Observing runway fashion's assortment migration from 1988 to 2023: Through the lens of computer vision

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Backgrounds

A retailer's assortment is defined by the set of products carried in a store at a time to specify an arrangement that maximizes sales or gross margin, which is subject to various constraints, such as a limited budget for purchasing products and limited shelf space for displaying products (Kök et al., 2015). When retailers conduct product assortment planning, they determine (1) the number of clothing categories, (2) the number of stock-keeping units (SKUs), such as styles, colorways, and sizes, within a category, and (3) the number of individual items of a particular SKU, based on consumer perceptions and preferences, retailer constraints, and environmental factors (Mantrala et al., 2009). Consumer preferences represent an individual's choices about representing themselves to the world. While some choices are genuinely unique, fashion is heavily driven by trends, some of which are seasonal, and others pop up more sporadically, often appearing first on the runway and then filtering quickly into the real world (Vittayakorn et al., 2015). Therefore, fashion runway trends have been an essential source for retail practitioners to capture changing customer tastes and translate those desires into new products or services (Mantrala et al., 2009).

The fashion industry has seen a huge expansion of interest in applying computer vision techniques to solve fashion tasks (Cheng et al., 2021). Convolutional Neural Network (CNN) models have been used to conduct trend forecasting, product search, style recommendation, and try-on image synthesis, to name a few. Such models can analyze hundreds of images in minutes, exponentially improving fashion professionals' working efficiency. While most off-the-shelf CNN models were not designed for fashion applications, they can be transfer-learned from fashion images to adapt to the fashion domain. The most famous fashion image dataset is DeepFashion2, a comprehensive fashion dataset containing 491K diverse images of 13 popular clothing categories from commercial shopping stores and consumers (switchnorm, 2019/2023). While computer vision has been used in fashion trend forecasting, existing research either covers a short period (Zhao et al., 2021) or focuses on clothing design features such as color and motif (Mall et al., 2019). Al-Halah et al. (2017) studied the clothing style change from 2010-2018 and predicted the trend for 2019 and 2020. However, their research was based on Amazon fashion product images, which is different from our setting.

Objective

To help fashion retailers make better assortment planning decisions, this research uses computer vision techniques to study how runway fashion's assortment has changed over the years. Within all decisions for assortment planning, clothing categories usually change the least from year to year and will most likely follow the prediction. Therefore, we focus on the clothing category migration of runway images between 1988 and 2023 to answer the following research questions.

1. Has the arrangement of clothing categories changed over the years? If so, in which direction?
2. Based on the time series pattern of runway assortment, what are the predictions for the assortment trends in 2023?

Methodology

Runway images were collected from vogue.com. The images cover major runway shows from 1988 to 2023, including ready-to-wear and couture, menswear and womenswear, and the four major fashion shows and emerging fashion shows in cities such as Shanghai, Mexico City, etc. A total of 905,013 images were downloaded. Since clothing assortment varies across seasons, we focused on analyzing the fall-ready-to-wear collections for this research, reducing the number of analyzed images to 271,335.

The model used to analyze the runway images was a mask region-CNN model transfer learned from the DeepFashion2 data. The original model uses a Residual Network (ResNet) plus Feature Pyramid Network (FPN) backbone with standard convolutional and fully connected heads for mask prediction, allowing it to obtain the best speed/accuracy trade-off (*Facebookresearch/Detectron2*, 2019/2023). However, it could not identify clothing items in various categories. Therefore, we applied transfer learning on the original pre-trained model using the DeepFashion2 data. The learning process revised the neural network parameters to predict clothing categories based on labels defined in the training images. DeepFashion2 defines clothing into 13 categories: short-sleeve tops, long-sleeve tops, short-sleeve outwears, long-sleeve outwears, vests, slings, shorts, trousers, skirts, short-sleeve dresses, long-sleeve dresses, vest dresses, and sling dresses. The resulting model generated clothing category labels for each image in the fall-ready-to-wear collections. More than one label could be assigned from a single image to indicate the style for tops and bottoms. The labels were then aggregated based on year to see how the ratio of each category changes over time, the results of which were used to answer research questions 1 and 2.

Results and Discussion

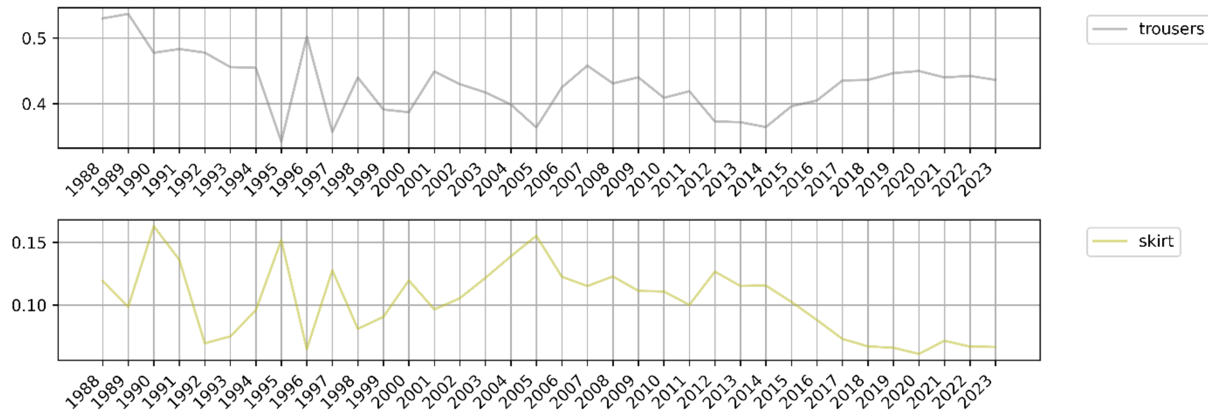
The ratio distribution of the trousers and skirts style category is illustrated in

Figure 1. It is detected that the ratios of trousers and skirts follow the trade-off theory, meaning that when one grows, the other declines. The ratio of skirts peaked in 2005, the prominent time of third-wave feminism. The same year, Ellen Johnson Sirleaf in Liberia became Africa's first elected woman leader, and Angela Merkel became Germany's first female chancellor. There is a noticeable trend that the skirts ratio started to decline in 2012, the same year when the ratio of trousers touched down and rebounded. It is predicted that the ratios of skirts and trousers will continue to be the same in 2024 as in 2023.

Conclusion and Future Research

This project used computer vision techniques to study the runway assortment change over the past 30 years. It provides insights into clothing style arrangement changes and links them to historical events. Limitations of the study include the limited styles available through the training dataset. It would be beneficial to select a different dataset, such as the Fashionpedia dataset (Jia, 2020/2023), and to analyze the design feature change over the years.

Figure 1. Time series plots of trousers and skirts



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