

# Tesla Stock Prediction Using News Sentiment Analysis



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# Overview

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# Problem Statement

## Research Question:

- Does **daily news sentiment** contain predictive signals for **Tesla's short-term stock price direction**?

## Approach:

- Predict **5-day forward trend (up vs. down)** using:
  - NLP sentiment analysis
  - Feature engineering
  - Traditional ML methods

# Why Predict 5-Day Trends (Not Next-Day)?

Daily movements are dominated by noise:

- Random market fluctuations, highly volatile
- Initial model attempt: Essentially random (coin flip accuracy)

5-day trends help filter volatility and capture signal:

- Sentiment takes time to propagate through market
- Improved model: Meaningful predictive signal

Result: More realistic, actionable predictions

# Data Sources

## Stock Prices:

- Yahoo Finance, Daily OHLCV data (2024-2025)

## News Articles:

- Google News feeds
- 25,398 articles across, 732 days (2024-2025)

## Earnings Calls:

- 9 quarterly transcripts (Q4 2023 - Q4 2025)

## SEC Filings:

- Collected from SEC EDGAR but not analyzed (time scope)

# Sentiment Analysis Tool

**FinBERT:** Financial domain-adapted BERT model

- Pre-trained on earnings calls, analyst reports, financial news
- Understands finance-specific language

Outputs:

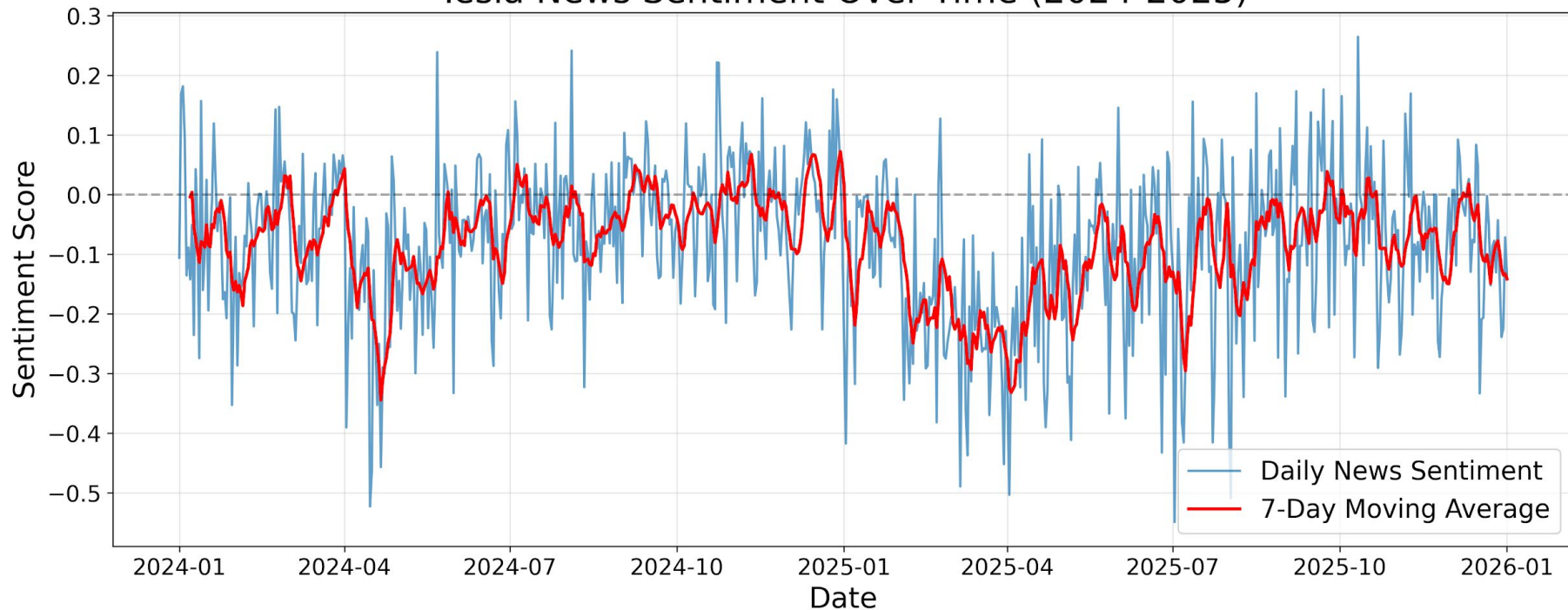
- Positive/negative/neutral sentiment and confidence score

Applied to:

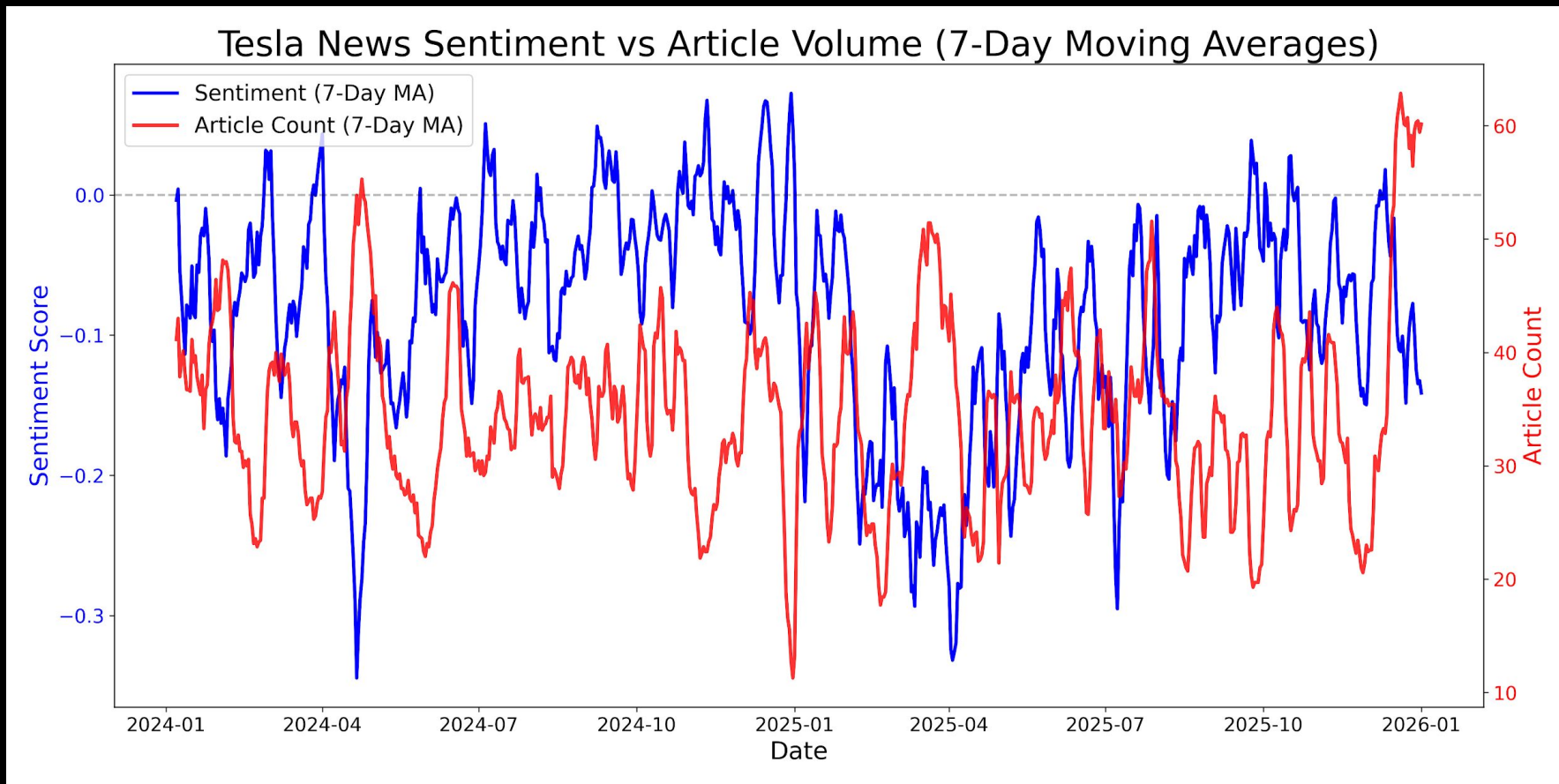
- News headlines (daily aggregation)
- Earnings transcripts (quarterly aggregation)

# News Sentiment Over Time

Tesla News Sentiment Over Time (2024-2025)

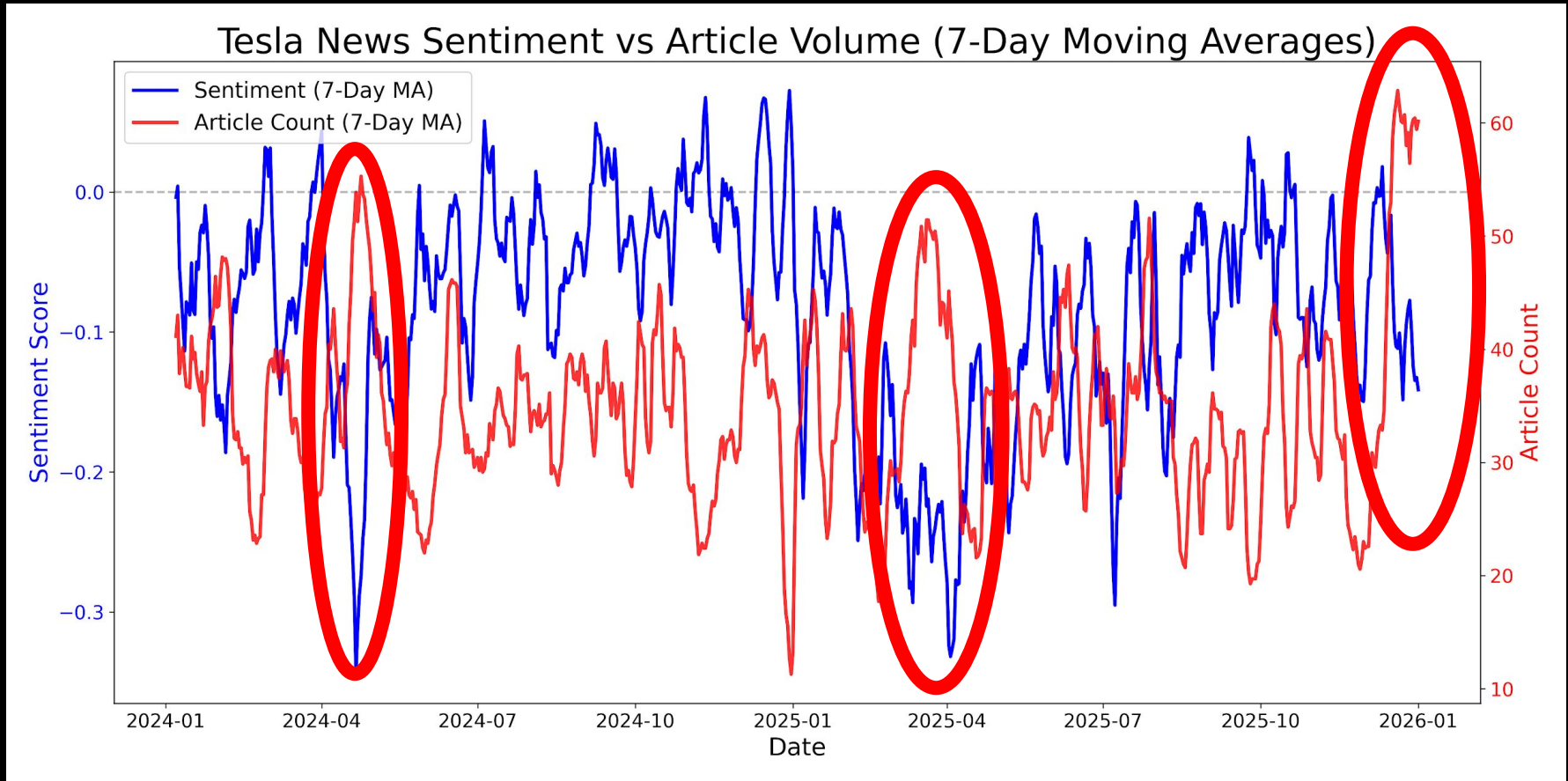


# Key Discovery: Sentiment vs. Volume

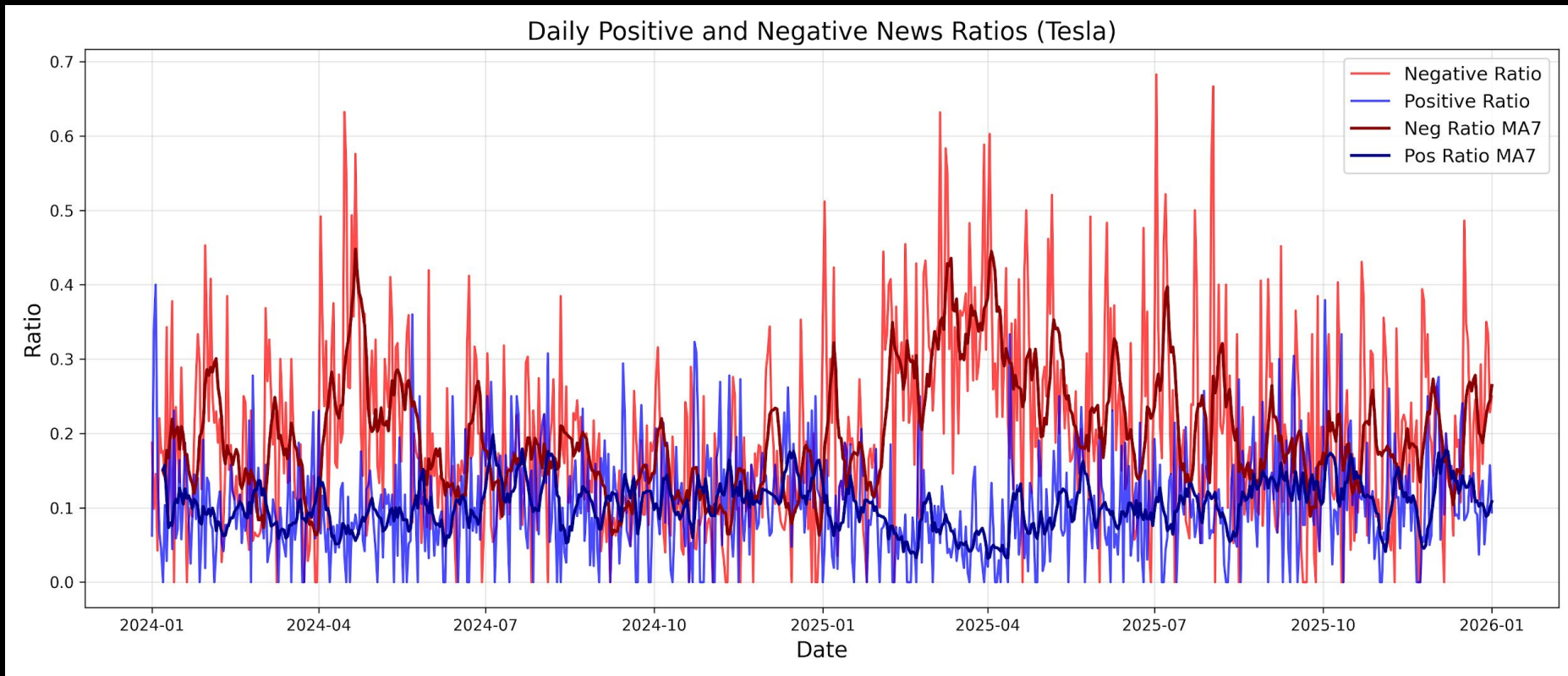




# Article Volume Spikes Align with Sentiment Drop



# Article Sentiment Distribution



Most Tesla news is negative: Explains high volume → negative sentiment

# Statistical Validation

A/B Test: High vs. Low Article Volume Days (split by median)

- High-volume days:
  - Average sentiment = -0.097
- Low-volume days:
  - Average sentiment = -0.071

Difference: -0.026

Statistical significance:  $p\text{-value} < 0.00001$

Conclusion: High-volume days are reliably more negative.

# Feature Engineering

## Sentiment Features:

- Average sentiment score: Daily, 7 day moving average, Previous day (lagged)

## Volume Features:

- Article count: Daily, 7 day moving average, Previous day (lagged)

## Interaction Term:

- **Sentiment × Article count** (captures effect: one is low/high vs the other)

## Stock Features:

- Daily return, 5-day moving average return, volume change

## Earnings:

- Latest quarterly earnings call sentiment score (forward-filled)

# Earnings Call Analysis

## Process:

1. Collected 9 earnings call transcripts (quarterly calls).
2. Chunked text into 512-character segments.
3. Analyzed sentiment per chunk (FinBERT).
4. Aggregated average sentiment to create quarterly score.

## Application:

Forward-filled quarterly scores between calls to provide management tone signal for daily predictions.

# Train/Test Split (Avoiding Data Leakage)

- **Training:**
  - Jan 1, 2024 - Jan 31, 2025 (257 samples)
- **Buffer (prevents overlap from 7-day moving averages):**
  - Feb 1-9, 2025 (10 days, discarded)
- **Test:**
  - Feb 10, 2025 - End of 2025 (225 samples)

Ensures no look-ahead or look-behind bias.

## Class Balance:

- Train: 50% up / 50% down
- Test: 52% up / 48% down

# Model Selection

Logistic Regression (L2): AUC 0.57 ✓

XGBoost: AUC 0.52

## Why Logistic Regression?

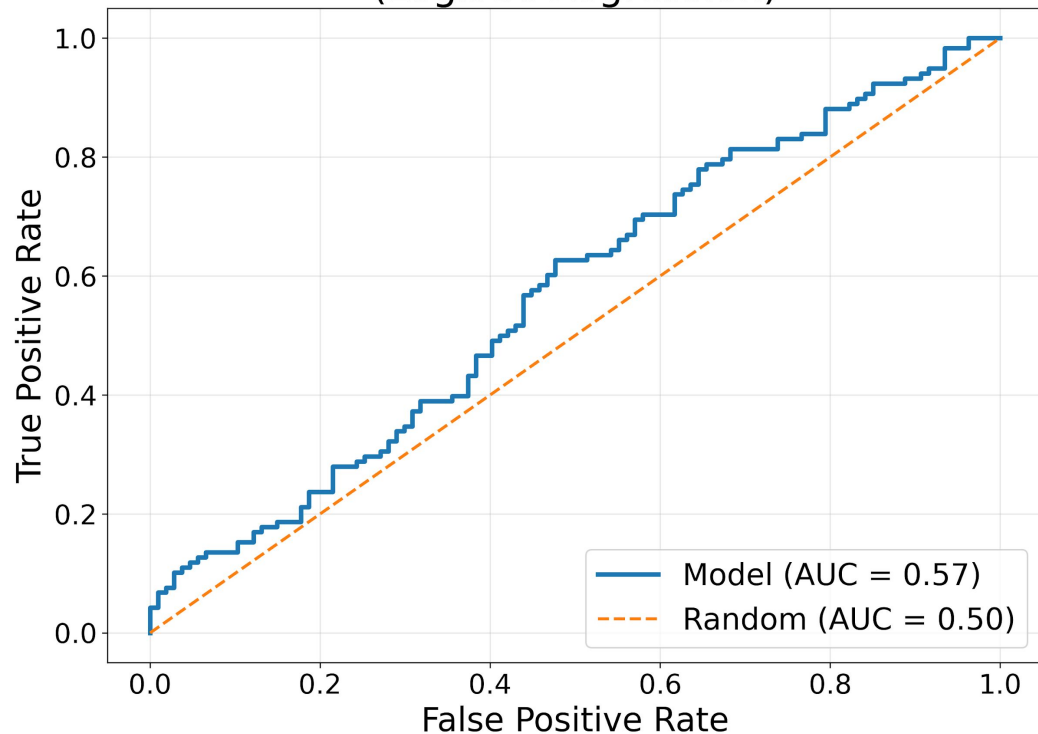
- Better performance on small dataset.
- Interpretable coefficients.
- Well-suited for linear relationships.

## XGBoost underperformed due to:

- Limited training data (257 samples).
- Linear feature relationships.

# ROC Curve (Receiver Operating Characteristic)

ROC Curve - Stock Trend Prediction  
(Logistic Regression)



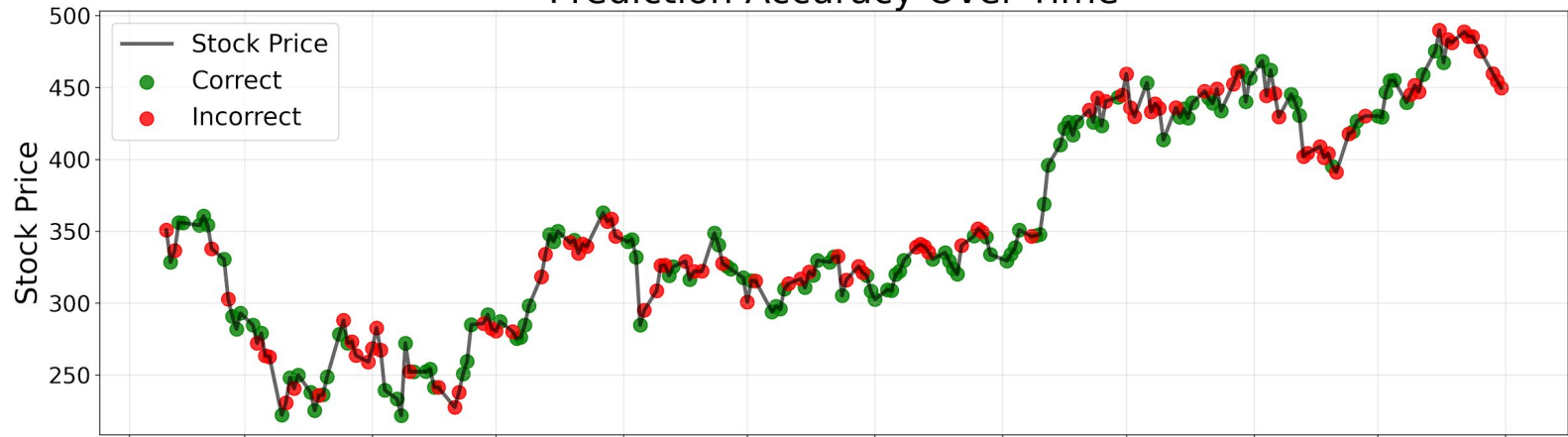
**AUC: 0.57** → 14% improvement  
over random guessing (0.50)

**Interpretation:**

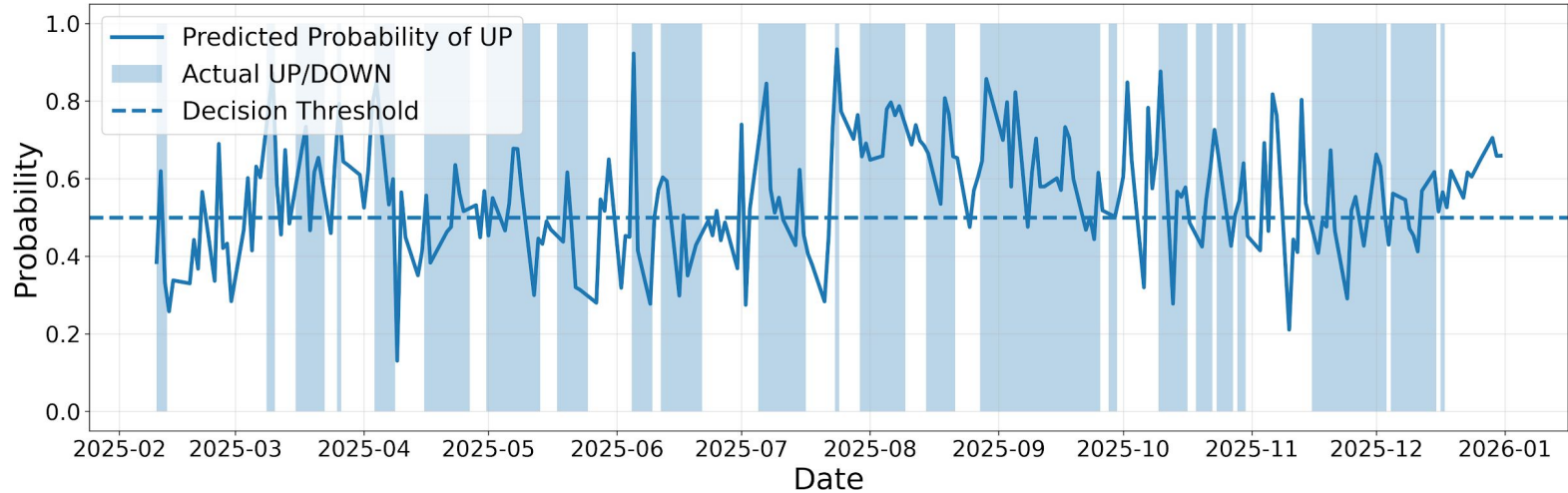
- Model successfully extracts  
signal from noisy data.



### Prediction Accuracy Over Time



### Model Predictions vs Actual Outcomes



# Confusion Matrix

Confusion Matrix

Actual \ Predicted	Down (0)	Up (1)
Down (0)	46	61
Up (1)	37	81

**Accuracy:** 56% (percent of correct predictions)

**Precision (Up):** 57%

(when predicting “Up”, correct 57% of the time)

**Precision (Down):** 55%

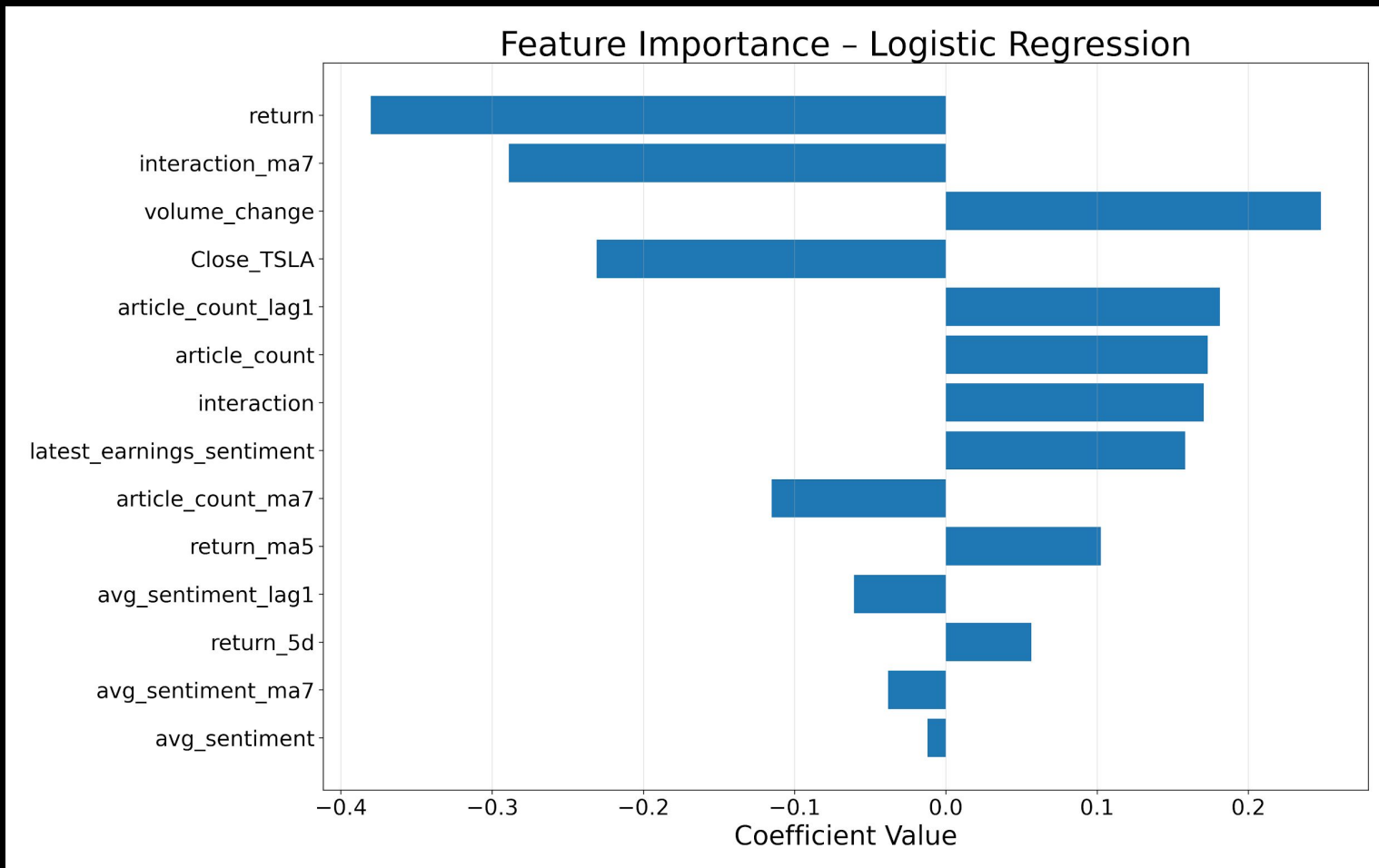
(when predicting “Down”, correct 55% of the time)

**Recall (Up):** 69% (catch 69% of actual “Up”)

**Recall (Down):** 43% (catch 43% of actual “Down”)

Model **better** at predicting **upward trends** (over downward).

# Feature Importance



# Conclusion

Does news sentiment contain predictive signals? YES.

Evidence:

- ✓ Sentiment  $\times$  article count interaction moving average: Top 5 feature
- ✓ Article count (lagged day): Top 5 feature
- ✓ Article count (current day): Top 5 feature
- ✓ Model AUC 0.57 vs 0.50 random (14% improvement)

Implication:

News sentiment is a valuable supplementary signal for short-term Tesla stock prediction.

# Business Applications

- **Early Warning System:**
  - Detect unusual negative sentiment spikes.
- **Investment Timing:**
  - Use sentiment as additional signal for investment.
- **Portfolio Monitoring:**
  - Track sentiment across multiple holdings.
  - Identify companies facing negative media attention.
- **Scalable Framework:**
  - Same approach works for any publicly traded company.
  - Can analyze simultaneously.
- **Automated System:**
  - Daily updates: new articles → sentiment scores → predictions

# Limitations & Next Steps

## Limitations:

- Small dataset (257 training samples).
- Single company (Tesla-specific patterns).
- News sentiment only (excludes social media).

## Next Steps:

- Expand to multiple companies/sectors.
- Add social media sentiment (Twitter/Reddit).
- Longer time horizons (weekly/monthly trends).