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Thomas Narock
University of Maryland Baltimore County, Department of Information Systems, tnarock@umbc.edu

Victoria Yoon
Virginia Commonwealth University, Department of Information Systems

Salvatore March
Vanderbilt University, Owen Graduate School of Management

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On the Role of Context and Subjectivity on Scientific Information Systems

Thomas Narock

University of Maryland Baltimore County, Department of Information Systems

tnarock@umbc.edu

Victoria Yoon

Virginia Commonwealth University, Department of Information Systems

Salvatore March

Vanderbilt University, Owen Graduate School of Management

Abstract:

The explicit representation of context and subjectivity enables an information system to support multiple interpretations of the data it records. This is a crucial aspect of learning and innovation within scientific information systems. We present an ontology-based framework for context and subjectivity that integrates two lines of research: data provenance and ontological foundations of the Semantic Web. Data provenance provides a set of constructs for representing data history. We extend the definition of these constructs in order to describe multiple viewpoints or interpretations held within a domain. The W7 model, the Toulmin model, and the Proof Markup Language (PML) provide the Interlingua for creating multiple viewpoints of data in a machine-readable and sharable form. Example use cases in space sciences are used to demonstrate the feasibility and value of our approach.

Keywords: knowledge management, Semantic Web, ontology, context, subjectivity, provenance

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I. INTRODUCTION

Context and subjectivity have always been important aspects of information system development and use. Context deals with the environment in which data has meaning. Subjectivity deals with multiple points of view and varying beliefs. In his seminal work on data representations Kent [1978] contends that the ability of an information system to communicate meaning depends on participants having a "common understanding" with which to interpret the recorded information. Information systems have historically been developed for specific organizational contexts, which are assumed to be understood by its users, each of which shares a common point of view and a common set of beliefs. Furthermore, the recorded "facts" are assumed to have a single interpretation, frequently determined by a process of organizational compromise among users. Thus, although the importance of context and subjectivity are well-recognized, information systems are typically confined to a single context and a single perspective for interpretation, both of which are maintained outside the information system itself.

While appropriate for organizational information systems, single-context, single-interpretation information systems are inadequate for emerging inter-organizational and interdisciplinary information system applications. The "facts" recorded in such information systems include subjective interpretations and inferences such as the quality of a production process or the level of customer satisfaction or the level of brand recognition. In such information systems the explicit representation of context and subjectivity has become crucial. For example, inter-organizational systems that support automated purchasing/sales require each participant to understand the other participant's context and interpretation of recorded "facts" such as product numbers, descriptions, unit of sale, packaging and shipping costs. If the buyer interprets prices to be per pound and include shipping but the seller interprets prices to be per box and shipping to be an additional cost, disputes will clearly arise.

Significant ongoing work in the standards community uses ontologies and frameworks to enable such business communication (e.g., RosettaNet and ebXML). However, more general representations of context and subjectivity are needed for interdisciplinary applications of information technology such as those envisioned by projects such as the cyberinfrastructure research environment [Atkins et al., 2003]. Cyberinfrastructure encompasses support for data acquisition, storage, management, integration, mining, and visualization over the Internet.

Many scientific disciplines view cyberinfrastructure as necessary, if not essential, to enabling the derivation of novel scientific theories and knowledge [Atkins et al., 2003]. Such scientists are attempting to develop capabilities for collaboration that far exceed what is available with current technology, even considering recent developments in the Semantic Web [Hey and Trefethen, 2005]. The goals of cyberinfrastructure research include the sharing of data and results across institutions and disciplines and the enabling of seamless integration and analysis of information from these distributed data sources. With multiple information sources, each having potentially different contexts and different subjective interpretations, the explicit representation and specification of context and subjectivity within the information system is crucial. Cyberinfrastructure has been endorsed as a major research effort of the National Science Foundation [Atkins et al., 2003] and has seen applications across a number of diverse disciplines, from biology [Stein, 2008] to environmental sciences [Govindaraju et al., 2009].

However, the "discovery" aspect of cyberinfrastructure, i.e., finding and assessing the relevance of existing information, has been identified as a difficult and unsolved problem [Stein, 2008; Govindaraju et al., 2009]. Many datasets relevant to scientific research are available over the Internet; however, the available services[1] utilize inconsistent vocabularies, assumptions, and contexts. Work being done on context-based reasoning [Bao et al., 2010] partially addresses this problem; however, as discussed below, use of this work requires the explicit assertion of which contexts are compatible. We argue that such a requirement is not feasible in highly dynamic environments such as cyberinfrastructure. Capabilities are needed to autonomously and automatically identify external contexts that are relevant to a given user.

Related work in the information systems community has focused on the concept of Knowledge Management for Innovation (KMI). KMI focuses on radical improvements in performance [Majchrzak et al., 2004] that result from exploiting diverse ideas and multiple perspectives, which may have been unknown or not considered by the

[1] We use the generic term *services* to refer to the heterogeneous set of available computational resources. This may consist of Semantic Web applications, Web services (both SOAP and REST), Grids, and other applications.

innovator [Armbrecht et al., 2001]. While KMI has been an active research area it has seen very little use in practice. Conjectured causes include a lack of understanding of the mechanisms of innovation [Grant, 1996; Majchrzak et al., 2004] and the disparity of approaches that are required. Existing Knowledge Management (KM) methods are insufficient and can even be counterproductive [Cheung et al., 2008]. Traditionally, KM has focused on "knowledge replication" [Gray, 2000; Swan, 2001] where best practices and past successes are documented and managed in order to increase future productivity and performance. While this form of KM has yielded many successes [Davenport et al., 1998] it also has numerous shortcomings. In particular, a number of researchers argue that "knowledge" is a fuzzy concept, largely dependent on the individuals involved in its development, i.e., it is subjective [Davenport et al., 1998; Bonifacio et al., 2002b]. Furthermore, recent research studies have revealed the distributed nature of knowledge [Bonifacio et al., 2002b]; yet KM implementations continue to advocate a centralized and structured approach [Bonifacio et al., 2002b].

Successful KMI, like successful cyberinfrastructure, requires the representation, interpretation, and integration of multiple perspectives and viewpoints. Moreover, theoretical constructs from KMI could lead to a more successful implementation of context and subjectivity on the Semantic Web, thus enhancing efforts in a critical Semantic Web research area [Hendler and Berners–Lee, 2010].

This article presents key components of a new framework for representing and identifying context and subjectivity. Our goal is to create a framework in which contexts can be identified and autonomously compared. This framework encompasses three main areas: (1) a means of declaring the existence of a context and formally encoding the facets of a context, e.g., creator of the context, definitions/relationships of concepts, and references, (2) a means of autonomously discovering contexts, and (3) a means of autonomously comparing context descriptions. This article focuses primarily on (1), with a discussion and preliminary results from (2) and (3). In doing so, we make two important contributions. First, we present a context ontology that allows for the semantic encoding of context rationale. Using this ontology, agents (human or software) can identify similar knowledge elements within a dynamic and evolving system such as cyberinfrastructure. Our approach is based on a provenance ontology; however, it does not require all component information systems to be Semantic Web applications. Second, our framework allows for the direct testing of KMI theories and provides support for Semantic Web-based initiatives such as cyberinfrastructure. As we will discuss, KMI theory predicts this will result in an enhanced user experience [Majchrzak et al., 2004; Cheung et al., 2008]; the Semantic Web is seen as the prime enabler of KMI [Joo and Lee, 2009]. However, KMI has yet to be formally tested in conjunction with the Semantic Web and it is unclear how the two will coexist.

The remainder of this work is organized as follows. First, we present a review of related research in knowledge innovation, context and distributed knowledge management, and efforts to address subjectivity on the Semantic Web. Second, we present an overview of our framework for knowledge innovation that explicitly represents subjectivity and context. Third, the formal design of our ontology is discussed and used to demonstrate the benefits that emerge from a system that incorporates it, particularly for complex and dynamic environments such as cyberinfrastructure. Fourth, we present an example use case in scientific computing to demonstrate the feasibility and value of our approach. Finally, we conclude with limitations, future research, and a summary of the benefits of representing subjectivity and context in knowledge management.

II. RELATED RESEARCH

Knowledge Inovation

Grant [1996] categorized knowledge management into two distinct groups: (1) efforts that focused on acquiring and storing knowledge such that ideas could be replicated in the future and (2) efforts aimed at knowledge innovation. The latter promise more significant benefits to an organization; however, their transfer to practice has been limited because knowledge innovation mechanisms are poorly understood and tools to implement research efforts are lacking.

Majchrzak et al. [2004] conducted a case study to better understand knowledge innovation, which resulted in a new framework for understanding this form of knowledge management. These results indicated that methodologies from knowledge replication could not be transferred to knowledge innovation. Subsequent work by Hahn and Wang [2009] reinforces this notion by describing convergent and divergent problem-solving processes and showing how each requires a knowledge management system with distinct capabilities. Cheung et al. [2008] have also pointed out deficiencies in current KM systems. They show that tools and technologies are available to find hidden patterns and find alternative solutions; however, where idea quality and innovation are important, such as in public policy and marketing, existing KM methodologies are inadequate.

Such results have led some [Joo and Lee, 2009] to suggest the use of newer and more intelligent technologies such as the Semantic Web for KMI. Majchrzak et al. [2004] argues that knowledge innovation should broaden the scope of knowledge management to include diverse and distinct sources of information. The Semantic Web is seen as an ideal technology to accomplish this goal, and Joo and Lee [2009] argue that the Semantic Web's capabilities align well with such knowledge management goals. However, currently the Semantic Web is incapable of reasoning with multiple contexts and presenting integrated information to users. One exception is Bao's [2010] context-based reasoning work, which includes a provenance component and is a significant contribution to the Semantic Web community. Yet, we argue that the theoretical underpinnings of context provenance are poorly understood. That is, KMI theory dictates that proper depiction of context rationale can induce innovation and creativity [Majchrzak et al., 2004; Cheung et al., 2008; Joo and Lee, 2009]. However, at present, KMI theory has yet to be fully integrated into the Semantic Web. As such, it is unclear which components of context are most important. We see our work in documenting and discovering contexts as an important validation of which context provenance constructs should ultimately be incorporated into a context-based Semantic Web (e.g., Bao et al., 2010).

Context and Distributed Knowledge Management

Our work follows the rationale of Distributed Knowledge Management (DKM) [Bonifacio et al., 2000; van Elst and Abecker, 2001; Bonifacio et al., 2002a, 2002b] where knowledge is viewed as inherently subjective and dependent upon local context. DKM represents a fundamental epistemological move from centralized knowledge management toward the notion of multiple local knowledge repositories. As such, DKM retains the subjective nature of knowledge and views knowledge management as the problem of codifying and managing multiple localized viewpoints. However, DKM is easier to describe in principal than it is to implement in practice. The fundamental technical challenge arises from trying to manage objects that are heterogeneous and diverse, yet on some level related. Several technical frameworks have been proposed to address this challenge [Bonifacio et al., 2000; van Elst and Abecker, 2001; Bonifacio et al., 2002a]. These have focused on defining sets of relationships between localized viewpoints. For example, van Elst and Abecker [2001] define a framework in which viewpoints are either distinct or exhibit some overlap. If overlap is found, then software agents attempt to map between the viewpoints. In a similar fashion, Bonifacio et al. [2002a] define four types of relationships for concepts within viewpoints: concepts are equivalent, concepts are disjoint, concept one is more general than concept two, concept one is more specific than concept two. Given these relationships, Bonifacio et al. [2002a] create a system in which queries are forwarded to other KM peers that have a similar view of the world. The initial work of Bonifacio et al. [2002a, 2002b] has since been extended into Contextual OWL [Bouquet et al., 2003], or C-OWL as it is commonly called. C-OWL is an extension to OWL and aims to formally encode viewpoint relationships in the Semantic Web.

However, current work in DKM still forces the user to make cognitive associations among retrieved information sets. For example, the work of Bonifacio et al. [2002a] and that of van Elst and Abecker [2001] informs the user of different viewpoints and is even capable of querying across multiple viewpoints in a distributed environment. However, neither addresses the notion of *why* the multiple viewpoints exist nor explains the inherent differences among viewpoints. In contrast, our framework is based on provenance research. By extending current provenance definitions, we address both how to find alternative viewpoints and *why* they exist.

As one moves from data integration to knowledge innovation, context moves from heterogeneous data definitions to heterogeneous conceptual models. Dougherty [1992] shows and Majchrzak et al. [2004] confirms that, in knowledge management innovation, new ideas are generated sporadically over time. This is in contrast to knowledge replication where idea generation and the recognition of opportunity occur at a single point in time and the acquired knowledge is codified and applied over time. This sporadic generation of ideas comes about from simultaneously viewing diverse and distinct ideas from multiple perspectives and viewpoints [Majchrzak et al., 2004]. Our framework provides the user access to this rationale and allows them to filter and interpret data based on the history and assumptions of its acquisition and representation.

Subjectivity and Semantic Web Technologies

Subjectivity deals with multiple points of view and varying beliefs. From this perspective the goal is not to find the "correct" view or belief, but rather to codify the multiple views and beliefs that exist and documenting why they exist. Two possible approaches to dealing with subjectivity are fuzzy logic [Dubois and Prade, 1997] and probabilistic logic [Giugno and Lukasiewicz, 2002]. However, neither approach is sufficient for representing multiple viewpoints. Fuzzy logic deals with imprecise boundaries, allowing a person, for example, to be "somewhat" tall or live "close" to a geographic location. However, fuzzy logic does not permit multiple perspectives to be "true" at the same time. Probabilistic logic uses probabilities to determine if an instance falls within a defined group. However, subjectivity is not concerned with validating the probability of different viewpoints being true. It is concerned with codifying different viewpoints and giving users the ability to see both the different viewpoints and the rationale behind them. Hence neither of these approaches is considered further.

A more promising approach involves reasoning over multiple localized ontologies. Work in this area is heavily influenced by the theory of Local Models Semantics [Giunchiglia and Ghidini, 1998], which describes local semantic points of views. There are three streams of research into multiple localized ontologies. Distributed Description Logics (DDL) [Borgida and Serafini, 2002] provide constructs to bridge between multiple ontologies. This work allows concepts and instances in various ontologies to be linked via several predefined relationships. The aforementioned C-OWL [Bouquet et al., 2003] was the first implementation of this. The second line of research, E-Connections [Kutz et al., 2002], focuses on connections lacking in DDL. While E-Connections may be more expressive than DDL they both require disjointedness between ontology modules. This means that concepts can be linked across ontologies; however, the reuse or extension of a concept from one ontology in another is forbidden, a significant limitation in its general applicability [Bao and Honavar, 2006], as well as its use in knowledge management innovation.

The third research stream in localized ontologies is Package-Based Description Logics (PDL) [Bao et al., 2006]. PDL proposes a selective import where selected pieces of one ontology can be imported into another. In this approach, users can have their own local viewpoints yet share common concepts, relationships, and individuals from other ontologies. Reasoning is done in a distributed manner over both local concepts and shared remote concepts. Building on PDL, Bao et al. [2010] have introduced the *isin* relation where isin(c, α) indicates that the statement α is true in context c. The isin relation can be used to divide OWL (or RDF) statements into contexts and explicitly state which statements are compatible.

$$\text{Compatibility:} \quad \mathrm{isin}(c_1, \alpha) \rightarrow \mathrm{isin}(c_2, \alpha) \qquad (1)$$

$$\text{Incompatibility:} \quad \mathrm{isin}(c_1, \alpha) \rightarrow \mathrm{isin}(\neg c_2, \alpha) \qquad (2)$$

For example, (1) indicates that context c_1 is compatible with context c_2, i.e., α is true in both c_1 and c_2 and (2) indicates c_1 is incompatible with c_2, i.e., the statement α is true in c_1, but is not applicable (should not be considered) in c_2. Functionality of this sort is greatly needed; however, manually specifying such conditions is infeasible in applications such as KMI or cyberinfrastructure environments. Such systems must automatically infer such relationships—either through direct inference or through higher-level processes and frameworks, which can determine such relationships.

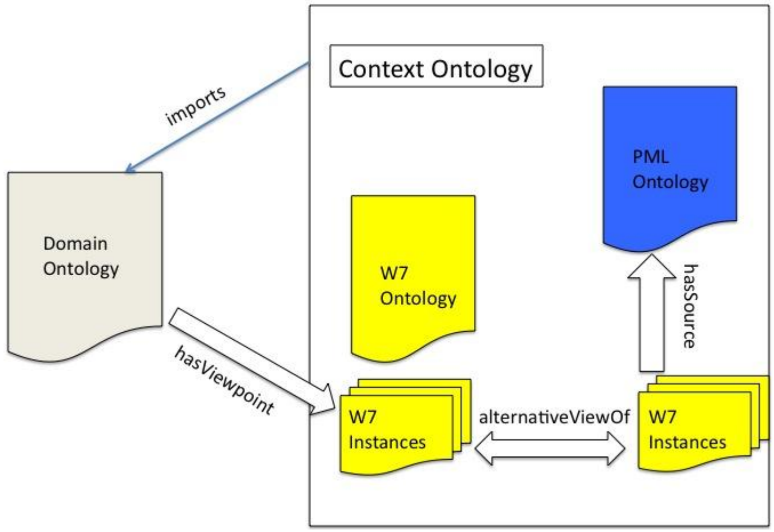
However, as our brief introduction indicates, the focus currently resides in how *known* modular ontologies should be linked. To our knowledge, existing research has not addressed the discovery of different contexts or incorporating *why* multiple contexts exist. We bring together ideas from the modular ontology community with provenance research to capture multiple points of view and to express the rationale underlying them.

III. A FRAMEWORK FOR REPRESENTING MULTIPLE PERSPECTIVES

Our proposed framework functions by using provenance to codifying multiple points of view and the rationale behind each point of view. Provenance is the documented history of an object or the documented processes in an objects lifecycle [Moreau et al., 2008]. We extend the role of provenance to include the documented history of an information system. Specifically, we create an ontology capable of describing the assumptions, beliefs, processes, and rationale used in the creation of the information system. Extending the role of provenance has two advantages. First, provenance is indispensible in many applications [Ram and Liu, 2007]. By using provenance to model subjectivity, we are not creating a new ontology that must be incorporated into an application; rather, we are extending the capabilities of existing highly utilized ontologies. More importantly, provenance allows us to justify our results. Not only are we able to return results from multiple contexts, but we are able to qualify those results by providing background information on the concepts under which those results were produced. This relieves the user of having to form their own assimilation of the results—a feature that is lacking in prior research efforts.

Our ontology is a reuse of an existing ontology and three models that are well-known from the literature: the W7 model [Ram and Liu, 2007], the Toulmin model of argumentation [Toulmin, 1958], and the Proof Markup Language (PML) [Pinheiro da Silva et al., 2004; McGuinness et al., 2007a]. The innovation, from this work, is that we now bring these models, and the areas of context, provenance, and knowledge management together to better address the context discovery challenges of cyberinfrastructure, as well as explore KMI theories. Further, this work produces a framework that can be reused within any domain. Figure 1 shows a high-level overview of our framework.

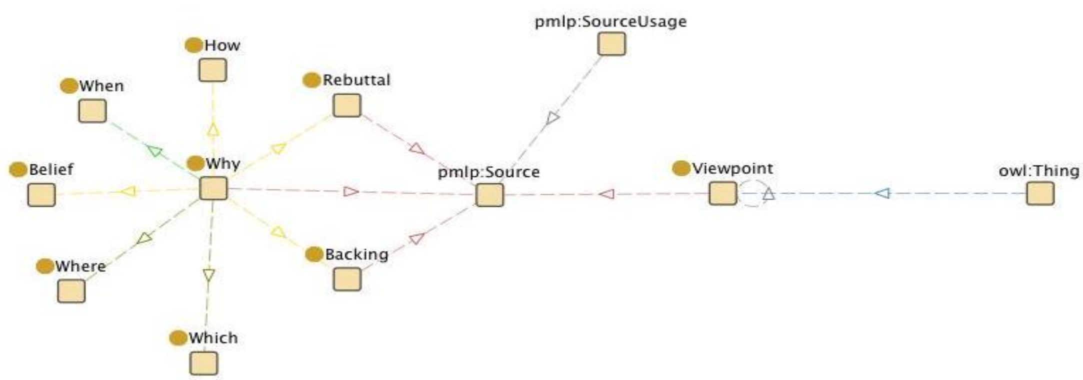
Ram and Liu [2007] proposed the W7 model as a means of dealing with data provenance. The authors intended the model to capture all the interrelated elements of data history—its creation, processing, modification, and storage. Here we use the model as a means for contextual representation. W7 garners its name from the “What,” “When,” “Why,” “Where,” “How,” “Who,” and “Which” elements that make up the model components. These components serve not only to describe the lineage of data, but also work well in describing the rationale for a particular viewpoint within a domain. To this end, we have utilized the W7 model as the basis of describing a context.



Multiple points of view in a domain ontology are expressed via the W7 ontology, and their sources are captured via the PML ontologies.

Figure 1. A High-Level Overview of Our Framework

Rather than codify the provenance of data, we use the W7 model to represent conceptual provenance within a domain. The "What" element of the W7 model is used as the basis for the *Viewpoint* class. This "What" element is combined with the Toulmin model of argumentation [Toulmin, 1958] to create a formal means of encoding the descriptive properties of a viewpoint. The W7 "Who" element has been dropped, as this pertains to the originator of the viewpoint and this construct is addressed by the PML ontology. Figure 2 shows an overview of the resulting ontology, and the Appendix provides a detailed description of the ontology components.



Squares represent ontology classes, and arrows depict relationships among classes. This figure was created via the Jambalaya Extension to the Protégé Ontology Editor.

Figure 2. A Graphical Depiction of the W7 Model as Used to Capture Viewpoints

Using the W7 model in this way, we can semantically encode the rationale behind the construction and usage of an information system. The assumptions and hypotheses that went into the information system are encoded in a standard and formal way. This provenance encoding can then be connected to data within a domain ontology to indicate that the data is associated with a particular context. In order to facilitate this connection, our context ontology contains *hasViewpoint* and *alternativeViewpointOf* object properties. The former is used to link domain ontology concepts to a particular viewpoint, while the latter is used in connecting related viewpoints. We next discuss how the framework incorporates the origin of each viewpoint.

In terms of source and lineage concepts, two possibilities emerged: the Proof Markup Language [Pinheiro da Silva et al., 2004; McGuinness et al., 2007a] and the Open Provenance Model (OPM) [Moreau et al., 2008]. OPM is a larger more community-directed approach to creating a provenance model. However, PML supports justification capabilities, which, at present, are lacking from OPM. KMI demands access to diverse points of view and the rationale behind those points of view [Armbrecht et al., 2001; Majchrzak et al., 2004]. In order to completely implement and test emerging theories, we chose PML for its abilities to expose users to the rationale behind the multiple viewpoints.

PML was designed to be an Interlingua for creating and sharing explanations generated by software agents. The language is broken into three components—a provenance module (PML-P), a justification module (PML-J), and a trust module (PML-T). Each is publicly available in OWL representations. We utilize these OWL representations with minor modifications that allow them to be integrated with our W7 ontology (see the Appendix for details). First, PML-P provides the concept of *Source* that documents the source of information. Our context ontology defines the W7 *Viewpoint* class as a subclass of this *Source* class in order to semantically express that a *Source* is the originator of a particular viewpoint. This connection replaces the "Who" component of the W7 model. That is, it encodes the origin and evolution of the information. We favor PML over W7 in this regard because of the PML justification properties that are described below. *Viewpoint*, as defined, can be the basis of a justification.

We have utilized the first two PML modules in our framework, but have not included the trust module. The trust module is intended to encode the trustworthiness of an agent and, while vitally important, the procedures for determining trust are beyond the scope of the current work. The provenance module replaces the "Who" component of the original W7 module. That is, it encodes the origin and evolution of information. We use this module to encode the origin of each viewpoint. The justification module is used when providing query results to users. Having multiple viewpoints linked to concepts in the domain ontology allows for applications to be built that filter certain viewpoints based on a user's preferences and beliefs. We utilize the justification module of PML such that results and the justifications surrounding how their conclusions where reached (which viewpoint) can be returned to users. Figure 3 graphically illustrates the relationships of our context ontology.

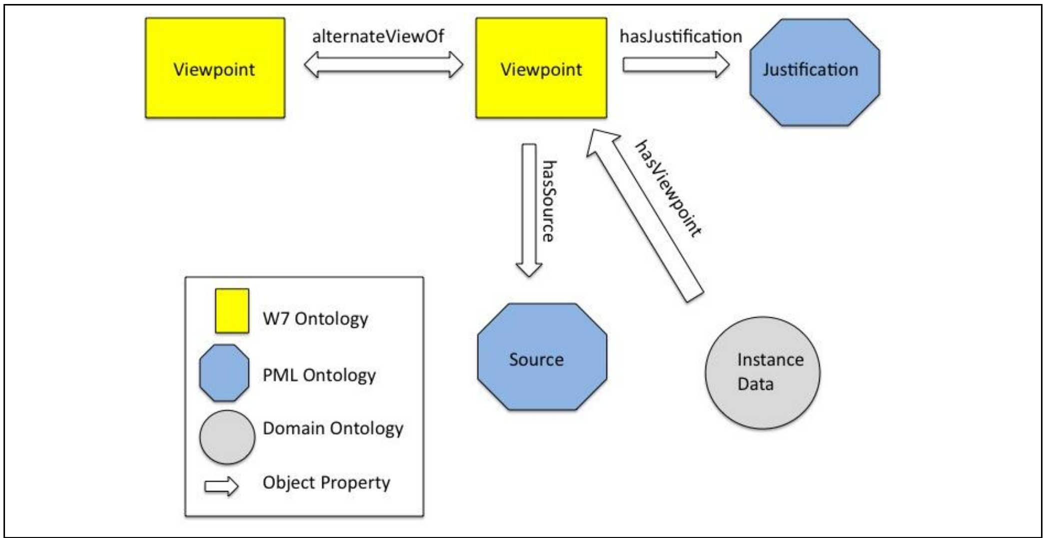


Figure 3. Illustration of How PML and W7 Ontologies Are Linked to Form the Context Ontology

PML allows for four types of justifications.[2] Two of these apply to our framework; however, at present only one is implemented, direct assertions. The first type of justification is an unproven conclusion. Our framework deals with contexts, and, as a result, all conclusions will be based on some context, and we do not support the unproven conclusion aspect of PML. The second type of justification is that of an assumption in which an agent assumes a conclusion to be true but cannot prove it to be so. Viewpoints are subjective phenomena, and we view all justifications as inherently assumptive. Hence we do not explicitly support this type of justifications. The third type of justifications is by direct assertions. It is this type of justification that is implemented in our framework. When responding to queries, our framework utilizes this type of justification in the response to users. An example of this approach is demonstrated in the use case section. The final type of justification deals with inferred conclusions. While we do not rule out the use of this justification type, at present we deal only with asserted contexts. This final type of justification will be the subject of future work.

[2] http://inference-web.org/2007/primer/#intro-pmlj

While PML has been publicly released in OWL, the W7 and Toulmin models exist only in conceptual form. To this end, we have taken the W7 model, as expressed in the literature, and have codified it as a formal OWL ontology. We further codified the Toulmin model as properties of our *Viewpoint* class. Having the two ontologies available in the same basis allowed for the final step of merger into a single ontology[3] expressed in OWL.

IV. EXAMPLE USE CASE

Among the early adopters of the Semantic Web were researchers in the physical sciences [Finin and Sachs, 2004], a community that the cyberinfrastructure environment explicitly seeks to support. This same community is also seen as benefiting the most from a contextual and subjective Semantic Web [Thomas and Sheth, 2006]. To this end, we provide an example use case from the space sciences. We highlight the need for, and show the benefit of, the ability to describe and access multiple contexts within a domain. The problem may be specific to the space sciences; however, the central issues regarding subjectivity are universal to KMI and cyberinfrastructure.

The Virtual Heliospheric Observatory (VHO) [Merka et al., 2008] and the Virtual Solar Terrestrial Observatory (VSTO) [McGuinness et al., 2007b] are two semantically enabled search and retrieval systems for space science data sets. Both systems utilize domain ontologies, and they encompass overlapping spatial regions. Both are vital to cyberinfrastructure within the space sciences; however, they were developed independently of each other, have different communities of users, and have disagreements in their ontological models of the domain. In addition to the context discrepancies there exists no mechanism, other than word of mouth, for users of one system to become aware of the information available in the other.

Utilizing our framework, the contextual provenance of these systems is formally encoded as an instance of our ontology. Developers of the VHO can utilize the ontology to document the context-based provenance of their system. They can describe concept definitions, inherent assumptions, and references (i.e., journal articles) through instantiations of the context ontology. This is done independent of other information systems. That is, the VHO need not be aware of the VSTO at the time of publishing their provenance documents. Software agents work behind the scenes to discover and compare provenance documents. Users of the VHO system would be altered to the existence of the VSTO system. Additionally, because we utilize machine-readable encodings, the provenance documents can be reasoned with and a detailed justification trace can be provided to users describing the contextual background of each system.

Space Sciences—Eruptions from the Solar Atmosphere

Our sun is the driver of a phenomenon known as “space weather.” This concept of space weather is in many ways analogous to Earth-based terrestrial weather and features the cosmic equivalent of storms, winds, and hurricanes. Interplanetary Coronal Mass Ejections (ICMEs) are remnants of violent eruptions from the solar atmosphere and can be classified as one of the most extreme events in space weather. ICMEs have been responsible for electrical power outages on Earth as well as damage to space-based communications satellites. Understanding the mechanisms of these events and their subsequent travel from the sun to the Earth is a prime objective of space physics.

The vast distance from the sun to Earth makes it difficult to track ICMEs once they leave the sun, and their evolution through space is poorly understood. As a result, a number of theories have emerged within space physics that attempt to define what one should see when an ICME passes by an Earth-orbiting satellite [Russell and Shinde, 2005]. Russell and Shinde [2005] have compared lists of events predicted by four ICME theories and have found little overlap. When the various theories are applied to spacecraft data on a yearly basis from 1995 to 2002, there is, at most, consensus on 40 percent of the identified events (1996) and less than 20 percent consensus for each of the remaining years. Thus, with this space physics phenomenon, we have an ideal case of subjectivity based on differing theoretical underpinnings. We have developed an implementation of our framework for this problem. Our goal is to produce a knowledge base of events that is linked to the theory from which it came and is searchable by the space physics community.

Because the concept of ICME has multiple definitions, it is difficult to create an ICME domain ontology using existing technologies. The Semantic Web standard OWL lacks the ability to state that two concepts are actually different manifestations of the same thing. Specifically, this means that we cannot formally state that the definition of ICME depends on which researcher we are currently dealing with. Further, applying essence and rigidity analysis [Guarino and Welty, 2002] reveals that having an ICME class with a sub-class for each theory is a common misuse of subsumption and is formally incorrect. Technically, the ICME theories constitute polysemy and are actually instantiations of ICME and not sub-classes of it. In formal ontological terms, the various theories need to be separate

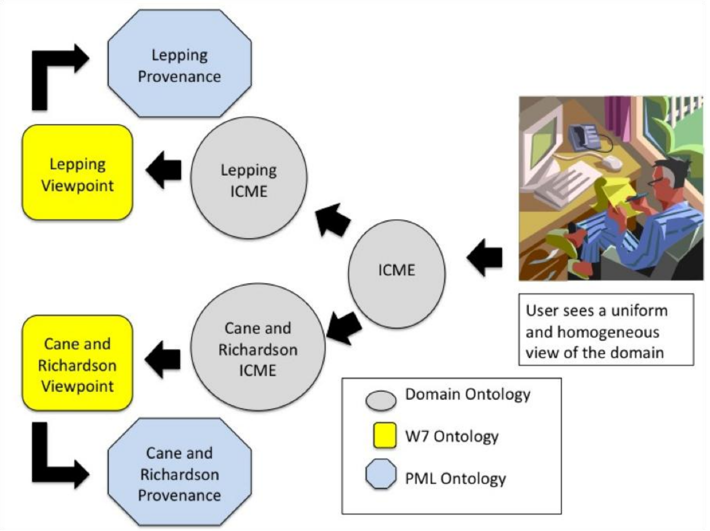
[3] http://userpages.umbc.edu/~tnarock/ontologies/context.owl

classes. However, without a meta-ontology, such as our context ontology, it is not possible to relate these concepts and show that they are unique manifestations of the same phenomenon. Thus, without the application of our framework we would be at a loss to include the concept of ICME and related data in our information system.

We begin by codifying the various ICME theories within space physics. For the purposes of this study, we have codified two ICME theories that are well-known to the space physics community. Our intent is to illustrate two clearly divergent theories and to illustrate how they can be captured and utilized within our framework. At present, this process is done manually through the graphical user interface of the ontology editor Protégé. The W7 component of our context ontology provides a general overview of each theory, expressed as a viewpoint. That is, each theory is contained in a respective instance of the “Viewpoint” class. These instances are then connected to instances of the “Why” component of the W7 model through object properties. The “Why” components provide a name and short description of each respective theory. The final use of the W7 component is to describe what makes each viewpoint unique. In this particular use case, we instantiate the “How” class because our present theories vary on preconditions. That is, they differ on the conditions that must exist prior to declaring an ICME to exist. Having completed this stage of development, we now have our distinct domain viewpoints in a computationally understandable format.

Building on the codification of our viewpoints, we now use the PML component, again via Protégé, to encode the provenance of the theory. That is, we describe who supplied this theory, when it was supplied, and any other lineage information deemed relevant by the application domain. We now have our viewpoints and their histories in a form that can be reasoned with, much like we reason with the domain ontology.

The final step is to link the viewpoint information with the data contained in the domain ontology. In our example, we have a default ICME class, as well as two additional ICME related classes; one for each of the viewpoints covered in our case study. By defining a default ICME class (and designating it so with a property in our ontology), we are able to provide a homogeneous view of the domain to users. In other words, interfaces to the knowledge base show users an integrated view of the domain by simply exposing the ICME class. Behind the scenes, this ICME class links, via object properties, to the two classes which instantiate the various ICME theories. These two classes, then, in turn, link to the viewpoints that describe them. Figure 4 shows a graphical depiction of these connections.



Users see a uniform view of the domain that actually links to several distinct definitions of the concept (which are named after their creators).

Figure 4. A Graphical Overview of a Subjective Concept Within our Domain Ontology

The connection described in this use case example can be generalized into a methodology for incorporating multiple points of view into a domain ontology. The methodology consists of the following steps.

1. Import our context ontology into the domain ontology.
2. Define default concepts in the domain ontology (ICME in our example).
3. Label these concepts as such using the isDefault property from the context ontology.
4. Define concepts for each variation of the default concept (the multiple ICME concepts in our example).

5. Use the context ontology to create provenance descriptions of the concepts in 4.
6. Relate concepts in 4 to default concepts in 2 via ontology properties provided in context ontology.

The user interface of our implementation is a Web browser that is connected to the knowledge base via the Semantic Web Java toolkit Jena. User based Web interactions are translated into SPARQL queries of the knowledge base. There are then two possible ways in which to query the system. The first is by a generic ICME query, which is expanded by the system to be a query over all subsequent ICME related classes. In our example implementation, this would be expanded into two queries; each of which would return a unique set of results. These result sets are each linked to provenance and viewpoint information. In this manner, the user can not only be given the two result sets, but these result sets can be accompanied by an overview of each viewpoint and the rationale of how the viewpoints differ. The effect is that the user is shown two possible scenarios and informed what the results would be under each scenario. Moreover, a user could qualify their query by naming a viewpoint, and the system could be made to ignore data relating to other viewpoints.

Our framework also effectively utilizes the reasoning capabilities of the Semantic Web. Figure 4 shows the two definitions of ICME used in our case study. Each is named for the author(s) who first proposed the theory. One of these, LeppingICME, defines the phenomenon of ICME as being equivalent to another space physics phenomenon, Magnetic Clouds. Our space physics domain ontology defines the classes LeppingICME and MagneticClouds as equivalent classes. In this manner, a query for all LeppingICMEs returns all instances of the MagneticCloud class. Thus, by basing our framework on the Semantic Web, we are able to address challenges in data integration.

The justification component of PML (PML-J) gives us the ability to provide machine understandable justifications for result sets. That is, we can output a PML-J OWL document that describes why the system gave the answer that it did. We view tremendous benefit in this output option. Previous sections have discussed outputting the results such that the user may view the various viewpoints as well as the result sets. While useful to human agents, this output format is incompatible with software agents. PML-J gives us the ability to output our justification in a form that can be used, and reasoned with, by intelligent software agents. The details of this output option, as well as use case scenarios, are left for future research.

Finally, we highlight one remaining element of our context ontology. The disputedIndividual property gives us the ability to specifically state that two individuals are actually different manifestations of the same thing. As an example, consider the two ICME classes shown in Figure 4. Occasionally, the same physical event is identified via both theories; however, due to the different criteria used in each theory, the start/stop times of the event are not the same. In these cases our framework is able to link these events and display to the user that they are manifestations of the same physical event, albeit with different temporal aspects.

V. CONCLUSIONS AND FUTURE WORK

Ambrecht et al. [2001] and Majchrzak et al. [2004] contend that KMI requires the integration of diverse and conflicting information. The Semantic Web is seen as a natural application of these theories [Joo and Lee, 2009]; however, at present there exist limitations in our ability to encode and manage truly diverse and conflicting information. As a result, emerging innovation theories are left without validation. Such theories could provide more benefit to Semantic Web adoption if we had a viable means of empirically validating such theories. Moreover, practical applications such as cyberinfrastructure require a mechanism to encode and ultimately to find other related contexts. Our framework is a first step in accomplishing these goals.

The provenance community is actively working to document the lineage of data. By extending the definitions of provenance to include the lineage of concepts and information systems, we can begin to create distributed systems that not only keep track of what they do, but keep track of how their interpretations align with the interpretations of others. As a result, users are no longer forced to integrate disparate results on their own. Rather, through provenance information, users have the ability to examine the conceptual models of subjective information systems. This work begins to bring together the provenance and DKM communities, and our ontology is the first step.

However, the ontology is only the first step in our proposed framework. Automated detection and comparison of contexts are vital to a complete implementation of our framework. Several approaches have been proposed (e.g Bunke and Shearer, 1998; Maedche and Staab, 2002; Li et al., 2003; Varelas et al., 2005; Sanchez et al., 2009; Viswanathan, 2010) for determining similarity of ontology graphs. We are currently exploring these various methodologies and are in the process of developing an algorithm that will autonomously identify viewpoint similarity within a given domain.

Yoon et al. [2005] studied the use of agents for knowledge management and found several advantages to this technology. One such advantage is that agents are autonomous and adaptable. That is, they can operate on their own and learn from previous experiences. Various DKM approaches have also focused on agents [van Elst and Abecker, 2001] as well as peer-to-peer technology [Bonifacio et al., 2002a]. The incorporation of agents is the next step in the development of our approach to KMI. Based on preliminary evidence, agents can significantly reduce the manual efforts that are currently required. We note that this work is currently focused on multiple viewpoints within the same domain.

Rapid innovation can result from access to diverse sources of data, and the knowledge management community has been eager to harness this ability. Previous technological abilities and methodologies are incapable of adequately addressing knowledge management for innovation. We have presented a more holistic view enabled by provenance. We have also shown that we are just scratching the surface of this research area and more questions and challenges wait. The creation of our context ontology has helped to clarify some of these issues and point us in a future research direction.

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1. These links existed as of the date of publication but are not guaranteed to be working thereafter.
2. The contents of Web pages may change over time. Where version information is provided in the References, different versions may not contain the information or the conclusions referenced.
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APPENDIX A: OVERVIEW OF CONTEXT ONTOLOGY

The *Viewpoint* class is the foundation of our ontology and is created by merging the W7 "What" element with the Toulmin Model of Argumentation. This class provides a mechanism for encoding general properties of the viewpoint and contains the following properties:

- Claim—a component of the Toulmin Model this property attempts to quantify the type of viewpoint being put forth. The allowed values are:
  - Fact—claims which focus on empirically verifiable phenomena
  - Judgment—claims involving opinions, attitudes, and subjective evaluations of things
  - Policy—claims advocating courses of action that should be undertaken

- Qualification—a component of the Toulmin Model that specifies the degree, or probability, of belief in the viewpoint. Probabilistic ranges are meant as a guideline as it is nearly impossible to assign an exact probabilistic belief value to a viewpoint. Allowed values are:
  - Strong—Steadfast belief given the available evidence. Roughly 0.7 to 1 on a probabilistic scale
  - Probable—Significant, but not steadfast, belief given the available evidence. Roughly 0.4 to 0.7 on a probabilistic scale
  - Weak—Little credence given the available evidence. Roughly 0.1 to 0.4 on a probabilistic scale
  - Unlikely—Given the available evidence the viewpoint has little support. Roughly 0 to 0.1 on a probabilistic scale

- Warrant—a component of the Toulmin Model that expresses the inference or reasoning that should result from evaluating the viewpoint/argument

- Name—a label by which this viewpoint can be referred

- The viewpoint class also has several object properties that link it to other classes in the ontology:
  - alternativeViewpointOf—this property links two viewpoints and states that they are unique viewpoints of the same topic. This property is an OWL transitive property meaning that it applies between successive members of a sequence.
  - disputedIndividual—a means of linking individuals that represent subjective interpretations of the same general concept
  - hasImplementations—a property for relating generic domain concepts to their multiple implementations
  - hasReference—a link between concepts and reference concepts

"Why" is used to express the reasons behind the viewpoint such as the goals, hypotheses, and assumptions that went into its formation. "Why" is comprised of the remaining W7 elements (When, Where, How, and Which) as well as three supporting classes—Belief, Rebuttal, and Backing. Belief is from the W7 model while Rebuttal and Backing are components of the Toulmin Model. Together these classes explain why a person has a particular viewpoint. Their usage is optional and used as needed in describing a viewpoint. These classes encode the actions, devices, and settings involved in a viewpoint, as well as the viewpoint holder's goals and assumptions. Belief, Rebuttal, and Backing are defined as follows:

- Belief—comprised of two subclasses, each with properties: *name*, *description*, and *hasReference:*
  - Assumption—a belief lacking any evidence or support
  - Hypothesis—a proposed explanation based on evidence

- Backing and Rebuttal are borrowed from the Toulmin Model and provide a means of encoding supporting and refuting evidence for a viewpoint. These classes are both comprised of *name*, *description*, and *hasReference* properties.

"Which" refers to the instruments, applications, and settings that are used. Some viewpoints are dependent on devices being used and the characteristics and capabilities of those devices play an integral role in the viewpoint. This dependence is captured by the "Which" element. The "Which" element is comprised of three additional classes—Device, Function, and Settings. By instantiating one, or more, of these three classes, the viewpoint creator encodes the role that instruments, applications, and settings play within the viewpoint.

- Device contains two subclasses that are used to describe the hardware, tools, and methodology on which a viewpoint is based—each subclass has a *name*, *description*, and *hasReference* properties:
  - Application—a software tool or methodology used in data collection or analysis
  - Instrument—a physical piece of hardware used to collect or analyze data

"When" is used to express temporal aspects of a viewpoint. This class is used when a viewpoint is dependent on (valid) during a certain period of time. The "When" class has two associated classes—Duration and Instant—which, respectively, encode a period of time and a single point in time.

The "Where" class describes spatial aspects of the viewpoint. Following the W7 model we utilize three supporting classes in order to encode various types of locations:

- Geographical Location—(W7 model) Location of points or places based on an area or boundary governed by common law—for example, a state or country

- Physical Location—(W7 model) Location of points or places based on a coordinate system

- Transaction Location—(W7 model) Location within a database or server. This is often represented as a URI.

The "How" element is used in conjunction with a viewpoint to express that the viewpoint originates via unique precursors, interpretations, or analysis. These analyses and interpretations may result in temporal and spatial discrepancies: however, we view these as consequences of the analysis ("How" element) and not instantiations of "Where" or "When" elements. The "How" class is comprised of one or more instantiations of the Action class. There are four types of actions, which are described by four associated classes—Precondition, Input, Resource, and Method:

- Precondition—conditions that must hold prior to enactment of an action. This class has properties: name, description, and hasReference.

- Input—objects that are manipulated by an action. This class has properties: name, description, and hasReference.
- Resource—available assets supportive of carrying out various actions. This class has properties: name, description, and hasReference.

- Method—descriptions of algorithms/actions that have been done. This class captures various action parameters and has properties: name, description, and hasReference.

ABOUT THE AUTHORS

Thomas Narock is a doctoral student in the Department of Information Systems at the University of Maryland, Baltimore County (UMBC). His primary research interests are in provenance, intelligent systems, information management, and knowledge discovery. He is particularly interested in the role of the Semantic Web in these research areas.

Victoria Yoon is Professor in the Department of Information Systems at Virginia Commonwealth University. Her primary research interest lies in the application of AI systems to decision making in organizations and the technical, as well as managerial, issues of such systems. She had been involved in building multi-agent systems for NASA Goddard Space Flight Center, as well as well as the Navy Postgraduate School. She is currently working on several projects in the field of Knowledge Management, Multi-Agent Systems, and Semantic Web.

Salvatore March is the David K. Wilson Professor of Management in the Owen School of Business at Vanderbilt University. He teaches courses on Information Technology and Internet Commerce, Database Management Systems, and Managerial Economics. His primary research interests are in the areas of Information System Development, Electronic Commerce, Logical and Physical Database Design, Distributed Database Design, and the Economics of Information. He is currently an Associate Editor for *Decision Sciences Journal, Information Systems Frontier,* and *Journal of Database Management* and a Senior Editor for *Information Systems Research.*

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