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Group 3

Project Proposal

LLM-Enhanced Stock Price Prediction:

Improving the Synergy of Price Prediction and Sentiment Analysis Models

Brenda Su, Cheryl Yeo, Chong Le Kai, Wong Swee Kiat, Tammy Lee, Trina Tan, Xavier Santimano

Motivation

- **Maximise Returns, Minimise Risks:**
  - Accurate stock price predictions can reduce exposure to large portfolio losses, helping investors make smarter financial decisions

- **LLM’s Potential:**
  - Sentiment analysis alone can already improve prediction accuracy by approximately 5% (Wang et al, 2019)

  - LLMs offer a richer, more context-aware understanding of financial news, potentially enhancing prediction models and providing a competitive edge in volatile markets

Problem Statement

This project explores **using LLMs for stock price prediction by integrating historical data with financial news sentiment** for better investment decisions.

While sentiment analysis is well-studied, the advantages of LLMs over traditional NLP methods remain under-studied. We evaluate text granularity, feature extraction, and multimodal architectures to assess their impact on prediction accuracy.

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Literature Review

EXISTING APPROACH

- Price Prediction Models
- Sentiment Analysis Models

ENHANCING MODEL

- Use of LLMs in Stock Prediction
- Multimodal Architecture

Existing Approach

Price Prediction Models

1. Integrating Sentiment Scores of Financial News and MLP-Regressor (Maqbool et al, 2024)

- Multilayer Perceptron (MLP) model combined sentiment scores and historical stock data
- Feature label to indicate if news articles were company-specific improved model accuracy

2. Comparative Study between Traditional Statistical Approach and Machine Learning Approach (Bhattacharjee et al, 2019)

- Predictions from traditional methods had higher Mean Squared Error
- RF, LSTM and MLP models produced the most accurate predictions

Sentiment Analysis Models

3. Stock market prediction analysis by incorporating social news opinion and sentiment (Wang et al, 2019)

- Addressed non-linear nature of financial data using voting method to aggregate scores calculated by NLTK and Vader
- Optimised model with window size selection and sentiment effect parameter

Enhancing Model

Use of LLMs in Stock Prediction

4. Assessing the Performance of LLMs for Target-Level Sentiment Analysis (Muhammad et al, 2025)

- Transformers outperform VADER
- LLMs excel in analysing sentiment without extensive labelled datasets
- Extensive pre-training on diverse and large-scale datasets

5. LLM Factor: Extracting Profitable Factors through Prompts (Wang, 2024)

- Use LLMs to analyse the news content and identify factors that affect stock prices
- Integrates background knowledge, stock-related factors and temporal data

Multimodal Architecture

6. Multimodal Stable Fusion via Gated Cross-Attention Mechanism (Zong and Zhou, 2024)

- Mechanism: MLP + pre-trained LLMs + graph attention neural network
- Higher prediction accuracy by filtering out noise

Summary

Source	Relevance to project
1 & 2	• Select top 3 models: RF, MLP, LSTM for baseline stock price predictions
3	• Integrate sentiment analysis with stock price predictions • Consider different window size (lags) • Compare using headlines vs abstract vs full text
4 & 5	• Try VADER, transformer models (DistilRoBERTa, deBERTa) and LLMs (Gemini, etc.) for sentiment predictions
6	• Explore different methods of combining stock price data and sentiment analysis

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Tools

PYTHON PACKAGES

APPLICATION PROGRAMMING INTERFACES (APIS)

LARGE LANGUAGE MODELS (LLMS)

Tools

standard packages

Row 1 (from left to right): Numpy, Pandas, Tensorflow
Row 2: Matplotlib, Keras, NLTK, BeautifulSoup
Row 3: Seaborn, Scikit-Learn, Yahoo! Finance, NY Times

Tools (LLMs)

Row 1 (from left to right): GPT, DeepSeek, LLaMA, Qwen
Row 2: Gemini

Note: We plan to utilise these models either through Hugging Face's API or via the respective LLM's direct API

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Datasets

STOCK PRICE DATA

NEWS DATA

For this proposal, we focus on the processing and usage of AAPL data only, but after will expand further to include other stocks.

Datasets

Stock Price Data

Method of retrieval:

- yfinance (retrieve Yahoo! Finance data)

Data:

- 30 companies (DJIA)*
- Will narrow down to 5-6 stocks
- 10 years: 2015 - 2024
- 2515 rows
- 6 columns (Adj Close, Close, High, Low, Open, Volume)

**Stock data from 30 companies in DJIA (Dow Jones Industrial Average), effective 15/02/2025*
***Focus on AAPL (Apple Inc) stock first, expand to other stocks once methodology and architecture is finalised*

Processing

Data Cleaning:

- Target stock: **AAPL****
- Check for null values (None)
- Target variable: **Adj Close**, drop other columns

Preprocessing:

- Drop rows depending on number of lags
- Transform index into Datetime
- MinMaxScaler (dependent on pricing model)
- Train Test Split (80:20)

Datasets

News Data

Method of retrieval:
- New York Times API: Article Search
  - Filter by organisation (e.g. “Apple Inc”)
- BeautifulSoup: scrape full text of articles

Data:
- NYT articles on Apple Inc**
- 10 years: 2015 - 2024
- 2125 rows
- 9 columns (pub_date, abstract, lead_para, headline, doc_type, section_name, type_of_material, rank, web_url)

***Focus on AAPL (Apple Inc) stock first, expand to other stocks once methodology and architecture is finalised*

Processing

Data cleaning/processing (only article search data):
- Target stock: **AAPL****
- Remove rows with Null/Empty Strings
- Transform pub_date into Datetime
- Drop column ‘snippets’ (duplicate of ‘abstract’)

Text Preprocessing:
- Visualisations
  - Tokenisation and removal of stopwords
  - Lemmatise tokens
  - Join lemmatised tokens back into a string
- Transformers: AutoTokenizer from pre-trained models

Datasets

Stock Price Data

Price	Adj Close						
Ticker	AAPL	AMGN	AMZN	AXP	BA	CAT	CRM
Date							
2015-01-02	24.320435	120.226593	15.4260	80.133865	113.657204	70.110153	58.910961
2015-01-05	23.635284	118.797897	15.1095	78.014641	112.870071	66.409309	57.846901
2015-01-06	23.637510	114.970551	14.7645	76.352020	111.540627	65.981995	56.882286
2015-01-07	23.968960	118.985886	14.9210	78.019562	113.272369	67.004478	56.613789
2015-01-08	24.889904	118.557266	15.0230	79.125473	115.275284	67.691254	58.264568

News data

	pub_date	abstract	lead_para	headline	doc_type
7	2015-03-31	A portrait of a volatile boy wonder and his path to technological vanguard.	In early 2009, Tim Cook presented Steve Jobs, his cancer-stricken mentor and friend, with a surprise offer: Cook wanted to donate a portion of his own liver to his ailing boss, who was stuck in dangerous limbo on California's waiting list for liver transplants.	'Becoming Steve Jobs,' by Brent Schlender and Rick Tetzeli	article

section_name	type_of_material	rank	web_url
Books	Review	6	https://www.nytimes.com/2015/04/05/books/review/becoming-steve-jobs-by-brent-schlender-and-rick-tetzeli.html

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Preliminary Results

PRICING MODEL EXPLORATION

- Stock Data (AAPL) EDA
- Baseline Pricing Model Exploration
  - Actual vs Predicted Plots
  - Mean Absolute Error and Mean Squared Error

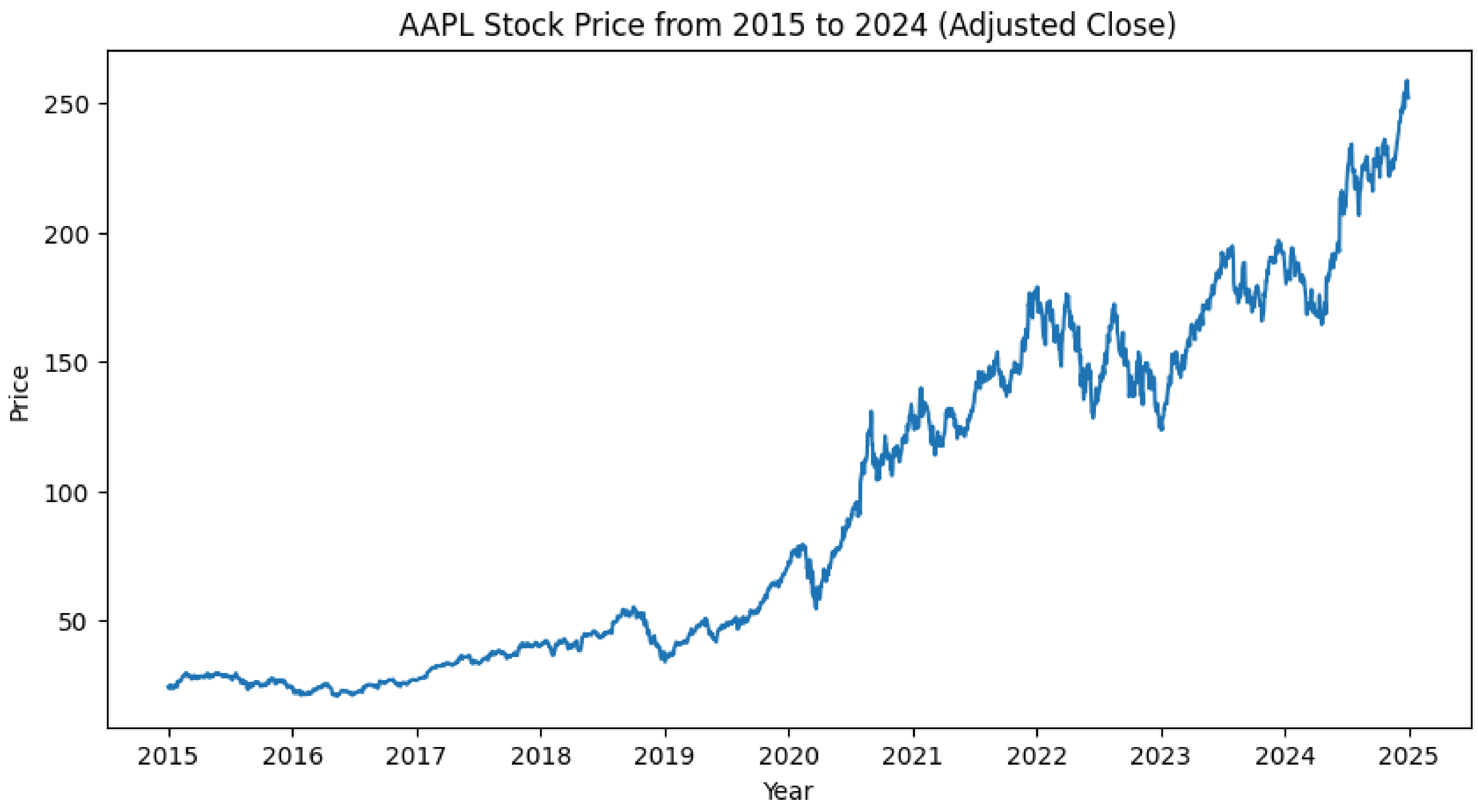
SENTIMENT MODEL EXPLORATION

- Baseline Sentiment Model Exploration
  - Word Cloud and Frequency Plots
  - Sentiment Distribution

Model Exploration

Pricing Models	Sentiment Models
Random Forest (RF)	VADER
Multilayer Perceptron (MLP)	DistilRoBERTa + DeBERTa
Long-Short Term Memory (LSTM)	To Do: LLMs

Stock Data EDA



summary statistics (AAPL):

count	2514.000000
mean	94.145636
std	65.602666
min	20.674534
25%	35.390480
50%	64.608204
75%	150.733929
max	258.735504

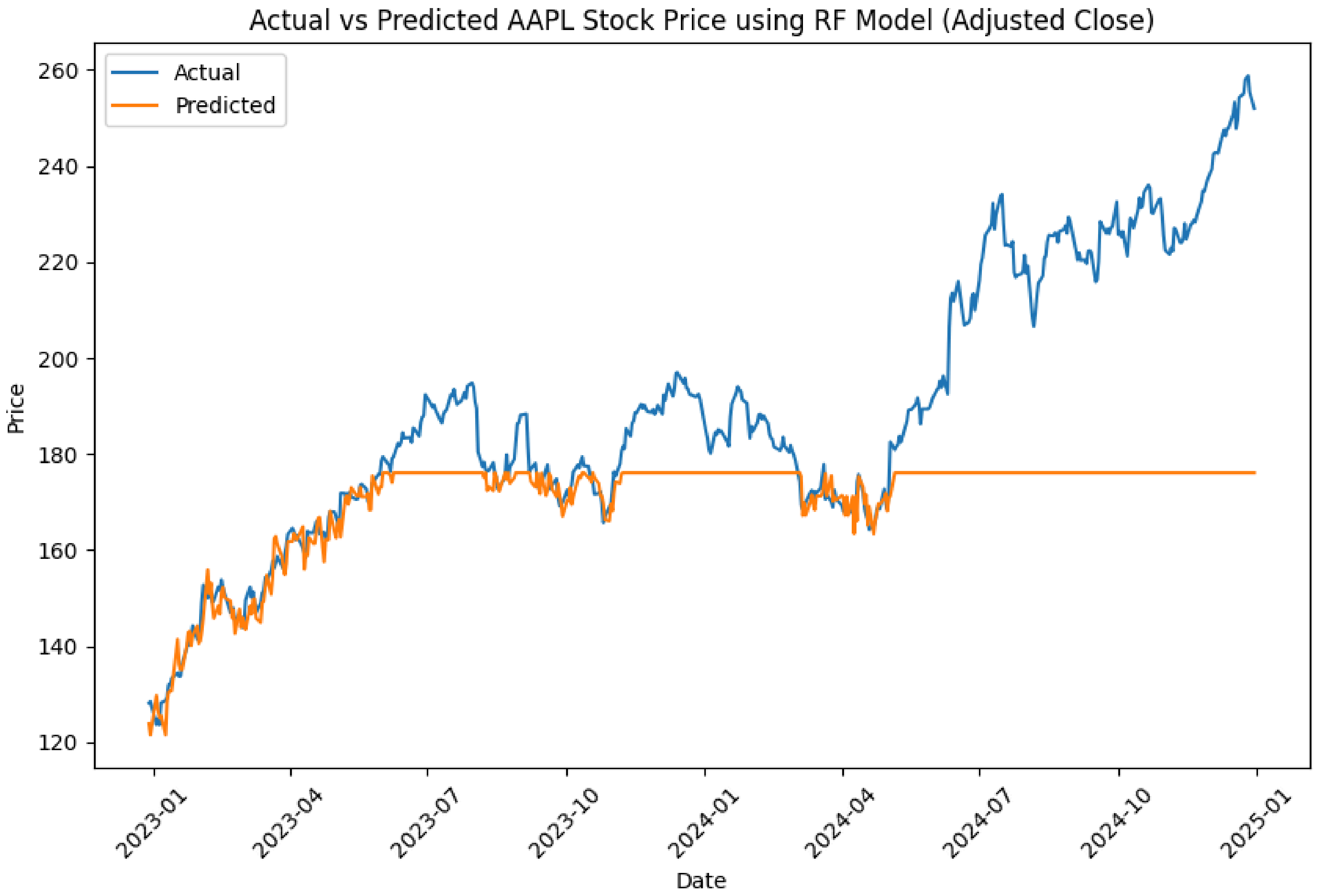
Pricing Model Exploration

Random Forest (RF)

Features:
Lag(-1) value of stock

Parameters:
100 estimators

Test Metrics:
Mean Absolute Error: 18.782
Mean Squared Error: 813.502



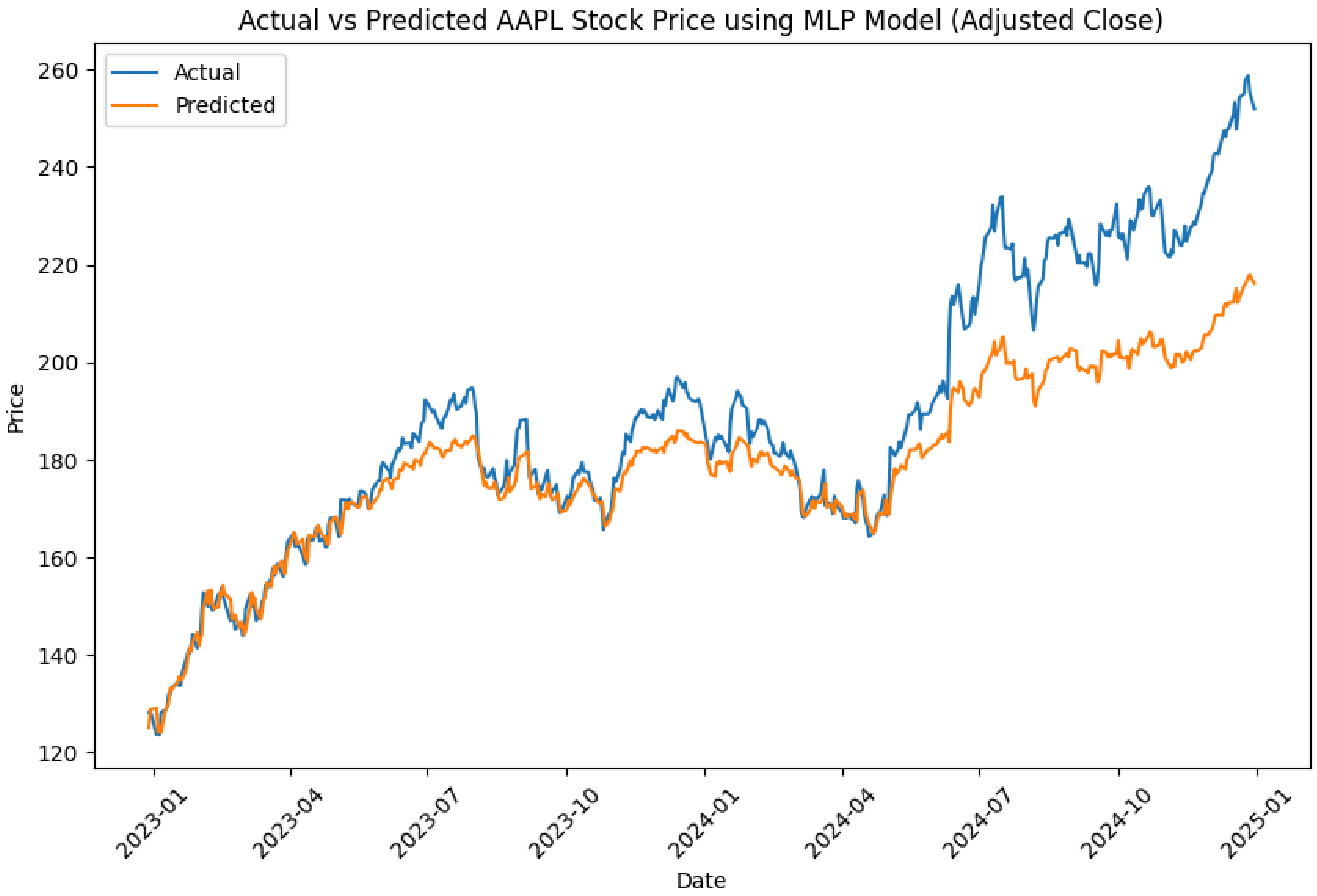
Pricing Model Exploration

Multilayer Perceptron (MLP)

Features:
Lag(-1) value of stock

Parameters:
150 hidden neurons (100, 50)
30 max iterations

Test Metrics:
Mean Absolute Error: 3.157
Mean Squared Error: 210.996



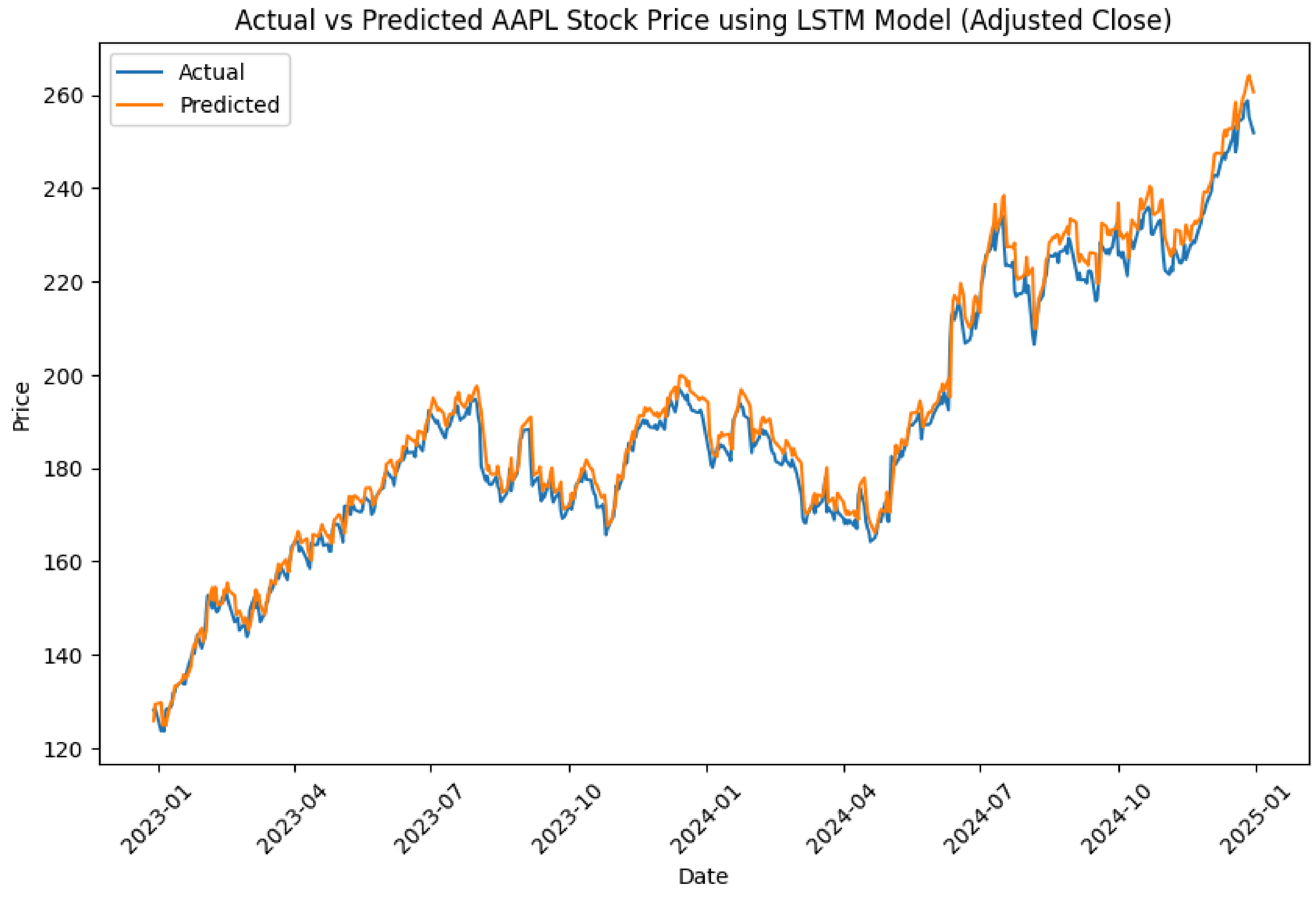
Pricing Model Exploration

Long-Short Term Memory (LSTM)

Features:
Lag(-1) value of stock

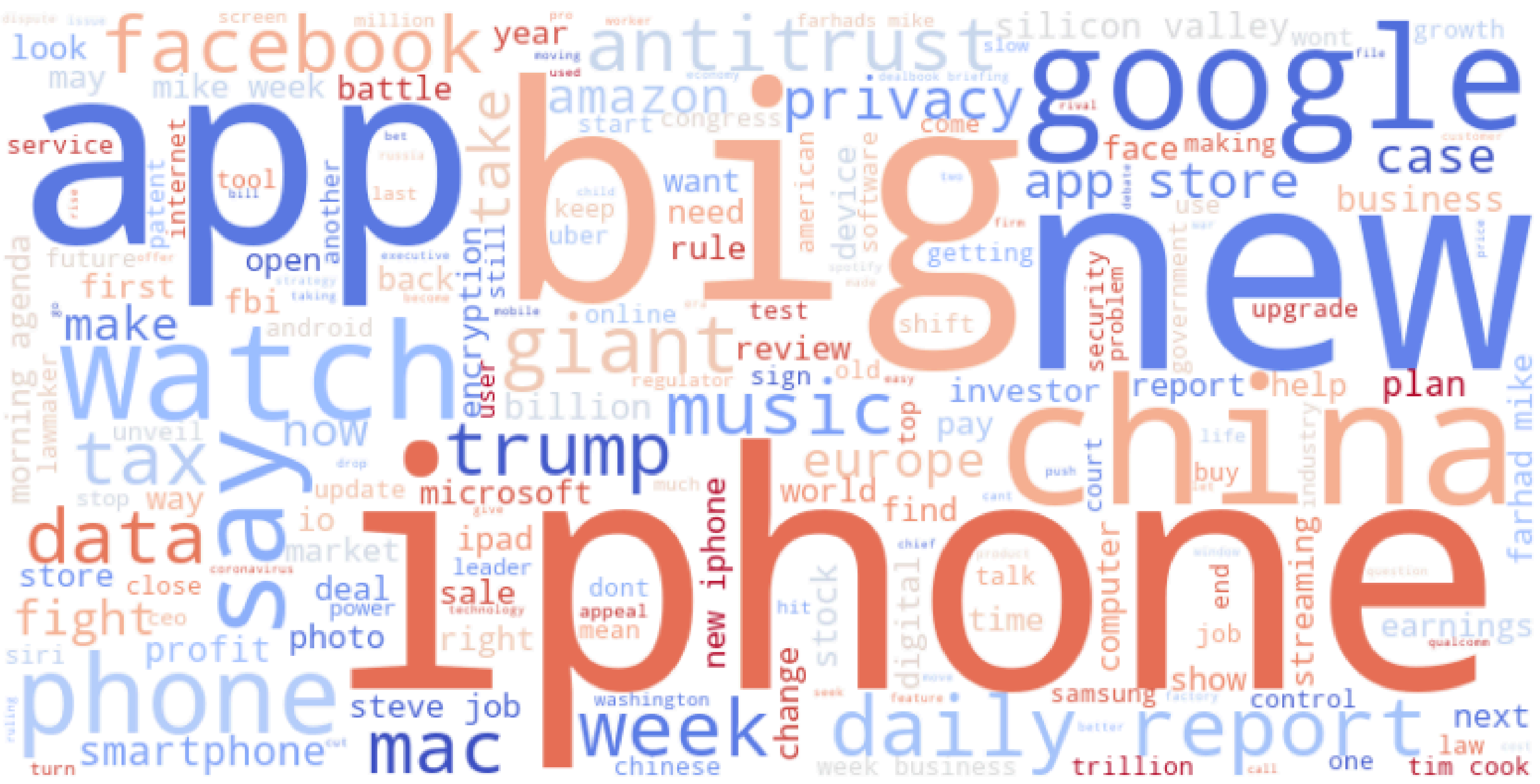
Parameters:
100 hidden neurons
96 batchsize
50 epochs

Test Metrics:
Mean Absolute Error: **1.713**
Mean Squared Error: **13.709**



Sentiment Model Exploration

Headlines

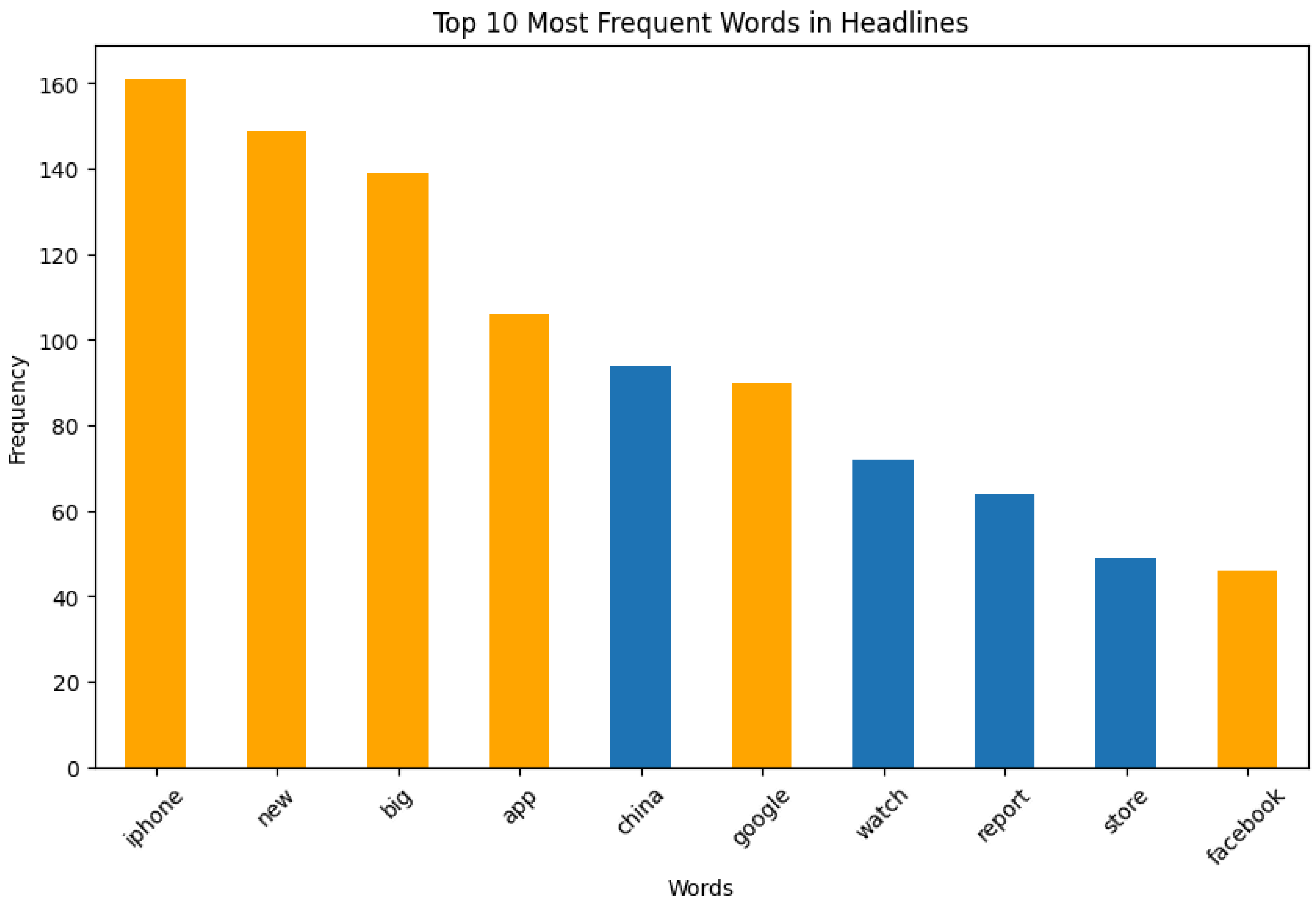


Abstract

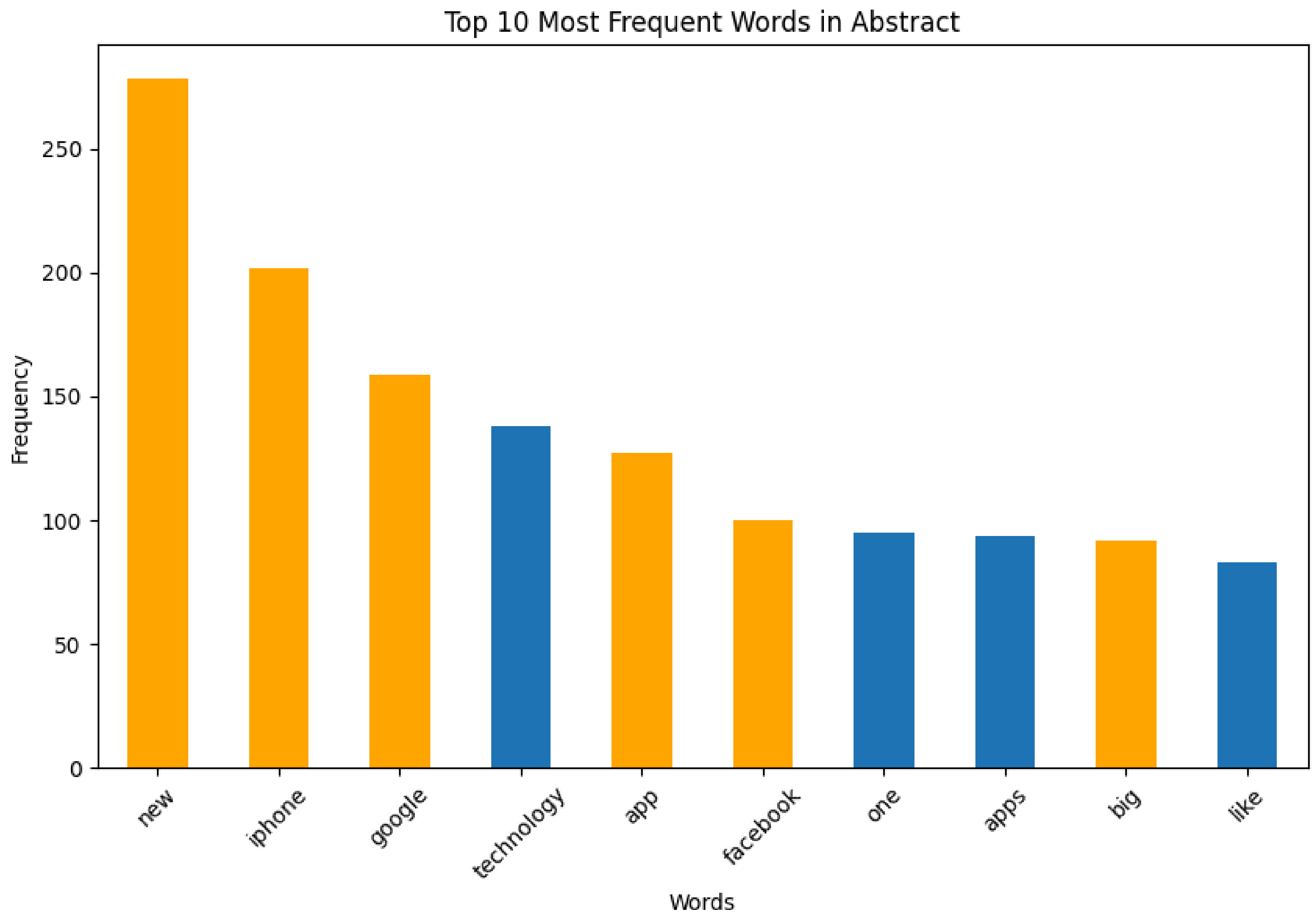
*Full text data has not yet been processed

Sentiment Model Exploration

Headlines



Abstract

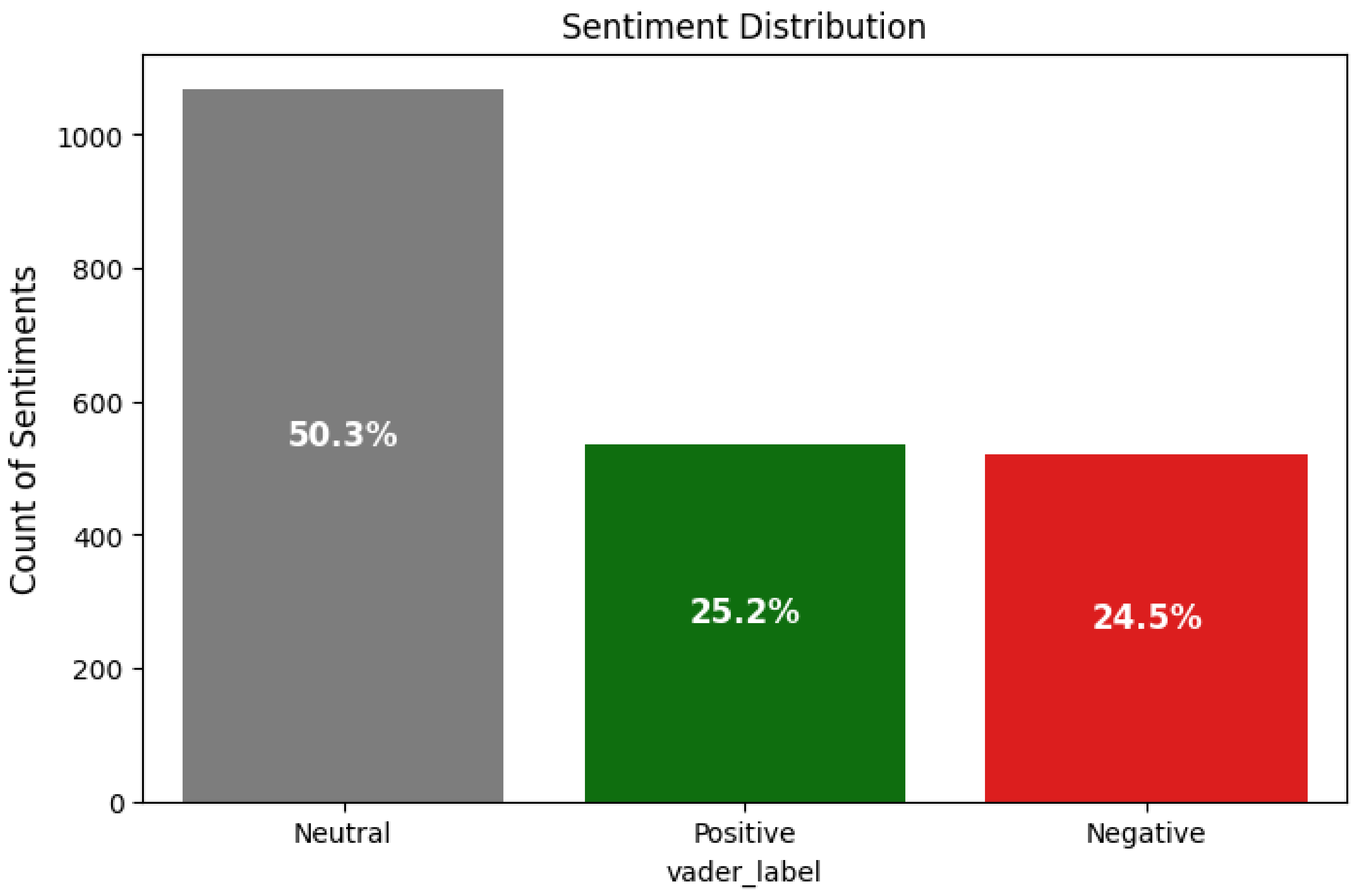


Sentiment Model Exploration

VADER

Data:
Headlines ONLY

Sentiment Classification Parameters:
Score > 0.05: Positive
Score < -0.05 : Negative
-0.05 <= Score <= 0.05 : Neutral

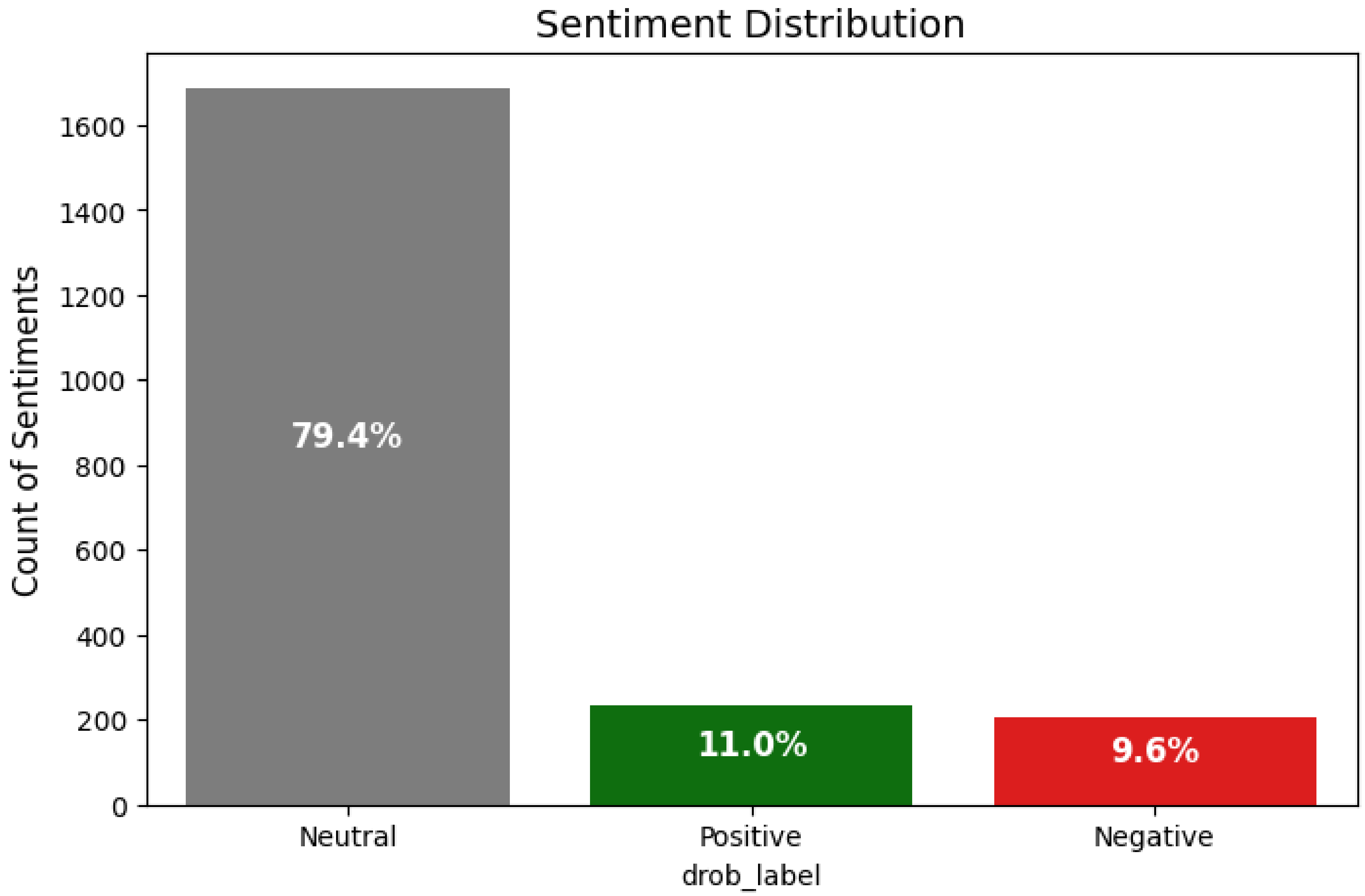


Sentiment Model Exploration

DistilRoBERTa

Data:
Headlines ONLY

Sentiment Classification Parameters:
Based on sentiment category with largest predicted value

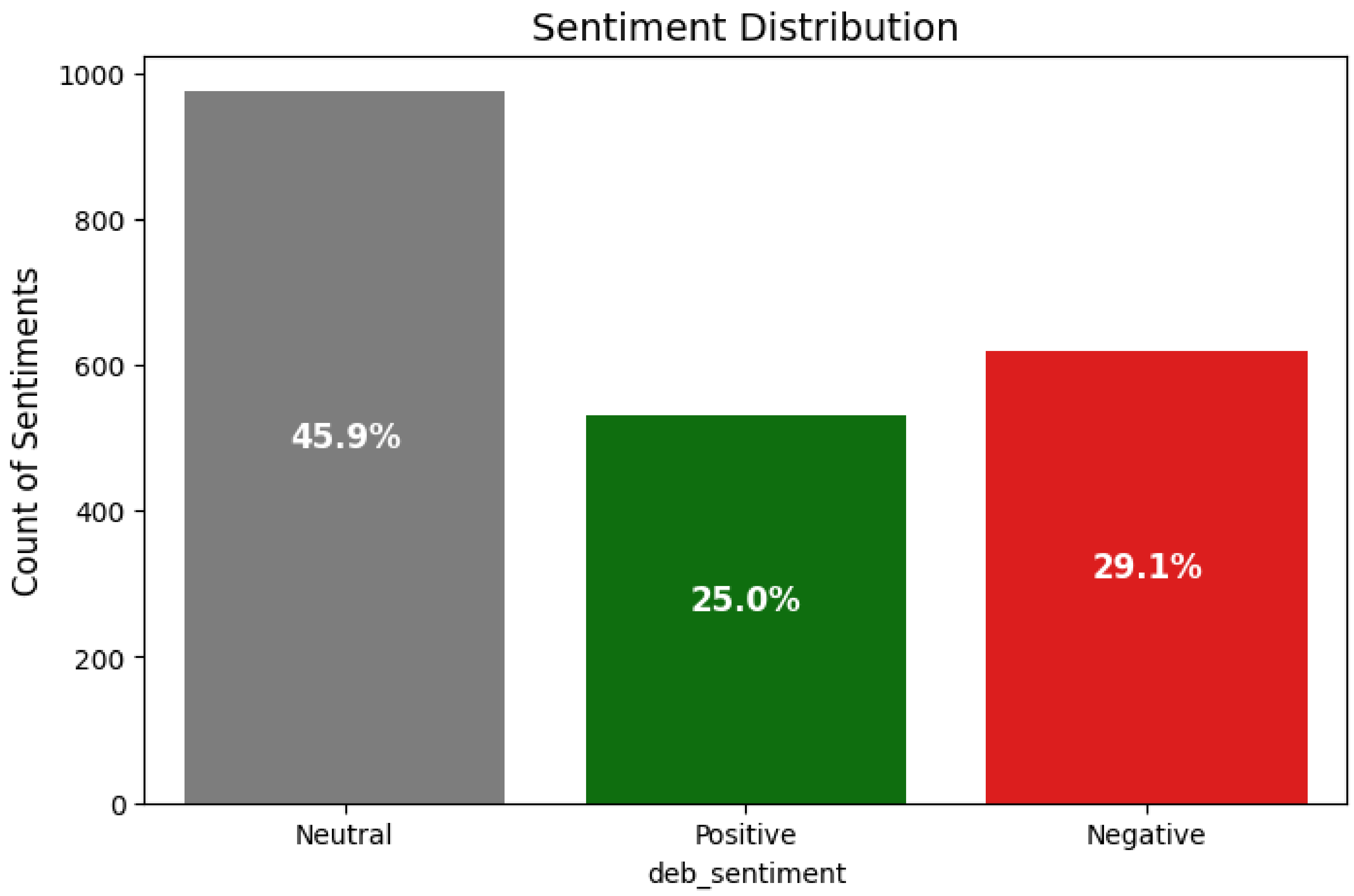


Sentiment Model Exploration

DeBERTa

Data:
Headlines ONLY

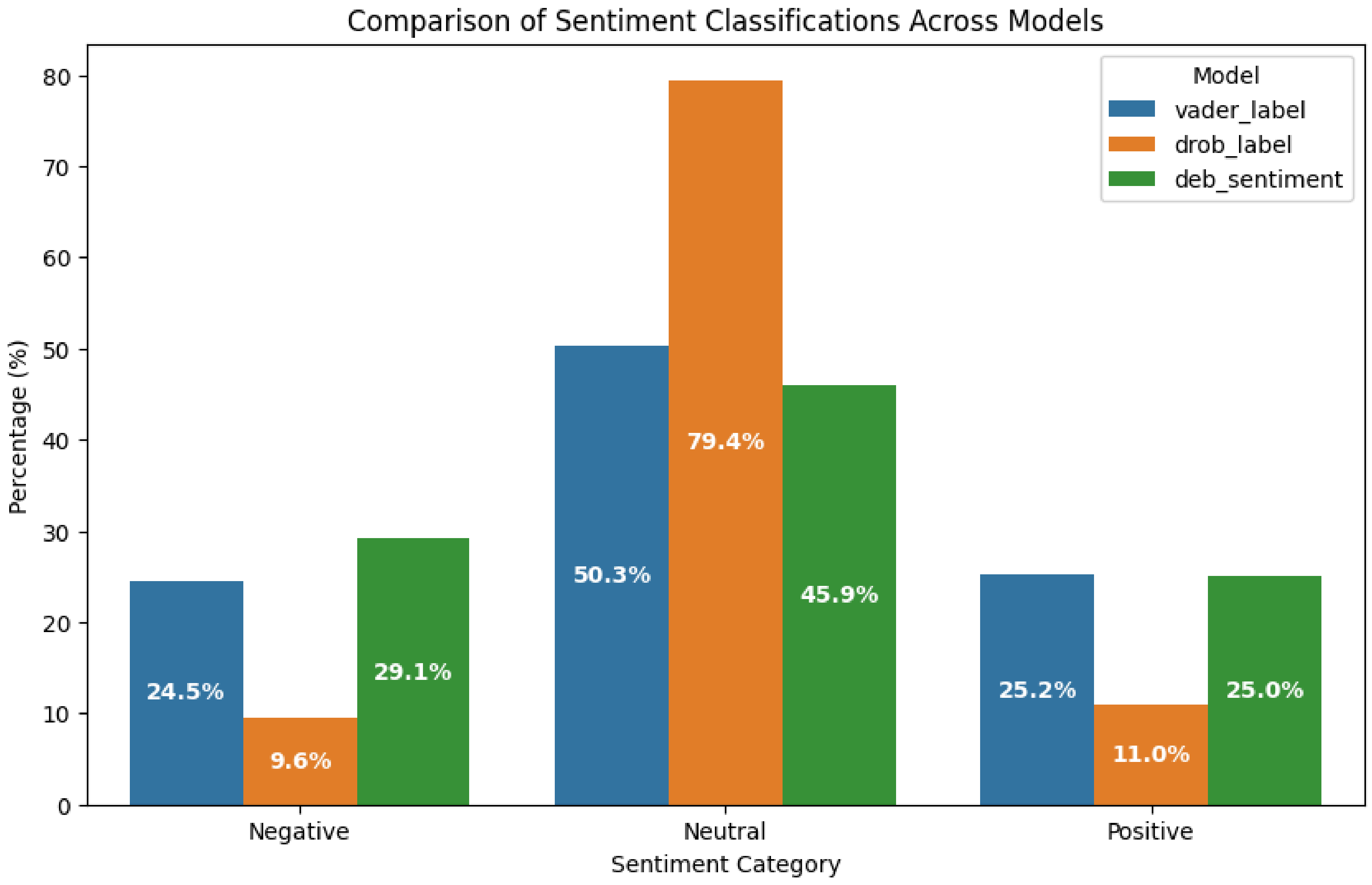
Sentiment Classification Parameters:
Based on sentiment category with largest predicted value



Sentiment Model Exploration

Comparing our models

- Sentiments are mainly classified as neutral across models
- Experiment on full text
- Implement Fine-Tuning



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Timeline

Timeline

Week 7

Present Proposal

Week 8

Collect remaining data
(5 other stocks*) +
LLM sentiment analysis (SA)

Week 9

Combine stock price
prediction with SA
(explore different
architectures)

Week 10 & 11

Compare performance of:

- Different model combinations
- Text granularity
- Window size
- Different stocks

+ Hyperparameter tuning

Week 12

Remaining changes +
slides/report writing

Week 13

Final Presentation

**5 other stocks are AMZN, CRM, IBM, MSFT, NVDA*

References

Literature Review

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Resources Used

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Thank You

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Tammy Lee Trina Tan Xavier Santimano