CausalAF: Causal Autoregressive Flow for Safety-Critical Driving Scenario Generation

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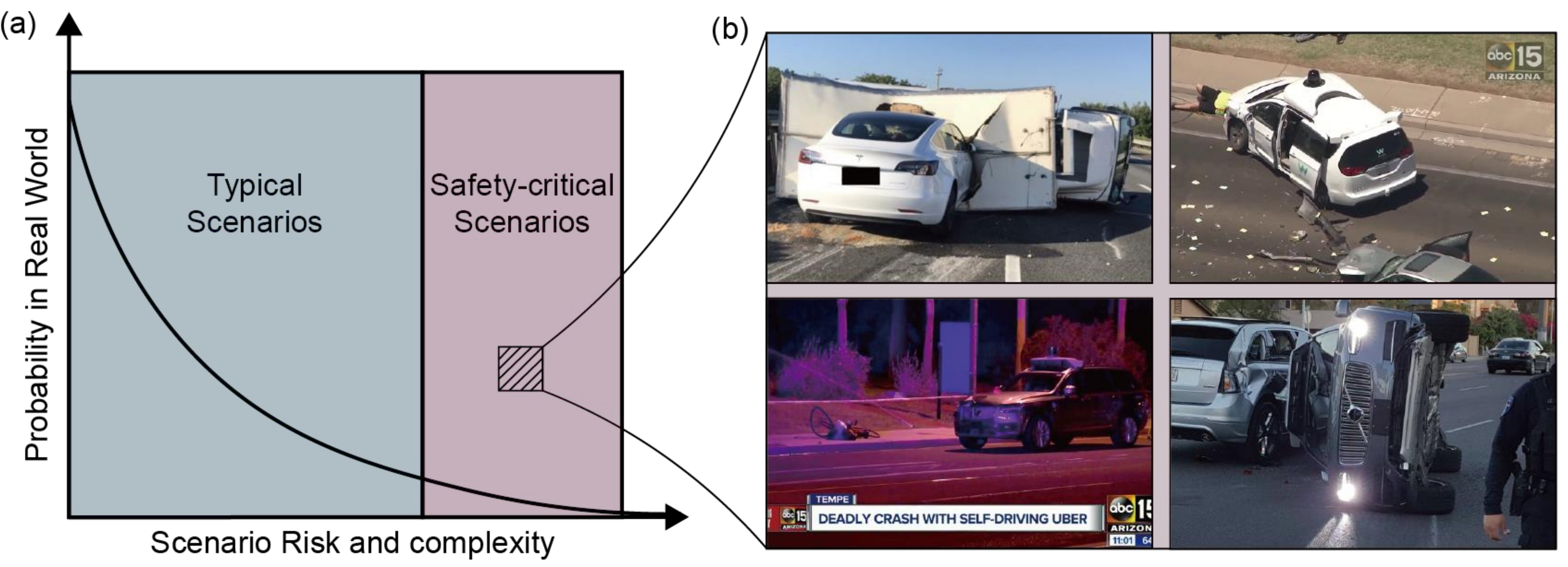
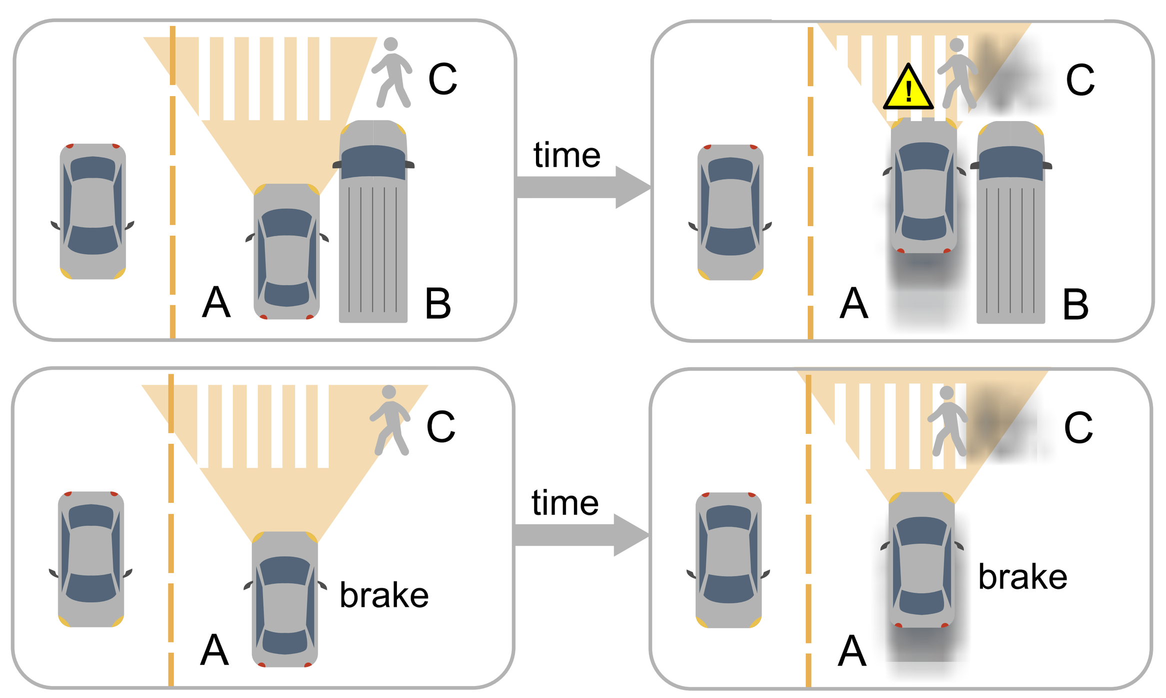
Motivation



- Autonomous Vehicles (AV) are usually developed and evaluated in typical scenarios, which are not enough for safety purpose.
- Adversarial Generation is one way to generate safety-critical scenarios as explored in existing works.
- However, adversarial attack is inefficient and lack of diversity.
- In this paper, we investigate how **causality** increases the efficiency.

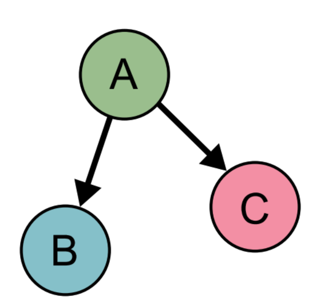
Safety-critical because the view of vehicle A is blocked by vehicle B

Not safety-critical if we remove vehicle B



Representation of Scenario

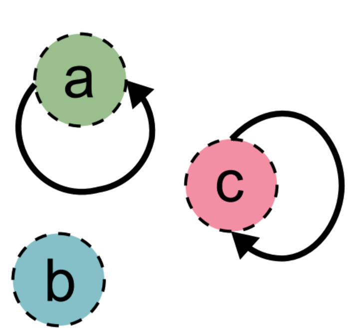
- Causal Graph (CG) $\mathcal{G}^C = (V^C, E^C)$



$$p(x_1, ..., x_n) = \prod_{j=1}^{n} p_j(x_j | \mathbf{pa}(x_j))$$

Assume global Markov property

- Behavioral Graph (BG) $\mathcal{G}^B = (V^B, E^B)$

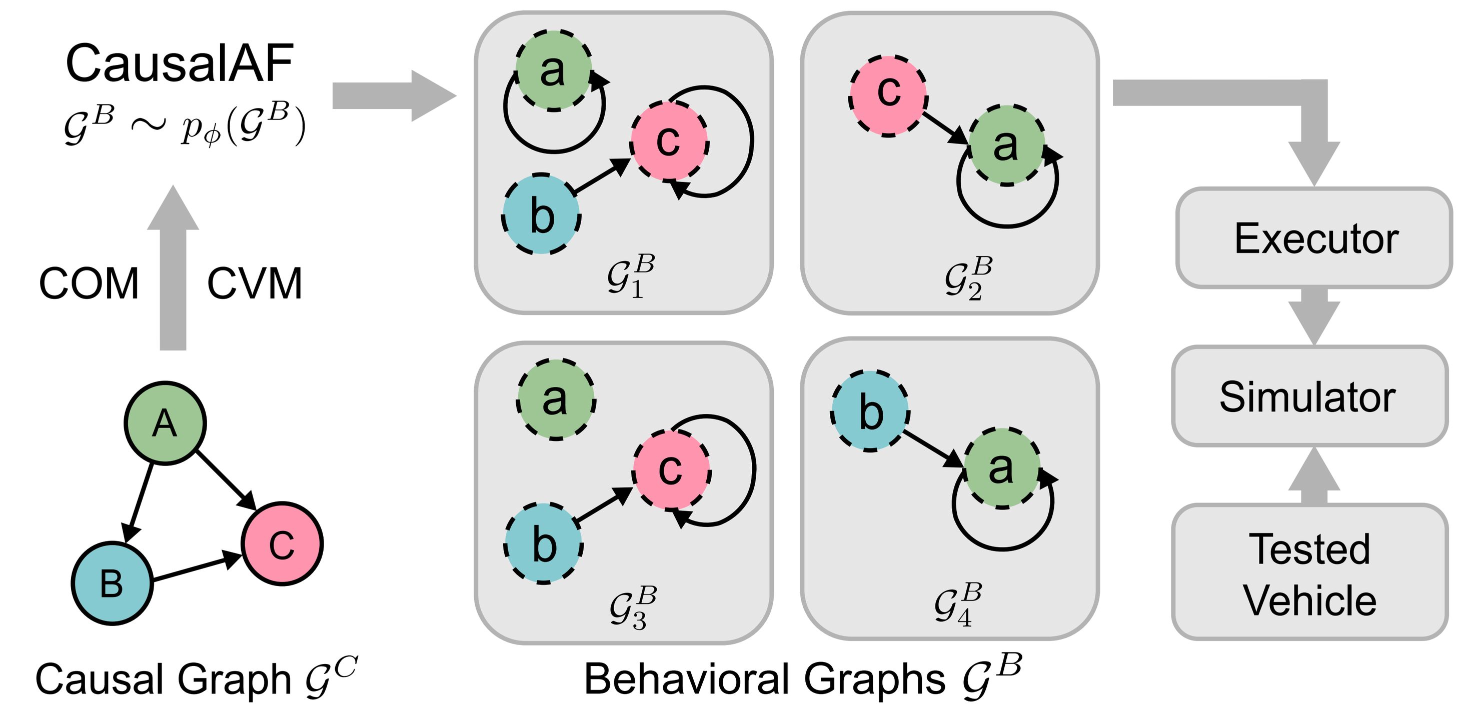


(i, i) means independent action

(i, j) means i influence j

Proposed Method (CausalAF)

1. High-level Framework



Use Normalizing flow as generative model

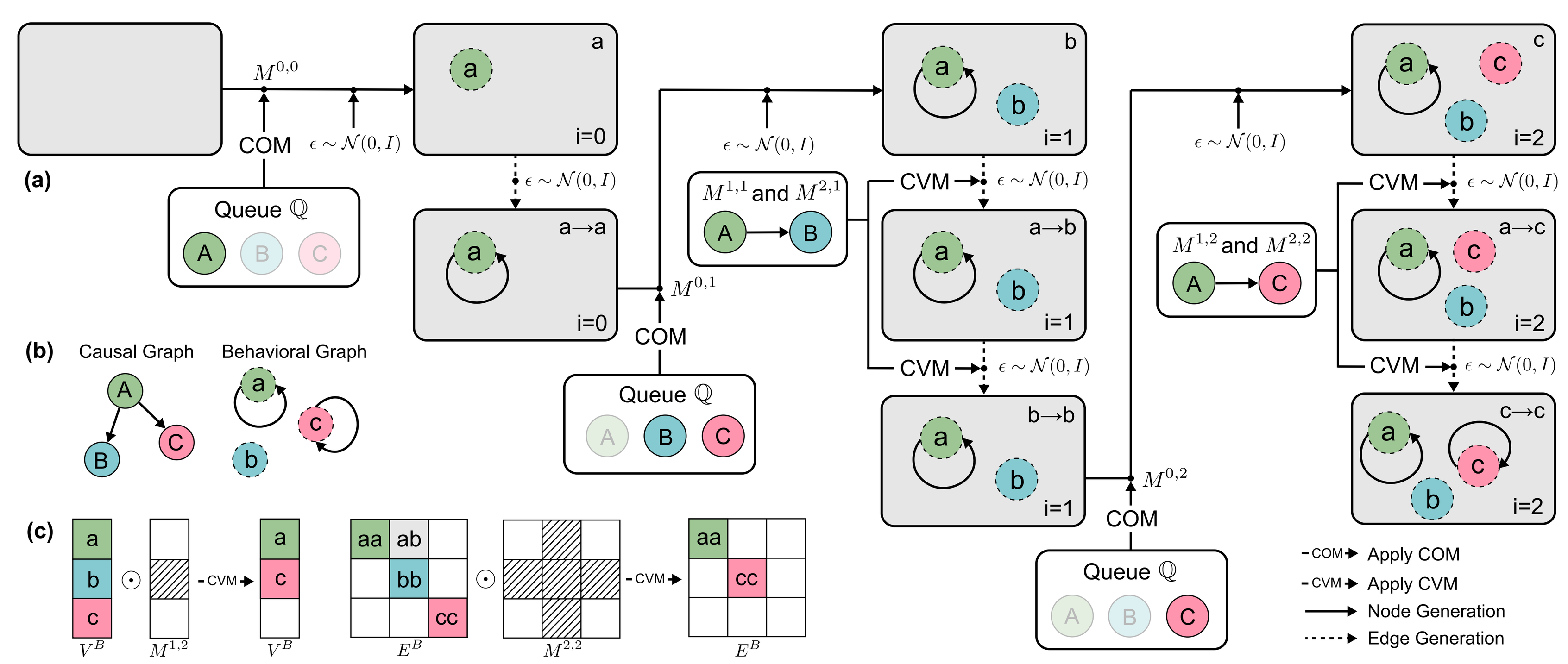
$$p_{\boldsymbol{x}}(\boldsymbol{x}) = p_0(f^{-1}(\boldsymbol{x})) \left| \det \frac{\partial f^{-1}(x)}{\partial \boldsymbol{x}} \right|$$

$$\boldsymbol{x} = \boldsymbol{z}_K = f_K^{-1} \circ f_{K-1}^{-1} \circ \cdots \circ f_0^{-1} = \mathcal{M}_\phi^{-1}(\boldsymbol{z}_0), \quad \boldsymbol{z}_0 \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$$

Node generation $\quad V^B[i,:] \sim \mathcal{N}\left(\mu_i^v, (\sigma_i^v)^2\right) = \mu_i^v + \sigma_i^v \odot \epsilon$

Edge generation $\quad E^B[i,j,:] \sim \mathcal{N}\left(\mu_{i,j}^e, (\sigma_{i,j}^e)^2\right) = \mu_{i,j}^e + \sigma_{i,j}^e \odot \epsilon$

2. Autoregressive Generation



Causal Graph works as two masks

- Causal Ordering Mask (COM) $M^o(\mathcal{G}^C)$

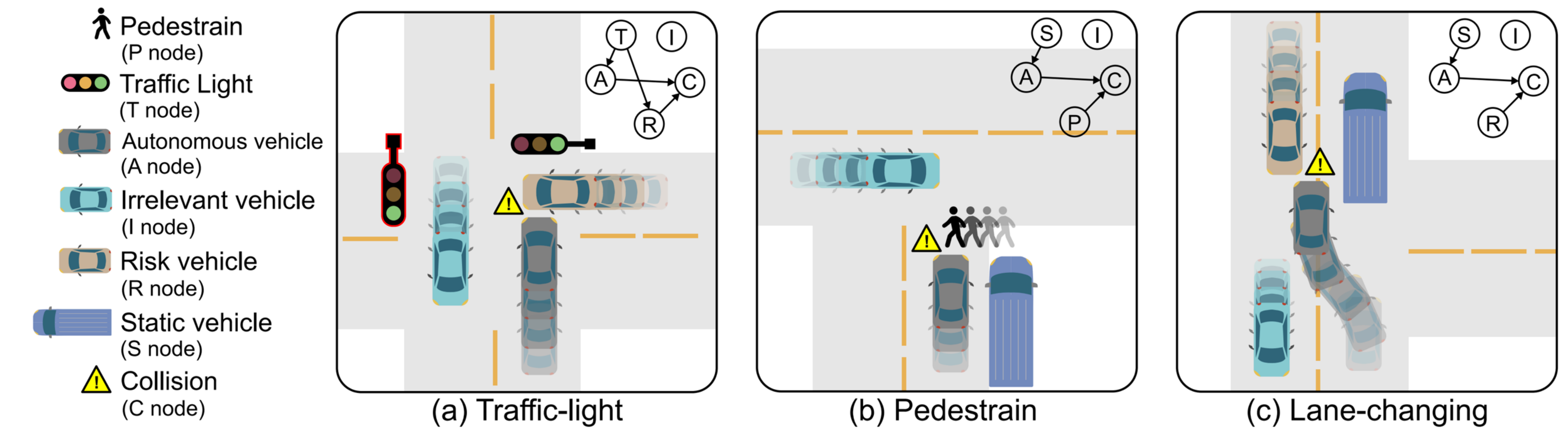
One-hot mask $\quad v_i = \arg\max(M^o(\mathcal{G}^C) \odot \mathrm{softmax}(V^B[i,:]))$

- Causal Visibility Mask (CVM) $M^x(\mathcal{G}^C)\ M^e(\mathcal{G}^C)$

Mask out non-cause nodes $\quad V^B(t) = V^B(t) \odot M^x(\mathcal{G}^C)$

$$E^B(t) = E^B(t) \odot M^e(\mathcal{G}^C)$$

Environment Scenario



Traffic-light. One potential safety-critical event could happen when the traffic light T turns from green to yellow to give the road right to an autonomous vehicle A.

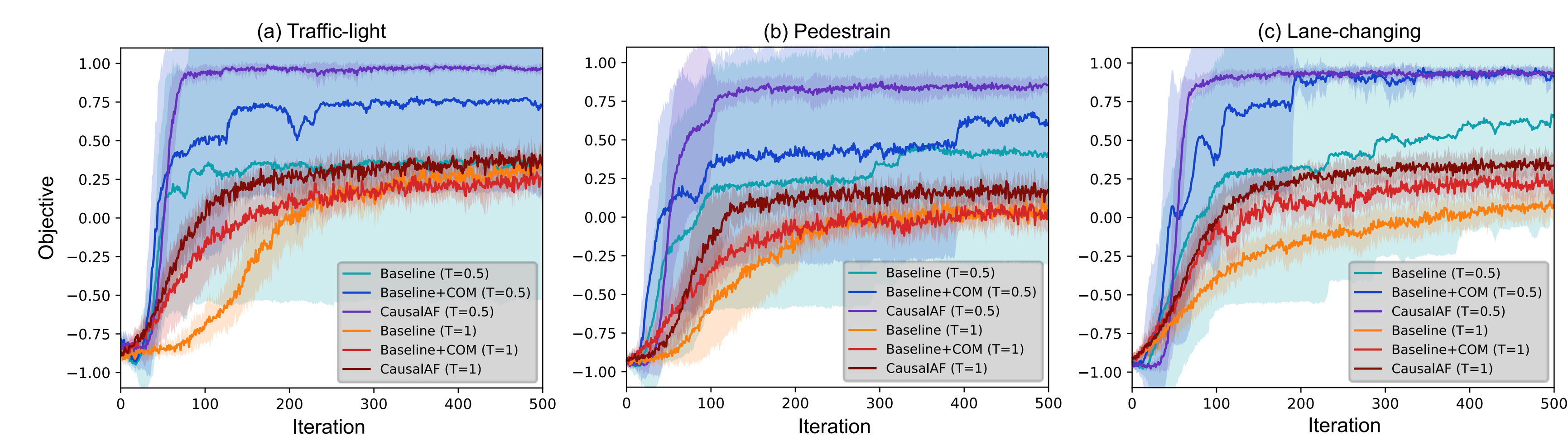
Pedestrian. A pedestrian P and an autonomous vehicle A are crossing the road in vertical directions.

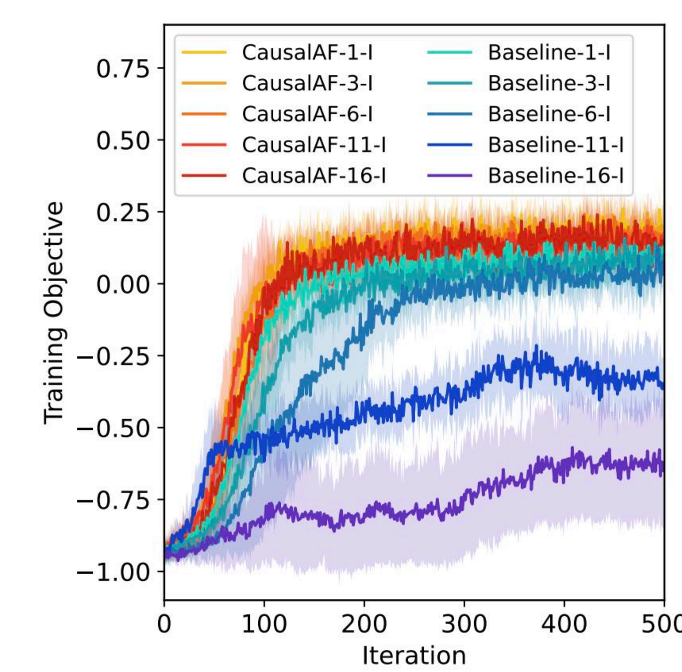
Lane-changing. An autonomous vehicle A takes a lane-changing behavior due to a static car S parked in front of it. Meanwhile, a vehicle R drives in the opposite lane.

Experiment

Table 1: Results of safety-critical scenario generation. **Bold** font means the best.

Environment	L2C [5]	MMG [4]	SAC [15]	Baseline	Baseline+COM	CausalAF
Traffic-light	0.63±0.28	0.31±0.54	0.47±0.61	0.29±0.84	0.69±0.52	**0.98±0.01**
Pedestrian	0.69±0.41	0.43±0.56	0.38±0.49	0.35±0.65	0.57±0.48	**0.83±0.13**
Lane-changing	0.85±0.10	0.56±0.36	0.58±0.41	0.53±0.69	0.88±0.04	**0.91±0.06**





- When the number of irrelevant vehicle increases, CausalAF shows larger advantages over the baseline

Evaluate 4 RL agents (trained with random or generated scenarios) on safety-critical scenarios.

Table 2: Comparison of RL algorithms evaluated on safety-critical scenarios

Method	Traffic-light Random	Traffic-light Generated	Pedestrian Random	Pedestrian Generated	Lane-changing Random	Lane-changing Generated
SAC [15]	0.35±0.23	**0.91±0.03**	0.30±0.41	**0.92±0.03**	0.49±0.37	**0.95±0.04**
PPO [16]	0.27±0.33	**0.86±0.10**	0.23±0.49	**0.80±0.12**	0.37±0.38	**0.92±0.04**
DDPG [17]	0.42±0.49	**0.89±0.07**	0.27±0.52	**0.85±0.09**	0.48±0.39	**0.95±0.02**
MBRL [18]	0.62±0.11	**0.98±0.02**	0.50±0.11	**0.97±0.01**	0.73±0.13	**0.98±0.01**