Machine Learning Nanodegree

Capstone Project

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I. Definition

Predicting the stock price has been researched for long. Now many people try to predict stock price with the machine learning algorithms, but there is not a single answer for this and it is still challenging problem.

It is also known that every country's stock market influences each other. In this project, I am going to predict the stock price in Japan with the data of US stock price and USD/JPY exchange rates.

Project Overview

The goal of this project is to predict the change rate of the close price of Nikkei 225 index compared to the previous day. Nikkei 225 is a stock market index for the Tokyo Stock Exchange in Japan.

I have an hypothesis that the Nikkei 225 has a strong correlation with the close price of US stock price and JPY/USD currency exchange rate. So, I am going to predict the change rate of the Nikkei 225 Based on its historical data, NASDAQ and USD/JPY exchange rates.

Problem Statement

The problem I try to solve is predicting the change rate of the Nikkei 225 and this is regression problem.

The target variable is the Nikkei 225's relative change rate from the previous day. For example, in case the Nikkei 225 index close price is "21450.04" and it was "21374.66" at the previous day, the relative change rate is ("21450.04" / "21374.66") ≒ 1.00352. Then, it is possible to know the error between the predicted rate and the actual rate.

From the Mitchell’s definition of a machine learning task, tihs problem can be defined as following.

> Definition: A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

- Task (T): Predict the change rate of Nikkei 225 of the next day.
- Experience (E): History data of Nikkei 225, NASDAQ and currency exchange (JPY/USD)
- Performance (P): Mean squared error between predicted value and the actual value

Metrics

I use MSE (Mean Squared Error) to evaluate the prediction. To lessen the error between the prediction and the actual, I think the MSE is suitable for this problem.
Because all datasets are normally distributed and so that the MSE will work correctly. (Please refer to the distribution histogram later.)

II. Analysis

Data Exploration

The data I am going to use is Nikkei 225, NASDAQ and USD/JPY currency data.

1. Nikkei 225

The data starts from January 1950 to current date. This data can be obtained at Quandl.

- https://www.quandl.com/data/NIKKEI/INDEX-Nikkei-Index

The input feature data is the change rate from the previous day of Nikkei 225.

2. NASDAQ Index

The data starts from January 2003 to current date. This data can be obtained at Quandl.

- https://www.quandl.com/data/NASDAQOMX/COMP-NASDAQ-Composite-COMP

The input feature data is the change rate from the previous day of the NASDAQ index.

3. Currency Exchange - JPY/USD

The data starts from March 1991 to current date. This data can be obtained at Quandl.

- https://www.quandl.com/data/CURRFX/USDJPY-Currency-Exchange-Rates-USD-vs-JPY

The input feature data is the change rate from the previous day of the JPY/USD exchange rate.

Exploratory Visualization

These are the example of the original data.

Nikkei data

	Date	Open Price	High Price	Low Price	Close Price
0	2017-11-24	22390.14	22567.20	22381.01	22550.85
1	2017-11-22	22601.55	22677.34	22513.44	22523.15
2	2017-11-21	22456.79	22563.25	22416.48	22416.48
3	2017-11-20	22279.98	22410.24	22215.07	22261.76
4	2017-11-17	22603.30	22757.40	22319.12	22396.80

Nasdaq data

	Trade Date	Index Value	High	Low	Total Market Value
0	2017-11-24	6889.16	6890.02	6873.74	1.032920e+13
1	2017-11-22	6867.36	6874.52	6859.28	1.029596e+13
2	2017-11-21	6862.48	6862.66	6820.02	1.029101e+13
3	2017-11-20	6790.71	6795.83	6779.49	1.018278e+13
4	2017-11-17	6782.79	6797.75	6777.43	1.017850e+13

	Dividend Market Value
0	81506001.0
1	536745500.0
2	169687729.0
3	151733686.0
4	284443422.0

Currency data

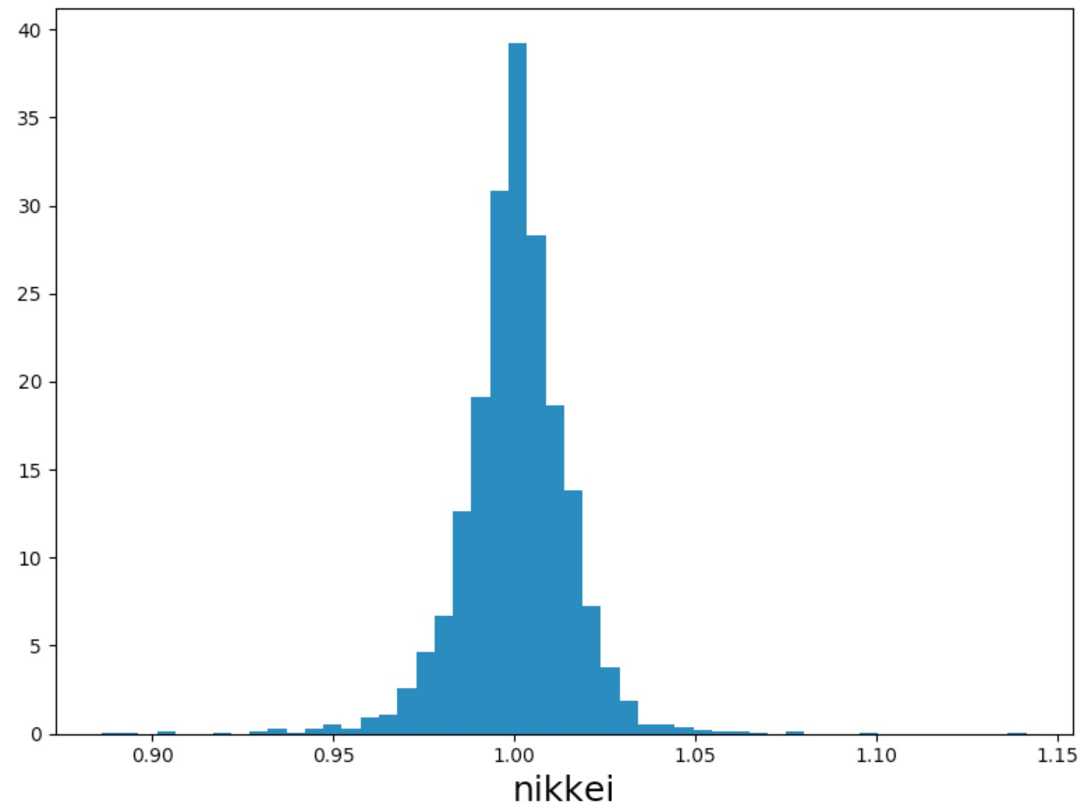
	Date	Rate	High (est)	Low (est)
0	2017-11-27	111.508003	111.540001	111.540001
1	2017-11-24	111.253998	111.571999	111.259003
2	2017-11-23	111.313004	111.376999	111.070999
3	2017-11-22	112.341003	112.343002	111.510002
4	2017-11-21	112.551003	112.699997	112.183998

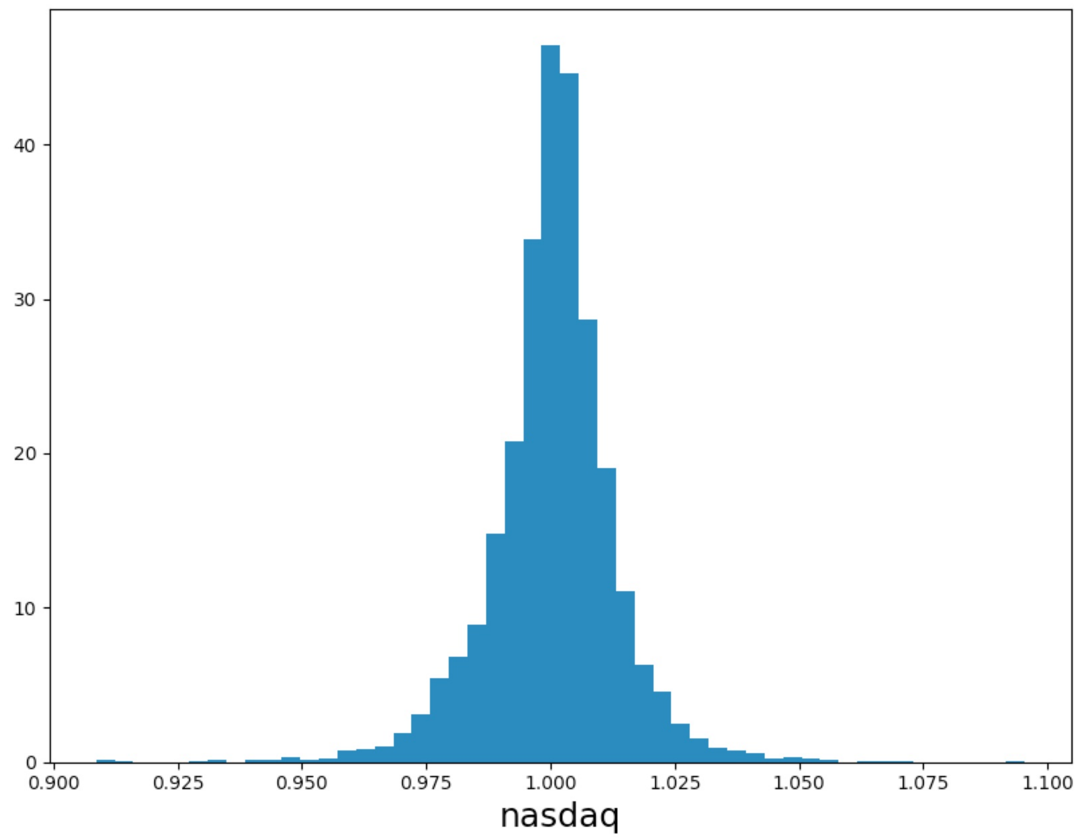
All these 3 data has the close price.

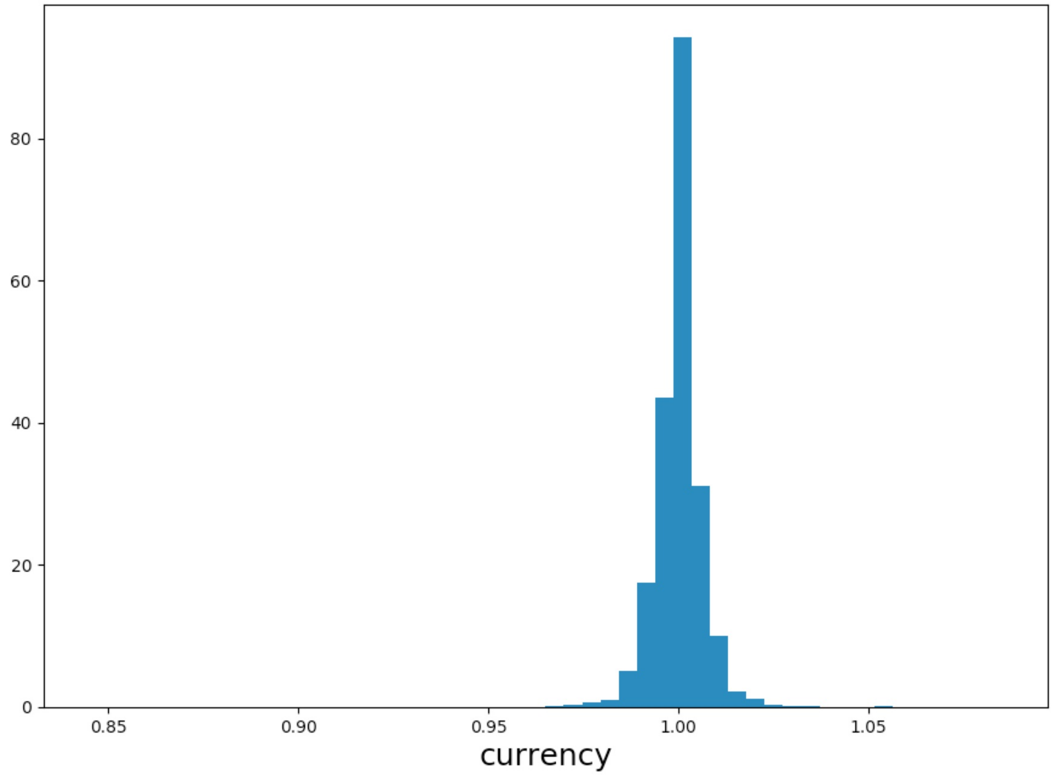
Usually each market opens for the weekday, but the market is closed for the holidays and it's different between Japan and US. So I remove the data if at lease one of the markets was closed.

Distribution of the datasets

I use the change rate as a feature data, so I plotted the distribution of the change rates.

- 
0
5
10
15
20
25
30
35
40
0.90
0.95
1.00
1.05
1.10
1.15
nikkei

- 
0
10
20
30
40
0.900
0.925
0.950
0.975
1.000
1.025
1.050
1.075
1.100
nasdaq

- 


```
[nikkei] Mean: 1.00030619031
[nikkei] Standard deviation: 0.0150312332318
[nasdaq] Mean: 1.00041836719
[nasdaq] Standard deviation: 0.0129797045167
[currency] Mean: 0.999975614903
[currency] Standard deviation: 0.00712121948432
```

As you can see the graph, the data are normally distributed.
The standard deviation for the currency is slightly smaller compared to nikkei & nasdaq, but the currency is also normaly distributed.
And I think there are not remarkable abnormalities in the datasets so I think I can use all of the datasets.

Algorithms and Techniques

The solution to this problem is to apply LSTM (Long short-term memory) to predict the Nikkei 225 index of the next day.

This is a type of time-series problem, so I need to consider which algorithms to apply here.

Neural networks assume that the each input data is independent. But this assumption does not suit for some kind of the problems. For example the prediction of the stock price, the data are not independent. The stock price on the day, say day T, it influences to the price of next day T+1 and T+2 or more future. So we need other algorithms to solve these problems.

RNN (Recurrent Neural Network) can deal those kind of problems. RNN remembers the information inside of it by making a internal loop (this is recurrent). But RNN has problem to handle a "long-term dependencies". If long context is needed for the problem, RNN could not solve it well.

LSTM is a one kind of the RNN (Recurrent neural network), capable of learning long-term dependencies. Both RNN and LSTM has the repeating module of neural network. RNN repeats it very simple structure, but LSTM repeats it with special way. So that LSTM can remember with longer context, and it is the reason to use LSTM for this problem.

Also, I apply the technique that is called "sliding window" for time series data. For example, sliding window size: N, it will input the feature data with N (days/units/etc).
This assume that the near past data influences a lot to the result. In this case, I will input the data within 10 days to train the model.

Benchmark

Benchmark model is made by the [DummyClassifier (http://scikit-learn.org/stable/modules/generated/sklearn.dummy.DummyClassifier.html)](http://scikit-learn.org/stable/modules/generated/sklearn.dummy.DummyClassifier.html). The MSE (Mean Squared Error) of the prediction should be less than the benchmark score.

III. Methodology

Data Preprocessing

First step is preprocess the each data (Nikkei 225, NASDAQ and USD/JPY currency data).

```
# main.py

# Data Preprocessing
dropping_features_for_nikkei = ['Open Price', 'High Price', 'Low Price']
dropping_features_for_nasdaq = ['High', 'Low', 'Total Market Value', 'Dividend Market Value']
dropping_features_for_currency = ['High (est)', 'Low (est)']

nikkei_data = 
DataPreprocessor(nikkei_data_org).preprocess_data(dropping_features_for_nikkei)
nasdaq_data = 
DataPreprocessor(nasdaq_data_org).preprocess_data(dropping_features_for_nasdaq)
currency_data = 
DataPreprocessor(currency_data_org).preprocess_data(dropping_features_for_currency)
```

Here DataPreprocessor class preprocess the data. (data_preprocessor.py)
preprocess_data method does:

- Drop the unnecessary features
- Rename columns (to 'date' and 'ClosePrice')
- Convert string 'date' to datetime 'date'
- Calculate change rate of the close price

Next, merge all 3 data to 1 data. After that, drop the rows if the data does not have a value (because of holidays).

```
# main.py

merged_data = DataPreprocessor.merge(nikkei_data, nasdaq_data, currency_data)
data = merged_data.dropna()
```

Preprocessed data is like this:

```
         date   nikkei   nasdaq  currency
0  2013-01-22  0.996482  1.002702  0.993557
1  2013-01-23  0.979184  1.003337  0.988047
2  2013-01-24  1.012766  0.992615  1.000576
3  2013-01-25  1.028790  1.006175  1.022330
6  2013-01-28  0.990634  1.001457  1.000000
7  2013-01-29  1.003918  0.999797  0.992114
8  2013-01-30  1.022751  0.996401  1.003648
9  2013-01-31  1.002223  0.999943  1.002544
10 2013-02-01  1.004729  1.011766  1.007537
13 2013-02-04  1.006166  0.984923  1.000000
```

Splitting the data

`DataSplitter` class splits the data to train, validation and test. (`data_splitter.py`)

```
# main.py

# Split the data
data_train, data_val, data_test = DataSplitter.split_to_train_val_test(data)
x_train, y_train = DataSplitter.split_to_x_and_y(data_train,
timesteps=timesteps)
x_val, y_val = DataSplitter.split_to_x_and_y(data_val, timesteps=timesteps)
x_test, y_test = DataSplitter.split_to_x_and_y(data_test, timesteps=timesteps)
```

Since this is time-series data, the data are not independent each other.
So it should be avoided to extract validation data or test data randomly.
Instead, I'm going to split the data by time.

I decided to split the data as following:

- Train: "2003-01-22" to "2015-12-31"
- Validation: "2016-01-01" to "2016-12-31"
- Test: "2017-01-01" to 2017-11-24"

Now the data samples are:

- 3060 samples for train
- 227 samples for validation
- 203 samples for test

Implementation

Building the model

I am going to build the model with LSTM (Long short-term memory).

```
# main.py
model = LSTMModel(timesteps, hidden_neurons).build()
```

At first, I build the simple model.

1st layer is LSTM with hidden units: 50. And flatten it and finally dense it with linear activation.

```
# Output of model.summary()
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 10, 50)            10800
_________________________________________________________________
flatten_1 (Flatten)          (None, 500)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 501
_________________________________________________________________
activation_1 (Activation)    (None, 1)                 0
=================================================================
Total params: 11,301
Trainable params: 11,301
Non-trainable params: 0
```

Fitting the model

```
# main.py
model.fit(x_train, y_train,
          batch_size=batchsize, epochs=epochs, validation_data=(x_val, y_val))
```

I fit the model with this configurations:

- timesteps = 10 (days: sequence of the sliding window)
- hidden_neurons = 50 (number of hidden units)
- epochs = 100 (300 later)
- batchsize = 10

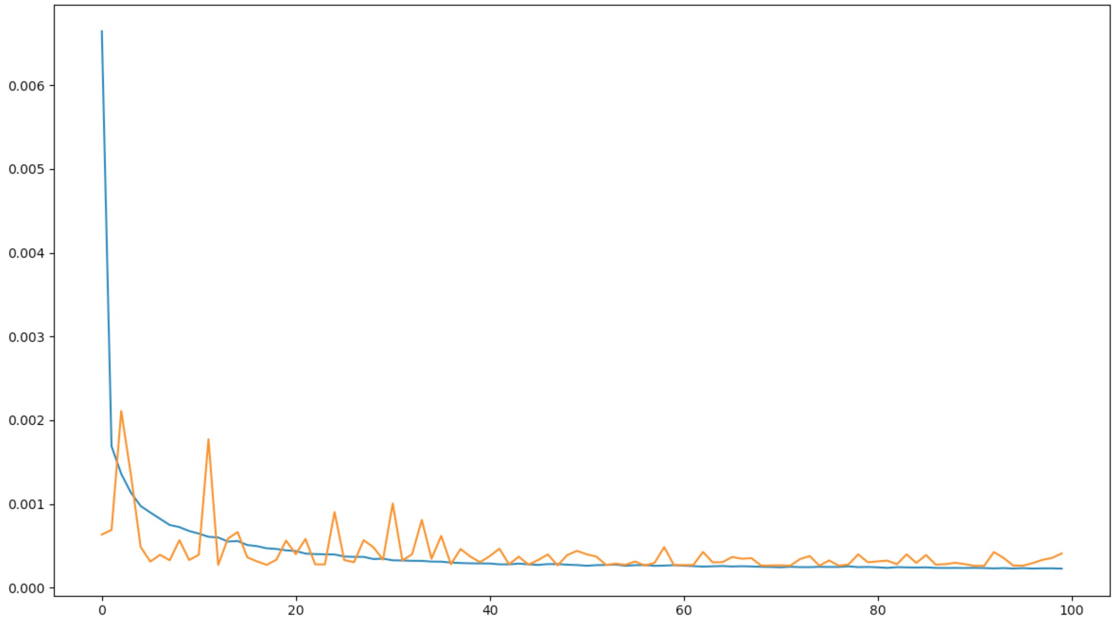
The difficult point is to decide the structure of the model and the configuration.
I thought I start with simple model first, but I need to consider what the simple model is.
I think the the model with only 1 layer is simple enough, so I set only 1 layer for this model.
And I set the configuration to reasonable round number.
The `timesteps: 10 (days)` is enough to consider the sequence of the data,
`hidden neurons: 50 (units)` is arbitrary but I believe the LSTM model can be built with 50 units.
For epochs and batchsize, I adjusted them looking how the metrics change.

Refinement

I started to fit the model with epochs: 10 but it's not enough to fit.
I could see the MSE score still keep going down so I changed it to 100, and I also tried epochs with 300.

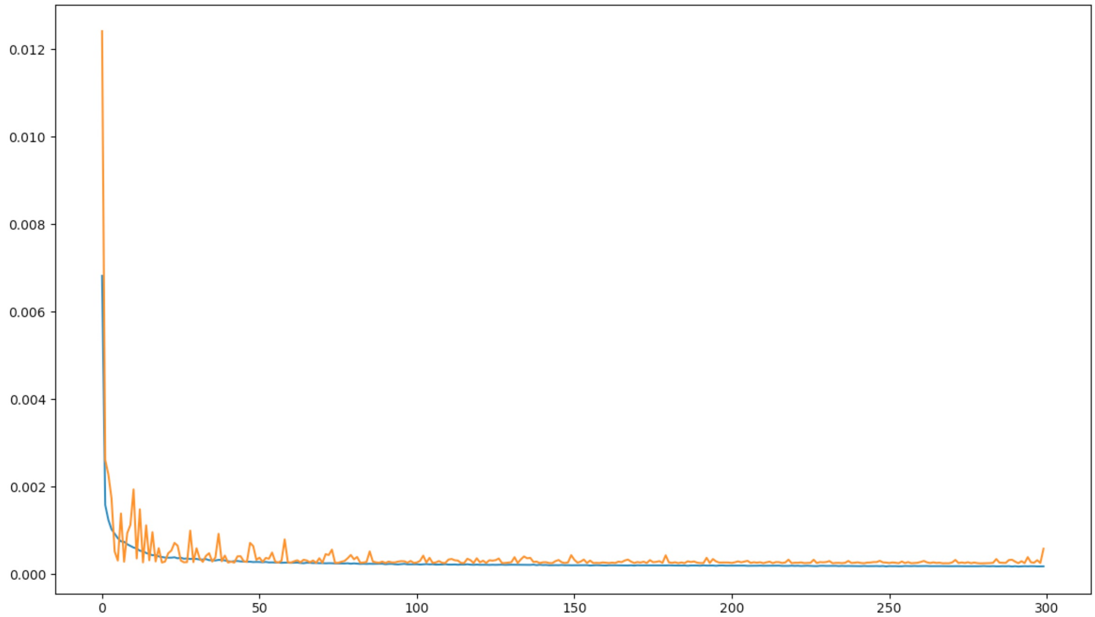
Here are the training histories graph.

- Epoch: 100, hidden_neurons: 50



(Blue: Training Loss, Orange: Validation Loss)

- Epoch: 300, hidden_neurons: 50



(Blue: Training Loss, Orange: Validation Loss)

As you can see, the metrics score calculated by MSE (Mean Absolute Error) is going down and converge. So I think it's good choice to train the model with epoch: 300.

IV. Results

Model Evaluation and Validation

Training with epochs: 100, hidden_neurons: 50

```
Completed Prediction.
(203, 2)
   predicted_nikkei  actual_nikkei
0          1.002065       1.003443
1          1.003285       0.987100
2          1.003638       0.994546
3          1.013035       1.014345
4          1.005125       1.018097
5          1.005163       1.003351
6          1.005462       0.994938
7          0.997152       0.983091
8          1.004840       1.005606
9          1.006951       0.987806

Evaluation score is 6.138374768395386e-05
Dummy evaluation score is 0.0002681380814638387
This prediction model's MSE is 22.892588530820866 percent compared to
benchmark. (smaller is better)
```

For epoch: 100, this means MSE (Mean Absolute Error) score is 22.8% of the MSE of benchmark dummy classifier.
So it could lessen the error 77.2%.

Training with epochs: 300, hidden_neurons: 50

```
Completed Prediction.
(203, 2)
   predicted_nikkei  actual_nikkei
0          0.997783       1.003443
1          0.998673       0.987100
2          0.998173       0.994546
3          1.008930       1.014345
4          1.002257       1.018097
5          1.001599       1.003351
6          1.000174       0.994938
7          0.991833       0.983091
8          0.999994       1.005606
9          1.002434       0.987806
203/203 [==============================] - 0s 221us/step
Evaluation score is 4.7810021372829685e-05
Dummy evaluation score is 0.0002681380814638387
This prediction model's MSE is 17.83037348213345 percent compared to benchmark.
(smaller is better)
```

For epoch: 300, this means MSE score is only 17.8% of the MSE of benchmark dummy classifier.
So this trained model could lessen the error 82.2%.

Training with epochs: 300, hidden_neurons: 100

I have tried with the hidden_neurons: 100 (units), but the predicted MSE was not good as expected.

```
Completed Prediction.
(203, 2)
   predicted_nikkei  actual_nikkei
0          0.990239       1.003443
1          0.992396       0.987100
2          0.994693       0.994546
3          1.002828       1.014345
4          0.995091       1.018097
5          0.993139       1.003351
6          0.995148       0.994938
7          0.986415       0.983091
8          0.995963       1.005606
9          0.995927       0.987806
203/203 [==============================] - 0s 248us/step
Evaluation score is 8.600796711214776e-05
Dummy evaluation score is 0.0002681380814638387
This prediction model's MSE is 32.07599854619936 percent compared to benchmark.
(smaller is better)
```

This MSE score with hidden_neurons: 100 is worse than the score of hidden_neurons: 50. This MSE score is 32.0% of dummy classfier, so it could lessen the MSE error only 68.0%.
I guess this is because the model has too many hidden neurons so that it overfitted to the training data.

From these results, I think the training with epoch: 300 and hidden_neurons: 50 is reasonable choice.

These are the configuration finally I chose:

- timesteps = 10 (days: sequence of the sliding window)
- hidden_neurons = 50 (number of hidden units)
- epochs = 300
- batchsize = 10

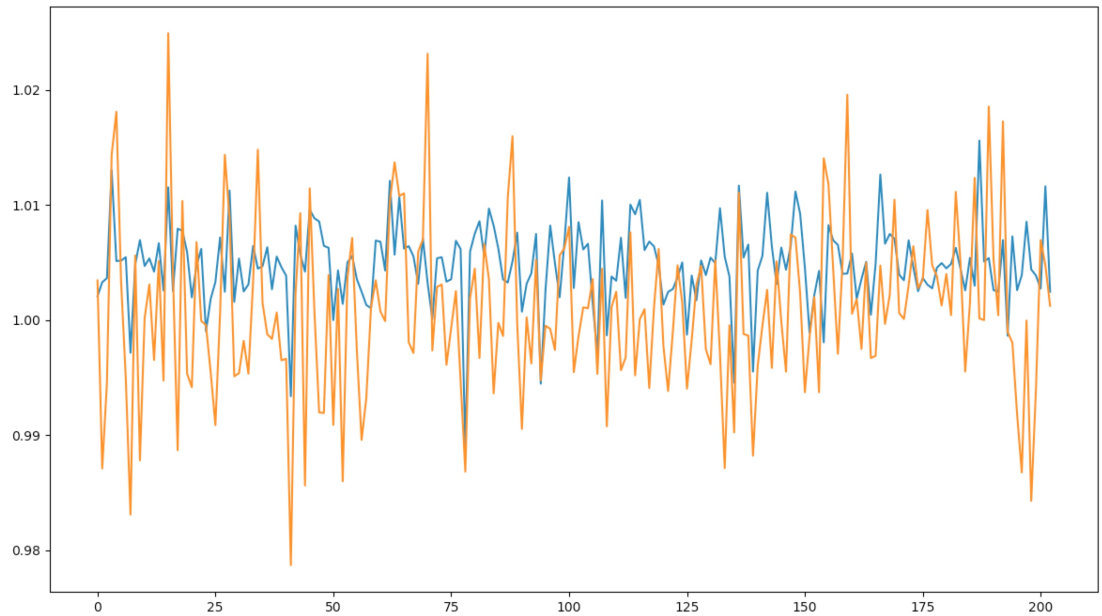
Justification

Compared to the benchmark (made by dummy classifier), this prediction model lessen the MSE (Mean Squared Error) more than 80%. I think this is significant result as it is quite difficult to predict the next day's change rate.

V. Conclusion

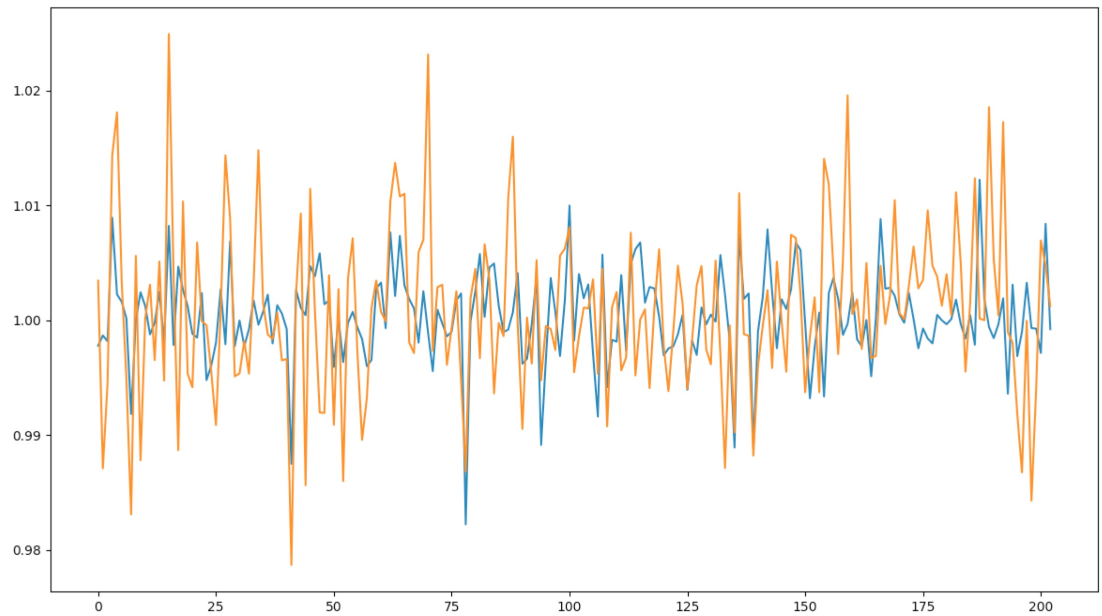
Free-Form Visualization

- Prediction result with Epochs: 100, hidden_neurons: 50



(Blue: Predicted, Orange: Actual)

- Prediction result with Epochs: 300, hidden_neurons: 50



(Blue: Predicted, Orange: Actual)

This is the comparison between predicted change rate and actual change rate.

I noticed that the actual change rate is high volatility and the predicted one is relatively low volatility. But the remarkable result is that it predicts very well for the big drop and some of the rising. Of course it does not work well for some days, but as I see the graph I think the prediction results fit with the actual very well.

For the reasons why the predicted change rate is relatively low volatility, I would assume it is because the model is trained with metrics MAE (Mean Absolute Error). To lessen the error, it is important to predict close to the actual, so it is likely to predict the low volatility because it will result with low error.

But I believe this does not matter in terms of the usefulness. Even the prediction is low volatility, it is still very useful to know the predicted change rate is positive or negative number.

Reflection

The important point to predict the time-series data is to avoid the look ahead bias. The time-series data affects each other. The values in the past affects to the value of the next day. This time, I split the data by the period so I believe I could avoid the look ahead bias.

And about building the model, I decided to train the model with the simpler model, but the difficult point is how to find the best model. This model has only 1 LSTM layer (with 50 hidden units) and dense it to output feature.
But, based on the purpose of this project, it is to investigate my hypothesis that there should be correlation between some countries stock price and currency data, and I believe I could achieve my target.

Improvement

It may improve the result by using another evaluation metrics. I evaluate the model by the mean squared error. To consider buying or not buying the stock, it is important to know the stock price will rise or fall. But this implementation minimize the error so that it may end up with incorrect conclusion. Even if the error is small, it is more important to know whether the stock rises or fall.

About generalization of this implementation, I think it can be generally used for other stock data. Just dropping the unnecessary data, and calculate the change rate then you can input those feature data and train the model.