CAT STREET: Chronicle Archive of Tokyo Street-fashion

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Abstract

The analysis of daily life fashion trends can help us understand our societies and human cultures profoundly. However, no appropriate database exists that includes images illustrating what people wore in their daily lives over an extended period. In this study, we propose a new fashion image archive, Chronicle Archive of Tokyo Street-fashion (CAT STREET), to shed light on daily life fashion trends. CAT STREET includes images showing what people wore in their daily lives during the period 1970–2017, and these images contain timestamps and street location annotations. This novel database enables us to observe long-term daily life fashion trends using quantitative methods. To evaluate the potential of our database, we corroborated the rules-of-thumb for two fashion trend phenomena, namely how economic conditions affect fashion style share in the long term and how fashion styles emerge in the street and diffuse from street to street. Our findings show that the Conservative style trend, a type of luxury fashion style, is affected by economic conditions. We also introduce four cases of how fashion styles emerge in the street and diffuse from street to street in fashion-conscious streets in Tokyo. Our study demonstrates CAT STREET’s potential to promote understanding of societies and human cultures through quantitative analysis of daily life fashion trends.

1. Introduction

Analysis of fashion trends is one of the hot topics in fashion research. Several studies in computer science have attempted to predict future fashion trends or evaluate long-term fashion trends [3, 27, 16, 5, 2, 20]. The motivation is mostly to predict the next fashion move for vendors production plans or improvement in recommendation engines in online stores. To achieve these objectives, many researchers created their own fashion image databases to determine fashion trends, and annotated a variety of auxiliary information to fashion images, such as color, fabric, shape, texture, location, and search queries [28, 12, 15, 21, 25, 26, 1].

The advantages of fashion image databases have continued to attract attention not only for business improvement but also for understanding our societies from a cultural perspective. In particular, the fashion style adopted in daily life is an important aspect of culture. As noted by Lancioni, fashion is a reflection of a society’s goals and aspirations [14]: people choose fashion styles within the social contexts in which they are embedded. The analysis of daily life fashion trends would provide a more in-depth understanding of our societies and human cultures.

However, the fashion databases proposed in previous studies have several limitations in terms of approach to daily life fashion trends. First, the level of details of location annotation in existing databases is not sufficient to analyze daily life fashion trends. Fashion is a way to express oneself and is affected by a wide variety of social factors, such as culture, economic conditions, historical events, and social position [14]. People belong to the social community, and some social communities have their own distinct fashion styles. In addition, social communities have their own territory. For instance, Shibuya Fashion is a fashion style for young ladies, originating from a famous fashion mall in Shibuya. The young ladies who are dressed in Shibuya Fashion frequent Shibuya, one of the famous fashion-conscious streets in Japan. Hence, we need fashion image data with location annotations at the street level to focus on what people wear in their daily lives [1].

Second, most databases consist of recent fashion images in the last decade because they are obtained from the internet. However, the periods covered by these databases might
not be sufficiently long to determine the fashion trends. Sociologists and anthropologists have found, by examining how fashion changes over extended periods, that fashion has decadal-to-centennial trends and cyclic patterns [13]. For example, the hemline index, which is a well-known index to measure economic conditions, indicates a cyclic pattern in which the skirt length becomes shorter when the economic condition gets better [7]. This pattern was determined based on observation of the skirt length in the 1920s and 30s. As an exception to the fashion database in computer science, Vittayakorn et al. collected fashion images from 1900 to 2009 to investigate how vintage fashion influenced fashion show collections in the period 2000–2014 [26]. However, the images labeled according to decades do not seem to capture how people choose fashion styles in their lives. From these previous findings and the limitations in several fields, it can be inferred that we need a fashion database in which images with more granular date labels cover a long period, at least a few decades, to determine the trends and cyclic patterns.

In this study, we propose a new fashion archive consisting of long-term fashion images with street location annotation to shed light on daily life fashion trends. Then, we corroborated the rules-of-thumb for two fashion trend phenomena, namely how economic conditions affect fashion style share in a long time span and how fashion styles emerge in the street and diffuse from street to street, to demonstrate the potential of our database.

This paper’s main contributions are as follows:

- We propose a new fashion image archive, CAT STREET, which includes images reflecting what women wore in their daily lives from 1970 to 2017. It contains timestamps and street location annotations.
- Our study demonstrates CAT STREET’s potential to promote understanding of our societies and human cultures through the quantitative analysis of daily life fashion trends.
- Our findings show that the Conservative style trend, a type of luxury fashion style, is affected by economic conditions.
- We introduce four cases to discuss how fashion styles emerge in the street and then diffuse from street to street in fashion-conscious streets in Tokyo.

2. Related work

The methodologies and fashion image databases proposed in previous studies help us to understand what fashion is. Table 1 presents the best-known public databases from fashion studies in computer science.

Fashionista is a representative fashion image database in the early stage of fashion analysis using computer vision techniques [28]. The images in Fashionista were collected from Chictopia.com, a fashion blog. They contain pose annotations for 14 body parts and clothing labels on superpixel regions. There are no location, timestamp, and fashion style annotations.

Subsequently, many fashion image databases with auxiliary information have been created, such as Hipster Wars [12], DeepFashion [15], Fashion 144k [21], Fashion-Style14 [25], When Was That Made? [26], and Fashion Culture Database [1].

Hipster Wars, DeepFashion, and FashionStyle14 have fashion style labels as training data for fashion style clustering. These fashion images were collected from Google Image Search [12], online shopping websites [15], and internet crawlers [21]. Furthermore, Fashion 144k, When Was That Made?, and Fashion Culture Database have location and/or timestamp annotations. Fashion 144k has city level location [25], When Was That Made? has decade labels such as 90s, 1954–1957, and 1920s [26], and Fashion Culture Database has city level location and time stamp [1].

These fashion databases have limitations that need to be overcome to shed light on daily life fashion trends. In this study, we define daily life fashion trends as trends of fashion styles that consumers adopt in their daily lives. We need data on how and what consumers wear to capture their fashion styles. Fashion photographs on the Internet, however, contain two types of fashion images: one type displays clothes that consumers themselves choose to wear and the other type is taken by professional photographers to promote a clothing line. Previous studies built their databases by collecting fashion images from the Internet; hence, existing databases do not reflect only the fashion styles chosen by consumers. In addition, no database has both long-term timestamps and location information. Daily life fashion exists in the street [11, 18], and it changes over time and exhibits some trends and cyclic patterns for an extended period. Building a new fashion image database with more granular, long-term timestamps and location information that reflects daily life fashion is required to analyze fashion from a cultural perspective.

3. CAT STREET: Chronicle Archive of Tokyo Street-fashion

We propose CAT STREET, a new fashion image archive that includes images reflecting what women wore in their daily lives from 1970 to 2017.

We created CAT STREET using the following steps. We took street-fashion photographs once or twice a month in fashion-conscious streets such as Harajuku, Shibuya, and Ginza in Tokyo from 1980 to the present. In addition, we used fashion photographs from a third-party organization taken in the 1970s at monthly intervals in the same fashion-conscious streets. Thence, by sorting images from the two data sources, we built a primary image database that has timestamps from 1970 to 2017. The photos from the third-
party organization do not have information about which photos were taken in which street, hence we annotated fashion images taken since 1980 with street tags.

Fashion styles are different for men and women. To focus on women's fashion trends in CAT STREET, we detected the subjects' gender and selected women's only images from the primary image database. Gender detection was performed manually by two researchers, and the detection results were validated reciprocally. Some images in the 1970s are in monochrome; therefore, we gray-scaled all images to align the color tone for all ages of the image.

Street-fashion photographs contain a lot of noise that hinders the precise detection of fashion styles that people wear. To remove the noise, we performed the following image pre-processing as the final step. We identified human bodies in the photographs using OpenPose [30] and clipped them to cut out the background images as much as possible. Then, we trimmed the subjects' heads to focus on the clothing items based on the head position, which is detected using OpenPose. Figure 1 gives an overview of the data of CAT STREET. The total number of images in the database is 14,679.

At the end of the database creation process, we checked whether CAT STREET met some requirements for a database to capture daily life fashion trends. First, CAT STREET comprises street-snap photographs in the fashion-conscious streets in Tokyo. It reflects the fashion style women choose in their real lives and does not include commercial fashion images for business purposes. Second, CAT STREET has necessary and sufficient annotations to track fashion trends: monthly timestamps from 1970 to 2017 and street-level location tags. Images in the 1970s do not have street tags; however, they belong to the same population as photos with street tags since 1980. Hence, we could use all the images in CAT STREET when we analyze the overall trends of daily life fashion in fashion-conscious streets as a representative case in Japan. From these features, we believe that CAT STREET has the potential to promote understanding of our societies and human cultures through the quantitative analysis of daily life fashion trends.

4. Analysis of daily life fashion trends

In this section, we demonstrate CAT STREET’s potential to promote understanding of our societies through the following process.
First, we created a fashion style clustering model using deep learning to analyze the fashion styles adopted in fashion images. Second, we applied the fashion clustering model to CAT STREET and calculated the extent to which people adopt the fashion styles in each year. Finally, we demonstrated that CAT STREET enables us to corroborate the rules-of-thumb for the fashion trend phenomena in our society by linking social contexts to the long-term evolution of fashion style share. It also allows us to investigate how fashion styles emerge in the street and move from street to street.

4.1. Fashion style clustering model

To build a fashion style clustering model, we selected FashionStyle14 as the training dataset. It consists of 14 style classes, as shown in the first row of Figure 2. Each class consists of approximately 1,000 images, and the database consists of a total of 13,126 images. The fashion styles of FashionStyle14 were selected by an expert as being representative of modern fashion trends in 2017. By applying the fashion clustering model to CAT STREET, we measured the share of each modern style in each year. We also found the beginnings of the characteristic modern fashion, such as when the Fairy style came into fashion. Some limitations of this approach will be discussed later.

We trained four deep learning (DL) network structures as options for our fashion clustering model, namely InceptionResNetV2, Xception, ResNet50, and VGG19. We set weights trained on ImageNet as the initial weights and fine-tuned them on FashionStyle14 using the stochastic gradient descent algorithm at a learning rate of $10^{-4}$. For fine-tuning, we applied k-fold cross-validation with k set as 5.

Subsequently, InceptionResNetV2 yielded the highest F1-scores among the DL network structures for most fashion styles. (The F1-scores are presented in Table 2.) Its accuracy is 0.787, which is higher than the benchmark accuracy of 0.72 established by ResNet50 trained on FashionStyle14 in the study by Takagi et al. Therefore, we adopted the DL network structure InceptionResNetV2 as the fashion style clustering model in this study.

4.2. Fashion styles in CAT STREET

We applied the fashion style clustering model to the images in CAT STREET. Figure 2 shows sample images classified into each fashion style using the fashion style clustering model.

The fashion style clustering model consisted of five models as we performed five-fold cross-validations when the DL network structure was trained, and each model estimated the style share for each image. To verify the clustering models robustness in terms of reproducing style shares, we evaluated the time-series correlations among the five models. Figure 5 shows the average correlation coefficients of the five models for fashion styles. Most fashion styles have high correlation coefficients of over 0.8, and the unbiased standard errors are small. Some fashion styles, such as Dressy, Feminine, and Gal styles, exhibit low correlations. These styles originally had low style shares, and hence low correlations this time. These results indicate that our fashion style clustering model is a robust instrument for reproducing the time-series patterns of style shares.

Figure 4 shows the averages of five style shares for the period 1970–2017 for each fashion style. Because there were no images for 1997 and 2009, we replaced the zeros with the averages of the adjacent values and considered the three-year moving average.

4.3. How social factors affect fashion style share

Social contexts prompt people to shape their social identities and choose adequate fashion styles to express their identities. It is said that economic conditions have an impact on peoples daily clothes. Sometimes people aspire to have a higher social status and are likely to purchase quality-guaranteed luxury items as a symbol of wealth. At the same time, these consumer behaviors rely on the economic conditions in the society.

To demonstrate the capability of CAT STREET to link social contexts to the long-term evolution of fashion style share, we investigated how economic conditions affect the Conservative share, which includes luxury fashion brands and items in the definition, as shown in Figure 5(a).

With the Conservative time-series share of the five models in CAT STREET as the dependent variable, we performed a one-way analysis of variance (ANOVA) to evaluate the difference in the share level in the business-cycle trough/peak period in the Japanese economy. We also used the vector autoregression (VAR) model to test the Granger causality between the averaged Conservative time-series share and the gross domestic product (GDP) growth rate in Japan. To construct the VAR model, we used the averaged Conservative time-series share from 1970 to 2008. The bankruptcy of Lehman Brothers occurred in 2008, and we assumed that it would hurt the business of luxury brands and change the business structure in the fashion industry.

Figure 5(b) shows the results of the one-way ANOVA. The average style shares of Conservative between the business-cycle trough and peak were significantly different ($p < .05$). This result indicates that the economic upturn prompted consumers to choose Conservative.

In terms of Akaike’s Information Criterion (AIC), we selected the VAR model with a lagged order of 2, and the F-test showed that the model was significant ($p < .05$). We also conducted the Granger-causality test, and it indicated that the GDP growth rate Granger-causes the Conservative share. To verify the effect size and significance of the
|                | InceptionResNetV2 | Xception | ResNet50 | VGG19 |
|----------------|------------------|----------|----------|-------|
| Conservative   | 0.754            | 0.758    | 0.708    | 0.620 |
| Dressy         | 0.940            | 0.936    | 0.938    | 0.898 |
| Ethnic         | 0.812            | 0.806    | 0.747    | 0.668 |
| Fairy          | 0.901            | 0.887    | 0.876    | 0.814 |
| Feminine       | 0.724            | 0.734    | 0.681    | 0.644 |
| Gal            | 0.782            | 0.779    | 0.757    | 0.710 |
| Girlish        | 0.640            | 0.629    | 0.603    | 0.523 |
| Casual         | 0.665            | 0.667    | 0.619    | 0.563 |
| Lolita         | 0.949            | 0.942    | 0.933    | 0.886 |
| Mode           | 0.748            | 0.754    | 0.721    | 0.650 |
| Natural        | 0.793            | 0.779    | 0.710    | 0.692 |
| Retro          | 0.701            | 0.700    | 0.644    | 0.590 |
| Rock           | 0.777            | 0.765    | 0.745    | 0.694 |
| Street         | 0.835            | 0.816    | 0.781    | 0.701 |
| Weighted Avg.  | **0.786**        | 0.781    | 0.747    | 0.689 |

Table 2. F1-scores of fine-tuned network architectures.

GDP growth rate on the Conservative share, we performed an analysis of the impulse response function (IRF) using the estimated VAR model. Figure 5(c) plots the IRF of the effect size of GDP growth rate over time and indicates a significant carry-over effect; the increase in the GDP prompted consumers to choose the Conservative style after a two-year delay.

The Conservative trend is originally represented by a combination of clothing items that have traditional and old-school aesthetics, and fashion experts often label items from highly recognized, quality-guaranteed luxury brands as the Conservative style [10, 17]. People who adopt this style exhibit a sense of credibility because the style projects a higher social status. The results in this section lead to the conclusion that consumers are likely to adopt the Conservative style more when business conditions are booming, and this definition of style qualitatively justified our results. To our knowledge, no study has shown the link between daily life fashion trends and social contexts quantitatively.
Figure 3. Average correlation coefficients among the five models for fashion styles. The error bars represent the unbiased standard error. Conserv. is abbreviation for Conservative.

Figure 4. Style shares of each fashion style.

4.4. How fashion styles emerge in the street and diffuse from street to street

There are two representative fashion-conscious streets in Tokyo: Harajuku and Shibuya. The fashion styles in Harajuku are famously compared with the fashion styles in Shibuya. One of the representative fashion styles in Harajuku is Harajuku Kawaii-kei fashion. This style emphasizes cuteness, and it is represented by the fashion style of a Japanese pop singer, Kyary Pamyu Pamyu. In contrast, one of the representative fashion styles in Shibuya is the Gal style. This style is a slightly sexy homegirl fashion [29].

Geographically, Harajuku and Shibuya are very close and only one station away from each other; however, they have different cultures and daily life fashion trends. We compared two daily life fashion trends in the fashion-conscious streets with CAT STREET to investigate how fashion styles emerge in the street and diffuse from street to street. Figure 6 shows the average style shares of four specific fashion styles, namely Ethnic, Fairy, Gal, and Retro, and their signature images in each street.

The first case in Figure 6(a) shows an example of style emergence in one street. The Fairy emerged in the late...
Figure 5. (a) Average style share for the Conservative style. The gray area indicates the recession periods in the Japanese business cycle. (b) ANOVA of the Conservative share with economic condition. The error bars represent the standard deviation. (c) Impulse response function for the effect of the GDP growth rate on the averaged Conservative time-series share over time. The dashed lines indicate the 95% confidence limits.

Figure 6. Average style shares and mentionable figures for four styles: (a) Fairy, (b) Ethnic, (c) Gal, and (d) Retro. All images in (a) and (b) were taken in Harajuku in 2008–2010 and 1999, respectively. For (c), the left four images were taken in Harajuku (i, ii) and Shibuya (iii, iv) in 1995–1996, and the right four images were taken in Harajuku (v, vi) and Shibuya (vii, viii) in 2010–2012. For (d), the left three images (i–iii) are one Retro taken in the early 1980s, and the right three images (iv–vi) are another Retro that came into fashion in the late 1990s.
2000s in Harajuku and disappeared in the early 2010s. The Fairy comprises the fashion coordination of frilly dresses that reminds one of a fairy [29]. The Fairy style is also called Harajuku Romantic style, which emerged around 2010 [29]. This movement is shown in the style share in Figure 6(a).

The next case in Figure 6(b) shows an example of style movement from street to street. Originally, the Ethnic style is a fashion inspired by native costumes [4]. Previous studies on fashion revealed that the share of Ethnic was sparked in the late 1990s by fancy goods stores located in the area near Harajuku, which deal in exotic fashion items. Figure 6(b) shows that this social background explains the Ethnic upward trend in the late 1990s in Harajuku. Lagging behind the trend in Harajuku, the Ethnic style in Shibuya gradually became accepted and reached the same share level in the mid–2000s. However, to our knowledge, there is no article or commentary that clarifies why the Ethnic style became accepted in Harajuku earlier than in Shibuya, and how and the means through which the style spread from street to street.

The third case is the Gal style. The style is a slightly sexy homegirl fashion; an iconic fashion mall in Shibuya, SHIBUYA109, prompted this styles trend [29]. This trend, known as maru-ky fashion, emerged in early 2000. Figure 6(c) shows an example of different style movements in each street. The Gal style came into fashion in 1995/1996 in Harajuku and Shibuya simultaneously. Namie Amuro, a Japanese pop singer, triggered this movement. She attracted many young girls as a fashionista of this style. The style remained in Shibuya, whereas it disappeared quickly and reemerged in Harajuku around 2012 with a slightly different taste.

The final case in Figure 6(d) shows an example of the same style movement in both streets. The Retro style is an abbreviation of retrospective style [4, 29]. According to the style definition, the overall downward trend in both streets in Figure 6(d) is plausible. Fashion revival is one of the relevant fashion trend phenomena of Retro, and there are a wide variety of substyles representing fashion revivals under Retro, such as 60s look, 70s look, and 80s look. In Figure 6(d), slight bounces can be observed in the early 1980s and late 1990s, which suggest that some type of fashion revival occurred. We need more detailed style tags to further investigate which Retro substyles reemerged in the two bounces; this is one of our future research areas.

We demonstrated how fashion styles emerge in the street and diffuse from street to street by mining daily life fashion trends in the fashion-conscious streets using CAT STREET. Some movements in the trends are supported by social contexts reported in previous fashion studies. However, the social contexts for some trends, such as the Ethnic movement from Harajuku to Shibuya, remain unclear. To clarify which social contexts prompt this style movement from street to street, we need to explore and link the existing knowledge in social science to these results.

These demonstrations suggest that CAT STREET can generate novel research questions and hypotheses that are lacking in existing approaches in the fashion research field and previous fashion databases to promote a more in-depth understanding of our societies and human cultures through quantitative analysis of daily life fashion trends.

5. Conclusion

In this paper, we proposed a new fashion image archive, CAT STREET, to capture daily life fashion trends using methodologies in computer science. CAT STREET comprises fashion images illustrating what people wore in their daily lives in the period 1970–2017, along with street-level geographical information. We demonstrated that two rules-of-thumb for the fashion trend phenomena, namely how economic conditions affect fashion style shares and how fashion styles emerge in the street and diffuse from street to street, can be quantitatively validated using CAT STREET.

Our work is not without limitations. We used the fashion style category of FashionStyle14 [29], which is defined by fashion experts and is considered to represent modern fashion. However, the definition does not cover all contemporary fashion styles and their substyles in a mutually exclusive and collectively exhaustive manner. Defining fashion styles is a complicated task because some fashion styles emerge from consumers, and suppliers define others. We must refine the definition of fashion styles to capture daily life fashion trends precisely.

Furthermore, prior to building CAT STREET, only printed photos were available for the period 1970–2009. Consequently, the numbers of images for these decades are not equally distributed because only those images from printed photos that have already undergone digitization are currently present in the database. The remainder of the printed photos will be digitized and their corresponding images added to the database in future work.

CAT STREET helps us to explore unresolved research questions by applying other quantitative analytical methods, such as unsupervised clustering, to extract fashion styles embedded in consumers daily lives. It can expand the boundaries of fashion studies in computer science and other fields.

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