# Urban Traffic

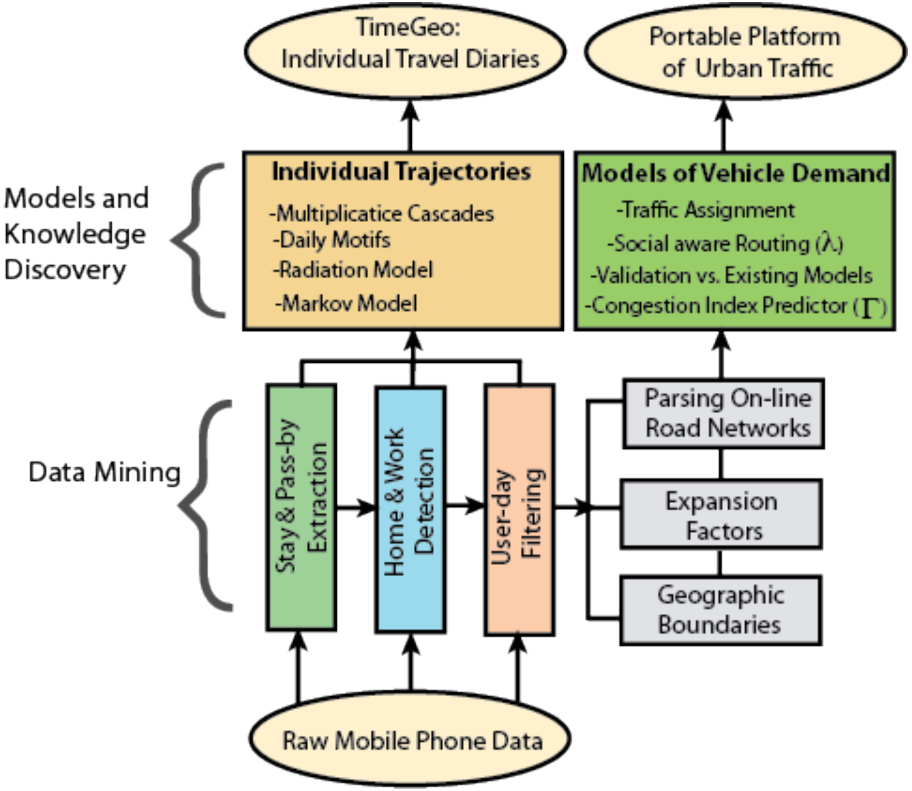
Marta C. Gonzalez

Associate Professor of Civil and Environmental Engineering,
Center for Advanced Urbanism

Civil and Environmental Engineering

Massachusetts Institute of Technology

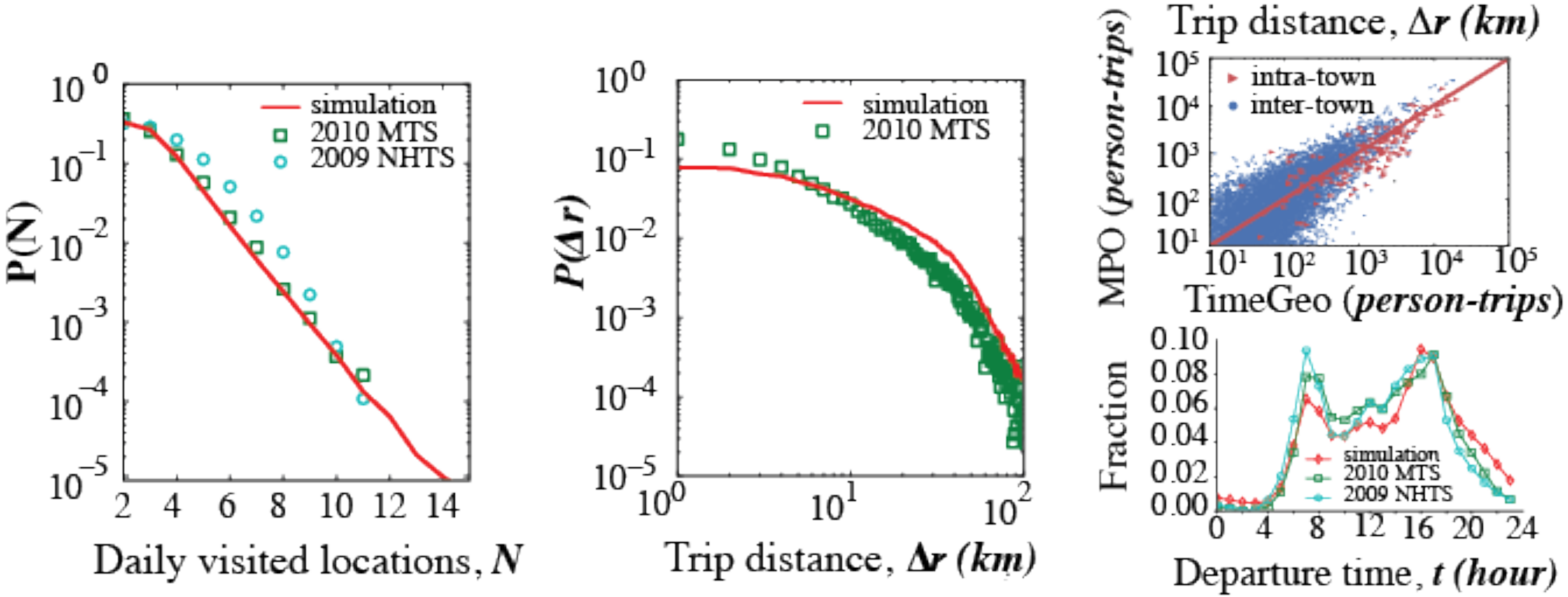
# From imperfect personalized data to Transportation models




**The TimeGeo modeling framework of urban mobility without surveys**
*PNAS* *(August)*, 2016

***Validated against Boston MPO 2007 and 2010 Urban Demand Models***

# Comparison with travel demand models based on travel surveys




**The TimeGeo modeling framework of urban mobility without surveys**
*PNAS* *(August)*, 2016

**Çolak, S.**, Schneider, C.M., Wang, P & Gonzalez, M. C., ***On the role of spatial dynamics and topology on network flows***, *New Journal of Physics (2013)*

In this work, we aim to analyze the phase transitions road networks go through to a state of congested transport.

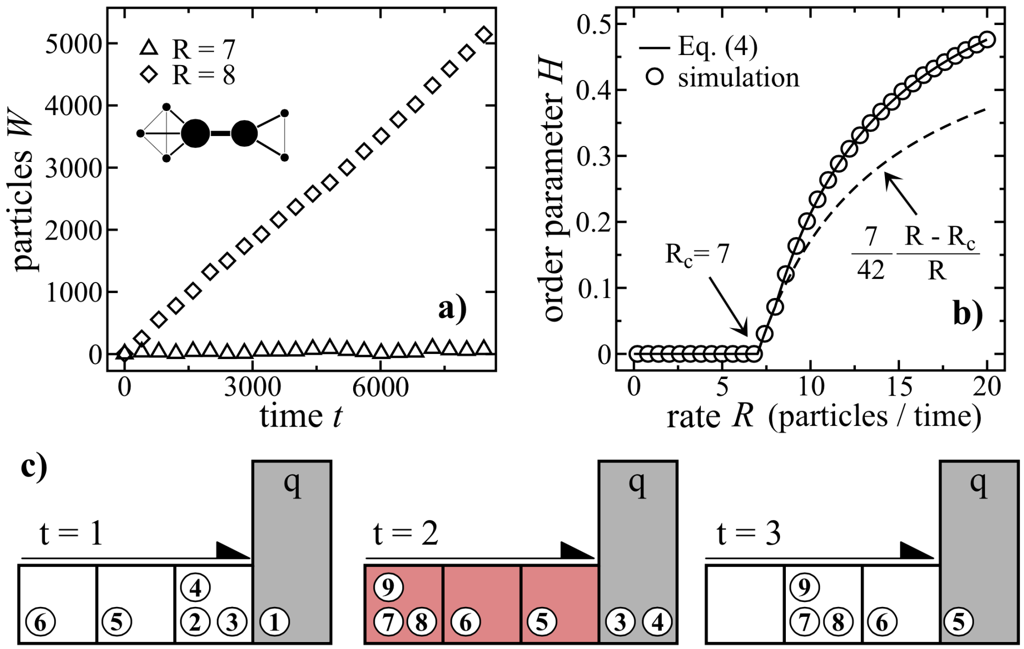
We implement a point-queue model to represent traffic.

We introduce an analytically solvable framework that includes simple topological measures of the network to estimate the response.

We explore the implications of our model for the San Francisco road network.

We load a network with **R** particles at every time step, with a randomly selected origin and a destination. Particles follow

$$H(R) = \frac{\langle \Delta W \rangle}{R}$$

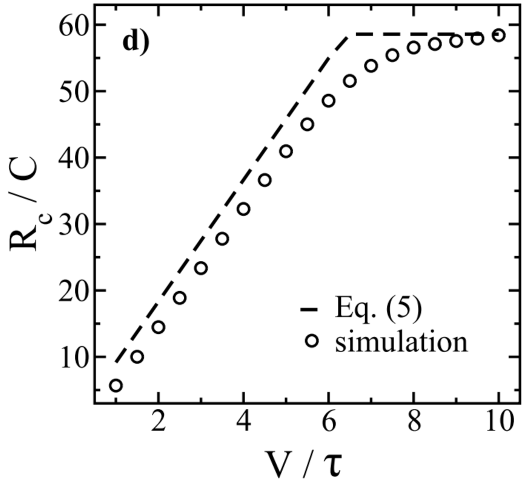



PQM : point queue model

SPQM: spatially constrained point queue model

$$R_c = N(N-1)\min\left(\frac{C}{B^{E*}_{max}}, \frac{V}{(\tau B^E + B^{E*})_{max}}\right)$$

The critical rate, Rc, depends on the critical element, which is the road segment with the smallest capacity to demand ratio. The element is determined by how many shortest paths it lies on, and is the origin of the congestion spread.




delay:

$$D_i(R) = \mathcal{H}(R_c^i - R) + \frac{C_i}{I_i(R)}\mathcal{H}(R - R_c^i),$$

inflow:

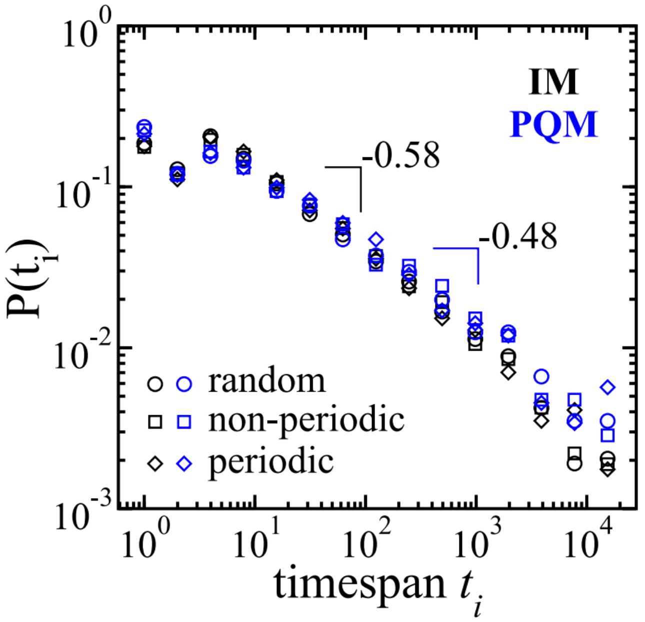
$$I_i(R) = \frac{\sum_{k\in\Gamma(i)}\prod_{j\in k} R D_j(R)}{N(N-1)},$$

order:

$$H(R) = \sum_{i\in\mathcal{N}}(I_i(R) - C_i)\mathcal{H}(I_i(R) - C_i),$$

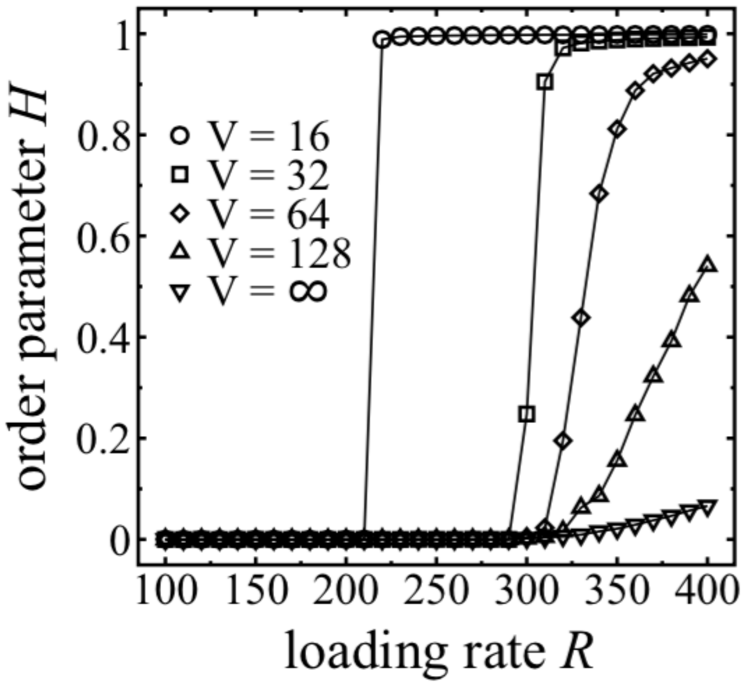
We analyze $t_i$, the length of the timespans at which the critical element is operating at its capacity. We observe *no-scale timespans*. This behavior agrees with phase transitions, as *fluctuations increase* and the network swings between the congested and uncontested state.

The distributions are *independent of topology*, but dependent on the traffic model.



We define **V**, number of particles that can fit on a link, to model space and how it affects congestion.

For lower **V** values, the nature of the transition shifts from a continuous to discontinuous one, highlighting the severity of traffic spillback.



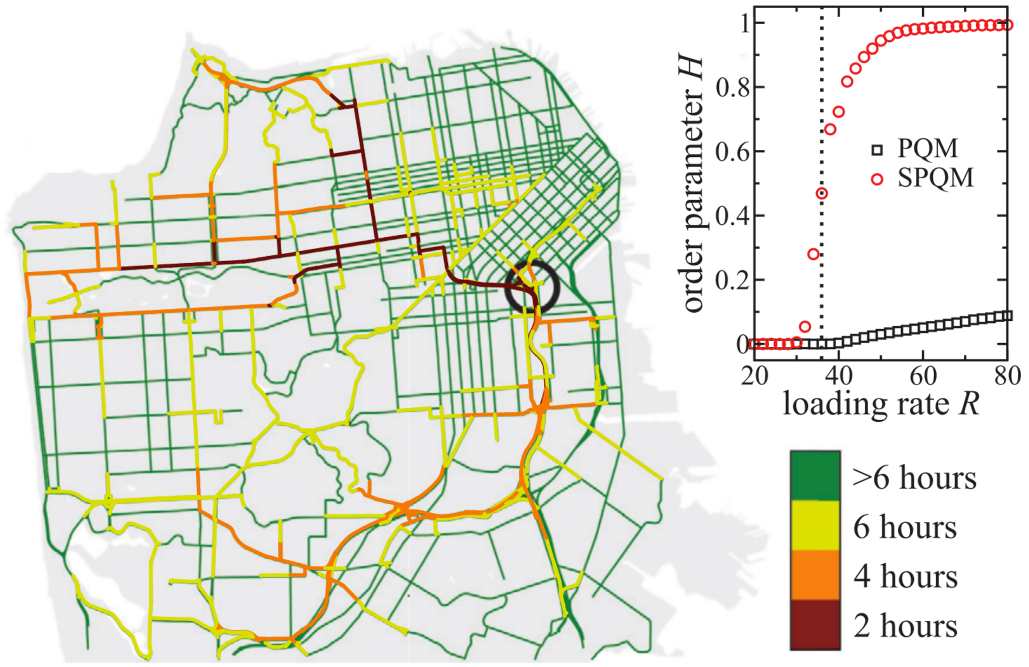



**Figure 4.** A congestion map of the San Francisco road network for $R = 36$ vehicles per timestep. Colors represent the times within which the road segments become congested as a consequence of the spillover. The black circle denotes the origin of congestion. (inset) PQM and SPQM transitions for the San Francisco road network, where $R_c^{\mathrm{PQM}} = 40$ and $R_c^{\mathrm{SPQM}} = 30$.

# Summary

We studied the phase transition to congestion as an interplay of supply and demand.

We showed that network topology and spatial constraints are determining factors that govern the nature of this transition.

- We consequently aim to analyze realistic demand and traffic conditions as they apply to a typical commuter.
- We hope to incorporate modifications to routing schemes and understand their implications.
- A final overarching goal is to be able to provide an understanding of congestion for many cities.

**Çolak, S.**, Lima, A. & Gonzalez, M. C., ***Understanding congested travel in urban areas***, *Nature Communications (2016)*

As cities grow, roads become increasingly burdened.

1. understanding the complex interplay between travel demand and the road infrastructure and,

2. modeling path-level travel times and overall congestion in not a single city but many at once

has been particularly highlighted challenges in this line of research.

In their 2013 report, TomTom stated in cities like Moscow, Rio, Mexico City and Beijing, commuters spend about 75% extra time traveling due to traffic.

The resulting loss of time, money and energy are borne by all citizens.

Continuing investment in more capacitated roads despite doubts relating to induced demand only provide short term relief.

| World rank | Filter rank | City | Country | Congestion Level | Morning peak |
|---|---|---|---|---|---|
| 1 | 1 | Istanbul | Turkey | 58% | 76% |
| 2 | 2 | Mexico City | Mexico | 55% | 93% |
| 3 | 3 | Rio de Janeiro | Brazil | 51% | 72% |
| 4 | 4 | Moscow | Russia | 50% | 77% |
| 5 | 5 | Salvador | Brazil | 46% | 62% |
| 6 | 6 | Recife | Brazil | 45% | 81% |
| 7 | 7 | Saint Petersburg | Russia | 44% | 67% |
| 8 | 8 | Bucharest | Romania | 41% | 78% |
| 9 | 9 | Warsaw | Poland | 40% | 69% |
| 10 | 10 | Los Angeles | United States | 39% | 60% |

In this work, we aim to couple travel demand profiles and travel time estimates to analyze how efficiently people move across cities.

We parse OpenStreetMap data, use OD information mined from CDR data and route trips in the road networks.

We explore the relationship between distance and travel time, and how it is influenced by aggregate characteristics of a city's supply and demand.

We measure the inefficiency of selfish routing and the potential benefits of routing schemes that take social good into account.

The typical traffic problem is formalized as follows:

$$\underset{x_e \forall e \in E}{\text{minimize}} \quad \sum_{e\in E} \phi_e = \sum_{e \in E} \int_0^{x_e} t_e(x)dx$$

$$\text{subject to} \quad \sum_p f_p^{st} = f^{st}$$

$$x_e = \sum_s \sum_t \sum_p f_p^{st} \delta^{st}(p,e),$$

$$x_e \geq 0, f_p^{st} \geq 0.$$

Algorithm B provides a fast and efficient origin-based solution to this problem.

**ALGORITHM B($N$)**

Initialize $B$ as the shortest path tree rooted at the origin.
Assign all flows to links to $B$.
**while** $r_g > 0.001$
**do**
- **for all** origins $o$
  **do**
  - Add to $B_o$ edges $e$ with negative reduced costs.
  - Solve the Restricted Master Problem for $B_o$.
  - Simplify $B_o$ by removing $\{e | x_e = 0\}$.

**RESTRICTED MASTER PROBLEM(Bush $B$, $\epsilon$)**

Update costs on all links on $B$.
Calculate the longest route tree with paths $P_i$ and costs $U_i$.
Calculate the shortest route tree with paths $p_i$ and costs $u_i$.
**if** $max\{U_i - u_i, \forall i\} \leq \epsilon$ , stop.
**else** *continue.*
**for all** $j$
**do**
- set of links in $p_i$ not in $P_i : S_j = p_i \setminus P_i$
- set of links in $P_i$ not in $p_i : L_j = P_i \setminus p_i$
- difference in costs to $j : g = (u_j - u_i) - (U_j - U_i)$
- total marginal cost of sets $S_j$ and $L_j h = \sum_{e \in S_j \cup L_j} c_e^{'}$
- flow to be shifted : $dx = min\{g/h, min\{x_e | e \in L_j\}\}$
- add flow to shorter path : $x_e = x_e + dx, e \in S_j$
- remove flow to shorter path : $x_e = x_e - dx, e \in L_j$
- update travel times : $t_e, e \in S_j \cup L_j$

# Route Assignment

1. Road networks from OpenStreetMap data.
2. Algorithm B, implements equilibration on a directed acyclic graph (DAG).
3. Keep track of where flow is sent two and from.

$$r_g = 1 - \frac{\sum_{o,d} t_{od} d_{od}}{\sum_{e \in E} t_e v_e},$$

where $t_{od}$ and $d_{od}$ represent the demand and the travel time between an origin and a destination, and $t_e$ and $v_e$ represent the travel time and the volume on a road segment $e$.

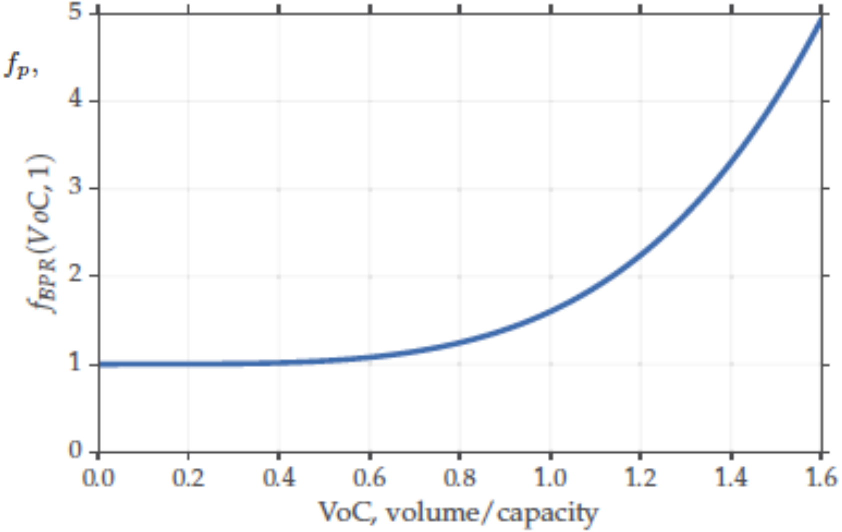
This ensures that all drivers in the system are in fact taking the shortest possible routes,

# travel times using a standard BPR function

$$f_p^{rio} = f_p^{boston} = f_p^{sfbay} = 1.3 \text{ and } f_p^{lisbon} = f_p^{porto} = 1.1.$$

$$f_{BPR}(VoC, f_p) = t_f * \left(1 + \alpha\,(VoC)^{\beta}\right) * f_p,$$

$\alpha = 0.6$ and $\beta = 4$




Note: The results of validated travel time at the level of routes act as a validation of the OD flows and show an application of the urban mobility platform to compare cities and the cause of their congestion.

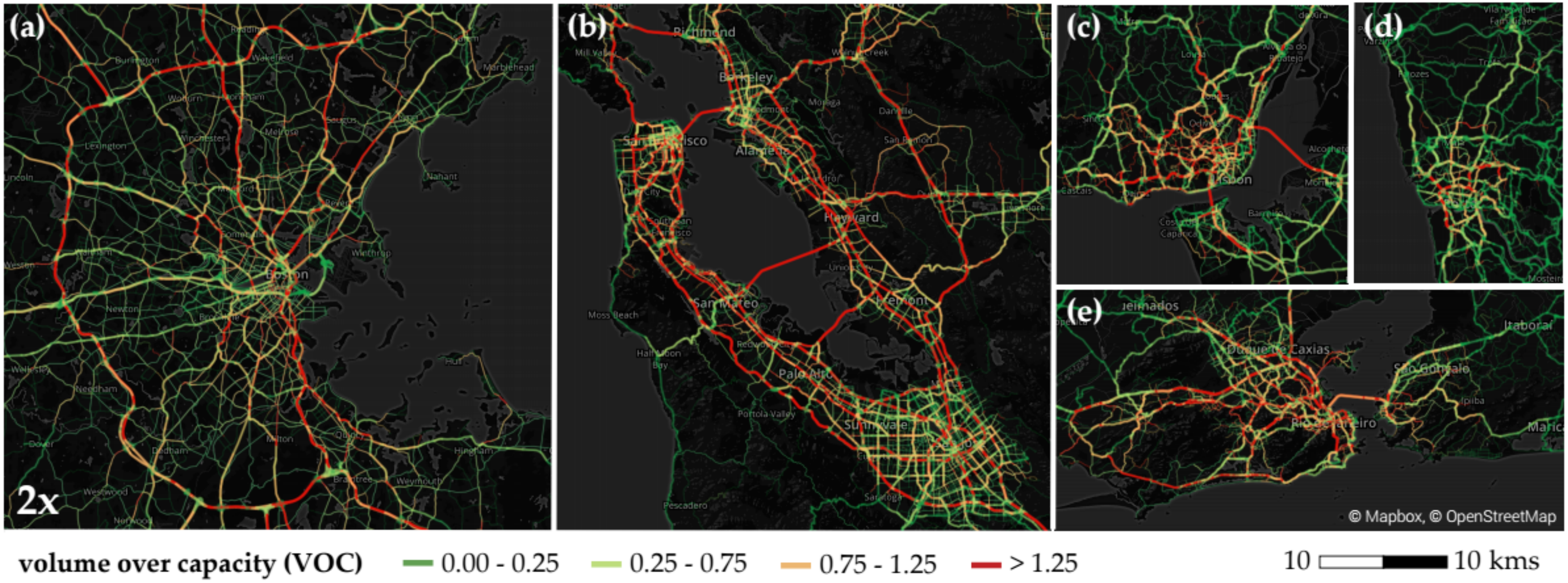
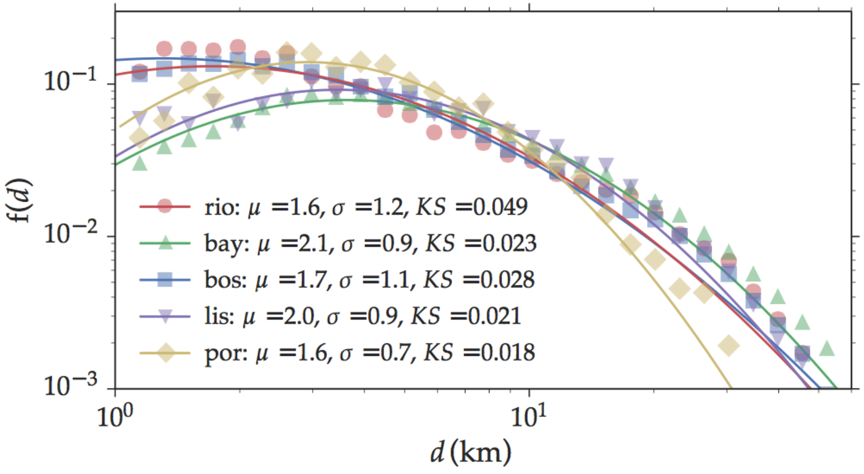
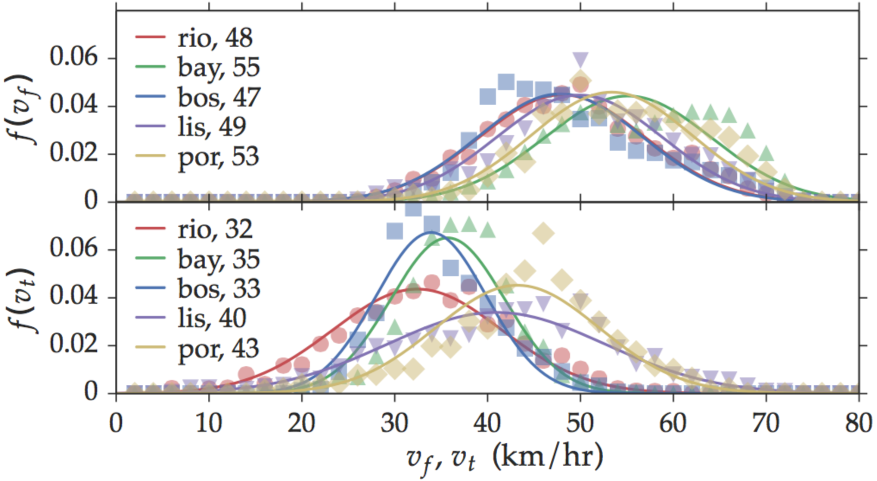


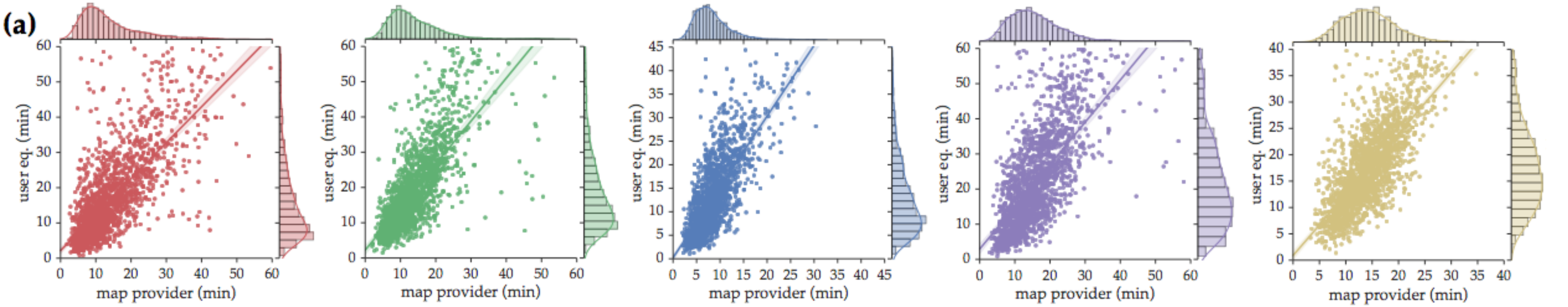

FIG. 2. **The maps of VOCs (volume over capacity) of the roads in the user equilibrium configuration.** The depicted cities are **(a)** Boston, USA, **(b)** San Francisco Bay Area, USA, **(c)** Lisbon, Portugal, **(d)** Porto, Portugal, and **(e)** Rio de Janeiro, Brazil. Higher VOCs are generally observed in highways as they provide faster means of travel. (Boston is 2x the distance scale.)

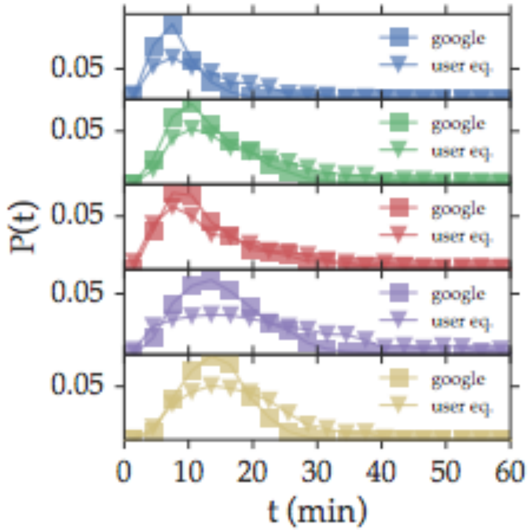



Commuting distances follow a lognormal distribution (with means ranging from 5 to 8 kilometers and standard deviations ranging from 2 to 4 kilometers) and exhibit similarity despite different city sizes.

Free and traffic speeds are normally distributed (with μ fluctuating around 50 km/hr). Under traffic conditions, the spread of speed distributions vary more.

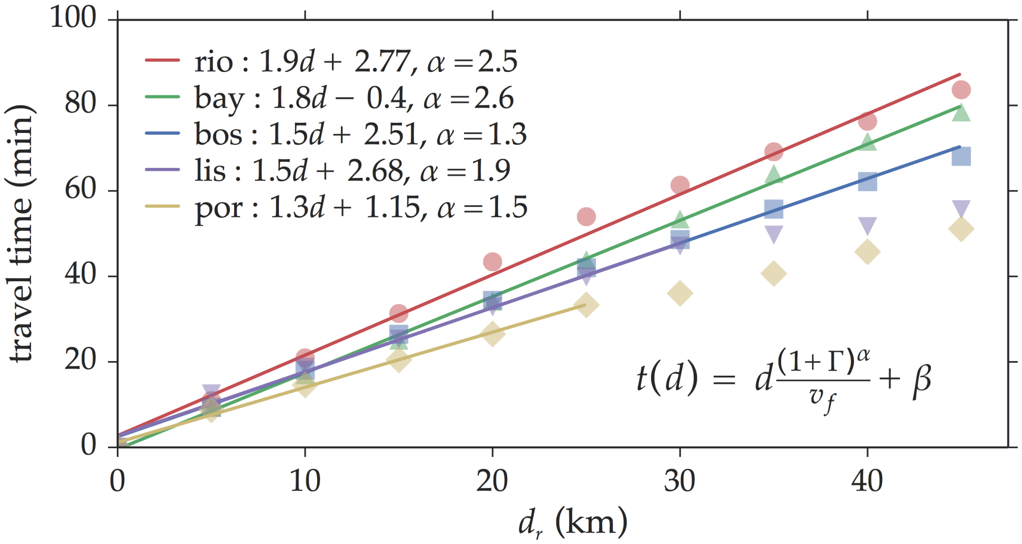



We generate the route travel times of commuters resulting from the demand profile and look at aggregate path properties.
These results demonstrate a

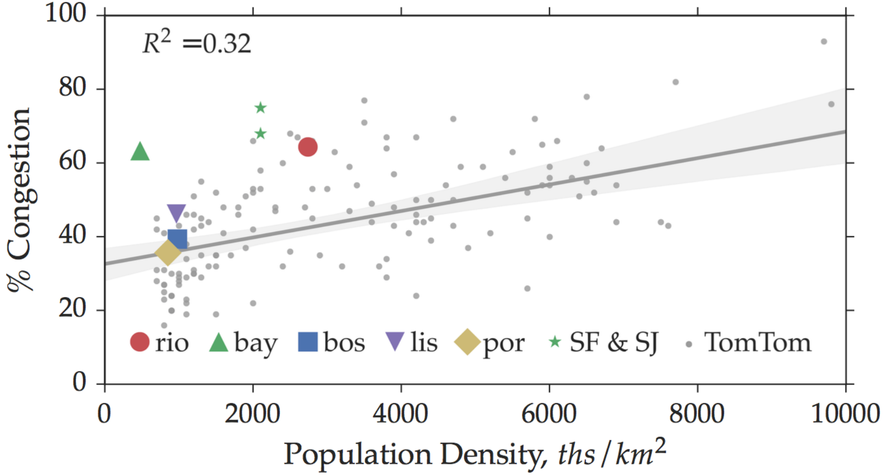
## demand-to-supply ratio

$$\Gamma = \frac{\sum_{e \in E} l_e x_e}{\sum_{x_e > 0, e \in E} l_e C_e}.$$

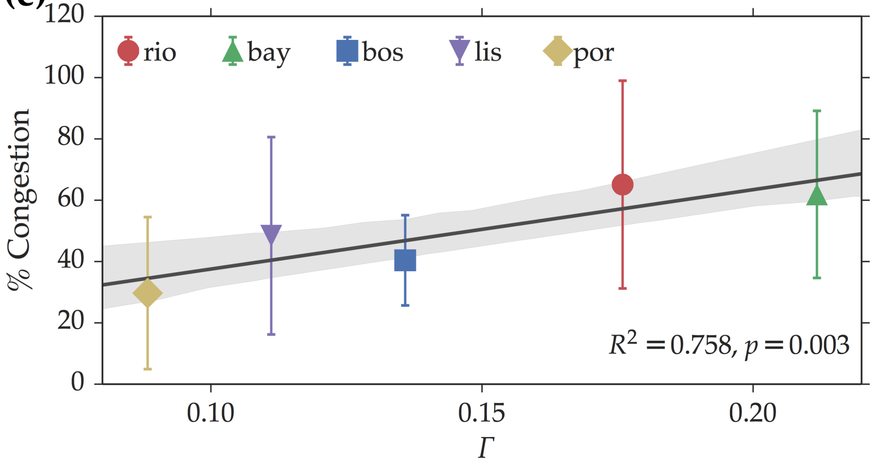



Γ, as a single dimensionless parameter, captures the load on the road infrastructure by bringing together trip distances, trip magnitudes, road capacities, and the distances they span.

It also helps explain navigation speed in cities for varying distances, with \alpha essentially describing the sensitivity of the city to the stress imposed by travel demand on its roads.




(e)




Here we investigate a typical relationship to test the common conception that cities with higher population densities tend to be more congested.

Our findings show that **Γ** is a better predictor than **ρ** as it lacks the outlier problem and provides a reasonable trend relating to overall congestion.

Next, we want to explore the potential of routing solutions on congestion alleviation.

To this end, we use a model that represents cost as a linear combination of the actual cost and the marginal cost of a selected path.

We refer to λ, the combination parameter in [0,1], as the weight of social good. λ=0 refers to UE, whereas λ=1 represents SO.

$$c_e^{\lambda}(x_e) = (1-\lambda)t_e(x_e) + \lambda \frac{d\left[x_e t_e(x_e)\right]}{dx_e}$$

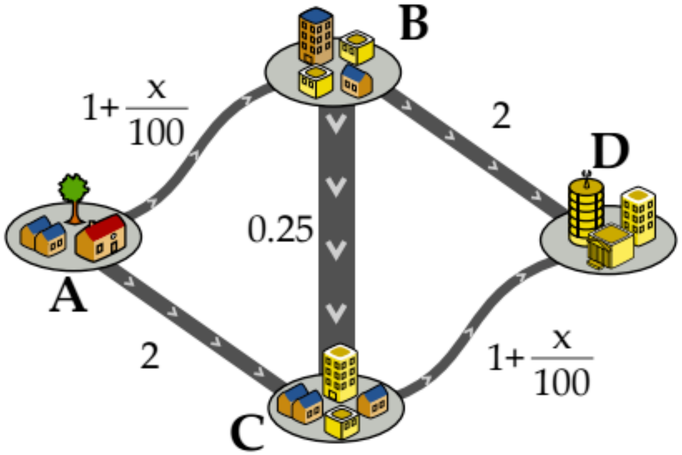
$$= \boxed{t_e(x_e)} + \boxed{\lambda x_e \frac{dt_e(x_e)}{dx_e}}$$

personal good

social good

$$\begin{aligned} \underset{x_e \forall e \in E}{\text{minimize}} \quad & \sum_{e \in E} \int_0^{x_e} c_e^{\lambda}(x_e) \cdot x_e dx_e \\ \text{subject to} \quad & \sum_p f_p^{st} = f^{st} \\ & x_e = \sum_s \sum_t \sum_p f_p^{st} \delta^{st}(p, e), \\ & x_e \geq 0, f_p^{st} \geq 0. \end{aligned}$$

100 drivers are going from **A** to **D**.

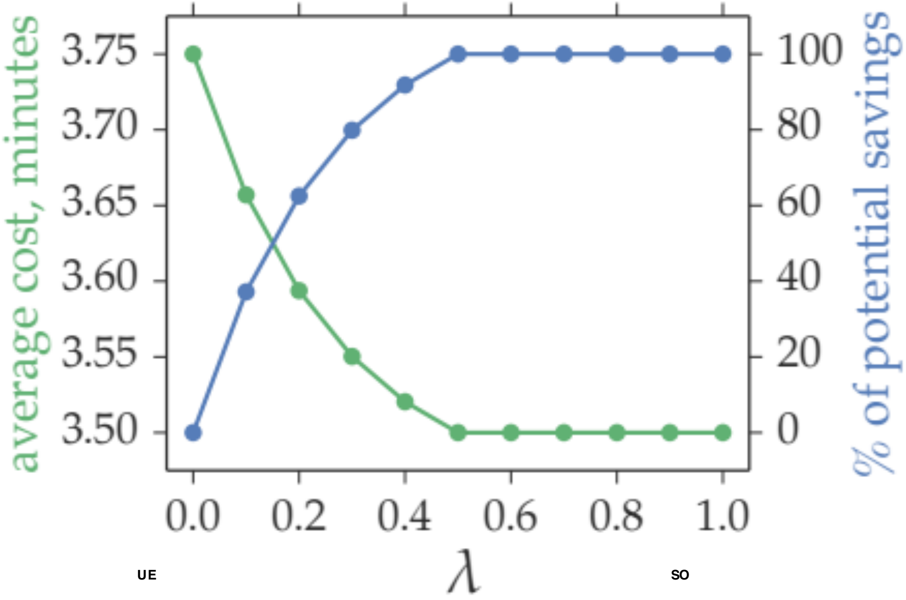



user equilibrium

$$f_{ABD} = f_{ACD} = 25$$
$$f_{ABCD} = 50$$

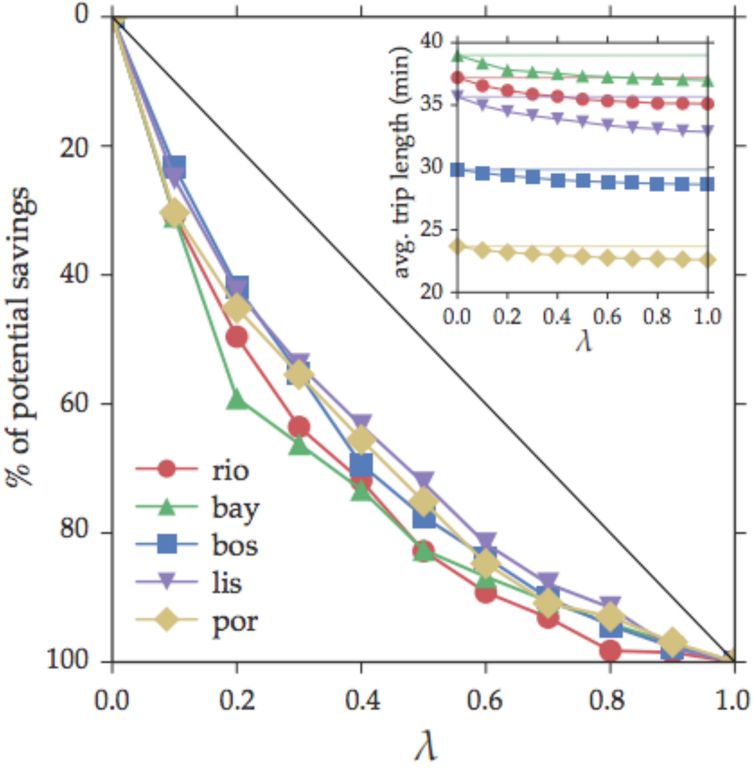
social optimum

$$f_{ABD} = f_{ACD} = 50$$



| | City | | | | |
|---|---|---|---|---|---|
| (min) | **Rio** | **SF Bay** | **Boston** | **Lisbon** | **Porto** |
| FTT | 20.6 | 21.1 | 19.3 | 22.4 | 15.3 |
| Loss | 14.1 | 12.5 | 8.2 | 8.0 | 4.0 |
| UE | 34.7 | 33.6 | 27.5 | 30.4 | 19.3 |
| Benefit | 2.6 | 2.6 | 1.3 | 2.1 | 1.1 |
| SO | 32.1 | 31.0 | 26.2 | 28.3 | 18.2 |
| % S | 18 | 21 | 16 | 27 | 28 |

15-30% of the time commuters lose in congestion on a typical morning peak is caused solely by selfish routing.




self $\boxed{t_e(x_e)} + \boxed{\lambda x_e \frac{dt_e(x_e)}{dx_e}}$ social

For λ = 0.2, an average of about 50% of all potential savings can be realized for our five subject cities.

The shape of the curves indicate that relatively modest social consideration weights λ can realize a significant portion of the potential travel time savings.

This raises the question: who is benefiting?

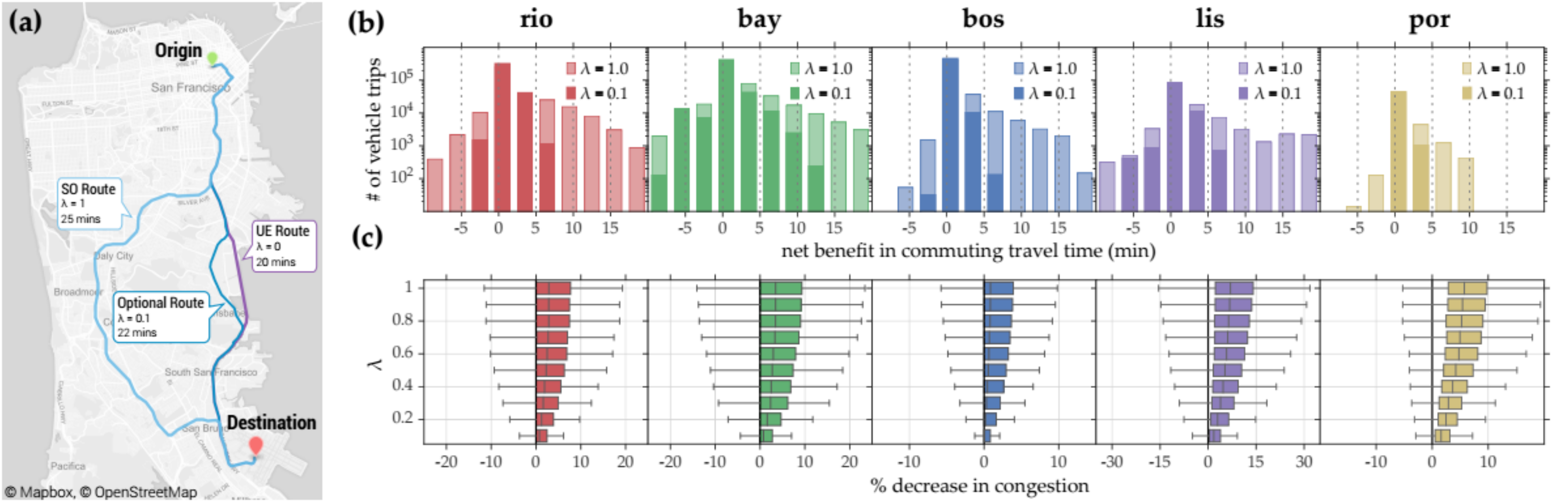



FIG. 5. **Benefit and congestion decrease distributions for different weights of social good. (a)** A depiction of three route alternatives with the corresponding travel times for a trip from Union Square to San Francisco Airport for $\lambda = 0$; $\lambda = 0.2$ and $\lambda = 1$, respectively. **(b)** Counts of vehicle trips and observed travel time benefits for $\lambda = 1$ and $\lambda = 0.1$. Negative benefits refer to increase in travel times for vehicles sacrificing for the social good. The spread of the distributions increase for higher $\lambda$. **(c)** The response of distributions of percentage decrease in time lost to congestion to increasing values of $\lambda$. The skewness towards positive values of congestion decrease indicate movement towards more optimal configurations.

Benefit distributions for commuters for λ = 0.1 exhibit less spread distributions compared to those for λ = 1, but the skewness towards the benefits remains inherent.

# Summary

### Takeaways

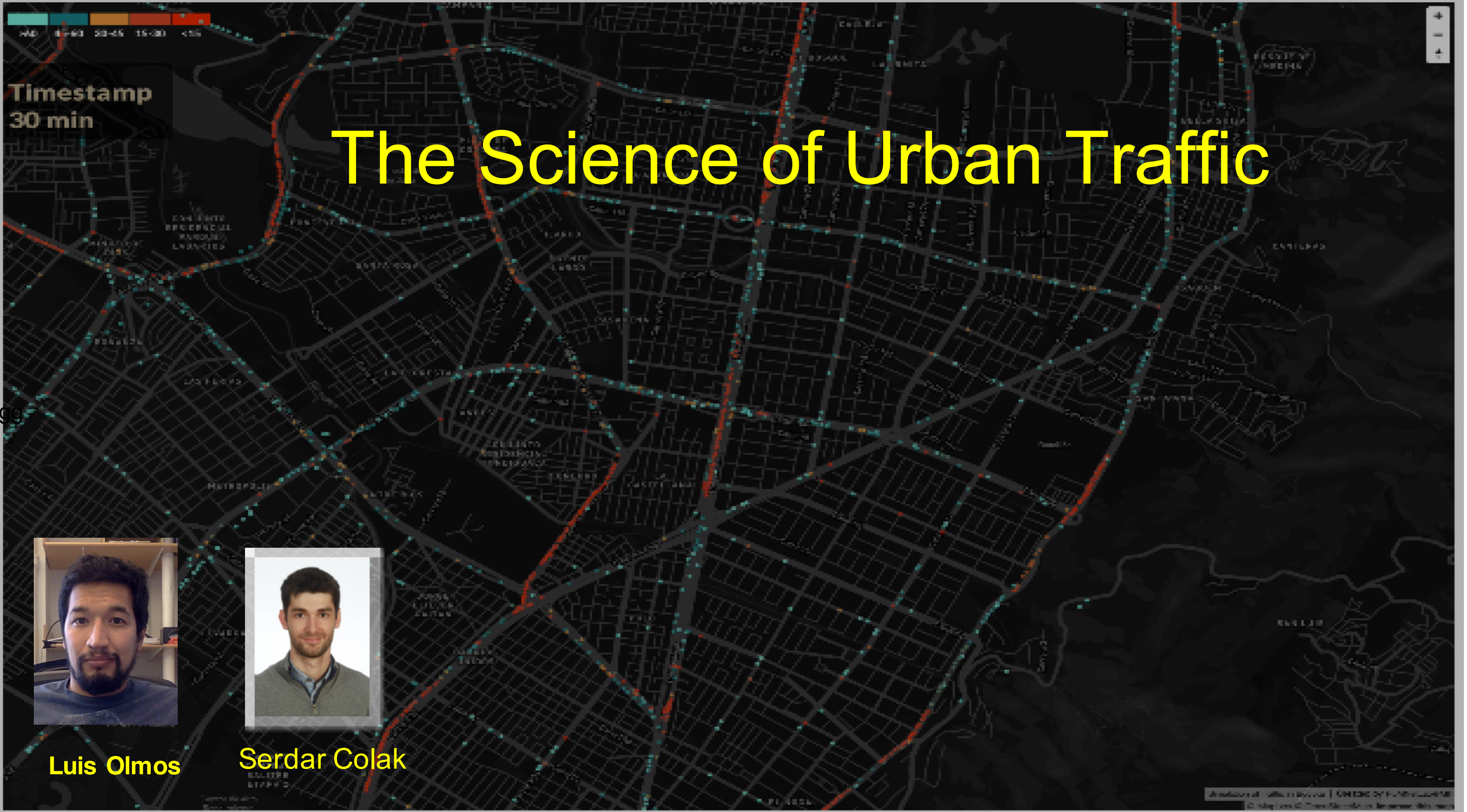
A city's congestion fingerprint is related to measurable characteristics, namely a ratio of total demand to total supply.

Lower λ will moderate the magnitude of benefits and losses while realizing most of possible benefits, making resulting policies fairer and easier to implement

### Future Work

- A more generalized approach that takes multi-modal transportation into account in the context of comparison of cities
- Shape findings to provide input of feedback for policies, for example, in the context of sociodemographics

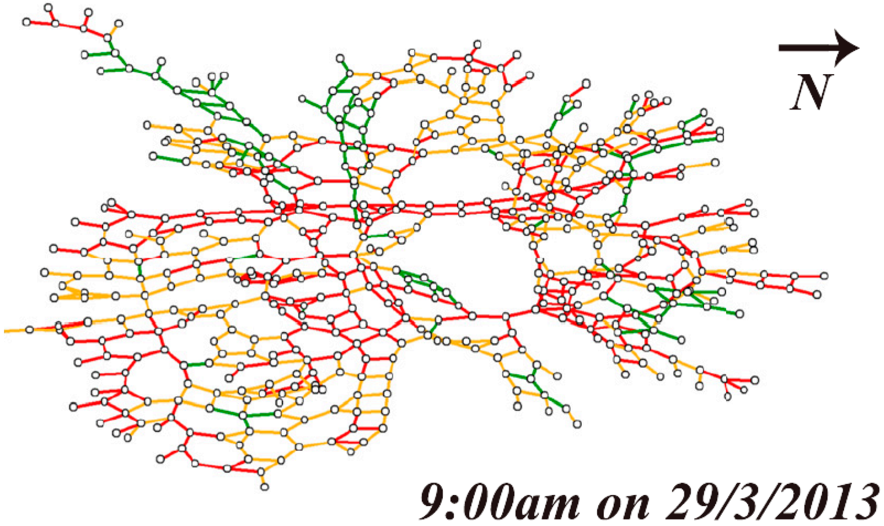
# The Science of Urban Traffic




Luis Olmos

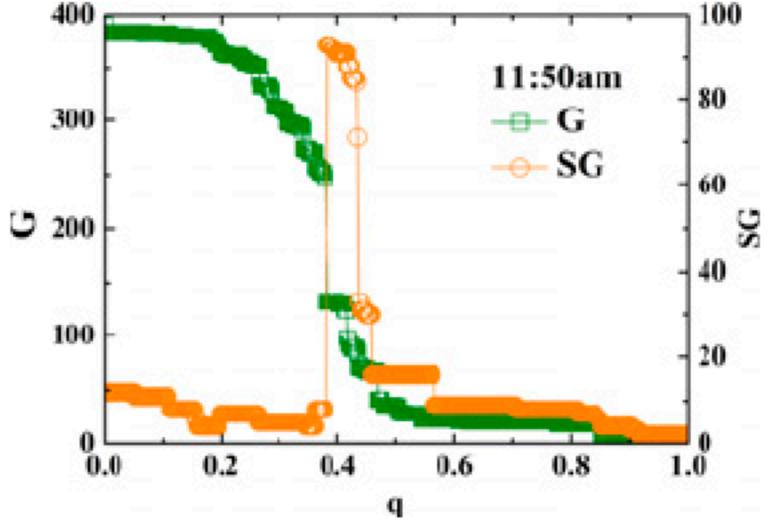
Serdar Colak

# Percolation transition in Dynamic Traffic Networks with evolving critical bottlenecks



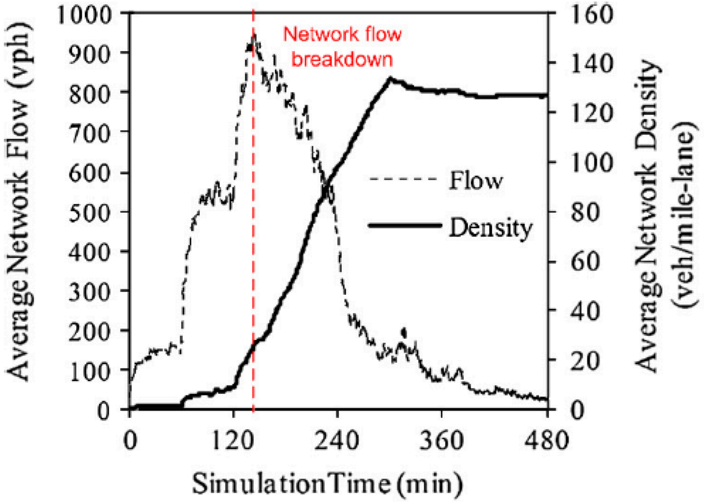

Links colored by
SPEED RATIO:

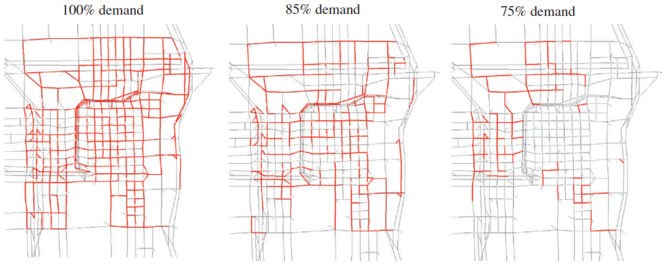
0.4 red
0.4-0.7 yellow
>0.7 green

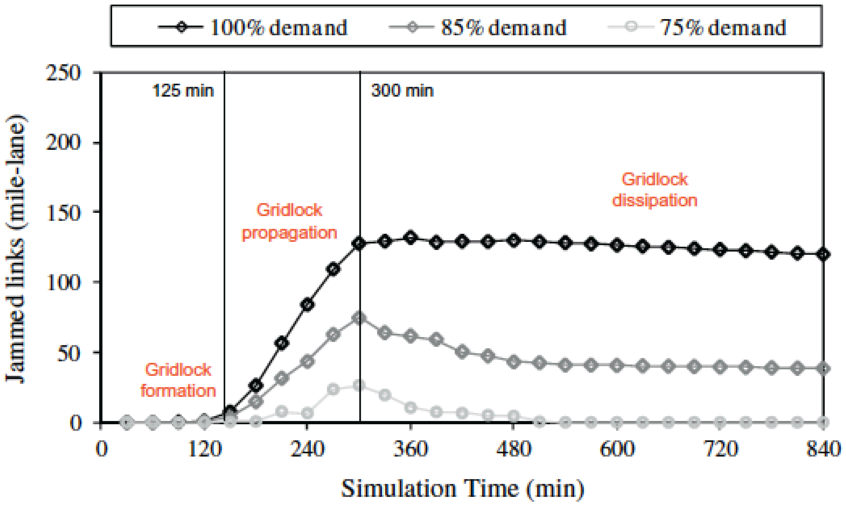



D. Li et. Al PNAS (2014)

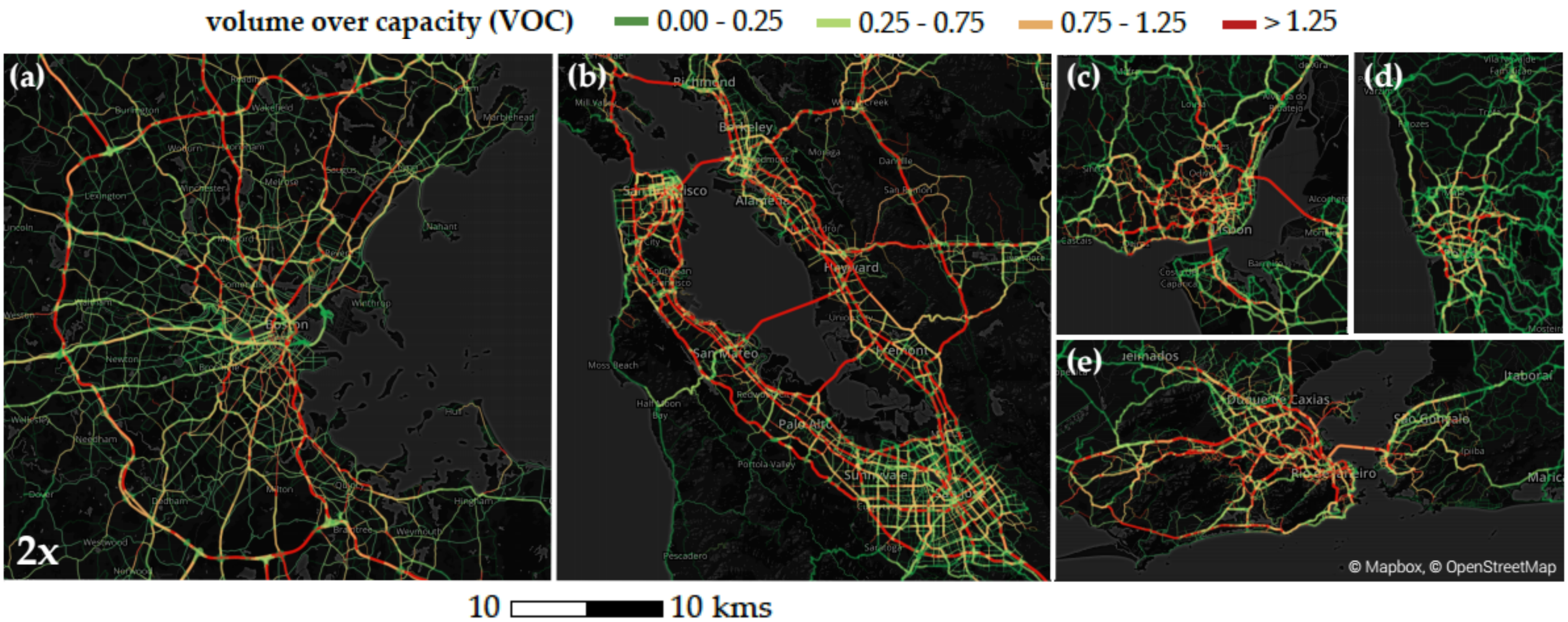
# Urban Networks gridlocks: Network characteristics and dynamics




*H.S. Mahmassani et al. / Transportation Research Part C 36 (2013) 480–497*




(a) Boston
(b) San Francisco Bay Area

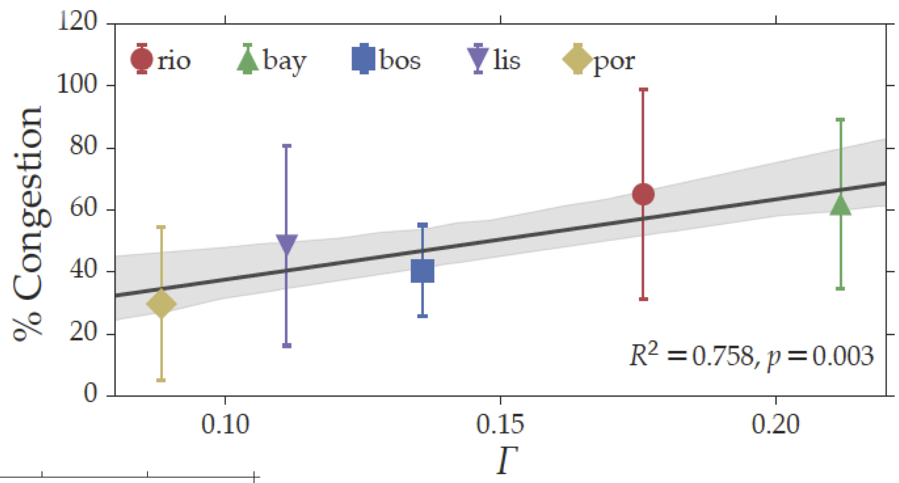
(c) Lisbon
(d) Porto

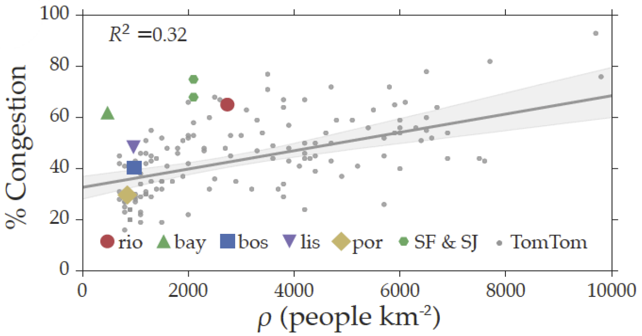
(e) Rio de Janeiro

Using 3 months of phone data
And Census Information on Population
and numbers of cars and their usage

Open Street Map data for the Streets when
not better data is available

# Better information based on our pipeline




$$\Gamma = \frac{\sum_{e \in E} l_e x_e}{\sum_{x_e > 0, e \in E} l_e C_e}.$$

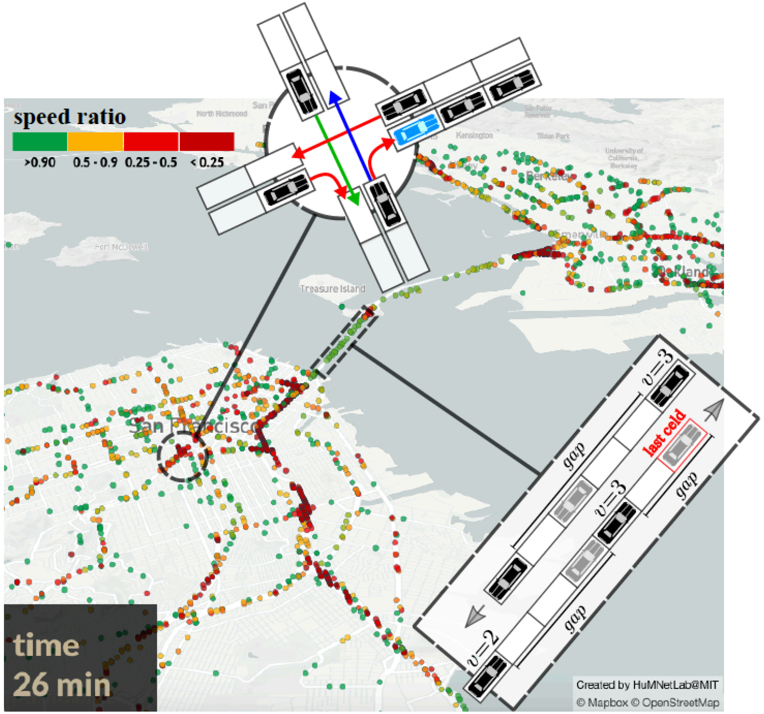
$x_e$ # Cars in the road link $e$

$l_e$ Road link length in miles

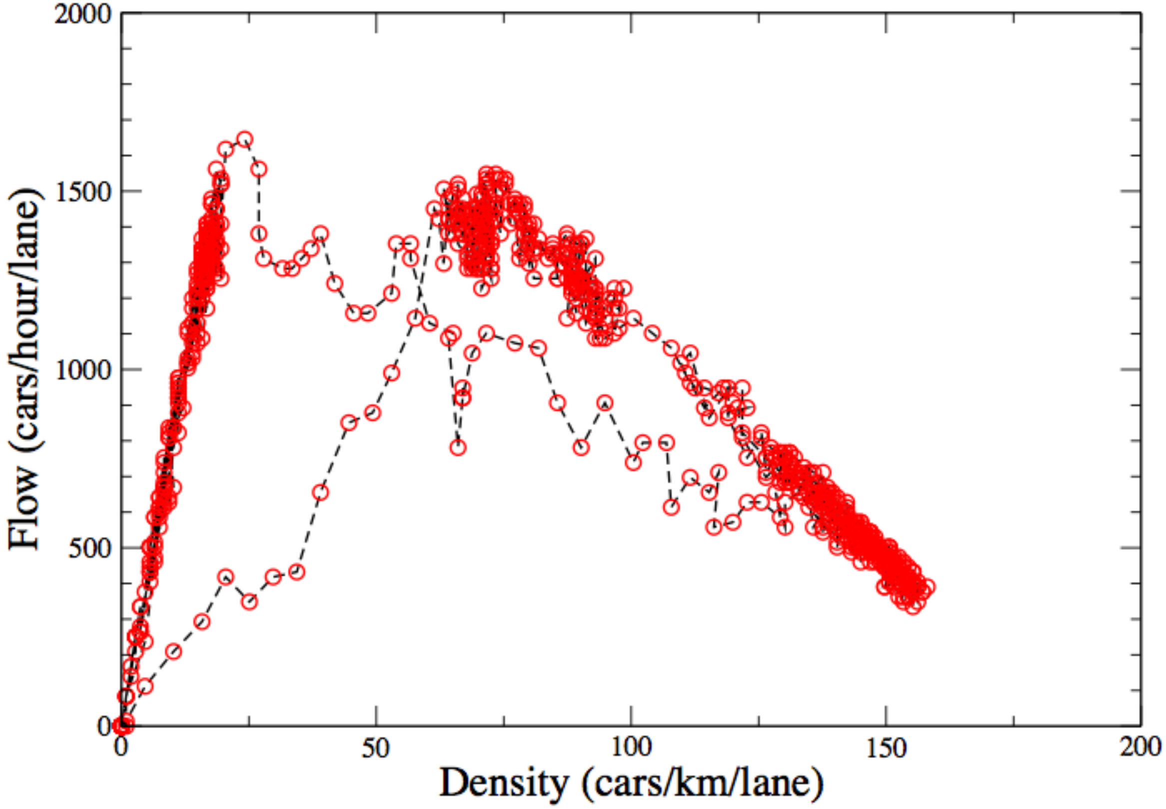
$C_e$ Capacity in the road link [cars/miles$^2$]

**Colak, Lima, Gonzalez, Nature Communications 2016**

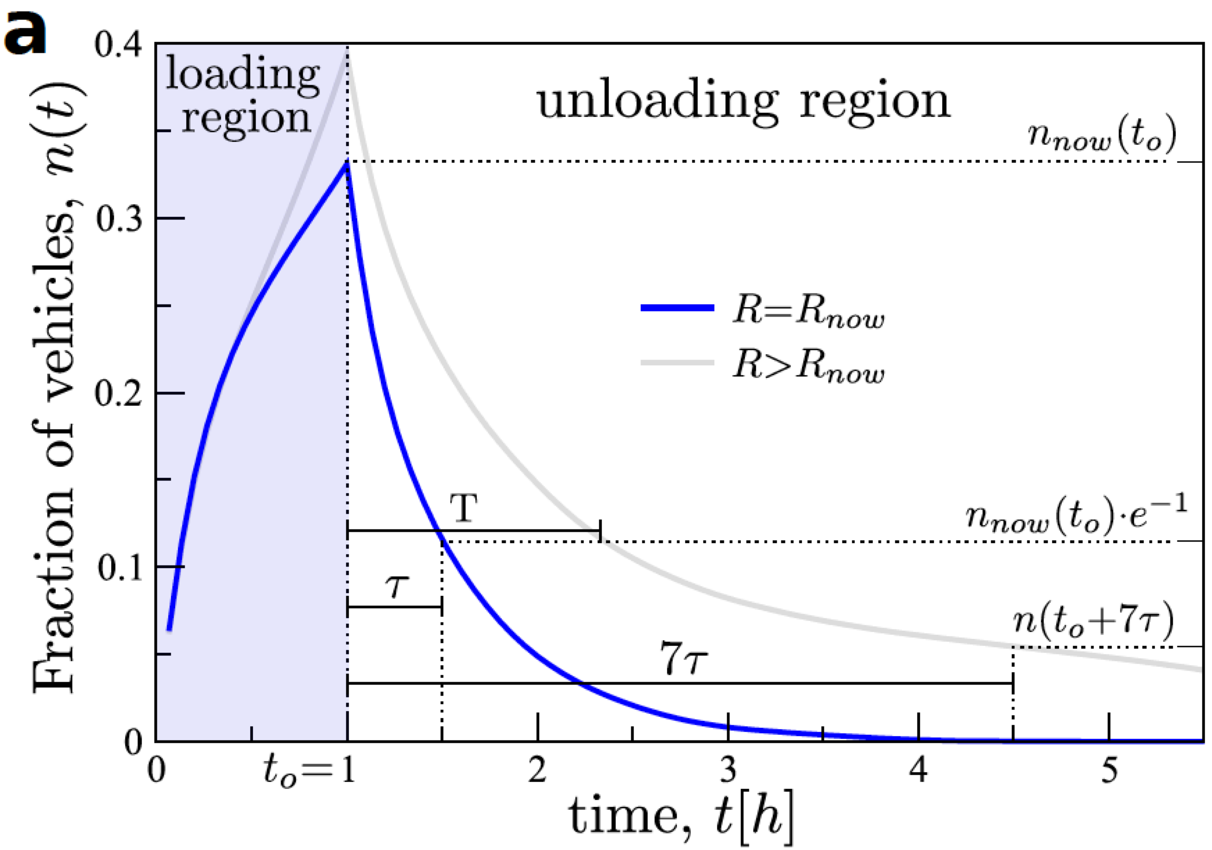

>60 45-60 30-45 15-30 <15
Timestamp
0 min
Bogota
Simulation of Traffic in Bogota | Created by HuMNetLab@MIT
© Mapbox © OpenStreetMap Improve this map


speed ratio
>0.90 0.5 - 0.9 0.25 - 0.5 < 0.25
Treasure Island
San Francisco
last cell
gap
gap
gap
$v = 3$
$v = 3$
$v = 2$
time
26 min
Created by HuMNetLab@MIT
© Mapbox © OpenStreetMap

# Traffic Fundamental Diagram

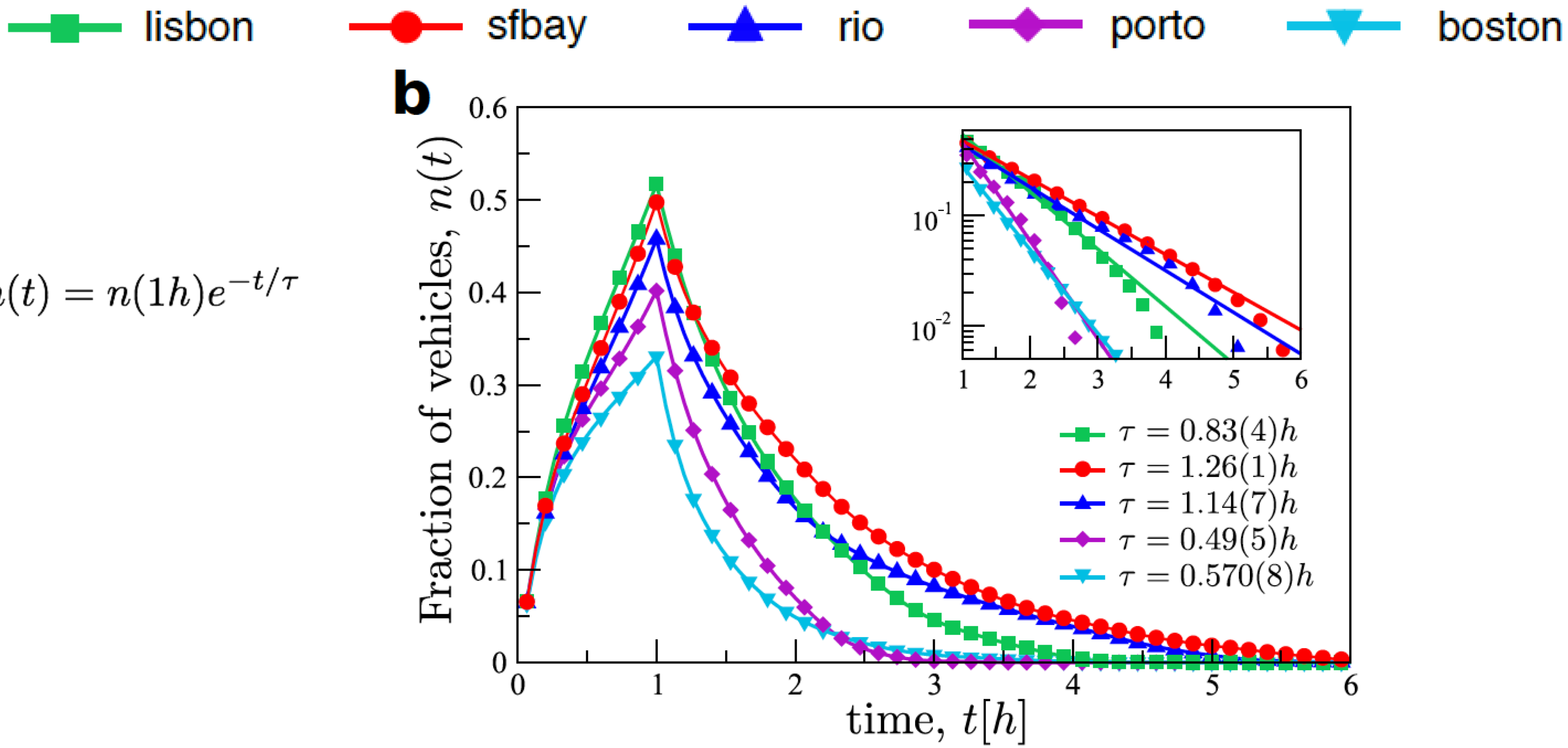


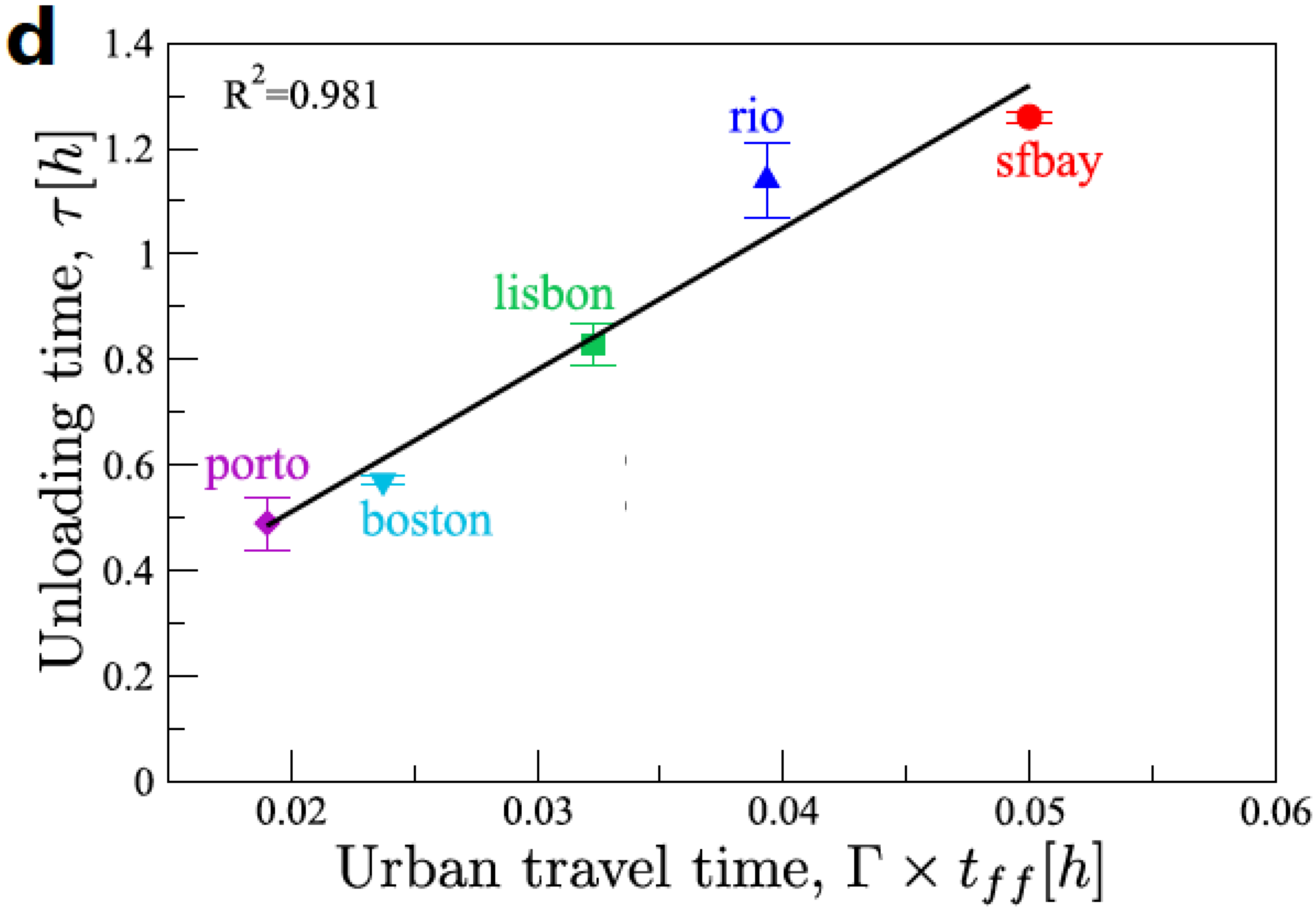
# Morning peak as a cycle of loading and unloading.



# How long does it take to unload?

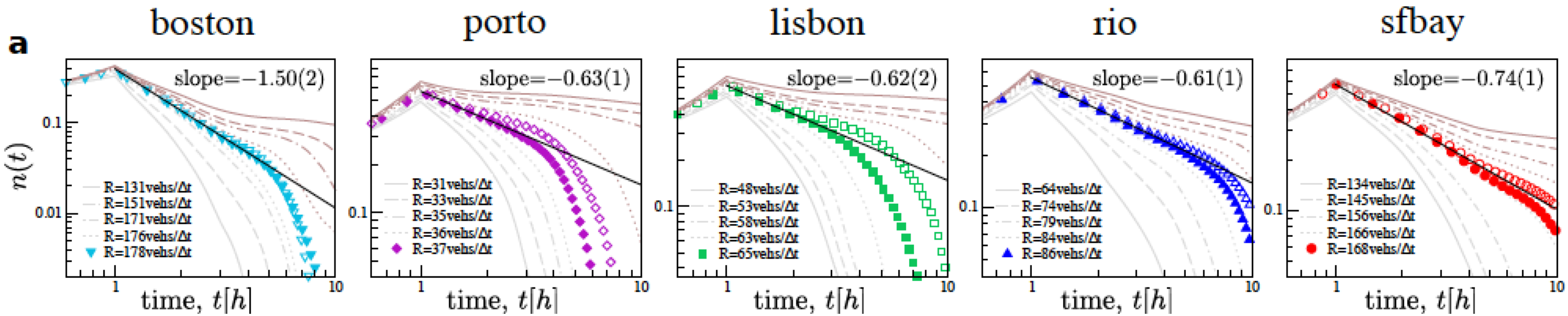
$$n(t) = n(1h)e^{-t/\tau}$$

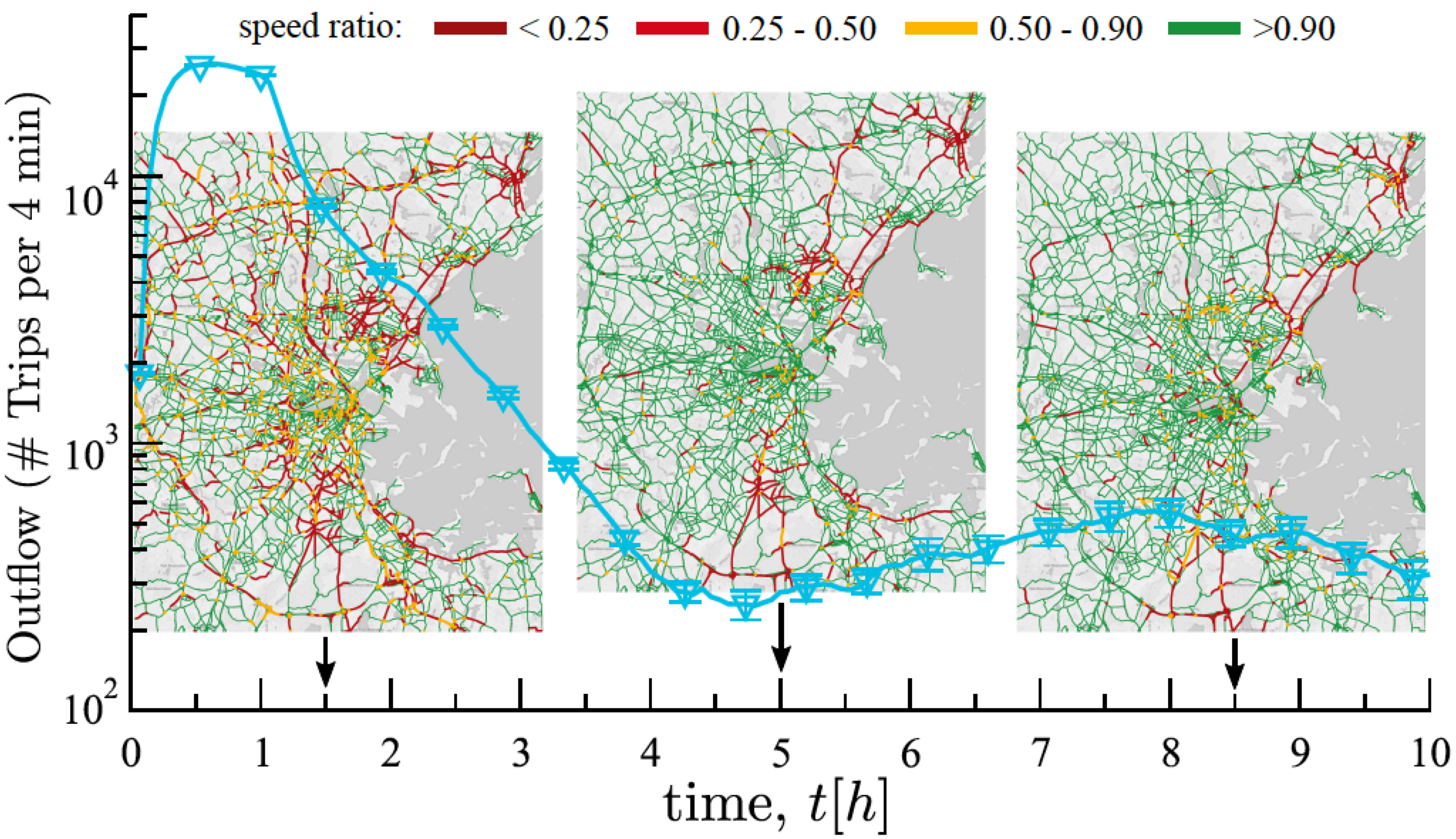




d
R²=0.981
rio
sfbay
lisbon
porto
boston
Unloading time, τ[h]
Urban travel time, Γ × t_ff[h]
0
0.2
0.4
0.6
0.8
1
1.2
1.4
0.02
0.03
0.04
0.05
0.06

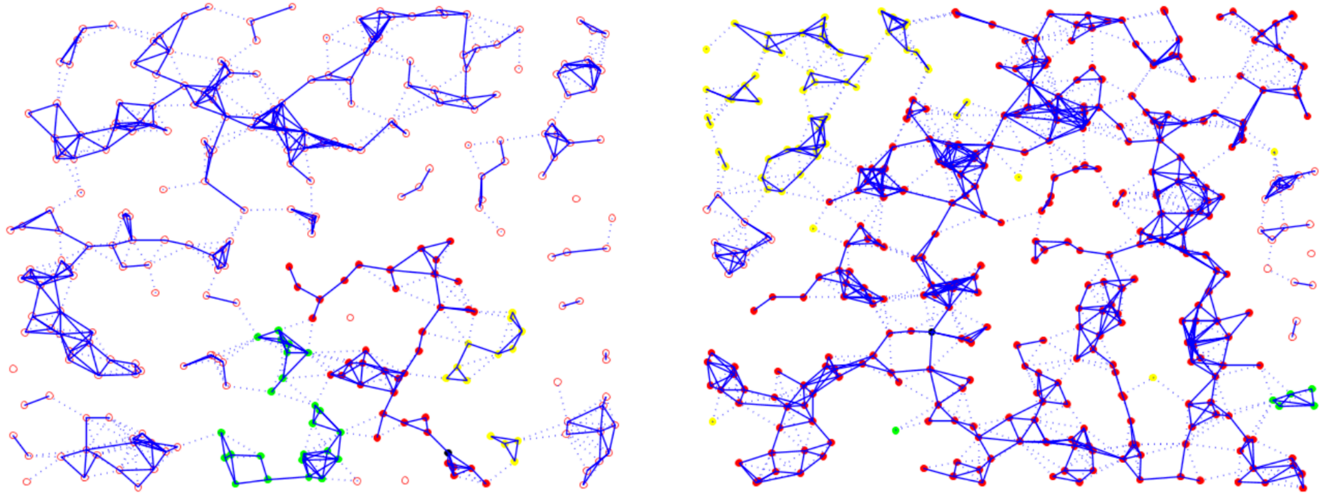
# Loading Rates





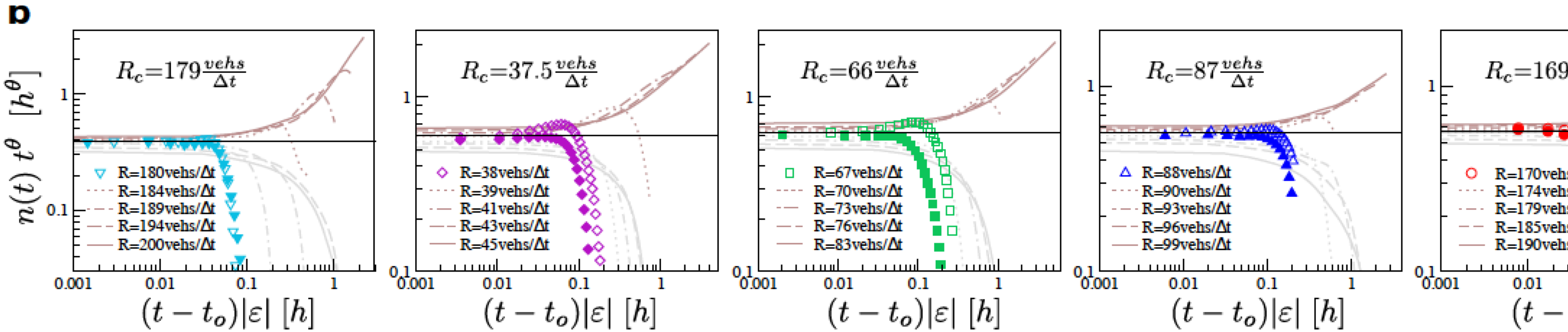
speed ratio:
< 0.25
0.25 - 0.50
0.50 - 0.90
>0.90
Outflow (# Trips per 4 min)
$10^2$
$10^3$
$10^4$
0
1
2
3
4
5
6
7
8
9
10
time, $t[h]$

***Nonequilibrium Critical Phenomena and Phase Transitions into Absorbing States***



(a) subcritical (b) supercritical

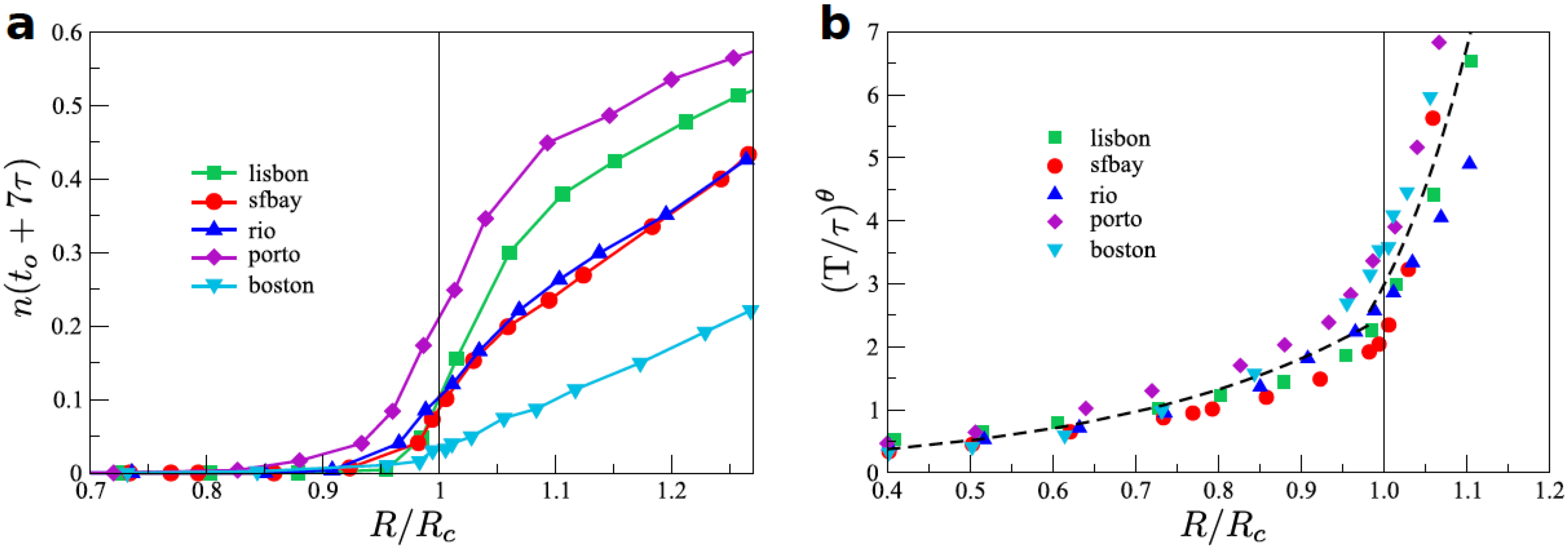
*H. Hinrichsen Review Article*
*Advances in Physics 49, 815-958 (2000); cond-mat/0001070*




$$\varepsilon = \frac{|R_c^2 - R^2|}{R_c^2}$$

**Olmos, Colak, Gonzalez: Non-equilibrium phase transition in Urban Traffic, in preparation**

# Number of cars in the network and relaxation time diverge after Rc



# Conclusions

- We studied urban traffic as an non equilibrium phase transition
- The control parameter is $\tau$ the relaxation time in which most of the cars have arrived to their destinations.
- $\tau$ is explained by $\Gamma$, the ratio of vehicles/space available and the median of the free flow travel time $t_{ff}$, determined by the commuting distances.

**Çolak, S.**, Lima, A. & Gonzalez, M. C., ***Understanding congested travel in urban areas***, accepted and to appear in *Nature Communications (2016)*

**Olmons L,** Çolak, S. & Gonzalez, M. C., ***Urban traffic as a no-equilibrium phase transition***, *In preparation (2016)*

# Demand Management for Large Events

Yanyan Xu PhD.
Postdoctoral Associate
Department of Civil and Environmental Engineering, MIT
Email: yanyanxu@mit.edu

# Rio Olympic Games

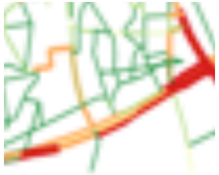
- Rio population: 6.4 millions
- International Olympic Committee (IOC) predicts 480,000 tourists in Rio for 2016 Olympics, that's about 7.5% of Rio population.
- How to evaluate the impact of Olympics to the travel of local population?
- How to manage the demand?

# Data from Companies

- Mobile Phone Data 
- Waze (extend the seed OD to weekdays)

# On-line

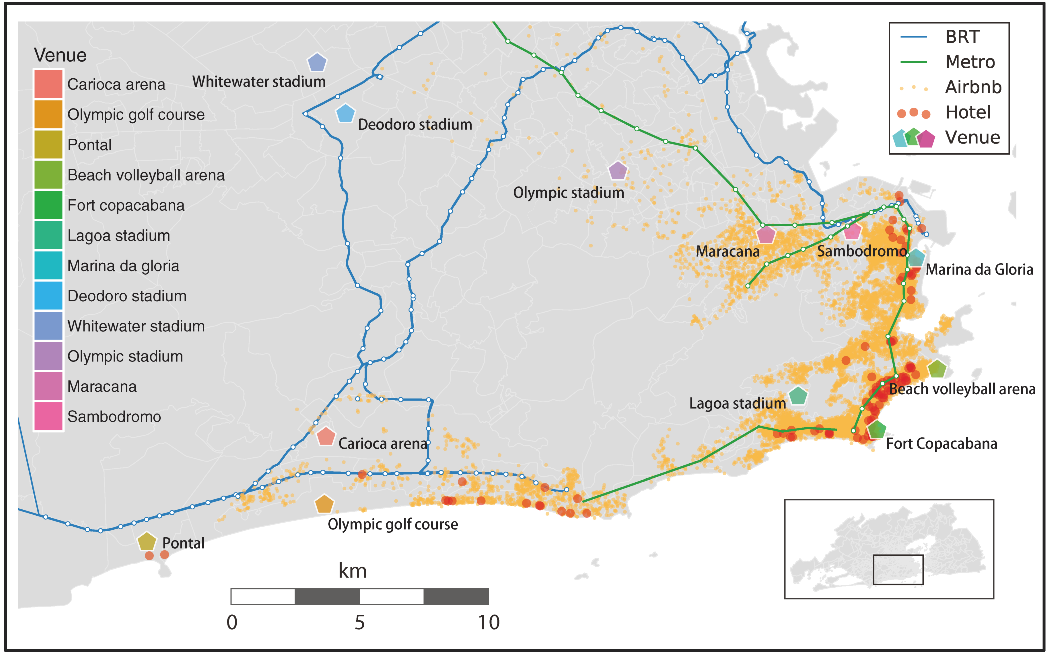
- Airbnb Supply
- GIS (OSM road network of Rio)

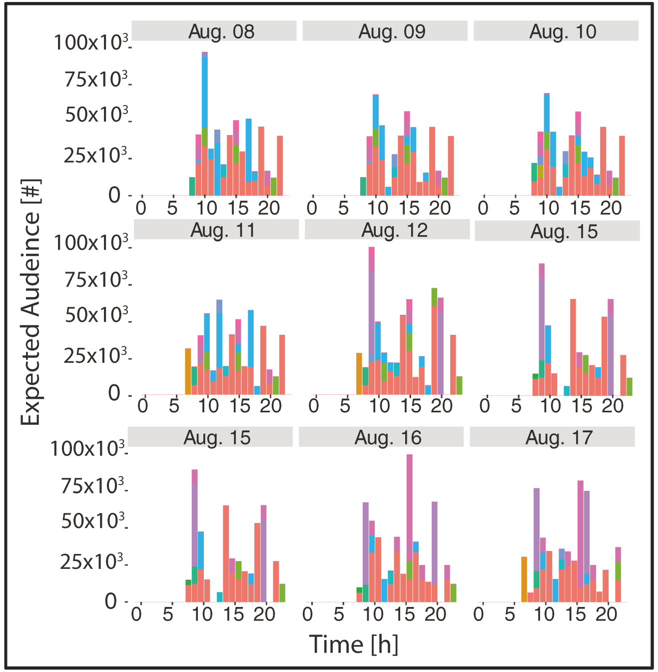


# Data from Government


- Hotel, Venues and Schedules
- Camera Data 

# Venues, Airbnb, hotels, BRT & Metro

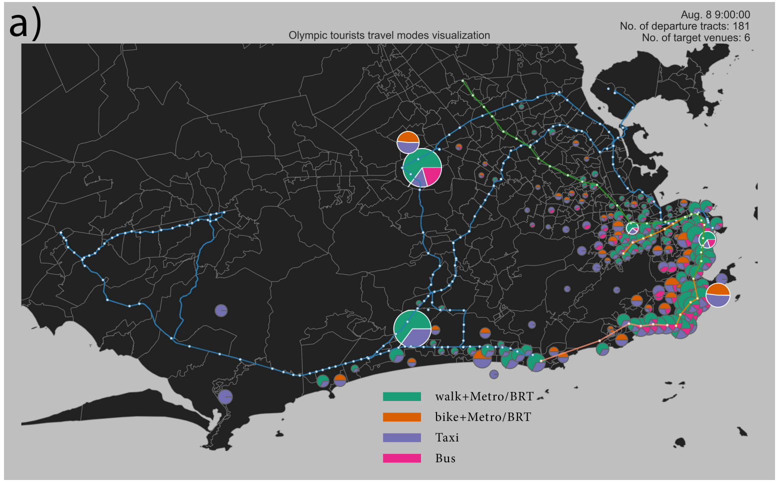


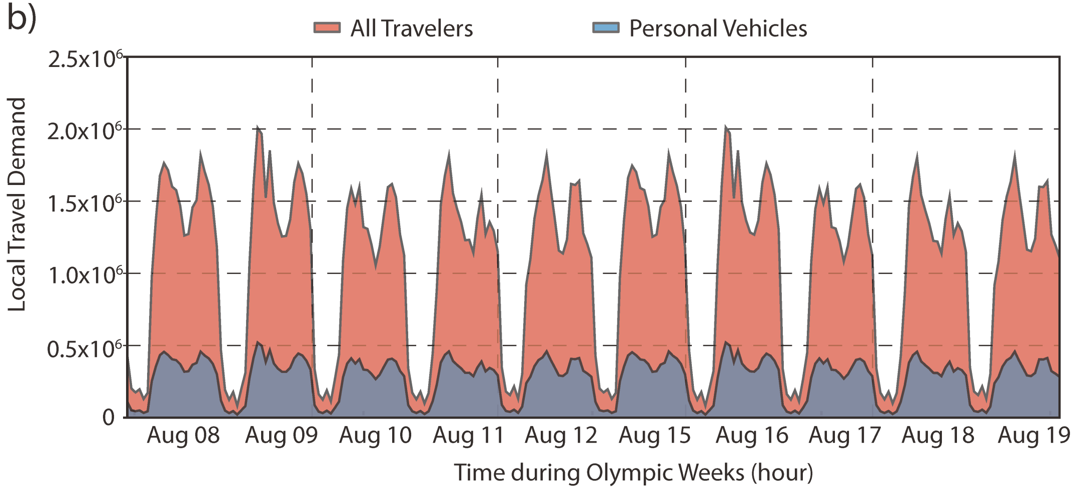




(a) Data Integrated

(b) Number of audiences arrive venues and when? (used data: Olympics schedule, capacity of venues )

# Travel demand prediction during Olympics

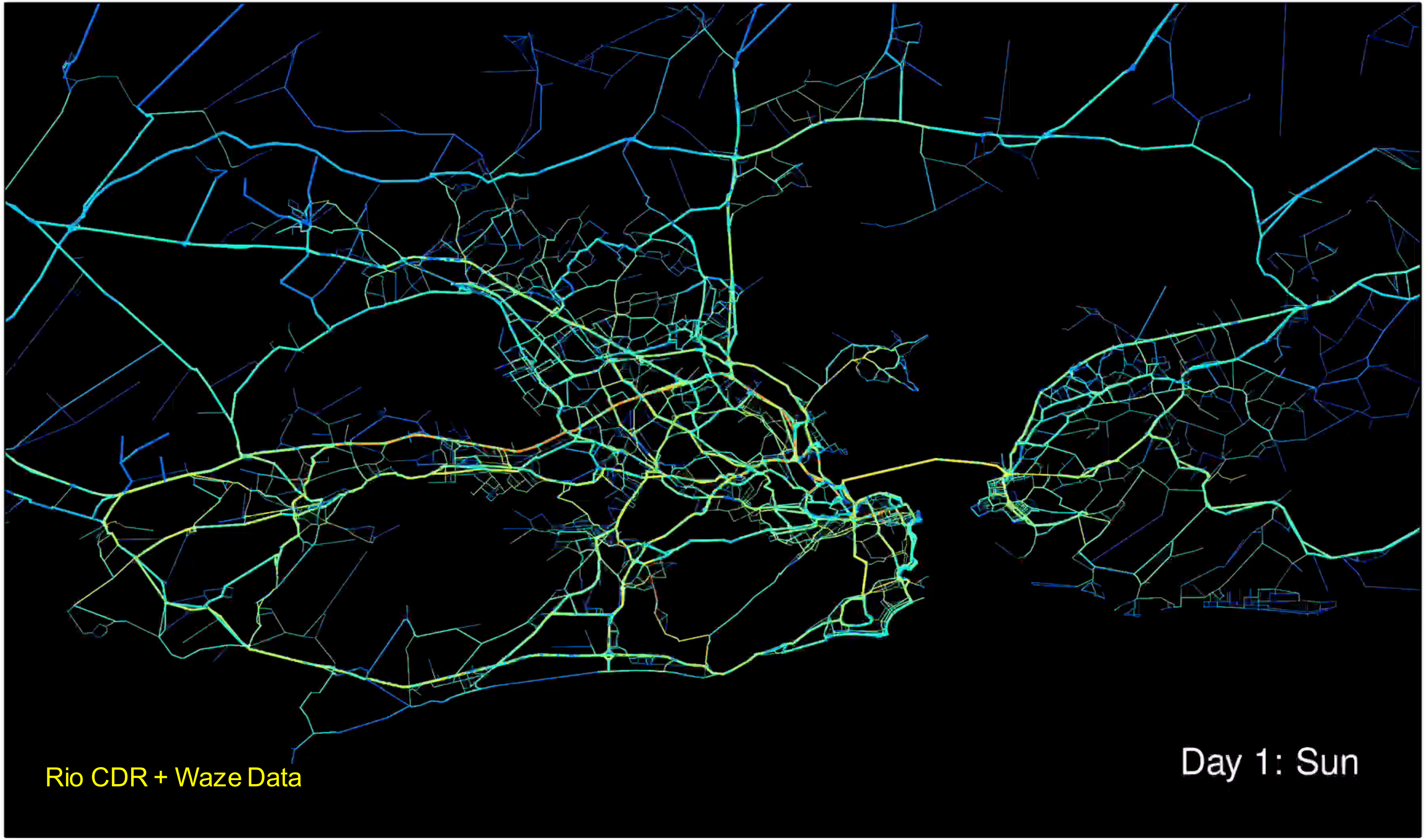



(a) Tourist travel mode split

(b) Total travel demand during Olympics: 1.8 million person / 0.5 million vehicles in peak hour.

# Traffic Model



# Smart-app (routing)

Modifications on the level of altruism:

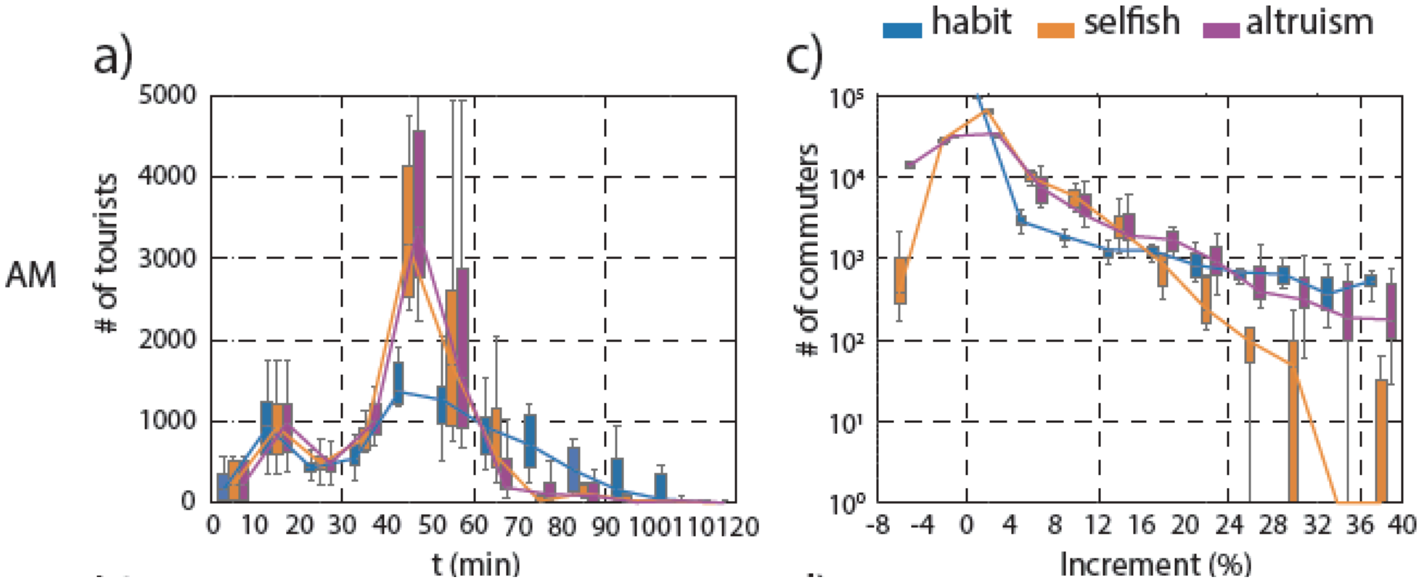
$$c_e^{\lambda}(x_e) = (1-\lambda)t_e(x_e) + \lambda \frac{d\left[x_e t_e(x_e)\right]}{dx_e}$$

$\lambda=[0..1]$

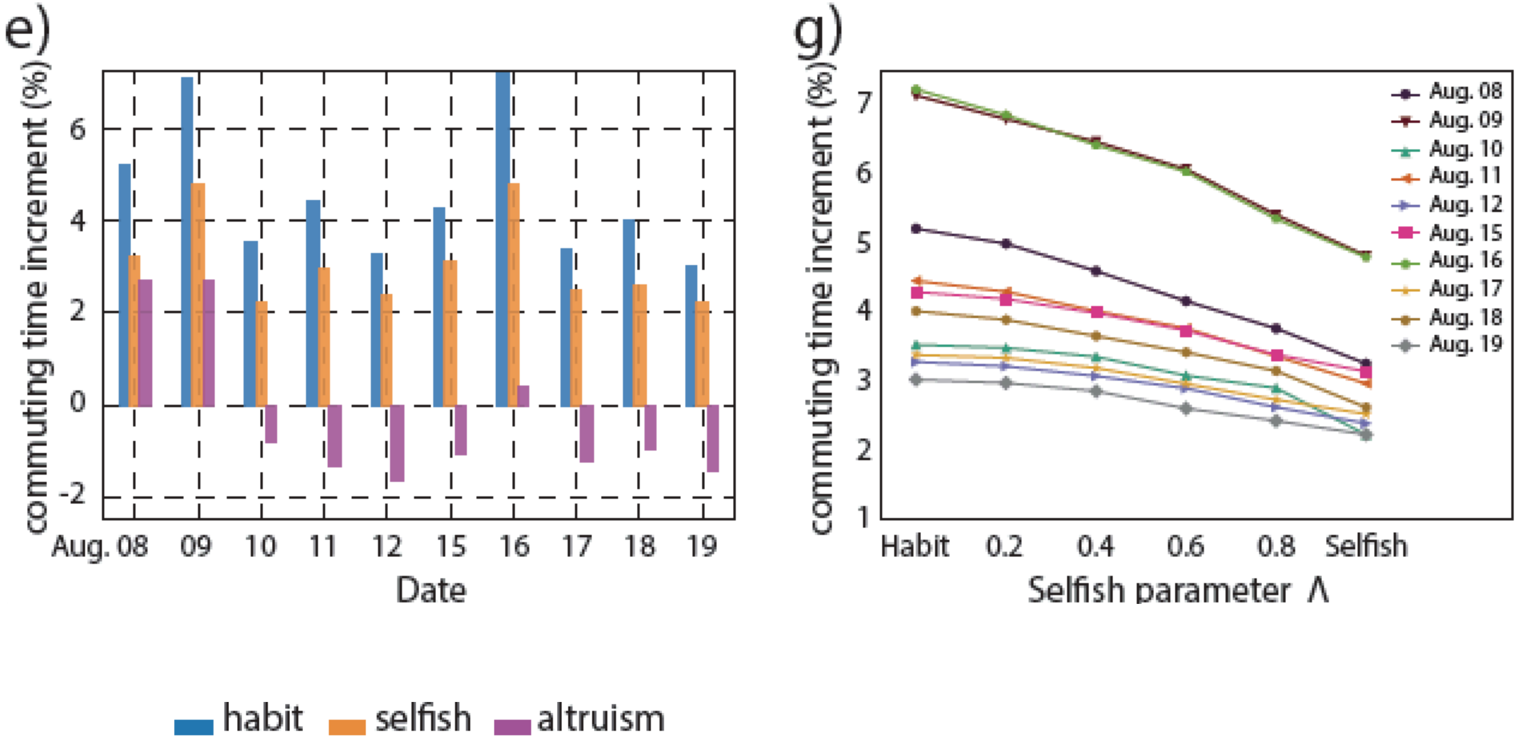
User Equilibrium component

Social Optimun component

# Travel time changes



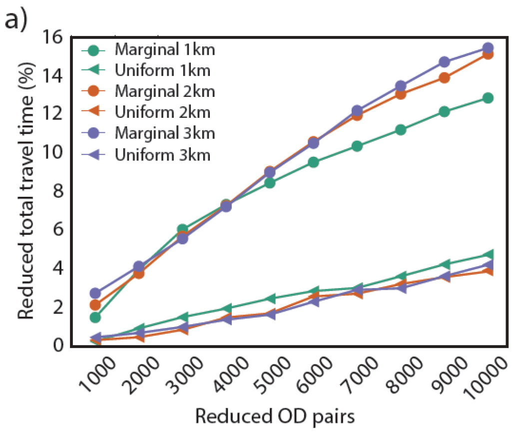
# Travel time changes per day

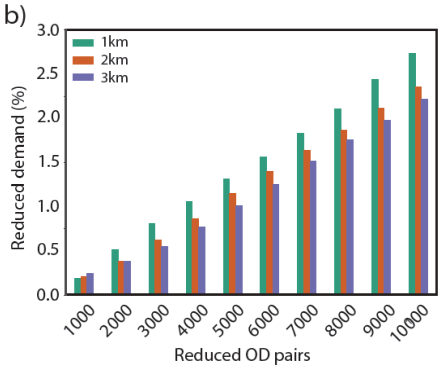


# Recommendations of Car reduction per Origin and Destination

Vehicle demand decrease: ~1.3%
Total travel time decrease: ~10.5%

# Collective demand Management




Travel time

$$t_e(v_e) = f_s \left[ 1 + \alpha \left( \frac{v_e}{C_e} \right)^{\beta} \right] \times t_e^f$$

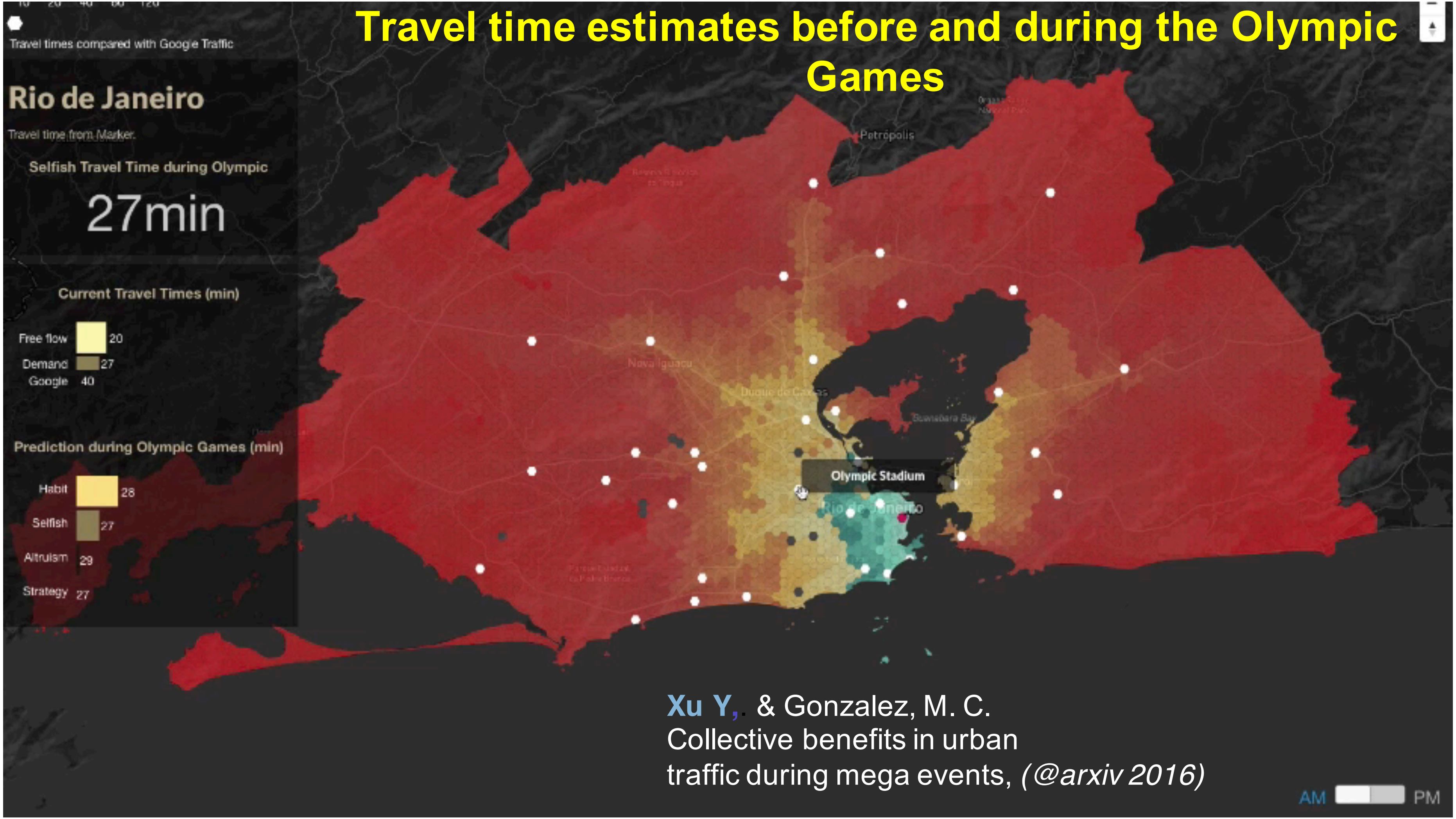
Marginal cost per link

$$MC_e = \frac{\partial (v_e t_e)}{\partial v_e}$$

We rank routes per total marginal cost

$$MC_p = \sum_{e \in \mathcal{E}} \delta_{ep} MC_e$$

# Travel time estimates before and during the Olympic Games




Xu Y,. & Gonzalez, M. C.
Collective benefits in urban
traffic during mega events, *(@arxiv 2016)*

# Conclusions

- Data integration allow us to model demands for mega events in a faster way.
- We can calculate the collective costs associated to each travel decision.
- There are smarter ways to reduce cars via feasible transit usage that show considerable benefits.
- Open questions:

  1-how to engage the population in games for social good?

  2- how can we envision mobility on demand and self-driving cars in planning for social good?
- Important quantities describe the response of the urban system. This understanding allows us to inform better decisions.