Information Design for Congested Social Services: Optimal Need-based Persuasion

Krishnamurthy Iyer

University of Minnesota

Joint work with **Jerry Anunrojwong** and **Vahideh Manshadi**

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Motivation

Most social services face the challenge of severe congestion leading to long waiting times and inefficiency.

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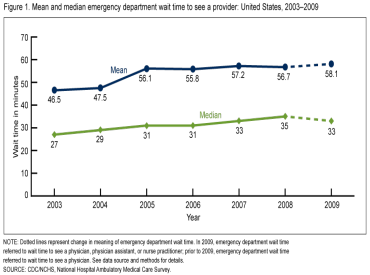

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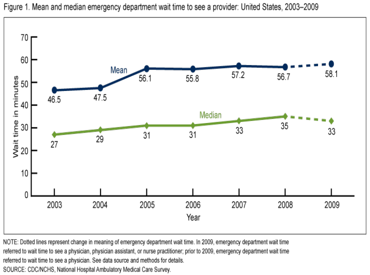

- limited capacity
- infeasibility of pricing
- inclusionary intent

Motivation

Given user heterogeneity, sharing wait-time information may incentivize users with lesser need to forgo (or delay using) the service.

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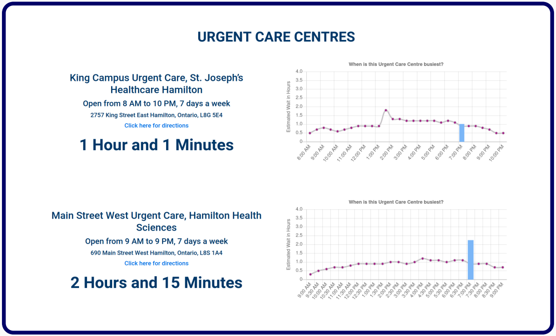

... especially useful for patients with less serious conditions who can use it to choose when and where to seek care.
[globalnews.ca]

Summary

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Criteria: (ex ante) Pareto dominance.

Take-away: With sufficient heterogeneity in need, information design can be powerful in improving overall welfare outcomes.

Related literature

We adopt the methodology of Bayesian persuasion.

Kamenica and Gentzkow (2011), Rayo and Segal (2010), Bergemann and Morris (2016), Dughmi and Xu (2016), . . .

Information design in operations:

- Lingenbrink and Iyer (EC'17)
- Das et al. (2017)
- Drakopoulos et al. (2018), Candogan and Drakopoulos (2019), Candogan (2019), etc.

Social goods allocation: Arnosti and Shi (2017), Leshno (2017)

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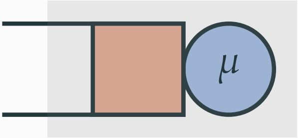
Social service provider:

- **unobservable** FCFS queue
- single server, rate μ



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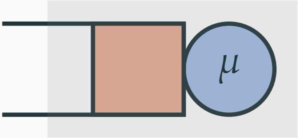
$\lambda_{\mathbf{H}}$

$\lambda_{\mathbf{L}}$



Heterogeneous need for service:

- high-need ($\mathbf{H}$)
- low-need ($\mathbf{L}$)

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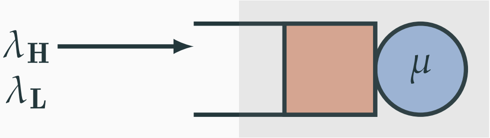

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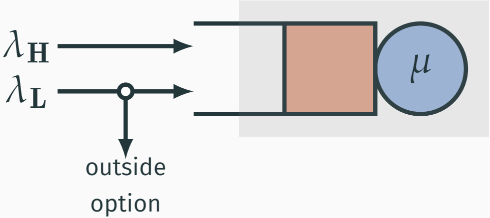

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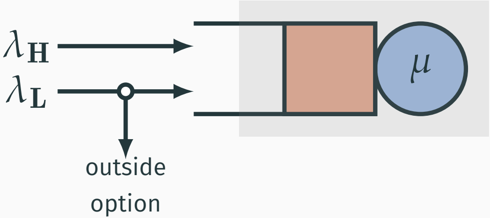

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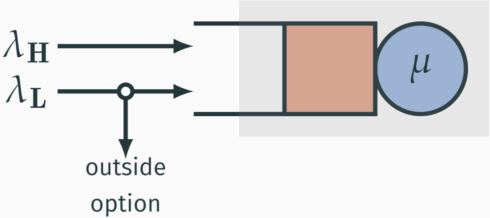

Resource sufficiency: $\lambda = \lambda_\mathbf{H} + \lambda_\mathbf{L} \leq \mu$

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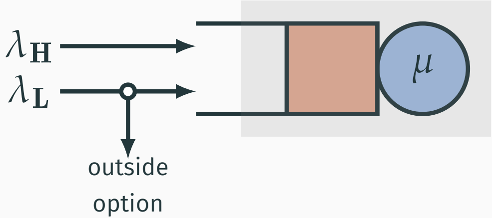

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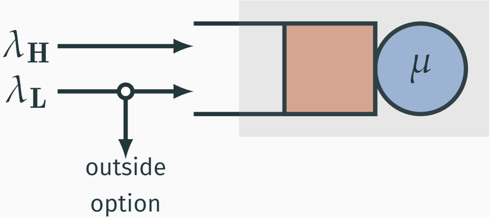

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Assumptions on utility:

- $u_i(k)$ strictly decreasing
- $u_{\mathbf{L}}(k) - u_{\mathbf{L}}(k+1)$ is non-increasing.

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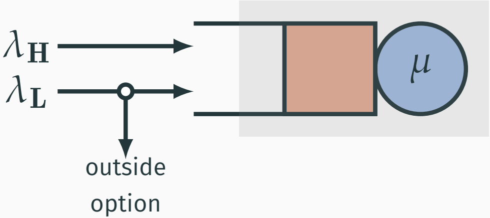

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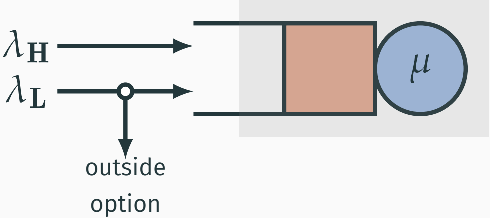

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SSP's goal: share information to reduce congestion.

Model: Signaling mechanisms

Signaling mechanism: A pair (S, σ) with

1. S = set of signals
2. σ = mapping from states to (distributions over) signals:

$$\sigma(s|n) = \mathbf{P}(\text{send signal } s | \text{queue size is } n).$$

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Revelation principle: suffices to consider $S = \{\mathbf{join}, \mathbf{leave}\}$, and σ such that **obedience** is optimal.

Model: Signaling mechanisms

Signaling mechanism: A pair (S, σ) with

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2. $\sigma = \{p_n : n \geq 0\}$

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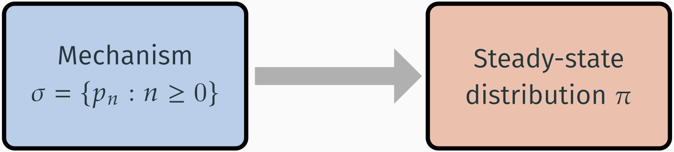

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$$\mathbf{E}_\pi[u_{\mathbf{L}}(X) \,|\, \textbf{join}] \geq 0, \qquad \textbf{(join)}$$
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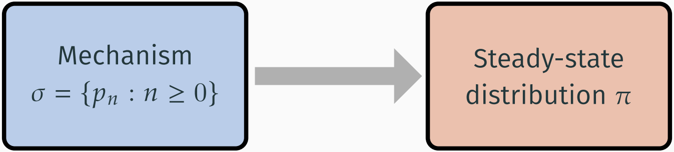

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Bayesian persuasion with **endogenous** prior.

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$\mathcal{SM}$ = set of all obedient signaling mechanisms σ.

Model: Welfare

Expected welfare of each type in steady-state:

$$W_{\mathbf{L}}(\sigma) = \lambda_{\mathbf{L}} \cdot \mathbf{E}_{\pi}[u_{\mathbf{L}}(X) \cdot \mathbf{I}\{\mathbf{join}\}]$$
$$W_{\mathbf{H}}(\sigma) = \lambda_{\mathbf{H}} \cdot \mathbf{E}_{\pi}[u_{\mathbf{H}}(X)]$$

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For $\sigma, \hat{\sigma} \in \mathcal{SM}$, σ **Pareto dominates** $\hat{\sigma}$ ($\sigma \succ_{\text{PD}} \hat{\sigma}$) iff

$$W_i(\sigma) \geq W_i(\hat{\sigma}), \quad i \in \{\mathbf{L}, \mathbf{H}\},$$

with at least one inequality strict.

$\sigma \in \mathcal{SM}$ is **Pareto dominant** iff $\hat{\sigma} \not\succ_{\text{PD}} \sigma$ for all $\hat{\sigma} \in \mathcal{SM}$.

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1. `full-info` mechanism
    - m_{fi} = smallest queue-size where "**leave**" is optimal for low-need users.
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3. **Admission policies**
   - Protocols $\psi = \{p_n\}_{n \geq 0}$ that need not honor obedience constraints.
   - $\mathcal{AP}$ = set of all admission policies ψ. Note: $\mathcal{SM} \subset \mathcal{AP}$.

Structural results

Structure of signaling mechanisms

Theorem

A Pareto dominant signaling mechanism has a threshold structure.

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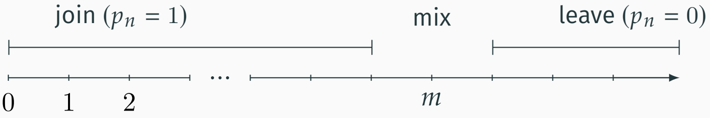

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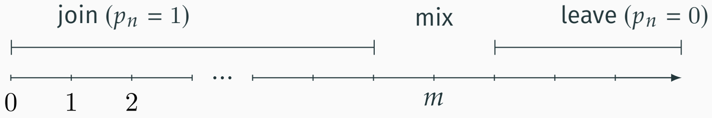

Proof: Perturb a non-threshold mechanism for Pareto improvement.

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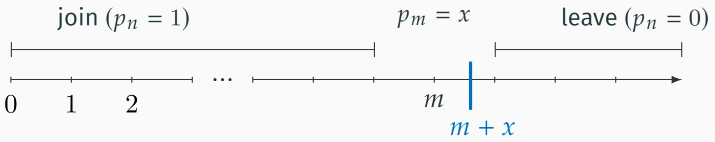

Notation: threshold $\sigma = m + x$ if $p_m = x \in [0, 1]$.

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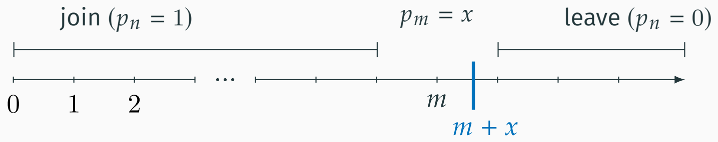

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Analogous result for Pareto dominant admission policies $\psi \in \mathcal{AP}$.

Structure of signaling mechanisms

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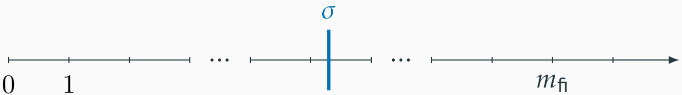
A Pareto dominant σ has a threshold below the `full-info` *threshold m_{fi}.*



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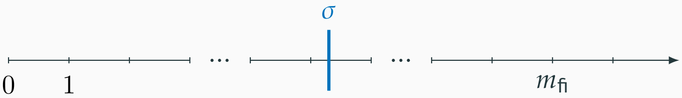

Proof: `full-info` Pareto dominates any mechanism with $\sigma > m_{\text{fi}}$.

Structure: Pareto dominance

Theorem

If the obedience constraint $(\textbf{leave})$ *does not bind for* $\sigma \in \mathcal{SM}$*, then*

$$\sigma \text{ is Pareto dominated in } \mathcal{AP} \implies \sigma \text{ is Pareto dominated in } \mathcal{SM}$$

Note: $(\textbf{leave})$ does not bind $\iff \mathbf{E}_\pi[u_\mathbf{L}(X) \,\big|\, \textbf{leave}] < 0.$

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Intuition:

- For any $\sigma \in \mathcal{SM}$ with $\sigma \leq m_{\text{fi}} \implies$ (**join**) does not bind.
- If (**leave**) does not bind, $\sigma \in \text{int}(\mathcal{SM})$.

Simple mechanisms

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Under `no-info`, all low-need users take the same action in equilibrium.

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Theorem: If $\lambda_{\mathbf{H}} < \bar{\lambda}$, then `no-info` is Pareto dominated.

Simple mechanisms: Full information

Under `full-info`, low-need users leave if and only if queue size is greater than m_{fi}.

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Theorem: Under sufficient demand for service, `full-info` is Pareto-dominated.

Comparison with first-best

Comparison with admission policies

Assumption: $u_{\mathbf{L}}(n) = u_{\mathbf{H}}(n) = 1 - c(n+1)$ for all $n \geq 0$.

- Linearity + homogeneity of inside option.

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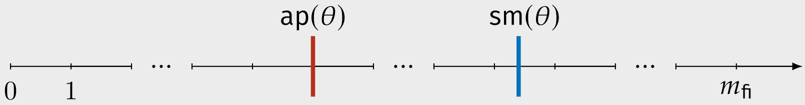
Lemma: $\text{ap}(\theta) \leq \text{sm}(\theta) \leq m_{\text{fi}}$.



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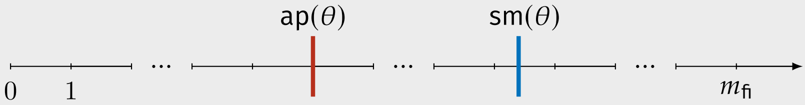

Users fail to internalize the negative externality. (Naor 1969)

Achieving first-best

Theorem

For any $\lambda_{\mathbf{H}} > 0$*, there exists a* $\bar{\theta} = \theta(\lambda_{\mathbf{H}}) \geq 0$ *such that*

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For small weights, the welfare outcome is **fixed** by the binding of $(\mathbf{leave})$.

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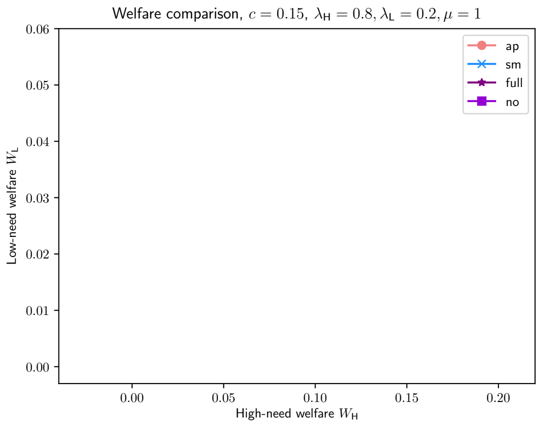
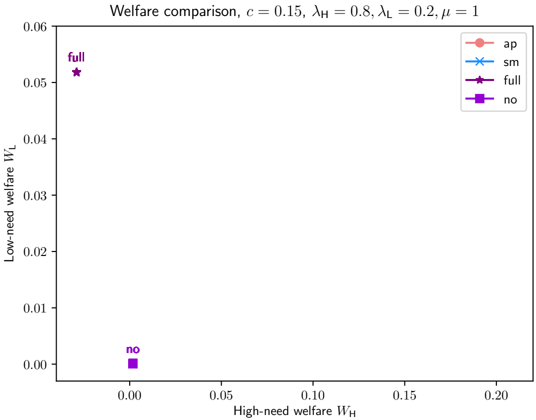
Information design plays a purely **coordinating** role to achieve first-best.

Numerics



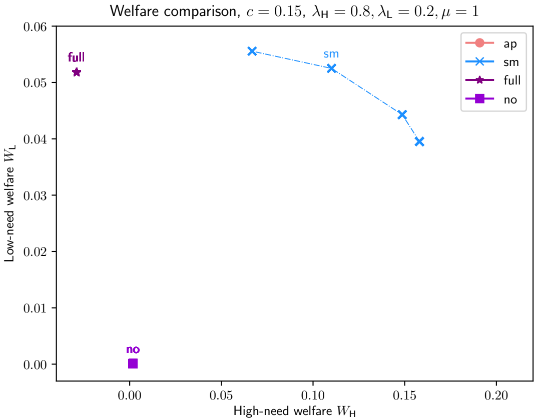
Welfare comparison, $c = 0.15,\ \lambda_H = 0.8, \lambda_L = 0.2, \mu = 1$
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Low-need welfare W_L
0.00
0.05
0.10
0.15
0.20
High-need welfare W_H
ap
sm
full
no

Numerics



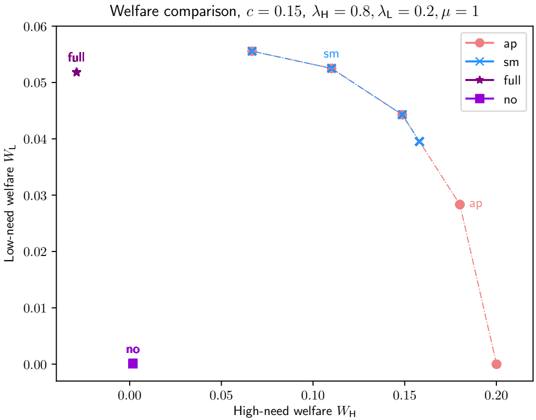
Welfare comparison, $c = 0.15,\ \lambda_{\mathrm{H}} = 0.8, \lambda_{\mathrm{L}} = 0.2, \mu = 1$
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Low-need welfare W_{L}
full
no
ap
sm
full
no
0.00
0.05
0.10
0.15
0.20
High-need welfare W_{H}

Numerics



Welfare comparison, $c = 0.15$, $\lambda_H = 0.8$, $\lambda_L = 0.2$, $\mu = 1$
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Low-need welfare W_L
full
sm
no
ap
sm
full
no
0.00
0.05
0.10
0.15
0.20
High-need welfare W_H

Numerics



Welfare comparison, $c = 0.15,\ \lambda_H = 0.8, \lambda_L = 0.2, \mu = 1$
Low-need welfare W_L
High-need welfare W_H
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0.00
0.05
0.10
0.15
0.20
full
no
sm
ap
ap
sm
full
no

Conclusion

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Information design provides Pareto improvement in welfare of all types over the simple mechanisms `no-info` and `full-info`

1. If $\lambda_{\mathbf{H}} < \bar{\lambda}$, then `no-info` is Pareto dominated.
2. With enough demand, `full-info` is Pareto dominated.

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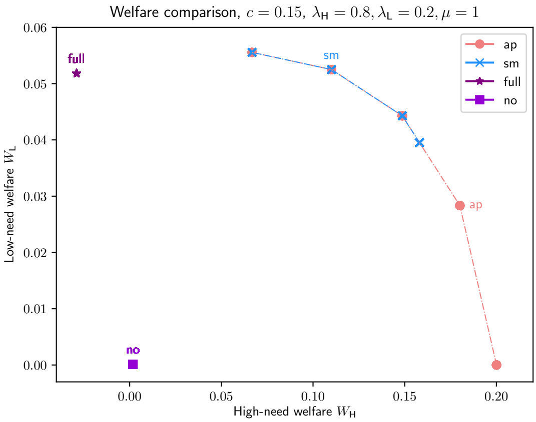
Under sufficient heterogeneity, information design can coordinate users' actions to achieve the **first-best**:

- same welfare outcomes as centralized admission policies

Conclusion



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0.06
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no

Thank you!

full paper: `https://arxiv.org/abs/2005.07253`