Information provision for managing a congestion-prone hub

Saurabh Amin
joint work with Sohil Shah and Patrick Jaillet

MIT

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Our focus

Q. How can a planner provision information to manage strategic agents who face choice to move to congested hotspot?

- Information governs agents' tradeoff of risk vs. value at hotspot
- Planner's utility defined in terms of ranges of preferred agent mass at hotspot and can depend on unknown state
- *Applications:* pandemic management (✹), ride-hailing (🚗)

- Study preferences for which optimal information mechanism has interval-based (esp. *monotone partitional* structure).
- Highlight how optimal information changes when dynamically provisioned to long-run agents over a uncertain time-hotizon

Part I: Hybrid work under risk of infectious disease at worksplace

Motivation

- Public health messaging and news reporting impacted individual activity/isolation levels during pandemic[1]
- Bayesian information design can be an effective tool for shaping agents' decisions, particularly in *post-peak* phase

Our setup:

- Information about risk of community transmission at workplace can be a soft intervention in hybrid work settings
- Planner aims to balance gains from in-person activity at workplace (hotspot) against costs from disease spread

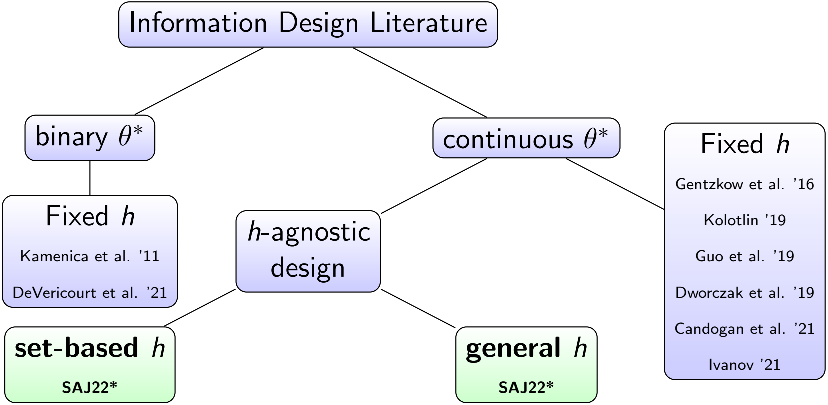
[1] Alcott et al. '20, Bursztyn et al. '20

Setup

- Planner discloses public information over uncertain state $\theta^* \sim F$ for **continuous** F to unit mass of strategic agents
- Mass (fraction) $1 - y$ elect to move to hotspot
- Each agent gains personal benefit and incurs uncertain cost that depends on θ^* and y

- We focus on design of optimal information provision for a broad class of **planner preferences** $h(y; \theta^*)$

Related work



Hard interventions:
Hu et al. '22, Birge et al. '20, Acemoglu et al. '20, Chernozhukov et al. '21, Moore '21, Drakopoulos et al. '14

Overview of results (Part I)

A. State-independent, set-based preference: $h(y;\theta^*) = \mathbb{I}\{y \in \mathcal{Y}\}$

- For most distributions F, optimal mechanism just signals which of two intervals that partitions Θ the true value lies in
- Monotone partitional and interval-based structure

B. State-dependent preference:

- Using discretization and linear programming for algorithmic design of mechanisms with approximation guarantees
  - **Scaled capacity:** $h(y;\theta^*) = \mathbb{I}\{y \geq a(\theta^*)\}$ for increasing, step function a
  - **Lipschitz preference:** $h(y;\theta^*)$ is Lipschitz continuous
- Mechanism satisfies interval-based structure by construction

Model: Uncertainty & Signalling

- Unknown state $\theta^* \in \Theta := [0, M]$ where $\theta^* \sim F$
  - F is commonly known and $\mu^\circ = \mathbb{E}_F[\theta^*]$
  - $\uparrow$ values of state $\Rightarrow \uparrow$ risk of community transmisison
- Planner *publicly* commits and discloses signalling mechanism:

$$\pi = \langle \{z_\theta(\cdot)\}_{\theta \in \Theta}, \mathcal{I} \rangle$$

  - $\mathcal{I}$ - set (alphabet) of signals
  - $z_\theta \in \Delta(\mathcal{I})$ - distribution over signals
  - Planner does not observe θ^* when commits/discloses

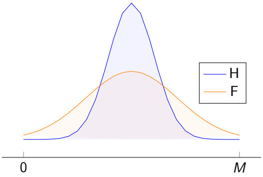
Model: Uncertainty & Signalling

- Signal $i \in \mathcal{I}$ is drawn from z_{θ^*}, and *publicly* shared with agents before they make their choices
- Signal i realized w.p. q_i and induces posterior mean belief μ_i

$$q_i := \mathbb{P}[\pi \to i] = \int_{\theta \in \Theta} z_\theta(i) dF(\theta)$$

$$\mu_i := \mathbb{E}[\theta | \pi \to i] = \frac{\int_{\theta \in \Theta} \theta z_\theta(i) dF\theta}{\int_{\theta \in \Theta} z_\theta(i) dF(\theta)}$$

- π has direct mechanism representation $\mathcal{T}_\pi = \{(q_i, \mu_i)\}_{i \in \mathcal{I}}$
- **Blackwell 1953**: A distribution over posterior means H is induced by some information structure if and only if: H is mean-preserving contraction of F, that is, $H \succeq F$

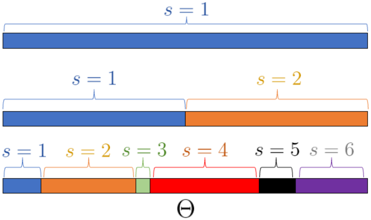


Monotone Partitional Structure

Monotone Partitional Structure (MPS)

A signaling mechanism π has MPS if:

- $\exists$ finite partition of Θ, $\mathcal{P} := \{\Theta_j\}_{j=1}^m = \{[t_{j-1}, t_j]\}_{j=1}^m$
- $0 = t_0 < t_1 < \cdots < t_{m-1} < t_m = M$
- $\mathcal{I} = [m]$ and for all $\theta \in \Theta$, $z_\theta(j) = \mathbb{I}\{\theta \in [t_{j-1}, t_j]\}$



Model: Agents

- Unit mass of non-atomic agents; each making simultaneous location choice: $a \in \{\ell_c, \ell_p\}$
  - ℓ_c: in-person work (communal/hotspot location)
  - ℓ_p: remote work (peripheral location)
- $y(\mathbf{a})$: aggregate mass choosing ℓ_p
- Each agent has private type from known distribution $v \sim G$

Model: Agents

Each agent earns reward

- $u^v(\ell_p, y; \theta^*) = 0$ if $a = \ell_p$
- $u^v(\ell_c, y; \theta^*) = v - \beta(y; \theta^*)$ if $a = \ell_c$, where $\beta(y; \theta^*) := \theta^* c_1(y) + c_2(y)$, with $c_1(\cdot), c_2(\cdot)$ decreasing and differentiable

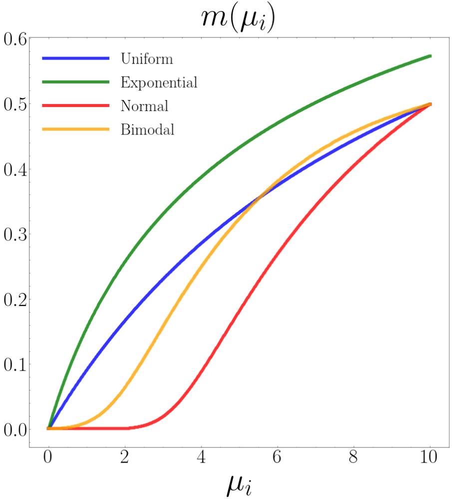
Remote agent mass at equilibrium: $y(a^*|\pi \to i) = y^*_\pi(i)$

Proposition

1. In equilibrium $y^*_\pi(i)$, $\exists v^*$ s.t. agents at $\ell_c \iff v > v^*$
2. $\exists$ weakly increasing, bounded, continuous $m : \Theta \to [0, 1]$ such that $y^*_\pi(i) = m(\mu_i)$

- v^*: private benefit of marginal agent indifferent over ℓ_c & ℓ_p

Remote mass for different G



- Larger remote agent mass needs (even) higher posterior means
- For simple preference and concave $m(\cdot)$, easy to maximize – try to induce "best" belief

Model: Planner Preferences

For given π, planner earns reward $h(y; \theta^*)$

Class	$h(y; \theta^*)$	Assumptions	Motivation
State-indpt, set-based	$\mathbb{I}\{y \in \mathcal{Y}\}$	$\mathcal{Y} \subseteq [0, 1]$	Capacity mandates, Essential workers
Scaled-capacity	$\mathbb{I}\{y \geq a(\theta^*)\}$	Increasing step function a	Safe capacity limits
Lipschitz	$h(y; \theta^*)$	jointly-Lipschitz	Community effects, Multiple workspaces

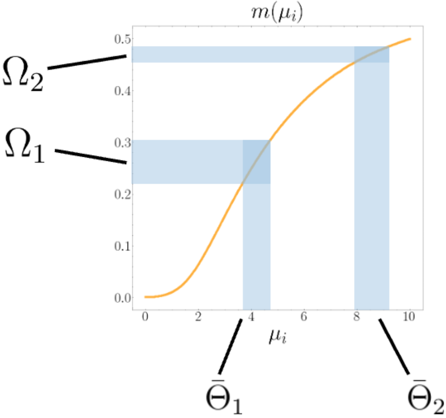
Planner's Design Problem

Optimal signalling mechanism

$$
\begin{aligned}
\pi^* &= \arg\max_{\pi} V(\pi) \\
&:= \arg\max_{\pi} \mathbb{E}_{\theta^* \sim F, i \sim z_{\theta^*}(\cdot)}[h(\pi, y^*(i); \theta^*)] \\
&= \arg\max_{\pi} \mathbb{E}_{\theta^* \sim F, i \sim z_{\theta^*}(\cdot)}[h(\pi, m(\mu_i); \theta^*)]
\end{aligned}
$$

State-Independent, Set-Based Preference

- $h(y;\theta^*) = \mathbb{I}\{y \in \mathcal{Y}\}$
- $\mathcal{Y} = \cup_{j=1}^{K} \Omega_j$ – union of K intervals $\Omega_j := [a_j, b_j] \subseteq [0,1]$
- For each j, "desirable" posterior means: $\bar{\Theta}_j := m^{-1}(\Omega_j)$



Equilibrium to Beliefs

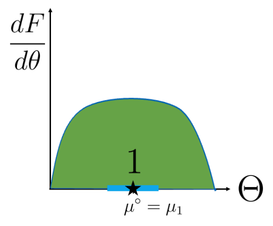
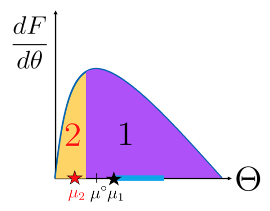
Planner seeks π^*:

$$\begin{aligned}\arg\max_{\pi} V(\pi) &= \max_{\pi} \mathbb{P}\{y^*_\pi(i) \in \mathcal{Y}\} \\ &= \max_{\pi} \mathbb{P}\{\mu_i \in m^{-1}(\mathcal{Y})\} \\ &= \max_{\pi} \sum_{i \in \mathcal{I}} q_i \mathbb{I}\{\mu_i \in \cup_{j=1}^K \bar{\Theta}_j\}\end{aligned}$$

- We analyze by position of prior mean μ° relative to $\cup_{j=1}^K \bar{\Theta}_j$ ($\underline{a} := \min \bar{\Theta}_1$, $\bar{b} := \max \bar{\Theta}_K$))
- Relative position of prior belief μ° to the desirable beliefs $\cup_{j=1}^K \bar{\Theta}_j$ is critical to structure of optimal design

Optimal Design

Theorem: Regimes with monotone partitional structure (MPS)

<table>
<tr><th>F</th><th>π^*</th><th>$V(\pi^*)$</th><th></th></tr>
<tr><td>$\mu^\circ \in \bar{\Theta}_i$</td><td>$\mathcal{I} = \{\mathbf{1}\}$
$[0, M] \to \mathbf{1}$</td><td>1</td><td>
</td></tr>
<tr><td>$\mu^\circ < \underline{a}$</td><td>$\mathcal{I} = \{\mathbf{1}, \mathbf{2}\}$
$[0, t^*] \to \mathbf{2}$
$[t^*, M] \to \mathbf{1}$</td><td>$1 - F(t^*)$</td><td>
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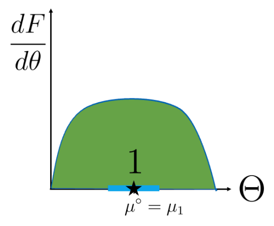
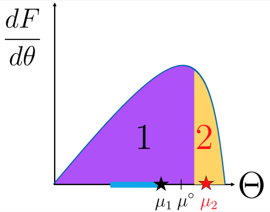
Optimal Design

Theorem: Regimes with monotone partitional structure (MPS)

F	π^*	$V(\pi^*)$	
$\mu^\circ \in \bar{\Theta}_i$	$\mathcal{I} = \{\mathbf{1}\}$ $[0, M] \to \mathbf{1}$	1	
$\mu^\circ > \bar{b}$	$\mathcal{I} = \{\mathbf{1}, \mathbf{2}\}$ $[0, t^*] \to \mathbf{1}$ $[t^*, M] \to \mathbf{2}$	$F(t^*)$	

MPS is not guaranteed

Example

- $F \sim \mathit{Unif}[0,1]$ ($\mu^\circ = 0.5$)
- $\bar{\Omega}_1 = [0.4 - \epsilon, 0.4 + \epsilon], \bar{\Omega}_2 = [0.6 - \epsilon, 0.6 + \epsilon]$

- No mechanism with MPS achieves objective 1
  - Consider first interval $[0, t_1]$ ($\mu_1 = \frac{t_1}{2}$, $\mu_i \geq \frac{1+t_1}{2}$ for all $i > 1$)

- $\mathcal{I} = \{1, 2\}$ with $z_\theta(1) = 0.7$ and $z_\theta(2) = 0.3$ for all $\theta \leq 0.5$, and $z_\theta(1) = 0.3$ and $z_\theta(2) = 0.7$ for all $\theta \geq 0.5$
  - $\mu_1 = 0.4$ and $\mu_2 = 0.6$
  - Achieves objective of 1

Optimal Design

- Let $\underline{s}(t) = \mathbb{E}[\theta|\theta < t]$ and $\bar{s}(t) = \mathbb{E}[\theta|\theta > t]$

Theorem

<table>
<tr><th>F</th><th>π^*</th><th>$V(\pi^*)$</th><th></th></tr>
<tr><td>$\underline{a} \leq \mu^\circ \leq \bar{b}$
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$\exists t, \quad \underline{s}(t), \bar{s}(t) \in \cup_{i=1}^K \bar{\Theta}_i$</td><td>$\mathcal{I} = \{\mathbf{1}, \mathbf{2}\}$
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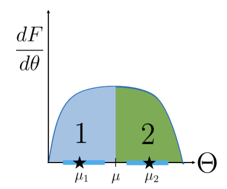
$[t, M] \to \mathbf{2}$</td><td>1</td><td>
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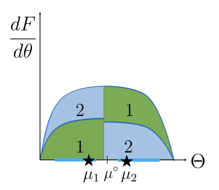
- Disperse mean belief; but can't do so if too tightly concentrated
- Can derive more general conditions without much complexity

Optimal Design

- $p(t, \lambda, \delta)$ and $q(t, \lambda, \delta)$ more diffused analogs of $\underline{s}, \bar{s}$

Theorem

F	π^*	$V(\pi^*)$	
$\underline{a} \leq \mu^\circ \leq \bar{b}$ $\mu^\circ \notin \cup_{i=1}^K \bar{\Theta}_i$ $\exists t,\ p(t,\lambda,\delta),$ $q(t,\lambda,\delta) \in \cup_{i=1}^K \bar{\Theta}_i$	$\mathcal{I} = \{\mathbf{1}, \mathbf{2}\}$ $[0, t] \xrightarrow{\text{w.p } \lambda} \mathbf{1}$ $\xrightarrow{\text{w.p } 1-\lambda} \mathbf{2}$ $[t, M] \xrightarrow{\text{w.p } \delta} \mathbf{2}$ $\xrightarrow{\text{w.p } 1-\delta} \mathbf{1}$	1	

Proof idea

- Part I: Require at most $K+1$ signals ($|\mathcal{I}| \leq K+1$)
  - $\bar{\Theta}_j$ are closed, convex intervals
  - For each j, $\mu_{i_1}, \mu_{i_2} \in \bar{\Theta}_j$ can be combined without loss
- Part II: Objective fn. of q_i, μ_i, so can search over $\mathcal{T}_\pi$'s
  - Search directly over all $H \succeq F$
  - Constraints: $\int_0^c H^{-1}(t)dt \geq \int_0^c F^{-1}(t)dt \ \forall c \in [0,1]$

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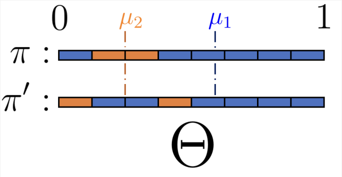
  - Search directly over all $H \succeq F$
  - Constraints: $\int_0^c H^{-1}(t)dt \geq \int_0^c F^{-1}(t)dt \; \forall c \in [0,1]$
- Part III: Know positions μ_i
  - If $\mu^\circ < \underline{a}$ or $\mu^\circ > \bar{b}$, know position of μ_{K+1} relative to other posterior means in $\bar{\Theta}_j$
  - If not, solve K convex optimizations for possible locations of μ_{K+1}
- Part IV: Combining (I) + (II) + (III)
  - Know that H must be discrete by (I)
  - Finite subset of constraints are sufficient so we reduce from an infinite # of constraints to finite constraint problem

State-dependent preferences

- Allowing preferences to depend on the state θ^* complicates the search problem (considering only $\mathcal{T}_\pi$ no longer sufficient)

Example

- $F \sim Unif[0,1]$ ($\mu^\circ = 0.5$)
- $h(y;\theta^*) = \mathbb{I}\{y \in \mathcal{Y}(\theta^*)\}$
- Desirable beliefs $\Omega(\theta^*) = m^{-1}(\mathcal{Y}(\theta^*)) = [\frac{2}{3}\theta^*, 1]$



- $\mathcal{I} = \{\mathbf{1}, \mathbf{2}\}, \mathcal{T}_\pi = \mathcal{T}_{\pi'} = \{(q_1 = \frac{3}{4}, \mu_1 = \frac{7}{12}), (q_2 = \frac{1}{4}, \mu_2 = \frac{1}{4})\}$
- $V_{F,h}(\pi) \neq V_{F,h}(\pi')$
  - If $\theta^* \in (\frac{3}{8}, \frac{1}{2})$, success only under π when induce belief μ_1

State-dependent preferences

- Allowing the preferences to depend on the state θ^* further reduces the possibility to obtain an optimal design with MPS

Example

- $F \sim \mathit{Unif}[0,1]$ $(\mu^\circ = 0.5)$
- $h(y;\theta^*) = \mathbb{I}\{y \in \mathcal{Y}(\theta^*)\}$
- Desirable beliefs $\Omega(\theta^*) = m^{-1}(\mathcal{Y}(\theta^*)) = [\frac{1}{3}\theta^* - \epsilon, \frac{1}{3}\theta^* + \epsilon]$
- $\pi = \langle \mathcal{I}, \{z_\theta\}_{\theta\in\Theta}\rangle$ where $\mathcal{I} = \{\mathbf{1},\mathbf{2},\mathbf{3}\}$ and $z_\theta(s)$ is as follows:

$$z_\theta(\cdot) = \begin{cases} \mathbf{1} \text{ w.p. } 1 \text{ if } \theta \in \mathcal{S}_1 := [0, 0.12] \cup [0.52, 0.56] \\ \mathbf{2} \text{ w.p. } 1 \text{ if } \theta \in \mathcal{S}_2 := [0.12, 0.30] \cup [0.80, 0.82] \\ \mathbf{3} \text{ w.p. } 1 \text{ if } \theta \in \mathcal{S}_3 := [0,1] \setminus \{\mathcal{S}_1 \cup \mathcal{S}_2\} \end{cases}$$

- $\mu_\mathbf{1} = 0.18, \mu_\mathbf{2} = 0.27$ and $\mu_\mathbf{3} = 0.65$
- $V_{F,h}(\pi) = 12\epsilon$
- Opt Mechanism with MPS: 6ϵ

Approximately Optimal Design

- Previous examples motivates need for *approximate* solutions

Definition

A mechanism π^ϵ is ϵ-optimal for a problem instance defined by distribution F over Θ and utility function h (under $V_{F,h}$) if:

$$V_{F,h}(\pi^*) - V_{F,h}(\pi^\epsilon) \leq \epsilon.$$

How to produce interval-based signalling mechanism π^ϵ?

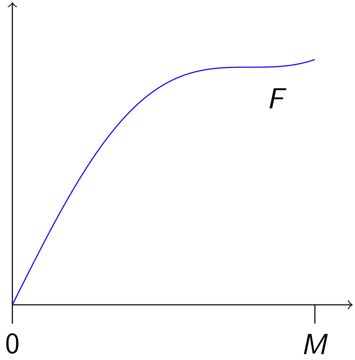
1. Discretize F appropriately to F_δ (intervals $\Theta_j \to$ points ν_j)
2. Reduce consideration to finite # of signals
3. Solve discrete analog using linear programming to get $\bar{\pi}^*$
4. Translate the discrete solution $\bar{\pi}^*$ to π^ϵ
   by applying $\bar{z}_{\nu_j}$ signal distribution to all states in Θ_j

Preferences

- **Lipschitz**: Preferences are smooth in the in-person mass and realized state
  - $h(y; \theta^*)$ is uniformly η_1-Lipschitz in y & η_2-Lipschitz in θ^*
- **Scaled-capacity**: Preferences specify an in-person capacity limit that gets progressively more strict as θ^* increases
  - $h(y; \theta^*) := \mathbb{I}\{y \in \mathcal{Y}(\theta^*)\} = \mathbb{I}\{y \geq a(\theta^*)\}$ where $a(\cdot)$ is weakly increasing step function

Discretization of F to F_δ

- Consider a finite number of states $\theta^* \in \{\nu_j\}_{j=1,..,N}$
- Partition Θ into $N = M\delta$ intervals Θ_j of width $\frac{1}{\delta}$
- Pick smallest point ν_j in each interval and assign all mass in Θ_j under F to point ν_j in F_δ



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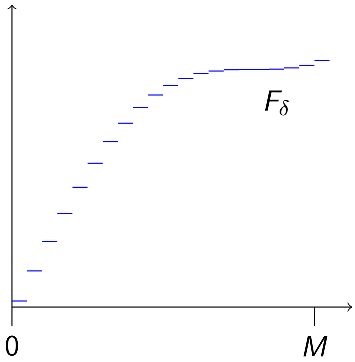
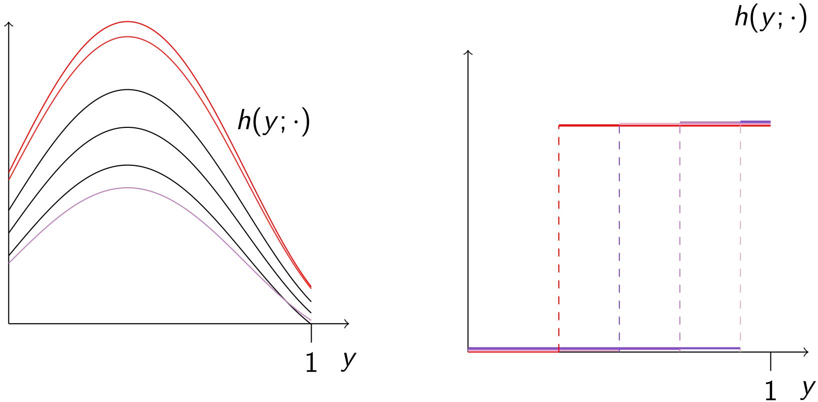
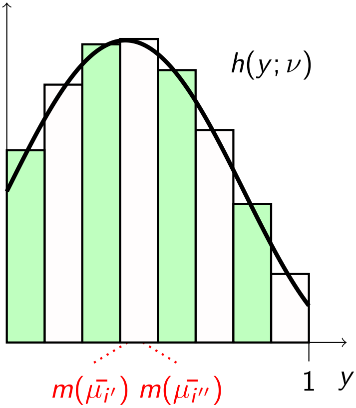


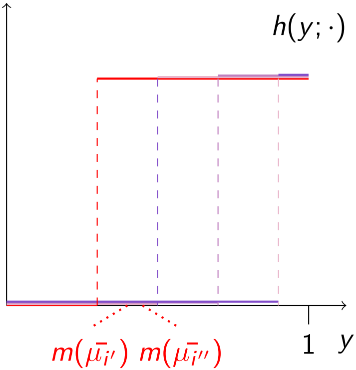
Reduce # of signals



- N curves
- Approximate h by piecewise const. fn. in y without much loss for Lipschitz preference

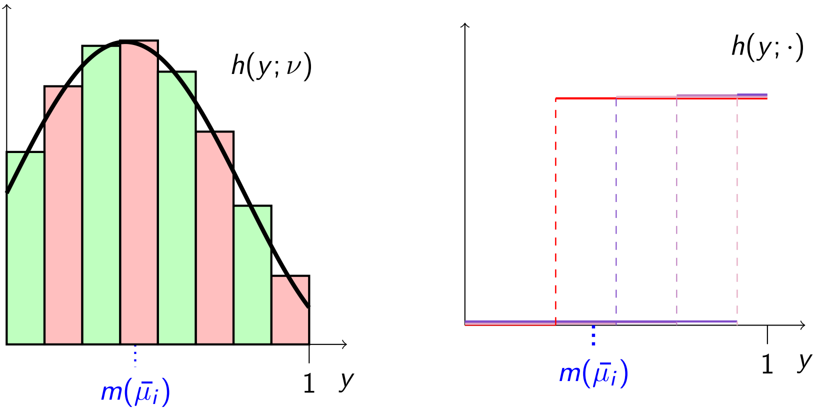
Reduce # of signals





- At most one signal will correspond posteriors that have equilibrium in each interval $\bar{\mu}_i \in [\gamma_i, \gamma_{i+1}]$

Reduce # of signals



- At most one signal will correspond posteriors that have equilibrium in each interval $\bar{\mu}_i \in [\gamma_i, \gamma_{i+1}]$

Solve Linear Program

- Variables x_{ji} to represent probability in state ν_j under F_δ and signal i is provisioned
  - $\bar{z}_{\nu_j}(i) = \frac{x_{ji}}{\sum_i x_{ji}}$
- Objective and constraints on posterior can all be made linear
  - Constraints on $\bar{\mu}_i$: $\gamma_i \sum_{j=1}^{N} x_{ji} \leq \sum_{j=1}^{N} \nu_j x_{ji} \leq \gamma_{i+1} \sum_{j=1}^{N} x_{ji}$
- LP algorithm outputs optimal *discrete* solution $\bar{\pi}^* := \pi^*_{F_\delta, h}$

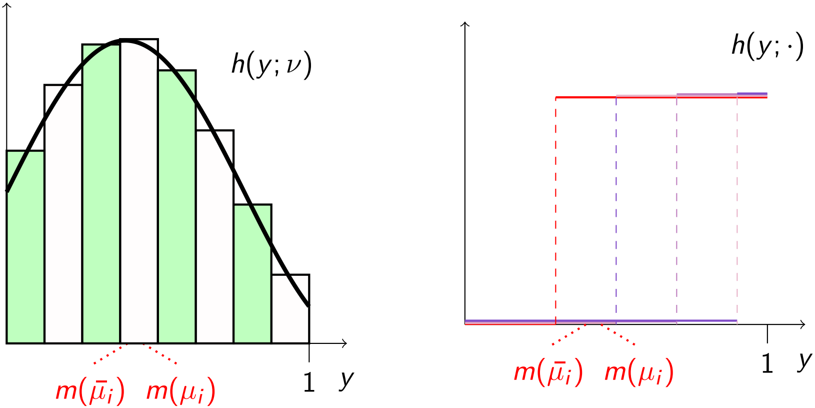
Translate from discrete to continuous solution

- Apply signal distribution $\bar{z}_{\nu_j}$ from $\bar{\pi}^*$ to every point in the corresponding interval Θ_j to get π^ϵ
- Similarly, unknown true optimal design $\pi^*_{F,h}$ has discrete analog $\bar{\pi}$ where aggregate signal distribution over interval Θ_j is applied to ν_j

Quality of π^ϵ error bounded by how lossless we transition from discretized to continuous signalling mechanisms:

$$
\begin{aligned}
V_{F,h}(\pi^*_{F,h}) - V_{F,h}(\pi^\epsilon) \leq & \big(V_{F,h}(\pi^*_{F,h}) - V_{F_\delta,h}(\bar{\pi})\big) \\
& + \big(V_{F_\delta,h}(\bar{\pi}^*) - V_{F,h}(\pi^\epsilon)\big)
\end{aligned}
$$

Translate from discrete to continuous solution



- Posteriors are close under discretization: $0 \leq \mu_i - \bar{\mu}_i \leq \frac{1}{\delta}$
  continuous signalling mechanisms induce higher posteriors

Translate from discrete to continuous solution

- Distribution over observed signals are identical
- This guarantees objective function values are also close

Theorem: For both Lipschitz and scaled-capacity

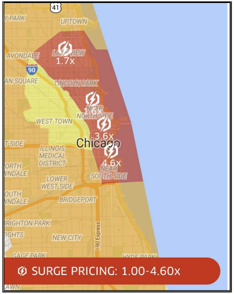
If cdf of G is Lipschitz, algorithm produces ϵ-optimal mechanism with runtime:
Lipschitz: $O(\frac{1}{\epsilon^5})$
Scaled Capacity: $O(\frac{1}{\epsilon^5})$

Part II: Dynamic information provision about demand surge in ride-hailing systems

Surge Pricing

Mobility service providers need to deal with uncertain demand

- **Wild Goose Chase (WGC):** Demand spikes
  $\Rightarrow$ drivers pick up far away passengers
  $\Rightarrow$ fewer trips supplied $\Rightarrow$ matching failure
  $\Rightarrow$ low welfare (Castillo et al. '17)
- **Surge Pricing:**
  - Subverts WGC
  - Lower prices when demand is low
  - $\uparrow$ total welfare and $\uparrow$ utilization rate



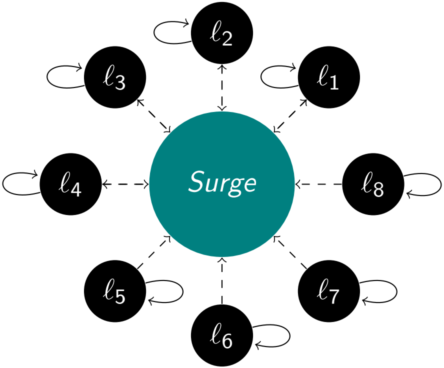
Rich literature on market design for ride-hailing systems:

- Bimpikis et al. '19, Besbes et al. '20, Borgs et al. '14, Castillo et al. '17, Castillo '20, Garg et al. '19

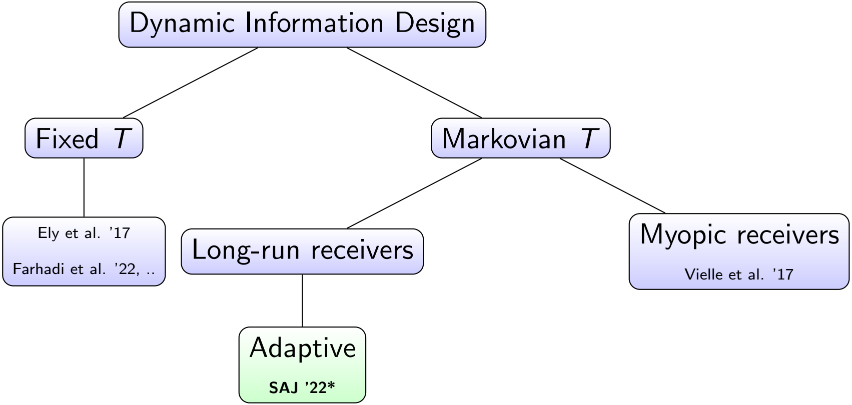
Managing Strategic Drivers

- **Key issue:** Strategic drivers with uncertainty over surge patterns (i.e. when and where) proactively chase/skip surges
  - Unreliable service and supply-demand imbalance
  - Congestive effect at surge hotspot

Q. How can platform dynamically provision information about uncertain demand surge to manage strategic drivers?



Related work



Our setting

- Planner seeks to maximize number of periods where desirable masses are maintained across two location types
- Under full-information disclosure, this is not possible as all agents only move just before surge onsets
- Under no-information disclosure, agents distribution immediately converges
- **Key point:** Optimal disclosure induces the mass in the desirable set that is closest to the no-information mass

Dynamic Model

- Discrete time $t = 1, 2, ..$
- Unit mass of non-atomic long-run agents; each make simultaneous location choice at time t: $a_t \in \{\ell_c, \ell_p\}$
  - ℓ_c is communal (demand hotspot)
  - ℓ_p is peripheral (remote)
  - Move from ℓ_p to ℓ_c is irreversible
- Mass y_t at ℓ_p at end of t

Model: Agents

- Each agent has private fixed per-period wage at ℓ_p from known distribution $v \sim G$
- Random time horizon $T \sim Geom(q)$ when surge onsets at congested hotspot
  - Horizon is memoryless
  - At end of period T, $1 - y$ agents at ℓ_c receive $\beta(1 - y)$ where $\beta(\cdot)$ is decreasing
- Agents seek to maximize total horizon wages

Dynamic Information Provision

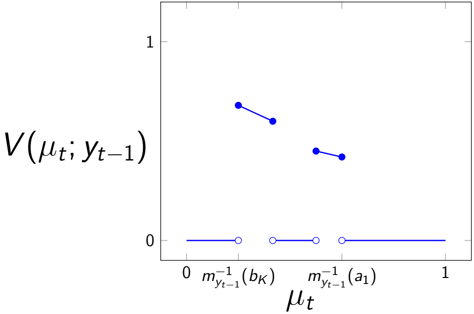
- Planner seeks to maintain driver distribution in a goal set $\mathcal{Y}$ i.e., maximize # of periods t with $y_t \in \mathcal{Y} := \cup_{j=1}^{K} \Omega_j$
- Each t, planner first *publicly* commits to and discloses *signalling mechanism* $\pi_t = \langle \mathcal{I}, \{z_\theta(\cdot)\}_{\theta \in \Theta_t} \rangle$
  - $\Theta_t = \{S_t, S_t^c\}$ where $S_t = \{T = t\}$ (e.g. $\mathbb{P}[S_t] = q$)
  - Planner can observe y_{t-1}, but not S_t
  - An adaptive, sequential model
- Signal then publicly shared with all agents before they make their decisions

Memorylessness

- By memorylessness, agents in t play stationary strategies that only depend on belief over $\mu_t(i) := \mathbb{P}[S_t|\pi \to i]$ and y_{t-1}
- Planner also uses stationary strategy to prescribe π_t that only depends on y_{t-1}
- Can characterize map from current beliefs to equilibrium in next period $m_{y_{t-1}}(\mu_t) := y_t^*$ (analogous to $m(\cdot)$ for Part I)

Value of information

- Solve for optimal strategy using dynamic programming on value functions $V(\mu_t; y_{t-1})$
- V is piecewise concave (linear) in μ_t
  - Concave regions correspond to the μ_t that yield y_t^* in Ω_j
- Planner benefits by not dispersing beliefs in these intervals

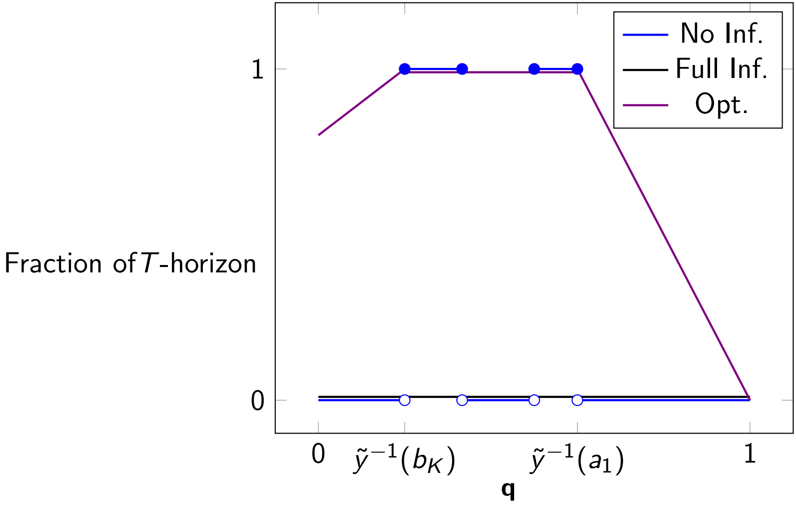


Full and no disclosure: Benchmarks

Lemma

- Under full disclosure, $y_1^* = .. = y_{T-1}^* > y_T^*$
  - Agents move to ℓ_c before T iff $v \leq \hat{v}_{FI}$ where $\beta(G(\hat{v}_{FI})) = \hat{v}_{FI}$
- Under no disclosure, $\tilde{y}^*(q) := y_1^* = .. = y_T^*$
  - Agents move (immediately) to ℓ_c iff $v \leq v_{NI}^*$ where $\beta(G(v_{NI}^*)) = \frac{v_{NI}^*}{q}$
  - $\tilde{y} : [0,1] \to [0,1]$ is weakly decreasing, bounded, and continuous.

Dynamic Information Provision: Result



Dynamic Information Provision: Result

Theorem

Optimal mechanism uses at most two signals and achieves values and posterior distributions:

$\mathbf{q}$:	$\mathbf{V}^*$:	(μ_1, μ_2) :
$\mathbf{q} < \tilde{y}^{-1}(b_K)$	$\frac{1+q-\tilde{y}^{-1}(b_K)}{q}$	$(0, \tilde{y}^{-1}(b_K))$
$\tilde{y}^{-1}(b_K) \leq \mathbf{q} \leq \tilde{y}^{-1}(a_1)$	$\frac{1}{q}$	$(\tilde{y}^{-1}(b_K), \tilde{y}^{-1}(a_1))$
$\mathbf{q} > \tilde{y}^{-1}(a_1)$	$\frac{1-q}{q(1-\tilde{y}^{-1}(a_1))}$	$(\tilde{y}^{-1}(a_1), 1)$

Conclusion

- New insights on structure and computation of optimal information mechanisms for managing congested hotspots
- Static and dynamic designs
- Future work: settings when planner needs to learn

thank you! feedback and questions?