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# Inferring preferences in ontology-based recommender systems using WOWA

**Miriam Martínez-García · Aida Valls · Antonio Moreno**

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**Abstract** In content-based semantic recommender systems the items to be considered are defined in terms of a set of semantic attributes, which may take as values the concepts of a domain ontology. The aim of these systems is to suggest to the user the items that fit better with his/her preferences, stored in the user profile. When large ontologies are considered it is unrealistic to expect to have complete information about the user preference on each concept. In this work, we explain how the Weighted Ordered Weighted Averaging operator may be used to deduce the user preferences on all concepts, given the structure of the ontology and some partial preferential information. The parameters of the WOWA operator enable to establish the desired aggregation policy, which ranges from a full conjunction to a full disjunction. Different aggregation policies have been analyzed in a case study involving the recommendation of touristic activities in the city of Tarragona. Several profiles have been compared and the results indicate that different aggregation policies should be used depending on the type of user. The amount of information available in the ontology must be also taken into account in order to establish the parameters of the proposed algorithm.

**Keywords** Preference Management · Semantic Data · Aggregation Operators · Ontology · Tourism.

M. Martínez-García
Departament d'Enginyeria Informàtica i Matemàtiques, Universitat Rovira i Virgili.
Av Països Catalans, 26. 43007 Tarragona, Catalonia (Spain). Tel.: +34-977559688
Fax: +34077559710
E-mail: miriam.martinez@urv.cat

A. Valls
Departament d'Enginyeria Informàtica i Matemàtiques, Universitat Rovira i Virgili.
Av Països Catalans, 26. 43007 Tarragona, Catalonia (Spain). E-mail: aida.valls@urv.cat

A. Moreno
Departament d'Enginyeria Informàtica i Matemàtiques, Universitat Rovira i Virgili.
Av Països Catalans, 26. 43007 Tarragona, Catalonia (Spain). E-mail: antonio.moreno@urv.cat

## 1 Introduction

In the current Knowledge Society, we are daily confronted with many hard decisions, in which an option must be chosen from a large set of alternatives. *Recommender systems* try to help us to make the best decision, taking into account our preferences, the context of the decision and the characteristics of the available options [1]. They are especially popular in e-commerce, as they may suggest to each user the items offered by an on-line store that fit better with his/her preferences. They have also been heavily used in the Tourism field in the last years to help visitors to select a set of leisure activities that they may enjoy and that fit in the context (dates, weather, budget, etc.) of the trip [6], [31]. The most common recommendation techniques are collaborative filtering and content-based. The former focus on the analysis of the ratings of users to products, and recommend to a user items that have been highly valued by similar users (or items that are similar to those that have received a high score by the user). On the contrary, *content-based recommender systems* (CBRS) have an explicit representation of the preferences of the users, which is stored in the *user profile* (UP). When a recommendation must be made, the options are ranked according to their similarity with the UP, and the best ones are shown to the user. Thus, in this kind of systems it is of paramount importance to have a good knowledge of the preferences of the user to suggest appropriate items.

Nowadays *ontologies* are one of the most popular mechanisms for knowledge representation and reasoning in intelligent systems. Among other components, they include a set of classes (which represent the main concepts of the domain) linked via binary relationships. In particular, taxonomic relationships allow building hierarchies of classes, in which each class is related to its super-classes and sub-classes. Thus, a *domain ontology* is an explicit conceptualization of a certain field. The hierarchical structure in which concepts are embedded allows the definition of *ontology-based semantic similarity* measures, which aim to compute how similar two concepts are, depending on their positions in the ontology.

The alternatives that may be recommended by a CBRS are usually described in terms of a set of characteristics, usually called *features*, *attributes or criteria*. The most commons kinds of attributes are numerical (integers or reals, in a particular range), nominal (list of predefined values, which may be ordered or not) and boolean (true or false). However, in the last years it has grown the interest on *semantic* attributes, which are those that may take as values the concepts of an ontology. It is common that semantic attributes are multi-valued, so that an item may have an associated list of concepts (instead of a single concept).

**Example**: in a recommender system of tourist destinations, each option could be defined in terms of numerical attributes (average temperature in summer, population, height), nominal attributes (language, weather), boolean attributes (presence of international airport) and semantic attributes (cultural and leisure activities available in the city, sports that may be practiced in the city). Thus, a particular destination like Tarragona could be defined as follows:

- Average summer temperature: 30 degrees Celsius.
- Population: 120,000
- Height: 0 (sea level)
- Languages: Spanish, Catalan (multi-valued attribute)

- Weather: Mediterranean
- Presence of international airport: true
- Cultural and leisure activities: Roman Amphitheatre, Roman circus, Museum of Modern Art, human castles, Cathedral, Archaeological Museum, etc.
- Sports that may be practiced in the city: Running, Swimming, Basketball, Volleyball, Skating, etc.

When the alternatives of a CBRS are defined in terms of semantic attributes it is interesting to consider the possibility of using domain ontologies. A new kind of ontology-based recommender systems is now recognized in the literature, in which ontologies are used not only to specify the possible values that these attributes may take (and the relationships between them), but also to represent the preferences of the user on those values [8], [43]. Thus, in the previous example, the UP could include an ontology of cultural and leisure activities and an ontology of sports. These ontologies could store, in some way, the interest of the user in each concept.

One of the main problems of ontology-based recommender systems is the initialization of the UP. The preferences of users may be discovered explicitly or implicitly. In the first case, the user should indicate directly the values of the semantic attributes which match his/her preferences; in the second case, the system analyses the interaction of the user with the system (e.g. which recommendations are stored, which recommendations are deleted, how the user rates a particular item) to try to infer which are his/her preferred values [24]. However, in both cases the preference discovery is hard if the number of concepts of the ontology is large. If there are hundreds or thousands of possible values for a semantic attribute, it cannot be expected that users will scan all of them to indicate their explicit preferences, or that they will interact with enough items to include all the possibilities. Thus, we can reasonably expect to have only a *partial* view of the tastes of the user, with preference values on a few ontology concepts.

This work is focused on *semantic CBRS*, in which alternatives are defined in terms of semantic criteria. The UP will be composed of an ontology for each semantic attribute, in which the preference of the user on some of the most specific concepts (i.e., the leaves of the ontological structure) will be stored. These initial partial preferences may have been given by the user in a short explicit questionnaire or may have been deduced from the interaction of the user with a small set of initially recommended items. The main contribution of this paper is the definition of a mechanism that permits inferring the preference of the user on *all* the specific concepts of the ontology, taking into account the known preferences and the structure of the ontology. This full preferential information could then be used by an ontology-based recommender system to provide the appropriate recommendations to the user. An interesting option would be the application of ELECTRE-SEM [25][26], an extension of ELECTRE-III that handles efficiently the preferential information on semantic attributes to establish preference relations between the set of alternatives, which can be later exploited to rank them. The novel inference procedure proposed in this paper is based on the use of the Weighted Ordered Weighted Average (WOWA) aggregation operator [44],[45].

The rest of the paper is structured as follows. The next section comments previous works on ontology-based recommender systems and gives a brief review of the main kinds of semantic similarity measures. Section 3 is the core of the paper. It describes how the preferences of the user on the values of a semantic attribute may be stored in the corresponding ontology, how the WOWA aggregation operators work and how they can be applied to complete a partial set of semantic preferences. Section 4 presents a case study related to the recommendation of leisure and sport activities to the visitors of Tarragona. Several user profiles are considered to evaluate the accuracy of the preference deduction procedure. This section also includes a comparison with the most similar works in the literature ([9], [38], [41]). The paper finishes with a conclusion and an outline of some points of future work.

## 2 Related work

This section is divided in two parts. The first one comments the use of ontologies to represent user profiles and reason about the preferences of the user in semantic recommender systems. The second one makes a brief introduction to the main kinds of semantic similarity measures that have been proposed in the literature.

### 2.1 Ontology-based recommender systems

Semantic (or ontology-based) recommender systems focus on the analysis of a set of alternatives defined on semantic attributes, in order to rank them or to select the ones that fit better with the user preferences [26]. A common option in this kind of recommenders is to use the domain ontologies both to structure the possible values of each semantic attribute and to store, in some way, the preferences of the user on those values [2], [46]. Usually a semantic attribute may take as value a list of the most specific concepts of the ontology (i.e., the leaves of the tree), and the score of an alternative depends on the preference of the user with respect to those specific concepts. For instance, in the example shown above, the score of Tarragona with respect to the Sports attribute would depend on the preferences of the user with respect to the values Running, Swimming, Basketball, etc.

There are several ways in which ontologies have been used to represent the user profile. The simplest way is to associate to each user an explicit list of the concepts (attribute values) in which he/she is interested (e.g. [4], [20], [37], [40]). This option is not very informative, since it is not possible to express levels of interest on different concepts. A more interesting and widespread approach is to represent the preferences of a user with a vector of real-valued features, in which each position contains the degree of interest of the user with respect to a concept of the ontology (e.g. [9], [17], [19], [28], [39], [41], [52]). Some works also add a measure of the credibility associated to the information stored in the profile. The preference rating values may be uncertain because in many cases they are not fully provided in an explicit way by the user, but have to be inferred or discovered in some way. These confidence degrees associated to each concept may be later used as weighting factors in the recommendation process [7], [12].

This paper presents a case study on the area of Tourism, which is one of the fields in which ontology-based recommender systems have been most heavily applied in the last years [6], [27]. For example, in [13] a Tourism taxonomy was designed to categorize attractions in classes like 'Gothic Art', 'Museums' or 'Religious Buildings'. The Tourism ontology defined in [30] had properties like 'part of', 'hasQuality,' 'location' or 'date.' The e-Tourism ontology defined in [13] also contained non-taxonomic properties like locatedIn, interestedIn or hasCurrency, that allowed the system to answer questions like which activities may be visited by a certain type of tourists, which is the location of interesting places or when they can be visited. Both [13], [23] used explicit rules to be able to deduce information from the ontology and to answer queries on it. For instance, a rule like 'fact(? X type architecture 0.9*?N) :- fact(? X type church ?N)' states that if an item belongs to the church category with a score N, it can also be considered a member of the architecture category with a score 0.9*N. In the SigTur recommender system [31] the authors defined a 5-levels Tourism ontology with over 200 concepts. The first level of the ontology contained 8 general categories (Events, Nature, Culture, Leisure, Sports, Towns, Routes and Viewpoints), which were refined in the subsequent levels. In [48] the authors described a recommender of tourist destinations based on Bayesian networks, which used an ontology on user profiles and another one on touristic information. Some works consider fuzzy ontologies, in which a concept may be related to a certain degree with another one (e.g. [10] use a fuzzy ontology on wines to recommend the most appropriate wine in a particular context). More complex recommender systems consider a set of ontologies; for example, [20] presents a semantic-based Tourism information system that employs a network of ontologies, called ContOlogy, composed by 11 ontologies, 86 classes, 63 properties and 43 restrictions. These ontologies represent the information about visitors, preferences, roles, activities, environment, devices, network, motivations, location, time and Tourism objects.

One of the key problems in ontology-based recommender systems is the initialization of the user profile, i.e. the acquisition of the preferences of the user with respect to the possible values of each semantic criteria. This preferential information may be acquired explicitly at the beginning of the recommendation session, by asking the user to complete some kind of form, to answer a questionnaire or to rate some alternatives (e.g. [5], [9], [32], [40]). This approach provides precise information, since it is given directly by the user; however, it is an intrusive elicitation mechanism, and most users are not keen on spending time providing this information. Moreover, if the number of concepts in the ontologies associated to the semantic attributes is large, it is not feasible in practice to ask the user to express his/her preference on each concept. A possible solution consists on using some kind of spreading procedure to propagate the scores given by the user to the rest of concepts of the ontology. For example, in the SigTur system [7] the user is initially asked to provide the preferences only on the top categories of the touristic ontology, and this information is spread to the subclasses (adding a certainty factor that decreases with the distance to these concepts). Another possibility is to try to learn the user preferences by analyzing his/her interaction with the system (e.g. the alternatives that are selected/viewed/deleted/purchased, the ratings given to the alternatives, or even the time spent with each alternative). SigTur [7] also employed this kind of techniques to update dynamically the information on the preferences of the user. The main advantage of this approach is that users do not need to spend time thinking about their preferences and making them explicit; however, more sophisticated computational approaches are required to try to understand the preferences of the user, and this information may have some associated uncertainty.

Since this paper is focused on the initialization step, a study of related methods has been done. Among the works in the literature, we can find different approaches to obtain the user's preferences in ontology-based recommender systems. Table 1 shows the main distinguishing features. There are papers that do not explain the process followed to initialize the user profile. Others assume that the user will explicitly give the initial preference scores. Six methods require additional information, e.g. the recommenders whose purpose is to filter documents. In many cases the user profile is completed by analyzing the user's actions on the recommender system. There are only three works comparable to the setting considered in this paper (without additional sources of information and without any user's feedback requirements), which are [9], [38] and [41]. In the experimental section they are compared with the method proposed in this paper.

Regardless of the method employed to acquire the user preferences, it is very unlikely that the system can have reliable and complete information on the interest of the user on each possible value of each semantic attribute. Thus, in this work it is assumed that it is more realistic to expect that, given a certain semantic attribute, the system will initially only have information on the preferences of the user with respect to a small set of concepts of the ontology. This hypothesis motivates the need to have a computational mechanism that is able to complete the preferential information, taking into account the initial partial information, the structure of the ontology and the definition of an appropriate preference learning policy.

## 2.2 Semantic similarity measures

Ontologies model the knowledge about the concepts in a certain domain using several types of relations, being the most common the taxonomical relations between a general concept and its sub-concepts (i.e. *is-a* relations). The exploitation of the information stored in ontologies is quite common in different fields, such as in Computational Linguistics for text analysis and text categorization, among others. In many of these tasks it is necessary to measure the semantic relatedness between two different concepts. Semantic similarity functions can be basically divided into two main categories: *distributional measures* and *ontology-based measures*. The distributional approaches use text corpora as the source to infer the semantics of the terms. They are based on the assumption that words with similar distributional properties have similar meanings [47]. Such measures take into account the co-occurrence of the words associated to the concepts in the same texts. The second approach relies on the relations between the concepts found in an ontology. Three types of ontology-based semantic similarity measures are distinguished [22]: edge-counting, feature vectors and information content. Edge-counting similarity functions use the number of edges separating two concepts to calculate the distance between them. The simplest measure is known as *Path Length* and it takes as similarity the minimum number of *is-a* links needed to connect two nodes of the ontology [35]. Such method to calculate the distance between terms has some weaknesses such as not considering the depth (i.e. the specificity) of the compared concepts. In this sense, other measures [21], [49] consider the depth of the concepts in the taxonomy, because concept specializations become less distinct the more they are refined. So, equally distant pairs of concepts belonging to an upper level of a taxonomy should be considered less similar than those belonging to a lower level. In case of multiple inheritance, it may be interesting to use a similarity measure that takes into account the number of common ancestors of the compared

**Table 1** Features of different ontology profile initialization methods

| Ref | Method of calculation | Additional sources | Implicit feedback |
|---|---|---|---|
| [3] | Given by user | None | Yes |
| [5] | Spreading by means of semantic associations parent-child | None | No |
| [7] | Downwards propagation of the interest scores given to the most general concepts | None | No |
| [9] | Constrained Spreading Activation (CSA) | None | No |
| [11] | Spreading activation | None | Yes, actions of users on the items |
| [14] | TD-IDF scheme | Documents and Open Directory Project | Yes, first documents searched |
| [15] | Train a learning model from examples of ratings | Linked Open Data | Yes |
| [17] | Given by the user | None | No |
| [18] | Spreading with contextual information | Context: time, place, people relationships (brothers, classmates, ...), etc. | No |
| [19] | Bayesian probabilistic propagation model | History of records of the user's Web searches | Continuous recalculation with decay factor |
| [28] | Estimation from the K-nearest users | Age of the publications used and set of similar users | No |
| [29] | Not explained | None | Yes, with previously browsed papers |
| [32] | Transformation to AHP decision model | None | No |
| [38] | Average of scores of the closest concepts | None | No |
| [39] | Not explained | Web documents | Yes, webs URL and its clicks |
| [40] | Given by the user | None | Yes, clicks to items |
| [41] | Spreading activation | None | Yes |
| [42] | All concepts with the lowest possible score (not liked) | None | Yes, from user's ratings to recommended items |
| [52] | TD-IDF scheme | Set of documents searched | Yes, first documents searched |
| [53] | Propagation only to the super-classes (ancestors) given scores of instances | None | No |

concepts, as proposed in [16]. Secondly, feature-based measures estimate the similarity according to other common semantic features between the two concepts, such as synonyms, meronyms or other semantic relationships [33]. Finally, a third approach consists on a conceptualization of information content of a term as the probability of its occurrence [36]. This probability can be computed from an external corpus or internally from the intrinsic information of the ontology structure [34].

## 3 Constructing the user profile based on ontologies

In this section a method to store the user preferences by means of an ontology is proposed. First, we define the user profile structure. Assuming that the user will introduce manually an interest score only for a subset of the concepts of the ontology, an algorithm to estimate the interest of the user on the rest of the concepts is presented. This novel algorithm has two main distinguishing features: on the one hand, it aggregates the information of the known scores taking into account the semantic relations of the concepts in the ontology; on the other hand, there is a set of weights that may be used to adjust the behavior of the aggregation operation.

### 3.1 The design of the ontology-based user profile with Tag Interest Scores

In this work we use a feature-based approach, in which each user has a personal profile that consists on a numerical preference score associated to the set of all possible tags that may appear in the alternatives. This set of tags is restricted to the most specific terms of the ontology (the ones that do not have descendants). The ontology is structured using taxonomical relations (is-a) where multiple inheritance is possible. Therefore, the tags (or concepts) may have multiple parents. Fig. 1 shows a portion of an ontology that classifies different aquatic sports. Notice that Boating and Fishing are sport activities made in the river or in the sea and, hence, they are subclasses of these two concepts. Subtypes of boating and sailing are defined in this ontology, although they are not displayed in the figure.

In a previous work [25] the concept of *Tag Interest Score TIS(t)* was defined, where $t$ is a tag corresponding to a leaf of the reference ontology. *TIS(t)* is a numerical score between 0 and 1 that indicates the satisfaction degree of the user with the corresponding tag $t$ according to the decision maker's goals. The tag score may have two possible directions: maximization (1 is the best score) or minimization (0 is the best score). The former is known as a gain criterion and the latter as cost criterion. The direction of *TIS(t)* must be decided according to the decision problem to be solved. In some problems, the concepts of the ontology may indicate negative features, such as environmental pollutants, hence the *TIS(t)* should be minimized if it is associated to the quantity of the pollutant. On the contrary, in other problems it may indicate elements that the user is searching for, like in e-commerce or recommender systems. In this case, *TIS(t)* is usually related to the degree of interest on the concepts and it is positively treated. Without loss of generality, in this paper we assume that *TIS(t)* has to be maximized. In Fig. 1 we can see an example of a tourist's profile with the interest scores, like $TIS(\text{Kayaking}) = 0.8$, $TIS(\text{Rafting}) = 0.7$ or $TIS(\text{Windsurfing}) = 0.3$, and we can see that this tourist prefers sports activities in the river (with tags with the highest scores), and he/she does not like surfing sports, except maybe banana rafting. In this example, there are three leaves without score: Canoeing, Scuba

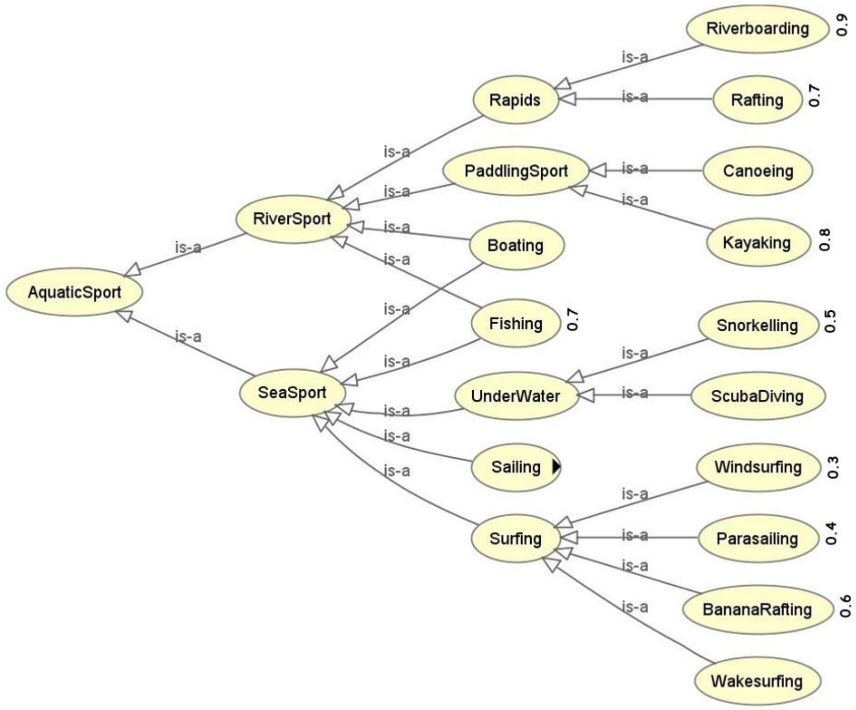


**Fig. 1** User profile ontology about aquatic sports with Tag Interest Scores

Diving and Wake Surfing. The estimation of missing TIS will be done using the WOWA aggregation operator, which is presented in the next section.

## 3.2 The WOWA operator

The *Ordered Weighted Average* (OWA) is a flexible aggregator operator that admits different degrees of conjunction/disjunction [50]. This technique has been widely studied and used in many decision-making problems [51]. Before defining the OWA operator, which is the basis for the WOWA operator, some preliminary concepts are formalized.

**Definition 1** A vector $v = (v_1 ... v_n)$ is a weighting vector of dimension $n$ if and only if $\forall_{i,1 \leq i \leq n}$, $v_i \in [0, 1]$ and $\sum_{i=1}^{n} v_i = 1$.

**Definition 2** A mapping $AM$: $\mathbb{R}^n \to \mathbb{R}$ is an arithmetic mean of dimension $n$ if $AM(a_1, ..., a_n) = \left(\frac{1}{n}\right) \sum_{i=1}^{n} a_i$.

**Definition 3** Let $p$ be a weighting vector of dimension $n$; then, a mapping $WM_p$: $\mathbb{R}^n \to \mathbb{R}$ is a weighted mean of dimension $n$ if $WM_p(a_1, ..., a_n) = \sum_{i=1}^{n} p_i a_i$.

The OWA operator is defined as a linear combination of the data with respect to a weighting vector, similarly to the weighted mean. However, in this case, a permutation of the values that are aggregated $a_{\sigma(i)}$ plays a central role in the definition and causes the weights to have a completely different meaning.

**Definition 4** Let $w$ be a weighting vector of dimension $n$; then, a mapping $\mathbb{R}^n \rightarrow \mathbb{R}$ is an Ordered Weighted Averaging *(OWA)* operator of dimension $n$ if $OWA_W(a_1, ..., a_n) = \sum_{i=1}^{n} w_i a_{\sigma(i)}$, where $\sigma(1), ..., \sigma(n)$ is a permutation of $1, ..., n$ such that the arguments are decreasingly ordered, i.e. $a_{\sigma(i-1)} \geq a_{\sigma(i)}$ for all $i = 2, ..., n$ (i.e., $a_{\sigma(i)}$ is the $i$th largest element in the collection $a_1, ..., a_n$).

With this definition, weights are assigned to the position of the values rather than to the values themselves. Therefore, one may define different aggregation policies that give different importance to the highest or lowest values that have to be aggregated. In fact, the weighting vector of the OWA operator allows to move continuously from the minimum (when $w_n = 1$ and the rest are 0) to the maximum type of aggregation (when $w_1 = 1$ and the rest are 0). The compensative behaviour of the aggregation operator can be fixed by the set of weights. Compensation is the property that a high degree of satisfaction in one criterion compensates a low degree of satisfaction in other criteria. The maximum operation (high orness) means full compensation or simultaneity (pessimistic aggregation policy), while the minimum operation (high andness) means no compensation or replaceability (optimistic aggregation policy). Those characteristics are especially suitable to combine the user's preferences in decision making processes and recommender systems.

In order to classify these OWA operators in relation to their conjunctive/ disjunctive degree, a measure of *orness* $\alpha$ may be calculated for any weighting vector $w$ of dimension $n$ with Eq.1. The range of $\alpha$ is [0,1]. When orness is near 1 the weights define a disjunctive behavior, while an orness close to 0 means that the aggregation is conjunctive (low orness implies high andness, since these two measures are complementary).

$$\alpha(w) = \sum_{j=1}^{n} w_j \left( \frac{n-j}{n-1} \right) \tag{1}$$

Another characterizing measure of OWA weights is the *divergence*, which is a number in the range [0, 0.5]. The maximum divergence, 0.5, corresponds to the case of arithmetic average (i.e. equal weight for all the input arguments). The minimum divergence, 0, happens when only one input value is used (when $w_j = 1$ for a unique position $j$). Divergence reduces if the weights are assigned to a small subset of consecutive values.

$$div(w) = \sum_{j=1}^{n} w_j \left( \frac{n-j}{n-1} - \alpha(w) \right)^2 \tag{2}$$

Later, in 1997, Torra proposed the Weighted OWA (WOWA), which combines the OWA operator and the weighted mean WM [44]. The WOWA operator was introduced to model situations in which both the importance of the information sources and the aggregation policy have to be considered. The operator aggregates a set of values using two weighting vectors: one corresponding to the vector $p$ in the weighted mean and the other corresponding to $w$ in the OWA operator. The WOWA operator is defined as follows.

**Definition 5** Let $p$ and and $w$ be two weighting vectors of dimension $n$; then, a mapping $WOWA : \mathbb{R}^n \to \mathbb{R}$ is a *Weighted Ordered Weighted Averaging (WOWA)* operator of dimension n if

$$WOWA_{p,\mathrm{w}}(a_1, ..., a_n) = \sum_{i=1}^{n} \omega_i a_{\sigma(i)}, \tag{3}$$

where $\sigma$ is defined as in the case of OWA (i.e., $a_{\sigma(i)}$ is the $i$-th largest element in the collection $(a_1, ..., a_n)$), and the weight $\omega_i$ is defined as

$$\omega_i = \mathrm{w}^*(\sum_{j \leq i} p_{\sigma(j)}) - \mathrm{w}^*(\sum_{j<i} p_{\sigma(j)}) \tag{4}$$

with $w^*$ being a monotone increasing function that interpolates the points $\left(\frac{i}{n}, \sum_{j \leq i} w_j\right)$ together with point (0,0). $w^*$ is required to be a straight line when the points can be interpolated in this way.

### 3.3 The inference procedure of new tag interest scores

In this section we present the procedure proposed to estimate the missing score for any leaf $c$ of the ontology. This method has 3 steps:

**Step 1. Find relatives.** We find concepts that are semantically similar to $c$ using the taxonomical relations of the ontology. Since only leaves have an associated TIS, we only retrieve concepts that do not have descendants. A set of related concepts is built by following the taxonomical relations in the ontology using Algorithm 1, where $n$ is the number of similar concepts we want to find. The function *fathers* receives a set of concepts and an ontology, and it returns the set of direct ancestors of all the concepts in the input set according to the ontology. The function *leaves* receives a concept and an ontology, and it returns the set of ontology leaves that have a known TIS and belong to the subtree whose root is the given input concept. In the union operations, no repeated elements are stored in the output set.

**Algorithm 1** Find Relatives

**Inputs:** ***concept c*, *user profile ontology* $\theta$, *int n***
**Output: set of neighbor concepts.**

$F$ = fathers $(\{c\}, \theta)$
$R$ = empty_*set*
$R = R \cup$ leaves $(f_i, \theta)$ for all $f_i \in F$
$m = |R|$
**while** (m < n) and (F $\neq \emptyset$) **do**
    $F' = \cup$ (fathers $(f_i)$,$\theta$) for all $f_i \in F$
    $R = R \cup$ leaves $(f_i, \theta)$ for all $f_i \in F'$
    $m = |R|$
    $F = F'$
**end while**
return $R$

In this algorithm we start searching for leaf concepts that are descendants of the fathers of $c$, which can be found at different depths. Moreover, if the number of elements is below the given input value $n$, we move to upper levels of the ontology to find leaf concepts descending from the hierarchy with root in a grandparent of $c$. Iteratively, if the number of neighbors with known score is still low, we continue exploring other regions of the ontology by going upwards in the chain of ancestors of the first concept $c$.

**Step 2. Concept Importance.** The determination of the importance of each relative is done according to its semantic similarity to the given concept $c$. As explained in section 2, there is a large set of semantic similarity measures available in the literature. The most appropriate measure depends on the purpose of each problem. In the formulation presented in Eq. 5, the semantic distance *dsem* is not specified.

Despite any semantic similarity could be used, we suggest the use of Path Length. A distance based on steps is appropriate taking into account that $c$ will be a very specific concept (located in the leaf of a branch). The more steps up and down are needed to find another leaf concept, the lower is their degree of semantic similarity.

Weights are defined in Eq. 5. The idea is that we want to give more importance to the concepts that are close to the target concept $c$, because they represent tags with a strong semantic similarity to $c$ and, thus, their interest scores are expected to be similar to the value that we have to estimate for $c$. For instance, concepts at distance 2 (i.e. brothers) are given more relevance than concepts at distance 3 (which are uncles or nephews). Concretely, for a concept $r_k$ found at distance $d$ with respect to the target concept $c$, the corresponding weight $p_k$ is calculated with the following expression, in which $D$ is the maximum distance at which a related concept has been retrieved, and $\#concepts(d)$ is the number of related concepts found at a certain distance $d$:

$$p_k = \frac{1}{\Omega \cdot dsem(c, r_k)}, where\ \Omega = \sum_{d=2\ldots D} \frac{\#concepts(d)}{d} \tag{5}$$

**Step 3. TIS calculation.** The estimation of the tag interest score of $c$ using the set of relatives $R$ and the weighting vector $p$ is done by means of the aggregation of the known scores of these relatives. The value of *TIS(c)* is calculated using the averaging operator on the known scores of the relatives of $c$. The WOWA operator with two weighting factors is proposed. As explained before, the classical OWA weights allow the definition of different aggregation policies. With conjunctive parameters, the resulting score is penalized when similar concepts have low scores (pessimistic approach), whereas with disjunctive parameters the score is based only on the highest scores of the similar concepts (optimistic approach). A neutral configuration is also possible, which leads to the classic arithmetic average.

In order to apply the operator, first the aggregation policy must be specified by defining a weighting vector $w$ of size $|R|$ . This vector can be manually defined by the user or it can be automatically constructed. Yager described that the weights can be obtained with Eq. 6 using a linguistic quantifier, which is a function $Q$ that is defined according to the quantity of simultaneous values to take into account (e.g."most", "at least half" or "all") [50].

$$w_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right) \tag{6}$$

Different linguistic quantifier functions may be obtained by setting a certain degree of orness. For example, $Q(r) = r^{\alpha}$ [50].

To summarize, the algorithm proposed in this paper is the following:

**Algorithm 2** TIS calculation

***Inputs: concept c, user profile ontology $\theta$, int n, OWA weights vector w***
***Output: score (TIS) for concept c***

1: $R =$ find relatives (t, $\theta$, n) with known TIS
2: sim= calculate weights with semantic distance ($R$, $\theta$)
3: score= $WOWA_{sim,w}$ ($R$)
4: return score

**Example:** Let us consider that Mr. Smith has the user profile shown in Fig. 2. We want to calculate the new TIS for the concept "Canoeing", which is unknown at the moment. We will use the information of the neighbor concepts following Algorithm 2, as explained. First, the aggregation policy of OWA must be chosen. In this example, a conjunctive model with small orness will be used, so we take $\alpha = 0.25$. The weights $w_k$ will be assigned later, depending on the number of relatives found in the ontology. In Step 1, we use the method Find Relatives (Alg. 1) and we get 5 relatives (grey area in Fig. 2): R = {Kayaking (TIS=0.8), Fishing (TIS=0.7), Boating (TIS=0.9), Riverboarding (TIS=0.7) and Rafting (TIS=0.4)}. As we now know that there will be 5 input arguments, we can establish the OWA weights:

$$w = (0.0, 0.0, 0.33, 0.33, 0.33)$$

In Step 2, we calculate the weight of each concept using path length as the distance with respect to "Canoeing". These distances are the following: Kayaking *dsem*=2, Boating *dsem*=3, Fishing *dsem*=3, Riverboarding *dsem*=4, Rafting *dsem*=4. Notice that Kayaking is a brother concept (smallest distance), while Riverboarding and Rafting are the less similar. The largest distance in this case is 4. Thus, using Eq. 5 we get $\Omega = 1/2 + 2/3 + 2/4 = 1.66$ and

$$p = (0.3, 0.2, 0.2, 0.15, 0.15).$$

In Step 3, the relatives are ordered in a descending way depending on their TIS. The three with less TIS will be used for the estimation of the interest on Canoeing, all of them with the same contribution according to $w$. Their weights on the final calculation depend on the semantic distance, being Rafting and Riverboarding less influent than Fishing. The WOWA operator can be applied with these input values:

$$WOWA_{(0.3,0.2,0.2,0.15,0.15),(0.0,0.0,0.33,0.33,0.33)}(0.8, 0.7, 0.9, 0.7, 0.4) = 0.61$$

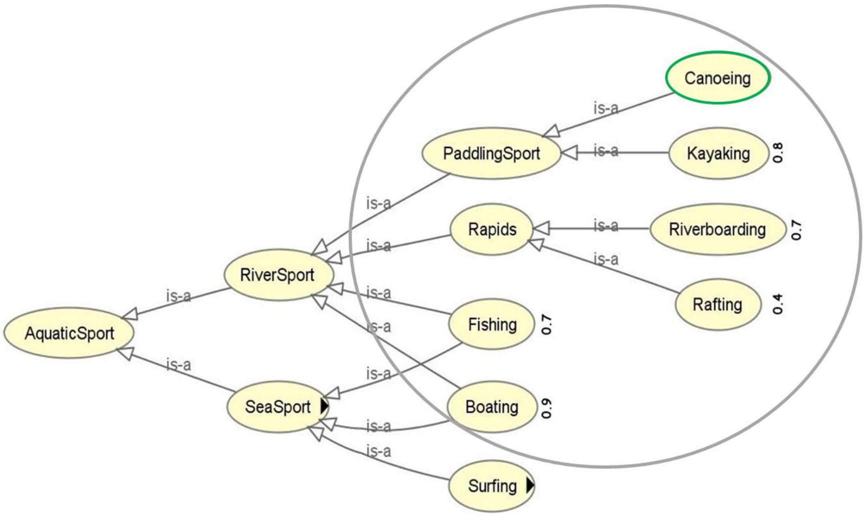


**Fig. 2** Set of relatives and TIS used for the calculation of the new tag interest score for Canoeing.

## 4 Experiments

To make the experiments we consider the case of a recommender system of touristic activities. In fact, the authors participate in the development of the Go-Tour Web recommendation system for people visiting the province of Tarragona, located in the region of Catalonia (north-east Spain). The system includes different types of cultural and leisure activities that can be done in this region. The activities are properly classified and labelled according to a specific ontology. Go-Tour takes into account many different kinds of data: demographic information, travel motivations, the actions of the user on the system, the ratings provided by the user, the opinions of users with similar demographic characteristics or similar tastes, etc. [31].

In order to validate the method for inferring missing scores that were not provided by the user explicitly, an experimentation procedure has been defined to perform multiple tests with different configurations. Several user profiles have been manually defined in order to deal with different situations, so they do not correspond to real people. The testing procedure is as follows:

1. Take a predefined user profile ontology that has a TIS for all the leaf concepts.
2. Remove a percentage of the TIS values randomly to simulate that the user has not entered some of the interest scores. These will be the missing values to estimate.
3. Use the estimation method based on WOWA to assign a TIS to each of the leafs without preference value.
4. Compare the original TIS with the calculated TIS.
5. Repeat steps 2-4 a certain number of times and calculate the average error.

Different parameters are used in this procedure. The repetition of the tests several times with different subsets of missing scores enables the calculation of a better quality indicator. The following subsections describe the experimental setting and the data used for the validation of the proposed method.

### 4.1 Experimental setting

The data used in the tests corresponds to people that is going to visit a touristic place in their holidays. Two ontologies that describe different types of activities (Leisure and Sports) have been used. It is worth noting that the ontology-based user profiles have a different ratio between the number of concepts that the user considers interesting (*likes*) and the number of concepts that the tourist is not interested in (*dislikes*). Some profiles correspond to tourists that are interested in a large variety of activities, while others search for a very specific type of touristic attractions. This will enable us to study the behavior of the proposed method to estimate the missing scores in different situations. After presenting the ontologies and profiles, the parameters used in the automatic testing procedure are given.

**Ontologies and user profiles**

- Leisure Ontology: it distinguishes 3 classes in the most general level: City Activities (Day Life and Night Life activities), Relaxation (Beach Activities, Spa and Wellness activities) and Amusement Parks (Natural Parks and Theme Parks). This ontology has 40 concepts and 18 intermediate concepts. Its maximum depth is 6 and the average branching factor is between 2 and 3.
  - Leisure Ontology - General Profile (L1): likes = 27, neutral = 4, dislikes = 9. This user prefers relaxation activities, especially beach walking, beach picnic, body care, massages, yoga, whirlpool bath and jacuzzi. He also likes amusement parks and day life city activities like sightseeing, gastronomy fairs and craft market. On the other hand, he dislikes music activities like concerts or discos, as well as game-related activities.
  - Leisure Ontology - Specific Profile (L2): likes = 9, neutral = 4, dislikes= 27. This case corresponds to a family with children that makes a visit for a weekend. This family is looking for amusement parks (water park, aquarium or jungle trek), and they also are interested on beach activities. This family does not want to do gastronomy-related activities, relaxation activities, botanical activities or shopping.
  - Leisure Ontology - Balanced Profile (L3): likes = 20, neutral = 3, dislikes = 17. This user has a similar number of likes and dislikes. The most preferred activities are sightseeing, craft market, gastronomy routes, typical food or national park visits. He is not interested in jungle trek parks, water parks, and relaxation or care activities.

- Sport Ontology: it divides sports in 3 main classes: Land Sports (sports in the forest, on the mountain, motor sports and shooting activities), Air Sports (gliding, parachuting and balloon activities), and Aquatic Sports (sea sports and river sports). This ontology has 60 concepts and 29 intermediate concepts. Its maximum depth is 7 and the average branching factor is between 3 and 4.
  - Sport Ontology - General Profile (S1): likes = 40, neutral = 3, dislikes = 15. This tourist is a sportive man who is eager to practice most kinds of sports. He only dislikes exploring and camping activities, archery and fishing.

  - Sport Ontology - Specific Profile (S2): likes = 15, neutral = 3, dislikes = 40. This user prefers mountaineering and river activities like trekking, wall climbing, rafting or canoeing. In his trip, he wants to avoid biking, picnic, horse riding and motor activities, among others.

**Parameters used in the test**

To run the experiments the following values have been used for the different parameters:

- Percentage of missing values: from 5% to 50%, in steps of 5%.
- Minimum number of relatives: 2, 4, 6 and 8.
- OWA aggregation policy with a divergence of 0.025 (which corresponds to the use of approximately half of the values) and with two degrees of orness:
  - Pessimistic aggregation with $\alpha = 0.2$ (conjunctive).
  - Optimistic aggregation with $\alpha = 0.8$ (disjunctive).
- Number of repetitions = 20 times.

## 4.2 Validation index

The quality of the new interest scores is measured as the *root-mean-square error* (RMSE) between the predicted scores and the original ones. As tags without score are selected randomly, each test has been repeated 20 times and the average and deviation of the RMSE have been calculated.

RMSE is a common validation index to measure the differences between the observed population values, $\hat{y}_i$, and the values predicted by a model, $y_i$. These individual differences are called residuals when the calculations are performed over the data set that was used for estimation, and they are called prediction errors when computed on new data (which is our case).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

## 4.3 Results

In this section, the obtained results are shown separately for each user profile. In particular, we focus on identifying the best number of relatives to use in pessimistic and optimistic aggregation policies. It is also interesting to know if the number of missing scores has any influence on the number of relatives needed for the estimation. After analyzing each user profile, we try to identify common guidelines that could be used to decide when to use the optimistic or the pessimistic approach, as well as the number of relatives to consider.

### *4.3.1 Analysis of the RMSE in different user profiles*

For each profile, two figures are presented: on the left, the RMSE obtained with the optimistic policy, and on the right, the RMSE with the pessimistic policy. The horizontal axis shows the different proportions of missing values studied, from a case where the profile is almost complete (only 5% missing scores) to a profile with just half of the possible interest scores available (50% missing TIS).

**Profile Leisure Ontology - General Profile (L1)**

In this first test, results are quite different for the optimistic and pessimistic types of aggregation. In the optimistic case, we can see that the best result (lowest RMSE) is obtained with 8 concepts, except when the number of missing scores is below 10%, where it is sufficient to use 2 or 4 concepts. This is probably because the ontology is full of TIS and, hence, we have good knowledge of the user's preferences and we do not need many additional evidence to predict a correct value for the missing scores. On the contrary, when using a pessimistic or conjunctive aggregation operator, we need a majority of concepts in agreement in order to assign a high score, therefore it is more probable to predict low scores, which is not appropriate for this tourist, because he is interested in many different types of activities. Consequently, in this case, it is better to use only 2 relatives for the conjunctive aggregation. Furthermore, we can see the error is lower in the optimistic setting (under 0.3 in most cases) while it is above 0.31 in most of the cases of the pessimistic approach, even with 2 relatives. Variance is similar for the different percentages of missing scores, but it is a bit larger for the pessimistic case.

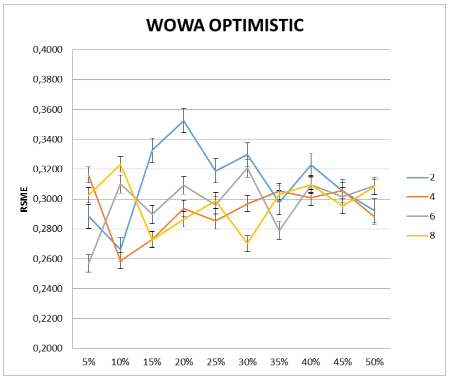


**Fig. 3** RMSE with an optimistic WOWA in profile L1

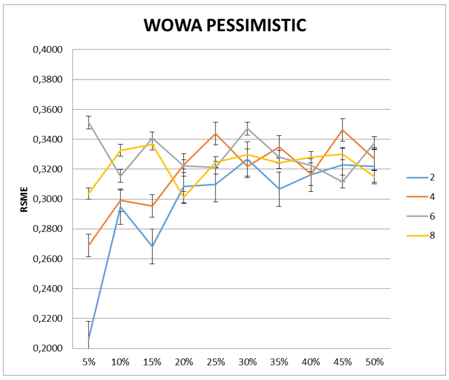


**Fig. 4** RMSE with a pessimistic WOWA in profile L1

**Profile Leisure Ontology- Specific Profile (L2)**

In this case the user has a small number of preferred activities. The worst error in the optimistic case (Figure 5) ranges from 0.27 to 0.29 and it is generally obtained with 2 concepts. It can be observed that, in this case, it is better to use 6 or 8 relatives in the optimistic approach. On the other figure (Figure 6) the conclusions are a bit different. It corresponds to the pessimistic (i.e. conjunctive) approach, where the minimum error is obtained with 2 or 4 neighbors (with a very small difference). In this case, 8 relatives give the worst RMSE. These results are similar to those obtained with user L1, in spite of the differences in the balance between likes and dislikes in L1 and L2.

Regarding the best RMSE levels, we can see that the minimum error is around 0.24 in both cases (optimistic and pessimistic). In Figure 6, the error changes depending on the amount of scores available in the user profile ontology. When the knowledge is large (5-20% of missing data values), the error is smaller than in the situations where the ontology has less information (above 25% of missing values). However, in the optimistic case, this difference is not appreciated. It can be seen that in the pessimistic case the error variance is larger than in the optimistic case, in which it is more stable.

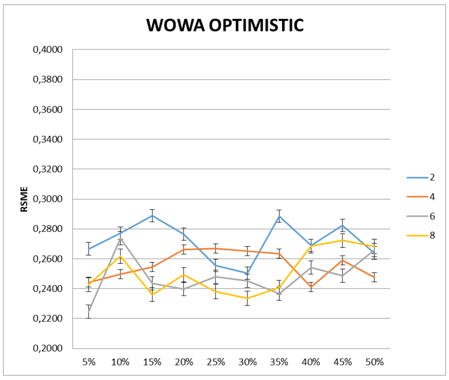


**Fig. 5** RMSE with an optimistic WOWA in profile L2

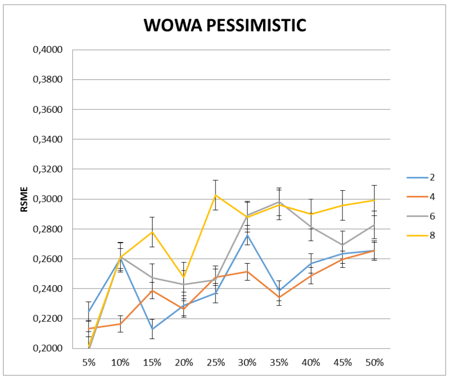


**Fig. 6** RMSE with a pessimistic WOWA in profile L2

**Profile Leisure Ontology- Balanced Profile (L3)**

In the Leisure ontology we tested a third type of user. In this user profile, L3, half of the tags are positively scored and the other half are negatively scored.

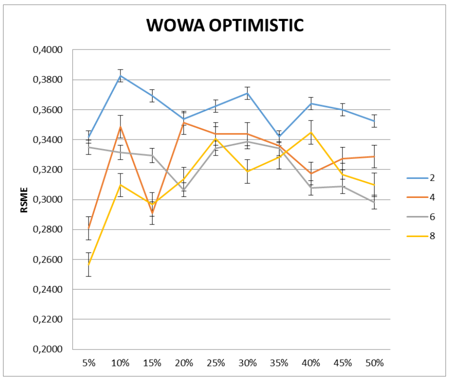


**Fig. 7** RMSE with an optimistic WOWA in profile L3

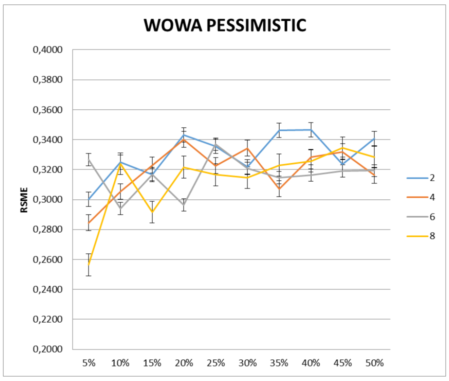


**Fig. 8** RMSE with a pessimistic WOWA in profile L3

In Figures 7 and 8 we can see that both versions (pessimistic and optimistic) get the best RMSE with 6 and 8 tags, with the best values between 0.30 and 0.32. In both cases, when the number of missing scores is large (above 40%), the results with 6 neighbors are a little bit better, although the difference is small. When 2 neighbors are considered the error is larger in the optimistic aggregation. This is not the case for 6 or 8 relatives. In both cases the RMSE is around 0.32.

**Profile Sport Ontology-General Profile (S1)**

This profile corresponds to the Sport semantic criterion, which has a different ontology, as described above. The first test with the Sport ontology corresponds to a tourist that is very keen on doing different types of sports.

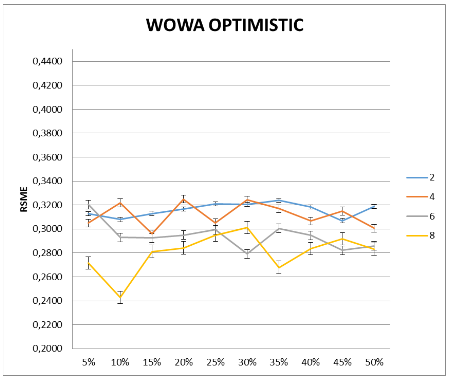


**Fig. 9** RMSE with an optimistic WOWA in profile S1

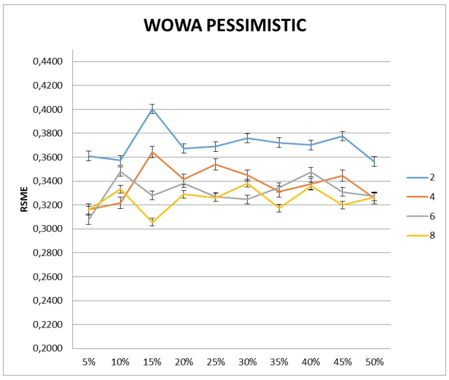


**Fig. 10** RMSE with a pessimistic WOWA in profile S1

The distribution of the taxonomical relations in the Sport ontology leads to different RMSE values. In Figure 9 and Figure 10 we can observe more stable and differentiated RMSE lines for each different number of relatives. Using only 2 values is the worst option, while using 8 is generally the best. In this case, with a user with a large number of concepts with high interest (TIS>0.5), we can see that the optimistic approach leads to a lower error, oscillating between 0.27 and 0.32. The conjunctive approach, which is more conservative, obtains errors between 0.31 and 0.40, clearly higher than the optimistic one.

**Profile Sport Ontology- Specific Profile (S2)**

The RMSE graphical lines are again quite stable, showing more clearly the difference in the error depending on the number of neighbors used for the prediction of the missing value. This is clearer in the optimistic approach (Figure 11) than in the pessimistic one (Figure 12). With more tags we reduce the error to values between 0.32 and 0.34 using the optimistic aggregation. Taking into account that this profile corresponds to a tourist searching for specific sports (likes=15), the error made with a conjunctive approach is smaller (with RMSE close to 0.3). In this pessimistic case, when the amount of missing data is large (above 30%), it is better to use 4 or 6 neighbors rather than 8, because they will be widespread in the ontology and they will be related to very different kinds of sports.

After this study of the five user profiles, four main conclusions are drawn:

- When the user is searching for specific tags, WOWA should use a pessimistic policy.
- In the pessimistic model, the number of relatives should be low when the percentage of missing scores is above 35% (to perform a local focused search).

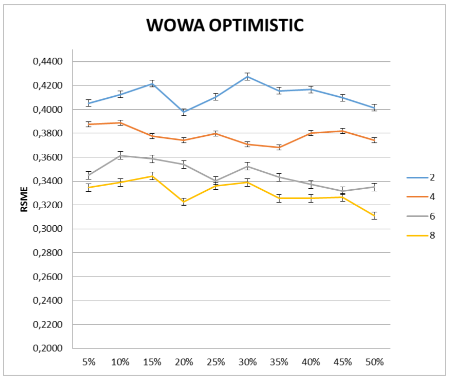


**Fig. 11** RMSE with an optimistic WOWA in profile S2

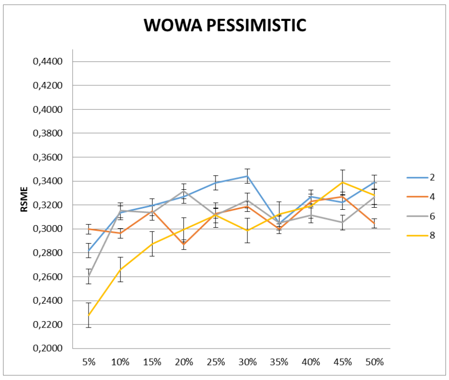


**Fig. 12** RMSE with a pessimistic WOWA in profile S2

In the case of a quite complete profile, we can increase the number of relatives to be used in order to improve the prediction.

- When the user has a profile with more likes than dislikes, WOWA should be optimistic and the use of more relatives is recommended (i.e. aggregate the information of 8 related concepts).
- The error may be different depending on the amount of missing scores in the user profile ontology. It is appreciated a difference between profiles with more or less than 20% of concepts without known TIS.

*4.3.2 Analysis of the number of concepts used for the calculation of a tag interest score*

In order to study in more detail the influence of the concepts used for the calculation of the unknown scores we have analyzed the number of relatives used in each calculation. The following bar charts show the averaged percentage of times that a certain number of relatives has been used during the 20 tests. Figures 13, 14, 15 correspond to the tests with the Leisure ontology and Figures 16, 17, 18 to the ones with the Sport ontology. Each figure displays the bar chart of 3 situations (with 10%, 30% and 50% of missing data). Each bar corresponds to the given number of minimum relatives to retrieve: 2, 4, 6, and 8.

We can observe that, even though a minimum of tags to use has been fixed, depending on the distribution of the TIS in the ontology the algorithm needs to go upwards in the taxonomy and consider sometimes many different branches. Therefore, the actual number of known scores may be larger than the minimum required.

Figures 13, 14, 15 show the histograms in percentages of the 3 different situations, from the best case (when we know most of the user's preferences) to the worst (with just half of the information). Analyzing the 3 situations, the following facts can be observed:

- 10% of missing data: indicates a situation with a lot of known information about the user (number of TIS available is high = 35). In this graphic, we can see that when fixing 2 or 4 neighbors, there is a high percentage of times that less than 5 concepts are used. When 6 or 8 concepts are the minimum, the distribution is quite stable until 14 concepts. It is worth noting that the whole set of available concepts (i.e. 35) is used in 20% of the WOWA calculations when we set a minimum of 8 neighbors. This situation corresponds to the case where the algorithm has to search in the whole ontology.

- 30% of missing data: indicates a situation in which we have 1 unknown preference for each 2 known TIS. In this case, the maximum number of available scores is 27 (see horizontal axis in the central graphic). 25% of the times in which 8 relatives were needed required the use of the whole set of tags. Again, fixing a lower number of relatives is directly related to using less concepts, especially for the cases of 2 and 4. We observe a gap between 14 and 27 concepts, which is directly related to the number of children of the root of the ontology.
- 50% of missing data: it is the worst case, corresponding to initial stages of the recommendation process, when the user has only introduced half of the tag interest scores (low number of TIS available). In this case, the proportion of used data is significantly higher in the last bar (when using all the 19 tags), especially with 8 neighbors, but also with 6.

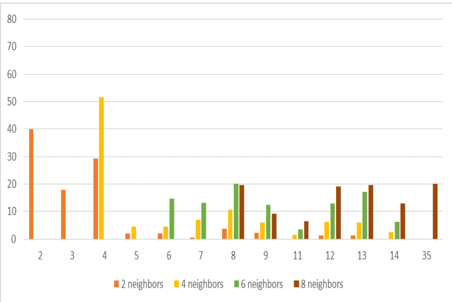


**Fig. 13** Missing values: 10% of 40=4 and TIS available: 35

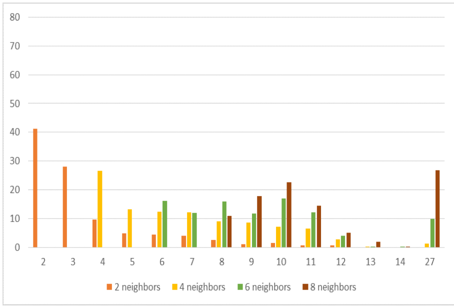


**Fig. 14** Missing values 30% of 40 = 12 and TIS available: 27

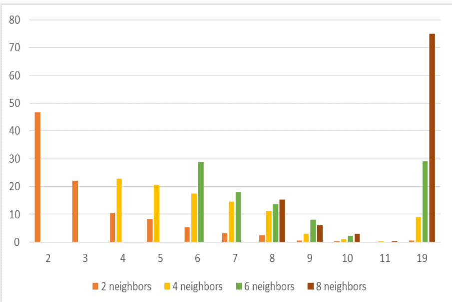


**Fig. 15** Missing values 50% of 40 = 20 and TIS available: 19

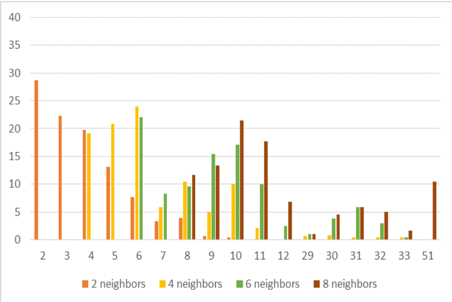


**Fig. 16** Missing values: 10% of 60 =6 and Tags available: 51

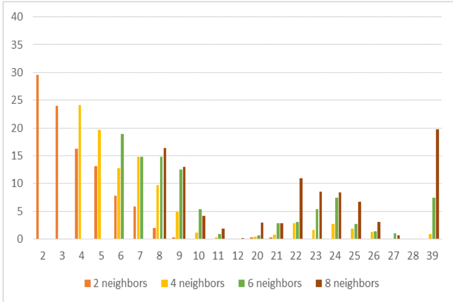


**Fig. 17** Missing values 30% of 60 = 18 and Tags available: 39

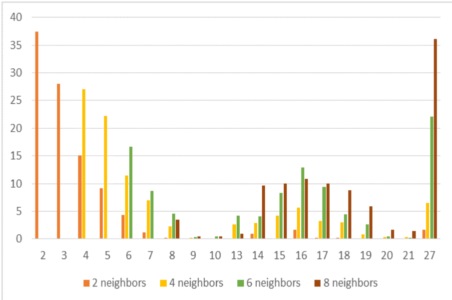


**Fig. 18** Missing values 50% of 60 = 30 and Tags available: 27

Likewise, in the case of the sports activities we also want to know the percentage of tags used in the three different situations (Figures 16, 17 and 18). The observations are analogous to the case of the Leisure ontology:

- 10% of unknown values: when the number of TIS available is high (51), we observe that the proportion of the concepts used when fixing 6 and 8 neighbors is similar, where the actual number of tags used is usually between 8 and 11 concepts. The whole set is only used 10% of times when 8 relatives are required.
- 30% of unknown values: indicates a situation in which we have 1 unknown preference for each 2 known TIS, as before. In this case, the bars are higher on the left of the graphic (low number of used tags). They decrease until 12 tags and then increase again to 22-25. A second gap without bars happens between 28 and 39. This is again related to the number of steps upwards that the algorithm must do until it finds the required number of concepts. The two first levels of the ontology have a great influence in these numbers because they form subgroups of related concepts.
- 50% of unknown values: it is the worst case, corresponding to initial stages of the recommendation process. In this graphic we note a large percentage of cases concentrated in the first bars. The distribution of the concepts in the different semantic subgroups modelled in the ontology makes that certain number of tags are not found (9-10 and 20-26) in this case.

### 4.4 Comparison with related works

Table 1 showed a list of 20 methods that deal with user profiles stored in ontologies. In order to compare the proposed WOWA-based method with the previous ones, we studied the characteristics of all the methods and selected the only three methods that work in the same conditions than our work: the user introduces a first subset of numerical scores on some of the most specific concepts and no other sources of knowledge are used, nor any other user interaction is considered. The selected methods are labelled as M1 [41], M2 [9] and M3 [38]. In all of them there is some kind of spreading (through an ontological structure) of a subset of initial preference scores given by the user.

In the work of [41] a weighted average is also used to estimate a missing score (M1). A set of close concepts is taken from the ontology. The weights considered in the averaging procedure are said to be based on the number of items under each concept, but, as no more details are given, they are not replicable. Therefore, we will use the same weights proposed in Eq. 5. The score of a concept is calculated from the scores of similar concepts.

Method M2 [9] also proposes a similar averaging procedure based on a set of weights that are interpreted as the probability that one concept is relevant to estimate the score of the other. The authors only indicate that the definition of the weights is critical and very hard to decide. In their experiments, weights were empirically fixed. The new score is obtained with a spreading activation mechanism over the semantic network. We have replicated this spreading activation to the leaves that do not have any score. The weight of the connection between concepts has been calculated as proposed in Eq. 5 in order to compare the effect of the activation process. Concepts with a missing score are set to zero, and then they are activated by performing an aggregation of the scores of the neighbor concepts. These concepts are ordered decreasingly by its interest score in vector $X$. Then, the following equation is used:

$$score(c_j) = score(c_j) + (1 - score(c_j) * w_i * score(x_i)) \ , \ for \ all \ x_i \in X \tag{8}$$

The initialization method M3 [38] consists in calculating a weighted average of the interest scores of the neighbor concepts using as weight a semantic similarity measure based on finding the Least Common Subsummer (LCA) and the distance of each neighbor ($c$ and $d$) to the LCA (Eq. 9).

$$dsim(c, d) = \rho * \frac{|ancestors(LCA(c, d))|}{|ancestors(c)|} + (1 - \rho) * \frac{|ancestors(LCA(c, d))|}{|ancestors(d)|} \tag{9}$$

In order to make these three methods comparable to the one proposed in this paper, we consider the same set of neighbors in all the cases. Neighbors are found as proposed before in Algorithm 1. Therefore, what we change is the way of aggregating the contribution of each of those similar concepts. We will use the ontology of Sports and the two user profiles S1 (general) and S2 (specific). As the best performance is obtained with 6 and 8 neighbors, we have fixed the number of neighbors to 7 for all the methods.

In Figure 4.4 we can see the performance of the 3 methods found in the literature and the new WOWA-based one. An optimistic WOWA was chosen for the most general profile (S1), whereas the pessimistic one was applied in the case of the specific profile S2, as they have been previously shown to be the most appropriate for each case. It can be seen that WOWA outperforms methods M1 and M2 in almost all the cases. The exception of M1 in S1 with 45% of missing values may be due to the randomness in the selection of the tags in the tests. Method M3 gives a performance comparable to WOWA in the S1 profile, being sometimes 0.02 points better or worse in RMSE. However, in profile S2, despite the fluctuations of the WOWA method, it is always the best one. We can notice that, in the case of profiles with more than 45% of missing information, WOWA is outperformed by M3 in both cases.

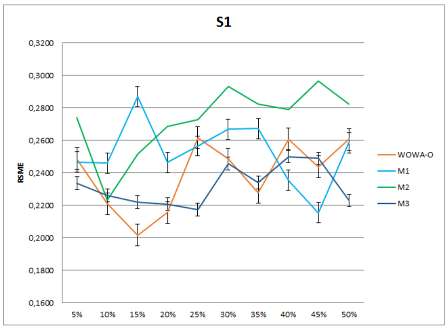


**Fig. 19** Comparison of RMSE in profile S1

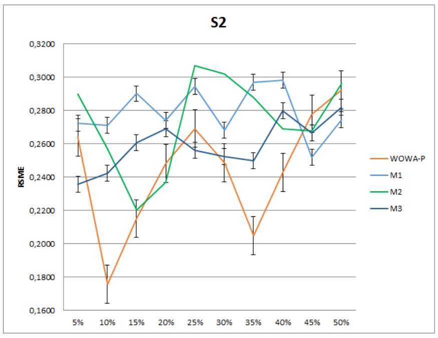


**Fig. 20** Comparison of RMSE in profile S2

## 5 Conclusion

In this paper, the initialization of semantic user profiles has been studied. The paper proposes the use of ontologies to represent the preferences of the user by means of a numerical indicator denoted as tag interest score (TIS) associated to the set of leaves of the ontology. The main contribution of the paper is the formalization of a method for estimating the interest score of a concept using information of other TIS available in the ontology. The proposed procedure is based on the WOWA aggregation operator that enables the modeling of the aggregation using two sets of weights. By means of a semantic similarity measure, the importance of the concepts whose preferences are known is introduced to guide the aggregation. This is a novel procedure to automatically adjust the weights depending on the concept studied in each case, exploiting the structure of the ontology, where multiple inheritance is possible.

In order to validate the method for inferring missing scores, two ontologies and several profiles have been defined. The testing domain is the recommendation of touristic activities, in the frame of the research projects of the authors. In particular, sport and leisure types of activities have been considered. Two types of users were defined: users that have multiple interests in many concepts and other users that are focused on specific types of touristic activities. A first study showed that the parameters of the WOWA operator must be appropriately defined according to these two differentiated types of users. It was also observed that it is generally recommended to use more information from related concepts, rather than just to focus on a specific neighborhood. However, the second study shows that when the knowledge about the user preferences is small, this may be problematic because many predictions will be done using all the scores of the ontology, which will lead to the same prediction for quite different concepts. The advantage of WOWA with respect to other methods in the literature is the ability of using the information provided by the neighbors in different ways so that it can be more optimistic or pessimistic in the predictions, while other approaches apply some kind of weighted average. Knowing the user's personality towards the recommended items, we can then adjust the WOWA parameters to better estimate the unknown preference scores.

Future work will consist on the integration of this procedure for completing the information of the user profile into a recommender system of touristic activities in the region of Tarragona, Spain. The recommendation procedure will be done using a multiple criteria decision aiding method called ELECTRE-SEM, which is able to exploit the information of the ontologies and TIS to make a ranking of a set of touristic attractions. The possibility of using other application fields is also open for consideration.

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