Modeling Traffic Congestion and an Examination of the Factors Influencing Chicago Public Transit Ridership in the City of Chicago

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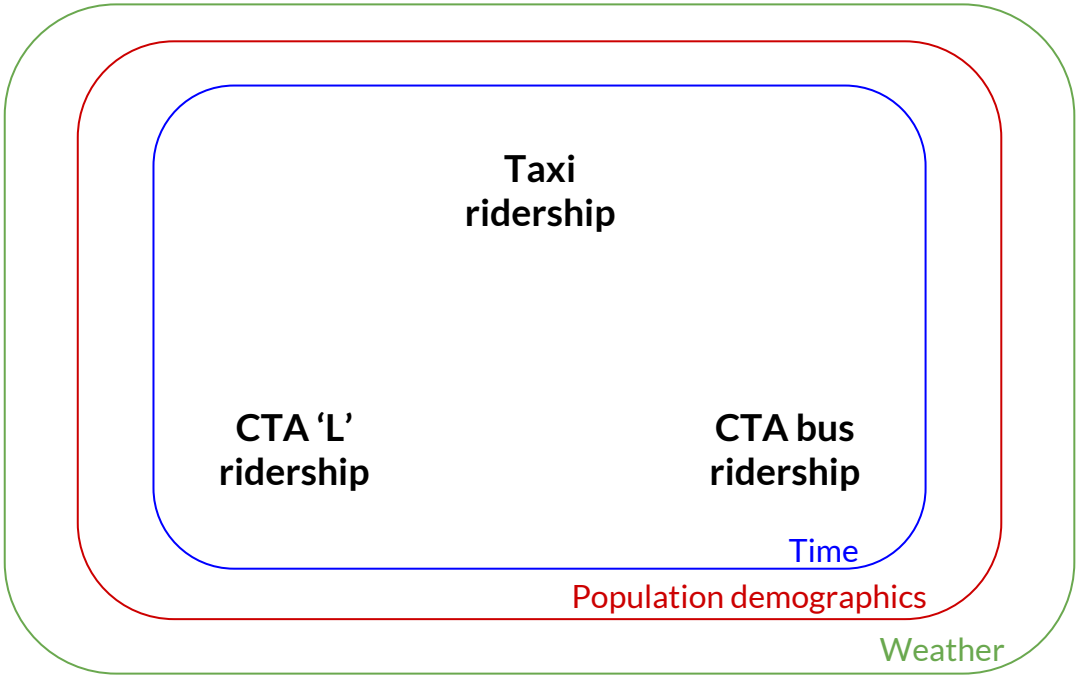
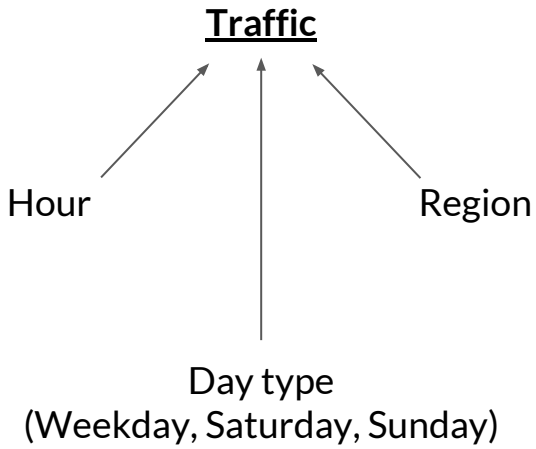
Objective: Explore public transportation behavior



Deliverable: Explore the factors influencing the ridership of each mode of Chicago public transportation

Objective: Model Chicago traffic congestion

Deliverable: Predict traffic congestion at a given time and location



Models chosen for testing:

- Simple linear regression
- Linear regression including second and third-order interaction terms
- kNN regression (resampled using repeated 10-fold cross-validation)

Validation: Final model applied to 12 days' worth of out-of-sample data.

Project management

Task delegation

Inferential	Taxi	Weather	Census	'L'	Traffic	Bus
Predictive	LR: training	LR: test	LR+: training	LR+: test	kNN: training	kNN: test

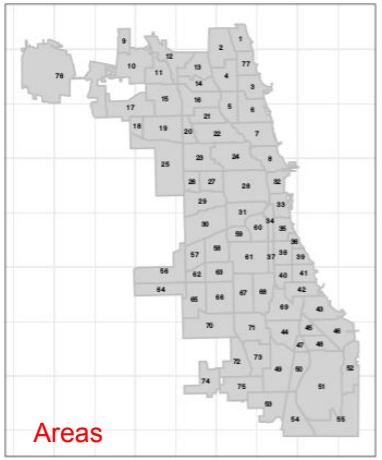
Timeline

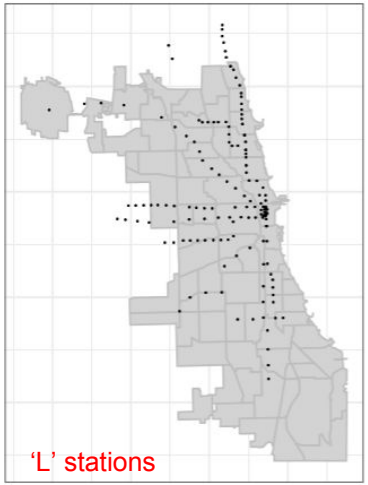
Study obstacles

Issue	Implications
Limitation: data for potentially relevant factors is unavailable • Ridesharing and Metra ridership • Geographical factors (e.g. number of intersections, total road length) • Public transit vehicle volume and timetable	Unable to account for these factors
Limitation: Traffic data encompassed the shortest timeframe (01/2013 - 01/2015) due to limited data collection	Investigation scope narrowed to the traffic data timeframe
Limitation: Valid timeframe for modeling further limited due to traffic data observation recording issues (01/2015)	• Model scope narrowed to the valid timeframe • Separate validation set scraped 4/10-4/22 • Unable to include weather in the model
Assumption: 2010 census results are representative of the study timeframe	Normalized responses by population counts that were not current

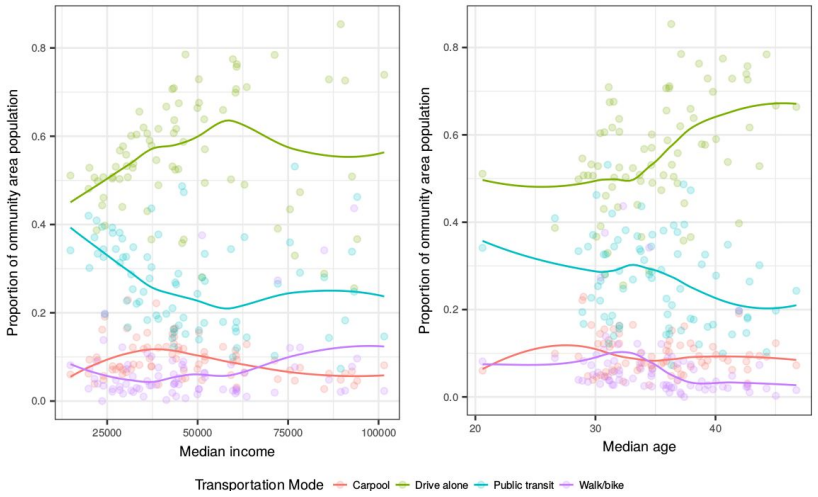
Data pipeline challenges

Issue	Solution
Location convention	Utilized *rgeos*, *rgdal*, *sp* R packages to align all datasets to community area
Taxi dataset size (~5GB/113M rows + 23 columns)	Aggregated taxi rides by day via Java
Time convention • Traffic: timestamp • Others: day	Aggregated traffic congestion by day via R





Public transportation factors: demographic

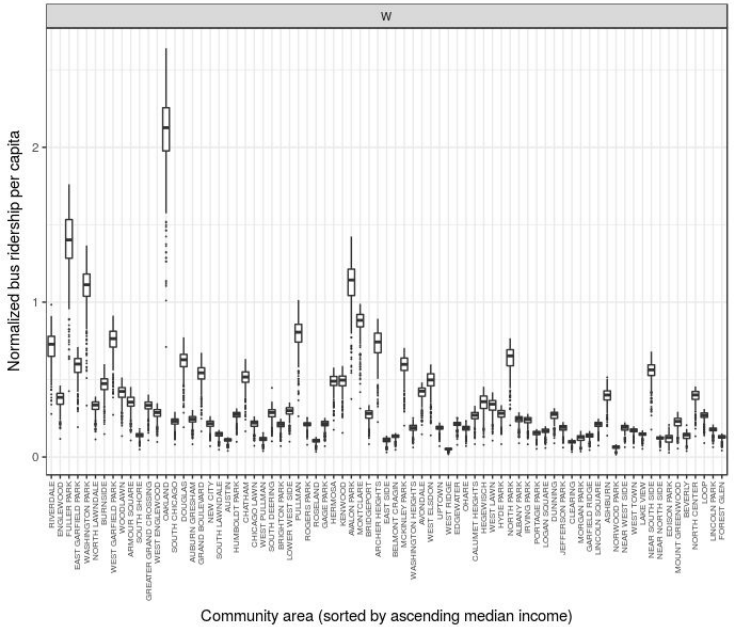


	Drive alone	Carpool	Public transit	Walk/bike
Median income ↑	↑	~	↓	~
Median age ↑	↑	~	↓	↓

Public transportation factors: demographic

Validating census observations on public transit ridership data:

- Areas with low median age did not exhibit lower ‘L’ or bus ridership per capita compared to areas with high median age
- Areas with low median income only showed the expected behavior when using bus ridership per capita as a response

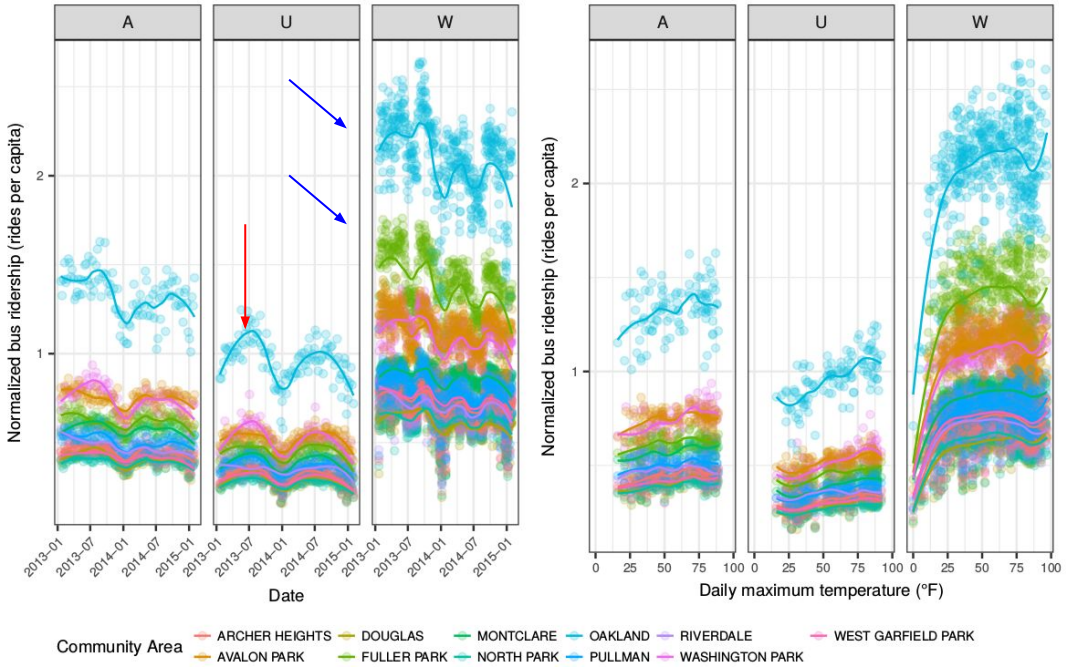


Public transportation factors: time/weather

Bus and 'L' ridership appears cyclic over the course of a year

- Case 1: sinusoidal
  - More typical/ of weekend ridership
  - Aligns with ridership trend with respect to temperature
- Case 2:
  - Jan - Jun: Relatively flat
    Jun - Aug: Step function down
    Aug - Nov: Step function up, potentially beyond initial baseline
    Nov - Dec: Steep decline
  - Likely driven by time-related factors (e.g. academic breaks, seasonal vacations)

Taxi ridership did not exhibit similar behavior



Predictive model results

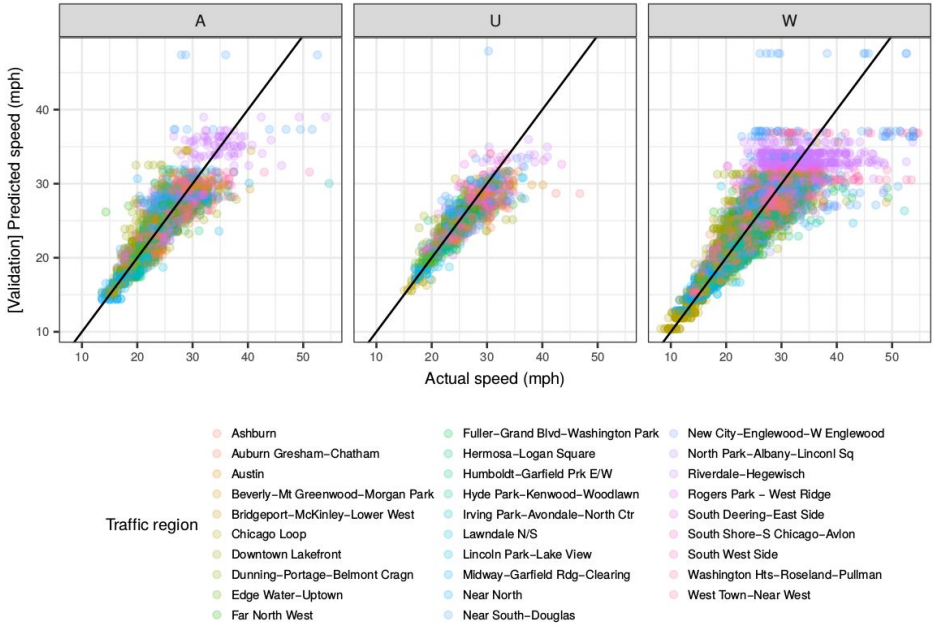
Model quality

- LR+ offers marginal fit improvement over LR at the cost of increasing DoF from 31 to 173.
- kNN improves training R^2 by **46%** and RMSE by 30% over LR! (...but is **SLOW**)
- Optimal $k = 9$

kNN residual analysis

- Model prediction accuracy and precision improves during periods of heavy congestion.
- Weekend observations exhibit this effects to a much lower degree.

Model	Training R^2	Training RMSE	Test RMSE	Validation RMSE
Linear regression	0.5245	3.348	3.2830	
Linear regression with interaction effects	0.542	3.288	3.2248	
kNN regression	0.7663	2.3465	2.2525	2.2129



Executive summary

Deliverable: Explore the factors influencing each mode of Chicago public transportation (taxi, CTA bus, and 'L')

Method: Qualitative analysis of responses with respect to meteorological, demographic and temporal factors

Findings:

- Distribution modality of all responses was defined by day of week and community area.
- Income and age connected to area-to-area distribution bias.
- Area distribution variation governed by time-related factors, with some influence by temperature.

Opportunities:

- Examine similar locations (e.g. NYC) that have published ridesharing data to use as an analog to Chicago
- Add bike-share (Divvy) data to investigation scope

Deliverable: Predict traffic congestion at a given time and location

Method: Prototype parametric (linear regression variants) and non-parametric (kNN regression) models

Results:

- kNN regression yielded the best fit quality, which was sustained in out-of-sample validation.
- All models tended to overestimate congestion when low.
- Model predictions were more precise during periods of heavy congestion.

Opportunities:

- Scrape current data for at least one year in order to enable weather to be added as a factor (current scope: one month)
- Change location resolution to the traffic segment level