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A Data-driven Approach for Garment Color Classification in On-line Fashion Images

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Abstract

Many different fashion related computer vision applications have been developed over the past few years. However, as an important attribute of fashion garments, color in fashion is rarely studied subject, and a color name matching algorithm is highly desired by the online fashion community that maps a garment color from an image to a verbal description . As a continuation of our previous nearest-neighbor-based fashion color matching method, in this paper, we propose a psychophysical experiment to collect fashion color naming data and a new data-driven classification model using random forest for color name classification. Our reversed color naming experiment uses a simple and straightforward procedure to extract users' color naming schema. The random-forest classifier utilizes a set of linear and non-linear features in CIELab color space. It achieves more than 80% accuracy, and shows great improvement over our nearest-neighbor-based model. Furthermore, this data-driven approach also has the ability of actively and dynamically learn and improve the algorithm; and it is also able to learn new users' color vocabularies.

Introduction

The online fashion market has shown a steady and strong growth in the past decade [1]. As one of the critical attributes of a fashion garment, missing or wrong color information can lead to miscommunications and even hinder sales performance. However, unfortunately, fashion garment color matching and color naming has not been regarded as one of the top topics for fashion imagery analysis. Most of the research interests in fashion imaging have been focused in other areas, including fashion parsing [2, 3], product matching and clothes retrieval [4, 5, 6, 7], human posture estimation [8], clothes synthesis [9], and fashion aesthetic quality analysis [10, 11]. As straightforward and easy as it may seem, fashion color naming and matching has always been a challenge for the online fashion industry.

Therefore, in this paper, we present a novel approach to draw fashion color naming and matching schema data from the online fashion community. A psychophysical experiment called *the Reversed Color Naming Experiment* is developed and conducted, to map verbal descriptions of colors to their corresponding color appearances, or color coordinates. More than 2,500 data entries are collected in our experiment, and a random forest classification model is trained to map color coordinates to color names.

The rest of this paper is organized as follows: Introduction reviews some existing color naming systems and, more specifically, color naming in fashion. We also summarize our previous work on fashion color naming. In the section of "Reversed Color Naming Experiment", we explain the experiment we conduct to collect users' color naming schema. Section 3 illustrates the random forest classifier approach to the fashion color naming problem.

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Color Naming Studies

Many computer vision works use color information of an image or video. Yet, the ability or complete theories to name individual colors, pinpoint objects with specific colors, and communicate the impression of a certain color composition is still under development [12]. A color naming system is desired to transform information from color spaces to color names.

So far there are several proposed works mapping color coordinates to a verbal description. One of the most commonly used color naming systems is the Munsell color standard [13]. It has been widely used in paint and textile production [12]. However, this proposed system lacks a color vocabulary and an exact transform from any color space to Munsell. To expand the vocabulary of the color naming system, Maerz and Paul [14] developed the first version of a color naming dictionary including 3000 English words and phrases. Later, the National Bureau of Standards (NBS) published a more detailed dictionary, including 7500 different names. It has been used in specific fields such as biology, textiles, dyes, and the paint industry. However, neither dictionary is organized in a systematic way, which makes the generalization more difficult.

To address this issue, derived from the Munsell system, the National Bureau of Standards developed the ISCC-NBS dictionary of color names according to the recommendations of the Inter-Society Council [15]. ISCC-NBS includes color names for 267 regions, and all the terms are sorted according to the dimensions of the color space: hue, lightness, and saturation. This system divides the lightness into 5 levels from (*very dark* to *very light*), and 4 levels for saturation ranging from (*grayish* to *vivid*), and three terms that consider both lightness and saturation (*brilliant*, *pale*, and *deep*). ISCC-NBS also expands to 28 basic sets (*red*, *orange*, *yellow*, *green*, *blue*, *violet*, *purple*, *pink*, *brown*, *brown*, *olive*,*black*, *white*, and *gray*).

Previous researchers have also derived mathematical models to match color values to color names. Lammens [16] used a Gaussian normal distribution to do color categorization. Belpaeme [17] built a another color categorization framework with fuzzy boundaries of the notion of color primitives and modeling via adaptive radial basis function networks [12].

Fashion Color Categories

For color management in the fashion industry, unlike other industries, where color names usually are objective and given based on the color appearance, most of the fashion color naming is done by the manufacturers individually before products are released. Other than that, seasonal trending color names are also predefined every season by the team at the Pantone Color Institute in the Pantone Fashion Color Trend Report [18]. For example, Fig. 1 shows the top 10 trending colors that are defined by Pantone fashion color experts. All the color names in Fig. 1 are updated regularly by the fashion experts, and they are not standard color names

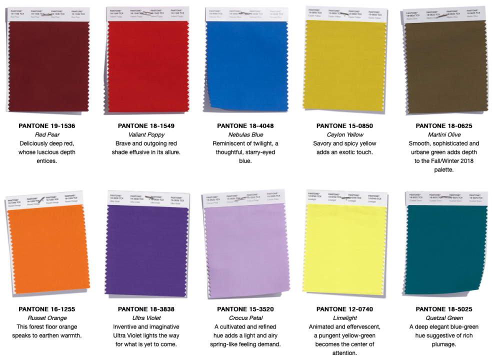

Figure 1: Pantone fashion color trend report – Fall/Winter 2018 New York top 10 color palette [18].

used in the previously mentioned color naming systems. Yet it is not a standard color naming system that is universally recognized by all fashion manufacturers.

Other than the problem of the lack of a universal standard fashion color system, fashion color naming has other challenges that are unique to it:

1. Different websites have different fashion palette definition. For instance, in Fig. 2, we show two palettes from Poshmark and Neiman Marcus, respectively. For example, neutral and pattern only exist on the Neiman Marcus website.
2. Some color families have more granular color descriptions. For example, on the Poshmark website, the yellow family has yellow, gold, and orange. For comparison, blue family only has one label.
3. Color can appear different on different websites. For example, Poshmark silver is much lighter than Neiman Marcus silver.
4. Color names can also represent texture, like silver and gold on the Neiman Marcus website.

Inspired by the previously proposed color naming methods [16, 17], in our previous work [2], we proposed a nearest-neighbor-based method to determine the color name. The workflow can be described as follow: first, our algorithm takes the predefined color values from the fashion website as the reference colors for each name category. Then, reference colors are converted to CIELab coordinates for more accurate calculation. For a query color value, the algorithm calculates the color differences ΔE between the query value and all the reference points and finds the color that has minimum color difference, i.e. the nearest neighbor.

Our nearest-neighbor-based algorithm is a straightforward answer to the color matching problem. And it is very computationally easy to use, as it only needs to store n reference colors and takes $O(n)$ to produce the final answer, which is a constant. In addition, for an online fashion marketplace or any online fashion retailer, the number of color choices offered is always limited. However, this NN-based method has some limitations:

- **Accuracy.** The model generally fails to provide accurate predictions due to oversimplification. Our algorithm only uses a limited number of reference points, and each class only has one point. The algorithm also oversimplifies the complexity by drawing hard decision boundaries in Lab color space.
- **Flexibility.** The model can only work for reference points from the website, and it cannot learn users' color naming schema to further improve the color naming algorithm.

(a) (b)

Figure 2: Two color palettes from online fashion websites. (a) is from Poshmark, and (b) is from Neiman Marcus.

Therefore, we want to build a data-driven color naming classification method that can learn color naming schema from the online fashion shoppers.

Reversed Color Naming Experiment

For the fashion marketplace, it is important to constantly and actively learn color descriptions from the online fashion community instead of from predefined labels. To further study how the online fashion community names colors, we design and conduct a psychophysical experiment called the *Reversed Color Naming Experiment*. We call the experiment reversed because instead of asking human subjects to name the color in a photograph, human subjects in our experiment are supposed to choose the color from the image based on a given color name.

For this experiment, we collected more than 2,500 images from a fashion P2P website; and they are also labeled by the seller while making the listing. Note that 1) For our specific case, up to two color labels are allowed per listing by the website. Therefore, sellers can only choose the top two predominant colors where there are more than two colors on the garment. You can see the full color palette in Fig. 2(a). 2) Each listing may contain multiple images, and all images within the same listing share the same color label.

We invited 6 human subjects to our experiment. They are 20-30 year-old adults with normal color vision. We chose the age range to reflect the demographic of online fashion shoppers, and color vision screening was done by using Color Blindness Test [19]. Although it was not a rigid requirement, all of our human subjects were avid online fashion shoppers. Their previous online fashion shopping experience helped human subjects understand each image and its color. Each human subject was assigned a set of fashion product images. On average, each person had 400 - 500 images to label within a week.

To keep our color experiment as simple and consistent as possible, we asked our human subjects use an Apple MacBook Pro with Retina Display to view the images and participate in the experiment. The experimental procedure can be described as follows: For a given image, we present the label(s) associated with the listing, and our human subject is expected to use the color picker to choose the color pixel(s) that is most representative of the color label. Then the selected color values are converted to CIELab and the subject moves on to the next image.

Color Naming Classifier Using Random Forest

In this section, we further discuss our paradigm of using the random forest algorithm to extract human viewers' fashion color naming schema.

Model Overview

We use a random forest [20] to match numerical color values to verbal description. Random forest is one of most widely used machine learning algorithms due to the good accuracy, robustness and ease of use. The algorithm is one type of ensemble classification method that combines a set of simple decision tree classifiers such that each tree is trained on a series of training data sampled independently and with the same distribution for all trees in the forest.

By running many decision trees and aggregating their outputs for prediction, the random forest algorithm fixes sub-par model robustness of a single decision tree; and it can also control over-fitting. A typical random forest classification training workflow can be described as follows:

1. Sample N different sets of training data from the original dataset using bootstrapping.
2. If there are M features, max split feature m ($m << M$) is determined such that at each node, m features are selected at random out of the entire set of M features and the best split on these m is used to split the node. The value of m remains unchanged during the forest growing.
3. Given each dataset, grow a decision tree to the largest extent possible. No pruning is required.

For inference, for each data point, we pass the M-dimensional feature vector to all the decision trees grown, and the final result is determined by majority vote.

It has been shown that the classification error resulting with random forest depends on two things [20]:

1. The correlation between any two trees in the forest. The more decorrelated trees are, the more accurate the forest is.
2. The strength of each individual tree in the forest. A strong tree has high accuracy, and increasing the strength of all the individual trees helps to improve the forest accuracy.

We can adjust m to change the between-tree correlation and individual tree strength. Larger m increases both the correlation and the strength. Therefore m should be further fine tuned to ensure optimal performance.

Feature Design

As previously stated, the key requirement of random forest is a large pool of features. We hereby introduce all features we engineer in this work.

We developed a set of seven features for our classifiers. All of our features are based in CIELab color space. The first three features are the L, a^*, and b^* values. Furthermore, we define chroma C as

$$C = \sqrt{a^{*2} + b^{*2}}, \tag{1}$$

and hue H as

$$H = \arctan\left(\frac{b^*}{a^*}\right) \tag{2}$$

where a^* and b^* are from the CIELa*b* color coordinates. We also introduce other quadratic features like La^* and Lb^*. We will further study the feature importance later.

Model Evaluation and Analysis

We split our data from the reversed color naming experiment into 70/15/15 for training, validation, and testing, respectively. Then, multiple combinations of hyper parameters (the number of trees, maximum split feature m) are proposed for model selection. After validation, we grow 25 trees for our classifier; and we follow the general practice and choose m as $\lfloor\sqrt{M}\rfloor = 2$. Figure 3 shows the confusion matrix on the testing set for our proposed algorithm. We have the following observations from our testing:

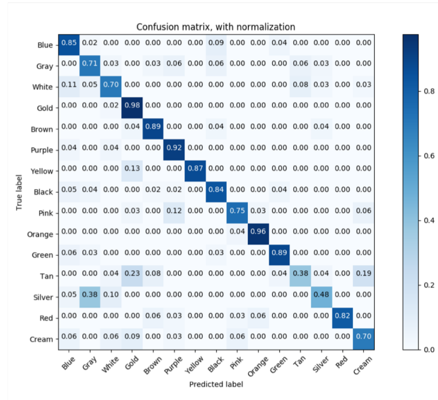

Figure 3: Confusion matrix for testing set based on trained random forest classifier.

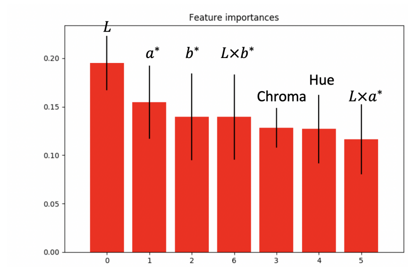

Figure 4: Feature importance for our trained random forest classifier.

- Overall, our algorithm performs very well with average testing accuracy of 80%. Compared with previous 60% accuracy from the previous nearest-neighbor method, a huge improvement can be gained by using random forest.
- Generally, focal colors like blue, purple, and orange have higher accuracy.
- Off-white colors (gray, cream, silver) create much confusion.
- There are also a couple of confusing pairs: pink-purple, tan-gold-brown, tan-cream, yellow-gold. These pairs can be shown to be very close to each other.

Furthermore, we study the importance of all the features. Feature importance is calculated as node impurity (here we use Gini impurity index in our work) decrease weighted by the probability of reaching that node. The node probability can be calculated by the number of samples that reach the node, divided by the total number of samples. The higher the value the more important the feature [21]. Figure 4 indicates the feature importance from the most to the least important. We can see that luminance value is the most important feature of all; and all other features share relatively similar importance. We can also see that by adding non-linear features to the classification system, we drastically improve the model complexity from the nearest-neighbor based color naming method.

Conclusion

Fashion color naming has been a crucial yet under studied problem for the online fashion market. In this work, we explore a new adaptive approach to match color values to descriptive color names. A reversed color naming experiment is proposed to collect color naming data; and a new random-forest based color classification system is used.

Our random forest classifier shows great improvement over our previous model and achieves high accuracy of color name prediction. Furthermore, the algorithm has the potential of further learning new fashion color vocabulary in the future if new trainable data is given.

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