

Algorithmic Sustainability for Resource Allocation in Large-scale Sociotechnical Systems

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The need for market mechanisms in allocating limited resources

Market mechanisms are a necessary tool to allocate limited resources in our resource constrained world

**We live in
a resource
constrained
world**



Limited Energy Resources



Limited Road Space



Limited Vaccine Availability

How do we **best** allocate scarce resources to **strategic** agents?

Market design involves designing mechanisms to set the rules of the marketplace, e.g., via pricing, to ensure the right resources go to the right people while aligning users' incentives

Pervasiveness of market mechanisms

Market mechanisms are pervasive and are undergoing major transformations in our increasingly data-driven society

Market mechanisms influence our everyday lives



Electricity Markets



Congestion Pricing



Vaccine Allocation

Computing advances have opened new avenues for market design



Online Advertising



Marketplace Platforms



Smart Mobility

Challenges for AI and data-driven market mechanisms

Fairness/Equity



Why congestion pricing is a tough sell, even if it's good policy

By Christian Hetrick June 10, 2024

Market mechanisms such as congestion pricing raise fairness/equity concerns and, hence, often remain **unimplemented**

Data Privacy and Uncertainty



DOT plans to implement V2X technology raise privacy concerns

Kimberly Adams | Aug 20, 2024

Data is often plagued with **uncertainty** and raises **privacy concerns** that render mechanisms relying on complete information inadequate

Security



GAO finds fraud in commuter program

It's a perk of federal employment: a free monthly subsidy that pays for commutes on public transportation. But scores of workers have been taking the government for a ride, selling their

Data abundance enables easy **information manipulation**, leading to novel security challenges

Societal considerations make resource allocation challenging

Traditional Market Mechanisms

Efficiency



Focus of classical resource allocation mechanisms

New Societal Considerations

Fairness/Equity

Security

Privacy/Uncertainty

New Technical Challenges

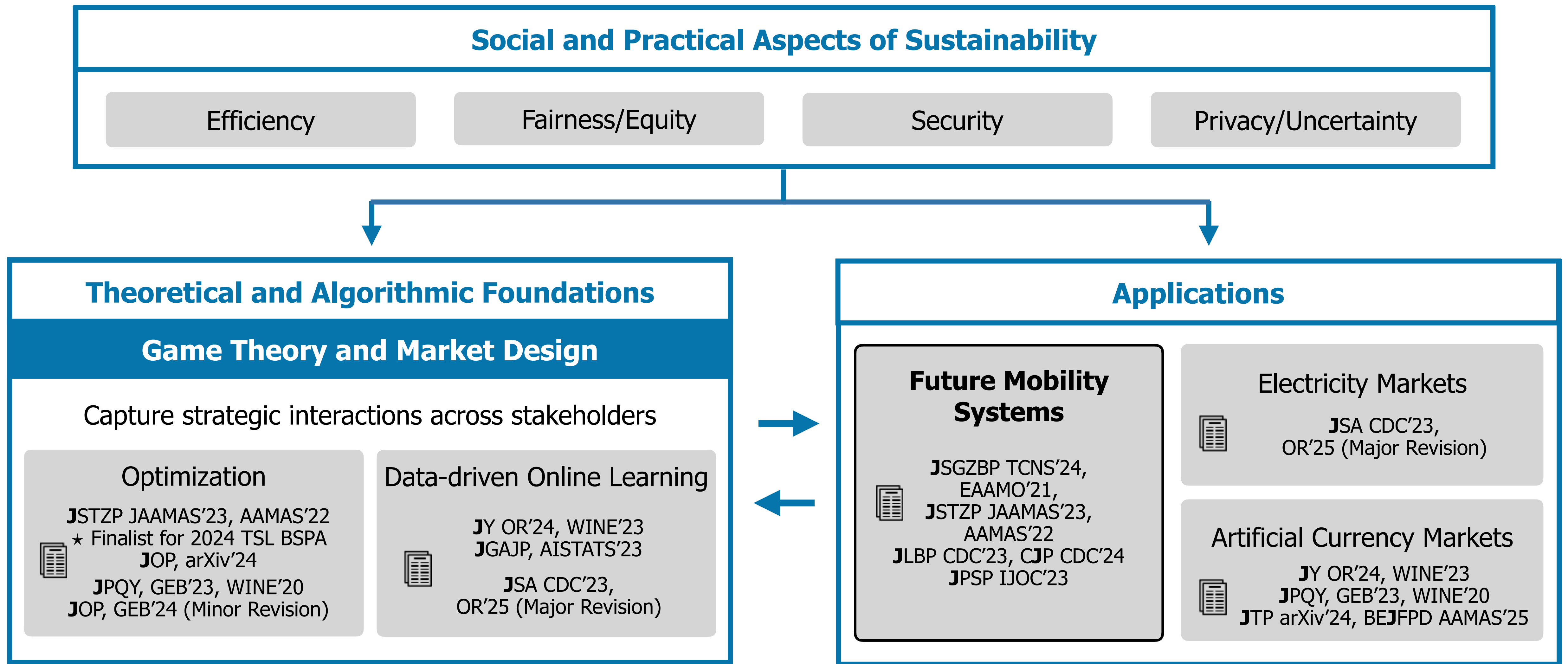
Computing optimal allocations or equilibria is often intractable under new constraints

Complete information on user attributes is often necessary for the efficacy of market mechanisms

➡ We need novel tools and methods to overcome these technical challenges

My Work: Sustainable resource allocation in socio-technical systems

My work leverages operations, CS, and economics to advance the **science** and **practice** of sustainable resource allocation



This talk: Addressing intractability under fairness & security constraints

Traditional Market Mechanisms

Efficiency

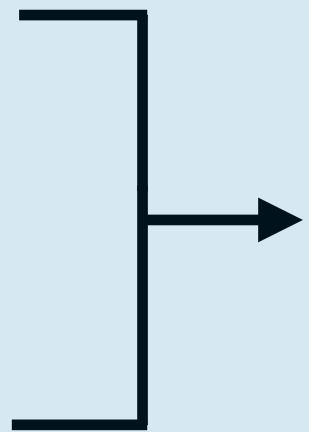


Focus of classical resource allocation mechanisms

Aspects of Social Sustainability

Fairness/Equity

Security



Computing optimal allocations or equilibria is often intractable under new constraints

Privacy/Uncertainty



Complete information on user attributes is often necessary for the efficacy of market mechanisms

➡ We need novel tools and methods to overcome these technical challenges

This talk: Fairness & security from approximation algorithm lens

We highlight two vignettes of this agenda focused on developing **approximation algorithms** for **NP-hard problems** arising under **fairness** and **security** considerations in **mobility** applications

Fairness (Congestion Pricing)

Jalota et al. JAAMAS’23

Finalist for the **2024 INFORMS TSL best student paper award**

Source of Hardness	Non-convexity of fairness constraints
Solution Method	Novel convex programming relaxation that also yields a natural pricing scheme

Security Games (Parking Enforcement)

Jalota et al. arXiv’24

Collaboration with **Stanford’s DPS** to demonstrate efficacy of our algorithms on enforcement data in increasing parking revenues by \$300,000 annually

Source of Hardness	Resource constraints on the available set of security officers
Solution Method	Optimizing a specific concave approximation of bi-level program yielding a natural greedy algorithm

Agenda

- Fairness in Congestion Pricing
- Security Games for Enforcement in Mobility Applications
- Future Directions



<https://sites.google.com/view/devanshjalota/>

Agenda

→ **Fairness in Congestion Pricing**

- Introduction and Motivating Example
- Model and Problem Setup
- Algorithmic Approach for Fair Traffic Routing: I-TAP
- Fair Congestion Pricing via I-TAP
- Conclusion

→ Security Games for Enforcement in Mobility Applications

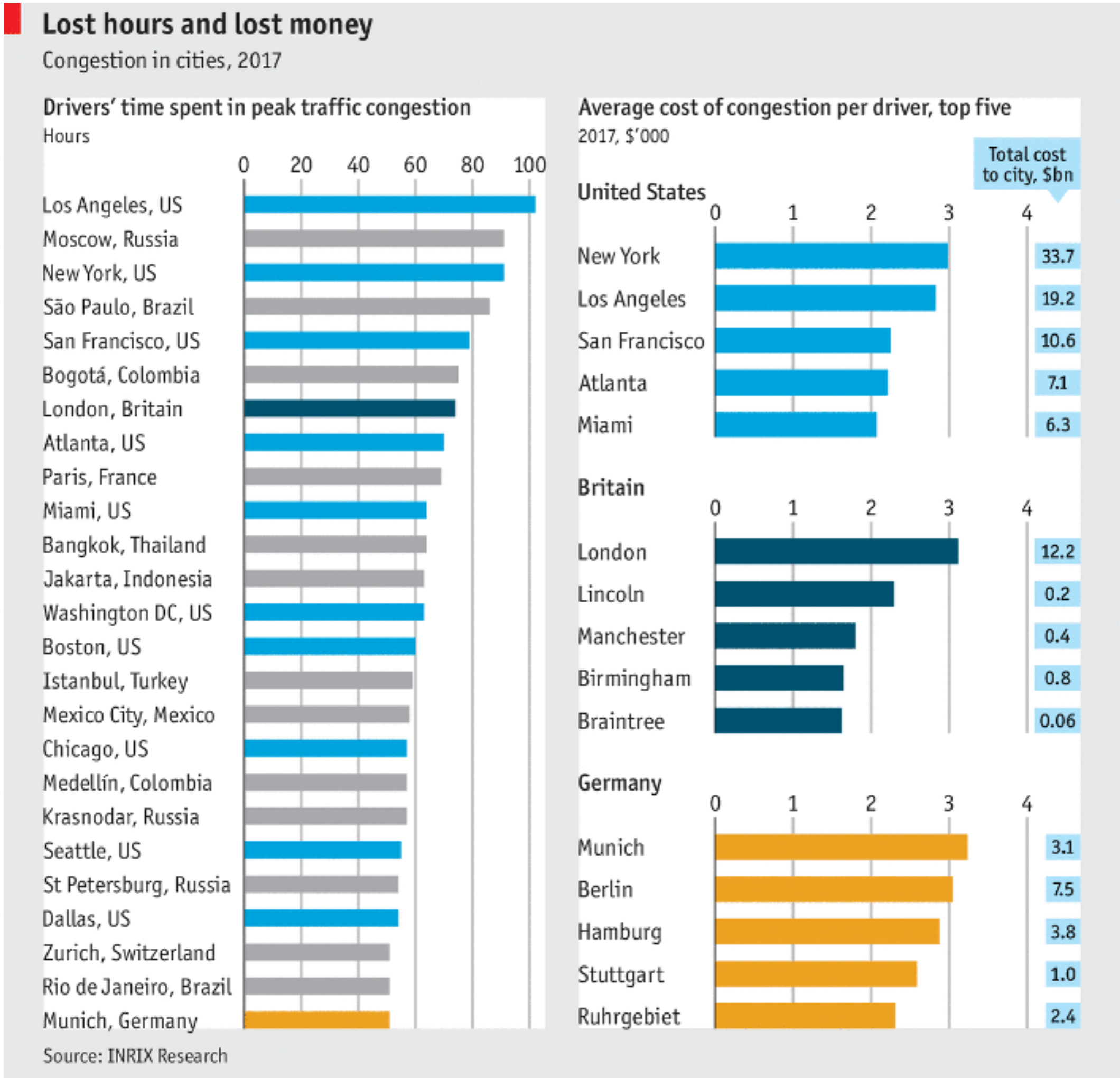
→ Future Directions

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Traffic congestion is a global challenge

Traffic congestion results in billions of dollars of economic losses, with commuters losing hundreds of hours, every year



Traffic congestion is ubiquitous



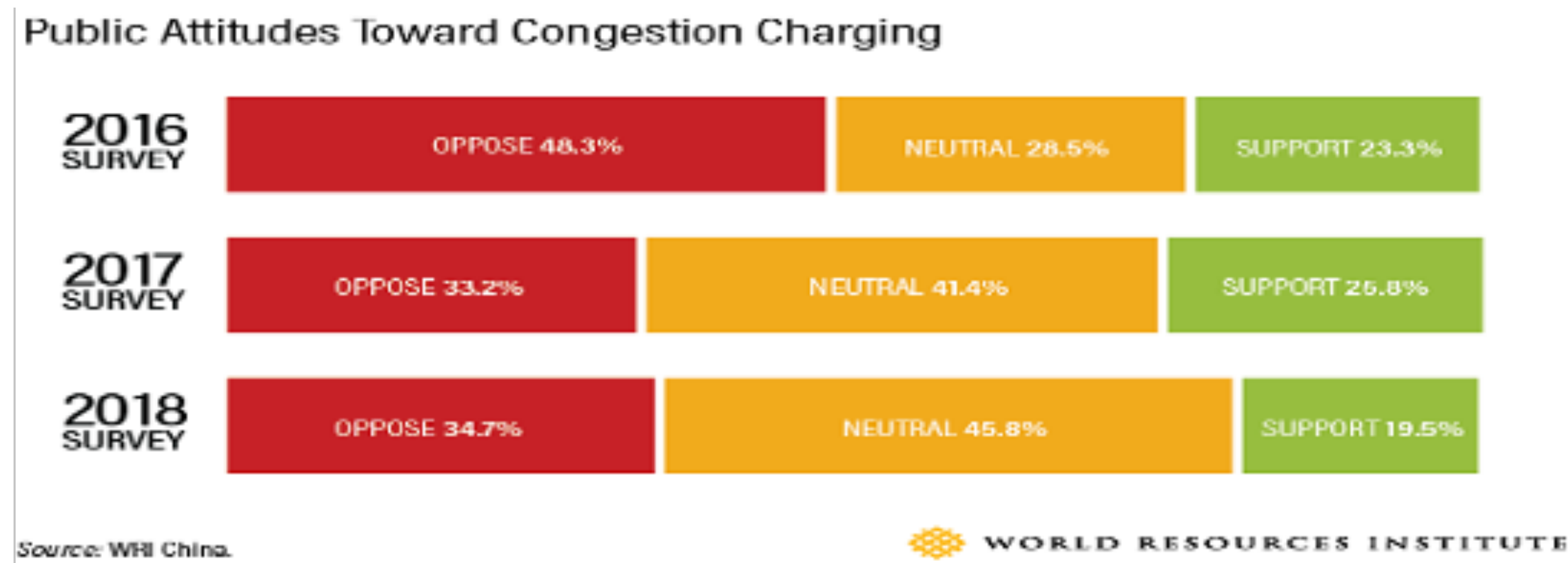
A Solution: Congestion Pricing (CP)



Fairness/Inequity Issues of Congestion Pricing (CP)

However, the real-world deployment of CP has been limited due to the resulting fairness/inequity issue

Regressive Nature of Congestion Pricing



Congestion fees have often been described as a **"tax on the working class"**

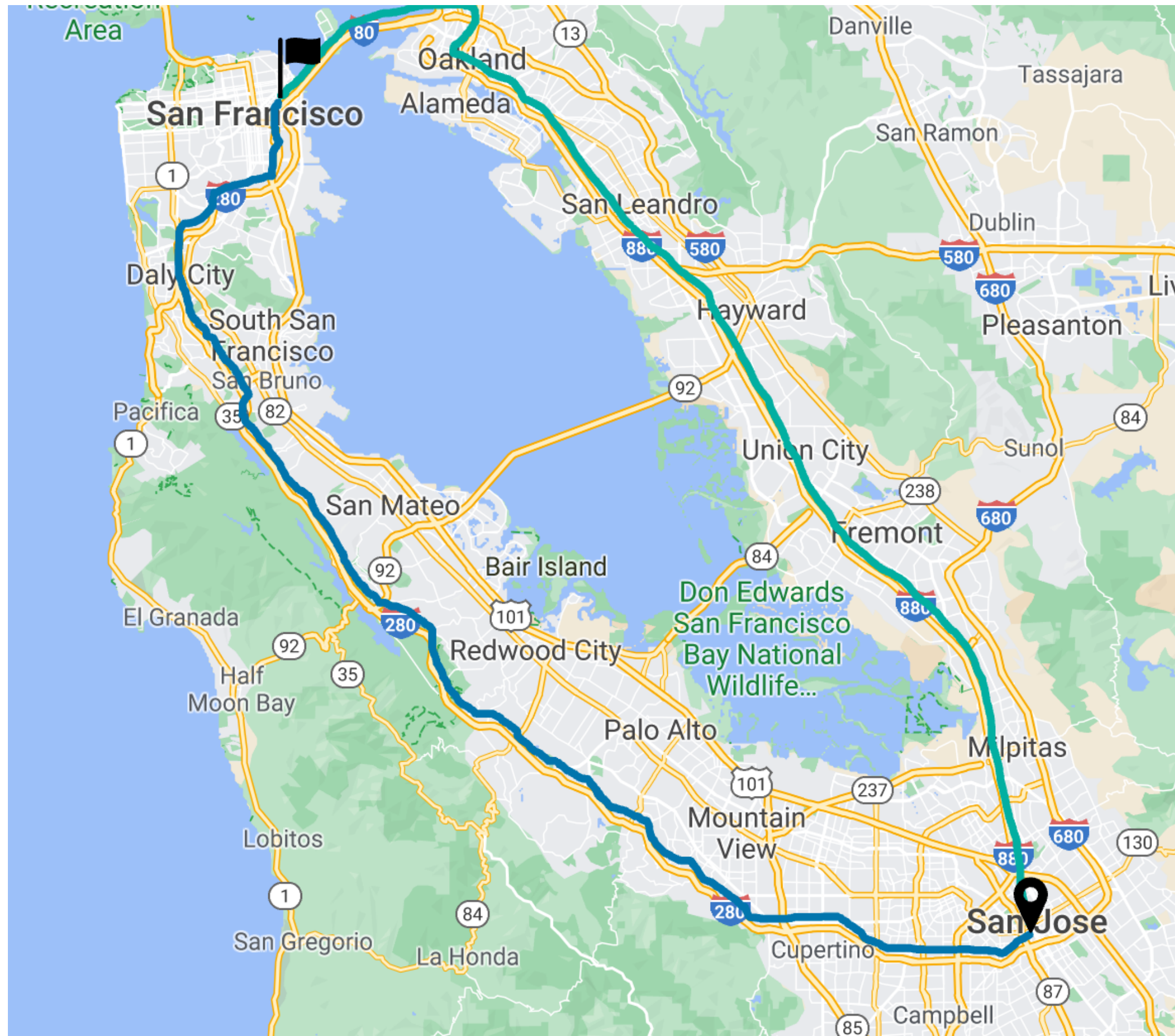
Limited Adoption of Congestion Pricing



➡ Tension between the efficiency gains of congestion pricing and its possible impact on low-income commuters

Example: A Traffic Routing Problem

Suppose we need to route five units of demand between San Jose and San Francisco



Problem Parameters

Travel Demand

x_1, x_2 : Flows on route 1 and 2

$$x_1 + x_2 = 5$$

Travel Time

$t_1(\cdot)$: Travel time function on route 1

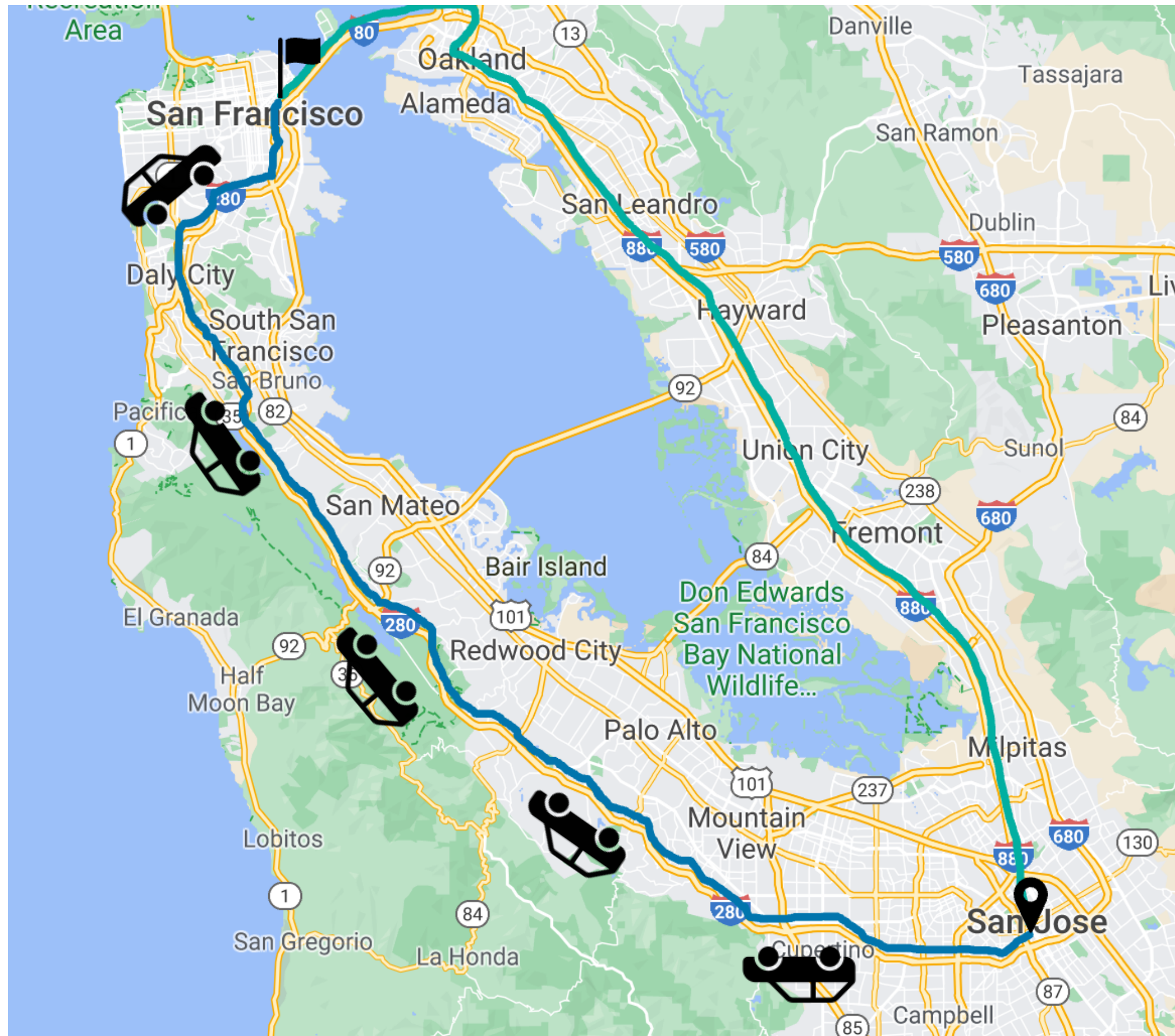
$$t_1(x_1) = 2x_1^2$$

$t_2(\cdot)$: Travel time function on route 2

$$t_2(x_2) = 50$$

Example: User Equilibrium (UE) without Tolls

Without tolls, users selfishly minimize their travel times, resulting in potentially large system travel times



User Equilibrium (UE)

No individual would be better off by deviating to another route

Route 1

$$x_1 = 5$$

$$t_1(x_1) = 2x_1^2 = 50$$

Route 2

$$x_2 = 0$$

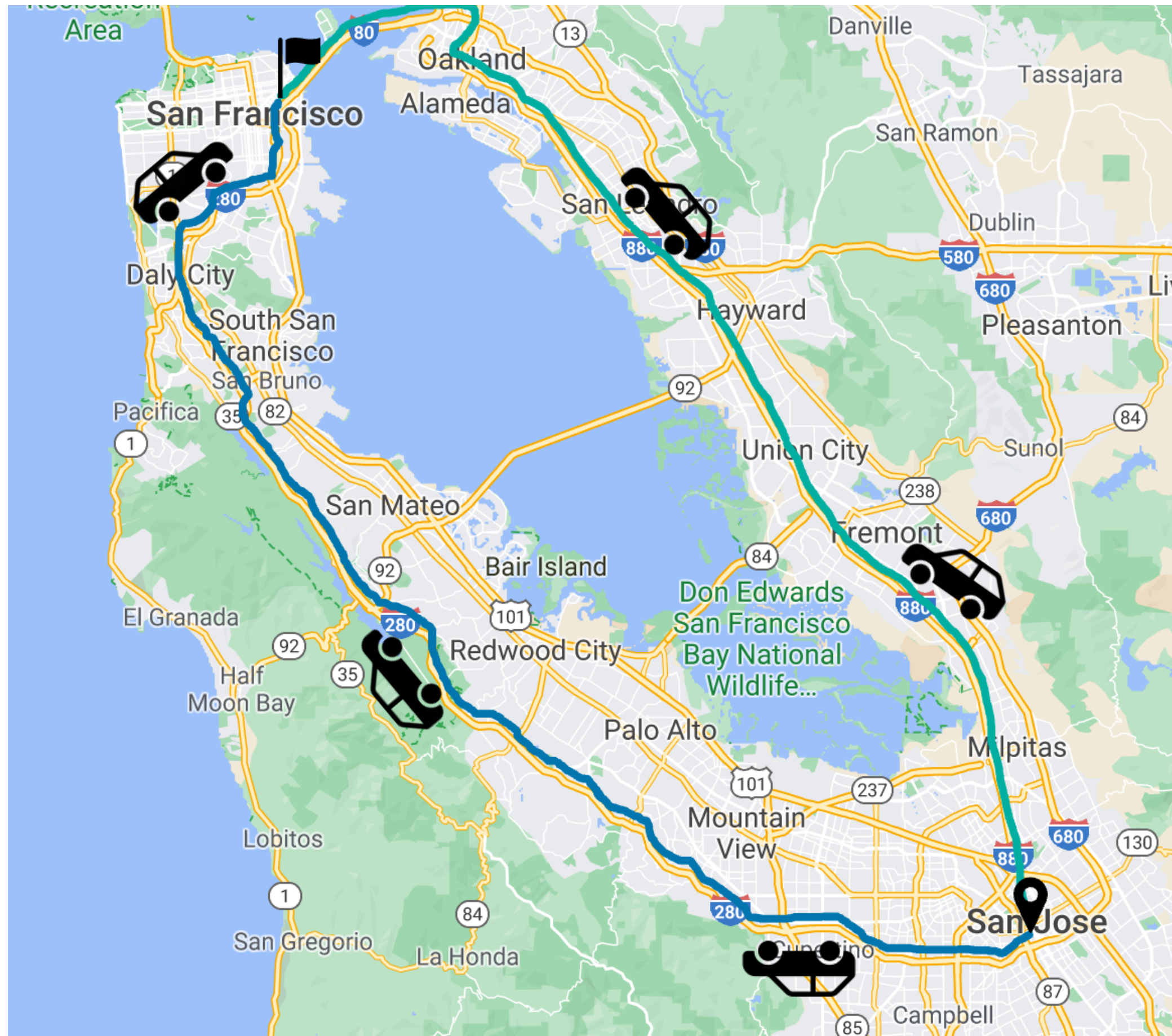
$$t_2(x_2) = 50$$

$$f^{SO}(\mathbf{x}) = x_1 t_1(x_1) + x_2 t_2(x_2) = 250$$

➡ The user equilibrium outcome can result in inefficient outcomes, with high total system travel times

Example: System Optimum (SO) with Congestion Pricing

Marginal cost pricing can be used to steer the traffic to the system optimum



System Optimum (SO)

The total travel time of all users is minimized

Route 1

$$x_1 = 3$$

$$t_1(x_1) = 2x_1^2 = 18$$

Route 2

$$x_2 = 2$$

$$t_2(x_2) = 50$$

$$f^{SO}(\mathbf{x}) = x_1 t_1(x_1) + x_2 t_2(x_2) = 154$$

➡ The system optimum outcome can result in unfair outcomes, with some users, typically those with lower incomes, incurring disproportionately high travel times in the pursuit of system efficiency

An Efficiency-Fairness Tradeoff

Comparing these two extreme solutions reveals an efficiency-fairness tradeoff

	UE (No Tolls)	SO (Marginal Cost Pricing)
Total Travel Time	250	154
Ratio of User Travel Times	1	≈ 3
	Fair but Inefficient	Efficient but Unfair

Contributions

We resolve this tradeoff through an novel traffic routing algorithm and price roads to enforce these flows

Computationally Efficient Routing Algorithm



Develop a novel convex program (I-TAP) that trades off efficiency and fairness

Fair Congestion Pricing Scheme



Present the first congestion pricing schemes for fair routing in general networks

Balance Fairness and Efficiency in Traffic Routing



Achieve sustainable transportation's efficiency and fairness objectives

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Performance Metrics

We evaluate the performance of a traffic routing policy in general road networks through two metrics

Efficiency

Ratio of total travel time of a traffic assignment $\mathbf{x}$ to that of the system optimum solution $\mathbf{x}^{SO}$

Inefficiency Ratio

$$\rho(\mathbf{x}) := \frac{f^{SO}(\mathbf{x})}{f^{SO}(\mathbf{x}^{SO})}$$

Fairness

Maximum ratio of the travel times of users traveling between the same O-D pair

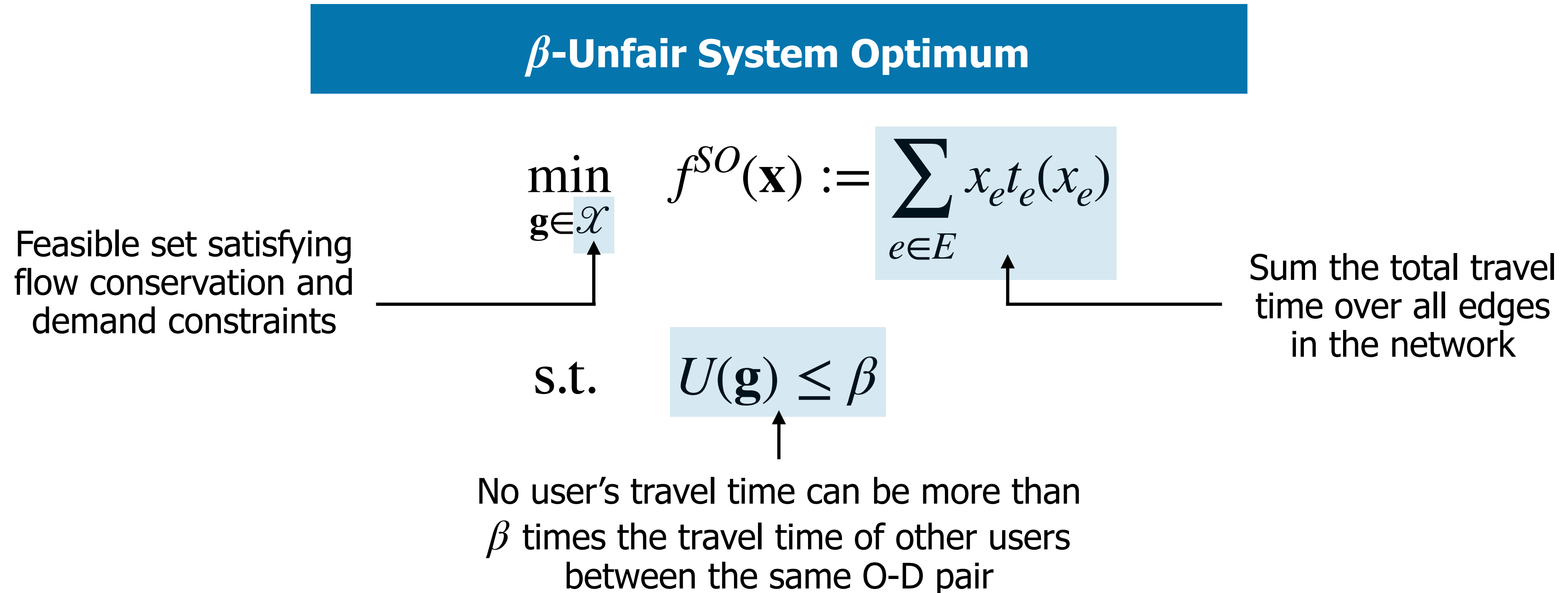
Unfairness

$$U(\mathbf{g}) := \max_{k \in K} \max_{Q, R \in \mathcal{P}_k^+} \frac{t_Q(\mathbf{x})}{t_R(\mathbf{x})}$$

Diagram illustrating the Unfairness metric $U(\mathbf{g})$. The formula is shown with annotations:
 - $U(\mathbf{g})$ is labeled "Path flow".
 - $k \in K$ is labeled "O-D pairs".
 - $Q, R \in \mathcal{P}_k^+$ is labeled "Paths with positive flow".
 - $t_R(\mathbf{x})$ is labeled "Travel time on route R".

Unfairness constrained system optimum

To balance efficiency and fairness, we study an unfairness constrained system optimum problem

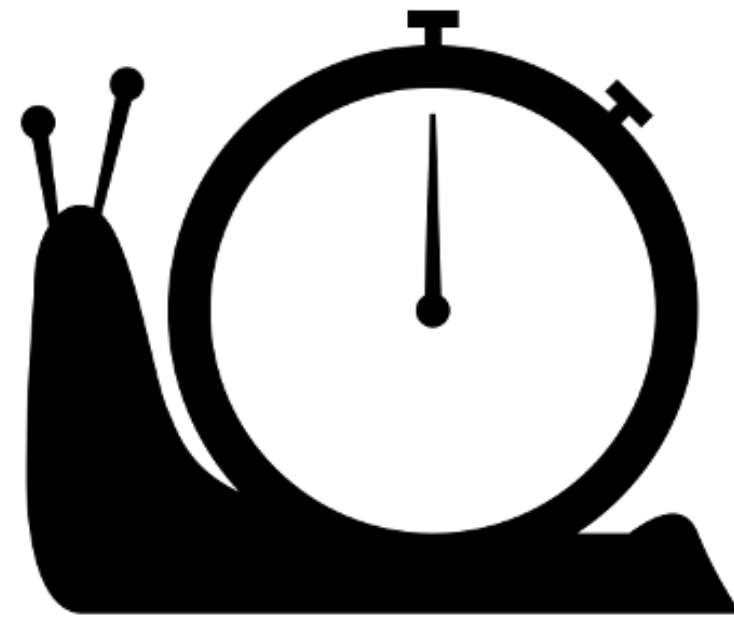


β -Unfair SO is NP-hard [Basu et al. 2017]: The unfairness constraints are non-convex

Related Literature

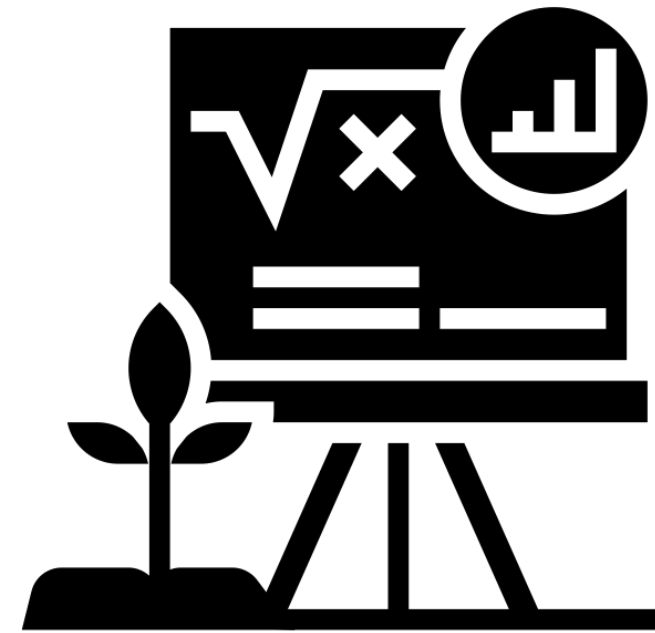
Past literature on fair routing to solve the unfairness constrained system optimum suffer from several drawbacks

Computationally Prohibitive



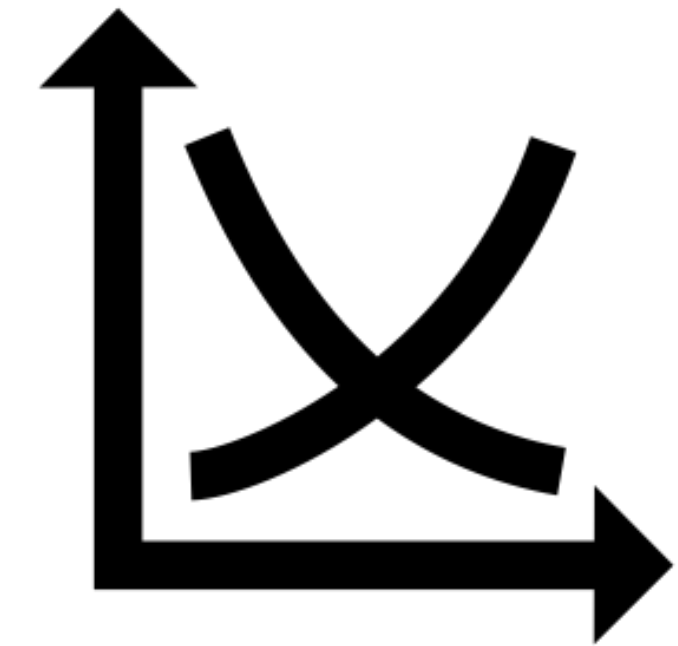
Unlike methods relying on solving MILPs or NP-hard sub-problems, we propose a computationally efficient convex programming approach

Lack of Theoretical Guarantees



We present theoretical bounds on the unfairness and inefficiency ratio to evaluate the performance of our algorithm

No Pricing Mechanism to Enforce Flows



Our convex program yields natural congestion pricing schemes, resulting in the first study of pricing for fair routing in general networks

➡ Our work overcomes several drawbacks of existing approaches to solve the unfairness constrained system optimum

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Our approach: Interpolated Traffic Assignment

Our approach interpolates between the UE and SO objectives to achieve a balance between efficiency and fairness

System Optimum Traffic Assignment Problem

Minimize Total Travel time

$$\min_{\mathbf{g} \in \mathcal{X}} f^{SO}(\mathbf{x}) := \sum_{e \in E} x_e t_e(x_e)$$

Inefficiency
Ratio: $\rho(\mathbf{x}) = 1$

Unfairness:
 $U(\mathbf{g}) \geq 1$

**Efficient
but Unfair**

User Equilibrium Traffic Assignment Problem

Users between each O-D pair
have same travel time

$$\min_{\mathbf{g} \in \mathcal{X}} f^{UE}(\mathbf{x}) := \sum_{e \in E} \int_0^{x_e} t_e(y) dy$$

Inefficiency
Ratio: $\rho(\mathbf{x}) \geq 1$

Unfairness:
 $U(\mathbf{g}) = 1$

**Fair but
Inefficient**

Interpolated Traffic Assignment Problem (I-TAP)

Interpolate between
UE and SO objectives

$$\min_{\mathbf{g} \in \mathcal{X}} f^{I_\alpha}(\mathbf{x}) := \alpha f^{SO}(\mathbf{x}) + (1 - \alpha) f^{UE}(\mathbf{x})$$

**Achieve best
of both worlds**

Approximation β -SO via I-TAP

I-TAP serves as a tractable approximation to the β -SO problem we seek to solve

β -Unfair System Optimum

$$\min_{\mathbf{g} \in \mathcal{X}} f^{SO}(\mathbf{x}) := \sum_{e \in E} x_e t_e(x_e)$$

$$\text{s.t. } U(\mathbf{g}) \leq \beta$$

NP-hard problem

Approximate



I-TAP

$$\min_{\mathbf{g} \in \mathcal{X}} f^{I_\alpha}(\mathbf{x}) := \alpha f^{SO}(\mathbf{x}) + (1 - \alpha) f^{UE}(\mathbf{x})$$

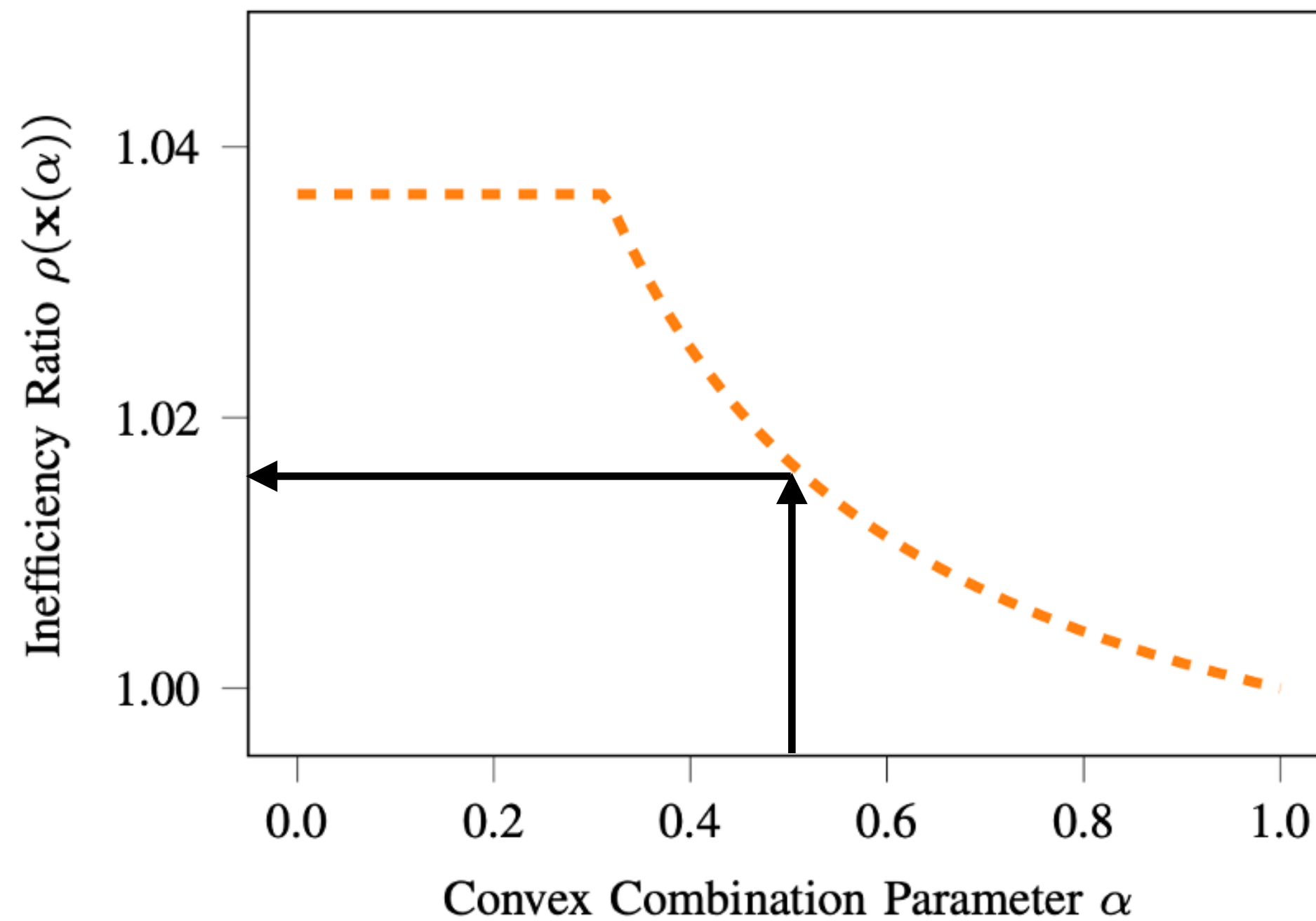
**Computationally tractable
convex program**

How good an approximation is I-TAP to the β -Unfair SO problem?

Theoretical Bounds for I-TAP

We obtain bounds on the total travel time and unfairness of I-TAP

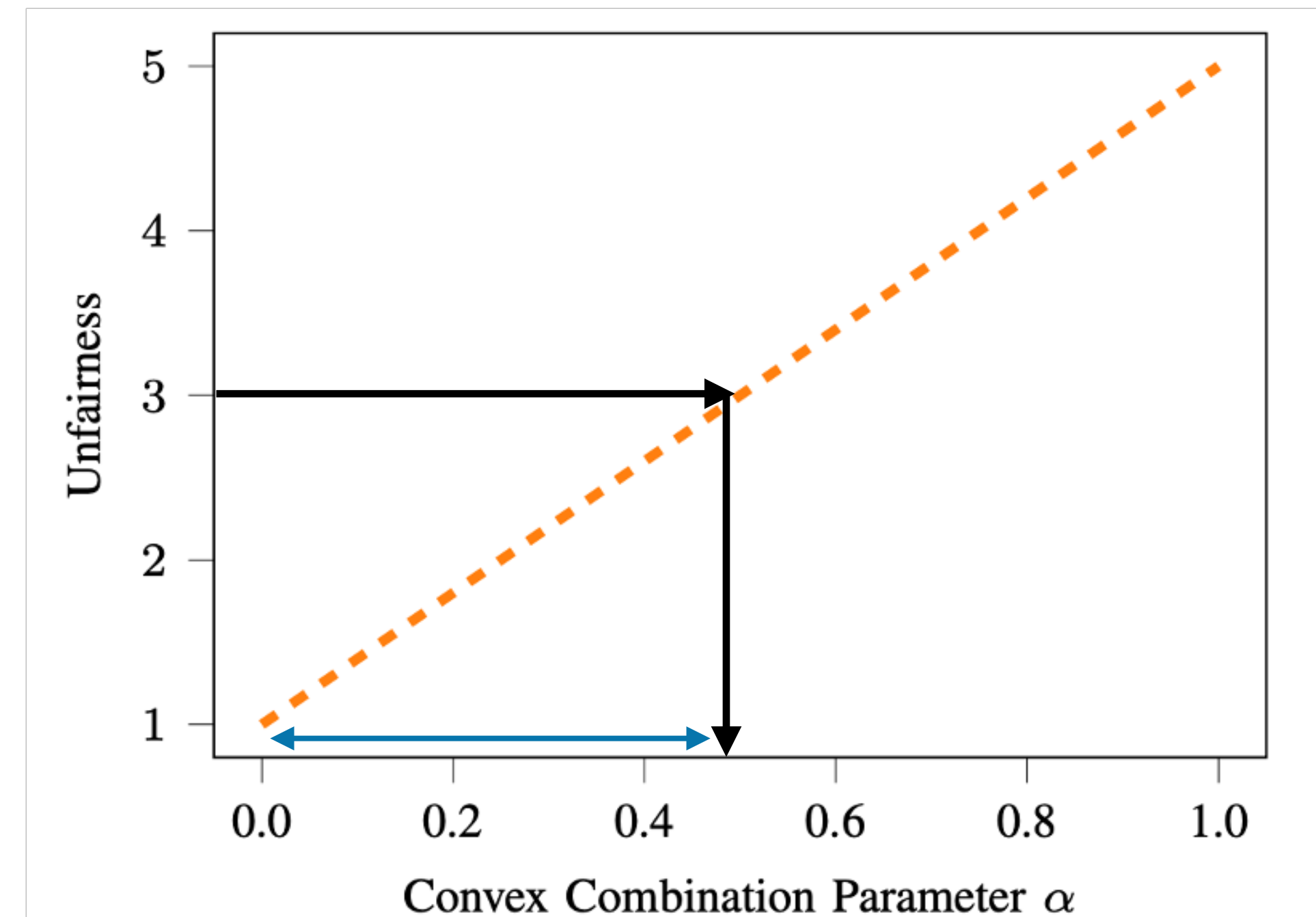
Inefficiency Ratio



Theorem: For any $\alpha \in [0,1]$, the inefficiency ratio

$$\rho(\mathbf{x}(\alpha)) \leq \min\left\{\text{PoA}, 1 + \frac{(1 - \alpha)(f^{UE}(\mathbf{x}(1)) - f^{UE}(\mathbf{x}(0)))}{\alpha f^{SO}(\mathbf{x}(1))}\right\}.$$

Unfairness



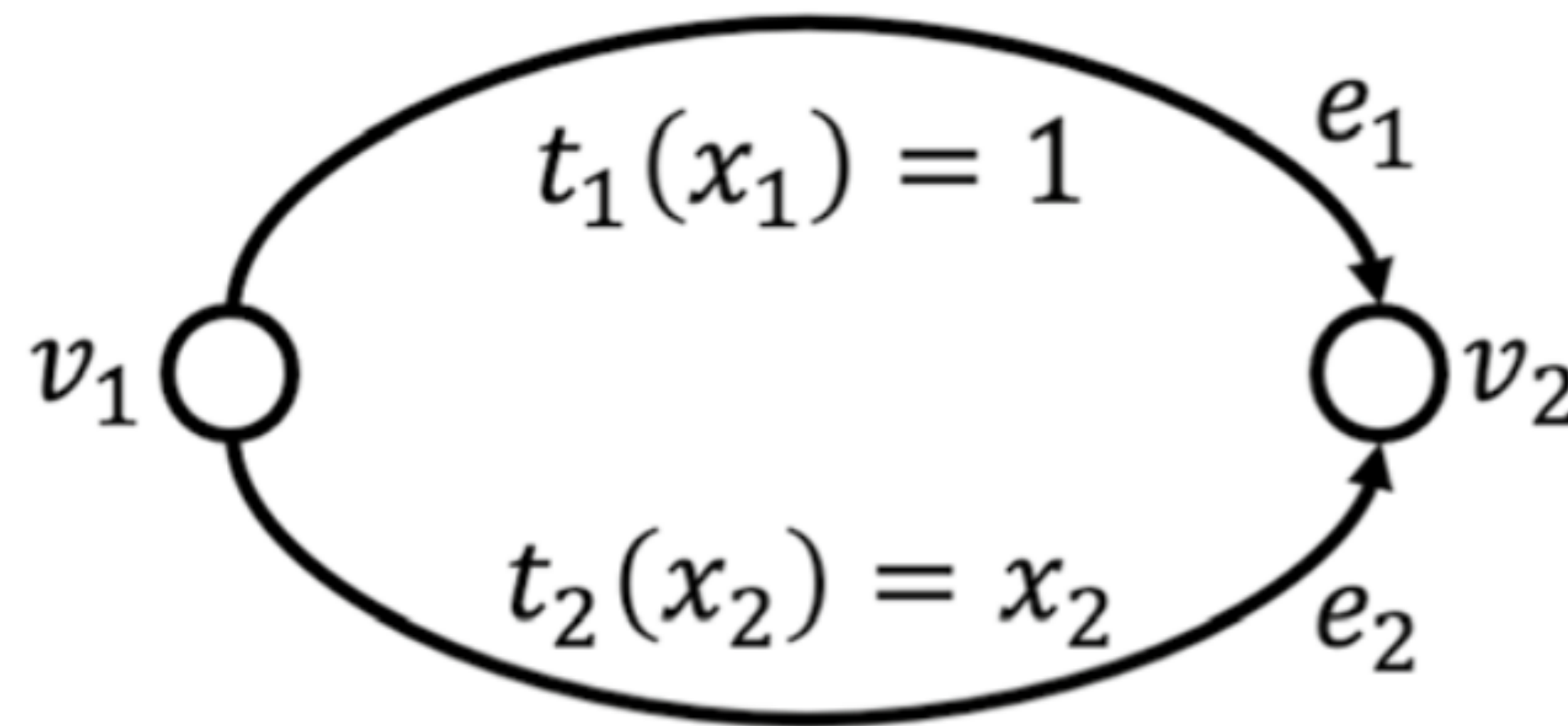
Theorem: Let m be the degree of the polynomial of the travel time functions. Then, $U(\mathbf{g}(\alpha)) \leq \beta$ if $\alpha \leq \frac{\beta - 1}{m}$.

This bound is tight.

Optimality of I-TAP

I-TAP achieves the optimal solution for the β -SO problem for any two-edge Pigou network

Theorem: For any two-edge Pigou network and unfairness parameter β , there exists some convex combination parameter α^* , such that the solutions of I-TAP with parameter α^* and that of the β -SO problem coincide



β -Unfair SO for Pigou Network



I-TAP for Pigou Network

Experiments: Computational Savings of I-TAP

Solving I-TAP is three orders of magnitude more computationally efficient than a state-of-the-art benchmark

Region Name	attributes			runtime (sec.)	
	$ V $	$ E $	$ K $	Jahn et al.	I-TAP
Sioux Falls (SF)	24	76	528	20.0	0.03
Anaheim (A)	416	914	1406	74.0	0.33
Massachusetts (M)	74	258	1113	24.3	0.09
Tiergarten (T)	361	766	644	18.2	0.20
Friedrichshain (F)	224	523	506	19.8	0.12
Prenzlauerberg (P)	352	749	1406	74.4	0.32

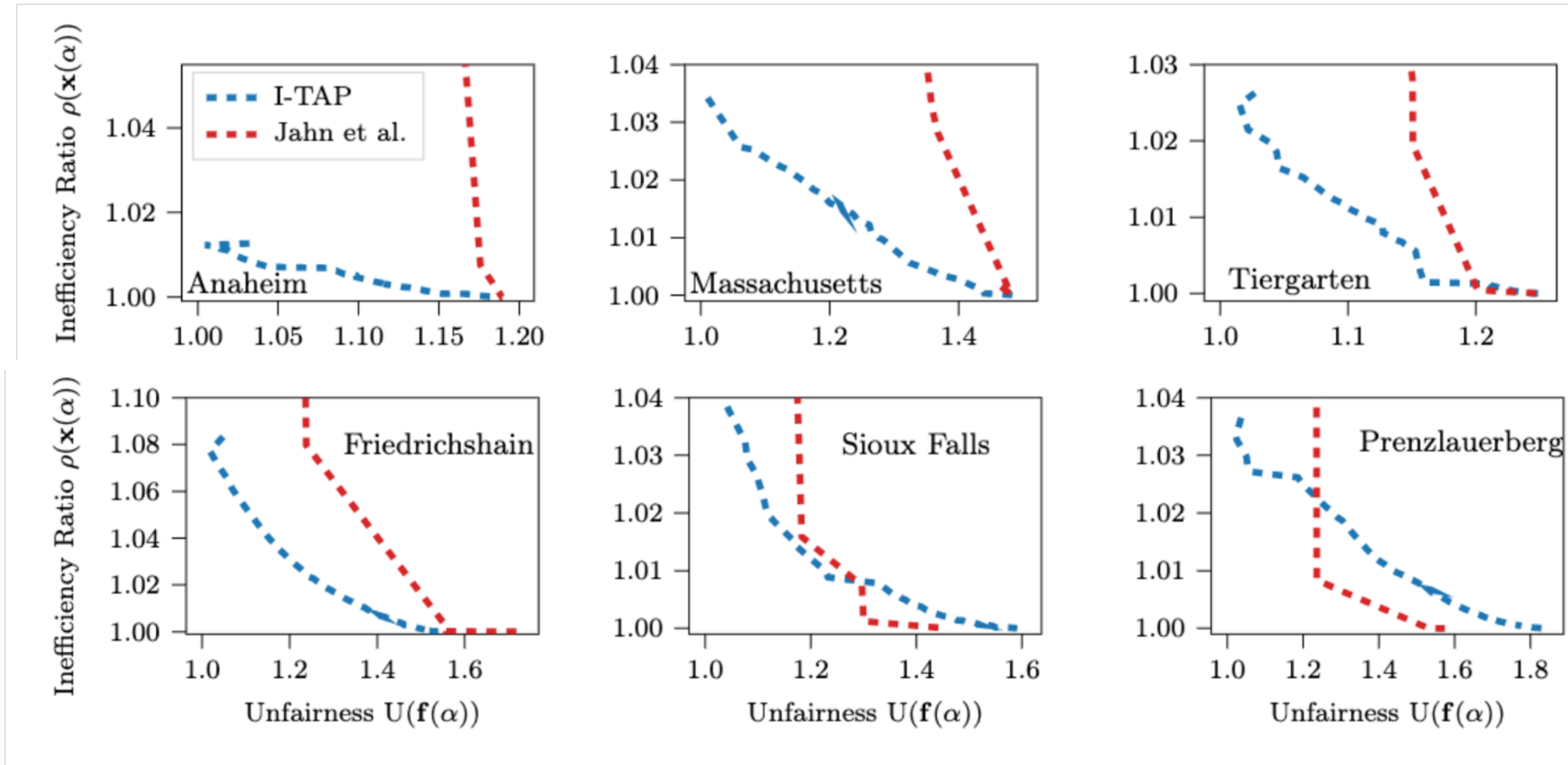


The superior runtime of I-TAP stems from the fact that it can be transformed into a UE-TAP, for which we have computationally efficient algorithms, e.g., Frank-Wolfe

$$f^{I_\alpha}(\mathbf{X}) = \alpha f^{SO}(\mathbf{X}) + (1 - \alpha) f^{UE}(\mathbf{X}) \xrightarrow{\text{Fundamental Theorem of Calculus}} f^{I_\alpha}(\mathbf{X}) = \sum_{e \in E} \int_0^{x_e} \underbrace{t_e(y) + \alpha y t'_e(y)}_{\text{UE-TAP with modified travel time function}} dy$$

Experiments: Efficacy of I-TAP

I-TAP outperforms a state-of-the-art benchmark in balancing efficiency and fairness in traffic routing



➡ For all desirable levels of unfairness, i.e., low unfairness, I-TAP achieves lower total travel times than the state-of-the-art benchmark

I-TAP has several advantages

I-TAP serves as a tractable and effective approximation to the β -SO problem we seek to solve

β -Unfair System Optimum

$$\begin{aligned} \min_{\mathbf{g} \in \mathcal{X}} \quad & f^{SO}(\mathbf{x}) := \sum_{e \in E} x_e t_e(x_e) \\ \text{s.t.} \quad & U(\mathbf{g}) \leq \beta \end{aligned}$$

NP-hard problem

Approximate



I-TAP

$$\min_{\mathbf{g} \in \mathcal{X}} \quad f^{I_\alpha}(\mathbf{x}) := \alpha f^{SO}(\mathbf{x}) + (1 - \alpha) f^{UE}(\mathbf{x})$$

**Computationally tractable
convex program**

Benefits of I-TAP

Computationally
Efficient

Theoretical bounds
to analyze efficacy

Superior numerical
performance compared
to benchmark

How do we set **prices** to induce fairness
constrained flows computed via I-TAP in practice?

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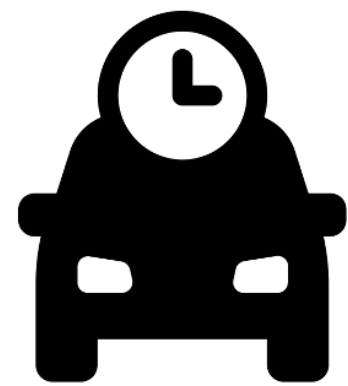
→ Security Games for Enforcement in Mobility Applications

→ Future Directions

Congestion Pricing via I-TAP

I-TAP yields a natural congestion pricing scheme to induce fairness-constrained flows in practice

User Behavior Model



Travel
time

+



Tolls

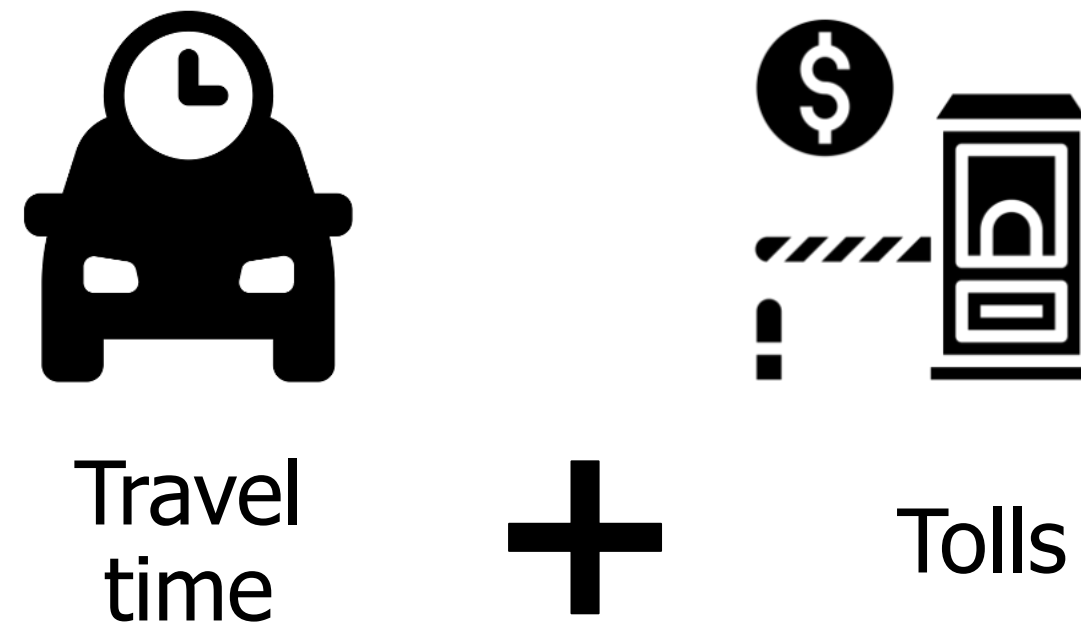
$$\boxed{v} \sum_{e \in P} t_e(x_e) + \sum_{e \in P} \tau_e$$

Value of Time

Congestion Pricing via I-TAP

I-TAP yields a natural congestion pricing scheme to induce fairness-constrained flows in practice

User Behavior Model



$$\sum_{e \in P} (t_e(x_e) + \tau_e)$$

Assume **homogeneous** users

Interpolated Marginal Cost Pricing with I-TAP

$$f^{I_\alpha}(\mathbf{x}) := \alpha f^{SO}(\mathbf{x}) + (1 - \alpha) f^{UE}(\mathbf{x})$$

$$f^{I_\alpha}(\mathbf{x}) = \sum_{e \in E} \int_0^{x_e} t_e(y) + \alpha y t'_e(y) dy$$

If there is positive flow on any path P , the following quantity is minimal for that O-D pair:

$$\sum_{e \in P} (t_e(x_e) + \alpha x_e t'_e(x_e))$$

**Interpolated
Marginal Cost Tolls**

➔ I-TAP can be used to derive a linear programming based congestion pricing scheme to induce fairness constrained flows with **heterogeneous** users

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Conclusion

We balance sustainable transportation's efficiency and equity goals

Computationally Efficient Routing Algorithm



Develop a novel convex program (I-TAP) that trades off efficiency and fairness

Fair Congestion Pricing Scheme



I-TAP yields natural congestion pricing schemes, namely interpolated marginal cost pricing

Benefits of I-TAP

Computationally Efficient

Theoretical Bounds to analyze efficacy

Superior numerical performance compared to benchmark

Extensions (Other Notions of Unfairness)

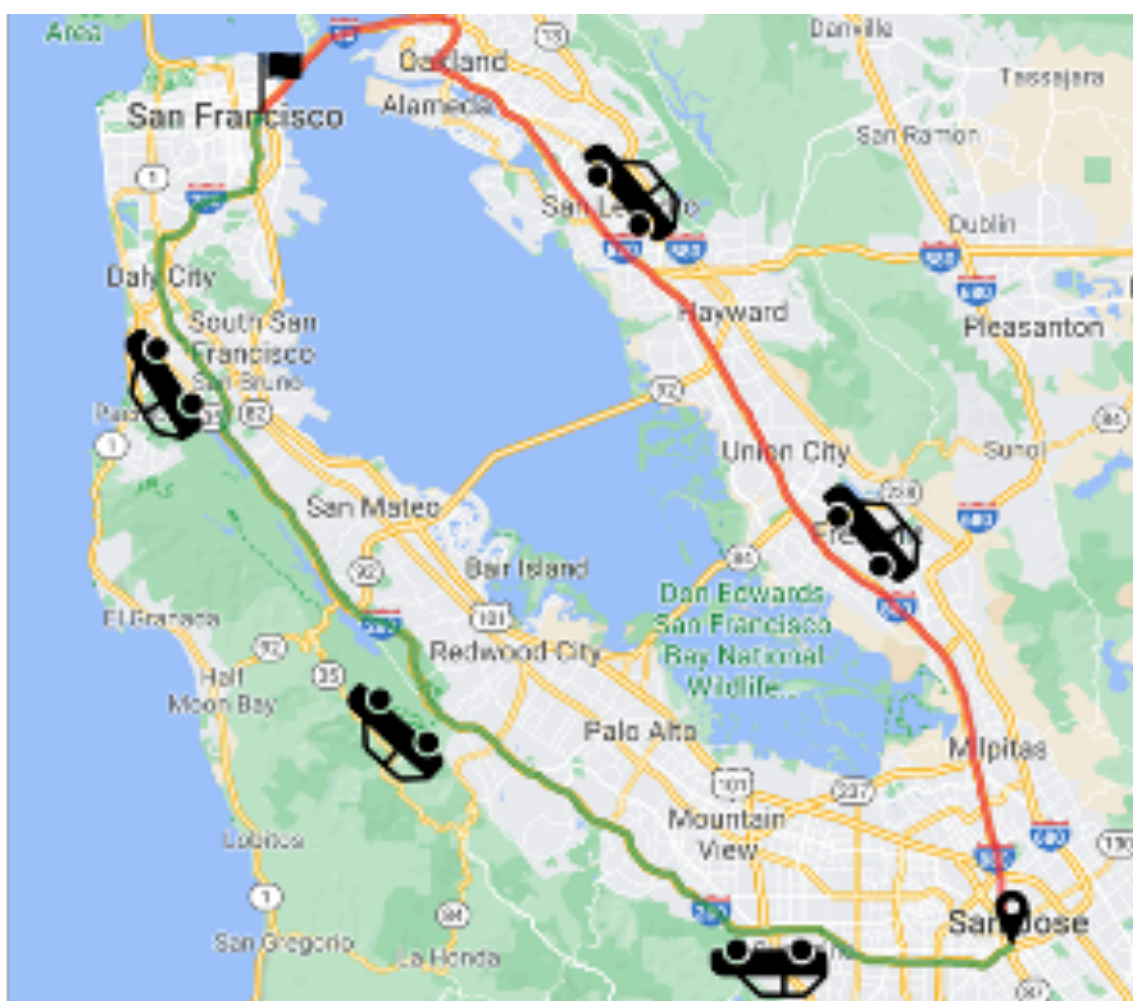
Numerical results show similar performance for other **intra-O-D pair unfairness** measures

Going **beyond** intra-O-D pair unfairness measures

Broader agenda on equitable congestion pricing

Our work paves the way for the design of sustainable and publicly acceptable congestion pricing schemes

Reduce low-income users' travel-time burden

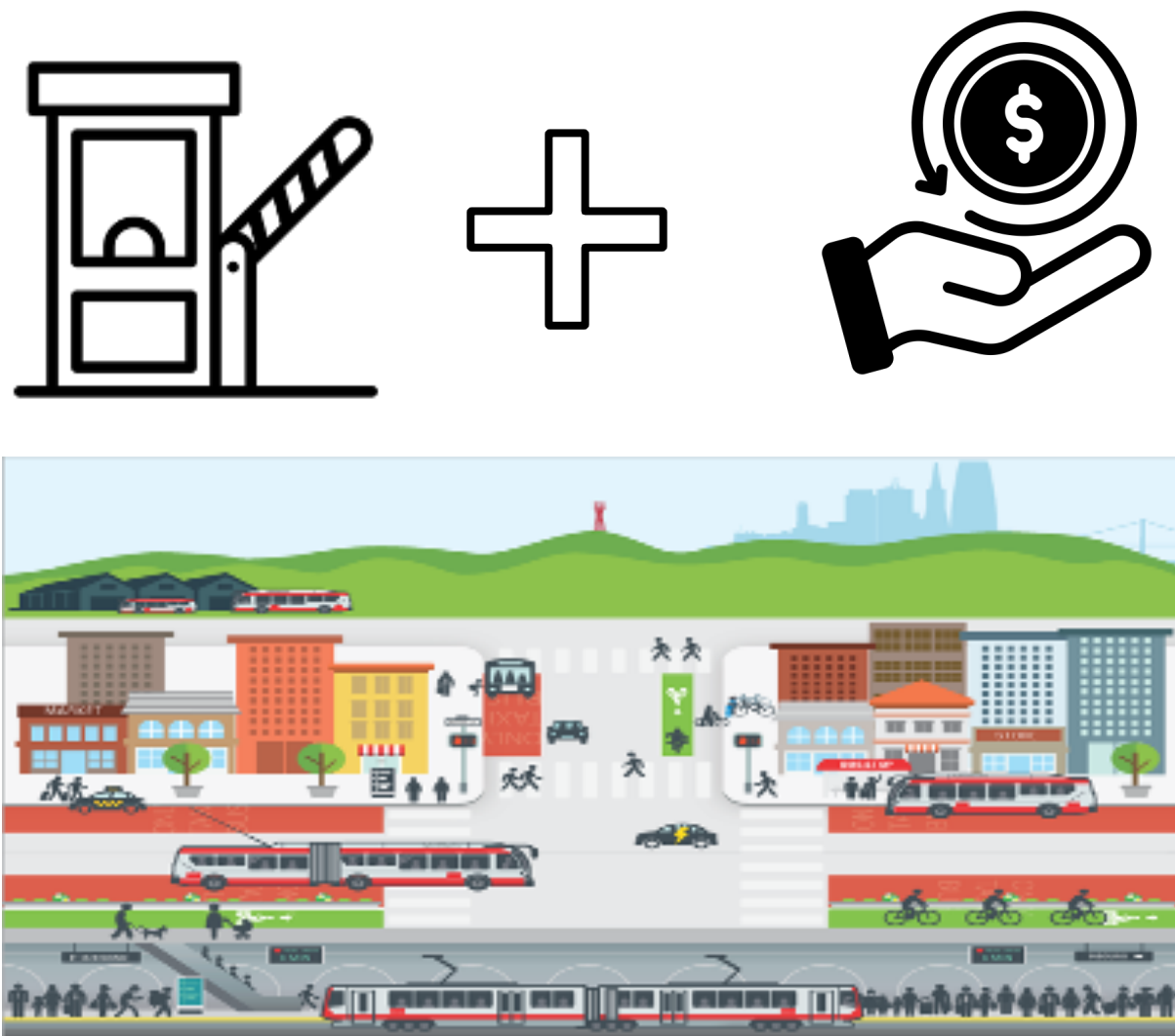


Convex program to overcome inefficiency of methods for fairness-constrained traffic assignment

 **JSTZP JAAMAS'23, AAMAS'22**

Finalist for the **2024 INFORMS TSL best student paper award**

Congestion Pricing with Revenue Refunding

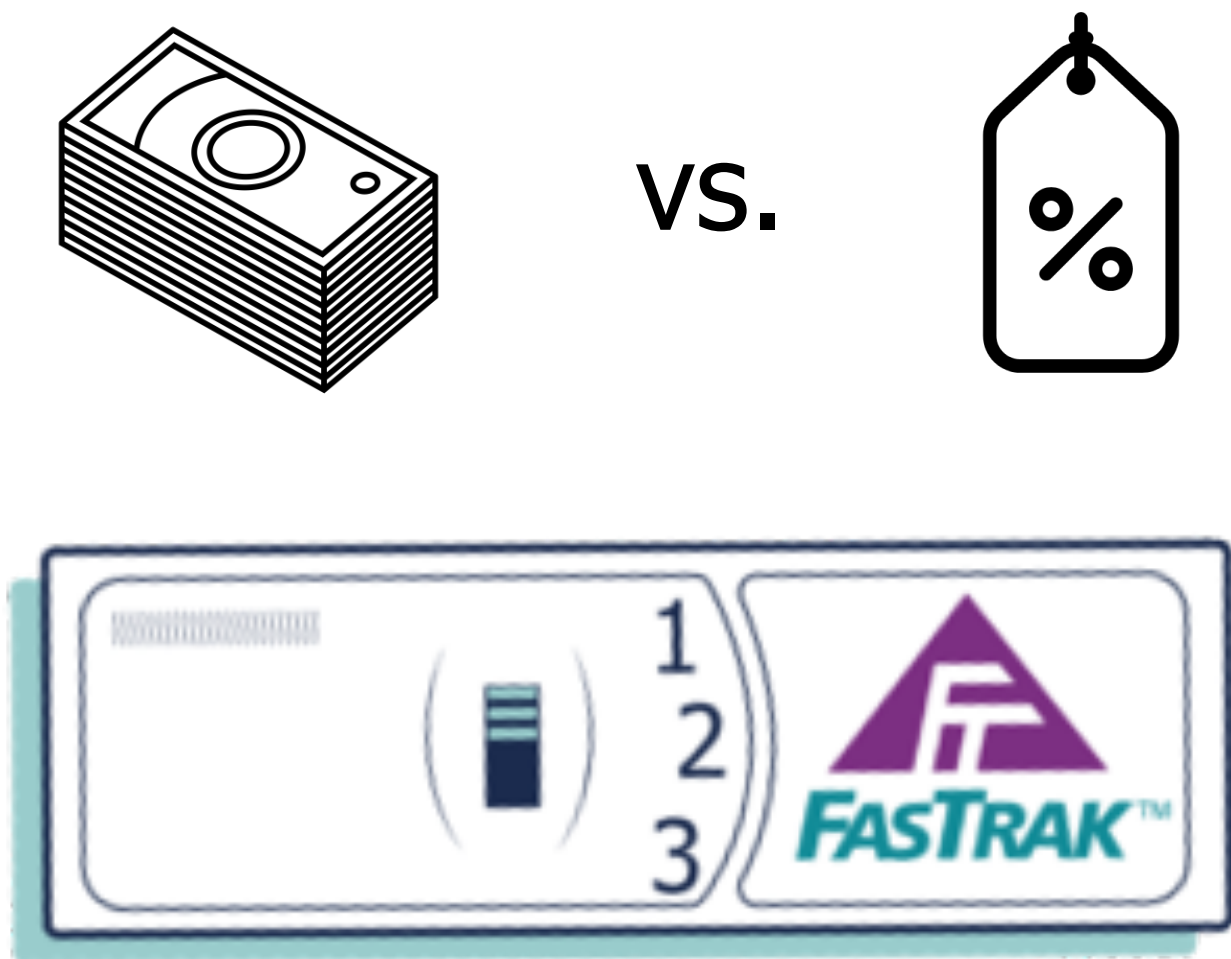


Provably increase system efficiency without worsening inequality

 **JSGZBP EAAMO'21, TCNS'23**

Covered by **New York Times**

Credit vs. Discount based Congestion Pricing



Game theoretic bi-level optimization framework to optimally design credit-based and discount-based schemes

 **JLBP CDC'23, CJP CDC'24**

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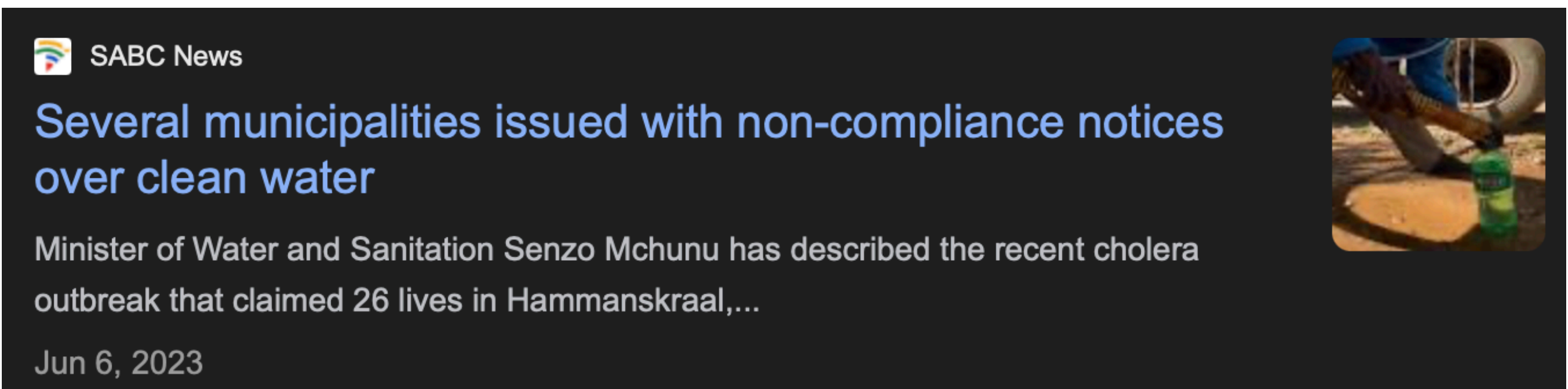
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- **Security Games for Enforcement in Mobility Applications**
 - Introduction
 - Model
 - Analysis of administrator strategies + equilibria
 - Numerical Experiments: Parking Enforcement
 - Conclusion
- Future Directions

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Fraud is ubiquitous and can be detrimental

Environmental Non-Compliance



Water treatment facilities have an incentive to save on compliance costs, which can put resident **lives at risk**

Traffic/Parking Violations



Commuters often engage in illegal parking practices or speeding, which can result in **traffic jams** and **compromise road safety**

Users engage in fraud to **strategically** obtain some benefit that would otherwise be unattainable within the bounds of lawful conduct

The prevalence of fraud raises a key security challenge

Effective enforcement requires **policing**, which poses a resource allocation problem

How do we best allocate a limited set of security resources to susceptible nodes or locations in a system?

Police Authority



Potentially susceptible nodes or locations



Outcome: More facilities complying with environmental regulations

The KETOS logo, featuring a stylized wave icon and the word "KETOS" in a bold, sans-serif font. To the right of the logo is the word "Processing" in a large, white, serif font, with the tagline "SOLUTIONS FOR THE PROCESS INDUSTRIES" in a smaller, white, sans-serif font below it. Below the logo and tagline is the text "Ensuring Compliance with Continuous Water Quality Monitoring" in a large, white, sans-serif font. The entire graphic is set against a background of blue water with bubbles.

The prevalence of fraud raises a key security challenge

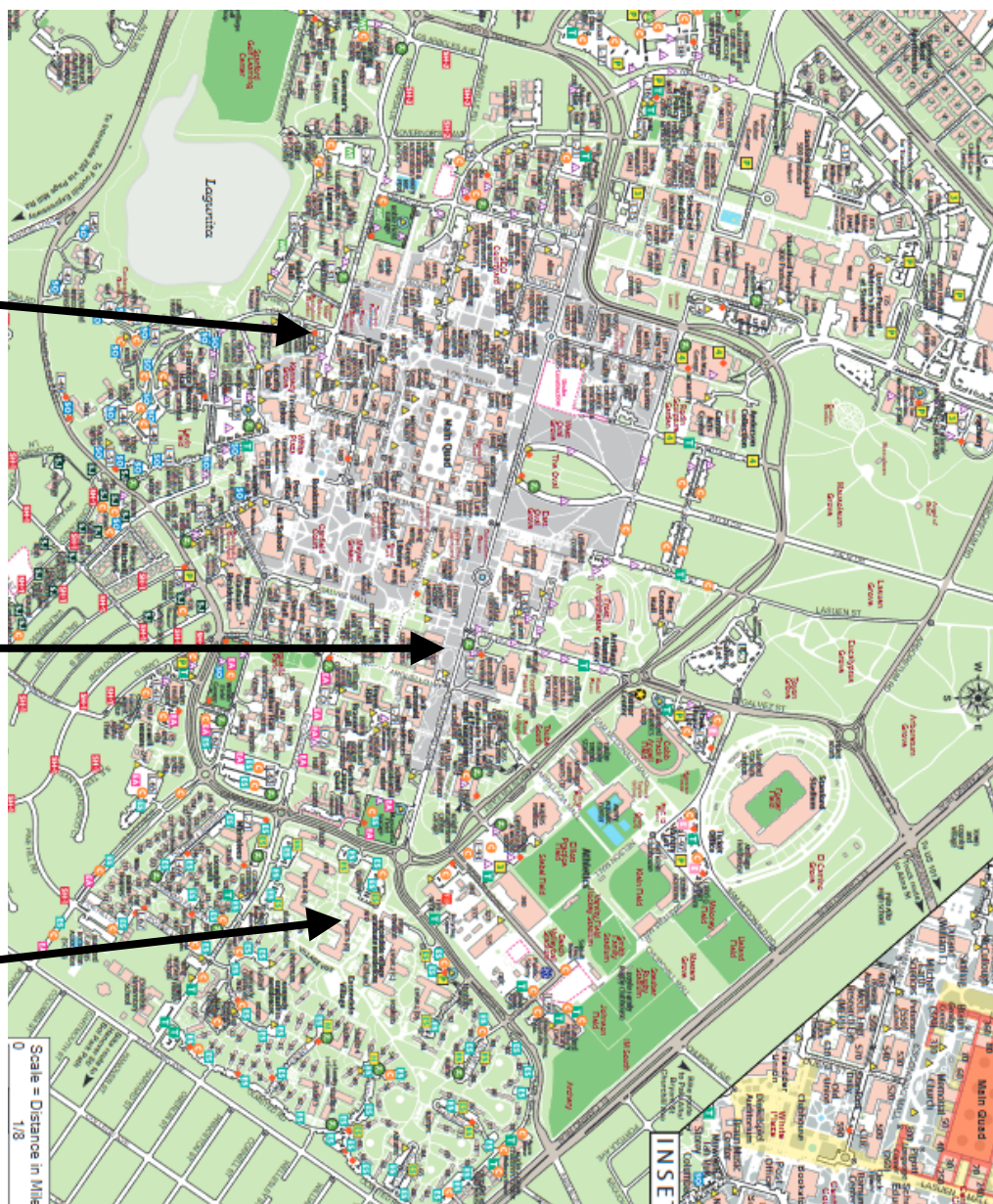
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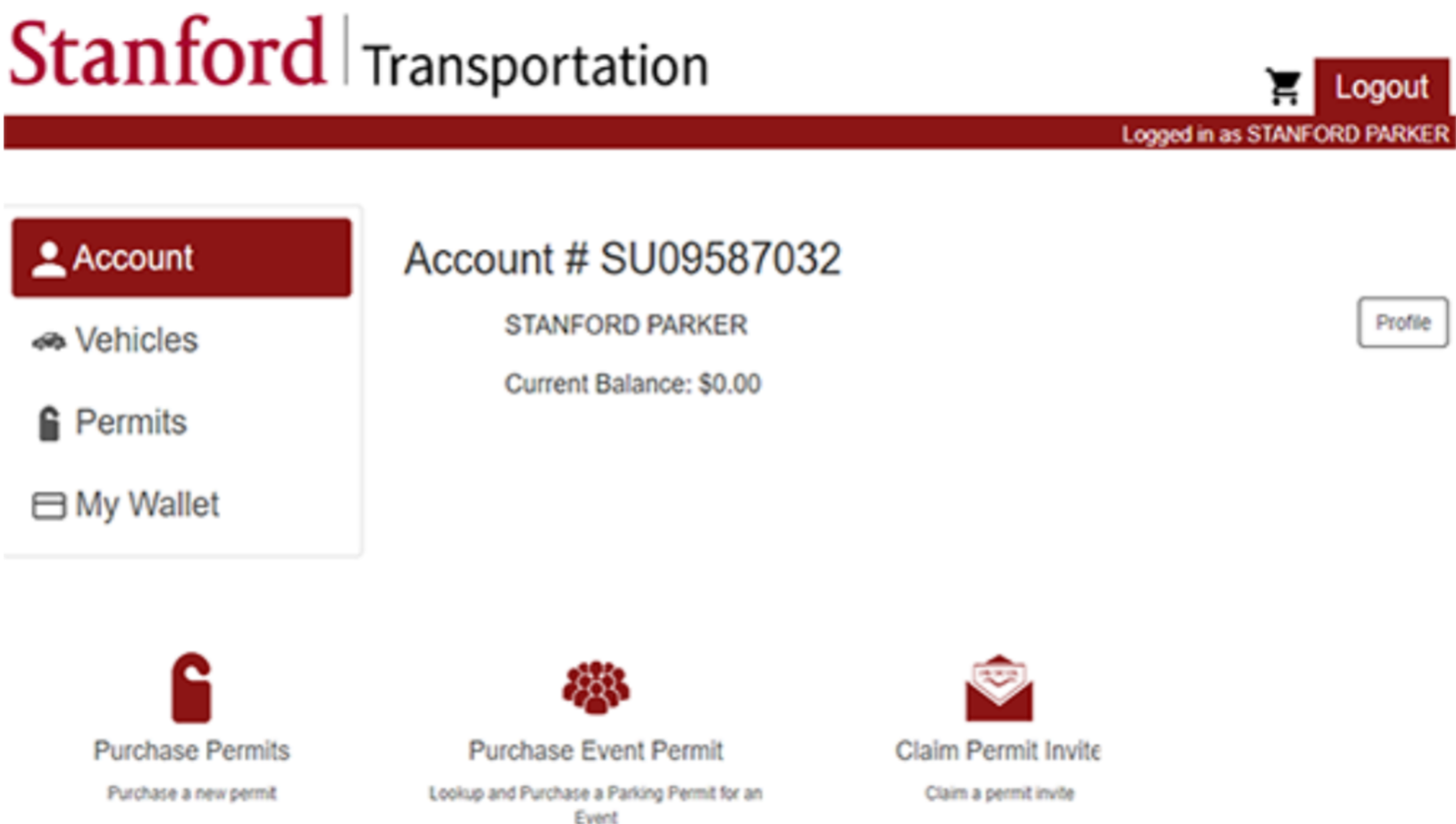
Police Authority



Potentially susceptible nodes or locations



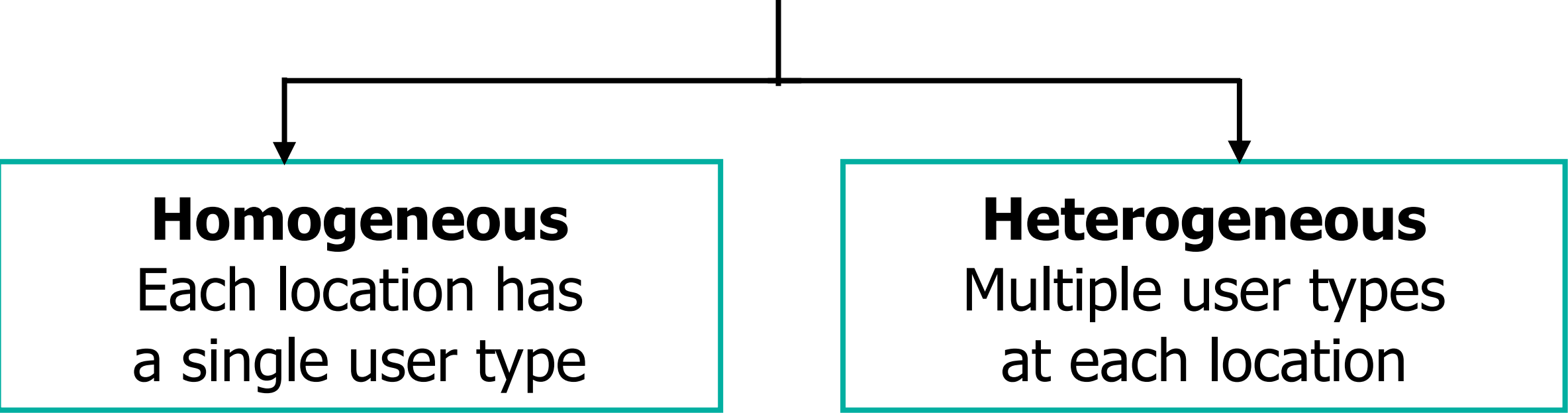
Outcome: Commuters purchase relevant parking permits



Contributions

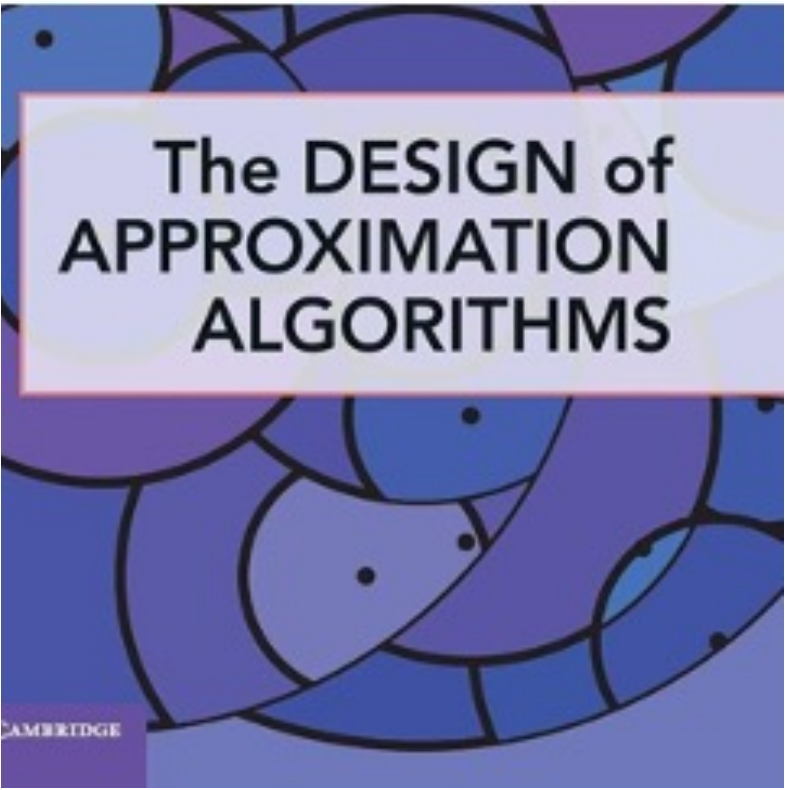
We study a security game between users and an administrator with a budget of security resources, where the administrator levies fines on users engaging in fraud

Equilibria and Optimal Strategies



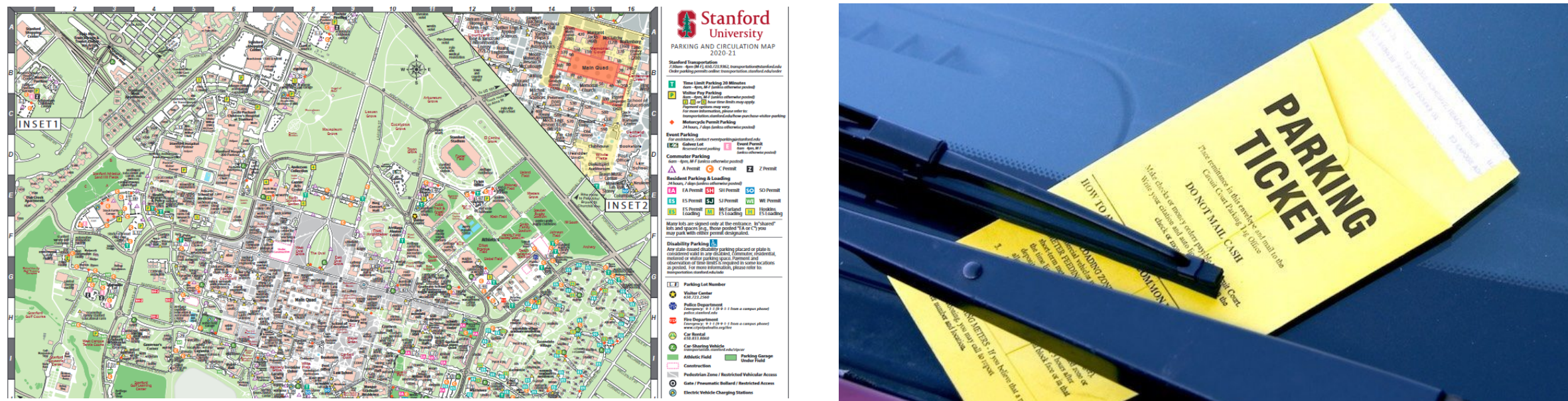
We study both revenue and payoff maximization objectives

Preview of Results



- NP-hardness** of computing optimal allocation strategies
- Approximation ratios** to optimal allocations
- Resource augmentation** guarantees

Numerical Experiments



Case study of Stanford’s parking enforcement system

Model Extensions

- Contract Game:** Payoff and revenue objectives at odds
- Additional Constraints** over allocation of resources
- Variability of Fines:** Administrator can optimize fines

Related Literature

Our work provides algorithms with provable guarantees for multi-resource Bayesian SSGs

Prior Work on Security Games

Single-resource
Bayesian Stackelberg
Security Games (SSGs)

Multi-resource
single type SSGs

Our Work

Our work provides the first algorithms with provable guarantees for **multi-resource Bayesian** SSGs

Administrator has a
budget of security
resources to prevent fraud

Adversary can
have multiple types

Agenda

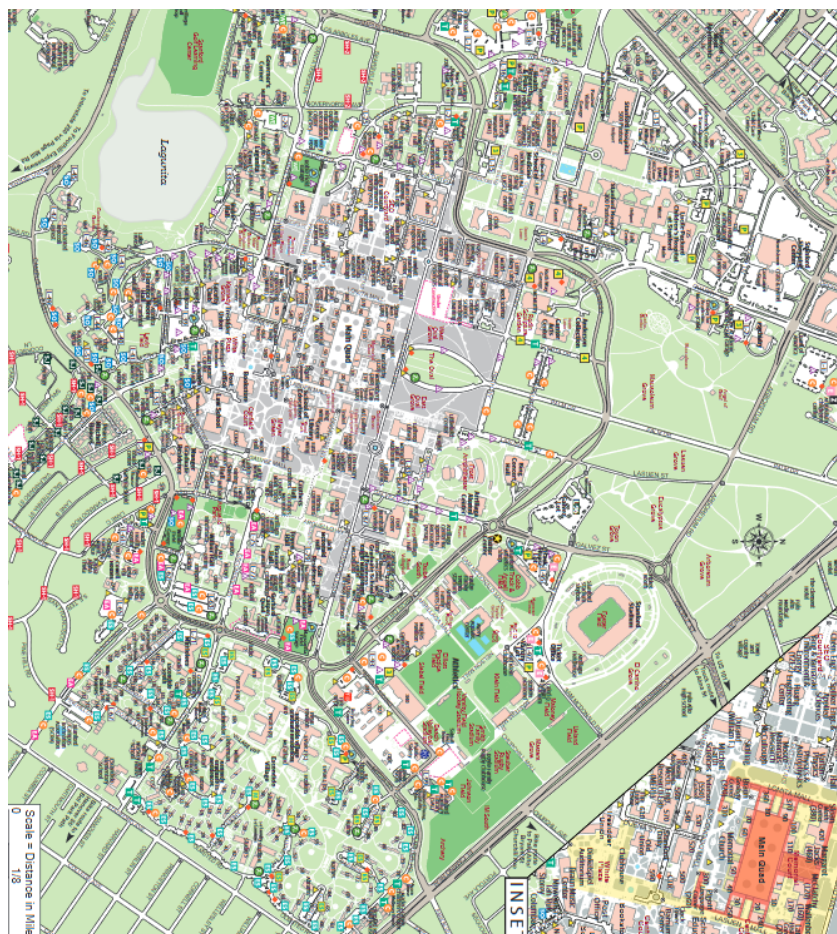
- Fairness in Congestion Pricing
- **Security Games for Enforcement in Mobility Applications**
 - Introduction
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Security Game Model

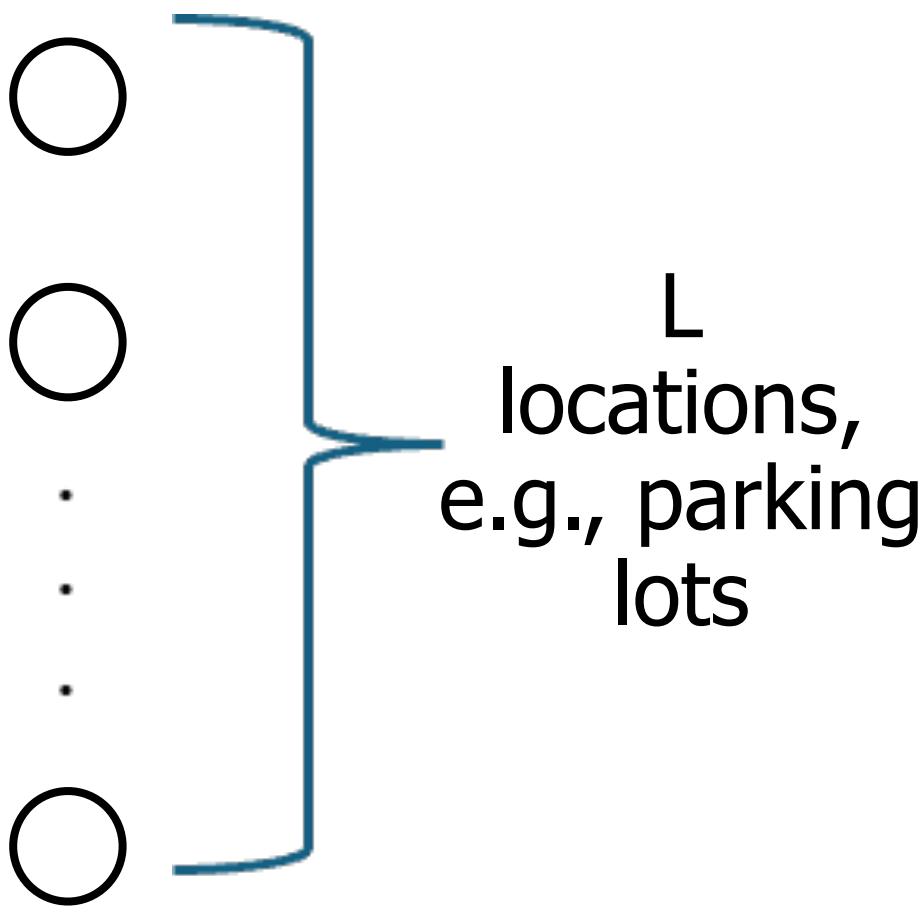
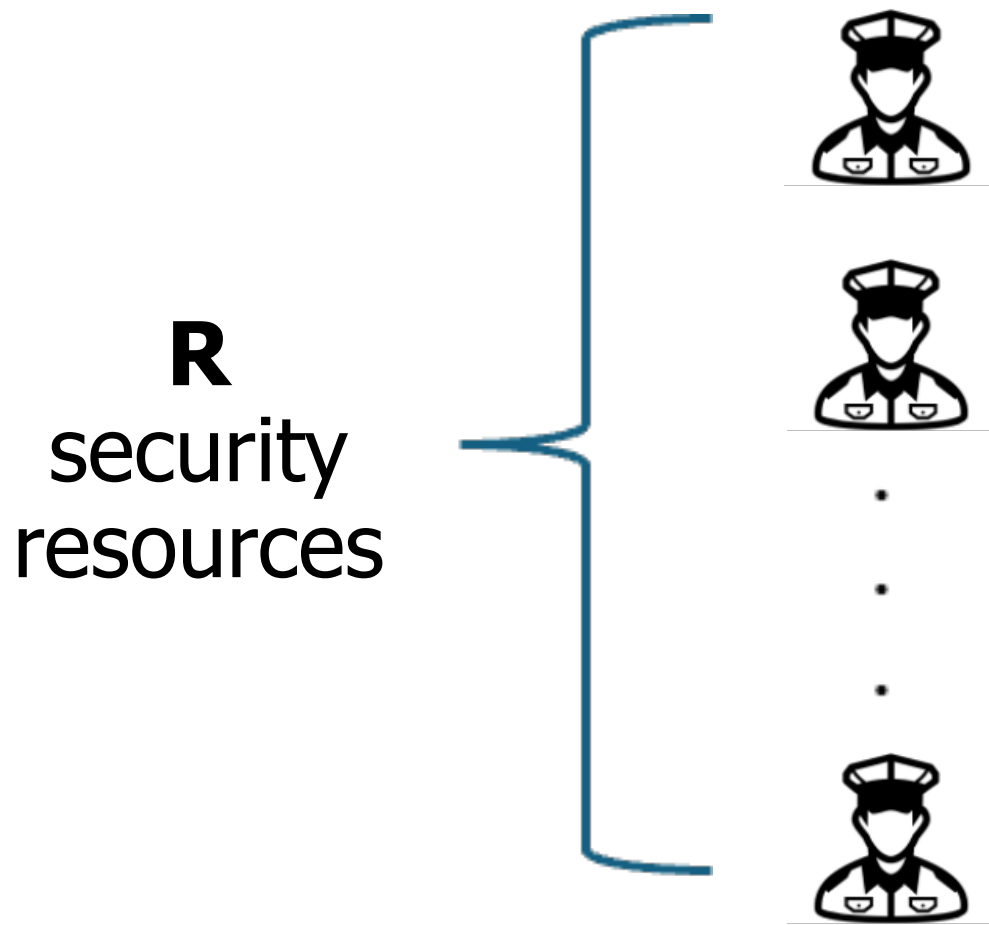
Administrator
(Police Authority)



Locations
susceptible to fraud



○ Location l



➡ Administrator levies a **fine k** if users are found engaging in fraud

$$\Theta_l^i = (\Lambda_l^i, d_l^i, p_l^i)$$

- Λ_l^i : Number of users
- d_l^i : Benefit from engaging in fraud
- p_l^i : Administrator payoff from reducing fraud

Administrator and User Strategies

Administrator Strategy

Administrator selects a mixed-strategy σ to allocate its budget of R security resources across the locations

σ_l = Probability security resource is allocated to location l

Feasible strategy set:

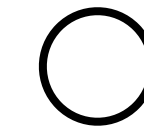
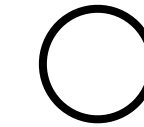
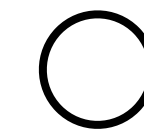
$$\Omega_R = \left\{ \sigma = (\sigma_l)_{l \in L} : \sigma_l \in [0,1], \sum_l \sigma_l \leq R \right\}$$



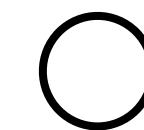
⋮



$\sigma_l \in [0,1]$



⋮



User Strategy

In response to administrator's strategy σ , users decide whether to engage in fraud

$y_l^i(\sigma)$ = Probability user engages in fraud at location l with type i given σ

$y_l^i(\sigma) \in [0,1]$ for all locations l and types i

Resource Constraint:
$$\sum_l \sigma_l \leq R$$

Administrator objectives

We study equilibrium outcomes under both revenue and payoff maximization administrator objectives

Revenue Maximization

$$\begin{aligned} \max_{\substack{\sigma \in \Omega_R \\ y_l^i(\sigma) \in [0,1], \forall l \in L, i \in \mathcal{I}}} Q_R(\sigma) &= \sum_{l \in L} \sum_{i \in \mathcal{I}} \sigma_l y_l^i(\sigma) k \Lambda_l^i, \\ \text{s.t. } y_l^i(\sigma) &\in \arg \max_{y \in [0,1]} U_l^i(\sigma, y) = y \left[\underbrace{(1 - \sigma_l) d_l^i}_{\text{Gains from fraud}} - \underbrace{\sigma_l k}_{\text{Losses from fraud}} \right] \\ &\text{for all } l \in L, i \in \mathcal{I} \end{aligned}$$

Police often maximize revenues from fine collections, e.g., highway speed traps may not target accident prone areas

Payoff Maximization

$$\begin{aligned} \max_{\substack{\sigma \in \Omega_R \\ y_l^i(\sigma) \in [0,1], \forall l \in L, i \in \mathcal{I}}} P_R(\sigma) &= \sum_{l \in L} \sum_{i \in \mathcal{I}} p_l^i (1 - (1 - \sigma_l) y_l^i(\sigma)) \\ \text{s.t. } y_l^i(\sigma) &\in \arg \max_{y \in [0,1]} U_l^i(\sigma, y) \\ &\text{for all } l \in L, i \in \mathcal{I} \end{aligned}$$

Administrators, such as owners of parking lots, may seek to minimize fraud, e.g., to maximize parking permit purchases

➡ **Goal:** Characterize optimal (or near-optimal) solutions to these bi-level programs, i.e., study **equilibrium** formation under both these administrator objectives

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Preview of Results

Homogeneous revenue maximization is polynomial time solvable while other settings are NP-hard

	Revenue Maximization	Payoff Maximization
Homogeneous (Each location has a single user type)	Polynomial time greedy algorithm to compute revenue-maximizing administrator strategy	NP-hard 1/2 Approximation: Greedy algorithm achieves at least half the optimal payoff Resource augmentation: Algorithm with R+1 resources achieves at least the payoff as optimal strategy with R resources
Heterogeneous (Each location has multiple user types)	NP-hard 1/2 Approximation Resource Augmentation	NP-hard 1/2 Approximation Resource Augmentation

Heterogeneous revenue maximization is NP-hard

No polynomial time algorithm can solve the heterogeneous revenue maximization bi-level program unless $P = NP$

Theorem: The problem of computing the revenue maximizing strategy with heterogeneous user types is NP-hard

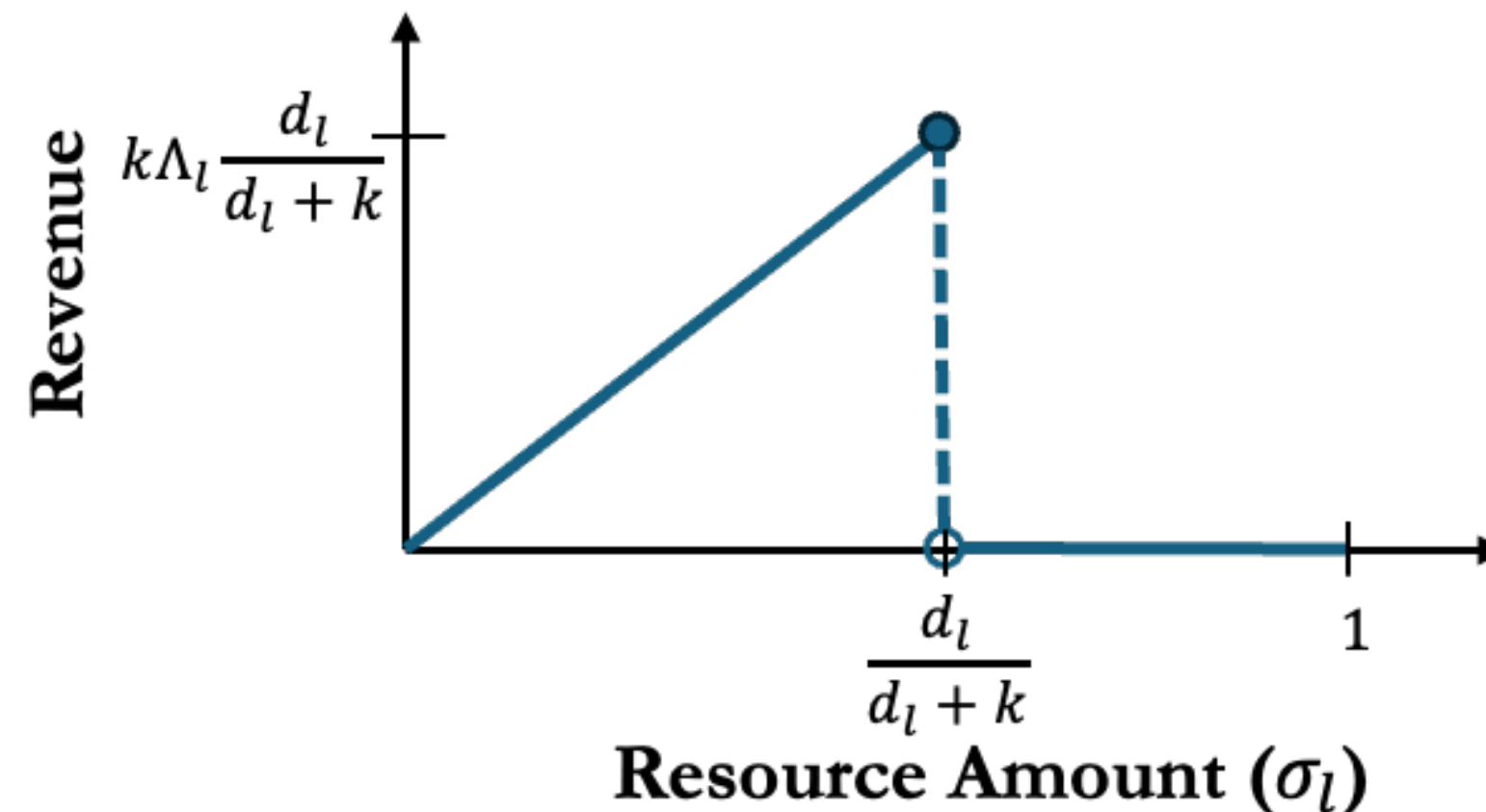


Geometric Intuition

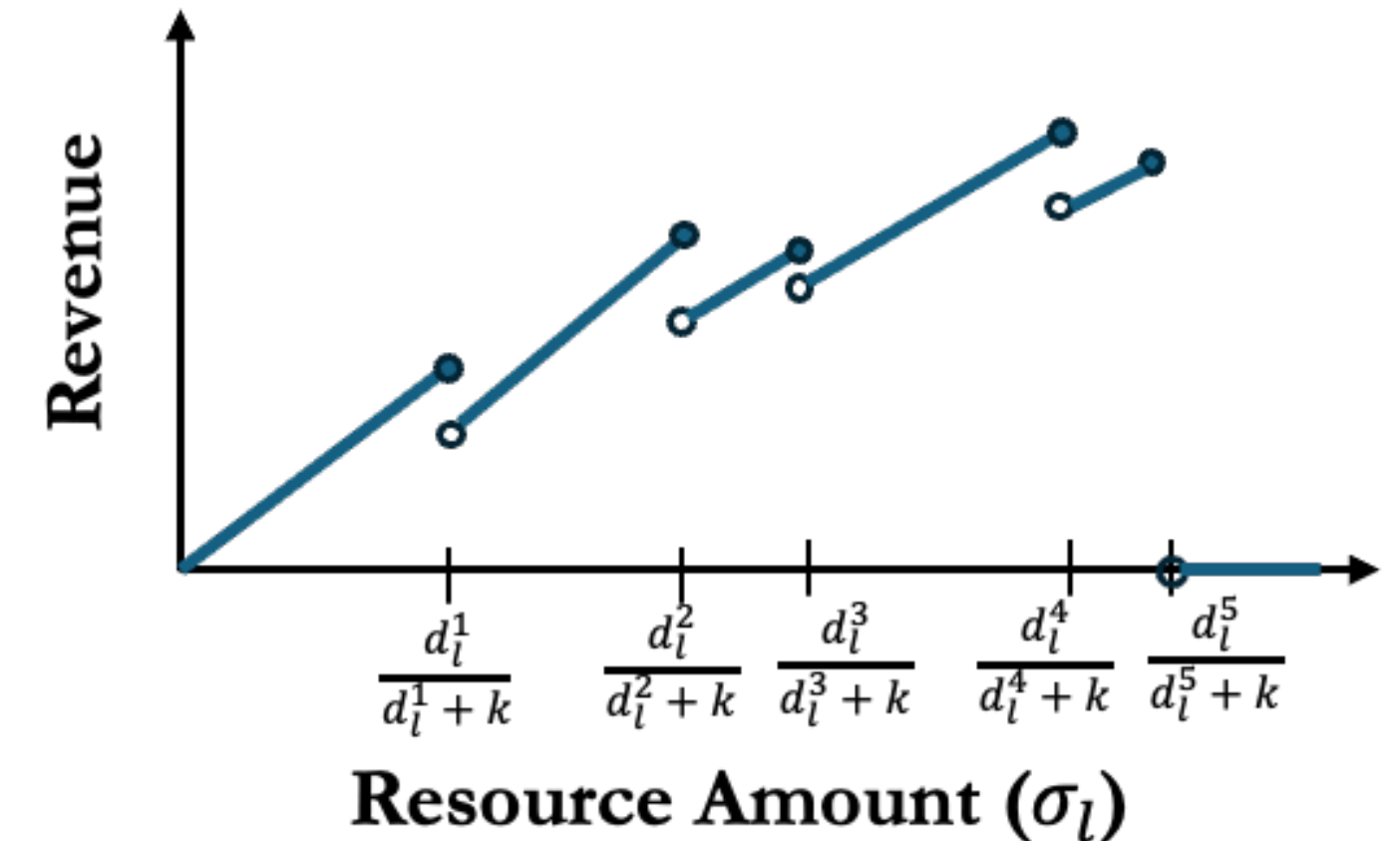
User best-response to revenue-maximizing administrator

$$y_l^i(\sigma) = \begin{cases} 0, & \text{if } \sigma_l > \frac{d_l^i}{d_l^i + k}, \\ 1, & \text{otherwise.} \end{cases}$$

Revenue function at location l
(**Homogeneous** User Types)



Revenue function at location l
(**Heterogeneous** User Types)



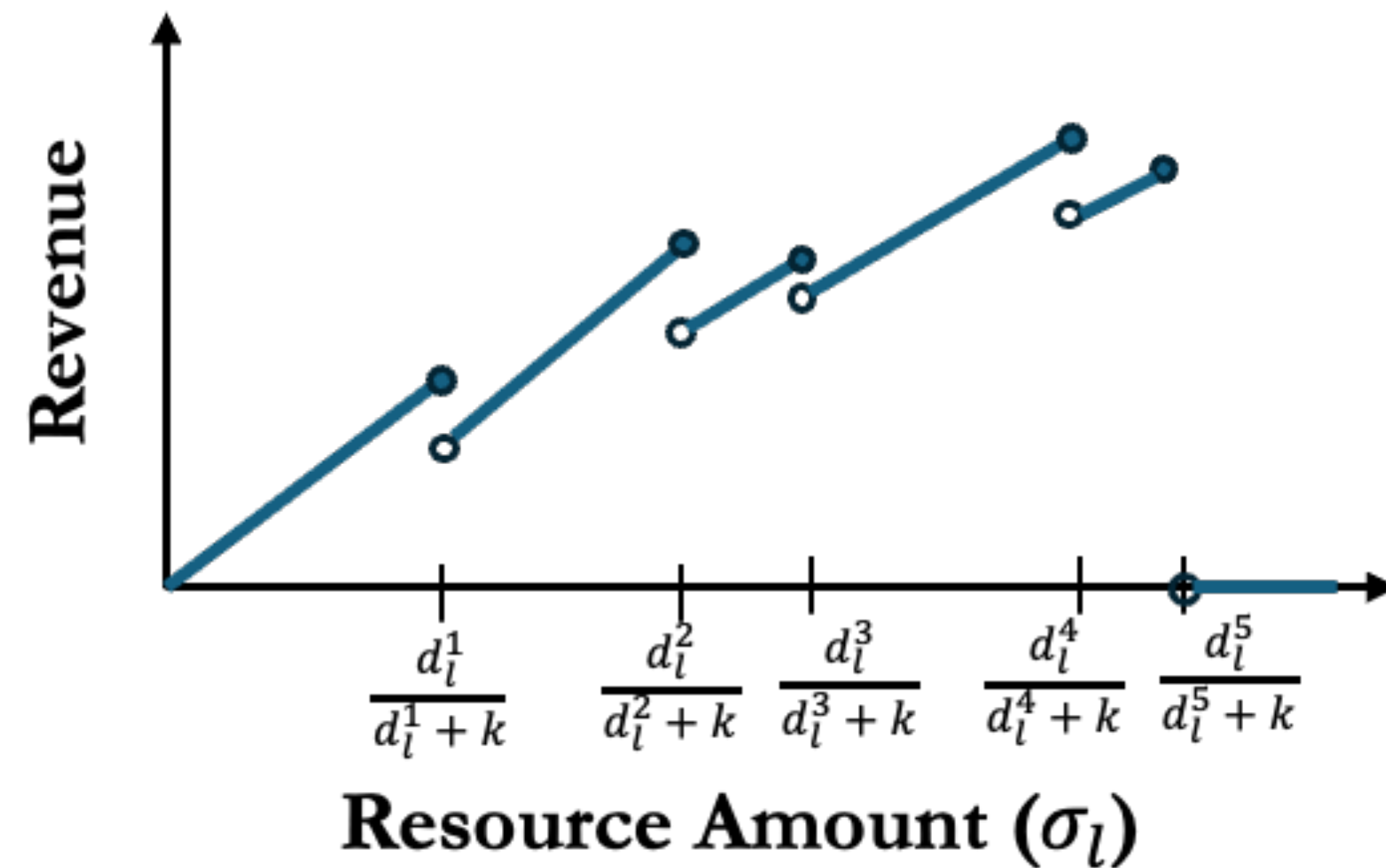
➔ Revenue function with **homogeneous** user types is **continuous** in the range $\sigma_l \in [0, \frac{d_l}{d_l + k}]$

➔ Revenue function with **heterogeneous** user types is **discontinuous** and **non-monotone** at $\frac{d_l^i}{d_l^i + k}$ for all i

Algorithm for heterogeneous revenue maximization

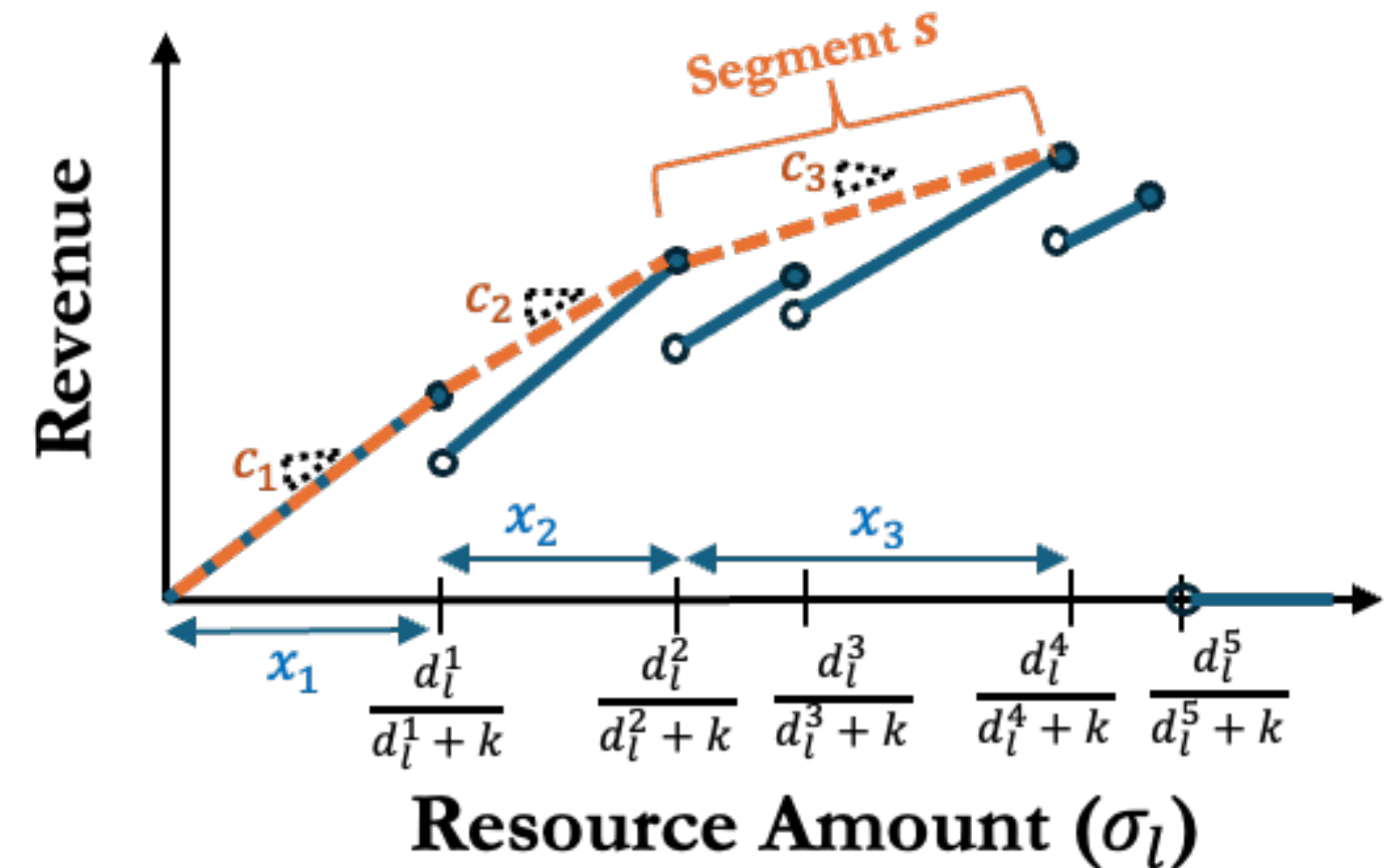
We maximize a monotone concave upper approximation (MCUA) of the revenue function

Revenue function



Revenue function is not
continuous and **non-monotone**

MCUA of revenue function



MCUA can be **optimized tractably** using a greedy procedure that orders segments in descending order of segment slopes

Guarantees for heterogeneous revenue maximization

Maximizing the MCUA of the revenue function motivates a natural modified greedy algorithm

Maximize MCUA of revenue function using greedy procedure

Optimal spending on single location

Select best of the two solutions

Algorithm 1: Greedy Algorithm for Administrator's Heterogeneous Revenue Maximization Objective

Input : Total Resource capacity R , User Types $\Theta_l^i = (\Lambda_l^i, d_l^i, v_l^i)$ for all locations l and types i

Output: Resource Allocation Strategy σ_A^*

Step 1: Greedy Allocation $\tilde{\sigma}$ Based on Slopes of MCUA of Revenue Function:

Define affordability threshold $t_l \leftarrow \min \left\{ R, \max_i \frac{d_l^i}{d_l^i + k} \right\}$ for all locations l ;

Generate MCUA of the revenue function in range $[0, t_l]$ for each location l ;

$\tilde{S} \leftarrow$ Ordered list of segments s across all locations of this MCUA in descending order of slopes c_s ;

Initialize allocation strategy $\tilde{\sigma} \leftarrow \mathbf{0}$;

for segment $s \in \tilde{S}$ **do**

if $x_s \leq R$ **then**

$\tilde{\sigma}_{l_s} \leftarrow \tilde{\sigma}_{l_s} + x_s$; Allocate x_s to location l_s ;

$R \leftarrow R - x_s$; Update amount of remaining resources ;

else

break ; Only allocate resources if $x_s \leq R$

end

end

Step 2: Find Solution σ' that maximizes revenue from spending on single location:

$\sigma^l \leftarrow \arg \max_{\sigma \in \Omega_R: \sigma_{l'} = 0, \forall l' \neq l} Q_R(\sigma)$ for all locations l ;

$\sigma' \leftarrow \arg \max_{l \in L} Q_R(\sigma^l)$;

Step 3: Return Solution with a Higher Revenue: $\sigma_A^* \leftarrow \arg \max \{Q_R(\tilde{\sigma}), Q_R(\sigma')\}$;

Theorem: Algorithm 1 achieves **at least half** the revenue as the revenue maximizing solution

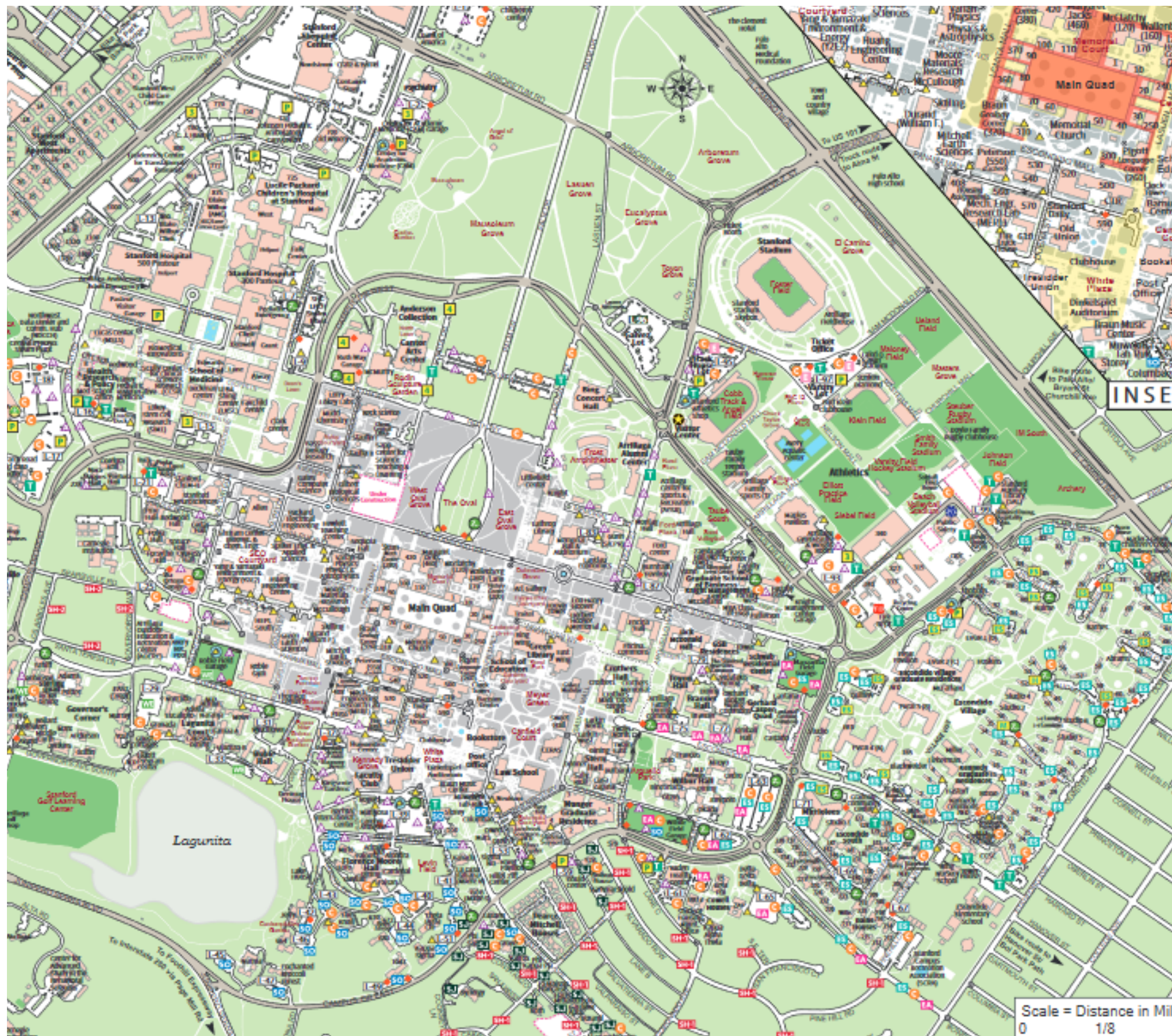
Theorem: Algorithm 1 with **R+1** resources achieves **at least** the revenue as the revenue maximizing solution with **R** resources

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Stanford parking enforcement setup and data-set

We obtained 7 months of parking enforcement and citation data from Stanford's Department of Public Safety



Setup

- Commuters are required to purchase permits and are issued citations if found violating regulations
- Citation fees go to Santa Clara County's Sheriff Department but earnings from permit purchases go to Stanford

Data-set

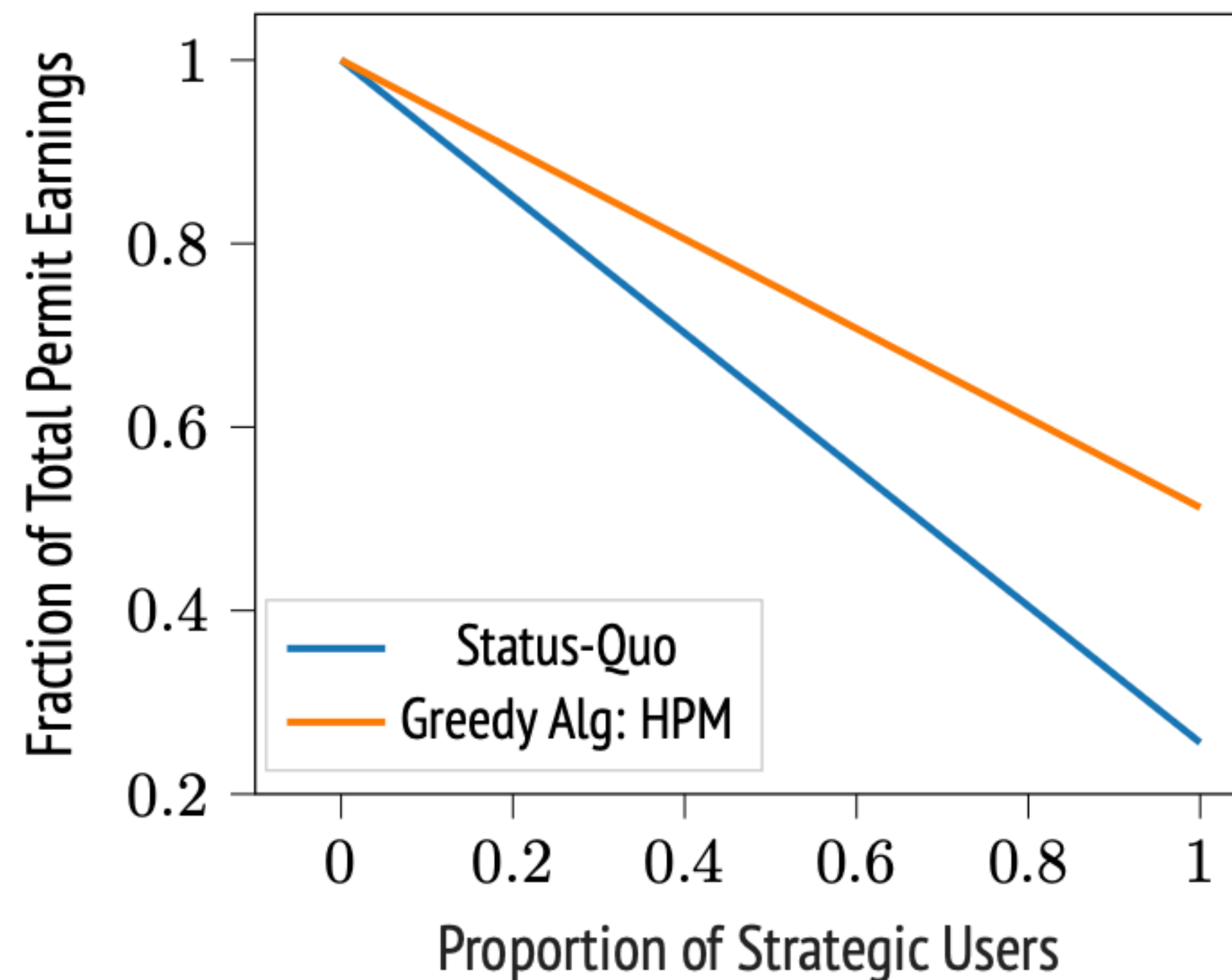
- 7 months of data from Sep 2022 - Mar 2023
- **Enforcement** data includes the time and period of enforcement
- **Citation** data includes the total number of citations issued in each parking lot in a given month

➡ We formulate Stanford's parking enforcement problem as a **heterogeneous payoff maximization** problem, where payoffs represent parking permit earnings

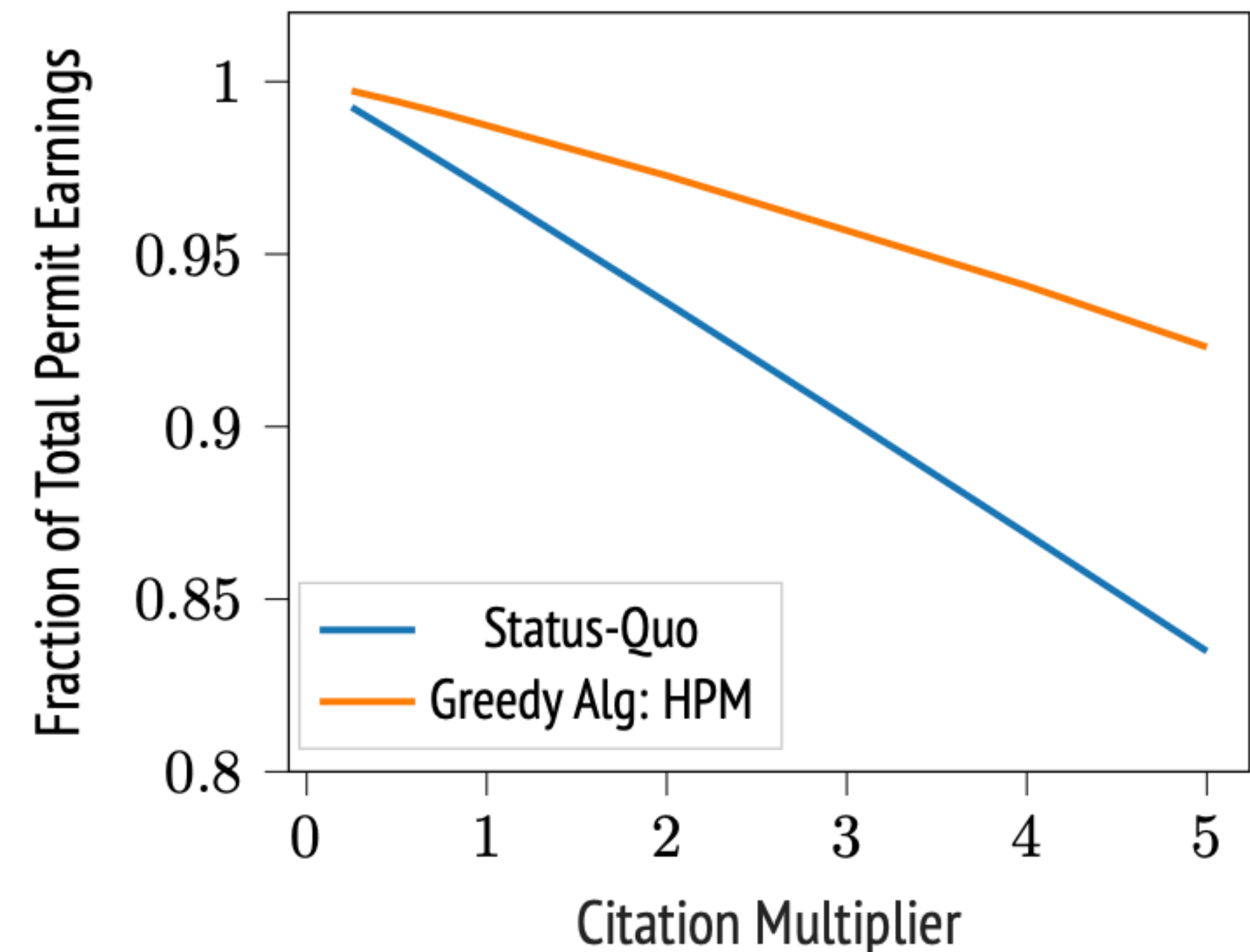
Results

Our approach achieves significant gains to the status quo, particularly as the proportion of strategic users increases

Counterfactual 1



Counterfactual 2



- ➡ Our approach has significant gains relative to the status quo as the **proportion of strategic users increases**
- ➡ Our approach achieves over **\$300,000** additional permit earnings per year relative to status quo

Agenda

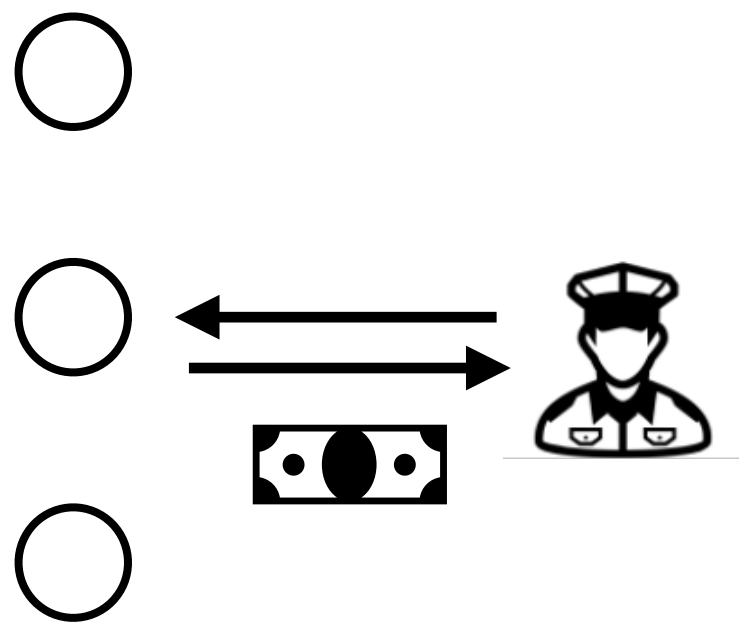
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Conclusion

We developed simple yet near-optimal algorithms to compute equilibria in our security game

Equilibria and Optimal Strategies

Studied a **multi-resource Bayesian** Stackelberg security game where fines are levied on fraudulent users



Numerical Experiments



Case study of Stanford’s parking enforcement system

Results on computation of administrator’s optimal strategies

	Revenue Maximization	Payoff Maximization
Homogeneous	Polynomial time algorithm	NP-hard 1/2 Approximation, PTAS Resource augmentation
Heterogeneous	NP-hard 1/2 Approximation Resource augmentation	NP-hard 1/2 Approximation Resource augmentation

Model Extensions

Contract Game

Additional Constraints

Variability of Fines

Summary: Fairness & security from approximation algorithm lens

We highlight two vignettes of this agenda focused on developing **approximation algorithms** for **NP-hard problems** arising under **fairness** and **security** considerations in **mobility** applications

Fairness (Congestion Pricing)

Jalota et al. JAAMAS'23
Finalist for the **2024 INFORMS TSL best student paper award**

Source of Hardness	Non-convexity of fairness constraints
Solution Method	Novel convex programming relaxation that also yields a natural pricing scheme

Security Games (Parking Enforcement)

Jalota et al. arXiv'24
Collaboration with **Stanford's DPS** to demonstrate efficacy of our algorithms on enforcement data in increasing parking revenues by \$300,000 annually

Source of Hardness	Resource constraints on the available set of security officers
Solution Method	Optimizing a specific concave approximation of bi-level program yielding a natural greedy algorithm

My Work: Sustainable resource allocation in socio-technical systems

My work leverages operations, CS, and economics to advance the **science** and **practice** of sustainable resource allocation

