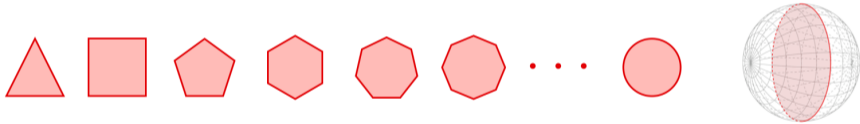# Escaping Flatland: Lessons learned from 2d "smart" urban spaces on protocol, policy, and mechanism design
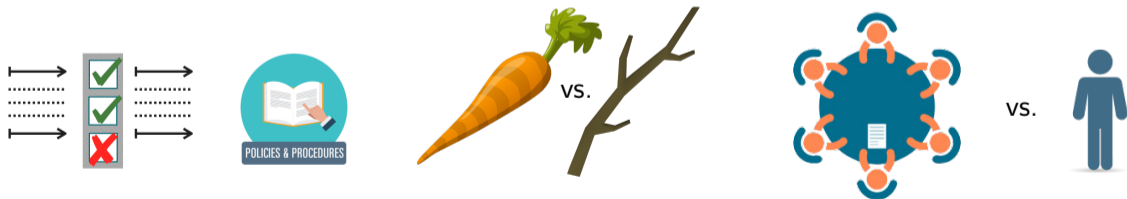

"Upward, not Northward" – E. A. Abbott, Flatland

Lillian J. Ratliff

Escaping Flatland While Leaving Behind its Vagaries

Key Question of Focus

Important for operations is the design of not just protocols and policies for assurances (safety, security, etc.), but also mechanisms to incentivize (carrot or stick) individuals and institutions to respect them.
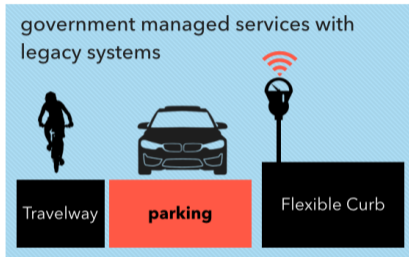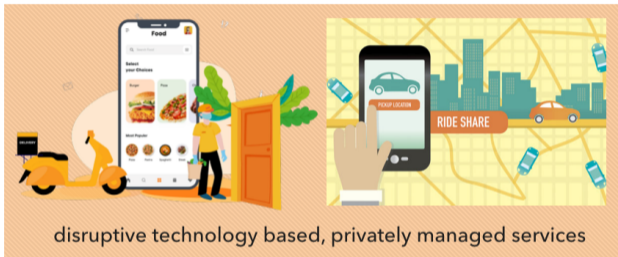
In the 2d Realm of Transportation and Peripheral Services...
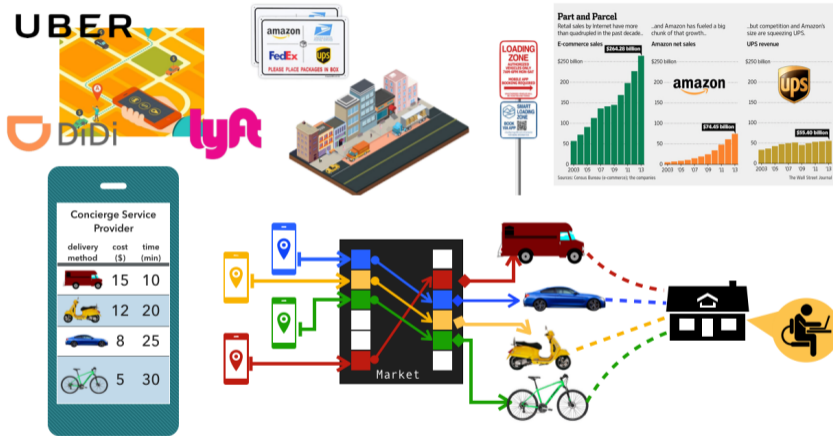
a tragedy of the commons: influx of new services w/o policy and regulatory mechanism in place to manage them

# Design Data-Informed Mechanisms in Intelligent Transportation

government managed services with legacy systems

disruptive technology based, privately managed services

Travelway | parking | Flexible Curb

Let's talk about some positive and negatives examples

Feedback Induced Distributional Shifts

Algorithmic mechanisms tend to be trained on past data without considering that the output of the algorithm may change the data distribution.
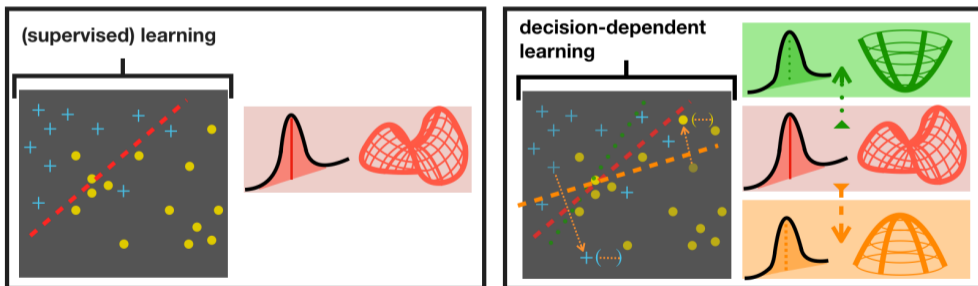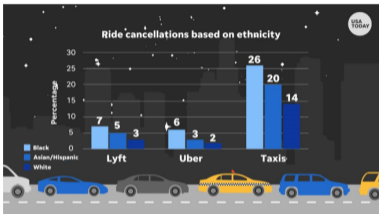
Biased, Censored, or Correlated Data

Algorithms tend to be trained on past data without considering bias (e.g., feedback induced distribution shift), censorship (e.g., privacy), or even correlations (e.g., implicit connections between sources).
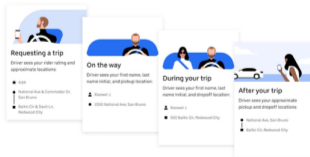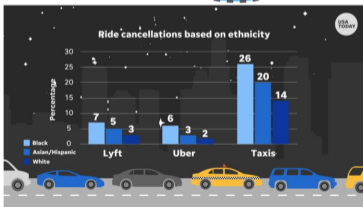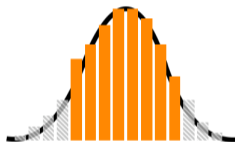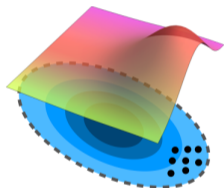
Example: Reinforcing Biases in the Gig Economy

- Gender wage gap: Uber, 7%[1]
- Discrimination based on race: wait times and fares higher for persons of color

Ride cancellations based on ethnicity

Lyft: Black 7, Asian/Hispanic 5, White 3
Uber: Black 6, Asian/Hispanic 3, White 2
Taxis: Black 26, Asian/Hispanic 20, White 14

Was your Uber, Lyft fare high because of algorithm bias?
Coral Murphy Marcos USA TODAY
Published 4:20 a.m. ET Jul. 22, 2020 | Updated 7:54 p.m. ET Jul. 22, 2020

Average hourly pay for Uber drivers in the U.S.

Data for gross pay
Source: Uber, data from Feb. 2015-Feb. 2017 • Get the data

Blacks face longer wait times on Uber, Lyft than other races – worse for taxis, study says
Marco della Cava USA TODAY
Published 1:08 p.m. ET Jun. 27, 2018 | Updated 4:12 p.m. ET Jun. 28, 2018

- indicates lack of consideration of feedback loops and how they may exacerbate institutional biases

[1]Cook et al. "The Gender Earnings Gap in the Gig Economy: Evidence from over a million rideshare drivers", NBER 2018

Strategic Data Sources

Data used to either train algorithms offline or as an input to an online decision-making algorithm may be generated by strategic data sources such as human users.
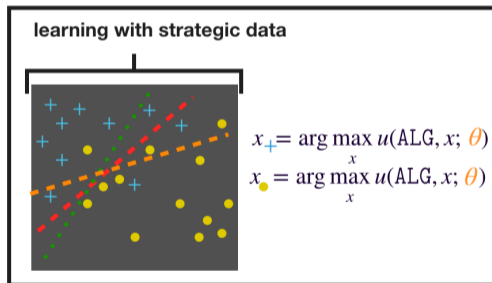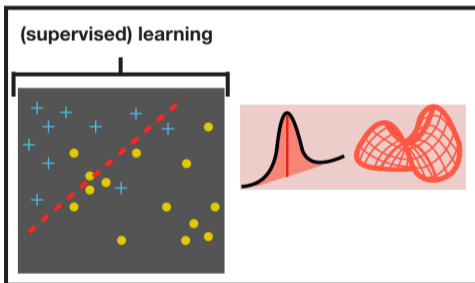
Ride-Share Price Gouging: Strategizing to trigger surges
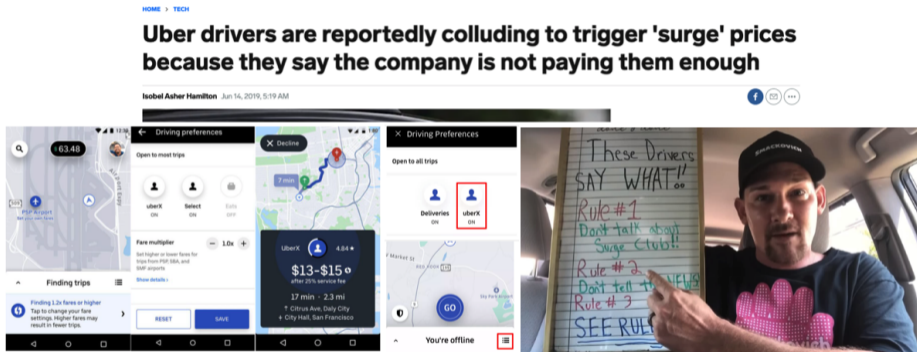
- Drivers strategically manipulate their location to trigger surge (e.g., at airports)
- Price increase is offloaded onto the demand (passenger) side of the market

- indicates misaligned incentives, and lack of consideration of collusion and other strategic behavior in mechanism design[1]

[1] Maheshwari, Chiu, Mazumdar, Sastry, Ratliff, 2021

Ride-Share Legal Battles

Technology

Uber and Lyft drivers strike for pay transparency — after algorithms made it harder to understand

Demonstrations took place in at least eight major cities nationwide Wednesday.

- not just questions at the level of mechanism design at the institutional level
- lack of self-regulation in these "democratized" labor markets requiring government to step in to prevent inequities and abuse

Algorithmic Competition

- **Gig Labor is a Competitive Market**: Drivers and riders may participate in multiple ride-share platforms, hence the pricing mechanism or other incentives on one platform influence the decisions and hence the data distribution a competitor sees

- **Forecasting Travel Time**: Multiple mapping applications (e.g., Waze or Google Maps) forecast the travel time between different locations, yet the realized travel time is collectively influenced by all their forecasts
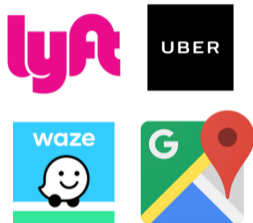
Some Questions:

- What are reasonable models of competition, and algorithm interaction?[1]
- What are the unintended consequences that can emerge in competitive settings?
- Can aforementioned biases be further amplified?

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[1] Narang, Faulkner, Ratliff, Drusvyatskiy, Fazel. Decision-dependent learning in the presence of competition, 2021

The Curb: Public vs private resource management

- Traditionally publicly managed, the curb is an essential component of city operations, impacting not just traffic flow but also supply chain (distribution), business district vitality, residential access, etc
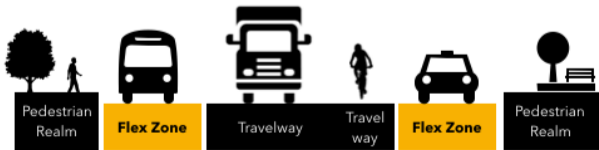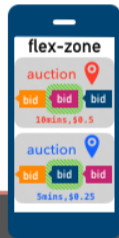
Timescales & Trust

- policy & regulatory changes operate on much slower timescales than "tech innovations"
- chicken and egg: adoption of new technologies or approaches often requires demonstration
- **Example**: After 6 yrs, SDOT now uses a model-based approach to price setting and auditing; took private-public-academic partnership
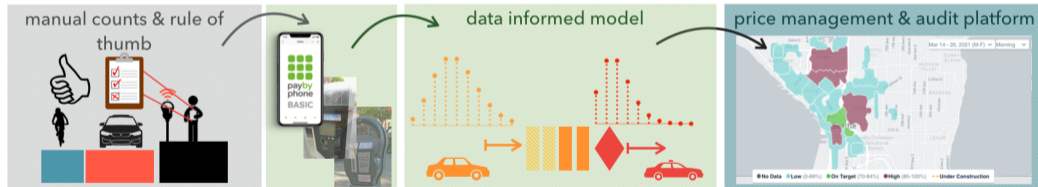
- needed to convince SDOT that the model was trustworthy

Sociological and community considerations

- privacy, bias, equity, fairness, recourse, etc. as they relate to access to services
- Q: are the services being introduced only for those with the means to access them? or, are we obligated to devise equitable access?
- The latter point raises issues with respect to the previous challenge on public vs private resource management
- Privacy: One of the emerging sources of data for curb management is probe data—namely, data from OEM head units that gives GPS location with temporal resolution ∼secs

Summary of Challenges in 2d: Can we head them off in 3d?

- designing mechanisms that account for decision dependent distribution shifts: strategically generated, biased, censored, correlated data
- Role of regulation and predicting unintended consequences, in particular with respect to algorithmic competition
- Timescales & trust: how to speed up the process from new development to deployment while engendering trust
- Public vs private ownership and management: what are the potential socio-technical challenges that might emerge
- Sociological and community barriers to adoption both at the individual and institutional level