Twitter and Fashion Forecasting: An Exploration of Tweets regarding Trend Identification for Fashion Forecasting

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Abstract

The fashion industry faces serious challenges in terms of accurate demand forecasting. While production decisions have to be made at an early stage, precise demand information only become available several months later. One main characteristic of the fashion industry is long time-to-market compared to short selling periods. Consequently, it is hardly possible to replenish successful products. Therefore, companies will have losses in terms of stock-outs or overstocked inventories. In order to avoid these losses accurate forecasts are needed. We suggest examining social media text data to support baseline forecasts. This research explores the question if the microblogging service Twitter can be an appropriate source for extracting relevant features in order to predict future fashion trends. Mainly we tackle the following questions regarding the Tweets: are fashion related topics discussed on Twitter? Can we extract information regarding colors, cuts, materials or fashion styles of a product? And if this is given how these words do occur together? For this purpose we collected Tweets which are either brand related, product type related or event related. The analysis is divided into two parts: In the first step, the pre-processing of the text data, we applied tokenization, stopword filtering, stemming and case transformation. In a second step, we applied Associations Rules in order to examine co-occurrences of the extracted words. The analysis shows that it is difficult to draw quantitative conclusions out of the data we obtained. This work is more a qualitative approach to the topic and we suggest validating our examination with bigger data set.

Keywords:
Twitter Fashion Forecasting

1. Introduction

The fashion industry faces several challenges in predicting the actual demands of their products. Inaccurate forecasts will have an impact on the companies success since it will lead weather to stock-outs or overstocked inventories. One major problem for fashion companies is placing their production orders without having the actual knowledge of demand. Due to the fact that most production plants are located in Asian countries, the production plans have to be placed early in advance. Therefore,these companies are faced with long time-to-market compared to their short selling periods of the fashion products. Due to this circumstances it is hardly possible to re-produce successful products. Moreover, the demand is influenced by additional factors such as the economic situation, public holidays or changing weather conditions [1]. Furthermore, items of a fashion collection are mostly replaced by following seasons collections, and therefore, companies often face a lack of historical sales data [2]. In summary, accurate forecasts are in particular necessary because of the short selling periods of fashionable items compared to their long time-to-market, the high variability in products

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and demand uncertainties.
Beheshti-Kashi and Thoben [3] suggest adding social media to the discussion of fashion forecasting. Following this argumentation the objective of this paper is to examine fashion related messages on Twitter.
Twitter is a microblogging service founded in 2006. It currently counts 288 million monthly active users and 500 million messages per day (Twitter, 2015). The service gives every user the opportunity to publish so called *tweets* limited to 140 characters. Originally developed for publishing status messages, Twitter has obtained the role of *an extensive real time information stream* [4]. Academic research on Twitter deals with different aspects. Recently, researchers have examined the relationship between online chatter on Twitter and real world outcomes in different application fields. These include political elections, predictions of entertainment goods, detection of influenza and the prediction of stock markets. The conducted works in these fields validated their models with reference data. In the case of political elections for instance with other election polls or the actual outcome. This approach is possible since the the actual outcome has a fixed date. Though, in fashion markets, there is a high variety on brands and designers. Moreover, in particular within the field of mass fashion, we hardly have fixed launching dates of products or collections. As a result, it is more challenging to validate the extracted information with real data.
Therefore, the objective of this paper is to explore the ability of Twitter to be an adequate source for the detection of future fashion trends. For examining this objective it is necessary to firstly demonstrate that we can extract attributes such as colors, materials or fashion styles out of the huge amount of daily messages. For this purpose, we selected three cases and collected brand related, product type related event related tweets.

The rest of the paper is organized as follows: First, we give a short overview of current fashion forecasting approaches. This is followed by works examining the predictive value of Twitter. Section 3 presents the research framework, including research questions, data collection, data description and data processing. In section 4 we will show and discuss the results. The last section will conclude the work, present some limitations and give an outlook for future work.

2. Related Work

2.1. Fashion Forecasting

Due to the described characteristics of the fashion industry standard forecasting approaches face challenges. Therefore, numerous researchers focus advanced models. In this section we will give a short overview of the current fashion sales forecasting approaches. A detailed survey of current fashion forecasting approaches is presented by Beheshti-Kashi et al. [5].
Sun et al. [6] apply the extreme learning machine (ELM) which was introduced by Zhu et al. [7] to fashion sales forecasting. Other studies such as in [8] apply the evolutionary neural network (ENN) to forecasting within fashion retail. Thomassey and Happiette [9] suggest a system for mean and short term forecasting.They apply fuzzy inference systems and neural networks. Nevertheless, it is difficult to implement such a system in real world apparel companies [2]. Looking at forecasting of new products: Xia and Wong[10] introduce a seasonal discrete grey forecasting model in order to handle the seasonality and lack of efficient data. Wong and Guo [11] suggest a hybrid intelligent sales forecasting model. Applying it to real world data they achieve improvements compared to for instance to ARIMA methods. The topic of color forecasting for fashion items with limited data is focused in [12]. The authors make a comparison of different forecasting models considering their performances and their ability to handle limited data. Choi et al. [13] focus on fast fashion strategies and introduce the Fast Fashion Forecasting algorithm (3F) which consists of the Grey model and the extended extreme learning machine. Applying it to three years of real sales data they report improved results. This paper follows the argumentation of [3] and adds the aspect of user generated content to the discussion of fashion sales forecasting.

2.2. Predictive Value of Tweets

In this section we will give an overview on research focusing on Twitter as a potential source for predicting forthcoming real world outcomes. This phenomena is mainly examined for the following fields: political opinion and elections, predictions of entertainment goods (box-office revenues, online music sales), detection of deceases and influenza as well as the prediction of stock markets.

Regarding elections political sentiments are used in order to predict future election outcomes [14] [15] [4]. Bermingham and Smeaton [15] for instance took the Irish General Election as a case study and validate their approach against traditional election polls and the final outcome of the election. They apply predictive measures and sentiment analysis and report that Twitter has a *predictive quality* for their case study. Likewise, [4] examine political discourse related to the German federal election in 2009. The authors consider Twitter as an *valid indicator of political opinion*. Nevertheless, they state some limitations of their work and purpose to capture the context of a message in future works. Similarly, [16] restrict their results and suggest to be more skeptical in the regard of predicting elections only based on Twitter raw data.
In context of entertainment goods, [17] demonstrate high correlations between Tweets and the real rank of box-office revenues. [18] suggest that Twitter is a good indicator for future sales of online music. Further research focuses on exploring sentiments from Twitter, examining potential correlations to the value of the Dow Jones Industrial Average [19] and on the prediction of stock markets in general [20] [21] [22].
[23] introduce a data collector for epidemic data from Twitter and demonstrate that user indeed publish messages about decease symptoms. They conduct simple predictions on these data. However, they suggest to further validate their results through statistical analysis and additional data collection. Similarly, [24] focus on tracking epidemic decease in order to detect an outbreak in advance. In contrast to [23] they validate their approach with further data from official health reports. Likewise, [25] investigate the potential of detecting the flu by examining tweets. They show high correlations in particular in the *early epidemic stage*.

3. Research Framework

In this section we will present the research questions, the data collections, the data description and the processing of the data.

3.1. Research Questions

As mentioned in the related work section, numerous works on Twitter and its predictive value mainly extract and discuss sentiments. However, within the fashion field there can be diverse topics that be discussed. Besides the high product variety, it can be discussed on different designers, brands, fashion shows, fairs, fashion companies, promotions, sales, fashion commercial. Therefore, in a first step it is needed to identify that the extraction of relevant features out of the huge amount of data is possible. Exploring fashion related data the following questions are possible:

- Can we identify fashion related discussion on twitter?
- Can we identify certain features of products such as colors, material or fashion styles?
- Can we identify certain features on brands?
- Can we identify associations between the mentioned attributes products/brands?

3.2. Data Collection

Following the research questions we selected three cases: *Brands, Product Type and Events*. For each of the cases concrete items and accordingly so called *hashtags* were chosen. A hashtag is a combination of the # and a word, a combination of words or numbers. Each user can create a hashtag on a any topic, event or product. Other users can use this in their tweets to reference to the discussion. For each of our cases we selected the adequate hashtags in order to extract the relevant tweets.
Brands: It is notable to mention that for this research we consider mass fashion products. The Alexa Analytics Tool served as reference for the brands selection. This tool provides rankings of websites measured by the user visits. With this in mind, we assume that high ranked brand websites will also be highly discussed in online communities. According to this assumption the brands *Mango, Gap, H&M, Zara and Abercrombie&Fitch* and their hashtags were chosen accordingly. The first four brands have similar target groups. In addition, they follow fast fashion strategies which enable them to react quicker to current trends. Therefore, the assumption is that for these companies it might have a added value to monitor Twitter since it is kind of promoted as real time news ticker. A&F have a slightly different target group and strategy.

Search queries	Returned Tweets
Abercrombie & Fitch	3621
Gap	58557
H&M	22074
Mango	61658
Zara	57458

Table 1: Brands related Tweets

Product Type: For the category product type *shoes* served as an example because of the high product variety. In addition, names of shoe types are mostly language independent. We selected a total number of 15 different shoe types, and accordingly their hashtags (see Table 2).
Events: The *Mercedes Benz Fashion Week Berlin* taking place in January 2014 served as case for this category . In this case we searched directly within Twitter for adequate hashtags with the search query *fashionweek berlin*. The *#MBFWB* hashtag is referencing directly to this event. Additionally, we selected the the hashtags which were used together with *#MBFWB* (see Table 3).
For each of the cases we identified corresponding hashtags to collect the data. The Software *Discover Text* served for our data collection. In the following part will give a detailed overview of the collected data set.

3.3. Data Description

3.3.1. Brand related Tweets

In this case we collected the data by using the brands names as search queries. The collecting period was in December 2013 two weeks before Christmas. Table 1 shows the search queries and accordingly the number of Tweets which had been returned. The search query on Abercrombie & Fitch returned considerably less tweets compared to the rest of the search keywords.

3.3.2. Product type related Tweets

Table 2 gives an overview of the 15 used hashtags and the number of returned tweets. As you can observe from the table the returned tweet numbers vary highly. The minimum of tweets is for the shoe type Peeptoe Ankle Boots and maximum number of extracted tweets if or the shoe type Flip Flops, followed by High Heel and Boots. In order to obtain valid information we only examined the cases with a minimum number of 1000 tweets. Therefore,

Shoetype	Hashtag	Tweets
Ankle Boots	#AnkleBoots	1000
Boots	#boots	30914
O'Orsay Pumps	#dorsaypumps	117
Flamenco	#flamenco	36
Flip Flops	#FlipFlops	31079
High Heel	#HighHeel	20400
Mules	#Mules	770
Overknees	#overknees	116
PeeptoeAnkleBoots	#peeptoe #ankleboots	2
Peeptoe Boots	#peeptoeboots	6006
Pony Heels	#pony #heels	36
Pumps	#pumps	36
Sandals	#sandals	593
Slipper	#slipper	260
Wedge Pumps	#wedges #pumps	255

Table 2: Shoetype related hashtags and Number of Tweets

Hashtag	Number of Tweets
#fashion	200000
#MBFWB	5673
#runway	25164
#fashionweekberlin	366

Table 3: Event related Hashtags

our actual data set includes the following shoe types: Ankle Boots (1000 tweets), Boots (30914 tweets), Flip Flips (31079 tweets), High Heel (20400 tweets) and Peeptoe Boots (6006 tweets).

3.3.3. Event related Tweets: Fashion Week

Table 3 presents the hashtags and their returned tweets on the Mercedes Benz Fashion Week Berlin. In total, four hashtags served for extraction of the relevant tweets. Also in this category the tweet numbers vary highly with the maximum number of 200000 tweets (#fashion) and the minimum number of 336 tweets (#fashionweekberlin). However, we have to mention that the actual number of returned tweets for the hashtag #fashion is 780133. Due to some export regulation of Twitter, we were limited to 200000 messages for the analysis.

3.4. Processing of the Tweets

From the collected data we focus on the actual messages, and ignore in this research the data on user related information such as the time or location. It is only the 140 characters which are of interest for this research.Therefore, we have to apply text processing analysis on the messages since we have unstructured data in form of the tweets. After extracting the pure text, we created for each of the hashtags a separated data set and applied the following processes on it:

- Tokenization
- Stopword Filtering
- Case Transformation (to lower case)
- Filtering Tokens by length

In a second step, we generated word vectors, counted words occurrences and applied association rules.

4. Findings

In this section we will give an overview of the most relevant findings of the analysis. We have to mention that during the analysis we encountered several challenges and problems. For instance, is was hardly possible to extract relevant information regarding the actual text in each category. It was difficult to find associations within the massages themselves. Therefore, we decided to use the data in order to explore the different hashtags and to examine their co-occurences. We suggest to examine the textual data with more elaborated text mining approaches which are tailored for micro massaging.

4.1. Brand related tweets

Since we did not collected data by hashtags in this category, we will only state some other insights which was demonstrated by this data set. As we have mentioned before, the number of returned tweets in this category varies highly. A possible explanation is that because of the word ambiguity of the brand names *Gap*, *Mango* and *Zara* not only messages in the context of the brands were extracted, but also tweets containing the context of the second meaning of the words, for instance the fruit mango. In particular, in these brands data sets, we identified a variety of languages. Since these brands are world wide sold, user do communicate from all over the world about these brands. Therefore, for the prediction of future trends, it is not only necessary to filter the language; probably, it is more relevant considering the users location, since most fashion trends are spread regionally. A fashion trend in Japan for instance, has not necessarily become a trend in Germany.

4.2. Product type related

In this category we will present the analysis on the three shoe types Flip Flops (31079), Boots (30915) and High Heels (20400), since they returned the highest number of tweets. In this category, it is noted that we do not have only a numeration of hashtags within a massage. In addition to the hashtags also the text take a role such as in *I can't wait for summer...dressing so simple, You can be fly in a tank top, shorts, and flip flops*. However, some combinations could be identified such as #red (19), #summer(33), and some occurrences of brands. In our data set, no references on the type of material could be identified. Though, in the case of the #Boots 1850 mentions of #leather could be counted. Moreover, also a fashion style in form of #vintage could be detected in 244 messages. Additionally, colors such as #black (597) and #brown(244) are used together with #Boots. The #HighHeel also occurs in different combinations. With colors it is mentioned for instance with #red (324), #blue (57), #black (281) or #gold (65). The #leather can be detected in 82 tweets. Also it occurs with other shoe types such as #pumps (114), since high heels can also be considered in this group. In addition, we can identify more describing attributes such as #glamour in 164 tweets.

4.3. Event related

For this category we selected the #fashion because the tweets mentioning the Fashion Week in Berlin, referenced also to this hashtag. However, the analysis shows that tweets including #fashion occur often with other more specified hashtags. In this way user somehow tag their 140 limited short massages. For instance, in 981 short messages the hashtag #ebay also appears. A qualitative analysis of these messages shows, that these tweets link to eBay shops and promote in this way their products. In 3675 tweets we find a combination of the hashtag #shoes, in 1921 #clothing, in 1359 #clothes and in 1632 handbags. In additon, even more detailed tags are combined such as

#womenfashion (13), #kidsfashion (42) or #mensfashion. A deeper examination of these tweets shows that by referring to several of such hashtags in most of the cases sales and promotions are stated. In some cases, a picture of a product is linked without giving further information on promotions. Looking at #MBFWB we can identify different combinations for instance with designer names, referring to coming or past fashion shows of these designers. A different reference is the appearance of the hashtag #outfit: in these cases visitors of the Fashion Week, in most cases, fashion bloggers, publish a picture of their own outfit visiting a certain show. Similarly, #outfit occurs together with the #runway. However, in this case, the user does not mentioned his or her own outfit. It is referring to a third person's outfit. However, most tweets with #run are also mentioning city names: #London (9099), #Milan (9461), #Paris (5118), #Amsterdam (28) and #NewYork (40).

5. Conclusion and future work

5.1. Conclusion

We analyzed in total over 535682 tweets, separated in 24 data sets. On the first question, if we can identify fashion related topics on twitter, we have to state that fashion is indeed a highly discussed topic. Only the hashtag #fashion returned 780133 tweets within three weeks. However, we have to mention that during January diverse fashion shows and events take place, which is a potential explanation for the huge number of tweets. The data collection with the #fashion should be repeated during a time with less events or shows, in order to examine if fashion related topics are also discussed on a regular basis or only occasionally. In addition, we can state that different types of fashion related topics are discussed. The analysis shows we can find product type messages, messages about brands and also about fashion shows. Though, these topics are discussed in several languages. It is needed to filter the language, and also the user location, in order to predict the right fashion trends for the corresponding region. The analysis shows that it is difficult to draw quantitative conclusions out of the data we obtained. It was difficult to find associations within the massages. Therefore, we explored the different hashtags and their co-occurences. We suggest to examine the textual data with more elaborated text mining approaches which are tailored for micro massaging. This work is more a qualitative approach to the topic and we suggest validating our examination with bigger data set.

5.2. Future Work

Since the topic fashion forecasting using social media text data is a complex topic, we see this paper as a starting point for our future research. Therefore, this work is still a work in progress and has some limitations. Firstly, in the analysis we did not divided the tweets into different languages. For the brand related and product type related tweets, we applied processes tailored for English. Therefore, the content of the rest of the short messages is not analyzed. As our next step we will also consider the different languages or only extract the English messages in order to have an one language based corpus. Secondly, as we already mentioned in our introduction, the purpose of this paper is not to present predictions and to validate their accuracy, we focus on the exploration of the raw data. The integration of the short messages in a prediction model will be one of the following tasks to fulfill.

6. References

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