PREDICTIVE MODELING & STATISTICAL ANALYSIS

Time Series Forecasting using Granger's Causality and Vector Auto-regressive Model

Multi-variate time-series data and Python programming

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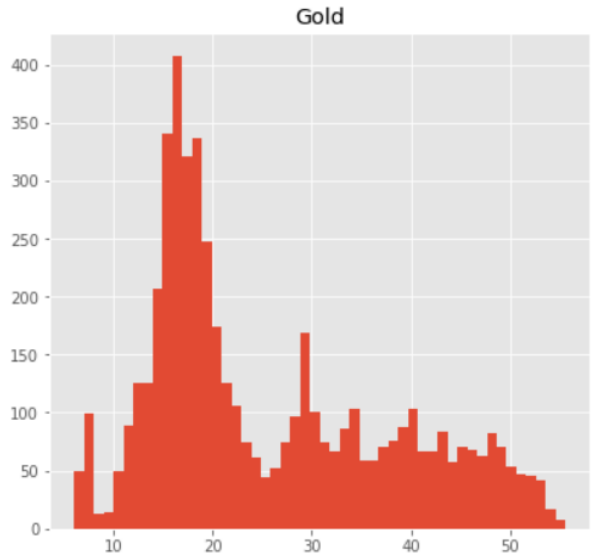
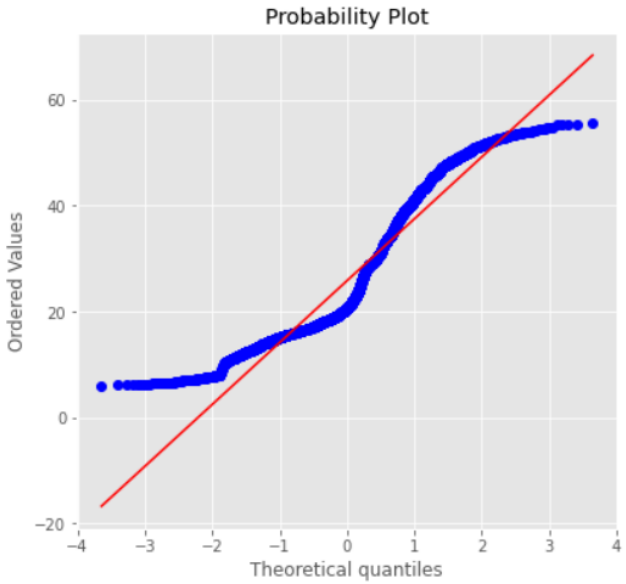




FORECASTING of ***Gold*** and ***Oil*** have garnered major attention from academics, investors and Government agencies like. These two products are known for their substantial influence on global economy. I will show here, how to use ***Granger's Causality Test*** to test the relationships of multiple variables in the time series and ***Vector Auto Regressive Model (VAR)*** to forecast the future ***Gold & Oil*** prices from the historical data of ***Gold prices, Silver prices, Crude Oil prices, Stock index , Interest Rate and USD rate***.

The ***Gold*** prices are closely related with other commodities. A hike in ***Oil*** prices will have positive impact on ***Gold*** prices and vice versa. Historically, we have seen that, when there is a hike in equities, ***Gold*** prices goes down.

- Time-series forecasting problem formulation
- Uni-variate and multi-variate time series time-series forecasting
- Apply ***VAR*** to this problem

Let's understand how a multivariate time series is formulated. Below are the simple K-equations of multivariate time series where each equation is a lag of the other series. X is the exogenous series here. The objective is to see if the series is affected by its own past and also the past of the other series.

$$y_{1,t} = f_1\left(y_{1,t-1}\ldots, y_{k,t-1}\ldots y_{1,t-p}, \ldots. y_{k,t-p}\ldots.X_{t-1}\ X_{t-2}\ldots.\right)$$

$$\vdots \qquad \vdots$$

$$y_{K,t} = f_k\left(y_{1,t-1}\ldots, y_{k,t-1}\ldots y_{1,t-p}, \ldots. y_{k,t-p}\ldots.X_{t-1}\ X_{t-2}\ldots.\right)$$

This kind of series allow us to model the dynamics of the series itself and also the interdependence of other series. We will explore this inter-dependence through ***Granger's Causality Analysis***.

Exploratory analysis

Let's load the data and do some analysis with visualization to know insights of the data. Exploratory data analysis is quite extensive in multivariate time series. I will cover some areas here to get insights of the data. However, it is advisable to conduct all statistical tests to ensure our clear understanding on data distribution.

> *Exploratory analysis is an iterative process where some of the tests (e.g. stationarity tests) might need to do repeatedly to ensure the required output.*

```
dataset = pd.concat([df1.Gold, df2.Silver, df3.USD, df4.Oil, df5.Interest, df6.Stock], axis=1) # combining dataframes
dataset.head()
```

Date	Gold	Silver	USD	Oil	Interest	Stock

1999-12-31	17.9375	NaN	NaN	NaN	6.377	6876.100098
2000-01-03	17.5625	NaN	99.89	NaN	6.498	6762.109863
2000-01-04	17.3125	5.335	100.10	25.55	6.530	6543.759766
2000-01-05	17.5625	5.170	100.05	24.91	6.521	6567.029785
2000-01-06	17.7500	5.127	100.34	24.78	6.558	6635.439941

Let's fix the dates for all the series.

```
dataset = dataset.loc['20000101':'20180501']
dataset.head()
```

Date	Gold	Silver	Oil	USD	Interest	Stock
2000-01-03	17.5625	NaN	NaN	101.39	6.498	6762.109863
2000-01-04	17.3125	5.290	25.20	100.18	6.530	6543.759766
2000-01-05	17.5625	5.170	25.50	100.09	6.521	6567.029785
2000-01-06	17.7500	5.127	24.80	100.05	6.558	6635.439941
2000-01-07	17.8125	5.150	24.65	100.18	6.545	6792.669922

```
dataset.isnull().sum() # missing values
```

```
Gold        519
Silver      130
Oil         477
USD         435
Interest    523
Stock       519
dtype: int64
```

```
dataset= dataset.fillna(method ='pad') # filling the missing values with previous ones
dataset.isnull().sum()
```

```
Gold        0
Silver      1
Oil         1
USD         0
Interest    0
Stock       0
dtype: int64
```

```
dataset = dataset.dropna()
dataset.head()
```

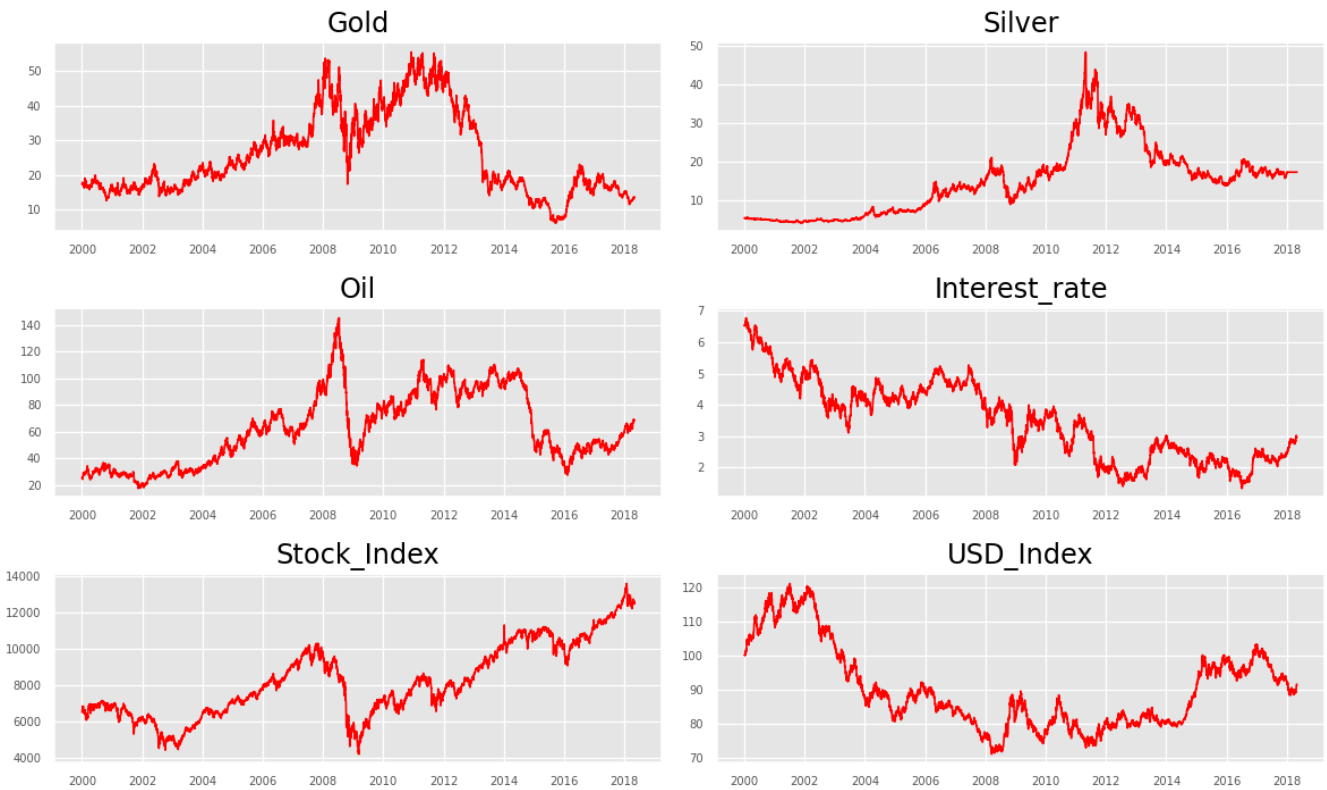
Date	Gold	Silver	Oil	USD	Interest	Stock
2000-01-04	17.3125	5.290	25.20	100.18	6.530	6543.759766

2000-01-05	17.5625	5.170	25.50	100.09	6.521	6567.029785
2000-01-06	17.7500	5.127	24.80	100.05	6.558	6635.439941
2000-01-07	17.8125	5.150	24.65	100.18	6.545	6792.669922
2000-01-10	17.4375	5.145	24.22	100.36	6.540	6838.450195

The NaN values in the data are filled with previous days data. After doing some necessary pre-processing, the dataset now clean for further analysis.

```
# Plot
fig, axes = plt.subplots(nrows=3, ncols=2, dpi=120, figsize=(10,6))
for i, ax in enumerate(axes.flatten()):
 data = dataset[dataset.columns[i]]
 ax.plot(data, color='red', linewidth=1)
 ax.set_title(dataset.columns[i])
 ax.xaxis.set_ticks_position('none')
 ax.yaxis.set_ticks_position('none')
 ax.spines["top"].set_alpha(0)
 ax.tick_params(labelsize=6)

plt.tight_layout();
```



To extract maximum information from our data, it is important to have a normal or Gaussian distribution of the data. To check for that, we have done a normality test based on the Null and Alternate Hypothesis intuition.

```
stat,p = stats.normaltest(dataset.Gold)
print("Statistics = %.3f, p=%.3f" % (stat,p))
alpha = 0.05
if p> alpha:
print('Data looks Gaussian (fail to reject null hypothesis)')
else:
print('Data looks non-Gaussian (reject null hypothesis')

output: Statistics = 658.293, p=0.000 Data looks Gaussian (reject
null hypothesis
```

```
print('Kurtosis of normal distribution: {}'. format(stats.kurtosis(dataset.Gold)))
print('Skewness of normal distribution: {}'. format(stats.skew(dataset.Gold)))
```

```
Kurtosis of normal distribution: -0.7547875128340102
Skewness of normal distribution: 0.6561298945285786
```

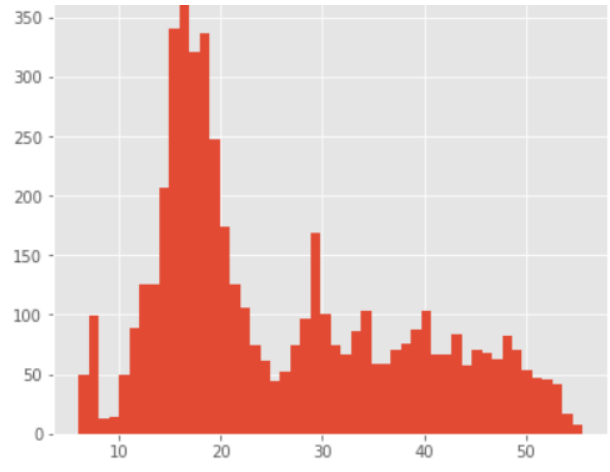
```
print('Kurtosis of normal distribution: {}'. format(stats.kurtosis(dataset.Oil)))
print('Skewness of normal distribution: {}'. format(stats.skew(dataset.Oil)))
```

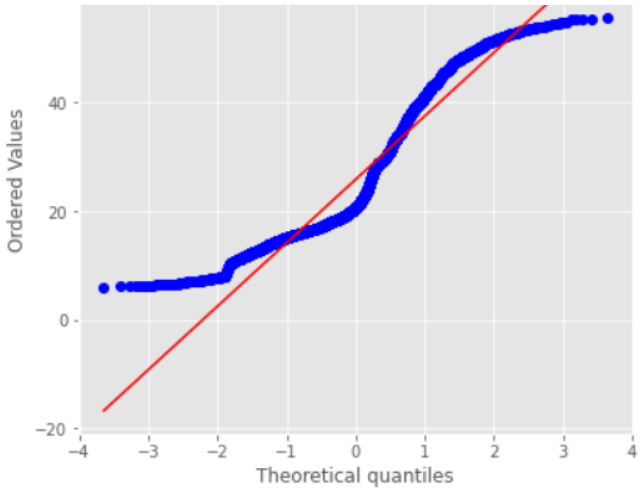
```
Kurtosis of normal distribution: -0.9559303293518187
Skewness of normal distribution: 0.2854153692916605
```

These two distributions give us some intuition about the distribution of our data. A value close to 0 for Kurtosis indicates a Normal Distribution where asymmetrical nature is signified by a value between -0.5 and +0.5 for skewness. The tails are heavier for kurtosis greater than 0 and vice versa. Moderate skewness refers to the value between -1 and -0.5 or 0.5 and 1.

```
plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
dataset['Gold'].hist(bins=50)
plt.title('Gold')
plt.subplot(1,2,2)
stats.probplot(dataset['Gold'], plot=plt);
dataset.Gold.describe().T
```

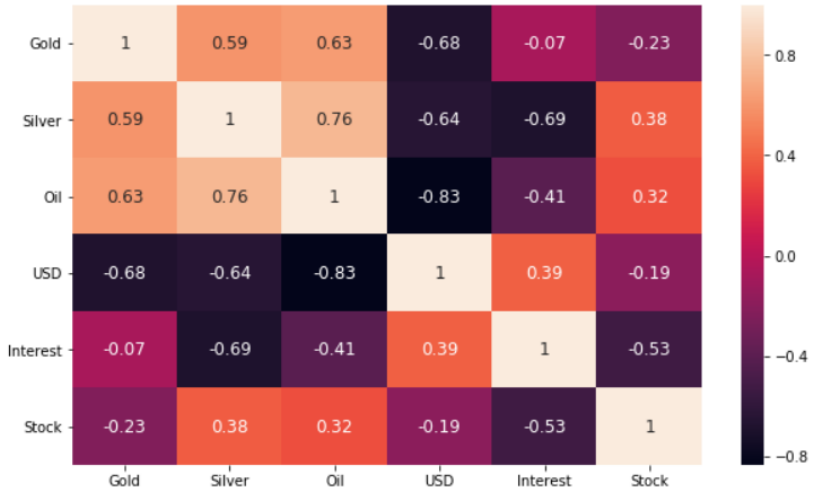
```
count    5129.000000
mean       25.828860
std        12.218568
min         6.080000
25%        16.379999
50%        20.700001
75%        34.980000
max        55.540001
Name: Gold, dtype: float64
```





Normal probability plot also shows the data is far from normally distributed.

```
corr = dataset.corr()
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.columns.values, annot = True, annot_kws={'size':12})
heat_map=plt.gcf()
heat_map.set_size_inches(10,6)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.show()
```



Steps to build VAR model

I will follow some procedural steps as mentioned below to achieve the goal here-

- Exploratory data analysis on training set
- Stationarity test
- Split the series into training and validation sets
- Transform the series
- Build a model on transformed series

- Model diagnostic
- Model selection (based on pre-defined criteria)
- Conduct forecast using the final, chosen model
- Inverse transform the forecast
- Conduct forecast evaluation

Auto-correlation

> Auto-correlation or serial correlation can be a significant problem in analyzing historical data if we do not know how to look out for it.

```
# plots the autocorrelation plots for each stock's price at 50 lags
for i in dataset:
plt_acf(dataset[i], lags = 50)
plt.title('ACF for %s' % i)
plt.show()
```

We see here from the above plots, the auto-correlation of +1 which represents a perfect positive correlation which means, an increase seen in one time series leads to a proportionate increase in the other time series. We definitely need to apply transformation and neutralize this to make the series stationary. It measures linear relationships; even if the auto-correlation is minuscule, there may still be a nonlinear relationship between a time series and a lagged version of itself.

Split the Series into Training and Testing Data

The VAR model will be fitted on X_train and then used to forecast the next 15 observations. These forecasts will be compared against the actual present in test data.

```
n_obs=15
X_train, X_test = dataset[0:-n_obs], dataset[-n_obs:]
print(X_train.shape, X_test.shape)

(5114, 6) (15, 6)
```

Transformation

Applying first differencing on training set should make all the 6 series stationary. However, this is an iterative process where we after first differencing, the series may still be non-stationary. We shall have to apply second difference or log transformation to standardize the series in such cases.

```
transform_data = X_train.diff().dropna()
transform_data.head()
```

Date	Gold	Silver	Oil	USD	Interest	Stock
2000-01-05	0.2500	-0.120	0.30	-0.09	-0.009	23.270019
2000-01-06	0.1875	-0.043	-0.70	-0.04	0.037	68.410156
2000-01-07	0.0625	0.023	-0.15	0.13	-0.013	157.229981
2000-01-10	-0.3750	-0.005	-0.43	0.18	-0.005	45.780273
2000-01-11	0.0000	0.050	0.49	0.29	0.060	-63.970215

```
transform_data.describe()
```

	Gold	Silver	Oil	USD	Interest	Stock
count	5113.000000	5113.000000	5113.000000	5113.000000	5113.000000	5113.000000
mean	-0.000886	0.002330	0.007452	-0.002080	-0.000730	1.141561
std	0.699671	0.359989	1.300758	0.460318	0.056205	84.506113
min	-5.310002	-5.677000	-11.490000	-2.545000	-0.522000	-990.589850
25%	-0.280001	-0.085000	-0.580000	-0.255000	-0.031000	-32.030274
50%	0.000000	0.002000	0.000000	0.000000	0.000000	0.000000
75%	0.280001	0.106000	0.640000	0.250000	0.029000	38.540039
max	6.309999	2.585000	9.770000	2.365000	0.334000	992.450200

Stationarity check

```
def augmented_dickey_fuller_statistics(time_series):
result = adfuller(time_series.values)
print('ADF Statistic: %f' % result[0])
print('p-value: %f' % result[1])
print('Critical Values:')
for key, value in result[4].items():
print('\t%s: %.3f' % (key, value))
```

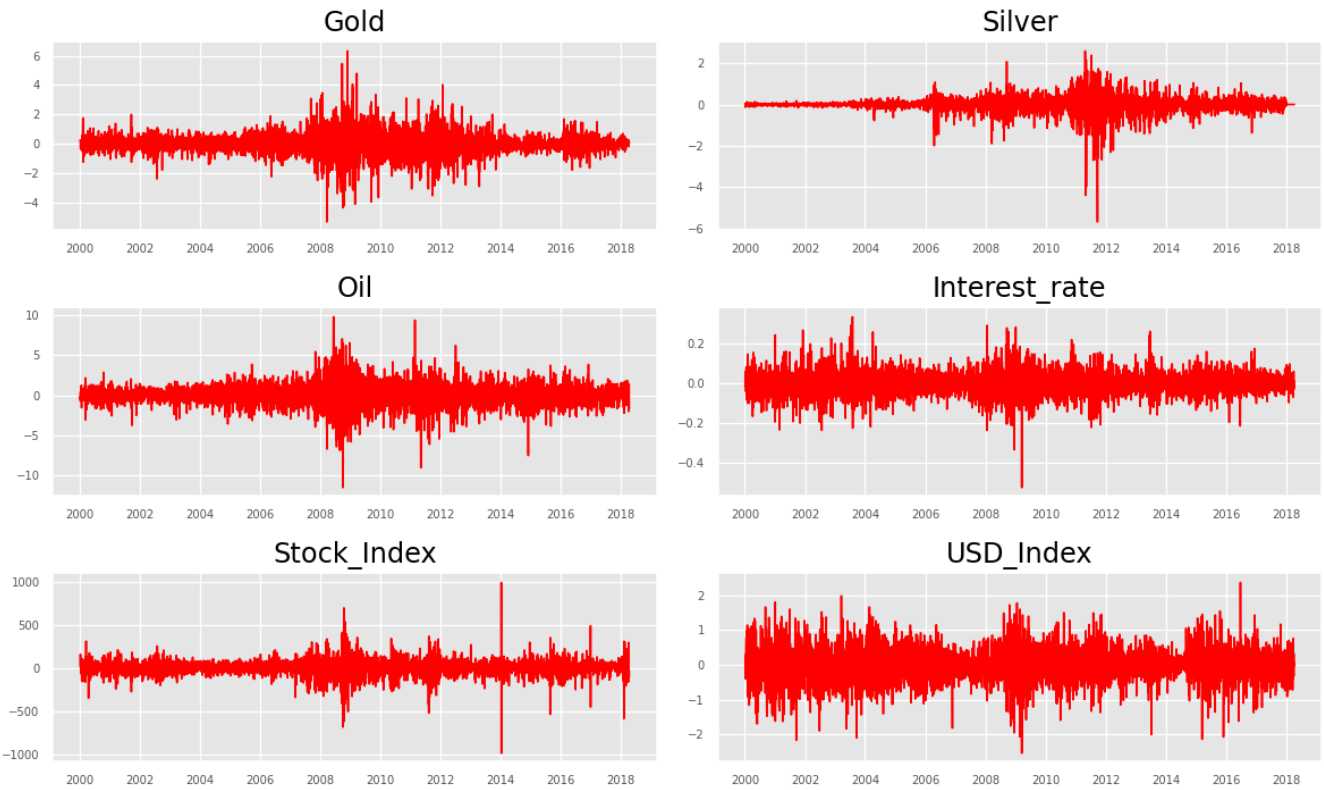
```
print('Augmented Dickey-Fuller Test: Gold Price Time Series')
augmented_dickey_fuller_statistics(X_train_transformed['Gold'])
print('Augmented Dickey-Fuller Test: Silver Price Time Series')
augmented_dickey_fuller_statistics(X_train_transformed['Silver'])
print('Augmented Dickey-Fuller Test: Oil Price Time Series')
augmented_dickey_fuller_statistics(X_train_transformed['Oil'])
print('Augmented Dickey-Fuller Test: Interest_rate Time Series')
augmented_dickey_fuller_statistics(X_train_transformed['Interest_rat
e'])
print('Augmented Dickey-Fuller Test: Stock_Index Time Series')
augmented_dickey_fuller_statistics(X_train_transformed['Stock_Index'
])
print('Augmented Dickey-Fuller Test: USD_Index Time Series')
augmented_dickey_fuller_statistics(X_train_transformed['USD_Index'])
```

```
Augmented Dickey-Fuller Test: Gold Price Time Series
ADF Statistic: -15.451920
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
Augmented Dickey-Fuller Test: Silver Price Time Series
ADF Statistic: -13.108853
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
Augmented Dickey-Fuller Test: Oil Price Time Series
ADF Statistic: -16.834911
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
Augmented Dickey-Fuller Test: Interest_rate Time Series
ADF Statistic: -53.527511
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
Augmented Dickey-Fuller Test: Stock_Index Time Series
ADF Statistic: -17.364640
p-value: 0.000000
Critical Values:
        1%: -3.432
```

```
        5%: -2.862
        10%: -2.567
Augmented Dickey-Fuller Test: USD_Index Time Series
ADF Statistic: -74.705481
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
```

```
fig, axes = plt.subplots(nrows=3, ncols=2, dpi=120, figsize=(10,6))
for i, ax in enumerate(axes.flatten()):
d = X_train_transformed[X_train_transformed.columns[i]]
ax.plot(d, color='red', linewidth=1)

# Decorations
ax.set_title(dataset.columns[i])
ax.xaxis.set_ticks_position('none')
ax.yaxis.set_ticks_position('none')
ax.spines['top'].set_alpha(0)
ax.tick_params(labelsize=6)
plt.tight_layout();
```



Testing Causation using Granger's Causality Test

The basis behind VAR is that each of the time series in the system influences each other. That is, we can predict the series with past values of itself along with other series in the

system. Using Granger's Causality Test, it's possible to test this relationship before even building the model.

Granger's causality Tests the null hypothesis that the coefficients of past values in the regression equation is zero. In simpler terms, the past values of time series (x) do not cause the other series (y). So, if the p-value obtained from the test is lesser than the significance level of 0.05, then, you can safely reject the null hypothesis. This has been performed on original data-set.

Below piece of code taken from stackoverflow.

```
maxlag=12
test = 'ssr-chi2test'
def grangers_causality_matrix(X_train, variables, test =
'ssr_chi2test', verbose=False):
dataset = pd.DataFrame(np.zeros((len(variables), len(variables))),
columns=variables, index=variables)
for c in dataset.columns:
for r in dataset.index:
test_result = grangercausalitytests(X_train[[r,c]], maxlag=maxlag,
verbose=False)
p_values = [round(test_result[i+1][0][test][1],4) for i in
range(maxlag)]
if verbose: print(f'Y = {r}, X = {c}, P Values = {p_values}')
min_p_value = np.min(p_values)
dataset.loc[r,c] = min_p_value
dataset.columns = [var + '_x' for var in variables]
dataset.index = [var + '_y' for var in variables]
return dataset
grangers_causality_matrix(dataset, variables = dataset.columns)
```

	Gold_x	Silver_x	Oil_x	Interest_rate_x	Stock_Index_x	USD_Index_x
Gold_y	1.0000	0.0000	0.0548	0.0342	0.0200	0.5159
Silver_y	0.0000	1.0000	0.1447	0.4335	0.4378	0.2418
Oil_y	0.0000	0.0000	1.0000	0.0000	0.0122	0.0018
Interest_rate_y	0.0082	0.0177	0.2292	1.0000	0.2153	0.2043
Stock_Index_y	0.0000	0.0000	0.0361	0.0000	1.0000	0.0263
USD_Index_y	0.0000	0.0000	0.2514	0.1879	0.3509	1.0000

The row are the response (y) and the columns are the predictor series (x).

- If we take the value 0.0000 in (row 1, column 2), it refers to the p-value of the Granger's Causality test for Silver_x causing Gold_y. The 0.0000 in (row 2, column 1) refers to the p-value of Gold_y causing Silver_x and so on.

- We can see that, in the case of *Interest* and *USD* variables, we cannot reject null hypothesis e.g. *USD* & *Silver, USD & Oil.* Our variables of interest are *Gold* and *Oil* here. So, for *Gold,* all the variables cause but for *USD* doesn't causes any effect on *Oil*.

So, looking at the p-Values, we can assume that, except USD, all the other variables (time series) in the system are interchangeably causing each other. This justifies the VAR modeling approach for this system of multi time-series to forecast.

VAR model

VAR requires stationarity of the series which means the mean to the series do not change over time (we can find this out from the plot drawn next to Augmented Dickey-Fuller Test).

Let's understand the mathematical intuition of VAR model.

$$y_{1,t} = c_1 + \Phi_{11,1} y_{1,t-1} + \Phi_{K2,1} y_{2,t-1} + \ldots\ldots \Phi_{1K,1} y_{K,t-1} + \varepsilon_{1,t}$$

$$y_{2,t} = c_2 + \Phi_{21,1} y_{1,t-1} + \Phi_{K2,1} y_{2,t-1} + \ldots\ldots \Phi_{2K,1} y_{K,t-1} + \varepsilon_{2,t}$$

$$\vdots$$

$$y_{K,t} = c_K + \Phi_{K1,1} y_{1,t-1} + \Phi_{K2,1} y_{2,t-1} + \ldots\ldots \Phi_{KK,1} y_{K,t-1} + \varepsilon_{K,t}$$

Here each series is modeled by it's own lag and other series' lag. y{1,t-1, y{2,t-1}…. are the lag of time series y1,y2,…. respectively. The above equations are referred to as a VAR (1) model, because, each equation is of order 1, that is, it contains up to one lag of each of the predictors (y1, y2, …..). Since the y terms in the equations are interrelated, the y's are considered as endogenous variables, rather than as exogenous predictors. To thwart the issue of structural instability, the VAR framework was utilized choosing the lag length according to AIC.

So, I will fit the VAR model on training set and then used the fitted model to forecast the next 15 observations. These forecasts will be compared against the actual present in

test data. I have taken the maximum lag (15) to identify the required lags for VAR model.

```
mod = smt.VAR(X_train_transformed)
res = mod.fit(maxlags=15, ic='aic')
print(res.summary())
```

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sat, 27, Jun, 2020
Time:                     09:48:57
--------------------------------------------------------------------
No. of Equations:         6.00000    BIC:                   -1.19025
Nobs:                     5111.00    HQIC:                  -1.25510
Log likelihood:          -40138.5    FPE:                   0.275259
AIC:                     -1.29004    Det(Omega_mle):        0.271096
--------------------------------------------------------------------
```

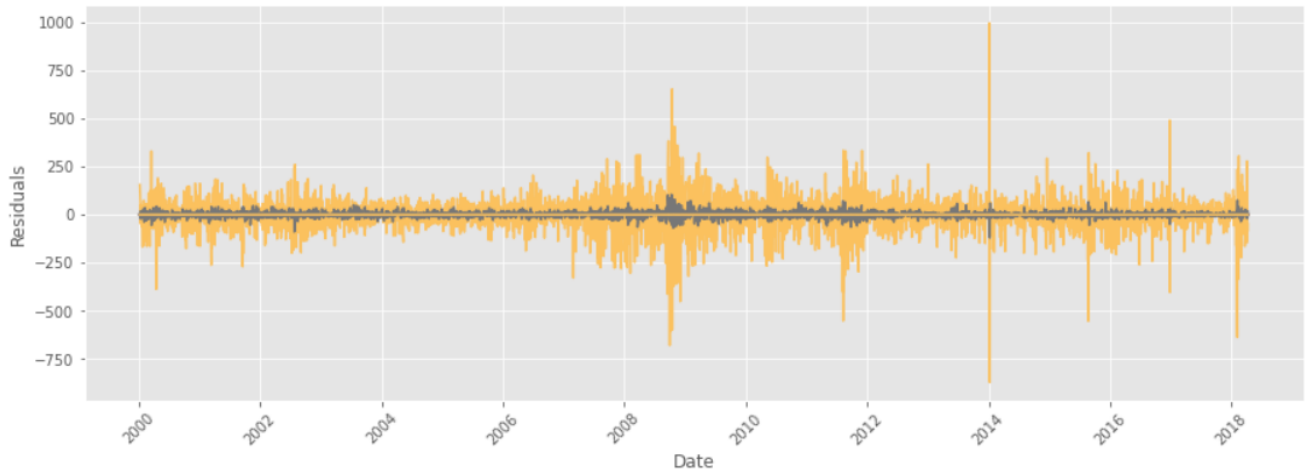
```
Correlation matrix of residuals
                Gold    Silver       Oil       USD  Interest     Stock
Gold        1.000000  0.387653  0.201638 -0.200735 -0.009341  0.161670
Silver      0.387653  1.000000  0.194438 -0.140164  0.004120  0.141765
Oil         0.201638  0.194438  1.000000 -0.199088  0.107060  0.280690
USD        -0.200735 -0.140164 -0.199088  1.000000  0.160394 -0.162544
Interest   -0.009341  0.004120  0.107060  0.160394  1.000000  0.209950
Stock       0.161670  0.141765  0.280690 -0.162544  0.209950  1.000000
```

The biggest correlations are 0.38 (Silver & Gold) and -0.19 (Oil & USD); however, there are small enough to ignore in this case.

Residual plot

Residual plot looks normal with constant mean throughout apart from some large fluctuation during 2009, 2011, 2014 etc.

```
y_fitted = res.fittedvalues
plt.figure(figsize = (15,5))
plt.plot(residuals, label='resid')
plt.plot(y_fitted, label='VAR prediction')
plt.xlabel('Date')
plt.xticks(rotation=45)
plt.ylabel('Residuals')
plt.grid(True)
```



Durbin-Watson Statistic

Durbin-Watson Statistic is related to related to auto correlation.

> *The Durbin-Watson statistic will always have a value between 0 and 4. A value of 2.0 means that there is no auto-correlation detected in the sample. Values from 0 to less than 2 indicate positive auto-correlation and values from 2 to 4 indicate negative auto-correlation. A rule of thumb is that test statistic values in the range of 1.5 to 2.5 are relatively normal. Any value outside this range could be a cause for concern.*

A stock price displaying positive auto-correlation would indicate that the price yesterday has a positive correlation on the price today — so if the stock fell yesterday, it is also likely that it falls today. A stock that has a negative auto-correlation, on the other hand, has a negative influence on itself over time — so that if it fell yesterday, there is a greater likelihood it will rise today.

```
from statsmodels.stats.stattools import durbin_watson
out = durbin_watson(res.resid)

for col, val in zip(transform_data.columns, out):
    print((col), ':', round(val, 2))
```

```
Gold : 2.0
Silver : 2.0
Oil : 2.0
USD : 2.0
Interest : 2.0
Stock : 2.0
```

There is no auto-correlation (2.0) exist; so, we can proceed with the forecast.

Prediction

In order to forecast, the VAR model expects up to the lag order number of observations from the past data. This is because, the terms in the VAR model are essentially the lags of the various time series in the data-set, so we need to provide as many of the previous values as indicated by the lag order used by the model.

```
# Get the lag order
lag_order = res.k_ar
print(lag_order)

# Input data for forecasting
input_data = X_train_transformed.values[-lag_order:]
print(input_data)

# forecasting
pred = res.forecast(y=input_data, steps=n_obs)
pred = (pd.DataFrame(pred, index=X_test.index,
columns=X_test.columns + '_pred'))
print(pred)
```

Date	Gold_pred	Silver_pred	Oil_pred	Interest_rate_pred	Stock_Index_pred	USD_Index_pred
2018-04-11	-0.002624	0.001585	-0.030177	0.002666	11.756011	0.036694
2018-04-12	-0.011787	-0.001876	0.013445	0.000837	3.269195	0.003336
2018-04-13	-0.001740	0.001800	0.003695	-0.001249	0.492346	-0.002411
2018-04-16	-0.001624	0.002012	0.005875	-0.000819	1.040094	-0.002270
2018-04-17	-0.000753	0.002307	0.007203	-0.000702	1.121373	-0.001844
2018-04-18	-0.000946	0.002386	0.007628	-0.000729	1.131713	-0.002042
2018-04-19	-0.000980	0.002357	0.007529	-0.000736	1.129534	-0.002059
2018-04-20	-0.000974	0.002352	0.007488	-0.000734	1.125906	-0.002042
2018-04-23	-0.000971	0.002353	0.007493	-0.000734	1.126257	-0.002042
2018-04-24	-0.000972	0.002354	0.007497	-0.000734	1.126638	-0.002043
2018-04-25	-0.000972	0.002354	0.007496	-0.000734	1.126575	-0.002043
2018-04-26	-0.000972	0.002354	0.007496	-0.000734	1.126550	-0.002043
2018-04-27	-0.000972	0.002354	0.007496	-0.000734	1.126556	-0.002043
2018-04-30	-0.000972	0.002354	0.007496	-0.000734	1.126557	-0.002043
2018-05-01	-0.000972	0.002354	0.007496	-0.000734	1.126557	-0.002043

Invert the transformation to get the real forecast

The forecasts are generated but it is on the scale of the training data used by the model. So, to bring it back up to its original scale, we need to de-difference it.

The way to convert the differencing is to add these differences consecutively to the base number. An easy way to do it is to first determine the cumulative sum at index and then add it to the base number.

This process can be reversed by adding the observation at the prior time step to the difference value. inverted(ts) = differenced(ts) + observation(ts-1)

```
# inverting transformation
def invert_transformation(X_train, pred):
forecast = pred.copy()
columns = X_train.columns
for col in columns:
forecast[str(col)+'_pred'] = X_train[col].iloc[-1] +
forecast[str(col)+'_pred'].cumsum()
return forecast
output = invert_transformation(X_train, pred)

#combining predicted and real data set
combine = pd.concat([output['Gold_pred'], X_test['Gold']], axis=1)
combine['accuracy'] = round(combine.apply(lambda row: row.Gold_pred
/row.Gold *100, axis = 1),2)
combine['accuracy'] = pd.Series(["{0:.2f}%".format(val) for val in
combine['accuracy']],index = combine.index)
combine = combine.round(decimals=2)
combine = combine.reset_index()
combine = combine.sort_values(by='Date', ascending=False)
```

	Date	Gold_pred	Gold	accuracy
14	2018-05-01	12.75	13.44	94.88%
13	2018-04-30	12.75	13.63	93.56%
12	2018-04-27	12.75	13.62	93.64%
11	2018-04-26	12.75	13.53	94.27%
10	2018-04-25	12.76	13.20	96.63%
9	2018-04-24	12.76	12.93	98.66%
8	2018-04-23	12.76	13.00	98.14%
7	2018-04-20	12.76	13.25	96.29%
6	2018-04-19	12.76	13.32	95.79%

5	2018-04-18	12.76	13.17	96.89%
4	2018-04-17	12.76	13.00	98.17%
3	2018-04-16	12.76	13.20	96.68%
2	2018-04-13	12.76	13.01	98.11%
1	2018-04-12	12.77	12.95	98.58%
0	2018-04-11	12.78	12.87	99.28%

Evaluation

To evaluate the forecasts, a comprehensive set of metrics, such as the MAPE, ME, MAE, MPE and RMSE can be computed. We have computed some of these as below.

```
#Forecast bias
forecast_errors = [combine['Gold'][i]- combine['Gold_pred'][i] for i
in range(len(combine['Gold']))]
bias = sum(forecast_errors) * 1.0/len(combine['Gold'])
print('Bias: %f' % bias)

print('Mean absolute error:',
mean_absolute_error(combine['Gold'].values,
combine['Gold_pred'].values))

print('Mean squared error:',
mean_squared_error(combine['Gold'].values,
combine['Gold_pred'].values))

print('Root mean squared error:',
sqrt(mean_squared_error(combine['Gold'].values,
combine['Gold_pred'].values)))
```

```
Bias: 0.448667
Mean absolute error: 0.4486666666666666
Mean squared error: 0.2647933333333332
Root mean squared error: 0.5145807354860199
```

Mean absolute error tells us how big of an error we can expect from the forecast on average. Our error rates are quite low here indicating we have the right fit of the model.

Summary

The VAR model is a popular tool for the purpose of predicting joint dynamics of multiple time series based on linear functions of past observations. More analysis e.g. impulse response (IRF) and forecast error variance decomposition (FEVD) can also be done along-with VAR to for assessing the impacts of shock from one asset on another to assess the impacts of shock from one asset on another. However, I will keep this simple here for easy understanding. In real-life business case, we should do multiple models with different approach to do the comparative analysis before zeroed down on one or a hybrid model.

I can be connected here.

Notice: The programs described here are experimental and should be used with caution. All such use at your own risk.