Sentiment Analysis on Instagram Threads Review Using VADER and RoBERTa

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*Abstract* **:- This study delves into sentiment analysis of Instagram Threads reviews, employing advanced natural language processing techniques. The research leverages VADER, a robust sentiment analysis tool, alongside RoBERTa, a state-of-the-art transformer-based model. Through this combination, the study aims to discern the overall sentiment of user-generated content within Instagram Threads reviews. The choice of VADER, known for its effectiveness in analysing short and informal texts, complements RoBERTa's proficiency in processing complex language structures. The integration of these tools offers a comprehensive approach to understanding the sentiments expressed in user reviews. This research contributes valuable insights into the sentiment landscape surrounding Instagram Threads, shedding light on user perceptions and feedback. Additionally, it showcases the potential of combining established sentiment analysis tools with cutting-edge models for nuanced analysis of social media content.**

Keywords—VADER, RoBERTa, threads, sentiment analysis, reviews .

INTRODUCTION

Sentiment analysis involves the extraction and comprehension of emotions expressed within a text document. The surge in data across various social media platforms such as Twitter, Facebook, and Instagram have empowered consumers to voice their opinions about products, individuals, and places in new ways. These opinions are typically conveyed through textual information. Each day, millions of textual messages are exchanged on social media and online shopping platforms. Assessing and dissecting the sentiment of these opinions is a highly crucial task. This is where Natural Language Processing (NLP) coupled with artificial intelligence and text analytics come into play, helping determine whether the sentiment is positive, negative, or neutral. Opinion mining and sentiment analysis are not restricted to any specific domain or platform. Furthermore, sentiment analysis offers valuable business intelligence that can inform impactful decision-making.

The behaviours of online users have evolved in tandem with the increasing volume of data on the internet. According to statistics [1], 70% of online users interested in purchasing electronics indicated that they read online reviews before making a purchase. This trend has spurred extensive research in sentiment analysis and opinion mining for online platforms like Instagram and Facebook. Several studies [2], [3], [4] have examined microblogging platforms such as Instagram and Facebook to discern people's opinions and categorize them based on sentiment. These resources yield a diverse range of information. For instance, manufacturers can gather insights about their products, while political parties and social organizations can shape their events based on the findings of these studies. While microblogging platforms like Twitter offer advantages such as a wide array of data and rapid information flow [1], it is worth noting that some tweets may contain sarcasm [5], making it challenging to label such a vast dataset based solely on certain features [6]. This can lead to suboptimal results and a reduction in the performance of machine learning models. In order to address these issues and enhance predictive accuracy, we have devised a novel approach.

Instagram Threads is a widely-used microblogging platform that enables users to share, convey, and interpret concise, real-time messages referred to as threads. At a glance, the Threads interface bears resemblance to Twitter. Both platforms offer a stream of text-based updates, allowing users to stay updated with global events and initiate their own discussions. With the capacity to incorporate images, videos, and links, Threads serves as an effective means to connect with your network and the wider audience. Each thread can extend up to 500 characters, nearly double the 280-character limit of Twitter. This extended length facilitates the articulation of comprehensive ideas or the narration of more intricate stories without requiring followers to sift through multiple posts for complete information. Threads amassed over 100 million users within a week of its launch, setting a record as the fastest-growing application in history. Consequently, Instagram Threads serves as a valuable data source employed in the realms of opinion mining and sentiment analysis.

The VADER (Valence Aware Dictionary and sEntiment Reasoner) Sentiment Analysis tool is a potent resource employed in the field of natural language processing. It empowers users to assess the overall sentiment expressed in a piece of text, typically characterized by brevity and informality, which makes it particularly adept at scrutinizing user reviews and comments. In this study, the SentimentIntensityAnalyzer from Python's Natural Language Toolkit (NLTK) library was employed. This analyser adopts a lexicon-based approach, wherein the lexicon encompasses the intensity levels of all sentiment-evoking words. These intensities are extracted, culminating in a sentiment score that determines whether the review is categorized as positive, negative, or neutral. Thanks to VADER's pretraining, results can be obtained more swiftly compared to many other analysers. However, a limitation of VADER lies in its ability to only discern sentiments for words present in its lexicon. Any new slang terms, if used in a review, will not impact the classification process as these slang words are not included in the lexicon and thus lack polarity. VADER shines brightest when handling short sentences, slang, and abbreviations commonly found in social media content.

The Robustly Optimized BERT Pretraining Approach (RoBERTa) is a pre-trained model developed by Hugging Faces. It undergoes training on an extensive dataset encompassing over 160GB of uncompressed text. RoBERTa represents an enhanced version of the Bidirectional Encoder Representations from Transformers (BERT) model, characterized by extended training periods, larger training batches, and an augmented volume of training data. BERT, a valuable technique in natural language processing (NLP), originates from the concept of pre-training contextual representations. It employs bidirectional Transformer training to grasp contextual associations among words within a given text. This methodology is applied to pre-train comprehensive bidirectional representations, conveyed as numerical vectors, to convey word meanings in the text through a multi-layer bidirectional Transformer. When presented with a text sentence, it produces a three-dimensional vector of sentiment scores, with each component corresponding to the likelihood of positive, neutral, and negative sentiments. Subsequently, we compute the RoBERTa sentiment scores as the disparity in probability between positive and negative sentiments.

LITERATURE REVIEW

In recent times, there has been a growing interest among researchers in the field of sentiment analysis. The following are earlier studies that have made significant contributions to this area in the past few years. Specifically, the assessment of the emotional content in text messages [7-10] to gauge their informational value [11], along with the identification of key user sentiments [12-14], a component of natural language processing, has captured the attention of the scientific community. This surge in interest can be attributed to the expanding range of potential applications. Text message sentiment analysis involves the extraction and interpretation of user evaluations of products and models, employing various approaches that utilize machine learning algorithms to categorize the emotions conveyed in the text [7]. For instance, this technique has been applied in sentiment analysis of tweets to comprehend public perception of specific news, evaluate interactions between humans and robots, and establish recommendation systems for product selection, among other applications [15, 16].

In their study [17], the authors discovered that employing a blend of machine learning alongside a lexicon-based approach yields greater accuracy than any single form of sentiment analysis. They employed a diverse range of sentiment analysis techniques, incorporating both machine learning models and dictionary-based methods, to assess and contrast the efficacy of user behaviour research.

In the study [1], extended BERT models are examined for their effectiveness in recognizing sentiment in tweets. To thoroughly assess the performance of Enhanced BERT, the Kaggle SMILE dataset is utilized. This dataset is assessed for emotions such as "happiness" and "sadness," among others, and sorted into specific categories. Experimental results indicate that this version of the model attains an impressive accuracy of 0.96.

Simultaneously, there have been several optimization models leveraging BERT, such as RoBERTa [18] and ALBERT [19]. RACSA maximizes the use of pre-trained language models and strengthens the connection between text and the specified aspect category by employing RoBERTa for feature extraction and fine-tuning. We propose the utilization of a cross-attention mechanism to guide the model's focus towards the text segment most relevant to the given aspect category. To tackle category imbalance, we incorporate a logarithmic balance factor to enhance the learning weight of sentiment polarity categories with fewer samples. Furthermore, RACSA operates as a multi-task learning model, treating each aspect category as an individual subtask.

Wagh et al. [20] introduced a versatile sentiment classification system designed for situations where no labelled data is available in the target domain. This method utilizes labelled data from a separate domain and was also employed to calculate term frequencies in tweets. The study focused on analysing a dataset consisting of four million publicly accessible tweets from Stanford University, which served as the foundation for predicting the sentiment expressed in individuals' opinions. While traditional classification algorithms can be used to train sentiment classifiers with manually labelled text data, this manual labelling process is both expensive and time-consuming. The research revealed that directly applying a classifier trained in one domain to other domains leads to notably lower performance. The study evaluated the accuracy of various algorithms across different quantities of tweets, including Naive Bayes, Multi-nominal NB, Linear SVC, Bernoulli NB classifier, Logistic Regression, and the SGD classifier. The results demonstrated that the proposed system exhibited superior efficiency compared to existing systems.

METHODOLOGY

In this paper, we present a comparative analysis of two distinct models applicable to sentiment analysis using a dataset comprised of thread reviews. During our investigation, it becomes evident that Google Play Store stands as the most widely employed platform for application downloads. An inherent advantage of Google Play Store is its feature that allows users to preview reviews before downloading any application. However, this presents a challenge for application owners as negative reviews can potentially harm an organization's reputation. The repercussions of a tarnished reputation persist over time, which is why organizations, regardless of their size, are concerned about their digital footprint.

1. *Data Set*

The Threads reviews dataset, sourced from Kaggle, underwent a cleaning process wherein extraneous columns were removed. Ultimately, the dataset comprised only two columns: "Review" and "Rating". This dataset was unsupervised. Subsequently, it was divided into two subsets based on the conditions: one containing solely positive reviews with ratings greater than 3, and the other consisting of negative reviews with ratings less than 3. The total dataset size used in the experiment was 2000.

1. *Data Processing*

Several preprocessing procedures were implemented to eliminate extraneous details from the tweets. This is crucial as cleaner data enhance their suitability for mining and feature extraction, consequently boosting result accuracy. Python's Natural Language Toolkit (NLTK) was employed for this data preprocessing task. The reviews underwent several steps: all characters except [! a-zA-Z] were eliminated using regular expressions; the text was then converted to lowercase, and common stop words (like "a," "an," "in," and "the") were subsequently removed.

1. *Proposed Method*

We utilized the VADER Lexicon module within Python's NLTK Framework, employing the entire dataset comprising 2,000 reviews for testing purposes. The model's output was structured as a dictionary containing scores for positive, negative, neutral, and compound sentiments. In the VADER Lexicon approach, when a sentence (or review) is input into the model, it identifies the emotional words and their respective intensities. Each word's polarity score falls within a range of -4 to 4, with -4 indicating extremely negative and +4 signifying highly positive sentiment. However, the overall sentiment score for a statement falls between -1 and 1. This is achieved by standardizing the sentiment scores of individual words, leading to the creation of a new metric referred to as the compound score. The compound score offers insights into both the intensity and polarity of the review. In cases where a sentence contains multiple sentiment words, their scores are aggregated and then normalized to yield the compound score.

1. *Calculation of compound Score*

Compound score =

In the equation, Alpha represents a constant typically set at 15, and 'x' signifies the cumulative polarity scores of all the words. Let us examine an example: "The food here is good and service is nice." In this case, 'good' and 'nice' are two sentiment words with polarity scores of 1.9 and 1.8, respectively. When we calculate the compound score, our 'x' value becomes (1.9 + 1.8) = 3.7. Consequently, our compound score amounts to 0.6907. Subsequently, we categorized the reviews based on the compound score derived from the VADER tool. If the Compound Score is greater than or equal to 0, the review is labelled as positive; otherwise, it is labelled as negative.

Sentiment Analysis() < ̶ File

For each row in rows

If sentiment Polarity Score(line)>0.05 then

Sentiment < ̶ Positive

Else

If sentiment Polarity Score(line)<=-0.05 then

Sentiment < ̶ Negative

Else Sentiment < ̶ neutral

end

end

end

Algorithm 1: Sentiment Classification using VADERS

|  |  |
| --- | --- |
| ***Word*** | ***Score*** |
| 😊 | 1.3 |
| thanks | 1.9 |
| lol | 2.9 |
| great | 3.1 |
| disaster | -3.1 |
| agrees | 1.5 |
| horrible | -2.5 |
| died | -2.6 |
| rejoiced | 2.0 |
| dangerous | -2.1 |
| conspiracy | -2.4 |

**Table 1: Example of different Vader lexicons**

In contrast to the previously discussed VADERS, we utilize the Robustly Optimized BERT Pretraining Approach (RoBERTa) [21] for analyzing the sentiments and emotions expressed in reviews. RoBERTa represents an enhanced version of the Bidirectional Encoder Representations from Transformers (BERT) model, characterized by extended training periods, larger training batches, and a more extensive training dataset. BERT [22] is a valuable tool in natural language processing (NLP), rooted in the concept of pre-training contextual representations. It employs bidirectional Transformer training [23] to grasp contextual associations among words within a text. This methodology is employed to pre-train intricate bidirectional representations, quantified as numerical vectors, to elucidate the meaning of words within the text using a multi-layer bidirectional Transformer [23]. When presented with a textual input, it yields a 3-dimensional vector of sentiment scores, with each component denoting the likelihood of positive, neutral, and negative sentiments.

We utilize Twitter-RoBERTa-base, a model pretrained on a vast dataset comprising more than 58 million tweets. For the execution, we employ the Python transformer module to apply the pretrained model obtained from an online machine learning platform (https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest) for the purpose of evaluating sentiment scores for reviews.

RESULTS

We extracted a total of 2000 reviews from the dataset. Subsequently, we split it into two distinct sets: one comprising exclusively positive reviews, and the other containing only negative ones. This division was based on the ratings, with reviews receiving 4 or 5 stars classified as positive, and those with 1 or 2 stars marked as negative. Following this process, we obtained a positive dataset with 707 entries and a negative dataset with 865 entries.

Results of VADER

This tabulated format displays the polarity, sentiment score, and percentage of the positive dataset, all derived through VADER sentiment analysis.

|  |  |  |
| --- | --- | --- |
| Polarity | Sentiment score | Percentage |
| Positive | 0.9306 | 93.06% |
| Negative | 0.0565 | 5.65% |
| Neutral | 0.0127 | 1.27% |

**Table 3: The tabular form for the positive set of data’s using VADER**

This tabular format displays the polarity, sentiment score, and percentage for the negative dataset.

|  |  |  |
| --- | --- | --- |
| Polarity | Sentiment score | Percentage |
| Positive | 0.4473 | 44.73% |
| Negative | 0.4751 | 47.51% |
| Neutral | 0.0774 | 7.74% |

**Table 4: The tabular form for the negative set of data’s using VADER**

Results of RoBERTa

This tabulated format displays the polarity, sentiment score, and percentage of the positive dataset, all derived through RoBERTa sentiment analysis.

|  |  |  |
| --- | --- | --- |
| Polarity | Sentiment score | Percentage |
| Positive | 0.7369 | 73.69% |
| Negative | 0.1471 | 14.71% |
| Neutral | 0.0565 | 5.65% |

**Table 5: The tabular form for the positive set of data’s using RoBERTa**

This tabular format displays the polarity, sentiment score, and percentage for the negative dataset.

|  |  |  |
| --- | --- | --- |
| Polarity | Sentiment score | Percentage |
| Positive | 0.0277 | 2.77% |
| Negative | 0.9167 | 91.67% |
| Neutral | 0.0138 | 1.38% |

**Table 6: The tabular form for the negative set of data’s using RoBERTa**

DISCUSSIONS

The positive dataset should exhibit a high positivity rate. According to Table 3, VADER achieves a positivity percentage of 93%, while RoBERTa achieves 73%. Conversely, the negative dataset should have a high negativity rate. In Table 4, VADER registers a negativity percentage of 47.51%, while RoBERTa reaches 91% in Table 5. Consequently, it is apparent that VADER is unsuitable for assessing negative reviews, as evidenced by the fact that in Table 4, the positive polarity percentage is 44%, a value quite close to the negative polarity percentage. This implies that VADER struggles to effectively differentiate between negative and positive reviews, potentially misclassifying negative reviews as positive. If dataset availability is limited and accuracy is not a primary concern, VADER could be an option. However, for more accurate results, RoBERTa is the superior choice.

CONCLUSION

In conclusion, our paper has introduced two sentiment analysis models and outlined the experimental methodology. Based on the dataset results, RoBERTa demonstrates higher accuracy than VADER, suggesting RoBERTa as the preferred choice for sentiment analysis.

REFERNECES

[1]:-Gordon, K.: Topic: Online reviews, https://www.statista.com/topics/4381/onlinereviews/

[2]:Pak, A., Paroubek, P.: Twitter as a corpus for sentiment analysis and opinion mining. In: LREc. vol. 10, pp. 1320–1326 (2010)

[3]:.Anjaria, M., Guddeti, R.M.R.: Influence factor based opinion mining of twitter data using supervised learning. In: 2014 Sixth International Conference on Communication Systems and Networks (COMSNETS). pp. 1–8. IEEE (2014)

[4]: Khan, F.H., Bashir, S., Qamar, U.: Tom: Twitter opinion mining framework using hybrid classification scheme. Decision support systems 57, 245–257 (2014)

[5]:-Bouazizi, M., Ohtsuki, T.: Opinion mining in twitter how to make use of sarcasm to enhance sentiment analysis. In: Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015. pp. 1594– 1597 (2015)

[6]:-C¸ oban, O., ¨ Ozyer, B., ¨ Ozyer, G.: T¨urk¸ce twitter mesajlarının duygu analizi. In: Signal Processing and Communications Applications Conference (SIU) (2015)

[7] S. Mann, J. Arora, M. Bhatia, R. Sharma, R. Taragi, Twitter Sentiment Analysis Using Enhanced BERT, in: A.J. Kulkarni, S. Mirjalili, S.K. Udgata, Intelligent Systems and Applications. Lecture Notes in Electrical Engineering, vol 959, Springer, Singapore, 2023, pp. 263-271. doi:10.1007/978-981-19-6581-4\_21.

[8] B. Albadani, R. Shi, J. Dong, A Novel Machine Learning Approach for Sentiment Analysis on Twitter Incorporating the Universal Language Model Fine-Tuning and SVM, Applied System Innovation, 2022; 5(1):13. doi: 10.3390/asi5010013.

[9] M. Bibi, W. A. Abbasi, W. Aziz, S. Khalil, M. Uddin, C. Iwendi, T. R. Gadekallu, A novel unsupervised ensemble framework using concept-based linguistic methods and machine learning for twitter sentiment analysis, Pattern Recognition Letters, Volume 158, 2022, pp. 80-86. doi: 10.1016/j.patrec.2022.04.004.

[10] A. P. Rodrigues, R. Fernandes, A. Aakash, B. Abhishek, A. Shetty, K. Atul, K. Lakshmanna, R. M. Shafi, Real-Time Twitter Spam Detection and Sentiment Analysis using Machine Learning and Deep Learning Techniques, Computational Intelligence and Neuroscience, vol. 2022 (2022). doi: 10.1155/2022/5211949.

[11] E. A. Manziuk, A. V. Barmak, Y. V. Krak, V. S. Kasianiuk, Definition of information core for documents classification, Journal of Automation and Information Sciences, 50(4), (2018) pp. 25-34. doi:10.1615/JAutomatInfScien.v50.i4.30.

[12] G. C.Huang, J. B.Unger, D. Soto, K. Fujimoto, M. A. Pentz, M. Jordan-Marsh, T. W. Valente, Offline Friendship Networks on Adolescent Smoking and Alcohol Use, doi:10.1016/j.jadohealth.2013.07.001.

[13] R. J. Moreira de Freitas, T. N. Carvalho Oliveira, J. A. Lopes de Melo, J. do V. e Silva, K. C. de Oliveira e Melo, S. Fontes Fernandes, Adolescents' perceptions about the use of social networks and their influence on mental health, 2021. doi:10.6018/eglobal.462631.

[14] B. Dave, Sh. Bhat, P. Majumder, IRNLP DAIICT@DravidianLangTech-EACL2021: Offensive Language identification in Dravidian Languages using TF-IDF Char N-grams and MuRIL, Proceedings of the First Workshop on Speech and Language Technologies for Dravidian Languages, Association for Computational Linguistics, 2021, pp. 266-269.

[15] L. Wei, S. Wei, J. Shaoxiong, E. Cambria, BiERU: Bidirectional emotional recurrent unit for conversational sentiment analysis, Neurocomputing (2022), pp. 73-82. doi: 10.1016/j.neucom.2021.09.057.

[16] N. Majumder, S. Poria, D. Hazarika, R. Mihalcea, A. Gelbukh, E. Cambria, DialogueRNN: An attentive RNN for emotion detection in conversations, Proceedings of the AAAI Conference on Artificial Intelligence, vol.33, 2019, pp. 6818-6825. doi: <https://doi.org/10.48550/arXiv.1811.00405>

[17] H. Li, Q. Chen, Z. Zhong, R. Gong, G. Han, E-word of mouth sentiment analysis for user behavior studies, Information Processing & Management (2022). doi: 10.1016/j.ipm.2021.102784.

[18]. Liu Y, Ott M, Goyal N, Du J, Joshi M, Chen D, Levy O, Lewis M, Zettlemoyer L, Stoyanov V (2019) Roberta: a robustly optimized bert pretraining approach. arXiv: Computation and language

[19]. Lan Z, Chen M, Goodman S, Gimpel K, Sharma P, Soricut R(2019) Albert: a lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942

[20] B. Wagh, J. V Shinde, and P. A. Kale, “A Twitter Sentiment Analysis Using NLTK and Machine Learning Techniques,” Int. J. Emerg. Res.

Manag. Technol., vol. 6, no. 12, pp. 37–44, 2018.

[21]. Liu Y, Ott M, Goyal N, Du J, Joshi M, Chen D, et al. RoBERTa: A robustly optimized BERT pretraining approach. arXiv preprint. 2019;arXiv:1907.11692.2019.

[22]. Devlin J, Chang M-W, Lee K, and Toutanova K. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 2019;1:4171–4186

[23]. Vaswani A, Noam S, Niki P, Jakob U, Llion J, Aidan N. G, et al. Attention is all you need. Advances in Neural Information Processing Systems. 2017; 30

[24]:- Devlin J, Chang M-W, Lee K, and Toutanova K. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 2019;1:4171–4186.

[25]:- Vaswani A, Noam S, Niki P, Jakob U, Llion J, Aidan N. G, et al. Attention is all you need. Advances in Neural Information Processing Systems. 2017; 30.

[26] C. J. H. E. Gilbert, “Vader: A parsimonious rule-based model for sentiment analysis of social media text,” in Eighth International Conference on Weblogs and Social Media (ICWSM-14). Available at (20/04/16)

[27] S. B. Mane, Y. Sawant, S. Kazi, and V. Shinde, “Real Time Sentiment Analysis of Twitter Data Using Hadoop,” Int. J. Comput. Sci. Inf. Technol., vol. 5, no. 3, pp. 3098–3100, 2014.

[28]. Pang, Bo, and Lillian Lee. "Opinion mining and sentiment analysis." Foundations and TrendsÂő in Information Retrieval 2.1âĂŞ2 (2008): 1-135

[29]: Comparison of VADER and LSTM for sentiment analysis R. Adarsh, Ashwin Patil, Shubham Rayar, [K. M. Veena](https://researcher.manipal.edu/en/persons/veena-k-m) [Department of Information and Communication Technology, Manipal Institute of Technology, Manipal](https://researcher.manipal.edu/en/organisations/department-of-information-and-communication-technology-manipal-in)

[30]: Sentiment analysis and causal learning of COVID-19 tweets prior to the rollout of vaccines Qihuang Zhang, Grace Y. Yi , Li-Pang Chen,Wenqing He Published: February 24, 2023 https://doi.org/10.1371/journal.pone.0277878