

# Evaluating Bike Share as A Solution to the “Last Mile Problem” in Public Transit

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Course: MACS 30200-Perspectives on Computational Research

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# Agenda

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- Background
- Research Question
- Data
- Model
- Summary

# Background: bike share

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- First introduced in the 1960s; became popular in the 2010s
- Historical development (DeMaio, 2009; Shaheen, Guzman & Zhang, 2010)
  - 1st gen: simply providing free bikes; no accountability
  - 2nd gen: docking stations, coin-deposit system; still little accountability
  - 3rd gen: incorporating information tech; preventing bike theft successfully
- Few studies quantitatively evaluating bike share usage (Faghih-Imani & Eluru, 2015)
- A complement or substitute for the existing public transit?

# Background: last mile problem

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- “Transit that offers frequent and rapid service along the main lines but leaves the travelers a mile from their destinations with poor connecting options is rarely the mode of choice” ( Zellner, Massey, Shiftan, Levine, & Arquero, 2016).
- Bike share is often seen as a solution to this last mile problem
  - Some survey studies provide evidence for this statement (e.g., Martin & Shaheen, 2014)
  - Few studies have evaluated the statement by examining actual bike share use

# Background: Divvy

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- First launched in summer 2013
- >6,000 bikes, >580 docking stations
- Annual membership and 24-hour pass
- A Chicago Department of Transportation (CDOT) program
- Per-trip data available at Divvy webpage ([www.divvybikes.com/system-data](http://www.divvybikes.com/system-data))



Image source: [City of Chicago official website](#).

# Research Question

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- Does bike share serve as a solution to the last mile problem in public transportation?
- For all trips made from and to Divvy stations in proximity with CTA stops, is the likelihood of trips that are potentially multimodal i.e., made in connection with the public transit rides, greater than by random chance? If so, to what extent?

# Data

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- Divvy trip data for the year of 2016
  - 3.6 million individual bike trips
  - Start and end time, start and end location, trip duration, user type, gender, birth year
  - 581 docking stations and their locations (longitude and latitude)
- CTA data
  - All CTA stops and their locations (11,487 stops)
  - Scheduled time for all bus routes and rail lines for all stops (2.8 million observations)
- Others
  - Weather in Chicago (temperature and precipitation)
  - Other geospatial features (CBD, community area, demographic data, etc.)

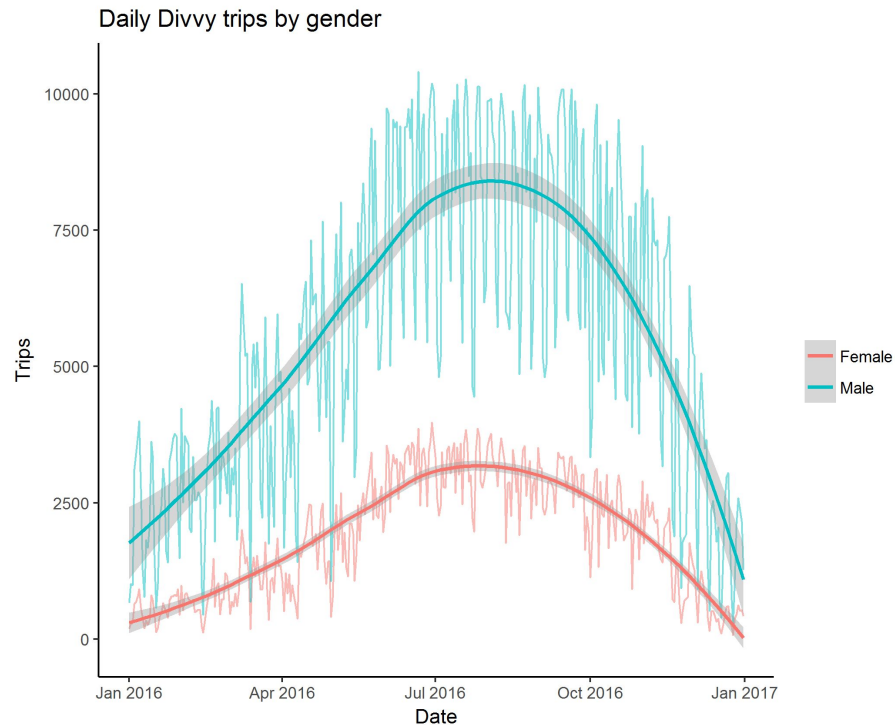
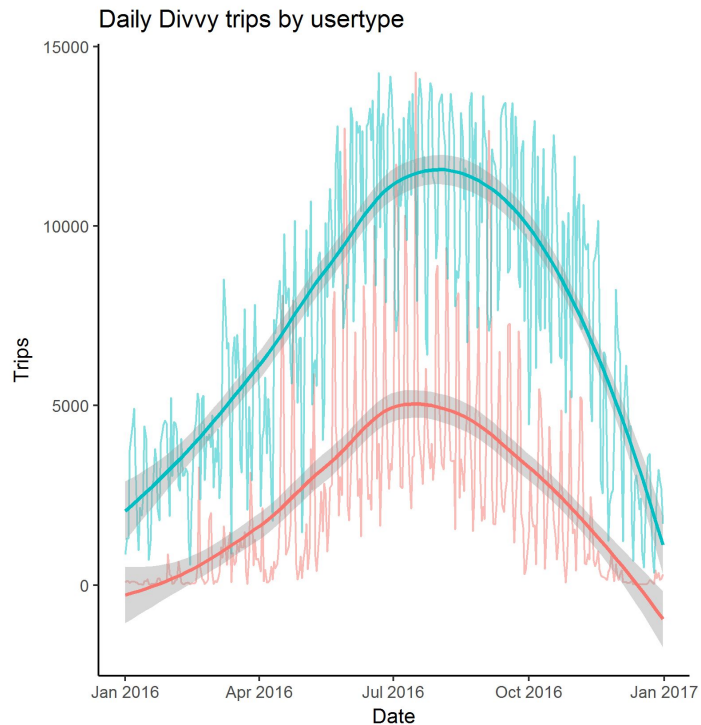
# Data: Divvy trips

Table 1: Descriptive summary of Divvy trips

Trip attributes	All Users		Members		Daily Customers	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Annual membership	76.1%	-	-	-	-	-
Gender	-	-	74.8%	-	-	-
Age	-	-	35.52	10.75	-	-
Weekday	72.5%	-	79.6%	-	49.6%	-
Rush hour	44.5%	-	52.7%	-	18.4%	-
Duration (min)	16.56	31.54	12.04	20.76	30.96	50.18
Duration (male)	-	-	11.57	19.87	-	-
Duration (female)	-	-	13.44	23.12	-	-
Proximity, from (50m)	46.8%	-	48.3%	-	42.0%	-
Proximity, from (100m)	72.5%	-	74.4%	-	66.5%	-
Proximity, from (200m)	88.0%	-	90.3%	-	80.9%	-
Proximity, from (300m)	92.5%	-	94.3%	-	87.1%	-
Proximity, to (50m)	47.0%	-	48.3%	-	42.9%	-
Proximity, to (100m)	72.6%	-	74.4%	-	66.8%	-
Proximity, to (200m)	88.2%	-	90.4%	-	81.1%	-
Proximity, to (300m)	92.6%	-	94.3%	-	86.9%	-



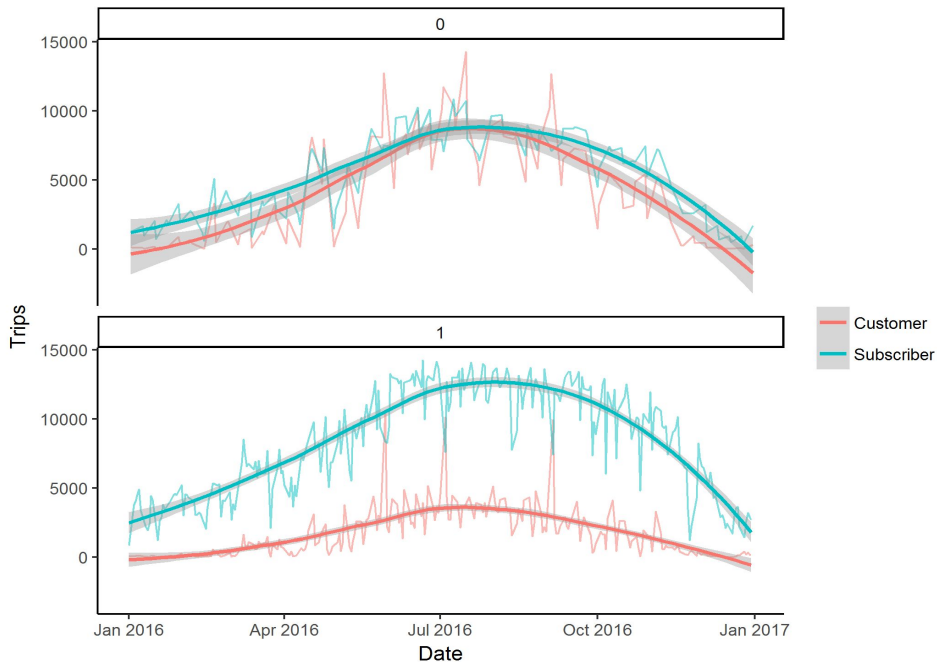
# Data: Divvy trips



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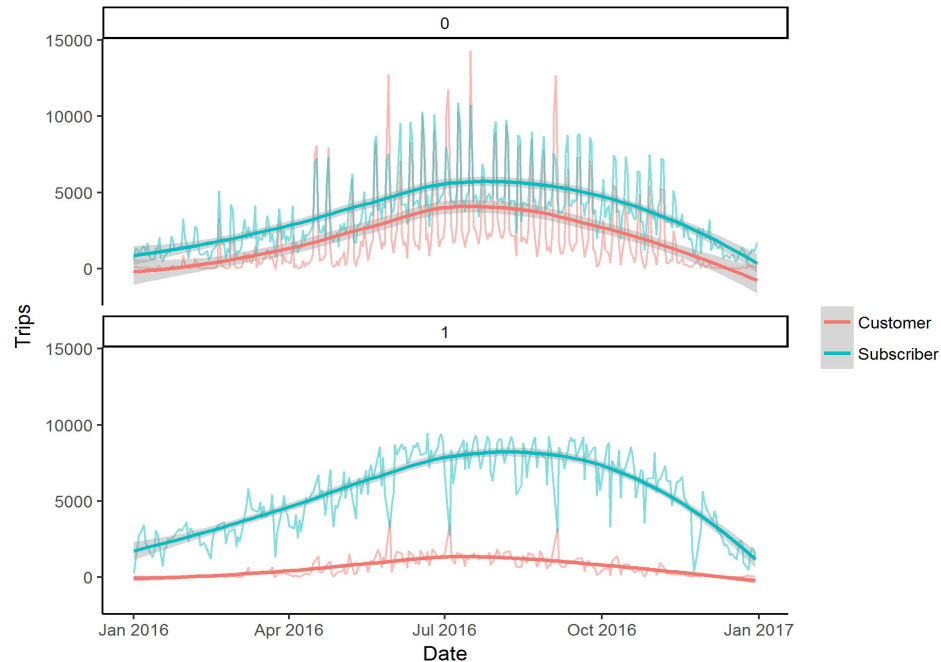
Daily Divvy trips by usertype and day of week

0 = weekends, 1 = weekdays



Daily Divvy trips by usertype and time of day

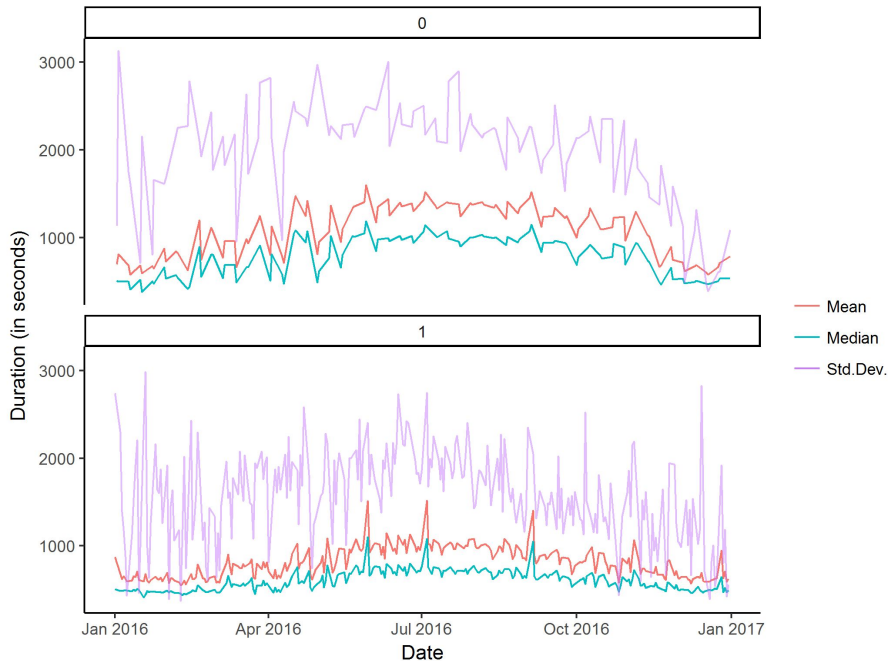
0 = not rush hour, 1 = rush hour



# Data: Divvy trips

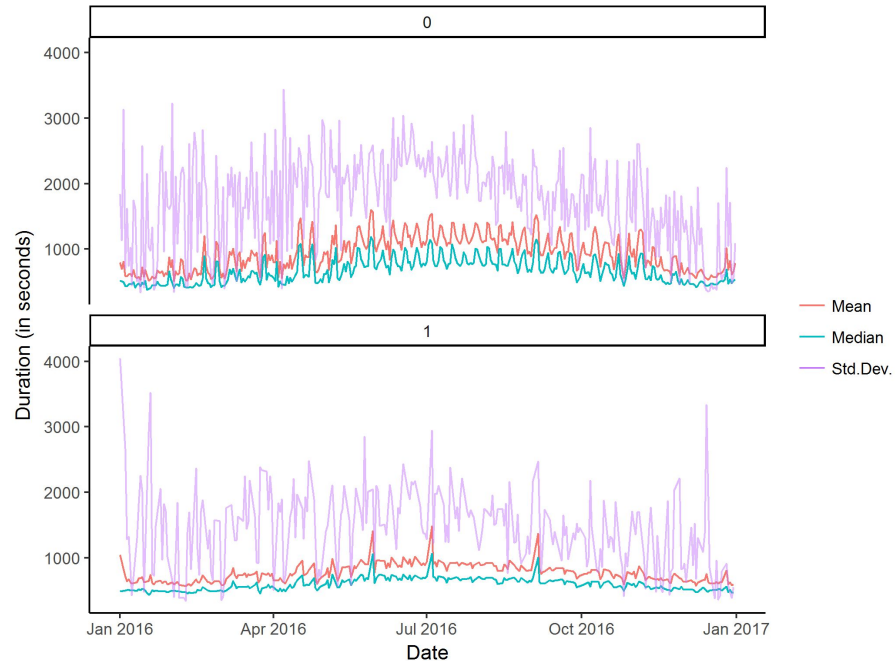
## Daily Divvy trip durations by day of week

Mean, median, and standard deviation; 0 = weekends, 1 = weekdays



## Daily Divvy trip durations by time of day

Mean, median, and standard deviation; 0 = not rush hours, 1 = rush hours



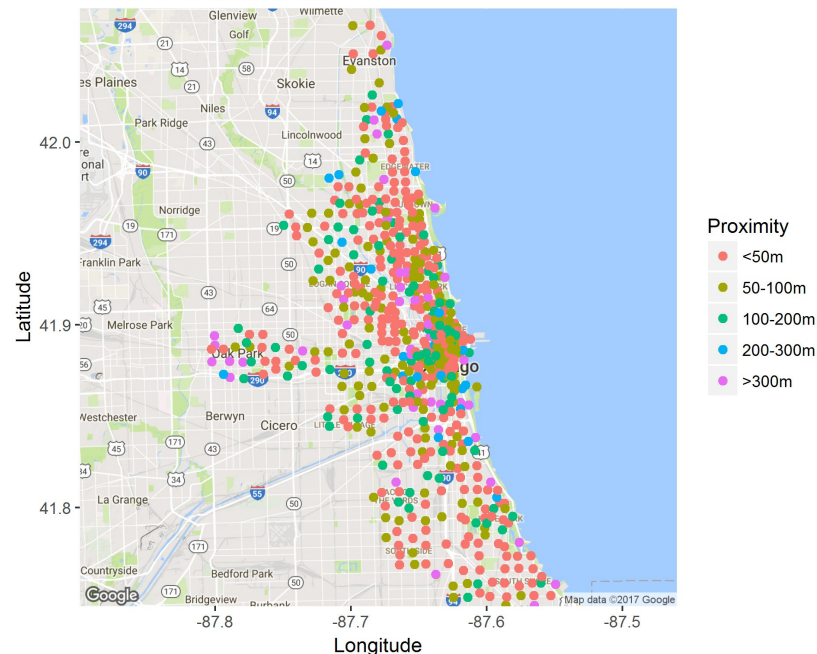
# Data: Divvy stations

Table 2: Descriptive summary of Divvy stations

Station attributes	Mean	Standard deviation
Number of trips originating	6188.27	8487.86
Number of trips terminating	6188.27	8655.73
Station capacity	17.19	5.56
Presence of CTA stops in proximity (50m)	48.4%	
Presence of CTA stops in proximity (100m)	73.1%	
Presence of CTA stops in proximity (200m)	88.8%	
Presence of CTA stops in proximity (300m)	92.6%	
Number of CTA stops in proximity (50m)	0.91	1.19
(only stations in proximity of CTA stops)	1.88	1.05
Number of CTA stops in proximity (100m)	1.98	1.82
(only stations in proximity of CTA stops)	2.70	1.60
Number of CTA stops in proximity (200m)	4.30	2.94
(only stations in proximity of CTA stops)	4.85	2.67
Number of CTA stops in proximity (300m)	7.66	4.60
(only stations in proximity of CTA stops)	8.27	4.22

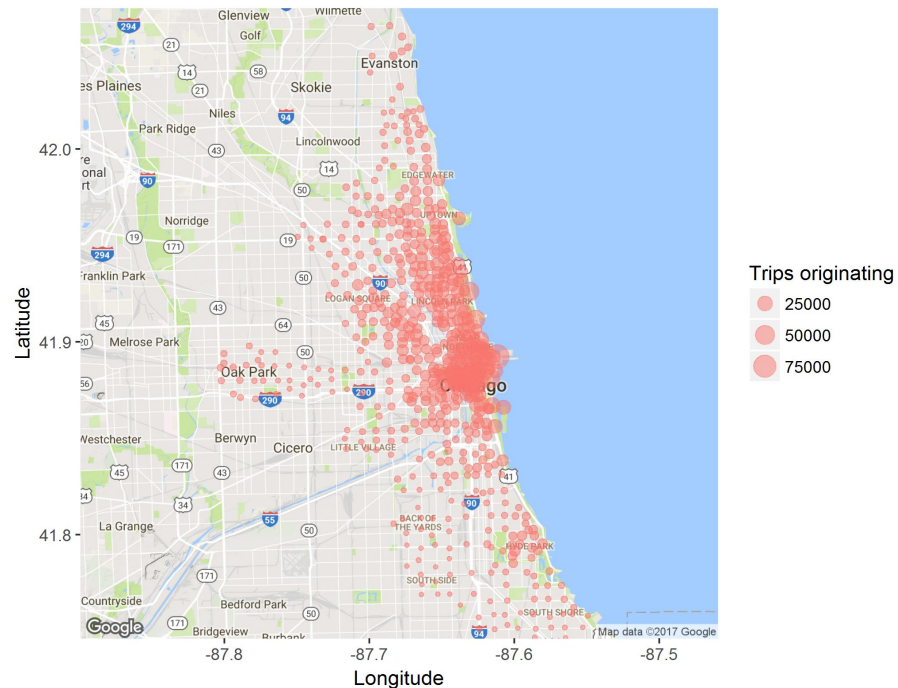
Divvy Stations by Proximity to CTA Stops

With different proximity standards

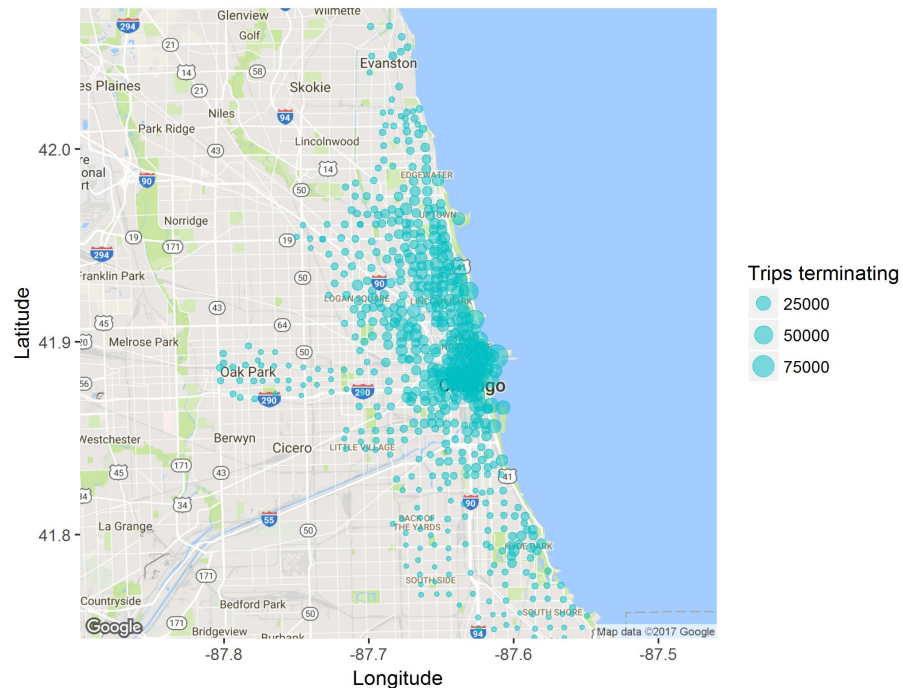


# Data: Divvy stations

Divvy Stations, Trips Originating



Divvy Stations, Trips Terminating



# Model

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## Outcome/dependent variable Y

- Potential multi-modality of each trip for the given proximity standard
  - If potentially multi-modal, the trip starts from/ends to a station in proximity with any CTA stops about the time when bus or rail arrive to/depart from such stops
  - Within the window of 1 to 5 minutes (assuming the trip was planned to be multi-modal)
- Proximity
  - Measured in Manhattan distance
  - Comparison of multiple proximity standards
    - 50m
    - 100m
    - 200m
    - 300m (used in most previous studies; e.g. Faghih-Imani & Eluru (2015))

# Model

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Attributes/independent variables  $\mathbf{x}$

- Trip-level attributes (user type, gender, age, trip duration)
- Temporal attributes (day of week, time of day, temperature, precipitation)
- Geographic attributes (CBD, population density, job density)

# Model

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Logistic regression (for each proximity standard)

- Outcome  $y$  for trip  $i$ :  $Pr(Y_i = y_i | p_i) = p_i^{y_i} (1 - p_i)^{(1-y_i)}$
- Probability function: 
$$p_i = \frac{\exp(\beta_0 + \beta' \mathbf{x}_i)}{1 + \exp(\beta_0 + \beta' \mathbf{x}_i)}$$
  - $p_i$  Probability that the trip  $i$  is potentially multi-modal
  - $\beta$  The vector of coefficients
  - $\mathbf{x}_i$  The vector of independent variables
- Likelihood function: 
$$L = \prod_{i=1}^N p_i^{y_i} (1 - p_i)^{(1-y_i)}$$



# Summary

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- Does Divvy offer a solution to the last mile problem for CTA rides?
- Comparison of various proximity standards

# Reference

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- DeMaio, P. (2009). Bike-Sharing: History, Impacts, Models of Provision, and Future. *Journal of Public Transportation*, 12(4), 41-56.
- Faghieh-Imani, A., & Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. *Journal of Transport Geography*, 44, 53-64.
- Martin, E. W., & Shaheen, S. A. (2014). Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two U.S. cities. *Journal of Transport Geography*, 41, 315–324.
- Zellner, M., Massey, D., Shiftan, Y., Levine, J., & Arquero, M. J. (2016). Overcoming the Last-Mile Problem with Transportation and Land-Use Improvements: An Agent-Based Approach. *International Journal of Transportation*, 4(1), 1-26.