A Mobile Context-Aware Proactive Recommendation Approach

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Abstract. The Proactive Context Aware Recommender Systems aim at combining a set of technologies and knowledge about the user context not only in order to deliver the most appropriate information to the user need at the right time but also to recommend it without a user query. In this paper, we propose a contextualized proactive multi-domain recommendation approach for mobile devices. Its objective is to efficiently recommend relevant items that match users' personal interests at the right time without waiting for users to initiate any interaction. Our contribution is divided into two main areas: The modeling of a situational user profile and the definition of an aggregation frame for contextual dimensions combination.

Keywords: Context modeling · Context-aware recommendation · User modeling · Proactive recommendation

1 Introduction

The development of mobile devices equipped with persistent data connections, geolocation, cameras and wireless capabilities allows current context-aware recommender systems (CARS) to be highly contextualized and proactive. They provide users with relevant information when it is most needed at the right time without waiting for the user to initiate any query. There are several context aware systems that attempted to meet the challenge of providing the right information at the right time without the interference of the user in a mobile environment. However,this requires good modeling of the dimensions of the context and especially the modeling of the user profile. Indeed, as mentioned by [1], several dimensions of context, such as location, time, users activities, needs, resources in the nearbies, light, noise, movement, etc., have to be managed and represented which requires a big amount of information and are time consuming. Besides, the incorporation of too many context dimensions generate complex context models. On the other hand, context models integrating few dimensions are unable to figure out the whole user context.

We propose, in this paper, a proactive context-aware recommendation approach that integrates the modeling of a situational user profile and the definition of an aggregation frame for contextual dimensions combination.

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The paper is organised as follows. We provide in section 2 an overview about the related work. Section 3 presents the proposed approach. We describe in section 4 the experiments done within the TREC 2014 Contextual Suggestion Track. We finish in section 5 with our conclusions and thoughts for future work.

2 Related Work

The user profile modeling covers broad aspects such as the cognitive, social and professional environment to determine the user intentions during a search session [1]. The user profile is an important dimension considered within context modeling. Indeed, context is defined as a set of dimensions that describe and/or infer user intentions and perception of relevance. Those dimensions cover situations related to factors such as location, time and the current application. Work in context-aware recommendation makes use of one or all of these dimensions to describe the user and integrate him forward in the various phases of the recommendation process. Proactive recommendation systems (PRSs) as described in [2], intend to sort among a large quantity of documents, the information that is most likely to be relevant to the user needs, and recommend that information without user requests. Several systems have been developed to support proactive recommendation. Various approaches relied on the user's past or actual behavior history to determine the user interests. Behavior history includes Web browsing history/clicks ([2]); previous visiting behaviors for location based systems ([4,5]) and previous reading patters for news recommendation systems ([6,7,8,9]). Other approaches dealt with user profiling from an activity centric angle. The common activities used to build the user profile in these systems might take the form of: Opened web pages or documents ([10,11,12]); Ongoing conversation or activity such as phone calls [13]; The social media activity of the user such as the user's tweet stream on Twitter ([14,15,16]). However, some approaches require that users express their interests and input keywords or tags which is, most of the time, inconvenient in a mobile environment since it entails extra efforts from the user such as tagging, searching, or clicking. Mobile systems can help keep track of user's activities, preference and location. Besides, many context aware systems dealt with user profiling from an activity centric angle. Nevertheless, we cannot reduce the user profile to some activities. One can simply open a document to work on without being related to it in any way or have a conversation about an issue that he/she is not concerned to know any recommendation about it. There are also the domain dependency issue. In fact, many of the actual contextualized systems are domain dependent (tourism, movie, news ...) and have specific context dimensions to apply according to the domain. However, most of them rely almost on the same context combination which includes location, time and user preferences with a slight difference on how to approach this information. Our approach tries to deals with these issues by integrating the modeling of a situational user profile and the definition of an aggregation frame for contextual dimensions combination.

3 Proposed Approach

We propose a multi-domain proactive context-aware recommendation approach that recommends the right item that match users personal interests at the right time without waiting for users to initiate any interaction or activity.

3.1 Context Modeling

We consider the context as a two-dimension representation
context=(profile,location).
These dimensions' instantiations form a situation S where recommendation is needed. We define in the following sections the different component of the context modeling process.

The User Profile. The user profile (UP) model is defined by two features, *Demographic data*; the user related information such as name,age,etc, C;the user's interests related to specific weighted categories :
$profile = \{C_i, w_i\}; i = 1..n$
A category is a set of weighted terms that are associated to the user preferences and to the interest that he expresses towards this particular category :
$C_i = \{t_j^{(i)}, w_j^{(i)}\}; j = 1..m$
The categories are predefined using the Open Directory Project Dmoz[1].

Location. The location is inferred according to GPS coordinates (*latitude and longitude*). Those GPS coordinates are not the only features that we can consider when defining a location. Indeed, as discussed by [16], there are different ways to characterize the location of the mobile user, *Absolute position*; *Relative* (next to, ...); *A Place name*; *A named class* that represents the type of the place, eg. museum, school, ... We consider the absolute position and the named class representation to characterize the spatial dimension of the user. We define two levels of the location dimension: *The actual location*, that refers to the user's actual location at a given time; *The user's related locations*, the places related to the daily life of the user (work, home, ...). The actual location can be recovered using several tools such as Geonames[2] or the Social Network Foursquare[3] which assign a location category to a given GPS coordinates.

3.2 The Recommendation Process

Type of Information to Recommend. We consider that the recommendation process entails a pack of situations which reflect a specific area of interest

[1] http://www.dmoz.org/docs/en/about.html
[2] http://www.geonames.org/
[3] https://fr.foursquare.com/

characterized by the instantiations of the context dimensions. The possible situations are organized within a knowledge database. A situation is then represented by two specific dimensions: the actual location (D_l) and the user's category of interests related to that location.

These values are used to assess the current situation need in information and the category type of the information to recommend. Our key idea is that the user's need in information changes according to the user's actual location. For instance, a user might want to check the news once he is at work or he might want to visit a specific shop if he's found to be near a mall.

The category of interest of the information to recommend is inferred from the current situation.

Information Extraction. In order to retrieve the information to recommend, a query q is formulated as : *q=(latitude, longitude, category_of_ interest)*
The query is sent to a geo-based service. The query result is represented by a set of items I : $I = \{i_1, ?, i_n\}$.
An item is defined as a weighted terms vector $i_j = \{t_k^j, w_k^j\}; j = 1..n, k = 1..p$
We filter out from the set I, the items suiting best the user's preferences by calculating a relevance score.
The relevance of an item with respect to the category of interest entails two components: the topic and the location relevance. The topic relevance assess to which degree the user preferences related to the given category are related to an item and is calculated as :

$$Topic_{rel}(VC_i, It) = \frac{\sum_{j=1}^{n} VC_i^j * It_j}{\sqrt{\sum_{j=1}^{n}(VC_i^j)^2} * \sqrt{\sum_{j=1}^{n}(It_j)^2}} \tag{1}$$

Where:
VC_i: the preferences keywords vector related to category C_i
It: the item keywords vector

The location relevance is only used in case where the user has to move to get to the suggested item. It is expressed by a score measuring the accessibility to the actual place's location and is calculated as the distance between 2 GPS coordinates corresponding to the user's current location and the suggested item location: ($P1(lat1, long1)$ et $P2(lat2, long2)$):

$$accessibility = R * c \tag{2}$$

Where:
R: The earth radius=6,371Km
$c = 2 * atan2(\sqrt{a}, \sqrt{(1-a)})$
$a = sin^2((lat2 - lat1)/2) + cos(lat1) * cos(lat2) * sin^2((long2 - long1)/2)$
The overall relevance for a result is calculated as :

$$Rel = \alpha * Topic_{rel}(C_i, It) + (1 - \alpha) * accessibility \tag{3}$$

The results are ranked according to their overall relevance scores. The recommendation process is summarized as follows :

```
Input: Profile{{C_i, w_i}^{i=1..n}}
        C_i = {(t^i_j, w^i_j); j = 1..m}
        Situation {UP, D_l}
        Situation Knowledge Database (KB)
Case of D_l
      item type(s)← get(KB,D_l)
      For each item type
         I← get(service,type,D_l)
         For each i ∈ {I}
            Compute topic-relevance of i
            If item type is accessibility sensitive
               compute geo-relevance of i
            End If
               Compute the overall relevance of i :
               R(i) ← f(topic − relevance(i), geo − relevance(i))
         End For
      End For
```

4 Experiments

We evaluated our approach using the TREC 2014 *Contexual Suggestion Track* task. We present in this section, a general description of the task, then we expose the obtained results.

4.1 The TREC 2014 Contexual Suggestion Track

This task offers an evaluation platform for search techniques that depend highly on the context and the user interests. The input to this task consist of a set of profiles, a set of sample suggestions (a set of venues evaluated by the profiles) and a set of contexts. Each profile corresponds to a single user, and indicates the preference of the user with respect to the set of suggestions. For example, one suggestion could be a recommendation to have a beer at the Dogfish Head Alehouse. The profile describes the negative or the positive preference of the user regarding the set of suggested venues.

Profiles Processing. The profiles are constructed using the list of the suggested venues evaluated by the user. Each suggestion is evaluated according to two ratings: a rating for the venue's title and description and a rating for the venue's website. The profile should indicate which venues a user likes or does not like. The ratings are fixed on a five-point scale based on how interesting a venue would be for the user if he was visiting the city the venue was in:
4, Strongly interested; 3, Interested; 2, Neutral; 1, Disinterested; 0, Strongly disinterested; -1, Website didn't load or no rating given

The suggestions (venues) representation :

```
id,title,description,url
1,Fresh on Bloor,"Our vegan menu ...",www.freshrestaurants.ca
```

The user's ratings :

```
id,attraction_id,description,website
1,1,1,0
```

In order to define the user's thematic profile, we identify for each suggested venue its category using Google Places API[4]. A profile is then expressed as a set of weighted categories under which there are terms set related to the liked suggestions :$profile = \{C_i, w_i\}; i = 1..n$

The categories are represented by a set of weighted terms extracted from the suggestions' descriptions. For each profile, the weight assigned to a particular category takes into account the two ratings of the suggested venues that were rated by users. One rating for the venue's title and description and the other one is for the venue's website.

$$weight(category) = \frac{\sum_{\forall s \in C} R_{td} + R_w}{N_p} \tag{4}$$

Where:
$\forall s \in C$: for each suggestion s belonging to this category C
R_{td}: The venue's title and description rating
R_w: The venue's website rating
N_p: the number of suggestions belonging to this category

Contexts Processing. The TREC task defines context according to GPS coordinates *context=(latitude,longitude)*. For each context, we gather possible venues by querying two geo-based services: Google Places and Foursquare. The query is modeled as:
Query=\{*(latitude,longitude),category*\}

A venue (query result) is modeled as an object having specific attributes and belongs to a specific category:

venue=\{*name,url,description,accessibility,category* \}

accessibility: Represents the distance separating the venue from the specified location. The venue accessibility is measured as the distance between 2 GPS coordinates(see formula number 2).

[4] https://developers.google.com/places/documentation/?hl=fr

(Profiles, Suggestions) Matching. The selection process of interesting places for each context-profile pair is summarized as follows:

```
For each p_i ∈ P
   For each c_j ∈ Cx
      - Calculate, for each suggestion s ∈ Cx_{j_suggestions}
        the relevance(Formula 3)
      - Normalize the relevance scores of the suggestions
        between 0 and 1
      - Extract the suggestions which relevance score
        is ≥ 0,5
        and that belongs to the categories of interest
        that are appreciated by the profile
        category_weight_normalised ≥ 0.5
```

Where:
P: The Profiles set
Cx: The Contexts set
$Cx_{j_{suggestions}}$: The set of suggestions related to context C_j
s: suggestion $\in Cx_{j_{suggestions}}$

4.2 Results

To measure the geographic relevance of the venues that we suggested for each context, we extracted a venues' sample V_g which involves the intersection of our venues collection with the venues that have been evaluated geographically in the TREC task for each context. We obtained $|V_g| = 4802$ venues across all contexts. Among these places, 4644 were evaluated geographically relevant which implies a total geographical precision equal to 0.97 and is calculated as:

$$geo\_relevance = \frac{Nb\_Geo\_Relevant\_Venues}{|V_g|} \tag{5}$$

To measure the profile relevance, there were two alternatives to note. A first alternative is to consider for each context, the intersection of our venues' collection with the venues provided by each run[5], however, this intersection almost gave the empty set. We opted for an intermediate solution of considering the intersection of our venues' collection with the union of the venues that each run has proposed across all profiles in order to get the suggested venues ratings. The cardinality of this intersection is $|V_p| = 889$ venues.

Then we measured for each venue the level of interest that it has requested from the profiles based on the number of profiles that have evaluated this venue

[5] A run represents the set of venues proposed by a team participating in the TREC 2014 Contextual Suggestion Track.

Table 1. Profile relevance (NBInV is the number of venues that were rated as interesting by the profiles; NbTotV is the total rated venues that were suggested by the run; Prec. stands for the precision)

id	run	NbInV	NbTotV	Prec.	id	run	NbInV	NbTotV	Prec.
1	BJUTa	352	1495	0,24	**20**	SScore	244	1496	0,16
2	BJUTb	327	1495	0,22	**21**	SScoreImp	254	1496	0,17
3	BUPT_01	81	671	0,12	**22**	tueNet	129	1497	0,09
4	BUPT_02	78	704	0,11	**23**	tueRforest	138	1497	0,09
5	cat	318	1496	0,21	**24**	UDInfo_1	201	1495	0,13
6	choqrun	196	1465	0,13	**25**	UDInfo_2	360	1495	0,24
9	dixlticmu	367	1496	0,25	**26**	uogTrBun	272	1495	0,18
10	gw1	58	1466	0,04	**27**	uogTrCsL	199	1496	0,13
11	lda	163	1496	0,11	**28**	waterlooA	260	1497	0,17
14	RAMAR2	260	1497	0,17	**29**	waterlooB	286	1497	0,19
15	RUN1	229	1494	0,15	**30**	webis_1	269	1477	0,18
16	run_DwD	181	1496	0,12	**31**	webis_2	230	1474	0,16
17	run_FDwD	262	1496	0,18					

as relevant compared to the total number of evaluations of the same venue. We obtained an average precision of 0,56 that is calculated as :

$$profile\_relevance = \frac{\sum_{v=1}^{|V_p|}(nb\_profiles_v / tot\_nb\_profiles_v)}{|V_p|} \tag{6}$$

where:
$nb\_profiles_v$: is the number of profiles that evaluated the venue v as interesting.
$tot\_nb\_profiles_v$: is the total number of profiles that evaluated the venue v.

In order to compare approximately the result that we obtained with the other participants'results, we also applied this method to the other runs in order to measure the profile relevance. Indeed, for each run we calculated the number of the venues that were rated interesting by the profiles compared to the total rated venues that were suggested by the run (see table 1).

As we can notice from Table 1, the profile relevance for each run does not exceed 0.25. This is explained by the fact that for each run, there is a large gap between the number of profiles that have judged a venue (belonging to a given context) as relevant and the number of the total judgments for the given venue.

The results that we obtained using our approach are promising and show that the use of the categories classification of a profile's preferences implies better thematic relevance compared to the profile interests. These results also indicate that the choice of the parameters that we have set such as the radius used for the definition of the premises of the venues for a given context, are effective. However, this evaluation has only indicted a part of our approach. Indeed, the time notion and the current activity of the user are not incorporated in the TREC task whereas these dimensions are considered in our approach.

5 Conclusion

The fundamental purpose of Context-Aware Recommender Systems consists in combining the user's context and environment in a same infrastructure to better characterize the user information needs in order to improve the recommendation process.We proposed a proactive context-aware recommendation approach that can help users deal with information overload problem efficiently by recommending relevant items that match users? personal interests at the right time without waiting for users to initiate any interaction or activity. More specifically, our contribution is divided into two main areas: The modeling of a situational user profile and the definition of an aggregation frame for social contextual dimensions combination. Actually, we are planning to participate in the RecSys 2015 Challenge *YOUCHOOSE* in order to validate our approach by incorporating, this time, the user's current activity and the time notions within the experiments.

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