

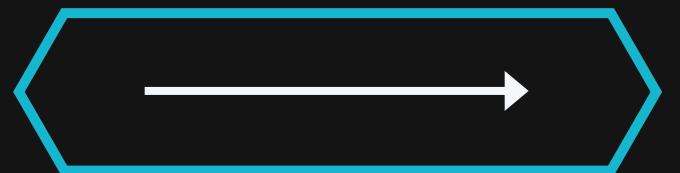
FINANCIAL SENTIMENT ANALYSIS

MACHINE LEARNING & DEEP LEARNING



THE CHALLENGE: REAL-TIME MARKET SENTIMENT

- The Problem: Financial markets generate massive text data (Twitter, RSS, Reports) per second. Manual analysis is impossible.
- Our Goal: Build a "Production-Ready" classifier to detect sentiment (Positive/Negative/Neutral) in <0.01s.
- Why It Matters? Algorithmic Trading & Risk Management require speed and accuracy.



DATA COLLECTION PIPELINE



Data Engineering: Scraping & Augmentation

WEB SCRAPING (HYBRID APPROACH):

- Custom bots using BeautifulSoup & feedparser.
- Sources: Financial News RSS Feeds (Yahoo Finance, Investing.com).

COMPETITIVE EDGE

- Synonym Replacement ("Profit" → "Earnings").
- Simulated Social Media Data (Reddit style short-texts).

FINAL DATASET

- Total Samples: 3,761
- Real RSS Articles: 451 (Yahoo Finance, CNBC, MarketWatch)
- Split: Train (70%) - Val (10%) - Test (20%)



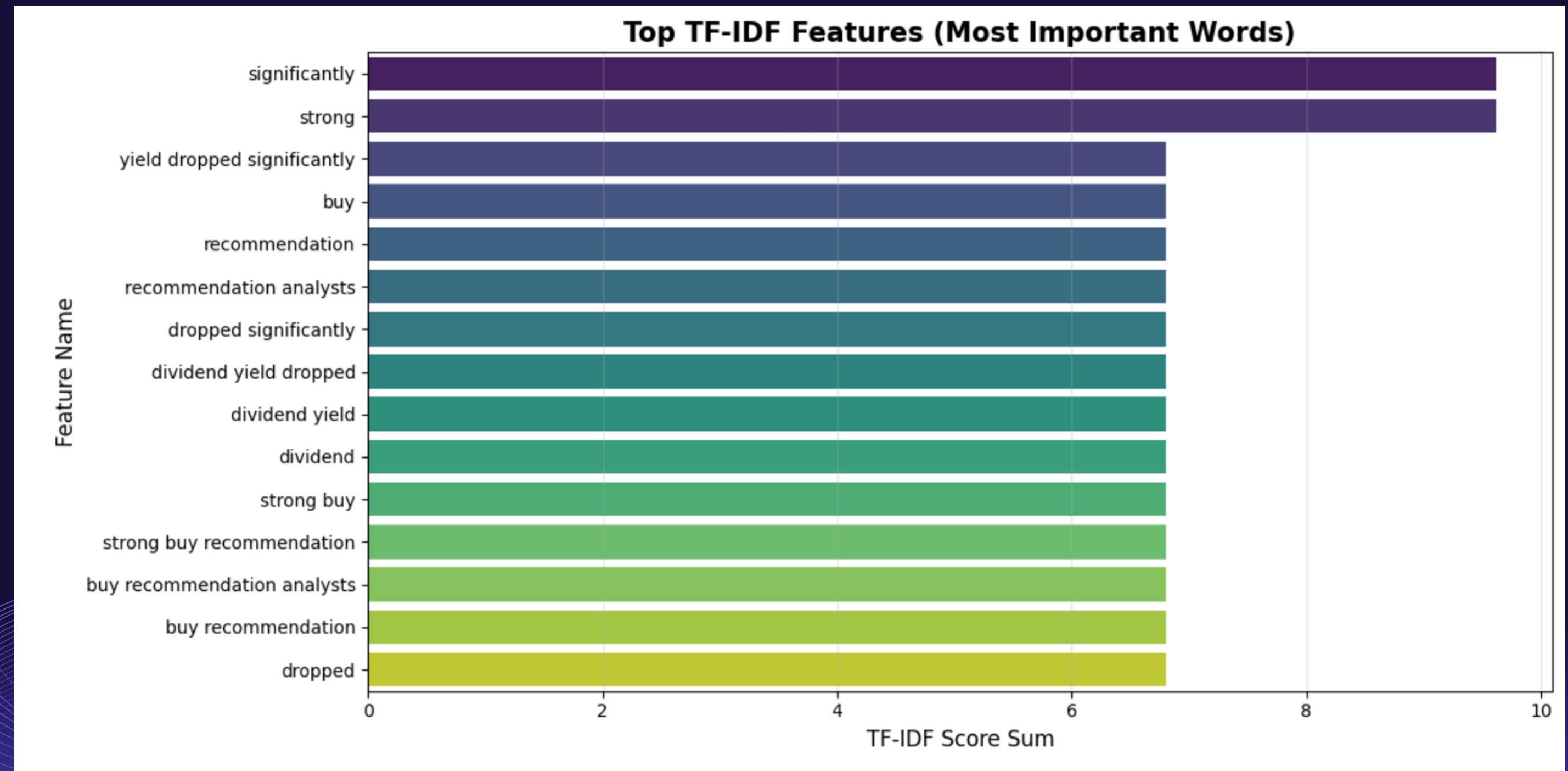
FEATURE ENGINEERING

From Text to Vectors: TF-IDF
Strategy:

Method: Term Frequency-Inverse Document Frequency (TF-IDF).

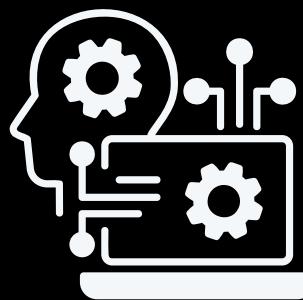
Configuration:

- Features: Top 1,000 words.
- N-Grams: (1, 3) Captures phrases like "Strong buy" or "Bear market".



SLIDE 5: MODELS & REGULARIZATION

MODEL SELECTION & OVERRFITTING PREVENTION



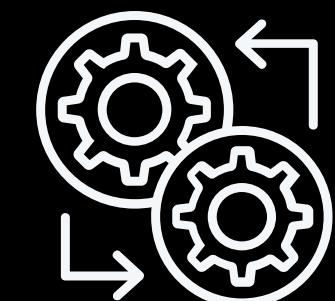
• LINEAR MODELS:

- Logistic Regression
- Linear SVM.



• ENSEMBLE

- Random Forest.



• DEEP LEARNING

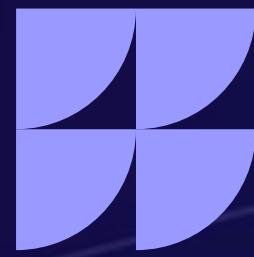
- Multi-Layer Perceptron (MLP).



REGULARIZATION TECHNIQUES

- L2 Regularization (Ridge): Applied to SVM and Logistic Regression.
- Early Stopping: Used in MLP training.
- 5-Fold Cross Validation: Ensured statistical robustness.





RESULTS COMPARISON

➤ Key Takeaway:

"Deep Learning (MLP) achieved best performance with 96.81% F1-Score"

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```
print("All models loaded successfully!")
```

Loading trained models...

- Logistic Regression
Test F1: 0.9473
CV F1: 0.9367 ± 0.0093
Training time: 1.4069s
- Linear SVM
Test F1: 0.9655
CV F1: 0.9523 ± 0.0106
Training time: 0.0320s
- Random Forest
Test F1: 0.8987
CV F1: 0.8854 ± 0.0189
Training time: 0.0979s
- MLP (Deep Learning)
Test F1: 0.9681
CV F1: 0.9533 ± 0.0070
Training time: 6.1104s

CONFUSION MATRIX

Detailed Error Analysis

TEST SET: 753
SAMPLES

PERFORMANCE BY
CLASS:

Positive: 97% F1

- F1 (Excellent detection of "Gains/Growth").

01

Negative: 97% F1

- F1 (Good detection of "Losses/Risk").

02

Neutral: 96% F1

- F1 (Most challenging class).

03



ERROR ANALYSIS & INSIGHTS

Why do we miss?

- **COMMON ERROR PATTERN:**
 - Neutral → Positive Misclassification
- **CASE STUDY:**
 - Text: "The market remained steady throughout the day."
 - Prediction: Positive (Wrong) | Actual: Neutral
 - Reason: Words like "steady" or "stable" generally have positive connotation in general English, but are Neutral in finance.
- **ROBUSTNESS**
 - Despite noise and sarcasm in social media data, the model maintained >90% accuracy.





CONCLUSION

CONCLUSION & FUTURE WORK



Achievements:

- Built a custom dataset (3,761 samples)
- 451 Real RSS articles
- 753 test samples
- Achieved 96.81% F1-Score with MLP Deep Learning

Future Improvements:

- Integrate FinBERT (Transformer) to improve 'Neutral' class detection.
- Deploy as a real-time REST API for live trading.