!pip install pandas

```
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-pack Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/pyt Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dis Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.7/dist-pa
```

Double-click (or enter) to edit

Importing 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 csv to pandas data frame
gold_data = pd.read_csv('/content/gld_price_data.csv')
```

#print first five rows
gold_data.head()

	Date	SPX	GLD	US0	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

#print last five data frame
gold_data.tail()

Date SPX GLD USO SLV EUR/U	USD
----------------------------	-----

X

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#number of rows and columns
gold_data.shape

(2290, 6)

#getting some basic info about data
gold data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 2290 entries, 0 to 2289 Data columns (total 6 columns): Column Non-Null Count Dtype # ------ - ------Date 0 2290 non-null object 2290 non-null float64 1 2290 non-null float64 2 GLD 2290 non-null float64 3 US0 2290 non-null float64 4 SLV EUR/USD 2290 non-null float64 5

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

#checking 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()

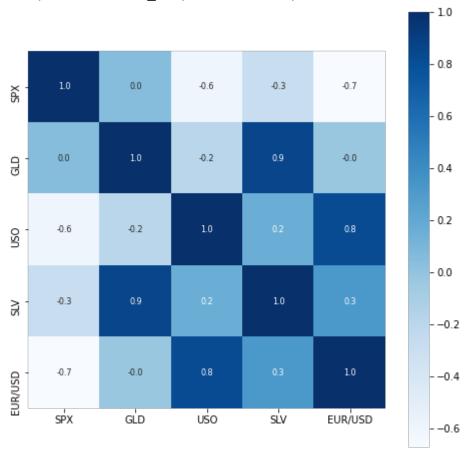
	SPX	GLD	US0	SLV	EUR/USD
count	2290.000000	2290.000000	2290.000000	2290.000000	2290.000000
mean	1654.315776	122.732875	31.842221	20.084997	1.283653
std	519.111540	23.283346	19.523517	7.092566	0.131547

correleation: 1.positive correlation 2.Negative correlation

correlation = gold_data.corr()

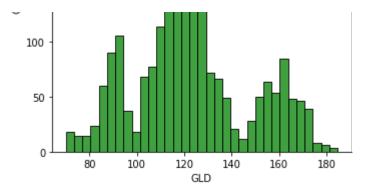
#constructing a heatmap to understand the correlation
plt.figure(figsize = (8,8))
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f',annot=True, annot_kws

<matplotlib.axes._subplots.AxesSubplot at 0x7fc9717b6ed0>



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

SPX 0.049345 GLD 1.000000



splitting the features and target (gold and date)

```
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
1	1447.160034	78.370003	15.2850	1.474491
2	1411.630005	77.309998	15.1670	1.475492
3	1416.180054	75.500000	15.0530	1.468299
4	1390.189941	76.059998	15.5900	1.557099
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]

```
model Training: Random forest Regressor
```

```
regressor = RandomForestRegressor(n_estimators=100)
#training the model
regressor.fit(X_train,Y_train)
```

Model evaluation

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

```
1//.183599/5 114.053899/5 119.238500022 94.0092004 125.4508
166.2639006 114.79080043 116.48660139 88.30239884 149.55870083
120.31389971 89.32329984 112.22320006 117.52550016 118.75680106
88.04179935 94.07690013 116.99959999 118.74670211 120.34000094
126.72729835 121.83909961 147.83840026 164.82509981 118.55569972
120.32310175 151.25430102 118.56999921 172.58109838 105.30009928
105.00220059 150.11530103 113.54730116 124.77520086 147.95020051
119.75630129 115.49720053 112.70910013 113.45340173 141.96240134
117.7650977 102.95310047 115.81740104 103.94700204 98.56550042
117.43340099 90.75380014 91.55400059 153.69229955 102.77949977
154.72820079 114.28770122 138.83100151 90.13569812 115.60169971
114.58449933 123.03300034 121.77270013 165.21610137 92.83459979
            121.43629898 120.90700049 104.77760014 140.45060319
135.127201
121.83209901 116.64780041 113.58400063 127.01209765 122.82469942
125.80669935 121.26220039 86.76309869 132.51220131 145.9791022
            159.18219961 159.50600246 126.35929908 164.97949922
92.6725994
108.86529956 109.54000102 103.90329871 94.38880039 127.80910279
107.09960039 161.64299963 121.75510044 132.20719989 130.2038021
160.27409968 90.18799843 176.20870169 127.47270027 126.67839891
86.36019928 124.4944992 150.60619729 89.55320025 106.85389964
109.02779995 84.41309903 136.06449885 155.10220289 138.41960359
74.34940021 152.71120143 126.10559995 126.66710051 127.4386992
            156.05550057 114.64670114 116.89190147 125.13259945
108.7787
154.00800162 121.35999979 156.38809867 92.8839007 125.44870155
125.80250019 87.78760045 92.11269925 126.14029967 128.2608033
```

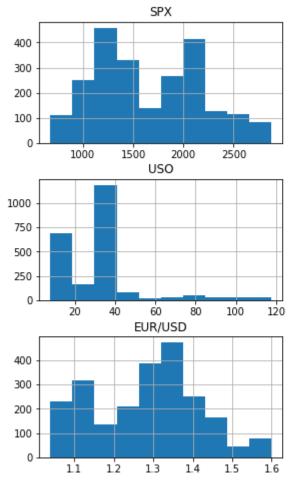
```
0 100 200 300 400
Number of values
```

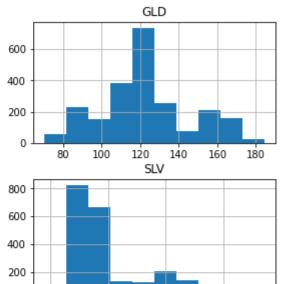
gold data.hist(figsize=(10,8))

0

10

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Stu	INGIN	319.111340	Z3.Z0334U	19.040011	7.092500	(
min	NaN	676.530029	70.000000	7.960000	8.850000	1
25%	NaN	1239.874969	109.725000	14.380000	15.570000	1
50%	NaN	1551.434998	120.580002	33.869999	17.268500	1
75%	NaN	2073.010070	132.840004	37.827501	22.882499	1
max	NaN	2872.870117	184.589996	117.480003	47.259998	1