Navigating Traffic Jams: Simplifying the Science of Bottleneck-Free Congestion with Cellular Automata

Tycho Stam (13303147), Mickey van Riemsdijk (13939432)

November 20, 2023

Introduction

Everyday traffic jams on highways and roads are a persistent source of frustration for commuters (ANWB, 2023). Often, the causes behind these jams remain unknown, with incidents like accidents or roadwork failing to account for their regular occurrence. While the precise reasons for these traffic jams are not fully understood, a widely accepted notion implicates bottlenecks as potential explanations. Bottlenecks, such as on-ramps, tunnels, and sags, are commonly recognized as areas where traffic jams can arise. Reasons for this can be the traffic flow.

Traffic flow refers to the movement of vehicles on roadways, encompassing the dynamic interactions and patterns that emerge as cars navigate from one point to another (Sugiyama et al., 2008). It is a complex system influenced by several factors such as vehicle density, road conditions, and driver behaviour. At its core, traffic flow is characterized by the continuous interplay between individual vehicles, each adjusting its speed and position in response to the surrounding traffic (Treiber & Kesting, 2013). The study of traffic flow involves understanding how these individual interactions contribute to collective phenomena, including the emergence of congestion or traffic jams.

Methode

To gain an understanding of traffic flow, a simple model is used to gain understanding. For this, the Cellular Automata (CA) Rule 184 is used. CA is a computational model consisting of a grid of cells, each in one of a finite number of states (Chopard & Droz, 1998). A CA is used instead of real cars, because of the ease of collecting data and the cheaper cost. Besides that, the simulation isn't prone to external variables like rain or the Sun.

Rule 184, specifically, operates on a one-dimensional binary array of cells, where each cell's state is determined by a set of predefined rules based on its own state and the states of its neighbouring cells (Wolfram, 1984). This rule is particularly apt for simulating traffic flow because it encapsulates the dynamics of vehicular movement, mirroring the way vehicles interact on a linear road Fuks-acute (1997). In this way, a road can be simulated without the mentioned bottlenecks, the result of which can be seen in Figure 1.

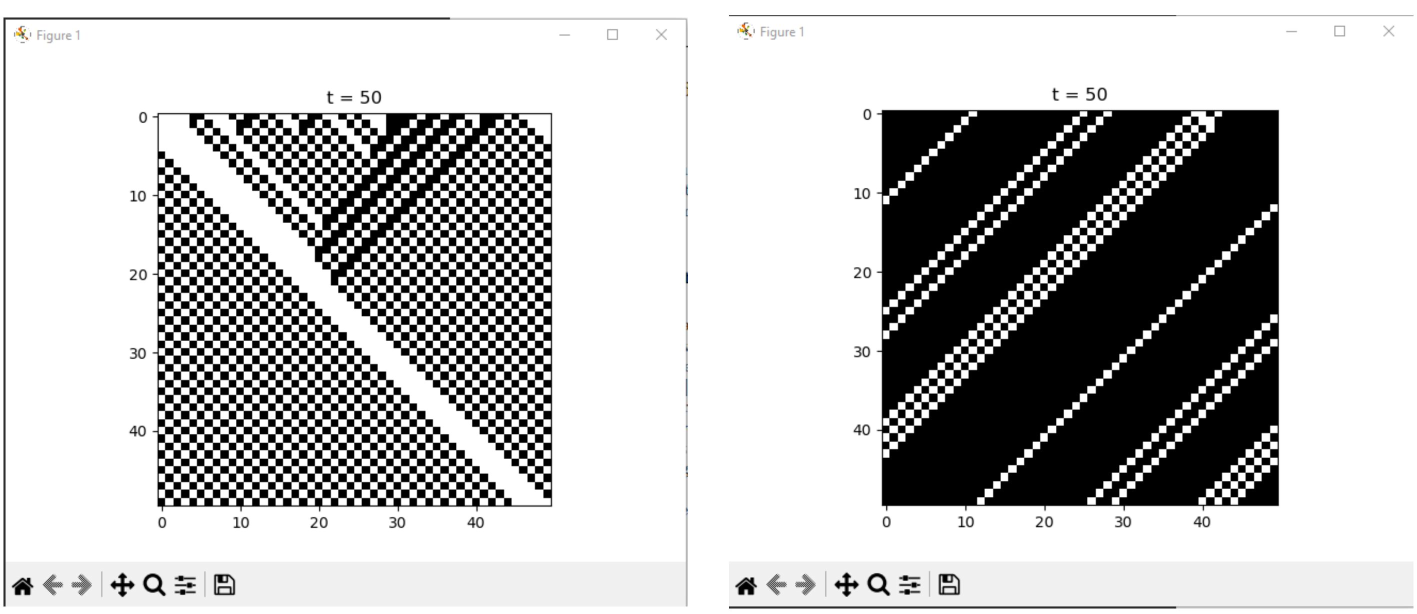

Figure 1: Evolution of a CA rule 184 of size $N = 50$ for $T = 50$ steps for the 'car' densities 0.4 (left) and 0.9 (right). Other parameters used are $k = 2$ and $r = 1$.

Within Figure 1, the simulation reveals that when the model exhibits a checker pattern, the 'car' moves smoothly without encountering issues. Notably, in the model with an initial density of 0.4, a small traffic jam occurs at the start, but subsequently, the 'cars' continue to move without impediment. However, at a higher density of 0.9, the simulation demonstrates a different scenario. The increased density leads to the heaping of 'cars,' resulting in the occurrence of traffic jams. For this assignment, the following parameters are used: $k = 2, r = 1, N = 50$ and $T = 50$. To run the code, the program needs to have the PyICS library included. Besides that, Plotly, NumPy and Pandas must be installed.

Traffic flow

To compute the traffic flow per unit of time within the CA, a car must traverse the right-hand side of the system boundary. This condition necessitates that the rightmost cell possesses a value of 1, while the leftmost cell possesses a value of 0. With an exclusion of the last generated row. Figures 2 and 3 illustrate the influence of density on the traffic flow within the system. The traffic flow is calculated thirty times for each density, and the resulting rounded mean is shown in the scatter plot. The mean is rounded, since the model can not simulate a percentage of a car. As observed in Figure 3, a phase transition occurs after the density of 0.5. This number is as expected because when enough time has passed, the 0.5 density will always produce the most amount of traffic due to the balanced nature of cars spread on the road. When a reduced number of time steps and lower road length are used in the model, the results may appear undersampled, as illustrated in Figure 2. This undersampling effect indicates a more limited temporal resolution, potentially impacting the accuracy and granularity of the observed traffic flow patterns.

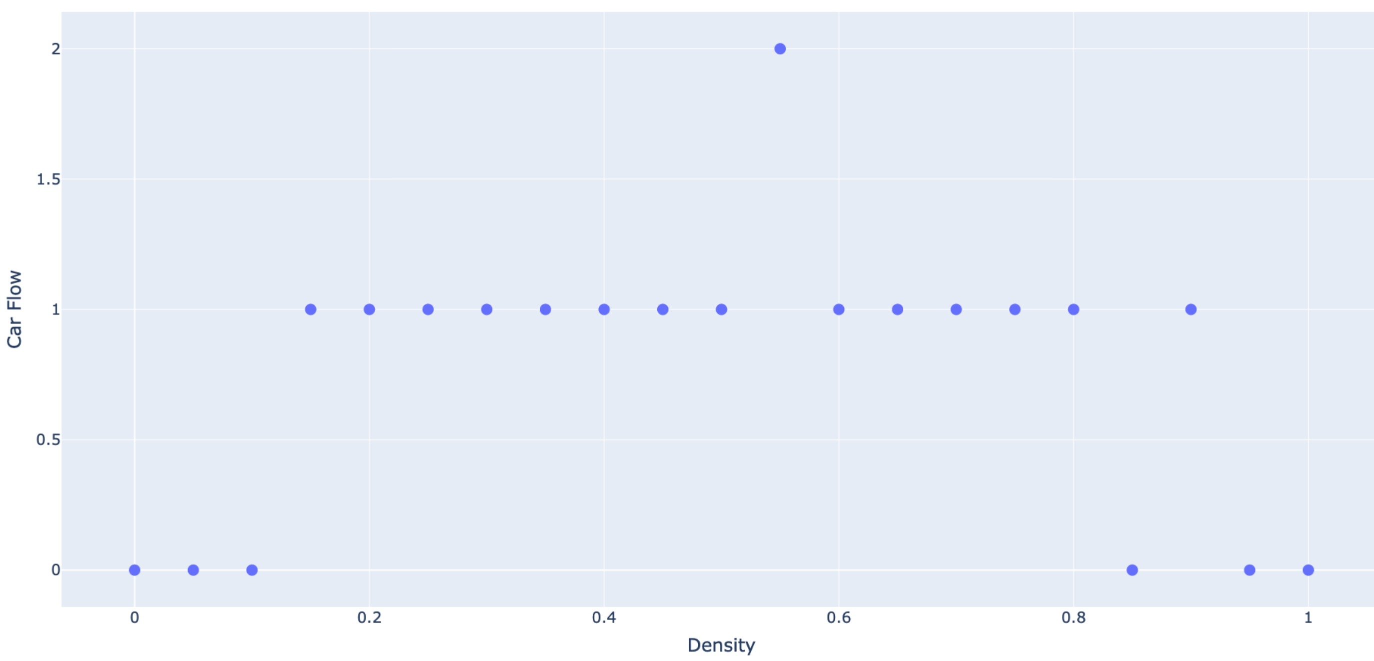

Figure 2: Scatter plot of Traffic Flow with Density range [0-1] with a road length of $N = 3$ and $T = 5$ time steps.

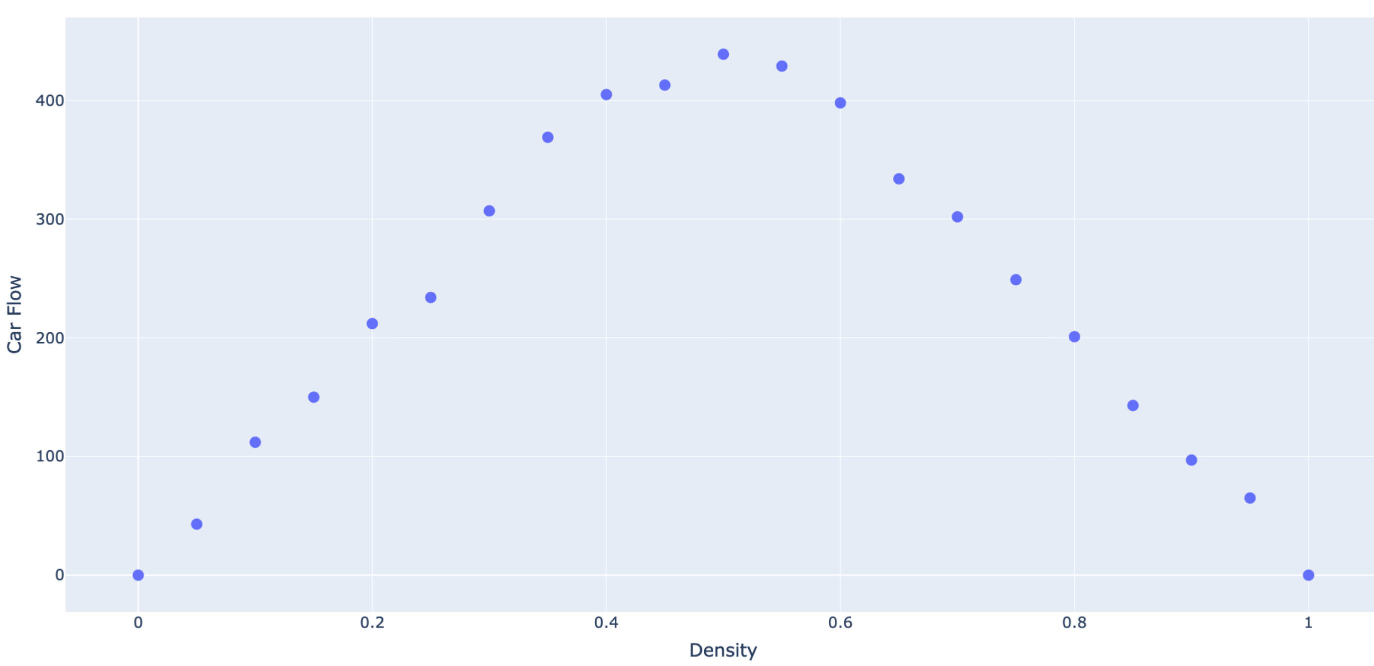

Figure 3: Scatter plot of Traffic Flow with Density range [0-1] with a road length of $N = 50$ and $T = 1000$ time steps.

Correctness probability

As seen in Figure 3 a phase transition starts after the highest amount of car flow in the graph. This exact point also equates to the critical density. In Figure 4 probability of correctness is measured according to the critical density. The following parameters are used: k = 2, r = 1. The time steps differ and each amount of time steps is repeated 20 times. The range of times steps is chosen according to the size of the array (in Figure 4, $N = 50$), the minimum amount of steps is half of the array and the maximum amount is the array times one and a half. These limits are chosen according to Figure 1 which shows a repeated pattern after half of the size of the array in time steps. The maximum is in this case twice a full iteration of the array. The density with the highest car flow of all repetitions per amount of time steps is set as the critical density. Afterwards, the density with the highest car flow is taken per repeat group. If the density falls in the range of 0.05 of the critical density, the density is 'correct'. The percentage of 'correct' marked densities is taken to bring forth the correctness probability. Figure 4 shows a consistent correctness probability of 0.90 and higher after 63 times steps.

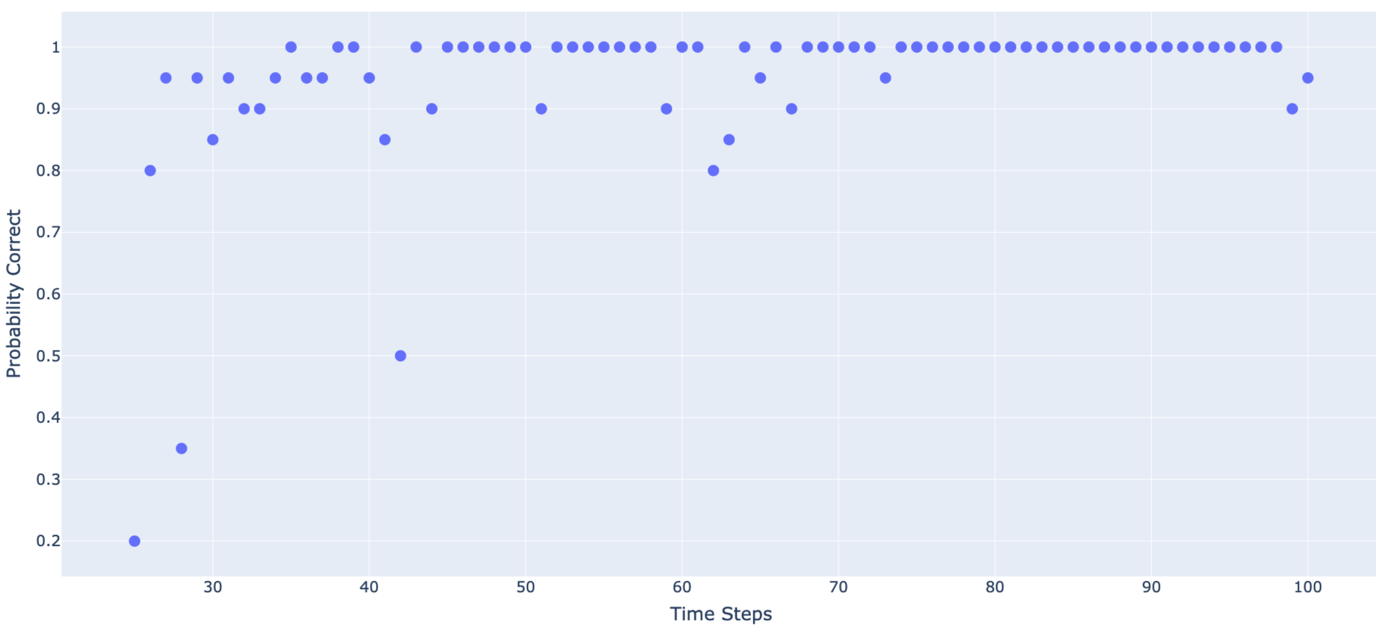

Figure 4: Influence time steps amount on correctness probability.

Conclusion

Traffic Flow

Based on Figure 3 an optimal traffic flow occurs around a density of 0.50. Around this point, a perfect balance is formed between how many vehicles there are and how smoothly the traffic moves. However, the graph also unveils a clear correlation: fewer cars correspond to diminished traffic flow, indicating that an excessively sparse road might not be conducive to optimal movement. Conversely, an increase in the number of cars results in a surge of traffic jams and a subsequent reduction in overall traffic flow. As mentioned earlier, a phase transition occurs around the highest point of the graph.

At the extremes of the graph, where the road is either fully occupied or completely empty, the calculation of traffic flow becomes non-existent. When the road is full of vehicles, there's little room for movement, causing traffic flow to come to a standstill. On the flip side, when the road is entirely empty, there's no traffic to measure.

Optimal parameters

In conclusion, the impact of undersampling is a crucial consideration in both real experiments and simulations. Determining the adequate number of cells or time steps necessary for a reliable measurement poses a challenge, especially in real-world experiments where factors like human drivers' preferences and constraints come into play. Often, it is challenging to ensure enough cars driving for an adequate duration due to practical limitations. In the realm of simulations, however, the advantage lies in the ability to precisely measure and adjust these parameters. As mentioned before, such a model is not prone to external or personal variables.

As depicted in Figure 4, the optimal time steps parameter for $N = 50$ appears to converge after $T = 63$. Beyond this point, a consistent influence on the correctness probability preceding 0.9 is observed. However, it's essential to note that as we extend the number of time steps and widen the cell dimensions, a higher runtime is expected. This indicates that while reaching optimal parameters is crucial for accuracy, there exists a trade-off between achieving precision and the computational resources required for simulations. Striking a balance between these factors becomes pivotal in designing simulations without compromising efficiency.

In the model, a density of 0.5 is the optimal density for a balanced traffic flow, but in the real world, traffic is not optimal. Personal and external factors can influence the flow of traffic, so it would be plausible to assume the optimal density would be lower in a real-world situation.

References

ANWB (2023). Dagelijkse drukke trajecten ochtend en avondspits. Retrieved November 16, 2023, from https://www.anwb.nl/verkeer/nederland/verkeersinformatie/dagelijkse-drukke-trajecten.

Chopard, B. & Droz, M. (1998). Cellular automata. *Modelling of Physical*, pages 6–13.

Fuks-acute, H. (1997). Solution of the density classification problem with two cellular automata rules. *Physical Review E*, 55(3):R2081.

Sugiyama, Y., Fukui, M., Kikuchi, M., Hasebe, K., Nakayama, A., Nishinari, K., Tadaki, S.-i., & Yukawa, S. (2008). Traffic jams without bottlenecks—experimental evidence for the physical mechanism of the formation of a jam. *New journal of physics*, 10(3):033001.

Treiber, M. & Kesting, A. (2013). Traffic flow dynamics. *Traffic Flow Dynamics: Data, Models and Simulation, Springer-Verlag Berlin Heidelberg*, pages 983–1000.

Wolfram, S. (1984). Universality and complexity in cellular automata. *Physica D: Nonlinear Phenomena*, 10(1-2):1–35.