Traffic Simulation

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CS166: Modeling, Simulation and Decision Making

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Introduction

In this paper, I discuss a cellular automata model for traffic flow. I assume a familiarity with cellular automata modeling and with a single lane traffic flow model (which is described in this paper: *Nagel, K., Schreckenberg, M. (1992)* <u>A cellular automaton model for freeway traffic.</u> *Journal de Physique I, 2(12), 2221–2229*).

I begin with a single lane model and subsequent analysis. I then move on to a two lane traffic model. Finally, I run simulations to provide analysis for changing driver behaviour. In all simulations run in this paper, the road length is 100 and maximum velocity is 5.

Section 1: Single Lane Highways

Update Rules

In this section, we implement a single lane highway traffic simulation. The rules can be defined as follows. A car will check if it is at its maximum velocity, and if it is not, will increase its velocity by one. A car then checks the distance between it and the car in front of it. If the distance is less than or equal to the cars current velocity, the car will lower its velocity to 1 - distance, in order to avoid a possible condition. Note that this is in many cases overly cautious as the car in front will most likely move forward. However, this rule prevents all collisions. Finally, there is an element of randomness, where if after the previous two steps a car's velocity is above zero, it will slow down by 1 with probability $p_{slowdown}$. With these simple rules, our traffic model can simulate traffic flow on a highway.

Visualization

The simulation of a single lane traffic flow can be visualized by printing the state at each time step, with time moving forward as one travels down the figure. A car is represented by its numerical velocity. In this way, the evolution and movement of traffic jams can be visualized. Note that the number 0 represents a car that is not moving.

The following four figures show traffic at four density levels.

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Figure 1.1: A traffic simulation with density = 0.1.

Figure 1.2: A traffic simulation with density = 0.3.

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Figure 1.3: A traffic simulation with density = 0.5.

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Figure 1.4: A traffic simulation with density = 0.7.

As the above figures show, the frequency and size of traffic jams increases as density increases. With low densities (Figure 1.1), the cars can often travel with little to no jams, while at high densities (Figure 1.4), the entire road is clogged by traffic jams. From these figures, it is clear how traffic jams slowly move against the movement of cars as time progresses. If the front car in a jam has a random slow down, which occurs quite frequently, the jam stands still, but gains size on the back. Once the front car leaves, the jam shrinks on the right side. This leads to the "walking backwards" behaviour of traffic jams.

Traffic Flow Analysis

In order to asses the state of a highway, the metric we will be using is traffic flow. This is defined as the average number of cars that move through one cell at each time step. It is recorded in the simulation, and it can be found at different densities. It is an important metric because it reveals how fast traffic is moving on the highway. It is especially interesting because if we were to imagine no traffic jams, we would expect to see traffic flow increase as density increases, as there are more cars on the road. However, from our analysis we see that traffic jams greatly changes this outcome.

I ran a simulation that measured the average traffic flow on 100 models at each density, and averaged the results, in order to have reasonable certainty that the change in traffic flow is due to changes in density and not just random occurrence. The results of the simulation can be seen below.

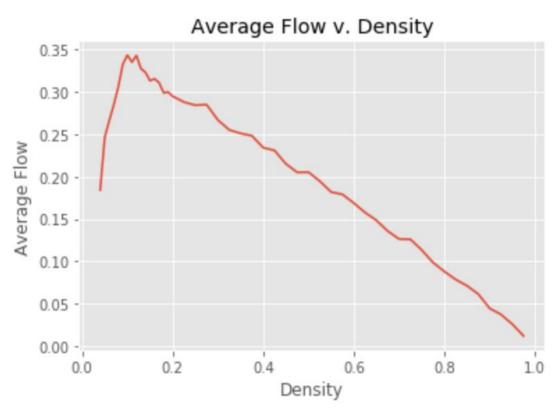


Figure 1.5: The Average Traffic Flow at varying densities.

From Figure 1.5, we can see that indeed average flow does increase as density increases at low densities, it reaches its maximum at around density = 0.13. After this, we see average flow decreasing approximately linearly as density approaches 1, where we see near average flow. From this, we can see that traffic jams are significantly decreasing the average flow of our road.

If we wanted to maximize the flow of traffic in a road, we would want a low density road. However, while this would mean cars are moving through the road fast, we would see a very small volume of traffic. If we want to have a large volume (high density) moving across the road, we should try to find a way to improve average traffic flow at the higher densities. This is attempted in the next section by creating a two lane highway.

Section 2: Two Lane Highways

Update Rules

In the one lane model, the car behaviour is quite simple. A car will accelerate if it is not at full speed, decelerate to ensure that it will never hit a car in front of it, and randomly slow down at a rate defined by an input parameter. The two lane model retains this car behaviour, while adding the added complexity of lane changes. Once a car has decided on its lane, it will follow the same acceleration, deceleration and random slow down behaviour as in the single lane model. The key difference is the lane changing behaviour.

While initially appearing difficult to implement, when broken down into clear steps, simulation lane changing behaviour is quite achievable. The car will go through a series of checks, and if all conditions are fulfilled, it will change lanes.

The first thing that car i checks is how far in front of it the next car is, which we will call gap(i). It then checks if gap(i) < l, where l is parameter of how far it looks ahead in its own lane. A base setting for l is l = v + 2, making l dependent on velocity (but accounting for the velocity it will increase and difference in measurement of distance and velocity). The car sees if the car in front of it is too close, and if it is, it decides it wants to switch lanes and moves to the next step.

The car then checks if the lane next to it is any better. It checks the distance between it and the next car in the other lane, which we will call $gap_o(i)$. It then checks if $gap_o(i) \ge l_o$, where $l_o = l$. Thus, in this state it is making sure that if it switches lanes, it will have an improvement as compared to its current lane.

Finally, the car checks if it will get in the way of cars in the other lane. It checks the distance between it and the closest car behind it in the other lane, which we will call $gap_{o,\,back}(i)$. Note that if there is a car in the neighboring site, $gap_{o,\,back}(i) = 0$, while a gap of X empty spaces between car i and the closest car behind it will give $gap_{o,\,back}(i) = X+1$. It then checks if $gap_{o,\,back}(i) > l_{o,\,back}$, where $l_{o,\,back}$ is the parameter of how far back it looks into the other lane.

A base case of $l_{o, back}$ is $l_{o, back} = v_{max} = 5$. Thus, car *i* is checking if there is a car behind it in the other lane that could potentially drive to where car *i* would switch to.

Finally, if all three previous conditions are fulfilled, the car will switch lanes with a probability p_{chanse} . This randomness is introduced to more accurately reflect real driver behaviour.

As explained earlier, each lane will perform simultaneous lane change updating. After cars change lanes, each lane will perform independent single lane updates according to the rules of single lane updates.

Assumptions

There are several key assumptions of the model that we have just explained. The first is lane symmetry. In many highway systems, one lane is designated as the "fast" lane, and cars that are passing are encouraged to use this lane. Our model, on the other hand, is assuming that both lanes are identical in terms of rules and preference. Another assumption is about driver behaviour. We have assumed that drivers will not switch lanes if there is a car behind them in the other lane that they would get in the way of. This is assuming good driver behaviour, which may not be an accurate assumption in the real world. Finally, as discussed, there is an element of randomness incorporated into the lane changing behaviour. Without this randomness, an unrealistic behaviour is observed where slow groups of cars all switch lanes at the same time, over and over. The vehicles all evaluate the other lane to be better, all switch, and the process repeats itself. The randomness leads to more realistic results, and is more reflective of real world behaviour.

Visualization

A two lane model can be visualized in much the same way as a one lane model. Each successive time step is printed below the previous, along with an empty line. The following two figures show this at two different densities.

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Figure 2.1: Two lane traffic with density = 0.3.

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Figure 2.2: Two lane traffic with density = 0.5.

From Figures 2.1 and 2.2, it is clear that as density increases, the number of traffic jams again increases. It is also apparent that larger traffic jams tend to occupy both lanes, which is a natural conclusion. What is harder to see from the graphs is that the lane switching behaviour is quite conservative, as a car has to fulfill a strict set of conditions (having space behind and in front when attempting to switch) and even then, only switches half the time. Thus, the switching behaviour is not very frequent. The question remains as to the effect of these switches on traffic flow.

Two Lane Traffic Flow

Just as in the single lane model, a parameter sweep with repeats at each parameter was conducted. The traffic flow was measured in the same way, and the following figure presents the results.

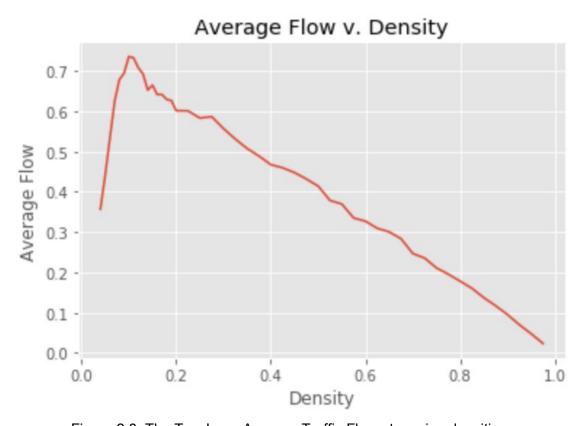


Figure 2.3: The Two Lane Average Traffic Flow at varying densities.

From Figure 2.3, we can see that the same trend as in the single lane model is present. The two lane model achieves its maximum traffic flow at roughly the same density, and traffic flow decreases at roughly linear rate as density increases to 1. What is hard to see from this figure is

a comparison with figure 1.5, to see how the two lane model compares with the single lane model.

In order to do this, I plotted Figure 2.3 alongside the traffic flow of the one lane model, except with the one lane model doubled. If the two lane model gave no improvement on traffic flow, we would expect the two lines to be equal.

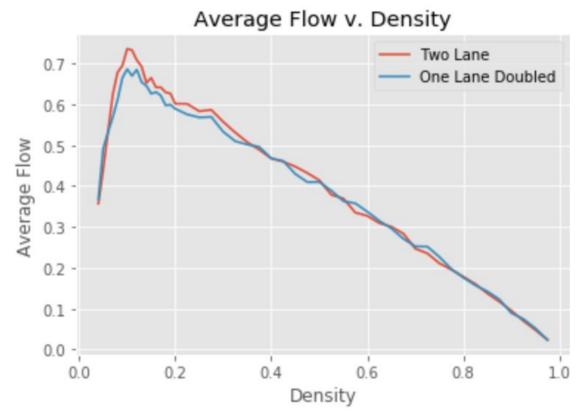


Figure 2.4: The Two Lane Average Traffic Flow Compared with One Lane Average Traffic Flow doubled.

From Figure 2.4, we can see that the two lane model does perform better, at least for certain densities. Firstly, it is important to note that while the difference between the lines is not huge, both simulations were repeated many times, meaning that the difference we see are significant and not simply due to chance. We can see that the two lane model increases average flow by about .04 at its maximum. We see fairly similar average flow for low densities, and gains in traffic flow from starting from around density = 0.08 and continuing until density = 0.38. After this density, the two lane and one lane doubled curves fluctuate between which is higher, but both follow a similar linear downward trend. Thus, we can conclude that at low to medium densities, allowing drivers to switch between lanes increases average flow, but at higher densities the effect is marginal to nothing. Another interesting thing to note is the similarity in the shape of the the two curves from the maximum traffic flow until about density = 0.28. Both are curved with slight fluctuations, and different from the more linear decrease seen after density = 0.28. This indicates that the marginal decrease in traffic flow from additional density is not linear

immediately after the maximum, but is instead curved, and becomes linear after about density = 0.28, which is still while the two lane model outperforms the doubled single lane model.

Extensions

Three lane model

In the real world, many highways have much more than two lanes. From the comparison between one and two lane models, I predict that an increase to three lanes would provide a further benefit. In the one lane model, there was just a single lane, and adding a second lane added one lane which had the ability to switch into one other lane and brough the original lane from having nowhere to switch to to having one lane to switch to. Going from two lanes to three lanes would not increase the number of possible lanes to switch to for the existing lanes but instead add a lane with two possible lanes to switch to. I predict that there would be an increase, but not by as large of an amount as the one to two lane increase. The two lane model introduced a radical new ability for cars as opposed to a one lane model. The three lane model extends this, but doesn't introduce a new concept, so will probably not have as strong an strong of an effect.

Relevance to Hyderabad, IN

This model was designed to simulate real world traffic, and it matches analysis done on aerial footage of real world highways. However, there are many roads in the world that do not behave like this. I am currently living in Hyderabad, IN, where the traffic is very different. Firstly, there are many small motorcycles and tuk-tuks that drive in between lanes and other cars, barely following any rules. The other cars try to mimic this behaviour but are not as nimble. Cars will rapidly go from full speed to stopped and vice versa, with trust in ability to break quickly outweighing a fear of crashing into another vehicle. In general, the traditional western "rules of the road" are much less of a concept. The model would need to be adjusted to account for these different real world behaviors. In truth, this is a good thing. A model that is applicable to extremely different real life situations is likely to be much to general, and may not be able to yield as pertinent results. The model we presented is quite accurate for western, urban to semi urban highways, and provides good insights as to how those systems behave under different conditions.

Section 3: Driver Behaviour

Changing $l_{o, back}$

In the first two sections of this paper, we only modified the density in order to assess the impact of the change on traffic flow. However, the model was built to be flexible, and it is possible to modify driver behaviour in order to understand the impact of the modifications on traffic flow. One way to change this is to modify $l_{o,\,back}$. $l_{o,\,back}$ is how far a car will look back while changing lanes. A high $l_{o,\,back}$ makes a car avoid cutting people off, while a low $l_{o,\,back}$ has no such consideration. Even with a low $l_{o,\,back}$, accidents are not possible, as the car that gets cut off will stop. However, it causes the car to stop and may increase traffic jams. On the other hand, this will likely lead to more cars being able to switch lanes, which could potentially decrease traffic jams. It is unclear what is the best behaviour.

The two lane model was used for this simulation. This simulation was done in a similar way as our previous simulations. However, it is possible that driver behaviour has different impacts at different density levels. Thus, a parameter sweep was done with two inputs, where each of a list of varied densities was paired with each of a list of varying $l_{o,\,back}$ levels (ranging from 6 to 0). This was carried out in AWS lambda. Due to AWS lambda constraints, the number of repeats had to be lowered. To counteract this, I sent three identical requests to AWS lambda to accomplish the same result. The following figure shows three dimensional plots for each request (named Data1, Data2, and Data3).

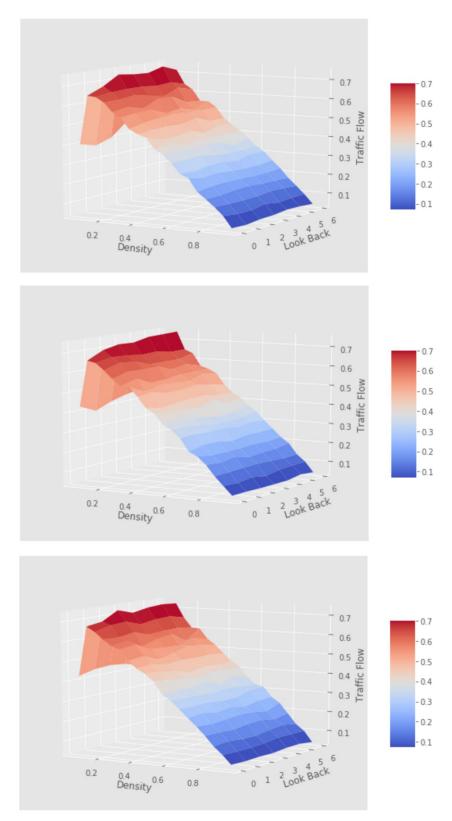


Figure 3.1: Three plots for the three data sets, each a parameter sweep of density and $l_{o,\,back}$.

From Figure 3.1, we can see that there are definitely interesting results. A single slice of the graph at constant $l_{o,\,back}$ is consistent with the curve we observed in figure 2.3. There also appear to be differing optimal $l_{o,\,back}$ for different densities. However, the three plots seem to have variance, and it is unclear if the observable trends are consistent throughout or due to variance. Thus, it is useful to look at the next figure, which is an average of the three plots.

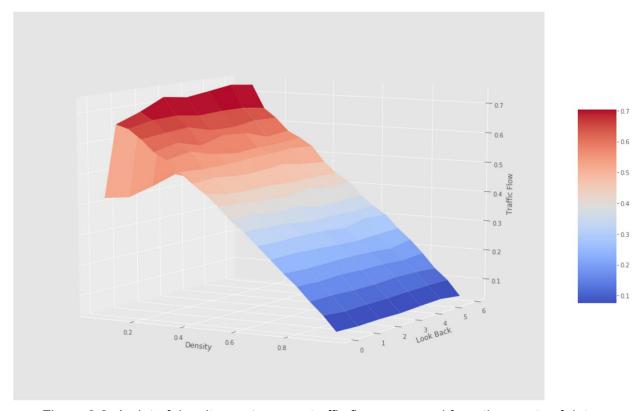


Figure 3.2: A plot of density vs. $l_{o.back}$ vs. traffic flow, averaged from three sets of data.

Figure 3.2 shows that much of the previously observed variance flattens out, especially as density increases. From this graph, it is unclear if the maximum traffic flow at low density (around density = 0.2) is achieved with a high $l_{o,\,back}$ or a low $l_{o,\,back}$. However it is clear that a $l_{o,\,back}$ = 0 produces the least desirable result. This makes sense, as at low densities there is less need to switch lanes as there are fewer traffic jams, so cutting people off is less necessary but still produces the negative result of a car having to stop short. For medium densities (between density = 0.3 and 0.5) it appears that there is a maximum traffic flow and a more intermediary $l_{o,\,back}$, with a look back of about 2 producing the maximum result. At high densities (larger than 0.5), it appears that whatever the optimal $l_{o,\,back}$ is, it has a lower impact, as the graph is quite flat.

Figure 3.2 has provided us with some useful analysis, but some things are still left unclear. I present another figure, which shows the optimal $l_{o,\,back}$ (produces the maximum traffic flow) at each density level.

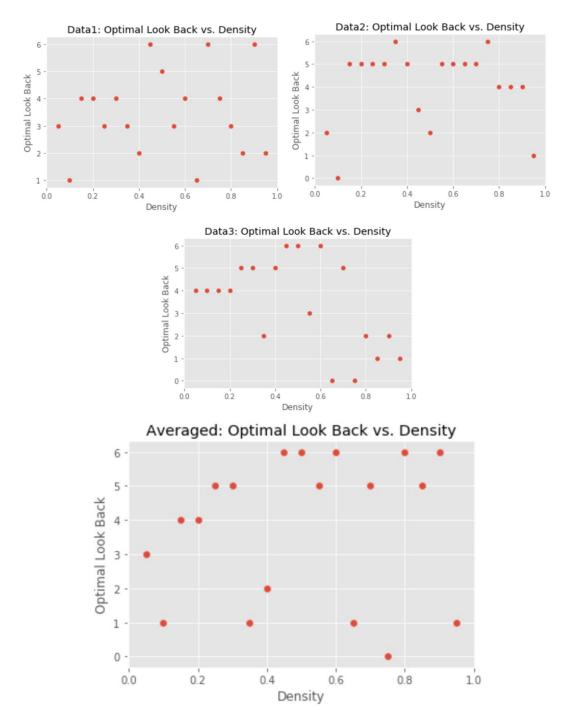


Figure 3.3: The top three plots show the optimal $l_{o,\,back}$ at each density for our three data sets, with the final plot showing the $l_{o,\,back}$ for each result the averaged dataset.

From Figure 3.3, we can see several things. At very low densities, it is unclear if a low or medium $l_{o,\,back}$ is optimal. At low densities, the optimal $l_{o,\,back}$ is at around 4. This indicates that

good driver behaviour at this density level is to not cut people off, but a $l_{o,\,back}$ of 5 is a bit too conservative, preventing people from switching where it would optimize traffic flow without making people slow down. At medium densities, we see that the lower $l_{o,\,back}$ of 1 to 2 produces the optimal traffic flow. This indicates that at this density level, cutting people by some amount (but not by the larger amount of even lower $l_{o,\,back}$) is worth it for optimizing traffic flow. This may be because the gains from more drivers switching lanes to avoid traffic outweigh the losses from drivers being cut off. Finally, at higher densities, we see the optimal $l_{o,\,back}$ fluctuating between low and high. This is indicative of the low impact that $l_{o,\,back}$ has on traffic flow that we observed from figure 3.2, as there is no clear trend as to which behaviour is better. This makes sense, as there are probably few lane changes in general as the roads are so crowded.

From the analysis of figures 3.1, 3.2 and 3.3, we can make some comments as to what good driving behaviour is. At all density levels, an extreme $l_{o,\ back}$ (either high or low) is not optimal. At smaller densities, a not cutting people off while avoiding being over cautious is preferable, while at medium densities, cutting people off while avoiding cutting them off too much is preferable, and at higher densities, how far back someone looks before switching lanes has a negligible effect.

This analysis, however, could still benefit from some further work. Specifically, analysis as to how consistent are the observed effects, and how relevant are the differences (is the difference between an optimal or suboptimal $l_{o,\,back}$ that big?) The first question could be addressed by either running large simulations with more repeated models, or by creating confidence intervals of the estimated traffic flow. This latter option could produce interesting graphs, with a graph like 3.2 including confidence intervals above and below, and trying to see if the lower bound of the interval is higher than the upper bound of the interval at another point. The second question could be addressed by analysis of how big of a real world impact small changes in traffic flow have.

Changing $p_{slowdown}$

While the $l_{o,\,back}$ is an important aspect of driver behaviour, there are other ways that driver behaviour can change. An important aspect of driver behaviour is $p_{slowdown}$, or the probability that a driver will slow down with no reason to. This is the key behaviour in the simulation that leads to accurate, real world results, namely traffic jams. However, it is still useful to analyze just how much of an impact this has on traffic flow. Using the same technique as previous simulations, a parameter sweep of different traffic densities combined with different $p_{slowdown}$ slow down values was run multiple times (25 repeats for each parameter set in this instance) and the traffic flows were averaged in order to get a average traffic flow at that specific set of parameters. The results are shown in the figure below.

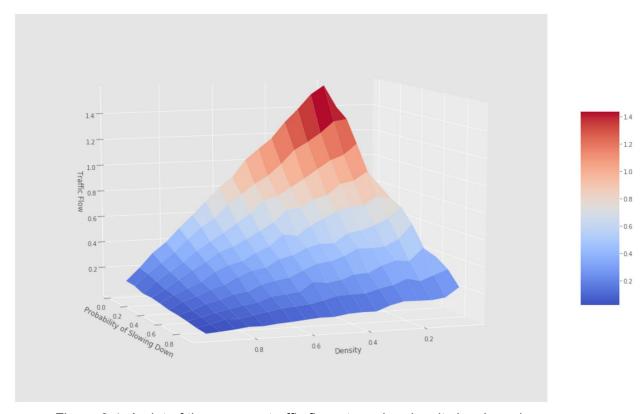


Figure 3.4: A plot of the average traffic flow at varying density levels and $p_{slowdown}$.

From Figure 3.4, we can see the enormous impact that $p_{slowdown}$ has on traffic flow. The effects are most pronounced at low densities but are consistent throughout all density levels. The effect is a huge increase in traffic flow, double and at low densities even more than double the traffic flow when decreasing from $p_{slowdown} = 0.5$ to $p_{slowdown} = 0$. We can also see that a high $p_{slowdown}$ can severely stunt traffic flow, even at low densities.

Autonomous Driving

The analysis from our previous two subsections can help to guide us if we want to program autonomous driving cars. We will first discuss $l_{o,\,back}$. If we had to choose one consistent $l_{o,\,back}$, the best course of action would be to program a high (although possible slightly less conservative than $l_{o,\,back}$ = maximum velocity) $l_{o,\,back}$, as this leads to the highest traffic flow in certain densities, while never giving us the lowest traffic flow like low $l_{o,\,back}$ at certain densities. However, what would be preferable would be a car that could detect traffic flow either through sensors or cameras viewing the road or through communicating with other cars. Thus, it would be able to adjust its $l_{o,\,back}$ to maximize traffic flow at the particular density it finds it self. This type of analysis could also be extended to more than 3 dimensions. An autonomous vehicle could have a huge dimensional space with of various parameters, some that it controls and some that are external, and it could optimize its controllable parameters based on its

environment by maximizing some set of outcomes, which could be much more than simply traffic flow, like individual speed or safety.

The larger conclusion that we can draw from our analysis is that autonomous cars should focus on minimizing unnecessary slowdowns. While a low $p_{slowdown}$ may be impossible for human drivers, autonomous cars may be able to have a much lower, if not zero level, which would dramatically increase traffic flow. This analysis shows that autonomous cars, by optimizing for things that humans can not do, could revolutionize driving and bring transportation to a level never before seen by humans.

A drawback of this analysis in terms of autonomous cars is that it is a cellular automata model. In reality, self driving cars may be able to communicate with each other, autonomous nature of the single cars, and instead act as one brain or organism, communicating its every wishes and truly maximizing traffic flow. This type of analysis is left for future research.

Future Work

While this model provides many useful insights, it is far from exhaustive. There are several ways in which this model could be improved. Firstly, the road itself could be added to. More than two lanes could be added, with some being present for only part of the road, to simulate a road adding or losing lanes. The model could also have a difference between the lanes, having one lane being a passing lane or a carpool lane. There could also be different speed limits in different sections, traffic lights or stop signs, and intersections. The model could also be changed to account for accidents. Cars could infrequently not brake properly and cause a collision. This could help to analyze how traffic responds to accidents blocking the road. Finally, driver behavior could be expanded even more. Finally, driver behaviour could be expanded even more. Instead of maximizing speed, cars could seek to stay exactly in between the car in front of and behind them. They could also speed faster than the maximum velocity or switch lanes recklessly. Even driver behaviours like drunk or otherwise impaired driving could be programmed in, to see how the rest of the road responds. The room for further analysis on this topic is rich and ready to be explored, especially as the advent of autonomous driving makes simulations like these invaluable.