Project Group - 06

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Research Objective

Requires data modeling and quantitative research in Transport, Infrastructure & Logistics

The driver is the most important parameter in the road traffic system and is the information decision maker and participant. The state of the vehicle on the road is the final result of the driver's cognition, psychology, decision making, and execution. The study of vehicle behavior only focuses on the outcome and ignores the entire process, which does not allow us to know the factors that influence the driver to make such a driving behavior. Therefore, it is important to analyze drivers' behavior of car following. The project first calibrates the IDM model based on the real observed vehicle trajectories through data processing. Then, heuristic genetic algorithms are used to obtain the optimal set of parameters for the driving characteristics of different drivers. Finally, the relationships between the driver's following behavior parameters and vehicle parameters are quantified and the selected quantitative model IDM model is analyzed for sensitivity in order to study the impact of driver behavior characteristics on traffic flow, which is of great significance for the future traffic development of cities and road safety.

In this project, we are very curious about the driving behavior of car drivers, so we model, optimize and analyze the vehicle following data from the ZTD data platform. We have chosen the following model algorithm and optimization algorithm as the goal of our course design. The car-following model algorithm adopts the intelligent driver model, and the optimization model chooses the genetic algorithm.

Contribution Statement

Be specific. Some of the tasks can be coding (expect everyone to do this), background research, conceptualisation, visualisation, data analysis, data modelling

Author Vincent Yang: Data sources searching, Data prcessing (Chapter 2), Genetic Algorithm (Chapter 3).

Author Eric Zhang: Correlation analysis using SPSS (Chapter 3), Partial visualisation and data analysis in Chapter 4.

Author Shenshen Sun: Result analysis and paritial visualisation in chapter 5, Research Objective.

Author Shuai Wang: Partial visualisation and data analysis in Chapter 4 and 5, Report layout.

1 IDM model

In this project, we will use the intelligent driver model with an explicit reaction time. Let's indicate the mathematical framework. We will fit the driving trajectory of a real car driver based on the intelligent driver model (IDM), **Equation 1**.

$$a_\alpha(t+\tau_\alpha) = a\left[1-\left(\frac{v_\alpha(t)}{v_0}\right)^4-\left(\frac{s^*\left(v_\alpha(t),\Delta v_\alpha(t)\right)}{s_\alpha(t)}\right)^2\right] \tag{1}$$

where we control the vehicle's driving state by the vehicle's acceleration $a_\alpha(t+\tau)$ at each moment *t* and τ_α denotes the driver's reaction time. v_0 denotes the free-flow speed of the vehicle and $S_\alpha(t)$ denotes the distance difference of the vehicle. s* is a distance consisting of three parts, given by the **Equation 2**:

$$s^*\left(v_\alpha(t),\Delta v_\alpha(t)\right) = s_0 + v_\alpha(t)T + \frac{v_\alpha(t)\Delta v_\alpha(t)}{2\sqrt{ab}} \tag{2}$$

$s*$ can be interpreted as a reference distance, composed of a static and dynamic term. S_0 indicates the minimum parking distance, and the $v_\alpha(t)T$ represents the speed of vehicle multiplied by the expected time headway. The third component represents a safety distance based on the speed difference $\Delta v_\alpha(t)$, which indicates the distance a vehicle needs to travel without hitting the vehicle in front of it (without reaching b) during non-emergency braking. a is the maximum acceleration of the vehicle, b is the comfortable deceleration of the vehicle.

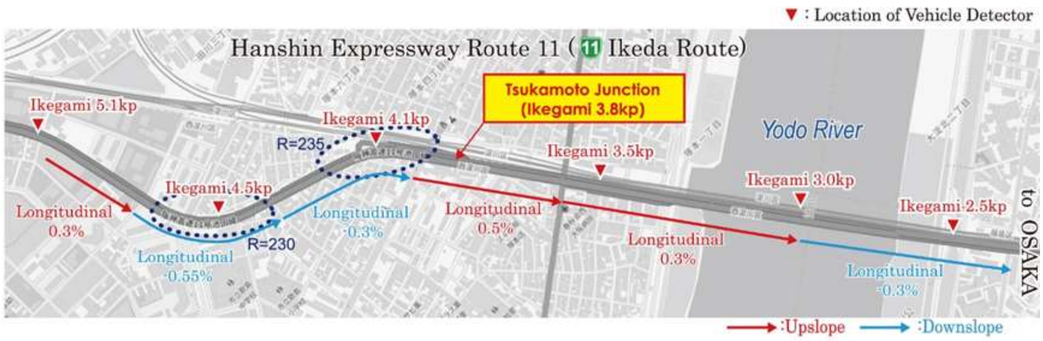
We modeled it according to the formula above, the file name is ***Intelligent Driver Model for assignment1.py.***

2 Data Processing

[https://zen-traffic-data.net/english/ (https://zen-traffic-data.net/english/)](https://zen-traffic-data.net/english/)

The vehicle trajectory data selected in this assignment comes from the Zen Traffic Data platform ([https://zen-traffic-data.net/ (https://zen-traffic-data.net/)](https://zen-traffic-data.net/)), which collects the movement of all vehicles on Hanshin Expressway Route 11 that stretches for several kilometers at 0.1 second intervals. Most sections of this expressway kilometer have 2 lanes, respectively, the passing lane and the driving lane, and there is an extra merging lane when it meets the merging gate.

The platform currently opens the track data of 3412 vehicles, We wrote a program(***Statistics information.py***) to count the number of rows in the raw data, and we also find the following time for every car(***find every car's time.py***), we got an average following time of 165.5 seconds. The data includes vehicle number, time, speed, lane,location, vehicle length and other information, it is worth noting that the vehicle length is rounded to 0.5 m. A portion of the Hanshin Expressway is shown in the figure below



To apply the car-following model, it is first necessary to find out information about the vehicles in front and behind. Since the original data (***L001_F001_trajectory.csv***) does not have the pairing information of the front and rear vehicles, we first need to pair the original data. We use the R language pairing program (***find_leaders.R***) given on the website to pair the vehicles and remove them. All vehicles with a vehicle length greater than 6.5 meters (***Remove vehicles over 6.5 meters.py***), got 1793 paired vehicle information (***Paired_L001_F001_trajectory.csv***).

COLUMN	TYPE	UNiT	DESCRIPTION	SAMPLE
vehicle_id	int		Vehicle ID	2341
datetime	string		Datetime	70216100
vehicle_type	int		1： normal vehicle 2： large vehicles (bus, truck, etc.)	1
velocity	decimal	km/h	Velocity	63.1
traffic_lane	int		1： driving lane 2： passing lane 3： entrance lane	1
longtiude	decimal	degree	Longitude measured as WGS84 system	135.45989
latitude	decimal	degree	Latitude measured as WGS84 system	34.720992
kilopost	decimal	meter	Distance from starting point of the expressway	5070.7
vehicle_length	decimal	meter	Estimated vehicle length from image recognition Value is rounded to 0.5 [m].	5.5
detected_flag	int		1： detected record by image recognition 2： interpolated record	1

We use kilopost as the vehicle location information, however, kilopost is calculated from the latitude and longitude of the rear center position of the vehicle, and the vehicle spacing S_α in the intelligent driver model is the distance from the rear of the previous vehicle to the front of the following vehicle, so the formula for calculating S_α in this assignment is shown in **Equation 3**.

$$s_\alpha = kp(\alpha - 1) - kp(\alpha) + length(\alpha) \tag{3}$$

where α is the current vehicle, $\alpha - 1$ is the previous vehicle, kp denotes kilopost, and $length$ denotes vehicle length.

3 Genetic Algorithm

We need to calibrate the model parameters of 1793 vehicles based on the improved intelligent driver model.

To this end, we use a genetic algorithm(***genetic algorithm.py***). We do so to fit the five parameters in the intelligent driver model, namely S_0, T, a, b, v_0 representing the driving behavior of the drivers. We use a library called geatpy, which has a built-in genetic algorithm kernel, and we need to set the parameters of the genetic algorithm.

The parameters are represented by a set of real numbers, and the quality of the model with these parameters by a value indicating the goodness of fit for the model with the parameter set. In this assignment, we chose to calculate the variation between the predicted car trajectory and the measured car trajectory as the root mean squared error between the measured position $y_{measured}(t)$ and predicted position $y_{IDM}(t)$, as indicated in **Equation 4**:

$$\min F(t) = \sum_{t}^{Time\ Interval} \left(y\_measured(t) - y\_predicted(t)\right)^2 \tag{4}$$

After determining the coding method and the fitness equation, we optimize the parameter set using a genetic algorithm.

For generating a next generation, we used the elite retention method. The initial generation was randomly generated within the range of values of each parameter. The population size was 20 individuals.

After that, we choose to use the two-point crossover method for the recombination of the parameter set with a recombination probability of 0.7. We use the variation operator of breeder GA as the variation algorithm for the parameter set. We set the variation probability to 1/decision variable dimensions.

Since there are five decision variables in total, we set the variation probability to 0.2. We set the condition for the termination of the algorithm to reach 50 evolutionary generations.

At the end, we do check the quality of the optimized result (see next subsection). Finally, we have to set a range for the calibration parameters to improve the calculation speed of the algorithm and to let the parameters fall within a reasonable interval, so we have to set a range for the five parameters to be calibrated, and the parameters are taken as follows.

$S_0 : 1 - 8m$ [Static Distance]

$T : 0.5 - 5s$ [Time Headway]

$a : 0.5 - 6m/s^2$ [Maximum Acceleration]

$b : 0.5 - 6m/s^2$ [Maximum Deceleration]

$v_0 : 0 - 50m/s$ [Free-flow Speed]

Now we have the value of the objective function and also the travel time of each vehicle, so we can calculate the error of each vehicle, we choose to eliminate the vehicles with an error greater than 10, and finally we get the data of 1231 vehicles(***result.csv***), also It's the driver's driving habits.

In [1]:
```
import pandas as pd
import plotly.express as px
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
```

In [2]:
```
# Result data
file_path = ".\\result.csv"
df = pd.read_csv(file_path, delimiter=',')
df
```

Out[2]:

	S	T	aMax	bMax	v0	least square	id	length	type	leader_id	leader_type	front_length	group	times	error
0	7.068824	1.160274	1.119538	4.133713	21.872616	1445.437292	3454	4.0	1	2376	2	7.5	1	713	1.423819
1	2.700226	1.699020	2.104446	2.820480	21.620178	1686.100051	3502	4.5	1	2763	2	8.5	2	701	1.550896
2	2.095893	1.755600	1.314833	3.444540	47.499037	1819.653283	3423	4.5	1	2041	1	5.5	2	746	1.561798
3	2.353956	0.579338	4.653707	3.689097	41.827202	2315.541396	3419	4.0	1	2008	1	4.5	1	877	1.624899
4	7.196570	1.325065	1.201248	0.500000	22.195339	2419.537743	3450	4.0	1	2923	1	3.5	1	768	1.774948
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1226	3.118927	1.582977	5.083557	1.203949	32.418823	113073.895500	145	3.5	1	143	1	4.0	1	1148	9.924536
1227	1.218109	2.281021	3.603653	4.311798	31.980896	153401.887700	865	3.5	1	862	1	4.5	1	1548	9.954739
1228	3.419281	1.898834	4.532684	5.868576	41.221619	178294.031400	1066	4.0	1	1065	1	3.5	1	1794	9.969128
1229	1.267029	1.875076	3.209045	0.974838	48.649597	160292.877100	987	4.5	1	985	2	11.5	2	1612	9.971824
1230	5.463654	1.319717	1.216370	3.205185	21.878052	111647.786400	751	4.0	1	749	2	7.0	1	1119	9.988724

1231 rows × 15 columns

Based on the data of the parameters given in the above table, 7 of them (S, T, aMax, bMax, v0, length(car), front_length(car)) are selected and correlation analysis is done using SPSS.

Correlations

[DataSet1]

Correlations

		S	T	aMax	bMax	v0	length	front_length
S	Pearson Correlation	1	-.228**	.014	.005	.004	.003	.042
	Sig. (1-tailed)		.000	.311	.424	.442	.453	.070
	N	1231	1231	1231	1231	1231	1231	1231
T	Pearson Correlation	-.228**	1	.167**	.120**	-.001	.142**	.181**
	Sig. (1-tailed)	.000		.000	.000	.491	.000	.000
	N	1231	1231	1231	1231	1231	1231	1231
aMax	Pearson Correlation	.014	.167**	1	-.093**	-.009	.013	.029
	Sig. (1-tailed)	.311	.000		.001	.380	.329	.156
	N	1231	1231	1231	1231	1231	1231	1231
bMax	Pearson Correlation	.005	.120**	-.093**	1	-.064*	-.025	.021
	Sig. (1-tailed)	.424	.000	.001		.012	.189	.233
	N	1231	1231	1231	1231	1231	1231	1231
v0	Pearson Correlation	.004	-.001	-.009	-.064*	1	-.018	.017
	Sig. (1-tailed)	.442	.491	.380	.012		.266	.277
	N	1231	1231	1231	1231	1231	1231	1231
length	Pearson Correlation	.003	.142**	.013	-.025	-.018	1	.393**
	Sig. (1-tailed)	.453	.000	.329	.189	.266		.000
	N	1231	1231	1231	1231	1231	1231	1231
front_length	Pearson Correlation	.042	.181**	.029	.021	.017	.393**	1
	Sig. (1-tailed)	.070	.000	.156	.233	.277	.000	
	N	1231	1231	1231	1231	1231	1231	1231

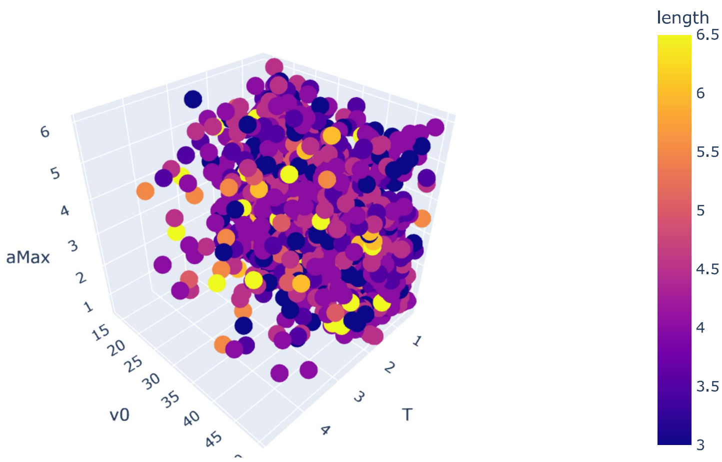
**. Correlation is significant at the 0.01 level (1-tailed).

*. Correlation is significant at the 0.05 level (1-tailed).

4 Basic Analysis

4.1 First, visualize the results of the above data

In [3]:
```
fig = px.scatter_3d(df, x='T', y='v0', z='aMax', color='length')
fig.show()
```



4.2 Then, we want to know the number of front vehicles in different length types.

In [4]:
```
# Each vehicle is marked with number = 1
df.insert(df.shape[1], 'number', 1)
df
```

Out[4]:

	S	T	aMax	bMax	v0	least square	id	length	type	leader_id	leader_type	front_length	group	times	error	number
0	7.068824	1.160274	1.119538	4.133713	21.872616	1445.437292	3454	4.0	1	2376	2	7.5	1	713	1.423819	1
1	2.700226	1.699020	2.104446	2.820480	21.620178	1686.100051	3502	4.5	1	2763	2	8.5	2	701	1.550896	1
2	2.095893	1.755600	1.314833	3.444540	47.499037	1819.653283	3423	4.5	1	2041	1	5.5	2	746	1.561798	1
3	2.353956	0.579338	4.653707	3.689097	41.827202	2315.541396	3419	4.0	1	2008	1	4.5	1	877	1.624899	1
4	7.196570	1.325065	1.201248	0.500000	22.195339	2419.537743	3450	4.0	1	2923	1	3.5	1	768	1.774948	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1226	3.118927	1.582977	5.083557	1.203949	32.418823	113073.895500	145	3.5	1	143	1	4.0	1	1148	9.924536	1
1227	1.218109	2.281021	3.603653	4.311798	31.980896	153401.887700	865	3.5	1	862	1	4.5	1	1548	9.954739	1
1228	3.419281	1.898834	4.532684	5.868576	41.221619	178294.031400	1066	4.0	1	1065	1	3.5	1	1794	9.969128	1
1229	1.267029	1.875076	3.209045	0.974838	48.649597	160292.877100	987	4.5	1	985	2	11.5	2	1612	9.971824	1
1230	5.463654	1.319717	1.216370	3.205185	21.878052	111647.786400	751	4.0	1	749	2	7.0	1	1119	9.988724	1

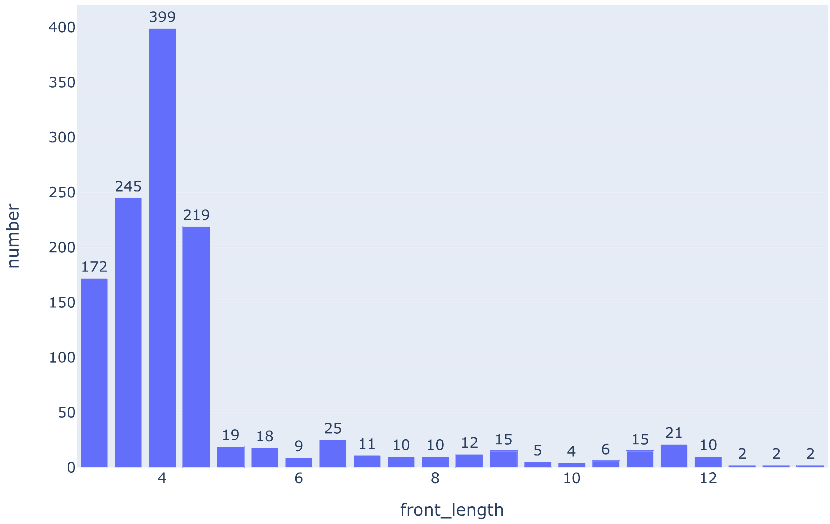
1231 rows × 16 columns

In [5]:
```
# Sorting vehicles of different lengths
df_4 = df.groupby("front_length").agg({"number": sum})
df_4
```

Out[5]:

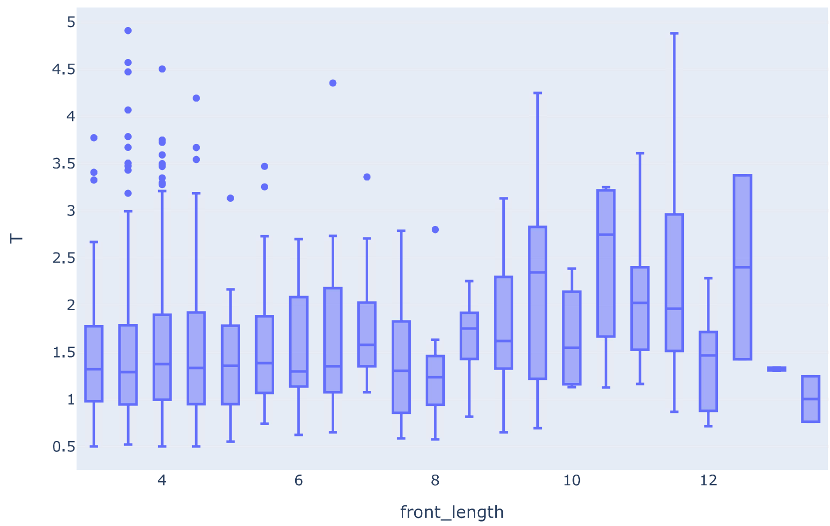
front_length	number
3.0	172
3.5	245
4.0	399
4.5	219
5.0	19
5.5	18
6.0	9
6.5	25
7.0	11
7.5	10
8.0	10
8.5	12
9.0	15
9.5	5
10.0	4
10.5	6
11.0	15
11.5	21
12.0	10
12.5	2
13.0	2
13.5	2

In [6]:
```
fig = px.bar(df_4, x=df_4.index, y="number", text_auto=True)
fig.update_traces(textposition = "outside")
fig.show()
```



4.3 Box figure on relationship between Expected Time Headway(T) and Front Car Length

In [7]:
```
fig = px.box(df, x="front_length", y="T")
fig.show()
```

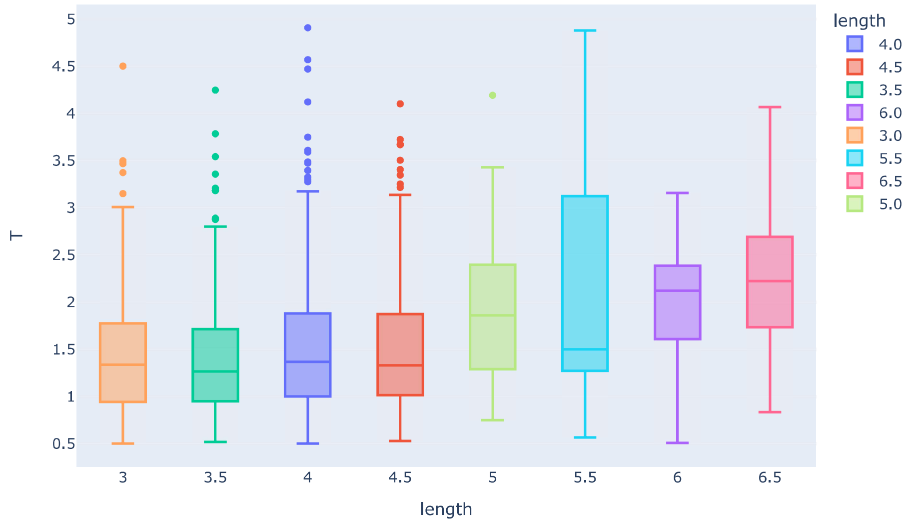


When the front vehicle length is between 3 and 6.5m, the expected time headway(T) is more stable, with values fluctuating between approximately 1.30 and 1.50.

When the front vehicle length is greater than 6.5m, the expected time headway(T) fluctuates greatly, indicating that the driver is unable to accurately determine the distance to the front vehicle.

4.4 Box figure on relationship between Expected Time Headway(T) and Car Length

In [8]:
```
fig = px.box(df, x="length", y="T", color='length')
fig.show()
```



A general trend can be drawn that the longer the length of the car the driver is driving, the expected time headway(T) becomes greater.

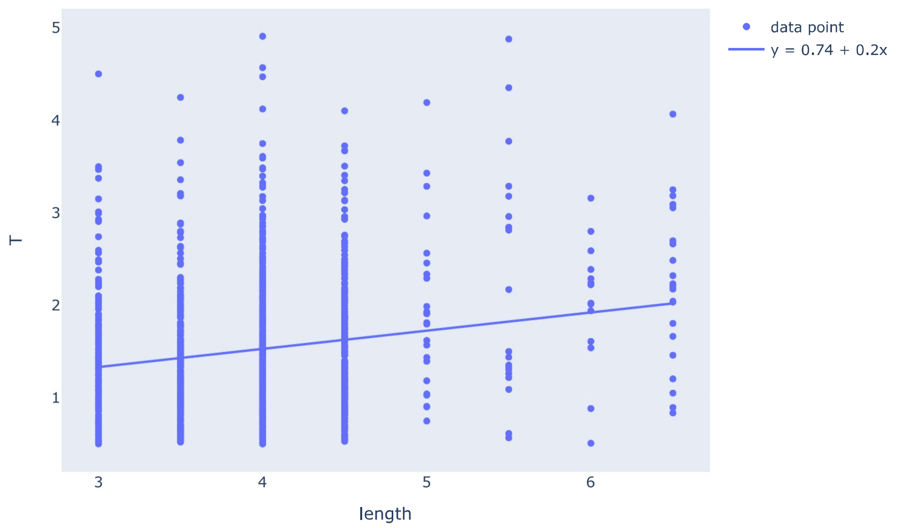
And according to the data results, when the car length is 5.5m, the expected time headway(T) is most unstable, with a large distribution range(1.27s to 3.12s).

4.5 Relationship between Expected Time Headway(T) and vehicle length

In [9]:
```
# T(Expected Time Headway) and Length Figure
fig = px.scatter(df, x="length", y="T", trendline="ols")

model = px.get_trendline_results(fig)
alpha = model.iloc[0]["px_fit_results"].params[0]
beta = model.iloc[0]["px_fit_results"].params[1]
fig.data[0].name = 'data point'
fig.data[0].showlegend = True
fig.data[1].name = fig.data[1].name + 'y = ' + str(round(alpha, 2)) + ' + ' + str(round(beta, 2)) + 'x'
fig.data[1].showlegend = True

fig.show()
```



According to the regression line, it can be seen that for every meter increase in the length of the car, the expected time teadway (T) increases by 0.2s.

4.6 Pick car No.45 and drow its trendline on acceleration

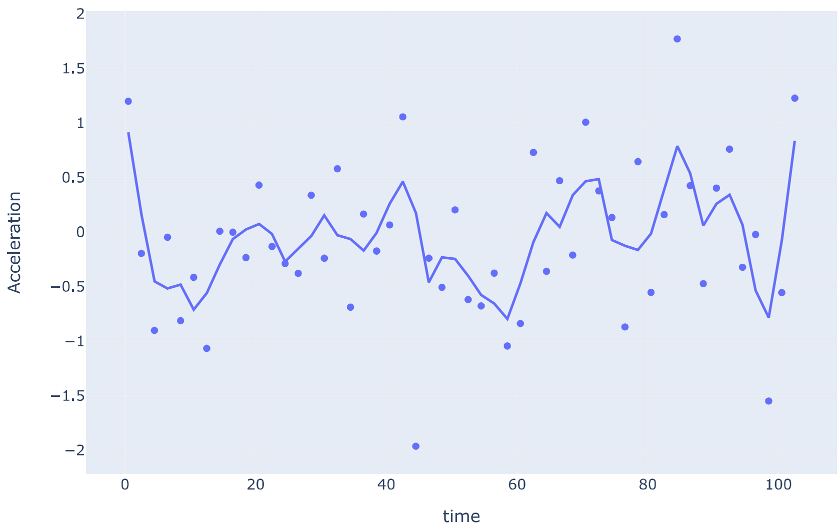
In [10]:
```
file_path_45 = ".\IDMdata_for_45.csv"
df_45 = pd.read_csv(file_path_45, delimiter=',')

a = []
for i in range(0, len(df_45), 20):
    a.append(i)
file_45 = df_45.iloc[a]
file_45
```

Out[10]:

	Unnamed: 0	Velocity	Acceleration	front car position	following car position	time
0	5	22.083333	1.197868	5013.3	5054.8	0.5
20	25	23.118247	-0.196055	4965.0	5009.5	2.5
40	45	22.512502	-0.901774	4921.4	4962.5	4.5
60	65	22.107790	-0.048463	4881.5	4918.0	6.5
80	85	21.317817	-0.812781	4840.6	4875.8	8.5
100	105	20.954422	-0.415862	4802.0	4830.4	10.5
120	125	20.154522	-1.066362	4761.3	4790.4	12.5
140	145	19.996274	0.007225	4721.4	4746.2	14.5
160	165	20.508522	-0.002056	4679.4	4705.3	16.5
180	185	20.378130	-0.234547	4639.4	4663.0	18.5
200	205	20.468841	0.430020	4598.4	4621.9	20.5
220	225	20.619558	-0.133235	4556.0	4580.9	22.5
240	245	21.289919	-0.289163	4510.8	4534.8	24.5
260	265	20.930060	-0.378803	4467.1	4489.3	26.5
280	285	20.956666	0.336937	4421.5	4446.5	28.5
300	305	21.440629	-0.240220	4380.0	4401.5	30.5
320	325	20.671536	0.579729	4341.9	4360.4	32.5
340	345	19.990073	-0.689199	4305.8	4322.9	34.5
360	365	20.015200	0.164555	4264.3	4286.2	36.5
380	385	20.163644	-0.174391	4221.3	4246.0	38.5
400	405	20.850204	0.064595	4182.7	4205.1	40.5
420	425	21.172419	1.055524	4137.6	4163.9	42.5
440	445	20.392953	-1.962937	4097.7	4119.6	44.5
460	465	19.917248	-0.239796	4058.6	4077.9	46.5
480	485	19.819847	-0.507157	4018.8	4038.1	48.5
500	505	19.890008	0.202378	3980.8	4000.0	50.5
520	525	19.728980	-0.619193	3943.3	3962.9	52.5
540	545	19.945782	-0.677604	3905.2	3925.9	54.5
560	565	20.367219	-0.376969	3866.0	3887.6	56.5
580	585	19.984638	-1.044514	3828.8	3854.8	58.5
600	605	19.538223	-0.839123	3789.6	3814.4	60.5
620	625	20.364766	0.729353	3746.4	3775.0	62.5
640	645	20.336822	-0.360694	3708.6	3735.7	64.5
660	665	19.677632	0.469789	3669.6	3696.3	66.5
680	685	19.075934	-0.211178	3630.7	3658.4	68.5
700	705	18.189714	1.006257	3598.1	3621.8	70.5
720	725	18.150366	0.376834	3560.0	3589.0	72.5
740	745	17.712193	0.132837	3525.4	3552.8	74.5
760	765	17.738428	-0.870324	3488.3	3517.5	76.5
780	785	17.601073	0.644647	3446.7	3479.1	78.5
800	805	17.175957	-0.554021	3414.5	3436.6	80.5
820	825	16.321673	0.159332	3381.9	3403.3	82.5
840	845	15.412308	1.769622	3358.8	3376.5	84.5
860	865	15.894708	0.424552	3325.0	3345.5	86.5
880	885	16.929529	-0.473399	3286.4	3311.7	88.5
900	905	17.351491	0.402146	3250.0	3273.8	90.5
920	925	18.667135	0.759388	3208.8	3238.9	92.5
940	945	19.168155	-0.322739	3171.4	3196.5	94.5
960	965	18.369076	-0.022981	3133.5	3160.0	96.5
980	985	17.547516	-1.548931	3100.6	3120.7	98.5
1000	1005	16.782025	-0.555282	3069.0	3087.5	100.5
1020	1025	16.282124	1.226687	3037.5	3058.0	102.5

```
In [11]: fig_45 = px.scatter(file_45, x='time', y="Acceleration", trendline="lowess", trendline_options=dict(frac=0.1))
fig_45.show()
```



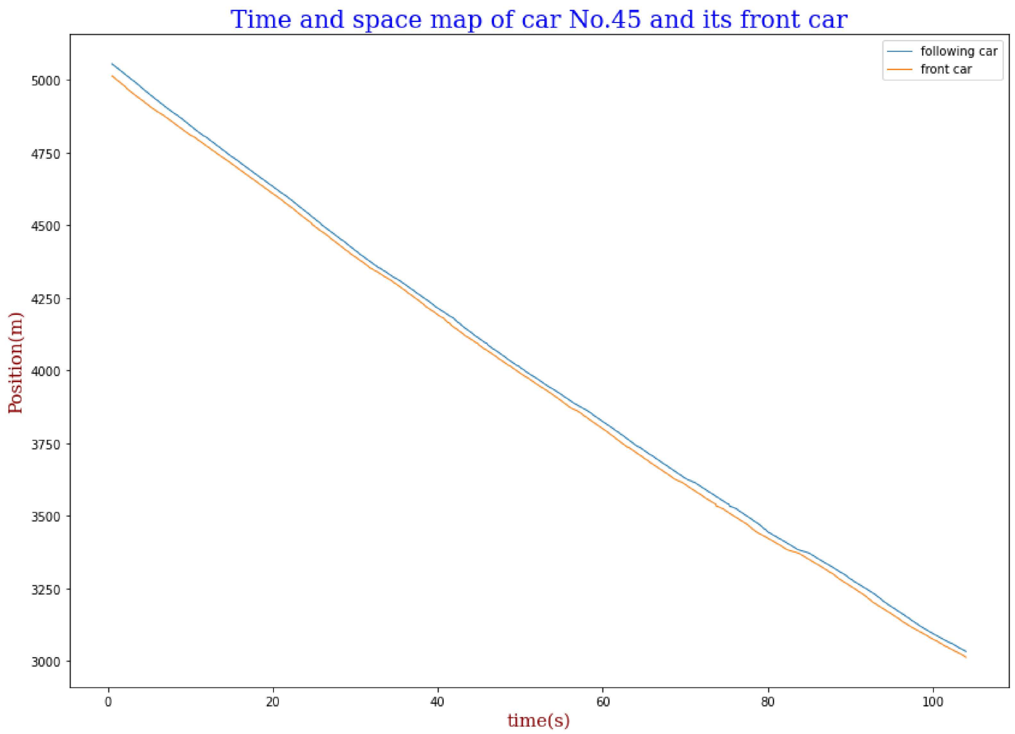
4.7 Time and space map of car No.45 and its front car

```
In [12]: # Draw picture about time and space map of car No.45 and its front car
x=df_45['time']
y1=df_45['following car position']
y2=df_45['front car position']

plt.figure(figsize=(14,10))
l1,=plt.plot(x,y1,linewidth=1)
l2,=plt.plot(x,y2,linewidth=1)

font1 = {'family':'serif','color':'blue','size':20}
font2 = {'family':'serif','color':'darkred','size':15}

plt.legend((l1,l2,),['following car','front car'])
plt.title("Time and space map of car No.45 and its front car", fontdict=font1)
plt.xlabel("time(s)", fontdict=font2)
plt.ylabel("Position(m)", fontdict=font2)
#
plt.show()
```



5 Sensitivity Analysis

After having a range for the five parameters of 1232 vehicles, we tried to make a sensitivity analysis of IDM model. A smoothly moving vehicle following the IDM model was selected from the filtered data and analyzed by adjusting the value of a parameter through the control variables method, leaving other parameters unchanged. The effect of different parameter settings on the model is analyzed and the results are visualized.

5.1 Sensitivity Analysis of Static Distance(s_0)

The third vehicle after filtering is selected as the target vehicle for sensitivity analysis.

The parameters after the third vehicle was calibrated are:

$$s_0 = 2.10,\ T = 1.76,\ aMax = 1.31,\ bMax = 3.45,\ v_0 = 47.50$$

The vehicle speed is updated every 0.1 seconds in python and the speed taken by the vehicle at different times is output separately. With other parameters kept constant, the value of s_0 was adjusted to obtain the $v - t$ image of the vehicle motion for different values of s_0 as shown in the **Figure 5.1**.

In [13]:
```
file_path_S = ".\S.csv"
df_S = pd.read_csv(file_path_S, delimiter=',')
df_S
```

Out[13]:

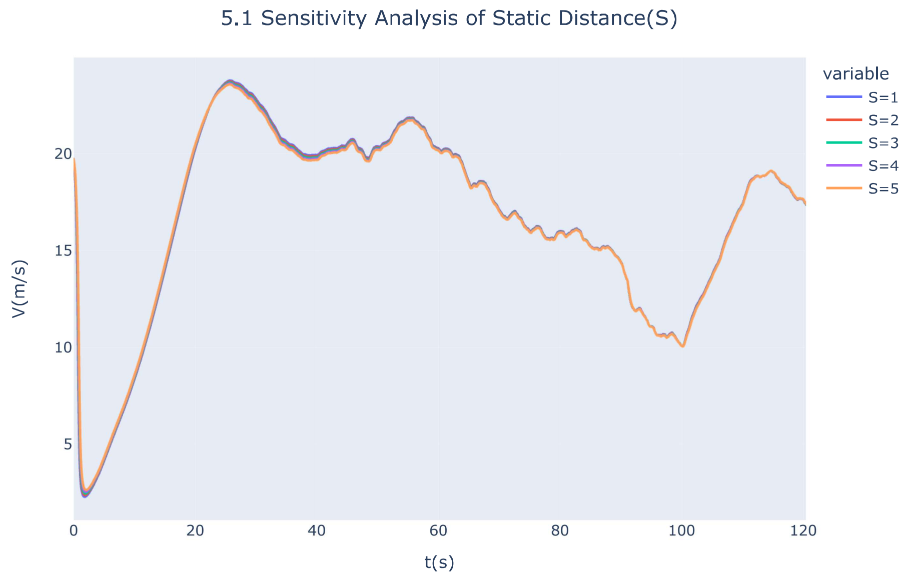
	S=1	S=2	S=3	S=4	S=5	t
0	19.722222	19.722222	19.722222	19.722222	19.722222	0.0
1	19.450406	19.472240	19.493460	19.514067	19.534060	0.1
2	18.999892	19.060428	19.118742	19.174861	19.228812	0.2
3	18.382873	18.504178	18.619833	18.729965	18.834705	0.3
4	17.346008	17.571916	17.785354	17.986659	18.176187	0.4
...	...	...	...	...	...	...
1200	17.604123	17.609539	17.615086	17.620766	17.626578	120.0
1201	17.519934	17.527409	17.534888	17.542380	17.549895	120.1
1202	17.452225	17.460860	17.469446	17.477996	17.486521	120.2
1203	17.461634	17.469158	17.476704	17.484278	17.491884	120.3
1204	17.363083	17.372707	17.382243	17.391704	17.401102	120.4

1205 rows × 6 columns

In [14]:
```
fig_S = px.line(df_S, x='t', y=df_S.columns[0:6])

fig_S.update_layout(
    title={
        "text":"5.1 Sensitivity Analysis of Static Distance(S)",
        "y":0.96,
        "x":0.5,
        "xanchor":"center",
        "yanchor":"top"
    }
)
fig_S.update_layout(xaxis_title='t(s)',yaxis_title='V(m/s)')

fig_S.show()
```



With the change of s_0 values, the $v - t$ image of vehicle 3 doesn't have too much difference. Apparently, changing the value of s_0 has less effect on motion of the vehicles which follow IDM model and s_0 has less effect on the sensitivity of the IDM model.

5.2 Sensitivity Analysis of Time Headway(T)

With other parameters kept constant, the value of T was adjusted to obtain the $v - t$ image of the vehicle motion for different values of T as shown in **Figure 5.2**.

In [15]:
```python
file_path_T = ".\T.csv"
df_T = pd.read_csv(file_path_T, delimiter=',')
df_T
```

Out[15]:

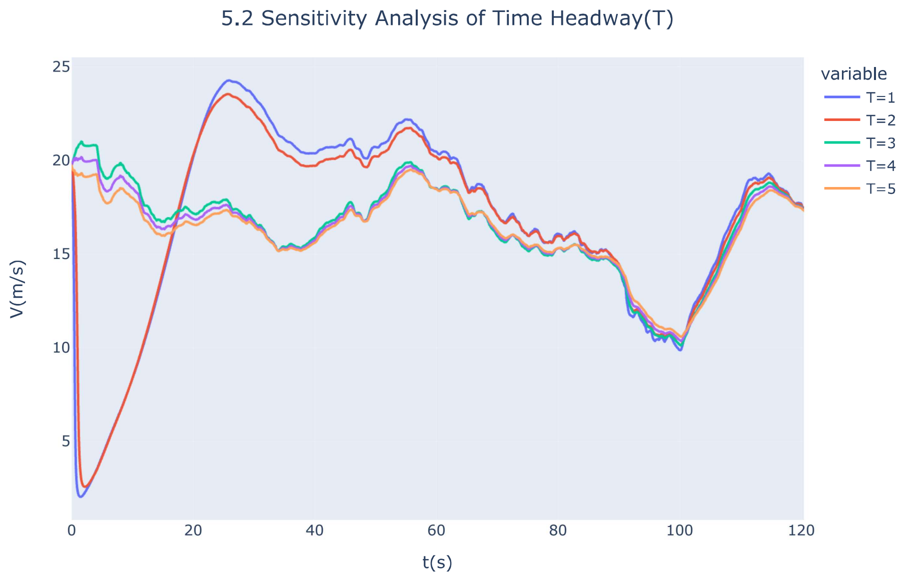
	T=1	T=2	T=3	T=4	T=5	t
0	19.722222	19.722222	19.722222	19.722222	19.722222	0.0
1	19.086235	19.570652	19.816358	19.823354	19.591640	0.1
2	17.943302	19.325391	19.919107	19.906056	19.486892	0.2
3	16.169206	19.017381	20.033912	19.979328	19.440440	0.3
4	13.192924	18.498050	20.141748	20.072961	19.465499	0.4
...	...	...	...	...	...	...
1200	17.639443	17.600972	17.509371	17.474398	17.435066	120.0
1201	17.520274	17.526069	17.451957	17.426960	17.394109	120.1
1202	17.434998	17.463991	17.401890	17.384390	17.356714	120.2
1203	17.461949	17.468998	17.399864	17.378647	17.349115	120.3
1204	17.329484	17.380208	17.330736	17.321468	17.299881	120.4

1205 rows × 6 columns

In [16]:
```python
fig_T = px.line(df_T, x='t', y=df_T.columns[0:6])
#fig.update_traces(line=dict(width=1.5))

fig_T.update_layout(
    title={
        "text":"5.2 Sensitivity Analysis of Time Headway(T)",
        "y":0.96,
        "x":0.5,
        "xanchor":"center",
        "yanchor":"top"
    }
)
fig_T.update_layout(xaxis_title='t(s)',yaxis_title='V(m/s)')

fig_T.show()
```



In **Figure 5.2**, the vehicle motion state varies considerably under the influence of different headway time distances, indicating that the values T has a large influence on the sensitivity of the IDM model and when the value of T goes larger, the more stable the change in vehicle speed.

5.3 Sensitivity Analysis of Maximum Acceleration(aMax)

With other parameters kept constant, the value of $aMax$ was adjusted to obtain the $v-t$ image of the vehicle motion for different values of $aMax$ as shown in **Figure 5.3**.

In [17]:
```
file_path_A = ".\A.csv"
df_A = pd.read_csv(file_path_A, delimiter=',')
df_A
```

Out[17]:

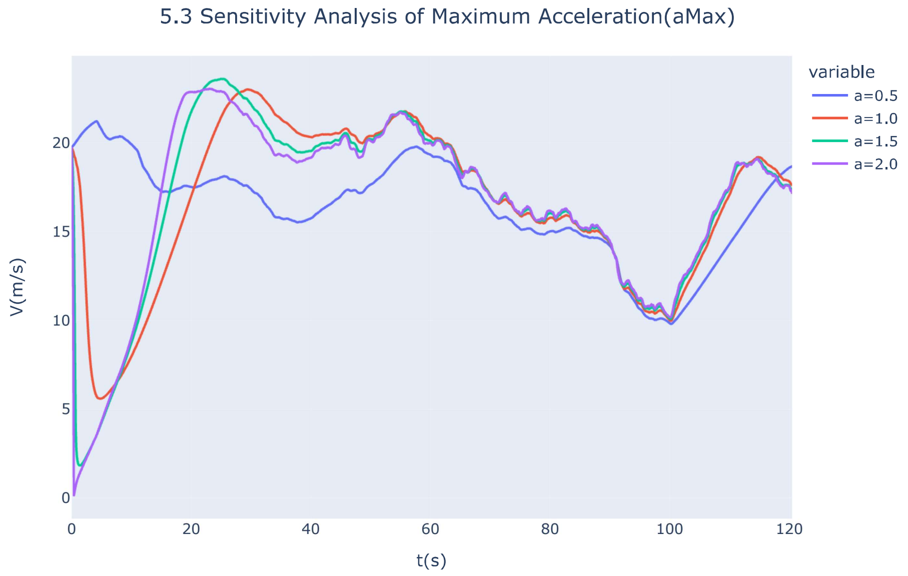
	a=0.5	a=1.0	a=1.5	a=2.0	t
0	19.722222	19.722222	19.722222	19.722222	0.0
1	19.764180	19.663777	19.311458	18.668128	0.1
2	19.806371	19.574539	18.561944	15.985045	0.2
3	19.849990	19.484389	17.375344	9.628673	0.3
4	19.890540	19.335345	15.165809	0.153603	0.4
...	...	...	...	...	...
1200	18.606443	17.809205	17.561126	17.504468	120.0
1201	18.623242	17.747391	17.465035	17.367358	120.1
1202	18.639692	17.693264	17.390964	17.277147	120.2
1203	18.661863	17.687899	17.407999	17.323868	120.3
1204	18.673791	17.614336	17.297296	17.173528	120.4

1205 rows × 5 columns

In [18]:
```
fig_A = px.line(df_A, x='t', y=df_A.columns[0:5])

fig_A.update_layout(
    title={
        "text":"5.3 Sensitivity Analysis of Maximum Acceleration(aMax)",
        "y":0.96,
        "x":0.5,
        "xanchor":"center",
        "yanchor":"top"
    }
)
fig_A.update_layout(xaxis_title='t(s)',yaxis_title='V(m/s)')

fig_A.show()
```



Similarly, from **Figure 5.3**, it can be seen that the maximum acceleration has a large effect on the sensitivity of the IDM model. When the value of $aMax$ goes smaller, the more stable the change in vehicle speed.

5.4 Sensitivity Analysis of Maximum Deceleration(bMax)

With other parameters kept constant, the value of $bMax$ was adjusted to obtain the $v - t$ image of the vehicle motion for different values of $bMax$ as shown in **Figure 5.4**.

In [19]:
```
file_path_B = ".\B.csv"
df_B = pd.read_csv(file_path_B, delimiter=',')
df_B
```

Out[19]:

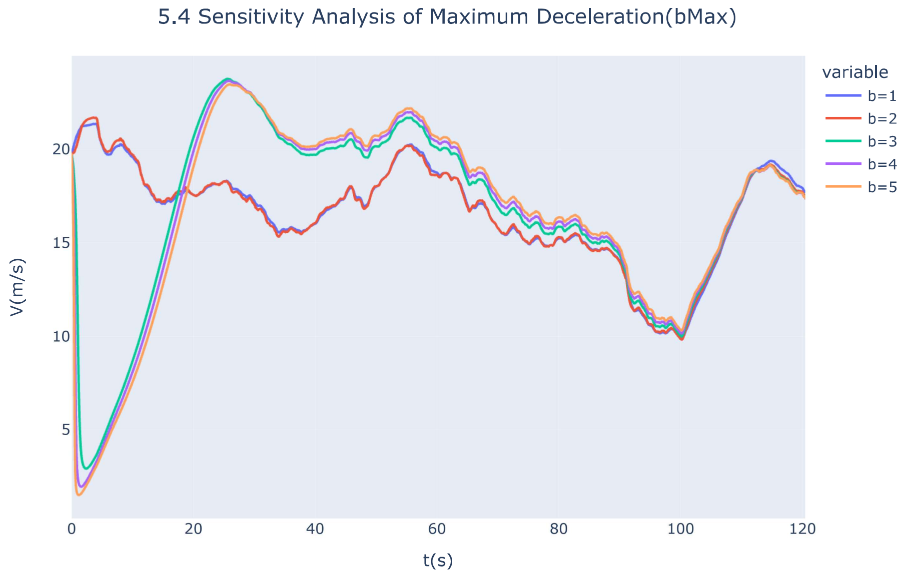
	b=1	b=2	b=3	b=4	b=5	t
0	19.722222	19.722222	19.722222	19.722222	19.722222	0.0
1	19.848674	19.751306	19.570030	19.345321	19.092855	0.1
2	19.976063	19.774566	19.328515	18.685328	17.852575	0.2
3	20.103159	19.811626	19.033487	17.694606	15.654617	0.3
4	20.230416	19.825352	18.553144	15.932928	11.429207	0.4
...	...	...	...	...	...	...
1200	17.894197	17.679640	17.620919	17.606706	17.620462	120.0
1201	17.832694	17.609544	17.542356	17.521014	17.529367	120.1
1202	17.777909	17.549950	17.477819	17.452512	17.458012	120.2
1203	17.765879	17.549011	17.483612	17.463291	17.472440	120.3
1204	17.695938	17.467064	17.391310	17.362708	17.365690	120.4

1205 rows × 6 columns

In [20]:
```
fig_B = px.line(df_B, x='t', y=df_B.columns[0:6])

fig_B.update_layout(
    title={
        "text":"5.4 Sensitivity Analysis of Maximum Deceleration(bMax)",
        "y":0.96,
        "x":0.5,
        "xanchor":"center",
        "yanchor":"top"
    }
)
fig_B.update_layout(xaxis_title='t(s)',yaxis_title='V(m/s)')

fig_B.show()
```



Similarly, from **Figure 5.4**, it can be seen that the maximum deceleration has a large effect on the sensitivity of the IDM model. When the value of $bMax$ goes smaller, the more stable the change in vehicle speed.

5.5 Conclusion

After the above analysis of the four parameters, s_0 has a small effect on the sensitivity of IDM model and T, $aMax$, $bMax$ has a large effect on the IDM model.