Uncertainty-Aware Distributionally Robust Model Predictive Control for Safe Autonomous Driving

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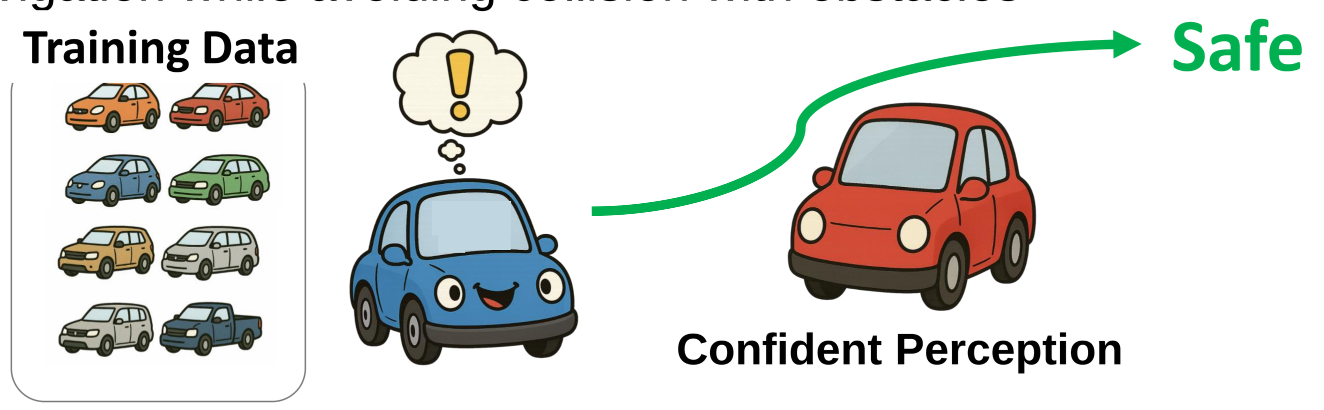
TL;DR

- We propose DRO-EDL-MPC, a **distributionally robust MPC** that leverages **evidential deep learning (EDL)** to **dynamically adjust conservativeness** based on perception uncertainty.

Introduction

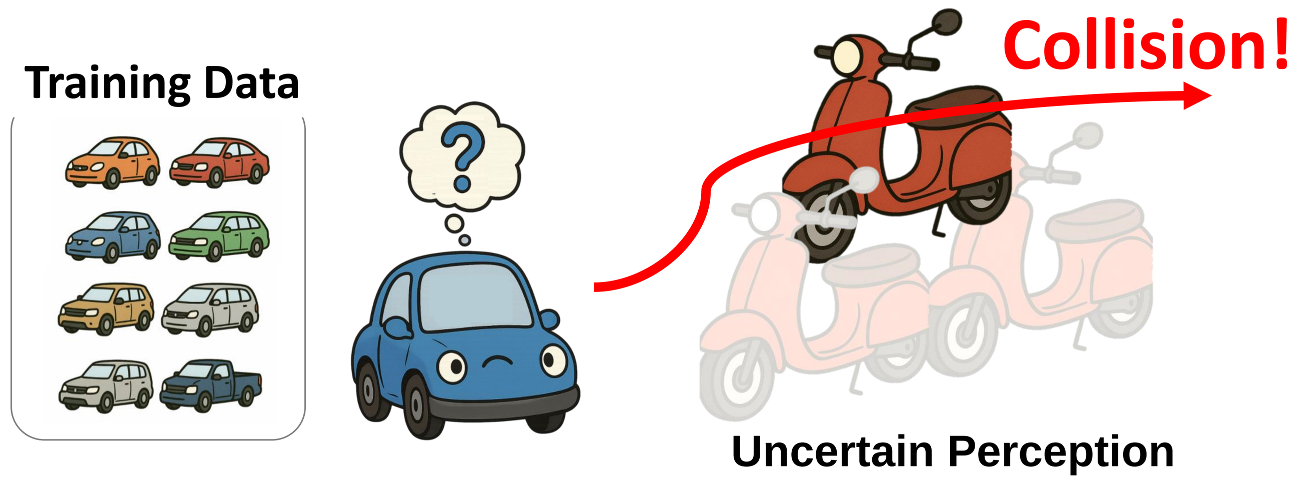
Goal

- Navigation while avoiding collision with obstacles



Challenges: Uncertainties in the Real World

- **Uncertain perception** leads to **failure in collision avoidance**



Motivation

- **We consider the uncertainty distribution** of perception results to utilize for use in **distributionally robust collision avoidance** control.

Problem Formulation

$$\min_{\mathbf{u}} \sum_{t=0}^{T-1} c(\mathbf{x}(t),\mathbf{u}(t)) + q(\mathbf{x}(T))$$

$$\text{s.t.}\quad \mathbf{x}(t)\in\mathbb{X},\ \forall t\in\mathbb{Z}_{0:T},\quad \mathbf{u}(t)\in\mathbb{U},\ \forall t\in\mathbb{Z}_{0:T-1}$$

$$\mathbf{x}(t+1) = f(\mathbf{x}(t),\mathbf{u}(t)) + g(\mathbf{x}(t),\mathbf{u}(t)),\ \forall t\in\mathbb{Z}_{0:T-1}$$

$$\max_{\mathbb{P}\in\mathbb{D}} \mathrm{CVaR}_{\epsilon}^{\mathbb{P}}[\ell(\mathbf{x}(t),\xi)] \le 0,\ \forall t\in\mathbb{Z}_{0:T}.$$

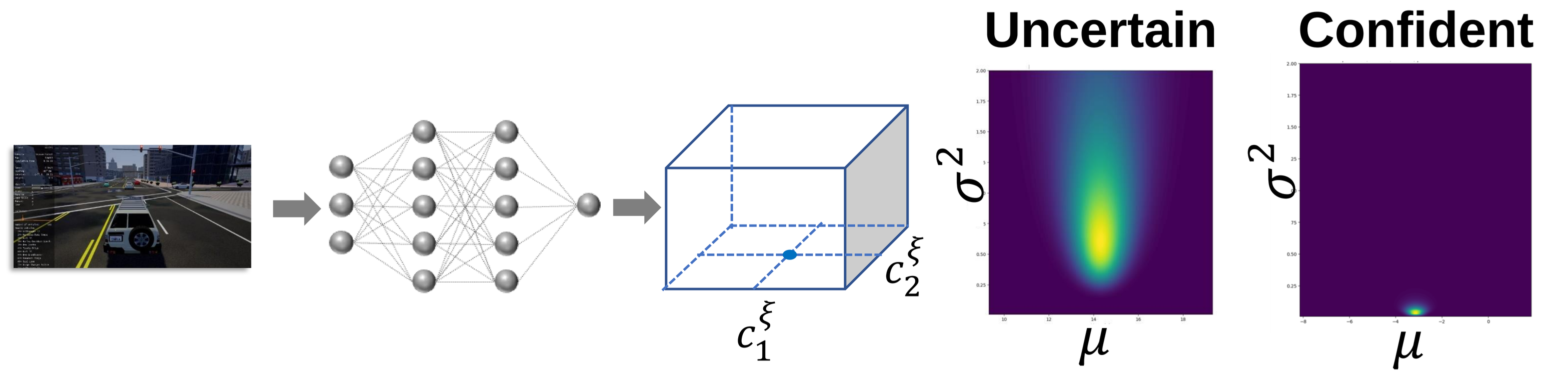
x: *ego state* c: *stagewise cost* f: *nominal dynamics* ℓ: *safety loss*
u: *control input* q: *terminal cost* g: *unknown dynamics* ξ: *obstacle state*
$\mathbb{P}$: *obstacle distribution* $\mathbb{D}$: *ambiguity set*

- **Safety constraint:** $\ell(x,\xi) = (r^x - r^\xi)^2 - \|c^x - c^\xi\|_2^2 \le 0$

r^x, r^ξ: *radii of the ego, obstacle vehicles*
$\mathbf{c}^x \coloneqq (c_1^x, c_2^x)$: *coordinates of the center of ego vehicle*
$\mathbf{c}^\xi \coloneqq (c_1^\xi, c_2^\xi)$: *coordinates of the center of obstacle vehicle*

Method

Evidential Deep Learning-based Perception



(a) Object detection procedure (Center position $c_i^\xi \sim \mathbb{P}_i \coloneqq \mathcal{N}(\mu,\sigma^2)$) (b) Uncertainty distribution of obstacle position ($\mathbb{P}_i \in \mathbb{D}_i$)

EDL-based Ambiguity Set

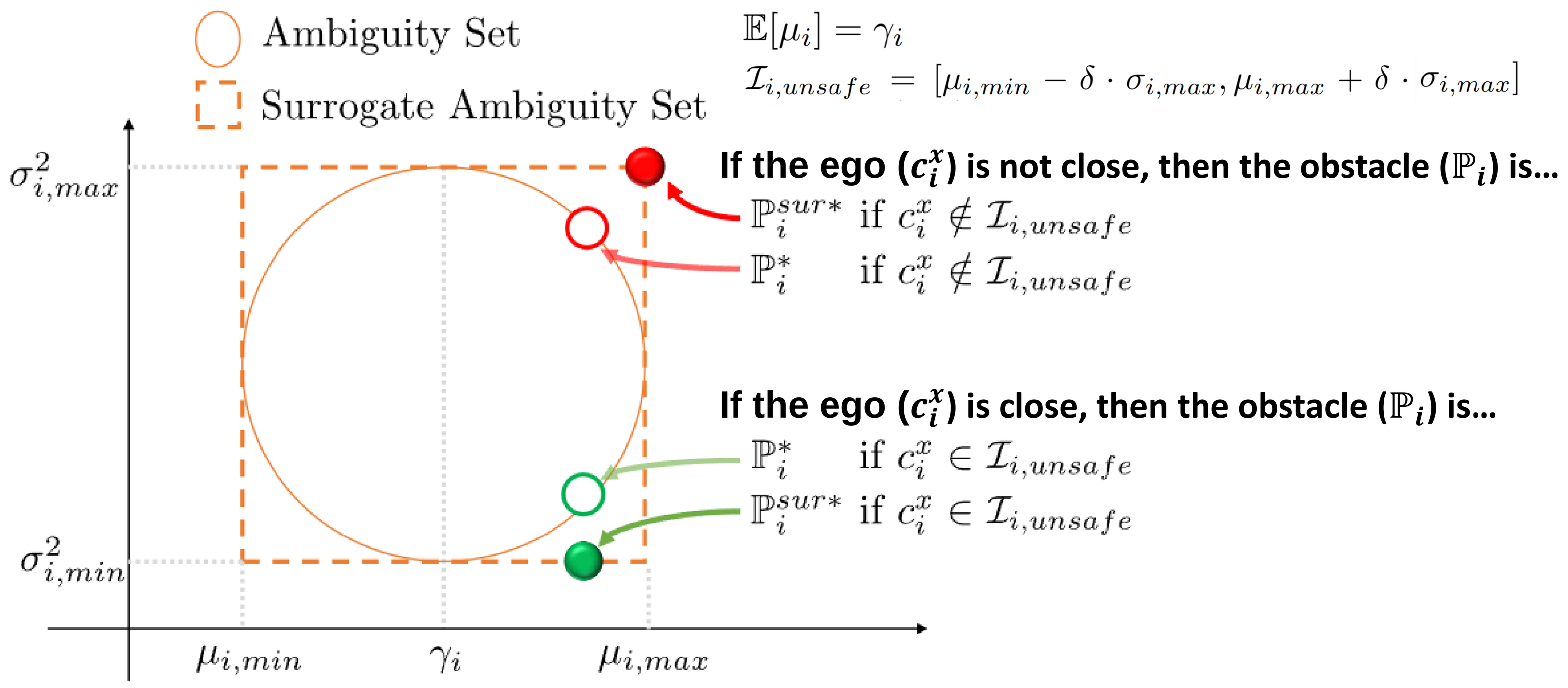
Definition 1

$$\mathbb{D}_i(\eta_i|m_i) \coloneqq \left\{ \mathcal{N}(\mu,\sigma^2) \,\middle|\, \int_{\theta=(\mu,\sigma^2)} NIG(\theta|m_i)d\theta = \eta_i \right\}$$

Definition 3

$$\mathcal{I}_{i,\mu} \coloneqq [\mu_{i,min}, \mu_{i,max}],\ \mathcal{I}_{i,\sigma^2} \coloneqq [\sigma^2_{i,min}, \sigma^2_{i,max}]$$

$$\mathbb{D}_i^{sur}(\eta_i|m_i) \coloneqq \{\mathcal{N}(\mu,\sigma^2) : \mu\in\mathcal{I}_{i,\mu}, \sigma^2\in\mathcal{I}_{i,\sigma^2}\}$$

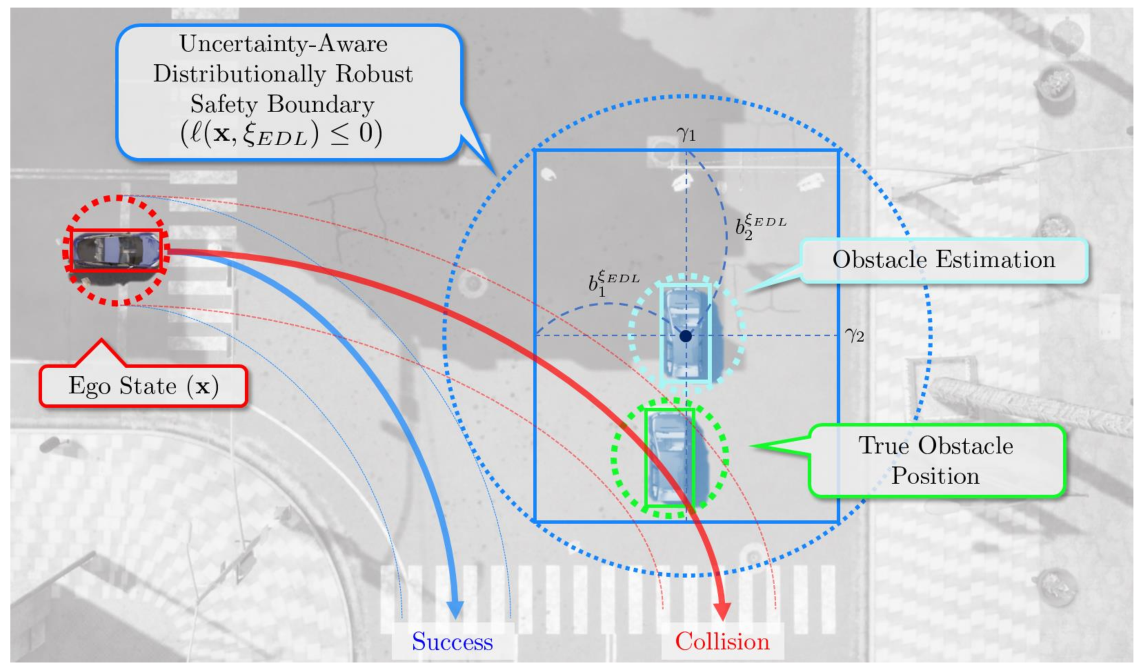


- Based on the **worst-case obstacle position** $\mathbb{P}^{sur*}$, we construct a **conservative obstacle state representation** ξ_{EDL}.

Conservative Constraint for Tractable MPC

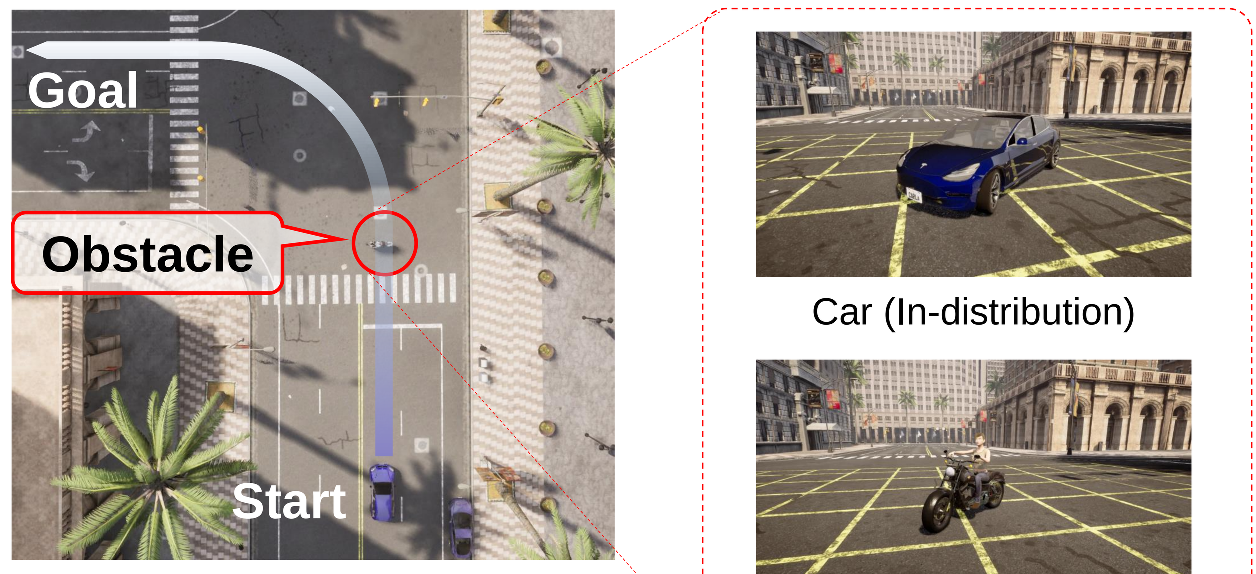
Theorem 1

$$\max_{\mathbb{P}\in\mathbb{D}} \mathrm{CVaR}_{\epsilon}^{\mathbb{P}}[\ell(\mathbf{x}(t),\xi)] \le 0 \Rightarrow \ell(\mathbf{x}(t),\xi_{EDL}) \le 0$$



Experiments

Experimental Settings



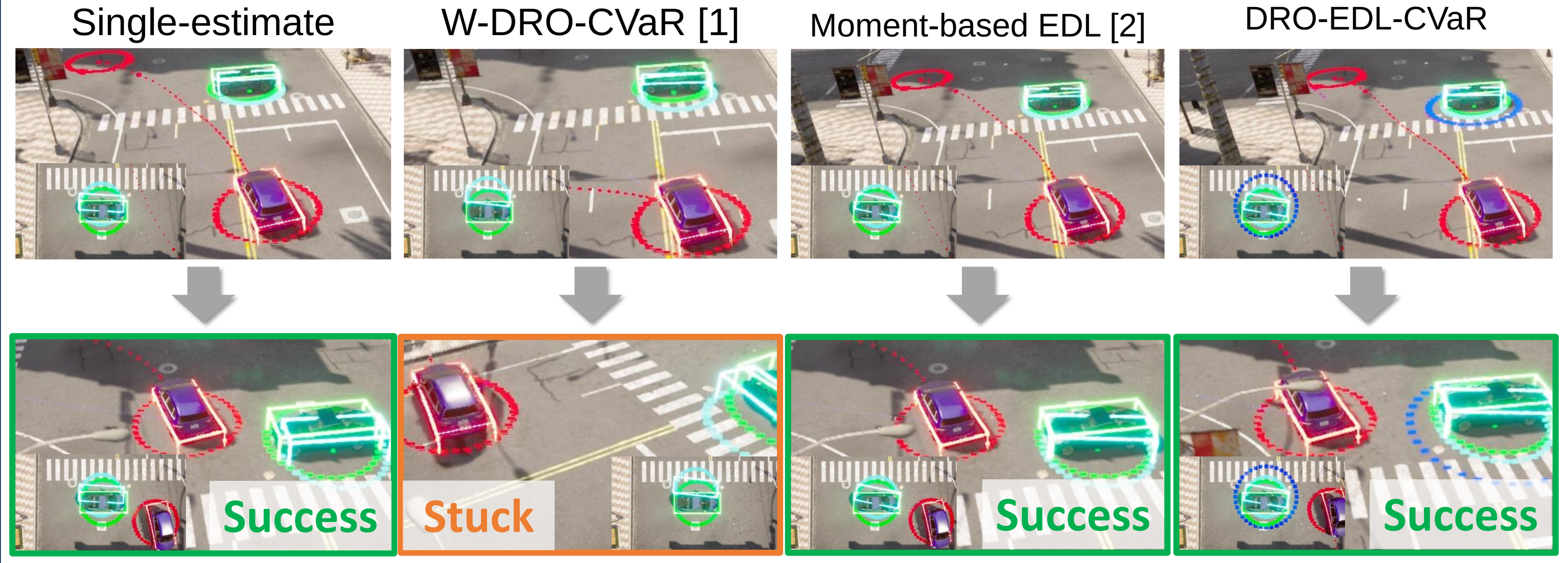
Driving environment (CARLA simulator)

Car (In-distribution)

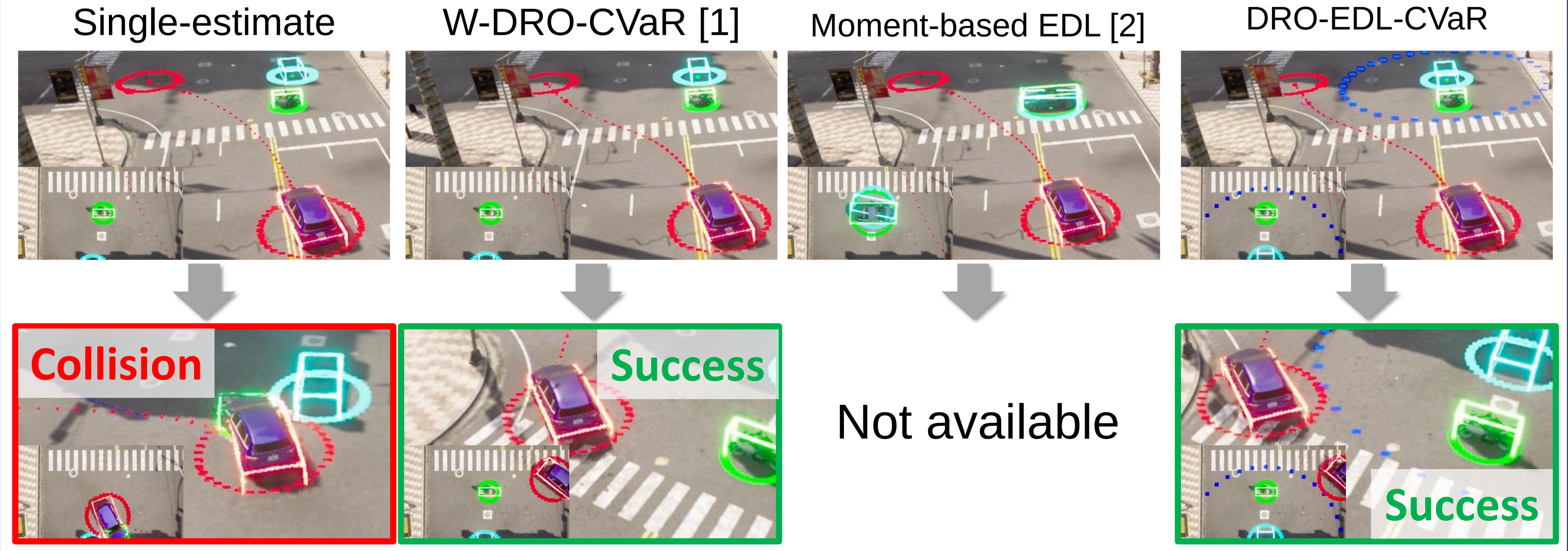
Motorcycle (Out-of-distribution)

Experimental Results

Confident prediction (In-distribution)



Uncertain prediction (Out-of-distribution)



Ground Truth Prediction (Proposed) Distributionally Robust Safety Boundary

References

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[2] Q. Wang, L. Pan, L. Heistrene, and Y. Levron, "Signal-Devices Management and Data-Driven Evidential Constraints Based Robust Dispatch Strategy of Virtual Power Plant," Expert Syst. Appl.,vol. 262, 2025.

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