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Deep Collaborative Filtering Approaches for Context-Aware Venue Recommendation

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ABSTRACT

In recent years, vast amounts of user-generated data have being created on Location-Based Social Networks (LBSNs) such as Yelp and Foursquare. Making effective personalised venue suggestions to users based on their preferences and surrounding context is a challenging task. Context-Aware Venue Recommendation (CAVR) is an emerging topic that has gained a lot of attention from researchers, where context can be the user's current location for example. Matrix Factorisation (MF) is one of the most popular collaborative filtering-based techniques, which can be used to predict a user's rating on venues by exploiting explicit feedback (e.g. users' ratings on venues). However, such explicit feedback may not be available, particularly for inactive users, while implicit feedback is easier to obtain from LBSNs as it does not require the users to explicitly express their satisfaction with the venues. In addition, the MF-based approaches usually suffer from the sparsity problem where users/venues have very few rating, hindering the prediction accuracy. Although previous works on user-venue rating prediction have proposed to alleviate the sparsity problem by leveraging user-generated data such as social information from LBSNs, research that investigates the usefulness of Deep Neural Network algorithms (DNN) in alleviating the sparsity problem for CAVR remains untouched or partially studied.

1 OVERVIEW

The goal of venue recommender systems is to find a specific and ordered list of venues that are most appealing to the users, known as the top-K venue recommendation task. Therefore, we plan to explore a number of ranking algorithms (e.g. Bayesian Personalised Ranking (BPR) [4], a pairwise approach) that exploit an MF-based approach to generate effective ranked list of venue suggestion to the users. Traditional BPR models typically suffer from the sparsity problem that hinders the quality of personalised venue suggestion. A common approach that enhances the performance of the BPR models under the sparsity condition is to extend the sampling criterion and pairwise ranking function of BPR to incorporate additional information (e.g. social links and geographical information of venues). To alleviate the sparsity problem, we we plan to 1) propose a novel Personalised pairwise Ranking Framework with Multiple sampling Criteria (PRFMC) for venue recommendation that exploits probabilistic models to effectively sample negative examples and generate personalised venues to users and 2) propose a sampling criteria and pairwise ranking approach that applies the state-of-the-art geographical and social probabilistic models to enhance the performance of the BPR model for venue recommendation.

Recently, Deep Neural Network models (DNN) have yielded success on tasks such as speech recognition, computer vision and natural language processing. However, the exploration of DNN in recommender systems has received relatively less scrutiny. Although some recent advances have applied DNNs to recommendation tasks and shown promising results, they mostly used DNNs to model auxiliary information, such as social links and the textual content of comments. In particular, we proposed simple yet effective approaches [1–3] that exploit word embeddings to model users' preference and the characteristics of venues based on textual content of comments. Various recent sophisticated DNN algorithms (e.g. Covolutional Neural Networks) that exploit word embeddings to represent textual contents have been shown to be effective in various applications (e.g. text classification). However, such learning algorithms have not widely applied to venue recommendation. Moreover, with regards to modelling the key collaborative filtering effect, our proposed approaches [1–3] are still based on MF, i.e. combining the users and items' latent factors using an inner product. To address the aforementioned challenges, we need to explore various sophisticated DNN techniques to 1) effectively model the users' preferences and the characteristic of venues based on user-generated data on LBSNs in a collaborative manner, 2) rank relevant venues that might interest users based on their preferences and surrounding context using learning-to-rank models and 3) incorporate implicit feedback and the user-generated data to enhance the effectiveness of CAVR. In particular, based on the previous successes of the DNN approaches for recommendation systems, which exploit convolutional and recurrent neural networks to model the user's temporal preferences, we plan to build a Collaborative DNN Framework for a CAVR system that learns the user's temporal preferences from their historical implicit feedback (e.g. check-ins), other additional information (social links and textual content of comments) and their current context (e.g. user's location).

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