

# Opinion-based User Profile Modeling for Contextual Suggestions

Peilin Yang  
Department of Electrical and Computer  
Engineering  
University of Delaware  
Newark, DE USA  
franklyn@udel.edu

Hui Fang  
Department of Electrical and Computer  
Engineering  
University of Delaware  
Newark, DE USA  
hfang@udel.edu

## ABSTRACT

The problem of contextual suggestion is defined as finding suggested places for a user based on the temporal and geographical context of the user as well as the user's preferences on example places. Existing studies model user preferences based on the descriptive information about the suggestions and might not generalize well. In this paper, we propose to model user profiles based on the opinions about the candidate suggestions. Instead of simply building a profile about "what a user likes or dislikes", we want to build the profile based on "why a user likes or dislikes" so that we can make a more accurate prediction on whether a user would like a new candidate suggestion. In particular, we propose to leverage the opinions from the comments posted by other users to estimate a user's profile. The basic assumption is that the reason why a user likes or dislikes a place is likely to be covered by the reviews posted by other users who share the similar opinions as the user. Experiments results over a TREC collection show that the proposed opinion-based user modeling can indeed outperform the existing description-based methods.

**Categories and Subject Descriptors:** H.3.3 [Information Search and Retrieval]: Information filtering

**General Terms:** Algorithms, Experimentation

**Keywords:** contextual suggestions, opinion, user modeling, recommendation

## 1. INTRODUCTION

Information Retrieval (IR) traditionally focuses on finding relevant information with respect to a query submitted by a search user. However, with the increasing use of mobile devices and information technology, it becomes possible to predict a user's information need based on the contextual information and user past activities collected by the mobile devices. Such prediction could enable IR systems to *proac-*

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [Permissions@acm.org](mailto:Permissions@acm.org).

*ICTIR '13*, September 29 - October 02 2013, Copenhagen, Denmark  
Copyright 2013 ACM 978-1-4503-2107-5/13/09 ...\$15.00.  
<http://dx.doi.org/10.1145/2499178.2499191>

*tively* provide relevant suggestions to the search users even before they submit any queries explicitly. For example, it would be useful to proactively send recommendations about the Beatles museum to a music fan who travels to Liverpool. This problem is referred to as *contextual suggestions* and has been identified as one of the IR challenges (i.e., "finding what you need with zero query terms") in the recent SWIRL 2012 workshop [1].

The TREC Contextual Suggestion Track [2] provides an evaluation platform for research efforts along this direction. Given a user's preferences on example suggestions and the user's geotemporal contexts, the task is to return a list of relevant suggestions based on both user profile and contexts. For example, we know that a user likes "Magic Kingdom Park" and dislikes "Kennedy Space Center". Assume that today is a Saturday and the user is in Philadelphia, the goal is then to automatically generate suggestions of the places for the user to visit, e.g., "Sesame Place". Most TREC participants first filtered out suggestions that do not satisfy the temporal and geographical constraints, and then rank candidate suggestions by using descriptions and categories information about the places to model the user profiles.

In this paper, we focus on the problem of user profile modeling for contextual suggestions. Since we know the places that a user likes and dislikes, a straightforward solution is to estimate a positive user profile to model what the user likes and a negative one to model what the user dislikes. Once we estimate such profiles for a user, we can then rank suggestions based on both their similarity to the positive user profile and their dissimilarity to the negative user profile. Existing studies estimated the user profiles based on the description and categories of the suggested places [4, 15, 16]. However, this method can only capture what kind of places a user like and may not be able to generalize well to infer the user preference on other places since their descriptions and categories may not match those in the user profile.

To address this challenge, we propose to model user profiles based on the reasons why the user likes or dislikes the places, i.e., their opinions about the suggestions. Since such information might not be available for every user and every place, our method is designed to take advantage of the wisdom of the crowd. In particular, we leverage the online opinions posted for each place and use them to approximate an individual user's opinion about the place. If a user likes a place, the positive profile of this user would be estimated based on the opinions about this place from similar users, i.e., those who also like the place. The negative profile could

be estimated in a similar way. We then explore several ways of estimating the profile based on the opinions. These methods are mainly different in what kind of information from the opinions is used for profile modeling.

Experiments are conducted on the TREC 2012 Contextual suggestions track collection. Results show that the proposed opinion-based method is more effective than existing description-based method for user profile modeling.

## 2. RELATED WORK

Most participants in TREC 2012 Contextual Suggestion track formulated the problem as a content-based recommendation problem since we only have a limited amount of information about user preferences [4, 12, 15, 16]. Thus, the user profile modeling is clearly the key challenge that needs to be solved. Various types of information about the example suggestions has been used to estimate user profile, and these information types include the descriptions of the places [4, 15], the categories of the places [15, 16] and the web sites of the places [4, 12]. However, none of the groups has tried to leverage the reviews about these places to estimate the user profile as what we propose in this paper.

Our work is also related to the studies on collaborative filtering [7, 14]. Collaborative filtering assumes that similar users would share similar ratings, and focuses on predicting the user rating based on such an assumption. Although our paper also leverages the information from similar users, we focus on estimating a better user profile based on the opinions from similar users.

Reviews have been utilized to improve the performance of recommendation systems [3, 6, 10, 11, 13]. Our paper is different from these previous studies because we directly use reviews to model user profile while others used reviews to predict the rating quality or the user intent.

## 3. PROBLEM FORMULATION

Following the problem set up of the TREC 2012 Contextual Suggestion track [2], given a user, we know the context (i.e., location and time) and his/her preferences on a few example suggestions (i.e., the ratings for each suggestion given by the user), the problem is to return a list of candidate suggestions based on both context and user preferences. Since this paper focuses on user modeling, we assume that we have filtered out the suggestions that are non-relevant to the context and the remaining suggestions will only need to be ranked based on the relevance to user preferences. This is a reasonable assumption since this two-step strategy was widely used among most participants of the track.

Formally,  $U$  denotes a user,  $ES(U) = \{es_1, es_2, \dots, es_k\}$  denotes a list of example suggestions that the user has rated, and  $R_U(es_i)$  denotes the rating of  $es_i$  given by  $U$ . The problem is, given a user  $U$  and a candidate suggestion  $CS$ , we want to estimate  $S(U, CS)$ , i.e., how likely user would like the suggestion, based on the similarity between the candidate suggestion and the user profile estimated based on  $ES(U)$  and the information about  $es_i$  such as  $R_U(es_i)$ .

## 4. OPINION-BASED USER PROFILE MODELING

### 4.1 Motivation

Existing studies on contextual suggestions estimated user profiles based on the descriptive information of the example

suggestions such as their names, descriptions and web sites [4, 12, 15]. However, one limitation of this approach is that the description could be very specific for one suggestion and might not be useful at all to infer the user’s preferences for other suggestions. Categories of the suggestions were then used by some groups to overcome the limitation [15, 16]. Although this method helps to improve the performance, the improvement is often small.

Instead of simply capturing what a user likes or dislikes, we propose to model the user profile based on his or her opinions about the example suggestions. Let us look at an example as shown in Figure 1. There are three suggestions: the first one is a museum and the last two are hotels. A user likes the first suggestion, but does not like the second one. Now we need to decide whether the user would like the third one. If we only consider the category information, we probably would not recommend the third one to the user because it seems that the user does not like hotels. However, if we know the opinions of the user for the two suggestions, i.e., “a small and clean museum that will take u less than an hour to see everything” for the first one and “dirty hotel, the room itself was filthy” for the second one, we could infer the user would prefer a place that is clean. Since the review of the third suggestion says “great hotel! clean and modern”, we could accurately infer that the user would like this suggestion. Clearly, opinion-based user profile modeling should be more effective than the description-based methods.

However, one challenge is users may not share their opinions explicitly by writing the reviews for each example suggestion. In fact, the problem formulation we described in the previous section does not contain such information at all. To address the challenge, we propose to leverage the opinions from similar users. More specifically, we assume that users who rated a suggestion similarly would share the same opinions about the suggestion. If a user likes a suggestion, we could identify all the other users who also like this suggestion and leverage their reviews about the suggestion as part of the user’s positive profile, i.e., the profile about what the user likes. We can build the negative profile in a similar way.

### 4.2 Matching User Profile with Candidate Suggestions

Given a user  $U$  and a candidate suggestion  $CS$ , the proposed method would compute their similarity score as follows:

1. Build a positive and negative user profile, i.e.,  $\mathcal{U}_{pos}$  and  $\mathcal{U}_{neg}$ , based on the information about example suggestions that the user has rated, i.e.,  $ES(U)$ ;
2. Build a positive and negative profile for the candidate suggestion, i.e.,  $\mathcal{CS}_{pos}$  and  $\mathcal{CS}_{neg}$ ;
3. Estimate their similarity, i.e.,  $S(U, CS)$ , based on  $\mathcal{U}_{pos}$ ,  $\mathcal{U}_{neg}$ ,  $\mathcal{CS}_{pos}$  and  $\mathcal{CS}_{neg}$ .

We now provide more details about this process. Figure 2 illustrates the main idea.

In the first step, we use positive reviews of the example suggestions that the user likes to build his or her positive user profile, and use negative reviews of example suggestions that the user dislikes to build negative user profile. The basic assumption is that the opinion of a user about a place can





	Category	Description (web site)	Review	Preference
	Suggestion 1	Museum	The X Museum is the oldest Holocaust museum in the United States...	A small and clean museum that will take you less than an hour to see everything... 
	Suggestion 2	Hotel	The Y Hotel is just moments from all tourists attractions and exciting things to do in Los Angeles both for business and pleasure...	Dirty hotel, the room itself was filthy... 
	Suggestion 3	Hotel	Hotel Z features an outdoor pool for hotel guests only and indoor/outdoor private event space...	? 

Figure 1: An example scenario when we know the user’s preferences for the first two suggestions and want to predict the preference for the third one

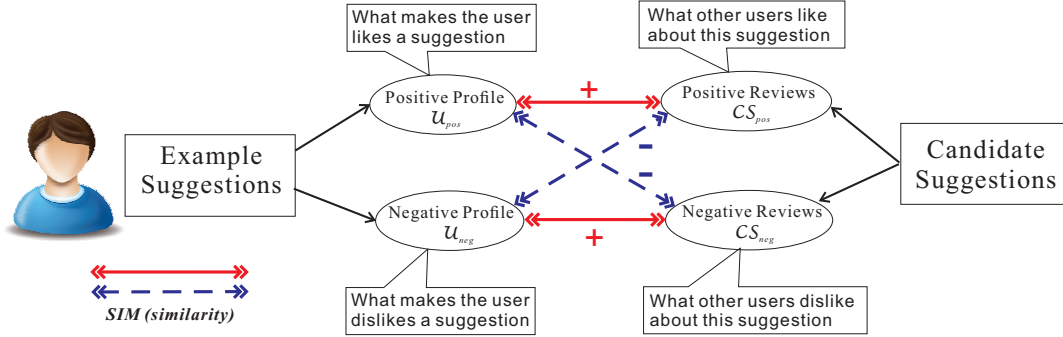


Figure 2: The main idea of the proposed approach

be inferred by the opinions of the users who give the same rating as the target user to the same place.

Formally, the user profiles are estimated as:

$$\begin{aligned}
 \mathcal{U}_{pos} &= \bigcup_{es_i \in ES(U) \cap R_U(es_i)=POS} REP(O_{pos}(es_i)) \\
 \mathcal{U}_{neg} &= \bigcup_{es_i \in ES(U) \cap R_U(es_i)=NEG} REP(O_{neg}(es_i))
 \end{aligned}$$

where  $O_{pos}(es_i)$  represents all positive reviews about  $es_i$ ,  $O_{neg}(es_i)$  represents all negative reviews, and  $REP(O(es_i))$  denotes how to represent opinion  $O(es_i)$  in the profile and we discuss several strategies in Section 4.3. Note that the original value of  $R_U(es_i)$  could be numerical, and we map these values into either POS or NEG.

In the second step, we could follow the similar strategy and build the positive and negative profile for a candidate suggestion CS as follows:

$$\begin{aligned}
 \mathcal{CS}_{pos} &= REP(O_{pos}(CS)) \\
 \mathcal{CS}_{neg} &= REP(O_{neg}(CS)).
 \end{aligned}$$

Finally, let us discuss how to compute the similarity based on all these profiles. Intuitively, a suggestion should have higher similarity with a user when the suggestion has the features that the user likes, or when the suggestion does not have the features that the user dislikes. This means that the similarity should be positively correlated with the similarity between two positive profiles and two negative profiles, i.e.,  $SIM(\mathcal{U}_{pos}, \mathcal{CS}_{pos})$  and  $SIM(\mathcal{U}_{neg}, \mathcal{CS}_{neg})$ . In the meantime, a suggestion should be penalized if it has the features that the user dislikes or does not have the features that the user likes, which means that the similarity should be negatively correlated with the similarity between positive and negative profiles, i.e.,  $SIM(\mathcal{U}_{pos}, \mathcal{CS}_{neg})$  and  $SIM(\mathcal{U}_{neg}, \mathcal{CS}_{pos})$ .

Following the above intuition, we can estimate the similarity between a user and a candidate suggestion as follows:

$$\begin{aligned}
 S(U, CS) &= \alpha \times SIM(\mathcal{U}_{pos}, \mathcal{CS}_{pos}) - \beta \times SIM(\mathcal{U}_{pos}, \mathcal{CS}_{neg}) \\
 &\quad - \gamma \times SIM(\mathcal{U}_{neg}, \mathcal{CS}_{pos}) + \eta \times SIM(\mathcal{U}_{neg}, \mathcal{CS}_{neg})
 \end{aligned} \tag{1}$$

where  $\alpha$ ,  $\beta$ ,  $\gamma$  and  $\eta$  are parameters that balance the impact of the four components to the final similarity score. Their values are chosen in interval  $[0,1]$  with the pace of 0.1.  $SIM(a, b)$  could be any text similarity measure.

### 4.3 Representation of Opinions

We describe a few strategies about how to represent user profiles based on the reviews of a suggestion  $s$ , i.e., how to represent  $REP(O_{pos}(s))$  and  $REP(O_{neg}(s))$ .

- *Use full reviews (FR)*: Use all terms occurred in the positive reviews about a suggestion  $s$  to build its positive profile, i.e.,

$$REP(O_{pos}(s)) = \bigcup_{t \in O_{pos}(s)} t,$$

where  $t$  is a term in the reviews. Similarly, use all terms occurred in the negative reviews of the suggestion to build its negative profile, i.e.,

$$REP(O_{neg}(s)) = \bigcup_{t \in O_{neg}(s)} t.$$

- *Use selective reviews (SR)*: Similar to FR but only include the most frequent terms in the profiles. This will reduce the computational cost significantly.

- *Use nouns (NR)*: Nouns from the reviews often correspond to aspects of suggestions. This strategy extracts only nouns in the reviews to build the profiles.

## 5. EXPERIMENTS

### 5.1 Data Set

We use the collection from the TREC 2012 contextual suggestion data set [2], which contains 34 users and 49 suggestions. Each suggestion has a short description and a URL which directs to the main site of that suggestion. Each user has preferences for all suggestions. There are two kinds of ratings available: ratings on descriptions and ratings on overall preference. In our experiments, we only use ratings on overall preference as ratings. As mentioned before, the ratings of this data set only has three levels: -1, 0, 1, which indicate dislike, indifference and like. We map -1 or 0 to negative (i.e., *NEG*) and 1 to positive (i.e., *POS*) for the value of  $R_U(es_i)$ .

### 5.2 Experiment Design

Our experiment design is different from the TREC official task because no judgments have been released for the official task. Thus, in this paper, we design our experiments to leverage the information available about the 34 users' preferences for the 49 suggestions.

Specifically, for each user, we randomly split 49 suggestions into three data sets, i.e., training, validating and testing. We hold  $\Theta_{profile}$  percentage of the suggestions that user has ratings as the base to model user profiles. We then tune the parameters on  $\Theta_{validate}$  percentage and test on  $\Theta_{test}$  percentage of data set. In our experiments, we use: ( $\Theta_{profile} = 60\%$ ,  $\Theta_{validate} = 20\%$ ,  $\Theta_{test} = 20\%$ ). Parameters of all the methods are trained on the validation set.

We use Mean Average Precision (MAP) [5] and Precision at 5 (P@5) [9] as the evaluation measures. More specifically, a suggestion with rating of -1 or 0 will be viewed as irrelevant, rating of 1 will be viewed as relevant.

We compare the proposed method with two baseline methods. The first one is to estimate the profile based on the descriptions of the suggestions, and the second one is based on the categories of the suggestions [15].

### 5.3 Results

Table 1 shows the cross-validation results of all the methods. It is clear that all the opinion-based methods perform significantly better than the two baseline methods in terms of both measures. In particular, the improvement of the opinion-based methods over the description-based method is much larger than the improvement of category-based method over the description-based one. Moreover, the performance of the three opinion-based methods are similar. Among all of them, the method using full reviews seems to be the best choice in terms of effectiveness.

## 6. CONCLUSIONS AND FUTURE WORK

In this paper, we propose an opinion based approach to user profile modeling for the contextual suggestion problem. Compared with the descriptions of suggestions, reviews contain more information about why users like the suggestions which makes the recommendation method generalize well in

different domains. Empirical results on TREC2012 data collections indeed show that the proposed opinion-based user

Table 1: experiment results on TREC2012 data

Method	MAP	P@5
Description	0.4588	0.5705
Category	0.4706	0.5886
Full Review	<b>0.6059</b>	<b>0.7372</b>
Selective Review	0.6054	0.6966
Noun Review	0.6058	0.7027

profile modeling is more effective than the state of the art method.

There are many interesting directions that we plan to pursue in the future. First, it would be interesting to evaluate the proposed method in the personalized local search problem [8]. Second, we only focus on the user modeling in this paper, and plan to study how to incorporate other context-related factors such as distances into the ranking process. Finally, how to automatically generate interesting descriptions that tailored for specific user is also an interesting topic that we plan to study.

## 7. REFERENCES

- [1] J. Allan, B. Croft, A. Moffat, and M. Sanderson. Frontiers, challenges, and opportunities for information retrieval: Report from swirl 2012 the second strategic workshop on information retrieval in lorne. *SIGIR Forum*, 46(1):2–32, 2012.
- [2] A. Dean-Hall, C. Clarke, and J. Kamps. Overview of the trec 2012 contextual suggestion track. In *Proceedings of TREC'12*, 2012.
- [3] N. Hariri, B. Mobasher, R. Burke, and Y. Zheng. Context-aware recommendation based on review mining. In *Proceedings of the 9th Workshop on Intelligent Techniques for Web Personalization and Recommender Systems*, 2011.
- [4] G. Hubert and G. Cabanac. Irit at trec 2012 contextual suggestion track. In *Proceedings of TREC'12*, 2012.
- [5] K. Järvelin and J. Kekäläinen. Ir evaluation methods for retrieving highly relevant documents. In *Proceedings of the SIGIR'00*, 2000.
- [6] A. Levi, O. Mokryn, C. Diot, and N. Taft. Finding a needle in a haystack of reviews: cold start context-based hotel recommender system. In *Proceedings of the RecSys'12*, 2012.
- [7] G. Linden, B. Smith, and J. York. Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing*, 7(1):76–80, Jan. 2003.
- [8] Y. Lv, D. Lymberopoulos, and Q. Wu. An exploration of ranking heuristics in mobile local search. In *Proceedings of the SIGIR'12*, 2012.
- [9] C. D. Manning, P. Raghavan, and H. Schütze. *Introduction to information retrieval*. Cambridge University Press, 2008.
- [10] R. Qumsiyeh and Y.-K. Ng. Predicting the ratings of multimedia items for making personalized recommendations. In *Proceedings of SIGIR'12*, 2012.
- [11] S. Raghavan, S. Gunasekar, and J. Ghosh. Review quality aware collaborative filtering. In *Proceedings of RecSys'12*, 2012.
- [12] A. Rao and B. Carterette. Udel at trec 2012. In *Proceedings of TREC'12*, 2012.
- [13] J. San Pedro, T. Yeh, and N. Oliver. Leveraging user comments for aesthetic aware image search reranking. In *Proceedings of WWW'12*, 2012.
- [14] X. Su and T. M. Khoshgoftaar. A survey of collaborative filtering techniques. *Adv. in Artif. Intell.*, 2009:4:2–4:2, Jan. 2009.
- [15] P. Yang and H. Fang. An exploration of ranking-based strategy for contextual suggestion. In *Proceedings of TREC'12*, 2012.
- [16] A. Yates, D. DeBoer, H. Yang, N. Goharian, S. Kunath, and O. Frieder. (not too) personalized learning to rank for contextual suggestion. In *Proceedings of TREC'12*, 2012.