Project

Building IOT application for Smart City to enhance urban mobility by harnessing the power of IoT to make cities smarter and more livable. The system will utilize ML to classify traffic conditions and LSTMs for forecasting pickup trends.

Models

Model 1: Machine Learning – Classify the traffic conditions (e.g., light, moderate, heavy) in different zones of NYC using ML.

Model 2: Time Series Prediction – Forecast the future demand for Uber pickups across NYC using LSTM.

Dataset

Dataset- Source of the dataset is NYC Taxi & Limousine Commission (TLC) - https://github.com/fivethirtyeight/uber-tlc-foil-response. It was obtained by FiveThirtyEight through a Freedom of Information Law request on July 20, 2015.

```
#import required libraries
import pandas as pd
import keras
import numpy as np
import matplotlib.pyplot as plt
import os
from datetime import datetime
from collections import Counter
from tensorflow import keras
from sklearn import preprocessing
from sklearn.metrics import confusion matrix, recall score,
precision score, fl score, accuracy score
from sklearn.model selection import train test split
from keras.models import Sequential, load model
from keras.layers import Dense, Dropout, LSTM
from keras.layers import Activation
from keras.utils import pad sequences
#from keras.wrappers.scikit_learn import KerasClassifier
#from keras.utils import np utils
from sklearn.model selection import cross val score
from sklearn.model selection import KFold
from sklearn.preprocessing import LabelEncoder
from sklearn.pipeline import Pipeline
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from sklearn.model selection import GridSearchCV
# from sklearn.preprocessing import MinMaxScaler
```

```
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.preprocessing import LabelEncoder
from sklearn.svm import SVC # The SVM Classifier from Scikit
from sklearn.tree import DecisionTreeClassifier
import seaborn as sns
import time

# Setting seed for reproducibility
np.random.seed(1234)
PYTHONHASHSEED = 0
```

Load the Uber Data for the month of Jan-June 2015

```
from google.colab import drive
drive.mount('/content/drive')
path_uber_15='/content/drive/My Drive/ColabNotebooks/IOT/Final
Project/uber-raw-data-janjune-15.csv'

Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

The dataset cosist for following columns -

- 1. Dispatching_base_num- The TLC base company code of the base that dispatched the Uber
- 2. Pickup_date- The date and time of the Uber pickup
- 3. Affiliated_base_num- The TLC base company code affiliated with the Uber pickup
- 4. locationID- The pickup location ID affiliated with the Uber pickup

```
df_uber = pd.read_csv(path_uber_15, delimiter = ",")
df_uber.head()
{"type":"dataframe","variable_name":"df_uber"}
```

Data Pre-processing

```
#convert datetime to epoch/unix time
from datetime import datetime
df_uber['unix']=df_uber['Pickup_date'].astype(int) / 10**9

df_uber.head()
{"type":"dataframe","variable_name":"df_uber"}

#Shape of uber data
df_uber.shape
(14270479, 5)
```

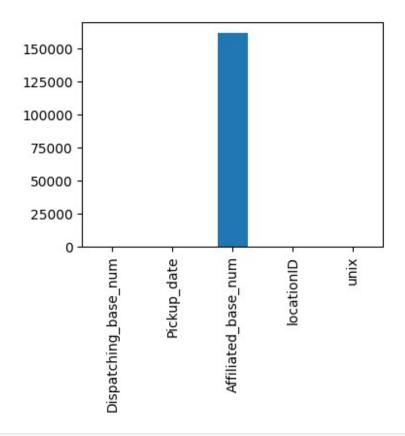
Check missing values

```
#Check number of rows with missing values
missing_value=df_uber.isna().sum()
missing_val = missing_value[missing_value > 0]
for missing_count in missing_val.items():
    print(f"Count of missing values {missing_count}")

Count of missing values ('Affiliated_base_num', 162195)

#Plot missing values
import matplotlib.pyplot as plt
f, ax = plt.subplots(figsize=(4,3))
missing_value.plot.bar()

<Axes: >
```



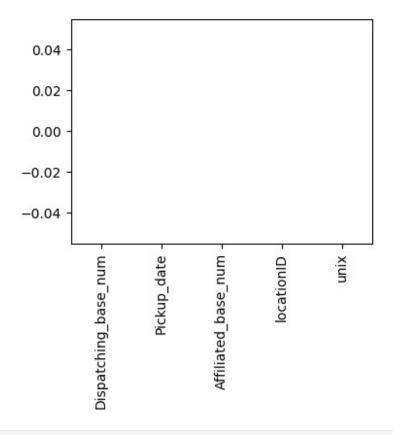
```
#Remove rows with missing values
df_uber = df_uber.dropna()

missing_value=df_uber.isna().sum()
missing_val = missing_value[missing_value > 0]
for missing_count in missing_val.items():
    print(f"Count of missing values {missing_count}")
else:
    print("Data do not have any missing values")

Data do not have any missing values

#plot after removing missing values
f, ax = plt.subplots(figsize=(4,3))
missing_value.plot.bar()

<Axes: >
```



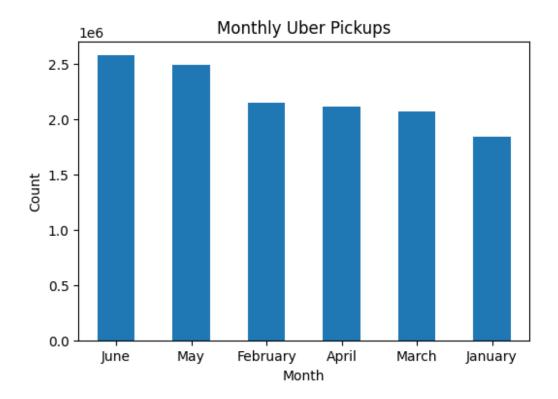
```
#Shape of data after removing missing values
df uber.shape
(14108284, 5)
#Check duplicate rows in the dataset
duplicate_count=df_uber.duplicated().sum()
print(f"Count of duplicate data {duplicate count}")
Count of duplicate data 896732
# Remove duplicate rows and check the sum of duplicate rows after
removing duplicate rows
df_uber.drop_duplicates(inplace=True)
duplicate count=df uber.duplicated().sum()
print(f"Count of duplicate data after removing duplicate rows
{duplicate count}")
Count of duplicate data after removing duplicate rows 0
#Shape of data after removing duplicates
df uber.shape
(13211552, 5)
```

Summary Data Pre-processing

- Uber data for Jan-June month contain 162195 missing values in Affiliated_base_num column.
- 2. Data contain **896732** duplicate rows
- 3. After pre-processing i.e. removing missing values and duplicate data, final dataset consist of **13,211,552** rows

Perform Exploratory Data Analysis

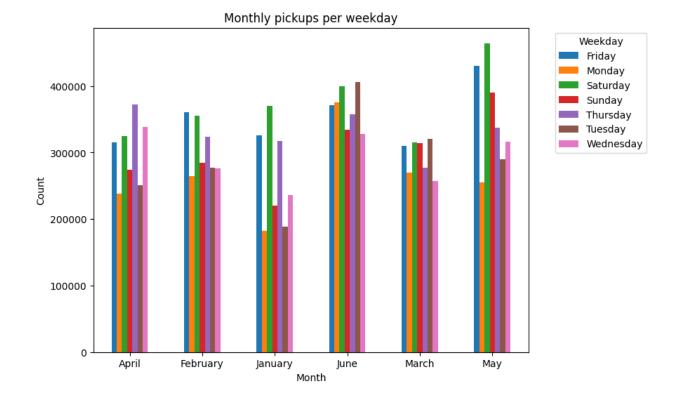
```
#Derive month name, name of weekday, hour of the day, month and day
numbers from Pickup date in uber dataset
df uber["month"] = df uber["Pickup date"].dt.month name()
df uber["weekday"] = df uber["Pickup date"].dt.day name()
df uber['hour'] = df uber['Pickup date'].dt.hour
df uber['month day'] = df uber['Pickup date'].apply(lambda pickup:
pickup.strftime('%m-%d').split('-'))
df uber['Monthumn'] = [month day [0] for month day in
df uber['month day']]
df uber['Day'] = [month day [1] for month day in df uber['month day']]
df uber.head()
{"type": "dataframe", "variable name": "df uber"}
#Uber pickup count by month
df uber["month"].value counts()
June
            2571771
            2483980
May
February
            2141306
April
            2112705
            2062639
March
            1839151
January
Name: month, dtype: int64
#Plot monthly pickup count
import matplotlib.pyplot as plt
# Plot data
counts = df uber["month"].value counts()
plt.figure(figsize=(6, 4))
counts.plot(kind="bar")
plt.xlabel("Month")
plt.ylabel("Count")
plt.title("Monthly Uber Pickups")
plt.xticks(rotation=0)
plt.show()
```



Highest pickups were performed in the month of June

```
#Count of monthly pickups per weekday
monthweek = pd.crosstab(index=df uber["month"],
columns=df uber["weekday"])
monthweek
{"summary":"{\n \"name\": \"monthweek\",\n \"rows\": 6,\n
\"fields\": [\n {\n
                        \"column\": \"Friday\",\n
\"properties\": {\n
                         \"dtype\": \"number\",\n
                                                       \"std\":
               \"min\": 309631,\n
315002,\n
45650,\n
                                       \"max\": 430134,\n
\"samples\": [\n
                                          360136,\n
                          \"num unique values\": 6,\n
430134\n
               ],\n
\"semantic type\": \"\",\n
                               \"description\": \"\"\n
           {\n \"column\": \"Monday\",\n \"properties\":
n
          \"dtype\": \"number\",\n
                                        \"std\": 62843,\n
{\n
                        \"max\": 375312,\n
\"min\": 182785,\n
                                                \"samples\": [\n
238429,\n
                 264693.\n
                                   255501\n
                                 \"semantic_type\": \"\",\n
\"num unique values\": 6,\n
\"description\": \"\"\n }\n
                                                 \"column\":
                                 },\n
                                         {\n
\"Saturday\",\n \"properties\": {\n
                                             \"dtype\":
\"number\",\n
                   \"std\": 54929,\n
                                           \"min\": 314785,\n
\"max\": 464298,\n
                        \"samples\": [\n
                                                324545,\n
                 464298\n
354962,\n
                                           \"num unique values\":
                                ],\n
           \"semantic_type\": \"\",\n
                                           \"description\": \"\"\n
6,\n
      },\n {\n \"column\": \"Sunday\",\n
}\n
                                                   \"properties\":
          \"dtype\": \"number\",\n \"std\": 58073,\n
{\n
```

```
\"max\": 390391,\n
\"min\": 219884,\n
                                                   \"samples\": [\n
                   284432,\n
273560,\n
                                      390391\n
                                                      ],\n
\"num_unique_values\": 6,\n
                                   \"semantic_type\": \"\",\n
\"description\": \"\n }\n },\n {\n
                                                    \"column\":
\"Thursday\",\n \"properties\": {\n
\"number\",\n \"std\": 33609,\n
                                                \"dtype\":
                                            \"min\": 277026,\n
                         \"samples\": [\n
\"max\": 372522,\n
                                                    372522,\n
                                              \"num unique_values\":
323955,\n
                   337607\n
                                   ],\n
            \"semantic_type\": \"\",\n
                                              \"description\": \"\"\n
6,\n
}\n },\n {\n \"column\": \"Tuesday\",\n
\"properties\": {\n \"dtype\": \"number\",\n
                                                          \"std\":
              \"min\": 188802,\n
\n 250632,\n
72429,\n
                                         \"max\": 405500,\n
\"samples\": [\n
                                             276956,\n
                         \"num unique values\": 6,\n
290004\n ],\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
                                                               }\
n },\n {\n \"column\": \"Wednesday\",\n
\"properties\": {\n \"dtype\": \"number\",\n \"std\":
41579,\n \"min\": 235869,\n \"max\": 338015,\n \"samples\": [\n 338015,\n 276172,\n 316045\n ],\n \"num_unique_values\": 6,\n
}\n ]\n}","type":"dataframe","variable name":"monthweek"}
#plot monthly pickups per weekday
plt.figure(figsize=(6, 4))
#monthweek.plot(kind="bar", figsize=(8, 6), cmap='coolwarm')
monthweek.plot(kind="bar", figsize=(8, 6))
plt.xlabel("Month")
plt.ylabel("Count")
plt.title("Monthly pickups per weekday")
plt.xticks(rotation=0)
# Show the plot
plt.legend(title="Weekday", bbox to anchor=(1.05, 1), loc='upper
left') # Add legend
plt.show()
<Figure size 600x400 with 0 Axes>
```



Summary of Weekday pickup analysis per month

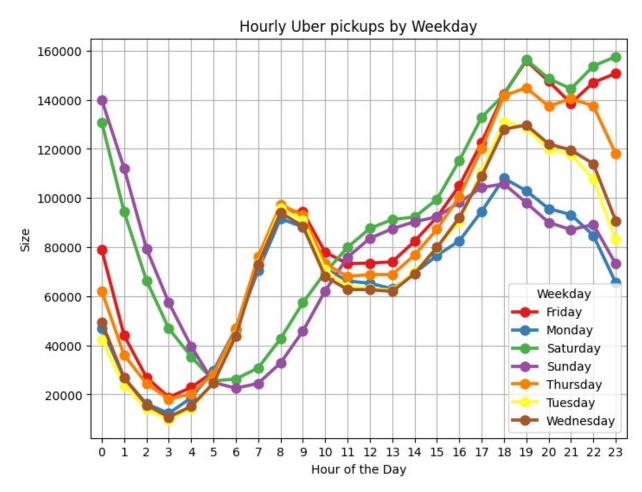
- 1. Highest number of pickups are performed Saturday in May compared to all other months
- 2. January, February Highest pickups are on Saturday
- 3. March Hightest pickups are on Tuesday
- 4. April Hightest pickups are on Thursday
- 5. May Highest pickups are on Saturday
- 6. June Hightest pickups are on Tuesday

```
#Hourly analysis
summary = df uber.groupby(['weekday', 'hour'], as index=False).size()
summary.head()
{"summary":"{\n \me\": \summary\n,\n \me\": 168,\n}
                  {\n \"column\": \"weekday\",\n
\"dtype\": \"category\",\n
\"fields\": [\n
\"properties\": {\n
                        \"Friday\",\n
\"samples\": [\n
                                              \"Monday\",\n
                               \"num unique_values\": 7,\n
\"Tuesday\"\n
                   ],\n
\"semantic_type\": \"\",\n
                                \"description\": \"\"\n
                    \"column\": \"hour\",\n
                                                \"properties\": {\n
    },\n {\n
\"dtype\": \"number\",\n
                         \"std\": 6,\n
                                                  \"min\": 0,\n
\"max\": 23,\n
                    \"samples\": [\n
                                                           16,\n
          ],\n
                    \"num unique values\": 24,\n
0\n
\"semantic_type\": \"\",\n \"description\": \"\"\n
                    \"column\": \"size\",\n
                                            \"properties\": {\n
    },\n {\n
\"dtype\": \"number\",\n \"std\": 38531,\n
                                                      \"min\":
```

```
9675,\n \"max\": 157588,\n \"samples\": [\n
110841,\n 46930,\n 118067\n ],\n
\"num_unique_values\": 168,\n \"semantic_type\": \"\",\n
\"description\": \"\"\n }\n ]\n
\"description\": \"\"\n }\n ]\n
\", "type": "dataframe", "variable_name": "summary"}

#plot Uber hourly analysis by weekday
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.pointplot(x="hour", y="size", hue="weekday", data=summary,
palette="Set1")
plt.xlabel("Hour of the Day")
plt.ylabel("Size")
plt.title("Hourly Uber pickups by Weekday")
plt.legend(title="Weekday")
plt.grid(True)
plt.show()
```



Summary of Hourly analysis by weekday

- 1. Friday and Saturday shows hightest numbers of pickups at 19 and 23 hour
- 2. Friday and Saturday shows upward trend in pickups after 21 hour vs Other days shows downward trend after 21 hour
- 3. Both Saturday and Sunday shows same trend between 0-14 hours however from 15 hours trend changes where Saturday has more number of pickups and pickup rise until 23 hours vs Sunday shows downward trend from 18 hour

```
#Unique location ids in uber data
unique locid=df uber['locationID'].unique()
len(unique locid)
262
#Mark the location ids by traffic contition base on number of pickups
performed per location ids
for loc in unique locid:
  df temp=df uber.loc[df uber['locationID']==loc]
  if (len(df temp) < 100000):
    df uber.loc[df uber['locationID'] == loc,
'Traffic conditions']='light'
  elif (\overline{\text{len}}(\text{df temp}) > = 100000 and \overline{\text{len}}(\text{df temp}) < = 250000):
    df uber.loc[df uber['locationID'] == loc,
'Traffic conditions']='moderate'
  elif (\overline{len}(df temp) > 250000):
    df uber.loc[df uber['locationID'] == loc,
'Traffic conditions']='heavy'
print(len(df uber.loc[df uber['Traffic conditions']=='light']))
print(len(df uber.loc[df uber['Traffic conditions']=='moderate']))
print(len(df uber.loc[df uber['Traffic conditions']=='heavy']))
df uber.head()
3284638
6028415
3898499
{"type": "dataframe", "variable name": "df uber"}
df uber.loc[(df uber['Traffic conditions']!='light') &
(df_uber['Traffic conditions']!='moderate') &
(df uber['Traffic conditions']!='heavy' )]
{"repr error": "cannot convert float NaN to
integer","type":"dataframe"}
df uber.to csv('/content/drive/My Drive/ColabNotebooks/IOT/Final
Project/uber-raw-data-janjune-15 trafficcond.csv', index = None)
```

Model 1 - Classify the traffic conditions (e.g., light, moderate, heavy) in different zones of NYC using Machine Learning Model

```
#Sample dataset to be used for ML model training
random sample = df uber.sample(frac=0.01, random state=42)
random sample.head()
{"type":"dataframe", "variable name": "random sample"}
light cond=len(random sample.loc[random sample['Traffic conditions']==
'light'])
moderate cond=len(random sample.loc[random sample['Traffic conditions'
]=='moderate'])
heavy cond=len(random sample.loc[random sample['Traffic conditions']==
'heavy'])
print(f"Sample data contain {light_cond} location ids with light
traffic condition")
print(f"Sample data contain {moderate cond} location ids with moderate
traffic condition")
print(f"Sample data contain {heavy cond} location ids with heavy
traffic condition")
Sample data contain 32901 location ids with light traffic condition
Sample data contain 60403 location ids with moderate traffic condition
Sample data contain 38812 location ids with heavy traffic condition
random sample.shape
(132116, 12)
```

Pre-processing data for DecisionTreeClassifier Model

```
# MinMaxscaling and LabelEncoding of data

X = random_sample[['unix','locationID']]
scaler = MinMaxScaler()
X_new = scaler.fit_transform(X)
y = random_sample['Traffic_conditions']
labelencoder_y = LabelEncoder()
y = labelencoder_y.fit_transform(y)
X_train, X_test, Y_train, Y_test = train_test_split(X_new, y, test_size = 0.2, random_state = 323)
```

Train DecisionTreeClassifier Model

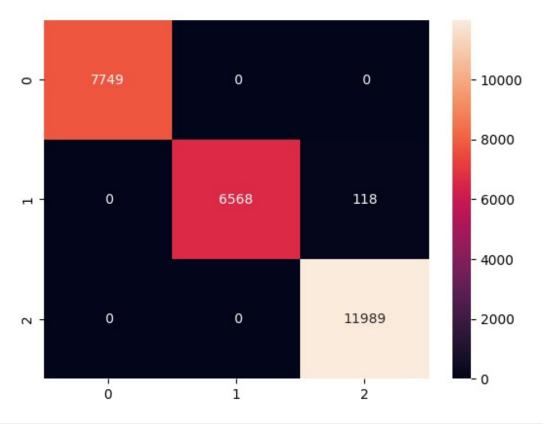
```
#Apply DecisionTreeClassifier ML model
classifier = DecisionTreeClassifier(max_depth=10)
classifier.fit(X_train, Y_train)
```

```
#Predicting the Test Set
Y_pred = classifier.predict(X_test)
```

Model Predictions

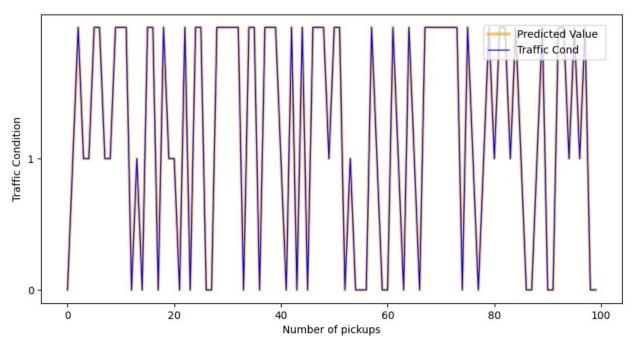
Plot Model Predictions

```
cm = confusion_matrix(Y_test, Y_pred)
sns.heatmap(cm,annot=True,fmt='2.0f')
<Axes: >
```

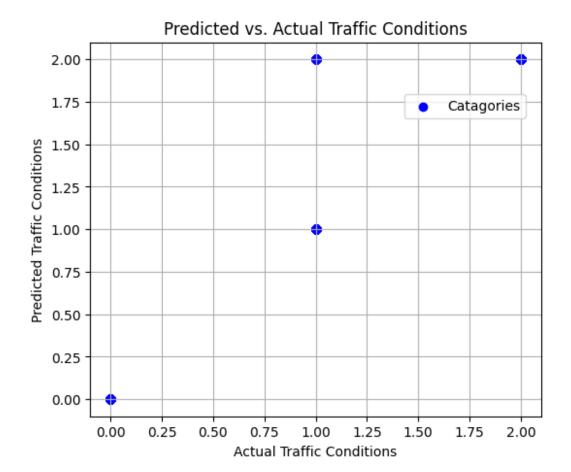


```
# Show predicted vs actual values for Traffic Condition for first 100
results
fig, ax = plt.subplots(figsize=(10,5))
fig.suptitle('Preiction of Traffic Condition on Location ids',
fontsize=22, fontweight='bold')
#ax.set_title('mu = %g, ph=%g' %(mu, ph))
ax.plot( Y_pred[0:100], label='Predicted Value', linewidth=3,
color='orange', alpha=0.6)
ax.plot(Y_test[0:100], label='Traffic Cond', linewidth=1, color='blue')
ax.set( yticks=np.arange(Y_pred.min(), Y_pred.max(), 1),
yticklabels=range(0, 2));
ax.set_xlabel('Number of pickups')
ax.set_ylabel('Traffic Condition')
ax.legend(loc='upper right', bbox_to_anchor=(0.98, 0.98))
<matplotlib.legend.Legend at 0x7dd23bdce9b0>
```

Preiction of Traffic Condition on Location ids



```
# scatter plot
plt.figure(figsize=(6, 5))
plt.scatter(Y_test, Y_pred, color='blue')
plt.xlabel('Actual Traffic Conditions')
plt.ylabel('Predicted Traffic Conditions')
plt.title('Predicted vs. Actual Traffic Conditions')
plt.grid(True)
plt.legend(['Catagories'], loc='upper right', bbox_to_anchor=(0.98, 0.88))
plt.show()
```



DecisionTreeClassifier Result Analysis

- Model is accurately predicting Traffic conditions light, moderate and heavy based on the input features location ids and unix date time
- Accuracy of Decision Tree Classifier: 0.9955343627005753
- Precision of Decision Tree Classifier: 0.9955778867115881
- Recall of Decision Tree Classifier: 0.9955343627005753
- F1-Score of Decision Tree Classifier: 0.995525418264997

```
#Save ML model predictions
df_ml_predict=pd.DataFrame()
df_ml_predict['Traffic_Condition_Actual']=Y_test
df_ml_predict['Traffic_Condition_Predicted']=Y_pred
df_ml_predict.to_csv('/content/drive/My Drive/ColabNotebooks/IOT/Final
Project/Final_Project_ML_Prediction.csv', index = None)
```

Model 2 - Time Series Prediction – Forecast the future demand for Uber pickups across NYC using LSTM

```
month_day_group = df uber.groupby(by = ['Monthumn',
'Day']).size().unstack()
month_day_group
{"type": "dataframe", "variable name": "month day group"}
## Aggregate results to form a time-series
month_day_series = [month_day_group.iloc[r,:] for r in
range(month day group.shape[0])]
month_day_list=[]
for month in month day series:
  for days in month:
    month day list.append(days)
print(f"Length of MonthDay time-series {len(month day list)}")
Length of MonthDay time-series 186
## When month is shorter than 31 days, there will be missing values in
series. Removing missing values from series.
nan indx=np.argwhere(np.isnan(month day list) == True)
print(f"number of missing values {len(nan indx)}")
remove inds = list(nan indx.reshape((1,len(nan indx)))[0])
print(f"ids tha are removed {remove inds}")
month_day_list_nonan = [month_day_list[i] for i,j in
enumerate(month_day_list) if i not in remove_inds]
print(f"Final Length of Monthday list {len(month day list nonan)}")
number of missing values 5
ids tha are removed [59, 60, 61, 123, 185]
Final Length of Monthday list 181
## Convert time-series into data-frame
df uber final = pd.DataFrame({'Davs':
range(1,len(month_day_list_nonan)+1), 'UberPickups':
month day list nonan})
df uber final.head()
{"summary":"{\n \"name\": \"df_uber_final\",\n \"rows\": 181,\n
\"fields\": [\n {\n
                          \"column\": \"Days\",\n
\"properties\": {\n
                          \"dtype\": \"number\",\n
                                                          \"std\":
            \"min\": 1,\n \"max\": 181,\n
                                                       \"samples\":
52,\n
[\n
            20,\n
                          43,\n
                                          154\n
                                                      ],\n
\"num_unique values\": 181,\n
                                    \"semantic type\": \"\",\n
\"description\": \"\"\n
                           }\n },\n {\n
                                                   \"column\":
\"UberPickups\",\n \"properties\": {\n
                                                  \"dtype\":
                    \"std\": 14006.144828848039,\n
\"number\",\n
                                                          \"min\":
```

```
24422.0,\n \"max\": 119208.0,\n \"samples\": [\n 52855.0,\n 80181.0,\n 85836.0\n ],\n \"num_unique_values\": 180,\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n ]\n ]\n}","type":"dataframe","variable_name":"df_uber_final"}
```

Pre-processing data for LSTM

Use last 2 weeks(14 days) to predict Uber Trips for current day

```
#Apply MinMax scalling to transforms data by scaling features to a
given range (0,1)
## Split into train-test set:
train uber series = df uber final.iloc[0:167,1:2].values
test_uber_series = df_uber_final.iloc[167:,1:2].values
print ('Training data: ', train_uber_series.shape)
print ('Testing data: ', test_uber_series.shape)
## Feature-scaling:
mms = MinMaxScaler(feature range = (0,1))
train uber series scaled = mms.fit transform(train uber series)
Training data: (167, 1)
Testing data: (14, 1)
x train = []
y train = []
for rides in range(14, train uber series.shape[0]):
    x_train.append(train_uber_series_scaled[rides-14:rides,0])
    y train.append(train uber series scaled[rides,0])
x train, y train = np.array(x train), np.array(y train)
x_{train} = np.reshape(x_{train}, newshape = (x train.shape[0],
x train.shape[1], 1))
```

Training LSTM Model

```
np.random.seed(11)
t_start = time.time()

def build_rnn(num_units, input_x, input_y, drpout, epochs,
size_of_batch, optimizer, loss):
    lstmmodel = Sequential()

## Adding first LSTM layer:
    lstmmodel.add(LSTM(units = num_units, return_sequences = True,
```

```
input shape = (input x.shape[1],1)))
   lstmmodel.add(Dropout(drpout))
   ## Adding second LSTM layer:
   lstmmodel.add(LSTM(units = num units, return sequences = True))
   lstmmodel.add(Dropout(drpout))
   ## Adding third LSTM layer:
   lstmmodel.add(LSTM(units = num units, return sequences = True))
   lstmmodel.add(Dropout(drpout))
   ## Adding fourth LSTM layer:
   lstmmodel.add(LSTM(units = num units, return sequences = True))
   lstmmodel.add(Dropout(drpout))
   ## Adding fifth LSTM layer:
   lstmmodel.add(LSTM(units = num units, return sequences = False))
   lstmmodel.add(Dropout(drpout))
   ## Adding o/p layer:
   lstmmodel.add(Dense(units = 1))
   ## Compiling RNN:
   lstmmodel.compile(optimizer = optimizer, loss = loss)
   ## Fitting RNN to training set:
   lstmmodel.fit(x = input x, y = input y, epochs = epochs,
batch size = size of batch)
   return lstmmodel
lstmmodel = build rnn(num units = 40, input x = x train, input y =
y train, drpout = 0.2, epochs = 1000, size of batch = 16, optimizer =
'adam', loss = 'mean squared error')
print (time.time() - t start)
Epoch 1/1000
10/10 [============= ] - 7s 21ms/step - loss: 0.2300
Epoch 2/1000
10/10 [============== ] - Os 19ms/step - loss: 0.0351
Epoch 3/1000
10/10 [============ ] - Os 22ms/step - loss: 0.0290
Epoch 4/1000
Epoch 5/1000
10/10 [============= ] - Os 20ms/step - loss: 0.0257
Epoch 6/1000
Epoch 7/1000
```

```
Epoch 8/1000
Epoch 9/1000
Epoch 10/1000
Epoch 11/1000
Epoch 12/1000
10/10 [============== ] - Os 21ms/step - loss: 0.0295
Epoch 13/1000
Epoch 14/1000
10/10 [============= ] - Os 21ms/step - loss: 0.0221
Epoch 15/1000
Epoch 16/1000
10/10 [============= ] - Os 20ms/step - loss: 0.0217
Epoch 17/1000
Epoch 18/1000
Epoch 19/1000
10/10 [============== ] - Os 20ms/step - loss: 0.0237
Epoch 20/1000
Epoch 21/1000
Epoch 22/1000
Epoch 23/1000
Epoch 24/1000
Epoch 25/1000
10/10 [============== ] - Os 23ms/step - loss: 0.0250
Epoch 26/1000
Epoch 27/1000
Epoch 28/1000
10/10 [============== ] - Os 22ms/step - loss: 0.0257
Epoch 29/1000
Epoch 30/1000
Epoch 31/1000
```

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Epoch 32/1000
10/10 [============= ] - Os 20ms/step - loss: 0.0207
Epoch 33/1000
Epoch 34/1000
Epoch 35/1000
Epoch 36/1000
Epoch 37/1000
Epoch 38/1000
Epoch 39/1000
10/10 [============== ] - Os 21ms/step - loss: 0.0237
Epoch 40/1000
Epoch 41/1000
Epoch 42/1000
10/10 [============= ] - Os 21ms/step - loss: 0.0244
Epoch 43/1000
Epoch 44/1000
Epoch 45/1000
10/10 [============== ] - Os 19ms/step - loss: 0.0224
Epoch 46/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0230
Epoch 47/1000
10/10 [============= ] - Os 21ms/step - loss: 0.0201
Epoch 48/1000
Epoch 49/1000
Epoch 50/1000
Epoch 51/1000
Epoch 52/1000
Epoch 53/1000
10/10 [============== ] - Os 19ms/step - loss: 0.0210
Epoch 54/1000
10/10 [============= ] - Os 20ms/step - loss: 0.0206
Epoch 55/1000
Epoch 56/1000
```

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Epoch 57/1000
Epoch 58/1000
Epoch 59/1000
Epoch 60/1000
Epoch 61/1000
10/10 [============== ] - Os 24ms/step - loss: 0.0235
Epoch 62/1000
Epoch 63/1000
10/10 [============= ] - Os 26ms/step - loss: 0.0233
Epoch 64/1000
Epoch 65/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0232
Epoch 66/1000
Epoch 67/1000
Epoch 68/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0211
Epoch 69/1000
Epoch 70/1000
Epoch 71/1000
Epoch 72/1000
Epoch 73/1000
Epoch 74/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0213
Epoch 75/1000
Epoch 76/1000
Epoch 77/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0197
Epoch 78/1000
Epoch 79/1000
Epoch 80/1000
```

Epoch 81/1000	-		•	10 ()			0.0015
10/10 [====================================	===]	-	0S	16ms/step	-	loss:	0.0215
10/10 [====================================	===]	-	0s	19ms/step	-	loss:	0.0207
Epoch 83/1000 10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0200
Epoch 84/1000 10/10 [====================================	1		0.5	17mc/sten		1000	0 0202
Epoch 85/1000							
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0187
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0199
Epoch 87/1000 10/10 [====================================	===1	_	05	16ms/step	_	loss:	0.0217
Epoch 88/1000				_			
10/10 [====================================				-			
10/10 [====================================	===]	-	0s	17ms/step	-	loss:	0.0212
Epoch 90/1000 10/10 [====================================	===]	-	0s	17ms/step	-	loss:	0.0202
Epoch 91/1000 10/10 [====================================				_			
Epoch 92/1000							
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0223
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0212
Epoch 94/1000 10/10 [====================================	1	_	0.5	17mc/sten	_	10551	0 0220
Epoch 95/1000				-			
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0208
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0218
Epoch 97/1000 10/10 [====================================	===1	_	0s	16ms/step	-	loss:	0.0218
Epoch 98/1000				_			
10/10 [====================================	=== j	-	US	Toms/step	-	1055:	0.0211
10/10 [====================================	===]	-	0s	17ms/step	-	loss:	0.0210
10/10 [====================================	===]	-	0s	17ms/step	-	loss:	0.0190
Epoch 101/1000 10/10 [====================================	1	_	0 c	16ms/sten	_	10551	0 0200
Epoch 102/1000							
10/10 [====================================	===]	-	0s	17ms/step	-	loss:	0.0196
10/10 [====================================	===]	-	0s	16ms/step	-	loss:	0.0228
Epoch 104/1000 10/10 [====================================	===1	_	0s	16ms/sten	_	loss:	0.0222
Epoch 105/1000				, 2.13 p			

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Epoch 106/1000
Epoch 107/1000
Epoch 108/1000
Epoch 109/1000
Epoch 110/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0190
Epoch 111/1000
Epoch 112/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0207
Epoch 113/1000
Epoch 114/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0193
Epoch 115/1000
Epoch 116/1000
Epoch 117/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0188
Epoch 118/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0201
Epoch 119/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0185
Epoch 120/1000
Epoch 121/1000
Epoch 122/1000
Epoch 123/1000
Epoch 124/1000
10/10 [============= ] - Os 24ms/step - loss: 0.0196
Epoch 125/1000
Epoch 126/1000
10/10 [============= ] - Os 24ms/step - loss: 0.0196
Epoch 127/1000
Epoch 128/1000
Epoch 129/1000
```

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Epoch 130/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0199
Epoch 131/1000
Epoch 132/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0192
Epoch 133/1000
Epoch 134/1000
Epoch 135/1000
Epoch 136/1000
Epoch 137/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0185
Epoch 138/1000
Epoch 139/1000
Epoch 140/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0206
Epoch 141/1000
Epoch 142/1000
Epoch 143/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0200
Epoch 144/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0230
Epoch 145/1000
Epoch 146/1000
Epoch 147/1000
Epoch 148/1000
Epoch 149/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0170
Epoch 150/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0178
Epoch 151/1000
Epoch 152/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0176
Epoch 153/1000
Epoch 154/1000
```

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Epoch 155/1000
Epoch 156/1000
Epoch 157/1000
Epoch 158/1000
Epoch 159/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0188
Epoch 160/1000
Epoch 161/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0184
Epoch 162/1000
Epoch 163/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0157
Epoch 164/1000
Epoch 165/1000
Epoch 166/1000
Epoch 167/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0161
Epoch 168/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0185
Epoch 169/1000
Epoch 170/1000
Epoch 171/1000
Epoch 172/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0164
Epoch 173/1000
Epoch 174/1000
Epoch 175/1000
Epoch 176/1000
Epoch 177/1000
Epoch 178/1000
```

Epoch 17							
]	-	0s	16ms/step	-	loss:	0.0160
Epoch 18			_			_	
]	-	0s	15ms/step	-	loss:	0.0189
Epoch 18			0.0	16mc/c+on		10001	0.0167
Epoch 18	======================================	-	05	Toms/step	-	toss:	0.010/
10/10 [=	=======================================	_	05	16ms/sten	_	1055.	0 0161
Epoch 18			03	10m3/3ccp			0.0101
	=======================================	_	0s	18ms/step	-	loss:	0.0152
Epoch 18	84/1000						
]	-	0s	16ms/step	-	loss:	0.0165
Epoch 18						_	
	=======================================	-	0s	16ms/step	-	loss:	0.0156
Epoch 18			ο -	16 / - 1		7	0.0146
10/10 [= Epoch 18]	-	υs	loms/step	-	loss:	0.0146
	=======================================		۵۵	16mc/cton		1000	0 0160
Epoch 18		-	05	Tollis/ Steb	-	1055.	0.0109
10/10 [=	=======================================	_	05	17ms/step	_	loss:	0.0171
Epoch 18	89/1000			-			
10/10 [=]	-	0s	17ms/step	-	loss:	0.0167
Epoch 19	90/1000						
]	-	0s	19ms/step	-	loss:	0.0145
Epoch 19			_	24 / /		-	0.0165
]	-	0S	24ms/step	-	loss:	0.0165
Epoch 19	92/1000 =========]		۵۵	25mc/cton		1000	0 0156
Epoch 19		-	05	231113/3 Leh	-	1055.	0.0130
	=======================================	_	05	25ms/step	_	loss:	0.0161
Epoch 19	94/1000						
10/10 [=]	-	0s	21ms/step	-	loss:	0.0154
Epoch 19							
]	-	0s	24ms/step	-	loss:	0.0136
	96/1000		•	25 / .		-	0 01 47
]	-	0S	25ms/step	-	loss:	0.014/
Epoch 19	=======================================		۵۵	20mc/cton		1000	0.0154
Epoch 19		-	05	Zuiis/step	-	1055.	0.0134
	=======================================	_	05	17ms/sten	_	loss:	0.0137
Epoch 19							0.0157
]	-	0s	16ms/step	-	loss:	0.0145
Epoch 20				-			
	=======================================	-	0s	17ms/step	-	loss:	0.0146
Epoch 20			^	16		1 .	0.0363
]	-	US	loms/step	-	loss:	0.0161
Epoch 20	======================================		0.0	17mc/c+c5		1000:	0 0122
Epoch 20		_	05	T/IIIS/2reb	•	(055)	0.0132
LPOCII ZO	03, 1000						

```
Epoch 204/1000
Epoch 205/1000
Epoch 206/1000
Epoch 207/1000
Epoch 208/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0144
Epoch 209/1000
Epoch 210/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0148
Epoch 211/1000
Epoch 212/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0152
Epoch 213/1000
Epoch 214/1000
Epoch 215/1000
Epoch 216/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0136
Epoch 217/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0146
Epoch 218/1000
Epoch 219/1000
Epoch 220/1000
Epoch 221/1000
Epoch 222/1000
Epoch 223/1000
Epoch 224/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0140
Epoch 225/1000
Epoch 226/1000
Epoch 227/1000
```

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Epoch 228/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0138
Epoch 229/1000
Epoch 230/1000
Epoch 231/1000
Epoch 232/1000
Epoch 233/1000
Epoch 234/1000
Epoch 235/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0139
Epoch 236/1000
Epoch 237/1000
Epoch 238/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0137
Epoch 239/1000
Epoch 240/1000
Epoch 241/1000
Epoch 242/1000
Epoch 243/1000
Epoch 244/1000
Epoch 245/1000
Epoch 246/1000
Epoch 247/1000
Epoch 248/1000
Epoch 249/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0132
Epoch 250/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0131
Epoch 251/1000
Epoch 252/1000
```

Epoch 253/1000		•	17 / 1		-	0.0120
10/10 [====================================	-	0s	1/ms/step	-	loss:	0.0138
10/10 [======]	-	0s	16ms/step	-	loss:	0.0146
Epoch 255/1000 10/10 [========]	_	05	16ms/sten	_	lnss	0 0126
Epoch 256/1000						
10/10 [====================================	-	0s	16ms/step	-	loss:	0.0137
10/10 [========]	-	0s	26ms/step	-	loss:	0.0125
Epoch 258/1000		0 -	22		1	0 0124
10/10 [===========] Epoch 259/1000	-	ΘS	23ms/step	-	loss:	0.0134
10/10 [=======]	-	0s	27ms/step	-	loss:	0.0140
Epoch 260/1000 10/10 [========]	_	0 c	22ms/sten	_	lnee	0 0133
Epoch 261/1000			-			
10/10 [====================================	-	0s	22ms/step	-	loss:	0.0124
Epoch 262/1000 10/10 [========]	_	0s	28ms/step	_	loss:	0.0141
Epoch 263/1000			-			
10/10 [====================================	-	0s	30ms/step	-	loss:	0.0142
10/10 [==========]	-	0s	17ms/step	-	loss:	0.0122
Epoch 265/1000 10/10 [========]		0-	17		1	0 0126
Epoch 266/1000	-	05	1/IIIS/Step	-	1055;	0.0120
10/10 [=======]	-	0s	16ms/step	-	loss:	0.0132
Epoch 267/1000 10/10 [========]	_	05	16ms/sten	_	loss:	0.0123
Epoch 268/1000						
10/10 [==========] Epoch 269/1000	-	0s	16ms/step	-	loss:	0.0130
10/10 [========]	-	0s	16ms/step	-	loss:	0.0136
Epoch 270/1000		0 -	10/		1	0 0140
10/10 [==========] Epoch 271/1000	-	ΘS	16ms/step	-	LOSS:	0.0140
10/10 [======]	-	0s	16ms/step	-	loss:	0.0146
Epoch 272/1000 10/10 [========]	_	0.5	16mc/cton		10001	0 01/13
Epoch 273/1000			·			
10/10 [====================================	-	0s	16ms/step	-	loss:	0.0127
Epoch 274/1000 10/10 [========]	_	0s	18ms/step	_	loss:	0.0128
Epoch 275/1000			·			
10/10 [==========] Epoch 276/1000	-	0s	16ms/step	-	loss:	0.0131
10/10 [=======]	-	0s	16ms/step	-	loss:	0.0115
Epoch 277/1000						

```
Epoch 278/1000
Epoch 279/1000
Epoch 280/1000
Epoch 281/1000
Epoch 282/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0127
Epoch 283/1000
Epoch 284/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0119
Epoch 285/1000
Epoch 286/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0128
Epoch 287/1000
Epoch 288/1000
Epoch 289/1000
Epoch 290/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0124
Epoch 291/1000
Epoch 292/1000
Epoch 293/1000
Epoch 294/1000
Epoch 295/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0138
Epoch 296/1000
Epoch 297/1000
Epoch 298/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0116
Epoch 299/1000
Epoch 300/1000
Epoch 301/1000
```

	302/1000						
	[=======] 303/1000	-	0s	16ms/step	-	loss:	0.0118
	[======================================	_	0s	16ms/step	_	loss:	0.0126
Epoch	304/1000						
	[=======]	-	0s	17ms/step	-	loss:	0.0125
10/10	305/1000 [=======]	_	05	17ms/sten	_	1055	0 0136
Epoch	306/1000						
	[======]	-	0s	16ms/step	-	loss:	0.0131
	307/1000 [=======]		0.5	17mc/cten		1000	0 0130
Epoch	308/1000			-			
10/10	[======]	-	0s	16ms/step	-	loss:	0.0147
	309/1000 [=======]		٥٥	16mg/g+on		1	0 0122
	310/1000	-	US	Tollis/Step	-	LOSS:	0.0133
10/10	[========]	-	0s	17ms/step	-	loss:	0.0126
Epoch	311/1000		•	10 / 1		,	0.0100
	[======] 312/1000	-	0S	16ms/step	-	loss:	0.0129
10/10	[======================================	-	0s	16ms/step	-	loss:	0.0119
Epoch	313/1000			-			
	[======================================	-	0s	17ms/step	-	loss:	0.0128
10/10	314/1000 [=======]	_	0s	16ms/step	_	loss:	0.0129
Epoch	315/1000						
	[=======]	-	0s	16ms/step	-	loss:	0.0112
	316/1000 [=======]	_	05	17ms/sten	_	loss:	0.0123
Epoch	317/1000						
	[=======]	-	0s	16ms/step	-	loss:	0.0106
	318/1000 [=======]	_	٩c	16mc/stan	_	1000	0 0120
	319/1000	_	03	101113/3 сер	_	1033.	0.0120
10/10	[======]	-	0s	16ms/step	-	loss:	0.0123
	320/1000 [=======]		0.0	16mc/c+on		10001	0 0126
	321/1000	-	05	10IIIS/Step	-	LUSS:	0.0130
10/10	[=======]	-	0s	16ms/step	-	loss:	0.0113
	322/1000		0 -	17		1	0 0105
	[=======] 323/1000	-	θS	1/ms/step	-	LOSS:	0.0125
	[========]	-	0s	17ms/step	-	loss:	0.0115
Epoch	324/1000						
	[=======] 325/1000	-	0S	25ms/step	-	loss:	0.0140
	[======================================	-	0s	24ms/step	-	loss:	0.0135
	326/1000			,			

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Epoch 327/1000
Epoch 328/1000
10/10 [============= ] - Os 27ms/step - loss: 0.0113
Epoch 329/1000
Epoch 330/1000
Epoch 331/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0124
Epoch 332/1000
Epoch 333/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0118
Epoch 334/1000
Epoch 335/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0123
Epoch 336/1000
Epoch 337/1000
Epoch 338/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0120
Epoch 339/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0128
Epoch 340/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0117
Epoch 341/1000
Epoch 342/1000
Epoch 343/1000
Epoch 344/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0118
Epoch 345/1000
Epoch 346/1000
Epoch 347/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0119
Epoch 348/1000
Epoch 349/1000
Epoch 350/1000
```

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Epoch 351/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0120
Epoch 352/1000
Epoch 353/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0107
Epoch 354/1000
Epoch 355/1000
Epoch 356/1000
Epoch 357/1000
Epoch 358/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0121
Epoch 359/1000
Epoch 360/1000
Epoch 361/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0139
Epoch 362/1000
Epoch 363/1000
Epoch 364/1000
Epoch 365/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0116
Epoch 366/1000
Epoch 367/1000
Epoch 368/1000
Epoch 369/1000
Epoch 370/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0127
Epoch 371/1000
Epoch 372/1000
Epoch 373/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0120
Epoch 374/1000
Epoch 375/1000
```

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Epoch 376/1000
Epoch 377/1000
Epoch 378/1000
Epoch 379/1000
Epoch 380/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0111
Epoch 381/1000
Epoch 382/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0106
Epoch 383/1000
Epoch 384/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0103
Epoch 385/1000
Epoch 386/1000
Epoch 387/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0110
Epoch 388/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0100
Epoch 389/1000
Epoch 390/1000
Epoch 391/1000
Epoch 392/1000
Epoch 393/1000
10/10 [============== ] - Os 22ms/step - loss: 0.0113
Epoch 394/1000
10/10 [============= ] - Os 26ms/step - loss: 0.0099
Epoch 395/1000
Epoch 396/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0113
Epoch 397/1000
Epoch 398/1000
Epoch 399/1000
```

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Epoch 400/1000
Epoch 401/1000
Epoch 402/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0113
Epoch 403/1000
Epoch 404/1000
Epoch 405/1000
Epoch 406/1000
Epoch 407/1000
Epoch 408/1000
Epoch 409/1000
Epoch 410/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0110
Epoch 411/1000
Epoch 412/1000
Epoch 413/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0103
Epoch 414/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0125
Epoch 415/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0107
Epoch 416/1000
Epoch 417/1000
Epoch 418/1000
Epoch 419/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0105
Epoch 420/1000
Epoch 421/1000
Epoch 422/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0100
Epoch 423/1000
Epoch 424/1000
```

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Epoch 425/1000
Epoch 426/1000
Epoch 427/1000
Epoch 428/1000
Epoch 429/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0115
Epoch 430/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0100
Epoch 431/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0114
Epoch 432/1000
Epoch 433/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0116
Epoch 434/1000
Epoch 435/1000
Epoch 436/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0091
Epoch 437/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0105
Epoch 438/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0110
Epoch 439/1000
Epoch 440/1000
Epoch 441/1000
Epoch 442/1000
Epoch 443/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0116
Epoch 444/1000
Epoch 445/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0100
Epoch 446/1000
Epoch 447/1000
Epoch 448/1000
```

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Epoch 449/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0104
Epoch 450/1000
Epoch 451/1000
Epoch 452/1000
Epoch 453/1000
Epoch 454/1000
Epoch 455/1000
Epoch 456/1000
10/10 [============== ] - Os 22ms/step - loss: 0.0107
Epoch 457/1000
Epoch 458/1000
Epoch 459/1000
Epoch 460/1000
Epoch 461/1000
Epoch 462/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0098
Epoch 463/1000
10/10 [============== ] - Os 15ms/step - loss: 0.0103
Epoch 464/1000
Epoch 465/1000
Epoch 466/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0103
Epoch 467/1000
Epoch 468/1000
Epoch 469/1000
Epoch 470/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0098
Epoch 471/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0090
Epoch 472/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0084
Epoch 473/1000
```

```
Epoch 474/1000
Epoch 475/1000
Epoch 476/1000
Epoch 477/1000
Epoch 478/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0117
Epoch 479/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0098
Epoch 480/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0093
Epoch 481/1000
Epoch 482/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0097
Epoch 483/1000
Epoch 484/1000
Epoch 485/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0110
Epoch 486/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0105
Epoch 487/1000
Epoch 488/1000
Epoch 489/1000
Epoch 490/1000
Epoch 491/1000
Epoch 492/1000
Epoch 493/1000
Epoch 494/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0095
Epoch 495/1000
Epoch 496/1000
Epoch 497/1000
```

```
Epoch 498/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0093
Epoch 499/1000
Epoch 500/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0093
Epoch 501/1000
Epoch 502/1000
Epoch 503/1000
Epoch 504/1000
Epoch 505/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0088
Epoch 506/1000
Epoch 507/1000
Epoch 508/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0105
Epoch 509/1000
Epoch 510/1000
Epoch 511/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0087
Epoch 512/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0095
Epoch 513/1000
Epoch 514/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0094
Epoch 515/1000
Epoch 516/1000
Epoch 517/1000
10/10 [============= ] - 0s 16ms/step - loss: 0.0091
Epoch 518/1000
Epoch 519/1000
Epoch 520/1000
10/10 [============= ] - Os 23ms/step - loss: 0.0099
Epoch 521/1000
Epoch 522/1000
```

```
Epoch 523/1000
10/10 [============== ] - Os 21ms/step - loss: 0.0102
Epoch 524/1000
Epoch 525/1000
10/10 [============= ] - Os 28ms/step - loss: 0.0095
Epoch 526/1000
Epoch 527/1000
Epoch 528/1000
Epoch 529/1000
Epoch 530/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0083
Epoch 531/1000
Epoch 532/1000
Epoch 533/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0085
Epoch 534/1000
Epoch 535/1000
Epoch 536/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0082
Epoch 537/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0091
Epoch 538/1000
Epoch 539/1000
Epoch 540/1000
Epoch 541/1000
Epoch 542/1000
Epoch 543/1000
Epoch 544/1000
Epoch 545/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0079
Epoch 546/1000
Epoch 547/1000
```

```
Epoch 548/1000
Epoch 549/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0105
Epoch 550/1000
Epoch 551/1000
Epoch 552/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0084
Epoch 553/1000
Epoch 554/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0097
Epoch 555/1000
Epoch 556/1000
Epoch 557/1000
Epoch 558/1000
Epoch 559/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0092
Epoch 560/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0088
Epoch 561/1000
Epoch 562/1000
Epoch 563/1000
Epoch 564/1000
Epoch 565/1000
Epoch 566/1000
Epoch 567/1000
Epoch 568/1000
Epoch 569/1000
Epoch 570/1000
Epoch 571/1000
```

```
Epoch 572/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0079
Epoch 573/1000
Epoch 574/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0085
Epoch 575/1000
Epoch 576/1000
Epoch 577/1000
Epoch 578/1000
Epoch 579/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0087
Epoch 580/1000
Epoch 581/1000
Epoch 582/1000
10/10 [============= ] - Os 24ms/step - loss: 0.0089
Epoch 583/1000
Epoch 584/1000
Epoch 585/1000
10/10 [============== ] - Os 28ms/step - loss: 0.0077
Epoch 586/1000
10/10 [============== ] - Os 26ms/step - loss: 0.0094
Epoch 587/1000
Epoch 588/1000
Epoch 589/1000
Epoch 590/1000
Epoch 591/1000
Epoch 592/1000
Epoch 593/1000
10/10 [============== ] - Os 29ms/step - loss: 0.0082
Epoch 594/1000
10/10 [============== ] - Os 27ms/step - loss: 0.0088
Epoch 595/1000
Epoch 596/1000
```

```
Epoch 597/1000
Epoch 598/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0083
Epoch 599/1000
Epoch 600/1000
Epoch 601/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0085
Epoch 602/1000
Epoch 603/1000
10/10 [============= ] - Os 19ms/step - loss: 0.0073
Epoch 604/1000
Epoch 605/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0067
Epoch 606/1000
Epoch 607/1000
Epoch 608/1000
10/10 [============== ] - 0s 16ms/step - loss: 0.0084
Epoch 609/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0098
Epoch 610/1000
Epoch 611/1000
Epoch 612/1000
Epoch 613/1000
Epoch 614/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0085
Epoch 615/1000
Epoch 616/1000
Epoch 617/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0087
Epoch 618/1000
Epoch 619/1000
Epoch 620/1000
```

```
Epoch 621/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0082
Epoch 622/1000
Epoch 623/1000
Epoch 624/1000
Epoch 625/1000
Epoch 626/1000
Epoch 627/1000
Epoch 628/1000
Epoch 629/1000
Epoch 630/1000
Epoch 631/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0077
Epoch 632/1000
Epoch 633/1000
Epoch 634/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0078
Epoch 635/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0075
Epoch 636/1000
Epoch 637/1000
Epoch 638/1000
Epoch 639/1000
Epoch 640/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0076
Epoch 641/1000
Epoch 642/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0068
Epoch 643/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0070
Epoch 644/1000
Epoch 645/1000
```

```
Epoch 646/1000
Epoch 647/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0069
Epoch 648/1000
Epoch 649/1000
Epoch 650/1000
10/10 [============= ] - Os 27ms/step - loss: 0.0068
Epoch 651/1000
Epoch 652/1000
10/10 [============= ] - Os 26ms/step - loss: 0.0072
Epoch 653/1000
Epoch 654/1000
10/10 [============= ] - Os 22ms/step - loss: 0.0082
Epoch 655/1000
Epoch 656/1000
Epoch 657/1000
Epoch 658/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0060
Epoch 659/1000
Epoch 660/1000
Epoch 661/1000
Epoch 662/1000
Epoch 663/1000
Epoch 664/1000
Epoch 665/1000
Epoch 666/1000
Epoch 667/1000
Epoch 668/1000
Epoch 669/1000
```

```
Epoch 670/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0064
Epoch 671/1000
Epoch 672/1000
Epoch 673/1000
Epoch 674/1000
Epoch 675/1000
Epoch 676/1000
Epoch 677/1000
Epoch 678/1000
Epoch 679/1000
Epoch 680/1000
Epoch 681/1000
Epoch 682/1000
Epoch 683/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0072
Epoch 684/1000
10/10 [============== ] - Os 15ms/step - loss: 0.0074
Epoch 685/1000
Epoch 686/1000
Epoch 687/1000
Epoch 688/1000
Epoch 689/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0089
Epoch 690/1000
Epoch 691/1000
Epoch 692/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0063
Epoch 693/1000
Epoch 694/1000
```

```
Epoch 695/1000
Epoch 696/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0064
Epoch 697/1000
Epoch 698/1000
Epoch 699/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0065
Epoch 700/1000
Epoch 701/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0067
Epoch 702/1000
Epoch 703/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0069
Epoch 704/1000
Epoch 705/1000
Epoch 706/1000
10/10 [============== ] - 0s 17ms/step - loss: 0.0064
Epoch 707/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0072
Epoch 708/1000
Epoch 709/1000
Epoch 710/1000
Epoch 711/1000
Epoch 712/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0066
Epoch 713/1000
Epoch 714/1000
Epoch 715/1000
10/10 [============== ] - Os 22ms/step - loss: 0.0059
Epoch 716/1000
Epoch 717/1000
Epoch 718/1000
```

```
Epoch 719/1000
Epoch 720/1000
Epoch 721/1000
Epoch 722/1000
Epoch 723/1000
Epoch 724/1000
Epoch 725/1000
Epoch 726/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0057
Epoch 727/1000
Epoch 728/1000
Epoch 729/1000
10/10 [============= ] - Os 19ms/step - loss: 0.0056
Epoch 730/1000
Epoch 731/1000
Epoch 732/1000
Epoch 733/1000
Epoch 734/1000
Epoch 735/1000
Epoch 736/1000
Epoch 737/1000
Epoch 738/1000
Epoch 739/1000
Epoch 740/1000
Epoch 741/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0066
Epoch 742/1000
Epoch 743/1000
```

```
Epoch 744/1000
Epoch 745/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0068
Epoch 746/1000
Epoch 747/1000
Epoch 748/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0060
Epoch 749/1000
Epoch 750/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0061
Epoch 751/1000
Epoch 752/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0054
Epoch 753/1000
Epoch 754/1000
Epoch 755/1000
Epoch 756/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0047
Epoch 757/1000
Epoch 758/1000
Epoch 759/1000
Epoch 760/1000
Epoch 761/1000
Epoch 762/1000
Epoch 763/1000
Epoch 764/1000
10/10 [============= ] - Os 19ms/step - loss: 0.0047
Epoch 765/1000
Epoch 766/1000
Epoch 767/1000
```

```
Epoch 768/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0056
Epoch 769/1000
Epoch 770/1000
Epoch 771/1000
Epoch 772/1000
Epoch 773/1000
Epoch 774/1000
Epoch 775/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0052
Epoch 776/1000
Epoch 777/1000
Epoch 778/1000
10/10 [============= ] - Os 22ms/step - loss: 0.0047
Epoch 779/1000
Epoch 780/1000
Epoch 781/1000
10/10 [============= ] - Os 23ms/step - loss: 0.0045
Epoch 782/1000
10/10 [============== ] - Os 21ms/step - loss: 0.0052
Epoch 783/1000
Epoch 784/1000
10/10 [============== ] - Os 28ms/step - loss: 0.0064
Epoch 785/1000
Epoch 786/1000
10/10 [============== ] - Os 16ms/step - loss: 0.0061
Epoch 787/1000
Epoch 788/1000
Epoch 789/1000
Epoch 790/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0044
Epoch 791/1000
Epoch 792/1000
```

```
Epoch 793/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0062
Epoch 794/1000
Epoch 795/1000
Epoch 796/1000
Epoch 797/1000
Epoch 798/1000
Epoch 799/1000
Epoch 800/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0043
Epoch 801/1000
Epoch 802/1000
Epoch 803/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0037
Epoch 804/1000
Epoch 805/1000
Epoch 806/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0047
Epoch 807/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0049
Epoch 808/1000
Epoch 809/1000
Epoch 810/1000
Epoch 811/1000
Epoch 812/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0053
Epoch 813/1000
Epoch 814/1000
Epoch 815/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0048
Epoch 816/1000
Epoch 817/1000
```

```
Epoch 818/1000
Epoch 819/1000
Epoch 820/1000
Epoch 821/1000
Epoch 822/1000
Epoch 823/1000
Epoch 824/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0068
Epoch 825/1000
Epoch 826/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0049
Epoch 827/1000
Epoch 828/1000
Epoch 829/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0091
Epoch 830/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0071
Epoch 831/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0077
Epoch 832/1000
Epoch 833/1000
Epoch 834/1000
Epoch 835/1000
Epoch 836/1000
Epoch 837/1000
Epoch 838/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0047
Epoch 839/1000
Epoch 840/1000
Epoch 841/1000
```

```
Epoch 842/1000
10/10 [============== ] - Os 25ms/step - loss: 0.0038
Epoch 843/1000
Epoch 844/1000
Epoch 845/1000
Epoch 846/1000
Epoch 847/1000
Epoch 848/1000
Epoch 849/1000
10/10 [============== ] - Os 24ms/step - loss: 0.0042
Epoch 850/1000
Epoch 851/1000
Epoch 852/1000
Epoch 853/1000
Epoch 854/1000
Epoch 855/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0037
Epoch 856/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0033
Epoch 857/1000
Epoch 858/1000
Epoch 859/1000
Epoch 860/1000
Epoch 861/1000
Epoch 862/1000
Epoch 863/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0047
Epoch 864/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0060
Epoch 865/1000
Epoch 866/1000
```

```
Epoch 867/1000
Epoch 868/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0049
Epoch 869/1000
Epoch 870/1000
Epoch 871/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0043
Epoch 872/1000
Epoch 873/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0046
Epoch 874/1000
Epoch 875/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0053
Epoch 876/1000
Epoch 877/1000
Epoch 878/1000
Epoch 879/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0029
Epoch 880/1000
Epoch 881/1000
Epoch 882/1000
Epoch 883/1000
Epoch 884/1000
Epoch 885/1000
Epoch 886/1000
Epoch 887/1000
10/10 [============== ] - Os 19ms/step - loss: 0.0048
Epoch 888/1000
Epoch 889/1000
Epoch 890/1000
```

```
Epoch 891/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0031
Epoch 892/1000
Epoch 893/1000
Epoch 894/1000
Epoch 895/1000
Epoch 896/1000
Epoch 897/1000
Epoch 898/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0038
Epoch 899/1000
Epoch 900/1000
Epoch 901/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0035
Epoch 902/1000
Epoch 903/1000
Epoch 904/1000
10/10 [============== ] - Os 19ms/step - loss: 0.0032
Epoch 905/1000
Epoch 906/1000
Epoch 907/1000
Epoch 908/1000
Epoch 909/1000
Epoch 910/1000
Epoch 911/1000
Epoch 912/1000
Epoch 913/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0032
Epoch 914/1000
Epoch 915/1000
```

```
Epoch 916/1000
Epoch 917/1000
Epoch 918/1000
Epoch 919/1000
Epoch 920/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0053
Epoch 921/1000
Epoch 922/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0039
Epoch 923/1000
Epoch 924/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0034
Epoch 925/1000
Epoch 926/1000
Epoch 927/1000
10/10 [============= ] - Os 16ms/step - loss: 0.0039
Epoch 928/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0032
Epoch 929/1000
Epoch 930/1000
Epoch 931/1000
Epoch 932/1000
Epoch 933/1000
Epoch 934/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0035
Epoch 935/1000
Epoch 936/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0043
Epoch 937/1000
Epoch 938/1000
Epoch 939/1000
```

```
Epoch 940/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0034
Epoch 941/1000
Epoch 942/1000
Epoch 943/1000
Epoch 944/1000
Epoch 945/1000
Epoch 946/1000
Epoch 947/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0033
Epoch 948/1000
Epoch 949/1000
Epoch 950/1000
Epoch 951/1000
Epoch 952/1000
Epoch 953/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0026
Epoch 954/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0029
Epoch 955/1000
Epoch 956/1000
Epoch 957/1000
Epoch 958/1000
Epoch 959/1000
10/10 [============== ] - Os 17ms/step - loss: 0.0040
Epoch 960/1000
Epoch 961/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0032
Epoch 962/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0039
Epoch 963/1000
Epoch 964/1000
```

```
Epoch 965/1000
Epoch 966/1000
Epoch 967/1000
Epoch 968/1000
Epoch 969/1000
10/10 [============== ] - Os 24ms/step - loss: 0.0023
Epoch 970/1000
Epoch 971/1000
10/10 [============= ] - Os 25ms/step - loss: 0.0041
Epoch 972/1000
Epoch 973/1000
10/10 [============= ] - Os 26ms/step - loss: 0.0040
Epoch 974/1000
Epoch 975/1000
Epoch 976/1000
10/10 [============= ] - 0s 18ms/step - loss: 0.0024
Epoch 977/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0030
Epoch 978/1000
Epoch 979/1000
Epoch 980/1000
Epoch 981/1000
Epoch 982/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0036
Epoch 983/1000
Epoch 984/1000
Epoch 985/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0024
Epoch 986/1000
Epoch 987/1000
Epoch 988/1000
```

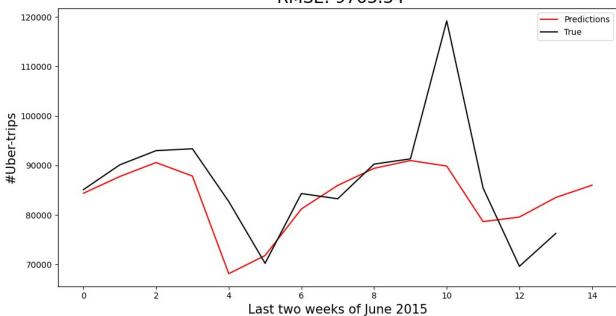
```
Epoch 989/1000
Epoch 990/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0030
Epoch 991/1000
10/10 [============= ] - Os 17ms/step - loss: 0.0038
Epoch 992/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0028
Epoch 993/1000
Epoch 994/1000
Epoch 995/1000
Epoch 996/1000
10/10 [============== ] - Os 18ms/step - loss: 0.0027
Epoch 997/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0043
Epoch 998/1000
Epoch 999/1000
10/10 [============= ] - Os 18ms/step - loss: 0.0040
Epoch 1000/1000
195.9479615688324
# using last 14 values to predict the next value
test uber series updated = df uber final[len(df uber final) -
len(test uber series) - 14:]['UberPickups'].values
test uber series updated = test uber series updated.reshape(-1,1)
test uber series updated = mms.transform(test uber series updated)
test uber series updated[0:10]
array([[0.65726947],
     [0.72960772],
     [0.81569131],
     [0.82318768],
     [0.68832419],
     [0.56061254],
     [0.61345546],
     [0.66073847].
     [0.79777604],
     [0.82472022]])
## Create properly structured test set:
x \text{ test} = []
for rides in range(14,29):
  x test.append(test uber series updated[rides-14:rides,0])
x \text{ test} = np.array(x \text{ test})
```

Plot LSTM Predictions

```
fig, ax = plt.subplots(figsize = (12,6))

e = [i*0.05 for i in pred]
ax.plot(pred, color = 'red', label = 'Predictions')
#ax.errorbar(x = range(15), y = pred, yerr = e, fmt = '*', color = 'r')
ax.plot(test_uber_series, color = 'black', label = 'True')
ax.set_xlabel('Last two weeks of June 2015', fontsize = 15)
ax.set_ylabel('#Uber-trips', fontsize = 15)
ax.set_title('LSTM Predicted vs Actual Values \n RMSE:
{}'.format(np.round(rmse,2)), fontsize = 20)
ax.legend()
plt.show()
```

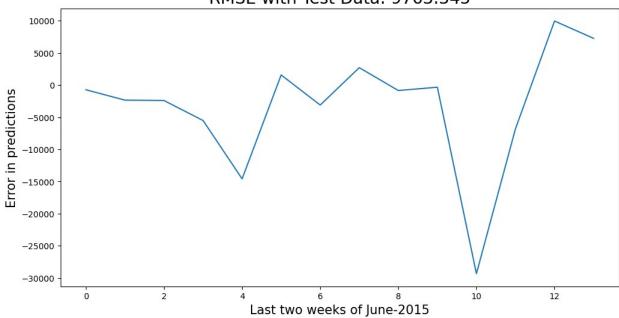
LSTM Predicted vs Actual Values RMSE: 9763.34



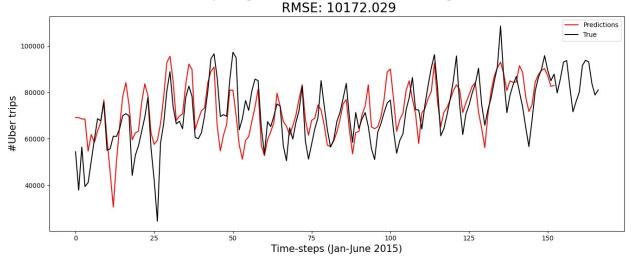
```
fig ,ax = plt.subplots(figsize = (12,6))
ax.plot(residuals)

ax.set_xlabel('Last two weeks of June-2015', fontsize = 15)
ax.set_ylabel('Error in predictions', fontsize = 15)
ax.set_title('RMSE with Test Data: {}'.format(round(rmse, 3)),
fontsize = 20)
plt.show()
```





Comparing LSTM-predictions with training data



```
#Export prediction results for LSTM
df_pred=pd.DataFrame()
df_pred['Actual_trips']=train_uber_series[0:-14].flatten()
df_pred['Predicted_trips']=pred_train

df_pred.to_csv('/content/drive/My Drive/ColabNotebooks/IOT/Final
Project/Final_Project_LSTM_Prediction.csv', index = None)
```

LSTM Prediction Analysis

- From the graph "LSTM predicted VS True Value" we can observe that the predicted values of uber trips followed the actual values of uber trips until 9th day.
- The predicted values for the 10th day deviated from the actual trip counts. Notably, on the 10th day, the actual trip count surged to 120,000, surpassing the range observed in the previous nine days, which typically fell between 70,000 and 95,000 trips.
- Predicted vaules on 10th day did not follow actual values of trips as the actual values are higher in number and could be outliers or anomalies.
- This proves that model is performing well and did not overfit with testing data.
- RMSE value(Test Data) 9763.345 indicates the average deviation between the predicted values generated by the LSTM model and the actual values in the training data
- We can see from RMSE with Test Data graph that the peak deviation occurred on 10th day with 30,000 trips, rest of the days deviation lies in range of 5000 to -10,000