Future Trends in AI Research, 2025, 2(1), 12-16
https://www.hillpublisher.com/Journals/ftair/
ISSN Online: 3066-3083

Analysis of the “Golden Corners, Silver Edges, and Grass Belly” Principle in Go from a Game Theory Perspective

Zhonghao Gao

International Department, Beijing Bayi School 29 Suzhou Street, Haidian District, Beijing 100080, China.

How to cite this paper: Zhonghao Gao. (2025) Analysis of the “Golden Corners, Silver Edges, and Grass Belly” Principle in Go from a Game Theory Perspective. *Future Trends in AI Research*, 2(1), 12-16.
DOI: 10.26855/ftair.2025.06.003

Received: September 11, 2025
Accepted: October 21, 2025
Published: November 14, 2025

***Corresponding author:** Zhonghao Gao, International Department, Beijing Bayi School 29 Suzhou Street, Haidian District, Beijing 100080, China.

Abstract

“Golden Corners, Silver Edges, Grass Belly” represents a crucial strategic principle in Go. This paper employs a Nash equilibrium-based strategy model to quantitatively evaluate the comparative value, validity, and efficiency of different placement positions throughout the game. Results demonstrate that corner placements yield significantly greater benefits than edge or center placements, confirming the mathematical rationale behind this rule. While the model accurately analyzes local formations, it remains limited in accounting for the dynamic evolution of the entire board.

Keywords

Go strategy; resource efficiency; Nash equilibrium; game theory

1. Introduction

Go is an ancient Eastern strategy game renowned for its profound complexity and artistic depth. The board holds approximately 10170 possible configurations—a number exceeding the total atoms in the universe—making it a pivotal domain for artificial intelligence research [1]. Alphago, for instance, achieved global fame by dominating the game just a few years ago [2]. Yet despite this immense complexity, players have traditionally relied on concise heuristic rules to guide their macro-level decisions [3]. Even AI systems initially adhere to these principles, though they demonstrate their validity through direct win rate metrics—indicating optimal placement [4]. However, current approaches lack a rigorous logical framework to deduce these insights or provide intuitive processes for human comprehension. Among all principles, the most macro-level and universally applicable rule in Go is famously known as: “Golden corners, silver edges, grassy middle.” [5] This principle states that placing stones in the corners yields the highest efficiency, creates the easiest territory to secure, and holds the most potential; the edges are next in value, while the middle is the least favorable. This principle primarily stems from the qualitative summarization of ancient masters’ experience. However, it lacks a rigorous quantitative mathematical framework to explain its validity. Thus, a core question arises: Can we use mathematical tools and thinking to transcend superficial empirical summaries and provide a solid argument for this classical wisdom?

This thesis aims to fill this gap by constructing a game theory model. Specifically, it abstracts the act of placing stones in Go into a strategic game, quantifying the payoffs associated with different placement locations (corners, edges, center) through the game’s inherent “eye count” system [8,9]. A payoff model is constructed, utilizing the core concept of Nash equilibrium to analyze players’ rational optimal strategy choices [10].

2. Literature Review

2.1 Summary of International Go and Game Theory Research

As an ancient strategic game, Go not only carries rich cultural connotations but has also become a significant subject in modern game theory research. With the advancement of artificial intelligence technology, Go has emerged as a crucial platform for testing algorithmic efficiency and intelligence levels. In recent years, the integration of Go and game theory has emerged as a hot topic in academia, particularly within the AI field where Go is regarded as a benchmark for evaluating machine learning algorithms [11,16].

2.2 Domestic Research on Go and Game Theory

Domestic research in recent years has also concentrated on Go and artificial intelligence. Gu Rong [4] conducted in-depth studies on several key issues in computer Go, proposing three influence models applicable to precise computation, static position evaluation, and dynamic search. Using machine learning methods, she automatically extracted joseki patterns from game records to build a joseki database, making the learned patterns more reasonable and consistent with human understanding [12]. Research perspectives and methodologies also encompass a CUDA-based Go game engine [7], the application of machine learning to Go machine games [6], and approaches combining deep learning with Monte Carlo tree search algorithms [5].

Domestic research has also explored other angles, such as compiling and summarizing historical game records [13] and mathematical models in Go [14]. In "Application of Nash Equilibrium in Multi-Level Game Search Strategies for Computer Go," Sheng Yijun [15,16] explored integrating Nash equilibrium theory into Go strategy search for positional evaluation and move selection. The study emphasized incorporating opponent models in multi-level search to avoid "one-sided" decision-making and enhance the program's competitive capabilities. This research provides game theory support for optimizing computer Go strategies, offering practical guidance.

In summary, Go games not only find extensive applications in computer science but also demonstrate immense research value and developmental potential in fields like cognitive science and artificial intelligence. However, insufficient quantitative research exists for certain widely applied Go strategies. For instance, little quantitative basis has been established for the Go strategy "gold corners, silver edges, grass belly." This paper attempts to achieve breakthroughs in this area.

3. Research Method Design

Game theory is a discipline that examines how rational decision-makers maximize their payoffs in strategic interaction scenarios. It finds broad application across economics, political science, sociology, biology, computer science, and other fields. Game theory analyzes situations where your decision outcomes depend not only on your actions but also on those of others. Consequently, you must predict others' behavior while recognizing that they are also predicting yours [17].

A game typically comprises the following fundamental elements:

1. Players: Rational individuals or entities (e.g., persons, companies, nations) participating in decision-making.
2. Strategies: The complete set of action options available to each player within the game.
3. Payoffs: The outcomes (utility, profit, welfare, etc.) each player receives after all players have chosen their respective strategies, typically represented by a payoff matrix or function.
4. Information: The degree to which players understand the game structure (e.g., payoffs) and the behavior of other players (e.g., perfect information vs. imperfect information).
5. Equilibrium: A core concept referring to a stable state where all players have chosen optimal strategies (based on predictions of others' actions), and no one has an incentive to unilaterally change their strategy.

The most renowned is the Nash equilibrium, proposed by mathematician John Nash. It describes a state where, given the strategies of other players, no single player can improve their payoff by unilaterally changing their strategy. The Nash equilibrium serves as the theoretical foundation for the value principle "gold corners, silver sides, grass middle." When constructing a simplified Go model using a reasonable value function (quantifying the value of corners, sides, and the middle), its Nash equilibrium strategy naturally reflects the behavioral pattern of "corners first, then sides, then the middle." This precisely demonstrates the power of game theory: it employs mathematical logic to explain and validate the experiential wisdom humans develop in complex strategic environments.

When designing research methodologies, the primary focus should be on numerically quantifying and analyzing the “golden corners, silver edges, grassy center” principle in Go. The objective is to use game theory models to validate optimal placement strategies in Go. The complex board is simplified into three zones: corners, edges, and center. Each zone’s efficiency and payoff are quantified using “eye count,” establishing a strategic game model. Within this model, players’ strategies involve selecting among these zones, while the payoff matrix represents changes in eye count after each move across different positions. To enhance realism and accuracy, a two-move scenario was incorporated to analyze the effects of different strategy combinations. This ensured the model directly addressed the research question. Through reverse reasoning, it was confirmed that the model should demonstrate corner placement yielding the highest target points in single-move scenarios and that these strategies remain optimal in two-move games, thereby validating the model’s validity. Finally, the entire modeling process, its connection to the research objectives, and the basis for validation are organized into a coherent document, clearly presenting the research design rationale.

4. Discussion

4.1 the Research Model

Given that the Go board is a relatively large analytical sample with 361 points across a 19×19 grid, this paper will segment the research process. The focus will be on the corners, edges, and central area of this 19×19 board, rather than a comprehensive analysis of all four corners, four edges, and the central area simultaneously. This is because such a comprehensive approach would result in an extremely large number of variables and choices. This approach is entirely feasible, as the principles often apply specifically to the opening layout phase.

The analysis proceeds in two distinct steps. The first involves simulating the initial move in a simulated game, considering three scenarios: placing a stone in a corner star point, placing a stone on a side line one space below the star point, or placing a stone in the central area. Each placement must occur at the locally optimal position. For example, the study stipulates that in the first analysis scenario: corner stone’s default to the star points in the corners, side stones to the next horizontal line from the star points on the side, and central stones to the center point (Tian Yuan). Each move is then compared based on the number of points it can capture, evaluating which position offers the highest efficiency and value. All specific point counts are obtained through Yifu Go（a Go website）’s positional evaluation.

Table 1. Single-Move Enclosure Value Analysis by Position

Player	corner（C）	sides（S）	center(M)
value	16points	6points	0points

The second analysis simulates the first two moves made by actual players during a game, permuting all possible combinations of these initial two moves. Each player has three options: corner, side, or center. Pairs are compared in groups—corner vs. corner, corner vs. side, corner vs. center—assuming each player optimally places stones in the best local positions (following common joseki patterns). The number of points captured by each player is then compared, recording the point values for both players under different positional scenarios. Go is fundamentally a zero-sum game, where one player’s gain is another’s loss. In other words, Player 2 aims to minimize Player 1’s gains. By collecting data on point values and applying the Nash equilibrium algorithm from game theory, the optimal strategy is derived. Player 1 aims to capture territory, while Player 2 seeks to secure their own territory while minimizing the opponent’s gains—aligning with the definition of Nash equilibrium. The study defaults to Player 1 as Black with the first move, disregarding komi rules.

During the process, the following rules apply: When both players target the same position on the board (e.g., “corner, corner”), they must place stones in the same corner—not in four distinct corners. The same principle applies to the sides and center. As previously stated, each player must choose the optimal position locally. Specifically: On the edge, the optimal positions are the star point one line down and the sharp thrust. In the center, the optimal positions are the center point and the move adjacent to the center point. If players choose different positions, such as “(corner, edge)”, they must follow the first positional strategy for that specific board layout. For example, the player in the corner must play the star point in the corner, and the player on the edge must play the star point on the edge.

Table 2. Quantitative Matrix of Dual-Move Strategy Payoffs

Player1/player2	corner（C）	side（S）	center(M)
corner（C）	Rc1: 6 Rc2: 3	Rc1: 16 Rc1: 6	Rc1: 16 Rc2: 0
side（S）	Rc1: 6 Rc2: 16	Rc1: 4 Rc2: 0	Rc1: 5 Rc2: 0
center（M）	Rc1: 0 Rc2: 16	Rc1: 0 Rc2: 5	Rc1: 0 Rc2: 0

4.2 Research Model Analysis

When Player1 chooses the corner (C): If Player2 also plays in the corner (C), Player1 gains 6 points while Player2 gains only 3 points, demonstrating a clear first-move advantage. If Player2 instead chooses the side (S), Player1's gain significantly increases to 16 points, and Player2's gain also rises to 6 points. However, Player1's gain remains substantially higher than Player2's and far exceeds other strategy combinations. If Player 2 chooses the center (M), Player 1 still gains 16 points while Player 2's gain becomes zero, highlighting the center strategy's weakness against the corner strategy.

When Player 1 chooses the side (S): If Player 2 plays in the corner (C), Player 1 gains only 6 points while Player 2 gains 16 points, indicating the side strategy is easily countered by the corner strategy. If Player 2 also chooses the side (S), Player 1's gain drops to 4 points while Player 2's gain becomes zero, yielding less than the corner strategy. If Player 2 chooses the middle (M), Player 1 gains 5 points while Player 2 still gains nothing, but the side's gain potential remains lower than the corner and fails to effectively suppress the opponent.

When Player1 chooses the center (M): Regardless of Player2's response, Player1 gains nothing. If Player2 chooses the corner (C), Player2 gains 16 points; if Player2 chooses the side (S), Player2 gains 5 points. Only when Player2 also chooses the center (M) do both players gain zero, highlighting the center strategy's disadvantage in the opening phase.

Analyzing the above data, we conclude that regardless of Player1's initial position, the primary and optimal choice for players is to play in the corner to either build territory or compress Black's space. Conversely, Player 1 should also prioritize corner placements as the first move to maximize territory expansion. In other words, this model structure demonstrates that the corner-first strategy yields significantly greater gains in equilibrium states, mathematically validating the adage "Gold in the corners, silver on the edges, grass in the middle."

4.3 Case Study Analysis

In the third game of the recent Strongest Go Players Tournament, the match between professional 9-dan players Tu Xiaoyu and Shin Jin-seon fully adhered to and demonstrated the research findings. The conclusion drawn from the study—that securing the corner first, then either playing in the opponent's corner to hinder their territory formation or playing in the corner itself, yields the highest resource efficiency—was put into practice. This case successfully bridges abstract model analysis with real-world gameplay, lending greater persuasiveness to our findings. It not only demonstrates the model's ability to explain top players' opening strategies but also highlights its practical value for guiding actual matches.

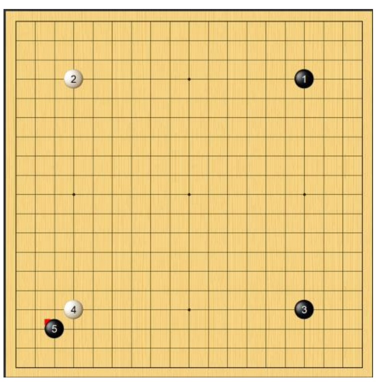

Figure 1. Opening Moves (First Five Steps) in Actual Game.

DOI: 10.26855/ftair.2025.06.003

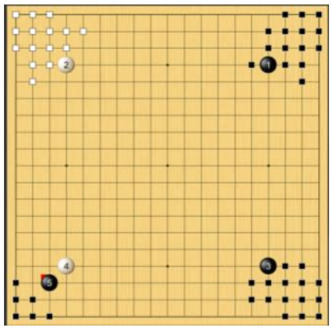

Figure 2. Comparison of Points Gained in Opening Moves (First Five Steps).

5. Conclusion

This research not only fills the gap in quantitative analysis of the classic Go principle "gold corners, silver edges, and grass in the middle," but also injects new vitality into the refinement of Go theory. Through mathematical modeling and game theory analysis, it provides a modern scientific interpretation for this ancient wisdom, deepening our understanding of the essence of Go strategy while offering new insights and theoretical support for the development of Go artificial intelligence. As this paper focuses solely on the opening phase and variations within two moves, it does not fully explore the diverse value gains that different placement options across the entire board might yield. Therefore, its findings are applicable only to analyzing resource efficiency gains in Go's opening stage.

Simultaneously, this research enriches Go scholarship while providing scientific grounds for practitioners' opening-phase decision-making. It advances the transition of Go from empirical to scientific understanding, holding significant theoretical value and practical implications.

References

[1] An B. Artificial Intelligence and Game Theory: Starting from AlphaGo. China Dev Watch. 2016;(06):13+17.

[2] Gao TT, Ding JH, Shu WA, Yin SQ. Research on AlphaZero-Based Go Game Systems. Intell Comput Appl. 2022;12(10):117-121.

[3] Gao X. Research and Implementation of Go Game Expert Systems [dissertation]. Beijing: Beijing University of Technology; 2002.

[4] Gu R. Research on Several Issues in Computer Go Game Systems [dissertation]. Beijing: Tsinghua University; 2003.

[5] Lin YC. Research on Go Game Based on Deep Learning and Monte Carlo Tree Search [dissertation]. Harbin: Harbin Institute of Technology; 2018.

[6] Tang Y. Research and Application of Machine Learning Algorithms in Go Gameplay [dissertation]. Chongqing: Chongqing University of Technology; 2012.

[7] Xiao F. Application Research and Experimentation of GPU High-Performance Computing in Computer Go Game Systems [dissertation]. Beijing: Beijing University of Posts and Telecommunications; 2011.

[8] Xie CH. The Role of Artificial Intelligence in Go Research. Inf Syst Eng. 2019;(01):105.

[9] Yu YB. Research on Computer Go Game Based on Monte Carlo Tree Search [dissertation]. Dalian: Dalian Maritime University; 2015.

[10] Yu L. Research on Computer Go Game Problems Based on Cognitive Science [dissertation]. Shanghai: East China Normal University; 2011.

[11] Zhou MM. Research on Computer Go Games Based on Expert Systems and Monte Carlo Methods [dissertation]. Nanjing: Nanjing University of Aeronautics and Astronautics; 2012.

[12] Gu R. Research on Several Issues in Computer Go Game Systems [dissertation]. Beijing: Tsinghua University; 2003.

[13] Zhu ZM. A Brief Discussion on the Evolution of Ancient Chinese Go Strategies. J Sichuan Univ Arts Sci. 2016;26(3):98-102.

[14] Shen JH. Mathematical Modeling Issues in Go. J Math Pract Theory. 1995;(3):45-50.

[15] Sheng YJ. Application of Nash Equilibrium in Multi-Level Search Strategies for Computer Go. Comput Eng Appl. 2006;42(19):80-82.

[16] Bouzy B, Cazenave T. Computer Go: An AI-Oriented Survey. Artif Intell. 2001;132(1):39-103.

[17] Tirole J. Game Theory. Renmin University Press; 2015.