Learning-Support Method for Professional Shogi Players Using Emotions of Others

Takeru Isaka and Iwaki Toshima
NTT Digital Twin Computing Research Center, Tokyo, Japan

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Abstract: Many methods have been proposed to support learning optimized for each learner. However, these methods mainly target novice to intermediate learners. We propose a method for further improving the abilities of advanced learners and professionals. At the advanced and higher levels, learners often target the behavior of more competent others. However, it is difficult to acquire the skills of such others simply by observing their behaviors. A learner must understand the thought processes to arrive at their behavior. Knowing the emotions that lead others to their behaviors could help learners understand others' thought processes. On the basis of this approach, we investigated a learning-support method that uses the emotions of others using Japanese chess (Shogi) as the subject. We obtained valences, arousals, and subjective-position scores (i.e., evaluation of whether black or white has an advantage for each position) for each move of Shogi from two professional Shogi players with different playing styles. We observed noteworthy gaps in valence and arousal between the two players, even with similar subjective-position scores. The players also gained new perspectives on complex moves by referring to each other's emotions. This suggests that awareness of the emotional gaps with others can broaden a professional's creativity.

1 INTRODUCTION

It is challenging for someone who has already reached the top to further advance, regardless of the competition, art, or industry in which they excel (Yelle, 1979; Argyris, 2002). Most learning-support methods are targeted at novice to intermediate individuals. The basic way for advanced individuals to further improve is through the learners' self-help efforts. We propose a learning-support method using the emotions of others to strengthen professional players of Japanese chess (Shogi).

Shogi is a popular board game that is also played professionally, and learning methods have been actively researched (Ito, 2018; Nishihara et al., 2018). Novices can steadily improve their abilities through manual learning methods such as memorizing the roles of pieces and mastering the standard moves. An example of a standard first move in Shogi is P76, which means to move the pawn to position 76.

In learning at this level, the optimal goal for a novice called the "zone of proximal development (ZPD)" (Vygotsky et al., 2011) can be clarified as a language. Clarifying goals as language means that goals can be described as specific actions to be taken by the learner (Skinner, 1954). The ZPD is defined as a task in which a learner cannot perform alone but with outside help. For example, a novice can understand the reason from a textbook: P76 is necessary to prepare to attack the opponent's position by opening the corner. Numerous learning-support methods for novices have been proposed to automatically provide manualized knowledge and an optimal goal (Siddiqui et al., 2022; Malaise and Signer, 2022; Dicheva et al., 2015; Rooein et al., 2022).

A typical method of learning Shogi played by professionals is to look back at the history of moves played in past games (hereafter referred to as "game record") and discover and learn decisive moves. Game records include moves played by the Shogi artificial intelligence (Shogi AI), which is more skilled than human Shogi players (Silver et al., 2018). In this learning, it is relatively easy to grasp the intention of the moves of others who are as competent as a learner or have a similar playing style because there is only a slight difference between their thoughts. However, it is difficult to grasp the intention of the moves played by others who are more skilled than a learner or have a different playing style because the difference between their thoughts is critical. Decisive moves by

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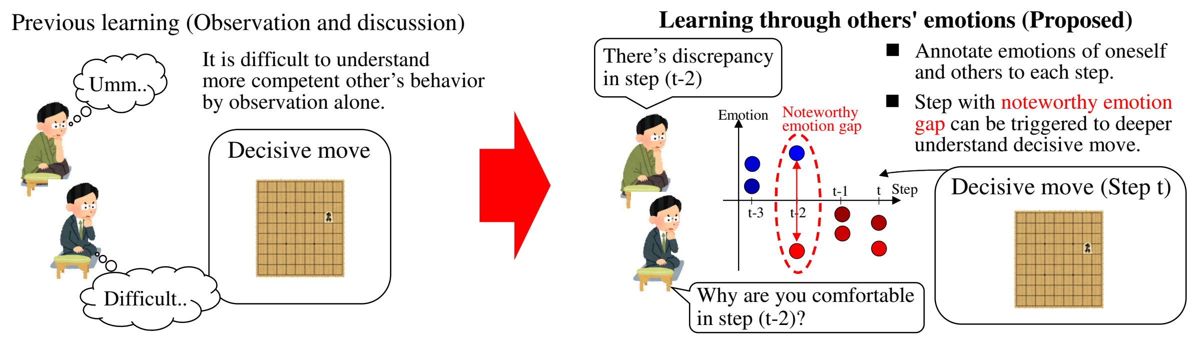


Figure 1: Overview of proposed learning-support method.

top professionals result from intuition and are difficult to explain logically, even for the top professionals who chose those moves (Ito et al., 2005). In other words, it is difficult to verbalize a learner's ZPD at the professional stages. The detection and presentation of professional tacit knowledge is also a common challenge not only in Shogi but also in a wide range of fields (Eraut, 2000).

1.1 Approach

We define emotion as how humans think about a situation one is facing. In Shogi, the situation is position and move. In Shogi and chess, technical terms have already been constructed to describe strategies and patterns of moves. However, they are only a verbalization of the typical thinking patterns of many players. Players with different playing styles have different ways of thinking about situations that cannot be explained in technical terms, and the higher the level of players, the more remarkable these differences become. The tacit knowledge we want to make effective use of is, for example, the way of thinking that professional players express when they say, "My fingers resist." Such words are not always uttered, and even if they are, it is difficult for others to understand their true meaning.

Previous studies have found that professional board-game players have specific brain-activity patterns compared with amateurs while playing (Wan et al., 2011; Tanaka, 2018). They efficiently search for the best next move by processing the positions and moves as a lumped spatiotemporal pattern (Ito et al., 2005; Ito and Takano, 2015). Ito and Matsubara (Ito, 2004) suggested that positive-negative emotions of the player accompany Shogi moves. Discussing with others and using their different perspectives is effective in problem-solving (Miyake, 1986; Dunbar, 1995). However, in discussions based on observation of game records, players do not always verbalize unconscious emotions.

If a learner can detect the transition of others' emotions leading up to a decisive move, and if they can identify the point of divergence with their emotions, they will be able to discuss and dig deeper into the differences in the way of thinking about the situation. Through this process (Fig. 2), it would be effective for professional players to develop and expand their own emotions by taking in others' emotions to fill in the gaps they have been unable to perceive. This learning cycle is an essential aspect of learning support, regardless of the level of the learner (Skinner, 1954; Berlyne, 1966). Fig. 1 shows an overview of the proposed learning-support method.

To provide a proof of concept for the above learning-support method, we collected the emotions of two female professional Shogi players (belonging to the ladies professional Shogi-player's association of Japan) during Shogi play using Russell's core affect (Russell, 1980). We then displayed the collected emotions of the two players in the time series and let them discuss the feedback on their Shogi play. Finally, we conducted a qualitative evaluation of whether referring to the collected emotions of others is effective in improving professionals' abilities. The contributions of this study are as follows.

- We propose a learning-support method for clarifying professional player's ZPD using the emotions of others.
- This study is the first proof-of-concept case to test the effectiveness of presenting the emotional differences between two professionals to enhance their learning.

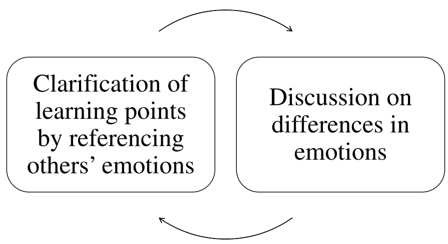


Figure 2: Learning cycle considered for this study.

2 RELATED WORK

2.1 Personalized Learning Optimization

Numerous studies have incorporated AI to provide optimized learning support for individual learners. An essential factor common to these studies is the automatic setting of optimal goals, referred to as the ZPD. Several studies (Zou et al., 2019; Baker et al., 2020) have shown that students' performance in school mathematics and English improves when they select from tasks in the ZPD. Siddiqui et al. (Siddiqui et al., 2022) proposed a method for university students that uses keywords of interest to trigger the recommendation of academic papers that the students are curious about and to expand their knowledge. Malaise and Signer (Malaise and Signer, 2022) proposed a method for a learner of table tennis that automatically suggests optimal exercises in the ZPD, taking into account the learner's knowledge and acquired skills. Methods for improving interfaces to support learning were also proposed using gamification (Dicheva et al., 2015) and chatbots (Rooein et al., 2022) to encourage students' spontaneous learning for individualized goals.

These studies targeted novice learners and stand on the condition that their goals have been clearly verbalized. It is difficult to verbalize and conceptualize the ideas and goals of professionals we focus on as learning targets (Eraut, 2000). Although vague and situational guidelines for learning to enhance professionals have been discussed (Eraut, 1994; Argyris, 2002), they are far from being protocolized for implementation as learning-support methods. The learning-support methods described above need to be extended to cover a broader range of learner levels and domains.

2.2 Game-Learning Support

Board-game learning support is a popular area of research. Methods have been proposed to assist Shogi novices by presenting predictive positions (Ito, 2018) and visualizing battlefields (Nishihara et al., 2018). There are also learning-support methods for recommending tasks tailored to the knowledge and abilities of individual chess novices on the basis of the ZPD (Guid et al., 2013).

Research has been conducted on chess (not Shogi) to explain the difference in ability between human experts and AI (Pálsson and Björnsson, 2023; Schut et al., 2023). However, to the best of our knowledge, no personalized learning-support methods for professional board-game players have been reported.

2.3 Collection of Emotions

Certain emotion-collection approaches use biometric data such as brain waves (Shen et al., 2009; Wan et al., 2011; Nakatani and Yamaguchi, 2014). However, it is difficult to decipher the emotion expressed from biometric details. We acquire emotions as annotations to words that can be obtained in and under various experimental environments and conditions that are easy for humans to interpret. As described in Section 3, we set representative words (comfortable - uncomfortable, dynamic - gentle) that express the emotion of the situation in playing Shogi and collected annotations of closeness degree between the words and players' emotions. The general purpose of collecting word annotations from experimental participants is to evaluate average human emotions (Plutchik, 1980; Scherer and Wallbott, 1994). In contrast, we focused on individual differences and aimed to record individual emotions in a format others could reference.

2.4 Using Emotion in Learning

Many researchers have explored the integration of emotions into learning-support methods. In school education, it is known that understanding students' emotional states has a meaningful impact on teachers (Shen et al., 2009; Tyng et al., 2017), and methods for communicating students' emotions in the classroom have been proposed (Sadiq. and Marentakis., 2023). However, few researchers have examined whether emotions effectively support learning among professional-level learners.

Professionals' tacit knowledge and intuition are difficult to verbalize, even for them both in Shogi (Ito et al., 2005) and other fields (Eraut, 2000). It has been suggested that tacit knowledge and intuition of Shogi professional players are encoded in their minds in a form similar to emotions (Ito, 2004). We investigated whether visualizing professionals' tacit knowledge and intuition via emotions can help them learn.

3 SELECTION OF ANNOTATION INDICATORS

We interviewed 17 advanced and the 2 professional Shogi players mentioned above to determine whether referring to emotion labels annotated by others for each move would help them understand decisive moves better than not referring to the annotation labels. All the advanced players held at least the rank of shodan (1-dan) or higher. The annotation labels used in this interview were Pulchick's basic emotions (joy, trust, fear, surprise, sadness, disgust, anger, and anticipation) (Plutchik, 1980) and Russell's core affect (valence, arousal) (Russell, 1980), which are commonly used emotion indices in the context of learning support. The interviews showed that 100% of the players indicated that referring to the emotion labels annotated by others is beneficial.

Next, we studied the two professional players (same as in the interviews) to determine which labels used in the previous step were valid. They played six Shogi games and annotated all the labels in seven levels for each move. We compared the validity of the annotated labels by interview and degree of variance. Fig. 3 shows the variance of annotated values per label obtained in all six games. The horizontal axis represents the annotation label, and the vertical axis represents the variance of the annotated value. Russell's core affects had relatively large variances for both labels, suggesting that the players were able to identify and annotate differences in emotions for each move. The interview results are summarized as follows.

- Pulchick's basic emotions make it difficult for players to determine which eight labels are the most critical for each situation.
- The labels of basic emotions other than joy and anticipation rarely occur while playing Shogi.
- Core affects are highly consistent with the emotions while playing Shogi, making them easy to annotate without much thought.

On the basis of the above findings between the two annotation indices, we considered that annotations by core affects were suitable for extracting the unspoken emotions expressed during Shogi games and used them as an annotation index in the experiment described in Section 4. Reflecting on the interview results, we set the label names of valence and arousal to "comfortable - uncomfortable" and "dynamic - gentle," respectively, which are words generally used in Shogi (e.g., "That move feels dynamic and comfortable.").

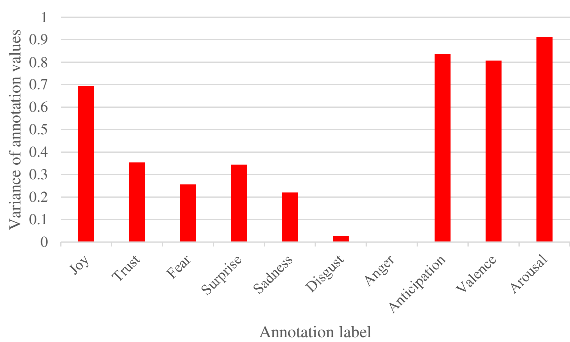


Figure 3: Variance of annotation values.

4 ANNOTATION METHOD AND EXPERIMENT

Using the annotation labels determined in the previous section, we conducted another experiment to annotate emotions to moves and positions in Shogi. The playing style of Shogi is generally expressed on two axes: strategy (offensive and defensive) and momentum (aggressive and passive). The same two professional Shogi players, with opposite playing styles shown in Table 1, were also annotators for this experiment to extract differences in emotion. Hereafter, we refer to them as annotators 1 and 2.

The annotators annotated 24 games, including a mix of three patterns: matches between pair of the annotators and the Shogi AI, past great matches (the annotators did not know the result of these matches), and matches between two Shogi AIs. In the first match pattern, the annotator pair doubles as black, and they discuss and decide on a move by consensus. In the other two match patterns, the annotators do not play; they only annotate. Hereafter, regardless of whether the annotator is a player, we refer to the player who makes the move first as black and the player who makes the move second as white. We used the graphical interface for Shogi (ShogiGUI, 2022) and the Shogi engine (Demura, 2017) as the Shogi AI and set it to a higher skill level than the annotators. Considering the results of the survey described in Section 3, we defined the following three annotation labels that are likely to express the traits of human emotion while playing Shogi.

- Valence (Comfortable - Uncomfortable): Subjective feeling of comfort or discomfort for a move from black's standpoint.
- Arousal (Dynamic - Gentle): Subjective feeling of aggressiveness for a move from black's standpoint.
- Subjective-position score: Subjective degree of advantage or disadvantage of black for a position.

Valence and arousal range from -1 to 1, where a lower value indicates a higher degree of "uncomfortable" or "gentle", while a larger value indicates a higher degree of "comfortable" or "dynamic". The subjective-position score ranges from -2000 to 2000. The upper and lower limits indicate a decisive win or

Table 1: Annotators' playing styles. They have opposite playing styles, both in strategy and momentum.

	Strategy	Momentum
Annotator 1	Defensive	Aggressive
Annotator 2	Offensive	Passive

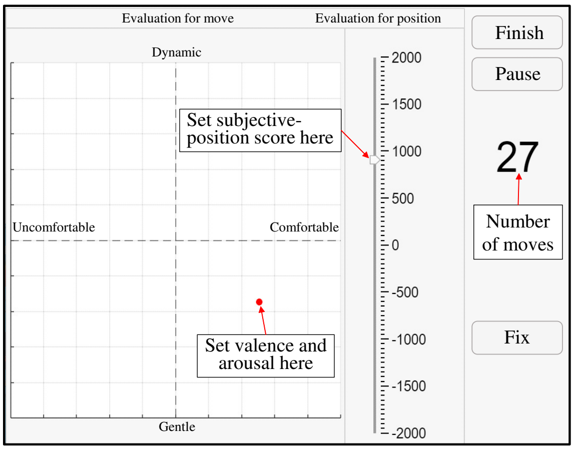


Figure 4: Interface of annotation tool designed to allow plotting indicators (Valence, Arousal, Subjective-position score) as continuous values selected to communicate emotions that are difficult to verbalize.

loss in the Shogi AI (Demura, 2017) we used in the experiment. Lower values indicate an advantage for white, while higher values indicate an advantage for black.

To enable the annotators to quickly and intuitively annotate after a move is determined, we developed an annotation tool with which an annotation can be completed with simple mouse operations, as shown in Fig. 4. We used a two-dimensional interface, which has been reported to allow intuitive and unloaded input (Sadiq. and Marentakis., 2023). Our tool has valence on the horizontal axis, arousal on the vertical axis, and a straight line next to them for subjective-position score. Annotation is completed with three clicks: clicking into the two-dimensional coordinates, clicking on the subjective-position score, and clicking on "Fix".

Fig. 5 shows the annotation procedure for Shogi situations using this annotation tool.

1. First, black or white makes a move.
2. Next, the annotators annotate this move with three types of emotions using the annotation tool from black's standpoint, regardless of whether it is a move of black or white.

These steps are repeated until the end of the game. After annotating each game, the annotators referred to the annotation results and had a feedback discussion about the game.

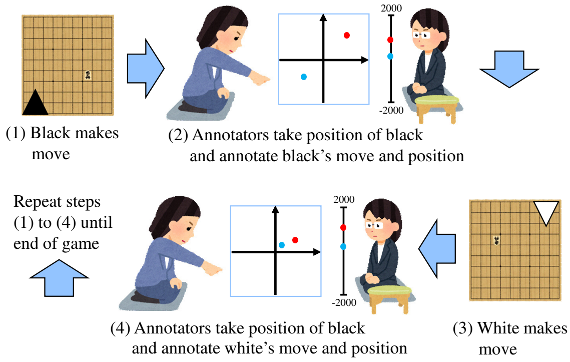


Figure 5: Annotation procedure.

5 RESULTS

The average number of moves played per game in all 24 games was 109.8. Of these, the average number of moves with different positive and negative signs (hereafter, referred to as "opposite") among the annotators was 13.5 in valence and 9.30 in arousal per game in all 24 games. We conducted a between-subjects analysis of variance (ANOVA) on the 2634 annotated emotions of all 24 games, and the results indicate a significant difference in valence between annotators ($F(1, 2633) = 6.595$, $p < 0.0001$ for valence, $F(1, 2633) = 1.151$, $p = 0.689$ for arousal, and $F(1, 2633) = 1.290$, $p = 0.529$ for subjective-position score).

Fig. 6 shows two annotation results of games with noteworthy differences between the two annotators. A between-subjects ANOVA was conducted from the results in Fig. 6 (a), and there was a significant difference in valence and subjective-position score between the annotators ($p = 0.00287$ for valence and $p = 0.00684$ for subjective-position score). Fig. 6 (b) shows the results that had opposite valences in 25 moves.

5.1 Emotion-Referenced Learning

The subjective-position scores in Fig. 6 (a) between annotators became reversed from around move 43 and remained opposite until the end of the game. In this game, white won, so the subjective-position score at the end of the game was expected to be negative. Therefore, annotator 1 who annotated the end of the game in Fig. 6 (a) with positive subjective-position scores greatly misread the situation. Annotator 1 should correct her thoughts to moves in this game. For annotator 1 to improve her skill, it is essential to detect which moves were decisive for the game's

(a)

(b)

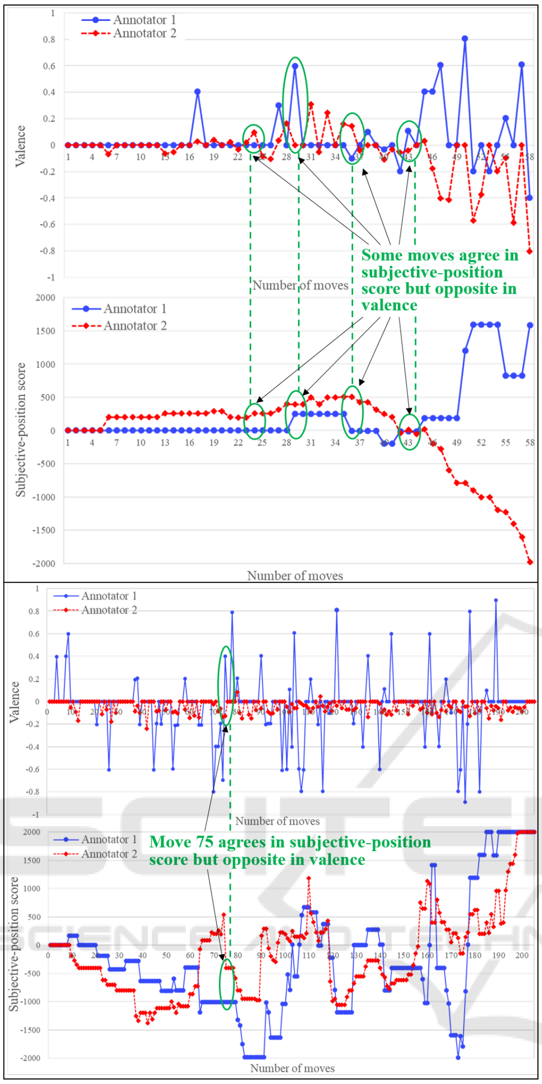


Figure 6: (a): Results that had significant differences among annotators. (b): Results that had many opposite emotions. Upper graph of each result shows valence, and lower shows subjective-position score, with horizontal axis representing number of moves.

misreading and modify her thoughts and criteria for evaluating the moves.

Fig. 6 (a) shows opposite valences in moves 22 to 37 despite the fact that the subjective-position scores of both annotators are on the same side of the graph. In such moves, the annotators had different ideas of the move's effect on the game. Annotator 1 may gain new perspectives in modifying her thoughts by hearing from annotator 2 about the reasons for the opposite emotions. In other words, these moves with opposite emotions are annotator 1's learning points based on the ZPD.

Table 2 lists dialogue excerpts from the annotators' discussion about the game in Fig. 6 (b) referring to annotated emotions. The annotators discussed move 75, which has an opposite valence. This move is superficially agreed upon, since the positive and negative signs of subjective evaluation coincide. In other words, it is a situation that should be explored in depth, which the annotators would have missed without the emotional annotation. Displaying the emotional transition of themselves and others enables annotators to detect the emotional gap and dig deeper into what annotator 1 evaluated and what annotator 2 did not evaluate. In Table 2, the discussion triggered by the emotional gap clarified what both sides perceive as benefits and what they consider risks. Thus, showing emotion can lead to complementary and better next moves when logic cannot be explained in words. With the proposed learning-support method, learners can proceed with their learning in the following steps.

- Learners annotate moves with their emotions and make a time-series list of emotions.
- Using a list of emotions, learners detect emotional gaps represented by moves with opposite emotions.
- Learners discuss and dig deeper into emotional gaps, focusing on the differences in thinking about the advantages and disadvantages. They can promote understanding to approach the emotions of others that they do not have, which leads to improved abilities.

By referring to a time-series list of emotions created by players with different playing styles, a player can actively learn and incorporate the perspectives one lacks, such as the risks and benefits of a move. This corresponds to an active learning cycle corresponding to the change from diffuse curiosity to particular curiosity (Berlyne, 1966).

6 EVALUATION

We obtained subjective evaluations from the annotators to subjectively evaluate the effectiveness of the proposed learning-support method regarding other's emotions by using a ten-point scale. The higher the score, the more effective our method, and the lower the score, the more effective the standard learning method of looking back at game records without referring to emotion. The two annotators gave an average evaluation score of 9.5 (Table 3).

We then interviewed a male professional Shogi player (an instructor of the annotators who did not participate in the experiment) about whether our

Table 2: Examples of actual discussions by annotators. The dialogues collected in this study are in Japanese and translated into English by one of the authors.

Annotator 2: Is move 75 of white that much advantageous?
Annotator 1: This was a pattern in which the attack from white was effective.
Annotator 2: Although white may feel comfortable, white had not regained the pieces lost during the attack. Thus, white has yet to achieve any practical result.
Annotator 1: I predict white's T37 (a move of Shogi) will reach the king in time.
Annotator 2: I don't have that prediction, because black's Silver General (a kind of Shogi piece) is effective and black has many pieces in hand.

method helped improve professional ability. He answered, "Professional players fight on a field beyond the resolution of language. This approach is effective in further strengthening those at a professional level. The stronger the player, the more effective the method is." These qualitative evaluations and the results of the interviews in presented in Section 3 suggest that our method is effective in improving the ability of professional Shogi players. It will be necessary to have more professional players participate in the experiment and conduct a statistical and long-term evaluation to determine if the proposed method improves their performance.

Table 3: Results of subjective evaluation by annotators using ten-point scale. Maximum score is ten.

Evaluation of annotator 1	10
Evaluation of annotator 2	9

7 DISCUSSION

The annotated results of the game in Fig. 6 (b) have a marked distribution difference between the valence and arousal shown in Fig. 7. From interviews with the annotators, this was a reasonable result representing the difference in aggressive and passive playing styles. The instructor of the annotators then commented on his interpretation of this distribution difference as "Aggressive players (e.g., annotator 1) focus on whether their attacks work (comfortable) or not (uncomfortable) and are sensitive to valence. On the other hand, passive players (e.g., annotator 2) are sensitive to the momentum of their opponent's attacks. This result shows such an emotional difference." Although the number of professional players

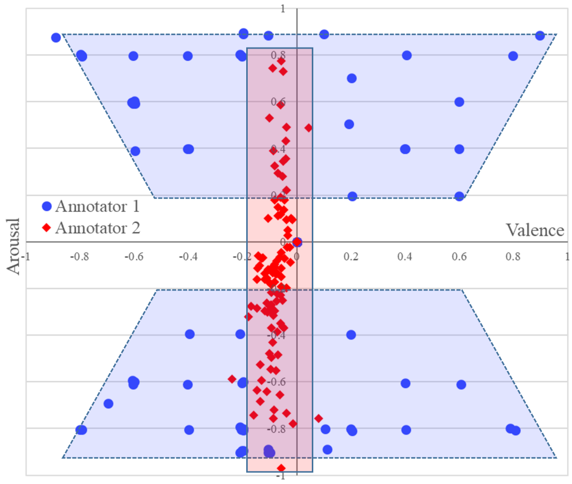
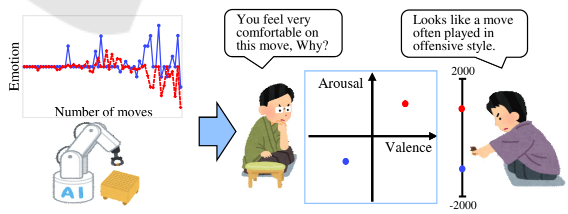


Figure 7: Distribution of variance and arousal between two professionals with different playing styles.

who participated in the experiment in Section 4 was small, these interviews supported that the annotated emotions reflect the tendency of professional players' thinking.

Whether the proposed method can be generalized to tasks other than board games is debatable. The proposed method is suitable for turn-based tasks with an objective evaluation axis for actions taken. It is impractical to directly apply the proposed method to tasks with continuously changing situations or tasks with many participants. These tasks require automation of emotion extraction. The choice of words to be used as annotation indicators may need to be modified depending on the task domain.

7.1 White Boxing of AI



(a) Annotating emotions for Shogi AI moves. (b) Collaborative translation of Shogi AI's complex moves triggered by emotional discrepancies.

Figure 8: Collaborative translation of Shogi-AI moves using emotional gaps.

With the increase in computational resources and evolution of computational Shogi algorithms (Silver et al., 2018), even top professional Shogi players have started to study the Shogi AI as a teacher (Nikkei Inc., 2022). However, the process leading up to the move decided by the Shogi AI is a black box. The proposed method can facilitate learners' understanding of complex Shogi AI moves by piecing together the emotions of those who understand one aspect of the move, as shown in Fig. 8.

- Several players with different playing styles annotate the moves decided by the Shogi AI with the emotions (Fig. 8 (a)).
- If each player can somewhat understand the AI's moves, they would be able to collaboratively translate its moves by connecting the emotions of multiple players (Fig. 8 (b)).

7.2 Learning with Emotion Estimator

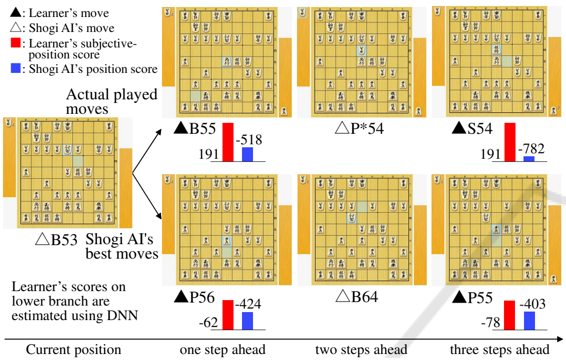


Figure 9: Learning Shogi AI moves with emotion estimator.

The learning-support methods described in Section 5.1 can only handle moves that were actually played. If we can estimate learner's emotions, we can find learning points on the basis of the ZPD from a wide range that includes moves that have not been played, represented by the Shogi AI's potential decisive moves.

Therefore, we created an emotion estimator that takes the Shogi situation (position and move) as input and outputs the emotions of the annotator. The data collected from annotator 1 described in Section 4 (2036 sets of inputs: positions and moves, output: emotions) were split into training, validation, and test data in the ratio of 4:1:1 to train a fully connected deep neural network (DNN) consisting of one input layer, four hidden layers, and one output layer. We set the number of epochs as 800. The amount of data is not yet sufficient and the accuracy of the estimation is not high, so the following results are for reference only. The top of Fig. 9 shows the branching by the moves selected by the annotators in the game in Fig. 6 (b), and the bottom shows the branching of the Shogi AI's (Demura, 2017) best moves (not actually played). We plotted the Shogi AI's position score and annotator 1's subjective-position score for each branch. Subjective-position scores on the lower branch were estimated with the DNN. For the best move of the Shogi AI, the difference between the Shogi AI's score and the learner's score is smaller than the upper branch. The lower branching suggests that the learner may have a similar mindset to the Shogi AI. Thus, the emotion estimator may help detect potentially optimal goals for the learner based on the ZPD.

8 CONCLUSIONS

To expand and develop a professional's ability, we proposed a learning-support method for extracting the emotions of others and incorporating other's thoughts triggered by emotional gaps into the thoughts of learners. We conducted an experiment to extract emotions about Shogi moves from two professional Shogi players and observed noteworthy emotional gaps between the two players, even with similar subjective-position scores. The players were then able to use the discrepancy in the others' emotions as a trigger for feedback discussions on the games. The qualitative evaluations suggested that referencing the emotion of others contributes to improving professional Shogi players' performance.

It will be necessary to conduct statistical and long-term evaluations to determine whether this method can be improved. We also plan to design a more appropriate interface using emotional information that can further enhance learning effects, as described in Sec. 7.2. The proposed method is not limited to Shogi but can be widely applied to other fields where professional tacit knowledge and intuition are difficult to verbalize.

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