Analysis of the Knowledge Structure of Go

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I. Introduction

In 2016, AlphaGo's defeat of Lee Sedol in a human-computer Go match sent shockwaves through the world, marking a landmark event in the history of AI. At the time, people were shocked by the outcome of the match. AlphaGo, powered by deep learning algorithms, quickly surpassed the level of human Go players, exceeding most people's expectations. Following the match, artificial intelligence quickly became a hot research area around the world. People began to study why AlphaGo was successful and where deep learning algorithms could bring breakthroughs in other fields.

After 2017, human-computer Go matches quickly faded away as AlphaGo's level soared beyond human reach. After that, leading AI researchers turned their attention to other fields. However AlphaGo's impact went beyond the mere outcomes of the matches and the Go AI that can help human players improve. The question of how AlphaGo actually won can be answered in two ways: one is to analyze AlphaGo's algorithms, the other is to analyze the knowledge structure of human Go. Only by combining these two aspects can we give a complete answer. There have been many discussions about the analysis and application of AlphaGo's algorithms. However, a deeper epistemological analysis of the knowledge structure of human Go, such as “What was the critical factor that led to humans losing to AI” is still lacking.

Unlike what people had previously imagined, Go AI does not play Go in a nearly exhaustive way with a large amount of computing power. Instead, it has reached a higher level in the field of "experience" such as "intuition" and "judgment," which humans once thought could not be described by computer language. On the other hand, in the knowledge areas of local life-and-death and forced sequences, AI does not have a huge advantage over human players. Even today, human players can still find better moves in some extreme game positions. Based on the understanding of Go AI algorithms, without a systematic breakdown of human Go knowledge, the explanation of this phenomenon can only remain superficial.

In fact, the Go knowledge passed down through generations, both orally and in writing, primarily consists of a collection of individual points. The Go knowledge in the minds of professional players is coherent, but it has not been systematically analyzed as an object. Only by conducting a structural and systematic analysis of Go knowledge can we give a more than superficial answer to the question “How did AlphaGo win?", and then accurately point out which parts of human Go knowledge revealed themselves as significant weaknesses against Go AI, which parts are reliable knowledge, and what caused such differences.

Analysis of the knowledge structure of Go can help us to further understand the limits of human cognitive abilities, as well as how these abilities are applied in the context of the game. It can also help us to identify areas where human Go knowledge is likely to be updated and improved in the future.

II. The Historical Generation of Go Knowledge

Human Go knowledge is the result of accumulated construction in history, and it is by no means an independent invention of modern Go players. To analyze the structure of Go knowledge, we must first review the history of the generation of Go knowledge. Books on Go knowledge have traditionally been divided into two categories: techniques and theories. From a historical perspective, the proportion of books on theories was higher before the Ming Dynasty, while books on techniques gradually became the majority after the Ming Dynasty. This is related to the historical evolution of the value and social form of Go.

In terms of specific knowledge content, Go technical books mainly list or enumerate the various technical aspects, such as opening, joseki, middle game, endgame, tesuji, life-and-death, and so on. With the continuous improvement of human overall level, the techniques of each knowledge category are also constantly updated. Go theory books can be traced back to [Dunhuang Classic of Weiqi] or [The Classic of Weiqi in Thirteen Chapters]. They mainly discuss the principles that should be followed in the game in the form of literary essays. Among them, the discussion of "strategy" is particularly important. Unlike technical knowledge, the language used in these strategy discussions does not rely on the professional terminology of Go. Their discourse often borrows from existing discourse systems. In terms of the goal of knowledge generation, part of the knowledge in the category of Go theories is to summarize the patterns of thinking in the game for people to follow, while another part attempts to use Go theories to discuss certain truths in the real world. This tradition began with [The Essence of Go](Yizhi), the earliest Go literary essay by Ban Gu from Han Dynasty. The tradition of Go literary theory is first based on a philosophical assumption that the principles contained in Go are the same as the principles in the world, and they all belong to "heavenly principles." Since the Han Dynasty, this assumption has been almost self-evident for the ancients. The form of knowledge argumentation used in Go articles is basically the same as that of ancient argumentative essays, often using a large number of analogies, and paying attention to the beauty of grammatical structure and the refinement of words. In general, traditional Go articles still belong to the category of ancient literary theory. After the 20th century, the concept of Go principles mainly refers to effective strategies and thinking methods for playing the game effectively, its extended meaning has faded. This is related to the strengthening of the competitive attributes of Go and the dominance of pragmatism. At the intersection of Go principles and techniques, there is another type of Go knowledge discourse called "Go commentary", which is a review of the game. Go commentary books and articles are not independent knowledge production, but can be seen as the comprehensive application of these two types of Go knowledge.

Modern people's understanding of Go is not out of thin air. Go knowledge has a history and is constantly generated on the basis of the contributions of our predecessors. The terminology used by modern Go players, the concepts and frameworks of thinking, and the generation of intuition, are all related to the overall historical accumulation of Go knowledge.

The knowledge of Go techniques is built on the foundation of "concepts". No matter how complex the technical knowledge is, it needs to be formed effectively on the basis of concepts. Concepts are used to represent the situations faced in the game. The most basic concept is the positional relationship between stones. These concepts are fixed as “terms”, such as “extend", "jump", and "knight’s move”. Single basic terms are combined into compound terms, such as "attach/pull back ", "hane/connect", etc. After there are enough terms to describe the positional relationships of stones, terms for "tactics" and "strategies" are generated, such as "reduction”, invasion", "three space jump from a iron pillar", and even "watch out our own weakness when attacking", "not to use thickness to enclose territory", etc. The structure extended by these Go terms is like the structure of "character-word-sentence" in language. Most of the terminology in Go is borrowed from existing cultural concepts, with only very few of newly generated jargon. In other words, the terms that form the basis of Go knowledge are largely consistent to the language symbols of the real world. The choice of which words to use to express the concepts in Go is also the accidental result of the generation of Go knowledge in the context of historical culture. The terms used by modern players and the Go knowledge that is constantly inherited and generated are based on these accidental choices of historical culture.

The 20th century witnessed an accelerated development of Go competition, leading to a rapid rise in the level of Go technique. Yet, our understanding of Go technical knowledge remains largely confined to an extension of existing conceptual frameworks. This lack of analysis of the nature and structure of Go knowledge persists even today. The encounter with AlphaGo cast doubt upon and challenged our inherent Go knowledge, prompting a necessary reflection. This reflection begins with a fundamental question: which parts of our Go knowledge can be trusted, and which parts warrant suspicion? Answering this question will inherently lead to a new classification of Go knowledge and reveal its internal, actual structure. The next crucial question then becomes: how did this knowledge come into being, and does it hold room for improvement? These are the core issues this paper seeks to address.

Ⅲ. Two Types of Go Knowledge

After AlphaGo-Master played the astounding early opening "3-3 invasion", and with the rapid popularization of Go AI, most of the josekis were eliminated in just a few years. It is clear that josekis, as a major category of Go knowledge, are clearly not definite knowledge. So, in the reflection of AlphaGo-Zero, which does not learn from human moves, what human Go knowledge is reliable?

It is easy to see that no matter how advanced Go AI becomes, human knowledge of basic life-and-death, endgame skills, tactics for capturing race, calculation of the outcome in the endgame etc, is still very reliable. In other words, not all human knowledge is unreliable. As long as the basic rules of Go do not change, knowledge such as "two eyes make a living group" is certain.

Therefore, from the perspective of the certainty of knowledge, Go knowledge can be divided into two categories: one is certain knowledge, the other is uncertain knowledge. The former is infallible, the latter is fallible. Next, we will examine their content, nature, and generation methods separately. In the past, the writing of Go knowledge was mostly a list of knowledge points. From this point on, we will re-examine, classify, and analyze these knowledge.

1, Definite Go knowledge

First, we will examine the content of definite Go knowledge. "A group with two eyes is alive" is a basic Go knowledge, "seki is alive" is a knowledge on the same level, and the implicit knowledge includes "a group that is surrounded with only one eye is dead". The knowledge about "life-and-death" is clearly certain. On this basis, tactics for “capturing race", "common life-and-death", "killing skills", etc, have formed a series of infallible knowledge. These knowledge is infallible because they are derived from the basic rules of Go.

The basic rules of Go include "stones without libraries are dead", which means that it determines what are dead stones on the board. Based on this, we can deduce that "stones that will not run out of liberties are alive." Continuing the deduction, we can derive the skills and knowledge of how to live and how to kill stones. Since this knowledge is directly deduced from the basic rules of Go using logic, as long as the logic deduction process is rigorous and flawless, the resulting insights are guaranteed to be accurate.

The knowledge about life-and-death problems also has different levels. The most basic ones like “make two-eyes to live” and shapes like "straight three" can be learned by beginners, while some complex life-and-death problems and intricate problems in real games may not be mastered even by top players. In theory, there are life-and-death problems that are beyond human level, but most of these problems can be solved by human players as long as they have enough time to think. The important feature of this knowledge is that once the problem is solved, as long as the process is logical and flawless, the knowledge is correct. In some complex life-and-death or capturing race problems, we still have the chance to see that human moves are better than AI's. This is because human knowledge in this area is based on logic, which is infallible, while AI algorithms are based on probability.

Beyond life-and-death problems, the knowledge of value of stones and calculating points, derived from basic rules of Go, is also infallible. For example, comparing the points in territories, endgame moves, how many points a certain endgame move worth etc. The way to decide the outcome of the game is to compare territory of both sides. The method is to count the points in the territories. Therefore, the knowledge obtained by using the method of numerical comparison in the game is homologous to the rules, it can also be said that it is produced by the logical deduction of the rules, and is therefore infallible. Based on this, at non-complex endgame stage, human players can also accurately find the optimal moves. When evaluating the situation, human players can get a accurate result by counting and comparing the points of both sides.

Besides the two types of certain knowledge mentioned earlier, there is another category of Go knowledge that is not as certain but can still be considered reliable. This knowledge is about "efficiency of stones", a measure that human players use to evaluate the situation and make decisions. Some aspects of stone efficiency are also infallible. For example, the side that can surround a territory using fewer moves is more efficient and is more likely to gain the lead. When we analyze efficiency of stones using only logic and math, we get definitive results. However, in actual games, there are situations where we cannot use logic and math alone. This is often because the positions on the board are too complex, and humans can only use logic and math to a certain extent. In these cases, we have to rely on our experience to make decisions.

The transposition method, a technique for comparing stone efficiency through different placements, perfectly exemplifies this type of knowledge. When the transposition steps are based solely on reliable principles, the resulting efficiency comparisons can be confidently considered accurate. While transposition excels at analyzing certain knowledge, real-game scenarios often present a blend of uncertainties. In these cases, the method serves more as an auxiliary tool, bolstering existing beliefs about stone efficiency rather than offering definitive judgments. Consequently, it is evident that in real games, human players' decisions often stem from a combination of established knowledge and uncertain beliefs.

From a different perspective, Go's technical knowledge is primarily concerned with comparison and judgment. This includes evaluating which move is better, determining which side has a better position, and so forth. The definitive knowledge within this realm can be understood as knowledge that has attained a precise degree of comparison and judgment. The definitions of “alive”, “dead”, and ko in Go, along with the numbers used to indicate points in a territory are all clear, unambiguous.

Overall, The core of indisputable knowledge in Go lies in its clearly defined rules, translated through logic and math into undeniable truths. This knowledge stands firm even when confronted by the elusive ideal of perfect play

2, On smaller boards like 7x7, human players can crack the code and find the perfect moves. However, humans are still very far from the optimal solution on 19x19 board. The cognitive methods employed and the knowledge acquired by human players differ significantly from different board size. On small boards where the optimal solution can be calculated, humans only use logic and math to calculate each move, without any vague understanding of "principles". On the 19x19 board, due to its complexity beyond the scope of human calculation and reasoning, humans can only use logic and math in a certain area, and adopt many empirical methods to obtain knowledge in other areas. In a broad sense, this knowledge is probabilistic knowledge.

Probabilistic Go knowledge encompasses a wide range of concepts, such as "thick/thin", "light/heavy", “good shape", "bad shape", "three space extension from a iron pillar", "entering the framework with caution", and so on. The number of such concepts is so large that it is impossible to list them all. The goal of these concepts is still to compare and judge the board position and make choices. The key difference between reliable Go knowledge and other types lies primarily in the methods used to generate it, followed by the clarity of its conceptual definitions.

Experience-based induction is the main method for generating this type of knowledge. For example, what is good shape, and what is bad shape? These are knowledge that human Go players have summarized over the years through empirical induction. Collective experience forms the core, with individual insights adding their unique flavor. The reason why humans need to use concepts like "shape" is because the number of possible moves on the 19x19 board exceeds the range that humans can reach with logical reasoning. Humans "cleverly" created some conceptual knowledge to deal with those situations. Good/bad shapes is one such concept.

Beyond logical reasoning, other human cognitive abilities play a role here, such as analogical and associative thinking. For example, concepts like "thick" and "light" are borrowed from their original meanings in culture. Although the actual situation of each game is different, we collectively describe some position as "thick", some shapes as "good shapes", etc, using these concepts to help us define and understand the situation, so that we can still get knowledge about the situation and determine good or bad moves even when we cannot accurately evaluate the situation. Although this knowledge is not as reliable as the first type of knowledge, they can be used to guide our decision-making in practice.

It is precisely on the basis of introducing these concepts to define the situation that the many "strategies" in Go can be carried out. For example, “Seek peace when in a weak position” from “The Ten Golden Rules of Go”. To understand this strategy, one must first understand what is “strong position”. The strength of positions cannot be accurately measured by specific numbers. Its degree is more of some "feelings" and "impressions". As experience grows and level improves, these feelings and impressions will become more coherent, effective, and closer to accurate.

However, no matter how effective this type of knowledge has been proven to be in practice, it is still some knowledge with uncertainty and cannot be accurately measured. In the match between human and AI, humans soon discovered that it was in these so-called "unquantifiable", vague situations that AI's ability far surpassed humans. For AI, there does not exist two types of knowledge with different properties. On any board, the algorithms called by AI are consistent, while the accuracy of human players when using these two types of knowledge capabilities varies greatly. This explains why in some special situations, human players can still surpass AI by exerting their logical reasoning ability to the extreme. However, in most situations, the knowledge obtained by human players relying on experience induction and feeling is completely unable to compete with AI algorithms. This reflects in the game, that is, the so-called "big picture" part that human players once boasted of (also known as the "whole board thinking" part), is now completely relying on AI to solve.

One interesting phenomenon that arises from this is that “a good sense of the whole board” used to be a common way to describe a player's style. However, this type of description has almost disappeared since AlphaGo. The reason is that the type of knowledge involved in "whole board thinking" is precisely the weakest part of humans compared to AI. In the post-AI era, if we truly describe a player's game as "very similar to AI," it is likely to a large extent a compliment to the player's "good sense of the whole board."

In the post-AI era, human Go players still need to use uncertain knowledge to process Go. This is determined by human’s cognitive limitations. It is worth noting that many of the cultural attributes of Go are generated on the basis of this type of imprecise knowledge.

In the language of epistemology in analytic philosophy, the first type of knowledge aligns with foundationalism. Here, knowledge arises through a process of deduction, where new knowledge is derived from established and justified foundational beliefs (Go rules) via logical reasoning. The second type of knowledge is consistent with coherentism. In this type of knowledge, each belief is justified by the way it fits into the entire belief system. Due to space constraints, a more in-depth analysis of this topic will be discussed in another article.

3, The cultural attributes of Go   knowledge

Many people say that “Go is a strategic game” or "Go is like life." As early as Han Dynasty in China, many scholars linked Go with military strategies, politics, and even the principles of heaven. The construction of these cultural attributes is directly related to the knowledge structure of Go.

If the realm of Go had been confined to small boards of 7x7 or less, the technical knowledge of the game would be limited to the first category: logical deductions derived from the game rules. In this case, Go would be considered a mathematical problem or a game that can be solved with certainty. Under this perspective, each move on the board corresponds to a final numerical value representing the difference in board positions. Concepts like "thick/thin", "light/heavy" are inaccurate redundancies and would not be used to solve the problem. The "strategic thinking" in Go would be completely replaced by calculation.

It is precisely because the size of the board goes beyond the range that humans can accurately solve, yet isn't so large that it entirely exceeds the range that humans can finish a game, that the cultural attributes of Go are generated on a 19x19 board. This is closely related to the second type of Go knowledge.

Non-quantitative Go knowledge is based on some binary concepts, such as "thick/thin", "unsettled /solid", "light/heavy" etc. These concepts come from existing language and are borrowed to define situations in Go that cannot be quantified. On the basis of these concepts, theories on how to act in different situations have been generated. This is the strategic knowledge of Go. For example, "Do not approach a thick position", "Sacrifice to gain initiative", and "The Ten Golden Rules of Go" are some of the strategic knowledge that people have summarized. The cultural attributes of Go, to a large extent, lie in the fact that non-quantitative Go knowledge is not specialized knowledge, but rather knowledge that is universally applicable.

People often say that "the principles of Go are the same as the principles of all things" or "the principles of Go can guide life." These statements actually express the idea that Go is not just a game with a mathematical answer, but rather contains universal knowledge. This perception has a very ancient tradition, dating back to Ban Gu's [The Essentials of Go](YiZhi). Why is this so? While other board games, such as Sudoku or Rubik's Cube, are also intellectual challenges, people do not say that they have the same function. The reason is that the non-quantitative knowledge in Go is based on existing cultural concepts, rather than being a completely new knowledge system that is independent of the world. The choice of words and concepts used in Go is closely related to the language system of the era in which the knowledge was generated. Therefore, the generation and development of the Go knowledge also reflect specific cultural traditions. On the other hand, they also reflect some of the characteristics of human thinking.

In the knowledge of Go, a clear distinction can be seen: for situations that humans can handle with mathematics and logic, people use this method to achieve as much accurate knowledge as possible. However, human rationality is limited, and it is impossible to handle the 19x19 board in this way. When faced with situations that cannot be processed with mathematics and logic, people use the method of experience induction to generate some concepts and strategies, which can also be called "principles." The disadvantage of this type of knowledge is that it is not as accurate as the previous type, and often there are errors. Its advantage is that it is universal and applicable to a wide range of situations. For similar situations or even similar conditions, people can use the same principles to deal with them, which is the so-called "inferring the general from the specific.

In the process of generating Go knowledge, people faced problems that could not be completely solved by logical reasoning. They introduced concepts such as "thick/thin", "light/

heavy", "urgent/non-urgent", and "unsettled/solid”. These are binary concepts that cannot be quantified, and they form the basis of the second type of knowledge. An interesting question is, if the early production of Go knowledge had taken place in a different language and cultural system, would it have generated the same set of concept knowledge? A related question that looks to the future is: With the help of AI, is it possible for humans to break through the old knowledge system and create more effective and accurate knowledge concepts?

To answer these questions, it is first necessary to analyze and compare the structure of human thinking and AI Algorithms in Go games.

IV. The nuances of human thinking in Go and the Structure of AI Algorithms

The application of human Go knowledge in practical games requires the specific cognitive activities of the subject to be realized. The types and nature of these cognitive activities are also worth studying. By comparing the thinking process of the game with the algorithmic structure of AI, we can not only see more clearly the differences and commonalities, advantages and disadvantages between humans and AI in the face of the game board, but also, through observing the way Go knowledge is used in practice, we can speculate on the future directions of human Go's progress, influenced and aided by AI.

Human thinking in Go can be divided into three main parts: intuition, calculation, and judgment. These are three elements that form the foundation of Go player’s decision-making.

No matter the level of the player, as long as they understand the rules of Go, the intuition will be shaped when facing a Go board. Intuition serves as an immediate response to a board position. A beginner's intuition may be more random, and their focus may be far from the correct choice, but beginners still have intuition (or instinct). As their level improves, their intuition will naturally become better. Intuition acts as a pruning technique, channeling computational resources towards the most promising lines of play, optimizing the decision tree's growth. This is a technique that is now shared by humans and AI. AlphaGo was trained to have intuition that is similar to or even surpasses that of human experts.

The improvement of intuition is mainly based on the accumulation of experience, rather than logical deduction. The sources of human intuition can be divided into individual experience and collective experience. The accumulation of individual experience mainly relies on game playing and reviews, that is, feedback from actual games; collective experience mainly comes from problem solving and replaying games, which respectively train the intuition in local positions (shapes) and the intuition of the whole board.

Calculation is the second element of the three parts of thinking in games. While past discourse in the Go world encompassed a broader definition of calculation, incorporating aspects of "judgment" within its scope. These two concepts have different properties and characteristics, and need to be considered separately. Calculation in the game is the process of forming a "strategy tree", that is, along the intuition, to think from the perspective of the other side, imagine one or more possible moves for both sides, and search for multiple branches. The process of searching and forming a strategy tree is calculation.

Calculation is the middle link of the three elements. It is first based on intuition. Without intuition, it will be difficult to find the starting point and clues. It connects with judgment. Go players make a comprehensive judgment on the many branches derived from the calculation, trying to analyze the pros and cons, and then make a choice of their moves.

Judgment is the final link of the three elements, directly influencing the decision making. It draws upon the deepest well of Go knowledge and both the two types of knowledge play a role in it, sometimes separately, sometimes together. When we judge life-and-death, value of moves, efficiency of stones, etc, the main knowledge used is the first type of knowledge, which is certain knowledge; when we judge thick/thin, light/heavy, and good/bad shapes, etc, the main knowledge used is the second type of knowledge, which is uncertain knowledge.

As mentioned earlier, the first type of knowledge is generated based on the rules, and is deduced in a logical and mathematical way. When applying it to new games, we stick to this approach, making further deductions based on existing knowledge. For example, knowing the “square four” shape cannot make two eyes, we would know whether a shape that can be simplified to "square four" can live or not. We can also use the logical deduction method to deal with more difficult problems of the same type. Whether the processing is successful mainly depends on our skill level versus the problem’s difficulty.

The second type of knowledge is mainly generated through the method of empirical induction. In the judgment process, this knowledge concepts is very commonly used. For situations that cannot be measured by precise concepts such as "life-and-death" or "value with actual points", we will use many imprecise concepts such as "thick/thin", "light/heavy", " territory/influence", "good/bad shapes" to judge the situation. As we already know, the judgment process, especially the ones that requires the use of the second type of knowledge, is a significant weakness of humans compared to Go AI. The imprecision of the second type of knowledge, which is not quantifiable, has not been fully recognized by humans before playing against AI. On the contrary, due to the attachment of many cultural attributes, it adds to the charm of related knowledge. AI has brought humans the opportunity to reflect on our knowledge and objectify the existing knowledge.

Interestingly, after the AlphaGo algorithm was released, we can find that from the initial paper to the AlphaGo-Master version, the structure of AlphaGo's neural network is almost in direct correspondence with the structure of the three elements of human thinking of the game: intuition corresponds to Policy network, calculation corresponds to Monte Carlo Tree Search, and judgment corresponds to Value network.

AlphaGo's Policy network allows AI to quickly find some key points through "intuition" on any board position. This part has reached and surpassed human level, and one example is that AI after Master will directly play 3-3 invasion in the early opening stage. This is a move that completely surpasses the intuition of human Go players at that time. Similar to how humans train their intuition, the training of Policy network is also essentially based on the accumulation of a large amount of experience, rather than logical reasoning.

Monte Carlo tree search is similar to human players' calculation in form, in that it also produces many branches of positions through searching for evaluation and decision making. However, there are significant differences in the specific methods of search. The Monte Carlo algorithm is mainly based on the statistical simulation method of probability and randomness, while human calculation is mainly based on thinking from the opponent's perspective along the intuition.

The main function of the Value Network for AlphaGo is to evaluate the situation, mirroring the human judgment. However, unlike humans, Value network works with pure data. It evaluates the win rate for each move, providing concrete numbers to guide decision-making. While humans can excel at small boards using logic and math to get an accurate result, but on large boards, they often need the combination of two types of knowledge, the inaccurate methods based on empirical induction are also used in the judgment, and in such cases, the accuracy of human's judgment is often greatly reduced.

Although the Police network and Value network were merged into a single network after the AlphaGo Zero version, the overall structure of the algorithm has not undergone fundamental changes. The correspondence between the algorithm of Go AI and the thinking of human players still exists. This actually validates a common view of current artificial intelligence: artificial intelligence based on neural networks partially simulates human brain.

On the basis of analyzing the knowledge structure, we can make a theoretical prospect for the future development of human Go knowledge. This prospect is no longer a vague feeling, but can be transformed into the following question:

Under the influence and help of AI, how much room for development and progress is there for the two types of Go knowledge used by humans in the three stages of game thinking?

First, consider intuition. Since the enhancement of intuition mainly relies on experience accumulation rather than logical reasoning, the overall experience of human Go games is obviously increasing, so the level of intuition in the history of Go has been constantly improving, but the speed of improvement has always been relatively slow. AI now has demonstrated more accurate intuition than humans, which is equivalent to providing humans with more and better conditions for experience accumulation. Therefore, AI will accelerate the growth of human intuition, pushing it to new heights, and the speed of improvement will exceed the era without AI. However, experience alone doesn't guarantee sudden leaps in skill, it simply boosts the efficiency of the learning process.

The second factor to consider is calculation. Human players' calculation abilities are mainly constrained by the limits of their rationality and intelligence. If the board is shrunk to a small enough size, or if human brain's ability is expanded to a large enough size, calculating all possible moves would become feasible. However, in reality, human rationality is limited, and the arrival of AI will not break through these barriers. So, in the realm of calculation, our ceiling is ultimately set by the collective limits of human reason. In the future, individual players might inch closer to this ceiling, but AI's impact won't be a game-changer.

Finally, consider judgement. This is where human players hold the most promising potential for advancement. The reason is that when human players face situations where they cannot make accurate judgment using the first type of knowledge, the accuracy of their judgment using the second type of knowledge falls short. AI can offer valuable assistance by providing comprehensive win rate data and move suggestions. This date is of great significance for the technical progress of human players. We will analyze them from the two aspects of experience accumulation and concept generation.

Go players are actively leveraging AI's win rate data to enhance their judgment of board positions, leading to a significant improvement in their accuracy. This is achieved through various methods, such as utilizing AI-generated position exercises where AI's win rate serves as the solution. Players then strive to understand and replicate this win rate by applying their own judgment methods. Just as AI aids in building intuition, it also accelerates the development of accurate judgment for Go players.

A currently unexplored avenue for advancement lies in restructuring and innovating concepts within the second type of Go knowledge. As previously discussed, concepts like "thick/thin," "unsettled/solid," "light/heavy," and even the "Ten Golden Rules of Go" and various proverbs represent "Go principles”, while valuable in practice, they lack precision and inevitability. Different cultural systems can generate diverse conceptual frameworks to describe and analyze the game, potentially leading to more accurate definition of positions. This could significantly improve human players' judgment and help them to find the best moves. The emergence of Go AI provides access to a new, foreign cultural system, facilitating a potential "Go theory reform." If successful, this reform has the potential to propel human Go skill to new heights. The key to reforming Go principles lies in crafting a robust discourse system for the second type of Go knowledge.