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Team Control Number
72333

Problem Chosen
C

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2017
MCM/ICM
Summary Sheet

With the new technologies arising in today's society, work needs to be done to analyze the affects the advancements have on the respective cities. Self-driving cars have already begun to be implemented in cities such as Pittsburgh and San Francisco. With these rapid advancements in transportation, there are many uncertainties present with the logistics and effect on existing systems. Our task was to define the effect on performance and efficiency self-driving cars have on the interstates and state routes that go through the counties of Thurston, Pierce, King, and Snohomish in Seattle, Washington.

To begin with the model, we first had to find an accurate representation that modeled normal forms of transportation without the use of self-driving cars. We started with finding traffic per hour on given stretches of road based on mileposts. This was found by finding the distribution of cars on a freeway at any given time of day. As an indicator on whether traffic were to occur, we looked at the capacity each segment of road had based on lane numbers and compared it with the total amount of cars on the road at the respective time. In order to calculate the capacity each road has, we looked at the length of each segment and the total amount of lanes. Once done doing so, we analyzed the space each type of car takes up. We assumed the average length of a car and estimated the car spacing between vehicles based on the average speed of sixty miles per hour. From this, a self-driving car will need less spacing between each other due to the communication between other self-driving cars and the self-driving car's decreased reaction time. The self-driving car would be able to react to sudden stops faster than a human would be able to react to visual stimuli, thus decreasing the amount of space needed between vehicles. In conjunction with the lesser space taken up by the cars, an increase in the amount of self-driving cars on the road would have an added benefit due to the increased amount of communication that cannot be represented spatially. This effect would become more present and visible as self-driving cars become more ubiquitous in society, and the communication between cars would negate the need for traffic signals and other signage. We believe that the aggregate between these two measurements of space will accurately describe the impact on efficiency that self-driving cars will have.

We focused on interstate 5 and looked at the density percentage of cars on the road at a given hour and analyzed the available space on the road with varying increments of self-driving cars. We found that our model showed an exponential increase in efficiency as the percentage of self-driving cars approached one-hundred. The curve followed a smooth slope which appears to have an inflection point at around 50 percent self-driving cars. Although our model does not include all of the variables that can occur while driving, we believe that it accurately describes the effect in efficiency that the implementation of self-driving vehicles will have.

Dear Governor Inslee,

In hearing about your uncertainties of the effects of allowing self-driving, cooperating cars on the roads in Thurston, Pierce, King, and Snohomish counties, we have conducted an analysis of traffic likelihood that takes into account the impacts that self-driving cars may have. Our analysis uses road volume as an indicator as to whether or not traffic will be likely to occur. It relies on the fact that self-driving vehicles will be able to sacrifice the time that it usually takes a human being to react. Additionally, as the number of self-driving cars increases, they will be able to efficiently communicate, further decreasing the amount of space needed between them by acting as one whole unit rather than separate vehicles. Our findings focused mainly on Seattle's section of interstate 5 because of the sheer amount of data we were given on it.

We began by defining traffic as when vehicles travel slower than the speed limit, 60mph. With further research online, we were able to break the total amount of cars based on hour and traffic density during a given hour. Using this information, we then found that looking at raw space available on the freeway as an indicator to whether or not you may drive below the speed limit. With the assumption of a 60 mph speed limit,the average length of a car, 14.7 feet, and the distance a car follows another we found the total amount of volume the cars on the road at a given hour would take up. To find the space available with the amount of cars present on the road, we had to subtract the volume of cars by the total area of the road, which was given to us by multiplying the stretch of road by the amount of lanes. This data was then averaged throughout the entire freeway by the hour and scaled to compute the likelihood traffic would occur at a given hour

Considering the task at hand, we moved to incorporate how adding self-driving cars would affect traffic flows. With an increase in self-driving cars, there are two spatial benefits; a primary and secondary effect. The primary effect takes into account the faster reaction times a computer would have over the average human. Because of this, the space required between two vehicles would be lessened due to the fact that a self-driving car is able to react faster to changes in speed. However, the following distance can still vary because the self-driving car would rely on sensors that would still be reacting to the movement of other non-self-driving cars. Although this reaction time is less than a human, it can be negated by the collaboration of self-driving cars adjacent to one another. This is defined as the secondary effect where a smaller and constant space between cars is needed due to the unity that is caused by the cooperation when self-driving cars communicate. For instance, a self-driving car followed by another self-driving car would accelerate and deccelerate in unison.

The results from our model display that an increase in self-driving cars would cause the likelihood for traffic to occur to exponentially decay. The primary and secondary effects followed a linear and exponential curve respectively, meaning that the primary effect caused a constant change while the secondary effect grew proportionally to the percentage of self-driving cars on the road. To put this in perspective, at peak traffic hour, 5pm, there is a 100% likelihood for traffic to occur. When self-driving cars comprise half of the total automobiles on the road, this percentage shrinks by an astounding 75%. When and if self-driving cars ever reach a point of where 90% of total cars are self-driving, the percent likelihood of traffic at the same peak hour is mere 7%.

With these results, you may be wondering how our simple spatial model can be applicable to the stark reality of traffic. Although our model is simple, we believe that the effects we analyzed can be generalized to any model, and the effects of an increase in self-driving cars is accurately depicted in our model. Because our model is only spatial, there are other factors that we did not consider that can further increase efficiency that other models may take into account. The results of our model lead us to believe that separate, designated lanes for self-driving cars could exploit the secondary effect we described above.

Thank you for looking into our analysis and we hope you embrace the increased efficiency self-driving cars could bring to the congestion that plagues the Seattle Metropolitan Area.

Sincerely,
Team 72333

Problem C: "Cooperate and navigate"

Introduction

We aimed to model the likelihood of traffic developing at a given time based on the number of cars on the road. We focused on the spatial density of cars on the road. To do this, we used car length in addition to following length. The distance a driver aims to leave for safe braking is normally a function of their velocity. Self-driving cars are able to drive closer to cars in front of them because they have quicker reaction times than humans, but the distance is still a function of velocity, as the human body has limits on what a comfortable deceleration looks like. In the case where a self-driving car is behind another and they are communicating, the space savings can be amplified as the cars can essentially brake and accelerate in sync. This means that the distance the cars drive from each other can be a constant, perhaps as close as a matter of inches with the cars behaving as one object. The difference between these two distances is what makes the efficiency of self-driving cars more optimal than normal vehicles.

Assumptions

The following assumptions were used to make our model

- Anything under the speed limit, 60mph, is considered traffic
- everyone follows the speed limit strictly
- no speeding is present in our model
- considered the freeway as a whole when calculating traffic, rather than splitting up data into Northbound/Southbound or Westbound/Eastbound
- state routes and interstates were handled the same
- did not account for entering/exiting vehicles on the freeways
- We used interstate 5 to generalize the data because this interstate comprised over half of the given data, making to focus on this stretch of road

Calculating Vehicle Density Numbers by Hour

We sought to characterize the conditions under which traffic is most likely to develop. To do this, we used a graph of average traffic volume based on time of day. When multiplied this percentage by the total volume of cars that passes a section of a road in a day to calculate the average volume of cars that passes a section of road during a given hour.

Quantifying Spatial Density

We chose to use data from the 5 freeway because more than half of the available data was for this freeway. We ran our calculations on the other freeways and got similar values in our calculations. In order to determine the physical capacity of a road to handle traffic, we developed a method that calculates the spatial capacity of a stretch of roadway, then uses the number of cars on the road to determine how likely it is for traffic to develop.

How Much Space on the Road

To calculate how much space exists on a given stretch of road, we used the data provided and read in the mile markers and calculated the distance between them before converting the distance to feet.

Then, using the fact that the average car is 14.7 feet long and needs 100 feet of stopping distance at 60 mph, we calculate the maximum number of cars that can safely fit on the freeway at that speed at the same time. We define safely as leaving adequate room to stop without causing a crash for the average driver.

How Much Space a Car Needs

In determining how much space the average vehicle leaves in front of them, we went to numerous sources before deciding on a metric. One of the existing heuristics according the DMV is to leave 3 seconds of space between you and the car in front of your Further empirical studies of this phenomenon would be helpful to determine how actual practices vary from suggested practices.

One of the current models available on the topic is the Optimal Velocity Model. This model incorporates additional variables such as individual driver sensitivity and speed that we did not have the time or resources to incorporate into our model. However, our model aims to model risk of traffic developing in the cases where all drivers are driving at their preferred speed. Thus, the additional variables are not critical.

Quantifying Spatial Savings of Self-Driving Cars, driving behind other Self-Driving Cars

When a self-driving car gets behind another self-driving car, communication between the two vehicles can allow them to travel as one unit. We wrote a program in Java to simulate the likelihood of a self-driving car ending up behind another self-driving car. We computed these percentages at different densities of self-driving cars, ranging from 0% self-driving cars to 100% self-driving cars, increasing in intervals of 5%. In the case of 100% self-driving cars, the maximum space savings are available, which changes the baseline density of cars that can fit on the freeway safely, which also lowers the likelihood of a traffic jam in our model.

Using Vehicle Density to find LikeliHood of Traffic Developing

Based on existing models of traffic, roadways can hold up to a certain number of vehicles traveling at full speeds. Once this threshold is exceeded cars are packed tighter and closer together, and can no longer safely travel at full speed. This threshold is an inflection point when representing likelihood of traffic on the y-axis and number of cars on the x-axis. We can see looking at the graph that the shape of the curve is follows logistic growth. At the far right end of the graph, the road is filled over-capacity, yet we cannot guarantee that there will be traffic. However, what we can say is that the road is overfilled and the more overfilled it becomes, the more likely a small perturbation, like someone accidentally tapping their brakes or an untimely lane change, is to cause traffic.

We read in the provided traffic data which included mile markers and daily traffic volumes. We then develop a method to determine the likelihood of traffic developing for regular cars depending on how many cars are on the road at a given time. We compute this number using our novel measurement for how many cars a given stretch of road can hold if all cars are going at full velocity and driving safely (defined as leaving ample room to not crash into the car in front of you.) Then, we calculate how self-driving cars would alter these spatial calculations, and then calculated how the likelihood of a traffic jam developing based on the available space on a stretch of a freeway..

Quantifying Spatial Savings on Self-Driving Cars

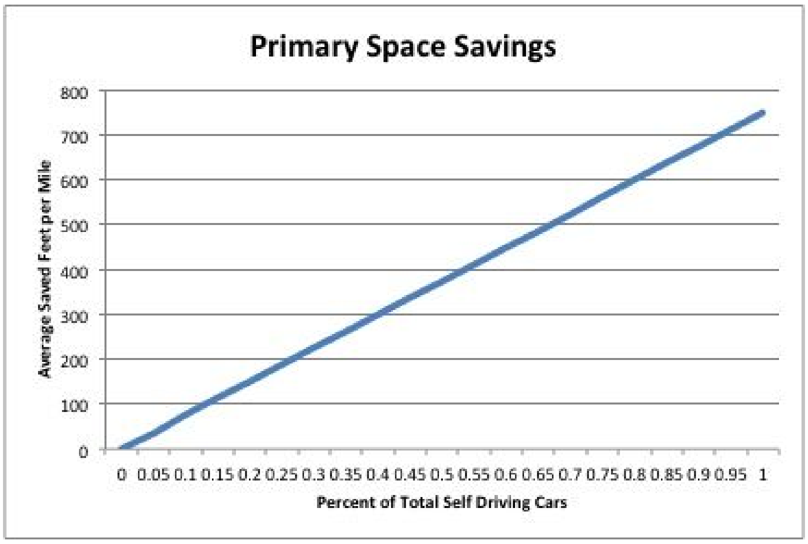
We postulated that each self-driving car on the road will result in space savings on the simple assumption that self-driving cars are able to drive closer behind the car in front of them as compared to human drivers. This is because self-driving cars rely on computerized sensors and systems to employ breaks, which can be deployed tens of times faster than human drivers. The human body can withstand a certain amount of deceleration safely, and thus the stopping distance a driver aims to leave takes this limit on deceleration into account, along with the driver's reaction time and other environmental variables like road wetness. Because of this, we postulated that the difference in reaction times between computer and human drivers can result in a decreased need for stopping distance that is proportional to the difference in reaction times.

Converting traffic scale into likelihood of traffic developing

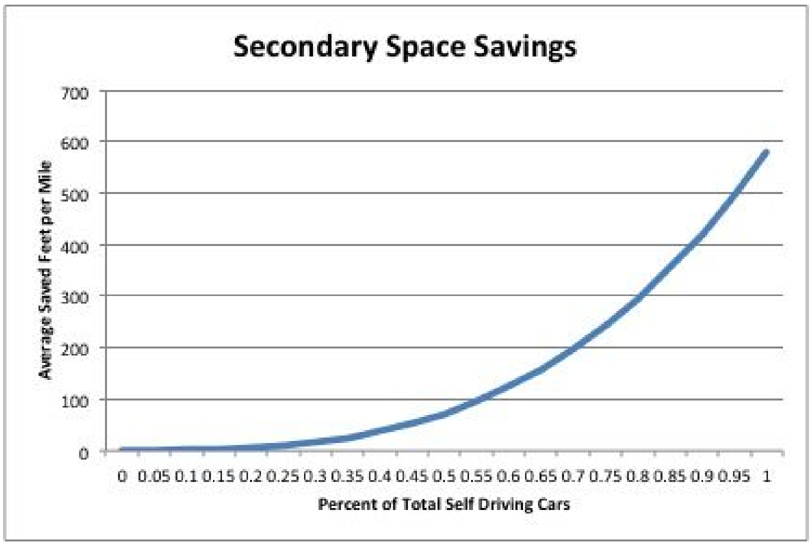
We used the data on total daily traffic volume and hourly traffic density distributions as well as the number of lanes on a freeway to calculate the average traffic density for a given section of road. In order to turn these numbers, in units of additional feet leftover on the road, into percentage likelihood of traffic developing, we needed to establish a scale to map the numbers into percentages. Our raw traffic number scale has a minimum represented by 100% self-driving cars on the road at 3A.M., where the traffic density is the lowest. This number corresponds to the lowest likelihood of traffic according to our model, around 1%. To find the maximum value, we calculated the traffic number at 5P.M (maximum traffic density) with 0% self-driving cars, which corresponded to nearly a 100% likelihood in traffic developing.

Results

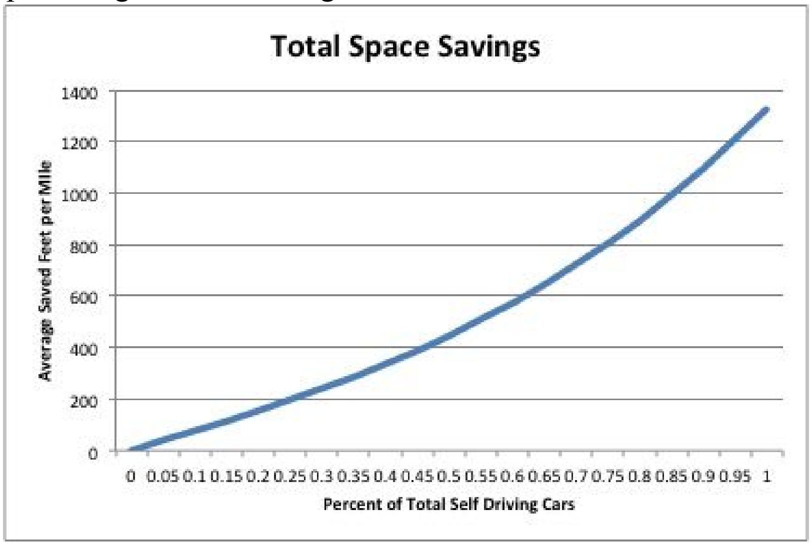
Our results show the likelihood of traffic decreasing as the percent of self-driving cars increases. To begin, we will analyze the spatial savings that an increase in self-driving cars results in. These savings allow vehicles to fit on the road, thus reducing the likelihood for traffic to occur. There are two different types of space savings that the implementation of self-driving vehicles create, the primary and secondary effect. The primary effect comes from the reduced reaction time a machine has over a human driver, while the secondary effect incorporates the cooperation a fleet of self-driving cars could achieve.



This graph above shows how an increase in self-driving cars affects primary space savings. The model is linear due to the flat reduction of space that the primary model pivots on. For every self-driving car on the road, the space needed for a vehicle would be reduced by 22 feet, which we calculated by taking into account the lack of a need for extra space caused by human reaction to visual stimuli. Although this reduction in space is a positive trend, it fails to incorporate the more advanced aspects a self-driving car brings to the table.



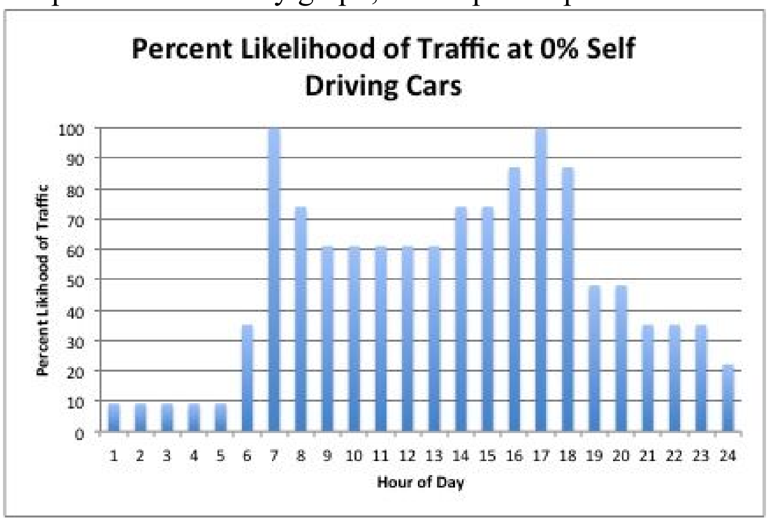
Differing from the primary model, we found that as self-driving cars increases, the secondary space saved will grow exponentially. This model relies on the probability that a self-driving car will be behind another self-driving car. If the two cars are in sequence, then the following distance for the trailing car will become a constant distance between the two due to the collaboration of the cars. To find this probability, we discovered that the probability of a self-driving car being trailed by another self-driving car is the percent of self-driving cars on the road squared divided by 10,000. This gave us a percentage of self-driving cars that we would be able to reduce the following distance for. This process results in an exponential difference, while the primary is linear. Together, these form a smooth transition curve for space saved by percentage of self-driving cars.



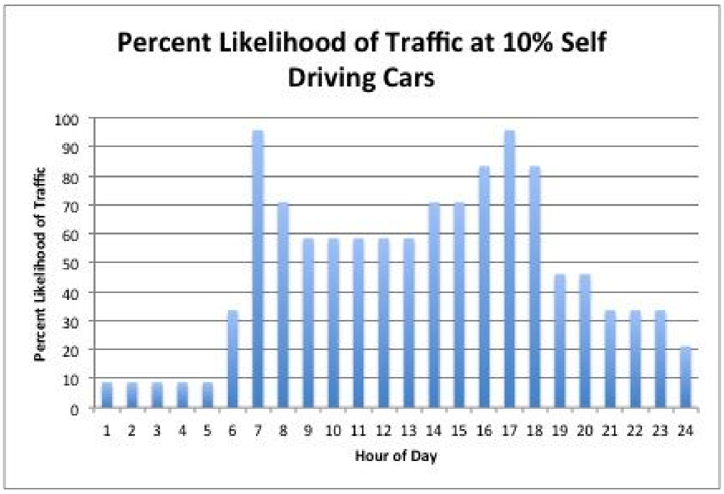
The total of the two effects creates a smooth curve that is not linear and not extremely exponential. The model closely represents logistical growth. The curve is so smooth that the inflection point is most likely located at 50%. The graph is expected to flatten out as there is no more space to be saved once reach 100% self-driving.

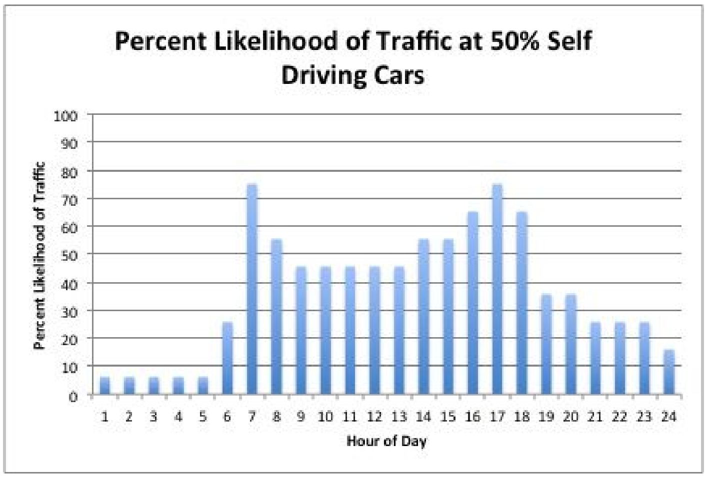
Conclusion

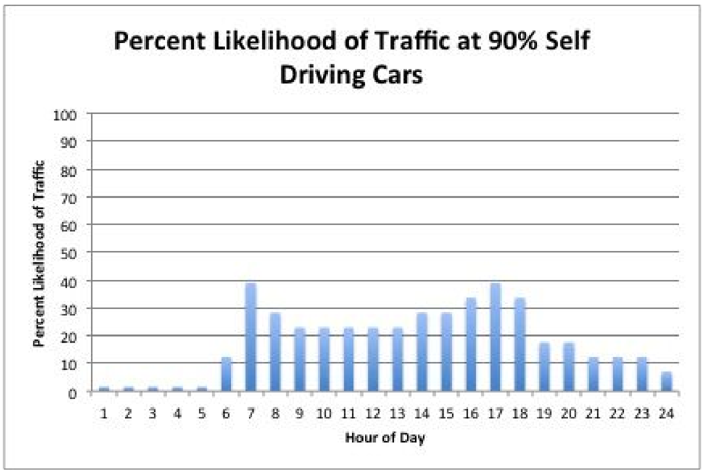
In conclusion, we were able to use the data above to discover how it will affect the efficiency of traffic flow. Due to the exponential nature of the savings, the implementation also allows for the decrease in traffic likelihood to follow an exponential model. The graphs below resemble the density curve we created based on the significant figures in the Department of Transportation's density graph, which placed peak hours of traffic at 8%.



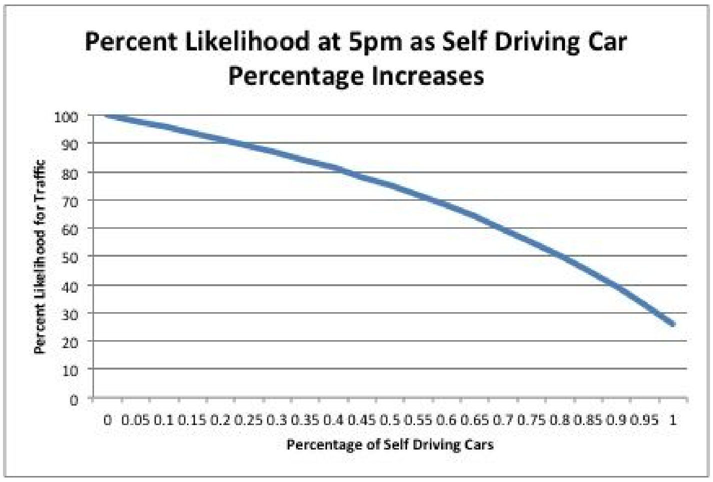
This is our baseline graph, which very closely resembles our density model.

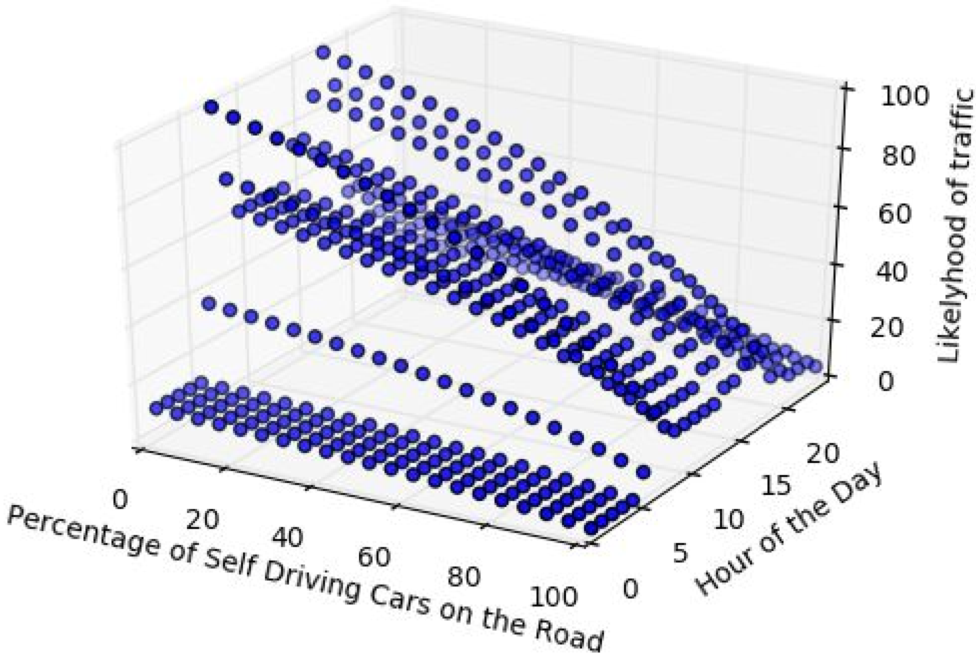






As our model predicted, the percent likelihood for traffic will exponentially decay as the percent of self-driving cars increases. Our model does not take into consideration many other factors that can cause traffic to occur. Although this is the cause, we believe that the overall trend of space savings caused by self-driving cars can encompass the change self-driving cars would have on a more thorough model. The graph below shows the general curve of the efficiency saved per percent of self-driving cars on the road. We believe that it is this curve that can be generalized to any model with the implementation of automated vehicles.





Our analysis of our model makes us believe that there could be another boost in efficiency if the secondary space saving effect was exploited through the use of designated lanes for automated vehicles. This would ensure that every self-driving car on the road can follow another self-driving car at a constant rate thus allowing a steeper exponential curve for efficiency at the lower percentiles. These lanes would need to be fazed out as the popularity of self-driving cars increases because the amount of self-driving cars would no longer be able to fit. An equilibrium of designated lanes would need to be found in order to maximize efficiency. The 3D graph above models likelihood for traffic to occur at each hour of the day as the percentage for self-driving cars increases. The downward slope can be matched to the graph above it, showing an exponential decay. This graph shows the trend with all the factors we analyzed displayed.

Source Code

```
//Program to calculate percent likelihood of traffic occurring on the 5 freeway

import java.util.*;
import java.io.*;
import java.lang.Math;

public class CarSim2 {
	// constants/globals to record average car length, percentage of
	// self-driving cars, car density per hour, and finalized data
	static double carLen = 14.7;
	static double percent_self_driving;
	static double[] car_density = { .01, .01, .01, .01, .01, .03, .08, .06, .05,
.05, .05, .05, .05, .06, .06, .07, .08,.07, .04, .04, .03, .03, .03, .02 };
	static double[] running;

	public static void main(String[] args) throws FileNotFoundException {
		// PrintWriter to write to our destination file
		PrintWriter p = new PrintWriter(new File("results1.txt"));

		// variables to hold data from given spreadsheet
		int ID;
		double start;
		double end;
		int avg_cars;
		int dec_lanes;
		int inc_lanes;
		String type;
		String line;

		// for loop that cycles through amount of self-driving cars on the
		road
		for (percent_self_driving = 0; percent_self_driving < 1.01;
	percent_self_driving = percent_self_driving + .05) {
			// creates a new final data storage array for each amount of
			// self-driving cars and initializes it to zero
			// last two indices represent primary and secondary saved space
			running = new double[26];
			for (int i = 0; i < 26; i++) {
				running[i] = 0;
			}

			// scanner to read from .txt containing excel info
			Scanner read = new Scanner(new File("dataMCM1.txt"));
			while (read.hasNextLine()) {
				// process and parse data
				line = read.nextLine();
				String[] s = line.split(",");
				ID = Integer.parseInt(s[0]);
				start = Double.valueOf(s[1]);
				end = Double.valueOf(s[2]);
				avg_cars = Integer.parseInt(s[3]);
				type = s[4];
				dec_lanes = Integer.parseInt(s[5]);
				inc_lanes = Integer.parseInt(s[6]);
				double distance = (end - start) * 5280;
				int total_lanes = dec_lanes + inc_lanes;

				double[] raw_milage_available =
			Chance_Calculations(avg_cars, car_density,
				total_lanes, distance);
				for (int j = 0; j < 26; j++) {
					running[j] += raw_milage_available[j];
				}
```

```
			}
			// for loop to convert raw milage to a percentage based on min
			// and max amount of space available
			for (int j = 0; j < 26; j++) {
				if (j < 24)
					running[j] = -100 * (((running[j] / 135) - 8000) /
				659000);
			}

			// print iterations worth of data to text doc
			p.printf("%.2f,", percent_self_driving);
			for (int k = 0; k < 26; k++) {
				if (k == 25)
					p.printf("%.2f\n", running[k]);
				else
					p.printf("%.2f,", running[k]);
			}
			read.close();
		}
		p.close();
	}

	// function that calculates raw milage available on roads
	public static double[] Chance_Calculations(int avg_cars, double
	car_density[], int total_lanes, double distance) {
		// calculate area available on section of highway
		double road_area = distance * total_lanes;
		double[] cars_at_hour = new double[26];

		for (int i = 0; i < car_density.length; i++) {
			// calculate amount of total cars are on the highway at a given
			hour
			cars_at_hour[i] = avg_cars * car_density[i];

			// calculate amount of self-driving and regular cars on the
			road
			double total_self_driving = cars_at_hour[i] *
		percent_self_driving;
			double num_norm = cars_at_hour[i] - total_self_driving;

			// calculate the extra space based on road size, number of
			cars, and
			// average car size
			double communication = SpaceChange(total_self_driving);
			cars_at_hour[i] = road_area - (num_norm * 54.7) -
		(total_self_driving * 32.7) + communication;

			// record saved space for analysis
			running[24] = running[24] + (22 * total_self_driving);
			running[25] = running[25] + communication;
		}
		return cars_at_hour;
	}

	// calculates additional space saved if two self-driving cars are next to
	// one another
	public static double SpaceChange(double total_self_driving) {
		// if cars are adjacent the following distance becomes a constant 1
		foot

		double percentage = Math.pow(percent_self_driving, 2);
		percentage *= total_self_driving;
		percentage = percentage * 17;
		return percentage;
}}
```

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