

Spontaneous Event Recommendations on the Go

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Abstract. In this paper, we summarize our previous work in the field of event recommendations and give an outlook on future work. We developed a recommender system which implements a hybrid recommendation technique to provide accurate recommendations. A two-week user study showed that our system delivers promising results. Nevertheless, we believe that this approach mainly supports users who are looking for recommendations a long time in advance. Other possible situations in which people could be open for recommendations are more spontaneous, for example, when they are already out exploring the city. We give an overview of aspects which have to be considered for such *spontaneous recommendations on the go* and the role of social context in this scenario.

Keywords: Event Recommendations, Collaborative Filtering, Context-Awareness, Mobile Application.

1 Introduction and Motivation

Recommending future events is more difficult than recommending items of other domains such as movies or points of interest. Events are often unique because they take place only one-time under the exact same conditions. Visitors cannot rate the event before it takes place and their ratings are no longer of importance for other potential visitors when the event is over [4]. These characteristics are the reason why more sophisticated techniques have to be identified and evaluated to ensure accurate event recommendations.

Our previous work presented first approaches to recommend events but these systems mainly support users who want to receive recommendations a long time in advance, before the actual event takes place. Nevertheless, when talking to selected experts from the event and ticketing industry, we found out that especially young people often decide spontaneously to join events they might like. One important factor in their decision making are the opinions of other important persons like close friends.

During our research in the field of event recommendations, we developed a mobile, context-aware event recommender system. In this paper, we present the results of our previous research which are the basis for our future work. Our goal is to find out under which circumstances (e.g., while driving a car or during a

sightseeing trip) users are open for joining recommended events spontaneously. After identifying the context for such spontaneous recommendations, we want to optimize them collaboratively, for example, by taking other people nearby or friends' opinions into account.

2 Previous Research Focus and Results

After conducting expert interviews with four selected representatives from the German event and ticketing industry, we developed our first event recommender system. In order to provide accurate recommendations, we implemented a hybrid recommendation algorithm based on Content-boosted Collaborative Filtering (CBCF). CBCF is a recommendation technique which uses the output from a content-based (CB) prediction to generate recommendations in the subsequent collaborative filtering (CF) phase. Studies show that this combination promises better recommendations than a pure CB or CF recommender [3]. Furthermore, we extended the traditional CBCF approach by contextual pre-filtering of events. Contextual pre-filtering is one paradigm for incorporating context into a recommendation process and allows to immediately exclude events which are impossible to recommend [1]. For example, an event taking place too far away from the user's location does not have to be considered for recommendation. Consequently, the final algorithm is composed of three phases:

1. Contextual pre-filtering
2. Content-based prediction
3. Collaborative filtering

The contextual pre-filtering reduces the number of possible recommendations before the actual recommendation process takes place. Events are filtered by a set of context factors we evaluated during the expert interviews like the geographical context, temporal factors and temporarily wanted or unwanted genres. The user can set thresholds like the maximum distance to a venue and if the context of a potential recommendation exceeds this threshold, the corresponding event will not be considered for recommendation.

After excluding events which do not satisfy the context constraints, the CB prediction phase takes place. For this, we adapt the classical CBCF approach to the special case of event recommendations. We analyze event attributes rated by the user in the past in order to estimate ratings for events comprising these attributes. Based on the expert interviews we conducted, events are mainly characterized by structured data. This is the reason why we propose a case-based approach for the CB prediction of ratings, as presented by [6]. For each event attribute (e.g., the venue), we count how often the user gave positive or negative feedback to previous recommendations comprising this attribute. If the user's history provides feedback for a sufficient number of attributes of an event, a prediction is called accurate. Similarity assessments can be used to calculate the similarity between the item and the query, in this case the user history. The output corresponds to the value of the recommended item for the user.

The calculated value is stored in the pseudo user-item rating matrix and used for the upcoming CF phase. Its goal is to extend the matrix by taking ratings of other users with similar preferences into account. For this purpose, we apply a *User-Based Nearest Neighbor* algorithm [5].

In the end, the events with the highest value for the user are recommended. Only recommendation with a value of at least 0.5 on a scale from 0 to 1 are considered. Furthermore, we limit the maximum number of recommendations at one request to 10 to avoid overwhelming the user with events.

We implemented the presented algorithm in a real working Android application we developed. A Munich based event and ticketing company provided a dataset with approximately 3700 real events which were used to conduct a two-week user study. During this study, 16 participants tested and rated the recommender system. Overall, they were satisfied with our solution (\varnothing : 3.75, σ : 0.83, on a scale from 1 to 5 with 5 representing the best possible rating). The recommendations met their expectations slightly above average (\varnothing : 3.38, σ : 0.60) and the study shows that they can be called sufficiently diversified (\varnothing : 3.63, σ : 1.05). A majority of the participants, 87.5%, mentioned that they would like to continue using the system to find interesting events in the future. In general, they were satisfied with the choice of settings which allowed them to modify the context-awareness, for example by defining thresholds like a radius or possible time slots. Nevertheless, the participants requested further options to modify the context-awareness, for example, the user's current budget for events which was not taken into account as this information was not available in our dataset.

3 Requirements for Spontaneous Event Recommendations on the Go

Even though the presented algorithm takes context into account, we believe that the recommender system mainly supports users in receiving recommendations a certain time before the actual event takes place. The developed application can be used at home and the geographical and temporal context settings allow to adapt the recommendations to future conditions. This approach covers a big share of potential visitors but it does not deliver further support for people who are open towards spontaneous event visits. Examples are tourists who visit a city for a few days and have some time left or young people going out in the evening without having any concrete plans.

As a next step in our event recommendation research, we want to focus on recommendations for events which take place in the same conditions as the current user context. We call these recommendations *spontaneous recommendations on the go* because the events take place shortly after the recommendation is generated and the venues have to be located in a reasonable distance to the user's current position. These kinds of recommendations demand the consideration of additional context factors which were less important in our previous work. For example, the current weather plays a critical role as bad weather may exclude some outdoor activities. In addition, the duration of events is critical as, for ex-

ample, tourists usually have only a little time for visiting events. The fact that the user is driving a car or taking the subway could have a significant influence on the acceptance of recommendations. Sensors in mobile phones area already precisely enough to determine which means of transportation the user is using [2]. We also want to try other solutions of context incorporation and compare the results to this work.

Social context is another relevant context factor which should be considered in future work. For example, the user's companions might influence her or his decisions in regard to spontaneous event visits. Furthermore, our solution could be improved by taking more sophisticated, collaborative methods into account. Instead of regarding all users in the user-item rating matrix, only friends or people nearby could be considered in some situations.

The goal of our research now is to identify all relevant context factors for *spontaneous recommendations on the go* and to understand which kinds of event recommendations are desirable under which circumstances. We want to implement the new algorithm in another prototype and test it again in a larger user study. The results of this study then can be compared to our previous results in order to measure the algorithm's performance.

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