Learning with Certificate Functions for Automotive Systems

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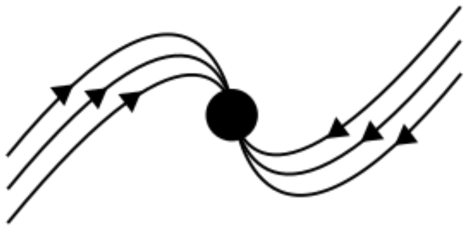
Control certificates functions

Certificate functions from **control theory** prove desired system properties.

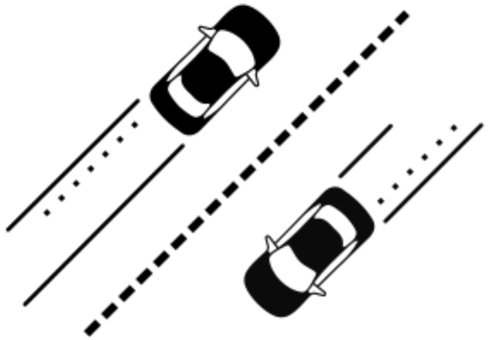
Lyapunov Function

> *Certifies stability of a fixed point*



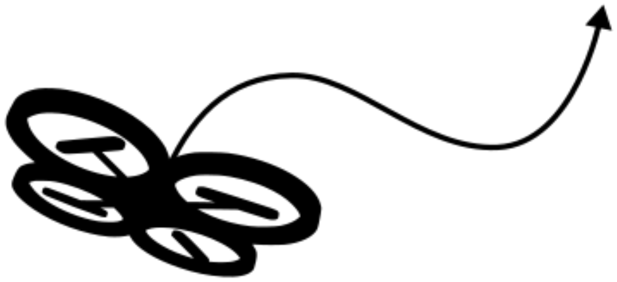
Barrier Function

> *Certifies invariance of a region*

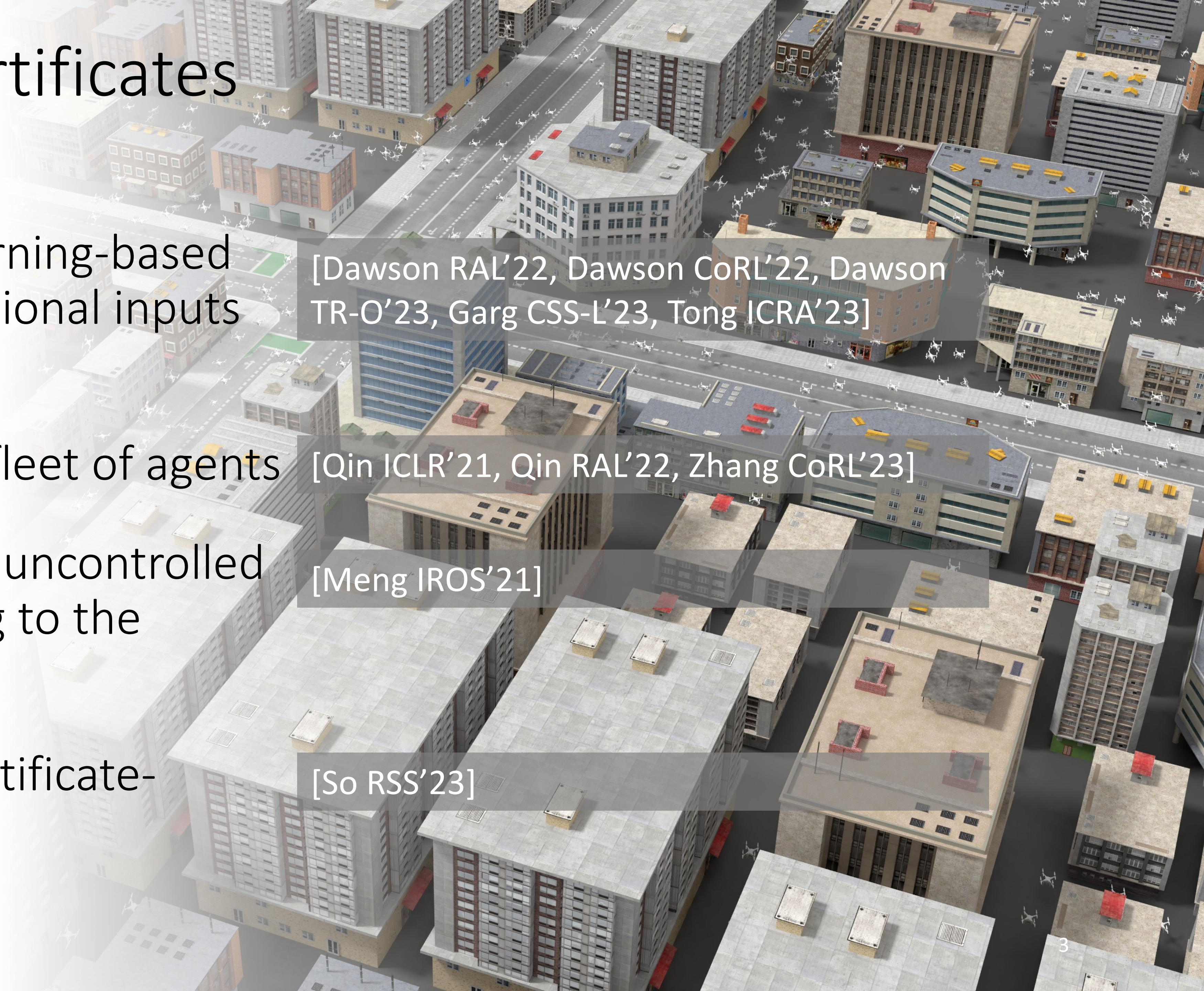


Contraction Metric

> *Certifies ability to track arbitrary trajectories*



Neural control certificates can help with



Single-agent certified learning-based control from high-dimensional inputs (robust, online, adaptive)

[Dawson RAL’22, Dawson CoRL’22, Dawson TR-O’23, Garg CSS-L’23, Tong ICRA’23]

Generalization in a large fleet of agents

[Qin ICLR’21, Qin RAL’22, Zhang CoRL’23]

Provide insights on other uncontrolled road participants reacting to the autonomous cars

[Meng IROS’21]

Combined with RL for certificate-carrying RL

[So RSS’23]

Neural certificate control

To solve LiDAR-based navigation, from a control certificate point of view, a robust Control Lyapunov Barrier function (rCLBF) can serve the purpose of certifying safe reach-avoid problems

Lyapunov

$$V(x_{\text{goal}}) = 0$$

$$V(x) > 0, \forall x \in \mathcal{X} \setminus x_{\text{goal}}$$

$$V(x) \leq c, \forall x \in \mathcal{X}_{\text{safe}}$$

$$V(x) > c, \forall x \in \mathcal{X}_{\text{unsafe}}$$

$$\inf_u L_{f_\theta} V + L_{g_\theta} V u + \lambda V(x) \leq 0,\ \forall x \in \mathcal{X} \setminus x_{\text{goal}}$$

Barrier

Theorem: If we can find such a V for a control policy u, then the closed-loop system is robustly safe and stable in terms of goal-reaching.

There are many approaches to find such a V, such as SoS, Simulation-guided synthesis. But the computational complexity has been a bottleneck so far.

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[Dawson 21] u and V can be represented as NNs, with loss $\mathcal{L}$ being

$$\inf_{V,u} \sup_{x \in \mathcal{X}} \Bigg(V^2(x_{\text{goal}}) + a_1 \frac{1}{N_{safe}} \sum_{x \in \mathcal{X}_{\text{safe}}} \max(V(x) - c, 0) + a_2 \frac{1}{N_{unsafe}} \sum_{x \in \mathcal{X}_{\text{safe}}} \max(V(x) - c, 0)$$

$$+ a_3 \frac{1}{N_{train}} \sum_{x \in \mathcal{X}} r(x) \sum_i \max(L_{f_{\theta_i}} V + L_{g_{\theta_i}} V u + \lambda V(x), 0) \Bigg)$$

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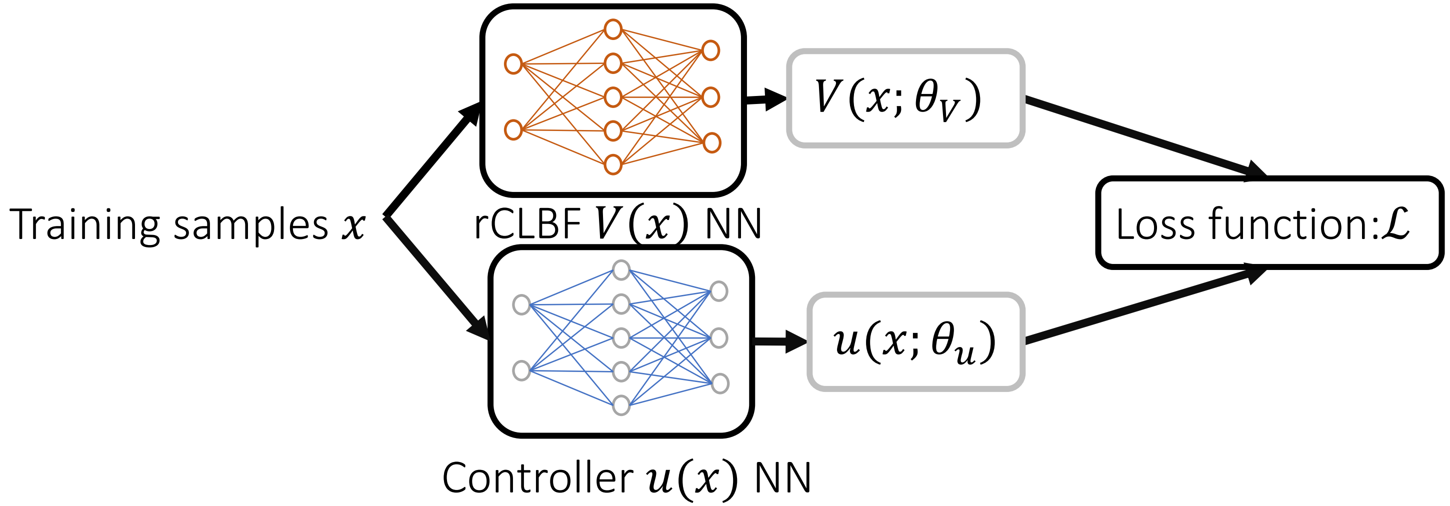

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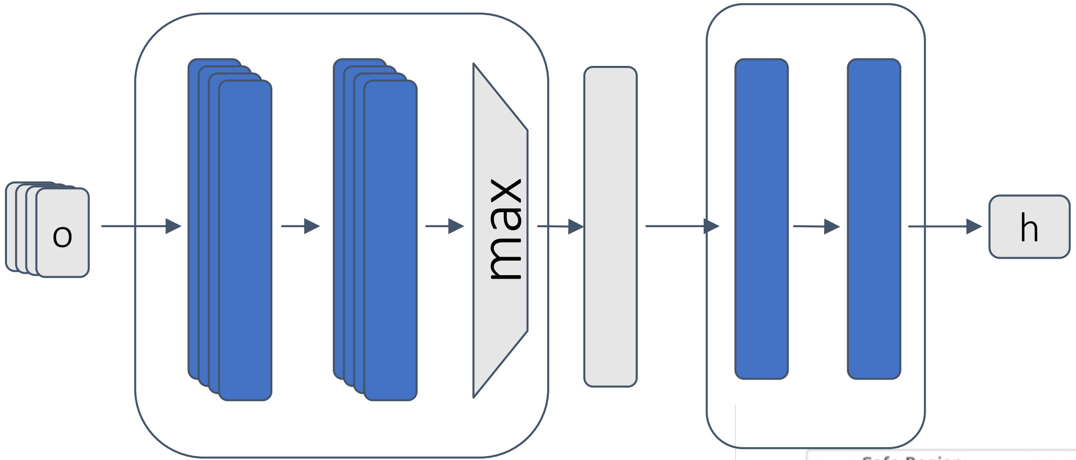
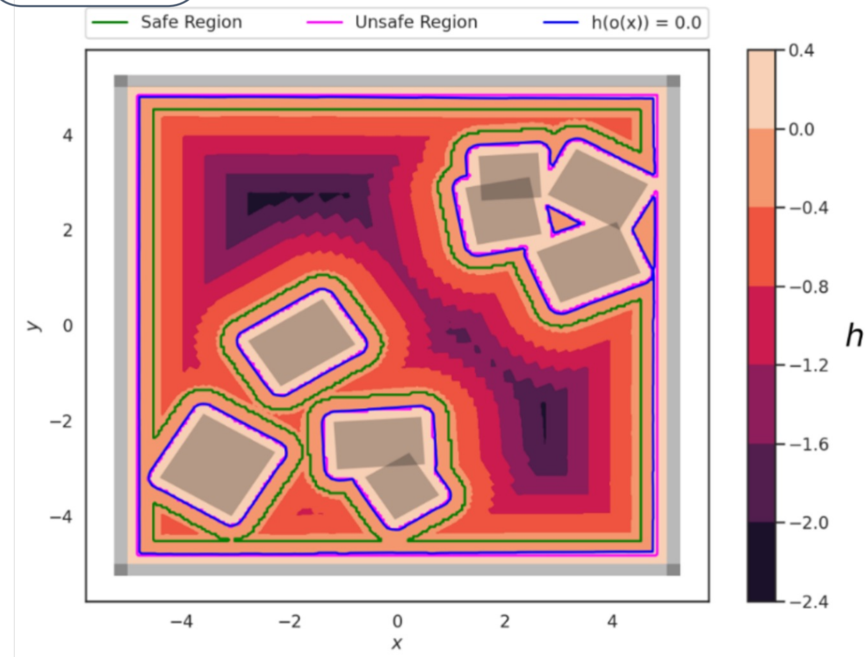
$$\inf_{V,u}\sup_{x\in\mathcal{X}}\Bigg(V^2(x_{\text{goal}}) + a_1\frac{1}{N_{safe}}\sum_{x\in\mathcal{X}_{\text{safe}}}\max(V(x)-c,0) + a_2\frac{1}{N_{unsafe}}\sum_{x\in\mathcal{X}_{\text{safe}}}\max(V(x)-c,0)$$

$$+\, a_3\frac{1}{N_{train}}\sum_{x\in\mathcal{X}} r(x)\sum_{i}\max(L_{f_{\theta_i}}V + L_{g_{\theta_i}}Vu + \lambda V(x),0)\Bigg)$$

Neural certificate control



Permutation-invariant embedding of lidar measurements

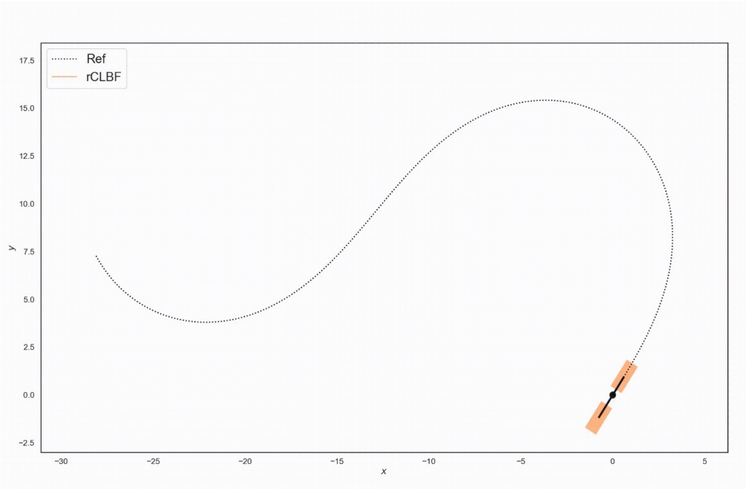


Observation-based CBF

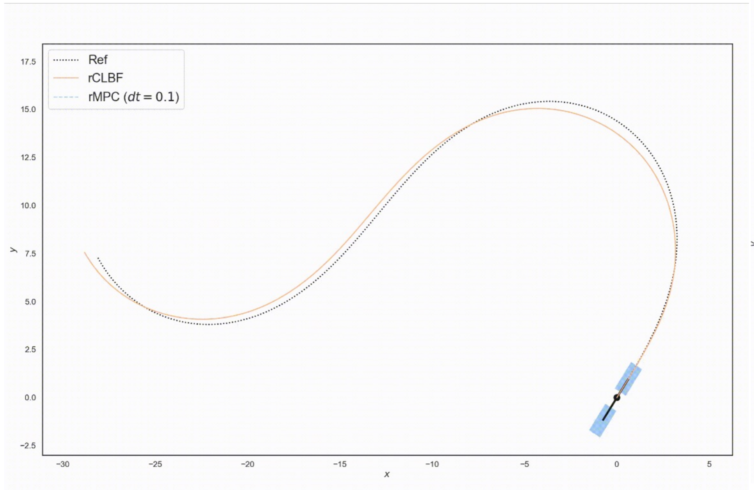
Observation-based CLF

Neural certificate control

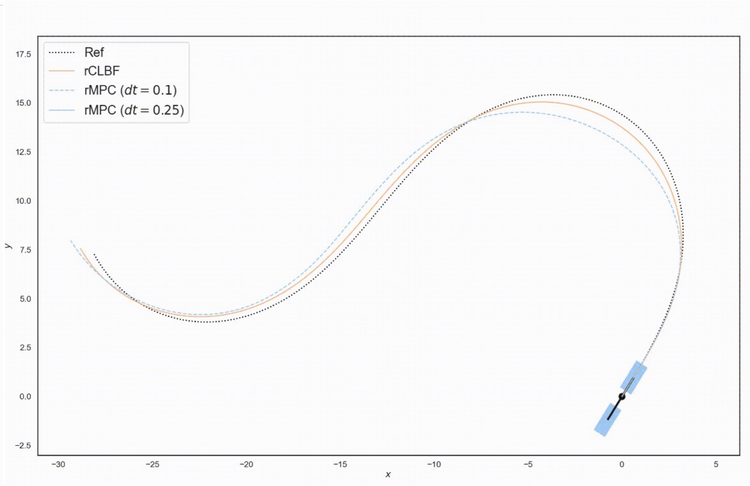
Neural certificate control can achieve 100 Hz (real-time) control, versus 4 Hz for robust MPC.



Our approach
(100 Hz)

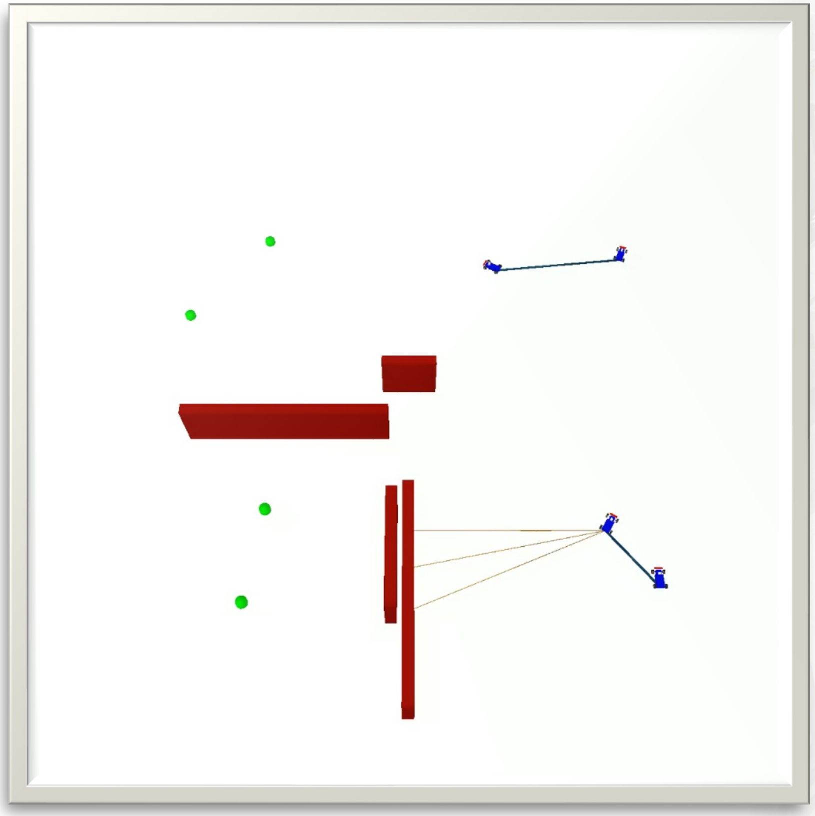


Robust MPC
(10 Hz, less than real-time)



Robust MPC
(4 Hz, real-time)

Neural certificate for multi-agent Systems



To handle multi-agent systems and generalize well to different settings, we need to fully decentralize the controller and neural certificates.

Songyuan Zhang, Kunal Garg, and Chuchu Fan, “Distributed Safe Multi-agent Control Using Neural Graph Control Barrier Functions.” *To appear at the Conference on Robot Learning 2023.*

Graph control barrier functions (GCBF)

A multi-agent system is naturally a graph $\mathcal{G} = (V, E)$

- $V = V_a \cup V_o$, where V_a are agents and V_0 are the hitting points of LiDAR rays in the observation
- The edges E are defined between each of the observed points and the observing agent when the distance between them is within the sensing radius R.

A GCBF for the graph is defined as

$$h(e_i, v_i) > 0 \text{ for } x_i \in S_{i,\,\text{safe}}$$

$$h(e_i, v_i) < 0 \text{ for } x_i \notin S_{i,\,\text{safe}}$$

$$\sup_{u_i}\left[\dot{h}(e_i, v_i) + \alpha\big(h(e_i, v_i)\big)\right] \geq 0 \text{ for } x_i \in S_{i,\,\text{safe}}$$

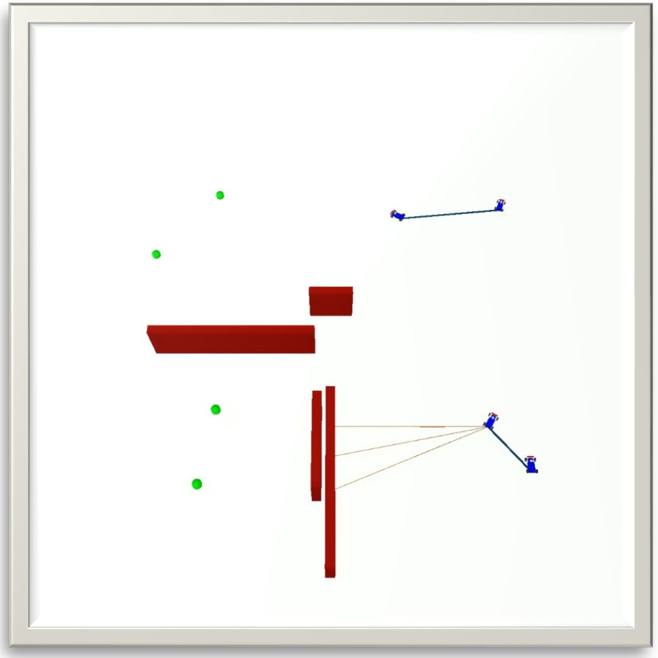
e_i: edge features

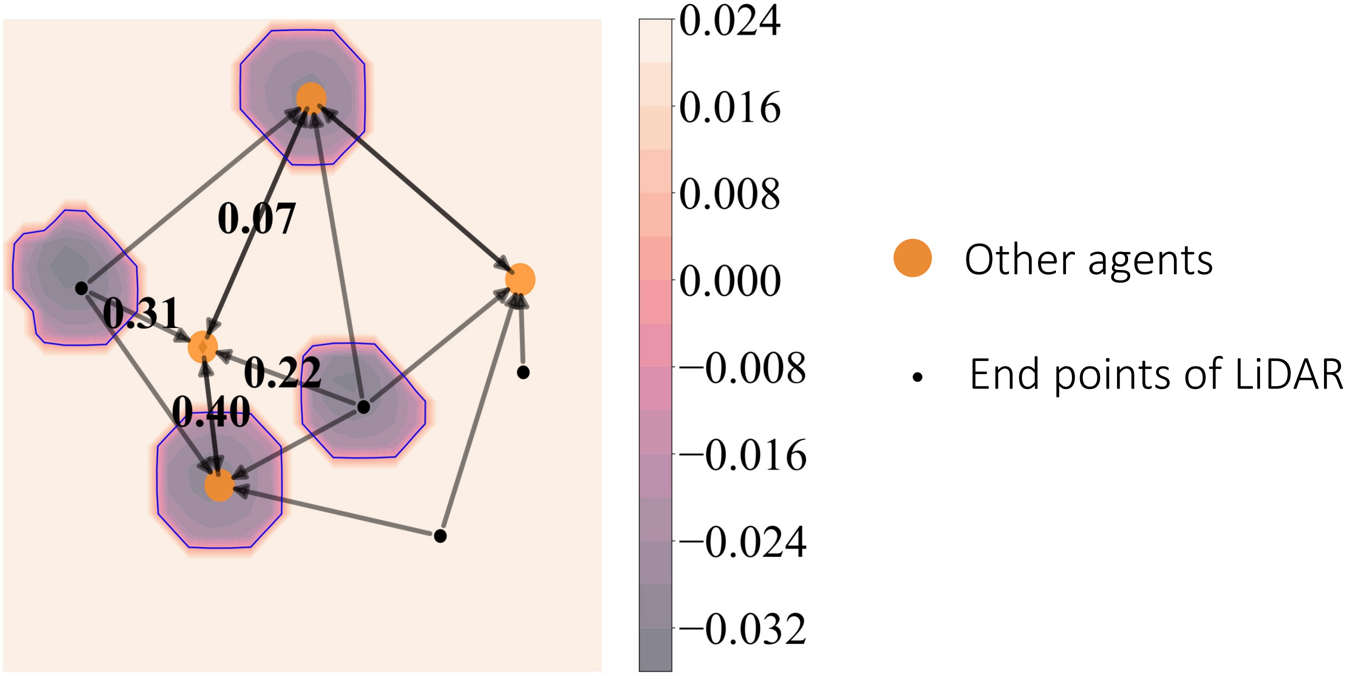
v_i: node features

α: class-$\mathcal{K}$ function

Theorem: Existence of a GCBF guarantees the safety of the multi-agent system from non-colliding initial conditions.

GCBF learned as Graph Neural Networks (GNN)

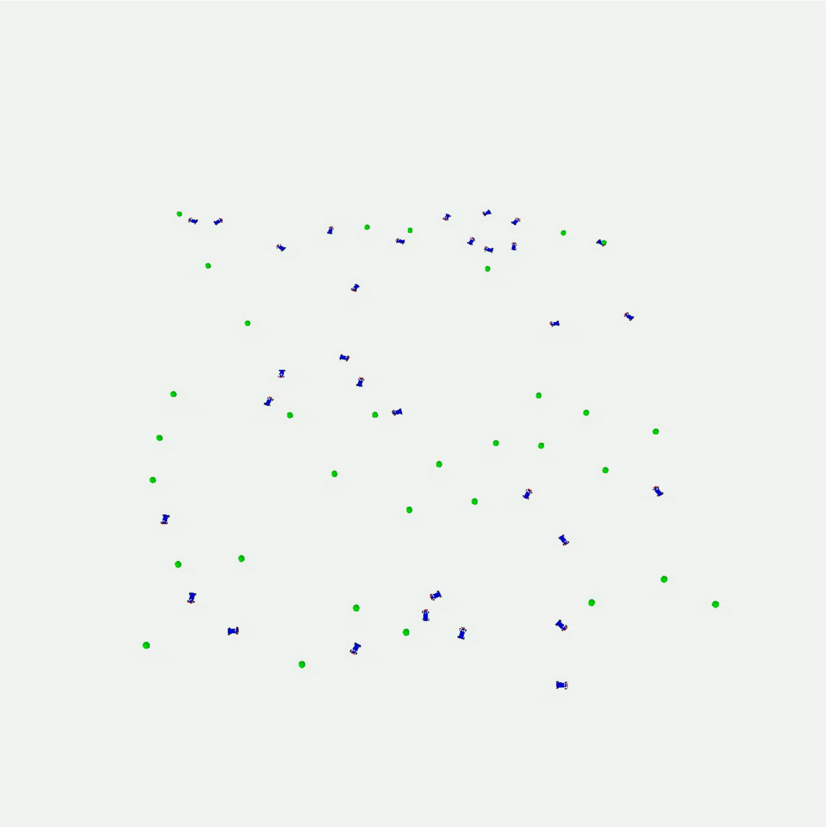
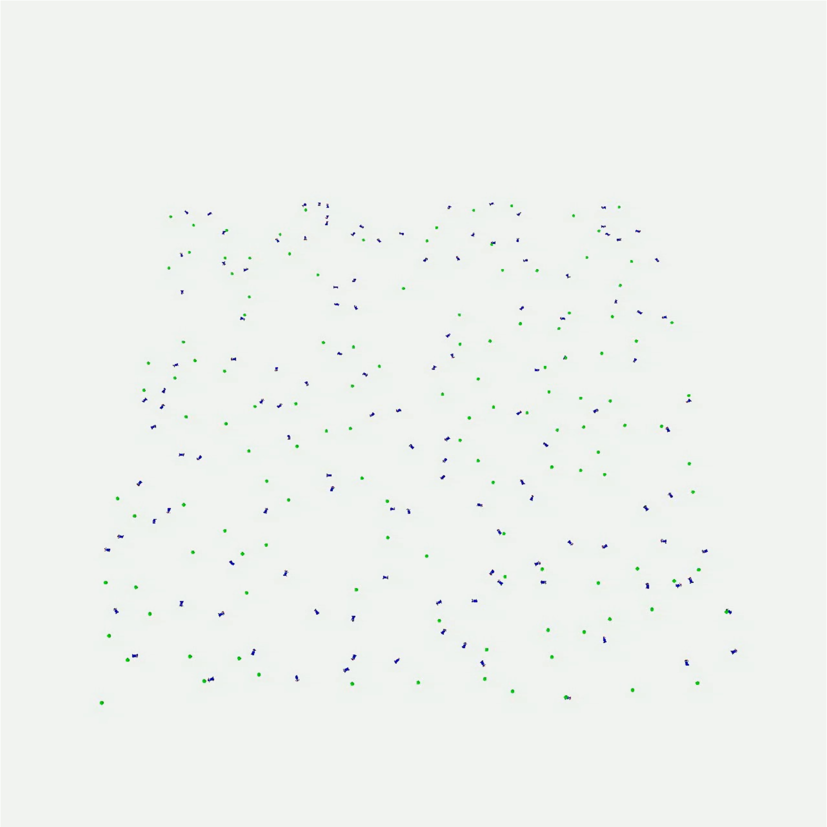
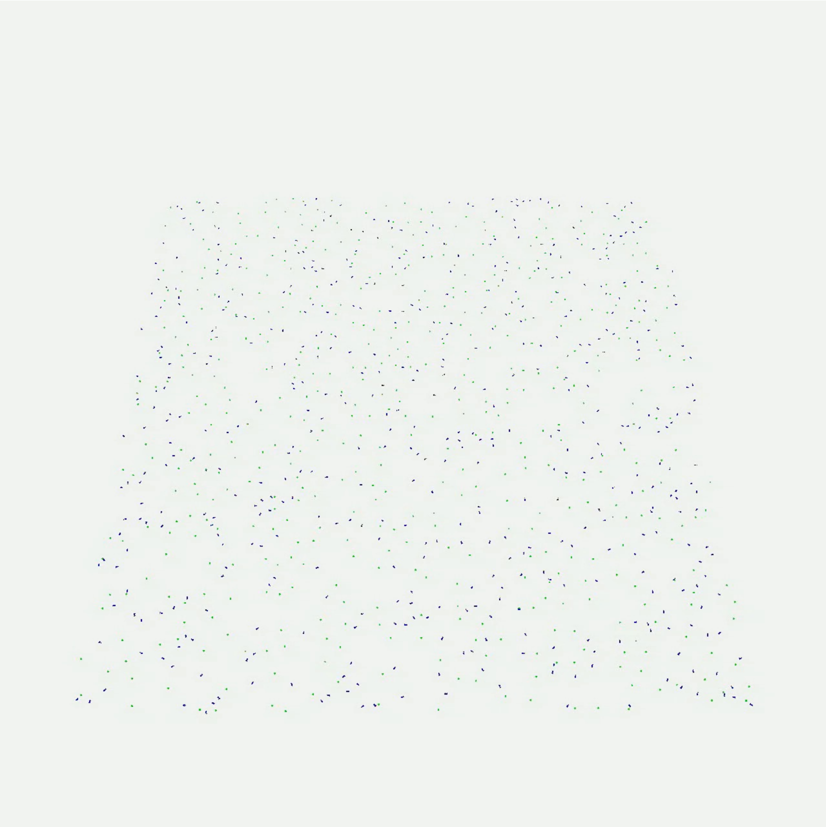




The GCBF is trained without explicit models of the obstacles, but some randomly sampled point in the point clouds.

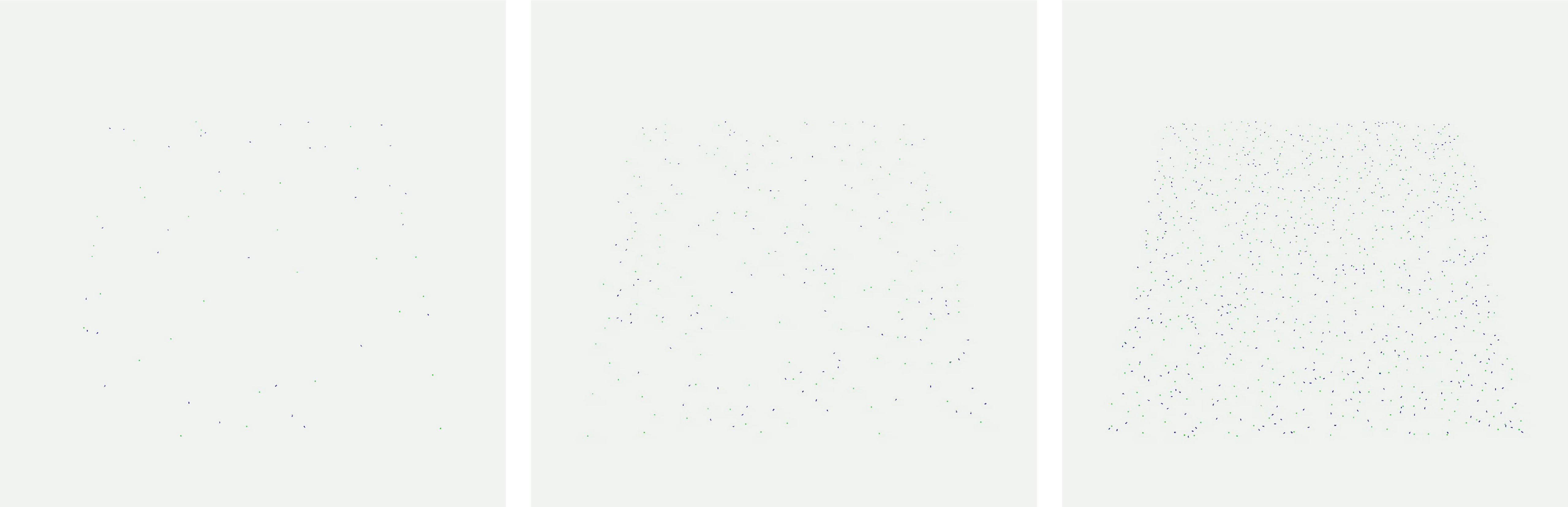
Graph control barrier functions (GCBF)

Trained with 16 Dubin cars, the resulting controller can be deployed on an arbitrary number of agents with the same dynamics.

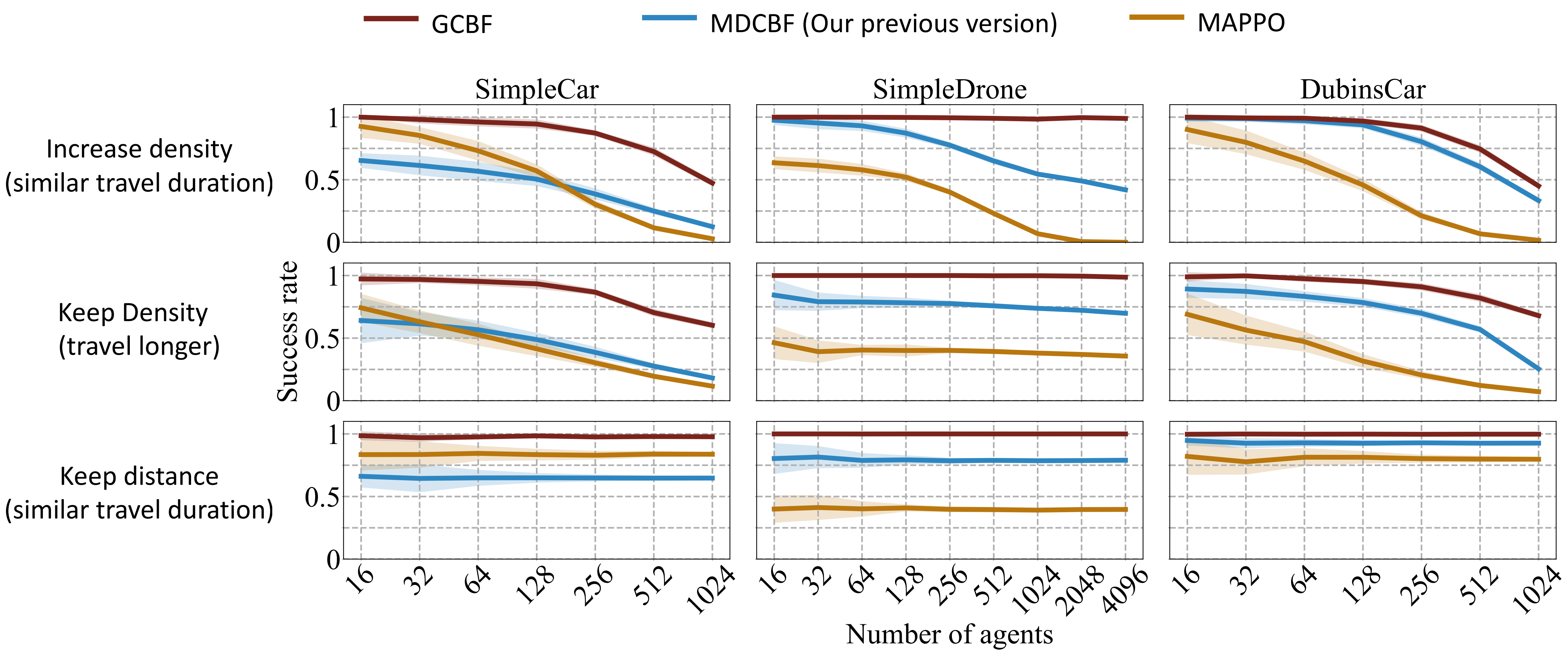




Graph control barrier functions (GCBF)

Trained with 16 Dubin cars, the resulting controller can be deployed on an arbitrary number of agents with the same dynamics, even with increased density.

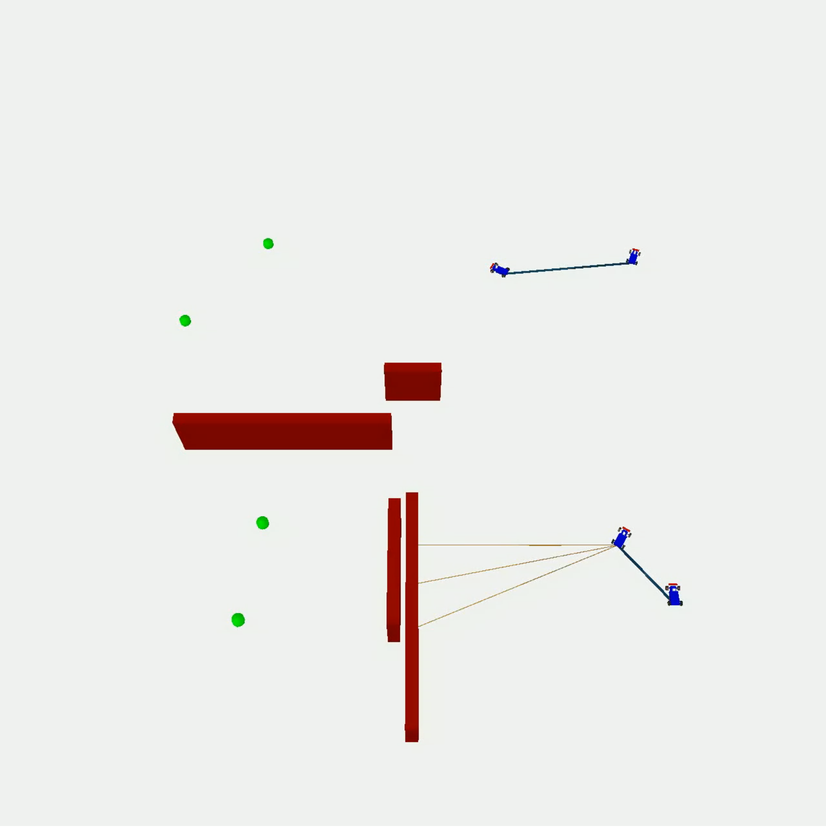
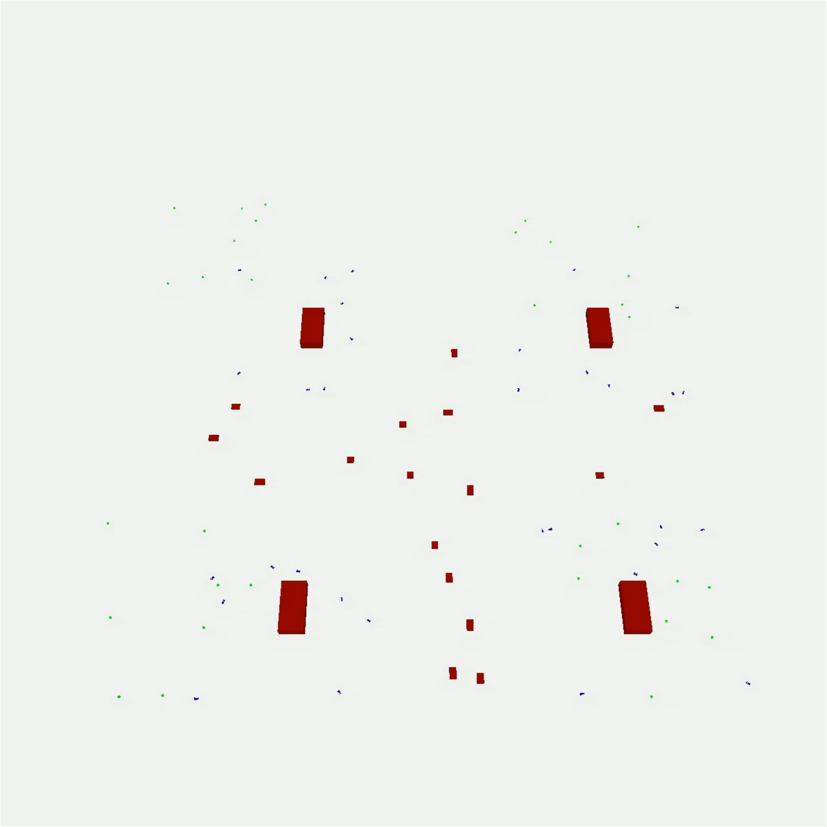
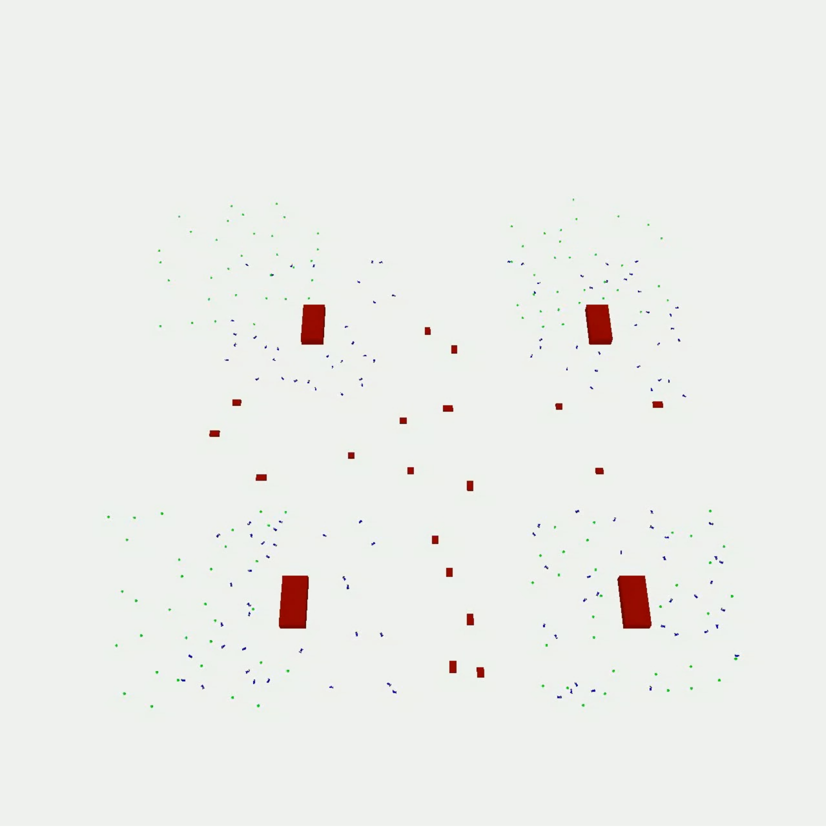


GNN-based neural CBF-based control



Graph control barrier functions (GCBF)

With LiDAR inputs, the decentralized controller can handle unseen (uncontrolled) obstacles of varying sizes and speed.

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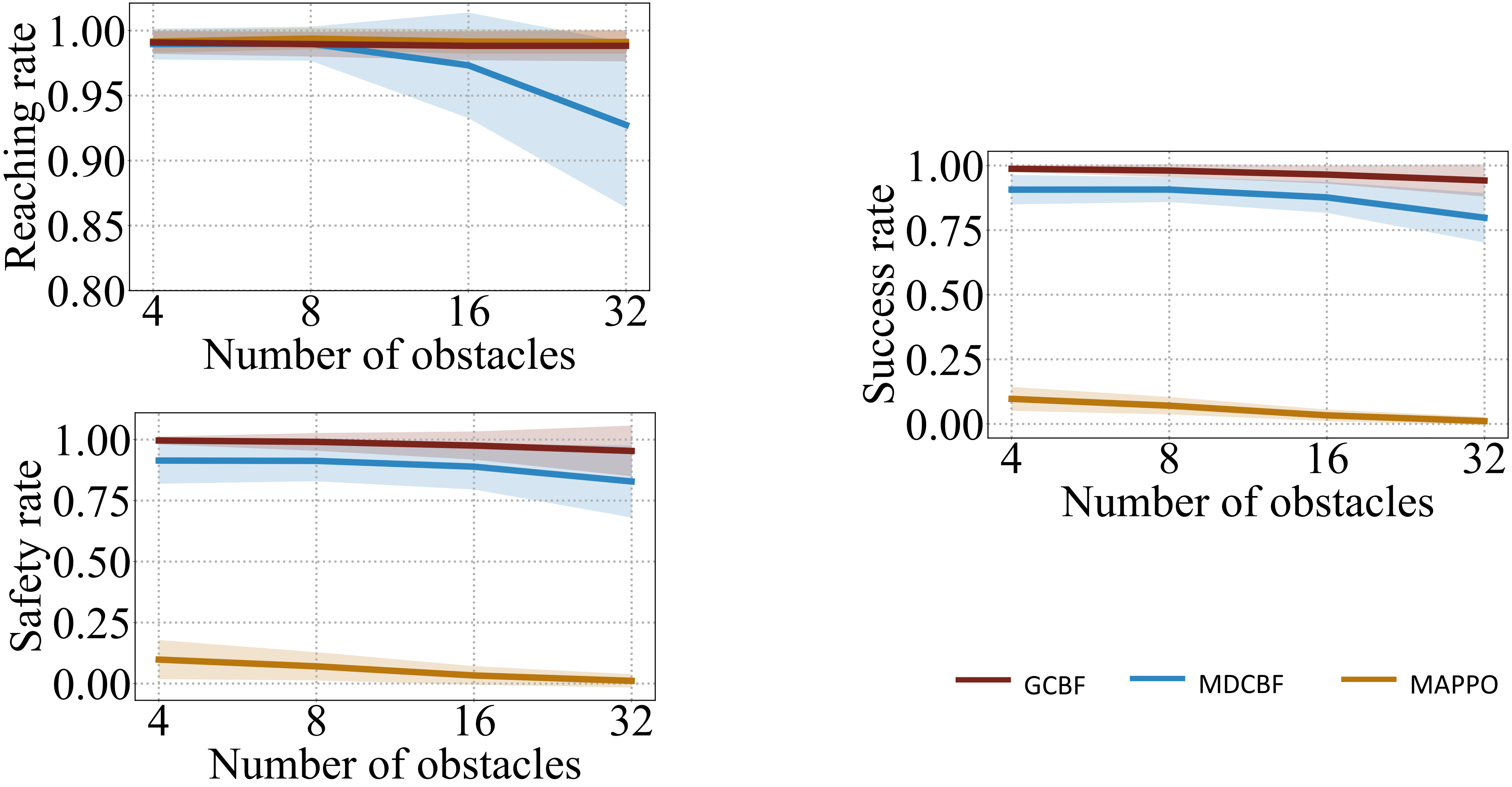
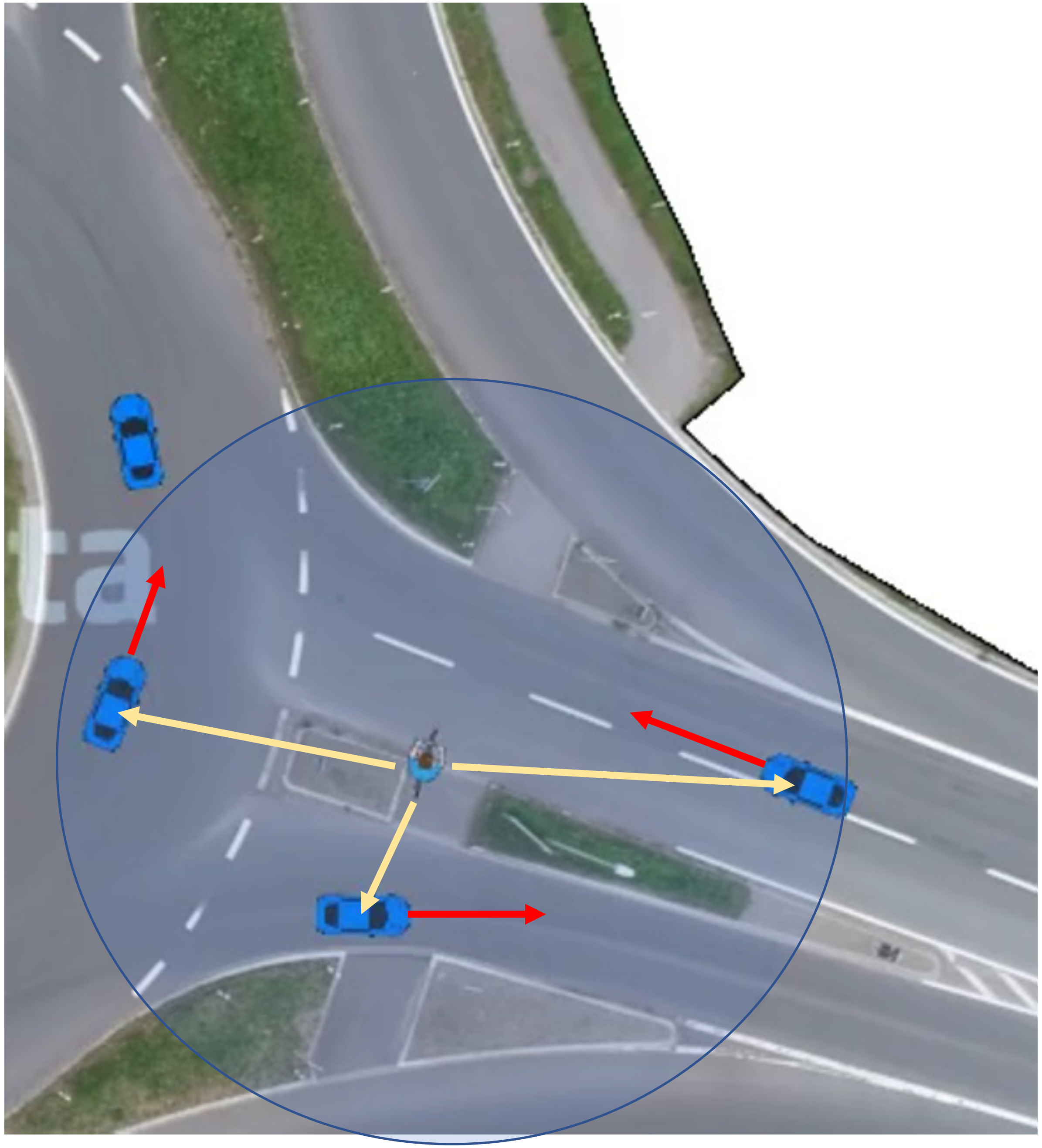


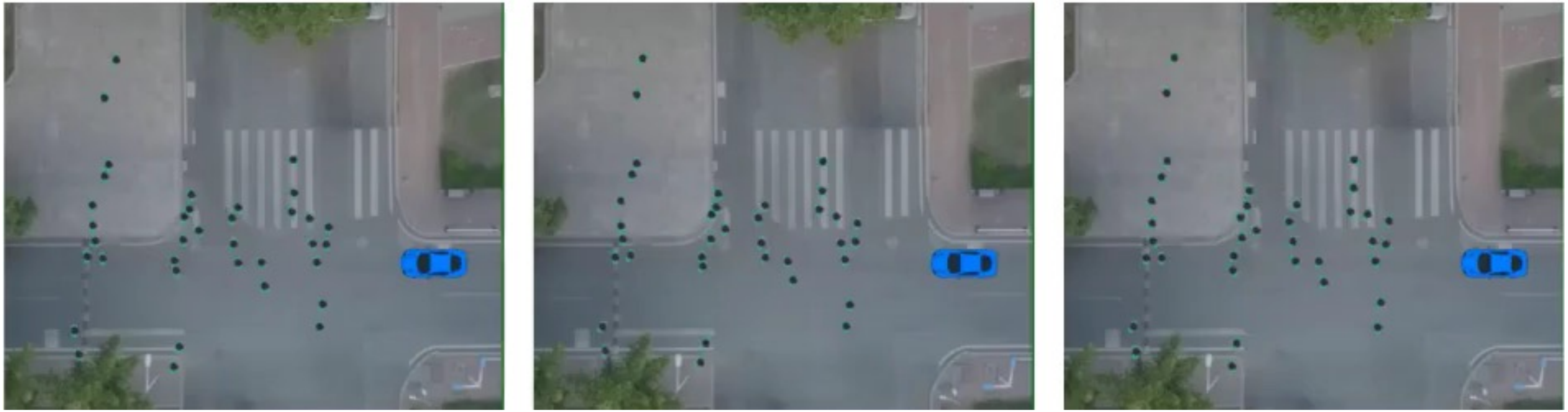
Neural certificates can help build reactive other road participants

Human intents (e.g., collision avoidance, traffic rules) can be learned as neural certificates from real-world traffic and be enforced in the learned human behavior models [Meng 21].



Inserting certificates in learned behavior models

It turns out the human behavior model learned in this way can generalize to unseen scenarios more realistically. [Meng 21]

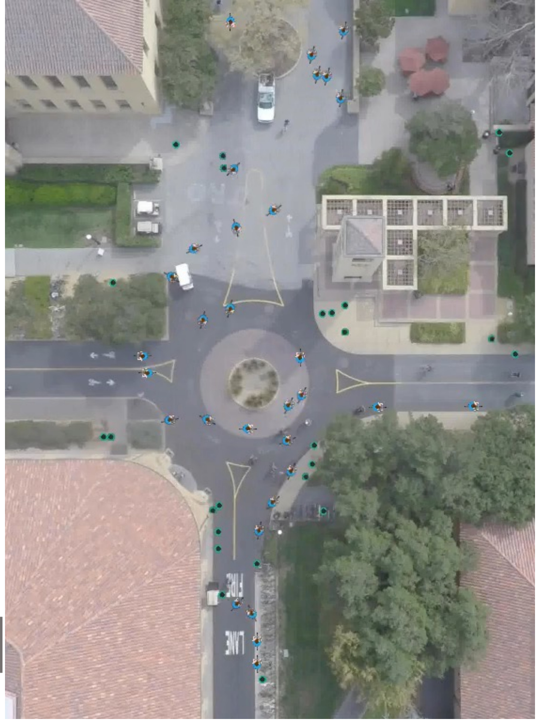


(a) Fixed trajectories (b) Imitation Learning (c) Ours

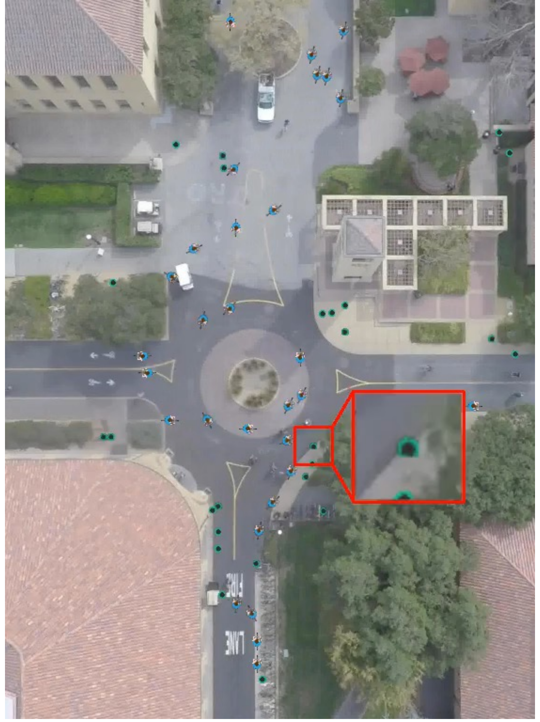
A (never seen before) vehicle attempts to drive through a crowd with different pedestrian models.

Ours

PS-GAIL [Bhattacharyya 18]



Ours



PS-GAIL

Ours

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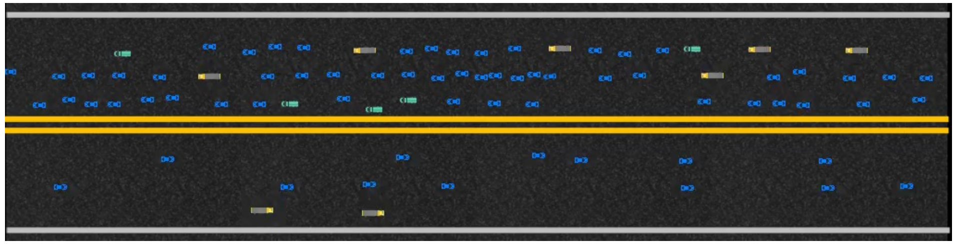

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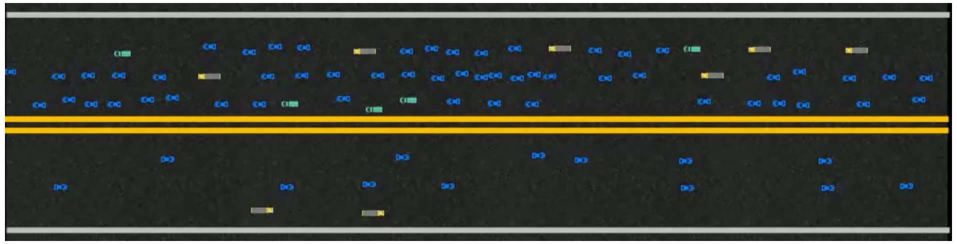

PS-GAIL

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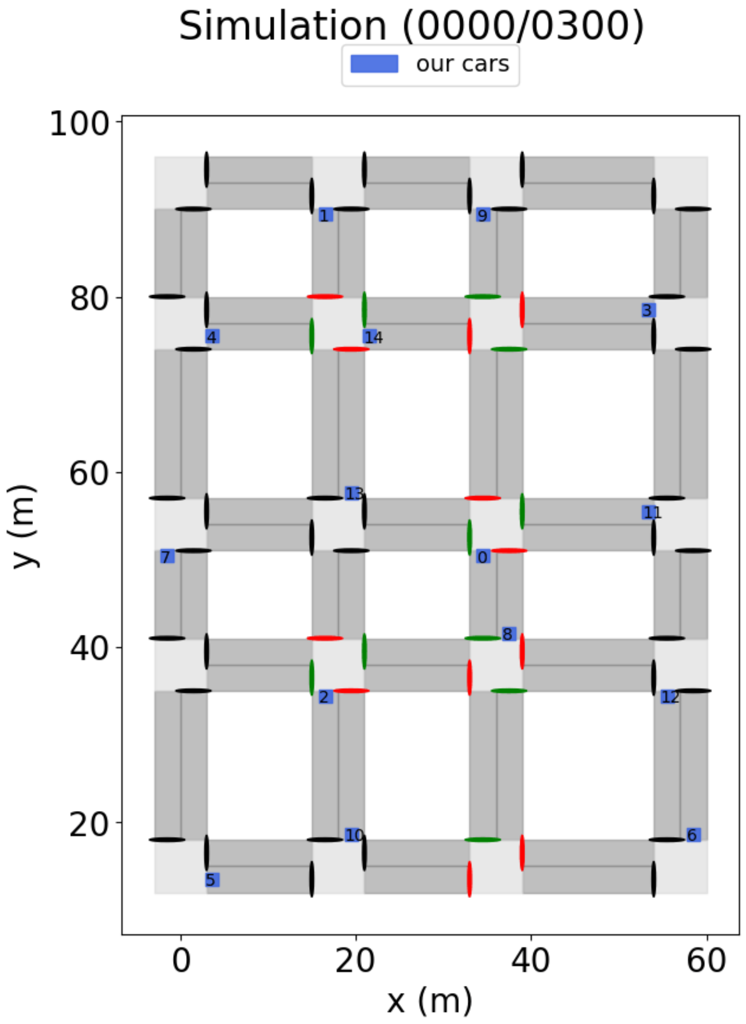

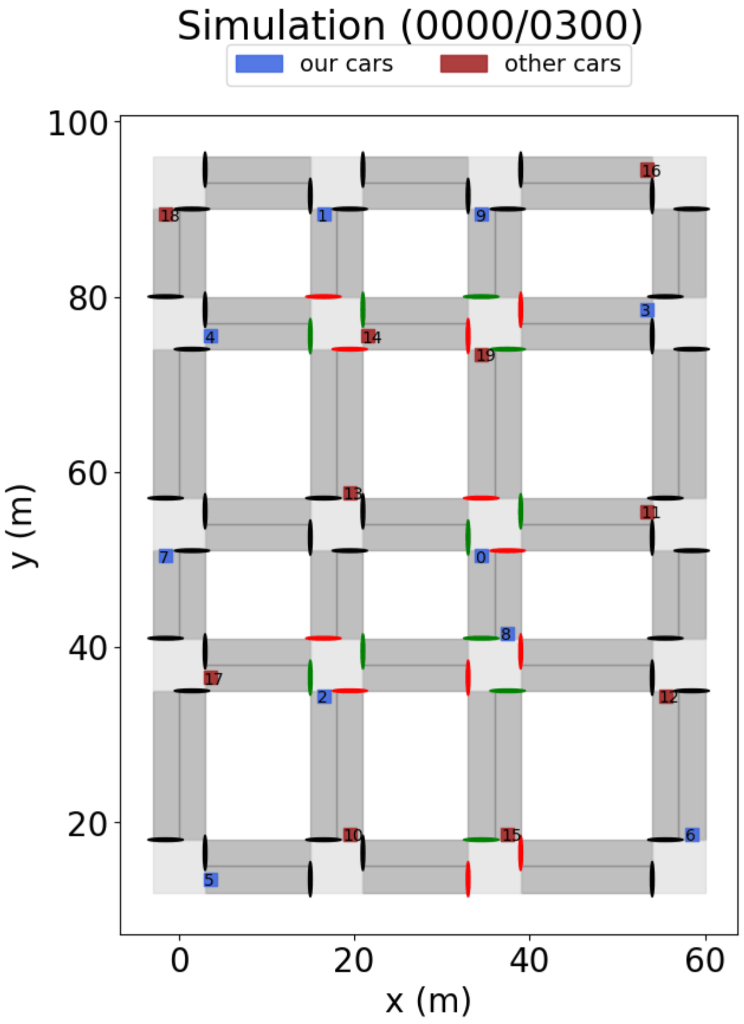

We can also insert traffic rules such as safety, stop signs, and traffic lights as neural certificates to each learned model.

Deployed on a more complex traffic scene, our agents always follow the traffic rules.

References

S. Zhang, K. Garg, and C. Fan, "Distributed Safe Multi-agent Control Using Neural Graph Control Barrier Functions." *Conference on Robot Learning,* 2023.

C. Dawson, Z. Qin, S. Gao, and C. Fan, "Safe nonlinear control using robust neural Lyapunov-barrier functions." Conference on Robot Learning, 2021.

Y. Meng, Z. Qin, and C. Fan, "Reactive and Safe Road User Simulations Using Neural Barrier Certificates." International Conference on Intelligent Robots and Systems, 2021.

C. Dawson, S. Gao, and C. Fan, "Safe Control with Learned Certificates: A Survey of Neural Lyapunov, Barrier, and Contraction Methods for Robotics and Control." *IEEE Transactions on Robotics*, 2023.

Realm Group

Realm GitHub

Neural certificates for automotive systems

Neural certificates provide a quantifiable way to certify learning-based control from sensor inputs.

Controllers from neural certificates can be designed to be robust, online, and adaptive.

Neural certificates can provide fully decentralized, scalable, and generalizable collision-avoidance control for vehicles.

Neural certificates can capture some human intents when building models for other road participants.

And many more applications using neural certificates!