

```
In [7]: import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn import metrics
from sklearn.ensemble import RandomForestRegressor

In [9]: gold=pd.read_csv("C:\\Users\\Pranav\\Desktop\\DATA SCIENCE DATA\\CVC file\\gld_price_data.csv")
gold.head()
```

Out[9]:

	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

```
In [10]: #shape of date
gold.shape

Out[10]: (2290, 6)
```

```
In [12]: ##describe mathamatical data
gold.describe()
```

Out[12]:

	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

```
In [13]: #information about data
gold.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: 187.5+ KB

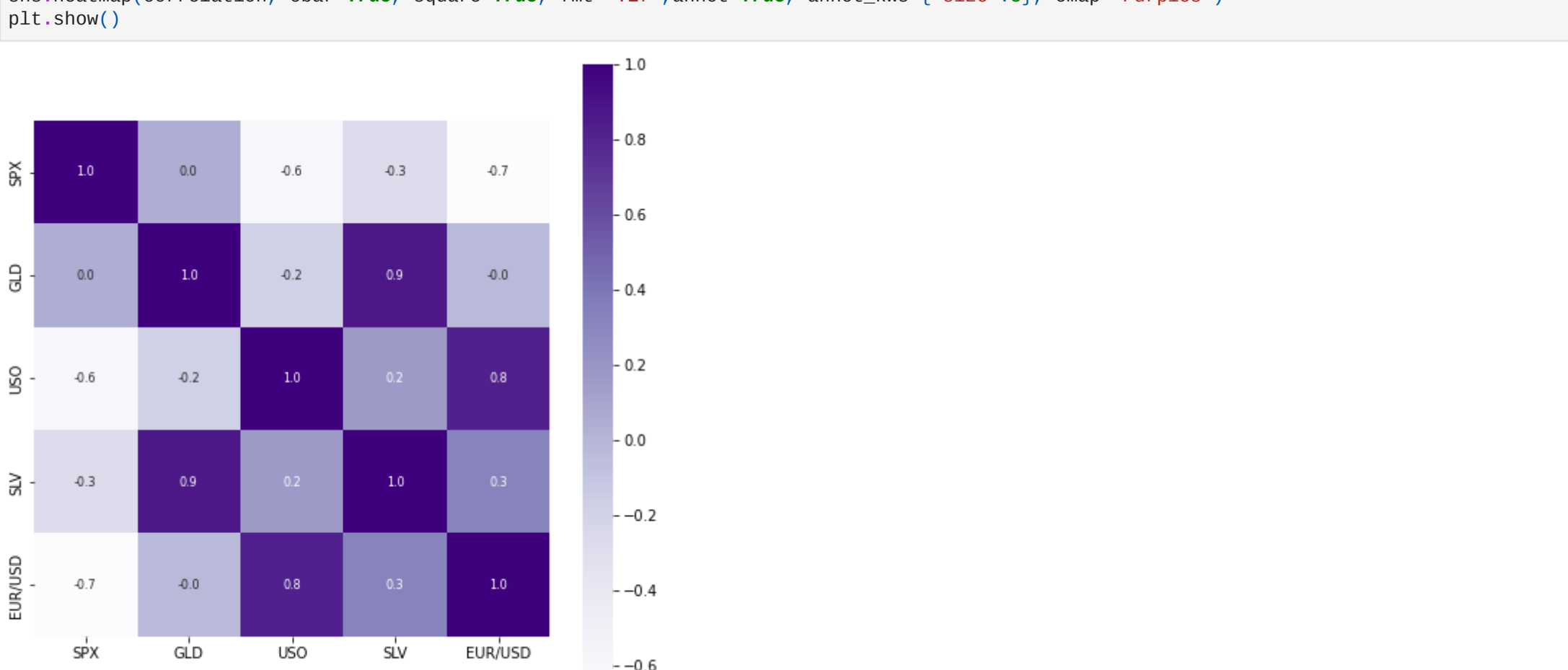
In [14]: #find the null value in data
gold.isnull().sum()

Out[14]:
Date      0
SPX        0
GLD        0
USO        0
SLV        0
EUR/USD    0
dtype: int64
```

```
In [19]: #Correlation:1-----Positive Correlation      2-----Negative Correlation
correlation=gold.corr()
print(correlation)

SPX      SPX      GLD      USO      SLV      EUR/USD
SPX      1.000000    0.049345 -0.591573 -0.274055 -0.672017
GLD      0.049345    1.000000 -0.186360  0.866632 -0.024375
USO     -0.591573   -0.186360  1.000000  0.167547  0.829317
SLV     -0.274055   0.866632  0.167547  1.000000  0.321631
EUR/USD -0.672017   -0.024375  0.829317  0.321631  1.000000
```

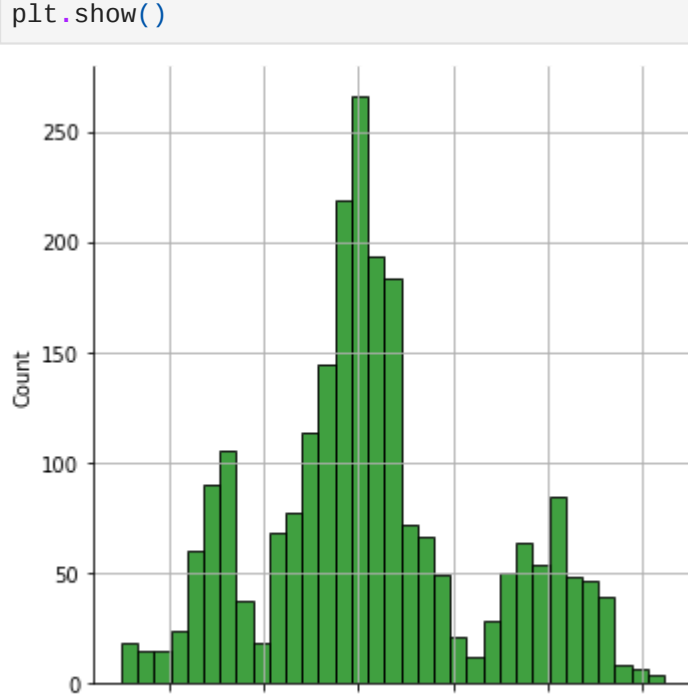
```
In [23]: # constructing a heatmap to understand the correlation
plt.figure(figsize = (8,8))
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f',annot=True, annot_kws={'size':8}, cmap='Purples')
plt.show()
```



```
In [27]: print(correlation['GLD'])

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

```
In [30]: #checking the distribution of gold price
sns.displot(gold['GLD'],color='green')
plt.grid(True)
plt.show()
```



```
In [35]: #Splitting the Features and Target
X=gold.drop(['Date','GLD'],axis=1)
y=gold['GLD']
print(X)
print(y)
```

[2290 rows x 4 columns]

0	84.860001
1	85.570000
2	85.129997
3	84.769997
4	86.779999
...	...
2285	124.589996
2286	124.380002
2287	125.180000
2288	124.489998
2289	122.543800

Name: GLD, Length: 2290, dtype: float64

```
In [34]: #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)
print("shape of X_train= ",X_train.shape)
print("shape of X_test= ",X_test.shape)
print("shape of y_train= ",y_train.shape)
print("shape of y_test= ",y_test.shape)

shape of X_train= (1832, 4)
shape of X_test= (458, 4)
shape of y_train= (1832,)
shape of y_test= (458,)
```

```
In [36]: #model training :Random forest regressor
regressor=RandomForestRegressor(n_estimators=100)
```

```
In [37]: #traing the model
regressor.fit(X_train,y_train)
```

Out[37]: RandomForestRegressor()

```
In [38]: #model evaluation
test_data_prediction=regressor.predict(X_test)
```

```
In [39]: print(test_data_prediction)

[168.78799915  81.9806998 116.27610001 127.53170076 120.62820169
154.82119761 150.3176988 126.226 117.48939894 125.84880126
116.58240062 171.93680054 142.20689822 167.97659851 115.19410017
119.05010008 149.48400297 170.2070002 159.93870353 158.22549947
155.16390023 125.31430012 175.55069994 158.93930344 125.15010058
93.62889973 77.16209998 120.18809997 119.16379956 167.44410017
87.96950029 125.16500021 91.21140057 117.72720021 121.11299927
136.67140068 115.49220098 114.95480084 147.43470003 107.23870079
104.18930273 87.30769784 126.48580062 118.1385999 153.80769898
119.52559985 108.36550011 108.05939829 93.18880043 127.22849736
75.39180037 113.58309896 121.28019994 111.39029921 118.91049889
120.87319917 159.51399985 168.30220077 146.8046968 85.90689857
94.31010058 86.89899871 90.48670013 118.83830092 126.44540059
127.47059987 169.43529938 122.23869924 117.22119907 98.61460038
168.16270129 142.90039893 132.41650223 121.06190239 121.23819955
119.78899039 114.52310158 118.07870088 107.27050075 127.87340092
114.02189939 107.52509975 127.16440049 119.70449872 88.79030048
88.39919884 146.66299934 127.39039929 113.38320016 110.41159817
108.26379891 77.68999896 170.32310179 114.26580922 121.65799893
127.96190174 154.86799806 91.72019914 136.09880099 158.67300378
125.35970103 125.38920063 130.93820106 114.99080098 119.99990002
92.12659987 110.2071988 166.91269857 156.91209869 114.34419965
106.80170138 79.1011 113.25890063 125.92190084 107.28179942
119.19200106 155.77920304 159.46679979 120.24039982 134.32790266
101.5321997 117.45819793 119.30329965 113.00610078 102.80789921
160.06799816 98.84580074 147.06139851 125.70870103 169.44699951
125.87549858 127.30539804 127.34100152 113.73869974 113.47500092
123.56299903 102.12969903 89.11609969 124.71609967 101.72819934
107.02049909 113.48470032 117.23940112 99.12879947 121.78690003
163.78439997 87.40269855 106.65629937 117.38610051 127.56420145
124.21980062 80.67859913 120.15440027 157.44919913 87.81429956
119.36679934 146.76679934 172.59449821 102.38259891 105.32430069
122.35570047 158.21120068 87.65599843 93.25750054 112.90470019
177.44359974 114.56239998 119.28419886 94.55890088 125.78470034
165.78470002 115.10010072 116.89110122 88.3933998 148.71320114
120.27909961 89.56119985 112.23259999 117.38650019 118.76790137
88.0105994 94.12700031 116.70049993 118.62190202 120.37800338
126.78959849 121.91469977 151.43749984 165.81790111 118.6174995
120.55730131 150.86000047 118.52659909 127.89469837 105.80009951
105.03230119 148.99200134 113.61520071 124.83680121 147.27169893
119.65690173 115.39080035 112.72600009 113.41490192 142.04030126
117.83909768 103.04960007 115.85510139 103.39490205 98.5913001
117.32600065 90.78900001 91.85870033 153.74959922 102.63939965
154.31980108 114.36050157 138.84950151 90.1951982 115.43089939
114.15079977 122.98560041 120.15440027 157.44919913 87.81429956
125.68940201 121.40449808 120.96049051 104.72609999 139.82750322
121.99020908 116.6211004 113.68270045 127.12259764 122.6367906
125.78300083 121.30810007 86.93279904 132.27030041 145.36880201
92.74929964 157.75299859 159.25890343 126.39649874 165.23010033
109.1324997 109.87660077 103.80589833 94.28900068 128.23070029
107.38610039 161.63949912 121.6690001 131.95770015 130.9020008
161.24979929 90.28149854 175.34500234 127.55580053 126.8877983
86.64179904 124.69999932 150.37239741 89.72120007 106.98269933
109.14179954 84.63699982 135.91819998 154.65190171 138.42640384
74.15970017 152.38010102 126.45819995 126.74109999 127.50879922
108.72079935 156.17040018 114.79270068 116.89990121 125.5915996
154.06100126 121.27669996 156.30079884 92.95670074 124.78930095
125.45930006 87.71140004 91.93689926 126.10639954 128.31990344
131.21790069 117.82979784 120.96259977 127.22339867 119.690407
136.40400076 93.80729915 120.96070041 113.06750126 94.28999922
109.0977999 87.0494992 109.61659956 89.61089995 92.51700016
131.79930281 162.55830987 89.35969993 119.35910084 133.40500172
123.73410037 128.29270229 101.98039862 89.06249881 131.30810001
119.63270046 108.35429989 169.10680076 115.23920037 86.59089906
118.76400088 90.90599965 161.82710075 116.59260047 121.64089999
160.150999 120.1190996 113.04789929 108.47689852 126.72519973
76.04070058 102.94409968 128.1457024 121.77499913 92.58760038
132.08320085 118.14970096 115.7975999 154.40660257 160.21070101
110.12309971 155.1752981 119.32850114 160.53850194 118.45220077
158.34299936 115.0484995 116.43060045 148.78349767 114.78930095
125.75059902 166.21510868 117.73169996 125.07549905 153.07320298
135.35600258 132.08439991 114.81730053 121.18740184 124.91140076
89.70510072 123.13489996 154.94930158 111.58670028 106.78229966
161.52270117 118.6622999 165.72620006 133.90930041 114.97879967
85.0260992 168.57090012 115.15679992 114.12280122 159.30020864
181.18949878 127.09120066 127.99090076 128.90930011 124.17450041
123.83400068 90.55200058 153.39850015 97.22609929 137.10769917
89.05919911 107.38429989 114.86410032 112.87290081 124.12749909
126.74049851 112.41100003 127.61339913 94.81199924 90.91260002
103.51489808 120.84199963 83.13419963 126.27129952 160.62640468
117.48280108 118.28030011 119.78189985 122.77179985 120.06570122
121.57289974 118.11080011 107.14789982 148.14840002 126.19829813
115.84330093 73.80589996 127.84010051 153.91070044 121.82650007
125.63160054 88.82240042 102.43959001 104.82430055 120.33110072
73.26330084 151.33310007 121.24899009 104.81240016 86.52679977
115.23299911 172.19599842 119.85910003 160.70169803 113.30659938
121.47870017 118.52720105 95.91579908 110.62940017 125.92390051
118.50169915 95.96830075 154.22340172 122.0560099 147.49879986
158.92740032 114.1210002 122.59419932 148.96869747 126.99430016
165.93350026 135.64640042 120.176699 167.6884976 108.31119895
121.90879851 140.88430121 106.94199905]
```

```
In [40]: # R squared error
error_square=metrics.r2_score(y_test,test_data_prediction)
```

```
In [44]: print("R squared error :", error_square)

R squared error : 0.989145707674411
```

```
In [45]: #compare the actual values and predict value in a plot
y_test=list(y_test)
```

```
In [55]: plt.figure(figsize = (20,7))
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.grid(True)
plt.show()
```

