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Identifying Future Demand in Fashion Goods: Towards Data Driven Trend Forecasting

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Abstract

Fashion is primarily based on adoption of trends by consumers in textiles, clothing, footwear, jewelry and art, inter alia. As fashion is based on human preferences, it is characterized by dynamic changes throughout seasons and years, short lifecycles, low predictability, high volatility of demand and impulse purchases. In the dynamic environment of apparel markets, fashion firms aim at successfully forecasting both the desirability of new collections and the volumes of each item produced and released to the market under terms of substantial levels of uncertainty. When demand for an item exceeds its supply, the firm is likely to lose additional profits that could have been collected had a sufficient volume of this item been present in the market. Alternatively, if the supply of an item surpassed its demand, it would remain unsold, thereby generating loss equal to its marginal production and distribution costs.

The paper suggests that accurate fashion trend forecasting in the context of multiple variants of color clothing can significantly enhance trend forecasting in textiles, consequently maximizing the profits of fashion companies while minimizing the forecasting error and reducing the costs that result from excess capacity of production or from loss of potential revenues due to low demand.

Keywords: Trend forecasting; Color variants; Excessive supply; Excessive demand

Introduction

The seasonal planning and pre-production of fashion collections involve a substantial risk, as textile producers are required to determine the colors, tones, pattern and contour, as well as the volume of items produced, for each model long before its release to the market. Rinallo D, et al. [1] and Kim E, et al. [2] state that fashion producers complete the design, planning and pre-production portfolios of upcoming seasons approximately 18 to 24 months before the beginning of the season.

Fashion trend forecasting is a complex process that aims at identifying future tastes and preferences of customers, as well as the underlying influences that foster them, in order to merge them into the insights of fashion designers, and by that to assist in enhancing the desirability of models in the market (see, for example, the analysis of the underlying motives of Chinese consumers of luxury goods [3]). Additionally, Stolze HJ, et al. [4] highlights the need for a supply chain that corresponds to the shopper's ecosystem in a more customized, rather than a generic, manner. However, the process is subject to several main sources of difficulty. Firstly, the identification of already-existing trends in the population is difficult by and of itself, and requires a broad spectrum of social, economic, design-oriented and cultural-monitoring specialization [5]. Secondly, the sample of customers examined by trendologists may not be a representative group, and hence may produce substantial biases when insights are generalized to a larger population. Thirdly, the analysis of current trends may not identify future occurrences and changes in preferences, which may arise in reaction to exogenous and unexpected events (for example, the rise of the "Arab Spring" in Tunisia, Syria and Egypt and its consequent cultural, social and economic effects).

Rinallo D, et al. [1] and Visconti LM [6] presents the forecasting of fashion trends as a process that mainly involves designers and social and cultural experts who predict the attributes of upcoming collections on the basis of cultural and societal developments. However, the forecasting of the success of new designs by the public provides only partial information to producers. The other variables in production decisions of companies are the quantities planned to be released to the market throughout the season (and the bulk is usually produced in advance) and the demand function of the population of potential customers in terms of "design" vs.

price (see [7] for exemplary model of these industrial and economic terms). The complex forecasting production processes may require sophisticated methods, such as flexible production planning models [8], social media trend analysis [9], and application of artificial neural networks [10]. In particular, the production plans of fast fashion companies, such as Zara, are intentionally lower than the expected demand: i.e. each model is produced only in a small series, in order to ensure that they completely sell every product that they offer [11-13]. Thereupon, these producers eliminate the risks of unsold items in terms of their unreleased revenues and logistics management [14-16]. Beyond the financial losses that fashion producers suffer for inaccurate sales forecasts, either due to inventory shortages or excess volume that remains unsold, unsold items generate negative environmental externalities, such as larger pollution during their production and waste [17-19].

Interestingly, most fashion-forecasting reports are produced by the milieu of designers and cultural experts, and rarely involve any insights from economists and engineers [20,21], despite the wealth of forecasting models and methodologies applied in statistical, demographic, and social analyses, as well as in economics and marketing research. However, recent works have applied analytical and quantitative tools and techniques to assist in assessing the predictability of customer tastes and to decrease forecasting errors ex ante [22].

Models that evaluate the impact of colors on consumer demand can be expanded and applied in other fields, where color selection is paramount to purchase decisions (such as furniture, jewelry and kitchenware), but may be less applicable where purchase decisions are driven by technical merits (such as speed in the case of automobiles or sound quality in stereo systems).

Expanding the Domains of Forecasting: From Demand to Trends

Trend forecasting is significant both for matching the introduced collection to the market's tastes and preferences, and for adapting the supply of produced goods to the demand. Well-founded forecasts can prevent the costs associated with excess inventory (that remains unsold) or lack of inventory (that translates into loss of potential profits). Additionally, forecasting is critical for enhancing production and procurement planning, lead times, and inventory management. In the fashion industry, forecasting is a difficult task because of the short life cycle of products and the high volatility of demand [23,24].

The main purpose of the forecasting process is to meet high volumes of demand, minimizing the risks associated with a surplus of goods remaining unsold at the end of the season, or a lack of popular items due to excessive demand. Fashion trend and demand forecasts are conducted where partial information of the market and customer preferences is present. Each season, designers produce and release to the market a multitude of new models (that can be perceived as relatively new products) without historical or complete information that can serve as a basis for assessment of the prospects of the success of products. Yet, as customer preferences do not drastically change between successive seasons or years (although major changes may take a place over longer periods of time), designs can be affected by the cumulative knowledge and know-how of the market that fashion firms acquire. For this reason, using historical data for the purpose of trend forecasting and assessment of the prospects of success of future products should only be approached with maximum caution.

Recently, artificial neural networks (ANNs) were applied to assist the complex processes of fashion trend forecasting and, in particular, to distinguish the relevant data upon market preferences from the stream of information that analysts and designers address [25,26]. These methods imitate the structure and functionality of biological processes and allow qualitative forecasting with a limited amount of data [27,28].

The Autoregressive Integrated Moving Average (ARIMA) is an additional statistical technique that combines a variety of statistical methods, such as integration of regression automatically moving average [29], to predict the demand for goods [28,30]. Even though ARIMA models are based on the assumption that linear relationships between variables exist (for example, between the volume of gray tones and the demand for the product), they provide a better clarity of the effects of independent variables on the resulting behaviour of fashion customers than ANN models do. Additionally, ANN models require long-time series (for the "training" or the calibration of the models) that may not be available, while ARIMA models are based on smaller volumes of data describing the market behavior over shorter periods [31].

ARIMA based models are typically applied due to the need to carry out forecasts with a normally distributed demand of fashion goods, and on the basis of representation of more restricted time periods. (For similar practices in various industrial sectors, see [32-34]).

Conclusion

The paper highlights the challenges associated with the introduction of new fashion collections to the market. These difficulties emerge due two source of uncertainty that fashion companies and designers confront. First, quantitative forecasting should be applied in greater scope and depth to prevent costly inventory errors that are associated with excessive or partial demand, both incorporating substantial operational and financial costs for fashion companies. Second, the rapid changes in consumer tastes suggests that design forecasting methodologies should be applied (beyond the seasonal reports of trend forecasting agencies) to cater to the developing preferences of customers with maximal success.

While the former domain is populated with advanced statistical and mathematical models aiming at the accurate forecasting of demand for the necessary inventory of fashion goods at any stage of the season, the latter is primarily based on qualitative methods, such as analysis of cultural, social and demographic changes. Thereupon, the paper highlights the importance of the application of well-based and traditional forecasting models that have proven

themselves in the domain of demand forecasting in the domain of trend forecasting, to assist in resolving multiple issues, such as forecasting the demand for textile colors and assessing the purchasing decisions of shoppers substituting the purchase of sold-out items with available goods.

Recent methods, such as ANN and ARIMA provide a quantitative toolbox of state-of-the-art statistical and mathematical models that can be implemented virtually for any type of fashion and apparel goods, should data upon purchases, orders and other attributes of consumer decisions be present. By applying these quantitative tools, which are currently restricted to forecasting demand volumes and inventory levels, fashion companies can gain valuable insights upon the dynamic and ever-changing consumer preferences.

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Conflict of Interest

Authors declare no conflict of interest.

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