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Quantitative Comparative Analysis of Traditional Go Joseki and AI-Recommended Moves

A Study of Twenty Fuseki Patterns Using KataGo Expected Score

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Abstract

AlphaGo's landmark victory over Lee Sedol in March 2016 triggered an unprecedented paradigm shift in the game of Go, prompting widespread re-valuation of joseki sequences—locally optimal opening patterns refined over centuries of human tradition. Despite this upheaval, systematic *quantitative* research into precisely how inefficient traditional joseki are—measured in concrete point (目) differentials—remains scarce in the academic literature. Most existing discourse has operated at the level of qualitative judgment ("this move is good/bad") without rigorously measuring the numerical stakes.

This study addresses that gap by extracting approximately **70 key moves from 20 fuseki patterns** widely used in the pre-AlphaGo era and quantifying the efficiency difference between traditional sequences and AI-recommended moves using KataGo's Expected Score metric. A central contribution is the independent design and development of **Joseki Analyzer—**a purpose-built program integrating a FastAPI backend with the KataGo engine—enabling automated, large-scale, reproducible analysis under standardized conditions

(1,000 visits, Chinese rule set, komi 7.5). The core metric **Δ Score** is defined as the Score Lead of the AI's top-recommended move minus the Score Lead of the traditional move at the same position; a negative value indicates that the traditional move is less efficient by the corresponding number of points.

Results show an **overall mean Δ Score of approximately −0.28 points** across 20 patterns, indicating that traditional moves incur an expected-score loss of roughly this magnitude per move relative to AI recommendations. The largest divergences occur in the *Komoku Approach–Pincer Response* (II) (−1.20 pts), *Komoku Approach–Aggressive Response* (−0.68), *Hoshi One-Space Pincer–3-3 Invasion* (−0.60), and *Komoku Corner Enclosure Fuseki* and Komoku Approach–High Extension (both −0.53). The single largest move-level loss is −2.59 points. Conversely, four patterns achieve Δ Score = 0—*Hoshi Approach–Knight's-Move Response, Komoku Enclosure–Development Variation, Hoshi Approach–Contact-Play Joseki*, and *Komoku Approach–Contact Play* (II)—indicating perfect alignment with AI evaluation.

A consistent typological finding emerges: corner-enclosure and extension patterns show the largest divergence from AI, while contact-play (붙임수) patterns show the smallest. Across all patterns, KataGo systematically prioritizes claiming empty corners over reinforcing one's own established

positions—a finding that runs counter to a core axiom of classical Go strategy. This study represents the first systematic, tool-assisted effort to quantify the inefficiency of traditional fuseki joseki in point-based terms, offering both empirical findings and a replicable methodological framework for evaluating classical Go theory against modern AI computation.

Keywords: Go, joseki, fuseki, KataGo, Expected Score, quantitative analysis, AlphaGo, AI efficiency, Δ Score, Joseki Analyzer

1. Introduction

1.1 Research Background

In March 2016, Google DeepMind's AlphaGo defeated world champion Lee Sedol 9-dan by four games to one—an event that was widely recognized not merely as a technical milestone but as a fundamental challenge to centuries of accumulated human knowledge about Go (Silver et al., 2016). Subsequent AI systems, including AlphaGo Zero (Silver et al., 2017) and KataGo (Wu, 2019), have further eroded confidence in a substantial portion of the traditional joseki (定石) canon, revealing that many sequences humans once considered locally optimal are, from an AI standpoint, second- or third-best plays.

Joseki are locally optimal corner sequences—patterns in which both Black and White played what was considered their best response—that form the building blocks of fuseki (布石), the strategic opening phase of a Go game. Before the AI era, the joseki corpus represented the apex of human inductive reasoning applied to the game over centuries of competitive play and analysis. The AI revolution has put this corpus under unprecedented scrutiny.

Yet despite the upheaval, scholarly discourse has remained largely qualitative, offering assessments of "good" or "bad" moves without rigorously measuring the numerical point differential involved. The question "by exactly how many points is traditional joseki X inferior to AI's recommendation?" has, to the author's knowledge, not been addressed in a systematic, large-scale, quantitative study. This gap has two practical consequences: (1) Go educators lack data-driven guidance on which traditional patterns remain reliable and which require revision; (2) the historical moment—AlphaGo's tenth anniversary—calls for an empirical reckoning with the gap between human intuition and AI computation.

1.2 Research Objectives and Questions

This study aims to quantify the efficiency gap between traditional fuseki joseki and KataGo's AI recommendations by extracting approximately 70 moves from 20 patterns widely used before AlphaGo and measuring the difference in expected score in point (目) units. Three research questions guide the investigation:

RQ1. What is the mean difference in Expected Score (Δ Score) per move between traditional fuseki joseki sequences and AI-recommended moves?

RQ2. Does the magnitude of divergence from AI recommendations vary systematically by joseki type (corner enclosure, extension, contact play, pincer response, etc.)?

RQ3. How does AI evaluate traditional moves in terms of Prior probability, and what strategic characteristics does KataGo consistently prefer?

1.3 Originality of the Study

This study differentiates itself from prior work in three respects. First, **a quantitative metric:** the study uses Score Lead rather than Win Rate to measure efficiency in point units. Win Rate is a nonlinear indicator in which small differences may be amplified or compressed; Score Lead offers a directly interpretable, linear measure of expected outcome. Second, **a purpose-built analysis tool:** the researcher independently designed and developed Joseki Analyzer, enabling automated analysis of 20 patterns and 70 moves under identical conditions—a scale of systematic comparison that was previously not feasible without dedicated tooling. Third, **cross-pattern comparison:** by applying a uniform measurement framework across 20 patterns, the study enables typological trend analysis that single-pattern studies cannot provide.

2. Theoretical Background

2.1 Joseki and Fuseki in Go

The opening phase of Go—the fuseki stage, typically the first 50 or so moves—is a contest for the most valuable territory. Classical theory holds that spatial value on a Go board follows a **corner** → **side** → **center** hierarchy: corners can be enclosed using only two board edges, yielding efficient territory with fewer stones; sides require one edge; the center requires no walls and is the hardest to convert into secure territory efficiently.

Within this framework, joseki are the locally agreed-upon optimal sequences in the corners, where both players played what was considered their best response, resulting in a locally balanced outcome. Fuseki is the art of combining these local joseki outcomes into a coherent global strategy. Before the AI era, the joseki canon—comprising hundreds of standard patterns—represented the highest level of human analytical achievement in Go theory. Players, coaches, and commentators treated joseki as a fixed reference system for understanding corner play.

2.2 The Rise of AI Go and KataGo

The development of AI Go can be understood in three phases. In the **first phase (2016)**, AlphaGo combined deep convolutional neural networks—building on advances in deep reinforcement learning (Mnih et al., 2015)—with Monte Carlo Tree Search (MCTS; Coulom, 2006; see Browne et al., 2012, for a comprehensive review), achieving superhuman performance against the world's strongest human players (Silver et al., 2016). In the **second phase (2017)**, AlphaGo Zero dispensed with human game records entirely, learning solely through self-play and rapidly surpassing its predecessor—in the process revealing that many canonical joseki were suboptimal (Silver et al., 2017). In the **third phase (2019–present)**, KataGo brought this technology to the open-source community, with efficient training algorithms and robust analysis tools making it the standard engine for Go research and education (Wu, 2019).

KataGo's Score Lead metric estimates Black's expected point advantage under Chinese counting rules, assuming optimal play from both sides. Positive values indicate a Black lead; negative values indicate a White lead. This metric provides a continuous, interpretable measure of positional efficiency appropriate for studying short-term move quality—the focus of this study.

Although the present study builds directly on the AI Go lineage outlined above, it differs from prior AI-driven revaluations of joseki in both scope and aim. AlphaGo Zero's self-play results (Silver et al., 2017) revealed that many canonical joseki are suboptimal, and subsequent discussions in the professional Go community broadly accepted this verdict at a qualitative level—new moves were adopted, certain sequences fell out of favor, and commentary literature shifted accordingly. However, these earlier revaluations were largely demonstrative (showing that AI plays differently) rather than measurement-based (quantifying by how many points traditional moves diverge from AI). The present study extends this lineage in two specific directions: (i) it replaces qualitative endorsement of AI moves with a continuous, point-based metric (Δ Score in 目 units) that is directly interpretable in Go's own scoring system, and (ii) it applies a uniform analytical framework across 20 patterns to detect typological trends rather than commenting on individual sequences. In this sense, the study is best understood not as a contradiction of AlphaGo Zero's findings, but as their quantitative continuation—moving from "AI plays differently" to "AI plays X points more efficiently in this pattern type."

2.3 Operational Definitions

Table 1. Key terms and operational definitions

Term	Definition
Score Lead	KataGo's estimate of Black's expected point advantage under Chinese counting. Positive = Black leads; negative = White leads.
Win Rate	KataGo's estimated probability that Black wins the game from the current position (0–1).
Prior	The neural network's prior probability assigned to a candidate move during MCTS, reflecting the network's intuitive preference before deep search.
Δ Score	Score Lead (AI best move) − Score Lead (traditional move). A negative value indicates the traditional move is less efficient by that many points.
Joseki (定石)	A sequence of locally optimal moves in the corner, resulting in a locally balanced outcome for both players.
Fuseki (布石)	The opening phase of Go (~first 50 moves), in which players establish strategic frameworks across the whole board.
Visits	The number of MCTS simulations allocated to each candidate move. Higher visits yield more accurate evaluations.
Contact play (붙임수)	A tactical sequence initiated by placing a stone directly adjacent to an opponent's stone.

3. Methodology

3.1 Analysis Tool: Joseki Analyzer

The central methodological contribution of this study is the independent design and development of **Joseki Analyzer** (Kim, 2026), a purpose-built program that automates the collection and structuring of KataGo evaluation data for arbitrary joseki sequences. The system architecture is as follows:

> **Joseki Analyzer — System Architecture** ① **Backend:** Python FastAPI REST API server ② **AI Engine:** KataGo (open-source Go AI, integrated via GTP protocol) ③ **Database:** SQLAlchemy ORM for structured result storage ④ **Output:** Automatic collection of Score Lead · Win Rate · Prior for top-15 candidate moves at each position; automated generation of structured HTML visualization reports

The analysis workflow proceeds as follows: (1) the user inputs a joseki sequence in GTP coordinate format (e.g., B4, C3, D16 ...); (2) Joseki Analyzer reconstructs each successive board position and calls KataGo; (3) KataGo returns Score Lead, Win Rate, and Prior for the top 15 candidate moves; (4) Joseki Analyzer records the rank and score of the traditional move and computes Δ Score against the AI's top recommendation; (5) results are automatically compiled into a structured HTML report. This automation made it feasible to analyze 20 patterns and 70 moves under identical, reproducible conditions.

3.2 Core Metrics

The primary metric of this study is defined as follows:

Δ Score = Score Lead (AI best move) − Score Lead (traditional move)

A Δ Score of 0 indicates that the traditional move and the AI's top recommendation achieve the same expected score. A negative value indicates that the traditional move is less efficient by that number of points. The *pattern-level mean Δ Score* is the arithmetic mean of Δ Score values across all analyzed moves within a pattern.

> ⚠ **Methodological caveat:** KataGo's Score Lead measures short-term expected efficiency, not absolute truth. The long-term strategic value of traditional joseki—particularly the exploitation of thickness (厚み) in the middle game, positional flexibility, and opponent-dependent variation—lies beyond the scope of this metric.
> Results should therefore be interpreted as evidence of short-term expected-score divergence, not a verdict on the overall value of traditional patterns.

3.3 Analysis Conditions

To ensure consistency and reproducibility, identical analysis conditions were applied to all 20 patterns. All analyses were conducted in February 2026.

Table 2. Standardized analysis conditions

Parameter	Setting	Rationale
Visits	1,000	Sufficient for systematic pattern-level analysis; consistent across all positions.
Rule set	Chinese	Area scoring; all stones and enclosed territory counted. Current international tournament standard.
Komi	7.5	Current official compensation for Black's first-move advantage.
Candidate moves	15	Top 15 moves reported per position, capturing the full competitive range.
Analysis mode	sequence	Moves reconstructed sequentially; each position analyzed independently.
Software	Joseki Analyzer v1.0	Custom-developed FastAPI + KataGo integration (see §3.1).

3.4 Pattern Selection

The 20 patterns were selected from Lee's (2007) *Joseki Selection* (정석 선택), published by Hyunhyungak Yangji—a widely used pre-AlphaGo reference textbook that systematically surveys fuseki joseki theory. Each pattern is identified using standard joseki nomenclature based on corner stone type (*hoshi / komoku*) and tactical method (approach, enclosure, pincer, contact play). Pure fuseki setup moves (where both players simply occupy corners without interaction) are excluded; analysis begins from the first interactive move in each sequence.

Table 3. The 20 analyzed joseki patterns

#	Standard Joseki Classification	Source Chapter Title (Korean)	Total moves	Analyzed
1	Komoku Corner Enclosure Fuseki	귀굳힘의 가치	9	4
2	Hoshi Approach–One-Space Pincer Response (Ⅰ)	협공에 대한 대응(Ⅰ)	10	4
3	Komoku Approach–Low Extension (3rd-line)	3선 돌의 가치	13	2
4	Komoku Approach–High Extension (4th-line)	4선 돌의 가치	21	6
5	Komoku Knight's-Move Enclosure Fuseki	날일자 굳힘의 가치	7	2
6	Hoshi Influence Fuseki – Side Extension	좌변 세력의 가치	21	2
7	Hoshi Approach–Knight's-Move Response	의문의 날일자	23	2
8	Komoku Enclosure – Development Variation	4선 돌의 발전성을 살려서	17	2
9	Komoku Approach–Context-Dependent Response	배석에 따른 변의 가치	21	2
10	Komoku Approach–Aggressive Response	적극적인 작전	20	2
11	Hoshi Contact-Play Stabilization Joseki	돌의 안정이 우선	13	2
12	Hoshi Approach–Contact-Play Joseki	붙임수 정석의 시기	13	7
13	Hoshi One-Space Pincer–3-3 Invasion Joseki	한칸 협공 이후	13	6
14	Komoku Approach–Contact Play (Ⅰ)	붙임수의 선악	15	3
15	Hoshi Approach–Contact Play	의문의 붙임수	16	3
16	Komoku Approach–Contact Play (Ⅱ)	붙임수의 선악은	18	4
17	Hoshi Approach–Contact-Play Timing	붙임수의 시기	21	7
18	Hoshi Approach–Contact-Play Direction	붙임수의 방향	16	6
19	Komoku Corner Development Fuseki	귀의 발전성과 변의 가치	13	2
20	Komoku Approach–Pincer Response (Ⅱ)	협공에 대한 대응(Ⅱ)	15	2
Total			335	70

Source: Adapted from Lee (2007), Joseki Selection (정석 선택), Hyunhyungak Yangji. Standard joseki classification names are based on corner stone type and tactical method; source chapter titles are the original Korean headings from the textbook.

4. Results

4.1 Overall Statistics

Metric	Value
Patterns analyzed	20
Total moves analyzed	70
Overall mean Δ Score (pts)	−0.28
Patterns with Δ = 0	4

Across 70 moves in 20 patterns, the overall mean Δ Score is approximately **−0.28 points**, indicating that traditional joseki moves incur a mean expected-score loss of this magnitude relative to KataGo's top recommendation. The pattern-level minimum is −1.20 points (*Komoku Approach–Pincer Response* II) and the maximum is 0.00 points (four patterns). The largest single-move loss recorded is −2.59 points (*Hoshi One-Space Pincer–3-3 Invasion*, move 9). Four patterns (20% of the sample) record a mean Δ Score of exactly 0, indicating full alignment between traditional sequences and AI evaluation.

4.2 Δ Score Across All 20 Patterns

Figure 1 presents the mean Δ Score for each of the 20 analyzed joseki patterns, sorted by absolute loss magnitude (descending). Detailed values and loss-category ratings are summarized in Table 4 below.

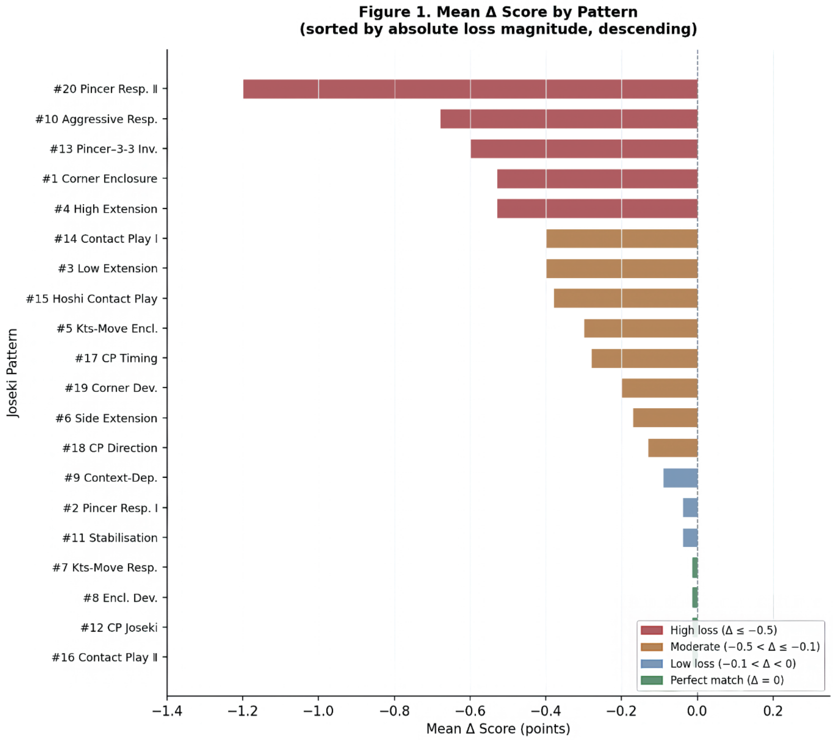

Figure 1. Mean Δ Score by pattern (points; sorted by absolute loss magnitude, descending). *Note: Negative values indicate the traditional move is less efficient than the AI recommendation by the corresponding number of points. Bar color indicates the loss-magnitude category as defined in Table 4 below (High loss / Moderate / Low loss / Perfect match).*

Table 4. Summary of Δ Score results across all 20 patterns

#	Standard Joseki Classification	Moves	Mean Δ	Min. Δ	Rating
20	Komoku Approach–Pincer Response (Ⅱ)	2	−1.20	−2.40	High loss
10	Komoku Approach–Aggressive Response	2	−0.68	−1.36	High loss
13	Hoshi One-Space Pincer–3-3 Invasion	6	−0.60	−2.59	High loss
1	Komoku Corner Enclosure Fuseki	4	−0.53	−1.46	High loss
4	Komoku Approach–High Extension (4th-line)	6	−0.53	−1.20	High loss
14	Komoku Approach–Contact Play (Ⅰ)	3	−0.40	−1.19	Moderate
3	Komoku Approach–Low Extension (3rd-line)	2	−0.40	−0.81	Moderate
15	Hoshi Approach–Contact Play	3	−0.38	−1.14	Moderate
5	Komoku Knight’s-Move Enclosure Fuseki	2	−0.30	−0.59	Moderate
17	Hoshi Approach–Contact-Play Timing	7	−0.28	−1.26	Moderate
19	Komoku Corner Development Fuseki	2	−0.20	−0.40	Moderate
6	Hoshi Influence Fuseki – Side Extension	2	−0.17	−0.33	Moderate
18	Hoshi Approach–Contact-Play Direction	6	−0.13	−0.77	Moderate
9	Komoku Approach–Context-Dependent Response	2	−0.09	−0.18	Low loss
2	Hoshi Approach–One-Space Pincer Response (Ⅰ)	4	−0.04	−0.18	Low loss
11	Hoshi Contact-Play Stabilization Joseki	2	−0.04	−0.07	Low loss
7	Hoshi Approach–Knight’s-Move Response	2	0.00	0.00	Perfect match
8	Komoku Enclosure–Development Variation	2	0.00	0.00	Perfect match
12	Hoshi Approach–Contact-Play Joseki	7	0.00	0.00	Perfect match
16	Komoku Approach–Contact Play (Ⅱ)	4	0.00	0.00	Perfect match

Patterns sorted by mean Δ Score (ascending). “Min. Δ»” denotes the largest single-move loss within each pattern.

4.3 Typological Trend Analysis

Grouping the 20 patterns by joseki type reveals a consistent and theoretically interpretable trend.

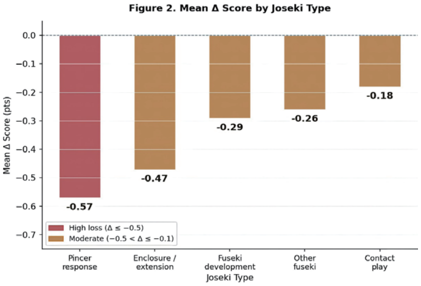

Figure 2. Mean Δ Score by joseki type. Pincer-response sequences exhibit the largest mean loss (−0.57); contact-play sequences show the smallest (−0.18).

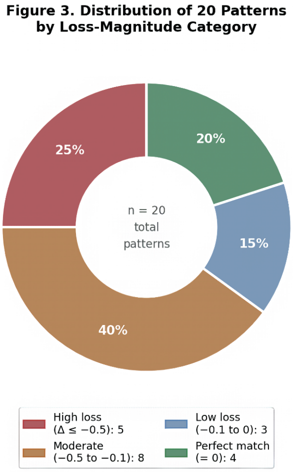

Figure 3. Distribution of the 20 patterns by loss-magnitude category, using the same Rating boundaries as Table 4: High loss (Δ ≤ −0.5) accounts for 5 patterns, Moderate (−0.5 < Δ ≤ −0.1) for 8, Low loss (−0.1 < Δ < 0) for 3, and Perfect match (Δ = 0) for 4.

Table 5. Mean Δ Score by joseki type

Joseki type	Patterns	Mean Δ Score	Patterns included
Pincer-response sequences	3	−0.57	#2, #13, #20
Corner-enclosure / extension sequences	5	−0.47	#1, #3, #4, #5, #6
Fuseki development variations	3	−0.29	#8, #9, #10
Other fuseki	2	−0.26	#7, #19
Contact-play (붙임수) sequences	7	−0.18	#11, #12, #14, #15, #16, #17, #18

Corner-enclosure and extension patterns (mean −0.47) and pincer-response patterns (mean −0.57) show the largest divergence from AI recommendations. Contact-play patterns show the smallest divergence (mean −0.18), with two achieving Δ = 0 across all analyzed moves. This trend suggests that AI and classical theory diverge most in situations where players have wide strategic freedom—choosing where and how to extend from an established corner position—and converge most when direct contact between stones narrows the locally feasible move space.

4.4 Deep Analysis: High-Loss Patterns

Four patterns share the largest mean Δ Scores in the dataset and are examined in detail below. They are ordered by mean Δ Score (descending in absolute value). Note that Pattern #4 (Komoku Approach–High Extension, mean Δ = −0.53) shares the same loss magnitude as Pattern #1 and belongs to the same typological category (corner-enclosure / extension); it is therefore represented in this section by Pattern #1 as a category exemplar.

① Pattern #20 — Komoku Approach–Pincer Response (II) | Mean Δ = −1.20 pts

The highest-loss pattern in the study. Of the two analyzed moves, the second (move 15, Black C7) incurs a loss of −2.40 points—the second-largest single-move loss observed. The traditional move C7 aims to claim a corner "territory" position in isolation; KataGo strongly prefers D5, a move that connects to neighboring groups and establishes a flexible, multi-purpose formation. KataGo's Prior for C7 is a mere 0.3%, compared with 52.9% for D5—a particularly large Prior gap that indicates the engine's learned intuition strongly disfavors the traditional choice even before deep calculation. Move 14 (White G3 vs. D3) records Δ = 0.00 in Score Lead, but still shows a Prior gap (0.9% vs. 25.9%), indicating that AI's overall strategic instinct points away from the traditional move even where short-term scores are identical.

② Pattern #10 — Komoku Approach–Aggressive Response | Mean Δ = −0.68 pts

Of the two analyzed moves, move 19 (Black F3) incurs −1.36 points; move 20 (White H3) achieves Δ = 0. The traditional Black F3 prioritizes speed and offensive pressure, but leaves adjacent groups inadequately connected, reducing overall positional thickness. KataGo prefers C3, which simultaneously secures solid thickness and strengthens the connection toward the center. The subsequent White H3, on which both tradition and AI agree, illustrates that moves satisfying thickness and connectivity simultaneously are consistently efficient.

③ Pattern #13 — Hoshi One-Space Pincer–3-3 Invasion Joseki | Mean Δ = −0.60 pts / Largest single-move loss: −2.59 pts

This pattern contains the largest single-move loss in the entire study: −2.59 points at move 9.

Across six analyzed moves, four achieve Δ = 0 and two record negative values, with high internal variance. This structure—where traditional moves initially align with AI and then sharply diverge at specific junctures—suggests that the traditional sequence is locally sound for several moves before committing to a strategic direction that AI evaluates as significantly suboptimal. The pattern has the widest per-move range of any pattern studied.

④ Pattern #1 — Komoku Corner Enclosure Fuseki | Mean Δ = −0.53 pts

Four analyzed moves yield losses at moves 7 and 9 (−0.67 and −1.46 respectively) and equality at moves 6 and 8. AI consistently responds to corner-enclosure positions by prioritizing empty-corner occupation elsewhere over reinforcing the enclosure already in progress. This is perhaps the most direct empirical illustration of the AI vs. classical divergence: what traditional theory treats as consolidating an advantage, AI treats as ceding initiative.

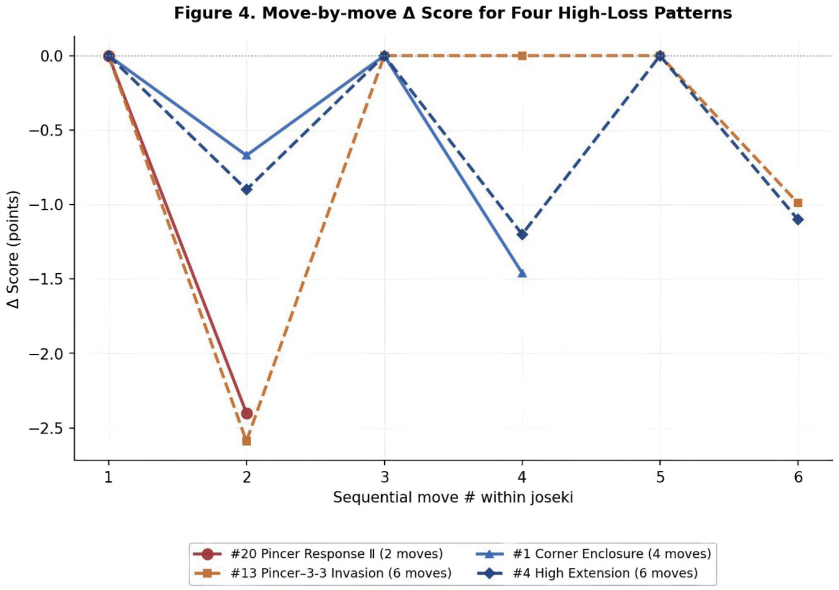
Figure 4. Move-by-move Δ Score for Four High-Loss Patterns

Figure 4. Move-by-move Δ Score for four representative high-loss patterns: #20 Pincer Response II, #13 Pincer–3-3 Invasion, #1 Corner Enclosure, and #4 High Extension.

Note: x-axis represents sequential analyzed move number within each pattern (not absolute game move number). Color encodes typological category — warm tones (red, orange) for pincer-related patterns, cool tones (blue) for enclosure/extension patterns. Pincer patterns exhibit sharp early losses at move 2 (−2.4 to −2.6), whereas enclosure/extension patterns show their largest losses at move 4 (−1.2 to −1.5).

4.5 Perfect-Alignment Patterns

The four patterns achieving Δ = 0 across all analyzed moves share a common structural characteristic: their locally optimal sequences are constrained enough that centuries of human analysis and AI computation arrive at the same conclusion. Patterns #12 (Hoshi Approach–Contact-Play Joseki, 7 moves) and #16 (Komoku Approach–Contact Play II, 4 moves) are the largest perfect-alignment sets, involving extended post-contact exchanges where both players have limited alternatives. Patterns #7 and #8 involve choice-restricted direction decisions following enclosure or approach moves.

Table 6. Characteristics of perfect-alignment patterns (Δ = 0)

#	Classification	Moves	Structural characteristic
7	Hoshi Approach–Knight's-Move Response	2	Directional choice post-approach; locally constrained
8	Komoku Enclosure–Development Variation	2	Enclosure development; limited alternatives
12	Hoshi Approach–Contact-Play Joseki	7	Post-contact formalized exchange sequence
16	Komoku Approach–Contact Play (Ⅱ)	4	Post-contact formalized exchange sequence

This finding is consistent with the broader typological trend: divergence between AI and traditional theory is smallest when the move space is narrowest. When human intuition is guided through a constrained, locally forced sequence, it tends to converge with AI computation. Divergence is largest precisely when human intuition must choose among a wide range of strategically plausible options—where AI's global pattern recognition and exhaustive search create an advantage over human heuristic reasoning.

5. Discussion

5.1 AI Strategic Preferences

The most consistent finding across all 20 patterns is that **KataGo systematically prefers claiming empty corners over reinforcing one's own established position**. In every corner-enclosure or extension pattern studied, AI's top recommendation is to play elsewhere—most often in an unoccupied corner—rather than continue the local sequence. This contradicts a foundational classical principle: that the purpose of a corner approach is to develop that corner, and that the responding player should prioritize local stability before moving elsewhere.

The Prior analysis reinforces this finding. In corner-enclosure patterns, the traditional move typically receives a Prior of 1–3%, while AI's preferred alternative—often a distant empty-corner play—receives 20–30%. This large Prior gap indicates that KataGo's trained neural network, before any deep search, strongly encodes the preference for global initiative over local consolidation. The implication is not simply that individual moves are suboptimal, but that the underlying strategic framework of pre-AI corner theory systematically underweights the value of early global positioning.

A second AI preference, visible across contact-play patterns, is **the acceptance of locally formalized exchanges**. When both players are committed to a contact sequence with limited alternatives, KataGo's top move frequently coincides with the traditional move, suggesting that classical theory succeeded in identifying locally optimal plays precisely where the move space was constrained enough for human analysis to be thorough.

5.2 Reassessing the Value of Traditional Joseki

The results of this study do not support the conclusion that traditional joseki are “wrong.” An overall mean Δ Score of −0.28 points per move is meaningful in aggregate over a full game of several hundred moves, but the interpretation requires important contextual caveats.

First, **educational value**. Traditional joseki sequences explicitly articulate strategic trade-offs—territory versus influence, corner versus side, speed versus thickness—in a pedagogically structured way. This function cannot be replicated by AI recommendations alone, which optimize outcome without articulating the trade-off. The tension illustrated in patterns like #10 (aggressive response) between a move that seeks immediate territory and one that builds thickness is precisely the kind of strategic decision that traditional joseki analysis was designed to teach.

Second, **the limits of the metric**. Score Lead measures expected outcome in the short term under the assumption of optimal play from both sides. This assumption is not a minor technical detail; it generates three distinct interpretive constraints that bear directly on how the present findings should be read.

The first is the thickness problem. In classical Go theory, thickness (厚み) denotes a wall or formation of stones whose immediate territorial value is small but whose latent power—projected influence, attacking potential against future invasions, and resilience under complex fighting—can decide games hundreds of moves later. Score Lead at the joseki stage cannot observe this latent power: it evaluates the position assuming both sides continue optimally, but the realized value of thickness depends critically on whether the resulting middle game contains the fighting situations in which thickness pays off. A traditional move that builds thickness at a Δ Score cost of −0.3 points may, in practice, return several points in a complex middle-game exchange that the local evaluator does not see.

The second is the *flexibility problem*. Some traditional moves are favored not because they are locally optimal but because they preserve multiple follow-up options against unknown opponent responses. KataGo's Score Lead, computed under the assumption of optimal play from both sides, systematically undervalues this kind of optionality: a move with three reasonable continuations against three different opponent plans may appear inefficient against a single best-line opponent yet outperform the AI-preferred move in the broader space of realistic games.

The third is *opponent-dependent variation*. AI evaluation assumes a symmetric optimal-opponent model. Human players, however, choose joseki partly to steer the game toward positions that exploit known weaknesses of specific opponents or styles. This strategic dimension is invisible to Score Lead by construction.

These three constraints do not invalidate the −0.28 mean Δ Score finding, but they constrain its interpretation. The finding should be read narrowly: under the assumption of optimal play from both sides and at a 1,000-visit search depth, traditional joseki moves incur this short-term expected-score loss. Translating this measured quantity into a broader verdict on the overall value of traditional joseki—across thickness deployment, flexibility against varied opponents, and full-game outcomes—requires evidence that this metric cannot, by construction, provide.

Third, **practical implications**. The study's results offer a data-driven guideline: **AI consultation is most valuable in corner-enclosure, extension, and pincer-response positions**, where divergence is large and consistent. In contact-play sequences, traditional joseki shows higher alignment with AI and can be followed with greater confidence.

5.3 Limitations

Five limitations constrain the generalizability of this study's findings. (1) **Analysis depth:** 1,000 visits, while sufficient for systematic pattern-level comparison, is substantially fewer than the hundreds of thousands of visits used in professional-level AI analysis; some evaluations may be inaccurate at this depth. (2) **Short-term metric:** Δ Score captures only short-term expected efficiency; long-term strategic value and opponent-dependent variation are not measured. (3) **Sample size:** 20 patterns and 70 moves represent a small subset of the several-hundred-pattern joseki corpus, and the present findings should therefore be read as evidence of trends within this sample rather than as conclusive claims about the joseki corpus as a whole. In particular, the typological pattern observed in §4.3—largest divergences in pincer-response and corner-enclosure sequences, smallest in contact-play sequences—is a hypothesis generated from this sample; confirmation requires a substantially expanded analysis corpus, which is identified as a primary direction for future work (see §6). (4) **Single source:** all patterns are drawn from a single textbook (Lee, 2007); other schools of joseki theory are not represented. (5) **KataGo's own limitations:** KataGo does not provide absolute ground truth; its evaluations reflect the biases of its training data and self-play regime, which cannot be fully controlled for in this study.

6. Conclusions and Future Directions

This study used a purpose-built analysis program—Joseki Analyzer—in conjunction with the KataGo AI engine to quantify the efficiency of 20 traditional fuseki joseki patterns (70 moves total) in point-based terms. Four principal conclusions emerge.

First, the overall mean Δ Score of approximately −0.28 points per move indicates that traditional joseki moves incur a measurable, consistent expected-score loss relative to AI recommendations. This is the first systematic, large-scale evidence of this magnitude in the academic literature.

Second, divergence varies significantly by joseki type. Pincer-response (mean −0.57) and corner-enclosure/extension (mean −0.47) patterns show the largest gaps; contact-play patterns (mean −0.18) show the smallest, with two achieving Δ = 0 across all moves. This typological finding has practical implications for educators and players deciding where to incorporate AI insights into traditional training.

Third, four patterns achieve complete alignment with AI across all analyzed moves, all sharing a common structural feature: locally forced sequences with limited alternatives. This finding supports the hypothesis that traditional joseki theory achieves its highest accuracy precisely where human analysis is guided by narrow choice spaces.

Fourth, AI consistently prioritizes global initiative—particularly the occupation of empty corners—over local consolidation. This finding, evident in both Score Lead and Prior data, represents a fundamental departure from a core axiom of pre-AI classical strategy.

Future research directions include, as the primary priority, (1) substantially expanding the analysis corpus to additional joseki textbooks, professional game records, and mid-game transition positions, in order to test whether the typological trends identified here generalize beyond the present 20-pattern sample. Further directions include: (2) incorporating multiple traditional sources beyond a single textbook to capture cross-school variation; (3) increasing visit counts for higher-precision evaluations; (4) tracing move-sequence efficiency curves to identify the precise juncture at which traditional and AI sequences diverge; (5) developing a quantitative framework for measuring the exchange ratio between influence (thickness) and territory; and (6) tracking changes in joseki adoption rates in professional games before and after the AlphaGo era.

On the occasion of AlphaGo's tenth anniversary, this study offers a concrete, point-based reckoning with the gap between human intuition and AI computation in Go—contributing both empirical findings and a replicable methodological framework to the emerging field of AI-assisted Go research.

References

Browne, C. B., Powley, E., Whitehouse, D., Lucas, S. M., Cowling, P. I., Rohlfshagen, P., ... & Colton, S. (2012). A survey of Monte Carlo tree search methods. *IEEE Transactions on Computational Intelligence and AI in Games, 4*(1), 1–43. https://doi.org/10.1109/TCIAIG.2012.2186810

Coulom, R. (2006). Efficient selectivity and backup operators in Monte-Carlo tree search. In H. J. van den Herik, P. Ciancarini, & H. H. L. M. Donkers (Eds.), *Computers and Games* (Lecture Notes in Computer Science, Vol. 4630, pp. 72–83). Springer. https://doi.org/10.1007/978-3-540-75538-8_7

Kim, J. (2026). *Joseki Analyzer v1.0* [Computer software]. Elite Open School. (Purpose-built analysis program developed for this study.)

Lee, H. (2007). *Joseki Selection* (정석 선택). Hyunhyungak Yangji.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Hassabis, D. (2015). Human-level control through deep reinforcement learning. *Nature, 518*(7540), 529–533. https://doi.org/10.1038/nature14236

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., van den Driessche, G., ... & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature, 529*(7587), 484–489. https://doi.org/10.1038/nature16961

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., ... & Hassabis, D. (2017). Mastering the game of Go without human knowledge. *Nature, 550*(7676), 354–359. https://doi.org/10.1038/nature24270

Wu, D. J. (2019). Accelerating self-play learning in Go. *arXiv preprin*t arXiv:1902.10565. https://arxiv.org/abs/1902.10565/

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Appendix

Go Board Diagrams: All 20 Joseki Patterns

Traditional Moves vs. AI-Recommended Moves

Source data: Joseki Analyzer + KataGo (1,000 visits · Chinese rule set · komi 7.5) · February 2026

Legend

Symbol	Meaning
T (orange circle)	Traditional move (only)
A (green circle)	AI best move (only)
Move # (blue circle)	Both agree (same move)
●	Black setup stone
○	White setup stone

How to read the boards: Each board shows the full 19×19 board, with the analyzed moves typically concentrated in one corner or side region. Markers indicate the analyzed moves: an orange circle with "T" denotes a traditional move only, a green circle with "A" denotes the AI's best move only, and a blue circle containing the move number indicates that the traditional move and AI recommendation coincide. When the AI recommends a distant tenuki—a move played elsewhere on the board, away from the local sequence—the move is listed in the table and is shown at its actual position on the full-board view. Setup stones are shown as standard black and white stones, representing the position before the analyzed sequence begins.

Note on Korean titles: The Korean titles provided for each pattern are descriptive labels for the standard joseki classification, not the original chapter titles in Lee (2007); see Table 3 of the main paper for the source chapter titles.

#1 — Komoku Corner Enclosure Fuseki

소목 귀굳힘 포석 · Δ avg = −0.53

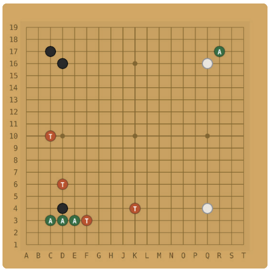

Figure A1. Board diagram for Pattern #1.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
6	○ W	F3	C3	0.00	1.7%	26.7%
7	● B	D6	E3	−0.667	3.4%	3.0%
8	○ W	K4	D3	0.00	1.4%	3.2%
9	● B	C10	R17	−1.455	0.8%	20.5%

#2 — Hoshi Approach–One-Space Pincer Response (I)

화점 날일자 걸침 한칸 협공 대응 (I) · Δ avg = −0.04

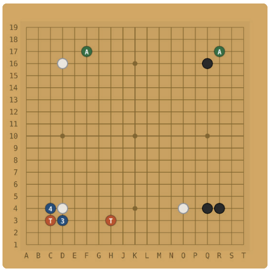

Figure A2. Board diagram for Pattern #2.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
7	● B	H3	R17	−0.178	2.4%	19.1%
8	○ W	C3	F17	0.00	23.7%	1.5%
9	● B	D3	D3	0.00	87.0%	87.0%
10	○ W	C4	C4	0.00	90.8%	90.8%

#3 — Komoku Approach–Low Extension (3rd-line)

소목 날일자 걸침 3선 벌림 · Δ avg = −0.40

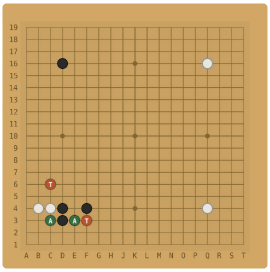

Figure A3. Board diagram for Pattern #3.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
12	○ W	F3	C3	0.00	1.9%	36.1%
13	● B	C6	E3	−0.806	2.3%	5.5%

#4 — Komoku Approach–High Extension (4th-line)

소목 날일자 걸침 4선 벌림 · Δ avg = −0.53

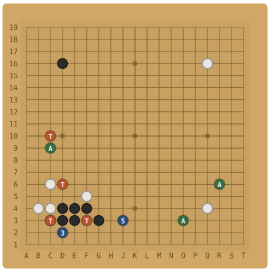

Figure A4. Board diagram for Pattern #4.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
16	○ W	F3	C3	0.00	1.6%	35.6%
17	● B	D6	C9	−0.900	4.1%	0.4%
18	○ W	D2	D2	0.00	25.9%	25.9%
19	● B	C3	O3	−1.200	15.2%	4.8%
20	○ W	J3	J3	0.00	27.9%	27.9%
21	● B	C10	R6	−1.096	0.3%	1.9%

#5 — Komoku Knight's-Move Enclosure Fuseki

소목 날일자 굳힘 포석 · Δ avg = −0.30

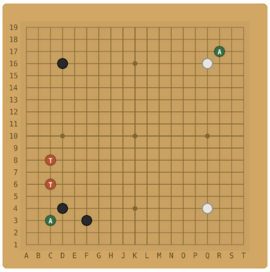

Figure A5. Board diagram for Pattern #5.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
6	○ W	C6	C3	0.00	1.0%	29.2%
7	● B	C8	R17	−0.593	3.1%	16.0%

#6 — Hoshi Influence Fuseki–Side Extension

화점 세력 포석 벌림 · Δ avg = −0.17

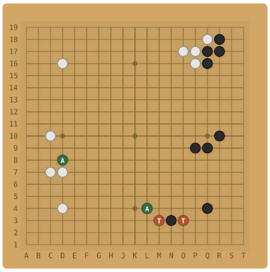

Figure A6. Board diagram for Pattern #6.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
20	○ W	O3	D8	0.00	1.2%	19.2%
21	● B	M3	L4	−0.334	12.1%	15.4%

#7 — Hoshi Approach–Knight’s-Move Response

화점 날일자 걸침 후 날일자 응수 · Δ = 0.00

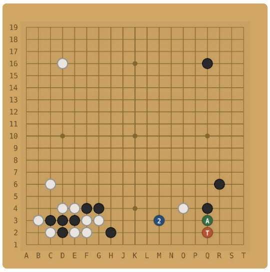

Figure A7. Board diagram for Pattern #7.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
22	○ W	Q2	Q3	0.00	15.7%	4.9%
23	● B	M3	M3	0.00	17.4%	17.4%

#8 — Komoku Enclosure–Development Variation

소목 날일자 굳힘 발전형 · Δ = 0.00

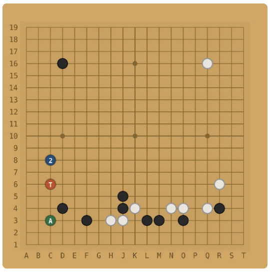

Figure A8. Board diagram for Pattern #8.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
16	○ W	C6	C3	0.00	1.9%	33.9%
17	● B	C8	C8	0.00	16.9%	16.9%

#9 — Komoku Approach–Context-Dependent Response

소목 날일자 걸침 배석별 응수 · Δ avg = −0.09

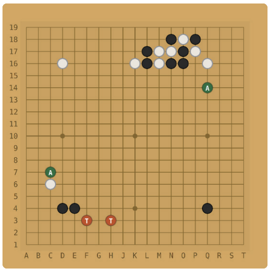

Figure A9. Board diagram for Pattern #9.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
20	○ W	F3	Q14	0.00	5.1%	1.3%
21	● B	H3	C7	−0.181	2.0%	8.1%

#10 — Komoku Approach–Aggressive Response

소목 날일자 걸침 적극 응수 · Δ avg = −0.68

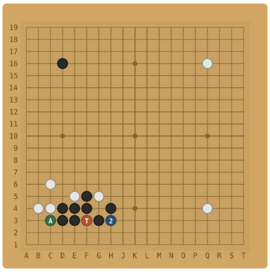

Figure A10. Board diagram for Pattern #10.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
19	● B	F3	C3	−1.364	3.1%	31.0%
20	○ W	H3	H3	0.00	52.0%	52.0%

#11 — Hoshi Contact-Play Stabilization Joseki

화점 붙임 안정형 정석 · Δ avg = −0.04

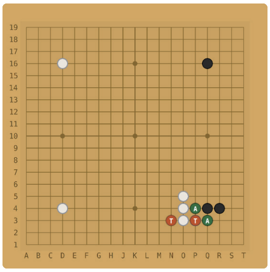

Figure A11. Board diagram for Pattern #11.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
12	○ W	P3	P4	0.00	36.1%	8.8%
13	● B	N3	Q3	−0.073	26.0%	23.3%

#12 — Hoshi Approach–Contact-Play Joseki

화점 날일자 걸침 붙임수 정석 · Δ = 0.00

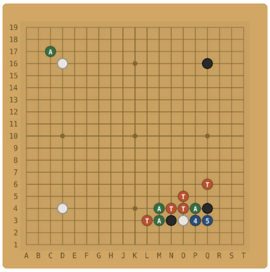

Figure A12. Board diagram for Pattern #12.

Mv#	Turn	Traditional	**AI Best**	**Δ Score**	T.Prior	AI.Prior
7	● B	O4	C17	0.00	1.1%	20.0%
8	○ W	N4	P4	0.00	51.8%	20.5%
9	● B	O5	P3	0.00	11.6%	62.9%
10	○ W	P3	P3	0.00	60.1%	60.1%
11	○ B	Q3	Q3	0.00	93.6%	93.6%
2	○ W	L3	M3	0.00	4.9%	10.9%
13	● B	Q6	M4	0.00	0.0%	14.5%

#13 — Hoshi One-Space Pincer–3-3 Invasion Joseki

화점 한칸 협공 3-3 침입 정석 · Δ avg = −0.60

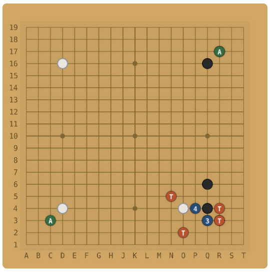

Figure A13. Board diagram for Pattern #13.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
8	○ W	R3	R17	0.00	30.1%	21.0%
9	● B	R4	Q3	−2.586	1.9%	86.1%
10	○ W	Q3	Q3	0.00	97.7%	97.7%
11	● B	P4	P4	0.00	84.5%	84.5%
12	○ W	O2	R17	0.00	0.2%	5.0%
13	● B	N5	C3	−0.986	29.6%	10.3%

#14 — Komoku Approach–Contact Play (I)

소목 날일자 걸침 붙임수 (I) · Δ avg = −0.40

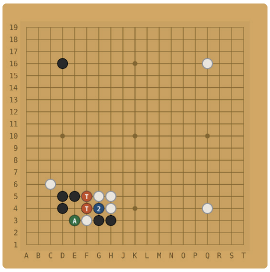

Figure A14. Board diagram for Pattern #14.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
13	● B	F4	E3	0.00	0.0%	19.7%
14	○ W	G4	G4	0.00	19.0%	19.0%
15	● B	F5	E3	−1.191	0.8%	66.8%

#15 — Hoshi Approach–Contact Play

화점 날일자 걸침 붙임수 · Δ avg = −0.38

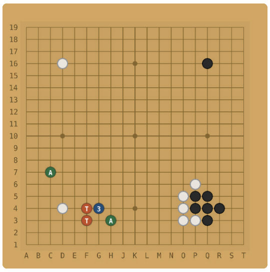

Figure A15. Board diagram for Pattern #15.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
14	○ W	F3	H3	0.00	5.8%	26.7%
15	● B	F4	C7	−1.139	0.2%	5.0%
16	○ W	G4	G4	0.00	57.9%	57.9%

#16 — Komoku Approach–Contact Play (II)

소목 날일자 걸침 붙임수 (II) · Δ = 0.00

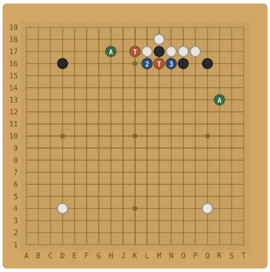

Figure A16. Board diagram for Pattern #16.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
15	● B	M16	H17	0.00	0.1%	2.8%
16	○ W	L16	L16	0.00	56.4%	56.4%
17	● B	N16	N16	0.00	13.9%	13.9%
18	○ W	K17	R13	0.00	62.7%	0.7%

#17 — Hoshi Approach–Contact-Play Timing

화점 날일자 걸침 붙임수 시기 · Δ avg = −0.28

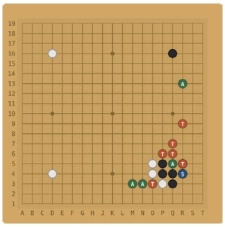

Figure A17. Board diagram for Pattern #17.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
15	● B	Q6	R13	0.00	0.3%	2.6%
16	○ W	Q7	Q5	0.00	60.4%	17.0%
17	● B	P6	R5	−1.255	2.2%	57.9%
18	○ W	R5	R4	0.00	33.1%	16.7%
19	● B	R4	R4	0.00	89.8%	89.8%
20	○ W	R9	N3	0.00	0.2%	6.0%
21	● B	O3	M3	−0.686	1.0%	17.3%

#18 — Hoshi Approach–Contact-Play Direction

화점 날일자 걸침 붙임수 방향 · Δ avg = −0.13

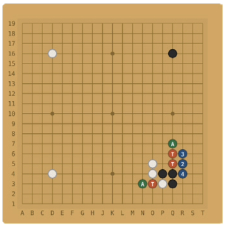

Figure A18. Board diagram for Pattern #18.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
11	● B	Q5	R5	0.00	7.5%	45.9%
12	○ W	R5	R5	0.00	17.4%	17.4%
13	● B	R6	R6	0.00	47.1%	47.1%
14	○ W	R4	R4	0.00	84.6%	84.6%
15	● B	Q6	Q7	−0.773	9.7%	62.7%
16	○ W	O3	N3	0.00	27.1%	25.6%

#19 — Komoku Corner Development Fuseki

소목 귀 발전 포석 · Δ avg = −0.20

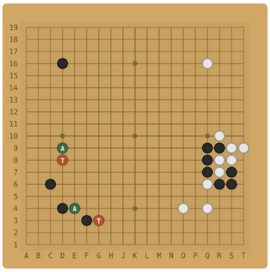

Figure A19. Board diagram for Pattern #19.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
12	○ W	D8	D9	0.00	2.3%	2.8%
13	● B	G3	E4	−0.402	0.9%	37.4%

#20 — Komoku Approach–Pincer Response (II)

소목 날일자 걸침 협공 대응 (II) · Δ avg = −1.20

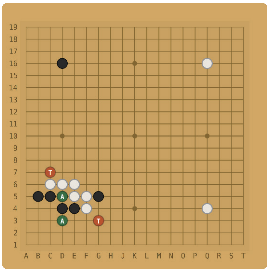

Figure A20. Board diagram for Pattern #20.

Mv#	Turn	Traditional	AI Best	Δ Score	T.Prior	AI.Prior
14	○ W	G3	D3	0.00	0.9%	25.9%
15	● B	C7	D5	−2.397	0.3%	52.9%

Δ Score = Score Lead (AI best move) − Score Lead (traditional move). T.Prior = neural-network Prior for the traditional move. AI.Prior = neural-network Prior for the AI's top recommendation.