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# Collaborative filtering with weighted opinion aspects

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ABSTRACT

Collaborative filtering (CF) aims to produce recommendations based on other users' ratings to an item. Most existing CF methods rely on the overall ratings an item has received. However, these ratings alone sometimes cannot provide sufficient information to understand users' behaviors. For example, a user giving a high rating may indicate that he loves the item as a whole; however, it is still likely that he dislikes some particular aspects at the same time. In addition, users tend to place different emphases on different aspects when reaching an overall rating. This emphasis on aspects may even vary from users to items, and has a significant impact on a user's final decision. To make a better understanding of a user' behavior and generate a more accurate recommendation, we propose a framework that incorporates both user opinions and preferences on different aspects. This framework is composed of three components, namely, an opinion mining component, an aspect weighting computing component, and a rating inference component. The first component exploits opinion mining techniques to extract and summarize opinions on multiple aspects from reviews, and generates ratings on various aspects. The second component applies a tensor factorization strategy to automatically infer weights of different aspects in reaching an overall rating. The last one infers the overall rating of an item based on both aspect ratings and weights. Experiments on two real datasets prove that our model performs better compared with the baseline methods.



## 1. Introduction

When online users make decisions such as seeing a movie, they often face a large amount of choices. Recommender systems can help them find the most relevant items that they might be interested in. Collaborative filtering (CF), a popular technique used in recommender systems, provides recommendations to users about items that people with similar tastes and preferences have liked in the past, usually in the form of ratings of items. However, relying on numerical ratings only is problematic. For one, having a lot of missing ratings may lead to the cold start and data sparsity problem, which may greatly affect the performance of CF. For another, the overall ratings are often of too coarse a granularity and cannot provide enough detailed information about user preferences.

Social networks present new opportunities as to further improve the accuracy of recommender systems. Nowadays, millions of users flock to social-networking sites such as *Epinion*, *Facebook*, connecting themselves with others, sharing their interests and opinions. These reviews are very useful for merchants and other users. For merchants, they can find out what users are concerned about from the reviews, and then make product improvement or sales plans accordingly. For users, they may be able to find products better by examining the preference implicit or explicit in the information reveled by prior purchasers of a product (e.g., via product reviews). At the same time, these reviews reflect users' behaviors on each of the aspects of the items.

For example, consider the two reviews shown in Fig. 1. They all discuss multiple aspects of the restaurant, such as *food*, *price*, and *service*. They both give the restaurant an overall rating of 2/5, but demonstrate different opinions on each aspect. The first reviewer dislikes the food, but the second reviewer is not pleased of the price. In order to help users tell this difference, it is necessary to understand a reviewer's behavior on each of the major aspects of the items for more accurate rating estimation in CF.

Furthermore, all aspects are not equal in forming a user's overall behavior. For example, consider a typical restaurant review shown in the left part of Fig. 1. This review comments on some aspects, i.e., *food, service* and *price*. It is obvious from the review that the user likes *service* and *price* but was not pleased of the *food*. However, the user gives the restaurant a 2/5 rating. One tenable explanation is that the user emphasizes different aspects when reaching the overall rating. That is, the user may put a heavier weight on *food* than *price* and *service*. Clearly, the weight users put on different aspects affects the overall ratings. Therefore, to

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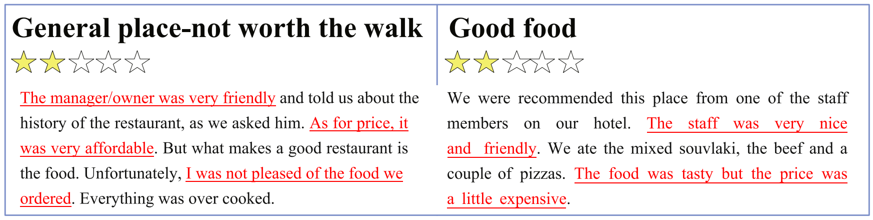


**Fig. 1.** Two examples of reviews about a restaurant.

understand such subtle differences, it is necessary to further reveal the relative importance weight that a user placed on each aspect when assigning the overall rating.

Users' opinion analysis and users' preference analysis, which are the component of users' behavior analysis, are the base of better recommending. So far, there exist some works exploiting the overall ratings to estimate the aspect weights, but little work has been done in exploiting opinions and weights for more accurate rating estimation in CF.

In this paper, we propose a new CF framework which incorporates users' behavior (including users' opinions and preferences) on different aspects into the CF process, in order to tap the rich sentiment information embedded in the reviews and the subtle differences between aspects, and also to alleviate the data sparsity/cold start problem. Our framework consists of three components, (1) opinion mining, (2) aspect weight computing, and (3) rating inference.

The first component infers numerical ratings on the multiple aspects of opinions expressed in the reviews when such ratings are missing or not explicitly presented. For this purpose, we first employ a double propagation method [1] to extract aspect terms and opinion words from the reviews. Double propagation is based on the observation that there are natural relations between aspect terms and opinion words due to the fact that opinion words are used to modify targets, which can be described through the dependency grammar [2]. Then, as some of those terms may carry the same meaning, we use Latent Dirichlet Allocation [3] to cluster those aspect terms into latent aspects. The corresponding opinion words can then be aggregated to get a user's ratings on each of these aspects. As each review has a lot of opinion aspects, the result of this component is a set of rating matrices, each corresponding to an aspect.

In the second component we compute the aspect weights based on the idea that the overall rating is "generated" based on a weighted combination of the latent ratings over all the aspects, where the weights are to model the relative emphasis that the user has placed on each aspect when giving the overall rating. At a first glance, it appears that given a dataset, we could easily build a regression model with the aspect ratings and the overall ratings being the variables and the weights being the parameters. However, this will make the number of free parameters (one for each combination of user, item, and aspect) too big to be tractable. In addition, this approach would inherently suffer from data sparsity because each user can hardly write more than one review on the same item, which makes it impossible to obtain sufficient training data to learn the weights reliably.

We hence propose a method based on tensor factorization, which aims to compute a concise representation of the underlying factors for weighting, taking into consideration the fact that many aspect ratings may be missing. Each element of this weight tensor corresponds to the weight a user puts on an aspect of an item. We use the HOSVD decomposition approach which computes the tensor into a core tensor multiplied (or transformed) by a matrix along each mode, subject to the constraint that the tensor reconstructed from those matrices and the core tensor have to consist of the optimal parameters to a linear regression problem that regresses the overall rating on aspect ratings.

The third component uses tensor factorization to infer the overall ratings, forming the basis of item recommendation. We get the weighted aspect ratings through the combination of the aspect weights and aspect ratings. The weighted aspect ratings, together with the overall ratings, constitute a tensor. Then we employ a tensor factorization approach to capture the underlying latent structure of the tensor and the result of the factorization can be used for inferring the unknown ratings. The tensor factorization process can be seen as a extension of matrix factorization in CF, but it can preserve the multi-dimension nature of the data and the result is better than the matrix factorization.

We evaluate our proposal on two datasets. We compare our model with some baseline methods, and the experiment results show that our model outperforms others.

The major contributions of this paper can be summarized as follows:

- We propose a new model that integrates users' behavior (including opinions and preferences) on multiple aspects into collaborative filtering for the overall ratings prediction.
- We employ a tensor factorization approach to capture the aspect weights, which alleviates the data sparsity problem and reduces the number of model parameters.
- We propose a method to predict the unknown overall ratings through (again) tensor factorization, where the tensor is constituted by weighted aspect ratings and overall ratings. A major advantage of this method lies in its ability to capture the intrinsic interactions among the three dimensions: user, item, and aspect.
- We conduct extensive experiments on some datasets to verify the effectiveness of our proposed approach.

The rest of this paper is structured as follows. Section 2 provides an overview of the related work. Section 3 defines the problem and presents the framework of our solution. Section 4 discusses the method to obtain the ratings on various aspects. Section 5 describes how to obtain aspect weights using tensor factorization. Section 6 discusses how to predict unknown overall ratings. Experimental results are presented in Section 7. Section 8 concludes this paper.

## 2. Related work

Our work is related to Aspect-based Opinion Mining, Aspect-based Weight Estimation, and Collaborative Filtering.

### 2.1. Aspect-based opinion mining

The main task of aspect-based opinion mining is extracting the aspects and learning the aspect ratings from a collection of reviews of a given item. The earliest attempt on aspect extraction is frequency-based. In the work proposed by Scaffidi et al. [4], the

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