Project 01: Gold Prices Prediction

#Day10 of #30DaysOfMachineLearning

> Getting Start with our Fir Project **Project 01: Gold Price Prediction** Dataset is Downloaded From Kaggel. The main Purpose to Build This project is to predict The Gold Pricess.By applying Some ML Algorithams.

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Importing the Libraries/dependacies

1. **Numpy:** It provides a multidimensional array object, as well as variations such as masks and matrices, which can be used for various math operations.
2. **Pandas:** Pandas has been one of the most commonly used tools for Data Science and Machine learning, which is used for data cleaning and analysis. Here, Pandas is the best tool for handling this real-world messy data.
3. **matplotlib:** Matplotlib is a library in Python and it is numerical – mathematical extension for NumPy library. Pyplot is a state-based interface to a Matplotlib module which provides a MATLAB-like interface. There are various plots which can be used in Pyplot are Line Plot, Contour, Histogram, Scatter, 3D Plot, etc.
4. **Seaborn** is a library for making statistical graphics in Python. It builds on top of matplotlib and integrates closely with pandas data structures. Seaborn helps you explore and understand your data.
5. **Sklearn:** It features various classification, regression and clustering algorithms including support-vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

Double-click (or enter) to edit

```
import numpy as np
#pandas is used to read the cvs file of our DataSet.
import pandas as pd
#matplotlib for making plots and graphs
import matplotlib.pyplot as plt
#next we will use seaborn and it is also usefull for making plots and graphs
```

```
import seaborn as sns
#from sklearn we will import model_selection so we need to split the orignal data into Tra
from sklearn.model_selection import train_test_split
#Now we will import our rendome forest regulator model
from sklearn.ensemble import RandomForestRegressor
#now from sklearn import matrices that is usefull for finding the performances of our mode
from sklearn import metrics
```

Data Collection and Processing

```
# loading our dataset (the csv data to a Pandas DataFrame) creat a variable and load data
data = pd.read_csv('../input/gold-price-data/gld_price_data.csv')
```

```
#after succesfully importing our csv to pd Dataframe. we will print out first 5 rows in th
data.head()
```

	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

We have the data from 2008 and **SPX**spx is also called Csmp index it is the capitalization index of 500 companies wich are publically trade. **GLD** Are Gold prices **USO** Uso Represents United State Oil Prices **SLV** Silver Price Value **EUR/USD** Currency pair of European and United States

```
# print last 5 rows of the dataframe
data.tail()
```

	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

```
#Printing Total number of rows and columns in Our Dataset/Data
data.shape
```

```
(2290, 6)
```

```
# getting some basic informations about the data
#the info function give us information about Number Of Entries and Number of Columns and D
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
```

```
# checking the number of missing values in our Data by applying isnull function
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. The describe function will give us some st
data.describe()
```

	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

Lets do Some Analysis on data so we will find the corellation between the various columns in dataset there are two types of correlation. while we are working on regressin projects we will

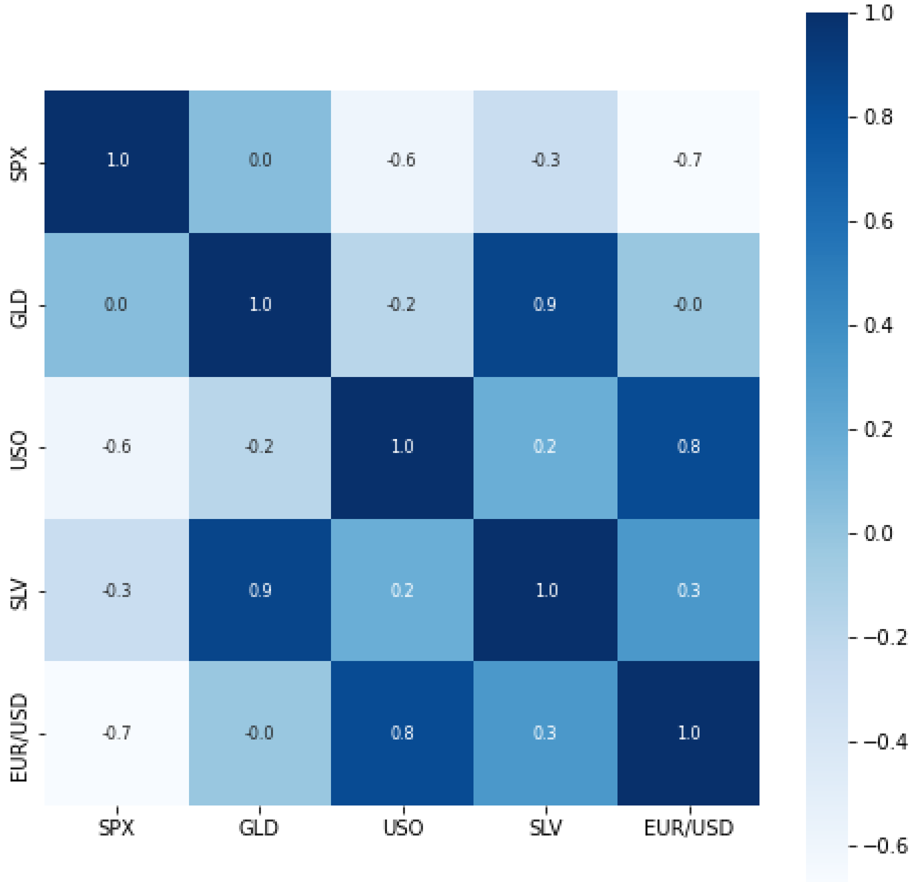
always check this correlation. so it tells us the which columns are related to which columns.
Correlation:

1. **Positive Correlation** in case of positive correlation when we take two variables, one variable will increase if the other variable decrease. so such kind of relations are known as positive correlation. we can say that these variables are directly proportional to each other.
2. **Negative Correlation** in Nagetive correlation if one value increases the other value decreases. So they are inversely proportional.

```
correlation = 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={'size':8
```

```
<AxesSubplot:>
```



In The plot above The Nagative Correlation have the Nagative Values and positive Correlation have Positive Values. In this Perticular Case the Values Lies between +1 and -0.6, Plus One means They are positively correlated as the value proceeds towards the nagative value it means they are nagative correlated. The feature we are intrested in is Gold And we see it is positive cirrelated. we can see the silver column. and the silver, Gold column has the value of

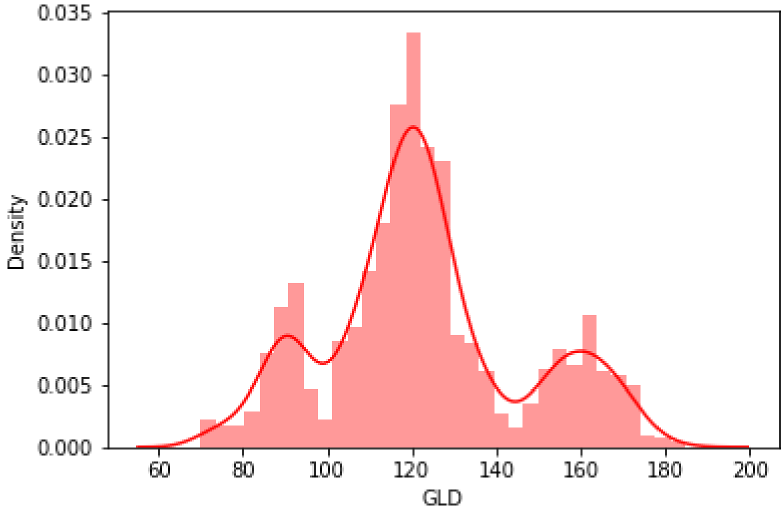
0.9 it means they are positively correlated. That Means if Gold prices Increases the Silver

```
# 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(data['GLD'],color='red')
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='GLD', ylabel='Density'>
```



So we Can See Here Most value lies in the range of 120.we have less values around 180,160

Splitting the Features and Target

Split the data to feed this in our machine learning algorithm, so column we are intrested in is Gold So we will be feeding this spx, Uso, Silver,EUR/USD columns with these columns we will try to predict the gold prices so we need to remove Date Column From our Datset.and Separate the Gold Column as well.

```
X = data.drop(['Date','GLD'],axis=1)
Y = data['GLD']
```

```
#printing The X to See That (Date, GLD) Columns are removed or not
print(X)
```

```
              SPX        USO      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]
```

```
#printing y For only printing The Gold 'GLD' column
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 into Training data and Test Data

> we will create four Varible so the "print(x) values Seperated into X_train and X test" The 80% of Values go to X_Train and remaining 20% of The values will go to X_test. and The Corresponding Gold Values will go to y_train and the corresponding gold prices for X_test will go this y_test. So we are just spliting the xand y into X_Train, X_test, Y_train, y_test by using **train_test_split function**

```
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: Random Forest Regressor model is an esamble model esamble means it consist of more then one models joined togeather so it is a non-symbol model of decsion tree

```
regressor = RandomForestRegressor(n_estimators=100)
```

```
# training the model
regressor.fit(X_train,Y_train)
```

```
RandomForestRegressor()
```

Model Evaluation

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

```
# printing ThePredicted values by our model
print(test_data_prediction)
```

```
[168.65859942  82.04259985 116.11520038 127.55760053 120.90280122
 154.75619792 150.72199852 126.23050035 117.67429884 126.1030005
 116.70320107 171.86160063 141.37929886 167.98319838 115.15780006
 117.28840038 138.86970262 170.06320148 159.0900034  158.68529927
 155.12800075 125.15750006 175.76789942 157.11870332 125.19450038
  93.79889978  77.88550013 120.86549986 119.18129953 167.52810052
  88.05260048 125.15779981  91.1029005  117.70070009 121.04849881
 136.03000039 115.54310106 115.40480097 148.1765993  107.2694007
 104.22370249  87.07549796 126.40580073 117.83789977 152.91259955
 119.60110006 108.37079978 108.00049819  93.24920086 127.2002979
  75.05810037 113.64409917 121.44269962 111.39799916 118.86459871
 120.5909994  159.50200021 167.92490189 146.98619688  85.9818986
  94.11110043  86.82539919  90.39390046 119.07670071 126.4722005
 127.57050023 169.65870001 122.33599921 117.48789907  98.25629991
 168.1439005  143.02929861 131.51640245 121.14050216 121.70619947
 120.00750054 114.60760172 118.24520044 107.30940086 127.80050026
 114.11599924 107.19719977 116.99560059 119.60489923  88.5911003
  88.22259857 146.46610188 127.22359978 113.54169986 110.27549841
 108.25199911  77.21669887 169.17700147 114.13239927 121.71219918
 127.69690214 154.85689804  91.75779911 135.3808014  159.161603
 125.83390078 125.11820047 130.64270223 114.91930135 119.97200005
  92.20760006 110.1768988  168.12759881 155.99079877 114.27749952
 106.2915014   79.47479976 113.35170055 125.90210066 107.17409945
 119.20260088 156.29650342 160.00459889 120.39890005 134.85970286
 101.47909978 117.52039798 119.25330018 113.06000072 102.79189926
 160.12029859  98.89310038 146.77179936 125.51300075 169.665499
 125.53039954 127.35379754 127.42120154 113.66539974 112.97720074
 123.53869909 102.20829939  88.95919965 124.60329978 102.19089936
 106.98929935 113.7014007  117.3144009   99.12809968 121.90960036
 163.06499838  87.40999881 106.85699963 117.36130036 127.60310099
 124.07220052  80.98529915 120.48030065 156.78739886  87.9197996
 110.35039941 118.86999935 172.27479878 103.092999   105.7897006
 122.56760045 157.27359833  87.69549832  93.39930044 112.95590008
 176.95489964 114.13829994 119.30930011  94.92780116 125.89170035
 165.64790067 114.96850083 116.91950123  88.33379863 148.6257005
 120.24949958  89.50420022 112.02950038 117.11520013 118.81020126
  88.05349947  94.24650007 116.90049988 118.55770187 120.30190055
 126.83839807 121.89199979 150.01280026 165.1947002  118.59669962
 120.20310153 150.74070028 118.46199942 172.99319844 105.39979952
 105.00290092 148.6558006  113.66040029 124.84090111 147.29140019
 119.61160123 115.3884004  112.78310027 113.50700196 142.06400065
 117.77349776 102.91280005 115.86980121 103.58870183  98.8081005
 117.34480054  90.60540003  91.55670036 153.40109873 102.79859988
 154.74040077 114.43170144 138.89980087  90.15719828 115.43829957
 114.29529972 123.17729963 121.79480024 165.36210109  92.93469934
```

```
135.15630111 121.26759964 120.90240034 104.75200022 141.07770297
121.78109908 116.57380038 113.68660118 127.01229738 122.71889941
125.71929889 121.1644005   86.93129907 132.75780071 145.76990152
 92.74059939 158.0257993  158.89480213 126.4729986  164.42489915
108.90179966 110.04510084 103.72969823  94.39470034 127.76840294
107.05720064 161.59109989 121.71550015 131.71790021 130.74670204
160.60150023  90.13169873 174.59960151 127.47010078 126.86179813
 86.6188993  124.50109944 150.65879724  89.54820031 106.85269944
108.95229976  84.5604989  135.86959972 154.91870206 139.27230351
 73.66460038 152.31080095 126.24299996 126.75090009 127.56169863
108.6183995  156.30360009 114.63240112 116.90230111 125.14319954
153.96830114 121.39019973 156.44819843  93.00190084 125.52860185
```

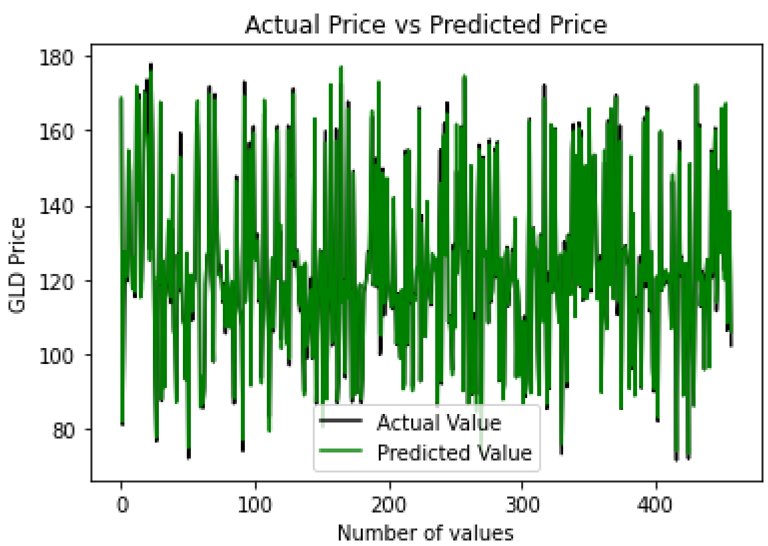
```
# So we need to compare predicted values with actual values by usnig R Square error
# error Score is a range that our model is performing
# R squared error
error_score = metrics.r2_score(Y_test, test_data_prediction)
print("R squared error Val : ", error_score)
```

```
R squared error Val :  0.9894290742935247
```

Comparing the Actual Values and Predicted Values in a Plot

```
Y_test = list(Y_test)
```

```
#Comparing the actual values with predicted values by labeling it.
# the actual values are labled with black color and The predicted values are Labled with G
plt.plot(Y_test, color='black', 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()
```



Thanks :) By Ahmed Ali