Fashion Life Cycle Forecasting: Popularity of Fashion Elements on Social Media

Completed Research Paper

Yifan Ren
Fordham University
New York, NY, USA
yren50@fordham.edu

Yilu Zhou
Fordham University
New York, NY, USA
yzhou62@fordham.edu

Heng Xu
American University
Washington, D.C., USA
xu@american.edu

Abstract

Understanding and forecasting fashion life cycle is of great importance in fashion industry. However, future trends that are full of uncertainty and fashion designers and brands are relying mostly on subjective judgement of fashion trends. The rise of social media has brought new opportunities in fashion industry. This study proposes to adopt a novel time series model, Prophet model, in predicting fashion life cycle. The Prophet model can be tuned to incorporate fashion industry domain knowledge such as seasonality and holiday occasions. Using data collected from Instagram, we compared the tuned Prophet model with traditional ARIMA model and untuned Prophet model on 25 fashion elements. Using a sliding window evaluation, we show that the tuned Prophet model performed significantly better than the benchmark models especially in longer term (12 months). Furthermore, we illustrate that Fad, Fashion and Classic can be quantitatively modeled with Instagram data. We believe this study bridges the gap between fashion industry and quantitative trend prediction.

Keywords: fashion life cycle, forecasting, prophet model

Introduction

Antiquated durables can be usable today, but few people wear them in outdated fashions. Fashion, is such a creative industry that is extremely sensitive to popular trends. This characteristic also makes practitioners in fashion industry wonder how to seize the future fashion trends, so as to develop boomed elements and significantly increase profits. To perceive such future trends that are full of uncertainty, in today's fashion industry, designers and brands are relying more on subjective experience accumulated over the years. However, the development of information technology and forecasting approaches are bringing some advanced potentials to this industry.

Product Life Cycle (PLC) has been an important support for designers and brands for a great while. This theory holds that products often undergo a process from birth to growth, to maturity, and finally to declines. Fashion style involves basic fashion elements of design including product shape, color, fabrics, print and pattern (Graves 1941). If a fashion element can be determined as in the growth stage, then following it will be more likely to attract customers. On the contrary, if brands rashly invest in fashion elements in a declining period, it may lead to great risks of loss.

PLC provides outstanding theoretical support, but also brings a new question: how to identify the current and future stages of a fashion element? In previous studies, sales often provided an answer as an intuitive

expression. However, collecting sales data from all fashion companies on the market is an impossible task. Besides, the sales performance of different companies may be affected by other factors such as retail channels, advertising, etc., and cannot simply reflect the popularity of the fashion element.

Fortunately, with the advent of Web 2.0, the rise of social media has brought new opportunities. Consumers not only produce but also share fashion-related content on social platforms such as Twitter and Instagram, allowing researchers to comprehensively grasp the popularity of different fashion elements in the consumer community. By combining with historical data, it is convenient to understand which fashion elements are short-lived fads and which are persistent classics. More importantly, grasping the future popularity will let people be aware of the general life cycle stage of this element, rather than specific bias based on sales performance, so as to widely provide supports with designers and brands.

In the development of information systems, there are various popularity forecasting approaches. However, these automated technical models lack a bridge to real-world business scenarios, especially to fashion industry. Despite the powerful strength of forecasting techniques themselves, fashion industry relies heavily on qualitative forecasting. There has been some limited quantitative work (Lin et al., 2014; Lin, et al., 2015). On the other hand, fashion domain knowledge is essential to make accurate predictions and guide need to be incorporated into quantitative analysis in the fashion business.

Therefore, in this study we test several quantitative forecasting models with a focus on the Prophet model (Taylor & Letham 2018). We choose Prophet model, because its "Analyst-in-the-Loop" feature allows analysts to better incorporate domain knowledge without falling into abstruse statistical and mathematical fields. We compared the Prophet model with the classic ARIMA model on 25 fashion elements. Data were collected from Instagram, including a comprehensive category of products, colors, printing, fabrics, and accessories. Empirical experiments are conducted to compare performances of different models. Results showed the superior performance of Prophet model with domain knowledge over ARIMA model and simple Prophet model. Furthermore, we illustrated prediction results that represent three type of life cycles in fashion: Fad, Fashion and Classic.

This study is devoted to building a bridge between technology and reality for designers and brands in the fashion industry in fashion life cycle forecasting by using social media data. We explore a novel way that uses predictive models to understand and forecast fashion trends. We believe that our work can zoom out the gap between the traditional qualitative studies in the fashion industry and the quantitative methods in the academic research. It also provides guidance to future large-scale digitization of traditional industries like fashion.

The remainder of this article is structured into five main sections: literature review that goes through the previous studies on life cycles, social media, and forecasting approaches; Methodology that elaborates the Prophet model, ARIMA model, and their core formulas; Experiment that shows the data collection and description, the preprocessing steps, the model fitting, the evaluations; Results and case study that compare multiple models and introduce the potential applications of our work; Conclusion and future work we expected.

Literature Review

In this section, we review previous studies on Product Life Cycle (PLC) and Fashion Life Cycle (FLC), studies on predictive power of social media, and appropriate forecasting approaches for fashion industry.

### *Product Life Cycles (PLC) and Fashion Life Cycles (FLC)*

Product Life Cycle, referred to as PLC, is the market life of a certain product, that is, the entire process from the emergence of a new product to the elimination of that in the market. Products have to go through cycles of four stages: emergence/development, growth, maturity/saturation, and decline/disappearance (Vernon 1966).

Researchers in the business field have been researching on how to contribute to making profitable strategies with PLC theory for a long time (Dean 1950; Levitt 1965; Cox 1967). More importantly, the capability to understand the product life cycle has remained a crucial impact on companies' marketing strategies to manage operational activities since it was introduced to the marketers (Rink 1979; Moon 2005). In other

business areas, there are also studies on the benefit of PLC in helping distributors and new product developments (Restuccia et al. 2016), option valuation (Bollen 1999), and the whole industry (Klepper 1997; Karniouchina et al. 2013).

The fashion industry is no exception. Fashion Life Cycles (FLCs) are very similar, but with its unique PLC curves (Wasson 1968). As shown in Figure 1, there are three types of FLC --fashion, fad, and classic—which are different in their duration length of saturation. The capability to grasp the product cycle stages is even more significant. Owing to the fact that, unlike durables (Cooper 2002), fashion products must preserve great innovations to attract customers due to high psychological demand in purchasing behaviors (Miller 1993; Pesendorfer 1995; Tassie 2004). Thus, the fashion industry should be more sensitive to product life cycles to avoid suffering losses from such declines.

However, studies on the traditional PLC may not be suitable for the FLC perfectly (Yoganarasimhan 2017); thus, some specific studies on fashion trends were conducted since Wasson's framework for the fashion industry (Wasson 1968). Some emphasized social signaling (Corneo & Jeanne 1999), some focused on diffusion routes (Crane 1999), some emphasized on a customer-behavior-based model (Tassier 2004), and some mined the color cycle in the fashion industry (Wong et al. 2016). The literature is largely qualitative or conceptual in nature (with Yoganarasimhan 2017 as an only exception in marketing research), which does not reflect the role of emerging technical development in fashion trend forecasting.

Figure 1. Three Types of Fashion Life Cycle
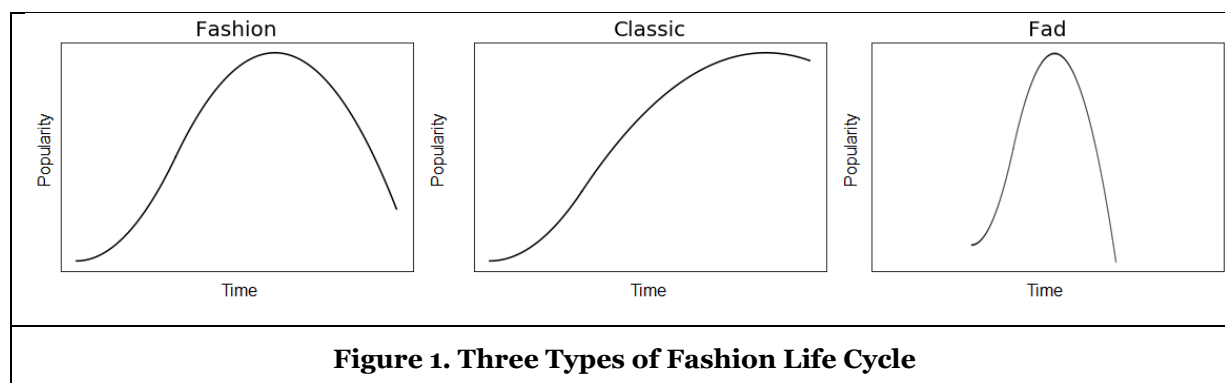
Forecasting Approaches and Social media

Forecasting popularity is crucial in identifying stages in the life cycle. Various diffusion models were proposed for such predictive tasks (Mahajan et al. 1990). The classic being the Bass diffusion model (Bass 1969). However, such models require variables such as total market and sales, which are very challenging to estimate in fashion industry. Fortunately, the emergence and popularity of social media are offering a couple of novel research opportunities in the IS field including trend forecasting (Kapoor et al. 2018), now people can directly find the popularity indicator of a certain product or a fashion element based on social media content. Meanwhile, the predictive power of social media is manifested widely, such as political elections (Tumasjan et al. 2010), the stock market (Bollen et al. 2011), and the cryptocurrency market (Mai et al. 2018).

More particularly, in terms of forecasting popularity on social media, there are many novel approaches. For examples, the classic diffusion model is extended as a self-exciting point process model for predicting popularity (Zhao et al. 2015) and studying content interactions (Yoo et al. 2019) on Twitter; the statistical method modeling the chronological popularity of events on social communities was introduced, considering the evolution of interests and contents (Lin et al. 2010); prediction in short-term popularity of burst and non-burstan viral topics in the internet forum (Hu et al. 2016); an analyst-in-the-loop framework developed at Facebook, with high flexibility and interpretability (Taylor & Letham 2018).

Social media platforms can also help us to understand the PLC (Roch & Mosconi 2016). The propagation sizes of products on social media platforms can strongly reflect customers' purchasing preferences (Dewan & Ramaprasad 2014). However, most of the studies on PLC on social media concentrate on the development stage in product cycles and utilize the rating and review tools most widely (Roch & Mosconi 2016), empirical forecasting of popularity on general social media platforms, such as Instagram and Twitter, is not involved. There are very limited studies that use social media to predict FLC.

Methodology

We propose to use two time-series models in FLC forecasting: ARIMA model and Prophet model. An autoregressive integrated moving average, or ARIMA, is a statistical analysis model that uses time series data to predict future trend (Box & Jenkins 1970). It is one of the most established models and has achieved excellent performance in previous cases.

One problem with ARIMA model is that it does not capture the dynamic and nonlinear time series of popularity of fashion elements on Instagram (Huang et al. 2019). Recently Facebook has proposed a Prophet model with an open-source framework (Taylor & Letham 2018). Compared to ARIMA model, a Prophet model does not require temporal dependence structure in time series data and is able to forecast both the linear and nonlinear trends embedded. And more importantly, human domain knowledge can be applied in tuning parameters and improvement after several iterations, so that makes the forecasting reflect and benefit the real business world more accurately. We introduce both models in this section.

ARIMA Model

ARIMA model is based on univariable empirically. It means that the forecasting of the future value of a variable is made by a linear function of the past values and random errors. The ARIMA model The basic form ARMA (p, q) model that has the following form:

$$\left(1 - \sum_{i=1}^{p} \emptyset_i L^i\right) y_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \tag{1}$$

Where L is a lag operator; y_t and ε_t are the actual value and random error at time period t. $\emptyset_i$ and θ_i are model parameters. Parameters p and q ($p, q \in Z_0^+$) are often treated as the order of the model. For ε_t, it is assumed that the random error is an independent and uniformly distributed variable whose average value is zero from the normal distribution. In some special cases, when the q is zero, it will present as an AR model of order p; when the p is zero, it will present as an MA model of order q.

Another particular case is that the left polynomial has a unit root of multiplicity d:

$$\left(1 - \sum_{i=1}^{p} \emptyset_i L^i\right)(1 - L)^d y_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \tag{2}$$

Parameter d is involved as the number of times the data have had past values subtracted, namely the degree of differencing. Hence, the ARMA (p, q) is extended as ARIMA (p, d, q).

In the steps of fitting an ARIMA model, the time series stationary should be firstly made by data transformation. For the resulting series, d is actually the number of differences required to render it stationary is the order of integration. And then, the parameters are estimated such that an overall measure of errors is minimized, by usually the Maximum Likelihood estimation.

Prophet Model

Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with seasonality and holiday effects (Taylor & Letham 2018). The basic model is as follows:
$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{3}$$

Here, $g(t)$ is used to model the noncyclical changes in the trend, instead of s(t), which catches the changes at fixed intervals, like seasonality. Those off-the-cuff holidays and events also have their influence on the trend, which is presented by $h(t)$. Additionally, there are some peculiar changes inevitably, which cannot be accommodated. ϵ_t is here to represent them.

However, $g(t)$ may differ caused by two types of trend. For nonlinear and saturating growth, $g(t)$ will be presented as a logistic growth model with time-varying capacity $C(t)$ instead of a fixed capacity of in the basic form, as presented in equation (4), otherwise, equation (7) will take effect for trends with a gradually

constant growth rate Meanwhile, at times s_j, S change points will have a growth rate adjusted by δ_j ($\delta \in R^S$).

$$g(t) = \frac{C(t)}{1 + \exp\left(-(k + \boldsymbol{a}(t)^{\mathrm{T}}\delta)\right)(t - (m + \boldsymbol{a}(t)^{\mathrm{T}}\gamma)))} \tag{4}$$

The parameter k is the growth rate, and m is an offset parameter. The rate k is adjusted at changepoints s_j as $k + \sum_{j:t>s_j} \delta_j$. A vector $\boldsymbol{a}(t) \in \{0,1\}^S$ is defined here, so that

$$a_j(t) = \begin{cases} 1, & \text{if } t \geq s_j, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

The offset parameter should be adjusted correspondingly by γ_j, where

$$\gamma_j = \left(s_j - m - \sum_{l<j} \gamma_l \right)\left(1 + \frac{k + \sum_{l<j} \delta_l}{k + \sum_{l\leq j} \delta_l} \right) \tag{6}$$

For trends with a gradually constant growth rate, an adjusted linear model is implemented as

$$g(t) = (k + \boldsymbol{a}(t)^{\mathrm{T}}\delta)t + (m + \boldsymbol{a}(t)^{\mathrm{T}}\gamma) \tag{7}$$

where the γ is set to $-s_j\delta_j$ so that the function is continuous.

In terms of seasonal influences, a flexible model using Fourier series is adopted, so that the periodical effects can be also included (Harvey & Shephard 1993). How quick fitting seasonal patterns is and the prior scale here should be defined by analysts so that have potentials for a contribution of domain knowledge. For seasonality, when P is the regular period, the arbitrary smooth seasonal impact is approximated with a standard Fourier series:

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi\, nt}{P}\right) + b_n \sin\left(\frac{2\pi\, nt}{P}\right) \right) \tag{8}$$

Holidays and events' effects are assumed as an independent. For holiday i, let D_i be the set of past and future dates for this holiday. An indicator function is added here to represent whether time t is during holiday i. For the corresponding change in the forecast, a parameter k_i is assigned to each holiday. Thus,

$$h(t) = [\mathbf{1}(t \in D_1), \dots, \mathbf{1}(t \in D_L)]\boldsymbol{k} \tag{9}$$

Experiment

In this section, we our efforts data collection and our empirical analysis of FLC on Instagram using ARIMA model and Prophet Model.

Data Description

For the fashion industry, "No other social media platform has come to define fashion with such visceral omnipotence as Instagram" (Ahmed 2019). We obtained the dataset from Instagram by web crawling based on a taxonomy constructed in advance. The overall dataset construction process is shown in Figure 2.

Figure 2. Dataset Construction Process
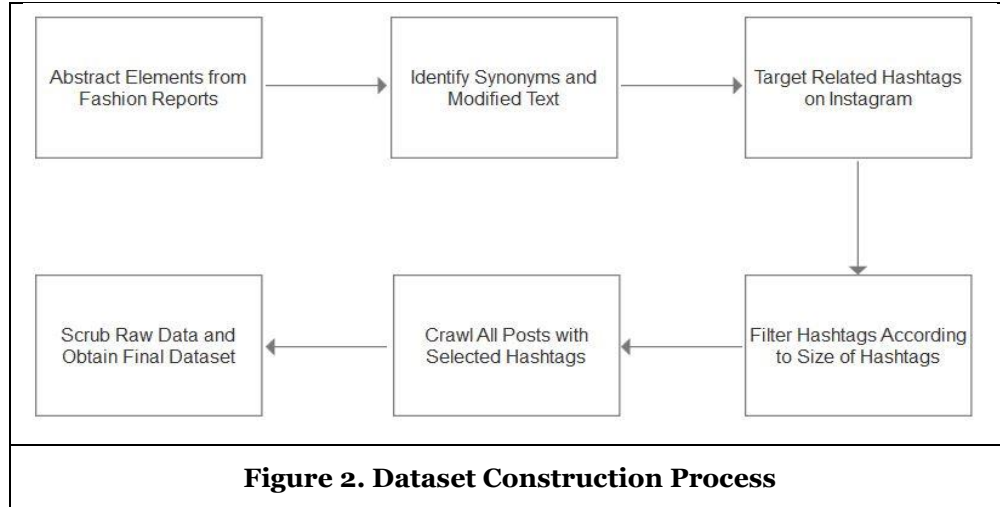
Fashion Taxonomy Construction

A fashion taxonomy is built to help us identify the most typical ones among a large number of fashion elements; such construction was also used widely in previous empirical studies on fashion analysis (Lin et al. 2014; Lin et al. 2015). There are several domain media in the fashion industry, including Cosmopolitan, InStyle, Vogue, Elle, and StyleCaster. The trends reports provided by them consist of a good reference for us to identify the focal elements, particularly those published in 2018 and 2019 to make us focus on the most recent popular fashion elements Additionally, compared to the previous studies on fashion trend, which only relied on the source of Style.com (incorporated in Vogue now) (Lin et al. 2014; Lin et al. 2015; Wong et al. 2016), the more diverse sources can offer a comprehensive pattern to us than before. After summarized those reports, 25 elements were identified in our empirical study (see Table 1 for fashion elements).

As fashion elements can be expressed in different ways, an expansion of the original taxonomy is conducted consequently to include synonyms and modified text based on domain knowledge. The taxonomy should include the synonyms of elements since when people are talking about a fashion element, sometimes they may refer to the synonyms instead of the element itself. Meanwhile, to narrow down to fashion domain color elements are treated with a phrase combination. People often mention colors with specific products in Fashion. For example, when people only mention beige in a conversation, they may be introducing their beige sheet or even the color itself. Nevertheless, a modified text, beige dress, is most likely to appear in the fashion-related context. Therefore, we use a couple of nouns of common fashion products to form modified text with each color and the synonyms of them. The nouns of common fashion products are dress(es), skirt(s), trouser(s), coat(s), outfit(s), suit(s), pant(s), sweater(s), jacket(s).

Data Collection from Instagram

To target information needed and fit the popularity on Instagram precisely, the initial taxonomy is adjusted and output as a set of corresponding hashtags for data crawling.

Firstly, the elements and their synonyms, as well as modified text, are regarded as hashtags to input into the search engine on Instagram, and the engine will show the size of our hashtags, and the related hashtags as well as their size in the drop-down box. The hashtags and their size are recorded. And then, so as to maximize the information gained and minimum noise, only the hashtag having a size between 10,000 and 1,000,000 are selected, unless the most popular hashtag of an element is still fewer than 10,000. In the latter case, the lower bound will become 1,000, but if there is still no hashtag meeting the bounds, the element will be removed from the taxonomy. If a hashtag and its other forms both meet the bounds, only the hashtag having a larger size will remain. Examples of a post with hashtag #baggypants and a search box for the puffer coat are shown in Figure 3 and Figure 4. After targeting the hashtags, web crawling script will start to record the HTTP response from the web in JSON as the raw data, which will be then scrubbed into structural format by preprocessing step that we will cover later. As we conducted this step totally rely on

the Instagram Web itself, so we have collected all the data presented within the user's search. However, it still shows few posts in the early years, which may be caused by the limited user scale on that time.

Finally, a mapping table of elements and hashtags, as shown in Table 1, and all posts with the hashtags targeted in the table on Instagram, are crawled. The final dataset contains 3,447,498 Instagram posts during the time range between 12/10/2010 and 04/08/2020. The specific time range for each element may differ slightly due to different crawling date and emerging date on Instagram.
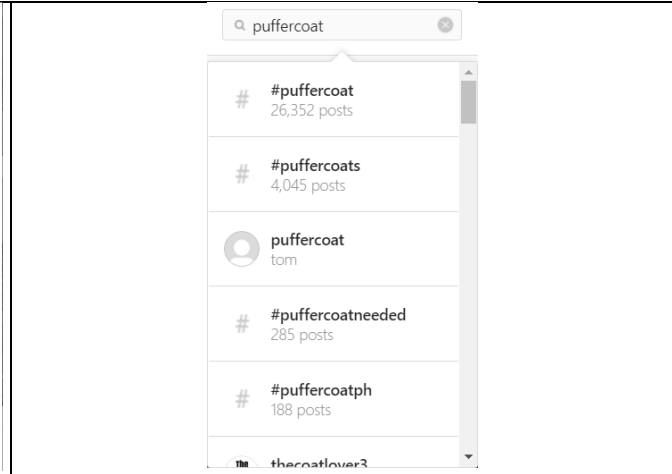

| Figure 3. Example of A Post with Hashtag | Figure 4. Example of A Search Box |

Table 1. Mapped Taxonomy of Elements and Hashtags			
Category	Element	Hashtag	Size
Product	baggy trousers	#loosepant, #baggytrousers, #baggypants, #widelegpants, #wideleg	409,406
	pleated skirt(s)	#pleatedskirt, #pleateddress	223,443
	puffer coat(s)	#puffercoat, #pufferjacket	109,293
	Jumpsuit(s)	#jumpsuits, #boilersuit, #coveralls, #salopette	470,028
	flared trousers	#flaredpants, #flaredjeans, #flarejeans, #bootcut, #bellbottoms	304,546
	velour tracksuit(s)	#velourtracksuit	4,246
	cape	#capecoat, #capelet	20,244
	denim skirt(s)	#denimskirt, #jeanskirt	287,379
Color	coral	#coraldress	14,675
	violet	#violetdress	6,766
	beige	#beigedress, #beigecoat, #beigeoutfit	35,348

	color block	#colorblockdress, #colorblocksweater	9,544
Print	floral(s)	#flowerprint	183,831
	leopard	#cheetahprint	292,556
	houndstooth	#houndstooth	215,059
Fabrics	see through	#seethrough	292,375
	fake fur	#fakefur	201,414
	shiny fabric	#shinyfabric	1,335
	shearling	#shearling, #fleecejacket	120,600
Accessories	Clear heels	#clearheels	26,612
	Micro bag	#microbag	9,113
	Fanny pack	#fannypacks	180,361
	Hermes Birkin Bag	#hermesbirkinbag	12,956
	Baguette Bag	#baguettebag	10,923
	Manolo Blahnik Hangisi	#manoloblahnikhangisi	4,619
Total			**3,447,498**

Preprocessing

A number of preprocessing was performed on the dataset. As shown in Figure 3, a post on Instagram may include many types of data, such as the image and textual content. But only a few of these details are useful in this experiment. And the sporadic post-level data cannot present the general trend. Hence, we firstly drop any temporarily useless variables in the dataset, like the image, the user id, and textual content.

Monthly aggregations are made in element-level afterward, so that only the year and month, the sum of counts of posts, the sum of counts of comments, the sum of counts of likes, the maximum count of comments, and the maximum count of likes remain. The year and month are taken as index "ds," and the sum of counts of posts is actually our target variable, showing the popularity of a certain element. The rest ones are not involved in common forecasting, but according to our domain knowledge, these variables are very likely to affect the trend. Therefore, they are generated for potential usage in the next steps.

Besides, Instagram was actually not popular until the large emergence of the mobile internet and Facebook's acquisition in 2012, people were also not used to talk and show the fashion content on this platform. So, rare posts before the time cannot represent the fashion trend, and their distribution is absolutely sparse. On the other hand, various web crawling date leads to multiple ending date of the dataset. When monthly aggregation was made, incomplete daily data in a month cannot be reliable. In summary, in order to solve the above problems, we decide to truncate the dataset in the time range between 01/01/2012 and 01/31/2020. Finally, the preprocessing has been done, and an example is shown in Table 2.

An external dataset of holidays and events are concluded as well. In addition to common national holidays, it is more important that we identify and add a series of events that may affect fashion trends based on domain knowledge. For example, awards ceremonies of the Emmy, the Grammy, the Oscar, and the Tony. Celebrities and some fashion influencers' apparels during the events and the after-parties tend to spark a heated discussion and imitation.

Table 2. Example of Pre-processed Element-level Dataset					
Ds	Sum of Posts	Sum of Likes	Sum of Comments	Maximum of Likes	Maximum of Comments
01/2012	1	10	2	10	2
02/2012	14	353	16	41	6
...	...	...	...	...	...
12/2019	8828	2131638	114495	34988	10506
01/2020	8728	2112949	105786	45555	782

Fitting

ARIMA model: ARIMA model requires multiple steps in model preparation that is highly time-consuming, including parameter tuning. It is necessary to have the series stationary and to pick the appropriate p value and q value. Thus, here we are using pmdarima to help us avoid the problems. Pmdarima is a Python API for auto-ARIMA modeling, like auto.arima, a traditional package in R.

Differencing tests have been done first so that the order of differencing d can be defined. Afterward, a series of pre-defined ranges of p value and q value will be used to fit models. The seasonality is also considered by identifying the optimal P and Q hyperparameters after the optimal order of seasonal differencing D is decided by Canova-Hansen testing (Canova & Hansen 1995). The best ARIMA model will be handed over after an optimization based on Akaike Information Criterion (AIC) (Akaike 1974).

Prophet (non-tuned): The type of growth is a required parameter assigned manually, thus even though manual intervention is not expected, a visualization should be done first to decide the most possible growth type. When the growth is assigned as logistic, the constant capacity and floor will be added. We also define an external dataset only containing the general national holidays, such as New Year, Christmas Day, and so on, which is used in this fitting. In terms of other hyperparameters, the default setting will remain as they perform well in the prediction of Facebook events (Taylor & Letham 2018). An embedded Stan program (Carpenter et al. 2017) in Prophet will take on the task of model fitting, as Stan's L-BFGS is used to discover a maximum a posteriori estimate.

Prophet (tuned): The main changes compared to the non-tuned model are settled in four components: location and number of changepoints, the smoothing parameters, adjusted external holiday dataset and time scales of seasonality, and capacity and floor in logistic growths.
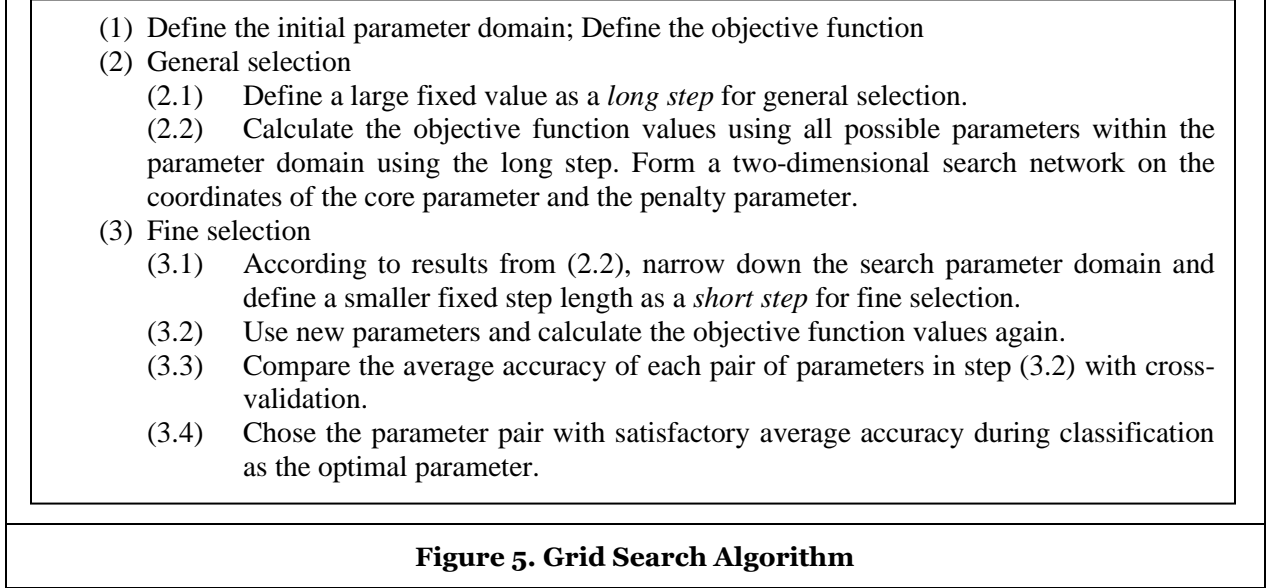
Location and number of changepoints are also defined as a possible range based on the visualization and related fashion events. The processed fashion-associated holiday dataset before is used here as a tuned part as well. Besides, fashion trend is highly fickle and sensitive to seasonality, so that the default smoothing parameters and seasonality scales trained from mass data cannot be applied in this model well; on the contrary, they should be able to reflect intense ebbs and flows by manual tuning. Thus, a couple of possible ranges of them are also defined here.

For this model, we define a new method to obtain the capacity and floor in each time point t_i by rolling window $T(t_1, t_2, \dots, t_{i-1})$. A possible range of ζ_f and ζ_c ($\zeta_c > 1 > \zeta_f$) are determined as well. At time point t, the floor $F(t)$ will be the product of ζ_f and the minimum of the sum of posts in the previous rolling window T, and the capacity $C(t)$ will be a product of ζ_c and the maximum one.

Another significant change here is additional regressors. Prophet provides an approach for additional regressors working similarly with holidays and events. The features related to likes and comments are left in preprocessing but never used in previous steps. But they can be good regressors as we made an ordinary least-squares linear regression, in which features about likes and comments are regarded as independent variables and the sum of posts is the target variable. A R^2 of 0.988 is obtained from the whole dataset and a mean R^2 of the element-level datasets is 0.809.

Finally, a Grid Search will be done within a pinch of possible parameters defined according to domain knowledge. The Grid Search algorithm is a non-linear parameter estimation method. The Grid Search algorithm of estimating parameters is an exhaustive search process and contains two steps: general selection and fine search. The detailed process is provided in Figure 5.

In this fitting process, the domain knowledge is incorporated mainly as the holiday and events dataset construction, additional regressors, and the initial parameter range for grid search. It correspondingly states the attribute of the Prophet model, "Analyst-in-the-Loop".

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(1) Define the initial parameter domain; Define the objective function
(2) General selection
    (2.1)   Define a large fixed value as a *long step* for general selection.
    (2.2)   Calculate the objective function values using all possible parameters within the parameter domain using the long step. Form a two-dimensional search network on the coordinates of the core parameter and the penalty parameter.
(3) Fine selection
    (3.1)   According to results from (2.2), narrow down the search parameter domain and define a smaller fixed step length as a *short step* for fine selection.
    (3.2)   Use new parameters and calculate the objective function values again.
    (3.3)   Compare the average accuracy of each pair of parameters in step (3.2) with cross-validation.
    (3.4)   Chose the parameter pair with satisfactory average accuracy during classification as the optimal parameter.

Figure 5. Grid Search Algorithm

Simulated Historical Evaluation

The mainstream k-fold cross-validation and train-test splitting method cannot be directly used in our prediction, because it is absolutely meaningless to randomly split our time series data into multiple parts. Fortunately, Prophet provides a simulated historical forecast (SHFs) method based on "rolling origin" (Tashman 2000) for evaluation. There is no same method embedded in ARIMA, but we repeat the same evaluation procedure for ARIMA so that the future comparison can be conducted.

In an evaluation process, firstly, a number of C cutoff points should be determined in historical data. At each cutoff point c, the model is trained based on the historical data before the cutoff date and tested in the future horizon period H_c. For each horizon point h_c in the period, a predicted value $yhat_{h_c}$ and the true value y_{h_c} can be observed and evaluated.

The Median Absolute Percentage Error (MdAPE) is used here as the main error metrics to evaluate and compare the various models, with its more reliability and better protection against outliers rather than Root Mean Square Error (RMSE) and MAPE (Armstrong & Collopy 1992). Nonetheless, MAPE is also provided as ancillary metrics for its interpretability. These two measures are defined by the formulas:

$$APE_{h_c} = \left| \frac{y_{h_c} - yhat_{h_c}}{y_{h_c}} \right| \tag{10}$$

$$MdAPE = median\left(APE_{h_c}\right) \tag{11}$$

$$MAPE = \frac{\sum_{c=1}^{C} \sum_{h=1}^{H} APE_{h_c}}{C * H} \tag{12}$$

Where the y_{h_c} and $yhat_{h_c}$ is actual value and forecast value, separately; and the value 1 of h and c is the first horizon point and first cutoff point instead of numerical meaning.

In our experiment, we choose the spacing between cutoff dates is 180 days (6 months), and the forecast horizon is 365 days (12 months).

Meanwhile, although many time-series forecasting tends to calculate their performance based on the whole period, this method may not reflect the model's strength at different cutoff points. Thus, we also utilize another evaluation approach to present the model's performance at multiple horizon points. Let the number of elements is N (N is 25 in our dataset), and remain the horizon h at the same point, so that the model's performance based on the whole dataset rather than element-level can be:

$$Mean\ MdAPE = \frac{1}{N}\sum_{n=1}^{N} MdAPE \tag{13}$$

$$Mean\ MAPE = \frac{1}{N}\sum_{n=1}^{N} MAPE \tag{14}$$

Result

We present here results from two models with evaluation metrics on the whole dataset and on each element level respectively.

Comprehensive Predictive Power

To comprehend the overall performances of models, we rely on a comparison analysis at different horizon period as shown in Figure 6. This vertical comparison can present more significant information, comprehensive predictive power.

In a PLC analysis, the ability to grasp the trend in a very short term is less helpful than that in a long term. Even though short term predictions reflects the current market trend, this trend may be caused by seasonality, and fashion firms are less likely to adjust their production and sales strategies in such a short time window. The prediction of long-term trends will allow fashion market participants to cope with changes in a more orderly manner without losing opportunities. In this case, obviously the tuned Prophet model performed the best among the three models. However, to our surprise, the untuned Prophet model does not show a clear advantage over ARIMA model in long term predictions. On the contrary, ARIMA model 's performance in short-term predictions shows superior performance.

Figure 6. Performance Comparison in Multiple Forecast Horizon (Left: Mean MdAPE; Right: Mean MAPE)
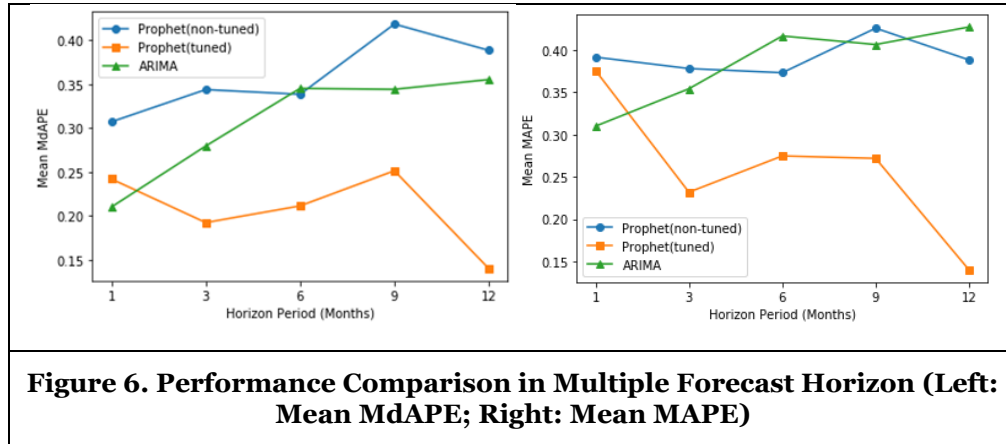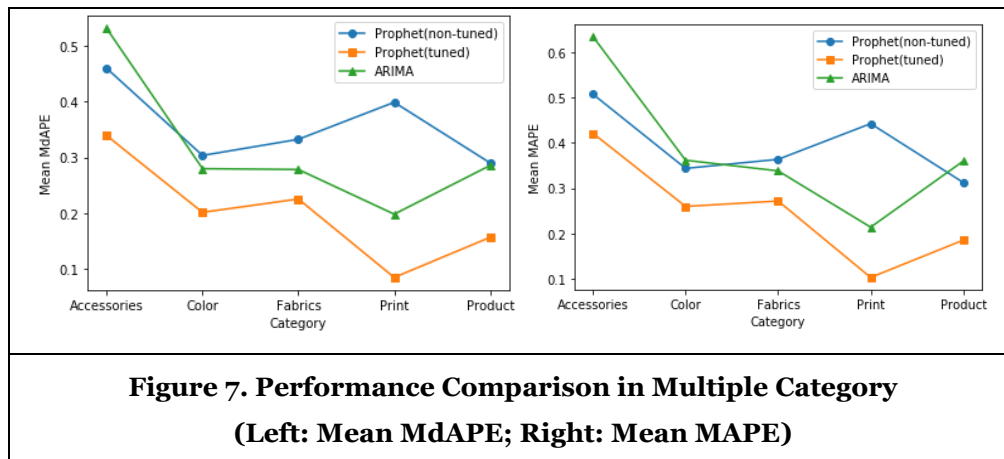
Specific Applicability

A more detailed comparison is exhibited in Table 3. According to this table, we can more specifically understand the applicability of different models in various fashion categories. In order to provide more intuitive information, Figure 7 is also shown below.

Table 3. Comparison of Different Models' Performance at Element-level							
Category	Element	ARIMA		Prophet (non-tuned)		Prophet (tuned)	
		MdAPE	MAPE	MdAPE	MAPE	MdAPE	MAPE
Product	baggy trousers	0.246	0.293	0.273	0.277	0.123	0.142
	pleated skirt(s)	0.293	0.312	0.356	0.365	0.090	0.108
	puffer coat(s)	0.457	0.662	0.304	0.380	0.255	0.298
	Jumpsuit(s)	0.215	0.290	0.303	0.347	0.181	0.213
	flared trousers	0.126	0.182	0.152	0.169	0.104	0.149
	velour tracksuit(s)	0.482	0.612	0.305	0.337	0.259	0.294
	cape	0.209	0.238	0.275	0.291	0.145	0.169
	denim skirt(s)	0.256	0.287	0.353	0.334	0.094	0.107
Color	coral	0.167	0.256	0.219	0.245	0.122	0.143
	violet	0.247	0.253	0.241	0.254	0.183	0.203
	beige	0.295	0.305	0.352	0.359	0.114	0.183
	color block	0.410	0.632	0.402	0.516	0.386	0.509
Print	floral(s)	0.119	0.133	0.197	0.227	0.085	0.103
	leopard	0.278	0.296	0.733	0.790	0.112	0.138
	houndstooth	0.197	0.212	0.267	0.310	0.056	0.067
Fabrics	see through	0.140	0.153	0.255	0.263	0.072	0.099
	fake fur	0.314	0.363	0.293	0.359	0.256	0.260
	shiny fabric	0.424	0.468	0.350	0.378	0.323	0.449
	shearling	0.235	0.368	0.432	0.454	0.250	0.278
Accessories	Clear heels	0.469	0.567	0.472	0.513	0.172	0.199
	Micro bag	0.470	0.508	0.402	0.427	0.221	0.243
	Fanny pack	0.884	0.821	0.459	0.475	0.432	0.463
	Hermes Birkin Bag	0.514	0.717	0.519	0.610	0.565	0.829
	Baguette Bag	0.445	0.651	0.496	0.546	0.296	0.390
	Manolo Blahnik Hangisi	0.408	0.541	0.412	0.472	0.349	0.401

Figure 7. Performance Comparison in Multiple Category

(Left: Mean MdAPE; Right: Mean MAPE)

According to the above table and figure, it is clearly seen that all three models fail to bring about advantages in predictions on the category of accessories. This circumstance may be caused that the customer behaviors about accessories are less likely to be affected by seasonality, and the customer base of each accessory is not as diverse as other categories, which means, for example, Hermes Birkin Bag has is so expensive that the discussion has to be limited in a small affordable group. This capacity limitation makes the process of popularity much random and full of subjective factors about customers themselves.
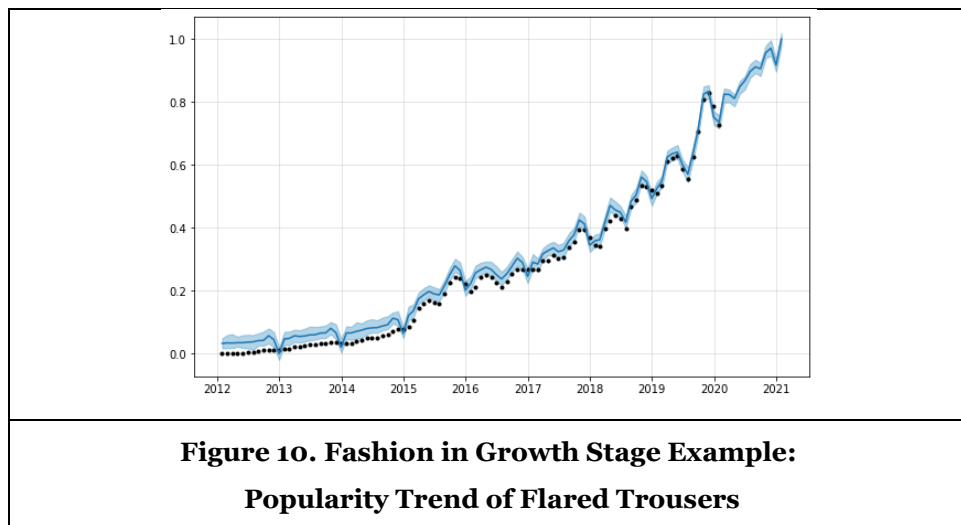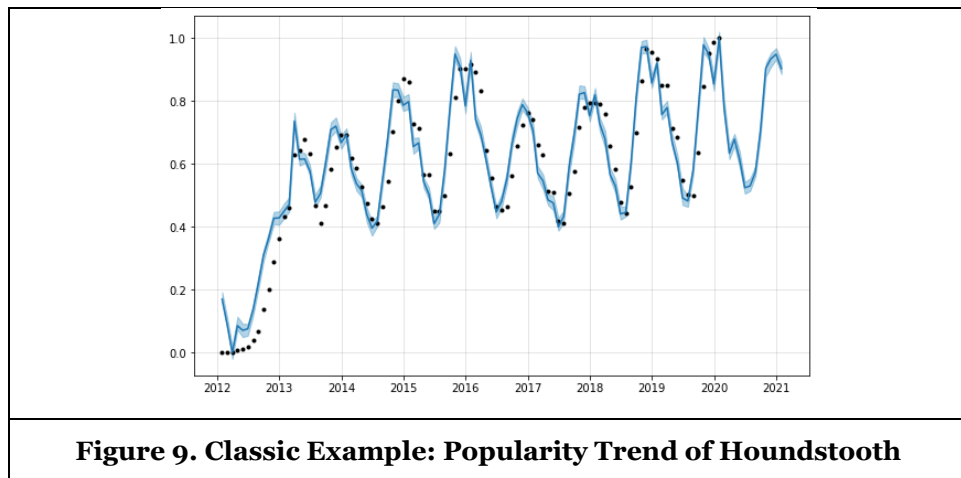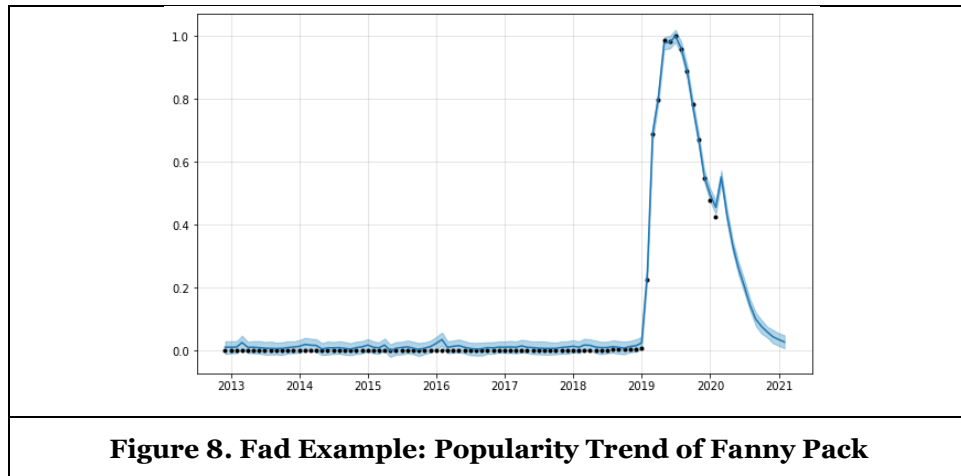
Anyway, the table and figure still proclaim the advantage of the tuned Prophet model. Actually, when this model is not tuned, those default parameters that trained from a more general trend (Taylor & Letham 2018), is not able to perform better than the traditional ARIMA model. However, the domain knowledge targeting a certain type of elements can make the Prophet better. This is exactly what Taylor and Letham emphasized when they proposed the Prophet model, "Analyst-in-the-Loop."
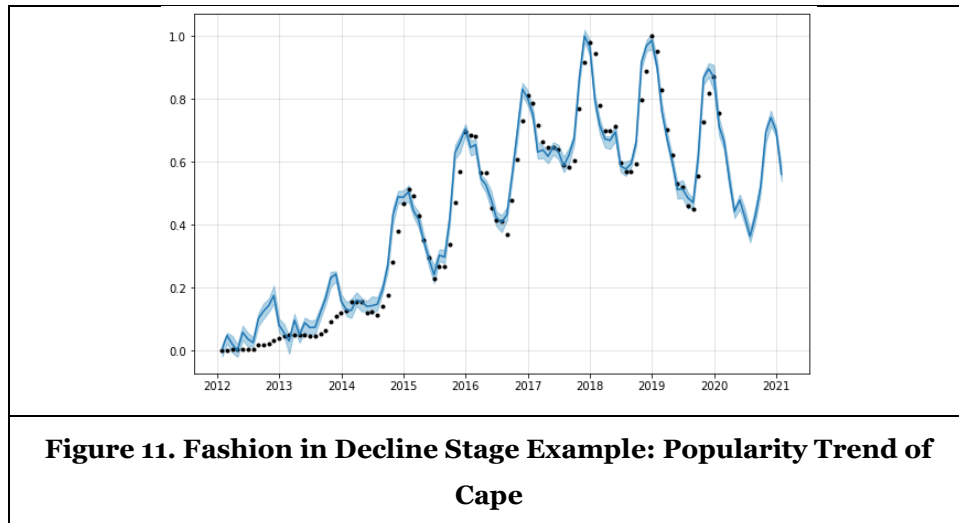
FLC identification: Case Study

The performance of the model provides an endorsement of its ability to predict the future trend of fashion elements. Here we select four typical elements presenting multiple types of FLCs as examples, as shown in from Figure 8 to Figure 11. In each figure of them, the trend actually is made up of two components. The scatter subplot shows the true value points, and the line subplot shows the trend line predicted.

As we introduced in the literature review, there are three typical fashion trends, Fashion, Fad, and Classic, presented by different FLC curves. Among our examples, it is apparently seen that the fanny pack here is most likely to be a fad, with the rapid growth of popularity in the short term and short maturity period from Figure 8. Based on Figure 9, houndstooth can be accepted as a classic fashion element because of its stable popularity at a fairly high level, even though this popularity may undulate due to seasonality.

Flared trousers and cape, these two elements are both having the common type of fashion trends, but in different stages, as shown in Figure 10 and Figure 11. The element, flared trousers, has always shown a clear upward trend, and there is no sign of slowing down so that it tends to be regarded as in the growth stage. By the way, another interesting phenomenon is that this element is not affected by seasonality well, which may be caused that this is a fashion element for all seasons, after all. Another element, cape, is most likely in the maturity stage of its life cycle. And it also shows a little downtrend. Thus, for fashion firms or designers, it is wiser is to focus on elements like flared trousers and reduce the attention to elements like the cape. It will be very useful for avoiding market risks and seizing opportunities.

Figure 8. Fad Example: Popularity Trend of Fanny Pack

Figure 9. Classic Example: Popularity Trend of Houndstooth

Figure 10. Fashion in Growth Stage Example:

Popularity Trend of Flared Trousers

Figure 11. Fashion in Decline Stage Example: Popularity Trend of Cape

Conclusion and Future Work

In this study, we explore the potentials of FLC identification of fashion elements on social media by three various models, ARIMA, Prophet (non-tuned), and Prophet (tuned). It is accepted that the Prophet (tuned) model can be most helpful owing to its much better prediction performance compared to the baseline models. This also further illustrates the role of "Analyst-in-the-Loop" in the prediction process of the Prophet model, as the Prophet (non-tuned) model does not perform more powerful than ARIMA model as we expected.

More importantly, its predictive strength validated by our experiment can be used to predict the future trend of fashion elements, which make the identification of FLC types and stages more approachable, like what we do in our case study. For participants in the fashion industry, whatever the designers, brands, or market consultants, this approach is able to make them seize the future opportunity, which gains profits from the rising elements and avoids possible losses from declining elements. Additionally, for other products that are sensitive to life cycles as same as fashions, the Prophet model can also be utilized in studies on the popularity of them.

However, there are still lots of future work, having the study more stable and helpful. For example, although our dataset contains about 3,447,498 historical posts on Instagram, a larger dataset will be more helpful for validation if it can be obtained. Besides, in the fashion industry, high-end fashion, such as runway, affect the market and trend deeply. Thus, the catwalk data can also be an appropriate and excellent supplement. Sales data, as the most intuitive response to the market, can also play an important role in validation, and complement the popularity. Therefore, in the future, we expect to combine our work with high-end fashion data, which have been studied well and helpfully (Lin et al. 2014; Lin et al. 2015; Wong et al. 2016); and validate the forecasting approach in more intuitive indicators, such as sales data and Google trend. We hope the future work can help the current study contribute much more to the traditional fashion industry, by some novel big-data approaches.

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