PriMera Scientific Engineering
Volume 6 Issue 6 June 2025
ISSN: 2834-2550

Proposal for a New Evaluation Index for Human Fallibility in Shogi

Type: Research Article
Received: April 30, 2025
Published: May 28, 2025

Citation:
Kazushi Mizuta., et al. "Proposal for a New Evaluation Index for Human Fallibility in Shogi". PriMera Scientific Engineering 6.6 (2025): 08-18.

Kazushi Mizuta*, Tetsuhiko Kinebuchi and Takeshi Ito

The University of Electro-Communications, Chofu Tokyo, 1828585, Japan

***Corresponding Author:** Kazushi Mizuta, The University of Electro-Communications, Chofu Tokyo, 1828585, Japan.

Abstract

This paper proposes a new evaluation index for evaluating human fallibility in shogi. By analyzing the differences between the decision-making processes of AI and humans, we found that while humans rely on intuition and decisions made within a limited timeframe, AI often makes different decisions because it carries out exhaustive searches. In this study, we developed a new evaluation index that extracts features prone to human error using a policy network trained based on professional game records. This evaluation model uses logistic regression to predict the probability of making a mistake in the endgame. We have shown that the proposed indicator is effective through testing with test data. In the future, we plan to construct similar evaluation indicators for the opening and middle game phases and verify their effectiveness.

Keywords: Shogi AI; Human Fallibility; Policy Network

Introduction

In research on games, chess-like games such as Shogi and Chess have been a central theme in artificial intelligence. In the field of shogi, AI began to win against professional shogi players in the early 2010s. In 2017, the shogi software "ponanza" and then Meijin Amahiko Sato played two games. As a result, ponanza won the two games, showing that Shogi AI can surpass humans. Since then, shogi AI has been getting stronger and stronger every year, so much more vital that it far exceeds the top human players.

Shogi AI has come to be recognized for its capabilities, and in recent years, there has been a growing movement to take advantage of its power. Many top professional shogi players active in the title tournaments use Shogi AI for their research. Also, it has become commonplace to show AI's thoughts on live game broadcasts. It is not uncommon for humans to feel discomfort with the evaluation values and win rate. Even if the AI judges that one of the players will win, from a human point of view, the game is challenging to solve, and even professional Shogi players often fail to make the best moves and lose the game.

Figure 1 shows the game between Yoshiharu Habu 9-dan and Masayuki Toyoshima, the then Ryuoh, on December 25, 2020, at the Class A Ranked Tournament, in which the game was played on move 129. The ABEMA Shogi Channel's Shogi AI, which was broadcasting the game, showed Habu 9-dan's winning rate at 94%, but at this point, Habu 9-dan resigned and lost the game in a significant upset. In this position, if the player plays ▲+B 8c, ▽Nx8c, ▲Gx7h, he will win if he does not make a mistake in a series of long moves. However, these changes are so varied that it is almost impossible for a human not to make a mistake when the time limit is one minute.

Figure 1: The position in which the AI rated the game as winnable, but the human resigned.

We believe that this discomfort with the Shogi AI's evaluation values and reading moves may be due to the difference in how the AI and humans decide which move to make. Ito investigated the difference in the way Shogi AI and humans decide which move to make and showed that while humans try to find the best move within a limited search range by narrowing down candidate moves and performing linear anticipation based on intuition, Shogi AI conducts an exhaustive search to determine the next move [1]. While humans have excellent intuition and can efficiently anticipate a long sequence of moves ahead, they may ignore moves that deviate from their intuition. On the other hand, Shogi AI can evaluate moves that are even off-intuitive to humans because it performs a comprehensive move-ahead. This may be why humans feel uncomfortable with Shogi AI moves.

Moves that are difficult for humans to play in the limited thinking time humans can process may be neglected and overlooked. We hypothesize that complex moves for humans to play in the limited thinking time available for human processing may be downplayed and ignored. Humans may be more likely to make mistakes if the moves have high AI evaluation values but are contrary to human intuition.

Therefore, this study will use a policy network learned from human game records to express moves humans can select as move probabilities. This collaborative approach, involving both human and AI decision-making, will be the basis for our proposed index to evaluate the moves in which humans are more likely to make mistakes.

In recent years, AI outperforming humans has begun to appear, and systems supporting our actions have also emerged. For example, an AI-based driving support system not only conveys AI decisions but also has the potential to prevent accidents by indicating human-specific errors that humans tend to overlook. This research is thought to lead to the possibility of such AI applications.

Mistake-prone positions in Shogi

Ito's unique approach involved comparing the thinking methods of human professional players and Shogi AI and investigating the characteristics of their thinking [1]. He had amateur players, professional players, and a then-prominent program solve a next-move problem and then examined the programs' thought logs and the professional players' speech data. His findings revealed that the computer made an exhaustive look-ahead from the given position and calculated the move based on the search result. In contrast, humans instantly narrowed down candidate moves to a few by intuition based on their experience and knowledge and then decided which move to make by linear search from a limited number of candidate moves. This suggests that humans narrow down the possible candidate moves and perform anticipation due to their difficulty in exhaustive searches. The question then arises: could the move probability by a policy network that learns human moves using a convolutional neural network be used to simulate this process?

Imahashi et al. proposed one solution to humans' discomfort with the win rate indicated by a Shogi AI [2]. They introduced a new evaluation index for gameplay close to human values. To develop this index, they analyzed the characteristics that make humans prone to making mistakes and studied the games in which top professional players made mistakes. From this analysis, they extracted five factors that could be related to human errors.

- Variation of the evaluation value depends on the depth of the search.
- Changes in the best move depending on the depth of the search.
- The existence of multiple promising moves.
- Remaining time.
- Number of legal moves.

Imahashi et al. proposed a new index that is a linear sum of these characteristics with appropriate weights. Then, to verify whether this index can discriminate the game where human players are prone to make mistakes, they conducted an evaluation experiment where top professional Shogi players made mistakes. As a result, we suggested that this index tends to be higher in the games where professional Go players make mistakes. We also showed that the five features used in the index are valuable in extracting the games in which they are likely to make mistakes.

In this study, we aim to propose a better indicator by using these features, the new features, and the output of the policy network described earlier.

Predictor of professional players' moves

Purpose

Using a convolutional neural network (hereafter, CNN), we construct a predictor that predicts the moves played by a professional Shogi player with as high a probability as possible by building a policy network using the professional Shogi player's game record as the teacher data.

Method

Here, CNN is used to train a policy network that predicts the pointing moves. The output is the pointing probability of each legal move (hereafter, the pointing probability by production is referred to as "policy"). By learning the actual game records of professional players as teacher data, the policy network outputs the pointing probability of each legal move and, by using these values, mimics the narrowing of professional players.

In learning, we referred to the book by the developer of "dlshogi," which won the 32nd World Computer Shogi Championship [3]. The game records used for training were all official games from 1976 to 2020 provided by the Japan Shogi Federation. However, we excluded the games that ended in ways other than "resignation, thousand day move, or declared win" (e.g., foul win/loss) because we considered their particular games. In addition, KIF files were converted to CSA files using the Shogi application "Electron Shogi" (now "ShogiHome") to create files for training [4]. The training data used was 11678287 positions (103196 games) and 1291209 positions (11491 games) for testing data. A total of 100 epochs were trained.

Evaluation for overlearning

Figure 2 shows the evolution of the cross-entropy error for the test data. The horizontal axis indicates the number of steps, and the vertical axis shows the value of the cross-entropy error.

Figure 2 shows that the value of loss for the test data is decreasing with the same trend as that for the training data. Therefore, we believe that overlearning should not occur.

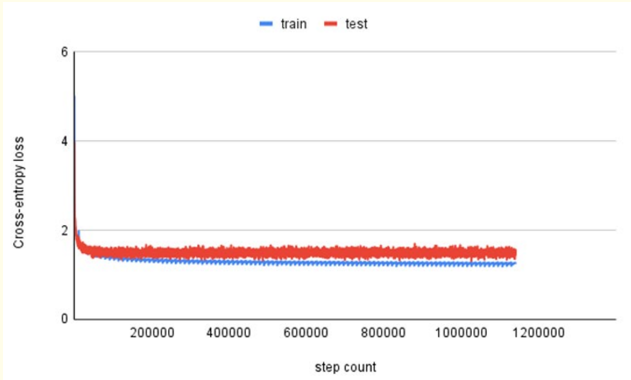


Figure 2: Transition of cross-entropy error.

To verify the validity of the output policies, we compared the agreement rate between the moves corresponding to the largest policy value of the position against the test data and the actual moves. As a result, the model learned for 100 epochs showed the most considerable agreement rate of 53.2%. Furthermore, we measured the agreement rate of the 100-epoch learned model in 20,000 randomly selected games from the test data and the percentage of actual moves in the top three positions of the policy (hereafter referred to as the "inclusion rate"). The results showed that the agreement rate was 52.2%, and the inclusion rate was 80.1%. These values exceeded the agreement and inclusion rates (50.0% and 78.1%, respectively) of the moves made by advanced human players using a move predictor that takes "flow" into account, as proposed by Kinebuchi et al. The agreement and inclusion rates from the trained model accompanying the book used as a reference were 49.7% and 79.2%, respectively. This model uses a game record superior to that of a professional player for training and is therefore considered to output a player's move probability superior to that of a professional player. Since the created model outperformed this model in both agreement and inclusion rates, it is considered less likely to predict powerful moves than professionals. Based on the above results, we believe that the 100-epoch learning model is a predictor that can predict professional players' moves with a reasonably high probability.

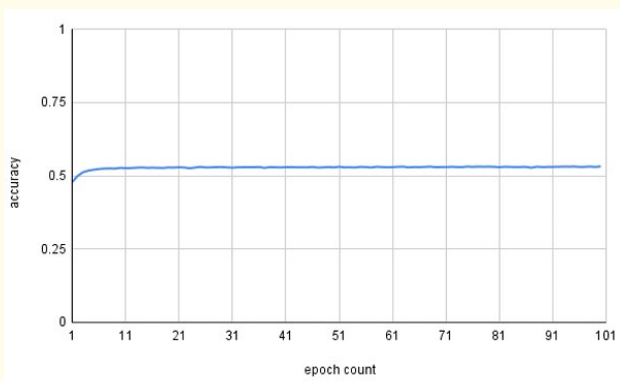


Figure 3: Transition of the agreement rate to the number of epochs.

Figure 3 shows the transition of the agreement rate between the moves corresponding to the largest policy value in the test data and the actual game moves for each epoch of the learning model. Since the agreement rate is almost saturated, we decided to use the 100-epoch learning model from now on.

Analysis using actual game records

Purpose

The purpose here is to extract wrong moves from professional Shogi players' actual game records and to look for valuable features for the index.

Definition of wrong moves and loss of winning rate

In this section, as a criterion for determining mistakes, we assume that the correct move is the move of a Shogi AI that outperforms humans. This study will use "Suisho 5" as that Shogi AI [6]. "Suisho 5" is an improved version of 'Suisho 4,' which won the 2nd Denryu Sen TSEC and is considered to be at a level that sufficiently outperforms humans.

Shogi AI outputs evaluation values using an evaluation function to judge whether the position is good or bad. Still, we calculated the degree of error by losing the estimated win rate before and after the pointing move. The reason for not using the loss of evaluation value is that there are cases in which the impact of a mistake differs even for the same difference in score. For example, an error with a loss of 1000 points, such as going from a 0-point game to a -1000-point game, can have a significant impact on the win or loss, while a mistake with a loss of 1000 points, such as going from a 5000-point game to a 4000-point game, still leaves the player ahead. The impact of the mistake is considered small. By using the difference in winning rate, we could express this in a way that was easy to understand regarding the impact on winning and losing.

The following sigmoid function was used to calculate the win rate. The input is the evaluated value, the output is the estimated winning rate, and a is a constant.

$$f(x) = \frac{1}{1 + e^{-ax}}$$

We decided the loss of win rate using the following equation. The x_{before} is the evaluation value before the move, and x_{after} is the evaluation value after the move.

$$loss\ of\ win\ rate = f(x_{before}) - f(x_{after})$$

There are various theories about the value of the constant a. However, we will use the most famous Ponanza constant (a = 1/600). This constant was determined statistically by having two players of similar game strength play from a specific rating to the end of the game. We decided to use this constant in this study.

ShogiGUI" is used to analyze the game record [7], and the evaluation value and the reading of candidate moves in each game can be obtained on ShogiGUI. We decided to use the concept of "superior position " for convenience. However, the evaluation value is not output when the move sequence of the checkmate is found. The superior position is where the captured pieces increase unilaterally, even though positions on the board are the same. In this case, the value was set to 31111 points to break the reading [8]. When the move sequence of the checkmate is found, we put the evaluation value at this time to 1 greater than the "superior position" evaluation value.

Features to be associated with mistakes using policies

The following features and these related hypotheses were developed to explain the relationship between the output of the policies created by the learning model and human fallibility.

<Feature 1> Policy value for the best move indicated by Suisho 5

When the value of Feature 1 is small, the best move at the position is considered difficult.

<Feature 2> The value of the largest policy at the position.

When the value of Feature 2 is small, it is considered a position with multiple candidate moves, and the player is still determining the best move to make.

<Feature 3> The product of features 1 and 2

When the value of feature 2 is small, the difference between features 1 and 2 is large, i.e., there are more attractive moves than the best move.

Since features 1 and 2 are real values between 0 and 1 and feature 2 has a value greater than or equal to feature 1, the more significant the difference between features 1 and 2, the smaller the value of feature 3. To test these hypotheses, we analyzed official professional game records.

Analysis of the game records of Meijin A-rank league

The Meijin A-rank league is a league of 10 top professionals that determines the challenger to Meijin, the most famous title game in Shogi. Here, we analyzed 57670 positions from the 69th to the end of the 79th season (2020), excluding the final positions of the game end.

The analysis condition was 10 million node searches per move using Suisho 5. The win rate that decreases with each move is called the loss of win rate. Here, we classified the stations using the win-loss due to moves as a threshold and obtained the average value of the features above. Table 1 shows the results for the games with a loss of 10% or more, and those with a loss of less than 50%, and Table 2 shows the results for the games with a loss of 50% or more and those with a loss of less than 50%.

	Win-loss ≥ 0.1	***Win-loss< 0.1***
Feature 1	0.186	0.393
Feature 2	0.461	0.599
Feature 3	0.100	0.284

Table 1: Results when the threshold for loss of winning percentage was 10%.

	Win-loss ≥ 0.5	***Win-loss< 0.5***
Feature 1	0.182	0.395
Feature 2	0.440	0.593
Feature 3	0.102	0.277

Table 2: Results when the threshold for loss of winning percentage was 50%.

In both Tables 1 and 2, the value of each feature differed between the positions in which mistakes resulted in a win-loss greater than the threshold and the positions in which mistakes were not made. Based on these results, we believe the hypothesis may be correct.

Proposed index using logistic regression

A model was created using logistic regression to output the probability of a mistake occurring in the endgame with a win-loss of 30% or more. Logistic regression makes it possible to predict the likelihood of an event occurring by using several explanatory variables. This model was created using the game records of Meijin A-rank, B-rank, and C-rank from the 78th to the end of the 79th season (2020) and the NHK Cup from 2015 to the end of 2020. In training, label 1 and label 0 data were split into training and test data in the 80% and 20% ratio, respectively. We used 13 explanatory variables, including Feature 1 and the number of legal moves in the position. The explanatory variables and their coefficients were those listed in Table 3.

Difference in win rate due to difference in number of search nodes	0.284
Change in candidate moves due to difference in number of search nodes	-0.170
Number of total turn	-0.157
Number of legal moves	0.255
Number of check legal moves	0.451
Consumption time (m)	-0.341
Maximum difference in win rate between 5 candidate moves	0.905
Difference in win rate between best move and next best move (Feature 4)	-0.594
Feature 1	-0.409
Feature 2	0.00694
Feature 3	-0.632
(1 -Feature 1) ×Feature 4	0.627
Feature 1×policy of the third move in best move's reading	-0.630
Intercept	-6.12

Table 3: Coefficients of each explanatory variable.

An example of using the model is described. Figure 4 shows the endgame of an actual game in which a mistake with a winning rate loss of 30% or more occurred. The player's turn is the second move turn.

Figure 4: A position in which a mistake with a winning rate loss of 30% or more occurred.

The correct move was ▽S*8h, but the player made the move ▽Lx9f in the actual game. The move of ▽S*8h is a move that has many changes, even if it is taken or escaped, and it also uses pieces with a high value. The ▽Lx9f is a move that takes advantage of the strength of the rook but also disrupts the defensive pieces, so it isn't easy to make the correct move.

Using the model, the probability of a mistake resulting in a loss of 30% or more was 8.10% for the position shown in Figure 4. The average probability of a mistake occurring in all test data was 0.998%. This indicates that the model can predict that this position is much more error-prone than the average. Out of the nine error-prone positions in the test data, the model accurately predicted eight with an error probability exceeding 0.998% (see Appendix). These findings suggest the practicality of the model in predicting error-prone positions.

Conclusion and future works

In this report, we proposed an index using logistic regression in the "endgame." The results suggest that this index may be effective. We will also create indexes using logistic regression in the "opening game" and "mid-end game." We will evaluate the validity of these indexes using actual game records and subjective evaluation by amateurs with high dan or higher.

This time, we tried constructing a prediction index by building a policy network using a professional player's game record, which is relatively close to the top level, as the training data. However, professional players make very few mistakes, so they may not be suitable as a target for creating a prediction model for errors. Therefore, in the future, we will construct a policy network model that predicts moves using amateur players' game records and create a probability index of the occurrence of amateur players' mistakes. Then, we propose a more affluent index to predict mistakes by evaluating the same position using the probability index of professional players' errors and the probability index of amateur players' mistakes.

Acknowledgments

We want to thank the Japan Shogi Federation for providing the game record database for a fee.

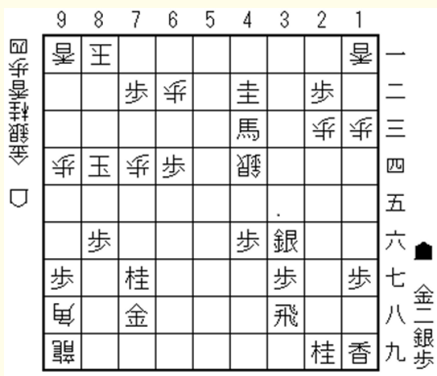
References

1. Ito T. "Thinking of Computers vs. Professional Players -Contemporary and Future of Computer Shogi". Journal of Information Processing Society of Japan 48.12 (2007): 4033-4040. in Japanese
2. Imahashi H and Ito T. "A Proposal of a New Position Evaluation Index in Shogi that Close to the Human Sense of Value". IPSJ SIG Technical Report GI-51.2 (2024): 1-9. in Japanese
3. Yamaoka T and Kanou K. "How to Create Strong Shogi Software - Deep Learning Shogi AI Implemented in Python". Mynavi Publishing Inc (2021). in Japanese
4. ShogiHome. https://sunfish-shogi.github.io/electron-shogi/
5. Kinebuchi T and Ito T. "A Method to Improve the Agreement Rate with Human Moves in Shogi by Considering the Flow". Journal of Information Processing Society of Japan 58.9 (2010): 1549-1554. in Japanese
6. Suisho 5. https://drive.google.com/file/d/1T-Go2KImMfKD_4m_j4fQFXrEfaGgAcS_/view
7. ShogiGUI. http://shogigui.siganus.com
8. What is the evaluation value 31111 output by the Shogi software?. https://yaneuraou.yaneu.com/2022/06/03/evaluation-value-31111/

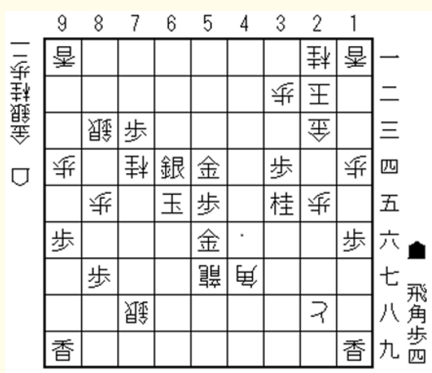
Appendix

The output of the index in the position in which a mistake was made in the endgame.

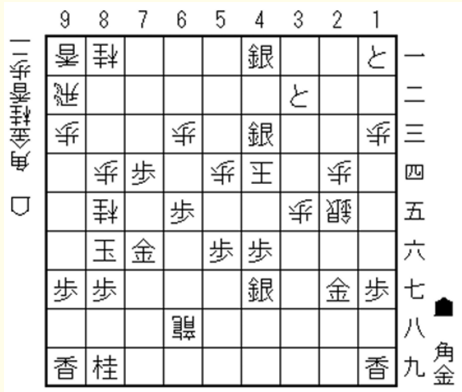
Probability of error occurrence: 1.68% (1st move turn).



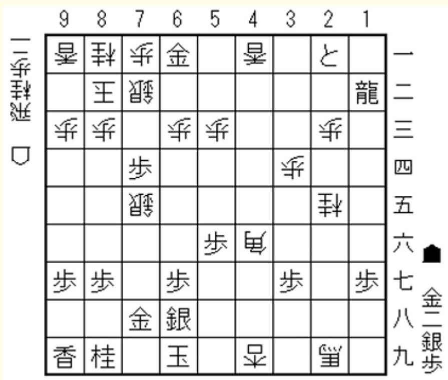
Probability of error occurrence: 12.6% (2nd move turn).



Probability of error occurrence: 6.32% (1st move turn).

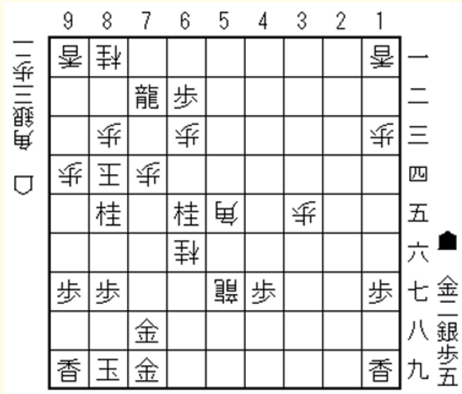


Probability of error occurrence: 0.939% (1st move turn).

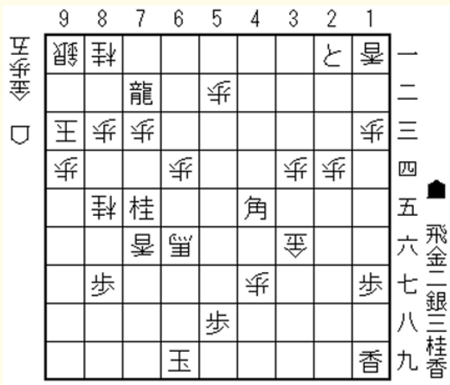


Probability of error occurrence: 4.60% (1st move turn).

Probability of error occurrence: 8.66% (2nd move turn).



Probability of error occurrence: 1.80% (1st move turn).



Probability of error occurrence: 1.40% (2nd move turn).