CSE 573 Group 9: Stance Detection

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***Abstract*—Stance detection is an automated process that involves predicting an individual's position or attitude towards a particular topic or issue based on their comments or statements. Specifically, stance detection focuses on identifying whether an individual is in favor of or against a particular topic [1]. This is better than sentiment analysis in terms that while sentiment analysis focuses on the polarity of sentiment, stance detection aims to identify the attitude or position expressed towards a particular topic or target. Opinions are ubiquitous. In this paper, we aim to determine their stance by employing the SemEval dataset and real-time tweets related to those topics. We perform this analysis using deep learning models such as Bidirectional Long Term Short Term Memory, Bidirectional Encoder Representations from Transformers along with Support Vector Machines. Later, we discuss and compare the findings from the various techniques used in this study.**

***Index Terms*—Stance Detection, Natural Language Processing, Web scraping, Bidirectional Long Term Short Term Memory (Bi-LSTM), Bidirectional Encoder Representations from Transformers (BERT), Support Vector Machines (SVM), classification**

I. Introduction

According to the 2021 report by Hootsuite and We Are Social, there are currently 4.9 billion social media users worldwide, which is an increase of 13 % compared to the previous year. This means that approximately 63% of the world's population is now using social media. Each platform has its own unique way of providing users with information, verifying account authenticity, and handling any disruptions that may impact user trust and usability. As Social Media continues to be an integral part of American daily life, researchers now have the ability to utilize the vast amounts of data generated by these platforms' users. This data can be used to build models that better understand human behavior and interactions, as well as to detect an individual's opinions, beliefs, or stances on a particular topic. By analyzing the data provided by Social Media, researchers can gain insights into how people communicate, what motivates them, and how they form opinions, which can be useful in various fields such as psychology, marketing, and politics.

Stance detection is a natural language processing task that involves identifying the attitude or perspective of the author of a piece of text towards a particular target. The target can be a person, an organization, a policy, a product, or any other entity that is the subject of the text. In the case of Social Media stance detection, we plan to identify the stance over a large variety of targets or 'topics'. Stance detection is often applied to text inputs from social media platforms like Twitter, where users express their opinions on various topics using short messages or tweets. These tweets often include hashtags, mentions, or other platform-unique characters that can provide additional context for stance detection. The text is then evaluated over some topic (topic detection methods allow the model to decide on the subject discussed at the same time) and an output is provided as either positive, negative, or neither.

The SemEval-2016 Stance Detection Task was a shared task in the field of natural language processing that focused on detecting the stance of users on various controversial topics, including the 2016 US presidential candidates. [2] The task involved developing machine learning models that could classify the stance of tweets into one of three categories: favor, against, or neutral. We propose several methods for improving the accuracy of such models (supervised), including broadening the scope of the dataset. To increase the reach and accuracy of the model we propose real-time fetching of data from the Twitter API for timely retraining of the model.

II. Dataset

We have opted to use the SemEval-2016 Task 6A dataset for our project. This dataset contains 2,914 Tweets related to five different topics: atheism, climate change, the feminist movement, Hillary Clinton, and the legalization of abortion. Each Tweet has been manually annotated by humans and assigned a stance label of positive, negative, or none. In order to address the limited coverage of pressing issues in the SemEval dataset, we propose to expand the range of topics by scraping Twitter for tweets related to gun laws, racial injustice, and immigration laws. By collecting data from Twitter, we intend to include a more varied range of topics. This incorporation of burning issues will enable a comprehensive view of language usage and sentiment regarding present-day events.

Our plan to expand the SemEval dataset also involves real-time tweet scraping to collect tweets related to the same topics as the original dataset. We intend to use a tool such as Tweepy or Twitter API to gather these tweets and then preprocess and clean the data to ensure its quality and relevance. After processing, we will combine the new data with the SemEval dataset to create a larger and more diverse dataset that can be used to train and evaluate models more effectively.

III. STATE-OF-ART METHODS & ALGORITHMS

A. Supervised Machine Learning

In supervised machine learning for stance detection, the model is trained on labeled data that contains examples of text with labeled stances toward specific topics. The training data is usually pre-processed to extract relevant features from the text, such as bag-of-words, n-grams, or word embeddings. The labeled data is used to train a machine learning model, such as a support vector machine (SVM), logistic regression, or a deep neural network. During the training phase, the model learns patterns in the text that are associated with each stance category, and it uses these patterns to classify new text into one of these categories.

B. Deep Learning

Deep learning models have become increasingly popular for stance detection, as they offer a powerful and flexible approach to modeling the complex relationships between text and stance. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two of the most widely used deep learning models for stance detection. These models use neural network architectures to learn representations of the input text that capture the relevant features for stance detection. More recently, transformers, such as the BERT model, have emerged as a promising approach to stance detection, due to their ability to capture contextual relationships between words in the input text.

C. Transfer Learning

Transfer learning for stance detection involves using pre-trained models on a large corpus of text and then fine-tuning them on a smaller annotated dataset for stance detection. This allows models to leverage the vast amount of knowledge captured in the pre-trained models to improve their performance on the smaller, task-specific dataset. Methods such as ULMFiT, OpenAI GPT, ELMo, and Google AI's BERT have recently revolutionized the field of transfer learning in NLP by using language modeling during pre-training, significantly improving on the state-of-the-art for a variety of natural language understanding tasks.

IV. RESEARCH PLAN

A. Prepossessing

a) Data Expansion: To broaden the scope of topics and address current issues, we aim to scrape Twitter for tweets related to gun laws, racial injustice, and immigration laws. The SemEval dataset has limited coverage of some hot topics, so we hope to include a more diverse range of subjects by gathering data from Twitter. By incorporating these burning issues into our dataset, we can provide a more comprehensive view of language use and sentiment in relation to current events

b) Data cleaning: To ensure the quality of our Twitter dataset, we will perform several data cleaning tasks. These tasks include removing URLs and mentions, as they may not contribute to the analysis. To make the data more informative, we also plan to replace emoticons with their corresponding sentiment. Furthermore, we will correct any spelling errors in the text to ensure that the data is accurate and reliable. Overall, these steps will help us to obtain a high-quality Twitter dataset for analysis.

c) Tokenization: Our approach involves tokenizing the text at the word level, which involves splitting the text into individual words. This tokenization step is critical because it enables us to represent the text as a numerical vector.

d) Removal of stop words: When it comes to stance detection, stop word removal can be a valuable technique to preprocess the text data before building the model. This is because stop words are generally used frequently and are not informative when it comes to understanding an author's stance or opinion. By removing these common words, we can improve the accuracy of the model by focusing on the more meaningful and informative words in the text. However, it's important to be cautious when removing stop words, as some may carry important nuances and context that can affect the author's stance or opinion.

e) Stemming and Lemmatization: Stemming and lemmatization are widely used techniques in natural language processing that can be advantageous for stance detection. These methods aid in decreasing the complexity of the text data by clustering similar words together, which can enhance model accuracy and efficiency. For stance detection, these techniques are especially valuable for pinpointing pertinent keywords and extracting significant features from the text. Grouping related words aid in decreasing data noise and enhancing model precision.

B. Data Augmentation

a) Synonym expansion: Including synonyms in a text analysis can help capture a greater diversity of opinions and viewpoints on a topic and provide a more nuanced understanding of the meaning of the text, which in turn can improve the accuracy of stance detection models.

b) Phrase expansion [5]: Expanding the use of related phrases in a text can help to improve the comprehensiveness of the analysis by capturing a broader range of opinions and perspectives, while also providing additional context and background information about the topic. This can lead to a more precise and specific understanding of the individual's opinion or stance

c) Query reformulation [4]: By reformulating the query, the stance detection model can become more adaptable to different contexts and structures of similar tweets. Additionally, it allows the model to predict the stance regardless of the specific way in which the opinion is expressed.

C. Models

a) BERT with SVM: With its ability to analyze word and phrase relationships in a sentence, BERT is an ideal tool for capturing the context and meaning of the text. This makes it a strong candidate for stance detection, as it can identify subtle language nuances and important features relevant to the task. Our approach involves using the pre-trained BERT-Base model to generate a set of features, which will then be input to an SVM classifier for predicting stance. SVM is a suitable choice for this task because it can establish clear decision boundaries for the three stances (Favor, Against, and None), allowing for accurate predictions.

b) Bidirectional LSTM: Bidirectional Long Short-Term Memory Networks (Bi-LSTMs) are useful for stance detection tasks due to their ability to handle sequential text data by processing it in both forward and backward directions. This allows them to capture contextual information from the entire input sequence. Furthermore, Bi-LSTMs can overcome the issue of vanishing gradients in deep neural networks by utilizing LSTM cells, which maintain information over time. Additionally, Bi-LSTMs have achieved impressive performance in several natural language processing tasks, including sentiment analysis, machine translation, and named entity recognition. As a result, they are a reliable option for stance detection, which involves determining an author's stance on a particular topic or issue.

V. Evaluation Plan

The aim of this project is to identify the stance for each of the above-mentioned topics in favor, against, or neutral. In order to train the model, we divide the data into splits in an 80:20 ratio, with 80% of the data being used for training the model and 20% for validation. It will be ensured that the class distribution remains consistent across both the training and validation datasets.

We will be using accuracy, precision, recall, and F1 score as metrics to evaluate the developed model. In our case accuracy would be the total number of correctly classified tweets to the total number of tweets used.

Precision is assessed by calculating the proportion of tweets that are correctly classified as "favor", "neutral", or "against" among all the tweets that the model predicted to belong to these categories. This evaluation measure is used to gauge how well the model can make accurate tweet label predictions while reducing the frequency of incorrect label predictions.

When evaluating recall, the model's ability to accurately predict the number of "favor", "neutral", and "against" tweets is determined by dividing the number of correctly predicted tweets in each category by the total number of actual tweets in that category. This metric is used to assess how well the model can predict each of the true tweet labels.

F1 Score is a combination of both precision and recall, this will be used in case the data is imbalanced, i.e. that one class is much more prevalent than the others.

As we are using augmented datasets, we would also like to compare the effect of data augmentation on the above-mentioned metrics.

VI. Project Timeline: Tasks, Descriptions and Deadlines

Task	Description	Timeline
Web Scraping	Scrape tweets pertinent to gun laws, racial injustice and immigration laws.	9 March
Data cleaning and pre-processing	Perform data expansion, data cleaning, tokenization, stop words removal, stemming and lemmatization.	18 March
Data Augmentation	Perform synonym expansion, phrase expansion and query reformulation	28 March
Model Training	Implement BERT with SVM and Bidirectional-LSTM	5 April
Performance evaluation	Evaluate the performance of the algorithms with proposed metrics	10 April
Final Report	Prepare final report	28 April

VII. Division of Work

Task	Assigned Team Member
Web Scraping	Baibhav Phukan
Data cleaning and preprocessing	Tanuja Renu Sudha
Data Augmentation	Sai Rathnam Pallayam Ramanarasaiah
Model Training	Sai Vikhyath Kudhroli, Avish Khosla
Performance evaluation	Gautham Maraswami
Final Report	All

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