Context Aware Recommendation on Missing not at Random Contextual Texts

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Abstract.

1 Introduction

Context Aware Recommendation System (CARS) has recently attracted interest from both academy and industry. CARS is welcomed by enterprises and users because it delivers more accurate and reasonable recommendation by taking contextual information into account. The contextual information includes and is not limited to when, where and with whom the user is to purchase an item. CARS has been successfully applied in a bunch of areas, including travel [6], music [8], web news [31] and so on.

The input of CARS is user feedback (i.e. user-item ratings) and the corresponding contextual information. Contextual information can be gathered from various sources. The era of Web 2.0 has kindled massive growth of opinions and reviews on the web. Therefore more and more researchers explore the feasibility of building CARS based on online reviews [17, 15, 11, 19, 35]. They adopted text mining techniques to extract contextual information from online reviews and transform a rating into a contextual rating. Then conventional recommendation models are built on contextual ratings.

Generally CARS suffers from the data sparsity problem. We have to deal with two challenges related to sparse contextual user feedback. First of all, **the missing of contextual information in ratings and reviews**. Even with powerful text mining techniques, the amount of user feedback with contextual information is far from sufficient to train a promising recommendation model. Users do not always provide contextual information when they give ratings and reviews. Below we show several examples of online reviews with and without implications on the contexts.

Existing research efforts simply discard reviews without any contextual information. They fail to make full use of user feedback, because the rating could still be informative even that the context is not given. We show here that this strategy is problematic when the contextual information in reviews are missing not at random. For example, many social studies have found that users write online reviews to "brag or moan" [], therefore online users give the contextual information on purpose in respond to an extreme experience under the given contexts. Consider the illustrative example in Fig 1. On the left the user is satisfied with ... under context ... On the right, the user is ...

Fig. 1. Selected reviews for two restaurants from www.yelp.ca. Reviews are shortened for the limited space. Number of starts for each indicate user rating. Reviews in violet rectangles are context explicit feedback, reviews in yellow rectangles are context implicit feedback

To address the above problem, we propose a novel model which is based on missing not at random assumptions. To connect the dots among ratings, non-contextual reviews and contextual reviews, we borrow the ideas of marginal utility theory [34]. Utility surplus is an economic concept to measure consumer's "satisfaction" or "pleasure". We expand the definition of utility surplus to a context aware setting: when a consumer obtains more satisfaction from a purchase under a certain context (contextual utility) than a general purchase under any context (general utility), he/she is more likely to post a piece of positive review regarding the context. Otherwise, if a consumer obtains less contextual utility than general utility, he/she is likely to post a piece of negative review regarding the context. If the consumer considers the satisfactions are equivalent under any context, he/she is more likely to give a non contextual review.

The second issue is **the high dimensionality of context space**. Most prior works modeled the ratings as a hypercube. With the massive number of possible values for each contextual dimension, the data sparsity problem is more severe. Take the location context for example, the purchase could happen at any place, thus it is very difficult to collect enough ratings which occur in the same place.

A strategy that departs from data cube approach is to project contextual ratings into hidden lower dimensional contextual spaces which consist of a set of contextual scenarios. We follow this path because it can be naturally incorporated into our models. The utility is the aggregation of user preferences over several commodity features of interest. We assume that the contextual utility is associated to a contextual scenario and the contextual information in the review texts are distributed depending on the contextual scenario.

Our contributions are three folds. (1) To the best of our knowledge, our work is the first in literature to apply MNAR properties to CARS and text mining based recommendations. We incorporate the utility theory in this novel model. (2) We address the data sparsity problem by exploiting non contextual reviews and embedding in a dimension reduction models. (3) We deliver recommendations that are both accurate and more explainable.

The rest of this paper is organized as follows. We provide a brief discussion on related work in section 2. We introduce the model on missing not at random contextual texts in section 3. We then detail the application of this model in context aware recommendation in section 4. The experimental results are described and analyzed in section 5. Finally, we conclude our work in section 6.

2 Related Work

This work is related to two areas: contextual aware recommendation systems and online review mining.

2.1 Context Aware Recommendation Systems

CARS is an emerging topic in recommender community [2]. The performance of CARS has been verified by a live controlled experiment [9]. There are three types of approaches to incorporate contextual information in the recommendation process. The first type is to pre-filter, i.e. select contextualized ratings data and factorize each context specific rating matrix [1]. The second type is to post-filter, i.e. split the resulting items to different contexts after recommendation [4]. The third type is to model the context, i.e. as a latent variable in BNN [22], or as a latent factor in matrix factorization [3]. or as tensor factorization [31, 13]. Empirical study has shown that which approach is better depends on the application [23]. The sparsity of rating data is an obstacle for CARS. A typical improvement is to integrate other resources, i.e. demographic information [16], sequential patterns [10], or, as we might review in the next subsection, texts in online reviews [17, 15, 11, 19].

2.2 Online Review Mining

Online review mining has been an active research area. Most existing researches are efforts that summarize reviews and extract certain information, i.e. opinion polarities [18], user groups according to their interests [30], aspects of products [20], and so on. Online review mining often requires a skillful combination of natural language processing (NLP) and machine learning models. An omnipotent model does not exist for every domain. Information extracted from online reviews is helpful in recommender systems. For example, identifying product aspects and user opinions is crucial for predicting a user's rating [24], estimating the review quality can "up-weight" or "down-weight" the importance of individual rating while performing collaborative filtering [25]. For CARS, online review mining also assists the recommendation process in POI recommender [6], hotel recommender [15], and restaurant recommender[17], etc.. For RGCARS, most researches in literature directly utilize the extracted conextual opinions to form preference data, and then pipe the explicit feedback with a CARS model. For example, a tensor factorization model is presented in [15], which imitates a user who favors reviews written by people with the same intent, nationality and tasts. An extended LDA is presented in [11], which jointly models users, items and contexts. In [17], the contextural information is integrated into a probabilistic latent relational model, which factorizes ratings to item specific features, as well as a combination of the current context and a user's long term preference. In [19] a simple recommendation model is used to aggregate opinions over each product feature.

3 Model

3.1 Utility Surplus

In Economics, utility is an important property of any commodity. It measures the satisfaction consumers get by purchasing an item. Money, as a special case of commodity, can also be measured by a utility function. If the consumer is willing to pay a certain amount of money, which is the price v_p, to purchase an item v, then the utility surplus $US(u,v) = UC(u,v) - UM(u_p, v_p)$, which is the commodity utility UC minus the money utility UM, will be positive. Usually, the commodity utility can not be directly counted, but can be inferred from observed consumptions. Moreover, a common assumption is that the commodity utility can be modeled as a linear combination of user preferences over commodity features. We extend this theory to the CARS problem. Suppose the user preference is represented by u, and contextual preference is represented by a, then the commodity utility under context k is measured by a combination of user specific utility and context aware utility: $UC_k(u,v) = \sum_c (\alpha a_{k,c} + (1-\alpha)u_c)v_c$, where $a_{k,c}$ is the contextual preference under context k to the commodity feature c, u_c is the user preference to c, and v_c is the quality of item v on feature c. The utility function of money could be more complicated. However, in this scenario, the consumers are paying a very small portion of money, compared to their incomes. So according to the law of diminishing marginal utility, a linear function can be adopted to measure the decrease of consumer satisfaction by losing the money, i.e. $UM(u_p, v_P) = u_P v_P$. Here u_P can also be interpreted as users' sensitiveness to price. We make the following manipulation to ensure that the score coincides with a probability.

$$p(x_{u,v,k} = 1|\mathbf{u}, \mathbf{a}, \mathbf{v}) = g(UC_k(\mathbf{u}, \mathbf{v})) = \frac{1}{1 + \exp -UC_k(\mathbf{u}, \mathbf{v})} \tag{1}$$

The economic interpretation is clear. If the user is satisfied with the consumption for the context, $US_k(u,v) > 0$, then $p(c|x) > 0.5$, which suggests that it is possible to choose the write a positive review.

4 Application

4.1 Recommendation

4.2 Contextual Information Extraction

5 Experiment

6 Conclusion

In this paper, we mainly focus on exploring the potencial of implicit feedback in a review guided context aware recommender system. We present new models, based on the utility surplus theory, to tackle the implicit feedback problem by treating them as complete observations or missing not at random observations. We systematically compare the assumptions and performances of thes models. The most important academic contribution of this paper is that, to the best of our knowledge, the unique types of implicit feedback (both context free and context aware) have not yet been studied by the community. Therefore our research might shed some insight into mining online reviews for recommender system, and other applications. Further research issues include adapting and testfying more assumption in the missing not at random model. For example, the inter homogenity of online communities, and applying the CPP model to appropriate contexts.

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