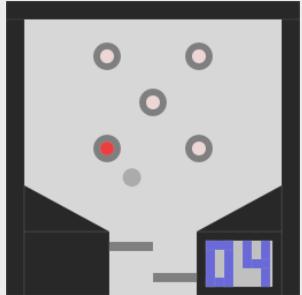
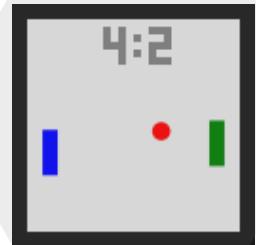
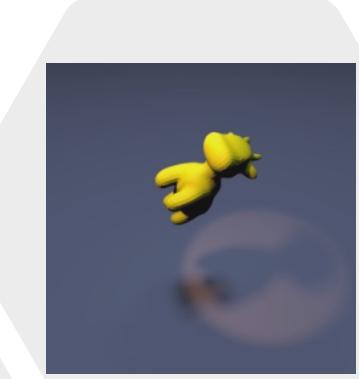


Learning Causal Variables from Temporal Observations

Phillip Lippe

PhD Student, University of Amsterdam

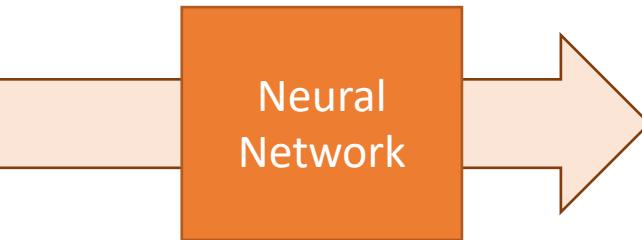
21. February 2023



Introduction

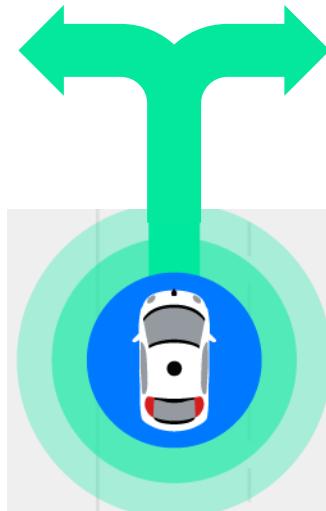
Representation Learning

Vision



Not interpretable
Unknown robustness

...



*Autonomous
driving*

Figure credits:

[1] Waymo tech block, 2017

[2] Cordts et al., The Cityscapes dataset. CVPR 2016.

Learning Causal Variables from Temporal Observations - Phillip Lippe

Slide 2

Introduction

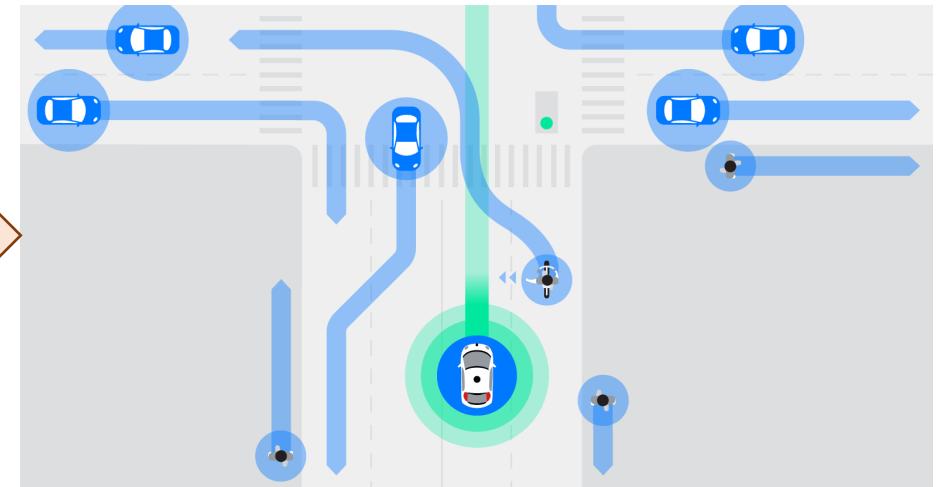
Representation Learning

Vision



Neural Network

Structured Representation
AD: Human guidance what to model, causal factors



Interpretable
Generalizable
Robust

Reasoning-oriented
Structure learned?

Causal Representation Learning

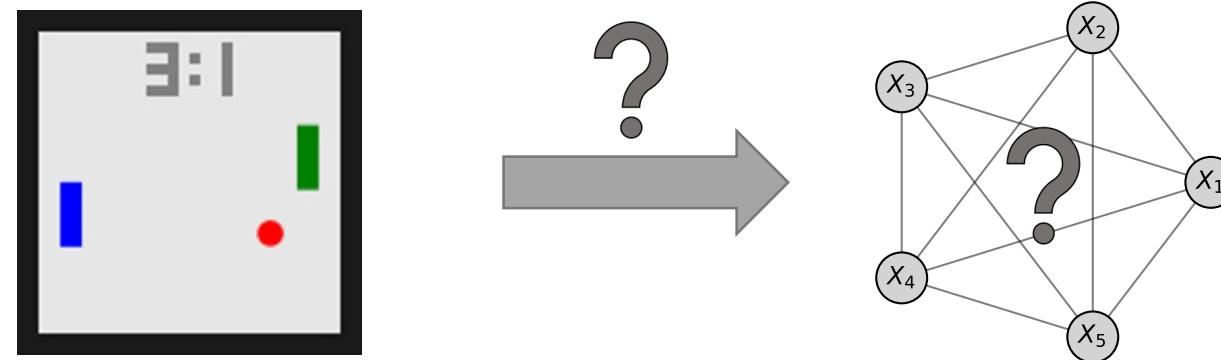
Figure credits:

[1] Waymo tech block, 2017

[2] Cordts et al., The Cityscapes dataset. CVPR 2016.

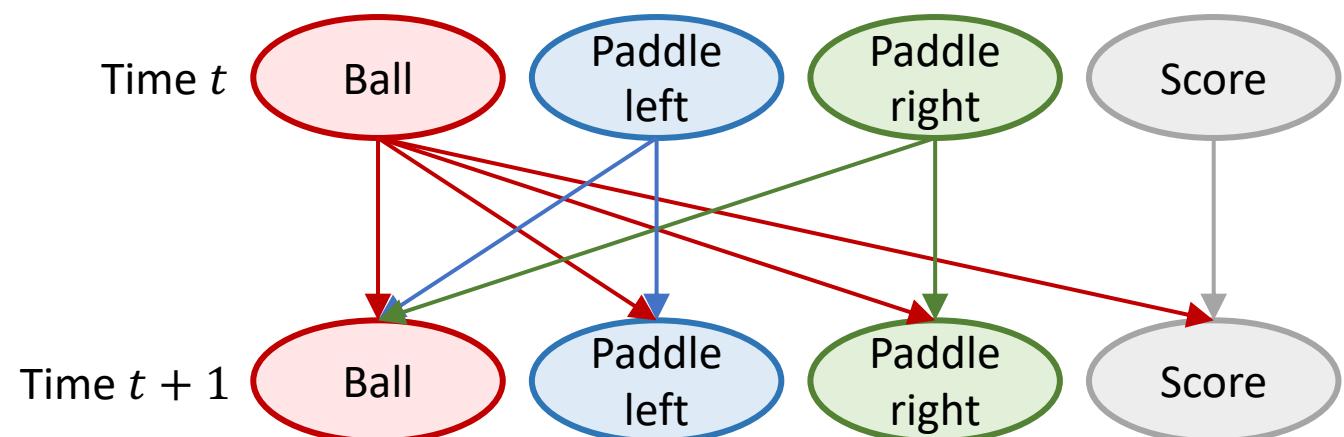
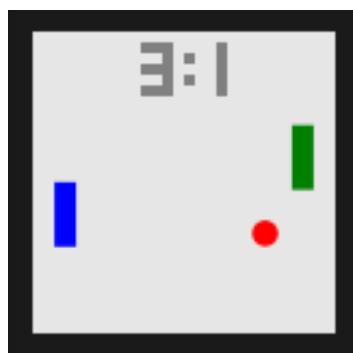
Causal Representation Learning

- Given high-dimensional observations of a (dynamical) system, what is its latent causal structure?
 - Causal variables
 - Their cause-effect relations



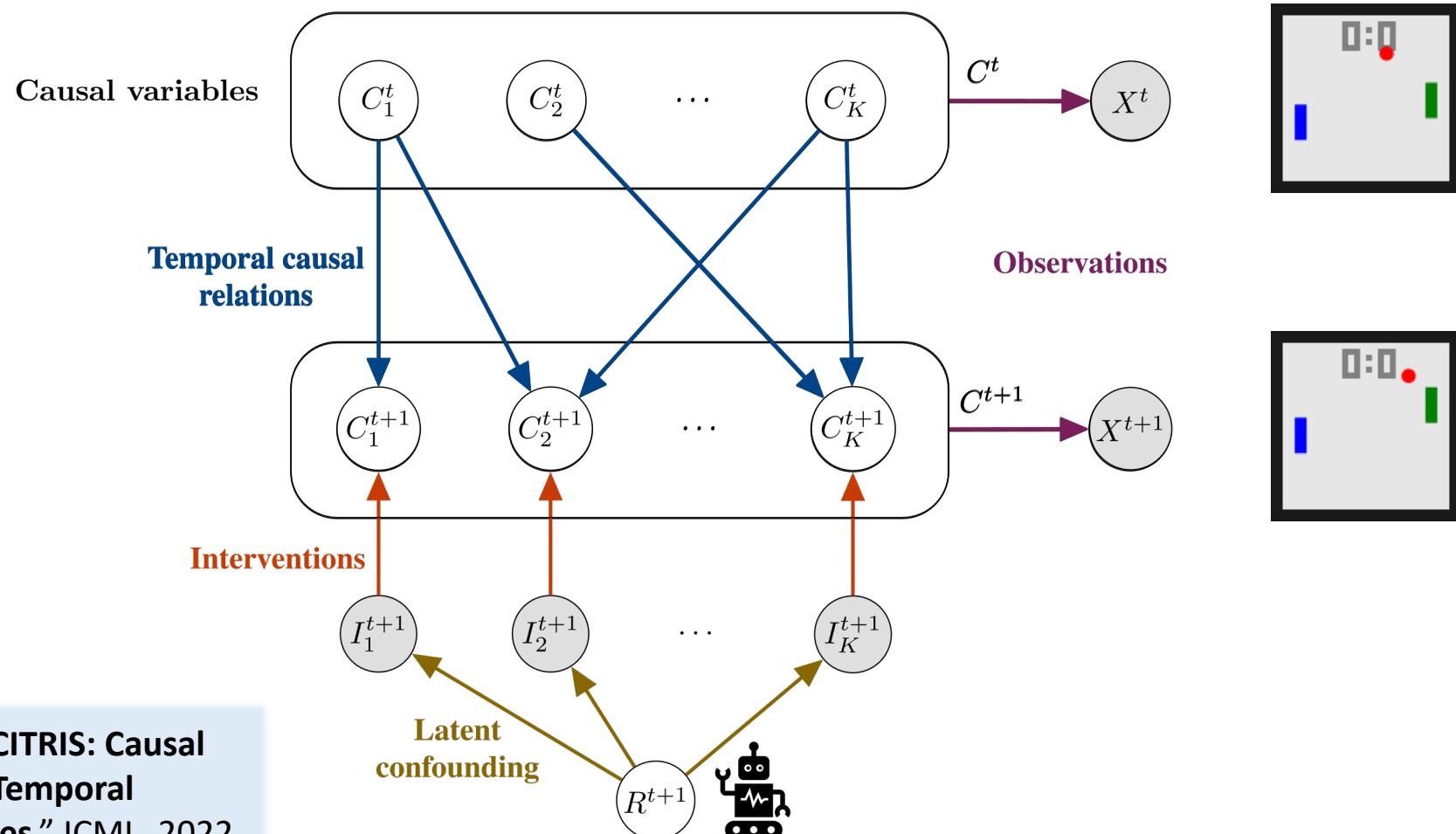
Causal Representation Learning

- Given high-dimensional observations of a (dynamical) system, what is its latent causal structure?
 - Causal variables
 - Their cause-effect relations



CITRIS: Causal Identifiability from Temporal Intervened Sequences

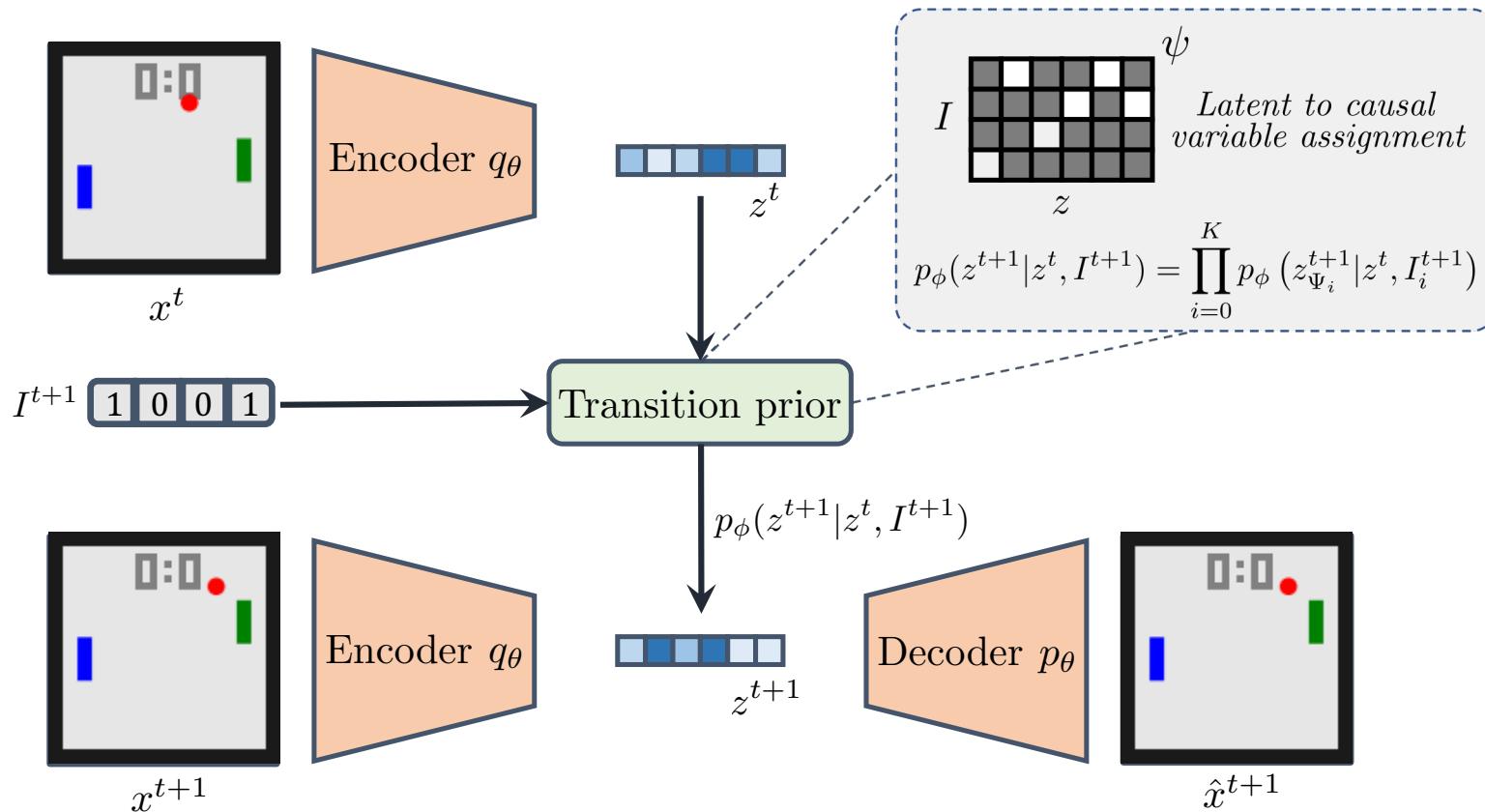
Setup



Lippe, Phillip et al. "CITRIS: Causal Identifiability from Temporal Intervened Sequences." ICML, 2022.

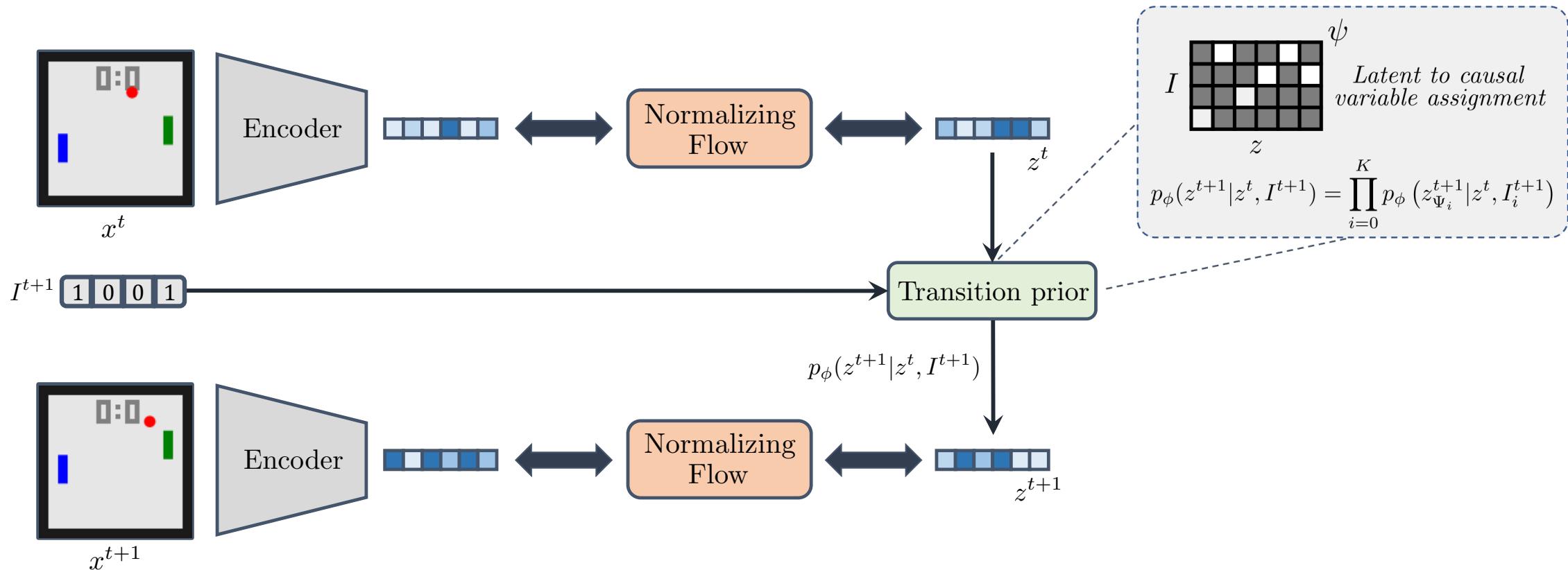
CITRIS Architecture

CITRIS-VAE



CITRIS Architecture

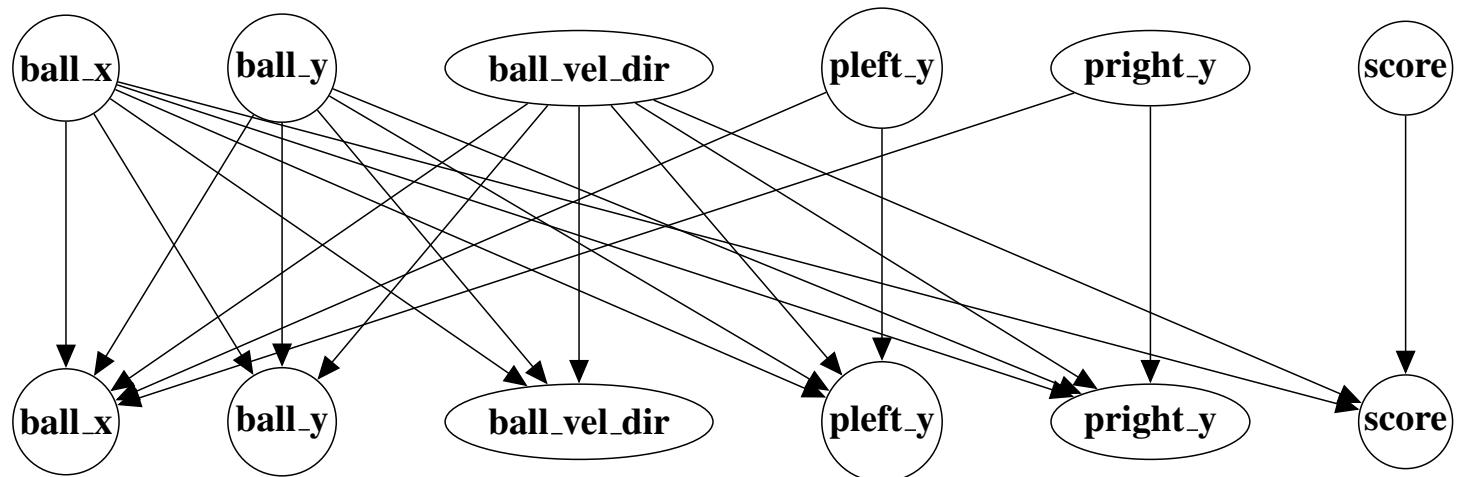
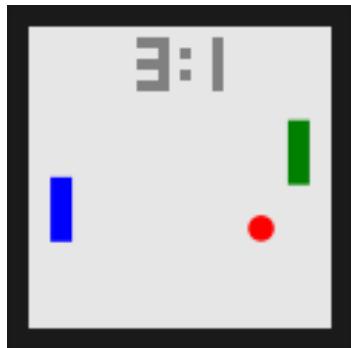
CITRIS-NF



CITRIS Experiments

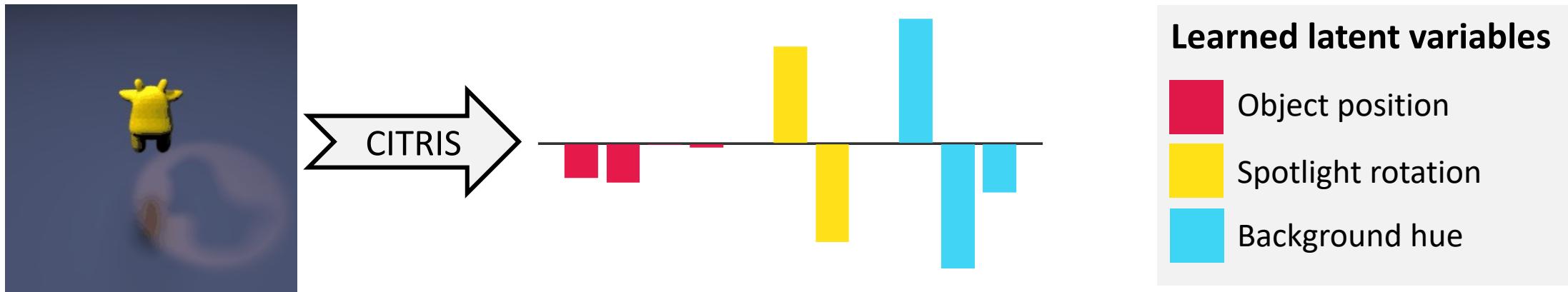
Pong

- CITRIS identifies the causal variables accurately
- Identified cause-effect relations closely follow ground truth

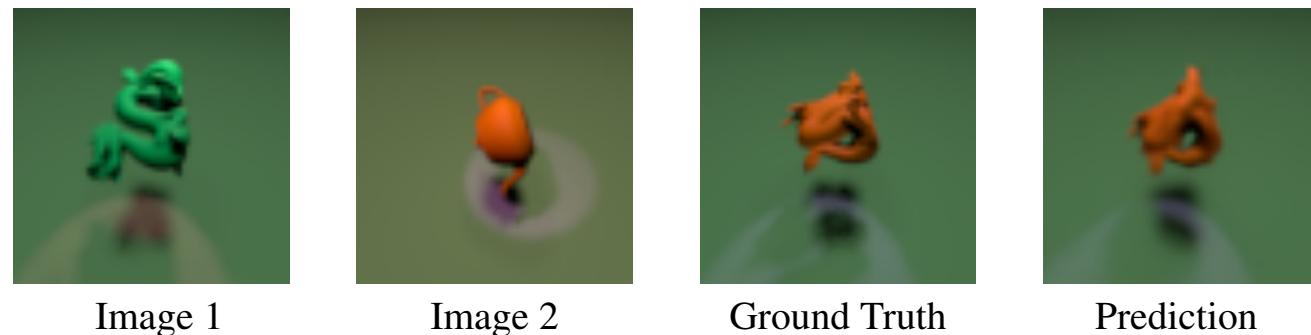


CITRIS Experiments

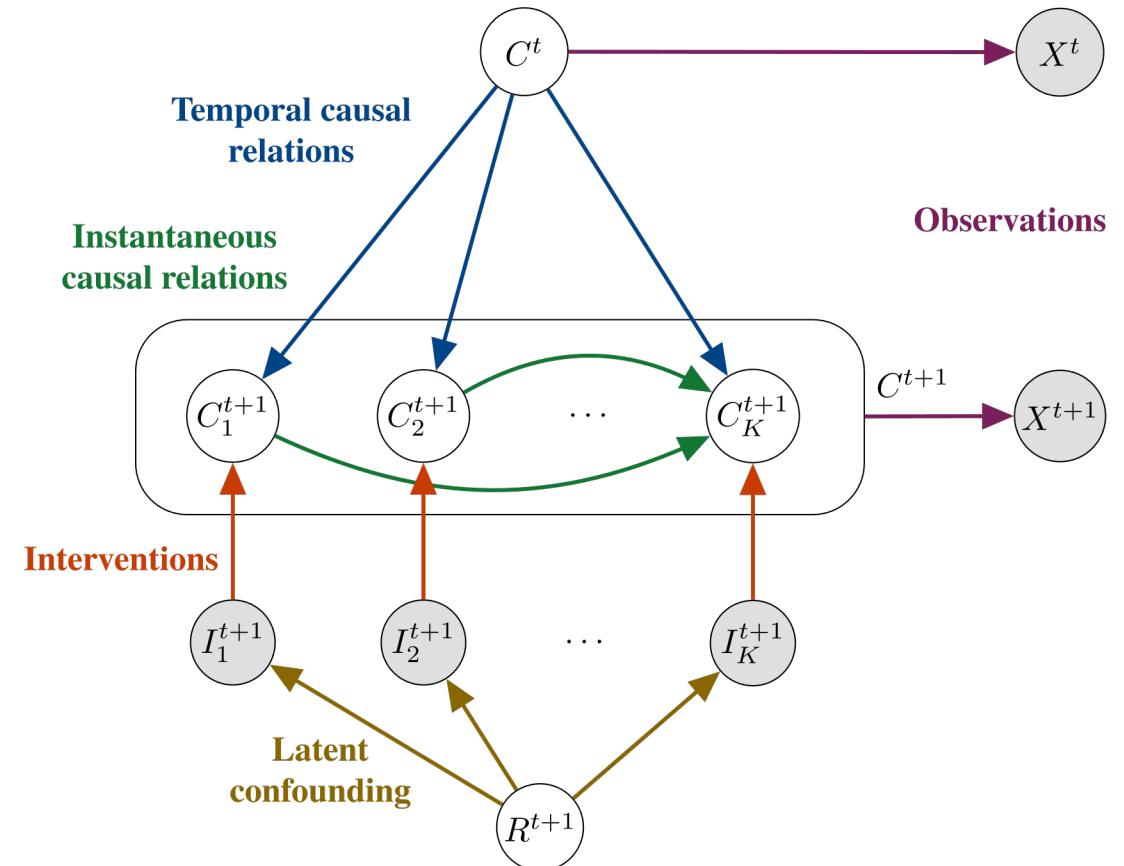
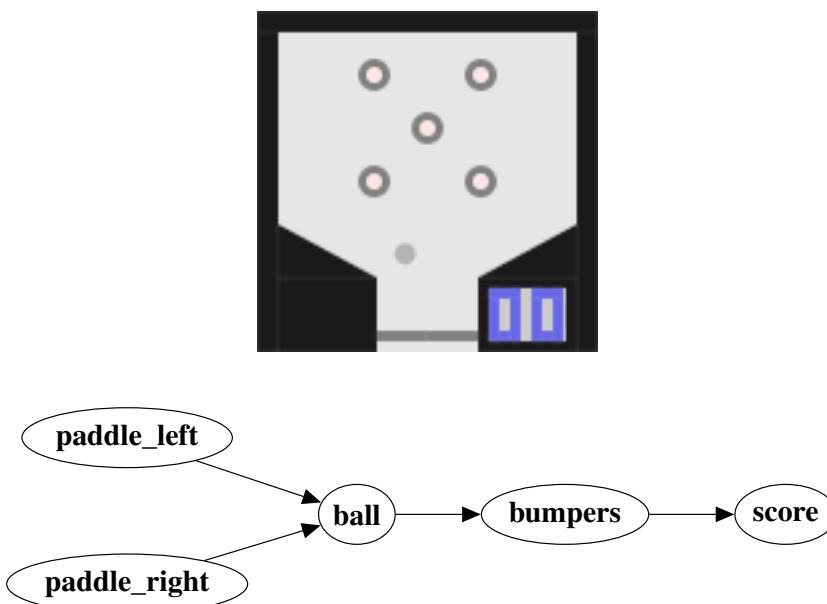
Visualizing the latent space



Novel combinations of causal factors



Causal Representation Learning for Instantaneous Effects



Lippe, Phillip et al. "Causal Representation Learning for Instantaneous and Temporal Effects." ICLR, 2023.

Summary

- **Causal Representation Learning** aims to learn generalizable, robust representations of causal variables in an environment
- **CITRIS** identifies causal variables in variety of environments by information about interventions
- Allows for interpretable, controllable latent spaces
- Opportunity for learning representations in complex, interactive environments like Embodied AI



Figure credit: [1] Szot, Andrew, et al. "Habitat 2.0: Training home assistants to rearrange their habitat." NeurIPS 2021.

References



Phillip Lippe, Sara Magliacane, Sindy Löwe, Yuki M. Asano, Taco Cohen, and Efstratios Gavves. "**CITRIS: Causal Identifiability from Temporal Intervened Sequences.**" In International Conference on Machine Learning (ICML). PMLR, 2022.



Phillip Lippe, Sara Magliacane, Sindy Löwe, Yuki M. Asano, Taco Cohen, and Efstratios Gavves. "**Causal Representation Learning for Instantaneous and Temporal Effects.**" In International Conference on Learning Representations (ICLR), 2023.



Johann Brehmer, Pim de Haan, Phillip Lippe, Taco Cohen. "**Weakly supervised causal representation learning.**" In Advanced in Neural Information Processing Systems (NeurIPS), 2022.

Slides and Papers

