NREL Transforming ENERGY

Factors Influencing Willingness to Share in Ride-Hailing Trips

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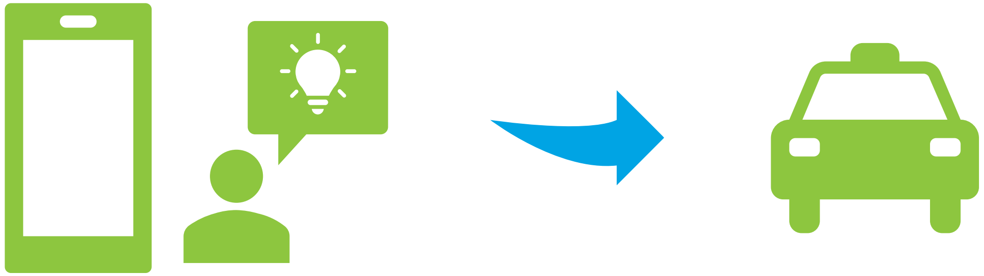
Motivation

- With the construction of the U.S. interstate system, the private car became the dominant travel mode—making our cities increasingly auto-dependent and congesting our roads.
  - Congestion in the U.S. cost an estimated $305 billion in 2017[1]
- With this orientation towards private cars, other (perhaps more energy- and space-efficient) modes have struggled to compete on cost and convenience.



- **Transportation Network Companies** (TNCs) offer a potential solution:
  - Offering cheap, on-demand, rapid, comfortable, and flexible travel

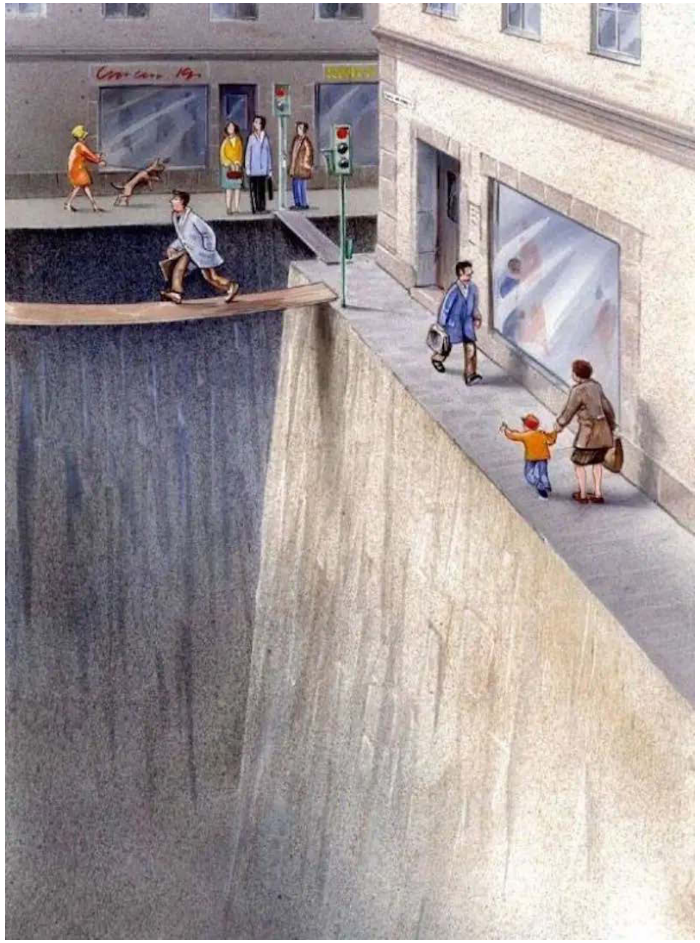
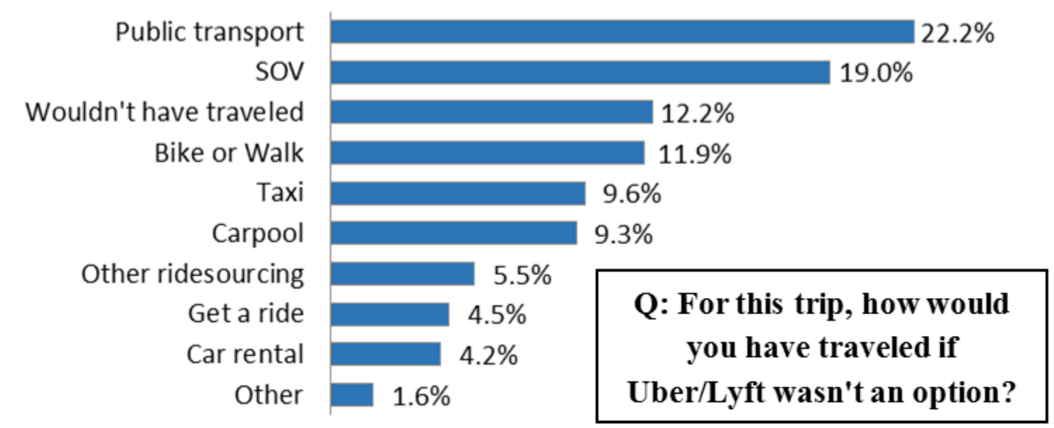


Illustration from Karl Jilg, Swedish Road Administration

1. Pishue, B. US Traffic Hot Spots: Measuring the Impact of Congestion in the United States, 2017

Impact of TNCs on Travel Behavior: Previous Findings

- Riders may be **shifting** from more sustainable modes to TNCs[1,2]



Source: Henao, 2017

- **Deadheading** may be increasing overall vehicle miles traveled in a given system by as much as 83%[3]
- Average **vehicle occupancy** of 1.3 riders per TNC vehicle (not considering deadheading)[3]

How can occupancy be increased?

1. Alejandro Henao, "Impacts of Ridesourcing—Lyft and Uber—on Transportation Including VMT, Mode Replacement, Parking, and Travel Behavior," (PhD diss., University of Colorado at Denver, 2017).
2. Steven R. Gehrke, Alison Felix, and Timothy G. Reardon, "Substitution of Ride-Hailing Services for More Sustainable Travel Options in the Greater Boston Region," *Transportation Research Record* 2673, no. 1 (2019): 438–446.
3. Alejandro Henao and Wesley E. Marshall, "The impact of ride-hailing on vehicle miles traveled," *Transportation* 46, no. 6 (2019): 2173–2194, https://doi.org/10.1007/s11116-018-9923-2.

Our Question

What factors might influence a customer’s propensity to share a TNC trip?

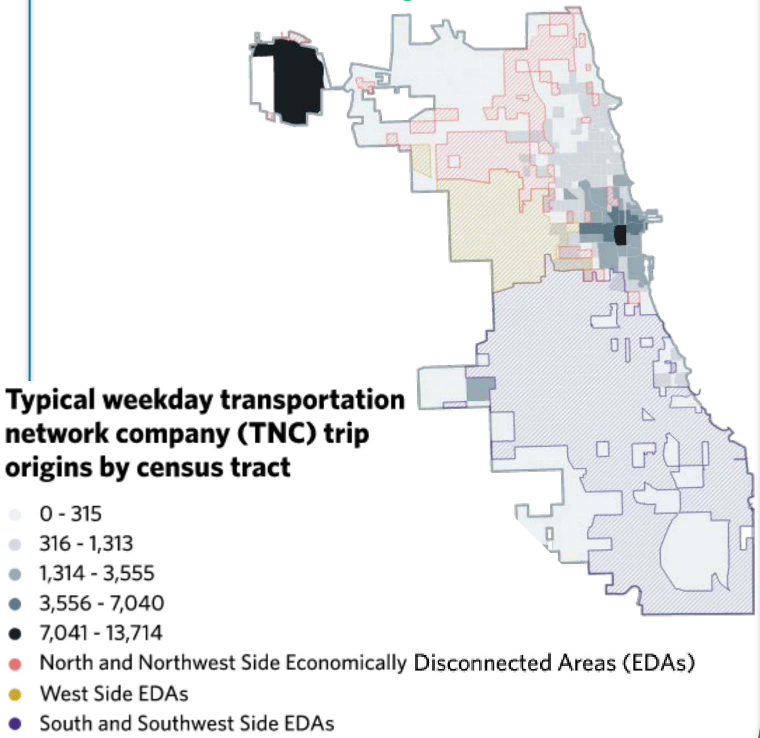
- **Ride Sharing** is when multiple TNC trip requests are combined into a single vehicle for some portion of a rider’s trip. The influences on a customer’s decision to share have thus far been unaddressed in related research.

- Touted benefits of ride sharing include:
  - Reduced congestion
  - Lower greenhouse gas emissions from transportation
  - Lower local pollutant emissions
  - Increased rideshare trip efficiency

The Dataset

- In April 2019, Chicago released the anonymized **trip**, **vehicle,** and **driver** data associated with citywide TNC operations[1]

101 Million Trips



5.9 Million Vehicle-Months

Photo from Free-Images.com [3]

5.8 Million Driver-Months

Photo from Free-Images.com [2]

1. Chicago Metropolitan Agency for Planning, "New Data Allows an Initial Look at Ride Hailing in Chicago," May 4, 2019, https://www.cmap.illinois.gov/documents/10180/1005256/PU-0026_TNC+POLICY.pdf/06def1f1-b0b1-0365-2386-2011dfb96fa9.
2. https://free-images.com/display/driving_navigation_car_road.html
3. https://free-images.com/display/cars_traffic_road_street.html

Trips Table Description

- This work focuses on the **trips table** for rides in Chicago between November 2018 and April 2019:
  - Start and end timestamps
  - Trip fare, duration, and distance
  - Pickup/drop-off census tract
  - Trips pooled: number of trips pooled (shared) from the time the first passenger was picked up until the car was empty again
  - **Shared Trip Authorized**: whether the customer agreed to a shared trip with another customer, regardless of whether they were actually matched

Number of Trips	45,338,599
Number of Trips After Filtering	38,983,953
Average Trip Distance	4.67 miles
Average Trip Duration	16 minutes

17.5 mph average speed!

Hypothesis

- Three categories of influential characteristics determine a customer's **willingness to share**.
- This work investigates the relative importance of these factors:

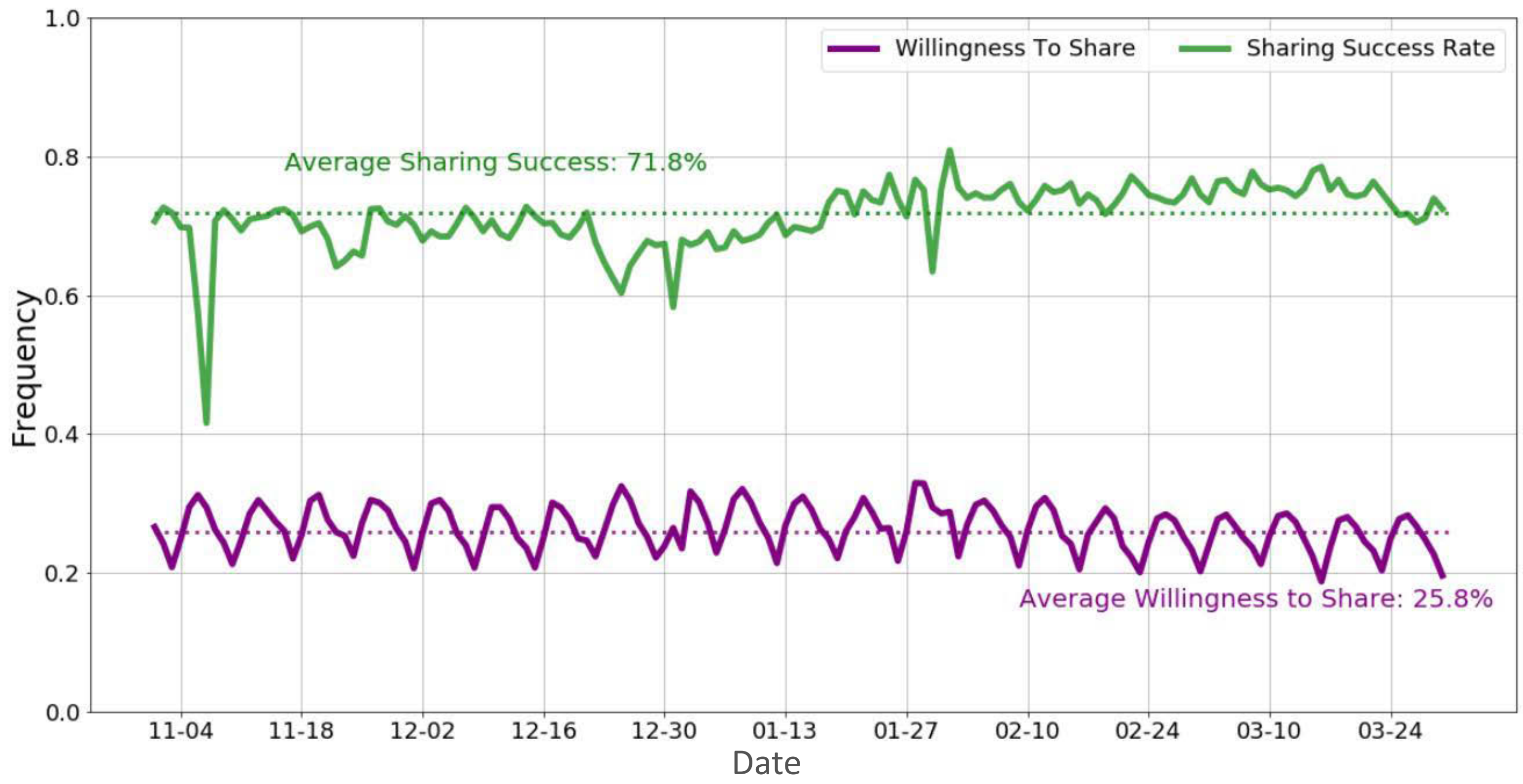
1. Trip-specific
   (e.g., trip distance/duration)

2. Temporal-environmental
   (e.g., time of day)

3. Location-based
   (e.g., population/job density)

Photo from Free-Images.com

Trip Aggregation



- Periodic trends in **willingness to share** (WTS) across all trips
  - Highest WTS midweek
- Among those trips that were authorized for sharing, there is an average match rate of 71.8% (18.5% of total trips are pooled)

Methodology and Results

Multiple Linear Regression

- Data binned by:
  - Census tracts of origin-destination pairs
  - Trip time of day
  - Weekend (including Friday) or weekday
  - Airport trip (Boolean)

- Then modeled the ***WTS Ratio***: "proportion of trips in which individuals have indicated a willingness to share"
  - $WTS\ ratio = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_i X_i \ldots + \beta_{10} X_{10} + \epsilon$
  - β_i coefficients indicate the explanatory power of each variable X_i

- The model assessed relevance of **ten explanatory factors**:
  - Duration, distance, weekend vs. weekday, time of day, average percent difference in fare (shared vs. private trips), airport trip, median income, population density, job density, and weather

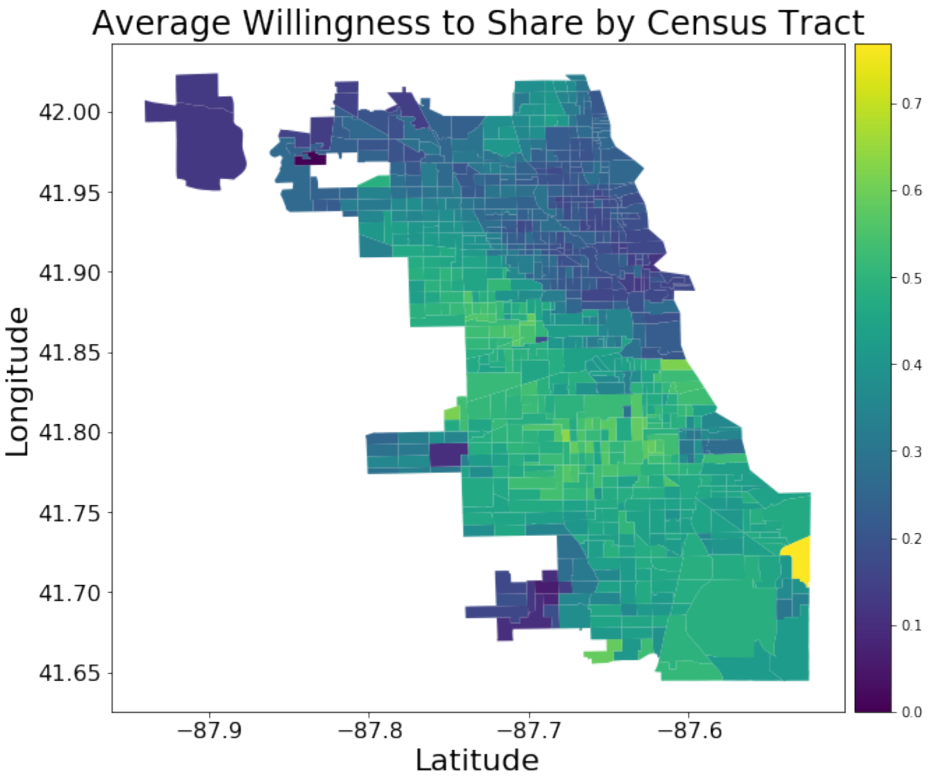
Regression Results

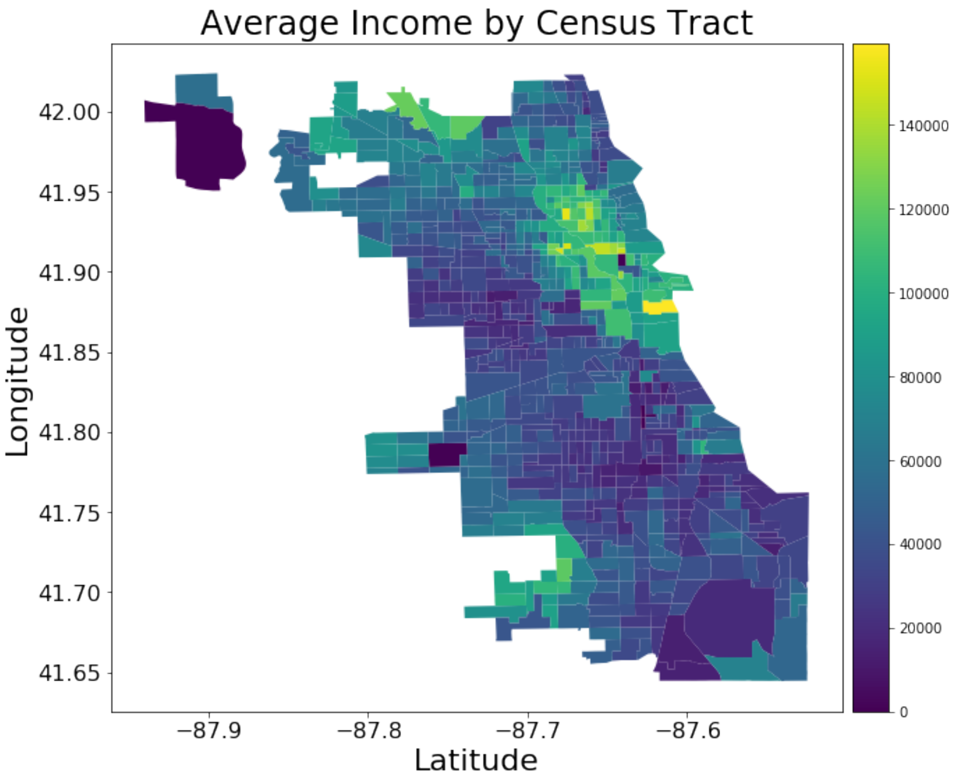
Variable	Estimate (β_i)
(Intercept)	0.540
airport_dropoff	-0.455
income_at_dropoff	-1.67E-06
airport_pickup	-0.360
income_at_pickup	-1.37E-06
weekend	-0.048
pop_density_at_pickup	-3.43E-06
pop_density_at_dropoff	-3.42E-06
job_density_at_dropoff	-4.62E-07
fare_diff_ptg	0.082
job_density_at_pickup	-2.12E-07
distance	0.006
night	-0.021
duration	2.30E-05
m_peak	0.014

$10,000 increase in median income = 1.67% decrease in WTS

- Shown in order of variable significance
  - All tested variables were significant except weather (wind, temperature, precipitation)
- Most significant: **trips to the airport**
  - Perhaps due to baggage, people in a rush to catch flights, family travel, etc.
  - 45% lower likelihood of WTS than a non-airport trip

Visualizing WTS Factors – Income





- Significant relationship between WTS and income by census tract (with a correlation of -0.714)
- The median shared ride cost is **~66%** of the cost of a private ride
  - The correlation above indicates a greater price sensitivity in low-income areas

XGBoost

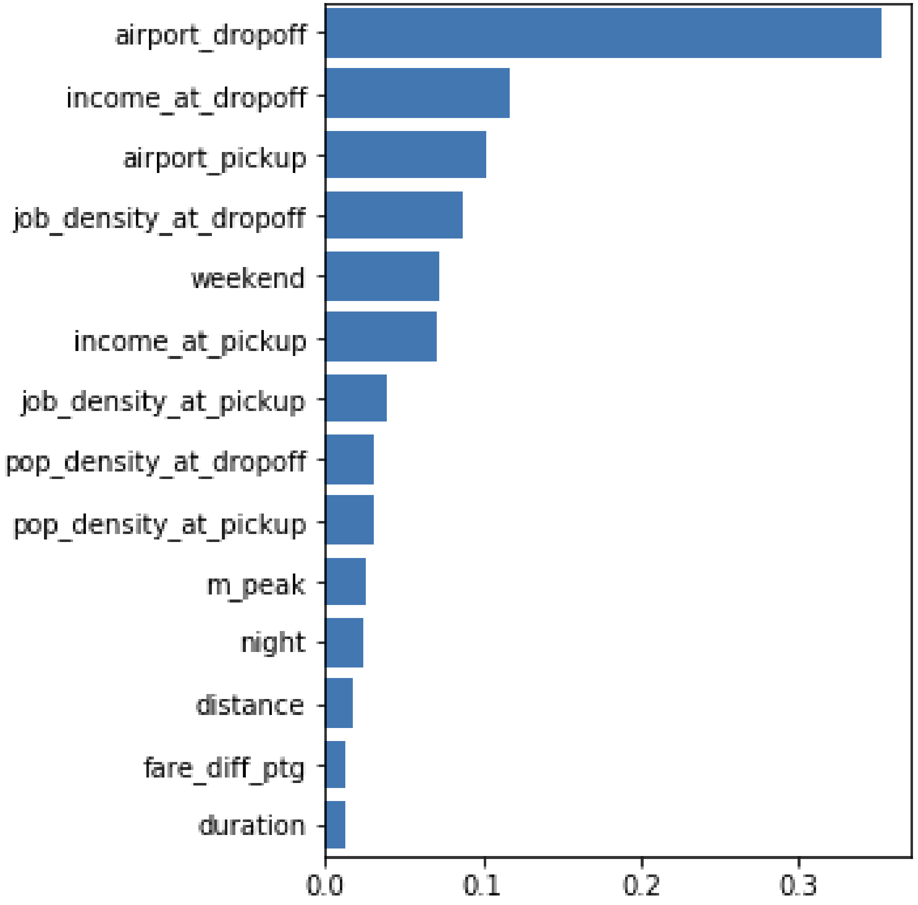
- One of the most successful machine-learning algorithms for prediction
- Applied in travel demand and travel time predictions

- Advantages:
  - Does not require detailed mathematical forms and assumptions on variable distributions
  - Suitable for capturing the **underlying relationships** among different variables in an environment of uncertainty
  - Fast and scalable to **large datasets**

- Disadvantage:
  - Only predicts within bounds of training – no extrapolation

XGBoost

- XGBoost model was estimated using the **same variables** as in the regression so that the results could be compared
- Results below show the relative significance of each variable for explaining different outcomes in the *WTS Ratio:*



XGBoost

- There are clear parallels in the order of significance of the variables between models
  - Income at pickup/drop-off and airport trips are most significant
  - Duration, distance, and time of day round out the end of the list

Linear Regression

Variable	Estimate (β_i)
(Intercept)	0.540
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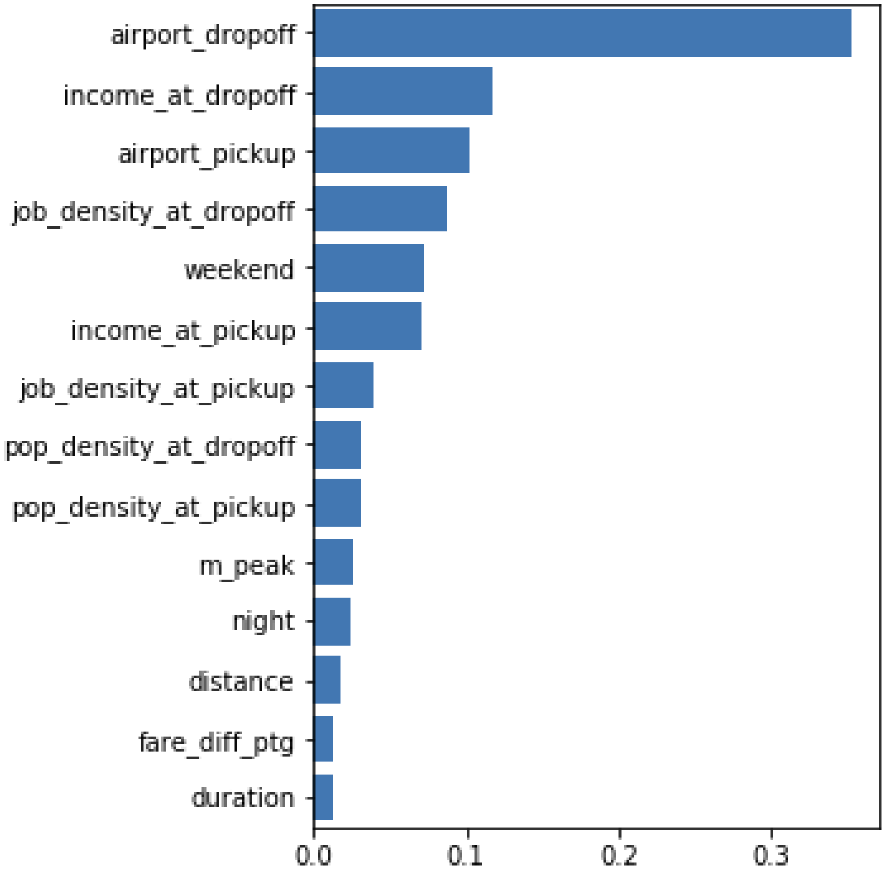
XGBoost

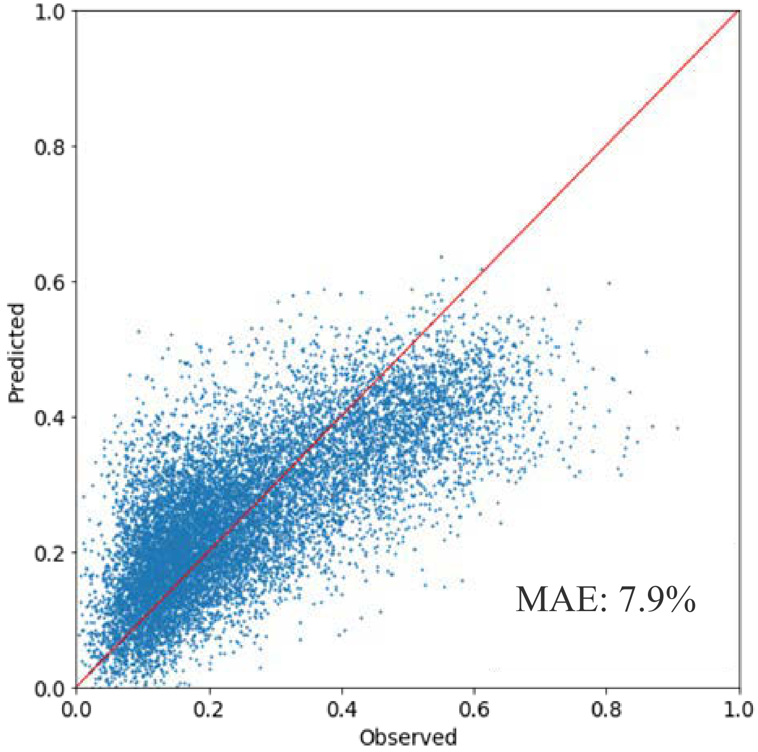


Model Verification

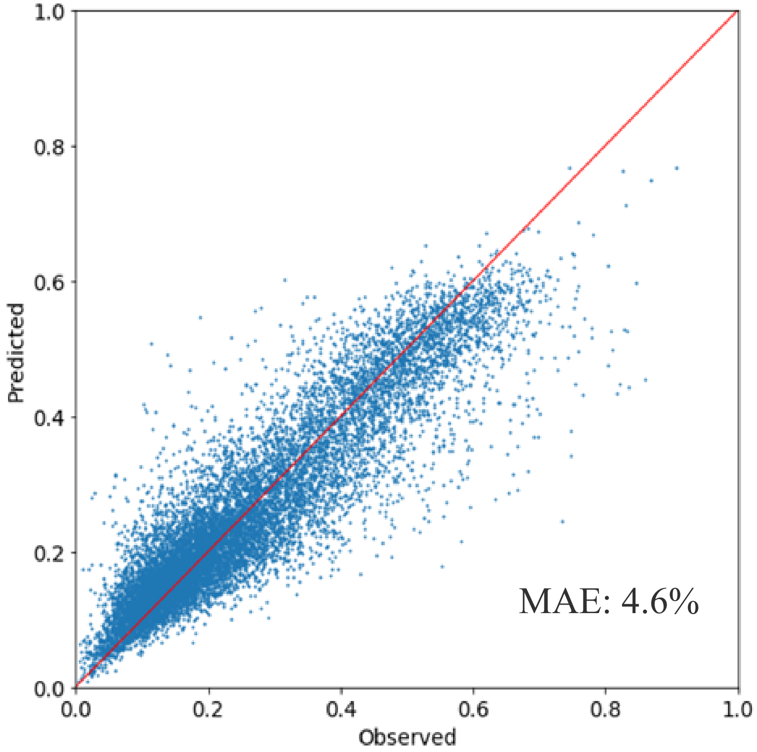
- Both models were constructed and **trained on 80%** of the data and then verified against the remaining 20%
- The XGBoost model predicted the *WTS Ratio* with a mean absolute error (MAE) of 4.6%, outperforming the regression (MAE of 7.9%)

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

Linear Regression Residuals



XGBoost Residuals



Conclusions

Takeaways

- So far, pooled rides have made up a **small portion** of TNC trips (~18%)
- Learning what factors make an individual more or less willing to share a trip could be beneficial for both **governments** and **TNC companies**
- Predictive modeling could enable more accurate **targeted pricing** to incentivize and increase overall WTS
  - An incremental 10% increase in the difference in fare between shared/private trip corresponds to a 0.82% increase in WTS (based on this regression model)

Future Research Questions for this Dataset

- Impact of the 2020 ride sharing tax (see table below)
  - Starting January 6th additional fees on private TNC trips with additional charges for rides starting in highly congested areas (downtown, airport, etc…)
- Driver Data
  - Who and where are the drivers serving the most trips?
- Surge Pricing Analysis
  - Identifying past large events in Chicago based on TNC trip patterns?

	Current Tax	New tax (Downtown)	New tax (Outside Downtown)
Private Trip	$0.72	$1.25 (+$0.53)	$3.00 (+$2.28)
Shared Trip	$0.72	$0.65 (-$0.12)	$1.25 (+$0.53)
Private Trip (Airports, Navy Pier, McCormick Place)	$5.72	$6.25 (+$0.47)	$8.00 (+$1.75)
Shared Trip (Airports, Navy Pier, McCormick Place)	$5.72	$5.65 (-$0.07)	$6.25 (+$0.47)

Source: City of Chicago Public Vehicle Industry Vehicle Notice No. 19-039

Thanks! Questions?

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