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A Style-Aware Collaborative Filtering-Based Recommender System

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Abstract
Online shopping for clothing products is growing rapidly. In order to avoid choice overload and match consumers with the most suitable products, retailers use recommender systems. However, unlike other products, recommending clothes can be challenging. Most customers not only search a clothes by their popularity or price but also by style. We present a Collaborative Filtering recommender system based on the traditional Matrix Factorization which incorporates items' contextual information in order to discover users' aesthetic preferences. We apply a style-aware recommender model in a real-world dataset of Amazon for experimental evaluation, demonstrating that our algorithm outperforms the state-of-the-art CF-based recommender approach.
Keywords: Recommender Systems, E-commerce, Collaborative Filtering

1. Introduction

Over the last decade there has been tremendous interest towards recommender systems from e-retailers. Recommender systems (RSs) can be defined as information filtering system that predicts the relative products that might be of interest to consumers (Adomavicius & Tuzhilin, 2005).

Collaborative Filtering (CF) technique is being applied extensively in e-commerce recommender systems (Zhao et al., 2015). CF analyzes relationships between users and between items in order to discover new user-item patterns (Koren et al., 2009). However, unlike books or technology products, recommending clothes can be challenging. Majority of customers not only search a clothing product by its popularity or price but also by style (such as, vintage, boho, classic, modern). Therefore it is necessary to develop a personalized recommender system that predicts the items that are relevant to user's aesthetic preferences (Viriato de Melo et al., 2015) (Hu et al., 2014).

In this paper, we describe a Collaborative Filtering-based recommender system in terms of its ability to discover *user's aesthetic preference*. We obtain this feature by building a set of item similarities using items' contextual information, then we implement these results to compare the recommending item with the set of users' purchased items, and incorporate these similarities into our recommendation model. Finally, for our experimental evaluation, we apply the proposed model in a real-world dataset of Amazon, demonstrating that our model outperforms the state-of-the-art CF-based recommender approach.

The rest of the article is organised as follows. In the following section, we discuss related work, while the proposed Style-Aware CF model is described in Section 3. In Section 4, we present experimental evaluation on the Amazon dataset, after which Section 5 concludes.

2. Related Research

For several years great effort has been devoted to the study of overcoming major drawbacks of CF. For example, majority existing clothing recommender systems implement visual appearances of items (He, 2015) in order to capture users' fashion requirements. Wang et al. (2015) proposed a human-perception-based fashion recommender system using fuzzy cognitive maps that treats both consumer's body shape and the fashion style. An interesting approach to this issue has been proposed by He, R. and McAuley, J. (2016) using users' past feedback and items' visual features which also aims to prevent cold-start problem. Whereas, an approach proposed by Viriato et al. (2015) combines visual features, textual attributes and human visual attention. Meanwhile, McAuley et al. (2015) had stressed a focus on identifying topics in the product reviews and descriptions which are useful as features for predicting links between products which detects substitutes and compliments network. Also, He (2015) proposed a similar approach which retrieves fashionable items creating an image-based query system which extends standard matrix factorization by modeling visual dimensions and latent features simultaneously. Etsy.com[1] recommender system uses Latent Dirichlet Allocation (LDA) to discover trending categories and styles in order to match with user's preference profile.

Our approach for recognizing style is different from all other approaches that use visual features. Our goal is to create a recommender system for a clothing online store which extracts style preference from the user's

[1] an e-commerce website focused on handmade or vintage items and supplies

previously purchased items and recommends items based on these preferences.

Hence, our proposed model is built based on the following concerns about (a) the ability of our recommendation approach to achieve better accuracy in predictions than the traditionally recognized models. (b) whether our recommendation approach will achieve better accuracy in recommendations.

3. A Style-Aware Collaborative Filtering Recommender System

The notion of style is difficult to be described. However, we regard rated items as signals of individual tastes. Hence there is a linear relationship between individual preferences and product purchases, (Banks, 1950) individuals reveal their styles by purchasing the items.

Our approach, in order to recommend items to a user, extracts styles from the user's activity patterns and recommends the items which have similar styles. Therefore, in this section we concentrate on the formulation of three main parts of our model:

1) Creating a dictionary of item styles (using TF-IDF topic modeling technique);
2) Discovering users' style preferences (using Cosine similarity measure);
3) Incorporate the outcome in a traditional Matrix Factorization model.

3.1. Model Formulation

Consider a model (Adomavicius & Tuzhilin, 2005) where *U* is the set of all users of a recommender system, and let *I* be the set of all thousands of items of Clothing department data, such as shoes, dresses, or jeans, that can be recommended to users in U . 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 $i \in I$ by user $j \in U$ is defined as $u: U \times I \rightarrow R$ 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 $j \in U$, we want to choose such item $i \in I$ that maximizes the user's utility.

To formulate mathematically:

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

Moreover, in order to distinguish between the actual and predicted ratings of the recommender system, we let the $R(i,j)$ denote a known rating (i.e., the actual rating that user j gave to item i, and make the $\hat{R}(i,j)$ notation to represent a predicted rating (i.e., the predicted rating for item i that user j has rated before). Each user in the user space U has a unique element, such as User ID. Similarly, each item in the item space I can be represented by its ID, title and description. For the mathematical simplicity, let $Content_i$ be the title and description of the item i .

3.2. Discovering user's style

3.2.1. TF-IDF: Creating a dictionary of item styles

In order to model users' preferences, we describe each item's contextual information as *keywords.* The importance of each keyword is represented with a *weight*. In turn, to identify keyword weights, we choose the *term frequency-inverse document frequency (TF-IDF)* measure (Adomavicius & Tuzhilin, 2005). TF-IDF converts the contextual information of items into a vector space model, which represents each item's information as a vector of numbers i.e. $f_{k,Content_i}$ - the number of times keyword k appeared in $Content_i$. Let's mathematically formulate our problem:

For each item *i,*

i) *Compute* $TF_{k,Content_i}$: We create a dictionary of keywords existent in $Content_i$ - $f_{k,Content_i}$. First, we select all keywords from the item *i*'s content and convert it to a dimension in the vector space. It is important to note that stopwords such as "the, at, on, etc." are ignored. Therefore, $TF_{k,Content_i}$ is defined as below:

$$TF_{k,Content_i} = \frac{f_{k,Content_i}}{\max_z f_{z,Content_i}} \tag{2}$$

ii) Compute *Inverse Document Frequency (* IDF_k *) defined as:*

$$IDF_k = \log \frac{I}{i_k} \tag{3}$$

IDF_k decreases the weight of frequently detected keywords in $Content_i$ and increases the weight of rarely detected keywords.
iii) Finally, compute *TF-IDF weight:*

$$w_{k,Content_i} = TF_{k,Content_i} \times IDF_k \quad (4)$$

Once we get each item's TF-IDF results, we calculate the Cosine Similarity between the first item content with each of the other item contents of the set in the next section.
3.2.2. Identifying users' style preference
The Cosine Similarity is a common way to compute item-to-item similarity in the traditional Item-based CF (Deshpande, 2004). This metric is chosen because, in a normalized *Content* space, cosine similarity measure treats each *Content* as a vector and then takes the cosine angle between the two Content vectors as a similarity measure between the two items (Al-shamri, 2014). For example, suppose in $Content_i$ the keyword "suede" appears 6 times and in $Content_m$ the keyword "suede" appears 2 times. Although, the Euclidean distance between $Content_i$ and $Content_m$ will be high but the cosine angle between contents will be small.
We define the cosine similarity measure as below:

$$\cos(\xi) = \frac{\vec{v}(Content_i)\,\vec{v}(Content_m)}{\left\|\vec{v}(Content_i)\right\|\left\|\vec{v}(Content_m)\right\|} \quad (5)$$

Having retrieved the item-to-item similarity matrix, our next problem is to define user j's style by comparing the similarity value of the recommending item to the each of items which user j rated before.

Formula (10) calculates average style similarity score, where $S^{(i,j)}$ is the average style similarity score of user j with the item i. Average style similarity score will be close to 1, if an item i is similar to the user j's previously purchased items, otherwise the score will be close to 0. M^j is the set of all user j's rated items in the category.

$$\overline{S^{(i,j)}} = \frac{\sum S_{m \in M}{}^{(i,m)}}{\sum M^j} \quad (6)$$

Similarity values of a recommending item to each user's style $style^{i,j}$ can be represented in a matrix $\phi \in Q^{i \times j}$ wherein the dimension and cells of this matrix are the same as the matrix $R \in Q^{i \times j}$.

Thus, we assume that there is a linear relationship between users' style and users' given ratings, we input this criteria in a classic MF model.

3.3. Matrix Factorization
In MF (Koren et al. 2009), user and item interactions are modeled as dot products in a joint latent factor space i.e. users and items are represented by feature vectors inferred from user-item rating patterns. Each item i in a set of I and each user j in a set of U are attributed to vectors x^i and θ^j feature vectors, respectively. The resulting inner products of vectors, which in turn, is associated with the overall interest of user j in the item i, thus estimating user j's rating to the item i. Moreover, μ is the overall average rating, while bias parameters b^j and b^i in turn, corresponds user and item effects.
The traditional MF can be expressed as therefore:

$$\min_{\theta,x} = \sum_{i,j\in\delta} (r^{i,j} - (\theta^j)^T(x^i) - \mu - b^j - b^i)^2 + \lambda((b^j)^2 + (b^i)^2 + \left\|\theta^j\right\|^2 + \left\|x^i\right\|^2) \quad (7)$$

The last part of the equation represents the regularization of learnt parameters in order to avoid overfitting. Hence, $\left\|\theta^j\right\|^2$ and $\left\|x^i\right\|^2$ are the Frobenius norms of θ and x, respectively. λ in turn, is the regularization parameter.

3.4 Style-Aware Collaborative Filtering Recommender Model (Style-Aware CF)
Having generated users' preferences, we now incorporate it in MF model. The parameters can be estimated by

solving the following minimization problem.

$$L(\theta,x) = \min_{b,\beta,\theta,x} \sum_{i,j\in\delta} (r^{i,j} - (\theta^j)^T(x^i) - \mu - b^j - b^i - \beta^j(style^{i,j}))^2 + \lambda((b^j)^2 + (b^i)^2 + (\beta^j)^2 + \left\|\theta^j\right\|^2 + \left\|x^i\right\|^2). \tag{8}$$

Minimization of the loss function in Equation (8) can be solved by a well-acknowledged technique - Stochastic Gradient Descend (SGD) with fixed θ and x which produces a local minimum solution (Bottou, 2010). Therefore, the gradients of Equation (8) with respect to θ and x are computed as follows:

$$\frac{\partial L}{\partial b^j} = b^j + \alpha(2e^{i,j} - \lambda b^j) \tag{9}$$

$$\frac{\partial L}{\partial b^i} = b^i + \alpha(2e^{i,j} - \lambda b^i) \tag{10}$$

$$\frac{\partial L}{\partial \theta^j} = \theta^j + \alpha(2e^{i,j}x^i - \lambda\theta^i) \tag{11}$$

$$\frac{\partial L}{\partial x^i} = x^i + \alpha(2e^{i,j}\theta^{jT} - \lambda x^i) \tag{12}$$

$$\frac{\partial L}{\partial \beta^j} = \beta^j + \alpha(2e^{i,j}style^{i,j} - \lambda\beta^j) \tag{13}$$

Algorithm1: Style-Aware Collaborative Filtering-based Recommender System

Input: R - User-Item rating matrix $N \times M$, δ - set of known rating in matrix R, θ^j - User feature matrix $N \times l$, x^i - Item feature matrix $N \times l$, b^j - bias of user j, b^i - bias of item i, μ - average rating of all users, l - number of latent features to be trained, ϕ - Normalized user style similarity matrix, β^j - style weight, $e^{i,j}$ - error between predicted and actual rating, α - learning rate, λ - overfitting regularization parameters, stop condition - ε.

Output: Style-Aware recommendation list.

1: procedure INITIALIZE θ^j, x^i AND VECTORS β^j, b^j, b^i WITH RANDOM VALUES

2: Fix values of l, α, and λ

3: Compute $L^{(t)}$ as in Equation (8)

4: repeat till error converges $[error(step-1) - error(step) < \varepsilon]$

$$error(step) = (r^{i,j} - (\theta^j)^T(x^i) - \mu - b^j - b^i - \beta^j style^{i,j})^2 + \lambda((b^j)^2 + (b^i)^2 + (\beta^j)^2 + \left\|\theta^j\right\|^2 + \left\|x^i\right\|^2)$$

5: for each $R \in \delta$ do

Compute $e^{i,j} = (r^{i,j} - (\theta^j)^T(x^i) - \mu - b^j - b^i - \beta^j style^{i,j})$

Modify training parameters: $\frac{\partial L}{\partial \theta^j}, \frac{\partial L}{\partial x^i}, \frac{\partial L}{\partial \beta^j}, \frac{\partial L}{\partial b^j}, \frac{\partial L}{\partial b^i}$.

6. end for

7. return θ^j, x^i, β^j, b^j, b^i

8. for each $R \in \delta$ do predict the rating for user and item $\hat{r}^{i,j}$

9. end for

10. end procedure=0

Style-Aware Collaborative Filtering based recommender system algorithm is depicted in Algorithm1. This completes the formulation of the model in order to use in an experimental setup in the following section.

4. Experimental Evaluation

4.1. Experimental Setup

4.1.1. Data description

The e-commerce dataset we use for our experiments is from Amazon (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 a subset of the data. We consider a clothing category, namely Women's and Men's Clothing, Shoes and Jewelry. The subset of data consists of 19491 ratings given by 4462 users to 1446 items. The rating sparsity is defined as below (Guo, 2014):

$$Sparsity = (1 - \frac{\#Ratings}{\#Users \times \#Items}) \times 100\% \tag{14}$$

The data is found to be 99.7% sparse, it means users only rated a small number of items.

The dataset is randomly divided into 80/20% split into training and test data. 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.

Table 1. The characteristics of experimental data

Category	**Clothing, Shoes and Jewelry**
Number of Users	4462
Number of Items	1446
Total ratings	19491
Rating sparsity	99.7%

4.1.2. Evaluation Metrics

We shall compare our model's performance to the baseline algorithm Item-based CF and Popularity-based model. In order to evaluate the models, we choose standard approaches for evaluating the quality of our model, namely Precision and Recall measure and root-mean-squared error (RMSE) metric.

(1) Precision and Recall measure. This metric is a good indicator of the recommender performance.

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:

$$P(k) = \frac{|a \cap p_k|}{k} \times 100 \tag{15}$$

While, recall at k is:

$$R(k) = \frac{|a \cap p_k|}{a} \times 100 \tag{16}$$

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:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{R_i} - R_i)^2} \tag{17}$$

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

4.2. Experimental Results and Discussions

In our experiment, the number of latent features and regularization parameters are kept constant and values are selected in such a way that they achieve the best results: $l = 8$, $\lambda = 1e - 009$ and $\beta = 1e - 009$. (The results with high number of latent features ($l = 32$) did not achieve high accuracy.)

4.2.1. Accuracy in predictions.

The results of RMSE derived using (17) on two datasets are presented in Table 2. According to Table 2, the $RMSE_{test}$ value of our approach in Clothing, Shoes and Jewelry dataset is 1.446, while Item-based CF $RMSE_{test}$ value is 1.516. By comparing our model, we find that discovering unique tastes in items' contextual information and implementing in RS improves recommendation quality.

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	**0.675**	**1.446**	Style-Aware CF
Clothing, Shoes and Jewelry	0.718	1.516	CF

Best results are highlighted.

4.2.2. Accuracy in recommendations.

The overall accuracy measurement results are summarized in Table 3 and Table 4. The results show that Style-Aware RS attains best precision and recall values compared to CF approach. By contrast, as revealed from the Popularity based RS results, recommending popular items lead to zero values of Precision and Recall. This means that, users' purchase intention is not based on items' popularity, but on users' aesthetic preferences.

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

Dataset	**Recommender Method**	**Number of Recommendations**		
		5	10	20
Clothing, Shoes and Jewelry	Style-Aware CF	0.1	0.1	0.1
	CF	0.1	0.1	0.09
	Popularity-based	0	0	0

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

Dataset	**Recommender Method**	**Number of Recommendations**		
		5	10	20
Clothing, Shoes and Jewelry	Style-Aware CF	0.6	1	1
	CF	0.4	0.6	1
	Popularity-based	0	0	0

Consider Figure 1, which represents a comparison of Precision and Recall at $top - 10$ recommendations of our model versus Item-based CF and Popularity based approaches calculated using (15) and (16). As shown in Figure 1, our approach achieved a better performance than the other models. The figure also indicates that Popularity-based model achieved worse results than two other methods; therefore the outcome is consistent with other studies which have shown that users' aesthetic tastes are more important in purchasing behavior.

It is also important to comment that, small differences between the driven results are associated with the data sparsity (Sparsity in Clothing, Shoes and Jewelry dataset is 99.7%) i.e. the percentage of rated items per user is very small and also, we selected a small amount of data for our technical convenience.

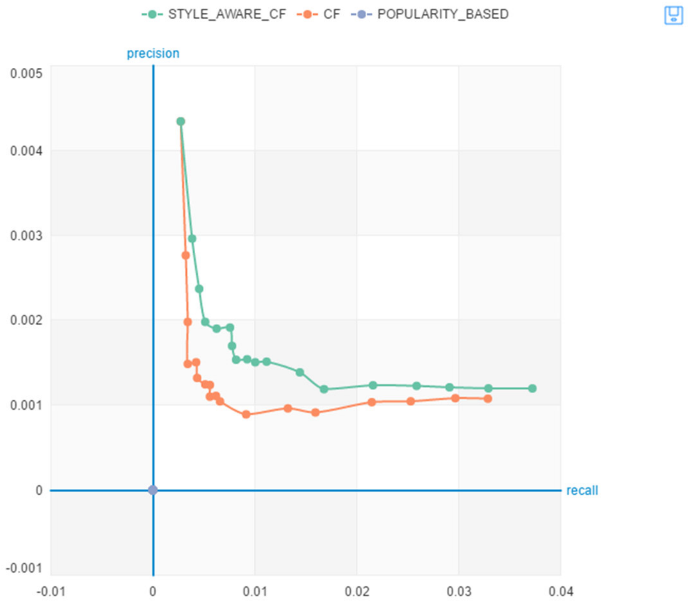

Figure 1. Precision and recall at top-10 recommendations for Clothing, Shoes and Jewelry dataset.

4.2.3. Discussions

These notable findings provide important insights for clothing e-stores and researchers to overcome limitations of CF technique. First, advantage of our algorithm is that, under data sparsity problem, and small amount of data, our algorithm is able to discover users' tastes and generate recommendations. The results derived from our model revealed that using contextual information of purchased items helps discovering unique tastes of a user. Second, item cold-start problem in e-commerce RSs still remain to be a salient part of research. Although we have not tested diversity of recommending items on our approach, we believe that recommending items based on users' aesthetic preferences may mitigate item cold-start problem.

Therefore, establishing a style detector in RSs would be a key strategy for online retailers to promote diverse products. Thus, we conclude that the proposed Style-Aware recommender approach has been validated by a real-world dataset evaluation with RMSE and precision-recall metrics.

5. Conclusion

This paper presented a Style-Aware Collaborative Filtering based recommender system for Clothing e-stores. We model user preferences using TF-IDF metric incorporating the outcome in CF. Specifically, for each user-item pair our model derives an estimate whether the item is close to user's preference while adding this feature in traditional CF model. We deployed our approach on a real-world Amazon dataset, showing our model achieves better recommendation accuracy than the traditional CF model. Moreover, our attention was focused not only improving recommendation performance, but also alleviating data sparsity problem. Although the proposed method can be readily used in practice, more experiments will be needed to verify the diversity of a recommending list. Therefore, work on the remaining issues is continuing and will be presented in future papers.

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