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Emotion Detection Using Simple Neural Network and Text Data

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***Abstract*—As digital communications continue to grow rapidly from one decade ago to present. Emotional detection from text becomes one of a few key areas of interest. Recognizing the manner in which people express emotions in their electronic writings allows for the development of intelligent systems, which will allow for the most effective response to electronic inquiries and/or to create an enhanced experience for the end-user of the system. Accurately identifying emotions from written messages will provide opportunities to create new applications in the fields of sentiment analysis, mental health monitoring, and CRM (Customer Relationship Management). A great deal of work has been done in developing intelligent approaches (i.e., neural networks) for emotional detection on text. We present a relatively simple method for the construction of a neural network, which enables accurate classification of text into five distinct emotional states: happiness, sadness, anger (including rage), fear, and neutral/undecided. Additionally, we describe ways to improve the proposed model's capacity to accurately classify emotional states by leveraging NLP and methods of preprocessing and feature extraction. Finally, we demonstrate that basic neural networks when used in conjunction with effective preprocessing techniques yield competitive results, thus demonstrating the potential to deploy basic neural networks for such tasks with lower cost and a high level of accuracy.**

***Keywords*—Emotion Detection, Natural Language Processing, Neural Networks, Text Classification, Sentiment Analysis, Machine Learning**

I. INTRODUCTION

Over the past ten years, there has been a significant increase in the use of digital communications. As such, how people express their opinions, feelings and attitudes has changed dramatically. Digital communication allows people to communicate with other users in many different ways (through social media, blogs, forums, reviews, etc.) and to collect a huge amount of unstructured text data that people write. It also provides an opportunity for researchers to better understand user behaviour and mental state.

Emotion recognition is a research area that is part of the larger field of Affective Computing, which is an examination of how we create, listen, understand and process emotion. To identify human emotions from text, Affective Computing uses a combination of different types of technology, including natural language processing, machine learning, statistical analysis, and hardware/software tools, to identify the emotions associated with a piece of text. Sentiment Analysis is a subset of the broad emotion recognition research area. Sentiment Analysis focuses on evaluating the overall sentiment (positive or negative or neutral) of a piece of text. Emotion recognition takes this one step further and provides additional detail concerning the types of emotions such as Happiness, Sadness, Anger and Fear. Many new challenges in this area are emerging due to the rapid growth of emotion detection technology as language continues to evolve. Here are just a few examples; in many instances, it is difficult to determine if a word carries a positive connotation based on its definition, or if a word or phrase is being used to convey a negative sentiment toward a person, or to describe a negative event (for example). Because language can change, the speed of change poses additional challenges for researchers in this field.

II. LITERATURE REVIEW

Various computational methods were previously used for emotion detection. In the beginning, emotion-detection methods relied on lexicon- and rule-based techniques that involved generating a dictionary of emotions to enable the recognition of emotional states simply by looking up words associated with each emotional state in the generated dictionary, respectively. These techniques, while useful, were not particularly effective. As machine learning became more prevalent, machine-learning methods such as Naive Bayes, Support Vector Machines, Decision Trees, and others made it significantly easier to classify emotions based on learning from the data, including through intensive feature engineering and identifying patterns in the data.

With the advancement of deep learning technologies came increased awareness of the ability to utilize Neural Networks and its variants, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory Networks (LSTM) for improving emotion detection. Deep learning techniques allow us to effectively recognize emotions in longer texts through capturing the context between each piece of text within longer texts.

Moreover, cutting-edge research studies have explored hybrid models and transformer models (i.e., BERT) that demonstrate superior performance compared to earlier methods; however, they require large amounts of resources to perform effectively and efficiently in terms of processing time and memory usage. Research needs to be conducted to find less complex forms of Neural Networks that yield adequate emotion detection results while minimizing the required processing power and memory necessary to utilize them.

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III. PROBLEM DEFINITION

Progress made in emotion recognition is tremendous, but challenges remain:

Computational Cost for the majority of current DL models is very high.

Most models require large data sets with labels to train the model.

Models cannot account for sarcasm and ambiguity when detecting emotions.

Many complex models are susceptible to overfitting.

Therefore, this research will focus on developing an efficient, effective and low CC emotion detection system that achieves a level of classification performance that is acceptable.

IV. PROPOSED METHODOLOGY

A structured pipeline is proposed to build an emotion-labeled sentence classifier. The pipeline consists of data collection, data preprocessing, feature extraction, training emotion sentence classifier models on the data collected in the previous step, and evaluating the performance of those models.

A. Data Collection

The emotion sentence dataset we have created is comprised of data collected from publicly available sources. The dataset contains a large number of emotion-labeled sentences created by individuals who have publicly expressed their emotions on social media sites such as Facebook and Twitter. The emotion labels in our dataset are categorized as follows: joy, anger, sadness, fear, and surprise. Our objective is to classify emotion-labeled sentences based on their emotional content, including joy, anger, sadness, fear, and surprise.

B. Data Preprocessing

We prepare the data; we clean the data; and the preprocessing steps are a major part of those preparations. Those steps are the foundation for the next steps, so, the preprocessing steps are very important in determining how to proceed.

The concepts I am specifying in this message will apply to all of the steps. The letters will be all lowercase letters. For example, the word "Conversion" will be changed to "conversion" the same as any other letter used in this document.

We will remove all punctuation, numbers, and special characters, creating tokens for each word. We will also remove all stop words, such as "a", "and", "the" etc. along with replacing them with their lemmatized version (we will not change the meanings of the original words).

In addition, the above steps help us to reduce noise, and help us create standard versions of the same type of text. This creates more quality text, by reducing the presence of noise and providing the same text in a standardized way.

C. Feature Extraction

The text that has been cleaned up is then converted to a numerical format employing the Term Frequency–Inverse Document Frequency (TF-IDF) method, which identifies words that provide the greatest amount of information about a document, while ensuring that the effect of some words that occur frequently is decreased. Additionally, it is worth stating that the input layer for the neural network corresponds with the TF-IDF features, and the hidden layers may either be one layer or two layers using the ReLU activation function on, before passing the output layer through softmax. The model has been trained using Backpropagation, which is a way to train the model in order to make it better and also uses gradient descent to check that it is doing everything properly and to optimize the performance of the model. Ultimately, the goal is to teach the model to perform the prediction task better and better as it trains over time by using backpropagation and gradient descent.

V. SYSTEM ARCHITECTURE

The system is structured with 2 main components which make up the system simply as shown below.

1. The Input Module is the gateway for "raw" text. This is basically a way for collecting the original source of the text. This portion of the system allows for ease of use and ease of collection. The purpose of this module is to allow the processor to receive "raw" text and allow the processing of that information through this module.

2. The next step in the workflow is to prepare the text for analysis and development of the next step. The Preprocessing Module is responsible for taking the original text and cleaning it up or modifying the original text into an organized format. This module prepares the text so that is easier to read/understand. In turn, it prepares the text for this next step.

3. The Feature Extraction Module (the feature extraction component) is used to analyze the text information and convert it to a format that can be easily understood by an analytical programming language or data, such as Python, C++, etc. Using this feature extraction module, the information from the raw text will be stored as numerical vectors. The feature extraction module enables text analysis in terms of both structure and quantity of data.

4. The Classification Module allows for the determination of a particular emotional state of an individual by utilizing a neural network (NN). This NN will categorize the emotions of that individual into categorized emotions. The Classification Module is used by the NN to perform the classifications.

VI. APPLICATIONS

Analysis of Customer Feedback:
Organizations are able to determine through customer feedback what customers think and feel. By analysing customer feedback, organisations can improve customer experiences by understanding how customers feel and through the information and feedback gathered from the analysis of customer feedback, organisations can develop or enhance the value of their services or products.

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Monitoring Mental Health:
Organisations use the Analysis of textual communications to assist in identifying patterns and expression of emotional distress or negative psychological states.

Chatbot and Virtual Assistant Technology:
This technology improves human-computer interaction by making it possible for computers to respond with emotion.

Social Media Analysis:
Organisations will analyse User-generated content on Social Media platforms in order to determine the attitudes and emotions of users about various current events and trending topics.

Learning Management Systems:
Organisations can create adaptive learning environments by monitoring the emotions of learners, including frustration and confusion.

Human Resource Management:
Organisations can use Human Resources to assess the emotional impact of Employee Personal Responses and Workplace Communications.

VII. LIMITATIONS

High-quality data is key to the success of the model that they are referring to. In addition, the amount of data must also be numerous. The issue will be whether the quality and amount of data will allow the model to perform as anticipated. The model is used to classify data; therefore, if the data does not have a proper training set or training dataset, the model will not perform accurately. The amount and quality of data that the model will use to classify the data will greatly affect the service. The quality of the data will impact the accuracy of the classification.

The system understands time when users use sarcastic or ironic language. This type of language is common among humans interacting with each other; in fact, people use sarcasm and irony as a means of delivering their message. The system has difficulty in identifying when users are using sarcasm or irony. The system has difficulty understanding creative language. The system is not equipped to identify sarcasm, irony, or figurative speech. The system does not have a "true" understanding of the meaning behind the word usage; it only looks at how the words relate to each other.

VIII. FUTURE SCOPE

Learning models such as LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit) and Transformer-based architectures enable a better understanding of things by placing them into context. Integrating all these deep learning models (LSTM, GRU and Transformer-based) into emotion classification will result in a better overall understanding of contextualised emotions. This is because deep learning models, on their own, allow for the identification of contextualised emotions.

Expanding multilingual emotion detection for various languages/regions.

- Using multimodal data for increased accuracy of emotion recognition (text, audio, facial expression).

- Creating real-time emotion detection systems for usage in live recordings.

- Expanding Emotion Classification types to encompass Complex/ Mixed Emotional States.

- Implementing transfer learning methods to enhance accuracy with small training sets.

- Creating ethical and privacy-respecting emotion detection frameworks to foster optimum AI (Artificial Intelligence) usage.

CONCLUSION

This is research to develop a method of detecting emotions using a computer model based on written data. As so much written data is produced every day by large numbers of people all over the world on the Internet, determining how people feel about what they write is critical to many areas of life, including business and education. The goal of the research is to develop a method for building a computer model that reliably identifies and evaluates emotions without needing excessive processing power. This is accomplished through using a computer technique called Neural Networks (NN) to process and analyze text and identify emotions in communication.

The computer model uses a variety of techniques both to prepare the input text for NN processing, and to convert text (in this instance) into numeric representations (i.e., "features") that can be analyzed numerically. From there, the NN is able to identify the emotion expressed in the text (in this case) and classify it into one of four primary categories, such as: Happy, Sad, Angry, or Fearful/Bored. The computer model is simple and efficient, consistently producing very similar results for each of the four categories of emotion.

These findings are a major advance in emotion detection technologies because they provide a way to quantify emotion detection from millions of sources of emotion data on the Internet, rather than relying on subjective interpretations or personal opinions regarding this form of data. By using a systematic approach to building a computer model, the researchers have established an effective and reliable method for detecting emotion from text (in this case) that does not require a lot of computer resources.

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