Machine Learning Centralized Traffic Control System for City Intersections

Final Report

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March 20, 2023

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1. Abstract

The motivation for this research is to investigate an alternative method to reduce traffic congestion in cities different from automated traffic lights by utilizing AI with the anticipation that all vehicles will become autonomous in the future. This paper aims to answer the following research question: How can AI be leveraged to develop a centralized traffic control system (CTCS) and can it outperform standard traffic lights? A CTCS can direct traffic through intersections removing the responsibility from independent AI to coordinate with other cars that could potentially be following different protocols. Faced with a conflict of interest, two autonomous vehicles may cause delays, congestion on roads, or safety concerns.

For this paper, an experiment is conducted within a closed simulation of a figure-8 track to compare the efficacy of four traffic control methods based on their throughput of cars, safety (car crashes), efficiency, and qualitative factors. It is anticipated that a CTCS will outperform standard traffic signals and results collected from this study can serve as supportive evidence for the possible implementation of this type of system. The visual simulation can also innovate on typical numerical simulations by incorporating more realistic driving conditions and providing qualitative analysis of different traffic control algorithms.

The field of machine learning vehicles and intersection control to reduce congestion is well explored, but in the race for car brands to develop self-driving AI behind closed doors, research into systematic city-wide strategies for reducing congestion is limited. This alternative's results to solving city congestion may demonstrate the feasibility of a machine learning CTCS that may drastically minimize city congestion, thereby reducing the need for road work, lane expansions, or complex AI communication to counteract increasing traffic. This could save city budgets billions of dollars and assist people to reach their destinations more efficiently.

2. Introduction

Machines equipped with artificial intelligence are rapidly overtaking inefficient algorithms and humans at completing complex tasks in today's society. In 1997, IBM's Deep Blue chess AI defeated Garry Kasparov, and more recently, car manufacturers are competitively developing AI capable of superior decision making to drive vehicles on their own. While impressive, an inherent issue arises when different companies develop AI to perform identical tasks: Faced with a conflict of interest, which system's protocol is preferred? Traffic control systems and vehicles prioritize safety above all else, and ambiguity around this ethical issue is cause for concern. The theorized solution analyzed in this paper is to align everybody's interests and have insistent communication and compromise between each active body in the system by subjecting all decisions to a centralized traffic controller.

The key research being conducted in this paper is comparing the performance of different traffic control methods quantitatively and qualitatively at an intersection when all cars are autonomous. It is also to develop a visual simulation environment useful to researchers seeking to evaluate traffic control methods more realistically and gather qualitative data largely unavailable in numerical simulations.

The key results in this paper present the efficacy of four different traffic control systems: Basic AI, Master AI, Traffic Lights + Basic AI, and Traffic Lights + Master AI. In order to develop a centralized traffic control system (CTCS), two AIs were created in a hierarchical structure with the Basic AI as the base and the Master AI as a controller. Each car is equipped with the Basic AI, a neural network that gathers information about its surroundings and autonomously drives a car around a figure-8 track. The Master AI is activated for a vehicle approaching the intersection and determines if it is on a crash course. When two cars are on a collision course, the Master AI decides for one to slow down and allows the other to pass. Together, these AI effectively simulate one cohesive fleet of AI vehicles, and thus, a CTCS. The traffic light methods for traffic control still use the Basic AI in each car. The Traffic Lights + Master AI method incorporates the Master AI for added safety, and the Traffic Lights + Basic AI method does not. The traffic lights are on fixed timers and are not controlled by AI.

The simulation developed is effective in serving as a proof of concept for CTCSs and leaves room to incorporate more complex scenarios regarding road conditions, pedestrians, and emergency vehicles.

This report is structured to first analyze related research, then outline research objectives, then explain the development of the simulation, present results comparing and contrasting the four traffic control methods, and finally discuss the work and form conclusions.

3. Background and Related Research

3.1 Problems with current traffic control systems.

- Rising population creates capacity issues for roads and expanding roads is costly [1-8].
- Many traffic-related issues, like congestion and pollution largely have fixed traffic signal timers to blame [2-6].
- High priority emergency vehicles struggle to pass through intersections [3, 4].
- High frequencies of idle cars contribute massively to pollution and greenhouse gasses [2].
- Human drivers induce mistakes and latency into traffic systems causing delays [7].

3.2 Theorized traffic control solutions

3.2.1 Adaptive Traffic Signals

- Real-time traffic monitoring to assist drivers with finding available parking, plan efficient routes, and increase throughput of intersections using historical patterns [2-7].

3.2.2 Smart Cities

- Information is continuously shared between buildings, infrastructures, vehicles, and sensors to provide autonomous vehicles with perception of surroundings necessary for decision making [5].
- Autonomous vehicles are exclusively used to safely and effectively transport passengers. Maximal throughput is theorized to increase from 2,000 vehicles per hour per lane to 10,000 or 20,000 [7].

3.2.3 Computer Communication and Accurate Information

- In [7], accurate information concerning public transportation like travel time and seat availability can assist with spreading peak loads and finding people alternatives to personal vehicles.
- Advanced computer software can also enhance safety by warning drivers about weather, speed limits, taking turns too quickly, etc. [7].

3.3 Power of AI

- In [9], researchers predict AI will outperform humans in many activities in the next ten years, such as translating languages (by 2024), writing high-school essays (by 2026), driving a truck (by 2027), working in retail (by 2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053).
- Computing power of machine-learning systems (based on their information-processing speed) doubled approximately every 3.43 months. This equates to an 11x increase in power each year [10].
- While theoretically effective, relying solely on cooperative coordination among autonomous vehicles presents a problematic subset of scenarios [11].

3.4 Unity ML-Agents Package (Tool for Machine Learning)

- Can define agents, behaviours, sensors, and reinforcement criteria [12].
- Supports Proximal Policy Optimization (PPO) training algorithm which is best suited for generalization tasks [12, 13]. Also supports Soft Actor-Critic (SAC) algorithm.

3.5 Analysis

Modern traffic control systems lack the scalability and capacity for growing populations in cities [1-8]. Typical solutions such as increasing lanes and smart traffic signals are unable to optimize throughput due to human error and latency in computer communication [2, 4-7]. Traffic control alternatives have been proposed to reduce reliance on humans and optimize computer networks and communication. Increased accuracy of real-time information and cohesive traffic signals may increase throughput slightly by improving public transit and individual autonomous vehicles, but the core problem with traffic signals will remain [2, 11]. Articles [3, 4, 6, 7, 8] are optimistic about the increase in efficiency obtained by optimizing traffic light control signals but other articles [2, 5, 11] are looking farther into the future and suggesting that traffic lights will become an outdated mechanism that can be replaced by autonomous vehicles. Autonomous vehicles are widely regarded to usher in the future of transportation by minimizing human decision making and improving road throughput by multiples of 5-10x once all vehicles are replaced [7].

For training and visualization, Unity's machine learning package (ML-Agents) is a suitable tool capable of implementing advanced training algorithms such as PPO and SAC [12]. For the purposes of this research paper, utilizing the PPO algorithm is preferred for its ability to train car driver agents to generalize and more straightforward implementation compared to SAC as discussed in [12, 13].

3.6 Research Gap

A scenario where all vehicles are autonomous and communicating offers the possibility to remove all current coordination mechanisms (traffic lights, signs, and rules) [9, 11]. This scenario gives rise to a particularly difficult problem to solve—optimal and safe coordination of autonomous vehicles through intersections. This problem is amplified when a conflict of interest occurs between two different policies in separate vehicles, or three policies, or ten, or fifty. Different car manufacturers are incentivised to develop a program that optimally transports their passenger between two points, but which vehicle is given priority when faced with a 50/50 decision. Centralized control schemes have been considered, but most place heavy emphasis on safety and collision avoidance without simultaneously addressing efficiency [11]. Previous techniques for developing algorithms for autonomous vehicles traversing intersections [2, 14] rely on numerical simulations which overlook several variables such as tire and air friction, visibility, and signal transmission times. Traffic control system simulations also lack qualitative evaluation to determine abstract performance metrics such as the perceived feeling of safety for a passenger in the vehicle which are more difficult to determine from a table of numbers.

A prototype system where one can observe agent behaviours and interactions will be an immensely useful provision to the community of researchers where AI can be evaluated in a rich environment. Throughout development, hidden qualitative considerations invisible to numerical simulations will be revealed and strategies for implementation can be discussed.

4. Research Objectives

O1: Compare and contrast traffic control methods based on their throughput of roads, safety, efficiency, and potential when all vehicles are autonomous.

O2: Develop a visual simulation that can assist with introducing realism into traffic control algorithms and provide a means to qualitatively analyze them.

4.1 Significance:

The research objectives above reveal the efficacy of the proposed central traffic control system and offer useful consultations for future development. Unity among car companies, developers, and traffic systems is a daunting task, but perhaps this research can serve as supportive and persuasive evidence for the success of centralized traffic control for a safe, efficient, and harmonious driving experience. Previous research is unable to provide qualitative analysis of algorithms on their perceived safety. Developing this simulation can serve researchers seeking to perform traffic control experiments with more realism and qualitative potential missing in numerical simulations.

5. Methodology

5.1 Overview

This research paper compares and contrasts the efficacy of traffic control methods at a city intersection based on throughput of roads, safety, efficiency, and potential for future development. The primary methods being compared are traffic light signals and a CTCS responsible for coordinating the safe travel of independently autonomous vehicles controlled by the Basic AI. The CTCS, or master controller (Master AI), evaluates the positions and velocities of each vehicle approaching the intersection and overrides their decisions when a collision is imminent.

Figure 1. Traffic control matrix showing methods being compared.

	No Traffic Lights	Traffic Lights
Master AI	Master AI	Traffic Lights + Master AI
Basic AI	Basic AI	Traffic Lights + Basic AI

5.2 Environment

5.2.1 Track Configurement

The experiment is carried out within a controlled, 3D system simulated in Unity (v2020.3.35f1 Personal) which includes one bi-directional track configured as a figure-8 with two lanes on each side. Walls were added along the outside edges of the track and along the centerline to separate the two sides. 146 checkpoints were placed along the track to trigger a reward signal when training the Basic AI.

5.2.2 Car Model and Controller

A car model was built using several physics components to simulate a realistic driving experience. A rigidbody component was used to interact with physics, collide with other objects, and obey gravity. Wheel colliders were attached to each wheel to introduce suspension and friction forces that elevate the realism of the simulation while also achieving a more satisfying driving experience (see **Appendix A** for relevant property values used for the car model and colliders).

A car controller was built to support keyboard inputs to drive (arrow keys for steering and accelerating, and space bar to brake). The car controller also specifies important limitations of the vehicle such as maximum speed, turning angle, motor force, and brake force (see **Appendix A, Image 3A** for the property values used).

5.2.3 Traffic Light System

The traffic light system, also known as a traffic signal, is a device that controls the flow of traffic at the intersection by using colored lights. This simulation's system consists of two traffic light statuses, red light on, and red light off (visually represented as a green light). Each status indicates a different action that drivers should take:

Red light on: Vehicles must stop and wait for the light to turn green before proceeding.

Red light off : Drivers may proceed through the intersection if it is safe to do so.

The traffic light system is controlled by a script that operates on a fixed cycle, with the length of time that each light remains on being determined by a constant variable. Congruent with modern traffic light signals, there is also a short period of time between each switching of the permissible direction when all lights are set to red in order to give drivers time to exit the intersection. The traffic signal is only used in the traffic control methods (i.e. it is only used for the Traffic Lights + Basic AI and Traffic Lights + Master AI methods). The traffic signals are represented in the simulation as triggers that span the width of the road and are detectable by ray casts originating from vehicles. See **Figure 4** for a visual.

5.3 Training the Basic AI

5.3.1 Training Algorithm

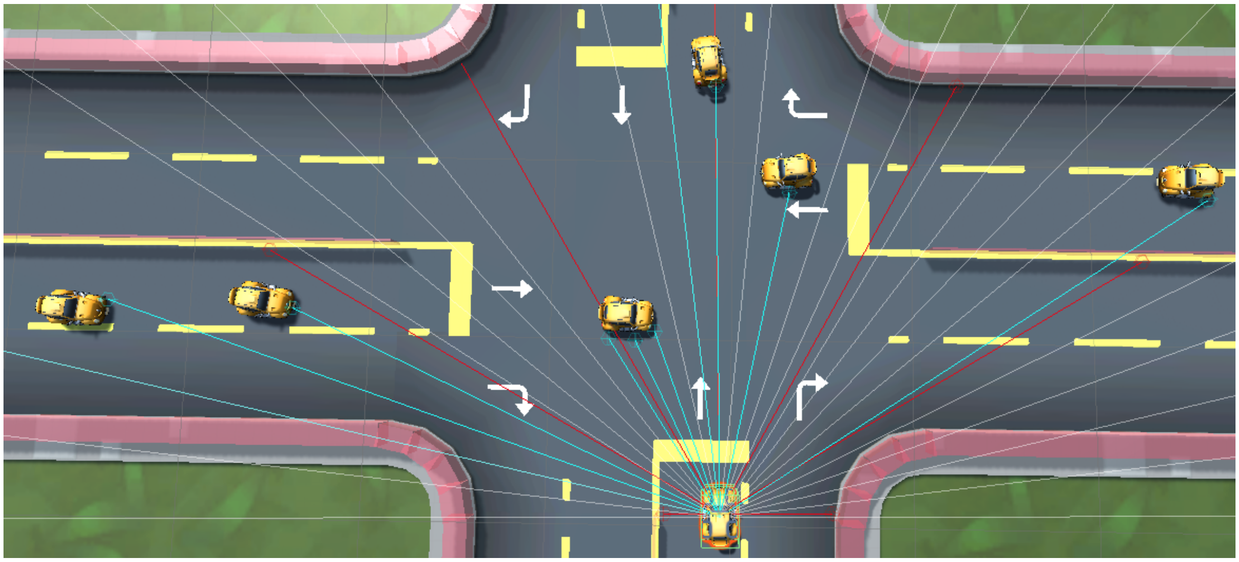
The autonomous vehicles are trained using an open source machine learning package called ML-Agents (v2.0.1) available for use inside the Unity game engine. The reinforcement training algorithm used was Proximal Policy Optimization (PPO) as suggested in [12], [13], and [15]. This training algorithm is more straightforward to implement due to having a smaller set of configuration settings and greater ability to generalize learnings to many situations. Recommended configuration values provided in the official GitHub documentation of the package [15] were consulted and usually followed (See **Appendix B** for configuration settings used).

5.3.2 Inputs and Outputs

The vehicle's perception of its environment is provided by a collection of ray casts originating from the center of the car model retrieving data about its proximity to other cars, walls, checkpoints, and traffic lights. These values are the inputs for the training model. The outputs are three discrete decisions: accelerate forwards or backwards, brake or do not brake, and direct the wheels left, right, or straight. The traffic signal also has a publicly accessible variable for how much time is left before switching colours. This value is used by the AI as an input to give it more context and encourage preserving momentum while approaching a red light. If it knows when the red light switches, it can brake and accelerate accordingly in advance.

Moreover, some raycasts were "stacked". Ray Perception Sensors can use the "stacked" observations from previous time steps as input to the agent's neural network. This allows the agent to incorporate information about how objects in the environment or itself are moving over time and make more informed decisions based on that information. Wall and car sensors were stacked twice to give the agent a more detailed perception of its surroundings.

Figure 2. Image depicting sensors each car uses to perceive its surroundings.



Rays are used to detect agent surroundings. Red rays represent a detection of a wall, blue rays are detections of another car, and white rays are missed car perception rays that did not detect another car. Checkpoint and traffic signal rays are not shown for clarity.

The ML-Agents package supports several agents using the same brain concurrently to train the AI faster. During training, between 10 and 40 cars would be placed around the track in the right lane on either side of the road. A wide range of reinforcement values were tested for the actions listed below, but the following rewards and penalties achieved the most successful behaviour policy:

Figure 3. Rewards and penalties for agents performing certain actions.

Action	Reward/Penalty
Pass through a correct checkpoint	+0.7
Pass through a wrong checkpoint	-3.0
Speed (~25 feedbacks/second)	$+(\text{CurrentSpeed}^{1.5} \times 10^{-6})$
Hit a wall	-2.0
Hit a car	-6.0
Pass through a red light	-3.0
Pass through a green light	+2.0

5.3.3 Optimizations

Five major optimizations were made to the agents to improve their performance and training times:

- Improving checkpoint and wall detection.

Each car originally had one set of sensors for checkpoints and walls. This structure of perception unfortunately made agents nearsighted when approaching a checkpoint and unable to see walls beyond it. The sensors were seperated into two sets to specifically detect checkpoints or walls by their tag (“checkpoint” or “wall”). This vastly improved the agent’s spatial awareness of walls and improved its ability to steer around turns more accurately.

- Resetting cars after collisions.

  Agents were reset to their original position on the track after hitting a wall, wrong checkpoint, red light, or car. This practice was implemented after noticing some cars flipping over after a hard collision and causing roadblocks.

- Reducing the number of outputs.

  Another optimization was reducing the number of outputs from 3 to 2. Originally, the agent made 3 decisions: accelerating forwards or backwards, braking or not braking, and steering left, right, or straight. There is never a need to reverse for this simulation so cars were set to always be accelerating forwards (until reaching their maximum speed set by the car controller) and only decide whether or not to brake and which direction to steer. This noticeably improved training times and performance of the AI due to a smaller set of possible outputs.

- Increasing the number of hidden layers in the neural network from the default 2 to 3.

  [15] recommends having 1-3 hidden layers of neurons with a default of 2. Less hidden layers results in faster training and efficiency, but more hidden layers are necessary to learn more complex control problems. After experimenting with 1-4 hidden layers, 3 was the most optimal.

- Adding a second box collider.

  Many collisions of two cars are caused by only one, but both cars were being reset and penalized. To encourage giving the right of way to vehicles ahead, a second box collider was positioned at the very front of each car and used to determine if a car was responsible for causing an accident. For each car, only collisions involving this collider resulted in a penalty and reset while the other affected vehicle was allowed to proceed normally.

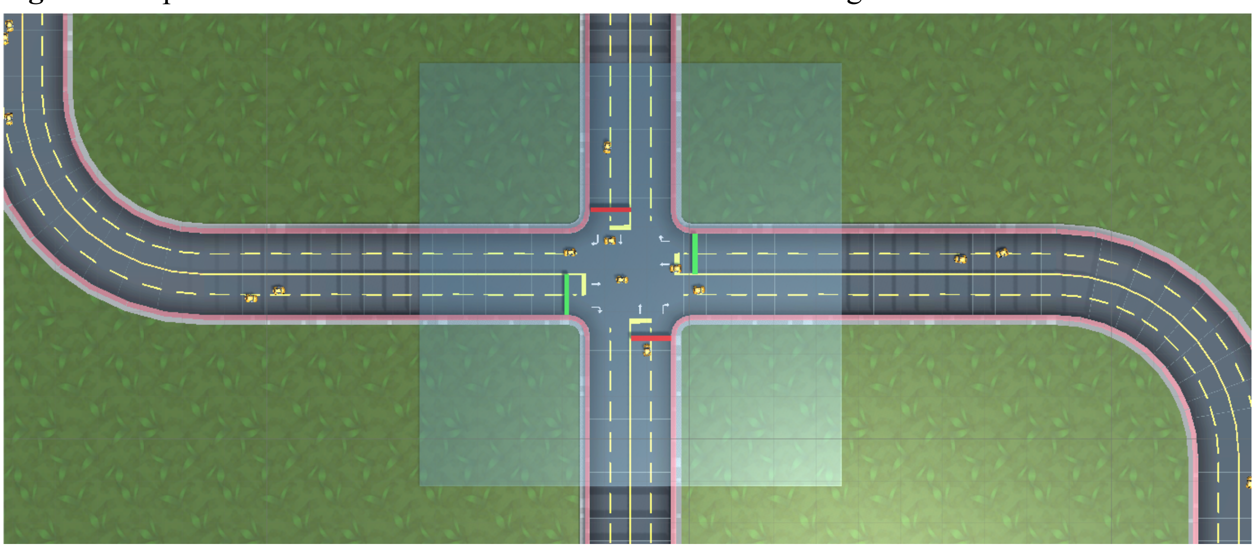
As of this point, the basic AI is accurately able to drive around the track, overtake slow cars in front of itself, and avoid collisions. However, there is virtually no communication or negotiation between vehicles when approaching the intersection and many either crash, or come to a standstill showing that the agent is unreliable to safely transport passengers. A higher level controller is necessary to conduct traffic.

5.4 Master AI

The goal is to have one central controller for all vehicles on the track in order to wisely conduct traffic. An attempt was made to handle several cars with one AI model but developing a functional policy proved to be too complex for the size of the inputs and outputs beyond three cars. A more optimal solution is to use a hierarchical architecture in which every car is equipped with an independent driver AI (Basic AI described in the previous section), and upon entering the proximity of an intersection, submitting control to a higher level conductor capable of predicting crashes and overriding the basic AI decision-making.

The master AI was implemented by placing a large box collider called the "Collision Detector" (CD) that covers the intersection and extends slightly beyond. When a car enters the CD, it is entered into a FIFO priority queue. Its future position (0.5s) is predicted by an algorithm using its current coordinates and velocity 25 times per second. During each loop, if any two cars have a future position within a certain distance deemed to be safe (2 units for this simulation), the lower priority car will be forced to brake. This algorithm was inspired by research conducted in [11] regarding position prediction and space availability in the intersection. This method was extended to include detecting collisions with red lights because the basic AI still had difficulty managing its speed when approaching a traffic signal. See **Appendix C** for more screenshots of the simulation environment.

Figure 4. Top-down view of intersection with master and traffic lights.



The blue tinted square represents the Master AI and it is present in two methods: Master AI, and Traffic Lights + Master AI (shown in image). The traffic light signals alternate which direction of traffic is permitted to proceed.

6. Results

6.1 Overview

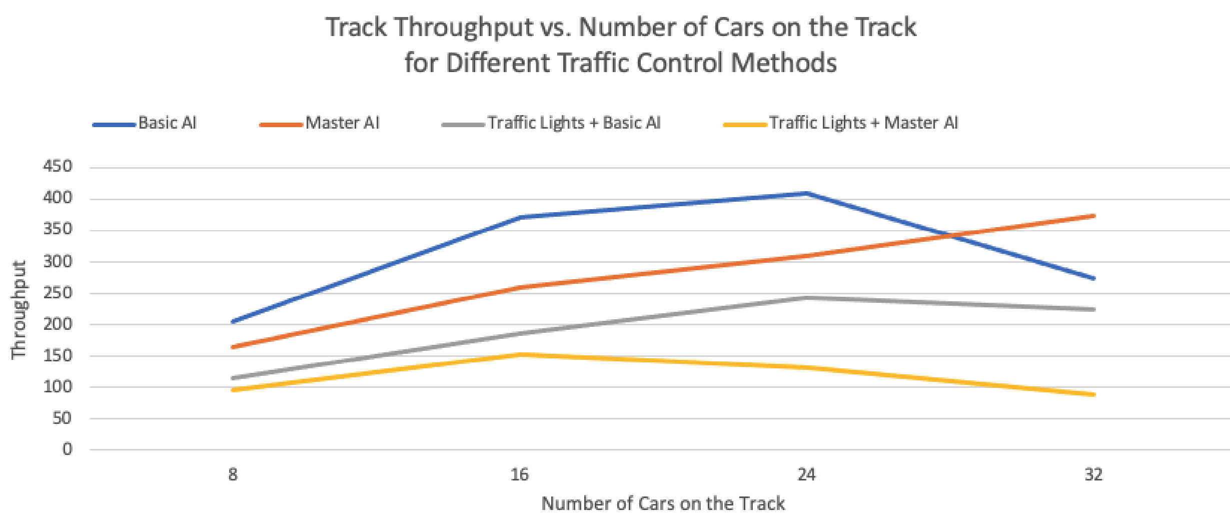
The efficacy of each method is judged based on its relative quantitative and qualitative performance. While the simulation is far from real-world conditions, each method can still be conceptually compared and analyzed to make inferences about their possible implementation. After the quantitative and qualitative analysis sections, an overall score will be determined for each of the four traffic control methods (Basic AI, Master AI, Traffic Lights + Basic AI, Traffic Lights + Master AI) to determine which has been the most effective and shows promise for future implementation. The following results were obtained by tracking throughput, crashes, average speed of the vehicles, and average stopped time per vehicle. Each trial consisted of one of the four traffic control methods being run for approximately 12 minutes with 8, 16, 24, or 32 cars on the grid for a total of 16 trials. The data was collected periodically every 3 seconds and accumulated throughout each trial.

6.2 Quantitative Comparisons Between Traffic Control Methods

This category of results presents performances of laps completed (throughput), car crashes, and efficiency (average car speed and stopped time) for each traffic control method.

6.2.1 Throughput

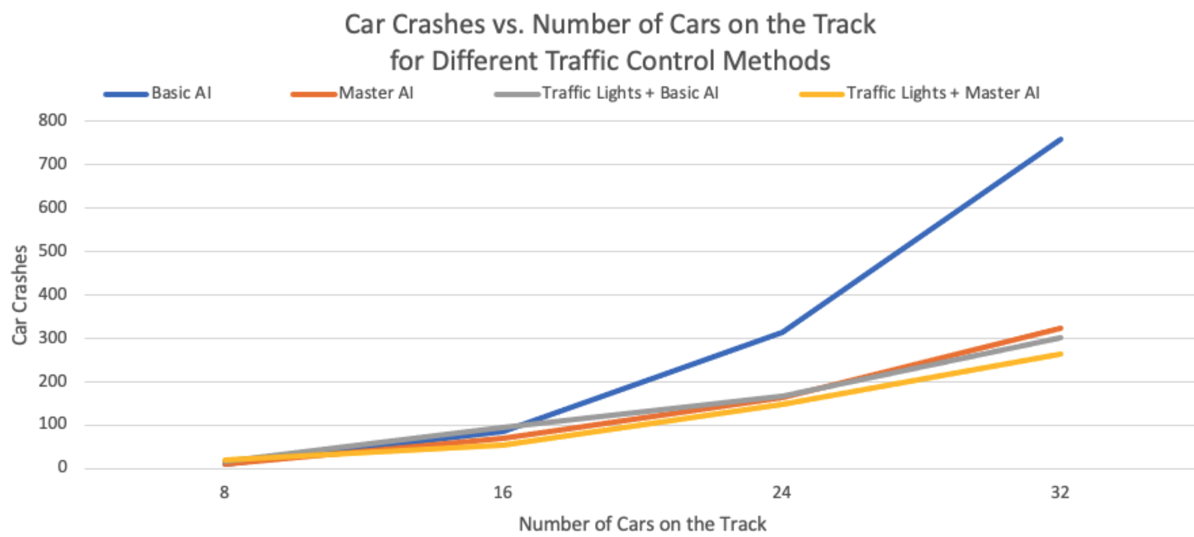
Figure 5. Track Throughput vs. Number of Cars on the Track for Different Traffic Control Methods.



Based on the graph above, the Basic AI is able to achieve the highest throughput after 12 minutes when 8-24 cars are on the track, but the Master AI outperforms the Basic AI when there are 32 cars. The Master AI also shows potential to increase as more cars are added while its competition all declined from 24 cars to 32. Across all four trials, the traffic light methods underperformed compared to the methods that exclude their use. At 32 cars, the Master AI achieved a throughput of 3.6x that of the Traffic Light + Master AI method.

6.2.2 Car Crashes

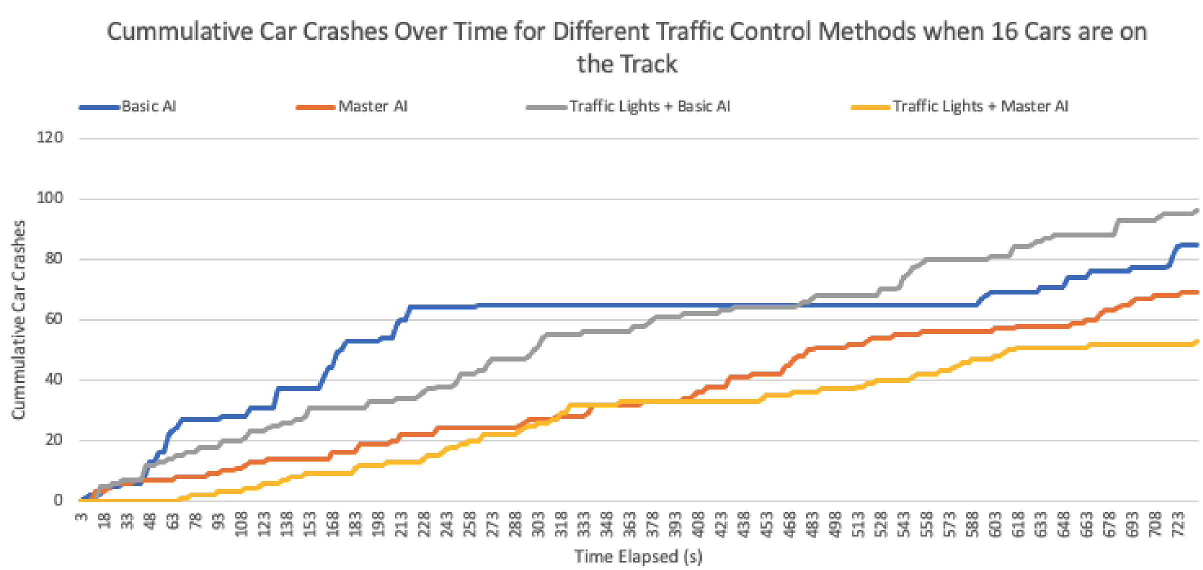
Figure 6. Car Crashes vs. Number of Cars on the Track for Different Traffic Control Methods.



The Basic AI stands out among the field as being the most unsafe method of traffic control due to its lack of collaboration between car agents and decision making protocol. The other three methods all achieve significant reductions in collisions with the Traffic Light methods marginally performing better than the Master AI as more cars use the track.

Upon further exploration, it became apparent that the Basic AI on its own becomes reliant on luck to pass through the intersection at a high speed without being hit causing an interesting phenomenon to emerge. The following graph shows the number of crashes over time for each traffic control method when 16 cars are on the grid.

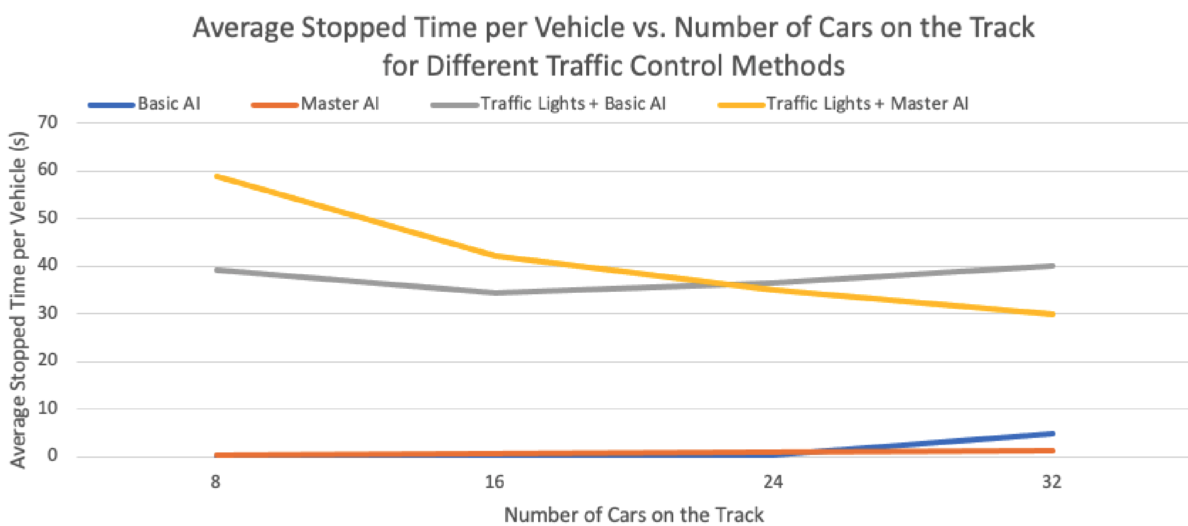
Figure 7. Cumulative Car Crashes Over Time for Different Traffic Control Methods when 16 Cars are on the Track.



This graph looks normal compared to every other trial; the number of car crashes steadily increases over time for each method, except for the Basic AI's line in this trial. The Basic AI appears to have run perfectly from 213 seconds to 590 seconds which is nearly 6 and a half minutes long. This unusually strong performance can be attributed to a phenomenon known as "self-organization" [14]. All the agents on the track managed to coordinate space between one another to form a stable network allowing them to pass through the intersection without adjusting course. This would not be possible in the other control methods because a higher power influences vehicles to slow down or make course adjustments breaking their coordination.

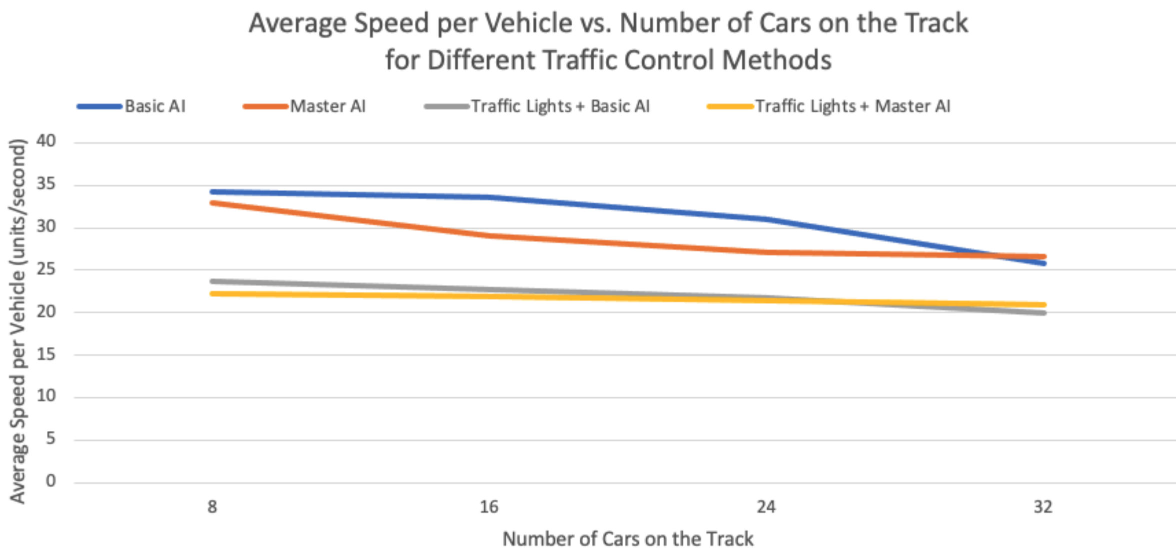
6.2.3 Efficiency

Figure 8. Average Stopped Time per Vehicle vs. Number of Cars on the Track for Different Traffic Control Methods.



This graph illustrates the stark contrast in protocol for how agents should behave when approaching the intersection. Out of the 12 minutes of runtime, flow being controlled by the traffic lights held cars at a full stop for roughly 40 seconds on average (5.67% of the time), while cars running without lights nearly never came to a full stop. The efficiency of removing traffic lights from the intersection is even more apparent in the next graph.

Figure 9. Average Speed per Vehicle vs. Number of Cars on the Track for Different Traffic Control Methods.



The average speeds per vehicle is a powerful metric by which to measure efficiency because it closely relates to throughput and congestion reduction [2, 6]. The Basic AI and Master AI were able to reach average speeds of over 25 units/second while the traffic light methods hovered close to 21 units/second showing a 19% improvement in speed when no traffic lights were used. A higher average speed reduces transit times between two points, improves fuel efficiency, and is more eco friendly.

6.3 Qualitative Comparisons Between Traffic Control Methods

As previously remarked, the most disorderly method was the Basic AI due to its inability to produce coordination with other vehicles except for its remarkable 6.4 minute performance when 16 cars were on the track. In other scenarios, the Basic AI appeared reckless and reliant on luck to successfully traverse the intersection.

The other traffic control methods improved safety and performed equally well at avoiding car crashes during each trial. The methods involving the Master AI were superior to the methods without it at organizing traffic and ensuring the safe traversal of the intersection. The Master AI can be adjusted to prioritize emergency vehicles that enter the intersection and likely outperform the other methods in their throughput.

When comparing congestion, it was clear that the traffic signals contributed to the problem. Lines would accumulate behind red lights that sometimes could not fully pass through a green light before the next red came on. The trials ran without traffic lights looked smoother and more effective at handling clusters of vehicles approaching an intersection. There was, however, an increased feeling of trust in the traffic lights to coordinate the traffic due to their familiarity and predictability.

6.4 Overall Scores

The following formula was used to capture the overall quantitative performance of each Traffic Control System:

$$Score = (Throughput) + (CarsOnTheTrack/2*AverageCarSpeed) - (3*Crashes) - (CarsOnTheTrack/2*AverageStoppedTime)$$

A crash is more severe than a successful pass through the intersection so the formula weighs throughput at 1x and crashes at -3x. The efficiency values (Average Car Speed and Stopped Time) are multiplied by half the number of vehicles on the track to scale with the increased numbers of cars on the road.

Figure 10. Graph of Overall Score vs. Number of Cars on the Track for Different Traffic Control Methods.

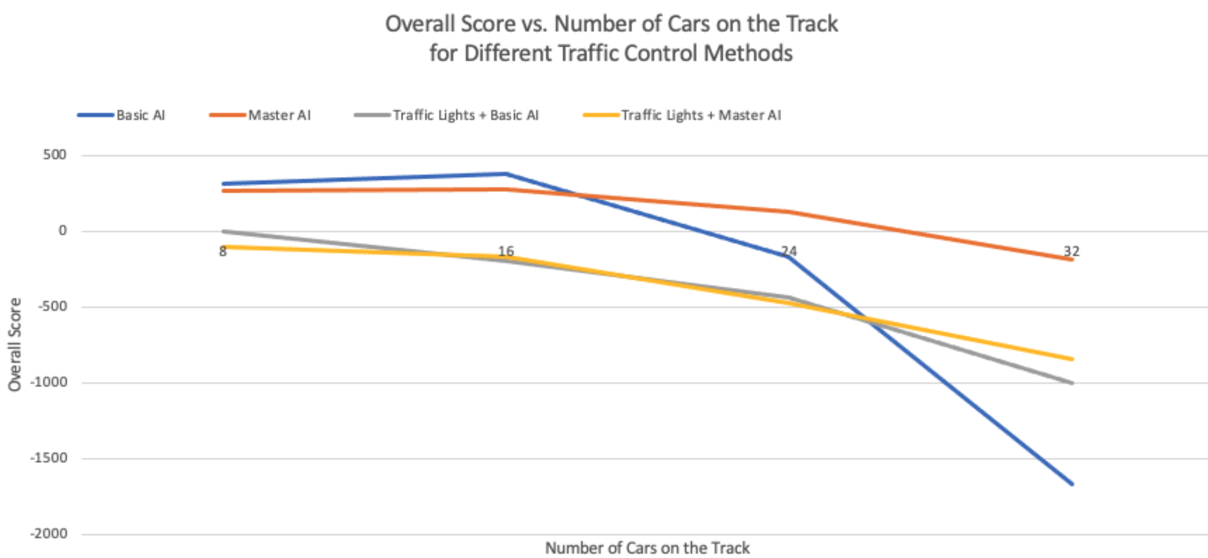


Figure 11. Table of Overall Score vs. Number of Cars on the Track for Different Traffic Control Methods.

Number of Cars on the Track	Basic AI	Master AI	Traffic Lights + Basic AI	Traffic Lights + Master AI
8	309	268	-2	-108
16	383	278	-195	-169
24	-167	132	-437	-478
32	-1666	-189	-1007	-847
Grand Total	**-1141**	**489**	**-1641**	**-1601**

Figure 10 and **11** illustrate the superiority of the Basic AI when small amounts of cars are on the track because the probability of a collision is low, but as the fleet size increases, it rapidly declines as crashes rise. The performances of the traffic light methods are similar because the Master AI had little effect on collision avoidance when the traffic signals already prevented perpendicular traffic from entering the intersection. Their performance starts poor and continues to decline as the number of collisions rise because of their poor efficiency. They cause many cars to be at a full stop for extended periods of time while they wait for the traffic signals to change.

The Master AI emerged as the top performer with a grand total score of 489 and signs of continuing to be superior beyond 32 cars on the track. It managed to keep the number of collisions as low as the traffic signal methods while achieving much stronger efficiency and throughput values suggesting that traffic lights are replaceable. Pedestrians and bikers are not present which would complicate the Master AI's protocol for handling vehicles passing through the intersection and a hybrid method with traffic lights may be necessary. Qualitatively, the Master AI also showed the most coordination and stable network performance. It was better able to break up clumps of cars and prevent congestion due to the priority queue managing backed up cars.

6.5 Validation

The data collected from the simulation was validated by running the trials several times and obtaining similar trends. Trials were also left to run for a sufficiently long period (12 minutes) in order to accumulate data that represented a close average over time. Running each trial for only one minute would be less reliable and valid because there is a higher possibility of an outlier performance that exaggerates the advantages or disadvantages of a certain method as was the case for the self-organization of the Basic AI when 16 cars were on the track. This outlier performance was mitigated by having the trial run for sufficiently long.

7. Discussion

Data collected was largely reliable and valid due to the long run times of each trial. There were occasional emergences of patterns that elevated performances but these were contained by leaving the simulation running long enough to approach expected averages.

The observed results demonstrate the potential for a centralized traffic control system capable of coordinating traffic flow more effectively than standardized traffic signals. In the real world where pedestrians, bikers, emergency vehicles, and other disruptors are present, the Master AI would require tweaks and improvements, but this simulation provides a reasonable proof of concept. The simulation created is also a useful starting point for researchers seeking to perform experiments where behaviours can be visualized and evaluated more closely. Previous techniques for developing algorithms for autonomous vehicles traversing intersections [2, 14] rely on numerical simulations which overlook several variables such as tire and air friction, visibility, and signal transmission times. Traffic control systems should also be evaluated qualitatively to determine abstract performance metrics such as the perceived feeling of safety for a passenger in the vehicle which are more difficult to determine from a table of numbers.

This research is anticipated to inspire more complex CTCSs that rival the performances of other practices like traffic signals, stop signs, or independent coordination between autonomous vehicles on the road. Faced with conflicts of interest, two autonomous vehicles may cause an accident or be overly cautious causing congestion and delays on the road.

8. Conclusions

As autonomous vehicles improve, questions surrounding their safe traversal of intersections become more pressing. Many research papers continue to explore traffic signal optimization algorithms as a means of directing traffic [3, 4, 5, 6] while others propose central control algorithms capable of directing traffic [2, 14]. This paper compared the potential of traffic signal control and centralized traffic control AI by developing a closed simulation using Unity's ML-Agents machine learning package while also incorporating more realistic variables such as tire and air friction with the potential for more (weather, road conditions, etc.).

Figure 5 indicated that the centralized traffic control system (Master AI) was the most successful in achieving the highest throughput as more cars were added to the track. It also managed to keep car crashes as low as the traffic light methods as shown in **Figure 6**. The traffic light methods were more inefficient than their counterpart methods which did not use any light signals. The average speed of a car on the track without traffic lights was 19% higher than with the lights, and the stopped time per car was nearly zero without traffic lights compared to over 40 seconds with the traffic lights after 12 minutes of run time.

Overall scores were calculated in **Figure 10** and **11** which determined that the Master AI was the most successful traffic control method achieving an overall score of 489. Basic AI had an overall score of -1141, Traffic Lights + Master AI scored -1601, and Traffic Lights + Basic AI scored -1641. Qualitatively, the Master AI was the most successful in breaking up clumps of vehicles and carefully reducing congestion making for the most harmonious driving fleet out of all the methods; although, the familiarity and predictability of traffic lights did feel safer and more in control.

The simulation lacks real-world complexity; however, it serves as a reasonable proof of concept to show that a CTCS has merit over standard traffic lights. It is anticipated that this research inspires more complex CTCSs that rival the performances of other practices like traffic signals, stop signs, or independent coordination between autonomous vehicles on the road. A visual simulation like the one developed for this paper is also important for evaluating the qualitative performance of algorithms that are difficult to obtain from typical numerical simulations in this field.

9. Future Work and Lessons Learned

9.1 Future Work

The simulation developed for this research is simplistic and lacks several real-world scenarios that may impact the effectiveness of each traffic control method differently. Currently, vehicles only travel straight through the intersection. More routes can add realism and complications that require the AI to adapt to a larger set of possibilities. Weather and road conditions can also be implemented and used as inputs for the Basic and Master AI to adapt to their environment and make more informed decisions. Pedestrians and bikers are perhaps the most complex addition to make due to the inability for AI to communicate with humans. A hybrid approach to traffic control may be the optimal solution in this scenario where a traffic signal is used to stop all traffic and allow pedestrian crossing or stop all pedestrian crossing and allow vehicles through the intersection. Emergency vehicles need special attention from the CTCS in order to maximize their speed through intersections and would be a useful addition to this simulation.

Lastly, safety must be improved in order to make a CTCS viable in the future. More work is needed to develop safer protocols for the AI which may involve a higher complexity neural network with more nodes and hidden layers, more accurate input data collection, error handling, and rigorous training.

9.2 Lessons Learned

AI can take a significant amount of time to train. Inputs and outputs should be minimized to only critically important requirements to optimize training times. This can also require a single task to be broken down and handled by separate AIs in order to reduce the number of inputs and outputs for each. This strategy was successful in the case of coordinating several independent vehicles using the Master AI.

By far the most effective period of testing occurred during the Basic AI trial when 16 cars were present on the road that managed to self-organize for half the duration of the trial. The emergence of self-organization in natural systems can be a powerful tool. In a complex system like traffic, leveraging this phenomenon may be the most effective method at coordinating participants but requires a deep understanding of probabilities and patterns. Further research in this field and its connection to AI could revolutionize traffic control due to its ability to maximize efficiency and even safety.

10. References

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Appendix A:

Properties of components used for Car models.

Image 1A. Relevant Rigidbody properties used for the Car model.

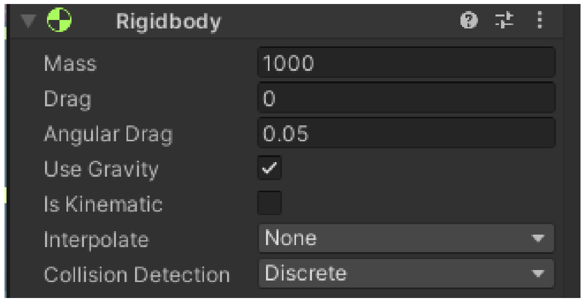


Image 2A. Wheel Collider properties for each wheel on a Car.

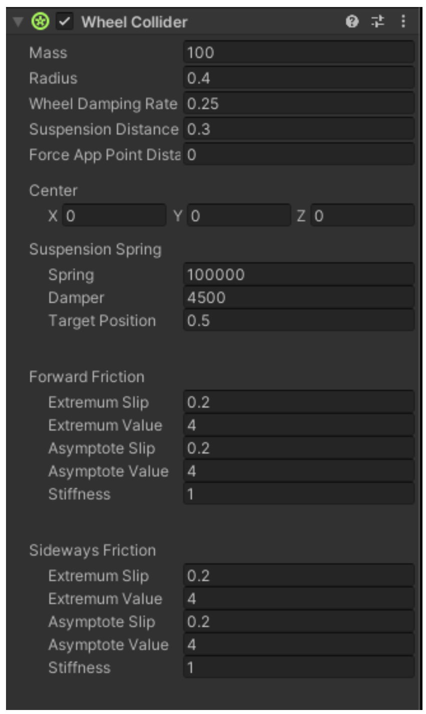
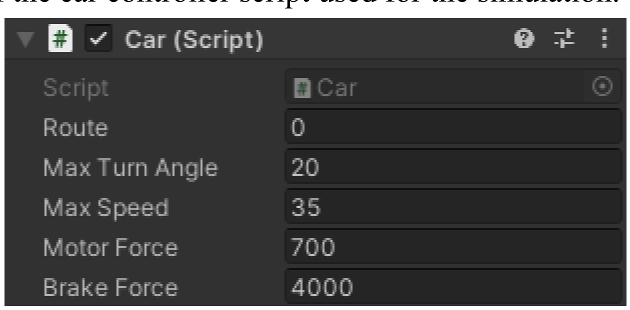


Image 3A. Properties of the car controller script used for the simulation.



Route was either set to 0 or 1 depending on the direction of travel.

Appendix B:

Image 1B. Properties of hyperparameters used for machine learning vehicles.

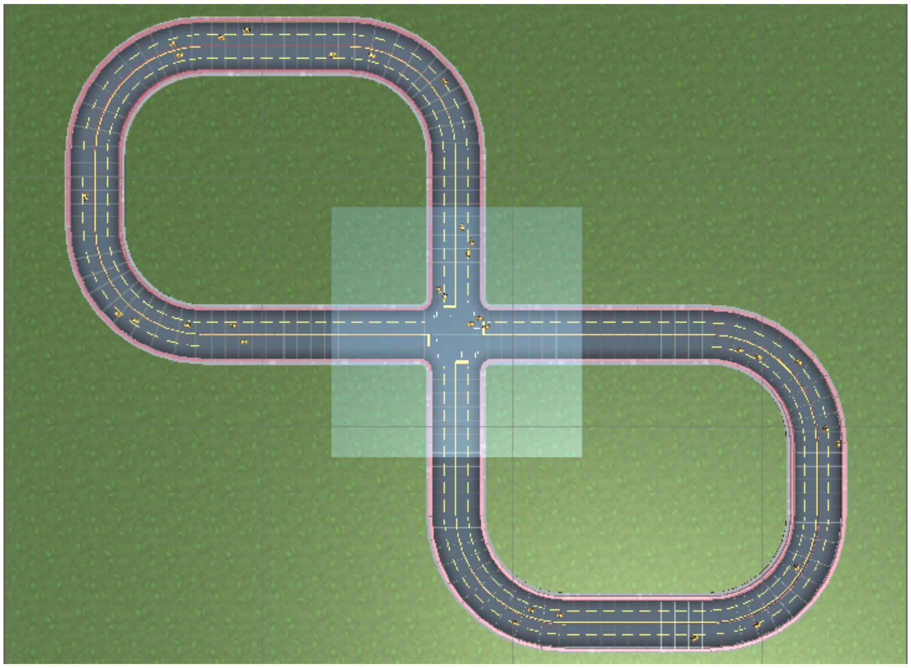
CarDriverAgent.yaml

```yaml
default_settings: null
behaviors:
  CarDriverAgent:
    trainer_type: ppo
    hyperparameters:
      batch_size: 1024
      buffer_size: 10240
      learning_rate: 0.0003
      beta: 0.005
      epsilon: 0.2
      lambd: 0.95
      num_epoch: 3
      learning_rate_schedule: linear
      beta_schedule: linear
      epsilon_schedule: linear
    network_settings:
      normalize: false
      hidden_units: 256
      num_layers: 3
      vis_encode_type: simple
      memory: null
      goal_conditioning_type: hyper
      deterministic: false
```

Appendix C:

Screenshots of simulation environment.

Image 1C. Top-down view of the Master AI simulation environment.



Shown here is the Master AI control method depicted by the blue tinted square around the intersection. The figure-8 track is meant to simulate traffic flow through a city intersection by reusing cars even after they've traversed.

Image 2C. Many environments are simulated concurrently inside Unity.