Dress Up Like a Stylist? Learning from A User-Generated Fashion Network

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ABSTRACT
Fashion is a fast growing industry, where it is no longer just the overall trends that is important, but also how individuals personalize their fashion styles. Fashion brands and retailers have been developing fashion clothing recommendation systems based on individuals’ filled-out survey, purchase and browsing history. However, few has taken outfits posted on social networks into consideration. In this preliminary study, we leverage a fashion social network, lookbook.nu, to study the fashion outfits from the perspective of brands, items, and colors. We study the stylists on the social network, and use topic modeling to learn the underlying topics of brands, items, and colors. We then investigate the learned topics and how they correlate with the outfits posted by the stylists. The goal of this paper is to provide an insight of how one can leverage the information of user-generated outfit information on social networks to better help individuals dress like stylists. To the best of the authors’ knowledge, we believe this is one of the first works studying fashion outfits from the perspective of outfit components and user-generated social networks.

CCS CONCEPTS
• Information systems → Social recommendation; Web applications; • Applied computing → Electronic commerce; Marketing;

KEYWORDS
fashion, outfit personalization, brand recommendation

1 INTRODUCTION
Fashion outfit recommendation and personalization has been emphasized in recent years. Such emphasis comes from various potentially improved performance metrics such as a deeper connection between the brand and customers\(^1\), return shoppers\(^2\), or better shopping experience\(^3\). Though studies have strived to provide recommendation or personalization solutions, one of the main discussed topics on major fashion magazines, such as Vogue and Marie Claire, and blogs that has drawn less attention is how to dress like a stylist.

From this perspective, this study attempts to explore the dress-up patterns of stylists. However, this is generally not directly observable without interviews and suggestions. To address this issue, we turn our attention to social media, which provides us an opportunity to capture the dress-up patterns of stylists through their posts. Our research site is Lookbook.nu. It is the largest global online style community and has been mentioned in major fashion and media outlet such as Elle and the Chicago Tribune. Using the posts by stylists from this research site (shown in Figure 1), we conduct thorough data analyses of the stylists’ fashion styles. Also, with the latent Dirichlet allocation (LDA) method, we are able to preliminarily identify several major topics of brands, outfit items, and colors from stylists’ dress up patterns. These topics are then shown to have specific combination relationships and are related to demographic information.

This study contributes to the literature by providing a solution to demonstrate the dress-up patterns of stylists which has the potential to be combined with existing fashion outfit personalization systems to further enhance the shopping experience or branding effects.

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\(^1\)https://fashionista.com/2014/06/customization-apparel-fashion  
\(^2\)https://www.invespcro.com/blog/online-shopping-personalization/  
2 RELATED WORK

There are several works studying the idea of outfit recommendation. Iwata et al. propose to use photographs from fashion magazines to recommend coordinations of fashion outfits with probabilistic generative models [3]. Shen et al. develop a recommender with which users can specify a scenario where they need appropriate clothing items [7]. Zhao et al. also develop a recommender that recommends fashion items based on users’ specified scenarios, while also incorporating collaborative filtering [8]. Similarly, Liu et al. develop a closet recommendation system with desired scenario as user input, and support vector machine (SVM) as the core model for the system [5]. In 2014, Ebay Inc. also patented the design of personalized clothing recommendation system, which aims to serve customers’ needs of automated clothing shopping [6]. However, none of the work above leverage the resource of user-generated social network.

There has been limited research done on studying fashion styles. One of the closest work is done by Hu et al., using latent Dirichlet allocation (LDA) to find the underlying aesthetic styles of products online shops through a collaborative filtering approach [2].

Regarding to the data source of study in this paper, lookbook.nu, there has been a lack of research focusing on it except Lin, Xu, Zhou and Lee [4] demonstrating whether people with similar styles connect with each other on online social networks.

In this work, we aim to fill the gap between fashion outfit recommendation and user-generated social network contents from the perspective of brands, items, and colors by studying individuals’ fashion tastes and styles.

3 DATA ANALYSIS

We created a crawler using script written in Python to collect data from Lookbook.nu. Our collected data consists of 707 stylists with their 120K posts of outfits (or looks). For each stylist, we collect the countries they locate in, ages, occupations, and fashion styles. For each outfit, we collect the brands, clothing items, and colors used in the outfit. The summary of our dataset is shown in Table 1.

To provide a better understanding of the stylists and their posted outfits on lookbook.nu, we conduct a thorough data analysis on the collected data. In the following, we first analyze the stylists’ factors, such as their demographic information. We then analyze the outfit components from the aspects of brands, items, and colors.

3.1 User Demographics Analysis

We first analyze the stylists on lookbook.nu with their demographic information and their fashion styles assigned by lookbook.nu.

Region: Among the 707 stylists, 155 (21.92%) are from United States, 73 (10.32%) are from United Kingdom, and 48 (6.78%) are from Germany. From the continent’s point of view, we find that most of the stylists on Lookbook.nu are from Europe (54.31%), with second most being North America (26.02%), and third most being Asia (13.01%), as shown in Figure 2.

There are several works studying the idea of outfit recommendation. We first analyze the stylists on lookbook.nu with their demographic information and their fashion styles assigned by lookbook.nu.

Age: The ages of stylists range from 16 to 38, with most between 20 and 25, as shown in Figure 3.

Occupation: Out of the 707 stylists, 451 of them declared their occupations. In total, there are 51 unique occupations in the dataset, with most users being bloggers (33.26%), students (19.73%), photographers (7.09%), models (5.99%), and fashion designers (3.99%).

Style: Lookbook.nu assigns these 707 stylists with styles based on the outfits they post. In total, there are 32 styles, and each stylist can belong to more than one style. The most common style is effortless (13.58%), minimal (10.18%), edgy (8.77%), playful (8.63%), and feminine (8.20%). There are also rare styles such as lolita (3.39%) and punk (2.12%). As shown in Figure 4, the occupations of the three selected fashion styles are significantly different from each other. For example, preppy mostly consists of students, while no student in our dataset belongs to the glam style. By definition, preppy is the style of expensive prep school students, and glam is the style of

<table>
<thead>
<tr>
<th>Table 1: Lookbook.nu dataset summary</th>
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<td>Type</td>
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</table>

Figure 2: Continent v.s. Figure 3: Age v.s. number of number of stylists on Lookbook.nu

Figure 4: Stylists’ occupations in different styles.

Figure 5: Fashion style v.s. Figure 6: Brand v.s. number of looks including that brand
night-outs and red carpets, which correspond to the composition of the two styles’ main occupations.

We also examine how age varies among fashion styles. As shown in Figure 5, the age range differs significantly among styles. The preppy style has a narrower age range, between 22 and 24 years old, while the street style includes stylists from a wide range, from 21 to 28 years old.

### 3.2 Outfit Analysis

In a fashion outfit, there are three major components: brands, items, and colors, as shown in Figure 1. All of these information are declared by the stylists. Here we analyze each of them, including consideration of the stylists’ demographic information discussed earlier.

**Brands:** Among the 120K posted looks, there are 288 brands adopted in the outfits’ items. The twenty most popular brands in terms of adoption in outfits are shown in Figure 6, with Zara being the most popular (24.35%), H&M being the second popular (13.44%), and Mango and Asos being third and fourth popular brands (4.62% and 4.45%, respectively). One interesting thing to note is that, among the twenty most adopted brands, only Chanel is the high fashion brand, and the rest are all fast-fashion and mass-market brands. We also find that in terms of adopting brands into the looks, users from all the continents behave similarly, except that users from South Africa do not use any high fashion brand. To further examine this phenomenon, we look at the overall types of brands. We adopt the brand type defined by [1], which classifies brands into high fashion, fast fashion, and mass fashion. Figure 9 shows that generally on lookbook.nu, users tend to incorporate clothing items from fast fashion brands into their outfits, which might be due to the age group of users. As shown in Figure 10, we find that even for all age groups, fast fashion is the mostly adopted type of brands. Also, users above 25 years old are more likely to incorporate items from high fashion brands compared to users below 25 years old.

However, when investigating the users’ number of fans versus the brands they use in their outfits, we find that there is an extremely small overlap between the top twenty brands in Figure 6. A closer look at the correlation between number of looks a brand is involved, and the average number of fans users who leverage that brand receives, we can see that in Figure 8, although fast fashion brands are involved with the most looks, they do not receive the most popularity in terms of number of fans. While high fashion are adopted in less looks, the users who incorporate high fashion items are slightly more popular than those using items by fast fashion brands. Finally, sports-related mass market brands are similar as the high fashion brands, while indie mass market brands tend to be adopted by less looks due to its uniqueness, and the popularity they associate with are not specific to a certain range.
As mentioned earlier, there are three major components in fashion lookbook.nu will be assigned with a brand topic $z$. For example, for a stylist $m$, a corresponding $z$ will be drawn from $\theta$ for each outfit history. $\theta$ can then serve as the brand topic distribution for all stylists, and $\phi$ is the topic distribution for all brands.

We follow this idea and train three LDA models, one for each component, which we call LDA-brand, LDA-item, and LDA-color. Each model will obtain parameters $\theta$ and $\phi$, which can later be used to conduct outfit recommendations.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$\alpha$</td>
<td>parameter of the Dirichlet prior on $\theta$</td>
</tr>
<tr>
<td>$\beta$</td>
<td>parameter of the Dirichlet prior on $\phi$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>topic distribution</td>
</tr>
<tr>
<td>$\phi$</td>
<td>object distribution</td>
</tr>
<tr>
<td>$z$</td>
<td>(latent) topic for the n-th object in the m-th stylist</td>
</tr>
<tr>
<td>$w$</td>
<td>(observed) object: brand/item/color</td>
</tr>
<tr>
<td>$M$</td>
<td>number of stylists</td>
</tr>
<tr>
<td>$N$</td>
<td>number of objects</td>
</tr>
<tr>
<td>$K$</td>
<td>number of topics</td>
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</tbody>
</table>

### 4.2 Evaluation

To evaluate the effectiveness of LDA in capturing the topics of each outfit component, we conduct the validation experiment as follows. For each component, we construct the outfit history as $H = (m, w)$, indicating the stylist $m$ incorporating object $w$ in an outfit. A 10-fold cross validation is conducted, and the performance of each LDA model is assessed by the following three metrics.

\[
\text{precision}@N = \frac{|\{\text{top } N \text{ recommendations}\} \cap \{\text{true items}\}|}{|\{\text{top } N \text{ recommendations}\}|} \quad (1)
\]
\[
\text{recall}@N = \frac{|\{\text{top } N \text{ recommendations}\} \cap \{\text{true items}\}|}{|\{\text{true items}\}|} \quad (2)
\]
\[
\text{f}_{1}@N = 2 \times \frac{\text{precision}@N \times \text{recall}@N}{\text{precision}@N + \text{recall}@N} \quad (3)
\]

where $N$ is the number of retrieved items, i.e., brands, items, and colors, from the recommendation list.

An important factor when learning LDA is the choice of $k$. Through empirical experiments, we find that LDA-brand performs the best when $k = 4$, LDA-item performs the best when $k = 10$, and LDA-color performs the best when $k = 13$.

The performance of each LDA model based on the value of $k$ is shown in Figures 16, 17, and 18. As shown, using LDA to predict the outfit components significantly outperform random guessing.
5 LEARNED MODEL ANALYSIS

After obtaining the topics for the outfit components, we analyze the learned topics of each component in this section.

5.1 Brand Topics

There are four topics for the brands in the lookbook outfits. We show the top five brands with their corresponding weight of each brand topic in Table 3. As shown, brand topic #0 and #2 both consist of fast fashion brands. However, #0 also include brands that do not design clothing but rather carry fashion clothing with no brand, such as Romwe and Sheiside. Brand topic #3 consist of mostly high fashion brands that are luxurious. As for brand topic #1, it consists of mainly sport and athleisure brands. Figure 19 shows three outfits that correspond to one brand topic to illustrate the difference between their underlying styles.

Table 3: Top five brands of each brand topic

<table>
<thead>
<tr>
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<th>#0</th>
<th>#2</th>
<th>#3</th>
<th>#1</th>
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<tbody>
<tr>
<td>Zara</td>
<td>(0.21)</td>
<td>Zara (0.17)</td>
<td>Choies (0.205)</td>
<td>Vans (0.02)</td>
</tr>
<tr>
<td>Topshop</td>
<td>(0.039)</td>
<td>Topshop (0.117)</td>
<td>Chanel (0.016)</td>
<td>Diesel (0.017)</td>
</tr>
<tr>
<td>Romwe</td>
<td>(0.059)</td>
<td>H&amp;M (0.082)</td>
<td>Givenchy (0.008)</td>
<td>Nike (0.014)</td>
</tr>
<tr>
<td>asos</td>
<td>(0.057)</td>
<td>Mango (0.045)</td>
<td>Nastygal (0.007)</td>
<td>Levis (0.013)</td>
</tr>
<tr>
<td>Sheinside</td>
<td>(0.042)</td>
<td>Forever21 (0.034)</td>
<td>AlexanderWang (0.006)</td>
<td>Lacoste (0.011)</td>
</tr>
</tbody>
</table>

5.2 Item Topics

There are ten item topics in the lookbook outfit. We show the top five items of three selected item topics in Table 4. As shown, item topic #1 shows items that are more of the hipster style, #3 shows items that are used in more sleek and biker style, and #7 shows items that are more likely to be incorporated into feminine outfits. Figure 20 shows three outfits that use these three item topics. As
one can see, the styles among the three outfits are significantly
different, and correspond with the items in their item topics.

<table>
<thead>
<tr>
<th>#1</th>
<th>#3</th>
<th>#7</th>
</tr>
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<tbody>
<tr>
<td>Sweater (0.008)</td>
<td>Jeans (0.016)</td>
<td>Dress (0.019)</td>
</tr>
<tr>
<td>Creepers (0.005)</td>
<td>Boots (0.012)</td>
<td>Heels (0.010)</td>
</tr>
<tr>
<td>Tights (0.004)</td>
<td>Hat (0.011)</td>
<td>Skirt (0.010)</td>
</tr>
<tr>
<td>Cardigan (0.004)</td>
<td>Coat (0.006)</td>
<td>Necklace (0.007)</td>
</tr>
<tr>
<td>Beanie (0.003)</td>
<td>Leather jacket (0.004)</td>
<td>Clutch (0.004)</td>
</tr>
</tbody>
</table>

5.3 Color Topics
There are thirteen topics for the colors in the lookbook.nu outfits.
We demonstrate three of the thirteen topics in Figure 21, where
we color the boxes to show the representative colors of each color
topic, and use the width of the boxes to indicate the weights of the
colors in each topic.

As shown, the three color topics are distinguishably different
from each other. To see how the outfits in each color topic look like,
we show the selected outfits with the corresponding color topics in
Figure 22. These outfits further show the difference between the
color topics and even carry implications of different fashion styles.

6 CONCLUSION
In this paper, we study the fashion outfit personalization from the
perspectives of the three components of outfits: brands, items, and
colors using the fashion social network, lookbook.nu. To unveil the
underlying topics of the three components, we use latent Dirichlet
allocation (LDA) to learn the outfit history. The usage of LDA shows
that we are able to identify the topics of brands, items, and colors,
and further successfully predict components in unseen outfits by
learning part of the stylists’ outfits. We finally study the learned
topics of the three components, and find that these topics further
indicate the individuals’ fashion styles.

For future work, we aim to leverage the connections on social
network to establish collaborative filtering on outfit recommenda-
tion. We also plan to utilize information in the images to better
capture more components in the outfits.

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