Twitter Sentiment Classification

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August, 2024

Background & Problem Statement

Background

- Social media platforms like Twitter have become rich sources of real-time information, capturing the diversity of human expression across various contexts. This project leverages the Sentiment140 dataset, a large collection of tweets annotated with sentiment labels, to develop a sentiment analysis tool.

Problem Statement

- The primary challenge is to accurately classify the sentiment of tweets (positive or negative) using a combination of linear and non-linear machine learning models. This classification must be effective even for texts that do not contain explicit emoticons.

Application

- The classification model developed through this project could be used by Brand for Social Listening, allowing them to understand customer sentiment towards their products and services, even when limited context is available.

Objectives

1. **Develop a Sentiment Analysis Tool**
   Create a tool that can classify sentiments in tweets using both traditional and advanced machine learning models.
2. **XAI Techniques**
   Use XAI methods like LIME and SHAP to make the models decision-making process transparent and interpretable.
3. **Evaluate Model Performance**
   Use cross-validation and independent test sets to assess the performance of the models.
4. **Causal Analysis**
   Apply causal inference techniques to uncover and understand causal relationships within the data.

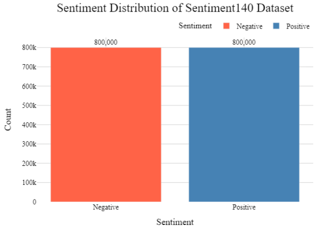
1. Background & Objective
2. Data & EDA
3. Literature Review
4. Model Engineering
5. Results
6. XAI
7. Future Work
8. References

Data Description

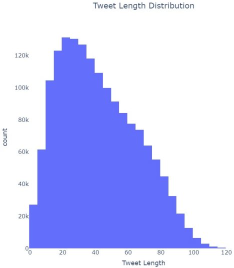
Data Source Description
The Sentiment140 dataset consists of 1.6 million tweets, each annotated with a sentiment label (positive or negative) based on the presence of emoticons. The dataset was collected using the Twitter API between April 6, 2009, and June 25, 2009. Each tweet in the dataset includes the tweet text, the sentiment label, and other metadata such as the date of the tweet, the query used to collect the tweet, and the user ID.

Key Features of the Dataset:

- **Size & Balance**: The dataset contains 1.6 million rows, evenly split between positive and negative sentiment.
- **Variance**: Tweets in the dataset contain a variety of words and expressions, reflecting the diverse nature of Twitter content.
- **Real-World Applicability**: The data was collected directly from Twitter, making it applicable to real-world scenarios.



Exploratory Data Analysis



- The chart shows that most tweets are relatively short, with a median character length of 38.
- This highlights both the importance and challenge of classification, as shortform text has less room for context than longform text.

- The word clouds illustrate the most common words associated with positive and negative sentiments in the dataset.
- While it is not shocking to see words like love and thank prominently featured in the positive word cloud, the words work and now being the most prominent in the negative word cloud are more surprising.

Sentiment Analysis in Twitter Using Machine Learning Techniques

Challenge

- Informal language & short tweets present difficulties for classification models

Proposed Solutions

- **Preprocessing:** Removing URLs, handling slang, and correcting misspellings
- **Feature Extraction:** Extraction of Twitter-specific features like hashtags
- **Classification Models post Preprocessing & Feature Extraction:**
  - Naive Bayes (NB)
  - Support Vector Machine (SVM)
  - Maximum Entropy (ME)
  - Ensemble Classifier: Combines NB, SVM, and ME using a voting mechanism

Relevance / Adaptability

- Preprocessing & Feature Extraction are used in the model in this presentation

Source: Neethu M S, Rajasree R, "Sentiment Analysis in Twitter Using Machine Learning Techniques," 4th ICCCNT 2013, IEEE, 2013.

ABCDM: An Attention-based Bidirectional CNN-RNN Deep Model for Sentiment Analysis

Challenge

- Individual sentiment classification techniques can have limitations, especially when translating short form methods to long form text

Proposed Solutions

- **CNNs and RNNs:** Identify word & phrase relationships over longer passages.
- **Attention Mechanism:** Understands the context and semantics of the text.
- **Bidirectional Processing:** Provides enhanced context by considering words before and after the target word.
- **Deep Architecture:** Incorporates multiple CNNs and RNNs for greater data processing and comprehension.

Relevance / Adaptability

- Provides a set of advanced techniques that can be employed if effectiveness of initial approach is limited or if model is scaled to be effective on long form text

Source: Basiri, Mohammad Ehsan, et al. "ABCDM: An Attention-based Bidirectional CNN-RNN Deep Model for Sentiment Analysis." Expert Systems with Applications 149 (2020): 113240.

Sentiment Analysis in the Age of Generative AI

Challenge

- Initial sentiment classification models may have limitations from being trained in a specific, closed environment; LLMs may not have this limitation

Proposed Solutions

- Compare classification from GPT-3.5, GPT-4, and Llama 2 against traditional transfer learning models like SiEBERT and fine-tuned RoBERTa
- The LLMs were able to perform similarly to SiEBERT and fine-tuned RoBERTa, showing that they are a viable alternative for sentiment classification

Relevance / Adaptability

- GPT-4 and Llama 2 were considered as a supplement to the project in case there was a need to simplify the process of adapting the model to new types of text data by leveraging the pre-trained capabilities of these models.
- The paper stressed the importance of preprocessing to handle text complexity and structured content

Source: Krugmann, Jan Ole, and Jochen Hartmann. "Sentiment Analysis in the Age of Generative AI." Customer Needs and Solutions (2024): 1-19. doi:10.1007/s40547-024-00143-4.

Logistic Regression

Model

- Logistic Regression model was trained on vectorized forms of the words in the dataset to find the probability that each word would contribute to a tweet having a positive or negative sentiment.

Accuracy

- Model returned a balanced accuracy of 0.75, with all precision and recall values falling between 0.72 0.78.

XAI

- SHAP XAI provides insight into the most important words in predicting/classifying user sentiment.
- Of the top 20 words identified by SHAP, 12 were words associated with negative sentiment, suggesting that the group of words related to negative sentiment is more concentrated than that related to positive sentiment.

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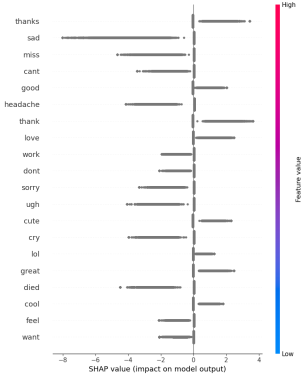
Model Accuracy on Full Dataset: 0.75

Classification Report:
              precision    recall  f1-score   support

           0       0.77      0.72      0.74    796302
           1       0.74      0.78      0.76    795668

    accuracy                           0.75   1591970
   macro avg       0.75      0.75      0.75   1591970
weighted avg       0.75      0.75      0.75   1591970
```



Model Engineering

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- In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat.
- Fusce mauris. Vestibulum luctus nibh at lectus. Sed bibendum, nulla a faucibus semper, leo velit ultricies tellus, ac venenatis arcu wisi vel nisl. Vestibulum diam.
- Aliquam pellentesque, augue quis sagittis posuere, turpis lacus congue quam, in hendrerit risus eros eget felis. Maecenas eget erat in sapien mattis porttitor. Vestibulum porttitor. Nulla facilisi.

XAI Techniques

Future Directions

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Thank You