Understanding and Developing Equitable and Fair Transportation Systems

PI: Weizi Li University of Memphis E-mail: wli@memphis.edu

1 Introduction

The transportation system is an interplay between infrastructure, vehicles, and policy. During the past century, the rapid expansion of the road network, blended with increasing vehicle production and mobility demands, has been stressing the system's capacity and resulting in annual expenditures of \$90 billion (traffic congestion) [20], \$900 billion (traffic accidents) [1], and \$100 billion (infrastructure maintenance). In order to alleviate these costs while providing passengers with safe and efficient travel experiences, we need to better design and plan our transportation system.

To start with, the design of our road network isn't the most efficient. Topologically, roads are by large linearly coupled and lack fail-safe redundancy, which is commonly found in other safety-critical systems [17]. One incident involving two vehicles can completely disable streams of roads and cause traffic jams to spread for miles. Geographically, our road network not only embeds but likely facilitates inequality: roads and bridges are found to better connect affluent sectors, while excluding the poor [2]. In addition, our road network is constantly under the stressors of extreme conditions such as wildfires, hurricanes, tornadoes, floods, which further challenge its resilience and threaten essential mobility activities.

While exhausting transport policies and control methods [16] to contain the increasing costs of the transportation system, technological advancements such as connected and autonomous vehicles (CAVs) and novel operation modes such as shared economy have offered new opportunities. However, many questions remain. First, what is the relationship between the road network, community development, demographics, and mobility behaviors? Second, by leveraging the insights from studying the first question, can we better plan, coordinate, and optimize vehicles in different modalities such as human-driven and autonomous to construct safe, efficient, and resilient traffic flows? Third, how can we build an intelligent transportation system to promote equity and fairness in our community development?

This proposal is the first step towards answering these questions. Specifically, we plan to leverage the unprecedented traffic data as a result of various lockdown policies implemented in 2020–2021. By comparing pre-lockdown and post-lockdown traffic data, we aim to reveal the connections between road network features, demographic factors, and traffic dynamics including traffic accidents and congestion. Next, we will integrate the obtained insights with advanced simulation and machine learning techniques to explore the potential of using CAVs to build safer, more resilient, and more equitable intelligent transportation systems.

2 Background and Preliminary Study

As a preliminary study, we investigate the influence of lockdown, i.e., reduced traffic flows, on traffic accidents. In this section, we will briefly introduce our findings (unpublished), upon which the proposed research will be conducted.

Demographic Inequality

In Fig. 1, we show the change of daily traffic accidents in different demographic groups before and after lockdown. Age, race, and gender are considered. The top row presents the changes in daily accident counts, which are mostly negative, meaning the number of accidents decreases across nearly all groups. However, the share of the accidents of each group (i.e., the fraction of accidents of one group divided by the total number of accidents) shows a different pattern at the bottom row. This observation demonstrates the disproportional impact of the pandemic on different demographic groups. To assess the robustness of the results, we consider three time windows: 15 days, 30 days, and 60 days, before and after lockdown. We have also removed seasonal shift in the changes and provided 95% confidence interval for statistical significance.

Regarding age, all groups except 70–79, 80–89, and 90–99 have significant reductions in daily accident counts. For groups older than 70, the changes are insignificant, which may due to the fact that seniors in general travel less and hence are impacted less by the mobility change. The groups 20–29 and 30–39 have the largest decrease in accident counts, but their shares do not change significantly. Only the group 10–19 has a significant decrease of 3.2% in its share. Overall, the pandemic does not seem to have a largely biased impact across all age groups. Regarding race, all groups experience a significant reduction in accident counts, among which Hispanic has the largest decrease followed by an increase after 15 days. In comparison, White has a significant reduction in both the number of accidents and fraction of accidents. Lastly, for gender, both Male and Female have significant reductions in the number of accidents. However, in terms of the share of accidents, Male has increased about 4%, while Female has decreased about 5%. In sum, the distribution of accidents has shifted its mass towards Hispanic and Male.

Spatial Irregularity

We have also identified the spatial irregularity of traffic accidents during the pandemic. Fig. 2 shows the distributions of traffic accidents in Los Angeles and New York City, before and after lockdown. There are two hot spots of traffic accidents in Los Angeles prior to the pandemic with as high as 80 accidents per month: one around the Hollywood area and the other around northern downtown Los Angeles. In contrast, during lockdown, the hot spots have shifted to southern Los Angeles, with the number of traffic accidents increased to more than 110. The distribution shift is also observed in New York City. Prior to the pandemic, the accident hot spots are distributed around Midtown Manhattan and Lower Manhattan, which are shifted to Upper East Side, West Bronx, and southern Brooklyn during the pandemic.

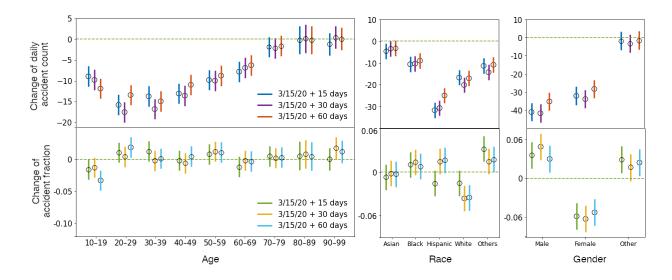


Figure 1: Change of daily accidents after lockdown across various age, race, and gender groups. Top: Change of daily accident count in each demographic group. Bottom: Change of daily accident fraction in each demographic group. 95% confidence intervals are shown. Also shown are estimates from three time windows, namely 15 days, 30 days, and 60 days, before and after lockdown.

Accident Severity

Lastly, we have analyzed the changes in traffic accidents of New York City in terms of severity. As severity levels are typically associated with transportation modes, we further divide the accidents into three types: ones without other transportation modes, ones involving pedestrians, and ones involving motorists. While the counts of accidents with and without injuries drop significantly, we find the number of fatal accidents remained the same across all three types under the reduced traffic flows. Another observation is that the share of no-injury accidents increases significantly after lockdown. However, this shift appears to be reversing as we progress longer (e.g., 60 days) into the pandemic.

3 Research Description

Our first research goal is to understand the relationship between the road network, community development, demographics, and mobility behaviors. In our preliminary study, we have analyzed the relationship of reduced traffic flows and traffic accidents. Next step is to bring in road networks and community statistics, and integrate them with our preliminary study. In particular, we believe that the road network is entangled with community development and mobility dynamics, and its features such as network topology and roadway functional classification have intricate relationships with other components in the intelligent transportation system that are not yet fully understood. So, using the traffic data before and after the pandemic outbreak. We plan to conduct the following research: 1) develop change-point detection algorithm; 2) conduct difference-in-differences analysis; 3) analyze

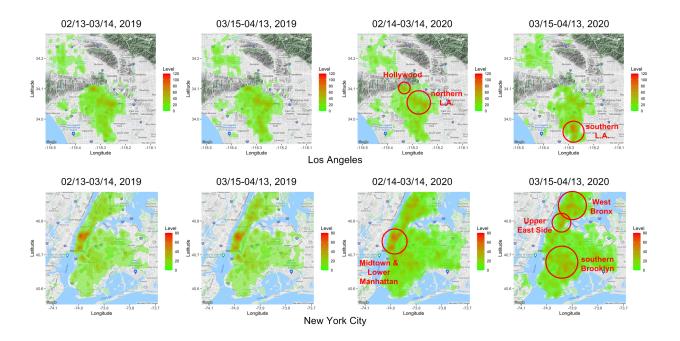


Figure 2: The distributions of traffic accidents in Los Angeles (TOP) and New York City (BOTTOM). Four 30-day analyses are shown before and after lockdown, in 2019 and 2020, respectively. In Los Angeles (L.A.), the accident hot spots have shifted from the Hollywood area and northern L.A. to southern L.A. In New York City, the accident hot spots have shifted from Midtown and Lower Manhattan to Upper East Side, West Bronx, and southern Brooklyn.

dynamic distribution shifts; and 4) integrate obtained insights with advanced simulation and machine learning techniques to better plan and coordinate CAVs.

Change-point detection. Populace may not react in synchronization with government guidance and policies. So, instead of using the lockdown date from the government, we plan to develop an algorithm to detect change-points in time series data, including traffic data such as flow and accidents, and pandemic-related data such as confirmed cases. Formally, we consider a non-stationary time series $m = \{m_t\}_{t=1}^T$, which may have abrupt changes at K unknown time steps $1 < t_1 < t_2 < \cdots < t_K < T$. And our goal is to automatically find these unknown time steps via solving the following optimization program:

$$\min_{\tau} V(\tau) + \beta K,\tag{1}$$

where β is the weighting factor; $\tau = \{t_1, t_2, \dots, t_K\}$ represents the segmentation of the time series. Both τ and K are unknown and will be identified using our algorithm. $V(\tau)$ is defined as:

$$V(\tau) = \sum_{k=0}^{K} c(m_{t_k} .. m_{t_{k+1}}), \tag{2}$$

where we additionally set $t_0 = 1$ and $t_{K+1} = T$; $c(\cdot)$ is the cost function that measures the similarity of the elements in the time series segment $m_{t_k}..m_{t_{k+1}} = \{m_t\}_{t_k}^{t_{k+1}}$.

Difference-in-differences analysis. In order to statistically test the correlations between road network features, demographics, and traffic behaviors. We need to remove possible seasonal changes in our study to ensure an unbiased analysis. This can be achieved via

difference-in-differences (DID) analysis. We will develop our version of DID algorithm to better suit the study of traffic data. As control, pre-pandemic road network, demographic, and traffic data will be used. One way to design the algorithm is to use the following regression model:

$$y \sim time * lockdown * x$$
 (3)

where y is the dependent variable; time indicates the year; lockdown indicates whether a day implements lockdown or not; and x is the independent variable, which could be factors such as age, gender, race, etc. This formula considers not only individual variables but also their two-way and three-way interactions. The interaction coefficients can be used to analyze changes in variables of interest before and after the pandemic outbreak.

Dynamic distribution shifts. To study the potential distribution shifts of various factors, we plan to develop an algorithm based on kernel density estimation. Specifically, we will split the available data regarding the factors of interest in multiple time periods. Again, pre-pandemic data will be used as control. Then, in each time period, we will fit a statistical distribution, e.g., the bivariate normal kernel, to pursue the estimation.

We plan to deliver both qualitative results through visualizing the resulting distributions and quantitative results in the form of statistical comparisons of the distributions. In particular, for the quantitative results, we will conduct a global two-sample test with respect to the integrated squared error (ISE) between the two density functions:

$$ISE = \int (f_1(x) - f_2(x))^2 dx,$$
(4)

where the null hypothesis is $H_0: f_1 = f_2$.

Integration with Simulation and Machine Learning. After gathering the analysis results from aforementioned studies. We would like to explore the use of connected and autonomous vehicles (CAVs) to improve our transportation systems' safety, equity, and resilience. Specifically, we plan to simulate city-wide traffic demand, and leverage deep reinforcement learning (DRL) to generate policies for distributing CAVs to meet the traffic demand, while reducing traffic congestion. DRL is a promising technique for large-scale, complex optimization problems, which are challenging for conventional control methods. By unifying human factors such as travel safety and community equity, and system factors such as network resilience as reward signals, we expect DRL to minimize traffic accident rates (an example of safety) and network travel time (an example of resilience), and maximize the number of satisfied trips (an example of equity). We will compare the performance of DRL with traditional vehicle dispatching algorithms under different CAV market penetration rates.

Qualifications

The PI has extensive experiences on intelligent transportation systems [6, 7, 11, 12, 14, 18, 19, 21], traffic simulation [8, 26], urban mobility [13, 15, 24], machine learning [9, 22, 23, 25], and multi-agent systems [4, 5, 10]. The PI also co-authored a popular survey paper on traffic simulation [3].

References

- [1] Lawrence Blincoe, Ted R Miller, Eduard Zaloshnja, and Bruce A Lawrence. The economic and societal impact of motor vehicle crashes, 2010 (revised). Technical report, 2015.
- [2] Robert Doyle Bullard, Glenn Steve Johnson, and Angel O Torres. *Highway robbery: Transportation racism & new routes to equity.* South End Press, 2004.
- [3] Qianwen Chao, Huikun Bi, Weizi Li, Tianlu Mao, Zhaoqi Wang, Ming C. Lin, and Zhigang Deng. A survey on visual traffic simulation: Models, evaluations, and applications in autonomous driving. *Computer Graphics Forum*, 39(1):287–308, 2020.
- [4] Weizi Li and Jan M. Allbeck. Populations with purpose. In *Proceedings of the 4th International Conference on Motion in Games (MIG)*, pages 132–143, 2011.
- [5] Weizi Li, Zichao Di, and Jan M. Allbeck. Crowd distribution and location preference. Computer Animation and Virtual Worlds, 23(3-4):343–351, 2012.
- [6] Weizi Li, Meilei Jiang, Yaoyu Chen, and Ming C. Lin. Estimating urban traffic states using iterative refinement and wardrop equilibria. *IET Intelligent Transport Systems*, 12(8):875–883, 2018.
- [7] Weizi Li, Dong Nie, David Wilkie, and Ming C. Lin. Citywide estimation of traffic dynamics via sparse GPS traces. *IEEE Intelligent Transportation Systems Magazine*, 9(3):100–113, 2017.
- [8] Weizi Li, David Wolinski, and Ming C. Lin. City-scale traffic animation using statistical learning and metamodel-based optimization. *ACM Trans. Graph.*, 36(6):200:1–200:12, 2017.
- [9] Weizi Li, David Wolinski, and Ming C. Lin. ADAPS: Autonomous driving via principled simulations. In *IEEE International Conference on Robotics and Automation (ICRA)*, pages 7625–7631, 2019.
- [10] Weizi Li, David Wolinski, Julien Pettré, and Ming C. Lin. Biologically-inspired visual simulation of insect swarms. *Computer Graphics Forum*, 34(2):425–434, 2015.
- [11] Lei Lin, Weizi Li, Huikun Bi, and Lingqiao Qin. Vehicle trajectory prediction using LSTMs with spatial-temporal attention mechanisms. *IEEE Intelligent Transportation Systems Magazine*, 14(2):197–208, 2022.
- [12] Lei Lin, Weizi Li, and Srinivas Peeta. Efficient data collection and accurate travel time estimation in a connected vehicle environment via real-time compressive sensing. Journal of Big Data Analytics in Transportation, 1(2):95–107, 2019.
- [13] Lei Lin, Weizi Li, and Srinivas Peeta. Predicting station-level bike-sharing demands using graph convolutional neural network. In *Transportation Research Board 98th Annual Meeting (TRB)*, 2019.

- [14] Lei Lin, Weizi Li, and Lei Zhu. Network-wide multi-step traffic volume prediction using graph convolutional gated recurrent neural network. In *Transportation Research Board* 101th Annual Meeting (TRB), 2022.
- [15] Lei Lin, Feng Shi, and Weizi Li. Assessing inequality, irregularity, and severity regarding road traffic safety during covid-19. *Scientific Reports*, 11(13147), 2021.
- [16] Gábor Orosz, R Eddie Wilson, and Gábor Stépán. Traffic jams: dynamics and control, 2010.
- [17] Charles Perrow. Normal accidents: Living with high risk technologies-Updated edition. Princeton university press, 2011.
- [18] Bibek Poudel and Weizi Li. Black-box adversarial attacks on network-wide multi-step traffic state prediction models. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 3652–3658, 2021.
- [19] Bibek Poudel, Thomas Watson, and Weizi Li. Learning to control direct current motor for steering in real time via reinforcement learning. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, 2022.
- [20] Urban Mobility Scorecard. The texas A&M transportation institute—urban mobility scorecard, 2015.
- [21] Yu Shen, Weizi Li, and Ming C. Lin. Inverse reinforcement learning with hybrid-weight trust-region optimization and curriculum learning for autonomous maneuvering. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2022.
- [22] Yu Shen, Laura Zheng, Manli Shu, Weizi Li, Tom Goldstein, and Ming C. Lin. Gradient-free adversarial training against image corruption for learning-based steering. In *Thirty-fifth Conference on Neural Information Processing Systems (NeurIPS)*, 2021.
- [23] Michael Villarreal, Bibek Poudel, Ryan Wickman, Yu Shen, and Weizi Li. Autojoin: Efficient adversarial training for robust maneuvering via denoising autoencoder and joint learning. 2022.
- [24] Songhe Wang, Kangda Wei, Lei Lin, and Weizi Li. Spatial-temporal analysis of COVID-19's impact on human mobility: the case of the united states. In *The 20th and 21st Joint COTA International Conference of Transportation Professionals*, 2021.
- [25] Ryan Wickman, Xiaofei Zhang, and Weizi Li. Sparrl: Graph sparsification via deep reinforcement learning. In *IEEE International Conference on Data Mining (ICDM)*, 2022.
- [26] David Wilkie, Jason Sewall, Weizi Li, and Ming C. Lin. Virtualized traffic at metropolitan scales. Frontiers in Robotics and AI, 2:11, 2015.