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Machine Learning for Colour Palette Extraction from Fashion Runway Images

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Abstract

An important aspect of colour forecasting is the process of generating colour palettes to represent collections at fashion shows. Humans have traditionally done this manually, and can do it well, but there are often too many images and it becomes an unmanageable task. In this paper, automatic machine-learning methods are developed to generate colour palettes for a fashion show based on the runway images. A set of ground-truth data to test the models was constructed based on asking each of 22 participants to select three colours to represent each of the 48 images from a particular fashion show. A close agreement was shown between these data and the colours automatically generated using a model that incorporated both supervised and unsupervised machine learning. The work could be extended to analyse millions of images from social media feeds to provide data-driven insights for colour forecasting.

Keywords: colour palette, runway images, colour extraction

Introduction

Colour forecasting is an important aspect of textile and fashion global supply chains (Diane & Cassidy, 2005; Noh & Ulrich, 2013; Cassidy, 2020). However, there are concerns about its effectiveness (Cassidy, 2007; Whitfield & Whelton, 2015). Improvements in colour forecasting could reduce the amount of waste that results from unsold goods. Traditionally colour forecasting has been, and largely remains, heavily dependent upon intuition and human critical analysis. However, tools for forecasting trends using big data are starting to emerge with some interesting results (DuBreuil & Lu, 2020).

One aspect of colour forecasting involves analysis of fashion images to develop valuable insights. There is currently growth in the use of data and AI techniques to achieve this since, although humans may be able to do this this task well, the analysis of hundreds or thousands of images can become a herculean task (Saponaro *et al.*, 2019). Social media marketing has become an indispensable part of today's advertising and marketing landscape (Chen, 2017) and it has been suggested, for example, that over 100 million images are uploaded every day to the social-media application Instagram (Aslam, 2020) and these images are thought to influence consumers (Chen, 2017). However, the fashion forecasting industry is in a period of change being driven by changes in technology and connectivity (Gaimster, 2012). Recently there has been interest in using machine vision tools for the automatic analysis of fashion images and fashion show runway images in particular (Vittayakorn *et al.*, 2015; Zhang *et al.*, 2018). One study, for example, considered learned similarity between images and suggested that this could be useful for predicting trends in fashion (Vittayakorn *et al.*, 2015). Another study used a novel semi-supervised machine-learning approach to process unlabeled fashion show images to automatically generate text-based attributes of garments (including colour attributes such as red) (Zhang *et al.*, 2018). Of course, there is also interest in analyzing images uploaded to social media (Mall *et al.*, 2019) since the number of these images is huge and is increasing daily (Aslam, 2020).

Various computational techniques can be applied in image analysis for colour forecasting and Artificial intelligence techniques may herald a revolution in the apparel industries (Guo *et al.*, 2011). Some researchers have explored the colour data in digital photos of ready-to-wear luxury brands from websites to generate insights about colour trends (Xiong, Kitaguchi, & Sato, 2017). Some researchers have extracted perceptually dominant colour names of images by web image search (Wang *et al.*, 2012). Also, a learning-based fuzzy colour prediction system was designed for apparel image analysis (Hui *et al.*, 2005) and showed that the fuzzy system, combined with a basic knowledge of colour prediction methods, outperformed traditional prediction methods. Another study compared fashion products; unsupervised learning methods were used to compare different types of data on 80000 fashion products sold across six years on the Amazon platform and found that their fashion product prediction works better in visual analysis than textual and meta-data cue on products (Al-Halah, Stiefelhagen, & Grauman, 2017).

Some studies have used colour expert participation. For example, a trend score was proposed as a standard value to show how trendy a product is (Stefani, 2019). IN this study both fashion experts and registered users were invited to evaluate like or dislike scores for fashion-related images and the trend scores were calculated from these. Classification machine-learning networks method have been shown to distinguish fashion style better than non-experts, but not as well as experts (Takagi *et al.*, 2018). There is still space to improve the performance of machine-learning algorithms in colour and fashion applications.

Fashion runway images provide particularly important images from which visual analysis may yield important colour trend insights (Lin and Yang, 2019). As mentioned earlier, colour forecasters in manufacturing or retail companies collect inspirations from fashion shows and create their colour prediction storyboards. Colour forecasters frequently gain valuable colour insights from fashion shows by their observation and extrapolation (Wong *et al.*, 2016). Colour databases extracted from runway data are vital for trend forecasting. Koh and Lee (2013) compared the colour data difference extracted from four ready-to-wear women fashion shows and categorised the colour data. Gu and Liu (2010) used machine learning to develop a colour database that could be used to develop more accurate systems for colour forecasting.

This study is specifically concerned with analysis of fashion runway images, using some simple machine-learning techniques, to extract colour palettes that represent the clothes that are on display at the show. A set of psychophysical data are generated to use as ground-truth data for the work. The contribution of the work is threefold: (1) to express the idea of using simple off-the-shelf machine-learning methods to extract colour palettes from a set of fashion runway images; (2) to demonstrate that the technique is effective; (3) to provide psychophysical data that will allow other researchers to test algorithms and to compare their performance with the performance of the algorithms described in this paper.

Methods

A set of 48 images were obtained from a fashion show of Burberry products. There was no specific reason to select Burberry for this case study; the Burberry show was selected randomly from those shows where images were easily available for download from the internet. Each image was displayed on an sRGB-calibrated display, and each of 22 participants was asked to select three colours (using a simple colour-picker tool) to represent the fashion show for each image separately. Figure 1 shows a typical image and the colours selected by the 22 participants. In right-hand part of Figure 1 the 66 colours (22 participants × 3 colour selections) are arranged so that the colours in each row were those chosen by a single participant. These colour data will be used as ground-truth data to evaluate the performance of machine-learning models. In other words, we would like to use the machine-learning algorithms to determine colours for each image and compare them to the psychophysically-derived target colours.

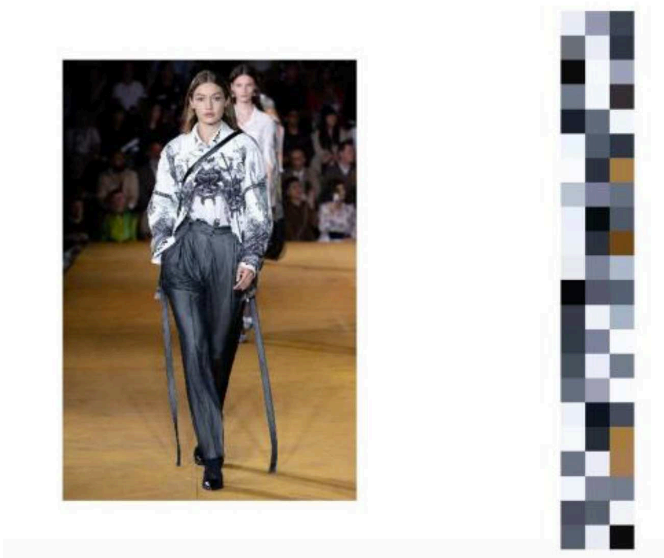

Figure 1. Example image (left) and colour selections from the participants (right). Each row (right) shows the colours selected by one of the participants. Most participants chose colours from the clothes and ignored the background.

Two methods were used to automatically extract colour palettes from each image. The first method (Model 1) was a simple clustering method based on k means. Cluster analysis is a simple technique for grouping a set of data into groups that share common features. In this case the features are the RGB colour data that define each colour and in this work the particular clustering algorithm used was the k-means algorithm implemented in MATLAB software. The algorithm allows for the numbers of groups or cluster to be specified and in this work four clusters were sought. Each cluster consists of a membership number (the number of colours that are in the cluster) and a centroid (the RGB values in the centre of the cluster that define it). For each image, four clusters were sought and the three centroids with the largest membership were taken as the colour palette representing the image. The reason that four clusters were sought rather than three was to allow for the fact that the images all contain more than three colours. In some sense this technique finds the dominant colours in the image. Since Model 1 was applied to all of the colours in each image including the background and audience (as well as the fashion garments and the model) we might expect the cluster analysis to generate some dominant colours in the image that are not necessarily associated with the fashion garments worn by the model.

The second method (Model 2) consisted of three steps: (1) use of a people-detection algorithm to create an exclusion box around the model in the image and pixels outside of this box were discarded; (2) the use of a foreground detection algorithm to perform a binary classification of the remaining pixels into foreground and background pixels; (3) use of the standard k-means algorithm to calculate three centroids from the foreground pixels. In all cases, image processing was carried out using MATLAB (Version: 9.6.0.1072779 R2019a).

The people detection algorithm was implemented using the *detect* command with MATLAB's peopleDetectorACF detection method. This method uses a pre-trained neural network that was built using 750,000 images from the CalTech Pedestrian dataset (Dollár *et al.*, 2012). The foreground/background segmentation was implemented using MATLAB's *activecontour* command. Figure 2 illustrates the steps that were used in Model 2.

Figure 2. Example image processing showing (from left to right) original image showing people-detection box; cropped image to include only the people-detection box; grayscale, R plane, G, plane, and B plane of the image; foreground detection to show foreground (white) and background (black). The first method applied k-means clustering to the second image from the left. The second method applied k-means clustering to the same image but ignoring those pixels that were deemed as background (according to the rightmost image).

In this work we wish to compare the visual similarity of colour palettes generated using the algorithms (Model 1 and Model 2) with those selected by humans (see Figure 1). Such a method has previously been published (Pan & Westland, 2018) and is described as follows for two palettes (A and B) each of which contain *N* colours or patches:

(1) For each of N patches in palette A, find the closest patch in palette B and calculate the colour difference ΔE using the CIELAB colour model (Westland *et al.*, 2012).

(2) For each of *N* patches in palette B, find the closest patch in palette A and calculate the colour difference.

(3) Calculate the visual difference ΔEp as the sum of the 2*N* colour differences divided by 2*N*.

The original work was carried out using the CIELAB colour difference formula and for palettes where $N = 25$. A good agreement was reported between ΔEp and the psychophysically derived visual colour differences between the palettes. A subsequent study added psychophysical data for palettes where $N = 5$ and found that the best agreement with psychophysical data was using the CIEDE2000(2,1) colour-difference equation (Yang *et al.*, 2020). The ΔEp metric (using the CIEDE2000(2,1) colour-difference equation) was used in this study was a measure of performance. Colour palettes generated automatically were compared, using this metric, to those ground-truth data derived from the psychophysical experiments.

Results

The variation in colour palettes chosen by the 22 participants shown in Figure 1 for one image is representative of the variation within and between participants for the other images. However, inter-observer variability was quantified by comparing each participant's 3-colour palette with the 3-colour palette from each other participant (for each image) and calculating ΔEp in each case. The distribution of these ΔEp values is shown in Figure 3.

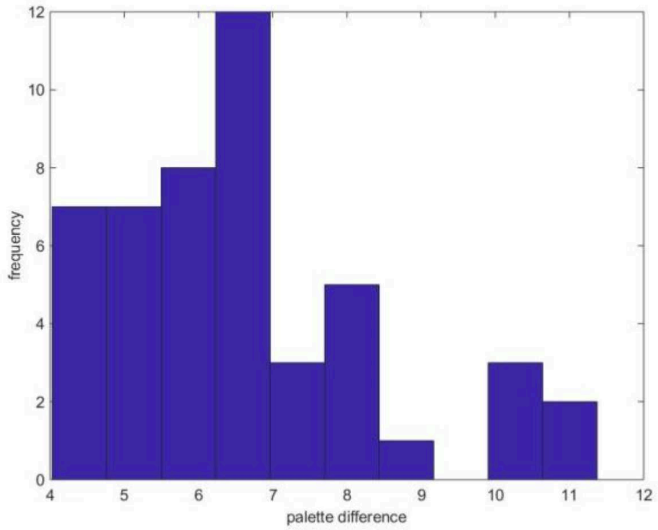

Figure 3. Inter-observer variability for each of the 48 Burberry images. For each image, the palette from each observer was compared to the palette from each other observer and the difference calculated as ΔEp. The mean ΔEp was calculated for each image and the frequency distribution of these mean values is shown in the figure. The mean pooled over all 48 images was 6.6 CIEDE2000(2,1) units.

Pooled over all 48 images the inter-observer variability was 6.6 colour difference CIEDE2000(2,1) units. This is not only a measure of inter-observer variability but suggest a limit on algorithm performance. For each of the algorithms used in this work the 3-colour palette produced for each image was compared to the 3-

colour palettes produced by each of the 22 participants and the values were averaged over all participants and all images. Since for any one image there is variability between the participants (6.6 CIEDE2000(2,1) units) in terms of the colours selected, it is not possible for the algorithms to generate a 3-colour palette that matches all participants’ 3-colour palettes simultaneously without error.

The performance of the two models can be seen visually for one example image in Figure 4. It is evident that Model 1 (k means applied to the whole image) does not result in a colour palette that represents the clothes particularly well. On the other hand, Model (segmentation of the image using a people detection algorithm followed by foreground/background segmentation and clustering) is more effective.

Figure 4. Colour palettes generated automatically an example image (top) for the model using Model 1 (left) and for Model 2 (right). Note that Model 2 is more effective at representing the colours of the garments themselves.

Table 1 shows the quantitative performance of the two models. These were calculated by calculating ΔEp between the 3-colour palettes from Model 1 and Model 2 and the 3-colour palettes produced by each of the 22 participants; mean performance values were obtained by averaging over all 22 participants and 48 images.

Table 1: ΔE_P Performance

Method	**ΔEp**
Inter-Observer Variation	6.6
Model 1 – applying k means to the whole image	14.9
Model 2 – segmentation of the person followed by k means	7.7

It is evident from Table 1 that the mean ΔEp for Model 2 is smaller than that for Model 1. Model 2 was therefore applied to each of the 48 images (see Figure 5) to produce 144 (48 images × 3 colours) colours that represent the whole show; k means was then applied to these 148 colours to generate a smaller colour palette that represents the show (Figure 6). In this case, a 16-colour palette has been produced. This is justifiable since the variation in colours across a whole collection is likely to be greater than that for any one garment.

Discussion

This work has introduced and tested a method for automatically extracting a colour palette representing a fashion collection based on a set of runway digital images. This process could replace the manual process that takes place when designers attend fashion shows to gain insights into emerging colour trends. The advantage of the new method would be that it is both objective and quick. Although the method has been applied here to runway images, in fact it could be applied to the many millions of images available, for example, on social media to develop colour palettes that represent geographically or temporally defined collections.

In this work a set of 49 images were used from a single fashion show. A set of ground truth data were obtained from a psychophysical experiment and two models were tested. Participants were asked to select colours that represent the show. Perhaps, it would have been better had the participants been instructed to select colours that represent the clothes rather than the show since it is not clear whether participants would interpret the background and context of the images as part of the show. Nevertheless, as illustrated for one particular image in Figure 1, participants did, in the main, ignore the background and selected colours relating to the clothes. The work has shown that Model 2 is effective for analysing the 49 images from the Burberry show that was selected for this case study; however, further psychophysical data are urgently needed to evaluate whether the algorithm in Model 2 works more generally. For example, note that in these Burberry images there was always one dominant figure (the model) and that made it relatively easy for this person to be identified by the people-detection algorithm. The algorithms may not work quite so well in more cluttered scenes or in those that have unusual or brightly coloured lighting.

The straw-man approach of applying clustering analysis to the whole image (Model 1) was unsurprisingly shown to be ineffective since the background tends to dominate the images in terms of pixel frequency. The application of a people detector followed by foreground/background segmentation was shown to be effective and the colour palettes produced by this method were shown to be about as similar to each participant's palettes were sent to each other's. This method using two machine-learning techniques: (1) cluster analysis and (2) a pre-trained neural network that is capable of reliable detection of upright unoccluded people. Neither of these AI techniques required intensive training by the authors (cluster analysis is unsupervised and the people-detection method using a pre-trained publicly available method). The use of such 'off-the-shelf' machine-learning methods in this study demonstrated that such methods are becoming commonplace and are accessible to almost anyone.

One limitation of this work is the observation that although the segmentation method effectively isolated the model wearing the fashion garments) it does ignore skin colours. This is an important limitation of the work. Although the colour gamut of skin is known (Xiao *et al.*, 2017), simply removing pixels that are within the gamut of skin colour could fail if the garments were also within that gamut. Further work will explore this and will also explore performing the segmentation in other colour spaces, such as CIELAB (Bansal & Aggarwal, 2011), and methods for segmentation beyond the simple k-means approach.

Figure 5: Example images from the 48-image collection using in this study.

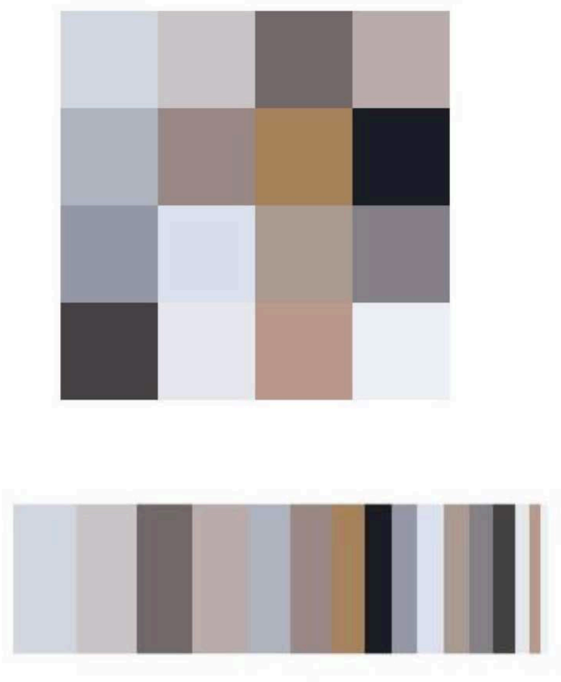

Figure 6: Colour palettes generated from the collection. In the top diagram the 16 colours generated from the show are shown. In the bottom diagram the colours are shown where the area of each cluster is related to the membership size of each centroid in the clustering analysis.

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