Color Trend Forecasting with Emojis

Wenwen Li(✉) and Michael Chau

The University of Hong Kong, Pokfulam Road, Pok Fu Lam, Hong Kong
liwwen@connect.hku.hk, mchau@business.hku.hk

Abstract. Color trends are fickle components of clothing styles. It's a tough task to predict trendy colors for the fashion industry. Meanwhile, excess inventory of certain colors and stock out of popular colors both lead to extra costs. Intense competition and short product life cycles require fashion apparel retailers to be flexible and responsive to the change of market trends. As a consequence of limited historical data, many studies focus on employing advanced and hybrid models to improve forecasting accuracy. These studies ignore abundant user interaction data on social media, which is an important source to understand consumer need, as well as advanced methods to deal will multivariate data in the forecasting model. Thus, this study aims to fill this research gap by applying Bayesian Neural Networks model and incorporating user interaction data, especially emojis, into the model. The evaluation results show that Bayesian Neural Networks outperform baseline model (Neural Networks and Support Vector Regression) and the model with emoji performs better than the one without emoji. The paper demonstrates the predictive value of emoji and provides an advanced method to process multivariate data.

Keywords: Emojis · Bayesian Neural Networks · Color trend

1 Introduction

As retail competition in the fashion industry around the world continues to intensify, fashion apparel firms have to improve their management abilities that support marketing strategies and decisions [1]. Retail inventory management is a fundamental part of management operations, which heavily relies on deep understanding of market trends. Fashion retailing industry mainly includes two types of market trends, which are color trend and style trend. Color trend forecasting is an important dimension of understanding customer needs [2] and avoiding unnecessary inventory cost.

Color trend forecasting relates closely to sales forecasting but heavily depends on market information and customer preference. Even if the product is well designed, its unpopular color will prevent potential customers from making a purchase. Despite the attention that retailers have devoted to color trend forecasting, the field of information system has not yet studied the opportunities that an integrated system incorporating abundant external information offers to improve efficiency and accuracy of color trend forecasting. In this study, we develop an integrated system that applies internal transaction information from the retailer and external market information from social media to predict color trend for retailers.

J. J. Xu et al. (Eds.): WEB 2018, LNBIP 357, pp. 171–181, 2019.
https://doi.org/10.1007/978-3-030-22784-5_17

There are two challenges that may baffle many retailers and researchers during color trend prediction. The first is to obtain the market and consumer data and decide valuable information. Color trend is a kind of collective selections by consumers. Besides inner operational data, market-related and consumer-related data are important for improving the accuracy of prediction. To predict color trends is a tough work because of all the uncertainties associated with industries and customer tastes. Color trend forecasting depends on drawing on market information from multitudes of industries like brands, designers, magazines and celebrities. Social media provide firms and experts a platform to present their ideas on fashion products and color trends. On the other hand, customer preference has great impact on color trends, and customers can interact with individuals in fashion industry on social media. Therefore, we collaborate with experts and deliberately design the data collection process to extract highly-valued information from social media. User interactions on Facebook can be separated into two categories: one is general interactions, such as "Likes", "Comment", and "Share"; another one is reactions (including "Love", "Haha", "Wow", "Sad", and "Angry") that offers users more choices than "Likes" to directly show their feeling for the post. Reactions are line-up of emojis, and we directly call them emoji in this paper. We categorize "Likes" as a general interaction because Facebook Likes are very popular [3]. It contains richer meaning than simple emojis. General interactions have played an important role in online marketing campaign. However, emojis as a relative new function on social media do not draw much attention.

The second challenge is efficiently incorporating limited operational data and abundant external data into an integrated predictive system. Offline sales often generate daily or weekly transactional data. While various information is available on the social media platforms, monthly or weekly operational data decides a small sample size and results a relatively large dimensional dataset. Dataset with too many features can easily make machine learning methods overfitting and influence the accuracy of forecasting. However, reducing features is not an ideal solution because it will lose some information. Different from medical and astronomical data, the number of features in business data is not tremendous, but most features are valuable for decision making. Features extracted from social media data are also convey different information. Hence, we choose a variation of standard Neural Networks, which is Bayesian Neural Network (BNNs), to incorporate various features. Because of its specific way to represent parameters, BNNs can efficiently avoid overfitting problem.

The aim of this paper is twofold: on the one hand, we investigate the operational and predictive value of user interaction data, especially emojis, in a context of the fashion industry. On the other hand, we compare the performance of three main machine learning methods on multivariate data and demonstrate the advantage of Bayesian Neural Networks of avoiding overfitting problem.

2 Research Background

Researchers have developed the measurement and system for fashion color in product designing [4, 5]. Before product designing, companies need to understand color trends in the market and try to predict the future trend. Some research on color trend forecasting has been conducted in textile field [2, 6]. There are two streams of literature that are relevant to our work: the literature related to emojis and the literature on forecasting methods in fashion industry.

2.1 Emojis

Forecasting in fashion industry requires deep understanding of the market and consumers. Operational data provided by firms have been widely applied in previous studies, whereas it covers very limited information about the market and consumers. Thus, other data sources are needed. Social media data has been widely adopted as one of the most important and ubiquitous sources to reach consumers and the market. User interactions on social media has become valuable information for marketing and operation management. Besides general interaction methods (e.g. comment, share, and "Likes"), emoji is an interesting way for users to express their feeling.

Emojis are "picture characters" or pictographs [7] that can be inserted into electronic communication platforms, such as text messages, email messages and social media posts. Due to emoji's popularity and broad usage, the Oxford Dictionary named 2015 the year of emoji [8]. The main objective of emojis is to convey conversational context, like happiness, sadness, frustration, sarcasm, etc. Emojis are essentially fulfilling the function of nonverbal cues in spoken communication [9]. Besides general sentiment expression, emojis have become a popular way for consumers to express their opinions and purchase intentions. Therefore, it is feasible to detect consumers' opinion through emojis that are used in reviews and posts. In a food context, emojis are an easy and intuitive way to express emotions on meals, and consumers spontaneously express food-related emotions in tweets [10].

In this paper, we focus on Facebook reactions that are expressed as emojis including five different animated emotions: Love, Haha, Wow, Sad, and Angry. With reactions, people can react to posts in a more accurate way. Before 2016, there was only the "Like" button on Facebook. However, a thumbs-up may not be an appropriate choice for every post. The appearance of reactions allows people to express their nuanced sentiments to posts. The reactions feature has become popular among Facebook users. On February 24th, 2017, Facebook revealed that people shared 300 billion reactions at the one year mark of the feature launch. Reactions can drive user engagement and reflect people's opinions to posts. Companies are able to learn the preference of customers by their reactions record. In addition, Facebook weights reactions more than "Likes" to determine the sequence of posts on user's News Feed. Facebook reactions provide opportunities for more precise sentiment analysis. A variety of different reactions represent people's emotional responses and are much easier to analyze than textual contents. In this paper, we use the word "emoji" instead of "reaction".

2.2 Forecasting Methods in Fashion Industry

The predicting methods applied in fashion studies differ widely from traditional statistical methods to machine learning techniques. One of the earliest and useful methods is exponential model, which uses the exponentially weighted moving average to forecast the expected value of a stochastic variable [11]. The advantage of this method is requiring little information storage and slight time to compute and making relative accurate forecasts. Subsequent studies examined and extended this method, especially in the field of sales prediction [12]. Other traditional statistical methods include linear regression and auto regression integrated moving average (ARIMA), which are good at analyzing time series data. However, real data in the company may not be perfect time series data and contains much noises, and these traditional statistical methods are unlikely to perform well.

Therefore, some more complicated and powerful methods, such as machine learning, have been adopted [13, 14]. When there is an absence of theory to guide model identification, machine learning methods, such as neural networks (NN) and support vector machines (SVM), can provide accurate prediction. Comparison between NN and statistical based models has been conducted and the result shows that NN outperforms in fashion retail sales forecasting [15]. Besides NN, SVM and random forest (RF) are also important methods in fashion prediction. SVM, a semiparametric technique, performs well on predictive tasks where the relationship between predictors and target is complex [16]. SVM has one variant call support vector regression (SVR), which is an advanced method for predicting. The development of this rich class of nonlinear models inspired researchers and organizations to dig large amounts of internal and external data and obtain much more accurate prediction results [17]. Bayesian Neural Network (BNN) is a combination of probabilistic model and a neural network. In 1987, researchers have come up with an idea of Bayesian integration over network parameters [18]. BNN can be regarded as an extension of standard networks with posterior inference. Because of incorporating Bayesian inference, BNN can avoid overfitting problem.

With the advent of big data, firms always encounter large amount of external data. One the other side, the core operational data may be very limited. Machine learning methods are fit to do large dimensional or multivariate data modelling. However, when facing large dimensional data, overfitting is hard to avoid and thus causes poor performance. One kind of popular methods to process large dimensional data is variable reduction. For instance, correlation analysis, principal component analysis, and chi-square are widely applied in Information System studies. Nevertheless, dimension reduction suffers from information loss and low accuracy.

In this paper, we use BNN to overcome this problem. Standard neural network with backpropagation has some disadvantages, such as many hyperparameters that require specific tuning and a tendency to overfitting [19]. Using Bayesian inference to learning neural networks can avoid these disadvantages. BNN has been proved to be a good choice to prevent overfitting when data is scarce [20, 21].

3 BNN and Forecasting Framework

3.1 Forecasting Framework

The forecasting framework includes both operational information and social media information. Social media information is extracted from Facebook posts and consists of general interactions and emojis. Sales data provides operational information. As shown

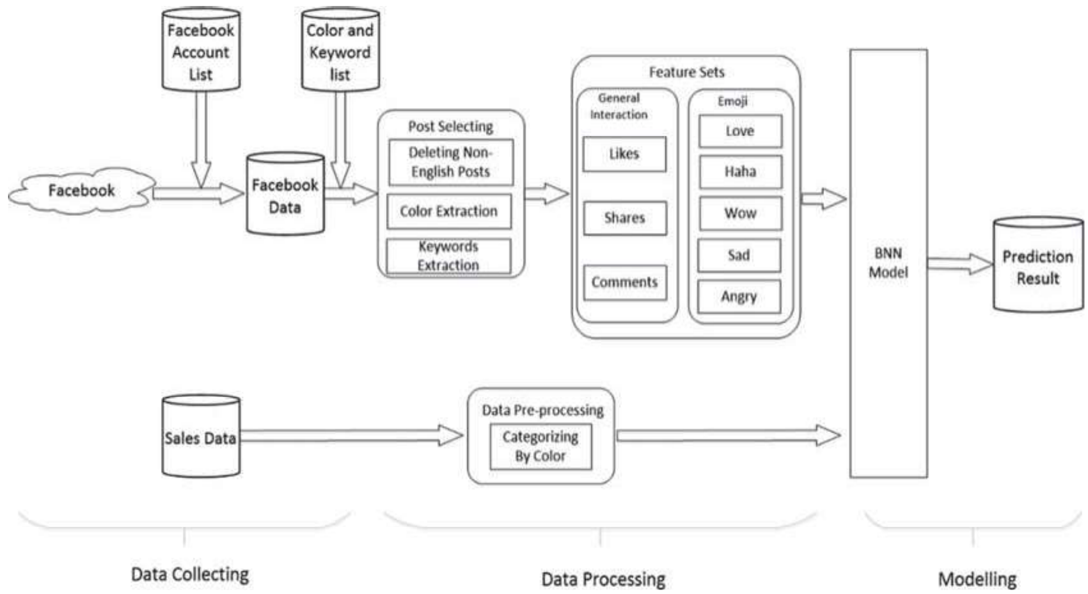

Fig. 1. The forecasting framework.

in Fig. 1, our framework consists of three phrases: data collection, data processing, and modelling.

In the first phrase, we built a Facebook account list according to the criteria we will introduce in Data Section and collect posts of all accounts on the list using Facebook application programming interface (API). Since we focus on fashion industry, four types of accounts are considered: brands, magazines, designers, and fashion influencers. Then we cleaned the data by removing hash tags, non-English characters and URLs in the text. Although accounts are related to fashion, we cannot guarantee that all posts published by these accounts are about fashion and color. To reduce noise, we built a color dictionary and a keyword dictionary with experts' help and selected posts that contain words in both of these two dictionaries. The color dictionary included all color words that can be used to describe clothing color. We categorized these color words into general nine color groups: White, Black & Gray, Blue, Green, Yellow, Red, Brown, Purple, and Orange. The keyword dictionary consisted of words that are related to clothing and fashion. There are 954 words in color dictionary and 870 words in keyword dictionary. The second phrase is data processing. As we discussed before, user interactions on Facebook can be categorized into two groups: general interactions and emojis. According to the data provided by Facebook, there are three types of general interactions ("Likes", share, and comment), and five types of emojis ("Love", "Haha", "Wow", "Sad", and "Angry"). The number of these user interactions is public and accessible via the Facebook API. In the last phrase, we deployed BNN model to process multivariate input data and demonstrated that the prediction accuracy of color trends can be improved by including user interactions, especially emojis. We utilize social media features and combine with previous sales data as inputs of the model. Two baseline models were also implemented.

3.2 Bayesian Neural Networks

There are two reasons for us to apply BNN in this paper. The first one is that a careful probabilistic representation of uncertainty is needed. For prediction problem, limited knowledge is obtained, and it is impossible to exactly describe outcomes. Also, the lack of training data causes epistemic uncertainty. The second one is preventing overfitting. Many machine learning methods are data hungry. Much business-related data is scarce and makes the model tend to overfitting. Although lots of studies have applied machine learning methods to solve practical business problem, few of them notice the potential problem of overfitting. In this paper, we demonstrate the poor performance of standard neural networks and SVR on scarce business data and introduce BNN to solve this problem.

From a probabilistic perspective, standard NN training is a kind of maximum likelihood estimation (MLE) for the weights. Bayesian inference helps to generate a complete posterior distribution and provide parameters (e.g. w) a distribution instead of a single value. Therefore, BNN combine the strengths of stochastic modelling and standard neural networks. In this paper, BNN helps to estimate uncertainty of limited data, learn the model structure automatically, and avoid overfitting.

4 Data

This study uses a weekly sales dataset provided by an international clothing retailer. Sales data includes 31 styles and records transaction details of each style, such as color, sales quantity, sales amount, and average price. We obtained this data for the period between January 2015 and December 2016 (106 weeks).

We chose Facebook to get social media information. The most important reason is that Facebook allows users to react to posts by emojis. It provides us a valuable opportunity to study the operational value of emojis. Most companies have both Facebook and Twitter account to do marketing and always publish similar posts on these two platforms. Thus, we only need to choose one platform as the data source. Besides, Facebook offers public application programming interface (API) to access post information of public pages.

We obtained a collection of public posts from Facebook via the Facebook API. For each post, the API provided the text content, the created time, a unique post ID, the number of “Likes”, the amount of interactions (e.g. shares and comments), and the amount of reactions (e.g. “Love”, “Angry”, “Haha”, “Sad”, and “Wow”). We predicted clothing sales using Facebook posts, which are all from one of the four types of Facebook public pages. They are brands, magazines, designers and influencers. We also set two criteria to choose qualified pages. First, “Likes” count of the page should be larger than 1,000. Second, the page must be authentic page for public figures, media companies and brands. In this way, we can get highly relevant posts and exclude useless information. Finally, we had 951 accounts in total. The data collection period for sales amounts is from January 2015 to December 2016, giving a total of 106 weekly sales amounts. Then we collect Facebook data recorded from December 2014 to December 2016 (totally 145,741 posts). The details of categorization of Facebook data are shown in Table 1.

Table 1. Facebook data source.

Category	No. of accounts	No. of posts
Brand	469	70,336
Magazine	93	15,207
Influencer	260	44,315
Designer	129	15,883
Total	951	145,741

Table 2 describes the social media features used in this paper. We constructed features on color level, since the purpose is predicting color trend. We observed the data carefully and decided not to consider “Angry” in this paper. Because we focus on posts related to fashion product, almost no one feel angry with these posts. All posts in our dataset have zero “Angry” emoji.

Table 2. Feature description.

Category	Item	Description
Post	Count	The number of selected posts mentioned certain color for one week
General interaction	Like	The total number of Like of selected posts
	Share	The total number of Share of selected posts
	Comment	The total number of Comment of selected posts
Emoji	Love	The total number of Love of selected posts
	Haha	The total number of Haha of selected posts
	Wow	The total number of Wow of selected posts
	Sad	The total number of Sad of selected posts

5 Evaluation

In this section, we report an experiment conducted to achieve our research purpose. To show the operational value of abundant social media data, we choose six different combination of inputs (Table 3). According to the retailer’s suggestion, four-week (one month) ahead forecast is acceptable. Four prediction time windows (one to four weeks) were tested to achieve the best performance. We denote sales in week t in color m as Smt, the number of total posts as Countmt, the number of share as Sharemt, the number of “Likes” as Likemt, the number of comments as Commentmt, the number of “Love” as Lovemt, the number of “Wow” as Wowmt, the number of “Haha” as Hahamt, and the number of “Sad” as Sadmt. To demonstrate the performance of the Bayesian Neural network, we evaluate it against popular machine classification methods, including support vector regression (SVR) and neural networks (NN). We choose a two-layer neural network with one hidden layer and one output layer as baseline model. Because the Bayesian neural network adopted in this paper has two layers.

Table 3. Input description.

Name	Input	Description
Input 1	(Sm(t-4))	One-week sales data
Input 2	(Sm(t-4), Countm(t-4), Sharem(t-4), Likem(t-4), Commentm(t-4))	One-week sales and general interaction data
Input 3	(Sm(t-4), Lovem(t-4), Wowm(t-4), Haham(t-4), Sadm(t-4))	One-week sales and emoji data
Input 4	(Sm(t-4), Countm(t-4), Sharem(t-4), Likem(t-4), Commentm(t-4), Lovem(t-4), Wowm(t-4), Haham(t-4), Sadm(t-4))	One-week sales, general interaction, and emoji data
Input 5	(Sm(t-4), Countm(t-4), Sharem(t-4), Likem(t-4), Commentm(t-4), Lovem(t-4), Wowm(t-4), Haham(t-4), Sadm(t-4), Sm(t-5), …, Sadm(t-5))	Two-week sales, general interaction, and emoji data
Input 6	(Sm(t-4), Countm(t-4), Sharem(t-4), Likem(t-4), Commentm(t-4), Lovem(t-4), Wowm(t-4), Haham(t-4), Sadm(t-4), Sm(t-5), …, Sadm(t-5), Sm(t-6), …, Sadm(t-6))	Three-week sales, general interaction, and emoji data

The experiment results are presented in Table 4. The dataset is divided into training sets (80%) and testing sets (20%). All input data has been normalized. We use the root-mean-square error (RMSE) to evaluate models. 10-fold cross-validation is also used in evaluation. The results show that BNN outperforms all the other methods in terms of RMSE. Furthermore, the results demonstrate the BNN's ability of prevent overfitting. User interactions have significant impact on the performance of predictive models. In the following, we discuss the evaluation results in more detail.

Table 4. RMSE for different methods and variables.

Model data	BNN	NN	SVR
Input 1 (1 variable)	0.0533	0.0599	0.0736
Input 2 (5 variables)	0.0518	0.0525	0.0696
Input 3 (5 variables)	0.0498	0.0512	0.0644
Input 4 (9 variables)	0.0471	0.0510	0.0643
Input 5 (18 variables)	0.0425	0.0600	0.0647
Input 6 (27 variables)	0.0460	0.0702	0.0645

5.1 Bayesian Neural Networks

Considering the poor performance of SVR, we only compare BNN with NN in this part. As shown in Table 4, models with general interactions (Input 2) perform better than the ones without general interaction (Input 1). It is an expected result and coincides with previous studies. The Table 4 also shows that, adding emoji information can improve the performance. BNN and NN with Input 3 outperforms the same model with Input 1. In addition, the model with emoji data (Input 3) performs better than the model with general interaction data (Input 2). These results have significant practical implication. General interactions on social media have been regarded as valuable indicators in operational forecasting. Our results show that emojis are more helpful in color trend forecast. The value of a better color trend forecasting to fashion retailers can be substantial, since accurate forecast can help retailers to adjust the quantity of product in different colors, reduce inventory cost, and avoid stock out situation. We also test the model with both general interaction and emoji data (Input 4). The result shows that the combination of general interaction and emoji data can further improve the accuracy of forecasting. Every function on social media is well designed to satisfy user's different social demands. These functions help retailers and researchers understand potential customers from various aspects.

To further study the predictive power of each type of emojis, we conducted a follow-up experiment. The predictive model is Bayesian Neural network. Experiment setting is the same as the previous experiment. Forecast lead time L is four weeks. We denote sales in week t in color m as Smt, and other variables follow the same format. As Table 5 shown, the model with "Love" performs better than others.

Table 5. RMSE for different emojis.

Input	Sm(t-4), Lovem(t-4)	Sm(t-4), Wowm(t-4)	Sm(t-4), Haham(t-4)	Sm(t-4), Sadm(t-4)
RMSE	0.0485	0.0524	0.0516	0.0553

5.2 BNN vs NN vs SVR

The overall superior performance of BNN reveals the advantage of BNN on multivariate problem, especially when it comes to large dimensional data. For the two baseline models, the performance of SVR is relatively stable when the number of inputs increases. NN performs well using limited inputs. When the dimension of inputs becomes relatively high, the performance is poor because of overfitting. Compared to NN, BNN is much better when dealing with high-dimensional data. Although the RMSE increases for Input 5 and Input 6, BNN still works better than NN and SVR.

6 Conclusions and Future Work

In this paper, we conduct color trend prediction and improve the performance of the forecasting framework by two steps. The first one is that we incorporate emojis into our framework and demonstrate the predictive value of emoji data. The second one is that we apply Bayesian Neural Network to prevent overfitting problem that is caused by the increase of features.

Improving color trend forecasts accuracy can help companies in retail inventory management and thus lead to operational benefits. As an important element of fashion product, colors have significant impact on product sales. Color trend forecasts provide more fine-grained results compared to sales forecasts on product-level. At the same time, color trend forecasts need more market information to follow the trend. Many fashion retailers, especially "fast fashion" companies, require accurate forecasts to make response to the market quickly. Thus, accurate color trend forecasts are essential in the fashion industry. Our study shows that emojis on social media can significantly improve the accuracy of color trend forecasts. Besides novel variables, we also consider the multivariate data analysis and apply Bayesian Neural Network to avoid overfitting problem. Our work can inspire companies and researcher to apply various user interaction data in the forecasting model. We will continue to dig the operational value of emojis and apply other machine learning methods.

Acknowledgements. The authors thank to reviewers and colleagues for their constructive comments on the paper.

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