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Modeling user preferences through adaptive fuzzy profiles

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Abstract

Adaptive software systems are systems that tailor their behavior to each user on the basis of a personalization process. The efficacy of this process is strictly connected with the possibility of an automatic detection of preference profiles, through the analysis of the users' behavior during their interactions with the system. The definition of such profiles should take into account imprecision and gradedness, two features that justify the use of fuzzy sets for their representation. This paper proposes a model for representing preference profiles through fuzzy sets. The model's strategy for adapting profiles to user preferences is to record the sequence of accessed resources by each user, and to update preference profiles accordingly so as to suggest similar resources at next user accesses. Profile adaption is performed continuously, but in earlier stages it is more sensitive to updates (plastic phase) while in later stages it is less sensitive (stable phase) to allow resource suggestion. Simulation results are reported to show the effectiveness of the proposed approach.

1 Introduction

The last decades have registered a growing interest for adaptive software systems, which are able to take into account the peculiarities of the distinct users in order to provide for personalized content [1]. These systems rely on a personalization process that is basically founded on two steps: (i) the automatic construction of models (user profiles) which encode the user preferences, and (ii) the automatic selection of the resources to be proposed, on the basis of the previously identified user models. The efficacy of a personalization process, therefore, is strictly connected with the possibility of automatically identifying user profiles, through the analysis of the navigational behavior that users exhibit during their interactions with the system.

Personalization processes have been adopted in several real-world applications, with the realization of e-commerce infrastructures, information retrieval systems, digital libraries, e-learning, etc. [2, 3, 4]. Several approaches have been proposed for personalization, however few of them take into account the perceptual nature of preference, which is pervaded by imprecision and graduality [5].

To deal with imprecision and gradedness, Fuzzy Set Theory (FST) [6] can be considered as a good candidate as mathematical paradigm for representing preferences into user profiles. FST, indeed, provides for basic elements (fuzzy sets) that are appropriate for the representation of imprecise and gradual concepts, and fuzzy operators to combine, aggregate and infer knowledge from fuzzy sets.

In [7], we proposed ProfileMatcher (PM), a system for recommending resources to users on the basis of their profiles. Two are the main features of PM: (i) deep profile structure, and (ii) the use of fuzzy sets. In particular, the deep structure of user profiles enables the representation of complex profiles, including user competences, preferences and knowledge. However, this version of PM has only static profiles, which do not evolve during time in order to capture the change of user preferences.

In this paper, we propose a model for representing and learning preference profiles through fuzzy sets. The proposed profile model is compatible with PM profiles, so they can be seamlessly integrated within this system to extend its capabilities. The model's strategy for adapting profiles to user preferences is to record the sequence of accessed resources by each user, and to update preference profiles accordingly so as to suggest similar resources at next user accesses. Profile adaption is performed continuously, but in earlier stages it is more sensitive to updates (plastic phase) while in later stages it is less sensitive (stable phase) to allow resource suggestion.

The proposed approach enables the introduction of dynamic profiles within PM, yet preserving the ability of representing imprecision and gradedness of user profiles. The

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two-phase learning process guarantees model convergence to a profile that can be used to suggest new resources that meet user preferences.

The paper is organized as follows. In Section 2, the profilation model is briefly described, along with the basic mechanism to associate preferences to users. In Section 3, the preference learning algorithm is formalized. In Section 4, some simulation results are reported to show the effectiveness of the proposed approach. Finally, Section 5 closes the paper by drawing some conclusive remarks.

2 The profilation model

The profilation model provides for a mechanism that associates resources to users on the basis of a compatibility degree. To make this possible, both resources and profiles are described through metadata, where each metadata describes an attribute in terms of a fuzzy set of values.

The employment of fuzzy metadata characterization enables the definition of different properties related to a resource. In particular, we can distinguish among: simple properties (regarding the punctual evaluation of an attribute by determining a single value inside the set of possibly infinite values); collective properties (regarding the extensional specification of a discrete set of values for an attribute); gradual properties (i.e. properties that apply to values to a degree rather than in a yes/no fashion).

It should be noted how this kind of approach produces a granulation of the attribute domains, where fuzzy sets are adopted to represent each information granule. This favors a mechanism of elaboration of concepts that is in agreement with the human reasoning schemes [8]. In this way, gradual associations can be realized between users and resources, on the basis of a compatibility ranking. As a result, each user can be ultimately addressed to the most compatible resources, without arbitrarily discarding those characterized by a lower degree of compatibility.

In the following subsections, the description of both resources and user profiles is detailed.

2.1 Resource description

Each resource is defined by a collection of fuzzy metadata, i.e. a set of couples <attribute, fvalue> where "attribute" is a string and "fvalue" is a fuzzy set defined on the domain of the attribute. An example of fuzzy metadata is :

$$\langle Complexity, \{Low/1, Medium/0.8, High/0.2\}\rangle$$

being "Complexity" the name of the attribute, "Low", "Medium" and "High" the values with membership degrees 1, 0.8 and 0.2 respectively.

More formally, we will denote a metadata as a couple $\langle a, \mu\rangle$ being $a \in A$ and $\mu : Dom\,(a) \longrightarrow [0,1]$. Here, we denote with A the set of all attributes used in an applicative context, and $Dom(a)$ is the set of all possible values of attribute a.

$$\boxed{\begin{array}{c}\langle DOI, \{10.1142/97898127096770204/1\}\rangle \\ \langle topics, \{fst/1, rs/0.5, um/0.8\}\rangle \\ \langle target, \{ug/0.2, gr/0.7, rs/1\}\rangle \\ \langle style, \{th/0.8, ap/0.4, sv/0.1\}\rangle\end{array}}$$

Figure 1. An example of resource description

A resource R is described by a set of metadata, i.e.

$$R = \{\langle a, \mu\rangle\, | a \in A\} \tag{1}$$

with the constraint that each attribute occurs at most once in the description.

A very simple example of resource description is reported in fig. 1. Here, the application context concerns the suggestion of papers. As we note from the example, fuzzy metadata generalize classical metadata because they are able to describe precise as well as imprecise properties characterizing the description of papers. The attribute DOI, for example, is the identifier of the paper and it is represented as a singleton fuzzy set with unitary membership degree. The covered topics, target and style of the paper have an imprecise and gradual nature. Hence they are described by a fuzzy set enumerating values with nonzero membership degrees. In the example, the considered paper is mainly focused on user modeling (um), with a significant reference to fuzzy set theory (fst) and, to a lesser extent, to recommender systems (rs). Also, from the description we deduce that the paper has a sharp scientific target – as being strongly suggested to researchers (rs) and graduate students (gr) – but it is not very recommended for undergraduate (ug) students. It has a neat theoretical (th) style, with some references to applications (ap), but it cannot be intendend as a survey (sv) of the state-of-the-art.

2.2 User profile description

User profiles are used to represent preferences of users accessing the system. In this work, the user profiles are formalized as collections of profile components. Analogously to the metadata specification in the resource description, the profile components are characterized in terms of fuzzy sets: this homogeneity expedites the matching process aiming at defining a compatibility degree between profile components and resources.

In particular, preference profiles reflect the interests users have for one or more properties of the accessed resources. They are initially empty and are modified at every access of the users on some resources. Each preference pro-

$\langle topics, \{fst/1, um/0.5, nn/0.8\}\rangle$
$\langle style, \{th/1, ap/0.1, sv/1\}\rangle$

$\langle topics, \{C++/0.2, Java/0.8, Smalltalk/0.3\}\rangle$
$\langle target, \{rs/0.1, ug/1, gr/0.5\}\rangle$

Figure 2. An example of profile with two profile components

file component represents an elementary preference (e.g. a user may prefer resources on "fuzzy sets" and "C++").

Formally, a user profile is defined as:

$$P = \{p_1, p_2, \ldots, p_n\} \tag{2}$$

where each profile component p_i is defined as a resource description as in (1).

In fig. 2, an example of profile with two components is reported. We may interpret this profile as describing a user with two different types of interests. The first profile component concerns theoretical or survey papers mainly focused on fuzzy set theory (fst) and, to a lesser extent, neural networks (nn). Also papers on user modeling (um) are of interest, but to a minor extent. The second profile component describes the interest of the user in papers on Java and, to a minor extent, to Smalltalk and C++. Interesting papers should be mainly targeted to undergraduate students (ug), while papers written for researchers (rs) are not of main interest in this case. Papers for graduate students (gr) are also of partial interest.

2.3 Matching mechanism

Given a resource description R defined as in (1) and a user profile description P defined as in (2), the matching mechanism computes a compatibility degree $K(R, P) \in [0, 1]$ that is as high as the resource is deemed compatible with user interests and preferences.

The compatibility degree $K(R, P)$ of a profile P to a resource R is defined in terms of the compatibility between the resource and each profile component, i.e.

$$K(R, P) = \max_{p \in P} K(R, p)$$

We choose 'max' as aggregation operator because we characterize the overall compatibility as disjunction of elementary compatibilities between the resource and the single user profile components.

The compatibility degree of a profile component to a resource is defined in terms of the matching of the common metadata between the profile component and the resource, that is:

$$K(R, p) = AVG\{K(\mu_R, \mu_p) | \exists a \in A \; s.t. \; \langle a, \mu_R\rangle \in R \wedge \langle a, \mu_p\rangle \in p\} \tag{3}$$

where, AVG is the standard mean which is used as a particular case of aggregation operator and $K(\mu_R, \mu_p)$ is the compatibility degree computed between two fuzzy sets.

Finally, to evaluate the compatibility degree between two fuzzy sets, we use the possibility measure [9] that evaluates the overlapping between fuzzy sets as follows:

$$K(\mu_R, \mu_P) = \max_{x \in Dom(A)} \{\min(\mu_R(x), \mu_P(x))\} \tag{4}$$

More specifically, the possibility measure evaluates the extent to which there exists at least one common element between two fuzzy sets. This measure reveals to be particularly suitable to quantify compatibility between fuzzy metadata, since we assume that two metadata are compatible if they share at least one value of a given attribute.

3 Learning preference profiles

Preference learning is a process to derive the preference profile of a user on the basis of her interaction with the system, synthesized by the resources she accesses to.

Let P be the preference profile associated to a user. Initially, this profile is empty but is dynamically updated as the user accesses to the resources. The approach used in the paper for learning preference profiles resembles to a competitive learning procedure [10], with the necessary variations for dealing with profile components.

Initially, the preference profile is defined by an empty set, i.e. $P \leftarrow \emptyset$. We denote as R_1, R_2, $R_3, \ldots$ the sequence of resources accessed by a user. Whenever a resource R_i is accessed by the user, the profile is updated. For each profile component $p \in P$, the compatibility degree is computed and the profile component with maximum degree is selected, that is:

$$p_i^* = \arg\max_{p \in P} K(R_i, p)$$

We use a threshold δ_i to decide if the preference profile is compatible with the resource. Specifically, if the compatibility degree $K(R_i, p_i^*) < \delta_i$, we deduce that no profile component is compatible with the resource R_i and a new profile component is added to P with the same metadata of R_i, i.e.:

$$P \leftarrow P \cup \{R_i\}$$

Conversely, if $K(R_i, p_i^*) \geq \delta_i$, the profile component p_i^* is updated so as to resemble to R_i. The update rule concerns all attributes in A following the subsequent rules. For each $a \in A$ and for each $x \in Dom(A)$, we denote as $\mu^a_{p_i^*}$ the fuzzy set in metadata $\left\langle a, \mu^a_{p_i^*}\right\rangle \in p_i^*$ or the degenerate fuzzy set $\mu^a_{p_i^*}(x) = 0$ if a is not used in the profile component. Similarly, we define the fuzzy set $\mu^a_{R_i}$. The fuzzy set $\mu^a_{p_i^*}$ is updated as follows:

$$\mu^a_{p_i^*}(x) \leftarrow (1 - \alpha_i)\mu^a_{p_i^*}(x) + \alpha_i \mu^a_{R_i}(x)$$

The new fuzzy set $\mu^{a}_{p_i^*}(x)$ is a linear combination of its older version and the fuzzy set $\mu^{a}_{R_i}(x)$. We observe that if $\alpha_i = 0$ no learning takes place; on the other hand, if $\alpha_i = 1$ the previous definition of $\mu^{a}_{p_i^*}$ is replaced with $\mu^{a}_{R_i}$. We tune α_i dynamically so that in earlier learning stages adaption is favoured (plastic phase). As i increases, adaptability decreases so as to stabilize the profile components. To achieve this behavior, the parameter α_i varies according to the following law:

$$\alpha_i = \exp(-\alpha(i-1))$$

An empirical rule for choosing the value of α could be the following. According to the frequency of user access to the resources, we estimate that the first 10% of time is used only for training, i.e. resources are not suggested on the basis of the preference profile. If N is the estimated number of total accesses a user makes on the system, then we set α so that α_i is greater than 0.5 for $i < 0.1N$. This can be achieved by setting:

$$\alpha = \frac{10 \log 2}{N - 10} \approx \frac{7}{N - 10}$$

To complete the design of the learning strategy, we need to define the thresholds δ_i that are needed to establish whether to create a new profile component or update an existing one. We observe that for $\delta_i = 0$ no new profile component is created, independently from the compatibility degree. On the other hand, for $\delta_i = 1$ new profile components are created for every distinct resource a user accesses to, provided that they have different descriptions. In this work we choose $\delta_i = 0.5$ for $i \leq 0.1N$ and $\delta_i = 0$ for $i > 0.1N$, so that new component profiles are generated only in the plastic phase whenever incompatible resources are accessed by the user.

(a)

(b)

Figure 3. Box-whiskers plot of the membership degrees of preference profiles for $N = 11$ (a) and $N = 100$ (b).

4 Simulation results

We tested the proposed approach for deriving user preference profiles in a simulated environment.

Two simulations were run. The first simulation was aimed at verifying the convergence property of the learning algorithm to a correct preference profile. The second simulation was aimed at verifying the ability of the proposed approach in creating multiple profiles that correspond to distinct user preferences.

4.1 Convergence

We assume the presence of five attributes, conventionally named a_1, a_2, a_3, a_4 and a_5. Each attribute has a three-valued domain, i.e. $Dom(a_i) = \{v_1, v_2, v_3\}$. We randomly generate 100 resources, each with all five attributes and three values per attribute. The membership degree attached to each value is generated randomly in $[0, 1]$.

To test convergence, we assume that a user has preference for value v_1 of attribute a_1. We first estimate that the total number of resources a user accesses is $N = 11$. In consequence of this choice, only one profile component is created. This simulation follows the case of typical occasional users that make a small number of accesses to the system, where it is important a quick learning of the preference profile.

We simulate user choices by randomly picking resources with a probability distribution directly proportional to the membership value of v_1 of attribute a_1. More specifically, the probability of picking a resource R_j from the set is:

$$Prob(R_j) = \frac{\mu^{a_1}_{R_j}(v_1)}{\sum_{h=1}^{100} \mu^{a_1}_{R_h}(v_1)} \qquad (5)$$

being $\langle a_1, \mu^{a_1}_{R_j} \rangle \in R_j$. We repeat this simulation 100 times,

$\langle a_1, \{v_1/1\}\rangle$	$\langle a_2, \{v_2/1\}\rangle$
$\langle a_3, \{v_3/1\}\rangle$	$\langle a_4, \{v_3/1\}\rangle$
$\langle a_2, \{v_2/1\}\rangle$	$\langle a_4, \{v_3/1\}\rangle$

Figure 4. The reference preference profile, made up of three profile components

so as to record enough data that represent the distribution of each membership degree of any value of each attribute.

In fig. 3(a), we observe a convergence towards the ideal preference profile $\langle a_1, \{v_1/1\}\rangle$ even if the number of accesses is very small (For each box, the lower bound indicates the 25-th percentile, the higher bound the 75-th percentile and the mid-line the median; whiskers indicate minimum and maximum values). Convergence is witnessed by the higher value of the median for value v_1 of attribute a_1 compared to other values. As the number of user accesses increases, the convergence property becomes more marked. In fig. 3(b) we plot the results of simulations when $N = 100$[1].

4.2 Multiple profiles

As for the previous simulation, we assume the existence of five attributes, with three values each, and 100 randomly generated resources. In this simulation we are interested at verifying the ability of the proposed learning procedure to learn different preference profile components from the same user. For this purpose, we define an ideal preference profile made up of three profile components, as depicted in fig. 4. A linguistic interpretation of the profile might be the preference of either one of the following types of papers:

- technical papers ($\langle a_1, \{v_1/1\}\rangle$) on fuzzy logic ($\langle a_2, \{v_2/1\}\rangle$);
- undergraduate ($\langle a_3, \{v_3/1\}\rangle$) short papers ($\langle a_4, \{v_3/1\}\rangle$);
- short papers ($\langle a_4, \{v_3/1\}\rangle$) on fuzzy logic ($\langle a_2, \{v_2/1\}\rangle$).

We assume $N = 50$ so that up to five profile components can be created. We generate three probability distributions for the random pick of resources to simulate user behavior. The following rule defines the first probability distribution, which is related to the first ideal profile component:

$$Prob(R_j) = \frac{\mu_{R_j}^{a_1}(v_1) \cdot \mu_{R_j}^{a_2}(v_2)}{\sum_{h=1}^{100} \left(\mu_{R_h}^{a_1}(v_1) \cdot \mu_{R_h}^{a_2}(v_2)\right)} \tag{6}$$

[1] In this case, we define $\delta_i = 0$ for $i > 0.01N$ to force the creation of only one profile component.

Figure 5. Difference distribution in resource compatibility degrees with ideal and learned preference profile.

The remaining probability distributions are defined accordingly. The simulation proceeds as follows:

1. First, an integer number in $\{1, 2, 3\}$ is selected randomly (uniform distribution);
2. Then a resource is selected according to the corresponding probability distribution;
3. The user preference profile is updated as described in Section 3. Eventually, a new profile component is created if incompatible with the existing ones.

The three steps are iterated N times. At the end of the learning stage, for each resource R_j we compare the compatibility degree of R_j to the ideal profile with the compatibility degree of R_j to the actual profile. We expect that the two compatibility degrees do not differ too much.

The entire simulation is run 100 times to gather statistically significant results. Fig. 5 shows the distribution of average values of the differences between the compatibility degrees of each resource with the ideal and the learned profile. As it can be observed, about in 50% of trials differences between compatibility degrees is less than 0.15, and this percentage increases to about 75% if we consider a difference of 0.2. These results indicate a good performance of the learning algorithm, in consideration of the random pick of the resources (6) that prevents the learned profile to converge exactly to the ideal one.

In tab. 1 we report the distribution of the number of profile components generated in the simulation. In the most frequent case (55 tests) three profile components were generated, thus reflecting the structure of the ideal profile. In some cases (18 tests) the number of profile components was

Table 1. Number of profile components (pc) versus number of tests

	1 pc	2 pc	3 pc	4 pc	5 pc
N. of tests	2	16	55	21	6

less than required. Expectedly, in these cases the matching performances are not as satisfactory as in the remaining cases, where more than three profile components indicate an unnecessary redundancy without hampering accuracy.

5 Conclusions

In this paper we have proposed an approach for learning preference profiles described in terms of profile components to deal with the multiplicity of user preferences, where each profile component is defined in terms of fuzzy sets to cope with imprecision and gradedness. Since preference learning is carried out on line with user interaction, we have defined the learning procedure so as to recognize a first plastic phase in which preference profiles are quickly learned; in the successive, stable phase, preference profiles are refined but can be used to suggest new resources to users.

Simulation shows comfortable results in terms of convergence of the learning procedure even if a small number of accesses is estimated, although a higher number of user accesses allows for a sharp convergence of the learned profile to the real preferences of the user. Also, in case of more complex preferences, the proposed approach enables the learning of multiple profile components reflecting elementary preferences.

Future research in the direction outlined in this paper will investigate on methods for further refining the learning procedure by taking into account several issues, such as merging similar profile components, pruning useless profile components and, more importantly, coping with the natural tendency of users in changing their preferences during time.

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