Impacts of Travel Demand Information Diffusion on Reducing Empty Vehicle Miles Traveled by Ridesourcing Vehicles

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Background

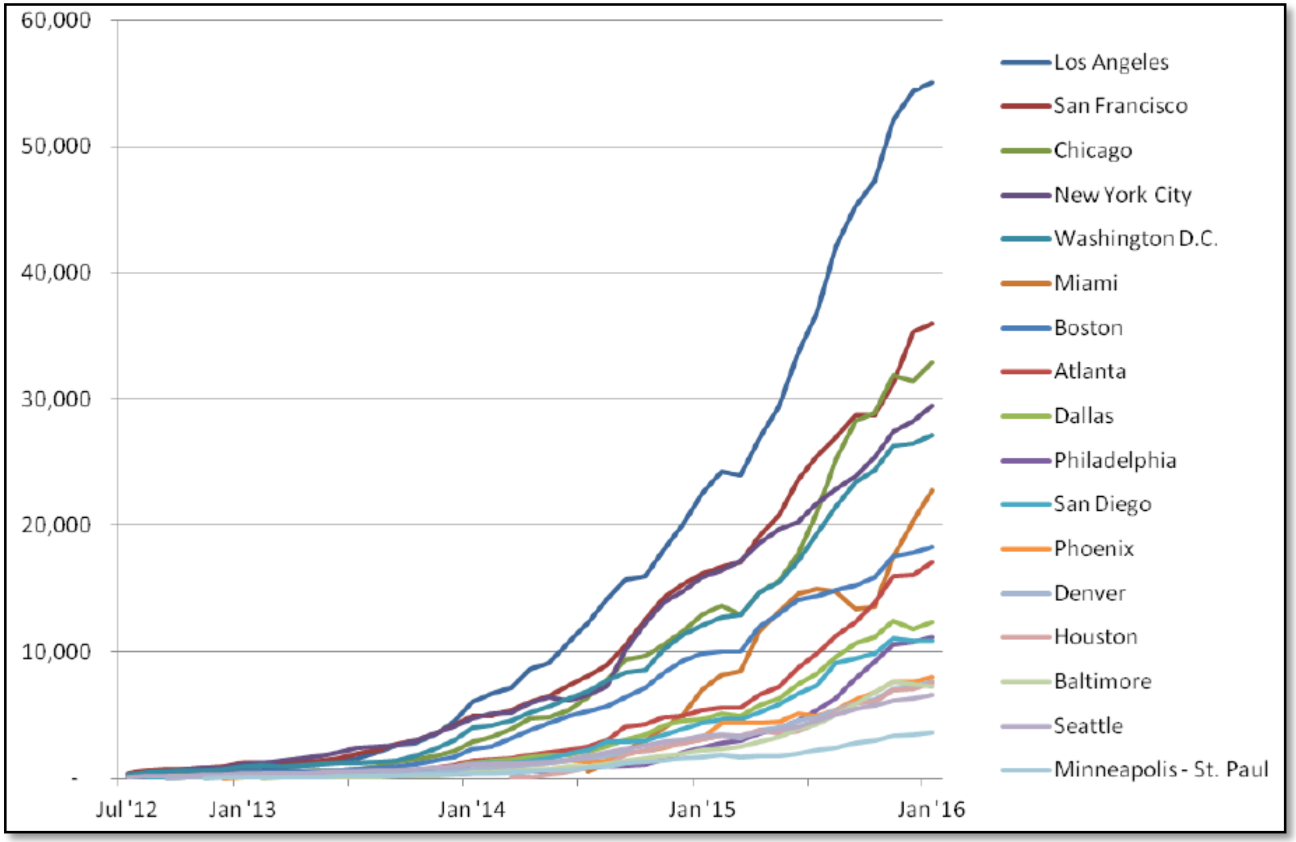
- Transportation Network Companies (TNCs) are rapidly gaining market share.

- Available in several cities in North America and are prevalent transportation mode alternatives in large metropolitan areas.
  In 2017, Uber had 375.5 million rides in North America (1)

- TNCs are redefining the way people travel, but are also causing new transportation and energy problems that require immediate attention.

TNC Are Experiencing Exponential Growth

No. of Uber drivers making at least 1 trip/month



Source: Uber

TNCs are Increasing Mobility – But at What Cost?

Ride-Hailing Apps Are Clogging New York's Streets
The city's traffic woes owe in part to more people choosing private transit over public.
The Atlantic

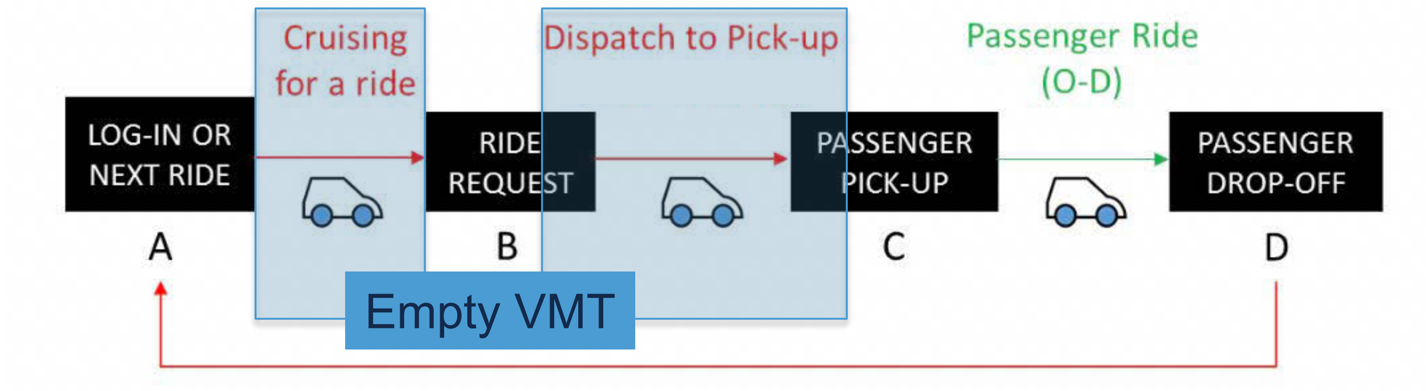
TNC growth has added 976 million miles of driving to city streets, citywide, since 2013.
-Schaller Consulting Report

Studies are increasingly clear: Uber and Lyft congest cities
Chicago Tribune

Evidence From Boston That Uber Is Making Traffic Worse
STREETSBLOG USA

Research Motivation: Reducing Empty TNC Mileage

TNC services → empty vehicle miles



Example Cases: San Francisco (SFCTA, 2018) – INRIX data

47% of the increase in vehicle miles travelled from 2010 to 2016

Denver (Henao and Marshall, 2018) – Collected by driver data

41% empty miles share for a single Uber/Lyft driver in Denver

Austin (Komanduri et al., 2018) – RideAustin TX data

37% empty miles of total vehicle miles traveled (VMT)

Empty VMT Scenarios

- Once the passenger is picked up and dropped off at their destination, the TNC driver (assuming they are still in service) can do one of four things:
  - **P**ark in a close-by location and wait for the next trip request
  - **A**ccept another request and travel to pick up the next passenger
  - **C**ruise around until they find another trip to serve
  - **T**ravel to a known demand pocket such as the airport or the central business district (or a suggested high-demand location) while waiting to be assigned to a customer

Future Travel Demand Information: Impact on Empty VMT

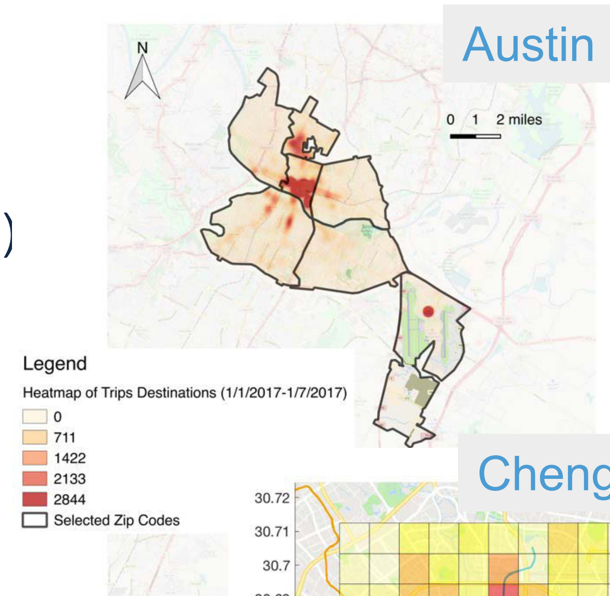
- What if ride-hailing drivers received information on future demand?
  - Hypothesis:
    - Reduction of cruising without passengers & empty mileage
    - Energy & environmental savings
  - Assumption:
    - Information on high future demand within next β minutes incentivizes drivers to wait in place for next ride
  - Method: Machine learning applications to forecast demand
  - Constraints: Cap drivers waiting time β to 5−20 minutes between rides
  - Ride assignment: Next closest ride within ZIP code of recent rider drop-off

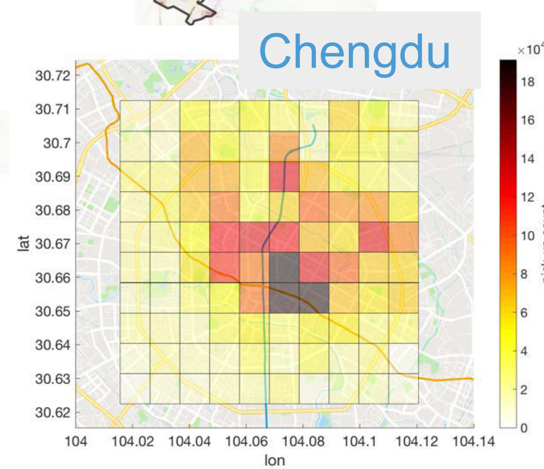
Application – Data Sources

Travel info diffusion effects on vehicle empty mileage case studies

Trip-level analysis using 1 week data from:

- RideAustin (Austin, TX, USA)
  - 28,586 trips, 16,930 drivers
- DiDi Chuxing (Chengdu, Sichuan, China)
  - 1,048,575 trips, 216,927 drivers





Brief Data Overview

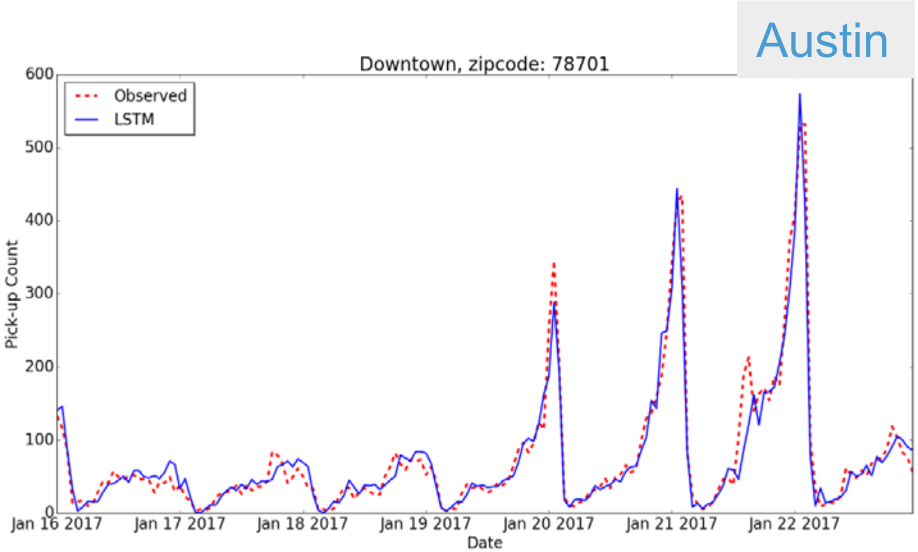
	Descriptive Statistics	Trip Distance (mi)	Estimated Deadheading Distance (mi)
RideAustin Sample	Mean	4.27	3.91
	Median	2.81	2.31
	Std. Dev.	4.12	3.12
DiDi Chuxing Sample	Mean	1.96	1.52
	Median	1.72	0.84
	Std. Dev.	1.29	1.66

TNC Demand Forecasting

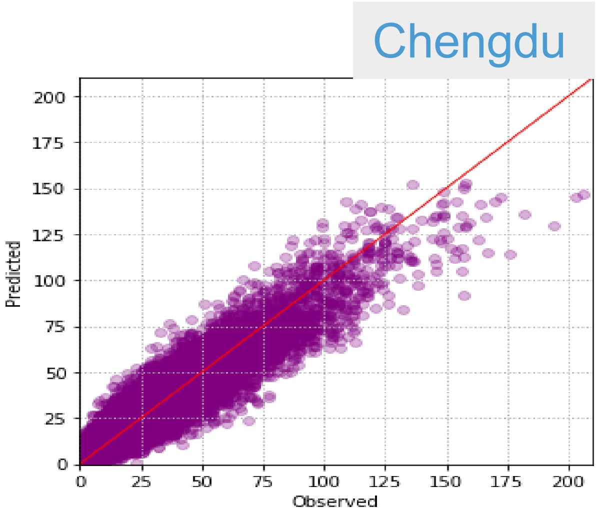
Long Short-Term Memory (LSTM) network for demand prediction

Recurrent neural network architecture learning time series data with long time spans and high dimensions

- 1-hour ahead prediction for RideAustin, 10-minute ahead prediction for DiDi
- Performance check based on RMSE and MAE



Ride-hailing trip demand prediction results for Austin TX, RideAustin 1 week data – Details in Hou et al. (2019)



Ride-hailing trip demand prediction results for Chengdu, DiDi 1 week data – Details in Chao and Hou (2019)

Drivers Waiting in Place – Heuristic Algorithm

Which drivers are more likely to wait in place after receiving future travel demand info?

Probability that a driver waits for a trip j to be generated at zd_i of their last trip destination i is binomially distributed with maximum probability of success equal to a threshold a

Algorithm 1 Algorithm for determining trips' destinations where information provision is provided to ridesourcing drivers

```
Initialize: Import trip destinations i ∈ I & zd_i the zip codes of trip destinations, PT_{zd_i t} the trips predicted at destination i during time, day, and month t (hourly categorization). Assume threshold a and r_it ∈ [0,1] uniformly distributed.
for t ∈ T do
    max PT_t
    for i ∈ I do
        X_it = a * PT_{zd_i t} / max PT_t
        if X_it > r_it then
            W_it == 1
        else
            W_it == 0
        end if
    end for
end for
```

$$X_{it} = a \cdot \frac{P_{zd_i t}}{\max PT_t}$$

$PT_{zd_i t}$: predicted trips at zone (from ML application)

$\max PT_t$: the max. number of trips predicted the following hour t

- r_{it} random $\in [0,1]$
- Driver of a trip where $X_{it} > r_{it}$ waits in place for the next rider pickup
- $X_{it} \leq r_{it}$ trip i ineligible for the following trip-matching process

Assignment - Heuristic

Determine next trip origin to assign driver who is waiting in place

Conditions

- Next trip candidates adhere to temporal and spatial constraints
- Candidate origin should be within the same ZIP code or grid cell as the previous trip's destination
- Driver is willing to wait in place for the next trip to arrive for less than a specific time threshold β
- Trip's origin k meets constraints and minimizes deadheading distance, then it occurs next

Algorithm 2 Algorithm for minimizing deadheading while matching trips based on information provision

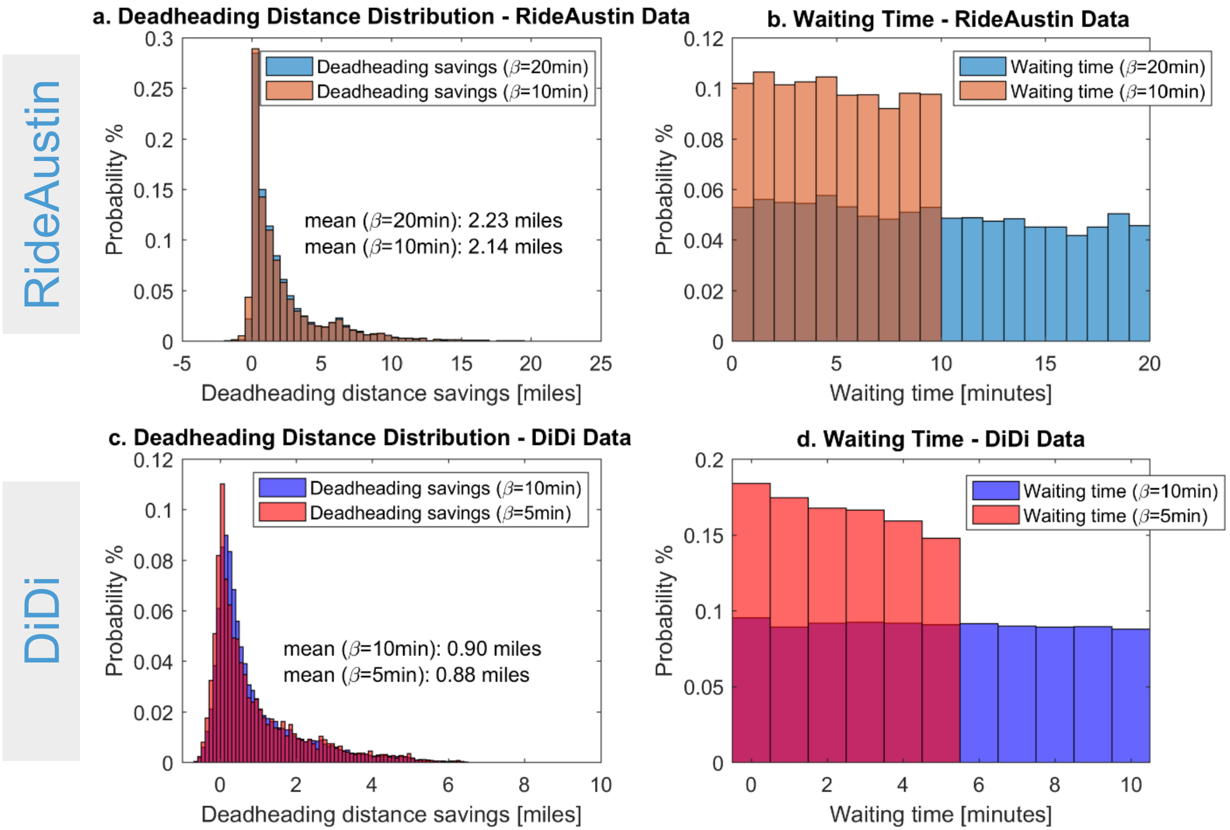
Initialize: Import trip destinations i & trip origins j, zd_i and zs_j as zip codes of trip destinations and trip origins, and td_i, ts_j as time reaching destination i and time of pick up at origin j.

for $i \in C : C \leftarrow i$ where $W_i = 1$ **do**
    $minD_i = 100000, minA_i = -1$
    for $j \in J$ **do**
        $\text{haversine}(i, j) = dh_{ij}$
        if $ts_j > td_i + \frac{dh_{ij}}{s}$ *and* $szd_i = zs_j$ *and* $ts_j - (td_i + \frac{dh_{ij}}{s}) \leq \beta$ **then**
            $j \in O$
        else
            $j \notin O$
        end if
        for $j \in O$ **do**
            if $temp < dh_{ij}$ **then**
                $minD_i = temp$
                $minA_i = j$
            end if
        end for
    end for
end for

Note:
Drop-off and pick-up times are not flexible

Empty Mileage Reductions & Energy/Cost Savings

Application outputs: **Average Trip-Level Savings**



VMT: 67.7% – 78% empty VMT reduction/trip

Energy: drivers save 0.08 – 0.10 gallons/trip

Cost: cost savings 23 – 26 cents/trip

VMT: 55% – 59% empty VMT reduction/trip

Energy: between 0.035 – 0.05 gallon per trip

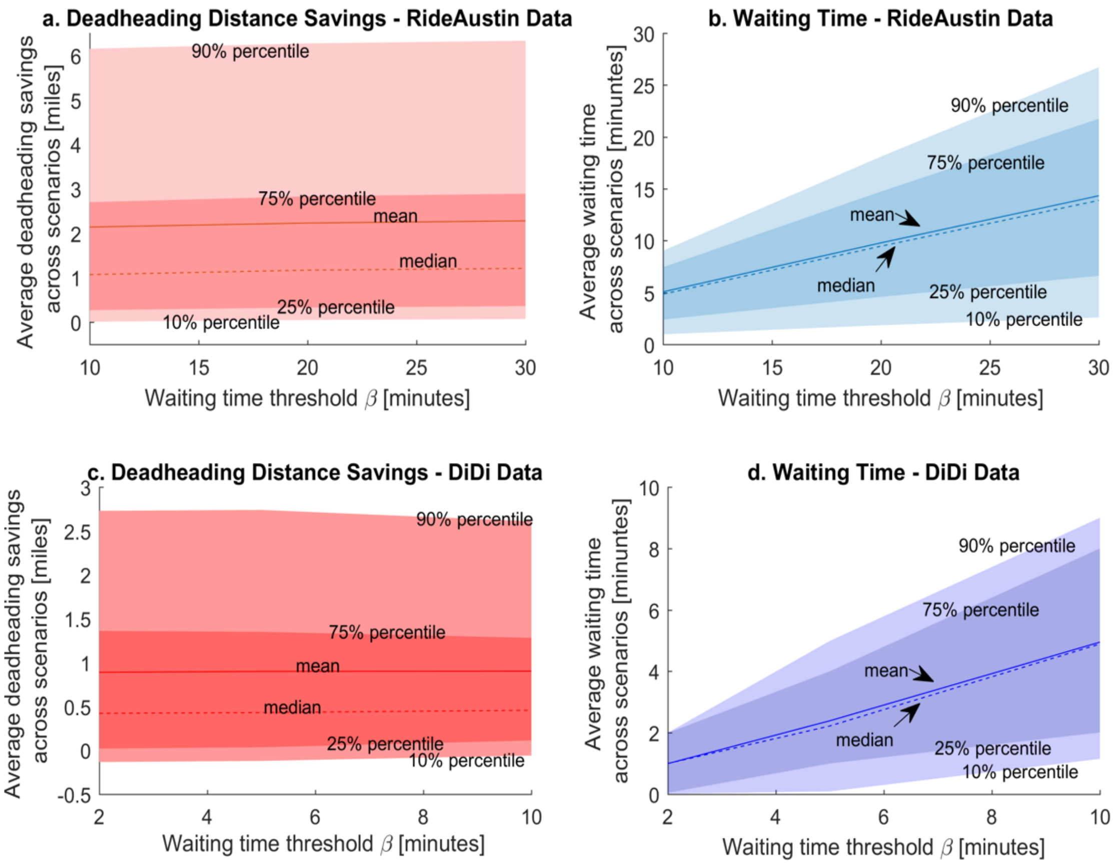
Cost: drivers save 11 – 13 US cents/trip

Sensitivity Results – Waiting Time Parameter Impact

Application outputs: **Distribution of Trip-Level Savings**

RideAustin

DiDi

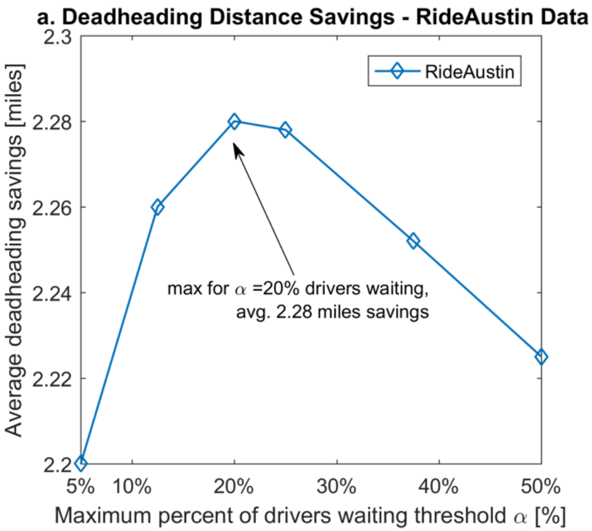


- Waiting time ↑ then deadheading VMT ↑
- Distribution uncovers avg. trip-level deadheading savings vary -0.1 – 6 mi

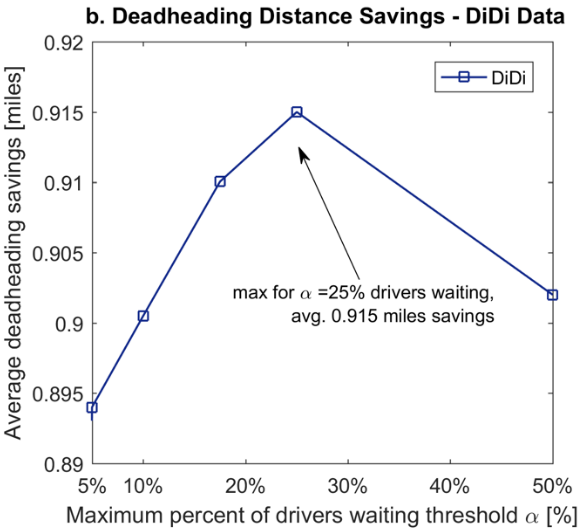
- Distribution uncovers avg. trip-level deadheading savings vary -0.08 – 2.7 mi

Sensitivity Results – Max Drivers Waiting Parameter Impact

RideAustin



DiDi



Scenario: Driver is willing to wait up to a threshold of β equal to 20 and 10 minutes for the RideAustin and DiDi data, respectively

Application: Varying threshold a, where a denotes the maximum percent of drivers that will be waiting based on the information received

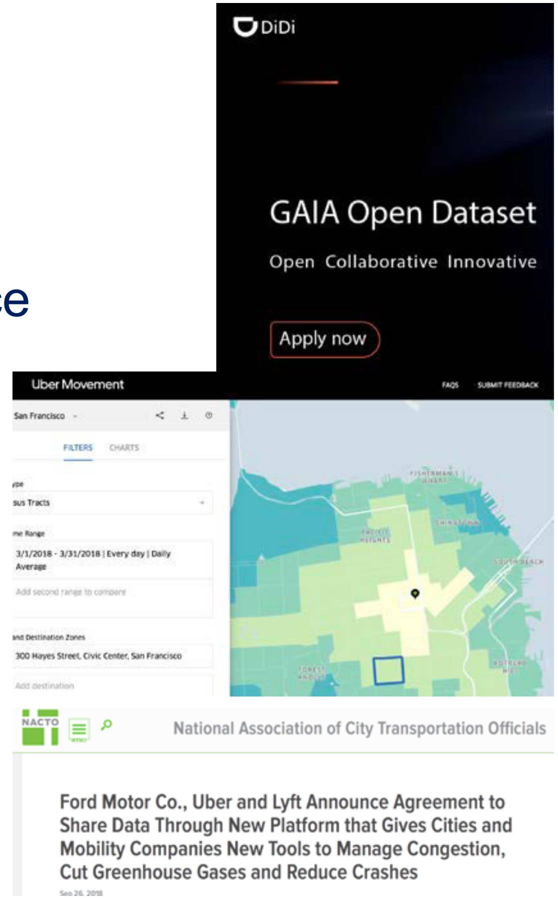
Results: 20% and 25% threshold results in max savings for the regions examined respectively, but heavily dependent on data

Conclusions & Future Research

- Travel demand information diffusion can help:
  - Curb empty vehicle miles [up to 78% per trip]
  - Reduce drivers operational costs, wear & tear, energy consumption
  - May require provisions for designated curb space for ride-hailing vehicles

- Extend application of the algorithm to different datasets

- Explore variability in driver behavior and impact on passenger wait time



Thank you!

Questions?

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