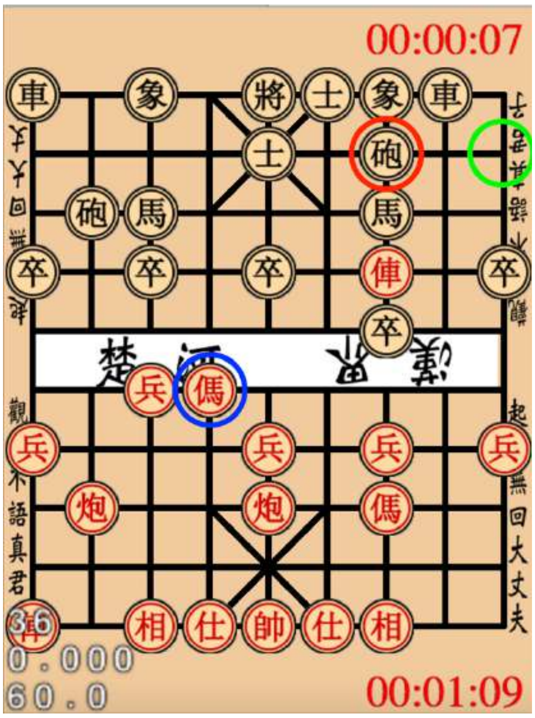
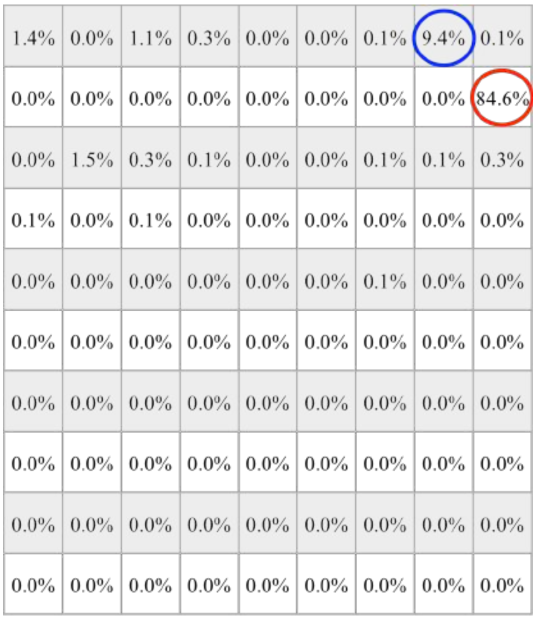
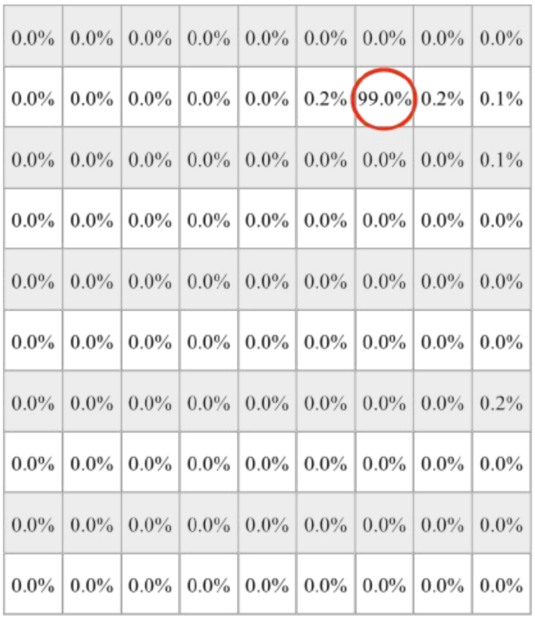


Figure 7.9. (a) Status after four moves



1.4%	0.0%	1.1%	0.3%	0.0%	0.0%	0.1%	9.4%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	84.6%
0.0%	1.5%	0.3%	0.1%	0.0%	0.0%	0.1%	0.1%	0.3%
0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 7.9. (b) Output of Piece Selector



0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	99.0%	0.2%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 7.9. (c) Output of Move Selector

7.2.3. Game-Playing Case 3

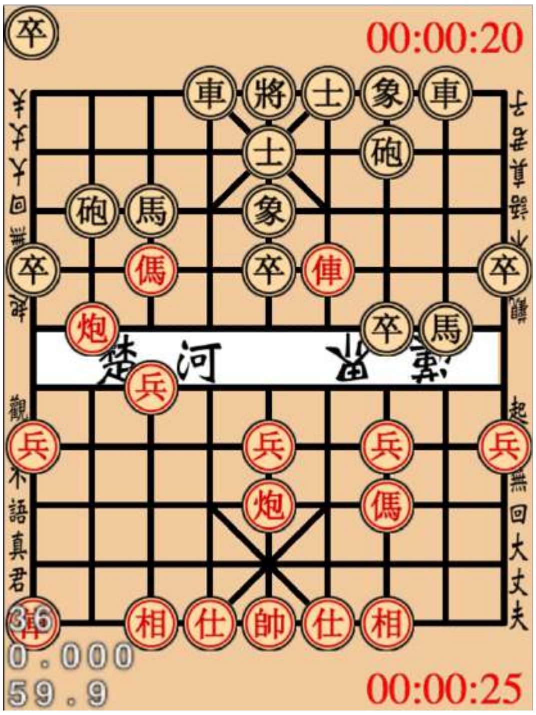


Figure 7.10. (a) Initial Status

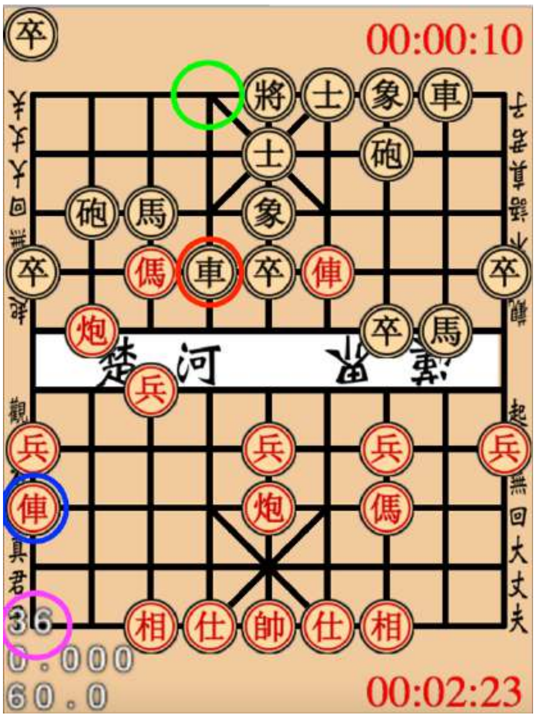
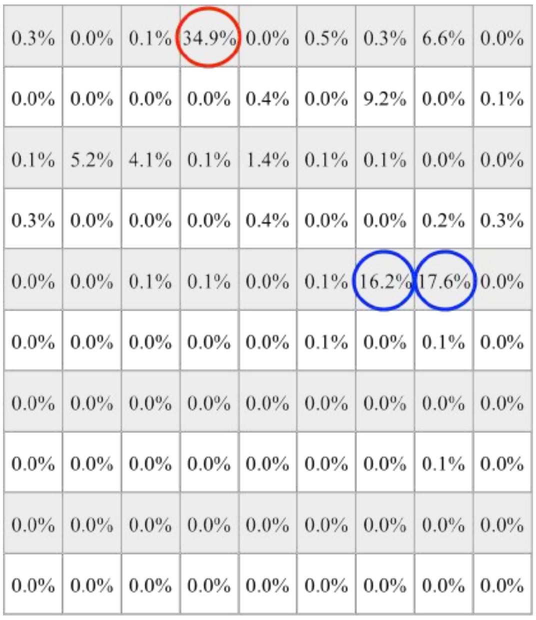
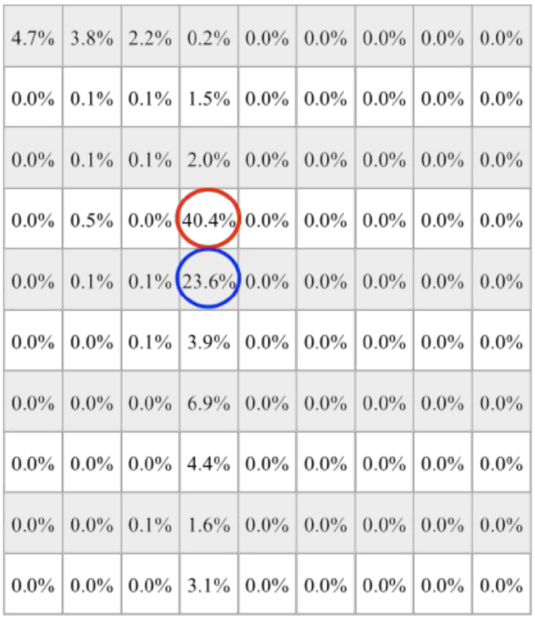


Figure 7.10. (b) Status after one move



0.3%	0.0%	0.1%	34.9%	0.0%	0.5%	0.3%	6.6%	0.0%
0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	9.2%	0.0%	0.1%
0.1%	5.2%	4.1%	0.1%	1.4%	0.1%	0.1%	0.0%	0.0%
0.3%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%	0.2%	0.3%
0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	16.2%	17.6%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

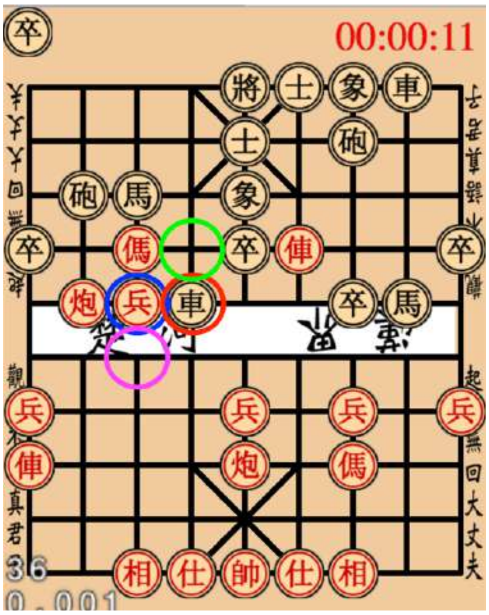
Figure 7.10. (c) Output of Piece Selector



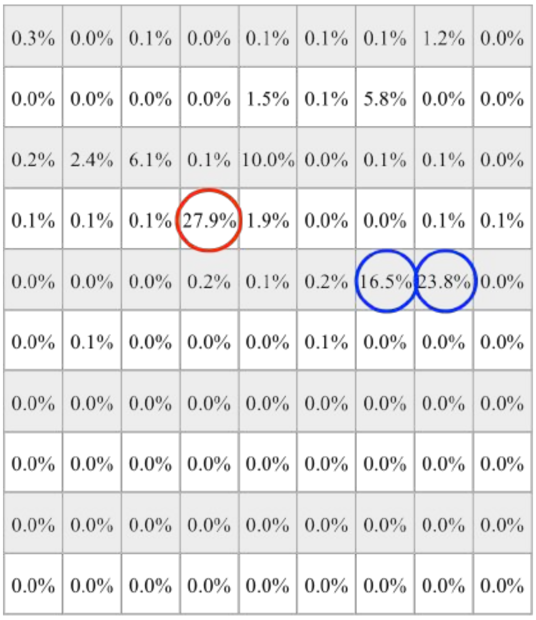
4.7%	3.8%	2.2%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.1%	1.5%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.1%	2.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.5%	0.0%	40.4%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.1%	23.6%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	3.9%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	6.9%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	4.4%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	3.1%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 7.10. (d) Output of Move Selector

And here is an example of bad performance of our AI. The initial status is as shown in Figure 7.10. (a). After we moved the red rock forward, the AI chose to move the black rock forward, from the green cycle to the red cycle, as shown in Figure 7.10. (b), so that it could attack the red knight in next turn and it also protected the black bishop in fifth column from being attacked by that red knight because that move would be illegal by the moving rules of knight, which appeared to be good in the first place but turned out to be a bad move later.

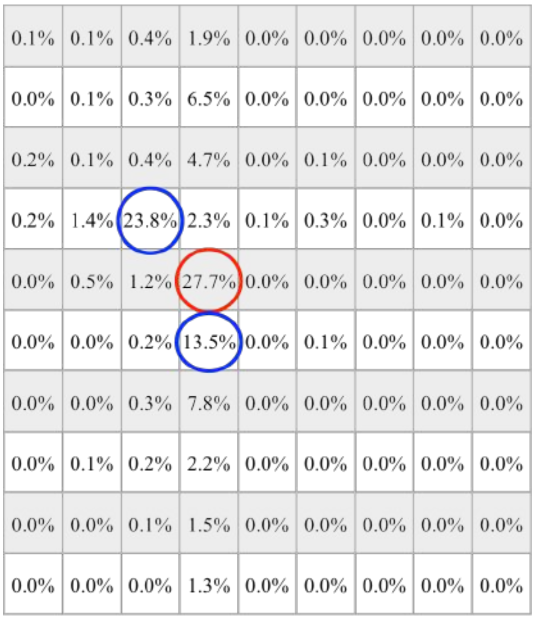


(a) Status after two moves



0.3%	0.0%	0.1%	0.0%	0.1%	0.1%	0.1%	1.2%	0.0%
0.0%	0.0%	0.0%	0.0%	1.5%	0.1%	5.8%	0.0%	0.0%
0.2%	2.4%	6.1%	0.1%	10.0%	0.0%	0.1%	0.1%	0.0%
0.1%	0.1%	0.1%	27.9%	1.9%	0.0%	0.0%	0.1%	0.1%
0.0%	0.0%	0.0%	0.2%	0.1%	0.2%	16.5%	23.8%	0.0%
0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector



0.1%	0.1%	0.4%	1.9%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.3%	6.5%	0.0%	0.0%	0.0%	0.0%	0.0%
0.2%	0.1%	0.4%	4.7%	0.0%	0.1%	0.0%	0.0%	0.0%
0.2%	1.4%	23.8%	2.3%	0.1%	0.3%	0.0%	0.1%	0.0%
0.0%	0.5%	1.2%	27.7%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.2%	13.5%	0.0%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.3%	7.8%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.2%	2.2%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	1.5%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	1.3%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

Figure 7.11.

In next turn, however, we chose to move the red pawn forward, from the purple cycle to the blue cycle. And unbelievably, our AI chose to move the rock forward again, leaving it under attack by the left red cannon, as shown in Figure 7.11. (a). As shown in Figure 7.11. (b) & (c), especially the Piece

Selector prediction results, this choice was not a clearly good one. Piece selector gave only 27.9% possibility to choose this rock piece, while it also gave 23.8% and 16.5% possibility to move the knight and pawn respectively. Similarly, Move Selector gave only 27.7% possibility for the rock piece to move to the position of red cycle, while it also gave 23.8% and 13.5% possibility for other two choices respectively, which could be a little bit better.

Seen from the example above, we can find that always selecting the piece with highest possibility given by Piece Selector and then selecting a move for it doesn't work well in some situations, especially when the possibilities of several pieces, given by Piece Selector, are quite close, which also means that none of them is much better than others.

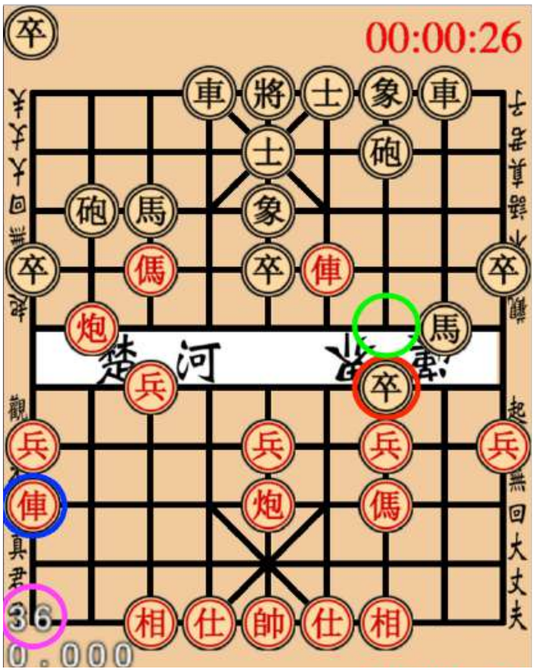
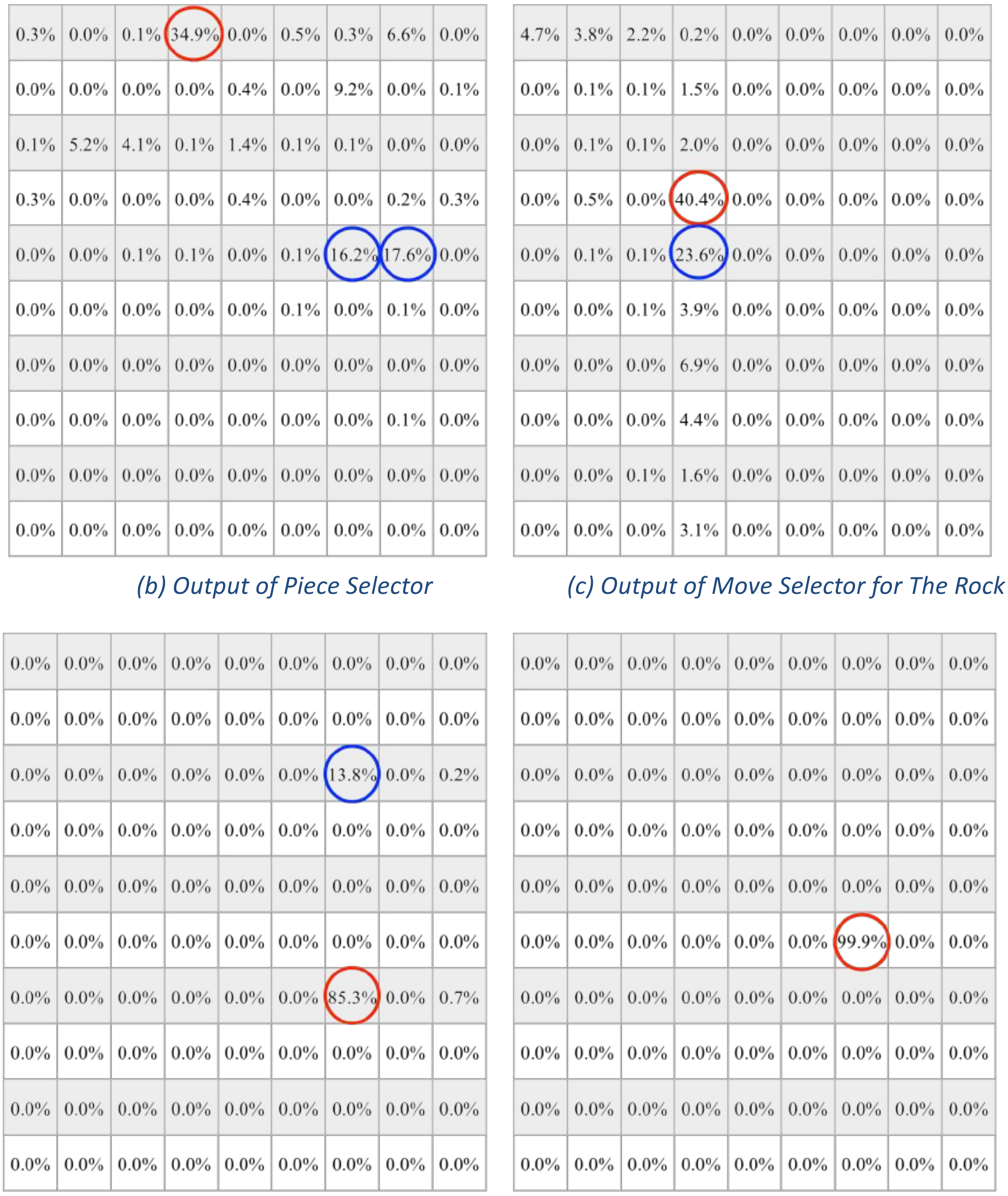


Figure 7.12. (a) New Status after two moves



0.3%	0.0%	0.1%	34.9%	0.0%	0.5%	0.3%	6.6%	0.0%
0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	9.2%	0.0%	0.1%
0.1%	5.2%	4.1%	0.1%	1.4%	0.1%	0.1%	0.0%	0.0%
0.3%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%	0.2%	0.3%
0.0%	0.0%	0.1%	0.1%	0.0%	0.1%	16.2%	17.6%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

4.7%	3.8%	2.2%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.1%	1.5%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.1%	2.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.5%	0.0%	40.4%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.1%	0.1%	23.6%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	3.9%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	6.9%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	4.4%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	3.1%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector for The Rock

0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	13.8%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	85.3%	0.0%	0.7%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(d) Output of Move Selector for the Knight

0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	99.9%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(e) Output of Move Selector for the Pawn

Figure 7.12.

Then, we modified the selection strategy of our AI as: select the best three choices, i.e. pieces with the highest three possibilities, then generate the move possibilities for each of them by our Move Selector, multiply the piece possibilities and move possibilities respectively, and at last pick the move with highest possibilities. As a result, the AI would choose to move the black pawn this time, from the green cycle to the red cycle, as shown in Figure 7.12. (a). The output of Piece Selector is as shown in Figure 7.12. (b). And the outputs from Move Selector for three different pieces, which are highlighted in Figure 7.12. (b), are as shown in Figure 7.12. (c) & (d) & (e) respectively. This is a good, or much better move. First of all, the left black rock wouldn't be under attack. Secondly, no matter whether this black pawn captured the red pawn in front of it or that red pawn captured it, the right red knight would be under attack by the right black cannon, or even better, by that black pawn as well.

7.2.4. Game-Playing Case 4

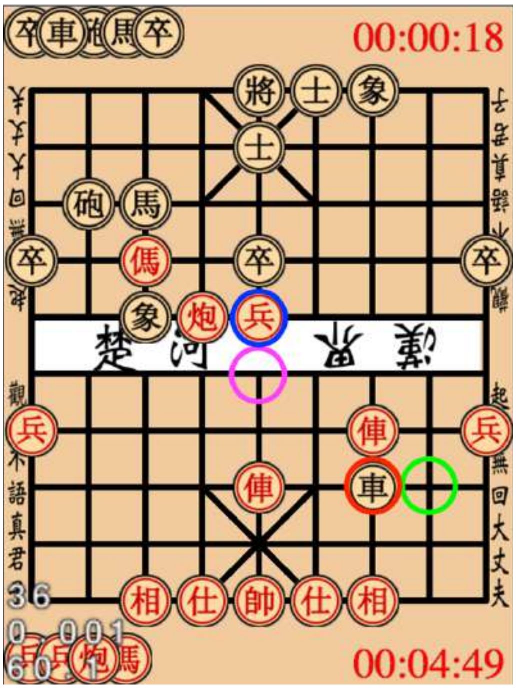
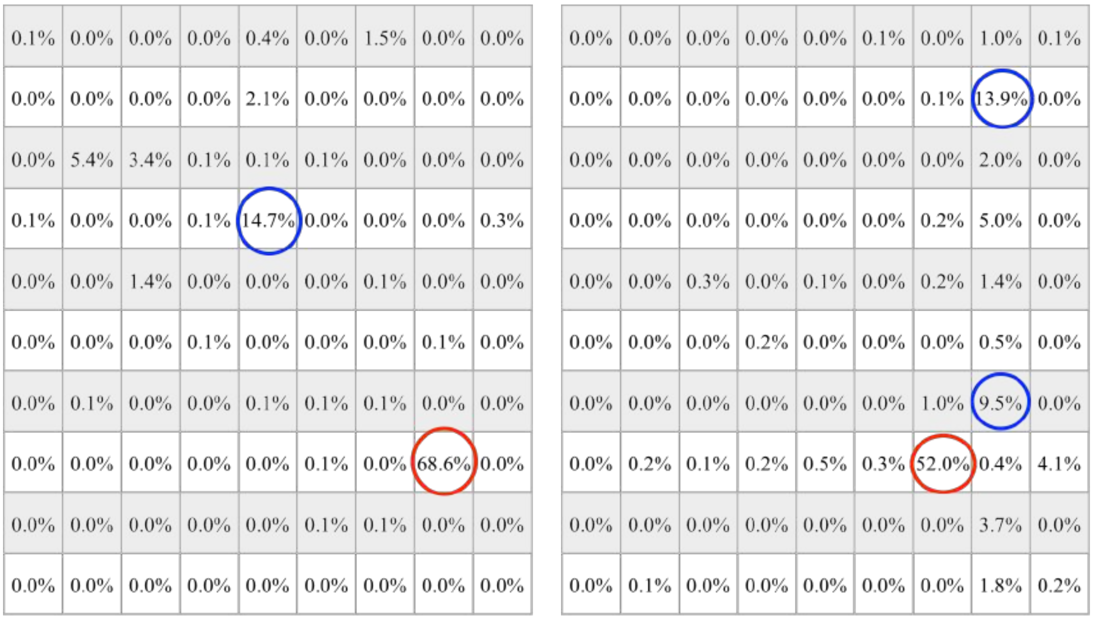


Figure 7.13. (a) Chessboard Status



0.1%	0.0%	0.0%	0.0%	0.4%	0.0%	1.5%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	2.1%	0.0%	0.0%	0.0%	0.0%
0.0%	5.4%	3.4%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
0.1%	0.0%	0.0%	0.1%	14.7%	0.0%	0.0%	0.0%	0.3%
0.0%	0.0%	1.4%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%
0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	68.6%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	1.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	13.9%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	5.0%	0.0%
0.0%	0.0%	0.3%	0.0%	0.1%	0.0%	0.2%	1.4%	0.0%
0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.5%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.0%	9.5%	0.0%
0.0%	0.2%	0.1%	0.2%	0.5%	0.3%	52.0%	0.4%	4.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.7%	0.0%
0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	1.8%	0.2%

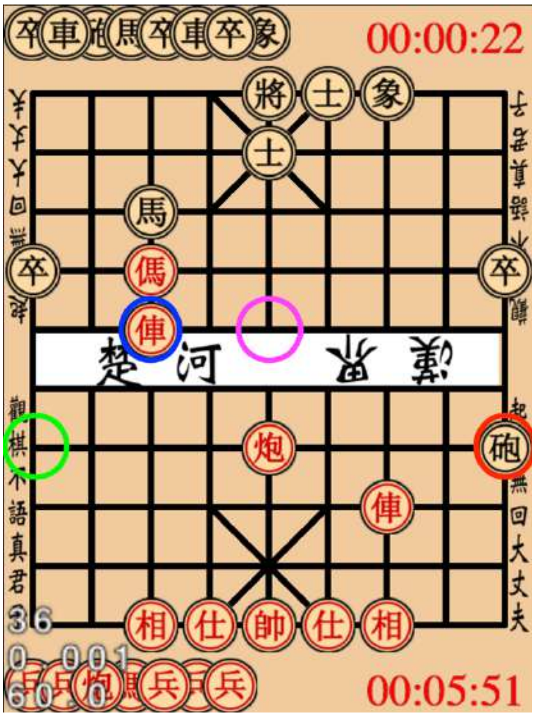
(c) Output of Move Selector

Figure 7.13.

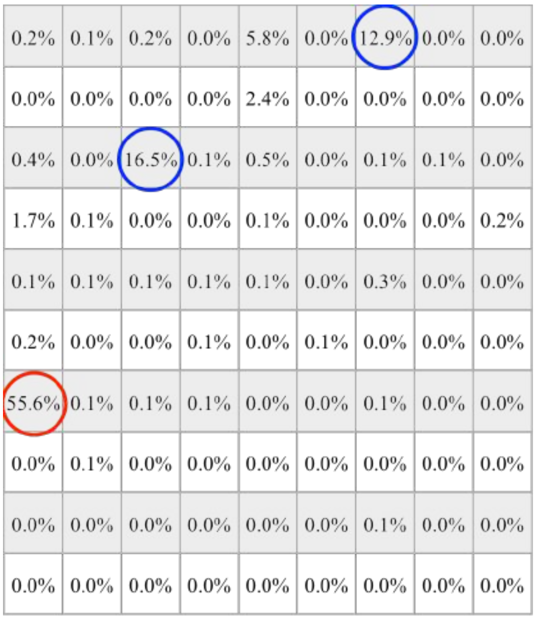
In this turn, we chose to move the red pawn forward, from purple cycle to blue cycle. Then, the AI chose to move the black rock left, from green cycle to red cycle, as shown in Figure 7.13. (a), which was a definitely bad move. First of all, that black rock was under attack by the left red rock. We did not choose to capture it and wanted to see how the AI would react. The expected move is that the AI would choose to move that black rock to capture the red rock and could check the red side as well. Or at least, the AI would move the black rock away to avoid being attacked by red rock. However, the AI moved the black rock to the red cycle, leaving it under attack by both red rocks, not checking the red side and even did not save the middle black pawn which was under attack by the middle red pawn.

In a word, this is an example where the AI performed quite bad.

7.2.5. Game-Playing Case 5

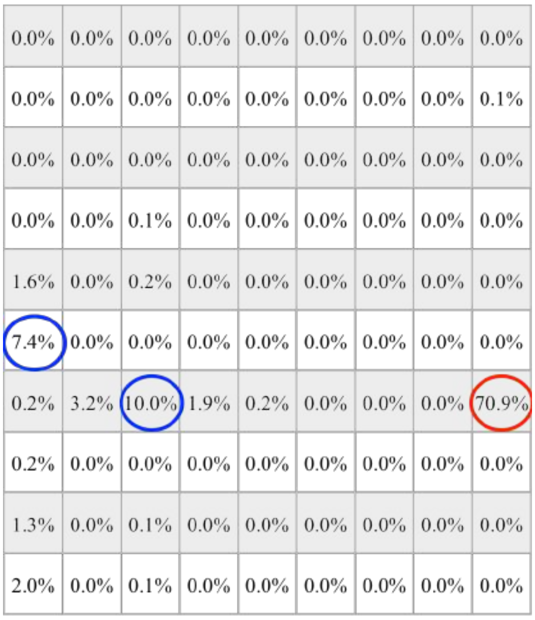


(a) Chessboard Status



0.2%	0.1%	0.2%	0.0%	5.8%	0.0%	12.9%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	2.4%	0.0%	0.0%	0.0%	0.0%
0.4%	0.0%	16.5%	0.1%	0.5%	0.0%	0.1%	0.1%	0.0%
1.7%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.2%
0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.3%	0.0%	0.0%
0.2%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%
55.6%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%
0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector



0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1.6%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.2%	3.2%	10.0%	1.9%	0.2%	0.0%	0.0%	0.0%	70.9%
0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1.3%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

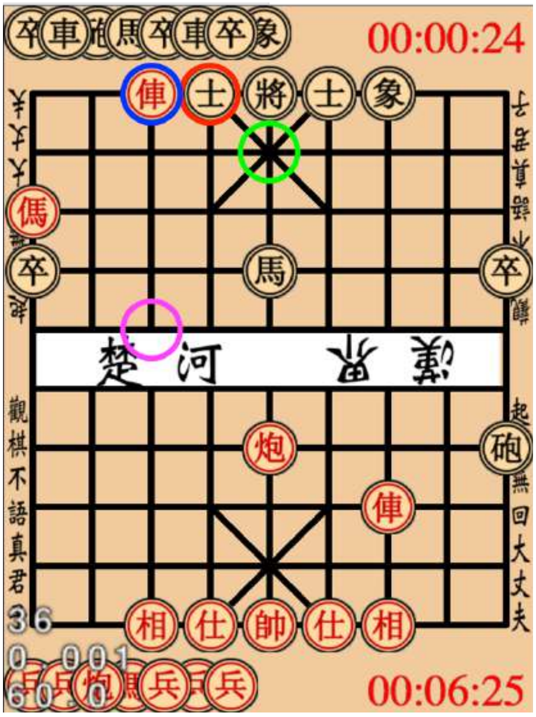
Figure 7.14.

After several turns, pieces left on the chessboard became much less. And after we chose to move the red rock from purple cycle to blue cycle, the black side was under check by the red cannon. However, the AI chose to move the black cannon from green cycle to red cycle to capture a red pawn, as shown in Figure 7.14. (a), with 55.6% possibility given by Piece Selector and 70.9% possibility given by Move Selector, as shown in Figure 7.14. (b) & (c).

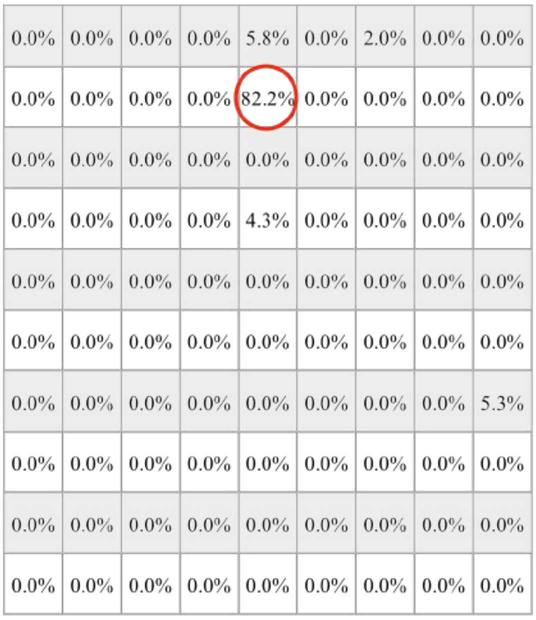
Obviously, this was a terrible move. After all, in next turn, we could use the red cannon to capture the black king and the AI would lose the game. This shows that our AI are not very responsive to the situation of being checked, which is a vital problem.

To further test its responsiveness to being checked, we did not capture the black king directly, but moved the red rock forward, from purple cycle to blue cycle, to check the black side again, as shown in Figure 7.15. (a). This time, the AI appeared to a little smarter and chose to move the advisor down to protect its king, with 82.2% possibility given by Piece Selector and 84.4% possibility given by Move Selector, as shown in Figure 7.15. (b) & (c), which was quite high, indicating that the AI was quite sure about this move.

Even though it was still being checked by the red cannon, it performed better in this situation. And this actually leads us to think why the AI responded effectively to being checked by rock but responded terribly to being checked by cannon. And more testing moves were made.

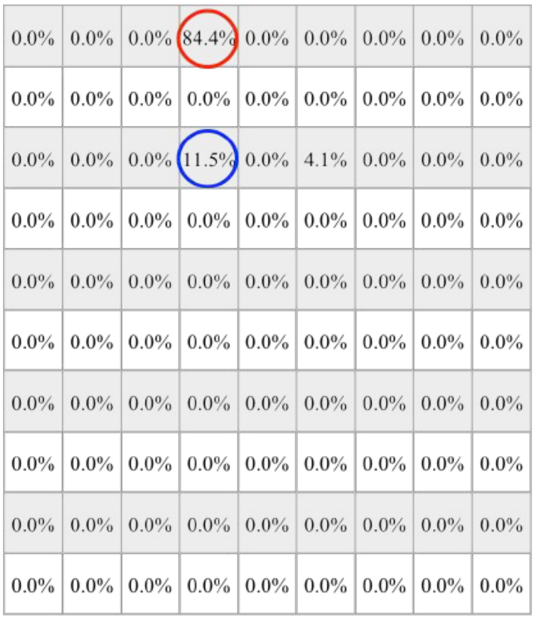


(a) Chessboard Status



0.0%	0.0%	0.0%	0.0%	5.8%	0.0%	2.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	82.2%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	4.3%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.3%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

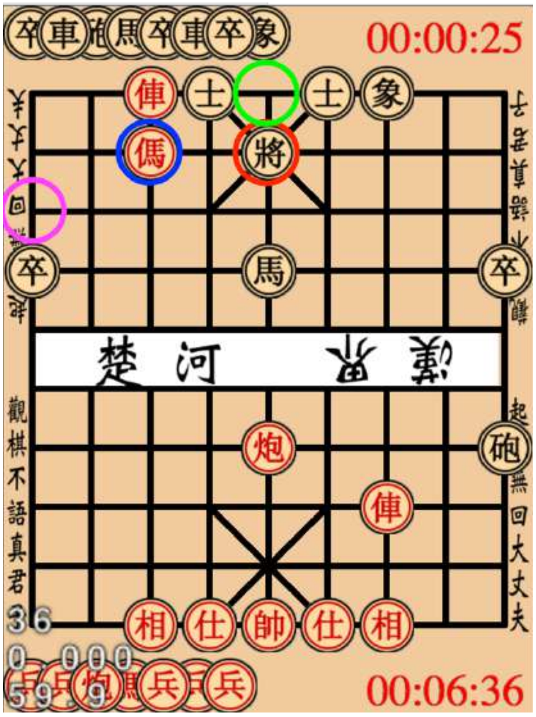
(b) Output of Piece Selector



0.0%	0.0%	0.0%	84.4%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	11.5%	0.0%	4.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

Figure 7.15.



(a) Chessboard Status

0.0%	0.0%	0.0%	0.4%	91.1%	0.3%	1.9%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.1%	0.0%	0.0%	0.0%	1.3%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.3%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

0.0%	0.0%	0.0%	0.1%	0.1%	0.8%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.1%	98.5%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.3%	0.0%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

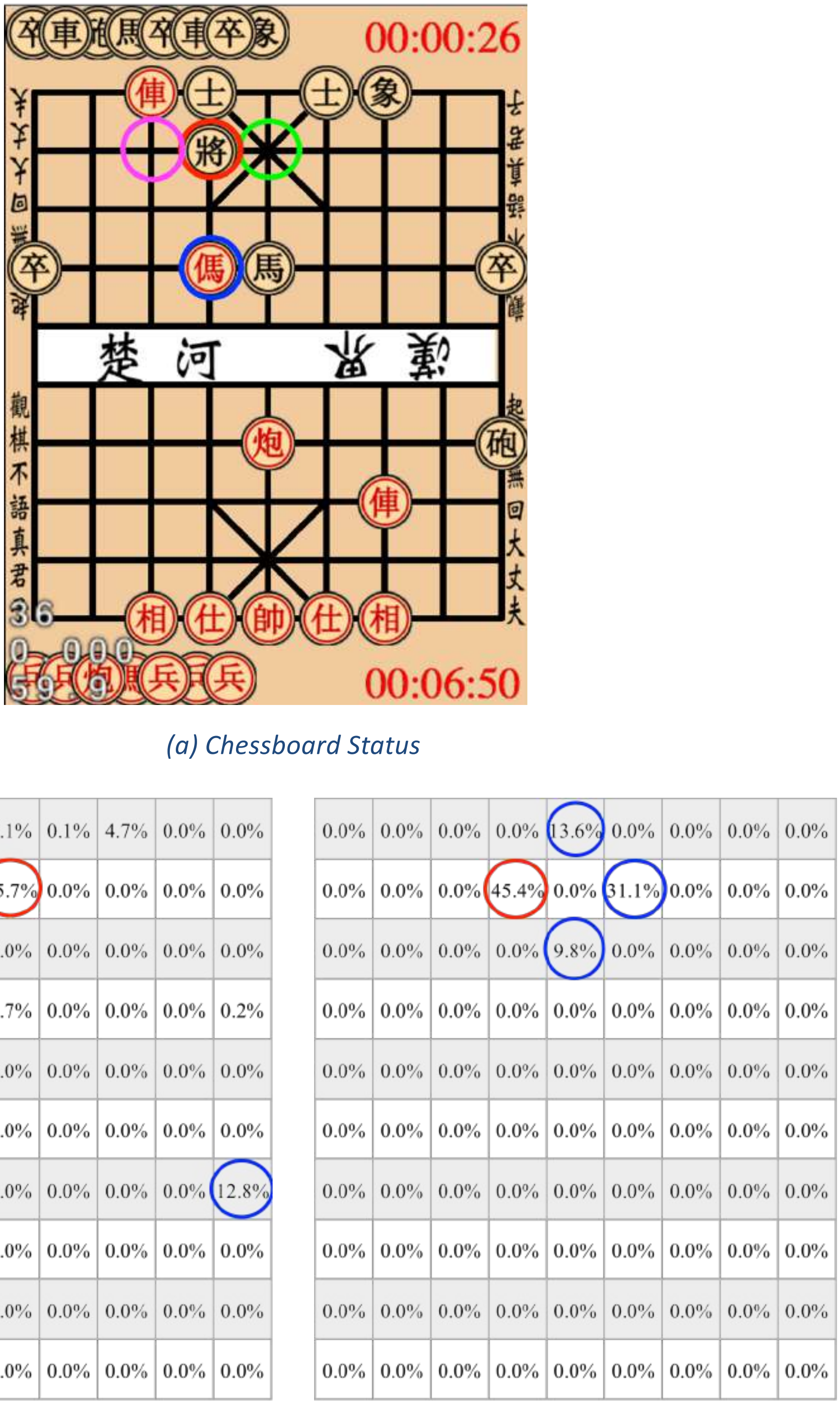
(c) Output of Move Selector

Figure 7.16.

In this turn, we chose to use the red knight to check the black side, moving it from purple cycle to blue cycle. Surprisingly, the AI chose to move the black king forward to avoid being attacked by the red knight, as shown in Figure 7.16. (a), with 91.1% possibility given by Piece Selector and 98.5% possibility given by Move Selector, as shown in Figure 7.16. (b) & (c), which indicated that the AI was almost 100% sure about this move. So, in this move, the AI also performed quite good.

However, the AI still did not respond to being checked by the red cannon. After all, it could choose to move the black knight downward, to protect the king from being attacked by both the red knight and the red cannon.

Again, we continued to use the red knight to check the black side, and the AI also responded well and moved the black king left, with 75.7% possibility given by Piece Selector and 45.4% possibility given by Move Selector, as shown in Figure 7.17.. Eventually, it escaped from being checked by the red cannon. But obviously, it was not due to that the AI realized it was checked by the red cannon. It was just a coincidence.



(a) Chessboard Status

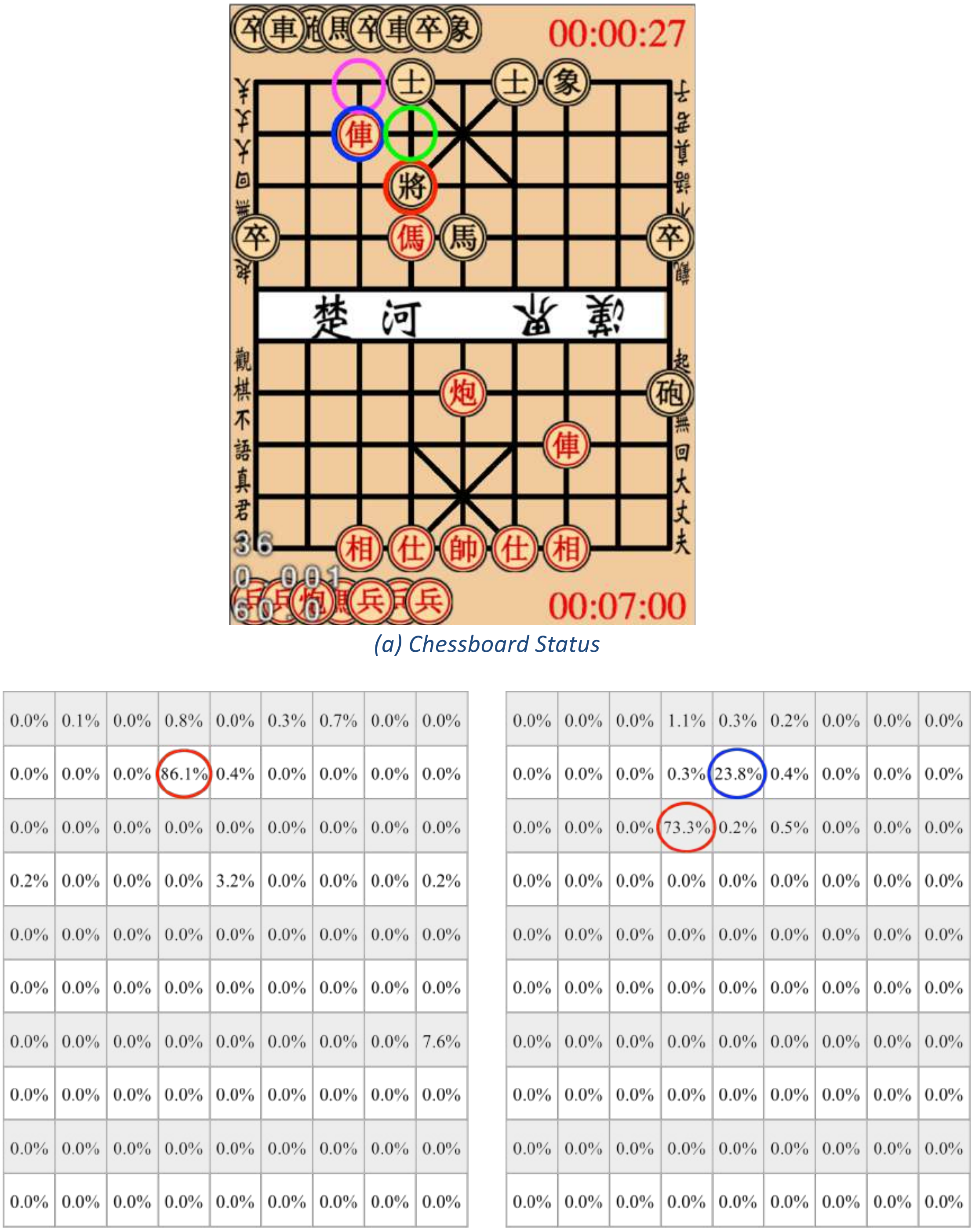
0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	4.7%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	75.7%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.3%	0.0%	0.0%	0.0%	5.7%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	12.8%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

0.0%	0.0%	0.0%	0.0%	13.6%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	45.4%	0.0%	31.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	9.8%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

Figure 7.17.



(a) Chessboard Status

0.0%	0.1%	0.0%	0.8%	0.0%	0.3%	0.7%	0.0%	0.0%
0.0%	0.0%	0.0%	86.1%	0.4%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.2%	0.0%	0.0%	0.0%	3.2%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.6%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

0.0%	0.0%	0.0%	1.1%	0.3%	0.2%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.3%	23.8%	0.4%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	73.3%	0.2%	0.5%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

Figure 7.18.

After that, we moved the red rock backward, from the purple cycle to the blue cycle, and checked the black side again. This time, the AI chose to move the black king forward again, as shown in Figure 7.18. (a), to escape from being attacked by the red rock and avoid from being attacked by the red knight at the same time, with 86.1% possibility given by Piece Selector and 73.3% possibility given by Move Selector, as shown in Figure 7.18. (b) & (c). Up to this point, the AI had responded well to being checked by the red rock and the red knight, twice for each. So, we came up with a hypothesis that the AI could respond well if it is checked in a shorter distance, but cannot perform reasonably if it is checked in a longer distance.

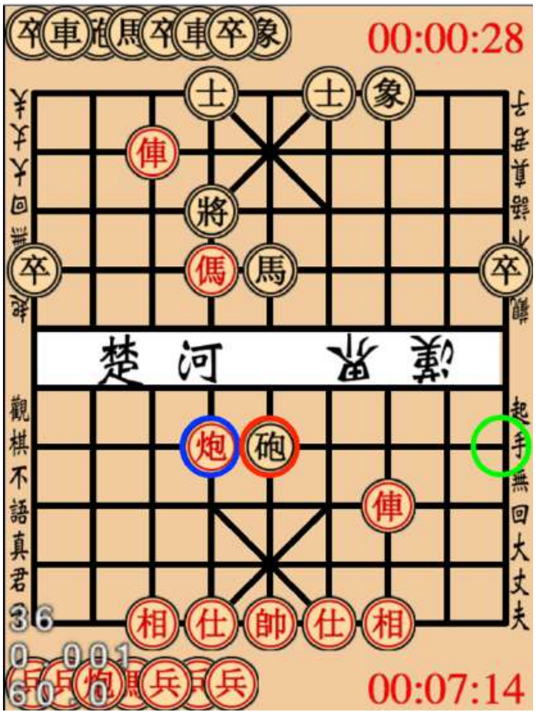
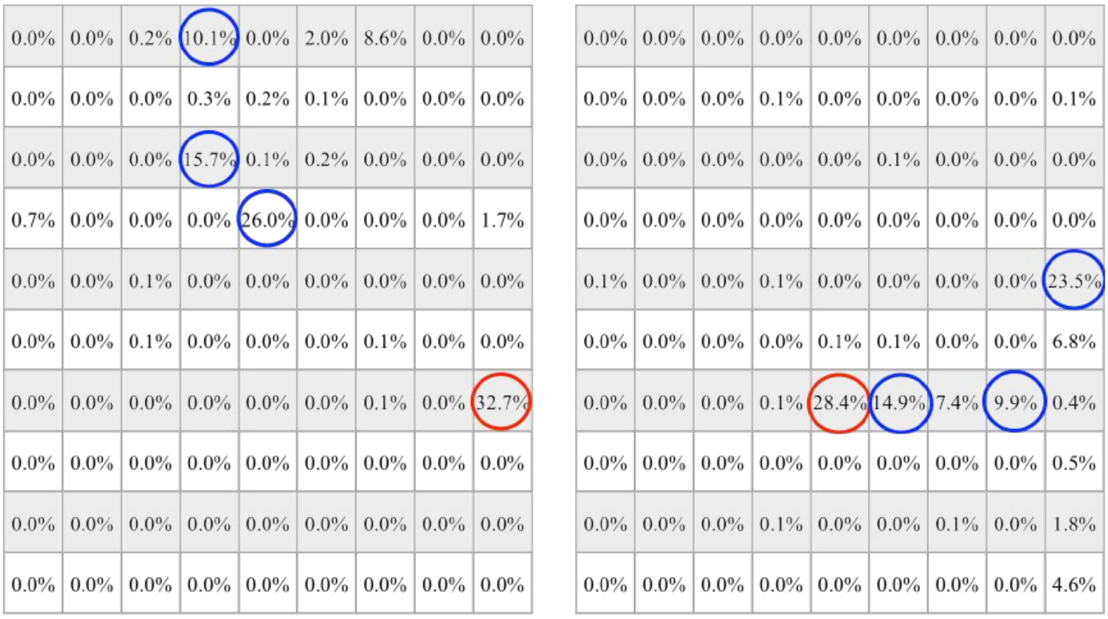


Figure 7.19. (a) Chessboard Status



0.0%	0.0%	0.2%	10.1%	0.0%	2.0%	8.6%	0.0%	0.0%
0.0%	0.0%	0.0%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	15.7%	0.1%	0.2%	0.0%	0.0%	0.0%
0.7%	0.0%	0.0%	0.0%	26.0%	0.0%	0.0%	0.0%	1.7%
0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	32.7%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

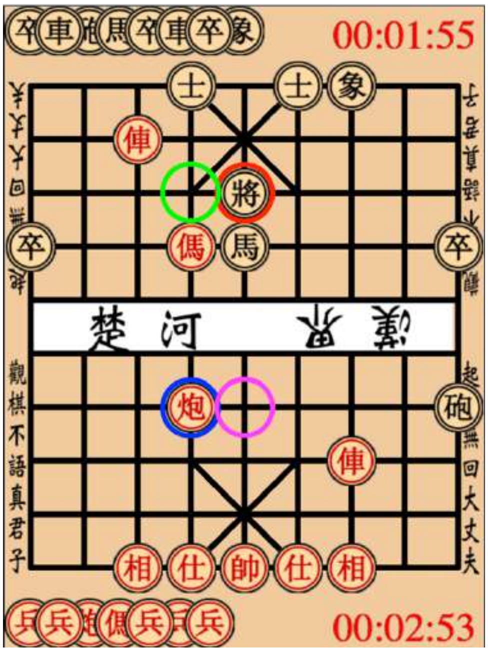
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	23.5%
0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	6.8%
0.0%	0.0%	0.0%	0.1%	28.4%	14.9%	7.4%	9.9%	0.4%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%
0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	1.8%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.6%

(c) Output of Move Selector for the Cannon

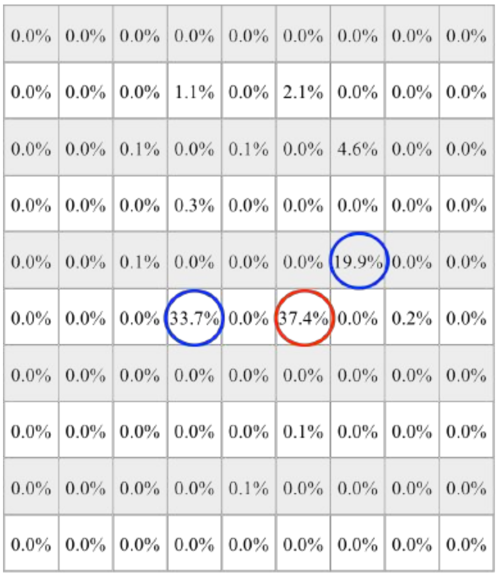
Figure 7.19.

To prove our own hypothesis, we chose to move the red cannon to check the black side again, from purple cycle to the blue cycle. As expected, the AI did not perform well and did realize that it was being checked. It chose to move the black cannon from the green cycle to the red cycle, as shown in Figure 7.19. (a). But we noted that the possibility of this move was not clearly better than other choices, as Piece Selector only gave it 32.7% possibility but also gave other pieces 26.0% and 15.7% possibilities respectively, as shown in Figure 7.19. (b).

Therefore, we decided to apply the other selection strategy again, which would consider the possibilities given by Piece Selector and Move Selector together. By this selection strategy, the AI chose to move the black king right, from the green cycle to the red cycle, as shown in Figure 7.20. (a), so that it successfully escaped from being checked by the red cannon and avoid from being attacked by the red rock and red knight at the same time. Using this selection strategy, the AI performed much better in this situation and even responded well to being checked by the cannon in longer distance.

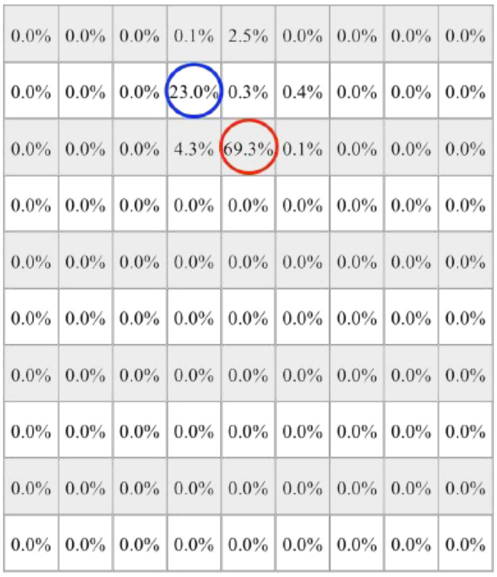


(a) Chessboard Status



0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	1.1%	0.0%	2.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	4.6%	0.0%	0.0%
0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	19.9%	0.0%	0.0%
0.0%	0.0%	0.0%	33.7%	0.0%	37.4%	0.0%	0.2%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Move Selector for the Knight

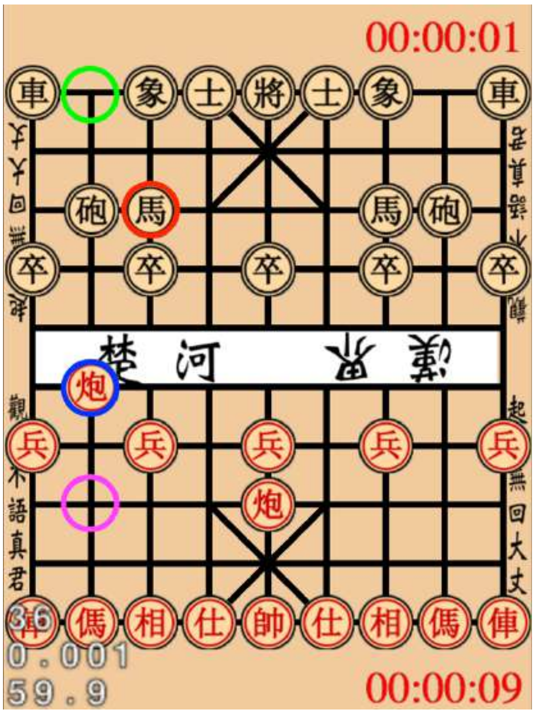


0.0%	0.0%	0.0%	0.1%	2.5%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	23.0%	0.3%	0.4%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	4.3%	69.3%	0.1%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

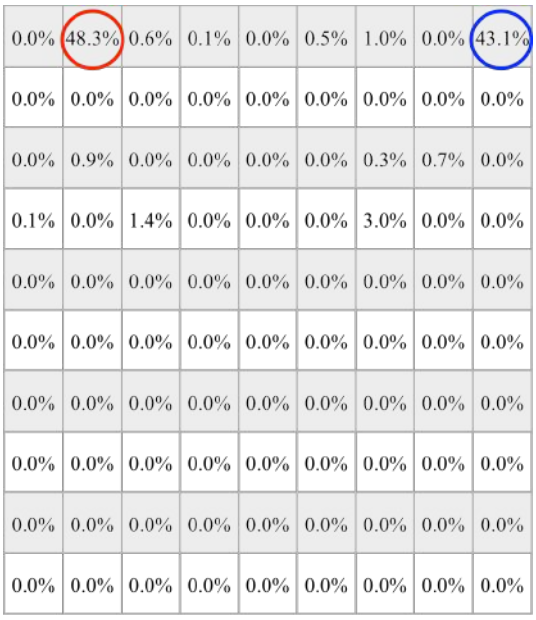
(c) Output of Move Selector for the King

Figure 7.20.

7.2.6. Game-Playing Case 6

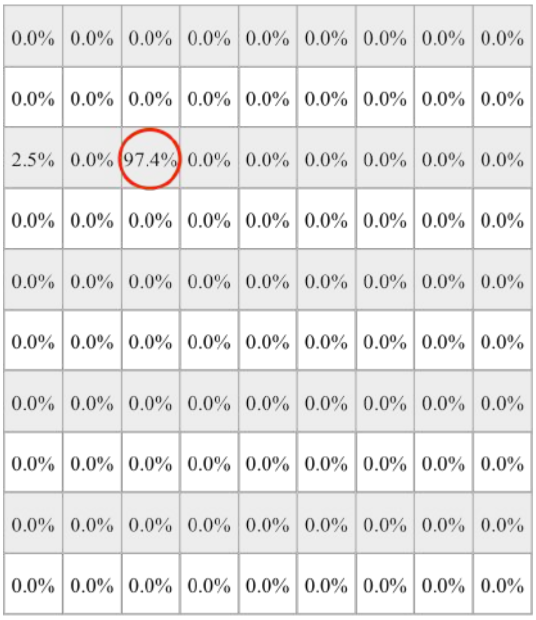


(a) Chessboard Status



0.0%	48.3%	0.6%	0.1%	0.0%	0.5%	1.0%	0.0%	43.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.9%	0.0%	0.0%	0.0%	0.0%	0.3%	0.7%	0.0%
0.1%	0.0%	1.4%	0.0%	0.0%	0.0%	3.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector



0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2.5%	0.0%	97.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

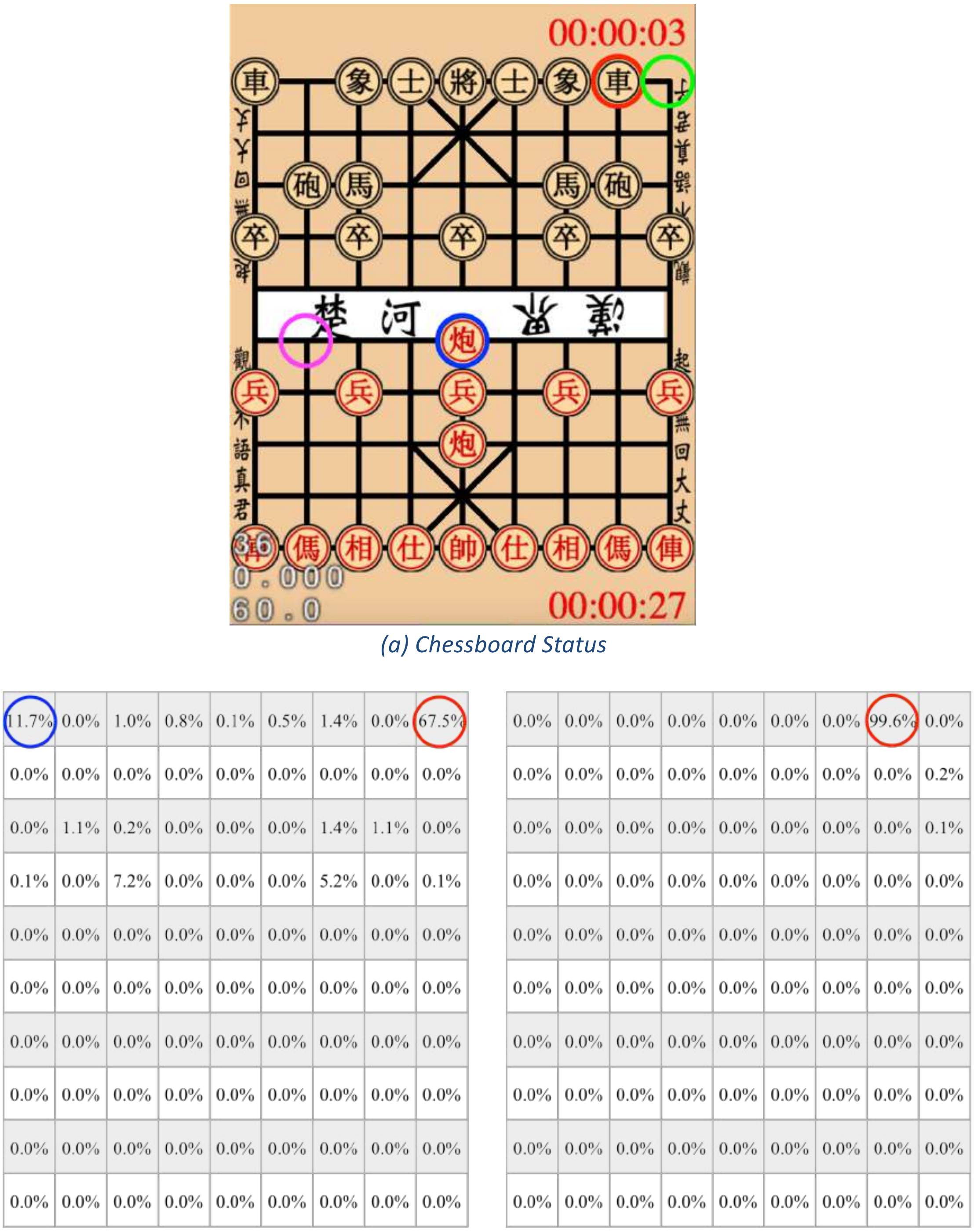
Figure 7.21.

This is another example where AI performed bad. We noted that in the game records we collected for model training and testing, the most common opening moves were roughly always to move one cannon to the middle, move one knight forward and then move one rock out. So, we used another very common opening way which was seldom used in professional competitions since it was not that effective actually.

Here, we moved one red cannon to the middle and then moved anther cannon forward, from the purple cycle to the blue cycle. And the AI seemed still to follow the fixed opening way, move the black knight first, with 48.3% possibility given by Piece Selector and 97.4% possibility given by Move Selector, as shown in Figure 7.21.. It is still fine up to this point.

In next turn, we moved the another red cannon to the middle as well, from purple cycle to the blue cycle, also known as “双炮将”. However, the AI chose to move the black rock out, from the green cycle to the red cycle, with 67.5% possibility given by Piece Selector and 99.6% possibility given by Move Selector, as shown in Figure 7.22..

Indeed, the AI still stuck to the most common fixed opening moves, but did not respond well to being checked by the cannon again. This time, even after we used the second selection strategy, the AI still made the same choice.



(a) Chessboard Status

11.7%	0.0%	1.0%	0.8%	0.1%	0.5%	1.4%	0.0%	67.5%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	1.1%	0.2%	0.0%	0.0%	0.0%	1.4%	1.1%	0.0%
0.1%	0.0%	7.2%	0.0%	0.0%	0.0%	5.2%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(b) Output of Piece Selector

0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	99.6%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

(c) Output of Move Selector

Figure 7.22.

One important reason is that this situation has never appeared in our training dataset as it has seldom happened in realistic professional Chinese chess competitions. So, in this aspect, the result is acceptable but still not satisfying.

Another issue is that the AI could not respond well to being checked by cannon, or more generally, being checked by pieces in long distance. This may be due to that the training dataset is not larger enough, or more likely, due to that the CNN in Piece Selector and Move Selector is not deep enough.

8. Discussion

In the beginning, there were two more feature channels to be extracted from the chessboard status and fed into the NN model as input, which represented some high-level information like attack-defend map and liberties of each piece. The training results, however, were not very satisfying. One possible reason would be that the values in these two feature channels could be much different from the values of other feature channels which mainly contained -1's, 0's and 1's. So, in our final model design, these channels were not included.

Although our trained models have achieved quite good accuracy, there is one issue to be further discussed. Given one certain chessboard status, there may exist different move choices even in our training dataset, as different people would apply different strategies which may all be quite good. It would affect our training results, and more importantly inspired us to encourage exploration of different choices and add randomness when deciding the move per the output of our models.

Despite the high accuracies, after we played against with our game AI to test its real behavior, it could hardly make effective responses when it was in check or it could capture the opposite King. It may be due to that in our training dataset, there is no training example where a King is captured, as our training dataset is extracted from realistic Chinese chess matches where the games would always end before that move is made. Besides, there are some cases where one player resigned in the middle of the game.

Another problem is the reaction to rarely seen chessboard statuses. The Piece selector performs well in a situation with large number of appearances in the training dataset like initial chessboard position. And it can deal with normal unseen situation if player think normally that the Neural Network can recognize those features learned from datasets. However, in some special cases that a player did a new move which never happened before, it would be a challenge to the game AI. In fact, in the 4th game of AlphaGo VS Lee Sedol, Lee's 78th move is out of AlphaGo's mind. Neither its Neural Network nor search tree had considered this move, which led to its failure. In our plan, the policy network trained by supervised learning cannot deal with the problem, which is reserved for next semester. Figure 8.1. below shows the decisive move 78 by Lee Sedol.

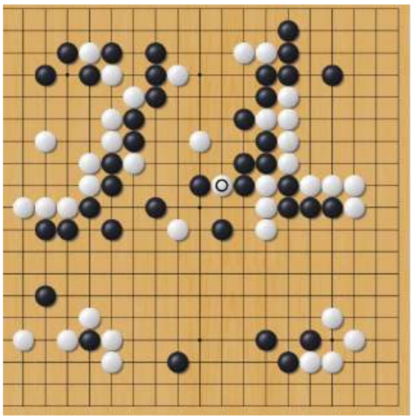


Figure 8.1. The Decisive Move 78 by Lee Sedol

In our project, the parameters of Neural Network must be carefully treated because a tiny change in these parameters can lead to different result. For instance, the size of filter is a key parameter. Applying 3*3 filters, the Neural Network had relative poor performance to detect long-distance threats from cannons and rocks. When we changed the size of fields to 5*5, the result is improved. Based on this phenomenon, we suppose that larger filters can read the global situation better because it can detect features with large size, which means it can do better in detecting long-distance moves of cannons and rocks.

9. Conclusion

As discussed in the section above, we can safely conclude that the current results of our project, i.e. the behavior of our current game AI, are within our expectation. It has learned the basic rules of Chinese chess and achieved quite high accuracy when predicting possible move choices of professional players in Chinese chess given certain chessboard statuses. And for normal situation, the move made by it is reasonable.

However, though it has high accuracy, its performance on real game is not such satisfying. For some specific situation like long-distance check from cannon, the AI may have no reaction and move some pieces irrelevantly. Also, the selection strategy will also affect the performance. A strategy combining the possibility of Piece Selector and Move Selectors would make more reasonable move when there is more than one move with close probability, while a simple strategy would choose a worse one.

In conclusion, our game engine performs well in common situation and needs to be improved to deal with special cases.

10. Plan for Second Term

In next semester, our object is to improve the performance of our game engine. And we have three major approaches to do that.

The first way is to use reinforcement learning to improve the performance of policy network. In the development of AlphaGo, the policy network with reinforcement learning played much better than previous one. We hope that by using the same method, the new network will have a good winning rate on online Chinese chess playing platform against human and cannot be distinguished as AI.

The second method is training a value network for evaluation. It will improve the speed and accuracy of searching. In this phase, we want the network to predict the winning rate of the situation on the game board correctly and consistence with humans' judgement, and it should outperform humans in situation with little difference.

Also, we need to implement a searching strategy combining the result from both neuron networks. In our plan, MCTS may be a better choice rather than minimax. And use it to find the best move as final output.

With these improvements, we will test our game engine against free and commercial Chinese chess engine, and use the winning rate to calculate the level of it. We hope that our AI can achieve a high-level competency in

Chinese chess. In our expectation, our game engine should have better performance on opening phase comparing to those AI without opening libraries. And for whole game, if the searching depths are same, it should play slightly better because the evaluation of neural network is more flexible than hard-code evaluation function.

11.Reference

[1] Edwards, S. J. (1994). Portable Game Notation Specification and Implementation Guide.

[2] Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2012). Foundations of machine learning. MIT press.

[3] Geman, S., Bienenstock, E., & Doursat, R. (1992). Neural networks and the bias/variance dilemma. Neural computation, 4(1), 1-58.

[4] James, G. M. (2003). Variance and bias for general loss functions. Machine Learning, 51(2), 115-135.

[5] Nielsen, M. (2016). Neural Networks and Deep Learning

[6] Hahnloser, R. H., Sarpeshkar, R., Mahowald, M. A., Douglas, R. J., & Seung, H. S. (2000). Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit. Nature, 405(6789), 947-951.

[7] Anzai, Y. (2012). Pattern Recognition & Machine Learning. Elsevier.

[8] [Online]. Available: https://www.tensorflow.org

[9] [Online]. Available: https://github.com/leenmie/chinese-chess

[10] Oshri, B., & Khandwala, N. Predicting Moves in Chess Using Convolutional Neural Networks.

[11] Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., ... & Dieleman, S. (2016). Mastering the Game of Go with Deep Neural Networks and Tree Search. Nature, 529(7587), 484-489.

[12] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. Nature, 521(7553), 436-444.

[13] Lai, M. (2015). Giraffe: Using Deep Reinforcement Learning to Play Chess. arXiv preprint arXiv:1509.01549.

[14] O'Shea, K., & Nash, R. (2015). An Introduction to Convolutional Neural Networks. arXiv preprint arXiv:1511.08458.

[15] Schmidhuber, J. (2015). Deep Learning in Neural Networks: An Overview. Neural Networks, 61, 85-117.

[16] [Online]. Available: https://en.wikipedia.org/wiki/Convolutional_neural_network

[17] [Online]. Available: https://en.wikipedia.org/wiki/Supervised_learning

[18] Tromp, J. (2016). Number of legal Go positions. preprint http://homepages cwi.nl/tromp/go/legal. html.