A survey on retail sales forecasting and prediction in fashion markets

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Sales forecasting is an essential task in retailing. In particular, consumer-oriented markets such as fashion and electronics face uncertain demands, short life cycles and a lack of historical sales data which strengthen the challenges of producing accurate forecasts. This survey paper presents state-of-the-art methods in the sales forecasting research with a focus on fashion and new product forecasting. This study also reviews different strategies to the predictive value of user-generated content and search queries.

Keywords: manufacturing; data mining; prediction; planning

1. Introduction

Sales forecasting can have a crucial impact on the success and performance of companies. Inaccurate forecasts presumably lead to stock-outs or over stock inventories which result in losses for the companies. In particular, within the retail and consumer-oriented industries, such as the electronic market or the fashion industry, accurate forecasts are essential. Companies face several challenges regarding accurate forecasts. For instance, they have to place their production plans before exact knowledge about future demands is available. This is required due to the fact that most production plants are located in Asian countries and therefore the time-to-market is longer than the selling period of fashionable products. Therefore, accurate forecasts are crucial because the production of successful products is hardly possible (Fissahn, 2001). In addition, other factors, such as changing weather conditions, holidays, public events as well as the general economic situation, can have an impact on future demands (Thomassey, 2010). Moreover, fashion items are replaced mostly for the following season; therefore, there is a huge lack of historical sales data (Thomassen, 2014). Summing up, due to short life cycles, high variability in products and demand uncertainties, fashion companies often face high challenges with regard to precise forecasts.

For sales forecasting purposes, statistical techniques, such as exponential smoothing, ARIMA, Box & Jenkins model, regression models or Holt-Winters model, are often applied. Newer approaches introduce the application of advanced techniques such as neural networks or data mining models. In order to increase the forecasting performances, more often hybrid models are developed to use the advantages of different models for a new combined approach (Liu, Ren, Choi, Hui, & Ng, 2013). Especially, hybrid models seem to be accurate in sales forecasting (Aburto & Weber, 2007; Khashei & Bijari, 2011; Lee, Shih, & Chen, 2012). Xia and Wong (2014) proposed the differences between classical methods (based on mathematical and statistical models) and modern heuristic methods. In the first group, they name exponential smoothing, regression, Box–Jenkins, autoregressive integrated moving average (ARIMA), generalized autoregressive conditionally heteroskedastic (GARCH) methods. Most of these models are linear and are not able to deal with the asymmetric behaviour in most real-world sales data (Makridakis, Wheelwright, & Hyndman, 1998). In contrast, the modern heuristic methods are mostly able to handle these challenges. In the field of fashion forecasting, these statistical techniques in their original forms face challenges in producing accurate forecast results, due to factors such as irregular patterns and high variability (Choi, Hui, & Yu, 2011) of fashion sales data. In order to handle these variables, more advanced models were developed in the literature. However, due to the idiosyncrasies of the fashion industry and requirement of historical data, these methods can be hardly adopted by apparel companies (Thomassen, 2014).

This survey paper gives an overview of recent sales forecasting research with a focus on retail and fashion sales forecasting. Introducing new products to the market, com-
panies have to deal with a lack of historical sales data. Motivated by this problem, researchers have proposed different forecasting models for this special scenario. These works will also be presented. Other review papers on sales forecasting do not consider user-generated content as a potential factor within this research field. However, the fashion market is a highly consumer-oriented market, and these consumers publish content online on different social media applications. Therefore, their opinions, experiences and expectations might play a relevant role within fashion forecasting processes (Beheshti-Kashi & Thoßen, 2014). The last section of the paper explores the application of user-generated content for prediction purposes and gives an overview of works within different domains.

2. Fashion sales forecasting

The literature discusses different approaches on the adequate dealing with the difficulties of the fashion industry concerning accurate forecasting. Mainly two different aspects are the focus of these works. The first approach is about statistical methods and the combination of new methods as well as the comparisons of their performances. The second research stream focuses more on the adequate integration of expert judgement and the combination with statistical forecasts (Davydenko & Fildes, 2013). They discuss, for instance, questions such as the added value of including expert knowledge (Franses & Legerstee, 2013). Moreover, they examine the integration of past knowledge of experts for adjustment purposes of statistical models and stated that in cases of poor performance of the model, the experts’ judgement leads to more accurate forecasts. Some new features for forecasting support systems such as the inclusion of past sales data and in addition to past judgements have been suggested (Franses & Legerstee, 2013). This paper will primarily examine the first mentioned research stream. For a detailed overview of the judgemental forecasting research, it is recommended to look at Lawrence, Goodwin, O’Connor, and Önkök (2006).

Within the first field, recent studies have focused on artificial neural networks (ANNs) for sales forecasting and report better performance compared to conventional approaches (Sun, Choi, Au, & Yu, 2008). Therefore, Sun et al. introduce the application of the so-called extreme learning machine (ELM) for fashion sales forecasting. The ELM was proposed by Zhu, Qin, Suganthan, and Huang (2005) due to its advantages such as faster learning compared to the standard gradient-based learning algorithm. Other studies apply the evolutionary neural network (ENN) for forecasting in fashion retail. Conducting real data analysis, they show promising results, especially in the case of noisy data (Au, Choi, & Yu, 2008). Similarly, Wong and Guo (2010) base their model on the ELM and propose a hybrid intelligent model for mid-term forecasts for fashion retailers.

Thomassey and Happi (2007 and Thomassey (2010)) introduce a model that consists of two automatic systems (mean- and short-term forecasting). In order to deal with the idiosyncrasies of the apparel industry such as the lack of historical data, they also propose to apply soft computing methods: fuzzy inference systems and neural networks. This approach handles the challenges in an effective way and shows promising results (Thomassey, 2010). However, the author reports that these methods can be hardly adopted by apparel companies (Thomassey, 2014). Nevertheless, a large number of commercial software tools often apply these techniques for their predictions (Jain, 2007), although most sales experts use these forecasts only as a baseline for their own estimations.

Mostard, Teunter, and de Koster (2011) introduce in their work a new approach which differs from the described models. They focus on pre-order demand information and apply three methods to advance demand forecasting: preview division, equal division and top-flop division. Their findings reveal promising forecasts for all three methods, among which, the top-flop approach produces the most robust predictions.

Similarly, Teucke, Ait-Alla, El-Berishy, Beheshti-Kashi, and Lütjen (2014) focus on pre-orders of seasonal clothing items and suggest a two-step prediction model which is able to estimate the additional post-orders before the actual production is started. They apply a decision tree approach in a first step to determine those articles which are likely to be re-ordered, and a support vector machine for the forecasts of the actual post-orders in a second stage. Applying this hybrid approach, more accurate results have been achieved (Teucke et al., 2014).

Ait-alla et al. (2014) suggest a mathematical model for robust production planning for apparel suppliers. The focus is to support the decision-making on the distribution of articles on different production plants. Results show that the model performs robustly and can successfully deal with constrains of uncertain consumer demands. Tan, Guan and Karimi (2013) proposed the relationship between the subsidy policy and the agricultural total factor productivity. And the authors provided some policy implications in the paper. Moreover, the problem of local capacity control for production networks with autonomous work systems has been addressed in Karimi, Duffie and Dashkovskiy (2010). The main focus was on both the stability of the production network and the local capacity adjustments in order to maintain the work-in-progress (WIP) in each work system in the vicinity of planned levels.

Given the complexity and necessity of the problem, various authors presented reviews on fashion sales forecasting with different focuses. In addition, an overview on older research on fashion sales forecasting, the work of Liu et al. (2013) and that of Thomassey (2014) are recommended. Nenni, Giustiniano, and Pirolo (2013) give also a review of the actual sate of fashion sales forecasting, however, with the focus on the different supply chain strategies. While these authors have not considered the possibility of applying user-generated content for prediction purposes,
this survey paper adds this perspective into the discussion of sales forecasting.

3. New product forecasting

This section presents an overview of recently published works focused on forecasting of new products applied on various real-world scenarios. Kahn (2014) underlines the difference of forecasting new products compared to the forecasting process of existing products. He considers quality assumptions, judgements and processes as crucial factors and concludes that following this approach, new products will be more successful. In this section, real-world examples from other markets in addition to the fashion market will be demonstrated. The electronic market, for instance, shares similar characteristics such as short life cycles or high product variability and therefore, approaches from this market are interesting within the research of fashion sales forecasting in order to adapt these methods to the fashion market. Another research suggests a standard forecasting procedure and additionally introduces a decision support system for new products. The New Product Forecasting System (NPFS) performs accurately for products with a stable demand and long life cycles. The precision is still higher than conventional methods having only one series of data. The system was tested for three real-world scenarios: tee, soft drink and cosmetics. In all these scenarios, the forecast results were precise. However, the authors conclude that the NPFS should be applied to more real-world scenarios such as electronics or fashion markets in order to test the system’s capability to deal with varying demand and short life cycles (Ching-chin, Ao, Wu, & Kung, 2010).

Lee, Kim, Park, and Kang (2014) focus on the pre-launch forecasting of new product demand based on the Bass model. They apply statistical and machine learning techniques for the prediction of the Bass model parameters and test six algorithms separately in a first step. In addition, they create a combined measure. Both approaches have been tested for 3D television sales and outperform traditional methods with more accurate results. Also, Tanaka (2010) applies his model on the electronic market. He focuses on new released products and designed his model to meet mainly the conditions of accuracy, timing of forecast release, and the broad coverage of items. He grounds his forecast model on accumulated sales data of similar product groups, for both short- and long-time sales and reports more accurate results in contrast to existing methods. In Lee, Lee, and Lee (2012), the focus is on consumer reservation prices taken from consumer surveys and applied for new product forecasting. In order to obtain more precise forecasts, the preliminary forecasts are updated using the MAP estimator. They calculate forecasts before a product is launched and shortly thereafter. The model is tested with real data from the South Korean broadband internet market and benchmarked against the Bass model and the logistic growth model. It is reported that the new approach outperforms both methods for pre-and-post launches.

In order to deal with the seasonality and limited data problems of fashion products, a seasonal discrete grey forecasting model is introduced by Xia and Wong (2014). Since the original grey model is not able to face the seasonality of time series, the authors suggest pre-processing the time-series by using the new method of cycle truncation for accumulated generating operation (CTAGO). Three cases of real sales data were used to validate the model. It outperforms some other forecasting models amongst others: the AR model, ANN model or the fuzzy grey regression model. Similarly, Wong and Guo (2010) assume that data pre-processing (in this case, detecting and removing outliers, interpolating missing data, normalization) of sales data is an effective approach dealing with real fashion sales data. Therefore, they suggest a hybrid intelligent sales forecasting model for fashion products which is conducted in a first step pre-processing of sales data and in a second step, the hybrid intelligent forecast model produces the actual forecasting. Applying this model on real sales data, it shows more accurate forecasts than, for instance, ARIMA models (Wong & Guo, 2010).

For fashion items, the colour is a main characteristic factor (King, 2012). Therefore, colour forecasting is a crucial task for fashion companies. Choi, Hui, Ng, and Yu (2012) focus on colour forecasting for fashionable products with limited data. For this purpose, they examine several different forecasting methods and compare them with regard to the performances on how they deal with the constraint of few data. Artificial neural networks (ANN), the grey model (GM), the Markov regime switching (MS) and GM + ANN hybrid models were applied on sales data of a cashmere garment company. The authors report that the hybrid models produce the most accurate forecasts in comparison to the other models since they can produce reasonable forecasts even with very little data. The GM also has the capability of precise estimates; however, it requires at least 3 years of data series.

Similarly, Gu and Liu (2010) consider colour forecasting as a crucial task for fashion companies and purpose a computer-assisted colour database for colour forecasting. The main parts of their model are: (1) Colour information selecting and arrange, (2) Colour information transfer and processing, (3) Colour data optimization. They report that, in particular, for image recognition, still human intervention is necessary.

Choi, Hui, Liu, Ng, and Yu (2014) focus on fast fashion which is a strategy conducted mostly by retailers and describe the phenomenon of constantly introducing new articles to the market. Companies such as Zara and Beneton are good examples for this strategy. Choi et al. (2014) work is motivated by this strategy in which a forecasting model faces data and time constrains. They suggest the Fast fashion forecasting algorithm (3F) and apply it to 3 years of real sales data as well as on an artificial
Table 1. Summary of selected literature on new product sales forecasting.

| Paper                        | Domain                          | Focus                          | Contribution                                      |
|------------------------------|---------------------------------|--------------------------------|---------------------------------------------------|
| Ching-Chin, Ao, Wu, and Kung (2010) | Beverages, Cosmetics            | Stable demand long life cycles | New product forecast system (NPFS)                |
| Lee et al. (2014)            | Electronics                     | Pre-launch forecasting         | Pre-launch forecasting based on the Bass model and statistical and machine learning algorithms |
| Tanaka (2010)                | Books, Consumer electronics     | Short- and long term           | Forecast model (NM model) for irregular and nonlinear sales items |
| J. Lee et al. (2012)         | Electronics                     | Consumer reservation prices    | Forecast model based on consumer reservation prices |
| Xia and Wong (2014)          | Fashion products                | Pre-processing time series     | Seasonal discrete grey forecasting model          |
| Wong and Guo (2010)          | Fashion products                | Pre-processing sales data      | Hybrid intelligent sales forecasting model        |
| Choi et al. (2012)           | Fashion products                | Colour forecasting             | Comparison of different forecast methods          |
| Gu and Liu (2010)            | Fashion products                | Colour forecasting             | Computer-assisted colour database                 |
| Choi et al. (2014)           | Fashion products                | Fast fashion                   | Fast fashion forecasting algorithm (F3)           |
| Ni and Fan (2011)            | Fashion products                | M-Commerce                     | Two-stage forecasting model Integration of customers |
| Piller and Lindgens (2012)   | Fashion products                | Co-creation                    |                                                   |

database. The 3F is a hybrid model consisting of the grey model (GM) and the extended extreme learning machine (EELM). While the GM estimates the main time series, the EELM is responsible for the residual series. They report reasonable forecast results, in particular under the lack of efficient time and data.

A growing part of fashion sales forecasting is M-Commerce which enables the consumer to purchase their products, for instance, from their smart phones online. Ni and Fan (2011) introduce a framework for sales prediction within a mobile environment. Their approach consists of a two-stage forecasting model: the first step is producing long-term forecasts quarterly and monthly for the current year and is based on historical sales data and information related to external factors such as the climate or region. For these long-term forecasts, they suggest the improved adjustment model which is based on the ART model and multi-variables error forecasting model which is grounded on neural networks. Applying this model on two years data from an apparel company, it is reported that the improved adjustment model outperforms the traditional ART methods with a higher accuracy of 17%. In the second stage, real-time sales data, as well as exogenous variables such as weather or promotion information, are applied to predict weekly and daily sales. Following the two-stage approach, the authors report precise forecasting results, in particular for fashion products.

In comparison to the described methods, Piller and Lindgens (2012) focus on a different approach for sales forecasting. They illustrate the application of co-creation for demand forecasting purposes and show Threadless.com as a best practise for this strategy. This website integrates ordinary customers and independent designers in the design process of their T-shirts. Customers take over the role of decision-makers and decide which models will go for production. Moreover, the clients have additional responsibilities such as advertising or selecting photographers.

A different perspective is followed by Mehrsai, Karimi, and Thoben (2013): they look at the increased demand for individualized products and suggest a collaborative framework consisting of modularity structure, cloud computing and make-to-upgrade strategies in order to overcome the challenges of manufacturing individual products.

Table 1 gives a summary of research on new product sales forecasting with different focuses.

4. Predictive value of user-generated content

Within this chapter, a different approach on how to predict future outcomes is presented. With the rise of the Web 2.0 and the emerging technologies, the ordinary user obtained a new role: He is an active and producing entity and not anymore passive and purely consuming. For this role, literature introduced the term produser (Bruns, 2006). Especially, fashion is a widely discussed topic in the communities and many fashion blogs publish different fashion-related topics. Kaplan and Haenlein (2010, p.
61) define Social Media as group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User-Generated Content. In contrast, Boyd and Ellison (2007) suggest a more detailed definition of social network sites:

We define social network sites as web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection and (3) view and traverse their list of connections and those made by others within the system. The nature and nomenclature of these connections may vary from site to site”. (Boyd & Ellison, 2007, p. 211)

Table 2. Summary of selected literature on predictive value of user-generated-content.

| Paper                              | Domains            | Research stream         |
|------------------------------------|--------------------|-------------------------|
| Aramaki, Maskawa and Morita (2011) | Epidemiology       | User-generated content  |
| Asur and Huberman (2010)           | Box office revenues | User-generated content  |
| Bermingham and Smeaton (2011)      | Elections          | User-generated content  |
| Bollen et al. (2011)               | Stock market       | User-generated content  |
| Boulos et al. (2010)               | Health/surveillance| Search queries          |
| Choi and Varian (2012)             | Consumer goods, consumer confidence, travel and unemployment benefits | Search queries |
| Connor et al. (2010)               | Elections          | User-generated content  |
| Corley, Cook, Mikler, and Singh (2010) | Epidemiology       | User-generated content  |
| Dhar and Chang (2009)              | Online music sales | User-generated content  |
| Ettredge, Gerdes, and Karuga (2005) | Unemployment       | Search queries          |
| Eysenbach (2006)                   | Epidemiology       | Search queries          |
| Gayo-avello et al. (2011)          | Elections          | User-generated content  |
| Gilbert and Karahalios (2008)      | Stock market       | User-generated content  |
| Ginsberg et al. (2008)             | Epidemiology       | Search queries          |
| Goel et al. (2010)                 | Entertainment goods| Search queries          |
| Hultin and Rydevik (2011)          | Epidemiology       | Search queries          |
| Kulkarni et al. (2012)             | Box office revenues | Search queries          |
| Polgreen, Chen, Pennock, and Nelson (2008) | Epidemiology | Search queries |
| Tumasjan et al. (2010)             | Elections          | User-generated content  |
| Vosen and Schmidt (2011)           | Private consumption | Search queries          |
| Zhang et al. (2011)                | Stock market       | User-generated content  |

Recently, more authors have examined the relationship from online chatter to real-world outcomes and the predictive power of such user-generated content. The microblogging service Twitter has served as the data source for most of the works. For instance, Asur and Huberman (2010) focus on movie box-office revenues and Twitter data and demonstrate high correlations between online data and the real rank of a movie. Dhar and Chang (2009) suggest that user-generated content is a good indicator for future sales of online music sales. Further research focuses on exploring sentiments from Twitter data examining potential correlations to the value of the Dow Jones Industrial Average (Bollen, Mao, & Zeng, 2011) and on the prediction of stock markets in general (Gilbert & Karahalios, 2008; Zhang, Fuehres, & Gloor, 2011). Likewise, Twitter posts were used to examine the platform’s role in predicting the outcome of future elections (Bermingham & Smeaton, 2011; Connor, Balasubramanyan, Routledge, & Smith, 2010; Gayo-avello, Metaxas, & Mustafaraj, 2011; Tumasjan, Sprenger, Sandner, & Welpe, 2010).

A further research stream is the usage of search keywords for prediction. Google Flu trends, for instance, estimate influenza distributions based on search keywords related to the topic influenza two weeks quicker than other system (Boulos, Sanfilippo, Corley, & Wheeler, 2010). They assume a relationship between these keywords and people indeed showing flu symptoms (Google, 2014). Goel, Hofman, Lahaie, Pennock, and Watts (2010) have a similar approach: they focus on entertainment goods, and assume that consumers which are interested in a specific movie or game might search for it online. They report higher correlation between movie revenues and online activity in contrast to search queries related to songs. Similarly, Kulkarni, Kannan, and Moe (2012) consider search volume as product interest and a significant indicator for future box-office revenues. Eysenbach (2006) even names search engine queries demand in order to emphasize the relevance of these keywords. Beheshti-Kashi and Thoben (2014) understand search queries also as a sort of user-generated content and therefore suggest the combination of both research streams within the exploration of integrating user-generated content within the fashion forecasting process. However, they propose this approach as a judgemental adjustment of baseline forecasts.

Table 2 gives a summary of more research focusing on the predictive value of user-generated content and search queries.
5. Conclusions

This survey paper conducted an overview of recent progress in the field of sales forecasting with the focus on fashion and new product sales forecasting. Conventional forecasting methods face challenges in producing accurate sales data for new products and consumer-oriented goods. In particular, uncertain demand, seasonality, product variability as well as a lack of historical can hardly be handled. Within the recently introduced approaches, hybrid forecasting models perform more precisely. Moreover, this study gave an overview of the literature focusing on the predictive value of user-generated content and search queries. For future work, different aspects of fashion forecasting can be followed: Most reviewed works propose complex models in order to produce precise forecasts, and validate them in most cases with real sales data. However, still fashion companies face challenges in adapting these complex models. Therefore, one interesting aspect is to explore models which are accurate and at the same time applicable for the daily work of fashion companies. Furthermore, it is worth to focus more on the diverse impacting factors which have been described. Different aspects such as the general handling and the reduction possibilities on the forecast results can be examined. Finally, the measurement of the predictive value of user-generated content in real life is a valuable aspect, which is currently followed and explored by the authors of this review.

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