Import Liberaries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings('ignore')
```

Load Data

In [2]:
```
Gold_Data = pd.read_csv("gld_price_data.csv")
```

Data Pre Processing

In [3]:
```
Gold_Data.head()
```

Out[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

In [4]:
```
Gold_Data.describe()
```

Out[4]:

	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 [5]:
```
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
```

In [6]:
```
Gold_Data['Date'] = pd.to_datetime(Gold_Data['Date'], format='%m/%d/%Y')
```

In [7]:
```
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
```

In [8]:
```
Gold_Data.isnull().sum()
```

Out[8]:
```
Date       0
SPX        0
GLD        0
USO        0
SLV        0
EUR/USD    0
dtype: int64
```

Checking Correlation

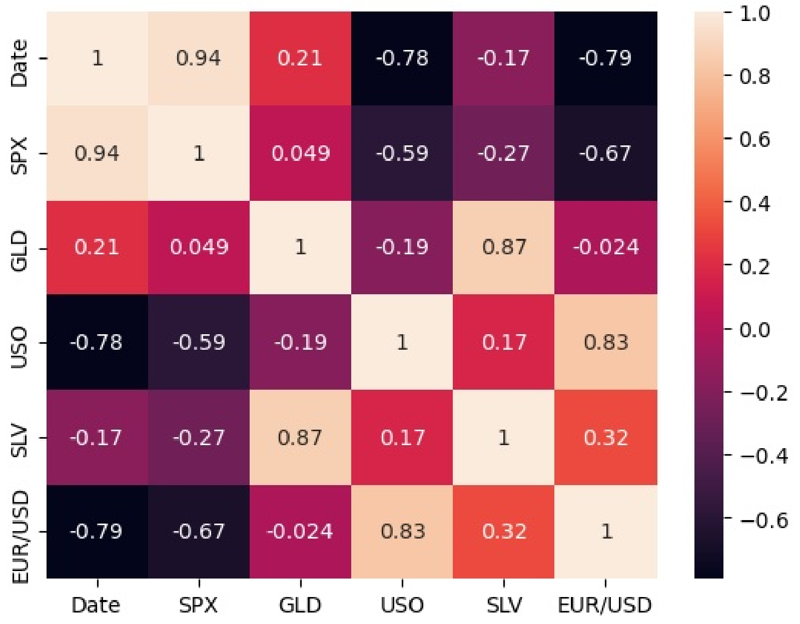
1. Positive Correlation

2. Negtive Correlation

In [9]:
```
correlation = Gold_Data.corr()
```

In [10]:
```
sns.heatmap(data = correlation,annot=True)
```

Out[10]:
```
<Axes: >
```



In [11]:
```
print(correlation['GLD'])
```

```
Date       0.209118
SPX        0.049345
GLD        1.000000
USO       -0.186360
SLV        0.866632
EUR/USD   -0.024375
Name: GLD, dtype: float64
```

In [12]:
```
Gold_Data.drop(columns='Date',axis=1)
```

Out[12]:

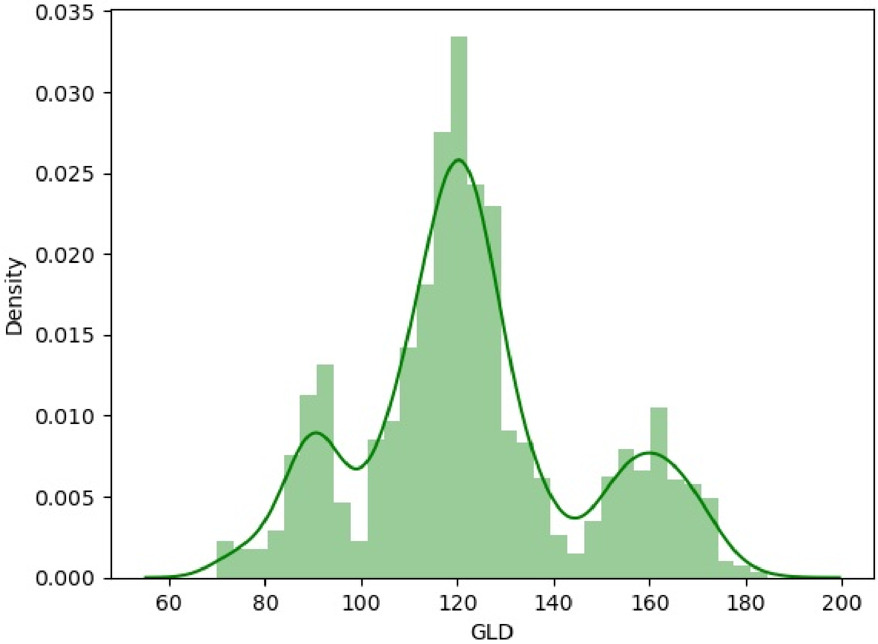
	SPX	GLD	USO	SLV	EUR/USD
0	1447.160034	84.860001	78.470001	15.1800	1.471692
1	1447.160034	85.570000	78.370003	15.2850	1.474491
2	1411.630005	85.129997	77.309998	15.1670	1.475492
3	1416.180054	84.769997	75.500000	15.0530	1.468299
4	1390.189941	86.779999	76.059998	15.5900	1.557099
...	...	...	...	...	...
2285	2671.919922	124.589996	14.060000	15.5100	1.186789
2286	2697.790039	124.330002	14.370000	15.5300	1.184722
2287	2723.070068	125.180000	14.410000	15.7400	1.191753
2288	2730.129883	124.489998	14.380000	15.5600	1.193118
2289	2725.780029	122.543800	14.405800	15.4542	1.182033

2290 rows × 5 columns

In [13]:

```
# checking the distribution of the GLD Price
sns.distplot(Gold_Data['GLD'],color='green')
```

Out[13]: <Axes: xlabel='GLD', ylabel='Density'>



Segregeting X and y

In [14]:

```
X = Gold_Data.drop(["GLD","Date"],axis =1)
y = Gold_Data["GLD"]
```

In [15]:

```
X
```

Out[15]:

	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 × 4 columns

In [16]:
```
y
```

Out[16]:
```
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
```

Train Split Test

In [17]:
```
from sklearn.model_selection import train_test_split
```

In [18]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=1)
```

In [36]:
```
print("X_train shape :",X_train.shape)
print("y_train shape :",y_train.shape)

print("-"*30)

print("X_test shape :",X_test.shape)
print("y_test shape :",y_test.shape)
```

```
X_train shape : (1832, 4)
y_train shape : (1832,)
------------------------------
X_test shape : (458, 4)
y_test shape : (458,)
```

Build the Model

Using Random Forest

In [19]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [20]:
```
model = RandomForestRegressor(n_estimators=100)
```

In [21]:
```
model.fit(X_train,y_train)
```

Out[21]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [22]:
```
y_pred = model.predict(X_test)
```

In [23]:
```
pd.DataFrame(y_pred,columns=['Predicted'])
```

Out[23]:

	Predicted
0	113.207400
1	147.273901
2	139.206298
3	112.638602
4	113.918600
...	...
453	115.571899
454	101.163598
455	129.596498
456	165.055598
457	119.145103

458 rows × 1 columns

In [24]:
```
pd.DataFrame(y_test)
```

Out[24]:

	GLD
1971	110.820000
1163	151.050003
693	137.660004
1651	113.070000
508	114.629997
...	...
1524	115.779999
363	98.900002
1272	130.559998
1053	164.860001
1814	120.589996

458 rows × 1 columns

Evalution Matrics

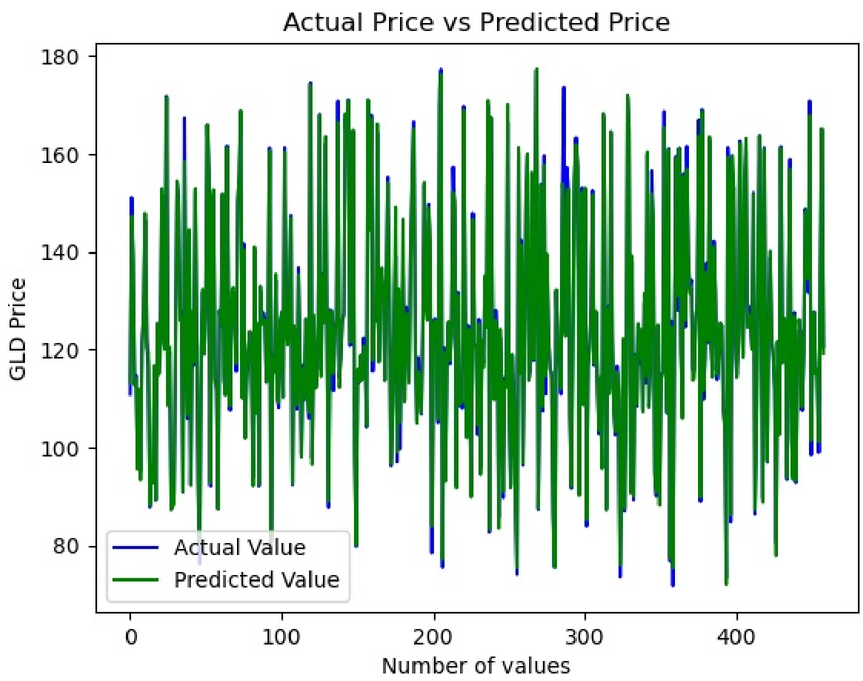
In [25]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score,root_mean_squared_error
```

In [26]:
```
print("mean absolute error : ",mean_absolute_error(y_test,y_pred))
print("mean squared error : ",mean_squared_error(y_test,y_pred))
print("root mean squared error : ",root_mean_squared_error(y_test,y_pred))
print("R squared error : ",r2_score(y_test,y_pred))
```

```
mean absolute error :  1.2703565508951964
mean squared error :  6.513854942298864
root mean squared error :  2.552225488137532
R squared error :  0.9876573180130552
```

In [27]:
```
Y_test = list(y_test)
```

In [28]:
```
plt.plot(Y_test, color='blue', label = 'Actual Value')
plt.plot(y_pred, 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()
```



- Actual Value and predicted values are slightly diffrents And R square we have 0.98 that means our model performing well

Making Prediction System

In [38]:

```
input_data = (1447.160034,78.370003,15.2850,1.474491)
input_data_as_numpy = np.asarray(input_data)

input_data_reshaped = input_data_as_numpy.reshape(1,-1)

Predicted  = model.predict(input_data_reshaped)
print(Predicted)
```

```
[85.55729996]
```