Calhoun: The NPS Institutional Archive

DSpace Repository

Faculty and Researchers | Faculty and Researchers' Publications

2019-12

Modeling Large-Scale Warfighter Cognitive Reasoning and Decision- Making Using Machine Learning (ML), Artificial Intelligence (AI), and Game Theory (GT)

Zhao, Ying; Kendall, Tony A.

Monterey, California: Naval Postgraduate School

http://hdl.handle.net/10945/70017

This publication is a work of the U.S. Government as defined in Title 17, United States Code, Section 101. Copyright protection is not available for this work in the United States.

Downloaded from NPS Archive: Calhoun

DUDLEY KNOX LIBRARY

Calhoun is the Naval Postgraduate School's public access digital repository for research materials and institutional publications created by the NPS community. Calhoun is named for Professor of Mathematics Guy K. Calhoun, NPS's first appointed -- and published -- scholarly author.

Dudley Knox Library / Naval Postgraduate School
411 Dyer Road / 1 University Circle
Monterey, California USA 93943

http://www.nps.edu/library

NAVAL RESEARCH PROGRAM
NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

Modeling Large-Scale Warfighter Cognitive Reasoning and Decision-Making Using Machine Learning (ML), Artificial Intelligence (AI), and Game Theory (GT)

Executive Summary Type: Final Report
Period of Performance: 10/15/2018–10/14/2019

Researchers:
Principal Investigator (PI): Dr. Ying Zhao, GSOIS, Information Sciences (IS)

Prepared for:
Topic Sponsor Lead Organization: N8
Topic Sponsor Name: LCDR Khoa Nguyen
Topic Sponsor Contact Information: khoa.h.nguyen@navy.mil, 703-695-4871

Distribution Statement: Approved for public release; distribution is unlimited.

Modeling Large-Scale Warfighter Cognitive Reasoning and Decision-Making Using Machine Learning (ML), Artificial Intelligence (AI), and Game Theory (GT)

Report Date: 10/08/19 Project Number (IREF ID): NPS-19-N091-A

Naval Postgraduate School / Graduate School of Operational and Information Sciences (GSOIS)

EXECUTIVE SUMMARY

Project Summary:
This project is a continuation of previous studies in which we leveraged theory and practice of Soar, a cognitive architecture, and reinforcement learning (RL), a class of machine learning (ML) and artificial intelligence (AI) algorithms, to model warfighters' cognitive functions such as reasoning and decision-making in a combat identification (CID) task.

The goal of the current project is to extend the Soar and RL technologies to other areas of warfighting applications such as war games and mission planning (MP); no previous researchers have been able to successfully apply ML/AI/game theory (GT) methods in this way. We first developed a generic representation of a multi-segment war game with two opposing asymmetrical players. We then developed game-theoretic frameworks and tested tools suitable for reasoning and decision-making in war-game or mission-planning tasks. We then designed ML/AI/GT components needed for a player to leverage AI to learn, optimize, and win (LAILOW) and showed how to apply LAILOW to a real war game in the context of over-the-horizon targeting. We confirmed that when modeling large-scale warfighter cognitive functions such as reasoning and decision-making, we need to combine technologies in ML, AI, and GT to best help warfighters, learn from them, and reduce their cognitive burden.

Keywords: *machine learning, ML, artificial intelligence, AI, game theory, GT, war game, mission planning, MP, genetic algorithms, decision-making superiority, readiness, cognitive functions, cognitive reasoning, optimization*

Background
There has recently been tremendous advancement in commercial applications of big data and deep analytics, including ML and AI methods; these technologies have the potential to address the unique challenges of modeling complex functions of warfighters, including reasoning and decision-making.

In our previous work, we studied the theory and practice of Soar, which is a cognitive architecture (Laird, 2012), and RL (Sutton, 2014), which is a class of ML/AI algorithms shown to be capable of automating some cognitive functions of warfighters, such as the decision-making of a tactical action officer in a CID task (Zhao, 2016; Mooren, 2017; Zhao et al., 2017, 2018).

Soar-RL is a rule-based reinforcement learning algorithm based on Soar. The original hypotheses for this project were that 1) the Soar and RL technologies can be extended to other areas of warfighting applications; and 2) that we would need to integrate GT techniques with ML/AI to simulate a wider spectrum of warfighters' cognitive functions. For example, when warfighters make decisions, they need to take into considerations all possible states of different types of opponents and adversaries' intentions,

Distribution Statement: Approved for public release; distribution is unlimited.

strategies, decisions, and actions. This is especially true for warfighting functions in strategic, operational, and tactical war games and MP.

The objective of this project was to study the potential to apply Soar and other ML/AI/GT techniques to new areas of military applications, including C-C4ISR, Assured C2, modeling & simulation, war games, and MP, to achieve decision-making superiority and improve readiness in the vast, complex, and uncertain domains of cybersecurity and information warfare.

Findings and Conclusions

In this research, we developed a process for leveraging AI to learn, optimize, and win a general asymmetrical war game; no previous researchers have been able to successfully apply ML/AI/GT methods in this way. We confirmed that when modeling large-scale warfighter cognitive functions such as reasoning and decision-making, we need to combine technologies in ML, AI, and GT to best help warfighters, learn from them, and reduce their cognitive burden. We also showed using a simulation data set that LAILOW is essential to improve the performance of mission planning capabilities for an AI assistant because it allows holistic learning, automation, and optimization of the whole kill chain or kill web operations in a war game environment, whereas traditional methods can only study small portions of the process. The white paper is accepted as a poster in the AAAI 2019 fall symposium (Zhao & Nagy, 2019).

War game communities such as commanders in the Naval War College (NWC) and mission planners in the air wings of a carrier could benefit from our research. The sequential asymmetrical war game design can be also extended to other areas of defense applications, including C-C4ISR, assured C2, and modeling & simulation to achieve decision-making superiority and improve readiness.

We first developed a generic representation of a multi-segment sequential war game with two opposing asymmetrical players. For one player—the self-player of a blue force—actions are placed into categories that represent actions or tactics in five typical warfare domains or cross-domains familiar to military strategists and mission planners: Intelligence, surveillance, and reconnaissance (ISR); command control (C2); mission planning (MP); platforms; and information operations (IO). Probabilistic rules—"events to actions" and "actions to events"—define the valid actions for each player. The two opposing asymmetrical players have their own sets of rules guiding their corresponding valid actions; valid actions can be defined by subject-matter experts (top-down) or data-mined from war game logs and data from doctrines and from the mission planning communities (bottom-up). Events generated by the players' actions happen sequentially in each segment. Events are discrete and do not consume time but result in observable outcomes that have value, i.e., probabilities or propensities for a player to win the game, while actions consume time and other costs. The two players interact only at mutual events. Their actions are evaluated by a set of equations to determine the expected win, lose, or draw status for the asymmetrical opponent.

We then developed game-theoretic frameworks and tested tools suitable for reasoning and decision-making in war-game or mission-planning tasks, using these results to design ML/AI/GT components needed for the war game; our aim was for a player to leverage AI to learn, optimize, and win (LAILOW) the game. To select relevant ML/AI/GT algorithms and design LAILOW, we had to consider the nature of the war game. For example, discovering predictive or anomalous patterns from data using ML/AI algorithms often requires big data; in a war game, however, there is usually little to no available data about the opponent's intent and actions because the opponent tries to hide this information; likewise, what data are available are often misleading. It was therefore imperative to include relevant modeling and simulation with physics, engineering knowledge, and warfare expertise to generate synthetic data. Moreover, the war game requires a player to search and optimize in a huge action space to counter the opponent's dynamic and ever-changing states and actions; we therefore needed to incorporate various scalable search and optimization techniques.

We also modified the Soar-RL algorithm in important ways for the war game. For one, we modified it so it can be used inside the loop of the game frameworks and be combined with a genetic coevolution AI algorithm. We also modified Soar-RL in the form of online learning and adaptation toward a trusted AI. When cognitive functions of warfighters are to be automated by an AI assistant, one needs to implement an AI assistant to gradually learn from a human master and so improve—not only to achieve better machine learning but also to allow it to gain the trust of humans through an interactive process. We thereby showed that machine learning techniques such as online learning and adaptation of Soar-RL can be used as a tool to bridge the "trust" between human and machine (Zhao et al., 2018).

We then applied LAILOW to a real war game in the context of over-the-horizon targeting. We showed that, because LAILOW is used under a game framework, it needs to constantly look at the self-player in a war game environment and suggests winning actions based on the nature of an opponent as follows (Zhao & Nagy, 2019):

- Case 1: opponent performs random actions (e.g., weather or other uncertain environmental factors)
- Case 2 (strategic complement game): opponent's actions show interest in the actions taken by the self-player (e.g., allies respond to self-player's actions).
- Case 3 (strategic competition game): opponent takes deliberately adversarial actions minimizing the effect of the self-player's actions (e.g., a cyber attacker's opponent counters an attack).

By applying the combined frameworks and techniques to our sequential war game with asymmetrical players, we demonstrated an advancement in state-of-the-art of ML/AI/GT theory and practice.

Distribution Statement: Approved for public release; distribution is unlimited.

Recommendations for Further Research

Two recommendations for future research are as follows:

1. Continue the research on, development of, and investment in modeling large-scale (with both big data and no data), trusted, adaptive, and causality-conscious warfighter cognitive functions using ML, AI, and GT algorithms or the LAILOW system.
2. Improve the technology readiness level (TRL) towards achieving module and/or subsystem validation in a relevant environment and module and/or subsystem validation in a relevant end-to-end environment (Blanchette, Albert, & Garcia-Miller, 2010).

References

Blanchette, S., Albert, C., & Garcia-Miller, S. (2010). *Beyond technology readiness levels for software: U.S. Army workshop report* (Report No. CMU/SEI-2010-TR-044 / ESC-TR-2010-109). Retrieved from Carnegie Mellon Software Engineering Institute website: https://resources.sei.cmu.edu/asset_files/TechnicalReport/2010_005_001_15305.pdf

Laird, J. E. (2012). *The Soar cognitive architecture*. Cambridge, MA: MIT Press.

Mooren, E. (2017). *Reinforcement learning applications to combat identification* (Master's thesis). Retrieved from https://calhoun.nps.edu/handle/10945/53020

Sutton, R. S., & Barto, A. G. (2014). *Reinforcement learning: An introduction*. Cambridge, MA: MIT Press.

Zhao, Y. (2016). *Applying the SOAR architecture to model cognitive functions in a kill chain* (Report No. NPS-N16-N273-A). Retrieved from Naval Postgraduate School Institutional Archive website: https://calhoun.nps.edu/handle/10945/57743

Zhao, Y., Derbinsky, N., Wong, L., Sonnenshein, J., & Kendall, T. (2018). Continual and real-time learning for modeling combat identification in a tactical environment. *Proceedings of the NIPS 2018 Workshop on Continual Learning,* Montreal, Canada. Retrieved from https://sites.google.com/view/continual2018/submissions

Zhao, Y., Mooren, E., & Derbinsky, N. (2017). Reinforcement Learning for Modeling Large-Scale Cognitive Reasoning. *Proceedings of the 9th International Conference on Knowledge Engineering and Ontology Development, (KEOD 2017),* Funchal, Portugal. Retrieved from http://www.scitepress.org/DigitalLibrary/PublicationsDetail.aspx?ID=b0ttus7UXek=&t=1

Zhao, Y., & Nagy, B. (2019). Causal learning in modeling multi-segment war game leveraging machine intelligence with EVE structures. Paper accepted as a poster in the AAAI 2019 Fall Symposium.

NPS NRP Executive Summary

Modeling Large-Scale Warfighter Cognitive Reasoning and Decision-Making Using Machine Learning (ML), Artificial Intelligence (AI), and Game Theory (GT)

Report Date: 10/08/19 Project Number (IREF ID): NPS-19-N091-A

Naval Postgraduate School / Graduate School of Operational and Information Sciences (GSOIS)

Acronyms

Artificial intelligence	AI
Comat identification	CID
Machine learning	ML
Mission planning	MP
Naval War College	NWC
Reinforcement learning	RL
Soar reinforcement learning	Soar-RL
Leverage AI to learn, optimize, and win	LAILOW

Distribution Statement: Approved for public release; distribution is unlimited.