A Brand-Aware Collaborative Filtering-Based Recommender System

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Abstract
Recommendig clothing products can be formidable: while making a purchase decision, of the many possible attributes, such as how fashionable or how popular the product is, customer's aesthetic preference plays a significant role. As the online retail marketplace is growing rapidly, making the available product range extremely diverse, capturing customer preference is also becoming more and more challenging. In this article we propose an extended Collaborative Filtering algorithm, using additional side information in order to capture products' styles, which are used to define a customer's preference.
Keywords: Recommender Systems, E-commerce, Collaborative Filtering

1. Introduction

Online retailers offer bewildering variety of products, which may overwhelm consumers to make right purchasing decisions.(Lee, 2007) In order to avoid choice overload and match consumers with the most suitable products, retailers use recommender systems (RSs), which predict the "relevancy" that corresponds individual preferences. (Adomavicius & Tuzhilin, 2005) (Koren et al., 2009)

There are mainly four types of recommender algorithms, namely, Content-Based Filtering, Collaborative Filtering, Hybrid Approaches and Popularity based recommenders. (Adomavicius & Tuzhilin, 2005) Content-Based Filtering (CB) approach analyzes user profiles and recommends items similar to the ones the user rated in the past, while Collaborative Filtering (CF) analyzes relationships between users or between items in order to determine new user-item patterns. (Koren et al., 2009)

However, both approaches entail several major drawbacks. For example, CF suffers from sparsity and cold start problems. Data sparsity refers to the condition of low percent of rated items over the whole number of items. Cold start problem means the condition where there are new users or items with little historical behavior.

CF is widely used in e-commerce RSs. However, little is known whether recommending products are consistent with the users' style preference.

Moreover, unlike books or technology products, recommending clothing products can be challenging. RS should recommend products not only if they match popularity or similarity, but also they should be relevant to users' preferences.

Majority of consumers not only search clothes by name, but also by brand. Brand is a key to influence consumers' purchasing decisions. Subsequently, each brand represents a certain style (such as, vintage, boho, classic, street style). (Grewal, 1998) For example, Hawes & Curtis evokes a style of luxury and classic. A man who frequently purchases this brand's products is a signal that he wears classic outfit. On the other hand, more purchase of brands such as Urban Wear denotes street style preference.

Therefore, multi-department online stores should concede human perceptive and cognitive elements of classical shopping. Resultantly, it is necessary to develop a personalized RS that recommends items that are relevant to user's brand preferences.

For this purpose, we develop a brand-aware recommender approach based on CF algorithm using brand information of products as an additional regularization term.
Our research questions are as follows:
(1) Whether including brand information in Clothing e-store increases RS performance and alleviates data sparsity.
(2) Whether or not, including brand information helps a better RS performance throughout different e-store departments?

Finally, we evaluate our model in a real-world dataset of Amazon, demonstrating the proposed algorithm improves recommendation accuracy.

The rest of this paper is organised as follows: Section 2 summarizes related work. The proposed Brand-Aware CF model is presented in Section 3. Subsequently, in Section 4, we perform experimental evaluation of our algorithm on the Amazon dataset. Finally, the last section concludes and gives some perspectives for future works.

2. Related Research

Several papers on clothing related RSs have been published in order to analyze major problems of traditional and non-traditional approaches. We find that the majority of related works rely on optimizing different objective functions. (Panniello et al., 2012) Many studies on the methods of improving the novelty and overcoming the weaknesses of CF were conducted. Whereas, Viriato et al. (2015) proposed a content-based approach which

combines visual features, textual attributes and human visual attention. Meanwhile, McAuley et al. (2015) presented an approach which identifies topics in the product reviews and descriptions which are useful as features for predicting links between products which identifies substitutes and compliments network. Also, He and McAuley (2016) propose a similar approach which retrieves fashionable items creating an image-based query system which extends standard matrix factorization (MF) by modeling visual dimensions and latent features simultaneously.

Our approach for recognizing brand names is different from other approaches that use visual features or other item information. Our goal is to create a RS for a clothing e-store which considers not only users' rating history, but also includes items' brand information. Once we can estimate the rating of the items through our model, we can recommend related items to the user with the highest estimated ratings.

3. A Brand-Aware Collaborative Filtering Recommender System

There is a strong linear relationship between individual brand preferences and product purchase intention, individuals reveal their styles by purchasing the items. (Banks, 1950)

In our approach, we assume purchased (rated) items as signals of individual styles (preferences). In order to recommend items to a user, our model extracts brand names from the user's activity patterns and recommends the items which have similar brand names. Therefore, in this section, we formulate two components of our algorithm, namely, traditional CF algorithm, and including additional input source such as Brand information.

3.1. Model Formulation

Consider a model where I is the set of all users of a recommender system, and let J be the set of all possible thousands of items from online store, such as shoes, dresses, or jeans, that can be recommended to users. We assume each individual has a consistent set of ordinal preferences with respect to her rated items which can be summarized by the utility function that represents the preference of item $j \in J$ by user $i \in I$ is defined as $u : I \times J \rightarrow R$ where R represents a numeric scale used by the users to evaluate each item, usually on the scale of 1 to 5. Then, for each user $i \in I$, we want to choose such item $j \in J$ that maximizes the user's utility (as indicated earlier, utility is represented by $rating$ R and initially defined only on the items previously rated by the users). Formally:

$$\forall i \in I, j_i = argmax_{j \in J} u(i, j). \tag{1}$$

Also, in order to distinguish between the actual ratings and the predictions of the RS, we let the $R(i, j)$ denote a known rating (i.e., the actual rating that user i gave to item j, and make the $R^*(i, j)$ notation to represent an unknown (i.e., the system-predicted rating for item j that user i has rated before). Each user in the user space I has a unique element, such as User ID. Similarly, each item in the item space J can be represented by its ID.

3.2. A Brand-Aware Collaborative Filtering-based Recommender Model

CF-based RSs recommend an item for a particular user based on the items previously preferred by other users. (Adomavicius & Tuzhilin, 2005) We exploit CF technique's Model-based algorithm – Matrix Factorization by exploring latent features of user ratings in order to predict the most preferable item which a user may wish to purchase. More formally, we minimize the following cost function:

$$\min_{w, a, b, V, U} \sum_{(i, j)} (r_{i,j} - score(i, j))^2 + \lambda_1 (\|w\|_2^2 + \|a\|_2^2) + \lambda_2 (\|U\|_2^2 + \|V\|_2^2) \tag{2}$$

Correspondingly, $r_{i,j}$ is the rating that user i gave to item j. U and V are, respectively user's and item's latent factors. λ_1 denotes the linear regularization parameter, while λ_2 is the regularization parameter. While, $\|\cdot\|$ are the Frobenius norms, that are implemented in order to alleviate overfitting.

The predicted score for user i on the item j is defined as:

$$score(i, j) = \mu + w_i + w_j + a^T brand_i + u_i^T v_j \tag{3}$$

Where μ is a global bias term. While, w_i and w_j are the weight term for user i and item j, respectively. $brand_i$ is the user's side information vector, i.e. the user's purchased items' brand information, hence it refers user i's brand preference. While a is the weight vector for $brand_i$ vector. Therefore, u_i and v_j are latent factors.

The model is solved using Adaptive Gradient Algorithm, a modified Stochastic Gradient Descent (SGD) with per-paramenter learning rate. This completes the formulation of the model to use in an experimental setup in the following section.

4. Experimental Evaluation

4.1. Experimental Setup

4.1.1. Dataset

The dataset we use for our experiments is from Amazon.com (McAuley et al., 2015) The data is gathered in the span of 2003–2014, the characteristics of dataset are given in TABLE 1. For technical convenience, we select two subsets of the data. We consider two categories, namely Women's and Men's Clothing, Shoes and Jewelry and Home and Kitchen.

Table 1. The characteristics of experimental data

Category	Clothing, Shoes and Jewelry	Home and Kitchen
Users	30523	7600
Items	8871	2780
Ratings	81320	53861
Rating sparsity	99.9%	99.7%

4.1.2. Evaluation Metrics

We conduct an offline evaluation and compare our model to the state-of-the-art CF approach. We choose standard approaches for evaluating the quality of our model:

(1) Precision and Recall measure.

Precision at k is defined as below:

Let p_k be a vector of the k highest ranked recommendations for a user i, let a be the set of items for that user. Hence, the precision is:

$$P(k) = \frac{|a \cap p_k|}{k} \times 100 \qquad (4)$$

While, recall at k is:

$$R(k) = \frac{|a \cap p_k|}{a} \times 100 \qquad (5)$$

In order to evaluate precision and recall, a recommendation list of $top - k$ items has been performed for each user based on the baseline model CF and our proposed model for both datasets.

(2) The RMSE measure.

In order to evaluate our model's rating prediction accuracy, we use root-mean-squared error (RMSE) metric. We compute the average difference between the estimed and actual ratings, as below:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2} \qquad (6)$$

While, y and $\hat{y}$ are vectors of length N, where y is the actual ratings, and $\hat{y}$ is the predicted ratings of the items.

4.2. Experimental Results

Each dataset is divided into 80/20% split into training and test data by a random selection. The recommendation approaches are applied to the training data, while test data is used to evaluation of our approaches. Experimental procedure is repeated 50 times, and generated the average of the evaluation metrics.

In our experiment, the number of latent factors U and V are chosen to be 32. Also, regularization parameters λ_1 and λ_2 are set to be $1e-009$.

4.2.1. Accuracy in predictions.

The results of RMSE on two datasets are presented in Table 2. By comparing our model and baseline algorithm CF, we find that adding a feature of items' brand information improves recommendation quality. According to Table 2, $RMSE_{test}$ values Clothing, Shoes and Jewelry and Home and Kitchen datasets are 1.5124 and 1.1535, respectively.

Table 2. Experimental results on real-world datasets. Performance measure by RMSE, lower RMSE

indicates better prediction accuracy.

Dataset	$RMSE_{training}$	$RMSE_{test}$	Recommender Method
Clothing, Shoes and Jewelry	**0.3112**	**1.5124**	Brand-Aware CF
Home and Kitchen	**0.3784**	1.1658	Brand-Aware CF
Clothing, Shoes and Jewelry	0.6389	1.8739	CF
Home and Kitchen	0.7957	**1.1535**	CF

Best results are highlighted.

4.2.2. Accuracy in recommendations.

The results in Table 3 and Table 4 show that, Brand-Aware RS attains best precision and recall values compared to CF approach. It is important to notice that, small values of measures are due to the data sparsity (Sparsity in Clothing, Shoes and Jewelry dataset is 99.9%, and 99.7% in Home and Kitchen dataset) and less amount of data i.e. the number of purchases per user is small.

Table 3. Accuracy in Recommendations. Precision at k (in percentage)

Dataset	Recommender Method	Number of Recommendations		
		5	10	20
Clothing, Shoes and Jewelry	Brand-Aware CF	0.04	0.03	0.04
	CF	0.03	0.02	0.03
Home and Kitchen	Brand-Aware CF	0.08	0.09	0.09
	CF	0.1	0.09	0.09

Table 4. Accuracy in Recommendations. Recall at k (in percentage)

Dataset	Recommender Method	Number of Recommendations		
		5	10	20
Clothing, Shoes and Jewelry	Brand-Aware CF	0.1	0.3	0.6
	CF	0.1	0.2	0.5
Home and Kitchen	Brand-Aware CF	0.2	0.4	0.9
	CF	0.2	0.4	0.9

Moreover, from Figure 1 and Figure 2, it is observed that our approach performs better than traditional CF model in both datasets.

Thus, we conclude that the proposed Brand-Aware recommender approach has been validated by two datasets evaluation with RMSE and precision-recall metrics.
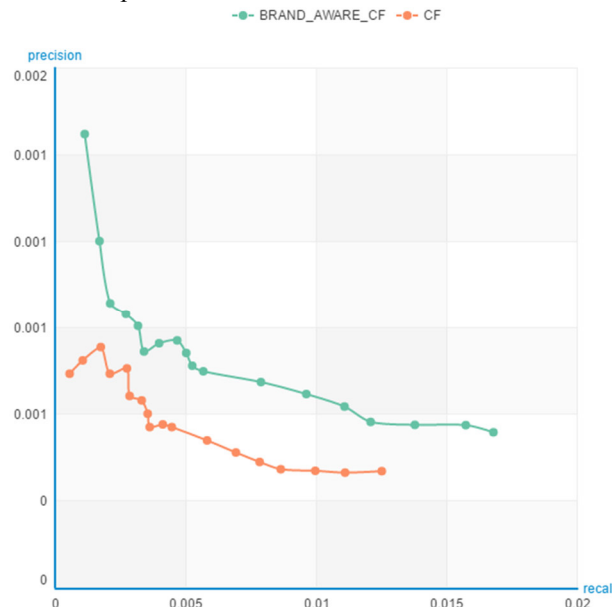

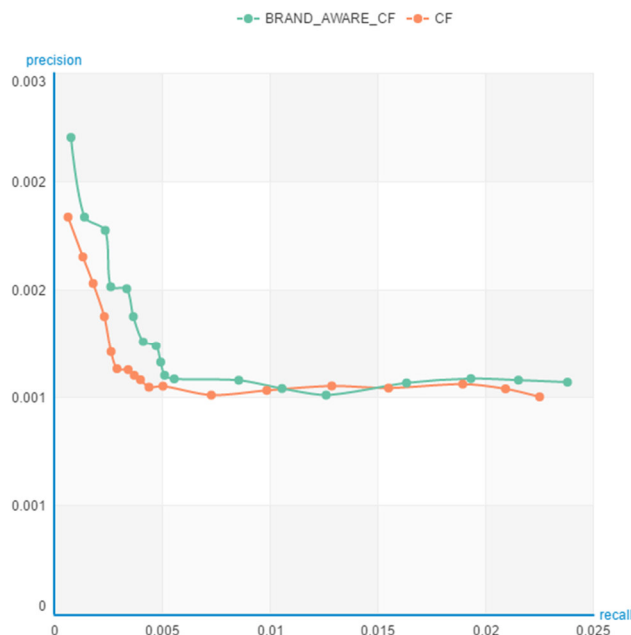Figure 1. Precision and recall at top-10 recommendations for Clothing, Shoes and Jewelry dataset.

Figure 2. Precision and recall at top-10 recommendations for Home and Kitchen dataset.

4.3. Discussions

The results of our analaysis support past findings that brand name is a key component in the consumer purchasing decision process. Brand-Aware RS achieves a better accuracy than state-of-the-art CF approach. We believe that, consumers are loyal to brands when making a purchasing decision, thus brand information is an important feature when building a clothing RS. Our second experiment, Home and Kitchen category also implies a brand name importance in RS. Although, the influence of brand name in Home and Kitchen dataset is minimal, this result indicates that unlike recommending other department items, clothing recommendation is more challenging. Therefore, it is highly recommended to add brand information in a clothing recommender system.

5. Conclusion

This paper presented a Brand-Aware Collaborative Filtering based recommender system. We combined products' brand information contained in each user's purchased list with Collaborative-Filtering approach. From the evaluation results, we conclude that brand information appears to be an important component in improving recommendation quality in a sparse data.

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