Fashion Recommendations Using Text Mining and Multiple Content Attributes

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ABSTRACT

Many online stores actively recommend commodities to users for facilitating easy product selection and increasing product exposure. Typical approach is by collaborative filtering, namely recommending the products based on their popularity, assuming that users may buy the products that many others have purchased. However, fashion recommendation is different from other product recommendations, because people may not like to go with the crowd in selecting fashion items. Other approaches of fashion recommendations include providing suggestions based on users' purchase or browsing history. This is mainly done by searching similar products using commodities' tags. Yet, the accuracy of tag-based recommendations may be limited due to ambiguous text expression and nonstandard tag names for fashion items. In this paper we collect a large fashion clothing dataset from different online stores. We develop a fashion keyword library by statistical natural language processing, and then we formulate an algorithm to automatically label fashion product attributes according to the defined library by text mining and semantic analysis. Lastly, we develop novel fashion recommendation models to select similar and mix-and-match products by integrating text-based product attributes and image extracted features. We evaluate the effectiveness of our approach by experiment over real datasets.

Keywords

Fashion recommendation, Text mining, Mix-and-match

1 INTRODUCTION

Due to the continued growth in the acceptance of e-commerce, the clothing products selling online has a rapid increase in the past two decades, not only in terms of sales volume but also in term of product types [1]. Recommendation technologies suggest users with products by analysing users' interests and purchase behaviors [2]. Content-based methods recommend items based on a comparison between the content of the items and a user's profile [3]. Recommender systems are widely used in e-commerce websites, such as amazon.com, netflix.com, taobao.com, and zalora.com.

Unlike traditional recommendation methods that focus on similarity search, we propose in this paper a method that makes recommendations in two dimensions, suggesting similar and mix-and-match clothing items from a content-based approach. In similar clothing recommendations, products that are similar to the target product are recommended to users; it helps users to quickly search for their needed products. For example, assuming the target product is a dress, the recommender system will suggest users other dresses that are similar to the given dress in colour, brand, description, and/or price range. All recommended products belong to the same product category, i.e., dress in this example. In mix-and-match clothing recommendation, the system gives outfit ideas that users are suggested with other clothing items or accessories that match well with the given product; and users can choose to buy these products together. Taking the dress example above, recommender system will suggest users with other products (e.g. jacket, handbag, shoes) that match well with the target dress. These matching products may match the target product in brand, colour, size, and/or style; all matching products belongs to categories different from the specific category of the target product.

The main contribution of this paper is that we propose a recommendation system that provide users with similar and mix-and-match clothing product recommendations based on a selected item. The rest of the paper is organized as follows. In the next section, we will look at previous work in the related areas. In Section 3, we will discuss the overall structure and detail of the proposed recommendation system. Section 4 describes the detailed metrics used in the experiments and experimental methodology for the proposed methods. In Section 5, we will present our experimental results and relevant discussion.

2 RELATED WORK

With the rapid development of computer and internet technologies, the key problem has been changed from how to obtain the required information in the past to how to help users get the necessary knowledge from the massive information today. There are two branches about clothing product recommendations, similar clothing recommendation and mix-and-match clothing recommendation. In the literature, methods for computing similarity can be classified as semantic-based methods and case-based reasoning methods [7]. The existing methods calculate the similarity of different clothing items by extracting features from these clothing, evaluating the similarity of different features and summarising all features with a weighted average score [8]. There are a number of measures calculating the feature similarity, such as Euclidean Distance, Manhattan Distance, Cosine Similarity, Hamming distance, and Correlation coefficient [9]. Therefore, recommendation of similar clothing has turned out to be a problem of feature extraction from clothing products, including modeling and formulation. In [10], similarity among clothing items is measured based on the semantic description of clothing products, in which a lightweight fashion ontology is developed based on expert knowledge. In [11], a method is proposed to recognize clothing attributes from clothing images, but only upper-body clothes are analysed. It is found that image backgrounds affect the final results of clothing attribute recognition, and the recognition accuracy is difficult to ensure [12].

In mix-and-match recommendations, [13] proposed to calculate the compatibility of clothing items and attributes. Inter-object or inter attribute compatibility are considered, and Conditional Random Field (*CRF*) is used to calculate the most compatible combinations. Most reported studies on mix-and-match recommendations are content-based techniques using prior knowledge. Some researchers design mix-and-match rules based on experts who are familiar with clothing coordination and styling, but users' personal requirements are not considered [14]. Other researchers provide recommendations by mining association rules from massive transaction records, finding the frequent mode of clothing matches [15]. This method can capture the fashion trends of clothing but can not give professional clothing matches.

There are also some work on context-based personalized clothing recommendations. Wearing occasion is one of the most important factors to consider when people select clothes.

3 METHOD

In this paper, clothing recommendations for both similar products and mix-and-match products are proposed. All tests are based on real dataset crawled from online fashion websites. We consider the description of clothing products, using *Natural Language Processing* to extract keywords and features of clothing products. Then products are re-grouped and groups are encoded, match rules are defined by fashion stylists and clothing experts. On the other hand, a domain ontology about clothing is constructed. Based on this, product similarity is calculated and sorted. Finally, recommendations are made, including similar products and mix-and-match products.

We will describe three parts of development in this section. In Section 3.1, the structure of the proposed recommendation system is described, which follows with dataset used in this study (Section 3.2) and our clothing product data re-categorization (Section 3.3). In Section 3.4 introduces how similar recommendations are computed. In Section 3.5, the mix-and-match clothing product recommendation is explained.

3.1 Recommendation Structure

There are four modules in the recommendation system, including attribute extraction module, clothing product recommendation module, sorting module and user feedback module.

The first phase is attribute extraction. In this phase, description of clothing products are analyzed by *NLP* tools. The second phase is the recommendation module. Similar recommendation and mix-and-match recommendation are put forward in this phase. The third phase is the sorting module, the similarity score and mix-and-match score are calculated between the target product and all candidate clothing products. The result is sorted and clothing products with the highest scores will be selected in to the final recommendation list. Lastly, a method is used to improve the performance of the structure using user feedback. The ontology library and keyword extraction method will be adjusted according to the feedback. The proposed fashion recommendation structure is shown in Figure 1. In the flowing subsections, similar clothing product recommendation and mix-and-match clothing product recommendation will be introduced in details.

3.2 About the Dataset

The data used in this paper are crawled from online fashion websites, including zalora.com.hk, hm.com/hk

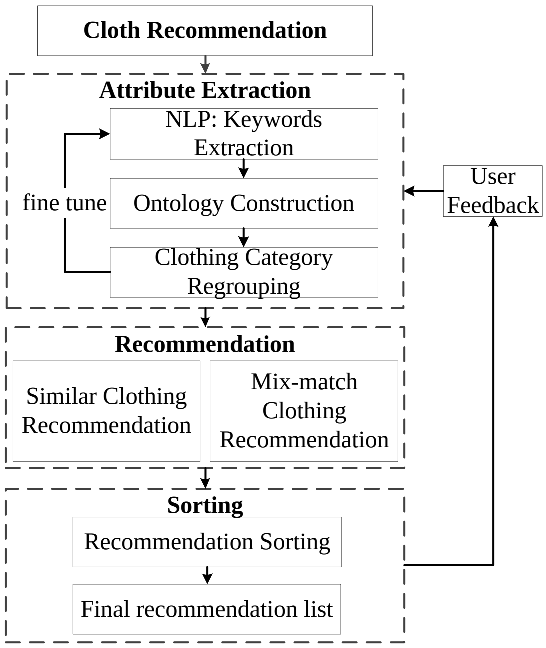

Figure 1: The structure of proposed recommendation method

and asos.com. There are a total of 158,211 products crawled from these websites, among which 91,491 are women products and 66,720 are men products. The main features we have got from online websites including product breadcrumbs, crawled time, product brand, product gender, product title, product price, product description, product details. The breadcrumbs of clothing products from different websites are different. In order to recommend products across websites and unify the breadcrumbs of all clothing products, we propose a product re-categorization method in Section 3.3 to map all products from the old breadcrumbs to our new redefined breadcrumbs.

3.3 Clothing Product Re-categorization

Since we crawled product data from different websites, the product classification vary among these websites. We therefore need to map products from the old categories to our new organized categories.

There are three kind of information we can use: clothing description, transaction data, clothing image. Description of clothing products is usually text information. In description of clothing products, including clothing category, which the product belongs to, product colour, price, materials. We use *NLTK* to extract nouns keywords from text description. *NLTK* is a leading platform for building Python programs to work with human language data. Transaction data are the records that users buying the products, including user name, product name, transaction data. A lot of information can be obtained from clothing images. Using pattern recognition techniques, information including colour, clothing type, clothing style can be mined from clothing images, which can make up the lack of text description of clothing products.

According to clothing products data we have got, we organize all clothing products into 101 categories, including 42 men's categories and women's 59 categories. Each category is assigned a unique identification code. Women's clothing category codes start with 'P3' and men's clothing category codes start with 'P2'. Table 3.3 shows the examples of keywords dictionary and the keywords list mapping that category.

For example, category code of bags (for women) is 'P302', and category code of bags (for men) is 'P202'. For each category, a list of keywords is found, if the keyword exists in one clothing description, the cloth product is assigned as the new category. For example, there is a bag(for women) product, if the text description of the product contains keywords in the keywords list of Category P302, the product is assigned as 'P302'. But there exist misclassified situation. The text description of clothing product is divided into three parts, product title, product breadcrumbs, product description. For each part, if the keywords list hit the text segment, the record will be recorded and scored. Category with the highest score would be selected.

A method is used to adjust and fine tune the keywords list of each category. The final result shows that more than 95% of the products are correctly categorized. After clothing product re-categorization, all clothing products are recategorized to 101 new categories. For each new category, a list of features are selected, which is also coded, features are selected and assigned to each product according to the text description of the product. Similar product recommendation and mix-and-match recommendation will be on basis of the new categories and features.

3.4 Similar Clothing Recommendation

3.4.1 Similarity Calculation Metrics

Similar clothing recommendation selects the most similar products in the same category. There are a list of features in each clothing product. Similarity calculation metrics of features can be represented as a vector,

$$C = \{f_1, f_2, f_3 \cdots f_m\} \tag{1}$$

where m is the number of features. f_i is the ith feature of the feature list. The main content of similarity computation is feature similarity computing and weight coefficient. There are three kinds of feature similarity computation, for explicit and continuous features, discrete features, and boolean features.

Category Name	Category Code	Keywords List
Bags	P302	Bags;Bag;Backpacks;Backpack;Clutches;Clutch;Handbag;Handbags;
Beachwear	P30401	Beachwear;Bikinis;Swimsuits;Bikini;Swimsuit
Dresses	P30402	Dresses;Dress
Pants_Leggings	P30406	Jobbers;Jobber;Leggings;Legging;Pants;Pant;Trousers;Trouser;Sweatpants
Bags	P202	Backpacks;Backpack;Bags;Bag;Clutches;Clutch;Duffle,Bags;Duffle Bag;Handbags
Beachwear	P20401	Beachwear;Bikinis;Bikini;Swimsuits;Swimsuit
Pants_Joggers	P20406	Chinos;Chino;Cropped,Pants;Cropped Pant;Cropped Trousers;Cropped,Trouser
Poloshirts	P20407	Poloshirts;Poloshirt;Polo,Shirts;Polo shirt;Polo;Long,Sleeved;Long-sleeved; Long-sleeves;Long-sleeve;Long sleeves;Long sleeve
Underwear	P20411	Boxers;Boxer;Bras;Bra;Briefs;Brief;Hipsters;Hipster;Lingerie,Sets;Lingerie Set; Lingerie;Panties;Pantie;Underwear

Table 1: Category re-categorization: examples of keywords dictionary

The similarity of explicit and continuous features can be computed with the nearest neighbor algorithm by Equation 2.

$$Sim(f_i, f_j) = 1 - \frac{|f_i - f_j|}{\beta - \alpha} \tag{2}$$

where $f_i \in [\alpha, \beta]$ and $f_j \in [\alpha, \beta]$ are the corresponding features in two clothing products. α is the minimum value and β is the maximum value in the corresponding clothing feature set.

The similarity of discrete features can be calculated using fuzzy mathematics:

$$Sim(f_i, f_j) = \frac{f_i \cap f_j}{f_i \cup f_j} = \frac{f_i \cap f_j}{f_i + f_j - f_i \cap f_j} \tag{3}$$

The similarity of boolean features can be either 1 or 0, and the similarity can be calculated as:

$$Sim(f_i, f_j) = \begin{cases} 1, f_i = f_j \\ 0, f_i \neq f_j \end{cases} \tag{4}$$

Lastly, the product similarity is calculated by integrating all available features:

$$Sim(C_i, C_j) = \frac{\sum_{i=1}^{m} w_i Sim\left(C_{f_i}, C_{f_j}\right)}{\sum_{i=1}^{m} w_i} \tag{5}$$

where C_i and C_j are two feature vectors of clothing products, w_i is the weight for the ith feature, while $Sim\left(C_{f_i}, C_{f_j}\right)$ is the similarity of ith feature of clothing product C_i and C_j. A method combining nearest neighbor method and fuzzy similarity retrieval method is proposed in this paper.

3.4.2 Color Similarity Calculating

One of the goals of the similar product recommendation is to calculate the similarity of product colors. Color is one of the most difficult areas to normalize. In fact, one single colour has different possible descriptions. However, it is difficult to calculate the similarity of these descriptions. These colours can be understood by people, but it is very difficult for computers. Even simple colours such as *snakeskin* or *periwinkle* can be difficult to handle automatically. In this paper, a method is proposed to cluster colours into a list of color categories. After cleaning all the color descriptions, there are 6,700 different colour descriptions in the dataset. All these colour descriptions are mapped into 11 categories.

3.5 Mix-and-match Clothing Recommendation

As mentioned in Section 3.3, we have 42 men categories and 59 women categories; each category has various features. In this section, mix-and-match rules are defined by fashion expert. Women's and men's mix-and-match are set respectively. Two match levels are defined, category level and feature level. A mix-and-match matrix is constructed for women's categories and men's categories. For example, a 59×59 matrix is constructed, if there exist match possibility in two categories, there would be a none zero score in the cross position of the mix-and-match matrix. The scores are divided into six levels,0, 0.2, 0.5, 0.8, 1 and 3 respectively, which 0 means the two categories do not match, while 1 means two categories match well. Score 3 means there exits feature level mix-and-match. Feature level match is also defined by fashion expert.

4 EXPERIMENT

4.1 Experiment Setup

In this section, the proposed method is tested on real online dataset by experiment. A total of 50 human subjects, mainly undergraduate students of The Hong Kong Polytechnic University participated in the experiment. The experiment is set as follows: 200 products are randomly selected involving various product categories. These products are divided into two groups: Group I with 50 products that computed recommendations are not shown, and Group II with 150 products that computed recommendations are shown

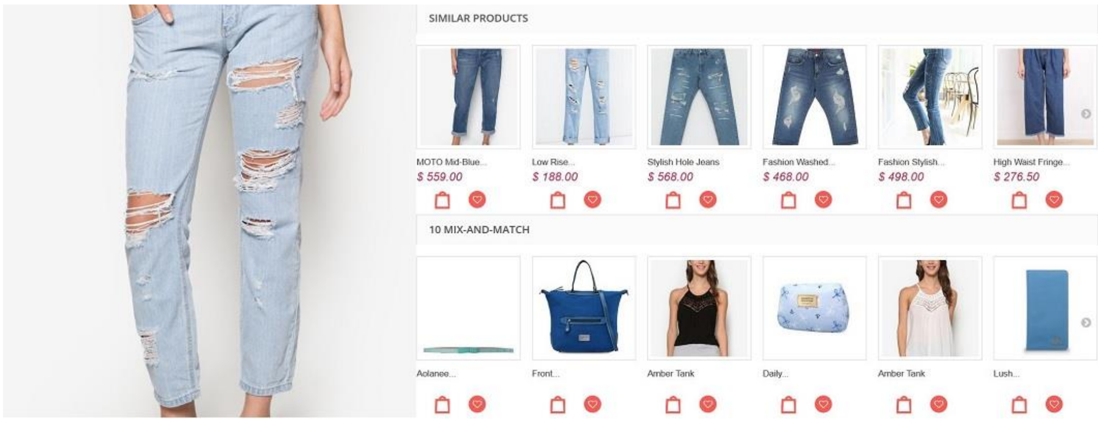

Figure 2: An example of similar and mix-and-match recommendation

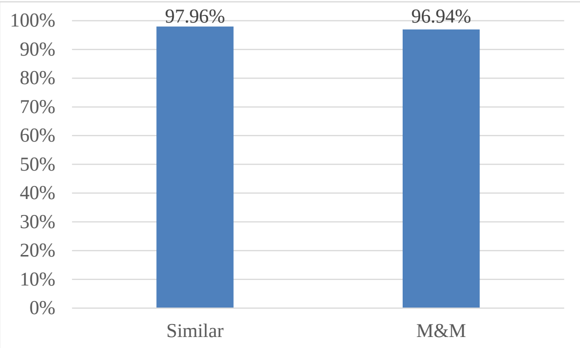

Figure 3: Similar products and mix-and-match recommendations volunteers selected

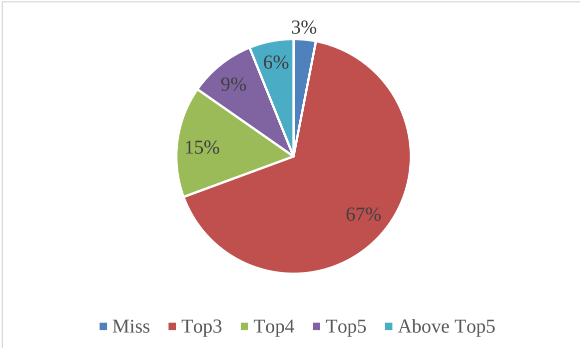

Figure 4: Distribution of products volunteers selected *VS* similar products recommendations

to the subjects. Subjects were asked to recommend 3 similar products and 4 mix-and-match products for each product of Groups I and II.

4.2 Experimental Results

There are 4820 product recommendations results in the experiment, during the period from 6th Feb to 18th Feb 2017. After data cleaning, there are 1323 records, including 441 Group I and 882 Group II ratings.

In Group I, subjects were asked to choose 3 similar products and 4 mix-and-match products without any recommendation suggestions. In Group II, subjects were asked to choose 3 similar products and 4 mix-and-match products from the recommendation list. If what subjects choose on their owns are happened same as those suggested by the recommendation system, it is an indicator that the system can generate very effective recommendations that are comparable to humans.

We judge the recommendation effectiveness by the sequence of what the users have chosen. Figure 3 shows that most users can select similar and mix-and-match items from the recommendation lists, which the hit rates are 97.96% and 96.94% for similar and mix-and-match items, respectively. Figure 4 shows which products users selected from the similar recommendation list, which are compared to the system calculated most similar items. We randomized the recommendations before showing to the subjects, and what the subjects selected are compared to the score (score sorting the similarity of the products by the system). If users selected items are the most similar ones among the randomized recommendations, it means the similar recommendations are effective. The results showed that over 67% of users selected similar items are the top 3 recommended items. Considering that users are asked to select 3 most similar items form the list, the similar recommendation is quite successful. Top 4 and top 5 rates are 15% and 9% respectively, meaning the users selected 3 items are among the top 4 most similar and top 5 most similar items in the recommendation list. Only 3% of selected items are not recommended by the system. Figure 5 shows the mix-and-match recommendations, which is more challenging problem as people are subjective about what products mean to be good match with the given items. The results show that less than half of the users selected mix-and-match are top 4 best match items suggested by the system. Considering that users are required to pick 4 items, it means 100% hit rate

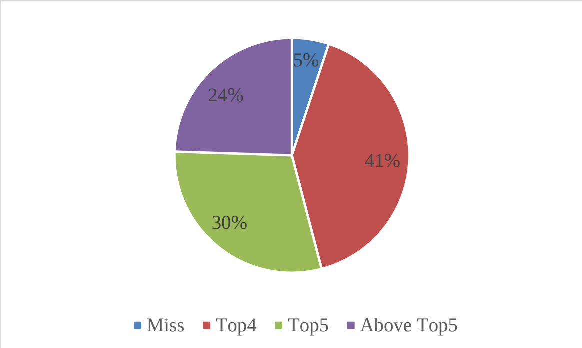

Figure 5: Distribution of products volunteers selected *VS* mix-and-match products recommendations

for these top 4 hit rate. Apart from full hit (top 4), around 30% of users selected mix-and-match items are among the top 5 suggestions of the system. Only 5% of the mix-and-match are not on the system generated recommendations, but some random 'noise' items given by the system. The results of mix-and-match hit rates are quite promising. Two examples of similar and mix-and-match recommendation is shown in Figure 2. More instances can be found in http://www.tozmart.com/.

5 CONCLUSIONS AND FUTURE WORK

In this paper, a hybrid recommendation structure on fashion clothing products is proposed, including similar and mix-and-match recommendations. Results show that the method get a good result both in similar recommendations and mix-and-match recommendations. In this paper, images of fashion products are not fully used, however many useful information for product recommendation cannot be extracted from text descriptions. In the future, we will focus on extracting features from clothing product images. A deep learning framework will be used to parse fashion photos, after which we will extract multi-features from parsed regions to describe product attributes like pattern, colour and style details. On the other hand, user context information and personalized recommendation will also be considered.

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