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Application Analysis of Intelligent Gaming in the Context of Go

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Abstract:

The swift evolution of Artificial Intelligence (AI) technology has ignited fervent discussions, particularly regarding its integration into the strategic game of Go. A landmark event was the unveiling of AlphaGo in 2017, an AI entity that swiftly ascended to an unassailable position against the world's top human Go players. This scholarly exploration delves into the intricate application of AI in the realm of Go, meticulously analyzing the trajectory of AI model development. Through a comparative examination of various models, the paper meticulously identifies both the shared attributes and the unique distinctions that define each AI system. The paper underscores the indispensable influence of deep learning and reinforcement learning methodologies in propelling AI advancements. Furthermore, the paper deliberates on the iterative enhancements made to the underlying algorithms, which have been instrumental in elevating AI's prowess in Go. In conclusion, the paper also thoughtfully addresses the emerging challenges that AI presents to the Go community, with a particular emphasis on the implications for human players. The paper concludes with a set of prescriptive recommendations aimed at fostering the continued ethical and beneficial advancement of AI technology within the Go domain.

Keywords: Intelligent Gaming; Go; Artificial Intelligence.

1. Introduction

Go, an ancient board game with a rich history spanning thousands of years is played by two players on a grid of intersecting lines, known as the Go board. This game, with its profound depth and elegant simplicity, has long been revered as a pinnacle of intellectual pursuit, challenging the minds of scholars, strategists, and enthusiasts alike for centuries. The game's complexity arises from the vast number of possible board configurations, which has made it a formidable challenge for Artificial Intelligence (AI) to master [1].

AI, a field that has seen exponential growth and development in recent decades, has permeated various aspects of human life, offering innovative solutions

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to complex problems and significantly enhancing working efficiency. The integration of AI into the realm of Go has been a topic of great interest and debate since 2015 when the AI program AlphaGo made headlines by defeating the human professional Go player Fan Hui. This event marked a significant milestone in the history of AI, showcasing its potential to excel in areas traditionally dominated by human expertise [1].

The rapid advancement of AI technology in the context of Go continued at an unprecedented pace, culminating in 2017 with the emergence of AlphaZero. This AI system, developed by DeepMind, demonstrated an extraordinary level of proficiency in not only Go but also in chess, a game with a long-standing tradition of AI research. AlphaZero's success in achieving superhuman performance in these games has sparked a renewed interest in the potential of AI to revolutionize the way people approach strategic thinking and decision-making in complex, rule-based environments [2].

This paper explores AI's impact on Go, detailing how technologies like deep learning and reinforcement learning have enabled AI to outperform humans. It discusses AI's role in education, cultural spread, and professional training, offering suggestions for optimizing AI in Go. The paper contributes to discussions on AI integration in Go and provides a framework for future development, highlighting AI's potential for innovation and human advancement.

2. Methodology

This paper delves into the intricate application of intelligent gameplay in the context of Go, providing a comprehensive exploration of the development of AI technologies within this domain. A significant portion of the paper is dedicated to examining the key technologies that have been instrumental in propelling AI to surpass the abilities of human players. This includes an in-depth analysis of deep learning, reinforcement learning, matrix algorithms, and Monte Carlo tree search, which have been pivotal in enabling AI systems to achieve and maintain a competitive edge over human experts. This section is dedicated to examining the operational functions of the diverse technologies integral to the development of AlphaGo.

2.1 Basic Models

The AI system, AlphaGo, is fundamentally constructed upon the thorough analysis of a substantial corpus of Go game records. These records, which are the bedrock of the AI's learning process, are customarily preserved in the Smart Game Format (SGF) within computer systems. The computer then meticulously processes these records, taking into account the strategic interplay between black and white pieces. By employing computer programming to emulate each SGF file, researchers meticulously construct a 19×19 matrix, which serves as the analytical framework for the AI to interpret and learn from the game data. Table 1 shows the specific matrix of AlphaGo evaluating the records.

Table 1. The Value Network Feature Representation of AlphaGo [3]

Feature Names	Number of Input Channels	Feature Description
Stone Colors	3	Player's color, opponent's, empty points
Constant 1 Channel	1	Constant channel, all values are 1
Move Number	8	Number of moves since the stone was placed
Liberty Count	8	Number of liberties of the stone
Capture Count	8	Number of opponent's stones that will be captured after the move
Atari Count	8	Number of our stones that will be captured after the move
Liberty Count After Move	8	Number of liberties of the stone after the move
Is Ko Point	1	Whether the move forms a ko
Is Approach Move	1	Whether the move forms an approach
Is Legal Move	1	Whether the move is a legal move or whether the move fills the player's own eye
Constant 0 Channel	1	Constant channel, all values are 0
Player's Color	1	Whether the current player is playing with black stones

In Table 1, the evaluation metrics used by AlphaGo are distinctly different from human players' criteria. The matrix, resulting from a thorough analysis of game records, quantifies each move in Go, taking into account the strategic positioning of the players. Notably, the matrix includes specific Go rules, including the ladder attack, a common and complex scenario in the game that goes beyond mere piece capture, requiring an evaluation of the board's overall state.

Moreover, artificial neural networks are integral to AI's application in Go. Leveraging the matrix's detailed representation of Go's subtleties as a robust platform for machine learning, researchers have chosen to employ deep neural networks to enhance the computational learning capabilities of AI systems. Fig. 1 shows a simple process of machine learning.

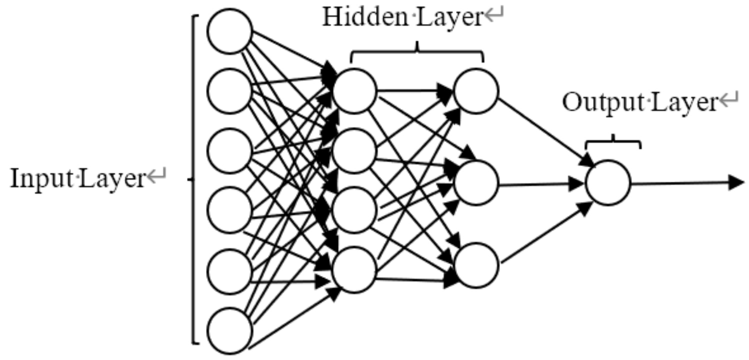

Fig. 1 Multi-layer neural networks [4]

In Fig. 1, the input layer consists of only six inputs. However, the hidden layer undergoes processing twice before yielding the final output. It is evident that the input layer will receive a significantly larger volume of information in the context of machine learning, thereby geometrically increasing the computational demands.

Consequently, by integrating policy functions and value functions, optimal strategies and situational assessments can be encapsulated within the two functions, denoted as $Q(s, a)$ and $V(s)$, respectively. The Q function evaluates the desirability of taking action in given state s, while the V function assesses the overall value of states. It is clear that a higher value attributed to a single move within these functions correlates with an increased likelihood of victory [4].

2.2 Model Development

Regarding AI in Go games, three pivotal iterations have emerged in the field's development: AlphaGo Lee, AlphaGo Zero, and AlphaZero. The subsequent sections of this paper will provide a detailed exposition of these models.

2.2.1 AlphaGo Lee

AlphaGo represents a model that integrates supervised and reinforcement learning mechanisms with multi-layered neural networks. It seeks to identify an effective function for assessing the state of play in Go games. Fig. 2 shows a simple relationship between agent and environment in reinforcement learning.

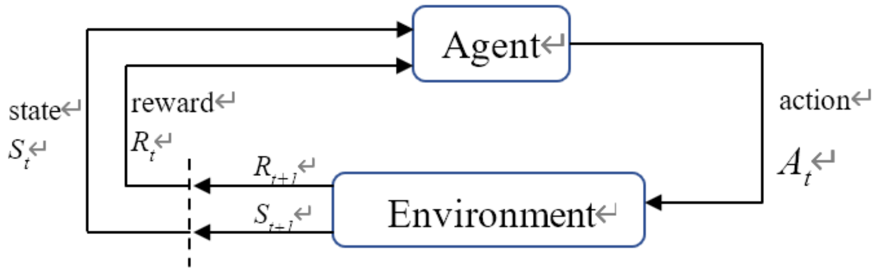

Fig. 2 The agent-environment interaction in reinforcement learning [5]

In Fig. 2, upon the selection of an action by an autonomous agent, the ambient environment absorbs the action, thereby effectuating a transition to a subsequent state. Then, a reward is dispensed as a consequence of the executed action. The agent recalibrates its decision-making process and proceeds to make further decisions within the confines of the new state.

What is more, AlphaGo utilizes Monte Carlo tree search techniques, as known as MCTS, to establish a new search algorithm with great efficiency [6]. Precisely, MCTS prioritizes records with a level as high as possible in order to reduce the simulation times. Fig. 3 introduces the working

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function of MCTS.

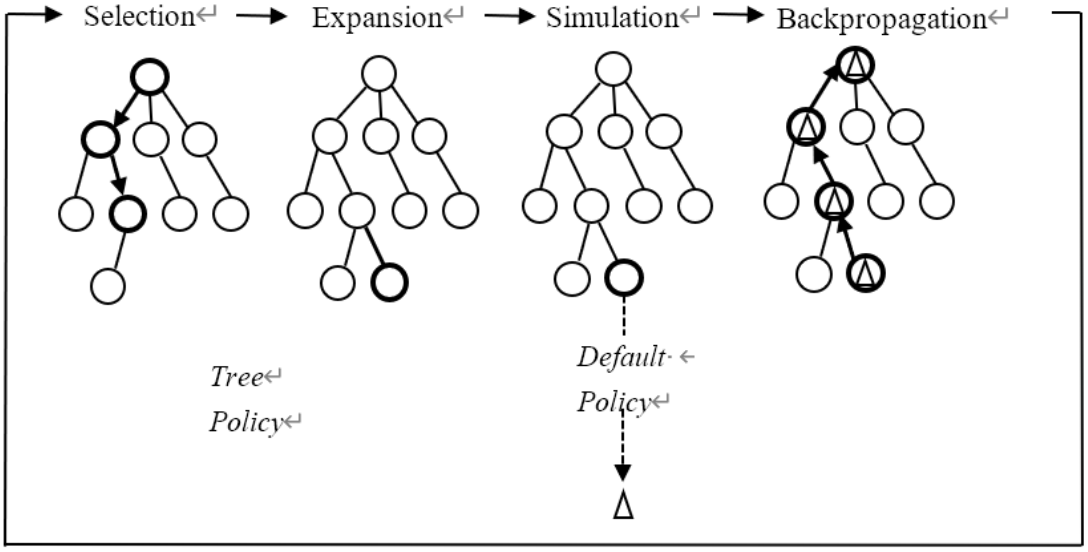

Fig. 3 Process of MCTS searching algorithm [7]

In conclusion, the Monte Carlo Tree Search (MCTS) serves as the foundational framework for AlphaGo, with reinforcement learning enhancing its learning algorithms. Lastly, neural networks are employed to emulate the necessary functions [4]. The synergy of these three components is inextricably linked to an immense computational effort. Leveraging Google's vast array of GPUs, TPUs, and parallel computing resources, AlphaGo Lee achieved a monumental victory against renowned Korean professional Go player Lee Sedol in 2016.

2.2.2 AlphaGo Zero

In October 2017, the model underwent a significant upgrade, resulting in the emergence of AlphaGo Zero. Starting with no prior knowledge of Go beyond the fundamental rules, AlphaGo Zero engaged in self-play and utilized reinforcement learning to hone its skills. Remarkably, within a mere 3 days, AlphaGo Zero surpassed the capabilities of its predecessor, AlphaGo Lee, demonstrating an extraordinary learning capacity [8]. The paper "Mastering the game of Go without human knowledge," published by DeepMind, posits that expert datasets are often costly, unreliable, or even redundant. Even when reliable, the training systems based on such data are limited in scope. However, AlphaGo Zero transcends these limitations due to its more complex residual neural networks composed of 40 hidden layers. Fig. 4 shows the structure of residual neural networks:

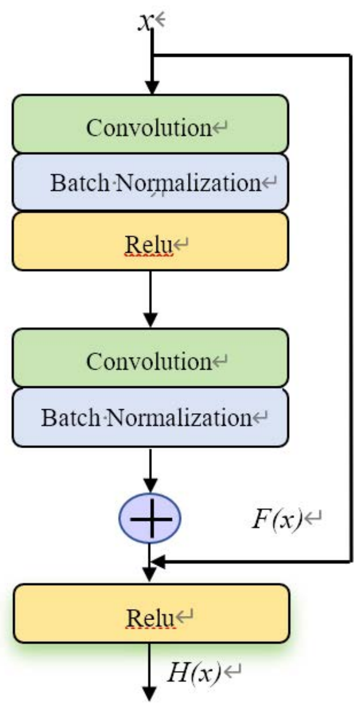

Fig. 4 Structure of residual networks [1]

In addition, AlphaGo Zero had only one 'brain' instead of both policy networks and value networks. The efficiency of AlphaGo Zero is far higher than AlphaGo Lee, which can be obviously seen in Fig. 5 showing the performance of each program on an Elo scale:

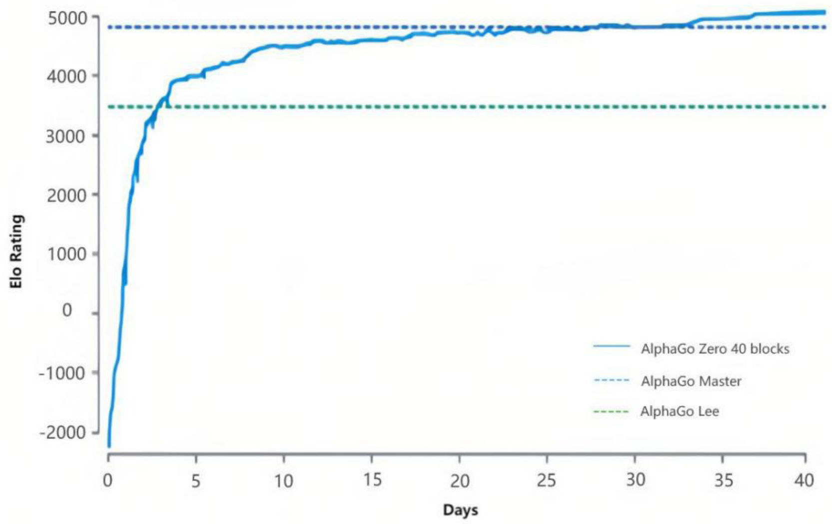

Fig. 5 Training time and chess performance of different versions of AlphaGo [4]

Despite AlphaGo Lee boasting a consistently high Elo Rating of approximately 3500, and AlphaGo Zero starting with an initial rating of merely -2000, the latter managed to outperform its predecessor in just 3 days, a testament to its remarkable learning capabilities. The exponential growth in AlphaGo Zero's Elo Rating within this short span underscores the prodigious computational prowess of its AI architecture.

Subsequently, AlphaZero made its debut, emerging as the preeminent AI system in the realm of board games. Equipped with functionalities akin to those of AlphaGo Zero, AlphaZero required only 150 hours to surpass the achievements of its predecessor [2]. In AlphaZero, strategy value network training is implemented. This training paradigm utilizes a Convolutional Neural Network (CNN), which is composed of a public network layer, an action strategy layer, and a state value network layer. The accompanying Fig. 6 illustrates the intricate training process of the strategy value network.

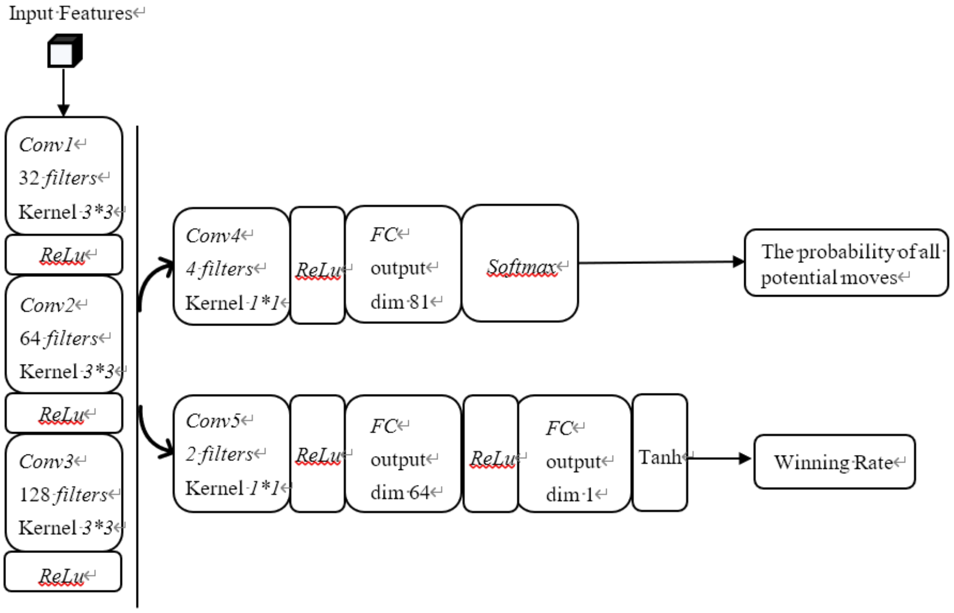

Fig. 6 Strategy value network training flow chart [9]

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3. Limitations and Future Outlooks

The advent of AlphaZero has revolutionized the Go community, establishing a new benchmark that is virtually unbeatable by human players. This development has prompted a paradigm shift, with human players increasingly turning to AI for training purposes. A prime example of this trend is the South Korean Go player Shin Jinseo, whose world ranking skyrocketed following his adoption of AI-assisted training methods. His opening strategies have become a de facto standard, mirroring AI's approach to the game. The success of Shin Jinseo has inspired other players to embrace AI, leading to a homogenization of opening moves in high-level Go matches.

Under the influence of AI, the Go community faces a potential conundrum. The uniformity in opening strategies may stifle the unique styles that have historically characterized individual players. For example, the once innovative and graceful openings of Chinese player Ke Jie, which were celebrated for their beauty and elegance, now risk being overshadowed by the precision of AI strategies. Furthermore, AI's unconventional yet optimal moves can perplex amateur players, as these choices, while theoretically sound, may not align with human intuition or traditional play.

As AlphaZero has ascended to the pinnacle of Go proficiency, there is growing anticipation for the emergence of a technology that caters to moves within the realm of human comprehension and acceptance. While this technology may not match the supremacy of AlphaZero, it could offer a more relatable and instructive platform for players to learn and grow. Such an approach would not only preserve the diversity of human play but also foster a more inclusive and engaging environment for the Go community, where players at all levels can benefit from AI's insights without feeling overwhelmed by its inscrutability.

4. Conclusion

AlphaGo's remarkable progress is intrinsically linked to the application of cutting-edge models and theoretical frameworks that have been developed to date. Its rapid evolution over a span of three years is also inextricably tied to the utilization of CPUs and GPUs, which provide the immense computational power necessary for its complex algorithms. This paper begins by encapsulating the foundational logic that underpins AlphaGo, irrespective of the various stages of its development. It then delves into the specific models that have been refined and improved upon over time.

In conclusion, AlphaGo has indeed achieved a level of proficiency that is currently unmatched by human players. However, from the author's perspective, there remains an unresolved issue concerning the sometimes counterintuitive and unpredictable nature of AlphaGo's playing style. It is an undeniable fact that an ideal technology, designed to be accessible and beneficial for human players, may not reach the same heights of excellence as AlphaZero, which stands as the epitome of Go technology today. Nevertheless, such a technology, while potentially less dominant in competitive terms, would undoubtedly offer a more suitable and effective platform for training purposes. It would bridge the gap between AI and human understanding, providing a valuable tool for players to enhance their skills and foster a deeper appreciation of the game's strategic nuances. The future of AI in Go, therefore, lies not only in the pursuit of victory but also in the enrichment of the human experience within this ancient and revered game.

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