Enhancing Traditional Local Search Recommendations with Context-Awareness

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Abstract. Traditional desktop search paradigm often does not fit mobile contexts. Common mobile devices provide impoverished mechanisms for text entry and small screens are able to offer only a limited set of options, therefore the users are not usually able to specify their needs. On a different note, mobile technologies have become part of the everyday life as shown by the estimate of one billion of mobile broadband subscriptions in 2011.

This paper describes an approach to make context-aware mobile interaction available in scenarios where users might be looking for categories of points of interest (POIs), such as cultural events and restaurants, through remote location-based services. Empirical evaluations shows how rich representations of user contexts has the chance to increase the relevance of the retrieved POIs.

Keywords: context-awareness, local search, location-based services, mobile devices.

1 Introduction

Internet location-based services such as Yelp (`www.yelp.com`), Where.com (`where.com`), Zagat (`www.zagat.com`) or Google Maps (`maps.google.com`) are information services accessible with mobile devices that utilize the ability to make use of the current location, acquired by common embedded GPS units, to answer requests about businesses, general information or objects of interest. With 486 million of estimated location-based services users by 2012[1], context awareness makes LBS applications very interesting compared to other mobile technologies. According to the Kelsey Group[2], local search spending forecasts for 2008-2013 are estimated in 130.5% annual growth rate while incomes from local search will surpass 50% of mobile search revenues.

Context is any information that can be used to characterize the current situation of the user environment (1). The whole user context cannot be easily

[1] `www.emarketer.com/Report.aspx?code=emarketer_2000510`
[2] `www.kelseygroup.com/press/pr090224.asp`

Joseph A. Konstan et al. (Eds.): UMAP 2011, LNCS 6787, pp. 335–340, 2011.

identified, analyzed and used during human-computer interaction. Current user needs and goals are complex and dynamic factors to represent, therefore the location becomes the only element of the context that can be easily measured more or less accurately depending on the positioning system. Even though there are several additional factors that potentially affect the interaction with the location-based service and the ranking of search results, a few prototypes provide a better representation of the user context and evaluate the potential benefits in real scenarios.

The paper introduces a neural network approach to make context-aware mobile interaction available in LBSs. Users are able to obtain POIs related to the current context in traditional map-based user interfaces. In the following section (Sect. 3) we describe the proposed approach, while results of the experimental evaluation is provided in Section 4.

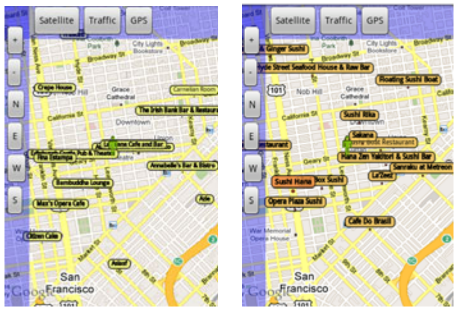
2 Related Work

To the best of our knowledge, there are very few attempts to investigate the integration of context-awareness technologies in location-based services for mobile environments. SmartCon (2) shares some ideas with the proposed approach, namely, the feature-based representations of POIs and neural networks to match them with the current user context. The authors do not take into consideration a traditional scenario where mobile phones interact with web LBSs but they consider customized mobile services and sensors in health monitoring context. The social pervasive recommender named SPETA (5) uses vector representations to draw distances between POIs and user preferences. It collects features of frequently visited POIs and use them for user profiling. Console *et al.* (4) devise and architecture for providing personalized services on-board vehicles. The recommendation is performed according with stereotypes of users. *CareDB* (8) follows a similar approach, where a so-called query rewriting module translates preferences and context into db query operators. Unfortunately, both of the approaches do not include any evaluation in real mobile scenarios.

3 Context-Aware Recommendation for LBS

The proposed context-aware recommendation engine is based on artificial neural networks. In this case, context-aware recommendation gives high weights to objects which are the most relevant to the given context. The highly ranked results are shown highlighted on the map-based user interface (see for example Fig. 3). The advantage of this approach is to employ machine learning algorithms to automate the process of determining the connections between the contextual factors and features related to the available POIs. Domain experts do not have to write long hand-coded rules or triggers used to specify how context-aware influence the selection criteria of POIs.

Almost any information available at the time of an interaction can be seen as context information. Examples are spatial and temporal information, e.g.,



(a) (b)

Fig. 1. A snapshot of the Google Maps GUI during a search for restaurants (a) and restaurants suggested by our recommender system where darker colors are associated to the most important results (b) (©2011 Google - Map data ©2011 Google)

current location, orientation and current time. Further factors of these kinds can be induced by querying public information services, such as weather, traffic reports and forecast services, or inferred by analyzing the obtained information, e.g., speed and day of the week.

As the user activity is crucial for many applications, context awareness has been lately focused more deeply in the activity recognition field (3). An activity is a sequence of actions conducted by human beings aimed at achieving a certain goal. Along with location and time, the activity is account to be one of the most important contextual factors in understanding mobile user needs (9).

We employ a richer contextual description that besides traditional physical and environmental factors focuses also on the classification of basic human activities or scenarios. In spite of the obvious relevance of this information for providing tailored results, location-based services for mobile devices based on activity recognition approaches have still to be deeply investigated. One of the reasons is undoubtably the complexity of representations and analysis of multiple specific sensor data in the recommendation task.

Even though there are accurate algorithms to estimate the user's physical activity or his social environment (e.g., sitting, standing, walking, in a restaurant or lecture), most of them analyze data collected by wearable sensors such as accelerometers or microphones. One requirement of the system is traditional smart phones as standard devices.

For our purpose, we limited our activity representation to coarse locations and user situations, namely: *1.* working, when the user is engaged in work or he is in the neighborhood of the office; *2.* traveling, when the user is moving between two places; *3.* other, that is, unknown activities or known activities with likelihoods under a given threshold.

The approach proposed by Liao *et al.* (7) is based on Relational Markov Networks (RMN) and raw location data collected by embedded GPS units of mobile devices to build personal maps and associate one of the above-mentioned activities to the current context. The rest of factors included in the context representation correspond to information about the weather and the time of the day. We can summarize them as follow:

– *Current activity*: (working, traveling, other)
– *Time of the day*: (morning, lunch, afternoon, dinner, night)
– *Mode of transportation*: (foot, car)
– *Weather*: (bad, good)

Pre-processing of the raw data having the characteristic of consecutive data, for instance, time and speed, is done in order to abstract them into a set of concepts, for example, *bad weather* or *traveling by car*.

In order to match the current context with the POIs of a LBS, we first use the location as query to retrieve the list of POIs in the user neighbor. The user is able to select one of the available categories, such as restaurant, night club and event. For each category of objects there is a set of features that characterizes some of the relevant information that has the chance to alter the recommendation ranking. For the sake of argument, in the case of restaurant recommendation, we queried Yelp services via its API obtaining 10 features. The available boolean features are: *restaurants with a private parking*, *fastfood/restaurant*, *dress code*, *take-out*, *waiter service*, *outdoor sits*, *take reservation*, *breakfast*, *lunch*, *dinner*. Two more features, namely, the *distance* and *time before closing*, are drawn assessing the two contextual features *user location* and *current time* along with the user location and opening hours of the restaurant.

The contextual features and the above-mentioned features of POIs are given as input to the neural network. The output layer is composed of 5 nodes representing how much close a given restaurant is to the current user context. Basically, the first node is associated to a *not interesting* recommendation and the fifth to *very interesting*. A supervised learning algorithm based on gradient descent and 10-fold cross-validation trains the neural network organized with a feed-forward multi-layer perceptron with one hidden layer.

As for training data used during the unsupervised learning, we collected the user feedback on a set of restaurants from a group of users according with random combinations of contextual factors.

4 Evaluation

We chose restaurants as popular points of interest users usually look for on mobile devices. A group of 15 college students familiar with mobile interfaces were asked to rate three lists of 20 restaurants, each list built querying the Yelp LBS. The three lists are related to restaurants in the neighbor of one specific location (i.e., an intersection road) in three U.S. cities respectively. The same evaluation can be performed with different LBSs so long as they provide a developer interface for obtaining POIs and related features given a location.

Table 1. Comparison of recommendation algorithms in term of NDCG@n

	$NDCG$@1	$NDCG$@5	$NDCG$@10
$Distance$	$0,097$	$0,269$	$0,295$
$YelpLBS$	$0,079$	$0,309$	$0,252$
$Context-Aware$	$0,324$	$0,564$	$0,737$

Each tester were asked to rate the three lists order according with three different contexts: *1.* You are going by car in the evening, you want to have dinner and weather is good, restaurants will be open for at least two hours; *2.* You are going on foot in the evening, you want to have dinner and weather is good, restaurants will be open for at least two hours; *3.* You are going on foot, you want to have lunch, and weather is good, you are just out of your place of work/study or in its surroundings, restaurants will be closed in 30 minutes, one hour. A preliminary analysis of mobile interactions with a popular LBS performed by some testers let us choose these three common contexts that represent quite different situations.

The order of restaurants to rate were previously randomized. The testers were free to browse Internet to acquire additional information useful for the task, e.g., price, photos, reviews. Of course, there is no overlap between contexts used for training and testing.

The rates are in Likert scale: *non-significant*, *significant*, *very significant*. The performance is evaluated by means of the Discounted Cumulative Gain NDCG of the top n items NDCG@n (6), a popular measure for search engine algorithms. The limit of the top n is justified since it is unlikely that mobile users will scroll long lists of retrieved items.

A comparison with a location-based ranking (Distance) and with the rank provided by Yelp, which likely balances distance and number positive reviews, shows that the gain for context-aware ranker is the largest. In other words, the recommendations provided by the system get closer to the ideal ranking proposed by users. All results were tested for statistical significance by using a paired 2-tailed t-test with p-value < 0.05.

5 Conclusions

We have presented a recommender system for context-aware mobile services. The system infers contextual data to provide users with personalized recommendations about POIs in the surroundings of the current position. The results of an evaluation performed on users show that the proposed approach provides significant benefits in terms of effectiveness of recommendations in comparison with traditional location-based services. In other words, the highly ranked results are the ones judged more appropriate for the current context. We are currently investigating the utility of information extraction and social network analysis to exploit networks of relationships in the recommendation process.

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