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Study on the Application of Weak Go AI in Go Education: the Balance between Go Progress and Emotional Value

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Abstract

With the continuous advancement of artificial intelligence (AI) technology, the application of AI in Go education and training has become a hot research topic. This article explores the important role of weak Go AI in Go education, especially its application in beginner teaching. We analyzed the current Go education methods and research status, and based on this, proposed a technological innovation: by adjusting the difficulty of AI, it can promote the improvement of beginners' Go skills while maintaining their enthusiasm for Go. Further experiments have shown that when the AI's Go power is appropriately higher than the tester's, it can effectively improve Go power while also considering emotional value. The research in this article proves that this innovation has profound significance for Go education.
Keywords: Weak Go AI, Go education, Teaching efficiency, Educational innovation

1 Introduction

Regarding the research background of this study, with the rapid development of artificial intelligence, AI has made significant breakthroughs in the field of Go. After AlphaGo defeated top human Go players, AI not only had a huge impact on the professional Go world, but also provided new opportunities for Go education and amateur Go.

Although AI has been widely applied in Go training, current research is mostly focused on the analysis of matches between professional and high-level amateur Go players, neglecting the educational needs of beginners. Finding suitable AI opponents for beginners is an urgent issue that can help improve Go skills while maintaining learning interest.

This paper first examines the current approaches to Go education and relevant research in Japan[1][2], assessing the use of AI in teaching and identifying limitations in current practices. We propose a new technological approach that can adjust the difficulty of AI games based on the actual go skills of beginners, which can promote the improvement of Go players' skills while maintaining their learning enthusiasm. We found through experiments that when the AI's Go power is appropriately higher than the tester's, the tester can not only achieve significant improvement in Go power, but also maintain a positive attitude towards Go emotionally. This innovation not only enhances the practical application of AI in Go education but also offers a fresh perspective on how AI can support learning. It also avoids the learning inconvenience caused by the shortage of Go teachers [3]. Ultimately, this study highlights the potential impact of this innovation on improving the efficiency of Go education and its broader significance for the field [4].

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2 Research method

2.1 Experimental Design

2.1.1 Selection of experimental subjects

The experimental subjects are beginners of Go at different levels, and the selection of participants should ensure that they are in a relatively beginner stage at the beginning of the experiment. Determine the starting level of the experimental subjects through preliminary Go skill evaluation (such as self-evaluation level or winning rate against AI), ensuring that the participants' level is within a controllable range for subsequent comparative analysis. Participants were randomly divided into multiple experimental groups, and each group would face AI opponents of different difficulty levels (AI had Level18, 17, -10%, 0%, 10%, 20%, 30% higher Go power than the tester).

2.1.2 AI difficulty setting

In order to better quantify the data, we adjust the level of the AI and the testers. In the case that all five testers agree that level 18 is weaker than the average beginner, we expressed the relationship between AI difficulty and beginner ability more intuitively. level 18 is quantified as -10% difficulty compared to the beginner human, Level 17 is set at 0% difficulty, level 15 is set at 10% difficulty, level 13 is set at 20% difficulty, and level 10 is set at 30% difficulty. These five quantified difficulties -10%, 0%, 10%, 20%, 30% as the five AI difficulties for testing. As shown in the following Figure 1.

The Go power of AI is designed to be a certain percentage stronger than that of participants. Specifically, different experimental groups correspond to different difficulty ranges, and the intensity of AI is -10%, 0%, 10%, 20%, and 30% higher than that of participants. This setting can be achieved by adjusting the AI's win rate or strategy complexity. By analyzing the game between the tester and AI, the experiment explores the impact of AI with different difficulty levels on the tester's Go ability improvement and emotional response. Each group of testers will have a fixed number of matches (10 matches per group) with AI of specified difficulty to ensure sufficient data support for analysis.

2.1.3 Experimental process

Before the experiment begins, a baseline evaluation of each tester's Go ability is conducted (such as through initial game winning rate, game strategy analysis, etc.) to provide reference for subsequent data comparison. Each group of testers engages in multiple rounds with AI, with consistent rules, times, and conditions for all rounds. Record the results of the game, including wins and losses, number of steps in each game, game duration, participants' strategy changes, etc., to ensure the reproducibility of the experimental process and the accuracy of the data. Monitor the progress of Go skills and emotional changes of each group of testers to ensure that they can capture the real reactions under different AI difficulty levels.

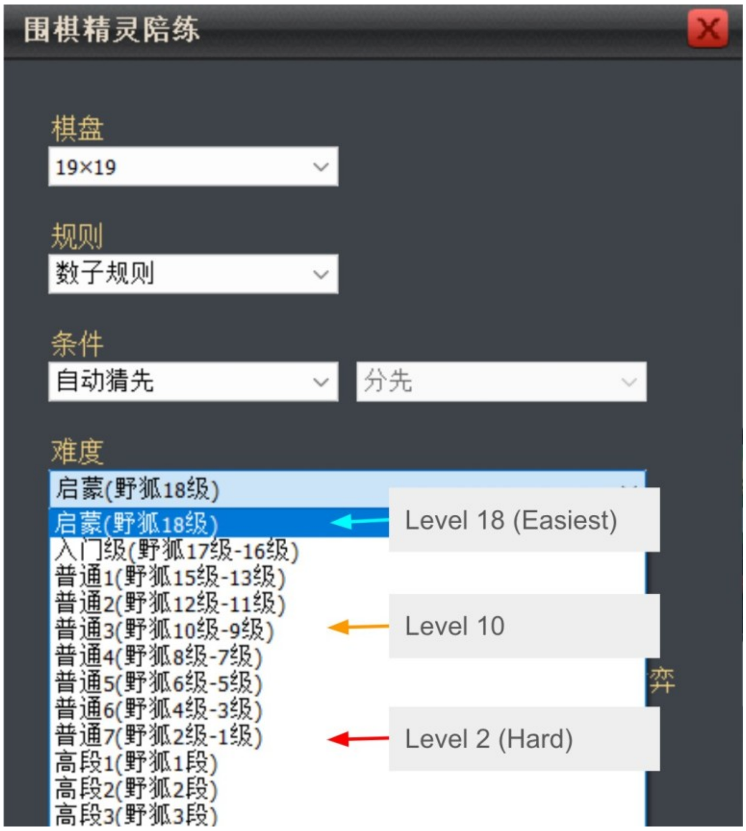


Figure 1: Selecting difficulty level. https://webigojp.com/

2.2 Data Acquisition

2.2.1 Data collection for improving Go skills

Go skill evaluation is conducted through pre and post tests. Firstly, conduct a baseline test of Go power before the experiment begins, and collect initial Go power data from each tester. Quantify Go skills through methods such as game winning rate, rank evaluation, and fixed form testing. After the experiment, each tester was evaluated for their Go skills again, and their changes from baseline data were recorded. The focus was on analyzing the impact of AI with different difficulty levels on improving Go skills. The specific data includes indicators such as changes in win rate, decrease in steps, and win loss ratio. Throughout the entire experiment, every game data of the tester will be recorded, including wins and losses, game steps, game duration, etc. These data will help researchers quantify the effectiveness of AI with different levels of difficulty in improving Go skills.

2.2.2 Data collection of emotional value

The assessment of emotional state will be conducted through an emotional value questionnaire after completing the daily rounds, ensuring that changes in emotions during the experimental process can be captured. The questionnaire design will cover participants' feedback on their interest, sense of achievement, frustration, challenge, and other aspects of Go. The questionnaire uses a Likert scale (1-5 points) to quantify emotional changes, facilitating data analysis. By monitoring the changes in questionnaire data each time, we can track the emotional changes under different AI difficulty levels and determine whether AI difficulty has a positive or negative impact on learning interest and enthusiasm.

2.3 Data Analysis Methods

2.3.1 Analysis of improving go skills

Analyze the improvement of Go skills of each group of participants during the experimental period by comparing the data of Go skills before and after testing. The specific analysis methods include calculating the percentage of win rate improvement, the extent of rank improvement, and the change in average steps. Use statistical methods to verify the significant differences in the improvement of Go skills among different AI difficulty levels. Analyze which group of AI difficulty can bring the most significant improvement in Go skills, and visualize the results for easy understanding.

2.3.2 Analysis of Emotional Value

Quantitatively analyze the data from the emotional questionnaire and calculate the average emotional scores (such as sense of achievement, frustration, interest, etc.) of participants under different AI difficulty levels. Use charts to display trends in emotional changes and identify patterns in how different levels of AI difficulty affect emotions. By conducting cross analysis and combining data on the improvement of Go skills with emotional changes, we aim to find a balance point where AI difficulty can enhance Go skills while maintaining learning interest. Specific analysis can use correlation analysis or regression analysis to demonstrate the relationship between AI difficulty and emotional response.

2.3.3 Exploration of the Best AI Difficulty Range

By combining data on improving Go skills and emotional value, determine how many percentage points the AI difficulty is higher than that of the tester, and effectively improve Go skills while maintaining positive feedback on emotional value. Through cross data analysis, the “optimal difficulty range” can be identified, which is the range where AI difficulty is most balanced with Go progress and emotional value.

3 Technological Innovation

3.1 The Balance Mechanism between Challenges and Achievements

Avoiding the problems of “excessive challenge” and “low challenge”: In traditional Go teaching, many beginners face the problem of excessive or low challenge. Our system ensures that learners are always in a state of moderate challenge through adaptive adjustment. In this state, AI is a certain percentage stronger than learners, providing enough pressure to push learners forward while also giving them a sense of achievement through appropriate victories, maintaining their interest and enthusiasm for Go. The innovation of the dynamic feedback mechanism: This system combines precise data on improving Go skills and real-time feedback on emotional states, gradually adjusting to find the learner’s “optimal difficulty range.” This data-driven dynamic adjustment mechanism has not been fully implemented in existing Go education AI, which is one of the core innovations of this article.

3.2 The Significance of Technological Innovation

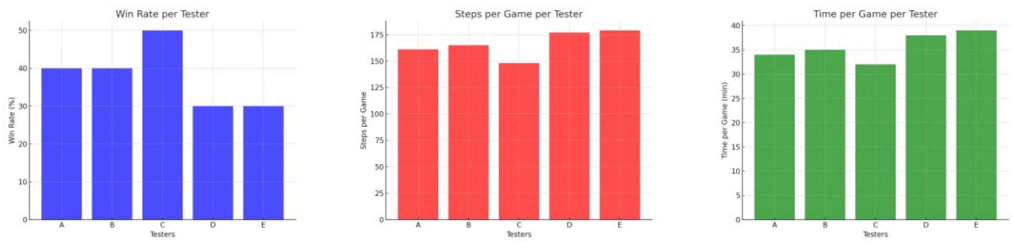
A new mode of personalized Go teaching: The traditional Go teaching mode is difficult to provide personalized training plans for every beginner. Our adaptive AI system can provide each beginner with the most suitable gaming experience for their level through personalized adjustments. It can not only promote the improvement of Go skills, but also provide emotional support to learners, thereby greatly enhancing the effectiveness of Go education. New exploration of emotional value in Go teaching: This article systematically introduces emotional value into the difficulty regulation of Go AI education for the first time. Through the emotional feedback mechanism, our system not only enhances players' Go skills, but also ensures that learners maintain their enthusiasm and interest in Go. This technological breakthrough provides new ideas for future AI applications in Go teaching, and also serves as a reference for intelligent educational technology innovation in other fields.

4 Experimental Results and Analysis

4.1 Experimental Results of Improving Go Skills

4.1.1 Preliminary competition testing

Before the experiment began, baseline assessments were conducted on the Go skills of each participant. Through preliminary competition testing, we conducted a statistical analysis of the participants' initial Go strength, including winning rate, number of steps taken, and duration of the competition. We asked the participants to play 10 games. The results of the preliminary competition testing are shown in Figure 2a–Figure 2c. Figure 2a shows the Win Rate of the participants were ranged from 30% to 50%. But we consider there were no significant difference of Go skill levels between testers. Therefore we mechanically assigned different AI levels to the testers in the following training session.



(a) Win Rate (b) Average of Steps (c) Average Time

Figure 2: Results of preliminary competition testing

4.1.2 Training session

After the preliminary competition testing, we asked the participants to train with fixed level of AI. participants engaged 20 matches with AI. We assigned each participants a fixed difficulty level of AI. When allocating AI levels, we took into consideration the Win Rate from the pre-testing and assigned AI Level 10 to C, which had the highest Win Rate, and assigned the easiest AI to D and E, which had the lowest Win Rate.

4.1.3 Testing session

After the training session, we moved to the evaluation session. In the evaluation session, we assigned 20 games with the difficulty level of AI randomly to five participants.

The method of testing learning results is to have five testers play another 20 games against the AI in the first step of testing to determine the progress level. And we recorded the winning rate, number of steps, and duration of the game.

We firstly discuss the result of Figure 3. For groups with AI difficulty levels -10% and 0% higher than participants, the win rate has decreased. For the groups with AI difficulty levels 10% and 20% higher than the participants, the testers' winning rates significantly increased (15% and 20%, respectively). For groups with difficulty levels above 30%, the winning rate of participants remains almost unchanged.

Figure 3: Comparison of win percentage before and after training

Secondly, we describe the result of Figure 4. In AI games with difficulty levels ranging from 10% to 20%, participants reduced their average number of steps by 8-13 steps, indicating that their strategic decisions were more effective. In a 30% difficulty game, the reduction in steps is not significant.

Finally, we analyze the result of Figure 5. In AI games with difficulty ranging from 10% to 20%, participants reduced their average time by 3-5 minutes, indicating that their strategic decisions were more effective. In the -10%,10% and 30% difficulty game, the reduction in time has not been significantly reduced.

4.1.4 Result analysis

Experimental data shows that within the range of 10% 20% higher difficulty than the tester, the improvement in Go power is most significant for AI. At this point, the winning rate, step

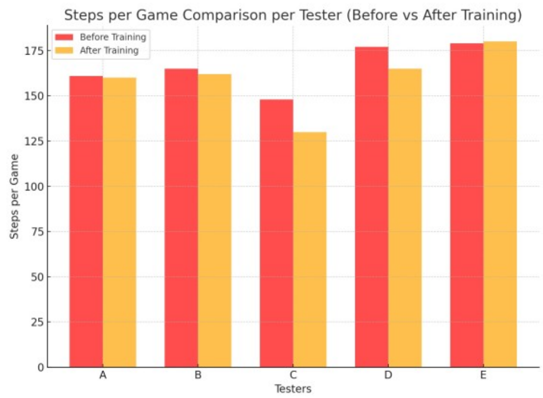


Figure 4: Comparison of steps before and after training

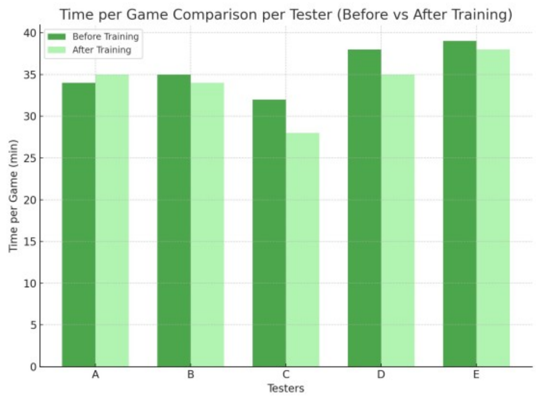


Figure 5: Comparison of game time before and after training

count, and error rate of the participants have significantly improved, indicating that the AI challenge for beginners within this difficulty range is both sufficient and not excessive. When the difficulty of AI exceeds that of the tester by more than 30%, the effect of improving Go power weakens, and the learning effect deteriorates when participants face higher difficulty opponents. (There was no improvement in win rate, only a small reduction in game time and game steps.)

Balance point: From the perspective of improving Go power, the optimal difficulty range for AI is 10% 20% stronger than the tester. At this point, the learning curve for beginners is the steepest.

4.2 Experimental Results on Emotional Value

4.2.1 Baseline emotional assessment

Before the experiment began, all participants were evaluated for their interest, sense of achievement (The quantified emotions are divided into 1-10), and learning motivation in Go through a questionnaire. The data shows that most participants have a high interest and curiosity in Go, but low confidence in their own Go skills.

4.2.2 Emotional changes under different AI difficulty levels

In the experiment, participants filled out an emotional feedback questionnaire after each game to evaluate their feelings towards the AI game, including sense of achievement, frustration, challenge, and motivation to continue learning Go.

The emotional feedback results under different AI difficulty levels are shown in Figure 6. The data shows that when the difficulty of AI is 10% -20% higher than that of participants, learners' sense of achievement and challenge remains at a high level, while their sense of frustration is lower. This indicates that AI within this difficulty range can provide moderate challenges, allowing learners to maintain a positive emotional experience while continuously improving. Balance point: From the perspective of emotional feedback, the optimal difficulty range for AI is also 10% -20% higher than that of testers. At this point, the learner's sense of achievement and challenge are maintained at their optimal state, with less frustration and the strongest learning motivation.

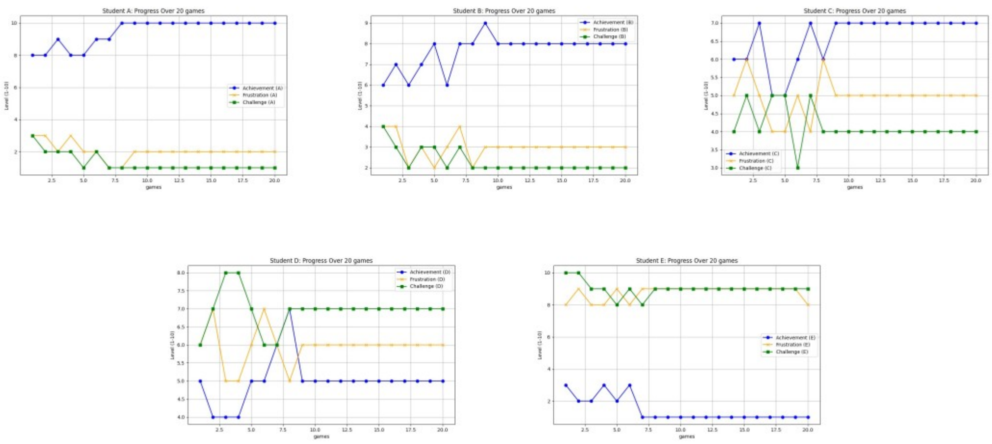


Figure 6: Five participants' sense of achievement, frustration, and challenge in 20 training games

4.3 Balance Point between Improving Go Power and Emotional Value

By cross analyzing data on improving Go skills and emotional feedback, the optimal range of AI difficulty can be determined. In the range where the difficulty of AI is 10% -20% higher than that of participants, there is a significant improvement in Go skills and emotional value is also maintained at a good level. Within this range, participants not only gained substantial improvement in their Go skills, but also maintained their love for Go and enthusiasm for learning. Balance point determination: Experimental results show that when the difficulty of AI is 10% -20% higher than that of participants, it is the best balance point for improving Go skills and maintaining emotional value. This difficulty level can provide sufficient challenges to promote learning without losing interest in learning due to excessive frustration.

5 Discussion and Summary

This study provides compelling evidence that weak Go AI, when adapted to learners' skill levels, serves as an effective tool for personalized education. By identifying the optimal difficulty range of 10%-20% above learners' baseline, the research demonstrates that AI can significantly improve cognitive outcomes, such as Go skills, while simultaneously preserving emotional engagement—a critical factor in fostering sustained interest and motivation in learning. Unlike traditional Go teaching methods, this adaptive AI approach offers beginners moderate and manageable challenges, enabling them to maintain a sense of achievement and enthusiasm.

However, this research is not without limitations. The experiment primarily focused on novice players, with a relatively small sample size and limited diversity in terms of age, cultural background, and skill levels. Emotional responses and the optimal AI difficulty range may vary across different player demographics, as well as among intermediate or advanced Go learners. Consequently, future studies should expand the participant pool and explore the adaptability of this framework in more diverse learning contexts to enhance the generalizability of the findings.

These insights extend beyond the realm of Go education, offering a scalable model for applying adaptive AI to a variety of skill-based training scenarios. By effectively balancing cognitive development and emotional engagement, this approach lays a solid foundation for more holistic, AI-driven educational paradigms that can support learners across diverse disciplines and contexts.

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