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New Product Design with Popular Fashion Style Discovery using Machine Learning

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Abstract. Fashion companies have been always facing a critical issue to design products that fit consumers' needs. On one hand, fashion industries continually reinventing itself. On the other hand, shoppers' preference is changing from time to time. In this work, we make use of machine learning and computer vision technologies to automatically design new "must-have" fashion products with popular styles discovered from fashion product images and historical transaction data. Products in each discovered style share similar visual attributes and popularity. The visual based fashion attributes are learned from fashion product images via a deep convolutional neural network (CNN). Fusing together with popularity attributes extracted from transaction data, a set of styles is discovered by Non-negative matrix factorization(NMF). Eventually, new fashion products are generated from the discovered styles by Variational Autoencoder (VAE). The result shows that our method can successfully generate combinations of interpretable elements from different popular fashion products. We believe this work has the potential to be applied in the fashion industry to help to keep reasonable stocks of goods and capture most profits.

Keywords: Fashion Style Discovery, Deep Learning, VAE Generator.

1 Introduction

Fashion industries live on the cutting-edge of design, continually reinventing itself. Every season, fashion companies launch new styles into the market and try to be the trend-setters who produce most "must-have" products. Which product will become the "must-have" one? It is totally decided by the market. We define the "must-have" popular fashion product as the product that has high sales. However, customers' needs are difficult to interpret. Different people have different preference and their taste may also change from time to time. How to design new styles that meet customers' needs is an open research question. Currently, fashion companies offer styles based on designer choices, which rely on their knowledge of social situation or cultural phenomena and guess what will be popular in the next season. However, the stakes are high, since unsold products at the end of season are either sold at huge discounts, or destroyed to protect the exclusivity of a brand name. In this paper, in order to complement the traditional investigation on future fashion trend, we aim to discover the style pattern of historical fashion products and consider customer's needs by machine learning and computer vision techniques. Variations or evolutions of design leading trend can be explored by learning through continuous selling items. We believe that information from image data goes beyond the knowledge boundary of human and captures more precise characteristics. With our method, new products could be automatically designed based on the discovered style pattern along with transaction information, such that they will have higher probability to become popular and lead to more profits.

Specifically, given a set of fashion product images with transaction history, our objective is to discover the style of "must-have" fashion products and automatically generate new fashion products with "must-have" styles. The contribution of our work contains two folds:

- We propose a new approach to successfully discover popular fashion product styles from product images and transaction history without supervision.
- Our approach could automatically generate new "must-have" fashion products that may have higher probability to meet customers' needs than traditional designer choices.

Applying this work into fashion industries, fashion companies could launch new products into markets based on customers' needs, which would benefit targeted marketing incentives with higher successful rate, capture most profits and keep reasonable stocks of goods.

2 Related Works

In the fashion industry, the majority of sales forecasting models are using statistical methods [1], which however, depend on many manually designed attributes other than attributes extracted from images. Even with big data analytics, the fashion industry still extracts feature from the product description and sales data [2] to infer the preferred styles and color for the next season.

Currently, there are several studies on customer preferences using image data, such as catalog image recommendation [3]. However, most of the recommendations are based on image retrieval e.g. find similar clothes with a given image. This kind of recommendation neglects customers' preference in styles of products. To capture the market scale preference, modeling style characteristics has become a popular computer vision task (e.g. categorize images with similar latent features) nowadays [4]. However, the popularity of each fashion style is still missing. Therefore, to figure out fashion product styles along with their popularity, we extended the existing style discovery method [4] to incorporate both visual contents and popularity information. And to take a step forward, we generate new products based on the discovered styles, which are not attempted in previous fashion design studies using generative models [5].

3 A Machine Learning Approach for New Products Design

There are two challenges in solving the problem of automatically generating the next "must-have" fashion products. One challenge is how to discover fashion product styles sharing similar visual attributes and popularity. Popularity here refers to high sales. Another challenge is how to automatically generate new fashion product matching customer's preference. We proposed a new approach based on historical product images and transaction data. It first trains a CNN based deep attribute model to learn the visual based fashion attributes from fashion product images and fuse together with popularity attributes extracted from transaction data. Then it discovers a set of styles that are sharing similar visual attributes and popularity from product images without supervision. Finally, new "must-have" fashion products are automatically designed by Variational Autoencoder (VAE) with images of discovered popular styles. The framework for the proposed approach is presented in Fig.1.

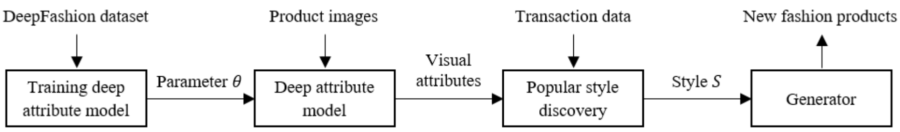

Fig. 1. The proposed framework for generating popular fashion products.

To better extract the visual attributes from fashion product images, robust representations of fashion products need to be learned from images first and they should be interpretable in visual elements. Thus, a deep convolutional model would be trained for attribute prediction using the DeepFashion dataset [6], which contains more than 200,000 images labeled with 1,000 semantic attributes collected from online fashion websites.

Inspired by [4], we proposed a deep attribute model based on CNN. The model is composed of 11 convolutional layers with 3×3 filter size followed by 3 fully connected layers and 2 dropout layers with the probability of 0.5. Additionally, all the layers in our model are followed by a batch normalization layer and a rectified linear unit (ReLU) except the first two fully connected layers are followed by a scaled exponential linear unit (SeLU). We implemented our model in Keras with the weighted binary cross entropy loss to train the network for binary attribute prediction. The network is trained using SGD for stochastic optimization.

Given a set of images $C = \{c_i\}_{i=1}^{N}$, the probability of M attributes for i^{th} image is a_i. With the deep attribute model, we can get the trained model parameters θ and have $a_i = f_a(c_i|\theta)$. That is to say the probability of semantic attributes such as floral print, stripe and arrow collar etc. in a given fashion product image can be obtained, and we adopt it as the visual attributes for representing a given product image.

The deep attribute model yields a matrix $A \in \mathbb{R}^{\{M \times N\}}$ representing the probability of M visual attributes for N images. The sales data for each product are simply treated as an additional attribute. By augmenting matrix $A \in \mathbb{R}^{\{M \times N\}}$ to $A \in \mathbb{R}^{\{(M+1) \times N\}}$, the sales information can also be considered for discovering latent styles. To discover the

Table 1. Total transactions for each discovered style.

Style	1	2	3	4	5	6	7	8	9	10
Sales	111	20	18	22	29	16	66	16	29	43
Popular	Yes	No	No	No	Yes	No	Yes	No	Yes	Yes
Style	11	12	13	14	15	16	17	18	19	20
Sales	16	17	33	15	25	11	77	14	54	15
Popular	No	No	Yes	No	Yes	No	Yes	No	Yes	No
Style	21	22	23	24	25	26	27	28	29	30
Sales	31	65	25	19	24	22	14	20	22	15
Popular	Yes	Yes	Yes	No	Yes	No	No	No	No	No

set of K latent styles $S = \{s_k\}_{k=1}^{K}$, we use a nonnegative matrix factorization (NMF) method to infer nonnegative matrices $W \in \mathbb{R}^{\{M\times K\}}$ and $H \in \mathbb{R}^{\{K\times N\}}$ such that $A \approx WH$. In this way, the discovered styles could share the similar visual attributes and popularity at the same time.

To produce products that are similar to those discovered styles but not the same, we formalize it as a problem that aims to learn a model $\hat{P}$ that is as similar as possible to P which is an unknown distribution where examples X follows [7]. Generative Adversarial Nets (GAN) [8] and Variational Autoencoder (VAE) [9] are two state-of-art machine learning generative models. GAN is to find the Nash Equilibrium between discriminator net from true distribution $P(X)$ and the generator net from model distribution $\hat{P}(X)$. VAE, on the other hand, is a probabilistic graphical model rooted in Bayesian inference. After comparing the performance between both, VAE is more suitable in our cases. It can generate combination of interpretable elements from different products. This might because the scale of training samples is small and VAE can learn the latent variables that are interpretable.

4 Experiment Results

Our model is evaluated on a real world data that is collected from a Hong Kong company. The data for the experiment contain 950 T-shirts images with 2058 transactions including online and offline purchases from year 2015 to 2017.

Evaluation for Deep Attribute Model. We trained our deep attribute model on cropped upper body images from the DeepFashion dataset. Due to the nature of the T-shirts, we only consider upper body clothes. Therefore, we cropped upper body images in the DeepFashion dataset and only use 533 attributes, which frequently appear in the upper body dataset (we take attributes that appear more than 100 times in this experiment). We split the DeepFashion dataset into 80% for training, 10% for validation and 10% for testing. Our attribute predictions average 77% AUC on a held-out DeepFashion test set.

Style Discovery. The NMF method in sklearn package in python has been used to learn K = 30 styles. For each style, we ranked top 10 images ordered by their attributes' similarities. As we can see in Fig.2, the colors in style 1 tend to be cold and dark, while in style 10 the colors tend to be pinky. Two styles that have average popularity in Fig.3

Fig. 2. The product images for the discovered styles with high popularity.

Fig. 3. The product images for the discovered styles with average popularity.

Fig. 4. Examples of new fashion products generated from style 1 and style 10.

both have very complicated prints compared to the styles with higher popularity in Fig.2. From this observation, we can say that customers in our data prefer simple and refreshing styles than complicated design with detailed prints.

The average transaction for each product in our data set is 2.29. Hence, the transactions for a style (10 products) with average popularity should be 22.9. From Table 1, we can find that half of the styles we discovered have transactions higher than 22.9, which shows that our style discovery can find styles that have higher popularity.

"Must-have" Product Generation. The images from style 1 and style 10 are fed into the VAE with concrete latent distribution [10] respectively. As we can see from Fig.4, the generated T-shirts have mixture elements from the original ones but are consistent with the original styles. Some obvious changes are: long sleeves to short sleeves, new color, mixture of graphic prints and the design of the collar transfer from one shirts to another. For example, the generated shirt in the first column in style 1 from Fig.4 contains the stripes and prints from the shirt in the fourth column in style 1 in Fig.2, and the color mixture from shirts in the fifth and sixth column in style 1 in Fig.2.

5 Conclusions

In this paper, we proposed a new approach for generating the next “must-have” fashion products. We first learn the visual attributes from an existing large dataset with fashion product images. Secondly, we incorporate visual attributes and popularity together from real world product images with transaction data. We then discover a set of styles that are sharing similar visual attributes and popularity in an unsupervised manner. Finally, new “must-have” fashion products that have interpretable elements are automatically designed from images of discovered popular styles. With our method, by replacing transaction data to investigation data (votes on fashion products that will be in the market), we can also visualize designs that contain the fashion leading components. In the future, we are going to apply our method on bigger dataset and evaluate the popularity of new generated products in the real world. The current dataset of generated products is not in a big variety. With more data, we would like to validate that our method can also generate more creative products from the discovered styles.

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