Online Consumers’ Opinions Analysis for Marketing Strategy Evaluation

Elena Ektoros[1], Andreas Gregoriades[1] and Michael Georgiades[2]
[1]Cyprus University of Technology, Limassol, Cyprus
[2]Primetel PLC, Limassol, Cyprus

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Abstract: With over two billion users having access to social media accounts, people increasingly choose to express themselves online. Electronic word of mouth generates large amounts of data, making it a valuable source for big data analytics. This provides organisations with key capabilities for improved decision-making through mining insights directly from online sources. In this work we gathered and analysed the sentiment of consumers’ tweets regarding the release of two smartphone products. Tweeter data was collected using a custom-made Android application. The research question addressed in this study focused on whether the marketing positioning strategy of the company under investigation was successful after the release of two of its new products. To evaluate this, we compared the product positioning strategy of the firm before and after the release of the product. Consumers’ opinions were analysed to identify possible discrepancies between planned consumers’ reactions and sentiments, as strategized by the company, and how these were altered with the release of the product.

1 INTRODUCTION

A new challenge for companies is how to discover hidden information in big data sources to remain competitive advantage through effective data processing (Khade, A. A., 2016). Micro-blogs represent one type of big data that is available for analysis and complements other forms of human interaction (Chamlertwat, W., et al., 2012). They gained popularity from the inherent need of people to express their views on a wider scale. The internet empowers consumers to gain access to information sources, enabling them to be “active co-producers of value” (deChernatony 2000) and sometimes referred as prosumers. Consumers give their opinion freely through micro-blogs and “reviews”. Micro-blogs are viewed as an electronic word-of- mouth (eWOM) which could trigger discussions on products or services. Companies realised the potential from eWOM analysis and use micro-blogging as a part of their marketing strategy (Jansen et al., 2009).

This work aims to analyse whether Huawei’s product release, positioning and marketing strategy for the Huawei P20 and Huawei P20 Pro products was successful by evaluating tweets before and after their release. To answer this research question, we utilised public opinion data obtained via a custom-made Twitter collection tool.

2 LITERATURE REVIEW

To improve the process of new product release that aim to satisfy new customers’ needs, it is important to evaluate alternative ways to retrieve information regarding customers’ opinions that could highlight those needs (Jung, J. J., 2012). According to a statement made by Scott Cook, co-founder of Intuit, “A brand is no longer what we tell a customer it is- it is what customers tell each other it is” (Nayab G et al, 2016). Twitter and other social networks became valuable resource for mining sentiment in fields such as customer behaviour. Around 20% of microblogs mention a brand name (Jansen, B. J., et al., 2009), hence, companies should include in their marketing strategy the management of brand perception on Twitter and other social media platforms. Several studies investigate the use of Twitter and other social networks to mine consumer-sentiment in field as customer behaviour.

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The role of online communities, particularly in the context of new product development, has been discussed by many studies (e.g., Franke and Piller, 2003). Pang (2007) highlighted that online product reviews enable marketers and manufacturers to gain more complete understandings of customers. Zhu and Zhang (2010) proved that online customer reviews can be a good proxy for communicating customer experience by word-of-mouth.

In order to achieve successful product development, product positioning is a critical technique to help firms better understand the underlying relationships between product features, competing alternatives and diverse consumers' needs (Lilien and Rangaswamy 2003; Petiot and Grognet 2006; Cha, et al., 2009). Product positioning is not what companies do to a product but is what companies do to prospective customers.

In strategic marketing, 'positioning' refers to implementing a set of tactics to ensure that a product and its characteristics occupy a unique position in the minds of customers (Lilien and Rangaswamy 2003). Optimal product positioning corresponds to determining which attributes and configurations should be used to satisfy customer requirements (Kwong, Luo, and Tang 2011). According to (Chih-Hsuan W., 2015) product positioning is implemented through a series of steps: (1) visualising competitive alternatives and product features (2) constructing a forecasting model to estimate how potential buyers will react to marketing stimulus and (3) specifying optimal position of new product(s) and identifying niche segment(s). A perceptual map is a powerful tool to visualise the relationships between competing products and their associated features in a comprehensible way. Moreover, perceptual maps can help firms assess the strengths and weaknesses of competing alternatives. According to (Hair J. et al, 2009), two ways are mainly used to construct a perceptual map: the first is multi-dimensional scaling and the second is correspondence analysis. The latter can use categorical variables to project on a plot the relationships between benchmarks and associated product features, without requiring multiple regression. Due to its simplicity correspondence analysis is adopted in this study to evaluate Huawei's P20 & P20 pro products' positioning.

Traditional approaches for studying consumer behaviour, such as marketing survey, interviews, focus groups, experiments and other, require a great amount of time and resources. Moreover, some products, such as smartphones, have a short-term product life cycle, hence this approach could not be appropriate due to the time required to perform these analyses and the lifespan of the product. Smartphone's market competition is fierce due to the constant advancement of technology, hence new updated versions are hitting the market at lightening speeds. According to HTC, the average shelf life for smartphones has decreased from three years in 2007 to around six to nine months in 2011 (Ferreira, 2011). Another important statistic from Statista.com shows that the average number of months for people to change their smartphones is less than two years (≈22 months). Therefore, producers have too little time to research market by traditional way. Referring to Technology Adoption Life Cycle, each model of smartphones has limited time to prove their product adoption using conventional means.

Twitter represent a useful platform for micro-blog analysis due to the amount of data that is generated from the public (Chamlertwat W. et al., 2012). Due to these platforms, sentiment analysis and topic extraction have been very hot research fields recently. These capabilities make it possible to automatically identify user's emotions regarding a subject (Al-Obeidat F. et al., 2018). Therefore, these methods are more appropriate in fast changing domains such as the smartphone market.

3 METHODOLOGY

The diagram in figure 1 illustrates the steps followed to answer our research questions. The first step in the method was to examine Huawei's marketing strategy for both P20 products and their associated positioning. An important element of the marketing strategy was the target customer segment and the keywords for promoting particular features of new products.

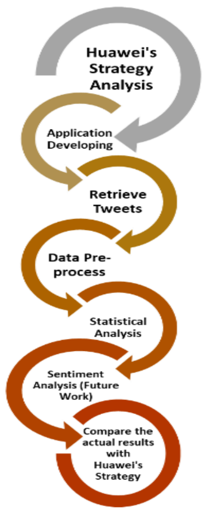

Figure 1: Methodology.

The second step of the methodology concentrated on the building of an application to dynamically collect data regarding the target customers of the company. In this stage an android application was developed to gather data based on specific geolocation coordinates of the microblogs and specific theme.

The next step in the methodology was data pre-processing, which involved data cleaning, dimensionality reduction and irrelevant data elimination. This was a necessary step to enable the processing of the data and the extraction of meaningful insights.

Following data pre-processing, the sentiment and statistical analysis on the dataset was performed. For these tasks open source tools were used. Specifically, a frequency analysis of the main themes in the dataset and polarity of sentiment analysis were performed.

In the final step, the obtained quantitative and qualitative data was analysed further to map the observed data against the planned company's strategy. During this step, the results obtained were compared with planned positioning to examine whether the marketing strategy of the firm matched the opinions of its customers. Therefore, identifying if consumers perceived positively the features of the new products and their quality.

4 STRATEGY ANALYSIS

The analysis of Huawei's marketing strategy was necessary to examine if the consumers' perception of the new products was analogous to the expectations of the company prior to the smartphones release. Based on the conducted analysis, it seems that Huawei adopted a product and cost differentiation strategy for the promotion of Huawei P20 and Huawei P20 Pro. The company aimed to target consumers that look for high specification smartphone, usually provided by iPhone, at a lower price. Based on this, Huawei's marketing strategy promoted the unique and competitive features of photography that Huawei Pro series smartphones has. The company tried to emphasise on the quality of the camera resolution in order to differentiate itself in their target market and use specific keywords to emphasise on this feature. Samsung and iPhone constitute Huawei's major competitors, with, iPhone as the leading brand owned 19,2% market share on smartphone sales and Samsung second with 18,4%. Huawei concentrated its efforts on the triple-camera feature introduced in the smartphone market for first time, utilising intelligent photography, hence differentiating Huawei from the other brands in smartphone industry. As part of their promotion the firm uses the "See Mooore" slogan clearly referring to the Leica triple-lens system presented in all advertisements that the smartphone has.

The assumption made here is that if the company manages to satisfy the needs of the market segment they targeted, this will be reflected in the eWOM of its consumers. In this study we explore the effect of the strategy on eWOM, before and after the release of the products.

5 THE DATA GATHERING TOOL

A data gathering tool was used to collect relevant tweets for the analysis. A custom Twitter application was developed for this process for Android mobiles. To have access to Twitter's APIs, a mobile app using Android studio was built. This is a typical procedure required by Twitter to secure access to Tweeters database by authorised users. In order to have the right data from the microblogs, the corresponding data entries of interest were specified in each query. i.e. data for sentiment and statistical analysis. The best feature that Twitter offers for this purpose is the "Search Tweets". Twitter offers two options to retrieve tweets. The Rest API and the Streaming API. For this task the Rest API was used, that allowed for searching of specific tweets using certain criteria specified in the queries searched for. The timeframe of the data gathering was 7 days due to API limitations. Figure 2 shows a screen shot of the developed Android app.

The specification of the tweets query keywords was based on preliminary analysis of the two products features and company positioning and strategy. For the two smartphones, terms such as #HuaweiP20, #HuaweiP20Pro, #Huawei, #SeeMore etc. were used. These keywords yielded 436 tweets with 140 characters length each. The #SeeMore and other related keywords related to the products' positioning strategy, with emphasis on being perceived by consumers as a product equipped with improved mobile photography. This was the key feature of the firm's marketing campaign.

Tweets were restricted to English language, and the target market for this study was the United Kingdom, since UK is one of the top 10 countries with active Twitter users worldwide according to Statista.com. Four main cities in the UK were targeted: London, Birmingham, Liverpool and Manchester.

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Figure 2: Screenshot of the developed tweet collector Android application retrieving tweets for keyword "Huawei" in London area for a specific date.

The data collection was held between 27th of March 2018 and 11th of April 2018. On the 27th of March the Huawei smartphones were official introduced in an event that took place in Paris. This date was treated as a key milestone in classifying the data in two categories: before and after product release.

In order to address the problem of customers referring to product features using different terms, it was necessary to create an ontology to enable the grouping of similar terms under different categories. This was manually developed based on products' features categories obtained from the Huawei's website.

6 DATA PRE-PROCESSING

Filtering of tweets was a necessary step prior to the analysis, to eliminate useless metadata information, and keep tweets as simple format. The filtering criteria for the Tweets were: inclusion of related keywords in tweets without information of author's username and other irrelevant punctuation symbols. The evaluated tweets were all in the English language.

The data gathering tool downloaded tweets in txt file-format, categorised based on their location and hashtag keywords. Tweets were organised in sixteen folds for all four UK cities. For each city the tweets were organised in four categories based on their keyword's hashtags.

The following process describes the data processing performed over each of the folders mentioned above as well as on the whole set of files. A custom tweet cleaner program was specified as a batch file executed from Windows command prompt and whose purpose was to consolidate all the *.txt files placed within the same folder into a single merged .txt file (named merged.txt).

Figure 3: Example Tweet after cleansing from irrelevant content.

Following the file merging procedure, the data was processed to include one tweet per line for better text manipulation and that included the elimination of irrelevant information such as characters, usernames, links, protocols. An example pre-process tweet is depicted in figure 3.

7 ANALYSIS

The keywords frequency analysis was performed using an opensource tool that disclaims automatically unknown symbols (i.e @, #, emojies), words in other languages and other misleading information. This process was repeated for each of the 16 files (4 cities and four keywords).

Table 1: Ranking of the top 10 words that users mentioned most frequently.

A/A	Word	Percentage
1	huaweip20	9.29
2	pro	7.32
3	huawei	5.63
4	p20	3.93
5	seemoore	2.24
6	paris	2.24
7	new	2.01
8	seemore	1.74
9	smartphone	1.33
10	unboxing	1.03

The first analysis was conducted using the WriteWords.com and yielded 1142 unique words in all tweets. Most words appeared in tweets more than once, so the overall sum of the words was 7581. Words were subsequently classified according to a number of themes. For instance, words that were relevant to the Huawei brand included keywords such as: Huawei P20, Pro, P20, HuaweiMobile etc.

Similarly, words that were referring to the phone's camera were filtered based on keywords: photography, triple-camera, Leica and so on.

The top 10 most popular words, as mentioned by users in their tweets are listed in Table 1. The word "HuaweiP20" was mentioned 9,29% of the time and the word "pro" 7.32%. The words "seemore" and "seemooore", were ranked 5th and 6th positions, and referred to the slogan used during the promotion of the products. The word Paris ranked in the top ten and denoted the place of the product release. This however had no relevance to how consumers perceived the new product and hence was ignored during the analysis.

Overall, 1174 out of the 4070 words were directly related to Huawei. Manchester emerged as the city with the highest number of relevant tweets. This could be attributed to the fact that it has the highest proportion of student population among the rest of the cities that were examined.

Some of the words were written in different spelling, such as "top" and "toop", so we considered these as identical. Each of the words were categorised as either positive, negative or neutral. This was performed using the Opinion Lexicon, which constitutes a list of positive and negative words or sentiments, compiled by (Hu and Liu, KDD-2004). All tweets have been evaluated against their polarity with 28 classified as positive, 10 negative and 12 neutral. The results from this analysis could indicate that the Huawei P20 release, triggered a positive reaction by consumers as indicated from the ratio of the positive over negative words.

Huawei's strategy as has been evaluated and analysed in previous section is mainly based on product-differentiation. Hence, its marketing plan was to promote the differentiating feature of their products. In the P20 and P20pro smartphones this was the triple-camera. From the tweets' analysis, forty unique words were detected in the dataset that described the camera in a positive way. While, from the overall tweets mentioning the camera, 15% referred positively to the triple-camera feature.

7.1 Sentiment Analysis

Sentiment analysis (SA) was a necessary component of this work. Considering the sentiment analysis methods available, this work assessed tweets that reflect public opinion regarding the new products and how this changed with time. SA literature (Pang and Lee, 2008) provided methodologies from other studies that utilised information from public opinions to extract their polarity and content categorisation (Gamon et ad., 2005).

SA is used to extract static data patterns and discover dynamic trends (Lei, N. and Moon, S.K., 2015) based on the emotional state of the author of a text. SA is a useful for research into online opinions due to their ability to automatically measure emotion in online texts. SA includes algorithms to automatically detect sentiment in text (Pang and Lee, 2008). Certain algorithms assign an overall polarity to a text while others identify topics that users discussed along with the polarity of the sentiment expressed in topics (Gamon et ad., 2005). Three common sentiment analysis approaches are: Machine Learning approaches, Lexicon-based methods and Linguistic Analysis techniques.

A Machine Learning (ML) approach utilises machine learning techniques and statistics. According to (Witten et al.,2016), training texts annotated by human coders in terms of polarity are used to train an algorithm to detect features that associate with the three positive, negative or neutral emotions. The trained algorithm can then look for the same features in new texts to predict their polarity (Thelwall et al., 2011). Sets of words, are also used for the algorithm training.

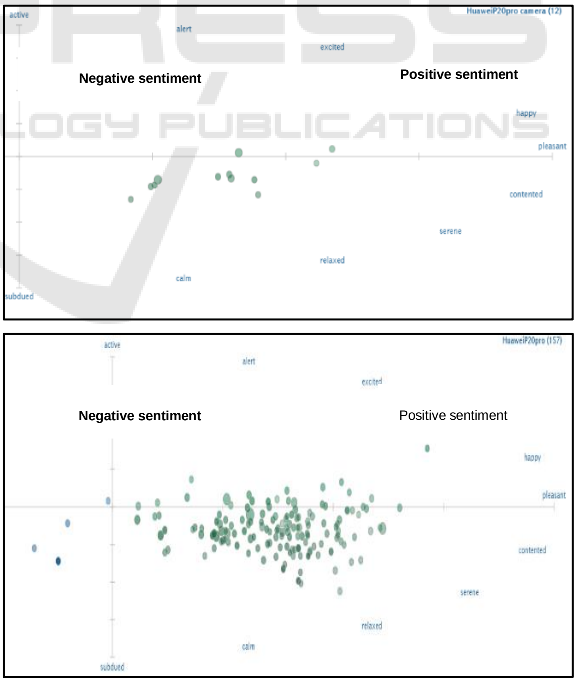

Figure 4: Sentiment analysis for the keywords: "HuaweiP20Pro" (bottom) and "HuaweiP20Pro Camera" visualised with the sentiment Viz tool.

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The Lexicon Approach is divided into two further techniques. The first one is the dictionary technique and the second is the corpus-based approach. It starts with lists of words that are pre-coded for polarity and strength, and are used as prior knowledge to evaluate the overall polarity of a paragraph based on occurrences of these know words (Thelwall et al., 2011)

The linguistic analysis method exploits the grammatical structure of text to predict its polarity, using a lexicon. For example, linguistic algorithms identify context and idioms as part of the polarity prediction process (Thelwall et al., 2011).

From the above three techniques in the field of Sentiment Analysis we selected the ML approach since it produces more accurate results. There are two basic ML methods that can be used for polarity classification, which are considered as the most efficient and simple to use:

- Naïve Bayes classification
- Support Vector machines

For these techniques it is important to train the classifier using supervised learning techniques. A set of training datasets should be used with cases that already have been assigned as negative, positive or neutral. In our case we used the tweeter sentiment corpus.

The Naïve Bayes Model is more commonly used in cases when we examine the polarity of a sentence by recognising the polarity of each word individually. The support vector machines is better for large texts (phrases) or combinations of words. However, since in Twitter, we deal with short texts, we initially decided to use the first model.

Despite its popularity, SA and its techniques have been criticised of their accuracy and specifically with regards to the detection of polarity of plain text contents. For example, in certain domain the accuracy of sentiment analysis was lower than 50% with less precision in detecting negative sentiments (Jongeling et al, 2015). To escape from this problem, we concentrated on positive and negative words alone, as they appear in tweets and referred to the product under study. This process identification was performed automatically. Plus, we constrained the search criteria to specific keywords and hence eliminated irrelevant tweets that could have influenced the results.

To validate our results with other methods, we used the SentimentViz tool to obtain the overall sentiment of consumers with regards to Huawei's P20 for the same period of analysis. Figure 4 illustrates the overall sentiment for the "HuaweiP20Pro" keyword. This represents the distribution of the keywords across the sentiment scale. The tweets in Figure 4 lean towards the positive side of the spectrum indicating that consumers perceived positively the new product and its differentiating features. Similarly, the camera keyword shows a positive sentiment as indicated also in figure 4. Both observations confirm the results performed from our preliminary analysis. Each tweet is shown as a circle positioned by sentiment, an estimate of the emotion contained in the tweet's text. Circles correspond to tweets. Negative tweets are drawn as blue circles on the left, and positive tweets as green circles on the right.

8 RESULTS

From the analysis of the data, we identified preliminary evidence which could indicate that Huawei's marketing strategy had a positive impact on their targeted users. The product positioning plan of the firm was to differentiate on price and technological features such as the use of the Leica triple-camera. Preliminary results showedthat consumers received well the new triple camera feature of P20 and referred to it in their tweets with positive connotations. The new phones triggered people's interest as it was also witnessed by Google Trends search queries in Germany, Spain and Italy for the same period, that could also indicate an increase in reputation.

Secondary data regarding company's sales performance, verified our preliminary results regarding the success of the company's positioning strategy by targeting consumers and addressing their needs. Both products were positively received by consumers and the trend of this effect was not declining after the first couple of weeks when consumers had a chance to experiment with the products. The overall opinion of users' tweets analyzed in this paper was positive throughout the specified time-frame and the ratio of positive over negative tweets was relatively constant.

This exercise showed that Twitter could be a valuable tool for predicting and analyzing costumer behaviour on product release. People through social media express their views about their experiences with products. Sentiment Analysis is an important tool for textual data investigation and marketing managers should include these capabilities in their portfolio of tools during analysis of public opinion. However, analysis of big data should be executed with consistency and accuracy to produce useful results.

9 CONCLUSIONS

Product positioning is key in targeting the right consumers. Commercial organisations continuously monitor their product positioning by gathering data online and offline. Products mispositioning however, could jeopardise the marketing strategy of a company and should be avoided. Validating strategies early in the product release cycle constitute a vital process for effective sales performance. Therefore, companies in addition to other information sources, should also utilise data from the blogosphere to understand customers' opinions in real time and accordingly respond to their needs (Al-Obeidat, F., Spencer, B. and Kafeza, E., 2018). Data mining can help enterprises resolve marketing issues and improve product positioning through quicker analysis of online consumers opinions.

This work presented a technique for evaluating product positioning using eWOM analysis. An application of eWOM analysis was also presented, for the marketing strategy of two Huawei smartphones. Limitations of this work lie in the small sample size which concentrated on specific geographical regions. For future work the authors are considering expanding on the methodology to evaluate the impact of marketing strategies using more sophisticated sentiment analysis techniques with less false positives and false negatives rates and hence require less manual evaluation.

REFERENCES

Jung, J. J., 2008. Taxonomy alignment for interoperability between heterogeneous virtual organizations. Expert Systems with Applications, 34(4), pp.2721-2731.de Chernatony, L. (2000). Succeeding with brands on the Internet. *Brand Management, 8(3), 186-195.*

Forbes, 2018 (https://www.forbes.com/companies/twitter/) Retrieved 10 April 2018

Statista, 2018 (https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/) Retrieved 13 April 2018

Huawei, 2018 (http://www.huawei.com/en/about-huawei/corporate-information/milestone) Retrieved 14 April 2018

Sagolla, D. (2009). 140 characters: A style guide for the short form. *Hoboken: Wiley*.

Jansen, B. J., Zhang, M., Sobel, K., & Chowdhury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science, 60(11), 2169-2188*.

Zhang, M., Jansen, B. J. and Chowdhury, A., 2011. Business engagement on Twitter: a path analysis. *Electronic Markets, 21(3), p.161*.

Wauters, R. (2009). Twitter spawned 50,000 apps to date, will open up firehose for more. Retrieved January 6, 2010, from http://www. techcrunch.com/2009/12/09/twitter-le-web-2009/.

Keller, E. (2007). Unleashing the power of word of mouth: Creating brand advocacy to drive growth. *Journal of Advertising Research, 47(4), 448–452*.

Chamlertwat, W., Bhattarakosol, P., Rungkasiri, T. and Haruechaiyasak, C., 2012. Discovering Consumer Insight from Twitter via Sentiment Analysis. *J. UCS, 18(8), pp. 973-992*.

Lei, N. and Moon, S. K., 2015. A Decision Support System for market-driven product positioning and design. *Decision Support Systems, 69, pp.82-91*.

Jung, J. J., 2012. Evolutionary approach for semantic-based query sampling in large-scale information sources. *Information Sciences, 182(1), pp.30-39*.

Ferreira, A., 2011. Android OS changes smartphone life cycle. *The Vista, February*.

Mostafa, M.M., 2013. More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications, 40(10), pp.4241-4251*.

Olobatuyi, M. E., 2006. A user's guide to path analysis. *Lanham: University Press of America, Inc. p.32*.

Thelwall, M., Buckley, K. and Paltoglou, G., 2011. Sentiment in Twitter events. *Journal of the Association for Information Science and Technology, 62(2), pp.406-418*.

Huang, J., Thornton, K. M. and Efthimiadis, E. N., 2010, June. Conversational tagging in twitter. In *Proceedings of the 21st ACM conference on Hypertext and hypermedia (pp. 173-178). ACM*.

Honey, C. and Herring, S. C., 2009, January. Beyond microblogging: Conversation and collaboration via Twitter. In *System Sciences, 2009. HICSS'09. 42nd Hawaii International Conference on (pp. 1-10). IEEE*.

Franke, N. and Piller, F. T., 2003. Key research issues in user interaction with user toolkits in a mass customisation system. *International Journal of Technology Management, 26(5-6), pp.578-599*.

Zhu, F. and Zhang, X., 2010. Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of marketing, 74(2), pp.133-148*.

Lilien, G. L. and Rangaswamy, A., 2003. New Product and Brand Management: Marketing Engineering Applications. *Prentice Hall*.

Boyd, D., Golder, S. and Lotan, G., 2010, January. Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *System Sciences (HICSS), 2010 43rd Hawaii International Conference on (pp. 1-10). IEEE*.

Petiot, J. F. and Grognet, S., 2006. Product design: a vectors field-based approach for preference modelling. *Journal of engineering design, 17(03), pp.217-233*.

Kwong, C. K., Luo, X. G. and Tang, J. F., 2011. A methodology for optimal product positioning with engineering constraints consideration. *International Journal of Production Economics, 132(1), pp.93-100*.

Pang, B. and Lee, L., 2008. Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval, 2(1–2), pp.1-135*.

Gamon, M., Aue, A., Corston-Oliver, S., & Ringger, E. 2005. Pulse: Mining customer opinions from free text. *Lecture Notes in Computer Science, 3646, 121–132*.

Witten, I. H., Frank, E., Hall, M. A. and Pal, C. J., 2016. Data Mining: Practical machine learning tools and techniques. *Morgan Kaufmann*.

Kim, S. M. and Hovy, E., 2004, August. Determining the sentiment of opinions. In *Proceedings of the 20th international conference on Computational Linguistics (p. 1367). Association for Computational Linguistics*.

Martinčić-Ipšić, S., Močibob, E. and Perc, M., 2017. Link prediction on Twitter. *PloS one, 12(7), p.e0181079*.

Khade, A.A., 2016. Performing customer behavior analysis using big data analytics. *Procedia computer science, 79, pp.986-992*.

Jongeling R, S. Datta, and A. Serebrenik. Choosing your weapons: On sentiment analysis tools for software engineering research. In *Proceedings of the International Conference on Software Maintenance and Evolution, pages 531–535, 2015*.

Nayab G , Bilal M , Shrafat A, 2016, “A brand is no longer what we tell the customer it is - it is What customers tell each other it is: Validation from lahore, *Pakistan, Sci.Int. (Lahore), 28(3),2757-2762*.

Chih-Hsuan W, 2015, A market-oriented approach to accomplish product positioning and product recommendation for smart phones and wearable devices, *International Journal of Production Research, 53:8, 2542-2553*.

Hair, J. F., Black, W. C.,Babin, B. J., & Anderson, R. E. 2009. Multivariate data analysis (7th Ed.). Upper Saddle River, *NJ: Prentice Hall*.

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