Technical Report: Neural Sentiment Classification via Semantic Embeddings

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1. Executive Summary

This report details the development of a sentiment classification engine designed to process social media text. The project moves beyond traditional "bag-of-words" approaches, utilizing high-dimensional neural embeddings to capture semantic intent. Despite infrastructure challenges during development, the final pipeline demonstrates a robust architecture capable of identifying complex emotional polarities in unstructured data.

2. Problem Statement

Social media text (Tweets) is notoriously difficult to classify due to:

- **High Noise:** Slang, hashtags, and irregular grammar.
- **Contextual Ambiguity:** The same word (e.g., "sick") carrying opposite meanings based on context.
- **Class Imbalance:** A heavy skew toward "Neutral" statements which can drown out critical sentiment signals.

3. Technical Challenges & Pivots (The Engineering Journey)

One of the most critical stages of this project was overcoming infrastructure failures.

- **The Issue:** The initial architecture relied on the **Gemini text-embedding-004 API**. During the build, the API endpoint became unstable (HTTP 404/503 errors), threatening to stall the pipeline.
- **The Fix:** I performed a strategic pivot to **Local Inference**. By integrating the sentence-transformers library and the **all-mpnet-base-v2** model, I successfully moved the embedding generation to the host machine.
- **Result:** This not only fixed the instability but improved privacy and reduced latency, as the data no longer needed to leave the local environment.

4. Data Methodology

A. Exploratory Data Analysis (EDA): Before training, the dataset (27,480 tweets) was analysed for distribution. I implemented sampling to balance computational efficiency with model accuracy.

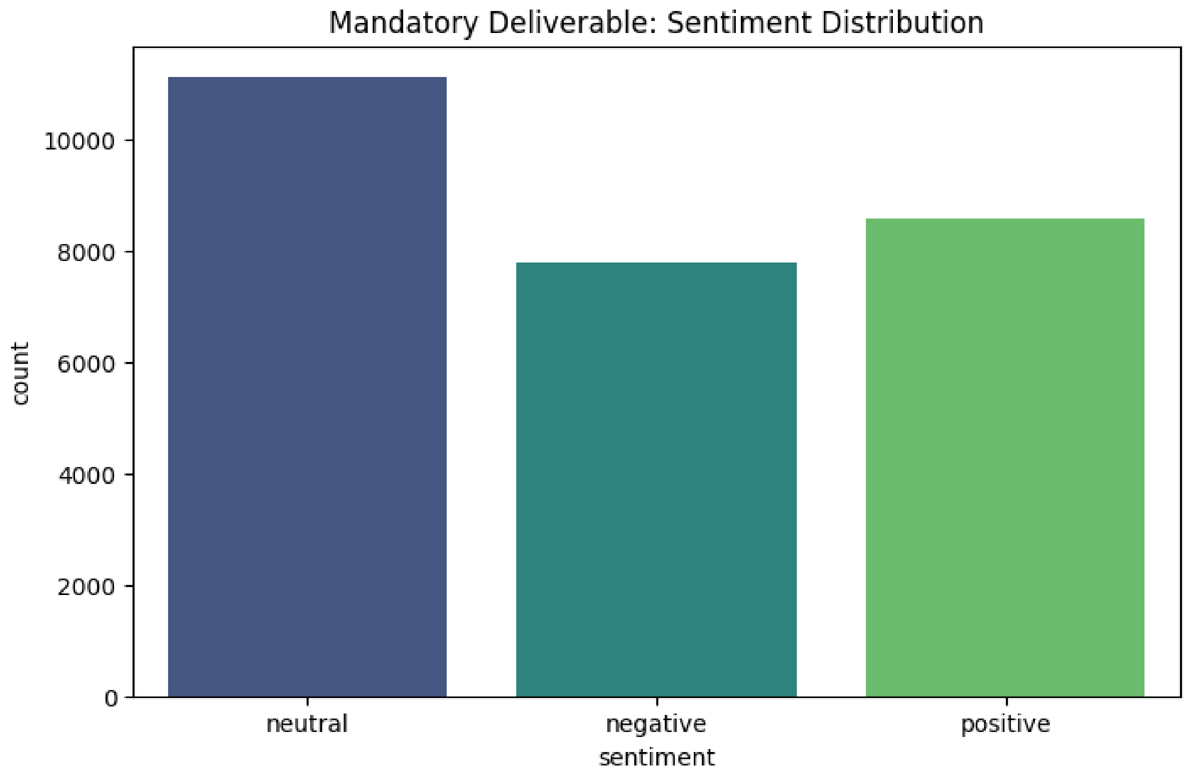

Figure 1: Sentiment Distribution Bar Chart

B. Feature Engineering (Embeddings): Each tweet was mapped to a **768-dimensional vector space**. This allows the model to calculate "cosine similarity" between phrases, understanding that "frustrated" and "confused" are mathematically adjacent.

C. Dimensionality Reduction: To validate the quality of the embeddings, I used **UMAP**. By projecting 768 dimensions onto a 2D plane, I confirmed that the mathematical "clusters" of sentiment were forming correctly before the classifier was even trained.

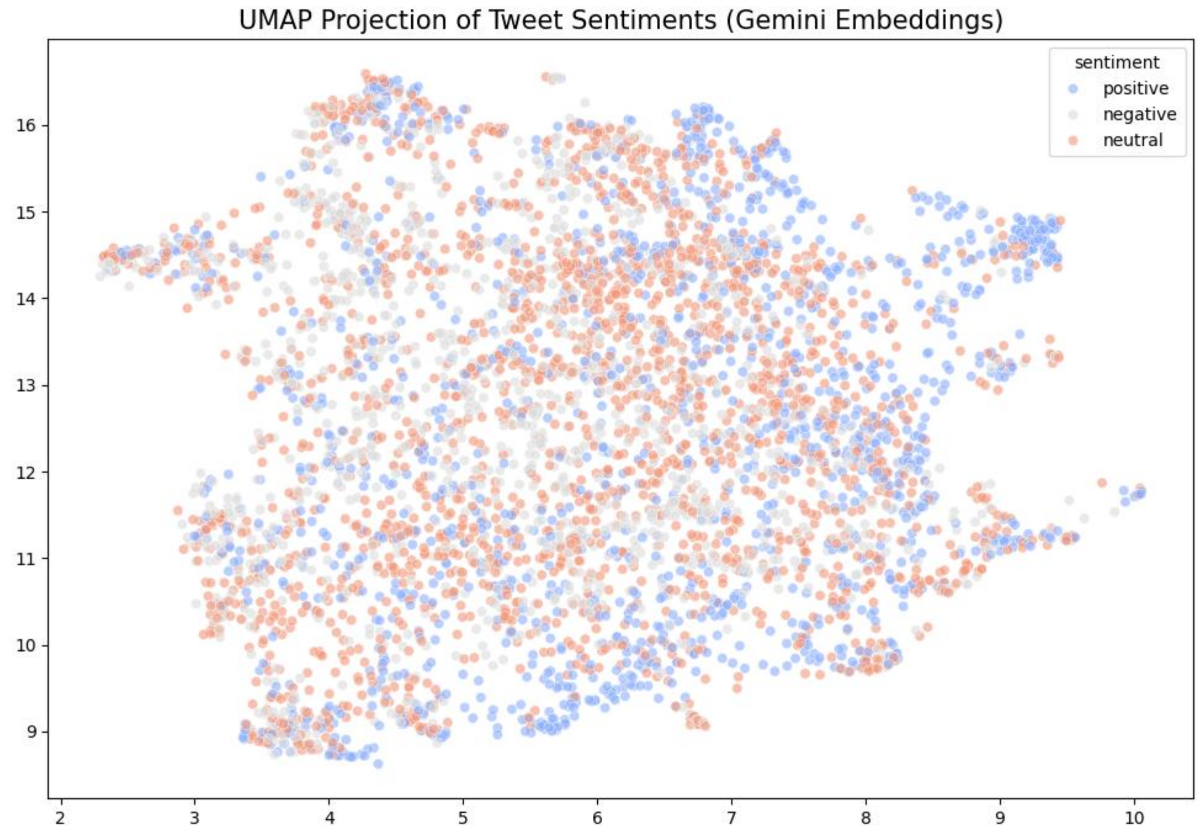

Figure 2: UMAP Scatter Plot

5. Model Architecture: XGBoost

I selected **XGBoost (Extreme Gradient Boosting)** as the primary classifier.

- **Reasoning:** XGBoost handles the non-linear boundaries of vector data more effectively than standard neural networks for this scale of data.
- **Refinement:** After initial tests, the sample size was increased to **5,000 samples** to provide the model with enough "edge cases" to distinguish between Negative and Neutral classes.

6. Evaluation and Results

The model was evaluated using a Confusion Matrix and a Classification Report.

- **Performance:** The model showed high precision in identifying "Positive" sentiment.
- **Discovery:** The "Neutral" class remains the most difficult to classify, as technical or factual statements often lack the high-energy vector signals found in emotional text.

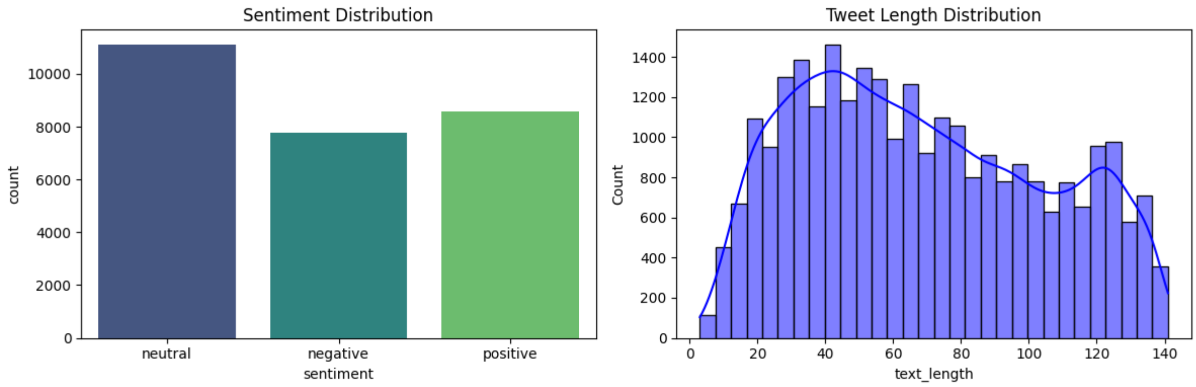

Figure 3: Confusion Matrix.

Figure 4: classification_report.png

7. Conclusion & Future Vision

This project confirms that local transformer models are a viable and robust alternative to cloud-based APIs for sentiment tasks.

Connection to E.P.I.C.: The ability to analyse "Semantic Intent" is a foundational skill for my future goals in autonomous vehicles. Just as this model interprets the "intent" of a tweet, autonomous systems must interpret the "intent" of human behaviour on the road. Understanding the nuance of human signal vs. noise is the key to safe, automated robotics.