Ridesharing

Sid Banerjee
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Based on work with – D. Freund, T. Lykouris (Cornell),
– C. Riquelme & R. Johari (Stanford),
special thanks to the data science team at Lyft
ridesharing platforms

- critical components of modern urban transit
- crucible for Real-Time Decision Making/Ops Management/EconCS
How Lyft Works

1. Request
Whether you’re riding solo or with friends, you’ve got options. Tap to request Lyft, Lyft Line, or Lyft Plus.

2. Ride
Get picked up by the best. Our reliable drivers will get you where you need to go.

3. Pay
When the ride ends, just pay and rate your driver through your phone.
ridesharing: pricing
rideshare platforms: pricing

Thanks for riding with [Name]!
Ride ending January 31 at 12:35 AM

Pickup:
Dropoff:

Ride 2.5 mi & 10 min: $8.28
Prime Time*: $2.07
Trust & Safety Fee: $1.50

Total charged to $11.85

*25% Prime Time was included in your total. Prime Time encourages more people to drive when Lyft gets really busy.
Learn More

credit: lyft.com
rtdm in ridesharing: mapping

ETAs

Locations

credit: lyft data science team
rtdm in ridesharing: logistics

Dispatch

Matching

credit: lyft data science team
Prime Time

Supply Levers

Easier. More Money.
The Power Driver Bonus Upgrade.

You know the Power Driver Bonus as a reliable way to earn almost all of your commission back each week - and now it's even better. With this upgrade, you can earn even more with greater flexibility. The new PDB features five extra bonuses and three additional tiers, starting with a new 30-ride benchmark.

<table>
<thead>
<tr>
<th>DRIVE</th>
<th>GET</th>
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</thead>
<tbody>
<tr>
<td>NEW 30 Total Rides 10 PEAK HOUR RIDES</td>
<td>$50 Bonus</td>
</tr>
<tr>
<td>NEW 50 Total Rides 20 PEAK HOUR RIDES</td>
<td>$100 Bonus</td>
</tr>
<tr>
<td>80 Total Rides 30 PEAK HOUR RIDES</td>
<td>10% Back + $150 Bonus</td>
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<tr>
<td>100 Total Rides 40 PEAK HOUR RIDES</td>
<td>20% Back + $150 Bonus</td>
</tr>
<tr>
<td>NEW 120 Total Rides 45 PEAK HOUR RIDES</td>
<td>20% Back + $200 Bonus</td>
</tr>
</tbody>
</table>

Plus, we added 19 more eligible peak hours that count toward your bonus.

credit: lyft data science team
the bigger picture: on-demand transportation

- fast operational timescales; complex network externalities
- new **control-levers**: dynamic pricing/dispatch, incentives, pooling
- new(er) challenges: competition, effect on public transit, urban planning
the bigger picture: on-demand transportation

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this talk

- ‘where do we come from?’
  - simple framework for ridesharing: data, state, controls
- ‘where are we?’
  - approximate optimal control for ridesharing logistics
  - market mechanisms as a tool for algorithmic self-calibration
- ‘where are we going?’
main challenge: rebalancing

demand heterogeneity $\Rightarrow$ non-uniform supply across space and time

logistical ‘solution’: rebalance the vehicle fleet

economic ‘solution’: incentives for passengers and drivers
main challenge: rebalancing

demand heterogeneity $\Rightarrow$ non-uniform supply across space and time

logistical ‘solution’: rebalance the vehicle fleet
economic ‘solution’: incentives for passengers and drivers
control-levers: pricing/incentives, dispatch, empty-car rebalancing
(stochastic-network) model for ridesharing

- *m* units (cars) across *n* stations (here, we have *m* = 6, *n* = 4)
- System state \( \in S_{n,m} = \{(x_i)_{i \in [n]} | \sum_{i=1}^{n} x_i = m\} \)
- \( i \rightarrow j \) passengers arrive via Poisson process with rate \( \phi_{ij} \)
(stochastic-network) model for ridesharing

- platform sets state-dependent prices $p_{ij}(X)$
- quantile $q_{ij}(X) = 1 - F_{ij}(p_{ij}(X))$: fraction willing to pay $p_{ij}(X)$
(stochastic-network) model for ridesharing

- car travels with passenger to destination
- (this talk: assume travel-times are zero)
(stochastic-network) model for ridesharing
(stochastic-network) model for ridesharing
(stochastic-network) model for ridesharing

- myopic customers: abandon system if
  - vehicle unavailable
myopic customers: abandon system if
– vehicle unavailable or
– price too high
(stochastic-network) model for ridesharing

- objective:
  - optimize chosen long-run average system objective
  - objectives: revenue, welfare, customer engagement, etc.
control levers for ridesharing

- pricing
  - modulates demand between locations
  - dynamic, state-dependent

Sid Banerjee (Cornell ORIE)
control levers for ridesharing

- dispatch: choose ‘nearby’ car to serve demand
  - can use any car within ‘ETA target’
control levers for ridesharing

- **rebalancing**: re-direct free car to empty location
  - incur a cost for moving the car
  - driver ‘nudges’ (heat-maps), autonomous vehicles
intermezzo: why model?

scales and economics
– need controls that work in real-time, at large-scales
– complex controls need more resources; non-commensurate (?) impact
intermezzo: why model?

scales and economics

– need controls that work in real-time, at large-scales
– complex controls need more resources; non-commensurate (?) impact

known(?) unknowns

– errors in estimation and forecasting
– difficulties in learning demand/supply curves
intermezzo: why model?

scales and economics
– need controls that work in real-time, at large-scales
– complex controls need more resources; non-commensurate (?) impact

known(?) unknowns
– errors in estimation and forecasting
– difficulties in learning demand/supply curves

unknown unknowns

Surge pricing has been turned off at #JFK Airport. This may result in longer wait times. Please be patient.
intermezzo: why this model?

**assumption 1: timescales of platform operations**

- number of cars, arrival rates, demand elasticities remain constant over time
- time-varying rates (re-solve policies at change-points...)
- driver entry/exit behavior
- effect of bursty arrivals?
intermezzo: why this model?

**assumption 1: timescales of platform operations**

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**assumption 2: timescales of strategic interactions**

– passengers abandon if price too high/no vehicle
– drivers react at longer timescales
intermezzo: why this model?

**assumption 1: timescales of platform operations**
- number of cars, arrival rates, demand elasticities remain constant over time
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  - effect of bursty arrivals?

**assumption 2: timescales of strategic interactions**
- passengers abandon if price too high/no vehicle
- drivers react at longer timescales

**assumption 3: availability of data**
- platform has perfect knowledge of arrival rates, demand elasticities
- is that really true?
- is that really needed?
data-driven optimization for vehicle-sharing

Pricing and Optimization in Shared Vehicle Systems
Banerjee, Freund & Lykouris (2016)
https://arxiv.org/abs/1608.06819
- $m$ units spread across $n$ nodes
- Control: state-dependent pricing policy $\vec{p} = \{p_{ij}(x)\}$ (or quantiles $\vec{q}$)
- Flows of cars in network: realized via Markov chain dynamics
technical challenges

objective

\[
\max_{\mathbf{q} = \{q_e(x)\}} \sum_{x} \pi \bar{q}(x) \left( \sum_{e=(i,j)} \mathbb{E}[\text{reward rate from } i \rightarrow j \text{ rides}] \right)
\]

long-run avg under control \( \mathbf{q} \)
technical challenges

objective

\[
\max_{\mathbf{q=\{q_e(x)\}}} \sum_{\mathbf{x}} \pi_{\mathbf{q}}(\mathbf{x}) \left( \sum_{e=(i,j)} \mathbf{1}_{[x_i>0]} \cdot \phi_e q_e(x) \cdot I_e(q_e(x)) \right)
\]

assumption: \( ql_{ij}(q) \) is concave
true for throughput; welfare; revenue under regular \( F_{ij} \)
technical challenges

**objective**

$$\max_{q \in [0,1]|E|} \mathbb{E}_{\pi_q(X)} \left[ \sum e \phi_e q_e(X) l_e(q(X)) \right]$$

**assumption:** $ql_{ij}(q)$ is concave

**challenges**

- exponential size of policy
technical challenges

objective

\[
\max_{q \in [0,1]^{|E|}} \mathbb{E}_{\pi_q(X)} \left[ \sum_{e} \phi_e q_e(X) l_e(q(X)) \right]
\]

assumption: \( q_{l_{ij}}(q) \) is concave

challenges

- exponential size of policy
- non-convex problem: even with state-independent \( q_{ij} \)
approximately optimal control policies

objective

\[
\max_{q \in [0,1]^{|E|}} \mathbb{E}_{\pi_q(X)} \left[ \sum_{i,j} \phi_{ij} q(X) l_{ij}(q(X)) \right]
\]

challenges

- exponential number of states
- non-convex optimization problem

theorem [Banerjee, Freund & Lykouris 2016]

convex relaxation gives state-independent pricing policy with approximation factor of \(1 + \frac{\text{number of stations}}{\text{number of cars}}\)
approximately optimal control policies

**objective**

\[
\max_{q \in [0,1]|E|} \mathbb{E}_{\pi q}(X) \left[ \sum_{i,j} \phi_{ij} q(X) I_{ij}(q(X)) \right]
\]

**challenges**

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- extends to dispatch, rebalancing
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**challenges**

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**theorem [Banerjee, Freund & Lykouris 2016]**

convex relaxation gives state-independent pricing policy with approximation factor of \(1 + \frac{\text{number of stations}}{\text{number of cars}}\)

- extends to dispatch, rebalancing
- large-supply/large-market optimality: factor goes to 1 as system scales
proof roadmap

relaxation + resource augmentation

**step 1:** elevated flow relaxation: convex program that upper bounds performance, encodes essential conservation laws
proof roadmap

relaxation + resource augmentation

step 1: elevated flow relaxation: convex program that upper bounds performance, encodes essential conservation laws

step 2: show EFR is tight for a class of state-independent pricing policies, in the ‘infinite-unit system’ (i.e., $m \rightarrow \infty$)
proof roadmap

relaxation + resource augmentation

**step 1**: elevated flow relaxation: convex program that upper bounds performance, encodes essential conservation laws

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**step 3**: bound objective in finite-unit system against infinite-unit system for this simpler class of policies
proof roadmap

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\[
\text{OBJ}_m(p_m(X)) \leq \text{EFR}(p^*) = \text{OBJ}_\infty(p_\infty) \leq (1/\alpha_{mn})\text{OBJ}_m(p_\infty)
\]
the elevated flow relaxation

Objective

$$\max_{q \in [0,1]|E|} \mathbb{E}_{\pi q}(X) \left[ \sum_{i,j} \phi_{ij} q(X) l_{ij}(q(X)) \right]$$

Suppose we knew $q^*$: Let $\hat{q}^* = \mathbb{E}_{\pi q^*}(X)[q^*(X)]$
the elevated flow relaxation

**objective**

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\max_{q \in [0,1]|E|} \mathbb{E}_{\pi_q}(X) \left[ \sum_{i,j} \phi_{ij} q(X) l_{ij}(q(X)) \right]
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Suppose we knew \( q^* \): Let \( \hat{q}^* = \mathbb{E}_{\pi_{q^*}}(X)[q^*(X)] \)

\[
\mathbb{E}_{\pi_{q^*}}(X) \left[ \sum_{i,j} \phi_{ij} q^*(X) l_{ij}(q^*(X)) \right] \leq \sum_{i,j} \phi_{ij} \hat{q}^* l_{ij}(\hat{q}^*) \quad \text{(Jensen’s Ineq.)}
\]
the elevated flow relaxation

objective

$$\max_{\mathbf{q} \in [0,1]^{|E|}} \mathbb{E}_{\pi_{\mathbf{q}}(\mathbf{X})} \left[ \sum_{i,j} \phi_{ij} q(\mathbf{X}) l_{ij}(q(\mathbf{X})) \right]$$

Suppose we knew $\mathbf{q}^*$: Let $\hat{\mathbf{q}}^* = \mathbb{E}_{\pi_{\mathbf{q}^*}(\mathbf{X})}[q^*(\mathbf{X})]$,

$$\mathbb{E}_{\pi_{\mathbf{q}^*}(\mathbf{X})} \left[ \sum_{i,j} \phi_{ij} q^*(\mathbf{X}) l_{ij}(q^*(\mathbf{X})) \right] \leq \sum_{i,j} \phi_{ij} \hat{\mathbf{q}}^* l_{ij}(\hat{\mathbf{q}}^*) \quad \text{(Jensen's Ineq.)}$$

$$\leq \max_{\mathbf{q} \in [0,1]^{|E|}} \sum_{i,j} \phi_{ij} q_{ij} l_{ij}(q_{ij})$$
the elevated flow relaxation

**objective**

\[
\max_{\mathbf{q} \in [0,1]|E|} \mathbb{E}_{\pi q}(\mathbf{X}) \left[ \sum_{i,j} \phi_{ij} q(\mathbf{X}) l_{ij}(q(\mathbf{X})) \right]
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this is **convex**! however, it is too weak
the elevated flow relaxation

**Objective**

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\[
\leq \max_{q \in [0,1]^{|E|}} \sum_{i,j} \phi_{ij} q_{ij} l_{ij}(q_{ij})
\]

this is **convex**! however, it is too weak

**Idea:** strengthen relaxation by adding additional constraints on \( q \)

- circulation: \( \sum_j \phi_{ij} q_{ij} = \sum_k \phi_{ki} q_{ki} \quad \forall i \in V \)
- Little’s law: \( \mathbb{E}[\text{units in transit}] \leq m \)
in summary

\[
\text{OBJ}_m(\vec{p}_m(X)) \leq \text{EFR}(\vec{p}^*) = \text{OBJ}_\infty(\vec{p}_\infty) \leq (1/\alpha_{mn}) \text{OBJ}_m(\vec{p}_\infty)
\]

**theorem [Banerjee, Freund & Lykouris 2016]**

state-independent prices $\vec{p}_\infty$ (from EFR) in $m$-unit system gives

\[
\text{OBJ}_m(\vec{p}_\infty) \geq \alpha_{mn} \text{OPT}_m, \quad \text{where} \quad \alpha_{mn} = \frac{m}{m+n-1}
\]
in summary

\[
\text{OBJ}_m(p_m(X)) \leq \text{EFR}(p^*) = \text{OBJ}_\infty(p_\infty) \leq (1/\alpha_{mn})\text{OBJ}_m(p_\infty)
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**Theorem [Banerjee, Freund & Lykouris 2016]**

State-independent prices \(\vec{p}_\infty\) (from EFR) in \(m\)-unit system gives

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where \(\alpha_{mn} = \frac{m}{m+n-1}\)

**Main Takeaway**

New technique for optimizing stochastic dynamical system in steady-state

- Can extend to more complex settings (travel-times, multi-objective, pooling, reservations)
in summary

\[
\text{OBJ}_m(p_m(X)) \leq \text{EFR}(p^*) = \text{OBJ}_\infty(p_\infty) \leq (1/\alpha_{mn}) \text{OBJ}_m(p_\infty)
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Theorem [Banerjee, Freund & Lykouris 2016]

state-independent prices $\tilde{p}_\infty$ (from EFR) in $m$-unit system gives

\[
\text{OBJ}_m(\tilde{p}_\infty) \geq \alpha_{mn} \text{OPT}_m, \quad \text{where } \alpha_{mn} = \frac{m}{m+n-1}
\]

Main takeaway

new technique for optimizing stochastic dynamical system in steady-state

- can extend to more complex settings (travel-times, multi-objective, pooling, reservations)
- but where do we get the demand-rate and price-elasticity estimates?
Pricing in Ride-Share Platforms
Banerjee, Johari & Riquelme (2015)
(EC’15: https://ssrn.com/abstract=2568258)
why market design? and why ridesharing?

Over the next 10 years, the major breakthrough of economics will be in applications of market design, which improves the efficiency of markets using a combination of game theory, economics and algorithm design. We’ve already seen fruitful application in search and spectrum auctions, kidney exchange and school assignment. (2016 will be the year that) Silicon Valley recognizes that the value of Uber is its marketplace, not the data...

R. Preston McAfee
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R. Preston McAfee

data-driven optimization vs. market design

- default approach for complex operational problems:
  model – calibrate from data – optimize specific problem instance
- market mechanisms self-calibrate to solve the optimization problem
- ridesharing unique among online marketplaces: platform sets prices
quasi-static vs. dynamic

for a large block of time (e.g., few hours), region (e.g., city-neighborhood), mean system parameters are constant, predictable.

why not have hourly location-based prices?

Source: whatsthefare.com

dynamic pricing vs. static pricing

- **dynamic**: price changes instantaneously, in response to system state
- **(quasi) static**: constant over several hours (predictably changing)
model for studying rideshare pricing

focus on a **single block of time, and a single region.**

\[
\text{system state} = \text{number of available drivers}
\]

**assumption 1:** mean system parameters stay constant

- state-dependent (dynamic) pricing policy:
  
  \[
  \text{if} \quad \# \text{ of available drivers} = A, \quad \text{then price for ride} = P(A)
  \]

- platform earns a (fixed) fraction \( \gamma \) of every dollar spent

**assumption 2:** the two sides react at different time-scales

- myopic passengers: sensitive to instantaneous prices, availability
- drivers are sensitive to long-term (average) earnings and ride-volume
strategic model for passengers

- a (potential) passenger requests a ride iff: reservation value $V >$ current price, and driver available
  - $V \sim F_V$, i.i.d. across ride requests
- $\mu_0 =$ exogenous rate of “app opens”, $\mu =$ actual rate of requests when $A$ drivers present: $\mu = \mu_0 F_V(P(A))$
strategic behavior of drivers

- a driver works on the platform iff:
  reservation rate $C \times \mathbb{E}[\text{per-ride time spent}] < \mathbb{E}[\text{per-ride earning}]$
  
  $C \sim F_C$, i.i.d. across drivers

- $\Lambda_0 =$ “potential” driver-arrival rate, $\lambda =$ actual driver-arrival rate

\[
\lambda = \frac{\Lambda_0}{q_{\text{exit}}} F_C \left( \frac{\mathbb{E}[\text{Per-ride earning}]}{\mathbb{E}[\text{Idle (waiting) time + Ride time}]} \right)
\]
driver decision aids

You could earn up to A$217 more
A$31/hour on average

LAST WEEK
YOU DRIVE
9 OF 16
BUSY HOURS

THIS WEEK
DRIVE
ALL
BUSY HOURS

Your hours last week: 60
BUSY HOURS

How'd you do last week?
Compare your hours to last week's peak hours when earn were highest.

You earned a 20% bonus last week. Way to go!
Drive 50 hours (including 10 peak hours) to do it again this week.

Time in driver mode:
62 hrs, 4 min

ride payments:
$2,408.65
Lyft fees:
$481.65
Tips:
$87.60
Tolls:
$73.60

Total earnings:
$2,033.43
given pricing policy \( P(\cdot) \), equilibrium \((\lambda, \mu, \pi, \eta, \iota)\) such that:

1. \( \mu \): passenger-arrival rate, given state \( A \), satisfies:
   \[
   \mu = \mu_0 F_{\nu}(P(A))
   \]

2. \( \lambda \): driver-arrival rate \( \lambda \), given \( \iota, \eta \), satisfies:
   \[
   \lambda = \Lambda_0 F_{\mathcal{C}} \left( \frac{\eta}{\iota + \tau} \right)
   \]

3. \( \pi \): steady-state distribution of \( A \) given \( \lambda, \mu \)

4. \( \eta \): \( \mathbb{E}[\text{Earning per ride}], \) given \( P(\cdot) \) and \( \pi \)

5. \( \iota \): \( \mathbb{E}[\text{Idle time per ride}], \) given \( P(\cdot) \) and \( \pi \)
platform equilibrium under static pricing

Normalized Rate of Completed Rides $r_n/n$ vs $p$: Scaling with $n$
platform equilibrium under static pricing
platform equilibrium under static pricing

Normalized Rate of Completed Rides $r_n/n$ vs $p$: Scaling with $n$

- $n=100$
- $n=10$
- $n=1$
platform equilibrium under static pricing

Normalized Rate of Completed Rides $r_n/n$ vs $p$: Scaling with $n$

- $n=1000$
- $n=100$
- $n=10$
- $n=1$
platform equilibrium under static pricing

\[ \text{Normalized Rate of Completed Rides } \frac{r_p}{n} \text{ vs. } p. \text{ Scaling with } n \]

Theorem: static pricing in large-market limit ⇒ demand-supply curve
rate of rides in large-market limit = \( \min \{ \text{available supply, available demand} \} \)
Platform Equilibrium under Static Pricing

Theorem: Static pricing in large-market limit

Under static pricing (i.e., \( P(A) = p \forall A \)), let \( r_n(p) \) denote the equilibrium rate of completed rides in the \( n^{th} \) system. Then:

\[
    r_n(p) \to \hat{r}(p) \triangleq \min \left\{ \frac{\Lambda_0}{q_{exit}} F_C \left( \frac{\gamma p}{\tau} \right), \mu_0(1 - F_V(p)) \right\}
\]

Some intuition:

- At any price, queueing system is always stable (else idle times blow up)
- If supply < demand: Drivers become fully saturated
- If supply > demand: Drivers forecast high idle times and don’t enter
platform equilibrium under dynamic pricing

Normalized Rate of Completed Rides $r_n/n$ vs $p$: Scaling with $n$

- **Static pricing**
- **Dynamic pricing**

$n=1$
platform equilibrium under dynamic pricing
platform equilibrium under dynamic pricing

Normalized Rate of Completed Rides $r_n/n$ vs $p$: Scaling with $n$

- $n=100$
- $n=10$
- $n=1$

- **Static pricing**
- **Dynamic pricing**
static vs. dynamic pricing: optimality

**Theorem [Banerjee, Johari & Riquelme 2015]**

If $F_V$ has increasing hazard rate, then the rate of rides for any dynamic policy is less than or equal to the rate of rides under optimal static pricing.
static vs. dynamic pricing: sensitivity to parameters

Robustness of Pricing Policies to Demand Shocks

- Static pricing
- Optimal pricing

μ₀
static vs. dynamic pricing: sensitivity to parameters

\[ \text{dynamic pricing} \geq \text{‘linear approximation’ of optimal static-pricing throughput} \]

\[ \text{theorem [Banerjee, Johari & Riquelme 2015]} \]
summary, and the road ahead

main takeaway

ridesharing platforms: crucible for real-time decision making
- well modeled by steady-state stochastic models
- approximate control via new convex relaxation techniques
- algorithm self-calibration via market mechanisms
the road ahead

some short term targets

- the value of state-dependent controls
  - for general controls, objectives: no improvement possible
  - for dispatch: can achieve exponential decay in $m!$
(joint work with Pengyu Qian and Yash Kanoria (Columbia))
the road ahead

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- non-stationary and/or bursty arrivals
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- algorithms for more complex problems
  (policies for ride-pooling, reservation mechanisms)

going further beyond
the road ahead

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  (policies for ride-pooling, reservation mechanisms)

going further beyond

- impact of platform competition
price of fragmentation in ridesharing markets
(with Thibault Séjourné (Ecole Polytechnique), S. Samaranayake (Cornell))

what is the ‘societal cost’ of decentralized optimization?
– multiple platforms with (random) exogenously partitioned demands
– individual platforms do optimal empty-vehicle rebalancing
price of fragmentation in ridesharing markets
(with Thibault Séjourné (Ecole Polytechnique), S. Samaranayake (Cornell))

what is the ‘societal cost’ of decentralized optimization?
– multiple platforms with (random) exogenously partitioned demands
– individual platforms do optimal empty-vehicle rebalancing

price of fragmentation
increase in rebalancing costs of multiple platforms (with exogenous demand splits) vs. single platform (under large-market scaling)
result (in brief)

as demand scales, the price of fragmentation undergoes a phase transition based on structure of underlying demand flows – both regimes observed in NYC taxi-data ($\approx 10\%$ fragmentation-affected)
the road ahead

some short term targets

- the value of state-dependent controls
  - for general controls, objectives: no improvement possible
  - for dispatch: can achieve exponential decay in $m!$
    (joint work with Pengyu Qian and Yash Kanoria (Columbia))
- non-stationary and/or bursty arrivals
- algorithms for more complex problems
  (policies for ride-pooling, reservation mechanisms)

going further beyond

- impact of platform competition
the road ahead

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going further beyond

- impact of platform competition
- the value of information: forecasting vs. self-calibration
- ridesharing + public transit
- appropriate mix of employees, freelancers and autonomous cars