Technical Report: Sentiment Analysis of US Airline Tweets

1. Problem Introduction

Airline companies receive thousands of customer tweets daily, ranging from praise to complaints. Manually going through all these tweets to understand public sentiment would be time-consuming and inefficient. Understanding sentiment patterns can help airlines improve customer service, spot common problems, and monitor their reputation.

The dataset used contains 14,640 tweets about six major US airlines. Each tweet is labelled as **positive**, **negative**, or **neutral**. The data is imbalanced, with **negative tweets** being the largest group.

This is a text classification task, where the goal is to train machine learning models that can automatically predict the sentiment of new tweets. Machine learning is well-suited here because:

- It can process large amounts of text quickly.
- It can learn patterns in language from past labelled examples.
- It can adapt to detect subtle tone differences in tweets.

2. Model Selection and Methodology

Chosen Models

1. **Support Vector Machine (SVM)** – Works well with high-dimensional text features like TF-IDF vectors.
2. **Weighted SVM with n-grams** – Adds class weights to help with imbalance and uses word pairs for more context.
3. **Neural Network (MLP Classifier)** – Can capture more complex patterns but needs careful tuning.

Preprocessing Steps

1. Cleaned tweets (removed punctuation, links, numbers, and stopwords).
2. Tokenized tweets into words.
3. Used **TF-IDF** to convert text into numeric features, giving more weight to rare but informative words.
4. Applied feature scaling for neural network input.

Feature Engineering

- For the weighted SVM, used **bigrams** (two-word sequences) to capture short phrases like “delayed flight” or “great service.”
- Applied **class weights** so the model paid more attention to positive and neutral tweets, which were underrepresented.

Evaluation Metrics

- **Accuracy** – Percentage of correct predictions.
- **Precision, Recall, F1-score** – To measure how well each sentiment was predicted.

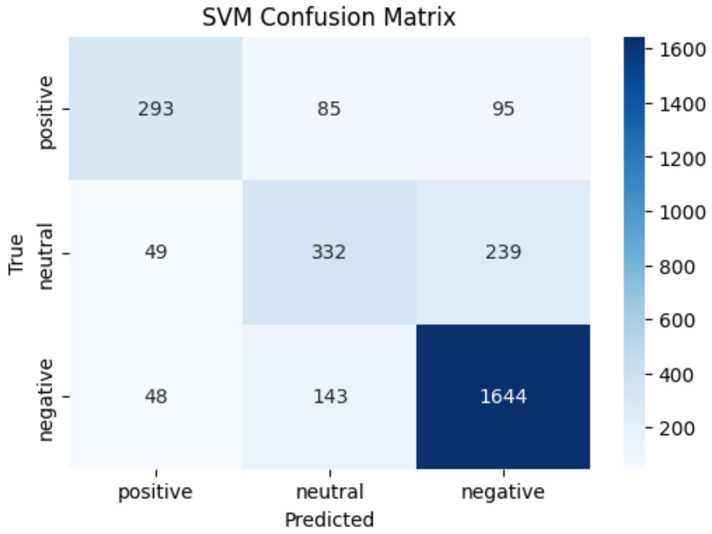
- **Confusion Matrix** – To see the exact classification breakdown for each model.

3. Results and Analysis

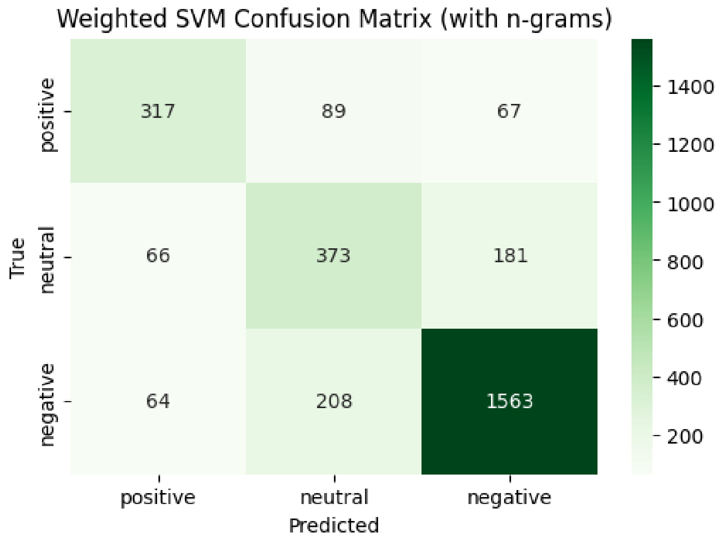
Model	Accuracy	Best Performing Class	Weakest Class	Notes
SVM	77%	Negative (Precision: 0.83, Recall: 0.90)	Neutral	Struggles with neutral tone detection
Weighted SVM (n-grams)	77%	Negative & Neutral balance	Slight drop in Negative recall	Class weights improved neutral detection
Neural Network (MLP)	76%	Negative	Positive	Needs more tuning for improvement

Confusion Matrices:

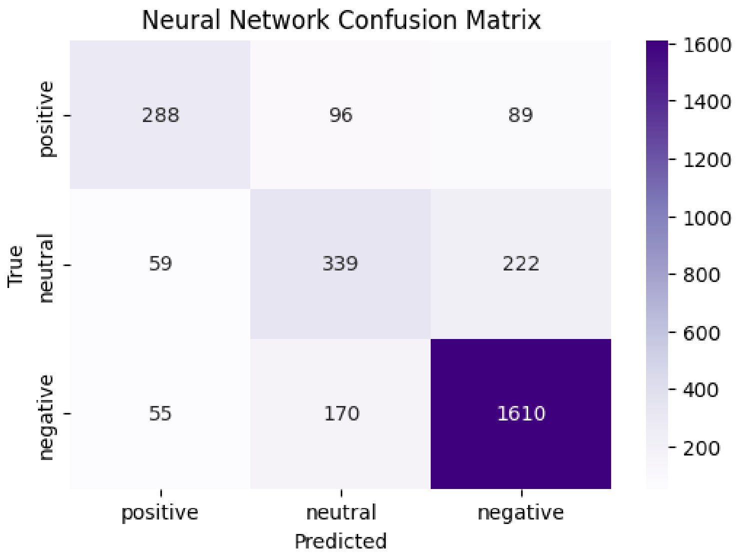
- **SVM**:



- **Weighted SVM (n-grams)**:



- **Neural Network (MLP)**:



Practical Interpretation

- SVM models are strong at detecting negative tweets, which is useful for spotting customer complaints quickly.
- Weighted SVM improves neutral classification, which could help in distinguishing between mixed-tone and complaint tweets.
- The neural network performed similarly to SVMs but didn't outperform them - probably needs more data or parameter tuning.

Limitations

- Class imbalance hurts performance for neutral and positive tweets.
- Only tweet text was used - adding metadata like airline name, time of day, or location might improve predictions.

4. Conclusion

This project showed that machine learning models can effectively classify airline-related tweets into sentiment categories. The Weighted SVM gave the best balance between classes, while the regular SVM was best for detecting negative tweets.

In practice, airlines could integrate such a model into a dashboard to monitor sentiment in real time, helping them respond faster to service issues. Future improvements could include trying ensemble methods, adding metadata, and experimenting with deep learning models.

References

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3. Manning, C. D., Raghavan, P., & Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge University Press.