Redefining human Go experts in the post-AI era: a perspective from sociology of professions

Jiuheng He

Abstract:

This paper outlines the transformation of human professional Go players from being seen as authoritative knowledge holder to becoming interpreters of AI strategies and gatekeepers of human Go knowledge. The article also examines how the expertise of Go AI becomes possible, identifying which actors and what arrangements enable Go AI to make expert statements and become a productive contributor to human Go community. Utilizing concepts from professional sociology, such as jurisdictional struggle, the article offers insights into AI's broader impact on professional communities. The role of human experts needs to be redefined in the post-AI era, where human experts remain indispensable mediators between AI and the public, tasked with navigating new knowledge and interpretations that AI introduces.

The revival of interests in the sociology of professions with the appearance of AI comes from the profound changes AI is introducing to professional roles and structures. As AI technologies become increasingly integrated into various sectors, they disrupt established practices, necessitate new skills, and raise ethical questions that professionals must navigate (Susskind & Susskind, 2015; Wexler & Oberlander, 2021). This shift not only alters the landscape of professions but also challenges the definitions of expertise, authority in knowledge, and the nature of professions themselves. Consequently, the sociology of professions becomes relevant again as it provides critical insights into how professions evolve in response to challenges, how professional identities and norms are renegotiated, and how professional knowledge is produced, which are all affected by AI.

The sociology of professions represents a rich theoretical tradition for understanding how occupational groups acquire status, power and jurisdictional authority in societies. Early foundational works by Talcott Parsons viewed professions as occupations centered on disinterested service ideals and socially approved technical knowledge (Parsons 1939). Other scholars highlighted how professions sought to professionalize by meeting certain structural criteria like formal training, licensing, codes of ethics and occupational closure (Carr-Saunders & Wilson 1933; Wilensky 1964).

However, a uniform and normative model of professionalization faced criticisms from many scholars. The concept “professionalization” risks losing its meaningfulness if applied indiscriminately in every profession without considering their intricacies and unique structures in the occupational landscape (Wilensky, 1964). Sciulli (2005), from the perspective of European scholars, reflects on the functionalist approach taken by Anglo-American sociologist of profession in identifying essential qualities of professions and their associations. Sciulli argues for a new sociology of professions that acknowledges the complexities of professional work within societal structures, which can move beyond the narrow definitions of professions and consider the broader social context that professions are situated in.

Andrew Abbott's 1988 book "The System of Professions" provided a seminal theoretical framework for understanding the social dynamics and power relations surrounding expert occupational groups in modern societies. Instead of providing accounts of how professionalization works, Abbott criticized the ‘life history’ style of literature on professions and conceptualized professions not based on fixed traits or a process of professionalization, but as actors competing through abstract knowledge systems and professional practices to control jurisdictions of tasks. Instead of viewing professions in isolation, Abbott analyzed them as an interdependent system where jurisdictional boundaries are continually negotiated and contested (Abbott 1988). A key source of professional power lies in abstracting knowledge, allowing occupations to define “cultural" and "cognitive" jurisdiction over certain tasks and services. The more a profession can codify and monopolize an expert knowledge system, the more powerful and expansive its jurisdiction can become. Abbott also highlighted the importance of examining adjacent professional actors that "hinder" or provide competition for jurisdictional claims over specific areas. New technologies, organizational innovations, or the emergence of new knowledge domains create spaces for professionalizing projects and jurisdictional reconfigurations.

More recent work has tried to expand what counts as professions or professional expertise beyond traditional definitions. One debating topic is whether a demarcation between professions and other uncredentialed occupations is necessary. Anteby et al. (2016) analyzed "formal and informal jurisdictional boundaries" between credentialed experts and uncredentialed specialists. Eyal (2013) examined "expert professionals" whose credentials derive more from experience and pragmatic mastery, not from an institutionalized system. Many scholars have illustrated the resistance and struggle towards an institutionalized professions from uncredentialed participants like lay people or social activists (Epstein, 1995; Wynne 1996).

Another major critique on the field of sociology of professions is on the idea of reducing expertise to matters of credentials, jurisdictions and monopolies, rather than focusing on the actual performance and practice of expertise (Collins and Evans 2007; Eyal and Pok, 2015). In sociology of professions, expertise is a quality that the experts possessed by the virtue of recognition granted by others. The analysis of expertise was reduced to how to secure the recognition of others through credentialing, licensing and so on. Eyal (2013) argues for a sociology of expertise to replace the sociology of professions, which suggests separating two modes of analysis. One is of experts that includes the classic topics in the sociology of profession: credentialing, licensing, jurisdictional struggles, etc. The other is about expertise, which is regarded as a network “linking together agents, devices, concepts, and institutional and spatial arrangements.” (Eyal, 2013)

While the sociology of professions has faced critiques regarding its narrow scope and theoretical limitations, the rise of artificial intelligence (AI) systems has catalyzed a revival of some research questions this field has been grappling with. AI’s increasing capabilities in domains traditionally dominated by human experts raises inquiries about how non-human actors might disrupt and renegotiate existing professional jurisdictions and hierarchies of expertise. This paper will analyze how Go community respond to the advent of Go AI since 2016, through the lens of Abbott's (1988) system of professions, and to potential jurisdictional battles and struggles as human professional players trying to defend their knowledge territories from taken away by Go AI. This paper will also reflect on the theoretical transition from a sociology of professions focused on professionalization to a broader sociology of expertise (Eyal, 2013) capable of accounting for diverse forms of specialized knowledge, whether institutionalized or not. The empirical case of Go AI like DeepMind's AlphaGo, which achieved superhuman performance in the game of Go, presents an opportunity to interrogate the positioning of non-human participants within expert knowledge domains and practices long governed by human professionals. Departing from the substantial view of expertise (Collins and Evans, 2007), Eyal's (2013) conceptualization of expertise as a heterogeneous network, connecting all agents associated with the task, provides a productive analytical lens for examining Go AI's disruptive impacts among the Go community. This networked perspective emphasizes how expertise emerges through dynamic interplays between diverse participants - including non-human actors like AI systems – that focuses on “what arrangements that must be in place for a task to be accomplished and through what processes these arrangements were created.” (Eyal, 2013) Viewing AI not as a technological black box but as an embedded participant within shifting expertise networks allows for interrogating how AI potentially destabilizes existing assemblages and politics of professional knowledge production. In doing so, this paper aims to bridge between the sociology of professions and perspectives on expertise to grapple with the emerging interactions between human and AI systems.

Emerging jurisdictional vacancies with AI

In March 2016, the AI system AlphaGo developed by Google's DeepMind achieved a significant milestone by defeating legendary Go grandmaster Lee Sedol in a five-game challenge match. Go, an ancient strategy board game, had long been viewed as a grand challenge for AI due to its vast computational complexity – with more potential board positions than atoms in the observable universe. However, AlphaGo applied deep neural networks and Monte Carlo tree search to intuitively evaluate Go positions rather than rely on brute-force calculation alone. Its 4-1 victory over Lee Sedol was a stunning demonstration of AI's increasing ability to master cognitive skills and forms of expertise that had been considered exclusively human domains. The emergence of AlphaGo significantly disturbed the Go practices and opened a jurisdictional vacancy. **The vacancy of jurisdiction over the game: who is legitimized to offer authoritative interpretations of what occurs during a Go game? Whose knowledge and viewpoints hold the authority within the Go community?**

The concept of jurisdictional vacancy originates from Abbott (1988), who argues that external forces, including technological advancements and organizational transformations, disrupt the professional landscape. This disruption leads to the dissolution of established jurisdictions and the emergence of new tasks, thereby creating jurisdictional vacancies. These vacancies set up stages where professional groups negotiate and redefine the boundaries of their jurisdictions. The following section will delve into the emergence of the jurisdictional vacancy following the AlphaGo challenge match and illustrate how Go AI effectively occupied the vacated space.

Let's first look at how professional Go players exercise their jurisdiction in the practice of Go. For professional players, their practice of Go is not just about playing the game; it also includes providing real-time commentary for professional matches, writing reviews about specific games, teaching students, and writing Go books. Almost all professional Go players, in one way or another, discuss what exactly happens on the board during a game. Even the players who are most focused on their own games will still review the game with their opponents after it ends, thus forming a 'objective' conclusion about everything that occurred in the match. Discussing what happens in a game is the most important aspect of a professional Go player exercise their jurisdiction because the Go game is not self-explanatory. The difference between intellectual games like Go and other competitive sports lies in the fact that audiences cannot intuitively understand the complex strategies and tactical plays unfolding in the game. For audiences of a basketball game, the score and the players' spectacular actions on the court allow them to have an individualized experience of the game's progress and to quickly grasp what is happening on the court. Although their understanding may not align with the interpretations of professional basketball insiders, this does not affect the audience's enthusiasm for the game. Yet, in the case of Go, without the commentary from professional players, most amateur Go players would find it difficult to understand the strategic play in a high-level professional match. For audiences, a Go match without commentary would turn into a mysterious ritual: after hundreds of moves have been made on the board, suddenly one player decides to concede and end the game. In some respects, a Go game is similar to an X-ray image in medical practice: the patient is unable to grasp what is underlying an X-ray image, only the doctor can interpret the information in the image, and this process is precisely how doctors exercise their jurisdiction. Here is an example of how a Go game is constructed by professional player Younggil An, who wrote the comments for the game between Fan Hui and AlphaGo in 2015. This game served as a private challenge match between AlphaGo and the European Champion, Fan Hui, aimed at testing AlphaGo's capability prior to its much-anticipated challenge against Lee Sedol. In this five-game challenge, AlphaGo defeated Fan Hui with a score of 5-0, which became the confidence foundation for the DeepMind team to decide to challenge Lee Sedol. Shortly after announcing the challenge match with Lee Sedol, the DeepMind team released the five games played between AlphaGo and Fan Hui. The Go community paid great attention to these five games, and many professional Go players provided commentaries and analysis to assess the level of AlphaGo at that time. Younggil An was among these analysts, and the following is an excerpt from his commentary on the fifth game between AlphaGo and Fan Hui.

Black (Fan Hui) resigned at move 214. White (AlphaGo) was winning by about 10 points on the board and Black couldn't find a way to catch up……

The opening up to White 34 was even, but Black 35 was questionable and White was slightly ahead up to 52. Black 57 and 65 were mistakes, and White took the lead.

White 70 and 74 were wrong, but Black 75 missed a great chance to take advantage of them. White was an overplay, but Black 93 was premature and can be regarded as the losing move.

White established a clear lead with 94 and didn't give Black any chances to catch up afterwards. (An, 2016)

Younggil An begins with an overview of the board's state at Black's resignation, then proceeds to analyze the course of game. Move 35, 57 and 65 by black were identified as the mistakes made by Fan Hui in the early stage of the game, which resulted in White taking the lead. Subsequently, the leader of the game went back and forth as Black and White all committed several mistakes. Next, we reach the game's most crucial moment: Black's move 93, which An identifies as the "losing move". These concluding remarks not only highlight the crucial moment of the game, but also construct a situated representation of the game: the course of the game is transformed from merely a sequence of black and white stones placed on the board to a trajectory of intellectual and strategic contest between two players. The game becomes a compelling narrative, including well-considered tactics, attacks that succeed or fall short, brilliant moves that turn the game around, and decisive blunders that determine the outcome. The discursive practices by commentators, mobilizing the specific language shared by Go community, represent an "objective" interpretation of the game. The objectivity is endorsed by their expertise and the specialized knowledge professional players have. Their expertise grants professional players the authority to exercise jurisdiction over Go games, as they are credentialed by the Go community to be the most capable of performing these tasks. Just like any other professions (Abbott, 1988), The Go community has established a set of organizations to educate and certify professional players through highly competitive qualifier tournaments while maintaining their authority as Go experts.

Yet the emergence of AlphaGo disrupted the authority of professional Go players. Not only did AlphaGo win the challenge match against Lee Sedol with a score of 4-1, but it also challenged the expertise of human professional players by playing a series of moves that contradicted human Go theory, one of which is the famous move 37 in the second game. In the second game, move 37, when AlphaGo first played it on the board, almost all human professional players thought it was an amateurish bad move. Yet, AlphaGo still managed to defeat Lee Sedol, even though it made many moves that professional players disagreed with. Chinese professional Go player Gu Li commented about move 37 after the match: “If it is okay to play this move (37), the way of playing Go might need to change.” When one of the strongest human players is defeated by artificial intelligence, and when human players realize that the Go theories summarized by humans over thousands of years might contain errors, the foundation of professional players' jurisdiction began to shake. What follows is the jurisdictional vacancy: who is authorized to interpret and construct what happens in a game?

A prevalent narrative about AI is that when AI reaches or even surpasses the capability of human experts, AI will replace the role of human experts and perform their duties in their professional fields. However, the actual situation in Go community or perhaps any other realms, is much more complex than this narrative suggests. First, regarding the challenge match, the Go AI surpassed human players only in the ability of playing the game, and playing ability is just one part of Go practices. Many other tasks that professional Go players perform, such as discussing the progress of games and teaching, which rely on the use of Go language for communication, are areas where AlphaGo has not reached the average level of human players. This assertion doesn't imply that AI cannot interpret the content of a game, but rather that the way AI interprets it cannot be understood by human players. The first underlying reason is the opacity of its artificial neural networks (ANNs) algorithm (Burrell, 2016). ANNs, especially deep learning models, consists of millions of parameters that interact in complicated ways. This immense complexity makes it impossible to trace how inputs are transformed into outputs or to understand the role of individual parameters in the decision-making process. Consequently, human players are unable to decipher the rationale behind each move played by AlphaGo. The second reason is that AlphaGo's algorithm does not actually include the language humans use to understand Go, such as strategy, purpose, territory, attack, defense, etc. Instead, its algorithm consists only of probability-based selections for the next move and the corresponding win rate. To better understand this point, let's look at a specific example of how AI interprets a game situation. Figure.1 is a screenshot of AI analyzing a tournament game.

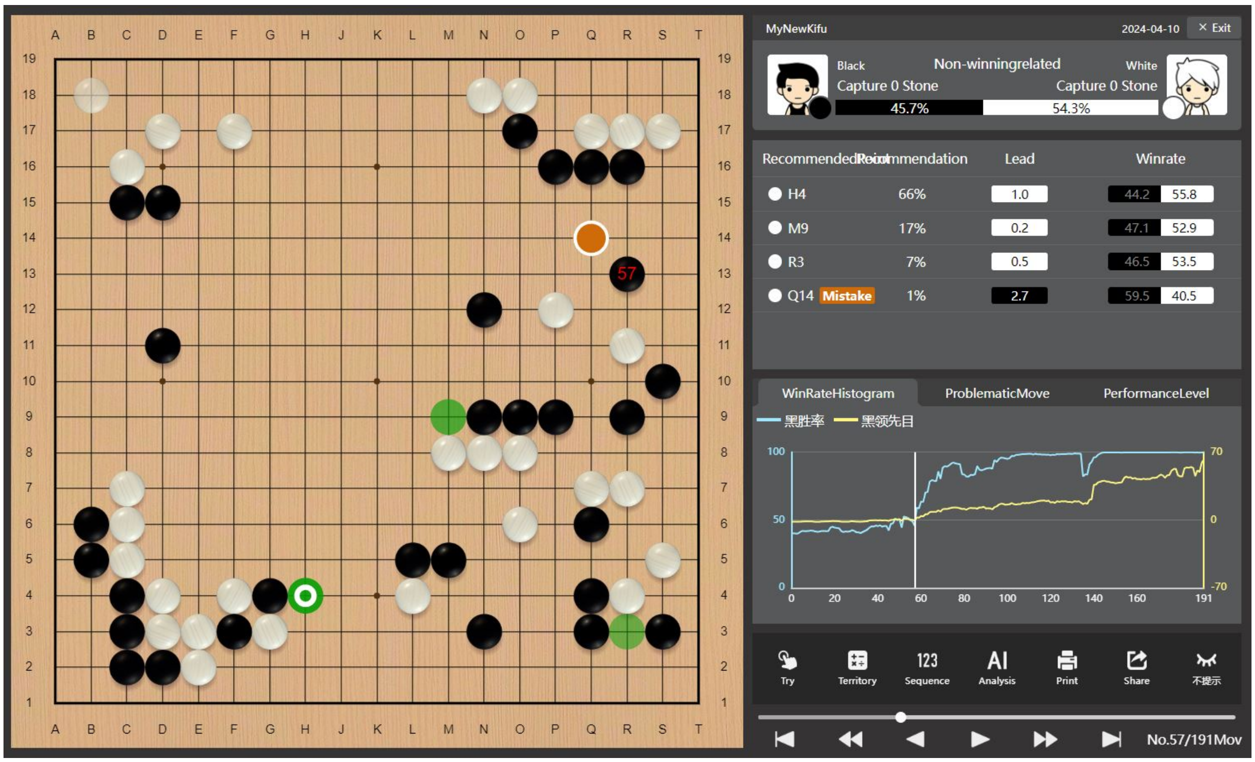

Figure.1 Go AI (Golaxy) analysis of the game between Park Junghwan 9-dan and Dang Yifei 9-dan on Feb. 12th 2023

In this screenshot, Golaxy[1] provides the best next move for White (marked with a white circle on a green circle), as well as two other potential good moves (in light green). However, in the actual game, White chose to play in the top right corner (marked with an orange point), a move considered incorrect by the AI. The information box on the right includes win rate evaluations for these moves: the best move has a win rate of 55.8% for White, indicating a slight advantage for White in the current situation; but after choosing

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[1] Golaxy is a Chinese Go AI.

the mistaken move, White only has a win rate of 40.5%. The curve chart at the bottom right describes the trend of Black's win rate throughout the game. According to the AI's analysis, Black was slightly behind at the beginning, but gradually gained an advantage during the mid-game battles. White made a series of mistake during move 53 to move 70 that leads to a very tough situation for White. Eventually, Black secured a winning position around move 100 (approaching a 100%-win rate), ultimately securing the victory. This appears to be a very convincing description of the game, yet the information it contains is quite limited. Human players want to know not just where the next move should be placed, but why it should be placed there. Similarly, in analyzing the game, human players are interested not only in the trend of overall win rates (who is leading and who is behind) but in why Black falls behind during the opening phase, why White made mistakes in the mid-game, and what allows Black to secure a winning position around move 100. Without exception, Go AI cannot answer any of these questions. Therefore, following human professional players losing the jurisdiction to interpret game positions, the capabilities of Go AI are insufficient to fill this jurisdictional vacancy. Thus, a new form of jurisdiction has emerged: a collaborative interpretation of the game between human professional players and Go AI. In this arrangement, AI is responsible for providing an answer that requires interpretation, while human professionals are tasked with explaining AI's provided answers using the Go language that is comprehensible to humans.

The following example demonstrates how professional Go players collaborate with AI to interpret a game. Professional Go player Li Zehao served as the commentator for the match between Park Junghwan and Dang Yifei, and he summarized the game as follows:

"A complete victory for Park Junghwan. The opening was quite even for both players. White 34 on the right side might have been a bit too aggressive, leading to Black 35 pinching and forcing White to activate a lonely group.

Black 45 flying move is somewhat questionable; it might have been better placed in the center. White 46 would have been in a much better position if it turned in the middle *abdomen rather than the actual game move, which seemed a bit slow and, without seeing a brilliant move suggested by FineArt (Go AI) in the lower right, this move was almost valueless. Black 52's small fly seems a bit slow and completely differs from the sacrificing strategy of FineArt.*

Starting from move 58, Dang Yifei's subsequent judgment had some issues, persisting in activating small-value stones, leading to a problem of thinness.

The move at 62 can be considered a losing move, neglecting the severity of Park Junghwan's move at 63, and after Black's upper side breakout, the situation was already terrible for White. Following this, Dang Yifei fought hard, attempting to fight a Ko in the lower right, but still lost due to significant losses earlier. I am today's commentator, Li Zehao. See you next time." (Li Zehao's commentary on FoxGo on Feb. 12th 2023)

In this summary, Li Zehao first describes the game as a complete victory for Park Junghwan, a conclusion also reflected in the win rate curve provided by AI. After about 50 moves, White fell into a losing position and never had a chance to turn the game around. Building on the judgments provided by AI, Li Zehao offers a strategic explanation for White's mistaken moves: the move at 52 was "slow," contradicting the sacrificing tactic suggested by AI, representing a tactical mistake; the move at 58 was a judgmental mistake, as White insisted on saving these valueless stones that should be sacrificed according to FinaArt. And the final losing move, White's move at 62, also considered by AI as White's biggest mistake, is interpreted as a calculating error: because White overlooked the severity of Black's move at 63. Li Zehao deconstructed the course of the game into several crucial moments, analyzing the strategic thinking that occurred at these times, and thereby reconstructing the progression of the game. It is noteworthy that AI does not frequently appear in Li Zehao's summary, seemingly making the Go AI invisible. However, all the conclusions relied upon in his summary are provided by AI. What Li Zehao has done is merely to interpret AI's conclusions in the human language of Go.

Certainly, within the Go community, there exists a resistance to sharing the jurisdictional authority for game interpretation with Go AI. During an interview, a player illustrated this point through an anecdote.

*“When AlphaGo first emerged, *** (a famous old professional player) fell seriously ill for a year, and thus, he was not able to follow the AlphaGo challenge match. Upon his recovery, it coincided with the publication of my book analyzing AlphaGo's games. After reading it, he became very upset and gave me a call, questioning, "Meng, how could you write a book like this? Was all the Go we learnt and played wrong?" Because I hold great respect for him and considered about his health, I couldn't rebut him over the phone. Instead, I reluctantly admitted he was right. But I also encouraged him to play against FineArts or Golaxy.” (Interview with Meng Tailing, 7-dan professional player)*

In this jurisdictional struggle, the resistance from human Go players partly stemmed from their skepticism about AI’s capability. Players were reluctant to believe that the game of Go, studied by humans for thousands of years, could be conquered by Go AI with such rapid progress. This skepticism persisted only for about a year after the challenge match between Lee Sedol and AlphaGo, during which time human professional players did not have access to freely playing against AI. With the publication of the AlphaGo algorithm and the introduction of open-sourced Go AI in the Go community, professional players gradually recognized the significant gap in skill between human and AI. As a result, they stopped questioning AI and instead began to embrace this shift in sharing jurisdiction with AI.

Another participant of the jurisdictional struggle is the group of amateur Go players. Before the advent of Go AI, professional Go players held absolute authority, meaning their insights into the game were beyond any questions. The professionalization and credential system of Go also created a natural divide between professional and amateur players. Yet with the emergence of Go AI, amateur players can also interpret the game with the aid of AI and challenge, with the endorsement of AI, the conclusions provided by professional players. In an interview, Gu Li, 9-dan world championship, described some awkward situations he encountered:

"After the emergence of AI, I've become more cautious when doing commentary in public. In the past, when I say Black is in a good position and, even if it might not be that strong, people wouldn't really challenge me. Now, if I say Black is leading, someone might pull up AI analysis and say, 'Teacher Gu, Golaxy, KataGo, FineArt all say you've got it wrong, and now Black's win rate is not looking good.' Obviously, that's embarrassing for me, so now we're much more cautious about assessing the situation. If we must make a judgment on the position, we definitely need to look at the win rates provided by AI." (interview with Gu Li)

Gu Li's concerns stem from his professional knowledge and expertise being challenged by Go AI, as any amateur player with AI assistance can easily defeat a top professional player. Therefore, despite being a top professional player, Gu Li's judgments on the game constantly require AI's endorsement to avoid being questioned by other players. However, a consensus among the professional Go player community is that they are not concerned about amateur players threatening their authority to interpret the game with the assistance of AI. This is because the expertise of professional players enables them to interpret AI's judgments with strategic significance. In other words, they are better at understanding Go AI.

"There's plenty of explainable aspects behind Go AI that most people (amateur Go players) fail to grasp. They do not understand what the professional players are thinking during the game, nor do they comprehend the significance of AI's moves. AI provides you with just one piece of information, which then requires your own understanding and digestion. While it appears to be a standard answer, in reality, there are many underlying pieces of information

that need to be discerned. Professional players are more capable at understanding and assimilating it." (interview with Hu Yaoyu, 8-dan professional player)

"The higher the level of the player, the deeper their understanding of AI, especially among top players, who are capable of providing a relatively reasonable explanation after observing AI's moves. Although this "understanding" is also just a human interpretation, we speculate on what objectives AI might have with this move and how the subsequent variations unfold." (interview with Meng Tailing, 7-dan professional player)

In summary, the jurisdictional struggle occurring within the professional Go community following the emergence of Go AI is not as conflicted and contentious as described by Abbott (1988). This is because the legitimacy of the professional players' jurisdiction is entirely dependent on their expertise in playing the game. Once Go AI defeated professional players in the AlphaGo challenge match, this legitimacy collapsed immediately. Despite some resistance, Go AI successfully took over the jurisdiction of interpreting game positions, although it still requires contributions from professional players to accomplish this task. The role of professional Go players has undergone a fascinating transformation: they still possess the power of interpretation, but the object of interpretation has changed. In the past, professional players interpreted the game positions on the board, and their authoritative knowledge allowed them to construct a game with objectivity; now, they interpret conclusions provided by Go AI, using their own expertise to construct the AI's strategy (even though such a thing does not exist in AI's algorithms) and the mistakes made by human players. The expertise of professional Go players ensures that they still maintain authority in this new form of interpretation.

Go AI's expertise as a network

When discussing how Go AI has disturbed the role of professional Go players in the practice of Go, we inevitably face a set of questions: how to position the expertise of a non-human participant in the map of human's expertise? Are we going to assign expertise to an AI system that can perform tasks that used to be only done by human experts? This paper does not intend to engage in the philosophical debate about the nature of expertise and whether non-human actors can possess expertise, but would like to reframe the question into a different one: **what arrangements must be in place for Go AI to become part of Go knowledge production and to produce expert statements in Go community?** This question arises from the network model of expertise proposed by Eyal, who suggests that "Expertise is better analyzed as a network connecting all these diverse elements" (Eyal & Pok, 2015), including experts, laypersons, institutional and spatial arrangements. Unlike the substantive model of expertise (Collins & Evans, 2007), the network of expertise encompasses more than merely experts and their skills because the successful performance of expertise needs a set of arrangements and negotiations that are frequently obscured. The advantage of regarding expertise as a network is that it breaks the black box of the ready-made expertise, the process of assembling which is often invisible to the public. Go AI serves as an example of applying this analytical framework, because in popular narratives, Go AI is often portrayed as an independent ready-made black box that possesses super-human capability in playing Go. However, discussions rarely focus on the arrangements behind the scenes that enable Go AI to function effectively. The following section will delve into the three dimensions of networks of expertise regarding Go AI.

Dimension 1: the materiality of Go AI

We can start with two pictures, the first (figure.2) of which is a scene from the AlphaGo challenge match. On the left side of the image is Dr. Aja Huang from the DeepMind team, who is responsible for executing the moves on the board based on AlphaGo's output displayed on a monitor. In this image, AlphaGo is almost invisible, with only a small monitor visible to us. However, in the second picture (figure.3), AlphaGo becomes much more tangible. In this photo of the DeepMind team's control room, more than 6 monitors are actively tracking AlphaGo's operation in real-time during the challenge match. Although we cannot ascertain what the parameters on these screens specifically represent, it is clear that the DeepMind team pays close attention to the backstage monitoring, ensuring that AlphaGo can perform to its fullest capability in the challenge match.

Figure.2 The picture of AlphaGo Challenge Match

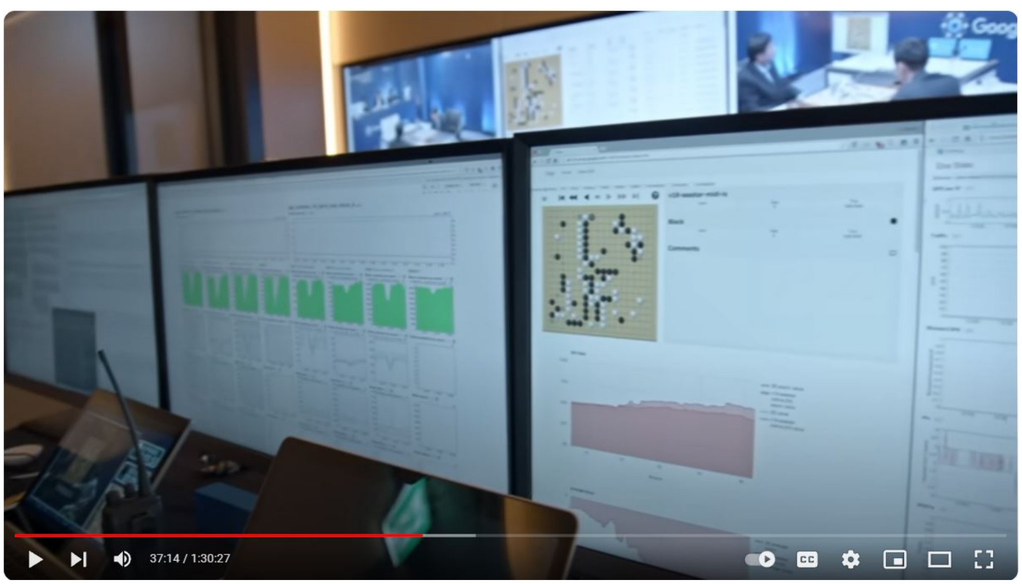

Figure.3 The backstage control room of DeepMind team during the challenge match (a screenshot from *AlphaGo* documentary)

What’s not shown in these two images is the Google Cloud Platform, which served as the computing resources that AlphaGo mobilized during the challenge match. Computational resources are crucial for the capabilities of Go AI, and currently, Go AI adopts two approaches to address the issue of computational resources. One approach, like AlphaGo, utilizes cloud computing resources. Commercial Go AI platforms such as Golaxy and FineArt rely on cloud computing and charge users based on usage duration. The other approach is represented by the open-sourced Go AI KataGo, where users can download the KataGo software for free. However, users must have their own computational resources, such as high-performance graphics processing unit (GPU), for subsequent use. Due to the majority of Go players having very limited computer knowledge, the development of Go AI has given rise to a new industry, which provides a paid service to professional Go players, assembling computers with high-performance GPU and installing and updating the open-sourced KataGo software for them.

Dimension 2: the interpreter/gatekeeper

As discussed in the previous section, the conclusions provided by Go AI are not ready-made knowledge but require interpretation by human professional Go players. Interestingly, the interpretations made by professional Go players are selective rather than fully accepting every piece suggested by AI. The following conversation with a professional player suggests that some AI moves are just too difficult to be interpreted.

“Many (AI) moves are completely beyond our understanding; everyone on our national team fails to comprehend them, truly incomprehensible. We can only learn from the parts that we do understand… It's mostly because the calculations are too deep. AI might calculate many variations for each move far beyond what we can manage… When we study the games played by AI, our main focus is on learning about the opening strategy.”

（Interview with an anonymous 9-dan professional player）

When professional Go players encounter AI moves that they cannot understand, they selectively ignore those moves. In game commentaries, it is common to see professional players make comments like, "FineArt suggests making the next move this way, but I believe the player in the game couldn't possibly have thought of that. It's too counterintuitive for humans." In their training, players choose AI moves that they can interpret to learn from. When they use such moves in tournaments, these AI moves thus receive attention from the Go community and possibly enter the domain of human Go knowledge. From this perspective, professional Go players are not just interpreters; they are also gatekeepers. Through their expertise, professional players set boundaries for human Go knowledge, incorporating certain contributions from AI into the realm of human Go knowledge, while discarding others as too complex to understand.

Dimension 3: the audience

According to Eyal, one significant dimension of the network of expertise is the relationship between those who are authorized to speak as experts and those who listen to them (Eyal & Pok, 2015). Due to the competitive nature of Go, the right to speak within the Go community is highly hierarchical. When two players talk about Go, if there is a clear difference in their skill levels, it is often the more skilled player who dominates the conversation, while the other can only listen passively. This was also reflected in the Go community before the emergence of AI, where professional players enjoyed absolute authority in speaking about Go due to their skills in the game. However, after the emergence of AI, professional Go players completely lost this privilege, and the only entity that now enjoys this authoritative right to speak within the Go community is the Go AI. In other words, both professional Go players and amateur Go players have become the audience of Go AI. In the following excerpt from an interview, a world champion complaint to me about the current situation of professional Go players.

"Nowadays, every amateur player has access to AI, and many people use AI to criticize your moves in tournaments. Everyone is using AI to comment on your play, not realizing how much thought we put into each move, why we make them; they don't understand. They only see the number (win rate) provided by AI, whether it has increased or decreased significantly. That's all they see. Everyone watches the games from this god-like perspective and then criticizes how badly you played." (interview with an anonymous world champion, 9-dan professional player)

In the current Go community, the prevailing consensus is that AI has become the gold standard for evaluating all aspects of Go, and any Go knowledge not endorsed by Go AI is questionable. An interesting example is that an amateur player who is analyzing the game records of all famous historical players, comparing their moves to those recommended by Go AI to produce a comprehensive ranking of all players throughout history. Meanwhile, AI itself also becomes the subject of evaluation. A topic that has persisted in the Go community since 2017 is which Go AI is the strongest. Various official and unofficial Go AI competitions have emerged consistently. However, few people in Go community realize that today's Go AI has far surpassed human levels of play, to the extent that even the Go AI ranked last in AI competitions is still much stronger than the best human player. The pursuit of the strongest AI has transcended practical considerations of how to improve human Go skills and has become a quest for absolute objectivity in Go.

Conclusion

With the development of large language models and various AI applications, the use of AI in various professional settings is rapidly increasing. Five years ago, professional Go community was among the few professional communities deeply affected by AI, but the number of fields experiencing similar impacts is expected to rise quickly in the coming years. This article explores how Go AI has transformed the role of human professional Go players, shifting them from being authorities of knowledge to interpreters of AI Go strategies and gatekeepers of human Go knowledge. The article also examines how the expertise of Go AI becomes possible, identifying which actors and what arrangements enable Go AI to make expert statements and become a productive contributor to human Go community. Although professional sociology has been relatively quiet over the past two decades, concepts, such as jurisdictional struggle, provide significant insights in analyzing the impact of AI on professional communities. The research questions discussed in this article can be applied to any professional field affected by AI, by simply replacing professional Go players with other professional groups. Another focus of this article is on redefining the role of human experts in the professional setting after AI surpasses human capabilities. As Abbott (1988) points out, technological advancements disrupt existing jurisdictions and create new tasks and problems. Human experts will not get replaced in the professional realm with the advent of AI; they will instead find new tasks to grapple with, especially since AI does not provide ready-made knowledge. Human experts will continue to be the most crucial mediators between AI and the public.

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