Comparing Deep Learning Transformers To Naive Bayes and Random Forest Models in the Context of Emotion Detection

Graduate Project Proposal

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1 Introduction

In the CSCI 6350 graduate project[1], the focus of research and student learning is on implementing a Deep Learning Transformer model for Emotion Detection (ED) and comparing its prediction accuracy with previous work by Hoehn et al.[3] that employed Naive Bayes and Random Forest ML models. Additionally, we intend to compare our transformer model with that of Lim et al.[5], a transfer learning-based ED model, ensuring a thorough comparative analysis of pre-built Transformers to one we are building from scratch.

2 Background

Emotion detection (ED) has garnered significant interest and investment in recent years, emerging as an important tool for understanding human behavior and enhancing communication effectiveness[7, 3]. Through the analysis of text, speech, or facial expressions, ED processes, and underlying machine learning (ML) models, aim to accurately identify and classify emotions expressed by individuals or groups, often in real-time.

ED ML which, incorporate natural language processing (NLP) through the use of deep learning architectures, can detect emotions with high precision given sufficient data[1]. The introduction of the Transformer model by Vaswani et al.[8] in 2017, through the paper "Attention is All You Need"[8], marked a significant advancement for transformers, establishing it as the state-of-the-art model for various NLP tasks, including machine translation, text summarizing, and question & answering tasks.

3 Motivation & Specific Aims

This graduate project's motivation is two-fold. **First**, it aims to build upon Hoehn[3] et al work for the COMS[2] PhD program which focused on ML models like Naive Bayes and Random Forest for ED. **Second**, it seeks to extend CSCI 6350's exploration into the use of Deep Learning for NLP[3] tasks, leveraging a dataset from Hoehn's study[3] based on 2021 Twitter data annotated with emotions[4] and comparing to others.

To complete the project, data from Hoehn's[3] paper that uses labeled emotions will serve as the basis for comparison. The dataset[4] itself is from 2021 Twitter, a simple collection of tweets annotated with emotions. There are 13 different labeled emotions and corresponding text with over 40,000 rows in a `csv` file.

Using a Transformer for Emotion Detection has four (4) main goals:

- Build, Train, and Validate a Transformer for Emotion Detection, using PyTorch[6].
- Display the learning rates and validation results in graphical forms using plots.
- Evaluate the Transformer's results against those from Hoehn[3] et al.'s paper on Naive Bayes & Random Forest results.

[1] The purpose of the graduate project is to afford students the opportunity to research modern technologies used in the field of natural language processing (NLP).
[2] COMS - Computational Data & Science Department
[3] NLP - Natural Language Processing

- Compare the constructed transformer with Lim et al.'s transfer learning-based emotion detection model[5] to ensure comparative results in ED.

Visual aids, like plots, will be utilized to display learning and validation outcomes, crucial for refining the Transformer's performance, in addition making necessary adjustments to hyperparameters in order to enhance performance.

A thorough comparison with Hoehn et al.'s and Lim et al.'s works[3][5] will validate our Transformer model's capability in capturing emotional nuances, showcasing its advantage over traditional ML models in understanding contextual dependencies.

4 Proposed Methods

The methodology to achieve the objectives outlined involve three primary components. Initially, the dataset will undergo pre-processing to cleanse the tweets by eliminating irrelevant characters or words. Subsequently, tokenization will be employed to transform the tweets into a format comprehensible by the model, utilizing BERT Tokenization[2] for this purpose.

Upon completion of tokenization, the transformer model, likely BERT[2] due to its proven efficacy in understanding human language context, will be deployed. The dataset, consisting of labeled records, will be divided using an 80/20% split to create training, validation, and test sets.

The model will be trained on the training set to facilitate learning the mapping of input text to accurate emotion labels. Optimization of the model's parameters will be achieved through back-propagation and gradient descent techniques. Performance will be evaluated on the validation set, focusing on F1 score(s) to assess its effectiveness in emotion prediction.

Finally, the transformer model's predictive outcomes will be compared with the Naive Bayes and Random Forest results from Hoehn's study[3] to establish comparative accuracy.

5 Expected Results

In the context of this Graduate Project on Emotion Detection from text data, it is anticipated that a Deep Learning Transformer model will outperform the Naive Bayes and Random Forest Machine Learning (ML) approaches described in Hoehn's paper[3].

This expectation is based on the premise that transformers, designed to capture the contextual nuances of human language through their attention mechanisms, are more adept at recognizing the intricacies of spoken and written language, such as sarcasm and idioms[5]. Therefore, when applied to a dataset of labeled records for emotion detection, the Transformer is likely to achieve higher accuracy rates than the Naive Bayes and Random Forest approaches, illustrating its robustness and effectiveness in capturing the emotions conveyed in text, surpassing the capabilities of traditional ML classifiers.

References

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