Unemployment LSTM Model - Training (1997-2020), Training (2021-2023)

In [ ]:
```python
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Input
from sklearn.model_selection import TimeSeriesSplit

import gdown
import time
```

In [ ]:
```python
# Load the dataset
url = 'https://drive.google.com/uc?id=1iJ-fXzt1maahR-_YH36yFBrHQ7lYQWf9'
output = 'data_unemployment.csv'
gdown.download(url, output, quiet=False)

# Check the file content
with open(output, 'r') as file:
    content = file.read()
    print("File content preview:")
    print(content[:500])

# Load the CSV file
try:
    data_unemployment = pd.read_csv(output, delimiter=',')
    print(data_unemployment.head())
except pd.errors.ParserError as e:
    print("Error parsing CSV file:", e)
```

```
Downloading...
From: https://drive.google.com/uc?id=1iJ-fXzt1maahR-_YH36yFBrHQ7lYQWf9
To: d:\OneDrive (Personal)\OneDrive\~ TMU 2023\CIND 820 - Big Data Analytics Project
\06 - Initial Results & Code (10%)\data_unemployment.csv
100%|██████████| 799k/799k [00:00<00:00, 3.66MB/s]
```

```
File content preview:
ref_date,geo,labour_force,sex,age_group,uom,value,industry_classification,naics,sex_
binary,age_group_numeric,geo_code,date_ordinal
1997,newfoundland and labrador,unemployment rate,males,25 to 54 years,Percentage,12.
1,"fishing, hunting and trapping",114,1,1,210,729025
1998,newfoundland and labrador,unemployment rate,males,25 to 54 years,Percentage,9.
0,"fishing, hunting and trapping",114,1,1,210,729390
1999,newfoundland and labrador,unemployment rate,males,25 to 54 years,Percentage,9.
4,"fishing, h
```

	ref_date	geo	labour_force	sex	age_group	uom	value	industry_classification	naics	sex_binary	age_group_numeric	geo_code	date_ordinal
0	1997	newfoundland and labrador	unemployment rate	males	25 to 54 years	Percentage	12.1	fishing, hunting and trapping	114	1	1	210	729025
1	1998	newfoundland and labrador	unemployment rate	males	25 to 54 years	Percentage	9.0	fishing, hunting and trapping	114	1	1	210	729390
2	1999	newfoundland and labrador	unemployment rate	males	25 to 54 years	Percentage	9.4	fishing, hunting and trapping	114	1	1	210	729755
3	2000	newfoundland and labrador	unemployment rate	males	25 to 54 years	Percentage	11.4	fishing, hunting and trapping	114	1	1	210	730120
4	2001	newfoundland and labrador	unemployment rate	males	25 to 54 years	Percentage	20.7	fishing, hunting and trapping	114	1	1	210	730486

In [ ]:
```python
# Convert 'ref_date' to datetime
data_unemployment['ref_date'] = pd.to_datetime(data_unemployment['ref_date'], forma

# Label encode the 'industry_classification' column
data_unemployment['industry_classification'] = data_unemployment['industry_classifi
label_encoder = LabelEncoder()
data_unemployment['industry_code'] = label_encoder.fit_transform(data_unemployment[
```

In [ ]:
```python
# Normalize the data
scaler = MinMaxScaler(feature_range=(0, 1))
features = ['value', 'date_ordinal', 'sex_binary', 'age_group_numeric', 'geo_code',
scaled_data = scaler.fit_transform(data_unemployment[features])

# Function to create sequences for forecasting
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, 0]
        xs.append(x)
        ys.append(y)
    return np.array(xs), np.array(ys)

# Define sequence length
SEQ_LENGTH = 3
```

```
# Split the data into training and testing sets based on the date
train_data = data_unemployment[data_unemployment['ref_date'] < '2021']
test_data = data_unemployment[data_unemployment['ref_date'] >= '2021']

# Normalize training and testing data separately
scaled_train_data = scaler.fit_transform(train_data[features])
scaled_test_data = scaler.transform(test_data[features])
```

In [ ]:
```
# Create sequences for training and testing
X_train, y_train = create_sequences(scaled_train_data, SEQ_LENGTH)
X_test, y_test = create_sequences(scaled_test_data, SEQ_LENGTH)

# Define cross-validation procedure
tscv = TimeSeriesSplit(n_splits=5)
cv_mse_scores = []

# Perform cross-validation
for train_index, val_index in tscv.split(X_train):
    X_train_cv, X_val_cv = X_train[train_index], X_train[val_index]
    y_train_cv, y_val_cv = y_train[train_index], y_train[val_index]

    # Define the LSTM model for forecasting
    model = Sequential()
    model.add(Input(shape=(SEQ_LENGTH, X_train.shape[2])))
    model.add(LSTM(50, activation='relu'))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mse')

    # Train the model
    start = time.time()
    history = model.fit(X_train_cv, y_train_cv, epochs=200, batch_size=32, validati
    end = time.time()

    # Evaluate the model
    val_loss = model.evaluate(X_val_cv, y_val_cv, verbose=0)
    cv_mse_scores.append(val_loss)

    print(f"Validation Loss: {val_loss}, Training time: {end - start} seconds")

print('Cross-Validation Mean Squared Error:', np.mean(cv_mse_scores))
```

```
Validation Loss: 0.02954861707985401, Training time: 26.910234928131104 seconds
Validation Loss: 0.019256656989455223, Training time: 32.976601362228394 seconds
Validation Loss: 0.012774420902132988, Training time: 39.478280544281006 seconds
Validation Loss: 0.02630561962723732, Training time: 47.53340983390808 seconds
Validation Loss: 0.017802385613322258, Training time: 55.34806728363037 seconds
Cross-Validation Mean Squared Error: 0.02113754004240036
```

In [ ]:
```
# Train the final model on the entire training set
model = Sequential()
model.add(Input(shape=(SEQ_LENGTH, X_train.shape[2])))
model.add(LSTM(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
```

```
print(model.summary())

start = time.time()
history = model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0
end = time.time()

# Convert elapsed time to minutes and seconds
elapsed_time = end - start
minutes = int(elapsed_time // 60)
seconds = int(elapsed_time % 60)

print(f"\nTraining time: {minutes} minutes and {seconds} seconds")
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
lstm_5 (LSTM)	(None, 50)	11,400
dense_5 (Dense)	(None, 1)	51

Total params: 11,451 (44.73 KB)

Trainable params: 11,451 (44.73 KB)

Non-trainable params: 0 (0.00 B)

```
None
Epoch 1/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0835 - val_loss: 0.0241
Epoch 2/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0176 - val_loss: 0.0190
Epoch 3/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0177 - val_loss: 0.0194
Epoch 4/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0156 - val_loss: 0.0176
Epoch 5/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0162 - val_loss: 0.0179
Epoch 6/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0145 - val_loss: 0.0179
Epoch 7/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0137 - val_loss: 0.0178
Epoch 8/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0146 - val_loss: 0.0171
Epoch 9/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0145 - val_loss: 0.0171
Epoch 10/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0141 - val_loss: 0.0171
Epoch 11/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0139 - val_loss: 0.0172
Epoch 12/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0141 - val_loss: 0.0174
Epoch 13/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0144 - val_loss: 0.0171
Epoch 14/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0130 - val_loss: 0.0167
Epoch 15/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0143 - val_loss: 0.0166
Epoch 16/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0131 - val_loss: 0.0166
Epoch 17/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0137 - val_loss: 0.0166
Epoch 18/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0167
Epoch 19/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0136 - val_loss: 0.0170
Epoch 20/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0126 - val_loss: 0.0172
Epoch 21/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0139 - val_loss: 0.0163
Epoch 22/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0133 - val_loss: 0.0165
Epoch 23/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0131 - val_loss: 0.0165
Epoch 24/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0130 - val_loss: 0.0161
Epoch 25/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0135 - val_loss: 0.0168
Epoch 26/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0126 - val_loss: 0.0158
Epoch 27/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0127 - val_loss: 0.0161
Epoch 28/100
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151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0161
Epoch 29/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0121 - val_loss: 0.0166
Epoch 30/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0126 - val_loss: 0.0160
Epoch 31/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0157
Epoch 32/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0123 - val_loss: 0.0155
Epoch 33/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0159
Epoch 34/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0125 - val_loss: 0.0157
Epoch 35/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0134 - val_loss: 0.0160
Epoch 36/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0125 - val_loss: 0.0157
Epoch 37/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0126 - val_loss: 0.0169
Epoch 38/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0121 - val_loss: 0.0160
Epoch 39/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0125 - val_loss: 0.0158
Epoch 40/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0126 - val_loss: 0.0153
Epoch 41/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0128 - val_loss: 0.0159
Epoch 42/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0117 - val_loss: 0.0155
Epoch 43/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0156
Epoch 44/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0130 - val_loss: 0.0160
Epoch 45/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0119 - val_loss: 0.0153
Epoch 46/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0121 - val_loss: 0.0152
Epoch 47/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0129 - val_loss: 0.0155
Epoch 48/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0156
Epoch 49/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0121 - val_loss: 0.0151
Epoch 50/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0155
Epoch 51/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0114 - val_loss: 0.0152
Epoch 52/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0118 - val_loss: 0.0161
Epoch 53/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0117 - val_loss: 0.0150
Epoch 54/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0120 - val_loss: 0.0151
Epoch 55/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0114 - val_loss: 0.0154
Epoch 56/100
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151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0150
Epoch 57/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0117 - val_loss: 0.0156
Epoch 58/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0118 - val_loss: 0.0153
Epoch 59/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0117 - val_loss: 0.0154
Epoch 60/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0113 - val_loss: 0.0158
Epoch 61/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0125 - val_loss: 0.0154
Epoch 62/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0113 - val_loss: 0.0152
Epoch 63/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0152
Epoch 64/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0114 - val_loss: 0.0160
Epoch 65/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0122 - val_loss: 0.0153
Epoch 66/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0151
Epoch 67/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0108 - val_loss: 0.0157
Epoch 68/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0111 - val_loss: 0.0156
Epoch 69/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0112 - val_loss: 0.0152
Epoch 70/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0111 - val_loss: 0.0160
Epoch 71/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0118 - val_loss: 0.0153
Epoch 72/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0152
Epoch 73/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0159
Epoch 74/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0113 - val_loss: 0.0154
Epoch 75/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0115 - val_loss: 0.0155
Epoch 76/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0115 - val_loss: 0.0153
Epoch 77/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0110 - val_loss: 0.0159
Epoch 78/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0106 - val_loss: 0.0152
Epoch 79/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0109 - val_loss: 0.0152
Epoch 80/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0113 - val_loss: 0.0158
Epoch 81/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0115 - val_loss: 0.0152
Epoch 82/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0109 - val_loss: 0.0151
Epoch 83/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0113 - val_loss: 0.0153
Epoch 84/100
```
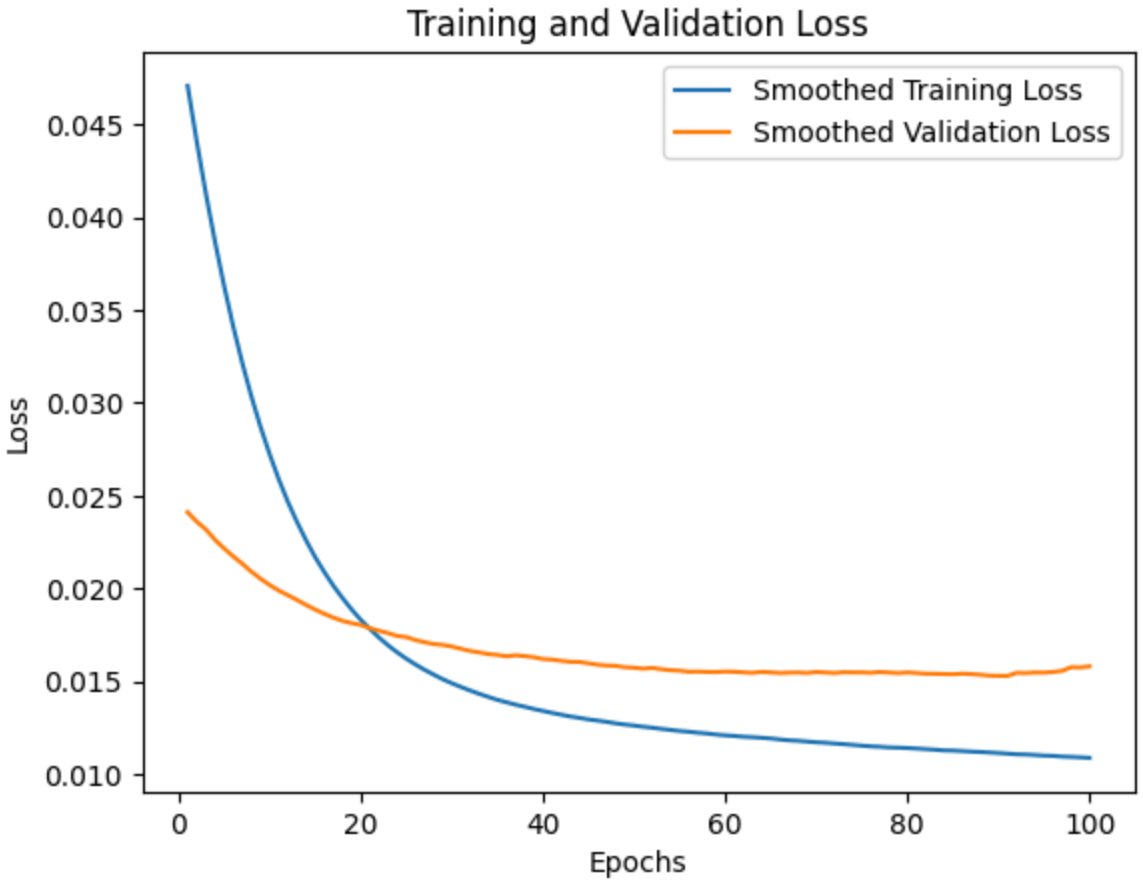

```
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0109 - val_loss: 0.0153
Epoch 85/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0111 - val_loss: 0.0153
Epoch 86/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0157
Epoch 87/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0111 - val_loss: 0.0152
Epoch 88/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0118 - val_loss: 0.0151
Epoch 89/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0109 - val_loss: 0.0149
Epoch 90/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0108 - val_loss: 0.0152
Epoch 91/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0113 - val_loss: 0.0152
Epoch 92/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0104 - val_loss: 0.0170
Epoch 93/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0153
Epoch 94/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0158
Epoch 95/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0111 - val_loss: 0.0154
Epoch 96/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0114 - val_loss: 0.0158
Epoch 97/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0161
Epoch 98/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0112 - val_loss: 0.0176
Epoch 99/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0114 - val_loss: 0.0156
Epoch 100/100
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0104 - val_loss: 0.0163

Training time: 0 minutes and 27 seconds
```

In [ ]:

```python
# Retrieve loss and validation loss from history
loss = history.history['loss']
val_loss = history.history['val_loss']

# Define the smoothing function
def smooth_curve(points, factor=0.9):
    smoothed_points = []
    for point in points:
        if smoothed_points:
            previous = smoothed_points[-1]
            smoothed_points.append(previous * factor + point * (1 - factor))
        else:
            smoothed_points.append(point)
    return smoothed_points

# Smooth the loss curves
smoothed_loss = smooth_curve(loss)
smoothed_val_loss = smooth_curve(val_loss)

# Plot smoothed training and validation loss
```

```
plt.plot(range(1, len(smoothed_loss) + 1), smoothed_loss, label='Smoothed Training
plt.plot(range(1, len(smoothed_val_loss) + 1), smoothed_val_loss, label='Smoothed V
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

# Identify the epoch with the lowest validation loss
best_epoch = np.argmin(smoothed_val_loss) + 1
print(f"Best epoch based on validation loss: {best_epoch}")
```




```
Best epoch based on validation loss: 91
```

In [ ]:

```
# Refine the LSTM model
model = Sequential()
model.add(Input(shape=(SEQ_LENGTH, X_train.shape[2])))
model.add(LSTM(50, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')

print(model.summary())

# Train the model
start = time.time()
history = model.fit(X_train, y_train, epochs=best_epoch, batch_size=32, validation_
end = time.time()

print(f"\nTraining time: {minutes} minutes and {seconds} seconds")
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
lstm_6 (LSTM)	(None, 50)	11,400
dense_6 (Dense)	(None, 1)	51

Total params: 11,451 (44.73 KB)

Trainable params: 11,451 (44.73 KB)

Non-trainable params: 0 (0.00 B)

```
None
Epoch 1/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0711 - val_loss: 0.0195
Epoch 2/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0169 - val_loss: 0.0183
Epoch 3/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0164 - val_loss: 0.0178
Epoch 4/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0146 - val_loss: 0.0174
Epoch 5/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0144 - val_loss: 0.0179
Epoch 6/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0136 - val_loss: 0.0169
Epoch 7/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0148 - val_loss: 0.0171
Epoch 8/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0137 - val_loss: 0.0168
Epoch 9/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0137 - val_loss: 0.0175
Epoch 10/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0142 - val_loss: 0.0170
Epoch 11/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0141 - val_loss: 0.0167
Epoch 12/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0135 - val_loss: 0.0165
Epoch 13/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0133 - val_loss: 0.0164
Epoch 14/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0130 - val_loss: 0.0162
Epoch 15/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0134 - val_loss: 0.0168
Epoch 16/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0129 - val_loss: 0.0161
Epoch 17/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0139 - val_loss: 0.0165
Epoch 18/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0130 - val_loss: 0.0161
Epoch 19/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0143 - val_loss: 0.0167
Epoch 20/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0139 - val_loss: 0.0161
Epoch 21/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0132 - val_loss: 0.0162
Epoch 22/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0128 - val_loss: 0.0162
Epoch 23/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0136 - val_loss: 0.0162
Epoch 24/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0134 - val_loss: 0.0162
Epoch 25/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0124 - val_loss: 0.0157
Epoch 26/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0126 - val_loss: 0.0163
Epoch 27/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0133 - val_loss: 0.0156
Epoch 28/91
```

```
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0135 - val_loss: 0.0156
Epoch 29/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0134 - val_loss: 0.0155
Epoch 30/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0123 - val_loss: 0.0169
Epoch 31/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0157
Epoch 32/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0131 - val_loss: 0.0161
Epoch 33/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0128 - val_loss: 0.0161
Epoch 34/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0139 - val_loss: 0.0157
Epoch 35/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0120 - val_loss: 0.0155
Epoch 36/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0122 - val_loss: 0.0160
Epoch 37/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0124 - val_loss: 0.0153
Epoch 38/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0124 - val_loss: 0.0153
Epoch 39/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0117 - val_loss: 0.0154
Epoch 40/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0122 - val_loss: 0.0151
Epoch 41/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0132 - val_loss: 0.0155
Epoch 42/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0123 - val_loss: 0.0153
Epoch 43/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0129 - val_loss: 0.0151
Epoch 44/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0113 - val_loss: 0.0154
Epoch 45/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0118 - val_loss: 0.0150
Epoch 46/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0118 - val_loss: 0.0154
Epoch 47/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0127 - val_loss: 0.0152
Epoch 48/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0111 - val_loss: 0.0152
Epoch 49/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0120 - val_loss: 0.0160
Epoch 50/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0119 - val_loss: 0.0148
Epoch 51/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0115 - val_loss: 0.0155
Epoch 52/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0119 - val_loss: 0.0149
Epoch 53/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0116 - val_loss: 0.0149
Epoch 54/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0120 - val_loss: 0.0148
Epoch 55/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0114 - val_loss: 0.0158
Epoch 56/91
```

```
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0113 - val_loss: 0.0152
Epoch 57/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0118 - val_loss: 0.0148
Epoch 58/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0122 - val_loss: 0.0151
Epoch 59/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0117 - val_loss: 0.0154
Epoch 60/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0115 - val_loss: 0.0152
Epoch 61/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0119 - val_loss: 0.0147
Epoch 62/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0112 - val_loss: 0.0152
Epoch 63/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0115 - val_loss: 0.0149
Epoch 64/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0116 - val_loss: 0.0147
Epoch 65/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0111 - val_loss: 0.0148
Epoch 66/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0119 - val_loss: 0.0147
Epoch 67/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0107 - val_loss: 0.0149
Epoch 68/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0107 - val_loss: 0.0147
Epoch 69/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0121 - val_loss: 0.0148
Epoch 70/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0118 - val_loss: 0.0147
Epoch 71/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0112 - val_loss: 0.0148
Epoch 72/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0109 - val_loss: 0.0151
Epoch 73/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0148
Epoch 74/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0112 - val_loss: 0.0155
Epoch 75/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0109 - val_loss: 0.0148
Epoch 76/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0111 - val_loss: 0.0150
Epoch 77/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0114 - val_loss: 0.0149
Epoch 78/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0117 - val_loss: 0.0152
Epoch 79/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0111 - val_loss: 0.0147
Epoch 80/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0108 - val_loss: 0.0153
Epoch 81/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0105 - val_loss: 0.0148
Epoch 82/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0106 - val_loss: 0.0154
Epoch 83/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0150
Epoch 84/91
```

```
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0110 - val_loss: 0.0156
Epoch 85/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0115 - val_loss: 0.0147
Epoch 86/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0109 - val_loss: 0.0147
Epoch 87/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0107 - val_loss: 0.0147
Epoch 88/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0108 - val_loss: 0.0146
Epoch 89/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0102 - val_loss: 0.0147
Epoch 90/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0107 - val_loss: 0.0149
Epoch 91/91
151/151 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0106 - val_loss: 0.0147

Training time: 0 minutes and 27 seconds
```

In [ ]:

```python
# Evaluate the model
loss = model.evaluate(X_test, y_test)
print(f'Test Loss: {loss}')

# Make predictions
predictions = model.predict(X_test)

# Inverse transform the predictions and the actual values
predictions_inv = scaler.inverse_transform(np.concatenate((predictions, np.zeros((p
y_test_inv = scaler.inverse_transform(np.concatenate((y_test.reshape(-1, 1), np.zer

# Compare the first few predictions with the actual values
comparison = pd.DataFrame({'Actual': y_test_inv, 'Predicted': predictions_inv})
print(comparison.head())
```

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 898us/step - loss: 0.1112
Test Loss: 0.09980463981628418
21/21 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
   Actual  Predicted
0    19.7  16.837419
1    15.1  17.222478
2    15.7  18.404970
3    16.0  18.723281
4    10.9  17.777026
```