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PREDICTIVE ANALYTICS AND TIME SERIES DATA

Future Price Prediction Beyond Test Data Using Vector Auto Regression

Simple steps to multi-step future prediction

Sarit Maitra · Follow

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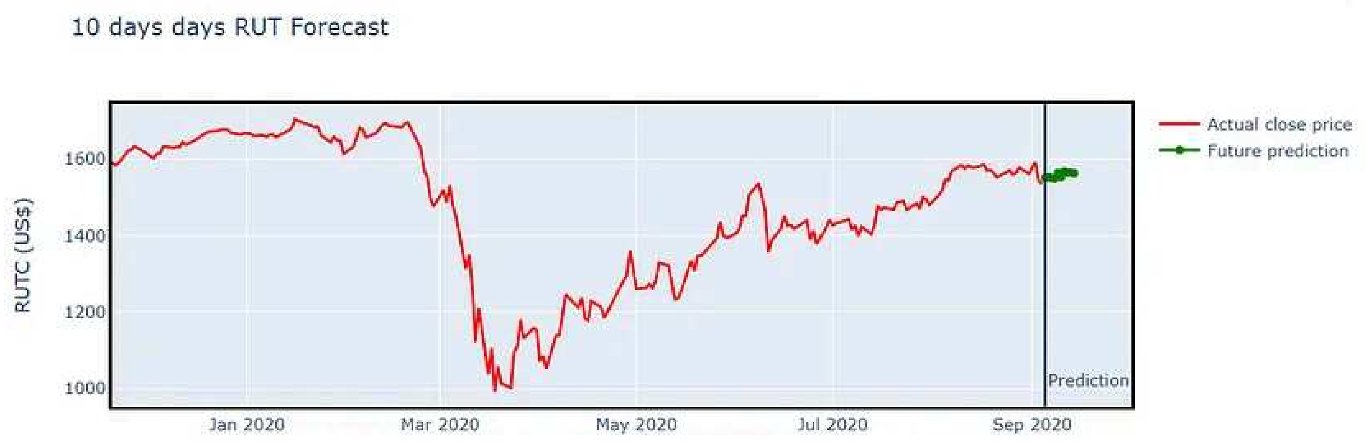

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Vector Auto Regression (VAR) comes with an advantage in easy implementation. Every equation in the VAR has the same number of variables on the right-hand side, the coefficients {α1, α2, …, β11, β21, …, γ 11, γ 21, … } of the overall system can be easily estimated by applying (OLS) regression to each equation individually. We could estimate this model using the ordinary least squares (OLS) estimator computed separately from each equations. Since the OLS estimator has standard asymptotic properties, it is possible to test any linear restriction, either in one equation or across equations, with the standard t and F statistics. The VAR models have the advantage over traditional machine learning models in that the results are not hidden by a large and complicated structure ("black box"), but are easily interpreted and available.

Testing of Granger causality helps to know whether one or more variables have predictive content to forecast and Impulse-response function and variance decomposition are normally used to quantify the effects over time. I already have written in the past about VAR and how multivariate time series can be fitted to generate prediction covering both.

Here, I will discuss simple steps to predict unknown future using VAR.

```
stock = ['^RUT', '^GSPC', '^DJI', '^IXIC' ]
start = pd.to_datetime('1990-01-03')
df = web.DataReader(stock, data_source = 'yahoo', start = start);
print(df.tail());
```

```
Attributes    Adj Close                                                  Close                                                  High                  \
Symbols            ^RUT        ^GSPC          ^DJI         ^IXIC          ^RUT        ^GSPC          ^DJI         ^IXIC          ^RUT        ^GSPC
Date
2020-08-31  1561.880005  3500.310059  28430.050781  11775.459961  1561.880005  3500.310059  28430.050781  11775.459961  1577.550049  3514.770020
2020-09-01  1578.579956  3526.649902  28645.660156  11939.669922  1578.579956  3526.649902  28645.660156  11939.669922  1578.579956  3528.030029
2020-09-02  1592.290039  3580.840088  29100.500000  12056.440430  1592.290039  3580.840088  29100.500000  12056.440430  1595.040039  3588.110107
2020-09-03  1544.680054  3455.060059  28292.730469  11458.099609  1544.680054  3455.060059  28292.730469  11458.099609  1592.469971  3564.850098
2020-09-04  1535.300049  3426.959961  28133.310547  11313.129883  1535.300049  3426.959961  28133.310547  11313.129883  1563.380005  3479.149902

Attributes                                    Low                                                    Open                                                    \
Symbols             ^DJI         ^IXIC          ^RUT        ^GSPC          ^DJI         ^IXIC          ^RUT        ^GSPC          ^DJI         ^IXIC
Date
2020-08-31  28643.660156  11829.839844  1561.880005  3493.250000  28363.550781  11697.419922  1577.550049  3509.729980  28643.660156  11718.809570
2020-09-01  28659.259766  11945.719727  1554.189941  3494.600098  28290.720703  11794.780273  1561.099976  3507.439941  28439.609375  11850.959961
2020-09-02  29162.880859  12074.059570  1567.430054  3535.229980  28713.529297  11836.179688  1578.780029  3543.760010  28736.789062  12047.259766
2020-09-03  29199.349609  11894.400391  1538.530029  3427.409912  28074.759766  11361.360352  1592.469971  3564.739990  29090.699219  11861.900391
2020-09-04  28539.750000  11531.179688  1501.520020  3349.629883  27664.679688  10875.870117  1546.640015  3453.600098  28341.050781  11396.240234

Attributes    Volume
Symbols         ^RUT       ^GSPC       ^DJI       ^IXIC
Date
2020-08-31  43422900  4342290000  517320000  3596980000
2020-09-01  40831100  4083110000  423410000  3480780000
2020-09-02  42851900  4285190000  539510000  3966140000
2020-09-03  48986800  4898680000  650080000  4437500000
2020-09-04  44314400  4431440000  694640000  4269190000
```

Here, we have data from Russell 2000 (^RUT), S&P 500 (^GSPC), NASDAQ Composite (^IXIC) and Dow Jones Industrial Average (^DJI). Let us separate Adj Close columns for all variables.

```
data = df['Adj Close']
data.tail()
```

Symbols	^RUT	^GSPC	^DJI	^IXIC
Date				
2020-08-31	1561.880005	3500.310059	28430.050781	11775.459961
2020-09-01	1578.579956	3526.649902	28645.660156	11939.669922
2020-09-02	1592.290039	3580.840088	29100.500000	12056.440430
2020-09-03	1544.680054	3455.060059	28292.730469	11458.099609
2020-09-04	1535.300049	3426.959961	28133.310547	11313.129883

Let us visually compare these series in one chart after applying normalization. We can see high correlation among all the variables selected here. This makes a good candidate for multivariate VAR.

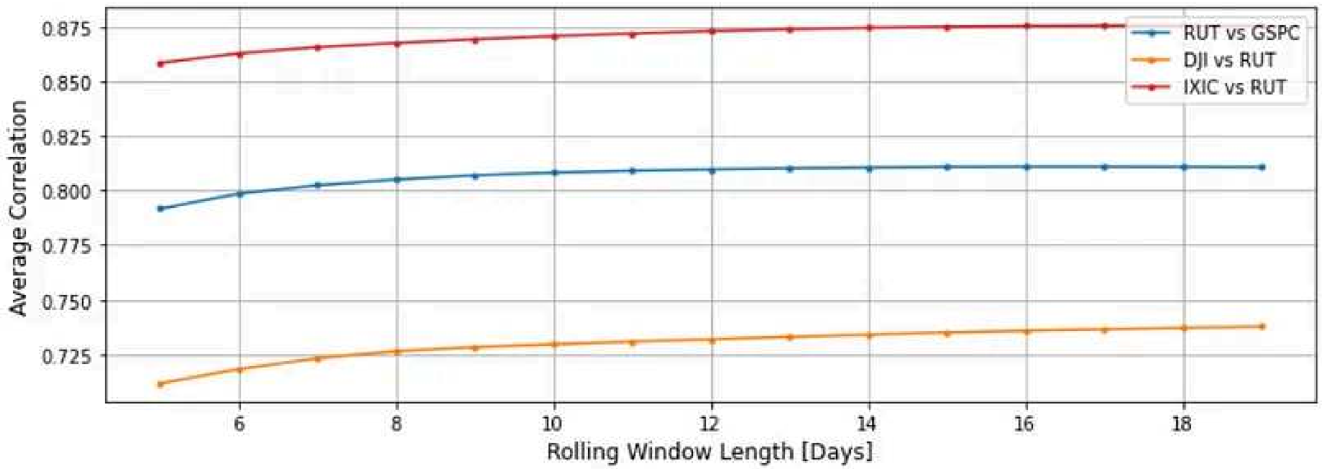
```
scaler = MinMaxScaler(feature_range=(0, 1))
sdf_np = scaler.fit_transform(data)
sdf = DataFrame(sdf_np, columns=data.columns, index=data.index)
plt.figure(figsize=(12,6))
plt.grid()
plt.plot(sdf)
plt.legend(sdf.columns)
plt.show()
```

Our goal here is to predict expected future prices of ^RUT and a motivation for the selection of DJI, GSPC and IXIC is their high correlation with RUT.

We can also diagnose the correlation by measuring the average linear correlation over the rolling window in a function of rolling window size; here I have taken window size of 5 and 20 days for visual display.

```
blue, orange, red = '#1f77b4', '#ff7f0e', '#d62728'  # color codes
plt.figure(figsize=(12,4))
plt.grid()
cor1, cor2, cor3 = list(), list(), list()
# average correlation for increasing rolling window size
for win in range(5, 20):  # Days
cor1.append(data['^GSPC'].rolling(win).corr(data['^RUT']) \
.replace([np.inf, -np.inf], np.nan).dropna().mean())
cor2.append(data['^DJI'].rolling(win).corr(data['^RUT']) \
.replace([np.inf, -np.inf], np.nan).dropna().mean())
cor3.append(data['^IXIC'].rolling(win).corr(data['^RUT']) \
.replace([np.inf, -np.inf], np.nan).dropna().mean())

plt.plot(range(5, 20), cor1, '.-', color=blue, label='RUT vs GSPC')
plt.plot(range(5, 20), cor2, '.-', color=orange, label='DJI vs RUT')
plt.plot(range(5, 20), cor3, '.-', color=red, label='IXIC vs RUT')
plt.legend()
plt.xlabel('Rolling Window Length [Days]', fontsize=12)
plt.ylabel('Average Correlation', fontsize=12)
plt.show()
```



In the context of variables or features selection, we need to decide which variables to include into the model. Since we can not and should not include all variables of potential interest, we have to have a priori ideas when choosing variables.

ADFuller to test for Stationarity

We need to get rid of trend in the data to let the model work on prediction. Let us check the stationarity of our data set.

```
def adfuller_test(series, signif=0.05, name='', verbose=False):
r = adfuller(series, autolag='AIC')
output = {'test_statistic':round(r[0], 4), 'pvalue':round(r[1], 4),
'n_lags':round(r[2], 4), 'n_obs':r[3]}
```

```
p_value = output['pvalue']
def adjust(val, length= 6): return str(val).ljust(length)

print(f'Augmented Dickey-Fuller Test on "{name}"', "\n   ", '-'*47)
print(f'Null Hypothesis: Data has unit root. Non-Stationary.')
print(f'Significance Level = {signif}')
print(f'Test Statistic = {output["test_statistic"]}')
print(f'No. Lags Chosen = {output["n_lags"]}')

for key,val in r[4].items():
  print(f' Critical value {adjust(key)} = {round(val, 3)}')
  if p_value <= signif:
     print(f" => P-Value = {p_value}. Rejecting Null Hypothesis.")
     print(f" => Series is Stationary.")
  else:
     print(f" => P-Value = {p_value}. Weak evidence to reject the
Null Hypothesis.")
     print(f" => Series is Non-Stationary.")

# ADF test on each column
for name, column in data.iteritems():
  adfuller_test(column, name = column.name)
```

```
Augmented Dickey-Fuller Test on "^RUT"
    -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -0.3981
No. Lags Chosen = 35
 Critical value 1%     = -3.431
 Critical value 5%     = -2.862
 Critical value 10%    = -2.567
 => P-Value = 0.9104. Weak evidence to reject the Null Hypothesis.
 => Series is Non-Stationary.
Augmented Dickey-Fuller Test on "^GSPC"
    -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = 1.1281
No. Lags Chosen = 36
 Critical value 1%     = -3.431
 Critical value 5%     = -2.862
 Critical value 10%    = -2.567
 => P-Value = 0.9954. Weak evidence to reject the Null Hypothesis.
 => Series is Non-Stationary.
Augmented Dickey-Fuller Test on "^DJI"
```

```
Augmented Dickey-Fuller Test on "^DJI"
    -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = 0.5528
No. Lags Chosen = 36
 Critical value 1%     = -3.431
 Critical value 5%     = -2.862
 Critical value 10%    = -2.567
 => P-Value = 0.9864. Weak evidence to reject the Null Hypothesis.
 => Series is Non-Stationary.
Augmented Dickey-Fuller Test on "^IXIC"
    -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = 2.5676
No. Lags Chosen = 36
 Critical value 1%     = -3.431
 Critical value 5%     = -2.862
 Critical value 10%    = -2.567
 => P-Value = 0.9991. Weak evidence to reject the Null Hypothesis.
 => Series is Non-Stationary.
```

It is clear that our existing data set is non-stationary. Let us take 1st order difference and check the stationarity again.

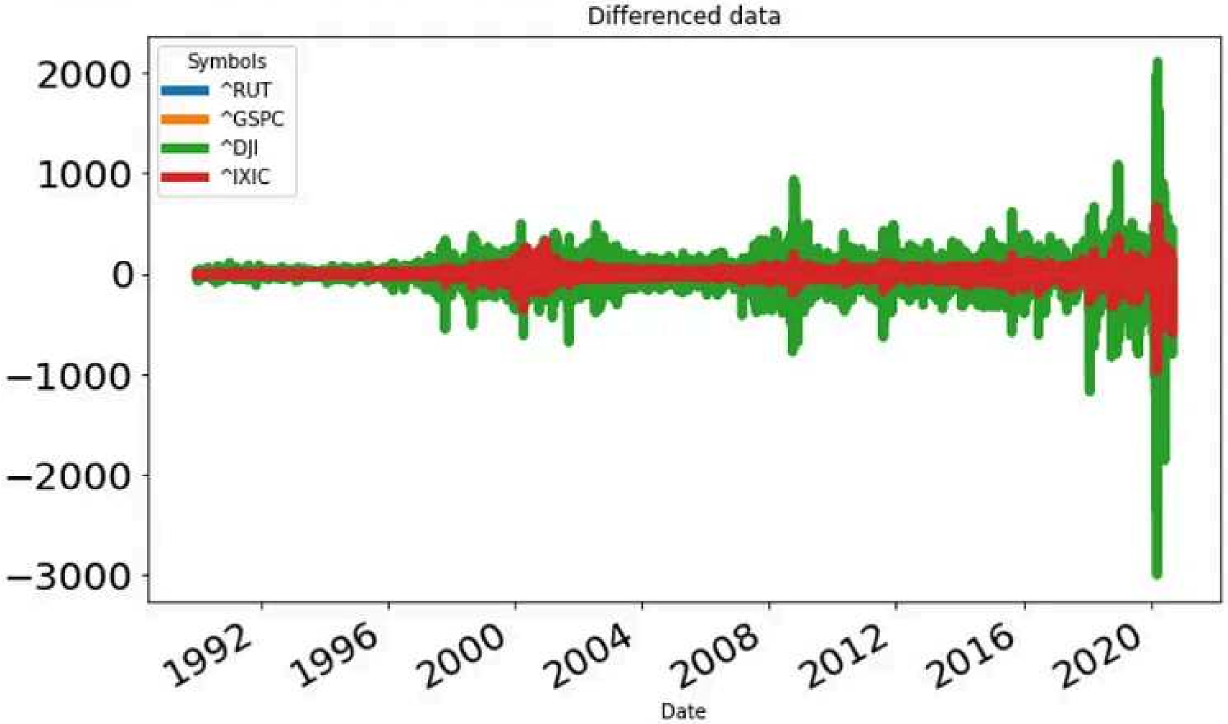
```
nobs = int(10) # number of future steps to predict

# differenced train data
data_diff = data.diff()
```

```
data_diff.dropna(inplace=True)
print('Glimpse of differenced data:')
print(data_diff.head())

# plotting differenced data
data_diff.plot(figsize=(10,6), linewidth=5, fontsize=20)
plt.title('Differenced data')
plt.show()
```

```
Glimpse of differenced data:
Symbols          ^RUT     ^GSPC       ^DJI     ^IXIC
Date
1990-01-04 -0.699997 -3.089996 -13.649902 -1.500000
1990-01-05 -0.440002 -3.470001 -22.830078 -1.199982
1990-01-08 -0.099991  1.589996  21.120117  0.500000
1990-01-09 -0.250000 -4.170013 -28.370117 -1.900024
1990-01-10 -1.360001 -2.309998 -15.360107 -6.099976
```



From the plot, we can assess that 1st order differenced has made the data stationary. However, let us run ADF test gain to validate.

```
# ADF Test on each column
for name, column in data_diff.iteritems():
```

```
adfuller_test(column, name=column.name)
```

```
Augmented Dickey-Fuller Test on "^DJI"
    -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -15.8337
No. Lags Chosen = 35
 Critical value 1%     = -3.431
 Critical value 5%     = -2.862
 Critical value 10%    = -2.567
 => P-Value = 0.0. Rejecting Null Hypothesis.
 => Series is Stationary.
Augmented Dickey-Fuller Test on "^IXIC"
    -----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level = 0.05
Test Statistic = -14.6937
No. Lags Chosen = 36
 Critical value 1%     = -3.431
 Critical value 5%     = -2.862
 Critical value 10%    = -2.567
 => P-Value = 0.0. Rejecting Null Hypothesis.
 => Series is Stationary.
```

Our data is stationarized to fit into regression model.

Vector Auto Regression

One model is specified, the appropriate lag length of the VAR model has to be decided. In deciding the number of lags, it has been common to use a statistical method, like the Akaike information criteria.

```
var_model = smt.VAR(data_diff)
res = var_model.select_order(maxlags=15)
print(res.summary())

results = var_model.fit(maxlags=15, ic='aic')
print(results.summary())
```

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	22.27	22.27	4.692e+09	22.27
1	22.24	22.25*	4.543e+09	22.24
2	22.22	22.26	4.482e+09	22.23
3	22.22	22.26	4.459e+09	22.23
4	22.21	22.27	4.435e+09	22.23
5	22.21	22.29	4.432e+09	22.24
6	22.20	22.29	4.385e+09	22.23
7	22.18	22.29	4.310e+09	22.22
8	22.17	22.29	4.257e+09	22.21
9	22.16	22.30	4.221e+09	22.21*
10	22.16	22.31	4.205e+09	22.21
11	22.16	22.32	4.212e+09	22.22
12	22.15	22.33	4.183e+09	22.21
13	22.15	22.34	4.172e+09	22.22
14	22.15	22.36	4.165e+09	22.22
15	22.15*	22.37	4.156e+09*	22.22

Correlation matrix of residuals

	^RUT	^GSPC	^DJI	^IXIC
^RUT	1.000000	0.868357	0.834560	0.813366
^GSPC	0.868357	1.000000	0.966471	0.895372
^DJI	0.834560	0.966471	1.000000	0.813201
^IXIC	0.813366	0.895372	0.813201	1.000000

Future predictions

Now that the model is fitted, let us call for the prediction.

```
# make predictions
pred = results.forecast(results.y, steps=nobs)
pred = DataFrame(pred, columns = data.columns+ '_pred')
print(pred)
```

Symbols	^RUT_pred	^GSPC_pred	^DJI_pred	^IXIC_pred
0	-1.111631	-3.210144	-54.811203	-18.877887
1	2.102828	8.201075	40.130150	25.051525
2	-2.482367	1.747004	-3.403546	-2.523552
3	-1.419123	3.711129	1.150103	14.349551
4	14.423217	18.877488	134.556490	65.639334
5	-10.781957	-22.649263	-201.510033	-72.717388
6	14.871588	26.855996	237.667891	78.530426
7	-3.151807	-5.778967	-53.187367	-15.475223
8	0.008099	1.054497	22.572021	10.507356
9	-1.555348	-4.087194	-11.226234	-19.971864

Similar observations can be obtained with the below lines of codes. In both cases we get the output but on differenced scale because our input data was differenced in order to stationarize.

```
# forecasting
lag_order = results.k_ar
DataFrame(results.forecast(data_diff.values[-lag_order:], nobs))
```

	0	1	2	3
0	-1.111631	-3.210144	-54.811203	-18.877887
1	2.102828	8.201075	40.130150	25.051525
2	-2.482367	1.747004	-3.403546	-2.523552
3	-1.419123	3.711129	1.150103	14.349551
4	14.423217	18.877488	134.556490	65.639334
5	-10.781957	-22.649263	-201.510033	-72.717388
6	14.871588	26.855996	237.667891	78.530426
7	-3.151807	-5.778967	-53.187367	-15.475223
8	0.008099	1.054497	22.572021	10.507356
9	-1.555348	-4.087194	-11.226234	-19.971864

Invert transform data to original shape

```
pred = DataFrame(pred, columns=data.columns+ '_pred')

def invert_transformation(data_diff, pred):
  forecast = pred.copy()
  columns = data.columns
  for col in columns:
    forecast[str(col)+'_pred'] = data[col].iloc[-1] +
forecast[str(col) +'_pred'].cumsum()
  return forecast

output = invert_transformation(data_diff, pred)
print(output.loc[:, ['^RUT_pred']])
output = DataFrame(output['^RUT_pred'])
print(output)
```

	^RUT_pred
0	1551.368349
1	1553.471177
2	1550.988810
3	1549.569688
4	1563.992905
5	1553.210948
6	1568.082536
7	1564.930729
8	1564.938828
9	1563.383480

Above are the future 10 days prediction; let us assign future dates to these values.

Assigning future dates

```
d = data.tail(nobs)
d.reset_index(inplace = True)
d = d.append(DataFrame({'Date': pd.date_range(start =
d.Date.iloc[-1], periods = (len(d)+1), freq = 'd', closed =
```

```
'right')}))
d.set_index('Date', inplace = True)
d = d.tail(nobs)
output.index = d.index
print(output)
```

```
             ^RUT_pred
Date
2020-09-05  1551.368349
2020-09-06  1553.471177
2020-09-07  1550.988810
2020-09-08  1549.569688
2020-09-09  1563.992905
2020-09-10  1553.210948
2020-09-11  1568.082536
2020-09-12  1564.930729
2020-09-13  1564.938828
2020-09-14  1563.383480
```

So, here we can see future prediction. Let us draw a plot to visualize with the historical data.

```
fig = go.Figure()
n = output.index[0]
fig.add_trace(go.Scatter(x = data.index[-200:], y = data['^RUT']
[-200:], marker = dict(color ="red"), name = "Actual close price"))
fig.add_trace(go.Scatter(x = output.index, y = output['^RUT_pred'],
marker=dict(color = "green"), name = "Future prediction"))
```

```
fig.update_xaxes(showline = True, linewidth = 2, linecolor='black',
mirror = True, showspikes = True,)
fig.update_yaxes(showline = True, linewidth = 2, linecolor='black',
mirror = True, showspikes = True,)
fig.update_layout(title= "10 days days RUT Forecast", yaxis_title =
'RUTC (US$)', hovermode = "x", hoverdistance = 100, # Distance to
show hover label of data point spikedistance = 1000,shapes = [dict(
x0 = n, x1 = n, y0 = 0, y1 = 1, xref = 'x', yref = 'paper',
line_width = 2)], annotations = [dict(x = n, y = 0.05, xref = 'x',
yref = 'paper', showarrow = False, xanchor = 'left', text =
'Prediction')])
fig.update_layout(autosize = False, width = 1000, height = 400,)

fig.show()
```

Here, we see how close VAR can predict future prices.

Key takeaways

VAR is easy to estimate. It has good forecasting capabilities; VAR model has the ability to capture dynamic structure of the time series variables and typically treat all variables as a priori endogenous. However, fitting standard VAR models to large dimensional time series could be challenging primarily due to the large number of parameters involved.

We have covered here as how to find the maximum lags and fitting a VAR model with transformed data. Once the model is fitted, next step is to predict multi-step future prices and invert the transformed data back to original shape to see the actual predicted price.

In the final stage, plotting the historical and predicted price gives a clear visual representation of our prediction.

I can be reached ***here***.

Note: The programs described here are experimental and should be used with caution for any commercial purpose. All such use at your own risk.

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Linear Regression Python

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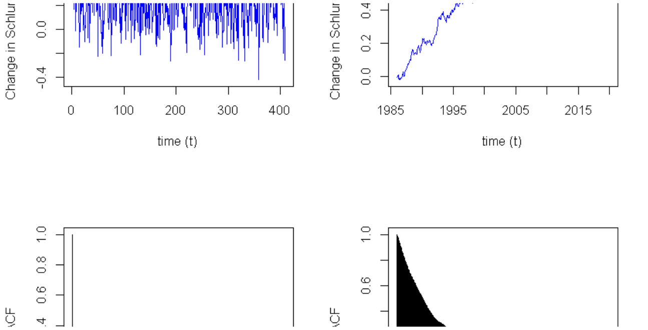

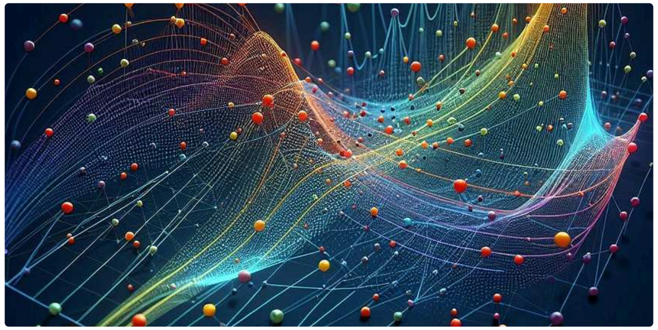

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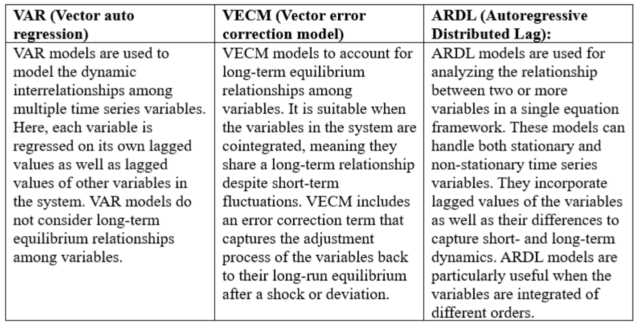

VAR (Vector auto regression)	VECM (Vector error correction model)	ARDL (Autoregressive Distributed Lag):
VAR models are used to model the dynamic interrelationships among multiple time series variables. Here, each variable is regressed on its own lagged values as well as lagged values of other variables in the system. VAR models do not consider long-term equilibrium relationships among variables.	VECM models to account for long-term equilibrium relationships among variables. It is suitable when the variables in the system are cointegrated, meaning they share a long-term relationship despite short-term fluctuations. VECM includes an error correction term that captures the adjustment process of the variables back to their long-run equilibrium after a shock or deviation.	ARDL models are used for analyzing the relationship between two or more variables in a single equation framework. These models can handle both stationary and non-stationary time series variables. They incorporate lagged values of the variables as well as their differences to capture short- and long-term dynamics. ARDL models are particularly useful when the variables are integrated of different orders.

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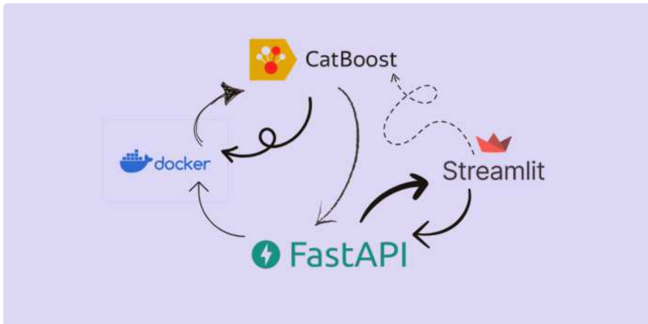

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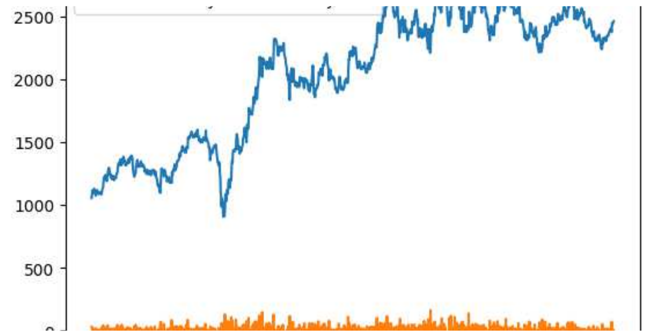

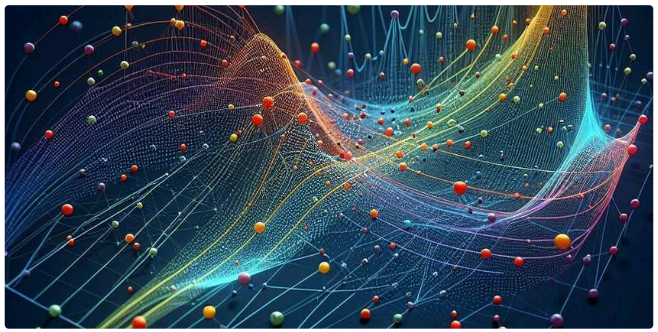

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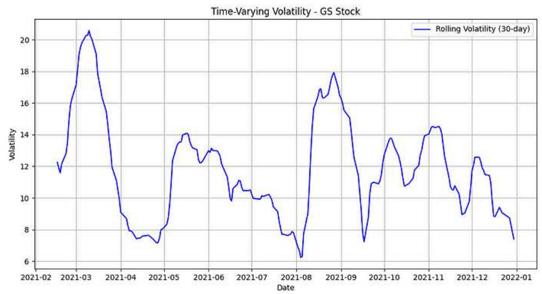

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