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Enabling Understanding of Artificial Intelligence (AI) Agent Wargaming Decisions through Visualizations

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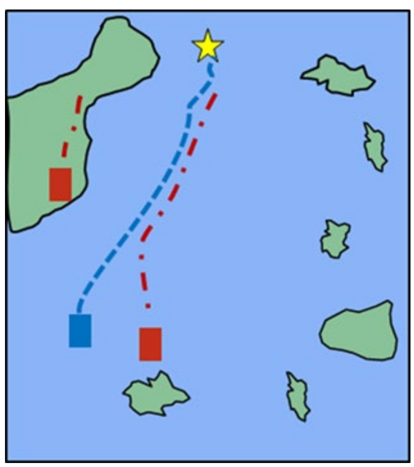

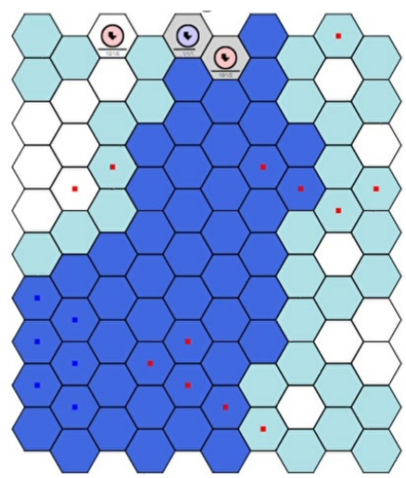

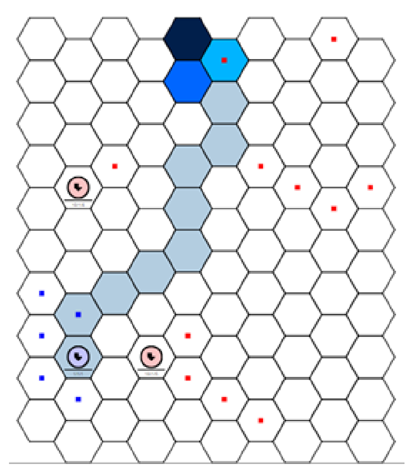

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Port Hueneme, CA 93043

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Abstract

The process to develop options for military planning course of action (COA) development and analysis relies on human subject matter expertise. Analyzing COAs requires examining several factors and understanding complex interactions and dependencies associated with actions, reactions, proposed counteractions, and multiple reasonable outcomes. In Fiscal Year 2021, the Institute for Systems Engineering Research team completed efforts resulting in a wargaming maritime framework capable of training an artificial intelligence (AI) agent with deep reinforcement learning (DRL) techniques within a maritime scenario where the AI agent credibly competes against blue agents in gameplay. However, a limitation of using DRL for agent training relates to the transparency of how the AI agent makes decisions. If leaders were to rely on AI agents for COA development or analysis, they would want to understand those decisions. In order to support increased understanding, researchers engaged with stakeholders to determine visualization requirements and developed initial prototypes for stakeholder feedback in order to support increased understanding of AI-generated decisions and recommendations. This report describes the prototype visualizations developed to support the use case of a mission planner and an AI agent trainer. The prototypes include training results charts, heat map visualizations of agent paths, weight matrix visualizations, and ablation testing graphs.

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Preface

This study was conducted for the Naval Surface Warfare Center, Port Hueneme Division, under MIPR N6339422MP00081. The technical monitor was Mr. Gregory DeVogel.

The work was performed by the Institute for Systems Engineering Research branch of the Computational Science and Engineering Division, US Army Engineer Research and Development Center–Information Technology Laboratory (ERDC-ITL). At the time of publication, Mr. Willie H. Brown was branch chief; Dr. Jeffrey L. Hensley was division chief; and Dr. Robert M. Wallace was the technical director. The deputy director of ERDC-ITL was Dr. Jackie S. Pettway, and the director was Dr. David A. Horner.

COL Christian Patterson was commander of ERDC, and the director was Dr. David W. Pittman.

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1 Introduction

1.1 Background

The Navy Planning Process consists of a six-step process that includes Mission Analysis, Course of Action (COA) Development, COA Analysis (Wargaming), COA Comparison and Decision, Plans and Orders Development, and Transition (US Navy 2021). Both COA development and COA analysis rely on human expertise and may become time intensive. Fiscal Year 2021 Engineer Research and Development Center (ERDC) Institute for Systems Engineering Research (ISER) research used advances in artificial intelligence (AI), machine learning (ML), and deep learning to facilitate Navy mission planning within a military wargaming framework using a maritime scenario. This prior work established a baseline maritime wargaming framework for continued agent training and scenario updates. Introducing AI methods into the planning process can benefit COA development and analysis but may not be an acceptable method if leaders and COA developers do not understand the AI "behaviors" and corresponding AI decisions. The maritime wargaming framework allows for incorporation of visualizations to support decision-maker understanding of agent behavior. Based on stakeholder feedback, this research focused on incorporating visualizations and techniques to assist decision-makers with understanding agent behaviors and actions taken.

1.2 Objectives

The project consisted of two main objectives: (1) explore the expansion of the previously developed proof of concept prototype to incorporate additional use cases and (2) develop visualization methods to assist decision-makers in understanding the results of AI-enabled COA analysis, to include better understanding of AI decision-making and recommendations.

1.3 Scope

The following constraints, limitations, and assumptions provided scope and bounds to guide this program of research and provide context for the research performed.

This research had one primary constraint:* the final products for this research required completion within an 8-month timeframe.

The research contained one primary limitation:† the research team's access to engagements with warfighting subject matter experts was limited.

The research team made three assumptions‡ to enable expanding upon the proof of concept prototype and visualization development:

- Access to stakeholders within the Naval Surface Warfare Center–Port Hueneme Division and from external organizations will be sufficient to inform the problem, gain understanding of data and operational context, and receive feedback on products. The research team made this assumption in order to support the development of the visualization prototypes for completion within a shortened timeframe.
- Unclassified development using open-source resources (e.g., Python / OpenAI Gym) is acceptable. The research team made this assumption because the wargaming model uses similar open-source resources, which were integral to the completion of deliverables within the condensed research timeframe.
- The number of factors considered and varied in experimentation was sufficient to inform research findings.

1.4 Approach

This research used the approach detailed in Figure 1 to accomplish the objectives. Initial research served to refine the problem and work direction as well as to guide literature reviews. Next, research focused on requirements analysis and interviews with stakeholders to identify use cases and scenarios. Once identified, the team determined use case requirements and identified visualization options to fit those use cases. This information supported the next two aspects of the research related to prototype investigation and framework integration. Investigations focused on identifying visualization options (indicated by the down arrow), such as developing

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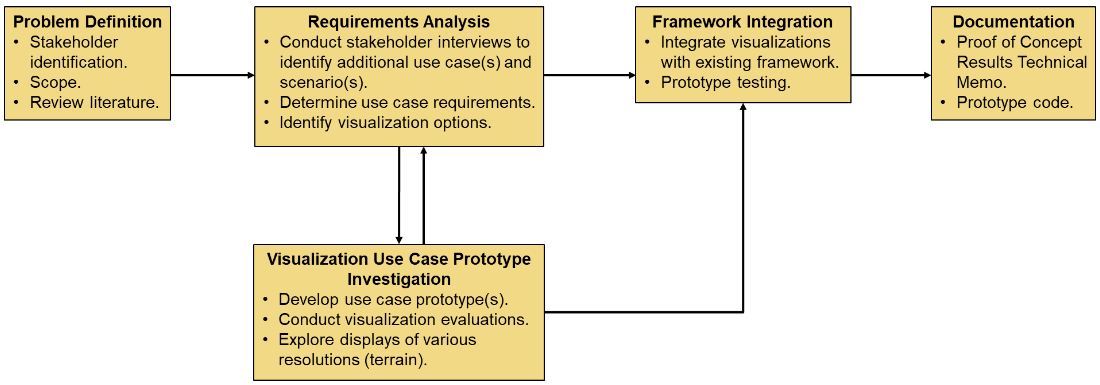
* A constraint is "[a] restriction imposed by the research sponsor that limits the research team's options in conducting the research" (Center for Army Analysis 2015).

† A limitation is "[a]n inability of the research team to fully meet the research objectives or fully address the research issues" (Center for Army Analysis 2015).

‡ An assumption is "[a] statement related to the research that is taken as true in the absence of facts, often to accommodate a limitation" (Center for Army Analysis 2015).

the use case prototype(s) and conducting reviews of the visualizations. This process iterated between requirements analysis and prototype investigation as visualization drafts changed in response to increased understanding of requirements. After development, research included evaluating the prototype visualizations and then integrating the new visualizations with the existing baseline framework.

Figure 1. Approach for artificial intelligence agent visualization integration.



1.5 Report Organization

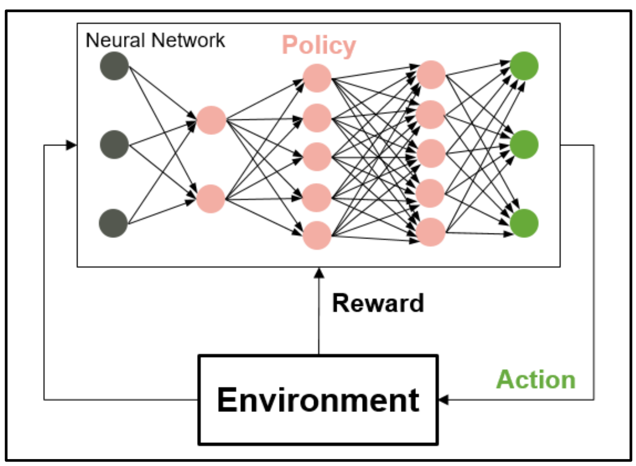
The remainder of the report follows the following outline. Section 2 of this report provides a brief overview of military wargaming as related to military doctrine and the potential role of AI agents for COA development and analysis. Section 3 provides an overview of the resulting visualization prototypes and ablation testing results. The report closes with a summary and way ahead.

2 Agent Decision-Making Overview

AI/ML includes the associated subcategories of supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning (RL) (Allen 2020). RL consists of rewarding agents with positive or negative rewards based on actions taken as the AI agent learns through trial and error (Sutton and Barto 2015). AI agents use inputs determined from the environment under exploration for making future action decisions (Russell and Norvig 2002).

One of the subcategories within RL, known as deep RL (DRL), combines RL and deep learning together. This wargaming framework relies on using a neural network (see Figure 2) for DRL. Each node in a neural network incorporates weights and biases that allow the network to calculate and determine how much to consider individual features of state data to make decisions.

Figure 2. Reinforcement learning with integrated neural network.



A major difficulty with using neural networks relates to understanding the agent's selection of specific actions. Because the AI agent learns through multiple iterations of trial and error, the decision-making process for an agent becomes less straightforward. As a result, stakeholders using AI agents for particular applications may not understand why the agent performs specific actions.

3 Visualization Use Cases

This section introduces the Navy's doctrine related to the COA development and analysis process (Section 3.1) as well as how integrating AI agents could support aspects of the COA development and analysis process using this wargaming framework. Section 3.2 details stakeholder feedback related to visualizations to potentially support understanding.

3.1 Course of Action (COA) Development and COA Analysis (Wargaming) Doctrine

Of the six steps in the Navy's planning process, the research team focused on steps 2 and 3, COA development and COA Analysis (wargaming), respectively, for developing AI agents that might facilitate Navy planning. These two distinct steps in the planning process have different implications associated with the use of AI agents and different requirements for visualizing AI actions to facilitate leader understanding.

3.1.1 COA Development

In step 1 of the Navy's planning process, Mission Analysis, planners gain a full understanding of their situation, the military problem they must solve, and the objectives they must achieve. With direction from the commander to guide them, the planning staff typically develops two or three COAs to solve the military problem.

Developing COAs requires expertise from a variety of functional experts, who provide input on a range of functions such as reconnaissance, logistics, personnel, and fires. COA development remains resource intensive in terms of the personnel required to develop two or three distinct COAs and the time needed to develop feasible, acceptable COAs. When developed, the COAs consist of a series of actions the unit will perform to achieve their mission objectives.

A planning team could use a blue AI agent, in conjunction with red AI agents, to produce candidate COAs for potential execution. Visualizing blue agent behavior and enhancing understanding of agent performance could be informative to decision-makers.

3.1.2 COA Analysis

COA development typically results in two or three COAs that the planning staff analyzes. The staff analyzes the COAs from, for example, a feasibility perspective, but the staff also wargames each COA.

In wargaming a COA, the staff considers the actions prescribed in the COA. For each action, the staff identifies what reaction the red force might have to the action, and, based on that reaction, develops blue counteractions. As with COA development, COA analysis (wargaming) requires expertise from a variety of functional experts and is also time intensive due to the large number of potential action-reaction-counteraction sequences for consideration.

A planning staff could use a red AI agent to generate more reactions to a blue counteraction, expanding the staff's understanding of potential outcomes for each of the actions. Being able to visualize the red AI agent's reactions could be helpful with understanding the red agent's behaviors.

3.2 Stakeholder Feedback for Artificial Intelligence (AI) Visualizations

This research gathered feedback from a variety of stakeholders to include previous interviews with mission planners and discussions with students conducting agent training using the same wargaming framework infrastructure. Initial analysis resulted in the identification of two initial use cases for visualization. The first use case involves the mission planner. These users could use a new visualization to understand the path of the agent, as this could relate to the COA development or the COA analysis as mentioned in Section 3.1.

The second use case relates to conducting agent training. This use case includes individuals who train agents to perform and act in a credible and reliable manner for eventual use in the maritime wargaming framework. The current training analysis process requires manual creation of training graphs using the comma-separated values (CSV) data generated after training iterations. Users primarily produce graphs with Microsoft Excel. However, the process to convert to an Excel graph becomes limited with higher numbers of training iterations. Another portion of the training process involves the agent trainers reviewing the resulting trained agent behavior in a game replay browser window. The replay allows for viewing of the actions taken during a game, which provides the trainer with visuals of the general behavior of the agent. However, the replay shows a move-by-move replay of the gameplay between the red and blue agents; the framework infrastructure lacks the ability to summarize the paths taken by each agent across multiple gameplays.

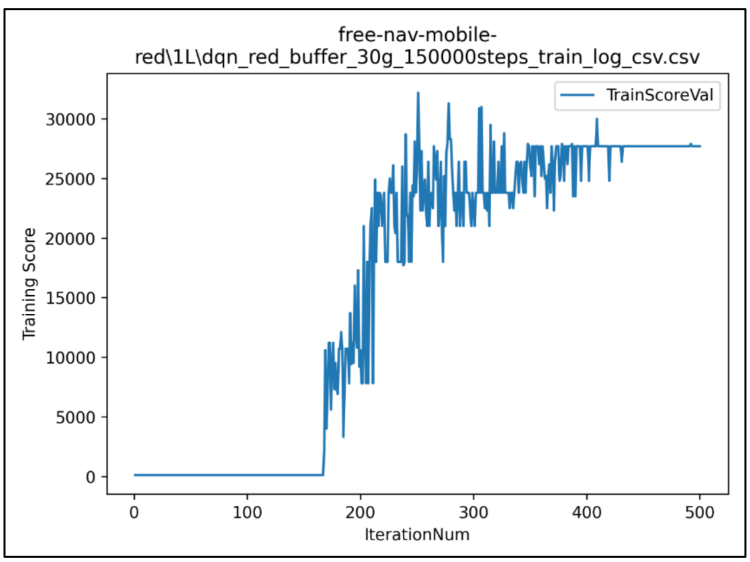
4 Results of AI Visualization

This section provides an overview of visualization prototypes developed to support understanding agent training and agent movement. The visualizations leveraged data generated from red and blue agent training excursions that considered 18 state data features. The visualizations support the use cases identified during stakeholder feedback discussions mentioned in Section 3.

4.1 Training Graphs

Researchers constructed a streamlined means to evaluate agent training performance over time by using the existing CSV output generated during training. The integrated Python script automatically converts a log file of a trained agent's per-game rewards achieved over time into associated graphs (Figure 3).

Figure 3. Example training graph.

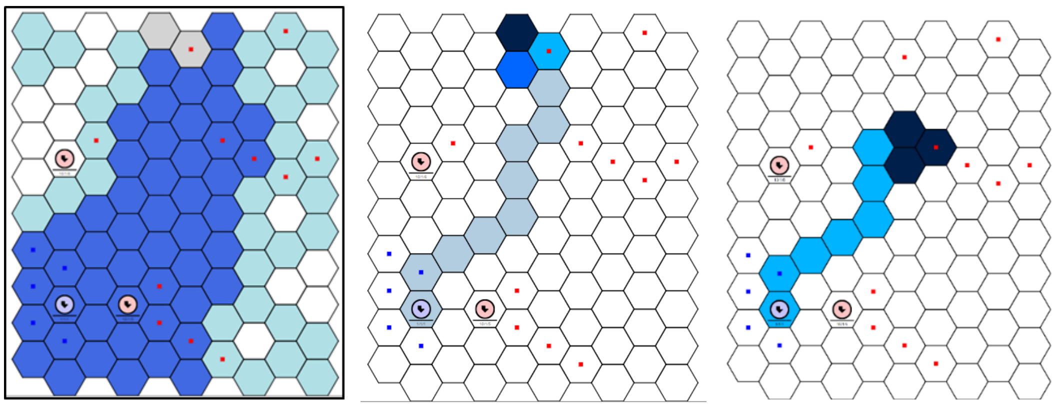


The graph plots the agent's training score (y-axis) versus its current iteration number (x-axis). This graph allows the training results to be quickly viewed and compared across multiple training iterations. The graph visualization helps to understand the agent training results and to identify when the agent reaches a plateau, or ceiling, in the rewards, signifying that more training does not result in a demonstrable increase in the training score (rewards) acquired.

4.2 Heat Maps

Awareness of the hexes that an agent travels along and how many turns an agent spends in each hex supports understanding AI agent actions and decisions. The hex-based heat map (reference Figure 4) serves as a summary to count all the paths taken by a specific agent after multiple gameplay sessions.

Figure 4. Scenario map along with two example heat maps of blue agent movement.



The heat map color aligns with the agent color (e.g., a blue agent generates a blue heat map); a darker shade symbolizes a relatively large quantity of phases in which an agent occupied the hex, while white shows that an agent never occupied the hex. The heat map functions by analyzing the replay files created by batch runs of the gameplays and storing the location data for each agent during each phase. Using the location data, the heat map capability calculates the highest number of visits to a particular hex and uses that data as the maximum value to create a color gradient with six breakpoints with which to label the hexes of the map. The heat map illustrates the path that each agent takes over a period of gameplays, overlaid onto a hex-grid map. Figure 4 depicts the baseline scenario (*left*) and two blue agent heat maps (*center* and *right*). For example, in the baseline scenario (Figure 4, *left*), one blue agent competes against two red agents in multiple sets gameplays. The blue agent seeks to reach the destination (appearing as the gray hexes in the scenario image). In the first set of gameplays, the blue agent reaches the destination, and the heat map (Figure 4, *center*) depicts the path most prominently followed by the blue agent across multiple gameplays. The blue agent follows the same path primarily and then shifts positions toward the end of the game while near the destination (gray hex). In another set of gameplays, the blue agent spends a larger amount of time in a specific group of hexes but never reaches the destination based on the heat map summary. Review of the actual replay file reveals that the red agent continuously attacked the blue agent until ultimately removing the blue agent from the simulation midway to the destination.

The heat map capability demonstrates a clear means for stakeholders to discover whether agents seem to be moving in a reasonable fashion and visually depicts paths taken and significant events (reaching destination or removal from simulation). These visualizations could support human experts' understanding of AI agents' actions in COA development and analysis. The heat map could also identify areas of potential future consideration for a mission (e.g., probability of defeat at a specific hex location).

4.3 Weighted Matrices

One approach to support understanding of agent decisions involves analyzing statistics of chosen weight matrices in a trained agent's neural network. This type of analysis highlights features within the neural network with high overall weights, which may signify importance to agent decisions while also isolating state-data features with weights near or at zero as potentially unimportant. Table 1 outlines the 18 specific state-data features used during agent training.

Table 1. State data and definitions.

State Data	Definition
Red unit strength	Location and health points for each red unit
Blue unit strength	Location and health points for each blue unit
Unit types (7)	Infantry, artillery, mechanized infantry, armor (tanks), frigate, small boat, and cruiser
Terrain types (5)	Land, rough land, water, deep water, and urban areas
Current phase	Current timestep within the game
Unit on move	Unit allowed to take action during turn
Legal moves	The set of allowable moves for each unit
Units able to move	The set of units that have yet to take action during the phase

Attempting to identify the value associated with each individual state-data feature first required analysis of the size and shape of the values in the neural network. The framework seems to have saved each parameter as a tensor in which each layer contains a variety of image and channel values, as well as a matrix with unique numbers of rows and columns. Converting the top level's data to an array of values and then taking the absolute value of each element enabled the construction of a convolution matrix. This matrix could help to provide initial insight as to how each input feature affected the three output nodes.

The AI-enabled trained agent leverages information using 18 specific types of state data that correspond to features such as the nearby terrain types (e.g., water), agents' unit types (e.g., artillery), and individual units' strength levels. The trained agent model data saves each state-data feature (parameter) in the form of a tensor in which each layer contains both image and channel values. This research converted the available data into the form of an array of values and used the absolute value of each element to develop the weight matrix (Figure 5), which consists of 3 rows and 18 columns. The 3 rows correspond to selected elements from the first layer of convolutions for the neural network, while initial observations imply that the 18 columns correspond to the number of state-data features.

Figure 5. Example weight matrix (notional).

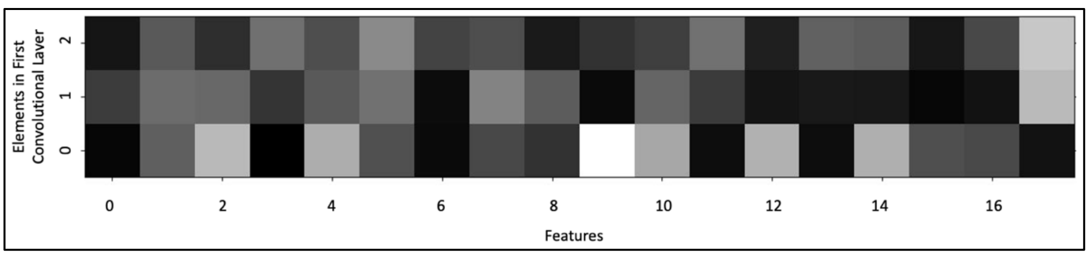
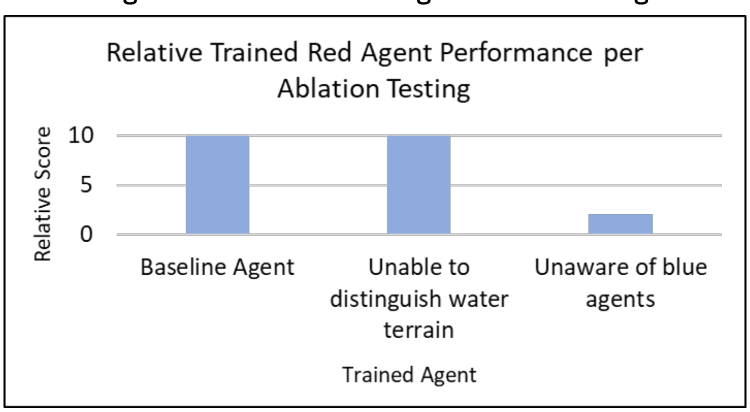


Figure 5 could provide potential insight as to how each of the input features affected agent training, assuming that the 18 columns do correspond to the individual state-data features. In this notional example, the darker colors would correspond to features of lower importance, and lighter colors would correspond to features of greater importance. A weight matrix allows for stakeholders to potentially visually identify the most influential features upon the agent's decision-making. For example, with respect to the scenario shown in Figure 4 (*left*), the proximity of opposing agents might have a more influential effect on the trained agents' actions than the type of terrain nearby. Researchers could alternatively produce a similar visualization for more values (such as the mean, median, and maximum values of weights from the first layer of convolutions) to try to gather additional insights. However, because the processing of data through multiple neural-network layers with varying numbers of nodes may skew the matrix's display of the data, extracting additional details to improve stakeholder understanding using this method would require additional study. Most importantly, additional investigation related to the columns' correspondence with the state-data features is required.

4.4 Ablation Tests

Another option for understanding agent behavior includes investigating features important to agents' learning. This approach requires training new agents without knowledge of specific features from Table 1 and then identifying any deterioration in performance, a concept referred to as ablation testing (Vinyals et al. 2019). For ablation testing, researchers removed knowledge of one feature of the scenario board, retrained an agent without that knowledge, and then compared the new agent's performance to the baseline agent's performance. As an example, one might train a baseline red agent to delay and harass the blue agent and experience decent performance with the original 18 state-data features. Then, one might train the red agent again with only 17 features by removing knowledge of one feature (e.g., location of opposing agent). By removing an individual feature from the 18 features initially used to train the baseline agent and then retraining the agent from the beginning, the research team identified a factor with significant effect on agent performance. Figure 6 demonstrates initial ablation testing results with the separate removal of two initial features.

Figure 6. Results from red agent ablation testing



For the ablation testing, researchers conducted an experiment in which the red agent no longer knows the blue agent's location on the game board during each training iteration. Since the red agent's reward function incentivizes the red agent to delay and harass the blue agent, the initial hypothesis predicted poor red performance when the red agent lacks awareness of the blue agent's location during training. The experimental results supported the initial hypothesis. As the bar chart in Figure 6 illustrates, compared to the baseline, the red agent trained without awareness of blue agents' location scored much lower than the baseline agent (on the far left of the chart). Also, some features are not as relevant and do not result in a significant decrease in scoring per the bar chart. When training a red agent without state-data knowledge about the type of water terrain, the agent still performed well, with a score very similar to that of the baseline agent. This indicates that the awareness of the opposing agent impacts the agent behavior more than the awareness of the type of water terrain. Stakeholders may gain a better understanding of the AI-trained red agents' decision-making by visually understanding which features' removal results in detrimental agent performance. Stakeholders may also evaluate whether their existing decisions and associated features considered align with the features used by the agent.

4.5 Integrating Gameplay Output with Unity Software

In collaboration with the Missouri University of Science and Technology (MS&T) research team, the ERDC ISER research team supplied hex-based AI gameplay output for visualization within a 3D Unity visualization environment. This visualization provides an alternative mode of viewing the AI agent performance during a gameplay session. The collaboration goal included translating the Python agent behavior from the framework for representation in the Unity environment. The research team provided replay output files to the MS&T research team. In turn, MS&T incorporated the agent movements from a saved gameplay file and then visualized the scenario in a 3D format within Unity.

5 Conclusions and Future Work

This research developed capabilities to improve understanding of agent training and gameplay through a variety of visualizations. An integrated graphing capability automatically generated training output visualizations to support analyzing agent learning. Investigations to understand features of importance resulted in a convolution matrix visualization potentially corresponding to elements from the neural network. Researchers developed heat maps to support understanding of agent movements taken during gameplays. Additionally, integrating the capability to perform and analyze ablation testing allowed for understanding the impact of removing state-data features upon agent performance. Ablation testing revealed the importance of knowing the blue agent's location on trained red agents' performance. Overall, the instantiated visualization prototypes provide options for stakeholders to potentially gain additional insight into agent training performance and agent decisions.

Several opportunities exist to expand upon the visualization capabilities generated. For example, tracking features of importance with a convolution matrix requires further investigations to translate the values produced with the convolution matrix into identifying which features could potentially be more or less important for agent success during training. In addition, the examination of the importance of state-data features with ablation testing only removed one feature at a time. Future research could investigate removing combinations of different features that might result in a more significant effect than simply removing individual features. Although the present use case for the heat-map functionality examines movement paths by a trained agent during gameplay, future research could potentially expand the functionality to illustrate the paths taken by agents during training. The future research could map the trial-and-error exploration of the entire space by an agent throughout the training process.

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Abbreviations

AI	Artificial intelligence
COA	Course of action
CSV	Comma-separated values
DRL	Deep reinforcement learning
ERDC	Engineer Research and Development Center
ISER	Institute for Systems Engineering Research
ML	Machine learning
MS&T	Missouri Science and Technology
RL	Reinforcement learning

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14. ABSTRACT
The process to develop courses of actions (COAs) for military planning COA development and analysis relies on human subject matter expertise. Analyzing courses of action requires examining several factors and understanding complex interactions and dependencies associated with actions, reactions, proposed counteractions, and multiple reasonable outcomes. In Fiscal Year 2021, the Institute for Systems Engineering Research research team completed efforts resulting in a wargaming maritime framework capable of training an artificial intelligence (AI) agent with deep reinforcement learning (DRL) techniques within a maritime scenario where the AI agent credibly competes against blue agents in gameplay. However, a limitation to using DRL for agent training relates to the transparency of how the AI agent makes decisions. If leaders were to rely on AI agents for COA development or analysis, they would want to understand those decisions. In order to support increased understanding, researchers engaged with stakeholders to determine visualization requirements and developed initial prototypes for stakeholder feedback in order to support increased understanding of AI-generated decisions and recommendations. This report describes the prototype visualizations developed to support the use case of a mission planner and an AI agent trainer. The prototypes include training results charts, heat map visualizations of agent paths, weight matrix visualizations, and ablation testing graphs.

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