MLND Capston Report

S&P 500 Predictor

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Definition

Project Overview

Inverstment companies use financial model to predict stocks. Some useful feature informations are hidden behind the historical data and other relative performance. However, stock price is not explicitly depend on these features, the prediction problem has never been well solved by any current math model.

Machine learning has the potential to create a complex statistical model for stock price prediction. In the recent years, machine learning has been widely used in trading. There are many papers about this topic:

- In Application of Deep Learning to Algorithmic Trading (http://cs229.stanford.edu/proj2017/final-reports/5241098.pdf), historical data and and deep learning algorithm have been used to develop price predictions.
- In Application of Machine Learning: Automated Trading Informed by Event Driven Data (https://dspace.mit.edu/bitstream/handle/1721.1/105982/965785890-MIT.pdf), event driven data has been used to to the prediction.
- etc.

In this project, we are going to use machine learning algorithms to predict S&P 500 index (https://en.wikipedia.org/wiki/S%26P_500_Index)(Standard & Poor's 500). S&P 500 is a very important index in stock trading market. It reflects the bahavior of U.S. stock market and has been widely used for financial analysis. The prediction of S&P 500 index is much helpful for investors to build trading strategies and avoid the risks.

Problem Statement

In this project, we will create and train a Linear Regression model and two LSTM (https://en.wikipedia.org/wiki/Long_short-term_memory) (Long Short-Term Memory) models. We use these models to predict the closing price of S&P 500 index (https://en.wikipedia.org/wiki/S%26P_500_Index).

Our data comes from Yahoo Finance (https://finance.yahoo.com/quote/%5EGSPC/), we download the data of recent 20 years (from 1998/08 to 2018/07) for training and testing.

Each data instance of one day includes: Date, Open, High, Low, Close, Adj Close and Volume. Adj Close (https://www.investopedia.com/terms/a/adjusted_closing_price.asp) is Adjusted Closing Price, and will be eliminated if it is all the same with Closing Price. For each instance:

- Input:
  - Open, High, Low, Close, Adj Close and Volume
- Output:
  - The Closing price in the next day, that means the data['Close'] shifted by -1 day.

We will build 3 different machine learning algorithms for the prediction, below are the algorithms and related package functions:

- Linear Regression (https://en.wikipedia.org/wiki/Linear_regression) based on the date and Closing price.
  - Sklearn.linear_model.LinearRegression()
- LSTM (https://en.wikipedia.org/wiki/Long_short-term_memory)(Long short-term memory) network for price prediction, based on the data in the recent 50 days.
  - keras.layers.recurrent.LSTM()
- Modify the LSTM (https://en.wikipedia.org/wiki/Long_short-term_memory) network for price change prediction, and calculate the price based on the price change.
  - keras.layers.recurrent.LSTM()

Metrics

In this project, we are going to predict the S&P500 Closing price in the next day. We will characterise the model performance based on the prediction error, which is the difference between real Closing Price and our prediction. The error for each instance could be positive or nagative. To accumulate the error, we square each error and find the mean value, then take the square root to make the dimension be the same with the price.

This is so called the RMSE (https://en.wikipedia.org/wiki/Root-mean-square_deviation)(Root-mean-square deviation), which is the square root of the mean of squared errors.

We will calculate the RMSE for the scaled data prediction, and magnify the RMSE for unscaled original price, and then use RMSE to compare the performance of different models.

Analysis

Data Exploration, Visualization

The data has been downloaded from Yahoo Finance (https://finance.yahoo.com/quote/%5EGSPC/), and saved in the path: 'data/SP500_199808_201808.csv'.

Each data instance of one day includes: Date, Open, High, Low, Close, Adj Close and Volume. As shown below:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1998-08-03	1120.670044	1121.790039	1110.390015	1112.439941	1112.439941	620400000
1	1998-08-04	1112.439941	1119.729980	1071.819946	1072.119995	1072.119995	852600000
2	1998-08-05	1072.119995	1084.800049	1057.349976	1081.430054	1081.430054	851600000
3	1998-08-06	1081.430054	1090.949951	1074.939941	1089.630005	1089.630005	768400000
4	1998-08-07	1089.630005	1102.540039	1084.719971	1089.449951	1089.449951	759100000

Check the descriptive statistics of these features:

	Mean	Max	Min	Stdev
Open	1460.50	2867.23	679.28	466.43
High	1469.20	2872.87	695.27	466.49
Low	1451.16	2851.48	666.79	466.33
Close	1460.74	2872.87	676.53	466.51
Adj Close	1460.74	2872.87	676.53	466.51
Volume	2.89e+09	1.15e+10	2.47e+08	1.57e+09

Now data['Date'] is in string format, so we use pandas.to_datetime() function convert it into datetime format.

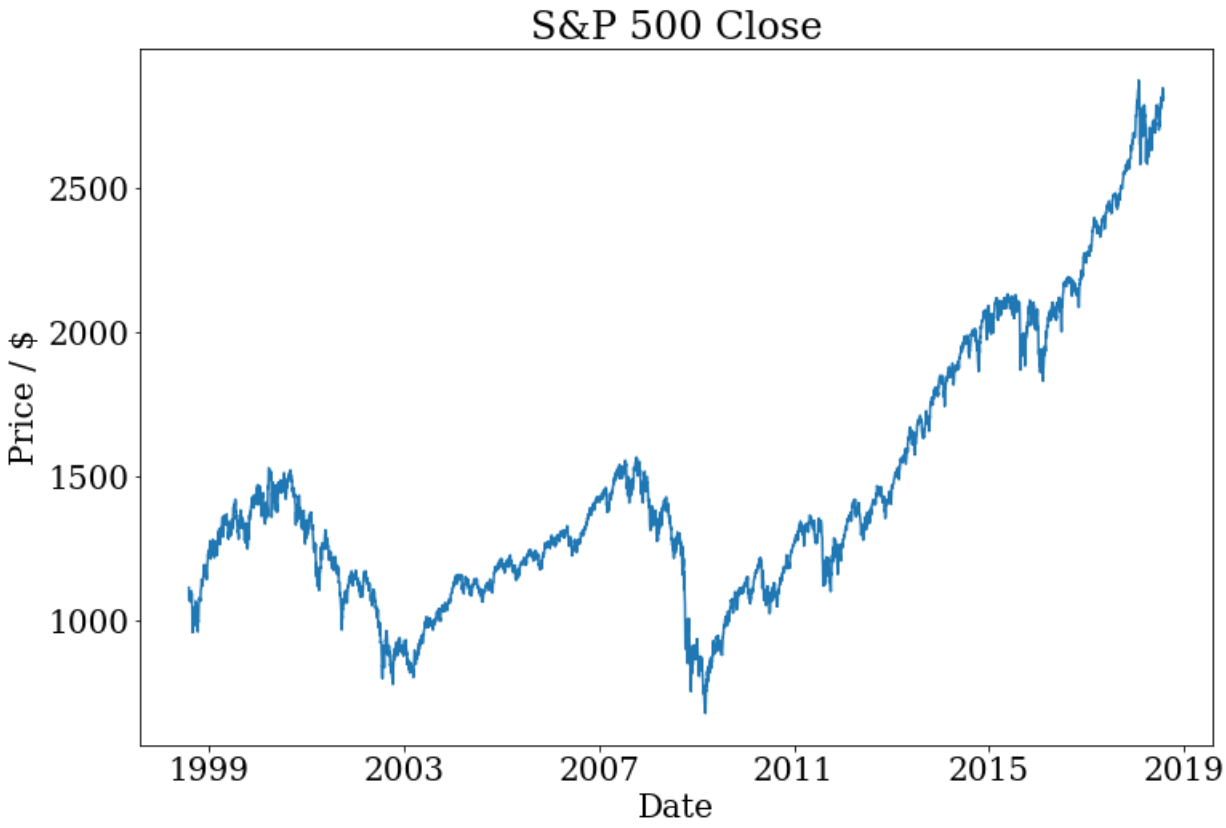
We find that data['Adj Close'] and data['Close'] are exactly the same. Below is the summation of the abs difference between data['Adj Close'] and data['Close']:

```
Out[2]: 0.0
```

So we drop the data['Adj Close'] column.

	Date	Open	High	Low	Close	Volume
0	1998-08-03	1120.670044	1121.790039	1110.390015	1112.439941	620400000
1	1998-08-04	1112.439941	1119.729980	1071.819946	1072.119995	852600000
2	1998-08-05	1072.119995	1084.800049	1057.349976	1081.430054	851600000
3	1998-08-06	1081.430054	1090.949951	1074.939941	1089.630005	768400000
4	1998-08-07	1089.630005	1102.540039	1084.719971	1089.449951	759100000

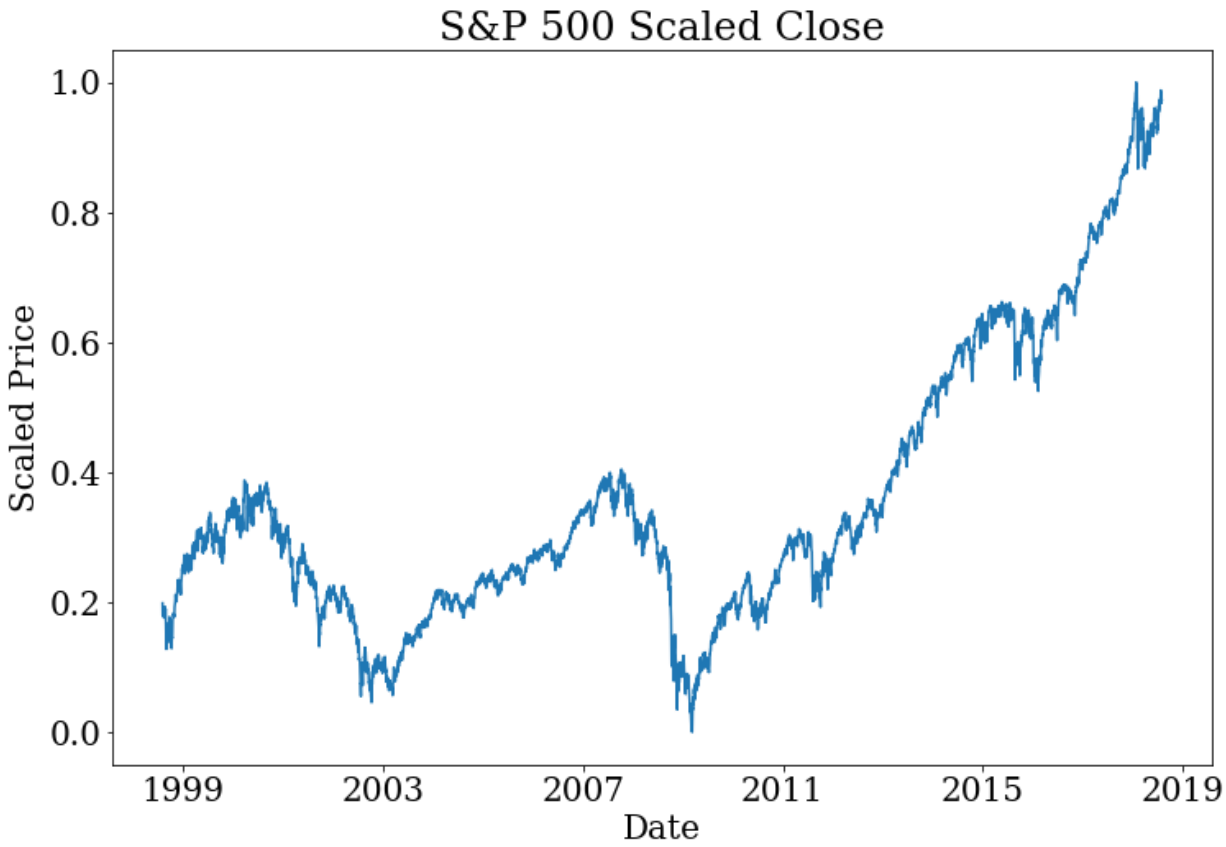
The original closing price of S&P 500 in the recent 20 years is shown in graph below:



The data is in a wide range. In order to get a better performance in machine learning, we scale the data in these columns: ['Open', 'High', 'Low', 'Close', 'Volume'], as shown below:

	Date	Open	High	Low	Close	Volume
0	1998-08-03	0.201737	0.195867	0.203049	0.198471	0.033314
1	1998-08-04	0.197975	0.194921	0.185395	0.180113	0.054029
2	1998-08-05	0.179547	0.178880	0.178771	0.184352	0.053939
3	1998-08-06	0.183802	0.181705	0.186823	0.188086	0.046517
4	1998-08-07	0.187550	0.187027	0.191299	0.188004	0.045687

Plot the scaled data, we can find that all the Closing Prices are located in the range of [0,1]:



We save the scaled data in 'data/SP500_199808_201808_scaled.csv' for further using.

Algorithms and Techniques

In this projest, we will use three supervised learningmodels:

- Linear Regression (https://en.wikipedia.org/wiki/Linear_regression), we will simply build a linear model to characterize the time dependence of the Closing price.
  - We use Date and Closing Price as input, and the Closing Price of the next day as output.
  - Split the data into training dataset and testing dataset.
  - Create the model by using function Sklearn.linear_model.LinearRegression()
  - Training: feed the training dataset to the Linear Regression model
  - Prediction: apply the trained model on the testing dataset, and check the performance.

- LSTM (https://en.wikipedia.org/wiki/Long_short-term_memory)(Long short-term memory) network for price prediction, based on the data in the recent 50 days. LSTM is a technique that can learn the long-short term depend of the historical data, and provide a reasonable prediction based on the data in the recent period.
  - We use the data of the recent 50 days as input, and the Closing Price of the next day as output.
  - Split the data into training dataset and testing dataset.
  - Create the model by keras.models.Sequential(), add the keras.layers.recurrent.LSTM() layer, Dense layers into the model, and add some Dropout() layers to avoid overfitting.
  - Set the parameters: batch_size = 100, epochs = 5
  - Training: feed the training dataset to the LSTM model

    - Prediction: apply the trained model on the testing dataset, and check the performance.

- Modify the LSTM (https://en.wikipedia.org/wiki/Long_short-term_memory) network for price change prediction, and calculate the price based on the price change.
    - We use the data of the recent 50 days as input, and create a new column data: Closing price change everyday, as output.
    - The model details are similar with the previous LSTM
    - After training the new model, we predict the price change on the testing dataset, and calculate the predicted Closing Price based on the price change. And compare with the real value.

At last, we compare the performance of these two models and choose the best one.

Benchmark:

Linear Regression Model

We will create the Linear Regression model as a benchmark. Let's import the scaled data from 'data/SP500_199808_201808_scaled.csv'.

Out[12]:

	Date	Open	High	Low	Close	Volume
0	1998-08-03	0.201737	0.195867	0.203049	0.198471	0.033314
1	1998-08-04	0.197975	0.194921	0.185395	0.180113	0.054029
2	1998-08-05	0.179547	0.178880	0.178771	0.184352	0.053939
3	1998-08-06	0.183802	0.181705	0.186823	0.188086	0.046517
4	1998-08-07	0.187550	0.187027	0.191299	0.188004	0.045687

To make a simple Linear Regression model, we select two columns from data:

```
data['Date'], data['Close']
```

Since data['Date'] is in datetime format, so we create a linear array, from 0 to len(data['Date']), to represent the Date.

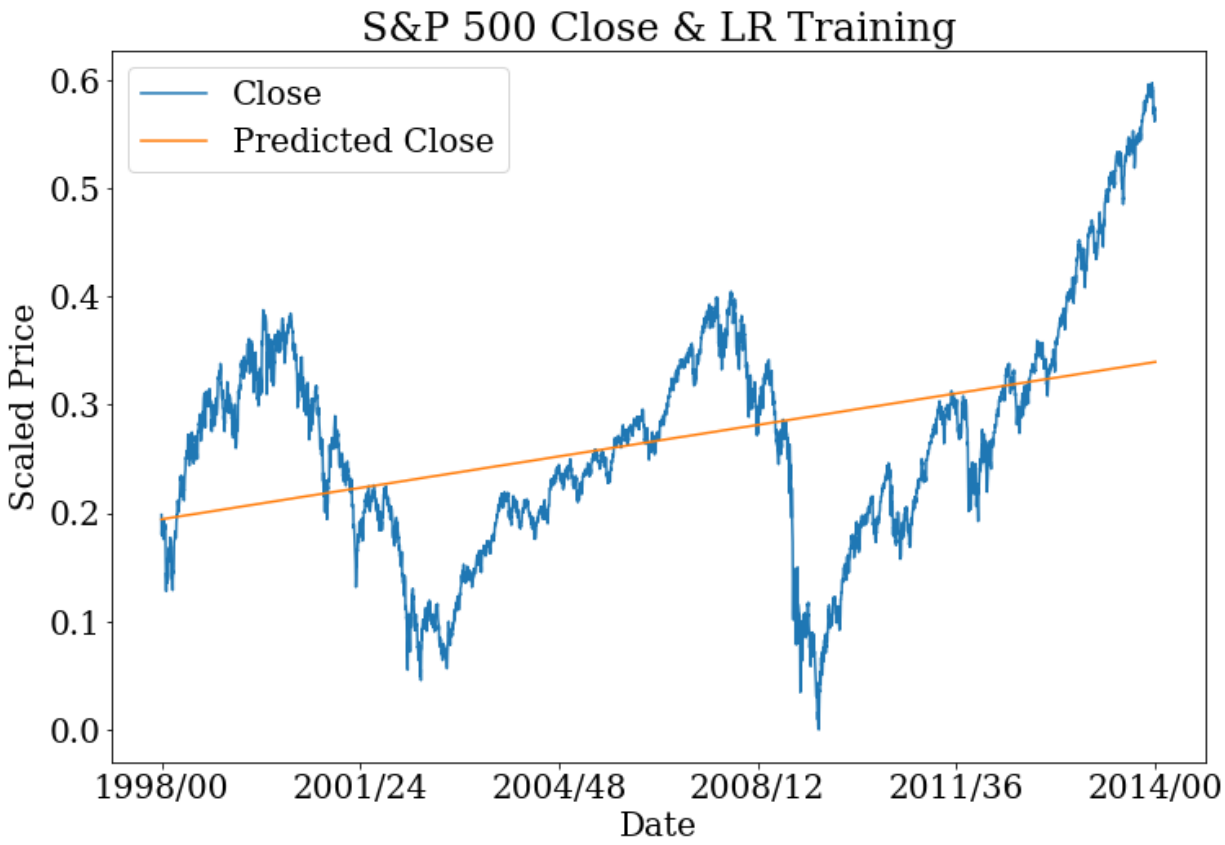
We split the datesets into training dataset and testing dataset. The last 1000 instances are for testing, and others are for training.

And we copy the data['Date'] for ploting later.

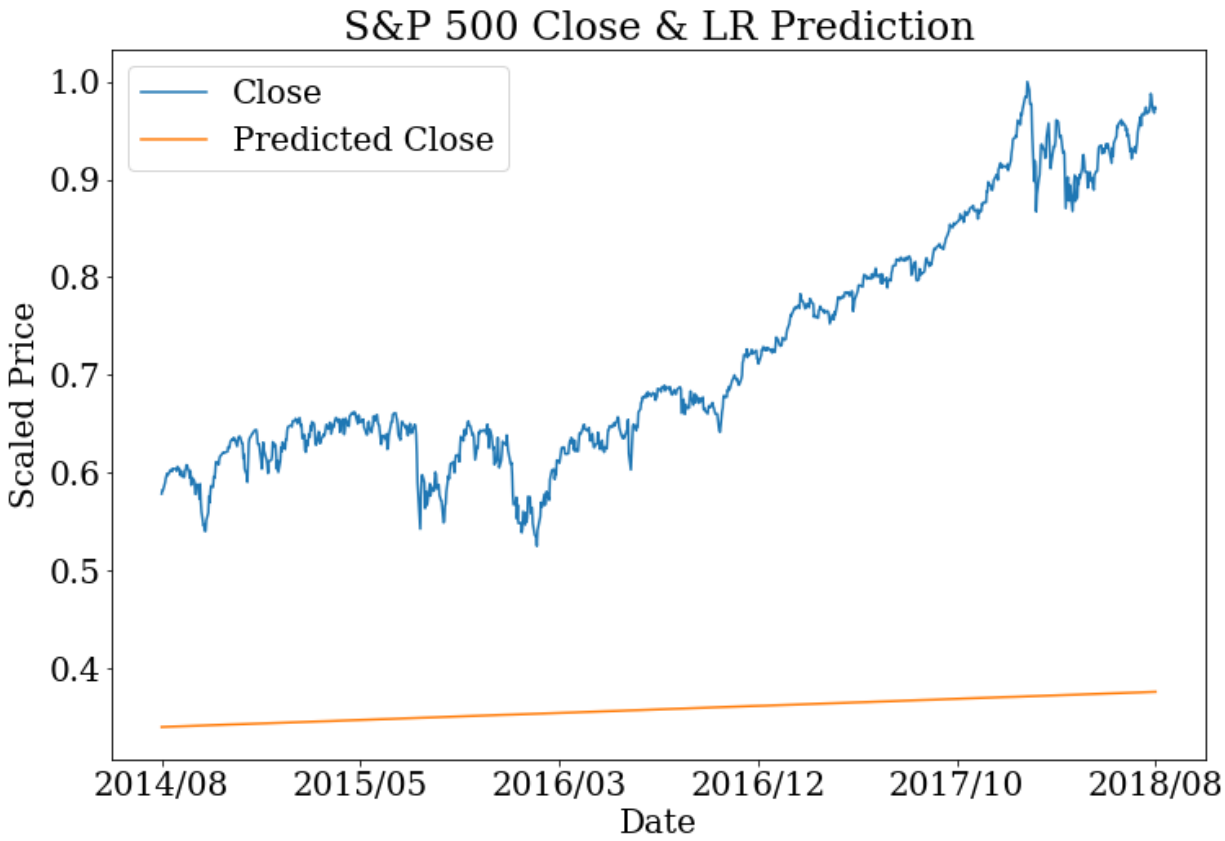
```
Size of X_train (4033, 1)
Size of y_train (4033,)
Size of X_test (1000, 1)
Size of y_test (1000,)
```

From sklearn, we import sklearn.linear_model as our model, and fit the model on our training dataset. Then use this model to predict the targets value in the testing dataset.

Plot the fitting result on the training dataset:



Plot the prediction result on the testing dataset:



The prediction result is not good in the graph. We can see the RMSE performance is vary bad.

```
RMSE on training dataset:  0.116004
RMSE on testing dataset:  0.383239
```

```
Original RMSE on testing dataset:  841.723179
```

The RMSE on the un-scaled original data is unbelievablly large, about 1/3 of the highest price value.

In conclusion, a simple linear regression is not valid in this problem.

Methodology

LSTM Model

In these Chapter, we will build a LSTM (https://en.wikipedia.org/wiki/Long_short-term_memory) (Long Short-Term Memory) model. And then try to improve it to get a better prediction.

Data Preprocessing

In LSTM model, the input is no longer a single instance in one day.

For each instance here, we will include the date of recent 50 days as a input, that means each input is a data matrix.

The Closing Price data['Close'] in the next day is the target.

We also copy the data['Date'] for ploting later.

```
Shape of the input dataset:
(4983, 50, 5)
Shape of the output dataset:
(4983, 1)
```

We split the datesets into training dataset and testing dataset. The last 1000 instances are for testing, and others are for training.

```
Size of X_train (3983, 50, 5)
Size of y_train (3983, 1)
Size of X_test (1000, 50, 5)
Size of y_test (1000, 1)
```

Implementation

Now we use keras to build a LSTM model, train the model and make the prediction. Here are the steps:

(code details of each step can be find in the the ipython notebook "./Predictor.ipynb":)

- Step 1: Import the relative functions in the package keras;
- Step 2: Build the architecure:
  - model = Sequential()

    - add layer: LSTM() based on the input size
    - add layer: Dropout(0.2)
    - add layer: LSTM(128)
    - add layer: Dropout(0.2)
    - add layer: Dense(units = 1)
    - add layer: Activation('linear')

      Notice that some other activiation functions are also good, such as 'relu' if the result is a positive number. But if the result can be neative (like we will show in the improved LSTM), we should use 'linear' or some other activiation functions.

- Step 3: Set the other hyperparameters:
    - input_shape is based on the size of input instance
    - unites is the how many days included in each input instance, here is 50
    - batch_size = 100
    - epochs = 5

      The choice of hyperparameters is depend on the performance and running time. If the running time is too long, you may have less time to try other parameters.

- Step 4: Compile the model based on the size of input instance.

- Step 5: Train the LSTM model on our training dataset for 5 epoches, below is the training result.

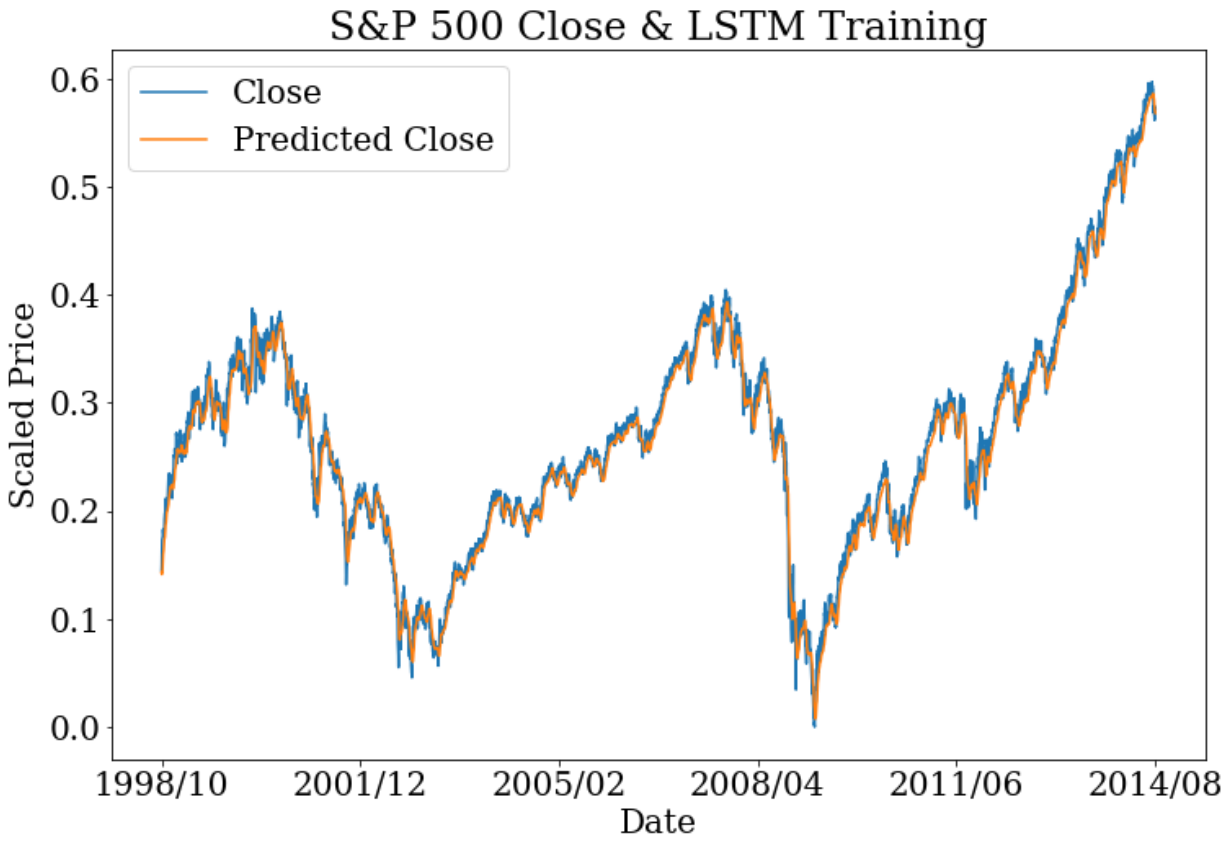
```
Train on 3783 samples, validate on 200 samples
Epoch 1/5
 - 43s - loss: 0.0042 - val_loss: 5.8551e-04
Epoch 2/5
 - 45s - loss: 6.7066e-04 - val_loss: 7.8203e-04
Epoch 3/5
 - 48s - loss: 5.3625e-04 - val_loss: 2.9757e-04
Epoch 4/5
 - 52s - loss: 5.0779e-04 - val_loss: 1.0400e-04
Epoch 5/5
 - 49s - loss: 4.7341e-04 - val_loss: 1.8065e-04
```

```
Out[52]: <keras.callbacks.History at 0x1a381ee198>
```

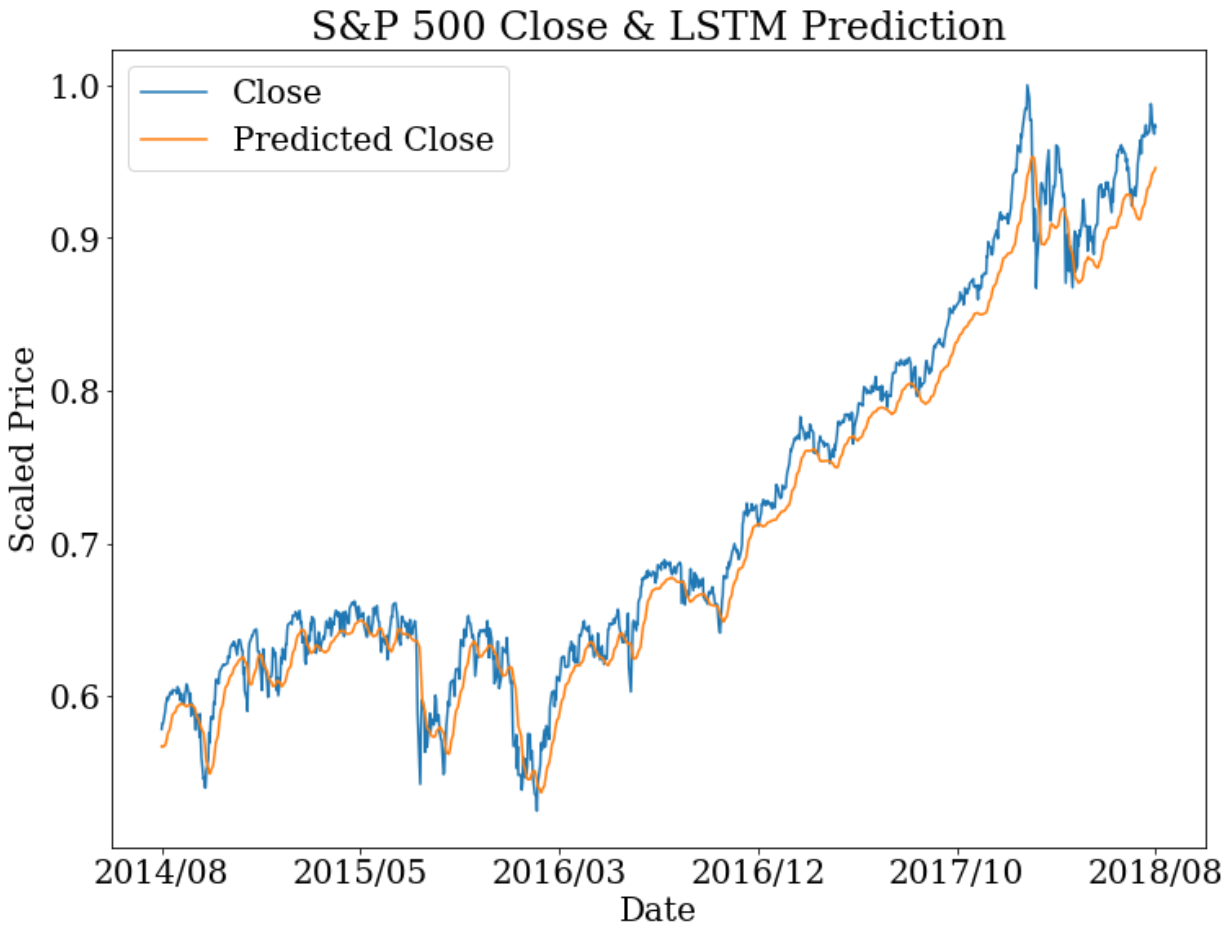
The trained model is been saved in 'saved_model/lstm.h5'.

- Step 6: Check the output performance on training dataset and make a prediction on testing dataset.

Plot the fitting result on the training dataset:



Plot the prediction result on the testing dataset:



The prediction result is much better than the Linear Regression model.

We can see the RMSE is very small on the training dataset.

However, on the testing dataset, the RMSE is not small enough, there is a bias that most of the prediction value is less than the real value. And obviously, the model is overfitted since RMSE on testing is much larger than training.

```
RMSE on training dataset:  0.013485
RMSE on testing dataset:  0.021833
```

All the values above is based on the scaled data.

For the original data, the RMSE should be magnified by a factor: max(data['Close']) - min(data['Close'])

```
Original RMSE on testing dataset:  47.953439
```

This is still not a good performance. It needs to be improved.

Refinement

To improve the LSTM model for a better performance, we have tested and tuned some hyper parameters:

- To avoid overfitting, we add Dropout() layers with the 0.2 drop rate.
- To make our model more applicable for the complex data, we increase the hidden nodes from 64 to 128
- We tried the Batch_Size from 10 to 500, if the Batch_Size is too low, the model cannot convergent, and when the Batch_Size is too large, we need more time finish the training. We set the Batch_Size as 100 based on the balence of convergence and time spending.
- We set the number of epochs = 5, too few epochs will cause underfitting and too many epochs cost more time in training.

After refinement, we decreased the RMSE on training set from 0.06 to 0.013, and decreased the RMSE on the testing sets from 0.1 to 0.0218

Use LSTM on Price Change

In the previous model, we didnot get a good performance in the testing dataset. There are several reasons:

- The data in the recent 1000 days is the higher than anytime in history. That's why we got a negative bias on prediction.
- The Price everyday is changed from the Open Price today or Closing Price yesterday. That means we don't need to know what the price is, we just need to know the price change everyday. And the closing price can be derived from the price change amount. Then the prediction of the Closing Price tomorrow will not be far away from that today.

We generate another target: increasing rate everyday, and prepare the training and testing datasets as we shown in previous.

We still applied the LSTM model in previous. The only difference is we use increasing rate as the target.

Compile the model and training the model on the training dataset.

Result

Model Evaluation and Validation

Based on the training result , the validation performance is much better than the previous LSTM.

```
Train on 3783 samples, validate on 200 samples
Epoch 1/5
 - 44s - loss: 3.7539e-04 - val_loss: 1.0599e-04
Epoch 2/5
 - 45s - loss: 8.6071e-05 - val_loss: 2.9931e-05
Epoch 3/5
 - 47s - loss: 7.4710e-05 - val_loss: 4.7925e-05
Epoch 4/5
 - 51s - loss: 6.3652e-05 - val_loss: 2.9682e-05
Epoch 5/5
 - 47s - loss: 5.8748e-05 - val_loss: 3.1733e-05
```

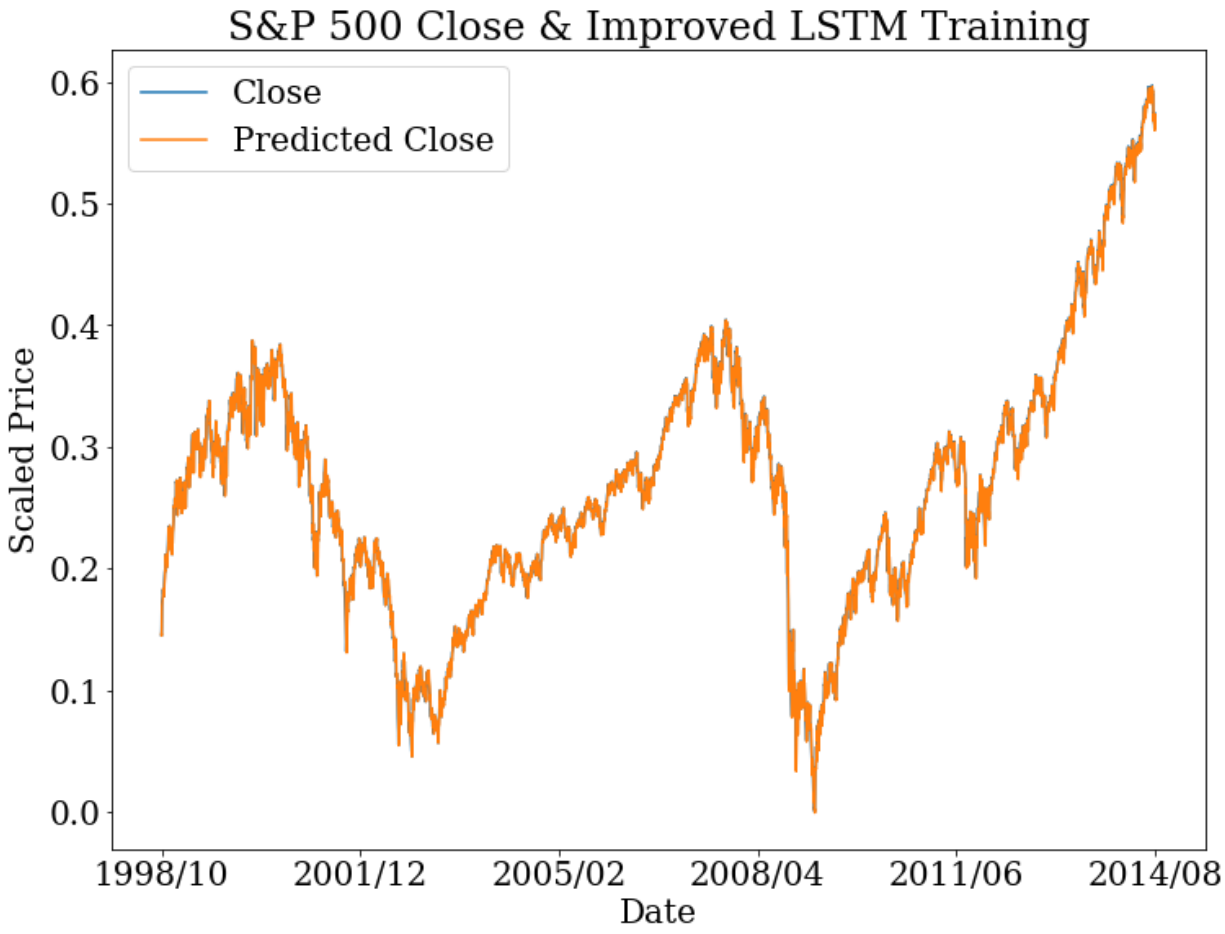
Out[91]: <keras.callbacks.History at 0x1a3f7a5b38>

Save the new LSTM model into 'saved_model/lstm2.h5'

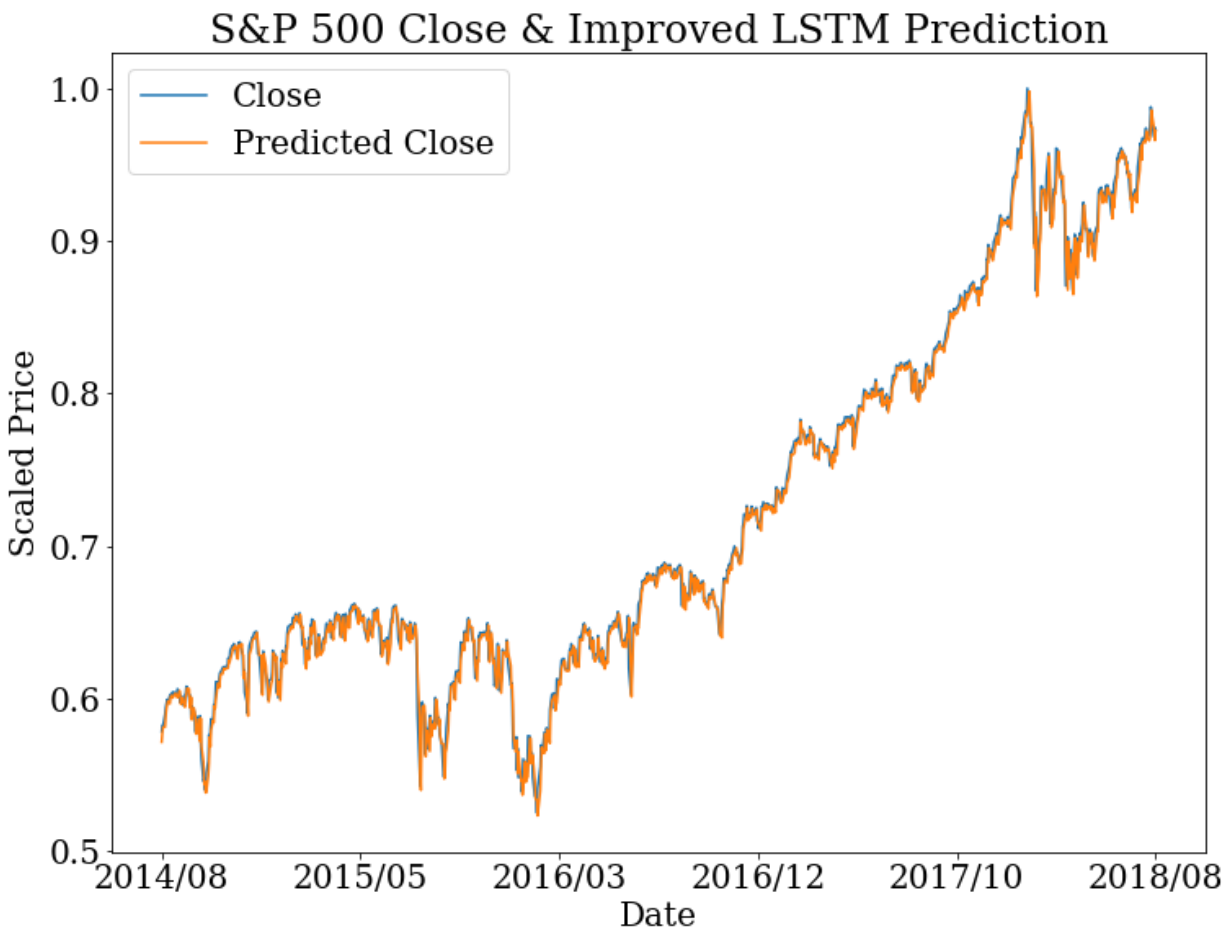
For the price change, we calculate the prediction on training dataset, and make a prediction on testing dataset.

Then calculate the scaled price value prediction, on both training set and testing set.

Plot the fitting result on the training dataset:



Plot the prediction result on the testing dataset:




```
RMSE on training dataset:  0.006712
RMSE on testing dataset:  0.008394
```

Now the prediction result has been improved much better.

We can find that RMSE becomes very small on both training and testing datasets.

For the un-scaled original data, the RMSE is also been decreased more than half.

```
Original RMSE on testing dataset:  18.435910
```

Justification

Compare with the benchmark result in Linear Regression model, our improved LSTM model improve the un-scaled RMSE from 841.723179 to 18.435910, decrease 97.8% RMSE.

```
The average closing price in the recent 1000 days is: 2259.413251
```

```
So the average percentage error, is: 18.435910 / 2259.413251 = 0.815960 %
```

Robustness

To check the robustness of our model, we will use our model to predict the closing price of S&P 500 during 1988/08 to 1998/08. The data has been downloaded in 'SP500_198808_199808.csv', below is the head of the data:

	Date	Open	High	Low	Close	Adj Close	Volume
0	1988-08-01	272.029999	272.799988	271.209991	272.209991	272.209991	138170000
1	1988-08-02	272.190002	273.679993	270.369995	272.059998	272.059998	166660000
2	1988-08-03	272.029999	273.420013	271.149994	272.980011	272.980011	203590000
3	1988-08-04	273.000000	274.200012	271.769989	271.929993	271.929993	157240000
4	1988-08-05	271.700012	271.929993	270.079987	271.149994	271.149994	113400000

```
Shape of the input dataset:
(2479, 50, 5)
Shape of the output dataset:
(2479, 1)
Size of X_train (1479, 50, 5)
Size of y_train (1479, 1)
Size of X_test (1000, 50, 5)
Size of y_test (1000, 1)
```

Lets check the performance of our model on the new dataset:

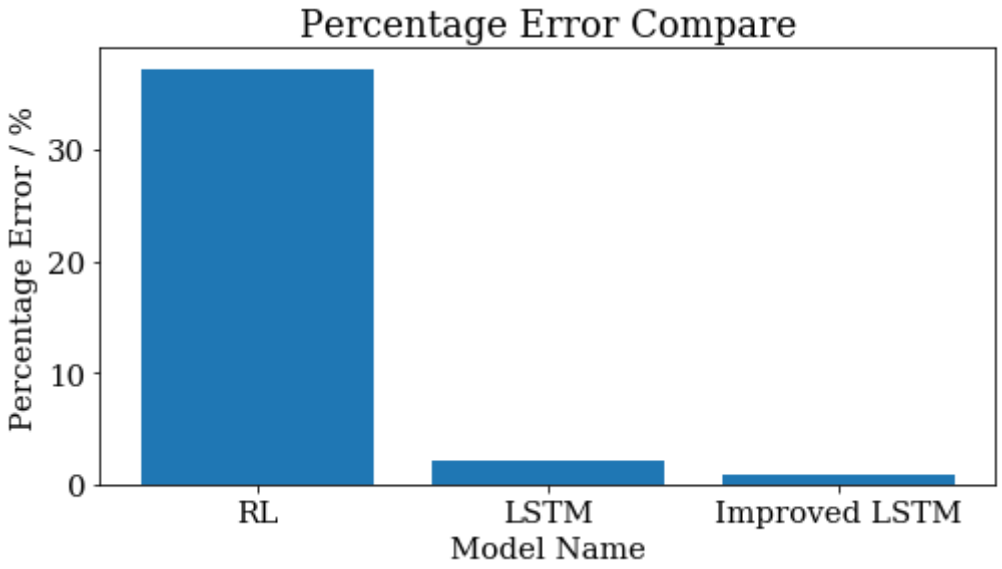
```
RMSE on training dataset:  0.003090
RMSE on testing dataset:  0.007758

Original RMSE on testing dataset:  7.213043
```

We can find that our model is very robust on other new datasets.

Conclusion

Free-Form Visualization

We compare the percentage error for the three models, the improved LSTM model has the best performance.



Reflection

Step by step recap of the process:

- Software:
  - We use Jupyter to run the ipython notebook. You can use the Jupyter in Anaconda, or download directely.
- Packages we use:
  - Pandas, Numpy, Sklearn, Matplotlib, Keras, Time, Datetime.
- Dateset:
  - Download the historical data from Yahoo
  - Import data by Pandas dataframe
  - Drop the duplicate columns, Scale the value
  - Prepare the dataset for LSTM: each input instance is matrix include the data of recent 50 days
  - Split the data into training set and testing set. We use the data of the last 1000 days as testing set, and others as traning set.
- Create a Benchmark model: Linear Regression
- Create a LSTM model:
  - Use the dataset prepared above for trainning and testing
  - Magnify the RMSE on the unscaled original data and Check the performance
  - Refine the parameters and repeat
- Modify the LSTM model:
  - Create another data column of closing price change, as use it as a new target;
  - Train the LSTM model in the new dataset, and predict the closing price change.
  - Calculate the
  - Magnify the RMSE on the unscaled original data and Check the performance
- Compare different models and choose the best one
- Write the report

In the improved LSTM model, our percentage error seems very small, but for a single day prediction, it is still unacceptabl. It is interesting that even if you just simply predict that the price tomorrow is the same with today, you can get a very good performance in RMSE. Because a single day

predicted price will not be to far from the current price.

For a better model, we should check the performance on long term prediction. In conclusion, this is just a toy model for machine learning practice, it cannot be used in real trading.

Improvement

Some improvement has not been used here, but might be useful:

- More features can be find from more datasets.
  - S&P 500 index comprises about 500 stocks, pick up some stocks and include them into input.
  - Different market interact with each other. We may add some other datasets like: Index Futures, CL Price.
- Stock price is determined by human behavoir, and human behavior is based the information they access. Internet informations, such as hot news and google search trends, indicats the potential behavior of people. An ideal model should include Natural Language Processing(NLP) on internet information.
- We may not need to create the wheel from the beginning, transfer learning from another well trained model could be another choice.

Out[45]: Click here to toggle on/off the raw code.