In [1]:
```
import yfinance as yf
import numpy as np
import matplotlib as plt
import pandas as pd
from scipy.optimize import Bounds
from scipy.optimize import minimize
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
from copy import deepcopy as dc
from sklearn.preprocessing import MinMaxScaler
```

Downloading Adjusted Close Data for MSFT,AAPL, & NVDA tickers

In [2]:
```
tickers = ['MSFT','AAPL','NVDA']
```

In [3]:
```
df = yf.download(tickers,start='2024-01-1', end='2024-10-17',interval='1d')['Adj Cl
```

```
[**********100%**********]  3 of 3 completed
```

In [486…
```
ret_df = np.log(df/df.shift(1))
ret_df
```

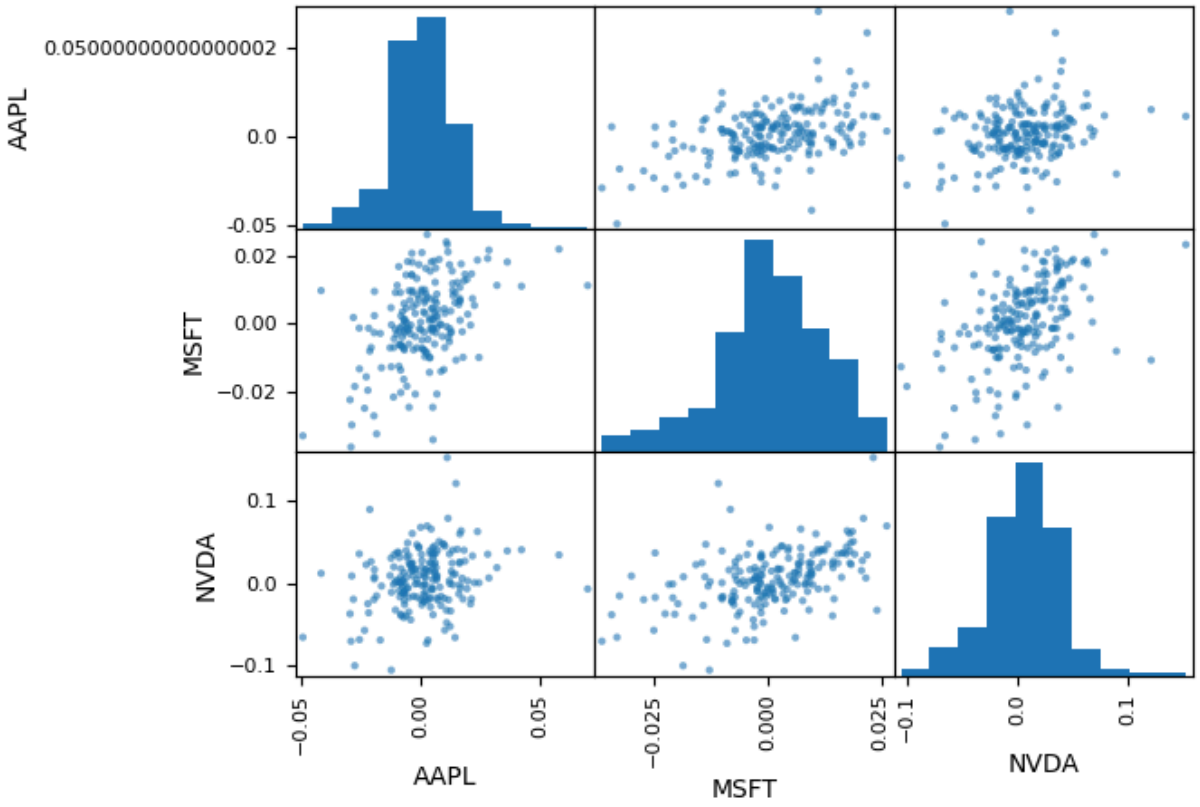
Out[486…

Ticker	AAPL	MSFT	NVDA
Date			
2024-01-02	NaN	NaN	NaN
2024-01-03	-0.007516	-0.000728	-0.012514
2024-01-04	-0.012781	-0.007203	0.008978
2024-01-05	-0.004021	-0.000517	0.022638
2024-01-08	0.023887	0.018696	0.062299
...	...	...	...
2024-10-10	-0.002181	-0.003888	0.016152
2024-10-11	-0.006527	0.001154	-0.000074
2024-10-14	0.016346	0.006751	0.023969
2024-10-15	0.010964	-0.000955	-0.047994
2024-10-16	-0.008891	-0.006277	0.030827

200 rows × 3 columns

Scatter matrix plot of the three stocks:

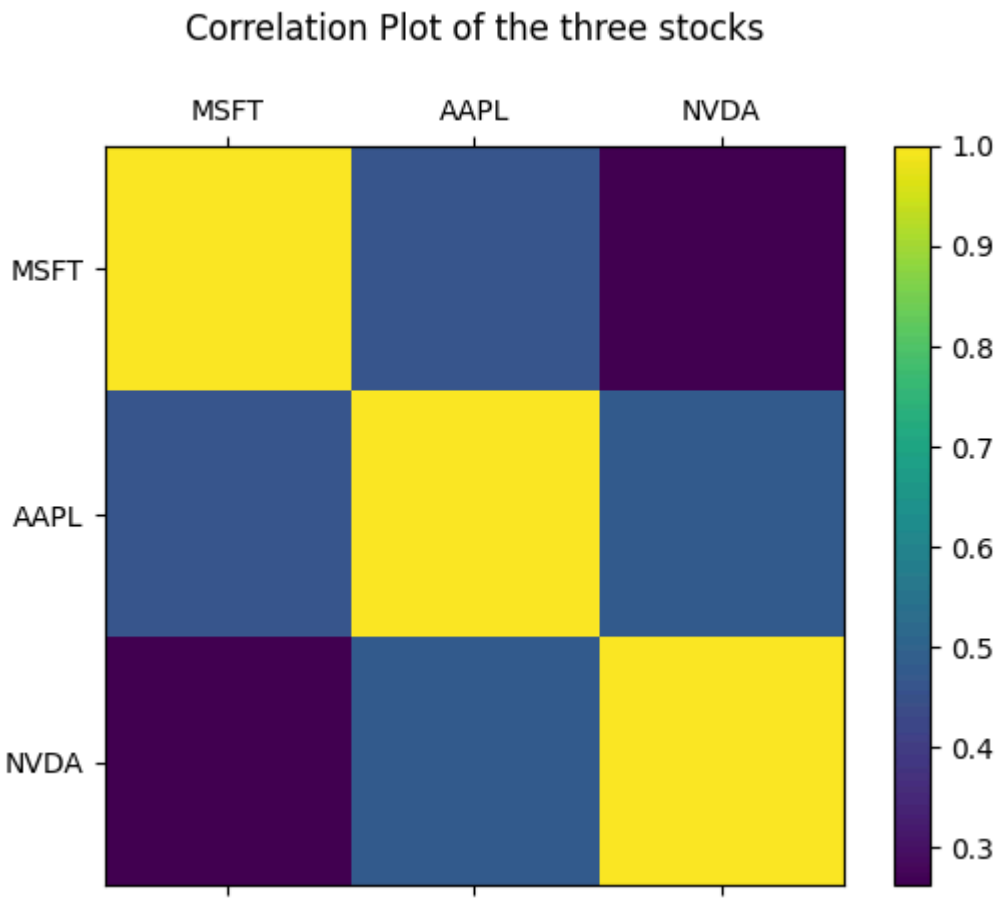
In [325…
```
pd.plotting.scatter_matrix(ret_df,alpha = 0.6);
```



Correlation Plot of the three stocks:

In [484…
```
figure = plt.figure()
axes = figure.add_subplot(111)

# using the matshow() function
caxes = axes.matshow(ret_df.corr(), interpolation ='nearest')
figure.colorbar(caxes)

axes.set_xticklabels(['']+tickers);
axes.set_yticklabels(['']+tickers);
plt.title("Correlation Plot of the three stocks\n")
plt.show();
```

```
C:\Users\hamad\AppData\Local\Temp\ipykernel_10912\1261348413.py:8: UserWarning: Fixe
dFormatter should only be used together with FixedLocator
  axes.set_xticklabels(['']+tickers);
C:\Users\hamad\AppData\Local\Temp\ipykernel_10912\1261348413.py:9: UserWarning: Fixe
dFormatter should only be used together with FixedLocator
  axes.set_yticklabels(['']+tickers);
```

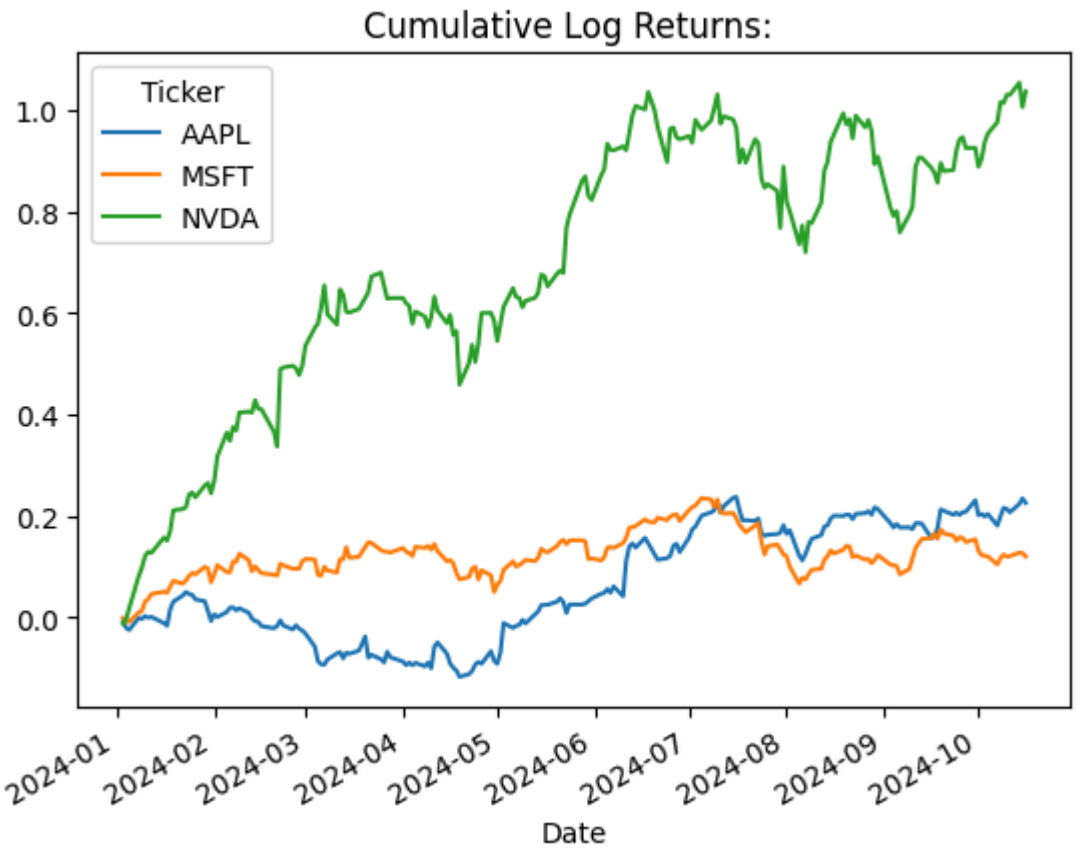


Mean & Standard Deviation of log returns of the three stocks:

In [8]:
```
print("\nMean of log returns: \n\n",ret_df.mean(),"\n")
print("Standard deviation of log returns: \n\n", ret_df.std())
```

```
Mean of log returns:

 Ticker
AAPL    0.001135
MSFT    0.000606
NVDA    0.005207
dtype: float64

Standard deviation of log returns:

 Ticker
AAPL    0.014931
MSFT    0.012186
NVDA    0.034985
dtype: float64
```

In [479…
```
ret_df.iloc[:,].cumsum().plot(title = "Cumulative Log Returns: ");
```



In [275…
```
W = np.ones(len(ret_df.columns))/np.ones(len(ret_df.columns)).sum()
```

In [11]:
```
def sharpe(W,returns):
    pf_risk = ((W.dot(returns.cov())).dot(W)) ** 0.5
    SR = W.dot(returns.mean())/pf_risk
    return -SR
```

Sharpe Ratio of Portfolio using equal weights:

In [12]:
```
sharpe(W,ret_df)
```

Out[12]: -0.14056243809216973

Expected return of portfolio containing equal weights for the three stocks:

In [13]:
```
ret_df.mean().dot(W)
```

Out[13]: 0.002315666578879068

Optimizing weights to reduce Sharpe Ratio

In [14]:
```
cons = ({"type":"eq","fun": lambda x: np.sum(x)-1})
```

In [327…
```
opt_w = minimize(sharpe,W,ret_df,bounds = Bounds(0,1),constraints = cons)
```

In [300…
```
print(opt_w.x)
```

```
[0.39927461 0.         0.60072539]
```

Sharpe Ratio of Portfolio with Optimized weights:

In [328…
```
print(sharpe(opt_w.x,ret_df))
```

```
-0.15365637567938248
```

Expected return of portflio given optimized weights;

In [16]:
```
opt_w.x.dot(ret_df.mean())
```

Out[16]:
```
0.0035807171929123317
```

Loading 207 Days of Adjusted Close Data for MSFT,AAPL, & NVDA tickers

In [17]:
```
tickers_dj = pd.read_html('https://en.wikipedia.org/wiki/Dow_Jones_Industrial_Avera
```

In [18]:
```
data_dj = yf.download(tickers_dj[0].Symbol.to_list(),start='2024-01-1', end='2024-1
```

```
[**********************100%**********************]  28 of 30 completed

3 Failed downloads:
[**********************100%**********************]  28 of 30 completed['HD', 'MCD',
'TRV']: ReadTimeout(ReadTimeoutError("HTTPSConnectionPool(host='query2.finance.yaho
o.com', port=443): Read timed out. (read timeout=10)"))
```

In [20]:
```
 device = 'cuda' if torch.cuda.is_available() else 'cpu'
device
```

Out[20]:
```
'cuda'
```

In [476…
```
data1 = data_dj[['MSFT','AAPL','NVDA']].iloc[176:]
final_3mo_return = np.log(data1/data1.shift(1))
```

Out[476…
```
30
```

Forecasting Adjusted Close Prices Using LSTM Modeling:

- Preparing Dataframe for LSTM model Input:

In [21]:
```
def prepare_dataframe_for_lstm(df,n_steps):
    df = dc(df)


    for i in range(1,n_steps+1):
        df[f'adj close(t-{i})'] = df[df.columns[0]].shift(i)

    df.dropna(inplace=True)
    return df
```

In [332…
```
df_MSFT = data_dj[['MSFT']]
```

In [333…
```
MSFT_lstm = prepare_dataframe_for_lstm(df_MSFT,7)
print(len(MSFT_lstm))
```

```
200
```

- Normalizing Data and Creating Train and Test Datasets for Model Training

In [334…
```
scaler = MinMaxScaler(feature_range = (-1,1))
```

In [335…
```
norm_MSFT_lstm = scaler.fit_transform(MSFT_lstm)
```

In [336…
```
X = norm_MSFT_lstm[:,1:]
X = dc(np.flip(X,axis=1))
Y = norm_MSFT_lstm[:,0]
```

In [337…
```
split_index = int(len(X)*0.8)
```

In [338…
```
X_train = X[:split_index]
X_test = X[split_index:]

Y_train = Y[:split_index]
Y_test = Y[split_index:]

np.shape(X_train),np.shape(X_test),np.shape(Y_train),np.shape(Y_test)
```

Out[338…
```
((160, 7), (40, 7), (160,), (40,))
```

In [339…
```
lookback = 7
X_train = X_train.reshape((-1,lookback,1))
X_test = X_test.reshape((-1,lookback,1))
```

```
Y_train = Y_train.reshape((-1,1))
Y_test = Y_test.reshape((-1,1))

X_train.shape,X_test.shape,Y_train.shape,Y_test.shape
```

Out[339… ((160, 7, 1), (40, 7, 1), (160, 1), (40, 1))

In [340…
```
X_train = torch.tensor(X_train).float()
X_test = torch.tensor(X_test).float()

Y_train = torch.tensor(Y_train).float()
Y_test = torch.tensor(Y_test).float()
```

In [341…
```
from torch.utils.data import Dataset

class TimeSeriesDataset(Dataset):
    def __init__(self,X,y):
        self.X = X
        self.y = y
    def __len__(self):
        return len(self.X)
    def __getitem__(self,i):
        return self.X[i],self.y[i]

train_dataset = TimeSeriesDataset(X_train,Y_train)
test_dataset = TimeSeriesDataset(X_test,Y_test)
```

In [342…
```
from torch.utils.data import DataLoader

batch_size = 20

train_loader = DataLoader(train_dataset,batch_size=batch_size,shuffle=True)
test_loader = DataLoader(test_dataset,batch_size=batch_size,shuffle=True)
```

- LSTM Model Architecture

In [343…
```
class LSTM(nn.Module):
    def __init__(self,input_size,hidden_size,num_stacked_layers):
        super().__init__()
        self.hidden_size = hidden_size
        self.num_stacked_layers = num_stacked_layers

        self.lstm = nn.LSTM(input_size,hidden_size,num_stacked_layers,batch_first=T

        self.fc = nn.Linear(hidden_size,1)

    def forward(self,x):
        batch_size = x.size(0)
        h0 = torch.zeros(self.num_stacked_layers, batch_size, self.hidden_size).to(
        c0 = torch.zeros(self.num_stacked_layers, batch_size, self.hidden_size).to(
        out, _ = self.lstm(x,(h0,c0))
        out = self.fc(out[:,-1,:])
        return out
```

```
model = LSTM(1,4,1)
model.to(device)
```

Out[343…

```
LSTM(
  (lstm): LSTM(1, 4, batch_first=True)
  (fc): Linear(in_features=4, out_features=1, bias=True)
)
```

In [344…

```
def validate_one_epoch(model,test_loader,val_losses):
    model.train(False)
    running_loss = 0.0

    for batch_index, batch in enumerate(test_loader):
        x_batch,y_batch = batch[0].to(device),batch[1].to(device)

        with torch.no_grad():
            output = model(x_batch)
            loss = loss_function(output,y_batch)
            running_loss += loss.item()


    avg_loss_across_batches = running_loss / len(test_loader)
    val_losses.append(avg_loss_across_batches)

    print('Val Loss: {0:.3f}'.format(avg_loss_across_batches))
    print('***************************************************')
    print()
```

In [345…

```
def train_one_epoch(model,train_loader,train_losses):
    model.train(True)
    print(f'Epoch: {epoch + 1}')
    running_loss = 0.0
    train_loss = 0.0

    for batch_index, batch in enumerate(train_loader):
        x_batch,y_batch = batch[0].to(device),batch[1].to(device)

        output = model(x_batch)
        loss = loss_function(output,y_batch)
        running_loss += loss.item()
        train_loss += loss.item()

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        if batch_index % 3 == 2:
            avg_loss_across_batches = running_loss / 3
            print('Batch {0}, Loss: {1:.3f}'.format(batch_index+1,avg_loss_across_b
            running_loss = 0.0
    train_losses.append(train_loss/len(train_loader))

    print()
```

- Training LSTM Model On MSFT Dataframe

In [346…

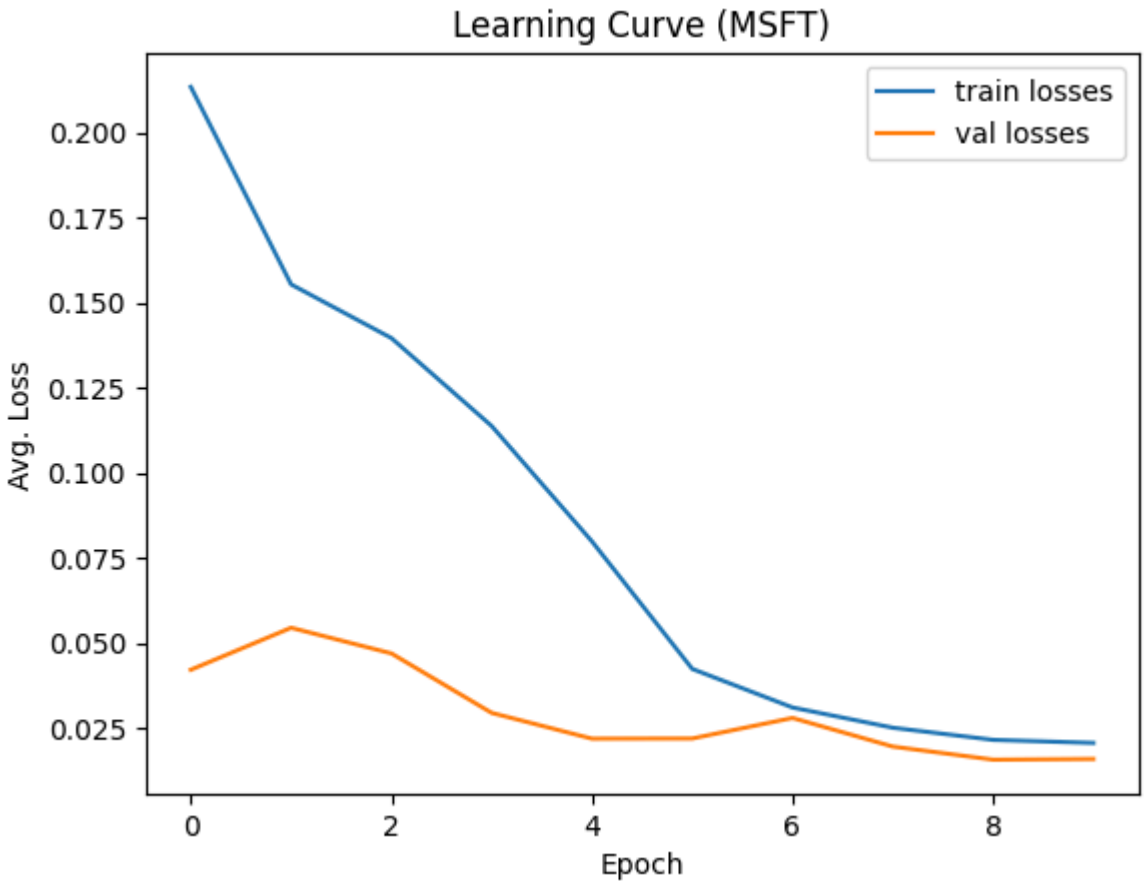
```
learning_rate = 0.01
num_epochs = 10
loss_function = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(),lr=learning_rate)
MSFT_val_losses = []
MSFT_train_losses = []

for epoch in range(num_epochs):
    train_one_epoch(model,train_loader,MSFT_train_losses)
    validate_one_epoch(model,test_loader,MSFT_val_losses)
```

```
Epoch: 1
Batch 3, Loss: 0.247
Batch 6, Loss: 0.176

Val Loss: 0.042
**************************************************

Epoch: 2
Batch 3, Loss: 0.158
Batch 6, Loss: 0.174

Val Loss: 0.054
**************************************************

Epoch: 3
Batch 3, Loss: 0.133
Batch 6, Loss: 0.136

Val Loss: 0.047
**************************************************

Epoch: 4
Batch 3, Loss: 0.113
Batch 6, Loss: 0.121

Val Loss: 0.029
**************************************************

Epoch: 5
Batch 3, Loss: 0.096
Batch 6, Loss: 0.084

Val Loss: 0.022
**************************************************

Epoch: 6
Batch 3, Loss: 0.061
Batch 6, Loss: 0.038

Val Loss: 0.022
**************************************************

Epoch: 7
Batch 3, Loss: 0.026
Batch 6, Loss: 0.033

Val Loss: 0.028
**************************************************

Epoch: 8
Batch 3, Loss: 0.027
Batch 6, Loss: 0.025

Val Loss: 0.020
**************************************************
```

```
Epoch: 9
Batch 3, Loss: 0.026
Batch 6, Loss: 0.016

Val Loss: 0.016
************************************************

Epoch: 10
Batch 3, Loss: 0.023
Batch 6, Loss: 0.017

Val Loss: 0.016
************************************************
```

In [376…

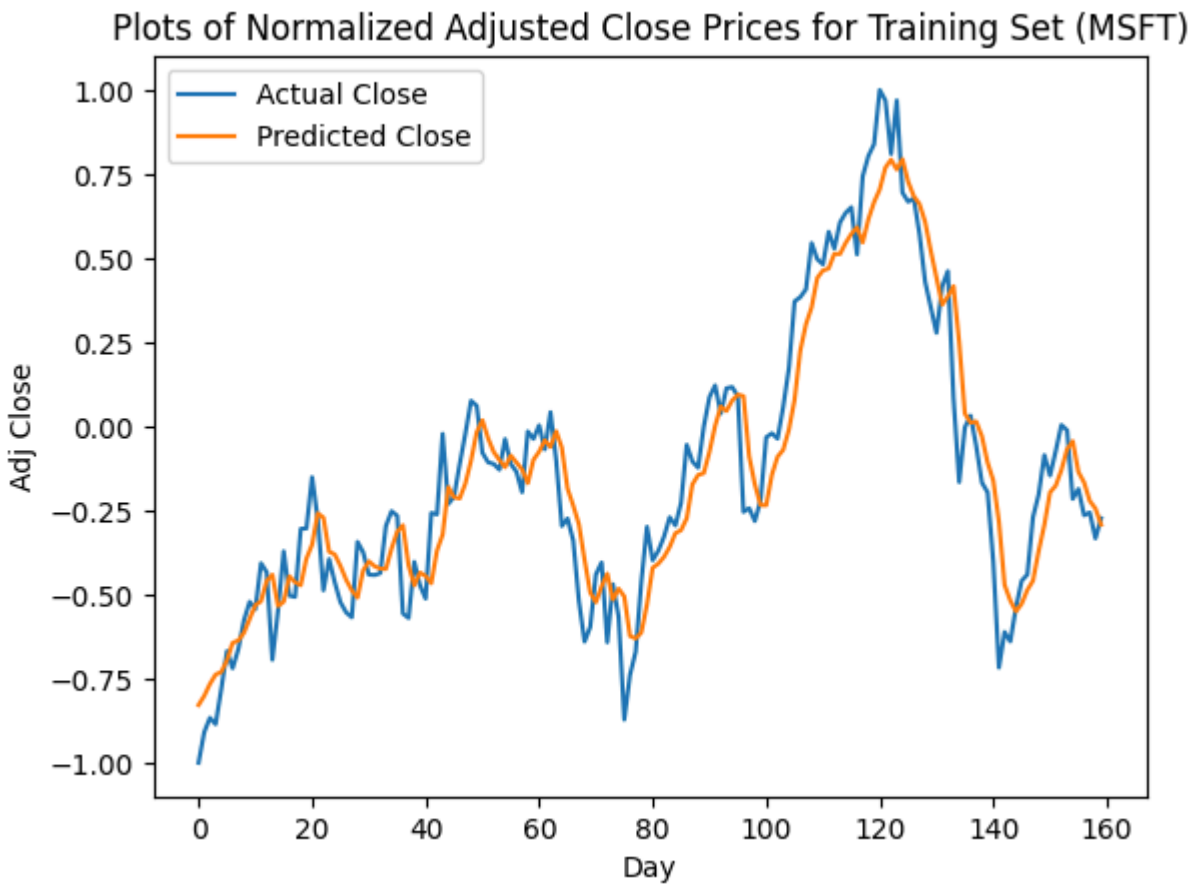
```python
plt.plot(MSFT_train_losses, label = 'train losses')
plt.plot(MSFT_val_losses, label='val losses')
plt.xlabel('Epoch')
plt.ylabel('Avg. Loss')
plt.title('Learning Curve (MSFT)')
plt.legend()
plt.show;
```



In [377…

```python
with torch.no_grad():
    predicted = model(X_train.to(device)).to('cpu').numpy()

plt.plot(Y_train, label = 'Actual Close')
plt.plot(predicted, label='Predicted Close')
```

```
plt.title("Plots of Normalized Adjusted Close Prices for Training Set (MSFT)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```

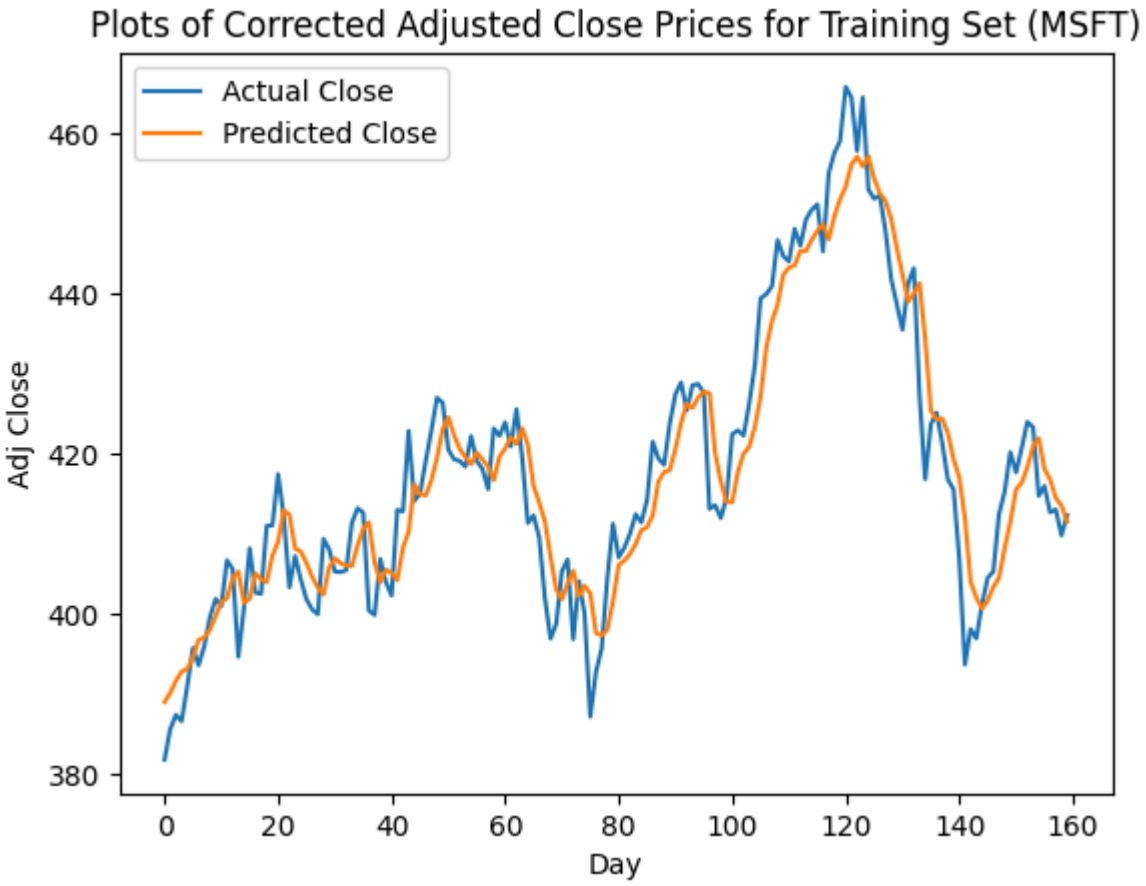


In [350…
```
train_predictions = predicted.flatten()

dummies = np.zeros((X_train.shape[0], lookback+1))
dummies[:,0] = train_predictions
dummies = scaler.inverse_transform(dummies)

train_predictions = dc(dummies[:,0])
```

In [351…
```
dummies = np.zeros((X_train.shape[0], lookback+1))
dummies[:,0] = Y_train.flatten()
dummies = scaler.inverse_transform(dummies)

new_y_train = dc(dummies[:,0])
```

In [378…
```
plt.plot(new_y_train, label = 'Actual Close')
plt.plot(train_predictions, label='Predicted Close')
plt.title("Plots of Corrected Adjusted Close Prices for Training Set (MSFT)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show
```

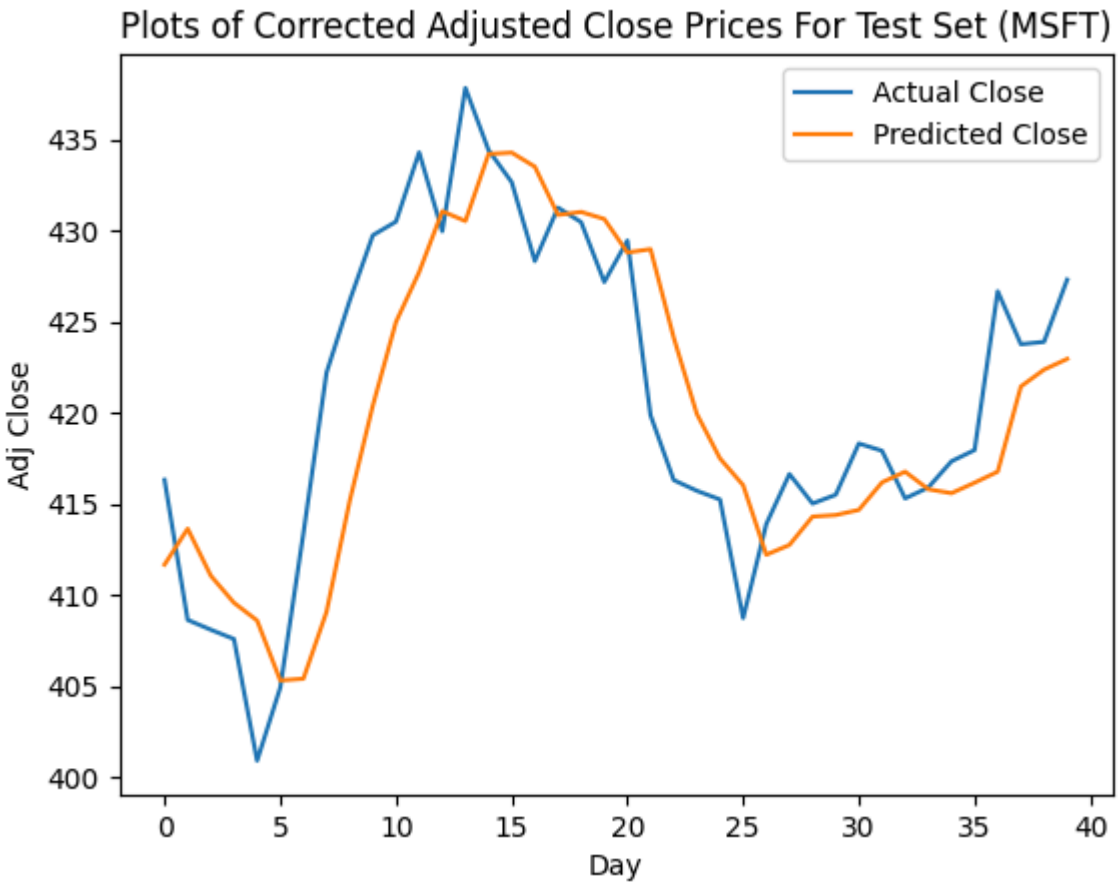
Out[378… <function matplotlib.pyplot.show(close=None, block=None)>



In [353…
```
test_predictions = model(X_test.to(device)).detach().cpu().numpy().flatten()
dummies = np.zeros((X_test.shape[0], lookback+1))
dummies[:,0] = test_predictions
dummies = scaler.inverse_transform(dummies)

test_predictions = dc(dummies[:,0])
```

In [354…
```
dummies = np.zeros((X_test.shape[0], lookback+1))
dummies[:,0] = Y_test.flatten()
dummies = scaler.inverse_transform(dummies)

new_y_test = dc(dummies[:,0])
```

In [379…
```
plt.plot(new_y_test, label = 'Actual Close')
plt.plot(test_predictions, label='Predicted Close')
plt.title("Plots of Corrected Adjusted Close Prices For Test Set (MSFT)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```

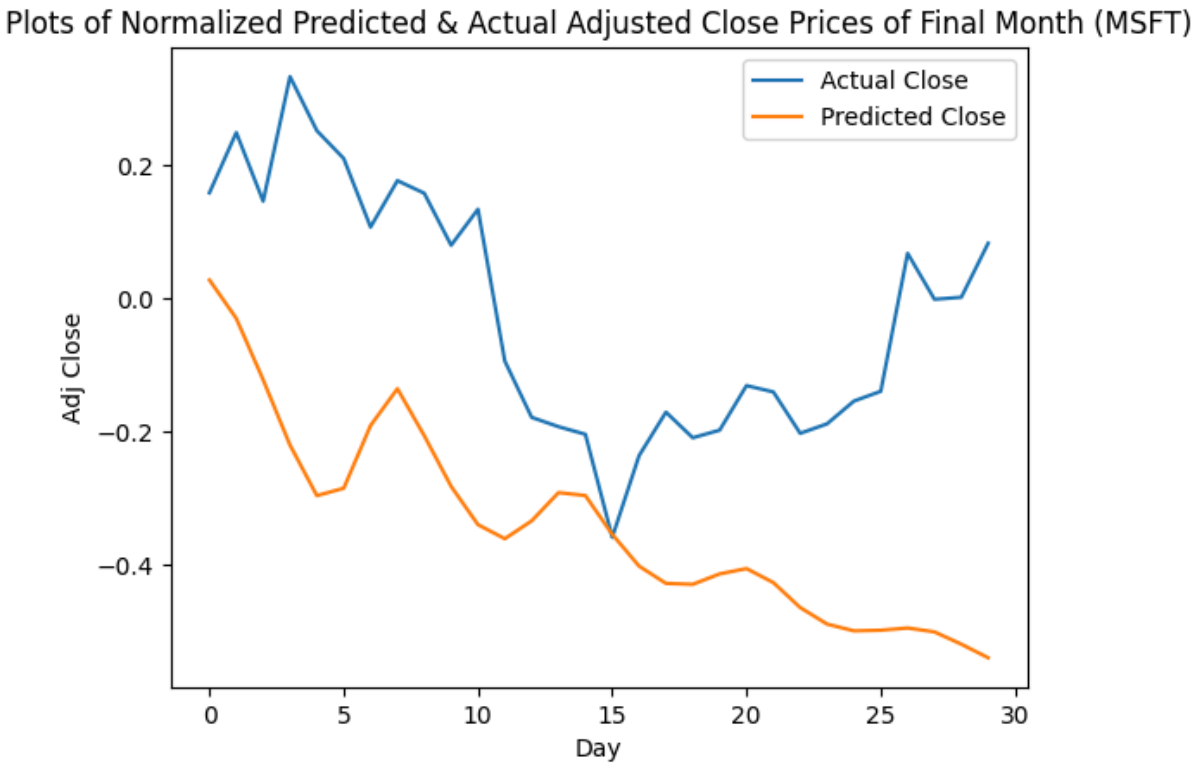


In [367…

```
np.shape(norm_MSFT_lstm)



pred_next_month = dc(norm_MSFT_lstm[170,1:])
#print(np.shape(pred_next_month))

for i in range(len(norm_MSFT_lstm[170:,:])):
    pred_next_month = pred_next_month.reshape(1,-1)
    X = np.concatenate(((pred_next_month[0,i:i+7]).reshape(1,-1),np.zeros((1,7))))
    X = dc(np.flip(X,axis=1))
    lookback = 7
    X=X.reshape((-1,lookback,1))
    X = torch.tensor(X).float()

    day_predictions = model(X.to(device)).detach().cpu().numpy().flatten()

    pred_next_month = np.append(pred_next_month,day_predictions[0])
```

In [380…

```
plt.plot(norm_MSFT_lstm[170:,0], label = 'Actual Close')
plt.plot(pred_next_month[7:], label='Predicted Close')
plt.title("Plots of Normalized Predicted & Actual Adjusted Close Prices of Final Mo
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```



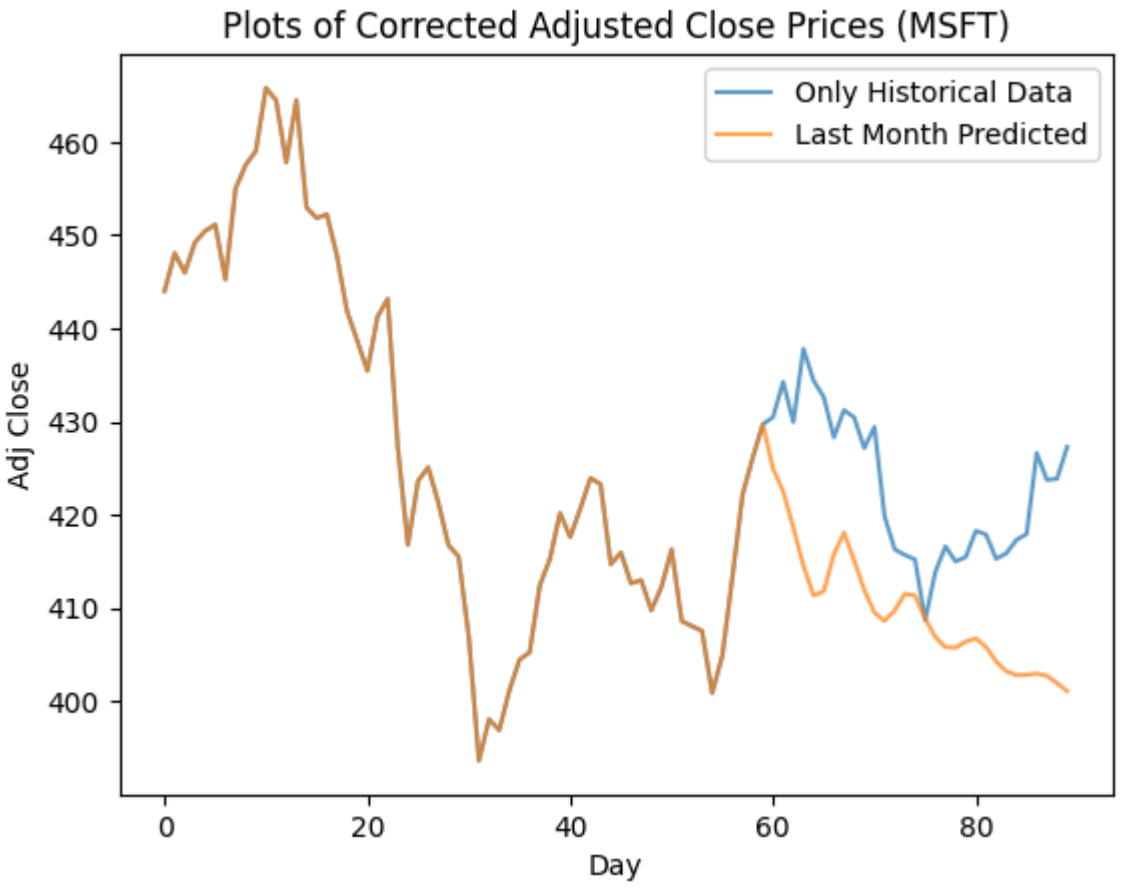
In [369…
```
new_norm_MSFT = np.concatenate((norm_MSFT_lstm[110:170,0],pred_next_month[7:]))
```

In [370…
```
dummies = np.zeros((new_norm_MSFT.shape[0], lookback+1))
dummies[:,0] = new_norm_MSFT
print(np.shape(dummies))
dummies = scaler.inverse_transform(dummies)

new_MSFT = dc(dummies[:,0])
```

```
(90, 8)
```

In [381…
```
MSFT_lstm_actual = MSFT_lstm.iloc[110:,0].to_numpy()
print(len(new_MSFT))
plt.plot(MSFT_lstm_actual, label = 'Only Historical Data',alpha=0.7)
plt.plot(new_MSFT, label='Last Month Predicted',alpha=0.7)
plt.title("Plots of Corrected Adjusted Close Prices (MSFT)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```

```
90
```



- Repeating Same Process for AAPL Ticker:

In [383…
```
df_AAPL = data_dj[['AAPL']]
```

In [384…
```
AAPL_lstm = prepare_dataframe_for_lstm(df_AAPL,7)
```

In [385…
```
scaler2 = MinMaxScaler(feature_range = (-1,1))
```

In [386…
```
norm_AAPL_lstm = scaler2.fit_transform(AAPL_lstm)
```

In [387…
```
X = norm_AAPL_lstm[:,1:]
X = dc(np.flip(X,axis=1))
Y = norm_AAPL_lstm[:,0]
```

In [388…
```
X_train = X[:split_index]
X_test = X[split_index:]

Y_train = Y[:split_index]
Y_test = Y[split_index:]

np.shape(X_train),np.shape(X_test),np.shape(Y_train),np.shape(Y_test)
```

Out[388…
```
((160, 7), (40, 7), (160,), (40,))
```

In [389…
```
lookback = 7
X_train = X_train.reshape((-1,lookback,1))
X_test = X_test.reshape((-1,lookback,1))

Y_train = Y_train.reshape((-1,1))
Y_test = Y_test.reshape((-1,1))

X_train.shape,X_test.shape,Y_train.shape,Y_test.shape
```

Out[389…
```
((160, 7, 1), (40, 7, 1), (160, 1), (40, 1))
```

In [390…
```
X_train = torch.tensor(X_train).float()
X_test = torch.tensor(X_test).float()

Y_train = torch.tensor(Y_train).float()
Y_test = torch.tensor(Y_test).float()
```

In [391…
```
train_dataset = TimeSeriesDataset(X_train,Y_train)
test_dataset = TimeSeriesDataset(X_test,Y_test)
```

In [392…
```
train_loader = DataLoader(train_dataset,batch_size=batch_size,shuffle=True)
test_loader = DataLoader(test_dataset,batch_size=batch_size,shuffle=True)
```

In [393…
```
model_AAPL = LSTM(1,4,1)
model_AAPL.to(device)
```

Out[393…
```
LSTM(
  (lstm): LSTM(1, 4, batch_first=True)
  (fc): Linear(in_features=4, out_features=1, bias=True)
)
```

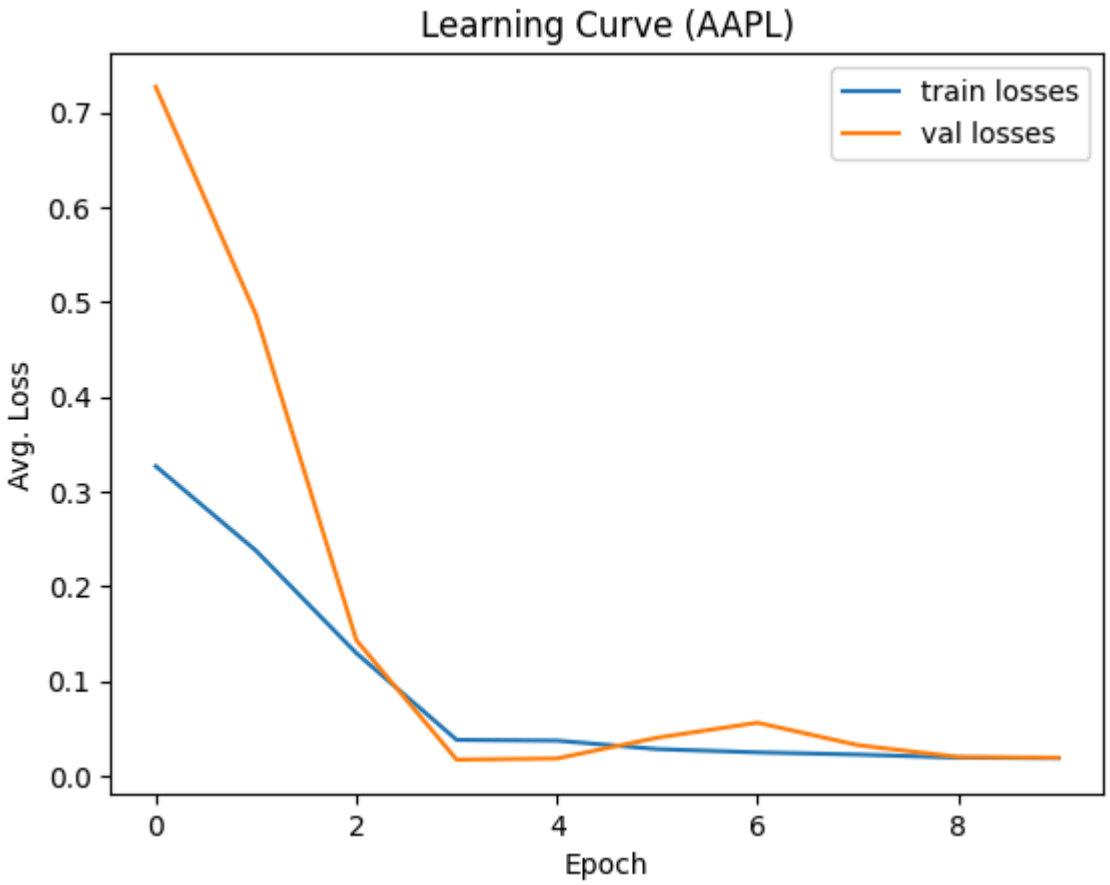
In [394…
```
learning_rate = 0.01
num_epochs = 10
loss_function = nn.MSELoss()
optimizer = torch.optim.Adam(model_AAPL.parameters(),lr=learning_rate)
AAPL_val_losses = []
AAPL_train_losses = []

for epoch in range(num_epochs):
    train_one_epoch(model_AAPL,train_loader,AAPL_train_losses)
    validate_one_epoch(model_AAPL,test_loader,AAPL_val_losses)
```

```
Epoch: 1
Batch 3, Loss: 0.392
Batch 6, Loss: 0.294

Val Loss: 0.727
**************************************************

Epoch: 2
Batch 3, Loss: 0.271
Batch 6, Loss: 0.216

Val Loss: 0.486
**************************************************

Epoch: 3
Batch 3, Loss: 0.171
Batch 6, Loss: 0.111

Val Loss: 0.143
**************************************************

Epoch: 4
Batch 3, Loss: 0.048
Batch 6, Loss: 0.034

Val Loss: 0.017
**************************************************

Epoch: 5
Batch 3, Loss: 0.031
Batch 6, Loss: 0.039

Val Loss: 0.018
**************************************************

Epoch: 6
Batch 3, Loss: 0.029
Batch 6, Loss: 0.025

Val Loss: 0.040
**************************************************

Epoch: 7
Batch 3, Loss: 0.020
Batch 6, Loss: 0.027

Val Loss: 0.056
**************************************************

Epoch: 8
Batch 3, Loss: 0.024
Batch 6, Loss: 0.021

Val Loss: 0.032
**************************************************
```

```
Epoch: 9
Batch 3, Loss: 0.020
Batch 6, Loss: 0.020

Val Loss: 0.020
************************************************

Epoch: 10
Batch 3, Loss: 0.019
Batch 6, Loss: 0.015

Val Loss: 0.019
************************************************
```

In [405…

```python
plt.plot(AAPL_train_losses, label = 'train losses')
plt.plot(AAPL_val_losses, label='val losses')
plt.xlabel('Epoch')
plt.ylabel('Avg. Loss')
plt.title('Learning Curve (AAPL)')
plt.legend()
plt.show;
```



In [396…

```python
test_predictions = model_AAPL(X_test.to(device)).detach().cpu().numpy().flatten()
dummies = np.zeros((X_test.shape[0], lookback+1))
dummies[:,0] = test_predictions
dummies = scaler2.inverse_transform(dummies)
```

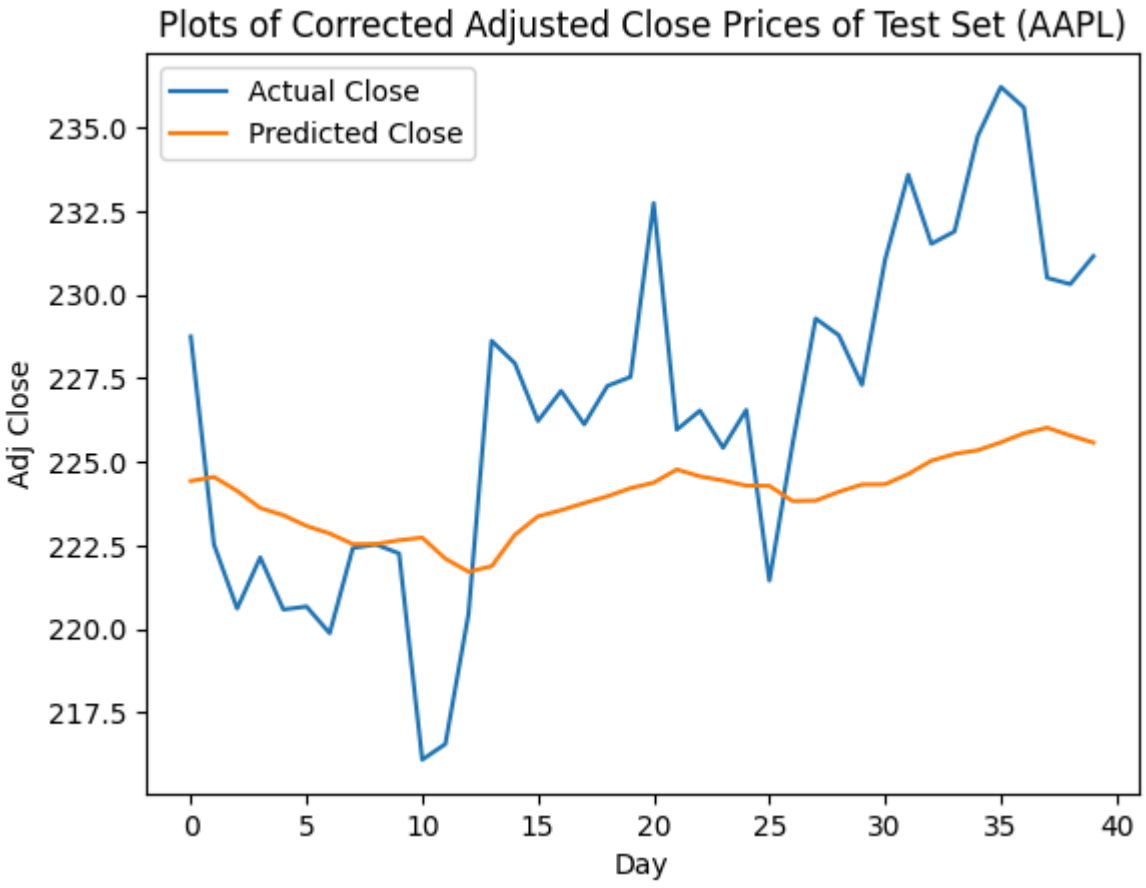
```
test_predictions = dc(dummies[:,0])
```

In [397…

```
dummies = np.zeros((X_test.shape[0], lookback+1))
dummies[:,0] = Y_test.flatten()
dummies = scaler2.inverse_transform(dummies)

new_y_test = dc(dummies[:,0])
```

In [400…

```
plt.plot(new_y_test, label = 'Actual Close')
plt.plot(test_predictions, label='Predicted Close')
plt.title("Plots of Corrected Adjusted Close Prices of Test Set (AAPL)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```



In [401…

```
np.shape(norm_AAPL_lstm)



pred_next_month = dc(norm_AAPL_lstm[170,1:])
#print(np.shape(pred_next_month))

for i in range(len(norm_AAPL_lstm[170:,:])):
    pred_next_month = pred_next_month.reshape(1,-1)
    X = np.concatenate(((pred_next_month[0,i:i+7]).reshape(1,-1),np.zeros((1,7))))
    X = dc(np.flip(X,axis=1))
```

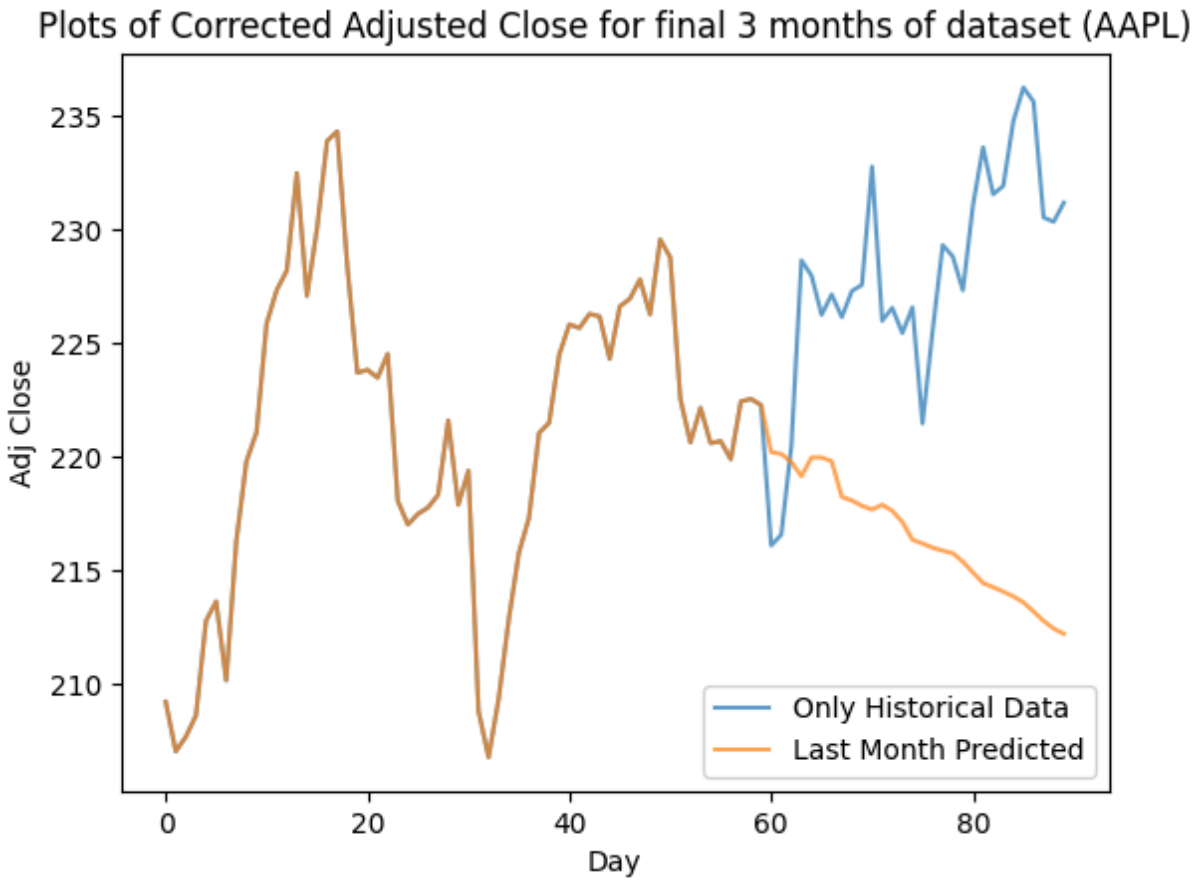
```
    lookback = 7
    X=X.reshape((-1,lookback,1))
    X = torch.tensor(X).float()

    day_predictions = model(X.to(device)).detach().cpu().numpy().flatten()

    pred_next_month = np.append(pred_next_month,day_predictions[0])
```

In [402…
```
new_norm_AAPL = np.concatenate((norm_AAPL_lstm[110:170,0],pred_next_month[7:]))
```

In [403…
```
dummies = np.zeros((new_norm_AAPL.shape[0], lookback+1))
dummies[:,0] = new_norm_AAPL
print(np.shape(dummies))
dummies = scaler2.inverse_transform(dummies)

new_AAPL = dc(dummies[:,0])
```

```
(90, 8)
```

In [404…
```
AAPL_lstm_actual = AAPL_lstm.iloc[110:,0].to_numpy()
plt.plot(AAPL_lstm_actual, label = 'Only Historical Data',alpha=0.7)
plt.plot(new_AAPL, label='Last Month Predicted',alpha=0.7)
plt.title("Plots of Corrected Adjusted Close for final 3 months of dataset (AAPL)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```



- Repeating Same Process for NVDA ticker:

In [406…
```
df_NVDA = data_dj[['NVDA']]
```

In [407…
```
NVDA_lstm = prepare_dataframe_for_lstm(df_NVDA,7)
```

In [408…
```
scaler3 = MinMaxScaler(feature_range = (-1,1))
```

In [409…
```
norm_NVDA_lstm = scaler3.fit_transform(NVDA_lstm)
```

In [410…
```
X = norm_NVDA_lstm[:,1:]
X = dc(np.flip(X,axis=1))
Y = norm_NVDA_lstm[:,0]
```

In [411…
```
X_train = X[:split_index]
X_test = X[split_index:]

Y_train = Y[:split_index]
Y_test = Y[split_index:]

np.shape(X_train),np.shape(X_test),np.shape(Y_train),np.shape(Y_test)
```

Out[411…
```
((160, 7), (40, 7), (160,), (40,))
```

In [412…
```
lookback = 7
X_train = X_train.reshape((-1,lookback,1))
X_test = X_test.reshape((-1,lookback,1))

Y_train = Y_train.reshape((-1,1))
Y_test = Y_test.reshape((-1,1))

X_train.shape,X_test.shape,Y_train.shape,Y_test.shape
```

Out[412…
```
((160, 7, 1), (40, 7, 1), (160, 1), (40, 1))
```

In [413…
```
X_train = torch.tensor(X_train).float()
X_test = torch.tensor(X_test).float()

Y_train = torch.tensor(Y_train).float()
Y_test = torch.tensor(Y_test).float()
```

In [414…
```
train_dataset = TimeSeriesDataset(X_train,Y_train)
test_dataset = TimeSeriesDataset(X_test,Y_test)
```

In [415…
```
train_loader = DataLoader(train_dataset,batch_size=batch_size,shuffle=True)
test_loader = DataLoader(test_dataset,batch_size=batch_size,shuffle=True)
```

In [416…
```
model_NVDA = LSTM(1,4,1)
model_NVDA.to(device)
```

Out[416…

```
LSTM(
  (lstm): LSTM(1, 4, batch_first=True)
  (fc): Linear(in_features=4, out_features=1, bias=True)
)
```

In [417…

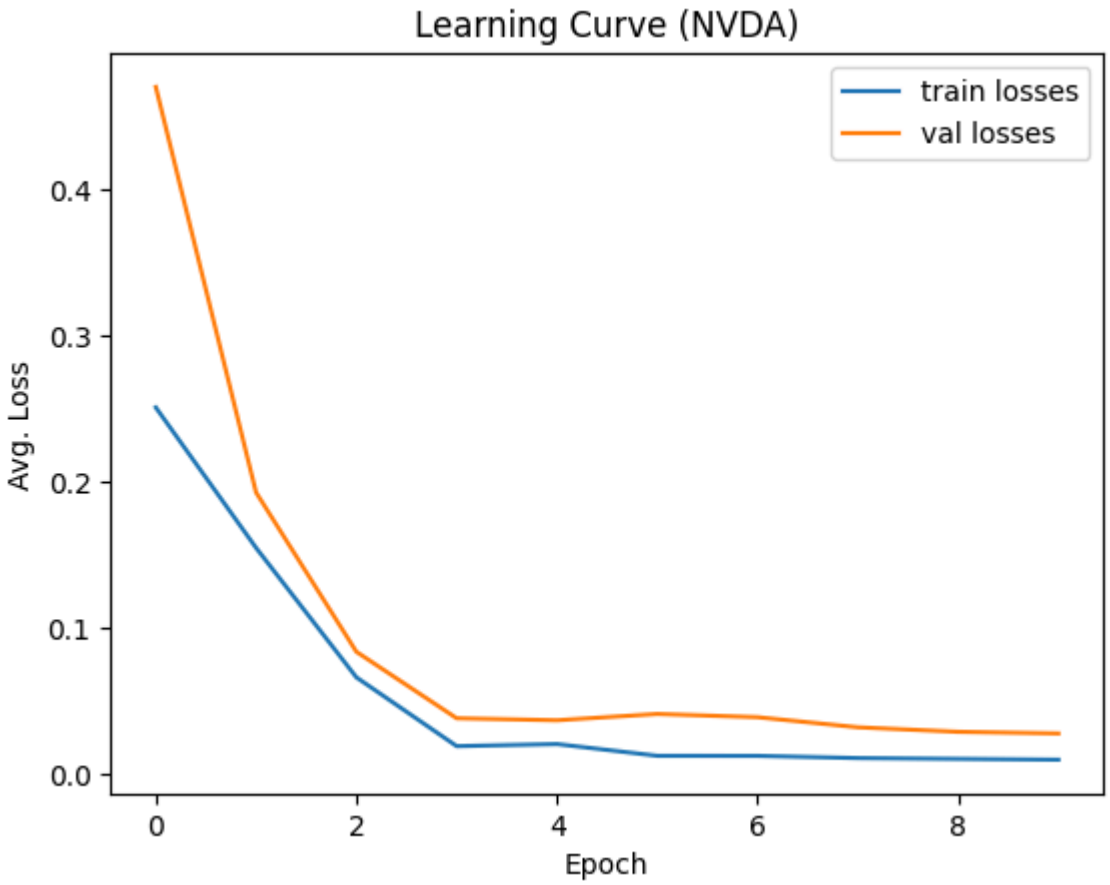
```
learning_rate = 0.01
num_epochs = 10
loss_function = nn.MSELoss()
optimizer = torch.optim.Adam(model_NVDA.parameters(),lr=learning_rate)
NVDA_val_losses = []
NVDA_train_losses = []

for epoch in range(num_epochs):
    train_one_epoch(model_NVDA,train_loader,NVDA_train_losses)
    validate_one_epoch(model_NVDA,test_loader,NVDA_val_losses)
```

```
Epoch: 1
Batch 3, Loss: 0.205
Batch 6, Loss: 0.277

Val Loss: 0.470
**************************************************

Epoch: 2
Batch 3, Loss: 0.177
Batch 6, Loss: 0.155

Val Loss: 0.193
**************************************************

Epoch: 3
Batch 3, Loss: 0.097
Batch 6, Loss: 0.060

Val Loss: 0.084
**************************************************

Epoch: 4
Batch 3, Loss: 0.019
Batch 6, Loss: 0.019

Val Loss: 0.039
**************************************************

Epoch: 5
Batch 3, Loss: 0.028
Batch 6, Loss: 0.017

Val Loss: 0.037
**************************************************

Epoch: 6
Batch 3, Loss: 0.012
Batch 6, Loss: 0.010

Val Loss: 0.042
**************************************************

Epoch: 7
Batch 3, Loss: 0.016
Batch 6, Loss: 0.012

Val Loss: 0.039
**************************************************

Epoch: 8
Batch 3, Loss: 0.011
Batch 6, Loss: 0.012

Val Loss: 0.032
**************************************************
```

```
Epoch: 9
Batch 3, Loss: 0.010
Batch 6, Loss: 0.011

Val Loss: 0.029
************************************************

Epoch: 10
Batch 3, Loss: 0.010
Batch 6, Loss: 0.012

Val Loss: 0.028
************************************************
```

In [419…

```
plt.plot(NVDA_train_losses, label = 'train losses')
plt.plot(NVDA_val_losses, label='val losses')
plt.xlabel('Epoch')
plt.ylabel('Avg. Loss')
plt.title('Learning Curve (NVDA)')
plt.legend()
plt.show;
```



In [421…

```
test_predictions = model_NVDA(X_test.to(device)).detach().cpu().numpy().flatten()
dummies = np.zeros((X_test.shape[0], lookback+1))
dummies[:,0] = test_predictions
dummies = scaler3.inverse_transform(dummies)
```

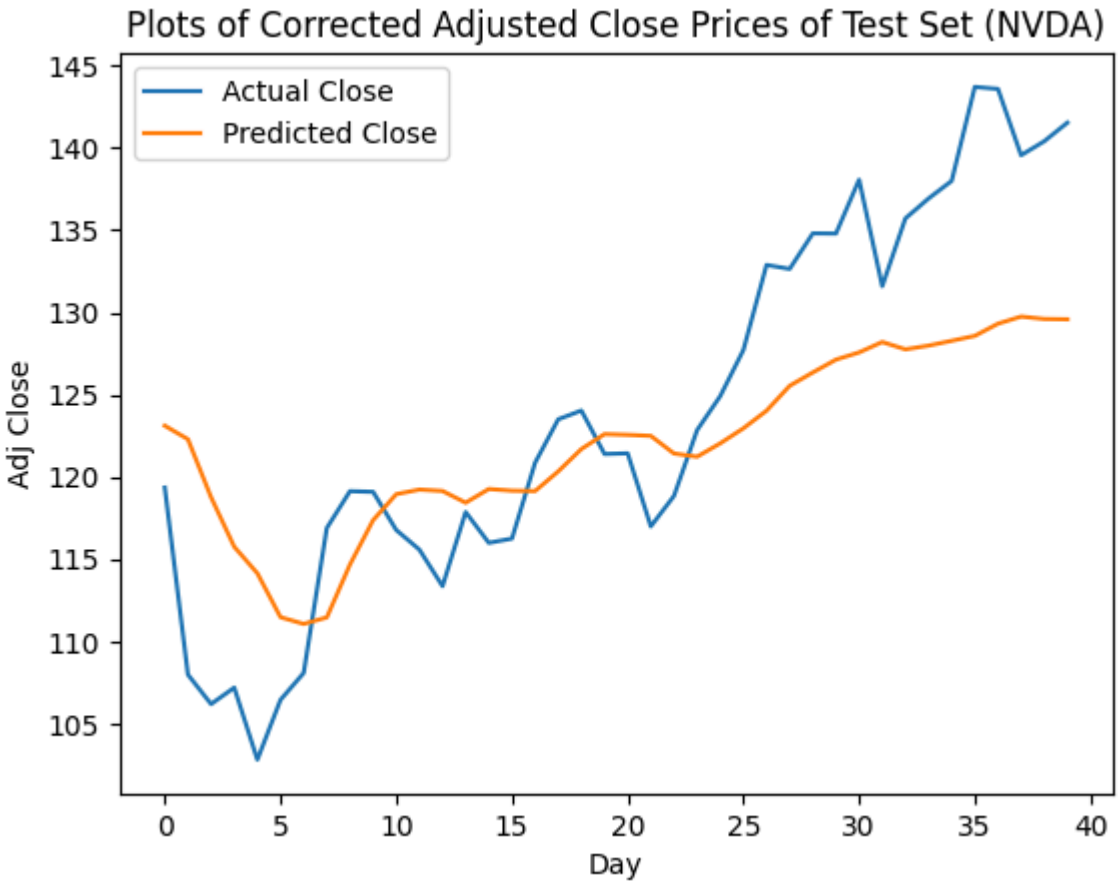
```
test_predictions = dc(dummies[:,0])
```

In [422…

```
dummies = np.zeros((X_test.shape[0], lookback+1))
dummies[:,0] = Y_test.flatten()
dummies = scaler3.inverse_transform(dummies)

new_y_test = dc(dummies[:,0])
```

In [449…

```
plt.plot(new_y_test, label = 'Actual Close')
plt.plot(test_predictions, label='Predicted Close')
plt.title("Plots of Corrected Adjusted Close Prices of Test Set (NVDA)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```



In [424…

```
pred_next_month = dc(norm_NVDA_lstm[170,1:])
#print(np.shape(pred_next_month))

for i in range(len(norm_NVDA_lstm[170:,:])):
    pred_next_month = pred_next_month.reshape(1,-1)
    X = np.concatenate(((pred_next_month[0,i:i+7]).reshape(1,-1),np.zeros((1,7))))
    X = dc(np.flip(X,axis=1))
    lookback = 7
    X=X.reshape((-1,lookback,1))
    X = torch.tensor(X).float()
```

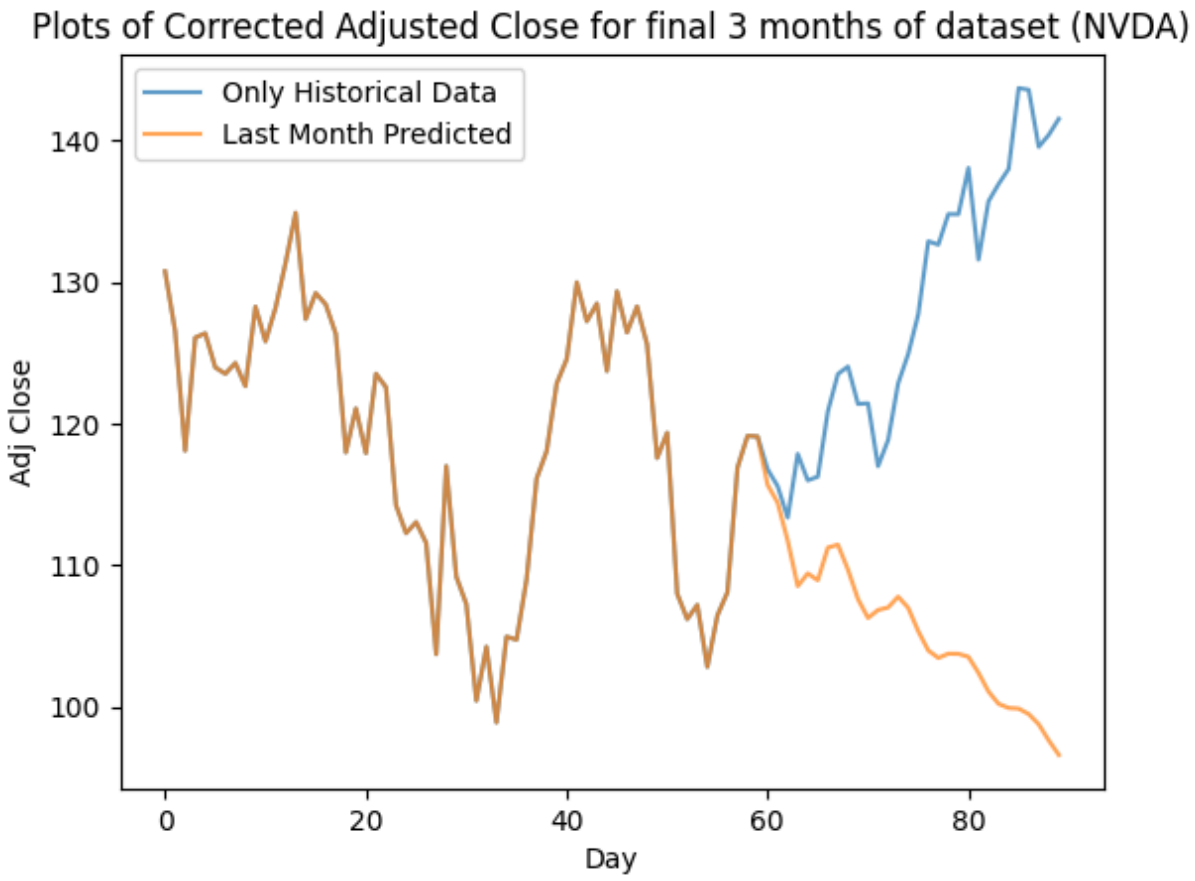
```
    day_predictions = model(X.to(device)).detach().cpu().numpy().flatten()

    pred_next_month = np.append(pred_next_month,day_predictions[0])
```

In [425…
```
new_norm_NVDA = np.concatenate((norm_NVDA_lstm[110:170,0],pred_next_month[7:]))
```

In [426…
```
dummies = np.zeros((new_norm_NVDA.shape[0], lookback+1))
dummies[:,0] = new_norm_NVDA
print(np.shape(dummies))
dummies = scaler3.inverse_transform(dummies)

new_NVDA = dc(dummies[:,0])
```

```
(90, 8)
```

In [448…
```
NVDA_lstm_actual = NVDA_lstm.iloc[110:,0].to_numpy()
plt.plot(NVDA_lstm_actual, label = 'Only Historical Data',alpha=0.7)
plt.plot(new_NVDA, label='Last Month Predicted',alpha=0.7)
plt.title("Plots of Corrected Adjusted Close for final 3 months of dataset (NVDA)")
plt.xlabel('Day')
plt.ylabel('Adj Close')
plt.legend()
plt.show;
```



Generating Log Return Dataframes for Our two datasets of Adjusted Close Prices:

In [430…
```
MSFT_3mo = NVDA_lstm.iloc[80:170,0].to_numpy()
new_MSFT;
AAPL_3mo = NVDA_lstm.iloc[80:170,0].to_numpy()
new_AAPL;
NVDA_3mo = NVDA_lstm.iloc[80:170,0].to_numpy()
new_NVDA;
```

In [431…
```
data = {'MSFT_3mo': MSFT_3mo, 'AAPL_3mo': AAPL_3mo, 'NVDA_3mo': NVDA_3mo}
df_3mo = pd.DataFrame(data);
```

In [482…
```
ret_df_3mo = np.log(df_3mo/df_3mo.shift(1));
ret_df_3mo.dropna(inplace=True);
```

In [271…
```
data2 = {'new_MSFT': new_MSFT, 'new_AAPL': new_AAPL, 'new_NVDA': new_NVDA}
df_new = pd.DataFrame(data2)
```

In [435…
```
ret_df_new = np.log(df_new/df_new.shift(1))
ret_df_new.dropna(inplace=True)
```

In [444…
```
W = [1/3,1/3,1/3]
opt_w1 = minimize(sharpe,W,ret_df_3mo,bounds = [[0,1],[0,1],[0,1]],constraints = co
opt_w2 = minimize(sharpe,W,ret_df_new,bounds = [[0,1],[0,1],[0,1]],constraints = co
```

Calculating Sharpe Ratios and Expected Returns of Our Two Optimized Portfolios with Respect to the actual return of the last month

In [477…
```
print("\n\nSharpe ratio of portfolio weights optimized with historical data: ", -sh
print("\n\nSharpe ratio of portfolio weights optimized with 2 months of historical
```

```
Sharpe ratio of portfolio weights optimized with historical data:  0.185940769888651
2


Sharpe ratio of portfolio weights optimized with 2 months of historical data & predi
cted data for the last month:  0.0888757967412012
```

In [478…
```
print("\n\nExpected return of portfolio weights optimized with historical data for
print("\n\nExpected return of portfolio weights with 2 months of historical data &
   opt_w2.x.dot(final_3mo_return.mean())  )
```

```
Expected return of portfolio weights optimized with historical data for the final mo
nth of our data:  0.002291111893429098


Expected return of portfolio weights with 2 months of historical data & predicted da
ta for the last mont for the final month of our data:  0.0013087974935228166
```