```
#declare variables and imports
import requests
import json
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import os
from torch.utils.data import Dataset, DataLoader, Subset
from tqdm import tqdm
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

ALPACA_KEY = ''
ALPACA_SECRET = ''


#helper functions for getting rsi and ema
def calculate_rsi(data, window=14):
    delta = pd.Series(data.flatten()).diff(1)

    gain = (delta.where(delta > 0, 0)).fillna(0)
    loss = (-delta.where(delta < 0, 0)).fillna(0)

    avg_gain = gain.rolling(window=window, min_periods=1).mean()
    avg_loss = loss.rolling(window=window, min_periods=1).mean()

    rs = avg_gain / avg_loss
    rsi = (100 - (100 / (1 + rs)))/100
    rsi = rsi.fillna(method='bfill')
    return rsi.to_numpy().reshape(-1, 1)

def calculate_ema(data, window=20):
    data = pd.Series(data.flatten())
    ema = data.ewm(span=window, adjust=False).mean()
    return ema.to_numpy().reshape(-1, 1)


#define class dataset
class StockDataset(Dataset):
  def __init__(self, ticker,lookback,lookforward):
    url = "https://data.alpaca.markets/v2/stocks/bars?symbols=" + ticker  +"&timeframe=1D

    headers = {
    "accept": "application/json",
    "APCA-API-KEY-ID": ALPACA_KEY,
    "APCA-API-SECRET-KEY": ALPACA SECRET
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    }

    response = requests.get(url, headers=headers)
    bars = response.json()['bars']
    df = pd.DataFrame(bars)

    # get unnormalized data
    close_prices = pd.json_normalize(df[ticker])['c'].values.reshape(-1, 1)
    volumes = pd.json_normalize(df[ticker])['v'].values.reshape(-1, 1)
    rsi = calculate_rsi(close_prices)
    ema = calculate_ema(close_prices)

    #normalize all data
    scaler_close = MinMaxScaler(feature_range=(-1, 1))
    scaler_volume = MinMaxScaler(feature_range=(-1, 1))
    scaler_ema = MinMaxScaler(feature_range=(-1, 1))
    norm_close_prices = scaler_close.fit_transform(close_prices)
    norm_volumes = scaler_volume.fit_transform(volumes)
    norm_ema = scaler_ema.fit_transform(ema)
    norm_data = np.hstack((norm_close_prices, norm_ema))

    #save to class
    self.ticker = ticker;
    self.data = norm_data
    self.times = pd.json_normalize(df[ticker])['t'].values
    self.lookback = lookback
    self.lookforward = lookforward
    self.scaler_close = scaler_close
    self.scaler_volume = scaler_volume

    #error checking
    if(lookback > len(self.data)):
      raise ValueError("Lookback cannot be greater than the length of the data")

  def __len__(self):
    return len(self.data) - self.lookback;

  def __getitem__(self, idx):
    input = self.data[idx:idx+self.lookback]
    label = self.data[idx+self.lookback]

    return {
        'input': torch.tensor(input,dtype=torch.float32),
        'label': torch.tensor(label,dtype=torch.float32)
    }


#define neural network
class StockPredictionLSTM(nn.Module):
  def __init__(self,input_size,output_size,dropout):
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      super(StockPredictionLSTM, self).__init__()

      self.input_size = input_size
      self.output_size = output_size
      self.hidden_dim = 32
      self.num_layers = 2

      self.lstm = nn.LSTM(input_size,self.hidden_dim,self.num_layers,batch_first=True,dropo
      self.fc1 = nn.Linear(32, output_size)
      #self.fc2 = nn.Linear(32, 16)
      #self.fc3 = nn.Linear(16, output_size)

      self.dropout = nn.Dropout(dropout)

    def forward(self, x):
      #initialize hidden layers
      h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_dim).requires_grad_()
      c0 = torch.zeros(self.num_layers, x.size(0), self.hidden_dim).requires_grad_()
      out, (hn, cn) = self.lstm(x, (h0.detach(), c0.detach()))
      out = out[:,-1,:]
      out = self.fc1(out)
      #out = self.fc2(out)
      #out = self.fc3(out)
      return out

#defining training loop
def train_loop(model, data_loader, criterion, optimizer, num_epochs=5):
  train_losses = []
  train_directions = []

  model.zero_grad()
  for epoch in range(num_epochs):
      # Main training loop
      model.train()
      train_loss = 0
      train_direction = 0
      for batch in tqdm(data_loader):
        input = batch['input']
        label = batch['label']

        output = model(input)
        label = label.view_as(output)
        loss = criterion(output, label)
        train_loss += loss.item()

        #checks if direction is correct (model predicts stock value increases and label a
        ref_value = input[:, -1][:, 0].flatten()
        label_differences = label[:, 0] - ref_value
        output_differences = output[:, 0] - ref_value
        for i in range(len(label_differences)):
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          if ((label_differences[i] > 0) and (output_differences[i] > 0)) or ((label_diff
            train_direction += 1

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

      # Calculate losses and direction accuracy
      train_loss /= len(data_loader)
      train_direction /= len(data_loader.dataset)
      train_losses.append(train_loss)
      train_directions.append(train_direction)

      print(f'Epoch [{epoch + 1}/{num_epochs}], Normalized Train Loss: {train_loss:.4f},
  print(f'Aggregate Data, Normalized Train Loss: {sum(train_losses)/len(train_losses):.4f
  return train_losses, train_directions

# load data, load model, load criterion, load optimizer, and train data
def get_model(ticker,lookback,lookforward, batch_size,num_epochs):
  data = StockDataset(ticker, lookback, lookforward);
  #train test split
  train_indices, test_indices = train_test_split(range(len(data)), test_size=0.2, random_
  train_dataset = Subset(data, train_indices)
  test_dataset = Subset(data, test_indices)
  train_loader = DataLoader(train_dataset, batch_size, shuffle=True)
  test_loader = DataLoader(test_dataset, batch_size, shuffle=False)

  #call model, loss function and optimizer
  model = StockPredictionLSTM(input_size=data.data.shape[-1],output_size=data.data.shape[
  criterion = nn.MSELoss()
  optimizer = optim.Adam(model.parameters(), lr=1e-3)

  #if model path exists use it, otherwise train
  model_path = f'{ticker}_{lookback}_{batch_size}_{num_epochs}.pth'
  if os.path.exists(model_path):
    print("Loading existing model...")
    train_losses = []
    train_directions = []
    model.load_state_dict(torch.load(model_path))
  else:
    print("Training new model...")
    train_losses, train_directions = train_loop(model, train_loader, criterion, optimizer
    torch.save(model.state_dict(), model_path)

  return data, model, train_losses, train_directions, test_loader, test_indices

# plot the losses and direction
def plot_data(train_losses,train_directions):
  plt.plot(train_losses, label='Train Loss')
  plt.xlabel('Epoch')
  plt.ylabel('Loss')
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  plt.ylabel('Loss')
  plt.legend()
  plt.show()

  plt.plot(train_directions, label='Train Direction')
  plt.xlabel('Epoch')
  plt.ylabel('Direction Correct %')
  plt.legend()
  plt.show()

#get predictions + plot predictions
def get_predictions(model, data, test_loader):
  scaler = data.scaler_close

  #unnormalize to get actual values
  actual = scaler.inverse_transform(data.data[:,0].reshape(-1,1)).flatten()
  predictions = []

  criterion = nn.MSELoss()
  test_loss = 0
  unnormalized_test_loss = 0

  model.eval()
  with torch.no_grad():
    for batch in tqdm(test_loader):
      input = batch['input']

      label = batch['label']
      output = model(input)
      loss = criterion(output, label)

      #unnormalize outputs, label, and loss to get unnormalized loss
      unnorm_label = torch.tensor(scaler.inverse_transform(batch['label'][:,0].detach().nu
      unnorm_output = torch.tensor(scaler.inverse_transform(output[:,0].detach().numpy().re
      unnormalized_loss = abs(unnorm_output-unnorm_label).item()

      test_loss += loss.item()
      unnormalized_test_loss += unnormalized_loss
      predictions.extend(unnorm_output.flatten().tolist())

  #get future predictions
  future_predictions = np.array(data.data[-data.lookback:])
  for i in range(data.lookforward):
    input = torch.tensor(future_predictions[-data.lookback:], dtype=torch.float32).unsquee
    output = model(input).detach().numpy().flatten()
    future_predictions = np.append(future_predictions, [output],axis=0)
  #unnormalize future predictions
  future_predictions = scaler.inverse_transform(future_predictions[:,0].reshape(-1, 1)).fl

  print(f'Normalized Test Loss: {( test_loss/len(test_loader)):.4f}, Unnormalized Test Los
  return predictions, actual, future_predictions
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def plot_results(predictions, future_predictions, actual, data, test_indices):
  train_len = len(actual) - len(test_indices)
  total_len = len(actual)

  #get years, months, and dates formats to display graphs
  times = pd.to_datetime(data.times).to_pydatetime()
  years = [time.year for time in times]
  months = [time.strftime('%Y-%m') for time in times]
  dates = [time.strftime('%Y-%m-%d') for time in times]

  #displays the entire graph with an overlay of the predictions
  unique_years_all = sorted(set(years))
  plt.title(f'{data.ticker} Actual vs Predicted')
  plt.plot(range(total_len), actual, label='Actual')
  plt.plot(range(train_len, total_len),predictions, label='Predicted')
  plt.xlabel('Time')
  plt.ylabel('Price')
  plt.xticks([years.index(year) for year in unique_years_all], unique_years_all)
  plt.legend()
  plt.show()

  #displays a zoomed in graph of the section we predicted overlayed on the actual graph
  unique_years_zoomed = sorted(set(years[train_len:total_len]))
  unique_months_zoomed = sorted(set(months[train_len:total_len]))
  unique_dates_zoomed = sorted(set(dates[train_len:total_len]))
  plt.title(f'{data.ticker} Zoomed In Actual vs Predicted')
  plt.plot(range(train_len, total_len), actual[train_len:total_len], label='Actual')
  plt.plot(range(train_len, train_len + len(predictions)), predictions, label='Predicted')
  plt.xlabel('Time')
  plt.ylabel('Price')
  #we want to use months if the entirety of stock data takes place in a year, and likewise
  if len(unique_years_zoomed) > 1:
    plt.xticks([years.index(year) for year in unique_years_zoomed], unique_years_zoomed)
  elif len(unique_months_zoomed) > 1:
    plt.xticks([months[train_len:total_len].index(month) for month in unique_months_zoomed
  else:
    plt.xticks(range(train_len, total_len), dates[train_len:total_len], rotation=45)
  plt.legend()
  plt.show()

  #displays a graph that also predicts the future
  #add buffer in case len(predictions) < len(lookback)
  predictions_focused = predictions[-data.lookback:]
  actual_focused = actual[-data.lookback:]
  future_predictions = future_predictions[-data.lookforward:]
  buffer = len(actual_focused) - len(predictions_focused)
  predictions_focused = np.concatenate((predictions_focused, future_predictions))

  unique_years_future = sorted(set(years[-data.lookback:]))
  unique_months_future = sorted(set(months[-data.lookback:]))
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  unique_months_future = sorted(set(months[-data.lookback:]))

  plt.title(f'{data.ticker} Future Predictions')
  plt.plot(range(len(actual_focused)), actual_focused, label='Actual')
  plt.plot(range(buffer, len(actual_focused) + len(future_predictions)), predictions_focuse
  plt.xlabel('Time')
  plt.ylabel('Price')
  if len(unique_years_future) > 1:
    plt.xticks([years.index(year) for year in unique_years_future], unique_years_future)
  elif len(unique_months_future) > 1:
    plt.xticks([months[-data.lookback:].index(month) for month in unique_months_future], ur
  else:
    plt.xticks(range(len(actual_focused)), dates[-data.lookback:], rotation=45)

  plt.legend()
  plt.show()

  print(future_predictions)



def main(ticker,lookback=15,lookforward=5,batch_size=1,num_epochs=5):
  data, model, train_losses, train_directions, test_loader, test_indices = get_model(tick
  if(len(train_losses) != 0):
    plot_data(train_losses,train_directions)
  predictions, actual, future_predictions = get_predictions(model,data, test_loader)
  plot_results(predictions, future_predictions, actual, data, test_indices)

main("AMZN",lookback=60,lookforward=20,batch_size=1,num_epochs=20)
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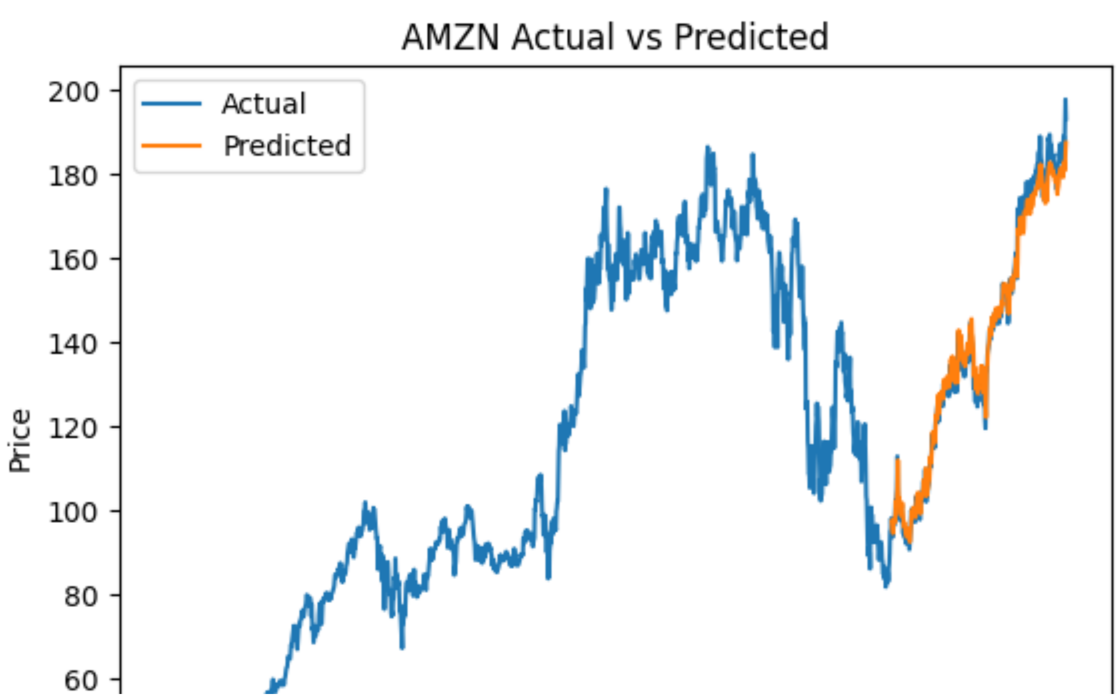
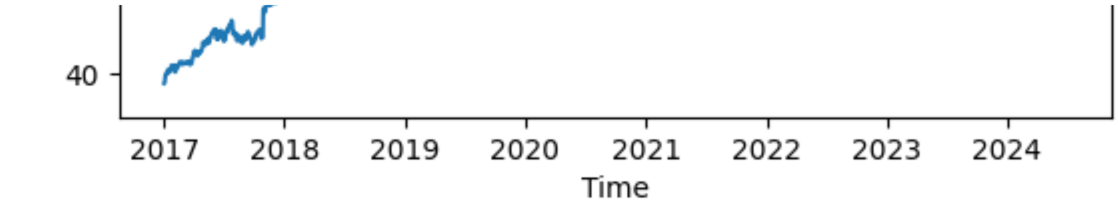
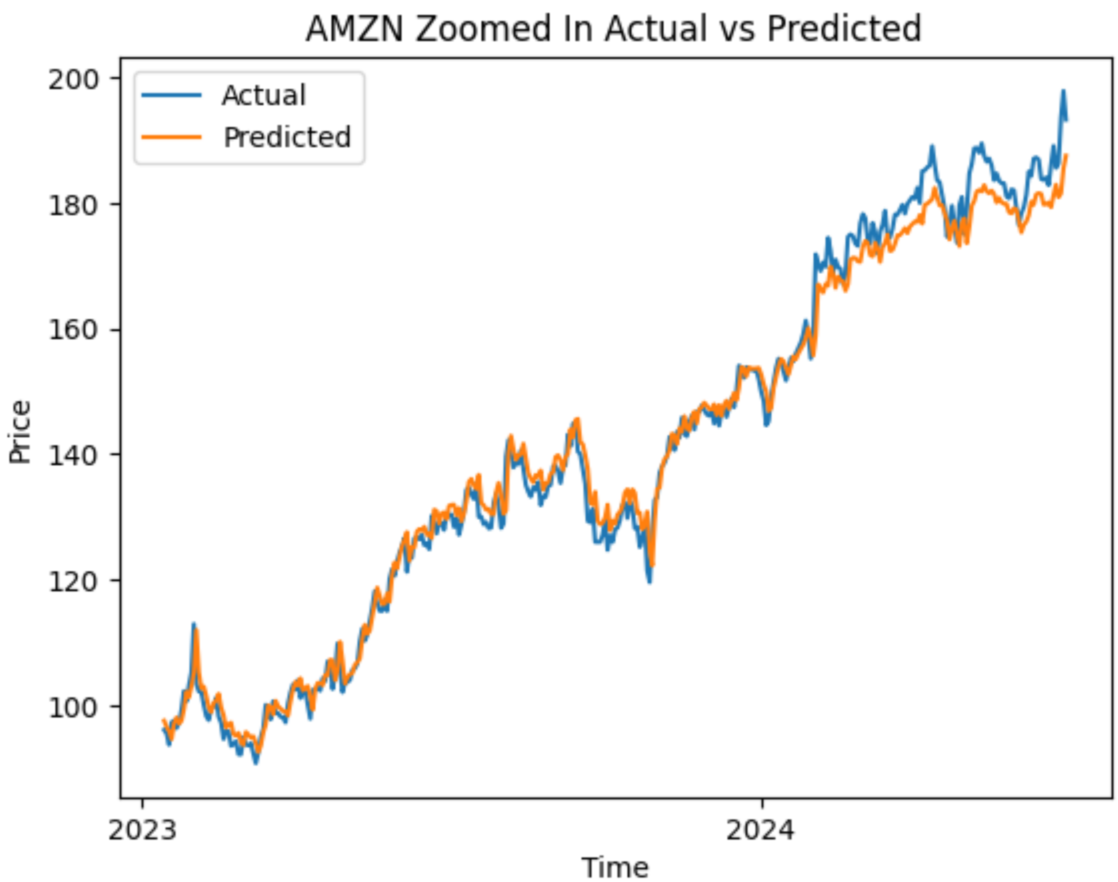
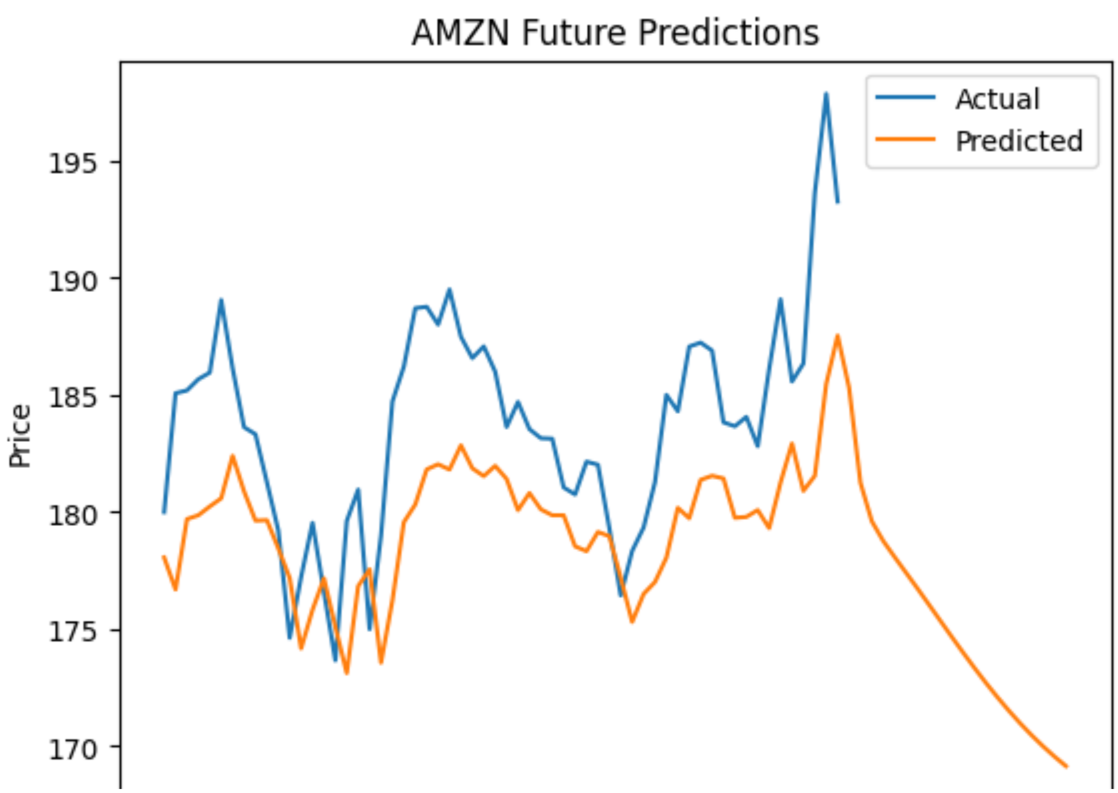
```
Loading existing model...
100%|██████████| 365/365 [00:01<00:00, 280.02it/s]
Normalized Test Loss: 0.0012, Unnormalized Test Loss: 2.6491
```




40
2017
2018
2019
2020
2021
2022
2023
2024
Time


AMZN Zoomed In Actual vs Predicted
Actual
Predicted
200
180
160
140
120
100
Price
2023
2024
Time


AMZN Future Predictions
Actual
Predicted
195
190
185
180
175
170
Price