Traffic Simulation

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Single Lane Traffic Simulation

The single lane traffic simulation I implemented follows the rules detailed in Nagel and Schreckenberg's paper including acceleration, slowing down due to cars ahead, and slowing down randomly to introduce some stochastic elements to the simulation for realism (1992).

1) **Acceleration:** if the velocity v of a vehicle is lower than v_{max} and if the distance to the next car ahead is larger than $v+1$, the speed is advanced by one $[v \rightarrow v+1]$.
2) **Slowing down (due to other cars):** if a vehicle at site i sees the next vehicle at site $i+j$ (with $j \leq v$), it reduces its speed to $j-1$ $[v \rightarrow j-1]$.
3) **Randomization:** with probability p, the velocity of each vehicle (if greater than zero) is decreased by one $[v \rightarrow v-1]$.
4) **Car motion:** each vehicle is advanced v sites.

Fig. 1: Ruleset from Nagel and Schreckenberg (1992)

Explanation

1) A car accelerates if the driver determines there is room to do so.
2) A car negatively accelerates if the driver sees a car ahead and anticipates the need.
3) A car randomly slows down due to a cell phone text, billboard, or other random event. This is to ensure the model actually behaves with some sort of human behavior otherwise the cars would reach an equilibrium with their velocities and barely fluctuate. The random slow down introduces the emergence of traffic jams.
4) After all of those rules are evaluated and executed, cars move according to their velocity.

Strategies

I implemented both the regular strategy detailed in the paper, as well as a strategy which uses knowledge of the car behind the driver to enable the driver to place themselves in the middle of the two cars beside them in a more equidistant manner. As I will show in my flow analysis, the middle strategy helps increase flow overall while hurting flow at the critical point. This is probably due to adjusting to be in the middle when not completely necessary, slowing down a car and reducing flow. I show that we can make the model more realistic and increase flow by adding in random use of the middle strategy to form a mixed middle strategy.

Flow Analysis

In class we calculated flow by counting the number of periodic boundary crossings; however, in my simulation I calculated the total distance moved by all cars, then divided by the road length. I tested one hundred different densities, five times each, that is randomly generating five roads for each density to make sure we had an even more representative sample instead of just one simulation per density. The following graph shows the Flows vs. Density for both the regular and middle strategies.

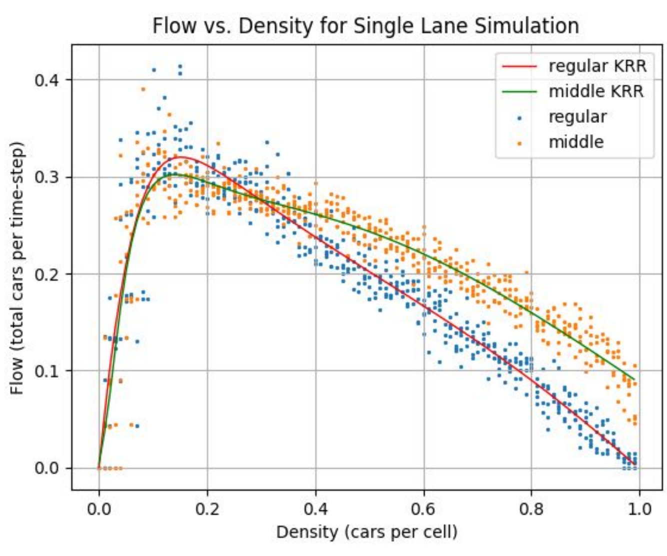

Fig. 2: Comparing strategies for the single lane simulation

First, let's look at the flows for the regular strategy. Fig. 14 in the appendix visualizes the flow of cars over time using the regular strategy. Using a kernel ridge regression I fit the red model to the blue data. The flow rapidly increases as we increase the density and reaches a critical point for total cars per time-step at around a density of 0.15 cars per cell. The flow decreases almost linearly as we increase the density, showing the negative effects of adding more cars to a road. As we add more cars to a road, the chance one of those cars randomly slows down greatly increases, which then increases the chances for a traffic jam. If we added more cars without a random slowdown rule we would get the graph below.

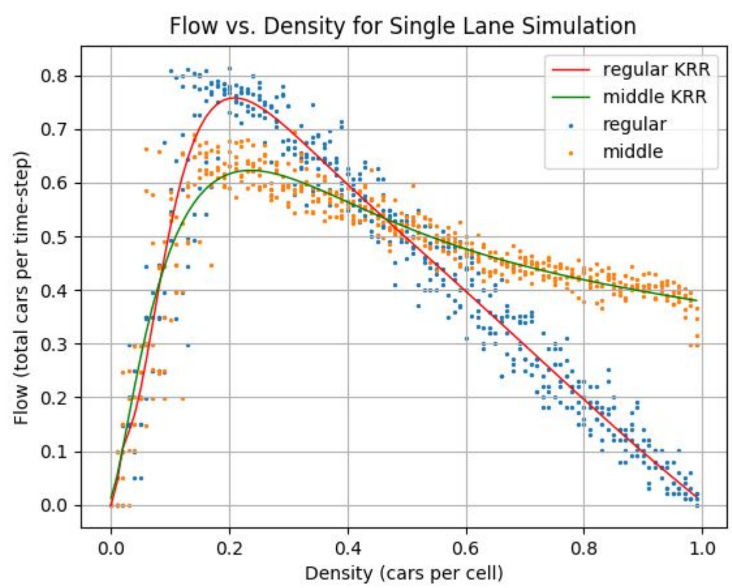

Fig. 3: Flows of both strategies without random slowdown rules

The flow skyrockets from around 0.3 in the original simulation at a critical point of around 0.15 cars per cell to a flow of 0.8 total cars per time-step at a critical point of around 0.2 cars per cell. The middle strategy lowers the flow at the critical point, yet helps ease traffic at higher densities.

This is probably due to the fact that a car may try to place itself in between two cars at the critical point while not necessarily needing to slow down, and later on, when the density is higher, being able to place the car in between cars, and as a result not needing to rapidly slow down, which would cause traffic jams. The problem in reality is that all people definitely do not use the middle strategy, so let us look at a mixed middle strategy where half of the people use the regular strategy and the other half use the middle strategy (graph below).

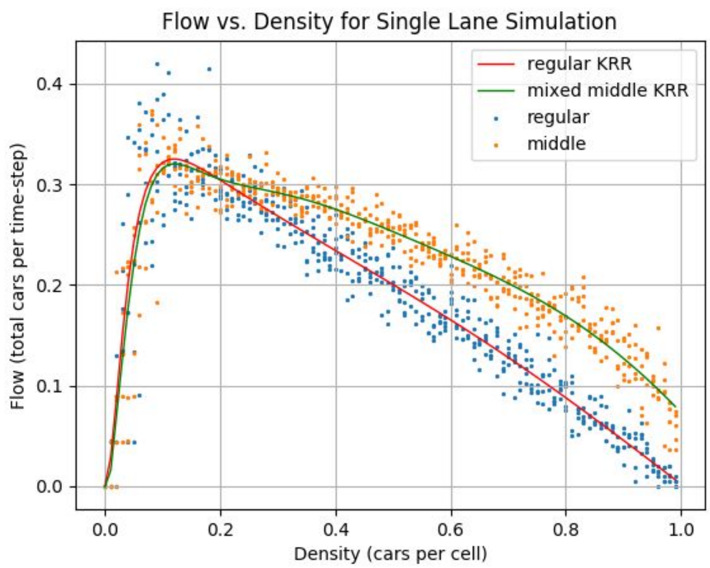

Fig. 4: mixed middle strategy performs better than middle at critical point

With this graph we can see the mixed middle strategy performs much more like the regular strategy, just with a bit of an improvement out towards the higher density values, and actually almost matches the flow of the regular strategy at the critical point. This can be seen as a mixed model which is shown to optimize traffic behavior. I will be keeping the non-mixed model but wanted to show how a mixed model would perform.

Multiple Lane Traffic Simulation

The multiple lane traffic simulation I implemented uses two single lane simulations described earlier, and includes the lane switching mechanism detailed in the paper by Rickert, Nagel, Schreckenberg, and Latour (1996). As outlined in the assignment description, my model is symmetric, uni-directional, and variable speed.

- $gap(i) < l$ (**T1**),
- $gap_o(i) > l_o$ (**T2**),
- $gap_{o,back}(i) > l_{o,back}$ (**T3**), and
- $rand() < p_{change}$ (**T4**).

Fig. 5: Rules for changing lanes in the 1996 paper

Explanation

- If a car sees a another car in its way, and
- If a car sees enough space in the other lane looking ahead, and
- If a car sees no other cars behind in the other lane, and
- If a car randomly “commits” to changing lanes

If all of the above conditions are met, the car will change lanes. This model assumes a symmetric form which, as detailed in the paper, means that no one lane has a magnetic quality to it. In some countries such as Germany the left lane is strictly used for passing, and the laws are enforced. In other countries like the United States, people drive in both the left and right lanes normally, and don’t necessarily use it for passing. This model also assumes that people don’t always change lanes when they attempt or have the opportunity to on an individual basis. I included a p_change (probability of changing lanes) parameter to add randomness to the lane changing and ensure that “ping-pong” behavior described in the paper does not occur. The model takes parameters allowing the user to set initial states, verbosity, etc. but most importantly, it allows users to set the lane threshold values which will determine the thresholds for drivers in the model to change lanes. With a low *l_o_back* we expect cars to cause more traffic jams because of their disregard for cars going fast in the other lane. Similarly, with a low *l_o* cars switch lanes even though it may not be better at all to do so, causing the car to rapidly slow down on the next time-step if there is a car closely ahead in the other lane. I will test these hypotheses in the below section.

Flow Analysis

I compared the single lane and multi-lane simulations and found the multi-lane simulation to have higher flows and throughput (average integral of flow vs. density model). Below both graphs compare the regular and middle strategies for the single and multiple lane simulations respectively holding the lane threshold values constant at three (*l*, *l_o*, *l_o_back* = 3).

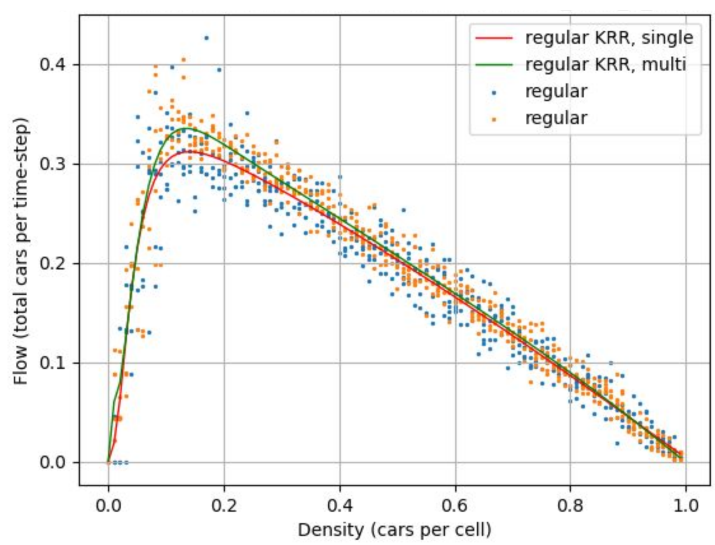

Fig. 6: Single vs. Multi-lane simulation for the regular strategy

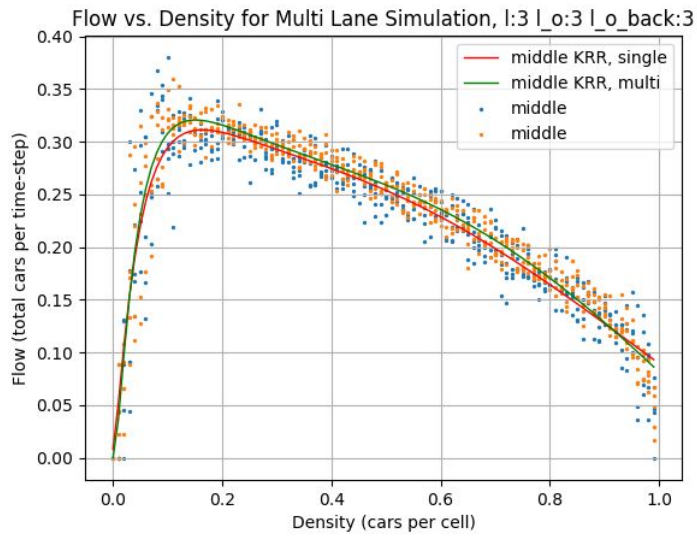

Fig. 7: Single vs. Multi-lane simulation for the middle strategy

For a point of comparison I averaged the density values for the critical flow values and found the “approximate critical point” using an average critical density of 0.145. The table below compares the max flow for the different strategies keeping the lane thresholds constant.

	Regular	Middle	Difference
Single	0.322656	0.294273	-0.02838
Multi	0.335806	0.300222	-0.035584
Difference	0.01315	0.005949	

Fig 8: Flow values at constant density near critical points

Results

These values show a decrease in flow when using the middle strategy over the regular strategy at critical points, as discussed earlier, and show a slight increase in flow when there are two lanes available with the same density. To get a more accurate picture of the performance of the strategies *on average* we can take the integral of the curves from 0 to 1 and subtract them to find the average difference in throughput as discussed earlier; in the class simulation it would be total number of cars crossing the periodic boundary over all densities (Note: to find the average over all densities, we are just dividing the integral by $b - a$, which in this case is one). This of course is an estimation, but gives us a good idea of how much the throughput and flow will increase when two lanes are present on average instead of just at the critical points.

	Regular	Middle	Difference
Single	89.816405	107.301064	17.484659
Multi	93.108135	108.849531	15.741396
Difference	3.29173	1.548467	

Fig. 9: Average throughput values ($\frac{1}{1-0}\int_0^1 f_{str,\, m}(x)\, \partial(x)$ where *str* is the strategy, *m* is single or multi, and *f(x)* is the model for the flow vs. density data corresponding to the *str* and *m*)

Fig. 9 shows that overall the multi-lane simulation using the middle strategy has the highest throughput of the other strategies, and that the switch from single lane to multi-lane as well as the switch from regular to middle both improve average throughput of cars and flow. We can conclude that having multiple lanes and the ability to change lanes with the same density as a single lane simulation improves flow at the critical point and overall.

Key Questions

Testing hypotheses about driver behavior in the multi-lane simulation

Earlier in this paper I hypothesized what would happen as I modified certain lane threshold parameters. It turns out extremely aggressive driver behavior results in much lower flows and throughput, and negatively affects traffic. The general idea was that a high *l*, low *l_o*, and low *l_o_back* all lead to short-sighted lane changes, which in turn cause rapid slow downs and traffic jams. A high *l* means a driver feels the need to move from their lane even if they may not need to, a low *l_o* means a driver doesn't look very far ahead in the other lane to determine if there will be room to speed up, and a low *l_o_back* means little to no consideration for the other lane when changing lane (this is the equivalent of checking your mirrors and blind spot). In the graph below we see what happens with extreme lane threshold parameters to test my hypotheses.

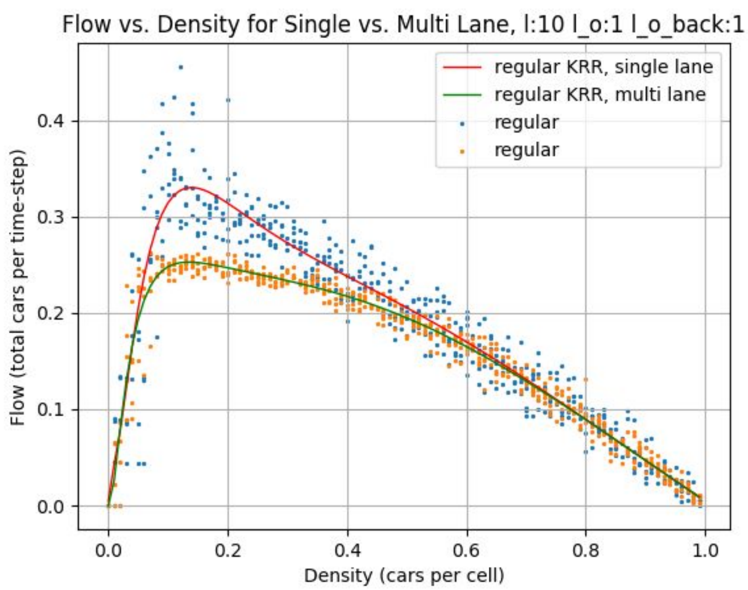

Fig. 10: Single vs. Multi-lane simulation with extremely aggressive lane changing parameters

	Throughput	Flow at Critical Point
Single	91.127687	0.330164
Multi	80.847917	0.252622
Difference	10.27977	0.077542

Fig. 11: Data showing impact of aggressive driver behavior

Clearly, the behavior of the driver for the multi-lane simulation caused by extremely bad lane threshold parameters decreases flow. Fig, 11 shows that in this case the multi-lane simulation underperformed the single lane simulation by 0.077542 total cars per time step at their respective critical points, which is nothing to scoff at. The graphs in the appendix compare different lane threshold values (for time-saving purposes I test 20 densities five times instead of 100 densities five times like I have previously).

Predicting Effect of Adding More Lanes

As I am not completely comfortable with developing probability equations and which type of analysis for this sort of simulation would fit best, I cannot say exactly how adding another lane would impact flow. A naive way of predicting would be to look at the percentage increase in flow keeping *l*, *l_o*, *l_o_back* constant, which according to Fig. 8, using a regular strategy we improved flow by approximately 4%, so maybe one additional lane would improve flow by 4% on top of the two-lane simulation flow. My intuition tells me every time we add a lane to the "highway" the benefit get smaller and smaller partly because of the low chance that cars from the middle lanes would reap benefits of a lane that is not directly adjacent to it. This would be an interesting extension.

Model Validity in Hyderabad

This model falls *hard* when applied to the reality of Hyderabad traffic. Hyderabad traffic could use this model strictly when talking about highways without traffic lights, and even then it may be a stretch. The reality is that in Hyderabad traffic would be better modeled in a fluid dynamics simulation using high viscosity parameters. Cars, autos, motorbikes, buses, and even ambulances act as molecules on a two-dimensional slice of a pipe with a diameter equivalent to the width of the road and driveable space combined. This sort of model would have to use more advanced mathematical concepts like differential equations and probably use a physics or fluid dynamics engine to more accurately and realistically model Hyderabad traffic.

Appendix

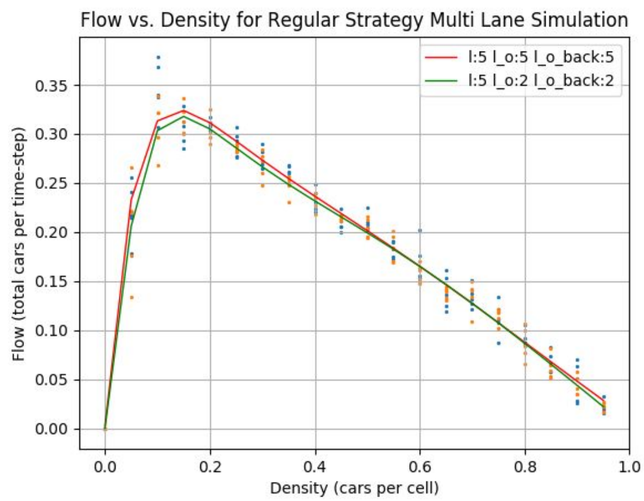

Fig. 12: lower *l_o* and l_o_back decrease flow

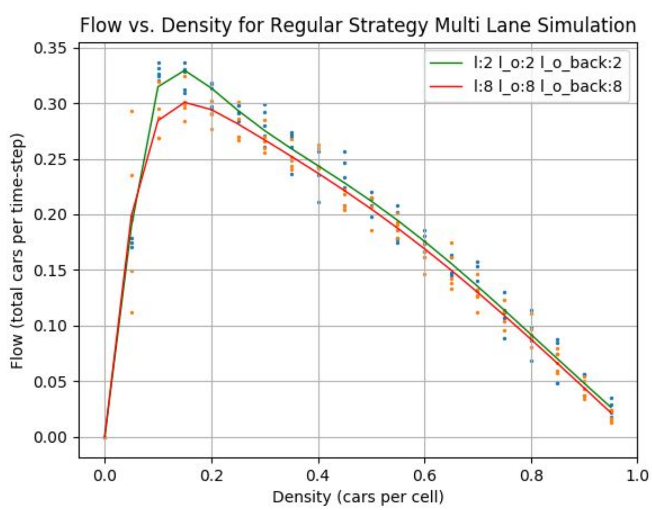

Fig. 13: high l, l_o, and l_o_back inhibits benefits of lane changing, cars change lanes less

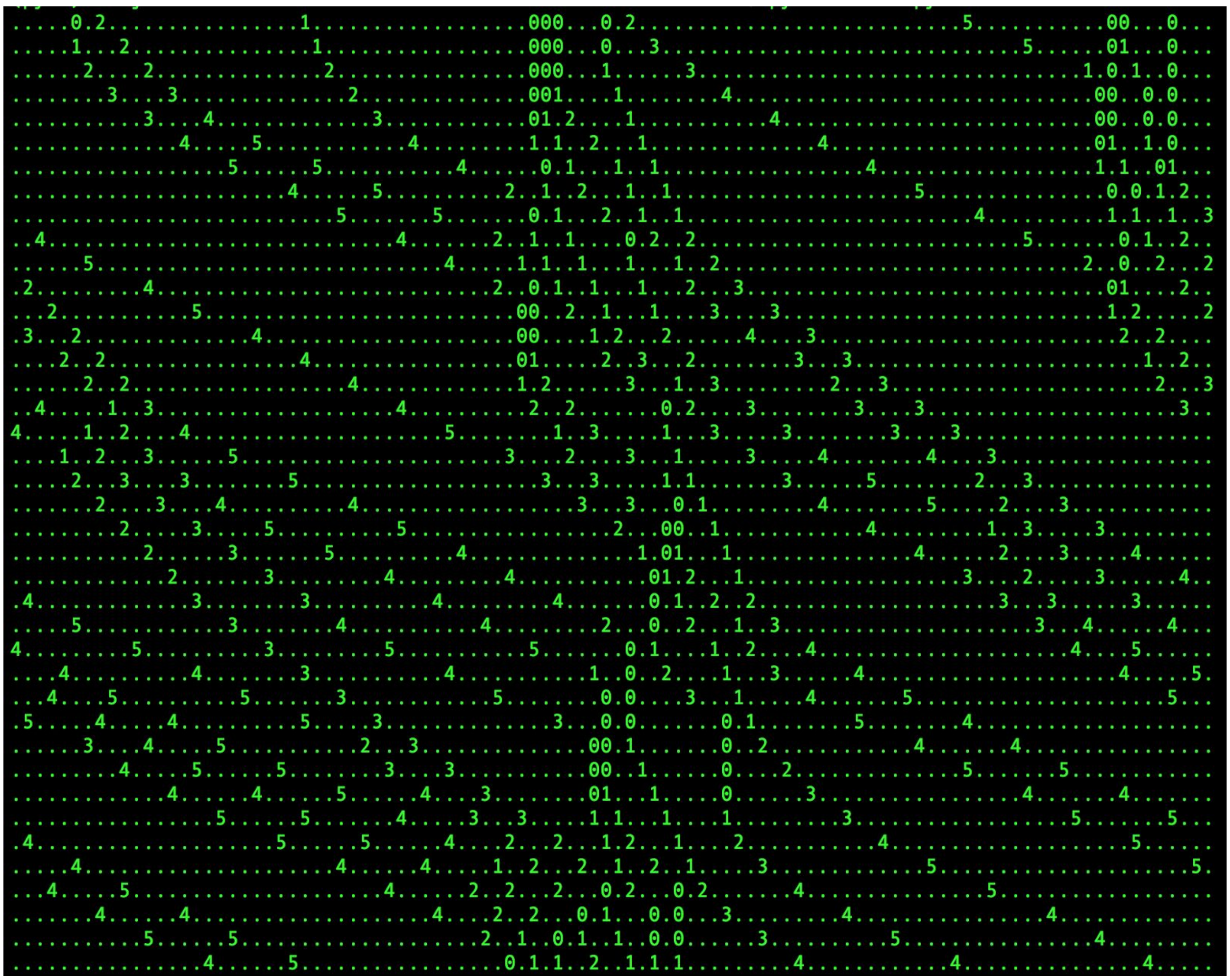

Fig. 14: Regular strategy single lane sim with a 0.1 density, groups of zeros are traffic jams

References

Nagel, K., Schreckenberg, M. (1992). A cellular automaton model for freeway traffic. Journal de Physique I, EDP Sciences, 1992, 2 (12), pp.2221-2229.

Rickert, M., Nagel, K., Schreckenberg, M., & Latour, A. (1996). Two lane traffic simulations using cellular automata. *Physica A: Statistical Mechanics and its Applications,231*(4), 534-550. doi:10.1016/0378-4371(95)00442-4