Technological Institute of the Philippines	Quezon City - Computer Engineering
Course Code:	CPE 019
Code Title:	Emerging Technologies in CpE 2 - Fundamentals of Computer Vision
2nd Semester	AY 2023-2024
ACTIVITY NO.	**PRELIM EXAMINATION**
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OBJECTIVES

In this exam, you will show the application of the following algorithms:

Part 1: Linear Regression

- Singular Linear Regression
- Multiple Linear Regression
- Polynomial Linear Regression

Part 2: Logistic Regression

Part 3: Decision Tress

Part 4: Random Forest

SCENARIO / BACKGROUND

In this exam, we will show each application of algorithms that listed above, including the datasets which contains the 2,516 entries.

The tasked is to analyzed historical stock market data for the past 10 years to identify patterns and build predictive models for stock price movements.

The goal is to develop models that can accurately predict wheter the stock price increase or decrease in the future based on various factors.

REQUIRED RESOURCES

- PC / Laptop with Internet Access
- **Python libraries:** pandas, sklearn, IPython.display, numpy, and seaborn.
- **Additonal application:** Graphviz
- **Datafiles:** Meta Stock Price Technical Indicator.csv

The datasets contain the following variables:

Variable	Description
1. Date	Date for which data is recorded
2. Open	Opening price stock on trading day
3. High	Highest price at which stock traded on during trading day
4. Low	Lowest price at which stock traded on during trading day.
5. Close	Final price at which stock is valued for the day
6. Volume	No. of shares or contrast traded in the security/market during a given period.
7. RSI_7	**7-day Relative Strength Index** • Measure the magnitude of recent prices changes to evaluate overbought/oversold conditions in price of stock
8. RSI_14	**14-day Relative Strength Index** • Calculated over 14 days
9. CCI_7	**7-day Commodity Channel Index** • Measure the difference between current price and historical average price
10. CCI_14	**14-day Commodity Channel Index** • 14 days for medium-term trends
11. SMA_50	**50-day Simple Moving Average** • Average the closing prices of stock over the past 50 days.
12. EMA_50	**50-day Exponential Moving Average** • Weight to recent prices
13. SMA_100	**100-day Simple Moving Average** • Average of closing prices of stock for over the past 100 days
14. EMA_100	**100-day Exponential Moving Average** • Responsive to recent price changes
15. MACD	**Moving Average Convergence Divergence** • Show the relationship between 2 moving averages of stock price
16. Bollinger	Price envelope
17. TrueRange	Measure the volatility that consider the range between high, low, and close of stock
18. ATR_7	**7-day Average True Range** • measures the market volatility by decomposing the entire range of stock for that period
19. ATR_14	**14-day Average True Range**

Import the libraries and data

```
#importing the important libraries that needed in the study
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
#load the Dataset and named as "stock"
stock = pd.read_csv("/content/Meta Stock Price Technical Indicators (10 Years).csv")
```

```
#select the first 20 rows of the data
stock.head(20)
```

	date	open	high	low	close	volume	rsi_7	rsi_14	cci_7	cci_14	sma_50	ema_50	sma_100	ema_100	macd	bollinger	TrueRange	atr_7	atr_14	next_day_close
0	2014-01-02	54.830002	55.220001	54.189999	54.709999	43195500	51.917475	58.077822	-64.312117	-13.517101	50.2818	50.740946	47.6654	46.914555	1.828901	53.2450	1.030002	1.652052	1.710739	54.560001
1	2014-01-03	55.020000	55.650002	54.529999	54.560001	38246200	50.604988	57.387622	-40.054734	-17.361246	50.3194	50.890719	47.8288	47.066897	1.687987	53.5420	1.120003	1.576045	1.668543	57.200001
2	2014-01-06	54.419998	57.259998	54.049999	57.200001	68852600	67.483917	65.221525	43.907749	42.364730	50.4254	51.138151	48.0306	47.268784	1.768947	53.9850	3.209999	1.809467	1.778647	57.919998
3	2014-01-07	57.700001	58.549999	57.220001	57.919998	77207400	70.672584	67.003189	150.620136	117.886980	50.5348	51.404115	48.2433	47.480966	1.869653	54.4840	1.349998	1.743829	1.748030	58.230000
4	2014-01-08	57.599998	58.410000	57.230000	58.230000	56682400	72.049420	67.768804	107.795942	101.415192	50.6604	51.671806	48.4600	47.695073	1.951977	54.9535	1.180000	1.663282	1.707456	57.220001
5	2014-01-09	58.650002	58.959999	56.650002	57.220001	92253300	61.139242	62.667059	67.348891	72.506466	50.8002	51.889389	48.6614	47.884774	1.913662	55.3020	2.309997	1.755670	1.750495	57.939999
6	2014-01-10	57.130001	58.299999	57.060001	57.939999	42449500	65.485896	64.706800	56.148766	68.897572	50.9710	52.126676	48.8627	48.085014	1.919270	55.7300	1.239998	1.682002	1.714031	55.910000
7	2014-01-13	57.910000	58.250000	55.380001	55.910000	63010900	47.872555	55.499705	-32.374938	0.494863	51.1090	52.275046	49.0377	48.240824	1.739855	55.9340	2.869999	1.851716	1.796600	57.740002
8	2014-01-14	56.459999	57.779999	56.099998	57.740002	37503600	59.366740	60.900791	-11.118995	38.260302	51.2596	52.489364	49.2319	48.429949	1.725443	56.1550	1.869999	1.854328	1.801843	57.599998
9	2014-01-15	57.980000	58.570000	57.270000	57.599998	33663400	58.220894	60.297824	47.470053	71.421641	51.4166	52.689787	49.4224	48.612501	1.683320	56.3445	1.300000	1.775138	1.765997	57.189999
10	2014-01-16	57.259998	58.020000	56.830002	57.189999	34541800	54.619116	58.472055	-20.009636	48.980431	51.5960	52.866270	49.5888	48.783240	1.598428	56.4610	1.189998	1.691547	1.724854	56.299999
11	2014-01-17	57.299999	57.820000	56.070000	56.299999	40849200	47.220911	54.606761	-92.207533	12.225818	51.7198	53.000930	49.7384	48.932848	1.442705	56.4975	1.750000	1.699897	1.726650	58.509998
12	2014-01-21	56.599998	58.580002	56.500000	58.509998	48669200	62.094919	61.425729	83.958821	70.064884	51.9076	53.216977	49.9271	49.123446	1.480554	56.6705	2.280003	1.782769	1.766175	57.509998
13	2014-01-22	58.849998	59.310001	57.099998	57.509998	61352900	54.053307	57.235969	90.891013	71.521682	52.1066	53.385335	50.0967	49.290333	1.413564	56.7900	2.210003	1.843803	1.797877	56.630001
14	2014-01-23	56.369999	56.680000	55.689999	56.630001	47951800	47.709888	53.760842	-135.833543	-74.865840	52.2886	53.512580	50.2502	49.436373	1.274770	56.7330	1.819999	1.840402	1.799457	54.450001
15	2014-01-24	56.150002	56.419998	54.400002	54.450001	55200700	35.626341	46.266576	-154.817590	-194.409048	52.4536	53.549342	50.3818	49.536121	0.977598	56.5575	2.229999	1.896059	1.830210	53.549999
16	2014-01-27	54.730000	54.939999	51.849998	53.549999	73924100	31.752850	43.566434	-159.282566	-244.337521	52.5924	53.549368	50.4986	49.615972	0.661836	56.3485	3.090001	2.066622	1.920195	55.139999
17	2014-01-28	54.020000	55.279999	54.000000	55.139999	48191200	44.246842	49.206285	-60.188711	-119.745178	52.7210	53.611747	50.6322	49.725855	0.533739	56.3335	1.730000	2.018533	1.906610	53.529999
18	2014-01-29	54.610001	54.950001	53.189999	53.529999	92995600	36.379188	44.370792	-76.810279	-137.418378	52.8118	53.608541	50.7409	49.801519	0.298862	56.3245	1.950000	2.008743	1.909709	61.080002
19	2014-01-30	62.119999	62.500000	60.459999	61.080002	150178900	67.751280	62.821640	167.461057	210.288091	53.0532	53.901545	50.9122	50.025829	0.713716	56.6460	8.970001	3.003208	2.414016	62.570000

```
#Calculating the summary statistics of data
stock.describe()
```

	open	high	low	close	volume	rsi_7	rsi_14	cci_7	cci_14	sma_50	ema_50	sma_100	ema_100	macd	bollinger	TrueRange	atr_7	atr_14	next_day_close
count	2516.000000	2516.000000	2516.000000	2516.000000	2.516000e+03	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000	2516.000000
mean	178.035517	180.328621	175.826359	178.129122	2.617010e+07	54.339039	54.047585	13.860957	21.786028	175.350939	175.391728	172.714407	172.828966	0.787792	177.025524	5.009948	4.998040	4.981088	178.245012
std	81.123720	82.200952	80.118216	81.166653	1.782460e+07	15.808831	11.486580	99.506607	107.431270	79.621484	79.101923	78.246631	77.120070	4.869274	80.479297	4.338035	3.045084	2.912425	81.198518
min	54.020000	54.939999	51.849998	53.529999	5.467500e+06	14.083263	21.934202	-233.333333	-422.479783	50.281800	50.740946	47.665400	46.914555	-29.046311	53.245000	0.529999	1.095919	1.276304	53.529999
25%	115.787498	117.452497	114.007502	115.565003	1.563175e+07	43.513651	46.359166	-68.969530	-57.372272	115.554749	115.484737	112.843875	112.552245	-0.881898	114.901500	2.087497	2.292068	2.379389	115.792499
50%	170.114998	172.110001	168.224998	170.245002	2.106275e+07	55.357801	54.679774	27.716116	35.250491	170.474200	170.871460	170.365500	171.015576	1.032127	169.461749	3.904995	4.305433	4.363978	170.264999
75%	220.297504	221.827499	216.492501	219.864994	3.022008e+07	66.148583	62.652629	95.153139	102.728473	210.956750	216.288210	203.539550	214.056316	2.855147	216.494625	6.619995	7.373164	7.530707	220.222496
max	381.679993	384.329987	378.809998	382.179993	2.323166e+08	93.579562	86.065371	233.333333	418.499830	363.754401	362.957061	351.029901	347.213736	15.623524	373.422003	87.250000	22.274682	16.665167	382.179993

```
#Provides the summary of Dataframe.
#Including the index, columnss, data type, and non-null values.
stock.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2516 entries, 0 to 2515
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   date            2516 non-null   object
 1   open            2516 non-null   float64
 2   high            2516 non-null   float64
 3   low             2516 non-null   float64
 4   close           2516 non-null   float64
 5   volume          2516 non-null   int64
```

```
 6   rsi_7          2516 non-null   float64
 7   rsi_14         2516 non-null   float64
 8   cci_7          2516 non-null   float64
 9   cci_14         2516 non-null   float64
 10  sma_50         2516 non-null   float64
 11  ema_50         2516 non-null   float64
 12  sma_100        2516 non-null   float64
 13  ema_100        2516 non-null   float64
 14  macd           2516 non-null   float64
 15  bollinger      2516 non-null   float64
 16  TrueRange      2516 non-null   float64
 17  atr_7          2516 non-null   float64
 18  atr_14         2516 non-null   float64
 19  next_day_close 2516 non-null   float64
dtypes: float64(18), int64(1), object(1)
memory usage: 393.2+ KB
```

```
#Checking if there's a missing or null values in Dataframe.
#isnull() and sum() calculates the total number of missing values for each column.
stock.isnull().sum()
```

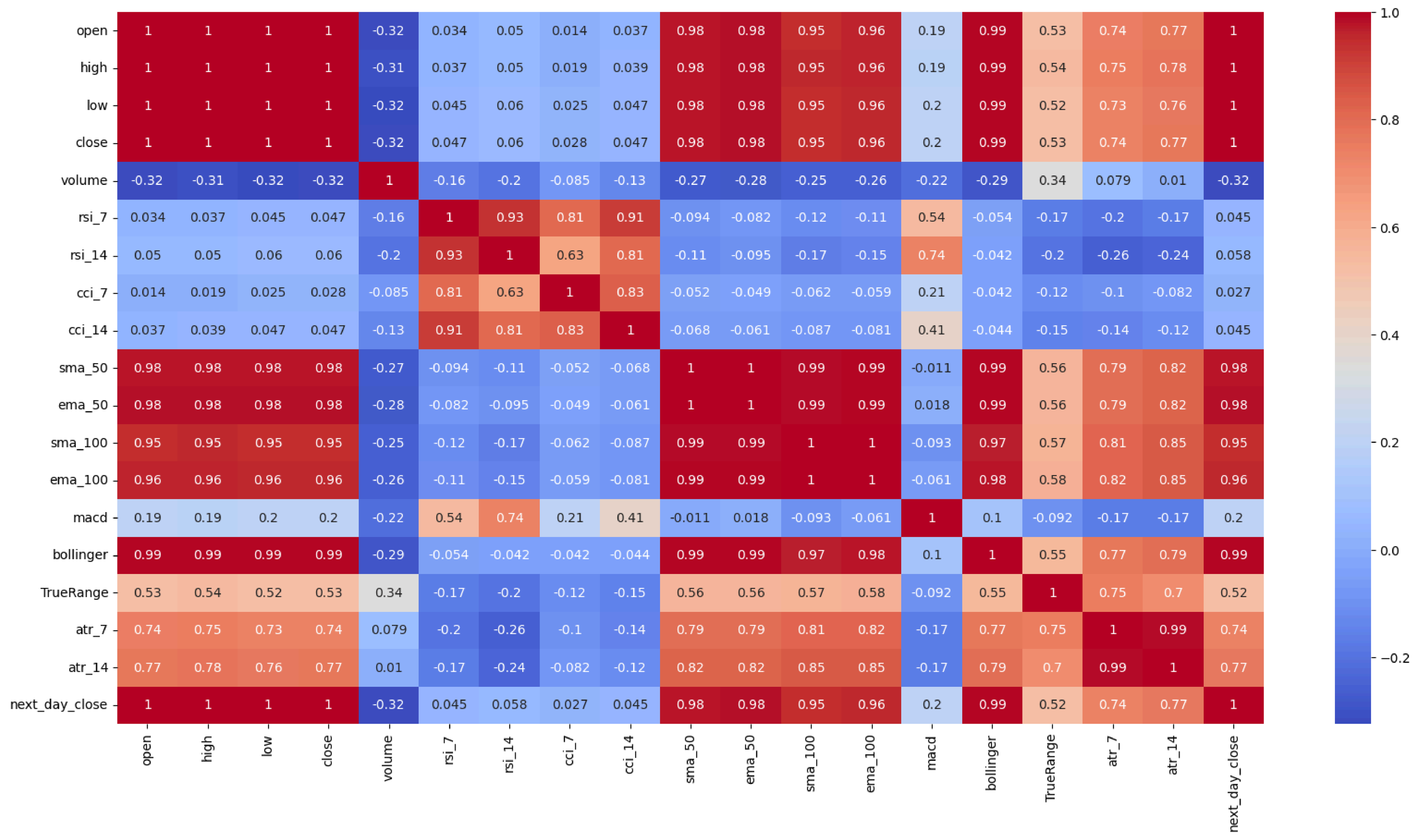
```
date              0
open              0
high              0
low               0
close             0
volume            0
rsi_7             0
rsi_14            0
cci_7             0
cci_14            0
sma_50            0
ema_50            0
sma_100           0
ema_100           0
macd              0
bollinger         0
TrueRange         0
atr_7             0
atr_14            0
next_day_close    0
dtype: int64
```

Analysis

Once there's missing values the statistic analsyis can leads to inaccurate results and predictions. That's why we check if there's a missing value above to fill the missing values to ensure that the analysis will be based on realible information. Also, there's algorithms cannot handle missing values and produces errors.

```
#importing seaborn for better visualization with color palettes that looks professional
import seaborn as sns
import matplotlib.pyplot as plt

#annotation - used to display actual values by each cell
#color map - 'coolwarm' for better visualization
plt.figure(figsize=(20,10))
sns.heatmap(stock.corr(),  annot= True, cmap='coolwarm')
plt.show()
```

```
<ipython-input-25-d23ea36618d7>:6: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(stock.corr(),  annot= True, cmap='coolwarm')
```



Analysis

We used heatmap with coolwarm tone to easily visualized the correlation coefficient of the data that indicates the relationship between 2 or more variables if they are closely related to each other.

Here in the visual aids, when the diagonal indicate as 1 it signifies a perfect positive correlation. The independent variables (open, high, low, close) have a perfect positibe correlation with dependent variable (next_day_close) that can used to predict or explain the values with high certainty.

Part 1: Linear Regression

In this part of exam, we will build and evaluate 3 types ofLinear Regression: **Singular Regression, Multiple Regression, Polynomial Regression**. These models will be trained on labeled dataset containing technical indicator for stock prices over the past 10 years.

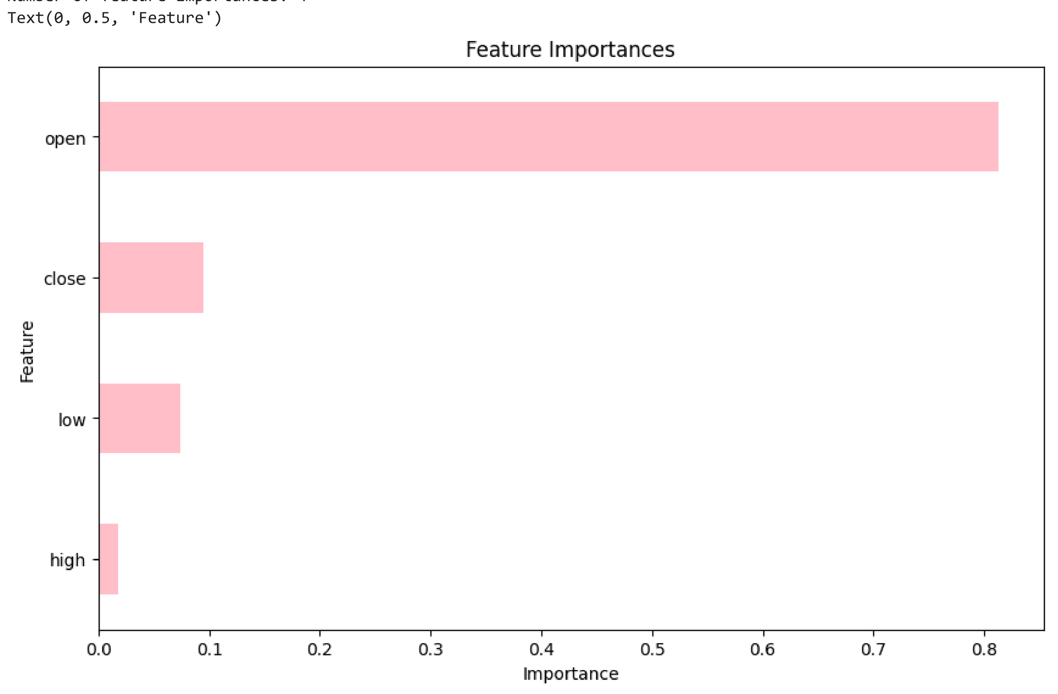
Our goal is to predict the classification of Meta Stock Price Movements from 2014 - 2023 based on indicators.

Singular Linear Regression

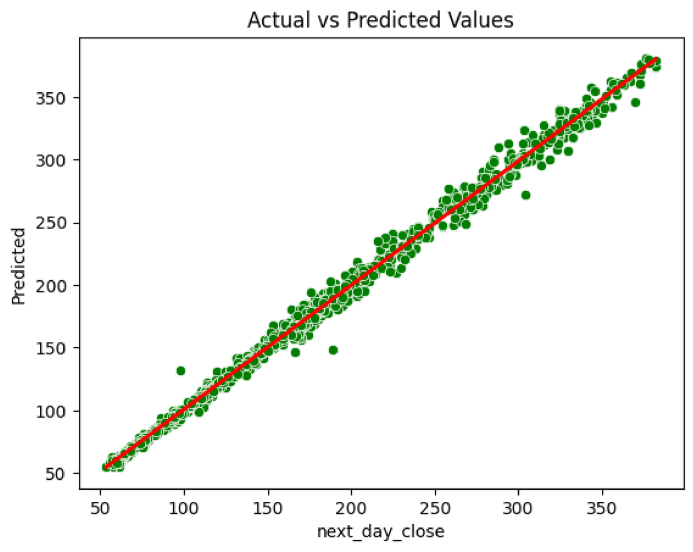
Statistical method used to model relationship between dependent variable (target or response) and independent variables (predictors or features). It assumes if there's a linear relationship between the independent and dependent variables.

```
#Column name
feature_names = ['open','high', 'low', 'close', 'volume', 'rsi_7', 'rsi_14', 'cci_7', 'cci_14','sma_50', 'ema_50', 'sma_100', 'ema_100', 'macd', 'bollinger', 'TrueRange', 'atr_7', 'atr_14', 'next_day_close']

#Display the Feature name and important variables
print("Number of features:", len(feature_names))
print("Number of feature importances:", len(feature_importances))

# Create horizontal bar plot
plt.figure(figsize=(10, 6))
ax = model_ranks.plot(kind='barh', color='pink')

# Set plot title and labels
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')
```

```
Number of features: 19
Number of feature importances: 4
Text(0, 0.5, 'Feature')
```




```
import seaborn as sns

# Define predictors and target variable
X = stock[['open']]  # Independent variables
y = stock['next_day_close']  # Dependent variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=23)

# Create a linear regression model
model = LinearRegression()

# Fit the model to the training data
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Plot actual vs predicted values
sns.scatterplot(x=y_test, y=y_pred, color='green')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted Values')

# Plot regression line
sns.regplot(x=y_test, y=y_pred, scatter=False, color='red')
plt.show()
```



Analysis

We can visually assess the performance of linear regression model in predicting the 'next_day_closing' prices based on the opening prices. The points are closely align along diagonal line which indicates that the model's prediction closely match to actual values.

Evaluate the model (Singular Linear Regression)

```
#Computation for MSE and R-squared score
mse = mean_squared_error(y_test, y_pred) #ave sqr diff. between actual and predicted values
r_squared = r2_score(y_test, y_pred) #measure the proportion of variance in x and y

print("Mean Squared Error:", mse)
print("R-squared Score:", r_squared)
```

```
    Mean Squared Error: 27.762230502330063
    R-squared Score: 0.995662789441985
```

Analysis

MSE is approximately 27.76 which is low value indicating that the model's prediction are close to actual values on average, which suggest a good accuracy.

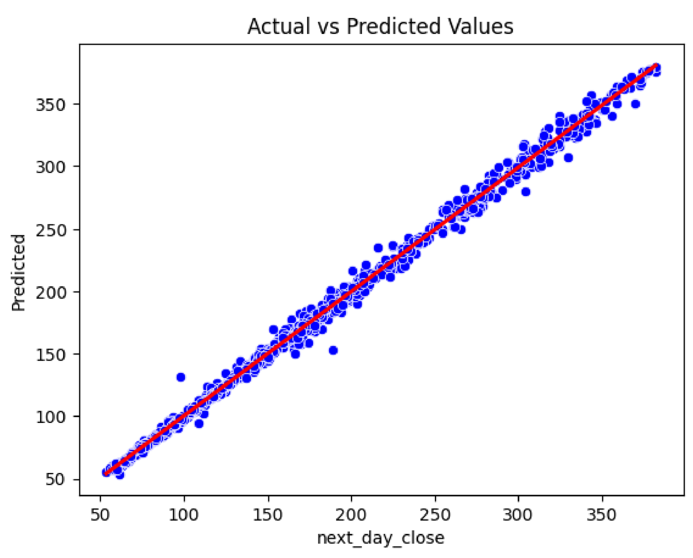
The ranges of r2-score from 0 to 1, the r-squared score of the data was 0.996 closes to 1. Which suggest that 99.6% of independent variables in model are effective in explaining the variation in dependent variable.

Note: Closes to 1 means a perfect fit for the variability of response data around it mean

Multi-linear Regression

Statistical technique used to analyzed relationship between two or more independent variables and dependent variables by fitting a linear equation to observed data.

```
import seaborn as sns

# Define predictors and target variable
X = stock[['open', 'high', 'low', 'close']]  # Independent variables
y = stock['next_day_close']  # Dependent variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=23)

# Create a linear regression model
model = LinearRegression()

# Fit the model to the training data
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Plot actual vs predicted values
sns.scatterplot(x=y_test, y=y_pred, color='blue')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted Values')

# Plot regression line
sns.regplot(x=y_test, y=y_pred, scatter=False, color='red')
plt.show()
```



Analysis

The points closely follow the red line, which suggests that the model's prediction are accurate and have a strong linear relationship between the independent variable (open, high, low, close) and dependent variable (next_day_close)

Note: If the points from tigh cluster around the regression line, it indicates that the model's prediction closely match the actual values and model capturing the patterns in data effectively.

Evaluate the model (Multi-linear Regression

```
# Calculation of MSE and R2-score
mse = mean_squared_error(y_test, y_pred)
r_squared = r2_score(y_test, y_pred)
print("Mean Squared Error:", mse)
print("R-squared Score:", r_squared)
```

```
    Mean Squared Error: 19.765984763393266
    R-squared Score: 0.9969120190901752
```

Analysis

The MSE is approximately 19.77 - low value which means the predicted values are close to the actual values. While the r2-score is equivalent to 0.997 or 99.7% which explains the model effectively captures the relationship of independent and dependent variable as evidenced by the high R-squared and low MSE.

Polynomial Regression

Regression analysis used to model the relationship between a dependent variable and one or more independent variable by fitting the polynomial function to observed data.

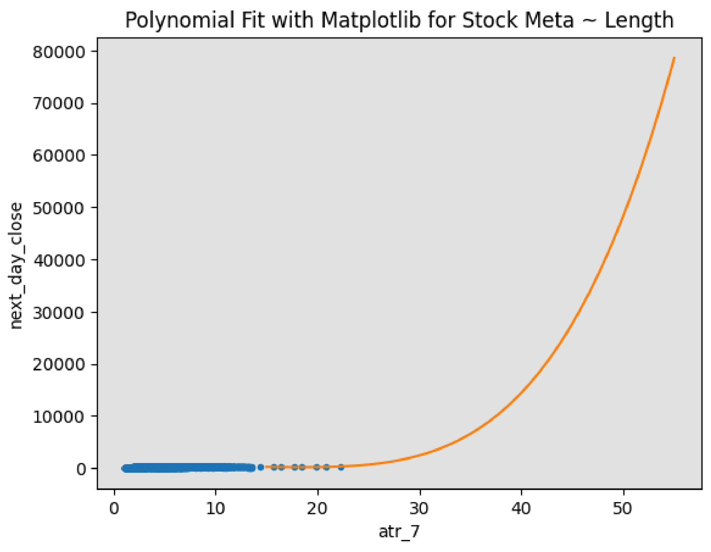
Note: Polynomial Regression fits a curve.

```
# Plotpolly - visualization of polynomial regression models.
# model - callable variable that can pass to independent and get vack the predicted values of dependent variables
# independent - used in regression / dependent - observed values
# name - label for x-axis (independent variable)
def PlotPolly(model, independent_variable, dependent_variabble, Name):
    # Genearte 100 space between 15 & 55, used to create smooth curve
    x_new = np.linspace(15, 55, 100)
    # predict the dependent variable based on model and x variable
    y_new = model(x_new)

    # Plots the original data points as dots and polynomial curve
    plt.plot(independent_variable, dependent_variabble, '.', x_new, y_new, '-')
    #Title Plot
    plt.title('Polynomial Fit with Matplotlib for Stock Meta ~ Length')
    # Current axes instance
    ax = plt.gca()
    # Set the background color
    ax.set_facecolor((0.898, 0.898, 0.898))
    # Current figure instance
    fig = plt.gcf()
    # label for x-axis as name
    plt.xlabel(Name)
    # plot y-axis as next_day_close
    plt.ylabel('next_day_close')
    # display plot
    plt.show()
```

Analysis

Designed that provide a convenient way to visualized the polynomial fit for regression model along side the original data points. It helps to capture the relationship between independent and dependent variable

```
# Two important variables that set as example for this model
x = stock['atr_7']
y = stock['next_day_close']

# Inside the polynomial model 'p' used to predict values of dependent based on independent values
f = np.polyfit(x, y, 4)
p = np.poly1d(f)

# Plot the polynomial fit
PlotPolly(p, x, y, 'atr_7')
```



Analysis

The graph show the relationship between 2 variables: 'atr_7' and 'next_day_close'. The dots represent as actual stock prices. The blue lines represents the polynomial fit that capture the general trend of stock as 'atr_7 changes.

This suggest that the volatility of stock increases ('atr_7' value), the prices tend to decrease or show movement.

```
y_pred
```

```
array([100.49389125,  98.99541718, 103.73844079, ..., 237.93001415,
       229.14277395, 234.43512425])
```

Evaluation of Polynomial Linear Regression

```
# Calculate predicted values using the polynomial regression model
y_pred = p(x)

# Calculate R-squared score
r_squared = r2_score(y, y_pred)
print('R-squared score:', r_squared)

# Calculate Mean Squared Error (MSE)
mse = mean_squared_error(y, y_pred)
print('Mean Squared Error:', mse)
```

```
R-squared score: 0.6170762448390501
Mean Squared Error: 2523.689159316617
```

Analysis

The MSE was equivalent to 2523.689, indicate the squared difference between the actual and predicted stock prices.The higher MSE suggest a larger predictions error, so there's another factor aside from 'atr_7' that affecting the stock prices.

r2-score of 0.617 or 61.7% of the variation in dependent variable (next_day_close) is explained by indepdent variable ('atr_7'), which suggest that the model doesn't not explain much of variability in the data.

Part 2: Logistic Regression

Statistical method used for binary classification task, where target variable has 2 possible outcomes. It used when dependent variable is categorical.

Note: Linear Regression - predicts continuous values, while Logistic Regression - is a binary classification algorithm, it requires the target variable to be categorical with two classes.

Rigde Regression instead of Logistic Regression

(continuous values are not suitable for logictic regression)

vaariant of linear regression that used when the data suffers from multicollinearity (high correlation among predictor variables) or when overfitting im the model. It adds penalty term to ordinary least objective function, which helps to reduce thecomplexity of model and prevent overfitting.

```
from sklearn.metrics import r2_score

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Creating and fitting the Ridge regression model
ridge_model = Ridge(alpha=1.0)  # You can adjust the regularization strength by changing the alpha parameter
ridge_model.fit(X_train, y_train)

# Making predictions on the test set
predictions = ridge_model.predict(X_test)

# Calculating Mean Squared Error
mse = mean_squared_error(y_test, predictions)

# Calculating R-squared score
r_squared = r2_score(y_test, predictions)

print("Mean Squared Error:", mse)
print('R-squared score:', r_squared)
```

```
Mean Squared Error: 1.7115637211977852
R-squared score: 0.9997318045506529
```

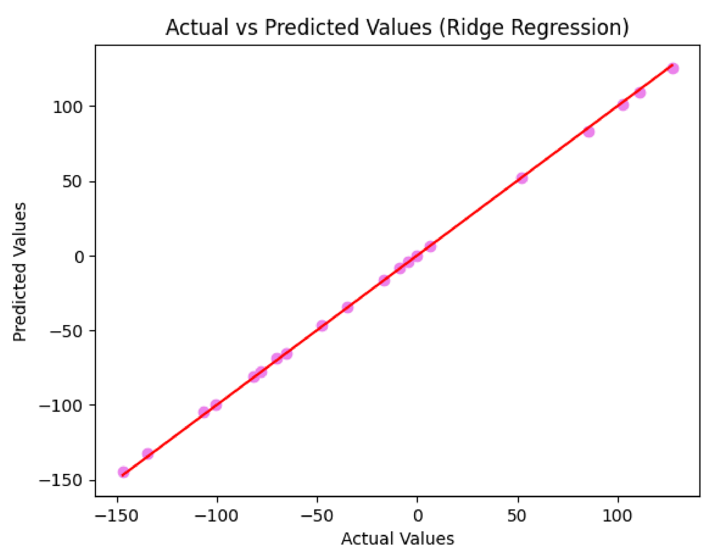
Analysis

Our target variables are continuous that's why we used ridge regression as a substitue for the logistic.

The MSE value of approximately 1.71 indicates that, on average, the squared difference between the actual and predicted target values is 1.71 clsoer to actual value

R-squared score of approximately 0.9997 suggests that the Ridge regression model explains about 99.97% perfectly explain the variance in the target variable.

```
# Plotting the actual vs predicted values
plt.scatter(y_test, predictions, color='violet')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='-')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values (Ridge Regression)')
plt.show()
```



Analysis

The visual aod seems that the Actual Value was 50 and 100. Then the Predicted Values are: 100, 50, -50, -100, -150, -150. The model's predictions seem to be lower that actual in some instances and higher to others, However the Actual value of 100 was accurate. Since that all feautures are on the same scale then it capturing the true relationship between the features and target variable accurately.

Part 3: Decision Trees

A flowchart structure used for classification or regression, where each internal node represents a test on an attribute (feature), branches represent the outcome of the test, and leaf nodes represent the class label (classification) or numerical value (regression).

Decision tree or if-else statements used to determine the best feature and decision rule for splitting data, minimizing squared error at each node.

Installing graphiz for displaying the image

```
!pip install graphviz
```

```
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (0.20.1)
```

Importing Libraries

```
from sklearn.tree import DecisionTreeRegressor, export_graphviz
from IPython.display import display, Image
import graphviz
```

```
#data["condition"].fillna(data["condition"].mean(), inplace = True)
```

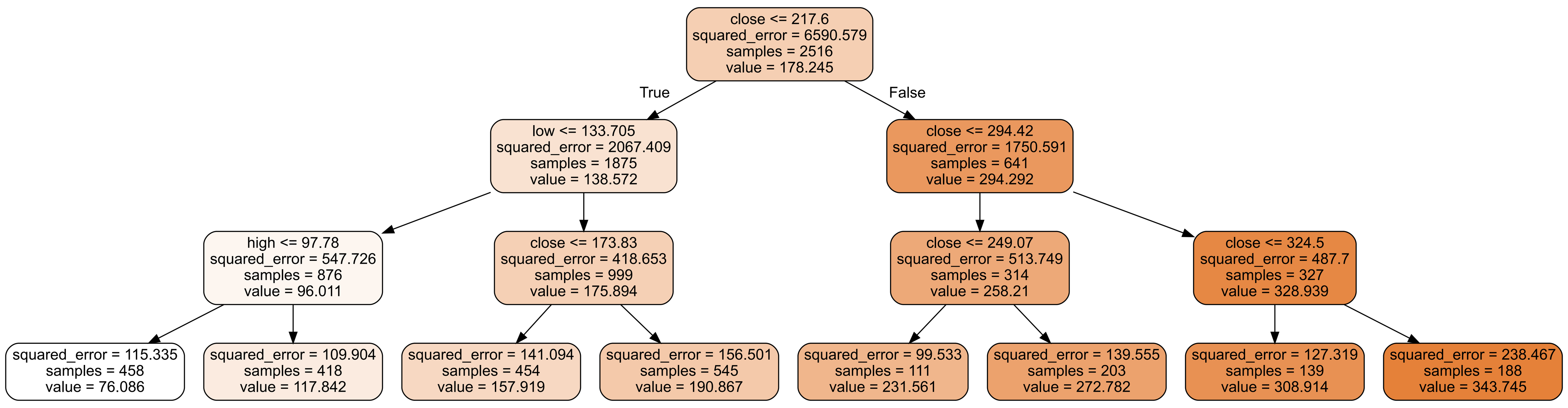
```
# Dependent variable
y_target = stock["next_day_close"].values
```

```
# 4 important variables
columns = ["open", "close", "low", "high"]
X_input = stock[list(columns)].values
```

```
# Creating Decision Tree Regression
regressor = DecisionTreeRegressor(max_depth=3) # depth 3 meand that tree will make split up to 3 levels deep.

#used to make prediction on new data
regressor.fit(X_input, y_target)
```

```
▾       DecisionTreeRegressor
DecisionTreeRegressor(max_depth=3)
```

```
# exporting the train decision tree model into textual representation in DOT format which is a graph description.
dot_data = export_graphviz(regressor, out_file=None, feature_names=columns, filled=True, rounded=True)
# represent the decision tree graph from DOT data
graph = graphviz.Source(dot_data)

# set the length and width of the graph
graph.format = 'png'  # or 'pdf', 'svg', etc.
graph.render("decision_tree_graph", format='png', cleanup=True, view=True, directory=None, quiet=False, quiet_view=False) # Save the graph to a file

# Displaying the decision tree
display(graph)
```



Analysis

The squared errors for specific condition and no. of samples indicates as data points that meet that condition.

For the first line the condition is met (high <=97.78), the squared error is 115.335 calculated based on 458 samples.

For the second line the condition is met (high <=97.78) is true, used in calculation 76.086

The squared errors and no of sample are calculated in different consditions for ex. "high <=97.78", low <= 133.705", and "close <=173.83" represent different rules or threshold for splitting data based on values of features.

The true condition lead to one branch of decision tree as true, false lead to another branch as false.

Evaluation for Decision Tree

```
# Predict the target variable using the trained model
y_pred = regressor.predict(X_input)

# Compute Mean Squared Error (MSE)
mse = mean_squared_error(y_target, y_pred)
print("Mean Squared Error:", mse)

# Compute R-squared (R2) score
r_squared = r2_score(y_target, y_pred)
print("R-squared:", r_squared)
```

```
    Mean Squared Error: 139.11747590258972
    R-squared: 0.9788914628869912
```

Analysis

Since we used Decision Tree Regressor, the evaluation metrics will be MSE and R2 score.

Results suggest that the regression model has performed well, with a relatively low MSE as 139.12 and a high R2 score as 0.979 0r 97.9%. It indicates that the model's predictions are close to the actual values, and the model explains a large portion of the variability in the target variable.

Note:

- y_test or y_pred containeed continuous values instead of dicrete class we can't used confusion matrix for that.
- Decision Tree Classifier used for classification problems where target variable is categorical "class labels".

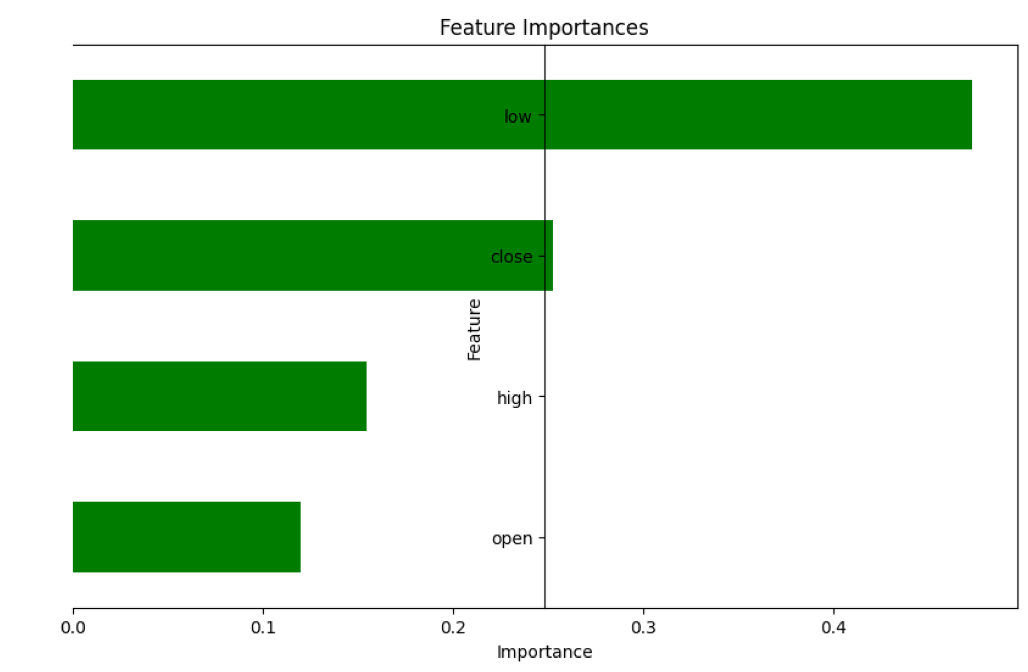
Part 4: Random Forest

An ensemble learning method that combines multiple decision trees to improve prediction accuracy and prevent overfitting.

```
# Contain the values of all columns in data except 'date'
X = stock.drop(["date"],axis=1).values
```

```
# Removing rows with missing values
x = stock.dropna(inplace = True)
```

```
# Train the random forest regressor model
regressor = RandomForestRegressor()
regressor.fit(X_train, y_train)

# Get feature importances from the trained random forest regressor model
feature_importances = regressor.feature_importances_

# Get the names of the features
feature_names = ['open','high', 'low', 'close']

# Create a Series with feature importances and their corresponding column names
model_ranks = pd.Series(feature_importances, index=feature_names, name='Importance')

# Sort feature importances
model_ranks = model_ranks.sort_values(ascending=True)

# Create horizontal bar plot
plt.figure(figsize=(10, 6))
ax = model_ranks.plot(kind='barh', color='green')

# Set plot title and labels
plt.title('Feature Importances')
plt.xlabel('Importance')
plt.ylabel('Feature')

# Move x-axis to the center
ax.spines['left'].set_position('center')

# Show plot
plt.show()
```



Analysis:

It's very essential to know what's the important variable in the model. So it's easy to identify what features contribute the most model's predictions. Which variables have little to no impact on prediction.

We used to display the importance variable in order for us to provide insight in the relationship between features and target variables that can useful for feature selection.

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

X = stock[['open','high', 'low', 'close']]  # Independent variables
y = stock['next_day_close']  # Dependent variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)

# Calling the module
# 100 = parameters/ reproducibility
rf = RandomForestRegressor(n_estimators = 100, random_state=42)
rf.fit(X_train, y_train)

# Generates the predictions in given data
y_train_pred = rf.predict(X_train)
y_test_pred = rf.predict(X_test)
```

```
import pandas as pd

# Contains predicted values of training set in y_train_pred
y_train_pred = pd.DataFrame(y_train_pred, columns =['yPredict'])
y_train_pred
```

	yPredict
0	337.834301
1	180.930000
2	111.489999
3	231.566498
4	167.470501
...	...
1756	175.202799
1757	275.835602
1758	127.633797
1759	148.666199
1760	233.130495

1761 rows × 1 columns

Analysis

it's important the know the y_train_pred for evaluating the performance model on training data. By comparing the predicted values with actual values.

This information can be sued to fine-tune the model to prevent overfitting.

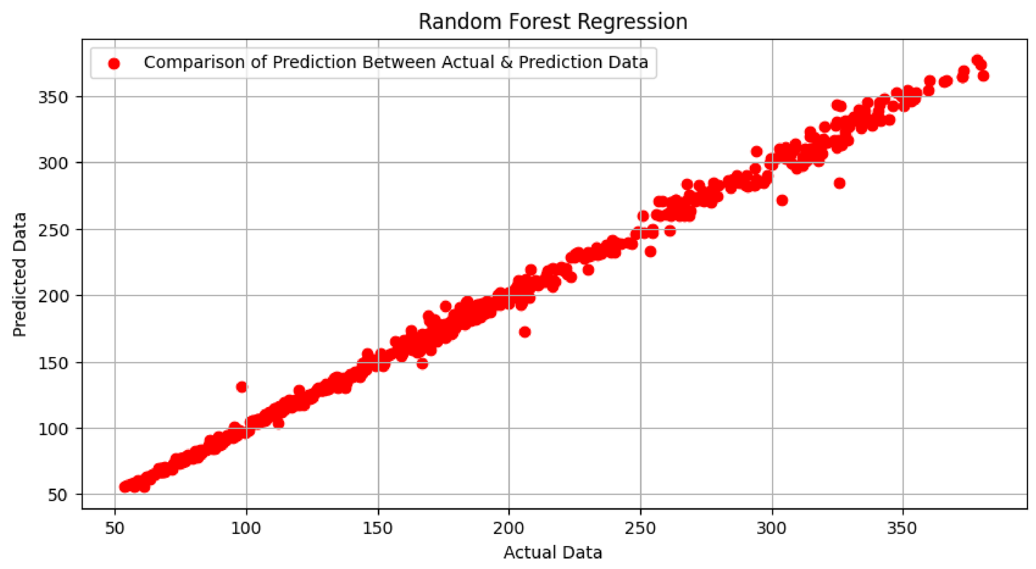
```
# Generates prediction in x_test that stored to y_test_pred
y_test_pred
```

```
array([149.75509966, 141.69479818, 111.30600024, 168.43439985,
       136.57419855, 170.65679782, 165.66380099, 330.44920589,
       151.69659998, 222.6278997 ,  83.57120116, 179.40290157,
        68.50380026,  93.79530192, 111.50920074,  82.30570015,
       287.62649971, 113.232799  , 277.64359465, 187.2568986 ,
       176.69480213, 274.51760347, 304.42720034, 200.98479955,
       130.10230006, 148.18960102,  79.59409949, 124.09210148,
       192.52709883, 177.96520099, 176.90250444, 291.49739723,
        68.67709995, 180.60070153, 218.80610069, 185.21649659,
        91.46140064, 150.74800034, 105.91259894, 165.94729936,
        79.82539921,  94.2900996 ,  95.27829986, 155.20690171,
       250.19520151, 318.29900137, 205.60779767,  76.65639989,
       170.45299855, 169.17669876, 285.3403985 , 237.19129811,
       135.43799957, 112.17849897, 163.54820015, 111.19049966,
       172.49170094, 163.82680081, 269.34699625, 107.53799987,
       309.7386973 , 163.02799984, 282.00040102, 175.11720201,
        77.77760072, 310.50220187, 196.08479935, 122.11489856,
       226.96189908, 162.47469871, 227.42099927, 208.17180081,
       209.91310334,  75.02969859, 193.09459778, 350.65000259,
       283.70010126, 178.98920216, 262.2841953 ,  66.04709924,
       202.7309978 , 210.931499  , 118.57330026, 309.63889695,
       196.77379455,  93.65810025,  94.48980204, 128.51600156,
       106.8713009 , 312.41389954, 129.96559815, 194.26849877,
       331.21380017, 131.51279712, 194.23079652, 293.84929986,
       184.28419791,  77.53909944, 296.76800292, 132.02469719,
       310.69130002, 329.46899701, 152.67840237, 267.76909041,
       190.3531017 , 170.13209813, 118.2513001 ,  74.09200016,
       117.73070021, 187.13199872,  64.44709975, 167.7391013 ,
       283.65260041, 108.65399914, 114.59009923, 182.43809794,
       350.68809674, 165.58799909, 248.52590098, 236.69580278,
       231.48479849, 173.73740032, 273.65230188,  74.89309915,
       176.68279904, 371.44210258, 183.00999995, 128.99020389,
        76.99379906, 221.79140303,  62.45869997, 232.24279948,
       270.38750043, 150.50570028,  79.91209952, 272.00830252,
       269.84610635, 124.14580071,  75.58610031, 318.31989737,
       187.58079662, 309.49439682, 160.37800105, 201.96329762,
       182.44879822, 130.01819866, 121.8761987 , 217.4258029 ,
        79.6393995 , 340.88730362, 182.46260082, 199.62970199,
       199.69380106, 165.9782001 , 167.49280034, 167.78119972,
        64.40759817, 165.84219773, 273.7391    , 136.03499762,
       203.533999  ,  93.25569982, 129.1775033 ,  64.90730032,
       175.84779955, 207.43900133, 175.83039933, 114.82120043,
       116.86279934, 297.0730967 , 318.85119821,  82.61090017,
       133.13959878, 199.36920154, 156.63580027, 106.27280021,
       272.25930561, 272.32650165, 161.62779957, 131.36840007,
       123.89170079, 335.91589807, 366.88620471, 164.79730161,
        88.97740022,  73.06299918, 115.28489842, 123.2331012 ,
       182.37560089, 103.04140077, 130.68800005, 131.8172985 ,
        58.2303003 , 176.69319816,  82.02180012, 176.53830015,
       110.38100126, 253.7178958 , 170.3923009 , 201.16839889,
       324.48259953, 166.44899919, 184.03189929, 331.76900251,
       162.24899943, 164.76899991, 196.90119955, 189.99859979,
       293.71330679, 128.3147972 ,  95.34039921,  73.5619993 ,
       161.29669977, 166.87670181, 162.56379889, 340.71050868,
       118.73249853, 220.8908019 , 180.26669941, 186.22569957,
       175.37249996, 198.43890119, 227.95970058, 182.61959922,
       119.04609856, 187.68189861, 176.59579995,  94.90230099,
       117.12109873, 360.04730753, 262.17209203, 133.67209682,
```

```
# Size of data and numbers of features.
stock.shape
```

```
(2516, 21)
```

```
plt.figure(figsize=(10, 5))
plt.scatter(y_test, y_test_pred, color='red', label='Comparison of Prediction Between Actual & Prediction Data')
plt.legend()
plt.grid()
plt.title('Random Forest Regression')
plt.xlabel('Actual Data')
plt.ylabel('Predicted Data')
plt.show()
```



Analysis

The visual aid compares the actual and predicted data for random forest regression. It suggest that the model was able to predict values for the test set with accuracy.

Evaluation for Random Forest (Actual vs. Predicted)

```
from sklearn.metrics import mean_squared_error, r2_score

# Make predictions on the training and testing data
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

# Calculate MSE for training and testing data
mse_train = mean_squared_error(y_train, y_train_pred)
mse_test = mean_squared_error(y_test, y_test_pred)

# Calculate R-squared for training and testing data
r2_train = r2_score(y_train, y_train_pred)
r2_test = r2_score(y_test, y_test_pred)

# Print results
print(f"Random Forest Train MSE: {mse_train:.2f}")
print(f"Random Forest Test MSE: {mse_test:.2f}")
print(f"Random Forest Train R2 Score: {r2_train:.2f}")
print(f"Random Forest Test R2 Score: {r2_test:.2f}")
```

```
Random Forest Train MSE: 22.96
Random Forest Test MSE: 19.77
Random Forest Train R2 Score: 1.00
Random Forest Test R2 Score: 1.00
```

Analysis

MSE values for both training and testing datasets are relatively low, with test MSE (19.77) being slightly low than train MSE (22.96). Indicates that the model generalizes well to unseen data.

Both train and test of R2 score are equal to 1, indicates that the model explains nearly variability in data.

It suggest that the model captures the patterns in data effectively without memorizing it, allowing to make accurate predictions on new data samples (unseen data that hasn't been trained on).

```
# Generating a sample dataset
X, y = make_regression(n_samples=100, n_features=4, noise=0.1, random_state=42)

# Creating a random forest regressor model
regressor = RandomForestRegressor(n_estimators=100, random_state=42)

# Fitting the model to the data
regressor.fit(X, y)

# Visualizing the decision trees in the random forest
dot_data = export_graphviz(regressor.estimators_[0],
                           out_file=None,
                           feature_names=['open', 'high', 'low', 'close'],
                           filled=True,
                           rounded=True)
graph = graphviz.Source(dot_data)
display(graph)
```