PART II:
IMPLICATIONS FOR ARMY AND JOINT CAPABILITIES

CHAPTER 3

GO AND ARTIFICIAL INTELLIGENCE: POTENTIAL FOR STRATEGIC DECISION-MAKING

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Go is the world's oldest board game.[1] Played on a square game board with a grid of 19x19 lines, two players take turns placing black or white stone pieces. To surround an opposing player's stones, results in the capture of those stones. At the end of the game, the player who surrounds the most space on the board and has the least captured stones is the winner.[2] The overall goal of the game of *Go* is to apply initiative in order to maximize one's own strengths while exploiting an opponent's weaknesses to achieve strategic and tactical encirclement. Short of that, it leads to a situation characterized by stability and balance.

While seemingly simple, *Go* is amazingly complicated. It is a game of initiative, maneuver, balance, and a clash of human wills to control the game board geography. *Go* is essentially a 2,500-year old "abstract war simulation."[3] Because of this, several prominent political thinkers have suggested that *Go* is a viable model for understanding geopolitics and strategy.[4] Still, few know how to apply it to their own decision-making. They can see *Go* as illustrative, informative, and even eye-opening, but are unable or unwilling to take the next steps and learn what *Go* teaches in order to apply it to their own strategic thinking. Teaming humans and computerized artificial intelligence (AI) is a potential solution that will allow a human to act like an expert at *Go* or similar decision-making processes, without the experience or in-depth study otherwise required. Recent developments in AI show this is now possible.

In 2016, a computer program resoundingly defeated two of the world's best *Go* players. The program was AlphaGo, written by computer scientists at Deepmind, a Google-owned AI research company.[5] AlphaGo did this, not through pre-programmed expert knowledge of the game, but by learning from the games played by expert human players and improving through self-play.[6] This approach is both revolutionary and wide reaching. While AI will be useful in many places, its application to the ancient strategy game of *Go* shows how it can help improve foreign and security policy decision-making. Combining the strategic lessons of *Go* with AI has the potential to make those lessons more broadly applicable and improve decision-making without requiring a cultural background or expertise in the game. It will allow human decision-makers to focus on their strengths and overcome their cognitive weaknesses. By creating a model of the world based on a *Go* framework, an AI algorithm like AlphaGo can become an expert in that world, understand a given situation, and then look far into the future, across many possible courses of action (COA), to help human decision makers determine which next move will best meet their objectives. By teaming with human decision makers to think faster, deeper, and more accurately, this type of AI can provide a decisive strategic advantage to those most willing to use it.[7]

MAN-MACHINE TEAMING FOR DECISION-MAKING

Moravec's Paradox states that what humans do effortlessly can be very difficult for computers.[8] This is especially true with basic tasks like motor skills and visual or audio recognition. The converse is also true, especially when it comes to human cognitive thinking. A complex strategic environment can be (too) difficult for the human mind to accurately process. There can be too much information, too much complexity, and too rapid a change in a situation. However, this is the exact environment in which strategic decision makers must operate. They cannot afford to make mistakes or succumb to the weaknesses inherent in human decision-making. This is what makes man-machine teaming complementary. Teaming an AI computer mind with the human mind combines human strengths with AI strengths to offset the weaknesses of both.

Where AI may struggle is when it encounters a situation beyond its learned experience or model. It may have difficulty thinking creatively beyond its database or programming. It may not be able to think ethically, especially in situations where the most ethical solution may not be the most efficient or effective solution. In addition, AI needs a goal to work toward (AI does not day-dream). This is where the human part of the man-machine team comes in. In this model of man-machine teaming, humans will provide objectives, creativity, and ethical thinking, while AI will provide self-taught experience, intuition, and forecasting abilities. An algorithm with these elements was key to the breakthrough that enabled AlphaGo to outthink the world's best *Go* player.

ALPHAGO, AN ARTIFICIAL INTELLIGENCE BREAKTHROUGH

AlphaGo is an AI breakthrough, different from many other attempts at game AI. Previous game AI like International Business Machine's (IBM) Deep Blue, a computer that first beat a world chess champion, did so with very specialized software and hardware.[9] It had large libraries of pre-programmed expert knowledge that it applied using computational brute force.[10] However, *Go* is estimated to be 300 times more complicated than Chess.[11] The techniques used by Deep Blue are impractical for a computer playing *Go*.

Since pre-programmed expert game knowledge is impractical for *Go*, the AlphaGo programmers took a different route.[12] Using deep learning and reinforcement learning artificial with neural networks coupled to a Monte Carlo Tree Search, AlphaGo was essentially self-taught.[13] Using a deep learning artificial neural network, it studied expert human games and then used that knowledge to improve itself through self-play. It developed its own experience, formed a type of intuition, and used that intuition to focus its forecasts in order to evaluate a sequence of likely best moves.[14] The algorithm then chose the move with the highest probability of winning the match.[15] In doing so, it made better game decisions than world's best *Go* players. This was a revolutionary achievement.

The self-learning decision-making algorithm used by AlphaGo is noteworthy because it does not just apply to *Go*—it can extend to other types of decision-making.[16] The elements required are a historical library of data for study and a basic model applicable to that data for improvement through self-play. Given relevant data and an applicable model, this process can be extrapolated from the abstract game of *Go* to real-world strategic decision-making. Then, as computer scientists have noted, "Deep learning has the property that if you feed it more data, it gets better and better."[17]

GO AND STRATEGIC DECISION-MAKING

The same thinking process that makes a mind (human or AI) successful in a strategic war simulation like *Go* will make that mind successful in geopolitical strategy. This implies that any strategic leader would benefit from learning *Go* and incorporating the way of thinking that *Go* stimulates into his or her decision-making framework. Even if unable to learn the intricacies of the game itself, a basic level of understanding and appreciation for its concepts will enhance decision-making. Additionally, if the *Go* way of thinking is integrated into the programming of an AI-assisted decision-making process, one need not be an expert to play like an expert. This is the key benefit of man-machine teaming through AI-assisted decision-making.

Go may apply directly in some cases and may serve as a useful analogy in others. Placing pieces on a *Go* board may provide direct insight on where to place equivalent pieces in the real world. Figure 3-1 shows an example for Europe and the Middle East.

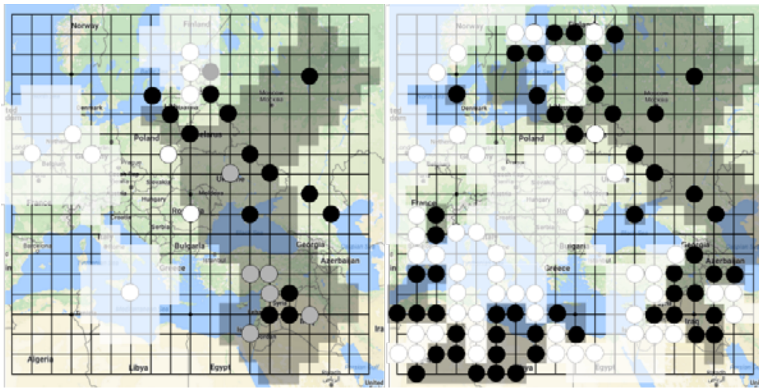

Figure 3-1. ***Go*** **Game Overlaid on Europe and Middle East Map.**[18]

The left map shows a constructed position based on a notional map of relative influence in Europe and the Middle East. White represents the United States and the North Atlantic Treaty Organization (NATO), black Russia and Russian allies. The map on the right shows the results of a relatively simple *Go* computer program, much less sophisticated than AlphaGo, playing both black and white positions through computer self-play. While this very basic *Go* model has several limitations, computer self-play does imply strategic benefits to Russia by applying additional influence activity in the Middle East, North Africa, and Northern Europe. It also highlights that the United States and NATO should strengthen their own influence throughout Europe and into the Middle East. This simple experiment illustrates the promise and applicability of *Go* as a basis for understanding and making decisions in a strategic environment.

STRATEGIC DECISION-MAKING THROUGH ARTIFICIAL INTELLIGENCE

Like AlphaGo, a decision-making AI tool would be composed of three minds. The first is the experience mind, based on an artificial neural network trained by history, doctrine, and examples from human strategists, able to recognize expert moves in a given area. The second is an intuition mind, formed by an artificial neural network trained through reinforcement learning, based on a relevant game model, and able to tell a winning position from a losing one, using a reward function based on a human-specified goal or objective. The third, a forecasting mind, would use the experience and intuition minds to narrow down possible options, forecast multiple possible future sequences of events, and make recommendations to meet given objectives.

The first two minds would always be learning. The experience mind would receive continuous updates of news, intelligence, and other relevant information. The intuition mind would continue to improve through reinforcement learning self-play and reward criteria that could update as objectives change. The forecasting mind would continue to run simulations and update probabilities of success as a situation develops. It would continuously extend the decision tree to cover more actions that are possible and improve the fidelity of previous estimates. Much like human strategic decision-making, the overall concept is a continuous cycle of evaluation and improvement.[19]

APPLICATIONS FOR AI-ASSISTED DECISION-MAKING

The basic approach for any application would be to create a simulation (game model) for the situation, to define success criteria, and then build and train a neural network for that simulation. AI-assisted decision-making could help leaders at all levels rapidly design, plan, and evaluate operations. Planners could test multiple operational approaches against a realistic AI-based adversary. Through a continuous deliberative planning process, the AI could update and evaluate the plans against the operational environment. The AI would continuously monitor the environment and warn planners when assumptions are no longer valid or if there is an opportunity to improve the plans.

Another application would be an AI-assisted common operating picture (COP).[20] It would catalog and display a disposition of friendly and enemy forces, automatically built and updated through a big data approach. Despite incomplete intelligence, an AI-supported COP could tell where an enemy should be with a corresponding level of confidence. In real-time, the AI would continuously interpret the situation, explore multiple lines of effort, and determine which is most likely to meet the given success criteria.

Based on this, the COP would recommend next actions and predict likely enemy responses. A commander could rapidly explore the situation and various COA, choosing hypothetical actions to see what the AI thinks would be a likely enemy response. In a complicated, multi-domain, anti-access area-denial future operating environment, this type of AI would find and predict “windows of superiority” for friendly forces to exploit.[21] It would show threat avoidance routing and recommend an optimized multi-domain fires tasking order. Essentially, this is a real-time situational awareness tool coupled to a forecasting, real-time, and AI-driven war game.

RECOMMENDATIONS

As part of the Third Offset Strategy, the Department of Defense (DoD) should fund research and development that will enable AI-supported human-machine teaming for strategic decision-making. Additional efforts should experiment with integrating AI into decision-making processes at all echelons. These efforts should be incremental, demonstrating basic capabilities before attempting more complicated ones.

The DoD and military services should begin a rapid prototyping effort to determine which aspects of AI can achieve the most near-term success. They should fund groups of programmers, strategists, and war-gaming experts to explore what is possible with this AI-assisted decision-making approach. Research into man-machine teaming processes should determine the best way to integrate, train with, and scale these AI tools. Organizations that would use these AI tools should apply change management principles to incorporate them into their processes and culture.

The true power of AI will be in the teaming of the human mind with the AI mind. This type of man-machine teaming will combine human strengths of goal-setting, creativity, and ethical thinking with AI strengths of rational thought through self-taught experience, intuition, and deep forecasting. A decision-making process that incorporates man-machine teaming through self-learning AI will overcome the weaknesses inherent in human decision-making and give those who use it a unique and decisive advantage over those who do not. This could be used to create a real-time, forecasting COP that could advise a decision maker on the next best move, while predicting the likely moves of an adversary. It could help strategists at all levels rapidly plan operations and quickly update those plans as facts change. In the end, by teaming with human decision makers to think faster, deeper, and more accurately, this type of AI will provide a decisive strategic advantage to those most willing to use it.

ENDNOTES - CHAPTER 3

1. David Lai, *Learning From the Stones: A Go Approach to Mastering China's Strategic Concept, Shi*, Carlisle, PA: Strategic Studies Institute, U.S. Army War College, 2004, p. 6, available from *http://ssi.armywarcollege.edu/pubs/display.cfm?pubID=378*, accessed August 1, 2017.

2. For a more detailed explanation of the rules of *Go*, see "Learn To Play," American *Go* Association, n.d., available from *http://www.usgo.org/learn-play*, accessed Mar 13, 2017.

3. Christopher Moyer, "How Google's AlphaGo Beat a Go World Champion," *The Atlantic*, March 28, 2016, available from *http://www.theatlantic.com/technology/archive/2016/03/the-invisible-opponent/475611/*, accessed November 30, 2016.

4. Scott A. Boorman, *The Protracted Game: A Wei Chi Interpretation of Maoist Revolutionary Strategy*, London, UK: Oxford University Press, 1969, is the seminal work in this regard. However, these ideas languished until 2002, when the following work was written, David Lai and Gary W. Hamby, "East Meets West: An Ancient Game Sheds New Light on US-Asian Strategic Relations," *Korean Journal of Defense Analysis*, Vol. 14, Iss. 1, Spring 2002. With later works like Lai, *Learning from the Stones* in 2004, and subsequent publications and presentations, Dr. Lai brought *Go* to the attention of U.S. diplomatic and defense circles. He continues to apply this game to examine U.S.-China and U.S.-Asia interactions in the Western Pacific. Dr. Henry Kissinger learned about *Go* from Dr. Lai's work and subsequently used these ideas to put U.S.-China relations in a new perspective in, Henry Kissinger, *On China*, New York: The Penguin Press, 2011. See the following,

Boorman; Lai and Hamby; Lai, *Learning From the Stones*; David Lai, "China's Strategic Moves and Counter-Moves," *Parameters*, Vol. 44, No. 4, Winter 2014-15; Kissinger, p. 201.

5. Google acquired Deepmind in 2014 for $650M, see, Samuel Gibbs, "Google buys UK artificial intelligence startup Deepmind for £400m," *The Guardian*, January 27, 2014, available from *https://www.theguardian.com/technology/2014/jan/27/google-acquires-uk-artificial-intelligence-startup-deepmind*, accessed December 18, 2016.

6. David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe1, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel, and Demis Hassabis, "Mastering the game of Go with deep neural networks and tree search," *Nature*, Vol. 529, January 28, 2016, p. 484, available from *https://storage.googleapis.com/deepmind-media/alphago/AlphaGoNaturePaper.pdf*, accessed December 19, 2016.

7. See, Kareem Ayoub and Kenneth Payne, "Strategy in the Age of Artificial Intelligence," *Journal of Strategic Studies*, Vol. 39, Iss. 5-6, pub. online November 23, 2015, pp. 805-806, available from *http://dx.doi.org/10.1080/01402390.2015.1088838*, accessed November 28, 2016.

> In many of these respects a domain specific AI [artificial intelligence] could radically shift military power towards the side that develops it to maturity. Domain-specific AI will be transformative of conflict, and like previous transformations in military capability, it has the potential to be profoundly disruptive of the strategic balance.

8. As highlighted in, Garry Kasparov, "The Chess Master and the Computer," *The New York Review of Books*, February 11, 2010, available from *http://www.nybooks.com/articles/2010/02/11/the-chess-master-and-the-computer/*, accessed December 19, 2016; and, Hans Moravec, *Mind Children, The Future of Robot and Human Intelligence*, Cambridge, MA: Harvard University Press, 1988, p. 9.

9. Feng-hsiung Hsu, *Behind Deep Blue: Building the Computer That Defeated the World Chess Champion*, Princeton, NJ: Princeton

University Press, 2002, pp. 172, 257, available from *https://archive.org/details/Behind_Deep_Blue_gnv64*, accessed December 19, 2016.

10. From the International Business Machine (IBM) Deep Blue information page: "There is no psychology at work" in Deep Blue, says IBM research scientist Murray Campbell. Nor does Deep Blue "learn" its opponent as it plays. Instead, it operates much like a turbocharged "expert system," drawing on vast resources of stored information (for example, a database of opening games played by grandmasters over the last 100 years) and then calculates the most appropriate response to an opponent's move. See, "Frequently Asked Questions: Deep Blue," IBM Research, n.d., available from *https://www.research.ibm.com/deepblue/meet/html/d.3.3a.html*, accessed December 19, 2016. Deep Blue and its difference from AlphaGo are further described here, Christof Koch, "How the Computer Beat the Go Master," *Scientific American*, March 19, 2016, available from *https://www.scientificamerican.com/article/how-the-computer-beat-the-go-master/*, accessed December 21, 2016.

11. Danielle Muoio, "Why Go is so much harder for AI to beat than chess," *Business Insider*, March 10, 2016, available from *http://www.businessinsider.com/why-google-ai-game-go-is-harder-than-chess-2016-3*, accessed on December 19, 2016.

12. Silver et al., p. 489.

13. Ibid., p. 484.

14. The idea of AlphaGo and intuition came from the following article, Christopher Burger, "Google DeepMind's AlphaGo: How it works," TasteHit, March 16, 2016, available from *https://www.tastehit.com/blog/google-deepmind-alphago-how-it-works/*.

15. Silver et al., p. 489.

16. Ibid.

17. Nicola Jones, "The Learning Machines," Nature, Vol. 505, January 4, 2014, p. 148, available from *http://www.nature.com/polopoly_fs/1.14481!/menu/main/topColumns/topLeftColumn/pdf/505146a.pdf*, accessed December 24, 2016.

18. Images created by the author, using computer self-play from app, see Patrick Näf Moser, designer, "Little Go," Version 1.3.1, updated January 19, 2017, available from *https://itunes.apple.com/us/app/little-go/id490753989?mt=8*; influence map from the computer program "Leela," available from *https://sjeng.org/leela.html*.

19. "Appendix I: Guidelines for Strategy Formulation," in J. Boone Bartholomees, ed., *The U.S. Army War College Guide to National Security Issues, Volume II: National Security Policy and Strategy*, 5th Ed., Carlisle, PA: Strategic Studies Institute, U.S. Army War College, 2012, pp. 417-418, available from *http://ssi.armywarcollege.edu/pubs/display.cfm?pubID=1110*, accessed August 1, 2017.

20. This idea of a Big Data generated Common Operating Picture (COP) is also captured in the Air Force's *Future Operating Concept*, see Headquarters, Department of the Air Force, *Air Force Future Operating Concept: A View of the Air Force in 2035*, Washington, DC: Department of the Air Force, September 2015, p. 9, available from *http://www.af.mil/Portals/1/images/airpower/AFFOC.pdf*, accessed January 8, 2017.

21. Sean Kimmons, "With multi-domain concept, Army aims for 'windows of superiority'," U.S. Army, November 14, 2016, available from *https://www.army.mil/article/178137/with_multi_domain_concept_army_aims_for_windows_of_superiority*, accessed March 14, 2017.