Leveraging Machine Learning for Financial Sentiment Analysis

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Intro

Introduction

- Topic Overview:
  - Exploring the use of machine learning techniques in analyzing financial news sentiments.
- Relevance in the Financial Sector:
  - Understanding market trends and investor sentiments.
  - Enhancing financial decision-making processes.
- Objective:
  - To demonstrate how advanced analytics and data-driven approaches can provide deeper insights into financial markets.

Research Question

Research Question

What Are We Addressing?
”How can machine learning be utilized to accurately classify the sentiment of financial news and predict stock market trends?”

Why Is It Important?

- Impact on Financial Decision-Making:
  - Enhances the understanding of market dynamics.
  - Aids in the development of data-driven investment strategies.
- Advancement in Financial Analytics:
  - Demonstrates the potential of machine learning in extracting meaningful insights from large volumes of financial data.

Data Sources and Preparation

Data Sources

Data Sources

- Financial Sentiment Analysis Dataset from Kaggle.[2]
- Sentiment Analysis for Financial News Dataset from Kaggle[3]

Sentence	Sentiment
The GeoSolutions technology will leverage Bene...	positive
$ESI on lows, down $1.50 to $2.50 BK a real po...	negative
For the last quarter of 2010 , Componenta 's n...	positive
According to the Finnish-Russian Chamber of Co...	neutral
The Swedish buyout firm has sold its remaining...	neutral

Data Preparation Steps

- Combining Data:
    - Merged both datasets into a single DataFrame.
- Label Encoding:
    - Encoded sentiments as Positive (1), Negative (0).
- Preprocessing:
    - Lowercased text, removed punctuation and numbers.

Machine Learning Techniques

Rationale for Model Selection

Model Selection Overview

- **Baseline Models**:
  - *KNeighborsClassifier*: Ideal for small datasets.
  - *LogisticRegression*: Strong baseline for binary classification.
- **Decision Trees and Ensembles**:
  - *DecisionTreeClassifier*: Clear interpretability, feature importance.
  - *RandomForestClassifier*: Manages overfitting, captures complex patterns.
  - *GradientBoostingClassifier*: Handles imbalance, offers high accuracy.
  - *XGBClassifier*: Enhanced version, suitable for large datasets.
- **Text Classification**:
  - *MultinomialNB*: Optimal for discrete features (e.g., word counts).
  - *SGDClassifier*: Flexible for large-scale, sparse data.

Data Analysis and Results

Evaluation Metrics

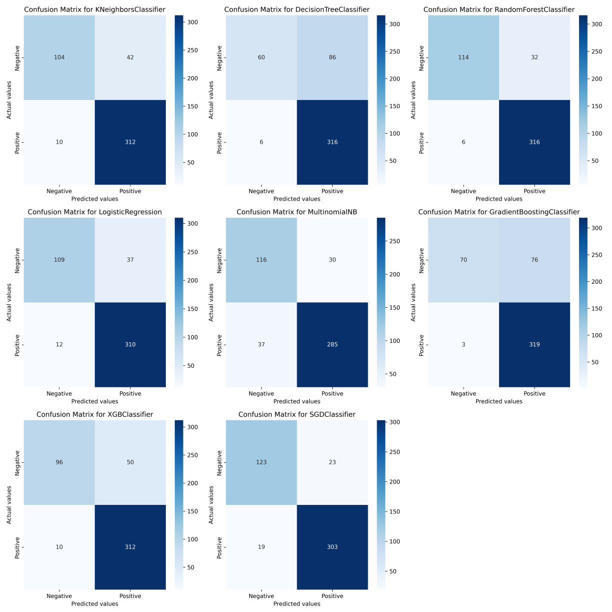
- Accuracy, Precision, Recall, F1 Score.
- Performance assessment for each model.

Results Summary

Model	F1 Score	Recall	Precision	Accuracy
RandomForestClassifier	0.943	0.981	0.908	0.919
SGDClassifier	0.935	0.941	0.929	0.910
LogisticRegression	0.927	0.963	0.893	0.895
KNeighborsClassifier	0.923	0.969	0.881	0.889
XGBClassifier	0.912	0.969	0.862	0.872
MultinomialNB	0.895	0.885	0.905	0.857
GradientBoostingClassifier	0.890	0.991	0.808	0.831
DecisionTreeClassifier	0.873	0.981	0.786	0.803

Table 1: Model Performance Metrics

Confusion Matrix



Application to Unseen Data

Application to Unseen Data

Unseen Data Source

- Massive Stock News Analysis DB for NLPBacktests from Kaggle.[1]

Preprocessing and Analysis

- Preprocessing of new data similar to training data.
- Sentiment analysis using trained models, FinBERT and random sentiment as a benchmark.

Insights and Observations

- Analysis of top stocks with the most unique news stories.
- Integration of sentiment scores with historical stock data from Yahoo Finance.
- Comparison of model predictions with actual market trends.

Headline	Publisher	Date	Stock
Stocks That Hit 52-Week Highs On Friday	Benzinga Insights	2020-06-05 10:30:54-04:00	A
Stocks That Hit 52-Week Highs On Wednesday	Benzinga Insights	2020-06-03 10:45:20-04:00	A
71 Biggest Movers From Friday	Lisa Levin	2020-05-26 04:30:07-04:00	A
46 Stocks Moving In Friday's Mid-Day Session	Lisa Levin	2020-05-22 12:45:06-04:00	A
B of A Securities Maintains Neutral on Agilent...	Vick Meyer	2020-05-22 11:38:59-04:00	A

Table 2: News Headlines and Stock Information

Trading Simulation and Model Edge

Sentiment Analysis and Trading Decisions

Sentiment Analysis as Basis

- Utilizes machine learning models to predict sentiment in financial news.
- Influences buy or sell decisions based on sentiment analysis outcomes.

Position Sizing Strategy

- Position sizes calculated based on model edge, adjusting for confidence.
- Dynamic adjustment based on consecutive positive/negative sentiments.

Risk Management and Trading Execution

Stop Loss and Take Profit Implementation

- Implementing stop loss and take profit to manage risks and gains.
- Automated triggers for selling at predefined price points.

Trading Actions

- Buy orders executed on positive sentiment detection.
- Sell orders executed on negative sentiment detection.
- Decisions consider cash, stock holdings, and current pricing.

Performance Tracking and Visualization

Portfolio Value Assessment

- Monitoring changes in portfolio value over time.
- Reflecting the impact of each trading decision.

Visualization of Trading Performance

- Charting portfolio value and stock holdings progression.
- Visual representation of trading performance and strategy effectiveness.

Calculation of Trading Edge

How the Trading Edge is Calculated

- The trading edge is calculated by assessing the predictive accuracy of each model.
- It measures the advantage of model predictions over random guessing in influencing trading decisions.
- This metric is critical for evaluating the effectiveness of sentiment analysis models in a real-world trading scenario.

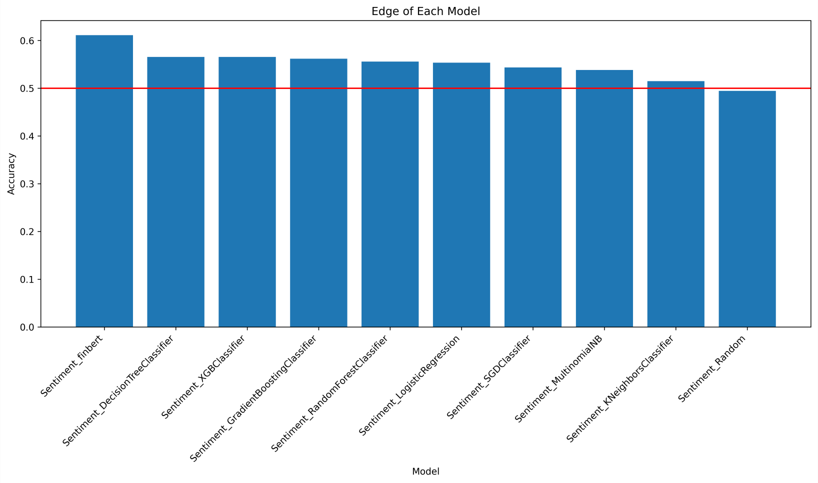
Analysis of Model Edge on Morgan Stanley Stock

Model Edge Performance

Model	Edge
finbert	61.12%
DecisionTreeClassifier	56.57%
XGBClassifier	56.57%
GradientBoostingClassifier	56.19%
RandomForestClassifier	55.58%
LogisticRegression	55.35%
SGDClassifier	54.37%
MultinomialNB	53.83%
KNeighborsClassifier	51.48%
Random	48.83%

Table 3: Edge of Sentiment Analysis Models for MS

Model Edge Graph



Model Value Counts

Model	0	1	2
DecisionTreeClassifier	127.0	3111.0	0.0
finbert	492.0	699.0	2047.0
LogisticRegression	647.0	2591.0	0.0
KNeighborsClassifier	230.0	3008.0	0.0
MultinomialNB	988.0	2250.0	0.0
SGDClassifier	938.0	2300.0	0.0
GradientBoostingClassifier	175.0	3063.0	0.0
XGBClassifier	262.0	2976.0	0.0
RandomForestClassifier	263.0	2975.0	0.0
Random	1564.0	1674.0	0.0

Table 4: Value Counts of Sentiment Analysis Models for MS

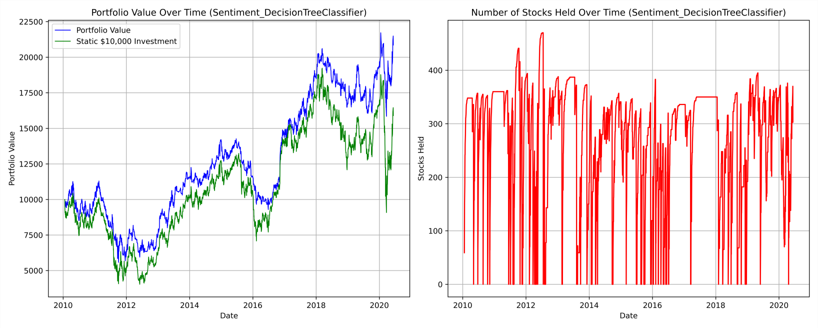
Trading Performance on Stock Morgan Stanley

Portfolio Performance

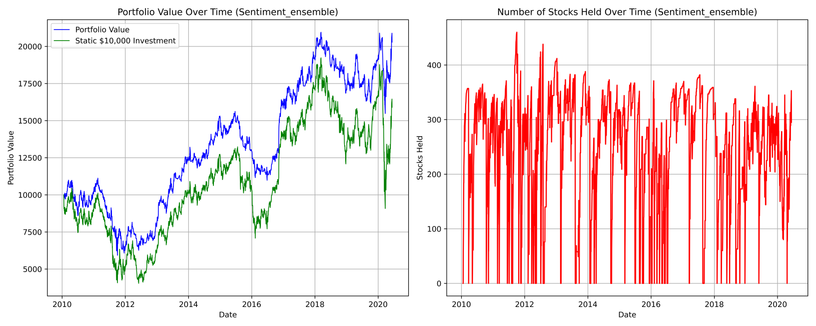
Model	ROI	Sharpe Ratio	Portfolio Value Change	Price vs Portfolio
Sentiment_finbert	129.16%	0.0285	129.16%	70.20%
Sentiment_DecisionTreeClassifier	108.59%	0.0258	108.59%	49.63%
Sentiment_ensemble	102.88%	0.0265	102.88%	43.92%
Sentiment_RandomForestClassifier	102.86%	0.0260	102.86%	43.90%
Sentiment_KNeighborsClassifier	102.56%	0.0266	102.56%	43.60%
Sentiment_LogisticRegression	100.87%	0.0292	100.87%	41.91%
Sentiment_GradientBoostingClassifier	98.82%	0.0251	98.82%	39.86%
Sentiment_SGDClassifier	64.43%	0.0247	64.43%	5.47%
Sentiment_MultinomialNB	55.16%	0.0225	55.16%	-3.81%
Sentiment_XGBClassifier	50.31%	0.0180	50.31%	-8.65%
Sentiment_Random	37.20%	0.0164	37.20%	-21.76%

Table 5: Portfolio Performance on Stock MS

Simulated Trading DecisionTreeClassifier



Simulated Trading ensemble



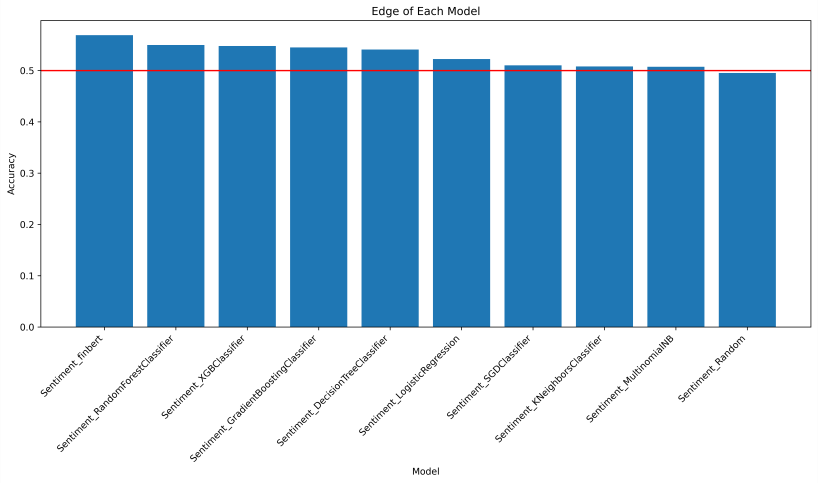
Analysis of Model Edge on Merck Co Inc Stock

Model Edge Performance

Model	Edge
Sentiment_finbert	56.89%
Sentiment_RandomForestClassifier	54.97%
Sentiment_XGBClassifier	54.76%
Sentiment_GradientBoostingClassifier	54.49%
Sentiment_DecisionTreeClassifier	54.08%
Sentiment_LogisticRegression	52.23%
Sentiment_SGDClassifier	50.99%
Sentiment_KNeighborsClassifier	50.79%
Sentiment_MultinomialNB	50.72%
Sentiment_Random	49.51%

Table 6: Edge of Sentiment Analysis Models on MRK

Model Edge graph



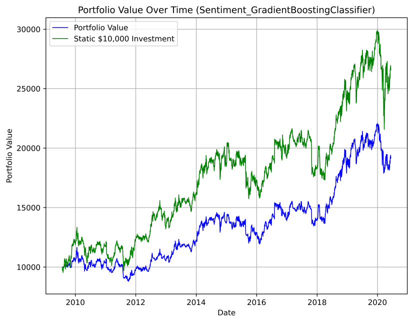
Trading Performance on Stock Merck Co Inc

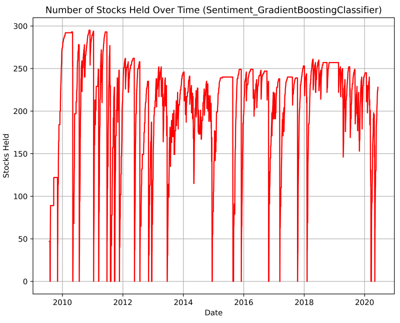
Portfolio Performance

Model	ROI	Sharpe Ratio	Portfolio Value Change	Price vs Portfolio
Sentiment_GradientBoostingClassifier	91.53%	0.0288	91.53%	-74.21%
Sentiment_ensemble	86.08%	0.0288	86.08%	-79.67%
Sentiment_DecisionTreeClassifier	81.80%	0.0267	81.80%	-83.95%
Sentiment_RandomForestClassifier	75.43%	0.0258	75.43%	-90.31%
Sentiment_XGBClassifier	74.45%	0.0257	74.45%	-91.29%
Sentiment_finbert	59.81%	0.0276	59.81%	-105.94%
Sentiment_Random	56.60%	0.0290	56.60%	-109.14%
Sentiment_SGDClassifier	55.24%	0.0245	55.24%	-110.51%
Sentiment_LogisticRegression	49.26%	0.0211	49.26%	-116.49%
Sentiment_KNeighborsClassifier	40.92%	0.0184	40.92%	-124.82%
Sentiment_MultinomialNB	36.90%	0.0190	36.90%	-128.85%

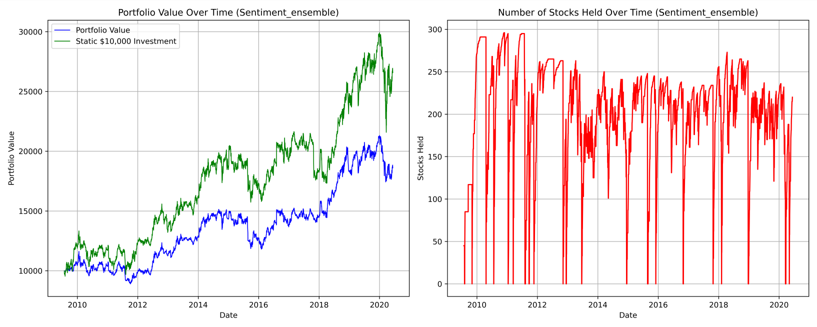
Table 7: Portfolio Performance on Stock MRK

Simulated Trading GradientBoostingClassifier





Simulated Trading ensemble



Detailed Analysis

Model Performance vs. Trading Simulation

Accuracy Edge and Trading Performance

- Models outperform the baseline random sentiment in accuracy.
- Simulated trading performance is not always directly correlated with model accuracy.
- Factors affecting trading performance:
  - Position sizing strategies.
  - Timing of market entry and exit.
  - The impact of transaction costs and slippage.

Specialization of Models

- FinBERT excels due to its specialization in financial contexts.
- Its understanding of nuanced financial language contributes to its strong performance.

Data Aggregation and Preprocessing

Aggregated Sentiments and Preprocessing

- Aggregation methods (min, mode, mean) yield different sentiment scores and influence accuracy.
- Preprocessing techniques and their impact:
    - Including vs. excluding stop words.
    - The decision to retain duplicates suggested overfitting issues.

Pairing Datasets and Overfitting

- Challenge of matching multiple news stories to a single trading day.
- Removal of duplicate stories led to decreased performance, indicating potential overfitting.

Limitations and Future Research

Study Limitations

- Data availability for each stock was limited.
- Generalizability of Results: The extent to which findings can be applied to different financial markets or conditions.

Future Research Avenues

- Expanding Data Sources: Incorporating a wider range of news sources and alternative data for enhanced accuracy.
- Advanced Analytical Techniques: Exploring transformer-based models and hybrid machine learning approaches.
- Real-Time Analysis and Scalability: Researching the applicability of models in real-time and high-frequency trading scenarios.

Practical Implications

Simulated trading

Understanding of market sentiment

References

References i

- Daily financial news for 6000+ stocks. `https://www.kaggle.com/datasets/miguelaenlle/massive-stock-news-analysis-db-for-nlpbacktests`.

  Accessed: [20/11/2023].
- Financial sentiment analysis dataset. `https://www.kaggle.com/datasets/sbhatti/financial-sentiment-analysis`. Accessed: [20/11/2023].
- Sentiment analysis for financial news dataset. `https://www.kaggle.com/datasets/ankurzing/sentiment-analysis-for-financial-news`. Accessed: [20/11/2023].

Thank you for watching my presentation