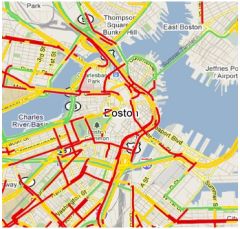
Urban Mobility: Learning, Behavioral Modeling, & Incentives

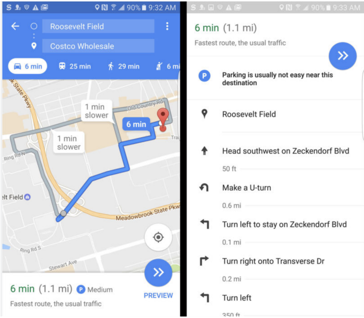
Lillian Ratliff**, Eric Mazumdar†, Chase Dowling**,
Tanner Fiez**, Dan Calderone†, Baosen Zhang**

**University of Washington; † University of California, Berkeley

Challenges in Urban Mobility

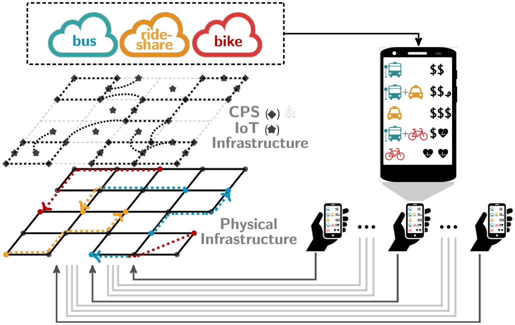
- Transportation infrastructure is being strained by rapid urbanization.
- Mobility related inefficiencies negatively impact public health, the environment, and general quality of life.
- Moreover, advances in technology have lead to the creation of new mobility modes, most of which are independently operated
- Users receive information from a variety of sources that provide solutions optimized for the individual without considering system-level impacts (e.g., Google's new parking feature)





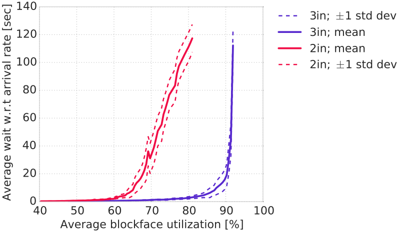
Urban Mobility: Learning, Modeling, & Incentives

- Learn plausible models of human behavior and preferences, with theoretical foundations, by drawing on "smart" infrastructure data
- Build incentive schemes & policies that promote efficient use of transportation resources
- Make use of new technologies to develop novel ways of deploying incentives and information



Integrating Parking into Routing Games

There is a lack of understanding of the fundamental relationship between parking related behaviors and congestion



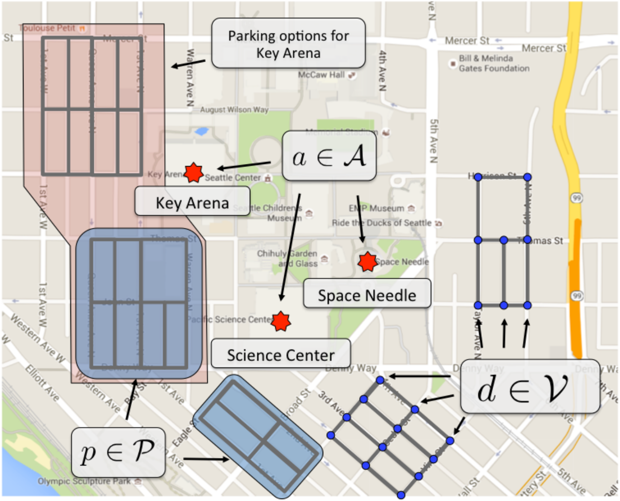
Simulations show network characteristics (e.g., topology) highly impact congestion-occupancy relationship.

- In analyzing data from SDOT, we found data-informed queuing models capture parking behaviors well.
- Routing games offer us a way to look at the how traffic populations choose their paths through a road network.

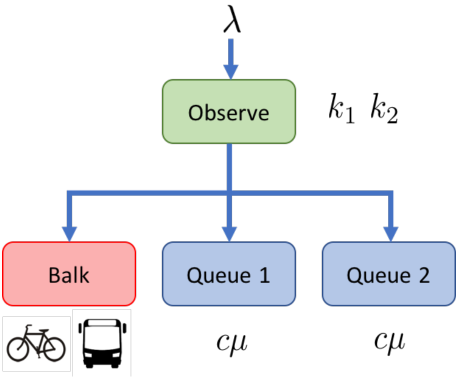
We couple a queuing model for parking with classical routing games in order to analyze the impact of parking-related behaviors on overall congestion.

Queue-Routing Game Abstraction

Seattle Center in Downtown Seattle



Queuing-Routing Game Formulation—Queue Model



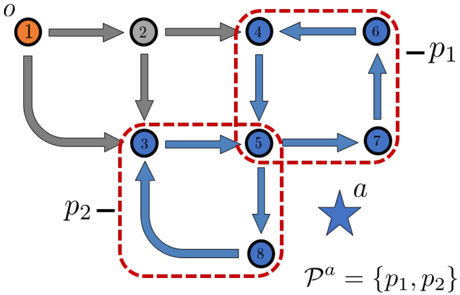
Parking customers have full information and their utilities are given by

$$U_{\text{balk}} = \text{cost of outside option}$$

$$U_{k_i} = \underbrace{\text{reward/satisfaction}}_{R_i} - \underbrace{\text{cost for waiting}}_{\frac{C_w(k_i+1)}{c_i\mu_i}} - \underbrace{\text{cost for parking}}_{\frac{C_{p,i}}{\mu_i}}$$

Integrating Queue Model with Routing Game

- Heterogeneous drivers: through traffic and potential parkers
- Circling is modeled as added latency in parking areas: static game model & in equilibrium circling behavior is distributed over edges of a parking area

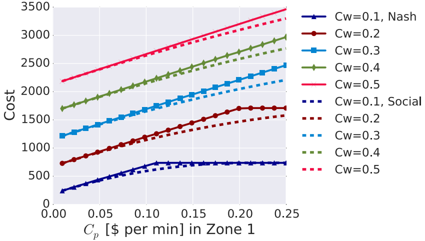


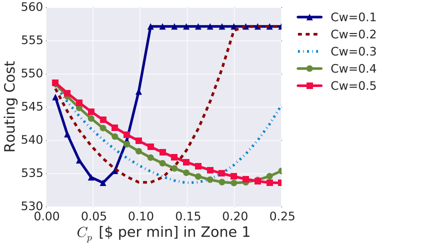
- **Solving for the equilibrium:**
  - Queue-Routing game is a Potential Game
  - With linear latencies, finding the Wardrop equilibrium requires solving a convex optimization problem.
  - Socially optimal solution can be found similarly.

Queue-Routing Game—Key Insights

We use data from Seattle and SDOT to derive queue–routing game parameters.

- Parking pricing can be used to manage congestion.
- Changing the price of parking C_p can reduce overall cost in the network.
- There exists an optimal price, C_p^*, for parking that minimizes the routing cost (congestion).
- There is a threshold after which C_p, can no longer be used as a control input for congestion.



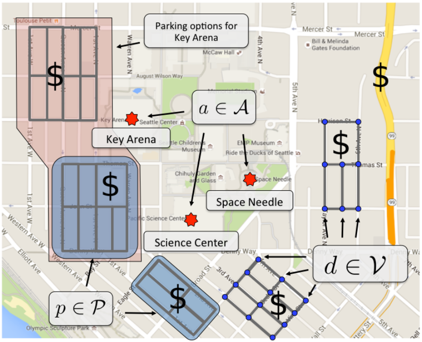


Calderone, et al. Understanding the Impact of Parking on Urban Mobility via Routing Games on Queue-Flow Networks. IEEE CDC 2016

Extension 1—Designing Tolls and Parking Prices

Simultaneously design tolls on a subset of the roads and design parking prices in order to induce more efficient, fair outcomes.

Seattle Center in Downtown Seattle



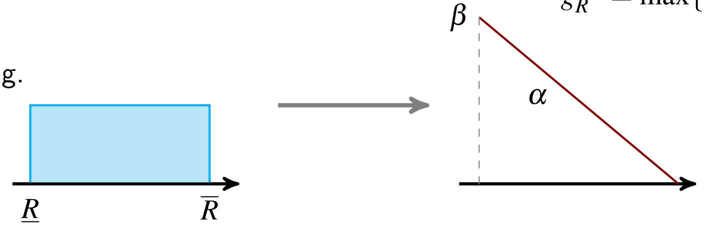
We write the tolling/pricing problem as a bilevel optimization problem:

- Challenge: nonlinear interaction between slack variables and tolls/parking prices.
- Solution: reformulate as a hybrid optimal control problem
- Add constraints derived from policy/regulations (e.g., Seattle parking price$\leq$ \$7/hour)

Extension 2—Balking via Variable Demand

$$g_R^{-1} = \max\{0, \alpha y + \beta\}$$

e.g.



$$P(x,d) = \underbrace{\text{latency}}_{\sum_e \int_0^{x_e} \tau \ell_e(y)\ dy} + \underbrace{\text{parking cost}}_{\sum_p \int_0^{d_p} C^p(y)\ dy} + \underbrace{\text{inverse 'demand'}}_{\sum_p \int_0^{d_p} g_R^{-1}(y)\ dy}$$

Key Insights

- Parking Routing with balking is also a potential game
- This framework allows us to investigate the impact of different distributions of player characteristics on the solution

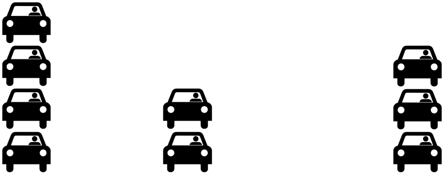
Supermarket Game & the Value of Information

Value of Information: expected reduction in expected waiting time due to a gain in information

$ for Info: mean service time, arrival rate, expected occupancy, price, etc.

balk

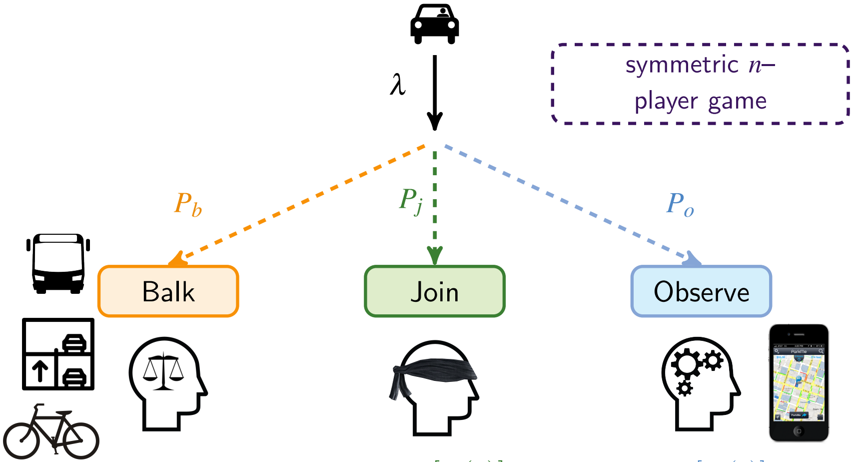
off street parking



queue 1 | queue 2 | $\cdots$ | queue n

Neighborhoods

To Observe or Not to Observe



$U_j = \mathbb{E}_{\pi_k}[u_j(k)]$

$U_o = \mathbb{E}_{\pi_k}[u_o(k)] - C_o$

$U_b = 0$

(or outside opt)

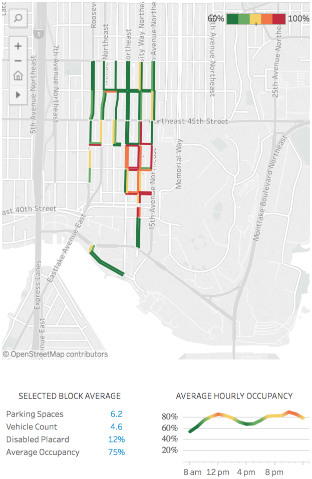
Ratliff, et al. To Observe or Not to Observe: Queuing Game Framework for Urban Parking. IEEE CDC 2016

Key Insights

Given the queuing game framework, . . .

- Nash is less efficient not only in terms of social welfare, but also more commonly used metrics—e.g., average wait time and utilization.
- With a *cost of observing*, at the social optimum
  - less than 100% of the population needs to opt in to observing
  - even at low traffic intensities (arrivals/service), it is better for a non-zero portion of the population to use an alternative mode
- Simulations indicate there is a highly non-linear relationship between congestion and occupancy when agents act selfishly. We are conducting studies to verify this.

U-District

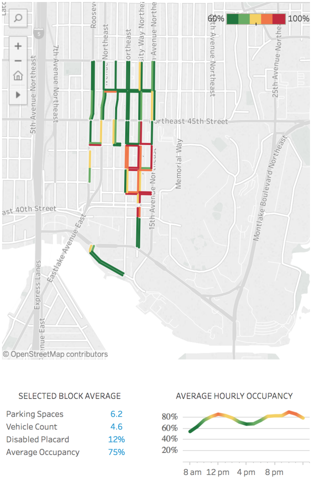


Key Insights

Given the queuing game framework, . . .

- Nash is less efficient not only in terms of social welfare, but also more commonly used metrics—e.g., average wait time and utilization.
- With a *cost of observing*, at the social optimum
  - less than 100% of the population needs to opt in to observing
  - even at low traffic intensities (arrivals/service), it is better for a non-zero portion of the population to use an alternative mode
- Simulations indicate there is a highly non-linear relationship between congestion and occupancy when agents act selfishly. We are conducting studies to verify this.

U-District

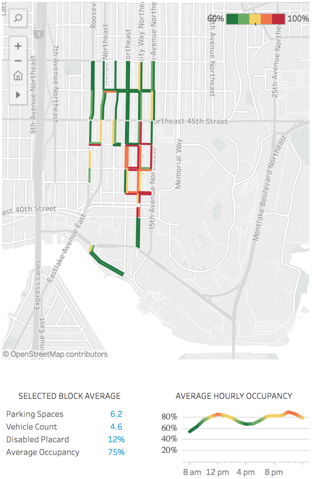


Key Insights

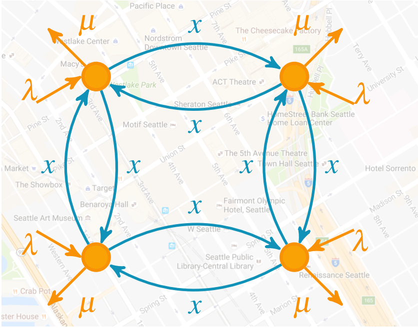
Given the queuing game framework, . . .

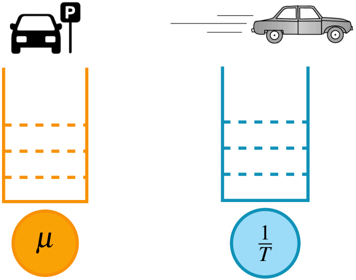
- Nash is less efficient not only in terms of social welfare, but also more commonly used metrics—e.g., average wait time and utilization.
- With a *cost of observing*, at the social optimum
  - less than 100% of the population needs to opt in to observing
  - even at low traffic intensities (arrivals/service), it is better for a non-zero portion of the population to use an alternative mode
- Simulations indicate there is a highly non-linear relationship between congestion and occupancy when agents act selfishly. We are conducting studies to verify this.

U-District



How do parking behaviors impact local congestion?





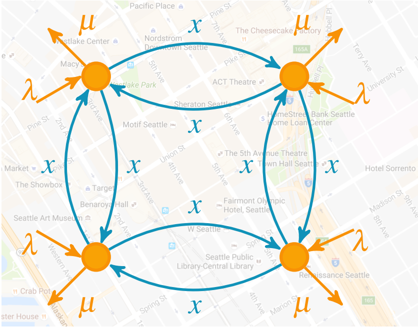
parking queue driving queue

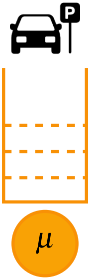
Fundamentally new type of multi-class queuing network in which rejections are exchanged instead of services

Natual Question: What conditions guarantee the system is stable (people eventually park & congestion does not grow w/o bound)?

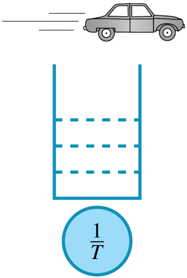
Preliminary Results — Symmetric Queue–Flow Network

Thm: Network is a symmetric d-regular graph s.t. the arrival rate is less than the parking service rate ($\lambda < \mu$) & the road service rate is sufficiently large $\left(\frac{1}{T} > \frac{\lambda^2}{d(1-\lambda)}\right) \implies$ system is stable & average wait time is $\frac{\lambda}{1-\lambda}T$.





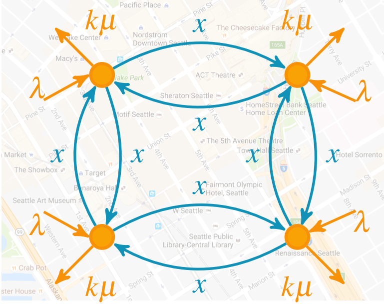
parking queue

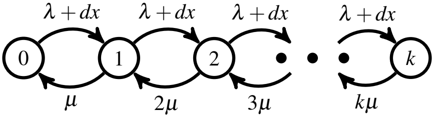


driving queue

Dowling, Zhang, Ratliff. Stability of Queue-Flow Networks. 2017 (in prep)

Preliminary Results — Multi-Server d–regular Networks





$$\begin{cases} \pi Q = 0 \\ \mathbf{1}^T \boldsymbol{\pi} = 1 \\ dx = \pi_k(\lambda + dx) \end{cases}$$

Thm: If $0 < \lambda < k$ & the road service rate is sufficiently large, then the system is stable. (proof idea: if $0 < \lambda < k$, then Descartes' rule of signs $\Longrightarrow \exists$ a unique positive solution to above equations)

Dowling, Zhang, Ratliff. Stability of Queue-Flow Networks. 2017 (in prep)

Looking Forward

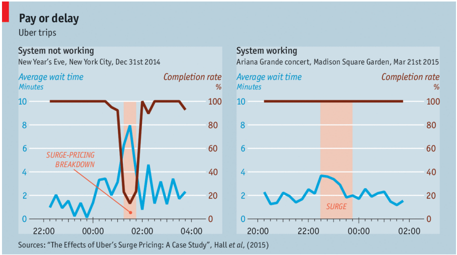
- Arbitrary network topology
  - In the symmetric case, we leveraged the structure of the graph to simplify the problem.
  - Stability can be assessed by determining if a set of polynomial equations has a real, positive solution; e.g.,

$$V(f_1,\ldots,f_n) = \{\text{common zeros of stationarity equations}\} \subset \mathbb{C}^n$$

$$V_{\mathbb{R}}(f_1,\ldots,f_n) = V(f_1,\ldots,f_n) \cap \mathbb{R}^n_+ \neq \emptyset?$$

  - We expect that we will be able leverage topological structure in sub-graphs to make simplifications
- Strategic sources/users
  - To design incentive or information dissemination policies, we need to merge the game theoretic results with the data informed models.
  - Testing and validation

Ongoing & Future Work



Economist.com

- Human decision-makers are often not perfectly rational—reference points, distortions of event probabilities, and risk play a significant role in decision outcomes
- Traditional rational, utility maximization models tend not to capture these effects, particularly in short-horizon decisions where there is little time for cogitation.

Risk in Parking & Routing—Leveraging "Information Tolls"

- We have derived new heterogenous routing game models where a user's type is drawn from a distribution that characterizes the risk sensitivity in the population.
- e.g., the risk-sensitive latency for type θ

$$\ell_e^{\theta}(x_e) = \underbrace{\text{expected cost}}_{\ell_e(x_e)+C^p(x_e)} + \underbrace{\text{degree of risk aversion}}_{g_i(\theta)} \cdot \underbrace{\text{perceived delay/cost}}_{\delta_e(\theta)}$$

- Initial Insight: the larger the propoportion of risk adverse users, the more costly it is to induce a particular set of edge flows (e.g., the socially optimal flow)
- Goal: assess user perceptions of costs (travel delays, waiting time, etc.) and identify where to target information in order to reduce uncertainty.

Risk Sensitive Reinforcement Learning

- People treat gains & loses differently—losses loom larger than gains.
- Goal: leverage fine grained data about mode/route choices (collected in Seattle, Bay Area, Los Angeles, and Nashville) in developing (real-time) algorithms for simultaneously learning and designing incentives in closed loop.

"internal state"

risk sensitive decision-making

$$\text{e.g., } u(x) = \begin{cases} k_+(x-x_0)^{\alpha_+}, & x > x_0 \\ -k_-(x_0-x)^{\alpha_-}, & x \le x_0 \end{cases} \quad \text{or} \quad u(x) = \exp(\lambda x)$$

prospect theory

entropic map

Thanks

ratliffl@uw.edu
mazumdar@berkeley.edu