Safety-aware Causal Representation for Trustworthy Reinforcement Learning in Autonomous Vehicles

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Motivation

Autonomous driving systems…

- Desires safety & generalizability
- Lacks structural awareness of the world

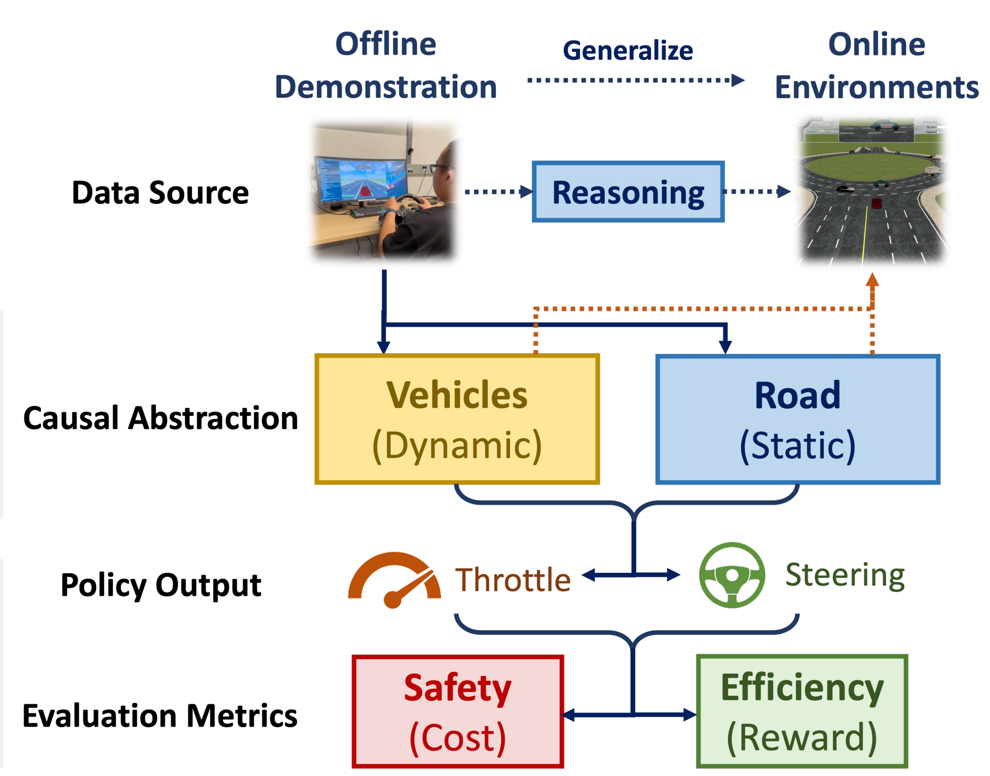
Existing approach along the pipeline…

- End-to-end solutions that are scalable?
- Balance safety and efficiency?

Simulator: *CARLA, MetaDrive*
[Dosovitskiy et al., CoRL 17'], [Li et al., TPAMI 22']
Dataset: *Waymo, Argoverse*
[Sun et al., CVPR 20'], [Chang et al., CVPR 19']

Explicit: *CDL, GRADER*
[Wang et.al. ICML 22'], [Ding et al., NeurIPS 22']
Implicit: *DBC, Denoised MDP.*
[Zhang et al., ICLR 21'], [Wang et al., ICML 22']

Explicit Constraints: *InterFuser*
[Shao et.al. CoRL 22']
Value-based: *SaFormer, CPQ*
[Xu et al., AAAI 22'] [Zhang et al., ICLR 23']



Problem Formulation

Constrained optimization:

$$\max_{\pi} \; J_r(\pi,\omega) \qquad r = w_1^r r_{forward} + w_2^r r_{speed} + w_3^r r_{term}$$

$$s.t. \;\; J_c(\pi,\omega) \le \kappa_c \qquad c = w_1^c c_{collide} + w_2^c c_{out\_road} + w_3^c c_{speed}$$

Structured Causal Model

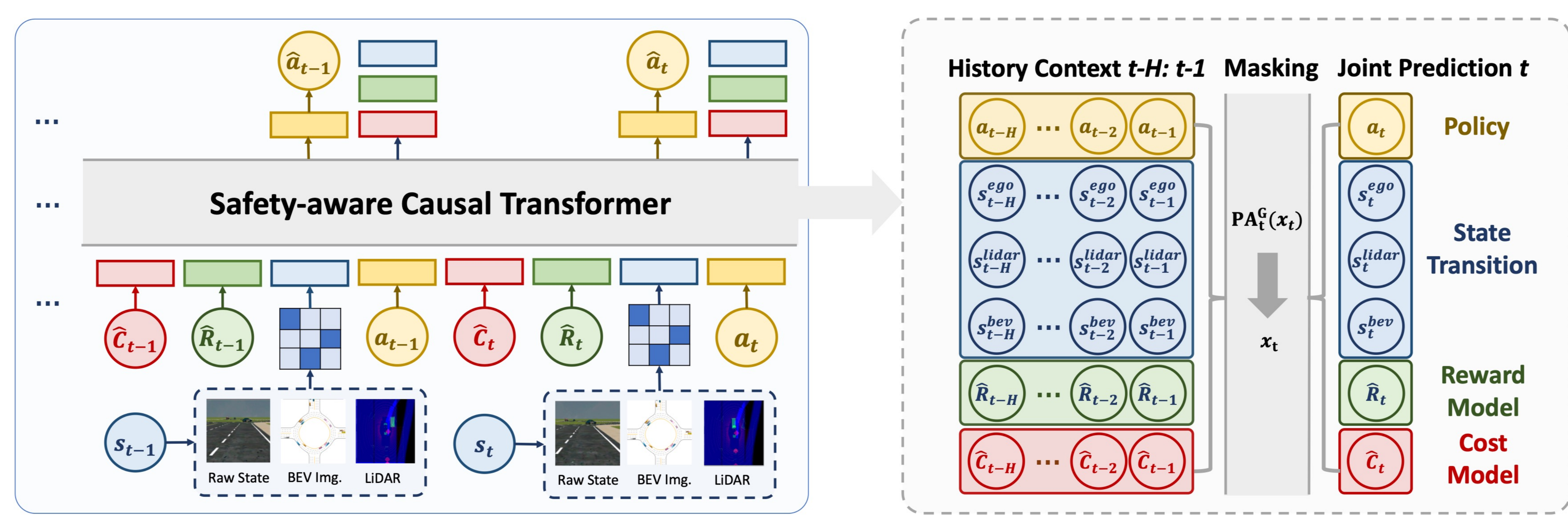
$$s_j := f_j(\mathbf{PA}^{\mathcal{G}}(s_j), \epsilon_j), \quad j \in [d],$$

Set of variables | Aggregation function | Parental Nodes in Causal Graph G | Exogenous Noise Variables

Methodology

FUSION: saFety-aware strUctural Scenario representatION

Step I: Causal Ensemble World Model



$$p(\tau_{t+1}|\tau_{t-K:t}) = p(a_{t+1}, s_{t+1}, R_{t+1}, C_{t+1}|a_t, s_t, R_t, C_t, \cdots)$$
$$= \underbrace{p\Big(r_t|\mathbf{PA}^G(r_t)\Big)}_{\text{Reward-to-go}} \underbrace{p\Big(c_t|\mathbf{PA}^G(c_t)\Big)}_{\text{Cost-to-go}}$$
$$\underbrace{\prod_{i\in\dim(S)} p(s^i_{t+1}|\mathbf{PA}^G(s^i_{t+1}))}_{\text{Factorized Dynamics}}$$
$$\underbrace{p(a_{t+1}|\mathbf{PA}^G(a_{t+1}))}_{\text{Policy Optimization}}$$

$$\mathcal{L}_{traj} = \log p(\tau_{t+1}|\tau_{t-K:t})$$
$$= \log p(r_t|\mathbf{PA}^G(r_t)) + \log p(c_t|\mathbf{PA}^G(c_t))$$
$$+ \sum_{i\in\dim(S)} \log p(s^i_{t+1}|\mathbf{PA}^G(s^i_{t+1}))$$
$$+ \log p(a_{t+1}|\mathbf{PA}^G(a_{t+1}))$$
$$= \underbrace{\mathcal{L}_{rtg}}_{\text{Reward Critic}} + \underbrace{\mathcal{L}_{ctg}}_{\text{Cost Critic}} + \underbrace{\mathcal{L}_{dyn}}_{\text{Transition Dynamics}} + \underbrace{\mathcal{L}_{act}}_{\text{Policy Optimization}}$$

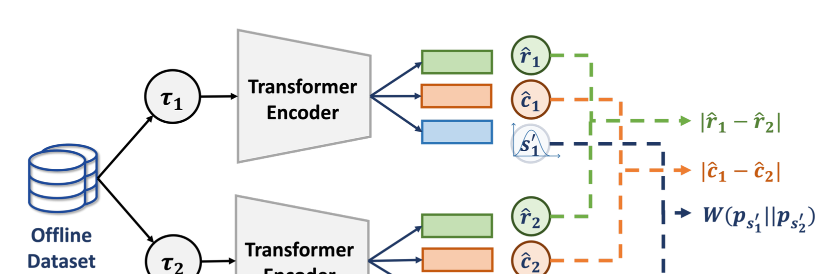
Step II: Causal Bisimulation Learning

Definition: Safety-aware Bisimulation Relationship

- $\forall a \in \mathcal{A}, r(s_1, a) = r(s_2, a)$
- $\forall a \in \mathcal{A}, c(s_1, a) = c(s_2, a)$
- $\forall a \in \mathcal{A}, s' \in \mathcal{S}, p(s'|s_1, a) = p(s'|s_2, a)$

Definition: Safety-aware Bisimulation Metrics

$$d^\pi(s_1, s_2) = \mathbb{E}_{\substack{a_1\sim\pi(\cdot|s_1),\\ a_2\sim\pi(\cdot|s_2)}} \Big[|r(s_1,a_1) - r(s_2,a_2)|$$
$$+ \lambda|c(s_1,a_1) - c(s_2,a_2)| + \gamma W_2(\hat{p}(\cdot|s_1,a_1), \hat{p}(\cdot|s_2,a_2))\Big]$$



Algorithm 1: Training and Inference of FUSION

Data: Context length H, Reward target R_0, Cost limit C_0
Result: Policy $\pi_{\theta,\phi}$
`/* Offline Training */`
for $k = 0, \cdots, N-1$ **do**
  Update Transformer θ with CEWM by (4);
  Update Encoder ϕ with CBL by Alg. 2;
`/* Online Inference with context H */`
$s_0 \leftarrow$ env.reset();
$\mathbf{o} \leftarrow \{C_0, R_0, s_0\}$;
$a_0 \leftarrow \pi_{\theta,\phi}(\mathbf{o})$;
for $t = 1, \cdots, T-1$ **do**
  Rollout: $s_t, r_t, c_t =$ env.step(a_{t-1});
  Predict reward value: $\hat{R}(s_t, a_t) \leftarrow \phi^r(s_t)$;
  Predict cost value: $\hat{C}(a_t, s_t) \leftarrow \phi^c(s_t)$;
  Update rtg token:
   $R_t \leftarrow \max\{\hat{R}(s_t, a_t), R_{t-1} - r_t\}$;
  Update ctg token:
   $C_t \leftarrow \min\{\hat{C}(s_t, a_t), C_{t-1} - c_t\}$;
  Update context: $\mathbf{o} \leftarrow \{\{a_{t-1}, C_t, R_t, s_t\}\}_{t-H:t}$;
  Predict action: $a_t \leftarrow \pi_{\theta,\phi}(\mathbf{o})$;

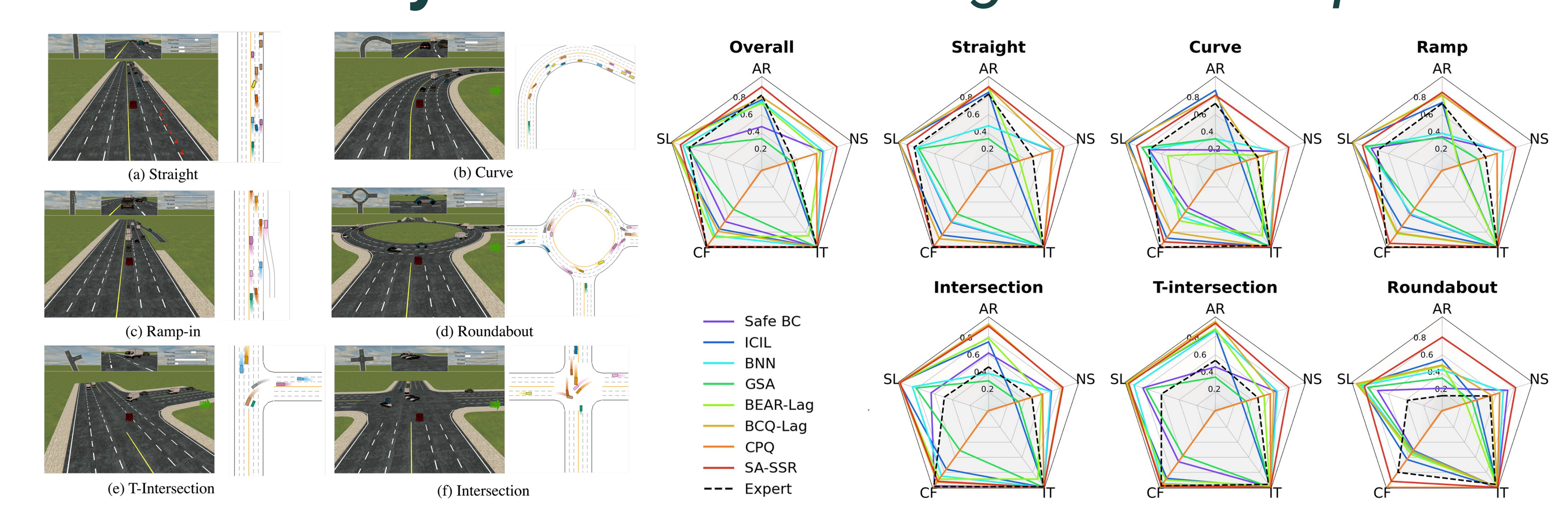
Experiments and Analysis

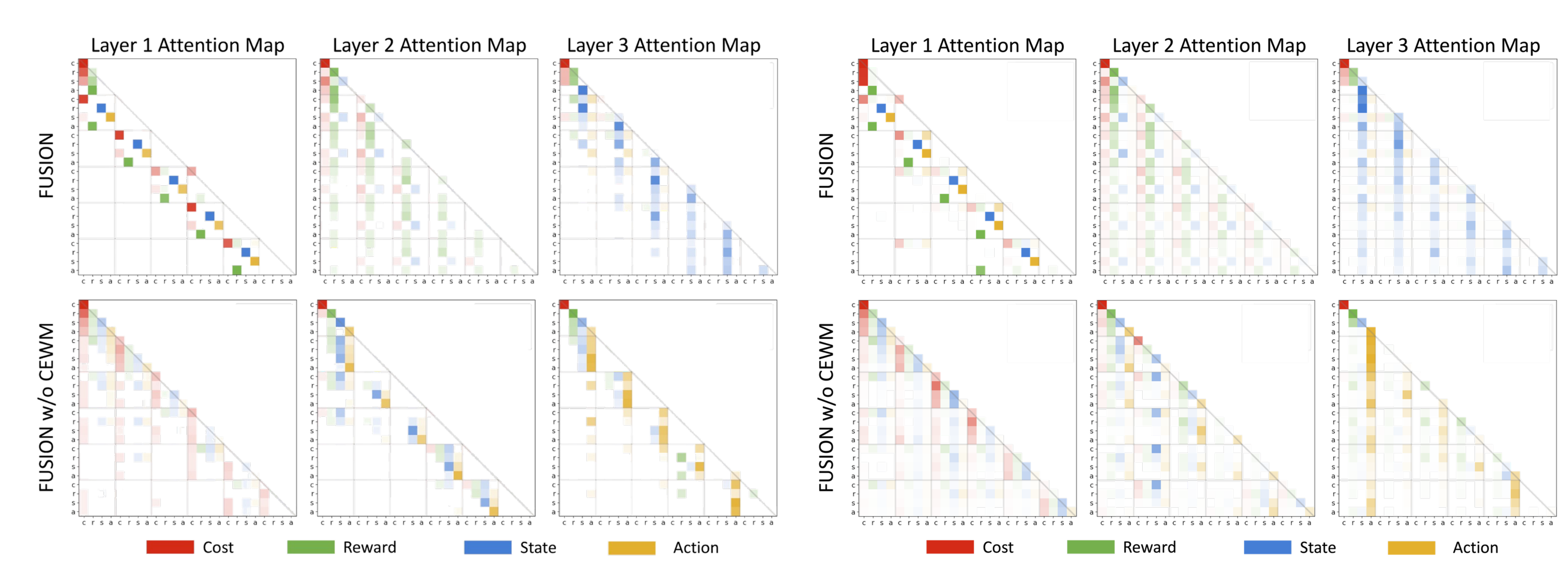
Evaluation Settings ($\kappa_c = 1$):

- Policy Mismatch (imperfect demonstration)
- Dynamics Mismatch (dense traffic)

Method	Policy Mismatch			Dynamics Mismatch		
	Reward (↑)	Cost (↓)	Succ. Rate (↑)	Reward (↑)	Cost (↓)	Succ. Rate (↑)
Safe BC	106.28±7.49	12.79±0.70	0.47±0.10	81.07±3.80	9.44±0.55	0.12±0.06
ICIL	122.66±4.85	11.07±1.11	0.76±0.05	88.21±5.30	7.29±0.72	0.32±0.05
BNN	118.61±3.09	4.46±0.41	0.74±0.11	113.35±5.68	19.16±0.55	0.59±0.06
GSA	89.94±6.84	13.18±1.26	0.34±0.08	102.40±6.44	11.88±0.98	0.03±0.02
BEAR-Lag	109.62±3.91	4.46±0.29	0.72±0.06	113.38±5.25	7.86±0.66	0.32±0.05
BCQ-Lag	111.36±5.26	**0.89**±0.08	0.79±0.08	122.72±7.64	6.22±0.76	0.39±0.08
CPQ	9.01±0.87	1.05±0.18	0.00±0.00	7.47±0.59	0.71±0.09	0.00±0.00
FUSION (Ours)	**139.95**±4.24	**0.52**±0.06	**0.90**±0.03	**117.40**±4.30	**0.90**±0.14	**0.82**±0.04
FUSION-Short	100.86±3.40	0.77±0.09	0.34±0.07	98.63±2.36	0.79±0.06	0.34±0.04
FUSION w/o CEWM	94.24±6.50	**0.67**±0.11	0.41±0.06	81.70±3.82	**0.60**±0.04	0.24±0.04
FUSION w/o CBL	104.54±4.04	3.46±0.21	0.58±0.09	90.34±4.28	5.60±0.32	0.08±0.01
FUSION	**139.95**±4.24	**0.52**±0.06	**0.90**±0.03	**117.40**±4.30	**0.90**±0.14	**0.82**±0.04
Expert Policy	131.32±29.60	16.02±9.46	0.81±0.15	129.71±28.84	17.58± 9.71	0.72±0.20

Result Analysis: *Diverse Config. / Attn. Map*





Take-aways

- CEWM transforms the offline RL as a sequence modeling problem, while adding more sequential awareness accounts for better results.
- CBL empowers the structural dynamics by enforcing extra sparsity.
- Comprehensive empirical evaluations with safety-aware LfD baselines