The Impending Data Literacy Crisis Among Military Leaders

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INTRODUCTION

You would be hard pressed to find a room full of office typists in any present-day corporate setting. Office typists (who reached an apex in the mid-20th century) employed fast typing skills, a mastery of language and grammar, and the ability to take real-time dictation through shorthand.[1] However, with the advent of personal computers and email, the speed of business required leaders to improve their own typing and communication skills. Those that embraced these skills quickly outperformed those that failed to adapt. Today, office typists are obsolete; their skills are now integral to everyone in an organization.

Similarly, today's business leaders rely on teams of data scientists[2] to manage, analyze, and model large amounts of data to inform decisions. Will data scientists one day sustain a fate similar to office typists? It may be too early to make such a prediction. Nonetheless, to compete in the near-future global market, leaders–military and civilian alike–will need to adapt these skills and become data literate with deep knowledge of data capabilities.

Data provide a competitive advantage[3] to the businesses and governments who know how to use them. The private sector employs cross-functional data science teams to analyze and build valuable prediction models from large clusters of data that are used to drive business decisions and maximize outcomes. The ubiquitous use of personal devices that capture our every step, social media post, and internet search, along with rapidly improving infrastructures to handle such large-scale structured and unstructured information, have given rise to machine learning (ML) and artificial intelligence (AI). We interact with ML algorithms daily; these techniques allow for endless possibilities to make data-driven decisions to enhance nearly any aspect of life. Amazon recommends items to purchase based

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on the purchase history of people similar to you. Google Maps provides routes based on your route preferences along with current traffic, speed, and accident data. Digital assistants, such as Siri and Alexa, use language processing to predict what information you are requesting. On discount travel sites, you may even find different prices based on an algorithm that predicts those using Apple computers are less price sensitive than those that use Windows PCs. With these relatively low-risk examples, the cost of getting the prediction wrong is fairly low. Data scientists tune parameters to improve the algorithm's performance based a context specific optimization of precision, sensitivity, and specificity.

MILITARY APPLICATION OF ML/AI TECHNOLOGIES

The U.S. Army is actively building advanced data capabilities that leverage ML and AI to revolutionize the future of warfare against increasingly capable adversaries. The potential for AI to drastically change the speed of decisions, and thereby the speed of war, will be revolutionary. Unfortunately, without a focused effort to improve military leaders' understanding of the data science field, commanders will lack trust in these technologies or, far worse, will over-rely on amoral machines to make decisions for them.

A quick search of the military's use of ML/AI results in numerous, cutting-edge efforts to revolutionize warfare. Project Maven[5] is one example where the U.S. Special Operations Command (SOCOM) is leveraging AI to assist in analyzing surveillance video using visual detection algorithms. The initial foray into AI-supported analysis has the potential to drastically improve SOCOM's ability to analyze vast amounts of raw video data and reduce the intelligence analyst's time needed to conduct this task. Although tactical-level leaders acknowledge the potential, the science fiction-like expectation is inconsistent with the reality, thus hindering the full integration.[6]

Project Convergence[7] is a second example where the U.S. Army is leveraging AI. With Project Convergence, the goal is to dramatically reduce the time needed to identify enemy forces and employ lethal munitions. This initiative demonstrated some success recently in an exercise where the Fires Synchronization to Optimize Responses in Multi-Domain Operations (FIRESTORM)[8] recommendation algorithm was used to support rapid decision-making to deliver lethal effects on identified targets. This project has the potential to dramatically improve the targeting cycle and quickly overwhelm our adversaries. However, leaders must have intricate knowledge[9] of how these systems work to understand the inherent biases that may exist within the algorithms and the potential clashes between moral values and AI-based decision-making.

The Operations Research/Systems Analysis (ORSA) is a functional area within the Army that traditionally supplied data analysts to support data-driven decision-making on strategic level staffs.[10] ORSA personnel are evolving their role from data analysts (analyzing data to produce new insights) into data scientists[11] (building predictive models and visualizing data to produce new insights) to support strategic-level decision-makers. Currently, however, neither ORSA personnel nor other data scientist teams are consistently available to support tactical- and operational-level decision-makers. Yet, leaders still find themselves making decisions in data-rich environments. Because of this, it is imperative that leaders at all levels improve their data literacy to operate in conflicts of both today and well into the future.

ML/AI IMPLICATIONS FOR LEADERSHIP

New military leaders are often told to "trust but verify,"[12] a phrase made popular by former President Ronald Reagan when discussing nuclear disarmament. This notion is usually followed by, "don't expect what you don't inspect," a mantra that is paramount to anyone employing ML algorithms and AI in a high-risk context. Given quality data, properly trained algorithms can find patterns and make predictions far better than humans.[13] However, many applications of ML/AI use "black box" approaches that obfuscate the decision-making rules that are used. In high-risk environments, when making data-driven decisions, leaders must understand why decisions are being recommended, think critically about potential biases, and verify the tradeoff[14] between precision (out of those predicted as A, how many are really A), sensitivity (out of those that are A, how many were predicted to be A), and specificity (out of those that are not A, how many were predicted to not be A).

Compared to the low-risk predictions involved in Google Maps and Amazon shopping, in the military, the cost of getting a prediction wrong could be catastrophic. Decision-making algorithms need to be informed by subject matter experts and be trained on the same type of data that leaders would utilize to make decisions. As an example, team leaders would never use a Google Maps algorithm to conduct route planning from a forward operating base to a target location unless they knew numerous variables were considered, such as historic enemy activity, friendly force location, and the potential to encounter deeply buried improvised explosive devices. The team leader would still want to verify the recommended route based on their own experience, mission objectives, and organizational capability.

WHAT DO LEADERS NEED TO UNDERSTAND?

At a minimum, military leaders employing ML/AI technologies must understand[15] the data pipeline, as well as algorithm development and underlying assumptions to identify the strengths (when it should work well), limitations (when it will be unreliable), and indicators of drift (when reinforcement learning algorithms in production become less reliable over time).

Data Pipeline

Algorithms are only as good as the data upon which they are trained. If these data are biased in any way, the algorithm will also be biased.[16] It is important for leaders to understand how data are obtained and processed so that they can appreciate the limits of an ML/AI application. Raw data must be processed and transformed before it can be used in ML/AI. Turning raw data[17] into usable data can be as complex as the algorithm-building process itself. When data engineers clean and transform raw data, the decisions they make will impact the performance of the algorithm. For leaders to fully appreciate what decisions, and ultimately what biases underlay the algorithm, they must have some knowledge of this data-cleaning process.

When unbalanced data sets are used for training, it can also introduce bias into detection algorithms. For example, one of the most popular data sets used to train algorithms to predict age and gender from a static image is based on the 100,000 most popular actors and actresses.[18] The data set contains a disproportionate number of Caucasian men, as well as images that appear much younger than their true age. As a result, most algorithms trained on these data can accurately detect Caucasian men, but have a substantially harder time classifying minority women, and almost always predict their age as older than they actually are. If diverse groups are not equally represented in a military object detection algorithm,[19] the results could disproportionately misclassify and endanger under-represented individuals. Leaders must critically think through potential biases inherent within training data sets to understand the limits of ML/AI algorithms.

When ML/AI applications are designed to continue learning as new data are considered–also called reinforcement learning algorithms–it is important for leaders to identify when contextual changes or data quality changes may impact the accuracy of the prediction models. By understanding how often new data are introduced and how often an algorithm's performance is tested, leaders can better identify this drift in accuracy.

Algorithm Development

Similar to data engineers making decisions about data processing, ML engineers make decisions when determining what algorithms to use and how to optimally tune them. Leaders employing ML/AI capabilities would certainly benefit from understanding how an algorithm makes decisions. The interpretability of an algorithm is an important consideration for ML engineers and leaders alike. Black box approaches, such as deep neural networks,[20] may provide a slight improvement in performance over more interpretable approaches, such as decision-tree classification algorithms. However, black box approaches come at a cost. Leaders that cannot articulate why an algorithm concluded what it did will either not be able to fully trust the recommendation or, perhaps more dangerously, blindly trust the decision.

FINAL THOUGHTS

As technology changes, all leaders (military and civilian) must learn the capabilities and limitations of the tools that they employ. The United States Military Academy was founded on a desire to bring the technical expertise of civil engineering and artillery[21] into our fledgling Nation's military officer corps at the turn of the 19th century. The technical expertise needed during today's information age is data literacy.

Across the country, most, if not all, colleges and universities are developing data science undergraduate and graduate degrees. Educational settings[22] may be an opportune context to develop data literacy and many initiatives are currently underway. In fact, West Point has several initiatives that are building this knowledge among our young military leaders. All current Cadets take a two-course core information technology program,[23] in which faculty members recently began to incorporate data science into the curriculum.[24] The Center for Data Analysis and Statistics,[25] the Applied Statistics and Data Science Major,[26] and the Computer Science Major[27] also provide additional opportunities for Cadets to further learn about data science and develop their knowledge and skills. Even within the behavioral sciences, I have introduced the R programming language[28] in an attempt to improve each Cadet's data literacy and algorithmic thinking.

With such training becoming increasingly prevalent across both military and civilian educational settings, in the near future, junior leaders will have a basic understanding of data and data-driven technologies. Mid- to senior-level leaders will need to embrace and consider ways to improve their own understanding of these technologies or risk these advances outpacing our leader's ability to employ them. This concept is not new or without support. As discussed in the *2019 ADP 6-22: Army Leadership and the Profession*, "The adaptable leader remains aware of the capabilities and shortcomings of advanced technology and ensures subordinates do as well."[29] We no longer need office typists, but we will always need adaptable leaders.

DISCLAIMER

Views expressed here are those of the authors and do not reflect the official policy or position of the United States Military Academy, the Department of the Army, or the Department of Defense.

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