

The script used to acquire all of the following data can be found in this GitHub repository. This repository also contains the modeling codes and will be updated continually, so welcome starring or watching!

Stock market data can be interesting to analyze and as a further incentive, strong predictive models can have large financial payoff. The amount of financial data on the web is seemingly endless. A large and well structured dataset on a wide array of companies can be hard to come by. Here provided a dataset with historical stock prices (last 12 years) for 29 of 30 DJIA companies (excluding 'V' because it does not have the whole 12 years data).

['MMM', 'AXP', 'AAPL', 'BA', 'CAT', 'CVX', 'CSCO', 'KO', 'DIS', 'XOM', 'GE',

'GS', 'HD', 'IBM', 'INTC', 'JNJ', 'JPM', 'MCD', 'MRK', 'MSFT', 'NKE', 'PFE',

'PG', 'TRV', 'UTX', 'UNH', 'VZ', 'WMT', 'GOOGL', 'AMZN', 'AABA'] Content The data is presented in a couple of formats to suit different individual's needs or computational limitations. I have included files containing 13 years of stock data (in the all_stocks_2006-01-01_to_2018-01-01.csv and corresponding folder) and a smaller version of the dataset (all_stocks_2017-01-01_to_2018-01-01.csv) with only the past year's stock data for those wishing to use something more manageable in size.

The folder individual_stocks_2006-01-01_to_2018-01-01 contains files of data for individual stocks, labelled by their stock ticker name. The all_stocks_2006-01-01_to_2018-01-01.csv and all_stocks_2017-01-01_to_2018-01-01.csv contain this same data, presented in merged .csv files. Depending on the intended use (graphing, modelling etc.) the user may prefer one of these given formats.

All the files have the following columns: Date - in format: yy-mm-dd

Open - price of the stock at market open (this is NYSE data so all in USD)

High - Highest price reached in the day

Low Close - Lowest price reached in the day

Volume - Number of shares traded

Name - the stock's ticker name

In [2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.preprocessing import MinMaxScaler
from torch.utils.data import DataLoader, TensorDataset

# Load dataset
data = pd.read_csv('/Users/vbaderdi/Downloads/IBM_2006-01-01_to_2018-01-01.csv')
data = data[data['Name'] == 'IBM']  # Selecting Apple stock as an example
data['Date'] = pd.to_datetime(data['Date'])
data.set_index('Date', inplace=True)
data.head()
```

```
/var/folders/g9/462975h55wnbq3d8yms_36lm0000gr/T/ipykernel_47578/3483396422.py:13: UserWarning: Could not infer format, so each element will be parsed individually, falling back to `dateutil`. To ensure parsing is consistent and as-expected, please specify a format.
  data['Date'] = pd.to_datetime(data['Date'])
```

Out[2]:

Date	Open	High	Low	Close	Volume	Name
2006-01-03	82.45	82.55	80.81	82.06	11715200	IBM
2006-01-04	82.20	82.50	81.33	81.95	9840600	IBM
2006-01-05	81.40	82.90	81.00	82.50	7213500	IBM
2006-01-06	83.95	85.03	83.41	84.95	8197400	IBM
2006-01-09	84.10	84.25	83.38	83.73	6858200	IBM

In [16]:
```python
# Selecting Close price for prediction
prices = data[['Close']].values

# Normalize data
scaler = MinMaxScaler(feature_range=(0, 1))
prices_scaled = scaler.fit_transform(prices)

# Prepare data for LSTM
```

```
look_back = 60  # Number of past days used for prediction
X, Y = [], []
for i in range(len(prices_scaled) - look_back):
    X.append(prices_scaled[i:i + look_back, 0])
    Y.append(prices_scaled[i + look_back, 0])
X, Y = np.array(X), np.array(Y)
X = np.reshape(X, (X.shape[0], X.shape[1], 1))

# Convert to PyTorch tensors
X_tensor = torch.tensor(X, dtype=torch.float32)
Y_tensor = torch.tensor(Y, dtype=torch.float32)
```

In [23]:

```
# Split into training and testing sets
split = int(0.8 * len(X))
X_train, X_test = X_tensor[:split], X_tensor[split:]
Y_train, Y_test = Y_tensor[:split], Y_tensor[split:]

# Create DataLoaders
train_dataset = TensorDataset(X_train, Y_train)
test_dataset = TensorDataset(X_test, Y_test)
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```

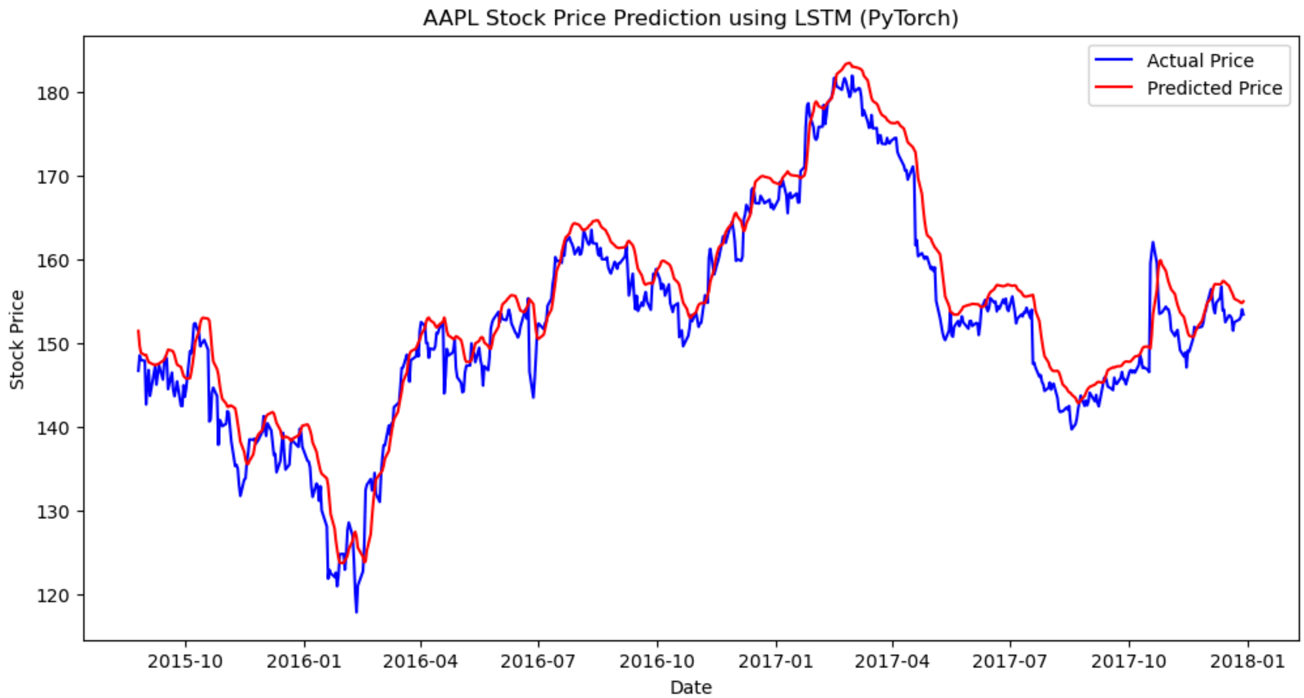
In [24]:

```
# Define LSTM model
class LSTMModel(nn.Module):
    def __init__(self, input_size=1, hidden_size=50, num_layers=2, output_size=1):
        super(LSTMModel, self).__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers, batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        lstm_out, _ = self.lstm(x)
        return self.fc(lstm_out[:, -1, :])
```

In [25]:

```
# Instantiate model, define loss function and optimizer
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = LSTMModel().to(device)
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Train model
epochs = 20
for epoch in range(epochs):
    model.train()
    for batch_X, batch_Y in train_loader:
        batch_X, batch_Y = batch_X.to(device), batch_Y.to(device)
        optimizer.zero_grad()
        predictions = model(batch_X)
        loss = criterion(predictions, batch_Y.view(-1, 1))
        loss.backward()
        optimizer.step()
    print(f"Epoch {epoch+1}/{epochs}, Loss: {loss.item():.6f}")

# Evaluate model
model.eval()
predictions, actuals = [], []
with torch.no_grad():
    for batch_X, batch_Y in test_loader:
        batch_X = batch_X.to(device)
        batch_predictions = model(batch_X).cpu().numpy()
        predictions.extend(batch_predictions)
        actuals.extend(batch_Y.numpy())

# Inverse transform predictions and actual values
predictions = scaler.inverse_transform(np.array(predictions).reshape(-1, 1))
actuals = scaler.inverse_transform(np.array(actuals).reshape(-1, 1))

# Plot results
plt.figure(figsize=(12, 6))
plt.plot(data.index[split + look_back:], actuals, color='blue', label='Actual Price')
plt.plot(data.index[split + look_back:], predictions, color='red', label='Predicted Price')
plt.legend()
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.title('IBM Stock Price Prediction using LSTM (PyTorch)')
plt.show()
```

```
Epoch 1/20, Loss: 0.003144
Epoch 2/20, Loss: 0.000781
Epoch 3/20, Loss: 0.000823
Epoch 4/20, Loss: 0.000477
Epoch 5/20, Loss: 0.000708
Epoch 6/20, Loss: 0.000637
Epoch 7/20, Loss: 0.000764
Epoch 8/20, Loss: 0.000820
Epoch 9/20, Loss: 0.000724
Epoch 10/20, Loss: 0.000978
Epoch 11/20, Loss: 0.000413
Epoch 12/20, Loss: 0.000650
Epoch 13/20, Loss: 0.000337
Epoch 14/20, Loss: 0.000570
Epoch 15/20, Loss: 0.000303
Epoch 16/20, Loss: 0.000806
Epoch 17/20, Loss: 0.000366
Epoch 18/20, Loss: 0.000250
Epoch 19/20, Loss: 0.000422
Epoch 20/20, Loss: 0.000663
```



In [ ]: