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The technological drama of AI

From private power to player engagement with AlphaGo

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Abstract

Introduced in 2016 as a watershed moment in AI development, the announcement of AlphaGo – the first AI system to beat a human professional in the board game of go – garnered a range of mass publicity, and this media coverage often forms the core of scholarly analysis, too. Drawing on a novel dataset of online discussions by professional and amateur players from 2016-2020 which covers the introduction and retirement of AlphaGo, as well as the construction of alternative systems, I outline a new perspective of the impact of the system on the playing community. Moving beyond recognition of audience-centric responses of enchantment/disenchantment by these players, I articulate a process of engagement through which meaning-making and reconstruction occurred within the go community. These findings emphasize the importance of including multiple perspectives in analysis and draws attention to the influence of impacted constituencies in AI construction.

Keywords: algorithms, public engagement, resistance, science and technology studies (STS), politics of technology

1. Introduction

While the klaxon of AI hype sounds most loudly for systems like ChatGPT and DALL-E today, eight years ago, similar claims for general purpose AI emerged around the announcement of the go-playing AI system AlphaGo, developed by the organization Google DeepMind. Long held as a "grand challenge" of AI and often analogized as the "holy grail" of the field, the success of a system that could beat a human professional in the board game of go occurred a decade earlier than expected (Silver et al., 2016).

At the time, news media reliance on corporate publications to make sense of this announcement put forward a dominating narrative of superhuman capacity, a narrative which empirical works since then have continued to center by analyzing media and corporate representations while overlooking local and responsive engagements by players within the go community (Bory, 2019; Curran et al., 2020; Oh et al., 2017; Sormani, 2023). Even assessments which challenge claims about AlphaGo's machine learning technique, or illustrate elements of enchantment (claims of superhuman, general AI) and disenchantment (claims of machinic, narrow AI) reinforce the public presentation of AlphaGo by leaving corporate-produced silences around the go community's engagement with the system untouched (Binder, 2022; Broussard, 2019; Campolo & Crawford, 2020). In this way, the current scholarly discourse of AlphaGo places the impacted constituency of go players in a position shared by the "users" conceived of in critical data and algorithm studies: "Whereas this critical body of scholarship has defined algorithms as objects to fear, a pressing question is still the extent to which everyday media users are only subjects and victims of algorithmic power. Are they so powerless against the workings of algorithms?" (Velkova & Kaun, 2019, p. 526). In other words, "The game is not over yet," as now, "The next task for the Go community is to find new narratives for winning plans informed by the output of deep learning AIs, no matter whether these plans are present in the AIs or not" (Egri-Nagy & Törmänen, 2020, p. 15). While existing studies make it seem as though passive, audience-based reactions are the only possible responses to AlphaGo (and AI broadly), studying the discursive practices of players here shows alternative processes of engagement too.

Moving from a critical position which recognizes the agency of impacted constituencies when facing an overwhelming force, I draw on empirical materials from a larger project which includes peer-reviewed publications and public blog posts from the development company DeepMind, monthly newsletters from the American Go Association, and over 800 posts from the online community forum r/baduk from 2016-2020 to illustrate the engagement processes which go players developed after the announcement and various iterations of AlphaGo. Borrowing the conceptual language of Pfaffenberger's (1992) *Technological Dramas*, I understand engagement as both "technological adjustment:" the myth-, context-, and artifact-altering practices players use in accommodating the AlphaGo system; as well as "technical reconstitution:" the conscious attempts to change the system, or in the case examined here, create an alternative system (which I term reconstruction). This empirical analysis adds a novel interpretation of the system, and identifies a wider repertoire of responses to AlphaGo than is currently present in the literature, while the focus on engagement will be of interest to wider audiences in critical data/algorithm studies and social studies of AI broadly. Overall, this work emphasizes the importance of a processual lens in assessing discourse around AI systems over a long timeframe, and the need to include multiple perspectives grappling with or making claims for what the impact of an AI system is, will, or should be.

The next sections explore possibilities of engagement and resistance with technology before introducing various dramaturgical perspectives which have been employed to understand AlphaGo itself. I then analyze the case of AlphaGo and the reconstruction of an alternative system – LeelaZero – through my empirical materials and the conceptual lens of a "technological drama," with a focus on players themselves. Working through the introduction, responses, and challenges to this system, the conclusion reflects on the importance of studying engagement and how it reasserts an important kind of agency: employing an asset-based understanding of impacted constituencies, and including more than system owner and developer perspectives when studying, changing, or challenging AI systems.

2. Beyond an audience: Engaging with AI

While both the sociology of technology literature and contemporary studies of AI emphasize "developers" or "users" in most instances of changing or challenging technology, here I instead employ the notion of impacted constituencies. Evoking an impacted constituency emphasizes two dimensions: that access to the AlphaGo system in particular, and other AI systems generally, is usually out of the reach of most, meaning they do not have an actual opportunity to use the system-as-such; and secondly, even without using these systems, these social groups are still impacted by the developments themselves. Initially conceived as "the people who lose when a new production process or artifact is introduced" (Pfaffenberger, 1992, p. 286), impacted constituencies is broadened here to include all those who feel the effects of a new AI system, without direct avenues of redress available, in contrast to users, developers, and system owners who all express differing agencies and opportunities for interaction (Kline & Pinch, 1996; Pinch & Bijker, 1984). As an analytic category, the import of impacted constituency is that it captures the position in which many of us find ourselves in relation to AI systems in society broadly: not using them, but certainly impacted by them (e.g. Calo & Citron, 2021). An impacted constituency is not like a public-in-general, that is, it is not an imagined evocation of a grouping 'out there' made by developers or others (Marris, 2015; Oudshoorn et al., 2004), but refers to a public-in-particular (Michael, 2009), namely a group or groupings that are affected (impacted) by the system under consideration, while still being unable to access it for their own uses. Instead of capturing this relationship to the technology as "bystanders" which resembles a more passive role (Humphreys, 2005), this categorization also taps into the literature on public engagement with science and technology which has shown the various ways in which groups excluded from technical decisions are able to have their knowledge validated as legitimate and gain a voice in developments which impact them (Feinstein, 2011).

In general, publics are separated from those who produce science and technology developments by an "expertise barrier," which blocks those who lack specialized, technical knowledge from full participation (Parthasarathy, 2010). This, however, should not be taken to mean that impacted constituencies do not have their own legitimate expertise and knowledge, merely that it tends to be devalued as it is non-technical. As this literature has importantly shown, members of the public are still able to break past this barrier and their knowledge contributions can reshape how science or technology is practiced. Broadly this happens in two ways: when members of the public show that their own experiences provide a certain kind of expertise which makes them "lay-experts" in the domain of concern (Epstein, 1995), or when technical experts attempt to over-extend their specialist knowledge into another domain in which the public can show greater expertise (Wynne, 1992). Importantly, while these localized knowledges are eventually realized as legitimate, it often occurs after sustained periods of activism and engagement by impacted constituencies and the enrollment of others to support their cause (Brown, 1992). In the case of AI systems generally, a lack of technical expertise (i.e. being unable to code or understand the concepts of machine learning) is often held up as a key barrier, which also means that attempts to remedy this gap come in the form of having those who design these systems include a variety of standpoints in their developments or to build some kind of algorithmic literacy (e.g. Costanza-Chock, 2020; D'Ignazio & Klein, 2020). While these are laudable goals, they also elevate design as the sole solution, once again relegating those without technical knowledge to a passive position (Benjamin, 2019). What a focus on engagement here will show is how even impacted constituencies without technical knowledge can still meaningfully engage, question, and help realize alternative AI systems.

In the ways in which engagement involves impacted constituencies challenging barriers to participation and the meanings foisted upon them, these practices of redress can also be understood as kinds of resistance (Pfaffenberger, 1992). Studying how go players respond to the AlphaGo system by reshaping the corporately-constructed meanings of the system that was produced by the developers and their media coverage reveals practices of both engagement and resistance. Within the discursive spaces of monthly newsletters and a global (though predominantly North American) online forum, the interaction and aggregation of players comments results in a series of "activist publics" which challenges the developer's actions and public narrative with counter-narratives and alternative meaning-making processes (Minocher, 2018). Identifying counter-narrativizing as one form of resistance and understanding engagement by those without formalized expertise as possible illustrates a new repertoire of practices that can be studied and expressed, challenging our own imaginaries of what is possible in response to the increasing digitalization and controlling of our social worlds (Benjamin, 2016). But, before exploring these potentials, we must first understand how players and the public-at-large is placed into a passive position, both socially and in academic studies of AlphaGo.

3. The drama of board game AI

Beyond associations of intelligence which valorize board games and a computer's ability to play them, we must also account for the media events that surround these kinds of matchups (Dayan & Katz, 1994). It is within these sets of arrangements - cultural connotations of intelligence and media production - that AI systems often attain their special status and impacted constituencies are placed into a passive audience or bystander position. Without the enrollment of media support and publicization, such outcomes are not guaranteed. For example, Garry Kasparov vs. the chess-playing system DeepBlue version two (for Kasparov won the first matchup in 1996) often stands out as a success of AI development, even though we now recognize it not as general artificial intelligence, but a kind of narrow *spectacular* intelligence. As Hamilton writes in her analysis of the media event surrounding Kasparov vs. DeepBlue II,

> Spectacular intelligence is an ends rather than a means, awarded for successful performance rather than essential identity […] Spectacular intelligence is, rather, the *discursive construction of something or someone as an intelligent agent* as a result of a publicly endorsed performance of intellect (2000, p. 346, italics added).

It is not enough for a computer to beat a human opponent in the game of chess. The meaning of that matchup itself must denote the winner as a kind of "intelligent agent" which is then validated by those witnessing the event who are placed into the role of bystander audience or separated spectators. As Hamilton notes, the role of the media event comes to the fore here, as these are performances which are carefully constructed in cooperation between organizers and various broadcast/mass media, all working to produce the "event-ness" of an event - breaking through everyday life, perceptibly interrupting routines, and producing a particular public profile - while also shaping the cultural meaning of the event by providing a script through which interpretations are made. In this way, "A public event has a table of contents that we [the public] must memorize, it relies on a cultural repertoire with which we must become acquainted. Spectators are helped to prepare themselves for the ceremony" through narrators, event introductions, itinerary descriptions, a rehearsal of highlights, and participant profiles (Dayan & Katz, 1994, p. 109). Without over-determining this influence, the meaning of the event comes about from the particular narrative framing which the media co-produce, while also widening the public endorsement of intelligence beyond one opponent to a global audience.

Alongside this building up of public attention and acclaim, it is also necessary to reduce the possibility that "spectators" might take on an alternative interpretation and decry the investment of resources and use of the newest computing technology of the time for mere gameplay. In order to address this concern, "This risk of trivialization is contained in the public presentation of chess machines by the careful promotion of chess-playing as a means to other ends" (Hamilton, 2000, p. 343). So, it becomes important not only that success in a board game signals some kind of spectacular intelligence, but also what this feat foretells or portends for other future applications and AI developments. With the case of DeepBlue II, IBM handled this dynamic by emphasizing the many other reapplications and possibilities of the system, notably touting developing pharmaceuticals, identifying DNA, managing nuclear arsenals, and a wide array of "more significant" (though undisclosed) activities as spaces of re-application for their chess system (Guly, 1998). These are similar to the domains that DeepMind would tout decades later in their own discussion of AlphaGo (e.g. protein folding and "drug discovery").

3.1 The dramas of go AI

It is these tendencies of spectacle around board game AI which seem to strongly influence scholarly responses to AlphaGo, too. Brief engagements by Broussard, Campolo & Crawford, Moss & Schüür, for example, all oppose the fantastical claims DeepMind makes about its technique, claiming it is the hyping up of "mathematical achievement" and computing developments (Broussard, 2019, p. 36), that it extends a form of "enchanted determinism" which obscures these dimensions (Campolo & Crawford, 2020, p. 8), and that it reinforces a myth that needs to be debunked (Moss & Schüür, 2018, p. 266). Bory begins to go further in his analysis of "The shifting narratives of artificial intelligence from DeepBlue to AlphaGo" (2019). Drawing clear dividing lines between the two systems and companies, Bory argues that Kasparov vs. DeepBlue II was a "conflictual and competitive form of struggle between human kind and a *hardware-based*, *obscure*, and *humanlike* player," while a matchup against AlphaGo "conveyed a cooperative and fruitful interaction with a new *software-based*, *transparent*, and *unhuman*-like form of AI" (italics original, p. 627). These convenient binaries of hardware/software, obscure/transparent, and humanlike/unhumanlike certainly appear at the surface-level comparison of both media events, but we should not take this to mean that AlphaGo itself is only or best understood as having these qualities. Much of the media coverage and public discourse around the event still evoked the competitive theme of (hu)man vs. machine regardless of what Bory notes (Curran et al., 2020; Oh et al., 2017), and especially when AlphaGo does still rely heavily on hardware, is obscured and locked away from the go community and public, and is recognized as exhibiting both human and non-human-like qualities, seeking to compare only against DeepBlue can lead to unproductive paths. As already indicated, there are also many continuities between these two systems and their media events, rather than simple oppositions.

More recent and detailed engagements by Sormani (2023) and Binder (2021, 2022) with AlphaGo similarly recognize issues with Bory's comparative approach, and stand out for at least a partial inclusion of perspectives from the go community itself. Drawing on Ziewitz's (2016) "algorithmic drama," Sormani employs a stepwise ethnomethodological approach to detail how one particular and well-known move in one particular game of AlphaGo (Move #37 in the second game of Lee Sedol vs. AlphaGo) attains its scenic intelligibility, that is, how human/machine interfacing made possible an "event that subsequent media coverage would interpret as a telltale sign of AlphaGo's 'superhuman intelligence'" (2023, p. 687). This fulfills the algorithmic drama by first making the AI system seem all-powerful, before sealing its character as inscrutable and opaque (Ziewitz, 2016). Including the professional and amateur English commentators of this game in analysis, Sormani provides a rich and in-depth examination of AlphaGo in a particular scene. While this importantly reveals details overlooked by other scholars (a significant one being other studies misrepresent when the human opponent would step out for a smoke break – *before* move 37, not after, which impacts interpretation of the event), such a methodology remains unsuitable for exploring how go players as a wider community and impacted constituency engage with the AlphaGo system over time.

In his own work, Binder (2022) focuses attention on establishing how the AlphaGo narratives attain both enchantment/disenchantment (cf. Campolo & Crawford, 2020), and elsewhere writes of the "social drama" of AlphaGo as a way to question the qualities of thinking the system may represent and what this means for the fluidity of boundaries in how we understand intelligence, creativity, and humanity (2021). But, first concerned more on media representation and professional go player perspectives, he overlooks lay players and their experiences grappling with AlphaGo, while in the second case his abstractions step further away from the playing community itself. However, his work also points in a direction which this article extends – namely, the role of 'local' knowledge producers (go players) in the meaning-making process of AlphaGo. As Bory and co-authors later note elsewhere, the role corporations play in crafting "mono-dimensional" narratives can "Result in disregarding other relevant trajectories in media change," something that can only be challenged or redefined through "a different narrative, based on a multidimensional perspective" (Natale et al., 2019, p. 12). While this call is made in order for critical media and communication scholars to challenge the positioning of corporate actors broadly, I take up this same approach in questioning the AlphaGo system in particular, seeking out what alternative narratives, understandings, and indeed even systems, emerge when we engage a multidimensional perspective that goes beyond only a corporate, developer lens.

Recognizing the dramatic elements of this case but wanting to go further, I draw on a third perspective, offered by Bryan Pfaffenberger's (1992) *Technological Dramas*, which directs explicit attention to both the politics of technology, and the agency of groups impacted by the introduction of the technology itself. While Sormani's use of the "algorithmic drama" explains the construction of AlphaGo as superhuman and Binder's use of the "social drama" draws attention to the constitution of cultural boundaries, I use the "technological drama" here to emphasize the engagement of go players in relation to AlphaGo and its various iterations. In doing so, I aim at a different contribution than these earlier authors as well. I am not seeking to provide a "metanarrative" of AlphaGo (Binder, 2022, p.1), nor am I attempting to craft an argument that "a fortiori applies to narrative interpretations" (Sormani, 2023, p.703). Rather, between the breadth provided by Binder's overview, and the depth of Sormani's explication, I am adding texture to

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this case by illustrating two significant ways in which the impacted constituency of go players engaged with the AlphaGo system during its introduction and ongoing successes (Flyvbjerg, 2006). This as-yet discussed element of the case highlights a more nuanced understanding of the system by players than we can glean from existing studies, while the findings and analysis of engagement and resistance by this particular impacted constituency generalizes to contemporary development of AI across domains.

4. The technological drama of AlphaGo

Through an ideal-typical model, Pfaffenberger (1992) introduces *Technological Dramas* as a means to examine the politics of technology through three processes: technological regularization, technological adjustment, and technological reconstitution. The first occurs when a "design constituency" produces or interacts with technology in a way which alters "the allocation of power, prestige, or wealth in a social formation. The technological processes or objects that embody these aims are cloaked in myths of unusual power" (p.285): myths, which in the case of AlphaGo, existing studies have challenged, dissected, and explained (Binder, 2022; Bory, 2019; Campolo & Crawford, 2020; Sormani, 2023).

The two remaining processes which I examine here as forms of engagement occur when impacted constituencies "engage in strategies that try to compensate for the loss of self-esteem, social prestige, and social power that the technology has caused" (Pfaffenberger, 1992, p. 286). This can occur through "technological adjustment:" controlling and altering the discourse, and/or "technological reconstitution:" trying to reverse implications of the technology. Both of these engagement processes can recursively feed back into further technological regularization by the design constituency. Overall, the technological drama functions as a way to study this recursive technical politics, characterizing technology as a "systemic formation constituted by discourses embedded in social, political, historical, and material relations" (Selber, 2004, p. 174). While Selber provides a fuller inventory of Pfaffenberger's framework to establish it as a critical meta-discourse heuristic, for my purposes in this paper, I focus on technological adjustment and technological reconstitution. In what follows, I briefly introduce the context of analysis before further detailing these engagement processes and illustrating their presence in the meaning-making and reconstruction processes of players engaging with AlphaGo.

4.1 Materials, method, and context

The empirical material for the following analysis draws from a larger project which includes peer-reviewed publications and public blog posts from the development company DeepMind, monthly newsletters from the American Go Association (AGA), and 837 posts from the online community forum r/baduk which include mentions of "AlphaGo" in the title. An abductive approach was employed (Tavory & Timmermans, 2014), moving from the open and axial coding stages of grounded theory and forms of situational analysis towards humanistic interpretation as analysis iterated (Biernacki, 2014; Clarke & Charmaz, 2019). Collecting these sources and placing them in conversation with one another reveals a range of meaning and reality-making around the AlphaGo system from actors which represent the different categories of system owners, developers, users, and impacted constituency. While news media representations have figured largely in existing analyses of AlphaGo (Curran et al., 2020; Oh et al., 2017), and have also been combined with game analyses (Binder, 2022; Bory, 2019), this is the first study to combine discussions from go players both from a real-time online setting and the circulation of the AGA e-journal in assessing the arrival and impact of AlphaGo.

Following a monthly circulation, AGA "E-Journals" represent a community sharing space where members of the AGA update and unite the larger US Go community (and other subscribers or visitors to their online pages) on the state of play in the field and other notable occurrences. For my purposes, I began looking at issues in October 2015 when the first human was invited to play against AlphaGo, under a signed non-disclosure agreement at DeepMind headquarters. The first mention of AlphaGo begins with the January 2016 issue, and I looked at each monthly issue from that point until the time of search. Overall, the monthly journal acts as a collection space for both the concerns and hopes that may be pinned upon AlphaGo and other AI variants, and as the subsequent years show, it highlights the ongoing analyses that come from the games that were released by DeepMind. More globally, the online community r/baduk represents a communal social space for many players of go across the world, with over 42,000 subscribers at the time of writing (including active and inactive members). Predominantly a US-based and English-speaking website, this particular online community (subreddit) r/baduk also includes posts linking to Chinese, Korean, and Japanese language sources with translations attached or requested. This particular inclusion of East Asian sources is reflective of the game's roots which trace back over millennia to China, and also reflects the predominance of professional players and leagues in the aforementioned countries too. When translated by members of the community, these sources are included as well. News sources posted by members of this community are included in analysis as well but are not sought out individually.

While approaches to having computers play go began in 1968, the following decades saw little improvement in the systems being constructed. The asymptotic growth of computer go programs was not merely limited by computing capacity, but also by the search and evaluation algorithms employed by these systems. Social choices and technical factors beyond each game's complexity were involved in this progression – namely the proximity of chess (vs. the distance of go) to Western AI developers as a well-known and intellectual game which narrowed their attention to only one kind of problem-solving, and the politics which marginalized a technical method (neural networks) with its associated data and hardware needs that would eventually be used in the construction of AlphaGo (Ensmenger, 2011; Olazaran, 1996). All to say, while go-playing computers did exist before AlphaGo, there was a clear delineation between top-ranking professional players (who often begin training in academies as young children) and the top-rated computer programs. While tournaments existed for various go programs to compete against one another, the limited capacity of these systems meant there was little perceived threat to in-person play with their presence, and common advice to beginner players was to play against humans rather than computers, lest one pick up bad habits and improper tactics. Given these features, the surprise arrival of AlphaGo in 2016 led to a series of engagements and resistance that sought to make sense of the system and its implications for the gameplaying community as a whole.

5. Technological adjustment to AlphaGo

Technological adjustment refers to the myth-, context-, and artifact-altering practices impacted constituencies engage in to accommodate the technology: "They try to control and alter the discourse that affects them so invidiously, and they try to alter the discursively regulated social contexts that regularization creates" (Pfaffenberger, 1992, p. 286). This can occur through *countersignification* where a more favorable frame of meaning in which self-esteem does not suffer is substituted, through *counterappropriation* where those deemed unsuited to the technology gain access anyways¸ and with *counterdelegation*, where impacted constituencies try to subvert the coercive functions of technological regularization. After the initial introduction of AlphaGo, the go community begins engaging in countersignification as they grapple with the purported qualities and impact of the system.

AlphaGo was first publicly announced on January 27, 2016, when the scientific journal *Nature* published an article entitled "Mastering the game of Go with deep neural networks and tree search." This article outlined the production of the AlphaGo system which beat European go champion Fan Hui in five private matches during October 2015. With an emphasis on the technique developed, the authors show evidence of their breakthrough development by reference to this defeat, claiming for the first time, the victory of a computer program over a professional human go player with no handicap (Silver et al., 2016). While the publication focuses on the technical dimensions of the system, editorial members of the journal enact their own kind of sensemaking in telling readers what AlphaGo represents, and what it foretells for our relationship to AI systems in the future.

Making their interpretation of the significance of this development explicit in a blog post published the same day as the article, *Nature* writes that a “Google AI algorithm masters ancient game of Go” (Gibney, 2016). Unlike human players who must play many matches in professional settings to attain a denotative level of mastery, the standards are clearly different here, as success against one human professional is presumed enough to “master” the game. In another editorial entitled “Digital Intuition” which was published the same day, the Nature team writes that “In what could prove to be a landmark moment for artificial intelligence, scientists announce this week that they have created an intuitive computer” (2016). Reflecting on the technique deployed to beat a go professional, they argue that AlphaGo employs “intuition” or “decision-making based on apparently instinctual responses; thinking without thinking.” In practice this also means that “a human can hardly check its [AlphaGo’s] working, or verify its decisions before they are followed through.” They recognize this will have an impact “for humans and their relationships with machines,” but rather than raising concerns about this inscrutability, the conclusion they draw is to bestow a special status to this and other kinds of future “intuitive” computers: “The machine becomes an oracle; its pronouncements have to be believed […] Intuitive machines will need more than trust: they will demand faith.”

In this way, *Nature* places AlphaGo outside the realm of humans, as both beyond comprehension and as above, producing judgment or insight from its privileged position which remains inaccessible to humankind. It is a significant claim to be made by the spokespeople for a prestigious journal such as *Nature*, and even though it is an editorial, the prophetic language and overall tenor of the article – valorizing without questioning or demanding forms of explainability – all helps to shape the image that is emerging of AlphaGo and the development organization DeepMind. In *Nature’s* presentation, AlphaGo becomes a powerful agent characterized by “deep neural networks” but with few other features. Overlooked remains the hardware, other software, and tens of millions of human gameplay moves the system is composed of. Instead, AlphaGo as oracle becomes a demand for faith rather than an opportunity for deeper interrogation. The relationship *Nature* puts forward between humans and machines is one of inaccessibility and inequality – imposing clear, separative dividing lines where the one option that remains for humans is faith without understanding.

The response from go players appears more firmly tempered. For the go community, without underplaying the announcement of AlphaGo, there is a generally shared sense across the British Go Association and American Go Association (AGA) journals, as well online r/baduk discussions of the time that Fan Hui is not the opponent who matters. Looking ahead to what would become the major global media event of AlphaGo, success against the renowned go champion Lee Sedol (who DeepMind and news media will often analogize as the Roger Federer of the go world due to his dominance) is seen as far from guaranteed, with professional and amateur players both expressing their skepticism of AlphaGo’s chances. While claims of spectacular intelligence have already emerged and been co-produced between DeepMind and *Nature*, one unpublicized match is not enough to prove AlphaGo’s mettle or “mastery” of the game for many in this community. With their emphasis more squarely on proving spectacular intelligence and what applications of AlphaGo means for other fields, DeepMind and *Nature* draw attention around the AlphaGo system away from the game itself. What is relatively overlooked is, as one user on r/baduk asks, “What can AlphaGo do for the game?” They raise a series of questions in their preamble, noting that “The potential benefits of AI are huge, but what is the potential for Go? Will AlphaGo, or another program, be able to answer some basic questions about go? […] Will programs be able to ‘explain’ why a certain move is better other than giving win percentages?”

The thread garners a series of responses, with the “top” (most upvoted) comment detailing three primary domains AlphaGo or a similar AI system could help with: analyzing yose (usually endgame moves which approach fairly stable territory to extend one’s position while minimizing the opponent’s), creating life and death problems (which are used to develop player ability to “read” a board situation and choose appropriate responses), and helping amateurs self-analyze games (by identifying what would be the recommended moves to play from an input board position). Crucially, in response to another set of

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the original poster's questions regarding the possibility of calculating absolute values for opening moves or one move in particular (tengen, the center star point), respondents are unequivocal in their belief that any AI system would be unable to achieve such outcomes because "That would require solving Go, which is beyond the scope of AlphaGo. It might help us get a closer approximation, but that would presumably *also* be based on win percentages" (italics original). As another respondent puts it,

> it's very unlikely it'll "solve" the game in a true [absolutely deterministic] sense. so even if it manages to become better than any human player, we still won't know if alphago's play is The Best Way To Play Go. it'll just be the best one we have available-- a role that is currently filled by the collective wisdom and experience of today's top professionals.

While there is a recognition that AlphaGo or any other AI system will not become an ultimate arbiter of go truths, it is also acknowledged that there are dimensions of the game which can be meaningfully changed or analyzed by such advanced computer programs. Much of this centers around players being able to use AlphaGo as a tool for their own training – to improve their ability to read patterns and determine moves, or to reconstruct the system's logic in order to determine why certain stone placements have higher win percentages than others. This suggests a more equitable relationship with the AlphaGo system – the system has defined limits, and also still has abilities that can be taken advantage of by other human players – not just as facts delivered from on high, but as a tool to extend each player's own skillset and practice.

There is also the suggestion of a displacement of expertise, with AlphaGo and similar AI possibly taking over a role currently represented by "the collective wisdom and experience of today's top professionals." A similar point comes up when, as part of a collective sense-making, the AGA interviews chess grandmasters about their experience with computer dominance in their gameplaying field. Noting that "players should not be afraid of the new age, but that things will be different," it is suggested that the role and form of game expertise will likely change. In the case of chess "Since strong computers can provide weak and middling players with solid and accurate analysis, the role of the chess master is different than it was;" with another grandmaster sharing that, before computer dominance "he might have seven or eight fellow players with him helping him prepare for the games. He doesn't need to do that now, since any questions he has or analysis he needs done can be done by computer." Here the abilities of the AI system are still affirmed, but it is not separated from humans. Instead, it takes on a familiar role that professional players often fill: a role of providing guidance and help in training. While replaying some of the same themes that DeepMind/*Nature* raises themselves, the distinction here is that the AlphaGo system is placed not as apart, but actually deep in the center of the go community, or in a hierarchical sense, in a space reserved for those at the top of the game. Even while acknowledging the dominance of the AlphaGo system, that is, while it may be at the "top," it is not separated as some kind of transcendent agent above the field. Placing the AlphaGo system at the top of the hierarchy instead of above the field acknowledges its deep connections to the go community, that it builds on all that has come before, while still recognizing its winning ability.

After its eventual victory against Lee Sedol in March 2016, the AlphaGo system was assigned an honorary 9-dan ranking by the Korean Baduk Association (KBA). Representing the highest-possible ranking attainable in the game, KBA's symbolic acknowledgment signals months later what *Nature* had claimed from the outset – that the AlphaGo system had "mastered" the game of go. What is significant here is that the claims of mastery *Nature* makes, and the actions taken by the KBA are in relation to two different systems, two different versions of AlphaGo. While for chess, DeepBlue was heavily hardware constructed and developed to face Kasparov in particular, AlphaGo-Fan Hui is composed of a makeup different than AlphaGo-Lee Sedol. A major difference is the kinds of games each system trained on. While the Hui system 'learned' only from amateur games (albeit high-ranking ones), AlphaGo-Sedol trained on a different dataset which included professional games alongside amateur ones, as well as other hardware differences (different CPUs and chipset configurations). It is worth noting that DeepMind uses this same naming convention in reference to their systems (calling them AlphaGo Fan and AlphaGo Lee), signaling an acknowledgment of significant qualitative differences not to mention quantitative, hardware ones. It remains widely accepted across discourses that Sedol would have beat AlphaGo Fan, with the original article even showing that AlphaGo's strength still remained well below Sedol's ranking (Silver et al., 2016). While this indicates the ease in which such systems can iteratively improve when given access to a wealth of resources that the aegis of a company like Google DeepMind provides, it also allows us to recast the claims being made by *Nature* months before.

Rather than representing the state of knowledge as-it-was, claims made in *Nature's* editorials and blog posts in January were actually helping lay out the form which AlphaGo would eventually fill with its "mastery." Their claims were made in response to the defeat of Fan Hui, DeepMind's own assertions about the system, and a handful of interviews, but also emerged before the go community itself had fully accepted any kind of mastery by AlphaGo. That a technical feat was achieved is certainly accurate at the time of *Nature's* commentary, but in asserting mastery over the game, the journal editors went further in speaking for the community and what this all represented. In this way, their claims made for new AI systems as being oracles that "demand faith" can also be read as both performative and normative statements, guiding interpretation in one direction, while silencing others.

It is especially worth noting that by the time the KBA symbolically acknowledged the mastery of AlphaGo-Sedol, they were not responding to the system on the basis of faith, but rather empirical evidence of success and the production of explanations – and therefore explainability around AlphaGo's moves – which had been built up by scores of commentaries from professional players and game analyses of both the Hui and Sedol matches. Contrary to claims made in *Nature*, the pronouncements of AlphaGo and other AI systems do not have to be believed. It is only after success has been consistently shown, against a meaningful opponent, after reflection and analysis, that the KBA endorsed the AlphaGo system. This acceptance was not predetermined or guaranteed, but rather built up and verified through gameplay and collective sensemaking. So, then, for whom does *Nature* speak when they argue that the AlphaGo system is an "oracle"? Accepting the claims of *Nature* means also accepting the inaccessible and inequal relationship they put forward between humans and machines. But this claim only comes about through their own assertion of the AlphaGo system as a distinctly separated agent and not an assemblage: by obscuring the wide webs of relationships between software, hardware, human gameplay, development, and more which help compose the system. Even with AlphaGo's success in gameplay, its elevated status is still not completely dominating as the players' negotiations above show.

These negotiations with AlphaGo make use of "contradictions, ambiguities, and inconsistencies in the hegemonic frame of meaning" around the system (Pfaffenberger, 1992, p.286), and the contexts its force supposedly extends to, in ways which retain and restore the power of those impacted by the system (players). In these technological adjustments, players seek to resist and alter the discourse to assert a new, more favorable frame of meaning upon the system rather than accepting the terms upon which it is presented. However, as shown by the victory of AlphaGo over Lee Sedol, at a certain stage, adjustment is no longer enough to minimize the felt influence of the system upon the playing community.

6. Technological reconstitution of AlphaGo

When it is not possible or enough to make accommodations and adjust to the system, technological reconstitution begins, as impacted constituencies try to reverse the implications of the system through *antisignification*: a symbolic inversion process which produces an alternative ideology around the technology, and results in *counterartifacts*: the active reshaping of technological production processes or artifacts "which embody features believed to negate or reverse the political implications of the dominant system" (Pfaffenberger, p. 286). In this manner, technological reconstitution aligns with the literature on *reconstruction* too, highlighting the ways in which the heterogeneous social construction of technologies retains latent affordances that emerge when different groups engage in the production process (Law, 1986; Taylor, 1995; Woodhouse, 2005). As the success of AlphaGo was firmly established, players engage in the production of their own systems, accessible to the playing community as a whole, without needing approval or sanction from any private development company.

DeepMind did not immediately dismantle or hide away their game-playing system after the match against Lee Sedol. Instead, they continued to bootstrap on this original development, eventually producing what they called AlphaGo Zero - an AI system that learned to play go and outperform its predecessors, all without the requirement of pre-existing datasets to begin training and learning from ("unsupervised machine learning"). In between AlphaGo-Sedol and AlphaGo Zero, there were also iterations known as "Master" which anonymously played 60 games against professionals online, winning all of them, and AlphaGo-Jie which defeated then-ranked number one go player Ke Jie before retiring May 2017 at what was dubbed the "Future of Go Summit," an event put on by DeepMind and the Chinese Weiqi Association (CWA) among other sponsors. Prefiguring this upcoming and final AlphaGo event, DeepMind declares, "We look forward with great excitement to AlphaGo and human professional striving together to discover the true nature of Go!" *The true nature of go*, as though there is an essence to be found, one that has been missing or out of reach until now. Until the arrival of AlphaGo. Not only does it replay the positivist notion of a calculative and pre-made reality out there waiting to be discovered, it also rhetorically shapes the field of go and its history as having been playing with the shadows on the cave wall instead of seeing the truth of the game in its actuality. What could be the "true nature" of a board game? What kind of essence would this be and which ways may it be "discovered"?

The grand metanarrative this mythical status of AlphaGo links to suggests an endpoint for go. Reaching the "true nature" is not only an achievement of "discovery" but also forecloses the possibility for future change and evolutions in gameplay. The danger/trick of playing with essences is that they are overdetermining, delineating and containing all that is while excluding and removing that which is not. Both incrementally and perhaps imperceptibly, the authors are positioning AlphaGo as the ultimate arbiter of go 'truths,' implicitly arguing that the coming age of go is one shaded by a kind of finality – one they embrace with the excitement that we could expect of those finding the "holy grail," while throughout their analysis removing the agency of humans beyond that of mimicry. As examples in their blog posts show, through DeepMind's lens, it is as though professionals merely become algorithms themselves and take on or follow the instruction sheet that AlphaGo lays down, and because this is closer to the truth of go than any knowledge before, they are likely to succeed. Eight years later, the game of go has certainly changed and the impacts of AlphaGo and many other AI systems are clearly visible, still felt, and now embedded within the go community and its practices. But no matter what 'truths' may have been found, games of go continue to produce their own microcosms of structured agency where variations continue to emerge and be created (Egri-Nagy & Törmänen, 2020; Nguyen, 2020).

This point is perhaps best summarized by a player of the game, responding to another user on r/baduk who was bemoaning the AI 'mastery' of go as taking away their interest in playing. Evoking the parallel example of computers playing chess, the user writes,

> Chess is still really, really far from solved by computers, in fact in the [past] decade computer programs […] have been able to improve more than in any other decade in history. This increase in playing strength **has not resulted in some clear best way to play**, on the contrary the top two engines, Stockfish and Komodo, have extremely differing playstyles with the former playing very creative sacrifices and the latter utilizing brilliant positional play to crush their respective opponents. With go being most probably a significantly harder game than chess I would not worry about the game losing [its] beauty, instead I would marvel that, just like in chess, computers might show the world a yet undiscovered depth and potential to the game [emphasis added].

Moving beyond DeepMind's rhetoric towards a plainer, less evocative, and more accurate language, AlphaGo is not leading towards a singular truth in the gameplay of go. As this user recognizes, there are new depths and potentials to the game that the AI system may "show" (help produce), but it is not an ultimate arbiter. While the original poster lamented some of the allure of go had gone now that it was "solved," which mirrors much of the solutionist rhetoric which DeepMind (and *Nature*) produces in their own writings and analysis, this user's response challenges such an assertion. Rather than approaching

AlphaGo as a wholesale erasure of humans, a more accurate and complicated story emerges when we continue to attend to the human interactions with and within the system, approaching the AI system as a sociomaterial assemblage being leveraged productively (and differently) by both DeepMind and other members of the go community.

The mere presence of the AlphaGo system, regardless of its unqualified success in oppositional gameplay, does not equate to knowledge transformation without human intervention. As a natural experiment of 1.3 million human move decisions among professional go players years after AlphaGo confirms, "decision quality significantly improved for the players with AI access after they gained access to *reasoning processes* of AI, but not for the players without AI access" (Shin et al., 2021, p. 1795, italics original). Comparing the gameplay results of those in mandatory military service in South Korea (and therefore not having access to go-playing AI) versus those not serving in the military (thereby having access), the authors show that "Human players learned from AI after the *open-source AI programs revealed the reasoning processes* of AI, rather than after AlphaGo *revealed actions* of AI" (p. 1800, italics added). DeepMind's occlusion of interpretability and understanding as important values for their go-playing system meant that gaining access to the reasoning process of AI could not occur with AlphaGo. Instead, much of what was promised with AlphaGo only became possible after players constructed an open-source program modeled after this system. In fact, all of the hopes and wants for what AlphaGo may mean for the game that users in the r/baduk thread mentioned above would not become possible with AlphaGo itself. Today there are a wide array of go AI programs one can choose to play and learn from, each varying in its level of openness and accessibility. Of the 19 different programs listed on the go website "Sensei's library," just under half of them are listed as open-source, with the others being either commercial programs or entirely unreleased. For my purposes, I choose to focus on one program in particular: LeelaZero, a crowdsourced and open-source version based off AlphaGo Zero (AlphaGo developed through unsupervised machine learning), which is widely discussed in my empirical materials, is used by amateurs and professional players globally, and is also the system used by South Korean players to make sense of AlphaGo in the natural experiment named above.

7. LeelaZero: The reconstruction of AlphaGo

LeelaZero is an open-source version of one of DeepMind's final AlphaGo iterations, AlphaGo Zero. Open source refers to source code that is made freely available for possible modification and distribution, often involving high levels of collaboration. LeelaZero is no exception, with the program's project page listing a total of 59 contributors. While this amount indexes the number of individuals who made code "commits," or at least some kind of modification/addition to the source code of LeelaZero, there are also countless others who contributed their own game records and personal computing processing capacity to help develop the system too. In this way, LeelaZero is not only an open-source project (making its code publicly visible and accessible), it is also crowdsourced: relying on the combined contributions of go players and other interested individual to get the project of the ground, running, and successful.

While LeelaZero is an open-source project, its effort was originally led by Gian-Carlo Pascutto (often referred to as GCP, his username on GitHub) who also authored the go shareware (copyrighted but free to use) program Leela among other chess engines too. On October 20, 2017, in an open letter first outlining the size of the task ahead of him and others to create a workable version of AlphaGo Zero, GCP notes that on consumer hardware "it would take ~9.3s to produce a self-play move, compared to 0.4s for them [DeepMind]." Adding up all the elements that help compose the system, he calculates that "They generated 29 million games for the final result, which means it's going to take me about 1700 years to replicate this [alone]," all of which is why he concludes that "I would be interested in setting up a distributed effort for this." Three and a half years later, on February 15, 2021, the project was declared finished and the server underpinning the training and development of LeelaZero was shut down, though the program remains accessible and widely used by players. By the end of this (re)construction process,

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a total of 21,219,288 self-play and 1,264,007 match games were played by the LeelaZero system (LeelaZero, n.d.), still falling short of DeepMind's 29 million mark (which took them three *weeks* to train, not years).

Though it is only one of many go programs available, LeelaZero is widely used today, much in the ways players hoped would be possible with AlphaGo, opening up new ways of self-analyzing, training, and even using the program to analyze AlphaGo's moves. The AGA series where Western commentators Redmond and Garlock analyze the games of AlphaGo, for example, relies not only on Redmond's professional acumen, but also access to LeelaZero which he uses to strengthen his own analysis. Professional across the globe now rely on different AI systems in their training and preparation, while tournaments now include cautions and restrictions against AI assistance. Much like different chess-playing systems differ from one another, LeelaZero also has its own playstyle distinct from the iterations of AlphaGo. One of the major factors for this is that DeepMind never released the weights for their neural networks, meaning that all other go-playing AI systems train and instantiate networks made of their own weights. Beyond playstyle, what sets LeelaZero apart from AlphaGo is its greater accessibility.

Being freely available, the LeelaZero system (and similar others) introduce further opportunities for explaining and understanding why AlphaGo and other AI systems choose the moves they do. As noted in the opening of this article, this means that "The game is not over yet," as now, "The next task for the Go community is to find new narratives for winning plans informed by the output of deep learning AIs, no matter whether these plans are present in the AIs or not" (Egri-Nagy & Törmänen, 2020, p. 15). Again, the success of AlphaGo and other go-playing AI systems is not being challenged. But, neither now, are such accomplishments being framed as out of humanity's reach. Instead of only a passive, receiving position, the role of go players here becomes one of active participation, active engagement in a co-construction process. Recognizing what their relationship with go-playing AI systems lacks (i.e. interpretability or understanding in the form of human narratives), the role of human players becomes the filling of this gap, not merely taking the output of these systems on blind faith, as though they are without recourse or critical reflection. While amateur players may use LeelaZero to assist in their training, they still seek out professional and more skilled player advice to understand what causes certain tactics to be successful (either through paid mentorship or requests on r/baduk), illustrating new co-producing roles with AI, rather than passive enchantment or disenchantment.

What LeelaZero helps reveal, too, is just how resource intensive AlphaGo and all its iterations were. While DeepMind emphasizes the software technique throughout their publications (and this is what Bory relays in his analytic comparison of AlphaGo to DeepBlue), we should not miss the level of hardware that the system relied upon. As GCP highlights, the DeepMind team had access to chipsets and processing units which enabled their AlphaGo system to make moves more than 23 times faster than existing consumer hardware would allow. Consider that the original AlphaGo-Hui distributed system involved 1,202 CPUs and 176 GPUs (central processing units, graphics processing units) while the closest competitor of the time, the "Crazy Stone" program, used only 32 CPUs. These constitute other layers of human involvement that are under-emphasized in DeepMind's presentation. In revealing these qualities, we are able to assert more accurately what AlphaGo represents and what this enactment means for understanding both of sophisticated computers, and for the game of go itself. What is clearer now is that much of the performative statement-making around the AlphaGo system which enacted it as a beyond-human, rupturing force able to make ultimate arbitrations came about not only because of qualities it exhibited, but because of the resources it was composed of as well. Technologies that require a high control of resources lend themselves towards an authoritarian or limited range of control (Winner, 1980). Contrasting the LeelaZero system to AlphaGo, much of what facilitated the separated status of the latter seems absent. Through an open and crowdsourced enactment, LeelaZero not only achieves what the AlphaGo system did, it is inherently more accessible. As a result, while still seen as playing beyond human skills, LeelaZero is not marked and therefore realized as wholly separated from humans.

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Much of the distance and allure of the AlphaGo system came about from the guarded quality and approach in which DeepMind demonstrated – but never made it available – to the world. With the accessibility that the LeelaZero system provides, as we've already seen, players are now able to incorporate the insights that go-playing AI systems help produce into their own training and gameplay with better understanding of the reasoning processes each system demonstrates (Shin et al., 2021). Even playing games online now includes an AI review available at the end, enabling opponents to review their matches immediately and even discuss their shared understandings if they want. Interpretability and explainability, key values which were absent with the AlphaGo system and added to much of its oracle/separated status, are present here. Players can continue to study the value of a variety of different moves and gameplay strategies with LeelaZero. Rather than being unattainable qualities of advanced AI systems in general, LeelaZero helps highlight these dimensions were missing because they were not priorities for DeepMind or its enrolled allies, and because access was never made possible with the AlphaGo system. Given access and reflection, human players show that superhuman go-playing AI systems are not as alien as we may perceive if we only attend to AlphaGo and official discourses around it. What this access has also revealed is that limits still exist for superhuman go AIs too. As a pre-print article released February 2023 shows, there are blind spots in superhuman go AI systems, such that playing moves which even human amateurs can respond to successfully unravels the current top-playing AI system (Wang et al., 2023). Not only are superhuman AIs not divinely incomprehensible, neither are they infallible.

The technological reconstitution/reconstruction of AlphaGo with LeelaZero highlights how the go community engaged in both inverting the supposed symbolism of AlphaGo, and how this resulted in the creation of a technological production process and artifact which negate and reverse the supposed implication of AlphaGo for the go-playing community – opening up whole new playstyles and opportunities for human players, rather than shifting into any stage of finality.

8. Conclusion

Subject to a substantial amount of attention, the media hype and attention around AlphaGo often influences scholarship on the system too. Moving from a critical position which recognizes the agency of impacted constituencies when facing an overwhelming force, I employed empirical materials from a multidimensional perspective to illustrate the engagement and resistance processes which go players developed after the announcement and various iterations of AlphaGo. Borrowing the conceptual language of Pfaffenberger's (1992) *Technological Dramas*, I illustrated engagement and resistance as both "technological adjustment:" the myth-, context-, and artifact-altering practices players use in accommodating the AlphaGo system; as well as "technical reconstitution:" the conscious attempts to change the system, or in the case examined here, create an alternative system (which I term reconstruction). This empirical analysis adds a novel interpretation of the system, and identifies a wider repertoire of responses to AlphaGo than is currently present in the literature, while the focus on engagement by impacted constituencies can be of interest to wider audiences in critical data/algorithm studies and social studies of AI.

Attending to the analytic category of impacted constituencies opens up the space to recognize these social groups as possessing a novel kind of agency which thus far has been theorized in narrow ways as passive enchantment or disenchantment. Employing an asset-based understanding of impacted constituencies reveals resistive practices where system owner narratives and curated meanings are challenged and reshaped by the engagement of those facing consequences without avenues of direct redress available. While technical programming skills are valuable in this repertoire of action, so too are communal-based, and supportive practices which involve interactions among the impacted constituency, such as sharing data, collective meaning-making through dialogue, and sharing strategies which minimize harmful or deleterious effects of the AI system. While the stakes may appear relatively low in the case of

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a go-playing AI system, the practices examined here can be analytically and empirically revealing of similar avenues of resistance and engagement in cases where serious harms are present. For example, in cases of so-called AI-enabled "predictive" policing, we can see a similar repertoire of action as impacted constituencies engage in counter-narrativizing, withholding data, and public education campaigns within communities to raise awareness of how new AI systems used by the police are transforming and intensifying harms (Coalition, 2021; Jefferson, 2020; Minocher & Randall, 2020). Moving beyond the predominant focus on the data going into these systems, and studies attempting to ameliorate expressed harms, studies of engagement with AI in domains such as these can challenge our own imaginaries of what is possible in response to the increasing digitalization and controlling of our social worlds. Overall, a focus on impacted constituencies and their engagement and resistances emphasizes the importance of a processual lens in assessing discourse around AI systems, and the need to include multiple perspectives grappling with or making claims for what the impact of an AI system is, will, or should be.

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