# Making Way: Using Vehicle-Vehicle Communication and A.I. to Clear a Path for an Ambulance through Heavy Traffic

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## Introduction

•We've all seen it happen: An ambulance is en route to an emergency with sirens blaring. It enters a congested roadway and must slow down to navigate the heavy traffic. Unfortunately, these delays could spell life or death for the patient in the back.

•Our research envisions a future when most vehicles are autonomous and equipped with vehicle-vehicle communication devices. With these devices, we can transmit data about incoming emergency vehicles (EVs) to cars in traffic.

•The goal is to get the cars to drive collaboratively to clear a path for the EV.

•We begin with simple models and later introduce A.I. methods to minimize the EV's travel time.

## Simulation Environment

• We need a powerful simulation tool to model traffic scenarios. For that, we use SUMO.

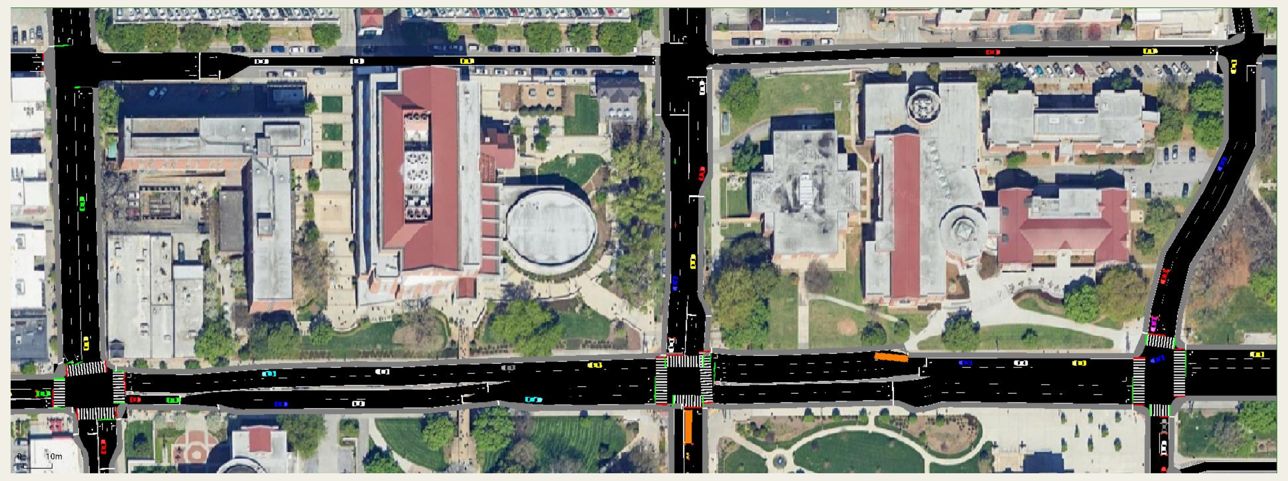

Fig. 1 - Cumberland Ave and surrounding streets, near UTK campus, modeled in SUMO (Simulation of Urban Mobility)

## Method 1: Mutable Vehicle Attributes

•Autonomous vehicles use vehicle following models to dictate their movements.

•Changing variables within these models can cause vehicles to drive more aggressively or collaboratively.

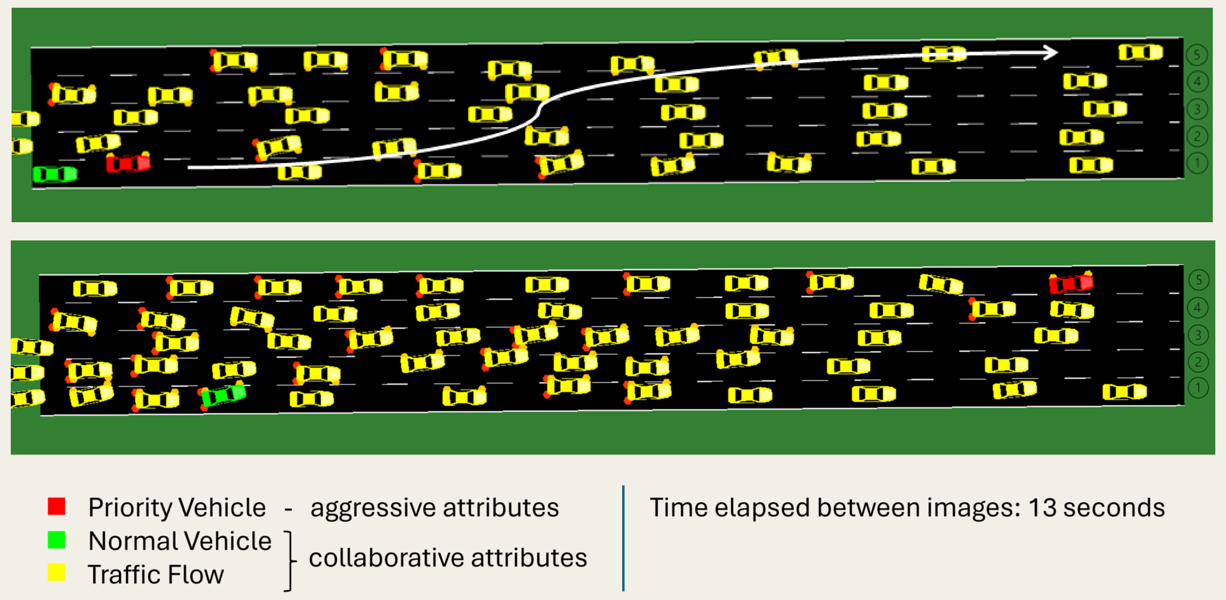


Fig. 2 - Vehicles spawn in the first lane and attempt to move over in heavy traffic

•The priority vehicle reaches the far lane with a 96.2% success rate, while the normal vehicle reaches the far lane with an 84.8% success rate.

•The priority vehicle experienced a 14.6% smaller time loss when attempting the same route as the normal vehicle.

## Method 2: Rule-based Vehicle Control

•Position and speed data is shared amongst vehicles in the network.

•When the distance between a car and the EV drops below a predetermined threshold, the car enters a preprogrammed sequence in which it pulls to the side of the road and stops until the EV has passed.

## Method 2: Continued

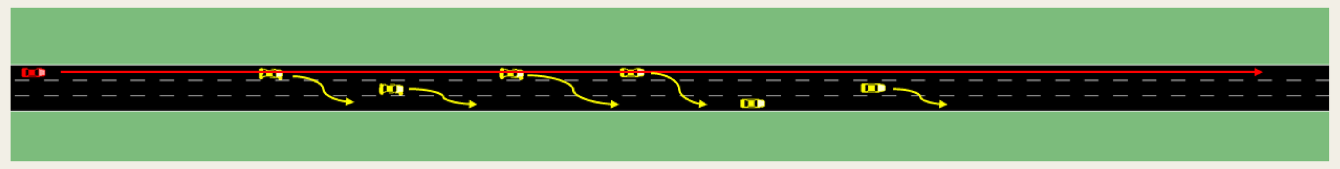

Fig. 3 - Emergency Vehicle approaches from behind

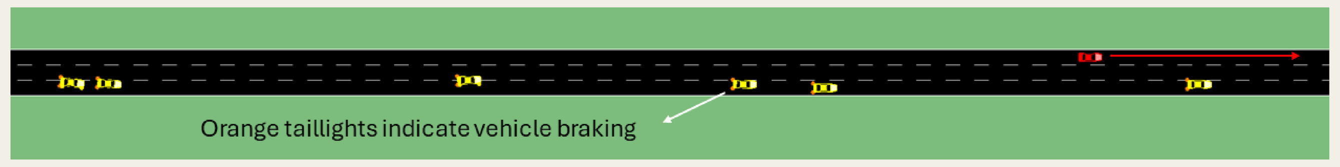


Fig. 4 - Traffic pulls to the right lane and stops

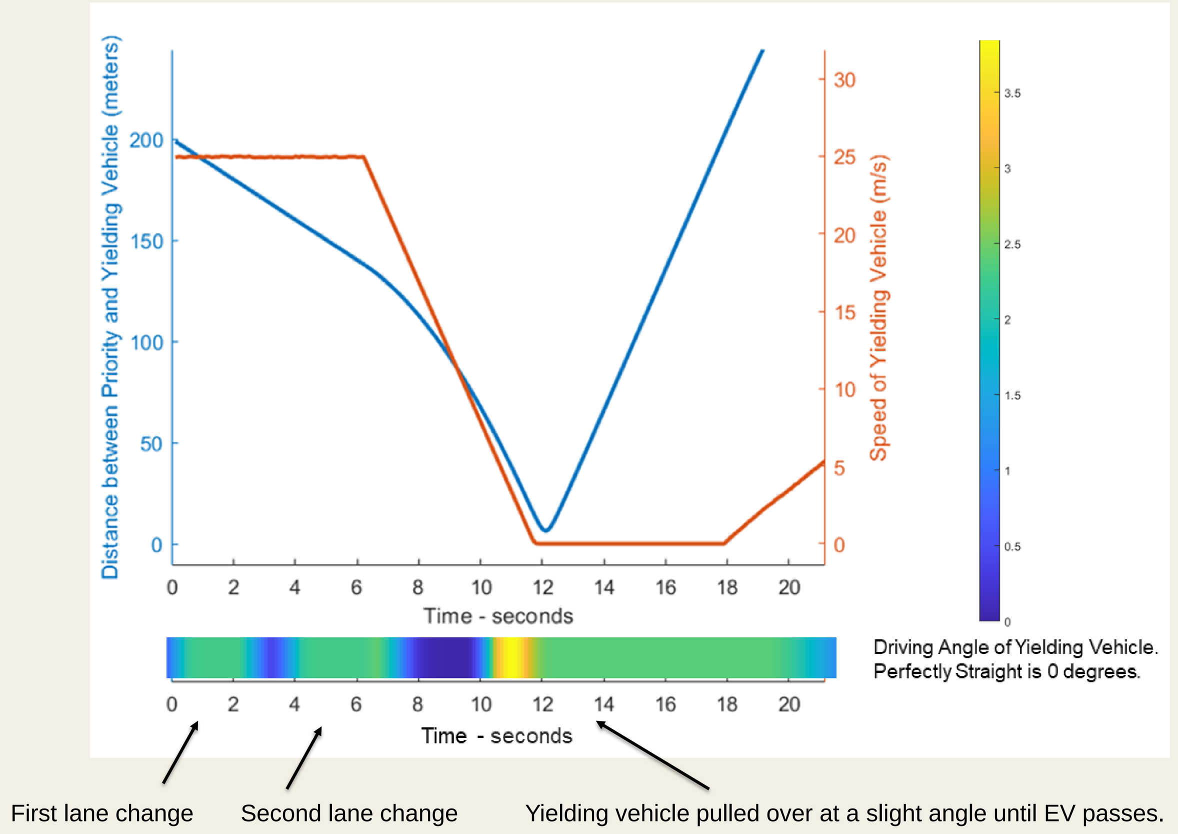


Fig. 5 - Speed, Distance from Priority Vehicle, and Driving Angle of the yellow vehicle during yielding maneuver

## Method 3: Deep Reinforcement Learning

•To introduce A.I. that outperforms Methods 1 & 2, the embedded agent needs two things: a state-space and an action-space.

•The state-space represents input the car receives from its environment, i.e., speed and location information about surrounding vehicles.

## Method 3: Continued

•The action-space represents the decisions the A.I. can make after observing its state.

•In our simulations, the state space is continuous, making a traditional Q-table approach infeasible.

•Instead, we trained a neural network to approximate our Q-values, following an approach similar to [1].

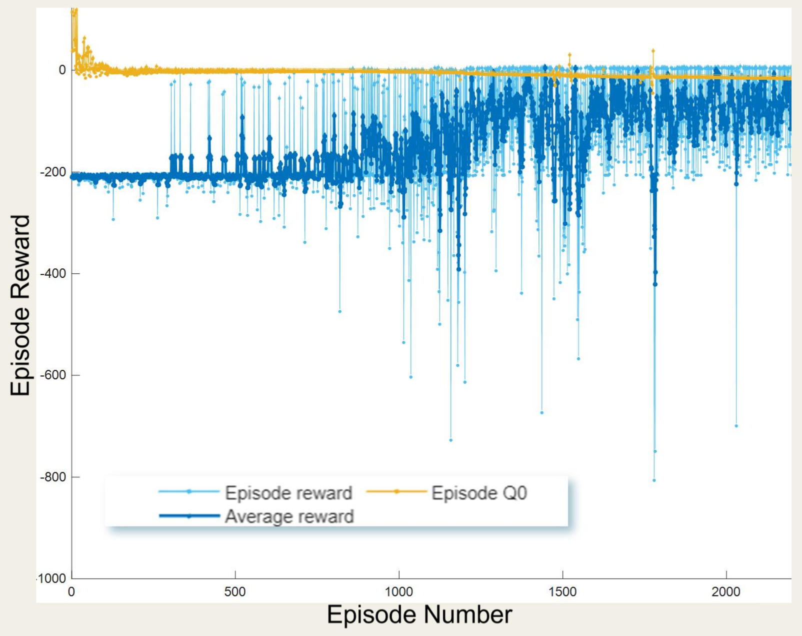


Fig. 6 – Episode reward for RL environment with DQN agent

## Future Research: Multi-agent collaboration

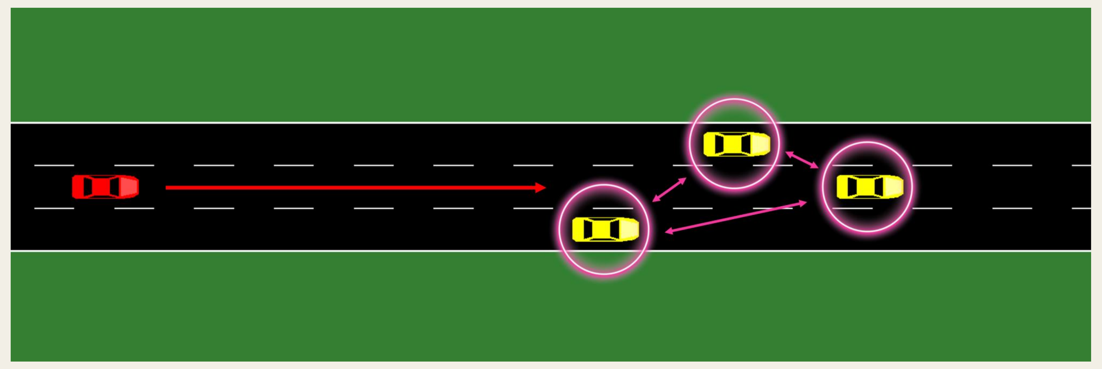

Fig 7. DQN agents collaborate their movement

•Our next step is to embed our A.I. into multiple vehicles at once.

•The cars will work together to minimize EV travel time with minimal disturbance to overall traffic.

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References: [1] H. Shoaraee, L. Chen and F. Jiang, "Decision-Making of an Autonomous Vehicle when Approached by an Emergency Vehicle using Deep Reinforcement Learning," 2021 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), AB, Canada, 2021, pp. 185-191, doi: 10.1109/DASC-PICom-CBDCom-CyberSciTech52372.2021.00041.

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