Style Recommendation for Fashion Items using Heterogeneous Information Network

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ABSTRACT

In the midst of vast amounts of available fashion items, consumers today require more efficient recommendation services. A system that sorts out items that form a stylish ensemble with already selected or possessed items would provide them with greater convenience. In this paper, we propose a fashion item recommendation method that learns the way the fashion items are matched from a large ensemble database. We empirically show that the proposed method can explain factors that affect item matching and recommend the most suitable items to the given set of items.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval

Keywords

Style recommendation, Clothing ensemble recommendation, Heterogeneous information network

1. INTRODUCTION

Today, as massive amounts of fashion items are available in both online and offline market, needs for efficient recommendation services has grown significantly. One of the most important factors in recommending a fashion item is how well the item combines with a set of other items to form stylish ensemble. A number of works have been proposed in matching fashion items using web-scraped outfit combination dataset from sites such as Pinterest. However, they are mostly based on color matching and are not flexible enough to exploit other relevant features[1, 2].

In this paper, we propose a fashion item recommendation method that learns from a large ensemble database. The items and their attributes, and the ensembles are modeled as a heterogeneous information network that allows for flexible semantic analysis. We define meta-paths on the network as patterns of relationships between items with respect to attributes and ensembles. Relative importance of each meta-path in matching items is learned from the ensemble database. We show through experiments that our proposed method outperforms baseline algorithms.

Figure 1: An example ensemble of fashion items

2. DATA COLLECTION

We have collected 18,449 fashion items and 7,458 ensembles from an online shopping mall. Each ensemble contains about 2.5 items. The ensembles, which are presented by professional fashion coordinators of the shopping mall, consists of clothes, shoes, and fashion accessories as shown in Fig 1. We extracted and refined 4 attributes - category, material, pattern, and color - from item descriptions and item images. Table 1 shows value sets of each attribute. Weighted multi-color vectors are extracted from data images using a color extraction tool. The color vectors are then grouped into 3000 clusters using k-means clustering.

Table 1: 4 attributes and value set of each

Attribute	Value Set
Category	Jacket, Suit, Coat, Shirts, T-Shirts, Sweater, Cardigan, Vest, Jeans, Slacks, Cargo, Baggy
Pattern	Striped, Checkered, Twisted, Printed, Dotted, Floral, Camoflage, Paisley, Herringbone
Material	Cotton, Leather, Denim, Wool, Linen, Suede, Corduroy, Fur, Spandex
Color	3000 color clusters

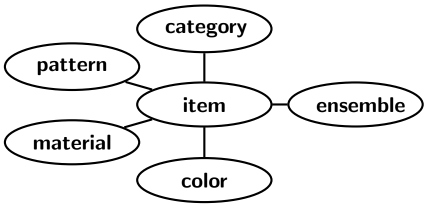

Figure 2: Network schema for fashion item ensemble

3. LEARNING PATH WEIGHTS

Fig 2 shows the network schema for fashion item ensemble dataset. There are 6 types of nodes, namely, **item**, **category**, **pattern**, **material**, **color**, and **ensemble**. Unlabeled edges represent direct associations between the nodes. We use the concept of meta-path[3] which can explain leverage factors related to clothing matching on the given network. Two kinds of meta-paths are used:

$$item \rightarrow X \rightarrow item \quad (1)$$

$$item \rightarrow X \rightarrow item \rightarrow ensemble \rightarrow item \rightarrow Y \rightarrow item \quad (2)$$

where $X, Y \in \{Category, Pattern, Material, Color\}$, so the total of 4+16=20 meta-paths are used. (1) is used based on intuition that the items which share the same attribute X would be matched together, and (2) is based on intuition that the items with the attributes that are frequently matched together on the network would be matched. For example with "*item* → *category* → *item* → *ensemble* → *item* → *category* → *item*" path, an item in the 'Jeans' category would be matched with an item in the 'T-Shirts' category, if the 'T-Shirts' category contains a lot of items that have been matched to 'Jeans' items.

To learn the coefficients of each meta-path, we sample 2,000 ensembles among 6,500 training ensembles (the rest is used for evaluation). Then for each sampled ensemble, we randomly choose one item as the target item and use the rest as query items. We choose to use normalized path count(NPC)[4] as path-based feature and prepare 20 dimensional feature vector for each ensemble as follows:

$$f_{Q,c} = (NPC_{p_1}(Q,c), NPC_{p_2}(Q,c), ..., NPC_{p_20}(Q,c))$$

$$where \quad NPC_{p_i}(Q,c) = \sum_{q \in Q} NPC_{p_i}(q,c)/|Q|$$

where $NPC_{p_i}(q,c)$ is normalized path count between q and c along meta-path p_i, Q is the set of query items, and c is the candidate item. The candidate items are sampled from the items that are released in the same month as the target item. And the according label becomes:

$$l_{Q,c} = \begin{cases} 1, & \text{if } c = target\,item \\ 0, & \text{otherwise} \end{cases}$$

The coefficient of each meta-path is learned using logistic regression on the feature vector and label pairs, $(f_{Q,c}, l_{Q,c})$.

Table 2 shows the important meta-paths and corresponding coefficients. Negative coefficient of (a) means the items that belong to the same category are rarely matched, which is trivial. In case of (d), the positive coefficient indicates that categories matched frequently on the network are actually important in item matching. Meta-paths for color attribute ((c) & (h)) show similar result with the meta-paths for category attribute ((a) & (d)), while those for the pattern attribute ((b) & (e)) turn out to be in the opposite. Also, we can infer from (f) and (g) that pattern and color are tightly related in styling.

Table 2: Important meta-paths and according coefficients (c denotes *category*, p denotes *pattern*, l denotes *color*, and e denotes *ensemble*)

No.	Meta-path	Coefficient
(a)	$i \rightarrow c \rightarrow i$	-6.897
(b)	$i \rightarrow p \rightarrow i$	1.090
(c)	$i \rightarrow l \rightarrow i$	-3.041
(d)	$i \rightarrow c \rightarrow i \rightarrow e \rightarrow i \rightarrow c \rightarrow i$	2.088
(e)	$i \rightarrow p \rightarrow i \rightarrow e \rightarrow i \rightarrow p \rightarrow i$	-0.607
(f)	$i \rightarrow p \rightarrow i \rightarrow e \rightarrow i \rightarrow l \rightarrow i$	0.565
(g)	$i \rightarrow l \rightarrow i \rightarrow e \rightarrow i \rightarrow p \rightarrow i$	0.652
(h)	$i \rightarrow l \rightarrow i \rightarrow e \rightarrow i \rightarrow l \rightarrow i$	3.826

4. EVALUATION AND CONCLUSION

The effectiveness of recommendation have been evaluated using the remaining 958 ensembles. As in the training stage, one item per ensemble is chosen as the target item and the remaining used as query items. Items nearest to the query items are recommended using the trained regression model. Random selection (Random) and personalized pagerank (PPR) based recommendations are used as baseline methods. Table 3 shows the results where performance is measured in terms of precision at k (k=1,3,5; P@1, ..., P@5) and mean reciprocal rank (MRR). The performance of PPR is lower than Random since PPR assigns higher scores to items near the query items. Consequently, the items of the same category or color with the query items tend to be recommended. Meanwhile, the meta-path based recommendation exploits the learned weights of the meta-paths, resulting in more effective recommendation.

Table 3: Result of each recommendation method

Method	P@1	P@3	P@5	MRR
Random	0.0715	-	-	-
PPR	0.0643	0.0602	0.0459	0.1983
Path	0.4004	0.2193	0.1621	0.5716

5. ACKNOWLEDGEMENTS

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