Who are the Devils Wearing Prada in New York City?

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1. INTRODUCTION

"The devil wears Prada" is a very popular fashion related movie which describes the story between a recent college graduated girl and the diabolic fashion magazine editor Miranda Priestly. Although Miranda’s grim manner of management is impressive, we also admire her unique foresight and aesthetics of fashion. In modern times, a growing number of people pay more attention to fashion and the mass has the penchant to emulate what large city residents and celebrities wear. Moreover, investigating fashion trends has become a great interest for the industry and academia [8][14][15][13] because of its promising opportunity for boosting many emerging applications such as clothing recommendation, advertising by clothing brand association, etc. Consequently, learning the fashion trends every year is very important for the industry as well as sociology and psychology.

Indisputably, New York City is one of the most famous fashion metropolises and the New York Fashion Week is one of the four most significant fashion weeks around the world [6][2][4]. The New York Fashion Show consists of almost 300 catwalk shows which are attended by more than 100,000 people [6]. The New York City Economic Development Corporation reported that the local economy is boosted by 850 million dollars by the New York Fashion Week [5].

A traditional way to discover fashion trend in the New York Fashion Week would be relying on the domain knowledge of the clothing designers and experts. However, it is very time consuming and the fashion trends vary with the...

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3. FASHION STYLE DISCOVERY

To provide a significant and specific clothing fashion reference, an effective framework for exploring clothing style representation is required. Using an appropriate clothing representation, we could offer a semantic and intuitive way for people to determine what fashion style they would like to choose. Inspired by the paper [10], a learning-based clothing attributes approach was carried out to describe clothing style. In the research [10], Chen et al. only detected 42 upper body clothing attributes. However, we observe the clothing information in the lower body is an essential clue for fashion trends understanding (e.g. wearing pants or skirt). Different from this research [10], we proposed to exploit a 60-attribute semantic representation to describe both upper and lower body clothing attributes. In the following, we briefly describe the adopted approaches for learning the clothing attribute. Table 1 shows the details of clothing attributes.

3.1 Feature Extraction

Before learning the 60 clothing attributes, we need to extract clothing features beforehand to train classifiers for every attribute. Thanks for Marcin Eichner’s team [11], we apply their pose estimation software to detecting the model’s pose and retrieve the body region of the model. More clearly, the pose estimation process is to segment body into nine parts: torso, upper left arm, upper right arm, lower left arm, lower right arm, upper left leg, upper right leg, lower left leg and lower right leg. Next, we extract four different kinds of features (e.g. color, texture, SIFT, and skin) and utilize two different aggregation methods to generate a visual feature vector for all the parts of the body. An example is illustrated in Figure 3.

3.2 Fashion Attribute Learning

In order to determine whether a fashion element is present in an image, we adopt a Support Vector Machine (SVM) [9] with a Chi-square kernel to learning fashion attributes (cf. Table 1). The most intuitive way for training each fashion attribute is concatenating 72 features (cf. Section 3.1) into a long vector that becomes the full body visual feature vector. However, the influence of different types of feature on each attributes may vary. For example, texture features might have a great effect on pattern based attributes. Consequently, we compute the classification performance of each feature to represent the importance of features as weights towards individual attributes. As a result, a weighting parameter can be applied to vectors from different features to emphasize the importance of different features.

3.3 Attribute Relation Inference

In section 3.2 the fashion elements are considered as isolated attributes. However, it is highly possible that some attributes appear in pairs (or groups). For example, we ob-
serve that a plaid shirt might have more than two colors. Note that inter-attribute dependencies are not always symmetric. For example, while a plaid shirt strongly suggests the presence of more than two colors, more than two colors do not necessarily suggest a shirt being plaid. We adopt a Conditional Random Fields (CRF) approach to infer the relation between attributes. More specifically, each attribute acts as a node in the CRF framework and the edge connecting every two nodes indicates the joint probability of these two attributes. We build a fully connected CRF with all the attributes pairwise connected.

4. EXPERIMENTAL RESULTS

We conduct experiments on a large clothing dataset collected from the New York Fashion Shows and Street-chic photos.

We conduct several experiments to gain understanding of the performance of the attributes. The overall accuracy of attributes is 62.6%. The examples in Figure indicate that the extracted attributes were effective for clothing style representation. An interesting observation is that some categories suffer from worse results (e.g., 42% accuracy of belt, 56% accuracy of accessories) since the objects are relatively small compared to the entire body. In the future, we could segment the body into more parts to improve the accuracy of the attributes detection. For example, we could segment the middle body for belt and the neck part for the accessories.

Table 2 shows the attributes percentage detected on the 2014 New York Fashion Shows and 2015 New York Fashion Shows. We divide these attributes into three categories, color, pattern and clothing style. We observe that there are always some classic colors, patterns or styles that have a large amount of clothing images in the fashion shows of every year. For example, in upper body color, both 2014 and 2015 fashion images have a large amount of white, gray and black colors. In upper body and lower body patterns, solid pattern is the classic pattern and solid pattern clothes always dominate every year’s fashion shows. In the style attribute category, there are many images with skirt in spring/summer fashion shows. These examples indicate that the results generated by attribute description methods are very reasonable and these results can be a very significant reflection for the fashion shows styles.

Besides these classic cloth styles, we are also interested in the changes in the fashion trend. These changes in attributes could indicate special fashion trends for the specific year. Note that we remove the classic style attributes, black, white and gray in the color category, solid pattern in the pattern category and skirts in the style category to present the changes more clearly. Figure 4 shows the change of fashion trend between the 2015 fashion shows and the 2014 fashion shows. From this figure, we could tell the unique fashion trends for 2015. In the color category, attributes with larger changes in the upper body are blue, multicolor, cyan and red; attributes with larger changes in the lower body are blue and purple. In the pattern category, attribute with larger changes in the upper body is striped; attribute with larger changes in the lower body is striped. In the style category, long knee length, tank top, outwear and collar are most significant attributes in 2015. These attributes with larger changes could be regarded as the unique fashion attributes trends shown in 2015.

In order to analyze the influence from the New York Fashion Shows on people’s daily life, we analyze the clothing attributes from the street chic images. As we mainly focus on the spring and summer fashion show influence, we collected 471 street chic images in 2014 and 575 street chic images in 2015 that were taken in New York from April to July and utilize these images as our street-chic data for fashion influence analysis. The changes of these attributes between 2014 and 2015 are shown in Figure 4. As shown in Figure 4, some changing trends of attributes are the same in fashion shows and in street chic. For example, there is a significant rise in both placket and top of the style category. In the pattern category, striped pattern in the upper body increased substantially. In the color category, blue in the lower body, blue, cyan, red and multicolor in the upper body showed an upward trend in both fashion show and street chic images. Consequently, we could tell that many people have the penchant to emulate clothing styles shown in the fashion shows. Some examples are shown in Figure 5. Interestingly, there are some different changes of fashion elements between the fashion shows and street chic images. For instance, we observe that the difference between the fashion shows and street chic lies in the long knee sleeve and outwear. We discovered that summer 2014 is the coldest in a decade, and people tended to wear outwear to keep warm. Another interesting observation is that people tend to wear bright-colored clothes in both the upper body and the lower body instead of wearing in only the upper body as shown in the fashion shows. A reasonable explanation is that light-colored clothes can absorb less sun light and keep people cooler; therefore, people are tempted to wear light color clothes in order to keep them cooler in the hotter weather in 2015. In summary, it seems clear that fashion trends from fashion shows indeed provide people a clothing reference and have significant influence on people’s daily life. However, so-
Figure 4: Quantitative fashion style changes in 2015 shown in the New York Fashion Shows (left column) and street-chic (right column). The correlation coefficients between the two columns are (style: -0.32, pattern: 0.64, color: 0.28). Note that the positively correlated attributes are marked red and the negatively correlated attributes are marked green. In terms of style, there are positively correlated attributes even though the overall correlation is negative, revealing both correlation and distance between stage and reality.

5. CONCLUSIONS

In this work, we construct a large dataset from the New York Fashion Shows and street-chic in order to investigate the possible clothing fashion trends in New York. In addition, we investigate a learning based method to automatically detect fashion attributes as the representation of fashion trends. We further demonstrate that the proposed framework is effective in fashion trend discovery. Furthermore, we compare the analysis result from the New York Fashion Shows and street-chic images in order to investigate whether and to what extent the fashion shows have influence on New York people. In the future, we plan to collect more images to increase the data set for more comprehensive studies. Moreover, there is also keen interest in exploring the proper fashion outfits to recommend users by aggregating user preference in clothing style and one future direction would be to incorporate these elements into the existing model and the scope will be extending and applying our system to practical applications, for example clothing style and product recommendation. Besides, the concept of clustering will also be one of the options as it will be interesting to automatically learning unseen clothing elements [12].

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