Sefamerve Research at The SIGIR eCom'22: Outfit Recommendation Based on Collaborative Filtering

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ABSTRACT

This paper describes our contribution to SIGIR eCom'22: Fashion Outfits Challenge. Given the real outfits produced by stylists and fashion experts, the task is to predict the most suitable missing item of a real outfit, out of a list of candidate products. Our approach considers the missing-item-prediction task as a neighborhood-based collaborative filtering problem. We experimented with several approaches both item and user-based (outfit-based) and reached the best prediction score of 0.68 by the "Item-based CF + Item-attribute model" which is ranked 3rd in the competition.

KEYWORDS

fashion outfits challenge, Farfetch outfit challenge, collaborative filtering, neighborhood-based collaborative filtering

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1 INTRODUCTION

The main goal of the Fashion Outfit Challenge is to develop a model that can generate outfits for each individual product. The organizers formed the competition by giving the real outfits produced by stylists and fashion experts and asked to predict the most suitable missing item of a real outfit, out of a list of candidate products [1].

We studied on the assumption that the outfit challenge task may be considered as a collaborative filtering (CF) problem. The CF recommendation system is the process of filtering or evaluating items through the opinions of other people [3]. One of the common methods of collaborative filtering (CF) is the neighborhood-based methods. Neighborhood-based CF algorithms rely on the assumption that similar users tend to display similar behavior patterns and similar items receive similar ratings [7]. These methods are used to determine the best item recommendations for the target user, or the best user recommendations for a target product.

Because the outfit combinations are chosen by certain designers, we have considered each outfit as a user choice. There is a possibility that more than one outfit can actually be created by the same designer/user. However, since there is no information on which combinations were created by the same stylists in the dataset, we consider using a user based approach in the training along with the item-based model. Hence, we designated our study to experiment the two main CF method both user-based (outfit-based) and item-based in the solution.

2 DATASET

The dataset consists of a list of outfits described by the products that compose it, and the Farfetch—leading platform for online luxury fashion shopping—product images and metadata, and outfits composition.

- # of products : 398670
- # of outfits: 300000
- # of products in training outfits dataset: 344797
- # of products not included training outfit dataset: 53873

Outfits consist of a minimum of 3 and a maximum of 14 products. Number of products distribution in the outfit dataset is provided below (Fig. 1).

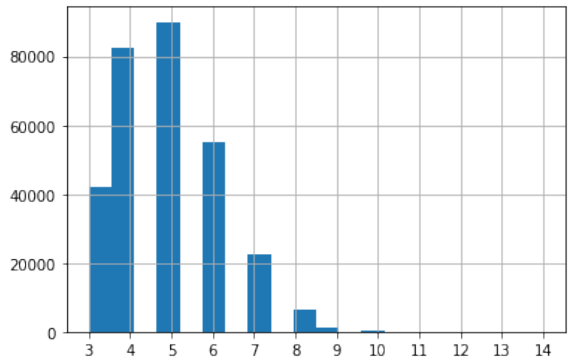

Figure 1: Distribution of products in outfit dataset

The provided candidate datasets in the study ranges from 4 to 41 with 26 average as provided below.

- mean: 26.04
- std: 8.91

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- min: 4.0
- 25% : 18.0
- 50: 26.0
- 75% : 34.0
- max: 41.0

3 METHODOLOGY

3.1 Outfit-Based CF

We have formulated our problem with the assumption that each outfit is a user in order to adapt the data we have into the user-based collaborative filtering problem. For this reason, we created a vector with the length of the number of products corresponding to each outfit. In this vector, if the relevant product is in the outfit set, it is defined as 1, otherwise it is defined as 0. Thus, a matrix with the size of 300K x 400K was formed, where the outfits were represented by rows and items by columns.

Due to the number of products in each outfit set is low, our matrix was formed in a sparse structure. In order to solve this sparsity problem, the dimension reduction process has been applied on the vector representing the similarity between the outfits. Unsupervised methods UMAP [6] and LDA (latent-dirichlet-allocation) [4] were used to find similar outfits in the dataset. We created a 64 length embedding vector for each outfit. Hyper parameters are used in the training is provided below:

- UMAP: n_components=64, metric:cosine,low_memory=True
- LDA: n_components=64, learning_method=online,verbose=1

As a result of training, we obtained a 64-dimension latent embedding representation for all the outfits. For the prediction stage, we generate a vector for the incomplete outfit subject to the recommendation by using UMAP/LDA model file as a vectorizer. Then, we need to find similarity between this vector and all other outfits. This converts the problem to similarity search problem.

In that step, we utilize Annoy—Approximate Nearest Neighbors—library [2] in order to search points in space that are close to a given query point. We expect from Annoy to find the most similar outfits that are closest to the evaluated incomplete outfit. Here, we selected the first 1000 outfits to provide candidates a reference list. After that step, we utilize score calculation algorithm provided in Alg. 1 to find the most relevant product for the incomplete outfit.

3.2 Item-Based CF

In this section, the item-based collaborative filtering (IB-CF) model has been tested which is the second approach in the neighborhood-based CF method. We calculated the co-occurrence of the products in the training dataset based on product_id. Accordingly, the candidate products for the incomplete_outfits were selected using the scoring calculation derived from frequency of co-occurrence with the products in the outfit dataset (Table 2). We used the score calculation algorithm provided in Alg. 1. The candidate product with the highest score was selected, if the candidates received equal score or zero, the first one was accepted as a recommendation.

First Product	Second Product	Count	Probability
15379678	15360881	4	0.4
	15781925	2	0.2
	16204075	2	0.2
	16260894	1	0.1
	14817366	1	0.1

Table 2: IB-CF Model Score Calculation

Score is calculated for each candidate products based on the co-occurrence of the evaluated product and each product in the incomplete outfits. The pseudo algorithm is provided in Alg. 1 which explains how scores are calculated.

Algorithm 1 Score calculation algorithm for candidates

Require:
Incomplete outfits: $InOutfits_{i=1}^{n}$, where $i = 1, 2, \cdots, n$, each element is a set of products,
Candidates: $Candidates_{i=1}^{n}$ where $i = 1, 2, \cdots, n$, each element is a list of candidate products,
Product Co-Occurence Matrix: $CoOccurence_{mxm}$, where $m = 1, 2, \cdots, m$, each element contains co-occurence information of all products (0 or 1)

Initilize $candidatescore_i = 0$, for all $candidate \in Candidates_i$
for each $candidate \in Candidates_i$ **do**
  for each $InOproduct \in \mathcal{I}Outfits_i$ **do**
    if $(candidate, InOproduct) \in CoOccurence_{mm}$ **then**
      $candidatescore_i \leftarrow candidatescore_i + 1$
    end if
  end for
end for

3.3 Item-based CF + Item-attribute model

The main disadvantage of the OB-CF model is that sometimes all candidates can get 0 score which is calculated based on the co-occurrence frequency of the outfit products and candidate products. Considering the 300K outfit in the training set, there are 53873 products (approximately 18%) that have never been used with any other combination before.

We proposed an item-attribute model to make a probabilistic estimation based on the characteristics of the products instead of suggesting a random product. For this purpose, we mapped all products to the new space produced as a combination of the Category, Main color and Gender features. Every product_id in the dataset converted to a new combined_attribute value such as "Shirts-GREEN-MEN", "Jackets-BLUE-UNISEX", "Trainers-WHITE-MEN" etc.

We utilized the same algorithm provided the previous section to calculate co-occurrence of these combined_attribute class. The probability values were obtained by normalizing frequencies dividing by the total number of observations as shown in Table 1. We applied the item-attribute model for those samples candidates get 0 or 1 scores from the Item-Based CF model. If the score from the

Co-occurred combined-attributes	candidate combined-attribute	Frequency	Probability
Shirts-GREEN-MEN & Jackets-BLUE-UNISEX	Trainers-WHITE-MEN	4	0.50
	Clutch Bags-PURPLE-MEN	3	0.375
	Trousers-BLACK-MEN	1	0.125
	TOTAL	**8**	**1**

Table 1: Calculation of combined-attributes

previous model is 1 or less, we select the product with the highest probability score.

3.4 OB-CF + IB-CF Hybrid Model (LightFM)

To reach a better estimation score, we suggest combining both outfit-based and item-based collaborative filtering models. We utilized LightFM, an effective recommendation system library which makes it possible to incorporate both item and user metadata into traditional matrix factorization algorithms. LightFM represents each user and item as the sum of hidden representations of their properties. This allows recommendations to generalize to new items (via item properties) and new users (via user properties) [5].

With LightFM, we apply a hybrid mode by providing the product attributes to the model together with the user defined outfit combinations.

The following variables are used as product attributes:

[product_family, product_category, product_sub_category, product_gender, product_main_colour, product_second_color]

We applied the following hyper parameters in the LightFM model:

- n_components: 30
- num_threads: 2
- num_epochs: 10
- item_alpha% : 1e-6
- loss: warp

4 RESULTS

As shown in the Table 3, we obtained the best test result by "IB-CF + Item-attribute" model as 0.68 percent accuracy. Outfit-based models that using UMAP-LDA embedding produced low accuracy values when we compared to the other models. However, implementation of "OB + IB Hybrid model (LightFM)" provides better than OB-CF model, but still quite far from "IB-CF" and "IB-CF + Item-attribute" models.

Model	Result (FITB)
OB-CF (LDA)[a]	0.148
OB-CF (UMAP) [b]	0.155
IB-CF [c]	0.65
IB-CF + Item-attribute model [d]	0.68
OB-CF + IB Hybrid Model (LightFM) [e]	0.515

Table 3: Model prediction results

[a] Embedding vector similarity with approximate nearest neighborhood. Vectorizer LDA with n_components = 64, similarity search with annoy model.
[b] Embedding vector similarity with approximate nearest neighborhood. Vectorizer UMAP with n_components = 64 similarity search with annoy model.
[c] Item based collaborative filtering. The number of outfits in which the products co-occurred were calculated as candidate scores.
[d] Winner model: Addition to IB-CF, co-occurrence scores calculated based on combined attributes for those samples candidates get 0 or 1 scores from the main IB-CF model.
[e] LightFM recommendation, OB-CF with item attributes.

5 CONCLUSION

Our approach considers missing-item-prediction-task as a neighborhood-based collaborative filtering problem. We experimented with several approaches both item and user based, and reached the best prediction score as 0.68 which is ranked 3td in the competition.

Regarding the OB-CF model, since there is no data about designers in the data set, we ignored the fact that more than one outfit can actually be created by the same designer/user. This obviously contradicted our assumption especially where the evaluation metric was defined as "Fill in the Blank (FITB)" in the research design.

We couldn't use the image dataset in our model due to time restriction, but we might have a suggestion for the future problem definition stage. For example; given incomplete outfits researchers might be asked to predict the most suitable item from a certain product category, despite about half of the candidates during training and test phase were like that. Using product images could have been more applicable for the problem if candidate category is provided.

REFERENCES

[1] Luis Baia, Eder Martins, Diogo Goncalves, Vanessa Marinho, Felipe Viegas, Ana Silva, and Tiago Otto. 2022. Farfetch Outfits Challenge on E-Commerce Workshop. In *SIGIR eCom 2022.*
[2] Erik Bernhardsson. 2018. *Annoy: Approximate Nearest Neighbors in C++/Python.* https://pypi.org/project/annoy/ Python package version 1.13.0.
[3] Jonathan L Herlocker, Joseph A Konstan, and John Riedl. 2000. Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work.* 241–250.
[4] Hamed Jelodar, Yongli Wang, Chi Yuan, Xia Feng, Xiahui Jiang, Yanchao Li, and Liang Zhao. 2019. Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tools and Applications* 78, 11 (2019), 15169–15211.
[5] Maciej Kula. 2015. Metadata embeddings for user and item cold-start recommendations. *arXiv preprint arXiv:1507.08439* (2015).
[6] Leland McInnes, John Healy, and James Melville. 2018. Umap: Uniform manifold approximation and projection for dimension reduction. *arXiv preprint arXiv:1802.03426* (2018).
[7] Tianqing Zhu, Yongli Ren, Wanlei Zhou, Jia Rong, and Ping Xiong. 2014. An effective privacy preserving algorithm for neighborhood-based collaborative filtering. *Future Generation Computer Systems* 36 (2014), 142–155.