Stock Prediction: Using PyTorch LSTM and KNIME

CS-52550, Fall 2024
Purdue Northwest University
10/26/2024

Prepared by:
Matthew Williams
Group Members:
Yash Singh, Jiuqiao Tao, Travis Thurn, Rui Zhang

Table of Contents

Table of Figures

ABSTRACT

Time series data is all around us with new data being produced as time goes on. Any data with a dependent time component can be analyzed using various time series modeling techniques. Some notable examples would be predicting temperature every hour or sales for the next month. Ways of modeling and analyzing this data are with autoregression, ARIMA (AutoRegression Integrated Moving Average), and LSTM (Long Short-Term Memory). There are more, but these three we use and discuss in this document.

In this document we analyze open, close/last, and high stock price values for Microsoft. We used KNIME for a linear regression model and forecast values for one month using a SARIMA (Seasonal AutoRegression Integrated Moving Average) model. We also used PyTorch to create a LSTM to forecast the same features during the same dates.

I. INTRODUCTION

We analyze open, close/last, and high stock price values for Microsoft between the dates January 2, 2020 to February 2, 2021. We then forecast up to March 3, 2021. The dataset is public and was downloaded from Nasdaq's website. All predictions are compared with historical ground truth data.

KNIME is an open-source, no-code software application for data scientists[2]. The installation for KNIME is a typical installation procedure and they provide set-up guides if one needs further assistance.

We created two different workspaces, one is using the provided link[1] in lecture (Figure 1) which was used to predict values of the dataset and the other workspace (Figure 1) was used to predict future values using a SARIMA model. In our ETL (Extract, Transform, Load) component, we transform the data type of our date column, add in missing rows, and then fill missing data using linear interpolation. The result is every data point being evenly separated, 1 day, and no missing values. We split the data in an 80/20 fashion, 80% test data and 20% validation data.

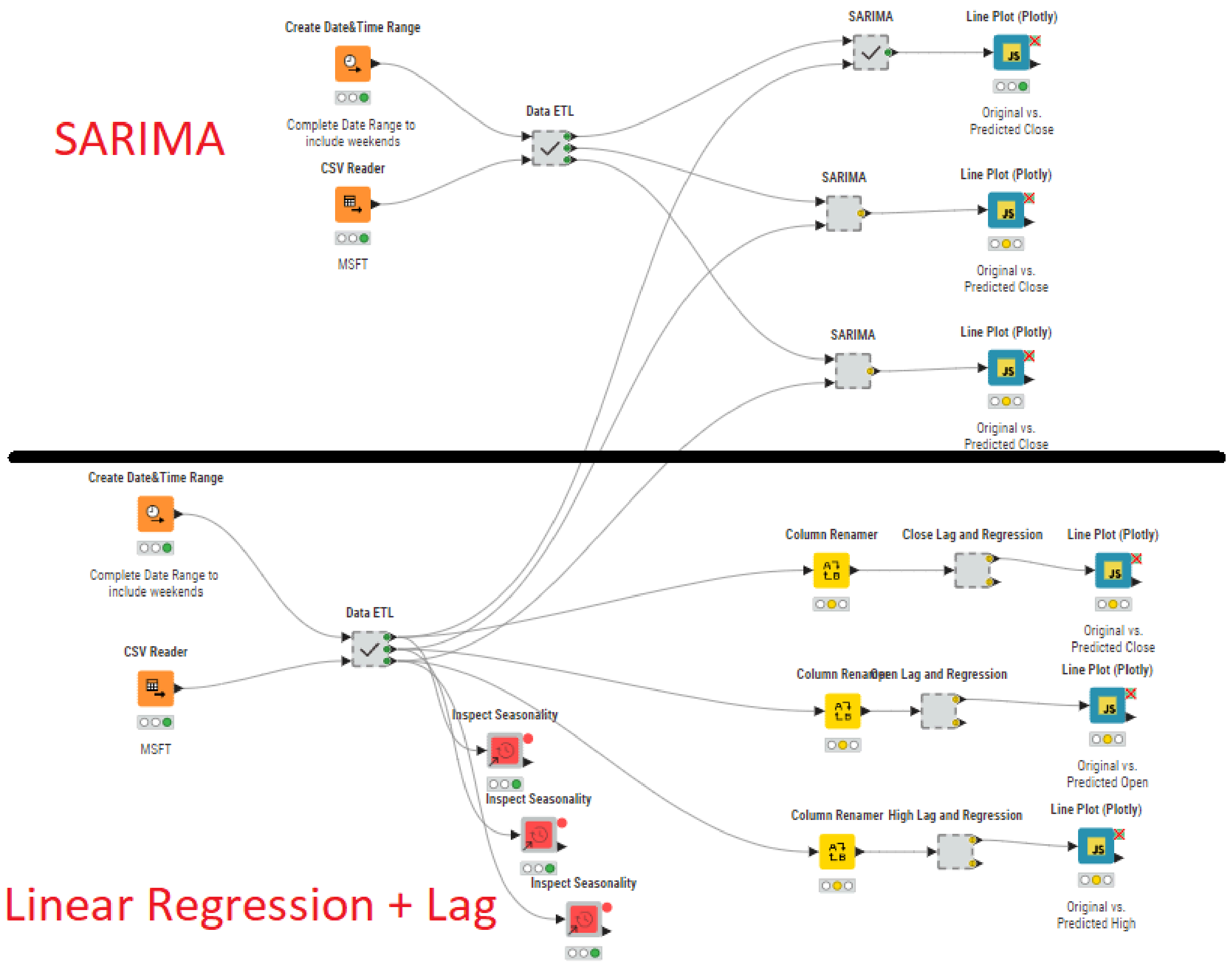


Figure 1 - KNIME Workspace; SARIMA(Top) and Linear Regression with Lag(Bottom)

Prior to setting up the SARIMA hyperparameters, we used the Inspect Seasonality module to analyze our dataset. With 150 lag values, this module produces an ACF (AutoCorrelation Function) plot which represents the correlation of the time series data versus the lagged values. Spikes in the plot indicate the seasonality of the data. Figure 2, 3, and 4 is the ACF plot using our data for close, open, and high stock price values respectively. The plot for the three features all look very similar and indicate that there is no seasonality within the data.

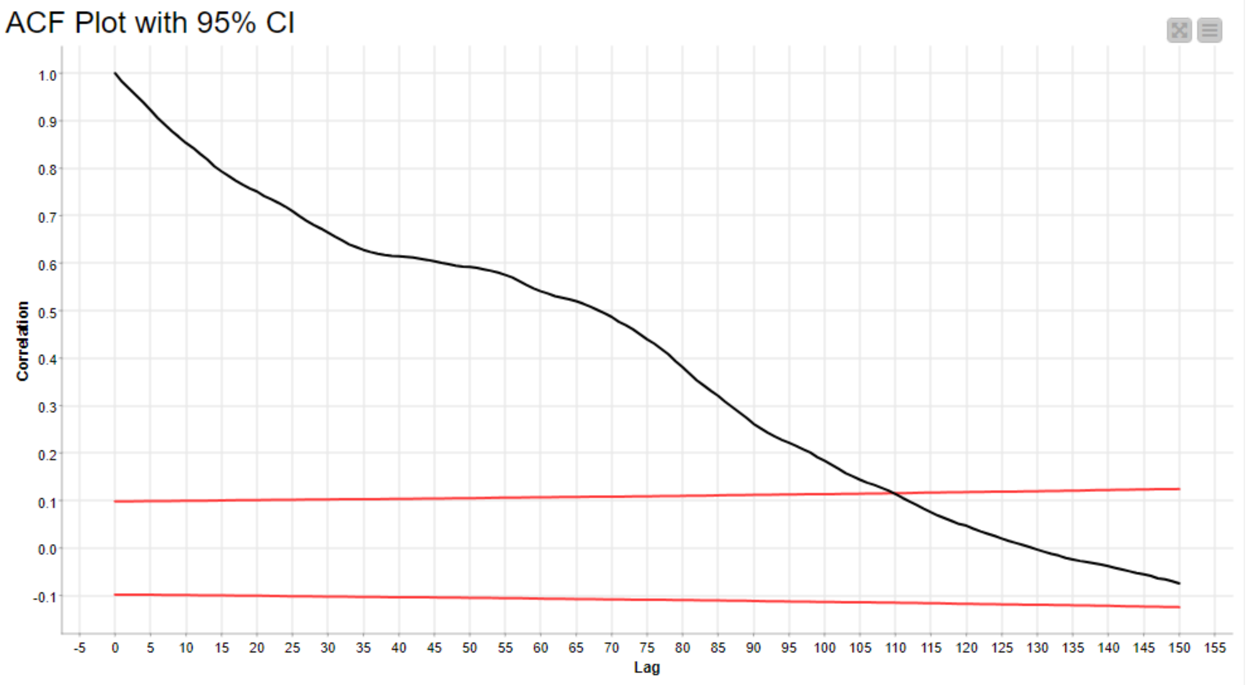


Figure 2 - Close ACF Plot

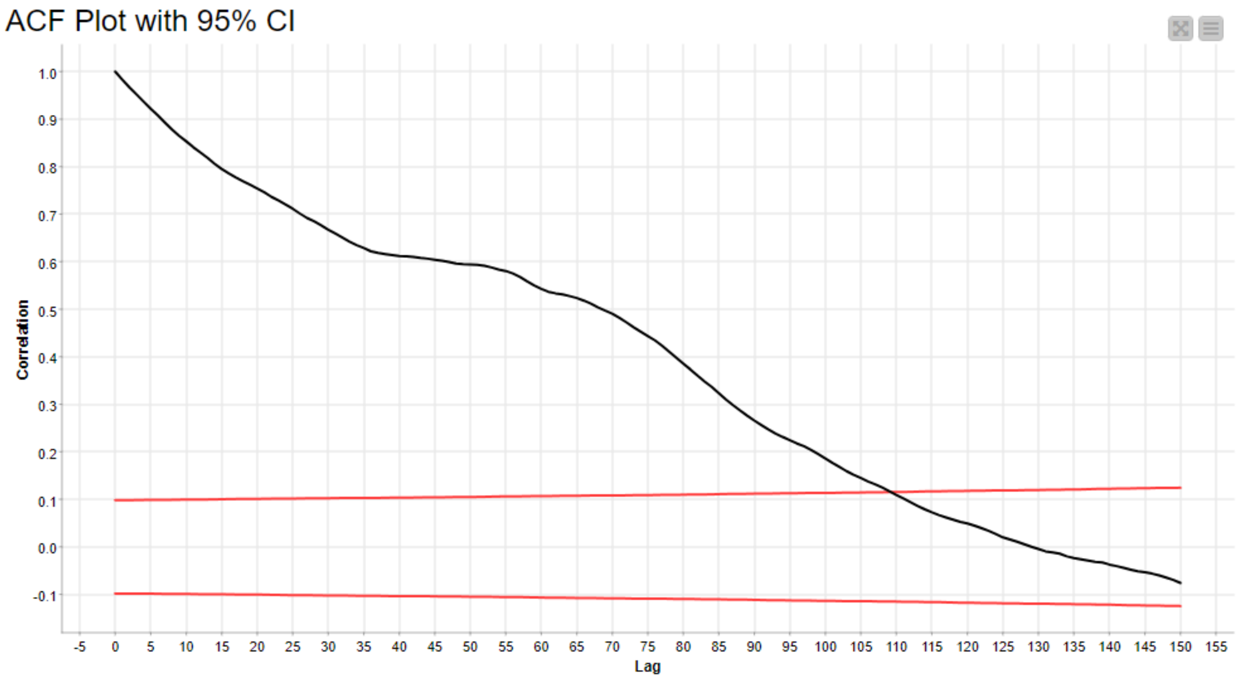


Figure 3 - Open ACF Plot

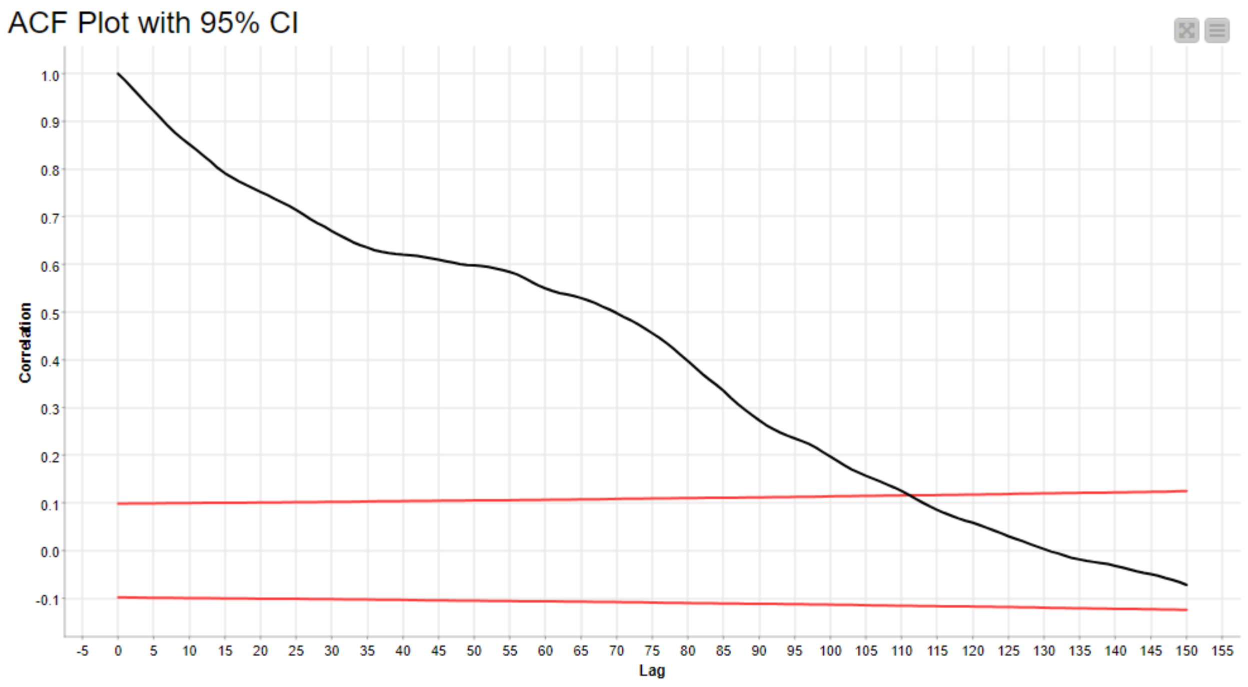


Figure 3 - High ACF Plot

If there was seasonality in the data you would see oscillations in the data with each spike indicating a season. Even with this, we decided to still select a seasonality of 30, one month, for our SARIMA season length parameter to match our PyTorch settings.

For the linear regression and column lag metanode, we lag the feature column by 30 and create 15 copies for the linear regression learner node to train on using an 80/20 split on training and validation data. The predictions on the validation data look good, however we were unable to forecast using this model. This is why we also have the SARIMA models in our workspace. Below will be the figures for the predictions on the validation data for each feature.

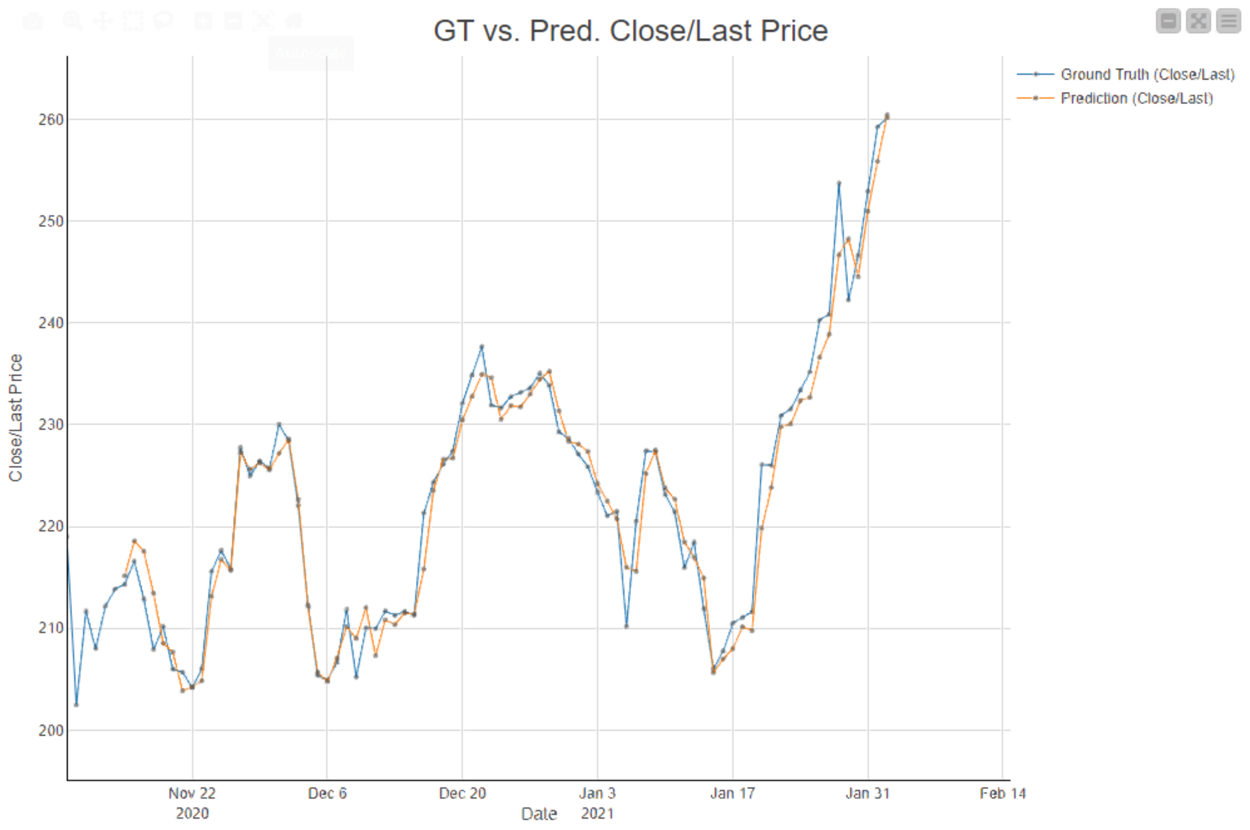


Figure 4 - Close Price Predictions on Validation

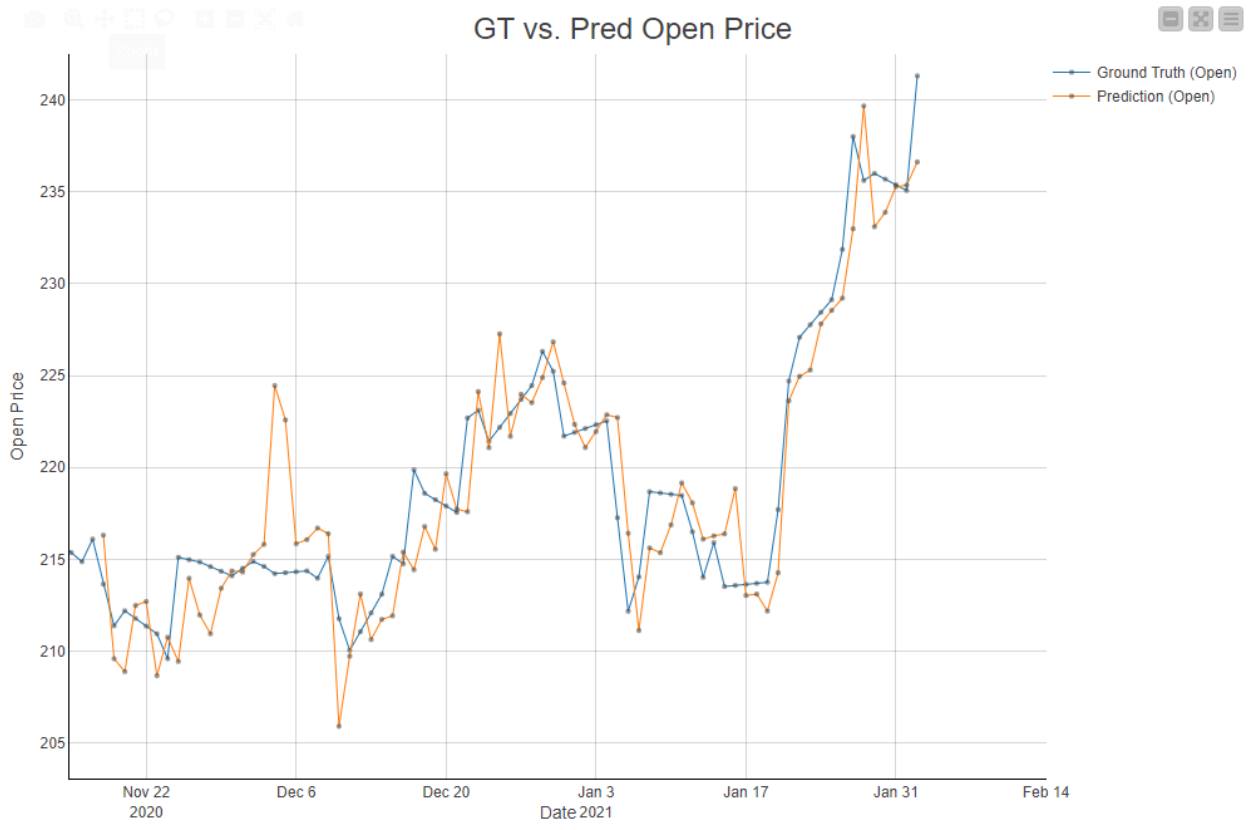


Figure 5 - Open Price Predictions on Validation Data

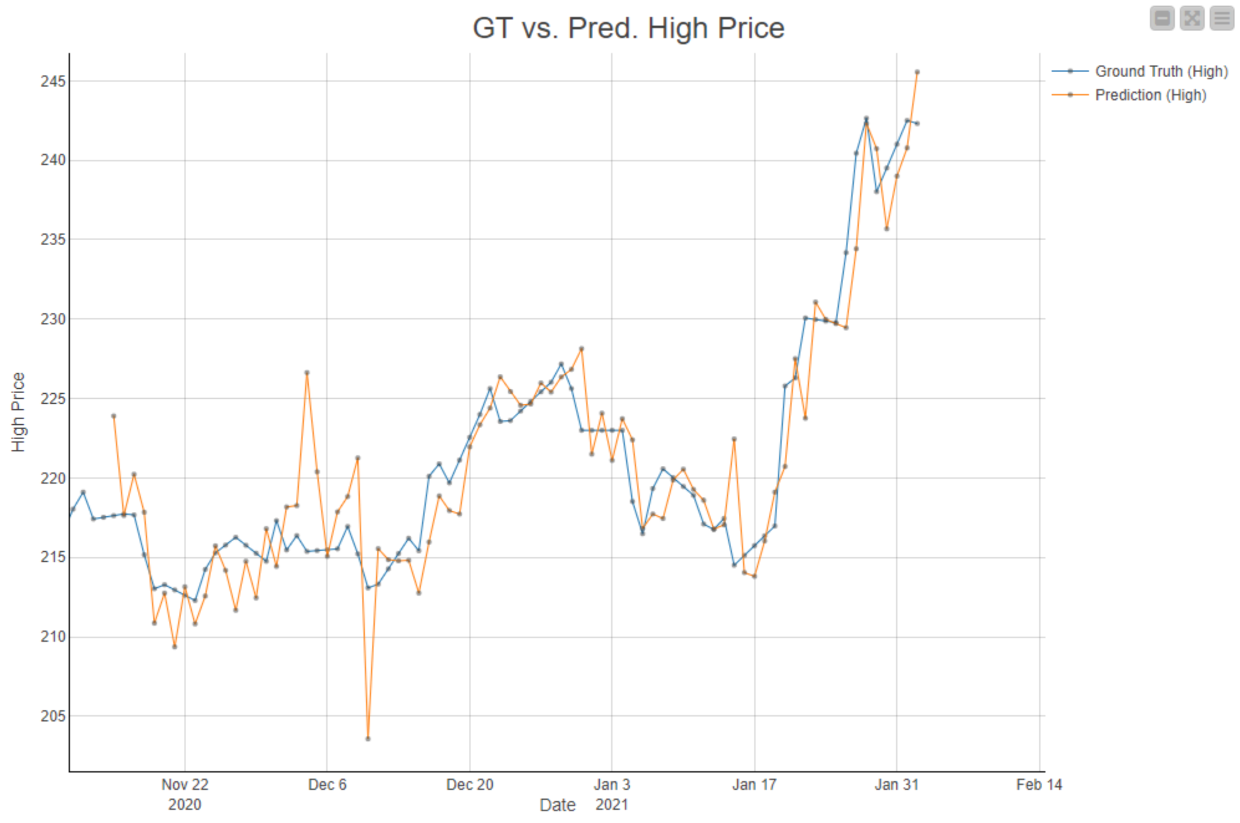
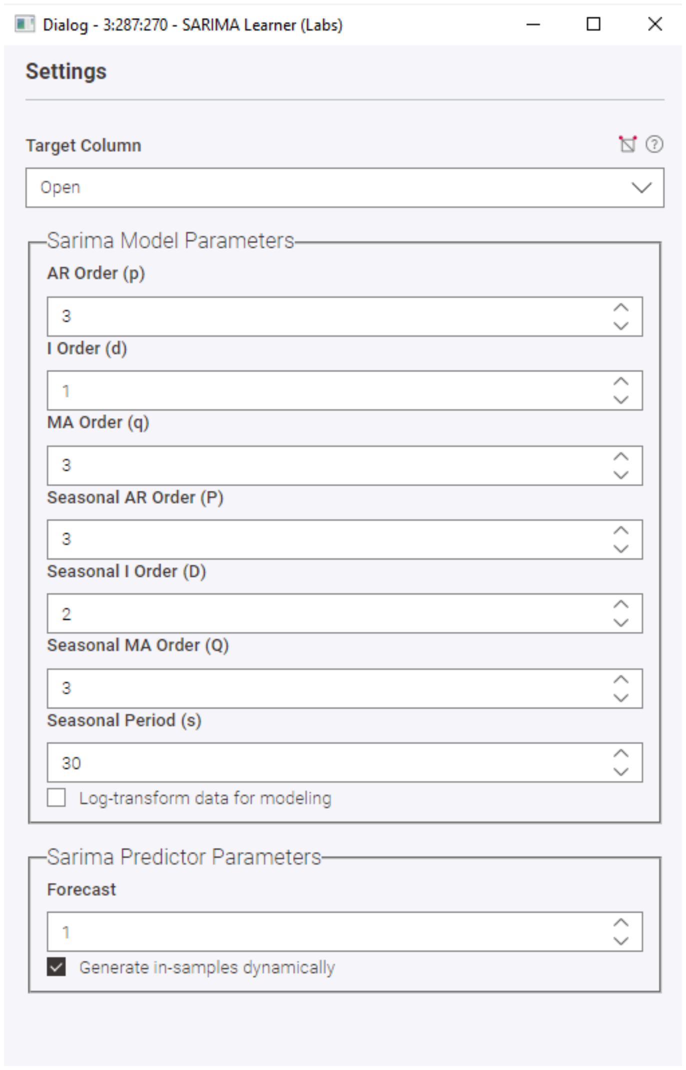


Figure 6 - High Price Predictions on Validation Data

When getting predictions, we will use the SARIMA component. Below are the parameters used for the SARIMA.



Dialog - 3:287:270 - SARIMA Learner (Labs)

Settings

Target Column: Open

Sarima Model Parameters

AR Order (p)	3
I Order (d)	1
MA Order (q)	3
Seasonal AR Order (P)	3
Seasonal I Order (D)	2
Seasonal MA Order (Q)	3
Seasonal Period (s)	30

☐ Log-transform data for modeling

Sarima Predictor Parameters

Forecast: 1

☑ Generate in-samples dynamically

Figure 7 - SARIMA Settings

Below are the predictions of our three features. The orange line represents our historical (ground truth) data that was used for training the model. The blue line represents ground truth data to be compared with our predictions. The green line represents our predictions.

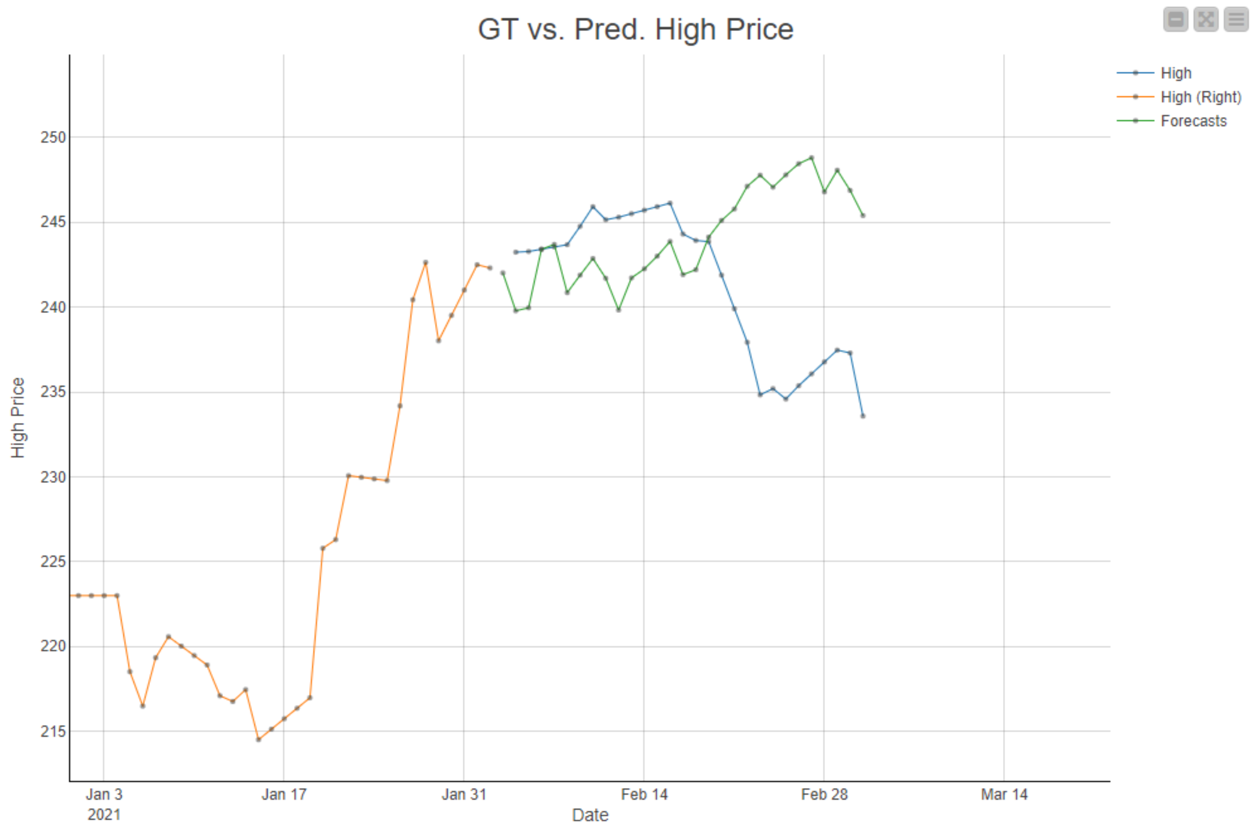


Figure 8 - Close Price Ground Truth vs Predictions

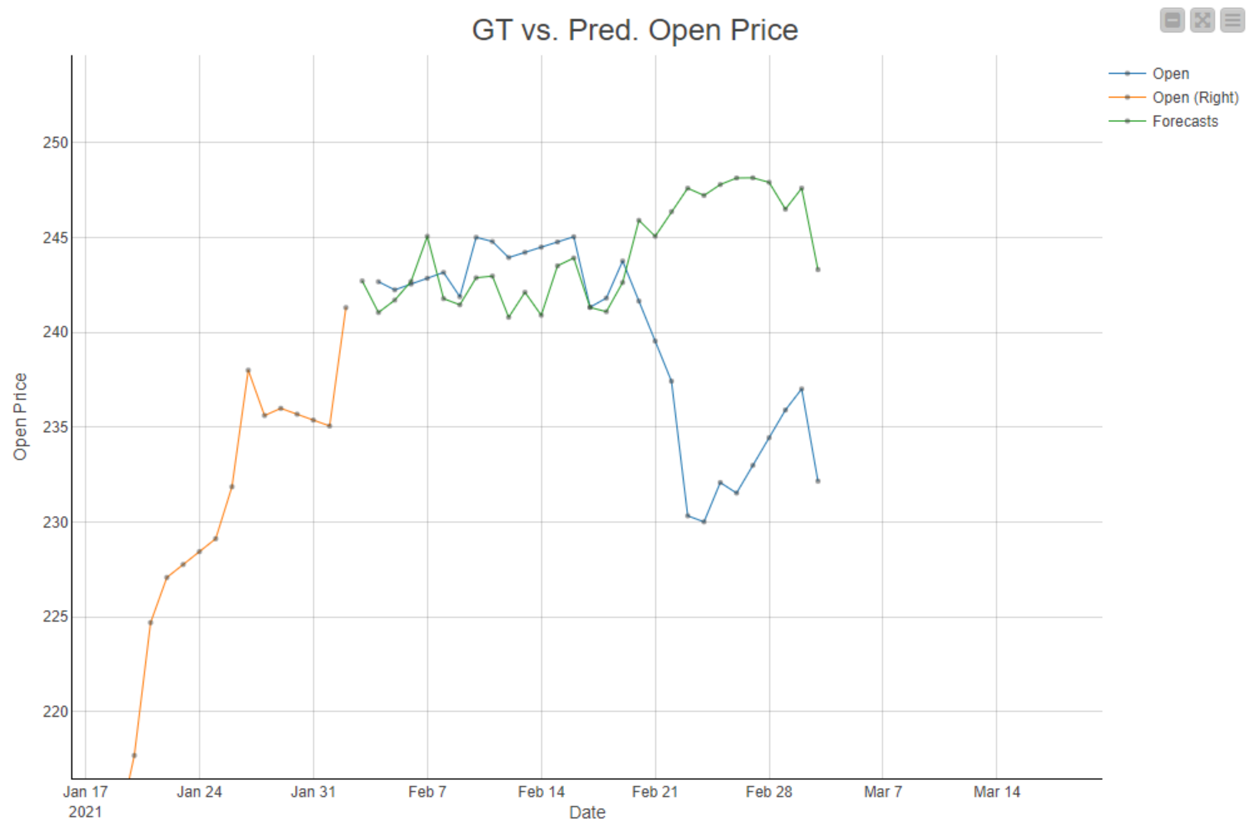


Figure 9 - Open Price Ground Truth vs Predictions

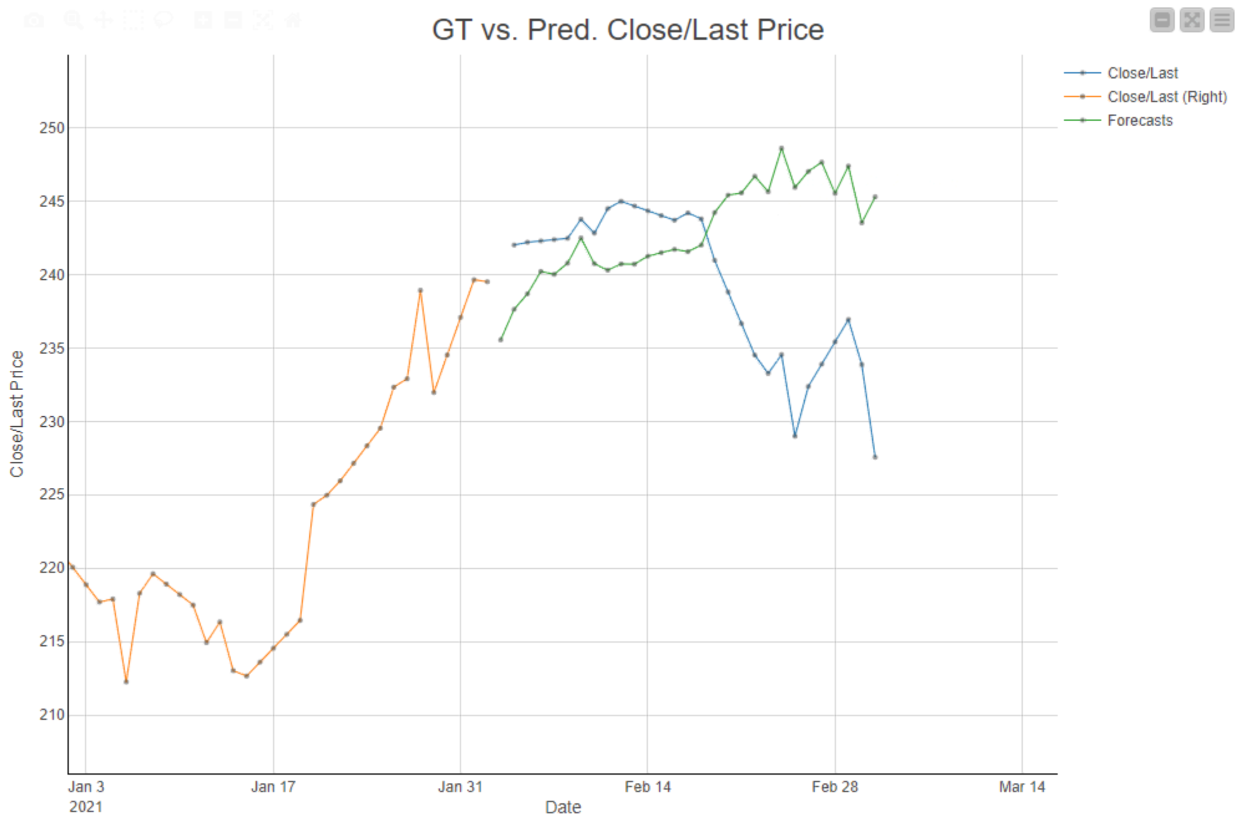


Figure 10 - Close/Last Price Ground Truth vs Predictions

II. LSTM

LSTM, also known as Long Short-Term Memory, networks are a special type of RNN (Recurrent Neural Network). LSTM networks have the ability to handle the long-term dependency problems that RNNs experience. LSTMs do this by introducing three gates in repeating modules. These gates compose of sigmoid neural net layers and multiplication operations. The three gates in LSTMs are the “forget gate layer”, “input gate layer”, and “output gate layer”.

The forget gate layer looks at the previous hidden state and the input and outputs a value between 0 and 1 (due to the sigmoid function) and this value represents how much of the previous data do we “forget” or throw away. A value of 1 meaning we keep everything and a value of 0 meaning we throw it all out or forget it. The old cell state gets scaled (multiplied) by the output of the sigmoid.

The input gate layer is responsible for determining what new data we are going to store. In this layer, we use a sigmoid function and a tanh function. The output of the sigmoid determines how much of the data we will use for updating the cell state value and the output of the tanh function gives us our potential new candidate values. The output of the sigmoid and tanh are multiplied together and added to the cell state. By this point in the process, we have removed or “forgot” information from the previous cell state to the current cell state and now added what we want to remember to the current cell state.

Finally, we need to determine what data we are going to output from the LSTM cell. This will be a filtered version of the cell state. A sigmoid is used to filter which parts to output. Then, use a tanh on the cell state (outputs values between -1 and 1) and multiply it by our sigmoid output. This is how it selects or filters which parts of the output to truly output.

Figure __ shows our data plotted out using Matplotlib.

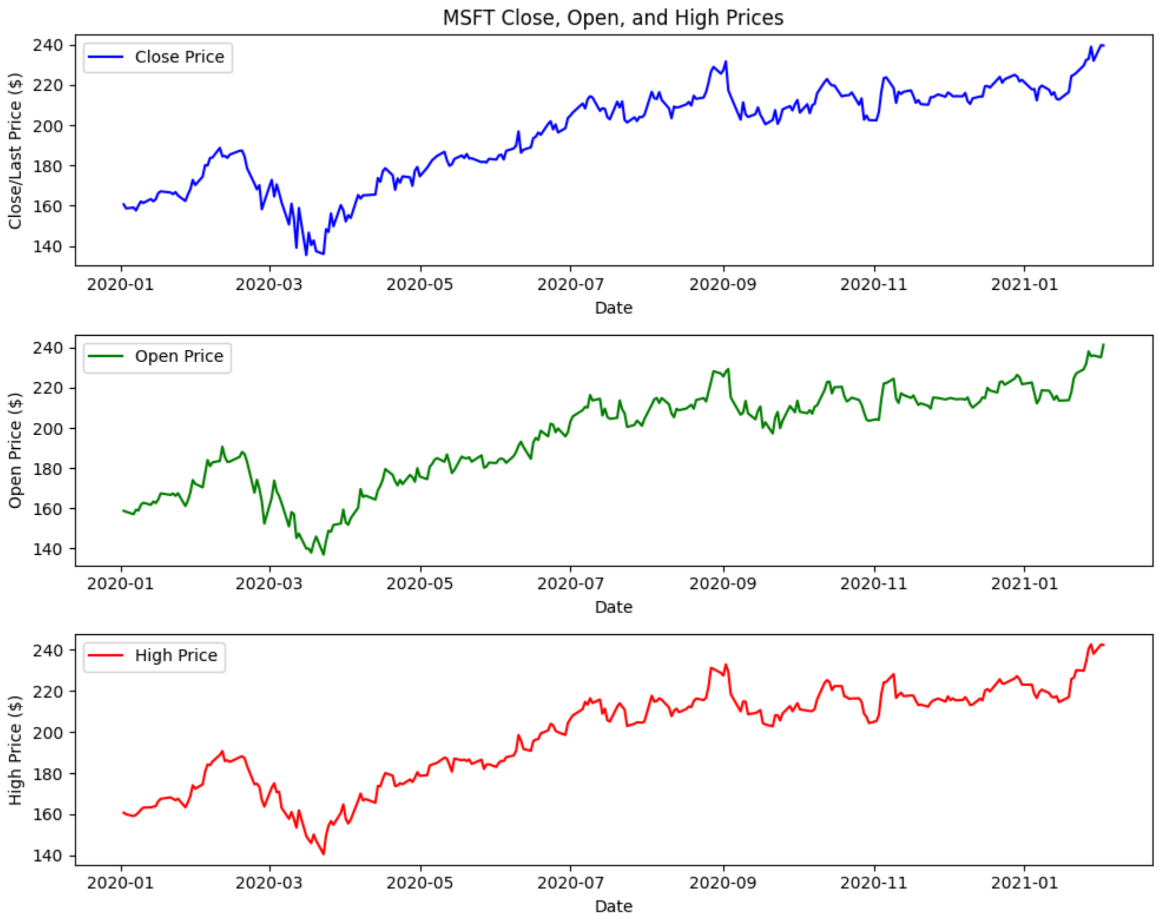


Figure 11 - Microsoft Close, Open, and High Prices

For data preparation, we scaled the data using MinMaxScaler from the sklearn library. We then split the data between 80% for training and 20% for testing.

For model training, we use a LSTM with 256 hidden nodes, 2 layers of hidden nodes, and a dropout of 0.2. The model is then run for 200 epochs with a learning rate of 0.0005. These were the final parameters after many trials with various parameter values and are applied to each feature. Figure __ displays the loss during training for each feature.

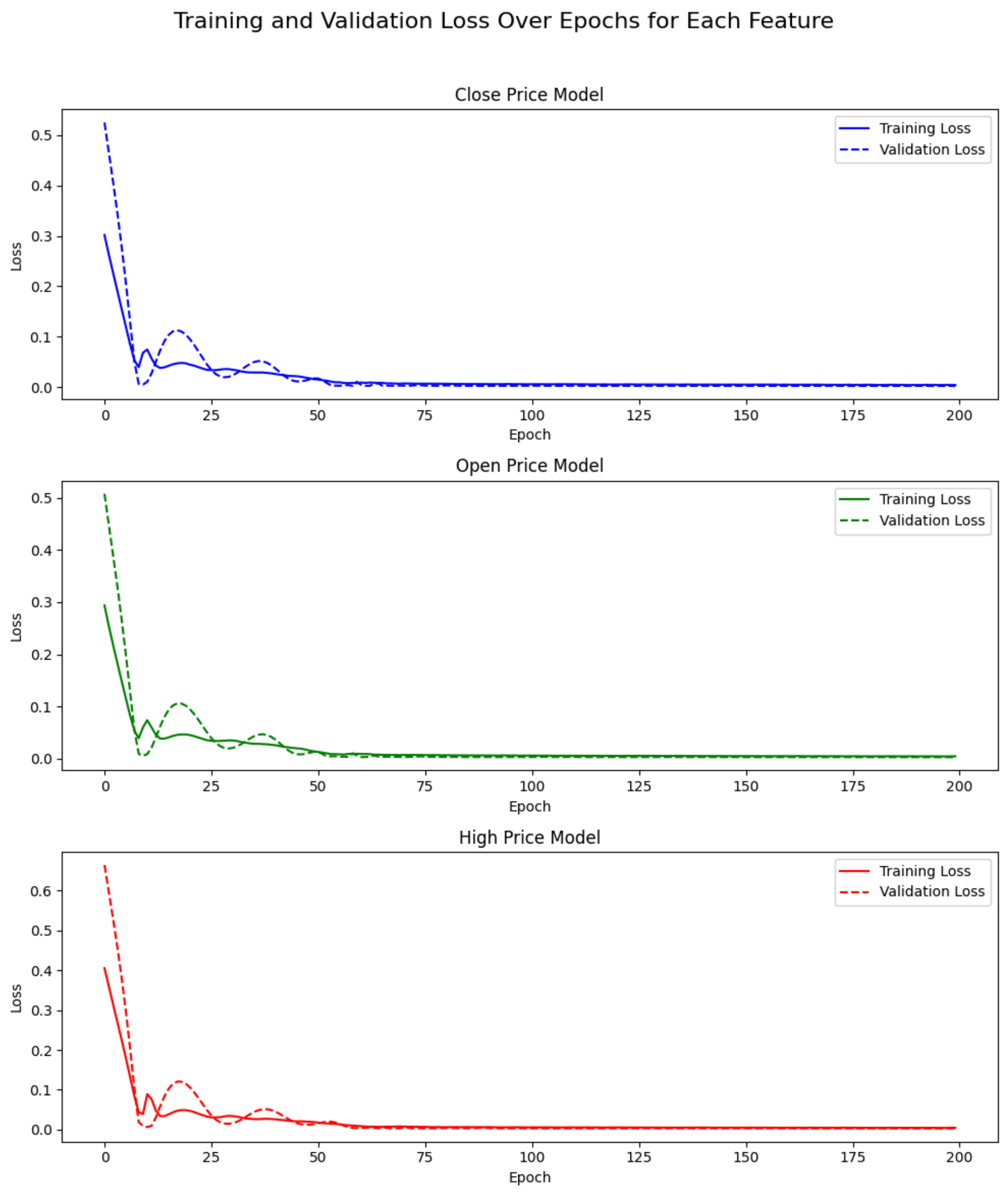


Figure 12 - Training and Validation Loss

The following figures are the predicted vs ground truth plot for our features, it also includes the MSE for the training set and testing set.

```
Evaluating model for Close prices
Close Training Set MSE: 48.0756
Close Testing Set MSE: 28.2235
```

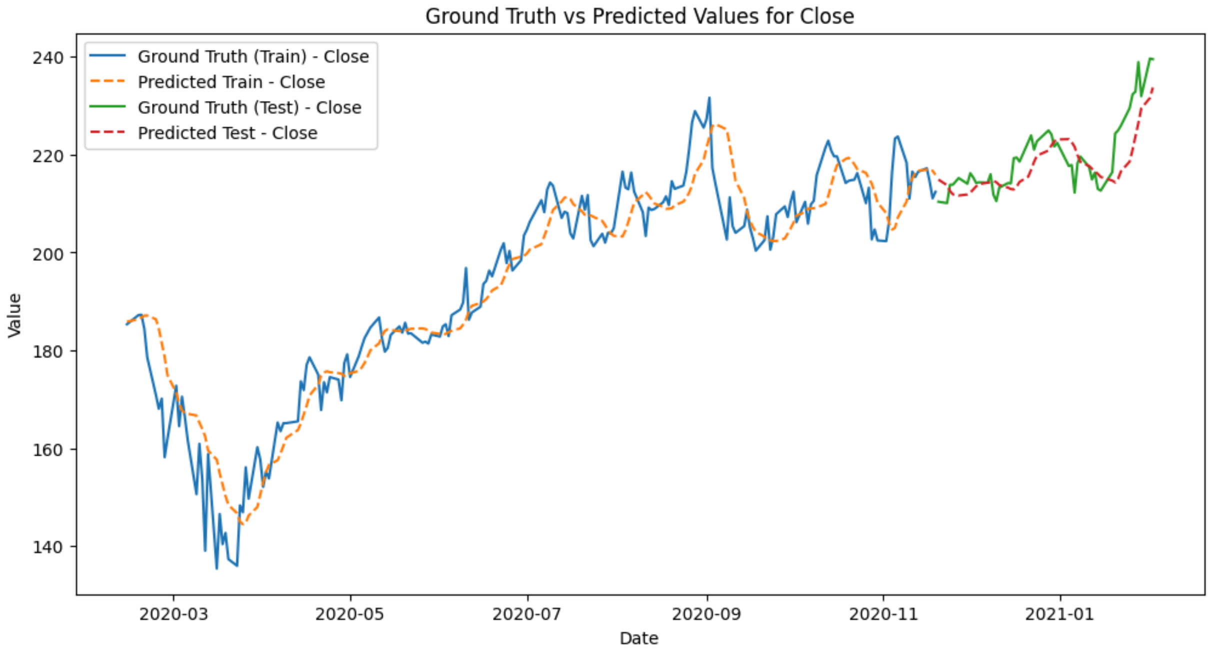


Figure 13 - Close Ground Truth vs Predicted Train and Test

```
Evaluating model for Open prices
Open Training Set MSE: 46.1359
Open Testing Set MSE: 29.5539
```

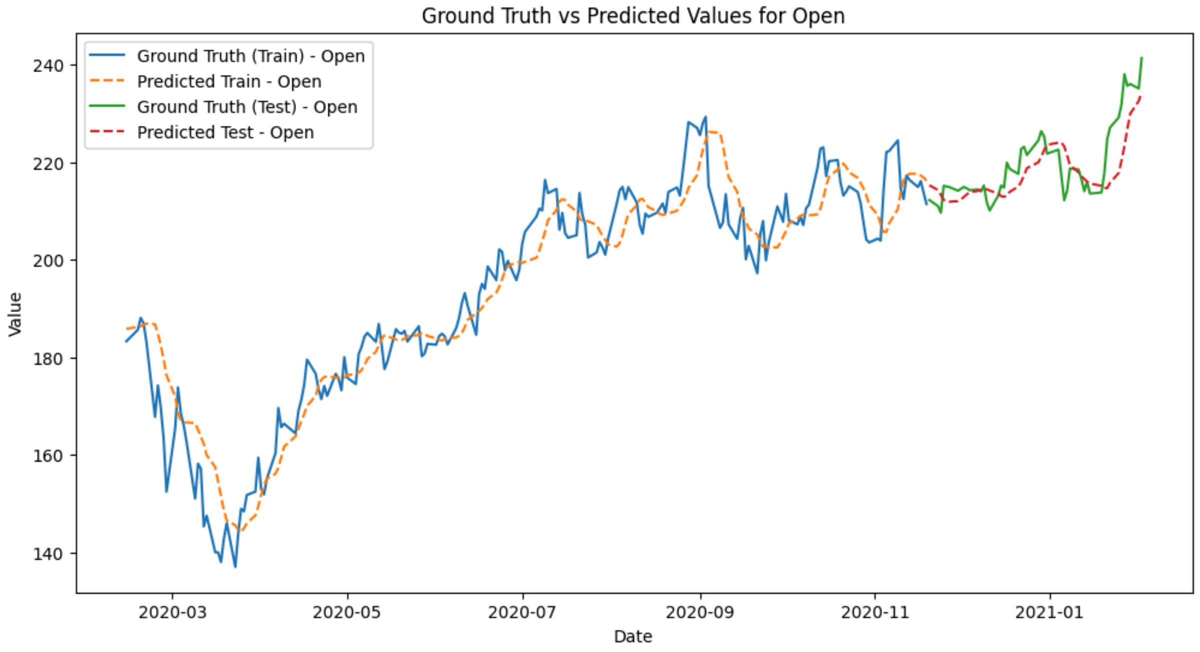


Figure 14 - Open Ground Truth vs Predicted Train and Test

```
Evaluating model for High prices
High Training Set MSE: 45.0685
High Testing Set MSE: 34.2393
```

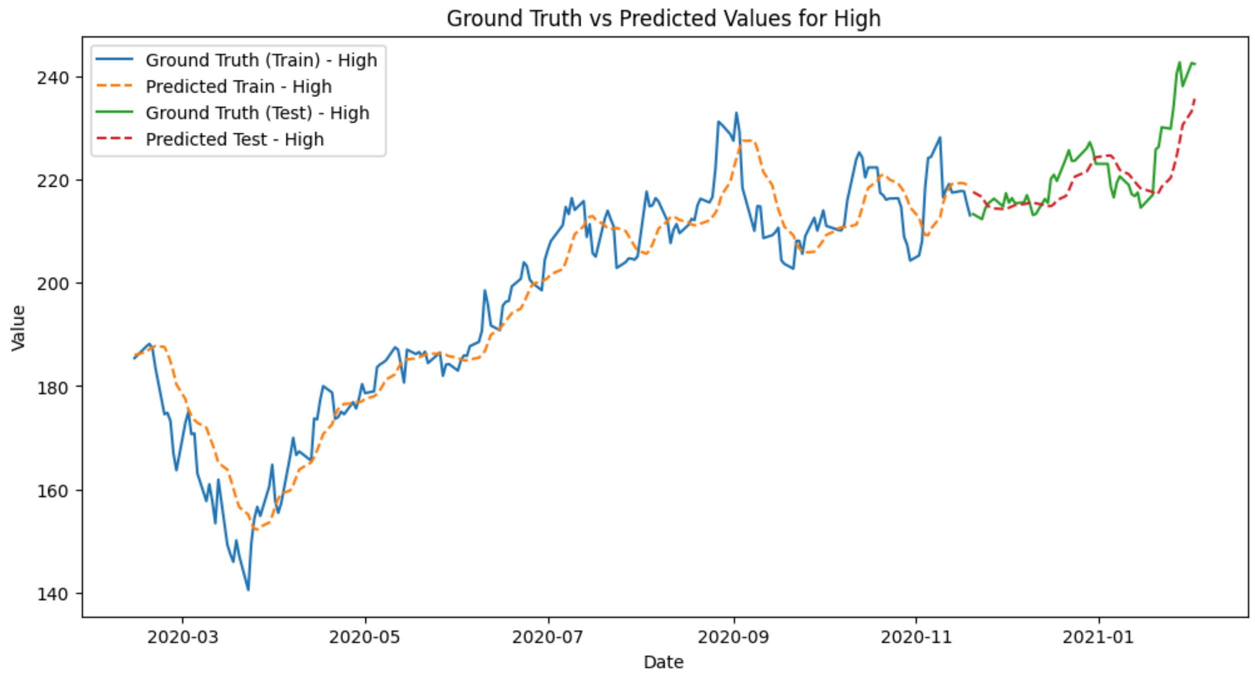


Figure 15 - High Ground Truth vs Predicted Train and Test

Using these models, we predict the next month.

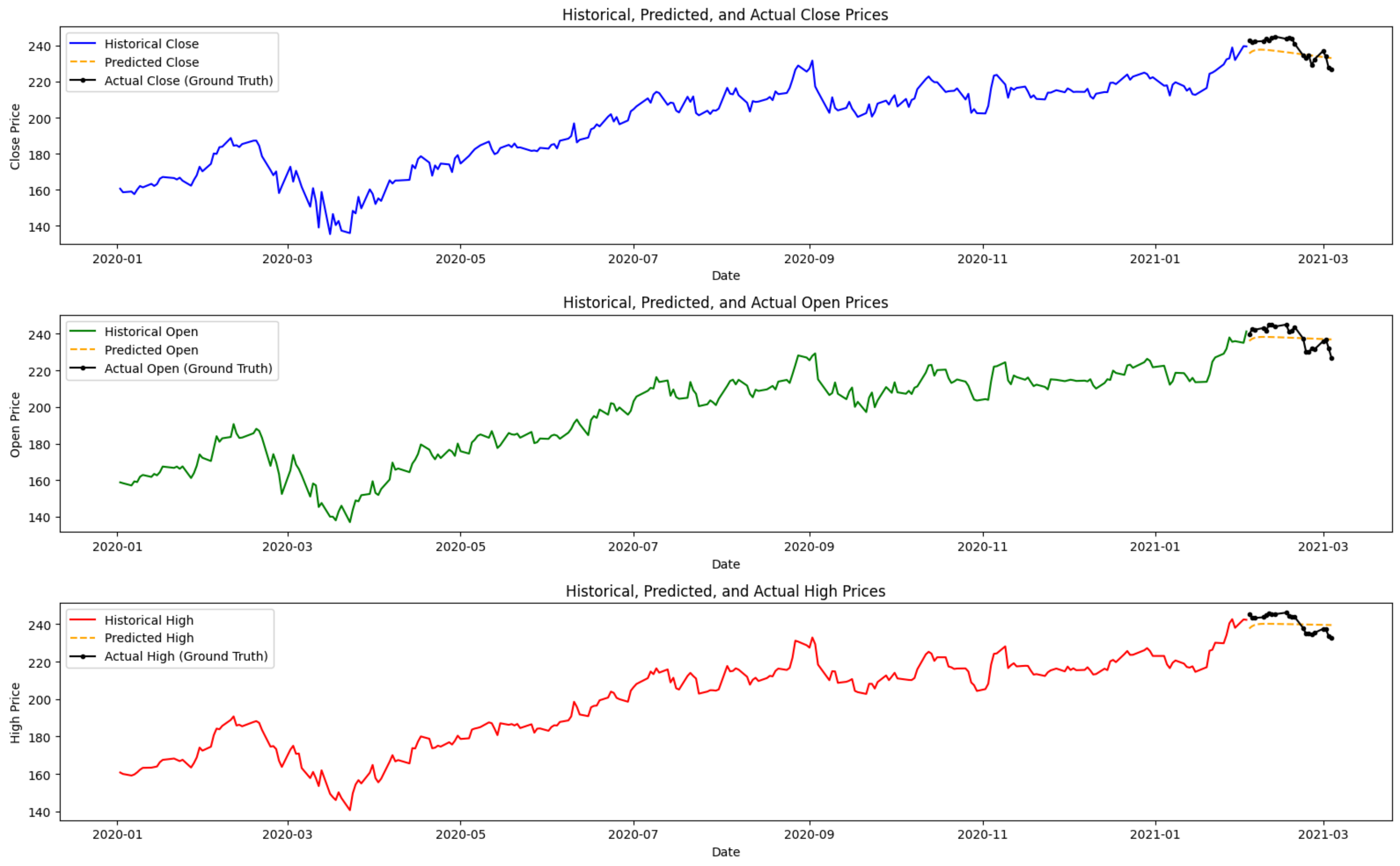


Figure 16 - Ground Truth vs Predicted

We can see from the predictions that it somewhat follows the trend of the ground truth data. However, the predictions seem to not be accounting for error terms considering the prediction line is pretty smooth.

III. DISCUSSION

The comparative analysis of SARIMA in KNIME and LSTM in PyTorch reveals distinct strengths and challenges in time series forecasting within non-seasonal stock data. The KNIME SARIMA model, constrained by the absence of seasonality, yielded less accurate predictions. Despite experimenting with various hyperparameters, SARIMA's accuracy was limited, reflecting its reliance on inherent periodicity, which was not present in our dataset as confirmed by the ACF plots.

These results also display the importance of data characteristics in model selection. While SARIMA is advantageous in clearly seasonal data, LSTM's dynamic nature proves better suited for financial data with less evident patterns. A potential direction for future improvement could include adding error correction mechanisms or refining hyperparameters for more volatile market data. Also, additional features could be considered such as stock indicators to better improve the predictions.

IV. CONCLUSION

In conclusion, this project highlights the effectiveness and limitations of using SARIMA and LSTM models for stock price prediction. While SARIMA struggled due to the lack of seasonality, the LSTM model provided a reasonable fit, demonstrating the strengths of deep learning for non-seasonal, complex time series data.

This project was run using GoogleColab. The codes and datasets can be found on this github: https://github.com/mltngpot/Stock-Prediction.

ACKNOWLEDGE

We would like to acknowledge the following for their useful resources: PyTorch documentation, TutorialsPoint time series section, and KNIME and their Community Hub. I, Matt Williams, would also like to thank my team members for their support and contributions on this project.

REFERENCES

[1]*KNIME Time Series Prediction*. [Online]. Available: https://hub.knime.com/knime/spaces/Examples/50_Applications/10_Energy_Usage/01_Energy_Usage_Time_Series_Prediction~kyzNLnmNn0WWLeaY/current-state./ [Accessed: 17-Oct-2024]

[2]PyTorch LSTM. [Online]. Available: https://pytorch.org/docs/stable/generated/torch.nn.LSTM.html [Accessed: 25-Oct-2024]

[3]TutorialsPoint Time Series. [Online]. Available: https://www.tutorialspoint.com/time_series/index.htm [Accessed: 24-Oct-2024]

APPENDIX

Below is the entire notebook; was ran in Google Colab:

```
# -*- coding: utf-8 -*-
"""P2_LSTM.ipynb

Automatically generated by Colab.

### Import resources and load data
"""

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
```

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

# Load your data into a DataFrame
df = pd.read_csv('/content/MSFT_1_2_20_to_2_2_21.csv')

# Parse the 'Date' column into datetime objects
df['Date'] = pd.to_datetime(df['Date'])

# Sort the DataFrame by date
df = df.sort_values('Date').reset_index(drop=True)

# Extract and clean columns as a NumPy array
data_Close = df['Close/Last'].str.replace('$', '').astype(float).values
data_Open = df['Open'].str.replace('$', '').astype(float).values
data_High = df['High'].str.replace('$', '').astype(float).values

# Visualize the data
plt.figure(figsize=(10, 8))

# Close/Last Price plot
plt.subplot(3, 1, 1)
plt.plot(df['Date'], data_Close, label='Close Price', color='blue')
plt.title('MSFT Close, Open, and High Prices')
plt.xlabel('Date')
plt.ylabel('Close/Last Price ($)')
plt.legend()

# Open Price plot
plt.subplot(3, 1, 2)
plt.plot(df['Date'], data_Open, label='Open Price', color='green')
plt.xlabel('Date')
plt.ylabel('Open Price ($)')
plt.legend()

# High Price plot
plt.subplot(3, 1, 3)
plt.plot(df['Date'], data_High, label='High Price', color='red')
plt.xlabel('Date')
plt.ylabel('High Price ($)')
plt.legend()

plt.tight_layout()
plt.show()

# Combine data for consistent scaling across all features
combined_data = np.array([data_Close, data_Open, data_High]).T

# Initialize and fit a single scaler
scaler = MinMaxScaler(feature_range=(0, 1))
data_scaled = scaler.fit_transform(combined_data)

# Separate the scaled data back into individual features
data_Close_scaled = data_scaled[:, 0]
data_Open_scaled = data_scaled[:, 1]
data_High_scaled = data_scaled[:, 2]


# Store the scaler for later inverse transformation
scalers = {"all_features": scaler}

# Use the scaled data for sequence creation
def create_sequences(data, seq_length):
    xs, ys = [], []
    for i in range(len(data) - seq_length):
        x = data[i:(i + seq_length)]
        y = data[i + seq_length]
        xs.append(x)
        ys.append(y)
    return np.array(xs), np.array(ys)

seq_length = 30
X_Close, y_Close = create_sequences(data_Close_scaled, seq_length)
X_Open, y_Open = create_sequences(data_Open_scaled, seq_length)
X_High, y_High = create_sequences(data_High_scaled, seq_length)

# Using the sequences generated in cell above
# Define test size
test_size = 0.2  # 20% for testing
```

```
# Split Close data
X_train_Close, X_test_Close, y_train_Close, y_test_Close = train_test_split(
    X_Close, y_Close, test_size=test_size, shuffle=False
)

# Split Open data
X_train_Open, X_test_Open, y_train_Open, y_test_Open = train_test_split(
    X_Open, y_Open, test_size=test_size, shuffle=False
)

# Split High data
X_train_High, X_test_High, y_train_High, y_test_High = train_test_split(
    X_High, y_High, test_size=test_size, shuffle=False
)

# Convert to tensors
# Close data
X_train_Close_tensor = torch.tensor(X_train_Close, dtype=torch.float32).unsqueeze(-1)
y_train_Close_tensor = torch.tensor(y_train_Close, dtype=torch.float32)

X_test_Close_tensor = torch.tensor(X_test_Close, dtype=torch.float32).unsqueeze(-1)
y_test_Close_tensor = torch.tensor(y_test_Close, dtype=torch.float32)

# Open data
X_train_Open_tensor = torch.tensor(X_train_Open, dtype=torch.float32).unsqueeze(-1)
y_train_Open_tensor = torch.tensor(y_train_Open, dtype=torch.float32)

X_test_Open_tensor = torch.tensor(X_test_Open, dtype=torch.float32).unsqueeze(-1)
y_test_Open_tensor = torch.tensor(y_test_Open, dtype=torch.float32)

# High data
X_train_High_tensor = torch.tensor(X_train_High, dtype=torch.float32).unsqueeze(-1)
y_train_High_tensor = torch.tensor(y_train_High, dtype=torch.float32)

X_test_High_tensor = torch.tensor(X_test_High, dtype=torch.float32).unsqueeze(-1)
y_test_High_tensor = torch.tensor(y_test_High, dtype=torch.float32)

# Define the LSTM model
class SimpleLSTM(nn.Module):
    def __init__(self, input_size=1, hidden_size=128, output_size=1, num_layers=1,
dropout=0):
        super(SimpleLSTM, self).__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers

        # Define the LSTM layer with dropout
        self.lstm = nn.LSTM(
            input_size,
            hidden_size,
            num_layers,
            batch_first=True,
            dropout=dropout
        )

        # Define the output layer
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # Set initial hidden and cell states
        h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size)
        c0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size)

        # Forward propagate through LSTM
        out, _ = self.lstm(x, (h0, c0))

        # Get the outputs from the last time step
        out = self.fc(out[:, -1, :])
        return out

# Train the model
num_epochs = 200 #200
learning_rate = 0.0005 #0.0005

# Create dictionaries to hold models, optimizers, losses, and data for each feature
models = {
    "Close": SimpleLSTM(hidden_size=256, num_layers=2, dropout=0.2), #256
    "Open":SimpleLSTM(hidden_size=256, num_layers=2, dropout=0.2),
    "High": SimpleLSTM(hidden_size=256, num_layers=2, dropout=0.2)
}

optimizers = {
    "Close": optim.Adam(models["Close"].parameters(), lr=learning_rate),
    "Open": optim.Adam(models["Open"].parameters(), lr=learning_rate),
    "High": optim.Adam(models["High"].parameters(), lr=learning_rate)
}

# Criterion
criterion = nn.MSELoss()

# Initialize lists to store training and validation losses for each feature
train_losses = {"Close": [], "Open": [], "High": []}
val_losses = {"Close": [], "Open": [], "High": []}

# Data for each feature
data = {
    "Close": (X_train_Close_tensor, y_train_Close_tensor, X_test_Close_tensor,
y_test_Close_tensor),
    "Open": (X_train_Open_tensor, y_train_Open_tensor, X_test_Open_tensor,
y_test_Open_tensor),
    "High": (X_train_High_tensor, y_train_High_tensor, X_test_High_tensor,
y_test_High_tensor)
}

# Training loop
for feature in ["Close", "Open", "High"]:
    print(f"Training model for {feature} prices")

    # Extract the corresponding model, optimizer, and data
    model = models[feature]
    optimizer = optimizers[feature]
    X_train_tensor, y_train_tensor, X_test_tensor, y_test_tensor = data[feature]

    for epoch in range(num_epochs):
        # Training phase
        model.train()
        optimizer.zero_grad()
        outputs = model(X_train_tensor)
        loss = criterion(outputs.squeeze(), y_train_tensor)
        loss.backward()
        optimizer.step()

        # Track training loss
        train_losses[feature].append(loss.item())

        # Validation phase
        model.eval()
        with torch.no_grad():
            val_outputs = model(X_test_tensor)
            val_loss = criterion(val_outputs.squeeze(), y_test_tensor)
            val_losses[feature].append(val_loss.item())

        # Print loss every 10 epochs
        if (epoch + 1) % 10 == 0:
            print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {loss.item():.4f}, Val Loss:
{val_loss.item():.4f}')

# Plot training and validation loss
fig, axes = plt.subplots(3, 1, figsize=(10, 12))
fig.suptitle('Training and Validation Loss Over Epochs for Each Feature', fontsize=16)

# Plot for 'Close' model
axes[0].plot(train_losses["Close"], label='Training Loss', color='blue')
axes[0].plot(val_losses["Close"], label='Validation Loss', linestyle='--', color='blue')
axes[0].set_title('Close Price Model')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
axes[0].legend()

# Plot for 'Open' model
axes[1].plot(train_losses["Open"], label='Training Loss', color='green')
axes[1].plot(val_losses["Open"], label='Validation Loss', linestyle='--', color='green')
axes[1].set_title('Open Price Model')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Loss')
axes[1].legend()

# Plot for 'High' model
axes[2].plot(train_losses["High"], label='Training Loss', color='red')
```

```
axes[2].plot(val_losses["High"], label='Validation Loss', linestyle='--', color='red')
axes[2].set_title('High Price Model')
axes[2].set_xlabel('Epoch')
axes[2].set_ylabel('Loss')
axes[2].legend()

# Leaving space for the main title
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()

# Evaluate the model
features = ["Close", "Open", "High"]

# Retrieve the combined scaler
scaler = scalers["all_features"]

# Evaluation loop for each feature
for i, feature in enumerate(features):
    print(f"Evaluating model for {feature} prices")

    # Retrieve the model and data tensors for the current feature
    model = models[feature]
    X_train_tensor, y_train_tensor, X_test_tensor, y_test_tensor = data[feature]

    # Set model to evaluation mode
    model.eval()
    with torch.no_grad():
        # Predict on training and test data
        train_pred = model(X_train_tensor).squeeze().numpy()
        test_pred = model(X_test_tensor).squeeze().numpy()

    # Prepare data for inverse transformation
    train_pred_stack = np.zeros((len(train_pred), 3))
    test_pred_stack = np.zeros((len(test_pred), 3))
    y_train_stack = np.zeros((len(y_train_tensor), 3))
    y_test_stack = np.zeros((len(y_test_tensor), 3))

    # Place predictions and actual values in the correct column (0, 1, or 2 for Close,
Open, or High)
    train_pred_stack[:, i] = train_pred
    test_pred_stack[:, i] = test_pred
    y_train_stack[:, i] = y_train_tensor.numpy()
    y_test_stack[:, i] = y_test_tensor.numpy()

    # Inverse transform the predictions and GT values
    train_pred_inv = scaler.inverse_transform(train_pred_stack)[:, i]
    y_train_inv = scaler.inverse_transform(y_train_stack)[:, i]
    test_pred_inv = scaler.inverse_transform(test_pred_stack)[:, i]
    y_test_inv = scaler.inverse_transform(y_test_stack)[:, i]

    # Compute Mean Squared Error (MSE)
    train_mse = mean_squared_error(y_train_inv, train_pred_inv)
    test_mse = mean_squared_error(y_test_inv, test_pred_inv)
    print(f'{feature} Training Set MSE: {train_mse:.4f}')
    print(f'{feature} Testing Set MSE: {test_mse:.4f}')

    # Correct date ranges for plotting
    dates_train = df['Date'].iloc[seq_length:seq_length + len(y_train_inv)]
    dates_test = df['Date'].iloc[seq_length + len(y_train_inv):seq_length + len(y_train_inv)
+ len(y_test_inv)]

    # Plot GT vs predicted values
    plt.figure(figsize=(12, 6))
    plt.plot(dates_train, y_train_inv, label=f'Ground Truth (Train) - {feature}')
    plt.plot(dates_train, train_pred_inv, label=f'Predicted Train - {feature}', linestyle='--')
    plt.plot(dates_test, y_test_inv, label=f'Ground Truth (Test) - {feature}')
    plt.plot(dates_test, test_pred_inv, label=f'Predicted Test - {feature}', linestyle='--')
    plt.xlabel('Date')
    plt.ylabel('Value')
    plt.title(f'Ground Truth vs Predicted Values for {feature}')
    plt.legend()
    plt.show()

def predict_future(model, initial_sequence, future_steps, scaler, feature_index):

    model.eval()
    predictions = []
    current_sequence = initial_sequence.tolist()

    for _ in range(future_steps):
        # Prepare the input sequence by reshaping to (1, seq_length, 1)
        input_seq = np.array(current_sequence[-seq_length:]).reshape(1, seq_length, 1)
        input_tensor = torch.tensor(input_seq, dtype=torch.float32)

        with torch.no_grad():
            prediction = model(input_tensor)

        # Extract the predicted value and add it to the sequence
        pred_value = prediction.item()
        current_sequence.append(pred_value)  # Use the predicted value as part of the
next input sequence
        predictions.append(pred_value)

    # Inverse transform predictions
    if scaler is not None:
        # We must fit predictions into a 3-column array for inverse transformation with the
scaler
        pred_stack = np.zeros((len(predictions), 3))
        pred_stack[:, feature_index] = predictions  # Populate only the relevant feature
column

        # Inverse transform and extract only the relevant feature column
        predictions = scaler.inverse_transform(pred_stack)[:, feature_index]

    return predictions

# Generate future predictions
future_steps = 30  # Predict the next 30 days

# Prepare initial sequences for each feature using the last sequence from the scaled
data
initial_sequence_close = data_scaled[-seq_length:, 0]  # "Close" feature
initial_sequence_open = data_scaled[-seq_length:, 1]   # "Open" feature
initial_sequence_high = data_scaled[-seq_length:, 2]   # "High" feature

# Predict future values for each feature
predictions_close = predict_future(
    model=models["Close"],
    initial_sequence=initial_sequence_close,
    future_steps=future_steps,
    scaler=scalers["all_features"],
    feature_index=0
)
predictions_open = predict_future(
    model=models["Open"],
    initial_sequence=initial_sequence_open,
    future_steps=future_steps,
    scaler=scalers["all_features"],
    feature_index=1
)
predictions_high = predict_future(
    model=models["High"],
    initial_sequence=initial_sequence_high,
    future_steps=future_steps,
    scaler=scalers["all_features"],
    feature_index=2
)

future_steps = 30

# Prepare initial sequences for each feature using the last sequence from scaled data
initial_sequence_close = data_scaled[-seq_length:, 0]  # "Close" feature
initial_sequence_open = data_scaled[-seq_length:, 1]   # "Open" feature
initial_sequence_high = data_scaled[-seq_length:, 2]   # "High" feature

# Predict future values for each feature
predictions_close = predict_future(model=models["Close"],
initial_sequence=initial_sequence_close, future_steps=future_steps,
scaler=scalers["all_features"], feature_index=0)
predictions_open = predict_future(model=models["Open"],
initial_sequence=initial_sequence_open, future_steps=future_steps,
scaler=scalers["all_features"], feature_index=1)
predictions_high = predict_future(model=models["High"],
initial_sequence=initial_sequence_high, future_steps=future_steps,
scaler=scalers["all_features"], feature_index=2)

# Generate future dates for predictions
last_date = df['Date'].iloc[-1]
future_dates = pd.date_range(start=last_date + pd.DateOffset(days=1),
periods=future_steps, freq='D')
```

```
# Load and prepare the ground truth data for the predicted period
truth_data_df = pd.read_csv('/content/HistoricalData_2_3_21_to_3_4_21.csv')
truth_data_df['Date'] = pd.to_datetime(truth_data_df['Date'])  # Ensure dates are in
datetime format
truth_data_df = truth_data_df.sort_values('Date').reset_index(drop=True)

# Clean up currency symbols and convert to floats
data_Close = df['Close/Last'].str.replace('$', '').astype(float).values
data_Open = df['Open'].str.replace('$', '').astype(float).values
data_High = df['High'].str.replace('$', '').astype(float).values

# Ground truth data for the prediction period
ground_truth_close = truth_data_df['Close/Last'].str.replace('$', '').astype(float).values
ground_truth_open = truth_data_df['Open'].str.replace('$', '').astype(float).values
ground_truth_high = truth_data_df['High'].str.replace('$', '').astype(float).values
ground_truth_dates = truth_data_df['Date']

# Concatenate historical and future data for continuous plotting
historical_dates = df['Date']

# Plot the results for each feature
plt.figure(figsize=(16, 10))

# Plot Close
plt.subplot(3, 1, 1)
plt.plot(historical_dates, data_Close, label='Historical Close', color='blue')  # Historical
data
plt.plot(future_dates, predictions_close, label='Predicted Close', linestyle='--',
color='orange')  # Predicted data
plt.plot(ground_truth_dates, ground_truth_close, label='Actual Close (Ground Truth)',
color='black', marker='.')  # Ground truth
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.title('Historical, Predicted, and Actual Close Prices')
plt.legend()

# Plot Open
plt.subplot(3, 1, 2)
plt.plot(historical_dates, data_Open, label='Historical Open', color='green')  # Historical
data
plt.plot(future_dates, predictions_open, label='Predicted Open', linestyle='--',
color='orange')  # Predicted data
plt.plot(ground_truth_dates, ground_truth_open, label='Actual Open (Ground Truth)',
color='black', marker='.')  # Ground truth
plt.xlabel('Date')
plt.ylabel('Open Price')
plt.title('Historical, Predicted, and Actual Open Prices')
plt.legend()

# Plot High
plt.subplot(3, 1, 3)
plt.plot(historical_dates, data_High, label='Historical High', color='red')  # Historical data
plt.plot(future_dates, predictions_high, label='Predicted High', linestyle='--',
color='orange')  # Predicted data
plt.plot(ground_truth_dates, ground_truth_high, label='Actual High (Ground Truth)',
color='black', marker='.')  # Ground truth
plt.xlabel('Date')
plt.ylabel('High Price')
plt.title('Historical, Predicted, and Actual High Prices')
plt.legend()

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```