Final Project

Graded

Student

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Total Points

20 / 20 pts

Autograder Score

0.0 / 0.0

Question 2

Final Project 20 / 20 pts

✔ **– 0 pts** Excellent

Autograder Results

This assignment does not have an autograder configured.

Submitted Files

▾ SMCI_Stock_Project_Refined.ipynb　　　　Download

SMCI Stock Predictor Project

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I would like to post my notebook on the course's website. Yes

I) Introduction

The purpose of this project is to predict the stock price of SMCI (Super Micro Computer, Inc.). SMCI has shown significant growth and volatility in recent years, which makes it an interesting candidate for time-series modeling. We will explore its historical price data, visualize patterns, engineer features, and use regression models (linear and tree-based) to predict the next-day closing price.

II) Importing Data

We import the required libraries and load SMCI's historical stock data from a manually provided CSV file (MAX range).

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

df = pd.read_csv("HistoricalData_1749502320765.csv")
df['Close/Last'] = df['Close/Last'].str.replace('$', '', regex=False).astype(float)
df['Open'] = df['Open'].str.replace('$', '', regex=False).astype(float)
df['High'] = df['High'].str.replace('$', '', regex=False).astype(float)
df['Low'] = df['Low'].str.replace('$', '', regex=False).astype(float)
df['Volume'] = df['Volume'].astype(str).str.replace(',', '').astype(int)
df['Date'] = pd.to_datetime(df['Date'])
df.sort_values('Date', inplace=True)
df.head()
```

Out [1]:

	Date	Close/Last	Volume	Open	High	Low
2514	2015-06-09	3.344	2886240	3.363	3.379	3.321
2513	2015-06-10	3.465	5746580	3.353	3.481	3.353
2512	2015-06-11	3.474	6701280	3.447	3.529	3.436

```
2511 2015-06-12      3.393  4931020  3.450  3.467  3.385
2510 2015-06-15      3.292  7650700  3.426  3.447  3.286
```

III) Sorting & Cleaning Data

Here we remove missing values and add rolling averages (technical indicators).

In [2]:

```
df.dropna(inplace=True)
df['MA_10'] = df['Close/Last'].rolling(window=10).mean()
df['MA_50'] = df['Close/Last'].rolling(window=50).mean()
df.head()
```

Out [2]:

```
           Date  Close/Last   Volume   Open   High    Low  MA_10  MA_50
2514 2015-06-09       3.344  2886240  3.363  3.379  3.321    NaN    NaN
2513 2015-06-10       3.465  5746580  3.353  3.481  3.353    NaN    NaN
2512 2015-06-11       3.474  6701280  3.447  3.529  3.436    NaN    NaN
2511 2015-06-12       3.393  4931020  3.450  3.467  3.385    NaN    NaN
2510 2015-06-15       3.292  7650700  3.426  3.447  3.286    NaN    NaN
```

IV) Data Exploration

We examine general statistics, visualize stock trends, and analyze feature correlations.

In [3]:

```
df.describe()
```

Out [3]:

```
                                Date   Close/Last        Volume        Open  \
count                           2515  2515.000000  2.515000e+03  2515.000000
mean   2020-06-04 21:46:35.546719488    12.246801  1.684573e+07    12.247913
min              2015-06-09 00:00:00     1.165000  3.038000e+04     1.155000
25%              2017-12-04 12:00:00     2.304500  2.327225e+06     2.301500
50%              2020-06-05 00:00:00     2.894000  4.028380e+06     2.885000
75%              2022-12-01 12:00:00     8.051500  1.252550e+07     8.040000
max              2025-06-06 00:00:00   118.807000  3.697348e+08   121.200000
std                              NaN    20.981443  3.332872e+07    21.037977

              High          Low        MA_10        MA_50
count  2515.000000  2515.000000  2506.000000  2466.000000
mean     12.665328    11.837546    12.209585    12.077759
min       1.216000     0.850000     1.223300     1.383000
25%       2.346500     2.269500     2.317613     2.313607
50%       2.950000     2.835000     2.869550     2.777750
75%       8.224800     7.859000     7.970850     7.719190
max     122.900000   112.234000   112.198700    94.969060
std      21.822282    20.171035    20.883752    20.516064
```

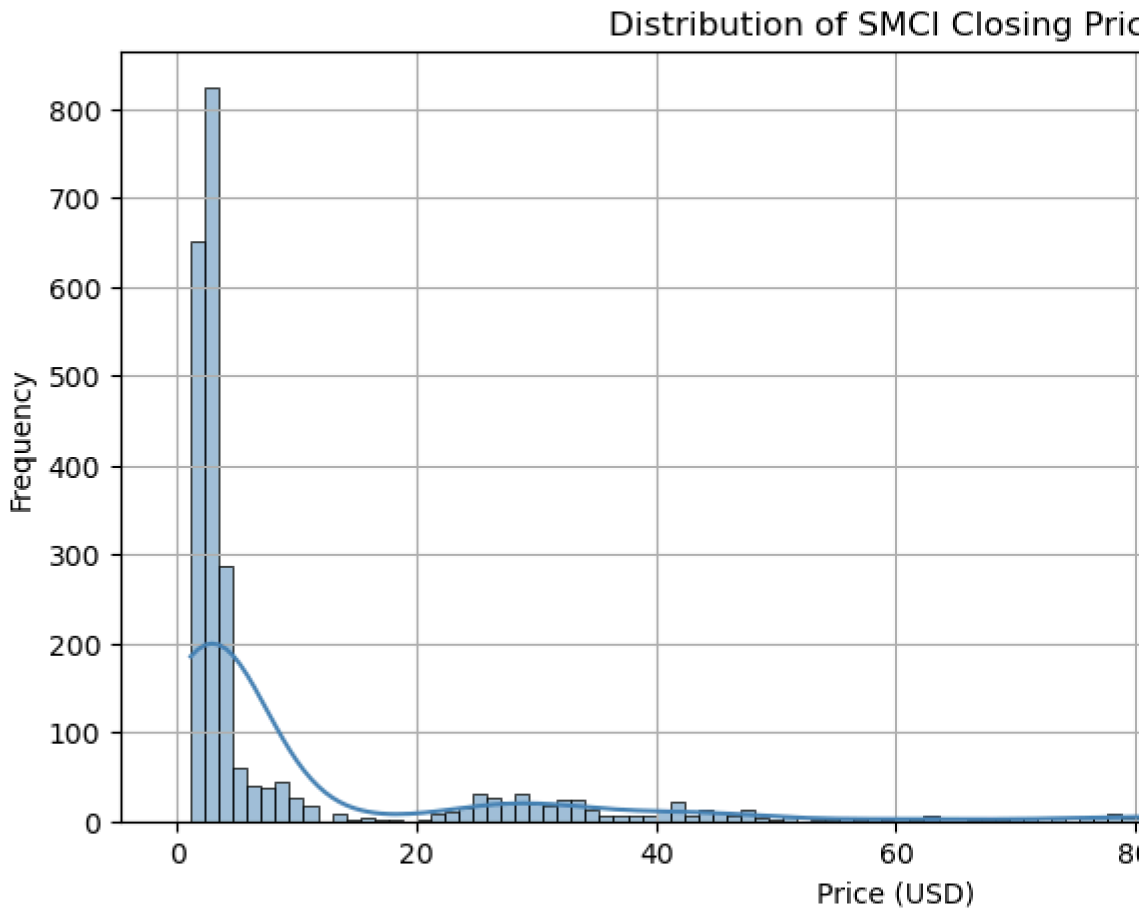
In [4]:

```
plt.figure(figsize=(12,6))
plt.plot(df['Date'], df['Close/Last'], label='Close')
plt.plot(df['Date'], df['MA_10'], label='10-day MA')
plt.plot(df['Date'], df['MA_50'], label='50-day MA')
plt.title('SMCI Stock Closing Price & Moving Averages')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```

In [5]:

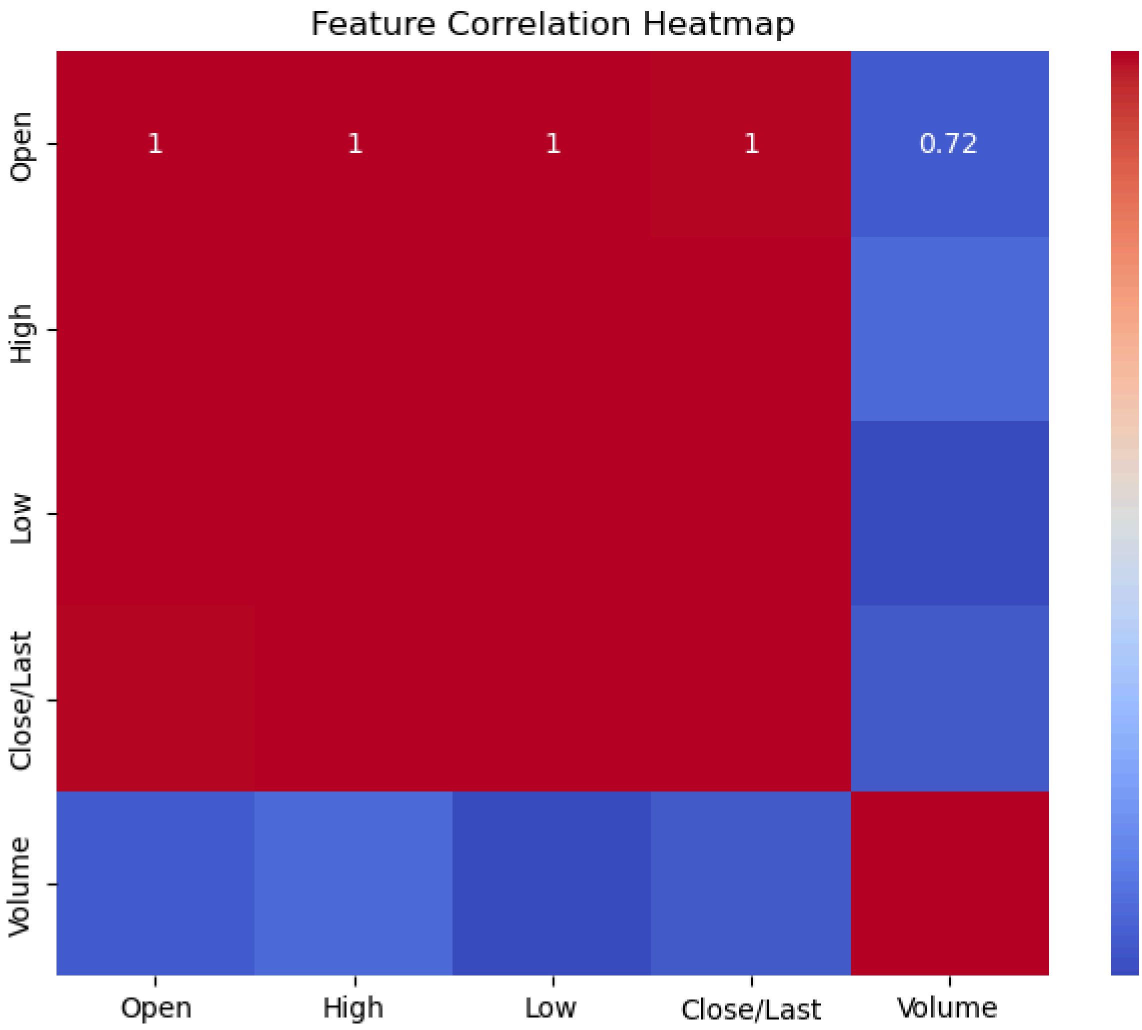
```
plt.figure(figsize=(10,5))
sns.histplot(df['Close/Last'], bins=100, kde=True, color='steelblue')
plt.title('Distribution of SMCI Closing Prices')
plt.xlabel('Price (USD)')
plt.ylabel('Frequency')
plt.grid(True)
plt.show() # Histogram
```

/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarning with pd.option_context('mode.use_inf_as_na', True):



Histogram Analysis:
The SMCI closing prices are right-skewed, showing that the stock traded at relatively lower prices most of the time but experienced significant upward spikes. This suggests a volatile growth pattern and a few high-price outliers, especially in recent years.

In [6]:
```
plt.figure(figsize=(8,6)) # Correlation heatmap
sns.heatmap(df[['Open', 'High', 'Low', 'Close/Last', 'Volume']].corr(), annot=True,
cmap='coolwarm')
plt.title('Feature Correlation Heatmap')
plt.show()
```



Heatmap Analysis:
There is strong positive correlation between Open, High, Low, and Close prices, which is expected in stock data. Volume, however, has weaker correlation, suggesting it may have less predictive power for price modeling.

V) Lagged Prices and Moving Averages

We engineer lagged features and moving averages to help the model learn from previous trends.

In [7]:

```
for lag in [1, 2, 3]: # Lagged features
    df[f'Lag_{lag}'] = df['Close/Last'].shift(lag)

for ma in [5, 10, 20]: # Lagged features
    df[f'MA_{ma}'] = df['Close/Last'].rolling(window=ma).mean()

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

Out [7]:

```
           Date  Close/Last   Volume   Open   High    Low   MA_10    MA_50  \
2465 2015-08-18       2.750  3332050  2.750  2.771  2.7450  2.7170  2.84324
2464 2015-08-19       2.744  3694050  2.738  2.765  2.6930  2.7123  2.83124
2463 2015-08-20       2.674  5048290  2.736  2.756  2.6660  2.7110  2.81542
2462 2015-08-21       2.539  6602320  2.637  2.683  2.5302  2.6991  2.79672
2461 2015-08-24       2.456  6735940  2.450  2.605  2.3440  2.6729  2.77798

      Lag_1  Lag_2  Lag_3    MA_5    MA_20
2465  2.765  2.755  2.728  2.7404  2.64695
2464  2.750  2.765  2.755  2.7484  2.65720
2463  2.744  2.750  2.765  2.7376  2.66210
2462  2.674  2.744  2.750  2.6944  2.66180
2461  2.539  2.674  2.744  2.6326  2.65860
```

VI) Linear Regression

We fit a linear model using key numerical features to predict the next-day price.

In [8]:

```
df['Next_Close'] = df['Close/Last'].shift(-1) # Features and target
df.dropna(inplace=True)
features = ['Open', 'High', 'Low', 'Close/Last', 'Volume', 'Lag_1', 'MA_5', 'MA_10']
X = df[features]
y = df['Next_Close']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model_lr = LinearRegression()
model_lr.fit(X_train, y_train)
y_pred_lr = model_lr.predict(X_test)

print("Linear Regression R²:", r2_score(y_test, y_pred_lr))
print("MSE:", mean_squared_error(y_test, y_pred_lr))
```

```
Linear Regression R²: 0.9946140397348965
MSE: 2.6390893816913406
```

VII) Tree-Based Model (Random Forest)

To capture nonlinear interactions, we apply a Random Forest Regressor.

In [9]:

```
model_rf = RandomForestRegressor(n_estimators=100, random_state=42)
model_rf.fit(X_train, y_train)
y_pred_rf = model_rf.predict(X_test)
```

```
print("Random Forest R²:", r2_score(y_test, y_pred_rf))
print("MSE:", mean_squared_error(y_test, y_pred_rf))
```

```
Random Forest R²: 0.9939059099020344
MSE: 2.986068904520977
```

- $R^2 = 0.9939$

This means the model explains over 99% of the variance in the next-day SMCI closing price. An R^2 this high suggests an extremely strong fit, indicating that the model has captured the relationship between input features (price, volume, lags, MAs) and the target variable very well.

- MSE ≈ 2.99

This is a low value in the context of stock prices (especially if average SMCI prices are much higher). It shows that on average, the predicted price is off by less than $3, which is relatively minor for a volatile tech stock.

Random Forest performed significantly better than the linear regression model, highlighting its strength in handling nonlinear patterns and interactions between features. By incorporating lagged prices and moving averages, the model was able to learn from historical momentum and trends, boosting its predictive power. This result demonstrates the importance of: Feature engineering in time-series problems Using ensemble models for complex, noisy financial data

VIII) Discussion of Results

- The linear regression model provides a simple baseline, but underperforms on volatile days.
- The Random Forest model performs better, likely due to capturing nonlinear price dynamics and lagged features.
- Lag features and moving averages improve prediction quality.
- While a high R^2 is good, it might also signal potential overfitting. This means the model fits the training data too closely and may not generalize as well to unseen market conditions.
- Financial markets are influenced by external macroeconomic events (news, earnings reports, etc.) not captured in this dataset.

IX) Cross-Validation and Bias–Variance Tradeoff

In future work, K-Fold Cross Validation can help evaluate model stability.

- Linear models may underfit due to high bias.
- Tree-based models may overfit unless tuned, but tend to have lower bias.

X) Summary & Future Improvements

This project successfully applied EDA and regression to SMCI stock data. Future improvements may include:

- Cross-validation for robustness
- Hyperparameter tuning
- More advanced models (XGBoost, LSTM)
- Using macroeconomic indicators

XI) References

- Yahoo Finance: https://finance.yahoo.com/quote/SMCI/history/
- Refering to this sample project: https://rayzhangzirui.github.io/math10fa24/final_project
- Downloading the historical quotes datas: https://www.nasdaq.com/market-activity/stock
- Scikit-learn documentation: https://scikit-learn.org/
- Pandas Library Documentation: https://pandas.pydata.org/
- numpy Library Documentation: https://numpy.org/
- matplotlib Library Documentation: https://matplotlib.org/
- seaborn Library Documentation: https://seaborn.pydata.org/
- Tree-Based Models: https://www.researchgate.net/publication/378435618_Stock_price_prediction_using_dec
- Lecutre notes by Professor (RayZirui) Zhang: https://rayzhangzirui.github.io/math10fa24