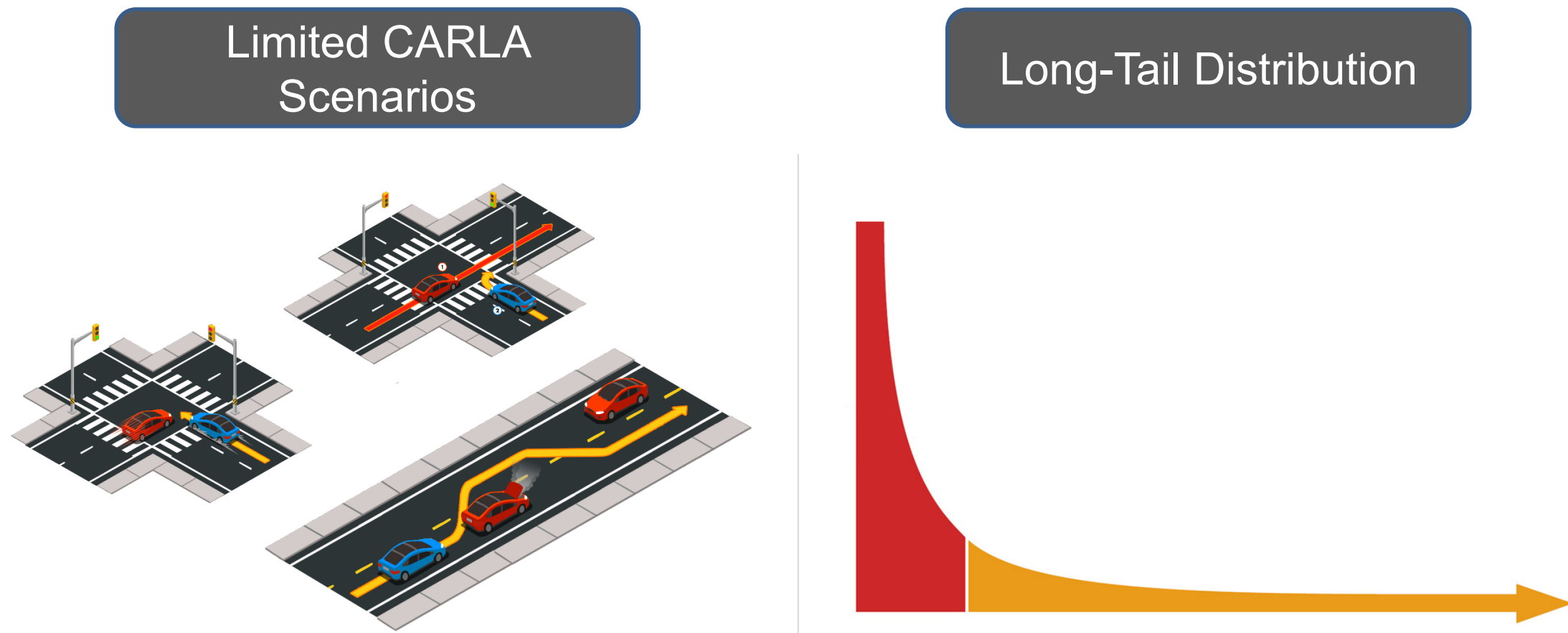


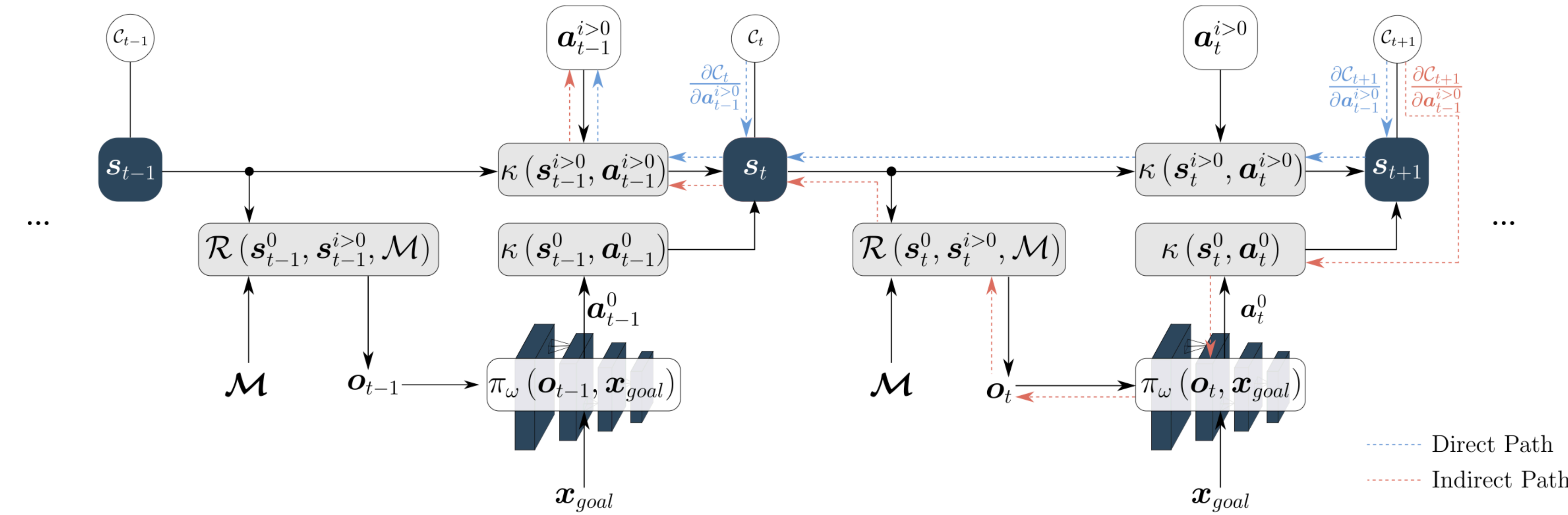
Motivation

Problem: Critical driving scenarios are extremely rare and *underrepresented* in real world data. Simulation is a promising solution but limited by *hand-crafted behavior* that does not permit the necessary *diversity*.

Goal: Efficiently generate safety-critical driving scenarios via optimization and use them to *augment* regular data to improve brittle driving policies.



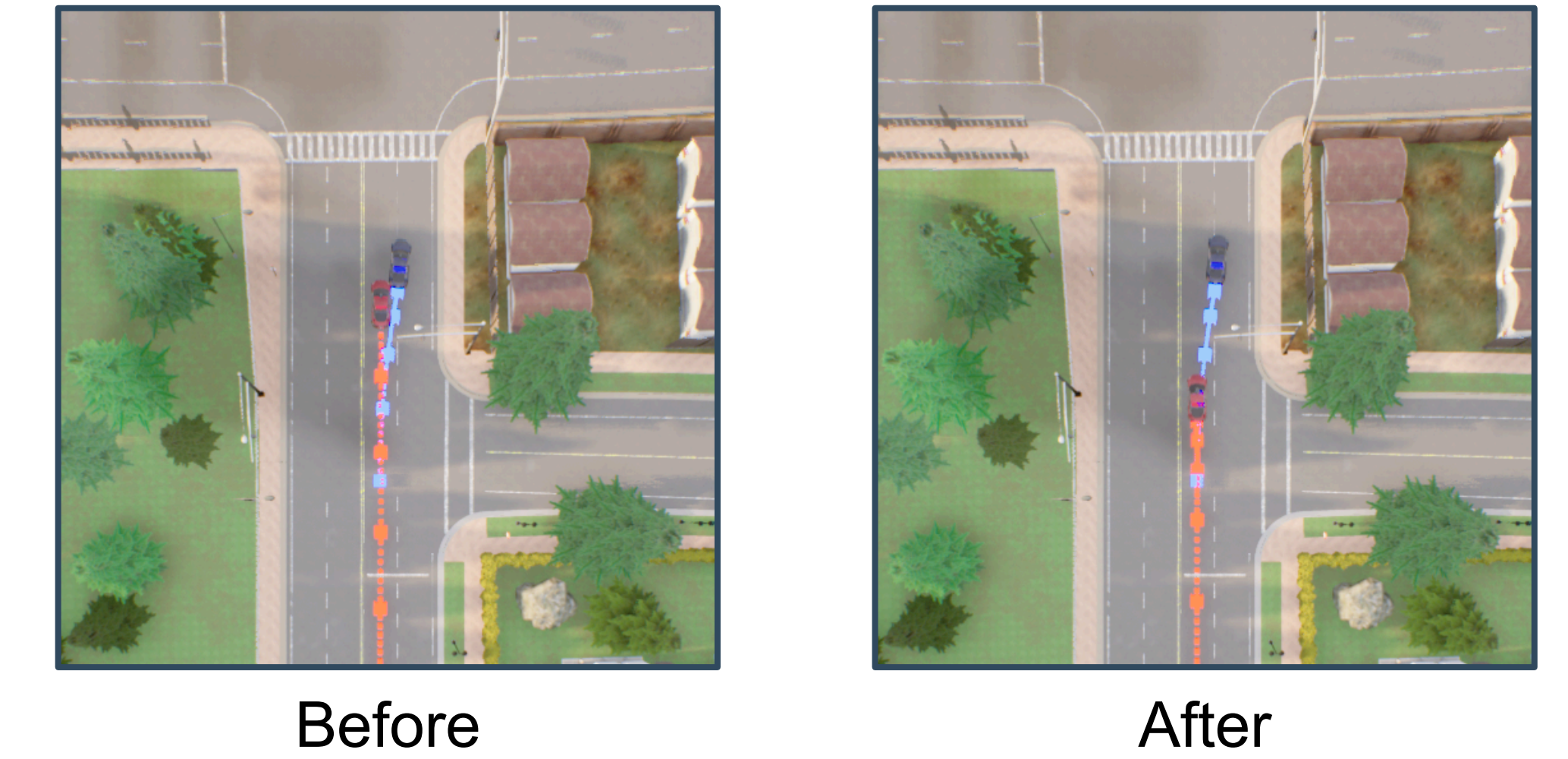
Optimization via Kinematics Gradients



Key Idea: Consider partial derivatives through the direct path only. This has two main advantages:

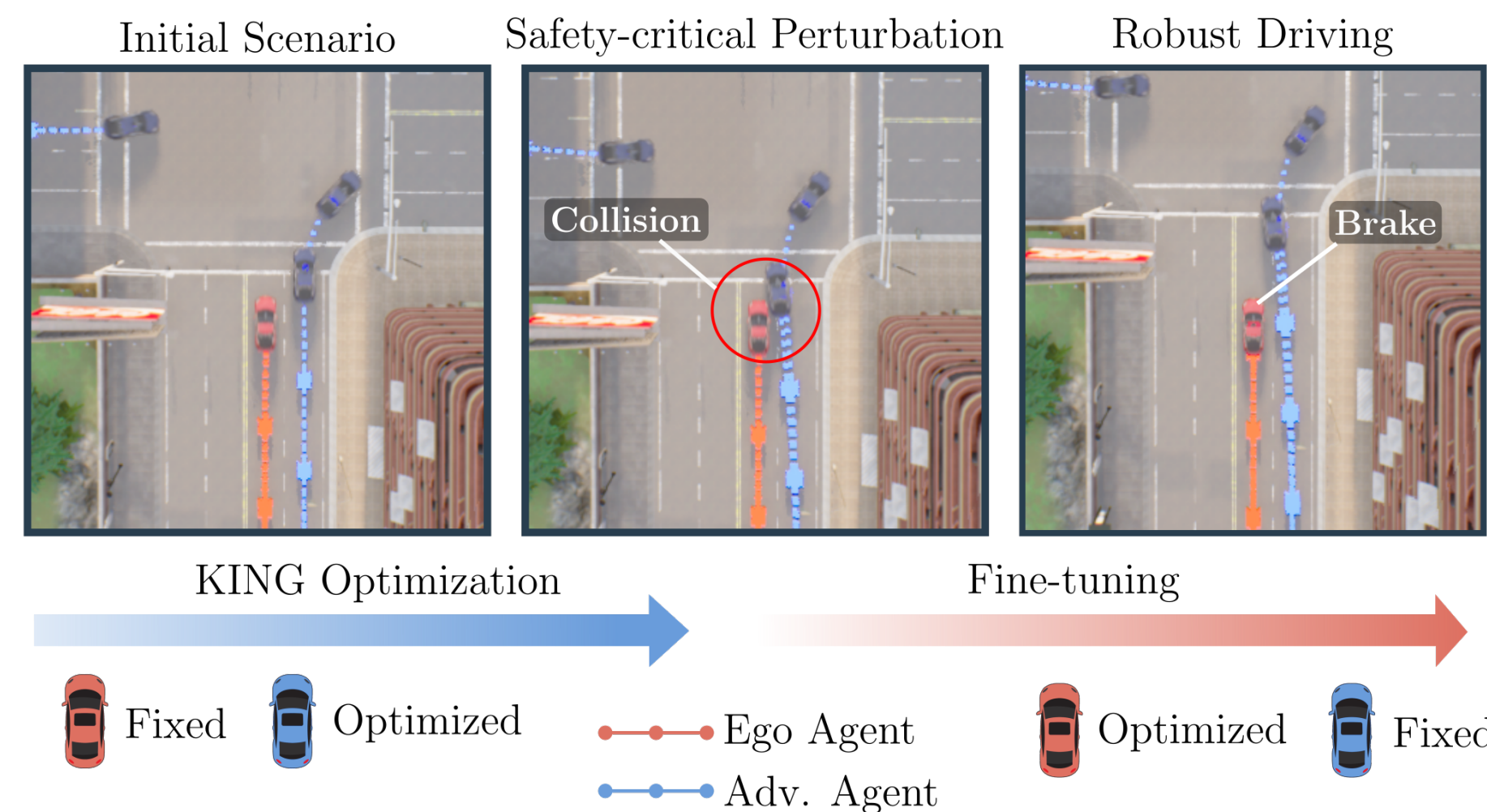
- > Renderer and driving model can be non-differentiable.
- > The backward pass is significantly less expensive.

Improved Robustness

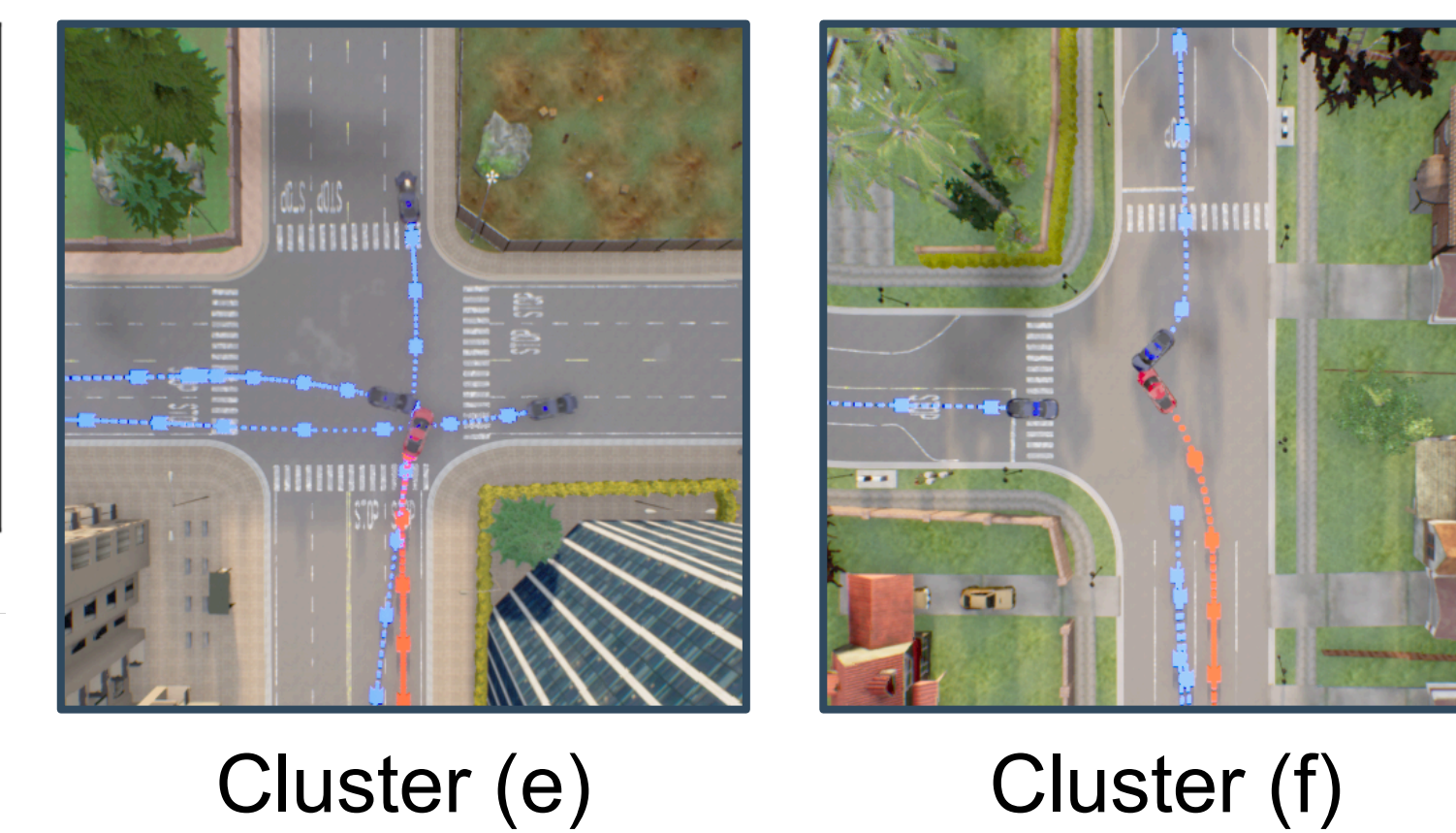
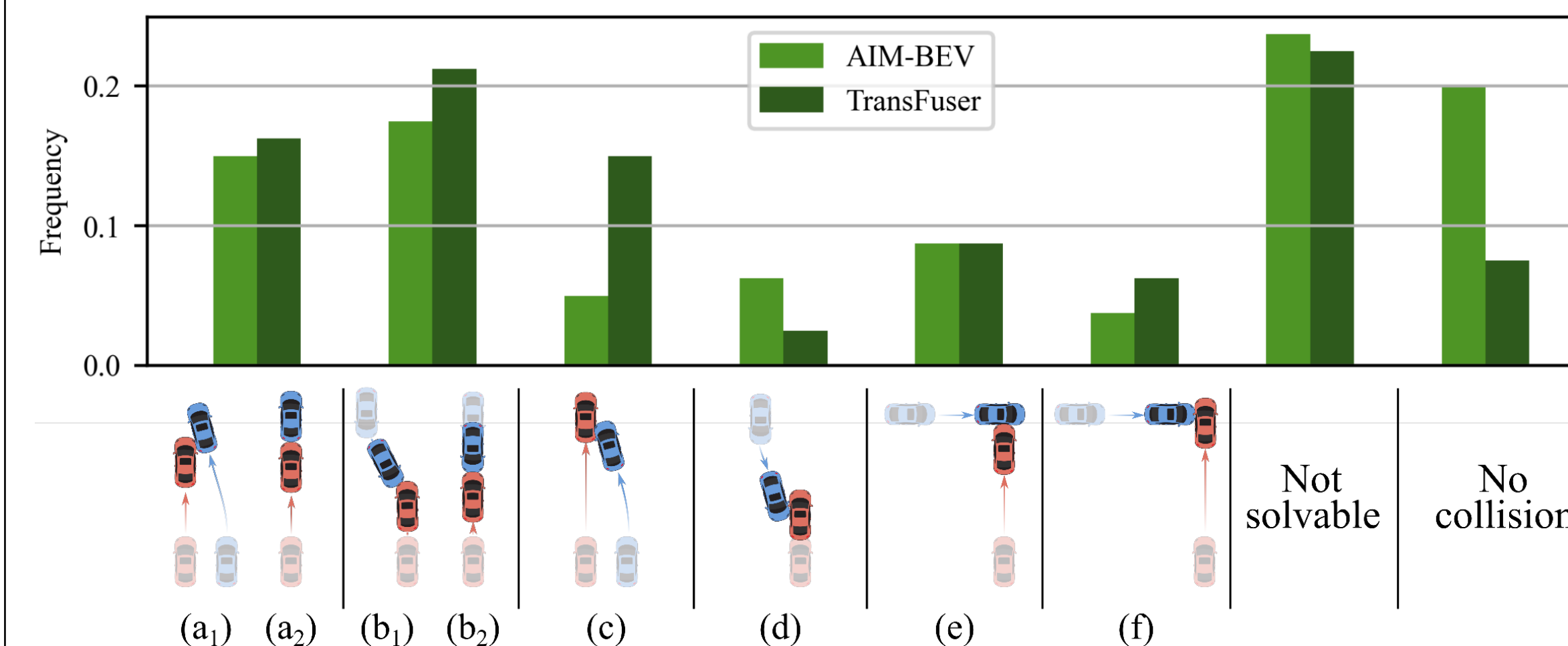


	Held-out KING scenarios	CARLA scenarios	
Dataset	CR ↓	DS ↑	CR ↓
No Fine-tuning	100.00±0.00	86.74±0.67	17.48±1.86
\mathcal{D}_{reg}	57.14±0.00	86.85±0.62	19.51±0.00
$\mathcal{D}_{crit} \cup \mathcal{D}_{reg}$	28.57±0.00	90.20±0.00	8.13±0.70

Procedure



Generation of Diverse, Safety-Critical Scenarios



Better and Faster

	4 Agents			Avg. {1,2,4} Agents		
Method	CR ↑	$t_{50\%}$ ↓	s/it ↓	CR ↑	$t_{50\%}$ ↓	s/it ↓
Random Search	68.75	15.22	1.48	66.67	9.66	1.38
Bayesian Optimization	63.75	22.12	2.06	65.00	14.34	1.73
SimBA [1]	61.25	19.68	1.48	64.17	15.84	1.38
CMA-ES [2]	62.50	9.39	1.52	68.33	8.17	1.40
Bandit-TD [3]	21.25	-	5.02	29.58	-	4.43
KING (ours)	78.75	6.40	2.03	82.50	7.78	1.90

[1] Guo et al., "Simple black-box adversarial attacks", ICML 2019
 [2] Hansen et al., "Completely derandomized self-adaptation in evolution strategies", Evolutionary Computing 2001
 [3] Ilyas et al., "Prior convictions: Black-box adversarial attacks with bandits and priors", ICLR 2019

