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Enhanced Research of Sentiment analysis Techniques in Social Media Content

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ABSTRACT

Human involvement is potentially the richest amount of information found on social media. Information received from internet consumers reflects their views on subjects or goods. It's almost hard for us to wade through any of such data. The study of social media communication has grown to be a critically significant part of social media work. However, most sentiment analysis is currently done on the gross stage, rather than the fine granularity and doesn't conduct the nuances required. Sentiment research has gained prominence. As several search engines seek out opinionated data and classify it as such, some text interpretation problems are more complex than with conventional text analysis. This is unequivocal about the need to resolve these issues and has opened the doors to potential polysemantic processing research. However, with data increasing in volume, the automated data processing is required. As extensive research is conducted into various sentiment analysis methods, a survey of these Sentiment measurements is provided.

Keywords: Sentiment analysis, Social Media, Emoticons, Challenges

Introduction

Over the last decade, social networking has expanded radically, such as Twitter, Facebook, WeChat, and Instagram. on other hand, Twitter claims to have over 320 million diverse users the Internet offers all the opportunity to post thoughts, ideas, loves, dislikes, and memories with ease and casualness never before possible in history [3]. We want to engage in this less structured manner. It motivates researchers to grasp and test new insights such as speech recognition and emotion analysis this way and with lexical, syntactic, and textual; this is correlated with the dynamic today; everybody is making use of social media to communicate their feelings. Thus, social media's created data may be used to look at users' reactions around the same time; some individuals held on to neutral positions on whether they could purchase an Apple Watch [7]. For the most part, marketers will like to know which demographic groups feel good towards their brands to drive more extraordinary sales efforts to increase their popularity. Furthermore, they can manipulate their mates' perceptions of their ideas by targeting consumers through social media [9].

Social media has transformed how people interact through posts, reviews, remarks, and evaluations. Customers are now allowed to check and discuss goods, regulations, and other issues via social networking. A Twitter account is a type of social media that gives users the freedom to express their views on any subject called "tweets." It has over 100 million users, and its primary purpose is to have enormous social networking info, of which tweets comprise the

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majority. Tweets cover nearly any kind of material, including users' personal lives (e.g., likes, dislikes, & items they're purchasing), recent events, and constant, relevant facts (e., earthquake). If finer distinctions can be made, it will produce more precise and more effective outcomes, such as angry, sad, anxious emotions, and happier ones [5].

This paper is structured in the following manner. In section 2, we discuss related research and our approach to other ones. This portion contains the Social Network Analysis section. In the fourth part, we present a discussion of the new framework. In closing, we leave additional observations and suggestions for future studies.

Background Study

Alam, M. et al. [1] Social networking has emerged as an integral component of the global communication process. This paper works with neural network hyperparameters to determine the sentiment of terms for social media use cases and show their ability to forecast and distinguish. The paradigm allows more competent community governments to make efficient use of indicators of their signature strengths. We first use specialized domain-specific word representation, which out-performs generalized data sets on a corpus.

Abid, F. et al. [2] The authors used domain-specific processing strategies on multi-specific databases and multi-source POS labeling to develop more efficient distributed representations.

Kolajo, T. et al. [4] Enhances content analytics approaches to allow for better comprehension, analysis, handling, and handling of slang, acronyms, abbreviations. These should be factors that lead to efficient and effective subsequent learning algorithms to work.

Mirtalaie, M. A., & Hussain, O. K. [6] The proposed method helps product designers identify and grouping features, helping them understand their importance, and guides them in the application of those tailored to their areas of interest. Also, a focused function considers dependencies are taken into account when assessing sentiment. It is different from other current emotion methods because it focuses on the finer aspects instead of the broad ones. Therefore, the techniques must be used more often when product designers choose to learn about the importance of a particular function. Our research showed that each step of SA-TF works better than those in the research literature. SA-TF also draws on these prior hypotheses of SM, facilitating decisions and decision making.

Shahare, F. F. [7] We have ingenious methods to compute emotion dependent on social network data to find press incidents. Our goal of using data journalism is to process news stories and research relevant emotions.

Tanna, D. et al. [8] To further understand how users' feelings impact others on the web, we focus on social networking and user actions usage of sentiment analysis to analyze and track. Still, it isn't essential for these activities various types of entities, including companies or colleges, may have access to interpret users' feelings toward their organizations. The report would allow universities to create social networking platforms that support their whole university and identify distressed users.

Wang, Z. et al. [11] This sentiment analysis research succeeded in devising an improved classifier for finding anomalies from social network data. The suggested approach has been seen to be effective using real-time Tweets as a case study. Using the proposed method, the various unusual anomaly trends were detected and interpreted. In the experiment, the process showed its efficiency and merit. The system was tested and found to have perfect consistency with human annotators' related classification tasks.

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Emoticons in Social Media

Social networking and instant messaging users utilize a wide range of emoticons. The majority of emoticons, such as ":)" and ":(" are commonly in usage, although a minority of the overall population uses other popular ones, such as. "and "?" Over the years, many different emoticons have been included in various experiments and collected the best of such expressions. Let's find an emoji (https://dev.twitter.com/apps/overview) in the full TwitterDecahosearch for some emoticons from March of 2015. (the Twitter Decahose API provides 10 percent of the total Twitter traffic). The message, which is just a one-tweet article, has a character limit of 140 characters. Twitter has almost one and a half billion messages in its database. Approximately 8,625,753 emoticons were discovered in that collection of results. If you look at most of the messages, most of them have just one emotion.

- **Emoticons and Sentiment**

For research purposes, such as polarities, such as optimistic or negative or neutral, such as unfavorable, In contrast, the emoticons, though, convey more nuanced feelings that cannot be described in terms of three groups. A lot of human activity does not fit into precisely one of space.

This study of emoticon sentiment validated the theory that certain emoticons are accurate markers of sentiment polarity, but a wide range of how people communicate emotions by emoticons and how they perceive the sentiment expressed through emoticons.

- **Clustering emoticons and words**

The sense in which feelings are typically used and the significance emoticons express are intriguing issues about their use. To address these queries, we used two machine learning algorithms in this study. First, we used a version of word2vec, a deep neural network-based algorithm, to describe the representation of the terms in the data collection, including emoticons.

- **Classifying sentiment with vs. without emoticons**

The findings of the previous study supported the role of emoticons in emotional communication. It's reasonable to ask whether deleting emoticons from the text would potentially damage emotion classification using machine learning algorithms. We used the bag-of-words model to train two Nave Bayes classifiers to evaluate this hypothesis. The 500 manually annotated tweets in subsection B served as training and testing info. On the initial tweets, one classifier was educated and checked. Another classifier was educated and contained the same sample of tweets but without the emoticons.

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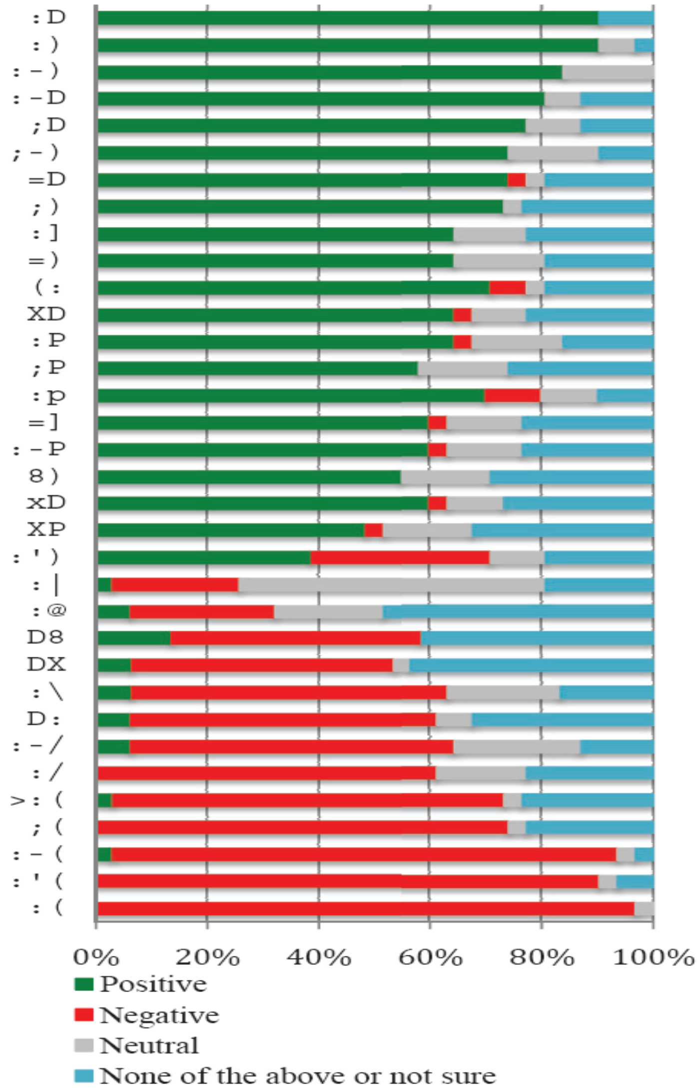

Figure 1. Survey of emotion expressed by emoticons

There are two possible reasons for the variations in accuracy and memory between positive and negative groups. For starters, drop the emoticons likely harmed the classifiers by making detail accessible to them. Second, it may be that the good and negative groups received fewer training tests in the no-emoticon scenario. Although this experiment may be enhanced by annotating further examples, current findings seem to support the claim that deleting emoticons from text hurts machine learning classifier efficiency.

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Comparative Analysis of Survey

Table 1: Evaluation of various authors' views.

Paper Name	Methodology	Limitations
Kolajo, T. et al. [4]	Social network streams are pre-processed for improved results. To accomplish this, an interconnected knowledge base (ikb) including a local knowledge source (Naijalingo), an urban dictionary, and internet slang were coupled with the adapted Lesk algorithm to enable semantic analysis of social network streams.	A word vector usage to describe a tweet in text classification has the disadvantage of preserving word order and does not correctly capture the textual meaning.
Mirtalaie, M. A., & Hussain, O. K. [6]	The architecture for sentiment aggregation for targeted features (SA-TF). SA- TF calculates the sentiment of a targeted part by assisting product designers in mapping the features addressed in feedback to the appropriate product elements, sentiment accumulation, and taking functionality dependencies into account to assess their polarity. The dominance of the various SA-TF phases is illustrated by tests and comparison with an actual approach.	The consumer feedback that is analyzed must come from reliable sources. Customers have input on a variety of social media sites. There might be cases where consumers' shared opinions are distorted or erroneous. If such feedback is taken into account, the product designer may have a distorted and inaccurate portrayal of the targeted functionality, contributing to incorrect decisions.
Tanna, D. et al. [8]	Users will gain access to a centralised network that allows them to do much more than the other social networking platform.	The services offered are minimal, and the correct kind of analysis costs a fortune. Sentiment research is seen in just a few areas in today's technological timeline.

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Wang, Z.et al. [10]	A social network analytics engine that uses a social adaptive fuzzy similarity-based classification system to automatically classify text messages into mood groups (positive, negative, neutral, and mixed), as well as the potential to distinguish their general emotion categories (e.g., satisfaction, happiness, excitement, anger, sadness, and anxiety).	The perspectives gained allow decision-makers to develop plans and improve the efficiency of their goods, services, and policies.
Wang, Z.et al. [11]	Emotion analysis can be used to identify patterns in social network results. We evaluated the method's applicability and robustness using sentiment analysis on tweet info. The results validate the proposed method's strengths and provide useful insights into this research area.	The training data must be broad enough to allow for adequate coverage of the whole target domain. It isn't easy to assess a training dataset's successful size in the real-world social network sense.

Discussion

Overall, we found that behavioral research parameters dependents on social networks would improve forecast accuracy Researchers profit from it in learning analytics, data analysis and learning technology. It offers an analytical workflow to analyze social network data that overcome the main limitations of manual qualitative analysis and computer-based analysis of textual content provided by users alike. Our research will educate school leaders, practitioners, and other related policy-makers to obtain more knowledge of people's college perceptions. Semantic functions are often beneficial from the agent's point of view to consider the influence parameters that affect the effects. Social networks built on Twitter provide a fantastic forum to measure popular sentiment with reasonable precision.

Some of the Challenges in Social Media Sentiment Analysis

- **Incremental Approach**

Real-time data analysis is not one-time. When adding data, we have to analyze whether we do not include the previous comments' results. The incremental methodology makes it possible to upgrade an ongoing outcome with only fresh individual data instances without re-processing previous models. This will be helpful as the whole dataset is not accessible if the data evolves.

- **Parallel Computing For Massive Data**

If we split the processing into tasks or continuous processes, performance improvements may be achieved by the concurrent application of sentiment analysis with tremendous social network results. Large instant messages are released daily for us to leverage the computational resources overall.

- **Grammatically Incorrect Words**

There are numerous ways to analyze feelings but hard work with grammatical errors. If these forms of mistake can be mapped to correct terms, sentimental analysis outcomes can be enhanced.

- **Review Author Segmentation**

Many people who can be named as review writers can have an opinion on a target. The writers must be classified according to their commentary style such that authenticity assessment is straightforward. This integrity assessment is helpful in decision-making.

- **Handling Noise and Dynamism**

Social networking data are vast, chaotic, unstructured and complex, creating new obstacles and presenting representative social media analysis issues. Identification and deletion of noisy data is a complicated process.

Conclusion

Sentiment analysis has become a widespread study domain, and many excellent studies have been conducted in this field. Several modern pieces of literature are analyzed in this survey. This study identified and graded feeling review in specific research from a variety of viewpoints, i.e., task-based, granularity-based and methodological. We have examined various forms of data and methods used in research on sentiment analysis and indicated their strengths and shortcomings. This survey developed a common vocabulary in numerous studies that enables people of diverse backgrounds to understand quickly and laid the foundations for advanced sentiment analysis testing.

References

[1] Alam, M., Abid, F., Guangpei, C., & Yunrong, L. V. (2020). Social media sentiment analysis through parallel dilated convolutional neural network for smart city applications. Computer Communications. doi:10.1016/j.comcom.2020.02.044

[2] Abid, F., Li, C., & Alam, M. (2020). Multi-source social media data sentiment analysis using bidirectional recurrent convolutional neural networks. Computer Communications. doi:10.1016/j.comcom.2020.04.002

[3] Cheng, L.-C., & Tsai, S.-L. (2019). Deep learning for automated sentiment analysis of social media. Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. doi:10.1145/3341161.3344821

[4] Kolajo, T., Daramola, O., Adebiyi, A., & Seth, A. (2020). A framework for pre-processing of social media feeds based on integrated local knowledge base. Information Processing & Management, 57(6), 102348. doi:10.1016/j.ipm.2020.102348

[5] Li, D., Rzepka, R., Ptaszynski, M., & Araki, K. (2020). HEMOS: A novel deep learning-based fine-grained humor detecting method for sentiment analysis of social media. Information Processing & Management, 57(6), 102290. doi:10.1016/j.ipm.2020.102290

[6] Mirtalaie, M. A., & Hussain, O. K. (2020). Sentiment aggregation of targeted features by capturing their dependencies: Making sense from customer reviews. International Journal of Information Management, 53, 102097. doi:10.1016/j.ijinfomgt.2020.102097

[7] Shahare, F. F. (2017). Sentiment analysis for the news data based on the social media. 2017 International Conference on Intelligent Computing and Control Systems (ICICCS). doi:10.1109/iccons.2017.8250692

[8] Tanna, D., Dudhane, M., Sardar, A., Deshpande, K., & Deshmukh, N. (2020). Sentiment Analysis on Social Media for Emotion Classification. 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS). doi:10.1109/iciccs48265.2020.9121057

[9] Wang, H., & Castanon, J. A. (2015). Sentiment expression via emoticons on social media. 2015 IEEE International Conference on Big Data (Big Data). doi:10.1109/bigdata.2015.7364034

[10] Wang, Z., Chong, C. S., Lan, L., Yang, Y., Beng Ho, S., & Tong, J. C. (2016). Fine-grained sentiment analysis of social media with emotion sensing. 2016 Future Technologies Conference (FTC). doi:10.1109/ftc.2016.7821783

[11] Wang, Z., Joo, V., Tong, C., Xin, X., & Chin, H. C. (2014). Anomaly Detection through Enhanced Sentiment Analysis on Social Media Data. 2014 IEEE 6th International Conference on Cloud Computing Technology and Science. doi:10.1109/cloudcom.2014.69

[12] Zhang, L., Yuan, H., & Lau, R. Y. K. (2016). Predicting and Visualizing Consumer Sentiments in Online Social Media. 2016 IEEE 13th International Conference on e-Business Engineering (ICEBE). doi:10.1109/icebe.2016.025

[13] M.Lingaraj, A.Senthilkumar, J.Ramkumar (2021). Prediction of Melanoma Skin Cancer Using Veritable Support Vector Machine1, Annals of Romanian Society for Cell Biology, ISSN:1583-6258, Vol. 25, Issue 4, 2021, Pages. 2623–2636.