SENTIMENT ANALYSIS OF TWEETS USING HETEROGENEOUS MULTI-LAYER NETWORK REPRESENTATION AND EMBEDDING

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1. Introduction

1.1 Task/ Research Question Description

For our project, we have selected a published paper, and in that paper, the authors have tried to solve several problems associated with the sentiment analysis of tweets with a heterogeneous multilayer approach (Singh et al., 2020). The researcher concluded that the proposed system is capable of outperforming other text-based counterparts. Hence, the author of this research will try to recreate the same results using a similar framework and validate the results obtained in the selected research.

Research Questions:

Is the proposed approach capable of addressing under-specificity issues due to text limitations in tweets?

Can the multilayer network embedding method capture the semantic relationships among hashtags, mentions, and keywords used in tweets?

Can the proposed approach overcome the challenges of noisy text, misspellings, and multilingual texts?

Does the centrality aware based random walk better represent tweets compared to other biased and unbiased frameworks?

1.2 Motivation and Limitation of Existing Work

Social media use has increased multifold in recent years, and we use social media to communicate more effectively with other human beings. Businesses use sentiment analysis methods to perform sentiment analysis on multiple social media platforms to gain insight into the minds of the users and design their products and services to better suit users. It has become essential to perform effective sentiment analysis on tweets to attain users' opinions and needs. Several pieces of research were undertaken to address this issue from different angles. However, prior research failed to mitigate all the issues related to the sentiment analysis of tweets. Here we are trying to develop a heterogeneous multilayer network representation and embedding to address these issues.

1.3 Proposed Approach

The proposed approach will house four separate constituents. These are listed below,

Using a multilayer network to represent one or more tweets.

Expanding and shrinking the network to lessen the presence of noise in tweets.

Classification of tweets with the use of multiple representations produced by several layered networks.

Application of centrality aware random walk on the multiple-layer network.

The researcher will combine the above-mentioned approaches in his/her multilayer network to perform sentiment analysis of tweets.

1.4 Likely Challenges and Mitigation

Tweets are short expressions and pose severe challenges over regular texts. There are several challenges that may be faced during the proposed research. Integrating a multi-layer heterogeneous network for the research will be challenging enough. Further recreating the main results of the selected research will be difficult considering the minutest details of the entire process. Creating and testing the framework from scratch will be quite challenging. Additionally, if the research will not go as planned the researchers will face severe challenges to find the issue and fix it. If the research appears to be harder than expected then the researcher will create a simpler network layer to test the feasibility of the research, and in the case of the research not going as planned, the researcher will try to find the issue by going through the chosen research once again and fix the issue.

2 Related Work

Two researchers working on tweets in the airline industry have tested Deep Intelligent Contextual Embedding (DICE) model for sentiment analysis of tweets and found that this model outperforms most of the classic classifier and various word embedding models (Naseem et al., 2019). The researchers proposed and tested a different model than that of the selected paper, and the approach was based on improving syntax, semantics, polysemy in context, and sentiment knowledge of words. Further, the researchers used Bi-directional Long Short Term Memory (BiLSTM) for sentiment determination of a tweet.

Another eminent researcher trying to improve the sentiment analysis of tweets denoted that traditional approaches fail to capture polysemy and sentiment information of words in a tweet (Naseem, 2020). To address this, the researcher proposed the use of (BiLSTM) and demonstrated that it performs better than other traditional sentiment capturing models. The researcher further denoted that this proposed model reduces information loss in the process and creates high-quality tweet representations. This research also differs from the proposed experiment due to the use of different frameworks and approaches.

Another prominent researcher performed a sentiment analysis on the Corona Virus Twitter Hashtag Dataset and found that deep learning models can improve sentiment analysis of social media applications (Alsayat, 2022). The researcher used advanced word embedding techniques and created a dedicated LSTM network for the study. The results of this study indicate that the model is capable of identifying prefixes and suffixes to understand social media tweets better. This research differs from the proposed research in terms of the approach and use of a multilayer network.

Another group of researchers proposed and tested a bidirectional GRU network with forward and backward propagation and found that the proposed framework showcases significant improvement over conventional sentiment analysis models (Fu et al., 2019). The results obtained by the researchers reinforce the simplicity and effectiveness of the model and may prove to be capable of sentiment analysis on various types of texts. This research is different from the proposed research as it employs a single network layer approach.

Two other researchers working in the same direction proposed a combination of separate deep learning methods such as LSTM, CNN, BiLSTM, and GRU for better comprehension of sentiment classification. The results of that study indicate that a combination of deep learning methods improves sentiment analysis of text multifold (Salur et al., 2020). This study differs from the proposed research as it utilizes multiple deep learning approaches instead of the multi-layer approach proposed in the research.

3 Experiments

3.1 Data Sets

In the selected research the researchers used a locally annotated dataset for the research. The researchers engaged two local annotators for annotating the data set and preparing for multilingual use. However, for the benefit of the proposed research and lack of resources, the researcher proposes to use similar datasets which are readily available with multilingual annotations. The researcher will use publicly available datasets in their research due to ease of access. The researcher will scour publicly available datasets and choose a suitable dataset for the research.

3.2 Implementation

Since the researcher of the proposed research has not finalized the data set selection, it will not be possible to provide a repository link at this stage of the report. However, the researcher will select a similar dataset from a publicly available resource. It will be beneficial for the researcher to select a similar dataset for result comparison. In the final project, the researcher will provide the repository link of the data set.

3.3 Results

In the selected research, the researchers applied two sentiment analysis classifiers namely CNN and BiLSTM on the chosen dataset, and tested four embedding models specified as MNE, SHE, MVE, and FT (Singh et al., 2020). Further, the researchers applied three types of Random walks specified as Biased RW, Unbiased, and Node2Vec. The Biased RW model outperforms other random walks. The Node2Vec embedding model provides the least satisfactory results, and the Biased RW model performs best among the embedded models (Singh et al., 2020).

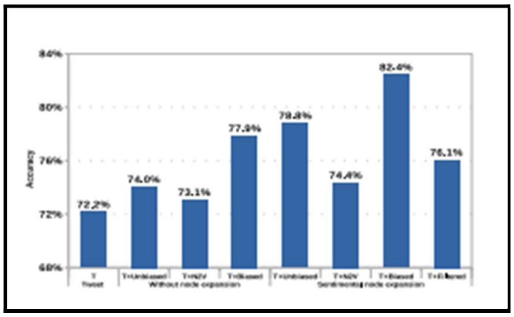

Figure: Performance of CNN Classifier on Tweets with Keywords (Singh et al., 2020).

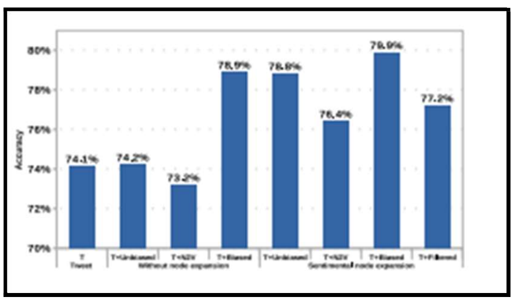

Figure: Performance of CNN Classifier on Multilingual Tweets (Singh et al., 2020).

The researcher proposes to present a table for comparing the results when the final research takes place.

3.4 Discussion

At this preliminary stage, it is difficult to predict any issues that the researcher might face during the detailed research. However, the researchers of the selected research did not face any significant issues in their research and the researcher of this project hope not to face any difficulty in their research.

The researcher will follow the process in the selected research and should not face any significant issues. Every available information suggests that the researcher will be able to reproduce the results of the selected research without any hindrance.

3.5 Resources

For the research, the researcher will require computers or laptops with high computational speed and capability. The researcher will be able to complete the proposed research within the time limits provided by the authority. With sincere planning, the researcher hopes to complete the tasks by himself within the time limit.

3.6 Error Analysis

At this preliminary stage of the research, the researcher was not able to perform a detailed error analysis. However, in the selected research, the researchers faced two errors during their research. These are round-off errors and loss of value due to the use of a classifier (Singh et al., 2020).

In the final research report, the researcher will perform a detailed error analysis and suggest mitigation efforts.

4 Conclusion

After considering the progress in the research direction and associated effort, the researcher hopes to recreate the selected process in his own research and compare the results of both researches. Considering the selected research approach and the feasibility of creating a similar model to test the accuracy and results of the selected research paper, it seems that the results can be reproduced to affirm positive or negative responses based on the comparison of results between two separate studies.

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