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차례

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Contents

인공지능(AI) 특집호를 펴내며

인류가 팬데믹의 어두운 터널을 벗어나자, 다양한 형태의 사회적 욕구가 곳곳에서 분출한다. 대안 사회에 대한 논의가 풍부해졌다 해도 여전히 선명하지는 않다. 뉴노멀이라는 신조어는 이러한 난맥상의 해결 수단으로 간주되는 기술적 도약뿐만 아니라, 새로운 비전 수립을 함축한다. 알파고의 강습(强襲)을 생생히 기억하고 있는 바둑계로서는 ChatGPT의 부상으로 후끈 달아오른 AI 담론이 의미심장한 '귀환'일 수밖에 없다. 국제바둑학회(ISGS) 집행부가 "7년의 세월 동안 우리가 AI로부터 무엇을 얻었는지, 그리고 이 거대한 시대적 요구가 갖는 의미는 무엇인지에 대한 사유와 성찰"을 촉구하는 학술 프로그램을 기획한 까닭이다.

지난 8월 31일 명지대학교 자연캠퍼스에서 '인공지능시대의 바둑(Go in the Age of Artificial Intelligence)'이라는 주제로 제1회 국제학술대회가 열렸다. AI 알고리즘으로 대변되는 새로운 '통치'의 전지구화를 반영하듯이, 현장 분위기는 뜨거웠다. 10편 발표의 빡빡한 일정이지만, 바둑이라는 단일 언어로 국적을 초월한 학술교류가 성사된 셈이다. 바둑의 형이상학적 불꽃이 사위어 가는 시대에, 지적 갈증을 해소하기 위해 펼쳐졌던 오아시스의 풍경을 지면으로 전한다.

특집논문은 모두 다섯 편이다.

첫 번째 논문에서 리저(李喆)는 인류가 축적해 온 바둑의 지식구조에 대한 이해가 필수적인 시대에 접어들었음을 강조한다. 중국의 역사서를 둘러보며, 기리(棋理)와 기술(技術)이 포괄된 바둑지식을 '필연적/개연적' 지식으로 구분하는데, 그 기준은 지식의 '확실성'이다. 문화적 속성과 불가분의 관계에 있는 개연적 비합리적이고도 계산불가능한 - 지식의 예로 "후박(厚薄)", "허실(虛實)", "경중(輕重)" 내지 "바둑십결(圍棋十訣)"을 들고 있다는 점이 흥미롭다. 결론은 그 개념적 한계를 올바르게 인식해야 인간이 AI에게 패하는 이유를 규명할 수 있고, 바둑이론의 지평을 넓힐 수 있다는 것으로 요약된다. 행동경제학의 핵심 개념인 제한적 합리성이나, 언어학 - 화용론 - 분야로 확장될 후속 연구가 기대된다.

리저가 인간이 축적한 바둑지식의 불완전성에 초점을 맞추었다면, 두 번째 논문에서 잭 개럿(Zack Garrett)은 2016년부터 이른바 '블랙박스 문제'를 해결할 유력 대안으로 부상한 '설명가능한 AI(Explainable AI)'의 틀을 적용해 AI의 착수를 설명할 수 있는지를 타진한다. AI가 둔 착수를 칼 헴펠과 폴 오펜하임이 처음 제시한 네 가지 원칙에 부합하는 방식으로 설명할 수 있는지를 추론하는 과정에서 등장하는 다양한 예시가 흥미진진하다. 그 비관적 결론과 무관하게, 비판에 대해 열려 있는 초학제적 연구를 지향하는 본지의 입장에서는 반가운 논문이 아닐 수 없다.

세 번째 논문의 저자 쿠엔틴 런디(Quentin Rendu)는 이제껏 누구도 시도하지 않았던 인간 승률(the human win-rate)을 계산하는 새로운 방법론을 제시한 뒤, 온라인게임에서 수집한 기보 데이터베이스에 기초해 인간 승률이 AI 승률보다 현저히 낮게, 그리고 일관된 추세로 나타나고 있음을 경험적으로 입증한다. 인간이 AI를 이길 수 없는 현실에서 어쩌면 당연하고도 불필요한 연구로 비칠 수 있지만, 반상에서 우리의 예측을 뒷받침하는 기초가 실은 매우 허약하다는 점, 그리고 대국 환경에 대한 세심한 고려가 없는 상태에서

AI 승률에 '맹목적으로' 의존하는 경우의 위험성에 대한 경고는 곱씹어볼만하다.

네 번째 논문에서 테오 바로에와 콜랭 르딕(Theo Barollet & Colin Le Duc)은 오픈소스 엔진의 선구적 분야에 속하는 바둑에서, AI 부정행위 탐지를 지원하기 위한 보완 장치로서 널리 사용되는 AI 유사성 지표(AI-likeness metric) 외에 점수손실 분포를 고려한 개별 선수의 경기력 분석을 제안한다. 놀랍게도 이 방식은 이미 두 개의 유럽바둑 공식 온라인리그에서 그 우수성이 검증된 바 있다. 그런데 이 논문이 선사하는 큰 울림은 논문 및 관련코드의 공개사유를 기술한 말미에 등장한다. "우리는 … 허위 고발을 최대한 방지하고, 안타깝게도 충분한 요소가 수집되면 부정행위 혐의자에게 신속하게 연락하여 혐의를 확인함으로써 부정행위 혐의자가 대면시합을 하거나, 다른 플레이어와 만나도록 유도할 수 있기를 바란다."

마지막으로, 다니엘라 트링스와 오치민(Daniela Trinks & Chi-min Oh)은 AI 엔진 도입이 바둑 교육에 미친 영향을 돌아본다. 현재까지 교육에 활용된 AI의 유용성과 미래 전망에 대한 교육자들의 의견이 엇갈리고 있다는 결론은 유사 도구로 볼 수 있는 ChatGPT를 주제로 쏟아져 나오고 있는 국내외 보고서와 비교할 수 있는 접점을 제공한다는 점에서 기여하는 바가 크다. 이 연구를 계기로 교육도구로서 AI가 갖는 잠재성에 대한 논의가 더욱 활성화되기를 기대한다.

일반논문 두 편도 유익하다.

심다운은 바둑진흥법을 '실효성'의 측면에서 접근해 그 문제점을 지적하고, 제정된 지 5년이 경과한 동법에 대해 새롭게 주의를 환기시키고 있으며, 온라인 바둑 대국에서의 '평등성' 개선을 위해 레이팅 점수와 대국 결과에서

승률, 대국 수를 산출한 뒤 레이팅 점수에 따른 승률과 대국수 변화를 분석한 김진환과 김채림은 의외의 재미를 선사한다.

바둑은 우리의 인지능력에 어떤 영향을 미칠까? 취미로 발레를 즐기는 멕시코의 10살 소녀 미셸 웡(Michelle Alejandra Wong Sámano) 또한 이런 의문을 품었나보다. 선물처럼 날아온 그녀의 특별논문은 바둑이 멕시코시티에서 바둑을 두는 인구의 인지능력에 어떤 영향을 미치는지를 보고한다.

놀이로서의 바둑이 거의 전지구인의 축제로 자리 잡은 역사는 따뜻한 연대를 매개한 ‘인간의 바둑’이 승부 귀신인 AI 바둑보다 훨씬 더 특별하다는 사실을 증언한다. 내년 여름에 제2회 국제바둑학술대회가 열릴 장소는 프랑스 툴루즈다. 많은 성원을 바라며, 실무에 많은 도움을 주신 김채림 사무국장, 그리고 소중한 시간을 할애해주신 여섯 분의 심사위원께 감사드린다.

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편집위원장 배인철

Introduction: Revisiting the nexus of human and AlphaGo

Escaping the dark tunnel of the pandemic, humanity wants to fulfill a wide range of social needs that have been pent up. We have explored a couple of alternative societies, but the prospect seems bleak. The term 'new normal' heralds the emergence of another type of cutting-edge technology, and implies the urgency of establishing 'the' vision to implement it as well. As a member of global Go circle who witnessed AlphaGo's 'reign', we see the AI discourse that has heated up with the rise of ChatGPT as a meaningful 'return'. Perceiving it as a social upheaval, the executive committee of the International Society of Go Studies (ISGS) planned an academic program calling for thinking and reflecting on what we have gained from AI over the past seven years.

On August 31, the 1st International Academic Conference on "Go in the Age of Artificial Intelligence" was held at Myongji University's Natural Campus. The atmosphere was hot, as if reflecting the globalization of the new 'governance' represented by AI algorithms. Having a tight schedule, it was a successful academic exchange transcending nationalities via the common language, Go. In this era when the metaphysical flame of Go withers, we gladly share the issues about the conference.

The special section consists of five papers.

In the first paper, Li Zhe emphasizes the importance of understanding the knowledge structure of Go, as we enter the era where such understanding is essential. By examining Chinese historical texts, Li categorizes Go knowledge, which encompasses principles (qili, 棋理) and techniques (jishu, 技术), into "inevitable/causal" knowledge, and "contingent" knowledge, with the yardstick of "certainty" of knowledge. It is interesting to note that contingent, irrational, and incalculable knowledge, which is inseparable from cultural properties, includes dualities such as "thick and thin," "empty and solid," "light and heavy," or the "Ten Principles of Go." It is summarized that recognizing the conceptual limits of Go theory can help identify the reasons why humans lose to AI and broaden the horizons of Go theory. This sets the stage for future research expanding into fields such as behavioral economics' core concept, the bounded rationality or linguistic pragmatics.

While Li Zhe focused on the incompleteness of the knowledge of Go in the first paper, in the second paper, Jack Garrett examines whether the framework of "Explainable AI," which has served as a promising solution to the so-called 'black box problem' since 2016, will be applied to explain AI's moves. Through the process of inferring whether AI's moves can be explained in a manner consistent with the four principles originally proposed by Carl Hempel and Paul Oppenheim, various intriguing analogies are presented. Apart from the pessimistic conclusion, we welcome this kind of paper, because our perspective pursues trans-disciplinary research that is open to various criticisms.

In the third paper, author Quentin Rendu presents a new methodology for calculating the human win-rate, which no one has attempted before. Based on a database of game records collected from online games, Rendu empirically proves that the human win-rate is significantly lower than the AI win-rate and consistently decreasing. While it seems like an obvious and redundant study in these days when humans cannot defeat AI, the paper offers valuable insights; it highlights the fragility of our cognitive foundations while attempting predictions on board, as well as the danger of blindly relying on AI win-rates without carefully considering the Go environments.

In the fourth paper, Theo Barollet and Colin Le Duc proposes an analysis of individual players' performance by considering the distribution of score loss as a complementary measure to the widely used AI-likeness metric in the field of open-source engines in Go. Surprisingly, this approach has already been validated in two European official online Go leagues. The huge impact comes at the end of the paper, when it states the rationale of the analysis: "By releasing this paper and the associated code publicly, we hope our work can inspire other organizations to adopt a similar process with medium or long-term analysis to avoid false accusations as much as possible, and, once enough elements are unfortunately gathered, allow them to quickly contact alleged cheaters to confirm the suspicions, encouraging them to play over-the-board games or to meet with other players."

Lastly, Daniela Trinks and Chi-min Oh reflect on the impact of AI engine integration on Go education. It highlights the divergent opinions among educators regarding the usefulness and future prospects of utilizing the AI-based tools in education. The contribution lies in providing a useful reference with the plethora of domestic and international reports on the comparative topics, particularly focusing on ChatGPT. We hope that this study will further stimulate discussion on the potential of AI as an educational tool.

Two general papers are valuable.

Shim Daun takes an approach to the Go Promotion Act from the aspect of 'effectiveness' and points out its problems. The author has rekindled attention to the law, which has been in effect for five years, and Kim Jinhwan and Kim Chaelim have analyzed the changes in win-rate and number of games according to rating scores and game results to improve 'equality' in online Go matches, arousing an unexpected fun.

What effects does Go have on our cognitive abilities? Michelle Alejandra Wong Sámano, a 10-year-old girl from Mexico who enjoys ballet, seems to have had this question in mind. Her special paper, an adorable gift, examines the impact of Go on the cognitive abilities of the population playing Go in Mexico City. We thank her for the interest in our journal.

The history of Go, which has become a global festival as a game, testifies to the fact that human Go, which mediates warm solidarity, is much more special than AI Go which actually has become 'the Lord of the Game'. The second International Go Academic Conference will be held in Toulouse, France next summer. We hope for a lot of support and would like to thank Kim Chaelim, the office director for her great help, and the six judges who have devoted their valuable time to review the papers.

2023 Nov.

Bae Incheol, Editor-In-Chief

특집

Special Section

인공지능시대의 바둑

Go in the Age of Artificial Intelligence

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围棋的知识结构分析
Analysis of the Knowledge Structure of Go

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Abstract: The potential implications of AlphaGo defeating a human player have not been fully discussed in the epistemological field. AlphaGo does not play in a nearly exhaustive way with a huge amount of computation, but has reached a higher level of “intuition” and “judgment”, which humans once thought was a difficult area for computer languages to break through. This phenomenon prompts us to rethink the structure of Go knowledge.

From the perspective of epistemology, what kind of knowledge of Go is indeed reliable? Based on this fundamental question, this paper attempts to analyze the structure of Go knowledge. The main thought processes in the game of Go can be summarized as “intuition”, “calculation” and “judge-

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ment", where rational deduction and empirical induction co-exist. In the past, the simple enumeration of knowledge points became the main focus of Go knowledge learning and teaching, now the nature of these knowledge points are distinguished, particularly the Go knowledge between"quantitative" and "non-quantitative", moreover, the correlation between knowledge generation and both inherent human cognitive abilities and cognitive limits is presented.

This paper analyzes the specific principles of how Go AI surpasses the human level of Go from the perspective of epistemology, provides theoretical support for how human players can leverage AI for new Go knowledge production in the future, and may serve as a bridge between Go and cognitive science research.

Keywords: Go knowledge, epistemology, intuition, calculation, judgement, rational deduction, empirical induction, quantitative

Ⅰ. 引言

2016年, AlphaGo在人机对决中击败李世石, 成为震撼全世界的标志性事件。在事件发生之初, 人们主要震撼于胜负的结果, 基于深度学习算法的AlphaGo将计算机围棋的水平迅速提升到了超过人类水平的程度, 超出了大多数人的预料。此后, 人工智能一跃成为全球热门的研究领域, 人们开始关注和研究AlphaGo为何能取得成功, 以及深度学习的算法应用还可以在哪些领域带来飞跃。

2017年之后, 由于AlphaGo的水平超出人类棋手太多, 人机对决的阶段迅速过去了。此后人工智能的前沿研究者们将注意力转移到了其它领域, 但AlphaGo在围棋领域留下的不仅仅是胜负结果和可以帮助人类棋手进步的围棋AI。AlphaGo究竟是怎么赢的？这个问题的回应包含两个方面, 一是关于AlphaGo算法的分析, 二是关于人类围棋知识结构的分析, 两者加起来才能构成完整的回答。关于AlphaGo算法的分析和介绍, 已有相当多的论述；而关于人类围棋的知识结构, 关于“人类棋手究竟输在什么地方”的认识论层面的反思, 目前仍旧匮乏。

与人们之前的设想不同, 围棋AI并不是用庞大的计算量以近乎穷举的方式来下棋, 反而是在“直觉”和“判断”这些人类曾认为难以用计算机语言描述的“经验”领域达到了更高水准。相反在局部死活、直线计算等知识领域, AI相比于人类棋手并没有巨大的优势, 时至今日仍可能在一些极端的棋局场景中被人类棋手的下法超越。在对围棋AI算法理解的基础上, 如果没有对人类的围棋知识进行系统性的结构分析, 对此现象的解释还是只能停留在表层。

事实上, 过往口耳相传或写于纸面上的围棋知识主要是一些知识点的罗列, 而职业棋手们脑海中的围棋知识虽然是融贯的, 但并未被作为对象进行系统地分析。只有对围棋知识进行结构性的系统分析, 我们在面对“AlphaGo赢在哪里”这样的问题时才能给出不只是“人工智能的计算能

力超过人类”这样浅显的回答，进而能够准确地指出在面对围棋AI时，人类的围棋知识里哪些部分形成了重大的弱点，而哪些部分是可以信任的知识，以及是何种原因造成了这样的差异。

对于围棋知识结构的分析，一方面可以进一步了解人类认知能力的限度，以及人类的诸认知能力在面对棋局时究竟如何施展；另一方面，也可以呈现未来人类的围棋知识在哪些方面有可能得到更新和飞跃。

II. 围棋知识的历史生成

人类的围棋知识是历史中层累建构的结果，绝非现代棋手独立的发明，要分析围棋知识的结构，首先应对围棋知识生成的历史进行梳理。历来关于围棋知识的书籍大体可分为两类，一曰技术，二曰棋理。从历史发展来看，明代以前棋理类书籍的比例较高，明代以后技术类书籍逐渐占据多数，这与围棋价值及其社会形态的历史演变相关。[1]

就具体的知识内容而言，围棋技术类书籍主要是各技术部分的并列或罗列，诸如布局、定式、中盘、官子、手筋、死活等等分门别类的技法，随着人类整体水平的不断提升，各知识门类的技法也得以不断更新。棋理类书籍则可上溯至《敦煌棋经》或《棋经十三篇》，主要以文论的形式来论述对弈所应当遵循的道理，其中尤以“策略”的论述为重，与技术类的知识不同，这些策略论述所使用的语言并不依赖于围棋的专业术语，其话语往往借用于已有的话语系统。[2]就知识生成的目标而言，棋理类知识中的一部分是概括总结对弈思维本身的脉络以供人沿习，另一部分则是试图用棋理来论述现实世界中的某些道理，此传统从汉代班固的《弈旨》这一最早的围棋文论即已起始。棋理文论的传统首先基于一种哲学思想上的

1) 李喆.中国围棋价值演变研究[J].中国围棋论丛,2015.
2) 例如《棋经十三篇》体例及语言皆仿《孙子兵法》而作。

预设，即围棋中蕴含的道理与世间万物的道理是相通的，它们共同从属于“天理”——自汉代以降，这种预设对于古人而言几乎不言自明。棋理文章所使用的知识论证的形式，与古代的说理文论基本相同，其中往往运用大量的类比，并注重文法结构的美感与词句的洗练。[3]大体来说，传统的棋理文章仍从属于古代文论这一大类。20世纪以后，棋理的概念主要是指面对棋局本身的有效策略与思考方法，其引申之义淡化，这与围棋的竞技属性增强、实用主义占据优势相关。在棋理与技术交界之处，还有一类围棋的知识话语是“棋评”，即对于棋谱的点评，棋评类的书籍与文章并非是独立领域的知识生产，而可以看做是这两类围棋知识的综合运用。

现代人对于围棋的诸多认知并非凭空而来，围棋知识具有历史性，是在前人贡献的基础上不断生成的。现代棋手面对棋局所使用的术语、思考的概念与框架、棋感的生成等等，都与围棋知识整体的历史积累有关。

围棋技术的相关知识，建基于“概念”的基础之上，无论如何复杂的技术知识，都需要在概念的基础上才能有效形成。概念用来表征对局中面对的状况，最基础的概念就是棋子与棋子之间的位置关系，这些位置关系的概念被语词定格为“术语”，例如“长”、“跳”、“飞”等。单个的基础术语组合成复合术语，例如“托退”、“扳渡”等，在有足够的术语描述棋子的位置关系之后，生成出“手段”和“策略”的术语，例如“侵消”、“打入”、“立二拆三”乃至“攻彼顾我”、“厚势不围空”等等，这些围棋术语所延展出的结构，就像语言中的“字-词-句”结构。围棋中的术语，大多借用于已有的文化概念，极少数是新生成的专有术语。也就是说，作为围棋知识之基础的术语，在很大程度上与生活世界的语言符号相通。选择采用哪些语词来表述围棋中的诸概念，亦是围棋知识生成于历史文化之中的偶然结果，现代棋手们所使用的术语和不断继承-生成的围棋知识，正是建基于这些文化历史的偶然选择之上。

围棋在20世纪加速了竞技化的发展，围棋技术的水平由此得到快速的

3) 例如，“围棋十诀”的每一诀都字数相同。

提升。对于围棋技术知识的认知，一方面仍是在旧有的概念基础之上的延伸，另一方面，直到今天仍然缺乏的是对于围棋知识之性质和结构的分析。在对阵AlphaGo之后，人类固有的围棋知识受到怀疑和挑战，产生了反思的契机；反思触及到的第一个问题是，人类的围棋知识中究竟有哪些部分是值得信任的，又有哪些部分是可疑的？对此问题的回答自然会形成关于围棋知识的新分类并呈现出其内在的实际结构。紧接着的问题是，它们曾经是如何生成的，又是否有改善的空间？本文试图处理的主要便是这些问题。

III. 两类围棋知识

在AlphaGo-Master下出令棋界震惊的开局“点三三”之后，随着围棋AI的快速普及，以往大部分的围棋定式在短短几年内都遭到淘汰。[4]可见，定式作为围棋知识中的一大类，显然并非确定无疑的知识。那么，在完全不学习人类下法的AlphaGo-Zero系围棋AI的映照下，还有哪些人类固有的围棋知识是可靠的？

人们很容易发现，不管作为他者的围棋AI达到多高的水平，人类自身对于围棋盘上的基础死活、封闭的官子大小、杀气的技巧、终局胜负的计算等等知识，仍然是十分可靠的。也就是说，在围棋盘上，并非“所有的知识都是不可靠的”，[5]只要围棋的基本规则不变，像“有两个真眼的一块棋是活棋”这样的知识就是确定无疑的。[6]

4) 例如，曾经十分流行的“妖刀”定式被AI判定为一方显著有利，从而失去定式之地位。

5) 在知识论中，某些怀疑主义会认为我们的信念不足以产生任何知识。参考理查德·费尔德曼《知识论》，中国人民大学出版社，2019年，第133页。

6) 怀疑主义者或许会质疑这里“真眼”和“活棋”等概念的清晰性，但这关系到的主要是术语定义是否清楚明白的问题。

由此, 从知识的确定性来区分, 可以分出两类围棋知识: 一类是确定无疑的围棋知识, 一类是不确定的围棋知识, 前者是不可错的, 后者是可错的, 接下来我们分别考察它们的内容、性质和生成的方式。以往对围棋知识的书写大多是知识点的罗列, 从此处开始我们将对这些知识进行重新的考察、分类和分析。

1. 具有必然性的围棋知识

首先考察确定无疑的围棋知识包含了哪些内容。"两眼活棋"是一个基础的围棋知识, "双活也是活棋"是与之平级的知识, 隐含的知识包括"被包围且只有一个眼的棋是死棋", 这些关于棋子"死活"的知识显然是确定无疑的。在此基础之上, 围棋里的"杀气技巧"、"常见死活"、"吃子方法"等等, 形成了一系列不可错的知识。这些知识之所以不可错, 因为它们是从围棋的基本规则演绎推理而来的。

围棋的基本规则包含"气尽棋亡", 也就是规定了棋盘上什么样的棋是死棋。以此作为基础开始推演, 可以得知"不会气尽的棋就是活棋", 继续推演, 则可以得出如何使自己的棋子成为活棋、如何使对方的棋子成为死棋等等的技巧知识。由于这些知识是从围棋的基本规则直接用逻辑的方式推演而来, 因此, 只要其逻辑推演的过程完整无误, 其产生的知识结果便是不会错的。

这一系列关于棋子死活的知识也有不同的难度层级, 最基础的两眼活棋和"直三"等形状的死活是入门阶段就能掌握的, 而一些复杂的死活题乃至错综复杂的实战死活, 则连最顶尖的人类棋手也不一定能掌握。完全超出人类计算能力的死活问题理论上也是存在的, 但大部分的死活问题对于人类棋手来说只要有足够的时间来思考都能够解决。这些知识的重要特点就在于, 一旦问题被解开, 只要过程是符合逻辑正确无误的, 那么这个知识就是不会错的。在一些复杂的死活或对杀问题上, 我们仍然

有概率看到人类的下法比AI推荐的更好，正是因为人类在这方面的知识一旦过程无误地达到了，就是正确无疑的，而当前围棋AI的算法主要基于概率，并非以不可错的逻辑推演为基础。

在死活问题之外，关于围棋盘上价值大小、目数多少的一些知识也不可错，这些知识是从围棋基本规则中计算胜负的规则推演而来的。例如，双方领地大小的比较（数目），两个官子大小的比较，一个封闭官子的价值等等。7)这些知识之所以不可错，也是因为它们与围棋的基本规则直接相连，围棋终局的胜负计算就是比较双方领地的大小，比较的方法是将双方的领地数字化，因此在对局中也采用数字比较的方法得到的一系列知识与规则同构，同样可以说是从规则逻辑推演而产生，因而是不可错的。据此，在一些不复杂的官子战中，人类棋手也可以准确地找到确定无疑的最优下法。在判断形势优劣时，有些局面也可以根据双方目数的对比得到准确无疑的结果。

在这两类确定知识之外，还有一些围棋知识的确定性要稍低一些，但或许仍可算作确定知识之类，这就是关于"棋子效率"（子效）的知识。"子效"是人类棋手对局时用来做决策和判断优劣的一个常用指标，有一些关于子效的知识也是不可错的，例如，围出同样的地域所花的手数不同，花费手数更少的一方显然子效更高、更有可能占据优势。当我们对子效的分析完全使用逻辑和数学的方式时，得到的结果就是确定无疑的知识，但在实际的对局中，有些局面并不能完全用逻辑和数学的方式来比较子效，这往往是由于局面的封闭性不强，以人类的计算能力只够部分地使用逻辑和数学的方法来比较和计算，剩余的部分交给了经验判断。

"手割法"8)作为比较子效的一种围棋技术，很好地展现了这类知识的性

7) 有一些官子的价值是人类无法准确描述的，也就是在通常意义的官子中存在一些人类达不到的知识（涉及"官子"的定义问题），但是还有很多官子的价值大小是人类可以用数字准确描述并进行比较的，这些是能够帮助棋手做决策的准确知识。

8) "手割法"相传为本因坊道策（1645-1702）创造的技术，其要点是通过假设性

质。当“手割法”运用的对象和过程全部是确定无疑的知识时，“手割”得到的结果也就是可以信任为正确的知识；但在实际的对局操作中，“手割”常常被用来处理的是混合了确定与不确定的知识，在这些情况下，“手割法”往往是作为子效分析的辅助方法来增强关于优劣的信念，而不能得到绝对准确的判断知识。由此也可以看出，在实际对局中，人类棋手的决策往往是由确定的知识与不确定的信念相结合。

换一个角度考虑，围棋中的技术知识，主要是关于比较和判断的知识：比较哪个选点好、判断哪方形势好等等，这其中的确定知识，可以理解为比较和判断达到了精确程度的知识。围棋里的死、活、劫，以及标记地域大小的数字，它们的定义都是清楚明白、没有模糊性的。

总体来说，围棋中确定无疑的、具有必然性的知识，主要是定义清楚明白、以围棋规则为基础前提、通过逻辑和数学的方式推演而成的知识，这些最坚固的知识即便在穷尽围棋的最优解面前也是正确的。

2. 具有或然性的围棋知识

在7*7或更小的围棋盘上，人类棋手可以算出其最优解；[9]而在常用的19*19棋盘上，人类距离最优解还有非常远的距离。面对不同大小的棋盘，人类棋手所使用的认知方法和得到的知识是有差异的。在可以算出最优解的小棋盘上，人类只使用逻辑和数学的方法算出每一个选点所对应的终局数字，而不存在“道理”的模糊认知；而在十九路棋盘上，由于其复杂度超出了人类计算推演的范围，人类只能在一定区域内使用逻辑和数学的方法，在另一些区域则采用了许多经验归纳的方法来获取知识，广义来说，这些知识就是具有不确定性的知识。

的改变次序，将需要判断优劣的棋形还原为已知优劣的棋形，再分析其中棋子效率的增减，由此判断局面。

9) 李喆.七路围棋最优解研究[J].围棋天地,2015(20):32-42

具有不确定性的围棋知识包含了很多内容，例如“厚薄”、“轻重”、“好形”、“愚形”、“立二拆三”、“入界宜缓”等等，其数量之多难以穷举，这些知识的目标仍然是用来比较和判断棋局及选点的优劣。与确定的围棋知识相比，两者的差别主要在于生成知识的方法，其次在于概念定义的清晰性。[10]

经验归纳是这类知识生成的主要方法。例如，什么是好的棋形，什么是不好的棋形，这些是人类棋手多年以来用经验归纳的方式总结出的知识，大部分来自集体的经验，少部分来自个体的经验。人类下棋之所以需要用到“棋形”这样的知识，是因为十九路棋盘上的变化数超出了人类用逻辑演算可以达到的范围，人类“聪明地”创造了一些概念知识来处理那些逻辑演算无法达到的局面，局部棋形的优劣就是其中一类概念。

在逻辑思维之外，人类其它的一些思维能力在这里发挥了作用，即类比和关联的思维。例如“厚薄”、“轻重”这样的概念，人们借用它们在文化中本有的词语意涵，用来定义棋盘上的状况。虽然每盘棋的实际状况都不完全相同，但我们将一些局面共同描述为“厚势”，一些棋形共同描述为“好形”等等，用这些概念来帮助我们定义和理解局面，使我们在不能精确衡量局面的时候仍然可以得到关于局面和选点优劣的知识，尽管这些知识不如第一类知识那么正确无疑，但在实践中可以用来指导我们的行棋决策。

正是在引入这些概念来定义局面的基础上，围棋里的诸多“策略”才能得以施展。例如，围棋十决里有“势孤取和”，要理解这种策略首先就要理解什么是围棋里的“势”，势的强弱大小无法用具体的数字来精确衡量，其程度更多是一些“感觉”和“印象”，随着经验的增多、水平的提高，这些感觉和印象就会更加融贯有效而接近准确。

10) 围棋中棋子的“死”和“活”、地域的“大”和“小”等等，定义都清楚明白，从而能进行准确的比较；“厚”和“薄”、“轻”和“重”等等，定义就相对模糊，只能进行大致的比较而无法精确衡量。

但是，无论这类知识在实践中被证明多么有效，它们仍然是一些无法精确测量的、具有不确定性的知识。[11]在人类与围棋AI的对决中，人类很快发现正是在这些所谓"虚"的、模糊不清的、无法量化处理的局面场景中，AI的能力远强于人类棋手。对于围棋AI来说，不存在这样两类性质不同的知识，面对任何局面，AI所调用的算法都是一致的，而人类棋手在运用这两类知识能力的时候精确度相差极大。这就是为什么在一些特殊的局面下，人类棋手将逻辑演算能力发挥到极致，仍有可能超越AI的下法和判断；而在大多数局面下，人类依靠经验归纳和感觉得到的知识完全无法与AI算法相抗衡，表现在对局中，就是在人类棋手曾经引以为豪的所谓"虚"的部分（也有人称为"大局观"的部分），如今完全依靠AI来解惑。

由此而来的一个有趣现象是，以往对棋手风格特点的评价中有一类是"大局观好"，但在AlphaGo之后，这类评价几乎消失了，其原因就在于"大局观"所涉及的知识类型正是人类相比于AI而言最弱的部分。在后AI时代，如果真实地评价一位棋手下的棋特别像AI，恐怕应有很大程度是在说这位棋手的"大局观好"。

后AI时代，人类棋手仍然需要用这一类知识来处理围棋，这是由人类思维能力的限度所决定的。值得一提的是，围棋的很多文化属性，正是在这类不精确的围棋知识基础上生成的。

如果用分析哲学中知识论（Epistemology）的话语来说，第一类围棋知识，契合"基础主义（Foundationalism）"，这一类知识都来自于已有证成的基础信念（围棋规则），由基础信念正确演绎而成。第二类围棋知识，契合"融贯论（Coherentism）"，这一类知识中，每个信念都以它融入整个信念系统的方式而获得证成。由于篇幅所限，对此的深入分析需以另一篇文章加以论述。

11）如果从怀疑主义的立场来考虑，这些认知内容更接近信念而非知识。

3. 围棋知识的文化属性

很多人会说“围棋是一种战略游戏”或者“棋如人生”, 早在中国的汉代, 就有许多文人将围棋与兵法、政治乃至天道（天理）联系起来, 这些文化属性的建构与围棋的知识结构有直接的关联。

如果人类一直在7*7以下的小棋盘上下棋, 那么围棋的技术知识就只会有第一类：从规则出发逻辑推演而成的知识。在这种情况下, 围棋会被认为是一个能够被人找到确定答案的数学问题或游戏, 从这个视角来看, 棋盘上的每一个选点都对应着一个最终表示双方盘面差距的数字。“厚薄”、“轻重”这些概念在小棋盘上是不精确的冗余, 不会被运用于解题, 而围棋中的所谓“策略”则完全由运算所代替。

正是由于棋盘的大小超过了人类能够精确解决的范围, 又没有大到完全超出人类能下完一盘棋的范围, 在19*19的棋盘上, 围棋的文化属性得以生成, 这与第二类围棋知识密切相关。

非定量的围棋知识以一些“二元对立”的概念为基础, 例如“厚薄”、“虚实”、“轻重”等, 这些概念来自于已有的语言, 被借用于围棋来定义无法量化处理的局面。在这些概念的基础上, 继续生成了在不同局面下应当如何行动的理论, 这就是围棋的策略知识。例如, “厚势勿近”、“弃子争先”、“围棋十决”等就是人们总结的一些策略知识。围棋的文化属性, 很大程度在于围棋的非定量知识并非特殊知识, 而是具有普遍性的知识。

人们会说“围棋的道理与万物道理相通”, “围棋的道理可以指导人生”等等, 实际上表达的是围棋不只是一个有数学答案的游戏, 而是蕴含着普遍性的知识, 这样的认知来自非常古老的传统, 最早可以追溯到班固的《弈旨》。为什么会这样？同样是智力游戏, 人们就不会说“数独”或者“魔方”这些游戏有这样的功能。其原因在于, 围棋里的非定量知识, 其语词和思想就来自于已有的文化概念, 而非完全独立于世界之外的新知识系统。借用哪些语词, 使用哪些概念, 与知识生成所处时代的语言系统密切

相关，因此这些围棋知识的生成与发展同时也反映出特定的文化传统。在另一方面，它们也反映出人类思维的一些特性。

在围棋知识中可以看到明显的分界：人类可以用数理和逻辑处理的局面，人们就采用这类方式以尽可能达到精确知识。但人的理性有限，无法对19*19路棋盘全部用这类方式来处理；面对无法用数理和逻辑处理的局面，人们就采用经验归纳的方法来生成一些概念和策略，也可称之为“道理”，这类知识的劣势是不如前一类精确，常常会有错误，其优势是具有普遍性和泛用性——类似的局面乃至类似的状况，人们都可以采用相同的道理来处理，即所谓“举一反三”。

在围棋知识生成的过程中，人们面对那些无法完全用逻辑推演处理的问题，引入了“厚薄”、“轻重”、“缓急”、“虚实”等等无法定量的二元概念，成为第二类知识的基础。一个有趣的问题是，如果围棋早期的知识生产是在另一套语言文化系统中完成的，还会生成出同一套概念知识吗？与这个问题相关联的一个问题朝向未来：在AI的帮助下，人类有没有可能突破旧有的围棋知识系统，创造出更有效、更精确的围棋知识概念？

要回应这些问题，需要先将人类对局的思维和AI对局的算法进行结构上的分析和对比。

IV. 人类对局思维与AI算法的结构

人类的围棋知识运用于实践的对局之中，需以主体的具体思维活动来实现，这些思维活动的类型与性质亦值得考察。将对局的思维过程与AI的算法结构进行对比，不仅可以更清晰地看出人与AI在面对棋局时的差异与共性、优势与劣势，并且，通过观察围棋知识在实践中的运用方式，可以推测在AI的影响和帮助下人类围棋未来可能的进步方向。

人类的对局思维主要可分为三个部分：棋感、计算、判断。我们可以称

之为对局思维的三要素。

面对任何一个围棋的盘面，无论任何水平的棋手，只要了解围棋规则，都会产生出棋感。棋感首先是在棋盘上第一时间关注到的位置，新手的棋感可能有更多的随机性，其关注点可能距离全局正确的选点很远，但新手仍然是有棋感（直觉）的。随着水平的提高，棋感自然会越来越好。棋感是一种“剪枝”方法，使计算资源投入于主干，使决策树的生长更优，这是如今人和AI共通的技艺——AlphaGo正是训练出了类似甚至超过人类棋手的棋感。

棋感的提升，主要基于经验的积累，而非逻辑的推演。人类棋感的来源可分为个体经验和集体经验，个体经验的积累主要依靠对局和复盘，即实践和反馈；集体经验主要来自做题和打谱，分别训练对于局部的棋感（棋形）和对于全局整体的棋感。

计算是对局思维三要素中的第二个要素。以往棋界的话语中略微扩大了“计算”的语义范围，将属于“判断”的部分也归入计算之内了，这两者具有不同的性质和特征，需分别加以考量。棋局中的计算，实际上是形成“策略树”的过程，即沿着棋感进行换位思考，设想双方可能的一种或多种下法，搜索出多个分支，这个搜索并形成策略树的过程是计算。

计算是三要素的中间环节，它首先基于棋感——如果没有棋感，计算将很难找到起始点和头绪；它连接着判断，棋手对计算得出的诸多分支进行综合判断，试图分析出优劣，从而决定落子选点。

判断是三要素中最终的环节，通常也是与落子决策最近的环节。判断中可以运用的围棋知识最多，两类围棋知识在这个环节都可以发挥作用——有时是分别发挥作用，有时是共同发挥作用。当我们去判断棋子的死活、目数的大小、子效的高低等等，所运用的主要是第一类围棋知识，即具有确定性的知识；当我们去判断棋子的厚薄、轻重、棋形的优劣等等，所运用的主要是第二类的围棋知识，即具有或然性的知识。

如前所述，第一类知识的生成是以规则为基础条件，以逻辑和数学的

方式推演而成的。在面对新棋局的具体运用中，仍然是沿着已有的这类知识，继续以逻辑和数学的方式向前推演。例如，当我们已经知道了“方四”这样的形状内部做不出两只眼，在对局中我们就可以判断出特定的可以简化为“方四”之眼形的棋子是否能存活。对于同一类型的更难的问题，在实战中我们同样可以用逻辑推演的方式来处理，处理是否成功主要取决于自身水平与问题难度的程度差异。

第二类知识的生成主要依靠经验归纳的方法，在判断环节，这些知识概念十分常用。对于我们无法仅仅用“死活”或“大小”等精确概念来衡量的局面，我们就会用到很多诸如“厚薄”、“轻重”、“实地与外势”、“好形与恶形”等等不精确的概念来处理和判断局面。我们已经知道，判断环节，尤其是需要运用第二类知识的判断环节，是人类相比于围棋AI时的显著弱点。第二类知识不可量化而具有的不精确性，在与AI对局之前尚未被人类充分认识，反而由于有许多文化属性附着其上，增添了相关知识的魅力，而AI为人类带来了反思知识、对已有知识进行对象化处理的契机。

有趣的是，在AlphaGo公布算法之后，我们可以发现，从最初的论文12)直到Master版本，AlphaGo神经网络的结构与人类对局思维的三要素的结构几乎是正相对应：棋感对应Policy network，计算对应Monte Carlo Tree Search，判断对应Value network。

AlphaGo的Policy network使AI面对任何盘面能迅速通过“直觉”找到一些要点，这部分通过训练达到并超过了人类水平，表现在棋谱上的一个例子是Master之后的AI都会在开局阶段直接考虑“点三三”的下法，这是完全超越当时人类棋感的下法。和人类训练棋感的方式相似的是，Policy network的训练在本质上也是依靠大量经验的积累，而非逻辑的推演。

Monte Carlo搜索在形式上接近于人类棋手的计算，同样是通过搜索产生出许多局面变化分支，以供判断和选择。只是搜索的具体方法有很大

12) Silver D, Huang A, Maddison C J, et al. Mastering the game of Go with deep neural networks and tree search[J]. nature, 2016, 529(7587): 484-489

差异, Monte Carlo算法主要是基于概率和随机性的统计模拟法, 人类的计算则主要是沿着棋感进行换位思考。

Value network对于AlphaGo的主要作用就是判断局势, 正对应人类对局思维的判断环节。不同之处在于, Value network生成的判断内容是胜率, 通过比较不同选点的胜率数字来帮助决策。而人类棋手的判断方法, 如前所述, 在类似于小棋盘的一些局面下可以完全用逻辑和数学的方式来得到准确的判断结果, 但在大棋盘上常常需要两类知识的结合, 基于经验归纳的不准确的方法也不得已用于判断之中, 通常在这样的情况下, 人类棋手判断的准确度就大幅下降了。

尽管在AlphaGo Zero版本之后, Police network和Value network两者合并为一个网络了, 13)但算法的整体结构并未发生根本性的改变, 围棋AI的算法与人类对局思维的对应关系仍然存在--实际上也验证了对于当前人工智能的一种常见观点：基于神经网络的人工智能部分地模拟了人类思维的结构。

在分析知识结构的基础之上, 我们便可以对人类未来围棋知识理论上可能的发展前景做出展望, 这个展望不再是模糊的感觉, 而可以转化为如下问题：

在AI的影响和帮助下, 人类的两类围棋知识运用于对局思维的三个环节, 分别有多少发展进步的空间？

首先考虑棋感。由于棋感的增强主要依靠的是经验积累而非逻辑推演, 人类整体的对局经验显然是不断增加的, 因此整个围棋史上棋感的水平是不断增强的, 但增强的速度也始终较为缓慢。如今AI展示出了比人类更加准确的棋感, 相当于提供给人类更多更好的经验积累条件, 因此, 在AI的影响下, 人类会训练出比以前更好的棋感, 且棋感增强的速度将超过没有AI的时代, 但是, 经验的累积也很难直接形成水平的飞跃, 只

13) Silver D, Schrittwieser J, Simonyan K, et al. Mastering the game of go without human knowledge[J]. nature, 2017, 550(7676): 354-359.

是经验积累的效率将会更高。

其次考虑计算。对于人类棋手而言, 计算能力主要受限于人类理性或智力的限度, 如果使棋盘缩小到足够小, 或者将人类大脑的能力扩张到足够大, 就可以将全局变化都纳入到计算的范围之内。但在现实中, 人类的理性能力有限, 人类的计算力并不会随着AI的出现而突破瓶颈。因此, 在围棋的计算领域, 限制人类上限的是人类整体的理性限度, 未来的棋手个人有可能更加接近上限, 而AI能够带来的影响不大。

最后考虑判断。未来人类棋手在判断方面的进步空间最大, 其原因在于, 人类棋手在面对无法使用第一类知识进行精确判断的局面时, 使用第二类知识判断局面的精确度很低。在判断环节, AI主要提供的是全覆盖的胜率数据和选点建议, 这些数据对于人类棋手的技术进步而言具有重大的意义, 我们分别从经验积累和概念生成两方面来分析。

当前已有不少棋手在做的, 是借观察AI的胜率数据来提升自己对局面的判断经验, 从而提高判断的准确度。其具体方法有很多种, 例如, 用AI生成大量的局面判断练习, 将AI的胜率视为练习题的答案, 而棋手要尝试用人类的判断方法去理解和接近AI胜率。与棋感经验的积累相似, 判断经验的积累也会因AI的帮助而加速提升。

另一个有可能但目前尚未开启的进步方向, 是对围棋第二类知识中的概念进行重新梳理和创造。如前文所述, “厚薄”、“虚实”、“轻重”乃至“围棋十决”和一系列围棋谚语所标示的“棋理”, 它们发挥了很强的实用性, 但都不具有精确性, 同时也不具有必然性。在不同的文化系统中, 有可能生成出不同的概念话语来描述和处理棋局, 很可能有些概念话语可以更精确地定义局面, 由此帮助人类棋手更准确地判断局面、更容易地找到精确选点。如今, 围棋AI的出现相当于使我们拥有了一个全新的、异域的文化系统, 这样的“棋理革新”便已成为可能, 而棋理的革新若能实现, 很可能会带来人类围棋水平的一次飞跃。棋理革新的空间, 就在第二类围棋知识的话语系统的创造之中。

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Explaining Go: Challenges in Achieving Explainability in AI Go Programs

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Abstract: There has been a push in recent years to provide better explanations for how AIs make their decisions. Most of this push has come from the ethical concerns that go hand in hand with AIs making decisions that affect humans. Outside of the strictly ethical concerns that have prompted the study of explainable AIs (XAIs), there has been research interest in the mere possibility of creating XAIs in various domains. In general, the more accurate we make our models the harder they are to explain. Go playing AIs like AlphaGo and KataGo provide fantastic examples of this phenomenon. In this paper, I discuss a non-exhaustive list of the leading theories of explanation and what each of these theories would say about the explainability of AI-played moves of Go. Finally, I consider the possibility of ever explaining AI-played Go moves in a way that meets the four principles of XAI. I conclude, somewhat pessimistically, that Go is not as imminently explainable as other domains. As such, the probability of having an XAI for Go that meets the four principles is low.

I. Introduction

The field of AI research has seen remarkable developments in recent years. Current large language models (LLMs) are capable of writing high quality passages of natural language text. Visual art generators like Dall-E 2 and Midjourney can make impressive digital paintings. In less than twenty years, we have gone from Deep Blue defeating Garry Kasparov in Chess to AlphaGo defeating Lee Sedol and Ke Jie in Go. AIs are now used to make important decisions that affect humans. Insurance companies can use them to determine whom to insure (Nieva 2023). Banks can use them to determine to whom they should lend money (Arun, Ishan, and Sanmeet 2016). Finally, judges can use them to evaluate the risk of recidivism in parole decisions (Ghasemi et al 2021).

With the rapid development of AI technology, a number of ethical issues have emerged. Since AIs are beginning to play larger roles in human societies, it is important that we understand how they make their decisions. That is to say, we want our AIs to be explainable. If someone's loan application is rejected, it is important to know why the application was rejected. Did the AI reject the applicant because of their race or because of their history with creditors? The former reason would be unethical, but the latter reason would just be good business. Determining the answer to this question can often be incredibly difficult. This is because there is often a tradeoff between accuracy and explainability. The more accurate our AI models, the harder it is to explain how they make their decisions.

The focus of this paper is not the ethical issues involving the explainability of AI. Instead, I will only focus on the explainability of Go-playing AIs like AlphaGo (and its offspring), KataGo, and Leela. In this context, many of the ethical issues with explainability go away. That being said, exploring the nature of explainability in the context of Go-playing AIs can shed light on the nature of explainable AIs (XAIs) in general.

In this paper, I explore how different theories of explanation apply to Go-playing AIs. In section 2, I briefly discuss the problem of XAI and its connections to Go. In section 3, I provide a brief introduction to some of the leading philosophical theories of explanation. In section 4, I consider the Deductive Nomological theory (DN) and the Inductive Statistical theory (IS), concluding that an explanation meeting the criteria of either view would not count as an XAI. In section 5, I consider how causal-counterfactual theories fair when dealing with Go-playing AIs. Causal-counterfactual theories offer better explanations of Go moves than DN explanations, but may be particularly difficult for non-experts to understand. In section 6, I take a brief detour to argue that the current explanatory capabilities of AI Go programs provide only inadequate explanations. Finally, I consider the pragmatic elements of explanation and how a Go-playing AI might differ from other AIs with regard to the possibility of giving generally accessible explanations.

II. Explaining AI

Most of the concern about explaining AI decisions comes from ethical concerns about the use of AI technologies for making decisions that affect people. The European Union recently passed the General Data Protection Regulation (GDPR), which contains articles pertaining to the use of AI for automated decision making. Many believe that the way the GDPR is written guarantees Europeans a right to an explanation.[1] So, when an AI makes a decision about a loan or about a person's eligibility for insurance, the compa-

1) See, for example, Selbst and Powles 2018.

ny that uses the AI must be able to provide an explanation of this decision.

Much of the philosophical discussion on explanation, however, comes from the philosophy of science. Philosophers in this area are concerned with the metaphysical and epistemological properties of primarily scientific explanations. The problem of XAI comes at the crossroads between discussions in the philosophy of science and those in ethics. Since the goal of this paper is to discuss the explainability of Go-playing AIs, I will stick to the former rather than the latter. Of course, there are still some ethical issues at play in explaining the moves of Go-playing AIs. If we can get an AI that is capable of explaining its reasons, then human Go players will have an invaluable resource for furthering their personal study of the game. This provides a benefit to Go players but could severely hurt many professional Go players who depend on the income they get from teaching the game. Attila Egry-Nagi and Antti Törmänen put the possibility in the following way:

> Scholars of the game benefit more clearly from the existence of good AI engines, as the computer can just 'tell the truth' about a debated board position. Previously, players would have to pay for teaching to get the same effect, but now it is enough to simply have a strong computer—or, in fact, even just a modern smartphone. Consequently, many Go teachers are now facing the danger of losing their jobs, even though they can still provide a big value that AIs cannot: they can explain why particular moves are good or bad. (Egry-Nagi and Törmänen 2020, p. 7)

They claim that teachers still have the advantage of being able to explain why a move is good or bad. If an XAI for Go could explain its moves, then there would be little room left for Go teachers. In this sense, there is an interesting ethical problem in the opposite direction. Normally we are driven to create explainable AIs because there is a moral obligation to know how the AI makes its decisions. In this case, there may be a moral reason to avoid knowing how Go-playing AIs make their decisions.

To make the discussion simpler, I will primarily focus on two particular examples of AI decisions throughout this paper: (i) a hypothetical scenario where an AI rejects a loan application and (ii) the 37th move of the 2nd game between AlphaGo and Lee Sedol.

Suppose that Sally has applied for a loan from a bank that uses an AI to evaluate loan applications. Sally's loan application is rejected, and she becomes curious why she was rejected. Was her credit score too low? Was her income too low? Or was it because of something out of her control like her race or her gender? The task of the bank is to provide Sally with an explanation that she can understand. Ideally, Sally should know what she could do to get a different result next time she applies for a loan.

Now, consider AlphaGo's move 37 depicted in Figure 1 below. The move stunned spectators when it was first played because it went against general wisdom about Go. Namely, playing a shoulder hit on the 5th line against a stone on the 4th line is inadvisable. Why did AlphaGo play its move at that point? Why, for example, did it play at P10 instead of D13—the move suggested by KataGo2)? In searching for an explanation of AlphaGo's move, we are looking for an explanation that can be understood by Go experts and the general Go playing community. Ideally, an explanation would allow us to understand the AI's moves well enough to potentially predict moves like it in the future and play them ourselves.

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2) KataGo 1.12.4 using 40x256 network s11101.

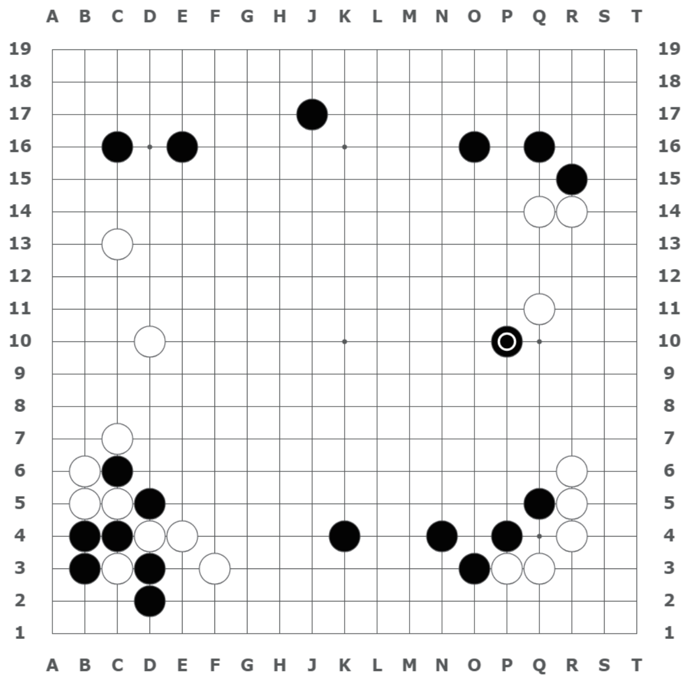

Figure 1: AlphaGo vs. Lee Sedol 2nd Game 37th move

Expert Go players have been using AI to train for a few years now. Doesn't this mean that there is no explainability problem with regard to Go? No. There are many things that humans can currently learn from AI. Many joseki have been discovered that, though they will make little impact in the games of beginner and intermediate players, can make a difference at the level of professional players. Even so, there are many situations where the AI picks a move that is minusculely better than alternative moves. The fact that the AI can do this repeatedly throughout a game leads to it playing at superhuman levels. Some moves made by the AI are apt for explanations. Maybe an AI plays at a vital point, or maybe it plays in an area that clearly negates the influence of the opponent's stones. These kinds of moves can easily be explained. The problem of XAI in the context of Go isn't explaining any given move the AI makes. Instead, the problem is explaining the AI's justifications for playing one move over another seemingly equal value move, like the decision between P10, D13, and E12 shown in Figure 2 below. The difference between the values of these moves is small, but small differences can build up over the course of a game. The issue of the explainability of Go-playing AIs is clearest in this domain, in the gap between human play and perfect play.

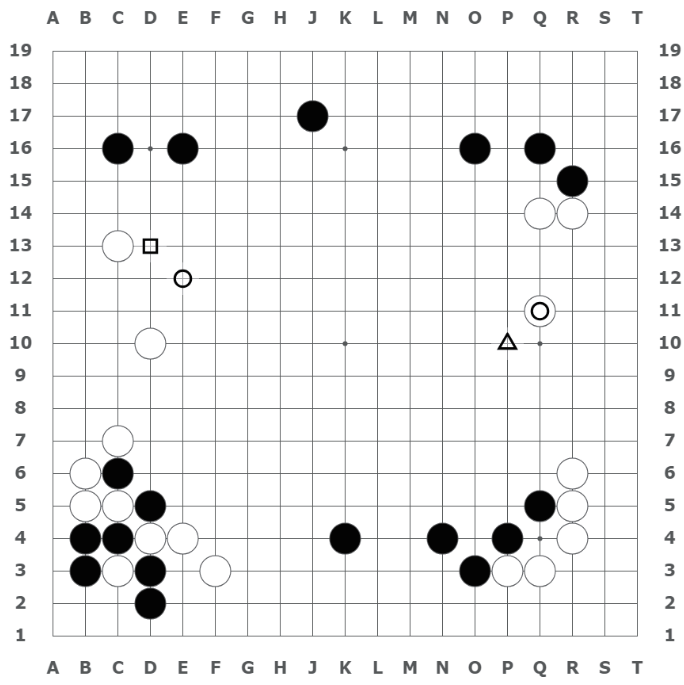

Figure 2: AlphaGo vs. Lee Sedol 2nd Game 37th move with additional potential moves.

That being said, the problem of XAI extends to beginners in Go as well. Supposing that we can make an explanation of AI-played Go moves that is understandable to experts, can we make one that is understandable to intermediate or beginner players? Consider Sally's loan application. If the bank gives Sally an explanation that contains tons of actuarial math in it, she won't be able to make heads or tails of it. But presumably the bank's duty is to explain their decision to Sally in terms she can understand. This paper will discuss explanations of AI-played moves given to experts, but it will also discuss the possibility of explaining AI-played moves to weaker players.

III. Theories of Explanation

The Deductive-Nomological theory (DN) was one of the first well-defined theories of explanation. It was first presented by Carl Hempel and Paul Oppenheim who describe four adequacy conditions for explanations.

1. The explanandum[3] must be a logical consequence of the explanans[4].
2. The explanans must contain general laws, and these must actually be required for the derivation of the explanandum.
3. The explanans must have empirical content; i.e., it must be capable, at least in principle, of test by experiment or observation.
4. The sentences constituting the explanans must be true. (Hempel and Oppenheim 1948, p. 247-248)

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3) The explanandum is the phenomenon or event to be explained.
4) The explanans is the facts that are meant to explain the explanandum.

According to the DN theory, then, an adequate explanation of a phenomenon or an event is a sound inference from at least two premises where the conclusion is the phenomenon to be explained. One premise is a general law and the other is a set of empirical claims. For example, consider the following explanation:

Empirical Claims: A thermometer made of glass and filled with mercury is submerged in heated water.

General Law: If a thermometer made of glass and filled with mercury is submerged in heated water both the glass and the mercury will expand, but the mercury will expand more, causing it to rise inside the thermometer.

Conclusion: The mercury in the thermometer rises.[5]

The DN theory need not be limited to just deductive inferences. We can also consider explanations that are based on statistical inferences. In particular, explanations involving inductive statistical inferences can be adequate. Hempel calls these explanations "Inductive-Statistical Explanations" (Hempel 1965), and the resulting theory of explanation can be called the Inductive Statistical theory (IS). The important difference between a DN explanation and an IS explanation is that the IS explanation only has a statistical law—one that only states a statistical relationship rather than a necessary one. As such, the premises of the inference do not guarantee the conclusion. Here is an example of an IS explanation:

Empirical Claims Winston had a blood alcohol level of .2 and drove his car at high speeds.

5) This example comes from Hempel and Oppenheim 1948, p. 246.

Statistical Law: If someone has an elevated blood alcohol level and drives at high speeds, they will probably crash.

Conclusion: Winston crashed his car.

The motivation behind both the DN and IS versions of the theory is that we can explain phenomena and events by reference to the propositions that guarantee the phenomenon/event or, in the case of IS explanations, make the event more likely to happen. There is, however, a common complaint against the DN theory. Among the class of DN explanations are ones that include irrelevant details. For example, no man who takes birth control medicine will get pregnant, but this generalization along with the knowledge that John Jones is a man who takes birth control medicine does not explain why John Jones does not get pregnant. Of course, the relevant feature of John Jones is not the birth control but is instead his biological sex. However, a DN explanation involving Jones' use of birth control can be given for why he is not pregnant. The problem of irrelevancies prompted the creation of the statistical relevance theory (SR) of explanation.

The SR model of explanation attempts to capture the idea of a successful explanation by measuring the statistical relevance of various parameters.[6] Consider a window that was broken when an errant baseball hit it. Aunt Gertrude, finding the wreckage later that day, may ask why the window broke. Of course, the correct explanation and answer to her question is that the baseball hit by little Timmy hit the window. It would be wrong to tell her that the window broke because there were flowers on the kitchen table.

We can capture this case easily enough by measuring the statistical relevance of the baseball's hitting the window and the statistical relevance of the

6) For more on the SR theory, see Salmon 1971.

flowers' being on the table. We do this by calculating the conditional probability of the different parameters.

P(Window breaks | Baseball hits the window & Flowers on the table) = *P*(Window breaks | Baseball hits the window)

Prior to the window's breaking, the probability of the window breaking given that it was hit by the baseball and the flowers were on the table is equal to the probability of the window breaking given that the baseball hit the window. This tells us that the flowers were statistically irrelevant, and hence their presence does not explain the breaking of the window.

Returning to John Jones, *P*(Jones doesn't get pregnant | Jones is a man) = *P*(Jones doesn't get pregnant | Jones is a man & he takes birth control). We can clearly see that Jones' taking birth control is statistically irrelevant to his not getting pregnant. So, the birth control is not part of an adequate explanation of why he doesn't get pregnant. His being a man, on the other hand, is statistically relevant, and does explain why he doesn't get pregnant. SR helps fill the hole left by DN by better connecting the explanans to the explanandum.

The SR theory is not the only way to capture the relevance between the explanans and the explanandum. As it turns out, many explanations do their explaining by identifying the causes of the explanandum. We can have, for example, a theory of explanation that states that ψ can be partially or wholly explained by φ if φ is a cause of ψ.[7] There are, of course, many different

7) In earlier years Nathan Salmon argued for the SR theory, but this changed in later years when he presented the causal mechanical theory, which says that explanation is not just a matter of statistical relevance, but it also requires causation. See Salmon 1984.

theories of causation. This paper cannot possibly cover every theory of causation and how those theories would interact with theories of explanation. Instead, I will focus here on just the counterfactual theory of causation. A counterfactual is a specific kind of conditional—one where we consider how the world would be different were some features changed. For example:

> If the allies had lost in WW2, then more people would speak German.

The sentence above is a counterfactual because it sets up a scenario that is counter to the facts (since the allies actually won), and then it draws some consequent about how the world would be. The counterfactual theory of causation identifies the causes of events with those things that cannot be changed without the event changing. Suppose that the cue ball in a game of billiards hits the 8 ball, causing it to drop into a pocket. We can generate a counterfactual like the following one:

> If the cue ball had missed the 8 ball, then the 8 ball would not have dropped into the pocket.

This counterfactual is true, and so we can determine that the cue ball was, at least, partially responsible for the 8 ball's dropping into the pocket—the cue ball was a partial cause of the event. David Lewis puts it succinctly as follows:

> We think of a cause as something that makes a difference, and the difference it makes must be a difference from what would have happened without

> it. Had it been absent, its effects – some of them, at least, and usually all – would have been absent as well. (Lewis 1973, p. 632)

Now, returning to a causal theory of explanation, how do we know that the baseball's hitting the window explains the window's breaking? Well, had the baseball not hit the window, then it wouldn't have broken. Had the baseball been lighter than it was, then the window would not have broken. Had the baseball been thrown with less force, then the window would not have broken.

The flowers, of course, are not part of the explanation of the window's breaking. This is because counterfactuals involving the flowers do not lead to the window's failing to break. Had the flowers been on the floor, had they been heavier, or had they been roses, the window still would have broken.

To get a complete explanation, we put together all or some important subset of the counterfactuals that result in a different event happening. So, to get a complete explanation of the breaking of the window, we need a list of all of the counterfactuals that result in the window remaining intact. Doing so will give us an understanding of what needs to change from the actual world to change the event with which we are concerned. In doing so, we understand why the event happened. The window broke because a ball carrying sufficient momentum hit the window.

Suppose that Sally's loan application has been rejected by the bank. The bank employs an AI to make decisions on loan applications. Sally reasonably expects an explanation from the bank. She worries that her application was denied because of her race or her gender. Sam Baron (2023) recently proposed one way that the bank can provide an explanation for its AI's decisions. The bank can make a list of counterfactuals of the form "If Sally's income had been $50,000, then the AI would have accepted her application." and "If Sally's credit score had been 700, then the AI would have accepted her application." Once Sally has been given a full list of the changes in her application that would be sufficient for the AI to change its decision, then she can extrapolate which features of her application contributed to its rejection.

The counterfactual analysis of explanation gives a pretty reasonable explanation to Sally, but it doesn't work in all cases. Consider the case of Aunt Gertrude when she asks for an explanation for her broken window. Suppose that she is told a list of counterfactuals about the momentum of the ball or the tensile strength of the window. Will she be satisfied with this explanation? Of course not. She may be concerned with who broke the window, not with the physics of window breaking. She may even struggle to understand an explanation that involves a list of counterfactuals. Perhaps she knows very little about tensile strength and momentum. A much better explanation would simply state that Little Timmy broke the window while playing ball.

Explanation is a method of communication—a means by which we give others understanding. A chemist may explain their research very differently when talking to a colleague than when talking to their parents. In turn, the explanation they give to their parents will differ from the one given to a five-year-old. To each audience the chemist gives a different explanation, but each conversation they have includes an explanation.

For another situation, suppose that a student receives a C on an essay she wrote. She demands an explanation from her teacher. If the teacher tells the student that she made some interesting points throughout the paper, and so she didn't deserve a D, the student will not be happy with the explanation. The student does not want to know why she got a C rather than a D—she wants to know why she got a C rather than an A or a B. A less successful student may be pleasantly surprised by receiving a C and ask for an explanation, hoping to find out what she did right. In the case of this second student, the teacher's explanation is accurate. She wants to know why she got a C rather than a D. The correct explanation is not merely a matter of giving understanding, it is a matter of giving the audience's desired understanding. All of this goes to show that what counts as an explanation is a pragmatic issue. The success conditions for explanations come from the audience of the explanation, and the factors at play include the audience's background knowledge and the contrast class they have in mind.

So far, I've presented several different approaches to explanations (DN, IS, SR, Counterfactuals, and some pragmatic concerns). Before we finally move to a discussion of Go-playing AIs, it is worth drawing the connection between theories of explanation and XAI. In 2020, Phillips et al put forward four principles of XAI.

1. Explanation: this principle states that an AI system must supply evidence, support; or reasoning for each decision made by the system.
2. Meaningful: this principle states that the explanation provided by the AI system must be understandable by, and meaningful to, its users. As different groups of users may have different necessities and experiences, the explanation provided by the AI system must be fine-tuned to meet the various characteristics and needs of each group.
3. Accuracy: this principle states that the explanation provided by the AI system must reflect accurately the system's processes.
4. Knowledge limits: this principle states that AI systems must identify cases that they were not designed to operate in and, therefore, their answers may not be reliable.[8)]

8) This is Angelov *et al* 2021's paraphrased version of the principles laid out in Phillips *et al* 2020.

In the subsequent sections of this paper, I will focus on how the different theories of explanation, as applied to Go-playing AIs, succeed or fail at living up to these four principles.

IV. DN, IS, and AlphaGo

I will start the discussion of XAI and Go by considering how the DN/IS model might work for explanations of AI-chosen moves in a game of Go. Remember that the DN model involves inferences from premises about lawlike regularities and empirical facts to the phenomenon or event to be explained. We will start with the conclusion of these inferences. Consider again move 37 in AlphaGo's game against Lee Sedol. This is exactly the kind of move for which we desire explanations. In our DN inference, we will take "AlphaGo plays P10 on move 37" as the conclusion—it is the explanandum for which we will seek an explanans.

We now need to construct the premises of such an explanation. First, the initial conditions. These are simple enough to lay out. We need to know the board position and how that is provided to AlphaGo as an input. The initial conditions may be different for different AIs, but in general they will involve the current board position or the current position plus the history of the game. Here, for example, are the inputs given to AlphaGo Zero, one of the successors of AlphaGo:

> The input to the neural network is a 19 × 19 × 17 image stack comprising 17 binary feature planes. 8 feature planes Xt consist of binary values indicating

> the presence of the current player’s stones (Xi t = 1 if intersection i contains a stone of the player’s colour at time-step t; 0 if the intersection is empty, contains an opponent stone, or if t < 0). A further 8 feature planes, Yt , represent the corresponding features for the opponent’s stones. The final feature plane, C, represents the colour to play, and has a constant value of either 1 if black is to play or 0 if white is to play. These planes are concatenated together to give input features st = [Xt , Yt , Xt-1, Yt-1, ..., Xt-7, Yt-7, C]. History features Xt, Yt are necessary because Go is not fully observable solely from the current stones, as repetitions are forbidden; similarly, the colour feature C is necessary because the komi is not observable. (Silver et al 2017, p. 27)

Things are much more complicated when we move to the lawlike premise. To make a deductive inference we will need an AI model that has no place for randomness. When it is presented with the same inputs it provides the same outputs. In the context of a competition, most AIs are not deterministic, and so some randomness will play a role. For example, under time constraints, engines may not be able to get to the depth necessary to play the same move every time. Because the numbers of visits to particular positions in a tree are not guaranteed to be the same on each run of the inputs, we cannot form a deductively valid argument from the initial conditions and the functioning of the AI to the actually played move.

Of course, the ways computers perform randomness is not actually random. The internal states of computers and the random numbers they generate are for our purposes deterministic. So, if we include the architecture of the model, the settings for all of the parameters in the model, and the internal states of the computer that are relevant for generating random numbers we can get the lawlike regularities necessary to create a deductively valid inference from the inputs to the output.

Once we have our deductive inference, we have our explanation of why the AI chose the move that it chose. But is it really an acceptable explanation of the move? Knowing the setup and the lawlike properties of the AI would be sufficient for us to determine the move it will play (given a large enough amount of time). So, in some sense we would understand why the AI made its move. This is not, however, what we mean by XAI. To see why, consider again the case of Sally who has had her loan application denied on the basis of an AI decision. She requests some explanation for why she was rejected. The bank gives her a list of the details from her loan application and maybe a report from a credit bureau. The bank also gives her all of the details of the AI model that was used, including the value of every parameter in the model. Would Sally be satisfied with the explanation? Would she understand why she was rejected? The answer to both questions is "no." The inner workings of neural networks and machine learning algorithms are still areas that require expertise that far exceeds the knowledge of the general public. Not only does the putative explanation in this case exceed the capabilities of the person whose loan is rejected—it also exceeds the knowledge of those who programmed or use the AI. After all, humans cannot keep track of all the parameters in the kinds of AI models in use in loan application adjudication or in Go playing. This is just the problem of XAI. If the weights of the parameters of the model were sufficient explanations of AI decisions, then there would be no need for making explainable AIs. Of course, the programmers can print out the weights of all of the parameters in a model, but that doesn't suffice as an explanation. The same, of course, holds in the domain of Go-playing AIs. Knowing the weights of the parameters does give us an explanation of a Go move, but it doesn't suffice for an average Go player, an expert, or the programmers. A DN explanation of an AI as complicated as AlphaGo will certainly fail to meet the 2nd principle of XAI.

An AI that allows for randomness could potentially be explained in terms of an IS inference. The difference between DN and IS is that IS allows for statistical inferences. So, we can allow for differences in the outputs of the model when fed the same inputs. This provides little help in explaining the moves of AI Go players. After all, if the lawlike premise still includes all of the weights of the parameters, it will still be too complicated to count as an adequate explanation. It doesn't matter that we accommodate the variability in the output of the model.

There may, however, be some more room for explanation when using IS. Consider the construction of AlphaGo Fan, AlphaGo Lee, and AlphaGo Master. All three of them have two networks, a policy network and a value network.[9][10] The policy networks were trained on thousands of games played by top players on the Kiseido Go Server. The task of the policy networks was to learn to predict the probability of a human playing a move in a given position. Suppose instead of training a policy network on games played by humans, we train one on games played by AIs. The goal of this new policy network would be to predict the probability of any given move in a position by an AI.

The new policy network can then be used to explain the moves of an AI using a statistical inference. The initial conditions, once more, are the inputs

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9) See Silver *et al* 2017, p. 21-22 for a breakdown of the differences between the versions of AlphaGo.

10) Note that Woosuk Park discusses the removal of the separate policy network in the move from AlphaGo Master to AlphaGo Zero. He considers whether this removal worsens the explainability of AlphaGo Zero's decisions. See Park 2022.

to the AI. The lawlike premise is now the predicted probability by the new policy network of given moves in similar positions to the ones on the board. We can then say that the AI was likely to pick the actual move given the board position because that is the kind of propensity that the AI has.

Note that we do not even need a sophisticated policy network to get inferences like this. We can see certain policies popping up in the AI that diverge from our human policies. For example, the AI has a habit of playing early 3-3 invasions. So, when an AI plays an early 3-3 invasion, we can explain this as a habit of the AIs. For an analogous situation, imagine someone who has built up an implicit bias towards things on their left. When offered two equally good pieces of cake, they choose the one on the left. When presented with two equally pleasant roads down which to walk, they choose the one on the left. When the person comes upon a choice in the future between an object on their left and another on their right. We can explain their having chosen the one on the left by means of their history of a left-leaning bias. Such an explanation doesn't get to the root cause of their bias, but it could suffice in some situations. The same can be said of explaining some AI-played Go moves. The AI has built up some bias and we can explain its actions by means of that bias. Such an explanation doesn't explain how the AI came to that bias, and so it fails to meet the first principle of XAI, but it does succeed at meeting principle 2. That is to say, an explanation like this would be understandable to most people. Unfortunately, this kind of explanation fails the 1st principle. Merely knowing the propensities of the AI does not tell us its justifications for its decisions.

We get a better explanation in this case than in the DN case. The average Go player can understand that the AI has picked up certain habits and that its choice in a given situation can, at times, be explained by these habits. Unfortunately, we cannot explain every move of the AI with surface level propensities. For some, we will need the much more complicated policy network trained on AI played games. In addition, the explanations we get in these cases are not really the kinds of explanations we are looking for. They tell us what kinds of moves the AI generally favors, but they fail to tell us why the AI likes those moves. They are only very surface level explanations of the moves of the AI. We may be able to do better with one of the other theories of explanation.

V. The Statistical Relevance of Go Moves

In this section, I consider both the SR theory and counterfactuals since both function similarly in the context of Go-playing AIs. Starting with the SR theory, we must consider how the conditional probability of the AI's playing the move it actually plays changes given different board positions. The focus here is on the board positions because they are the variables that can change between multiple runnings of the AI. Consider Figure 3:

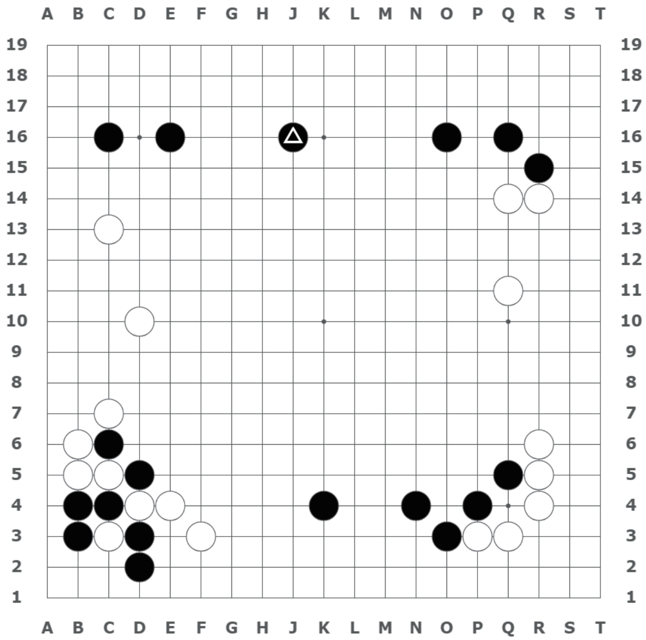

Figure 3: An altered version of the 2nd game between AlphaGo and Lee Sedol

The stone that was originally on J17 has been moved to J16. We can now consider how much different the AI's decisions are than they actually were. In this new position, KataGo gives roughly similar evaluations to the various candidate moves to the evaluations given when the stone was at J17. So, the probability that it will play one of those moves is mostly unchanged. This tells us that the stone's being at J17 is less relevant to the explanation.

This process can be repeated for each stone in the actual board position and the various places that stone could have been instead. By doing this we can determine which stones are most statistically relevant to the AI's decision. The explanation of the AI's move, then, is just the list of statistically relevant stones. That is to say, the AI made the move that it made because of the arrangement of a particular subset of the stones on the board.

Applying the counterfactual approach to a Go-playing AI, we get a similar kind of explanation to the one provided by the SR analysis. We need to make a list of counterfactuals that would result in the AI playing a different move than it actually did. In other words, we make a list of changes to the inputs to the AI that result in a different output. We can then combine that list to know exactly which stones on the board are important for the AI's decision. The stones that are most important for getting the move that was actually played are the ones that, when changed in a counterfactual scenario, result in a different AI-played move. Note that this will give us a list similar to the one given by the SR analysis.

These methods of explaining AI decisions are present in the attempts at explaining the decisions of image recognition AIs. When an image classifier tells the user that an image contains a cardinal instead of a robin, it can be asked to highlight which pixels played the largest role in determining its decision. This method has allowed programmers to find interesting loopholes discovered by the AI. For example, Ribeiro et al (2016) trained an image classifier to identify wolves as opposed to huskies in images. They purposely trained the network on biased data where all of the images containing wolves also contained snow. Their goal was to test how humans interpreted the outputs of the biased AI. As part of the process, they have the AI explain how it comes to its verdict on a given picture. This is accomplished by identifying the pixels in the image that were most important for the AI's decision. Of course, the pixels showing snow ended up being the AI's justification.

We are getting closer to an acceptable XAI for Go, but SR and the counterfactual approach aren't yet sufficient. An expert Go player may be able to glean something from data about which stones played the largest role in the AI's decision. For example, if a particular stone or subset of stones was relevant to the AI's move, then an expert may be able to couch that knowledge within their broader understanding of the game to learn something about the AI's decision. The stones on a Go board can bear complex relationships to one another. Moving one stone over can have drastic effects on the direction of the game. This means that the SR and counterfactual methods will often run into the problem that just about every stone is relevant. As such, if we were confused about why the AI took the current board position and output its actual move, then we will be just as confused knowing that every stone was relevant to that decision. This problem is particularly thorny when we consider that the goal is to explain why the AI makes one move over an ostensibly equal move elsewhere on the board. A small change in the inputs has a high chance of changing the output when the potential outputs are very close together.

In addition, the complexity of such an explanation would put it out of the reach of people who are not already Go experts. This reveals a dissimilarity between an XAI that evaluates loan applications and one that plays Go. A list of relevant counterfactuals regarding loan decisions are understandable to the layman. One can easily grasp the idea that they made too little income to qualify for a loan or that they have too many late payments in their credit history. A layman in Go, on the other hand, cannot understand why changing one stone on the opposite side of the board could have such drastic effects on the AI's decision.

To sum up this section, the SR theory and the counterfactual approach both meet the 1st principle, since they are fully grounded within the relationships between the inputs of the neural network and its output. They both fail on giving meaningful information, and so they both fail to meet the 2nd principle. All things considered; they still do better than the DN approach in this respect.

VI. Reading the Future

Before continuing to the pragmatic aspects of explanation, I will take a short detour to discuss the kinds of explanations that Go-playing AIs currently provide to players. At any point in a game, the player can ask the AI about its expected probability for either of the players winning. Players can also see data on the other moves that the AI considered and how many times it visited those parts of the tree. The players can see just how much the AI prefers one move over another. Most importantly, players can have the AI play out a sequence of moves from the current position.

All of these points of data count as partial explanations for why the AI made its move. We know that the AI made its move because it thought that move would increase its probability of winning. In particular, we know just how much more the AI thinks that the actual move improves its situation over alternative moves. We also can see how the AI thinks the game might proceed from the move it just played. Many top players learn from the AI by playing out sequences like this. They attempt to understand why the AI made a particular move by allowing the AI to play out the sequence until the proper consequences of the AI's move become clearer. Perhaps the AI played a move in order to set up a future attack. One way to find this out is to allow the AI to play out the sequence it saw until we get to that attack.

Is this a sufficient explanation for the AI's move? Perhaps in some cases this may be sufficient. When, for example, the payoff of the AI's move is only a handful of moves away. Unfortunately, we cannot use this method to explain every move an AI makes. Playing out individual sequences, even if they are the AI-determined optimal sequences, will give us too small of a view of the tree that the AI is searching. We may know one potential payoff of the AI's move, but not why this particular payoff is better than what the AI could receive from a different move. We have here the particularly tricky problem that I set up in section 2. Why did AlphaGo play at P10 instead of D13? We can play out sequences from both positions, but we will not be able to see why the many sequences that can result from P10 were preferable to those that result from D13 or other nearly equivalent moves. Once we have multiple board positions that are some number of moves after the AI's chosen move, we still must rely on the AI to output for us an evaluation of the position. All we have done is delay the inevitable request for clarification from the AI, and if we can't explain the AI's original decision, we won't be in a much better position trying to explain its evaluation of a slightly progressed board position. The kind of explanation described in this section would fail to meet principle 1 of the 4 principles of XAI. In many cases it doesn't give much justification for the AI's move.

VII. Useful Explanations

One recurring problem with the theories of explanation I have discussed so far is that they do not provide explanations that are accessible to non-experts. In the case of some of the explanations, they aren't even accessible to experts. Some in the literature on explanations, like Peter Achinstein (1983), have made the move to treating explanations as pragmatic entities. Explanations have purposes and audiences. What counts as an explanation of an event is determined by the knowledge and desires of the audience of the explanation.

Consider Sally, the woman whose loan application was rejected. She desires to know what she can change about her life to eventually be approved for the loan. She also wants to know whether the decision was made for potentially illegal reasons. Her background knowledge may not include any information about machine learning algorithms or the structures of neural networks. So, an attempt to explain to her the decision in terms of the weights of the parameters in the model would fail. It neither gives her actionable information nor any understanding at all.

The SR and counterfactual explanations of AI-played Go moves could be sufficient to give experts some understanding of the reasons why the AI makes some of its moves. Note that the understanding they get is not just an understanding of the habits of the AI, like they would get from the IS theory. Instead, they may be able to get knowledge of the underlying principles of Go that the AI has discovered. These approaches, however, fail to give non-experts a genuine understanding of why the AI makes its moves.

Is it even possible to give an explanation that is sufficient to give non-experts genuine understanding of AI-played moves? There is skepticism in the literature on XAI about the possibility of giving explanations of AI decisions. The source of this skepticism comes from human inability to explain our own decisions. Human decisions are heavily influenced by many factors that we cannot isolate and explain. For example, teachers grading student written essays may try to fit their decisions into a rubric, but a lot of the process is done based on the hard to articulate feelings of the teacher. Jocelyn Maclure puts this complaint thusly, “Those who seek to deflate the explainability problem argue that we should not be excessively troubled by the lack of transparency of automated decision-making because humans are equally opaque when they think and judge” (Maclure 2021).

Is the situation any better in Go? Well, let’s consider how Go players explain their moves. Sometimes the explanation is easy enough. Playing the vital point that saves or kills a group or playing a simple sente move during the endgame, are moves that humans can easily explain. But moves in the midgame that are out in the open board can be significantly harder to explain. As Egri-Nagy and Törmänen put it:

> On the one hand, we do not know exactly how we play the game. It is difficult to verbalize our Go knowledge. Explanations for a move often get replaced by an ‘it felt right’ statement. (Egri-Nagy and Törmänen 2020, p. 4)

This kind of explanation is even worse than the kinds of explanations that current AIs give. At least KataGo can explain its decisions in terms of a probability estimate for the winner of the game. A human who explains their move by saying “it just felt right” cannot even provide an estimate of how much their move has changed their probability of winning.

Our inability to explain our Go moves is clear from the abundance of Go proverbs. We have proverbs like “Don’t throw an egg at a wall” which informs us that we ought not play a weak stone near our opponent’s strength. Proverbs are by their nature vague and situational. There are times when one ought to go against the advice of a proverb, but they stand as good rules of thumb. It is impossible to condense complex and important pieces of Go knowledge into phrases that can be properly understood by beginners, and so we explain Go moves with pithy little sayings.

So, we already have an explainability problem in Go. Unlike explaining the decisions regarding loan applications, explaining Go moves is particularly difficult for humans. We develop intuitions that we often cannot express in words. For a similar example, consider the work of a chicken sexer. It is incredibly difficult to identify the sex of a chick, but some humans are able to quickly identify the sex and sort the chicks. Robert Brandom puts it this way,

> Industrial chicken-sexers can, I am told, reliably sort hatchlings into males and females by inspecting them, without having the least idea how they do it. With enough training, they just catch on. [...] At least in this way of telling the story, they are reliable noninferential reporters of male and female chicks, even though they know nothing about how they can do it, and so are quite unable to offer reasons (concerning how it looks or, a fortiori, smells) for believing a particular chick to be male. (Brandom 1998)

They are clearly identifying some features of the chick, but it is difficult for them to put into words what they are noticing.

What lesson can we draw from the pragmatic concerns about explanation? We should be skeptical about the possibility of making XAI for functions that are particularly complicated. In the case of Sally's loan application, the number of variables and the relevant changes to those variables are limited enough that a list of counterfactuals could be created that would give Sally enough understanding to make informed decisions in the future. A position in the middle of a Go game has too many parameters to keep track of and too many ways that those parameters could be changed for us to make a list of counterfactuals that would give a player enough understanding to make future decisions.

Albert Einstein supposedly said, “If you can’t explain it to a six-year-old, then you don’t understand it yourself.” Taking this quote at face value undermines its message. There are plenty of things that experts cannot explain to six-year-olds. A lot of background knowledge is needed to understand quantum mechanics. It is possible to explain some of the topic to a six-year-old, but they will only gain surface level understanding. The same is true of Go. To be able to understand the limited explanations that Go-playing AIs give, one must already have a sufficient amount of background knowledge. There isn’t much more an AI can do to explain its moves to a general audience than show the change in its expected territory and probability of winning. For experts, on the other hand, some of the methods of explaining AI-played Go moves described above may be sufficient to gain a limited understanding. For example, knowing which stones were the most important ones for the AI’s decision could shed some light on why the AI made its move, as opposed to a seemingly equal move. The understanding we can gain in this way will, unfortunately, be incomplete.

The function describing optimal Go play from a given position is so complicated that there is some reason to be pessimistic that an XAI for Go can be created. If humans could understand the function, we wouldn’t need to explain Go-playing AIs in the first place. Again, there is a substantial disanalogy between Go-playing AIs and loan adjudicating AIs. Humans can understand who would be a good debtor and who would not. The point of the AI in these cases is to cut down on human labor and make less biased decisions. The loan adjudicating AI isn’t meant to do something humans cannot do. Go-playing AIs, on the other hand, are designed to be superhuman in their abilities. It is no wonder they cannot explain their justifications to us—they are just that much better than us.

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Go players should not trust AI win rate

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Abstract: The advent of artificial intelligence (AI) has transformed the landscape of various strategic games, including Go. In 2016, the AIpowered engine AlphaGo defeated one of the world's strongest players. Since then, Go engines have routinely been used by amateur and professional Go players to analyse theirgames. In the early stages of AI analysis, Go players relied solely on the AI win rate, the only availableindicator. However, the AI win rate does not accurately reflect the win rate of human Go players and might be misleading.

Katago, first released in 2019, is the first engine to provide score predictions in addition to win rates. While it is now possible to evaluate board positions with a score, it remains unclear how this score translates into human win rates. In this work, a large database of online and professional games is analysed to extract the win rate of a human player based on their strength and the stage of the game. As expected, the human win rate is significantly lower than the AI win rate, even for 9dan professionalplayers. A general for-

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mula is provided to compute the win rate based on player strength and move number. This feature offers new insights into the relative importance of mistakes and can assist players in makingimproved decisions during games.

Keywords: Go, Baduk, Weiqi, AI, Katago, Win rate, Statistics.

Ⅰ. Introduction

Spoiler alert: humans are no longer the strongest Go players. Go is an abstract strategy board gamethat has been played for thousands of years. Nowadays, it is predominantly played on a 19x19 grid wheretwo players alternately place Black or White stones. The grid starts empty, with the stones not moving during the game, and the objective is to encircle a larger area than the opponent. At the game's conclusion, each player receives one point for each stone on the board and one point per intersection in controlled areas. An example of a finished game on a smaller board is shown in Figure 1.

Slightly before computers were a thing, artificial intelligence (AI) was born. Alan Turing, widely recognised as the father of modern computer science, designed an algorithm for a Chess engine as early as 1948 (Kasparov and Friedel, 2017). With the rapid increase in computational power, it soon became possible to explore millions of positions and determine the move leading to the best result. This tree search algorithm was an important part of Deep Blue (Campbell et al., 2002), the first Chess engine to defeat a World Chess Champion in 1997.

Go, on the other hand, is renowned among both players and computer scientists for its sheer num ber of possible moves. The branching factor in Go is significantly larger than that in Checkers, Chess, or Shogi, rendering pure tree search algorithms inefficient. A similar complexity in branching is also found in Backgammon, due to the numerous possible outcomes of dice rolls. To address this challenge, Tesauro et al. (1995) developed a Backgammon engine using artificial neural networks (ANN) trained through reinforcement learning. Starting with minimal knowledge, the engine played games against itself and adopted successful strategies. This approach enabled TDGammon to attain a worldclass level in Backgammon.

A similar concept found success in Go. The first Go engine to defeat a worldclass champion was AlphaGo (Silver et al., 2016), which relies on a database of human games and two ANN known as policy and value networks, refined through reinforcement learning. The policy network examines each move and provides the corresponding probability of winning for that move. Initially trained with human knowl

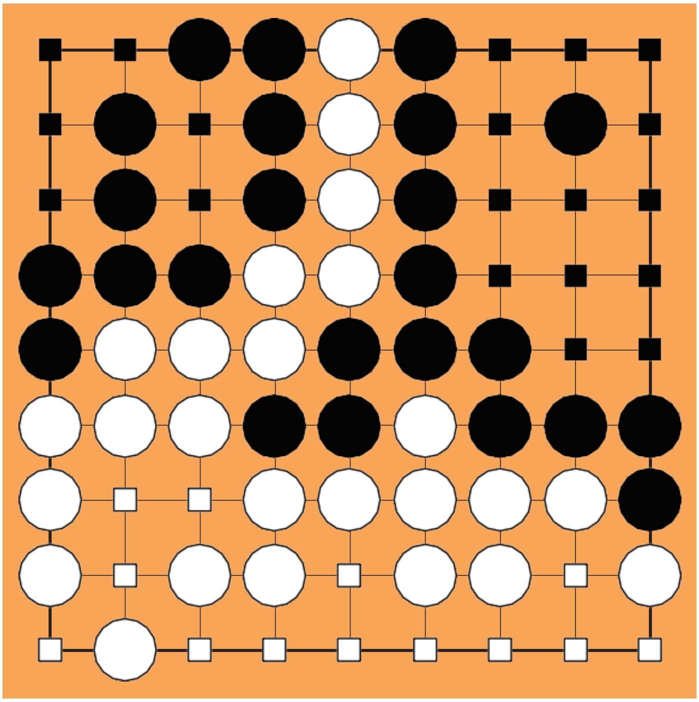

Figure 1 Finished game on a 9x9 Go board. Black player scores 43 points (24 stones and 19 controlledintersections) whereas White player scores 38 points (25 stones and 13 controlled intersections). Withoutkomi, Black wins the game by 5 points.

Level	Main time	AI visits	Games number
12k Fox	20 min	5	28,595
10k Fox	5 min	5	27,830
8k Fox	5 min	5	25,590
6k Fox	5 min	5	28,723
4k Fox	5 min	5	31,264
2k Fox	5 min	5	26,002
1d Fox	20 min	5	51,079
1d Fox	20 min	500	11,938
1d Fox	5 min	5	52,004
1d Fox	1 min	5	41,456
3d Fox	5 min	5	37,736
5d Fox	5 min	5	25,991
7d Fox	5 min	5	35,207
8d Fox	1 min	5	24,920
9d Fox	1 min	5	28,990
1p - 5p	-	5	23,159
9p	-	5	14,842
Total			515,326

Table 1 Details of the analysed kifu database

edge, it later underwent reinforcement learning. The value network reads the current board position and produces the probability of winning (AI win rate). A year later, a new engine named AlphaZero (Silver et al., 2017) was introduced, surpassing AlphaGo's performance with fewer computational resources and without using any human knowledge. AlphaZero was then extended to Chess and Shogi (Silver et al., 2018), once again outperforming the top AIpowered engines.

Since then, Go engines entered the daily routine of amateurs and professional Go players. While quite strong to serve as sparring partners, these engines aid in analysing games and positions. Shin et al. (2021) showed that players who utilise AI for reviewing their games exhibit improved performance during gameplay. AlphaZero even revisited fundamental sequences and principles taught to every Go player (Baker and Hui, 2017). Similar advancements occurred in Chess (Sadler and Regan, 2019), underscoring AI's potential to enhance game understanding.

Post game analysis is widely employed to improve at strategy games. The main idea involves review ing games and seeking feedback from opponents or stronger players to identify errors. Leela Zero (Pas cutto, 2017), an open-source implementation of the AlphaZero algorithm, attained superhuman strength in 2017, becoming a staple for Go players to analyse their games. Leela Zero exclusively provides AI win rates for evaluating board positions. In 2019, a novel engine called Katago (Wu, 2019) was relased. For a given position, Katago provides both AI win rate and score, a feature that quickly gained popularity. While AI win rates broadly represent the Go engine's probability of winning against itself, an abstract concept, scores offer a more tangible metric for Go players.

In games like Chess and Shogi, evaluating positions necessitates considering factors such as material advantage, piece activity, and king safety. These factors can be combined into a score, which is then transformed into a win rate using an evaluation curve (Takeuchi et al., 2007). The creation of an evaluation function based on heuristic features has also been assessed in the early stages of computer Go (Bouzy and Cazenave, 2001; Müller, 2002).

In Go, players directly evaluate score differences during games. This involves estimating the final state of the board and counting the intersections belonging to each player. However, knowing the score of the current position, even perfectly, is not enough. Predicting the game's outcome based on score is a complex task, depending on the strength of the players as well as the current stage of the game. Some strong amateur players might assert that overturning a 20point lead in the endgame is virtually impossi ble. Others might emphasise that resigning is the only move that guarantees a 100% chance of losing the game.

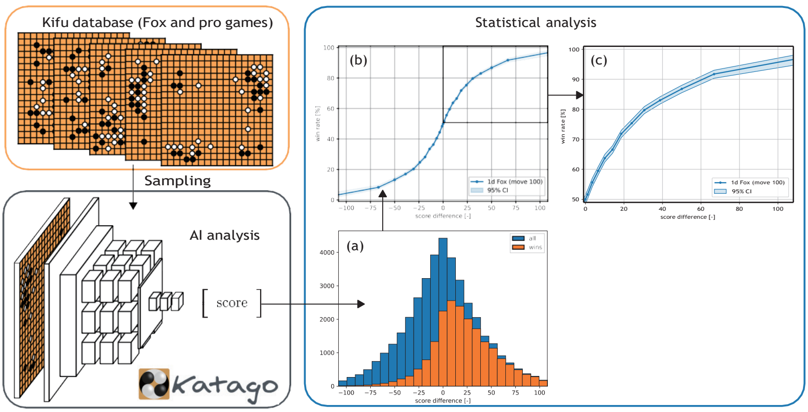

Figure 2 Summary of the developped method. A large set of games is selected and analysed with Katago, outputting score at each move. Distributions of total and won games are plotted against score (a). Ratio of wins on total games gives the average win rate at each score (b). 95% confidence interval is computed using Beta distribution (b). Symmetry is enforced (c). Plots at move 100 for a 1d Fox player.

In order to design a useful metric for analysing Go games, this study aims to compute win rates using an extensive database of Go games, encompassing varying player strengths.

Section II will delve into the methodology, AI settings, and game databases. In Section III, the human win rate will be compared to AI win rate, with an exploration of the game stage's influence. A general formula will also be proposed to calculate human win rates based on player strength and game stage (formally move number). In Section IV, we examine how the human win rate can enhance both the learning and decisionmaking processes of Go players.

Ⅱ. Methods

1. Building the Database

AIpowered Go engine Katago v1.12.4 (Wu, 2019) was used with the neural net ”b18c384nbtuec 20221121b” for game analysis. Most of the games underwent analysis with 5 visits, meaning that at each position, the tree search explored 5 additional positions. A smaller sample of games was analysed with 500 visits to validate the methodology. The computations were performed on a single laptop equipped with NVIDIA RTX A3000 Laptop GPU. Half a million games were analysed, requiring approximately 800 hours of computational time (≈ 33 days).

Go games database The statistical analysis conducted in this study requires an extensive collection of analysed Go games. To construct such a database, online Go games played on the Fox Go server between 2015 and 2019 were utilised (Featurecat, 2019). Only nonhandicap games featuring players of equal strength were selected. The players' strengths range from 12kyu to 9dan. The majority of games have a main time of 5 minutes per player. Games terminated by a draw, by connection loss or by time were excluded, considering only games won by score or resignation.

A total of 477,325 analysed kifu based on online games were compiled. This database has been made available online under an opensource license (Rendu, 2023). The quantity of games per skill level, along with the time settings and the number of visits, is provided in Table 1.

To evaluate the difference between online and real games, the Go4Go (https://www.go4go.net/

go/) database of professional games was employed. A total of 38,001 games were analysed using 5 visits, with player strengths either equal to 9p (14,842 games) or falling within the range 1p5p (23,159 games). These games were downloaded through a commercial license and could not be made available online.

2. From Go Games to Human Win Rate

In this section, the method developed to compute the human win rate is presented. A visual summary of the method is provided in Figure 2.

First, games that meet the criteria (no handicap, equal strength, etc.) are chosen from professional (Go4Go) and online games (Fox Go server) to create a kifu database. The games are then analysed by Katago, which produces the AI win rate and the score at each move.

Using the database of analysed games, one can select all the games for a given player strength (e.g., 1d) and generate a histogram of the score difference at a specified move number (e.g., 100). The resulting plot is shown in Figure 2a. Within each score bin, the histogram displays the number of won games (N_{wins} in orange) and the total number of games (N_{games} in blue).

The probability of a twooutcome event (winning and losing) can be estimated using the Beta distri bution, based on the count of previous successes (N_{wins}, the number of games won) and the total number of games (N_{games}). The expected win rate is calculated by the formula:

$$\text{win rate} = \frac{N_{wins}}{N_{games}} \qquad (1)$$

The uncertainty in the win rate primarily depends on the number of games (N_{games}) and can be readily calculated through the Beta distribution. Unless otherwise specified, the results presented in this work are derived from an average of 2000 games per bin, resulting in a 95% confidence interval of approximately

±2%. A typical win rate curve against the score is plotted along with its corresponding 95% confidence interval in Figure 2b.

Enforcing symmetry The win rates computed from data slightly differ between Black and White players. This disparity may be attributed to statistical noise or unaccounted factors, such as the correct komi

value for a fair game, the matching algorithm potentially favoring White for the stronger player, or evenpsychological effects. However, this kind of analysis is beyond the scope of this study.

To calculate the win rate without regard to the player's color, the win rate of the leading player in the game is sought. For each game, the absolute value of the score is calculated, as well as a boolean set totrue if the leader won the game. The range of positive scores is then divided into bins, where the countsof wins (N_{wins}) and the total number of games (N_{games}) are obtained. For symmetric win rate curves, all the information is contained in the upper right quadrant as shown in Figure 2c.

Dataset size and bins number Once the dataset is sufficiently large, the computed win rate should not depend on the dataset size. To assess the convergence of our statistical analysis, the win rate is plotted against the score for varying dataset sizes in Figure 3. The score range has been divided into 12 bins for this analysis. Using only 6,000 games (500 games per bin), the win rate curve appears noisy and does not follow a regular sigmoid curve. With 24,000 games (2,000 games per bin), a smooth win rate curve is obtained, nearly identical to the win rate derived from twice as much data (48,000 games). Unless otherwise specified, a minimum dataset size of 24,000 games will be employed in this study, ensuring the statistical convergence of the analyses.

To avoid binning the data, alternative methods for computing the win rate were explored. One ap proach involves fitting a parametrised probability density function to the score distribution of won games. Using Bayes' theorem, the win rate can then be computed. This approach yielded favorable outcomes for a limited range of move numbers and player strengths, yet failed to generalise across the entire rangeof investigation.

Relying on discrete bins to compute the win rate is not problematic, as long as the number of bins does not impact the results. Given a dataset of 24,000 games, the win rate is calculated for three different bin numbers: 6 (4,000 games per bin), 12 (2,000 games per bin), and 24 (1,000 games per bin). The resulting curves are displayed in Figure 4. Notably, employing 1,000 games per bin produces a win rate curve with significant noise and a wide confidence interval. With 4,000 games per bin, the curve is smoother, but the data points are relatively distant from each other. Consequently, a value of 2,000 games per bin was selected, corresponding to 12 bins for our minimal dataset of 24,000 games.

Impact of number of visits When analysing Go games with AI, one of the most crucial parameters is the number of visits, also referred to as playouts. The number of visits represents the maximum count of board positions evaluated during the Monte Carlo tree search. A higher number of visits ensures greater accuracy in score and AI win rate estimation, at the expense of increased computational costs. While a substantial number of visits is typically necessary for postgame analysis, it may not be essential for statistical analysis. If a lower number of visits augments the variance of AI predictions without introducing bias, it can be anticipated that errors in score predictions will offset one another. To examine this hypothesis, 12,000 games were analysed using 500 visits, requiring 288 hours.

Merely 12 hours (24 times less) are needed to analyse the same database with 5 visits. The calculated win rate is depicted in Figure 5 for both visit numbers. Only 12,000 games with 5 visits are used for a fair comparison, and the number of bins is set to 8 to ensure a sufficient number of games per bin. The outcomes are identical, aligning with expectations that the number

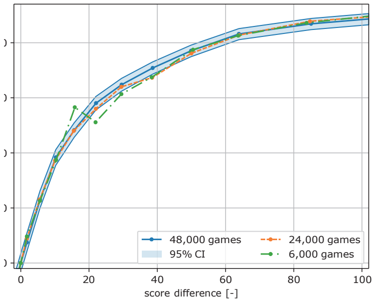

Figure 3 Influence of dataset size on win rate using12 bins (move 150, 1d fox player)

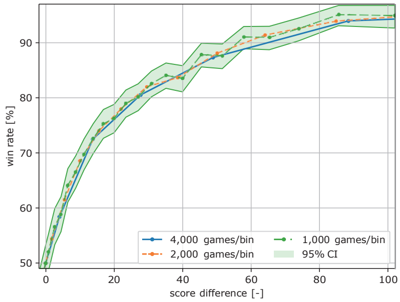

Figure 4 Influence of games per bin on win rate using24,000 games (move 150, 1d fox player)

of visits solely influences the variance of score predictions, without introducing bias. The results presented further in this study are obtained using 5 visits.

Impact of time settings Most of the collected games use a main time of 5 minutes. Nevertheless, for certain player strengths, insufficient data is available at this time setting. For 8dan and 9dan players, more data was accessible from shorter games with a main time of 1 minute. For 12kyu players, most games are played with longer time settings, including a main time of 20 minutes.

To assess the impact of time settings on the win rate, the win rate is plotted in Figure 6 for the threedistinct settings, considering a player strength of 1dan. A total of 50,000 games are collected for each time setting, ensuring a low level of uncertainty. It can be observed that the three curves are in strong agreement, signifying no influence of time settings on the win rate.

Ⅲ. Results

1. AI Win Rate or Score?

To evaluate a board position, Katago uses a neural network known as the value network. This network generates various scalar values, two of which are relevant for game analysis: win rate and score. From a given position, the AI win rate can be approximated as the probability that the AI will win the game when playing against itself.

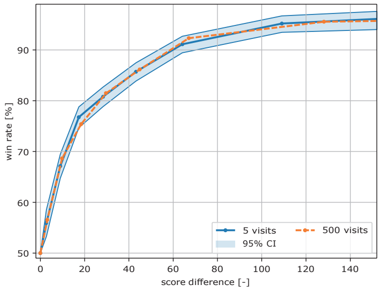

Figure 5 Impact of number of visits on win rate (move 150, 1d fox player)

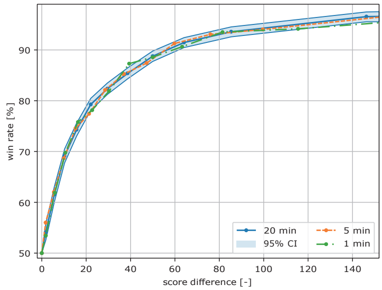

Figure 6 Impact of main time on win rate (move 150, 1d fox player)

On the other hand, the score is an estimation of the score at the end of the game. AlphaGo, Leela Zero and Katago utilise the AI win rate to train their neural networks. SAI used a two scalars output for its value network, and could be trained to maximise the score difference, but it was only assessed on small boards (Morandin et al., 2019). It is generally accepted that the win rate is a more reliable metric to train such neural networks than the score.

By considering all the analysed games, the AI win rate is plotted against score in Figure 7. It is apparent that the relationship between AI win rate and score is nonlinear. As anticipated, a 1point difference holds significant impact on the game's outcome when the score difference is near 0, but it has a minor effect on the win rate if the score difference is already substantial (e.g., 30).

Furthermore, the relationship between AI win rate and score is influenced by the move number. A 5point lead corresponds to an AI win rate of 85% at move 50 and 95% at move 200. This aligns with expectations, as overturning the game is easier during the opening and middle game phases, where numerous possible moves exist, compared to the endgame, where the range of viable moves is more limited.

2. Human Win Rate

As stated in the preceding section, the AI win rate is an estimate of the winning probability when the AI competes against itself. Similarly, the human win rate is defined as the probability of winning when playing against oneself or against an opponent of equivalent strength. Since AI strength greatly surpasses that of top professional players, we anticipate that the human win rate will significantly differ from the AI win rate, particularly for amateur Go players.

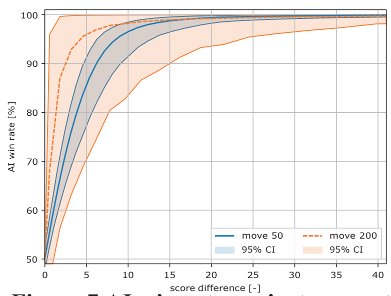

Figure 7 AI win rate against score at different move number (50 ≈ end of the opening, 200 ≈ endgame)

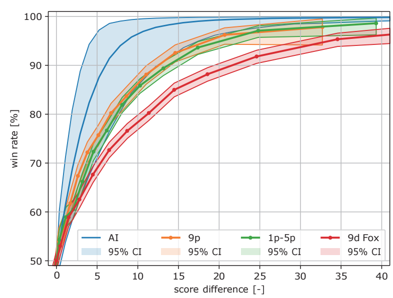

Figure 8 Comparison of AI and human win rate (9p, 1p5p are from professional games, 9d Fox are from online games, win rate is shown at move 100)

The comparison between AI win rate and human win rate is presented in Figure 8. As expected, the AI win rate considerably exceeds the human win rate, even when examining 9dan professional players. The win rate for professional players ranging from 1p to 5p is very similar to that of 9p players, althoughconsistently slightly lower. This suggests that our methodology and the number of analysed games suffice to capture the difference between 9p and 1p to 5p professional players, but this win rate distinction remains relatively small. The win rate is notably lower for 9d Fox players, whose strength is expected to be closeto that of professional players.

Several hypotheses can explain this disparity. The average skill level of 9dan Fox players might be notably lower than that of professional players. Time settings could potentially influence the win rate professional games span several hours, while the 9dan Fox games analysed here feature a mere oneminute main time. Moreover, it's plausible that players approach official professional games moreseriously compared to online games. Finally, players might adopt distinct playing styles during online games, exhibiting more aggressive or unconventional moves. Further studies would be necessary to assess these hypotheses.

3. Impact of Game Stage

Go games are typically divided into three stages: the opening (*fuseki*), middle game (*chuban*), and endgame. One of the authors of Li et al. (2019) analysed 500 Go games and extracted the move numbers at which the middle game and the endgame begin. Both distributions were found to be normal. Their results reveal that the middle game starts around move 49 ± 6, and the endgame at move 162 ± 19.

It is widely understood that as a game progresses toward its conclusion, it becomes easier to securevictory given a fixed score lead. For instance, with a 10point lead in score, the win rate is anticipated to

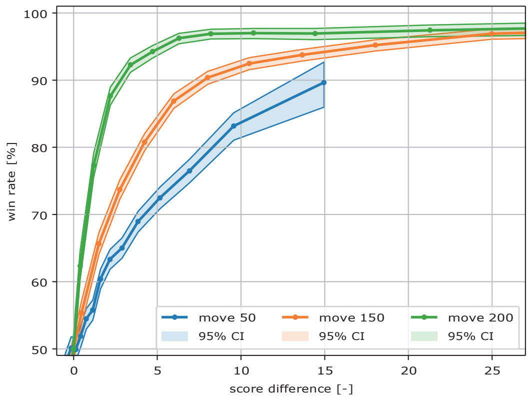

Figure 9 Win rate against score at different stages of the game for professional players

be higher during the endgame compared to the opening. To evaluate this effect, the win rate is plotted atmoves 50, 150 and 200 in Figure 9 for professional players (1p to 5p and 9p altogether). With a 10pointlead, the win rate stands at 84% at the end of the opening (move 50), rises to 92% at the end of the middlegame (move 150) and reaches 97% during the endgame. As a consequence, the shape of the win rate curves evolves with move number. It exhibits nearly linear behavior at move 50, becoming steeper as themove number rises, and culminating in an almost square step function by move 200.

4. One Fit to Rule Them All

In order to make win rates accessible to a wide audience of players, one would ideally need a simple formula. Win rate curves exhibit a distinctive sigmoid shape that can be characterised by the two parameters algebraic function:

$$f(x) = \frac{1}{2} * \frac{\gamma x}{(1+|\gamma x|^k)^{1/k}} + \frac{1}{2} \quad (2)$$

where x is the score, f (x) the win rate, and γ and k are real parameters. The parameter k governs the slope of the sigmoid function, enabling the modeling of both steep sigmoids (for higher move numbers) and quasilinear sigmoids (for lower move numbers). The value of k is displayed against move number in Figure 10 for various player strengths. A consistent decreasing trend is observed across all player strengths, indicating that k is mostly influenced by move number. A linear regression using the methodof least squares on the range $n_{move} \in [50; 200]$ yields the following formula for k:

$$k(n_{move}) = 1.99 - 0.00557 * n_{move} \quad (3)$$

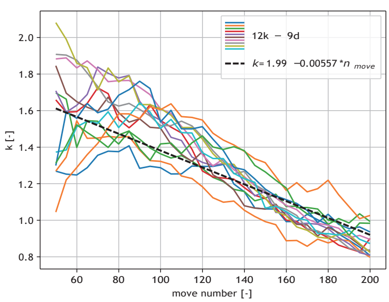

Figure 10 Value of parameter k againt move number for different player strengths

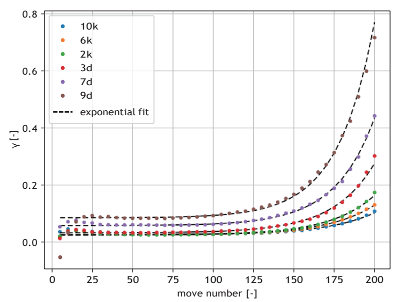

Figure 11 Value of parameter γ againt move number for different player strengths

The value of γ is plotted against move number for different player strengths in Figure 11. It can be observed that γ is dependent on both the number of moves and player strength. Each player strength curve can be adequately represented by the exponential fit:

$$\gamma\,(n_{move}, L) = 0.0001 * e^{w(L) * n_{move}} + \delta\,(L) \tag{4}$$

were w (L) and δ (L) are real parameters depending only on player strength. Applying least square minimization within the range $L \in [-11; 9]$ every 2 levels (with 11 corresponding to 12kyu and 9 to 9dan) yields the following coefficients:

$$w\,(L) = 0.0375 + 0.000543 * L \tag{5}$$

$$\delta\,(L) = 0.00292 * e^{0.354 * L} + 0.025 \tag{6}$$

The general formula is derived by substituting the fitted parameters from Equations 3 and 4 into Equation 2. The resulting win rate is compared to the data in Figure 12 for kyu players and Figure 13 for dan players. Four game stages were selected: moves 50, 100, 150, and 200. The comparison reveals a strong agreement between data and the formula, with an average absolute error of 1.2%. This suggests that the formula serves as a solid interpolation for win rates across player strengths ranging from 12kyu to 9dan and move numbers between 50 and 200. However, the validity of the formula outside these bounds has not been assessed.

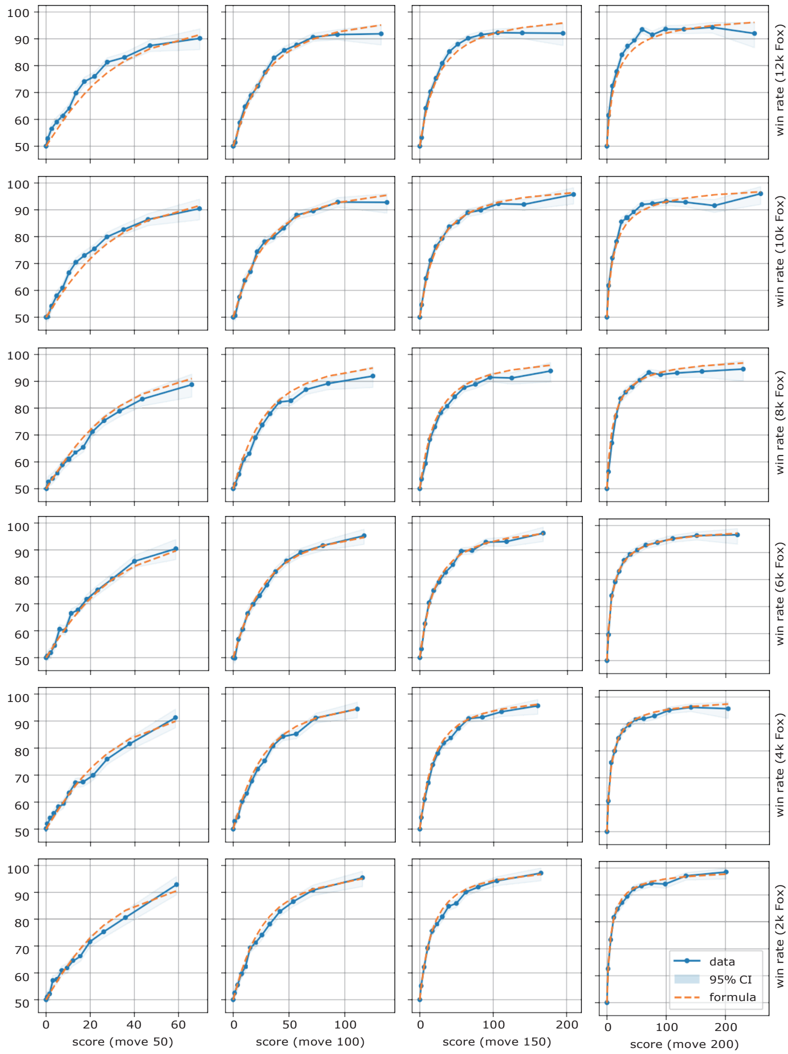

Figure 12 Win rate against score with respect to move number and player strength (kyu level)

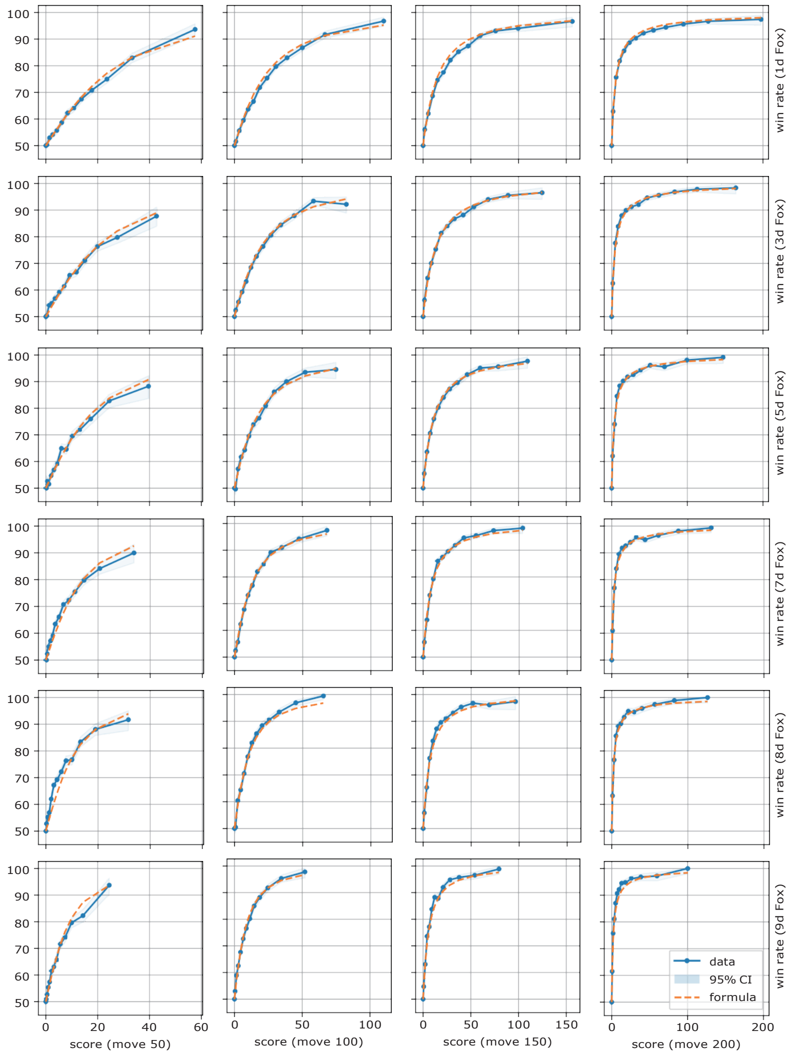

Figure 13 Win rate against score with respect to move number and player strength (dan level)

Ⅳ. Discussion

As pointed out by EgriNagy and Törmänen (2020), AI win rates can be misleading in certain situa tions. For instance, in a handicap game, Black might initially hold a score lead yet maintain a win rate of 50% if the handicap is wellchosen. Furthermore, the AI win rate is only meaningful for players of equiv alent strength. Following the methodology developped within this study, games involving handicaps or participants of differing strengths could be analysed. Such an approach would yield a novel metric that factors in the skilllevel disparity between players.

Even in balanced games, the AI win rate can lead to wrong conclusions, particularly for amateur players. A 5point lead at move 200 yields a 97% AI win rate, implying that the game is already decided according to Go engines. For a 5dan Fox player, the win rate is about 75%, suggesting a significant chance of turning the tide in the endgame. For a 8kyu Fox player, the win rate drops to 60%, indicating a more evenly matched game.

The strategic choices made during a game of Go hinge on the game's stage and score evaluation. When slightly behind, players should choose optimal moves and exploit every chance to secure a few points. Conversely, if a player is significantly losing, they might initiate difficult fights to create com plex scenarios where the odds could shift. Such strategies often involve suboptimal moves (colloquially termed trick plays) which might incur point losses on average but harbor a small possibility of overturning the game. The ability to estimate one's win rate is thus of crucial importance.

The human win rate derived in this study can be read directly on Figures 12 and 13. It can also be computed using the formula given by Equation 2. A small sample of human win rates associated to a score lead of 10, 20 and 30 points, are listed in Table 2 for illustration. They span a large range of player strengths and various stages of the game (moves 50, 150 and 200).

Rank (Fox)	win rate at move 50	win rate at move 150	win rate at move 200
12k	62 / 72 / 79%	64 / 73 / 79%	70 / 78 / 82%
8k	62 / 72 / 79%	66 / 75 / 80%	74 / 81 / 85%
4k	63 / 72 / 79%	68 / 77 / 82%	78 / 85 / 88%
2k	63 / 73 / 80%	69 / 78 / 83%	80 / 87 / 90%
1d	64 / 74 / 81%	70 / 80 / 85%	82 / 88 / 91%
3d	66 / 77 / 84%	72 / 82 / 87%	84 / 90 / 92%
5d	69 / 80 / 87%	75 / 84 / 89%	86 / 91 / 94%
7d	74 / 86 / 91%	78 / 87 / 91%	88 / 93 / 95%
8d	77 / 89 / 93%	80 / 89 / 92%	89 / 93 / 95%
9d	82 / 92 / 95%	83 / 90 / 93%	90 / 94 / 96%

Table 2 Human win rates for 10 / 20 / 30point lead for different player strengths at various stages of the game

Human win rates not only aid players in making informed decisions during gameplay but also in post game analysis for error review. Tools like AI Sensei (Teuber et al., 2023) already categorise moves as ’Good,’ ’Inaccuracy,’ ’Mistake,’ or ’Blunder,’ based on point drop and player strength. By incorporating the developed formula, the associated drop in human win rate could be provided to complete the analysis. The point drop offers retrospective insight into a move’s absolute value, whereas the win rate illustrates its impact on the game’s outcome. These metrics are synergistic and could be employed together to enhance the learning of Go players.

V. Conclusions

This study involves the analysis of a substantial collection of online games played on the Fox Go server, as well as professional games, using the Go engine Katago. The resulting database of analysed games has been made available online under an opensource license.

Within this study, a novel methodology has been developed for computing win rates using analysed Go games. The findings reveal a consistent trend: human win rates are notably lower than AI win rates, which applies to both professional and amateur players. This suggests that one should not rely blindly onAI win rates for game analysis.

A general formula has been derived to predict win rate curves at specific move numbers and playerstrength. The formula's accuracy has been validated across move numbers ranging from 50 to 200, as well as player strengths from 12kyu to 9dan. This innovative metric can serve to assess the importance of mistakes during game analysis, depending on the game stage and player strength. Furthermore, it can provide guidance for estimating one's probability of winning during a game of Go, leading to improved strategic choices.

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A statistical analysis of amateur go players to assist AI-cheating detection in online go communities

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Abstract: Since the democratization of powerful AI engines for the game of Go, it is not uncommon to see a drastic level increase of some players that must be explained with the help of AI. This is considered cheating and forbidden by most organizations.

When looking at online beginners and stronger amateur players, we discovered that they can display playing strength below professional level and still confidently win the game, as opposed to professional players. This makes using only AI-likeness metrics not sufficient to detect such players. We propose a method based on the analysis of a player's performance considering point loss distribution over several games, taking into account only relevant moves of a game. We still use an AI-likeness metric for analyzing individual games where the use of AI may not be consistent.

We evaluated our methods on two European go official online leagues, where cheating detection was already performed (for a total of about 150 unique regular players, with levels ranging from 20 kyu to 5 European dan). We show that our system confirmed 5 cases of players previously banned for cheating (out of 6). Our methods do not set out to categorize players between “cheaters” and “not cheaters,” but rather rank them in order of suspicion, for the sake of assisting referees and providing them a way to effectively investigate suspicious players over time.

Keywords: baduk, cheating detection, statistical method, online go

I. Introduction

Despite the ancient history of Go and its current prevalence nowadays, especially in Asian countries such as Korea, Japan, or China, it is only relatively recently that it reached other parts of the globe. For instance, the main cultural and technological events that brought attention to this game in Europe are the Japanese manga Hikaru No Go published in 1998, and DeepMind's work on AlphaGo in 2016 [5]. However, most countries and national federations lack a sufficient physical implementation through their territories, while still pursuing the goal of having national rated leagues and, eventually, professional players. In order to allow as many players as possible to play Go in an official way, it is not uncommon for federations to experiment with the creation of online leagues. However, since the recent improvements of AI in the field, cheating at the game, even at a high amateur level, is accessible to most players easily, thus artificially augmenting their rating. This led to leagues and communities to be wary of the integration of online games in official national ladders, either by creating a separate ladder [6] or even by ignoring such games altogether from the official ratings.

Therefore, such federations and affiliated online communities have been creating ethical and fair-play committees, whose goal is to make sure all the games are played in a regular fashion. Unfortunately, more often than not, the number of people doing this work and their available resources are quite low compared to the amount of games that need to be analyzed. This longing for resources and time optimization led to the development of automated tools and methods.

As members of such a committee, our team has been working towards the adaptation and development of such tools, and this paper presents the current state of our research in using analytical methods to provide useful metrics and information in detecting AI-assisted cheating in amateur games.

Ⅱ. State of the art in anti-cheating detection and related works

Contrary to what exists today in other disciplines such as chess and their FIDE/ACP Anti-Cheating Committee, there is no global organism overseeing cheating detection in Go. Indeed, each server, federation, and online leagues have their own cheating detection mechanisms and there is no global effort to mutualize resources and knowledge.

In fact, due to the lack of resources in some smaller organizations, some leagues and communities do not have any kind of anti-cheating systems at all, making them vulnerable to cheating, and sometimes preventing them from offering online rated games to their players (American Go Association, IGLO).

1. Related works

To our knowledge, only a few articles focus mainly on cheating detection in Go.

One of them from Egri-Nagy and Törmänen [1] tries to detect AI-assisted play with a single SGF file. We share some common hypothesis with their work:

Cheating detection cannot be made in a fully automatic way without getting many false positives, a human intervention is needed [3].

Their cheating-detection method is also based on several metrics derived from AI go engine and the combination of several suspicious metrics make them conclude an AI is used.

However, they quickly tackle the problem of looking at several games for a single player, by suggesting to detect a sudden increase in player strength in a single SGF-file to detect cheating. We believe this cannot detect many cheaters and that it would instead require a long term analysis. Our method uses many games of a player's history because we are not always able to detect such sudden increases. For example, a newer strong player in a league may already be a strong amateur player or a cheater. We also encountered the case of a player cheating for a long time and mimicking a plausible increase of player's strength over time.

Most of the cheaters we detected in the context of our cheating-detection work would have the benefit of the doubt of being strong players if we could only look at a single record of their games.

The other article from Park et al. [2] provides a way to compute an AI-likeness metric. Obvious moves are filtered out from the game, as well as moves played when the game is "decided'' (more than 95% win rate for either player). The remaining moves are considered "meaningful" and are considered "AI-like" when the score difference between the top AI-move and the played move is below a certain threshold. They apply their method to professional games and manage to observe a significant difference between top professional players and known cheaters in terms of "AI-likeness".

We adapted some of their methods in our work, for example by filtering moves and by computing an AI-likeness metric for a whole game. However, we cannot directly apply their method for several reasons. Firstly, they use a closed source AI engine and their score metric is derived from some internal values of their AI engine that are not standard in publicly available engines. Secondly, their metric is especially suited for professional players where a cheater would need to play very closely to AI-level in order to beat top professional players. In our amateur level context, a cheater can play many sub-optimal moves and still confidently win the game.

Ⅲ. Dataset and methodology

As members of an online club affiliated to the french go federation, our internal league made for a good practice ground to test and evaluate our methods, as the games played are rated on the national ladder. This online league, that has existed for 3 years now, gathers around fifty players monthly, each of whom play 3 games in that time period. That accounts for 1776 games at the time of writing.

The anti-cheating detection committee has detected 6 players with strong confidence over the past 3 years. This is the result of long term analysis of players' games with moderation tools used by go servers to detect cheating.

Once the committee believes the player strength cannot be explained without the help of an AI, the player is contacted and a meeting is planned. Only 2 players admitted cheating (at that time, we hired an European professional player to analyze the games; and he found that the performance displayed would be of a player above his own professional level, thus leading to the conclusion that an AI was used) and the other ones did not provide convincing explanations of their strength and refused to play over the board games. Only after these meetings took place and their refusalof playing over the board games (even friendly games) were they accused of cheating and suspended from the league. These cases serve as a reference baseline against which we can compare our findings and are identified in relevant figures by the “flagged” hue (the orange points).

For each player taking part in the league, we gathered up to 100 of their online games outside of the league, with the following filters :

- Ranked on the server ladder
- No handicap games
- No correspondence games

This brings our games count to 7225. Each of these games is then analyzed with Katago [4], an open-source go engine. Most of these analyses have been performed by AI Sensei [8], which is an online platform allowing players to execute free analysis up to 50 visits per move. Therefore, this is the number of playouts that we opted for in our own analyses, as this is the most likely settings that could have been used for cheating during live rated games, and because such a setting is still enough to beat all of the players included in our dataset, with levels ranging from 20 kyu to 5 dan on OGS.

An interesting side effect that occurred during the making of this dataset is that some games played against robot players ended up appearing. Such artificial players, many of which have been artificially made weaker to be of acceptable challenge against amateur players [7], are detected as suspicious players by our models without any intervention on our part, thus supporting our findings.

Ⅳ. Statistical analysis of amateur online games

In this section, we look at two different metrics and see if we can discriminate known cheaters from our dataset, as well as organizing other players according to these metrics.

1. AI-likeness metric

We adapted the method described in the Park et al. paper to be used with a different engine and in amateur games. The main difference is that we do not have access to the same metrics as their engine is proprietary. However, using the score lead AI estimation in Katago proved to be pertinent as a relative metric between moves. While we envisioned to use the utility metric provided by the analysis engine, which is derived from both the winrate and score lead metrics, the author has confirmed to us that this is not a pertinent metric to compare different moves, as there is no relation between turns with this metric.

In adapting the original paper to be implemented with this metric, we calculated that the threshold for considering a move to be “AI-like” is 0.6 on the score lead metric. Indeed, despite seeming high in the context of professional games, most amateur games present wide ranges of point loss within their moves, and choosing enough moves within the 0.6 score lead variation can still confidently lead to a win.

Another difference with the Park et al. paper is that we do not discard early game moves in our analyses, as the amateur players present in our dataset do not possess such a strong knowledge of the early games sequences as professional players. The repartition of moves considered to be “AI-like” after the various filters described in the Park et al. paper is shown in Figure 1. By plotting the AILR metrics with the winrate of each player included in our dataset, we are able to confirm that most of the known cheating players are gathered in the top-right corner of the plot, as shown in Figure 2.

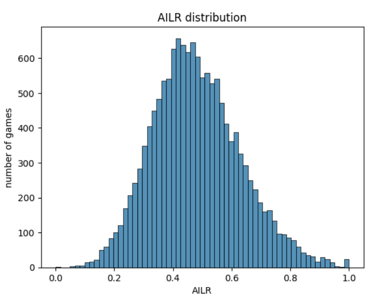

Figure 1

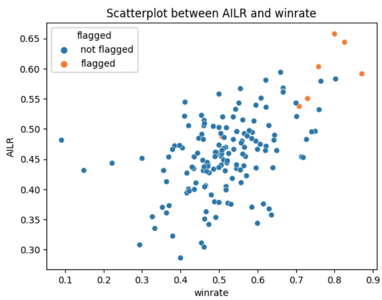

Figure 2

2. Move error metric

We detected several cheaters that do not blindly follow AI top moves. They often do not play the best moves but they almost never make mistakes, especially for amateur players and throughout many games.

We will look at the amount of points lost after each move compared to the top AI move and its distribution over several games. We consider the logarithm of this quantity, because the difference between a mistake of 1 and 2 points and 14 and 15 points is not the same in terms of impact on the game outcome.

Examples of distributions for this metric can be seen on Figure 3. These are only illustrative examples but the trend we can see in those cases is constated in the entire dataset: the stronger the player, the moreit looks like a decreasing exponential with a higher steepness. The convex parts that can be observed for the 10k player can also be observed for players around that strength as well as players with a lower level.

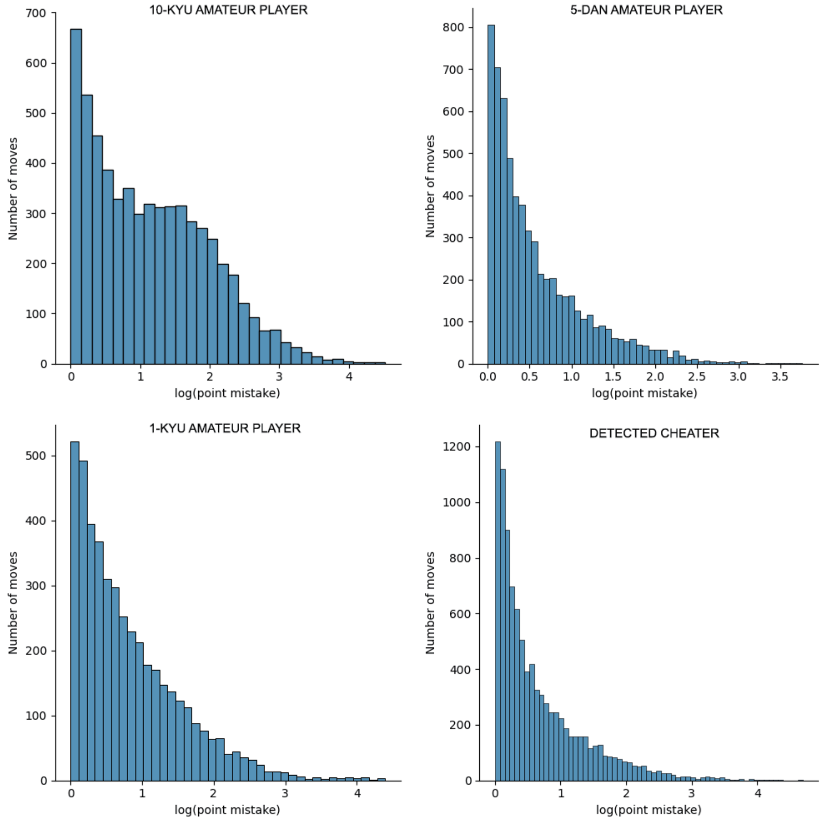

Figure 3: Examples of distributions of the logarithm of the point mistake for 4 different players.

First, we will look at the simple average for each player over all of their moves. This can be seen on Figure 4. The cheater in the cluster of supposingly non-cheating players is a player who got a sudden increase in strength and suddenly have beaten several dan players while being around 6k for a long time. We see that apart from this player, the cheaters we already detected all have one of the fewest mistakes among all players. Two players in this suspicious cluster are considered non-cheating, as they are already known dan players who have been playing over the board tournaments for a long time. The rightmost, bottommost point is a player with only 5 games in our dataset. Even if they could be qualified as suspicious, we would not consider this to be sufficient to qualify the player as "suspect" unless some other metrics are also suspicious.

The main issue with this method is that a player with a few games and supposingly not cheating can display values greater than known cheaters, and there is no clear and definite boundary between suspicious and non-suspicious games. We expend on this method to determine a more deciding criterion.

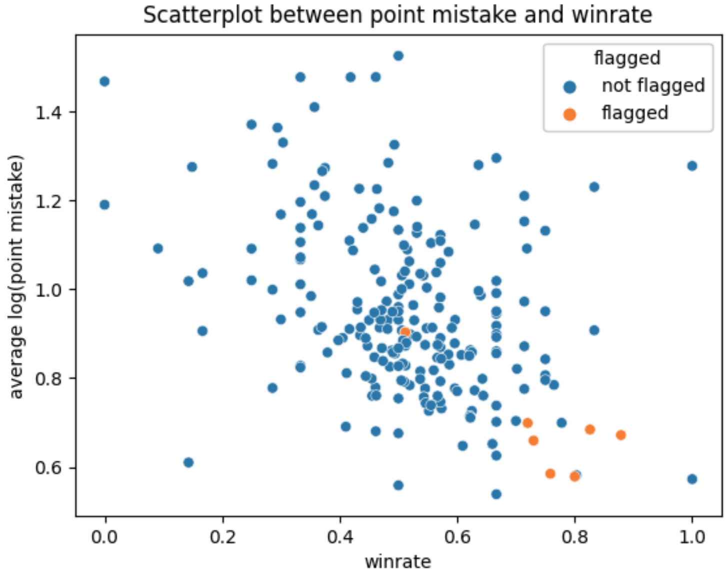

Figure 4

Our goal is to approximate the distributions seen on Figure 3 as an exponential curve. We define two coefficients a and b such that a*exp(-b*x) fits the distribution. A high value of b coefficient means that the exponential decreases quickly, and that the player only makes a few mistakes. As for players with lower ranks, where an exponential curve should not fit the distribution, we apply the fitting anyway and observe the variance ofthe parameters that should be especially high.

As an example, the parameters and their variance of this fit for our 4 examples can be seen on Table 1. We see that the value of the b coefficient (how fast the exponential decreases) is correlated with the strength ofa player, at least in our 4 examples. The values for the whole dataset can be seen on Figure 5.

	a	variance (a)	b	variance (b)
10k player	635	1113	0.65	0.00247
1k player	563	53	1.07	0.00039
5d player	840	188	1.87	0.00185
Cheater	1256	720	1.89	0.00324

Table 1: Fitting coefficients and their respective variance to approximate the error distributions as an exponential curve.

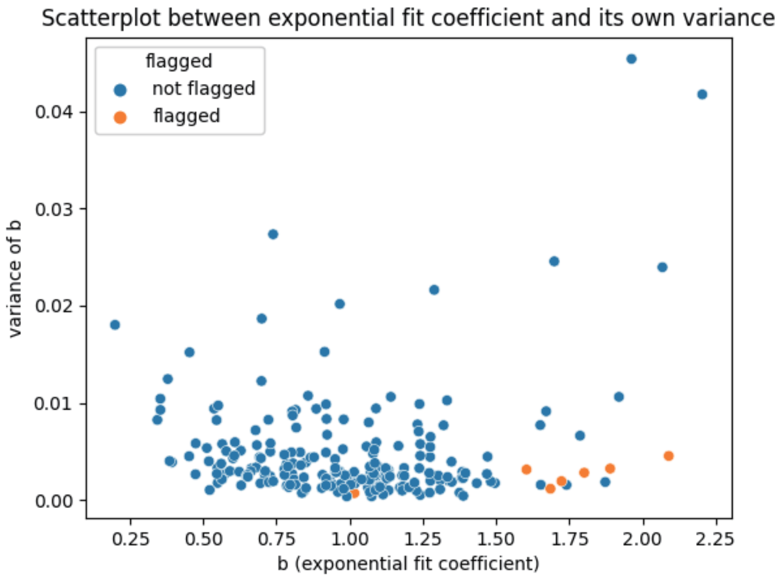

Figure 5

Compared to the previous method, we observe that the boundary between the “flagged” and “not flagged” cluster is clearer, although the two stronger dan players are still in the “flagged” cluster. The aforementioned outlier with only a few games in our dataset is not beyond the “flagged” cluster anymore. However, a supposedly non-cheating player appearedin this cluster, this player is a strong dan player who only plays a few online games. It is too early to become really suspicious about this player but this may suggest the need for further investigation in the future.

V. Discussions

The method described in the previous part has a major weakness that would need to be addressed: it cannot discriminate between a cheater and a strong dan player. This is where conventional and non-analytical methods come into play: for example, we may ask strong dan players in this cluster to play some over the board games ifthey are not already doing so. Moreover, it cannot detect players with sudden strength increases, but this can be detected if we look at each game individually and we see a major difference between some metrics.

This would also prove useful in discriminating against a player who only cheats in a few of their games. By using our metrics on only a few games that are believed to be of particular interest (such as rated league games), we can accidentally bias our results due to the potentially low number of games in that subset.

However, these metrics and the described methods can still be helpful in developing tools to assist fair-play committees, by gathering player-specific analyses efficiently, such as the AILR evolution over time shown in Figure 6.

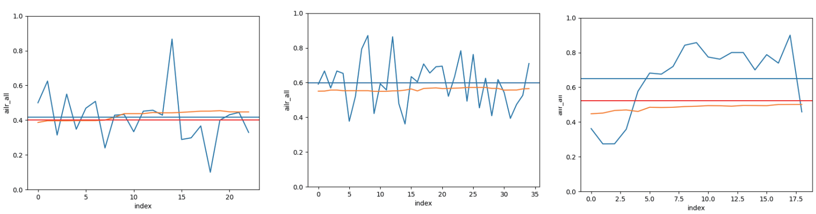

Figure 6

While the information conveyed in this figure is not directly helpful in detecting suspicious players or games, it can still provide useful information for referees when they investigate specific events, saving them some time and energy by automating this data collection.

VI. Conclusion and future works

We can expand on this method by including more games in our dataset, especially leagues with higher level players, and trying to take rating into account to discriminate against suspicious players more efficiently. By using an open-source engine and collaborating with other international leagues and go servers, we hope to offer a greater range of tools to them and allow them to independently improve on this method.

If we manage to gather more information on cheating players and games where cheating occurs, we should also be able to develop new methods that cover a greater range of cases and more subtle cheating, as well as per-player statistics even more useful for fair-play committees' investigations.

The findings in this research reinforced our knowledge of the benefits and limits of using analysis detection for amateur players, as other methods need to be developed as well, especially in the domains of game servers tooling and social investigation processes.

By releasing this paper and the associated code publicly, we hope our work can inspire other organizations to adopt a similar process with medium or long-term analysis to avoid false accusations as much as possible, and, once enough elements are unfortunately gathered, allow them to quickly contact alleged cheaters to confirm the suspicions, encouraging them to play over-the-board games or to meet with other players.

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Exploring the Impact of AI on Go Education: A Teacher Survey

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Abstract: In 2016, AlphaGo's advent transformed the world of Go as AI-powered tools began to surpass the world's top professional players. The rapid growth in AI's influence raises questions about the potential replacement of human players. This paper examines recent trends in Go education in light of the AI revolution and its future implications. To investigate these trends, we conducted a survey among Go educators, focusing on three key aspects: (1) the perceived benefits of learning Go, (2) the impact of AI on Go education, and (3) educators' satisfaction with Go AI tools. Data was collected through online questionnaires in English, Korean, and Chinese. Survey results indicate that Go teachers believe learning Go equips students with valuable skills, including critical thinking, resilience, and persever-

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ance, fostering character and cognitive development. However, educators' opinions on AI-based tools in the classroom are mixed. Approximately 41% of respondents have refrained from using AI tools, citing concerns about their suitability for lower-level and younger learners, as well as perceived difficulties in their implementation. Additionally, there are concerns about over-reliance on AI and its limitations in Go education. Conversely, educators who have integrated AI tools report overall satisfaction and optimism for further developments. This study highlights the growing acceptance of AI programs and their positive impact on Go education. While practical demands remain partially unmet, many educators, in general, express satisfaction with the available programs. The findings of this study shed light on areas for potential improvement in AI to further enhance Go education.

Keywords: Go, Baduk, Weiqi, Education, Artificial Intelligence, Educational Technology, Instructional Media, Teacher Survey

I. Introduction

Artificial Intelligence (hereafter AI) has been making major waves in the Go community ever since 2016 when AlphaGo, a product of Google DeepMind researchers, stunned the world by defeating human grandmaster Lee Sedol. Since that milestone event, several Go AI programs exhibiting superhuman proficiency have emerged. Professional Go players have turned to AI analyses for self-improvement, signaling a posthuman shift within the community (Jeon 2021). This means that theories and knowledge, which had been accepted and passed down for decades or even centuries, are now being challenged or replaced by data-driven recommendations of AI programs. Before the rise of AI, humans were the primary creators of techniques, standard sequences, and narratives in Go. In contrast, nowadays concerns are raised that human creativity and input might be devalued even though there is still a place for them.

The realm of Go education has not remained untouched by AI advancements. AI-powered teaching tools are now being used to train children and beginners, providing visual imagery to elucidate the abstract aspects of Go. Previously, these aspects were considered substantial barriers for many beginners attempting to understand the game. Nonetheless, the applicability and advantages of AI-powered programs are yet to be researched scientifically.

In light of the transformations triggered by the emergence of AI, Go educators now have an additional option – incorporating state-of-the-art technology into their classrooms. The hypothesis presented in this paper anticipates a range of reactions from Go instructors. While some might embrace AI tools to captivate more students, others might resist this shift due to challenges in adopting AI and their preference for traditional teaching methods.

This study aims to investigate the factors shaping teachers' decisions and the extent to which AI has altered Go teaching methods, addressing the following research questions.

1. What benefits of Go education for children do Go teachers perceive?
2. What is the impact of Go AI programs on Go educational practices?
3. Are Go teachers satisfied with the Go AI programs available?

Answering these questions will shed light on recent developments in Go education amid the emergence of AI as a novel learning and teaching medium while providing insights for future advancements in Go education.

II. Literature Review

The demand for incorporating AI in the field of Go education has been on the rise. Examining the changes in Go education brought about by the introduction of AI-assisted teaching tools may provide insights into the general field of education. The Google DeepMind Challenge Match garnered attention from both the media and individuals interested in AI. However, despite the emergence of numerous AI-based Go education tools recently, there is still limited research on their impact on Go teachers and their students.

1. Benefits of Go Education

While the literature on Go education is not extensive, several studies have highlighted its positive impacts on learners' development. Lim (2009) surveyed to investigate the competitiveness of Go education compared to other subjects in the school curriculum, advocating for institutional reform. Lee and Jeong (2007) revealed that learning Go improves students' emotional intelligence (EQ), while Kim and Cho (2010) found that Go has a positive influence on children's overall IQ, problem-solving abilities, and patience. Similarly, Kwon et al. (2010) concluded that long-term Go training enhances learners' cognitive capacities, while their subsequent study (Kwon et al. 2013) demonstrated improvements in intuitive decision-making and judgment skills. Gallup Korea (2016) investigated Korean adults' awareness of Go and the state of Go education in Korea. It reported that, despite Go enjoying a very positive image amongst all adult age groups, their interest level has been declining, indicating challenges in Go education.

After the advent of Go AI, Wakabayashi and Ito (2020) developed an AI-driven education model for beginners, who often require additional motivation due to the complexity of Go. Gürbüzel, Sadak, and Özdemir (2022) highlighted the positive impact of Go on teachers' problem-solving skills. In conclusion, while Go education enhances cognitive and intellectual development, further research is needed to explore the impacts of AI on Go education, providing insights into AI-induced phenomena both in the Go community and beyond.

2. Go AI Programs

Initially, the study of Go AI programs occupied a niche in the fields of Go studies and computer science, mainly exploring potential AI advancements regarding the Go-playing level. Despite some early skepticism about computers defeating humans at Go (Bouzy & Cazenave 2001; Friedenbach

2005; Mańdziuk 2007), others foresaw the potential of computer Go (Ramon & Struyf 2003; Park 2005) and predicted that AI would eventually surpass human skills in the game (Moskowitz 2013). These predictions about the importance of ‘machine learning’ (Ramon & Blockeel 2001; Doshay & McDowell 2005) and the ‘Monte-Carlo technique’ (Lewt 2006; Baudi & Gailly 2011; Gelly & Silver 2011) for AI’s future success proved accurate. Before AlphaGo was introduced to the public, research used to focus primarily on AI tools’ proficiency in Go.

The advent of AI Go programs surpassing human skills, particularly the development and success of Google DeepMind’s programs (Silver et al. 2016, 2017, 2018), has spurred multidisciplinary research. Computer scientists and mathematicians have delved deeper into topics such as the evolution of computing (Chen 2016), Monte Carlo tree search (Fu 2016), Bayesian optimization (Chen et al. 2018), in addition to deep learning, neural networks, and reinforcement learning (Holcomb et al. 2018). Subsequent studies have encompassed an exploration of AlphaGo’s innovative Go techniques (On & Jeong 2016), AI’s decision-making processes (Park et al. 2019), its applications in various fields like pathology and education (Wang et al. 2016; Granter, Beck & Papke 2017), as well as philosophical considerations and ethical questions, including AI-assisted cheating (Egri-Nagy & Törmänen 2020; Park et al. 2022). Binder (2022) emphasized AI’s influence as a cultural force, using AlphaGo as a case study. In summary, whereas earlier studies primarily focused on developing strong Go programs, recent studies have increasingly examined the philosophical and sociological implications of AI, expanding beyond a purely technological focus.

3. Artificial Intelligence in Education

Since the early 1990s, Artificial Intelligence in Education (AIED) has undergone significant advancements enriching student life and indicating a paradigm shift in education (Roll & Wylie 2016; Azoulay 2018). Contemporary research focuses on AI's role in secondary and higher education, highlighting innovations in personalized learning, creativity, emotion control, and computational thinking (Popenici & Kerr 2017; Cruz-Jesus et al. 2020; Ouyang & Jiao 2021; Su & Yang 2022; Ezzaim et al. 2022). AI-supported platforms enhance assessment and teaching quality (Hwang et al. 2020; Chen, Chen & Lim 2020), yet full personalization of AI and its acceptance among teachers remain unrealized (Jeon et al. 2021; Chen et al. 2022). Concerns arise regarding potential misuse, algorithm bias, and a departure from human-centered principles (Floridi et al. 2018; Yang et al. 2021). Educational researchers stress the need for robust policymaking to navigate opportunities and risks, emphasizing the importance of balancing the enhancement of human capacities with potential detriments to human skills and control in an AI-driven educational landscape.

The noticeable shift in classrooms due to AI-assisted teaching necessitates a discussion on its implications for Go education, especially in the context of AI's growing presence. The scarcity of studies on AI's impact in this field highlights the importance of this research. This paper aims to explore the extent to which AI has affected Go teachers' attitudes and practices, potentially providing insights for future advancements in Go education.

III. Research Method

This study aims to explore Go teachers' perceived benefits of Go for children, the impact of Go AI tools on Go educational practice, and Go teachers' satisfaction with the Go AI tools regarding their educational practice. To answer these questions, we developed an online questionnaire consisting of six sections, namely demographic information (4 questions), educational environment (5 questions), perceived benefits of Go education (3 questions), impact of AI on Go education (11 questions), applications of AI in Go education (16 questions) and evaluation of Go AI programs (11 questions). The questionnaire was provided in English, Korean, and Chinese. The convenience sampling method was utilized by asking Go teachers to participate in the survey via social media (Facebook, LinkedIn, Band, Reddit, etc.). Responses were collected from 2022.09.23 to 2022.10.22 via an English and Korean questionnaire, and from 2023.05.24 to 2023.06.23 after adding a Chinese version. A total of 193 people responded, with 188 of them submitting valid responses.

The survey data were analyzed mainly using statistical calculations in Excel, in addition to open-ended questions that were analyzed by using 'theme analysis' to identify recurring themes in the written responses.

1. Participants

Analyzing the demographic data of the 188 valid respondents showed that the majority of the survey participants were male (77.7%) compared to 20.2% female respondents (Table 1).

Table 1. Participants' Demographics

Variables	Values	N	%	Mean	SD
Gender (N=185)	male	146	77.66%		
	female	38	20.21%		
	non-binary	1	0.53%		
Country (N=187)	China	77	40.96%		
	South Korea	35	18.62%		
	USA	18	9.57%		
	Chinese Taipei	17	9.04%		
	Germany	9	4.79%		
	Others (17 countries)	31	16.49%		
Age (N=185)				38.44	13.35
Go Teaching Experience (N=188)				10.87	8.94
Position (N=188)	permanent teacher at a Go school	67	35.64%		
	freelance Go teacher	38	20.21%		
	part-time teacher at a Go school	27	14.36%		
	Go teacher at after-school classes	27	14.36%		
	Go Teacher at a higher education institute	11	5.85%		
	teacher at an online Go school	9	4.79%		
	other	9	4.79%		
	Go streamer (YouTube, Twitch, etc.)	5	2.66%		
Students' Age (N=188)	6-10 years	144	76.60%		
	11-15 years	111	59.04%		
	20-59 years	64	34.04%		
	16-19 years	59	31.38%		
	younger than 6 years	35	18.62%		
	older than 59 years	20	10.64%		

There were responses from 22 countries, with most responses from China (41.0%), followed by South Korea (18.6%) and the U.S.A. (9.6%). When mapping each respondent's country to its respective continental Go federation, it was revealed that 71.1% of the respondents belonged to the Asian Go Federation, 16.6% to the European Go Federation, and 9.6% to the North American Go Federation. The average age was 38.4 years with a standard deviation (SD) of 13.4, and the respondents reported an average Go teaching experience of 10.9 years (SD = 8.9). The majority of respondents teach children between 6 and 10 (76.6%) and the age group from 11 to 15 years (59.0%). 9 out of 10 respondents (93.1%) have been teaching Go to children, while about one-third have been offering lessons for adults (34.6%). Furthermore, it is notable that two-thirds teach more than one age group listed in the questionnaire (65.4%). When asked about their current position, 35.6% answered that they were permanent teachers at Go schools, followed by 20.2% freelance Go teachers, 14.4% part-time Go teachers, and 14.4% Go teachers at after-school classes.

IV. Results

1. Perceived Benefits of Go Education

First, we asked the respondents whether they consider Go to be helpful for children's development. The majority of respondents answered affirmatively (89.4%, Table 2). The follow-up question about the reason was open-ended, and the most frequently chosen reasons why Go teachers regard Go as beneficial for children's development are shown in Table 2.

Table 2. Go Teachers' view on educational benefits for children's development

Do you think learning Go is helpful for children's development? (N=188)	N	%
yes	168	89.36%
I don't know	20	10.64%
no	0	0%
Why do you think Go is helpful for children's development? (N=164)	**N**	**%**
Thinking skills	80	48.78%
Resilience, perseverance	60	36.59%
Character development	56	34.15%
Cognitive development	50	30.49%
Focus	31	18.90%
Math abilities	13	7.93%
Problem-solving ability	11	6.71%
Decision-making ability	10	6.10%

The responding Go teachers identified several benefits of Go education for children, including improved thinking skills (48.8%), resilience, and perseverance (36.6%), while Go is also perceived as supporting character development (34.2%), cognitive growth (30.5%) and improved focus (18.9%). Additionally, a minority noted enhanced math abilities (7.9%), problem-solving (6.7%), and decision-making (6.1%). In other words, Go teachers report that learning Go enhances some of the children's essential academic abilities and fosters their character development.

2. Impact of AI on Go Education

2.1. Importance of AI tools

We asked survey participants to rate the importance of AI-based teaching in Go across different learner levels, ranging from beginners to experts, using a 5-point Likert scale (1 not important, 5 very important). Table 3 displays their responses, along with the average importance score (M) for each Go level (maximum of 5 very important).

Table 3. Importance of using AI in Go education across all levels of learners

How important do you regard using AI tools in Go education? (N=188)	Not important at all		Not important		Neutral		Important		Very important		M	SD
	N	%	N	%	N	%	N	%	N	%		
for experts (stronger than 4 dan)	3	1.60%	1	0.53%	10	5.32%	37	19.68%	134	71.28%	4.61	0.76
for advanced learners (1-4 dan)	6	3.19%	10	5.32%	33	17.55%	92	48.94%	42	22.34%	3.84	0.95
for intermediate learners (9-1kyu)	18	9.57%	25	13.30%	81	43.09%	39	20.74%	20	10.64%	3.14	1.08
basic level (15-10 kyu)	46	24.47%	39	20.74%	63	33.51%	17	9.04%	18	9.57%	2.65	1.23
for beginners (weaker than 15 kyu)	69	36.70%	40	21.28%	43	22.87%	17	9.04%	17	9.04%	2.37	1.31

The majority of the respondents strongly support the integration of AI in Go instruction for expert learning, with ‘very important’ (71.3%) and ‘important’ (19.7%). Following this trend, Go teachers generally align with the adoption of AI for advanced players, with nearly half of the respondents rating it ‘important’ (48.9%) and more than a fifth classifying it as ‘very important’ (22.3%). For intermediate and basic level learners, however, ‘neutral’ was the most common response, accounting for 43.1% and 33.5% respectively. This reflects a degree of uncertainty about using AI for these groups, despite a generally positive trend for intermediate learners. In contrast, over half of the Go teachers express a negative view on employing AI for beginners, selecting ‘not important at all’ (36.7%) or ‘not important’ (21.3%). In sum, Go teachers regard the usage of AI in Go education as very important for experts (M=4.61), important for advanced learners (3.84), neutral for intermediate (3.14) and basic level (2.65), and unimportant for beginners (2.37). In other words, one could argue that Go teachers consider the use of AI more important as the learner’s level increases.

We designed six questions to explore how Go teachers view AI programs as instructional media. Table 4 illustrates their responses.

Table 4. Go Teachers’ overall perception of Go AI programs

Rate how much you agree to the following statements. (N=188)	Strongly Disagree		Disagree		Neutral		Agree		Strongly Agree		M	SD
	N	%	N	%	N	%	N	%	N	%		
Go teaching methods have changed after the emergence of Go AIs.	4	2.13%	15	7.98%	37	19.68%	88	46.81%	44	23.40%	3.81	0.95
The emergence of Go AIs is an opportunity for Go education.	7	3.72%	12	6.38%	44	23.40%	73	38.83%	52	27.66%	3.80	1.03
Go AI programs enhance my work efficiency.	9	4.79%	17	9.04%	58	30.85%	74	39.36%	30	15.96%	3.53	1.02
I am satisfied with the Go AI programs available.	3	1.60%	15	7.98%	72	38.30%	77	40.96%	21	11.17%	3.52	0.86
Integrating an AI program in Go education is seemingly impossible.	28	14.89%	66	35.11%	54	28.72%	26	13.83%	14	7.45%	2.64	1.12
In the future, human Go teachers will be replaced by Go AI programs.	51	27.13%	54	28.72%	50	26.60%	25	13.30%	8	4.26%	2.39	1.14

Primarily, most Go educators agree that the emergence of Go AI programs has led to changes in their teaching methods, with 46.8% selecting ‘agree’ and 23.4% choosing ‘strongly agree’ which calculates into an average agreement index of M=3.81 out of 5. While there is a slight variation in intensity, they also accept that the advent of AI programs provides an opportunity for Go education (M=3.80). Despite receiving an increasingly higher number of neutral responses for the next two questions, respondents tended to agree with the statements “Go AI programs enhance my work efficiency” (M=3.53) and “I am satisfied with the Go AI programs available” (M=3.52), with more positive responses (55.4% and 52.2%) than negative responses (13.8% and 9.6%). Notably, the Go teachers have a neutral stance regarding the negative idea that integration of AI programs in Go education is impossible (50% strongly disagree or disagree, 28.7% neutral, M=2.64). This disagreement becomes stronger with the prediction that human Go teachers will be replaced by Go AI programs (M=2.39), with more respondents choosing ‘strongly disagree’ (27.1%) and ‘disagree’ (28.7%). Overall, Go teachers appear to acknowledge and embrace chances in teaching methods and environments, seeing the potential for enhancing their teaching efficiency. Although most of them express satisfaction with the currently available AI programs, they are generally skeptical regarding the idea of AI taking over traditional teaching roles in Go education.

2.2. Usage of Go AI programs

In consideration of the use of Go AI programs, respondents were inquired about whether they had used AI for planning, conducting, or evaluating Go classes (Table 5). Nearly six out of 10 respondents have stated that they used AI programs as an educational tool (58.5%). Among the AI users, most Go teachers selected Lizzie (38.2%), followed by Golaxy (34.6%), Fine Art (23.6%), AI at YikeWeiqi (21.8%), and KaTrain (19.1%). It is also notable that the majority of the survey respondents have used more than one AI in their Go classes (64.7%).

Table 5. Go AI programs used in the classroom

Have you used AI programs for planning, conducting, or evaluating Go classes? (N=188)	N	%
yes	110	58.51
no	78	41.49

ich AI have you used in our Go class? (N=110)	N	%	Which AI have you used in your Go class? (Contin.)	N	%
Lizzie	42	38.18%	ZBaduk	5	4.55
Golaxy	38	34.55%	Kids Go Server	4	3.64
Fine Art	26	23.64%	Zen	4	3.64
AI at YikeWeiqi.com	24	21.82%	OGS	3	2.73
KaTrain	21	19.09%	Go Master	2	1.82
AI at 99weiqi	15	13.64%	KataGo	2	1.82
AI at Yike Children	15	13.64%	Tencent Children's Go	1	0.91
BadukPop	13	11.82%	IGOWIN	1	0.91
AI at 101weiqi	12	10.91%	Crazy Stone	1	0.91
AI Sensei	11	10.00%	Baduk Study	1	0.91
Baduk King	8	7.27%	AI at Tygem	1	0.91

It can be concluded that Go AI programs are gaining acceptance as an educational medium among Go teachers, with more than 20 programs being available to choose from.

Which program would be rated best from the educational point of view? As shown in Table 6, out of 110 respondents who have used a Go AI before, 42 respondents (38.2%) omitted to name the best Go AI for educational purposes, or noted that they could not choose one as the top AI:

> “Each has its strengths and weaknesses,” “Everything will do,” “I don’t know because I haven’t tried many programs yet.”

In addition, some respondents (6.4%) chose more than one AI as their best pick. The most popular Go AIs regarding their educational features were Golaxy (10%), followed by KataGo (9.1%), AI at 99weiqi (6.4%), as well as Fine Art and Lizzie with 4.6% each. It should be noted that as many as 25 different programs were chosen as best educational Go AI which demonstrates that quite a decent number of AI programs have been recognized in the educational field.

Table 6. AI program with the best Go educational features

Which AI program has the best Go educational features? (N=110) (Multiple answers possible.)	N	%
no answer/I don't know/none is best	42	38.18%
Golaxy	11	10.00%
KataGo	10	9.09%
AI at 99weiqi	7	6.36%
Fine Art	5	4.55%
Lizzie	5	4.55%
AI at YikeWeiqi.com	4	3.64%
BadukPop	4	3.64%
AI at Yike Children	3	2.73%
AI Sensei	3	2.73%
I'm the Baduk King	3	2.73%
Others (15)	18	16.36%

In addition to the general attitude and the preference for a certain AI program, we were also interested in how Go teachers would use AI in the educational environment. We provided twelve types of educational activities typically done by teachers and students in a Go classroom and asked the teachers to state the frequency of AI usage in that activity on a 3-point Likert scale (1 no usage, 2 occasional usage, 3 frequent usage). As shown in Table 7, only one activity, the teacher reviewing learners' games with AI assistance happens frequently with a mean score of 2.39 out of 3, followed by occasional activities such as teachers preparing classes using AI tools (M=2.21), AI assisting teachers in planning classes (M=2.15), learners reviewing their games with AI (M=2.05), and teachers using AI during a lecture (M=2.03). On the other hand, two activities were evaluated with a low-frequency score of M=1.65 which can be interpreted as ‘no usage’. These are assignments and tracking a student’s learning progress.

It must be noted that this survey targeted teachers only, which is why the learners’ actual usage of AI tools might not be evaluated accurately as learners might utilize AI at home without the teacher’s knowledge. Overall, it can be summarized that AI tools are utilized in a rather limited way compared to their affordances.

Table 7. Frequency of AI usage in the Go classroom

How often does the following	I don't know		No usage		Occasional		Freqent usage		Mean	
occur in your Go classes? (N=110)	N	%	N	%	N	%	N	%		
cher reviews learner's games with AI assistance	1	0.91%	6	5.45%	52	47.27%	51	46.36%	2.39	C
teacher prepares class using AI-based Go tools	2	1.82%	13	11.82%	55	50.00%	40	36.36%	2.21	C
assistance in planning classes	4	3.64%	16	14.55%	50	45.45%	40	36.36%	2.15	C
learners review their games with AI	3	2.73%	28	25.45%	39	35.45%	40	36.36%	2.05	C
teacher uses AI Go programs during lecture	1	0.91%	26	23.64%	52	47.27%	31	28.18%	2.03	C
learners play against AI	2	1.82%	31	28.18%	46	41.82%	31	28.18%	1.96	C
learners use Go AI during class to learn	3	2.73%	35	31.82%	46	41.82%	26	23.64%	1.86	C
learners play against other learners	6	5.45%	38	34.55%	33	30.00%	33	30.00%	1.85	C
to visualize Go concepts	3	2.73%	38	34.55%	46	41.82%	23	20.91%	1.81	C
learners solve Go problems	3	2.73%	53	48.18%	28	25.45%	26	23.64%	1.70	C
ırners get an assignment that requires AI usage	2	1.82%	54	49.09%	34	30.91%	20	18.18%	1.65	C
to track student's learning progress	5	4.55%	47	42.73%	39	35.45%	19	17.27%	1.65	C

3. Evaluation of Go AI programs

Part 3, the final section of the study, explores Go teachers’ evaluations of Go AI tools, covering positive and negative effects, satisfaction, improvements, and required support.

3.1. Positive Effects

In the survey, we asked Go teachers about the positive effects of using AI in Go education by utilizing an open-ended question. After analyzing the responses, seven major themes and recurring perspectives emerged from the survey responses (Table 8).

Table 8. Positive effects of using AI tools in Go education

What do you regard as the positive effects of using AI tools in Go education? (N=136)	N	%
Expert Insights and Guidance	65	47.79%
Enhanced Learning	40	29.41%
Efficiency & Convenience	28	20.59%
Improvement in Go Skills and Understanding	27	19.85%
Teaching Support	25	18.38%
Broader Perspective	25	18.38%
Facilitates Self-directed Learning	15	11.03%
Little or no effect	7	5.15%
Simulates Interest & Curiosity	5	3.68%

Firstly, nearly half of the teachers appreciate AI's expertise (47.8%): AI offers expert-level advice, which is especially beneficial when there are no strong players or teachers available. It also helps in reviewing games more effectively. For example, teachers stated:

> "Expert 'answers' when experts are not around. Good interfaces allow for the exploration of options. Contributions to Joseki libraries," "increased accuracy," "The Go strength of artificial intelligence in modern society is far higher than that of human beings," and "Artificial intelligence can find moves that humans cannot see."

Three out of ten respondents mentioned that AI can enhance the learning process (29.4%). AI tools allow students to learn higher-level moves, Go concepts, and strategies. They can find students' mistakes more easily and visualize and quantify winning percentages to clarify good and bad moves. AI tools serve as an excellent resource, especially for players in regions without access to strong players or professionals. They provide opportunities to study and improve despite the lack of in-person guidance:

> "An on-demand source of high-quality moves," and "Greater availability of opponents and games analysis."

One out of five respondents appreciate the efficiency and convenience of using AI in Go education (20.6%). AI tools increase efficiency in learning and analyzing games, saving time and reducing errors. They also provide a convenient on-demand source of high-quality moves and answers to difficult questions:

> "High efficiency," "Convenience can't go wrong," "Convenient lesson preparation," and "[AI] can provide accurate solutions and is easily accessible to anyone."

Nearly twenty percent noted that AI tools help improve Go skills and understanding of Go concepts (19.9%). AI aids in the learning process, providing guidance and solutions, which help students improve their Go skills more efficiently:

> "[AI] improves Go skills," "It can enable high-level students to learn newer knowledge," "[AI] helps students better understand and correct original

> mistakes," "Improvement in early opening moves and overall skills due to understanding artificial intelligence's way of thinking and techniques," and "Consistently improving strength. Enhancement in the understanding of Go concepts."

Another recurrent theme is AI's support in the teaching process (18.4%) by providing technical guidance, allowing teachers to delegate tasks such as game reviews, and easing the identification of proper alternatives during lessons:

> "Technical guidance is more reliable, allowing students to open their horizons," "By letting artificial intelligence take over teaching games and Go analysis, teachers have fewer tasks to do directly," and "Teachers can delegate some review work to the AI, such as having students play each other and then review with AI before coming to the teacher to discuss key moments in the game. A teacher doesn't necessarily have to review every move of every game, especially if the games come down to a few key mistakes that students can easily visualize with the help of AI."

The same number of teachers appreciate AI's benefit of expanding horizons and promoting breakthrough thinking (18.4%). AI introduces new moves, broadens the players' perspectives, fosters different thinking, and encourages flexible approaches:

> "Different thinking and flexibility with people," "[AI] expands ideas," "[AI] makes the dimension of thinking bigger," "AI has taught us that more moves are available and that there is no rigid way to play," and "Opening the mind of the students to a new (AI) way of thinking."

One out of ten teachers also pointed out that AI tools facilitate self-directed learning (11.0%). AI programs enable students to practice more efficiently, without any time or place constraints:

> "Students can engage in self-directed learning, and it is fun!" "[AI] opened a door for every player to review their own games and see the biggest mistakes right after the game," and "Students can study anytime and anywhere, rationally use artificial intelligence software."

A minority of respondents reported little or no effect of using AI in their classes (5.2%), while five teachers noted that AI may stimulate the learners' interest and curiosity (3.7%).

3.2. Negative Effects

In addition to the aforementioned positive effects, Go teachers also mentioned some negative consequences of using AI tools in Go education. First and foremost, more than half of the teachers (53.1%) are concerned that the use of AI makes students overly reliant on this new medium, causing them to prefer it over their own cognitive skills:

> "Since artificial intelligence suggests the best moves, the time for self-thinking is reduced, making it difficult to engage in creative thinking," "The immediate response of artificial intelligence deprives us of the luxury to think for ourselves," "Lack of pleasure due to excessive dependence," "The traditional theories of Go are being unjustly dismissed due to blind faith in artificial intelligence," and "I sometimes worry that newer players lean on AI too much. They can begin to look at the game as simply a series of good

> or bad moves, without thinking critically about [the] whole-board strategy or broader concepts behind why moves are strong or weak. The AI will tell you what moves it thinks are good, but it won't explain why. Stronger players can usually fill in the 'why', but like weaker players reviewing professional games, they may not understand the reasoning behind a strong or weak move. I also sometimes worry that the AI encourages people to focus on 'the single best move' or the 'single best line of play'at the expense of creativity or exploring fun, if suboptimal, lines of play. People quickly end up playing in the style they think the AI will approve of. They also may simply rely on the AI analysis of a move to determine if it's good or bad instead of learning to think critically and independently about the moves. I think it's best for most new players to review their games without AI first, then only after they have given the game some thought to bring in the AI. Basically, I worry that AI can become a crutch for some players."

The last quote contains two more aspects that are worthwhile discussing in more detail, which are AI's limitation in education and the loss of creativity. 4 out of 10 teachers argued that using AI in Go education faces limitations (41.5%) due to AI's inability to provide explanations and interactions with students, AI's raw information offered without any explanations of reasons, leading to potential misunderstandings:

> "[AI] takes away the 'why' and goes straight to the solution," "Lack of emotional communication," "Most players tend to mimic how AI would play without knowing the basis and logic behind it. Amateurs like myself would learn more from a strong human teacher explaining fundamentals rather than try to copy AI's moves," and "It lacks human explanations and interactions,"

> and "Having a human teacher with at least a basic understanding of didactics/teaching methods is far more useful than using AI for all but the most advanced students. Blindly copying the AI style might be harmful to developing one's understanding of the game."

Another serious educational limitation is the potential diminishing of the teacher's authority:

> "Students start to take the AI moves as gospel, often questioning principles that teachers teach. Specifically, if the AI somehow suggests a different move in a particular situation that is not aligned with the principles the teacher taught," and "The artificial intelligence software used by students before [reaching] 5 dan is almost useless, and some students will not listen to the content of the teacher because of this, which will affect the authority of the teacher."

A similar number of teachers addressed the potential danger of AI killing creativity (40%):

> "The monotonous and repetitive game sessions are stifling creativity, leading to the production of individuals who simply memorize without engaging in independent contemplation and reflection," "It can also lead to the formation of fixed ideas or preconceptions," "Too much reliance and lack of innovative exploration," and "The degree of freedom of Go will be limited."

Furthermore, some teachers argue that AI users are too weak to use this medium efficiently to learn or teach Go (25.4%):

> “It took up teaching time and did not achieve corresponding results,” “It doesn’t explain why it is a good move so it is hard to understand for ddk[1],” “If [the] teacher is too weak, it will be impossible [to use AI],” “Uncritical use of it can be dangerous depending on the situation, AI would recommend some solutions that have human meaning after a lot of moves and with a small margin. Blindly following those kinds of solutions would probably have a negative influence on weaker players,” “If everyone studies AI, I think that it will make everyone’s playing styles more similar. Unless your goal is to produce professional players, I don’t understand what the value is in using AI tools as opposed to learning from stronger players. Go can build relationships between people and introducing AI doesn’t magnify this at all. I sense it might actually interfere a little in the teacher/student relationship. All Go knowledge until very recently has been passed from person to person. It is new that a lot of learning now is ‘artificial’. I’m not against AI, but it feels unnecessary (unless you are training to be a pro),” and “(…) The second problem is less visible but probably more dangerous: humans should play Go at the level they understand (based on their slowly acquired knowledge and practice). Trying to mimic the top-level AI play and even worse, remembering the sequences without understanding the principles might lead to disasters visible in the world of international chess: top grandmasters are commenting their own games with sentences like ‘I forgot the sequence proposed by the computer (chess) program.’”

Some Go teachers are also concerned that the usage of AI might hinder students from developing essential skills through Go education as valued traditionally (21.5%) and discussed above in the part ‘perceived benefits of

1) Double-digit kyu (ddk) level refers to players ranging from 10 kyu (basic level) to 30 kyu (absolute beginner).

Go education':

> "There are concerns that the educational benefits of Go might be obscured, and the focus could solely be on skill improvement," "Mostly the use of computers hinders the cultivation of patience. Students click and try rather than read, and they want to see results fast as the computer replies almost instantly," and "Excessive reliance on AI in Go education could potentially hinder the cultivation of etiquette and character, which are among the advantages of Go education," and "Artificial intelligence causes some highly talented individuals, especially newcomers, to give up Go before they even start. Go itself is a game that pursues continuous thinking and surpassing challenges, but under the influence of many unknown individuals, artificial intelligence denies this essence. The teaching of artificial intelligence makes many highly gifted beginners think that Go's future will be dominated by AI, so they give up learning. Many strong professional Go players see their seniors defeated by AI and consider it a demon in their hearts. Losing the courage to challenge is like putting down their weapons, which is very fatal."

Moreover, Go teachers addressed the concern about losing the essence of the game played and enjoyed by humans (10.77%):

> "Children are very concerned about winning and losing. Go should be a pleasure to enjoy the game," "Human teacher and opponent are essential parts of the Go experience," and "forgetting that Go is a game played by two (or more) humans, that share a good time."

Last but not least, teachers also express worries about the unethical usage of AI (10%), as stated below:

> "It is very troublesome to control cheating in the game," and "The first problem is obvious: giving access to AI might cause student's 'addiction' and induce cheating (especially in the online environment). This problem needs to be taken very seriously and the code of conduct comes first, before the result of the game. It is extremely important at the adolescent age (between 11 and 18 years old)."

In sum, the foremost worries among respondents involve an excessive dependence on AI, coupled with AI's limitations in Go education and its potential to suppress creativity. Furthermore, some teachers expressed concerns about students or teachers not utilizing AI tools effectively and how AI could impede the development of traditional Go skills. Additional apprehensions encompass the potential loss of the game's essence and the difficulty in preventing and detecting cheating with AI.

Table 9. Negative effects of using AI tools in Go education

What do you regard as the negative effects of using AI tools in Go education? (N=130)	N	%
Overreliance on AI	69	53.08%
Limitations of AI in Go education	54	41.54%
Killing creativity	52	40.00%
Incompatible with students' or teacher's level	33	25.38%
Replacing traditional value	28	21.54%
Essence of Go vanishes	14	10.77%
Cheating and dishonesty	13	10.00%
Loss of human interaction and socialization	10	7.69%
Learners might lose respect for human efforts,	10	7.69%
Decreased enjoyment and fun of playing Go	9	6.92%

3.3. Satisfaction

In order to analyze how satisfied Go teachers are with the currently existing Go AI programs, we provided five statements and asked teachers to rate them on a 5-point Likert scale (1 strongly disagree, 5 strongly agree). Table 10 summarizes the responses.

Table 10. Satisfaction with AI programs for Go education

	Strongly disagree		Disagree		Neutral		Agree		Strongly Ag	
n with AI programs for Go education	N	%	N	%	N	%	N	%	N	%
further development of AI programs as an educational tool.	0	0%	0	0%	14	12.73%	43	39.09%	53	48.1
n satisfied with the functions current AI programs provide.	1	0.91%	6	5.45%	28	25.45%	45	40.91%	30	27.2
sound understanding about how to use AI programs in Go education.	0	0%	7	6.36%	42	38.18%	38	34.55%	23	20.9
costs for integrating AI programs in Go education are reasonable.	2	1.82%	7	6.36%	40	36.36%	42	38.18%	19	17.2
re sufficient resources to learn about AI and how to use them in Go education.	4	3.64%	16	14.55%	37	33.64%	32	29.09%	21	19.0

The majority of Go educators (87.3%) anticipate further developments in AI as an educational tool for Go. Two-thirds express satisfaction with current AI programs (68.2%). However, only half of the teachers feel proficient in using AI tools (55.5%) and believe they have adequate access to AI-related resources for Go education (48.2%). Regarding costs, many Go teachers find AI programs reasonable (45.4%), while 36.4% maintain a neutral stance. In summary, Go teachers who have used AI in their Go classes view existing AI programs positively but also see a need for further development and support.

3.4. Improvements

The following open-ended question inquired what improvements Go teachers wish to see regarding Go AI tools for educational purposes. Four frequent themes appeared when analyzing their responses (Table 11). The majority (56%) stated that they wished for explanations and educational content, followed by customization and diversification (42.9%). Some teachers hope for improvements regarding the interface and usability of the programs (27.4%). Lastly, multilingual support and enhanced accessibility (13.1%) was also a theme that occurred repeatedly.

Beyond the themes, it is worthwhile to look at some of the teachers' suggestions as they provide excellent concrete ideas of how to further develop AI to become a better educational medium. Below are some respondents' statements for each of the four themes, beginning with the most frequent theme, explanations, and educational content:

> "It would be great if there were explanations using comics or videos, etc., along with the text," "Explanations of the reasons why one direction of play is better than the other alternatives," "Firstly, provide understanding for the teacher. Secondly, for the pupils," "It would be really helpful if the AI could categorize moves/situations and output that as well. For example, moves could be categorized into: 1. good exchanges 2. asking moves 3. big (gote) moves. If that would happen all the time, you (as a learner) could much more readily find out why the AI plays a certain move at a certain time. Even better would be, if the AI could articulate a goal for the local or global situation, e.g., 'sacrificing a stone to build thickness' or 'gaining sente locally to play the last big move,'" and "AI Go promoter would be cool. AI for spreading the

> popularity of the game.”

The second frequent field of improvement was customization and diversification, described by Go teachers as follows:

> “Learning software for different age groups and one or two recommended moves need to be set,” “Testing [the] level of student for joseki, opening, middle game, endgame, problems, to help them improve smartly,” “The next big thing with AI tools would be the one for generating specific tsumegos (tesuji, yose, ko-fight, etc.) for a different level of knowledge. That would ease the preparation of learning materials, and maybe even allow efficient usage of tablets/smartphones as a personalized way for kids’ progress.”

The third frequent theme was interface and usability improvements, including customer support and administrative support, as stated below:

> “Especially for educational programs targeting novices and beginners, the learning sequence and difficulty should be more systematically organized. It should enhance convenience and interest in learning rather than serving solely as a means of learning,” “The interface design can be more concise, which is convenient for teachers and students who are not so proficient in computer use to get started quickly,” and “‘I’m the Baduk King’ faces the challenge of applying for and obtaining official certification from the Korea Baduk Federation (KBF). The problem is that to acquire the official dan or kyu, I have to apply separately. This should be transferred to the Korea Sports Council through KBF. We should no longer burden Go players with double applications!”

Lastly, the field of multilingual and affordable access was addressed by some teachers:

> "Affordable hardware that can be purchased in bulk," "More English literature in the subject," and "Development of affordable programs without any financial burden and active consideration of feedback from coaching sites is needed."

In sum, Go teachers suggest adding functions to enhance the educational efficiency of AI, such as explanations to make it easier to understand the outcome of AI's calculations. It seems to be required to personalize the tools and target all Go learners regardless of their age and level. User-friendly interface is desirable to enhance teachers' and students' satisfaction.

Table 11. Improvements of Go AI tools for educational purposes

What kind of improvements do you wish to see egarding AI Go tools for educational purposes? (N=84)	N	%
Enhanced explanations and educational content	47	55.95%
Customization and diversification	36	42.86%
Interface and usability improvements	23	27.38%
Multilingual support and enhanced accessibility	11	13.10%
None	11	13.10%
Anti-Cheating measures	3	3.57%
Restrict access to teachers only	1	1.19%

3.5. Required Support

In addition to the above improvements, the last survey question inquired about what kind of support Go teachers would need to use AI tools more often in the field of Go education. The most frequent answers are displayed in Table 12. The list is topped by the Go teacher's wish for financial (43.4%) and technical assistance (42.1%), followed by administrative support (14.5%). Similar to the former question, some respondents also stated their interest in further AI development (11.8%). In sum, increased accessibility, including more information on Go AI tools and how to use them effectively in class, along with financial support, is required to improve the usage rate and degree of satisfaction.

Table 12. Required support to use AI tools more often in Go education

What kind of support do you need in order to use AI tools more often in Go education? (N=76)	N	%
financial	33	43.42%
technical	32	42.11%
none/I don't know./No intention in using AI.	14	18.42%
administrative	11	14.47%
More AI development (more features, greater accessibilty, more programs)	9	11.84%

V. Discussion

1. Summary and Implications

The results of this study can be summarized as follows.

Firstly, Go teachers report numerous benefits of Go education for children, ranging from enhanced thinking skills to character and cognitive development.

Secondly, AI's importance in Go education varies: the higher the learner's level, the more important Go teachers perceive the usage of AI. For instance, while the use of AI provides expert knowledge to highly skilled players, the benefit of such knowledge is somewhat limited for beginners. Go AI has an impact on teaching methods, and work efficiency, and thus is mostly perceived as an opportunity. Most Go teachers incorporate AI in their classes for reviewing games, lecturing, and class preparation although not all affordances are in wide use yet.

Thirdly, the potential benefits of AI include extraordinary expert insights beyond human Go skills, improved learning experiences, and added convenience in the learning and teaching process. Nonetheless, concerns have emerged, including the risk of over-reliance on AI, its limitations in offering comprehensible explanations, and social interaction with the students, in addition to potential obstacles to the development of cognitive skills and character. Go teachers have been emphasizing the value of Go education in nurturing these skills for many years prior to AI's introduction into the classroom. Many Go educators eagerly await further AI advancements, although they expressed their overall satisfaction with the current state of AI in education.

In the context of recent research regarding AI in education, several studies have discussed its implications. Chatterjee and Bhattacharjee (2020) noted its benefits for higher education. Uzumcu and Acilmis (2023) observed that teachers using AI engage more with students. However, Salas-Pilco, Xiao, and Oshima (2022) highlight AI access disparities, advocating for inclusive education, especially for minorities. Kong, Cheung, and Zhang (2023) also report ongoing efforts to promote AI literacy and ensure equal access for all learners.

While this study focuses on current trends and challenges, historical development can also provide valuable insights. An (2021) describes how instructional media evolved from printed media to digital media over the last 120 years. Her analysis reveals a recurring pattern of initial enthusiasm followed by limited impact on teaching practices, influenced by factors such as poor instructional quality, cost, resistance to change, lack of integration guidelines, and systematic barriers. She argues that teachers need to become comfortable and confident when using new media, realize its value, and experience the positive effects of its integration to overcome the typical resistance to change (An 2021). These historical insights highlight the importance of addressing similar challenges and maximizing the benefits of AI in Go education.

Based on the findings above, several implications can be drawn.

Firstly, Go AI programs as a new instructional medium have shown potential to enhance Go education, particularly for advanced learners by providing expert insights, supporting teaching, and offering new learning opportunities. In other words, many Go teachers recognize the value of integrating this medium in their educational practices while some are reluctant to use AI in their classroom.

Secondly, Go teachers also point out the need for improvements in AI tools, such as enhanced explanations of recommended moves and sequences, as well as customization options.

Thirdly, addressing concerns and enhancing AI features can improve acceptance. This includes increasing accessibility through multilingual support, reducing costs, and ensuring user-friendliness, for instance, by providing user guidelines for Go teachers and learners.

Furthermore, Go teachers require customized training and resources to optimize AI use effectively. It would be beneficial to establish an institutional setting, such as Go teachers' professional development programs or collaborative platforms, in which Go teachers can engage in discussions, access resources, maximize work efficiency through shared best practices, and further develop their pedagogical skills. This institutional support is essential for advancing the integration of AI in Go education, ensuring that both teachers and students can fully harness the benefits of this technology.

Lastly, achieving a delicate balance between AI integration and traditional human-centered Go education appears to be crucial. That way the intrinsic benefits of Go education can be preserved and the positive image of Go as an educational tool that enhances learners' cognitive and character development can be maintained.

While this study provides valuable insights, it is essential to acknowledge its limitations and areas for future research.

2. Limitations and Future Studies

This exploratory study examined Go teachers' perceptions and usage of this technology in order to understand the potential of integrating AI tools into Go teaching. However, it is important to recognize the limitations and necessity for further research in this emerging area.

More studies are needed to provide scientific evidence for the findings. For example, the survey responses reveal Go teachers' perceived benefits of Go education. Some of them have been proved by scientific studies (Lee & Jeong 2007; Kim & Cho 2010; Kwon et al. 2010, 2013; Jeon 2021; Gürbüzel, Sadak, & Özdemir 2022) while other benefits stated are primarily based on the respondents' teaching experience and observations. Further studies revealing the educational benefits of learning Go by providing reliable scientific evidence will help elevate the status and importance of Go education.

Given that the usage of AI in Go classrooms is relatively novel, the literature is scarce. Being of an exploratory nature, this study utilized a survey research design to gain initial insights into the Go teachers' acceptance and actual usage of AI. However, one should keep in mind that the survey's sample size and demographics may not fully represent all Go teachers' perspectives. The survey design and the potential self-reporting bias may influence the reported attitudes. Similarly, the results may not fully capture the entire range of experiences and possibilities of using AI programs in Go education.

Strong Go AI tools have only emerged in the past seven years. In other words, due to the relatively short period of AI implementation of less than a decade, our study did not have the opportunity to examine the long-term effects of AI integration in Go education. In the past, Go professionals like Lee Sedol would spend hours meticulously reviewing their games to get closer to the optimal sequence of play. However, in today's practice, it has become common to quickly resort to AI tools to identify significant errors and consider AI-recommended alternatives. While this approach offers the advantage of greater efficiency in learning, it also raises concerns about reduced cognitive engagement, potentially leading to reduced cognitive benefits.

Additionally, it is worth noting that the survey focused exclusively on Go teachers and thus did not gather valuable feedback that learners could provide to AI developers. Finally, it is important to recognize that rapid advances in AI technology may cause some findings to become outdated. For example, in June 2023, a Chinese company introduced an AI robot that offers learners a fundamentally different learning experience than interacting with AI through a screen[2].

To address the above limitations and advance our understanding in this area, follow-up studies are required. These studies could include qualitative research methods such as in-depth interviews and observations, case studies examining specific AI applications, experimental studies, research with a primary focus on learners, longitudinal studies, and more. These efforts will contribute to ongoing research into the potential of AI in Go education and provide updated insights as the technology and educational methodology evolve.

3. Conclusion

In conclusion, this paper has explored the complex landscape of Go education in the age of AI. It is evident from the responses that Go teachers believe that learning Go equips students with a rich array of valuable skills, which include fostering critical thinking, resilience, and perseverance, ultimately contributing to character and cognitive development. This underscores the enduring significance of traditional Go education methods.

However, as the educational landscape evolves with the integration of AI, educators' opinions become more nuanced. Approximately 40% of the sur-

2) SenseTime has introduced an AI-powered Go version of "SenseRobot," combining advanced AI and robotics to offer real board practice and online gameplay for both novices and experts. (Wang 2023)

veyed respondents have chosen to refrain from the use of AI tools in their teaching. Their reservations primarily stem from concerns regarding the suitability of these tools for lower-level and younger learners, coupled with perceived implementation challenges. Furthermore, these educators express concerns about the potential risks of over-reliance on AI and its inherent limitations in the context of Go education.

Conversely, among the educators who have embraced AI tools in their classrooms, a notable trend emerges – a sense of overall satisfaction and optimism for the future. This group recognizes the benefits and potential of AI tools, paving the way for further developments in Go education. Their experiences highlight the growing acceptance of AI programs and shed light on their positive impact on Go education.

Despite this progress, it is important to acknowledge that practical demands, in some cases, remain unfulfilled, and the integration of AI into Go education has not been without its challenges. This, in turn, emphasizes the need for continuous improvement in AI tools to further enhance Go education.

In summary, the findings of this study illuminate the evolving dynamics in Go education. While traditional methods still hold significant value, the incorporation of AI introduces both opportunities and challenges. The delicate balance between these two realms becomes essential, ensuring that the intrinsic benefits of Go education are preserved while harnessing the potential of AI for more effective and engaging learning experiences.

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바둑진흥법의 실효성
Effectiveness of the Baduk Promotion Act

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Abstract: The Baduk Promotion Act, which was enacted for the purpose of contributing to the expansion of leisure opportunities for the people, the cultivation of healthy minds, and the globalization of Baduk, legally supported the policy of supporting the promotion of Baduk and the creation of Baduk culture, and prepared a legal basis for it. This has a significant meaning for Baduk community.

However, in order for the law to be effective, it must be practiced in real society. Therefore, the purpose of this study is to examine the effectiveness of the Baduk Promotion Act enacted on April 17, 2018 for its legislative purpose. The results of examining the characteristics and limitations of the Baduk Promotion Act are as follows.

First, there is an issue regarding the lack of clear definitions within the law for terms such as 'Baduk instructor,' 'Baduk professional player,' and

‘Baduk organization.’.

Second, there is an issue concerning the term ‘special circumstances’ used in defining cooperation with relevant agencies, as it leaves room for various interpretations.

Third, the provisions of the Baduk Promotion Act, which stipulate support policies such as funds, are meaningful in that they provide a legal basis for receiving financial support from the state budget. There is a problem that consists of regulations that are too comprehensive and abstract to be taken as a legal basis for materialization.

Lastly, there is an issue within the content related to the cultivation and support of Baduk professional players, which may prioritize a sports policy focused on fostering elite athletes and elevating the national stature rather than aligning with the primary objectives set forth by the Baduk Promotion Act.

Therefore, to enhance the effectiveness of the Go Promotion Act, it is necessary to enact legal provisions that specify clear criteria and procedures. Through such improvements, it is believed that effective support and development for the promotion of Go can be facilitated.

Keywords: Baduk, Baduk Culture, Baduk and Sports, Baduk Promotion Act, Korea Baduk Association, Korea Baduk Federation

Ⅰ. 서론

바둑진흥법은 2018. 4. 17. “바둑의 진흥 및 바둑문화 기반조성에 필요한 사항을 정함으로써 국민의 여가선용 기회 확대와 건강한 정신함양 및 바둑의 세계화에 이바지하는 것을 목적”으로 제정되었다.[1)]

바둑진흥법의 제정 경과는 바둑의 활성화와 진흥을 위해 김용섭 교수는 바둑진흥법의 제정 필요성에 관하여 여러 차례 논문[2)]을 발표하며 주장하였고, 체육계에서 2007. 12. 21. 태권도 진흥 및 태권도공원 조성 등에 관한 법률을 시작으로, 2008. 3. 28. 전통무예진흥법, 2012. 1. 17. 씨름진흥법 등이 제정돼 시행되고 있는 것에 아이디어를 얻은 한국기원이 당시 유력한 국회의원이었던 이인제 의원을 통해 2013. 8. 27. 바둑진흥법을 처음 발의한 것이다.[3)] 그러나 제19대 국회에서 심의되지 않아 2016. 5. 29. 만료 폐기되면서 제정되지는 못하였다. 바둑황제 조훈현 9단이 제20대 국회의 국회의원이 되면서 이인제 의원 대표발의 법률안의 기본골격은 유지하여 바둑진흥법안을 2016. 8. 4. 재차 제출하였고, 2016. 5. 29. 국회 토론회 및 2017. 2. 28. 국회 교육문화체육관광위원회 공청회를 개최하는 등 두 번째 시도 끝에 2018. 3. 30. 국회 본회의를 통과하여 비로소 결실을 보았다.[4)]

위와 같은 과정의 노력을 통해 바둑의 진흥 및 바둑문화 조성에 대한 지원정책을 법률적으로 뒷받침하고 그 법적 근거를 마련한 바둑진흥법이 제정되었다고 할 수 있다. 법은 사회생활을 규율하는 규범이므로 법의 생명은 그것을 현실 사회에서 실현하는 데 있다. 즉, 법의 효력은 법이 그 규범

1)「바둑진흥법」 제1조

2) 김용섭, “바둑문화의 진흥을 위한 법정책적 과제”, 스포츠와 법 제10권 제3호, 2007; 김용섭, “바둑문화의 진흥을 위한 특별법 제정의 필요성과 입법방향”, 행정법연구 제22호, 2008.

3) 남치형, 「바둑의 사회와 문화」, 명지대학교출판부, 2021, 278-279면.

4) ‘한국기원 특수법인화’와 ‘프로기사 등 기보에 관한 저작자의 권리보호’ 등 원안에 있던 ‘한국기원’에 관한 부분은 특정단체와 특수관계자 등을 보호하는 측면이 있음을 지적받아 전부 삭제되었다.

의미대로 실현될 수 있는 상태에 있는 것을 말한다.[5] 그러나 법규범이 사실상 실현되지 않는다고 하여 당장 법규범으로서의 의미를 상실하는 것은 아니지만, 실효성이 없다면 그 법은 아무런 존재 가치가 없는 것으로 해석되기도 한다. 따라서 법을 통해 실효성 있는 정책을 실현하기 위해서는 바둑진흥법 규정의 특징 및 한계를 분석하는 연구뿐만 아니라 바둑 진흥을 위해 국가는 어떠한 방법으로 정책을 수립하고 집행할 수 있는지, 또한 지원정책을 구체적으로 어떻게 실현해 나갈 수 있는지 등 다양한 각도에서 연구가 이루어져야 할 것이다. 이하에서는 바둑진흥법의 주요 내용을 정리하고, 동 법률에 대한 특징 및 한계를 지적하여 입법 목적에 따라 활용될 수 있는 실효성에 대해 논의하고자 한다.

Ⅱ. 바둑진흥법의 주요 내용

바둑진흥법의 내용을 구체적으로 살펴보면, 기본적인 사항을 규정한 총칙 규정은 제1조에서 제4조까지의 목적, 정의, 국가 및 지방자치단체의 책무, 다른 법률과의 관계 등 모두 4개 조항으로 구성되어 있다. 그리고 바둑 진흥을 위한 원칙적인 사항을 규정한 본칙 규정은 제5조에서 제13조까지로 바둑진흥기본계획, 관계 기관과의 협조, 바둑의 날, 바둑단체의 지원 및 바둑전용경기장의 조성, 기술개발의 추진, 창업, 연구 활동 지원, 바둑문화산업의 융합 및 연계, 국제교류 및 해외확산의 지원 등의 내용으로 모두 9개 조항으로 구성되었다.

1. 바둑진흥의 주체

바둑진흥법 제3조는 바둑 진흥을 위해 “국가 및 지방자치단체는 필요한

5) 최종고, 「법학총론」, 박영사, 2019, 103면.

시책을 마련하며, 국민의 바둑 활동을 보호하고, 바둑 교육을 받을 수 있도록 교육 기회의 확대에 노력해야 한다."라고 규정하여 바둑을 진흥시키기 위한 주체로서 국가와 지방자치단체를 명시하고 있다.

국가와 지방자치단체는 바둑의 진흥을 위하여 정책적으로 계획을 세워서 각종 사업을 통해 지원할 책무가 있다는 것이다. 스포츠 분야가 국가의 지원(정부 주도하에 육성)을 통해 발전된 역사로 비추어 볼 때 바둑의 발전을 위해서 바둑진흥법에 국가 등의 책무를 명시된 점은 의미가 있고, 국가의 주도적 역할이 중요하다고 할 수 있다.

2. 바둑진흥계획의 수립·시행

문화체육관광부장관은 바둑의 체계적인 보존 및 진흥에 관한 기본계획(이하 '기본계획'이라 한다)을 수립하여 시행하도록 하고 있다. 바둑진흥법 제5조 제2항에 의하면 기본계획에는 ① 바둑 진흥의 기본방향에 관한 사항, ② 바둑 진흥을 위한 조사·연구에 관한 사항, ③ 바둑의 기술개발 추진에 관한 사항, ④ 바둑의 교육·보급에 관한 사항, ⑤ 바둑지도사의 교육·보급에 관한 사항, ⑥ 바둑전문기사의 육성·지원에 관한 사항, ⑦ 바둑단체 및 바둑전용경기장의 지원에 관한 사항, ⑧ 바둑 국제 교류·협력 및 국제행사 개최에 관한 사항, ⑨ 바둑 진흥에 필요한 재원 확보에 관한 사항, ⑩ 기보의 상업적 활용 관련 입법 정책 동향 연구에 관한 사항 등이며, 기본계획은 5년마다 수립하여 시행하여야 한다.

바둑 진흥을 위한 계획에는 그야말로 다양한 계획이 규정되어 있다. 즉 규정을 찬찬히 읽어보기만 하면 바둑 산업을 위한 모든 계획이 법 규정 내에 모두 포함된 것을 알 수 있다. 그뿐만 아니라 동 법률에서 계획사항으로 규정하지 못한 계획이 누락되었을 것을 우려하여 입법자는 동 법률 제5조 제2항 제11호에서 "그 밖에 바둑 진흥을 위하여 필요한 사항으로 대통령령이 정하는 사항"은 대통령령에 위임하여 규정할 수 있도록 하는 근거

를 마련하고 있다. 제11호에서 대통령령으로 정하는 사항이란 ① 바둑 관련 자료의 발굴·수집·보존에 관한 사항, ② 바둑 진흥을 위한 콘텐츠 개발·보급에 관한 사항을 기본계획으로 포함하여 규정하고 있다.

3. 자금지원

바둑진흥법 제8조 "국가와 지방자치단체는 바둑 진흥을 위하여 행정적·재정적 지원을 할 수 있다." 제9조 "국가와 지방자치단체는 바둑과 관련된 기술개발과 기술 수준 향상을 위하여 스포츠산업 진흥법에 따른 지원[6]을 할 수 있다." 제10조 "문화체육관광부장관은 바둑에 관한 창업을 위하여 스포츠산업 진흥법에 따른 지원[7]을 할 수 있다." 제11조 "문화체육관광부장관은 바둑의 연구 활동 등에 대하여 필요한 자금을 지원할 수 있다." 제13조 "바둑의 국제교류와 해외확산 지원 사업을 추진하기 위하여 예산의 범위에서 경비의 전부 또는 일부를 보조할 수 있다."라고 하는 등 자금지원에 관하여 포괄적인 근거를 마련하고 있다.

4. 바둑전용경기장의 조성

바둑진흥법 제8조에서 "국가와 지방자치단체는 바둑 진흥을 위하여 필요하다고 인정되는 경우 바둑단체에 대하여 행정적·재정적 지원을 할 수 있고, 바둑전용경기장을 조성·운영"할 수 있도록 하고 있다.

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6) 「스포츠산업 진흥법」 제7조(실태조사) ① 문화체육관광부장관은 기본계획과 세부시행계획을 효율적으로 수립·시행하기 위하여 정기적으로 스포츠산업 실태조사를 실시하여야 한다. 「스포츠산업 진흥법」 제8조(연구개발의 추진) ① 문화체육관광부장관은 스포츠산업과 관련된 연구개발을 추진하기 위한 정책을 수립·시행하고, 연구개발을 수행하는 데 드는 자금을 예산의 범위에서 지원하거나 출연할 수 있다.

7) 「스포츠산업 진흥법」 제10조(창업 지원 등) 문화체육관광부장관은 스포츠산업과 관련된 창업을 촉진하고, 일자리를 창출하기 위하여 필요한 시책을 마련하며, 사업추진에 필요한 자금을 예산의 범위에서 지원할 수 있다.

그러나 바둑진흥법의 체계는 태권도 진흥 및 태권도공원 조성 등에 관한 법률(이하 '태권도 진흥법'이라 한다)과 달리 '장'의 구분이 없이 '조'로만 구성되어 있으며, 그 법 조항도 단 1개에 불과하다. 태권도진흥법의 경우 '태권도공원의 조성 및 운영'이라는 제목의 장을 구성하여 10개의 법 조항을 규정한 것에 비교하면, 상대적으로 바둑진흥법의 적용 범위가 좁고 조문이 구체적이지 않다는 문제가 있다.

5. 바둑 연구 활동 및 국제교류, 해외 확산 지원

그 외에도 바둑의 국제교류 및 해외확산의 지원할 수 있는 제도가 있다. 바둑진흥법 제13조에 따르면 문화체육관광부장관은 바둑의 국제교류와 해외확산을 촉진하기 위하여 ① 국제대회의 개최, ② 바둑지도사의 파견, ③ 해외 홍보 등의 사업을 추진할 수 있도록 하고 있다. 또한 사업을 효율적으로 추진하기 위하여 문화체육관광부장관은 대통령령으로 정하는 관련 기관이나 단체에 이를 위탁 또는 대행하게 할 수 있도록 하고 있다.

Ⅲ. 바둑진흥법의 특징 및 한계

1. 용어 정의

바둑진흥법 제2조에서는 법에서 사용하는 용어의 뜻을 정하여 규정하고 있는데 문제의 소지가 있는 정의는 다음과 같다.

(1) "바둑지도자란 국민체육진흥법 제11조에 따른 바둑 종목의 체육지도자 자격이 부여된 사람을 말한다."[8]라고 정하고 있지만, 국민체육진흥법 제11조 제2항 규정에 따라 국민체육진흥법 시행령 제9조 제2항에서 정한

8)「바둑진흥법」 제2조 1

체육지도자[9]의 자격 종목으로 바둑이 명시되어 있지 않다. 그러나 "그 밖에 문화체육관광부장관이 정한 심사기준과 심사 절차에 따라 자격 종목으로 인정하여 고시하는 종목"에 바둑 종목을 포함해 체육지도자 자격을 부여할 수 있을 것으로 보인다.

태권도진흥법은 태권도지도자에 관한 규정을 정하고 있으며, 국민체육진흥법 제11조 제2항에 따라 일정한 자격이 부여된 것에 더해, 태권도 진흥법 제2조에서는 국기원 승단 심사를 거친 4단 이상 태권도 단증을 보유한 사람으로 정의하고 있다. 이는 바둑진흥법에서 정의된 바둑지도자의 정의보다 더 구체화한 규정을 제공하며, 더 나아가 태권도지도자의 양성과 국외 파견에 대한 담당 단체를 국기원으로 정하여 규정하고 있다. 바둑진흥법상 바둑지도자에 관한 구체적인 규정은 없지만, 바둑지도사[10]라는 제도를 만들어 시행하고 있는 대한바둑협회는 바둑지도사의 자격요건을 1급·2급·3급으로 나누고 있으며,[11] 등급별로 다른 자격요건[12]을 정하고 있다.

(2) "바둑전문기사란 대통령령으로 정하는 바둑 실력 검증대회를 통과하여 바둑 전문가 집단의 바둑 경기에 참여할 자격을 부여받은 사람으로서 직업적으로 각종 바둑 활동에 종사하는 사람을 말한다."[13] 이 정의에서는 대통령령으로 정하는 바둑 실력 검증대회를 통과해야 한다는 조건이 제시되었는데, 바둑진흥법 시행령 제2조에서 규정하는 바둑 실력 검증대회는 "바둑의 보급, 교육, 국제교류 관련 업무를 수행하는 비영리법인으로

9) 「국민체육진흥법시행령」 제9조[별표1]에 따른 체육지도사(1.전문스포츠지도사, 2.생활스포츠지도사, 3.장애인스포츠지도사, 4.유소년스포츠지도사, 5.노인스포츠지도사)의 자격 종목 어디에도 바둑은 없다.

10) 「바둑진흥법」은 '바둑지도자', 대한바둑협회는 '바둑지도사'로 규정하여 명칭에서 차이가 있다.

11) 대한바둑협회, 바둑지도사 규정(2020) 제6조

12) 대한바둑협회, 바둑지도사 규정(2020) 제9조

13) 「바둑진흥법」 제2조 2

서 문화체육관광부장관이 정하여 고시하는 비영리법인이 바둑전문기사를 선발하기 위하여 주최하는 대회”라고 규정하고 있다.[14)]

이러한 정의는 한국기원이 선발하는 프로기사와의 관계를 명확하게 설명하고 있지 않은 문제가 있으며, 혼란을 없애기 위해서는 프로와 아마에 대한 추가적인 정의나 바둑전문기사에 대한 보다 구체적인 정보가 필요하다. 또한 바둑전문기사의 육성·지원 대상이 모호하다는 문제도 있다.

바둑지도자와 바둑전문기사 자격과 관련하여, 바둑진흥법에 규정을 명문화하였다는 것은 국가가 해당 자격을 인정하고 지원하는 제도를 만들었다는 것을 의미한다. 따라서 민간자격증을 공인된 국가자격증으로 제도화하였다고 할 수 있다. 이러한 자격제도는 헌법 제15조에서 규정하고 있는 직업선택의 자유를 제한하는 것이다. 즉 개인은 국가의 간섭을 받지 않고 자신이 원하는 직업을 선택하고 변경할 수 있는 것이 원칙이나, 바둑지도자와 바둑 전문기사같이 일정한 자격을 보유한 자 이외에는 권리행사를 할 수 없는 것을 의미한다. 이와 같은 자격제도는 헌법상 보장된 직업선택의 자유나 수행의 자유를 국회가 제정한 법률로 금지해 놓은 다음 일정한 자격을 갖춘 자에게만 직업의 자유를 회복시켜 주는 것이므로, 바둑진흥법에 자격을 취득하는 근거와 결격사유, 자격 취소사유, 징계사유 등 세부적인 사항이 명문의 규정으로 규율하여야 할 것인데[15)] 그러한 내용은 하나도 규정되어 있지 않아 법적 기준이 명확하지 않은 문제가 있다.[16)]

이러한 문제점을 해결하기 위해서는 자격검정 기관과 연수기관을 설립하고, 그들의 관리 및 평가 방법에 관한 사항을 정하며, 자격요건과 결격사

14) 해당 비영리법인이 국제 바둑 경기활동실적 등을 고려하여 바둑전문기사와 같은 수준의 바둑 실력을 갖추었다고 인정하여 바둑전문기사를 선발하는 방식을 포함한다.

15) 김용섭, “국가적 차원의 바둑진흥법의 입법적 방안”, 스포츠와 법 제20권 제1호, 2007, 36면.

16) 전통무예진흥법 시행령 제4조는 전통무예지도자의 자격검정은 규정하였는데, 전통무예의 종목 기준이 존재하지 않아 무예계에 혼란과 논쟁만 가열시킨 사례가 있다.

유, 취소사유, 징계사유 등에 대한 명확한 기준을 마련해야 한다. 구체적인 규정의 마련과 추가적인 법 개정을 통해 바둑의 발전과 진흥을 위한 목적을 달성할 수 있을 것이다.

(3) “바둑단체란 바둑의 발전·교육·국제교류 등을 주된 목적으로 설립된 국제기구·법인 또는 단체를 말한다.”[17] 바둑계에는 한국기원과 대한바둑협회와 같은 여러 바둑단체가 존재하며, 이들 간에는 업무 분담과 관련된 분쟁이 발생하기도 한다.

대한바둑협회는 한국기원과 한국의 바둑계가 바둑을 스포츠의 하나로 편입시킴으로써 여러 가지 법률적, 제도적, 행정적, 재정적 지원을 받고자 2005년 설립한 단체인데,[18] 한국기원은 주로 프로와 관련된 업무를, 대한바둑협회는 주로 아마추어 관련 업무를 맡았다. 그러나 2018년과 2019년 두 단체 간의 대립이 심화하면서 한국기원은 중단하였던 아마 단·급증을 발급하기 시작하였고, 어린이 바둑대회를 비롯하여 아마추어 바둑대회의 주최와 주관까지도 조금씩 재개하는 중이다.[19] 이러한 상황에서 바둑 진흥을 위한 기본계획을 수립하고 시행하기 위해서는 바둑단체에 대한 명확한 정의와 선정 절차, 지원 방안 등을 구체적으로 규정하는 것이 필요하다.

태권도에는 국기원이 임명하는 ‘대사부’와 태권도진흥법상 ‘대사범’이 존재한다. 태권도진흥법 제21조의2에 규정된 대사범의 경우, “국기원 승단심사를 거친 9단 태권도 단증을 보유한 사람 중에서, 국내외 태권도 보급에 기여하고 그 밖에 윤리성 등 대통령령으로 정하는 기준[20]에 부합한 조

신준철, “전통무예진흥법 시행령에 무예계 술렁”, 무카스미디어, 2009. 1. 27.

17) 「바둑진흥법」 제2조 3

18) 남치형, “한국 바둑 국제화에 따른 한국기원과 대한바둑협회의 역할”, 바둑학연구 제5권 제2호, 2008, 36면.

19) 남치형, 앞의 책, 136면.

20) ‘윤리성 등 대통령령으로 정하는 기준’이란 1. 「국민체육진흥법」 제2조 제11호의2에 따른 스포츠비리를 저지르지 않는 등 태권도 분야 종사자로서 직업윤리에 대한 기본 소양을 갖출 것, 2. 봉사활동에 적극적으로 참여하는 등 지역사회에서 모범이 될 것. (「태권도 진흥법 시행령」 제7조의2)

건을 갖추었을 때 태권도 대사범으로 지정될 수 있다"라고 명시하고 있다.[21] 이는 태권도 기술을 보존, 계승하기 위해 중요무형문화재처럼 태권도원로 가운데 중요 기능인을 선발, 우대하자는 취재에서 2020. 12. 4. 법의 개정을 통해 시행하고 있으며, 2021. 4. 29. 문화체육관광부가 태권도대사범의 지정 등에 관한 사무를 수행할 전담 기관을 공모하였으나 당시 국기원장의 취임으로 인한 내부 사정이 바쁘다는 이유 등으로 신청하지 않았고, 이에 문화체육관광부는 2021. 6. 17. 전라북도 무주에 있는 태권도진흥재단으로 지정 공고하였다.[22] 태권도의 총본산이자 태권도 9단 등 유단자에 대한 기록 및 각종 자격이나 경력 증명에 대한 근거 자료를 갖고 있는 국기원이 내부 사정으로 신청하지 않아놓고선 태권도진흥재단으로 지정 공고된 이후 '태권도 대사부'라는 태권도 진흥법과 비슷한 제도를 만들어 위촉하면서 양 단체 간의 영역 다툼의 사례가 있다.

태권도진흥법과 같이 태권도대사범의 제도를 명문화하여 시행하는 과정에서도 위와 같은 단체 간의 불협화음이 있기 마련인데 바둑진흥법은 너무 일반론에 치우쳐져 있어서 그 구체적 실효성이 담보되어 있다고 할 수 없다. 따라서 바둑단체의 선정 절차와 지원 방안 등을 명확히 규정하고, 양 단체의 협력을 촉진하려는 조치도 필요하다. 이를 통해 바둑단체의 역할과 책임이 명확히 정립되고, 바둑의 진흥과 발전을 위한 효과적인 제도가 마련될 수 있을 것이다.

2. 관계 기관과의 협조

기본계획의 수립·시행을 위하여 다른 중앙행정기관, 지방자치단체 또는 공공기관 등의 장에게 협조를 요청할 수 있고, 그 협조 요청받은 자는 특별

21) 서완석, "국기원 선임 4명 대사부 논란…태권도진흥법상 대사범과 차이는?", 노컷스포츠, 2021. 9. 14.

22) 남궁윤석, "국기원 대사부와 태권도진흥재단 대사범", 한국태권도신문, 2021. 9. 23.

한 사정이 없으면 이에 따르도록 하고 있다.[23] 이는 관계 기관과의 협조를 규정한 법 조항의 실질적 효력을 떨어뜨리는 요소일 수 있다. ‘특별한 사정’이라는 표현은 해석의 여지가 많고 관계 기관의 주관적인 판단에 따라 협조의 시기나 그 내용이 달라질 수 있으므로 응답에는 명확한 기준과 절차가 필요하다. 이를 통해 협조 요청과 협조 응답 사이의 일관성과 예측 가능성을 높일 수 있으며, 관계 기관과의 협조가 원활하게 이루어질 수 있을 것이다.

3. 자금 등의 지원정책

바둑 산업은 주로 대기업과 같은 사기업의 후원을 받아 자금을 지원받는 경우가 많았는데 바둑의 진흥을 위해 국가의 예산에서 재정적 지원을 받을 수 있도록 법률적 근거를 마련했다는 점에서 큰 의미가 있다. 다만 한 개의 법 조항으로 국가와 지방자치단체 그리고 문화체육관광부장관의 지원정책을 구체화하기 위한 법적 근거로 삼기에는 매우 포괄적이며 추상적인 규정으로 구성되어 있다.

바둑진흥법의 법 조항 대부분이 ‘행정청은 … 할 수 있다’라고 규정하여 행정 결정에 있어 행정청에 선택의 자유가 인정되는 행정행위, 즉 재량행위에 속한다.[24] 해당 법규가 일정한 요건을 갖춘 자에게 반드시 일정한 보조금을 지급하도록 규정한 경우라면 청구권이 발생한다고 할 것이지만 그렇지 아니하고 재량사항으로 예산의 범위 내에서 보조금을 지급할 수 있게 되어 있는 경우에는 법적 청구권이 인정되지 않으며, 어떠한 종류의 보조금을 누구에게, 어느 정도를 어느 정도의 기간 지급할 것인가는 행정청의 행위 선택의 자유에 속한다.[25] 또한 ‘필요하다고 인정하는 경우’라는 단서는 그 필요성의 판단기준이 없다는 한계를 갖고 있어 지원 주체가 필요

23) 「바둑진흥법」 제6조
24) 박균성, 「행정법 기본강의」, 박영사, 2016, 157면.
25) 김용섭, “스포츠 보조금의 법적 문제”, 스포츠와 법 제2권, 2001, 232-233면.

하지 않다고 판단할 때 수혜자는 지원을 요청하는 급부청구권 행사가 어렵다. 즉 바둑진흥법이 행정행위의 요건 및 법적 결과(효과)가 일의적으로 명확하게 규정되어 있어서 법을 집행하면서 행정청에 어떠한 선택의 자유도 인정되지 않고 법을 기계적으로 적용하는 기속행위에 속하여야 할 것인데, 국가와 지방자치단체 그리고 문화체육관광부장관이 노력 의무를 성실히 이행하지 않을 때 그러한 부작위에 대한 청구권을 인정하는 법적의무를 부과하는 조항으로 해석하는 것은 무리가 있어 보인다.[26]

또한 국민체육진흥법 제18조에서 국가가 회계연도마다 예산 범위에서 지방자치단체와 학교 등에 대하여 경비의 일부를 보조하고, 국가 및 지방자치단체는 대한체육회, 지방체육회, 대한장애인체육회 기타 그 밖의 체육단체에 대하여 필요한 경비나 연구비를 일부 보조하도록 하고 있으며, 동 법률 제19조에서는 국민체육진흥기금을 설치하고, 제22조의 사업이나 지원 등을 위하여 운영하도록 하고 있다. 이와 같은 스포츠 단체에 대한 지원금과 바둑진흥법에 따른 재정적 지원 사이에는 중복 지원의 문제도 발생할 수 있다.

따라서 법률을 통한 지원은 한정된 자원으로 운영되며, 예산의 배분 및 지원 대상자의 선정, 그리고 지원금의 효율적인 사용의 문제가 발생할 수 있으므로 지원 대상자의 선정 기준과 절차 등의 항목을 명확하게 정의하는 법조문의 개정이 필요하다.

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26)「바둑진흥법」 제8조 바둑단체의 지원 및 바둑전용경기장의 조성과 관련하여, 한국기원은 2015. 9. 2. 경기 화성시와 본원 이전과 관련 전략적 제휴 협약(MOU)을 체결하고 동탄2지구 여울공원 내 3,500㎡ 부지 내 세계바둑스포츠콤플렉스(2021년 2월 개장 목표) 건립 등을 진행하였다. 그런데 협의 애초에는 없었던 화성시의 경기장 사용료 요구와 단독 사용 불가라는 내용을 제기함에 따라 양측이 이견을 보이면서 한국기원의 화성시 본원 이전은 수포가 되었다. 이후 2020. 9. 3. 한국기원과 경기 의정부시는 ‘한국기원 이전 및 바둑 전용 경기장 건립 협약’을 체결하여 본원 이전을 재추진 중이다. 그러나 2022.5. 착공, 2023. 12. 준공할 계획이었으나 아직 착공하지 않은 상황이다.

4. 바둑전문기사의 육성·지원정책

바둑진흥법 제5조 제2항 제6호에서 “문화체육관광부장관은 바둑의 체계적인 보존 및 진흥을 위하여 바둑전문기사의 육성·지원에 관한 사항을 수립·시행하여야 한다.”라고 규정하고, 2021. 12. 발표된 바둑 진흥 기본계획에는 “바둑 영재발굴 체계 구축과 세계적인 스타 선수를 발굴·육성하고 기량 유지 및 향상을 위한 체계적인 훈련을 지원하여 국제경쟁력을 확보”해야 한다는 프로바둑 활성화 내용이 포함되어 있다. 이러한 규정과 계획들은 자칫 잘못하면 바둑진흥법이 달성하고자 하는 국민의 여가선용 기회 확대와 건강한 정신 함양의 목표보다는 엘리트 체육인을 양성하여 국가적 위상을 높이는 것에 우선시 되는 스포츠정책이 될 수 있다.

1962. 9. 17. 제정된 국민체육진흥법은 한국에서 학교체육, 생활체육, 그리고 전문체육 등의 기능을 조율하고 그 역할을 대표하는 스포츠에 관한 기본법적 성격의 법이라 할 수 있다.[27] “국민체육을 진흥하여 국민의 체력을 증진하고, 체육활동으로 연대감을 높이며, 공정한 스포츠 정신으로 체육인 인권을 보호하고, 국민의 행복과 자긍심을 높여 건강한 공동체의 실현에 이바지함”을 목적으로 한다.[28] 이 규정의 경우 1982. 12. 31. 전면개정을 통해 ‘국위 선양’이 추가되었다가,[29] 2020. 8. 18. 일부개정을 통해 ‘공동체의 실현’에 이바지한다고 제·개정하였다.

최철호의 국민체육진흥법의 문제점과 개선방안 연구에 따르면, 국민체육진흥법은 제11조 제1항에서 “국가는 국민체육 진흥을 위한 체육지도자의 양성과 자질 향상을 위하여 필요한 시책을 마련하여야 하고”, 제14조[30]

27) 손석정·신현규, “국민체육진흥법 제정 의도와 배경에 관한 연구”, 스포츠와 법 제11권 제3호, 2008, 136면.

28) 「국민체육진흥법」 제1조

29) 1982. 12. 31. 개정된 「국민체육진흥법」의 목적은 “국민체육을 진흥하여 국민의 체력을 증진하고, 건전한 정신을 함양하여 명랑한 국민 생활을 영위하게 하며, 나아가 체육을 통하여 국위 선양에 이바지함”

30) 「국민체육진흥법」 제14조 제4항도 엘리트 체육을 진흥하는 조항이었으나 2021. 8. 10. 일부개정을 통해 삭제됨 “국가는 올림픽대회, 장애인 올림픽대

에서 선수 등의 육성에 관한 제목하에 “국가와 지방자치단체는 선수와 체육지도자에 대하여 필요한 육성을 하여야 하고(제1항)”, “국가와 지방자치단체는 우수 선수와 체육지도자 육성을 위하여 필요한 표창 제도를 마련하여야 하며(제2항)”, “국가 등은 우수 선수에게 아마추어 경기 생활을 할 수 있게 하기 위하여 문화체육관광부장관이 요청하면 우수 선수와 체육지도자를 고용하도록 하고(제3항)”, 제15조에서 “국가는 스포츠 활동에서 약물 등으로부터 선수를 보호하고 공정한 경쟁을 통한 스포츠 정신을 높이기 위하여 도핑 방지를 위한 시책을 수립하여야 하고”, 제17조에서 체육 용구의 생산 장려 등에 관하여 규정하고 있는데, 이러한 규정들은 엘리트 체육진흥을 위해 규정되어 있는 대표조항이라 한다.[31] 이에 비해서 학교체육의 진흥에 관한 조항 1개[32], 직장 체육의 진흥에 관한 조항 1개[33], 노인 체육의 진흥에 관한 조항 1개[34], 그리고 여가 체육에 관하여도 1개 조항[35]에 그쳐 엘리트 체육을 육성하는 법 조항이 더 많은 것을 알 수 있다.

바둑진흥법은 제5조 제2항 제6호에 “바둑전문기사의 육성 및 지원”을 명시하고 있으며, 이는 위에서 살펴본 국민체육진흥법의 엘리트 체육진흥 관련 법 조항보다 적게 규정되어 있다. 그러나 2021. 12. 발표된 바둑 진흥 기본계획안의 세부 내용을 살펴보면, ‘지역연고제의 도입’, ‘바둑 영재와 스타 선수의 발굴 및 육성’, ‘바둑전용경기장 건설’ 등과 같은 프로바둑 활성화 방안이 추진 계획으로 제시되고 있다. 또한, 법에서 명시하고 있는 국민체육진흥법과는 달리 바둑진흥법은 학교·직장·여가·노인 체육을 진흥하기 위한 구체적인 법 조항을 명시하고 있지 않다. 다만, 바둑전문기사의 육성·지원과 같이 기본계획 수립·시행을 규정한 항목의 하나로 바둑의 교육·

회, 그 밖에 대통령령으로 정하는 대회에서 입상한 선수 또는 그 선수를 지도한 자와 체육진흥에 뚜렷한 공이 있는 원로 체육인에게 대통령령으로 정하는 바에 따라 장려금이나 생활 보조금을 지급하여야 한다.”

31) 최철호, 앞의 논문, 2009, 45면.

32) 「국민체육진흥법」 제9조

33) 「국민체육진흥법」 제10조

34) 「국민체육진흥법」 제10조의2

35) 「국민체육진흥법」 제16조

보급에 관한 사항을 규정[36]하고 있다. 기본계획안의 내용을 살펴보면, 바둑 보급 수단으로서 '유년기, 청소년기, 성년기, 노년기 등 세대별로 차별화된 맞춤형 바둑교육콘텐츠 개발'과 '바둑의 정규교육 과정'을 추진하고, 바둑 여가 활동 확대 방안으로 생활체육 기반 강화를 위한 '스포츠클럽', '지역스포츠클럽 리그', '학교스포츠클럽' 활성화를 추진하고, 사회 취약계층 대안 여가로서의 바둑 활용방안으로 '소외계층 대상 여가 활동 지원 확대'와 '장애인 교육·치료·여가 목적의 바둑을 향유' 할 수 있도록 바둑 교육·보급에 관한 사항을 구체화하여 발표하였다. 이처럼 바둑에 관한 지원은 특정단체 혹은 특수관계자보다는 근본적으로 바둑을 진흥하고, 바둑의 산업화 기반 조성을 위한 방식으로 지원되는 것이 바람직하다.[37]

IV. 결론

국민의 여가선용 기회 확대, 건강한 정신함양, 그리고 바둑의 세계화에 이바지하는 것을 목적으로 제정된 바둑진흥법은 바둑의 진흥과 바둑 문화 조성에 대한 지원정책을 법률적으로 뒷받침하고 그 법적 근거를 마련하였다는 점은 의미가 크다.

그러나 법이 효력을 갖기 위해서는 현실 사회에서 실현되어야 한다. 법이 실현되지 않더라도 법규범의 의미를 상실하지는 않지만, 법의 효력이 없다면 그 법은 존재 가치가 없는 것으로 여겨질 수 있기 때문이다. 따라서 이 연구는 바둑진흥법이 입법 목적에 따라 활용될 수 있는 실효성을 고찰하는 데 목적이 있다. 바둑의 진흥 및 바둑문화 조성에 대한 지원정책을 규정하고 있는 바둑진흥법의 내용을 중심으로 그 특징 및 한계를 검토한 결과는 다음과 같다.

첫째, 법에서 사용하는 '바둑지도자', '바둑전문기사', '바둑단체' 라는

36) 「바둑진흥법」 제5조 제2항 제5호
37) 김용섭, 앞의 논문, 35면.

용어의 정의에 관한 규정이 명확하지 않은 문제가 있다. 바둑관련 자격 및 단체에 대한 법적 근거를 확립해야 하며, 그에 따른 자격 조건, 결격사유, 자격취소, 징계 기준 등을 구체적으로 규정하는 것이 필요하다. 또한 바둑 단체 간의 협력을 촉진하고 역할을 명확히 정립하기 위한 제도나 기구를 마련하는 것도 하나의 방안이 될 것으로 보인다.

둘째, 관계 기관과의 협조를 규정하는데 '특별한 사정'이라는 표현은 협조에 대한 일관성 없는 판단을 초래할 수 있고 해석의 여지가 많다는 문제가 있다. 따라서 이를 해석하는 명확한 기준과 절차가 필요하다.

셋째, 자금 등의 지원정책을 규정한 바둑진흥법의 법 조항은 국가의 예산에서 재정적인 지원을 받을 수 있도록 법률적인 근거를 마련했다는 점에서 의미가 있다. 그러나 한 개의 법 조항으로 국가 등의 지원정책을 구체화하기 위한 법적 근거로 삼기에는 매우 포괄적이고 추상적인 규정으로 구성되어 있으며, 많은 법 조항이 행정청의 재량권을 인정하고 있고 이에 따라 부작위에 대한 급부청구권을 인정받을 수 없는 한계가 있다. 또한 국민체육진흥법에서 정한 스포츠 단체에 대한 지원금과 바둑진흥법에 따른 재정적 지원 사이에는 중복 지원의 문제도 발생할 수 있다.

마지막으로 바둑전문기사 육성 및 지원에 초점을 두는 대신, 바둑의 대중화 및 여가 측면을 강화하고 지역사회에서의 바둑 활동을 지원하는 균형 잡힌 스포츠정책을 채택해야 한다. 이러한 방향성이야말로 국민의 여가 확대와 건강한 정신 함양을 위한 목표에 더 부합하는 정책이 될 것이다.

따라서 바둑진흥법의 실효성을 높이기 위해서는 법조문을 구체화하고 명확한 기준과 절차를 마련하는 법제적 정비가 필요하다 할 것이다. 이러한 개선을 통해 바둑 진흥에 대한 효과적인 지원과 발전을 촉진할 수 있으리라 생각한다.

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온라인 바둑 레이팅 점수 차가 승률과 대국 수에 미치는 영향
The Effect of Online Go Rating Point Difference on Winning Rate and the Number of Matches

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Abstract: The purpose of this study is to contribute to the creation of a more equal environment for playing online Go. For this purpose, the results of the online Go server C company's 7 dan matches and 7 dan and 6 dan matches were used. The matches were divided into sections by rating score difference between the two players and the winning rate and the number of matches were analyzed. The results of analyzing 7 dan's 269,898 matches and 7 dan and 6 dan's 107,649 matches are as follows.

First, the winning rate on the side with the higher score (H ratio) increased by 10% for every 300 points in the 7 dan matches. As for the number of matches, 70% of the matches were distributed within the first 15 sections (point difference ranged 300), which is within H ratio of 50%, and

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about 90% of the matches were played within 25 sections (point difference ranged 500), which is within H ratio of 60%. In the 7 dan matches, when the difference was more than 300 points, the even game with 6.5 point komi seemed unequal.

Second, in the matches between 7 dan and 6 dan, overall, 10% increase in the H ratio was shown for every 450 points, and one-stone handicap seemed unequal from about 900 points difference. Looking at the distribution of the number of matches, about 80% of the matches were played between the 20th section (point difference ranged 400) and the 71st section (point difference ranged 1420), that is, the H ratio ranged from 50% to 60%.

Third, as a countermeasure against this inconsistency, komi subdivision and constant C value adjustment were proposed.

Keywords: online go, go rating point, online go level, go

I. 연구의 필요성

게임이나 스포츠에서 해당 종목을 얼마나 잘 수행하는가는 그 게임 활동에 매우 중요한 영향을 미친다. 게임의 흥미 요소 중 하나로서 자신의 게임 수행 수준을 향상시키는 것은 매우 중요하다(최일호, 2003). 신병식(2001)의 연구를 보면 이러한 현상은 바둑에서도 예외가 아니다. 인터넷 바둑 이용자들을 대상으로 한 설문조사에서 바둑을 두는 목적에 대해 32.3%가 바둑이 늘기 위해라고 응답하여 가장 많았고 그 뒤를 이어 20.1%가 승부를 즐기기 위해라고 답했다.

사람은 자신이 잘하는 것에 더욱 흥미를 느끼고 관심을 갖기 마련으로(최일호, 2003) 보통 게임을 할 때 실력 차이가 나면 게임의 흥미가 떨어지는 것이 일반적이다(김진환, 2002). 특히 바둑처럼 실력의 차이가 승리 요소의 대부분을 차지하는 종목에서는 더욱 그렇다. 이런 맥락에서 대국을 할 때 치석(Handicap)을 이용하는 것은 다른 게임에 비해 바둑이 갖는 커다란 장점 중의 하나이다. 바둑은 대국자 사이에 실력의 차이가 나더라도 치석을 활용하여 두 대국자 간의 전력을 비슷하게 만들 수 있기 때문에 흥미가 극대화되는 경향이 있다(김진환, 2002). 이러한 조정 매개가 없다면 실력이 낮은 대국자는 일방적인 승부에 흥미를 잃을 가능성이 있고 이는 실력이 높은 상대와의 대국을 피하는 현상으로 이어질 수 있다. 이런 현상은 기력이 많이 차이 나는 대국자 사이에서뿐만 아니라 같은 기력대의 대국자 사이에서 나타나기도 한다.

김기준(2013)의 연구에서 C사의 7단과 7단 간 30,000판의 대국 중 두 대국자의 레이팅 점수 차이가 500점 이하인 대국이 89%를 차지하였다. C사에서 매일 두어지는 대국 수에 비하면 30,000판이 많은 숫자라고는 볼 수 없다. 하지만 이 비율을 보았을 때 같은 기력 내에서 레이팅 점수 차가 크게 나는 두 대국자의 대국 수는 매우 적다는 것을 볼 수 있다. 이는 많은 이용자가 자신보다 레이팅 점수가 크게 높은 상대, 또는 그 반대로 크게

낮은 상대와의 대국을 꺼리는 경향이 있다고 볼 수 있다. 같은 기력 이용자끼리 대국을 한다고 해도 승부가 일방적이면 대국할 때 느끼는 재미가 반감되기 마련이다. 이러한 현상을 개선하기 위해 레이팅 점수와 승률, 그리고 대국 수가 실제로 관계가 있는지 확인할 필요가 있다.

이 연구는 레이팅 점수 차이에 따라 점수가 높은 쪽, 낮은 쪽의 승률 분포와 이에 따른 대국 수 분포를 살펴본다. 여기서 나온 결과를 바탕으로 이용자들의 점수 구간별 승률과 대국 수, 그리고 실제 기력 사이에 유의미한 차이가 있는지 확인하고, 그에 따라 더욱 대등하게 승부를 겨루는 방법을 제안하여 더욱 흥미로운 대국이 가능한 환경조성에 이바지하는 것을 목적으로 한다.

II. 연구문제

이 연구는 인터넷 바둑 사이트 C사 이용자의 레이팅 점수 차이에 따라 나타나는 승률 변화와 점수 차 구간 및 승률 대별 대국 수를 분석하여 현황을 분석하고 대국 환경을 좀 더 발전시킬 수 있는 방법 제안을 목적으로 한다. 이 목적을 달성하기 위한 연구문제는 다음과 같다.

1. 현황분석

C사의 7단끼리 대국했을 때 레이팅 점수 차 구간별 승률은 어떠한가?
C사의 7단끼리 대국에서 점수 차 구간 및 승률 대별 대국 수는 어떠한가?
C사의 7단과 6단이 대국했을 때 레이팅 점수 차 구간별 승률은 어떠한가?
C사의 7단과 6단의 대국에서 점수 차 구간 및 승률 대별 대국 수는 어떠한가?

2. 관계분석

레이팅 점수 차에 따라 승률에 변화가 있는가?
점수 차 구간에 따라 대국 수에 변화가 있는가?
승률에 따라 대국 수에 변화가 있는가?

III. 연구방법

1. 연구대상

이 연구의 대상은 C사의 7단 간 호선 대국, 7단과 6단 간 정선 대국 결과 자료이다. C사의 6, 7, 8단은 일정한 승률 이상을 유지해야만 승단할 수 있도록 강화된 기준을 적용한다. 고수로 올라갈수록 레이팅을 어렵게 하여 최고단은 명예와 희소성을 가질 수 있도록 고안된 기준이다. C사의 6~8단은 유지 또는 승단이 어렵고 이 범위의 기력을 유지하려면 실제로 실력이 뒷받침되어야 하므로 그만큼 기력이 안정적이라고 볼 수 있다. 기력이 안정적이고 기복이 심하지 않아야 실제 실력에서 나오는 결과를 얻을 확률이 높다. 8단의 경우 레이팅 점수의 상한선이 없어 범위를 정하는 데에 어려움이 있으므로 대상에서 제외하였다.

이 연구에서는 목적을 달성하기 위해 인터넷 바둑 사이트 C사로부터 7단 간 호선 대국 355,248국의 결과 자료와 7단과 6단 간 정선 대국 141,889국의 결과 자료를 제공받아 연구를 진행하였다. 이중 대국 내용과 관계없이 승부가 결정되어 승률을 왜곡할 가능성이 있는 시간승, 무승부, 수순 100수 이하의 자료는 제외하고 남은 7단 간 대국 269,898국, 7단과 6단 간 대국 107,649국을 분석하였다.

2. 분석방법

1) 레이팅 점수 구간 설정

C사의 기력별 레이팅 점수 범위는 1,000점 간격으로 기력을 구분하고 있다. 7단의 레이팅 점수 구간은 32,000점-32,999점이며 6단의 레이팅 점수 구간은 31,000점-31,999점이다. 레이팅 점수 차이에 따라 나타나는 승률의 차이를 정밀하게 파악하기 위해 7단인 두 대국자의 레이팅 점수 차이를 20점 간격, 총 50구간으로 나누어 승률을 분석하였다. 점수를 더 세분화하여 나누는 것은 크게 유의미하지 않다고 판단하여 각 구간을 20점 간격으로 설정하였다. 구간의 크기는 1구간이 0-19점 차, 2구간은 20-39점 차, 3구간은 40-59점 차로 정한다. 레이팅 점수가 같은 두 대국자가 둘 경우 두 대국자의 최소 점수 차이는 0이므로 0부터 19까지 20점을 한 구간으로 정한다. 예를 들어 32,500점의 이용자가 32,519점의 이용자와 대국하면 그 대국의 결과는 1구간에 포함된다. 32,500점의 이용자가 32,520점의 이용자와 대국하면 그 결과는 2구간에 포함된다. 1구간 범위인 0-19를 초과했기 때문이다.

승률의 기준은 레이팅 점수가 높은 대국자를 기준으로 한다(이하 'H비율'로 표기한다). 7단 대국은 모두 호선이므로 흑, 백 관계없이 레이팅 점수만을 기준으로 한다.

7단과 6단 간의 레이팅 점수 구간은 1부터 시작하여 20까지 20점을 한 구간으로 정하여 총 100구간으로 나눈다. 7단 간 대국과 구간 설정 점수가 다른 이유는 6단의 레이팅 점수 범위는 31,000-31,999점, 7단의 범위는 32,000-32,999점으로 6단과 7단이 대국할 경우 두 대국자의 레이팅 점수가 반드시 1점 이상 차이 나기 때문이다. 1구간은 1-20점 차, 2구간은 21-40점 차, 3구간은 41-60점 차 등의 순서이다. 예를 들어, 31,995점의 6단과 32,015점의 7단이 대국했다면 이 대국 결과는 1구간으로 포함된다.

레이팅 점수 차가 20점 이하이기 때문이다. 7단 대국자의 레이팅 점수가 32,016점이면 차이는 21점이 되고 1구간 범위인 1-20점 차를 초과하므로 2구간으로 분류된다.

2) 연구절차

이 연구의 절차는 다음과 같다.

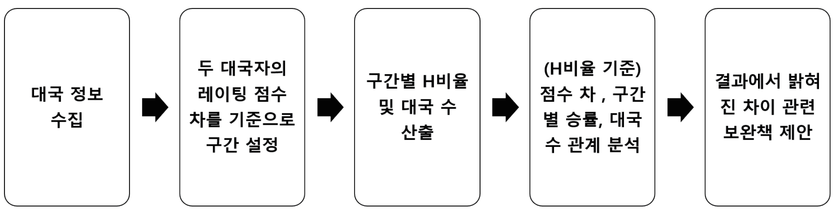

그림 1 연구절차도

먼저 분석 대상인 7단 간, 7단과 6단 간 대국 결과 자료를 수집한다. 모든 대국 결과를 두 대국자의 레이팅 점수 차이에 따라 구간별로 나누고 각 구간의 H비율과 대국 수, 전체 대국 수에서 차지하는 비율을 산출한다. 이렇게 나온 결과에서 구간별 승률 변화와 누적 대국 수를 살펴보고 레이팅 점수 차이와 어떤 관계가 있는지 분석한다. 분석한 결과를 바탕으로 이용자들이 지금보다 더 대등한 승부를 겨룰 수 있는 방법을 제안한다.

IV. 연구결과

7단 간 호선 대국과 7단과 6단 간 대국을 점수 차 20점 간격대로 분석하여 나온 결과는 다음과 같다.

1. 7단 간 호선 대국

모비율의 검정으로 계산한 H비율 임계치는 50.2%다. 1구간부터 3구간까지는 50%를 유지하다가 4구간부터 H비율이 51%대로 진입한 후에는 계속해서 높아지는 추세를 보였다. 15구간부터는 H비율 60% 이상을 유지하였으며 29구간부터는 70% 이상을 유지하였다. 레이팅 점수 차가 커짐에 따라 H비율이 연속적으로 높아지는 것을 확인할 수 있다. 레이팅 점수에 따른 승률 차이가 확연하다.

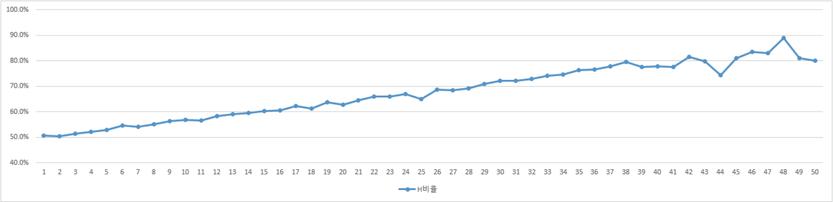

그림 2 구간별 7단 간 호선 대국 H비율 분포

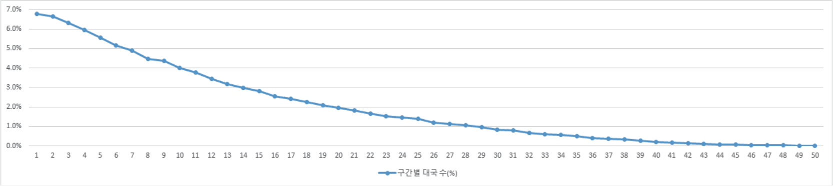

그림 3 구간별 7단 간 호선 대국 수 분포 (%)

구간별 대국 수를 보면 구간이 커질수록 꾸준히 대국 수가 줄어드는 것을 볼 수 있다. H비율이 60%가 넘어가는 구간인 15구간까지의 누적 대국 수는 전체의 70%이고 1구간부터 25구간까지 누적 대국 수는 전체의 89.4%를 차지한다. 약 90%의 대국이 레이팅 점수 500점 차 내에서 두어

지는 것을 확인할 수 있다. 이 구간은 H비율이 50%~60%대 구간이기도 하다.

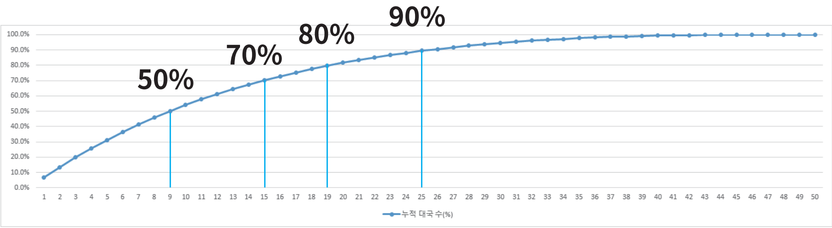

그림 4 구간별 7단 간 호선 누적 대국 수 분포 (%)

2. 7단과 6단 간 정선 대국

모비율의 검정으로 계산한 H비율 임계치는 50.3%다. 1구간부터 6구간까지 H비율은 30%를 밑돌다가 20구간에서 처음으로 50%를 넘겼다. 이는 6단과 7단 대국에서 400점 차 언저리까지는 정선 치수가 6단에게 조금이라도 유리하다는 것을 나타낸다. 24구간부터는 H비율이 50% 아래로 떨어지는 구간이 거의 없이 계속 증가하다가 44구간에서 60%를 돌파했고 52구간부터는 꾸준히 60%를 웃돌며 연속적으로 높아졌다. 72구간에서는 H비율이 70%를 넘겼고 계속해서 증가하는 추세를 보였다. 7단 간 호선 대국과 마찬가지로 H비율이 연속적으로 높아지는 추세를 보였고, 이 역시 레이팅 점수에 따른 확연한 승률 차이를 보였다.

대국 수 그래프를 보면 H비율이 처음으로 50%를 넘긴 20구간부터 70% 돌파 직전인 71구간까지의 누적 대국 수는 79.7%였다. 7단과 6단의 정선 대국 역시 H비율 50%~60%대에 대부분의 대국이 몰려있는 현상을 확인할 수 있다.

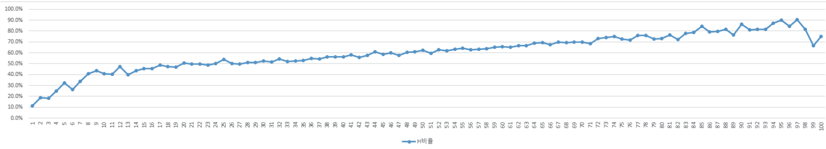

그림 5 구간별 7단과 6단 간 정선 대국 H비율 분포

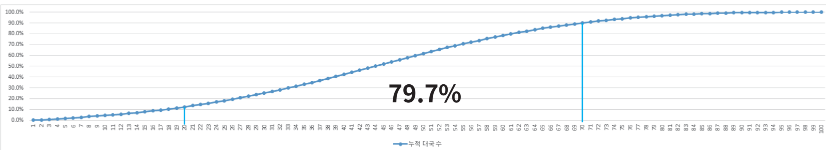

그림 6 구간별 7단과 6단 간 정선 누적 대국 수 분포 (%)

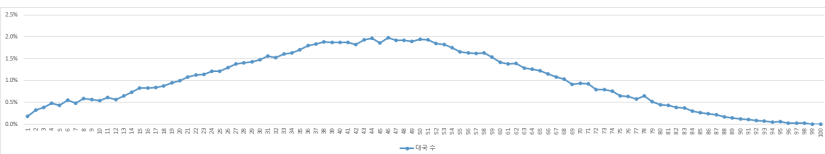

그림 7 구간별 7단과 6단 간 정선 대국 수 분포 (%)

V. 논의

1. 구간별 승률 변화

이 연구에서는 C사의 7단 간 호선 대국, 7단과 6단 간 정선 대국 결과를 레이팅 점수 차를 기준으로 구간별로 나누어 그에 대한 승률을 산출해 보았다. 그 결과 7단 간 호선 대국에서는 레이팅 점수가 높은 대국자가 이

기는 비율이 연속적으로 증가하는 추세를 보였다. 이는 레이팅 점수가 기력의 차이를 잘 반영한다고 볼 수 있다. 하지만 15구간부터 연속적인 60% 이상의 승률 차이, 29구간부터 70% 이상의 승률 차이로 대략 300점대마다 견고한 10% 승률 상승 현상이 나타났다. 이렇게 안정적이고 지속적인 차이는 호선 승부로 간주하기엔 다소 어려울 수도 있겠다.

7단과 6단 간 정선 대국에서는 7단이 20구간, 즉 400점 차이 구간이 되어서야 처음으로 승률 50%를 달성하였고 24구간부터 꾸준한 50%이상 승률을 유지하였다. 이는 레이팅 점수 400점 차 내에서는 정선 치수가 6단에게 유리하다고 볼 수 있다. 17구간부터 31구간까지는 H비율이 47%~52% 사이에서 요동치는 모습을 보이며 평균 승률도 50.2%로 임계치 50.3%와 거의 유사한 수치를 나타냈다. 이러한 수치를 보았을 때 이 구간이 7단과 6단의 정선 치수에 가장 적당한 구간이라고 할 수 있겠다. 구간별 승률을 점수대로 살펴보면 50%에 도달한 것이 400점 구간이었고, 50% 안팎을 유지하여 정선 치수에 적당하다고 생각되는 구간이 17구간부터 31구간, 즉 340점부터 620점 구간이다. 48구간(960점)에서 60%, 72구간(1420점)에서 70% 이상의 연속적인 승률 상승세가 이어지는 것을 볼 때 7단과 6단 간 대국에서는 대략 450점마다 승률에 현저한 차이가 나타나는 것으로 보인다.

2. 구간별 대국 수 변화

7단 간 대국 수를 살펴보면 H비율이 50%와 멀어지면서 대국 수가 줄어드는 추세다. 레이팅 점수 500점 차 내에 약 90%의 대국이 분포하는데 이 구간은 H비율이 50%~60%대 구간이다. 이 중에서도 15구간까지의 누적 대국 수가 70%인데 이 구간은 H비율이 60%에 처음으로 도달한 구간이기도 하다. 이를 보면 많은 이용자는 50%대 승률로 승부를 겨룰 수 있는 대국자와의 대국을 선호하는 경향이 있다고 볼 수 있다. 같은 7단끼리 대국

이긴 하지만 더 다양한 점수대 이용자끼리 좀 더 대등한 승부를 겨루기 위해서는 어느 정도 조정이 필요할 것으로 생각된다.

7단과 6단간 대국 수를 살펴보면 H비율이 50%에 도달한 20구간부터 70%가 되기 직전인 71구간까지 승률 50%~60%대에 약 80%의 대국이 몰려있다. 7단과 6단의 정선 대국에서도 호각의 승부를 선호하는 경향이 나타난다고 볼 수 있겠다.

승률이 명확하게 차이가 나는 레이팅 점수는 이용자의 실력을 반영해주는 훌륭한 척도가 될 수 있다. 하지만 승률이 확연하게 차이 나는 점수대의 이용자들이 한 기력대에 모여있다면 이는 승부의 재미를 반감시키는 요소도 될 수 있다. 그러므로 이러한 현상에 대해 종합적으로 두 가지 대안을 제안한다.

첫째, 같은 기력 내에서 구간을 나누어 덤을 조정한다. 현재 7단과 6단의 범위는 각 1,000점이고 앞에서 언급했듯이 7단 간은 약 300점, 7단과 6단 간은 약 450점마다 승률 차이가 명확하게 나타난다. 이에 300점, 450점대를 한 구간으로 정하여 1,000점을 총 3구간으로 나누고, 구간마다 덤에서 2집씩을 빼거나 더해주는 방법을 제안한다. 예를 들면 7단 1구간 이용자와 2구간 이용자가 대국할 때 1구간 이용자가 흑이면 4집 반을 공제하고 백이면 8집 반을 받는 방식이다. 1구간 이용자와 3구간 이용자가 대국하면 1구간 이용자 기준으로 흑이면 2집 반, 백이면 10집 반이 된다.

둘째, 한 판 대국에서 조정될 점수에 적용되는 상수 C값을 조정하는 것이다. C값을 올려서 1,000점의 간격을 다소 느슨하게 조정해주는 것이다. 현재는 7단 간은 300점, 7단과 6단 간은 450점마다 H비율이 10%씩 상승하는데, 점수 간격을 느슨하게 하여 승률이 상승하는 구간을 500점 정도로 조정하는 것이다. 한 기력대에서 전체적인 승률 분포가 50%~60%대가 되면 좀 더 다양한 점수 구간대의 이용자들이 서로 더 많이 대국할 것으로 예상된다.

VI. 결론 및 제언

1. 결론

이 연구는 두 대국자의 레이팅 점수 차와 승률, 대국 수의 관계를 분석하여 좀 더 대등한 승부를 겨룰 수 있는 대국 환경조성에 이바지하는 것을 목적으로 한다. 이를 달성하기 위해 C사의 7단 간, 7단과 6단 간 대국 결과를 레이팅 점수 차로 구간을 나누고 구간별 H비율과 대국 수를 산출하였다. 산출한 결과를 분석하여 얻은 결론은 다음과 같다.

첫째, H비율은 7단 간 호선 대국에서 1구간부터 50%를 시작으로 연속적인 상승세를 보였다. 이후 약 300점 구간마다 10% 승률 상승이 나타났다. 대국 수는 7단 간 호선 대국에서 70% 대국이 15구간(300점), H비율 50%대 내에 분포했으며 약 90% 대국이 25구간(500점), H비율 60% 내에 분포했다. 7단 간 대국에서는 300점 차 이상이 되면 호선 치수의 불일치가 나타난다. 약 300점 구간마다 H비율 견고한 10% 상승을 보였다.

둘째, 7단과 6단 간 정선 대국에서는 24구간(480점)부터 H비율이 50% 이상의 연속적인 상승세를 보였다. 17구간부터 31구간까지 승률이 50%안팎을 요동치는 구간이 7단과 6단 간 정선 치수와 일치하는 구간이다. 전체적으로는 약 450점 구간마다 10% 승률 상승이 나타났다. 이는 900점 차 정도가 되면 정선 치수의 불일치가 나타나고 점수 차가 커질수록 불일치 현상이 심화되는 것을 보여준다. 대국 수 분포를 보면 79.7% 대국이 20구간(400점)부터 71구간(1420점) 사이, H비율이 50%~60%대인 구간에서 두어졌다.

종합해 보면 7단 간, 7단과 6단 간 대국 모두 대략 300점, 450점 구간마다 10% H비율 상승이 나타났고 레이팅 점수 차가 적은 구간대, 승률이 50%~60%대에 대국이 몰리는 편중 현상이 나타났다.

이 연구는 이용자들에 의해 축적된 실제 자료인 레이팅 점수와 대국 결과에서 승률, 대국 수를 산출하여 레이팅 점수에 따른 승률과 대국 수 변

화를 분석하였다. 이를 통해 실제 기력 차이를 알아보고 이에 따른 많은 이용자가 점수 차가 적은 상대를 선호하는 경향이 있음을 밝혀냈다는 점에 의의가 있다.

2. 제언

이 연구의 제한점과 후속 연구를 위한 제언은 다음과 같다.

첫째, 이 연구에서는 대상을 C사의 7단 간 호선 대국, 7단과 6단 간 정선 대국으로 한정하였다. 후속 연구에서는 더욱 다양한 기력대를 대상으로 하여 전체 기력에 대한 승률 변화와 실제 현상을 밝혀냄으로써 더욱 정밀한 기력체계 구축 방안을 제시할 수 있겠다.

둘째, 치수 불일치에 대한 대안으로 덤 세분화 방법을 제시하였지만 이 방법이 효과가 있는지를 알아보려면 실제 검증 작업이 필요하다. 이에 대한 후속 연구가 진행되어 효과 검증이 이뤄지기를 기대한다.

셋째, 치수 불일치에 대한 또 다른 대안으로 매 대국에서 조정될 점수에 적용되는 상수 C값 조정을 제시하였는데 이 방법에 대해서도 효과를 알아보기 위해서는 기력 안정성 검증 연구가 진행되어야 하겠다.

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Special Feature Article

· The Game of Go as a Support in the Development of Cognitive Skills

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The Game of Go as Support for Cognitive Skill Development

Michelle Alejandra Wong Sámano
Mexico

Research Project of the “Adopt a Talent Program” (PAUTA), Category Social Sciences at the National Autonomous University of Mexico (UNAM)

Mentors: Dr. Reyes Manuel Pérez Sánchez (Workshop Teacher at PAUTA, translator of the paper)

Siddhartha Ávila Delgado (Go Teacher)

Abstract: Go is a strategy game of oriental origin that has spread to many countries. With an antiquity of more than 2,500 years, its influence has expanded to Mexico, where it is currently practiced by people of all ages, without distinction of gender. Information on the web and studies indicate that practicing Go can influence the strengthening of cognitive skills of the people who play it. Therefore, the interest in this project is focused on studying the influence of the game Go on the development and strengthening of cognitive skills in people who play it in Mexico City and the metropolitan area, based on the evaluation and comparison of two groups: a group of 22 people who play Go and a group of 22 people who do not. The study was carried out in June 2023. Four cognitive skills were chosen for evaluation: reasoning, creativity, mathematical ability, and emotional intelligence. The evaluations consisted of exercises designated by school levels: primary, secondary, and high school and beyond. The data obtained was compiled into a table to create comparative graphs. The interpretation of the results revealed that the group that played Go obtained higher percentages in the evaluation of cognitive abilities, with mathematical ability showing the most significant improvement.

Keywords: Go game (Baduk, Weiqi), cognitive skills, mathematical ability, decision-making, creativity, emotional intelligence

I. Introduction

Go is a strategy game of oriental origin, practiced worldwide. In China it is called Weiqi, in Japan, they call it Go, and in Korea, it is called Baduk. It is more than 2,500 years old and is considered one of the four traditional arts of ancient China, along with calligraphy, painting, and music. In Mexico it is known by the name Go. In eastern countries, Go is part of the curricular plan in schools (Gürbüzel, 2022).

In Mexico, there are schools and places where people teach how to play, practice, and participate in tournaments, mainly in Mexico City. At the National Autonomous University of Mexico (UNAM) Go has been a sports discipline since 2019.

There are scientific studies that indicate that practicing Go can influence the development or strengthening of cognitive skills of people who practice it, such as concentration, reasoning, analysis, problem-solving, creativity, decision-making, numerical ability, and emotional management, among others. It is even mentioned that it could help in the treatment of diseases such as Alzheimer's (Lin, 2015, in Gürbüzel, 2022) or in improving the cognitive functions of students with attention deficit and hyperactivity (Kim, 2014).

Cognitive skills are skills that the brain has to function with the information it receives from the environment (Lifeder, 2022). Among the 10 main cognitive skills mentioned by the author are: perception, attention, comprehension, memory, language, orientation, praxis, executive functions, reasoning, and behavior management. Pradas (2020) adds more skills to the list, including motivation, affective prediction, lateral thinking, and planning, among others.

I was interested in this topic because I want to check if these skills are enriched by practicing Go, because if so, it would be very useful to extend the practice of Go in educational centers and communities to strengthen the development of cognitive skills and, furthermore, as it is a game could be of more interest to practice.

Research question: Will people who play Go have greater development in their cognitive skills than people who have never played Go?

General objective: Check if practicing the oriental game of Go benefits people in strengthening their cognitive skills.

Particular objective: Check if the game of Go helps in strengthening the cognitive skills (mathematical reasoning, decision-making, creativity, and emotional intelligence) of people through a comparison between groups of people who play Go and people who do not play Go. Hypothesis: Playing Go helps strengthen people's cognitive skills, as it is a strategy game that requires putting into practice skills such as reasoning, analysis, decision-making, and creativity, among others.

II. Research Method and Materials

44 people participated, divided into 2 groups of 22 people each. One group practiced Go and the other group did not practice it. The two groups were evaluated on the skills of mathematical reasoning, decision-making, creativity, and emotional intelligence. The evaluations were assigned according to the participant's education (primary, secondary, high school, and above). The exercises were the same for both groups.

Materials: mazes, word search, mathematical calculation exercises, and a "cat" game with a small questionnaire to find out their emotions in the game.

- Exercises for mathematical reasoning: 5 exercises were applied and a score was established to evaluate: correctly answered = 1, poorly answered = 0.
- Decision-making exercise: labyrinth. They were given three minutes to resolve it. 1 point was scored for completing the maze or achieving more than ¾ parts, and 0.5 for achieving less than ¾ parts.
- Exercise for creativity: word search. They were given 3 minutes to find the greatest number of words. Those who managed to find 7 words or more were scored with 1 point, and 0.5 for those who managed to find 6 words or less.
- Exercise for emotional intelligence: They played CAT (5 attempts) and then answered a questionnaire with response options.

III. Data analysis and results

The results were recorded in two tables: IF you play Go and DO NOT play Go. Graphs were made to have percentages of the general comparisons, and the following was found:

Mathematical reasoning: The group that plays Go managed to solve a greater number of the exercises compared to the group that does not play Go, out of a total of 110 points, the group that does play achieved 82.72%, and the group that does not play 67.27% (see Figure 1).

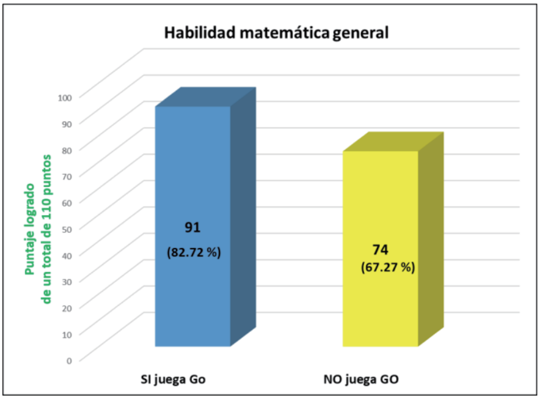

Figure 1. General mathematical ability

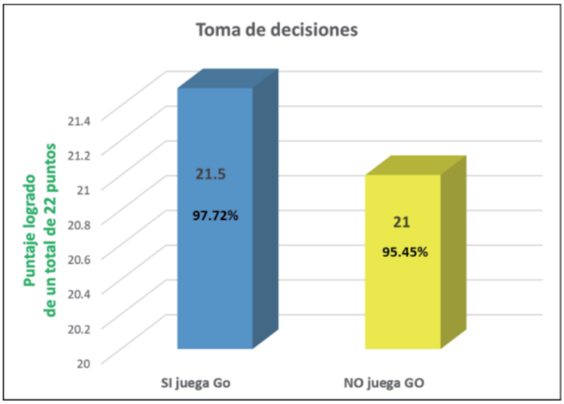

Figure 2. Decision-making

Decision-making (mazes): Of a total of 22 points, the group that plays Go achieved 97.72%, and the group that does not play Go achieved 95.45% (Figure 2).

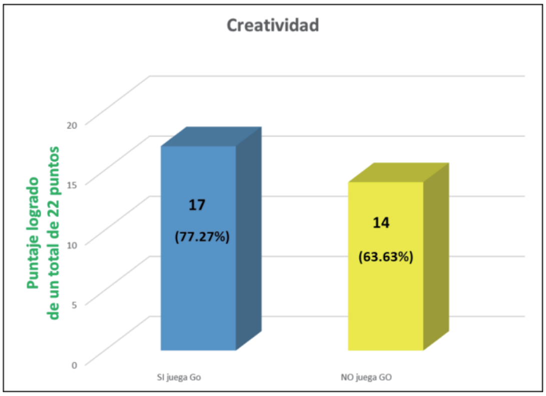

Figure 3. Creativity

Creativity (word search): Of a total of 22 points, the group that does play Go achieved 77.27% and the group that does not play Go 63.63% (Figure 3).

Emotional intelligence: the emotions that were most used to express how they felt when playing cat, winning or losing were the following:

1. The group that plays Go was more descriptive in expressing their emotions by using words such as: excited, satisfied, and calm.
2. The non-Go-playing group was less descriptive: calm.

IV. Conclusion

The skills were greater in the group that plays Go. In mathematical ability, the difference was 15.45% greater compared to the group that does not play Go. In decision-making, the difference was 2.27% greater in the group that plays Go, and in creativity, the difference was 13.64% greater in the group that plays Go. In emotional intelligence, a greater variety of emotions were used to express themselves in the group that plays Go. With the results I found, I can conclude that my hypothesis was fulfilled.

The social impact of my project is that with the practice of Go, we can strengthen the development of the skills necessary in school or in daily life and in the management of our emotions; therefore, in our self-esteem and in the relationship with our environment, and you can learn to play at any age, so its benefits are very broad. The best thing is that Go is a game and that makes it more fun.

In the future, I would like to know how the strengthening of cognitive skills happens now with a group of girls and boys who do not practice Go, first, evaluate them as I did with this project, then teach them to play Go and after a few weeks evaluate them again to know if there were changes that help their cognitive abilities.

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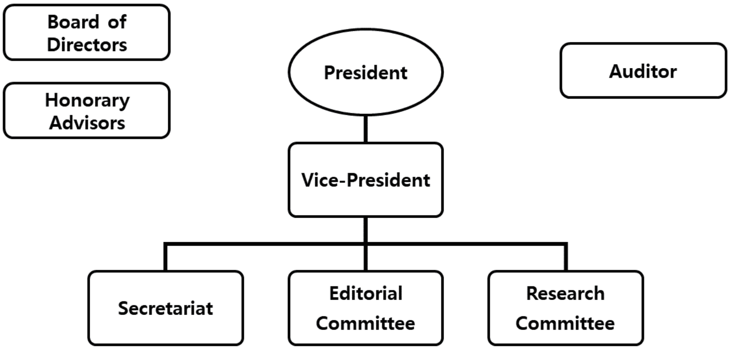
Author Introduction

Michelle Alejandra Wong Sámano is a ten-year-old from Ecatepec, Mexico, currently in the fifth year of primary school. Since 2017, she has been an enthusiastic participant in Siddhartha Avila's library Go workshop, where her dedication led her to secure first place in the intermediate category at the 2023 Baduk Festival.

As a student in the "Adopt a Talent Program" (PAUTA) at the National Autonomous University of Mexico (UNAM) since 2018, Michelle has conducted five research projects, one of which, "The Game of Go as Support for Cognitive Skill Development," is being published in this journal. Her research work has earned her a prestigious award, the 2020 ICN Women's Award. Her Go study spanned one year within the science program, culminating in a presentation at the finalist exhibition, where it was showcased alongside other children's science projects on August 19, 2023 (see Figure 1).

Figure 1: Michelle Alejandra Wong Sámano presenting her Go research project at a Science Fair.

Michelle's diverse talents extend beyond her academic pursuits. Since 2020, she has taken on the role of a children's presenter at the Centro Cultural de España en México, actively participating in children's radio programs where she discusses various topics, including children's rights, pets, Go, interviews, and more. Furthermore, her versatility shines as she provides voice-over work. Since 2021, Michelle has been a trained storyteller for children, and in 2022, she assumed the role of coordinator for a children's reading club. In her leisure time, Michelle enjoys ballet, aerial dance, reading, and drawing. She also values spending quality time with friends, going for walks, and watching TV. While she takes pleasure in playing chess as a casual pastime, her true dedication lies in her pursuit of Go, which represents a serious and deeply studied endeavor in her life.



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1. 논문투고자는 본 학회의 회원에 한한다. 단, 비회원은 공동연구자로 참여할 수 있다.
2. 논문은 본 논문지에 투고하기 전에 공개 출판물에 발표되지 않는다.
3. 투고 규정에 위배되는 원고는 접수하지 않는다.
4. 논문은 연중 수시로 접수하되, 학회지 발행 예정일 2개월 전에 해당호에 게재할 논문을 마감한다.
5. 논문의 심사는 전문가 심사과정(peer review processor)에 따라 진행하며, 본 학회의 심사규정에 따른다.
6. 논문의 채택여부는 본 학회지 편집위원회의 결정에 따르며, 논문의 부분적 수정을 요구할 수 있다.
7. 논문투고자는 1부를 작성, 투고신청서와 함께 사무국장의 공식 이메일로 제출한다.
8. 논문 첫 쪽에 제목, 성명, 소속기관 (모두 영문 포함), 연구분야, e-mail 등을 기입한다.
9. 논문은 영문초록(주제어 포함), 본문, 참고문헌의 순으로 한다.
10. 논문의 영문초록은 500단어 이내로 한다.
11. 논문은 [별첨1] 국제바둑학회지 투고논문 편집지침에 맞추어 제출한다.
12. 논문은 [별첨1] 을 기준으로 A4 20장 내외로 한다.

[별첨1] 국제바둑학회지 투고논문 편집지침

1. 한국어 논문은 한글과컴퓨터사의 한글로 작성하는 것을 원칙으로 한다.

2. 형식 지침

제출하는 논문의 형식은 아래와 같은 형식을 권고한다.

● 제목은 한글 함초록바탕 18, 굵은체, 그 다음 줄에 영문 제목은 Times New Roman 18, 굵은체, 중간 정렬로 한다.
● 저자 이름은 한글 함초롱바탕 12, 그 다음 줄에 영문 이름은 Times New Roman 12, 우측 정렬로 한다.
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3. 논문의 저자가 2인 이상인 경우, 논문 작성에 대한 참여 정도에 따라 책임저자(제1저자), 공동저자(제2저자) 등으로 공동 저자의 순위를 정하고 참여 정도가 동등한 경우 공동저자라고 밝히고 저자들을 ‘가나다’ 또는 ‘ABC’ 순으로 기재한다. 영문인 경우 책임(1st author), 공동(Co-author, 2nd author, 3rd author…) 등으로 명기한다. 모든 논문은 교신저자(Corresponding author) 표기를 해야 하며, 단독 저자 논문의 경우 단독 저자를 교신 저자로 표기하는 것을 원칙으로 한다.
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5. 원고 중 장에 해당되는 번호는 로마자(Ⅰ, Ⅱ …)로, 절에 해당되는 번호는 아라비아자(1, 2, 3,…)로 표시한다.
6. 그림과 표의 제목은 아래에 써넣고, 본문에서 그림과 표에 대한 언급은 괄호를 사용하지 않고 언급한다.
7. 참고문헌에서 문헌 나열은 한글을 먼저 ‘가나다’ 순으로 나열하고 그 다음에 외국어 문헌을 언어별로 분리하여 알파벳순으로 나열한다.

[별첨2] 연구윤리확약서

1. 저자(들)는 본 논문이 창의적인 것이며, 위조, 변조, 표절, 부당한 저자 표시, 중복 게재 등의 연구부정행위를 하지 않았음을 확인합니다.
2. 저자(들)는 본 논문에 실제적이고 지적인 공헌을 하였으며 논문의 내용에 대하여 책임을 함께 합니다.
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Journal of Go Studies

1. All submissions to the *Journal of Go Studies* should be limited to members of the International Society of Go Studies; Non-members are allowed to participate as joint authors.
2. Authors must not submit their manuscripts that have already been published in a domestic/foreign journal without disclosing the fact. Also, the same manuscript shall not be submitted to more than one journal at the same time.
3. The manuscripts that violate the submission rules will not be accepted.
4. Author(s) may submit manuscripts at any time of the year. However, the manuscripts to be published in the upcoming volume should be submitted no later than two months before the due date of publication.
5. The manuscript shall be reviewed according to the peer review process and the regulations of this society.
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7. Author(s) shall submit the manuscripts together with the submission application form via the official e-mail of the Secretary General.
8. All author(s) should also include the title, the author's name, and the details of their affiliation, and e-mail address on the first page of the manuscript.
9. The manuscripts should be written in the following order: abstract, keywords, body text, and references.

10. The abstract should be approximately 500 words.
11. Author(s) should conform to the guidelines in appendixes 1 and 2 in submitting manuscripts.
12. The length of the manuscript should not exceed A4 20 pages.

Appendix 1. General Guideline

1. File Format

   In principle, the manuscript shall be written in MS Word (.doc or .docx).

2. Specifications for Manuscripts

   All manuscripts should be formatted for publication according to the style notes below;

   · The title of the article: Times New Roman 18 bold, not indented, centered

   · Author's name: Times New Roman 14, line space above

   · Author's workplace or affiliation, nation: Times New Roman 12, italicized

3. Authors' Names & Corresponding Author

   If there are more than one author, their names should be listed sequentially, beginning with the author who has made the greatest contribution to the article followed by the other writers in descending order, the Primary author (1st author), Co-author, 2nd author, 3rd author, etc. If equal contributions to the article were made, names of co-authors should be provided in alphabetical order. Every article should have a corresponding author. Therefore, in the case of a single author article, he/she should be designated as the corresponding author.

4. Body of the Article

   In the case of English manuscripts, the font shall be Times New Roman, font size 11, 100% character spacing, and single line spacing.

5. Headings

   The level 1 headings shall use Roman numerals (I, II···), while other heading levels shall use Arabic numerals (1, 2, 3···).

6. Figures and Tables

   The title of the figures and tables should be placed below, and the in-text references mentioned without using parentheses.

7. In the reference list, the references should be sorted in the languages as following order; English and then the others in the alphabetical order.

Appendix 2. Research Ethics Guideline

1. The author(s) confirm that this manuscript is original and did not commit research misconduct such as forgery, falsification, plagiarism, unfair indication of authorship, or duplicate publication.
2. The author(s) have made practical and intellectual contributions to this paper and share responsibility for the contents of the paper.
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