Abstract. There are many connections among artificial intelligence, learning, reasoning and ontologies. The Ontology Summit 2017 explored, identified and articulated the relationships among these areas. As part of the general advocacy of the Ontolog Forum to bring ontology science and engineering into the mainstream, we endeavored to abstract a conversational toolkit from the Ontology Summit sessions that may facilitate discussion and knowledge sharing amongst stakeholders relevant to the topic. Our findings are supported with examples from the various domains of interest. The results were captured in the form of this Communiqué, with expanded supporting material provided on the web.

Keywords. artificial intelligence; machine learning; reasoning; ontologies

1. Introduction

We are currently witnessing increasingly widespread applications of Artificial Intelligence (AI), which deals with intelligent behavior, learning and adaptation in computational systems. Three of the most significant drivers and enablers of AI technology are the availability of increasingly massive amounts of data (Big Data); the rapidly dropping cost of storing and processing data; and advances in machine learning (ML) techniques. This situation has made it possible to exploit sophisticated ML techniques that require large amounts of data to be effective. The applications of ML have “boosted Android’s speech recognition, and given Skype Star Trek-like instant translation capabilities. Google is building self-driving cars, and computer systems that can teach themselves to identify cat videos. Robot dogs can now walk very much like their living counterparts” [1]. It is worth noting that while these may be very useful, they are types of what are called “narrow AI” technologies. These are AI Applications that allow computers to solve specific

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problems, like image recognition, or perform reasoning tasks that do not emulate the full range of human, self-directed, cognitive abilities.

The Ontology Summit 2017 was an attempt to survey the ways in which the AI techniques of ML, reasoning and ontology engineering are being used for their mutual benefit. These uses were classified into three tracks, but it was soon clear that the different tracks have significant overlap with each other, and there was considerable variety within each track. While “learning” was intended to be restricted to machine learning in the Ontology Summit, since it was in the context of AI, human learning was also explored to some extent, especially as it relates to machine learning. The term “reasoning” in the Ontology Summit theme was not intended to be restricted to formal, logical reasoning. Classifying the many techniques, determining the best practices, and identifying synergies have emerged as three key challenges for the exploitation of the relationships among ML, reasoning and ontology engineering.

The Ontology Summit 2017 surveyed the current state of the art among the major AI topics of learning, reasoning and ontologies with three tracks, summarized in Section 2 below. Each track focused on a relationships between two of the three AI topics, as illustrated in the Ontology Summit 2017 logo in Fig. 1. Some of the background for the theme of the Ontology Summit is presented in Section 3. This is followed, in Section 4, by a survey of the opportunities and challenges of the relationships among learning, reasoning and ontologies, and in Section 5 some prospects for the future are presented. The Communiqué ends with a conclusion and acknowledgments.

2. Track Summaries

2.1. Overview Session

The Overview Session began the Ontology Summit with a presentation introducing the Ontology Learning Layer Cake in Figure 2 which was used as a common touchpoint across all tracks. The highest layer represents logic and axioms, with lower layers depicting schemata, relations, concept hierarchies, synonyms and terms at the lowest layers for ontology learning. The layer cake presents a framework for describing the process for knowledge extraction. An example is the process of acquiring a concept hierarchy which can be depicted by graphs representing relationships among elements.
2.2. Track A: Using ML to extract knowledge and improve ontologies

This track addressed one of the big bottlenecks for AI; namely, how to create sufficient knowledge about the world for an intelligent agent. Handcrafting knowledge bases and ontologies is time and resource consuming. This track explored the use of automation and various ML approaches to extract knowledge and improve ontologies including their population.

The following are some of the highlights of the presentations in this track.

- Bottlenecks and obstructions in ontology engineering and ontology development.
- Ontology engineering is an iterative and spotty activity (i.e., non-uniform progress in its activities and processes).
- ML can be utilized to: (1) extract knowledge which facilitates the development and maintenance of ontologies, (2) filter noisy data to further improve the quality of developed ontologies, and (3) harmonize ontologies to manage dependence on peculiarities of the datasets.
- Ontology Learning: building domain ontologies by automatically extracting concepts and relationships.
- A layer cake of ontological primitives [3].

2.3. Track B: Using background knowledge to improve machine learning results

The mission of this track was to scope out challenges and opportunities in “using background knowledge to improve machine learning results,” the role of ontologies and comparable resources in achieving this, and the requirements for ontologies that may be used in these ways. Five speakers provided examples and insights, and there was lively discussion of the issues and ideas they raised. The sessions provided insights on the semantic, syntactic and contextual aspects of machine learning using ontologies. Relations with the themes of other tracks were discussed, along with common ideas and opportunities.

The following are some of the highlights of the presentations in this track.
Ontology Summit 2017

- With Machine Learning as focus, what are ontology and non-ontology background knowledge influences on ML?
- ML and NLP activities: how they use formal ontologies and how can we design ontologies that can be useful for them?
- What are non-ontology inputs are used in ML and NLP, e.g., vocabularies, hierarchies, taxonomies, thesauri.
- Where are these ML and ontology inputs being used? In domains such as financial business, intelligence, text processing and legal areas.

2.4. Track C: Using ontologies for logical reasoning and vice versa

The goal of track C was to discuss the techniques developed for reasoning using ontological foundations. Any intelligent agent has four basic components:

1. sensors which take external signals in various forms;
2. knowledge, which manifests in various forms (e.g., qualitative, quantitative and combinations of both);
3. inference mechanisms which reason about the world, given the sensor input, using knowledge; and
4. actuators, which execute various forms of action (e.g., physical and mental).

In addition, there are other attributes, such as feedback mechanisms, emotion and sentiment analysis, and social behaviors. Ontologies form the core for knowledge representation, which is used by the appropriate inference strategy. Many forms of inference strategies exist (e.g., backward and forward reasoning, inexact reasoning, constraint satisfaction, theorem proving). In the previous summits, an ontology spectrum, depicting a range from informal representations to formal representations, was presented (e.g., XML, OWL, modal logic, category theory). Ontologies are used for inference in a wide range of domains (e.g., medical, engineering design, finance). In this track, there were six presentations, which dealt with axiomatizations for ontologies, probabilistic reasoning for inferencing and for generating knowledge graphs (a kind of semantic network) from data, using ontologies for transferring from the biological domain to engineering domain, utilizing ontologies – standardized and new – for scientific discovery from large data repositories and for automating workflow. These are summarized below.

- Ontology interoperability ranges from lowest expressivity (e.g., taxonomy) at the syntactic level to intermediate (e.g., thesaurus) at the structural level with various levels of expressivity (e.g., conceptual models and logical theory), and to the highest semantic level with First Order Logic. See Figure 2.
- Tools and technologies also follow this progression.
- Reasoning requires disambiguation of terms from domain overlaps and irreducible structure implied by derived information. It progresses from more elementary computational uses of ontologies such as coordination (agents) and configuration (information management) to more sophisticated uses of ontologies for semantics.
- The anatomy of an Intelligent Agent includes not only sensors, knowledge and inference but also social and sentiment attributes.
- Processes and methods for knowledge acquisition range from visual (pictorial), linguistic and virtual to algorithmic.
Ontologies can aid in the discovery of scientific knowledge and automated workflow analysis.

Design engineering examples applicable for ontology inference relate to structural strategies, requirements and use cases including ecosystem requirements.

3. Background

Early success with machine translation as well as machine “learning” using statistical methods suggested that some progress could be made sub-symbolically [4], i.e., without specific representations of knowledge. However, sub-symbolic ML works by solving classification or regression problems on uninterpreted raw data. Systems devised to solve these problems can be said to “learn” in the sense of optimizing a set of model parameters to increase performance over time. Calling it “learning” makes it sound cognitive and mind-like, but computationally it generally has no resemblance to how humans think, learn and understand or how ontologies represent knowledge. An ML system includes a sub-symbolic layer which stores its sensed data as vectors of numbers. These may be understood as geometrical dimensions, but there is a leap to a symbolic level using formal logic representation. Some progress of inducing semantic relations from conceptual spaces based on ML of text however has been reported in [5].

More recent data-driven AI, also known as Empirical AI, also works sub-symbolically but uses biologically inspired neural net architectures along with optimizing and statistical approaches. Empirical AI takes more of a learning-oriented stance such that knowledge about the world is largely acquired/learned ground up from data such as text and images. Interacting with text and images like this is very different from the much broader, biologically inspired, experience of interacting with the world. While there are some smart systems, such as self-driving cars, that have a limited range of such interactions, learning on the job here seems risky. For an example of this, see [6].

Current AI progress has yet to master the broader forms of learning and understanding that comes from real-world, embodied experience. Some think that such embodied learning requires starting with a cognitive core and then successively developing more sophisticated cognitive models. The social aspect of real-world, embodied experience includes learning common knowledge from other intelligent agents along with their information bearing products such as text, data and physical actions. While acquisition of domain knowledge and domain reasoning methods continue to improve, it has proven very hard to “code” into machines or to learn bottom up without some seed knowledge. Some automated help is needed to handle the major bottleneck issues of domain and general knowledge, which can help with common sense and reasoning, such as the many daily inferences that humans make.

4. Opportunities and Challenges

There are a great many techniques that have been developed that make use of learning, reasoning and ontologies. This section is a attempt to survey some of the problems and opportunities of the relationships among learning, reasoning and ontologies.
4.1. Predictions using Biological Organization

The cell, along with body systems, is usually modeled using levels of organization, each of which can be represented using an ontology – from the molecular and biochemical level, to the cellular and tissue level, to the organ and organ system level, and to the level of biospheres. Biological organization is often called a “hierarchy,” but it is not a hierarchy in the ontological sense. By functionalizing the levels of organization, i.e., mapping from one level to another, one has a form of reasoning, called “biological inference.” An example is the genotype-phenotype map. ML guided by ontologies, such as the manually curated Gene Ontology (GO) [7], is the underlying technique for biological inference from genes to their protein products. This use of ML employs extensive measurement data on the network relation between genes and their protein products. GO is structured to handle this biological issue by means of the three GO domains: Biological Process, Cellular Component, and Molecular Function.

The biological inference technique leverages knowledge of gene co-expressions and protein-protein interactions to create a data-derived gene similarity network. An alignment process identifies which data terms are new and which recapitulate existing knowledge in GO. Taken together this knowledge can be reduced to an ontological hierarchy and aligned with the GO, suggesting names for new, data-driven terms. A majority, about 60%, of relations found by data derivation for cellular components are already in GO-Cellular Component, but only about 25% of these derived terms for Biological Process and Molecular Function were already found in GO, indicating that much potentially useful knowledge was uncovered [8].

Not every domain has the degree of agreement on base ontologies that has been achieved in the BioMedical domain. Likewise, not every area has the degree of agreement on levels of organization. Therefore, it is an open research issue whether something like this be achieved in other domains.

4.2. Context Identification

Words like “stock” and “bear” have many different interpretations that depend strongly on the context [9]. Thus in the context of a financial discussion that touches on stocks the term “bear” is likely referring to investor or stock market attitude as opposed to a type of mammal. Context is fundamental to interpretation yet it is difficult to formalize the notion of context and perhaps the best stance is to agree with Pat Hayes [10] that there is no single notion of context. At its core, a context includes the notions that some propositions, say “There are lots of bears in the stock market,” can be said to be true or false within a context. Saying, “There are lots of polar bears in the stock market” is most likely false due to context. What we understand as the context can depend on context itself. Important work in this area was done by John McCarthy and Pat Hayes in their situation calculus [10], and by Barwise, Perry and Devlin who developed situation theory [11], later formalized in the Web Ontology Language (OWL) [12,13]. Situation theory is very popular in many domains, especially military and business domains.

While situation theory is an effective formalization for context in many cases, it is not a complete solution to the notion of context. The challenge is to develop an effective formal notion of context that can be used to disambiguate the interpretation of words in human discourse and lead to what is called “understanding.” Both situation calculus and
situation theory support reasoning processes. Situation theory is especially versatile in this respect, allowing many forms of reasoning [14].

4.3. Cognitive Scaffolding

The relations of machine learning (ML), reasoning and ontological knowledge, within an AI context, have been the focus of the 2017 Ontology Summit. Extracting information and building knowledge bases and ontologies using ML and intelligent natural language processing (NLP) techniques, for example, was discussed in Track A. Machine learning has come a long way since Arthur Samuel’s 1959 definition of ML as a subfield of computer science that gives “computers the ability to learn without being explicitly programmed.”[15] In practice, this means developing computer programs that can make predictions based on data. ML, in this sense, has become much more feasible now that more and richer data has become available. Modern machine learning workflow often include routine tasks for: problem evaluation, data exploration, data pre-processing, model training followed by testing and deployment. One observation was that many of these techniques have become more cognitive, contextual and holistic rather than purely bottom up. Achieving this requires more intelligent processing and more knowledge.

Some knowledge is needed to handle ambiguity for words such as “pen” which have many senses. One sense of “pen” is of a writing instrument, but another is of a small enclosure for holding animals or children depending on context. But the context here isn’t really a statistical one. Understanding a sentence with “pen” in it often requires real world knowledge about the relative sizes of boxes and pens.

Even simple and less general tasks, such as reading, employ a knowledge “starter” or “seed” on which AI processes, such as supervised or semi-supervised learning, can be applied. An example of seeding knowledge for intelligent process was illustrated in the Never-Ending Language Learning (NELL) system for one important cognitive task: reading. The inputs to NELL include:

1. an initial ontology defining hundreds of categories (e.g., person, sports team, fruit, emotion) and relations (e.g., plays on team (athlete, sports team), plays instrument (musician, instrument)) that NELL was expected to read about, and
2. 10 to 15 seed instance examples of each category and relation.

Seeding knowledge in this case was helped by the topical focus of what NELL’s reading task was, for example, reading about sports or music.

A more general question is the ontological basis of sufficient knowledge needed by an autonomous, intelligent agent which observes and acts on an environment in a directed way to achieve goals. This remains an abiding question. No single architecture, technique or tool, for example, available to build or develop an intelligent agent, has proven adequate to address all the functionality needed for even relatively simple information agents such as envisioned in the original DAML effort [16]. Candidates approaches, however, abound from disciplines as diverse as Cognitive Development, Cognitive Science, Developmental Robotics and AI. There are, for example, many cognitive architectures proposed, including some from Cognitive Psychology such as SOAR [17,18,19] and ACT-R [20], as well as BDI architectures [21,22,23].

But such agent systems have difficulty accommodating common sense things like diverse spatio-temporal information, including quantitative and qualitative assessments.
within a single analytic context in a suitable period of time. Yet as part of the analytic process for understanding a situation, humans easily integrate both quantitative and qualitative information assessments to arrive at conclusions, and this happens before humans, for example, learn to read. That is, the seeding for something like NELL has already occurred for humans. How is this? It seems reasonable to assume that some degree of innate structure is needed to develop a cognitive system and relevant knowledge for some common things as part of an agent’s experience. Such cognitive development, particularly in the context of general intelligence, is sometimes discussed in terms of an early scaffolding with a core set of cognitive abilities providing a temporary structure to afford organizing more general knowledge and learning during the progressive development into a richer cognitive skill system.

In cognitive science, knowledge is conceived as the main outcome of the process of understanding [24,25]: by interacting with the environment, intelligent agents are able to interpret and represent world facts, suitably acting to preserve themselves and pursue specific goals accordingly. Representing knowledge is a necessary step for communication, but knowledge can be properly represented only insofar that world phenomena are previously presented to humans, namely experienced through cognitive structures. Such a cognitive scaffolding can be understood as a starter set: a type of dynamic building block.

Unfortunately, there are currently no accepted starter sets within domains nor a general theory as to what a starter set is or what the first recognizable knowledge and reasoning components are. The Cognitive Linguistics Hypothesis [26], for example, suggests that likely, common human experiences with the world are simple, limited and constrained. Given this, a core part of understanding is grounded in perception and action. This core semantics is represented in what some call “image schemata,” which act as metaphorical frames and cognitive building blocks. Candidates for what image schemata could be include such familiar ontological foundation notions as: Objects, Process and Part-Whole relations, Motion, Full-Empty, Container, Blockage, Surface, Path, Link, Collection, Merging, Scale and Emerge [27]. Some ontology design pattern work and reference ontologies have leveraged these notions, such as work on containment, motion and path.

This leads to many challenges:

- What are candidates for a set of knowledge that could provide adequate cognitive scaffolding. Various possibilities were discussed above.
- Some capability statements may also provide some idea, such the scaffolding and experience needed to handle the frame problem and to decide what is relevant when the world is constantly changing around us [28]. AI systems don’t just need common sense facts and knowledge about the world, they have to know what knowledge is relevant, from one situation to the next.
- As part of scaffolding, an intelligent agent must represent relevant knowledge so that it is accessible and usable for achieving the agent’s purpose. How is such meta-knowledge about representation learned?
- As part of scaffolding, intelligent agents need control mechanisms to find relevant pieces of knowledge in particular contexts. How is this learned and what knowledge is involved?
- Recognize existing patterns/entities, even with partial and/or noisy input.
- Determine what existing categories a pattern belongs to (and how well it fits).
• Predict the remainder and/or continuations of a given partial pattern (predict).
• Be able to learn new patterns/entities, and to be able to categorize them.
• Focus/selection/importance: Selecting pertinent information at the input level as well as during learning and cognition.
• Be able to learn new skills both mental and physical.
• Be able to learn via a wide range of modes, including: unsupervised, supervised, exploration, instruction, etc.
• Support integrated long-term memory, i.e., the knowledge base must be immediately available to all other abilities.

4.4. Probabilistic Semantics

There are several techniques for integrating probability with semantics. The following are from [29]:

• Statistical Relational Learning. Broad AI needs to deal with both relational structure and uncertainty. A particular line of work focusing on the combination of probabilistic models with description logic is known as Probabilistic Semantics [30].
• Probabilistic Soft Logic (PSL) is a machine learning framework for developing probabilistic models. PSL uses first order logic rules as a template language for graphical models over random variables with soft truth values from the interval \([0, 1]\). The underlying mathematical framework supports extremely efficient inference continuous optimization task, which can be solved efficiently. PSL includes the ability to reason holistically about both entity attributes and relationships among the entities, along with ontological constraints. In practice, PSL has produced state-of-the-art results in many areas spanning NLP, social-network analysis, and computer vision. With PSL, large-scale knowledge graph extraction problems with millions of random variables can be orders of magnitude faster than existing approaches.

4.5. Ontology Alignment

Currently, there is no agreement on ontologies to handle the range of heterogeneous information in the Big Data age. While we have seen numerous efforts to create domain ontologies, the vocabularies and ontologies behind various data sources are not generally interoperable. General methods to merge and align ontologies include such things as PROMPT, an algorithm for semi-automatic merging and alignment of ontologies [31]. But as noted more recently in Ontology Summits and related session [32,33], there are issues in reconciling and aligning ontologies with different assumptions and concepts. There is work on ontology integration which has produced algorithms and heuristics with some success in making such computations tractable [34]. However, as noted by [35], the effective use of ontology formalisms (i.e., rules and axioms) as part of an integration process “remains an open question.”

One of the things that makes the ontology integration process difficult is that as part of the process we need to understand the relationship between knowledge structures (classes and properties) and instance data in target ontologies. Existing ontology matching and alignment techniques are very restricted. They find similarities, equivalences and
subsumption relations between two (or more) ontologies which must, at least, be syn-
tactically and schematically integrated, have similar scope, and be no more expressive
than OWL. In contrast, semantic integration between existing domains like hydrology,
its ontologies and schemas additionally require translation between ontology languages,
and more rigorous specification of the semantics in each ontology. This can currently be
done only by manual integration of the ontologies, but use of a suitable reference ontol-
ogy may help automate this as in [33]. In addition, integration must have the capacity
to use the semantics of the ontology to model the relationships between the ontologies
being integrated, and to create a coherent and consistent integrated or aligned ontology.

Another abiding source of difficulty for matching parts of ontologies is that an on-
tology is designed with certain background knowledge (axiomized or not), for a pur-
posek, and within a specific context (explicit or implicit). The context for an ontology can
include the experience of the ontologists who developed the ontology, their preference
for particular upper level ontologies, domain vocabularies, ontology design patterns or
source data to model from. These may not be part of an ontology specification, and, thus,
are not available to aligning tools or entity/relation matchers. This lack of background
knowledge and context leads to ambiguities [36].

4.6. Knowledge Graph Identification and Extraction

The reality of Big Data allows querying from massive repositories of potentially inter-
related facts. Unfortunately, as noted in prior Ontology Summits [37,32], representing
this information in rich formation to make it useful knowledge is a formidable challenge.
One interesting thrust is to transform source material (typically natural language text)
into a knowledge graph form. A knowledge graph is a structure where entities are graph
nodes, categories are word labels associated with each node, and relations are directed
edges between the nodes. A knowledge graph is thus one simplified version of an on-
tology and something less formal than Sowa’s conceptual graphs. Such efforts to build
even this simple structure require resolving entity identification and entity relationships.
There is a degree of uncertainty and noise in and about such relationships targeted in
these extractions as well as the need to infer missing information, and determining which
candidate facts should be included into a knowledge graph as part of the identification
process. One approach is to:

1. associate extraction confidences along with candidate facts,
2. to identify co-referent entities, and
3. to incorporate ontological constraints.

This approach relies on probabilistic soft logic (PSL), a recently introduced probabilistic
modeling framework which easily scales to millions of facts such as demonstrated with
extractions from the NELL project containing over 1M extractions and 70K ontological
relations [38].

4.7. Processes

It should be obvious that learning, reasoning and ontologies occur within larger processes
where they, and the relationships between them, form steps of a process. John Sowa pro-
posed that “For intelligent systems, the cognitive cycle is more fundamental than any
particular notation or algorithm.” Then he concluded that “By integrating perception, learning, reasoning, and action, the cycle can reinvigorate AI research and development.”

[39] There are many examples of cognitive cycles where learning, reasoning and ontologies all occur. The scientific discovery process is an example with a long history. A great many other activities can be regarded as decision making cycles in which each iteration improves understanding and awareness by finding new knowledge as well as by rejecting some previous knowledge. In the past, a single iteration of a cognitive cycle, such as the scientific discovery process, could take decades. Today, cognitive cycles occur more quickly, much more data must be processed and the data is more complex. Learning, reasoning and ontologies, and the relationships between them that are the subject of this Ontology Summit, can play important roles in cognitive cycles. Several previous summits are also relevant to the cognitive cycle, including the need to deal with massive amounts of data [40] which come from large collections of sensors [41] and require many steps that must interoperate [42].

While combining learning, reasoning and ontologies within cognitive cycles has potential advantages, it is not commonly practiced. To the extent that such processes are automated at all, they are generally ad hoc and informal. To automate the scientific discovery process, it is necessary to use NLP to extract the materials and methods used by experiments [43] and the scientific hypotheses that are generated [44]. The challenge is to develop the required ontologies, to standardize them, to formulate best practices, and to convince communities to use them. In some cases, such as PROV-O for provenance [45], the ontology has been standardized, but other requirements of the cognitive cycle are less advanced. None of them are frequently used, and best practices are only starting to emerge.

5. Future Prospects

Among the interesting aspects of the work in Section 4.1 is that it illustrates not only the extraction of new knowledge using ML and reasoning, but also the value of leveraging existing quality knowledge such as in GO as part of this process and alignment with new knowledge with existing ontologies. A good prospect is to use upper domain reference (i.e., foundational) ontologies as starting points for developing quality ontologies.

Concerning the important issue of context in Section 4.2, there is an abundant amount of work in NLP to try and take a degree of context into account. See also Section 4.3 for a related discussion. In the case of language understanding, the context is often one of a discourse topic which can be represented as a larger knowledge structure where themes are formalized as Ontology Design Patterns. At its extreme, this work tends to looks at text and utterances not as having a unique, independent and objective information content, but as producing some understood content in the mind of the reader or hearer. In this sense, semantics is conceptualized as something to be constructed from propositions as ingredients along with a context.

With regard to the ontology alignment challenges in Section 4.5, the Ontology Alignment Evaluation Initiative (OAEI) continues to run contests on ontology alignment [46]. In the OAEI, ontology matchers are challenged with a robust set of ontology and data sources to be matched. For example, match the Adult Mouse Anatomy (2744 classes) with the National Cancer Institute Thesaurus (3304 classes) which describes the
human anatomy. As in past campaigns, they use a systematic benchmark series to be matched. The work of this benchmark series has been to identify the areas in which each alignment algorithm is strong and weak.

There are many roles that learning, reasoning and ontologies can play in the cognitive cycle discussed in Section 4.7.

- Reasoning is fundamental for each of the steps in the cognitive cycle as well as the transition from one step to another step. Reasoning determines which facts produced by sensors are relevant to a goal, whether scientific discovery or decision making. Reasoning is responsible for determining the best hypothesis or hypotheses that are supported by the relevant facts. Reasoning is used for making the decision about which hypothesis is the best and what should be done next.

- Learning can be used for processing the relevant sensor data. Learning can also be used for developing the ontology that organizes the data and makes it understandable. Learning can be used at a meta-level to optimize the cognitive cycle, to detect problems with the cycle, and to help correct problems. Still another use for learning is to develop a library of optimized modules that are available for constructing new cognitive processes. Ontologies and reasoning can be used to ensure that the modules interoperate with one another correctly in a new cognitive process.

- Ontologies play many roles in the cognitive cycle. They can formalize the whole process in a domain-independent manner which promotes reuse. Ontologies are closely connected with reasoning and interoperability. Ontologies can be the basis for maintaining provenance and for explaining the process, both of which promote human understanding.

6. Conclusion

Unfortunately, the history of AI is one of a series of boom and bust cycles, and there is risk that this will happen again. Indeed, AI is expanding so rapidly in so many sectors of the economy that the mainstream media are beginning to question whether AI technologies are worth the investment [47]. Big Data in general has been criticized for several years [48], and ML has many of the same problems:

1. Correlation does not imply causation.
2. Understanding the results is still essential. Indeed strong AI, thinking like a person, ultimately faces the challenge of representing and using the knowledge available to people.
3. It is common to game ML algorithms. Examples include “Google Bombing” and “Spamdexing” that can skew search engine results.
4. Lack of consistency and interoperability of data.
5. Data is seldom independent. ML depends on statistically independent data but much (and, in some cases, most) of modern web content is derived, not original, using many of the same ML techniques that are then applied to the derived data.
6. The Bonferroni correction [49] for statistical significance is rarely used.
7. Questions being asked are too imprecise.
8. Some occurrences are rare yet still significant. ML works best for commonly occurring events but does not work well for rare occurrences. For example, an automated translation of “dumbed-down escapist fare” to German and then back to English produced “scaled-flight fare.”


While ontologies cannot solve all of these problems, they can help with many of them. The Ontology Summit 2017 has examined a wide range of issues, opportunities, challenges and future prospects for the interconnections among learning, reasoning and ontologies in the context of AI. It is appropriate to consider whether the problems raised in the introduction have been addressed. Clearly, not all of them can be addressed. By grounding ML results in ontologies based on human experience, one can hope to eliminate at least the more implausible examples of inferring causation from correlation, and to discover some attempts to “game the results.” However, the problems that could be impacted the most are understanding, consistency, interoperability, and precise questioning. The issue of the Bonferroni correction problem could also be effectively addressed. By formalizing the entire discovery process, one can determine exactly how many attempts at statistical inference are being performed and hence can compute the correct significance level to use. Finally, the overhyping problem, being more of a sociological issue, cannot be addressed directly, but at least in this Communiqué we end with the caution that we do not claim to have surveyed solutions to the problems that were raised but only to have suggested avenues for potential solutions.

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Certain commercial software systems are identified in this paper. Such identification does not imply recommendation or endorsement by the National Institute of Standards and Technology (NIST); nor does it imply that the products identified are necessarily the best available for the purpose. Further, any opinions, findings, conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NIST or any other supporting U.S. government or corporate organizations.

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Ontology Summit 2017


