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 a consumer's "satisfaction" or "pleasure". Utility surplus is the difference between what a consumer pays and what a consumer gains. We expand the definition of utility surplus to a context aware setting: what a consumer benefits from a purchase under the specific context. We then assume that the user will compare the general utility surplus given no context and the context aware utility surplus under a specific context. The probability of he/she giving a contextual review is dependent on the result of the comparison.

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 model. (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. Let's denote the commodity utility a consumer u gains from item v $UC(u,v)$, the item's price p, the money utility for the user $UM(p,v)$, then the *utility surplus* in this particular purchase $US(u,v)$ is the difference between the commodity utility and the money utility $US(u,v) = UC(u,v) - UM(u,p)$,.

A common assumption is that the commodity utility can be modeled as a linear combination of user preferences over commodity features []. Without ambiguity the user preference is represented as $u \in R^K$ on K potential aspects, and the commodity feature is represented as $v \in R^K$ on K potential aspects. According to the law of diminishing marginal utility, $UM(p,v)$ is also a linear function of p. It is convenient to define an additional element in v for the price p and in u to depict how sensitive the consumer is to the price. Hence we can the money we have $US(u,v) = uv$

Usually the commodity utility can not be directly counted, but can be inferred from observed consumptions. In recommender systems, we have a collection of ratings. Suppose in preprocessing we polarize the ratings so a binary rating $x \in \{0,1\}$ indicates whether the user publishes a positive opinion. We make the following manipulation to ensure that the utility surplus coincides with a probability of generating a rating.

$$p(x_{u,v} = 1|\mathbf{u},\mathbf{v}) = \frac{1}{1+\exp\left[-uv\right]}, \tag{1}$$

The economic interpretation is clear. If the user is satisfied with the consumption, $US(u,v) > 0$, then $p(x_{u,v} = 1) > 0.5$, which suggests that u is likely to assign a positive rating.

We extend the definition of utility surplus to the CARS problem. Intuitively the user preferences under various contexts will be different. For example, if a couple is traveling in their honeymoon, then they are probably looking for a romantic resort hotel. Consider the same couple on a business trip, they are more likely to be interested in a chain hotel near the airport. We use similar notation to represent the contextual preference $a(c) \in R^K$ of any given *context scenario* c. Our assumption is that, the context aware utility surplus given a certain context scenario c is related to contextual preference $a(c)$ instead of individual preference $US_c(a, v) = a(c)v$.

Similarly, we observe user feedbacks on the contextual consumptions. Suppose $y_{c,v} \in \{0, 1\}$ is the binary user opinion on how good the commodity v is under a certain context scenario c, we have:

$$p(y_{c,v} = 1|\mathbf{a}(\mathbf{c}), \mathbf{v}) = \frac{1}{1 + \exp\left[-a(c)v\right]}. \tag{2}$$

3.2 Condition Contextual Missingness on Comparison

In a CARS based on online reviews, every user feedback consists of a rating and a piece of review. By adopting text mining techniques, we can extract contextual phrases from the reviews, i.e. phrases describing time, locations and companions. It is possible that not every piece of review contains contextual information. As we have shown in Sec. 1, it is problematic to discard user feedbacks without any contextual information. The rating is valuable. Although the rating can not be mapped to any context, it reflects user preference and commodity characteristics.

Our intuition is that the contextual information is not missing at random. The purchase is deemed to happen under a certain context scenario. However when the consumer is about to publish ratings and reviews, he/she could choose to not reveal the context scenario within which the purchases is made. The consumer will compare the contextual utility surplus (related to the contextual preference) and the general utility surplus (related to individual preference). When a consumer is significantly more satisfied by the contextual utility, he/she is likely to post a piece of positive review regarding the context. Otherwise, if a consumer obtains significantly 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, he/she is more likely to give a non contextual review.

The above intuition is modeled by an XOR operation. Suppose the binary variable $r \in \{0, 1\}$ indicates whether the review contains contextual information, the value of r is determined by the polarity of contextual satisfaction x and general satisfaction y: $r = x \bigoplus y$. In other words, the contextual information is present if and only if one of x, y is positive and the other is negative. $r = (1 - xy) - (1 - x)(1 - y)$.

Next we explore the relations between contextual phrases in a review and the context scenario. A user chooses the appropriate contextual phrases to describe the context scenario unknown to us. Therefore the context scenario can be inferred because observing a contextual phrase is probabilistically dependent on the hidden context scenario . For example, a business trip is likely to happen on weekdays, a family trip is likely to happen on weekends or holidays. Like many topic models, we mimic a generation process of the user producing a review. For simplicity, we denote any word or contextual phrase w. We use $\beta \in R^{(C+1)\times W}$ to represent the distribution, where C is the number of context scenarios, $\beta_{0,w}$ is the probability of observing a word w under no context scenario, $\beta_{c,w}, c > 0$ is the probability of observing a word w given the context scenario c.

Putting the utility surplus theory and the MNAR assumption on contextual information in a Bayesian probablistic model, we derive the following Conditional Contextual Comparison (CCC) model, depicted in Fig. 2. We assume the following procedure. Given user preference $u \sim \mathcal{N}(0, \sigma_u^2)$, commodity feature $v \sim \mathcal{N}(0, \sigma_v^2)$, contextual preference per context $a(c) \sim \mathcal{N}(0, \Sigma_a^2)$, context parameter $\alpha \sim Dirichlet(\pi)$, for any purchase made by user u on commodity v:

- A context scenario c is chosen. This is modeled by generating a $C-dimensional$ vector $s \in R^C$ where $s_c = 1$ and $s_j = 0, j \neq c$ for any other context scenario. Therefore in this step generate the switch $s \sim Mult(\alpha)$
- The user obtains a general rating $x_{u,v} \sim Bern(\frac{1}{1+\exp[-uv+m]})$
- The user obtains a contextual rating $y_{c,v} \sim Bern(\frac{1}{1+\exp[-a(c)v+m]})$
- Choose the response $p(r_{u,v} = 1|x_{u,v}, y_{u,v}) = (1 - x_{u,v}y_{u,v}) - (1 - x_{u,v})(1 - y_{u,v})$. If the response is positive $r_{u,v} = 1$, the contextual rating is displayed $y_{u,v}$ is observable; otherwise $r_{u,v} = 0$, the general rating is revealed $x_{u,v}$ is observed..
- Choose the words for N times. If the response is to not reveal any contextual information, the word is chosen from a general word distribution $p(w|\beta, r_{u,v} = 0, s_{u,v}) = \beta_{0,w}$. If the response is to depict the context scenario, the word is chosen from the context specific word distribution $p(w|\beta, r_{u,v} = 1, s_{u,v}) = \prod_c \beta_{s_{u,v,c},w}^{s_{u,v,c}}$

3.3 Inference

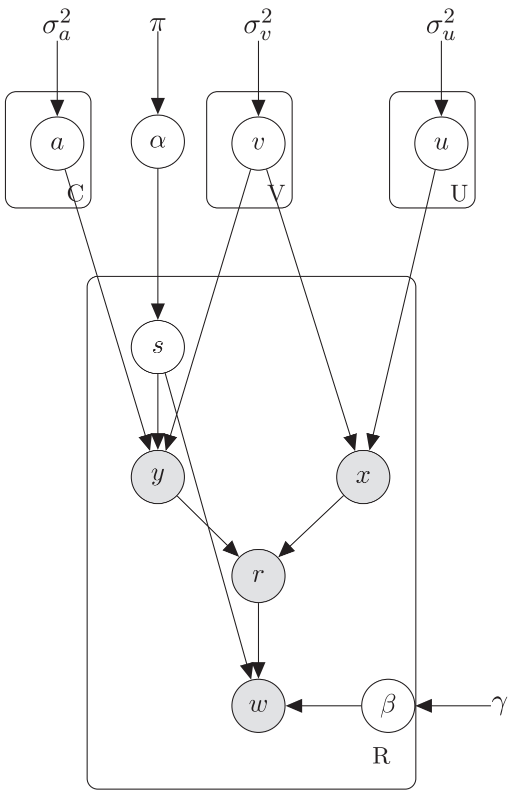
We aim to optimize the likelihood of generating the observations $D = \{< r, x, y, \{w\} >\}$, where r is the response indicating whether the review contains contextual information, x, y are partially observed ratings, $\{w\}$ is a set of words in the review. If the feedback does not have any contextual information, $r = 0$, x is observed, $y = 1 - x$ can be inferred easily. Given the parameter space $\Theta = (u, v, a, \alpha)$, we have:

$$\ln p(r = 0|\Theta) = \sum_{w \in r} \ln p(w|\beta_0) + \ln(\sum_c p(y|a_c, v)p(s = c|\alpha)) + \ln p(x|v, u). \quad (3)$$

If we can extract contextual information from the review, then $r = 1$, y is observed, $x = 1 - y$ can be inferred, we have:

$$\ln p(r = 1|\Theta) = \sum_{w \in r} \ln p(w|\beta_c)p(s = c|\alpha) + \ln(\sum_c p(y|a_c, v)p(s = c|\alpha)) + \ln p(x|v, u). \quad (4)$$

We use the general EM algorithm. In the E-step, for each feedback, we compute the posterior probability, denoted as $f(s, c) = p(s_{u,v} = c|x_{u,v}, y_{u,v}, \mathbf{w}, \Theta^{old}$.



(a) Plate notation for the CCC model

Parameter & Interpretation
$a(c) \in R^K$ Context aware preference
$u \in R^K$ User preference
$v \in R^K$ Commodity features
$\alpha \in R^C, \alpha_c \in (0,1), \sum_c \alpha_c = 1$ Global context distribution
$\beta \in R^{(C+1)\times\|W\|}$ Word distribution

Variable & Interpretation
$s \in R^C, s_c \in \{0,1\}, \Sigma_c s_c = 1$ Context indicators, not observable
$x \in \{0,1\}$ Context irrelevant rating, partially observable
$y \in \{0,1\}$ Context aware rating, partially observable
$r \in \{0,1\}$ response observation whether the review contains contextual information

Hyperparameters & Interpretation
σ_a Variance for a
σ_u Variance for u
σ_v Variance for v
π Dirichlet hyperparameter for α
γ Dirichlet hyperparameter for β

(b) List of notations for variables

Fig. 2. The Conditional Contextual Comparison (CCC) Model

$f(s,c)$ is average over all c for each s. Again, if the corresponding review contains contextual information $r=0$, we have:

$$f(s,c) \propto [\frac{1}{1+\exp(-a_c v))}]^{1-x_{u,v}} [\frac{\exp(-a_c v)}{1+\exp(-a_c v))}]^{x_{u,v}} [\frac{1}{1+\exp(-uv))}]^{x_{u,v}} [\frac{\exp(-uv)}{1+\exp(-a_c v))}]^{1-x_{u,v}}. \tag{5}$$

if the corresponding review does not contain contextual information $r=1$, we have:

$$f(s,c) \propto [\frac{1}{1+\exp(-a_c v))}]^{y_{u,v}} [\frac{\exp(-a_c v)}{1+\exp(-a_c v))}]^{1-y_{u,v}} [\frac{1}{1+\exp(-uv))}]^{1-y_{u,v}} [\frac{\exp(-uv)}{1+\exp(-a_c v))}]^{y_{u,v}}. \tag{6}$$

In the M-step, we first fix u, v, a and maximize over β.

$$\beta_{c,w} = \frac{\sum_{w \in s} f(s,c)}{\sum_w \sum_s f(s,c)} \tag{7}$$

Since maximizing over u, v, a is infeasible, we adopt a generalized EM to increase the likelihood. We fix β, v, a to update u.

$$u_k = u_k - p\{\sum_{s \in u} \sum_c f(s,c)[\frac{\sum_{r=1,y=1} \sum_{r=0,x=0} -v_k + \sum_{r=1,y=0} \sum_{r=0,x=1} v_k(\exp(-uv))}{1+\exp(-uv)}]\}, \tag{8}$$

where p is the step length.

We fix β, v, u to update a.

$$a_{c,k} = a_{c,k} - p\{\sum_s f(s,c)[\frac{\sum_{r=1,y=0} \sum_{r=0,x=1} -v_k + \sum_{r=1,y=1} \sum_{r=0,x=0} v_k(\exp(-a_c v))}{1+\exp(-a_c v)}]\}. \tag{9}$$

We fix β, a, u to update v.

$$v_k = v_k - p\{\sum_{s \in v} \sum_c f(s,c)[\frac{\sum_{r=1,y=0} \sum_{r=0,x=1} -a_{c,k} + \sum_{r=1,y=1} \sum_{r=0,x=0} a_{c,k}(\exp(-a_c v))}{1+\exp(-a_c v)} + \frac{\sum_{r=1,y=1} \sum_{r=0,x=0} -u_k + \sum_{r=1,y=0} \sum_{r=0,x=1} u_k(\exp(-uv))}{1+\exp(-uv)}]\}, \tag{10}$$

4 Application

4.1 Recommendation

4.2 Contextual Information Extraction

5 Experiment

5.1 Experimental Setup

5.2 Context Aware Recommendation

5.3 Contextual Phrases Distribution

5.4 Parameter Performance

5.5 Case Study

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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