Collaborative Research: CPS: Medium: An Online Learning Framework for Socially Emerging Mixed Mobility

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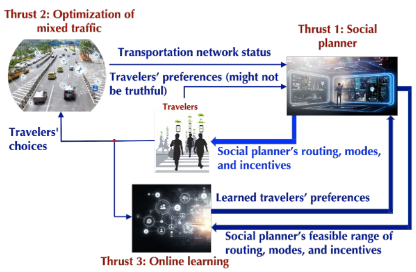
Objective

- The overarching goal is to develop an online framework that will aim at well distributing vehicle flow in a mixed traffic environment, where connected and automated vehicles (CAVs) co-exist with human-driven vehicles, resulting in a socially-optimal mobility system that travelers would be willing to accept.
- A "socially-optimal mobility system," is a mobility system that is efficient (in terms of energy consumption and travel time) and ensures equity in transportation.



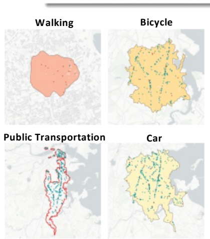
Technical Approach

Quantification of Mobility Equity

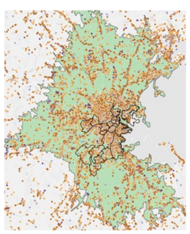
- We aim to design mobility equity metric (MEM) at a city-wide level that is agnostic to preferences of individuals, evaluable with publicly available data, and capable of capturing multi-modal transportation and other aspects such as accessibility, costs, and societal factors.
- Mobility index (MI) represents mobility (or accessibility) from an origin i with respect to the different parameters from social, economic, and spatial factors, i.e., price sensitivity κ, user cost c_m, and accessible services $\sigma^s_{i,m}(\tau_m)$ within a time threshold.

Mobility Index of Node $i \in \mathcal{O}$

$$\varepsilon_i = \sum_{m \in \mathcal{M}} e^{-\kappa_i c_m} \cdot \left\{ \sum_{s \in \mathcal{S}} \beta^s \sigma^s_{i,m}(\tau_m) \right\}.$$



Accessible Services with Different Modes



Services in Boston

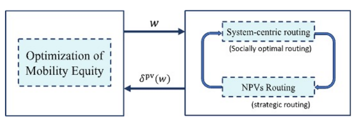
- Mobility equity metric (MEM) evaluates how emerging mobility systems are equitably provided at a city-wide level using Gini index.

Mobility Equity Metric (MEM)

Given MI ε_i for residential node $i \in \mathcal{O}$, MEM is

$$MEM = 1 - \frac{\sum_{i \in \mathcal{O}} \sum_{j \in \mathcal{O}} p_i p_j |\varepsilon_i - \varepsilon_j|}{2(\sum_{i \in \mathcal{O}} p_i)(\sum_{i \in \mathcal{O}} p_i \varepsilon_i)}.$$

Improving Mobility Equity via Routing in Mixed Mobility Systems



Mobility Equity Maximization

For a given compliance rate, we solve the following problem:

$$\underset{w}{\text{Maximize}} \quad \text{MEM}$$
$$\text{subject to:} \quad \delta^{pv}(w) \leq \gamma$$

Problem (System-Centric Routing)

$$\underset{\{x^{ij}_{m,n}\}}{\text{Minimize}} \sum_{m \in \mathcal{M}} w_m \left\{ \sum_{n \in \mathcal{N}} \sum_{(i,j) \in \mathcal{E}} t^{ij}(x^{ij} + q^{ij}) \cdot x^{ij}_{m,n} \right\}$$
$$\text{subject to : (flow constraints)},$$

where w_m is the weight for transportation mode m.

Problem (Strategic Routing of ℓ-Level NPV)

$$\underset{\{a^{ij}_{\ell,n}\}}{\text{Minimize}} \sum_{n \in \mathcal{N}} \sum_{(i,j) \in \mathcal{E}} t^{ij} \left(x^{ij} + \sum_{l=0}^{\ell-1} q^{ij}_l \right) \cdot a^{ij}_{\ell,n}$$
$$\text{subject to : (flow constraints)},$$

where $q^{ij}_\ell = \sum_{n \in \mathcal{N}} q_{\ell,n} \cdot a^{ij}_{\ell,n}$.

Cooperation Compliance Control

- Incentivize noncompliant vehicles to comply with the guidance by penalizing the noncompliant behaviors. We define a global cost C to control the behavior of all users, and local cost c_i to ensure individuals being priced based on their own behavior.

Goal: Achieve Desired Compliance Probability

$$P(k) = p(q_i + C(k) + c_i(k))$$

where $p : \mathbb{R} \to [0, 1]$ is a monotone increasing function, q_i is the agent's initial proclivity of compliance.

How: Adopt Cooperation Compliance Control

$$C(k+1) = C(k) + \alpha(Q^* - \frac{1}{N}\sum_{i=1}^{N} M_i(k))$$
$$c_i(k+1) = c_i(k) + \beta(Q^* - M_i(k))$$

Online Preference Learning

- Devise expert with clustering algorithm

Algorithm 1 Expert With Cluster

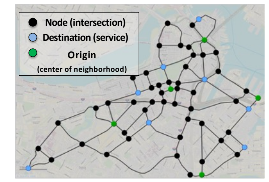
Require: Number of clusters K, offline training data $\mathcal{D}$, learning rate η
  Train with data $\mathcal{D}$, receive $\{\boldsymbol{\theta}_i\}_{i \in [N']}$
  Apply clustering on $\{\boldsymbol{\theta}_i\}_{i \in [N']}$, receive centroids $\{\mathbf{c}_k\}_{k \in [K]}$
  Initialize weight $\mathbf{p}_{i,1}(k) \leftarrow \frac{1}{K}$ for all $i \in [N], k \in [K]$
  for $t = 1, \ldots, T$ **do**
    for $i = 1, \ldots, N$ **do**
      Receive $x_{i,t}$
      Sample $E_{i,t} \sim \mathbf{p}_{i,t}$, submit $Rec_{i,t} = \hat{y}(\mathbf{c}_{E_{i,t}}, x_{i,t})$,
      Receive $y_{i,t}$, compute loss $\mathbf{l}_{i,t}(k) = l(\hat{y}(\mathbf{c}_k, x_{i,t}), y_{i,t})$ for all $k \in [K]$
      $\mathbf{p}_{i,t+1}(k) \leftarrow \frac{\mathbf{p}_{i,t}(k) e^{-\eta \mathbf{l}_{i,t}(k)}}{\sum_{k' \in [K]} \mathbf{p}_{i,t}(k') e^{-\eta \mathbf{l}_{i,t}(k')}}$ for all $k \in [K]$
    end for
  end for

Results

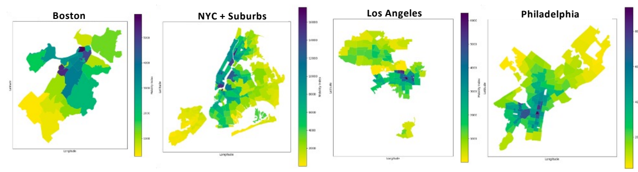
- MI tends to be better in downtown and worse in suburban areas and cities with better public transportation have higher MEM values.
- Numerical simulation shows that MEM can be improved via routing in emerging mobility systems or by having higher compliance rate.

City	MEM
Manhattan	0.881
Chicago	0.788
Boston	0.708
Philadelphia	0.643
NYC + Suburbs	0.623
LA	0.623

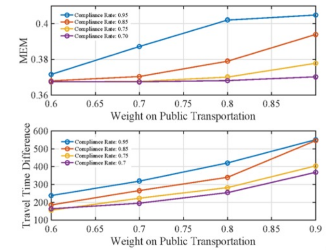
Mobility Equity Metric across Cities



Transportation Network in Boston City



Mobility Indices at Neighborhoods



Simulation Results with Different Compliance Rate

Scientific Impact

- Merging learning and control approaches for CPS and bridging the gap between optimal planning and safe-critical control in CPS.
- Develop a framework addressing societal challenges within CPS.

Broader Impact

- Develop a new mobility equity metric and equity-prioritized control framework for emerging mobility systems.
- Develop a holistic and rigorous framework to capture the societal impact of CAVs and provide solutions that enhance accessibility, safety, and equity in transportation.

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