Collaborative Research: RAPID: **Addressing Transit Accessibility and Public Health Challenges due to COVID-19**

PIs: Abhishek Dubey (Vanderbilt), Aron Laszka (University of Houston)

Collaborators: Philip Pugliese (Chattanooga Area Regional Transportation Authority), Dan Freudberg (Nashville Metro Transit Authority)

Project Motivation

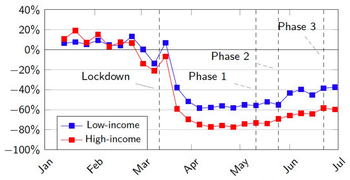
- Public transit services are the backbones of many communities, providing access to jobs and essential services.
- COVID-19 and associated social restrictions have radically changed ridership behavior in urban areas.
- Vehicle capacities have been reduced due to social distancing requirements.
- We ask three questions in this research project:

Question 1: **How has COVID-19 impacted ridership and what is the new normal?**

Question 2: **How has ridership varied spatiotemporally and between socio-economic groups?**

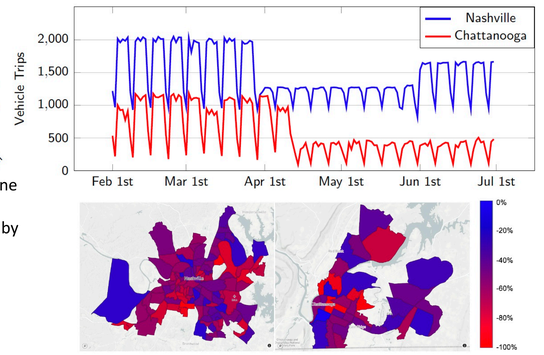
Question 3: **How can we manage transit operations and scheduling in this new normal of changing ridership patterns?**

Service Changes and Demographic Impact



Change in ridership compared to 2019 baseline for the 10% highest income and 10% lowest income census tracts in Nashville (measured by median household income).

Metric	Pearson Correlation
Median Income	0.21
Median Housing Value	0.35
Median Rent	0.15
% White	0.01
% African American	-0.02
% Hispanic	-0.19



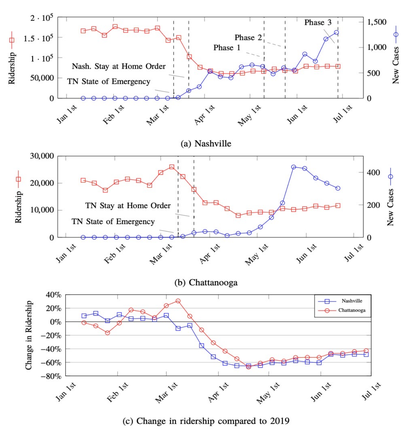
Change in ridership between pre-lockdown (January-February) and post-lockdown (May-June) 2020 per census tract for (left) Nashville and (right) Chattanooga.

Occupancy Estimation

- **Occupancy** is a composition of two random processes: **boarding** and **alighting**. The two random variables of interest for the trip are:
  - **board counts:** $\gamma_t(s_i) \sim Po(\lambda_b^{(t)})$ and
  - **alight counts:** $\alpha_t(s_i) \sim Po(\lambda_a^{(t)})$
- The goal is to learn a generative model that can estimate the board count and alight count conditioned on time of day, activity in the region, day of the week, month of the day, and the local weather.
- Thereafter, occupancy can be modeled as a composition of the two processes.
- We have developed regression count models: Poisson, ZIP, and Hurdle as well as neural network models.
- The models are learned per route, stop, and direction.

Our Key Findings

- We found peak ridership declines of 66.9% and 65.1% for Nashville and Chattanooga, respectively, between pre-pandemic and post-lockdown periods.
- Largest relative declines were on weekdays during morning and evening rush.
- We found a 19% greater decline in ridership in high-income areas than in low-income areas.



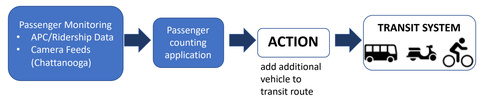
(a) Nashville

(b) Chattanooga

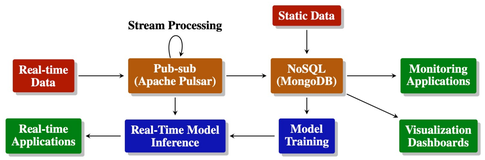
(c) Change in ridership compared to 2019

Scheduling Problem

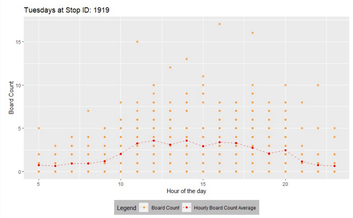
- Fixed-lines are scheduled weeks or months in advance and are static over that time-span.
- COVID-19 requires satisfying new and ever-changing capacity requirements on transit vehicles.
- Ridership patterns are changing rapidly across spatiotemporal and socio-economic dimensions.



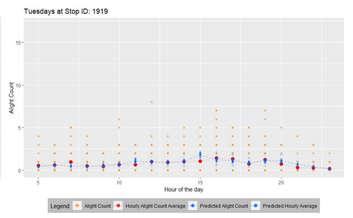
- *Key idea:* Monitor passenger counts on vehicles and dynamically add vehicles to a route to ensure capacity and system requirements are met.



Initial Results



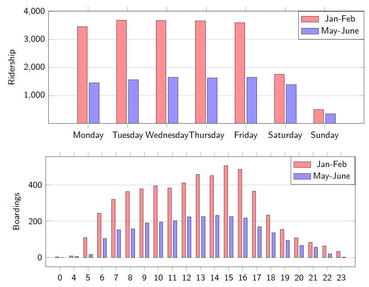
Board counts shown as orange dots (on unseen data). Red dots indicate their hourly average (Poisson rates).



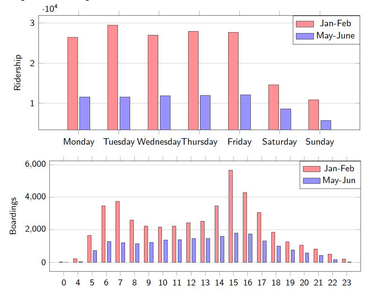
Alight counts shown as orange dots (on unseen data). Red dots indicate their hourly average (Poisson rates). Blue dots indicate predicted values.

Ridership Impact

Chattanooga

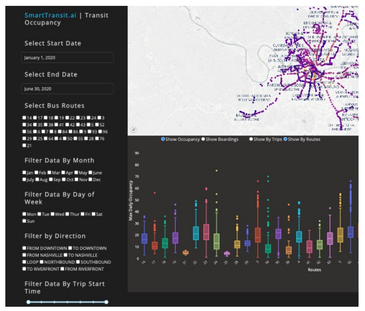


Nashville



- Largest relative declines in ridership was during weekdays and morning and evening commute times for both cities.

Occupancy Analysis and Likelihood Prediction

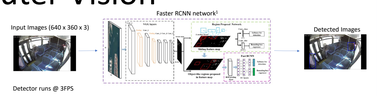


Nashville occupancy and delay

Chattanooga occupancy and delay

Computer Vision

- Automated Passenger Counter data is noisy.
- We can use on-board camera data from vehicles to estimate their occupancy.
- A benefit of this approach is the ability to obtain origin-destination data.



Detector runs @ 3FPS

Videos	Cameras	Mean Normalized Error across a video stream (in counting number of people)			
		Faster RCNN (mobilenet)	Faster RCNN (inception)	Faster RCNN (nas)	YoLo V3
Bus-126 stream 1	Driver	0.364	0.312	0.364	0.615
	Door	0.450	0.341	0.305	0.662
	Rear	0.445	0.390	0.395	0.618
	R/Door	0.462	0.459	0.407	0.281
Bus-126 Stream2	Driver	0.404	0.339	0.411	0.408
	Door	0.485	0.318	0.346	0.548
	Rear	0.334	0.483	0.291	0.344
	R/Door	0.325	0.275	0.184	0.246
Bus-126 Stream3	Driver	0.383	0.250	0.314	0.369
	Door	0.497	0.357	0.369	0.321
	Rear	0.411	0.340	0.214	0.307
	R/Door	0.385	0.219	0.233	0.152

Faster RCNN trained on inception and NAS datasets have the lowest mean normalized error across the video streams.