0 ．Analysis environment

Data editing was done in R, and post-editing analysis was done in Python. I would like to thank Rstudio.Clo ud and Google Colaboratory for their help.

1 ．Data to be analyzed

1.1. Nikkei 225

After looking into it, it seems that there are various peculiarities as a stock price index, but it is the most maj or, so I adopted it.

1.2. dow industrial stocks

There is also the S&P500. Somehow decided with a major feeling.

1.3. Japanese government bond 10 years

The reason I used 10-year government bonds as an interest rate indicator was because I was taught that w hen I was working at a stock market at the end of the market.

It's knowledge from 20 years ago, so I don't know if that feeling still remains.

1.4. 10 year US treasury bond

Since I chose a 10-year Japanese government bond, I set it to 10 years to match the consistency of the mat urity.

1.5. Yen US dollar exchange

Once I got the US and UK stocks and interest rates, I wanted a currency exchange that connects them.

1.6. others

I thought about gold as an escape from financial assets, but I didn't want to increase variables, so I gave up.

1.7. data editing program

Since the author is unfamiliar with python, I edited it with R. I'm not good at R anymore.

1.7.1. Joining method

In terms of SQL, the date is used as a join key, and it is a simple Inner Join, and it is a body that throws awa y all the days that are closed even if it is one. It's just a preliminary preliminary analysis, so I'm fine with this.

1 ．8 ．basic statistics

<Python-Code-Begin>

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
import statsmodels.api as sm
import datetime
#Data
!wget https://www.dropbox.com/s/********/TsData002.csv
df000 = pd.read_csv(    'TsData002.csv', parse_dates=['Date'])
df000.head(5)
```

	Date	JpyToUsd	N225Price	DawPrice	Y10	UsBondYr10
0	1987-08-13	151.45	25575.740234	2691.489990	5.645	8.634
1	1987-08-14	150.00	25494.009766	2685.429932	5.682	8.559
2	1987-08-17	149.91	25378.880859	2700.570068	5.718	8.587
3	1987-08-18	146.08	25344.339844	2654.659912	5.790	8.720
4	1987-08-19	145.10	25231.589844	2665.820068	5.626	8.815

df000.describe(include='all')

	Date	JpyToUsd	N225Price	DawPrice	Y10	UsBondYr10
count	7088	7088.000000	7088.000000	7088.000000	7088.000000	7088.000000
unique	7088	NaN	NaN	NaN	NaN	NaN
top	2007-09-10 00:00:00	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN
first	1987-08-13 00:00:00	NaN	NaN	NaN	NaN	NaN
last	2018-03-01 00:00:00	NaN	NaN	NaN	NaN	NaN
mean	NaN	112.428998	16842.068623	9557.841296	2.320669	4.946851
std	NaN	16.517309	6237.867098	5217.448975	1.908382	2.145243
min	NaN	75.718000	7054.979980	1738.739990	-0.297000	1.358000
25%	NaN	102.693000	11487.625244	4204.460083	1.033750	3.115500
50%	NaN	112.290000	16495.250000	10095.995117	1.552000	4.765500
75%	NaN	122.862000	19957.382813	12342.012451	3.466000	6.472500
max	NaN	159.910000	38915.871094	26616.710938	8.105000	10.222000

<Python-Code-End>

2．Univariate time series

2．1．fbprophet

It is a time series analysis tool made by facebook, which has already been tried by various people and reported on qiita. It seems that it is explained as a developed form of the Holt Winters method. It seems to work in both R and Python. It worked in my local environment in R, but it didn't work in Rstudio could. Is it because you use Stan? Also, it supports univariate, but does not seem to support multivariate. This time, I tried it with Python on Google Colaboratory.

First, prepare. It's easier to put the data edited in R in "share" mode on dropbox and use "!wget" instead of putting it on google drive.

<code_below>

#Install

```
!pip install pandas
!pip install numpy
!pip install pystan
!pip install matplotlib
!pip install fbprophet
#Import Data
!wget https://www.dropbox.com/*******（省略）***********/TsData002.csv
#Load Data
import pandas as pd
import numpy as np
df = pd.read_csv('TsData002.csv')
<code_above>
```

I tried all five series, but I will write about the Nikkei 225, which is the target variable that I want to predict as a representative.
Nikkei 225. Since the code has not been cleaned of redundant parts after copy and paste, it is not beautiful because it is imported twice, but please forgive me.

```
<code_below>
#N225Price
df2 =  df[['Date','N225Price']].copy()
df2 = df2.rename(columns={'Date': 'ds', 'N225Price':'y'})
from fbprophet import Prophet
model = Prophet()
model.fit(df2)
future_df2 = model.make_future_dataframe(365)
future_df2.tail()
forecast_df2 = model.predict(future_df2)
forecast_df2[['ds','yhat']].tail()
from matplotlib import pyplot as plt
model.plot(forecast_df2)
plt.show()
```

```
model.plot_components(forecast_df2)
plt.show()
```


```
# Calculate root mean squared error.
print('RMSE: %f' % np.sqrt(np.mean((forecast_df2.loc[:len(df2), 'yhat']-df2['y'])**2)) )
>>>RMSE: 1399.172808
```

<code_above>

Since the Great East Japan Earthquake, the annual trend has been on an upward trend. In terms of monthly periodicity, it can be read that the bottom will be around November. It was so beautiful that I began to wonder if it was true. If you think about it with a little statistics, you can think that this graph itself is "point estimation" in statistical inference. In other words, I think it would be even better if you could understand the confidence interval elements like the first graph. That way, you can analyze th e situation based on the “certainty” of trends and periodicity.

Perhaps such a function is also implemented and can be used with option commands etc.

I would like to investigate this in the future.

2．2．ARIMA changed to ARMA

Next, let's start working on ARIMA.

ARIMA is ARIMA. If you predict the number of daily page requests for a Japanese airline company in the pa st 20 months for one month in the future, and if the difference between the measured value and the actual v

alue is within 5%, then it is OK. I remember that I was able to handle the increase in the number of accesse s to . but···.
So, I have good memories of ARIMA, but I wonder if it will fit well and make predictions this time.
It was quite difficult, so only Nikkei 225.
Postscript: When the degree is automatically estimated, it becomes (2, 0, 2) and the sum is zero, so it is AR MA.

<code_below>

```
# Load Libraries
import numpy as np
import pandas as pd
from scipy import stats
# Draw Graph
from matplotlib import pylab as plt
import seaborn as sns
%matplotlib inline
# make graph horizontal
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6
# Statistical model
import statsmodels.api as sm
#Read Data
!get https://www.dropbox.com/*******TsData002.csv
#Load data to pandas
df000 = pd.read_csv(    'TsData002.csv',     index_col='Date', parse_dates=['Date'])

df000.head(5)
```

Date	JpyToUsd	N225Price	DawPrice	Y10	UsBondYr10
1987-08-13	151.45	25575.740234	2691.489990	5.645	8.634
1987-08-14	150.00	25494.009766	2685.429932	5.682	8.559
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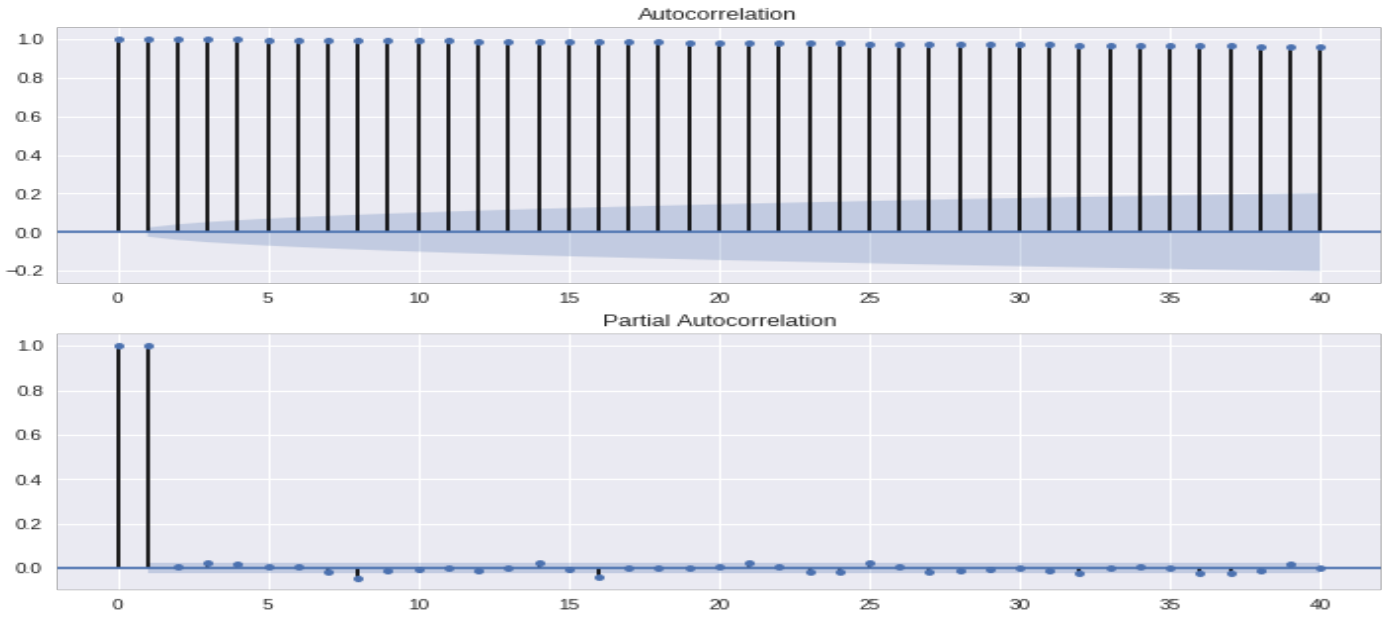
1987-08-18	146.08	25344.339844	2654.659912	5.790	8.720
1987-08-19	145.10	25231.589844	2665.820068	5.626	8.815

```
#Eliminate other than N225Pricew
df001 = df000[["N225Price"]]
plt.plot(df001)
```


```
# fix date type & delete null data
ts = df001['N225Price']
ts =ts.dropna(how='any')
plt.plot(ts)
```


```
# find the autocorrelation
ts_acf = sm.tsa.stattools.acf(ts, nlags=40)
ts_acf
array([1.        , 0.99903304, 0.99807604, 0.99716146, 0.99628441,
       0.99541629, 0.99456571, 0.99368822, 0.99272498, 0.99174111,
       0.9907543 , 0.98977139, 0.98876962, 0.98776901, 0.98681383,
       0.98584892, 0.98481014, 0.98377661, 0.98275179, 0.98173483,
       0.98073477, 0.97978321, 0.97884645, 0.97786696, 0.97685134,
       0.97588177, 0.97492482, 0.97393909, 0.97294024, 0.97193549,
       0.97092823, 0.96989444, 0.96882841, 0.96776806, 0.96671785,
       0.96567044, 0.96458989, 0.96346446, 0.96231421, 0.96119644,
       0.96008845])
# partial autocorrelation
ts_pacf = sm.tsa.stattools.pacf(ts, nlags=40, method='ols')
```

```
ts_pacf
array([ 1.       ,  0.9991194 ,  0.00818315,  0.0280301 ,  0.02071028,
        0.0013183 ,  0.013607  , -0.01082195, -0.05106348, -0.01921664,
       -0.00417685, -0.00259338, -0.01256579,  0.00143656,  0.03637976,
       -0.00937997, -0.05032874,  0.01730417, -0.00133815,  0.00239207,
        0.00287304,  0.02941132,  0.01823222, -0.02035991, -0.02390654,
        0.0302897 ,  0.01058523, -0.02155854, -0.01185044, -0.00838821,
        0.01829222, -0.00940945, -0.02990229, -0.00365188,  0.01271348,
        0.00676229, -0.02760578, -0.03823805, -0.01223098,  0.02425152,
        0.00206539])
#  graph of autocorrelation
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(ts, lags=40, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(ts, lags=40, ax=ax2)
```



<code_above>

Stationarity is not maintained at all, so take the difference and check again.

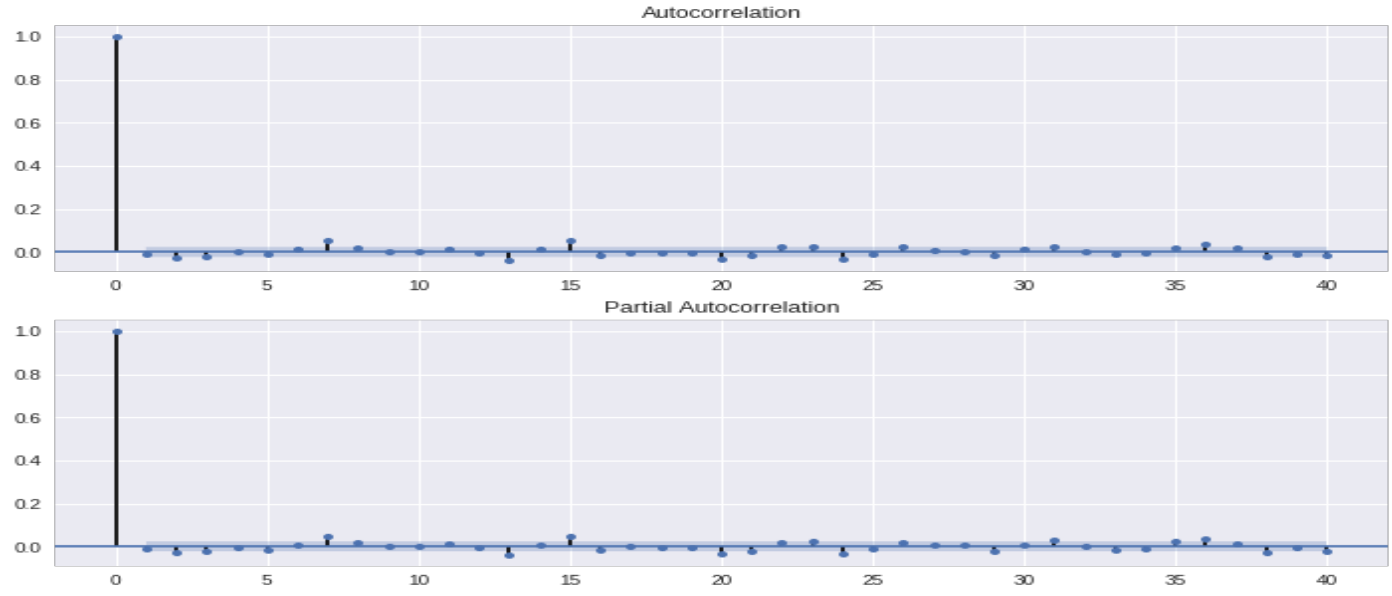
<code_below>

```
# Find Autocorrelation -- Difference Series
diff_acf = sm.tsa.stattools.acf(diff, nlags=40)
diff_acf
array([ 1.00000000e+00, -8.56775204e-03, -2.83136053e-02, -2.05382687e-02,
       -4.78423689e-04, -1.27270025e-02,  1.11971751e-02,  5.11723143e-02,
        1.76716610e-02,  5.70848634e-05, -8.64011700e-04,  1.08580893e-02,
       -3.39246954e-03, -3.64525666e-02,  1.24154735e-02,  5.34053751e-02,
       -1.73294737e-02, -1.33542265e-03, -2.02518812e-03, -3.51557212e-03,
       -3.37212820e-02, -1.57650077e-02,  2.68959547e-02,  2.48436907e-02,
       -3.21667294e-02, -1.14623499e-02,  2.27293990e-02,  6.84961528e-03,
```

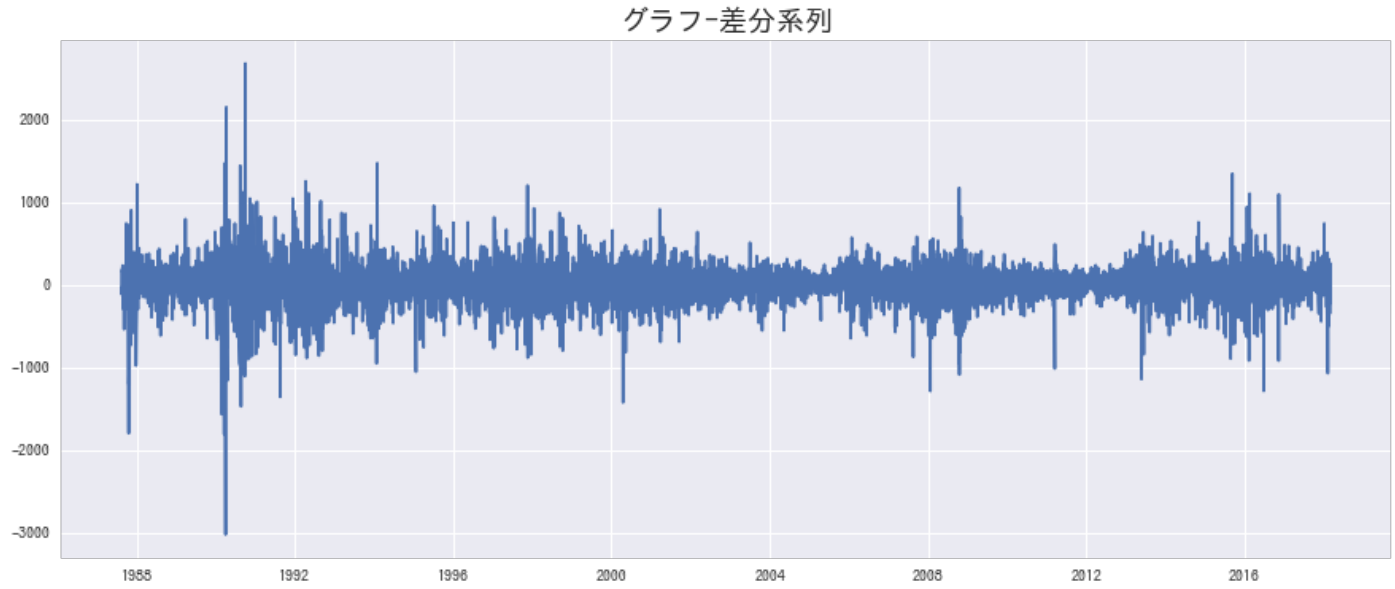
```
       1.21088533e-03, -1.45360878e-02,  1.27128918e-02,  2.36163318e-02,
       1.57196961e-03, -1.01756053e-02, -5.62132802e-03,  2.12029236e-02,
       3.36617272e-02,  1.74116668e-02, -2.19415752e-02, -8.91676238e-03,
      -1.82411280e-02])
```

```
# Partial Autocorrelation -- Difference Series
diff_pacf = sm.tsa.stattools.pacf(diff, nlags=40, method='ols')
diff_pacf
array([ 1.00000000e+00, -8.57009208e-03, -2.84061467e-02, -2.10647711e-02,
      -1.65929682e-03, -1.39443431e-02,  1.04836376e-02,  5.07049519e-02,
       1.88309961e-02,  3.77958746e-03,  2.19482478e-03,  1.21608835e-02,
      -1.84976411e-03, -3.67866197e-02,  8.99370605e-03,  4.99269490e-02,
      -1.77402781e-02,  9.12158614e-04, -2.81688612e-03, -3.28928769e-03,
      -2.98177973e-02, -1.86244868e-02,  1.99689538e-02,  2.34995752e-02,
      -3.06998449e-02, -1.09813533e-02,  2.11635527e-02,  1.14406190e-02,
       7.96925286e-03, -1.87216666e-02,  8.98208497e-03,  2.94635883e-02,
       3.19930522e-03, -1.31667808e-02, -7.20997457e-03,  2.71532271e-02,
       3.77610347e-02,  1.17298516e-02, -2.47507718e-02, -2.55091804e-03,
      -1.77858076e-02])
```

```
#  Autocorrelation Graph -- Difference Series
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(diff, lags=40, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(diff, lags=40, ax=ax2)
```




```
plt.plot(diff)
```



<code_above>
Stationarity is maintained... I feel.
So, let's try ARIMA parameter estimation for the difference series (diff).

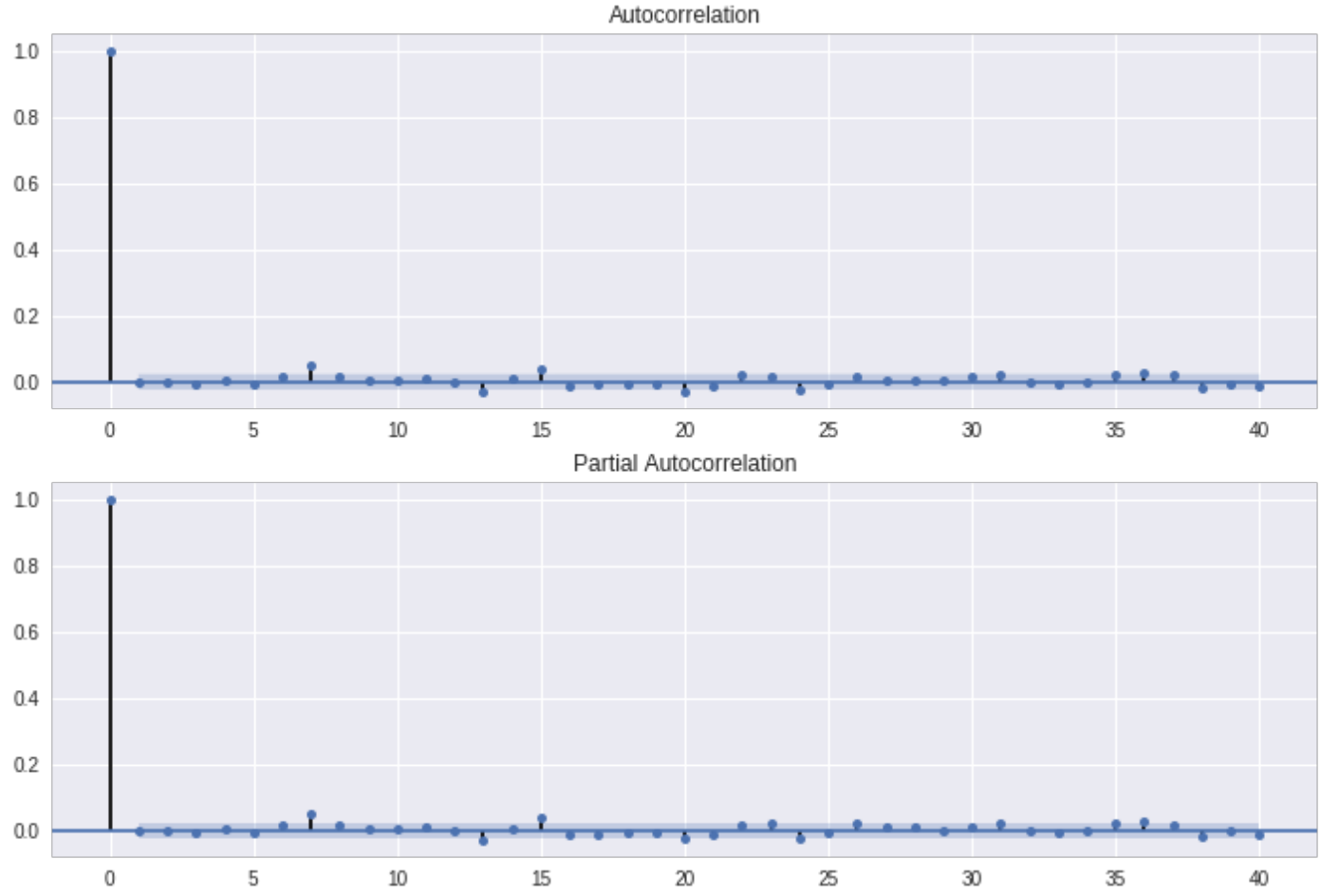
<code_below>
# Execution of automatic ARMA estimation function for differential series (first-order differential version)--Eli minates disturbing NaN with dropna
resDiff = sm.tsa.arma_order_select_ic(diff, ic='aic', trend='nc')
resDiff
>>>
{'aic': 0 1 2
 0 NaN 98218.905477 98215.050764
 1 98218.936947 98216.949365 98214.920125
 2 98215.221971 98214.741907 98201.920126
 3 98214.081072 98215.997405 98217.804338
 4 98216.061694 98217.371673 98218.641840, 'aic_min_order': (2, 2)}
<code_above>
I got "'aic_min_order': (2, 2)}" in the difference series, so I assumed that (2,0,2) would be good in the original series.
To be precise, ARMA instead of ARIMA because it does not take the difference

<code_below>
'aic_min_order': (2, 2)} in the first order difference sequence, so ARIMA(2,0,2) is the best, so simply apply it
P-2, q=2 was the best, so I modeled it -- but I couldn't calculate it with difference 1, but it worked with diffe rence 2
#In the graph of ACF, PACF, p=0,7,13,15,q=0,7,13,15 seems to be good. So 7, 1, 7 = NG assuming sum = 1
from statsmodels.tsa.arima_model import ARIMA
ARIMA = ARIMA(ts, order=(2,0,2)).fit(dist=False)

```
print(ARIMA.params)

#mod = sm.tsa.ARIMA(ts, order=(2,2,2)).fit(trend='nc')
#mod.params


# It's not SARIMA, but I don't see any periodicity
resid = ARIMA.resid
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(211)
fig = sm.graphics.tsa.plot_acf(resid.values.squeeze(), lags=40, ax=ax1)
ax2 = fig.add_subplot(212)
fig = sm.graphics.tsa.plot_pacf(resid, lags=40, ax=ax2)
>>>
const              -0.521828
ar.L1.D.N225Price  -0.867974
ar.L2.D.N225Price  -0.170238
ar.L3.D.N225Price   0.533285
ma.L1.D.N225Price   0.850380
ma.L2.D.N225Price   0.143486
ma.L3.D.N225Price  -0.564095
dtype: float64
```



<code_above>

I feel that the scale of the vertical axis of the graph is deceiving ("how to trick people with statistics"), Continue.
<>code_below>
# Prediction
pred = ARIMA.predict('1988-01-04', '2018-03-01')

# Visualization of actual data and prediction results--nice
plt.plot(ts)
plt.plot(pred, "r")

<code_above>
It fits so well that I was surprised if it was a drawing mistake. So, let's forecast the original series and the for ecast separately.

original series

predictor series

For real? I'm afraid that there are some big pitfalls to be FIT.

```
#validation
ts_pred = ts[len(ts)-len(pred):len(ts)]
#index for validation
# http://docs.w3cub.com/statsmodels/generated/statsmodels.tools.eval_measures.vare/
import statsmodels
rmse = statsmodels.tools.eval_measures.rmse(ts_pred, pred, axis=0)
mse = statsmodels.tools.eval_measures.mse(ts_pred, pred, axis=0)
print(mse)
print(rmse)
>>>59880.04082859314
244.70398613139332
```

2．3．RNN

I'm going to try RNN (LSTM) with keras because it's Nora deep learning.

This is also univariate, only Nikkei 225.

I used the code from https://qiita.com/yukiB/items/5d5b202af86e3c587843. Thank you.

<code_below>

```
# library
%matplotlib inline
import seaborn as sns
import numpy as np
import pandas as pd
import statsmodels.api as sm
import datetime
import matplotlib.pyplot as plt
import math
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
```

```
from sklearn.metrics import mean_squared_error
from sklearn import preprocessing
from keras.layers.core import Dense, Activation
from keras.layers.recurrent import LSTM

#data
!wget https://www.dropbox.com/*********/TsData002.csv
#
df000 = pd.read_csv(    'TsData002.csv',     index_col='Date', parse_dates=['Date'])
#save alias
df001 = df000.copy()
#Eliminate other than the Nikkei 225, which is the target variable
df002 = df001[["N225Price"]]
df002.head()
df003 = df002.apply(lambda x: (x-x.mean())/x.std(), axis=0).fillna(0)
df003.head()
df003["N225Price"].head()
df003.plot()
```

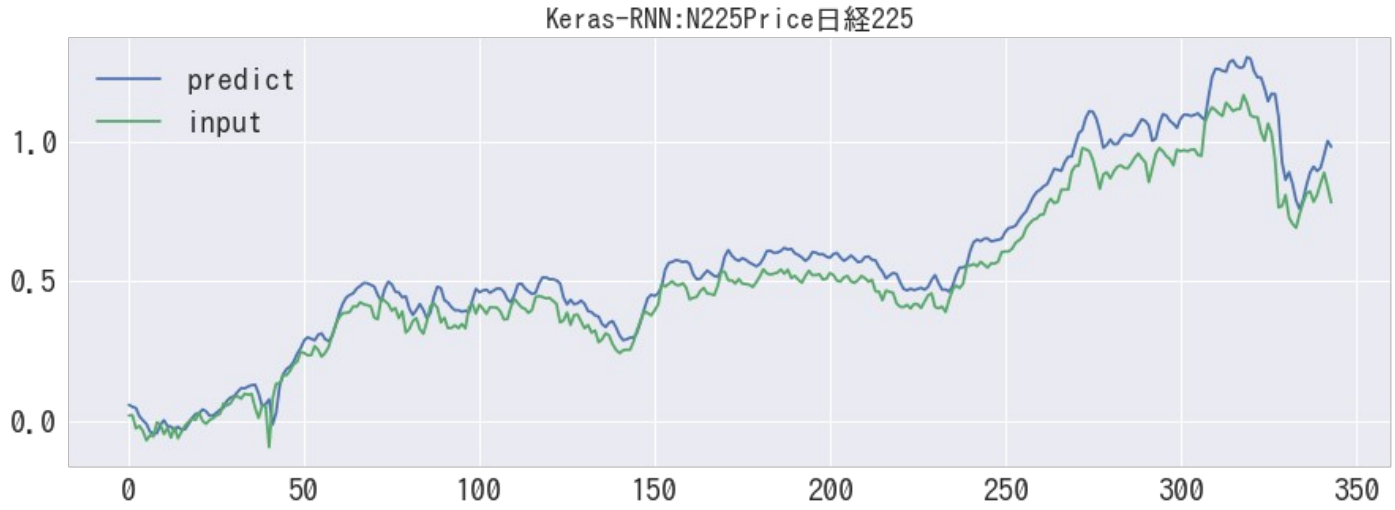

```
def _load_data(data, n_prev = 100):
    """
    data should be pd.DataFrame()
    """
    docX, docY = [], []
    for i in range(len(data)-n_prev):
        docX.append(data.iloc[i:i+n_prev].as_matrix())
        docY.append(data.iloc[i+n_prev].as_matrix())
    alsX = np.array(docX)
    alsY = np.array(docY)
    return alsX, alsY

def train_test_split(df, test_size=0.1, n_prev = 100):
    """
    This just splits data to training and testing parts
    """
    ntrn = round(len(df) * (1 - test_size))
```

```
    ntrn = int(ntrn)
    X_train, y_train = _load_data(df.iloc[0:ntrn], n_prev)
    X_test, y_test = _load_data(df.iloc[ntrn:], n_prev)
    return (X_train, y_train), (X_test, y_test)

length_of_sequences = 365
(X_train, y_train), (X_test, y_test) = train_test_split(df003[["N225Price"]], n_prev =length_of_sequences)

in_out_neurons = 1
hidden_neurons = 300
model = Sequential()
model.add(LSTM(hidden_neurons, batch_input_shape=(None, length_of_sequences, in_out_neurons), retu
rn_sequences=False))
model.add(Dense(in_out_neurons))
model.add(Activation("linear"))
model.compile(loss="mean_squared_error", optimizer="rmsprop")
# early stopping
early_stopping = keras.callbacks.EarlyStopping(monitor='val_loss', patience=2)
model.fit(X_train, y_train, batch_size=60, nb_epoch=15, validation_split=0.05, callbacks=[early_stopping])
predicted = model.predict(X_test)
dataf =  pd.DataFrame(predicted[:365])
dataf.columns = ["predict"]
dataf["input"] = y_test[:365]
dataf.plot(figsize=(15, 5))
```




```
#MSE
import statsmodels
statsmodels.tools.eval_measures.mse(dataf['input'],dataf['predict'], axis=0)
>>>0.004287546624338439
#RMSE
statsmodels.tools.eval_measures.rmse(dataf['input'],dataf['predict'], axis=0)
>>>0.06547936029267878
<code_above>
```

The kedo that I did by looking at it, the shape seems to be similar. Feels like it's vertical.

Some degree of deviation seems to be a realistic prediction.

3．Multivariate time series

From here, it is a multivariate time series that finally makes sense of data with 5 multivariate series.

3．1．VAR

I used Python halfway through (order estimation of VAR) and then used R.

<Python_code_below>

```
# Preparation
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
import statsmodels.api as sm
#import quandl  # API wrapper for downloading from data site Quandl. You can install it with pip install quan
dl.
import datetime
#data
!wget https://www.dropbox.com/s/gbpbbifrtnoyaq6/TsData002.csv
!ls
df000 = pd.read_csv(    'TsData002.csv',     index_col='Date', parse_dates=['Date'])
df000.head(5)
```

Date	JpyToUsd	N225Price	DawPrice	Y10	UsBondYr10
1987-08-13	151.45	25575.740234	2691.489990	5.645	8.634
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1987-08-17	149.91	25378.880859	2700.570068	5.718	8.587
1987-08-18	146.08	25344.339844	2654.659912	5.790	8.720
1987-08-19	145.10	25231.589844	2665.820068	5.626	8.815

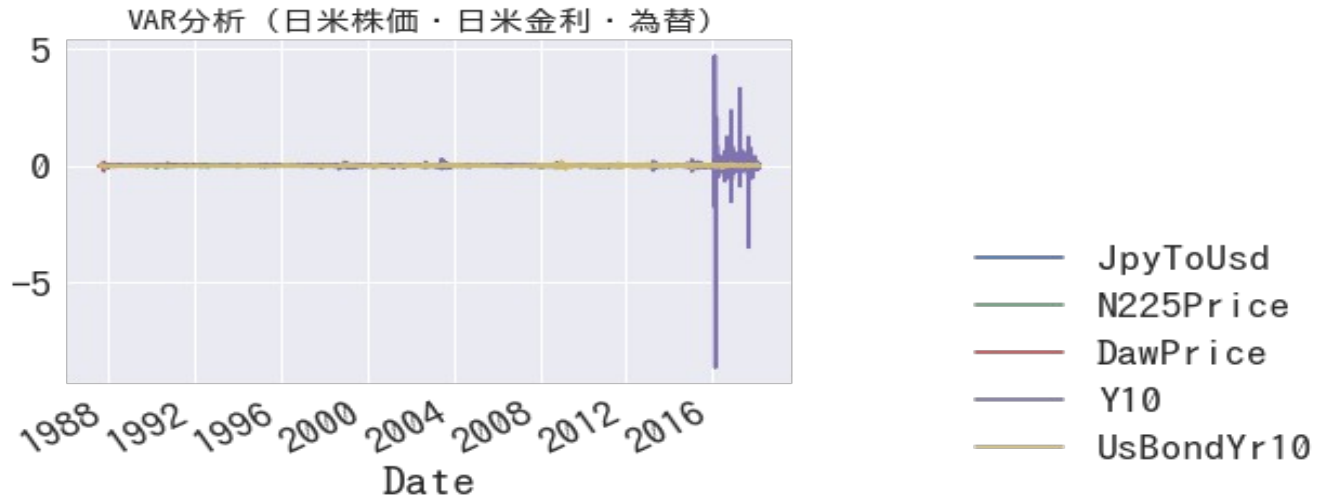
```
#Convert to differential series to achieve stationarity
df001 = df000.pct_change()
df002 = df001.dropna(how='any')
df002.head()
```

Date	JpyToUsd	N225Price	DawPrice	Y10	UsBondYr10
1987-08-14	-0.009574	-0.003196	-0.002252	0.006554	-0.008687
1987-08-17	-0.000600	-0.004516	0.005638	0.006336	0.003271
1987-08-18	-0.025549	-0.001361	-0.017000	0.012592	0.015489
1987-08-19	-0.006709	-0.004449	0.004204	-0.028325	0.010894
1987-08-20	-0.006547	0.006539	0.015369	-0.024351	-0.008622

# Take a look at descriptive statistics
df002.describe()

	JpyToUsd	N225Price	DawPrice	Y10	UsBondYr10
count	7087.000000	7087.000000	7087.000000	7087.000000	7087.000000
mean	-0.000025	0.000093	0.000380	0.000373	-0.000005
std	0.007035	0.015232	0.011621	0.164344	0.017542
min	-0.055494	-0.114064	-0.226102	-8.666667	-0.154944
25%	-0.003602	-0.007453	-0.004562	-0.010829	-0.008210
50%	0.000019	0.000278	0.000597	0.000000	-0.000446
75%	0.003784	0.007882	0.005793	0.009071	0.007610
max	0.036956	0.141503	0.166276	4.733333	0.204866

# try plotting. -The exchange rate has been fluctuating recently
df002.plot().legend(bbox_to_anchor=(1.2, 0.5))



#column sorting. Make the leftmost dependent variable N225Price.
df003= pd.concat([df002['N225Price'],df002['JpyToUsd'],df002['DawPrice'],df002['Y10'],df002['UsBondYr10']], axis=1)
df003.head()

Date	N225Price	JpyToUsd	DawPrice	Y10	UsBondYr10
1987-08-14	-0.003196	-0.009574	-0.002252	0.006554	-0.008687
1987-08-17	-0.004516	-0.000600	0.005638	0.006336	0.003271
1987-08-18	-0.001361	-0.025549	-0.017000	0.012592	0.015489
1987-08-19	-0.004449	-0.006709	0.004204	-0.028325	0.010894
1987-08-20	0.006539	-0.006547	0.015369	-0.024351	-0.008622

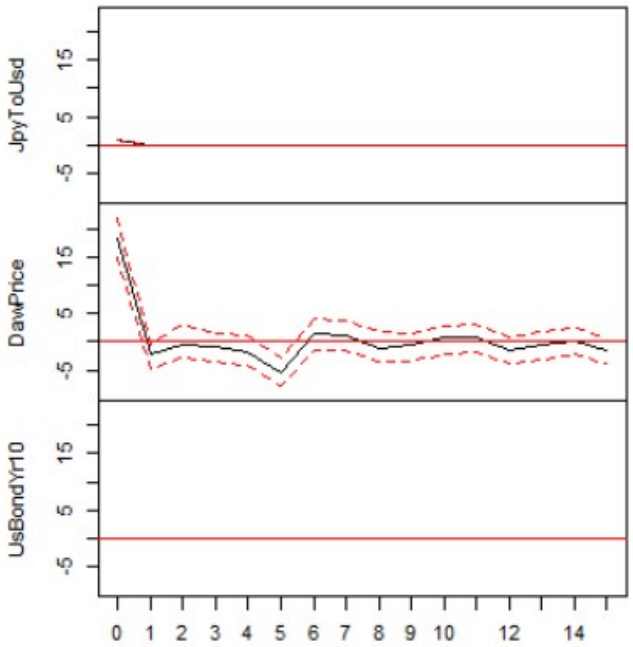
```
# make a VAR model
model = VAR(df003)
#Lag order selection
model.select_order(365)
>>>* Minimum
{'aic': 18, 'bic': 1, 'fpe': 18, 'hqic': 2}

#Set to 18 based on the result of model.select_order(365) above.
# -> Error could not broadcast input array from shape (18,5,5) into shape (11,5,5)
#I get an error, so change the order to 11
results = model.fit(11)
<Python_code_above>
```

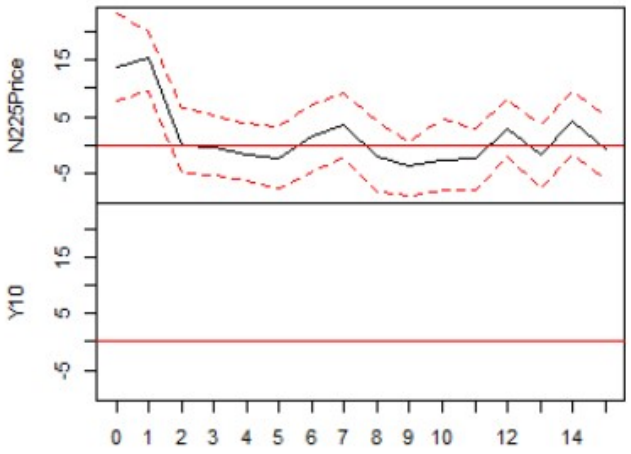
For some reason, I got an error at degree 18, so I decided to try it with R. (Unable to solve due to lack of ha cking ability of small job)

```
<R_code_below>
#setwd("~/project/20180304/20180304")
library(KFAS)
library(xts)
library(forecast)
library(urca)
library(ggplot2)
library(ggfortify)
library(tseries)
library(sqldf)
library(lubridate)
library(vars)
library(readr)

### read csv
TsData002 <- read_csv("TsData002.csv")

#data transformation
TsData002ts <- as.ts(TsData002, start=c(1987,8,13),freq=365)
```

```
XtsData002 <- as.xts(TsData002ts, start=c(1987,8,13),freq=365)
head(XtsData002)

#difference sequence for stationarity
XtsData002diff1=diff.default(XtsData002, lag=1, differences=1)
XtsData002diff1$Date <- NULL


#VAR(p=18) estimate model  p=18 is up to the analysis on google colab
XtsData002diff1var01=VAR(XtsData002diff1,p=18, type="const")

#VAR(p=11) model outline
summary(XtsData002diff1var01)
>>> ( omitted as it is very long )

#Test the model VAR(p=11)    for Granger causality.
#(Summary of output) Even with N225Price, which has the highest P-value, p-value = 0.009037, so it is don
e with a 5% rejection region (no null hypothesis)
causality(XtsData002diff1var01,cause="N225Price")
causality(XtsData002diff1var01,cause="JpyToUsd")
causality(XtsData002diff1var01,cause="DawPrice")
causality(XtsData002diff1var01,cause="Y10")
causality(XtsData002diff1var01,cause="UsBondYr10")


#draw the impulse response function of the model VAR(p=11)
#Since the model has an impulse response function p = 18, draw a lot up to n.ahead = 20
impulse_func <- irf(XtsData002diff1var01,n.ahead = 20,ci = 0.95,ortho = FALSE)
ortho_impulse_func <- irf(XtsData002diff1var01,n.ahead = 20,ci = 0.95,ortho = TRUE)
#plot(impulse_func)
plot(ortho_impulse_func)
```

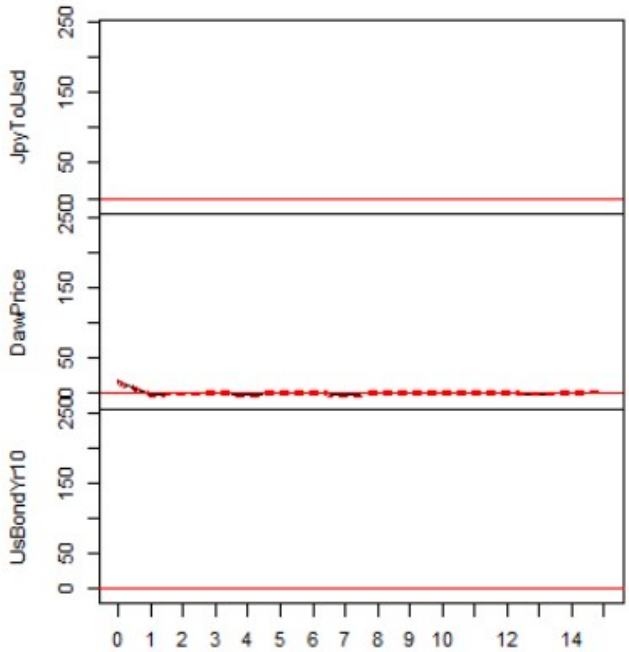
Orthogonal Impulse Response from JpyToUsd

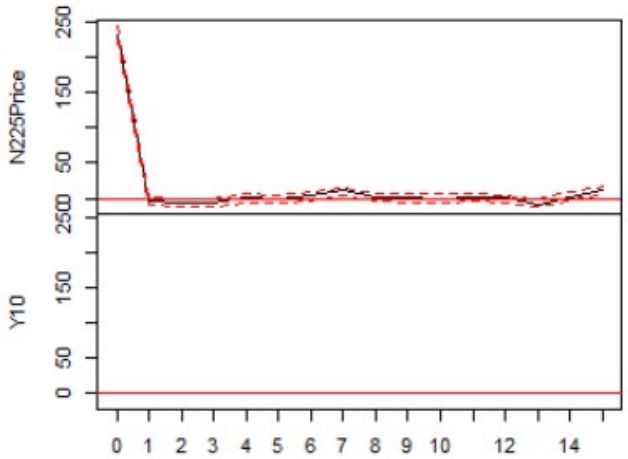




95 % Bootstrap CI, 100 runs

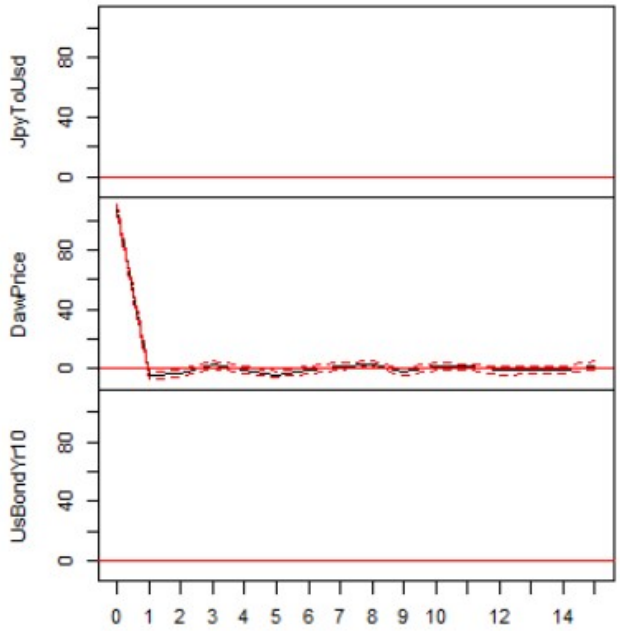
Orthogonal Impulse Response from N225Price

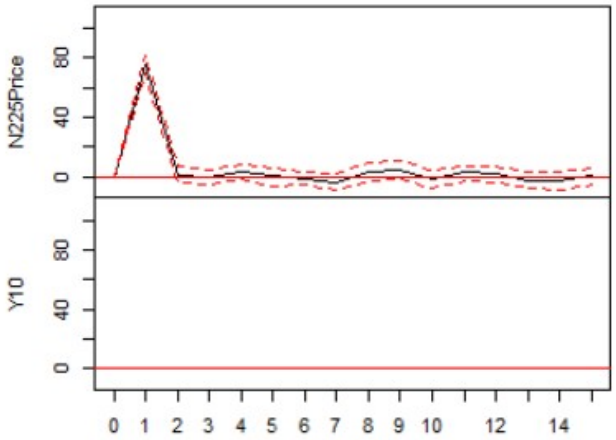




95 % Bootstrap CI, 100 runs

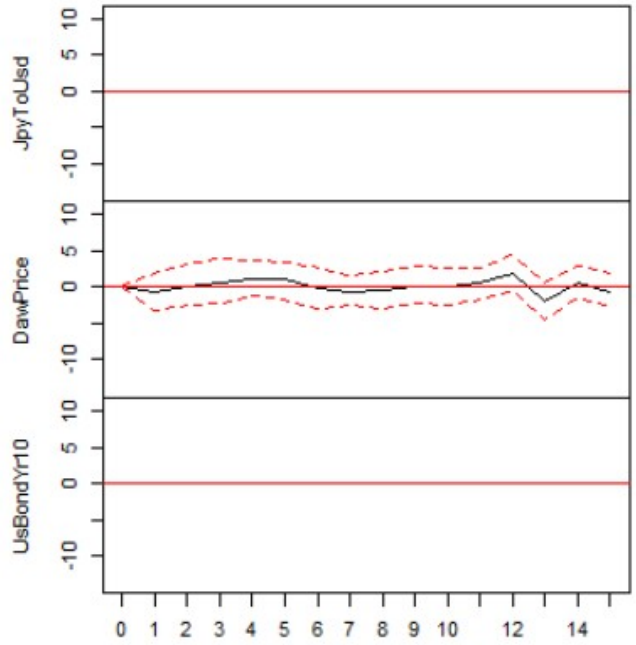
Orthogonal Impulse Response from DawPrice

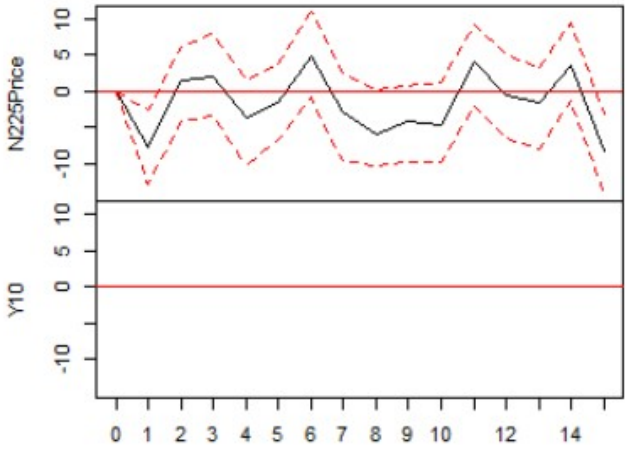




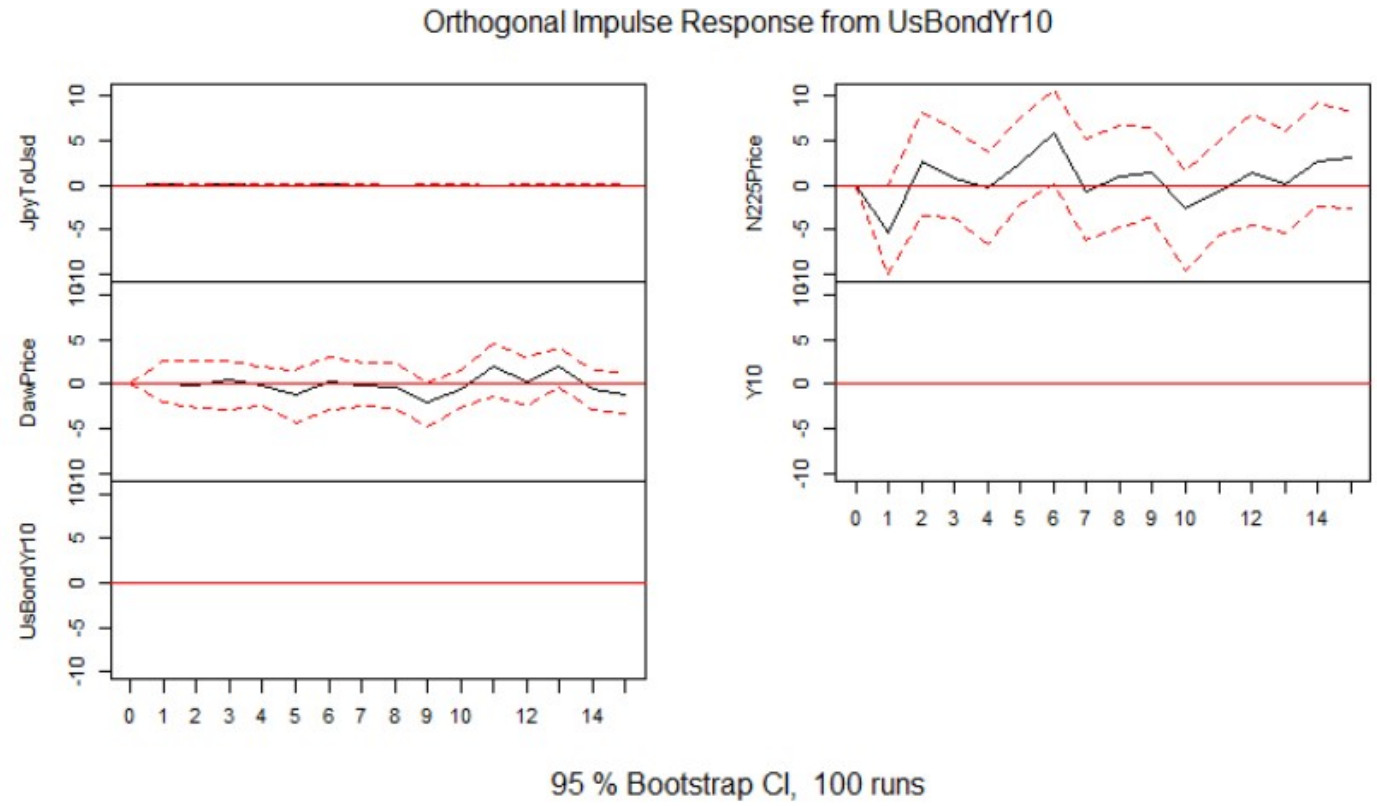
95 % Bootstrap CI, 100 runs

Orthogonal Impulse Response from Y10





95 % Bootstrap CI, 100 runs



<R_code_above>
The interpretation of the impulse response is
#JpyToUsd Forex: Impacting Dow and N225 Stocks
#N225: Affects self (N225) + slightly affects Dow
#Daw: Affects itself (Daw) and N225
#Y10 (JGB 10 Years): Impacting the Dow and N225
#UsBondY10: Impact on Dow and N225
So, in the end, I feel that modeling with this 5 series with N225 as the objective variable is good.

3．2．Multivariate LSTM
I was allowed to reference.
https://qiita.com/tizuo/items/b9af70e8cdc7fb69397f

<code_below>
```
# https://keras.io/
!pip install -q keras
# preparation
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
import statsmodels.api as sm
import datetime
import numpy
```

```
import matplotlib.pyplot as plt
import pandas
import math
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
#data
!wget https://www.dropbox.com/*********/TsData002.csv
df000 = pd.read_csv(    'TsData002.csv',     index_col='Date', parse_dates=['Date'])
#save alias
df001 = df000.copy()
#Move the target variable Nikkei 225 to the far left
df002 = df001[["N225Price","JpyToUsd","DawPrice","Y10","UsBondYr10"]]
#Standardization
df = df002.values
df = df.astype('float32')
# normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
df = scaler.fit_transform(df)
# split into train and test sets
train_size = int(len(df) * 0.67)
test_size = len(df) - train_size
train, test = df[0:train_size,:], df[train_size:len(df),:]
print(len(train), len(test))
#convert an array of values into a dataset matrix
# if you give look_back 3, a part of the array will be like this: Jan, Feb, Mar
def create_dataset(dataset, look_back=1):
   dataX, dataY = [], []
   for i in range(len(dataset)-look_back-1):
#Number of rows of data minus look_back minus 1 (because the last minus 1 means that the python loop co
unter starts from zero)
      xset = []
      for j in range(dataset.shape[1]): #Loop range specification meaning over all columns
         a = dataset[i:(i+look_back), j] # From line i to line i + look_back
         xset.append(a)
      dataY.append(dataset[i + look_back, 0])
      dataX.append(xset)
   return numpy.array(dataX), numpy.array(dataY)
# reshape into X=t and Y=t+1
look_back = 12
trainX0, trainY0 = create_dataset(train, look_back)
testX0, testY0 = create_dataset(test, look_back)
print(testX0.shape)
print(testX0.shape[0])
```

```
print(testX0.shape[1])
print(testX0.shape[2])
print(testY0.shape)
print(testX0[26,4,])
trainX = numpy.reshape(trainX0, (trainX0.shape[0], trainX0.shape[1], trainX0.shape[2]))
testX = numpy.reshape(testX0, (testX0.shape[0], testX0.shape[1], testX0.shape[2]))
trainY = trainY0.copy()
testY = testY0.copy()
#Developping mode
model = Sequential()
model.add(LSTM(4, input_shape=(testX.shape[1], look_back)))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
#It takes time, sodation try setting epoch=10 in the trial
#model.fit(trainX, trainY, epochs=1000, batch_size=1, verbose=2)
model.fit(trainX, trainY, epochs=10, batch_size=1, verbose=2)
#validation
trainPredict = model.predict(trainX)
testPredict = model.predict(testX)
pad_col = numpy.zeros(df.shape[1]-1)
def pad_array(val):
    return numpy.array([numpy.insert(pad_col, 0, x) for x in val])
trainPredict = scaler.inverse_transform(pad_array(trainPredict))
trainY = scaler.inverse_transform(pad_array(trainY))
testPredict = scaler.inverse_transform(pad_array(testPredict))
testY = scaler.inverse_transform(pad_array(testY))
#Calculation of standard deviation--RMSE varies considerably from run to run
trainScore = math.sqrt(mean_squared_error(trainY[:,0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = math.sqrt(mean_squared_error(testY[:,0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

Train Score: 577.90 RMSE

Test Score: 2113.18 RMSE

```
plt.plot(trainY ,"y")
plt.plot(trainPredict)
```

```
plt.plot(testY ,"y")
plt.plot(testPredict)
```

We were able to do reasonable modeling along with univariate RNN.

Summary.
After trying various things, I feel that my Python skills have improved a little. We will continue to learn by coll ecting, transcribing, interpreting, and modifying code that will serve as samples.
The challenge is performance evaluation comparing different methods. I haven't gotten around to it at all thi s time.
Next, it seems that I have obtained three years' worth of data on the level of one-ball breaking news in the major leagues (I haven't seen the contents yet), so
I'm wondering whether to try various things there, or to rush to performance evaluation with this topic.