Applying Machine Learning Methods to Forecast S&P 500 Market Behavior

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Introduction

Machine learning techniques have increasingly become an appropriate measure across various fields. In modern, daily financial markets, there is much value in prediction, although predicting stock developments is more complicated than it seems. Prices change due to microtransactions and terabytes of data create new patterns every day. For example, research done by Alzaman found that machine learning techniques predict stock movement based on Toronto Stock Exchange information, confirming that financial sets are appropriate to use this technique since there's relevant patterning.
In this research, I used a similar idea through different datasets. S&P 500 historical data was acquired through the yfinance library, and using closing price as a predictive measure seeks prediction based on minimal change relative to prediction. The main goal of this study is to see how well these methods work on S&P 500 data and whether they can be used to understand general market behavior.

Methods

Data Source: Daily closing prices for Apple (AAPL), Tesla (TSLA), Amazon (AMZN), Visa (V), and Microsoft (MSFT) were downloaded from Yahoo Finance using the yfinance API for the period 2017-01-01 to 2019-12-31.
Data Cleaning:
Feature Engineering: For the target stock (Apple), the prediction target was defined as the next day's price. Input features included today's price and 1- to 5-day percentage returns.
Train–Test Split: Data was split into 80% training and 20% testing.
Models: Two regression models were trained and evaluated:
– Linear Regression
– Random Forest Regressor
Evaluation Metrics: Data was cleaned, features were engineered, and models were trained using standard machine-learning preprocessing steps

Study Objective/Aim

Apply machine-learning methods to analyze historical S&P 500 stock prices.
Visualize sector distribution, price trends, and correlations among five major companies.
Build models that predict next-day Apple prices using return features.
Compare Linear Regression and Random Forest for accuracy.
Evaluate strengths and limitations of models to understand stock market behavior.

Findings

1. Price Trends Across Companies Showing volatility
The closing prices for all five companies trended higher. Apple's and Microsoft's trajectory is more stable and consistent than Tesla's fluctuations. This suggests a long-term outlook of big tech companies and amore short-term possibility that complicates predictions.

Five companies' trend in closing prices input

```
STOCK_DICT = {'Apple': 'AAPL', 'Tesla': 'TSLA', 'Amazon': 'AMZN', 'Visa': 'V', 'Microsoft': 'MSFT'}
START = '2017-1-1'
END = '2019-12-31'
LAG = 7
df = pd.DataFrame()
for name, symbol in STOCK_DICT.items():
 df[name] = yf.Ticker(symbol).history(start=START, end=END).Close
df.head()

df.dropna(inplace= True)
df.head()
```

Five companies' trend in closing prices output

...

Date	Apple	Tesla	Amazon	Visa	Microsoft
2017-01-03 00:00:00-05:00	26.770882	14.466000	37.683498	74.684151	56.299316
2017-01-04 00:00:00-05:00	26.740915	15.132667	37.859001	75.294792	56.047413
2017-01-05 00:00:00-05:00	26.876902	15.116667	39.022499	76.177818	56.047413
2017-01-06 00:00:00-05:00	27.176542	15.267333	39.799500	77.229996	56.533222
2017-01-09 00:00:00-05:00	27.425463	15.418667	39.846001	76.797844	56.353298

Data Cleaning: Remove Time from Index

Date	Apple	Tesla	Amazon	Visa	Microsoft
2017-01-03	26.770882	14.466000	37.683498	74.684151	56.299316
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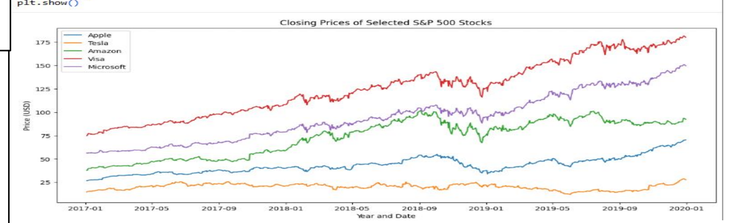
Closing Price Visualization

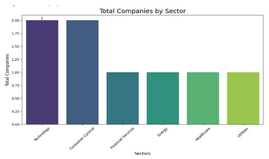
```
plt.figure(figsize=(14,6))
for col in df.columns:
  plt.plot(df[col], label=col)

plt.title("Closing Prices of Selected S&P 500 Stocks")
plt.xlabel("Year and Date")
plt.ylabel("Price (USD)")
plt.legend()
plt.show()
```

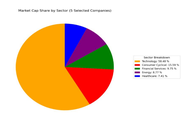


2. Sector Concentration and Market Capitalization

Next step is to find market sector and market capital.

	Symbol	Company	Sector	Marketcap
0	AAPL	Apple	Technology	3.000000e+12
1	TSLA	Tesla	Consumer Cyclical	8.000000e+11
2	AMZN	Amazon	Consumer Cyclical	1.500000e+12
3	V	Visa	Financial Services	5.000000e+11
4	MSFT	Microsoft	Technology	3.200000e+12
5	XOM	ExxonMobil	Energy	4.500000e+11
6	JNJ	Johnson & Johnson	Healthcare	3.800000e+11
7	NEE	NextEra Energy	Utilities	1.700000e+11

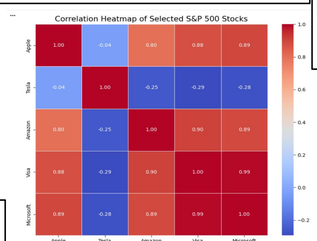




The selected stocks span Technology 58.48%, Consumer Cyclical15.59%, Financial Services9.75%, Energy8.77%, Healthcare7.4%, and Utilities. Technology companies (Apple and Microsoft) contributed the largest share of total market capitalization in the sample, illustrating the dominant role of large tech firms in the modern S&P 500. A sector countplot and market-cap pie and bar chart visually summarized how concentrated the sample is in technology-related sectors.

3. Correlation Patterns Revealing How Closely These Companies Move Together

The correlation heat map of adjusted daily closing prices showed the greatest positive correlation between Apple and Microsoft as well as a mediocre correlation among the other large-cap stocks with the exception of Visa and Tesla, who were less correlated to this group of major tech company names. These correlations suggest that some stocks tend to move together, which is important for diversification and portfolio design.



4. Train–Test Split and Temporal Structure

Using the ML Dataset that was built: Create tomorrow's targets and prices; Past 5 days, targets and prices returns

Train Test-Split Data

Data

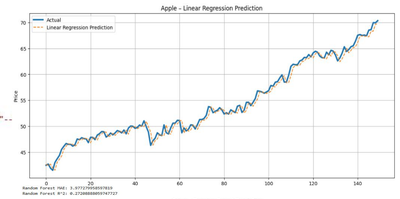
Date	Price	Target	Return_1	Return_2	Return_3	Return_4	Return_5
2017-01-10 00:00:00-05:00	27.453117	27.600630	0.001088	0.010177	0.021429	0.026633	0.025484
2017-01-11 00:00:00-05:00	27.600630	27.485388	0.005373	0.006387	0.015695	0.020927	0.032150
2017-01-12 00:00:00-05:00	27.485388	27.436987	-0.004175	0.001175	0.002165	0.011364	0.022640
2017-01-13 00:00:00-05:00	27.436987	27.658247	-0.001761	-0.005929	-0.000588	0.000420	0.009563
2017-01-17 00:00:00-05:00	27.658247	27.655945	0.008064	0.006289	0.002088	0.007472	0.008488

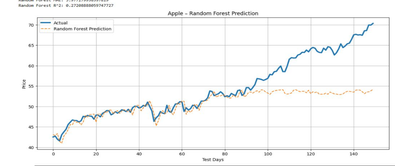
Visualization

Train Test Data Visualization shows the blue line(full dataset) and the red line is (train/ split)

5. Model Performance: Linear Regression vs Random Forest

```
# Linear Regressiin model
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score

lr = LinearRegression()
lr.fit(X_train, y_train)
lr_pred = lr.predict(X_test)
plt.figure(figsize=(14,6))
plt.plot(y_test.values, label="Actual", linewidth=3)
plt.plot(lr_pred, label="Linear Regression Prediction", linestyle="--
plt.title(f"{target_stock} - Linear Regression Prediction")
plt.xlabel("Test Days")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()
# Random forest
from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor(
    n_estimators=300,
    random_state=42,
    max_depth=None
)
rf.fit(X_train, y_train)
rf_pred = rf.predict(X_test)
rf_mae = mean_absolute_error(y_test, rf_pred)
rf_r2  = r2_score(y_test, rf_pred)
print("Random Forest MAE:", rf_mae)
print("Random Forest R^2:", rf_r2)
plt.figure(figsize=(14,6))
plt.plot(y_test.values, label="Actual", linewidth=3)
plt.plot(rf_pred, label="Random Forest Prediction", linestyle="--")
plt.title(f"{target_stock} - Random Forest Prediction")
plt.xlabel("Test Days")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()
```



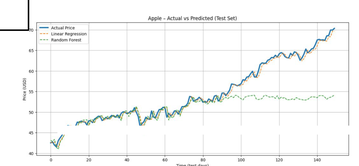


Both models were trained on the same features and evaluated on the same test set using MAE and R². Random Forest achieved a lower MAE and higher R² compared to Linear Regression, indicating better predictive performance. Visual plots showed that Random Forest tracked the shape of the actual price series more closely, especially during non-linear movements, while Linear Regression tended to under-fit periods of strong trend or volatility.

6.Overall Comparison and Interpretation

This shows stock prices contain non-linear patterns that cannot be captured fully by a simple linear model. Random Forest, by averaging many decision trees, can adapt to more complex relationships between past returns and future prices. However, prediction errors remain, underscoring that markets are influenced by many external factors not included in this model.

```
results = pd.DataFrame({
    "Model": ["Linear Regression", "Random Forest"],
    "MAE": [
        mean_absolute_error(y_test, lr_pred),
        mean_absolute_error(y_test, rf_pred)
    ],
    "R2 Score": [
        r2_score(y_test, lr_pred),
        r2_score(y_test, rf_pred)
    ]
})
results
```



Results

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	Model	MAE	R2 Score
0	Linear Regression	0.615027	0.988167
1	Random Forest	3.977280	0.272089

This research finds that machine-learning based tools can learn from the meaningful structure of historical prices of correlated stocks from the preeminent companies of the S&P 500. In addition, this study finds that the Random Forest Regressor learned better than Linear Regression when attempting to predict the next day closing price for Apple relative to MAE and R².
These results also indicate that the financial time series data is best transformed with non-linear operations. Yet, the MAE and deviations are still significant enough to indicate that stock markets are heavily impacted by news articles, macroeconomic conditions and investor decisions that cannot solely be predicted by historical prices.

Further Information Scan Here!

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References:
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Pedregosa et al. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research.
Hastie, Tibshirani, & Friedman (2009). The Elements of Statistical Learning.
Additional online documentation and tutorials on time-series forecasting and Random Forest regression.