Overview

Project Name: PeasAI-TweetAnalyzer

The Primary Objective

Objective

Develop a system to categorise tweets mentioning a specific business into three sentiment categories: negative (bad review), neutral (neutral review), and positive (positive review), while also identifying and labelling the specific aspects of the product or service being praised or criticised within each tweet

Tasks

Choosing the right Models

We have chosen the huggingface model - “cardiffnlp/twitter-roberta-base-sentiment” for the sentiment analysis tasks that we have to accomplish and “MoritzLaurer/deberta-v3-xsmall-zeroshot-v1.1-all-33” for zero-shot-classification of issues that are the subject of the review.

The Roberta model we have chosen is a roBERTa-base model trained on ~58M tweets and finetuned for sentiment analysis with the TweetEval benchmark. The zero-shot-classification model in use is a modified version of the foundation model, microsoft/deberta-v3-xsmall. The model only has 22 million backbone parameters and 128 million vocabulary parameters. The backbone parameters are the main parameters active during inference, providing a significant speedup over larger models. The model is 142 MB small. This model was trained to provide a small and highly efficient zeroshot option, especially for edge devices

Fine-tuning the Models

We use a fine-tuned version of the sentiment analysis model because fine-tuning one on airline reviews offers a significant advantage. Generic models trained on broad datasets may struggle with industry-specific language and nuances. Fine-tuning tailors the model to recognise the sentiment expressed within the context of airline travel. This leads to more accurate identification of positive experiences (e.g., praising in-flight service) and negative ones (e.g., complaints about delays), providing airlines with a clearer picture of customer sentiment.

We considered fine-tuning a zero-shot classification model for airline review sentiment analysis. However, the pre-trained model we selected achieved good results without further adjustments. This suggests the model is already strong in sentiment understanding, possibly due to its status as a top performer in zero-shot classification in small models. Additionally, exploring a larger model for fine-tuning wasn't feasible due to computational limitations on most computers. Given these factors, we decided to use the model without further fine-tuning to achieve good performance without the extra time and resources needed for fine-tuning.

Multiple steps were taken in the Fine-tuning process of the sentiment analysis model for decreasing instances of over-fitting . The Kaggle notebook used for fine-tuning is given in the Notes section. But some of the steps that were taken are:

- Prepping the data we have
- Basic analysis of the data have
- Making Training, Validation and Test datasets
- Fine-tuning
- Finding the statistics of how our model performed.

Building a GUI app for the ML models

We have built a clean, intuitive, user-friendly application that helps you analyse the sentiment and classify tweets. It has a simple interface with a single entry box where you can paste a tweet for analysis. Once you click the "Submit" button, the app utilises two machine learning algorithms: sentiment analysis and zero-shot classification.

- Sentiment Analysis: This algorithm determines the overall emotional tone of the tweet, classifying it as positive, neutral, or negative.
- Zero-Shot Classification: This algorithm goes beyond sentiment analysis and assigns a more specific class to the tweet based on its content.

The results are displayed in three designated sections of the app labelled "Positive Tweets," "Neutral Tweets," and "Negative Tweets." Each tweet is presented within a frame that includes the tweet text itself and two buttons.

- Change Sentiment: This button allows you to reclassify the tweet based on sentiment (positive, neutral, or negative). When you click this button, the tweet frame automatically moves to the corresponding sentiment section.
- Change Class: This button is for situations where you believe the zero-shot classification might be incorrect. Clicking this button allows you to manually assign a different class to the tweet, but it won't move the frame since the sentiment section is already determined.

Overall, offers a convenient and intuitive way to analyse and classify tweets, providing valuable insights into the emotional tone and content of social media communication.

Results

We get a rough idea of how the model works using the statistics collected in the 3-cross-validation that we implemented during the Fine-tuning process. The following is a confusion matrix that is obtained (The confusion matrix in this case is non-binary)

Labels	Predicted positive tweets	Predicted neutral tweets	Predicted negative tweets
Actual positive tweets	242	21	19
Actual neutral tweets	30	244	111
Actual negative tweets	39	65	1615

*We have taken average values of the 3 splits in the above matrix

sensitivity (true positive rate) = 0.8581560283687943

specificity (true negative rate) = 0.9449970743124634

false negative rate = 0.0744985673352436

true neutrality rate = 0.6337662337662338

The metrics for the zeroshot model can be found in the link of the huggingface model given in notes.

Conclusions

Goals and Achievements

Our project aimed to achieve a foundational level of tweet sentiment analysis and classification using machine learning. We opted for a pre-trained model with basic finetuning, because of our limited experience with extensive hyperparameter tuning. Despite this, we achieved fairly good results and focused on building a user-friendly GUI (Graphical User Interface) for real-time analysis.

We prioritised well-structured code using Object-Oriented Programming (OOP) principles. This modular design allows for easy modifications and future feature additions. The codebase is also flexible in accommodating different machine learning models if needed. We documented the fine-tuning process thoroughly.

Future Improvements

While Peach-TweetAnalyzer demonstrates its potential as a sentiment analysis and classification tool, several exciting possibilities exist for future development:

Fine-tuning improvements:

Our knowledge of hyperparameter tuning for machine learning models is still very limited. While we achieved good results with the chosen pre-trained model, there's a possibility that more extensive hyperparameter tuning could further improve the accuracy of the sentiment analysis and classification. This area presents a huge scope for improvement.

Additional Improvements:

- Integrate a Twitter API for live analysis of relevant tweets.
- Allow data export to CSV for further user analysis.
- The well-organised, object-oriented code facilitates future development of new features.
- Explore fine-tuning models for specific industries beyond airlines.
- Implement a system for user-defined class-based categorisation.
- Develop a dashboard to visually represent trends and insights.
- Refine the GUI for a more user-friendly experience.

PeasAI-TweetAnalyzer showcases the power of combining machine learning with a user-friendly interface. It serves as a foundation for a robust and versatile tool for understanding social media communication for various business domains.

Notes

- Kaggle Notebook - https://www.kaggle.com/code/jdhruvr/airlinetweetssentimentfinetuning/notebook
- Github Repository for the submission - https://github.com/JDhruvR/PeasAI-TweetAnalyzer
- Links for the pre-trained models used - https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest,