SIMULATION OF TRAFFIC FLOW

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Abstract

The population of vehicles has doubled over the past 20 years and with it did time that people spend stuck in traffic. The rate of growth of cars suggests that the problem of congestions is going to get only worse over the years. This project uses a "cellular automaton" model, which focuses on the motion of individual vehicles, to investigate the behaviour of traffic flow and provide potential solutions. Research on traffic flow distributions in single-lane model led to the conclusion that the probability of breaking is a more significant factor in contributing to the maximum traffic flow than speed limit. Analysing the two-lane model showed that the ability to change lanes does not impact the maximum traffic flow sufficiently and when the maximum traffic flow distributions of both models were compared, the values were within the uncertainties of each other. Implying, that the construction of wider roads can only increase the capacity of cars, but not the traffic flow per lane.

1 Introduction

Car is a revolutionary mean of transport that can take you from point A to point B in no time, and because of its usefulness and convenience the number of cars has been growing so dramatically, that the population of vehicles doubled in the past 20 years to reach a staggering number of 1.32 billion cars (Petit, 2017). This change highly impacted time that people spend on the

roads, in London drivers spend an average of 149 hours per year in congestions, that's more than 6 days spent stuck in traffic (Scorecard City, 2019). This figure suggests that the problem of congestions is going to get worse as the time goes by and immediate solutions are required.
There are two main approaches used to investigate traffic flow. One is "hydrodynamic" model, which ignores individual vehicles and treats traffic like a fluid. The other model, which we use, is called "cellular automaton", which is analogous to kinetic theory in that it treats the motion of individual cars. The model was first proposed in 1992 by Kai Nagel and Michael Schreckenberg and showed that a discrete model approach is computationally advantageous and contains some of the important aspects of the fluid-dynamical approach (Nagel and Schreckenberg, 1992). Not only that, but it also laid a foundation for a better understanding of traffic flow and potentially solving the problem of congestions. Using this model, we go a bit further and analyze traffic flow in one lane to see how the maximum flow depends on the parameters of the model. Also, the simple model is extended to two lanes, in order to see if the construction of multi-lane road can significantly increase the traffic flow and tackle the problem of congestions.
The methods for generating one-lane and two-lane models are discussed in the next subsections, third subsection describes the technique used to extract the uncertainties using Probability Density Function while the last part in methods describes the process of finding the best data quality against computing time ratio. The results are presented and discussed in section 3 for both one-lane and two-lane models.

2 Method

2.1 Generating a one-lane model

Before gathering the data on the traffic flow and expanding into a more complicated model of multi lanes, the simple model must be generated. This can be done using the steps provided in the K. Nagel and M. Schreckenberg's research paper:

1. **Accelerating**: if vehicle's speed 'v' is not at maximum allowed speed 'vmax' , then 'v' is increased by one at each time step $[v \to v + 1]$

2. **Slowing down**: if vehicle's speed 'v' is more than a distance 'd' to the car in front, then 'v' is set to the distance minus one [v → d – 1]

3. **Slowing down due to unforeseen events** (releasing clutch too fast, obstacle on the road, etc.): if vehicle is moving at speed "v", then there is a probability "p", that it can slow down

4. **Moving**: After the execution of previous steps, each car is advanced "v" number of cells per time step

Our simulated road is a 1D array of 200 cells where each cell holds an information on the speed of vehicle. Empty cell corresponds to value of 0 and cell that holds a car has a value from 1 to vmax, unless the velocity of a car is 0, then the value is set to -1. For each car in the array the steps above are executed accordingly, if the car's position plus it's velocity "v" is bigger than the length of the road, it subtracts the length of the road from its new position and places the car at the beginning of array, thus creating a circular road with a fixed number of cars.
Furthermore, when array is simulated, all the cars start with the minimum velocity of 0 and only after some time the system reaches an equilibrium. If the time frame is long this non-equilibrium state is negligible when it comes to average velocities, but since our computing power is very limited and we can't produce many time steps, the average velocities in this non-equilibrium state need to be ignored. This can be done by comparing average velocity at one time step and the next, if the difference between these velocities is sufficiently small, the data can be gathered.

2.2 Generating a two-lane model

The two-lane model uses the same instructions as introduced in the previous subsection, but also has some additional steps that go before the slowing down of cars. This comes from the fact, that in the two-lane road instead of slowing down due to the car in front, cars can change lanes without losing their velocity. However, it must comply with these rules:

1. **Checking for cars in front**: if car's position plus it's velocity "v" is more or the same as the position of the car in front, then it checks the other lane. If the car in front on the other lane is further than the car in front on the same lane, then it moves to the next rule, else it stays on the same lane and follows the steps of the simple model

2. **Checking for cars in back**: if there's a car behind on the other lane and its velocity plus position is less than the position of the car that we are interested in, then this car changes lanes, else it stays on the same lane and follows the steps of the simple model

2.3 Probability Density Function (PDF)

It's easy to get an uncertainty in traffic flow value, we must calculate the spread of all the traffic flows at each density and it provides us with error bars. But obviously there is an uncertainty not only in traffic flow values, but also in density, so how can this uncertainty be extracted? One of sophisticating methods is called Probability Density Function (PDF), it is used to specify the probability of random variable falling within a particular range of values. The procedure is as follows: every time the simulation runs, cars are distributed randomly across the road and because of this the traffic flow value is slightly different every time. With each distribution a maximum is found at some density, if we plot the number of counts the maximum was found at the specific density against densities, it should provide us with a histogram (Figure 1). Finally, from the best fit of normal distribution, it should be possible to extract the value of 1σ that gives a 68 % certainty that the maximum value will fall within that range. For this specific task origin was used because of its convenience in finding the best fit.

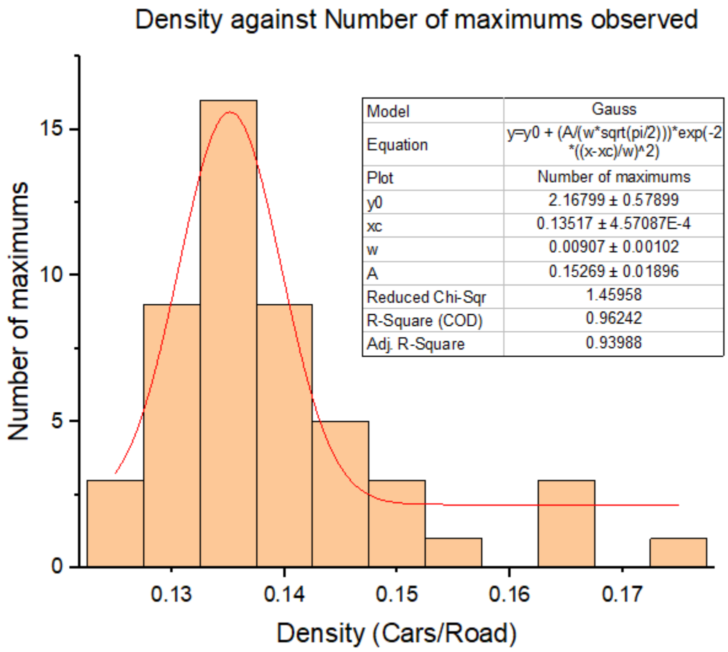

Figure 1: an example of PDF for a one-lane model

2.4 Quality/Computing time ratio

One of the biggest challenges in this project was to find optimal values for initial distributions and time steps, so that the data would be valid, and the computing time would be relatively short. This problem arose when the simulation for 1800 time steps and 10 initial distributions was ran to get an average traffic flow distribution. The simulation took 7 hours just to get the data for one graph of varying slowing probabilities p and maximum velocities v_max. To get all of the data it would have taken 168 hours , that's why an optimal parameters had to be found, so that the best quality/computing time ratio would be achieved.
To begin with, the averaged data of 1800 time steps was compared against the data of one sample for 200 time steps The difference can be seen clearly in

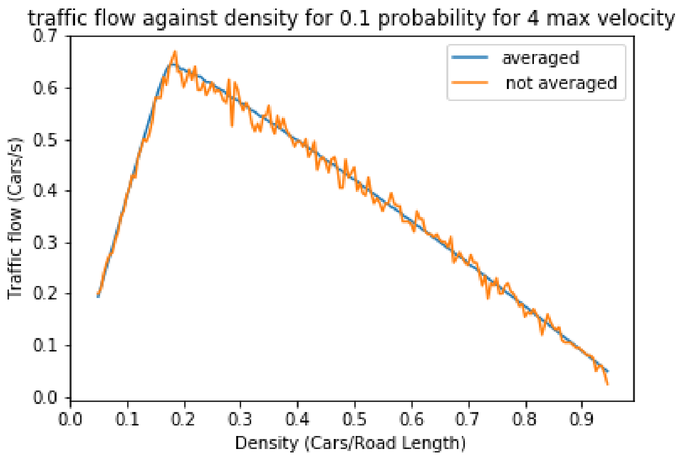

Figure 2: Comparison of two traffic flow distributions. One for 200 time steps and not averaged and the other for 1800 steps and averaged over 10 initial distributions

Figure 2. The unaveraged traffic flow is very noisy with frequent fluctuations, while averaged is steadily building up and then decreasing without any major fluctuations. The next obvious step, was to compare two averaged datasets over 10 initial distributions, one for 200 time steps and the other for 1800 time steps.

Figure 3 shows that averaging the traffic flow over 10 initial distributions extremely improves the quality of the traffic flow data, the fluctuations are not as frequent and occur only around the peak. Since increasing the number of initial distributions or time steps any further drastically increases computing time, another solution had to be proposed, the one that would save time and further improve the fit to the previous graph. The solution to this was to

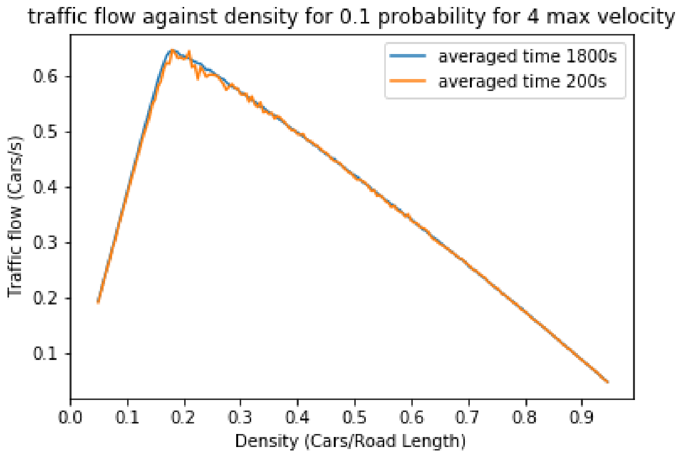

Figure 3: Comparison of two averaged traffic flow distributions

track the traffic flow not only at one location, but at many places on the road simultaneously, this doesn't increase computating time significantly and all of the traffic flow values can then be averaged to give an even better estimate of traffic flow against density.

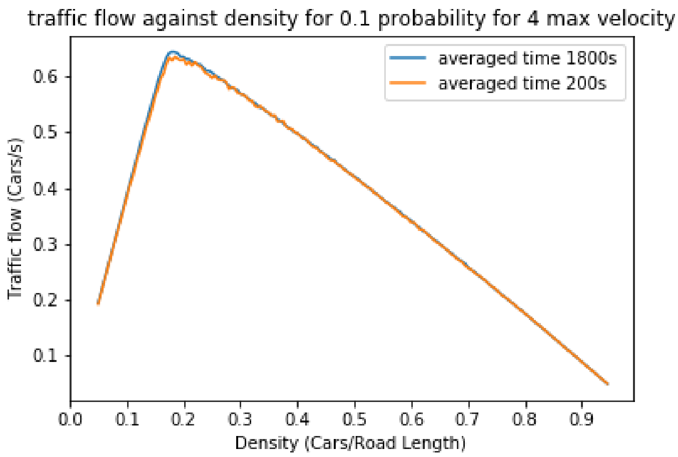

Figure 4: Comparison of two traffic flow distributions. The traffic flow distribution for 200 time steps is now averaged over many places along the road

Figure 4 illustrates how averaging traffic flow at many places along the road further improves the traffic flow against density graph. There are some mild fluctuations around the peak, but the Quality/Computing time ratio is the best that it can get to.

3 Results and Discussion

3.1 Varied maximum speed and slowing probability impact on traffic flow in one lane

Figure 5 shows how the distributions of traffic flow for different probabilities of slowing vary with different maximum speeds. All the graphs seem to follow a similar trend as the maximum velocity increases, the peak of the maximum traffic flow shifts to slightly lower densities. This happens because higher speed limits require cars to have bigger distances between each other in order to accelerate to maximum speeds. Now the maximum traffic flow can be observed at higher value as the velocity increases. On average the traffic flow increases by 0.03 cars per second between velocities. If we assume that

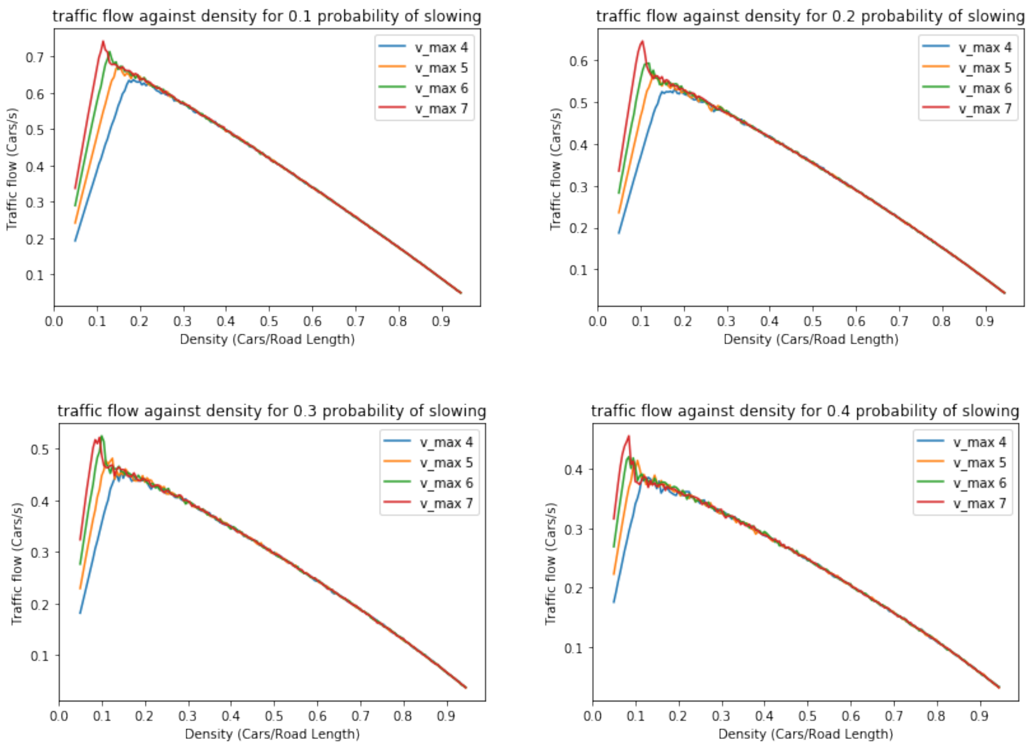

Figure 5: Distributions of traffic flow for varied speed limits

one cell is equivalent to 7.5 metres in real life, then increasing the velocity by 27km/h contributes to an addition to the traffic flow by approximately 108 cars per hour. It doesn't seem like much, but over time this number stacks up. Furthermore, another interesting result is that lower velocities seem to reach their maximum traffic flow on the higher velocities' distribution and then follow the exact same trends for higher densities. This might come from the fact that densities higher than the one for maximum traffic flow make it impossible for cars to accelerate to their maximum velocities and therefore all the distributions follow the same trend.

Figure 6 is an inverse of Figure 5, it shows varied probabilities of slowing against different maximum speeds. Just by looking at the graphs we can clearly see that the traffic flow distributions vary significantly as the probability of slowing is decreased. On average the difference between peaks is 0.09 ± 0.02 cars per second that's equal to 324 ± 72 cars per hour, which is around 3 times more than the figure for speed limit. This seems like an answer to the question of whether the journey time is best reduced by increasing the speed limit or reducing extraneous diversions that cause random breaking. However, even though it looks as though the obvious answer is decreasing the probability of breaking, it's hard to draw this conclusion, as these two parameters are very different.

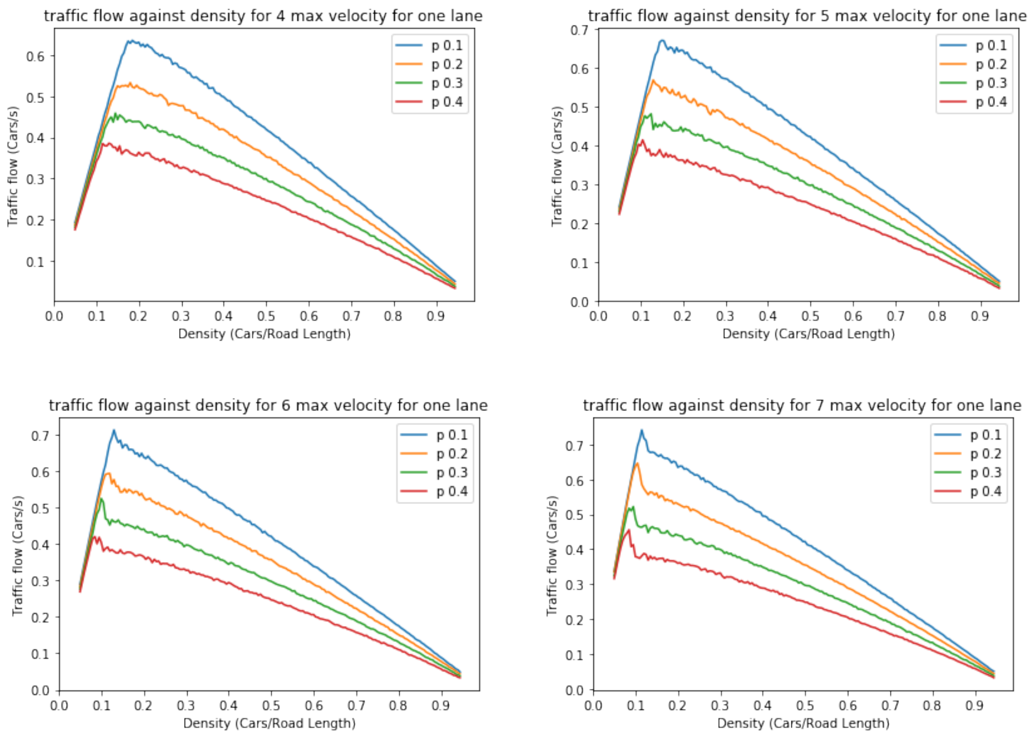

Figure 6: Distributions of traffic flow for varied probabilities of slowing

Implementing higher speed limit in real life is quite straightforward, however decreasing probability of slowing is not that simple. It would require an increase in reaction time and learning rate of a driver. There are two ways to achieve this: either we wait millions of years for evolution to do its work on humans or replace human drivers and give autonomous vehicles full control. In fact, the research done by Talebpour, A., & Mahmassani, H. S. on influence of autonomous vehicles on traffic flow, shows strong correlation between the percentage of autonomous vehicles and traffic flow(Talebpour and Mahmassani, 2016).. Furthermore, the traffic flow data for a road of 100% autonomous vehicles agrees very well with the traffic flow distribution for low probability of breaking. At density of 0.24 cars per road length they project an estimate of 2100 cars per hour, while at the same density using our simulation, we get 2124 ± 20 cars per hour.

3.2 Varied slowing probability impact on traffic flow in two-lane model

What makes the two lane model more advantageous than one lane is the possibility for cars to change lanes. Intuitively it seems as though it should highly increase traffic flow as we are getting rid of the bottleneck. If there's a car driving slowly in one lane, all the other cars can overtake it, thus not allowing the congestion to form. However, the data suggests otherwise. All the maximum traffic flow values for two lanes fall within the uncertainty of traffic flow for one lane (Figure 8). For one lane 10% probability of slowing the maximum traffic flow is 0.67 cars/s ± 0.02 cars/s, while with the same configuration for two lanes it's 0.68 cars/s ± 0.01 cars/s. For higher probabilities of slowing the difference between values gets bigger, but so do the uncertainties. One lane 30% and 40% probability of breaking, the values are

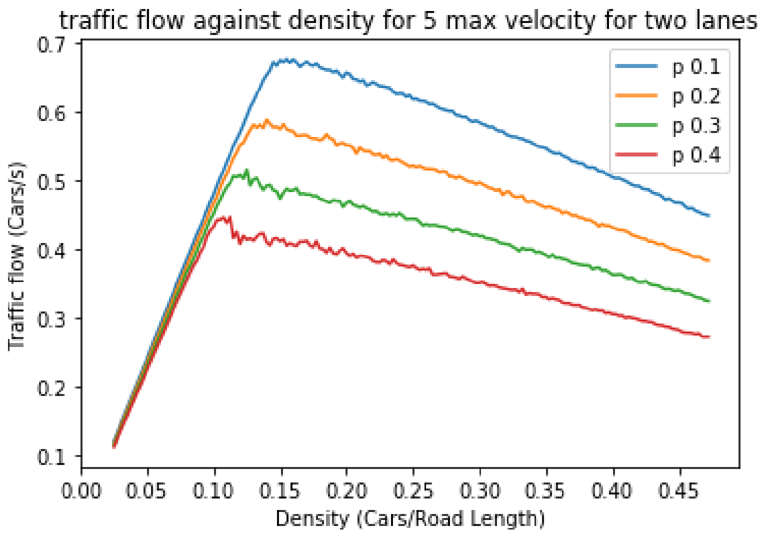

Figure 7: traffic flow distributions for two-lane model as probability is varied

0.48 cars/s ± 0.04 cars/s and 0.41 cars/s ± 0.03 cars/s and for two lanes the values per lane are 0.52 cars/s ± 0.02 cars/s and 0.45 cars/s ± 0.02 cars/s respectively

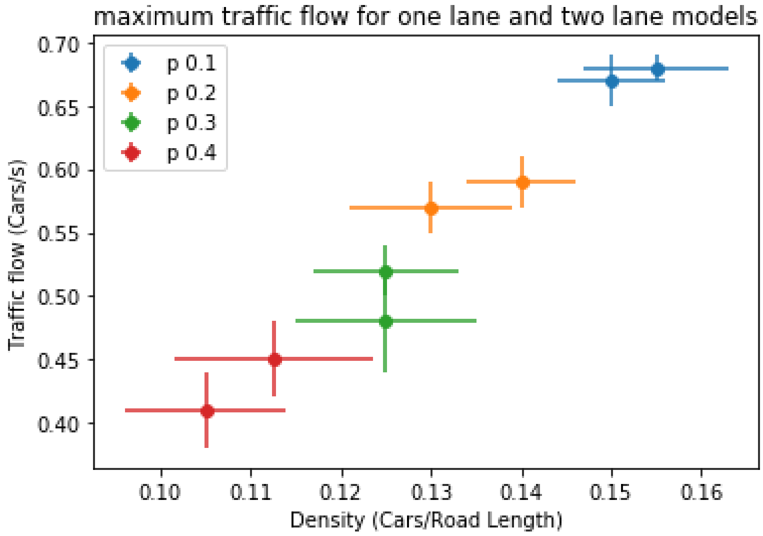

Figure 8: maximum traffic flows for two-lane and one-lane models

So, even though two-lane road can hold double the capacity, the maximum traffic flow per lane doesn't seem to be significantly different from the one in the one-lane model. However, there are some flaws with this model, in real life when a congestion starts forming in one lane, the cars in the other lane slow down to let the cars in, whereas in the simulation, the cars don't follow the situation in other lanes and don't slow down if a congestion starts forming in other lane.

4 Conclusions

Simulation of traffic using the "Cellular Automata" model proved to be a success in helping us extract some useful information on the traffic flow. By varying the parameters for one-lane road we have deducted that an increase in maximum speed limit, contributes to an addition to the traffic flow by approximately 108 cars per hour, while decreasing the probability of slowing by 10% adds up to 324 extra cars per hour. These figures suggest that decreasing probability is more significant for traffic flow than increasing speed limit. Furthermore, the ability to change lanes for two-lane model turned out to be insignificant in contributing to maximum traffic flow. The compared cases of both models for maximum velocity of 5, showed that for each probability of slowing, the maximum traffic flows were within the uncertainties of each other.

5 References

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