

# Market Predictions Using LSTM Network

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Data Sources:

[https://www.kaggle.com/camnugent/sandp500/version/4#all\\_stocks\\_5yr.csv](https://www.kaggle.com/camnugent/sandp500/version/4#all_stocks_5yr.csv)

The main source for this notebook was [Soumith's Github - Time Sequence Prediction](#) in which he goes through the problem of using a recurrent neural network to predict a sine wave.

```
[18] import numpy as np
import torch
import matplotlib.pyplot as plt
import cyclor
import time
import pandas as pd
import time

from __future__ import print_function
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib
#matplotlib.use('Agg')
import matplotlib.pyplot as plt

import datetime as dt
from matplotlib import style
import pandas_datareader.data as web

#Plotting
from IPython.display import display
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from matplotlib import cm

import matplotlib.dates as mdates
```

## Import and Prepare Data

---

```
[2] #Load .csv file
```

```

path = '/Users/spencerbertsch/Desktop/ENGG_192/RNNs/Data/AAPL.csv'
path2 = '/Users/spencerbertsch/Desktop/ENGG_192/RNNs/Data/all_stocks_5yr.'
#create a data frame from the data stored in the .csv file
df = pd.read_csv(path)
SP500_data = pd.read_csv(path2)
SP500 = SP500_data.values

print("We have 500 stocks in our training dataset and a total daily closing values of: 635795")
print("Which gives us", (SP500.shape[0])/505, "data points per stock")
SP500_data.head(5)

```

We have 500 stocks in our training dataset and a total daily closing values of: 635795

Which gives us 1259.0 data points per stock

	date	open	high	low	close	volume	Name
0	2/8/13	15.07	15.12	14.63	14.75	8407500	AAL
1	2/11/13	14.89	15.01	14.26	14.46	8882000	AAL
2	2/12/13	14.45	14.51	14.10	14.27	8126000	AAL
3	2/13/13	14.30	14.94	14.25	14.66	10259500	AAL
4	2/14/13	14.94	14.96	13.16	13.99	31879900	AAL

```

[3] close_price = SP500[:, 4]
#price_mat = close_price.reshape(500, 1238)#1259
price_mat = close_price.reshape(505, 1259)#1259

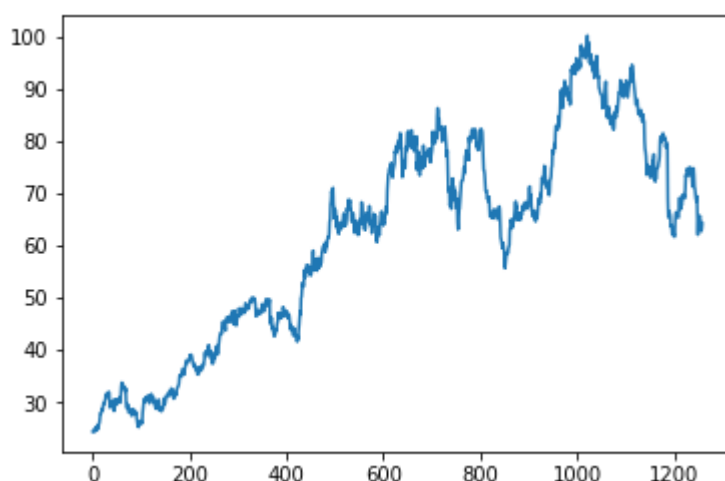
```

```

[4] plt.plot(price_mat[26,:])

```

[<matplotlib.lines.Line2D at 0x1a1c326710>]



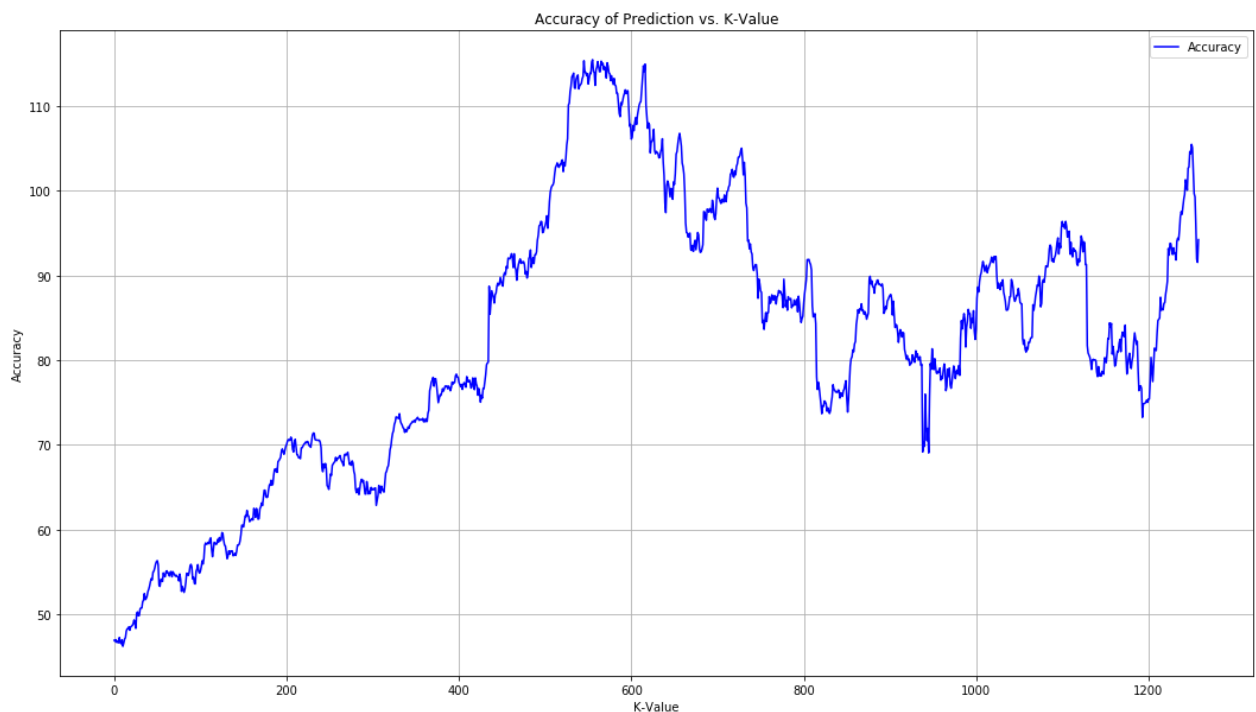
Only the first 26 stocks are the same length, which will not matter for training our RNN, but the stock price will jump inside our vectors if we go past 26 stock in our dataframe

```
[5] data = price_mat[:26,:]
data.astype(float)
data.shape

data2 = pd.DataFrame(data)
```

```
[6] x = range(0,500)
y = range(0,1)
fig = plt.figure(figsize=(18, 10))
ax1 = fig.add_subplot(111)

plt.plot(data[4,:], 'b', label='Accuracy')
plt.legend(loc='upper right');
plt.xlabel('K-Value')
plt.ylabel('Accuracy')
plt.title('Accuracy of Prediction vs. K-Value')
plt.grid()
```



```
[7] #calculate and store averages for window sizes of 25, 50, 100, and 200
W25 = data2.iloc[4,:].rolling(window=25,min_periods=0).mean()
W50 = data2.iloc[4,:].rolling(window=50,min_periods=0).mean()
W100 = data2.iloc[4,:].rolling(window=100,min_periods=0).mean()
W200 = data2.iloc[4,:].rolling(window=200,min_periods=0).mean()
```

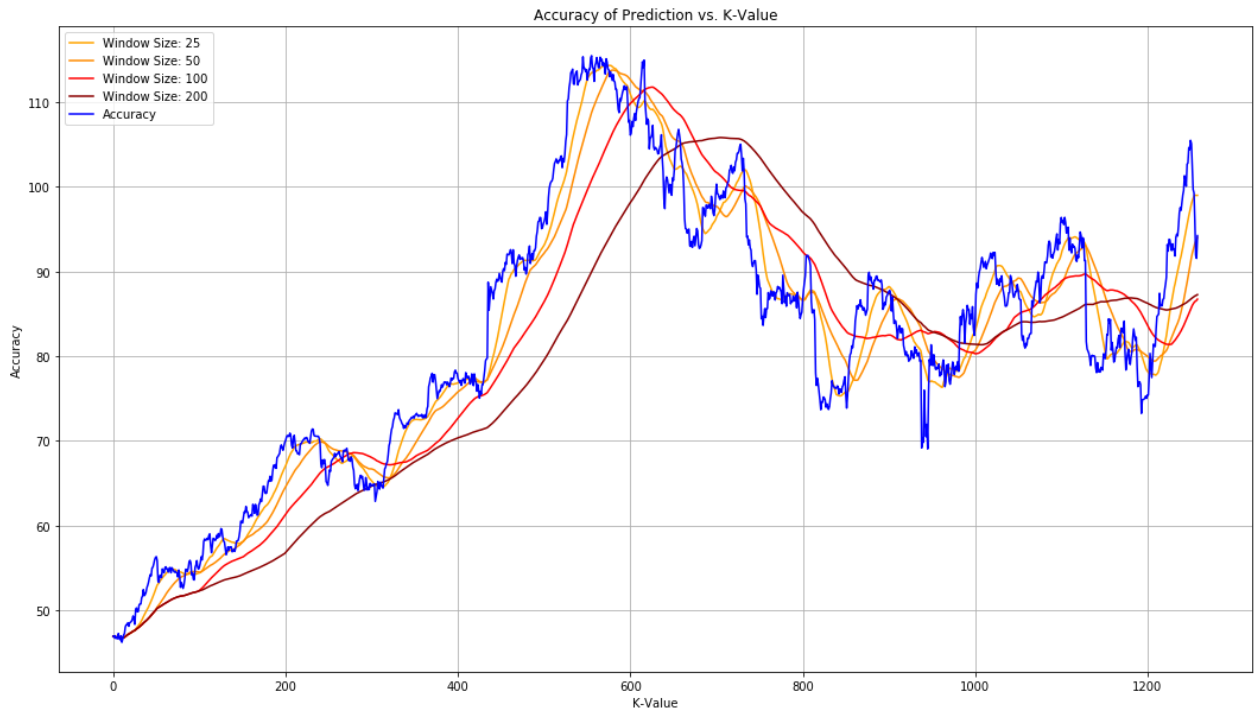
```
[8] x = range(0,500)
y = range(0,1)
fig = plt.figure(figsize=(18, 10))
ax1 = fig.add_subplot(111)

ax1.plot(data2.iloc[4,:].index, W25, color='orange', label=('Window Size: 25'))
ax1.plot(data2.iloc[4,:].index, W50, color='darkorange', label=('Window Size: 50'))
ax1.plot(data2.iloc[4,:].index, W100, color='red', label=('Window Size: 100'))
ax1.plot(data2.iloc[4,:].index, W200, color='darkred', label=('Window Size: 200'))
```

```

ax1.plot(data2.iloc[4,:].index, W200, color='darkred', label=('Window Siz
plt.plot(data2.iloc[4,:], 'b', label='Accuracy')
plt.legend(loc='upper left');
plt.xlabel('K-Value')
plt.ylabel('Accuracy')
plt.title('Accuracy of Prediction vs. K-Value')
plt.grid()

```



[9]

## Define Sequence Class

```

[13] units = 250

class Sequence(nn.Module):
    def __init__(self):
        super(Sequence, self).__init__()
        self.lstm1 = nn.LSTMCell(1, units)
        self.lstm2 = nn.LSTMCell(units, units)
        self.linear = nn.Linear(units, 1)

    def forward(self, input, future = 0):
        outputs = []
        h_t = torch.zeros(input.size(0), units, dtype=torch.double)
        c_t = torch.zeros(input.size(0), units, dtype=torch.double)
        h_t2 = torch.zeros(input.size(0), units, dtype=torch.double)
        c_t2 = torch.zeros(input.size(0), units, dtype=torch.double)

        for i, input_t in enumerate(input.chunk(input.size(1), dim=1)):

```

```

        h_t, c_t = self.lstm1(input_t, (h_t, c_t))
        h_t2, c_t2 = self.lstm2(h_t, (h_t2, c_t2))
        output = self.linear(h_t2)
        outputs += [output]
    for i in range(future):# if we should predict the future
        h_t, c_t = self.lstm1(output, (h_t, c_t))
        h_t2, c_t2 = self.lstm2(h_t, (h_t2, c_t2))
        output = self.linear(h_t2)
        outputs += [output]
    outputs = torch.stack(outputs, 1).squeeze(2)
    return outputs

```

```

[14] # set random seed to 0
      np.random.seed(0)
      torch.manual_seed(0)
      # load data and make training set

```

<torch.\_C.Generator at 0x110423290>

```

[15] #Prepare data
      input = torch.from_numpy(((data[3:, :-1]).astype(float)))
      target = torch.from_numpy(((data[3:, 1:]).astype(float)))
      test_input = torch.from_numpy(((data[:3, :-1]).astype(float)))
      test_target = torch.from_numpy(((data[:3, 1:]).astype(float)))

```

```

[16] # build the model
      seq = Sequence()
      seq.double()
      criterion = nn.MSELoss()
      # use LBFGS as optimizer since we can load the whole data to train
      optimizer = optim.LBFGS(seq.parameters(), lr=0.8)
      #begin to train

```

```

[17] epochs = 5
      tic = time.time()
      for i in range(epochs):
          print('STEP: ', i)
          def closure():
              optimizer.zero_grad()
              out = seq(input)
              loss = criterion(out, target)
              print('loss:', loss.item())
              loss.backward()
              return loss
          optimizer.step(closure)
          # begin to predict, no need to track gradient here
          with torch.no_grad():

```

```

        future = 500
        pred = seq(test_input, future=future)
        loss = criterion(pred[:, :-future], test_target)
        print('test loss:', loss.item())
        y = pred.detach().numpy()
    # draw the result
    plt.figure(figsize=(30,10))
    plt.title('Predict future stock values\n(Dashlines are predicted values)')
    plt.xlabel('Day', fontsize=20)
    plt.ylabel('Stock Price (USD)', fontsize=20)
    plt.xticks(fontsize=20)
    plt.yticks(fontsize=20)
    def draw(yi, color):
        plt.plot(np.arange(input.size(1)), yi[:input.size(1)], color, linewidth=2)
        plt.plot(np.arange(input.size(1), input.size(1) + future), yi[input.size(1):], color, linewidth=2, style='dashed')
    draw(y[0], 'r')
    draw(y[1], 'g')
    draw(y[2], 'b')
    plt.savefig('predict%d.pdf'%i)
    #plt.close()
    toc = time.time()

```

```

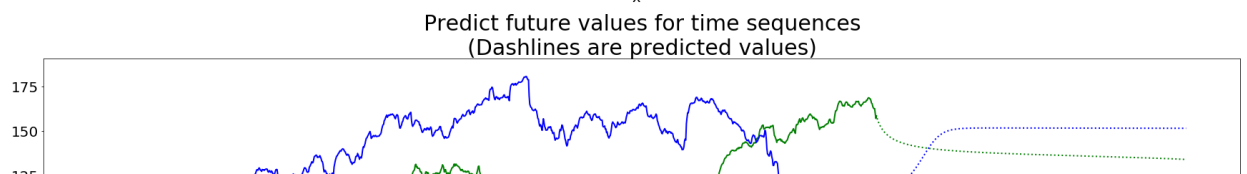
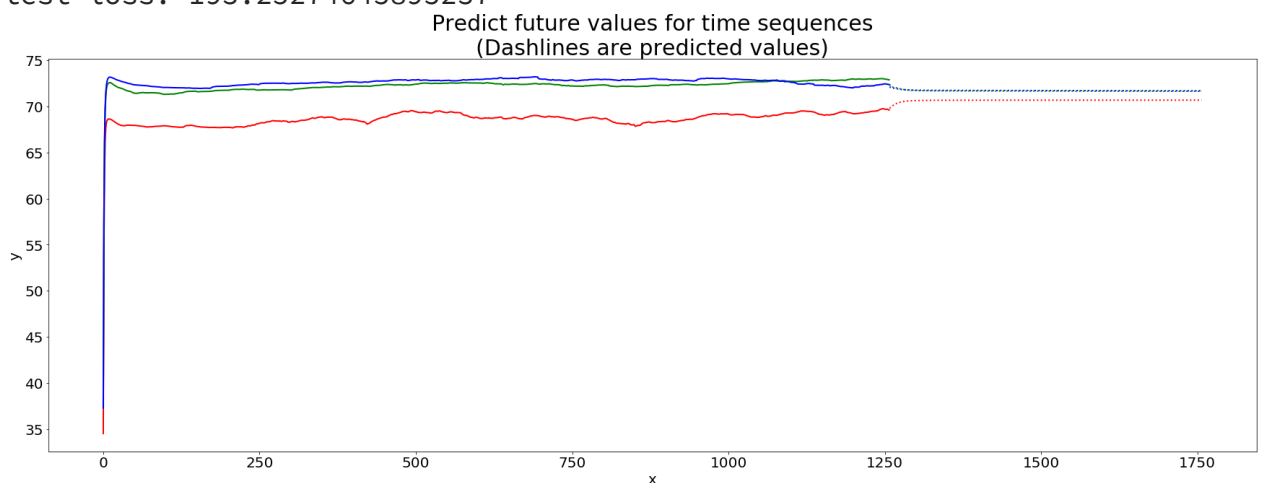
loss: 883.9363476544311
loss: 740.9950536672206
loss: 595.3078151803076
loss: 501.9678511231797

```

```

loss: 476.88602008944713
loss: 505.60466138515767
loss: 374.03119670159145
loss: 338.47528571883333
loss: 318.72074918099275
loss: 302.0269892265138
loss: 269.39137204796356
loss: 247.7981081791043
loss: 213.90648261628235
loss: 200.41307131704662
test loss: 193.25274645895237

```



```
[ ] train_time = toc - tic  
secs = train_time%60  
mins = (train_time - secs)/60  
  
print('Time taken to train on', epochs, 'epochs was:', mins, 'minutes and'
```