Simulation Based Training's Incorporation of Machine Learning

Ivar Oswalt, PhD
Alion Science and Technology Corporation
Norfolk, VA
Ioswalt@alionscience.com

Tim Cooley, PhD
DynamX Consulting
Oxford, MA
Tcooley@dynamx.com

ABSTRACT

Machine learning (ML) is all around us. From virtual assistants to automated testing, it provides capabilities that we now depend upon. Yet, while ML enables significant advantages in organizing and differentiating complex data in many domains, it has not yet made a significant impact on US Department of Defense (DoD) training systems or training methods. The question is not should ML be integrated into DoD training, but what techniques are efficient, effective, and feasible? The answer to these questions, and many others, are critical to developing the next generation of trainers and live, virtual, and constructive (LVC) training capabilities. The potential impact is vast, but well researched and intentional integration is crucial, as the costs will be significant. This paper describes ML and discusses emerging/innovative technological ideas on integrating ML into two categories of training systems. First are multi-person training simulators, such as convoy trainers, which - with the injection of ML - could realize decreases in training time and increases in proficiency. Second, the analysis expands these insights into the context of LVC training simulations. For LVC, it summarizes precursor semi-automated systems, highlights current ML applications, discusses the roles ML could play in future LVC environments, and describes how these systems could be wrapped in advanced training delivery approaches. This paper concludes with thoughts and considerations regarding ML topics that are critical in simulation-based training (uncertainty, metrics, DoD/commercial interaction, and data) and then recommends possible next steps.

ABOUT THE AUTHORS

Dr. Ivar Oswalt is a Senior Modeling and Simulation Analyst of Alion Science and Technology Corporation, supporting the Navy's Modeling and Simulation Office (NMSO) in the areas of plans, policy, education, standards, and outreach. He was a contributing author to the recent revision of the Secretary of the Navy Instruction on M&S and VV&A Management. With significant experience in multi-attribute utility theory, he has developed M&S metrics and measurement approaches for the Office of Naval Research Operations Analysis Program; analyzed overseas intelligence operations to assess the potential role of M&S-type predictive systems to forecast events for the Naval Research Laboratory's Adversarial Modeling and Exploitation Office; and has formulated composability requirements, a framework, and functional areas for the Department of Defense M&S Office (DMSCO).

Dr. Tim Cooley is President and Founder of DynamX Consulting, a veteran owned consulting firm. Dr. Cooley spent 17 years on the United States Air Force Academy faculty, both in uniform and as a civilian, holding numerous positions including the DMSO Modeling and Simulation Chair, Deputy Department Head, and Senior Researcher. As the principal investigator, he completed many innovative mathematical and cost analyses for the USMC, USAF, and OSD and has performed counter-terrorism research for Joint Staff. He has significant experience using Machine Learning and Neural Networks for pattern recognition/classification in the medical community and is currently researching standards development in Artificial Intelligence.

Simulation Based Training's Incorporation of Machine Learning

Ivar Oswalt, PhD
Alion Science and Technology Corporation
Norfolk, VA
Ioswalt@alionscience.com

Tim Cooley, PhD
DynamX Consulting
Oxford, MA
Tcooley@dynamx.com

INTRODUCTION

Machine learning (ML) and the resulting artificial intelligence (AI) are a part of our daily lives. From voice recognition and automated assistants on mobile phones to self-driving automobiles, ML/AI is all around us. And both have significant advantages: they don't experience fatigue, have personal error bias (although algorithms can be subjective), and can access information updates from the internet of things. However, ML/AI is scarcely utilized in DoD training systems or training methods, despite these and many other advantages. How, where, and to what degree should DoD training systems integrate ML/AI? In studying the problem of how to integrate ML-based AI into new innovative training systems, there are many potential directions that could be explored. Each one of these directions brings about many questions.

> *"There is a need to build simulations that are themselves learning agents - Able to compare their outcomes with actual results, assign "blame," and adjust parameters in a semi-automated or automated way" (Surdu, 2007)*
>
> *"We all know that with VA, AR, LVC, AI, and the development of machine learning, we in the military, in the DoD are just too slow to take advantage… It's a challenge we are all going to have to continue to face and work through." (Drummond, 2017)*
>
> *"Artificial Intelligence and Big Data capabilities must be organic to, and reside within, the STE (Synthetic Training Environment) Architecture and the Training Simulation Software from the beginning." (CAC-T, 2017)*
>
> *"Military officials and industry experts have long discussed how artificial intelligence can benefit the warfighter. … However, there has been much less emphasis on how it can improve modeling and simulations for training purposes…" (Tadjdeh, 2018)*

The answers to these questions are critical in developing the next generation of trainers; ones that incorporate AI and ML This area normally includes visual perception/facial recognition, speech recognition, language translation, system automation, and similar. Yet, our focus here is significantly narrower. It concentrates on ML/AI within US DoD training simulations. It does not address ML/AI in analytic simulations, simulation inputs (to train) ML/AI systems, or ML/AI use in automatous system control logic – even though these are all very important areas.

This paper describes ML/AI within a subset of US DoD simulation-based training systems. It discusses the current state-of-the-art and important relevant goals, These are, in the most general sense: 1) Improved simulation capabilities (e.g., better Blue, Red, and White/Neutral Force inclusion and decision making representation), 2) Training delivery enhancement (e.g., adaptation of learning systems to the training audience), and 3) Training scenario advancement based on insights from force employment alternatives/outcomes discovered within ML/AI based simulations (e.g., innovations in tactics, techniques, and procedures (TTP) / emergent behavior) – in real time (during mission execution), just in time (immediately prior to debarkation), and in post-event/exercise scenario development and employment (e.g., future in-garrison training). This article also includes a discussion of the current state-of-the-art, development potential, considerations, and possible ways ahead. The three quotes above exemplify the duration of this pursuit, current interest, and one Service's specific intent in this area, but they are a tiny subset of the statements of needs, requirements, goals, and similar that describe ML/AI within the US DoD simulation training community.

DESCRIBING ML/AI AND SOME OF ITS VARIANTS

To frame this discussion, a set of basic definitions are required – most are traditional; a few have been expanded to better apply to this domain. They are:

- Artificial Intelligence (AI): An area of study and a set of programs that accomplish complex tasks – or that generate insights – that would normally require a human (Widman, 1990). AI programs may: Generate behavior that is not completely described by an algorithm; Incorporate facts and relationships about the real world; Address ill-structured problems; and Maintain logic and data structures that allow explanation.

- Machine Learning (ML): An application of AI that provides systems the ability to automatically learn (or learn in an automated fashion) and improve from experience without being explicitly programmed. ML programs search for useful representations of input data, within a hypothesis space, using guidance from a feedback signal (Chollet, 2018).
- Types/Components of ML/AI:
    - Classic Machine Learning Approaches: Include probabilistic modeling, early neural networks, kernel methods, decision trees, random forests, and gradient boosting machines. They have less capability to adapt to data and improve their results in an automated fashion than modern methods.
    - Symbolic AI/Expert Systems (ESs): Programs that reproduce the behavior of a human expert within a specific area of knowledge (knowledge-based systems that capitalize on hindsight/experience)
    - Neural Networks (NNs): An information network consisting of input, hidden (if any) and output nodes. In single layer feed forward networks, inputs are fed directly to the outputs via a series of weights (there are no cycles). In neural networks, the most popular learning technique is back-propagation and its variants, in which output values are compared to the correct answer and weights are subsequently adjusted. Two types of NNs warrant additional definitions:
        - Deep Learning NNs (DLNNs): Multi-layered NNs that emphasize learning from successive layers of increasingly meaningful representations.
        - Generative Adversarial Networks (GANs): A system of at least two NNs (generative and discriminative) contesting with each other in a zero-sum/minimax game framework.
    - Dynamical ML: Machine learning that can adapt to variations over time. It requires real-time recursive learning algorithms and time-varying data models (Madhavan, 2017).
    - Genetic Algorithms: A metaheuristic inspired by the process of natural selection that relies on bio-inspired operators like mutation, crossover, and selection (Melanie, 1996).
        - Genetic Fuzzy-based AI: Programs that implement a Genetic Fuzzy Tree (GFT) methodology, using a collection of fuzzy inference systems that are trained.
    - Agent / Multi-Agent-Based Models: Systems that are composed of multiple interacting entities that may exhibit self-organized / emergent behavior.
    - Cognitive Models: Rule-based semantic networks / production rules that implement problem solving capabilities, some of which can form new operators/rules from those that exist as needed.
- Human-Level Artificial General Intelligence (AGI): The development and demonstration of systems that exhibit the broad range of general intelligence found in humans (Adams, 2012).

The overall goals of ML/AI application to simulation-based training have been summarized above. Yet, it is important to add that within each of these areas, there are many potential specific objectives. For instance, in decision maker representation/replication (Blue, Red, and White/Neutral), specific objectives include developing ML/AI systems that: mimic human cognition, replicate human biological systems, model human behavior (e.g., fatigue), include multi-human interactions, etc. Unfortunately, many are beyond the scope of this paper.

FOCUS AREA INSIGHTS

Possible applications of ML/AI will be examined within simulator-based training systems and Live, Virtual, and Constructive (LVC) training federations. These two case studies provide a set of "book-ends" – one focused on direct extensions to current capabilities that can provide near-term results. The second, LVC, is a much more complex simulation training environment, in which some types of ML/AI systems already exist, while at the same time there are sophisticated requirements that will require long-term planning and solution development.

Current and Potential ML/AI in Vehicle/Simulator-based Training

Here the focus is on simulators – that is "a machine with a similar set of controls designed to provide a realistic imitation of the operation of a vehicle, aircraft, or other complex system, used for training purposes (the virtual (V) in LVC). They are in the same category as emulators, computer-based embedded trainers, appended trainers, etc.

Simulators are used widely by the services to train personnel in vehicle operations. With respect to a convoy or driving training system there are four basic parts: the hardware (the vehicle emulator), the software (the scenarios and the part that analyzes the trainee's input), the trainee, and the trainer (see Figure 1). For instance, the US Marine Corps uses the Combat Convoy Simulator (CCS) and the Operating Driving Simulator (ODS) with the US Army using similar systems as well. The CCS facilitates training for convoy tactics, techniques and procedures, use of weapons in compliance with the rules of engagement, and verification and validation of unit standard operating procedures. On the order of 20,000 Marines are trained each year in the CCS. The ODS trains vehicle operators on multiple vehicle platforms. The trainer uses a manufactured cab with interchangeable dash sets that replicate the look and functionality of the vehicle chosen for simulation. The systems are equipped with three-degrees-of-freedom seat motion for the driver and 180 degrees of visual display via three electronic displays. Roughly 15,000 Marines are trained each year using the ODS. Incorporating ML/AI in either of these systems could have great advantages. The questions that arise focus around into what component do we inject AI and what are the expected benefits?

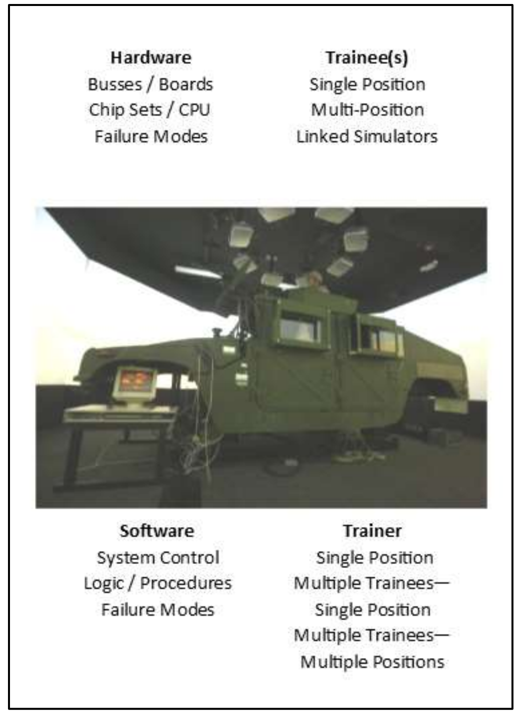

Figure 1. Components of a Simulator

Hardware can be considered in two forms: the physical structure of the simulator and the electronic devices embedded within the structure that control the simulation. Certainly, the physical structure would need to represent the actual vehicle as closely as is possible, as it does currently. The application of ML/AI would not affect that element. However, the embedded electronic hardware would be required to change. The embedded hardware would need to be powerful and fast enough, dedicated boards with multi-thread, parallel processing capability with multi-gigabyte on-board memory, to process the AI algorithms and data inputs in real-time. With current technology these types of boards are affordable and are in the $500-$1000 range. The AI algorithms could reside in firmware which would allow for updates to the algorithms. However, typically firmware only applies to the functioning of an individual component and not the more general software system. Therefore, the impact to embedded hardware would be to upgrade the components to possess significantly increased capability.

Software is the brains of a simulator system. The scenarios, input processing, and outputs are all controlled through extensive software modules. For ML/AI to impact training, it will have to reside in the software modules since it would process inputs and impact outputs of the simulator. This is not surprising. However, given the lack of AI in current simulators, it can’t just be appended to the current systems as an optional add-on. It has to be ingrained in the very fiber of the system to function most effectively: fully embedded in the software and a part of the algorithms that govern the simulator behavior. In other words, it isn’t just an upgrade to the current systems, it is a whole re-design. One might think that this level of processing can’t be done in real-time and the simulator will then be a poor reflection of the live system as the response time will lag. However, the relatively recent research on autonomous vehicles would cast doubt on that argument (Kendall, 2017). Given that vehicles are able to navigate even complex routes autonomously at prevailing traffic speeds, it would seem logical that simulators could process inputs and provide correct outputs in real-time.

This brings us to, how does ML/AI impact the trainee? One answer to that question is that the infusion of ML/AI should heighten the training experience and increase the effectiveness of the training. One such example would be “adaptive training”. Adaptive training is training that adapts to the trainee’s inputs and provides more training where needed. For example, if a trainee has a difficult time maintaining proper following distance under threatening conditions (the situation where an enemy is present or is expected to be present), then the AI in the system would present more of those situations and less of routine convoy driving. Or, if a trainee is not scoring well on using the 0.50 caliber machine gun, then the AI in the simulator puts that trainee into more situations where firing the 0.50 caliber is required. Conversely, if a trainee has mastered a certain task, climbing steep hills in rough terrain for example, then the AI presents less of those situations to that trainee. Additionally, the AI should provide feedback for why the trainee did not complete a task well so that training and learning are achieved and not just repetition of the same flawed tactics. By training in this fashion, a trainee becomes more proficient in a shorter period of time since they practice their weak areas more and their strong areas less. Therefore, the end result is more effective training as the trainee increases his/her proficiency in less time. While there are other potential uses for ML/AI in driving simulators, such as predicting trainee behavior based upon a larger training group, adaptive training seems to be one of the most useful (Hercenberg, 2008).

For the trainer, ML/AI would have significant impact. No longer could a trainer set a scenario and then sit back knowing each task presented and the sequence of that presentation. Each scenario would change based upon the trainee's responses. Some might say that the trainer could be replaced, or at least partially replaced, by the AI in giving feedback, providing suggestions, etc. More likely, the trainer will need to be better trained and more proficient than ever since the scenarios are no longer completely predictable. Currently, a trainer knows those tasks that a particular scenario trains and may just brush up on those items for that training session. A system with infused ML/AI is less structured and somewhat amorphous, requiring the trainer to be ready to critique and provide feedback for a much bigger task set, whether it be in real-time or as an after-action debrief. In this new mode trainers will need to be better prepared and more proficient at their craft to incorporate the new technology. H. J. Wilson posits that AI will bring about a new collection of jobs; one of those being an "Explainer" (Wilson, et al, 2017). In this case, the explainer would use the AI feedback and ensure the trainee interprets it correctly and knows how to correct the deficiencies in his/her task performance. This will require the trainer to have a higher level of proficiency in both the real and the simulated system.

The discussion thus far has focused on the simulator itself. However, there may be additional uses for AI in simulator-based training that do not impact the simulator operation. For example, applying AI in scenario development could assist in generating more efficient scenarios. In this case, the ML/AI system would input a list of tasks and be asked to build the most efficient set of scenarios that train all the tasks. While the tasks would contain terrain specific tasks (i.e. turning on hills, driving in very rough conditions, driving through shallow water, etc.), these scenarios wouldn't have to be tied to a specific geographic terrain. Currently, much driving training ***is*** tied to simulated terrain in geographic locations of interest. In the spirit of "train as you fight", it would be beneficial to use ML/AI to build efficient scenarios in geographic specific locations as well thus enhancing pre-deployment training. Training on more efficient scenarios would enhance, hasten, and improve training especially in the time-starved pre-deployment phase. Current plans are to include simulators such as the CCS in a persistent training framework utilizing the LVC model. The next section widens the aperture to envision ML/AI applied to an LVC framework and the corresponding efficiencies.

LVC-based Training

The nomenclature, "Live, Virtual and Constructive (LVC) simulation" was first introduced in 1989 and is a widely used taxonomy to describe the individual components or the aggregation of live, virtual, and constructive simulations. [1] While LVC may not be the most inclusive way to describe how simulations/synthetic systems can be used by humans (in this case for training) and incorporate ML/AI, it bounds this discussion using a construct that is both legitimately discriminating and currently popular. Hopefully, the increasing interest in ML/AI will allow the expansion of these LVC-oriented insights to other relevant areas.[2] A live simulation is one involving real people operating real systems; a virtual simulation is one involving real people operating simulated systems; a constructive simulation is one involving simulated people operating simulated systems (note: real people can be allowed to stimulate (make inputs) to such simulations) (DoD, 2016). It has been widely reported that Northern Edge 2017 - a joint training exercise involving all US military services - was the largest live, virtual and constructive air-to-air training event at that time and first to integrate all LVC elements for advanced personnel training.

[1] The term "LVC" was first used in 1989 (per 30 April 2007 informal communiqué by Gen. Paul Gorman (USA ret.) and Gen. Larry Welch (USAF ret)) and was officially published by the Defense Science Board on advanced simulation (Braddock, 1993).
[2] Other relevant areas include personal immersion and presence; virtual environments, reality, and worlds; synthetic environments; mixed and augmented reality, etc.

A generic LVC graphic has been developed (see Figure 2) to display the main components of an LVC event. It generally follows the format of an DoD Architecture Framework (DODAF) Operational Viewpoint (OV)-1, which describes a mission (in this case training) and displays interactions between and among the participants, the subject architecture and its environment, and also between the architecture and its external systems (DoD CIO, 2010). This graphic includes seven components that are critical to the delivery of all LVC-based training. Two, architecture and networks, provide connectivity and technical infrastructure. Two others, scenario and timing, control when and what is trained against. The environment represents the battle space and synthetic forces the complementary forces. The seventh component is the learning environment that manages the event and analyzes the results. Each of these components enable training to be delivered to the learning audience (the trainee). In subsequent sections, this structure will be used to describe ML/AI current and possible future LVC capabilities as well as possible future ML/AI enhanced training delivery capabilities.

Figure 2. LVC OV-1 for AI/ML Analysis

When one searches for AI or automated forces/capabilities in US DoD simulation-based training systems, the results often include historical examples, some of which continue to be developed and used (see table 1). Currently there are many software systems that provide AI, and in some cases ML, functionality to/within LVC simulations. Although significant research has gone into identifying and characterizing them here, it's acknowledged that this list is incomplete. To help describe these software systems it is useful to note that many provide decision maker representations or augment decisions made by simulation users (the Synthetic Forces box of Figure 2). These systems' representations of personnel (and sometimes groups) often apply to blue/friendly personnel, red/hostile/opposing forces (OPFOR), and white/neutral participant's cognitive, behavior, and/or decision processing. Examples include:

- Adaptive Character of Thought (ACT-R) – Combines a semantic net with rule-based representation to provide memory representation and inferencing (NRC, 2008).
- State, Operator, and Results (SOAR) – Uses production rules to implement problem solving and can create new operators/rules from preexisting constructs (NRC, 2008).
- ALPHA – An artificial intelligence that controls flights of unmanned air vehicles in aerial combat missions using genetic fuzzy tree / logic-based constructs (Ernest, 2016).
- Simulated Cognitive Cyber Red-Team Attacker Model (SC2RAM) – A synthetic, offensive, cognitive agent that emulates real attackers via modeling thoughts, decision making, and understanding (ONR, 2017b).

Table 1. US DoD M&S Semi-Automated Forces: History - Highlights

Name	Date	Reference
SIMNET	1983	Fawkes, 2017
SAF	1988	ibid.
ModSAF	1993	STRICOM, 2002
OneSAF	1996	PEOSTRI, 2018
JSAF	1997	AFRL, 2003
UMBRA	1997	SNL, 2018b
VR-Forces	1999	VT MAK, 2018
DANTE	2001	SNL, 2018a
OneSAF OOS	2005	Wittman, 2005
SE CORE	2005	PEOSTRI, 2018
STAGE	2008	Presagis, 2018
SLATE	2014	Noah, 2017

- Dynamic, Adaptive and Modular (DYADEM) Entities for Unmanned Aerial System Training – Creates individual ship behaviors and patterns of employment (ONR, 2017a).
- Hybrid AI/Cognitive Tactical Behavior Framework for LVC – Advances the areas of simulated people including path planning, team behavior, working memory, and attention (Xavier, 2012).

Along with these current ML/AI simulation capabilities, given LVC's requirement for an implementing infrastructure (distribution approach, federation, etc.) it is useful to note that current instantiations (Distributed Interactive Simulation (DIS), High-Level Architecture (HLA), Test and Training Enabling Architecture (TENA), etc.) allow for but do not explicitly include or enable ML/AI. It would be useful to extend to these current frameworks an approach previously developed to analyze AI within Distributed/Federated Architectures (Abdellaoui, 2008) to gain key insights in the:

- Availability of built-in AI modules or functionality (e.g., NNs)
- Ability to modify entity behavior pre and during runtime
- Presence of an external interface to enable entity control, information transfer, etc.

Since training events that combine L, V, and C require an architectural infrastructure, further research, using these criteria and others, is required.

There are many ways that ML/AI could provide additional capabilities within live, virtual, and/or constructive simulations used to train individuals and groups, across all US DoD echelons-of-command. First, LVC provides a more general case for the above discussion on vehicle simulators regarding the value of a training system adapting to the trainee / training audience (the Learning Environment oval in Figure 2). I.e., "It's a combination of very high simulation technology, very high-fidelity simulators, with feedback that is tailored to you." (Richardson, 2017). In the case of LVC, that tailoring needs to take place within numerous training systems, as they present content to hundreds of participants, across geographic locations and US Department of Defense and Department of Homeland Security military services. This exceptionally complex multi-variate domain provides an excellent environment for ML/AI, with its ability to ingest data and outcomes, and develop implementing rules.

Next, ML/AI can, similarly ingest data and outcomes, and develop (and extend) rules, that reflect a real-time understanding of the battlefield, especially the enemy's order of battle (strategy, operations, and tactics), relative to scenario and terrain variations (the Scenario box of Figure 2). Again, the battlefield is a complex multi-variate domain, within which ML/AI can provide a unique understanding. This is true for real-time (mission planning, rehearsal, and execution) but perhaps equally important to adapt LVC training systems to account for longer term red/threat/opposition order of battle (OOB), concepts of operation (CONOPs), concept of employment (CONEMP), etc. Similarly, this same concept applies to blue/friendly/coalition/partner's order of battle (OOB), course of action (COA), concept of operations (CONOP), and CONEMPs – all that can be provided to DLNNs, GANs, GFTs, and similar for analysis and insights. It is obvious that these techniques apply to the training of US DoD personnel in traditional warfare areas (air, land sea) but also to new areas (space, cyberspace, cognitive-space (the next version of information warfare, psychological operations, etc.). In all cases ML/AI is suited to providing deep and unique scenario insights which are able to provide a new level of training realism and, thereby, increase force readiness.

Third, US DoD LVC training events can benefit from the application of ML/AI to assess and understand the big data sets they generate (the Analytics component within the Learning Environment oval of Figure 2). Such big data analytics using ML/AI is currently being conducted in support of DoD operations via efforts like Project Maven. Project Maven is assisting military analysts as they sort through the vast amounts of data that are discovered by US sensors and drones. In fact, this ML/AI system and its utilization are designed to improve: "With AI, if you give that airman in the field an 80 percent capability, and a good user guide," both the user and the tech have room to grow, Floyd said. "You want to give them ability to improve it on the fly, and we're inventing some of those processes to do that. You deploy something that's not 100 percent, you know that on day one you're going to retrain it, and then you go from there." (McLeary, 2018) That advancement of ML/AI technology and supporting processes/personnel applies equally to LVC simulation-based personnel training.

Finally, ML/AI have potential to provide significant functionality within many other areas of LVC-based training. They could optimize networks, reduce latency, and efficiently distribute resource requirements as well as supporting the design, deployment, and use of required distribution/federation architectures (the Architectures Synthetic Forces boxes of Figure 2). They could advance the inclusion of environmental parameters in simulation-based training events by providing insights on when, where, and in what context the myriad of possible weather effects significantly impacts force employment outcomes (the Architectures Synthetic Forces boxes of Figure 2). Lastly ML/AI could aid in better understanding of the delivery, pace, and content of specific/just-in-time training, pre-deployment refreshers, and long-term educational opportunities.

THOUGHTS AND CONSIDERATIONS

The idea of infusing ML/AI into our daily lives used to be a science fiction topic, much like space travel. While space travel isn't presently an everyday occurrence, AI and ML are used by the average person virtually every day. However, neither AI or ML are currently embedded into DoD simulation-based training systems. What would it take to get there? Embedding ML/AI into the kinds of systems discussed above is not insurmountable, but will take deliberate, intentional, planned efforts. As a result, there are many relevant thoughts and considerations that arise.

While ML/AI will generate solutions and insights that are brilliant and potentially extremely innovative, they may – and currently are, especially DLNNs – doing so without their logic being amenable to inspection, understanding, or perhaps recreation / reproducibility (Ackerman, 2017). Thus, Lee SeDol's observation in the 37th move of the 2nd game of Go, that what AlphaGo produced – "It's not a human move. I've never seen a human play this move. So beautiful." (Metz, 2016). Such events violate the human need to maintain logic and data structures that allow explanation – for verification and validation with empirical data; and for control. This point is recognized for ML/AI generally, and here is highlighted for simulation-based training (Ilachinski, 2017). Given current directions in ML/AI where the ML system is being asked to both differentiate data and to build a ML network which is the most effective in training on that data, this inexplicability of how outputs are generated from inputs will only worsen. As a result, there is a need for uncertainty estimation/consideration and mitigation/remediation of that uncertainty. That is, advances that allow insight into the degree to which the results are inexplicable/incomprehensible, approaches for conditionalizing the answers generated (based on that degree), methodologies for decreasing the severity of the impact of these uncertainties, and approaches to decreasing the uncertainty itself; these will all be important in applying ML/AI to simulation-based training.

There are currently significant insights on how to measure the impact of simulation / LVC use; within training, assessment, and acquisition. These include metrics that reflect enterprise, application area, and program level impacts; key results, cost, timing, and risk dimensions; as well as how they correlate / cascade from the most global goals (win the war) to lower level impacts at operational, tactical, and mission levels (Tolk, 2017). Yet, these measures do not reflect or account for the degree to which a simulation/LVC environment can learn or innovate, improvise, and extrapolate – i.e., to embody some degree of human-level artificial general intelligence – to meet a service goal, like training. This idea is once again a subset of a larger conclusion, that there is a need to develop measures of merit for autonomous systems (Ilachinski, 2017). So, it is important to assess ML/AI qualities in simulation-based training, perhaps in part by adapting and extending measurement approaches found in education, business, technology development, and software engineering that are used to assess these qualities. Possible areas of investigation include measuring the initial and final state of a learning system (or person/student), its ability to adapt/incorporate newly discovered variables, and the degree to which the final ML/AI system accomplishes complex tasks – or generates new insights – both relative to the pre-existing condition and to some 'absolute' (Kelvin-type) scale.

There is no dispute that ML/AI technology is advancing rapidly in the commercial/corporate sphere and that DoD's relation to that world is tenuous at best. Earlier this year, project Maven was in the news after 3,100 Google employees signed a letter protesting their company's involvement (McLeary, 2018). In addition, DoD system design, development, and deployment timelines are also out of sync with the urgency associated with the need for improved training – it takes 8-14 years to develop and deploy a revolutionary system. This means it is critical to improve the mechanisms available to DoD for discovering, adapting/adopting, integrating, and deploying commercial ML/AI into its LVC training simulations. This is in addition to the need to decrease the elapse time in acquiring and employing these systems.

Regarding DoD's development and use of AI/ML, which many see as groundbreaking technologies, "The Decker-Wagner report advises the Army to manage risk in its acquisition portfolio by limiting the proportion of higher-risk programs to "only those [systems] that are truly urgently needed because they represent 'game-changing', revolutionary military capability…" "It also cautions that you should expect an 8- to 14-year development cycle … for such systems, even if you do everything right." (Tate, 2016 and Decker, 2011)

There are many issues relative to data. First, to infuse ML/AI into a system, data must be collected to so that the ML system has a data set from which to learn. It must learn a good response (the "gold standard") from a bad and the point at which the response changes from good to bad, understanding that in many cases there are levels of goodness as responses are on a continuum and not a digital scale. The gold standard response would be best coming from operational data on live systems, but potentially could be determined from mathematically based models of the live systems. Therefore, ML/AI systems must be designed, and the data collected for ML based upon these designs. Many of the ML/AI systems employ Deep Learning and most of the data sets used in these systems fall into the category of Big Data – at least terabytes. However, at an individual level and even perhaps a training system level, it would take an extremely long time to generate and collect that amount of data (e.g., in the CCS, which trains 21,000 Marines each year, if each Marine performs a task 5 times in the simulator that provides 105,000 data points, *in a year).* LVC events (some of which include thousands of service personnel, hundreds of pieces of equipment, all military services, etc.) on the other hand, could generate Big Data. This should enable the enhancements discussed above, but relative to LVC event generated data, it will need to be normalized since it will be generated under differing conditions (i.e., accuracy, periodicity, etc.). In either case, data sets, even smaller ones, can provide input into ML algorithms and can be useful (El Deeb, 2015), but the data first needs to be collected. After the collection of the data, some data analysis would need to be done to "clean" the data[3] and to understand the data's characteristics, more important for small data sets than for Big Data. Once this is complete, ML algorithms can be applied, and the results analyzed and tested.

CONCLUSIONS AND NEXT STEPS

ML/AI isn't new, but the current applications driven by hardware advancements are things only dreamed about 20 years ago. ML/AI has the potential to revolutionize how the DoD trains (and fights), however, current simulation-based training systems trail ML/AI use in industry. A well-planned, intentional, and methodical incorporation of ML/AI into simulation-based training, at the individual simulator level or the broader LVC level, could significantly increase training efficiency and efficacy. While the cost of incorporating ML/AI could be significant[4], the savings by reducing training time and improving proficiency would be substantial as well. Given the potential, studies that move this discussion to the next level and fill in some of the details are critical in developing the technology and increasing the DoD's readiness posture. After that, collecting key data will be necessary, followed by the implementation of ML and the integration of the AI algorithms into simulation-based training systems. The sooner the process starts the sooner the DoD will have next generation training capability.

Especially in an area as diverse and rapidly advancing like ML/AI there is an imperative to actively engage, collaborate, and coordinate with the performers and participants. For the DoD simulation-based training community this includes resident centers, laboratories, and facilities; training and training support processes and initiatives; as well as commands, organizations, and universities. But, as noted above, perhaps more important is proactive outreach and interaction with commercial, corporate, and industrial partners; academic, research, and non-profit organizations; along with non-DoD US Government entities. Effective outreach, engagement, and collaboration requires planning. There is a need to develop DoD simulation-based training road map, that includes these activities, but that also provides overall goals and objectives, sequencing of activities, and investment means and mechanisms.

As in any emerging research or technology area, focused analysis and technology demonstrations are extremely useful. The Australian defense establishment has recognized this and has begun a dedicated effort that includes ML/AI (Rowe, 2017). US DoD organizations like DARPA, IARPA, etc. provide and excellent environment (charter, skills, processes, and resources) to conduct such activities. In addition, the DoD community conducts technology and advanced concept demonstrations, challenges, feasibility experiments, etc., all of which could be used to expand the understanding and use of ML/AI in DoD simulation-based training.

In many ways, like the need for verification, validation, and accreditation (VV&A) in autonomous systems/robotics development and in automated testing, VV&A of training systems that employ ML/AI is extremely important. The delivery of negative training based on erroneous insights or actions of employed supporting systems is always a concern. This concern is magnified when these systems are very complex, interdependent, distributed, and heightened

[3] Cleaning the data is a process where obvious incorrect entries, garbled data, or blank records are deleted.

[4] Estimating the cost of building AI/ML into simulation-based training is outside the scope of this paper and would require a significant amount of details that are unknown at this time.

even further when they provide capabilities that would normally require a human, like M/AI provides. There have been VV&A framework developments for low-level VV&A activities that seek to "improve the consistency and efficiency of M&S federations in the support of autonomous system development" that should be extended/adapted to the use of ML/AI in simulation-based training (Tremori, 2017). In conclusion, as important as ML/AI are to DoD simulation-based training, and given the scope of the research, analysis, and implementation opportunities and challenges touched upon here, we look forward to future endeavors!

ACKNOWLEDGEMENTS

The authors would like to express their appreciation for insights provided by: Katherine Morse, John Hopkins University Applied Physics Laboratory; Steve Kasputis, Northrop Grumman Corporation; and Byron Harder, US Marine Corps; and for research and editorial inputs by Margaret Callahan, Alion Science and Technology Corporation.

REFERENCES

Abdellaoui, N., Taylor, A., & Parkinson, G. (2008). *Comparative Analysis of Computer Generated Forces' Artificial Intelligence*, NATO, RTO-MP-MSG-069.

Ackerman, E. (2017). *How Drive.ai Is Mastering Autonomous Driving with Deep Learning*. IEEE Spectrum. Retrieved from: https://spectrum.ieee.org/cars-that-think/transportation/self-driving/how-driveai-is-mastering-autonomous-driving-with-deep-learning

Adams, S., Arel, I., Bach, J., Coop, R., Furlan, R., Goertzel, B., … Sowa, J. (2012). Mapping the Landscape of Human-Level Artificial General Intelligence. *Association for the Advancement of Artificial Intelligence*.

Air Force Research Laboratory (2003). *Command, Control, Communications, Computer, Intelligence, Surveillance And Reconnaissance (C4ISR) Modeling And Simulation Using Joint Semi-Automated Forces (JSAF).*

Braddock, J., & Thurman, M. (1993). *Report of the Defense Science Board Task Force on Simulation, Readiness and Prototyping: Impact of Advanced Distributed Simulation on Readiness, Training and Prototyping*, Office of the Under Secretary of Defense for Acquisition.

Chollet, F. (2018). Deep Learning with Python. *Manning Publishing Company.*

Combined Arms Center - Training (CAC-T). (2017) *Synthetic Training Environment (STE) White Paper*. Retrieved from: https://usacac.army.mil/sites/default/files/documents/cact/STE_White_Paper.pdf

Decker, G., & Wagner, L. (2011). *Army Strong: Equipped, Trained and Ready: Final Report of the 2010 Army Acquisition Review*.

Department of Defense Chief Information Officer (DoD CIO) (2010). *DoD Architecture Framework Version 2.02 (DoDAF)*. Retrieved 2019 from: https://dodcio.defense.gov/Library/DoD-Architecture-Framework/

Drummond, F. (2017). Pentagon Looks to Paradigm Shift in Training Procurement. *I/ITSEC 2017 Show Daily*, 12.

El Deeb, A. (2015). What to do with Small Data. *Rants on Machine Learning*. Retrieved from: https://medium.com/rants-on-machine-learning/what-to-do-with-small-data-d253254d1a89

Ernest, N., Carroll, D., Schumacher, C., Clark, M., Cohen, K., & Lee, G. (2016). Genetic Fuzzy Based Artificial Intelligence for Unmanned Combat Aerial Vehicle Control in Simulated Air Combat Missions. *Journal of Defense Management*, 6(1).

Fawkes, A. (2017). *Developments in Artificial Intelligence: Opportunities and Challenges for Military Modeling and Simulation*. NATO, STO, STO-MP-MSG-149.

Hercenberg, M. (2008). *Dynamic Learning of AI in Gaming*. White Paper, Villanova University.

Ilachinski, A. (2017). *Artificial Intelligence and Autonomy; Opportunities and Challenges*. Center for Naval Analysis.

Kendall, A., Badrinarayanan, V., & Cipolla, R. (2017). *SegNet: A Deep Convolutional Encoder-Decoder Architecture for Robust Semantic Pixel-Wise Labelling*. Retrieved from: http://mi.eng.cam.ac.uk/projects/segnet/#publication

Madhavan, P. (2017). NEXT Machine Learning Paradigm: "DYNAMICAL" ML. *The Industrial IOT Community Newsletter*.

Mcleary, P. (2018). *Pentagon's Big AI Program, Maven, Already Hunts Data in Middle East, Africa*. Retrieved from: https://breakingdefense.com/2018/05/

Melanie, M. (1996). *An Introduction to Genetic Algorithms*. MIT Press.

Metz, C. (2016). The Sadness and Beauty of Watching Google's AI Play GO. *Wired*.

National Research Council. (2008). *Behavioral Modeling and Simulation: From Individuals to Societies*. Washington, DC: The National Academies Press.

Noah, D. (2017). *Secure LVC Advanced Training Environment (SLATE): Advanced Technology Demonstration (ATD)*. AFRL, 88ABW-2017-2171.

Office of Naval Research. (2017a). *Dynamic, Adaptive and Modular (DyAdeM) Entities for UAS Training*. Retrieved from: http://www.navair.navy.mil/nawctsd/pdf/2017-DyAdeM.pdf

Office of Naval Research. (2017b). *Simulated Cognitive Cyber Red-Team Attacker Model (SC2RAM).* Retrieved from: http://www.navair.navy.mil/nawctsd/pdf/2017-SC2RAM.pdf

Presagis. (2018). *Stage Scenario Technical Overview*. Retrieved from: https://www.edstechnologies.com/STAGE.pdf

Program Executive Office Simulation, Training and Instrumentation (PEO STRI). (2018). *One Semi-Automated Forces (ONESAF).* Retrieved from: http://www.peostri.army.mil/onesaf

Program Executive Office Simulation, Training and Instrumentation (PEO STRI). (2018). *Synthetic Environment Core (SE Core): 3D Geospatial M&S Summit Follow On*. Retrieved from: http://www.peostri.army.mil/synthetic-environment-core-se-core-

Richardson, J. (2017). *Chief of Naval Operations Master Chief Petty Officer of the Navy, All Hands Call - 5th Fleet*. 29 December 2017.

Rowe, C. (2017). *Modelling Complex Warfighting Strategic Research Investment*. Joint & Operations Analysis Division, DST 1936, Expression of Interest.

Sandia National Laboratories. (2018a). *Dante*. Retrieved from: http://umbra.sandia.gov/products.html#dante

Sandia National Laboratories. (2018b). *Umbra Simulation Framework*. Retrieved from: http://umbra.sandia.gov/

Surdu, J. (2007). Simulation Technologies: Thoughts and Pointers. *Proceedings from Behavior Representation in Modeling and Simulation (BRIMS).*

Tadjdeh, Y. (2018). Big Data, AI to Advance Modeling and Simulation. *National Defense Magazine*.

Tate, D. (2016). *Acquisition Cycle Time: Defining the Problem (Revised)*. Institute for Defense Analyses, Document NS D-5762 (Revised).

Tolk, A., & Oren, T. (2017). *The Profession of Modeling and Simulation: Discipline, Ethics, Education, Vocation, Societies, and Economics*. John Wiley & Sons, Inc.

Tremori, A., Sobrino, P.C., Vinas, A.C., Maglione, G.L., Solarna, D., Been, R., & Mansfield, T., *A Verification, Validation and Accreditation Process for Autonomous Interoperable Systems,* Modelling and Simulation for Autonomous Systems (MSEAS), 2017.

US Army STRICOM, Directorate for Research and Engineering. (2002). *Modular Semi-Automated Forces (MoDSAF)*. Retrieved 2002 from: http://www.stricom.army.mil/PRODUCTS/MODSAF/

VT MAK. (2018). *VR-Forces*. Retrieved from: https://www.mak.com/products/simulate/vr-forces

Widman, L., & Loparo, K. (1990). Artificial Intelligence, Simulation, and Modeling. *Interfaces, 20(2),* 48-66.

Wilson, H.J., Daugherty, P.R., & Morini-Bianzino, N. (2017). The Jobs that Artificial Intelligence Will Create. *MIT Sloan Management Review, 58(4).* Retrieved from https://sloanreview.mit.edu/article/

Wittman, R. L., & Surdu, J. (2005). OneSAF objective system: toolkit supporting user and developer lifecycles within a multi-domain modeling and simulation environment. Proceedings from *SimTecT 2005 Simulation Conference and Exhibition*. Sydney, Australia.

Xavier, P.G., Hart, B.E., Hart, D.H., Little, C.Q., Oppel III, F.J., Brannon, N.G., … Parker, E.P. (2012). *Hybrid AI/Cognitive Tactical Behavior Framework for LVC*. Sandia National Laboratories, SAND2011-9468.