We identify causal variables and their

causal graph from temporal sequences

with instantaneous effects.

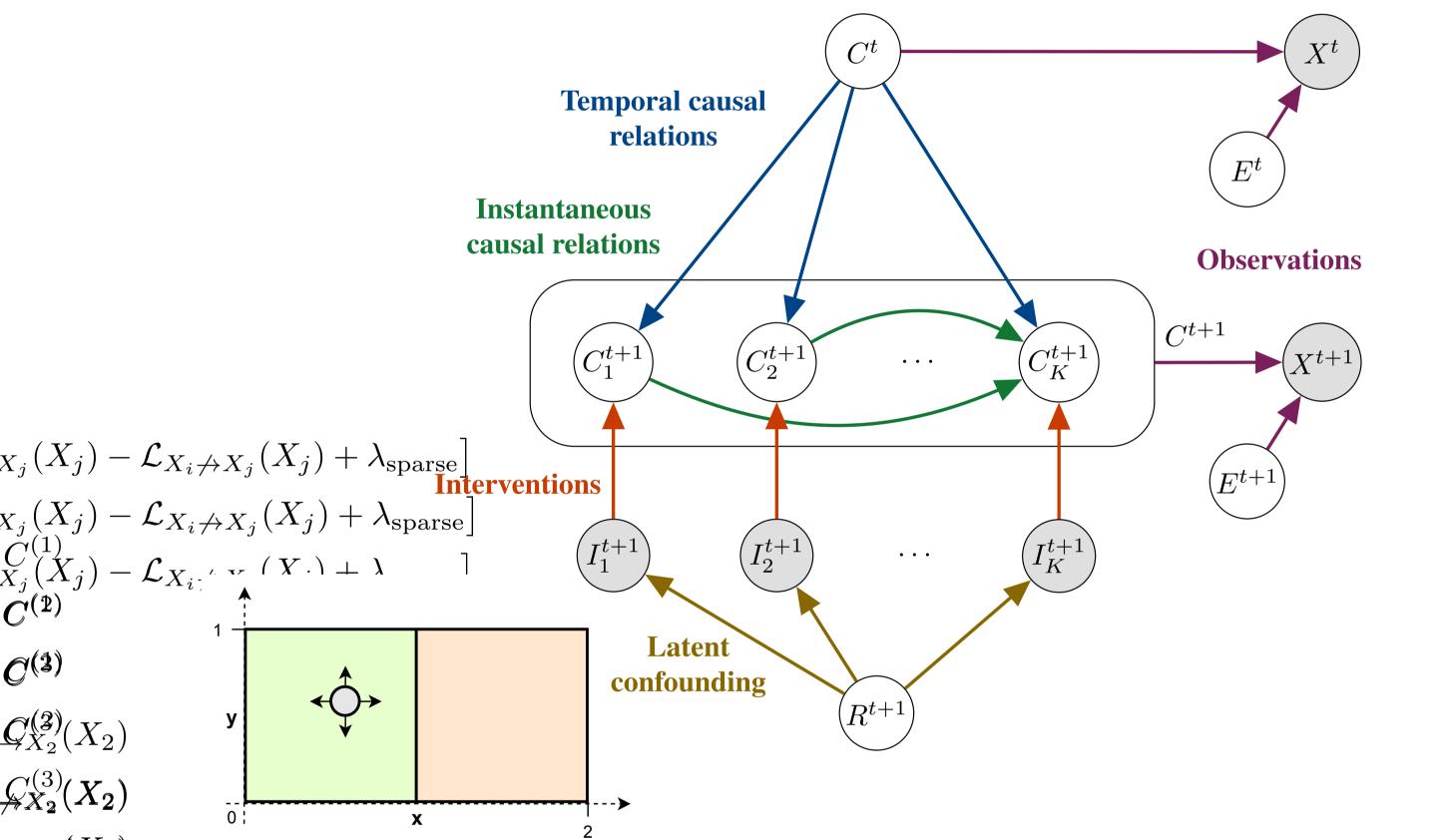
iCITRIS: Causal Representation Learning for Instantaneous Temporal Effects

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PROBLEM SETTING

- Causal effects faster than frame rate cause instantaneous effects \bullet
- Joint causal representation learning + causal discovery needed



OPTIMIZATION STABILIZATION

- Chicken-and-egg situation: without graph, no lacksquaredisentanglement; without variables, no graph
- Our solution:
 - Graph Learning Scheduling: freeze graph parameters for first several iterations
 - Mutual Information Estimator: no MI between \bullet intervened variables and previous time step

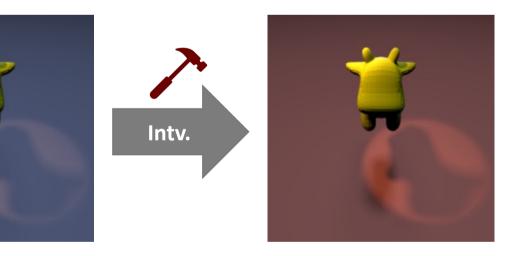
EXPERIMENTS

Instantaneous Temporal Causal3DIdent: 7 causal lacksquarevariables with temp. and instantaneous effects

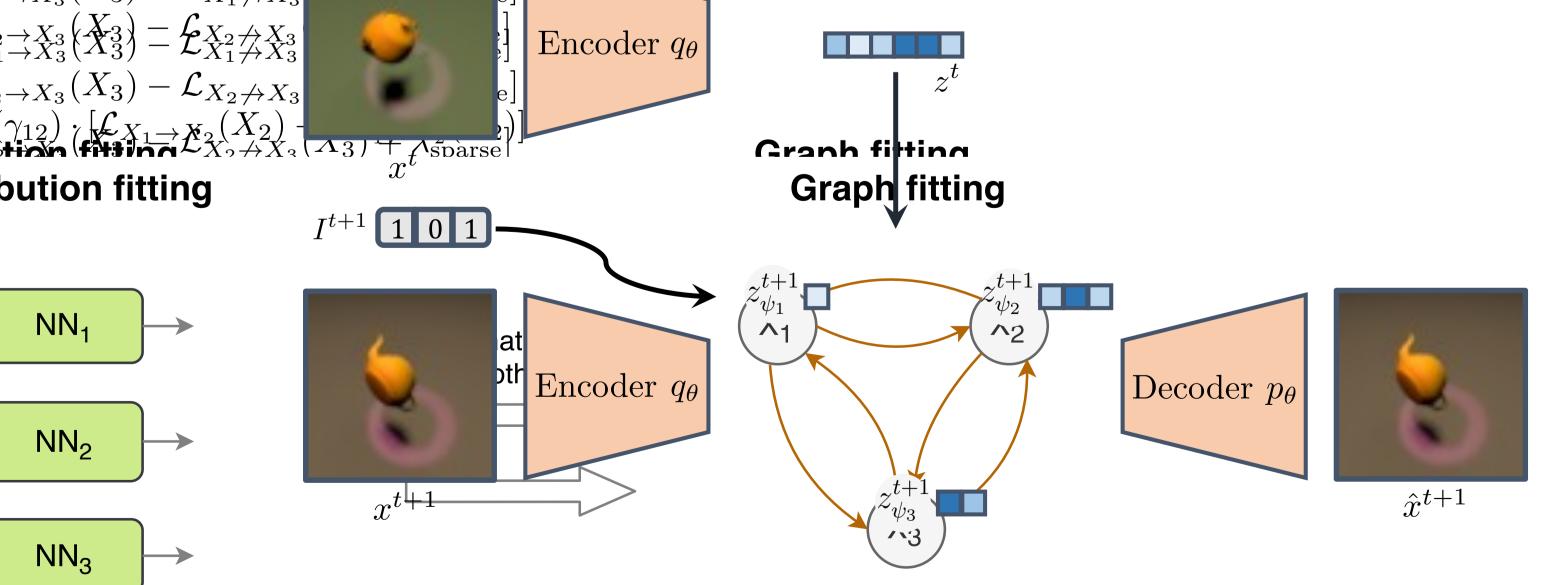
 $C^{(2)}$ $C_{X_2}^{(2)}(X_2)$ $\sum_{X_2}^{(3)} (X_2)$ $\not\Rightarrow X_2(X_2)$ $\neq X_2(X_2)$ $\neq X_2(X_2)$ $\neq X_3(X_3)$ $\neq X_3(X_3)$ $\neq X_3(X_3)$ $\neq X_3 \begin{pmatrix} X_3 \\ X_2 \end{pmatrix}$ $\stackrel{\not \to X_3}{\to X_2} \begin{pmatrix} X_3 \\ X_2 \end{pmatrix}$

ICITRIS: INSTANTANEOUS EFFECT IN CRL

Perfect interventions to distinguish instantaneous effects from entanglement in encoding function



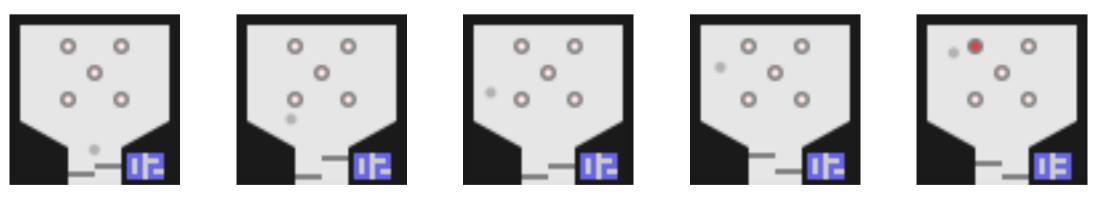
 $-\mathcal{E}_{X_1} \mathcal{A}_{Y_2} \mathcal{E}_{Y_1} \mathcal{A}_{Y_2} \mathcal{E}_{Y_1} \mathcal{A}_{Y_2} \mathcal{E}_{Y_1} \mathcal{A}_{Y_2} \mathcal{E}_{Y_1} \mathcal{A}_{Y_2} \mathcal{E}_{Y_2} \mathcal{A}_{Y_2} \mathcal{E}_{Y_1} \mathcal{A}_{Y_2} \mathcal{E}_{Y_2} \mathcal{E}_{Y_$ |1| are $-\mathcal{L}_{X_1}$ identifiable under a directed acyclic causal graph $\sum_{X_2} X_2(X_2) = \mathcal{L}_{X_1} + \mathcal{L}_{X_2}(X_2) + \mathcal{L}_{X_1} + \mathcal{L}_{X_2}(X_2) + \mathcal{L}_{X_2} + \mathcal{L}_{X_1} + \mathcal{L}_{X_2} +$ $\underset{X_{2}}{\xrightarrow{X_{3}}} \begin{pmatrix} X_{3} \\ X_{2} \end{pmatrix} = \mathcal{L}_{X_{3}}^{X_{1}} \not\subset X_{2}^{X_{3}} \begin{pmatrix} X_{3} \end{pmatrix} + \lambda_{\text{sparse}}$ (ENCO [2] or NOTEARS [3]) $_{\to X_3}(X_3) - \mathcal{L}_{X_1 \not\to X_3}$



Model	R^2 (diag \uparrow / sep \downarrow)	SHD (instant \downarrow / temp \downarrow)
iCITRIS-ENCO	0.96 / 0.05	1.33 / 5.00
iCITRIS-NOTEARS	0.95 / 0.09	4.00 / ${f 5.00}$
CITRIS	0.92 / 0.19	4.67 / 10.00
iVAE	0.82 / 0.20	6.67 / 15.33
iVAE-AR	0.79 / 0.29	11.00 / 12.67

Causal Pinball: game dynamics with 5 causal vars lacksquare

Model	R^2 (diag \uparrow / sep \downarrow)	SHD (instant \downarrow / temp \downarrow)
iCITRIS-ENCO	0.98 / 0.04	0.67 / 3.67
iCITRIS-NOTEARS	0.98 / 0.06	2.33 / 3.67
CITRIS	0.98 / 0.04	2.67 / 4.00
iVAE	0.55 / 0.04	2.33 / 4.33
iVAE-AR	0.53 / 0.15	4.33 / 6.33



iCITRIS identifies the causal variables and their temp.+instant. graph well in both datasets

References

[1] Lippe, Phillip, et al. "CITRIS: Causal Identifiability from Temporal Intervened Sequences." International Conference on Machine Learning. PMLR, 2022. [2] Lippe, Phillip, et al. "Efficient Neural Causal Discovery." *ICLR* 2022 [3] Zheng, Xun et al. "DAGs with NO TEARS: Continuous Optimization for Structure Learning." Advances in Neural Information Processing Systems, 2018.

