Item Recommendation with Veristic and Possibilistic Metadata: a Preliminary Approach

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Abstract

Item recommendation depends on metadata describing items as well as users through their profiles. Most currently used technologies use precise metadata because of the efficiency of the recommendation process. Nonetheless fuzzy metadata can be useful because of their ability to deal with imprecision and gradedness, two features pervading real-world applications. Fuzzy metadata can have both possibilistic and veristic interpretations, which are complementary and can simultaneously occur in a recommendation context. In this paper we describe a preliminary approach to deal with this double interpretation proposing an extension of the theory of veristic variables, that is specifically suited for item recommendation. Fuzzy metadata are used to calculate the interestingness of an item for a user computing possibility and necessity measures, which enable the ranking of items. As described in the illustrative examples, this approach effectively provides for semantically significant results that are useful for item recommendation with fuzzy metadata.

1 Introduction

The last decades have witnessed a growing interest for adaptive software systems, which are able to take into account the peculiarities of the distinct users in order to improve the interaction possibilities. The demand for adaptive systems directly follows the increasing development of Web applications: the huge number of users connecting on-line requires suitable tools for the personalization of Web contents [7]. The basic idea consists in realizing interactive systems with the capability of assigning to each user the contents which best match her interests and preferences.

Recommender systems are systems based on information filtering techniques that attempt to present resources or items that are estimated to be of interest to the user. Typically, a recommender system compares the user's profile to some reference characteristics, and tries to predict the degree to which an item is interesting for a user, even if the user has never accessed to the item. These characteristics may come from the information item (the content-based approach) or the user's social environment (the collaborative filtering approach) [1].

In the case of content-based approach, item recommendation can be effectively achieved through the use of metadata, i.e. data describing items according to several attributes. The use of metadata is widespread in computing literature, and several technologies have been standardized to support the development of systems based on metadata information[1].

Most currently used technologies offer "crisp" metadata, i.e. metadata that assign a precise value (or a collection of values) to each attribute describing an item. Whilst this solution is computationally efficient and effective for some types of attributes (e.g. the name of the item), it appears too limiting when the description of an item cannot be precise. In many cases attributes cannot be described precisely, because it is impossibile, unnecessary or inconvenient [11]. As humans, we treat such attributes as "fuzzy", i.e. we assign to such attributes sets of values with different degrees of membership. As a consequence, there is not any sharp boundary on whether a value applies to the attribute or not. The genre of a song, the topics covered by a scientific paper, the complexity of a learning objects are just few examples of attributes that cannot be precisely evaluated for their corresponding items.

Research on fuzzy metadata is in a steep progress in several directions. An an example, in [9] a fuzzy description logic is proposed, which has been applied in [8] to define

[1] see also `http://www.w3.org/Metadata/Activity.html`

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ontologies for reasoning with fuzzy metadata. In [5] the RDF standard is extended to represent fuzzy metadata. In [2] a formal model of learning object fuzzy metadata is introduced. In [4] an application to fuzzy metadata for library catalogation is presented, while in [6] a framework is proposed to deal with fuzzy metadata in an e-learning context.

In this work we are interested in the twofold interpretation of a fuzzy set when it is used as a value for an attribute in a metadata declaration. Suppose that for an attribute A a fuzzy set F is assigned. It is legitimate to assert that the current value is unknown but it is restricted within F with different degrees of possibility. Alternatively, the metadata can be interpreted as if *all* values of F apply to the attribute A. Actually, both interpretations are valid, and the selection of either one depends on the meaning of the attribute. As an example, the fruition time of a learning object is an attribute with the first type of interpretation: we do not know how much time a user will spend for the learning object, but we can reasonably restrict the possibile values within a fuzzy set, which may be linguistically labelled with terms such as "about an hour". On the other hand, the attribute describing the topics covered by a scientific paper can be interpreted as the set of *all* the topics actually covered by a paper, with different degrees of strength.

The two interpretations of fuzzy metadata have been studied in the context of linguistic variables by several authors, including Yager in [10]. Namely, the first interpretation is called *possibilistic* as the fuzzy set indicates the possibility that an attribute has a specific value; on the other hand, the second interpretation is *veristic* since the fuzzy set expressess all the values held for the attribute. Taking into account both veristic and possibilistic metadata in a recommender system is important to provide for a semantically significative ranking of items and overcomes usual approaches based on similarity evaluation (often based on Euclidean distance) which may not have any semantical support.

In this paper we outline a preliminary approach for using such a dual interpretation in the context of metadata representation and its use within a recommender system. The main issue to be addressed is how to combine information coming from user profiles and item descriptions if both are described by fuzzy metadata with the two interpretations. In other words, we study the definition of a matching mechanism that is semantically coherent with possibilistic and veristic interpretations, so as to assess the degree of interest of a user (with a specific profile) for an item, both described by fuzzy metadata with the two interpretations. For this purpose we extend the theory of veristic variables so as to derive possibility and necessity measures that are specifically suited for item recommendation. We illustrate the effectiveness of the proposed approach with an illustrative example.

2 Veristic and possibilistic metadata

In this section we introduce a representation of fuzzy metadata, and then we describe their basic computing machinery (with emphasis on veristic interpretation) based on Yager's theory of veristic variables.

2.1 Representation

For the purposes of our discussion, we treat a metadata as a linguistic assignment where the lefthand side is an attribute (eventually qualified by the item it describes) and the righthand side is the assigned value. For short, a metadata can be expressed in the form

$$Item.Attribute \text{ is}* \ Value$$

Here we use the soft-constraint notation proposed by Zadeh [11]. The copula "is*" can be declined to denote different interpretations for the assignment. In our work, we are interested in possibilistic interpretation (copula "is") and veristic interpretation (copula "isv"). For simplicity we will drop item qualification when unnecessary.

The simplest case of attribute assignment comes when $Value$ is a single value within a domain. In such assignment there is no uncertainty at all. Assignments of this type can be, for example, the title of a movie, the number of pages of a book, and so on.

A more complex case occurs if $Value$ is a subset of a domain (e.g. the authors of a book). An even more complex case (which we study here) occurs when $Value$ is a *fuzzy* subset of a domain. For discrete domains[2] this case leads to fuzzy metadata that can be denoted as

$$Item.Attribute \text{ is}* \ F$$

where:

$$F = \left\{ \frac{\mu_F(x_1)}{x_1}, \frac{\mu_F(x_2)}{x_2}, \ldots, \frac{\mu_F(x_n)}{x_n} \right\} \quad (1)$$

being $x_i \in U$, $\mu_F(x_i) \in [0,1]$ is the degree of membership of x_i within F (with 0 representing *"no membership"* and 1 representing *"full membership"*) and U is the attribute domain. Usually, if $\mu_F(x_i) = 0$, the value x_i is not explicitly represented in the fuzzy set. We immediately observe that fuzzy metadata provide for a straightforward extension of single and set-valued metadata.

The same fuzzy set can be interpreted in a veristic sense as well as in a possibilistic sense. An example will clarify this statement. We suppose to have a scientific paper that is moderately concerned with recommender systems (rs),

[2] For the sake of simplicity, we will not deal with continuous domains in this paper

highly concerned with verisitic variables (vv) and lightly concerned with metadata technologies (mt). A reasonable metadata description of the paper topics is

$$Paper.Topics \text{ isv } \left\{\frac{0.5}{rs}, \frac{0.8}{vv}, \frac{0.3}{mt}\right\}$$

We understand that all the topics included in the fuzzy set apply to the scientific paper, with different degrees of strength. Hence, the interpretation of the assignment is veristic.

On the other hand, we suppose that a user is moderately interested in recommender systems, highly interested in verisitic variables and lightly interested in metadata technologies. In this case we may provide for the following user description:

$$User.Topics \text{ is } \left\{\frac{0.5}{rs}, \frac{0.8}{vv}, \frac{0.3}{mt}\right\}$$

We observe the same fuzzy set applied to the same attribute (Topics) for both metadata. However, in the second case, the interpretation is possibilistic as any paper concerning recommender systems, veristic variables or metadata technologies are of interest for the user, with different degrees. Both interpretations are valid in the context of item recommendation.

2.2 Computation

Many authors have suggested remarkable approaches to compute information interpreted in a possibilistic sense (see, e.g. [3] for an authoritative reference), but fewer authors have addressed the problem of defining and computing veristic information. One approach is suggested by Yager [10], and is briefly described in this section.

We consider a veristic statement expressed in the form

$$M \text{ isv } F$$

where $F \in \mathcal{F}(U)$ is defined as in (1) and $\mathcal{F}(U)$ is the set of fuzzy sets in the domain U. Formally this statement induces a possibility distribution on $\mathcal{F}(U)$:

$$\Pi : \mathcal{F}(U) \to \{0, 1\}$$

The distribution Π characterizes the semantics of the veristic statement. In the "open" interpretation, the distribution is defined as:

$$\Pi(A) = Deg(F \subseteq A)$$

where $Deg(F \subseteq A)$ is the degree of inclusion of F in A. With this interpretation the veristic statement can be interpreted as "M is at least F". In the "close" interpretation, the distribution is defined as:

$$\Pi(A) = 1 \text{ iff } A = F$$

In this interpretation the veristic statement is interpreted as "M is exactly F".

The possibility distribution Π enables the re-definition of a veristic statement into a possibilistic statement of the form

$$M^* \text{ is } F^*$$

where $F^* \in \mathcal{F}(\mathcal{F}(U))$ such that:

$$\forall A \in \mathcal{F}(U) : F^*(A) = \Pi(A)$$

The strength of the possibilistic re-definition of a veristic variable stands in the possibility of manipulating both veristic and possibilistic statements within the same computational framework, without losing the semantics they carry. For a homogeneus representation, possibilistic constraints such as M is V can be redefined as M^* is V^* where:

$$\forall x \in U : \left\{\frac{\mu_V(x)}{x}\right\} \in V^*$$

In order to obtain information on individual elements of the universe U from the statement M^* is F^*, two measures on U are introduced: Verity and Rebuff. Verity quantifies the certainty that an element $x \in U$ belongs to all fuzzy subsets of F^*. It is formally defined as

$$Ver(x) = \min_{A \in \mathcal{F}(U)} [A(x) \vee \bar{F}^*(A)]$$

being $\bar{F}^*(A) = 1 - F^*(A)$. In the "close" interpretation, Verity reduces to:

$$Ver(x) = F(x)$$

Rebuff is the complement of the possibility that an element $x \in U$ belongs to at least one subset of F^*. Formally:

$$Rebuff(x) = 1 - \max_{A \in \mathcal{F}(U)} [A(x) \wedge F^*(A)]$$

Again, in the "close" interpretation, Rebuff reduces to

$$Rebuff(x) = 1 - F(x)$$

Verity and Rebuff give information on single elements of U. A more extended querying mechanism can be defined, which involves the computation of possibility and necessity of a veristic statement, given some other piece of knowledge. We assume the availability of a piece of knowledge as represented in the form M^* is W. A query can be formulated about the possibility or the certainty of a veristic statement given the available knowledge. Such a query can be resolved by re-defining the veristic statement into its possibilistic representation, and using the theory of conditional possibility distributions to calculate the degrees of possibility and certainty [3]. Formally:

$$\begin{aligned} &Poss[M \text{ isv } F | M^* \text{ is } W] = \\ &= Poss[M^* \text{ is } F^* | M^* \text{ is } W] = \\ &= \max_A [F^*(A) \wedge W(A)] \end{aligned} \tag{2}$$

Information on the certainty of the assignment is computed as

$$
\begin{aligned}
&Cert[M \text{ isv } F|M^* \text{ is } W] = \\
&= Cert[M^* \text{ is } F^*|M^* \text{ is } W] = \\
&= \min_A[F^*(A) \vee \bar{W}(A)]
\end{aligned}
\tag{3}
$$

The possibility measure quantifies the existence of at least one fuzzy set shared by both the available knowledge and the query. On the other hand, the necessity statement quantifies how much each fuzzy set belonging to the available knowledge also belongs to the query.

3 Item recommendation

In our approach for item recommendation, we use metadata both to describe items and to define user profiles. Thus, both profiles and items are represented within a recommendation system as collections of metadata. Matching profiles and items requires matching metadata sharing the same attribute and then merging all matching results to provide for a "compatibility" degree representing the interest of a user (belonging to a profile) for an item.

Given a metadata M, we can extract the following information:

- $Attr(M)$ is the attribute of the metadata;
- $Value(M)$ is the value assigned to the metadata, i.e. a fuzzy set;
- $Type(M)$ is the type of the metadata (v=veristic, p=possibilistic);

Given a metadata M_P in the profile and a metadata M_I in an item, such that $Attr(M_P) = Attr(M_I) = A$, a query is built so as to quantify the possibility and the certainty of a statement in the profile, given the knowledge represented by the item. More formally, the query translates in the problem of computing the quantities:

$$Poss[A \text{ is* } Value(M_P)|A \text{ is** } Value(M_I)]$$

and

$$Cert[A \text{ is* } Value(M_P)|A \text{ is** } Value(M_I)]$$

Here, "is$*$" depends on $Type(M_P)$ and "is**" depends on $Type(M_I)$. Depending on these two types, four situations may occur. All these cases, however, can be reduced to a single case by re-mapping statements in the possibilistic case. Thus, we translate the query in the computation of the following quantities:

$$Poss[A^* \text{ is } Value(M_P)^*|A^* \text{ is } Value(M_I)^*] \tag{4}$$

and

$$Cert[A^* \text{ is } Value(M_P)^*|A^* \text{ is } Value(M_I)^*] \tag{5}$$

These two quantities are both useful for item recommendation. A statement can be indeed possible (i.e. a user is potentially interested to an item) but nothing can be said about its certainty. On the other hand, for a statement that is not certain nothing can be said about its possibility. We derive the following situations, sorted by relevance for item recommendation:

1. A statement that is certain (hence possible) indicates that the item is actually interesting for the user;
2. A statement that is uncertain but possible indicates that the item is potentially interesting for the user;
3. A statement that is uncertain and impossible indicates that the item is actually *not* interesting for the user.

With fuzzy quantification of metadata, these three statemets are measured in the $[0, 1]$ interval. Thus, when a database of items is available, they can be sorted by certainty value. In case of equal certainty for different items, they are sorted by possibility.

If profiles and items are described by more than one metadata, then a query is computed for each couple of metadata sharing the same attribute. Then all results are aggregated to yield one degree of certainty and one degree of possibility. According to the least possibility principle [3], the "min" operator can be used to compute such an aggregation.

Possibility and Certainty, as defined respectively in (4) and (5) may be troublesome for item recommendation. Let us consider the case in which we have a statement asserting *"a user is interested only in papers concerning Fuzzy Logic and Artificial intelligence"* and another one that states *"a paper is concerned with Fuzzy Logic, Recommender Systems and Artificial intelligence at the same time"*. These statements will repectively induce the constraint on variables U and P, $U \text{ isv } UI = \{fl, ai\}$ and $P \text{ isv } PT = \{fl, rs, ai\}$ where elements in the sets represent topics, namely Fuzzy Logic (fl), Recommender Systems (rs) and Artificial Intelligence (ai). If we perform a query about the interestingness of the paper for a user known its topics, using Yager's machinery we will find that $Poss[U \text{ isv } UI|P \text{ isv } PT] = 0$ and $Cert[U \text{ isv } UI|P \text{ isv } PT] = 0$ while we expect surely the user will like the paper, as its topics include her preferences. In order to overcome this inconvenient, possibility and certainty measures are re-defined respectively as

$$
\begin{aligned}
&Poss[M^* \text{ is } F^*|M^* \text{ is } W] \\
&= \max_{A \in I^x, B \in I^x}[F^*(A) \wedge W(B) \wedge Deg(A \subseteq B)] \\
&= \max_{A \in I^x, B \in I^x}[F^*(A) \wedge W(B) \wedge \min_{x \in X}[\bar{A}(x) \vee B(x)]]
\end{aligned}
\tag{6}
$$

and

$$
\begin{aligned}
&Cert[M^* \text{ is } F^* | M^* \text{ is } W] \\
&= \min_{A \in I^x, B \in I^x} [F^*(A) \rightarrow (W(B) \rightarrow Deg(A \subseteq B))] \\
&= \min_{A \in I^x, B \in I^x} [\bar{F}^*(A) \vee (\bar{W}(B) \vee Deg(A \subseteq B))] \\
&= \min_{A \in I^x, B \in I^x} [\bar{F}^*(A) \vee (\bar{W}(B) \vee \min_{x \in X} [\bar{A}(x) \vee B(x)]]
\end{aligned} \tag{7}
$$

Differently from Yager's approach, these two measures allow to inspect the content of the fuzzy sets associated to the metadata.

4 Illustrative example

Let us consider an illustrative example to better explain the previous sections. Namely we are interested in showing the results of a user querying a system that stores and suggests scientific papers. We know that each paper is classified with respect to its topics and we suppose that a user is interested in one or more among them.

Hence let $U = \{fl, os, ai, rs, se\}$ be the universe of discourse related to a metadata M representing the topic of a paper having as elements Fuzzy Logic (fl), Operating Systems (os), Artificial intelligence (ai), Recommender Systems (rs) and software engineering (se).

Let us then consider four subsets of U: $A = \{fl, rs\}$, $B = \{fl, rs, ai\}$, $C = \{fl, se\}$ and $D = \{os, se\}$. Each of these sets can be regarded as a fuzzy restriction. If the restriction is interpreted in a veristic way we have the sets $A^*_v = \{\frac{1}{A}\}$, $B^*_v = \{\frac{1}{B}\}$, $C^*_v = \{\frac{1}{C}\}$ and $D^*_v = \{\frac{1}{D}\}$ (the close world assumption holds). On the contrary if the restriction is interpreted in a possibilistic sense we can map each set into its corresponding associated one $A^*_p = \{\frac{1}{\{fl\}}, \frac{1}{\{rs\}}\}$, $B^*_p = \{\frac{1}{\{fl\}}, \frac{1}{\{rs\}} \frac{1}{\{ai\}}\}$, $C^*_p = \{\frac{1}{\{fl\}}, \frac{1}{\{se\}}\}$, and $D^*_p = \{\frac{1}{\{os\}}, \frac{1}{\{se\}}\}$.

Taking into account the set A, the following query can be performed: *"a user is interested in resources concerning fuzzy logic and recommender systems at one time. How is it possible that a paper about fuzzy logic, recommender systems and artificial intelligence can be useful?"*. This query induces a veristic restriction both in the part concerning the preferences of the user and in the part representing the knowledge about the topic of the paper. Similar queries can be obtained taking into account sets C and D. The machinery provided in the previous sections allows to compute possibilities and certainties as:

$$
\begin{aligned}
&Poss[M^* \text{ is } A^*_v | M^* \text{ is } B^*_v] = 1 \\
&Poss[M^* \text{ is } C^*_v | M^* \text{ is } B^*_v] = 0 \\
&Poss[M^* \text{ is } D^*_v | M^* \text{ is } B^*_v] = 0
\end{aligned} \tag{8}
$$

and:

$$
\begin{aligned}
&Cert[M^* \text{ is } A^*_v | M^* \text{ is } B^*_v] = 1 \\
&Cert[M^* \text{ is } C^*_v | M^* \text{ is } B^*_v] = 0 \\
&Cert[M^* \text{ is } D^*_v | M^* \text{ is } B^*_v] = 0
\end{aligned} \tag{9}
$$

It can be seen that in the first case, when the metadata describing the topic of the paper includes the metadata describing the preferences of the user, her interest will be certain.

Another possible query can be of the type: *"a user is interested in fuzzy logic or in recommender systems. Knowing that the subjects of a paper are fuzzy logic, recommender systems and artificial intelligence at the same time, will the paper be of interest?"*. We are thus giving a possibilistic interpretation to the restriction representing a user's preferences and a veristic interpretation to the restriction representing the a priori knowledge (i.e. the topic of the paper). Hence we have possibilities:

$$
\begin{aligned}
&Poss[M^* \text{ is } A^*_p | M^* \text{ is } B^*_v] = 1 \\
&Poss[M^* \text{ is } C^*_p | M^* \text{ is } B^*_v] = 1 \\
&Poss[M^* \text{ is } D^*_p | M^* \text{ is } B^*_v] = 0
\end{aligned} \tag{10}
$$

and certainties:

$$
\begin{aligned}
&Cert[M^* \text{ is } A^*_p | M^* \text{ is } B^*_v] = 1 \\
&Cert[M^* \text{ is } C^*_p | M^* \text{ is } B^*_v] = 0 \\
&Cert[M^* \text{ is } D^*_p | M^* \text{ is } B^*_v] = 0
\end{aligned} \tag{11}
$$

In this example it can be seen that when the metadata describing the topic of the paper includes the metadata describing the preferences of the user, her preference is certain, while when the metadata have only some elements in common, the user preference for the paper will be only possible but nothing can be said about certainty.

Another query is of the type:*"a user is interested in fuzzy logic or in recommender systems. Knowing that the subjects of a paper are one among fuzzy logic, recommender systems and artificial intelligence, will the paper be of interest?"*. The interpretation of the restriction modelling both user preference and the a priori knowledge about the paper is possibilistic. In this case we have the following possibilities:

$$
\begin{aligned}
&Poss[M^* \text{ is } A^*_p | M^* \text{ is } B^*_p] = 1 \\
&Poss[M^* \text{ is } C^*_p | M^* \text{ is } B^*_p] = 1 \\
&Poss[M^* \text{ is } D^*_p | M^* \text{ is } B^*_p] = 0
\end{aligned} \tag{12}
$$

and certainties:

$$
\begin{aligned}
&Cert[M^* \text{ is } A^*_p | M^* \text{ is } B^*_p] = 1 \\
&Cert[M^* \text{ is } C^*_p | M^* \text{ is } B^*_p] = 0 \\
&Cert[M^* \text{ is } D^*_p | M^* \text{ is } B^*_p] = 0
\end{aligned} \tag{13}
$$

As it can be seen from the examples the situation is completely analogous to the previous case even if the interpretations of the restrictions change.

Finally, the last type of query can be expressed as:*"a user is interested both in fuzzy logic and in recommender systems at the same time. Knowing that the subjects of a paper are one among fuzzy logic, recommender systems and artificial intelligence, will the paper be of interest?"*.

The interpretation of the restriction representing user preferences is veristic while the interpretation of the restriction representing the a priori knowledge is possibilistic. In this case we have no information at all, as can be seen from possibilities:

$$\begin{array}{l} Poss[M^* \text{ is } A_v^* | M^* \text{ is } B_p^*] = 0 \\ Poss[M^* \text{ is } C_v^* | M^* \text{ is } B_p^*] = 0 \\ Poss[M^* \text{ is } D_v^* | M^* \text{ is } B_p^*] = 0 \end{array} \quad (14)$$

and certainties:

$$\begin{array}{l} Cert[M^* \text{ is } A_v^* | M^* \text{ is } B_p^*] = 0 \\ Cert[M^* \text{ is } C_v^* | M^* \text{ is } B_p^*] = 0 \\ Cert[M^* \text{ is } D_v^* | M^* \text{ is } B_p^*] = 0 \end{array} \quad (15)$$

Here it can be seen that is not possible neither certain that a user will like a paper if she looks for a whole set of topics but our knowledge about the subject of the paper is related to just one (unknown) topic in a set.

If we fuzzify elements in the sets we will find that the equations (6) and (7) lead to a consistent result. For the sake of simplicity let's consider the veristic-veristic case.

Let's now consider the above mentioned set A, C, D giving to their first element a partial membership of 0.3 to represent the fact that a user is much more interested in recommender systems and artificial intelligence than in fuzzy logic. In that case we will have possibilities:

$$\begin{array}{l} Poss[M^* \text{ is } A_v^* | M^* \text{ is } B_v^*] = 1 \\ Poss[M^* \text{ is } C_v^* | M^* \text{ is } B_v^*] = 1 \\ Poss[M^* \text{ is } D_v^* | M^* \text{ is } B_v^*] = 0 \end{array} \quad (16)$$

and certainties:

$$\begin{array}{l} Cert[M^* \text{ is } A_v^* | M^* \text{ is } B_v^*] = 0.3 \\ Cert[M^* \text{ is } C_v^* | M^* \text{ is } B_v^*] = 0 \\ Cert[M^* \text{ is } D_v^* | M^* \text{ is } B_v^*] = 0 \end{array} \quad (17)$$

The fuzziness associated with our knowledge smooths the result of the query. It's easy to see that the machinery performs in an analogous way with other three cases above mentioned.

5 Conclusion

According to the soft-computing principles, imprecision is an intrinsic feature of all real data and all tentatives of removing it yield to a loss of useful information. Fuzzy metadata allow imprecise description of objects by attaching fuzzy sets to attributes instead of single, precise, values. With such an extension, however, a question arises about the *meaning* of such metadata. In this paper, we have highligted two interpretations – namely possibilistic and veristic – that are equally valid in an item recommendation context and can simoultaneously occur in a query. We have outlined a preliminary approach for item recommendation by using an extension of the theory of veristic variables of Yager, which defines two measures to quantify a query: the possibility value and the certainty value. The proposed approach emphasizes the semantic significativity of the operations required to quantify the interestingness of an item for a user, as depicted in the illustrative example.

As a preliminary approach, it defines a line of research aimed at building a self-contained system for item recommendation with fuzzy metadata, by taking into account all the computational facets of calculating queries with veristic statements with "open" and "close" interpretation, so as to provide for item recommendation in presence of large volumes of data.

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