Introduction to Fuzzy-Ontological Context-Aware Recommendations in Mobile Environments

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Abstract. In the framework of context-awareness in mobile networks, handling both user and context in a homogeneous way is a key concern. It is particularly important in a recommendation process where imprecise user-defined values are compared with sensor inputs. This paper reports work in progress towards the realisation of a common representation framework for context- and user-related data, investigating the coupling of fuzzy theory and semantic web to deal with uncertainties and imprecisions issues faced by context-aware recommender systems in mobile environments. We propose a model allowing to represent ontology properties values as fuzzy sets linked with linguistic values. This model, pluggable onto any ontology, is meant in particular to be associated to context and user ontologies with the objective of enhancing context-aware recommendations quality.

1 Introduction

The mobile computing domain is still a wide field of study comprising lots of issues related, e.g., to the number and heterogeneity of networks, protocols, devices and communication interfaces of applications. While it is an inherent need for devices and applications in such an environment, bringing context-awareness in mobile networks remains an open problem. In our research work, we focus on problems related to context-awareness in hybrid networks, a class of mobile ad-hoc networks where nodes can be mobile or fixed [7]. This kind of network handles naturally social interactions since mobile end-users, through their devices, are seen as an integral part of the network in the form of mobile nodes. However, their inherent complexity makes them difficult to use when wanting to make applications context-aware: networks and information available to a user can be different at each moment, and so is it for information routing.

Fulfilling the needs of the end-user by providing targeted information and services in a seamless way, requires context-awareness to be also focused on the user profile and his preferences. In other words, this requires context-aware (and user-aware) recommendations. The state of the art shows however that context-aware research has focused more on sensors than on users [8], while in the personalization community, most of existing recommender systems does not fully consider context information [19]. This suggests open issues, that we would like to address.

Assuming that network availability and routing issues are solved at the network level, systems recommending information, content or services, designed for the web can still be used or adapted without heavy modifications. For example, a service-oriented approach for recommendations in the TV domain has been recently successfully applied in a mobile environment [11]. Indeed, when recommendation exploits only user profiles and occurs in the closed world formed by a provider and his customers, manipulated data are well formalized and adapted for the recommendation process. In this case, data sources are known and de-facto reliable. However when wanting to take the context into account, the multiplicity and heterogeneity of data sources must be considered. In mobile environments, context information sources include physical sensors as well as abstract ones like, e.g., web services or human-originated information. Issues related to Information Quality (IQ) arise, such as completeness, precision, currentness, provenance and trustworthiness [18] [20]. This becomes especially true when users themselves become (context) information providers through ad-hoc networks formed by their mobile devices. Like when expressing their preferences, information provided by users is often approximated or incomplete, and inherently fuzzy.

Context data sources heterogeneity induces interoperability issues, some of which can be solved using the common representation framework provided by ontologies [2]. But this allows only representing context data using a common vocabulary and concepts having a well defined semantics. While this brings a very good support for reasoning, limitations also exist, especially regarding uncertainty and imprecision. In the Semantic Web community, this has lead to research works on the joint use of Fuzzy Logic [23] and Semantic Web [15]. Regarding IQ issues on context data, the fuzzy theory could provide at least a partial answer. Indeed, it offers a framework to represent partial truth and imprecise valuations such as those represented with linguistic variables, and allows for approximate reasoning.

In order to set-up a common representation and reasoning framework, we investigate the coupling of fuzzy theory and semantic web for context-aware recommendations. Our main goal is to propose ontology-based models and algorithms grounded in fuzzy theory to deal with uncertainties in human related assumptions, confidence in predicted data, and management of trust, and more generally providing a framework for reliable context data whatever its kind and origin. In this paper, we first discuss briefly the handling of context and related quality issues in mobile environments (section 2). Then, as a first step towards the realization of our framework, we focus on the coupling of fuzzy sets and ontologies for modelling vague human-related data together with other machine-originated context data like, e.g., those provided by sensors. To this end, we propose in section 3 a model allowing to use fuzzy sets in ontologies and explain how it can be used to model contextual information. Section 4 concludes, relating to other similar works and brings some perspectives and future works.

2 Handling context in mobile environments

2.1 Context gathering processes

As suggested in the introduction, making recommendations in mobile environments cannot be achieved by only taking into account the user profile and preferences. Mobility implies considering contextual information concerning the user himself and his environment, but also the networks availability and physical constraints limitations, as well as any useful environmental and situational information. Achieving true context-aware recommendations bears some issues. According to [22], current approaches for bringing context-awareness to personalisation systems suffer from accuracy and reliability problems. User preferences and interests are indeed context-dependent and only few approaches try to take it into account, especially in an evolving context [12].

Personalised context-aware information delivery in mobile networks depends on a series of data gathering and aggregation processes, each being followed by a processing and analysis phase leading to adapt or recommend an item. These processes are related to the user and his context, the resources to be delivered, and the network:

- User profile building: the explicit user profile (containing characteristics like, e.g., demographic data) is completed with an implicit part that is inferred from the user behaviour. To be actually reliable, implicit profiling needs to consider user consumption or action context.
- Aggregation of user context: gathered from sensors surrounding the user or able to provide any relevant information about the user situation, but some elements could also be inferred from user behaviour (e.g. for determining mood or activity).
- Aggregation of data concerning the network properties and state to anticipate the Quality Of Service.
- Aggregation of data related to the information or resource to be transmitted: its source, its characteristics, its intended target, etc.

2.2 Context quality issues

Each of the above listed aggregation processes leads to implement dedicated interpretation and conversion methods. The latter bear some risks that are related to Information Quality (IQ). As suggested in [19], these risks can significantly impact the usability of profiles for personalized applications. The quality of context information is influenced by different factors from the network layer to the end-user application: data availability, completeness and reliability; data sources trustworthiness; transport reliability (data loss can occur in the network); aggregation reliability (including homogenization of data and conflict handling). Additionally, information can be irrelevant if used in a non-suitable context, or become obsolete over time. As emphasized by [18], IQ is sensitive to context changes, such as time and usage goal. A sensor could loose precision when it rains. A user preference can be misinterpreted in an improper context (e.g. "John Doe prefers to see action movies on weekends" [19].

In order to assess the quality and thus usability of aggregated information during a context retrieval phase, it is necessary to consider IQ-related issues and in particular the validity of each data regarding the context. A context layer must be added to the models used for personalization, not only to represent the current user context but also to identify the items which can be delivered in an optimal way given a specific context, and the dependence of user interests and preferences in context.

The particular IQ issue on which we focus here concerns data precision and completeness. In our mobile environment, information providers include digital sensors as well as humans. They provide data using different formalisms and influenced by different factors. In particular, humans have each their own specific mental model [16]. Not only they use rather qualitative terms (like, e.g., "cold", "fast", "near"), but also they have each their own subjective interpretation of these terms. Additionally, this interpretation is also context-dependent: a same person may not consider "cold" in the same way in the morning and at night, in the office or outside.

In order to assess the usability of information, the system must deal with the different formalisms of data providers and especially being able to compare explicit data with implicit ones influenced by humans internal mental models. The use of ontologies decreases ambiguity in context information aggregation by allowing raw explicit data to be mapped or described using concepts. It also enables inference mechanisms on the currentness or usability of information (e.g. an outdated measure of temperature should impact a context profile built with this information) [1]. Nevertheless, the imprecise and context-dependent data gathered from human information providers (including user interests) can be best represented using fuzzy sets. The coherent representation of information provided by digital sensors as well as human information providers in ontologies remains a challenge, to which we contribute to give an answer in the next section.

3 Using linguistic values in ontological representations

3.1 Motivations

Linguistic values are imprecise notions usually used by humans to characterize something. Terms like "young", "hot" or "far" are examples of such values, corresponding to so-called linguistic variables (respectively, "age", "temperature" and "distance"). When it comes to recommender systems, they can be used to simplify the expression of user interests and to more precisely express the behaviour of the system at the boundaries of an interest. The usual way of dealing with these linguistic values is using fuzzy sets [14][24].

The interest of fuzzy logic for recommender systems has been illustrated in, e.g., [21], [10] and in [9]. In combination with description logic, fuzzy sets can be used to represent the membership of an individual to a concept. However, in recommender systems, the user is a central element, and from a user point of view, having to define such a degree of belonging may not be intuitive. For example, what means for him being "young" at 80%, or that the weather is 20% cloudy? A more suitable approach would be to first define linguistic values such as "young" by defining their associated membership functions [17], and let the user use linguistic values only.

Such an approach has the advantage of preserving the users own mental models. For example, one can define the concept "young" as someone with an age between 0 and 15, while another person can define it as being between 0 and 40. This can be made even more precise by defining a membership function, specifying, e.g., some progressive transition to get from "young" to "old". With existing recommender systems, it is often not possible to express such complex preferences as "I am looking for a restaurant with prices up to 20EUR but I could accept up to 25EUR even if I would be less satisfied". This is illustrated by Figure 1, where the *johnCheap* concept is defined as a membership function specifying that the interest for restaurants is full (=1) until a price of 20 and decreases for higher prices, until 25 where it becomes null (=0). Using membership functions thus allows defining how the interest evolves when the recommended content deviates from an ideal preference. The system would then be able to map a standard (e.g. numerical) value into a user specific fuzzy representation and from a user to another one.

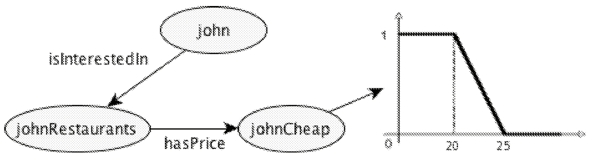

Fig. 1. Decreasing user interest represented by a fuzzy set.

3.2 Representing Linguistic Values within Ontologies

The two main research stakes are finding a way to store fuzzy information in combination with classic semantic web formats like OWL, and defining a mechanism to reason over this fuzzy Description Logic (DL). We retained two approaches. Straccia [17] proposes a new formalism different from OWL, to express fuzzy DL, together with a dedicated reasoner capable of dealing with common membership functions. This solution however lacks interoperability and usability: ontologies must be expressed using a dedicated syntax, and membership functions are described using parameters having no direct meaning for the user. The approach is slightly different in [6], as they tried to introduce fuzzy logic in such a way that they could still use a classic DL reasoner without extensive modifications. New predicates $\leq_{a\pm b}$ and $\geq_{a\pm b}$ have been added by defining new XML schema *simpleType*, and a modification of the Pellet reasoner integrating a fuzzy datatype reasoner is proposed.

The latter solution already brings wide possibilities and preserves interoperability with existing ontology languages, but the integration of fuzzy logic is limited to datatype properties in OWL. Based on this idea we propose a model, illustrated in Figure 2, to represent fuzzy sets directly into an ontology instead of using new XML datatypes. This is motivated by the need to allow personalised definition of fuzzy sets in ontologies, while preserving interoperability.

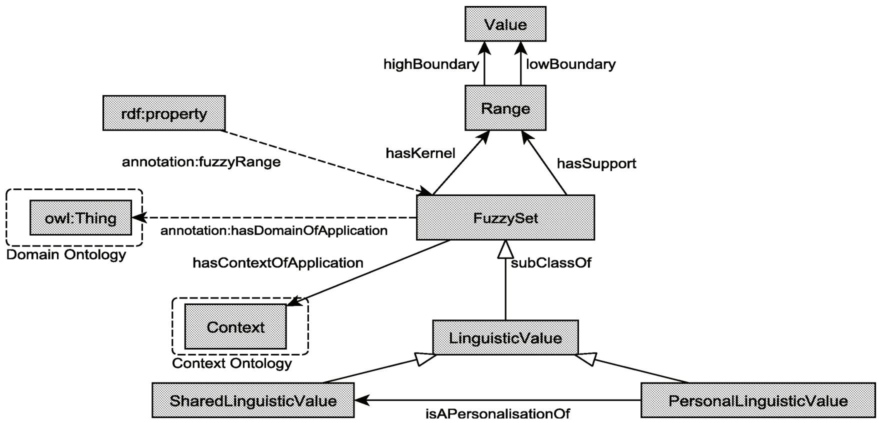

Fig. 2. The fuzzy sets model

Most commonly used membership functions (*e.g* triangular, trapezoidal, left or right shoulders) can be represented by defining only the kernel and the support of the fuzzy set. The kernel is the set of elements x where the membership function $\mu(x) = 1$; the support is the set of elements x where $\mu(x) > 0$. The *FuzzySet* concept is defined by two object properties, *hasKernel* and *hasSupport*, defining the associated membership function.

Because the meaning of a linguistic value can depend on the user context, each one can be associated to an application context by the *hasContextOfApplication* property. For instance, the meaning underneath the term "hot" depends on the season and on where the action takes place. The *Context* concept in our model represents the main class in a dedicated context ontology such as in [12], formalizing useful contextual elements.

Besides, the definition of linguistic values can be different from one user to another. The *personalLinguisticValue* concept aims at representing this possibility to have a personalised definition of a shared term, of which a common definition is given using *sharedLinguisticValue*. The property *isApersonalisationOf* allows keeping a link between this personalised value and the corresponding shared term. The shared values are meant to be pre-defined in ontologies, while the personal ones will be part of the user profile. Additionally, while the later could be defined by the user himself, it will most of the time be evaluated through an implicit profiling process. Machine learning techniques would typically be exploited in this case.

We also need to deal with the fact that the meaning of linguistic values also depends on the domain of application. The meaning of the term "tall" will be different whether it is applied to, e.g., jockeys or basket-ball players. The *hasDomainOfApplication* property is defined to solve this problem. With it we can define, e.g., a linguistic value "tall" which will be used when the subject of a property "height" is an instance of a "Jockey" class and another linguistic value "tallBasketPlayer" which will be used for instances of a "Basket-ball" class. As OWL-DL requires types separation the property *hasDomainOfApplication* is defined as an *owl:AnnotationProperty*.

After having conceptually modelled fuzzy sets and linguistic values, a way to integrate seamlessly with classic ontologies needs to be added. For example, let us assume an OWL ontology containing an *age* datatype property whose domain is a class *Person* and whose range is *xsd:Integer*. We would like now to add the possibility of using linguistic values, *e.g* "young", to describe the age of a person. A naive approach would be to modify the range of the *age* property to something like *xsd:Integer* $\sqcup$ *LinguisticValue*. There are two majors problems with this idea. First, it implies to modify the ontology. Secondly, OWL DL imposes a separation between object properties and datatype properties. Then we cannot have a property whose range is the union of a datatype and a class. To deal with these limitations, we finally propose to use again annotations. The *owl:Annotation fuzzyRange* will allow linking an existing linguistic variable defined by a property, *e.g age*, to our *LinguisticValue* class.

To summarize, the model of Figure 2 allows the representation of most usual membership functions, the personalised definition of linguistic values, the fuzzyfication of existing ontologies without modifying them directly, and the compatibility with existing OWL DL reasoners. It does not directly allow fuzzy description logic reasoning but it is possible to develop parsers mapping fuzzy ontologies represented using this model into the syntax supported by different fuzzy DL reasoners: fuzzyDL [4], DeLorean [3] or Pellet modified reasoner [6].

3.3 Application to a context ontology

In classic ontological context representations we usually find datatype properties such as *temperature* or *distance*, qualified with numerical values. Using our model for introducing linguistic values will allow a user to express a contextual information or a context of validity of his/her interests more intuitively. In the latter case, during the recommendation process, the current context of the user is compared to the user preferences. It is at this point that the crisp numerical values from sensors can be compared to the linguistic values thanks to the membership functions. For instance, consider a temperature sensor providing a value T. The system can compare this value to linguistic values related to temperature and, by using their membership functions, it can determine to which extent the value T corresponds to each linguistic value. The results is a list of linguistic values associated to a degree of membership. For example, a temperature T of 10°C could be represented as ("cold", 0.6);("moderate",0.2);("hot";0). Figure 3 illustrates the use of our model with an example where a "temperature" context element is defined using linguistic values. The values "hot" and "cold" are specified by shared membership functions, while the user John has a personal definition for "cold".

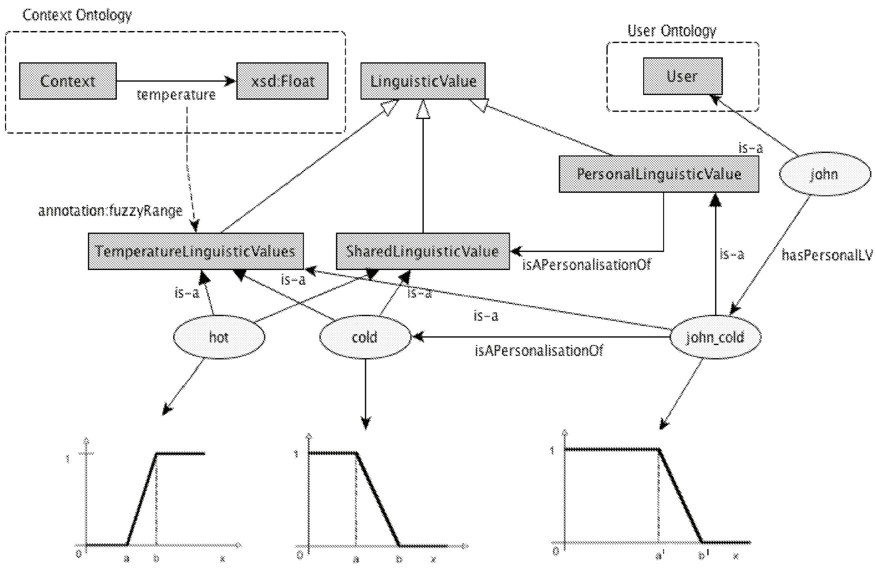

Fig. 3. The fuzzy sets model applied to a context ontology

4 Conclusion and perspectives

In this this paper, we have first discussed issues related to context-aware recommendations in mobile environments and quality of context in particular. One of these issues is the heterogeneity of data representation between humans and sensors. To start solving it, we have proposed a model allowing to introduce fuzzy sets and linguistic variables in ontologies. This model has the following characteristics: it can be used in an extension of an ontology without requiring any modifications of the latter; it allows assigning both default and specific fuzzy membership functions to a (rdf) property; it permits the mapping between crisp data and fuzzy sets in an obvious manner; and it moreover supports context and domain dependency.

Regarding the issues arising in mobile networks, we have shown this approach allows expressing user-specific interpretations of things. The model will allow us exploiting user-originated information expressed with linguistic variables. This will be particularly useful in ad-hoc networks where users exchanging information act themselves as abstract sensors regarding context data gathering. Moreover, it can be exploited to specify variable user interests following a fuzzy membership function. This allows defining the variation of user preferences and interests at their boundaries. In the same way we could specify variations of sensor inputs according to influence parameters.

Recently, Fuzzy logic has been used in [5] for situation-aware mobile recommendation of services. Situation is inferred with ontological reasoning, where a fuzzy layer allows dealing with vagueness in the inference rules antecedents. Like us, the authors have highlighted the need to offer users a more intuitive way to express interests and to deal with imprecision of context data. Their approach is however slightly different. Fuzziness is handled in rules and is related to specific properties in their ontologies, like "is-close-to", or "is-around". In our approach, we allow more flexibility by proposing a way to fuzzyfy any property of an ontology. Regarding linguistic values, [5] considers them as application-dependent. This is partially true, since they can also depend on the domain. But whatever the case, they are first of all user-dependent and might be defined differently depending on the user mental model, as we have explained.

The preliminary research reported here will serve as a modelling basis in the design of a framework for user- and context-aware information transmission in hybrid networks. By better capturing real life data, and exploiting the coupling of ontological and fuzzy reasoning to deal with context aggregation uncertainties, we aim at enhancing the quality of gathered and interpreted context, and thus the user perceived quality of recommendations. This goal could be facilitated by designing a common representation model for context data whatever its origins. We have explained that crisp values provided by sensors could be easily mapped to user-defined fuzzy sets, but another possibility is also to express any sensor input using fuzzy memberships associated to linguistic values. This has been exploited in [13] coupled with Bayesian networks in a context-aware music recommendation system. This option needs to be investigated.

Next steps in our research will be to exploit this model in previously developed user and context ontologies [12]; exploring also different crisp or fuzzy representation models for context data to ensure seamless mappings; and defining accordingly rules and appropriate extensions of a fuzzy DL reasoner. Remaining issues are also the handling of partial truth and uncertainties in context aggregation, as well as provenance and trustworthiness.

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