+ Code + Text

Time Series Analysis Assignment - Gold Prices (XAU/USD)

```
import pandas as pd
import matplotlib.pyplot as plt
```

1. Data Loading and Preparation:

Loading the data -

```
df=pd.read_excel(r"/content/Gold.xlsx", parse_dates=True)
df.head()
```

	datetime	open	close	average price
0	2010-01-03 18:00:00	1098.45	1099.95	1099.200
1	2010-01-03 18:05:00	1100.00	1099.75	1099.875
2	2010-01-03 18:10:00	1099.70	1099.45	1099.575
3	2010-01-03 18:15:00	1099.50	1099.45	1099.475
4	2010-01-03 18:20:00	1099.40	1098.90	1099.150

```
df.shape
```

```
(986004, 4)
```

Data Cleaning -

```
df['datetime']=pd.to_datetime(df['datetime'],errors='coerce')
delete_years=[2010,2011,2012]
df=df[~df['datetime'].dt.year.isin(delete_years)]
```

```
df=df.reset_index(drop=True)
```

```
df['date']=df['datetime'].dt.date
df.insert(0, 'date', df.pop('date'))
df.head()
```

	date	datetime	open	close	average price
0	2013-01-01	2013-01-01 17:00:00	1674.90	1674.90	1674.900
1	2013-01-01	2013-01-01 18:00:00	1675.11	1673.36	1674.235
2	2013-01-01	2013-01-01 18:05:00	1673.33	1673.33	1673.330
3	2013-01-01	2013-01-01 18:10:00	1673.37	1673.27	1673.320
4	2013-01-01	2013-01-01 18:15:00	1673.32	1673.16	1673.240

```
df=df.drop(columns=['datetime','open','close'])
df=df.rename(columns={'average price': 'avg_price'})
df.head()
```

	date	avg_price
0	2013-01-01	1674.900
1	2013-01-01	1674.235
2	2013-01-01	1673.330
3	2013-01-01	1673.320
4	2013-01-01	1673.240

```
data=df.groupby('date').agg({'date':'first','avg_price':'mean'}).reset_index(drop=True)
data.head()
```

	date	avg_price
0	2013-01-01	1674.672055
1	2013-01-02	1685.993943
2	2013-01-03	1671.660394
3	2013-01-04	1645.249338
4	2013-01-06	1658.975208

```
data.set_index('date',inplace=True)
```

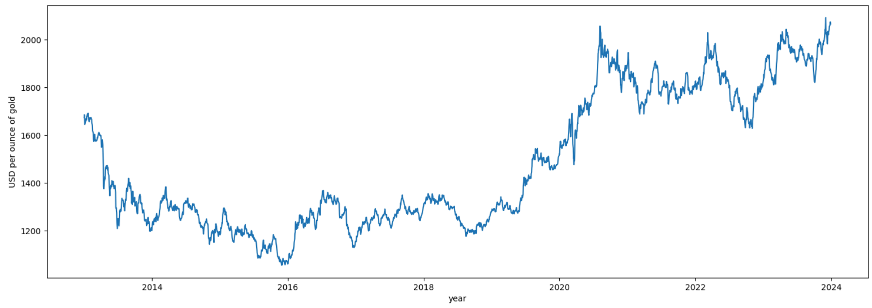
```
data.shape
```

```
(3418, 1)
```

2. Plot the Time Series.

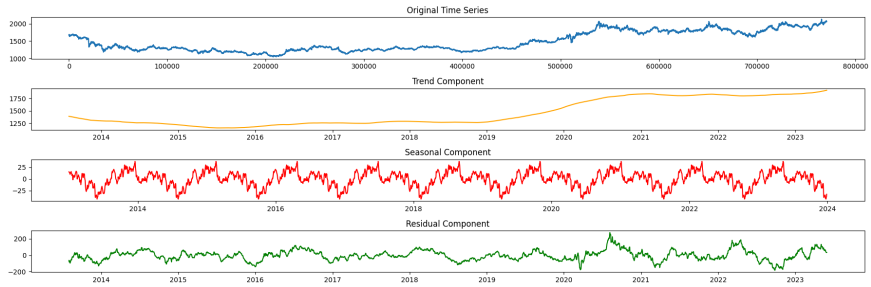
```
plt.figure(figsize=(18,6))
plt.plot(data)
plt.xlabel('year')
plt.ylabel('USD per ounce of gold')
```

```
Text(0, 0.5, 'USD per ounce of gold')
```



3. Extract the Components of Time series.

```
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib as mpl
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
decompose = seasonal_decompose(data['avg_price'], model='add', period=365)
trend=decompose.trend
seasonality=decompose.seasonal
residual=decompose.resid
fig, ax=plt.subplots(4, 1,figsize=(18,6))
ax[0].plot(df.index, df['avg_price'], label='Original')
ax[0].set_title('Original Time Series')
ax[1].plot(trend.index, trend, label='Trend', color='orange')
ax[1].set_title('Trend Component')
ax[2].plot(seasonality.index, seasonality, label='Seasonal', color='red')
ax[2].set_title('Seasonal Component')
ax[3].plot(residual.index, residual, label='Residual', color='green')
ax[3].set_title('Residual Component')
plt.tight_layout()
plt.show()
```



4. Check whether Stationary or Non-stationary.

```
from statsmodels.tsa.stattools import adfuller
import pandas as pd
import numpy as np
result=adfuller(data,autolag='AIC')
stats=pd.Series(result[0:4],index=['Test Statistic','p-value', 'No. of lags used', 'number of observations used'])
print(stats)
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
if result[0] < result[4]["5%"]:
    print ("Time Series is Stationary")
else:
    print ("Time Series is Non-Stationary")
```

```
Test Statistic                   -0.322953
p-value                           0.922190
No. of lags used                 21.000000
number of observations used    3396.000000
dtype: float64
        1%: -3.432
        5%: -2.862
        10%: -2.567
Time Series is Non-Stationary
```

5. Making the Data Stationary.

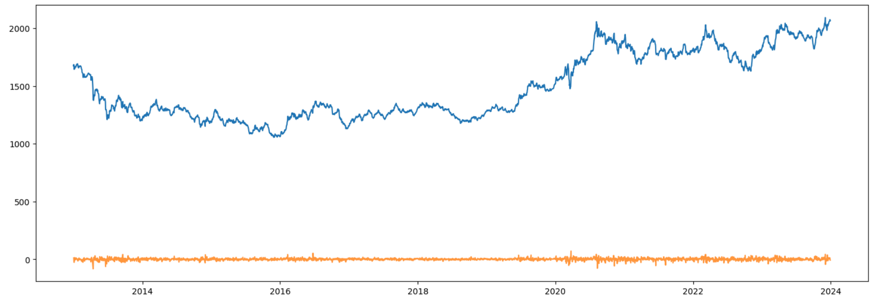
```
df=data[['avg_price']]
df['shift']=df.avg_price.shift()
df['shiftDiff']=df.avg_price - df['shift']
df.tail(8)
```

	avg_price	shift	shiftDiff
date			
2023-12-20	2035.847699	2034.484656	1.363043
2023-12-21	2041.605109	2035.847699	5.757409
2023-12-22	2055.809216	2041.605109	14.204107
2023-12-25	2059.837431	2055.809216	4.028215
2023-12-26	2062.703207	2059.837431	2.865776
2023-12-27	2074.760525	2062.703207	12.057319
2023-12-28	2074.235996	2074.760525	-0.524529
2023-12-29	2066.480270	2074.235996	-7.755727

```
from statsmodels.tsa.stattools import adfuller
result=adfuller(df.shiftDiff.dropna(),autolag='AIC')
stats=pd.Series(result[0:4],index=['Test Statistic','p-value', 'No. of lags used', 'number of observations used'])
print(stats)
for key, value in result[4].items():
    print('\t%s: %.3f' % (key, value))
if result[0] < result[4]["5%"]:
    print ("Time Series is Stationary")
else:
    print ("Time Series is Non-Stationary")
```

```
Test Statistic                 -1.386849e+01
p-value                         6.530501e-26
No. of lags used                2.000000e+01
number of observations used     3.396000e+03
dtype: float64
        1%: -3.432
        5%: -2.862
        10%: -2.567
Time Series is Stationary
```

```
plt.figure(figsize=(18,6))
plt.plot(df.index, df.avg_price)
plt.plot(df.index, df.shiftDiff, alpha=0.8)
plt.show()
```



6. Implementing ARIMA model

```
pip install pmdarima
```

```
Collecting pmdarima
  Downloading pmdarima-2.0.4-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_28_x86_64.whl (2.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.1/2.1 MB 8.5 MB/s eta 0:00:00
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.4.0)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.10)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.25.2)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (2.0.3)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.11.4)
Requirement already satisfied: statsmodels>=0.13.2 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.1)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: packaging>=17.1 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (24.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2.8
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2024.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->pmdarima)
Requirement already satisfied: patsy>=0.5.4 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13.2->pmdarima) (0.5.6)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.4->statsmodels>=0.13.2->pmdarima) (1
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.4
```

```
from pmdarima import auto_arima
import warnings
warnings.filterwarnings("ignore")
stepwise_fit=auto_arima(df['shiftDiff'].dropna(),trace=True,suppress_warnings=True)
stepwise_fit.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=25005.659, Time=9.87 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=25415.290, Time=0.17 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=25047.484, Time=0.35 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=25008.513, Time=1.68 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=25413.742, Time=0.15 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=25004.628, Time=6.26 sec
 ARIMA(0,0,2)(0,0,0)[0] intercept   : AIC=25009.596, Time=3.23 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=25009.645, Time=1.70 sec
 ARIMA(1,0,3)(0,0,0)[0] intercept   : AIC=25005.809, Time=9.96 sec
 ARIMA(0,0,3)(0,0,0)[0] intercept   : AIC=25011.178, Time=3.12 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=25011.427, Time=3.68 sec
 ARIMA(2,0,3)(0,0,0)[0] intercept   : AIC=25006.916, Time=12.35 sec
 ARIMA(1,0,2)(0,0,0)[0]             : AIC=25002.903, Time=1.91 sec
 ARIMA(0,0,2)(0,0,0)[0]             : AIC=25007.870, Time=0.42 sec
 ARIMA(1,0,1)(0,0,0)[0]             : AIC=25007.918, Time=0.38 sec
 ARIMA(2,0,2)(0,0,0)[0]             : AIC=25011.769, Time=0.92 sec
 ARIMA(1,0,3)(0,0,0)[0]             : AIC=25004.093, Time=2.71 sec
 ARIMA(0,0,1)(0,0,0)[0]             : AIC=25006.796, Time=0.47 sec
 ARIMA(0,0,3)(0,0,0)[0]             : AIC=25009.459, Time=0.55 sec
 ARIMA(2,0,1)(0,0,0)[0]             : AIC=25009.705, Time=0.66 sec
 ARIMA(2,0,3)(0,0,0)[0]             : AIC=25005.272, Time=2.26 sec

Best model:  ARIMA(1,0,2)(0,0,0)[0]
Total fit time: 62.901 seconds
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	3417
Model:	SARIMAX(1, 0, 2)	**Log Likelihood**	-12497.452
Date:	Wed, 17 Apr 2024	**AIC**	25002.903
Time:	07:01:25	**BIC**	25027.449
Sample:	0 - 3417	**HQIC**	25011.674
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.8458	0.084	-10.061	0.000	-1.011	-0.681
ma.L1	1.2095	0.084	14.400	0.000	1.045	1.374
ma.L2	0.3260	0.027	12.139	0.000	0.273	0.379
sigma2	87.9654	1.044	84.259	0.000	85.919	90.012

Ljung-Box (L1) (Q):	0.08	**Jarque-Bera (JB):**	6128.48
Prob(Q):	0.77	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.60	**Skew:**	-0.54
Prob(H) (two-sided):	0.00	**Kurtosis:**	9.47

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

7. Validating the Model.

```
train=df.iloc[:-18]
test=df.iloc[-18:]
print(train.shape,test.shape)
```

```
(3400, 3) (18, 3)
```

```
from statsmodels.tsa.arima.model import ARIMA
model=ARIMA(train['shiftDiff'],order=(1,0,2))
model=model.fit()
model.summary()
```

SARIMAX Results

Dep. Variable:	shiftDiff	**No. Observations:**	3400
Model:	ARIMA(1, 0, 2)	**Log Likelihood**	-12427.517
Date:	Wed, 17 Apr 2024	**AIC**	24865.034
Time:	07:45:15	**BIC**	24895.691
Sample:	0 - 3400	**HQIC**	24875.991
Covariance Type:	opg		

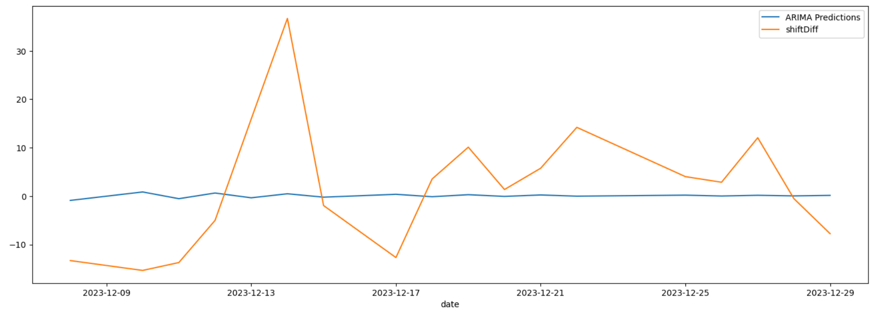
	coef	std err	z	P>|z|	[0.025	0.975]
const	0.1059	0.225	0.472	0.637	-0.334	0.546
ar.L1	-0.8425	0.089	-9.435	0.000	-1.017	-0.667
ma.L1	1.2035	0.089	13.482	0.000	1.029	1.378
ma.L2	0.3222	0.028	11.332	0.000	0.266	0.378
sigma2	87.7516	1.059	82.851	0.000	85.676	89.828

Ljung-Box (L1) (Q):	0.06	**Jarque-Bera (JB):**	6222.02
Prob(Q):	0.81	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.60	**Skew:**	-0.55
Prob(H) (two-sided):	0.00	**Kurtosis:**	9.53

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

```
start=len(train)
end=len(train)+len(test)-1
shiftDiff_pred=model.predict(start=start,end=end,typ='levels').rename('ARIMA Predictions')
print(shiftDiff_pred)
shiftDiff_pred.index=df.index[start:end+1]
plt.figure(figsize=(18,6))
shiftDiff_pred.plot(legend=True)
test['shiftDiff'].plot(legend=True)
```

```
3400   -0.885281
3401    0.860717
3402   -0.529932
3403    0.641627
3404   -0.345358
3405    0.486131
3406   -0.214360
3407    0.375772
3408   -0.121387
3409    0.297447
3410   -0.055402
3411    0.241857
3412   -0.008570
3413    0.202403
3414    0.024668
3415    0.174402
3416    0.048258
3417    0.154528
Name: ARIMA Predictions, dtype: float64
<Axes: xlabel='date'>
```



Double-click (or enter) to edit

```
from sklearn.metrics import mean_squared_error
from math import sqrt
test['shiftDiff'].mean()
rmse=sqrt(mean_squared_error(shiftDiff_pred,test['shiftDiff']))
print(rmse)
```

```
12.788660986749893
```

```
shiftDiff_pred=shiftDiff_pred+df['shift'][-18:]
```

```
Results=pd.concat([df['avg_price'][-18:], shiftDiff_pred], axis=1)
Results.rename(columns={0:'predictions'}, inplace=True)
```

```
Results
```

date	avg_price	predictions
2023-12-08	2016.916544	2029.341875
2023-12-10	2001.570069	2017.777262
2023-12-11	1987.853243	2001.040138
2023-12-12	1982.839583	1988.494869
2023-12-13	1998.771902	1982.494226
2023-12-14	2035.471268	1999.258034
2023-12-15	2033.524975	2035.256908
2023-12-17	2020.837222	2033.900747
2023-12-18	2024.372772	2020.715835
2023-12-19	2034.484656	2024.670218
2023-12-20	2035.847699	2034.429254
2023-12-21	2041.605109	2036.089556
2023-12-22	2055.809216	2041.596539
2023-12-25	2059.837431	2056.011619
2023-12-26	2062.703207	2059.862098
2023-12-27	2074.760525	2062.877608
2023-12-28	2074.235996	2074.808783
2023-12-29	2066.480270	2074.390525

8. Predictions and Original data.

```
plt.figure(figsize=(18,6))
plt.plot(Results)
plt.legend(Results)
plt.show()
```