A Collaborative Ranking Model with Contextual Similarities for Venue Suggestion

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Abstract. While recent studies have explored the idea of adopting collaborative ranking (CR) for recommendation, there has been no attempt to incorporate contextual similarities between venues. In this study, we explore the effect of incorporating contextual similarities into the learning strategy of a CR model. By enhancing the latent associations between users with contextual similarities, our experiments show that contextual similarities improve the performance of CR.

1 Introduction

Generating venue suggestions plays a crucial role in satisfying the user needs, for example when exploring a new city [2]. Recommendation algorithms can be divided into two categories: content-based and collaborative-based approaches. Content-based approaches build user and item profiles based on items' contents and measure the similarity between the profiles [3,6]. Many real-world problems limit the accuracy of venue suggestion. For instance, a major issue is the sparsity of users' check-in data. To address the data sparsity problem relevant studies exploit auxiliary information, such as user tags and temporal information [5,9]. Moreover, in relevant literature item recommendation, such as venue suggestion, is often treated as a rating prediction or matrix completion task [1]. However, considering the square loss as a measure of prediction effectiveness is not accurate in the top-N recommendation task [8]. In other words, being able to present a more accurate ranked list to a user should be rewarded. Collaborative ranking (CR) is based on this idea and focuses on the accuracy of recommendation at the top of the list for each user, by learning the individual's ranking functions in a collaborative manner [7].

In this study, we explore the effect of incorporating contextual similarities of venues into CR. We design the objective function of the CR model to include the contextual similarity measures in the loss function with a focus on ranking relevant venues at the top of the recommendation list. This enables our model to propagate venue contextual proximity to the users, thus addressing the sparsity

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problem that appears in the check-in data. For example, in the conventional collaborative filtering approaches, the latent associations are captured only if users have visited the same venue, whereas incorporating venue similarities in our CR model can capture the associations even if users have only visited contextually similar venues but not the same ones.

2 Proposed Method

Let $\mathcal{P} = \{\rho_1, \ldots, \rho_n\}$ and $\mathcal{L} = \{l_1, \ldots, l_m\}$ be the sets of n users and m venues, respectively. We consider user ratings 1, 2, and 3 on venues as negative feedback, while ratings 4 and 5 as positive one. For each user ρ_i, we define $\mathcal{L}_i^+$ as the set of relevant venues, and $\mathcal{L}_i^-$ as the set of irrelevant ones. Moreover, let $S_z \in \mathbb{R}^{m \times m}$ be the similarity matrix of venues based on a contextual feature z.

Contextual Similarities. In our approach we compute a contextual similarity between two venues l_i and l_j based on their content and location. In the following we briefly introduce three similarity measures, defining $S_{ij} = \{S_z(i,j) : z \in \{1, 2, 3\}\}$ as the set of contextual similarity functions.

- **Geographical:** first, we compute the geographical similarity between two venues to incorporate the geographical context while characterizing the user's geographical preferences. The similarity is inversely proportional to the distance between two venues, denoted by $S_1(i,j)$.
- **Review based:** for venue l_i, we train a Support Vector Machine (SVM) classifier with linear kernel to estimate the review-based similarity. We consider positive reviews as positive training samples and negative reviews as negative training samples to train the SVM and call the trained classifier SVM_i. Then, for each venue $l_j : j \in \mathcal{L}$ we classify the reviews of l_j using SVM_i. We take the value of the decision function as the similarity measure, denoted by $S_2(i,j)$.
- **Category based:** $S_3(i,j)$ is the cosine similarity between the category vectors of l_i and l_j.

Collaborative Ranking with Contextual Similarities. Here we present our model, called CRCS, which suggests venues for each user ρ_i placing relevant venues at the top of the recommendation list. Our goal is to understand the user's check-in behavior with the contextual similarities of venues explained in Section 2. For example, a user may like all venues that are in the city center and serve pizza. Building ranking functions considering different contextual similarities between venues also allows us to model latent associations between users with similar tastes who would not be considered in a traditional CR setting. This happens because CRCS takes into account the venue similarities as it updates the user and item latent matrices. CRCS can build the associations between users as it considers content- and context-based similarities while updating the latent matrices. Notice that our CRCS model does not rely on the type of contextual similarity and is not limited to a certain type of contextual features. Hence, it can be a general framework for incorporating any type of contextual features.

We focus on ranking the venues that a user likes higher than the ones she does not. Formally, we aim at ranking venues that belong to $\mathcal{L}_i^+$ higher than those that are in $\mathcal{L}_i^-$. Our goal is to rank the venues with emphasis on the top of the list. Let $H_i(l_j^-)$ be the "height" of an irrelevant venue, that is:

$$H_i(l_j^-) = \sum_{k \in \mathcal{L}_i^+} \sum_{z=1}^{3} \Big[\big(\alpha_z \times \mathbf{1}_{[f_i(l_k^+) \leq f_i(l_j^-)]} \big) / S_z(k,j) \Big] \ ,$$

where α_z is the weight of contextual similarity S_z and $\mathbf{1}_{[.]}$ is an indicator function. Dividing the indicator function by S_z allows the model to incorporate the contextual similarities into the model while constructing the height for irrelevant items. For example, if an irrelevant item is ranked higher than a relevant item, but they are contextually very similar based on S_z, then the denominator will be higher, which means the height of the irrelevant venue will be reduced accordingly. The objective function should aim at minimizing H_i for all irrelevant venues of user ρ_i. A lower value of H_i means that there are fewer irrelevant venues ranked higher than relevant ones, and those that are ranked higher are more similar to relevant items. However, indicator functions are not convex and they are not suitable to our optimization strategy. Therefore, we use the logistic loss of the difference between the two functions as a convex upper bound surrogate. We define the difference between the k^{th} venue and the j^{th} as follows:

$$\delta_i(k,j) = \mathbf{u}_i^T \sum_{z=1}^{3} \big[\alpha_z (\mathbf{v}_k - \mathbf{v}_j) / \exp(|S_z(k,j)|) \big] \ .$$

Therefore, the surrogate height function $H_i'(l_j^-)$ becomes:

$$H_i'(l_j^-) = \sum_{k \in \mathcal{L}_i^+} \log \big[1 + \exp\big(- \delta_i(k,j) \big) \big] \ .$$

Finally, the objective function is defined as follows:

$$R(U,V) = \sum_{i=1}^{m} \frac{1}{n_i} \sum_{j \in \mathcal{L}_i^-} \big(H_i'(l_j^-) \big)^2 \ .$$

3 Results

We evaluate our approach on a mixed dataset of two benchmark datasets, made available by the TREC. The datasets are for the TREC Contextual Suggestion Track (TREC-CS) 2015 and 2016. We used the publicly available crawls of [4].

Table 1 reports the performance of all the models on TREC-CS in terms of nDCG@k with k $\in \{1, 2, 3, 4, 5\}$. Our proposed CRCS model significantly

Table 1: Performance evaluation on TREC-CS in terms of nDCG@k with k $\in \{1, 2, 3, 4, 5\}$. Bold values denote the best scores, for p <0.05 in paired t-test.

	nDCG@1	nDCG@2	nDCG@3	nDCG@4	nDCG@5
P-Push	0.5635	0.5282	0.5188	0.4963	0.4775
RH-Push	0.4606	0.4561	0.4581	0.4611	0.4575
IRenMF	0.5037	0.4781	0.4806	0.4759	0.4689
GeoMF	0.4743	0.4842	0.4879	0.4801	0.4774
Rank-GeoFM	0.5662	0.5491	0.5445	0.5123	0.4976
CRCS	**0.6832**	**0.6226**	**0.5888**	**0.5522**	**0.5332**

outperforms all state-of-the-art methods in terms of nDCG@k for all values of k (according to pairwise t-test at $p < 0.05$). Compared to the state-of-the-art method, Rank-GeoFM, the improvements in terms nDCG@1 and nDCG@5 are 21% and 7%, respectively. This indicates that our proposed CRCS can address the data sparsity problem by incorporating different types of contextual similarities. While the geographical similarity includes the neighborhood influences in the model, the category-based similarity takes into account users with similar tastes when they do not share the same check-in records. In addition to that, the review-based similarity models venues similarities in terms of other users' opinions in various contexts. Fusing these similarity measures with a CR-based model enables CRCS to form complicated similarity affinities among venues and propagate it to the users. Hence, our proposed CRCS addresses the data sparsity problem better than other state-of-the-art models, indicated by the high recommendation accuracy.

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