LSTM model using PyTorch to predict the Volume of Starbucks stock price

- Source : https://bit.ly/2S8pHD7
- Data : https://bit.ly/3hCe5TS

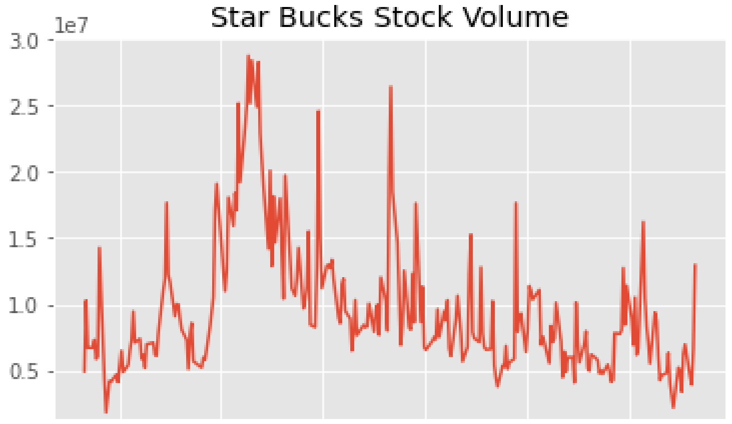
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('SBUX.csv' , index_col='Date', parse_dates=True)
```

```
df.head(5)
```

Date	Open	High	Low	Close	Adj Close	Volume
2019-12-11	86.260002	86.870003	85.849998	86.589996	84.145752	4921900
2019-12-12	88.000000	88.889999	87.540001	88.209999	85.720032	10282100
2019-12-13	88.019997	88.790001	87.580002	88.669998	86.167046	6714100
2019-12-16	89.139999	89.300003	88.430000	88.779999	86.273941	6705600
2019-12-17	88.870003	88.970001	87.470001	88.129997	85.642288	7296900

```
plt.style.use('ggplot')
df['Volume'].plot(label='CLOSE', title='Star Bucks Stock Volume')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffb4c279650>
```




```
X = df.iloc[:, :-1]
y = df.iloc[:, 5:6]
```

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler
mm = MinMaxScaler()
ss = StandardScaler()

X_ss = ss.fit_transform(X)
y_mm = mm.fit_transform(y)
```

```
#first 200 for training

X_train = X_ss[:200, :]
X_test = X_ss[200:, :]

y_train = y_mm[:200, :]
y_test = y_mm[200:, :]
```

```
print("Training Shape", X_train.shape, y_train.shape)
print("Testing Shape", X_test.shape, y_test.shape)
```

```
Training Shape (200, 5) (200, 1)
```

```
Testing Shape (53, 5) (53, 1)
```

```
import torch
import torch.nn as nn
from torch.autograd import Variable


X_train_tensors = Variable(torch.Tensor(X_train))
X_test_tensors = Variable(torch.Tensor(X_test))

y_train_tensors = Variable(torch.Tensor(y_train))
y_test_tensors = Variable(torch.Tensor(y_test))


#reshaping to rows, timestamps, features

X_train_tensors_final = torch.reshape(X_train_tensors,   (X_train_tensors.shape[0], 1, X_train_tensors.shape[1]))


X_test_tensors_final = torch.reshape(X_test_tensors,  (X_test_tensors.shape[0], 1, X_test_tensors.shape[1]))


print("Training Shape", X_train_tensors_final.shape, y_train_tensors.shape)
print("Testing Shape", X_test_tensors_final.shape, y_test_tensors.shape)
```

```
Training Shape torch.Size([200, 1, 5]) torch.Size([200, 1])
Testing Shape torch.Size([53, 1, 5]) torch.Size([53, 1])
```

```
class LSTM1(nn.Module):
    def __init__(self, num_classes, input_size, hidden_size, num_layers, seq_length):
        super(LSTM1, self).__init__()
        self.num_classes = num_classes #number of classes
        self.num_layers = num_layers #number of layers
        self.input_size = input_size #input size
        self.hidden_size = hidden_size #hidden state
        self.seq_length = seq_length #sequence length

        self.lstm = nn.LSTM(input_size=input_size, hidden_size=hidden_size,
```

```
                          num_layers=num_layers, batch_first=True) #lstm
        self.fc_1 =  nn.Linear(hidden_size, 128) #fully connected 1
        self.fc = nn.Linear(128, num_classes) #fully connected last layer

        self.relu = nn.ReLU()

    def forward(self,x):
        h_0 = Variable(torch.zeros(self.num_layers, x.size(0), self.hidden_size)) #hidden state
        c_0 = Variable(torch.zeros(self.num_layers, x.size(0), self.hidden_size)) #internal state
        # Propagate input through LSTM
        output, (hn, cn) = self.lstm(x, (h_0, c_0)) #lstm with input, hidden, and internal state
        hn = hn.view(-1, self.hidden_size) #reshaping the data for Dense layer next
        out = self.relu(hn)
        out = self.fc_1(out) #first Dense
        out = self.relu(out) #relu
        out = self.fc(out) #Final Output
        return out


num_epochs = 1000 #1000 epochs
learning_rate = 0.001 #0.001 lr

input_size = 5 #number of features
hidden_size = 2 #number of features in hidden state
num_layers = 1 #number of stacked lstm layers

num_classes = 1 #number of output classes


lstm1 = LSTM1(num_classes, input_size, hidden_size, num_layers, X_train_tensors_final.shape[1]) #our lstm class


criterion = torch.nn.MSELoss()    # mean-squared error for regression
optimizer = torch.optim.Adam(lstm1.parameters(), lr=learning_rate)


for epoch in range(num_epochs):
    outputs = lstm1.forward(X_train_tensors_final) #forward pass
    optimizer.zero_grad() #caluclate the gradient, manually setting to 0
```

```
    # obtain the loss function
    loss = criterion(outputs, y_train_tensors)

    loss.backward() #calculates the loss of the loss function

    optimizer.step() #improve from loss, i.e backprop
    if epoch % 100 == 0:
        print("Epoch: %d, loss: %1.5f" % (epoch, loss.item()))
```

```
Epoch: 0, loss: 0.01163
Epoch: 100, loss: 0.01051
Epoch: 200, loss: 0.01031
Epoch: 300, loss: 0.01019
Epoch: 400, loss: 0.01009
Epoch: 500, loss: 0.01001
Epoch: 600, loss: 0.00995
Epoch: 700, loss: 0.00990
Epoch: 800, loss: 0.00985
Epoch: 900, loss: 0.00981
```

```
df_X_ss = ss.transform(df.iloc[:, :-1]) #old transformers
df_y_mm = mm.transform(df.iloc[:, -1:]) #old transformers

df_X_ss = Variable(torch.Tensor(df_X_ss)) #converting to Tensors
df_y_mm = Variable(torch.Tensor(df_y_mm))
#reshaping the dataset
df_X_ss = torch.reshape(df_X_ss, (df_X_ss.shape[0], 1, df_X_ss.shape[1]))


train_predict = lstm1(df_X_ss)#forward pass
data_predict = train_predict.data.numpy() #numpy conversion
dataY_plot = df_y_mm.data.numpy()

data_predict = mm.inverse_transform(data_predict) #reverse transformation
dataY_plot = mm.inverse_transform(dataY_plot)
plt.figure(figsize=(10,6)) #plotting
plt.axvline(x=200, c='r', linestyle='--') #size of the training set
```

```
plt.plot(dataY_plot, label='Actuall Data') #actual plot
plt.plot(data_predict, label='Predicted Data') #predicted plot
plt.title('Time-Series Prediction')
plt.legend()
plt.show()
```