**FINAL PROJECT FOR COURSE MACHINE LEARNING**

***Establishment of neural network model and analysis of Radar Traffic Data***

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## 1 Introduction

This report is about our final project for the course Machine Learning [1]. We worked in a team of two members. Our task is to Build a deep learning model that predicts the traffic volume. The data that should be analyzed is called “Radar Traffic Data”, which can be download in Kaggle [2]. The traffic data is collected from radar sensors deployed by the city of Austin.

This report is developed by the following parts: data analysis and processing, model construction and parameter setting, experimental process and conclusions, personal experience (individual notes).

The following is our work plan:

|  |  |
| --- | --- |
| Duration | task |
| 16/11/2020 - 23/11/2020 | * Start the project: create a github project for our co-work, create a shared Google doc and a shared kaggle notebook for sharing ideas or articles referring to our project. * Conduct preliminary data analysis and read related papers |
| 24/11/2020 - 01/12/2020 | * Chose the appropriate time series analysis model: LSTM, GRU |
| 02/12/2020 - 08/12/2020 | (Weicheng HE) Construction of model LSTM and improve model.  (Linxue LAI) Construction of model GRU and improve model. |
| 09/12/2020 - 13/12/2020 | Improve codes, summarize experimental results, write report |

## 2 data analysis and processing

In order to facilitate data visualization and data analysis, we use the shareable notebook of the kaggle platform for data analysis and processing.

### 2.2 Data description:

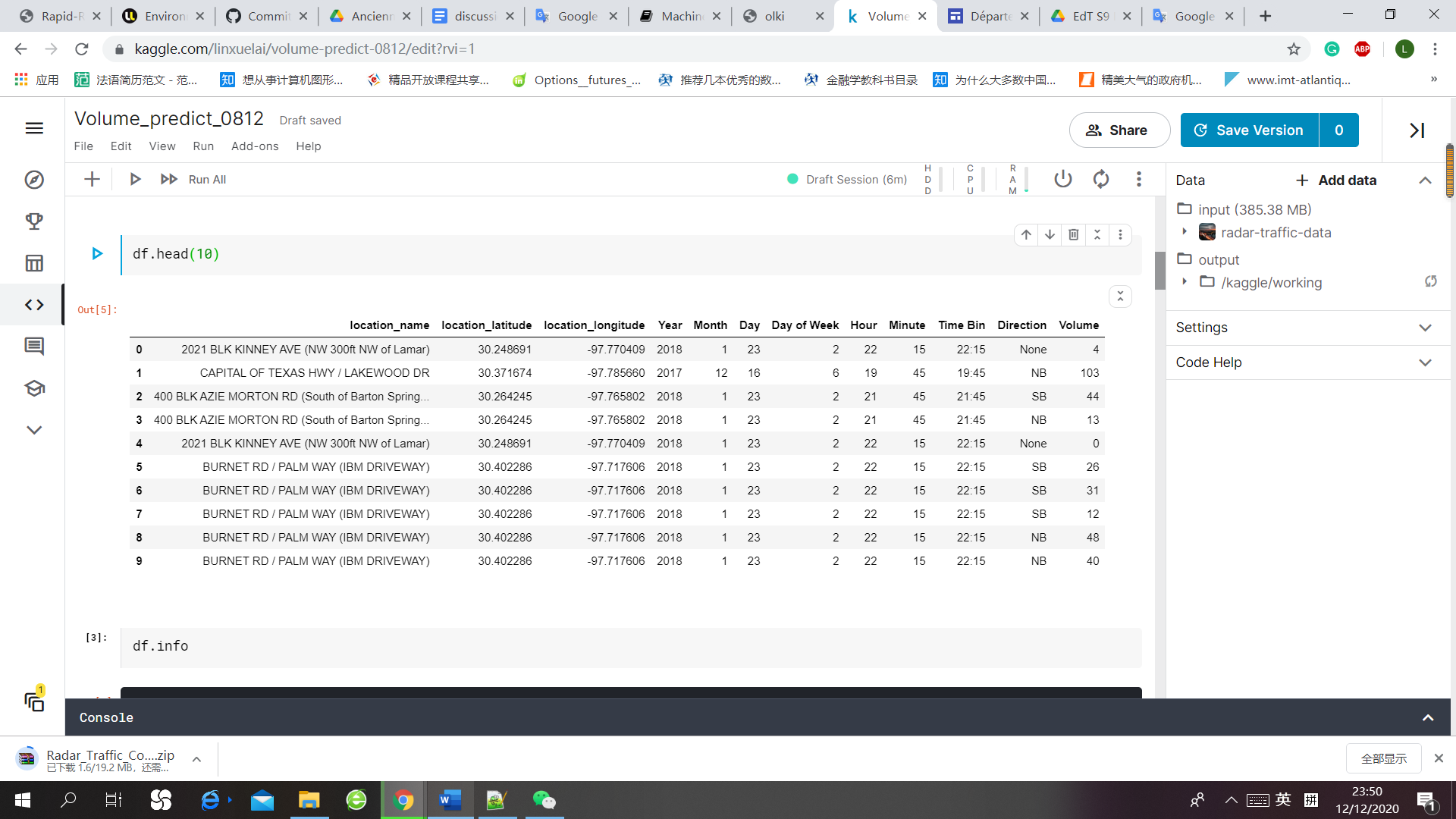
Traffic data collected from the several Wavetronix radar sensors deployed by the City of Austin. Dataset is augmented with geo coordinates from sensor location dataset.

# Load data

df = pd.read\_csv("/kaggle/input/radar-traffic-data/Radar\_Traffic\_Counts.csv")

df.head(10)

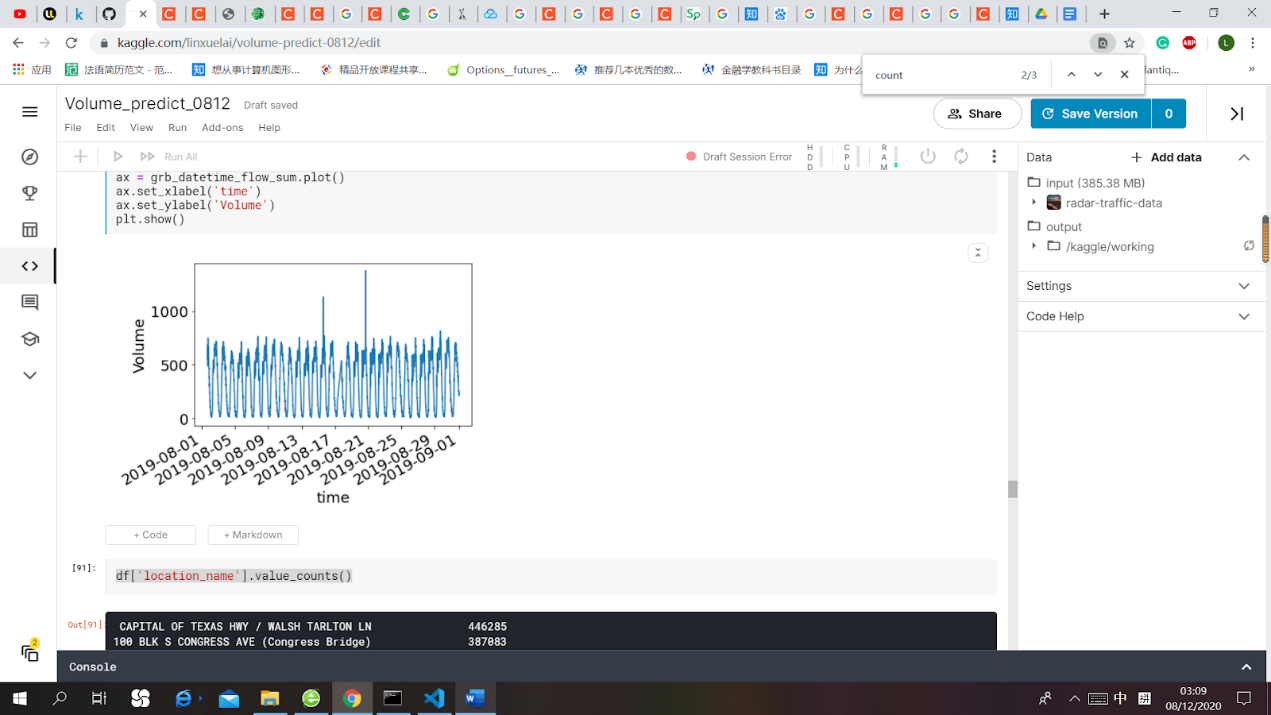
The following is an overview of some of the data:



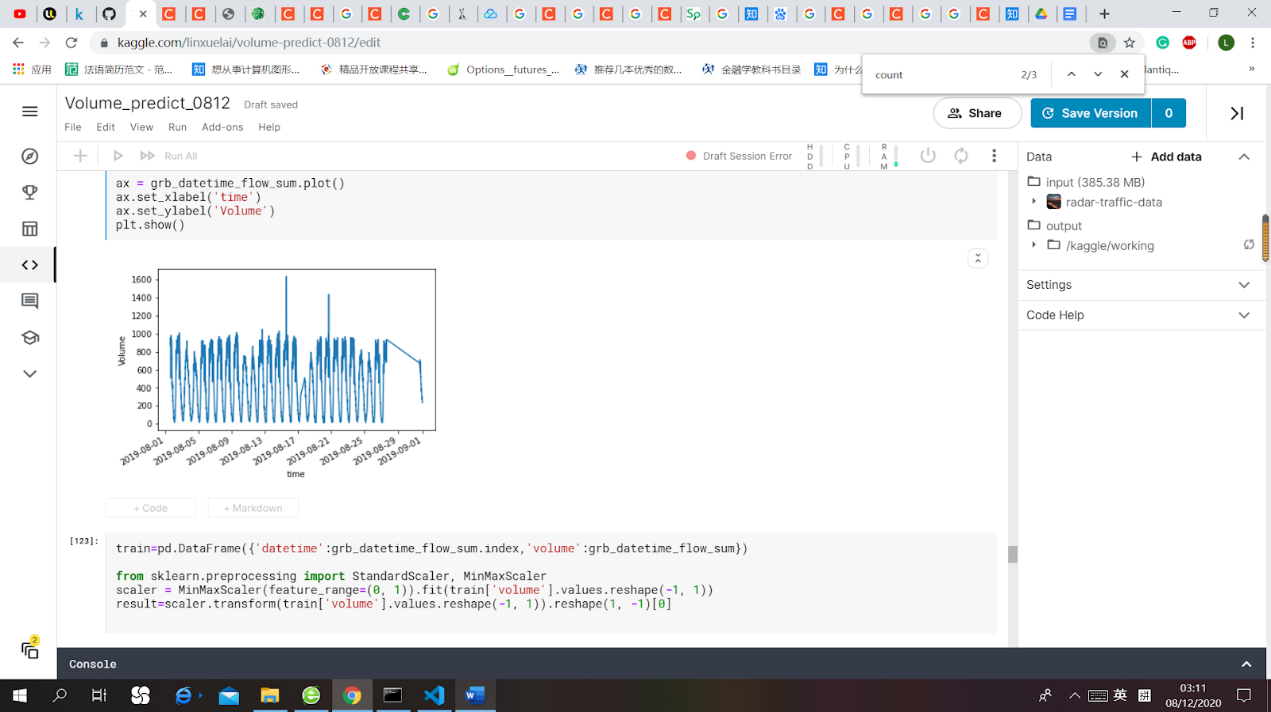
As traffic flow data has obvious periodic change characteristics, we consider using the commonly used LSTM model and GRU model for time series analysis.

There is a question to consider: Is it necessary to consider both time and space factors?

In order to simplify the problem and make it easier to understand, we first consider the changes of traffic volume at a single location over time. By looking at the data of a certain location in a certain period of time, we found that the data has an obvious cycle nature of daily changes. For example:



*Location 1： 3201 BLK S LAMAR BLVD (BROKEN SPOKE)*

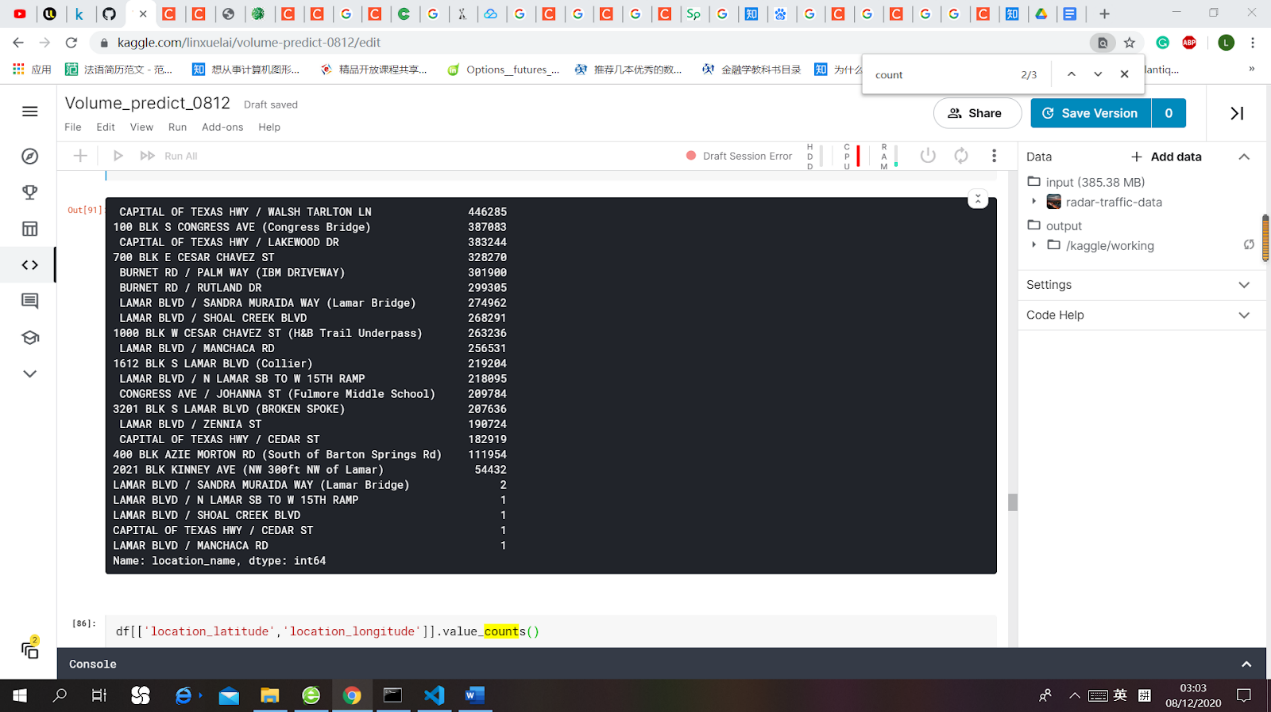
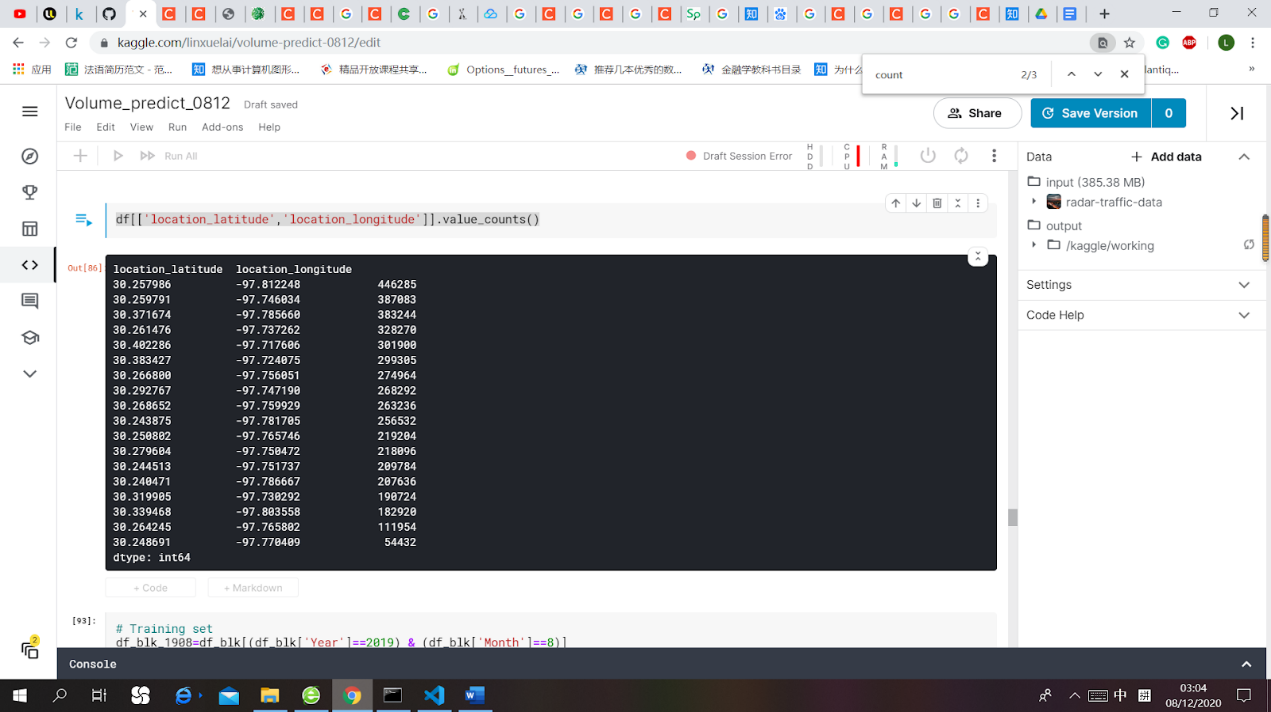


*location 2：100 BLK S CONGRESS AVE (Congress Bridge)*

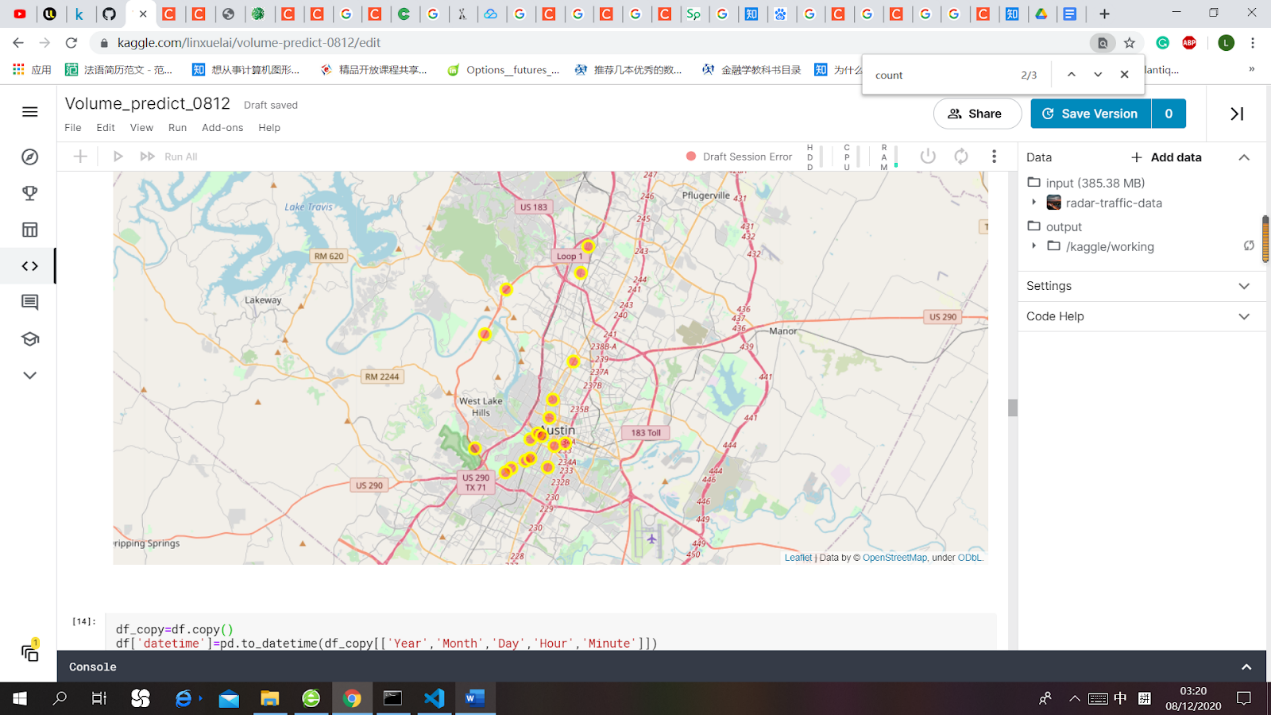
The number of locations: 23 different locations by location\_name; according to actual latitude and longitude: 18 different locations.

df['location\_name'].value\_counts()

df[['location\_latitude','location\_longitude']].value\_counts()

The following is a map-based visualization (see the codes in annexes 1):



We use the process\_data method in the code data/data.py for data processing:

First, take the data of location = '100 BLK S CONGRESS AVE (Congress Bridge)' from March to June 2018 as the training set. The July data will be used as the test set.

Second, we use the training set data to implement a standardized object *scaler*, and then use the *scaler* to standardize the training set.

Since the time series prediction task needs to use historical data to predict future data, we use the time lag variable *lags* to divide the data, and finally obtain a data set of (*samples, lags*).

The divided data set still has timing characteristics in the arrangement order. Although *keras* can choose to shuffle the data during training, the execution order is to sample the data first and then shuffle, and the sampling process is still in order. of. Therefore, we use the method *np.random.shuffle* to shuffle the data and disrupt the order of the data.

# Training set

    df\_street\_1836=df\_street[(df\_street['Year']==2018)&(df\_street['Month']<7)].copy()

    # sum of volume by time bin

    grb\_datetime\_flow\_sum=df\_street\_1836.groupby('datetime')['Volume'].sum()

    train=pd.DataFrame({'datetime':grb\_datetime\_flow\_sum.index,'volume':grb\_datetime\_flow\_sum})

    # Normalization of training set

    from sklearn.preprocessing import StandardScaler, MinMaxScaler

    scaler = MinMaxScaler(feature\_range=(0, 1)).fit(train['volume'].values.reshape(-1, 1))

    result=scaler.transform(train['volume'].values.reshape(-1, 1)).reshape(1, -1)[0]

    train=[]

    for i in range(lags, len(result)):

        train.append(result[i - lags: i + 1])

    train = np.array(train)

    np.random.shuffle(train)

    X\_train = train[:, :-1]

    y\_train = train[:, -1]

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

The processing of the test set is similar to the above process:

#Test set

    df\_street\_1807=df\_street[(df\_street['Year']==2018) & (df\_street['Month']==7)]

    grb\_datetime\_flow\_sum=df\_street\_1807.groupby('datetime')['Volume'].sum()

    validation=pd.DataFrame({'datetime':grb\_datetime\_flow\_sum.index,'volume':grb\_datetime\_flow\_sum})

    # Normalization of test set

    from sklearn.preprocessing import StandardScaler, MinMaxScaler

    scaler = MinMaxScaler(feature\_range=(0, 1)).fit(validation['volume'].values.reshape(-1, 1))

    result=scaler.transform(validation['volume'].values.reshape(-1, 1)).reshape(1, -1)[0]

    test=[]

    for i in range(lags, len(result)):

        test.append(result[i - lags: i + 1])

    test = np.array(test)

    np.random.shuffle(test)

    X\_test = test[:, :-1]

    y\_test = test[:, -1]

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

    y\_test = scaler.inverse\_transform(y\_test.reshape(-1, 1)).reshape(1, -1)[0]

## 3 Models

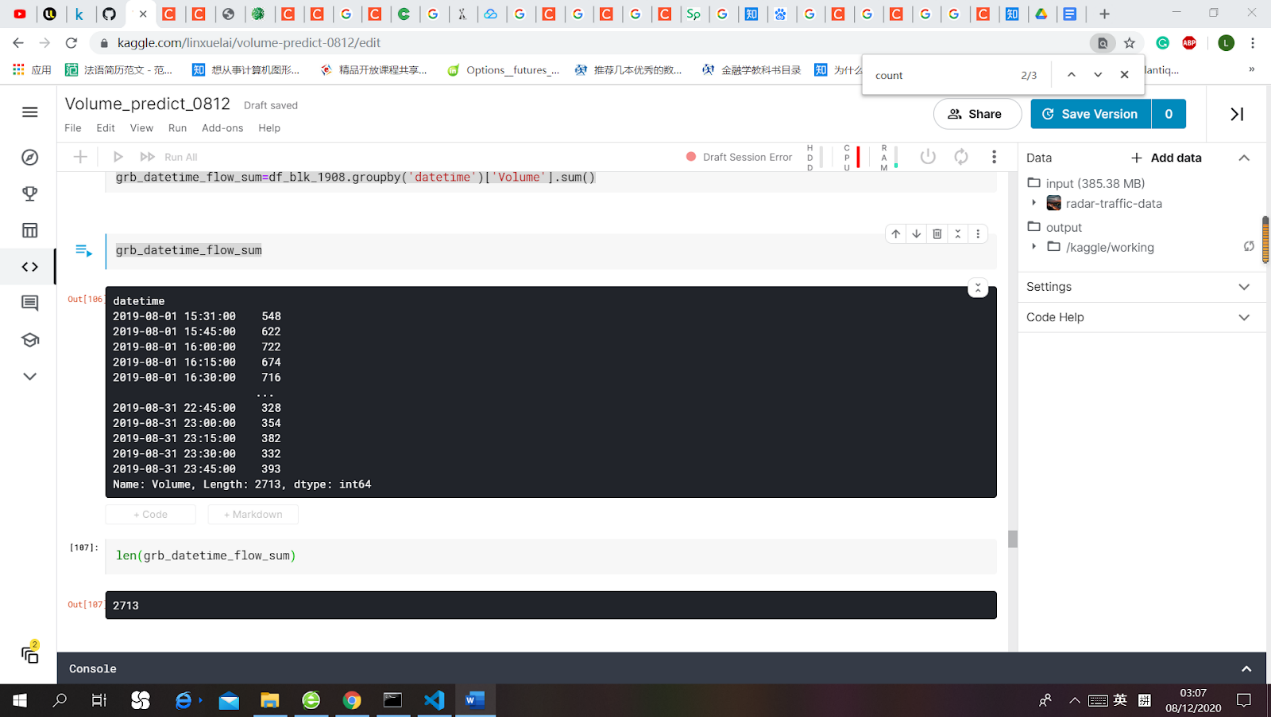
We built an LSTM model and a GRU model, trained and tested traffic flow data at a certain location, and compared the results of the two models.

### 3.1 LSTM

### 3.2 GRU

选择了其中一个位置，选择某时间段的某地点进行GRU的训练，只考虑时序性。

相邻数据以15min为间隔



# Training set

lags = 4

config = {"batch": 256, "epochs": 600}

raw\_data = 'data/Radar\_Traffic\_Counts.csv'

location='100 BLK S CONGRESS AVE (Congress Bridge)'

units=[lags,64,64,1]

pv=predict\_volume(raw\_data,location,units,lags,config)

pv.training()

pv.model\_evaluation()

测试结果：

### 3.3 Comparison

## 4 Conclusion

## 5 References

[1] course link: <https://members.loria.fr/CCerisara/#courses/machine_learning/>

[2] data link: <https://www.kaggle.com/vinayshanbhag/radar-traffic-data?select=Radar_Traffic_Counts.csv>

[3]

## Annexes 1: map visualization

import folium

import pandas as pd

df = pd.read\_csv("/kaggle/input/radar-traffic-data/Radar\_Traffic\_Counts.csv")

# define the world map

world\_map = folium.Map()

# display world map

world\_map

lat\_lon = pd.DataFrame(df,columns=['location\_name','location\_latitude','location\_longitude'])

lat\_lon.drop\_duplicates(['location\_name','location\_latitude','location\_longitude'], keep='first', inplace=True)

print(lat\_lon)

lat\_lon.drop\_duplicates(['location\_latitude','location\_longitude'], keep='first', inplace=True)

print(lat\_lon)

print(len(lat\_lon))

# get the data in map

limit = len(lat\_lon)

data = lat\_lon.iloc[0:limit, :]

latitude,longitude = lat\_lon['location\_latitude'][0],lat\_lon['location\_longitude'][0]

# Instantiate a feature group in the dataframe

index = folium.map.FeatureGroup()

# Loop through the data and add each to the feature group

for lat, lng, in zip(lat\_lon.location\_latitude, lat\_lon.location\_longitude):

index.add\_child(

folium.CircleMarker(

[lat, lng],

radius=7, # define how big you want the circle markers to be

color='yellow',

fill=True,

fill\_color='red',

fill\_opacity=0.4

)

)

# Add to map

v\_map = folium.Map(location=[latitude, longitude], zoom\_start=12)

v\_map.add\_child(index)