main

March 22, 2024

Importing the necessary libraries.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score,mean_squared_error, mean_absolute_error
import warnings
warnings.filterwarnings("ignore")
```

Data Collection and Analysis

[2]:
```
gold_data = pd.read_csv('gold_price_data.csv')
```

Displaying the first 5 rows of dataframe

[3]:
```
gold_data.head()
```

[3]:

	Date	SPX	GLD	USO	SLV	EUR/USD
0	1/2/2008	1447.160034	84.860001	78.470001	15.180	1.471692
1	1/3/2008	1447.160034	85.570000	78.370003	15.285	1.474491
2	1/4/2008	1411.630005	85.129997	77.309998	15.167	1.475492
3	1/7/2008	1416.180054	84.769997	75.500000	15.053	1.468299
4	1/8/2008	1390.189941	86.779999	76.059998	15.590	1.557099

Displaying the last 5 rows of dataframe

[4]:
```
gold_data.tail()
```

[4]:

	Date	SPX	GLD	USO	SLV	EUR/USD
2285	5/8/2018	2671.919922	124.589996	14.0600	15.5100	1.186789
2286	5/9/2018	2697.790039	124.330002	14.3700	15.5300	1.184722
2287	5/10/2018	2723.070068	125.180000	14.4100	15.7400	1.191753
2288	5/14/2018	2730.129883	124.489998	14.3800	15.5600	1.193118
2289	5/16/2018	2725.780029	122.543800	14.4058	15.4542	1.182033

No. of rows and columns

[5]:
```python
shape = gold_data.shape
print("Rows",shape[0])
print("Columns",shape[1])
```

```
Rows 2290
Columns 6
```

[6]:
```python
gold_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2290 entries, 0 to 2289
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Date     2290 non-null   object
 1   SPX      2290 non-null   float64
 2   GLD      2290 non-null   float64
 3   USO      2290 non-null   float64
 4   SLV      2290 non-null   float64
 5   EUR/USD  2290 non-null   float64
dtypes: float64(5), object(1)
memory usage: 107.5+ KB
```

[7]:
```python
gold_data['Date'] = pd.to_datetime(gold_data['Date'])
```

[8]:
```python
gold_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2290 entries, 0 to 2289
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Date     2290 non-null   datetime64[ns]
 1   SPX      2290 non-null   float64
 2   GLD      2290 non-null   float64
 3   USO      2290 non-null   float64
 4   SLV      2290 non-null   float64
 5   EUR/USD  2290 non-null   float64
dtypes: datetime64[ns](1), float64(5)
memory usage: 107.5 KB
```

[9]:
```python
gold_data['Day'] = gold_data['Date'].dt.day
gold_data['Month'] = gold_data['Date'].dt.month
gold_data['Year'] = gold_data['Date'].dt.year
```

[10]:
```python
gold_data.head()
```

```
[10]:          Date          SPX        GLD        USO     SLV   EUR/USD  Day  Month  \
0  2008-01-02  1447.160034  84.860001  78.470001  15.180  1.471692    2      1
1  2008-01-03  1447.160034  85.570000  78.370003  15.285  1.474491    3      1
2  2008-01-04  1411.630005  85.129997  77.309998  15.167  1.475492    4      1
3  2008-01-07  1416.180054  84.769997  75.500000  15.053  1.468299    7      1
4  2008-01-08  1390.189941  86.779999  76.059998  15.590  1.557099    8      1

   Year
0  2008
1  2008
2  2008
3  2008
4  2008
```

```
[11]: gold_data.drop(labels=['Date'],axis=1,inplace=True)
```

```
[12]: gold_data.head()
```

```
[12]:          SPX        GLD        USO     SLV   EUR/USD  Day  Month  Year
0  1447.160034  84.860001  78.470001  15.180  1.471692    2      1  2008
1  1447.160034  85.570000  78.370003  15.285  1.474491    3      1  2008
2  1411.630005  85.129997  77.309998  15.167  1.475492    4      1  2008
3  1416.180054  84.769997  75.500000  15.053  1.468299    7      1  2008
4  1390.189941  86.779999  76.059998  15.590  1.557099    8      1  2008
```

```
[13]: gold_data.tail()
```

```
[13]:             SPX         GLD      USO      SLV   EUR/USD  Day  Month  Year
2285  2671.919922  124.589996  14.0600  15.5100  1.186789    8      5  2018
2286  2697.790039  124.330002  14.3700  15.5300  1.184722    9      5  2018
2287  2723.070068  125.180000  14.4100  15.7400  1.191753   10      5  2018
2288  2730.129883  124.489998  14.3800  15.5600  1.193118   14      5  2018
2289  2725.780029  122.543800  14.4058  15.4542  1.182033   16      5  2018
```

Check for missing values

```
[14]: gold_data.isnull().sum()
```

```
[14]: SPX        0
GLD        0
USO        0
SLV        0
EUR/USD    0
Day        0
Month      0
Year       0
dtype: int64
```

Check for duplicate values

[15]:
```
gold_data.duplicated()
```

[15]:
```
0       False
1       False
2       False
3       False
4       False
        …
2285    False
2286    False
2287    False
2288    False
2289    False
Length: 2290, dtype: bool
```

[16]:
```
gold_data.duplicated().sum()
```

[16]: 0

Statistical measures of data

[17]:
```
gold_data.describe()
```

[17]:

	SPX	GLD	USO	SLV	EUR/USD
count	2290.000000	2290.000000	2290.000000	2290.000000	2290.000000
mean	1654.315776	122.732875	31.842221	20.084997	1.283653
std	519.111540	23.283346	19.523517	7.092566	0.131547
min	676.530029	70.000000	7.960000	8.850000	1.039047
25%	1239.874969	109.725000	14.380000	15.570000	1.171313
50%	1551.434998	120.580002	33.869999	17.268500	1.303297
75%	2073.010070	132.840004	37.827501	22.882500	1.369971
max	2872.870117	184.589996	117.480003	47.259998	1.598798

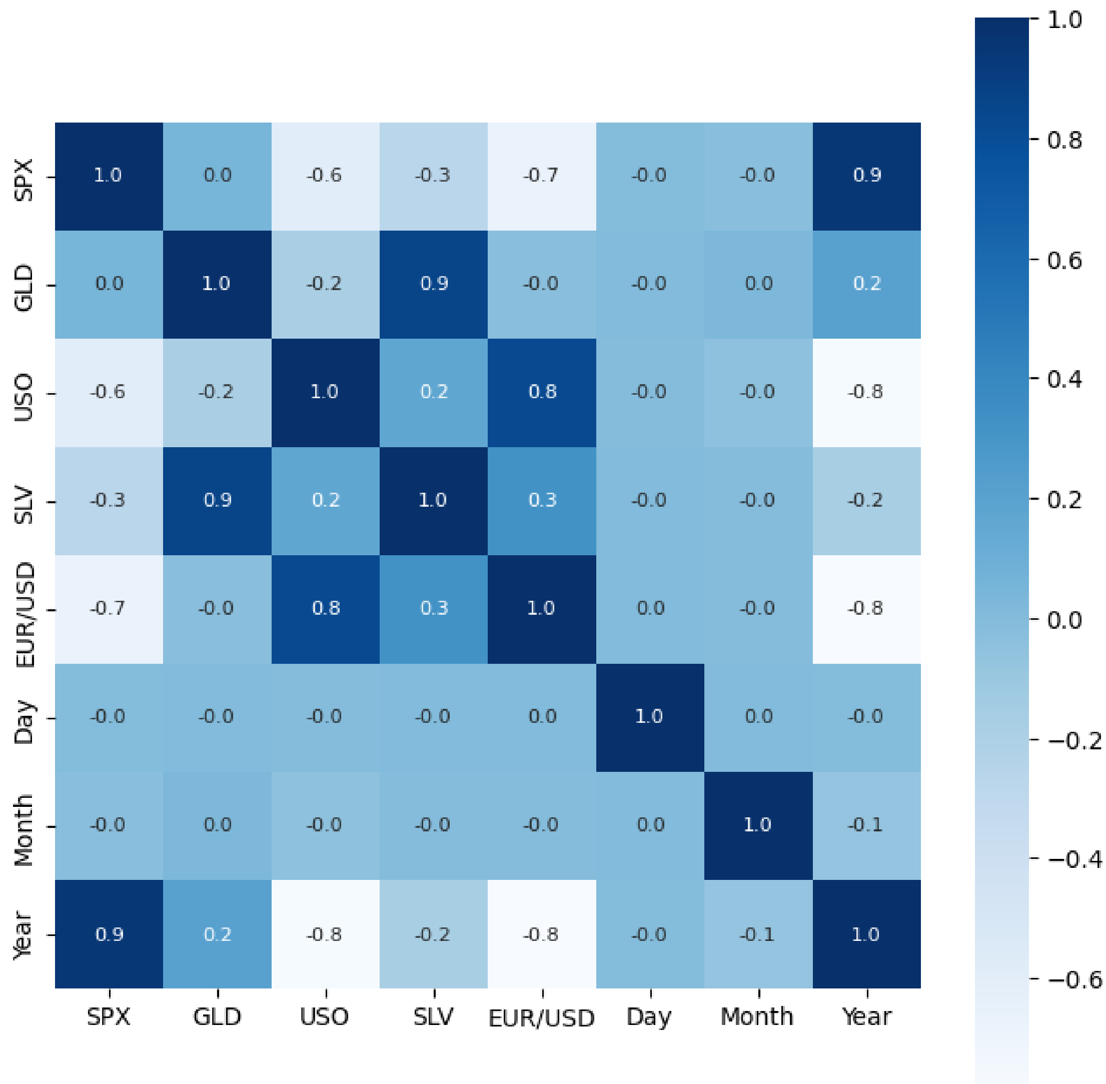
	Day	Month	Year
count	2290.000000	2290.000000	2290.000000
mean	15.644541	6.329258	2012.724891
std	8.746132	3.591149	2.993271
min	1.000000	1.000000	2008.000000
25%	8.000000	3.000000	2010.000000
50%	15.500000	6.000000	2013.000000
75%	23.000000	10.000000	2015.000000
max	31.000000	12.000000	2018.000000

Check for correlation 1. Positive Correlation -> if 2 variables are directly proportional 2. Negative Correlation -> if 2 variables are inversly proportional

[18]:
```python
correlation = gold_data.corr()
```

Constructing a heatmap for understanding correlation

[19]:
```python
plt.figure(figsize=(8,8))
sns.heatmap(correlation,cbar=True,square=True,fmt='.
 ↪1f',annot=True,annot_kws={'size':8},cmap='Blues')
plt.show()
```

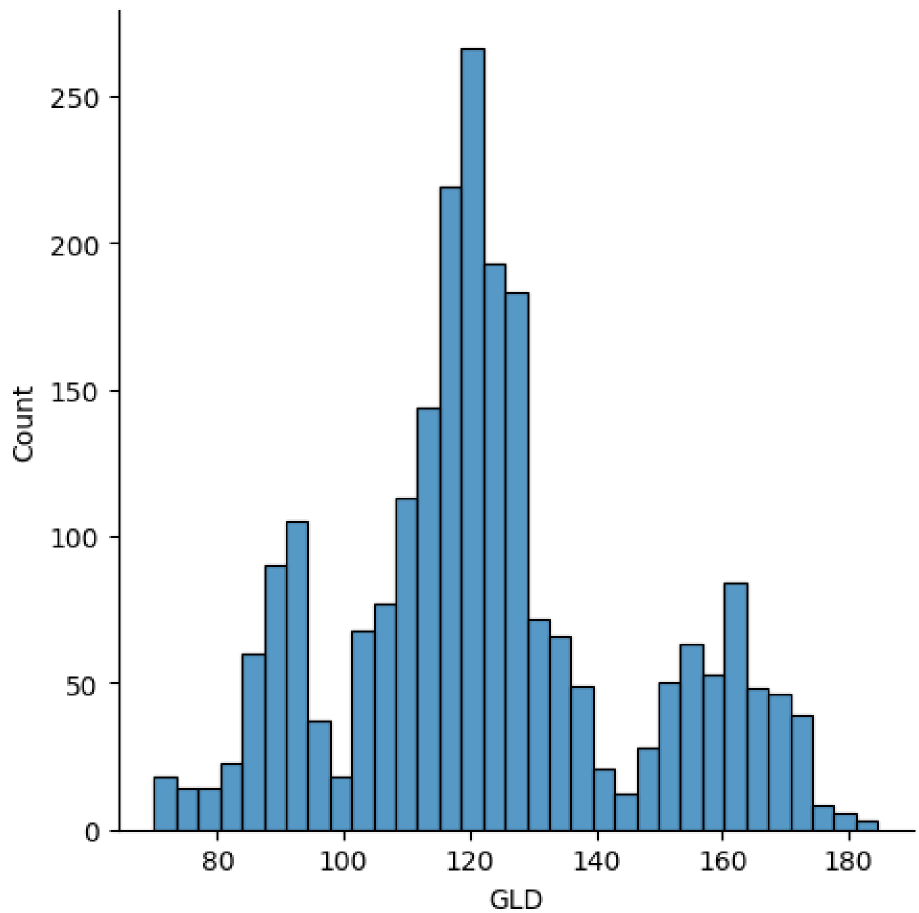


[20]:
```python
correlation['GLD']
```

[20]:
```
SPX        0.049345
GLD        1.000000
```

```
USO       -0.186360
SLV        0.866632
EUR/USD   -0.024375
Day       -0.000198
Month      0.020494
Year       0.206654
Name: GLD, dtype: float64
```

[21]:
```python
sns.displot(gold_data['GLD'])
plt.show()
```



Splitting the dataframe into independent and dependent features

[22]:
```python
X = gold_data.drop(labels=['GLD'],axis=1)
y = gold_data['GLD']
```

[23]:
```python
print(X)
```

```
                SPX         USO        SLV    EUR/USD  Day  Month  Year
```

```
0     1447.160034  78.470001  15.1800  1.471692   2      1  2008
1     1447.160034  78.370003  15.2850  1.474491   3      1  2008
2     1411.630005  77.309998  15.1670  1.475492   4      1  2008
3     1416.180054  75.500000  15.0530  1.468299   7      1  2008
4     1390.189941  76.059998  15.5900  1.557099   8      1  2008
…          …          …        …        …    …    …    …
2285  2671.919922  14.060000  15.5100  1.186789   8      5  2018
2286  2697.790039  14.370000  15.5300  1.184722   9      5  2018
2287  2723.070068  14.410000  15.7400  1.191753  10      5  2018
2288  2730.129883  14.380000  15.5600  1.193118  14      5  2018
2289  2725.780029  14.405800  15.4542  1.182033  16      5  2018

[2290 rows x 7 columns]
```

[24]:
```
print(y)
```

```
0        84.860001
1        85.570000
2        85.129997
3        84.769997
4        86.779999
           …
2285    124.589996
2286    124.330002
2287    125.180000
2288    124.489998
2289    122.543800
Name: GLD, Length: 2290, dtype: float64
```

Splitting the data into train and test data

[25]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
 ↪2,random_state=2)
```

Model Training

1. Linear Regression

[26]:
```
linear_reg = LinearRegression()
```

[27]:
```
linear_reg.fit(X_train,y_train)
```

[27]: LinearRegression()

[28]:
```
X_test_pred = linear_reg.predict(X_test)
```

[29]:
```
score = r2_score(y_test,X_test_pred)
print("R2 Score:",score)
```

```
mse = mean_squared_error(y_test,X_test_pred)
print("Mean Squared Error:", mse)

mae = mean_absolute_error(y_test,X_test_pred)
print("Mean Absolute Error:", mae)
```

```
R2 Score: 0.8951756144813316
Mean Squared Error: 55.28894085182888
Mean Absolute Error: 5.440993599415312
```

2. Decision Tree Regressor

[30]:
```
DTR = DecisionTreeRegressor()
```

[31]:
```
DTR.fit(X_train,y_train)
```

[31]:
```
DecisionTreeRegressor()
```

[32]:
```
X_test_pred = DTR.predict(X_test)
```

[33]:
```
score = r2_score(y_test,X_test_pred)
print("R2 Score:",score)

mse = mean_squared_error(y_test,X_test_pred)
print("Mean Squared Error:", mse)

mae = mean_absolute_error(y_test,X_test_pred)
print("Mean Absolute Error:", mae)
```

```
R2 Score: 0.9923888658867422
Mean Squared Error: 4.014443220640711
Mean Absolute Error: 1.2198552772925764
```

3. Random Forest Regressor

[34]:
```
regressor = RandomForestRegressor(n_estimators=100)
```

[35]:
```
regressor.fit(X_train,y_train)
```

[35]:
```
RandomForestRegressor()
```

[36]:
```
X_test_pred = regressor.predict(X_test)
```

[37]:
```
score = r2_score(y_test,X_test_pred)
print("R2 Score:",score)

mse = mean_squared_error(y_test,X_test_pred)
print("Mean Squared Error:", mse)
```

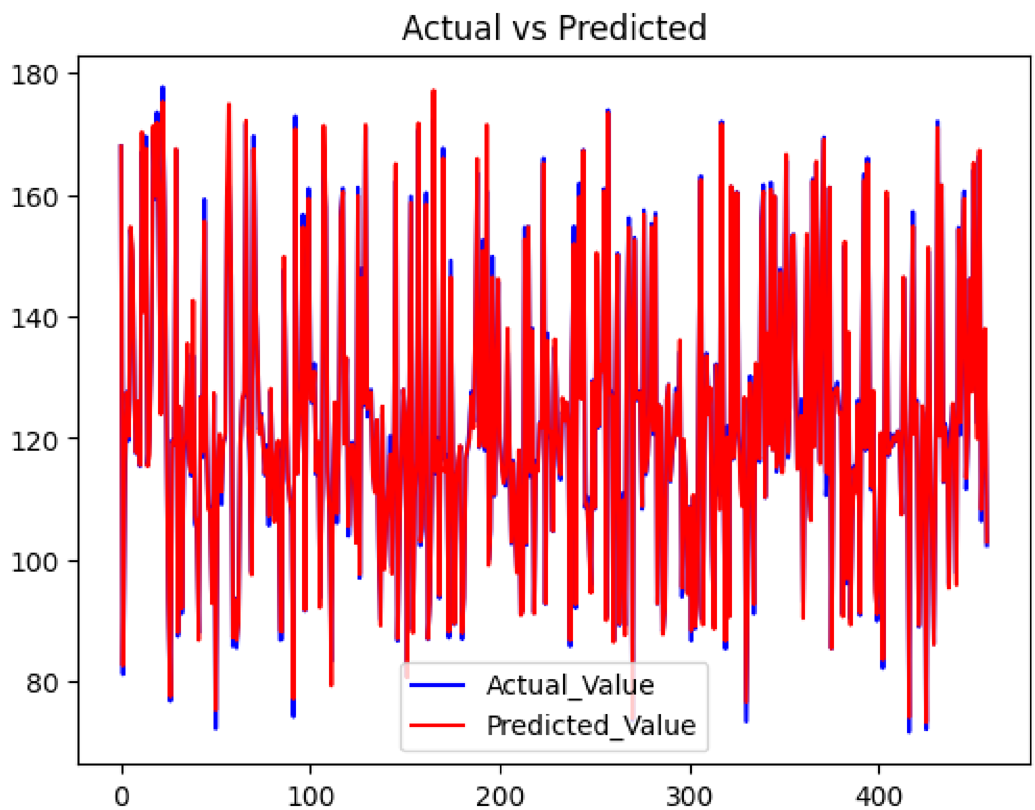
```
mae = mean_absolute_error(y_test,X_test_pred)
print("Mean Absolute Error:", mae)
```

```
R2 Score: 0.9953724047837169
Mean Squared Error: 2.4407950204842086
Mean Absolute Error: 0.9843287218340594
```

Compare the actual values and predicted values in plot

[38]:
```
y_test = list(y_test)
```

[39]:
```
plt.plot(y_test,color='blue',label='Actual_Value')
plt.plot(X_test_pred,color='red',label='Predicted_Value')
plt.title('Actual vs Predicted')
plt.legend()
plt.show()
```



As the Random Forest Regressor is predicting more accurately so we use it for creating the predictive system

Creating the predictive system

[40]:

```python
input_data = [1252.540039,101.459999,17.26,1.5673,2008,7,24] # y = 91.330002

# Convert the list to a numpy array for easy manipulation
input_data = np.array(input_data)

# reshape array as we are predicting for one instance
input_data_reshaped = input_data.reshape(1,-1)

prediction = regressor.predict(input_data_reshaped)
print("Gold price for given input is:",prediction)
```

```
Gold price for given input is: [90.91029921]
```