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A Semantic Framework for Harvesting Vague Enterprise Knowledge from Microposts

Panos Alexopoulos
Intelligent Software Components S.A.
Av. del Partenon, 16–18, 1–7, 28042, Madrid, Spain
palexopoulos@isoco.com

John Pavlopoulos
Department of Informatics, Athens University of Economics and Business,
76 Patission Str., 10434, Athens, Greece
annis@aueb.gr

Phivos Mylonas
National Technical University of Athens, Image, Video and Multimedia Laboratory
9 Iroon Polytechniou Str., 15773, Athens, Greece
fmylonas@image.ntua.gr

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The advent and wide proliferation of Social Web in the recent years has promoted the concept of social interaction as an important influencing factor of the way enterprises and organizations conduct business. Among the fields influenced is that of Enterprise Knowledge Management, where the increase and maintenance of the employees' active participation in the organization's knowledge management activities is pursued through the adoption of social computing approaches. In this paper we consider a prominent and increasingly applied such approach, namely enterprise microblogging, and we propose a novel way to exploit its knowledge generation and sharing capabilities in order to effectively capture and formalize enterprise knowledge that is vague. Application and empirical evaluation of the framework indicates significant potential towards this goal.

Keywords: Enterprise knowledge management; enterprise microblogging; vague knowledge; fuzzy ontologies.

1. Introduction

Knowledge Management evolved over the last years to a serious management discipline that aims to enable enterprises and organizations to fully leverage their knowledge in their effort to grow more efficient and competitive.[35,13] This leverage involves several key objectives such as identification, gathering and organization of existing knowledge, sharing and reusing of this knowledge for different applications and users and facilitation of new knowledge creation. Nevertheless, a dimension of enterprise knowledge that has so far been inadequately considered by the research community is that of *vagueness.*

Vagueness,[18,33] typically manifested by terms and concepts like *Tall, Strong, Expert* etc., is a quite common phenomenon in human knowledge and it is related to our inability to precisely determine the extensions of such concepts in certain domains and contexts. That is because vague concepts have typically fuzzy boundaries, that do not allow for a sharp distinction between the entities that fall within the extension of these concepts and those which do not. This is not usually a problem in individual human reasoning, but it may become one, (i) when multiple people need to agree on the exact meaning of such terms and (ii) when machines need to reason with them. For instance, a system could never use the statement "*This project requires many people to execute*" in order to determine the number of people actually needed for the project.

To deal with vague knowledge, a relatively new knowledge representation paradigm that has been proposed is Fuzzy Ontologies,[2] extensions of classical ontologies that, based on principles of Fuzzy Set Theory,[20] allow the assignment of truth degrees to vague ontological elements in an effort to quantify their vagueness. Thus, whereas in a traditional ontology one would claim that "*The project's budget is high*" or that "*Jane is an expert at Artificial Intelligence*", in a fuzzy ontology one would claim that "*The project's budget is high to a degree of 0.7*" and that "*Jane is an expert at Artificial Intelligence to a degree of 0.5*".

Unfortunately, an important bottleneck in the process of developing and applying fuzzy ontologies for knowledge management is that of vague knowledge acquisition. This kind of bottleneck in traditional ontology development has been well documented in the literature and several approaches towards automating the knowledge acquisition process have been proposed.[38,30] In fuzzy ontologies the problem is even more acute as the high level of subjectivity and context-dependence characterizing vague information makes the accurate definition of fuzzy degrees and membership functions a very difficult task. Yet only a few automatic approaches for fuzzy ontology population have so far been proposed, with the vast majority of them being based on text mining.[1,22,9]

Contrary to above approaches, we envision the active participation of users in the vague knowledge acquisition process through a corresponding framework based on the so-called Web 2.0; a technological paradigm that facilitates and supports the active participation and collaboration of people on the Web. Our approach is inspired from works in the area of "crowdsourcing"[37,29] where a large group of people solves implicitly a problem or carries out a task through proper incentive mechanisms. In our case such mechanisms are required since one of the biggest bottlenecks in typical Knowledge Management systems, where end-users are supposed to actively participate, is precisely the hurdles they encounter that discourage them for keeping involved. On the other hand, Web 2.0, where users participate in an active manner, and willingly generate new content, has been adopted by companies for their internal processes within the so-called Enterprise 2.0 framework.[25]

In particular, microblogging systems have been embraced as a way of fostering internal communication within the enterprise boundaries. Microblogging is one of the recent social phenomena of Web 2.0, being one of the key concepts that has brought Social Web to more than merely early adopters and tech savvy users. Simply put, microblogging is a light version of blogging where messages are restricted to less than a small number of characters. Yet, its simplicity and ubiquitous usage possibilities have made microblogging one of the new standards in social communication. There is already a large number of social networks and sites, with more blooming every day, that appear to have some microblogging functionalities, with Twitter[a] and Facebook[b] being the most famous.

Twitter, in particular, allows users to publish text limited to a maximum of 140 characters. On Twitter a user has two main roles, to publish tweets (writer) or to subscribe to other users and read their posts (reader).[6] As a writer you are allowed to: (1) republish or retweet other users' posts; (2) make reference to other users within the published content (a.k.a. mentions) by using the '@' character before the user's user name; (3) reply to another tweet, replies always start with '@'username (author of the tweet you are replying to); (4) include different types of resources to your post (i.e. hashtags and links); and (5) be listed by your followers. As a reader you can: (1) follow other users' posts; and (2) organise into groups (lists) the users you follow.

Given the above, in this paper we present a framework for automatic capture and conceptualization of vague knowledge, based on:

(1) A semantically enhanced microblogging system.
(2) A fuzzy ontology learning process that acts upon the social content produced by the enterprise's people within this system.

The key idea behind this process is that the content, the provenance and the structure of the user generated microposts, can provide useful information for the generation of the optimal degrees and membership functions of the enterprise's fuzzy ontology. An initial version of the framework has already been presented in Ref. 3; in this paper we substantially extend this work by providing a more detailed technical description of the framework as well as an evaluation of its ability in acquiring vague enterprise knowledge.

The remainder of this paper is organized as follows: in Section 2, we introduce necessary relevant background information utilized within this work while in Section 3 we provide an overview of related work. Section 4 describes the proposed vague knowledge acquisition framework, focusing on the semantic microblogging

[a] www.twitter.com
[b] www.facebook.com

platform that we use to generate the required social content and the methods we apply to it in order to create the fuzzy ontology. In Section 5 we evaluate the framework's ability to capture vague knowledge in an effective way and, finally, in Section 6, we summarize the key aspects of our work and we discuss the potential directions it could take in the future.

2. Background and Problem Setting

2.1. *Vagueness and ontologies*

In the relevant literature, vagueness is defined as a semantic phenomenon in which predicates admit borderline cases,[18] i.e. cases where it is unclear whether or not the predicate applies. For example, some people are borderline tall: not clearly "tall" and not clearly "not tall". This definition clearly separates the notion of vagueness from similar phenomena like inexactness or uncertainty. For example, stating that an object's distance from a certain point is between 10 and 20 meters is an inexact statement but it is not vague as its limits of application are precise. Similarly, the statement "*Today it might rain*" denotes the inability to know whether it will rain or not but this is due to lack of adequate information rather than because the phenomenon of rain lacks sharp boundaries. This latter fact means practically that vagueness cannot be really treated by means of probability theory.

Vagueness in an ontology appears typically in concepts, relations, attributes and datatypes.[2] A concept is vague if it admits borderline cases, namely if there are (or could be) individuals for which it is indeterminate whether they instantiate the concept. Typical vague concepts are those that denote some phase or state (e.g. Adult, Child) as well as attributions, namely concepts that reflect qualitative states of entities (e.g. High, Big, Strong, etc.). Similarly, a relation is vague if there are (or could be) pairs of individuals for which it is indeterminate whether they stand in the relation. The same applies for attributes and pairs of individuals and literal values. Finally, a vague datatype consists of a set of vague terms which may be used within the ontology as attribute values. For example, the attribute *Employee Experience*, which is normally measured by the number of working years, may also take as values terms like *junior, senior* and *veteran.*

2.2. *Fuzzy ontologies and problem definition*

A fuzzy ontology utilizes notions from Fuzzy Set Theory in order to formally represent the vague ontological elements described in previous paragraph. The basic elements it consists of include:

- **Fuzzy Concepts**, namely concepts to whose instances may belong to them to certain degrees (e.g. *Goal X is an instance of StrategicGoal to a degree of 0.8*). These degrees are called fuzzy and practically denote the extent to which entities should be considered as being instances of a given concept.

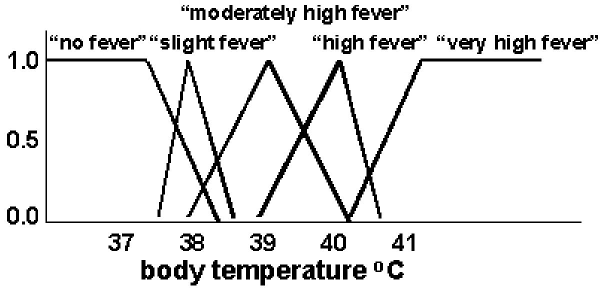

Fig. 1. Fuzzy datatype example.

- **Fuzzy Relations/Attributes**, namely relations and attributes that link concept instances to other instances or literal values to certain degrees (e.g. *John is expert at Knowledge Management to a degree of 0.5*).
- **Fuzzy Datatypes**, namely sets of vague terms which may be used within the ontology as attribute values (e.g. attribute *experience* mentioned above). In a fuzzy datatype each vague term is mapped to a fuzzy set that assigns to each of the datatype's potential exact values a fuzzy degree indicating the extent to which the exact value and the vague term express the same thing (e.g. *A body temperature of 38 degrees Celcius is considered a slight fever to a degree of 0.4*)

Based on that, the problem we wish to tackle can be informally defined as follows: *Given a fuzzy enterprise ontology, what are the optimal fuzzy degrees and membership functions that should be assigned to its elements (concepts, relations and datatypes) in order to represent their vagueness as accurately as possible?*

In particular, given a fuzzy concept (e.g. CompanyCompetitor) and a set of its instances (e.g. a set of companies), we practically want to learn the degree to which each of these instances belongs to this concept (e.g. to what degree each company is considered a competitor). Similarly, given a fuzzy relation (e.g. isExpertAt) and a set of related through it pairs of instances (e.g. persons related to business areas), we want to learn the degree to which the relation between these pairs actually stands. Finally, given a fuzzy datatype (e.g. ProjectBudget) and the terms it consists of (e.g. *low, average, high*), we want to learn the membership functions of the fuzzy sets that best reflect the meaning of each of these terms.

3. Related Work

3.1. *Vagueness theories*

The phenomenon of vagueness in human language and knowledge has been studied from a logic and philosophical point of view in a number of works,[18,33,34] and different theories and paradigms have been proposed to accommodate it. The most known of these paradigms are supervaluationism,[19] many-valued logics and fuzzy logic.[20]

The first regards the borderline cases of a vague predicate as a source of uncertainty and considers all the different ways in which these predicates can be made precise. This means that if an object's colour is somewhere in the border region between green and blue, then supervaluations allow you to say with certainty that the object is either green or blue but not both. In other words the one crisp threshold of classical logic is replaced by two crisp thresholds: one between green and the borderline area, and between the borderline area and blue.

Many-valued logics, in turn, define additional truth values that stand between the values of true and false in order to represent borderline cases. While this allows to model vagueness more subtly, it's difficult for one to decide how many additional truth values are sufficient to tackle the problem. Thus, fuzzy logic appeared, proposing a large range of truth values between 0 and 1, where 0 means 'completely false', 1 'completely true', and all other values are intermediate degrees of truth. Currently, this paradigm is the prevailing one when it comes to dealing with vagueness in semantic information and knowledge management systems[5] and, therefore, is a natural choice for the problem our work tackles.

3.2. *Automatic (fuzzy) ontology construction*

The task of automatic ontology construction,[12,44] seeks to discover ontological knowledge from various forms of data[23] automatically or semi-automatically in order to overcome the bottleneck of ontology acquisition in ontology development. Many works in this area try to tackle specific tasks, such as concept and relation extraction, extending existing ontologies, and ontology population.[4,27,36] For example, in Ref. 27 a methodology for semi-automatic ontology extension by glossary terms based on text mining methods and considering ontology content, structure and co-occurrence information is proposed. Another automated ontology extension system is SOFIE[36] that is able to parse natural language documents, extract ontological facts from them and link the facts into an ontology. Other works focus on learning more complex knowledge such as concept hierarchies. For example, in Ref. 11 this is done by means of Formal Concept Analysis while in Refs. 40 and 42 by means of Latent Dirichlet Allocation learning algorithm.

Coming to fuzzy ontologies, the task of generating them in an automatic way has been considered by some works in the literature, yet their approaches are quite different than the one presented in this paper. For example, the approach in Ref. 39 utilizes a fuzzy variation of Formal Concept Analysis[15] in order to generate fuzzy concepts. To do that, however, it requires the existence of fuzzy degrees in the level of statements, thus making it inappropriate for the problem this paper tackles. A similar problem has the approach of Ref. 43 where the generation of the fuzzy ontology is done from a fuzzy object-oriented database model.

On the other hand, the approach of Ref. 22 does generate such degrees for the fuzzy ontology it extracts from textual corpora (through a text mining approach), yet these degrees do not reflect the domain's vagueness but rather the uncertainty regarding the accuracy of the mined ontology elements. A text mining approach is also followed in Ref. 1 where detected fuzzy qualifiers (i.e. terms like "very", "slightly", "quite") in front of concepts in the text are used to generate fuzzy degrees and membership functions. In all cases, the main differentiating characteristic of our proposed framework is the adoption and exploitation of a social computing paradigm to engage people in the process of vague knowledge formalization, in an indirect way.

3.3. *Enterprise microblogging*

The question whether microblogging can offer benefits for individual knowledge workers and their organizations when deployed in the enterprise has been the subject of various works and systems.[14,26] In Ref. 26 the authors describe the process and results of deploying a microblogging service at Siemens. The service was provided as part of a larger knowledge management infrastructure, namely References@BT, and was used by around 500 users, revealing a high degree of acceptance by the user community. In another work,[17] topic extraction techniques were applied to content generated from the deployment of the enterprise microblogging system Yammer in a company, the goal being to determine whether the microblogging system is a potential platform to facilitate better knowledge sharing and knowledge creation among employees. A similar analysis is reported in Ref. 8 in order to provide insights on the structural properties of the extracted network of directed messages sent between users of a corporate microblogging service, as well as the lexical and topical alignment of users.

3.4. *Knowledge extraction from microposts*

The increased popularity of microblogging, both in the social web media and the enterprise, has led to a large number of works dedicated to the task of extracting useful information and knowledge from microposts. For example, in Ref. 24 advanced NLP techniques are used to analyze pre-election tweets and extract from them political opinions and while in Ref. 10 semantic entities and events are extracted from sports tweets. Also, the works in Refs. 21 and 31 focus on performing sentiment analysis in Twitter while in Ref. 41, microposts are used as a data source for automatic ontology construction.

4. Proposed Framework

Vague pieces of knowledge are characterized by the existence of blurry boundaries and by high degree of subjectivity. As such, they are expected to provoke discussions, disagreements and debates among the enterprise's members. For example, it might be that two product managers disagree on what the most important features of a given product are or that two salesmen cannot decide what amount of sales is considered to be low. Our approach is based on the facilitation and recording of such discussions and disagreements, through a microblogging platform, and their utilization for determining the optimal degrees and membership functions of a fuzzy ontology representing this knowledge.

In particular, the process we propose for performing vague knowledge acquisition within an enterprise consists of the following steps:

(1) Development of a fuzzy ontology that describes vague knowledge about the enterprise and its environment.
(2) Set up of a microblogging platform in which the members of the enterprise are expected to participate and perform discussions and information exchange on aspects regarding the enterprise and its environment.
(3) Detection and extraction from the user generated platform's content of vague knowledge assertions, namely statements related to the elements already defined in the fuzzy enterprise ontology.
(4) Calculation for each vague assertion of a strength value based on the utilization of various characteristics of the discussions they are involved in.
(5) Aggregation of these assertions and automated generation of fuzzy degrees and membership functions.

In the following paragraphs we elaborate on each of the above steps.

4.1. *Fuzzy ontology development*

This step involves the development of a fuzzy ontology that captures and conceptualizes vague enterprise knowledge, using the elements described in Section 2.2. For this task we consider the IKARUS-Onto methodology[2] which has been designed to cover the whole fuzzy ontology development lifecycle, from specification to validation and which defines a set of concrete steps and guidelines for transforming existing ontologies into fuzzy ones (Figure 2).

These steps are to be followed here as well with, nevertheless, an important difference: the fuzzy degrees and fuzzy membership functions of the ontology's elements are not to be defined by domain experts (as the methodology suggests in step 2); instead they are going to be automatically calculated by analyzing the user's microposts in the way explained in the subsequent sections.

4.2. *Enterprise microblogging platform*

For the purposes of this work we use an intra-enterprise semantic microblogging tool that allows its end-users to share short messages expressing what are they doing, or more typically in a work environment, what are they working at. Architecture-wise, the tool is divided in two main components, namely a microblogging engine and an ontology-based semantic engine that offers indexing and search functionalities over the platform's content. The microblogging functionalities of the system are quite similar to those of Twitter, with two important enhancements:

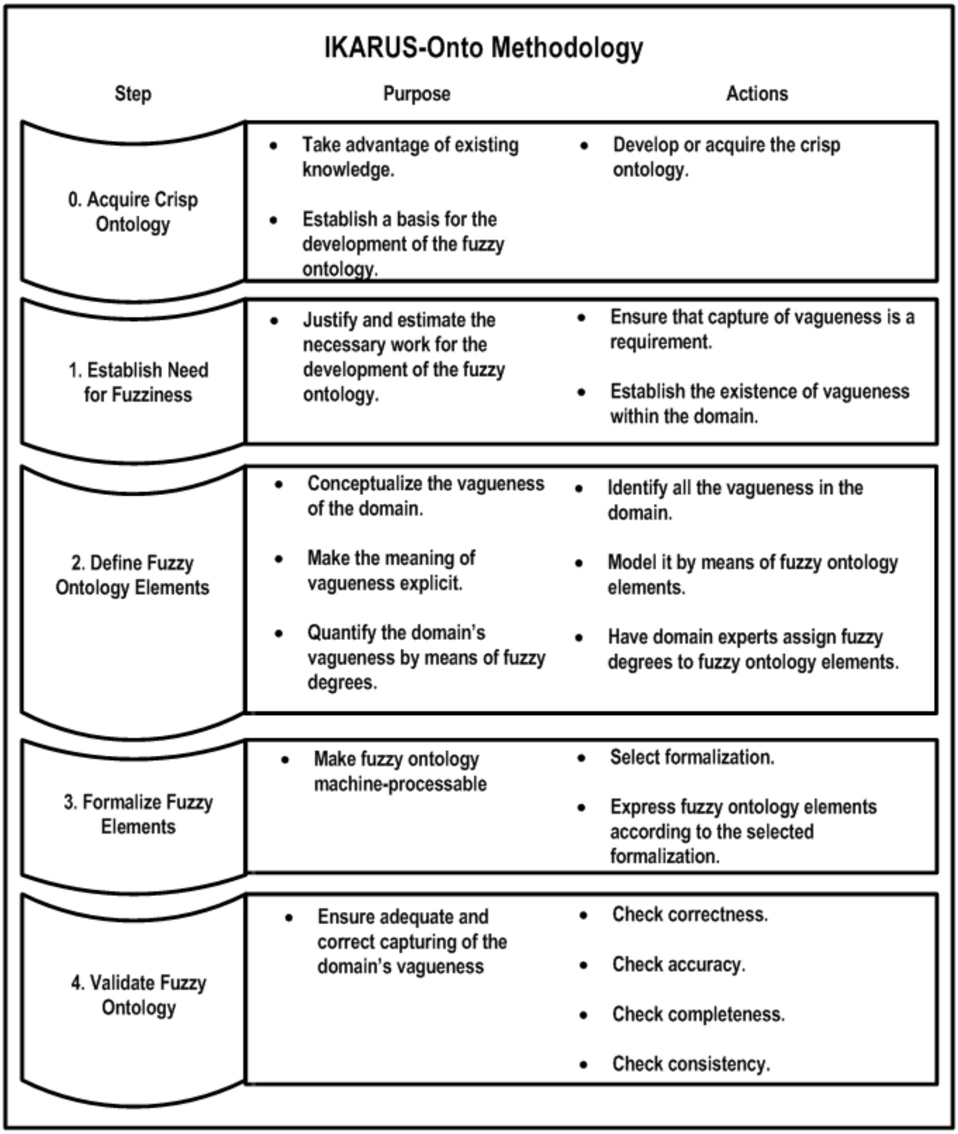

Fig. 2. The IKARUS-Onto methodology.

(1) When users reply to a message they are able to denote the nature of their reply by using the predefined hashtags *#support* and *#attack*.
(2) Users are also able to denote their agreement or disagreement to a message through a rating functionality (colored birds in Figure 3). This rating reflects the user's opinion on the overall message's content and has nothing to do with the linguistic hedges (i.e. terms like "very") that may be found in vague ontology elements as the one of Figure 1.

Fig. 3. (Color online) The microblogging platform.

These two features allow us to use the platform as an argumentation tool[32] and capture in a structured way the disagreements and debates that may occur among the users while sharing knowledge through the platform. As we will see in the next sections, the structure of these disagreements will play a key role in the generation process of the fuzzy ontology degrees and membership functions.

On the other hand, the semantic functionalities of the system are implemented in a three layered architecture:[7] (i) ontology and ontology access, (ii) keyword to ontology entity, and (iii) the semantic indexing and search as the top layer, as depicted in Figure 4. The main functionality is the performance of Named Entity Recognition on each new status update, allowing the extraction of some of the entities mentioned within the message. This process is performed by parsing each message using an enterprise ontology as well as additional vocabularies and thesauri like Wordnet. Each message is then tagged with the entities that have been extracted from that message.

As we will explain in the next section, the Named Entity Recognition capabilities of the platform enable the detection of vague ontological statements and assertions

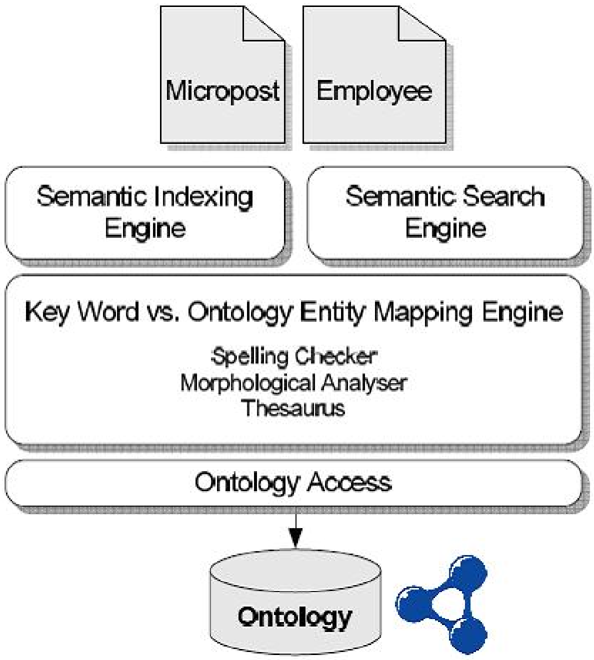

Fig. 4. System semantic architecture.

within the microposts. These statements, being related to the elements already defined in the fuzzy enterprise ontology, are going to be the second key input in the generation process of the fuzzy ontology degrees and membership functions.

4.3. *Detection and extraction of vague knowledge assertions*

Vague knowledge assertions are practically statements related to the elements of fuzzy ontology. For example, the assertion "*A budget of 100,000 euros is low*" is related to the fuzzy datatype "ProjectBudget" while the assertion "*John is expert in ontologies*" is related to the fuzzy relation "isExpertAt". Our goal in this step is to detect and extract such assertions from the messages generated by the platform's users so that we can use them to determine the fuzzy degrees of their respective elements.

To achieve this, we use the system's semantic analysis capabilities in order to, given the fuzzy ontology we have already developed in the beginning of the process, recognize such assertions within a piece of text. An important factor that contributes to higher levels of precision for this detection is the fact that microblogging messages are short. In any case, the detection process is to be performed in a semi-automatic fashion where the accuracy of the extracted assertions could be checked by the knowledge engineer.

Table 1. Example vague concept assertions.

Concept	Instance
Competitor	Autonomy
Competitor	IBM
Competitor	Indra
Competitor	Atos
Strategic Client	Coca Cola
Strategic Client	Endesa

Table 2. Example vague relation assertions.

Relation	Subject	Object
isRelevantToResearchArea	PARLANCE	Fuzzy Ontologies
isRelevantToResearchArea	PARLANCE	Open Information Extraction
isRelevantToResearchArea	PARLANCE	Dialogue Systems
isRelevantToResearchArea	K-DRIVE	Linked Data
isRelevantToResearchArea	K-DRIVE	Ontologies

More formally, for the purposes of this paper we consider a fuzzy ontology as a tuple $O_F = \{C, R, I, T, i_C, i_R, D\}$, where

- C is a set of fuzzy concepts.
- I is a set of instances.
- R is a set of fuzzy binary relations that may link pairs of concept instances.
- i_C is a fuzzy concept instantiation function $C \times I \to [0, 1]$.
- i_R is a fuzzy relation instantiation function $R \times I \times I \to [0, 1]$.
- D is a set of fuzzy datatypes. Each $d \in D$ is itself a tuple $\{T, X, f\}$ where T is the set of linguistic terms of the datatype that refer to a base variable whose values range over a universal set X and f is a function that, for each linguistic term $t \in T$, relates the values of X to a fuzzy degree.

Given that, the relevant assertions for fuzzy concepts form a set A_C where each $a \in A_C$ is a tuple $\{c, i\}$, $c \in C$, $i \in I$. Table 1 shows an example of A_C.

Similarly, for fuzzy relations the relevant assertions form a set A_R where each $a \in A_R$ is a tuple $\{r, i_1, i_2\}$, $c \in C$, $i_1, i_2 \in I$. Table 2 shows an example of A_R for the fuzzy relation "isRelevantToResearchArea". On the other hand, for fuzzy datatypes the related assertions form a set A_D where each $a \in A_D$ is a tuple $\{d, t, v\}$, $d \in D, t \in T, v \in X$. Table 3 shows an example of A_D for the fuzzy datatype "ResearchProjectBudget".

4.4. *Assertion strength assessment*

To calculate the strength of the extracted vague assertions we consider their so-called "social context". The latter includes all messages that are directly or indirectly

Table 3. Example vague datatype assertions.

Datatype	Vague Term	Value
ResearchProjectBudget	High	3 million
ResearchProjectBudget	Fairly high	1.2 million
ResearchProjectBudget	Fairly high	1 million
ResearchProjectBudget	Fairly high	0.8 million
ResearchProjectBudget	Average	0.85 million
ResearchProjectBudget	Low	0.6 million
ResearchProjectBudget	Average	0.6 million
ResearchProjectBudget	Low	0.2 million

related to these assertions and may influence their validity. More formally, a social context is a tuple $G = \{U, M, A, \textit{Incl, Pub, Att, Sup, Agr, Disag}\}$ where:

- U is a set of users.
- M is a set of messages.
- $A = A_C \cup A_R \cup A_D$ is a set of vague assertions.
- $\textit{Incl}$ is an assertion containment function $A \to M$ that returns for a given assertion $a \in A$ the messages it is included into.
- $\textit{Pub}$ is a message publishing function $M \to U$ that returns for a given message $m \in M$ the user that has published it.
- $\textit{Att}$ is a message attacking function $M \to M$ that returns for a given message $m \in M$ the messages that attack to it.
- $\textit{Sup}$ is a message supporting function $M \to M$ that returns for a given message $m \in M$ the messages that support it.
- $\textit{Agr}$ is a message agreeing function $M \to U$ that returns for a given message $m \in M$ the users that agree with it.
- $\textit{Disag}$ is a message disagreeing function $M \to U$ that returns for a given message $m \in M$ the users that disagree with it.

Given such a context, we calculate the strength of the assertions contained in it as follows:

Let $a \in A$ be an assertion and $M_a = \textit{Incl}(a)$ be the set of messages in which this assertion is contained. Then the strength of the assertion $S(a)$ is given by the average strength of these messages, namely:

$$S(a) = \frac{1}{|M_a|} \cdot \sum_{m_i \in M_a} s(m) \tag{1}$$

where $s(m)$ denotes the strength of each message and is calculated as follows:

$$s(m) = w_1 \cdot \textit{agr}(m) + w_2 \cdot \textit{sup}(m) + w_3 \cdot \textit{infl}(\textit{Pub}(m))\,. \tag{2}$$

In the above Eq. (2) w_1, w_2 and w_3 are (manually defined) weights denoting the relative importance, in calculating the message's strength, of the measures

$agr(m), sup(m)$ and $infl(Pub(m))$ respectively. All three measures get values between 0 and 1. In particular, $agr(m)$ denotes the relative agreement on the message m based on the number of agreements and disagreements it has received by the users. Thus, it is calculated as follows:

$$agr(m) = \frac{1}{2}\left(1 + \frac{|Agr(m)| - |Disag(m)|}{\sum_{m_i \in M}(|Agr(m)| + |Disag(m)|)}\right). \tag{3}$$

Similarly, $sup(m)$ denotes the relative support to the message based on the number and strength of attacking and supporting messages. As such, it may be recursively calculated as the difference between the average strength (as calculated by Eq. (4.4) of the message's supporting messages and the average strength of its attacking messages, normalized to the range $[0, 1]$:

$$sup(m) = \frac{1}{2}\left(1 + \frac{\sum_{m_j \in Sup(m)} s(m_j)}{|Sup(m)|} - \frac{\sum_{m_i \in Att(m)} s(m_i)}{|Att(m)|}\right). \tag{4}$$

For example, assume that we have a message A with two related messages B and C, the one attacking and the other supporting A. Then the relative support of A by B and C will be the difference between the strengths of these two. If A and B do not have any other supporting or attacking messages, then their strengths will be calculated based only on the relative agreement they enjoy (Eq. (3)) and the influence of their author (see below). If, however, A and B do have attacking or supporting messages, then their strengths will be calculated in the same way as the one of A, namely by considering the difference of these messages's strength . This process should be repeated until the leaf nodes of the message graph are reached.

Finally, $infl(Pub(m))$ denotes the overall influence of the user who has published the message (and thus has made the assertion). The intuition behind considering this factor for quantifying vagueness is that the perception of the latter is often based on social factors and, for example, if some person in the enterprise is very influential, then people tend to adopt his/her views on matters.

In this work we consider influence to be generally relevant to the number of users that follow the message publisher, the times the publisher's messages are republished by its followers and his/her overall expertise on the message's topic. For that, we derive the exact influence score using the Topic-Entity PageRank algorithm presented in Ref. 6. The particular algorithm builds upon the classical PageRank algorithm[28] and an extension of it called Topic-Sensitive PageRank.[16]

More specifically, according to PageRank, if a web page has a link to another, then the author of the first page is implicitly giving some importance to the second. Thus, by considering users instead of pages and the "follow" and "repost" relations as links between them, the same algorithm can determine the general influence of each user within the community. Moreover, given a set of domain-specific topics, the Topic-Sensitive PageRank algorithm may be used to bias the computation of a user's influence according to his/her expertise on these topics. Thus, by considering as topics the business areas in which the enterprise's users are considered expert, Topic-Sensitive PageRank can get a more accurate influence score for them. Finally, the Topic-Entity PageRank algorithm considers in addition the idea that the more a user u_1 republishes posts from another user u_2 about a given topic, then the higher the expertise (and thus the influence) of user u_2 is to this topic.

4.5. *Generation of membership functions and fuzzy degrees*

In this step our goal is practically to estimate the fuzzy instantiation functions i_C and i_R for fuzzy concepts and relations respectively as well as the fuzzy term meaning membership functions m for fuzzy datatypes. To do that we utilize the extracted assertion sets A_C, A_R and A_D along with their calculated strengths from the previous step.

In particular, given a concept $c \in C$ and an instance $i \in I$ we consider $A_C^{c,i} \subseteq A_C$ to be the set of the relevant vague assertions. Then, the fuzzy degree to which i belongs to c is calculated as the mean value of the strengths of these assertions:

$$i_C(c,i) = \frac{\sum_{a_j \in A_C^{c,i}} S(a_j)}{|A_C^{c,i}|} \,. \tag{5}$$

Similarly, for two given instances $i_1, i_2 \in I$ and a relation $r \in R$, we consider $A_R^{r,i_1,i_2} \subseteq A_R$ to be the set of the relevant vague assertions and the fuzzy degree of the pair to be the mean value of their strengths:

$$i_R(r,i_1,i_2) = \frac{\sum_{a_j \in A_R^{r,i_1,i_2}} S(a_j)}{|A_R^{r,i_1,i_2}|} \,. \tag{6}$$

Finally, given a vague term $t \in T$ belonging to a datatype $d \in D$ we consider $A_D^{d,t} \subseteq A_D$ to be the set of the relevant to the term vague assertions. Then, to determine the membership function of the fuzzy set that best describes this term, we perform regression analysis on the value-strength pairs $\{v_j, s_j\}$, v_j being the datatype value of the jth assertion and s_j being the strength of this assertion, and we generate the function that best fits this data. As possible membership function types we consider the triangular, the trapezoidal and the gaussian ones,[20] as these are the most common used in the relevant literature.

5. Framework Application and Evaluation

The evaluation of our framework took place as an experiment involving the development of a fuzzy enterprise ontology. The goal of this experiment was to assess the framework's ability to tackle effectively the problem defined in Section 2.2, i.e. to automatically derive the optimal fuzzy degrees and membership functions that should be assigned to the fuzzy ontology elements in order to represent their vagueness as accurately as possible. As we will explain in the rest of this section, a fuzzy degree is "optimal" when it helps minimize the disagreements over the truth of a vague statement.

Fig. 5. Examples of seed microposts.

The first phase of the experiment involved the actual application of the framework to generate the fuzzy ontology and the process we followed comprised the following steps:

(1) We applied IKARUS-Onto to develop an initial version of the fuzzy ontology which, as suggested in Section 4.1, did not contain any degrees or membership functions for its elements. A sample of these elements includes the following:
   - **Concepts:** Competitor, CompanyExpertiseArea, StrategicClient
   - **Relations:** *isRelevantToResearchArea*(Project, ResearchArea)
   - **Datatypes:** ResearcherExperience, ResearchProjectBudget

(2) We deployed the microblogging platform and 50 users were registered to it and started using it.

(3) To bootstrap the knowledge acquisition process we initiated discussions about vague elements by posting corresponding seed microposts containing relevant statements. Figure 5 shows such microposts as well as some responses to them.

(4) We allowed these discussions to go on for a period of time and then we used the platform's semantic analysis capabilities to detect and extract vague knowledge assertions from the generated microposts. Examples of such assertions are already shown in Tables 1–3.

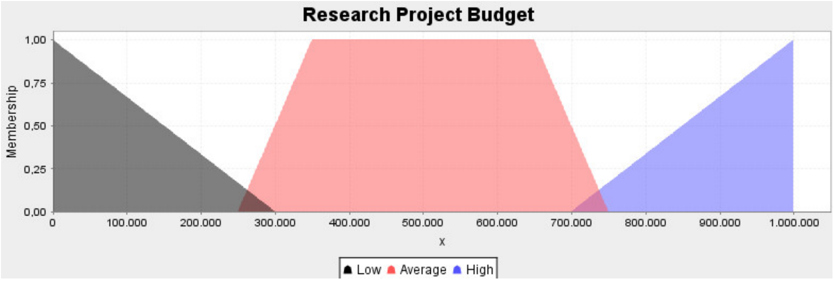

Fig. 6. (Color online) Example generated fuzzy datatype.

Table 4. Examples of generated fuzzy statements.

Statement	Degree
Competitor (Autonomy)	0.3
Competitor (IBM)	0.3
Competitor (Indra)	0.7
Competitor (Atos)	0.6
StrategicClient (Coca Cola)	0.9
StrategicClient (Endesa)	0.8
isRelevantToResearchArea (PARLANCE, Fuzzy Ontologies)	0.8
isRelevantToResearchArea (PARLANCE, Dialogue Systems)	1.0

(5) We applied the algorithms and methods of Sections 4.4 and 4.5 to evaluate the strength of the extracted assertions and generate the degrees of the corresponding fuzzy elements respectively. Figure 6 shows the outcome of this process for the fuzzy datatype "ResearchProjectBudget" while Table 4 shows the calculated fuzzy degrees for some of the ontology's statements.

In the above process the values of the weights w_1, w_2, and w_3 for Eq. (2) were set to be 0.2, 0.5 and 0.3 respectively. The reason we used a higher value for w_2 was that we considered the actual arguments made in favour or against a particular message to more informative about its validity than the other two aspects (agreement and influence).

The second phase involved the assessment of the generated fuzzy ontology's quality in terms of its accuracy. Practically, a fuzzy ontology is more accurate the more the degrees of its fuzzy elements are perceived as natural by those who use the ontology. For example, the fuzzy statement *Obama is a BlackPerson to a degree of 0.2* is highly unintuitive (and therefore inaccurate) while the statement *Sergey Brin is a RichPerson to a degree of 0.8* makes much more sense.

To perform this assessment we asked 20 people that had not participated in the microblogging process, to rate the **intuitiveness** of a random set of 20 fuzzy ontology statements in a scale from 1 to 10. Before that we had asked them to do the same for the same set of statements but without showing them the fuzzy

Table 5. Vague ontology statements for evaluation.

	Statement
S1	A budget of 760,000 Euros is high
S2	Coca Cola is a strategic client
S3	IBM is a competitor
S4	A researcher with 3 years of experience is junior
S5	Parlance is relevant to Vagueness
S6	The company is expert in Sentiment Analysis
S7	Telefonica is a strategic client
S8	A researcher with 3 years of experience is senior
S9	A budget of 710,000 Euros is average
S10	WF4Ever is relevant to the Semantic Web
S11	The company is expert in Semantic Search
S12	Daedalus is a competitor
S13	KDrive is relevant to intelligent information access
S14	The company is expert in Open Innovation
S15	Indra is a competitor
S16	Bankia is a strategic client
S17	A researcher with 3,5 years of experience is junior
S18	Telefonica is a strategic client
S19	KDrive is relevant to Problem Solving Methods
S20	A budget of 290,000 Euros is low

degrees. The reason we did that was that we wanted to use the non-degree grading as a baseline so as to verify two things:

(1) That the statements with the fuzzy degrees were actually more intuitive than the ones without.
(2) That the statements with the fuzzy degrees caused less disagreements among the people than the ones without.

Table 5 shows the 20 statements while Tables 6 and 7 their ratings, without and with fuzzy degrees respectively. For the first evaluation task, we computed for each statement the average ratings they received from the evaluators, with and without degrees. The results are shown in the plot of Figure 7 and clearly indicate an important increase in the average perceived naturalness of all the statements by the people.

For the second task, we computed for each pair of evaluators the **weighted kappa** value of their ratings, as a way to measure the level of their inter-agreement. Then we calculated the mean value of these inter-agreements as a measure of the overall group's agreement to the given statements' intuitiveness. Table 5 shows this overall agreement for the statements with degrees and the ones without. As the numbers indicate, the fuzzy degrees that our framework generated managed to

Table 6. Intuitiveness ratings of vague statements without fuzzy degrees.

Rater/Statement	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
R1	5	6	4	7	5	3	3	6	8	5
R2	3	8	6	3	2	1	1	2	4	2
R3	6	7	3	7	6	6	3	5	7	8
R4	3	2	5	6	7	8	3	5	5	3
R5	4	6	7	8	3	1	2	6	7	9
R6	4	6	3	4	4	6	2	2	6	4
R7	5	5	6	5	3	6	5	7	4	3
R8	2	4	3	4	3	1	2	6	7	5
R9	2	6	4	8	3	1	2	6	5	5
R10	3	2	6	8	7	8	3	1	6	5
R11	1	2	3	2	4	4	1	2	3	4
R12	3	8	6	5	2	3	1	3	4	2
R13	6	5	3	7	6	6	3	4	7	8
R14	3	2	5	6	7	8	3	5	9	3
R15	4	6	6	4	1	1	2	6	7	9
R16	4	6	3	4	4	6	6	2	6	4
R17	5	5	6	5	3	6	5	7	4	3
R18	2	4	3	2	3	1	2	6	4	5
R19	2	4	4	8	3	1	2	6	5	5
R20	3	2	6	7	7	5	4	8	6	6
	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
R1	5	7	3	7	5	6	3	6	5	7
R2	1	4	1	5	3	2	4	8	4	2
R3	6	8	1	5	5	4	4	8	4	2
R4	2	5	5	3	4	9	5	8	7	5
R5	4	5	6	2	7	8	4	7	9	3
R6	9	3	3	5	5	6	2	5	4	1
R7	4	4	2	7	5	6	5	6	4	7
R8	4	5	6	2	7	4	7	8	2	3
R9	4	5	2	2	4	3	4	3	9	3
R10	2	6	3	5	4	4	6	7	4	4
R11	2	3	5	2	1	2	1	2	3	2
R12	1	4	2	5	3	2	4	8	4	2
R13	3	8	1	6	5	3	4	5	4	2
R14	2	5	5	3	4	9	8	8	7	5
R15	4	5	6	2	7	8	4	7	9	3
R16	9	3	3	5	5	6	2	5	4	1
R17	6	4	2	7	5	6	5	6	4	7
R18	4	5	3	2	7	4	4	8	2	3
R19	4	5	2	2	4	3	4	3	9	3
R20	7	6	3	5	4	4	3	7	4	4

improve substantially the level of agreement among the evaluators' ratings and thus achieve a higher level of consensus on the statements' (and ultimately the whole ontology's) accuracy.

As already suggested, these results were obtained with $w_1 = 0.2$, $w_2 = 0.5$, and $w_3 = 0.3$ as the weight values of Eq. (2). These are by no means implied

Table 7. Intuitiveness Ratings of Vague Statements with Fuzzy Degrees

Rater/Statement	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
R1	7	8	7	9	7	7	7	8	8	7
R2	7	7	7	9	7	7	7	8	8	7
R3	8	8	7	8	6	7	8	7	6	7
R4	7	7	7	8	7	8	7	7	6	7
R5	7	8	8	9	7	8	7	7	8	6
R6	8	7	7	9	7	8	8	7	8	6
R7	7	8	7	8	6	7	8	6	8	7
R8	7	8	7	9	6	9	7	7	8	6
R9	8	8	7	9	7	8	8	7	8	7
R10	8	7	6	8	7	8	7	8	8	6
R11	7	8	7	9	7	7	7	8	8	7
R12	8	8	7	8	7	7	7	8	8	7
R13	8	8	7	9	7	8	7	7	8	7
R14	8	8	7	9	7	8	8	7	8	7
R15	8	7	7	8	7	7	8	8	8	6
R16	7	9	7	8	7	8	8	7	7	6
R17	7	8	7	9	7	8	7	8	8	7
R18	7	8	7	8	8	8	8	7	7	6
R19	7	8	8	9	7	8	8	7	5	7
R20	7	8	8	9	7	8	8	8	8	7
	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20
R1	8	9	7	9	8	8	8	7	8	7
R2	8	8	7	9	8	8	8	7	8	7
R3	7	6	6	8	6	7	8	7	8	7
R4	6	7	7	9	6	7	8	7	7	8
R5	7	6	7	8	7	8	7	7	9	7
R6	7	6	6	8	7	8	8	7	7	8
R7	7	6	6	8	6	7	8	8	6	7
R8	7	6	7	8	7	8	8	7	7	7
R9	6	6	7	8	7	8	7	7	9	7
R10	7	7	7	8	6	7	8	7	9	7
R11	7	9	6	9	8	8	7	7	8	7
R12	6	9	7	9	8	8	7	7	9	7
R13	7	8	6	8	8	8	7	7	7	8
R14	6	8	7	8	7	8	7	7	9	7
R15	7	9	7	9	8	8	8	7	9	7
R16	7	8	7	7	9	8	7	7	8	7
R17	7	8	7	8	7	7	8	7	9	7
R18	7	8	7	8	7	8	7	8	8	8
R19	7	6	7	8	7	8	7	7	8	7
R20	8	8	7	9	8	8	8	7	8	8

as the optimal ones and changing them would result in a different set of degrees for the fuzzy ontology that might be rated as better or worse by the evaluators. However, determining the exact relation between the weight values and the quality of the resulting fuzzy ontology is left as future work as it would require a significant number of rating sessions by the evaluators above.

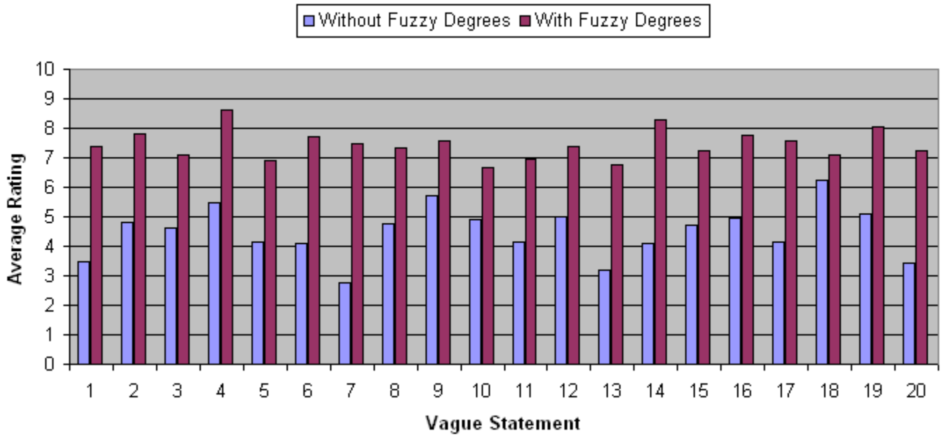

Fig. 7. (Color online) Average ratings for the vague statements.

Table 8. Overall agreement of the evaluators' ratings.

	Mean Weighted Kappa
Vague statements without fuzzy degrees	0.097
Vague statements with fuzzy degrees	0.29

6. Conclusions and Future Work

In this paper we proposed a framework for automatic vague knowledge acquisition in enterprise settings, based on a semantically enhanced microblogging system and a fuzzy ontology learning process that acts upon the social content produced by the enterprise's people. The key characteristic of our approach is the utilization of the content's social features, like the relative agreement and support that microposts enjoy or the status and influence of the users, in order to assign strengths to vague assertions and, ultimately, generate a fuzzy ontology that reflects the domains's vagueness.

Moreover, our framework is applicable not only to the task of constructing a fuzzy ontology but also to the ones of maintaining it and evolving it. Thus, for example, if at any point of the fuzzy ontology's lifecycle new vague elements are added (concepts, relations etc.), then the fuzzy degrees of these can be easily calculated based on relevant discussions and microposts involving them. The main requirement for that is that these elements are defined and initialized within the fuzzy ontology as described in Section 4.1; then the system's semantic engine will be able to extract relevant assertions about these elements from the content and populate their fuzzy degrees.

Of course, how fast and how effectively this may be achieved, depends highly on the amount and quality of the social content that the users generate in the microblogging platform. Therefore, an important line of future work is the study and application of incentive mechanisms that will engage more people in the knowledge sharing process within the enterprise.

Furthermore, the effectiveness of the framework can benefit from further development in the semantic analysis capabilities of the microblogging platform so that the detection and extraction of vague assertions is more accurate. Finally, an interesting (and more ambitious) direction for future work is to apply our vague knowledge acquisition approach in more open-ended scenarios where users' discussion topics are not limited to the matters of an enterprise but can be virtually about anything.

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