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Integrating Ontologies and Fuzzy Logic to Represent User-Trustworthiness in Recommender Systems

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Abstract

Recommender systems can be used to assist users in the process of accessing to relevant information. In the literature we can find sundry approaches for generating personalized recommendations and all of them make use of different users' and/or items' features. Building accurate profiles plays an essential role in this context, so that the system's success depend to a large extent on the ability of the learned profiles to represent the user's preferences. An ontology works very well to characterize the users profiles. In this paper we develop an ontology to characterize the trust between users using the fuzzy linguistic modelling, this way in the recommendation generation process we do not take into account users with similar ratings history but users in which each user can trust. We present our ontology and provide a method to aggregate the trust information captured in the trust-ontology and to update the user profiles based on the feedback.

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1. Introduction

Recommender systems seek to discover information items (movies, music, books, news, images, web pages, papers and so on) that are valuable to the user. Recommender systems may be considered personalized services because they have an independent profile for each user taking into account the particularities of each of them. These kinds of systems are becoming popular tools for reducing information overload and to improve the conversion rate in e-commerce web sites [1, 2]. The delivery of personalized recommendations, requires the system to have some information available about every user, such as the ratings provided by the users about the viewed or purchased items. Another aspect to take into consideration is which additional information is required by the system, and how this information is processed and managed to generate a list of personalized recommendations. One of the most used methods to generate recommendations is the collaborative approach [1] in which the recommendations to a particular user are based upon other users' recommendations with similar profiles, taking into account the ratings provided by those users.

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One key disadvantage of this approach consists of the need for a lot of ratings to obtain a good performance, which is usually difficult to achieve because users typically provide just a few ratings. Therefore, collaborative approaches tend to fail because they have difficulties to compute the similarity between two users. Thus, some improvements need to be introduced to overcome this situation and one promising direction is to focus on *trust*, which plays a crucial role in on-line social networks [3], extremely widespread and popular today. Trust networks are social networks in which users can assign trust scores to each other. In the literature, we can find some proposals about the incorporation of trust models in recommender systems [4, 5]. In these systems, the recommendation engine uses in one way or another the trusted network between users. Then, a key aspect to obtain good results is precisely storing the trusted network. For that reason, and because of the success they have demonstrated in similar scenarios, we propose to use ontologies as an efficient way to represent and exploit the information, especially trusted network.

Ontologies are very suitable to model different aspect of the world we live in. In the last decade, ontologies have been increasingly used within the field of recommender systems [6, 7]. In the collaborative approach, domain ontologies are mainly used to analyse the user behaviour according to this knowledge structure, building user profiles. There are even proposals including fuzzy logic in the ontological representations to allow for some uncertainty in them [8, 9, 10, 11]. In the same way that fuzzy ontologies have been used to represent user profiles, we consider them suitable for modelling the trust between users, extracted from a trusted network.

Our proposal relies on a combination of these approaches to improve the recommendation process, namely trust networks along with trust propagation mechanisms, and user profiles based on ontologies. Our proposal is therefore, a new recommender system whose main novelties are:

- We define an ontology that represents the degree of trust between users based on the evaluations provided according to their experiences. To keep the maximum flexibility to manage the information, we incorporate a multi-granular fuzzy linguistic modelling method [12, 13]. It allows the representation of the different concepts of the system with different linguistic label sets.
- We use a domain ontology to establish the relationships between users and their preferences about the recommendation subject.
- We present a method to estimate the trust score between two users, because the trusted network can be huge and most users do not know each other.
- We propose a new recommendation approach in which the recommendations are taken from trustworthy users, i.e., we do not consider users with similar ratings history but users in which each user can trust.

The paper is structured as follows. In Section 2, the preliminaries are presented. Next in Section 3, we describe our proposal, including the evaluation of the system. Finally, some concluding remarks and future works are pointed out in Section 5.

2. Preliminaries

2.1. Recommender systems

Recommender systems try to guide the user in a personalized way towards suitable tasks among a wide range of possible options [1, 2]. Personalized recommendations rely on knowing users' characteristics, which might be tastes, preferences about items as well as the ratings of previously explored items. The system has to maintain users' profiles updated in order to provide good recommendations, the way of acquiring this information may vary from implicit information, that is, analyzing users behavior, or explicit information, where users directly provide their preferences.

On the design of a recommender system an aspect to take into account is the way of generating recommendations. In the literature we can find them mainly pooled in two categories. In the first one authors consider two different approaches: On one side, *Content-based systems* where they generate the recommendations taking into account the characteristics used to represent the items and the ratings that a user has given to them. On the other side, *Collaborative systems* where the system generates recommendations using explicit or implicit preferences from many users, ignoring the items representation. The second one extends the categorization with another three approaches: *Demographic systems*, *Knowledge-based systems* and *Utility-based systems* [1, 14].

Since each approach has certain advantages and disadvantages, depending on the scope settings, the most adopted solution addressed in the literature is the combination of the previous approaches in what is known as an *hybrid recommender system* [14]. The aim of this hybridization is to combine different approaches to reduce the disadvantages of each one and to exploit their benefits.

2.2. Fuzzy linguistic approach

The fuzzy linguistic approach is a tool based on the concept of linguistic variable proposed by Zadeh [15]. This theory has given very good results to model qualitative information and it has been proven to be useful in many problems. We describe the 2-tuple fuzzy linguistic modelling and multi-granular fuzzy linguistic approach used to represent the linguistic information used in the system.

2.2.1. The 2-tuple fuzzy linguistic approach

In order to reduce the loss of information of other methods such as classical or ordinal, in [16] is proposed a continuous model of information representation based on 2-tuple fuzzy linguistic modelling. To define it both the 2-tuple representation model and the 2-tuple computational model to represent and aggregate the linguistic information have to be established.

Let $S = \{s_0, ..., s_g\}$ be a linguistic term set with odd cardinality. We assume that the semantics of labels is given by means of triangular membership functions and consider all terms distributed on a scale on which a total order is defined. In this fuzzy linguistic context, if a symbolic method aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, ..., g\}$, we can represent β as a 2-tuple (s_i, α_i), where s_i represents the linguistic label, and α_i is a numerical value expressing the value of the translation between numerical values and 2-tuple: $\Delta(\beta) = (s_i, \alpha)$ and $\Delta^{-1}(s_i, \alpha) = \beta \in [0, g]$ [16].

In order to establish the computational model negation, comparison and aggregation operators are defined. Using functions Δ and Δ^{-1}, any of the existing aggregation operators can be easily be extended for dealing with linguistic 2-tuples without loss of information [16]. For instance arithmetic mean, weighted average operator or linguistic weighted average operator could be used.

2.2.2. Multi-granular linguistic information approach

A problem modelling the information arises when different experts have different uncertainty degrees on the phenomenon, then several linguistic term sets with a different granularity of uncertainty are necessary. The use of different label sets to assess information is also necessary when an expert has to evaluate different concepts. In such situations, we need tools to manage multi-granular linguistic information [17].

In [17] a multi-granular 2-tuple fuzzy linguistic modelling based on the concept of linguistic hierarchy is proposed. A *Linguistic Hierarchy*, *LH*, is a set of levels $l(t, n(t))$, where each level t is a linguistic term set with different granularity $n(t)$. In [17] a family of transformation functions between labels from different levels was introduced. To establish the computational model we select a level that we use to make the information uniform and thereby we can use the defined operator in the 2-tuple model.This result guarantees that the transformations between levels of a linguistic hierarchy are carried out without loss of information.

2.3. Ontologies

Agarwal [18] states that "an ontology is the manifestation of a shared understanding of a domain that is agreed between a number of agents and such agreement facilitates accurate and effective communications of meaning, which in turn leads to other benefits such as inter-operability, reuse and sharing". This knowledge representation model provide a semantic structure and meaning to the unstructured data of Web [19]. Thanks to their popular use, nowadays we can find many services, methodologies and languages related to ontologies [20], and what is more important, there are many repositories of ontologies available to users [1].

Ontologies have been playing a relevant role in recommender systems. They are being widely used both at content-based and to represent the user profiles because they provide a common vocabulary with terms interrelated

[1] http://www.w3.org/wiki/Ontology_repositories

semantically [21]. There are recommender systems that use ontologies to expand the user interests in the items which are identified in the ontology. In general, most of the developed recommender systems proposals that involve domain ontologies use them to measure the preferences of users to the items of the content [21, 22, 23, 24, 25].

The use of fuzzy ontologies in recommender systems is shaping as an important research topic. A fuzzy ontology can be considered as a set of concepts (classes), relationships and axioms where each relation is measured with an uncertainly degree. We can find some formal definitions of a fuzzy ontology, fuzzy relationships and fuzzy inference process [8]. In this proposal we also deal with fuzzy knowledge in the ontology.

2.4. Trust networks

Trust networks are social networks in which users can explicitly express their level of trust in another users. In the actual information society, they are usually very large and therefore a lot of users don't even know the vast majority of other users. For this reason, we need to use a method to estimate the trust degree between two users. The idea is to search for a path between the two users and propagate the trust degrees found along the path. But usually, we can find several paths between two users, so we may select the most relevant and aggregate the propagated trust degrees into the trust degree estimation. Due to computational complexity and/or in order to eliminate less informative paths or to select the most relevant paths, an upper path length limit is typically imposed. It is called *horizon*, H, and typical values for H are 2 or 3.

To aggregate the propagated trust degrees of the paths found there are serveral alternatives [5]. Some of them are based in Ordered Weighted Average (OWA) operators [26]. To overcome the problems of the majority guided OWA operators, in [27] the authors propose a majority guided induced OWA (IOWA) operator [28]. In this case, the reordering of the set of values to be aggregated isn't induced by themselves (like in OWA operator) but this reordering is induced by means of a variable.

Using this operator in [29] is defined a majority guided linguistic IOWA operator, MLIOWA, that we adopt in our system, because it allows us to work with linguistic information and overcome the previous problem with the majority guided. It is defined according to the following expression:

$$\Phi_Q((u_1, p_1), \ldots, (u_n, p_n)) = s_k \in S \tag{1}$$

$$\text{with } k = round(\textstyle\sum_{i=1}^{n} w_i \cdot ind(p_{\sigma(i)}))$$

such that:

- $(u_{\sigma(i)}, p_{\sigma(i)})$ is the pair with $u_{\sigma(i)}$ the i-th lowest value in the set $u_1, \ldots, u_n$.
- $u_i = sup_i$, where sup_i is the overall support of value p_i, obtained as:

$$sup_i = \sum_{j=1}^{n} sup_{ij} | sup_{ij} = \begin{cases} 1 & if\ |ind(p_i) - ind(p_j)| < \alpha \\ 0 & otherwise \end{cases}$$

  with $\alpha \in \{0, 1, \ldots, \tau\}$ and sup_{ij} a binary support function that expresses the support from p_j for p_i or the similarity between both values.
- $ind(s_i) = i$.
- Q is a linguistic quantifier representing the concept of fuzzy majority in the aggregation. It is used to compute the weighting vector $W = (w_1, \ldots, w_n)$, such that $\forall i \in 1, \ldots, n$, $w_i\ in[0, 1]$, $\sum_{i=1}^{n} = 1$, and:

$$w_i = Q\left(\frac{sup_{\sigma(i)}}{n}\right) \Bigg/ \sum_{j=1}^{n} Q\left(\frac{sup_{\sigma(j)}}{n}\right)$$

  with $Q(sup_{\sigma(i)}/n)$ denoting the degree to which $p_{\sigma(i)}$ represents the majority.

With respect to the variable inducing the reordering of the set of values to be aggregated, the average global trust of all users of each of the founded path is chosen. To compute the global trust of a user we use PageRank [30] because is one of the most widely used global trust metric.

3. Proposal description

In this section we present a recommender systems based on trust and ontologies, designed using a multi-granular linguistic modelling. In order to represent the different concepts to be assesses by the system, we will use different label sets ($S_1, S_2, ...$) selected from a *LH* [17]. The system works with the following concepts:

- *Degree of trust* of a user relative to another, which is labelled in S_1.
- *Membership degree* of item scope with respect to each category used in the domain ontology, which is labelled in S_2.
- Predicted *degree of relevance* of item for an user, which is labelled in S_3.
- *Degree of satisfaction* with a recommended item expressed by an user, which is labelled in S_4.

We propose to use a *LH* composed by the following linguistic terms sets:

- $S^5 = \{b_0 = None = N,\ b_1 = Low = L,\ b_2 = Medium = M,\ b_3 = High = H,\ b_4 = Total = T\}$
- $S^9 = \{c_0 = None = N,\ c_1 = Very\_Low = VL,\ c_2 = Low = L,\ c_3 = More\_Less\_Low = MLL,\ c_4 = Medium = M,\ c_5 = More\_Less\_High = MLH,\ c_6 = High = H,\ c_7 = Very\_High = VH,\ c_8 = Total = T\}$

Level 2 is used to represent the degrees of trust, membership and satisfaction ($S_1 = S^5$, $S_2 = S^5$ and $S_4 = S^5$) and for the predicted relevance degrees we use the level 3 ($S_3 = S^9$).

3.1. Knowledge base representation using ontologies

The system architecture consists of the following elements:

- *On2Trust* is an ontology that holds users in the system according with their degree of trust. This concept is modelled in the ontology as an object property, whose existence represents the reliability relationship between two users. This property has an asymmetric value, because the reliability degree of one user to with respect to another particular user does not imply the opposite meaning. Values of this concept are represented using the level S_1 of the *LH*, i.e., S^5. So, these properties have been called *None_Reliable*, *Low_Reliable*, *Medium_Reliable*, *High_Reliable* and *Total_Reliable*.
- A domain ontology is included in the system to keep the items semantically organized. In this ontology, we represent items as instances of a generic class. The items establish a relationship with the domain ontology using a predefined object property that represents the concept of membership degree, assessed in S_2 (S^5) which is defined in the ontology as *MD_None*, *MD_Low*, *MD_Medium*, *MD_High* and *MD_Total*.
- Database: an ordinary database where the ontologies and data are stored.
- Recommendation engine represents the computing process that classifies information in the ontology and generates recommendations. It is widely described in section 3.2.

Domain and *On2Trust* ontologies are used together to establish the relationship between users and items in order to represent the degree of satisfaction and predicted degree of relevance. The former is explicitly defined by an user and stored in the ontology using these properties: *None_Satisfaction*, *Low_Satisfaction*, *Medium_Satisfaction*, *High_Satisfaction* and *Total_Satisfaction*. The later is refreshed each time the system computes the recommendations, using these properties: *None_Predicted_Relevance*, *Very_Low_Predicted_Relevance*, *Low_Predicted_Relevance*, *More_Less_Low_Predicted_Relevance*, *Medium_Predicted_Relevance*, *More_Less_High_Predicted_Relevance*, *High_Predicted_Relevance*, *Very_High_Predicted_Relevance* and *Total_Predicted_Relevance*.

3.2. Recommendation approach

To generate the recommendations, we do not take into account the users similarities, but the knowledge gained from the ontologies. The users explicitly express trust degrees to other users, and this knowledge is organized in *On2Trust*. However, a large number of users have not supplied the trust degrees to many other users. Therefore, to generate recommendations, we need a method to estimate the trust degree between users. To estimate the level in which a user u trust in other user v, $\tau_{u,v}$, we aggregate the propagated trust degrees by all paths found, applying the MLIOWA operator in this manner (see Section 2.4):

$$\tau_{u,v} = \Phi_Q((AT_1^{u,v}, t_1^{u,v}), ..., (AT_n^{u,v}, t_n^{u,v})) \tag{2}$$

where $AT_i^{u,v}$ is the average global trust of all users found in the path i between u and v, $t_i^{u,v}$ is the propagated trust in that path between the two users and according to the majority represented by the fuzzy linguistic quantifier Q. To apply this operator we follow the configuration established in [29], i.e., we assume that the linguistic quantifier $Q_1 = most_of$ defined by the parameters (0.3, 0.8) and $\alpha = 1$. In that paper a working example is available. The values of trust are explicitly supplied by the users or estimated with the described procedure. So, if we wish to estimate (if no evaluation is stored yet) or upgrade the relevance of a item i for a user u:

1. Identify the set of trusted users of u, Γ_u. To do that, we estimate the trust between u and all other users (see equation 2) taking into account the selected horizon, i.e. $\tau_{u,v}$ $\forall v \in \Upsilon$ with $v \neq u$ and Υ the set of users. As $S_1 = S^5$, we consider that the user v is a trusted user of u if $\tau_{u,v} > (s_2^5, 0)$, i.e., if the linguistic similarity degree is higher than the mid linguistic label.
2. To recovery the assessments provided by the trusted users of u over the item i, i.e., the linguistic satisfaction assessments $sat(y, i) \in S_4$, $\forall y \in \Gamma_u$.
3. The item i is recommended to u with a predicted relevance degree $p_{rel}(u, i) \in S_3 \times [-0.5, 0.5]$ which is calculated as follows:

$$p_{rel}(u, i) = \overline{x}_l^w((TF_{S_4}^{S_5}(sat(y_1, i), 0), TF_{S_4}^{S_1}(\tau_{u,y_1})), \ldots, (TF_{S_4}^{S_5}(sat(y_n, i), 0), TF_{S_4}^{S_1}(\tau_{u,y_n}))), \tag{3}$$

where $y_1, \ldots, y_n \in \Gamma_u$, $\overline{x}_l^w$ is the linguistic weighted average operator [17] and $TF_{t'}^t$ is the transformation function between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ [17].

Finally, when users have received the recommended items, they are asked to assess the relevance of these recommendations in order to update their profiles. Users communicate their linguistic evaluation judgements to the system, $rc \in S_4$, indicating their satisfaction with the recommendations (higher values of rc = greater satisfaction). This information is updated in the ontology to be taken into account in future recommendations.

4. Experiments and evaluation of the system

To perform these experiments we have used a variation of the Epinions dataset [2] [4]. The Epinions dataset was collected by Paolo Massa in a 5-week crawl (November/December 2003) from the Epinions.com Web site. The dataset contains the following information: 49290 users who rated a total of 139738 different items at least once, writing 664824 reviews; the total number of issued trust statements is 487181. Users and items are represented by anonymized numeric identifiers. We have used the ratings data and trust data files. The former has the following format <*userID itemID ratingValue*>. The second has the format <*sourceUserID targetUserID trustStatementValue*>. Due to performance reasons, we have slightly modified the original dataset. We've taken a reduced Epinion dataset containing a sample of the first 1000 users and 2000 items. The ratings subset for this reduced subset still contains 7841 ratings and 52548 trust statement values. The modified data set is loaded into the ontology to enable the experimentation according to the proposed approach.

4.1. Experiments description

To develop the experiments we implemented the approach proposed in this paper, considering $H = 2$, $H = 3$ and $H = 4$ (called *Trust-H2*, *Trust-H3* and *Trust-H4*). In order to compare the results with other techniques, we have implemented *item-based* and *user-based* collaborative approaches [1] (without use *On2Trust*) with different configurations. We've also analysed the impact of having a different number of neighbours on the similarity computation, achieved by using different values for the variable K, which represents the most similar k-users. In addition, we combined these values with two different similarity metrics, such as *Cosine* and *Pearson*. We name

[2] `http://www.trustlet.org/wiki/Epinions`

Col-It- or *Col-Us-* the algorithms *item* and *user* based respectively; likewise we added to the algorithm name the suffixes Cs or Ps for Cosine or Pearson metrics; the last suffix corresponds to the number of neighbours ($K10$, $K20$ or $K50$). It might well be considered that these approaches have a linear complexity.

We carried out a *5-fold cross validation process* in which the data set is divided into a training set with 80% of the data and a validation set with the additional 20%. Thus, we first performed the analysis on the training set and then we tested against the validation set. In order to minimize the bias introduce by the way of choosing these training and validation subsets, the process is performed 5 times but with different partitions.

To measure the accuracy, we adopted the *Mean Absolute Error (MAE)*, whose purpose is to quantify the degree of accuracy for the predictions generated by the recommender system vs. the real value created by the users. On the other hand, we also analysed the *coverage* achieved with each approach [31], i.e. the proportion of ratings of the validation set the system can generate a prediction for.

To complete our experiments, we studied the performance and coverage of different configurations on different portions of the input data, classifying users and items into different types [4]. The users are classified in these types: *cold start users* who provided from 1 to 4 ratings, *heavy raters* who provided more than 10 ratings, *opinionated users* who provided more than 4 ratings and whose standard deviation is greater than 1.5, *black sheep users* who provided more than 4 ratings and for which the average distance of their rating on corresponding item with respect to mean rating of the item is greater than 1. The items are classified in: *niche items* which received less than 5 ratings and *controversial items* which received ratings whose standard deviation is greater than 1.5.

4.2. Experiments results

In this section we describe the results of the set of experiments we carried out. Figure 1 shows the MAE and coverage for cosine/Pearson similarity measure for item-based and users-based collaborative approaches for the different user groups. The MAE obtained is similar for all combinations (except for small differences), but the coverage is better with the user-based collaborative approach. In both cases, the higher the number of neighbours, the better the results, especially in coverage.

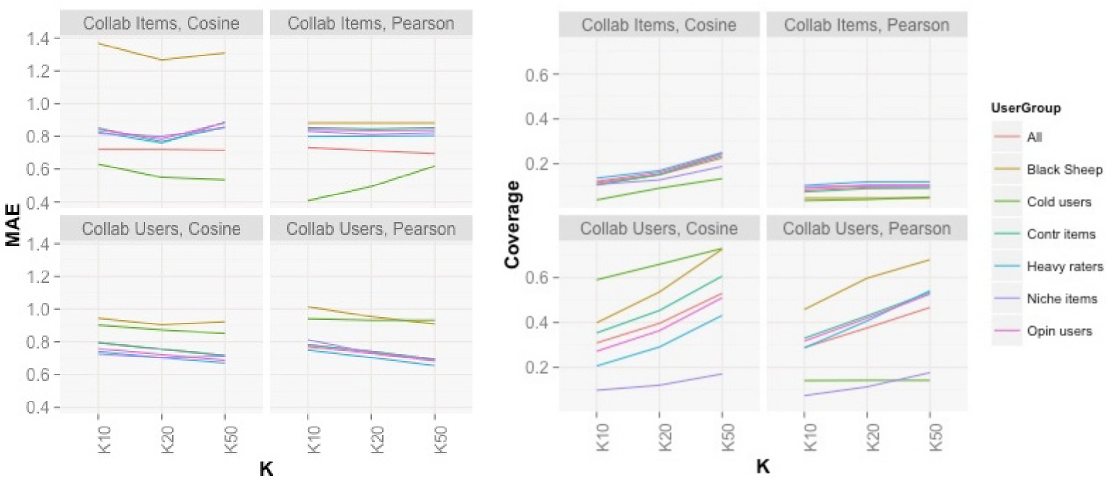

Fig. 1. MAE and Coverage obtained with differents configurations of collaborative approach.

Now we analyse the results obtained with our approach based on trust and ontologies. Figure 2 shows respectively the MAE and coverage obtained with our proposal for different horizons. These figures show that a higher horizon value does not guarantee better results in MAE terms (in fact, the better MAE is obtained with $h = 3$), but in coverage. Moreover, a higher horizon value penalizes the time to results as it implies much higher execution time.

Finally, we present the comparison of our proposal with the different recommendation approaches analysed. Figure 3 show the results of this comparison: on the left side the result with all the groups of users are presented,

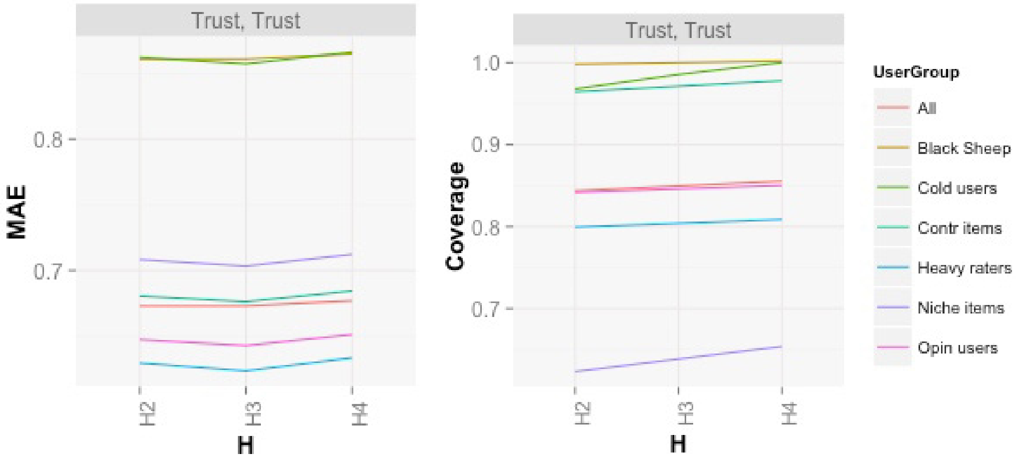

Fig. 2. MAE and Coverage obtained with our suggested approach for differents horizons.

while the right side shows the results for all users, not classified. We can see that the better MAE is obtained with item-based collaborative implementation for cold users, but only for very specific situations. However, in general terms, we see that *On2trust* clearly outperforms the other approaches. Beyond that achieved improvement in MAE, the best results of our proposal manifest in terms of coverage. In Figure 3 clearly see to which extent the coverage obtained with our proposal outperforms the other methods.

5. Conclusions and future work

We have presented a recommender system incorporating ontologies to improve the representation of user profiles. We have developed an ontology to efficiently characterize the trust network between users, using the fuzzy linguistic modelling to facilitate the representation of different concepts. The system also incorporates a domain ontology to represent the relationships between users and their preferences about the items. The main idea of our new recommendation approach consists of not taking into account users with similar ratings history in the recommendation generation process, but rather trustworthy users. To achieve this, we have proposed a method to estimate the trust score between a pair of users. This method finds all possible paths between the two users, exploring the ontology used to represent the trust network. Finally, it aggregates the trust information represented in the most relevant paths found between the pair of users. To evaluate the performance of our system, we have developed several experiments by comparing different configurations of the system parameters. We also compare the new recommendation approach with the collaborative ones. The obtained results reveals an improvement over previous proposals.

As further research we propose to explore the application of specific measures of the social networks analysis, exploiting the information represented in the developed ontologies, incorporating these measures into a new recommendation approach.

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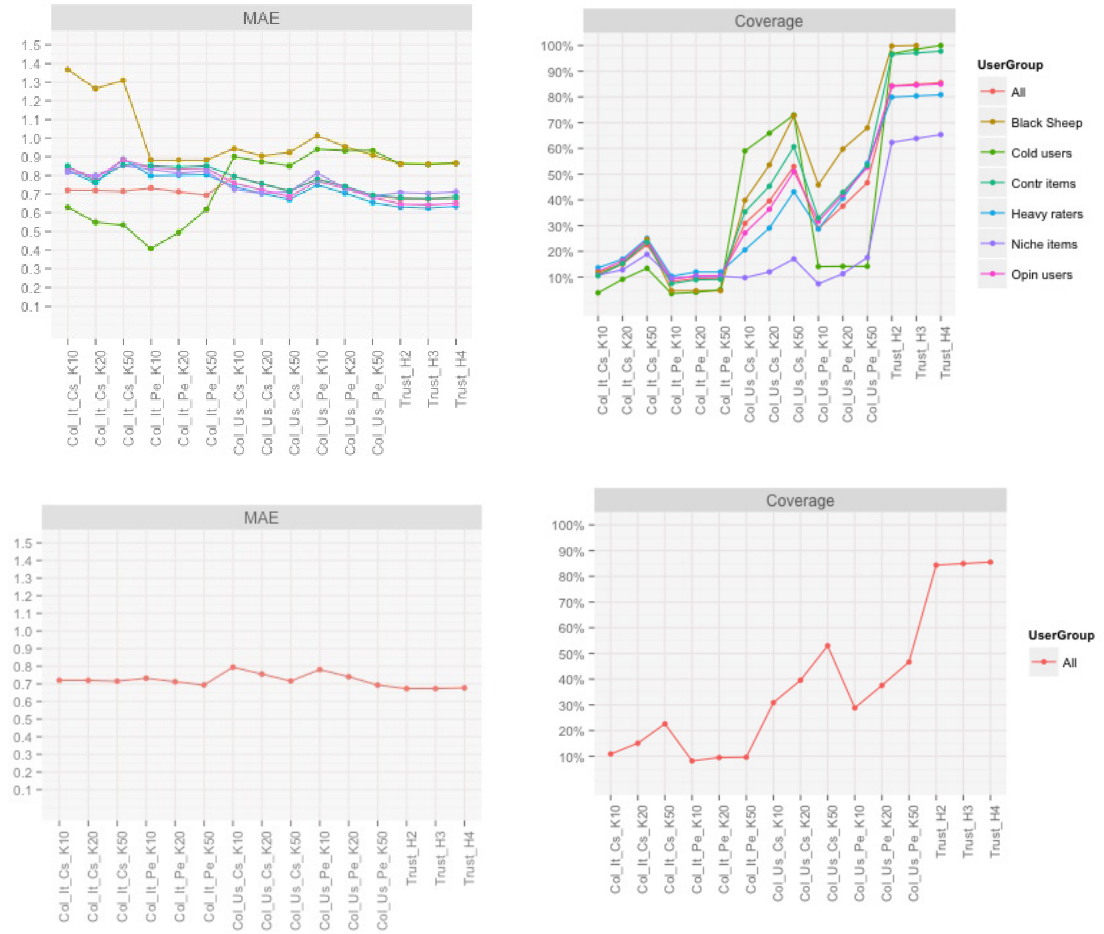

Fig. 3. Comparison of MAE and coverage between *On2trust* and the other schemes.

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