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

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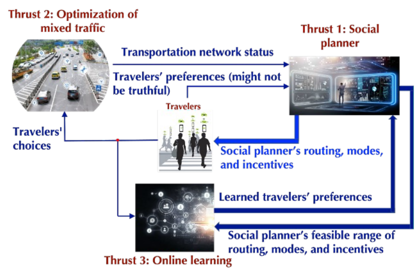
Objective

- The overarching goal is to develop an online framework that will aim at 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 fair distribution in transportation.



Technical Approach

Quantification of Mobility Fairness (Thrust 2)

- We aim to design mobility 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 (MI) of Node $i \in \mathcal{O}$

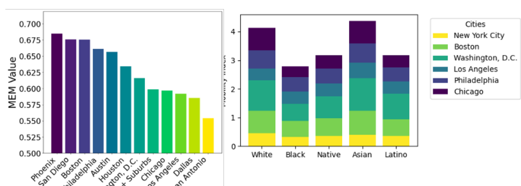
$$\varepsilon_i = \sum_{m\in\mathcal{M}} e^{-\kappa_i c_m} \cdot \left\{ \sum_{s\in\mathcal{S}} \beta^s \sigma^s_{i,m}(\tau_m) \right\}.$$

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

Mobility Metric (MEM)

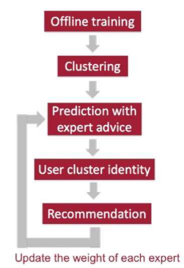
Given MI ε_i for residential node $i \in \mathcal{O}$, MEM is

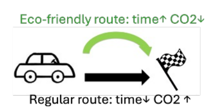
$$\mathrm{MEM} = 1 - \frac{\sum_{i\in\mathcal{O}}\sum_{j\in\mathcal{O}} p_i p_j |\varepsilon_i - \varepsilon_j|}{2(\sum_{i\in\mathcal{O}} p_i)^2(\sum_{i\in\mathcal{O}} p_i\varepsilon_i)}.$$

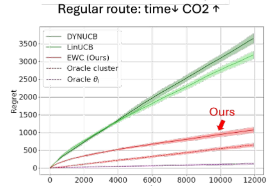


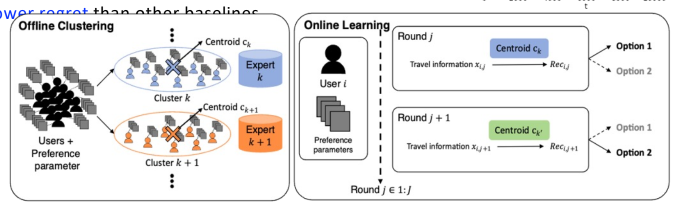
Online Preference Learning (Thrust 3)

- We aim to design hierarchical approach to capture user preference in travel route choice with low regret and data efficient way.
- We propose Expert with Clustering (EWC), a novel hierarchical contextual bandit approach, which combines clustering and prediction with expert advice.
- In experiments, we use travel route recommendation problem, where users are given eco-friendly longer route and regular shortest route.
- Our results show that EWC with offline training on preference and prediction with expert achieves the lower regret than other baselines.

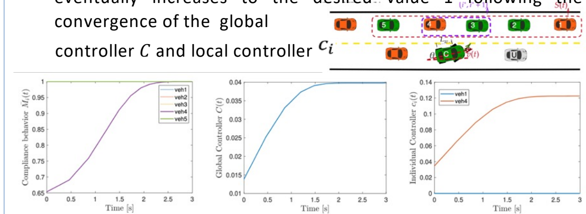








- Results: The compliance behavior of the non-compliant vehicle eventually increases to the desired value 1 following the convergence of the global controller C and local controller c_i



(a) Compliance behavior $\bar{M}_i(t)$. (b) Global Controller $C(t)$ (c) Individual Controller $c_i(t)$

Cooperation Compliance Control (CCC) (Thrust 1)

- Goal: Achieve desired compliance probability for all users by incentivizing noncompliant vehicles to comply with the guidance provided by the "Social Planner".

Goal: Achieve Desired Compliance Probability

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

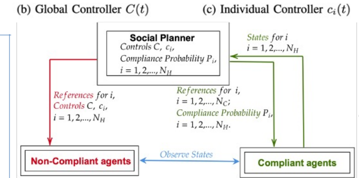
where $p : \mathbb{R} \to [0,1]$ is a monotone increasing function, q_i is the agent's initial proclivity of compliance.

- How: 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.

How: Adopt Cooperation Compliance Control

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

$$c_i(k+1) = c_i(k) + \beta(Q^* - \bar{M}_i(k))$$



- Approach: We apply the CCC scheme to the lane-changing problem, where a "Social Planner" provides references to all vehicles, measures their state errors, and induces cooperation compliance for safe lane-changing.

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 metric providing fair mobility service and a control framework for emerging mobility systems to achieve socially optimal solutions.
- Develop a holistic and rigorous framework to capture the societal impact of CAVs and provide solutions that enhance accessibility and safety in transportation.

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