Machine Learning for Sentiment Analysis

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Abstract

Emotional sentiment analysis can be used in a wide range of of applications, from gauging public opinion to studying the impact of social media on mental health. Despite the ease with which humans can perform sentiment analysis, the task poses a more substantial challenge for computers. We propose an investigation of state-of-the-art transformer-based machine learning methods to address this challenging task. We will also present an alternative solution based on more traditional machine learning techniques to evaluate performance against the state-of-the-art in both accuracy and inference time. Results and findings will be recorded in a final report.

Index Terms

Machine learning, sentiment analysis, natural language processing, transformers, support vector machines, BERT

I. Introduction

Humans possess an innate ability to determine emotion from conversation without explicit cues. We automatically collect samples of a speaker's speech patterns, body language, choice of vocabulary, and the surrounding context, for example, as data points from which we construct an overall picture of their emotion. This subconscious analysis then informs our decisions and actions as we interact with those around us. While this task is incredibly simple for humans, determining emotional sentiment is much harder for a computer.

Sentiment analysis is a branch of computer science that aims to use machine learning techniques to automatically determine emotion conveyed through text. This proposed work will explore sentiment analysis using Twitter status updates (tweets) as samples for evaluation. The problem being addressed, proposed solution, related work, and project timeline will be outlined in the following sections.

II. Problem Definition

Sentiment analysis can provide rich information about people's views and emotions on various issues, topics, or products. This information can be used to gauge public opinion and respond to consumer needs, as well as for the study of social media influence on individuals' moods and personal well-being. For these reasons, the problem of sentiment analysis is of significant interest. However, many challenges are associated with this task. Inconsistencies of spelling, slang, incomplete thoughts, non-traditional characters (such as emoticons), and cultural variations in written expression all make the task of classifying emotional sentiment from text difficult. The goal of this proposed work is to present and evaluate an implementation that addresses this this task and its difficulties and allows for high accuracy emotional sentiment analysis from text.

III. Proposed Solution

This section outlines the proposed solution to the problem identified in section II. The datasets that will be used, along with brief descriptions of each, is provided. That is followed by an overview of the methods that will be used for this work.

A. Dataset

The principal dataset that will be used for this project is the CARER dataset [1]. The dataset consists of approximately 20,000 tweets, each automatically labeled using the distant supervision approach outlined in [2]. This approach makes use of a tweet's emoticons as ”noisy labels” to classify tweets according to one of six labels: anger, fear, love, joy, sadness, or surprise. A similar dataset, prepared by Kaggle user Praveen Govi, uses the same techniques as the CARER dataset but has more code examples for ease of use [3]. These datasets will be used in conjunction to train and test our proposed methods.

B. Methods

In this proposed work we will implement and evaluate a machine learning model to classify the emotional sentiment of tweets. While the main focus of this work will be on designing the classifier, brief investigation into methods of feature extraction from text will be performed. Once a feature extraction method is chosen, the intent is that it will be used for all further tests. Classification will focus on established modern transformer based methods and will utilize the PyTorch open source machine learning library for development. The deliverable of this portion of the project will be a trained, validated, and tested transformer classifier tuned for optimal performance on data that is characteristic of our proposed datasets.

Further work will investigate the use of traditional machine learning methods, such as support vector machines (SVMs) or naive Bayes classification, for multi-class classification of emotion from tweets. As will be discussed in section IV, existing works utilizing these traditional techniques for sentiment analysis can perform only binary classification. This work will be compared to the transformer-based implementation to analyze classification accuracy and inference speed. A thorough, comparative analysis will be performed between all classifiers implemented and results will be reported. It is expected that transformer-based models will perform with higher accuracy; however, other implementations may provide faster inference and lower network sizes more amiable for use in embedded, compute-constrained applications.

IV. Related Work

Many different machine learning techniques have been proposed and implemented as approaches for natural language processing (NLP) and sentiment analysis. These approaches range from more traditional methods, such as naive Bayesian classifiers and support vector machines (SVMs), to newer methods, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and transformers. A brief survey of these related works is provided below.

Sentiment analysis in Twitter posts was studied in [4] where four different classification techniques (SVM, naive Bayes, maximum entropy, ensemble classifier) were used. The dataset used in this work contained 1,200 posts with each being classified as 'positive' or 'negative' in sentiment. The results showed that SVM and maximum entropy were the most accurate methods for classifying this binary sentiment. Of course, this work is limited by the use of only two classes, which cannot fully capture sentiment in complex posts; however, the results show the promise of machine learning for sentiment analysis.

A similar investigation was performed in [5], albeit with different methods and data. In this case, SVMs and variations of decision trees were utilized for classification of sentiment. This work shares the downside of only using a binary classification; however, it does utilize a much more extensive dataset, with over 1.6 million samples [5]. Results from this work show best achieved accuracy to be 84% when using a decision tree. In addition to the works presented in [4] and [5], other work has been done on more traditional methods for sentiment analysis from text, such as a study of product review sentiment analysis presented in [6].

Recently, more advanced methods for NLP and sentiment analysis have been proposed. A study of a combination of CNNs and LSTM networks is presented in [7]. This study showed that a LSTM-CNN combination performed best for binary sentiment analysis of a dataset of over 1.5 million Twitter posts.

A new machine learning architecture well-suited for NLP was presented in [8]. The architecture, termed a transformer, does not rely on recurrence, like LSTMs, or convolutions, like CNNs. Instead, the architecture is based on attention mechanisms and uses an encoder-decoder structure. A predominantly used implementation of transformers for NLP is BERT, a model introduced by Google AI [9]. BERT provides a pre-trained model that can then be fine tuned for a variety of NLP applications with state-of-the-art performance.

One final area that should be discussed, and that will be further investigated is the extraction of features from text. The paper that introduces the dataset to be used in this proposed work introduces a graph-based enriched feature patterns model [1]. Other feature methods such as term frequency-inverse document frequency, N-gram, word frequency, and character frequency also exist [1], [10]. It was shown that the method for extracting features can affect the performance of the classification of sentiment [10].

V. Project Plan

A. Timeline

Table I below contains a timeline estimate of the high-level tasks that we would like to undertake for this project. We will also be reviewing relevant literature weekly, as was instructed in the project guidelines. In our table, we have also included relevant class deadlines so that we may use this table as a comprehensive resource for the course schedule.

TABLE I
ESTIMATED PROJECT TIMELINE

Task Group	Task	Projected Completion Date
Understand existing sentiment analysis methods	Download models and datasets	10/8
	Run existing models	10/15
	Analyze results in progress report	10/22
Implementing existing and new methods	Run existing models on datasets	11/12
	Work on applying methods to multi-class classification	11/27
	Work on applying transformer methods	11/27
	Synthesize results into presentation	11/30
	Review slides and practice presentation	12/2
Class deadlines	Midterm exam	10/14
	Progress report	11/1
	Final report	First week of December
	Final presentation	12/9 or 12/14
	Final exam	12/16

B. *Project Responsibilities*

Since the topic of this project is rather exploratory in nature, most of the project's responsibilities can be shared equally. The collaborative nature of Google Colaboratory means that both team members can work together on running the existing sentiment analysis models, understanding their inner workings, and analyzing their results. Given each team member's preferences, Daniel will lead the implementation and testing of multi-class classification methods for sentiment analysis, while Avery will take the lead on the transformer methods. However, both team members will collaborate closely on these topics.

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