Sentiment Analysis Report

Introduction

This report outlines the sentiment analysis performed on an airline dataset using the DistilBERT model. The goal was to classify tweets into three sentiment categories: negative, neutral, and positive. The analysis involved data preprocessing, model training, and evaluation.

Data Preprocessing

Data Loading and Cleaning:

- The dataset was loaded from a CSV file containing 14,640 entries.
- Irrelevant columns such as negativereason_gold, airline_sentiment_gold, retweet_count, tweet_coord, tweet_location, tweet_created, user_timezone, and name were dropped.
- Duplicate rows were identified and removed, resulting in 14,601 unique entries.

Text Preprocessing:

- Stopwords were removed from the text data.
- Text was tokenized and converted to lowercase.
- The text data was further processed to ensure consistency and readiness for model input.

Handling Missing Values:

- Missing values were identified, particularly in the negativereason and negativereason_confidence columns.

Model Setup and Training

Model Selection:

- The DistilBERT model was chosen for its efficiency and effectiveness in text classification tasks.
- The model was initialized with the distilbert-base-uncased pre-trained weights.

Data Preparation:

- The dataset was split into training, validation, and test sets with a 70-15-15 split ratio.
- Labels were encoded using LabelEncoder to convert sentiment categories into numerical values.

Training:

- The model was trained for 7 epochs with a batch size of 32.
- The AdamW optimizer was used with a learning rate of 1e-5 and weight decay of 1e-2.
- Gradient clipping was applied to prevent exploding gradients.
- Dropout regularization was used with a dropout probability of 0.5 for both hidden layers and attention probabilities.

Training Results:

- The training loss decreased from 0.6683 to 0.1547 over the 7 epochs.
- Training accuracy improved from 72.09% to 95.15%.
- Validation accuracy peaked at 81.96% in the 4th epoch but slightly decreased to 80.73% by the 7th epoch.

Model Evaluation

Test Accuracy:

- The model achieved a test accuracy of 82.98%.

Classification Report:

- Precision: The model performed well in identifying negative sentiments (0.87 precision) but struggled slightly with neutral sentiments (0.70 precision).
- Recall: The recall was highest for negative sentiments (0.92) and lowest for neutral sentiments (0.60).
- F1-Score: The F1-score was highest for negative sentiments (0.90) and lowest for neutral sentiments (0.65).

Loss and Accuracy Curves:

- The training and validation loss curves showed a consistent decrease, indicating effective learning.
- The accuracy curves demonstrated steady improvement, with training accuracy surpassing validation accuracy, suggesting some overfitting.

Conclusion

The sentiment analysis using DistilBERT achieved a satisfactory test accuracy of 82.98%. The model performed exceptionally well in identifying negative sentiments but showed room for improvement in classifying neutral sentiments. Future work could involve further hyperparameter tuning, data augmentation, or exploring more advanced models to enhance performance, particularly for neutral sentiment classification.