Ann Arbor Traffic Optimization

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Abstract:

We developed a Markov chain–based model to optimize traffic flow in Ann Arbor, with a focus on high-congestion scenarios such as University of Michigan game days and adverse weather conditions. Using historical traffic data, we could determine the business of any given intersection. These classifications were used to construct a Markov transition matrix representing traffic movement patterns. By analyzing the steady-state distribution, we proposed alternate routing strategies aimed at reducing congestion on key streets. Our results demonstrate the potential of probabilistic modeling to inform more efficient urban traffic systems.

This steady state can be used for a number of applications, such as determining optimal advertisement locations, real estate pricing based on traffic and noise pollution, and developing an infrastructure budget. We chose an area to optimize, encapsulated by State Street, Williams Street, South Main Street, and East Washington Street. To create the transition matrix, we estimated the probability of a car going straight right or left at every intersection. We did this by using historical traffic data and creating proportions at each intersection.

Optimal Advertising Location

When placing advertisements, advertisers and businesses alike prioritize locations with a high expected traffic volume of their target audience. Because of this, an intersection that retains a large amount of traffic is an optimal location for advertisements. Using the steady-state we can predict intersections with high long-term retention of traffic, which will be the best places within Ann Arbor, or any given set of intersections, to advertise. These areas will be the most coveted. Hence, real estate agents can accurately price these higher than the real estate in surrounding areas. Additionally, if this does not occur, business owners who use our model can see inefficiencies in the market and find the best place to invest in advertising.

Real Estate

Real estate price evaluations have vastly different metrics for residencies and businesses. Business locations are similar to advertisements. Locations with higher predicted traffic retention based on the steady state will likely be evaluated at higher rates, assuming all else is equal. Inversely, residencies will likely be evaluated at lower rates due to noise pollution and traffic congestion. Residences under flight paths sell for much less than their counterparts. Especially in an active college town like Ann Arbor, peace and quiet are coveted. Hence, real estate that is not subject to loud noise from traffic will be priced much higher than the rest of the market.

Wear and Tear

Traffic and Road Wear: High-traffic intersections experience more rapid deterioration due to the constant pressure and friction from vehicles. This wear and tear isn't just surface-level; it affects the structural integrity of the road. Over time, this leads to issues like potholes, cracks, and uneven surfaces.

Steady State Analysis for Long-term Impact Assessment: Steady state analysis is a method used to predict the long-term effects of constant factors, like traffic and road conditions. By analyzing traffic patterns and road wear rates, it provides a more accurate picture of future road conditions. This type of analysis considers the continuous use of roads rather than just short-term or immediate impacts.

Infrastructure Bill Projections and Maintenance Schedules: Utilizing steady-state analysis, the city of Ann Arbor can more effectively plan for future expenses. This includes creating accurate projections for infrastructure bills, which cover the costs of road repairs and upgrades. Additionally, it aids in developing maintenance schedules, ensuring that road repairs are timely and efficient, reducing the likelihood of major road failures.

Improved Road Conditions and Traffic Flow: Regular maintenance informed by steady-state analysis keeps roads in better condition. This has a direct impact on travel efficiency and safety. Well-maintained roads reduce the likelihood of accidents caused by poor road conditions and allow for smoother, faster travel.

Reduced Need for Traffic Diversions: With fewer road hazards like potholes, drivers are less likely to seek alternative routes, leading to more consistent and predictable traffic patterns. This can result in reduced overall traffic congestion, as drivers won't need to divert to avoid poor road conditions.

Economic and Environmental Benefits: Better road conditions and reduced traffic congestion can lead to economic benefits. Less time spent in traffic means improved productivity and reduced fuel consumption. Environmentally, it can lead to lower emissions, as constant stopping and starting in traffic is more fuel-intensive than steady driving.

Community Impact: Beyond the immediate practical benefits, this approach can have a positive impact on the community's perception of the city's infrastructure management. Residents and businesses benefit from the reliability of road conditions, contributing to a more positive view of the city's governance.

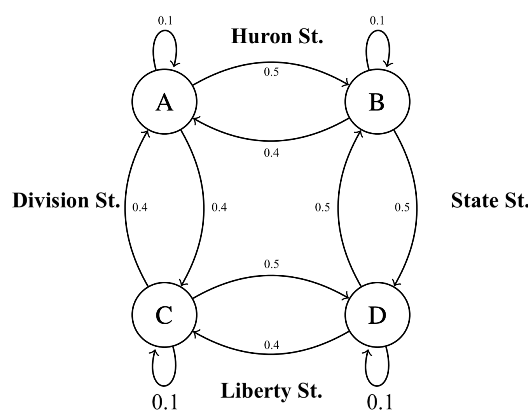
In summary, applying steady state and Markov chains analysis to traffic and road wear in Ann Arbor can lead to more effective infrastructure planning, improved road conditions, reduced traffic congestion, and overall economic and environmental benefits. This proactive approach in city planning reflects a commitment to sustainable and efficient urban management.

Implementation and Assumptions

We had to make many assumptions to create this model. We first assume that the traffic data we used to create the transition matrix was accurate. Additionally, we assumed that the system is a closed system. This means that the number of cars entering the system was equal to the number of cars exiting the system. Another assumption we made was that due to traffic signals, congestion, pedestrians crossing, and other outstanding factors, there is a 10% chance that a car would remain at the intersection it is currently at. Using these assumptions, we were able to create an accurate model for the seven-by-three collection of streets in Ann Arbor. This process can be scaled to the rest of Ann Arbor if need be by state and county legislators. We have created a fluid model, meaning that we can alter probabilities and instantly see the results. This can be used as a "guess and check" method for optimizing traffic flow. Additionally, it can be used as a safety net to double-check any decisions made by elected officials and see the implications on traffic in Ann Arbor.

Mathematical Background:

A Markov chain is a mathematical model that describes a sequence of events where the outcome of each event depends only on the previous state and not on the entire history of events. In other words, it is a dynamic process that moves from one state to another in a series of discrete steps. This model can be used to understand traffic flow and areas that have the most congestion. To give a more simple example, you can use the Markov model to look at just four intersections (see right).



Based on historical traffic flow data, a probability matrix can be produced that shows the likelihood of moving from one intersection to the next. For the purposes of understanding the Markov chain, we have simplified the probabilities.
The transition matrix is as follows:

$$A = \begin{bmatrix} 0.1 & 0.4 & 0.4 & 0 \\ 0.5 & 0.1 & 0 & 0.5 \\ 0.4 & 0 & 0.1 & 0.4 \\ 0 & 0.5 & 0.5 & 0.1 \end{bmatrix}$$

In this case, A_{11} refers to the probability of staying at intersection A. A_{21} refers to the probability of going from intersection A to intersection B. A_{31} refers to the probability of going from intersection A to intersection C and so on.

Using the Markov chain, we can determine the steady state of this system. This can be done in 2 ways. The first is eigenvectors. Firstly, find the eigenvectors of matrix A. They are as follows:

$$\mathbf{v}_1 = \begin{bmatrix} 4/5 \\ 1 \\ 4/5 \\ 1 \end{bmatrix}, \lambda_1 = 1 \quad \mathbf{v}_2 = \begin{bmatrix} 4/5 \\ -1 \\ -4/5 \\ 1 \end{bmatrix}, \lambda_1 = \text{-}4/5 \quad \mathbf{v}_3 = \begin{bmatrix} 0 \\ -1 \\ 1 \\ 0 \end{bmatrix}, \lambda_1 = 1/10 \quad \mathbf{v}_4 = \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}, \lambda_1 = 1/10$$

Next, determine the initial state. The beauty of the Markov Chain is that the initial state does not change the steady state. Let's say that an equal amount of cars start at each intersection.

$$\mathbf{v}_{initial} = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{bmatrix}$$

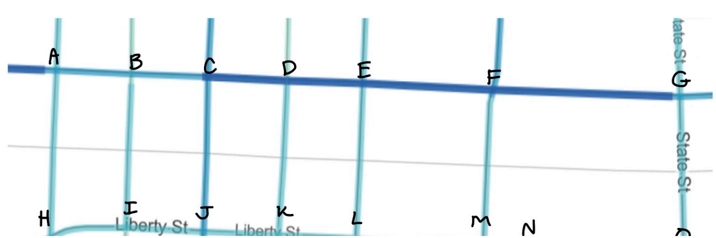
The eigenvectors can be written as a linear combination of v initial.

$$A \begin{bmatrix} 4/5 \\ 1 \\ 4/5 \\ 1 \end{bmatrix} + B \begin{bmatrix} 4/5 \\ -1 \\ -4/5 \\ 1 \end{bmatrix} + C \begin{bmatrix} 0 \\ -1 \\ 1 \\ 0 \end{bmatrix} + D \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{bmatrix}$$

Where A = 5/18, B = 0, C = 1/36, D = -1/36
Because the eigenvectors can be written as a linear combination and the largest eigenvalue equals 1, the steady-state vector can be found by finding the limit at t reaches infinity.

$$\mathbf{v}_t = \frac{5}{18}(1)^t \begin{bmatrix} 4/5 \\ 1 \\ 4/5 \\ 1 \end{bmatrix} + 0(\frac{-4}{5})^t \begin{bmatrix} 4/5 \\ -1 \\ -4/5 \\ 1 \end{bmatrix} + \frac{1}{36}(\frac{1}{10})^t \begin{bmatrix} 0 \\ -1 \\ 1 \\ 0 \end{bmatrix} - \frac{1}{36}(\frac{1}{10})^t \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

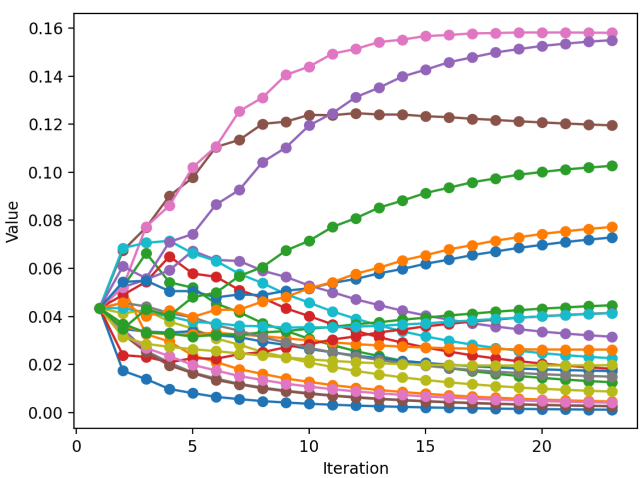
$$\lim_{t \to \infty} \mathbf{v}_t = \frac{5}{18} \begin{bmatrix} 4/5 \\ 1 \\ 4/5 \\ 1 \end{bmatrix} \approx \begin{bmatrix} 0.22 \\ 0.27 \\ 0.22 \\ 0.27 \end{bmatrix}$$



Based on our steady-state vector, intersections B and D will be more crowded. About 54 percent of cars will be at either B or D and about 44 percent of cars will be at either A or C. This is consistent with what we would expect to see in Ann Arbor since intersections B and D fall on State St., which is typically a crowded area.

The same principles can be applied to a larger traffic area. It can tell you which intersections are the busiest and how slight changes in traffic flow affect the overall system. However, to find the steady state using more intersections, we opted for an alternative process rather than eigenvectors. As mentioned before, the initial state does not change the steady state. Therefore, after some state changes, the system will converge to a steady state.

We used Python to simulate this. By storing each state, you can easily see where the values converge, which makes up our steady state. Each value in the steady state corresponds to a specific intersection. By comparing the values, we can determine which intersections have the most amount of traffic in the long-run, regardless of the amount of cars that start in each state.

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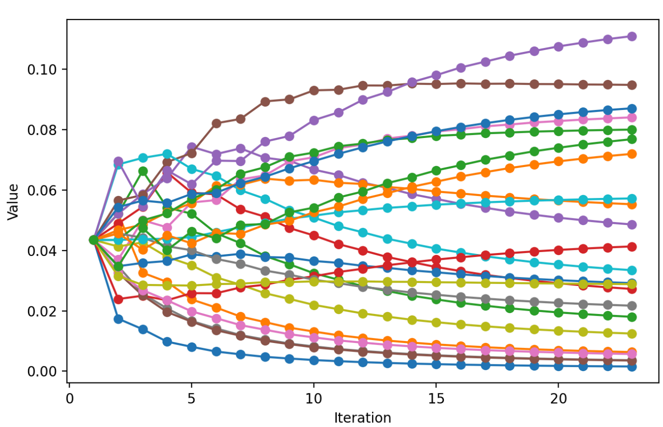
a 0.1326240656650363
b 0.509590152937988
c 1.371480127907992
d 1.9543106982752183
e 3.2863597775101483
f 12.02996459190864
g 15.820692219119852
h 0.3021971846828053
i 0.9443819457069627
j 2.389488783515772
k 1.7689113724577443
l 2.622457036993596
m 4.37645689961419
n 4.0622431467516265
o 15.353133791443756
p 0.2944470332390044
q 0.4508301313898573
r 1.5553341923511832
s 1.961722678720771
t 4.053110208766835
u 7.098607477938781
v 7.543426810920444
w 10.118227672181815
```

From the steady state, we see that intersections F, G, O, and W have the highest traffic volume. Beyond that, looking at intersections C, D, and E, we can see that traffic gets heavier when driving down Huron toward State St. This is consistent with what we would expect because G, O, and W all fall on State St.

We ran the simulation again to see if traffic could be directed away from State St by changing the timing of lights. After adjusting the transition matrix, we achieved a slightly more even distribution of traffic between intersections.

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a 0.1680627606387222
b 0.6731444055450773
c 1.8924704846972193
d 2.8409526321087437
e 5.001074926958437
f 9.49738260617151
g 8.33519790533204
h 0.38837693774539905
i 1.3070667937492189
j 3.4612693200917075
k 2.9789675860102367
l 5.604327572008492
m 7.975446629303486
n 4.061041783711669
o 10.883398336260871
p 0.37759531871367585
q 0.6007397478594745
r 2.2291246774204634
s 2.896435201623974
t 5.691672513677402
u 8.583719680435244
v 7.042913722543672
w 7.509616457393281
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Markov Chains such as this help to understand how each state will behave in the long run, regardless of initial conditions. In this case, it provides insight on traffic conditions at specific intersections and what adjustments can help reduce congestion.

Limitations

Factors such as weather conditions, road closures, accidents, and human behavior introduce complexities that a basic Markov model may not sufficiently account for. Additionally, the model assumes a constant transition probability, which can be an oversimplification since traffic patterns vary considerably throughout the day and on different days of the week. Therefore, while Markov Chains provide valuable insights into general traffic trends, they may not be fully reliable for predicting specific traffic conditions at a given time.

Another limitation is the scalability of the model. As the size of the traffic network increases, the size of the transition matrix grows exponentially, which can lead to difficulties in accurately estimating transition probabilities due to the sheer volume of data required. This can be particularly challenging in urban areas with complex traffic networks. Moreover, for a large-scale system, the assumption that the system reaches a steady state may not always hold true, or it may take a significantly long time to reach that state, limiting the model's practicality for dynamic traffic management and real-time decision-making.