CS 450 - Machine Learning & Data Mining

Name: Kwok Moon Ho | Github: https://github.com/kwokmoonho/Machine-Learning-SP500

Introduction:

The objective of this project was aimed at using Python and different machine learning algorithms(LSTM, KNN, Linear Regression) to conduct predictions on the S&P 500 index. This problem was especially interesting because it compared the performance of different machine learning algorithms and how it applied to the prediction of the S&P 500 index. At the end of the project, I was able to conclude which algorithms were better for the prediction of the S&P 500 index.

All of the data was obtained from Yahoo Finance S&P500 index. There was an 8850 row in the data set from the period 2/1/1985 to 3/13/2020. The reason this period was used was that it contained at least three economic recessions in USA history and the only used date and numeric data type.

The project experienced three different machine learning algorithms which included, LSTM, KNN, and Linear Regression. LSTM achieved a higher result than linear regression, based on my calculation and visualization below.

Data preparation:

Since stock data does not contain missing value and categorical data, the data preprocessing process for this project did not implement labels, use one-hot encoding, or handle missing value. Instead, this project applied feature scaling - “Scaling features to a range.” The purpose of this is to standardize the data so that the maximum absolute value of each feature is scaled to unit size. This is achieved by using ‘MinMaxScaler.’ The motivation to use this scaling included robustness to very small standard deviations of features and preserving zero entries in sparse data.

```
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(dataset)
```

Mining / Learning from the data:

In this project, three machine learning algorithms were used which included: Linear Regression, KNN, and Long Short-Term Memory (LSTM). The process of mining the data for these three different algorithms were: Data Preprocessing → Data Feature Scaling → Splitting 80% of data to train set and 20% to test set.

Linear Regression:

```
#implement linear regression
```

```
model = LinearRegression()
model.fit(x_train,y_train)
```

The code above creates a linear regression model and fits in the x_train and y_train dataset. The root means square error (rmse) is 727.06. This shows that this is not a good fit for using linear regression to predict the S&P 500 index.

KNN:

```
#using gridsearch to find the best parameter
params = {'n_neighbors':[2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20]}
knn = neighbors.KNeighborsRegressor()
model = GridSearchCV(knn, params, cv=5)
……….
```

In order to find the best k for KNN algorithms, the code above used GridSearchCV to find the best parameter of k from 2 to 20. Then the x_train and y_train data will fit in the KNN model. The root means square error (rmse) is 1478.34, which shows that this is not a good fit for using KNN regression to predict the S&P 500 index.

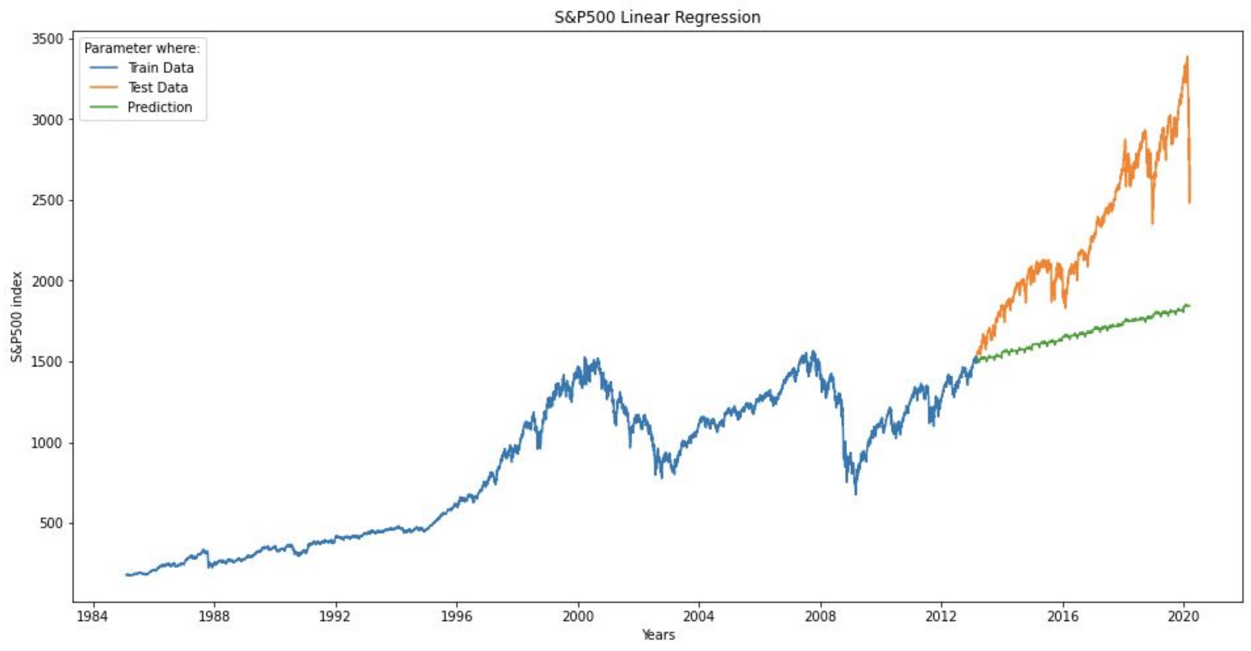
Long short-term memory (LSTM):

```
for i in range(60,len(train)):
    x_train.append(scaled_data[i-60:i,0])
……………..
# create and fit the LSTM network
myRMS = []
for p in range (40,60):
    model.add(LSTM(units=p, return_sequences=True, input_shape=(x_train.shape[1],1)))
    model.compile(loss='mean_squared_error', optimizer='adam')
    model.fit(x_train, y_train, epochs=10, batch_size=32, verbose=2)
```

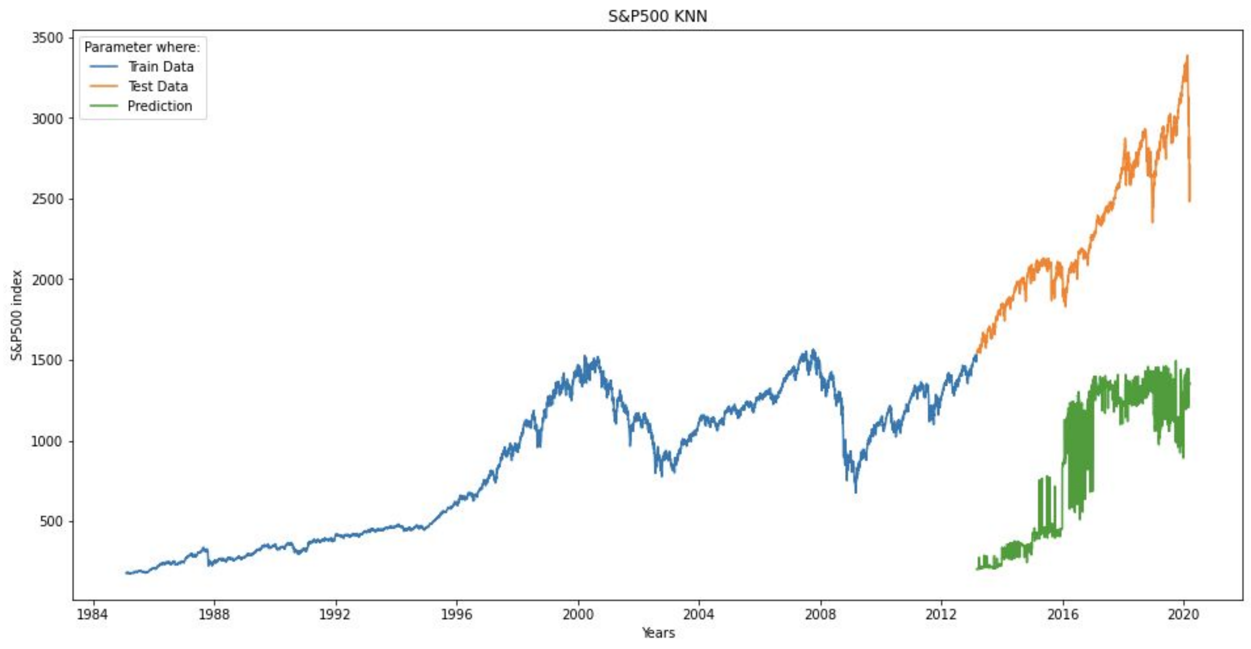
I used the past 60 days from the train data to calculate the predicted value. Therefore, when the data is split into x_train and y_train, the “for loop” starts from 60 and goes to the length of the train data set. In the LSTM function, the “unit” means the dimensionality of the output space. In this case, “units” are set into different values inside a “for loop” from 40 to 60, which means that there will be 40 to 60 hidden layers each loop. Since it is a regression problem, this LSTM model implemented the Mean Squared Error Loss, which calculated as the average of the squared differences between the predicted and actual values. An epoch is an iteration over the entire x_train and y_train. The variable “batch_size” means that the number of samples per “gradient” update in this LSTM model uses the default value 32. The variable “verbose,” which is 2 in this model, means that one line per epoch. The root means square (rmse) is 37.
This LSTM model tried different numbers of units, epochs, and batch_size.
The challenge for mining or learning from the data is that it takes a lot of time to understand the parameter of the function. I overcame these challenges by researching various documents in the Kears library.

Results:

Linear Regression:

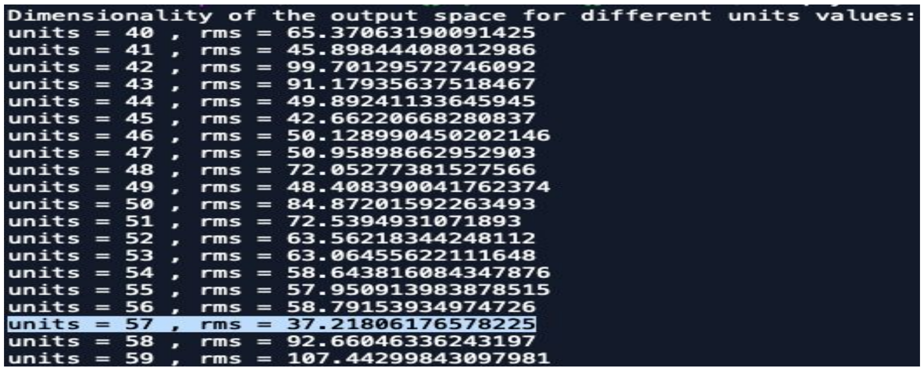


KNN:

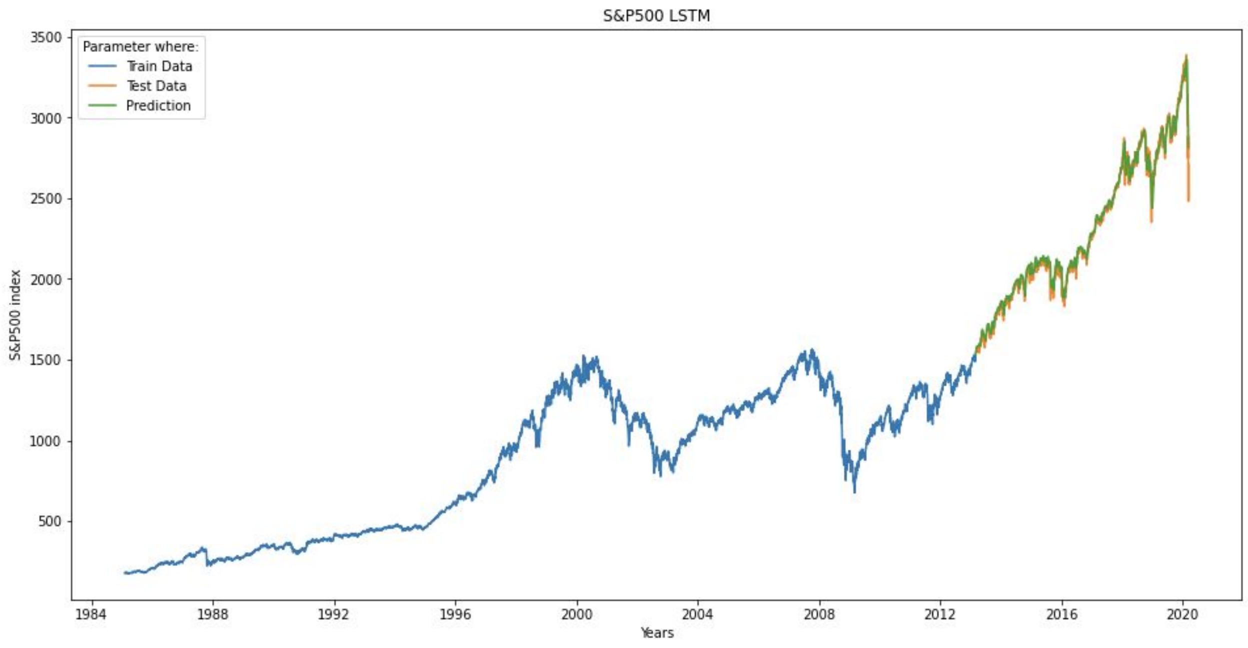


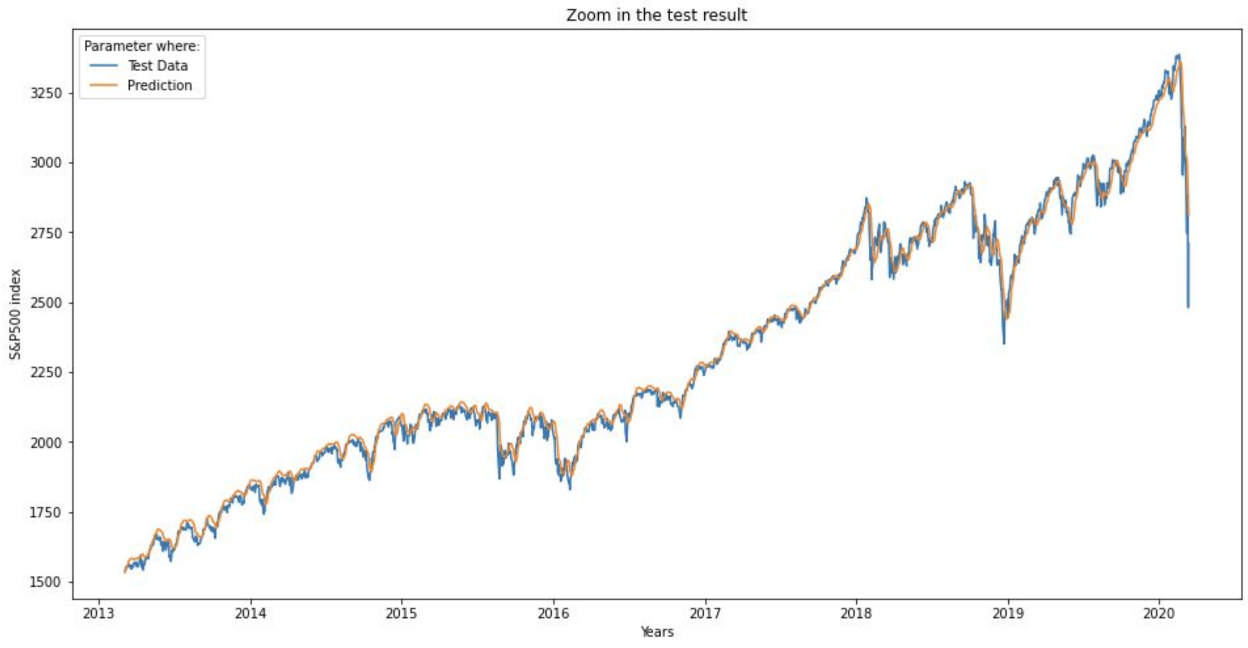
LSTM:

The best result for these variables are units = 57, batch_size = 32, epochs = 10.



```
Dimensionality of the output space for different units values:
units = 40 , rms = 65.37063190091425
units = 41 , rms = 45.89844408012986
units = 42 , rms = 99.70129572746092
units = 43 , rms = 91.17935637518467
units = 44 , rms = 49.89241133645945
units = 45 , rms = 42.66220668280837
units = 46 , rms = 50.128990450202146
units = 47 , rms = 50.95898662952903
units = 48 , rms = 72.05277381527566
units = 49 , rms = 48.408390041762374
units = 50 , rms = 84.87201592263493
units = 51 , rms = 72.5394931071893
units = 52 , rms = 63.56218344248112
units = 53 , rms = 63.06455622111648
units = 54 , rms = 58.643816084347876
units = 55 , rms = 57.950913983878515
units = 56 , rms = 58.79153934974726
units = 57 , rms = 37.21806176578225
units = 58 , rms = 92.66046336243197
units = 59 , rms = 107.44299843097981
```





Conclusions:

Values and outcome of the project:

After testing various methods, I found that the best-fit machine learning algorithms for prediction S&P 500 index were LSTM > Linear Regression > KNN. Investors or businesses may consider to include LSTM as one of the trend indicators to help them make strategic investment judgments or choose to include LSTM in their investment strategy plan.

Limitation:

Since the S&P 500 index is an integrated index by 500 stocks value, it may not really reflect the limitations of LSTM when predicting non-numerical issues. In another word, the stock price is affected by the news about the company and other factors like demonetization or merger/demerger of companies. There are certain intangible factors as well which can often be impossible to predict beforehand.

Lessons Learned:

I learned how to implement the concept and function of linear regression, KNN, and LSTM in Python to conduct a machine learning prediction. I learned a lot by doing research on the Kears library and looking up all the variables and meanings. I will continue my research by conducting “back-testing” to analyze the profit and loss ratio by using LSTM to trade.

If I could start over, I would only implement LSTM algorithms and try this model in different datasets. Then, I would explore the “machine trading” concept by implementing my model to trade and analyze the profit and loss ratio. Since I did not have any group members, I think I did a great job in this project by myself by implementing three different machine learning algorithms.