Towards Understanding and Predicting Emotions from Text

Tanvir Hasan, Amitabh Sarkar
M.Sc in CSE, University of Oulu

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Abstract

Artificial intelligence (AI) is permeating more and more aspects of our daily lives, with a rising emphasis on understanding the language that expresses human emotions. Natural Language Processing (NLP) is important in this endeavour. Our study utilizes NLP methods to analyze emotions using the International Survey on Emotion Antecedents and Reactions (ISEAR) dataset, encompassing basic emotions across 37 nations. Our findings reveal that specific words are associated with each emotion, giving insights into how people express their feelings. Sentiment analysis shows that most of the situations expressed by participants were negative, whereas positive was the lowest. Our study also presents different machine learning models' performance on the dataset and how feature selection affects emotion prediction, emphasizing its significant influence on model performance regarding the accuracy, precision, recall and F1 score metrics. This study adds to our understanding of how people express emotions through text and predict them accurately. Moreover, this study will assist future technology designers in creating emotion-aware technologies.

1 Introduction

Artificial intelligence (AI) is becoming increasingly interwoven into our daily lives, and can currently understand human language well, especially when it is spoken directly. However, the text is also used to transmit our feelings, and it is crucial for AI systems to be able to understand and comprehend these emotions in order to be really helpful. Text-based communication is now dominating, and emotions expressed in the text can provide vital insights into people's moods, attitudes, and behaviours. Natural Language Processing (NLP) is a promising area of research for leveraging the power of text data to understand and predict emotions. This research paper addresses the field of emotion analysis with a focus on employing NLP-based methodologies. The study employs the ISEAR (International Survey on Emotion Antecedents and Reactions) dataset [1], which contains examples of the seven primary emotions: joy, fear, anger, sadness, disgust, shame, and guilt. The dataset also includes the situational context of each entry, as well as the respondent's appraisal and response to each emotion.

A range of NLP methodologies, including feature extraction, data preparation, and machine learning, are utilized to fulfil these aims. In addition to employing well-known machine learning approaches like Multinomial Naive Bayes, the researchers also study cutting-edge methods like XGBoost, LightGBM, and CatBoost to evaluate how well they do in identifying emotions. Through this study, the researchers seek to enhance the field of emotion analysis and open the way to more precise and nuanced emotion prediction from text data. This research attempts to construct AI systems that can understand and respond to human emotions portrayed in text. This could have a wide range of uses, such as improving customer service [2], producing more effective mental health treatments, and creating more engaging social media experiences.

By examining the words associated with individual emotions and evaluating sentiment, this study aims to gain a deeper understanding of human emotional expression in text data. The study looks for particular word groups that are associated with various emotions, including joy, fear, anger, sadness, guilt, shame, and disgust. The study also aims to find the sentiments (e.g., positive) of each document, examine the impact of various feature selection strategies on text-based emotion prediction and evaluate the efficacy using a statistical model. The goal is to provide information that can enhance emotion classification models, increase the understanding of emotional patterns and point up potential directions for future research in text-based emotional analysis. It is crucial to comprehend the words associated with emotions, assess sentiment, and investigate feature selection techniques and machine learning models because these topics have real-world applications in a variety of fields. These research areas are essential for developing our knowledge of human emotions and increasing technologies' ability to handle human emotions and language.

2 Related work

Emotions are an integral part of the human. Emotions significantly influence human decision-making and enhance our communication skills. Over the first few years, researchers have made significant progress toward detecting emotions automatically. However, using different sensors researchers convey a person's emotional state, but emotion prediction from text is hard.

2.1 A journey from textual data to insightful perception

Emotion and sentiment from the text have become one of the hottest interests among researchers. It is often interchangeably used yet distinct and plays significant roles across various disciplines, including business, healthcare, education and many more. The significance and numerous applications of sentiment and emotion analysis offer insights into the obstacles faced by researchers in the development of effective methodologies. Similarly, Munezero et al. [3] found the interchangeability of terminology like 'emotion detection', 'affective computing', and 'emotion analysis'. Their study underlines the dynamic nature of language and its function in mood and emotion analysis. In healthcare, Singh et al. [4] explain how sentiment and emotion analysis can be used to identify patients battling with depression during covid-19 pandemic. Their study highlighted the usefulness of emotion analysis in providing mental support which aligns with our study. Furthermore, Sangeetha and Prabha [5] emphasize the significance of sentiment and emotion analysis in education for assessing teacher efficacy and enhancing teaching techniques through student feedback.

2.2 Machine learning models for emotion detection

A study [6] proposed multiple methods on how to extract meaningful words using semantic approaches such as POS tagger by identifying nouns, verbs, adverbs, and adjectives of sentences. They also proposed a Chi-square method to exclude the weak semantic features and achieved an improvement in the emotion recognition rate using the ISEAR dataset. Cecilia et al. [7] focused on different experiments on classifying the emotional tones in phrases from children's fairy tales. They employed different supervision to identify the stories' emotional undertones with promising outcomes when compared to a naive byes baseline and Bag of Words methods for distinguishing emotional and non-emotional stories. Similarly, the IBM Watson Tone Analyzer was used by Ahmed et al. [8] to analyze the linguistic and emotional tones in the lyrics of English songs. Five classification algorithms were used, and the decision tree was found to be the most accurate with respect to precision, recall and F1 score. The ability to apply emotions to complicated activities like creating discussion, deciphering participants' behaviour, and supporting multimodal interactions makes it crucial to interpret emotions in conversation. To anticipate Ekman's six universal emotions, Soujanya et al [9] constructed a conversational dataset of text, speech and video. A method for automatically identifying emotions in text was put out by Ezhilarashi et al [10] who used Wordnet to create an emotional ontology in English. Similar results were obtained using conversational text data by Waleed et al. [11], who predicted the three main emotions of joy, sadness, and anger.

3 Methodology

3.1 Dataset Description

We considered several open datasets for our study, including affective text, crowdflower_data, daily dialogue, EmoBank, and Goemotions. Most of these datasets have a large collection of emotional documents. However, we decided to use the ISEAR dataset. Individuals from 37 nations on five continents contributed to the ISEAR dataset. The ability to examine how emotions are perceived and expressed across many cultures helps researchers better grasp the similarities and differences in emotional experiences, making this global and cross-cultural component crucial. The dataset is annotated with seven emotions—joy, fear, anger, sorrow, disgust, humiliation, and guilt. This comprehensive portrayal of emotions offers a wide range of emotional data, making it appropriate for a variety of investigations on emotions. Multiple emotion data are necessary for a sophisticated study and detailed comparison of emotional reactions.

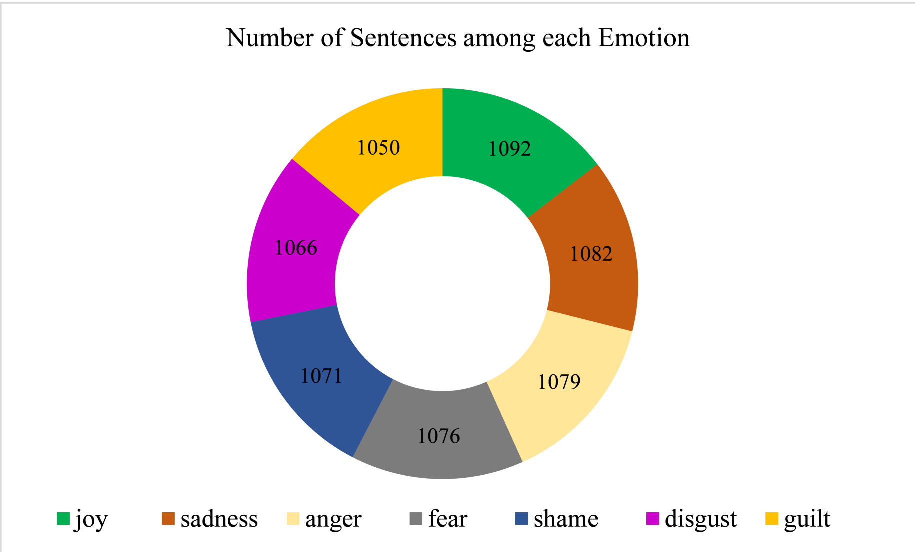

Figure 1: Number of documents among each emotion.

The dataset also contains details on how participants evaluated the events that caused these feelings as well as how they responded to them, in addition to information about the emotions they experienced. This additional information is essential for understanding the causes of emotions and their effects, greatly advancing studies on emotion prediction and the comprehension of underlying mechanisms. The dataset includes responses from over 3,000 participants, a bigger sample size that is frequently chosen in research since it can produce more reliable and generalizable conclusions, boosting statistical power and the accuracy of results. Concerning emotion prediction, the dataset's wealth of cross-cultural, multi-emotion, and contextual data makes it especially advantageous. Machine learning models and predictive algorithms can benefit from this dataset by utilizing appraisal and reaction information to forecast emotional responses in specific situations. This capability can be incredibly valuable in fields such as psychology, human-computer interaction, and affective computing, where the comprehension and prediction of human emotions are pivotal.

3.2 Text Preprocessing

Text pre-processing is a crucial step in natural language processing (NLP) that involves cleaning and standardizing textual input before analyzing and modelling it. We began by denoising data with the BeautifulSoap package. To remove any HTML tags from the text, the BeautifulSoup library is utilized. Text data in the present scenario may comprise HTML components that are irrelevant to our tasks. By removing them, only the written information remains. Contractions, like "didn't" (did not), are similarly enlarged to their full forms. This expansion can assist in standardizing the content and make it easier to work with downstream NLP algorithms. The text must first be tokenized into words before normalization can be applied. To separate the text into individual words, the tokenize function employs the Natural Language Toolkit (NLTK). Following that, we used various text-normalizing methods. Text normalization is the process of normalizing text data through the use of various transformations. To ensure uniformity, we converted all characters to lowercase using the to_lowercase function, removed punctuation from tokenized words using the remove_punctuation function, replaced numerical digits with their textual representations using the replace_numbers function, and removed stopwords from the text using the remove_stopwords function, such as "the" and "and." The remove_stopwords parameter determines this phase, which is optional.

Following that, we applied stemming and lematization to our dataset. Despite the fact that stemming and lemmatization are commonly used in text normalization. The stem_words function simplifies words to their root form, whereas the lemmatize_verbs function normalizes verbs to their base form. We ensured that the textual data was consistent, free of redundant parts, and fit for further analysis by following these steps. Text preparation has a big impact on the accuracy and effectiveness of NLP.

3.3 Ethical considerations

The exploration of the dataset was made accessible under a Creative Commons Attribution-NonCommercial-ShareAlike 3.0 (CC BY-NC-SA 3.0) license. In our study, we cited the dataset and we did not make any changes to the dataset and used it only for research purposes.

4 Findings

4.1 Words associated with individual emotions and sentiment analysis

Understanding the words associated with individual emotions not only offers valuable insights into human emotional expression but also serves as a foundation for the development of emotion classification models. Our finding has revealed fascinating insights into the words association with the individual emotions. The participants often associate each emotion with a distinct set of words that co-occur when they express these emotions. In the case of joy emotions, participants expressed their feelings with words like “get”, “friend”, “pass”, and “time”. These words reflect the positive nature of joy, often associated with social interactions and activities that bring happiness. Fear is often expressed through terms like “angry”, “die”, “alone”, and “afraid”. These words in the conversation highlighted the apprehension and unease that fear creates, touching on concepts of danger and silence. Anger is frequently conveyed with words like ”disgust”, ”ashamed”, and ”guilty.” These words reveal the complex and interrelated nature of negative emotions, as anger can often be accompanied by feelings of disgust and shame. Words associated with sadness include ”night”, ”sad”, ”people”, and ”mother”. Sadness typically encompasses feelings of sorrow, loss, and melancholy, often related to personal experiences and relationships. Disgust is a term characterized by words such as “die”, “time”, “friend”, and car. These words illustrate the diverse triggers of disgust, ranging from personal encounters to mundane situations like commuting. Shame, as an emotion, is conveyed through words such as ”friend”, ”one”, ”men”, and ”father”. Shame frequently revolves around personal experiences and self-perception, as individuals deal with inadequacy and self-worth. Lastly, guilt is strongly related to terms like ”tell”, ”first”, and ”would”. Guilt typically originates from moral and ethical difficulties, causing individuals to reflect on their actions and judgments.

Emotion name	**Tokens related to individual emotion**
Joy	Get, Friend, Pass, Time, Feel, Happy
Fear	Go, Night, Afraid, Alone, Home
Anger	Angry, Friend, Go, Tell, Come, Make
Sadness	Die, Friend, Go, Leave, Get
Disgust	See, Feel, People, Men, Go
Shame	Ashamed, Feel, Tell, Go, Say
Guilt	Feel, Guilty, Go, Mother, Time

Table 1: **Tokens related to individual emotion**

Apart from word association with individual emotions, we explored sentiment on the dataset. Sentiment analysis is vital for measuring and analyzing emotional patterns in the text, offering insights, assuring data quality, enabling comparison analysis and adding decision-making. For extracting sentiment names(e.g., positive) we employed the TextBlob library. The employment of the TextBlob library for sentiment analysis has shed light on the overall emotional tone of the participants. Our findings indicate the emotional tones conveyed by the participants are dispersed across the spectrum, with 30% tons expressing positive feelings, 33% being neutral and 37% tending towards negative emotional tones among the participants. This distribution shows a considerable amount of emotional diversity among participants. The predominance of negative emotions may imply that many participants experienced events that were emotionally balanced or less intense.

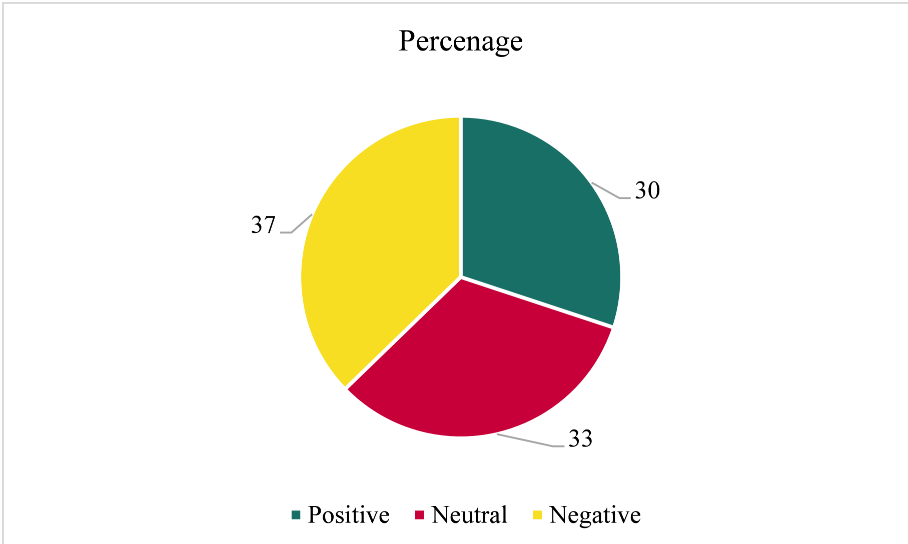

Figure 2: Percentage of different sentiments among participants.

4.2 Model performance and comparison with other models

In our dataset, we applied different feature selection methods such as Chi-Square, TF-IDF, Mutual Information, Chi-Square with Top-K, Feature Importance from Random Forest, L2 Regularization (Lasso), and Correlation-Based feature selection method on some common machine learning classifiers such as Logistic Regression, Random Forest, Support Vector Machine, k-Nearest Neighbors, XGBoost, Decision Tree, and Neural Network. Our finding shows that feature selection methods have a significant impact on model performance in Table 2. The results of the ANOVA test show that the choice of feature selection techniques significantly affects performance measures like Accuracy, Precision, Recall, and F1 Score. The performance differences across feature selection strategies are not due to chance and are in fact statistically significant, according to the extremely low p-values for all metrics. To get better results for your particular Emotion Prediction from Text work, it is necessary to carefully select the appropriate feature selection strategy.

The results of our testing of different machine learning algorithms for text data emotion analysis are compiled in Table 3. Performance parameters for each model are shown, including accuracy, weighted average precision, weighted average recall, and weighted average F1 score.

Table 3 provides key insights into model performance variations and the impact of the chosen machine learning method on the effectiveness of emotion analysis. While some models, such as Naive Bayes, SVM, and Logistic Regression, showed reasonably good accuracy and weighted average metrics around

Performance	**F-Statistics value**	**P-value**
Accuracy	22.32	0.0
Precision	2.87	0.012
Recall	22.32	0.0
F1 score	28.75	0.0

Table 2: Impact of feature selection methods on performance metrics: ANOVA test result

Model Name	**Accuracy(%)**	**Weighted avg Precision(%)**	**Weighted avg Recall (%)**	**Weighted avg F1 score(%)**
Multinomial Naive Bayes	54	54	54	54
Support Vector Machine	58	58	58	58
Logistic Regression	58	58	58	58
Random Forest	55	55	55	55
Decision Tree	48	48	48	48
K-nearest neighbours (KNN)	38	40	38	36
Convolutional Neural Network (CNN)	53	53	53	53
Naive Bayes	63	65	63	63
Xgboost	55	55	55	54
Light Gradient Boosting Machine(LightGBM)	53	53	53	53
CatBoost	55	56	55	55

Table 3: Performance of different ML algorithms on ISEAR dataset

58-63%, others, like K-nearest neighbours (KNN), performed worse. Another insight is consistency in weighted metrics. It is noteworthy that across many models, the weighted average precision, recall, and F1 scores remained constant, demonstrating a performance that strikes a balance between accurately classifying emotions and reducing false positives and negatives. Furthermore, the efficacy of emotion analysis is significantly influenced by the interplay between preprocessing methods, algorithms, and feature extraction techniques. To fully comprehend the subtleties of these relationships and how they affect performance, more research is required. Finally, the results imply that there is an opportunity for advancement in text-based emotion analysis. Better outcomes might be obtained by experimenting with more complex deep learning models or by fine-tuning hyperparameters. Different text-based models such as the Bidirectional Encoder Representation (BRET) model can be applied to find a good performance.

5 Discussion

In this study, we explored words associated with individual emotions. To our best knowledge, none of the studies explored previous word associations with emotions. However, we are aware that the words might be changed in the case of study sample changes. Furthermore, our research illustrates how essential feature selection is in the field of text-based emotion prediction and how these methods have a positive significant impact on how effective ML models are. Tripathy and Sharaff [12] conducted a study that has slight similarities with our findings. The novel hybrid approach for sentiment analysis exhibited outstanding results by considerably lowering the feature dimensions. In our study, we tried to present different feature selection methods on some common machine learning classifiers and found that feature selection has a significant correlation with the performance of ML models. We also found that Naive Bayes performed well in our case compared to other algorithms. A similar type of experiment was done by Başarslan and Kayaalp [13], though they utilized multiple word embedding methods, including Word2Vec (W2V), and BERT, alongside machine learning and deep learning models. Their models demonstrated outstanding performances with an accuracy of more than 75 percent. Our study takes a pioneering step in diving into the the links between words and certain emotions, emphasizing the critical role that feature selection plays in the realm of text-based emotion prediction.

6 Limitations and Future Work

When interpreting our findings, it is essential to keep certain limitations in mind. Although our study has offered insights into the efficacy of machine learning models and emotional analysis, it has limits. The effectiveness of the models varies, demanding further research on our models to boost our generability. Moreover, we did not validate the cultural sensitivity of the data. Our study provides a respectable paradigm for emotion analysis, although there is still room for improvement. Future research can examine multilingual and multimodal emotion analysis, increase model generality, boost interpretability, and concentrate on real-time applications such as customer service and mental health therapy.

7 Conclusion

Our study offers a ground-breaking inquiry into the links between words and particular emotions, exposing the crucial function of feature selection in text-based emotion prediction. We uncovered different word sets that were specifically connected to each emotion, revealing crucial information about how people transmit their feelings. Additionally, we looked at sentiment analysis, which showed that participants had a wide variety of emotional tones, with negative sentiments being more common. Additionally, our investigation of how different machine learning models fared on the ISEAR dataset illustrates the huge impact that feature selection strategies have on model performance. Notably, while K-nearest neighbours (KNN) demonstrated relatively poor performance, other models, including Naive Bayes, SVM, and Logistic Regression, displayed high accuracy and weighted metrics. Through further examination of intricate deep learning models and hyperparameter tuning, this study hints at the prospect of improving text-based emotion identification, suggesting new areas for future study. In the end, our findings establish the framework for the design of emotion-aware computers and increase our knowledge of how emotions are expressed through language.

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