

Following the User's Interests in Mobile Context-Aware Recommender Systems : The hybrid- ϵ -greedy algorithm

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Abstract— The wide development of mobile applications provides a considerable amount of data of all types (images, texts, sounds, videos, etc.). In this sense, Mobile Context-aware Recommender Systems (MCRS) suggest the user suitable information depending on her/his situation and interests. Two key questions have to be considered 1) how to recommend the user information that follows his/her interests evolution? 2) how to model the user's situation and its related interests? To the best of our knowledge, no existing work proposing a MCRS tries to answer both questions as we do. This paper describes an ongoing work on the implementation of a MCRS based on the hybrid- ϵ -greedy algorithm we propose, which combines the standard ϵ -greedy algorithm and both content-based filtering and case-based reasoning techniques.

Keywords—component; context-aware recommender systems; personalization; situation.

I. INTRODUCTION

Mobile technologies have made access to a huge collection of information, anywhere and anytime. Thereby, information is customized according to users' needs and preferences. This brings big challenges for the Recommender System field. Indeed, technical features of mobile devices yield to navigation practices which are more difficult than the traditional navigation task.

Recommender systems are systems that produce individualized suggestions concerning interesting content the user might like out of a large number of alternatives. Often, recommender systems using collaborative or content-based filtering algorithms are applied.

In mobile applications, information personalization is even more important, because of the limitations of mobile devices in terms of displays, input capabilities, bandwidth etc. It is then desirable to personalize not only using pre-defined user profiles, but also the user's context such as the current location.

We can find similar challenges in context-aware systems area. A general definition of context-aware systems is given in [4]: "A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task."

The key goal of context-aware systems is hence to provide a user with relevant information and/or services

based on his current context. This goal matches with the goal of recommender systems.

Both context-aware systems and recommender systems are used to provide users with relevant information and/or services; the first based on the user's context; the second based on the user's interests. Therefore, the next logical step is to combine these two systems within the so-called mobile context-aware recommender systems.

The notion of context is not new. In general, it refers to any information that is relevant to the user and his/her surroundings. The main difficulty when dealing with context is its high dynamicity and its constant change. A change in one contextual feature may generate changes in other contextual features. That's why context-aware systems have to be adapted to highly dynamic user situations and context models need to capture the dynamic interactions between contextual information.

Several works in context-aware systems have addressed the problem of context modeling and interesting single or hybrid models exist. Most of them are gathered in the survey done in [5]. However, these models have not been widely applied to the mobile application domain. The dynamic interactions between contextual dimensions and user profiles have not been fully represented by the existing models which often focus on modeling static associations among different contextual information.

In recommender systems, a considerable amount of research has been done in recommending relevant information for mobile users. Earlier techniques ([12], [15]) are based solely on the computational behavior of the user to model his interests regardless of his surrounding environment (location, time, nearby people). The main limitation of such approaches is that they do not take into account the contextual evolution of the user interests w. r. t. his context.

This study gives rise to another category of recommendation techniques that tackle these limitations when building situation-aware user profiles. Two key questions have to be considered, namely 1) how to recommend the user information that follows his/her interests evolution? 2) how to model the user's situation and its related user's interests?

In order to tackle these problems, our approach consists of:

- Capturing context through communication with diverse information sources: from the mobile device GPS capability, if it is possible, or by inferring a user's location based on the user's calendar or other devices in the neighborhood.
- Storing history for future use or user habit analysis.
- Reasoning and learning capabilities to be able to (i) use the collected contextual information for mapping low-level information to symbolic contextual information (e.g. mapping an exact coordinate to a symbolic location such as an address) or to deduce higher level information i.e. identify user situation and recommend the most relevant content according to the situation (e.g. determine that the user is in a room where a meeting is in progress so the cell phone should be switched to silent mode); (ii) learn the behavior based on reasoning and the history data (e.g. whenever the user enters a room which has a meeting in progress or where the next event is a meeting, the user turns the volume of the cell phone down and searches for the meeting agenda. The system may learn this behavior for the next time).

The remainder of the paper is organized as follows. Section II reviews some related works. Section III presents the user model. Section IV introduces the recommendation algorithm and the last section concludes the paper and points out possible directions for future work.

II. BACKGROUND

We mention now recent relevant recommendation techniques that tackle the two issues mentioned above, namely: following the evolution of user's interests and modeling the situation and user profile.

A. Following the evolution of user's interests

The trend today on recommender systems is to suggest relevant information to users, using supervised machine learning techniques. In these approaches, the recommender system has to execute two steps: (1) the learning step, where the system learns from samples and gradually adjusts its parameters; (2) the exploitation step, where new samples are presented to the system to perform a generalization [18].

These approaches suffer from the following drawbacks: (i) need for initial information about the user's interests provided by an expert; (ii) difficulty in following the evolution of the user's interests. Some works found in the literature [7, 8, 16] address these problems as a need for balancing exploration and exploitation studied in the "bandit algorithm". A bandit algorithm B exploits its past experience to select documents that appear more frequently. Besides, these seemingly optimal documents may in fact be suboptimal, due to imprecision in B's knowledge. In order to avoid this undesired situation, B has to explore documents by actually choosing seemingly suboptimal documents so as to gather more information about them. Exploitation can increase short-term user's satisfaction since some suboptimal

documents may be chosen. However, obtaining information about the documents' average rewards (i.e., exploration) can refine B's estimate of the documents' rewards and in turn increase long-term user's satisfaction. Clearly, neither a purely exploring nor a purely exploiting algorithm works best in general, and a good tradeoff is needed. The authors on [7, 8, 16] describe a smart way to balance exploration and exploitation. However, none of them consider the user's situation during the recommendation.

B. Modeling the situation and user profile

Few research works are dedicated to manage the user's situation on recommendation. In [2, 9, 10] the authors propose a method which consists of building a dynamic situation and user profile based on time and user's experience. The user's preferences and interests in the user profile are weighted according to the situation (time, location) and user behavior. To model the change on user's preferences according to his temporal situation in different periods, like workday or vacations, the weighted association for the concepts in the user profile is established for every new experience of the user. The user activity combined with the user's profile are used together to filter and recommend relevant content.

Another work [6] describes a MCRS operating on three dimensions of context that complement each other to get highly targeted. First, the MCRS analyzes information such as clients' address books to estimate the level of social affinity among users. Second, it combines social affinity with the spatiotemporal dimensions and the user's history in order to improve the quality of the recommendations.

In [1], the authors present a technique to perform user-based collaborative filtering. Each user's mobile device stores all explicit ratings made by its owner as well as ratings received from other users. Only users in spatiotemporal proximity are able to exchange ratings and they show how this provides a natural filtering based on social contexts.

Each work cited above tries to recommend interesting information to users on contextual situation; however they do not consider the evolution of the user interest.

To summarize, none of the mentioned works tackles both problems. As a result, our approach exploits the following new features:

- We consider user situations as a multi-dimensional space where each dimension is represented by a domain ontology. Unlike in [1, 2, 6, 10], where context items are low level data, in our approach they correspond to concepts of social, location and time ontologies. Each situation is associated to specific user profile and preferences.
- Inspired by models of human reasoning developed by [14] in robotic, we propose to consider user's situation in the bandit algorithm by using case-based reasoning technique, which is not considered in [7, 8, 9, 16].
- In [7, 8, 16] authors use a smart bandit algorithm to manage the exploration/exploitation strategy, however they do not take into account the content in

the strategy. Our intuition is that, considering the content when managing the exploration/exploitation strategy will improve it. This is why we propose to use content-based filtering techniques together with ϵ -greedy algorithm.

In what follows, we define the structure of the proposed user model and the methods for inferring the recommendation situations. Then, we explain how to build dynamic user profiles, and how to manage the exploration/exploitation strategy, according to the current situation.

III. THE PROPOSED USER'S MODEL

As stated in Section II, static approaches for building the user's profile [12, 15] are poorly useful in our context, so we rather focus on more dynamic techniques, capable of continuously adjusting the user's interests to the current situation.

Figure 1 depicts the diagram of the proposed user model.

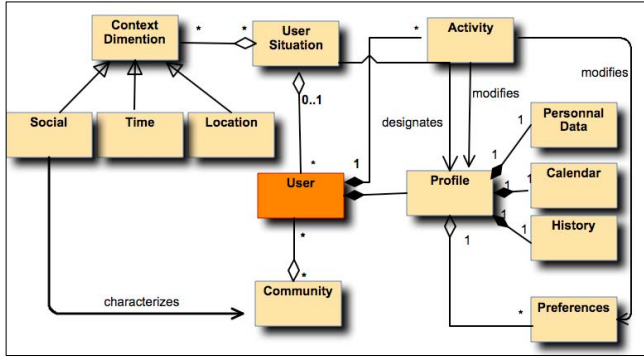


Figure 1. User model diagram

A. User Profile

The user profile is composed of the user's personal data and other dynamic information, including his preferences, his calendar and the history of his interactions with the system.

1) UserPreferences

The user preferences are contextual and might depend on many factors, like the location or the current task within an activity. Thus, they are associated to the user situation and the user activity. Preferences are deduced during user navigation activities. They contain the set of navigation documents used by the user in a situation. A navigation activity expresses the following sequence of events: (i) the user logs in the system and navigates across documents to get the desired information; (ii) the user expresses his preferences on the visited documents. We assume that a visited document is relevant, and thus belongs to the user's preferences, if there are some observable user's behaviors through 2 types of preference:

- The direct preference: the user expresses his interest in the document by inserting a rate, like for example putting stars ("*") at the top of the document.

- The indirect preference: it is the information that we extract from the user system interaction, for example the number of clicks on the visited documents or the time spent on a document.

Let UP be the preferences submitted by a specific user in the system at a given situation. Each document in UP is represented as a single vector $d=(c_1, \dots, c_n)$, where c_i ($i=1, \dots, n$) is the value of a component characterizing the preferences of d . We consider the following components: the total number of clicks on d , the total time spent reading d , the number of times d was recommended, and the direct preference rate on d .

2) History

All the interactions between the user and the system are stored as well as the situations in order to exploit this data to improve the recommendation process.

calendar Before each meeting, the user has to fill-up the calendar with information concerning the person(s) to meet, Time and Location instances are automatically inferred by the system.

B. User Situation

A situation S can be represented as a triple whose features X are the values assigned to each dimension: $S = (X_l, X_t, X_s)$, where X_l (resp. X_t and X_s) is the value of the location (resp. time and social) dimension.

Suppose the user is associated to: the location "38.868143, 2.3484122" from his phone's GPS; the time "Mon Oct 3 12:10:00 2011" from his phone's watch; and the meeting with Paul Gerard from his calendar. To build the situation, we associate to this kind of low level data, directly acquired from mobile devices capabilities, more abstracted concepts using ontologies reasoning means.

1) Location

There are different ways to characterize a location. As returned by location sensor systems (like GPS), location is a position in systems based on geographic coordinates, or may also be defined by an address. Simple automated place labeling systems are already commercialized (Google maps, Yahoo local...) and consist of merging data such as postal addresses with maps.

In our user model, we use a local spatial ontology to represent and reason on geographic information. Using this ontology, for the above example, we get, from location "38.86, 2.34", the value "Paris" to insert in the location dimension of the situation.

2) Time

The temporal information is complex: it is continuous and can be represented at different levels of granularity. To define the temporal aspects characterizing the user's situation, we suggest to abstract the continuum time into specific and significant periods (abstract time classes), which we expect having an effect on the user's behavior (e.g. morning, weekend). To allow a good representation of the temporal information and its manipulation, we propose to use OWL-Time ontology [11] which is today a reference for representing and reasoning about time. We propose to base our work on this ontology and extend it if necessary. Taking the example above, for the time value "Mon Oct 3 12:10:00

2011", we get, using the OWL-Time ontology, the value "workday".

3) Social connection

The social connection refers to the information of the user's interlocutors (e. g. a friend, an important customer, a colleague or his manager). To define the neighborhood people aspects characterizing the user, a clear model for the representation and reasoning on social clustering is necessary. We use the FOAF Ontology [13] to describe the social network by a set of concepts and properties. For example, the information about "the meeting with Paul Gerard" can yield the value "wine client" for the social dimension.

IV. THE PROPOSED RECOMMENDATION ALGORITHM

In our MCRRS, documents' recommendation is modeled as a multi-armed bandit problem. Formally, a bandit algorithm proceeds in discrete trials $t = 1, \dots, T$. For each trial t , the algorithm performs the following tasks:

Task 1. It observes the current user u_t and a set A_t of arms together with their feature vectors $x_{t,a}$ for $a \in A_t$. The vector $x_{t,a}$ summarizes information of both user u_t and arm a , and is referred to as the context.

Task 2. Based on observed rewards in previous trials, it chooses an arm $a_t \in A_t$, and receives reward r_{t,a_t} whose expectation depends on both the user u_t and the arm a_t .

Task 3. It then improves its arm-selection strategy with the new observation, $(x_{t,a_t}, a_t, r_{t,a_t})$. It is important to emphasize here that no feedback (namely the reward $r_{t,a}$) is observed for unchosen arms $a \neq a_t$.

In tasks 1 to 3, the total T-trial reward of A is defined as

$$\sum_{t=1}^T r_{t,a_t}$$

while the optimal expected T-trial reward is defined as

$$E \left[\sum_{t=1}^T r_{t,a_t^*} \right]$$

where a_t^* is the arm with maximum expected reward at trial t . Our goal is to design the bandit algorithm so that the expected total reward is maximized.

In the field of document recommendation, we may view documents as arms. When a document is presented to the user and this one selects it by a click, a reward of 1 is incurred; otherwise, the reward is 0. With this definition of reward, the expected reward of a document is precisely its Click Through Rate (CTR). The CTR is the average number of clicks on a recommended document, computed dividing the total number of clicks on it by the number of times it was recommended. Consequently, choosing a document with maximum CTR is equivalent, in our bandit algorithm, to maximizing the total expected rewards.

A. The ϵ -greedy algorithm

The ϵ -greedy strategy is sketched in Algorithm 1. For a given user's situation, the algorithm recommends a pre-defined number of documents, specified by the parameter N . In this algorithm, $UP^c = \{d_1, \dots, d_p\}$ is the set of documents corresponding to the current user's preferences; $D = \{d_1, \dots, d_N\}$ is the set of documents to recommend;

$getCTR$ (Alg. 1, line 6) is the function which estimates the CTR of a given document; $Random$ (Alg. 1, lines 5 and 8) is the function returning a random element from a given set; q is a random value uniformly distributed over $[0, 1]$ which defines the exploration/exploitation tradeoff; ϵ is the probability of recommending a random exploratory document.

Algorithm 1 The ϵ -greedy algorithm

```

1: Input:  $\epsilon, UP^c, N$ 
2: Output:  $D$ 
3:  $D = \emptyset$ 
4: For  $i = 1$  to  $N$  do
5:    $q = Random(\{0,1\})$ 
6:    $d_i = \begin{cases} \arg \max_{d \in (UP-D)} (getCTR(d)) & \text{if } q \leq \epsilon \\ Random(UP^c) & \text{otherwise} \end{cases}$ 
7:    $D = D \cup d_i$ 
8: Endfor
9: Return  $D$ 

```

To select the document to be recommended, there are several strategies which provide an approximate solution for the bandit problem. Here, we focus on two of them (as in [16]):

- the greedy strategy (Alg. 1, line 6), which estimates each document's CTR; then it always chooses the best documents, i.e. the ones having the higher CTR; thus it only performs exploitation;
- the ϵ -greedy strategy, which adds some greedy exploration policy to the greedy strategy, choosing the best document with probability $1-\epsilon$ (Alg. 1, line 6) or a randomly picked document otherwise (probability ϵ) (Alg. 1, line 8).

B. The proposed hybrid- ϵ -greedy algorithm

We propose a two-fold improvement on the performance of the ϵ -greedy algorithm: integrating case base reasoning (CBR) and content based filtering (CBF). This new proposed algorithm is called hybrid- ϵ -greedy and is described in Algorithm 4.

To improve exploitation of the ϵ -greedy algorithm, we propose to integrate CBR into each iteration: before choosing the document, the algorithm computes the similarity between the present situation and each one in the situation base; if there is a situation that can be re-used, the algorithm retrieves it, and then applies an exploration/exploitation strategy.

In this situation-aware computing approach, the premise part of a case is a specific situation S of a mobile user when he navigates on his mobile device, while the value part of a case is the user's preferences UP to be used for the recommendation. Each case from the case base is denoted as $C = (S, UP)$.

Let $S^c = (X_l^c, X_i^c, X_s^c)$ be the current situation of the user, UP^c the current user's preferences and $PS = \{S^1, \dots, S^n\}$ the set

of past situations. The proposed hybrid-ε-greedy algorithm involves the following four methods.

1) *RetriveCase()* (Alg. 4, line 4)

Given the current situation S^c , the *RetrieveCase* method determines the expected user preferences by comparing S^c with the situations in past cases in order to choose the most similar one S^s . The method returns, then, the corresponding case (S^s, UP^s).

S^s is selected from PS by computing the following expression as it done by [9]:

$$S^s = \arg \max_{S^s \in PS} \left(\sum_j \alpha_j \cdot \text{sim}_j(X_j^c, X_j^s) \right) \quad (1)$$

In equation 1, sim_j is the similarity metric related to dimension j between two situation vectors and α_j the weight associated to dimension j . α_j is not considered in the scope of this paper, taking a value of 1 for all dimensions.

The similarity between two concepts of a dimension j in an ontological semantic depends on how closely they are related in the corresponding ontology (location, time or social). We use the same similarity measure as [17] defined by equation 2:

$$\text{sim}_j(X_j^c, X_j^s) = 2 * \frac{\text{depth}(LCS)}{(\text{depth}(X_j^c) + \text{depth}(X_j^s))} \quad (2)$$

Here, LCS is the Least Common Subsumer of X_j^c and X_j^s , and depth is the number of nodes in the path from the node to the ontology root.

2) *RecommendDocuments()* (Alg. 4, line 6)

In order to insure a better precision of the recommender results, the recommendation takes place only if the following condition is verified: $\text{sim}(S^c, S^s) \geq B$ (Alg. 4, line 5), where B is a threshold value and

$$\text{sim}(S^c, S^s) = \sum_j \text{sim}_j(X_j^c, X_j^s)$$

In the *RecommendDocuments()* method, sketched in Algorithm 2, we propose to improve the ε-greedy strategy by applying CBF in order to have the possibility to recommend, not the best document, but the most similar to it (Alg. 2, line 8). We believe this may improve the user's satisfaction.

The CBF algorithm (Algorithm 3) computes the similarity between each document $d=(c_1, \dots, c_k)$ from UP (except already recommended documents D) and the best document $d^b=(c_1^b, \dots, c_k^b)$ and returns the most similar one. The degree of similarity between d and d^b is determined by using the cosine measure, as indicated in equation 3:

$$\cos \text{sim}(d, d^b) = \frac{d \cdot d^b}{\|d\| \cdot \|d^b\|} = \frac{\sum_k c_k \cdot c_k^b}{\sqrt{\sum_k c_k^2 \cdot \sum_k c_k^{b2}}} \quad (3)$$

Algorithm 2 The *RecommendDocuments()* method

```

1: Input:  $\varepsilon, UP^c, N$ 
2: Output:  $D$ 
3:  $D = \emptyset$ 
4: For  $i=1$  to  $N$  do
5:    $q = \text{Random}(\{0, 1\})$ 
6:    $j = \text{Random}(\{0, 1\})$ 
7:    $d_i = \begin{cases} \arg \max_{d \in (UP-D)} (\text{getCTR}(d)) & \text{if } j < q < \varepsilon \\ \text{CBF}(UP^c-D, \arg \max_{d \in (UP-D)} (\text{getCTR}(d))) & \text{if } q \leq j \leq \varepsilon \\ \text{Random}(UP^c) & \text{otherwise} \end{cases}$ 
8:    $D = D \cup \{d_i\}$ 
9: Endfor
10: Return  $D$ 

```

Algorithm 3 The CBF() algorithm

```

1: Input:  $UP, d^b$ 
2: Output:  $d^s$ 
3:  $d^s = \arg \max_{d \in UP} (\text{cosim}(d^b, d))$ 
4: Return  $d^s$ 

```

3) *UpdateCase()* & *InsertCase()*

After recommending documents applying the *RecommendDocuments* method (Alg. 4, line 6), the user's preferences are updated w. r. t. number of clicks and number of recommendations for each recommended document on which the user clicked at least one time. This is done by the *UpdatePreferences* function (Alg. 4, line 7).

Depending on the similarity between the current situation S^c and its most similar situation S^s (computed with *RetriveCase()*), being 3 the number of dimensions in the context, two scenarios are possible:

- $\text{sim}(S^c, S^s) \neq 3$: the current situation does not exist in the case base (Alg. 4, line 8); the *InsertCase()* method adds to the case base the new case composed of the current situation S^c and the updated UP .
- $\text{sim}(S^c, S^s) = 3$: the situation exists in the case base (Alg. 4, line 10); the *UpdateCase()* method updates the case having premise situation S^c with the updated UP .

Algorithm 4 hybrid- ϵ -greedy algorithm

```

1. Input:  $B, \epsilon, N, PS, S^s, UP^s, S^c, UP^c$ 
2. Output:  $D$ 
3.  $D = \emptyset$ 
4.  $(S^s, UP^s) = \text{RetriveCase}(S^c, PS)$ 
5. if  $\text{sim}(S^c, S^s) \geq B$  then
6.    $D = \text{RecommendDocuments}(\epsilon, UP^s, N)$ 
7.    $UP^c = \text{UpdatePreferences}(UP^s, D)$ 
8.   if  $\text{sim}(S^c, S^s) \neq 3$  then
9.      $PS = \text{InsertCase}(S^c, UP^c)$ 
10.  else
11.     $PS = \text{UpdateCase}(S^p, UP^c)$ 
12.  end if
13. else  $PS = \text{InsertCase}(S^c, UP^c);$ 
14. end if
15. Return  $D$ 

```

V. CONCLUSION

This paper describes our approach for implementing a MCRS. Our contribution is to make a deal between exploration and exploitation for learning and maintaining user's interests based on his navigation history.

In the future, we plan to evaluate our approach on real mobile navigation contexts obtained from a diary study conducted with collaboration with the Nomalys French company. This study will yield to know if considering the situation on the exploration/exploitation strategy significantly increases the performance of the system on following the user's interests.

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