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Sentiment Analysis on Social Networking: A Literature Review

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Abstract— Large numbers of users share their opinions on Social networking sites, making it a valuable platform for tracking and analyzing public sentiment. Such tracking and analysis can provide critical information for decision making in various domains. So, it has attracted attention in both academia and industry. Presently, the use of public sentiment analysis has spread to services and making applications and developments came into existence in this area and now its main target is to make computer able to identify and create emotions like human being. This paper aims to create a data bank to facilitate the referencing needs of researchers and practitioners in this area. To this end, this paper presents the literature review pertaining to this topic. The literature review is based on the data collected from various research papers, tools and web sources.

Keywords*-Sentiment analysis; public opinion; twitter.*

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I. INTRODUCTION

With the rapid growth of Internet, extremely large amount of product reviews are rapidly upward on the Internet. Customers can obtain these reviews and can decide to purchase for his/her desire product. As well as, product manufacturers can obtain these product reviews from customers to improve the quality of their products on timely fashion and opinion method bringing together these two so that both of them can do for their advancement and beneficent. So, to give reviews on the products and get feedback of these product reviews Social networking sites is the best resource for tracking and analyzing public sentiment. Such tracking and analysis can provide critical information for decision making in various domains. So, it has attracted attention in both academia and industry. Presently, the use of public sentiment analysis has spread to services and making applications and developments came into existence in this area and now its main target is to make computer able to identify and create emotions like human being. This paper aims to create a data bank to facilitate the referencing needs of researchers and practitioners in this area. To this end, this paper presents the literature review pertaining to this topic. The literature review is based on the data collected from various research papers, tools and web sources that will strongly assist in easy referencing

II. LITERATURE REVIEWS

It has been a widely used area over the years and still it leaves a lot to be researched. [Fried, Surdeanu, Kobourov, Hingle, Bell] investigated the predictive power behind the language of food on social media. They collected a corpus of over three million food-related posts from Twitter and demonstrate that many latent population characteristics can be directly predicted from this data: overweight rate, diabetes rate, political leaning, and home geographical location of authors. For all tasks, their language-based models significantly outperform the majority class baselines. [Logunov, Panchenko] generated Twitter sentiment indices by analysing a stream of Twitter messages and categorising messages in terms of emoticons, pictorial representations of facial expressions in messages. Based on emoticons they generated daily indices. Then they explored the time-series properties of these indices by focusing on seasonal and cyclical patterns, persistence and conditional heteroscedasticity. [Zhang, Parikh, Singh, Sundaresan] chosen a particular global ecommerce platform (eBay) and a particular global social media platform (Twitter). They quantified the characteristics of the two individual trends as well as the correlations between it. They provided evidences that about 5% of general eBay query streams show strong positive correlations with the corresponding Twitter mention streams, while the percentage jumps to around 25% for trending eBay query streams.[Gonçalves, Araújo, Benevenuto, Cha] There are multiple methods for measuring sentiments, including lexical-based approaches and supervised machine learning methods. Despite the wide use and popularity of some methods, it is unclear which method is better for identifying the polarity (i.e., positive or negative) of a message as the current literature does not provide a method of comparison among existing methods. Such a comparison is crucial for understanding the potential limitations, advantages, and disadvantages of popular methods in analyzing the content of OSNs messages. They developed a new method that combines existing approaches, providing the best coverage results and competitive agreement.

[Gomide, Veloso, Meira Jr] analysed how Dengue epidemic is reflected on Twitter and to what extent that information can be used for the sake of surveillance. Dengue is a mosquito-borne infectious disease that is a leading cause of illness and death in tropical and subtropical regions, including Brazil. They proposed an active surveillance methodology that is based on four dimensions: volume, location, time and public perception. First they explored the public perception dimension by performing sentiment analysis. This analysis enables their to filter out content that is not relevant for the sake of Dengue surveillance. [Hong and Davison] proposed several schemes to train a standard topic model and compare their quality and effectiveness through a set of carefully designed experiments from both qualitative and quantitative perspectives. They showed that by training a topic model on aggregated messages they could obtain a higher quality of learned model which results in significantly better performance in two real world classification problems.[Deitrick, Valyou, Jones, Timian and Hu] discussed two popular topics in the study of social networks are community detection and sentiment analysis. Community detection seeks to find groups of associated individuals within networks, and sentiment analysis attempts to determine how individuals are feeling. While these are generally treated as separate issues, this study takes an integrative approach and uses community detection output to enable community-level sentiment analysis. [Saif, Fernandez, He and Alani] presented an overview of eight publicly available and manually annotated evaluation datasets for Twitter sentiment analysis. Based on this review, they showed that a common limitation of most of these datasets, when assessing sentiment analysis at target (entity) level, is the lack of distinctive sentiment annotations among the tweets and the entities contained in them. [O'Connor, Balasubramanyan, R. Routledge and Smith] analysed several surveys on consumer confidence and political opinion over the 2008 to 2009 period, and find they correlate to sentiment word frequencies in contemporaneous Twitter messages. [Anjaria, Mahana and Guddeti] introduced the novel approach of exploiting the user influence factor in order to predict the outcome of an election result. They also proposed a hybrid approach of extracting opinion using direct and indirect features of Twitter data based on Support Vector Machines (SVM), Naive Bayes, Maximum Entropy and Artificial Neural Networks based supervised classifiers and combined Principal Component Analysis (PCA) with SVM in an attempt to perform dimensionality reduction. [Davies and Ghahramani] demonstrated on data from Twitter, modelling happy vs sad sentiment, and show that in some circumstances this outperforms similar Naive Bayes models by more than 10%. [Cha, Haddadi, Benevenuto and Gummadi] used a large amount of data collected from Twitter, they presented an in-depth comparison of three measures of influence: indegree, retweets, and mentions. Based on these measures, investigated the dynamics of user influence across topics and time. They made several interesting observations. [Saif, Fernandez, He and Alani] investigated whether removing stop words helps or hampers the effectiveness of Twitter sentiment classification methods. To this end, they applied six different stop word identification methods to Twitter data from six different datasets and observe how removing stop words affects two well-known supervised sentiment classification methods. They assessed the impact of removing stop words by observing fluctuations on the level of data scarcity, the size of the classifier's feature space and its classification performance. [Beauchamp] This paper employs a new dataset of over 500GB of politics-related Tweets from the final months of the 2012 presidential campaign to interpolate and predict state-level polling at the daily level. By modelling the correlations between existing state-level polls and the textual content of state-located Twitter data using a new combination of time-series cross-sectional methods plus Bayesian shrinkage and model averaging, it is shown through forward-in-time out-of-sample testing that the textual content of Twitter data can predict changes in fully representative opinion polls with a precision currently unfeasible with existing polling data. [Kooti and Mason] described the process in detail, highlighting the factors that come into play in deciding which variation individuals will adopt. Their classification analysis demonstrates that the date of adoption and the number of exposures are particularly important in the adoption process, while personal features (such as the number of followers and join date) and the number of adopter friends have less discriminative power in predicting adoptions. They discussed implications of these findings in the design of future Web applications and services. [Marchand, Keselj, Milios and Shepherd] compared seven opinion lexicons on six sentiment datasets (movie reviews and tweets) conducted. Results suggested that increasing the lexicon size by semantic expansion as well as assigning an interval value to the words of the opinion lexicon significantly increases the classification performance on short texts (e.g. tweets). [Bifet and Frank] discussed the challenges that Twitter data streams pose, focusing on classification problems, and then consider these streams for opinion mining and sentiment analysis. To deal with streaming unbalanced classes, proposed a sliding window Kappa statistic for evaluation in time-changing data streams. Using that statistic they performed a study on Twitter data using learning algorithms for data streams. [Ceron and D'Adda] analysed that the daily variation in the Italian 2013 election voting intentions expressed on Twitter to evaluate the effect of different campaign messages, measured through the hand coding of parties and leader's official Twitter account. [Signorini, Segre, Polgreen] examined the use of information embedded in the Twitter stream to track rapidly-evolving public sentiment with respect to H1N1 or swine flu, and track and measure actual disease activity. They also showed that Twitter can be used as a measure of public interest or concern about health-related events. Their results showed that estimates of influenza-like illness derived from Twitter chatter accurately track reported disease levels.[An, Ganguly, Fang, Scyphers, Hunter, and Dy] attempted to understand whether Twitter data mining can complement and supplement insights about climate change perceptions, especially how such perceptions may change over time upon exposure to climate related hazards. A combination of techniques drawn from text mining, hierarchical sentiment analysis and time series methods is employed for this purpose. [Tumitan and Becker] detected whether user comments on an on-line newspapers reflect external indicators of public acceptance (e.g. vote intention). The paper outlines the approach used to identify and classify sentiment in news comments written in Portuguese language and to correlate it to external indicators, and discusses the main results for this case study. [Hu, Tang, Gao and Liu] proposed study the problem of *unsupervised sentiment analysis with emotional signals*. In particular, they investigated whether the signals can potentially help sentiment analysis by providing a unified way to model two main categories of emotional signals, i.e., emotion indication and emotion correlation. [Myslín, Zhu, Chapman, Conway] developed a content and sentiment analysis of tobacco-related Twitter posts and build machine learning classifiers to detect tobacco-relevant posts and sentiment towards tobacco, with a particular focus on new and emerging products like hookah and electronic cigarettes. Using the collected 7362 tobacco-related Twitter posts at 15-day intervals from December 2011 to July 2012 data, machine-learning classifiers were trained to detect tobacco-related vs irrelevant tweets as well as positive vs negative sentiment, using Naïve Bayes, k-nearest neighbors, and Support Vector Machine (SVM) algorithms. Finally, contingency coefficients were computed between each of the categories to discover emergent patterns. [Paul and Dredze] applied the recently introduced Ailment Topic Aspect Model to over one and a half million health related tweets and discover mentions of over a dozen ailments, including allergies, obesity and insomnia. They introduced extensions to incorporate prior knowledge into this model and apply it to several tasks: tracking illnesses over times (syndromic surveillance), measuring behavioral risk factors, localizing illnesses by geographic region, and analyzing symptoms and medication usage. [Henderson and EliassiRad] applied LDA-G to several large graphs (with thousands of nodes) from PubMed (a scientific publication repository). They compared LDA-G's quantitative performance on link prediction with two existing approaches: one Bayesian (namely, *Infinite Relational Model*) and one non-Bayesian (namely, *Cross-associations*). On average, LDA-G outperforms IRM by 15% and Cross-associations by 25% (in terms of area under the ROC curve). Furthermore, they demonstrated that LDA-G can discover useful qualitative information. [Hu] discussed algorithms that extend LDA to accomplish tasks like document classification for text, object localization for images, and automatic harmonic analysis for music. For each domain, also emphasized approaches that go beyond LDA's traditional bag-of-words representation to achieve more realistic models that incorporate order information. [Moghaddam and Ester] addressed the problem of opinion question answering to answer opinion questions about products by using reviewers' opinions. Their proposed method, called Aspect-based Opinion Question Answering (AQA), support answering of opinion-based questions while improving the weaknesses of current techniques. [Arora and Srinivas] tried to characterize the opinion-mining landscape by proposing a faceted taxonomy of the different aspects of opinion mining. They then surveyed literature and place these in appropriate places in the proposed model. They also proposed a general purpose work flow required from any opinion mining engine. [Jiang, Zhang, Fu, Niu and Yang] defined several tree kernels for sentiment expression extraction and sentiment classification, which are subtasks of opinion mining. Their proposed tree kernels encode not only syntactic structure information, but also sentiment related information, such as sentiment boundary and sentiment polarity, which are important features to opinion mining. [Fu, Peng, Kuo and Lee] focused on different features with different scopes on facebook can be found by multi-level opinion-consistent hidden community(OCHC) framework that proposed in the paper. Communities of opinion-consistent users are clustered Multi-level OCHC model. [Deng, Xu, Zhang, Han and Zou] employed the concept of public opinion field, on which event information and public opinion in text corpus are distinguished. Based on this view, they focused on how does the public opinion affect the evolution of events, proposed a method to measure the influence, and represent it on the event evolution graph. [Lau, Lai and Yuefeng] illustrated of a novel opinion mining method underpinned by context-sensitive text mining and inferential language modelling to improve the effectiveness of opinion mining. Their initial experiments showed that the proposed the inferential opinion mining method outperforms the purely lexicon-based opinion finding method in terms of several benchmark measures. [Yongyong, Yanxiang, Xuegang, Peipei and Xindong] approached OFESP (Opinion Feature Extraction based on Sentiment Patterns) which takes into account the structure characteristics of reviews for higher values of precision and recall. With a self-constructed database of sentiment patterns, OFESP matches each review sentence to obtain its features, and then filters redundant features regarding relevance of the domain, statistics and semantic similarity. [34] There are many research works in opinion mining. However, all current methods are focusing on how to handling the opinion mining for English language, Chinese, Japanese and so on. There lacks works on how to conduct Cantonese Opinion Mining. To solve the problem, in the paper, we propose a method to handle sentiment analysis for Cantonese opinion mining. [Liu, Xu and Zhao,] compared to the traditional unsupervised alignment model, the proposed model obtains better precision because of the usage of partial supervision. In addition, when estimating candidate confidence, they penalized higher-degree vertices in our graph-based co-ranking algorithm to decrease the probability of error generation. Their experimental results on three corpora with different sizes and languages show that their approach effectively outperforms state-of-the-art methods. [Wang and Zhou] proposed a new approach based on opinion mining. Through the reviews customers have posted they can mining the evaluation of various Web site indexes quantitatively. To improve the accuracy of the mining results they used a approach called MRA (mutual reinforcement approach). [Cho, Ryu, Jeong, Hee Kim and Kim] proposed different methods of opinion mining from existing ones. The methods we present here enable credibility evaluation and result conversion using influence of each opinion holder on the Internet and their personal information, which are an analysis-result of LIWC, including their background information and tendency. [Jawale, Kyatanavar and Pawar] explored an idea of extracting real time dataset through provided Graphical User Interface (GUI). The summarization unit would generate opinion mining result in visualized form for further decision making process. [Yu Xiao ; Lin Xia] proposed a LeaderRank algorithm to identify opinion leaders based on community discovery and emotion mining methods. The performance of this algorithm is evaluated using real-world datasets and their experiments showed that the identification of interest groups and the emotion property shown in post/reply articles helps to find opinion leaders on Bulletin Board System (BBS). [Hu, Gong and Jingzhi Guo] presented how to mine product features. The proposed extraction approach is different from the previous methods because they only mined the features of the product in opinion sentences which the customers have expressed their positive or negative experiences on. In order to find opinion sentence, a SentiWordNet-based algorithm is proposed. [Xiaojun Li ; Lin Dai ; Hanxiao Shi] proposed a opinion mining system which mines useful opinion information from camera reviews by utilizing Semantic Role Labeling (SRL) and polarity computing method. Feature lexicon and sentiment lexicon are constructed to mine features and emotional items. [Han, Du and Chen] presented a web opining mining algorithm based on sentiment phrase classification vector. By the techniques of sentiment phrase classification, the algorithm compares the similarity between

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document vectors, mines the theme of the document and judges the document theme attributes. [Hai, Chang, Kim and Yang] proposed a novel method to identify opinion features from online reviews by exploiting the difference in opinion feature statistics across two corpora, one domain-specific corpus (i.e., the given review corpus) and one domain-independent corpus (i.e., the contrasting corpus). [Ahmad and Doja] presented the (Frequent Pattern) FP-growth method for frequent pattern mining from review documents which act as a backbone for mining the opinion words along with their relevant features by experimental data over two different domains which are very different in their nature. [Xu, Cheng, Tan, Liu and Shen] focused on how to improve aspect-level opinion mining for online customer reviews. They proposed a novel generative topic model, the Joint Aspect/Sentiment (JAS) model, to jointly extract aspects and aspect-dependent sentiment lexicons from online customer reviews. [Jusoh and Alfawareh] introduced the use of a fuzzy lexicon and fuzzy sets in deciding the degree of positive and negative. Their experimental result showed that the approach is able to extract opinions and present the opinions in a more efficient way. [JiangJiao Duan and Jianping Zeng] proposed a novel method to forecast stock returns by mining opinion and sentiment from Web forum messages. Opinion about the drop and rise of stock prices is firstly extracted from the messages posted by forum users. Then unhealthy sentiment is recognized by means of pattern matching. A Bayesian model that incorporates opinion and unhealthy sentiment is established to infer the relation between stock returns and the combination of opinion and sentiment. [Muangon, Thammaboosadee and Haruechaiyasak] proposed a framework of feature based opinion mining by using scores which essentially relies on the usage of two main lexiconizing levels, features and polar words. An approach for extracting features and polar words from textual opinion is based on syntactic pattern analysis. [Sohail, Siddiqui and Ali] presented a recommendation technique based on opinion mining to propose top ranked books on different discipline of the computer science. Based on the need of the customers and the reviews collected from them, we have categorized features for the books. They analysed the features on the basis of several characteristics that we have categorized and reviews of the users. Weights are assigned to categorized features according to their importance and usage, and accordingly the ranks are given. [Liang and Dai] proposed a new system architecture that can automatically analyze the sentiments of these messages. They combined this system with manually annotated data from Twitter, one of the most popular micro blogging platforms, for the task of sentiment analysis. In this system, machines can learn how to automatically extract the set of messages which contain opinions, filter out non opinion messages and determine their sentiment directions (i.e. positive, negative). [Yin-Fu Huang ; Heng Lin] presented a product ranking system using opinion mining techniques. Users can specify product features to get back the ranking results of all matched products. In that system, they considered three issues while calculating product scores: 1) product reviews, 2) product popularity, and 3) product release month. [Medagoda, Shanmuganathan and Whalley] investigated opinion mining and sentiment classification studies in three non-English languages to find the classification methods and the efficiency of each algorithm used in these methods. It is found that most of the research conducted for non-English has followed the methods used in the English language with only limited usage of language specific properties, such as morphological variations. The application domains seem to be restricted to particular fields and significantly less research has been conducted in cross domains.[Liu, Zhiqiang, Bing and Zhang] showed Logic Programming, particularly Answer Set Programming (ASP), that can be used to elegantly and efficiently implement the key components of syntax based aspect extraction. Specifically, the well-known double propagation (DP) method is implemented using 8 ASP rules that naturally model all key ideas in the DP method. [Rogovschi and Grozavu] described in this research provides topological clustering of the opinion issued from the tweets, each cluster being associated to a prototype and a weight vector, reflecting the relevance of the data belonging to each cluster. [Lima, Allan Diego Silva ; Sichman, Jaime Simao] presented a generic and domain independent opinion relevance model for a Social Network user. The Social Opinion Relevance Model (SORM) is able to estimate an opinion's relevance based on twelve different parameters. Compared to other models, SORM's main distinction is its ability to provide customized results according to whom the opinion relevance is being estimated for. [Dziczkowski, Wegrzyn-Wolska and Bougueroua] described functions of a system designed for the behaviour analysis of e-commerce clients. It enables user identification and client behaviour extraction for interacting with web site customers. Their system carries out an evaluation and rating of opinions, and their approach is based on linguistic and the statistic treatment of natural language. [Leopairote, Surarerks and Prompoon] discussed problem of different sentiment of the same sentence in different environment. To solve this problem, rule-based classification is used as their machine learning model. In this research, software quality extracted from user perspective with respect to ISO 9126 is selected to be the characteristic model and proposed a methodology for a software product reviews mining based on software quality ontology and a product software quality in use scores for software review representation. [Aldahawi and Allen] analyzed data collected from Twitter and investigate the variance that arises from using an automated sentiment analysis tool versus human classification. Their interest particularly, lies in understanding how users' motivation to post messages affects the quality of classification. The data set utilizes Tweets originating from two of the world's leading oil companies, BP America and Saudi Aramco, and other users that follow and mention them, representing the West and Middle East respectively. [Karkare and Gupta] discussed that most of the existing methods are processing the reviews in terms of positive and negative comments. But this approach is not enough for a customer to make decision about product. The proposed approach not only finding the positive and negative comments for any product or product features, but also rating them in the order of positivity and negativity. Also, the proposed approach gives the degree of comparisons for a particular product and product features. [Lavanya and Varthini] discussed that in order to get useful data it becomes necessary to apply NLP techniques which make it easy for the people to make decisions at the time of buying products or contracting services. All the users are not concerned with all features of a product. Hence this research proposed a feature based sentiment classification method that helps a user to make decisions easily based on their features of interest.

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III. CONCLUSION

Today social networking on Internet have become an essential part for everyone. By making Internet useful with the help of applying opinion or sentiment mining techniques, a customers and company manufacturers can get reviews of the product and get feedback from the customers so that the company can improve its product to satisfy his customers approximately 100% respectively. Even though a lot of work have been done in this area but still it acts as a fertile area for new researchers. Thus, this paper makes an attempt to present the literature review in an organized manner covering various aspects of mobile forensic analysis. The literature review is based on the data collected from various publications, books, tools and web sources. It has been realized from the study that even though the field has been researched a lot so far, but still it acts as a fruitful area for new researchers as it is very vast. It is anticipated that this paper will facilitate the reference needs of researchers and practitioners and hence will encourage research in this area.