Minerva Schools At KGI CS166 - Traffic Simulation Assignment Report

> Quang Tran CS166 Fall 2019

#### 2

## Introduction

The format of this report is that in each part, plots and *raw* results are simply presented without and accompanied explanations or interpretations. All the interpretations and discussions are at the very end of each part.

## Simulation Code

Link: https://gist.github.com/guangntran/fc0d12d2d9fb922770f30dfc8af5e417

# Part 1. Traffic jam on a circular road

 Write well-structured and well-documented Python code to implement the model described in the paper.

The code is available in my notebook as well as the gist link above.

 Visualize the state of this model over time, to show how traffic jams can appear when traffic density is high enough.

In all of the graphics below, the states over 20 time steps are displayed. Road length is set to 100, slow down probability 0.5, and max speed 5.

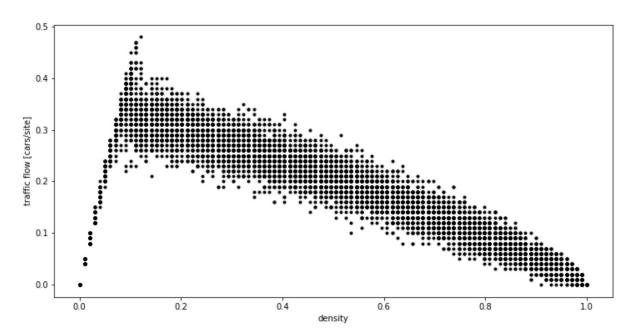
Car density 0.05
5
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44
5454545454
4
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444444
Car density 0.07
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54251.14 45340.244
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4

Car density 0.1
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221.1231
$\dots 1 \dots 3 \dots 0.2 \dots 3 \dots 3 \dots 2 \dots \dots 4 \dots 4 \dots 1.$
2002443
31.013453
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3 1 0 2 2 4 5 3 4
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1.1...1.....4.....0.000.....0..2.....00..0.2....4.....4.....4....3...2...1..

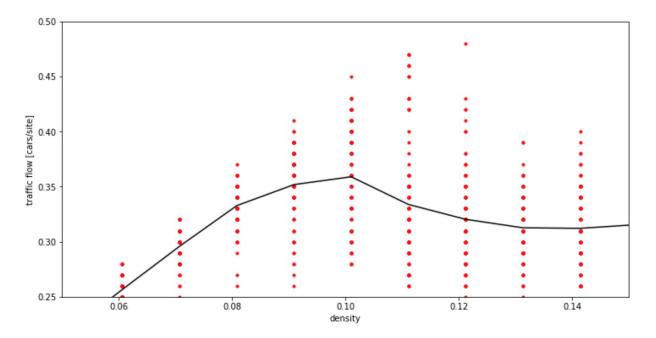
```
Car density 0.4
0.3.\dots..00002..0.0.001.1.00.3\dots.1\dots.01\dots02\dots..001..001..001.0\dots.01\dots.2\dots.1\dots02\dots...3\dots.2\dots00.1\dots
1....2...0000..01.1.00.0.001....1..2...1.0.1..2....00.1.00.00..1.2....1..0.1..2....2...001..0.
..2...1.001.1.1..001.0.000....0.1..0.0..2...1..001..001.1.1..2...1..1.1..1...3.....0001.00...
\dots \dots 1.001.1.0 \dots 001.0.000.2 \dots \dots 1.1.1.1 \dots \dots 1.000 \dots 00.01.1.1.2 \dots 1.1.1.1.2 \dots 2.\dots \dots 0000.00.2.\dots
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\dots \dots 0001 \dots 01.2 \dots 01.000 \dots 1 \dots 3 \dots 1.1.00 \dots \dots 2 \dots 001.0 \dots 1 \dots 2 \dots 0 \dots 1.2 \dots 2 \dots 2 \dots 3 \dots \dots 1 \dots 000.0001 \dots \dots
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```

 How the overall average traffic flow rate varies with traffic density and present your results in your report.



**Figure 1.** <sup>1</sup>Traffic flow depending on car density in a one lane model. The road length is 100, maximum speed is 5, and the probability of slowing down is 0.5. For each density point, 100 simulations are run. Traffic flow is averaged over 100 time steps.

To inspect the critical value of p at which there is a change-over of the traffic flow, I followed the code in the pre-class work solution for session 4.1 and zoomed in critical region:



**Figure 2**. Traffic flow depending on car density in a one lane model, with densities ranging from 0.05 to 0.15. The maximum is observed at around 0.10.

We see that the critical value is at around 0.10, slightly different from the critical value of 0.08 reported in the paper.

• Further exploration: How does traffic flow depend on road length?

<sup>&</sup>lt;sup>1</sup> **#dataviz:** clear graph with caption that provides details on the simulation set-ups. The color chosen is vanilla black and superfluous colors (like red, blue, etc.) were avoided.

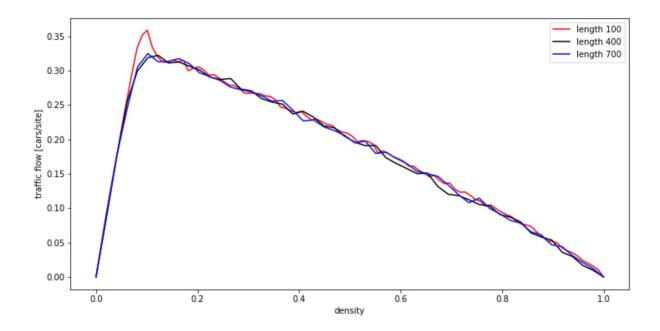


Figure 3. Traffic flow depending on car density in a one lane model with three values of road lengths. The maximum speed is 5, and the probability of slowing down is 0.5. For each density point, 100 simulations are run. Traffic flow is averaged over 100 time steps.

### Interpret and critique the results:

When we visualized states of the automata over time with different values of densities, we saw that, as expected, with low car densities (in the graphics for p=0.05 and p=0.07), cars are sparse and the road is almost jam-free. However, with higher densities (p=0.1, 0.2, and 0.4), traffic jam forms. Interestingly, we saw a backward movement of the jams in all these three cases. This speaks to reality: when a car stops or tailgates, the traffic jam gradually forms behind that car onwards and even when this car has escaped the traffic jam, the consequences still propagates throughout. This can be also seen as a visualization of a phantom chicken discussed in class.

- We observed a critical value of around 0.10 when we zoomed in the critical region, slightly different from the one reported on Nagel et al. paper (around 0.08). However, we are not too concerned about this discrepancy, because the simulation settings in the paper is vastly different from the one we implemented here: in the paper, the road length is set to  $L = 10^4$  (compared to only  $L = 10^2$ ), and the flow is computed with averages over  $10^6$  time steps, compared to only  $10^2$  here. This is not to claim, however, that the traffic flow depends on the road length or the number of time steps. I am just hypothesizing that the critical value I found by my own implementation may be not accurate because it still contains a lot of noise due to small road length and small time steps to average over. In fact, it is claimed in the Rickert et al. paper that large time steps like  $10^3$  have the effect of making the transients die out (p.5).
- In exploring whether the traffic flow depends on the road length, we found that the lines for both three lengths (100, 400, and 700) mimic each other very well, with the exception at around the critical point of density, where the red line for length 100 is higher than the other two lines, but this can be explained away by the fact that the traffic flows in the critical region have the most variance (Fig. 1) and therefore, the spike of the red line may be simply due to chance. One hypothesis is, all else equal, traffic flow does not depend on density. This makes sense, because intuitively, one can restrict the view to just part of a road of any length and one is effectively observing a different model of a different length while the traffic flow is, of course, still the same.<sup>2</sup>

<sup>&</sup>lt;sup>2</sup> **#hypothesisdevelopment**: the hypothesis developed is fully motivated by empirical results, data visualizations, and intuitive explanations.

# Part 2. Multi-lane highways

 A description, in your report, of how this model works. What are the assumptions, parameters, and update rules of the model? Do not just copy and paste from the paper. Explain the cellular automaton in your own words and as clearly as possible.

## 1. The assumptions

- The cars' lane switching behavior can be broken down into two discrete steps (called two-part update step). The first step is to switch to another lane (if any). The second step is adjusting the speed and moving.
- Because of the first assumption, it is also assumed that cars cannot move diagonally.
   Diagonal move can be broken down as a two-step move: sideways to get to another lane, and forward to get ahead.
- It is assumed that we make no distinction between 1) the time for cars that make a lane switch and move forward and 2) the time for cars that **don't** make a lane switch and move forward (i.e., simply move forward). Two types of time are encompassed in one time step in the simulation. This is sloppy, but tolerable.
- In the model implemented, the preference for any lane is the same (i.e., symmetric).

  That means, the drivers make no distinction between the lanes present in the model. In an asymmetric model, drivers can switch to a lane, but there is one lane that the drivers (or some of them), prioritize over the other whenever possible.

## 2. Rules

The set up about the sites, the cars occupying the sites, and the boundary condition is the same as that for the uni-lane model. Here, only the updating rules in one time step of this model is presented.

Any update is performed synchronously and is split into two parts:

### a. Part 1: Lane changing

A car will switch to the other lane (in case of a two-lane highway) if the following four conditions are satisfied:

- Condition 1: The car ahead of it is too close (g < l, with g being the gap between the car and the car ahead)
- Condition 2: In the other lane, the car ahead of it is far enough ( $g_0 > l_0$ , with  $g_0$  being the gap between the car and the car ahead in the other lane). This is to make sure it will get a benefit when switching to that lane (or else it'd better remain in the current lane)
- Condition 3: In the other lane, the car behind it is far enough ( $g_{0,back} > l_{0,back}$ ). This is a conservative move, to make sure that it will not crash into the car behind, based on the expected speed of the car behind.
- Condition 4: After all the above conditions are satisfied, it will switch to the other lane with probability  $p_{change}$ .

At the end of this part, the cars switch lanes (or remain at the current lanes) synchronously.

The above conditions are enough for 2-lane system.

For a model of MORE THAN TWO lanes, additional conditions must be established. The reasons are:

- in a 3+ lane model, there are lanes that have two bordering lanes, one on the left and the other on the right. There must be a scheme to help each car decide on which lane it switches to in case it is considering the two lanes.
- in a 3+ lane model, a car in a lane needs to look at not only at the lanes immediately beside it (lanes  $i \pm 1$ , with i being the number of the current lane), but only at the lanes one lane away from its lane  $(i \pm 2)$ . This is because cars on lanes  $i \pm 2$  may also choose to switch to the same lane that the car in the current lane chooses to switch to, resulting in a crash. Look at the graphic below for an example:

Lane 1				
Lane 2				
Lane 3				

According to the original conditions, both the cars in the green cell and the blue cell chooses to switch to the red empty cell in lane 2, resulting in a crash. There must be another condition to counter this.

Here I propose two additional conditions:

- Condition 5: If the car in lane i sees a car behind in lane i-2 with a gap no larger than  $l_{0,back}$ , the car won't switch to lane i-1. Similarly, if the car in lane i sees a car behind in lane i+2 with a gap no larger than  $l_{0,back}$ , the car won't switch to lane i+1.
- Condition 6: After checking all the above 5 conditions, if the car is allowed to switch to both lanes i-1 and i+1, break ties by randomly choosing a lane.

### b. Part 2: Speed updating and motion

The speeds of the cars in each lane are updated following the exact same rules as those for the uni-lane highway model. For the sake of completeness, these rules are:

- If the current speed has not reached maximum ( $v < v_{max}$ ), and the gap between this car and the car ahead is at least v + 1, increment the speed by 1 (v -> v + 1)
- If the gap between this car and the next car is less than v, update the speed to the gap (  $v \rightarrow g$  )
- The speed is decremented by 1 with probability p<sub>slow</sub>

At the end of this part, each car, synchronously with all the other cars, advances by v sites.

## 3. Parameters

This model includes parameters of the original one-lane model. These are:

- the length *L* of the road (number of sites)
- density of the road p (equals N/K, with K being the total number of sites. In a one-lane model, K = L)
- homogeneous maximum speed  $v_{speed}$
- slow down probability  $p_{slow down}$

The following are additional parameters:

- the number of lanes *M*
- the parameters for lane changing updates. These include:
  - *l* in condition 1
  - $l_0$  in condition 2
  - $l_{0,back}$  in condition 3
  - $p_{change}$  in condition 4

Note that in the Python implementation, of these four parameters related to lane changing rules, I only made  $l_{0,back}$  and  $p_{change}$  parameters, and the other two parameters are fixed (i.e., users can't set up these parameters.) This is due to the challenges involved in making all four parameters.

 Write well-structured and well-documented Python code to implement the model described in the paper.

The code is included in the gist linked at the beginning.

 Visualize the state of this model over time, to show the typical traffic patterns that can emerge. Your results will again depend on traffic density.

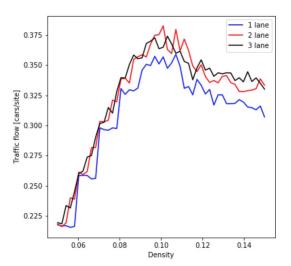
In all of the graphics below, the states over 20 time steps are displayed for each lane of the two-lane road. Road length is set to 50, slow down probability 0.5, max speed 5, l = v + 1,

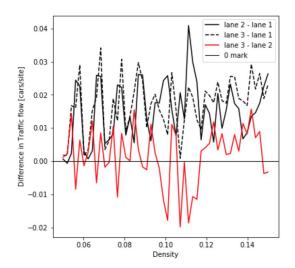
$$l_0 = l$$
,  $l_{0.back} = v_{max}$ ,  $p_{change} = 1$ .

Density = 0.05						
321	40					
442						
43	141.					
455						
54	.24					
45	235					
345	34					
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433	35543 35542.
533	233454
5444	344
54	.235454
555	344455
4555	.4453444
455444	543355.
5555	55435
444444	5
Density	
3.0240030.003	.5320.04115
01	440015224
022002.0.1233	5110133333
02	51.0024233
11	
.124.0.1200241	.4
122	440123513
223001.00.1	4.00223423
1233010.1.14.	310.112433
.134000.1021	4.00123543
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.1340011.0012	201.024245.
2400.11.0.0.123	.3.00102124
22.001.0.0.0.134	100002125
.5310.110.0113	00.10.13134
143.0000121.13	.0.01021333
Density	- 0.4
0.032.130.13.12422.0	2.0.020003.000.1.00.1.00.1.00.1
0111211.11.1221.0.0	.3.1.101.00.10.00.10.00.0.00.0.00.
.112.131.011232.10.0	30.0.00100110.100.0.10.00.0.0.1.100
1.121.14.102233.0.00 0230210.13333.0.00.1	0.10.0.100.1200.00.10.0.10.10.0100.1
.120030.1.132.010.01	.00.1.101.12000.00000.0010002
11.0.12.01.13.1.1.00.00	3001.1.001.000.10.10000.10.1000.1
111010.00110100.0	00001.111000.00.0000.10.1.1.00.1.1
.120.121.1.0110000	00001.120000.0.100.1100100.01
211.1310122000001.	00.1102.0000.10.00.1.1.00000.1.12 0.1.1110.000.100.0.1.1.10000.1.1.12.
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.21.012312.13.100.102.	1.1.000000.000.0.0.000.1212020
110232.11.10.000.0.11 $120.121.02020.00.102$	0.00.1.00.1.00.1000.0.1.1000.13.1.0000 $0.000.1.1.000.1.1.0.000.111.10.100$
2.0022010.130.0.10.12	1.11.10.1000.1.1.1.100.1.12200200
10.12112.1.1110.0012	1210.100001.10.00.1023.000000
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 How much more traffic can flow through a multi-lane road, compare to a single lane road, at the same traffic density.





**Figure 4.** Traffic flow vs. density for different number of lanes (left) and the pairwise difference in traffic flow of the models (right).

- Interpret and critique the results
- As with the one lane model, when the densities are low, we see that the cars are sparse and there is no traffic jams formed. However, as we increase the density, congestions start to form. In both lanes, we can observe the backward movement of the congestion, just as we did in the one-lane model.
- We also see no discernable difference between the two lanes in each value of the car density. This is due to the symmetric setting of the simulation: drivers have no preferences for either of the lanes.
- We saw that in figure 4, the lines for the three number of lanes seem to peak in around
  the same region. This suggests that the critical value at which the traffic flow reaches its
  maximum is the same for all number of lanes included in the model. However, more

- careful simulations with more iterations, more various road lengths, and more time steps needed to confirm this hypothesis.
- We saw that one lane has consistently lower traffic flow compared to two- and three-lane models. One explanation is that the agents involved in the automata (i.e., the cars) have more flexibility to adjust its locations in the system in the way that regulates better the flow. In other words, cars have the option to switch to another lane, and because they only switch lane if the switching is beneficial for them, this has a double effect: reduce the congestion in the current lane, and put the empty sites of another lane to a more effective use.
- Between two- and three-lane models: Up to and slightly after the critical region, there is no discernible difference in the traffic flows between two- and three-lane models (the two lines, red and black, keep intertwining each other). However, for densities that are larger than 0.12, we see that most of the time the three-lane model has a better flow. This suggests the following: going from one lane to two lanes is always beneficial (in terms of varied car densities), but for any additional lane, it's only beneficial when the density is high enough. This makes sense: if there are too few cars, having a bunch of lanes does not bring much profit, especially given that each car has its maximum speed, so even if one car occupies one entire lane, it cannot make much use of that. In order for the advantage of multiple lanes to exhibit, there must be enough cars on the road (i.e., the density is high enough.)

# Part 3. Key Questions

• How much more traffic can flow through a 2-lane road compared to a 1-lane road at the same traffic density? What about roads with more than 2 lanes? Either model 3 or more

lanes and report on your results, or predict how much larger the traffic flow through a 3+ lane road will be compared to a 1-lane road at the same traffic density.

This is addressed in the previous part.

• How applicable is this model to traffic in Berlin? (If you are not in Berlin, comment on how applicable the model is to traffic in your city.) Write a short paragraph and motivate why the model is suited to traffic in your city (or why it is not).

We need to look at the salient assumptions and rules to determine if this model is applicable to Berlin's traffic

- The assumption that each vehicle in the same lane has the same size (occupying the same slot) is applicable. In Berlin, there is not that various types of vehicles. Most people commuting (on the road) by either cars, or bikes. And since each of these types has its own lane (there is a lane for bikes and one for cars), this assumption is reasonable. Compared to a more adhoc traffic like that in Vietnam, where I come from, bikes, scooters, motorbikes, and cars are just mixed with each other in the road which would have made this assumption intolerable.
- The assumption that all vehicles update their behavior synchronously and based on local information is also reasonable, and I would argue that this is not specific to Berlin traffic but to all. This is because when driving, each driver makes sense of the world at the moment and using the information of drivers surrounding him/her (he/she is not capable of a more holistic view).
- However, the rule that allows the driver to tailgate the car ahead whenever possible is not applicable. Drivers in Berlin usually avoids this behavior. They, in fact, exhibit the "good driving behavior" proposed in one of the pre-class videos, that is, they try to keep a reasonable distance with the car ahead and the car behind. This rule, therefore, needs modifying.