future 30 days

7 days past

The dataset is sasional and Additive time series

https://medium.com/aiskunks/time-series-forecasting-using-deep-learning-ebe383913c5f

Import necessary libraries

In [13]:
```
from pyspark.sql import SparkSession
from pyspark.sql.functions import col, window, sum, lit, to_date
import matplotlib.pyplot as plt
import pyspark.sql.functions as psf
import pandas as pd
import seaborn as sns
import numpy as np
import keras
import math
import tensorflow as tf
from pyspark.sql import SparkSession
from pyspark.sql.functions import col, window, sum, lit
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
import pyspark.sql.functions as psf
from tensorflow.keras.layers import LSTM, Dense, Dropout, GRU, SimpleRNN
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error


import warnings
warnings.filterwarnings("ignore")
```

Create a spark Session

In [2]:
```
# Create a SparkSession
spark = SparkSession.builder.appName("CA01_Sem_02").config("spark.executor.memor
spark
```

```
24/03/22 15:06:36 WARN SparkSession: Using an existing Spark session; only runtim
e SQL configurations will take effect.
```

Out[2]: **SparkSession - hive**

SparkContext

Spark UI

Version	`v3.3.4`
Master	`local[*]`
AppName	`PySparkShell`

Data_Ingestion Module

To leverage the use of hadoop, this module was created to read the csv files into a pyspark dataframe and save on hadoop hdfs system

In [3]:
```
# data_ingestion function: Loads all CSV files in a directory using PySpark and
# Args:
    # path: Path to the directory containing CSV files
    # hd_path: Hadoop path on HDFS to save the processed files

def data_ingestion( path, hd_path):

    try:
        # Read all files in the directory matching the CSV extension (*.csv)
        df = spark.read.csv(path, header=True, inferSchema = True)

        # Save the DataFrame to Hadoop server - HDFS
        df.write.mode("overwrite").csv(hd_path, header=True)
        print('Data Ingestion Completed')

    except Exception as e:
        print("An error occurred:", e)
```

Running the data_ingestion function

In [14]:
```
# path to directory where the files are
path = "file:///home/hduser/Documents/CA01_Sem_02_MSc_Data_Analytics/*.csv"

# path where the files should be saved on hadoop
hd_path = "/user/hduser/bike_data/"

# Call the processing function
data_ingestion(path, hd_path)
```

```
[Stage 4:==================================================>     (9 + 1) / 10]
Data Ingestion Completed
```

Verifying the data on hadoop

In [5]:
```
!hdfs dfs -ls /user/hduser/bike_data
```

```
Found 11 items
-rw-r--r--   1 hduser supergroup          0 2024-03-22 01:43 /user/hduser/bike_da
ta/_SUCCESS
-rw-r--r--   1 hduser supergroup   96739828 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00000-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   93859490 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00001-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   93287714 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00002-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   89508134 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00003-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   86649859 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00004-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   86128007 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00005-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   78088682 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00006-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   66881784 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00007-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup  107554151 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00008-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
-rw-r--r--   1 hduser supergroup   78814057 2024-03-22 01:43 /user/hduser/bike_da
ta/part-00009-454d576a-1573-4842-95b4-4f7556e392f8-c000.csv
```

Load data from hadoop

In [41]:
```
hd_path = "/user/hduser/bike_data/"

try:


  # Read the CSV files using the specified path
  df = spark.read.csv(hd_path, header = True, inferSchema = True)

  # Print the first few rows of the DataFrame (optional)
  df.show(2)


except Exception as e:
    print("An error occurred:", str(e))
```

```
[Stage 41:==============================================>          (8 + 2) / 10]
```

```
+----------------+-------------+-------------------+-------------------+---------
-----------+----------------+--------------------+--------------+---------+------
----+-----------------+-----------------+-------------+
|         ride_id|rideable_type|         started_at|           ended_at|  start_s
tation_name|start_station_id|    end_station_name|end_station_id|start_lat| start
_lng|          end_lat|           end_lng|member_casual|
+----------------+-------------+-------------------+-------------------+---------
-----------+----------------+--------------------+--------------+---------+------
----+-----------------+-----------------+-------------+
|20CAF4CAD9186B1C|  docked_bike|2023-03-26 16:52:35|2023-03-26 17:22:08|Washingto
n & Inde...|           31272|15th St & Constit...|         31321|38.886978|-77.01
3769|        38.892244|        -77.033234|       casual|
|695D9110D59A0A42| classic_bike|2023-03-28 16:51:30|2023-03-28 17:06:32|      11t
h & C St SE|           31659|D St & Maryland A...|         31612|38.885908|-76.99
1476|38.89484064247075|-76.99591577053069|       member|
+----------------+-------------+-------------------+-------------------+---------
-----------+----------------+--------------------+--------------+---------+------
----+-----------------+-----------------+-------------+
only showing top 2 rows
```

In [42]:
```
df.printSchema()
```

```
root
 |-- ride_id: string (nullable = true)
 |-- rideable_type: string (nullable = true)
 |-- started_at: timestamp (nullable = true)
 |-- ended_at: timestamp (nullable = true)
 |-- start_station_name: string (nullable = true)
 |-- start_station_id: integer (nullable = true)
 |-- end_station_name: string (nullable = true)
 |-- end_station_id: integer (nullable = true)
 |-- start_lat: double (nullable = true)
 |-- start_lng: double (nullable = true)
 |-- end_lat: double (nullable = true)
 |-- end_lng: double (nullable = true)
 |-- member_casual: string (nullable = true)
```

Checking the shape of the dataframe\

In [43]:
```
print((df.count(), len(df.columns)))
```

```
[Stage 43:==============================================>          (8 + 2) / 10]
(4467334, 13)
```

When it comes to using RNNs for time series forecasting or analysis, the data structure must have some level of consistency, as each row of the dataset represents one trip, only a new column was created to represent the tripa and only date and trips were selected from the dataset

In [44]:
```
trips = df.select("started_at")
```

In [45]:
```
trips.show(5)
```

```
+-------------------+
|         started_at|
+-------------------+
|2023-03-26 16:52:35|
|2023-03-28 16:51:30|
|2023-03-28 19:25:55|
|2023-03-03 16:33:58|
|2023-03-11 14:31:24|
+-------------------+
only showing top 5 rows
```

In [46]:
```
trips = trips.withColumn("started_at",to_date(col("started_at")).alias("date"))
```

In [47]:
```
trips.show(5)
```

```
+----------+
|started_at|
+----------+
|2023-03-26|
|2023-03-28|
|2023-03-28|
|2023-03-03|
|2023-03-11|
+----------+
only showing top 5 rows
```

In [48]:
```
trips = trips.withColumn("trips", lit(1))
```

In [49]:
```
trips.show(5)
```

```
+----------+-----+
|started_at|trips|
+----------+-----+
|2023-03-26|    1|
|2023-03-28|    1|
|2023-03-28|    1|
|2023-03-03|    1|
|2023-03-11|    1|
+----------+-----+
only showing top 5 rows
```

In [50]:
```
trips.printSchema()
```

```
root
 |-- started_at: date (nullable = true)
 |-- trips: integer (nullable = false)
```

In [54]:
```
#window_spec = window(trips['started_at'], "1 day")
daily_df = trips.groupBy("started_at").agg(sum("trips").alias("total_trips"))
```

In [56]:
```
daily_df = daily_df.orderBy("started_at")
```

In [57]:
```
daily_df.show(10)
```

```
[Stage 55:==============================================>          (8 + 2) / 10]
```

```
+----------+-----------+
|started_at|total_trips|
+----------+-----------+
|2023-01-01|       6787|
|2023-01-02|       7240|
|2023-01-03|       7559|
|2023-01-04|       7791|
|2023-01-05|       8409|
|2023-01-06|       6719|
|2023-01-07|       7122|
|2023-01-08|       5176|
|2023-01-09|       6520|
|2023-01-10|       7303|
+----------+-----------+
only showing top 10 rows
```

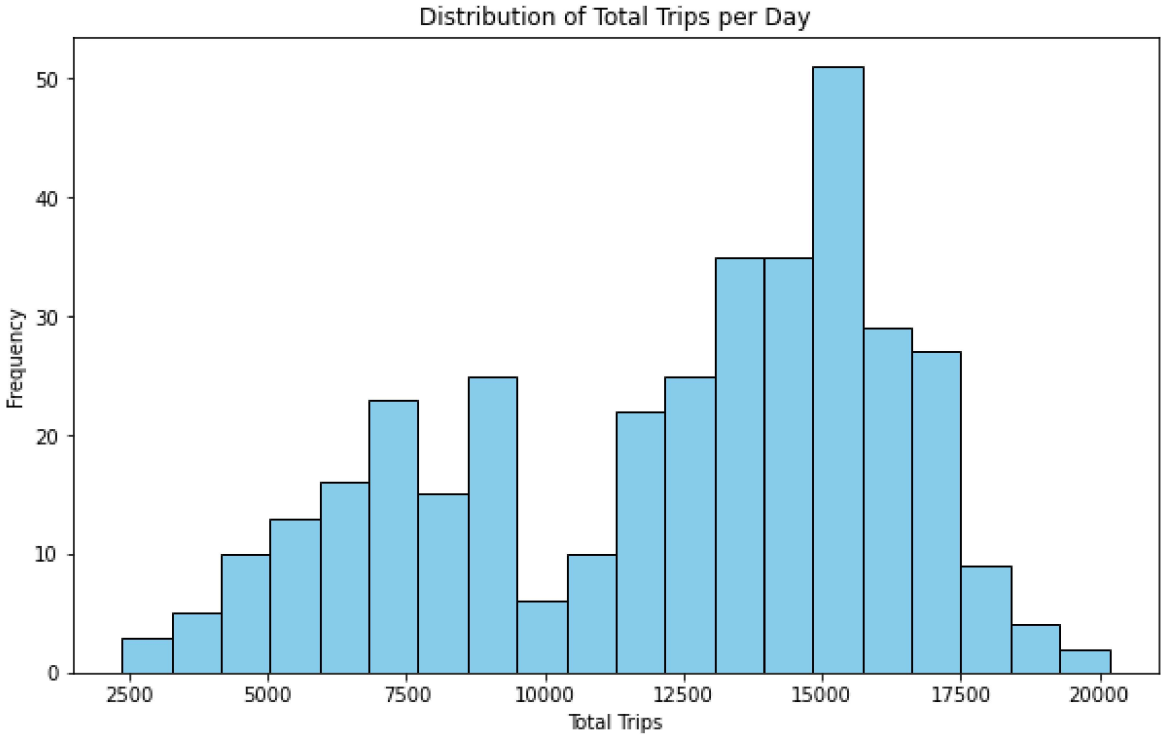
```
[Stage 55:=====================================================>     (9 + 1) / 10]
```

In [58]:
```
daily_df.describe().show()
```

```
+-------+------------------+
|summary|       total_trips|
+-------+------------------+
|  count|               365|
|   mean|12239.271232876712|
| stddev| 3983.046929307485|
|    min|              2369|
|    max|             20174|
+-------+------------------+
```

In [59]:
```
# Converting PySpark DataFrame to Pandas DataFrame
pandas_df = daily_df.toPandas()

# Plotting a histogram
plt.figure(figsize=(10, 6))
plt.hist(pandas_df['total_trips'], bins=20, color='skyblue', edgecolor='black')
plt.title('Distribution of Total Trips per Day')
plt.xlabel('Total Trips')
plt.ylabel('Frequency')
plt.grid(False)
plt.show()
```



In [192…
```
pandas_df = pd.read_csv("pandas_df.csv", index_col='started_at')
```

In [193…
```
pandas_df
```

Out[193…

started_at	total_trips
2023-01-01	6787
2023-01-02	7240
2023-01-03	7559
2023-01-04	7791
2023-01-05	8409
...	...
2023-12-27	2580
2023-12-28	7918
2023-12-29	8659
2023-12-30	7594
2023-12-31	7327

365 rows × 1 columns

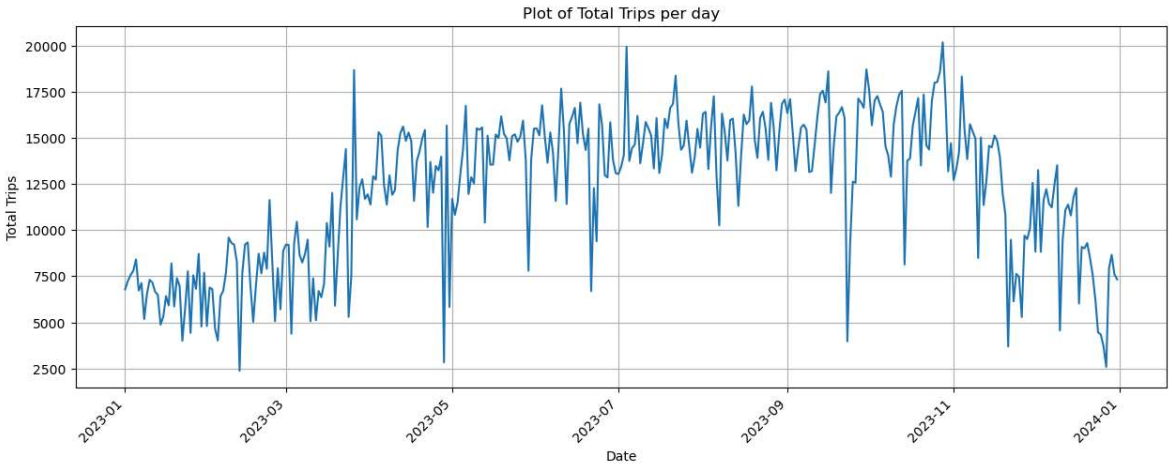
In [180…
```
pandas_df = pandas_df[["started_at","total_trips"]]
```

In [46]:
```
pandas_df['started_at'] = pd.to_datetime(pandas_df['started_at'])

plt.figure(figsize=(15, 5))
```

```
plt.plot(pandas_df["started_at"], pandas_df["total_trips"])

plt.xlabel("Date")
plt.ylabel("Total Trips")
plt.title("Plot of Total Trips per day")
plt.xticks(rotation=45, ha='right')
plt.grid(True)
plt.show()
```



In [183…

```
pandas_df
```

Out[183…

	started_at	total_trips
0	2023-01-01	6787
1	2023-01-02	7240
2	2023-01-03	7559
3	2023-01-04	7791
4	2023-01-05	8409
...	...	...
360	2023-12-27	2580
361	2023-12-28	7918
362	2023-12-29	8659
363	2023-12-30	7594
364	2023-12-31	7327

365 rows × 2 columns

In [187…

```
pandas_df = pandas_df.set_index('started_at')
```

In [190…

```
pandas_df
```

Out[190…

started_at	total_trips
2023-01-01	6787
2023-01-02	7240
2023-01-03	7559
2023-01-04	7791
2023-01-05	8409
…	…
2023-12-27	2580
2023-12-28	7918
2023-12-29	8659
2023-12-30	7594
2023-12-31	7327

365 rows × 1 columns

In [ ]:

In [ ]:

In [43]:
```
trips = pandas_df.iloc[:,-1]
```

In [44]:
```
type(trips)
```

Out[44]:
```
pandas.core.series.Series
```

LSTM Model Building:

```
For building a LSTM model, its important to observe some
parameters:
Input layer: This layer takes the sequence of past trip counts
as input. for this project, a window size of past 7 days was
chosen to feed into the LSTM.
LSTM layer: This layer is the core of the model, responsible for
learning long-term dependencies in the trip count data. The
model will be evaluated with different layers and numbers.
Output layer: This layer predicts the future trip count. It will
be used a single neuron with a linear activation for numerical
prediction.

TensorFlow is designed to work primarily with NumPy arrays.
Because of this, pandas.core.series will be transform into NumPy
arrays.
```

The next thing we need to do is to specify our number of timesteps. Timesteps specify how many previous observations should be considered when the recurrent neural network makes a prediction about the current observation.
We will use 7 (week based) timesteps. This means that for every day that the neural network predicts, it will consider the previous 7 days of trips to determine its output.

In [154…

```
def preprocessing(scaler, look_back):

    pandas_df = pd.read_csv("pandas_df.csv")
    trips = pandas_df.iloc[:,-1]


    # convert to numpy array
    np_trips = trips.to_numpy()
    np_trips = np_trips.astype('float32')
    np_trips = np_trips.reshape(-1,1)


    # convert an array of values into a dataset matrix
    def create_dataset(dataset, look_back):
        dataX, dataY = [], []
        for i in range(len(dataset)-look_back-1):
                a = dataset[i:(i+look_back), 0]
                dataX.append(a)
                dataY.append(dataset[i + look_back, 0])
        return np.array(dataX), np.array(dataY)

    # normalize the dataset
    np_trips = scaler.fit_transform(np_trips)

    # split into train and test sets
    train_size = int(len(np_trips) * 0.75)
    test_size = len(np_trips) - train_size
    train, test = np_trips[0:train_size,:], np_trips[train_size:len(np_trips),:]



    # reshape into X=t and Y=t+1
    trainX, trainY = create_dataset(train, look_back)
    testX, testY = create_dataset(test, look_back)

    # reshape input to be [samples, time steps, features]
    trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
    testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))




    trainX.shape, testX.shape
    return trainX, testX, trainY, testY, np_trips
```

In [155…

```
look_back = 1  # defining the look_back
```

Model 01

In [156…

```
# create and fit the LSTM network
model1 = Sequential()
model1.add(LSTM(8, input_shape=(1, look_back)))
model1.add(Dense(1))
model1.compile(loss='mean_squared_error', optimizer='adam')
model1.summary()
```

Model: "sequential_22"

Layer (type)	Output Shape	Param #
lstm_33 (LSTM)	(None, 8)	320
dense_33 (Dense)	(None, 1)	9

Total params: 329 (1.29 KB)

Trainable params: 329 (1.29 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:

```
# scaler to normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))

#call the function processing
trainX, testX , trainY , testY, np_trips = preprocessing(scaler, look_back)


model1.fit(trainX, trainY, epochs=300, batch_size=16, verbose=1)
```

In [158…

```
# make predictions
trainPredict = model1.predict(trainX)
testPredict = model1.predict(testX)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

In [159…

```
# invert predictions
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
```

In [160…

```
# calculate root mean squared error
trainScore = np.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = np.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

```
Train Score: 2682.08 RMSE
Test Score: 2698.48 RMSE
```

RMSE (Root Mean Squared Error):

```
It measures the difference between predicted and actual trip
counts.
Lower RMSE indicates better performance. Ideally, you want the
error to be as small as possible.
```

Training vs Test Score:

```
The training score (0.13) is slightly lower than the test score
(0.17), which is a good sign. It indicates that the model is not
overfitting to the training data and can generalize somewhat
well to unseen data (test set).
```

Interpretation:

```
An RMSE of 0.13 on the training data suggests that on average,
the model's predictions are off by about 0.13 times the scale of
your trip count data.
The test score of 0.17 indicates a slightly higher average error
on unseen data, but it's still relatively low.
```

Considering the Data Size:

```
With a limited dataset size of 365 days, achieving very low RMSE
scores might be challenging. The model might not be able to
capture all the complex variations in the daily trip counts.
```

Overall Assessment:

These scores suggest that the LSTM model is capturing some underlying patterns in the trip count data and can make reasonable predictions. However, there's still room for improvement.

In [161…

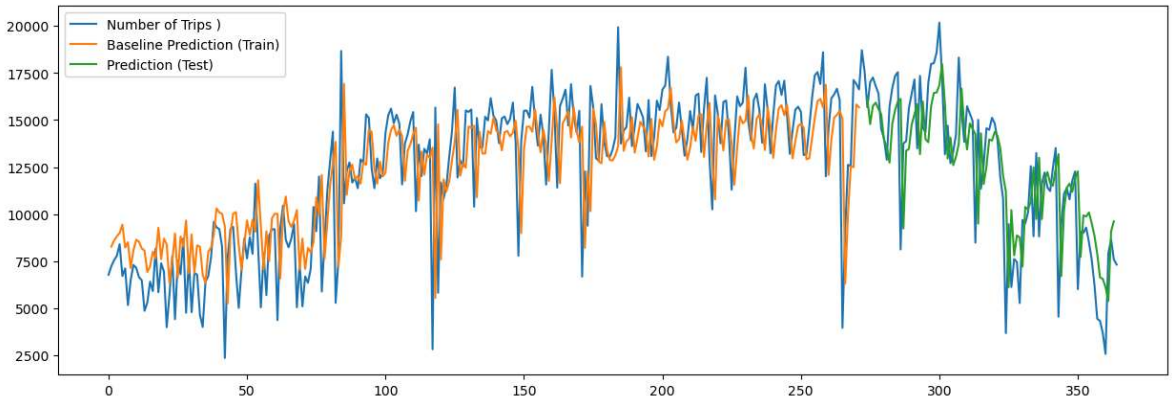
```
#shift train predictions for plotting
trainPredictPlot = np.empty_like(np_trips)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict


# shift test predictions for plotting
testPredictPlot = np.empty_like(np_trips)
testPredictPlot[:, :] = np.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(np_trips)-1, :] = testPred
```

In [162…

```
# plot baseline and predictions

plt.figure(figsize=(15, 5))
plt.plot(scaler.inverse_transform(np_trips))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.legend(['Number of Trips )', 'Baseline Prediction (Train)', 'Prediction (Tes
plt.show()
```



MODEL 02 - LSTM Hyperparameter

In [163…

```
from keras.regularizers import L2
model2 = Sequential()
model2.add(LSTM(128, return_sequences=True, input_shape=(1, look_back)))  # Look
model2.add(LSTM(units=64, return_sequences=True, kernel_regularizer=keras.regula
#model2.add(Dropout(0.2))  # Uncomment and adjust dropout rate
model2.add(LSTM(32))
#model2.add(Dropout(0.2))
model2.add(Dense(16))  # Added a dense layer
model2.add(Dense(1, activation='relu'))
model2.compile(loss='MSLE', optimizer='RMSprop')
model2.summary()
```

Model: "sequential_23"

Layer (type)	Output Shape	Param #
lstm_34 (LSTM)	(None, 1, 128)	66,560
lstm_35 (LSTM)	(None, 1, 64)	49,408
lstm_36 (LSTM)	(None, 32)	12,416
dense_34 (Dense)	(None, 16)	528
dense_35 (Dense)	(None, 1)	17

Total params: 128,929 (503.63 KB)

Trainable params: 128,929 (503.63 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:

```
# scaler to normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))

#call the function processing
trainX, testX , trainY , testY, np_trips = preprocessing(scaler, look_back)

model2.fit(trainX, trainY, epochs=300, validation_data=(testX,testY), batch_size
```

In [165…

```
# make predictions
trainPredict = model2.predict(trainX)
```

```
testPredict = model2.predict(testX)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 1s 52ms/step
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

In [166…

```
# invert predictions
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
```

In [167…

```
# calculate root mean squared error
trainScore = np.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = np.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

```
Train Score: 2822.42 RMSE
Test Score: 2842.10 RMSE
```

In [168…

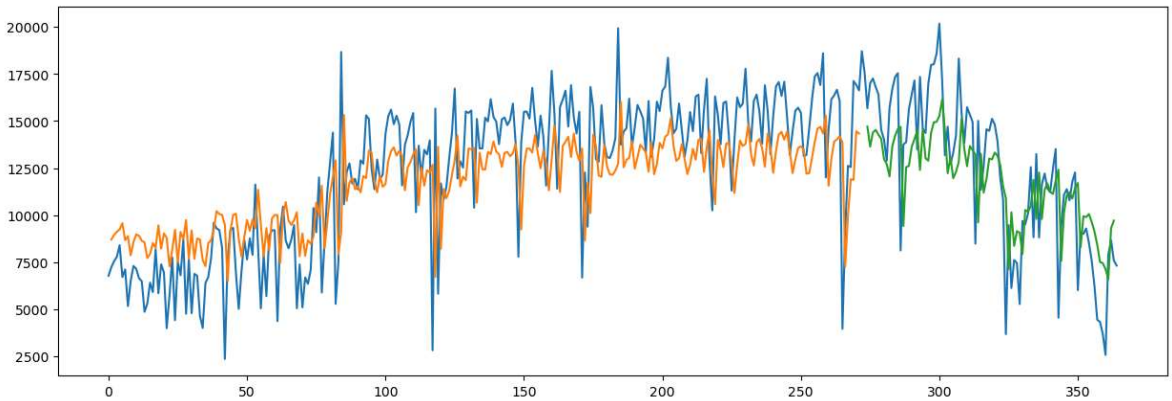
```
# shift train trainPredictPlot for plotting
trainPredictPlot = np.empty_like(np_trips)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict


# shift test testPredictPlot for plotting
testPredictPlot = np.empty_like(np_trips)
testPredictPlot[:, :] = np.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(np_trips)-1, :] = testPred
```

In [169…

```
# plot baseline and predictions
plt.figure(figsize=(15, 5))

plt.plot(scaler.inverse_transform(np_trips))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()
```



In [ ]:

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Model 03 - GRU

In [170…

```
# Define the GRU model
model3 = keras.Sequential()
model3.add(GRU(128, return_sequences=True, input_shape=(1, look_back)))  # Look_
model3.add(GRU(units=64, return_sequences=True, kernel_regularizer=keras.regular
model3.add(Dropout(0.2))  # Uncomment and adjust dropout rate
model3.add(GRU(32))
model3.add(Dropout(0.2))
model3.add(Dense(16))  # Added a dense layer
model3.add(Dense(1))
model3.compile(loss='mean_squared_logarithmic_error', optimizer='adam')
model3.summary()
```

Model: "sequential_24"

Layer (type)	Output Shape	Param #
gru_9 (GRU)	(None, 1, 128)	50,304
gru_10 (GRU)	(None, 1, 64)	37,248
dropout_6 (Dropout)	(None, 1, 64)	0
gru_11 (GRU)	(None, 32)	9,408
dropout_7 (Dropout)	(None, 32)	0
dense_36 (Dense)	(None, 16)	528
dense_37 (Dense)	(None, 1)	17

Total params: 97,505 (380.88 KB)

Trainable params: 97,505 (380.88 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:

```
# scaler to normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))

#call the function processing
trainX, testX , trainY , testY, np_trips = preprocessing(scaler, look_back)


model3.fit(trainX, trainY, epochs=300, validation_data=(testX,testY), batch_size
```

In [172…

```
# make predictions
trainPredict = model2.predict(trainX)
testPredict = model2.predict(testX)
```

```
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

In [173…

```
# invert predictions
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
```

```
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
```

In [174…

```
# calculate root mean squared error
trainScore = np.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = np.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
```

```
Train Score: 2822.42 RMSE
Test Score: 2842.10 RMSE
```

In [175…

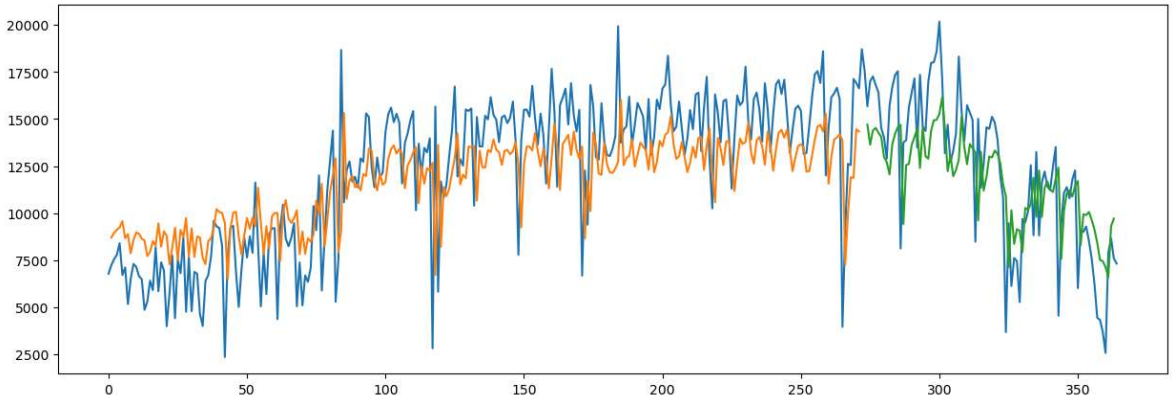
```
# shift train trainPredictPlot for plotting
trainPredictPlot = np.empty_like(np_trips)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict


# shift test testPredictPlot for plotting
testPredictPlot = np.empty_like(np_trips)
testPredictPlot[:, :] = np.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(np_trips)-1, :] = testPred
```

In [176…

```
# plot baseline and predictions
plt.figure(figsize=(15, 5))

plt.plot(scaler.inverse_transform(np_trips))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()
```



In [ ]:

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In [ ]: