**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.

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:

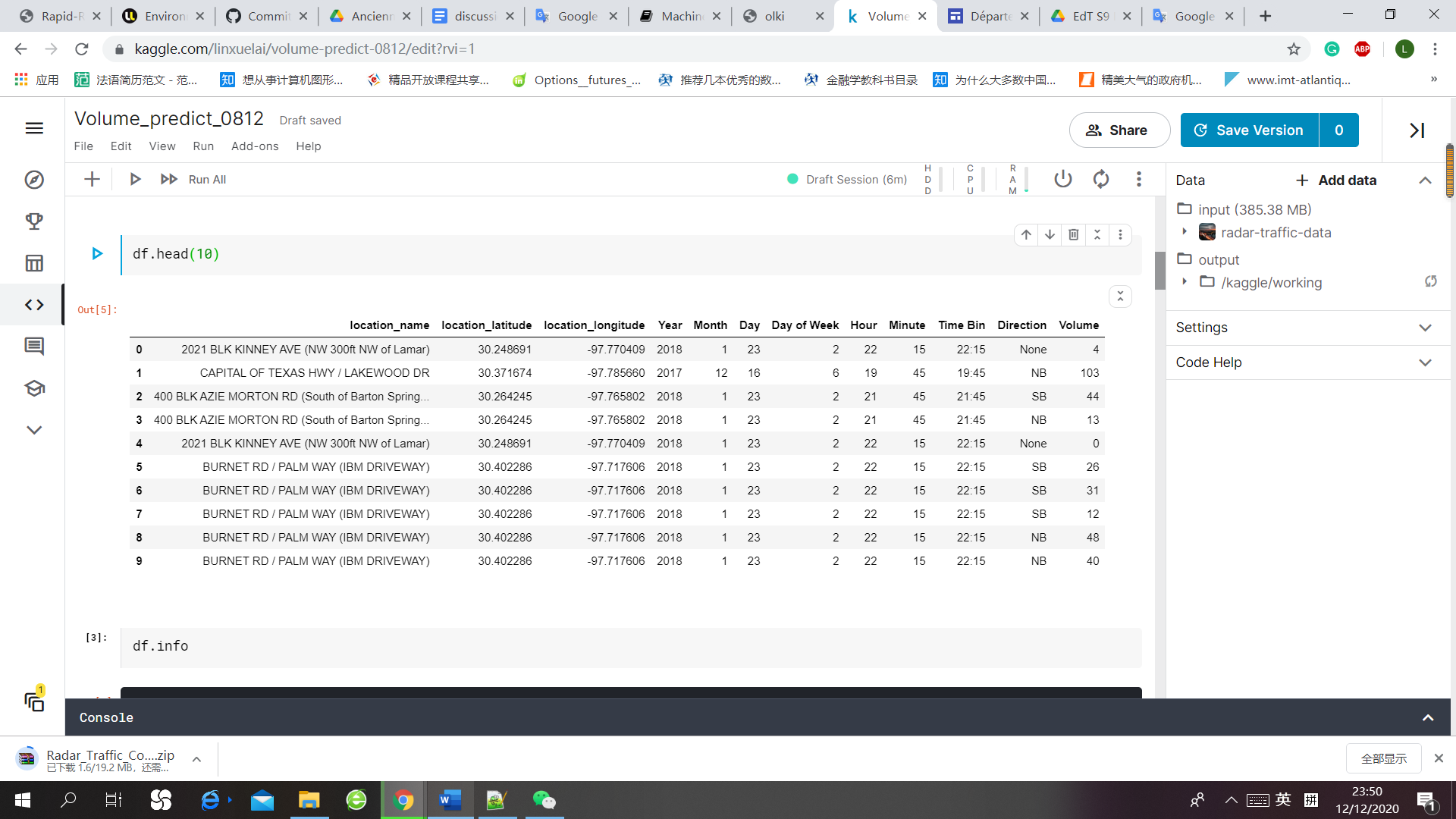
Traffic data collected from the several Wavetronix radar sensors deployed by the City of Austin. Dataset is augmented with geo coordinates from sensor location dataset.

# Load data

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

df.head(10)

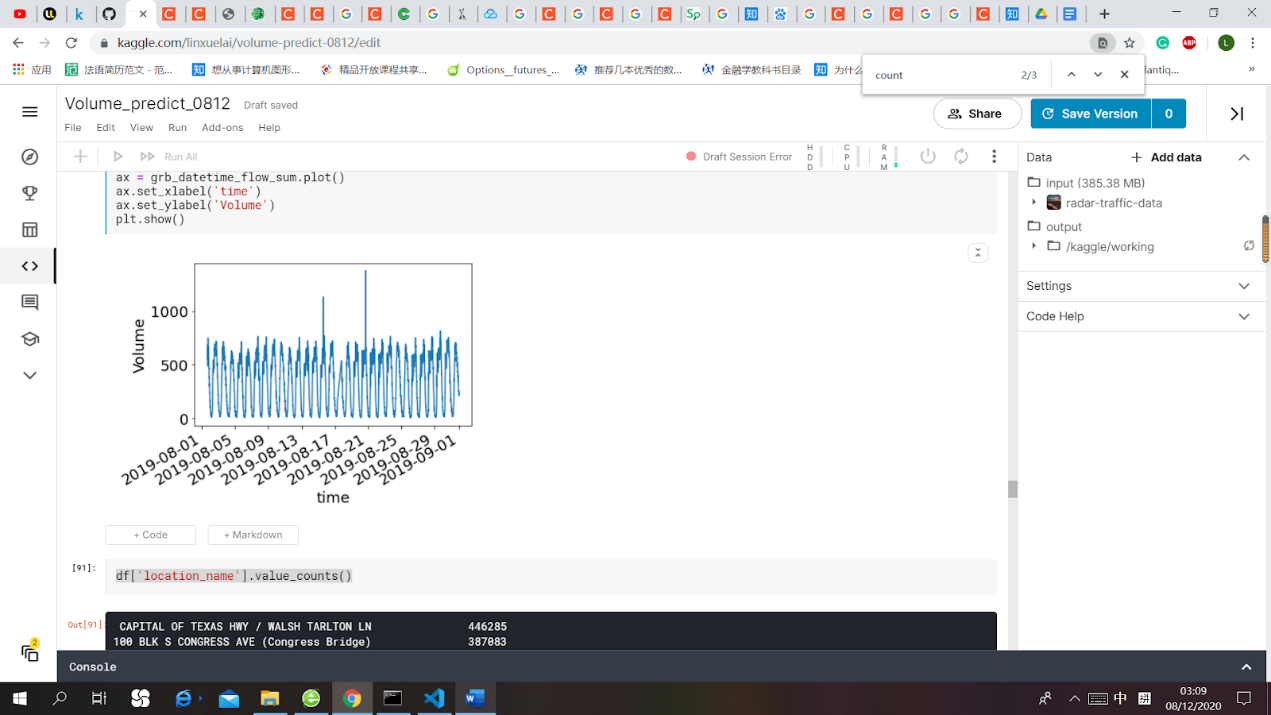
The following is an overview of some of the data:



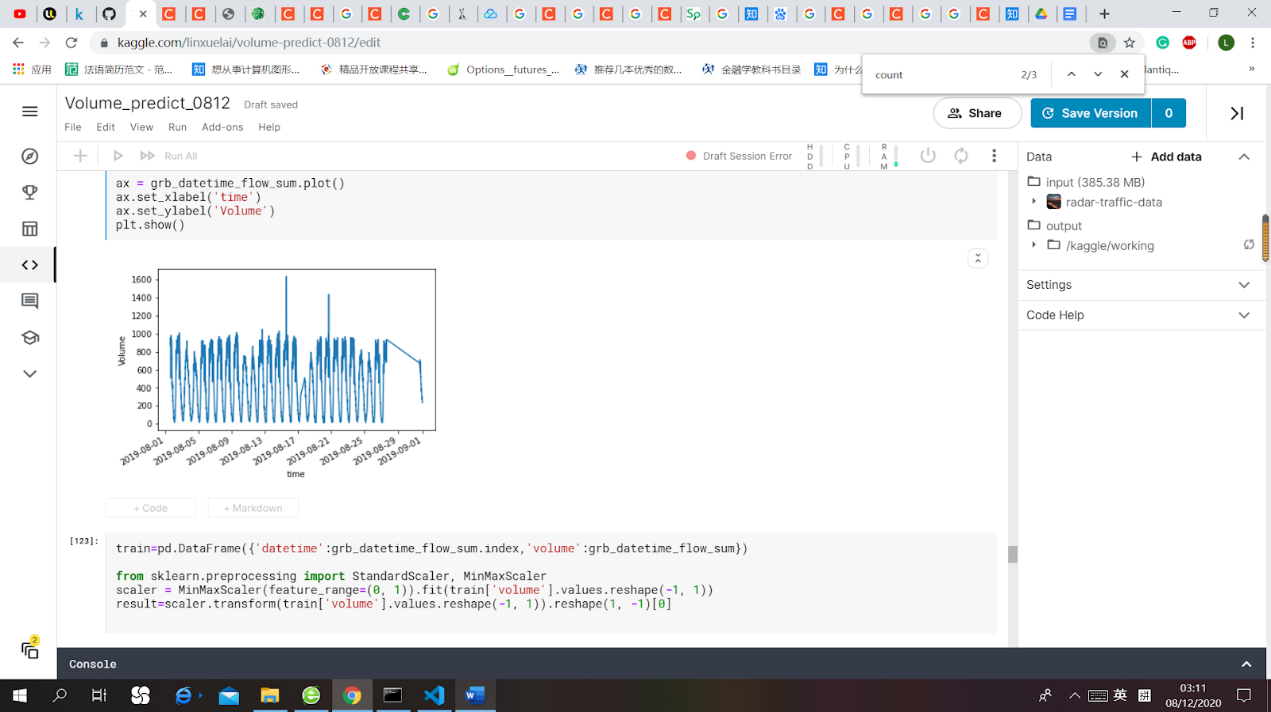
As traffic flow data has obvious periodic change characteristics, we consider using the commonly used LSTM model and GRU model for time series analysis.

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)*

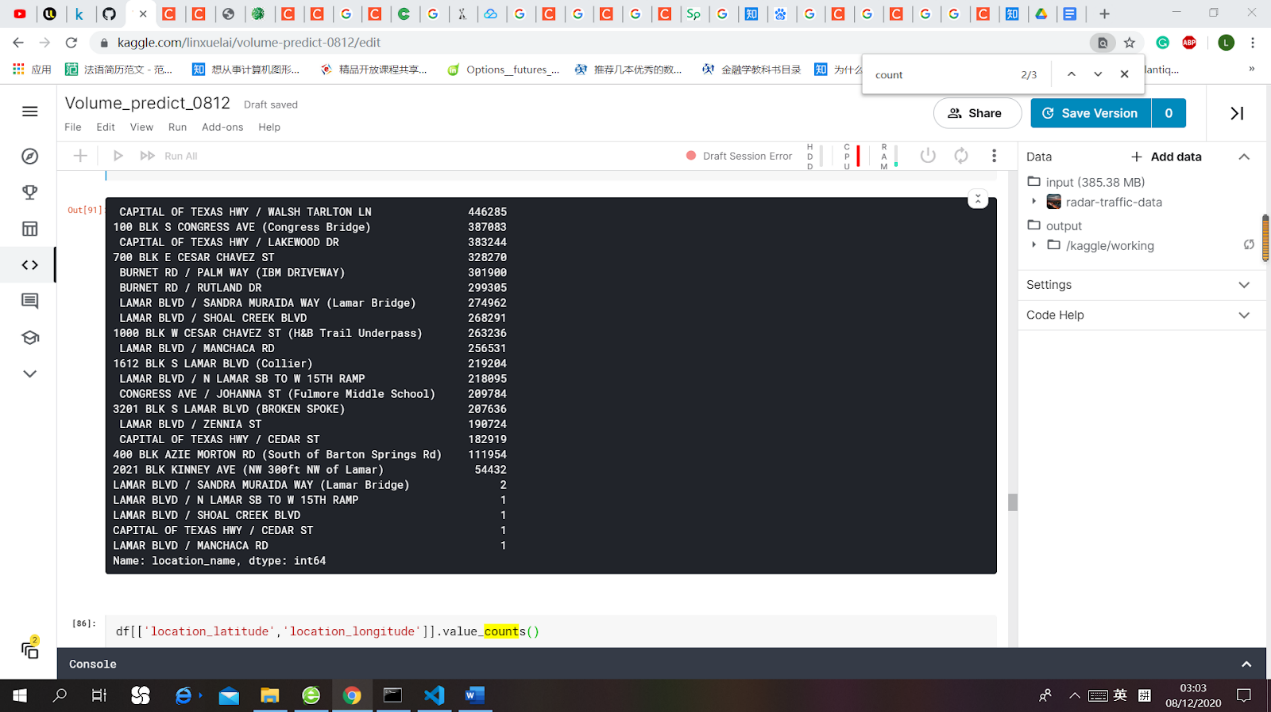
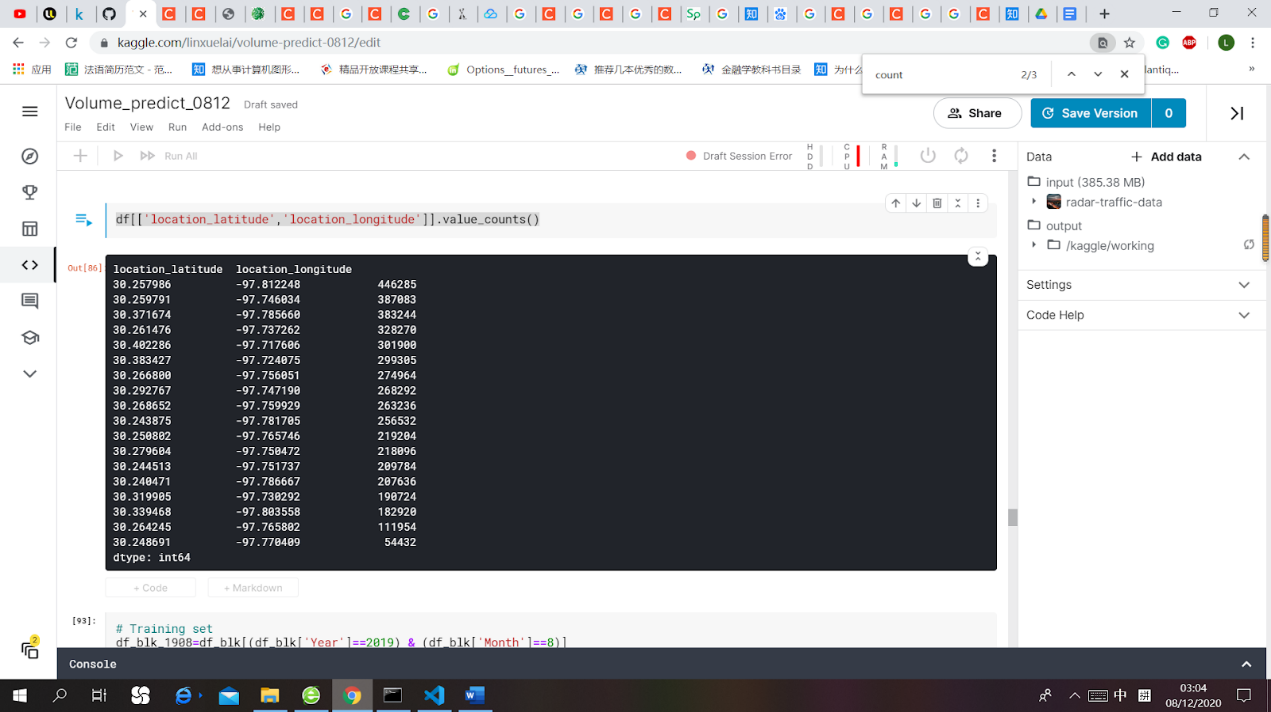


*location 2：100 BLK S CONGRESS AVE (Congress Bridge)*

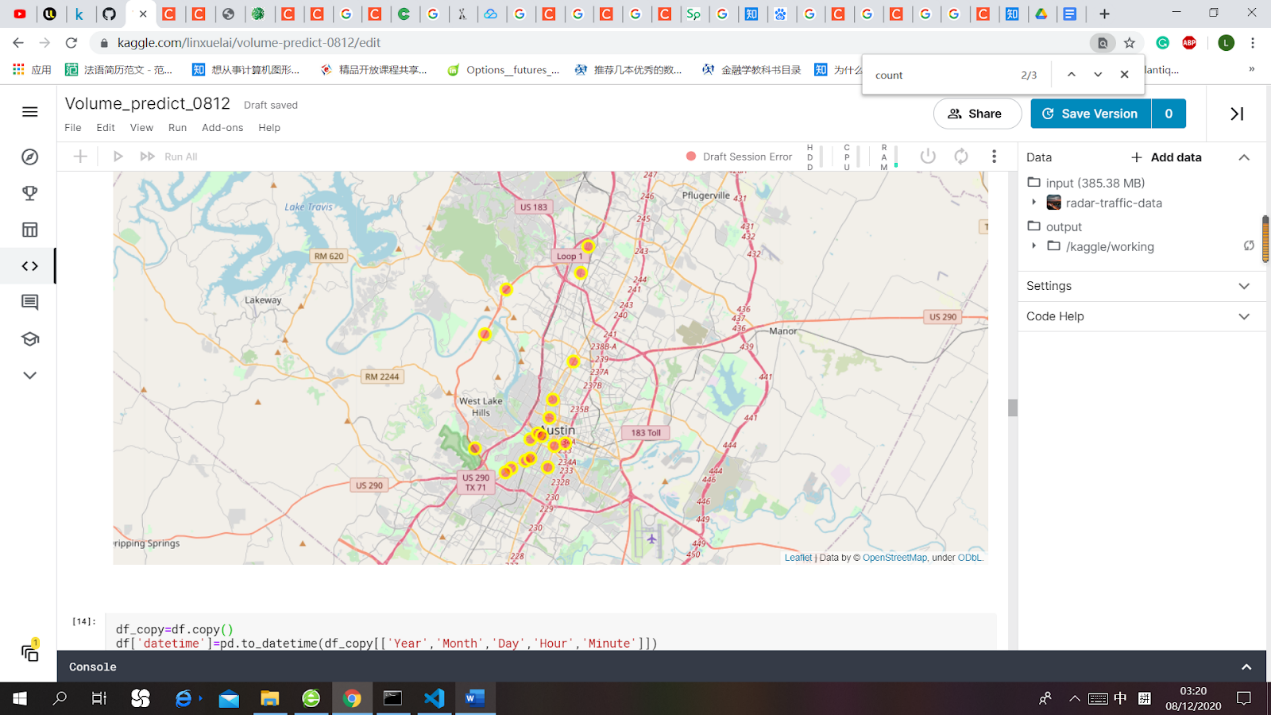
The number of locations: 23 different locations by location\_name; according to actual latitude and longitude: 18 different locations.

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.

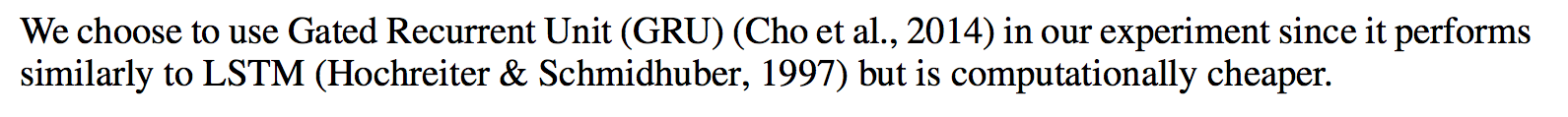
### 3.1 LSTM

### 3.2 GRU

3.2.1 Introduction to GRU

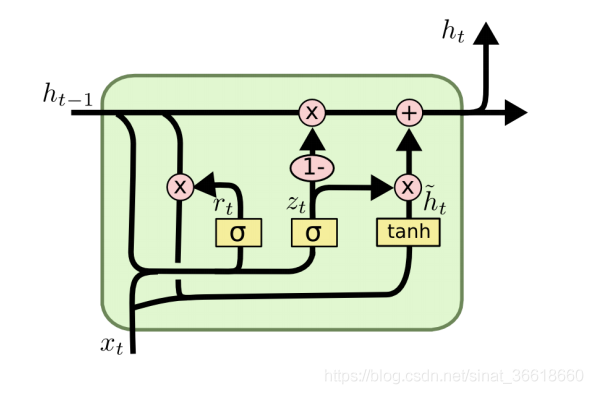
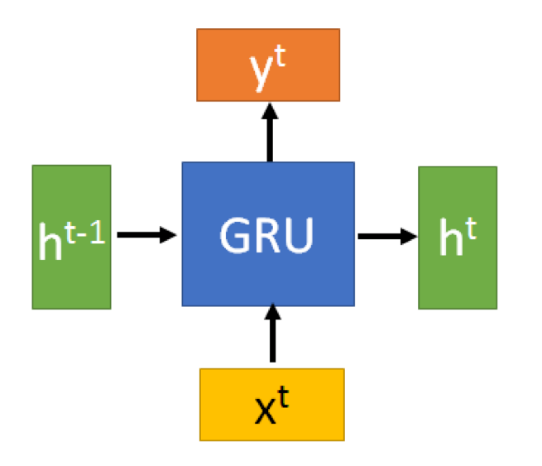
GRU (Gate Recurrent Unit) is a type of Recurrent Neural Network (RNN). Like LSTM (Long-Short Term Memory), it is also proposed to solve problems such as long-term memory and gradients in back propagation.

In many cases, GRU and LSTM are almost the same in actual performance, so why do we use the newcomer GRU (proposed in 2014).

Figure 1 below quotes a passage from the paper to illustrate the advantages of GRU. *Figure 1: R-NET: MACHINE READING COMPREHENSION WITH SELF-MATCHING NETWORKS（2017）*

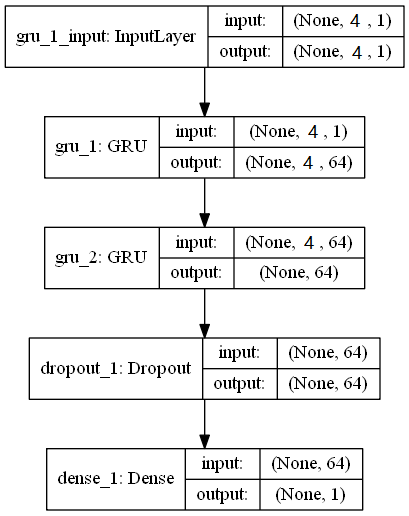
3.2.2 Structure of GRU model

The input and output structure of GRU is the same as that of ordinary RNN. There is a current input xt and a hidden state ht-1 passed down from the previous node. This hidden state contains information about the previous node. Combining xt and ht-1, GRU will get the output yt of the current hidden node and the hidden state ht passed to the next node.



*Figure 2: (a) GRU input and output structure (b) GRU network schematic diagram*

We use a 2-hidden layer GRU structure, as shown below:



*Figure 3 2-hidden layer GRU structure*

The model implementation code is as follows:

In the code *main.py*:

lags=4

units=[lags,64,64,1]

In the code model/model.py :

def get\_gru(units):

    """GRU(Gated Recurrent Unit)

    Build GRU Model.

    # Arguments

        units: List(int), number of input, output and hidden units.

    # Returns

        model: Model, nn model.

    """

    model = Sequential()

    model.add(GRU(units[1], input\_shape=(units[0], 1), return\_sequences=True))

    model.add(GRU(units[2]))

    model.add(Dropout(0.2))

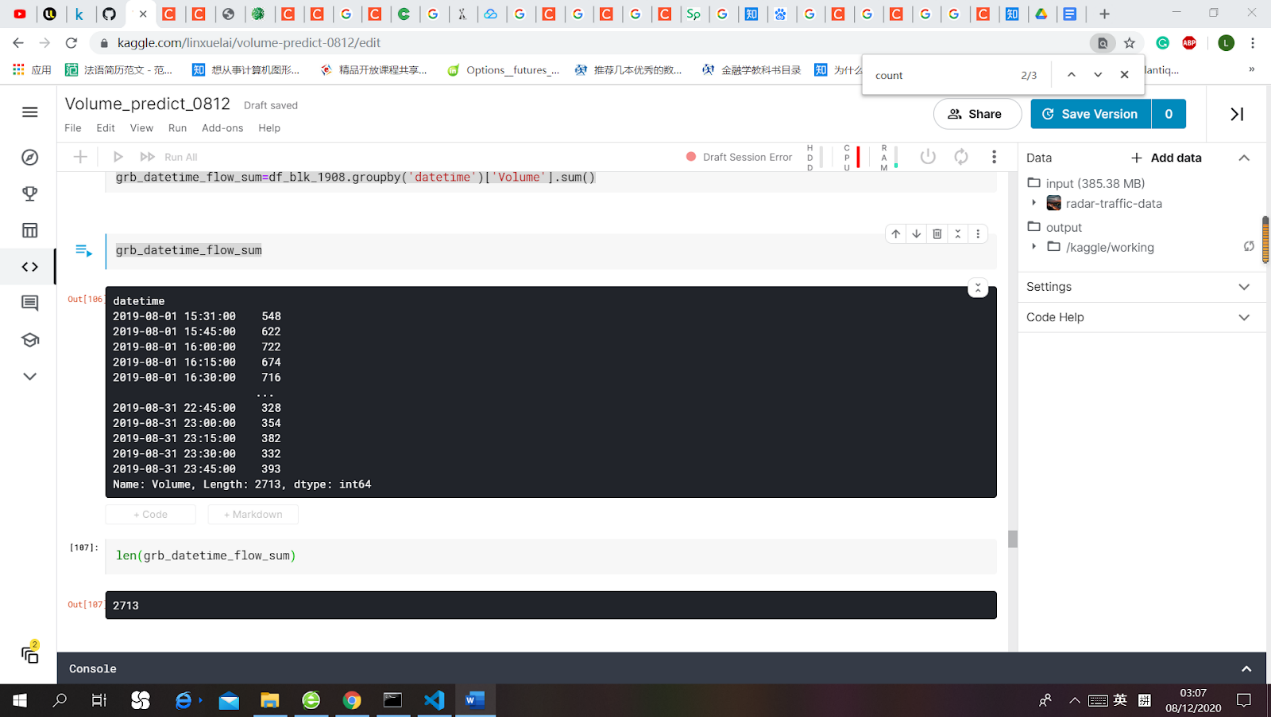
    model.add(Dense(units[3], activation='sigmoid'))

    return model

The experiment procedure (find code main.py in annexes 2):

One of the locations is selected, and a location in a certain period of time is selected for GRU training, and only time sequence is considered.

The data is at 15min intervals.



We run python main.py to do our whole experiment, the code will do firstly initialization of some important parameters in *Class predict\_volume*:

    def \_\_init\_\_(self,raw\_data,location,units,lags,config):

        self.raw\_data=raw\_data

        self.location=location

        self.units=units

        self.lags=lags

        self.config=config

        self.X\_train, self.y\_train, self.X\_test, self.y\_test, self.scaler = process\_data(self.raw\_data,self.location,self.lags)

Then train the gru\_model for our prepared dataset.

Finally，We use the trained model to make predictions on the test set and evaluate the results.

Here use MAE, MSE, RMSE, MAPE, R2, explained\_variance\_score several indicators to evaluate the regression prediction results.

def MAIN():

    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()

Values of the indicators：

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Metrics** | **MAE** | **MSE** | **RMSE** | **MAPE** | **R2** | **Explained variance score** |
| GRU | 26.00 | 1284.67 | 35.84 | 13.55% | 0.9671 | 0.9671 |

### 3.3 Comparison

## 4 Conclusion

In this project we proposes a LSTM model and a GRU model for traffic flow prediction. We compared the predictions of the LSTM and GRU models and found that in our research, the GRU NN model performed slightly better than the LSTM NN model. On average, the MAE and MSE of the GRU NN model are smaller than those of the LSTM NN model. The R-Squared of the GRN model is larger, about 0.9671, indicating that the model fitting effect is better than the LSTM model.

In future work, the influence of location factors can be considered. Combining the influence and relation of different locations and the factor of time, we can consider using methods such as Spatial-Temporal Graph Convolutional Networks for traffic flow prediction.

## 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] Find codes of this project in github: <https://github.com/LinxueLAI/FinalProject>

## 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)

## Annexes 2: main.py

import numpy as np

import pandas as pd

from data.data import process\_data

from evaluation import MAPE, eva\_regress, plot\_results

from model.model import get\_lstm, get\_gru

from train import train\_model

from tensorflow.keras.models import Model,load\_model

import matplotlib.pyplot as plt

class predict\_volume():

    def \_\_init\_\_(self,raw\_data,location,units,lags,config):

        self.raw\_data=raw\_data

        self.location=location

        self.units=units

        self.lags=lags

        self.config=config

        self.X\_train, self.y\_train, self.X\_test, self.y\_test, self.scaler = process\_data(self.raw\_data,self.location,self.lags)

    def training(self):

        gru\_model= get\_gru(self.units)

        train\_model(gru\_model, self.X\_train, self.y\_train, 'GRU', self.config)

        lstm\_model= get\_lstm(self.units)

        train\_model(lstm\_model, self.X\_train, self.y\_train, 'LSTM', self.config)

    def model\_evaluation(self):

        y\_preds = []

        lstm = load\_model('model/LSTM.h5')

        gru = load\_model('model/GRU.h5')

        models = [lstm, gru]

        names = ['LSTM', 'GRU']

        for name, model in zip(names, models):

            file = 'images/' + name + '.png'

            # plot\_model(model, to\_file=file, show\_shapes=True) # pydotplus.graphviz.InvocationException: GraphViz's executables not found

            predicted = model.predict(self.X\_test)

            predicted = self.scaler.inverse\_transform(predicted.reshape(-1, 1)).reshape(1, -1)[0]

            y\_preds.append(predicted[:120])

            print(name)

            eva\_regress(self.y\_test, predicted)

        plot\_results(self.y\_test[: 120], y\_preds, names)

def MAIN():

    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()

if \_\_name\_\_ == '\_\_main\_\_':

    MAIN()