LAB Assignment 5.1 - Univariate Time Series using LSTM

Objective - To forecast future values of a univariate time series using LSTM-based models

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Dataset Link - https://www.kaggle.com/datasets/anirudhchauhan/retail-store-inventory-forecasting-dataset?resource=download

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

from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout, Bidirectional
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

```
np.random.seed(42)
```

```
# Load dataset
df = pd.read_csv('/content/retail_store_inventory.csv')

# Display the basic information
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73100 entries, 0 to 73099
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Date                73100 non-null  object 
 1   Store ID            73100 non-null  object 
 2   Product ID          73100 non-null  object 
 3   Category            73100 non-null  object 
 4   Region              73100 non-null  object 
 5   Inventory Level     73100 non-null  int64  
 6   Units Sold          73100 non-null  int64  
 7   Units Ordered       73100 non-null  int64  
 8   Demand Forecast     73100 non-null  float64
 9   Price               73100 non-null  float64
 10  Discount            73100 non-null  int64  
 11  Weather Condition   73100 non-null  object 
 12  Holiday/Promotion   73100 non-null  int64  
 13  Competitor Pricing  73100 non-null  float64
 14  Seasonality         73100 non-null  object 
dtypes: float64(3), int64(5), object(7)
memory usage: 8.4+ MB
None
```

```
df.head(10)
```

	Date	Store ID	Product ID	Category	Region	Inventory Level	Units Sold	Units Ordered	Demand Forecast	Price	Discount	Weather Condition	Holiday/Promotion	Compe Pı
0	2022-01-01	S001	P0001	Groceries	North	231	127	55	135.47	33.50	20	Rainy	0	
1	2022-01-01	S001	P0002	Toys	South	204	150	66	144.04	63.01	20	Sunny	0	
2	2022-01-01	S001	P0003	Toys	West	102	65	51	74.02	27.99	10	Sunny	1	
3	2022-01-01	S001	P0004	Toys	North	469	61	164	62.18	32.72	10	Cloudy	1	
4	2022-01-01	S001	P0005	Electronics	East	166	14	135	9.26	73.64	0	Sunny	0	
5	2022-01-01	S001	P0006	Groceries	South	138	128	102	139.82	76.83	10	Sunny	1	
6	2022-01-01	S001	P0007	Furniture	East	359	97	167	108.92	34.16	10	Rainy	1	
7	2022-01-01	S001	P0008	Clothing	North	380	312	54	329.73	97.99	5	Cloudy	0	
8	2022-01-01	S001	P0009	Electronics	West	183	175	135	174.15	20.74	10	Cloudy	0	
9	2022-01-01	S001	P0010	Toys	South	108	28	196	24.47	59.99	0	Rainy	1	

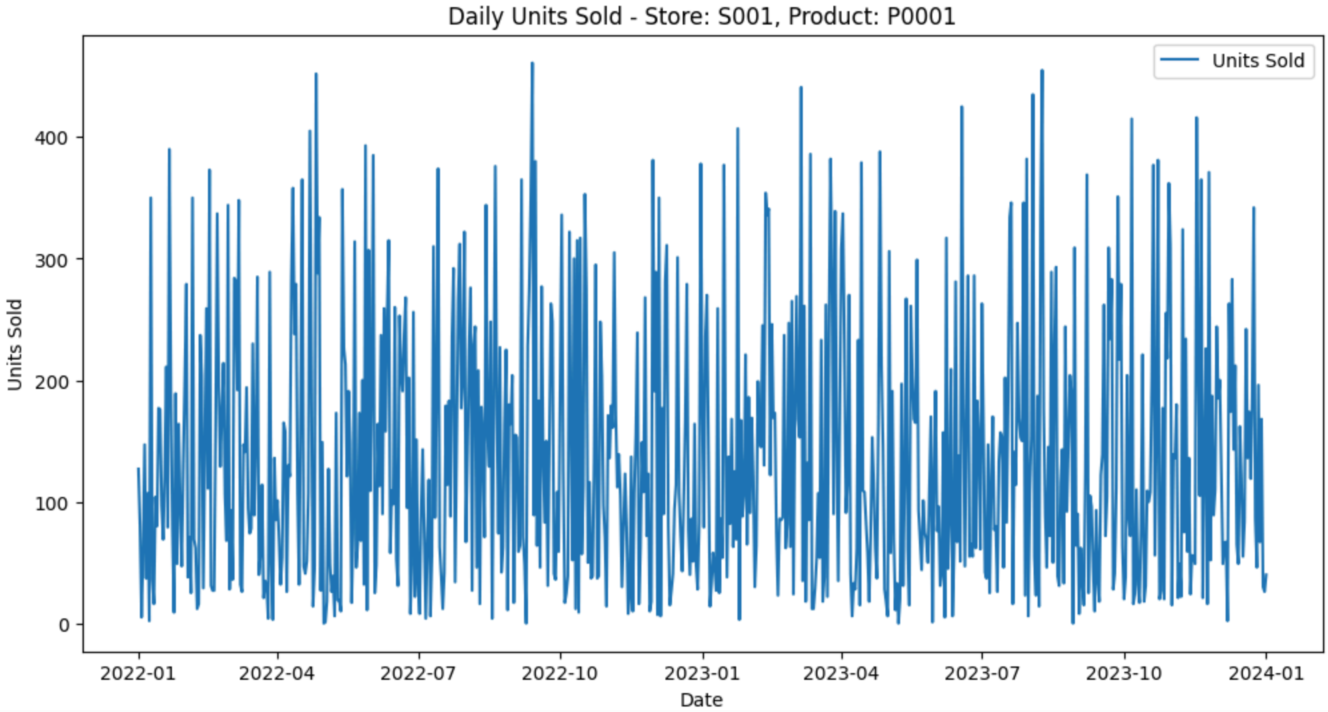
```
# Filter for a single store and product
store_id = "S001"
product_id = "P0001"

df_filtered = df[(df['Store ID'] == store_id) & (df['Product ID'] == product_id)].copy()

# Convert date, sort and clean
df_filtered['Date'] = pd.to_datetime(df_filtered['Date'])
df_filtered.sort_values(by='Date', inplace=True)
df_filtered.dropna(inplace=True)


# Prepare time series
time_series = df_filtered[['Date', 'Units Sold']].copy()
time_series.set_index('Date', inplace=True)

# Plot
plt.figure(figsize=(12,6))
plt.plot(time_series.index, time_series['Units Sold'], label='Units Sold')
plt.xlabel('Date')
plt.ylabel('Units Sold')
plt.title(f'Daily Units Sold - Store: {store_id}, Product: {product_id}')
plt.legend()
plt.show()
```




```
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(time_series)

scaled_data[:5]
```

```
array([[0.27548807],
       [0.17570499],
       [0.01084599],
       [0.12581345],
       [0.31887202]])
```

```
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(seq_length, len(data)):
        X.append(data[i-seq_length:i, 0])
        y.append(data[i, 0])
    return np.array(X), np.array(y)

sequence_length = 30  # 1 month of history
X, y = create_sequences(scaled_data, sequence_length)

X = X.reshape(X.shape[0], X.shape[1], 1)


split = int(len(X) * 0.8)
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]

print(f'Train shape: {X_train.shape}, Test shape: {X_test.shape}')
```

```
Train shape: (560, 30, 1), Test shape: (141, 30, 1)
```

```
model = Sequential()
model.add(Bidirectional(LSTM(64, return_sequences=True), input_shape=(X_train.shape[1], 1)))
model.add(Dropout(0.2))
model.add(Bidirectional(LSTM(64)))
model.add(Dropout(0.2))
model.add(Dense(1))

model.compile(optimizer='adam', loss='mean_squared_error')

# Callbacks
early_stop = EarlyStopping(monitor='val_loss', patience=5)
checkpoint = ModelCheckpoint('best_model.h5', monitor='val_loss', save_best_only=True)

model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/bidirectional.py:107: UserWarning: Do not pass an `input_shape`/`input_
  super().__init__(**kwargs)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
bidirectional (Bidirectional)	(None, 30, 128)	33,792
dropout (Dropout)	(None, 30, 128)	0
bidirectional_1 (Bidirectional)	(None, 128)	98,816
dropout_1 (Dropout)	(None, 128)	0
dense (Dense)	(None, 1)	129

```
 Total params: 132,737 (518.50 KB)
 Trainable params: 132,737 (518.50 KB)
 Non-trainable params: 0 (0.00 B)
```

```
history = model.fit(
    X_train, y_train,
    epochs=20,
    batch_size=32,
    validation_data=(X_test, y_test),
    callbacks=[early_stop, checkpoint]
)
```

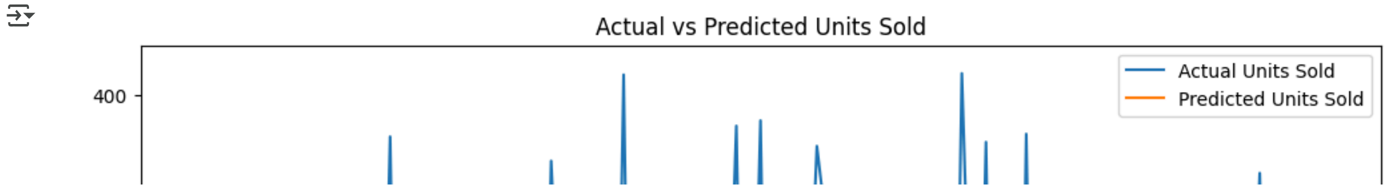
```
Epoch 1/20
17/18 ━━━━━━━━━━━━━━━━━━━━ 0s 55ms/step - loss: 0.0852WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `
18/18 ━━━━━━━━━━━━━━━━━━━━ 10s 113ms/step - loss: 0.0835 - val_loss: 0.0547
Epoch 2/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 2s 76ms/step - loss: 0.0579 - val_loss: 0.0550
Epoch 3/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 2s 64ms/step - loss: 0.0623 - val_loss: 0.0549
Epoch 4/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 62ms/step - loss: 0.0572 - val_loss: 0.0570
Epoch 5/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step - loss: 0.0555 - val_loss: 0.0564
Epoch 6/20
18/18 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step - loss: 0.0564 - val_loss: 0.0583
```

```
model.load_weights('best_model.h5')

predicted = model.predict(X_test)
predicted_values = scaler.inverse_transform(predicted)
actual_values = scaler.inverse_transform(y_test.reshape(-1, 1))
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 3s 354ms/step
```

```
plt.figure(figsize=(12,6))
plt.plot(actual_values, label='Actual Units Sold')
plt.plot(predicted_values, label='Predicted Units Sold')
plt.title('Actual vs Predicted Units Sold')
plt.xlabel('Time')
plt.ylabel('Units Sold')
plt.legend()
plt.show()
```




```
rmse = np.sqrt(mean_squared_error(actual_values, predicted_values))
mae = mean_absolute_error(actual_values, predicted_values)

print(f'Root Mean Squared Error (RMSE): {rmse:.2f}')
print(f'Mean Absolute Error (MAE): {mae:.2f}')
```

```
Root Mean Squared Error (RMSE): 107.85
Mean Absolute Error (MAE): 88.95
```

```
plt.plot(history.history['loss'], label='Train Loss')
```