## **Importing the Libraries**

```
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.ensemble import RandomForestRegressor
from sklearn import metrics
```

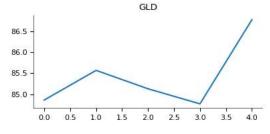
## **Data Collection and Processing**

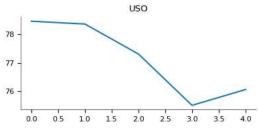
```
# loading the csv data to a Pandas DataFrame
gold_data = pd.read_csv('/content/gld_price_data.csv')
# print first 5 rows in the dataframe
gold_data.head()
```

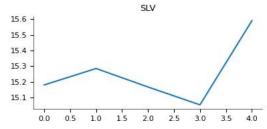
	Date	SPX	GLD	USO	SLV	EUR/USD	$\blacksquare$
0	1/2/2008	1447.160034	84.860001	78.470001	15.180	1.471692	11.
1	1/3/2008	1447.160034	85.570000	78.370003	15.285	1.474491	
2	1/4/2008	1411.630005	85.129997	77.309998	15.167	1.475492	
3	1/7/2008	1416.180054	84.769997	75.500000	15.053	1.468299	
4	1/8/2008	1390.189941	86.779999	76.059998	15.590	1.557099	

### Values

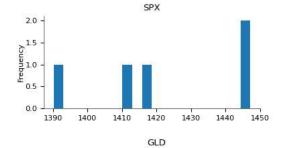


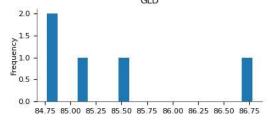


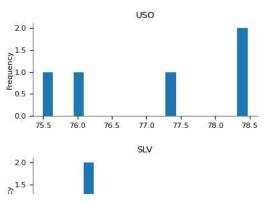




# Distributions



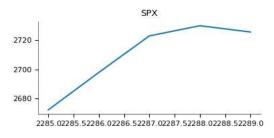


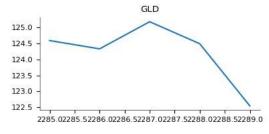


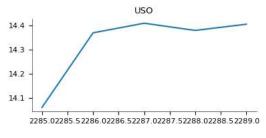
# print last 5 rows of the dataframe
gold\_data.tail()



#### Values

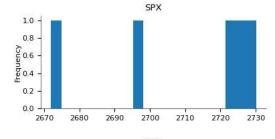


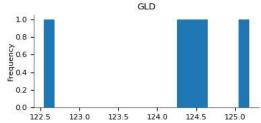


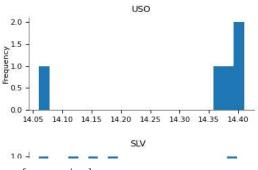




## Distributions







# number of rows and columns
gold\_data.shape

 $\mbox{\tt\#}$  getting some basic informations about the data  $\mbox{\tt gold\_data.info()}$ 

<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 SPX 2290 non-null float64 GLD 2290 non-null float64 US0 2290 non-null float64 3 SLV 2290 non-null float64 EUR/USD 2290 non-null float64

dtypes: float64(5), object(1)
memory usage: 107.5+ KB

# checking the number of missing values
gold\_data.isnull().sum()

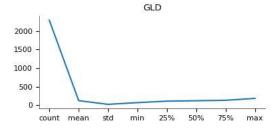
```
Date 0
SPX 0
GLD 0
USO 0
SLV 0
EUR/USD 0
dtype: int64
```

# getting the statistical measures of the data gold\_data.describe()

	SPX	GLD	USO	SLV	EUR/USD	=
count	2290.000000	2290.000000	2290.000000	2290.000000	2290.000000	11.
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	

## Values







# Correlation:

- 1. Positive Correlation
- 2. Negative Correlation

```
correlation = gold_data.corr()
# constructing a heatmap to understand the correlatiom
plt.figure(figsize = (8,8))
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f',annot=True, annot_kws={'size':8}, cmap='Blues')
```

```
<ipython-input-9-ac468a117088>:1: FutureWarning: The default value of numeric_only in Da
       correlation = gold_data.corr()
     <Axes: >
                                                                                            1.0
                                                                                            0.8
      SPX
                              0.0
                                            -0.6
                                                           -0.3
                                                                         -0.7
                                                                                            0.6
      GLD
                0.0
                                            -0.2
                                                                         -0.0
                                                                                            0.4
                                                                                            0.2
      JSO
                -0.6
                              -0.2
# correlation values of GLD
```

# correlation values of GLD
print(correlation['GLD'])

```
SPX 0.049345
GLD 1.000000
USO -0.186360
SLV 0.866632
EUR/USD -0.024375
Name: GLD, dtype: float64
```

# checking the distribution of the GLD Price
sns.distplot(gold\_data['GLD'],color='green')

<ipython-input-11-b94eac2e88dd>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

USO

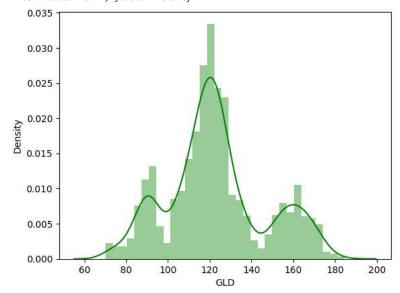
SLV

FUR/USD

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <a href="https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751">https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751</a>

sns.distplot(gold\_data['GLD'],color='green')
<Axes: xlabel='GLD', ylabel='Density'>



## **Splitting the Features and Target**

```
X = gold_data.drop(['Date','GLD'],axis=1)
Y = gold_data['GLD']
print(X)
                  SPX
                            US0
                                     SLV EUR/USD
    0
          1447.160034 78.470001 15.1800 1.471692
          1447.160034 78.370003 15.2850 1.474491
    1
          1411.630005 77.309998 15.1670 1.475492
     3
          1416.180054 75.500000 15.0530 1.468299
          1390.189941 76.059998 15.5900 1.557099
    4
    2285 2671.919922 14.060000 15.5100 1.186789
    2286 2697.790039 14.370000 15.5300 1.184722
     2287 2723.070068 14.410000 15.7400 1.191753
    2288 2730.129883 14.380000 15.5600 1.193118
    2289 2725.780029 14.405800 15.4542 1.182033
    [2290 rows x 4 columns]
print(Y)
    0
             84.860001
    1
             85.570000
             85.129997
    2
     3
             84.769997
             86.779999
    2285
            124.589996
    2286
           124.330002
    2287
            125.180000
    2288
            124.489998
            122.543800
    Name: GLD, Length: 2290, dtype: float64
```

### **Splitting into Training data and Test Data**

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state=2)
```

# **Model Training: Random Forest Regressor**

### **Model Evaluation**

```
# prediction on Test Data
test_data_prediction = regressor.predict(X_test)
print(test_data_prediction)
```

```
153.95100103 121.20859394 156.3489362 93.0493602 125.52400186
     126.14160044 87.84690022 92.31969906 126.26369918 127.96430337
     113.03239982 117.69269717 120.73140022 127.10859796 119.52300098
     137.32900041 93.98649926 119.81700042 113.36440105 94.29009927
     109.00550013 87.88449913 109.23489923 89.63409991 92.36150031
     131.91610263 162.32540003 89.36600005 119.40130098 133.5950017
     124.04670044 128.46710132 101.91449848 88.85149896 131.3031007
     119.7300001 108.61770002 168.15360125 115.25100064 86.58299949
     118.74960041 91.08919968 161.67280069 116.58740033 121.69999998
     160.36689843 120.17259969 112.69949964 108.48119877 126.73780022
      75.95280043 102.9959997 127.7304026 121.77789922 92.70440028
     132.02360078 118.18340097 115.80879991 154.95820267 158.66030046
     110.04349938 155.99279751 119.14970092 160.48320117 118.29040001
     157.87150015 115.1127992 116.37920034 150.20789946 114.81610075
     125.80409858 165.53399997 117.4625
                                          125.08299912 153.41130373
     153.46530238 131.8451002 114.80450061 121.26490215 124.78130062
      89.79290036 123.08979994 155.79400194 111.8201004 106.53159985
     161.82320134 118.38409992 165.54479947 134.22430075 115.06679969
     152.92089855 168.50970032 114.77780061 114.08420118 158.88149889
      85.2990989 127.1159006 127.81610082 129.01939999 124.33550064
     123.90940024 90.68310081 153.19219982 97.20069941 136.16799987
      88.84029931 107.53389998 115.16850045 112.78140112 124.5349993
      91.40079858 125.34960113 162.35019892 119.90629852 165.00090146
     126.87759788 112.34890017 127.55689917 94.77529915 90.79379975
     102.66239909 120.73169996 83.16679944 126.21380064 160.38650476
     117.16730083 118.25129994 119.91660003 122.74529944 120.1069014
     121.55900001 118.35560038 107.10579998 148.64770046 126.22659819
     115.72320088 73.94539988 127.82380128 154.66100061 122.12090012
     125.64720078 88.92320028 103.99009904 124.60220052 120.1938004
      73.37120093 151.81469969 121.07280041 104.70940007 86.29039784
     115.3047991 172.29169735 119.93780022 160.02799833 113.12859959
     121.01950013 118.39540099 95.89329981 118.7290003 125.86480057
     118.52849973 95.80380041 154.42520148 122.04080019 148.11149987
     159.90360216 114.01310009 122.55969933 149.95659826 127.26730018
     165.91240086 135.4577006 120.19619938 167.06889851 108.41759861
     121.77889852 138.92960088 106.82129904]
print("R squared error : ", error_score)
```

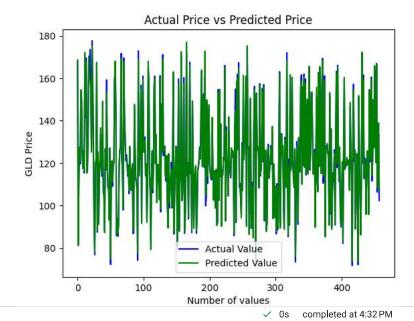
#### # R squared error

```
error_score = metrics.r2_score(Y_test, test_data_prediction)
```

R squared error : 0.9890515443068826

### Compare the Actual Values and Predicted Values in a Plot

```
Y_test = list(Y_test)
plt.plot(Y_test, color='blue', label = 'Actual Value')
plt.plot(test_data_prediction, color='green', label='Predicted Value')
plt.title('Actual Price vs Predicted Price')
plt.xlabel('Number of values')
plt.ylabel('GLD Price')
plt.legend()
plt.show()
₽
```



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