Generalizing Cooperative Eco-driving via Multi-residual Task Learning

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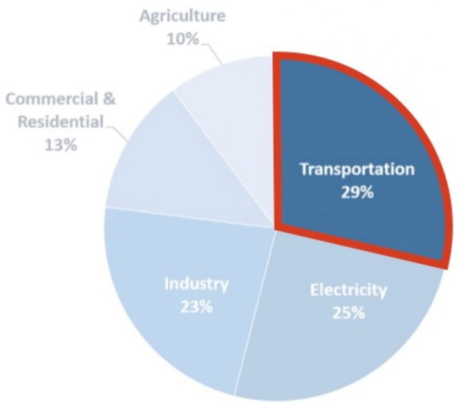
Autonomous Driving

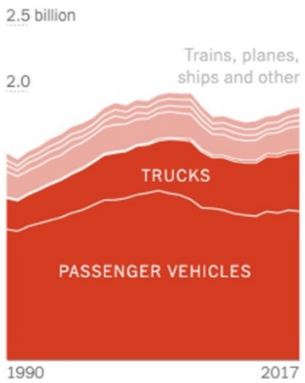
<u>Safety</u>: Drastically reduce roadway **fatalities**

43K annual US fatalities, a leading cause of death of young people

<u>Time</u>: Unlock the **hundreds of billions of hours** spent driving

1 hour each day / American driver





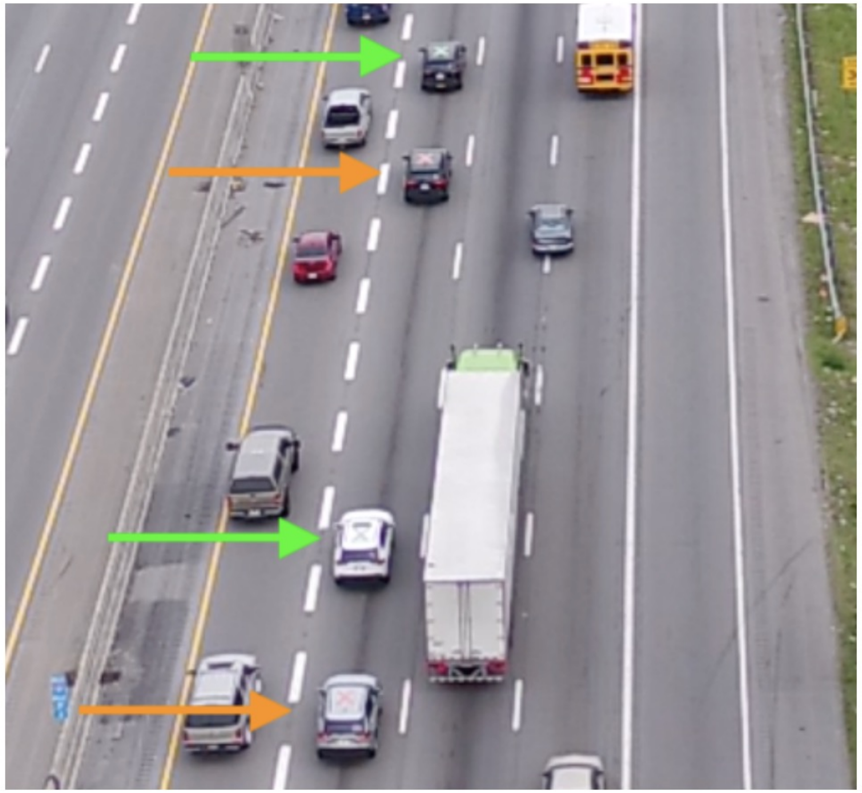
<u>Environment</u>: Mitigate **environmental harms**

Transportation is the largest contributing sector of greenhouse gas emissions in the US at 29%, mostly on roadways

Autonomous Vehicles for Lagrangian Traffic Control

Fixed Location-based Actuators

AVs as Mobile Actuators



I-24 highway traffic smoothing (Lichtle et al. 2023)

Autonomous Vehicles for Lagrangian Traffic Control

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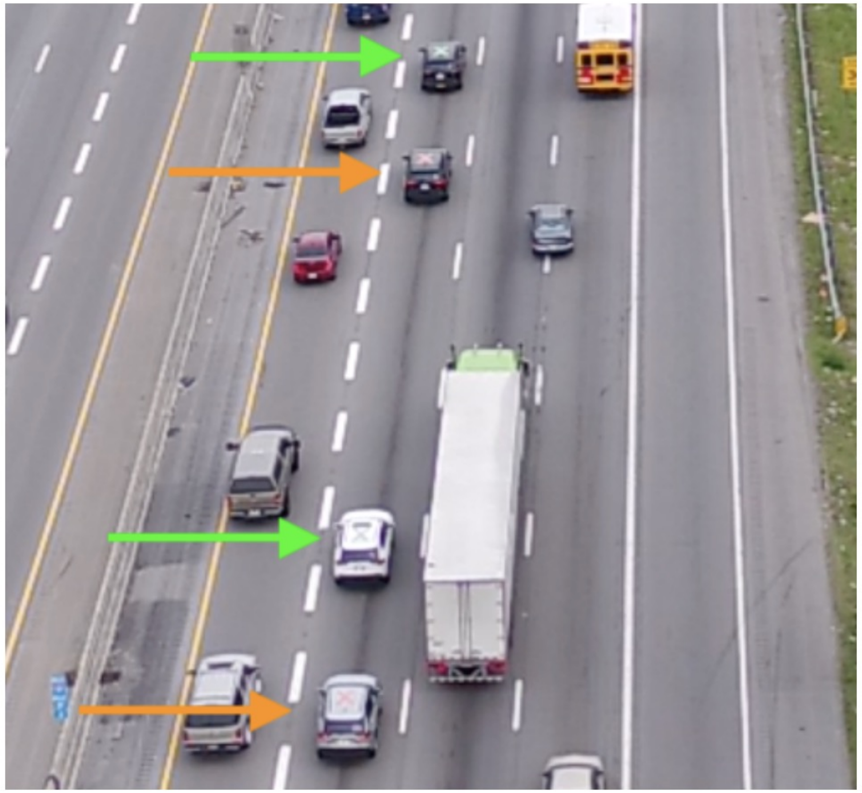

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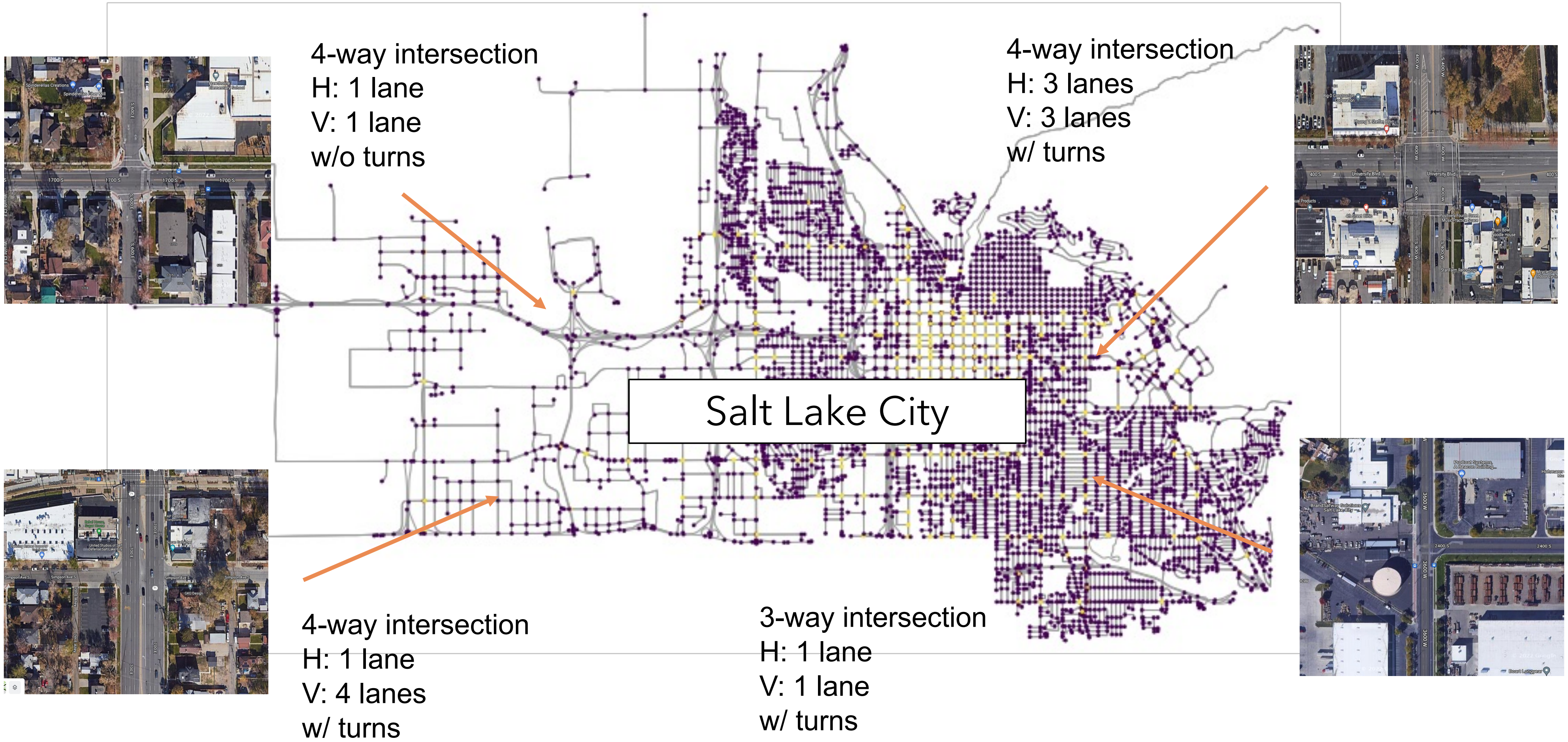
Cooperative multi-agent control problem

Mixed traffic control problem (AVs and human-driven vehicles co-exist)

Goal: Fleet-level traffic flow optimization

Generalization Challenge

Factors of variation: Topology, turn restrictions, road grade, weather, travel demand, vehicle types, age , etc.



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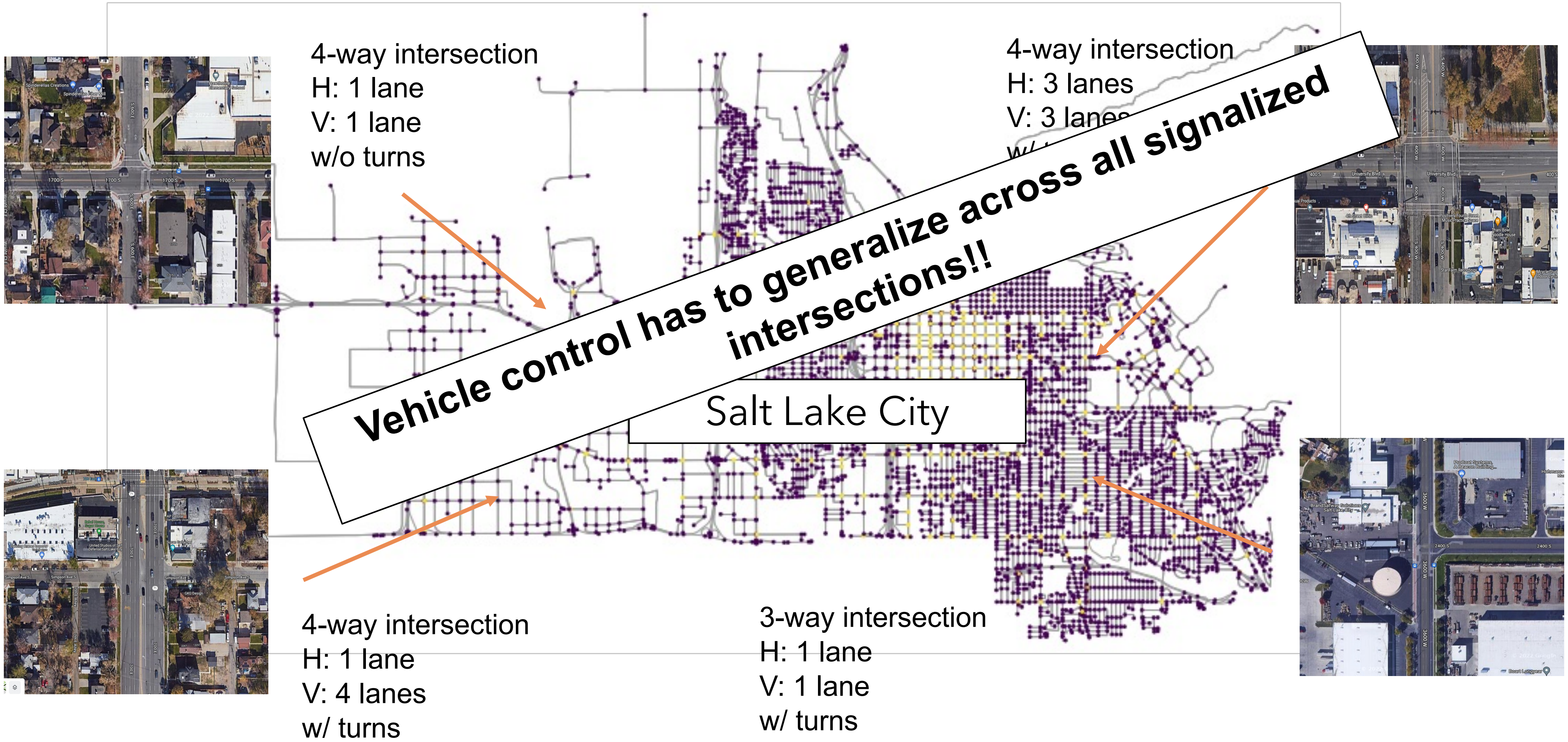
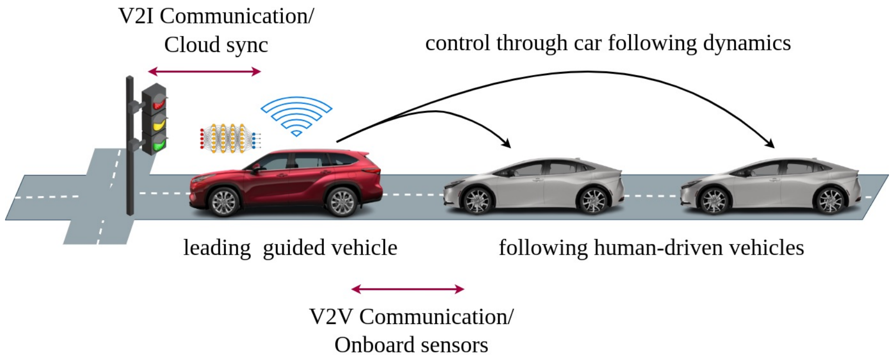


Contributions

Formalize generalization in Lagrangian traffic control as a Contextual Markov Decision Process (cMDP).

Propose Multi-residual Task Learning (MRTL) as a framework to solve the resultant cMDP.

Show the utility of MRTL in a demonstrative cooperative eco-driving application.



Contextual Markov Decision Process (cMDP)

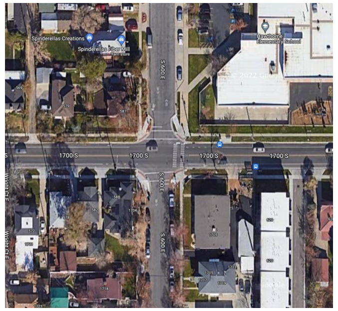
Markov Decision Process (**MDP**)

$$M = (S, A, \rho, T, r, \gamma)$$

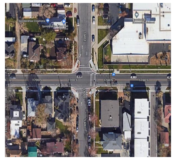
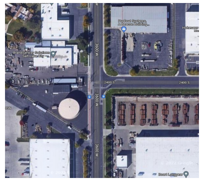
Contextual Markov Decision Process (**cMDP**)

$$M_{cMDP} = (S, A, C, \rho_c, T_c, r_c, \gamma)$$

C: Context space



Context: (lane count, lane configuration, …)

M_{cMDP} = (M() , M(), …)

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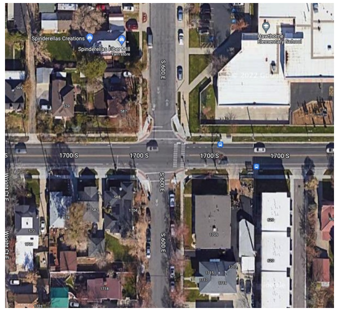

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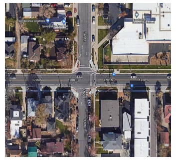
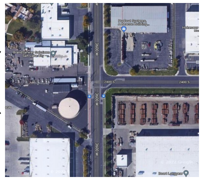
M_{cMDP} = (M() , M(), …)

$$\pi^* = \underset{\pi}{\operatorname{argmax}} \mathrm{E}\left[\sum_{c \in C} \sum_{t=0}^{H} \gamma^t r_c(s_t, at) \mid s_0^c, \pi \right]$$

Multi-residual Task Learning (MRTL)

$\pi(s, c) \longrightarrow$ 

Can be solved with
multi-task learning

Learning residual actions

$\pi(s,c)$	$=$	$\pi_n(s,c)$	$+$	$f_\theta(s,c)$
Multi-residual Task Learning policy action (superposition)		Nominal policy action (Initial suboptimal action)		Residual policy action (corrective residual action)

Generalizing Cooperative Eco-driving

Objective: Leverage AVs as Lagrangian actuators to improve fleet-level emission of a mixed traffic fleet.

MRTL outperform baselines

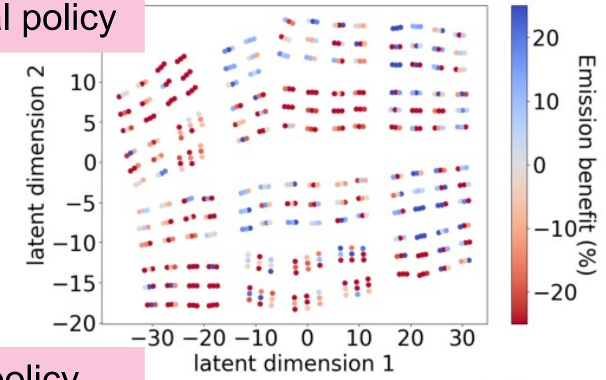
Emission benefits over 1200 traffic MDPs stem from 600 intersections

Baseline	Emission reduction % (lower the better)
Multi-task learning	64.08%
GLOSA (nominal policy)	13.13%
MRTL (ours)	**-13.95%**

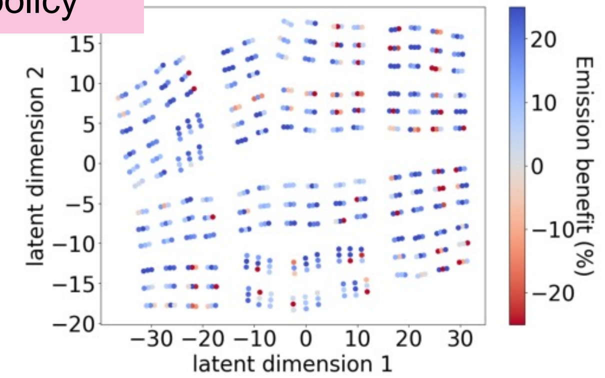
MRTL can overcome nominal policy limitations

t-sne visualization of intersection benefits

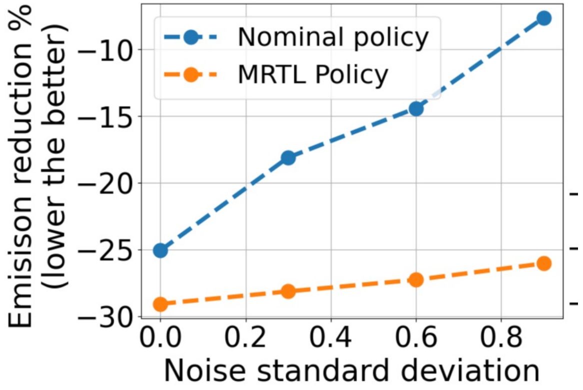
Nominal policy

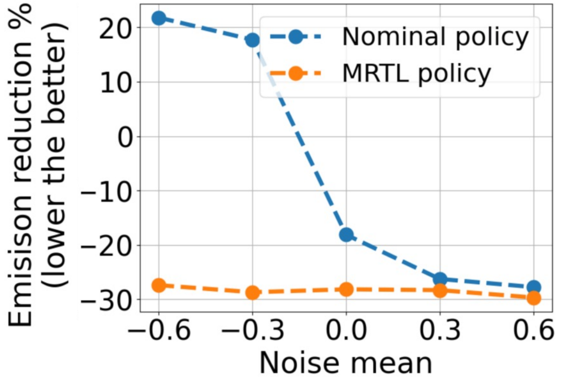


MRTL policy



MRTL is robust to control and bias noise





Takeaways

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The multi-residual task learning (MRTL) framework offers a promising approach for solving contextual markov decision processes.

Application of MRTL to cooperative eco-driving yields significant emission benefits, indicating greater generalization across traffic scenarios.

For questions and comments, please reach me at vindula@mit.edu

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