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The Avocado Paper: A Path Toward Ontology-based Predictive Models for Human–Autonomous Teaming

by Paul Shorter

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By Paul Shorter
Human Research and Engineering Directorate, CCDC Army Research Laboratory

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14. ABSTRACT The purpose of this report is to support one of four Human–Autonomous Teaming (HAT) Essential Research Program research areas that entails development of predictive models to evaluate HAT interaction. Predictive models would enable researchers to weigh the merits of a course of action pursuant to a given scenario or contingency in question, then apply time and resources to that action based on the strength of the model outcome. It is posited that an ontology framework could be developed to horizontally integrate data that are vertically defined within taxonomies. The data would then be directed to a data analytics module to evaluate HAT scenarios.			
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1. Introduction

This technical note describes an approach to developing a methodology to predict outcomes of human–autonomous interaction, based on a survey of current literature, pursuant to the US Army Combat Capabilities Development Command Army Research Laboratory (ARL) Human Research and Engineering Directorate (HRED) Human–Autonomous Teaming (HAT) Essential Research Program (ERP).

The military application of autonomous agents can arguably be traced back to the first and second world wars. Robotic platforms—for example, the Wickersham Land Torpedo, Kettering Bug, Leichter Ladungstrager Goliath, and FL-7 motorboat—were developed, and actually employed in some cases, in an attempt to gain military dominance on the land, sea, and air.[1] The development of GPS in the 1990s precipitated the modern concept of an autonomous agent.[2] Since then, aerial drones have been used for surveillance and target acquisition to great effect. US military ground and air robots number in the thousands and perform a variety of functions.

However, drones and robots have primarily been used as tools that augment Soldiers' capabilities, much like a truck, rifle, or other conventional equipment. In recent years, the US military has gained interest in developing agents that are truly autonomous by incorporating machine learning (ML) capabilities into various platforms. It is envisioned that autonomous agents will evolve from merely being Soldiers' tools to being functioning members of a military unit—a battle buddy.[3]

Toward that end, ARL/HRED initiated an HAT ERP to undertake related research in direct support of the Next-Generation Combat Vehicle (NGCV) and Soldier Lethality (SL) Cross-Functional Teams (CFTs). The HAT ERP approach conceives of not only the potential capabilities of future intelligent technologies, but the potential for completely novel interactions among heterogeneous teams of Soldiers and intelligent agents. It also reconceives approaches and requirements for training.

2. Ontology-based Predictive Models

The purpose of this technical note is to support one of four HAT ERP research areas that entails development of predictive models to evaluate HAT interaction. Predictive models would enable researchers to weigh the merits of a course of action pursuant to a given scenario or contingency in question, then apply time and resources to that action based on the strength of the model outcome. The statistician George Box is attributed with remarking that "all models are wrong, but some are useful”. Keeping Box in mind, this report provides an approach to developing predictive models for HAT interaction based on current literature.

Modeling and simulation (M&S) has a long history of use in a variety of fields to support resource decisions, training scenarios, engineering design, and the development of products, to name a few. Technology advancements in these fields necessitate that M&S methods evolve to accommodate these advancements to remain current and effective. To achieve this, practitioners often design M&S architectures that enable the M&S methods to meet their purpose while providing flexibility to support changes in technology. Herein a similar concept is entertained within the context of HAT interaction. The HAT ERP is expansive and constantly evolving. The various research undertakings, while all moving toward a defined goal, span multiple domains; for example, neurotechnology, brain–computer interface, complex environment models, and naturalistic technology. An effective HAT interaction predictive model requires an architecture that can accommodate the depth and breadth of this research program.[4–6]

The evolution of ML technology, integral to HAT interaction, has propagated the development and use of ontologies and taxonomies to define and integrate various domains that would otherwise be disjointed. It is posited that the same concept could be applied to HAT interaction M&S, in which taxonomies[7] are stand-alone entities that define a given domain and act as arguments within an ontological architecture. The ontology defines relationships[8] between or among taxonomies and enable the taxonomies to co-operate to achieve a goal; for example, predict HAT interaction outcomes.

2.1 Ontologies

Ontologies are commonly used by data analysts to integrate multiple concepts in a variety of ways. The ontologies provide a formal description of knowledge as a set of concepts within a domain, their attributes, and the relationships among them.[9] Whereas taxonomies only provide a set of vocabulary and a single relationship between the terms, an ontology provides a set of relationships, constraints, and rules that establishes context and inference. This provides an architecture that defines knowledge representations that are sharable and reusable, yet flexible enough to be augmented with new knowledge about the domain.

Current literature cites several examples where ontological constructs enable efficient and reliable data integration and information exchange between different agents or systems to overcome capability limitations.[10] For example, a given task may entail a team consisting of a human and two autonomous agents: one agent equipped with a visual sensor and the other designed for mobility. All activity is managed by a common ontology. The human initiates a task sequence to either agent, which then exchanges visual data and spatial orientation coordinates to negotiate delivery of a payload. The agents have their respective limitations; however, they achieve the goal because their common ontology coordinates their activity.

Ontologies are also used to facilitate multimodal data sources that fuse data to develop a full description of the environment, thereby providing the user a basis for inference.[11] Furthermore, the environment is made open by allowing the addition or removal of modalities at any time according to the needs of the user.[12] The result yields a higher degree of environmental affordance[13] where physical and digital properties enable cooperation and collaborative actions.

Having obtained a higher degree of affordance, inferences about the environmental state can be made through the exchange of information encoded in axioms and rules that provide a semantic foundation for dissimilar considerations;[14] for example, statutory constraints, business rules, and workflow models. The ontology may also support inferences about the environmental state through the use of model-based mathematical methods[15] that can also be encoded as intrinsic modeling capabilities[16] or designed to reference subconstructs that perform those functions.[14]

2.2 Taxonomies

A taxonomy is a classification system that organizes a body of knowledge based on an underlying set of principles, definitions, and other considerations that serve to standardize a set of unifying constructs that can be used to systematically describe and interpret the contents therein. While ontologies provide broader context and inference, as previously described, taxonomies tend to be hierarchical in a manner that defines elements within their knowledge domains and how they relate.

Taxonomies are used by practitioners from many diverse fields. The Canadian military developed a taxonomy of cyber effects and threats to their computer networks that is used as the foundation for various applications; for example, training simulation, policy, and procedure analysis.[17] Research on US Army intelligence training posited the use of a knowledge taxonomy to enhance intelligence training practices.[18] The Organization for Economic Cooperation and Development uses several taxonomies to monitor global economic activity.[19] The US Securities and Exchange Commission uses a taxonomy to standardize corporate financial information to support reporting across multiple entities.[20]

The list of taxonomy applications is extensive. However, in all cases the information a taxonomy provides is restricted to its own domain, as explained previously. To create synergies beyond its domain or across multiple taxonomy domains, a taxonomy would need to be integrated into an ontology-based scheme. For example, an intelligence officer may need economic information that relates to an intelligence taxonomy to support an assessment. That need could be satisfied by an ontological scheme that relates both taxonomy domains. Alternatively, one taxonomy would have to subsume the other, which would likely be arduous, inefficient, and not readily adaptive to change.

Research literature favors the ontology-based scheme. There are many examples that integrate taxonomies to achieve a stated goal. The structure, definitions, and domain standardization provided by the taxonomy are leveraged to execute operations that are encoded in the ontology. They can be relatively simple, translating a taxonomy across multiple agents, or very complex, converting differing taxonomies into common terms. They have been applied in a variety of fields, including robotics and automation, decision support systems, and collaborative engineering design. Furthermore, taxonomies have also been used to predict outcomes. In some cases a taxonomy can be constructed for modeling and analysis methods that can be employed when certain criteria are met. The idea is to use abstractions of an operational scenario in question to automatically select the appropriate method.[21] Alternatively, outcome predictions can be determined by applying appropriate methods to taxonomy instances that represent an operational scenario.

2.3 Data Considerations

The data used in ML and other data analytics applications are usually collected as a byproduct of normal business operations. Netflix serves as a common example of this evolution in which its business operations data are used to personalize movie recommendations, auto-generate thumbnails and artwork, scout locations for movie production, edit movies, and monitor streaming quality. Increasingly, businesses such as Netflix are starting to regard their data as a primary resource that can repurposed and leveraged beyond its original use.

As relevant research and ML practices have advanced, data used in these types of applications have been attributed with characteristics such as the following:

- Fine-grained in resolution and uniquely indexical in identification[22]
- Relationality: containing common fields that enable the conjoining of different datasets[23]
- Veracity: data can be messy and noisy, and contain uncertainty and error[24]

- Value: many insights can be extracted and the data repurposed[24]
- Variability: data whose meaning can be constantly shifting in relation to the context in which they are generated[24]

These data characteristics are further emphasized in a report by Abassi et al.[25] that defines an information value chain (IVC), which explains the relationship between technologies, skill sets, processes, and organizational factors in this new data-analytics paradigm. Relative to the HAT ERP, the IVC differs from conventional management information systems primarily in the amalgamation of technologies into “platforms” and processes into “pipelines” that make data more readily available to users. It is conceivable that platforms and pipelines could entail ontologies and taxonomies to perform their functions. The concept of the IVC may also be inferred when considering the development of the combat cloud by the US military.[26] The combat cloud will be populated by data collected from conceivably any combat system platform that would serve as both sensor and effector. Thus, the data collected by the combat cloud are a byproduct of and used to support combat operations.

Data generated from ARL research experiments could also be regarded as a byproduct of ARL operations collected from HRED and HAT ERP experiments, which could include experiments that explicitly entail HAT interaction scenarios. While the primary purpose is to support research questions and hypotheses for a given study, the data could conceivably be repurposed to support predictive modeling for HAT interaction or any other human sciences application.[27]

Therefore, in addition to supporting predictive models, these data considerations have cost–performance implications for human sciences research in general. If data can be repurposed to serve objectives in addition to their original application, ARL/HRED could use its resources more efficiently. Repurposing data, in effect, would be a budget multiplier.

2.4 Human Sciences Knowledge Domain

The intent of developing an ontology for human sciences research is to integrate information across the human sciences domain to support predictive models and other data analytics.

To conceptualize how an ontology-based framework might apply to the ARL/HRED research program, consider the Web Ontology Language (OWL), the syntax of which is designed to model a network of nodes and arcs based on three elements known as Classes, Individuals, and Properties, which form a “triple” taking the following form[28]:

Nominal: individual –> property –> individual (or value)

Syntactical: subject –> predicate –> object

The predicate is the primary mechanism with which domain information is integrated by either relating subjects and objects or subjects and values (numeric, strings, etc.).

To further this conceptualization, consider the schematic presented in a recent ARL information briefing, shown in Fig. 1, that illustrates the ARL human sciences program delineated into research areas related by organizational and budget considerations.

The Fig. 1 schematic could serve as the framework for an ontology representing the human sciences knowledge domain, wherein the Tier 2 and Tier 3 elements represent classes and subclasses, respectively. Actual data elements (electroencephalogram parameters, electrocardiogram parameters, etc.) considered in each Tier 4 research activity represent individuals in the ontology and also represent the data input to any data analytics to be performed. Predicates are contextually defined to relate individuals to each other or to a data value. These classes, subclasses, individuals, and properties are constructed in triples as previously described.

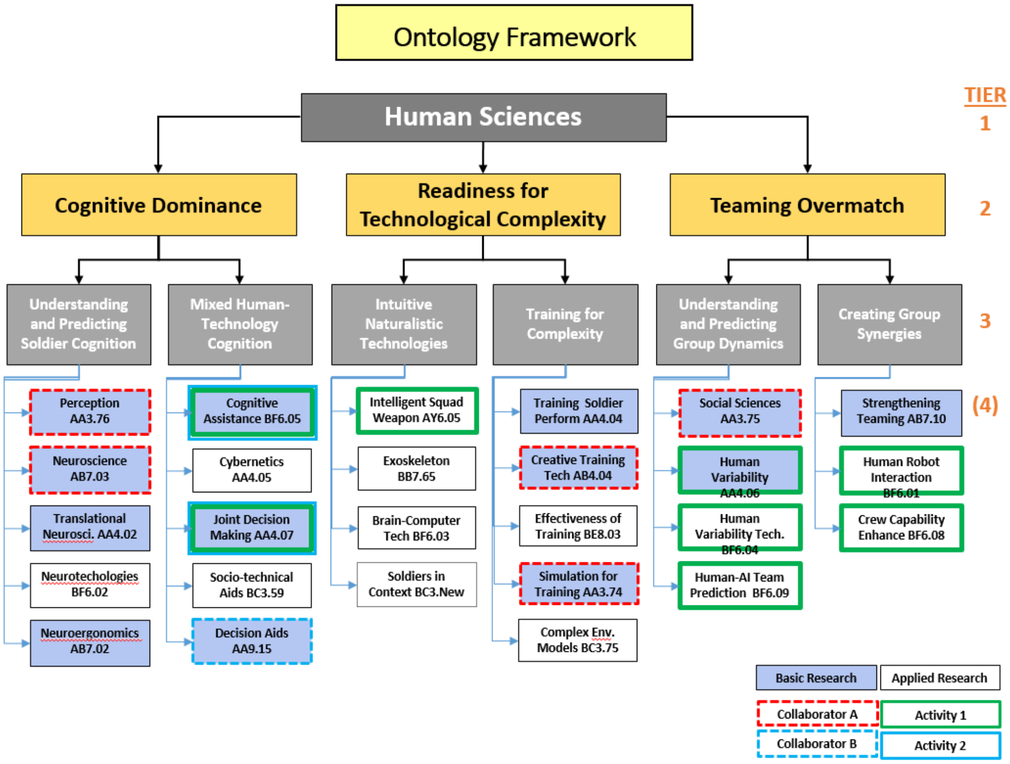

Fig. 1 Ontology framework for human-science knowledge domain

As indicated in the Introduction, an ontology-based framework would also require taxonomies as stand-alone entities that define a given domain and act as arguments within an ontological architecture. The ontology defines relationships between or among taxonomies and enables the taxonomies to co-operate to achieve a goal (e.g., predict HAT interaction outcomes).

Figure 2 presents a notional data taxonomy, based on Bloom's cognitive domain,[29] to illustrate how taxonomies would apply to the human sciences ontology framework described. Notionally, such a taxonomy would represent the hierarchy of data collected from ARL/HRED research experiments, irrespective of organizational, operational, or budget considerations. The lowest element of a given taxonomy (i.e., data elements $\{x_1, x_2 \ldots x_n\}$, $\{y_1, y_2 \ldots y_n\}$) represent the actual data collected and correspond to the individuals defined in the ontology (electroencephalogram parameters, electrocardiogram parameters, etc.). In this framework, data elements could be retrieved from across all research activities to perform data analytics. In addition, in their role in ontology-based analytics, data taxonomies perform several other important functions:

- Provide a centralized repository for standardized data

- Enable re-use of data beyond the original intended purpose, thereby improving organizational cost performance
- Eliminate redundancy in data retrieval and storage
- Facilitate augmenting or restructuring of strategic or tactical processes
- Enable governance processes for fixing inconsistencies or providing feedback to users
- Detail rules for automating remediation of predictable inconsistencies
- Offer tools for sanitizing and normalizing data
- Reduce ambiguity; ensure consistency in data definitions and inclusion/exclusion

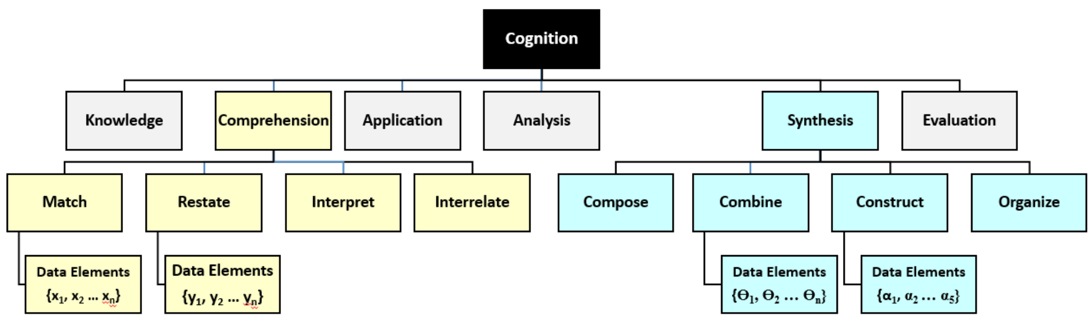

Fig. 2 Notional taxonomy based on Bloom's cognition domain

For illustrative purposes, assume that the taxonomical data elements shown in Fig. 3 represent actual data collected by the Tier 3 ontological research activities—Intuitive Naturalistic Technologies and Creating Group Synergies, indicated in Fig. 1. Triples can be formed based on the OWL syntax, as shown in Fig. 3.

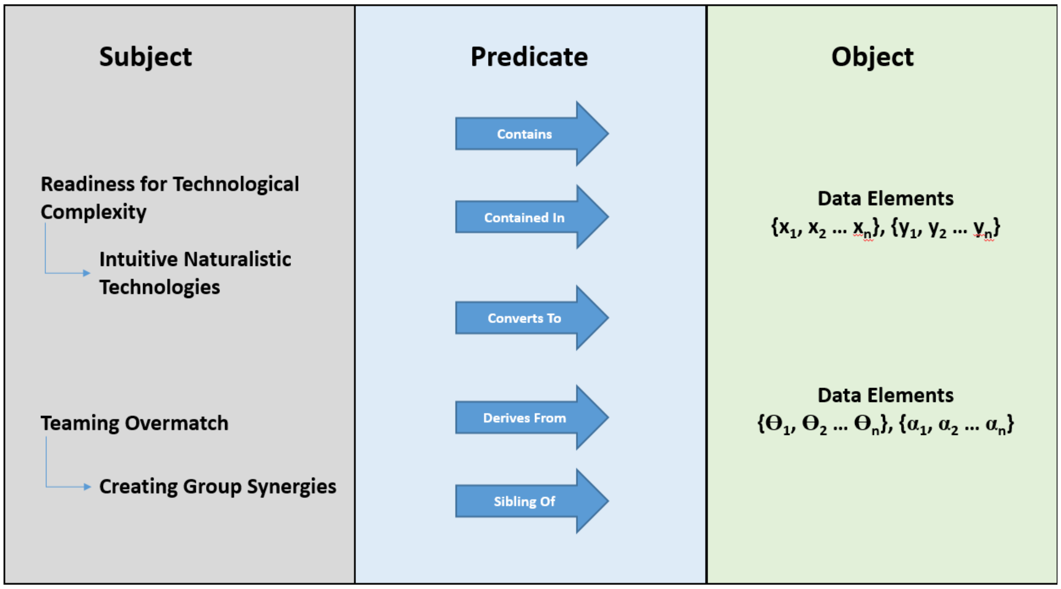

Fig. 3 Triples based on OWL syntax

Figure 4 presents a schematic of how the ontology and taxonomy combine to form the total framework for predictive models and data analytics. The predicates "Contains", "Contained In", and "Sibling Of" relate data elements across the human sciences knowledge domain, while the predicates "Converts To" and "Derives From" relate data values that would be used to perform predictive modeling and other data analytics.

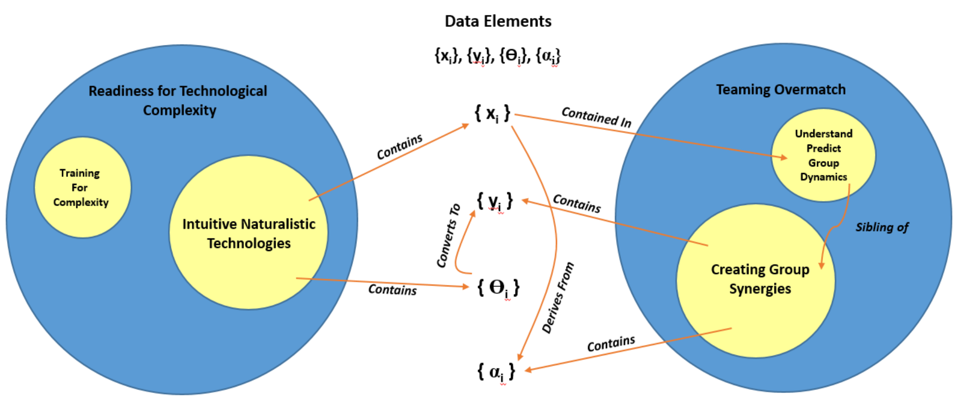

Fig. 4 Framework for ontology-based predictive models and data analytics

3. Conclusion and Path Forward

A survey of current literature indicates that artificial intelligence and data analytic practices entail the use of ontologies to integrate data, and taxonomies to define data, across one or more knowledge domains. The many benefits of an ontology-based approach include horizontally integrating knowledge across the entire knowledge domain, vertically standardizing data definitions within the knowledge domain, repurposing collected data in addition to their original intended use (thereby improving the cost-effectiveness of the organization as a whole), adapting to evolutions in research initiatives, and lending itself to more effectively employing ML methodologies.

A notional example is provided of how these practices and methodologies may apply to ARL/HRED, based on an ARL/HRED taxonomy of research activities that in turn serves as the ontological foundation, the "triples concept" employed in the OWL, and Bloom's taxonomy of the cognitive domain. While the example provided is notional, it will serve as the conceptual basis for ensuing efforts focus on a proof of principle and development of a working prototype. Toward that end, future efforts may also consider implications of CFTs, (e.g., NGCV and SL), and possibly initiatives undertaken by the US Army branches (i.e., Combat Arms, Combat Support, and Combat Service Support).

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List of Symbols, Abbreviations, and Acronyms

ARL	US Army Combat Capabilities Development Command Army Research Laboratory
CFT	Cross-Functional Team
ERP	Essential Research Program
HAT	Human–Autonomous Teaming
HRED	Human Research and Engineering Directorate
IVC	information value chain
ML	machine learning
M&S	modeling and simulation
NGCV	Next-Generation Combat Vehicle
OWL	Web Ontology Language
SL	Soldier Lethality

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