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Learning recency based comparative choice towards point-of-interest recommendation

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ABSTRACT

With the prevalence of GPS-enabled smart phones, *Location Based Social Network* (LBSN) has emerged and become a hot research topic during the past few years. As one of the most important components in LBSN, *Points-of-Interests* (POIs) has been extensively studied by both academia and industry, yielding POI recommendations to enhance user experience in exploring the city. In conventional methods, rating vectors for both users and POIs are utilized for similarity calculation, which might yield inaccuracy due to the differences of user biases. In our opinion, the rating values themselves do not give exact preferences of users, however the numeric order of ratings given by a user within a certain period provides a hint of preference order of POIs by such user. Firstly, we propose an approach to model users preference by employing utility theory. Secondly, We devise a collection-wise learning method over partial orders through an effective stochastic gradient descent algorithm. We test our model on two real world datasets, i.e., Yelp and TripAdvisor, by comparing with some state-of-the-art approaches including PMF and several user preference modeling methods. In terms of MAP and Recall, we averagely achieve 15% improvement with regard to the baseline methods. The results show the significance of comparative choice in a certain time window and show its superiority to the existing methods.

1. Introduction

Recent years have witnessed the booming of GPS-enabled smart phones, thus the gap between physical and real world has been blurred and location-based services emerge. Along with online social media, Location Based Social Networks (LBSN), such as Foursquare, Facebook Places, and Yelp, become prevalent in recent years. These LBSNs allow users to explore Points-of-Interests (POIs), such as restaurants and entertainment clubs for better services by sharing their experiences and opinions about the places they visited. For example, on Yelp website and with mobile apps, users can (1) check-in at POIs; (2) give ratings to such places; and (3) write reviews and tips for shops or restaurants to show their likes or dislikes about the places. Generally, "A Point-of-interest is a specific point of location that someone may find useful or interesting. Most consumers use the term when referring to hotels, campsites, the stations or any other categories used in modern navigation system" (extracted from Wikipedia entry). In this paper we treat POI as a Business or Merchant at a specific location, and utilize ratings and time stamps which are two common and easily accessible resources in LBSNs to model user preference in turn for recommendation, i.e., POI and merchant are used interchangeably. In a common sense, our proposed approach can be deployed in broader recommendation applications.

Both LBSN users and POI merchants can benefit from the recommendations. On one hand, LBSN users can gain better user experience and satisfaction in terms of quality and service by utilizing the recommendations of POI made. On the other hand, POI merchants will attract more customer visits and increase the business turnover given the appraisal voted by customers. Moreover, POI merchants can get additional benefit through the analysis of user check-in and review data in LBSNs, e.g., understanding their reputations or concerns in customers. Thus POI-recommendation becomes a hot topic in LBSNs research and application.

Traditionally, we can adopt conventional recommendation methods by simply treating POIs as ordinary items (Ye, Yin, & Lee, 2010). Thus, lots of models, such as *neighborhood-based* (Linden, Smith, & York, 2003) or *model-based* (Koren, Bell, & Volinsky, 2009; Hu, Koren, & Volinsky, 2008) approaches can be utilized seamlessly, such as *collaborative filtering* (CF) based POI

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recommendation. Likewise, such approaches mainly rely on the user-POI rating matrix, where each element represents a rating given by a user to a POI, to calculate similarity between users or POIs. Apparently, the rating value indicates a preference score of a user on specific POI, however, simply utilizing user-rating or POI-rating vectors alone to make the similarity calculation might yield inaccuracy due to the differences of user biases. Though some studies attempt to incorporate user bias into the models to alleviate the inappropriateness of modeling user preference, we argue that the user rating behavior is not sufficiently investigated and modeled. In contrast, we think although the rating values of users don't give the exact preference degrees of users to various POIs, the numeric order of ratings given by a user within a certain period of time at least provides a hint of preference order of POIs by this user, i.e., the higher rating denotes a more preferable judgment, and vice versa. With such observed preference orders by all users, we can train a POI preference prediction model by a learning process, upon which our POI recommendation model is initialized.

The aforementioned summaries shed light on us to give the following assumptions: (1) **Relativization**: By individually viewing the rating a user gives to a particular POI, we sometimes can not tell the actual user preference to this POI due to the user biases. For example, a user gives 4 star to a POI out of average rating 4.5, which indicates the preference to such POI is below the average. However, supposing that the same POI was rated 4 star by another user, whose average score is 3.5, we can say that this user may be more critical and prefers to this POI more than others. In such case, using the absolute ratings alone sometimes could not capture the accurate user preference, yielding unsatisfactory recommendation results POIs, which motivate us to take a relative view to address this problem. Our idea in this paper is to leverage the rating order rather than rating value from user rating history to accurately learn user preference. The intuition is quite straightforward - the order of ratings by users implies the underlying user preference information. Take a toy example shown in Fig. 1, we can see that the user prefers POI p_5 more than p_4 due to the higher rating on p_5 than p_4. (2) **Comparative Choice**: The user rating behavior is indeed a comparative process, where a rating given by a user is actually a choice making after the user compared the target POI with other visited POIs rather than a random determination. (3) **Recency**: Although the user rating is a comparative decision, not all rating history of the user should be considered due to the short-term memory effect, i.e., the user is more likely to compare the target POI with recently visited POIs rather than those visited a long time ago, and finally gives a rating. In other words, recency is the key factor in comparison and decision. Also known from the toy example in Fig. 1, the comparative relationship between p_5 and p_4 is more reliable than that between p_5 and p_3. Thus setting an appropriate time window to form the comparative POI set becomes another research question we need to tackle.

In this paper, we aim to address the problems based on the aforementioned assumptions and propose a new model to learn user preference from user rating behaviors through employing choice model from utility theory. Our idea is originated from the assumptions that user rating is mainly determined by recent comparative experiences of users, i.e., comparative choice and recency, the rating given to a POI by a user is a result of comparisons to other POIs recently visited by this user. The collection of all observed users' comparative choices forms a training set for us to learn the user preferences over various POIs in an aggregated view. More specifically, from the rating history of each user, we count in all POIs within a defined time window, e.g., previous K visits before the current POI, to form a POI collection. Naturally, in each collection, POIs can be sorted according to their ratings in a partial order, where through the view of economics, a higher rating indicates the more satisfaction of user to the POI, meanwhile implies the higher utility of a particular POI to a certain user. Hence, by employing choice model deduced from utility theory, we could simulate the user rating behavior from such partial order relationship, learn the user preference more precisely, and in turn, provide better recommendations.

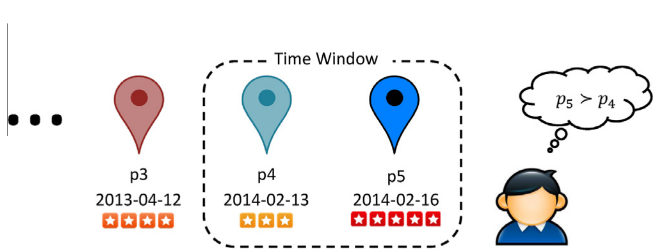

Fig. 1. Toy example.

In summary, we made the following contributions:

- We propose a novel approach to model user rating behavior by exploring comparative relationship between ratings within a certain time window.
- We design a choice model and employ collection-wised learning over partial orders through an effective and efficient stochastic gradient descent algorithm.
- We conduct extensive experiments to evaluate the performance of our model on two large-scale real datasets. The results show that our approach outperforms other state-of-the-art methods.

The remainder of the paper is organized as follows.Section 2 provides an overview of the related work. Section 3 gives the formulation for the problem we study. We detail our model in Section 4 and report the learning and inference in Section 5. The result of the experiments are presented in Section 6, followed by the conclusions and future work in Section 7.

2. Related work

In this section, we review a number of works on recommendations especially in POI recommendation, which are related to our approach.

2.1. Traditional recommendations

Traditional recommender systems mainly focus on user-item rating matrix by employing memory-based (Linden et al., 2003) or model-based collaborative filtering(CF) (Koren et al., 2009; Hu et al., 2008). The premise behind memory-based CF is to recommend items by like-minded user to a given user and the intuition of model-based CF like matrix factorization is that only a few latent factors are in control. Moreover, contextual information like social or trust network are embedded into models for further improvements of the prediction accuracy (Jamali & Ester, 2009; Xiang et al., 2010; Deng, Huang, & Xu, 2014). Text, Tags and temporal information are utilized for recommendation of music (Hyung, Lee, & Lee, 2014), news (Li, Zheng, Yang, & Li, 2014), product (Hong, Li, & Li, 2012) and tagging system (Zheng & Li, 2011). Our research topic is different from traditional recommendations since traditional methods rely much on the entire rating vectors to calculate similarities for estimating user preference while ignoring the differences of user biases. By using numeric order of ratings to depict user preference over POIs is more closer to the real situation and elaborating such mechanism is significant for understanding user behaviors, which needs to be explicitly modeled in our proposed approach.