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Pattern Acquisition and Comparative Analysis in the Game of Go

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Abstract

The game of Go represents a major challenge for artificial as well as human intelligences due to its profound complexity.

Although computer programs capable of playing Go have existed for decades, the period from 2015 to 2025 has marked a turning point, with these systems achieving—and even exceeding—professional human performance. A notable shift in gameplay strategy emerged around 2016, driven by the adoption of unconventional yet effective moves demonstrated by AI programs, challenging previous conventions of preferred moves.

Nowadays, the process of learning Go has evolved from traditional knowledge transfer, based on centuries of established conventions regarding strategy, positional judgement and move value to modern trends developed by AI playing style, lacking the explanatory heuristics inherent in both human style of playing and oral tradition.

Facing this new challenge, we rely on our curiosity to understand our opponents' moves beyond technological and language barriers as we continue to explore the mysterious depths of this timeless game.

Keywords: Statistical analysis, Pattern recognition, AI interpretability, Modern theory, Style evolution, Professional Games, Computational Go.

I. Introduction

For our investigation of this perceived evolution in the style of play, we first compiled a selection of academic literature published in the latest 50 years, regarding analysis of Go from a mathematical standpoint. Among other approaches, the work of Liu and Dou (2007) titled "Automatic Pattern Acquisition from Game Records in Go"[1] presented a simple and effective methodology that persisted in guiding our inquiries. Their study of frequency in patterns sampled the placement of each stone on the board statistically across 9,500 professional games from the early 2000s.

We focused our research in reiterating this simple but effective methodology with existing records of both current and previous professional games, expecting to find changes in the frequency of moves played then as opposed to now.

The scope of this work is as follows:

- First we present an updated algorithm for automatic pattern acquisition, building on the algorithm introduced in [1].
- Then we analyze high-frequency patterns from over 17,000 recent professional games, as well as 19,000 from a period before AlphaGo (2002-2011) in order to identify the evolution of most frequent patterns in professional play.
- Finally we provide a comparative analysis of the most popular patterns then and now, offering quantitative insights into the evolution of Go strategies.

II. Related Work

1. Literature

The acquisition and analysis of patterns in Go have been extensively studied, with early efforts focusing on manual compilation of patterns and language-based approaches denoting specific moves in relationship to their resulting shapes, such as: knight's jump (*keima*), hug (*hane*), kick (*tsuke*), corner enclosure (*shimari*), forcing move (*kikashi*), solid connection (*nobi*), one space jump (*ikken-tobi*), etc.

Studies published as early as 1990 have paved the way to explore the role of patterns in Monte Carlo tree search and move generation, [2] and the use of terminology to identify the essential components of whole board positions such as liberties, captures, ko situations, life and death of groups, etc. [3],[4]

A statistical method for automatic pattern acquisition was introduced in 2007 [1] defining patterns as spatial relationships within a fixed 5x5 grid. This approach demonstrated the feasibility of extracting repeatable patterns from game records and highlighted the importance of statistical usage in determining pattern urgency.

Recent advances in AI, particularly deep reinforcement learning, have shifted the focus toward end-to-end learning systems such as AlphaGo. Nevertheless, pattern-based approaches remain relevant for understanding human play and improving interpretability in AI systems.

Recent work involves combinatorial game theory applied to complex end-game positions [5], as well as measurements of the degree of complexity of several variants and rulesets relevant to the game of Go. [6] Despite these advancements, there is a lack of comparative studies analyzing the evolution of Go patterns over time.

Our research bridges that gap by revisiting the methodology of [1] and applying it to a modern dataset of professional games.

2. New Analysis

Evaluating patterns by extracting 5x5 grids, as per selected literature [1] results in what could be compared to "atomic" components of the whole board strategy inherent in the game of go. While this criteria yields interesting results, we decided to leverage today's availability of computing power to expand the area of possible patterns.

This enlargement allowed us to obtain a whole board perspective and detect the appearance of well-known joseki sequences, akin to "molecules" in a figurative sense. In order to achieve this, results obtained in [1] had to be replaced by our new analysis, in order to be consistent enough for a comparative analysis.

III. Methodology

1. Pattern Definition

A Go pattern is defined as a spatial configuration of stones where the most recent move is displayed in the center of a 19x19 grid. [1] Our primary objective was to construct a database of such patterns, extracted from every move in the sampled game records, and quantify their frequencies. To ensure accuracy, we also implemented a canonical representation function that groups equivalent patterns across the board and accounting for rotations, reflections, and color inversions of each pattern to produce a statistically coherent count, allowing for mirror images of the same pattern to be represented as variations of the same move, regardless of the color of the stones, orientation relative to the board's symmetries.

Note: This canonical representation implies that the color of the stones playing a certain move is arbitrary, as it groups together equivalent moves without differentiating the sequential turns that are customary in Go (i.e. black is followed by white)

Additionally, a function that differentiates the outermost (first) three lines of the board was necessary. This function becomes increasingly important as the most frequent moves are normally located in the corners of the board, and even more so with modern opening strategies, according to our findings.

2. Datasets

We compiled two datasets:

A) ~19,600 games played between 2002 and 2011

~17,300 pro games played between 2016 and 2025.

The records were downloaded using a simple python script and sourced from http://gokifu.com

After the datasets were examined for games containing illegal moves or corrupt data, dataset A consisted of 19,584 records, while dataset B totaled 17,173 records suitable for analysis.

3. Pattern Acquisition Algorithm

The script employs a python library called *sgfmill* that is able to parse SGF records and extract data one move at a time. Other libraries are necessary such as os, *pathlib* for accessing files and folders, as well as *collections* for efficiently cataloguing moves canonically. the core algorithm is based on the pseudocode presented in[1], and implemented using Python 3.

The algorithm processes each move in each game record using nested *for* loops as follows:

1. For each game record:

1.1 For each move:

1.1.1 Extract the 19x19 grid centered on the move.

1.1.2 Convert the grid into its canonical form.

1.1.3 Update count of pattern in the database1.1.4 Update count of game files containing the pattern

2. Sort database in descending order 3. Print top entries with overall frequency and # of game records

This algorithm has a complexity linear to the number of moves, making it highly efficient for large datasets)[1]

4. Statistical Analysis

We analyzed the frequency distribution of patterns across the dataset, identifying the 19 most frequent 19x19 patterns for cross-temporal analysis. This allowed us to visualize stylistic shifts in professional play statistics over the course of 18 years of professional Go matches.

In order to compute the data effectively, we designed a simple notation using the following symbols:

☻ (black smiley face): Player in turn.

☺ (white smiley face): Opponent.

+ (plus sign): Empty intersection.

/ (slash sign): Edge intersection (first line of the board).

. (dot) : Space outside the board.

These symbols allow for consistent pattern matching while performing transformations on matrices, while keeping track of plays near the edge of the board as different from patterns located in the central area, identifying plays in the 4,4 corner star point (*hoshi*) and its adjacent 3,4 intersection (*komoku*) separately.

IV. Findings

1. Change in Frequency of Patterns in Professional Games

Our analysis reveals patterns found in the professional dataset, with the new top 19 highfrequency patterns compared to pre-AI style of play (see Table 1).

We observe a significant rise in the early san-san invasion to a corner star point, a trademark aspect of AI style. Modern *joseki* sequences therefore appear considerably more often, displacing approaches to opponents' single stones in the corners of the board

2. Evolution of Go Strategies

Our results indicate that certain patterns have remained consistently popular, while others have declined in usage. For instance, the 3-3 invasion has become more frequent, signaling a preference for corner territory as opposed to developing the edges early in the game. However, corner enclosures appear to occur less frequently, with a two-space jump from the 3-4 point becoming more urgent than the classical knight's jump.

These trends effectively represent the evolving strategies in professional Go and the influence of AI on human play.

V. Discussion

By comparing a pattern's prevalence to that of its local follow-ups, we infer the relative frequency of moves outside the local area—a phenomenon consistent with *tennuki* (prioritizing a distant move over local continuation). For instance, when a pattern's frequency surpasses that of its immediate continuation, it implies players often prioritize global strategy over local battles.

Periodic replication of this study could deepen our understanding of professional play, challenge time-honored proverbs, and modernize pedagogical frameworks for learning and improving at Go.

For experienced players, these findings provide actionable insights into contemporary strategies, while beginners and intermediates gain a structured approach to studying professional games. Ultimately, this research bridges tradition and innovation, fostering a dynamic, datadriven culture within the Go community.

VI. Conclusion

This article presents a modern approach to automatic pattern acquisition in the game of Go. By analyzing large datasets of recent professional games, we identify key trends and shifts in pattern usage, offering new insights into the evolution of Go strategies.

Our results underscore the importance of pattern-based approaches in both human and AI play, and provide a framework for future research in game AI and pattern recognition.

VII. Acknowledgements

This work is dedicated to the memory of Professor José “Pepe Chac” Chacón, for his exemplary fighting spirit and invaluable contributions to Mexico’s Go community.

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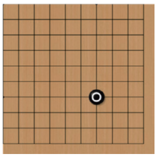
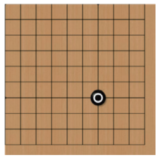
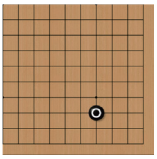
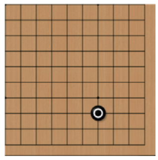
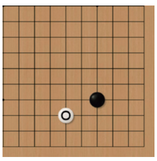
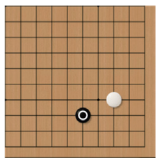
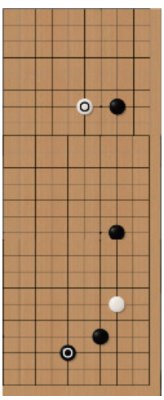
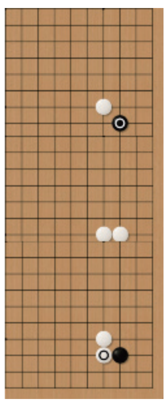
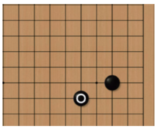
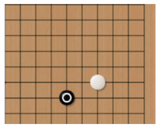
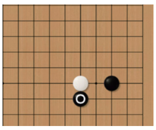
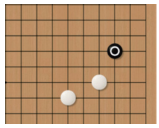
Table I.

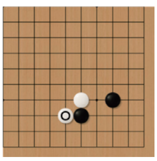
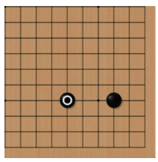
2007 (a)	2025 (b)	
		1. the 4-4 star point remains most frequent
		2. komoku (3-4) also remains as second most frequent pattern
		3. A low approach to a 3-4 point is nowadays more urgent than both a low approach to 4-4, (pattern 3a) and a high approach to a 3-4 (pattern 4a)
		4. A san-san invasion is more urgent than a high approach to an opponent's komoku 5. this standard sequence after a san-san invasion leaves the invader in gote, suggesting the invaded stone may reply with *tennuki* before extending 6. Once white extends, it its less likely that black will *tennuki*, considering the result of pattern 5b

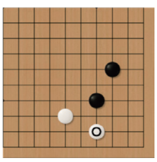
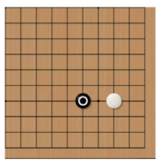
7A. low approach to the 4-4 is now less frequent than a san-san invasion, see pattern 5a

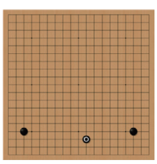
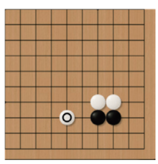
8. This approach resembles the joseki pattern in 6a but is actually a low approach to the opponent's enclosure from the 4-4 point. The fact that this encolsure pattern does not appear without the approach, suggests this move follows most of the time

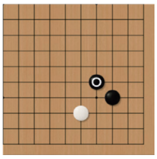
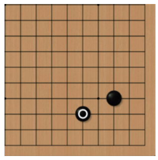
9. A *joseki* continuation to pattern 5b not as frequent
10Two space jump from komoku appears as the most urgent form of enclosing a corner

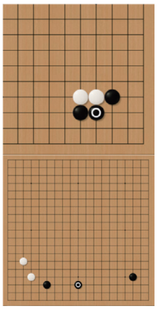
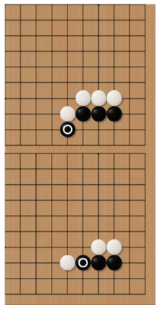
11. a high approach to komoku descends from 4th to 11th most frequent pattern

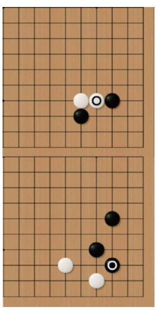
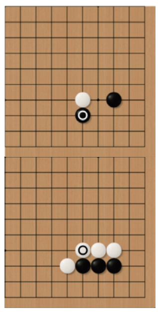
12. Another continuation from pattern 5b precedes its subsequent *joseki* moves in patterns 14b, 15b and 17b

13. This move is now less frequent, see pattern 7a

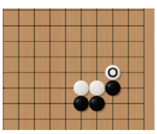
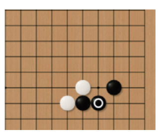



14. This joseki pattern naturally appears after a san -san invasion. but an extension from white's stone in the third line is not always the immediate follow-up, suggesting white's *tennuki* 15Though less frequent, this sequence from san-san invasion *joseki* also suggests white's *tennuki*, instead of following up with *hane* as in pattern 14b

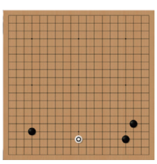
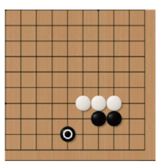



16 This pattern has become less frequent, see 8a

17 Similarly to pattern 14b, sequence suggests this black's *tennuki* immediately after white's hane.

18. This joseki pattern is less frequent in modern play, see 9a

19. Another continuation from pattern 9b

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