Just-In-Time Recommendation Approach Within A Mobile Context

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***Abstract*—Just-In-Time Recommender Systems involve all systems able to provide recommendations tailored to the preferences and needs of users in order to help them access useful and interesting resources within a large data space. The user does not need to formulate a query, this latter is implicit and corresponds to the resources that match the user's interests at the right time. In this paper, we propose a proactive context-aware recommendation approach for mobile devices that covers many domains. It aims at recommending relevant items that match users' personal interests at the right time without waiting for users to initiate any interaction.**

***Index Terms*—Context Modeling, Context-Aware Recommendation, User Modeling, Proactive Recommendation**

I. Introduction

A key aspect in recommendation approaches is the use of context which stands for factors such as location, time and the user's current activity that describe or infer the user's situation. 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: *the information need reformulation*, *the selection of information resources* and *the information relevance evaluation*. 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, resources in the nearbies, movement, etc., have to be managed and represented which requires a big amount of information and are time consuming. On the other hand, context models integrating few dimensions are unable to figure out the whole user context. Besides, relying on user's explicit rating data as feedback for recommendation put a certain burden on the users.
In this paper, we propose 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.

The paper is organized as follows. In Section 2, we provide an overview about the related work. Section 3 presents the proposed approach. In Section 4, we describe the experiments. In Section 5, We finish with our conclusions and summarize thoughts for future work.

II. Related Work

Several systems have been developed to support proactive recommendation. In order to recommend items related to user's interests, various approaches depend on the user's past or actual behavior history that includes previous visiting behaviors for location-based systems ([2], [3]); Web browsing history/clicks ([4]) and previous reading patters for news recommendation systems ([5], [6], [7], [8]). Other approaches considered recommendation from an activity centric angle. Indeed, they relied on triggers to launch the recommendation process. The triggers might take the form of ongoing conversation or activity such as text messages, phone calls [9]; opened web pages or documents ([10], [11], [12]) and the social media activity of the user such as the content of the user's tweet stream on Twitter ([13], [14], [15]).
Hao et al. [16] uses the user's social network in order to extract preferences data and friendship information. They use explicit ratings published in epinions[1] and Duban[2] social networks and thus do not infer the user's interests from his published content. Wang et al. [17] blend information from various SN that the user is registered to. Nevertheless, they rely on the user's explicit feedback based on the recommended activities rating.
Most of the above mentioned approaches encounter certain limitations regarding context acquisition, modeling and interpretation without the user's interference in order to initiate the recommendation process. They are generally domain dependent and deal with the recommendation process from an activity centric angle by focusing on the *opened web pages or documents* or the *ongoing conversation or activity* such as text messages or phone calls on the user's mobile phone. Besides, 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 searching, tagging or clicking. Mobile systems can help keep track of user's activities, preference and location. We believe that we can take advantage from the same context information without encumbering the user's mobile and recommend items related

[1] www.epinions.com
[2] www.duban.com

to different domains. 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.

III. Proposed Approach

We propose an approach for proactive context-aware recommendation that covers several domains and recommend the right item when it is most needed without waiting for the user to initiate any interaction or activity with his mobile device.

A. Context Modeling and Acquisition

A multi-dimension representation is considered for the context modeling
context=(profile,location,time) that entails three dimensions, which are:

- The user profile : user's related information and interests modeled as specific weighted categories C :
  $UP = \{C_i, w_i\}; i = 1, ..., n$
  The user's click-through on a recommendation is also considered as implicit feedback in order to enrich and update the user's preferences database.
- Location: the user's position extracted by GPS coordinates
- Time: numerical or temporal labels (morning, evening, ...). Precisely, a day is split into time slots of a certain length that help to determine the information type to recommend. Time is represented according to two levels:
  - Time of the day: A daily routine is divided into five periods (morning, midday, afternoon, evening and night) that are framed within 24 hours intervals.
  - Week day : defined by two main classes that are workdays (Monday to Friday) and rest days (week-end, vacations and public holidays)

These dimensions are instantiated using the sensors embedded in the user's smartphone in order to capture the context.

B. Information Extraction and Recommendation

We consider that user's daily routine is represented as a pack of situations organized within a knowledge database, that reflect a specific category of interest described by the the spatio-temporal dimensions' instantiations. A situation is characterized by three dimensions: the time of the day, the weekday and the actual location: $S = (D_t, D_w, D_l)$
Böhmer et al. [18] performed a study about user's behaviour and have shown that users tend to consult weather and news in the morning (from 7am to 9am), sports applications in the afternoon around (2pm-5pm) and read books at late evening. Thus, the category of interest of the information to recommend is inferred from the current situation, (Example :*Restaurant* for the situation *Lunch*).
We look for the information to recommend by extracting items from a social networking service that depends on the type of information that should be recommended. For instance, we use Feedly[3] in order to retrieve interesting news, and Foursquare to extract information related to restaurants and points of interests. The purpose of using social networking services for information retrieval lies in the fact that the information extracted is voted interesting by other users. Then, we will be filtering out from information already voted as interesting those suiting best user's preferences.
We represent the query result by a set of items $I : I = \{i_1, , i_n\}$ that are modeled as weighted terms vectors $i_j = \{t_k^j, w_k^j\}; j = 1, ..., n; k = 1, ..., p$
The set I is filtered out by calculating a relevance score, in order to extract the items that match the user's preferences.
The item relevance regarding the category of interest includes two components: the topic and the location relevance. The topic relevance estimates to which degree an item is related to the user's preferences with respect to the given category and is calculated by the cosine similarity :

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

Where:
VC_i: the preferences keywords vector related to category C_i
It: the item keywords vector
In the case where the suggested item is related to a location, we measure the location relevance by calculating the distance between the two GPS coordinates: $(P1(lat1, long1)$ et $P2(lat2, long2))$ that correspond to the suggested item location and the user's current location :

$$accessibility = R * c \quad (2)$$

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 used to rank the results is computed as

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

α is set to 0.6 according to experiments.

IV. Experiments

A. Dataset

Our approach was evaluated against the TREC 2012 Contexual Suggestion Track. This task explores search techniques that depend on context and user interests.
The task's input includes a set of suggested venues that were evaluated by a set of users on a five-point scale based on how much a user might find a venue interesting. The two sets are used to leverage the users' preferences regarding the kind of venues the users would like to visit. The task also includes a set of contexts that correspond to a particular location characterized by a city, day of the week, time of day, and season. For instance, a context might be *Los Angeles, California, on a weekday morning in the fall*. For each profile/context pairing, it is required to generate a list of venues that are deemed appropriate to the user's profile based

[3] http://feedly.com/index.html/discover

on his preferences and to the context. The user's profile are modeled as a set of weighted categories under which there are terms related to the liked suggested venues' descriptions.
In a second phase we proceed with gathering the venues related to each context using three geo-based services : Google Places[4], Foursquare[5] and yelp[6]. As we explained earlier, we consider each context as a situation characterized by a particular category of interest. For example, we believe that it would be more convenient to suggest to users to go to see a movie or to visit theaters in the evening.
In order to extract possible interesting venues for each context, we send a query to geo-based services having as parameters the GPS coordinates and the category of information needed. The query's results stands for a set of venues characterized by *a name, URL, a description, accessibility and a category*.
In a third phase we set the profiles/suggestions matching process for each context using the relevance score calculation explained earlier (see formula 3).

B. Results

As we could not be a part of the TREC 2012 Contextual Suggestion track evaluation and having our suggested venues being evaluated by the users, we extracted from our evaluation data the venues that were fully evaluated in the track for geographical, temporal and website relevance. Since there were some judgements missing for some profile/context pairs, we conducted a user study in which we asked participants to rate on a 3 point scale the venues that were suggested for these profile/context pairs: 0 for *non-relevance*, 1 *for marginal relevance* and 2 *for perfect relevance*. The set of venues judged within the user study includes not only the venues that had their evaluation missing within the TREC evaluation, but also those that were judged in the track. This is actually used, with other parameters, in order to evaluate the coherence of the judgements of the user study participants. Indeed, once we have finished with the user study, we calculated the *Fleiss KAPPA* [19] coefficient which measures the inter-agreement between the participants. A Kappa coefficient close to 1 indicates a perfect agreement. Table 1 presents the different KAPPA coefficients measured regrading the geographical, the temporal and the website judgements for all the participants. Those latters were given information about the users's preferences and the venues (name, description, location, website). We also tried to compare the participants judgements scores

GeoFleiss Kappa	1.000
TempFleiss Kappa	0.675
WebFleiss Kappa	0.853

TABLE I: The user study inter-agreemnt

with those given in the TREC evaluation for some venues in order to figure out if the particpants were really able to guess the profile's preferences and tastes regarding the suggested venues. Therefore, we measured the precision of the scores given by the participants regarding the TREC evaluation scores for the geographical, the temporal and the website aspects. Table 2 presents the precision scores.

Geo_precision	0.909
Temp_precision	0.818
Web_precision	0.727

TABLE II: The The users'study and the TREC evaluations scores matching

According to the precision scores that we obtained, we can deduce that the users'study that we conducted is reliable in order to fill up the remaining missing scores within the TREC evaluation.
There were two measures used for the TREC track evaluation : precision at rank 5 (P@5) and the mean reciprocal rank (MRR) up to rank 5 (MRR@5). The P@5 is the proportion of the top 5 relevant suggested places and the MRR@5 is the inverse of the rank of the correct suggestion among the first five suggested places according to a context/profile pair.
There were 10 scores computed by the P@5 and the MRR@5 measures, standing for : the geographical relevance (G), the temporal relevance (T), the website rating (W), the geo-temporal combined score (GT) and the web-geo-temporal combined score (WGT). Then, an overmean across all profile-context pairs was calculated for the approaches (runs) presented within the TREC 2012 Track[7]. We present, in Table 3 and Table 4, all runs ordered by P@5 and MRR@5 on the WGT score.
As we can notice from Table 3 and Table 4, the approach that we propose yield to promising results and prove that the classification method of the users's preferences and the suggested venues within time-related specific categories leads to a better contextual relevance. The results also reveal that the parameters set within the venue retrieval phase such as the radius defining the venue's premises for a context, are generally effective.

V. Conclusion

Context-aware Recommender Systems aim at combining the context and the user in the same framework to better characterize the information the user needs to improve the recommendation process. We proposed an approach for proactive context-aware recommendation that covers several domains and recommend the right item when it is most needed without waiting for the user to initiate any interaction or activity with his mobile device. The approach entails the modeling of a situational user profile and defines an aggregation framework for contextual and social dimensions.
Actually, we are working on integrating a situation assessment phase in which we will integrate mobile technologies and the user's context in order to figure out what are the different factors that make the user less open to recommendations.

[4]https://developers.google.com/places/
[5]https://www.foursquare.com/
[6]https://www.yelp.com
[7]http://trec.nist.gov/pubs/trec21/papers/CONTEXTUAL12.overview.pdf

run	P5_WGT	P5_GT	P5_G	P5_T	P5_W
Proposed approach	0,4125	0,4750	0,7750	0,6625	0,7875
iritSplitV1	0,3375	0,5625	0,8750	0,5750	0,4750
UDInfoCSTc	0,3000	0,6125	0,8625	0,6625	0,4000
gufinal	0,2875	0,7250	0,9250	0,7375	0,4125
ICTCONTEXTRUN2	0,2875	0,5250	0,8625	0,5250	0,3875
guinit	0,2500	0,6500	0,9375	0,6500	0,3625
udelp	0,2375	0,5750	0,9125	0,5875	0,4250
UDInfoCST	0,2375	0,6375	0,8375	0,7250	0,3750
udelnp	0,2125	0,5875	0,9500	0,5875	0,4125
baselineB	0,2000	0,6750	0,8875	0,6875	0,3125
PRISabc	0,2000	0,5750	0,8625	0,5750	0,3500
run02K	0,2000	0,5750	0,9000	0,5875	0,3500
hplcranki	0,1875	0,5875	0,8500	0,6250	0,3750
iritSplitV2	0,1875	0,5125	0,8250	0,5250	0,3375
run01TI	0,1875	0,6000	0,9000	0,6125	0,3875
baselineA	0,1750	0,4375	0,8250	0,5000	0,4500
ICTCONTEXTRUN1	0,1375	0,5500	0,8750	0,5500	0,3125
waterloo12a	0,1375	0,4625	0,9375	0,4625	0,3500
hplcratin	0,1250	0,4625	0,8875	0,4750	0,4250
waterloo12b	0,1250	0,5750	0,8875	0,5750	0,2125
csiroht	0,0750	0,4750	0,8000	0,4875	0,1875
csiroth	0,0750	0,5375	0,8500	0,5500	0,1375
UAmsCS12wSUM	0,0625	0,1750	0,4375	0,3500	0,2750
FASILKOMU01	0,0500	0,5625	0,9250	0,5625	0,0750
UAmsCS12wSUMb	0,0250	0,2000	0,5000	0,3625	0,3000
FASILKOMU02	0,0000	0,5750	0,9000	0,6000	0,0500
watcs12a	0,0000	0,0000	0,0000	0,7000	0,6125
watcs12b	0,0000	0,0000	0,0000	0,5000	0,6625

TABLE III: The 5 P@5 measures sorted by WGT

run	M_WGT	M_GT	M_G	M_T	M_W
gufinal	0,5885	0,8438	1	0,8438	0,6823
Proposed Approach	0,4833	0,5771	0,8719	0,7417	0,8021
iritSplitV2	0,4604	0,7813	0,9063	0,8125	0,5125
UDInfoCSTc	0,4583	0,75	0,9063	0,8125	0,4896
iritSplitV1	0,4385	0,6969	0,9375	0,6969	0,6167
guinit	0,4187	0,7396	1	0,7396	0,5177
PRISabc	0,4115	0,6927	0,9688	0,6927	0,5229
run02K	0,4104	0,7521	0,8958	0,7521	0,5406
ICTCONTEXTRUN2	0,401	0,7083	0,9688	0,7083	0,5229
UDInfoCST	0,401	0,8125	0,8594	0,9688	0,5469
udelnp	0,3594	0,6792	0,9688	0,6792	0,6667
hplcranki	0,3562	0,6979	0,875	0,7708	0,526
baselineB	0,3302	0,7813	1	0,7813	0,499
udelp	0,3281	0,651	0,9583	0,651	0,625
run01TI	0,3177	0,6406	0,875	0,6406	0,6615
hplcratin	0,3146	0,5781	0,9688	0,5938	0,6583
baselineA	0,3062	0,6354	0,9375	0,6979	0,651
ICTCONTEXTRUN1	0,2656	0,6615	0,8563	0,6615	0,5104
waterloo12a	0,2469	0,7031	0,9688	0,7031	0,4063
waterloo12b	0,2188	0,6719	0,9063	0,6719	0,3906
UAmsCS12wSUM	0,1688	0,2938	0,5906	0,5094	0,5906
csiroth	0,1302	0,625	0,875	0,625	0,2802
csiroht	0,1063	0,5104	0,8333	0,5229	0,2344
FASILKOMU01	0,0938	0,6615	0,9375	0,6615	0,1146
UAmsCS12wSUMb	0,0833	0,3094	0,6354	0,5333	0,526
FASILKOMU02	0	0,7052	0,9063	0,7365	0,0677
watcs12a	0	0	0	0,8719	0,6823
watcs12b	0	0	0	0,7781	0,6635

TABLE IV: The 5 MRR@5 measures sorted by WGT

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