

Using network science and data visualization to assess the potential of urban sharing economies

Technical University of Denmark, Copenhagen, Apr 4, 2017

Michael Szell

@mszll

Research with: P. Santi, G. Resta, R. Tachet, O. Sagarra, S. Sobolevsky, S.H. Strogatz, C. Ratti

Visualizations with: S. Bogner, B. Gross, J. Lee, T. Lauer, et al.

Urban transportation is facing serious issues

Pollution



Traffic jams



Fatalities



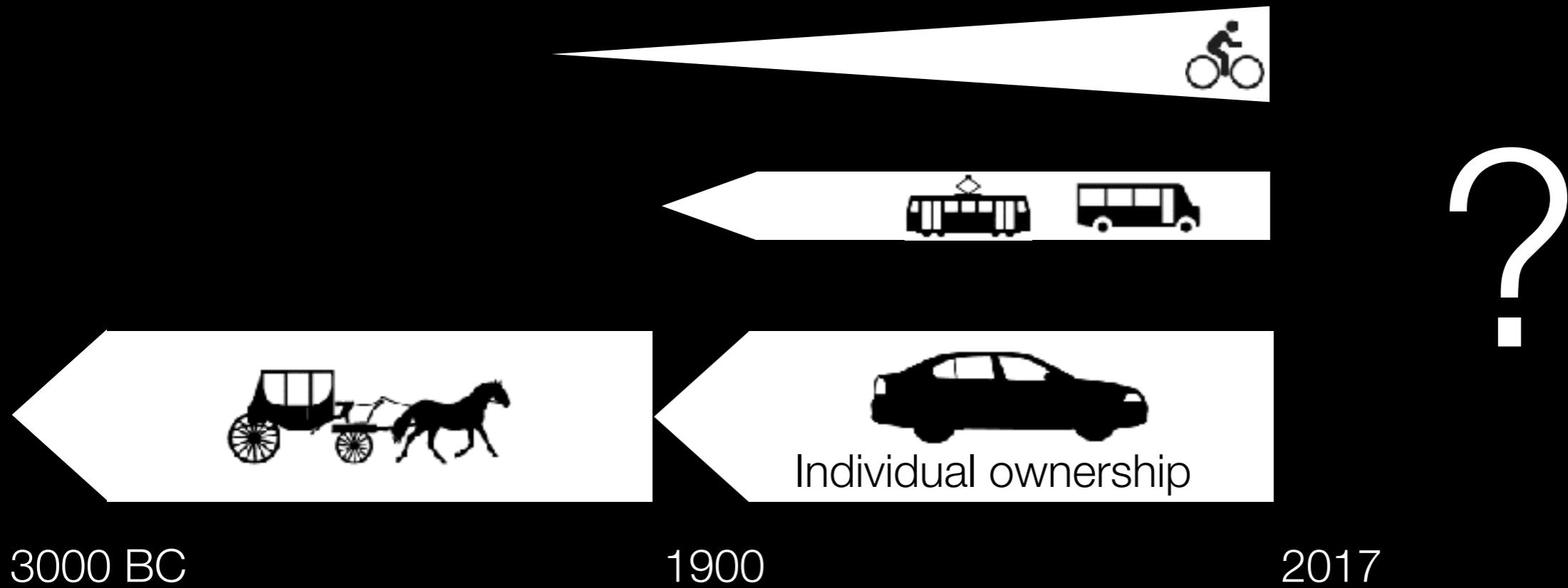
3.7 Mio.

1.2 Mio.

How efficient is urban transport?

We don't know.

Urban transportation is at a turning point



Urban transportation is changing

Vehicle sharing



Ownership → Accessibility

Botsman, R. and Rogers, R. HarperCollins, New York (2010)
Eckhardt, G.M. and Bardhi, F. Harvard Business Review (2015)

Urban transportation is changing

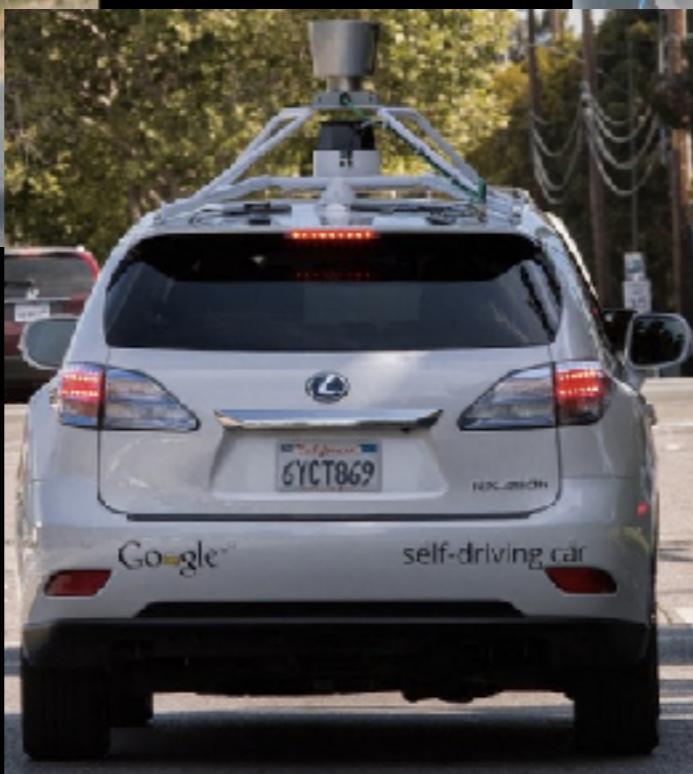
Algorithms and mobile technology
to improve existing services



Ownership → Accessibility

Urban transportation is changing

Self-driving cars



Lack of driver further motivates giving up ownership

The taxi system is inefficient



High emissions, cost, waiting times

Real-time data sets are available



Real-time data sets are available

Can we use realtime data and mobile technology to

- 1) Quantify existing taxi systems
- 2) Design an improved system?



NYC
13,500 cabs

Real-time data sets are available

Can we use realtime data and mobile technology to

- 1) Quantify existing taxi systems
- 2) Design an improved system?



Goals

- more efficient
- less emissions
- affordable alternative

NYC

13,500 cabs

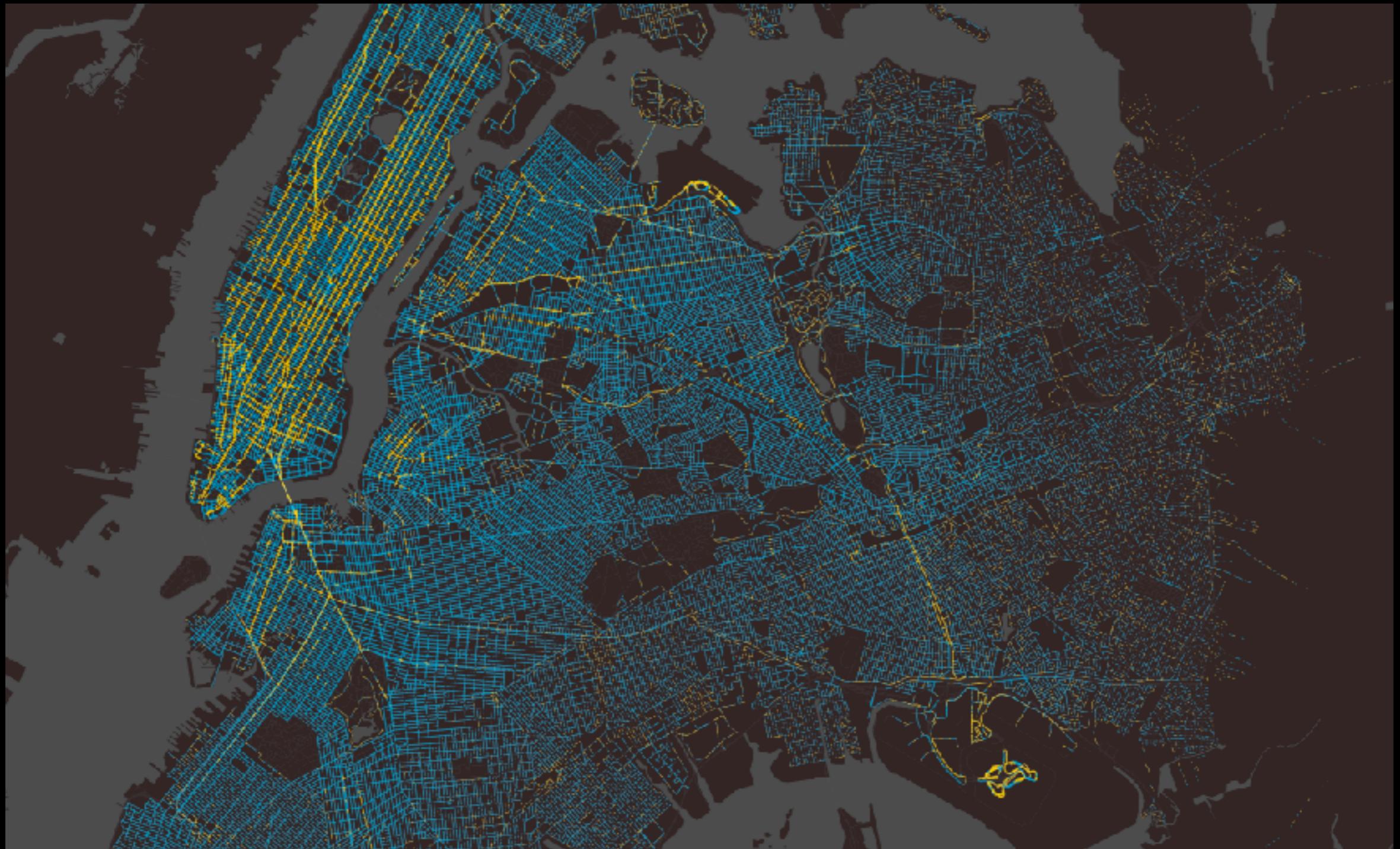
PAPER 1



Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S.H. and Ratti, C. PNAS 111 (2014)

Step 1: Analyze data

NYC taxi trips in 2011



13500 cabs

150 million trips ~400.000 per day

Pickups

Dropoffs

Step 1: Analyze data

Pickups

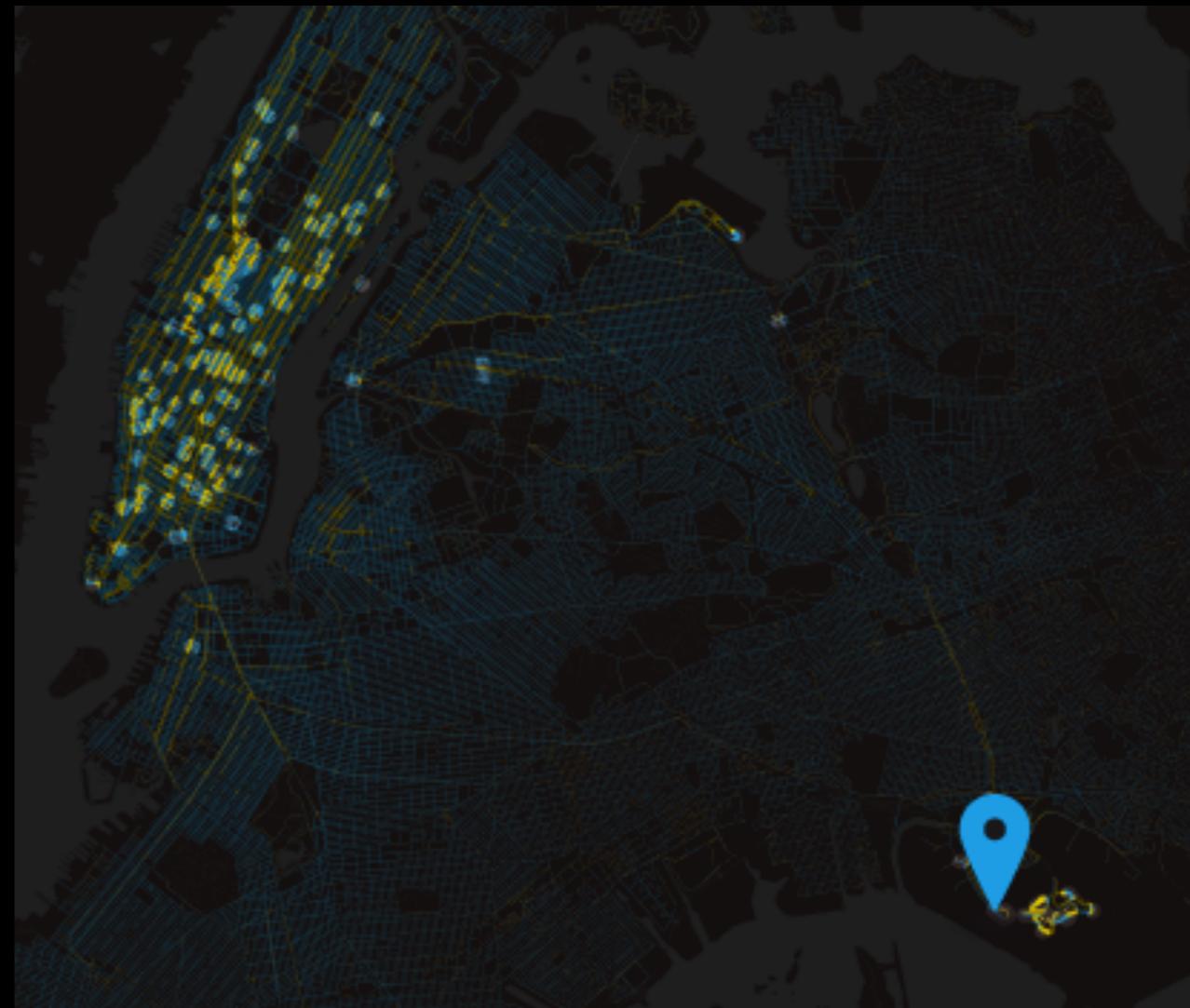
Dropoffs



Step 1: Analyze data



Destinations



Origins



Pickups



Dropoffs

Trips can be combined

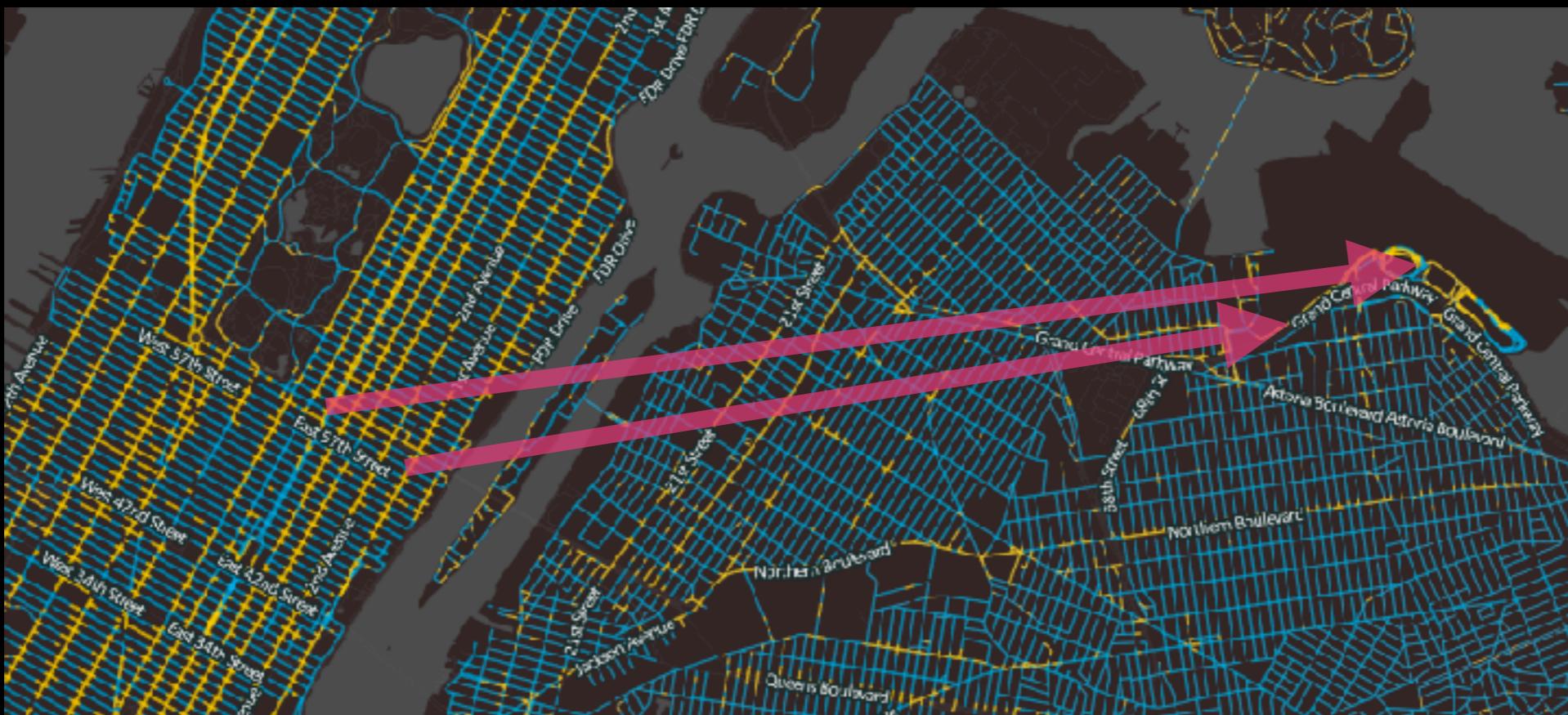


Pickups

Dropoffs

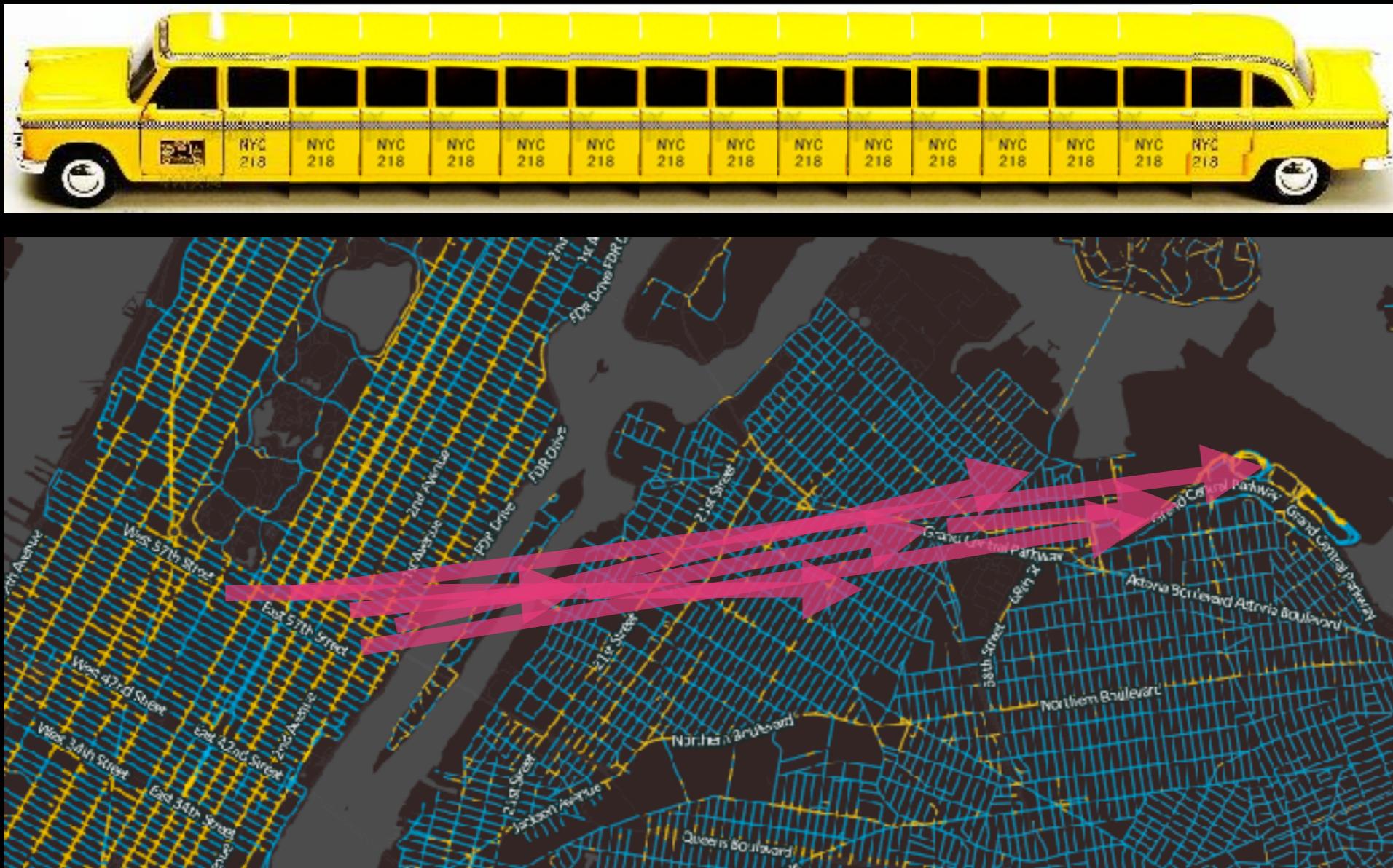
Step 2 : A new dispatch process

Combine 2 trips



Step 2 : A new dispatch process

Combine k trips



Street network

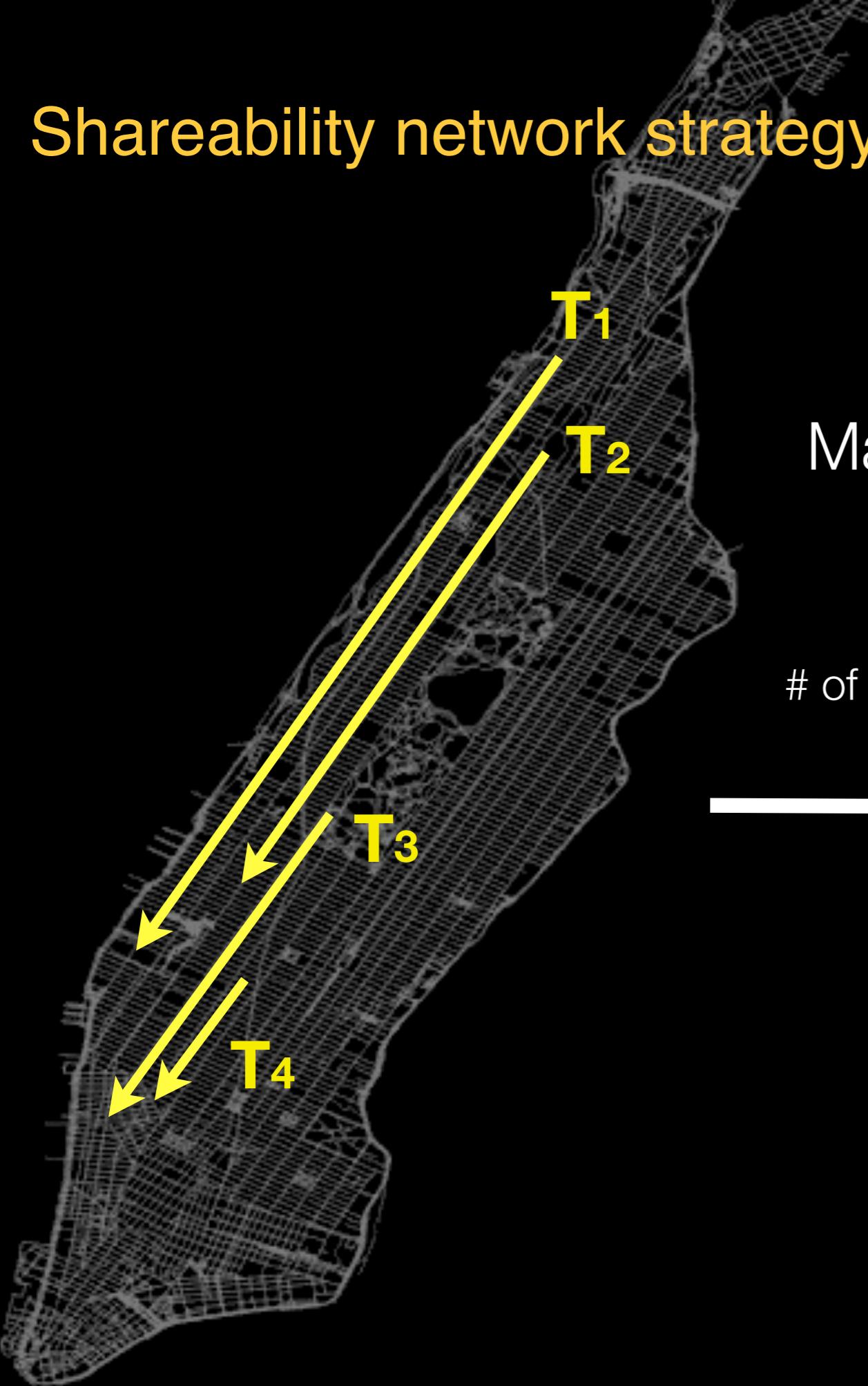


Extraction from
OpenStreetMap

9000 street
segments

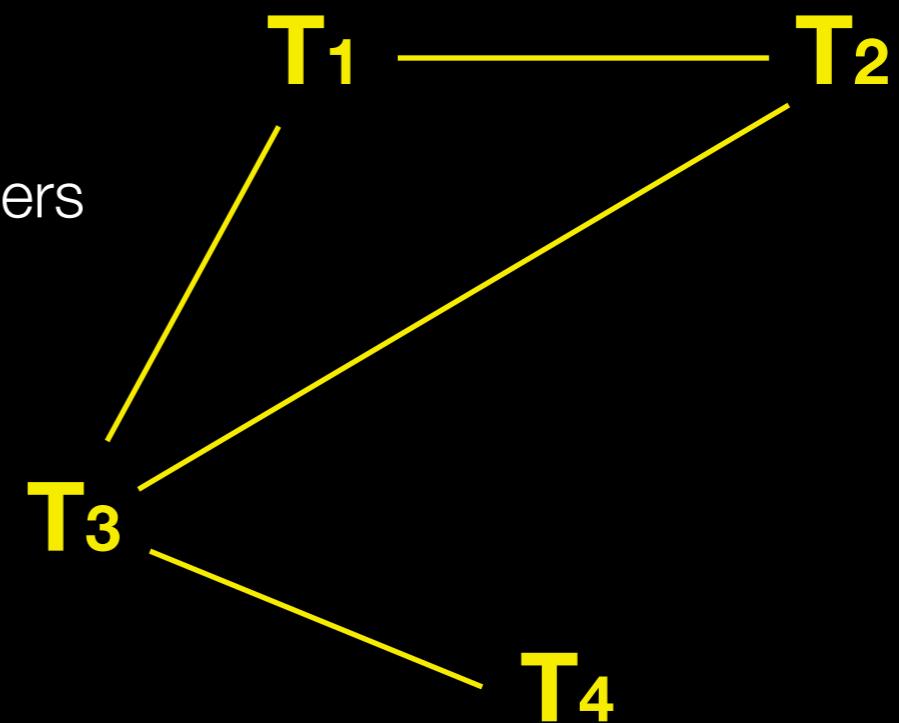
Matching GPS-
coordinates

Shareability network strategy

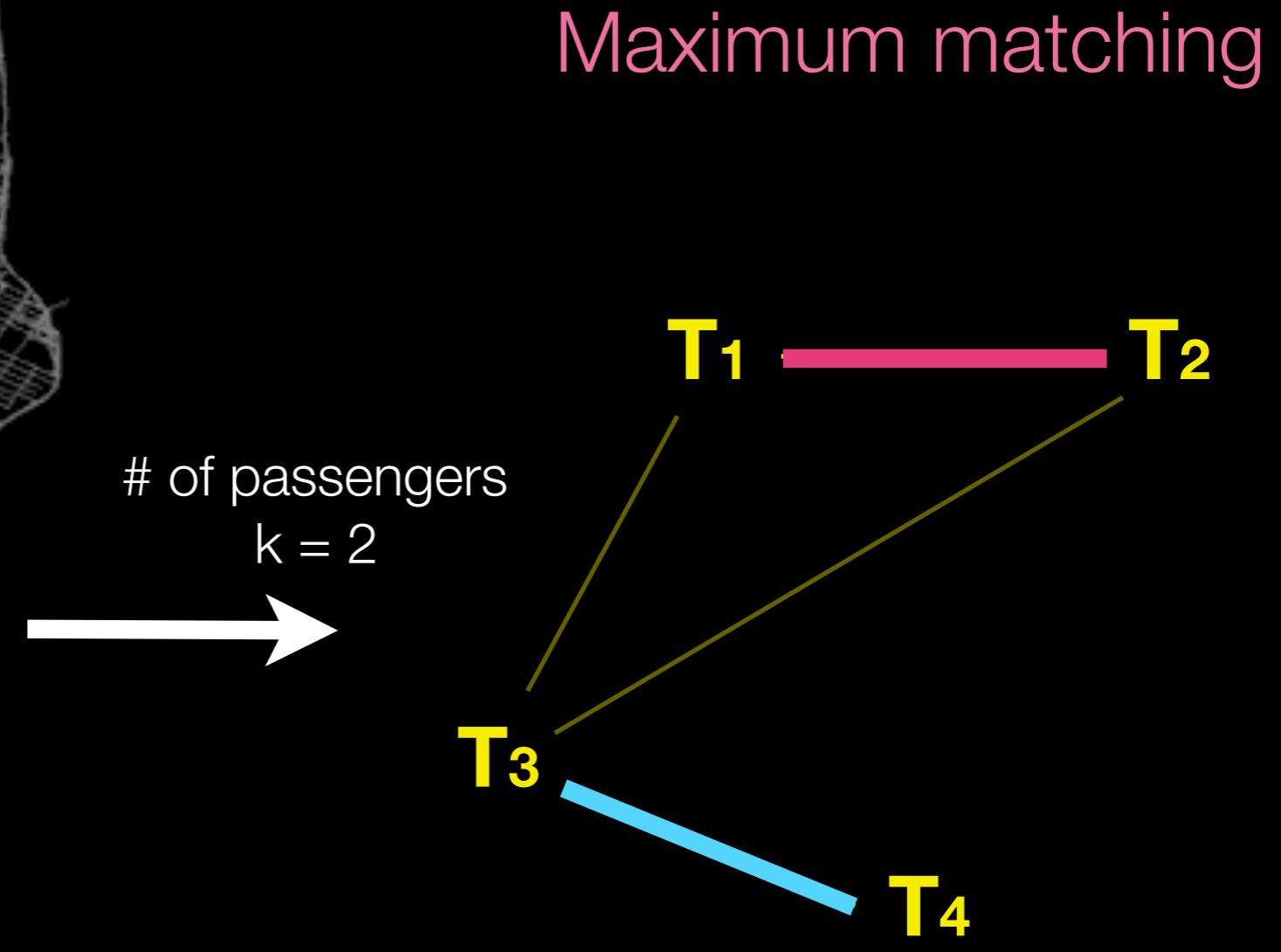
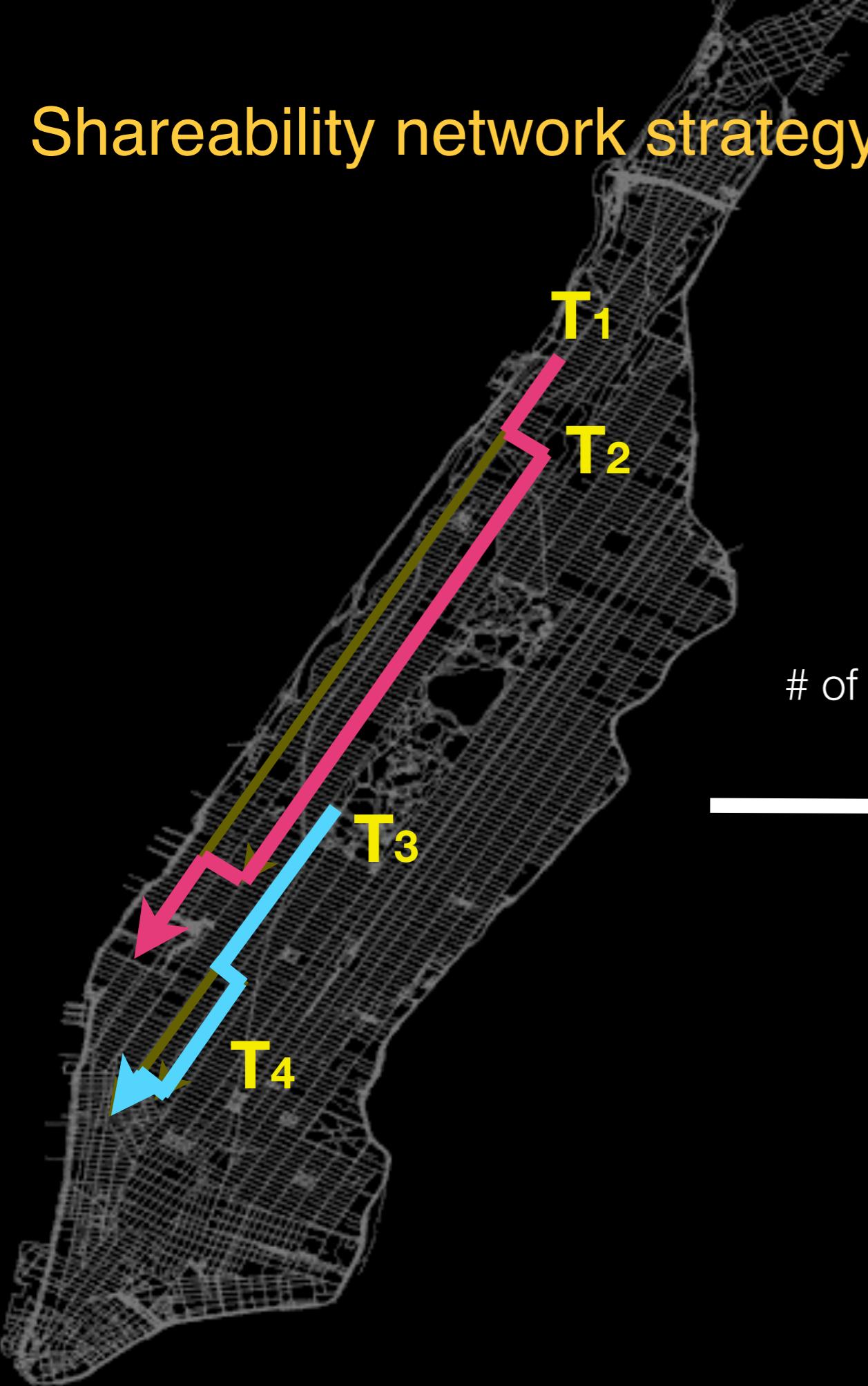


Mapping

of passengers
 $k = 2$

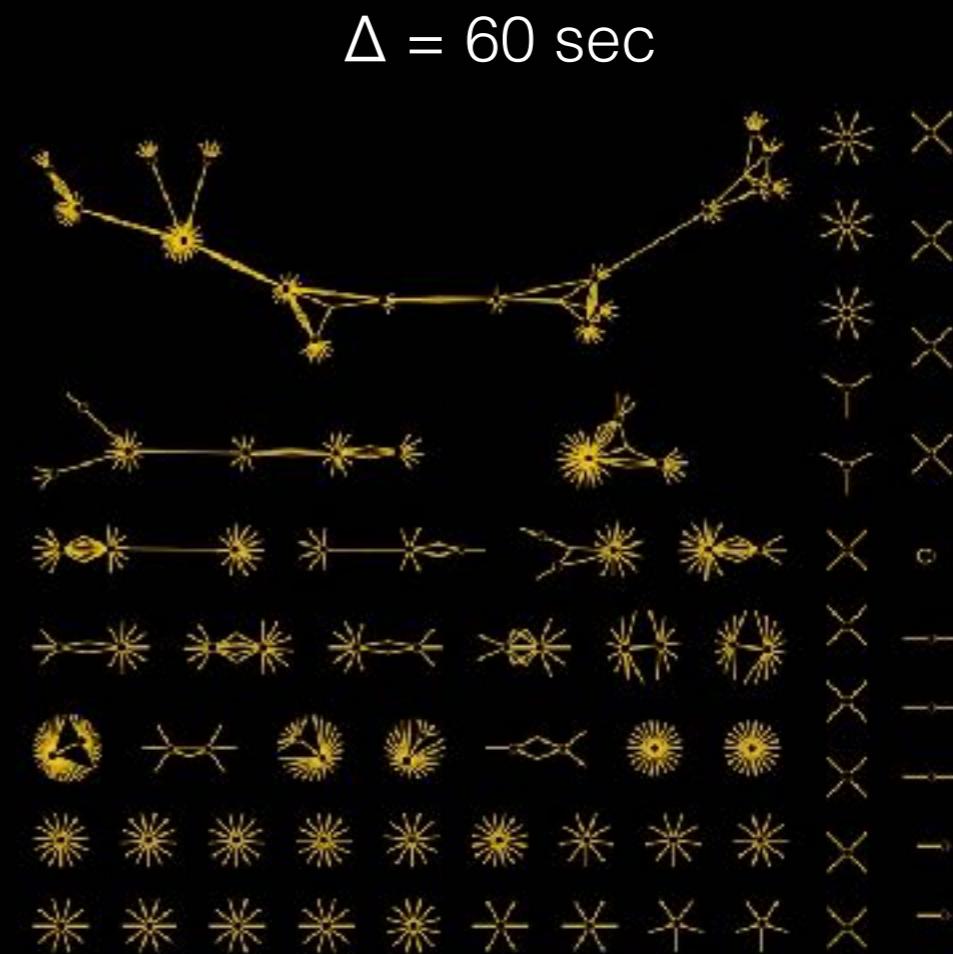
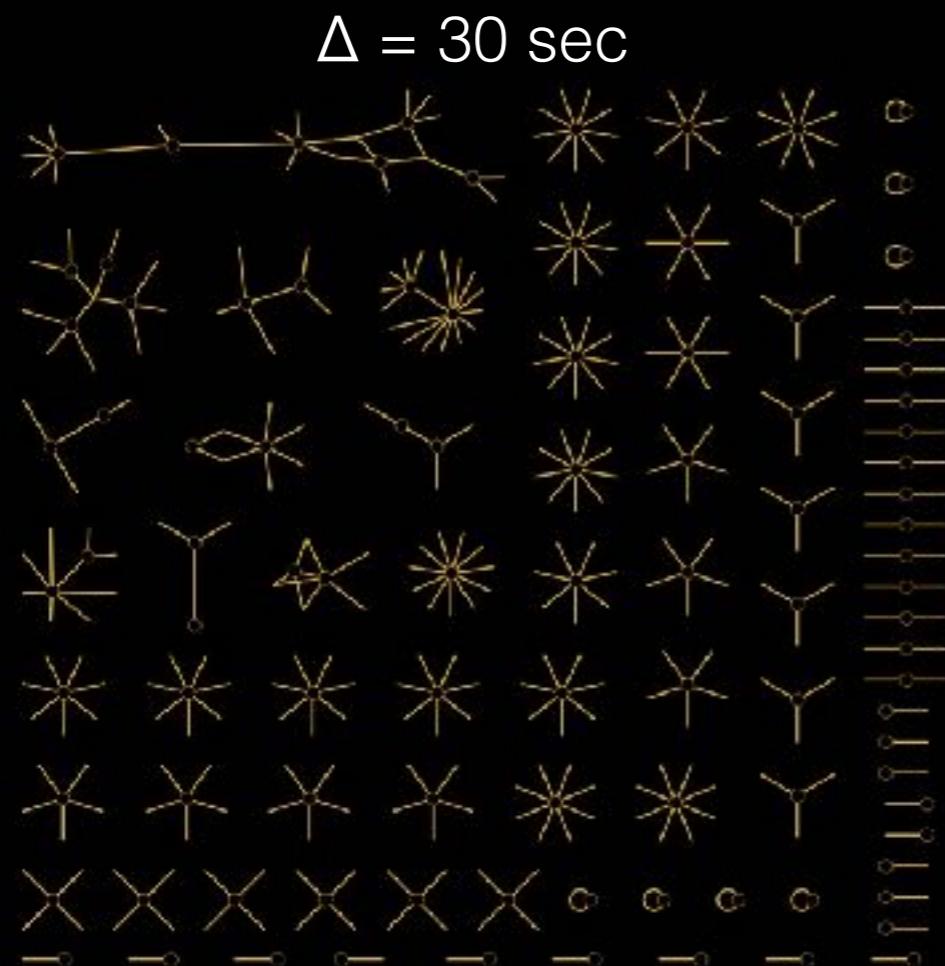


Shareability network strategy



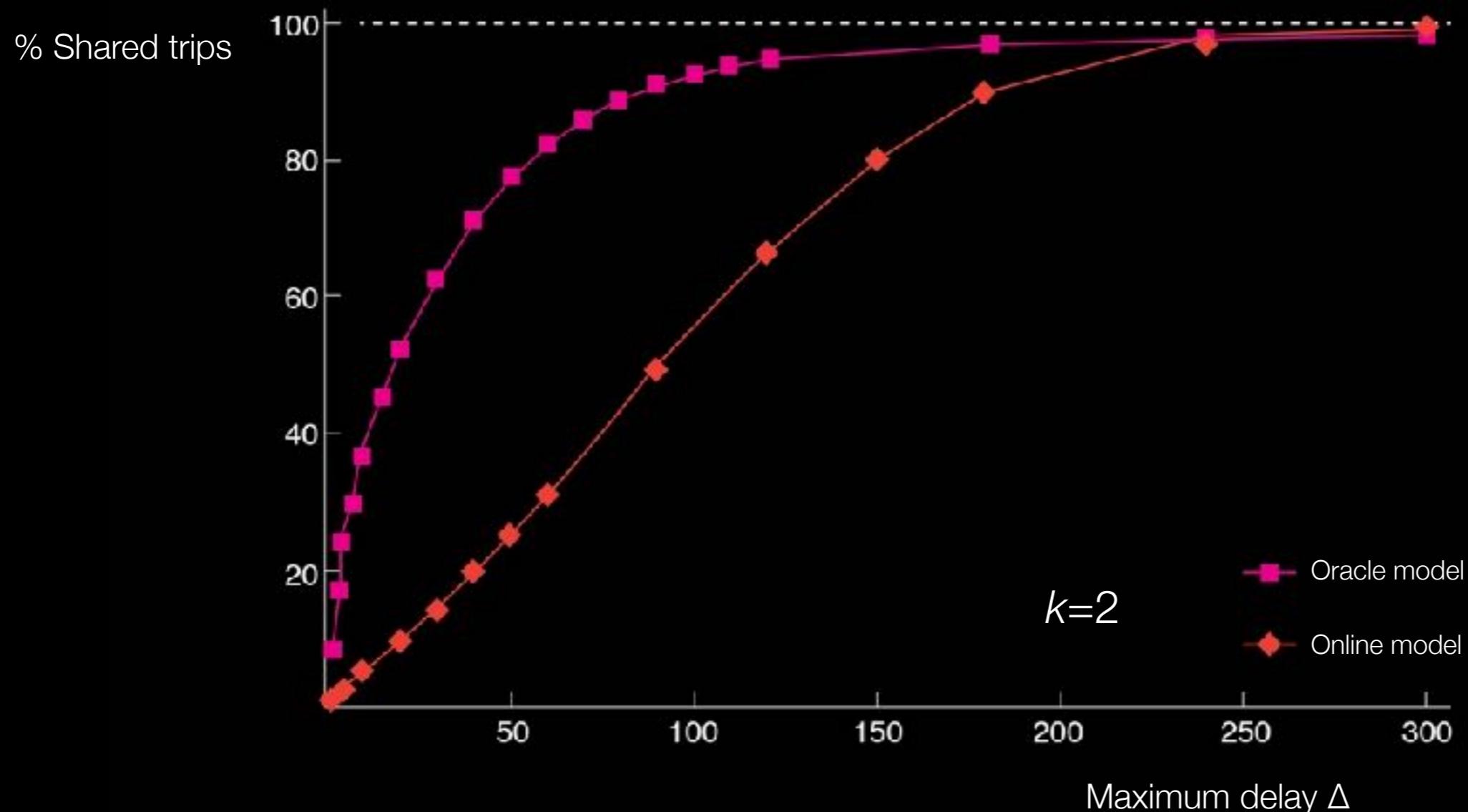
Shareability network densification

Maximum time delay Δ



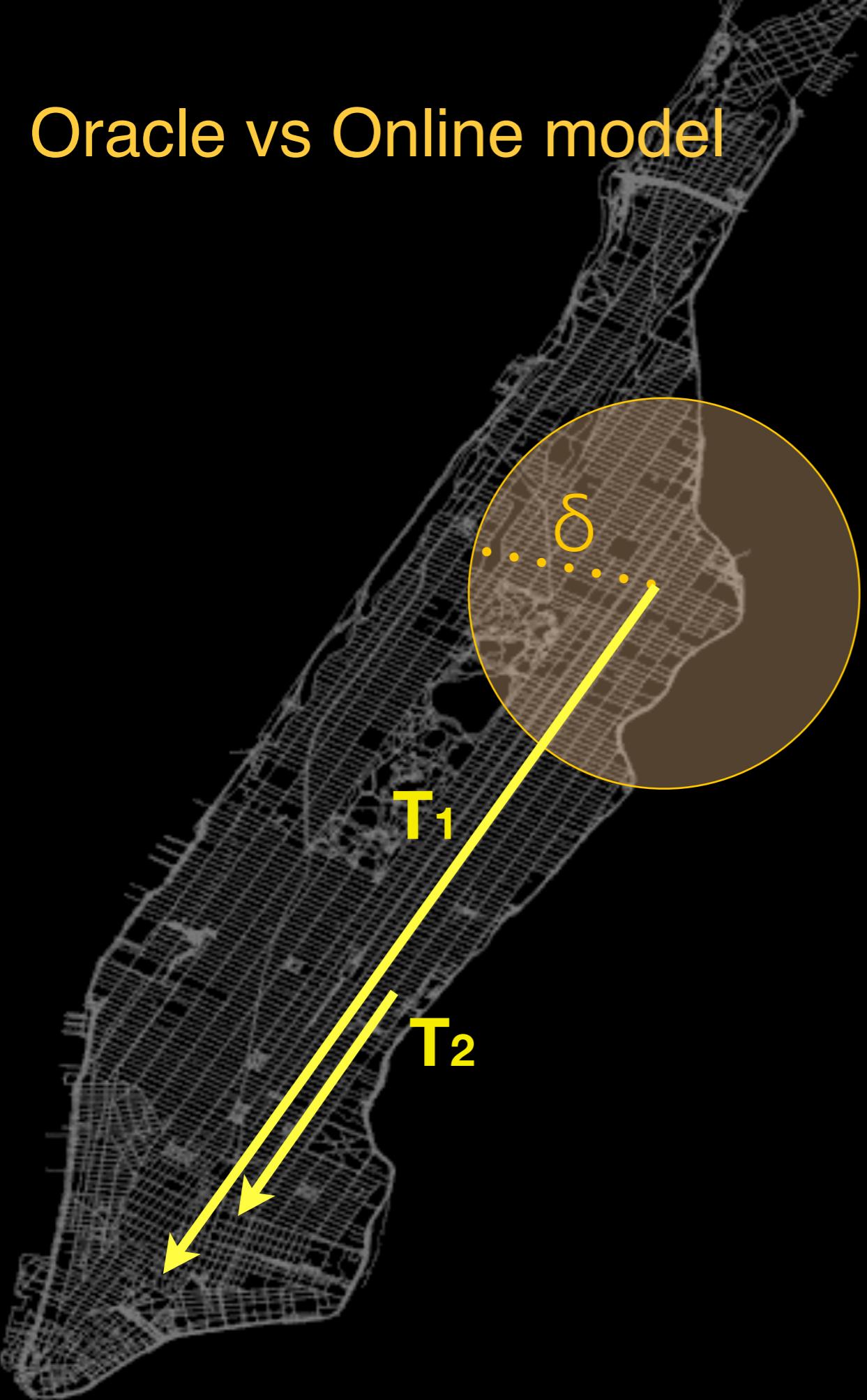
More tolerance = denser network = more sharing opportunities

The majority of trips is shareable!



The majority of trips is sharable with minimal passenger inconvenience

Oracle vs Online model

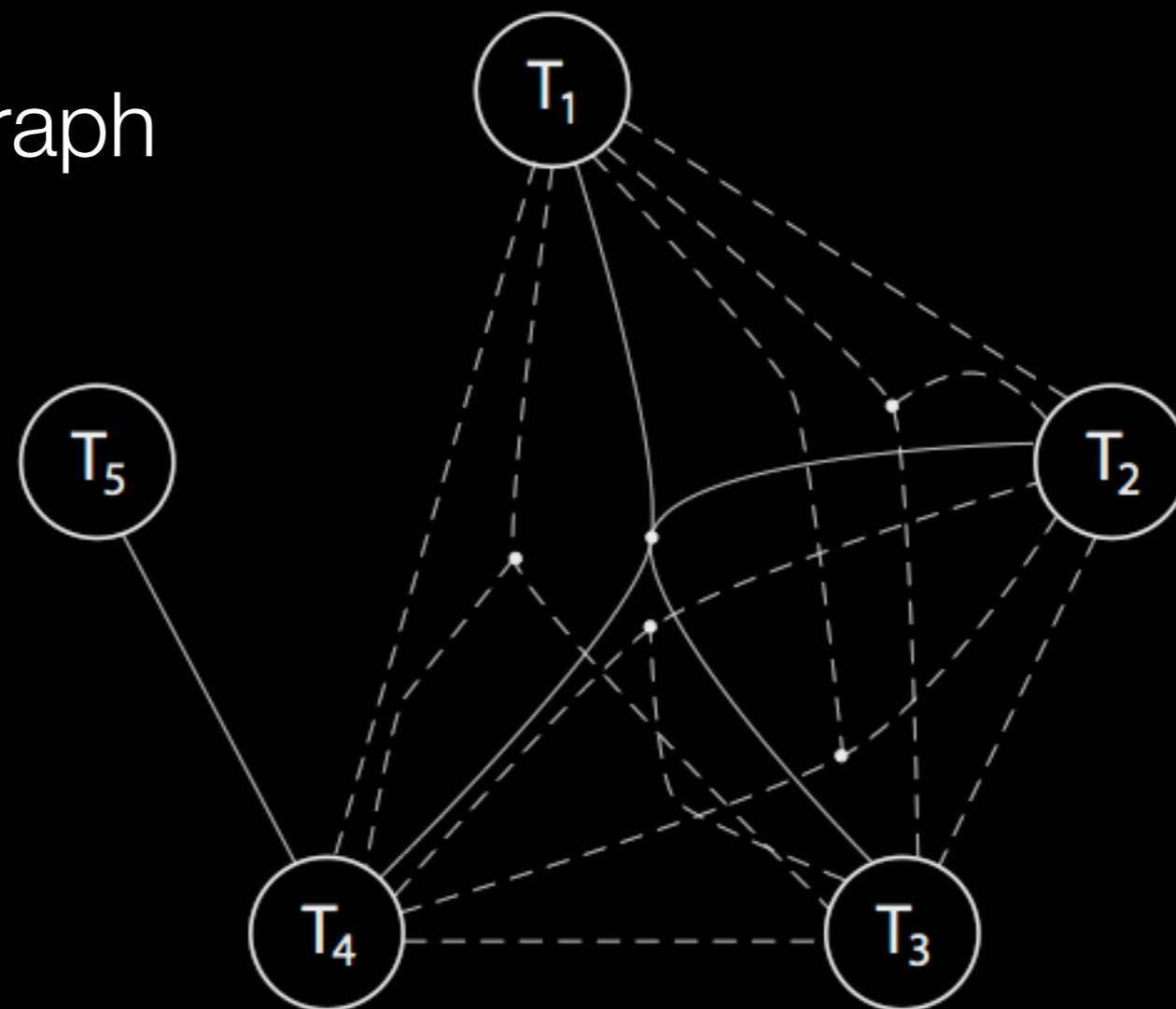


Oracle: omniscient

Online: realistic,
constrained by time
window $\delta = 1 \text{ min}$

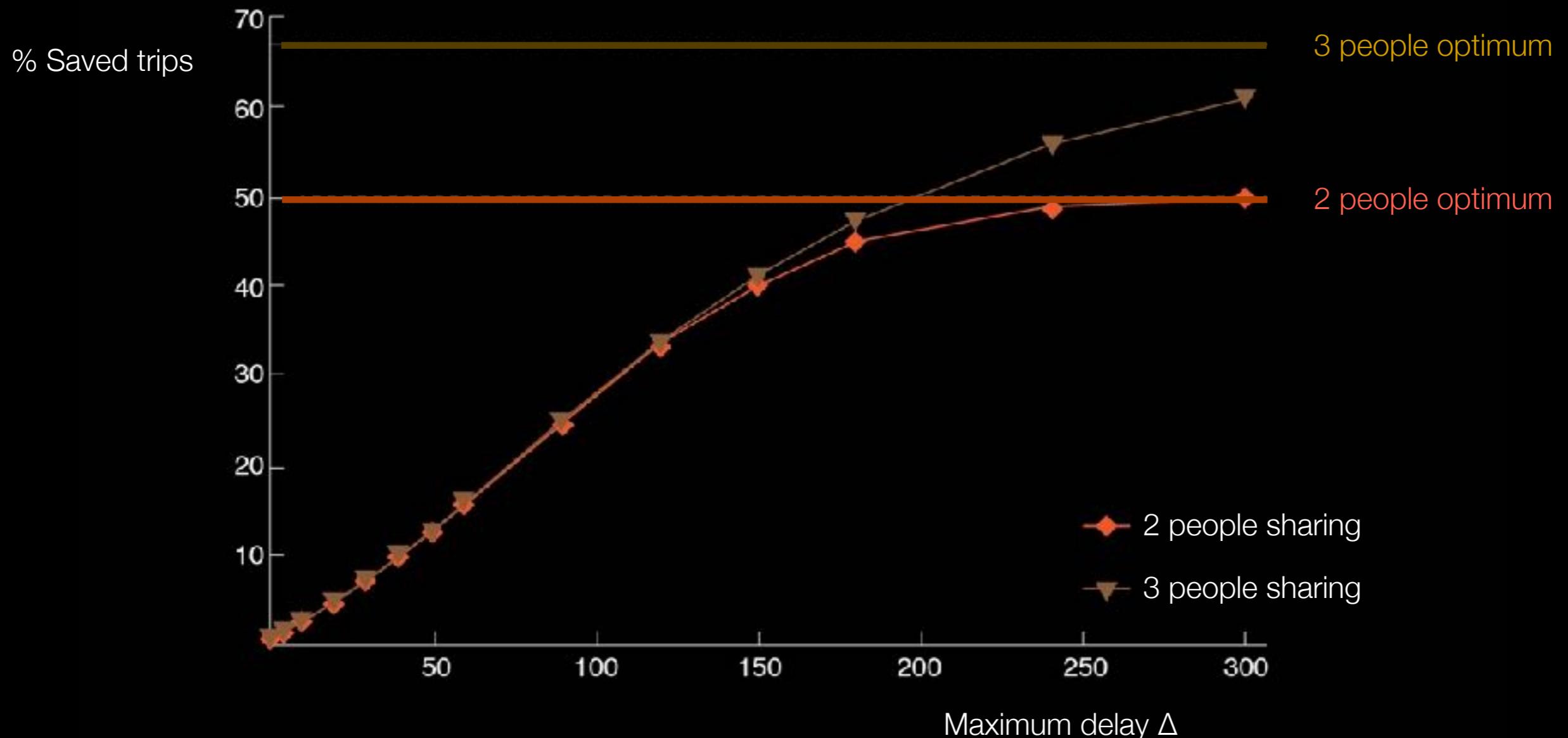
Approach can be extended to higher dimensions

Trip hypergraph



Approximation in $O(n \log n)$

From 2 to 3 people sharing



In NYC, benefits of 3 people sharing
increase only slightly

Consequences of trip-sharing

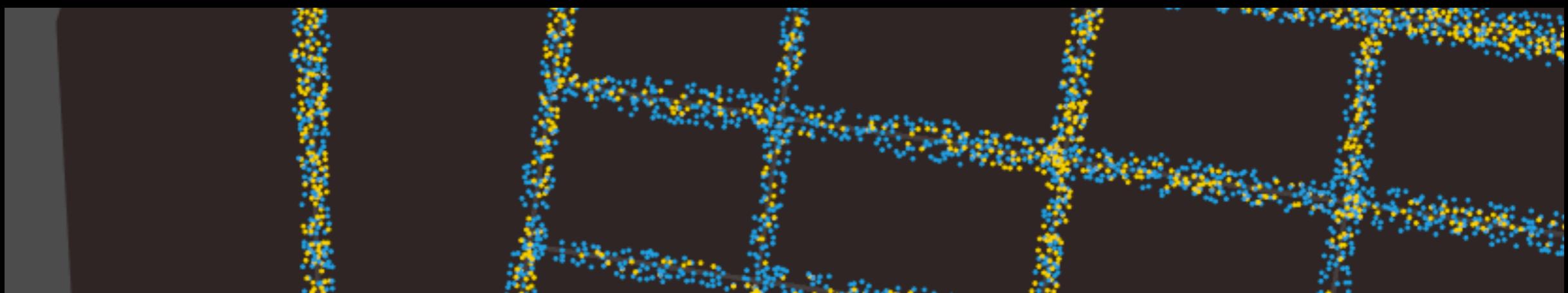
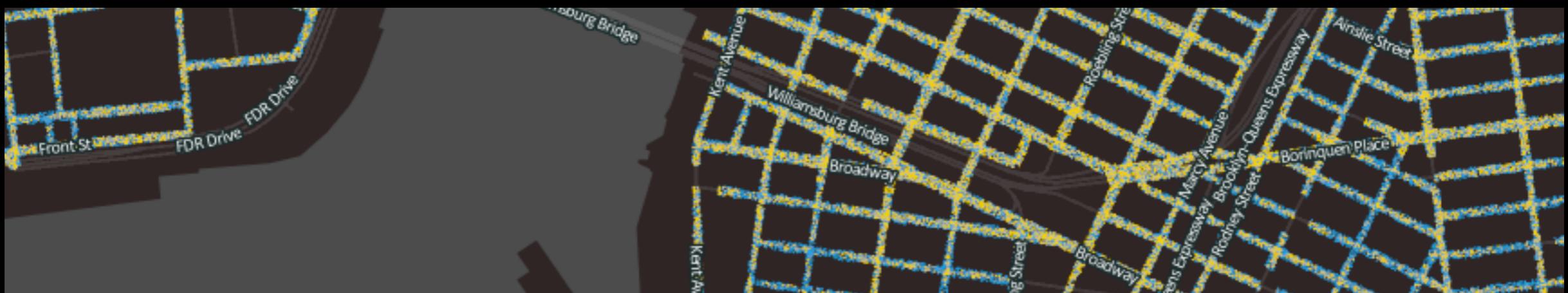
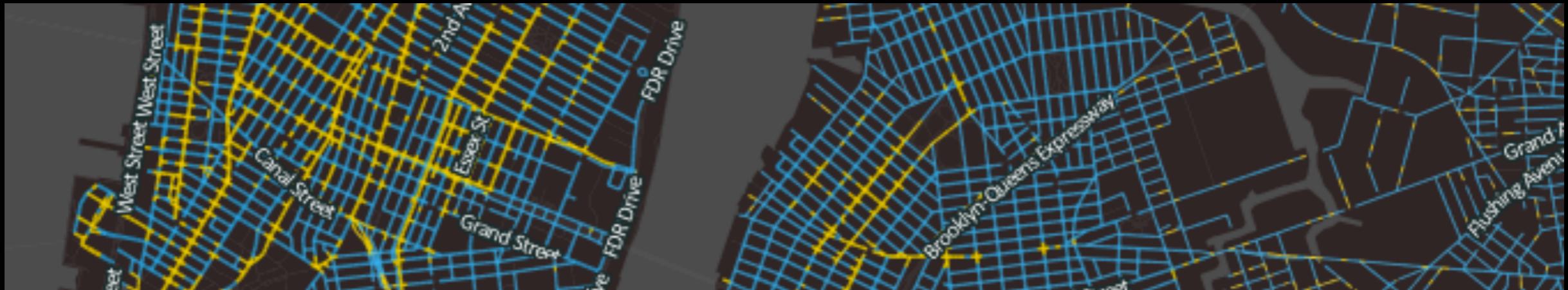
- More efficient use of vehicles: 40% decrease
- Decreased pollution and deaths
- Blurring line between private and public transportation
- New design of fare system

Online tool hubcab for interactive exploration of sharing benefits



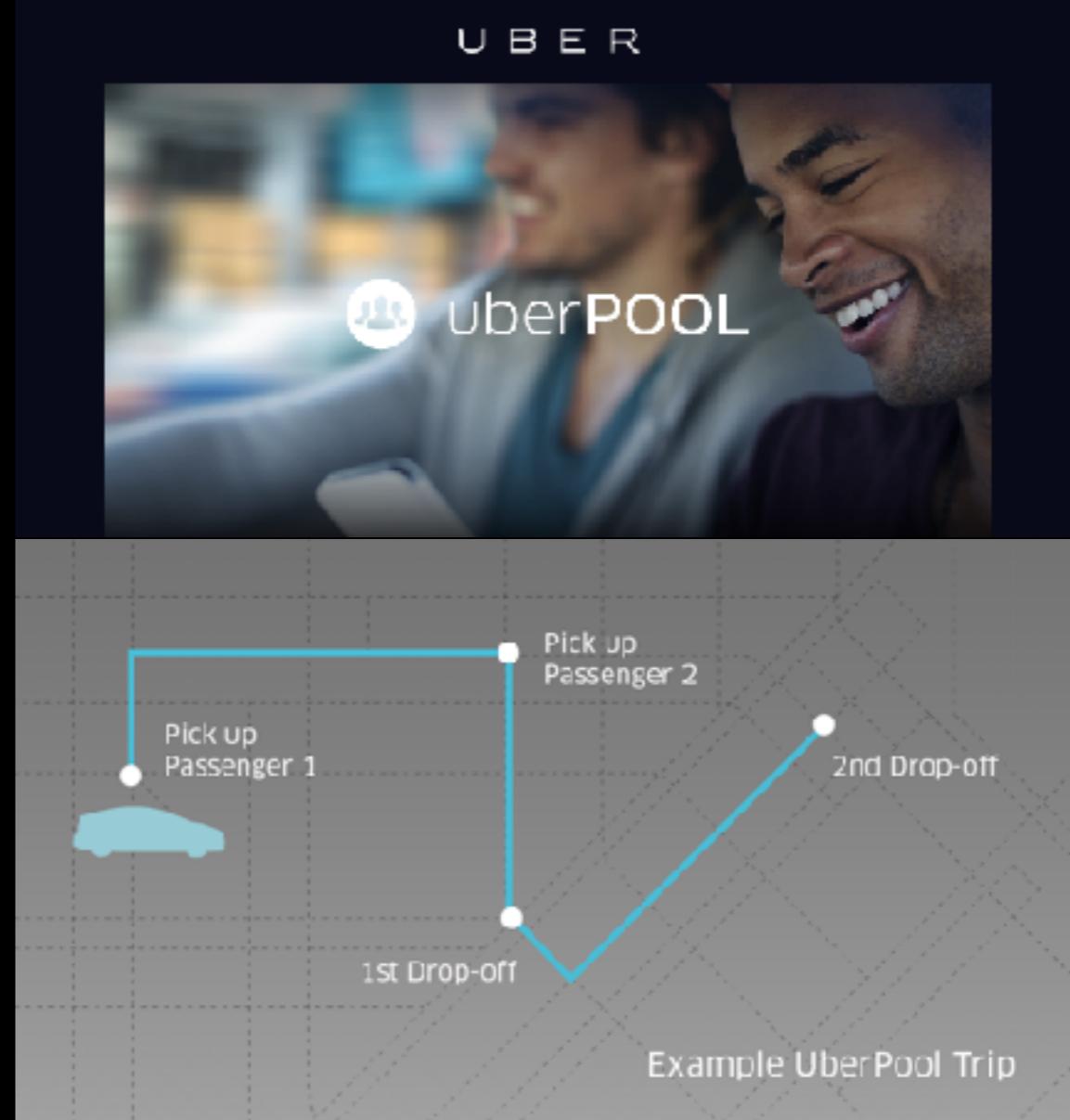
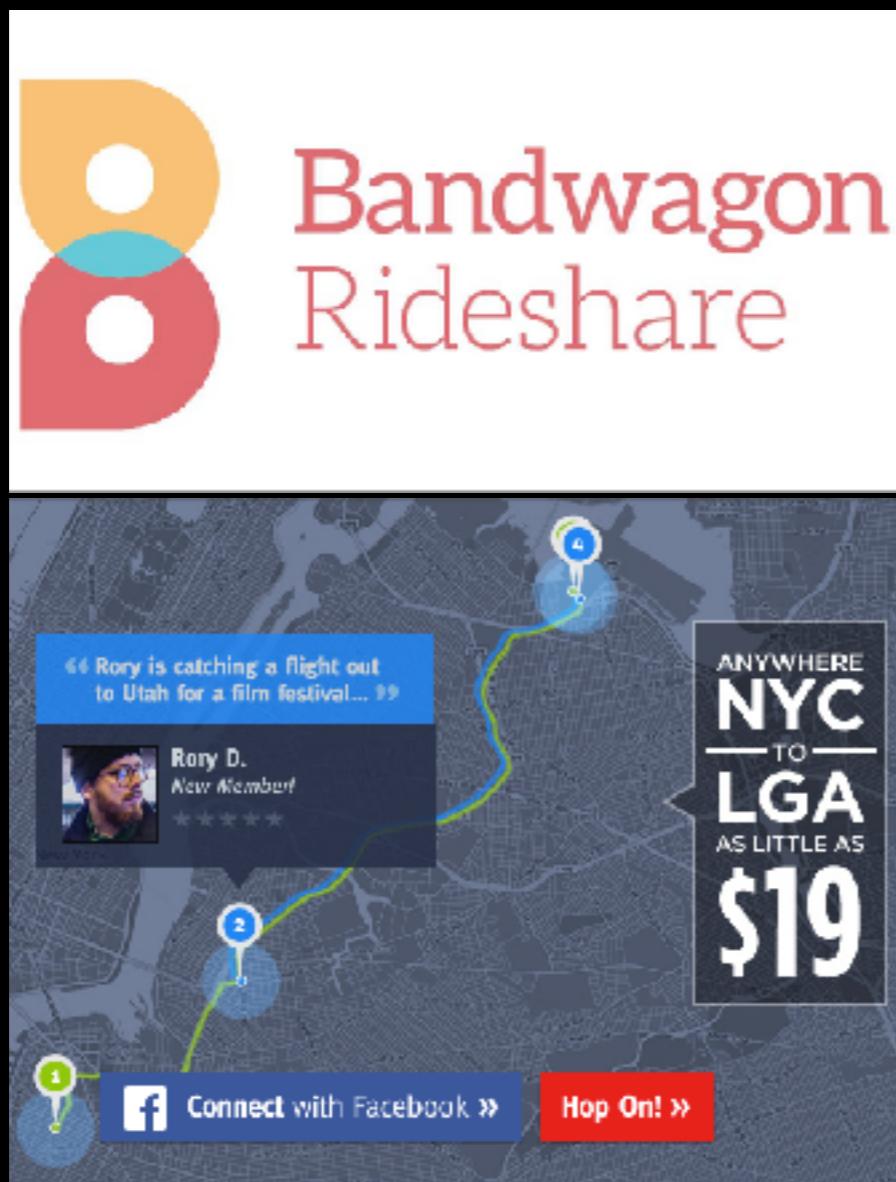
<http://www.hubcab.org>

Zoom into the data, flow exploration, time selection



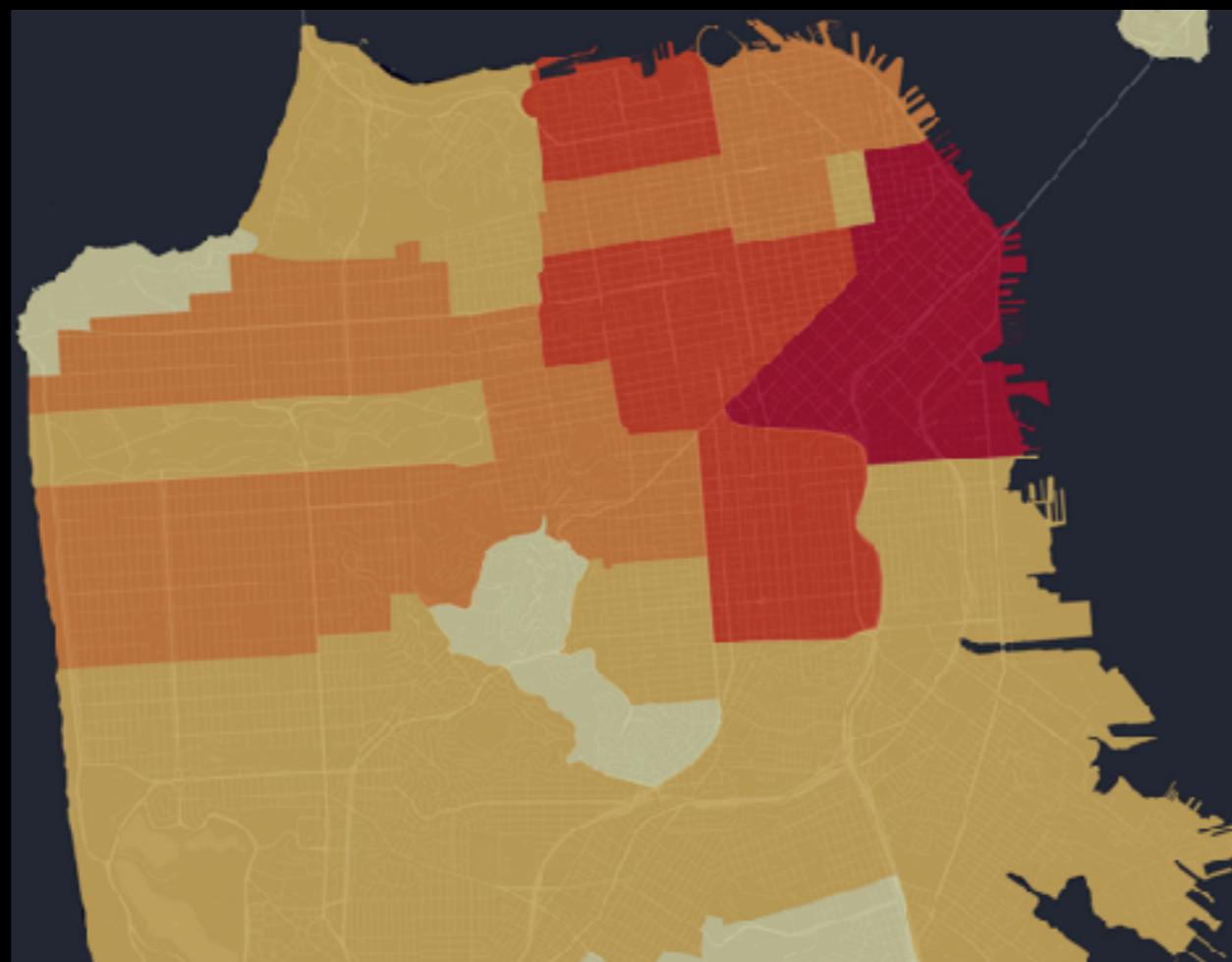
 Pickups Dropoffs

Trip-sharing is now implemented!



Trip-sharing is now implemented!

So far, uberPOOL saved 674,000 miles in San Francisco!



Source: <http://blog.uber.com/uberpool-update>

Beware of unintended consequences!

Cars become more attractive



Cities invest less in public infrastructure



MORE cars on the road = MORE problems

Sustainable implementation of sharing
requires understanding systemic effects

PAPER 2

SCIENTIFIC REPORTS

OPEN Scaling Law of Urban Ride Sharing

R. Tachet¹, O. Sagarra^{1,2}, P. Santi³, G. Resta⁴, M. Szell⁵, S. H. Strogatz⁶ & C. Ratti⁷

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Abstract Ride sharing services have become increasingly popular in recent years, but their scaling behavior is less well understood. In this paper, we analyze the scaling behavior of ride sharing services in New York City. Data from Uber, Lyft, and Sidecar are used to estimate the scaling behavior for each city, and a model is used to simulate ride sharing services under a range of universal access. We explore this scaling law theoretically with a scaling model that predicts the potential for ride sharing in a large, urban area. Key model parameters and modelable parameters. A better understanding of these will help planners, engineers, or companies, and society, to design sustainable public transportation.

Scaling of personal ground vehicles: what can ride sharing tell us about personal mobility? Indeed, the success, popularity, and flexibility of ride sharing is related to the efficiency of ride sharing services. However, there is still a gap between the quality of shared experiences, public transportation, and private automobile mobility. This work is justified as a first step towards understanding how ride sharing services can reduce the gap between public transportation and private car sharing services. Considering long-term planning is key to making ride sharing the future of personal mobility for the coming years.

The emergence of ride sharing services presents an opportunity to improve the efficiency of individual, on-demand transportation. By closing the gap between shared, low-carbon public transportation and mobile but non-shared private transportation, ride sharing needs to do more to provide for Uber¹, Lyft², and Sidecar³, are rapidly contributing to reducing personal car ownership. The scalability of such potential benefits depends on the success of ride sharing services. This is comparable to space and time – and thus ride sharing is not yet widely used by present.

With recent investments in automated and temporal regulation of individual mobility patterns, every city is becoming more efficient and flexible in its personal mobility. This is particularly true for ride sharing services, which are becoming more popular and more widespread. The results in the following sections show that ride sharing services have been more successful than traditional taxi services. They could become a major player in the future of urban mobility, due to their ability to collect and process data in a single ride from multiple entry points⁴. For the rideability index, it shows the number of individual trips that can be shared, the total of individual trips in New York City, the rideability and utilization for New York, and that it increases rapidly with the number of trips available for sharing.

As far as connectivity⁵ and trip duration are concerned, both the results are similar to New York City. There was no relation to trip size, but that trip size is regular in most respects, namely, at large proportions, to small geographical areas, and the maximum density of taxi traffic, in what follows, we study ride sharing in three major world cities — San Francisco, Singapore, and Mexico — for which data is available, although they are quite far from each other and from New York City. Urban traffic characteristics, population, and geographical traits, but also looks the same empirical behaviour, showing the potential for ride sharing. To the best of our knowledge, the existence of such a connectivity measure has not been reported before. It evaluates the connectivity, including the existence of ride sharing, using a simple mathematical model. The results indicate a clear trend in the number of ride sharing users over time, and does not follow any predictable pattern. When a report of how far or greater is the distance as it is needed, when the price, distance, age, or other things that rideability could have a large influence on rideability are observed in New York City.

Results

In New York City, the average daily distance (AD) is 10.6 km, the average traffic speed is 23 km/h, and the average number of trips per day is 10,333. Higher values than the empirical case of connectivity

¹Available at: www.uber.com (last visited: 20/02/2016). Accessed: 09/03/2016. © 2016 Uber Technologies, Inc. All rights reserved. ²Available at: www.lyft.com (last visited: 20/02/2016). Accessed: 09/03/2016. © 2016 Lyft, Inc. All rights reserved. ³Available at: www.sidecar.com (last visited: 20/02/2016). Accessed: 09/03/2016. © 2016 Sidecar, Inc. All rights reserved. ⁴Available at: www.singularityu.org (last visited: 20/02/2016). Accessed: 09/03/2016. © 2016 Singularity University, Inc. All rights reserved. ⁵Available at: www.civilandenvironmental.umich.edu (last visited: 20/02/2016). Accessed: 09/03/2016. © 2016 Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI, USA. Correspondence and requests for materials should be addressed to C.R. (email: charles.ratti@mit.edu)

New York is special - What about other cities?

NYC 13,500 cabs



San Fran 1,500 cabs



Singapore 26,000 cabs



Vienna 5,000 cabs



New York is special - What about other cities?

NYC 13,500 cabs



$25,846/\text{km}^2$

San Fran 1,500 cabs



$6,659/\text{km}^2$

Singapore 26,000 cabs



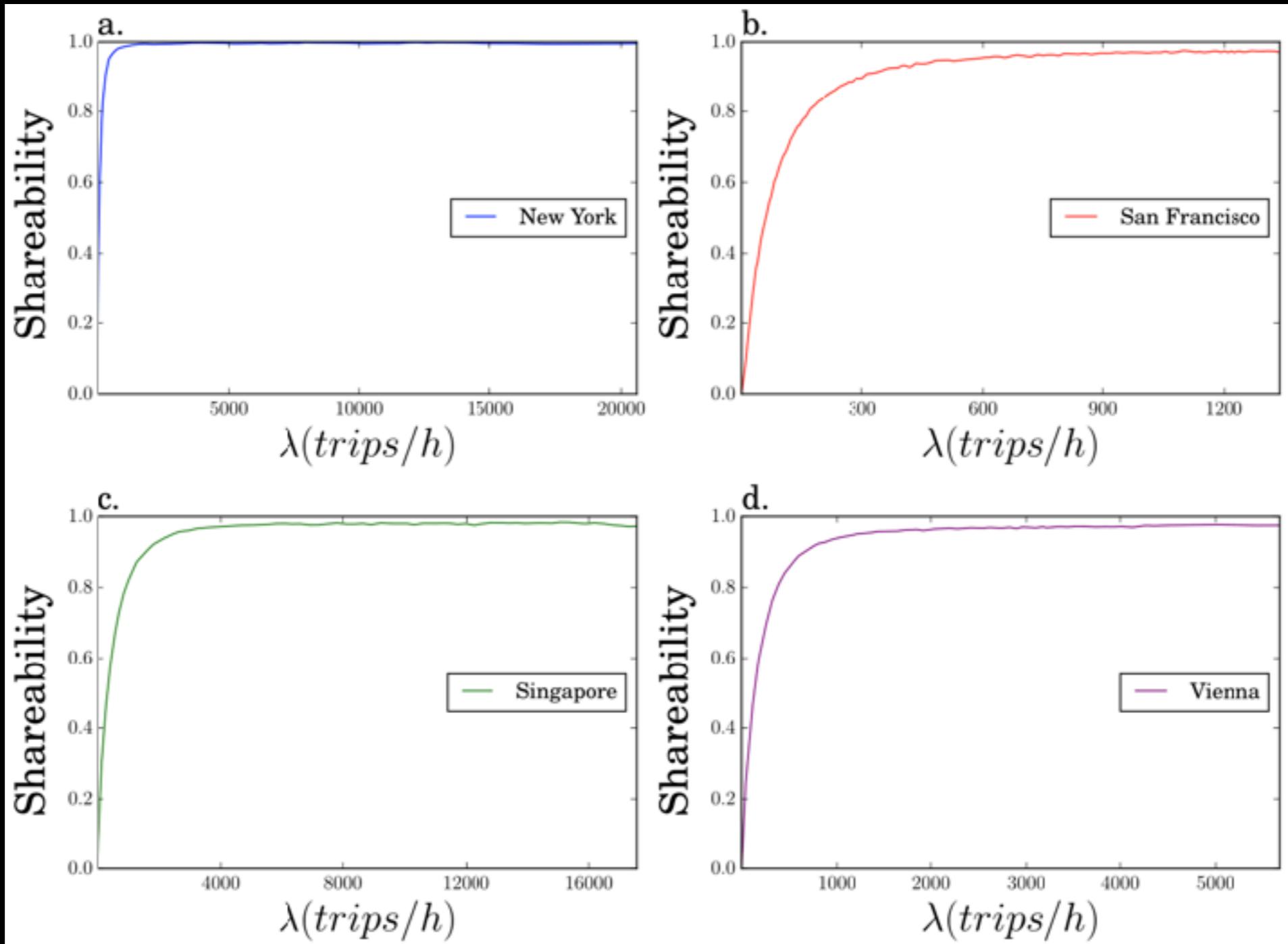
$7,988/\text{km}^2$

Vienna 5,000 cabs

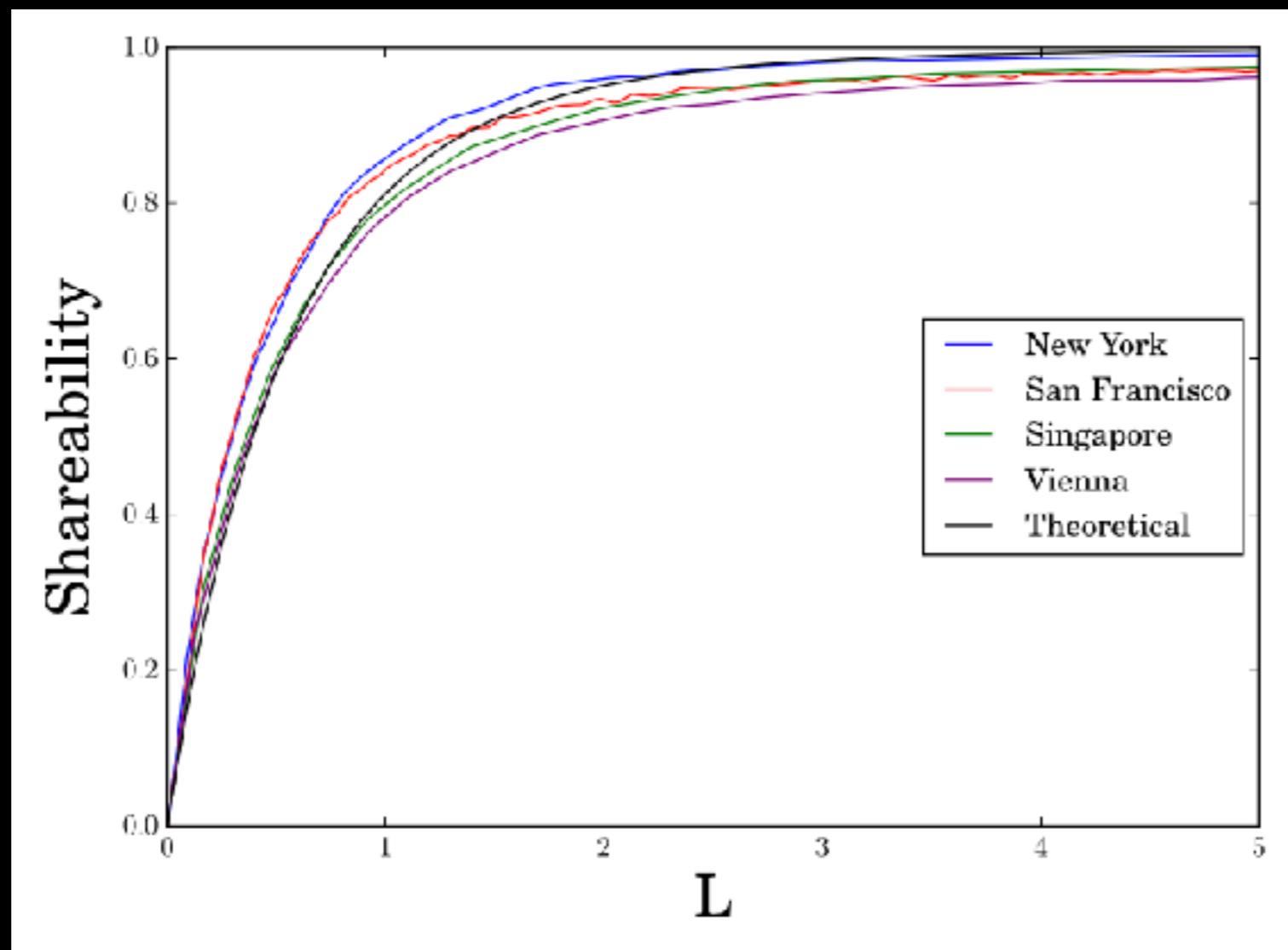


$4,002/\text{km}^2$

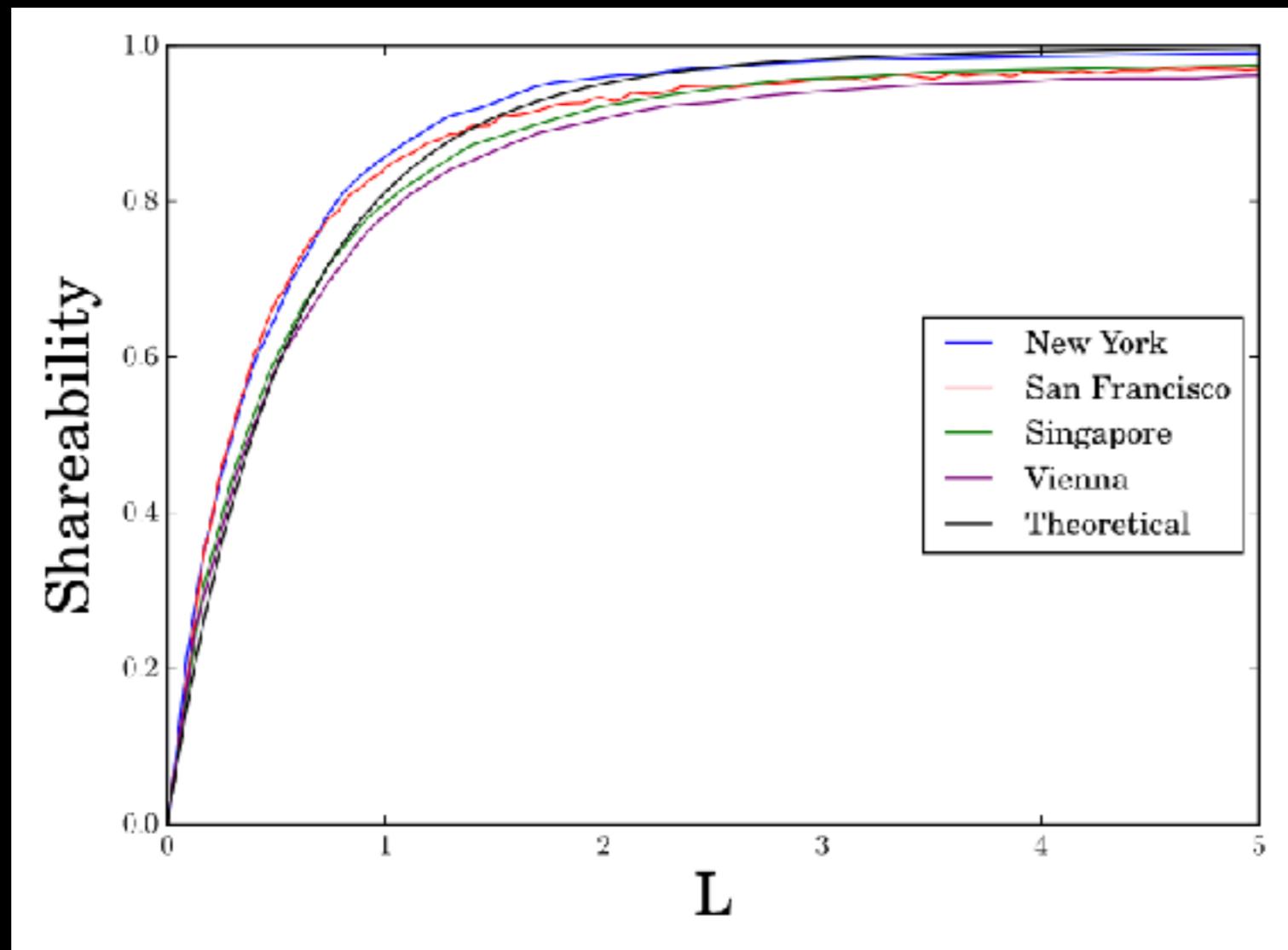
Different cities have similar shareability curves



All curves collapse onto a universal curve!



All curves collapse onto a universal curve!



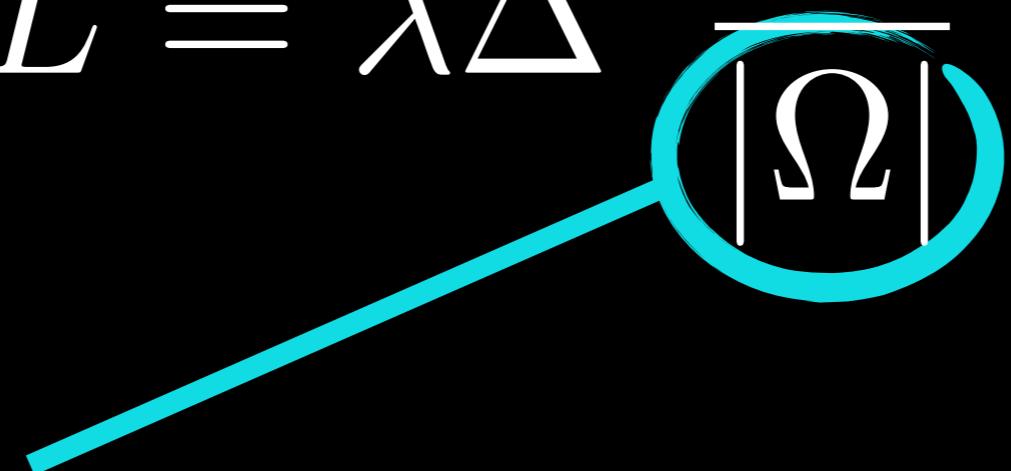
What is L?

Rescaling through L

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

Rescaling through L

$$L = \lambda \Delta^3 v^2$$



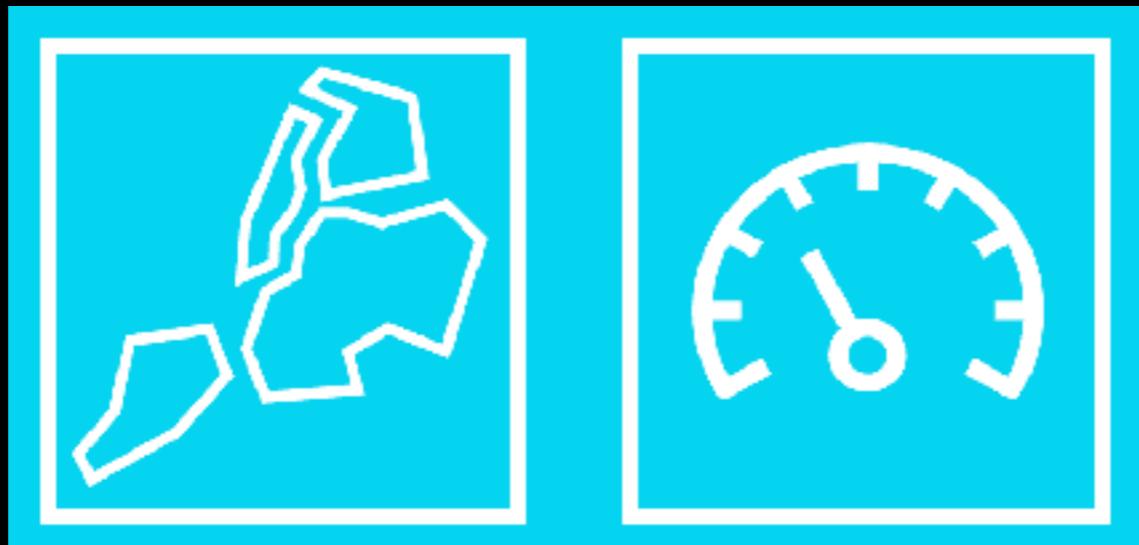
City area



Rescaling through L

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

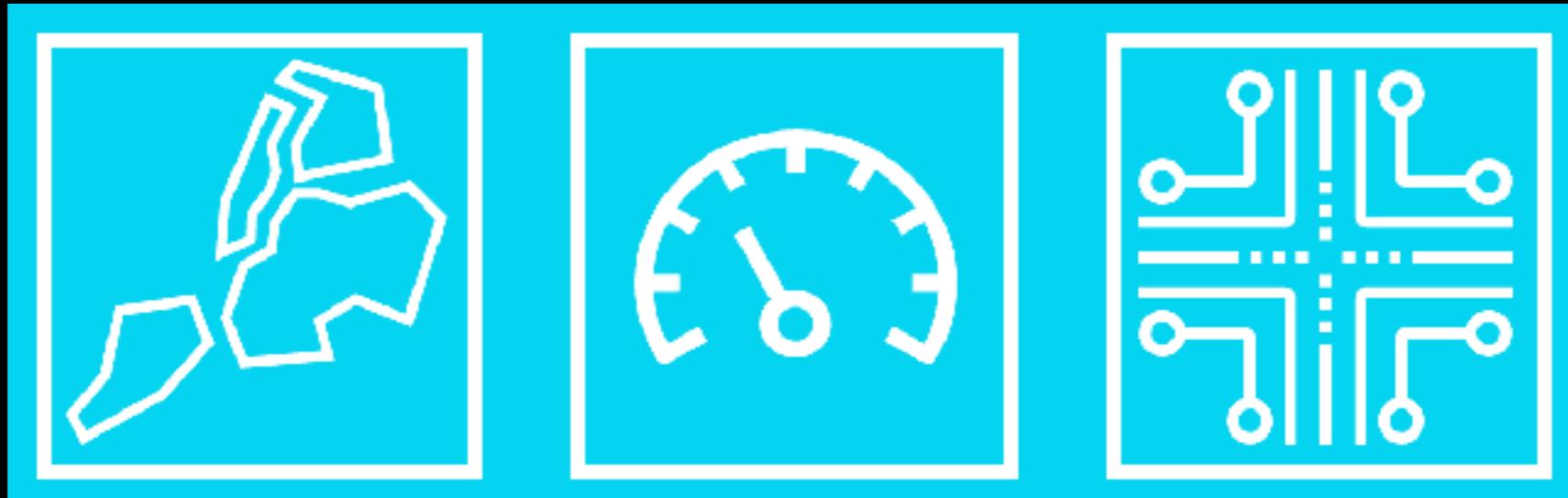
Avg speed



Rescaling through L

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

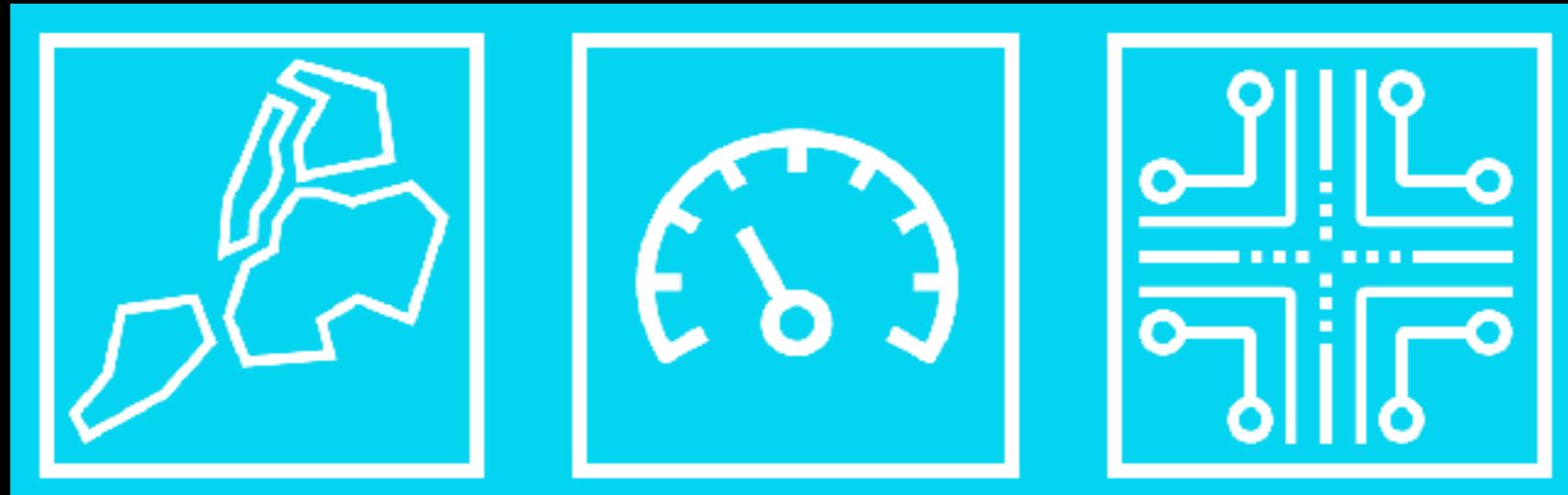
Trip density



Rescaling through L

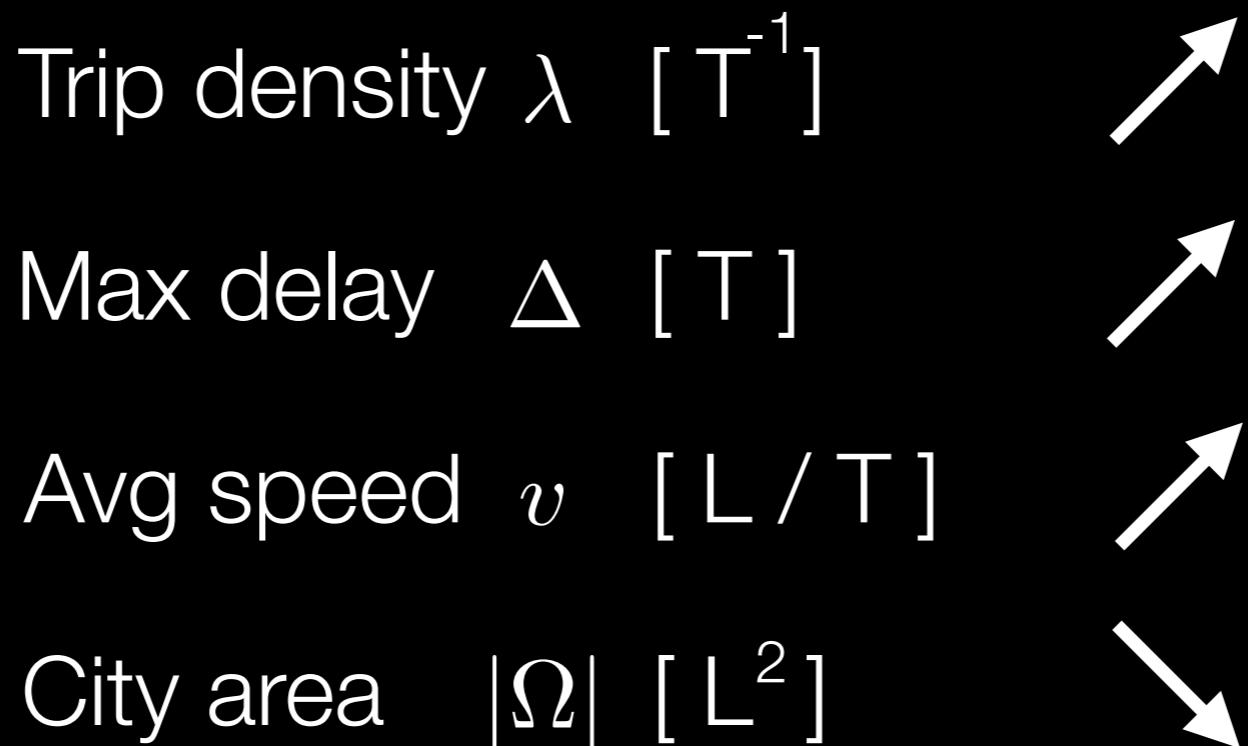
$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

City area Avg speed Trip density



L is dimensionless

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$



L is a ratio between two timescales

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

Tolerable delay time

Δ

vs

Expected waiting time

t_{wait}

L is a ratio between two timescales

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

Tolerable delay time

$$\Delta$$

vs

Expected waiting time

$$t_{\text{wait}} = \frac{1}{\lambda} \times \frac{|\Omega|}{(v\Delta)^2}$$

L is a ratio between two timescales

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

Tolerable delay time

vs

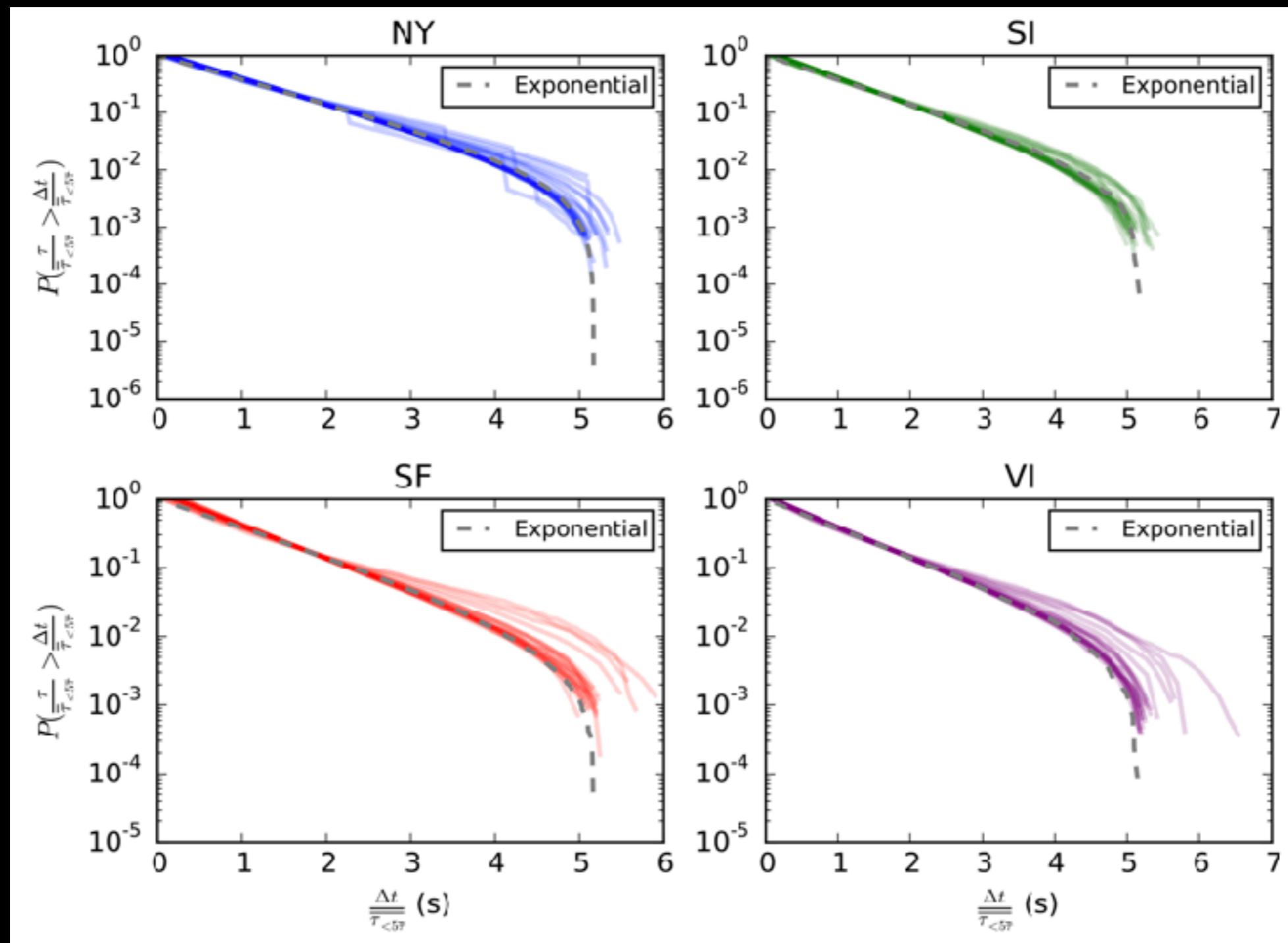
Expected waiting time

Δ

**Characteristic
time for new trip**

$$t_{\text{wait}} = \frac{1}{\lambda} \times \frac{|\Omega|}{(v\Delta)^2}$$

Trip generation is poissonian



L is a ratio between two timescales

$$L = \lambda \Delta^3 \frac{v^2}{|\Omega|}$$

Tolerable delay time

vs

Expected waiting time

Δ

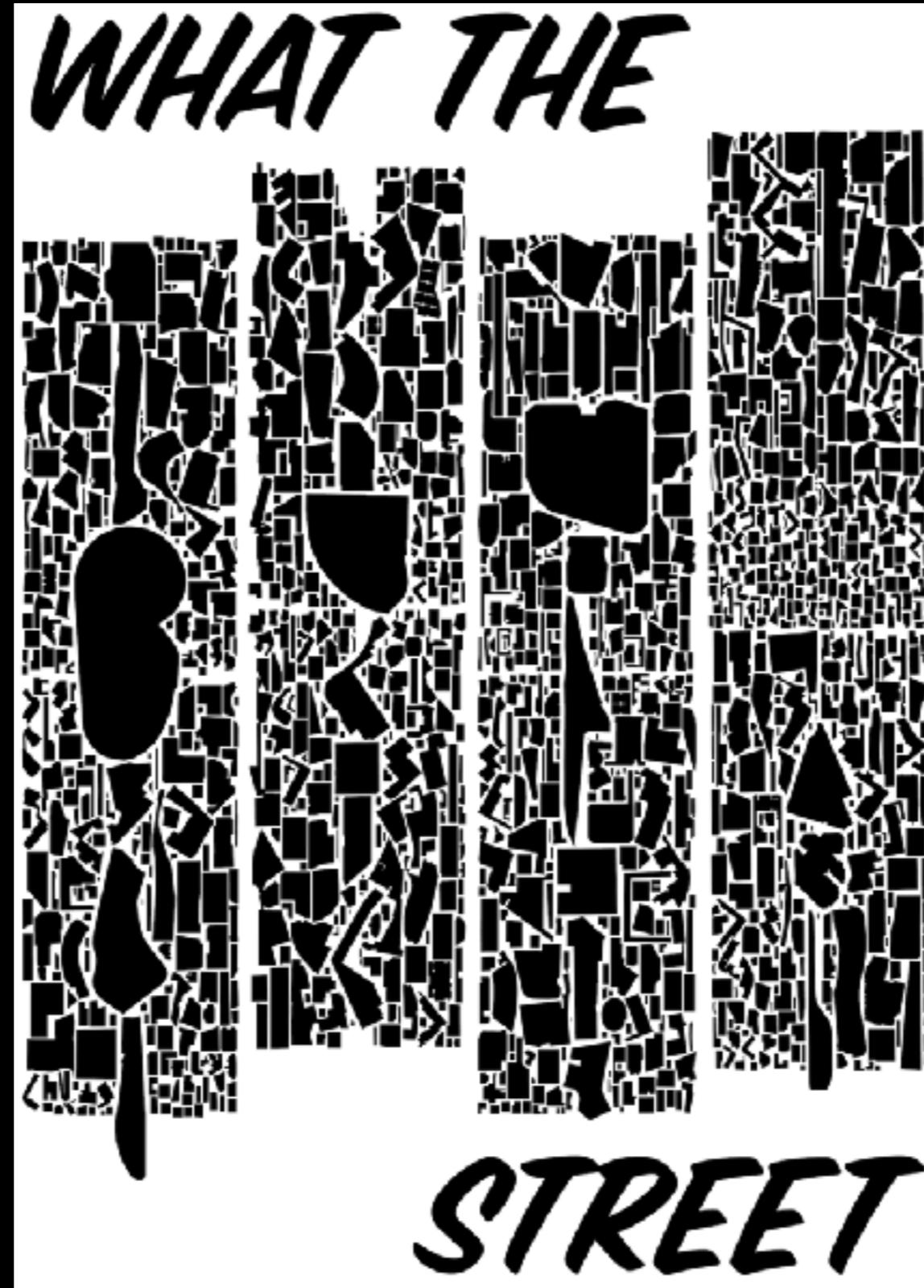
**Characteristic
scale of a vicinity**

$$t_{\text{wait}} = \frac{1}{\lambda} \times \frac{|\Omega|}{v \Delta^2}$$

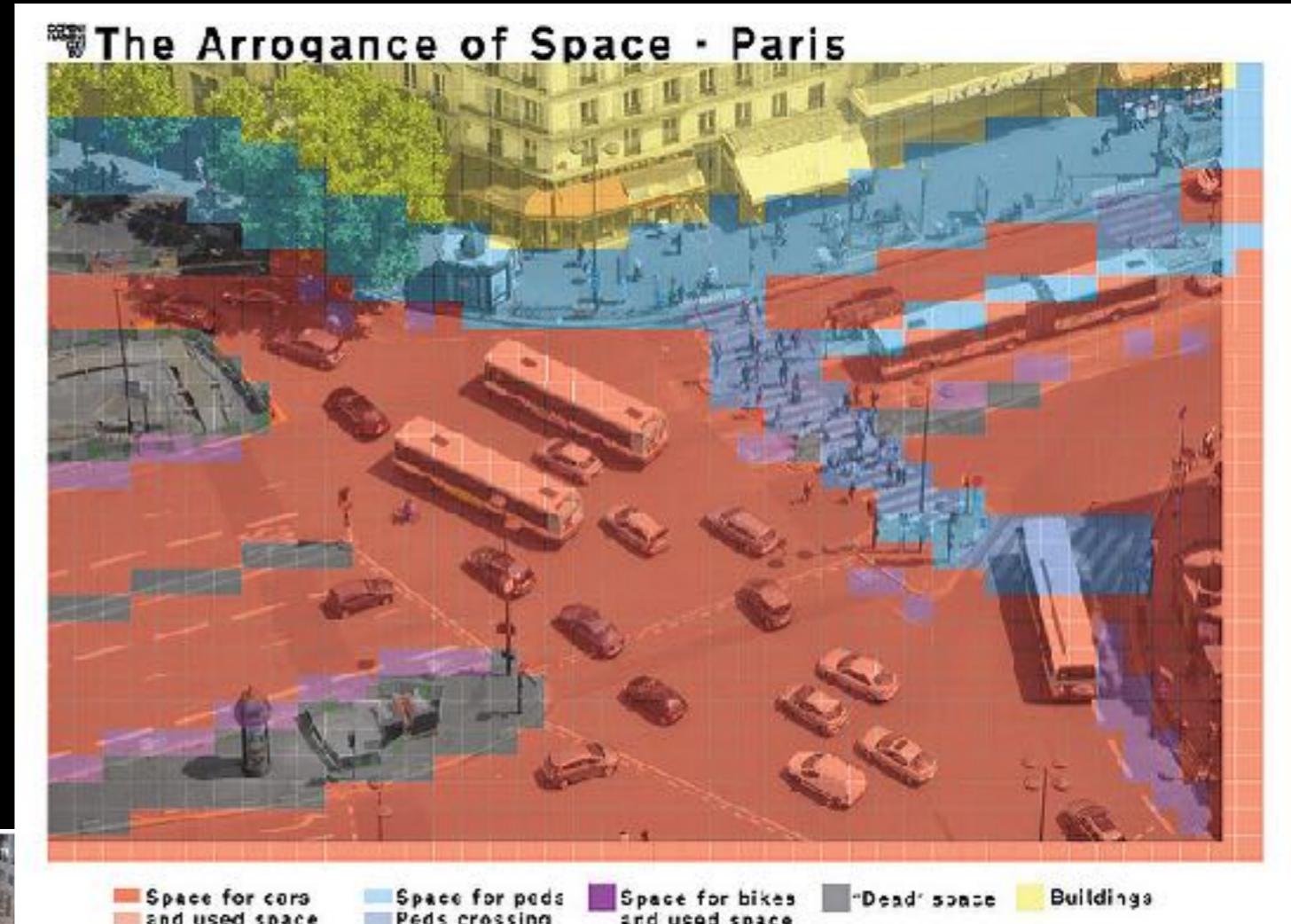
Sure, cities are different...

...but ride-sharing works well almost everywhere

<http://senseable.mit.edu/shareable-cities/>



Exploring "The Arrogance of Space"



Cars are used 36 min per day

They stand around 1404 min per day

Cars are used 36 min per day

They stand around 1404 min per day

A typical snapshot of Berlin
from space shows:

30,000 cars moving

1,200,000 cars parked

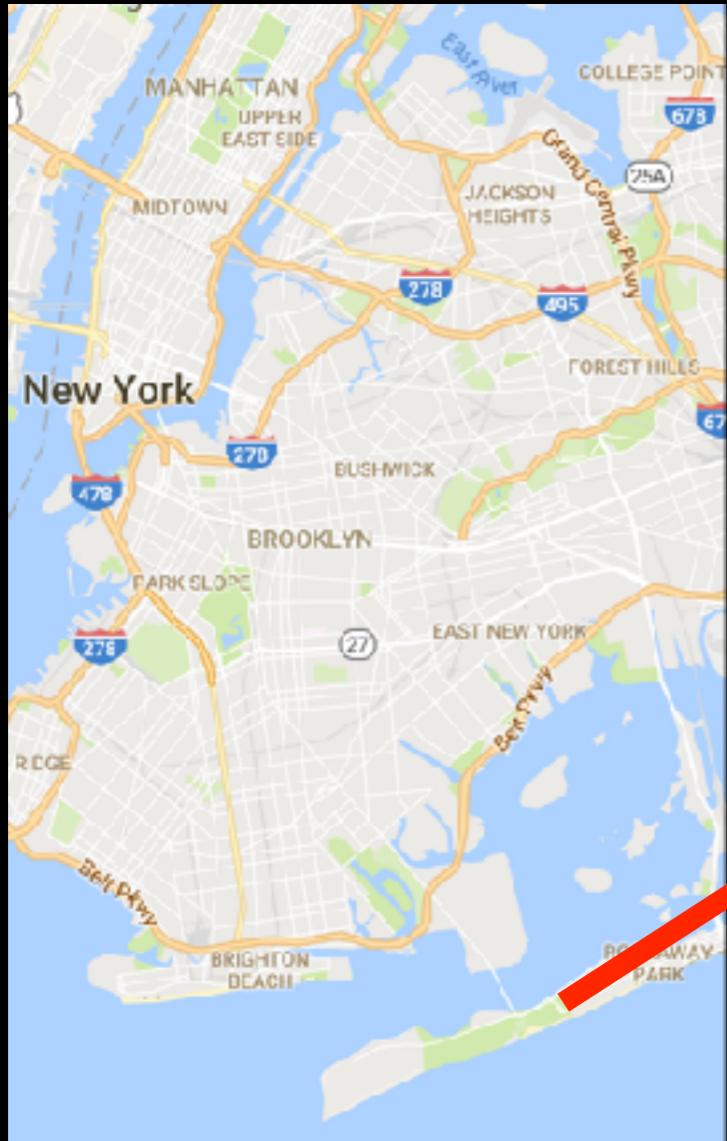
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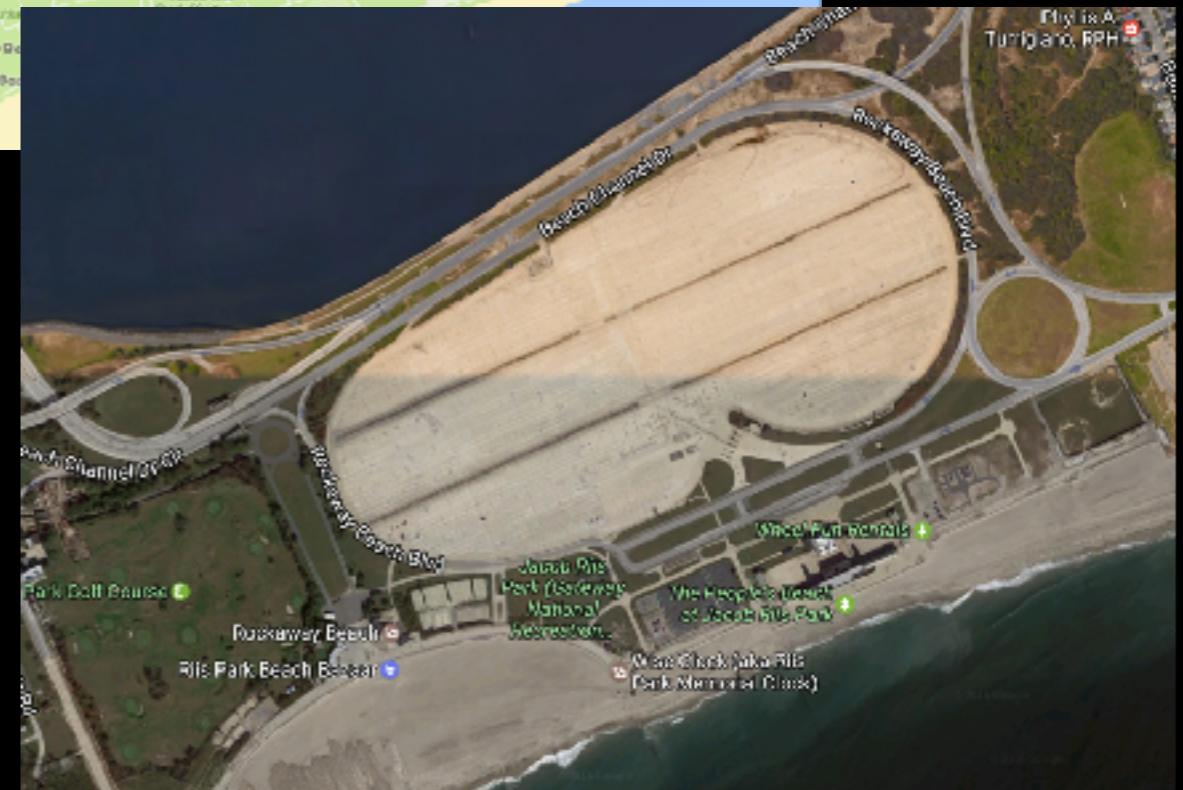
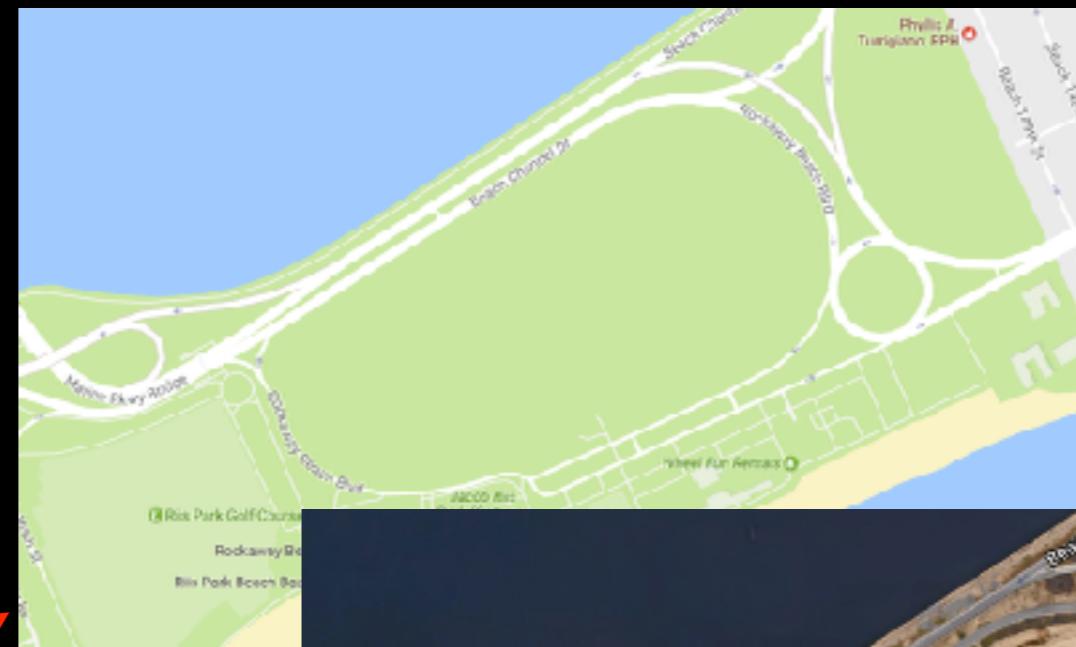
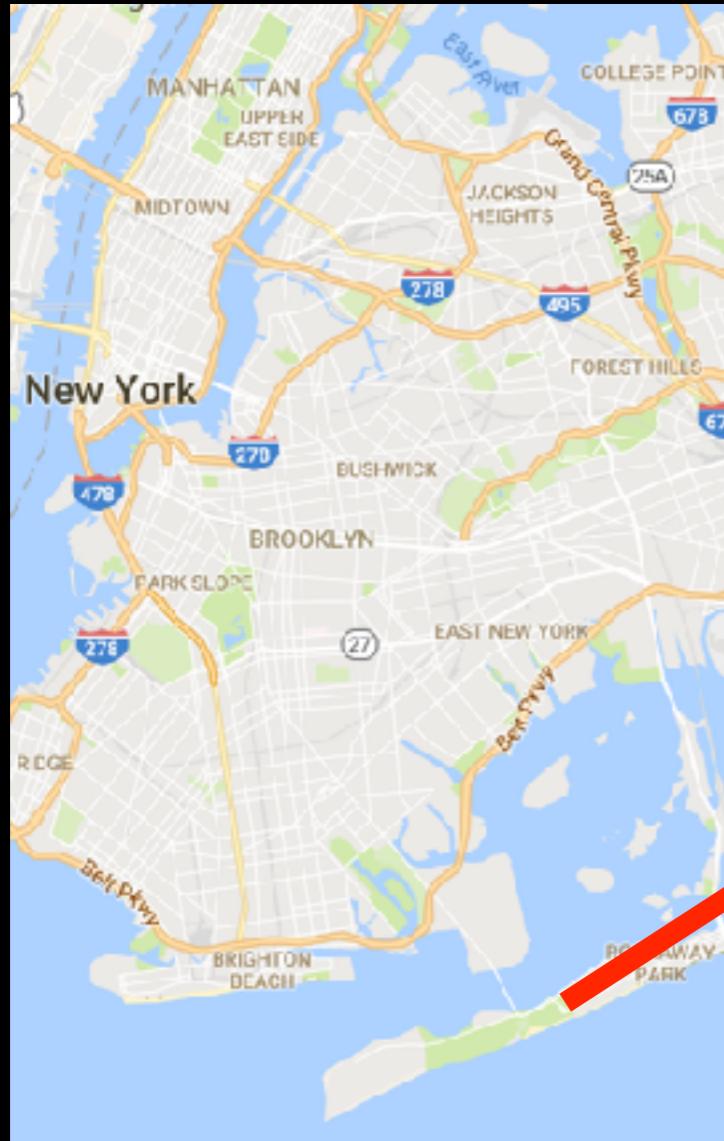
1,200,000 cars parked = 4 Central Parks
 = 64,000 playgrounds

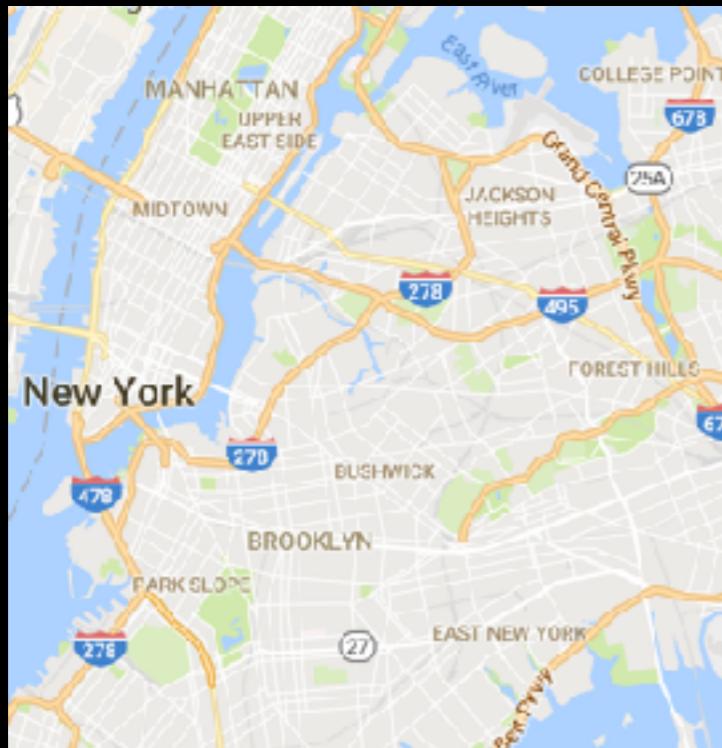


What a lovely green..

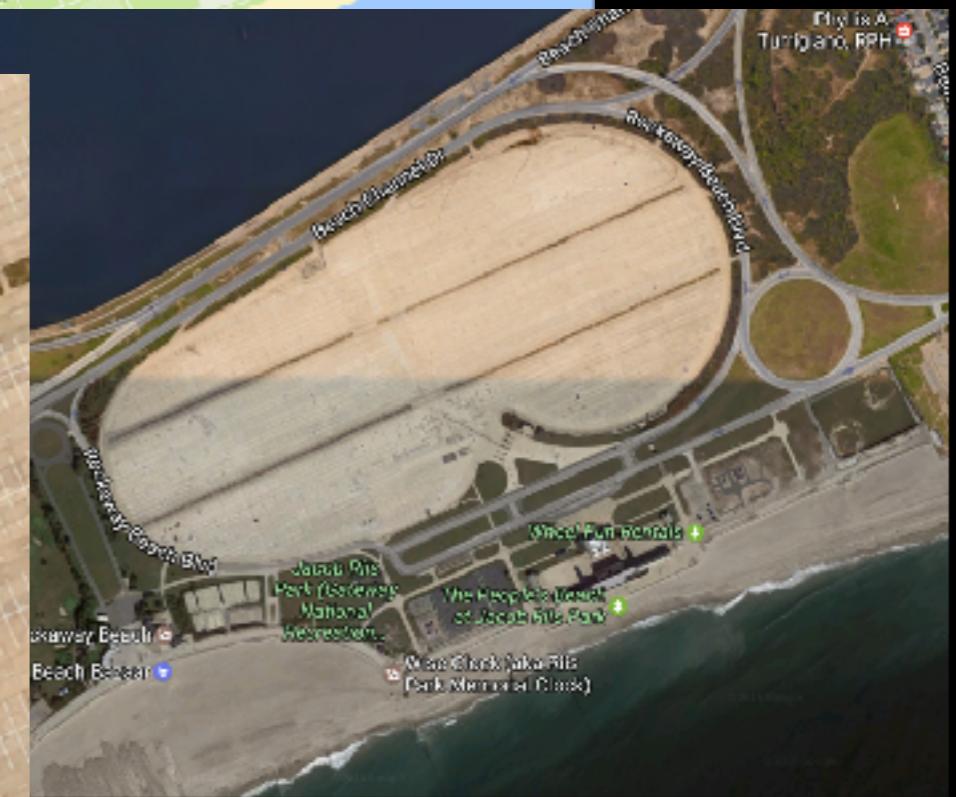
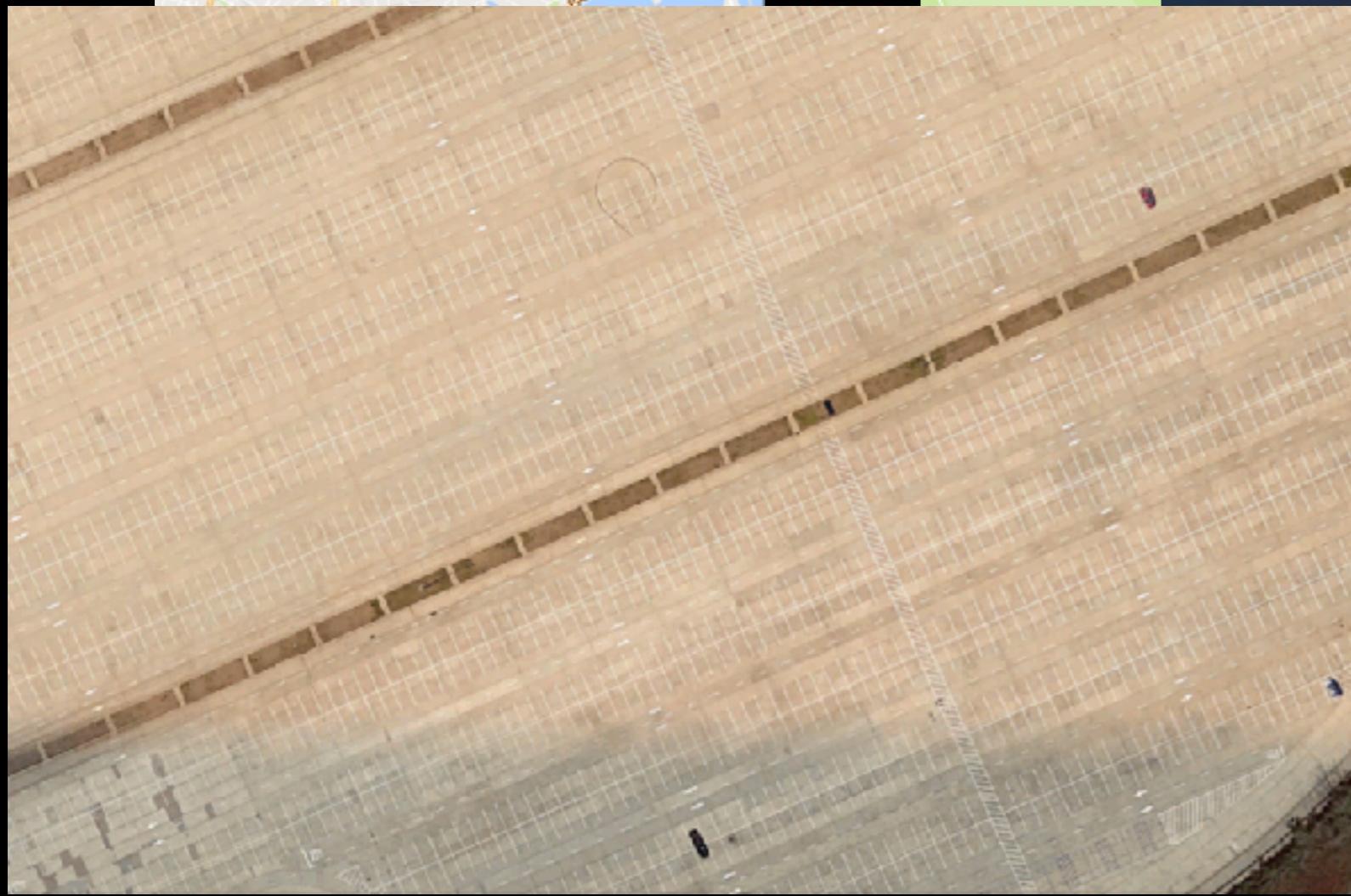
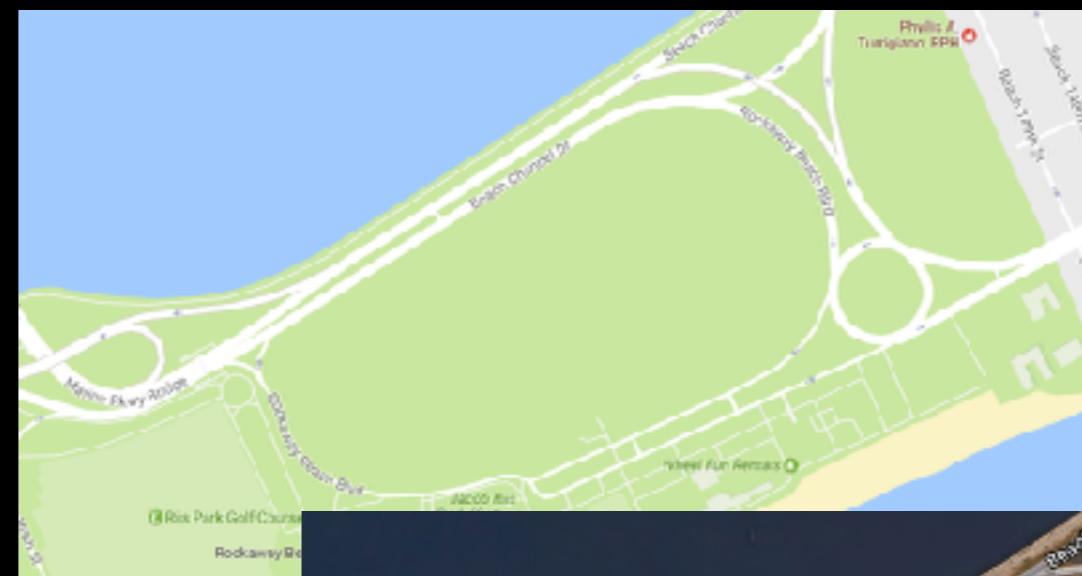


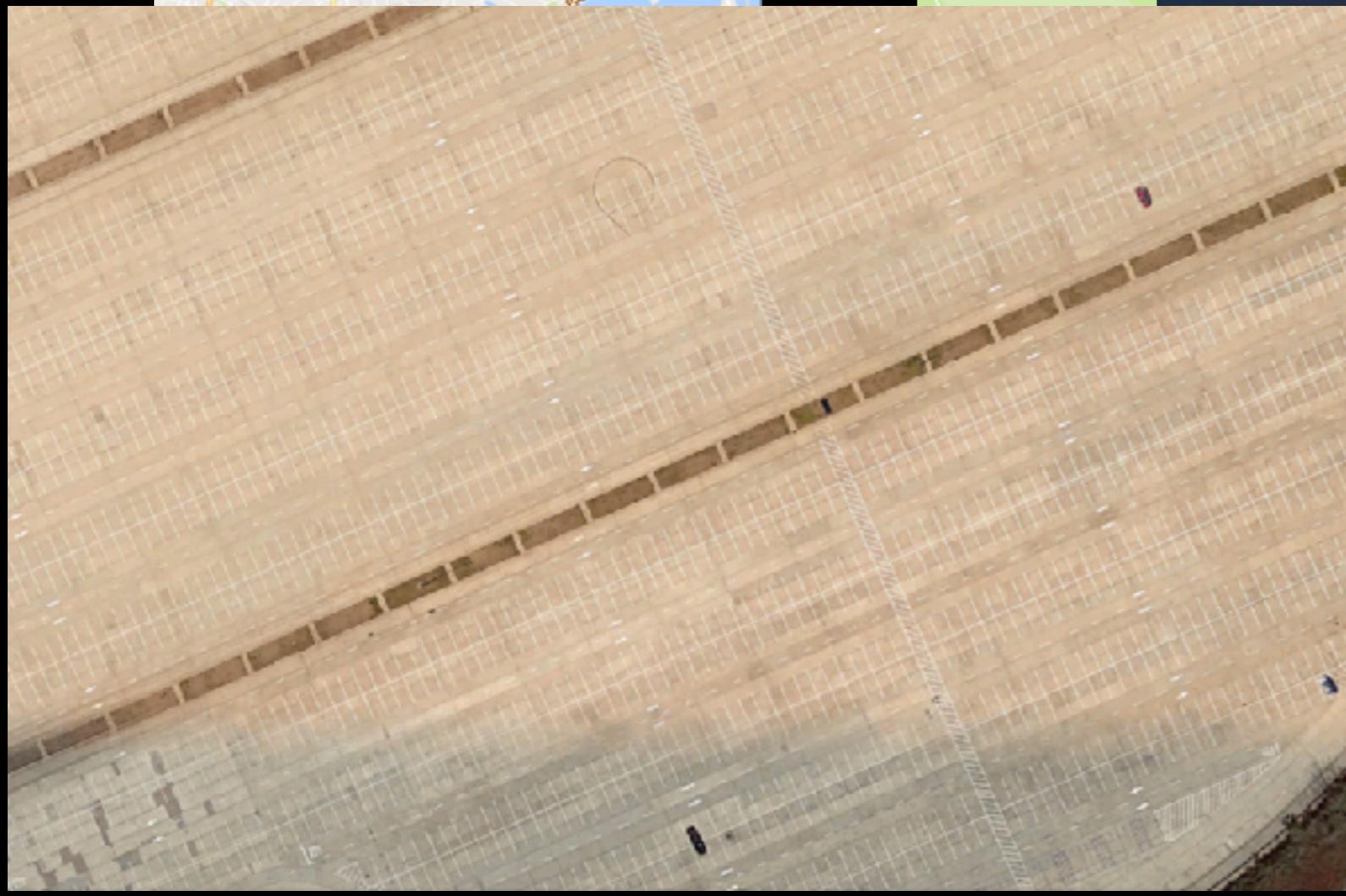
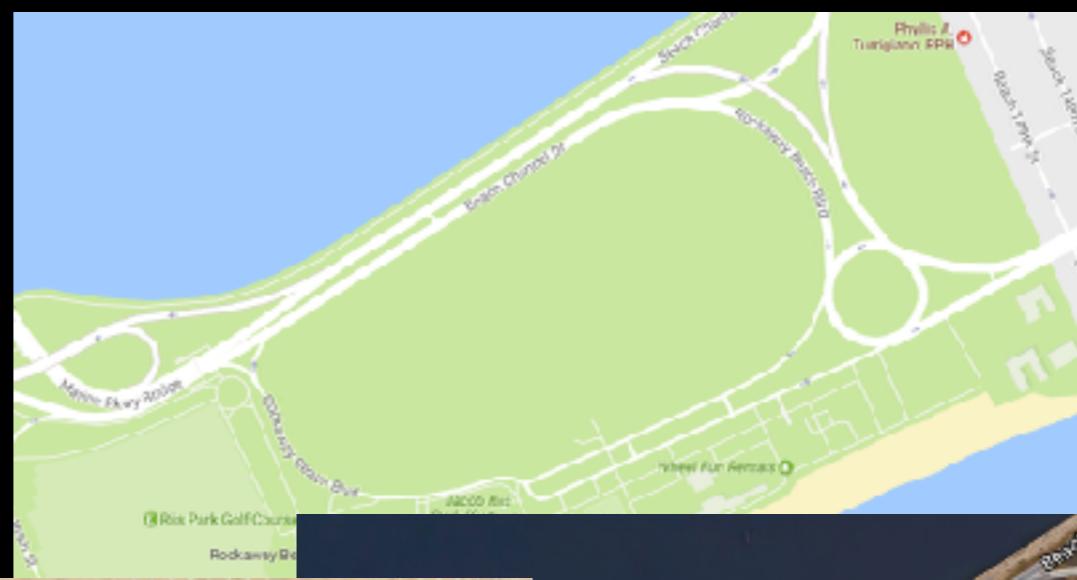
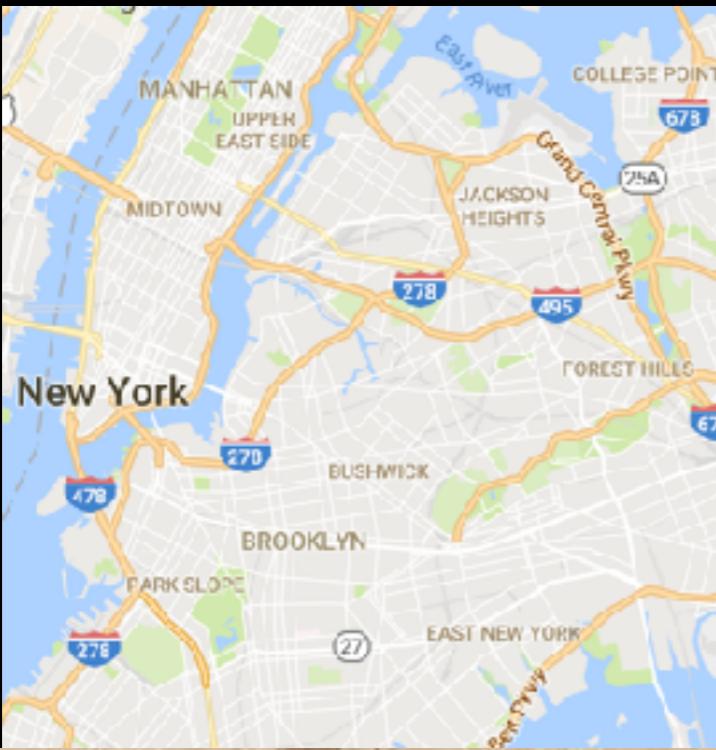
What a lovely green..





What a lovely green.. MONSTER

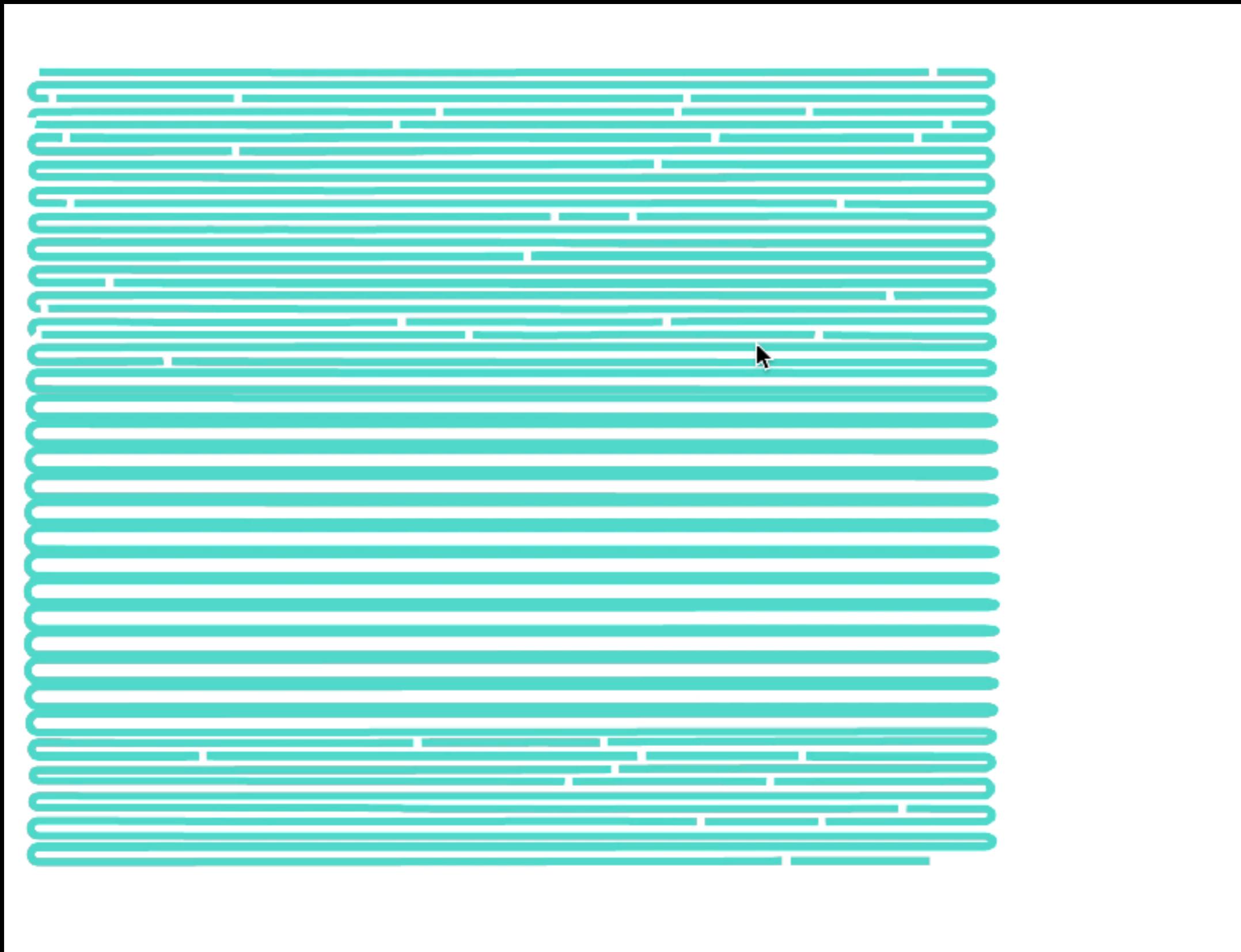




Use polygon packing to visualize ALL parking spaces



Use graph algorithms to roll up ALL streets and rails

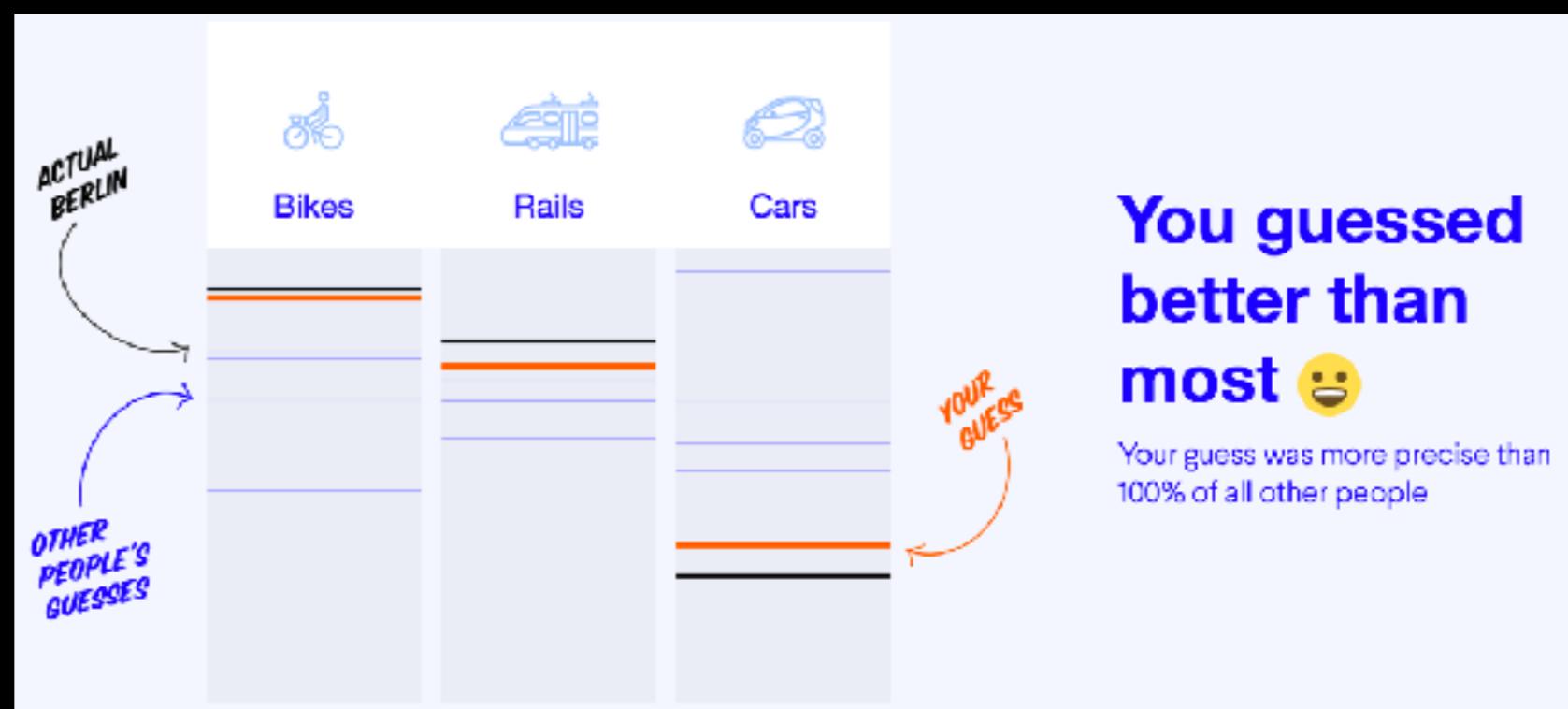
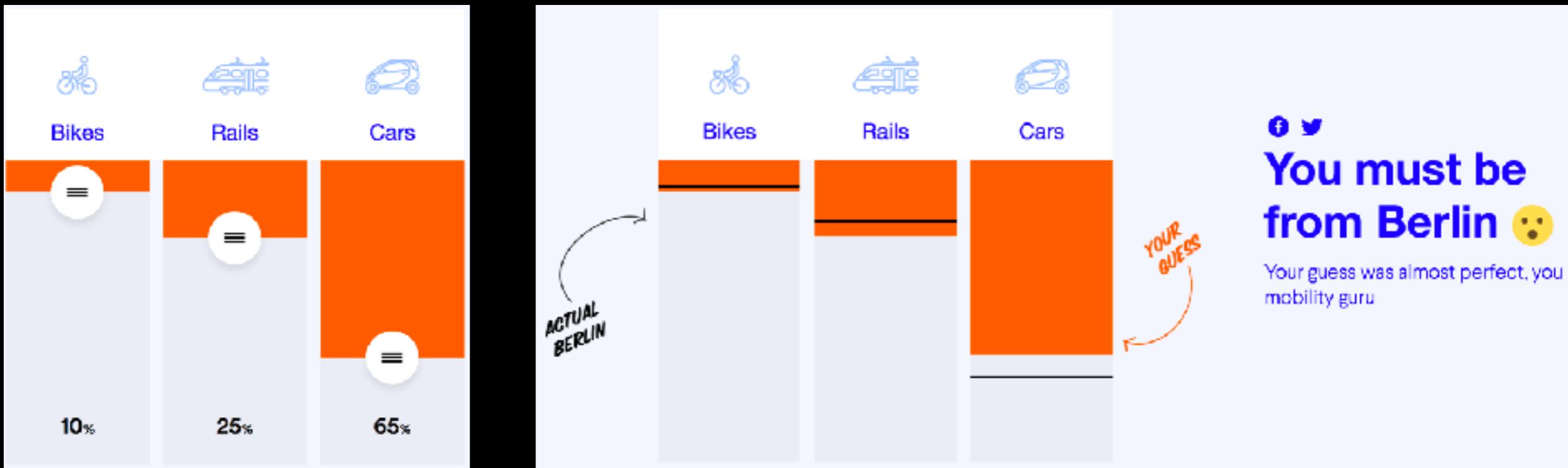


Shared self-driving cars

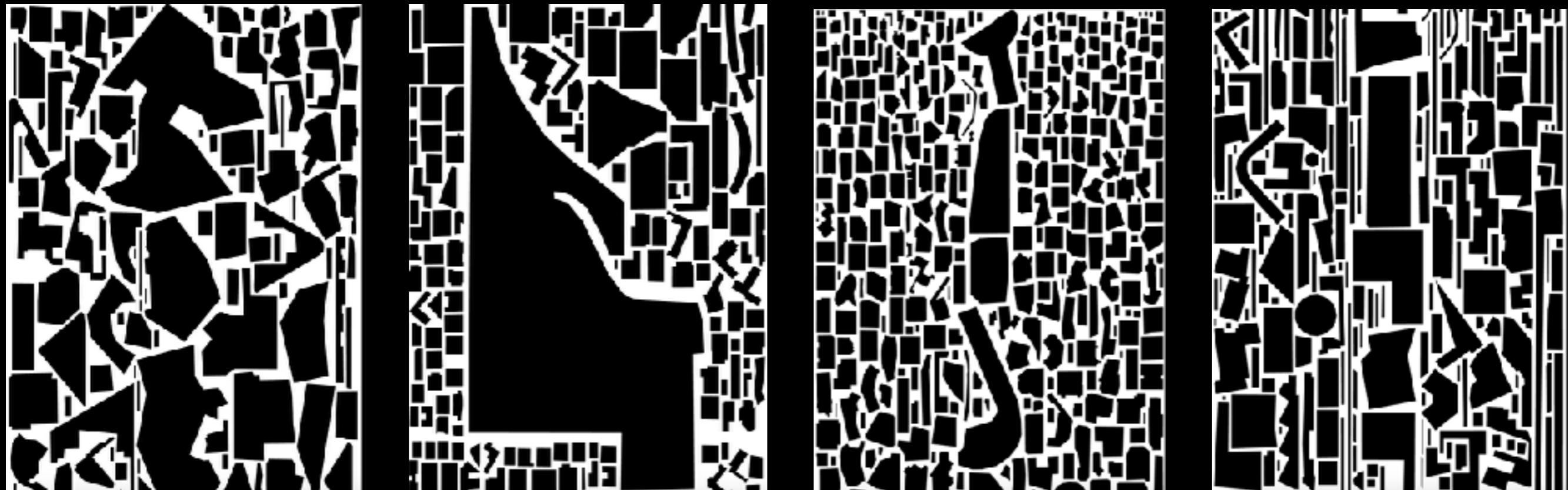
Same mobility can be delivered with 10% of cars



Exploring "The Arrogance of Space" interactively

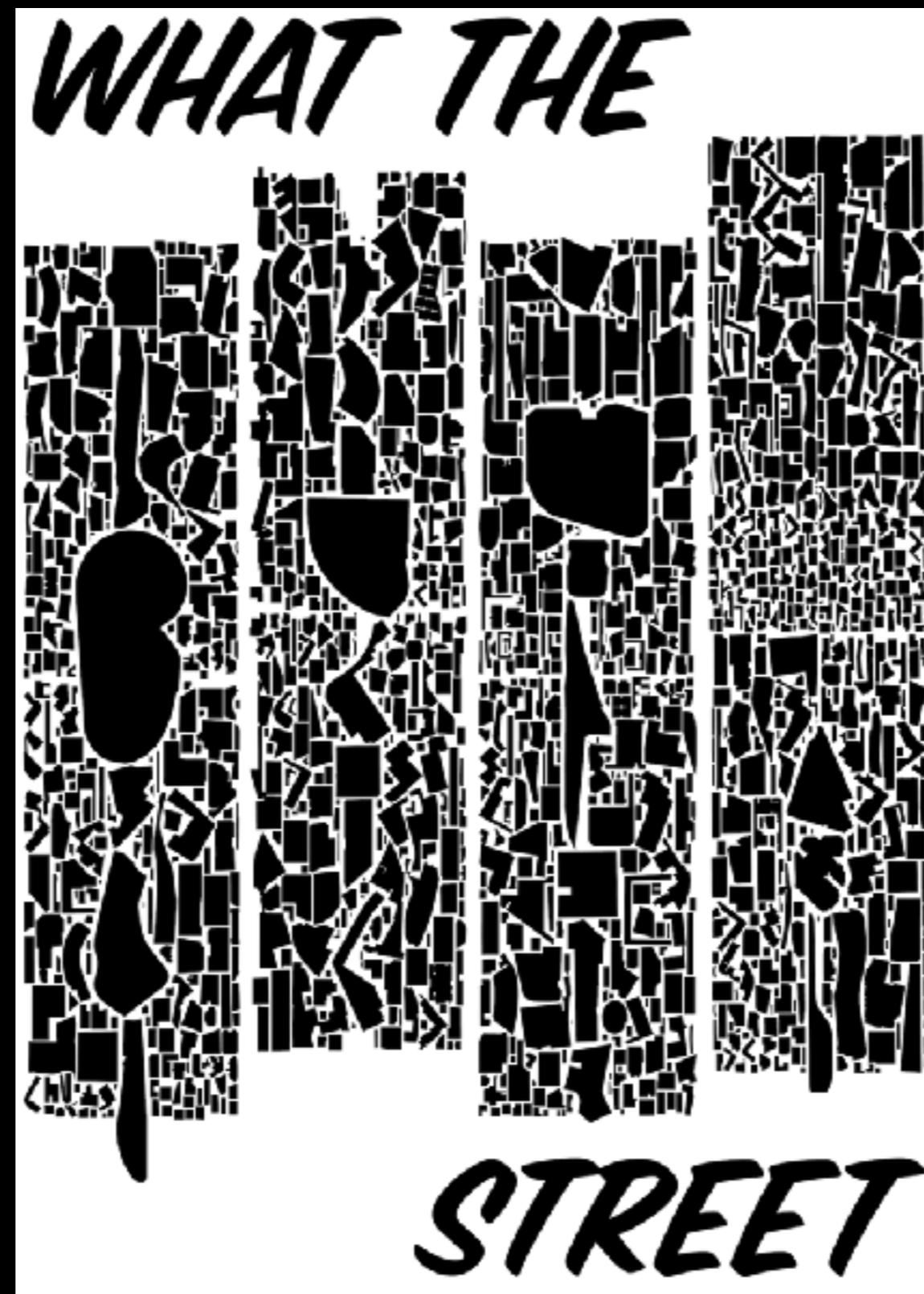


Cities have unique patterns



Which one is Copenhagen, and why?

Launching April 19, whatthestreet.com



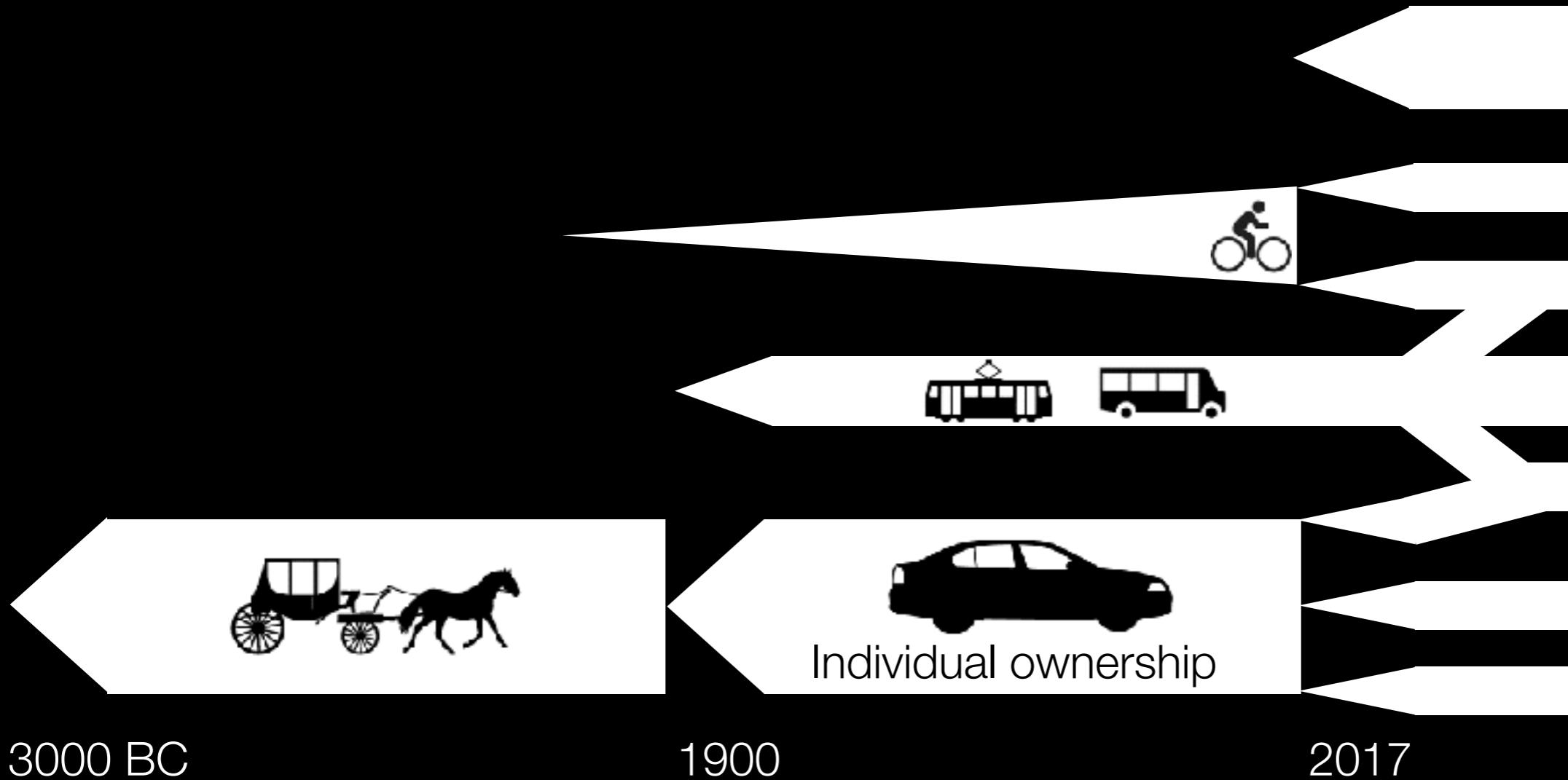
Let us prioritize + incentivize what works best for society

1. Bike
2. Metro, rail, tram
3. Bus

If cars needed, let them be shared and autonomous, to not waste space

Good scaling arguments why car-centric cities are not sustainable

Let us understand these developments towards sustainable solutions for living together



Research

Paolo Santi
Giovanni Resta
Remi Tachet
Oleguer Sagarra
S. Sobolevsky
Carlo Ratti
Steven Strogatz

Visualizations

Benedikt Groß
Joey Lee
Eric Baczkuk
Carlo Ratti
Andi Weiß
Stefan Landsbeck
Pierrick Thebault

Stephan Bogner
Tobias Lauer
Tilman Hauser
Raphael Reimann
Daniel Schmid
Johannes Wachs
Anagrama
Zoom7

Michael Szell

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