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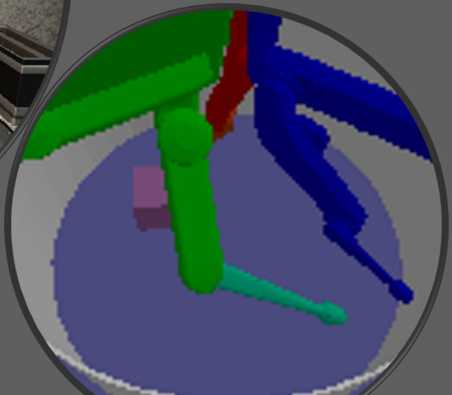
BISCUIT: Causal Representation Learning from Binary Interactions



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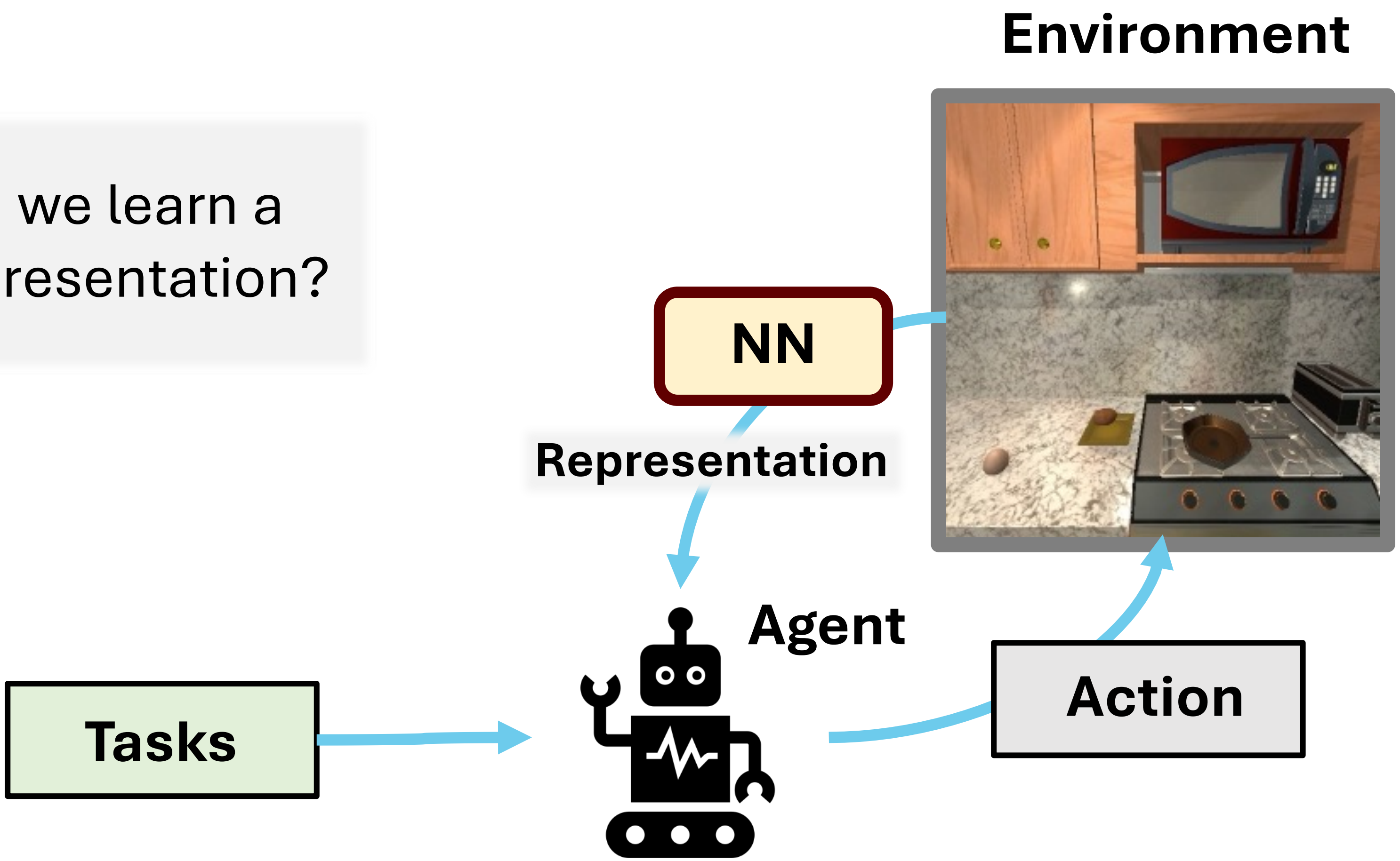
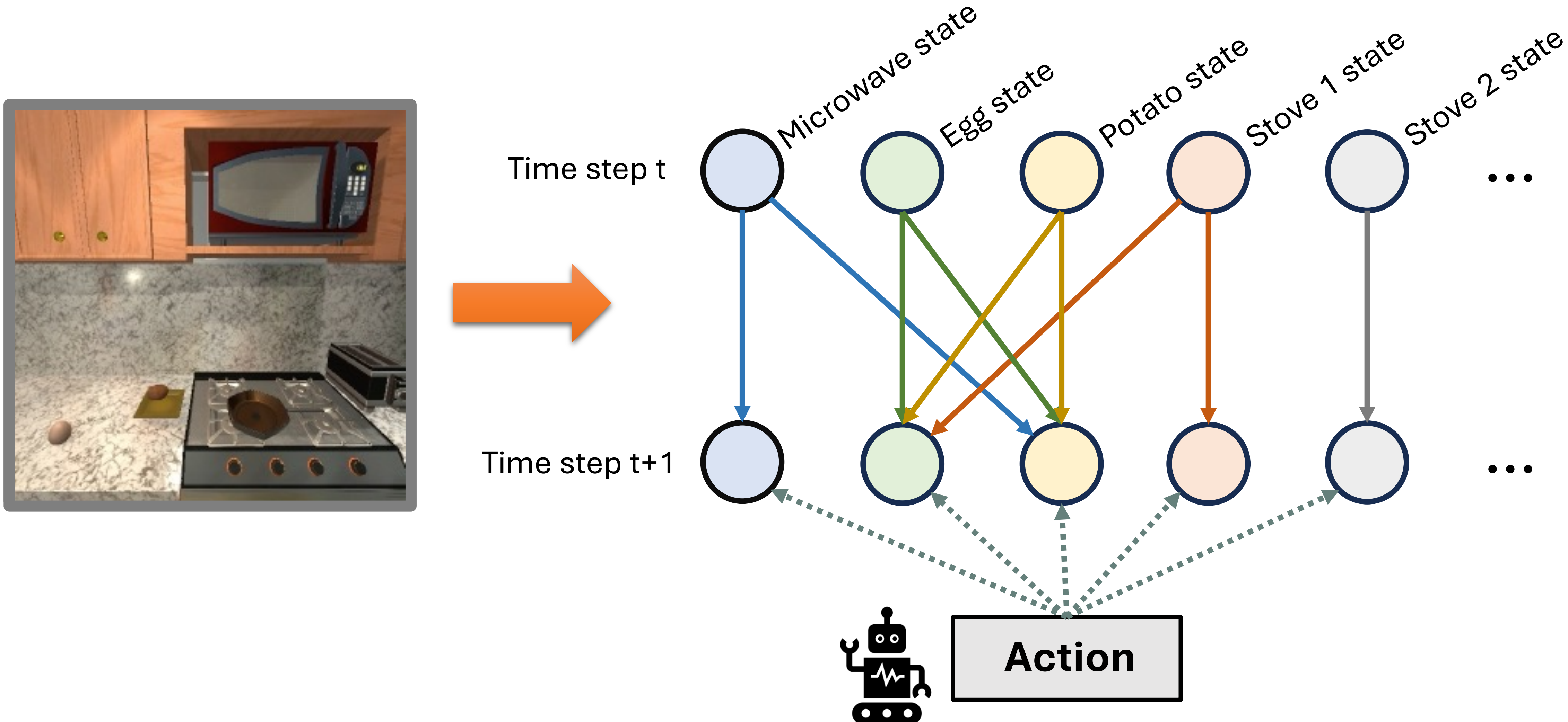
Problem Setup

How can we learn a causal representation?



Temporal Causal Representation Learning



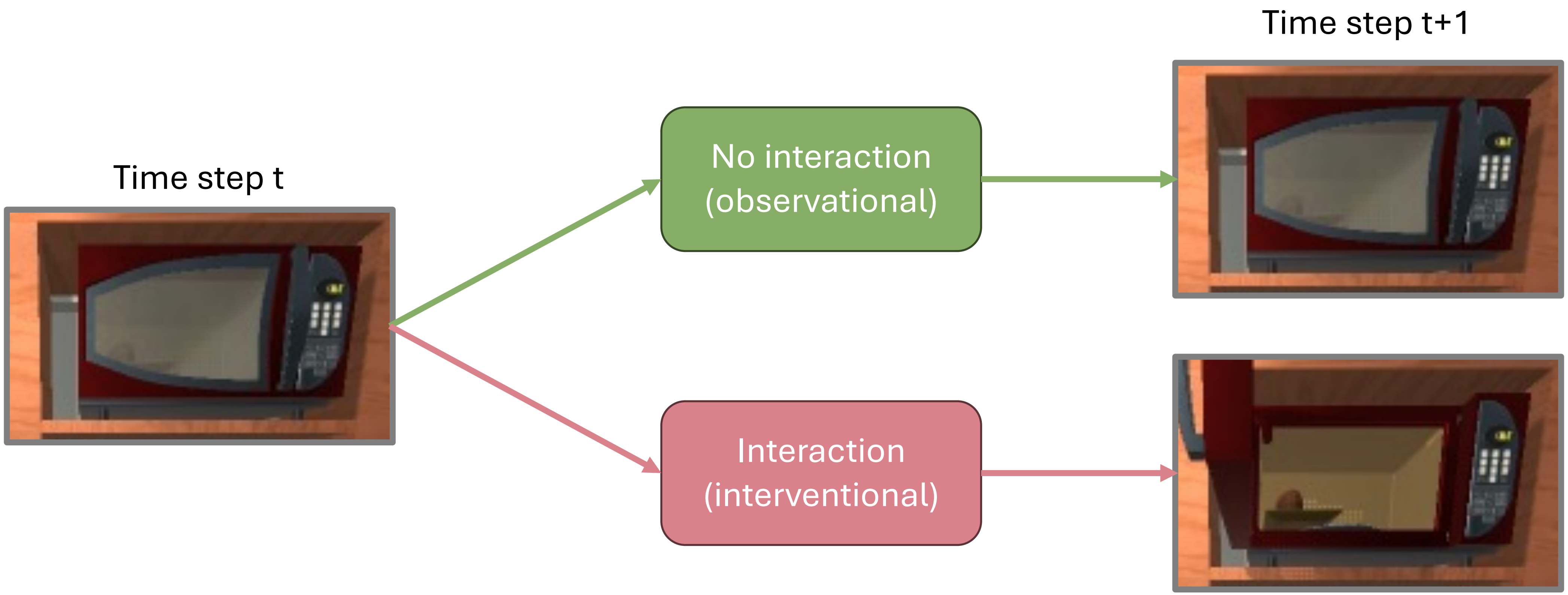
Temporal Causal Representation Learning

- **iVAE** [Khemakhem et al., 2020] – temporality as auxiliary variable, parametric assumptions
- **DMS** [Lachapelle et al., 2022] – graphical assumption (mechanism sparsity), exponential family
- **LEAP** [Yao et al., 2022ab] – sufficient mechanism variability over regimes/environments
- **Properties of Mechanisms** [Ahuja et al., 2022] – known functional form of mechanisms
- **CITRIS** [Lippe et al., 2022] – non-parametric, known intervention targets
  - **iCITRIS** [Lippe et al., 2023a] – instantaneous effects

BISCUIT – non-parametric, arbitrary graphs, unknown binary interactions

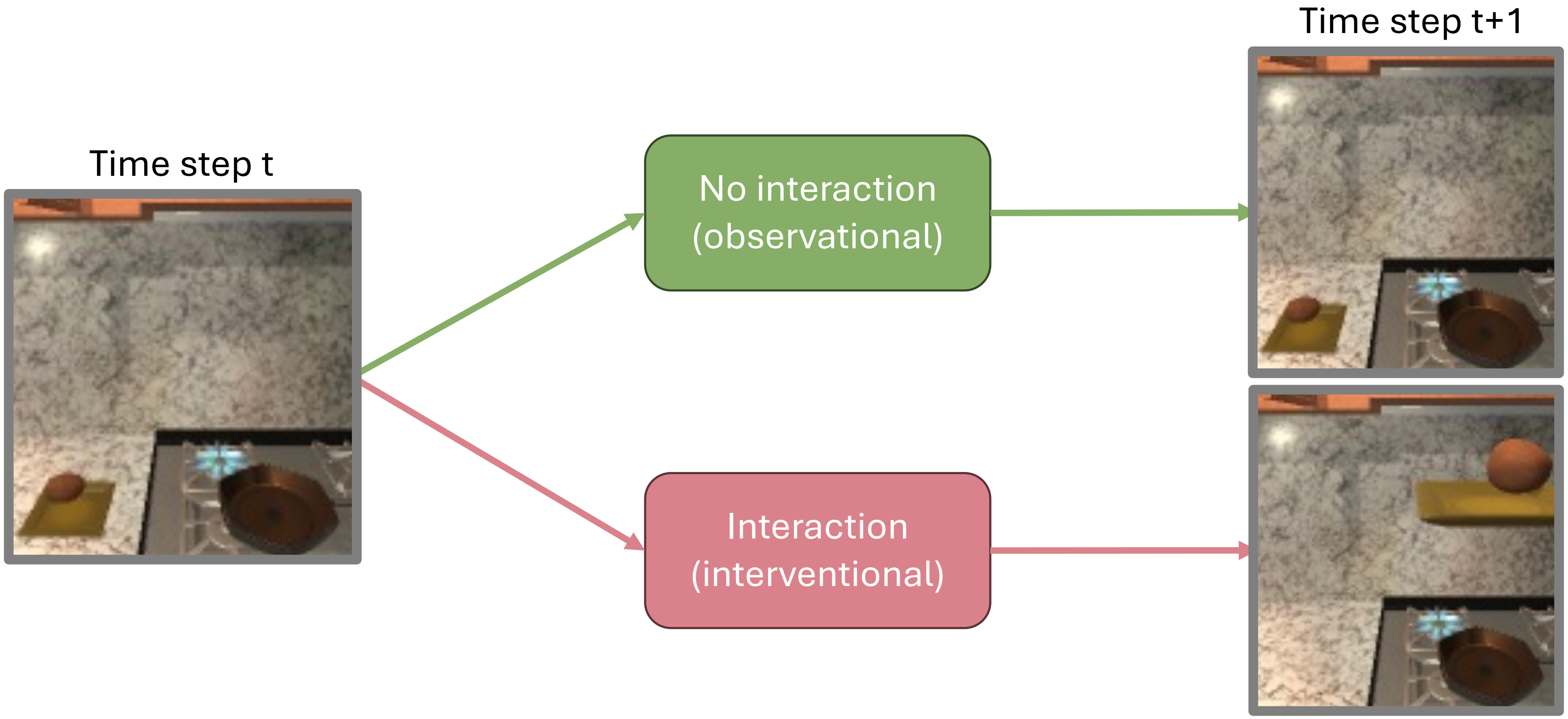
BISCUIT: Binary Interactions

Key assumption: Interactions between the agent and causal variables can be described by **binary variables**



BISCUIT: Binary Interactions

Key assumption: Interactions between the agent and causal variables can be described by **binary variables**

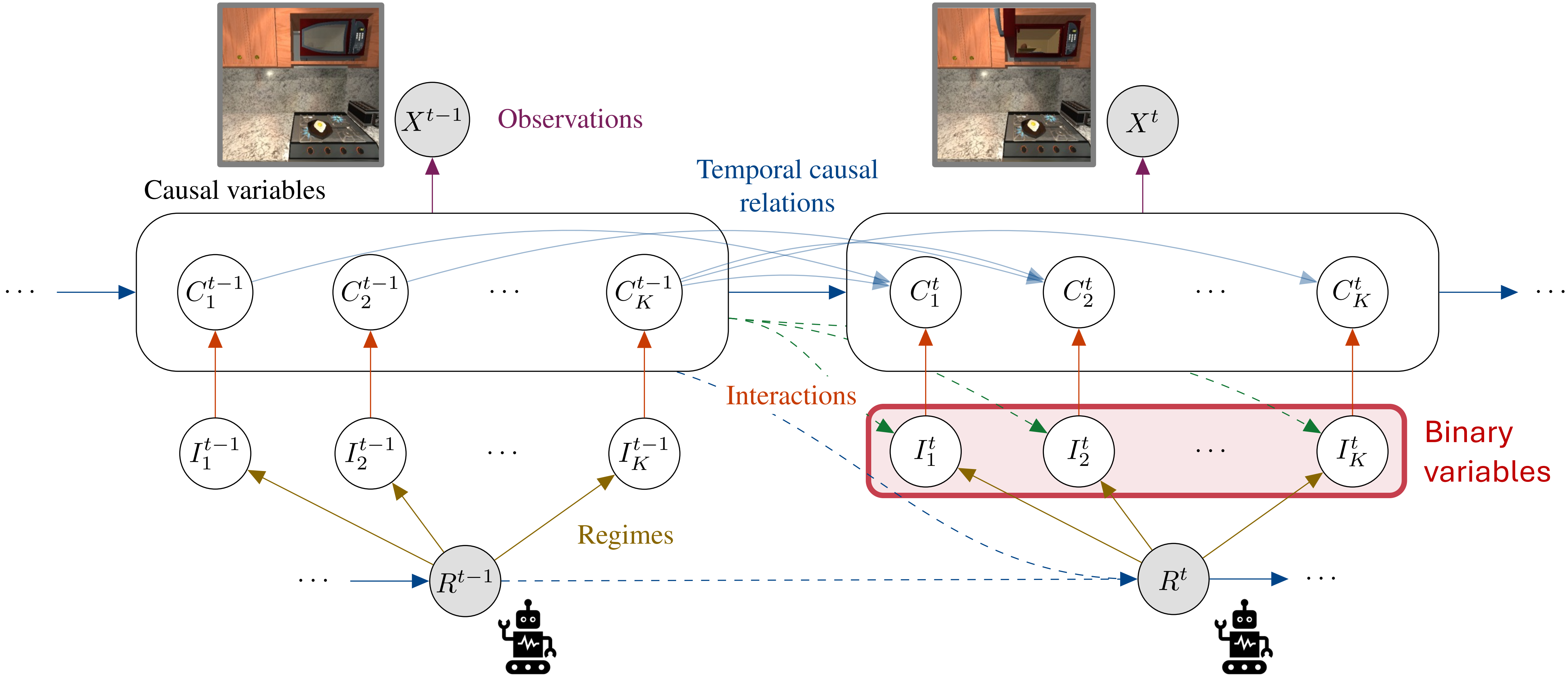


BISCUIT: Binary Interactions

Key assumption: Interactions between the agent and causal variables can be described by **binary variables**

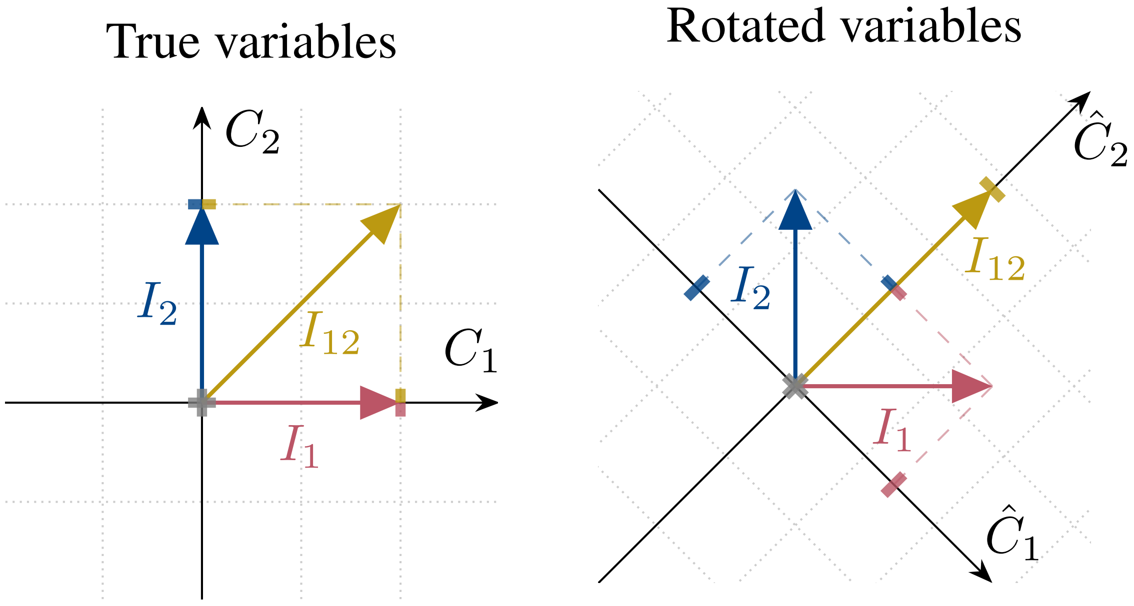
- Causal variables can be continuous values, evolving stochastically over time
- Certain interactions cause unknown interventions, changing corresponding mechanisms
- Realistic assumption in many RL environments:
  observational = no agent-variable interaction,
  interventional = agent interacting with variable

BISCUIT: Causal Model



Binary Interactions enable Identifiability

- Knowing each variable has only two mechanisms helps identify difficult cases
- Example: Additive Gaussian Noise – $C_i^t = \mu_i\left(C^{t-1}, I_i^t\right) + \epsilon_i,\ \ \epsilon_i \sim \mathcal{N}(0, \sigma^2)$
  - Both true and rotated variables model the same distribution, but under interventions, only the true variables have two means

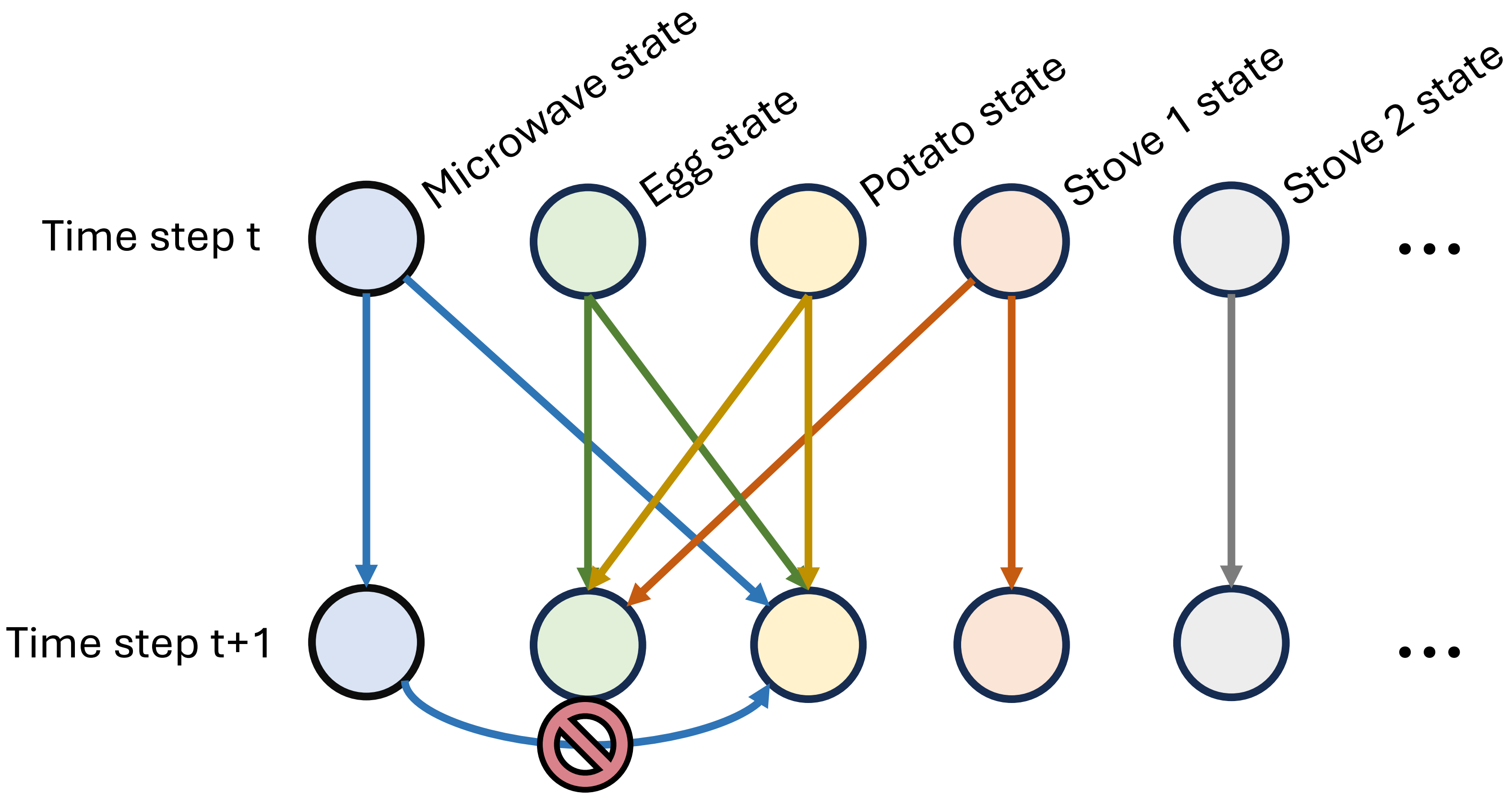


Identifiability Assumptions

- **Assumption 2**: interaction variables of different causal variables are not deterministic functions of each other
  - Implies that two variables are not always interacted with at the same time
  - Distinct interaction patterns
- If the interaction variables I_i^t are independent of C^{t-1}, only requires $\lfloor \mathbf{log_2} \boldsymbol{K} \rfloor + \mathbf{2}$ actions/values of R^t
  - Example: agent with random policy

Identifiability Assumptions

- **Assumption 3**: Causal Relations can be resolved over time



Identifiability Assumptions

- **Assumption 4**: The causal mechanisms vary sufficiently over time or on interactions
  - Prevents cases like interventional and observational distribution being identical
  - Supports many common setups like additive Gaussian noise models or more complex distributions

*A. (**Dynamics Variability**) Each variable's log-likelihood difference is twice differentiable and not always zero:*

$$\forall C_i^t, \exists C^{t-1}: \frac{\partial^2 \Delta(C_i^t|C^{t-1})}{\partial (C_i^t)^2} \neq 0;$$

*B. (**Time Variability**) For any $C^t \in \mathcal{C}$, there exist $K+1$ different values of C^{t-1} denoted with $c^1, ..., c^{K+1} \in \mathcal{C}$, for which the vectors $v_1, ..., v_K \in \mathbb{R}^{K+1}$ with*

$$v_i = \left[\frac{\partial \Delta\left(C_i^t|C^{t-1}=c^1\right)}{\partial C_i^t} \quad \cdots \quad \frac{\partial \Delta\left(C_i^t|C^{t-1}=c^{K+1}\right)}{\partial C_i^t}\right]^T$$

are linearly independent.

BISCUIT: Identifiability Results

Assumption 1: Interactions between agent and causal variables can be described by **binary variables**

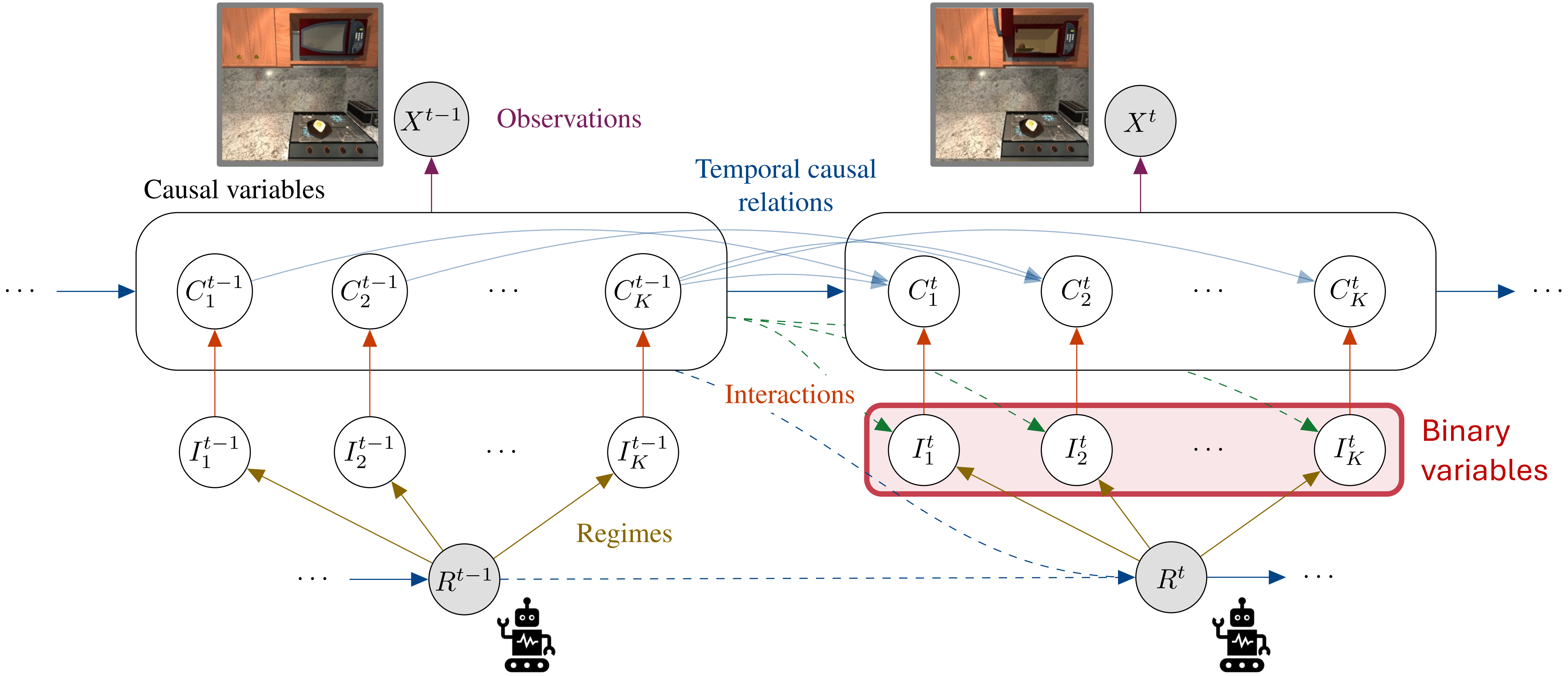
Assumption 2: All causal variables have different interaction patterns

Assumption 3: Causal Relations can be resolved over time

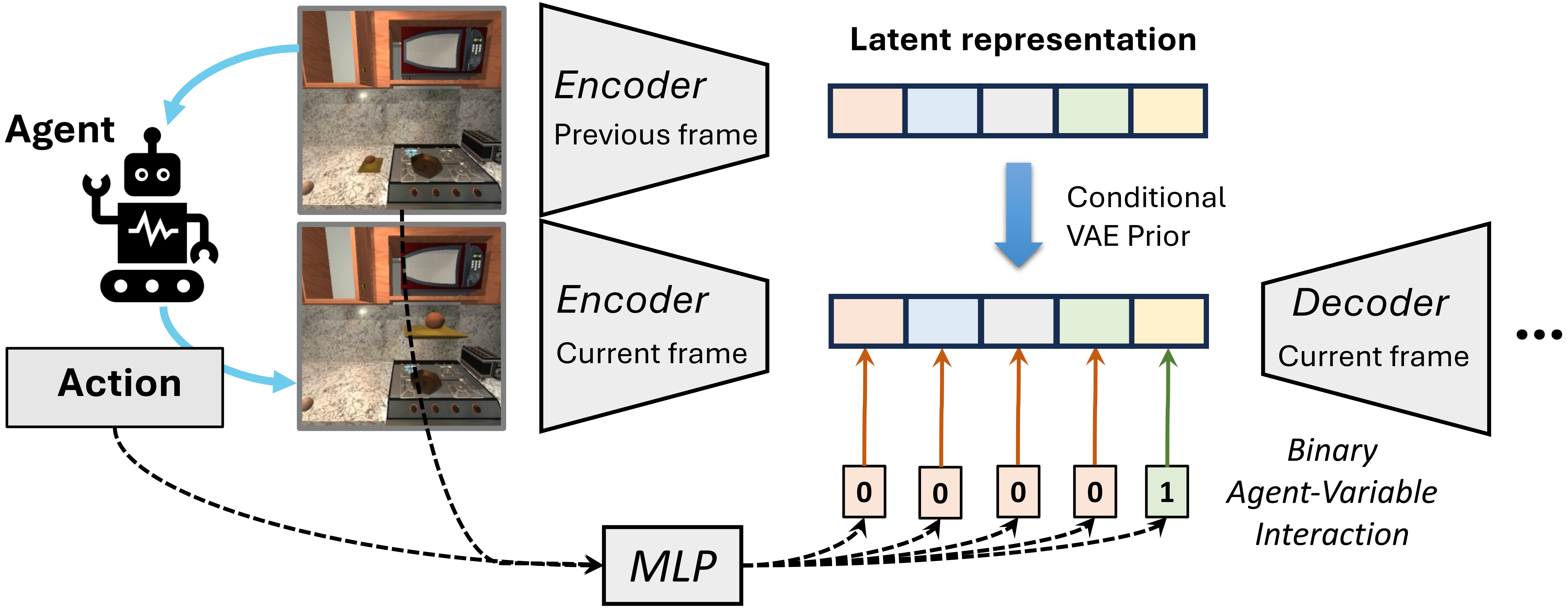
Assumption 4: The causal mechanisms vary sufficiently over time or on interactions

Identifiability Result
The causal variables can be identified up to permutation and element-wise transformations.

BISCUIT: Causal Model (Reminder)



BISCUIT: Architecture



BISCUIT: Architecture

- Loss function:

$$\mathcal{L}_t = \underbrace{-\mathbb{E}_{q_\phi(z^t|x^t)}[\log p_\theta(x^t|z^t)]}_{\text{Reconstruction}} + \underbrace{\mathbb{E}_{q_\phi(z^{t-1}|x^{t-1})}\left[KL\left(q_\phi(z^t|x^t)||p_\omega(z^t|z^{t-1},R^t)\right)\right]}_{\text{Prior modeling}}$$

Encoder Decoder Prior

- Prior structure:

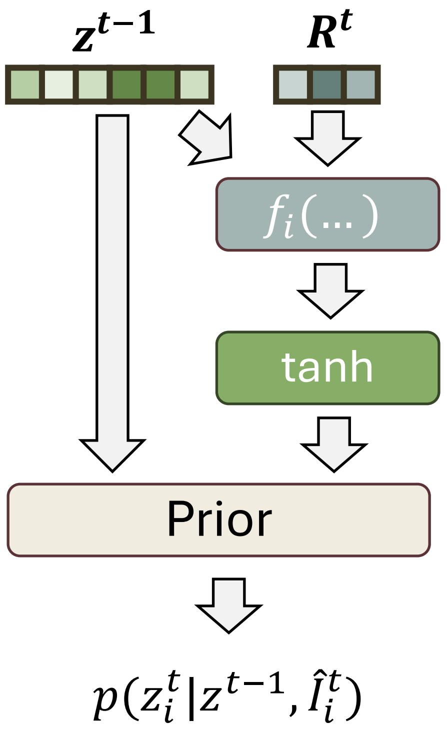
$$p_\omega(z^t|z^{t-1},R^t) = \prod_i p_\omega\left(z_i^t|z^{t-1}, f_i(R^t,z^{t-1})\right)$$

Binary function output

BISCUIT: Learning Binary Variables

- Prior $p(z_i^t|z^{t-1},\hat{I}_i^t)$
  - $\hat{I}_i^t = f_i(z^{t-1},R^t)$

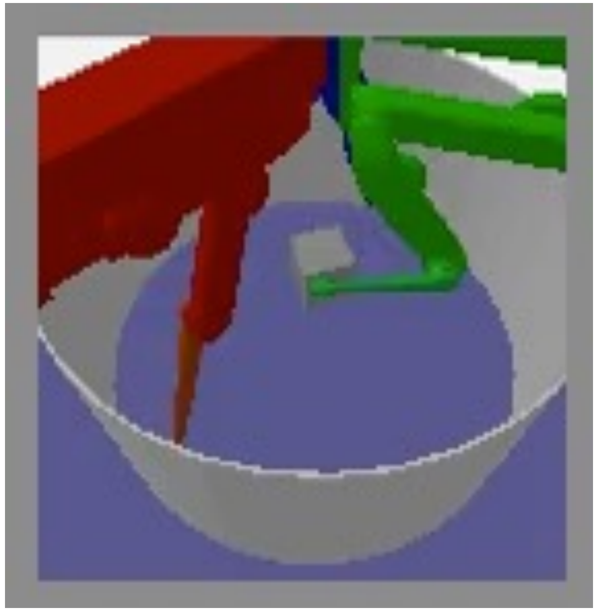
- Continuous Relaxation
  - $\hat{I}_i^t = \tanh\left(\frac{f_i(z^{t-1},R^t)}{\tau}\right)$
  - Smooth optimization
  - Decrease temperature over training



Experiments

Synthetic Environment

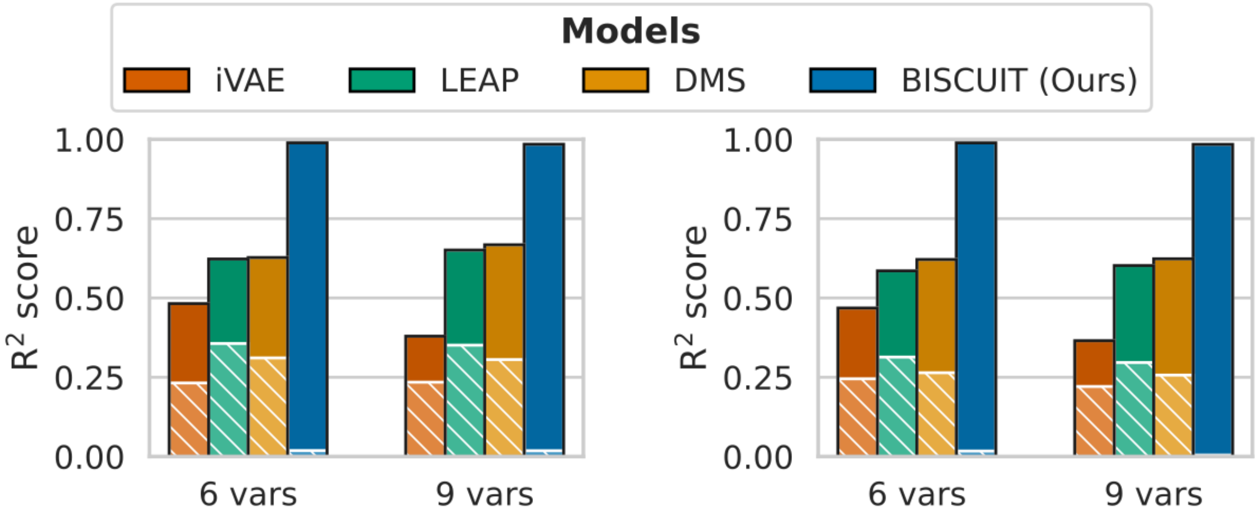
CausalWorld



iTHOR

Synthetic Environments

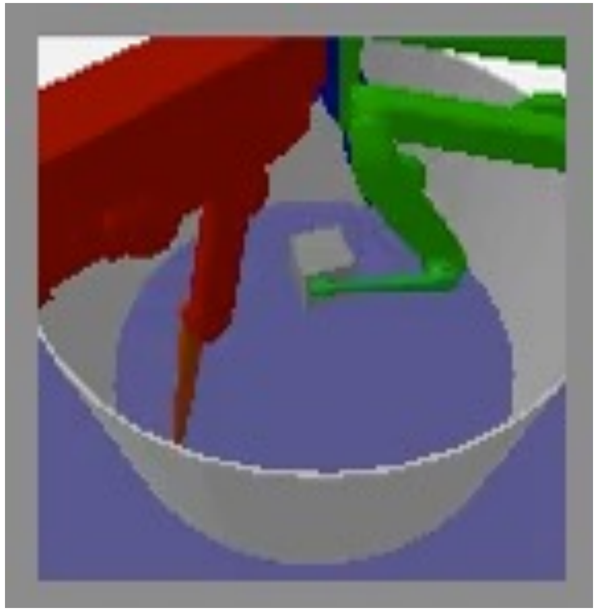
- Evaluated on synthetic dataset with additive Gaussian noise model
- Identifies causal variables well, also under mininal bound of interactions



(a) Random Interactions (b) Minimal Interactions

CausalWorld – Robotic Trifinger

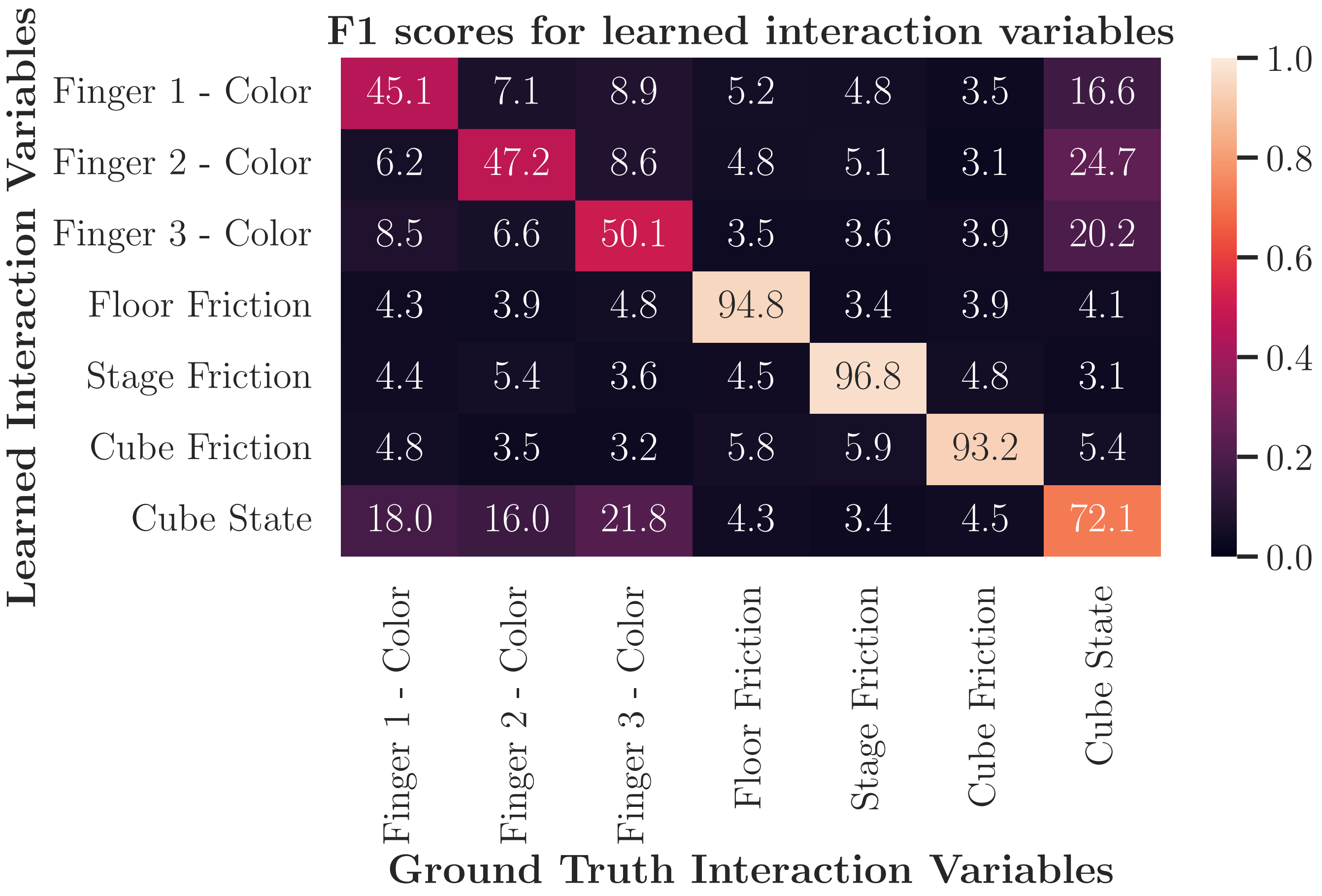
- Tri-finger robot interacting with its environment and objects
  - Causal variables include object position, frictions, colors, etc.
- Action: 9-dimensional motor angles (3 per finger)
- BISCUIT identifies causal variables accurately

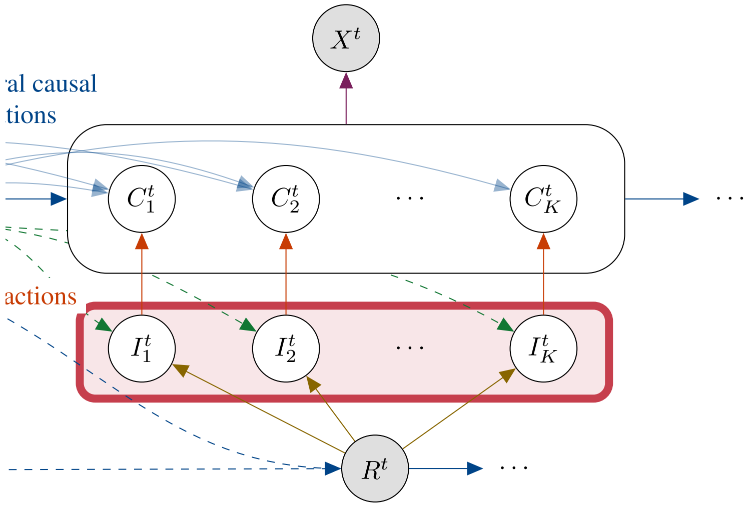


Accuracy of learned causal variables
(higher is better / lower is better)

Models	CausalWorld
iVAE (Khemakhem et al., 2020a)	0.28 / 0.00
LEAP (Yao et al., 2022b)	0.30 / 0.00
DMS (Lachapelle et al., 2022b)	0.32 / 0.00
BISCUIT-NF (Ours)	**0.97** / 0.01

CausalWorld – Learned Interactions





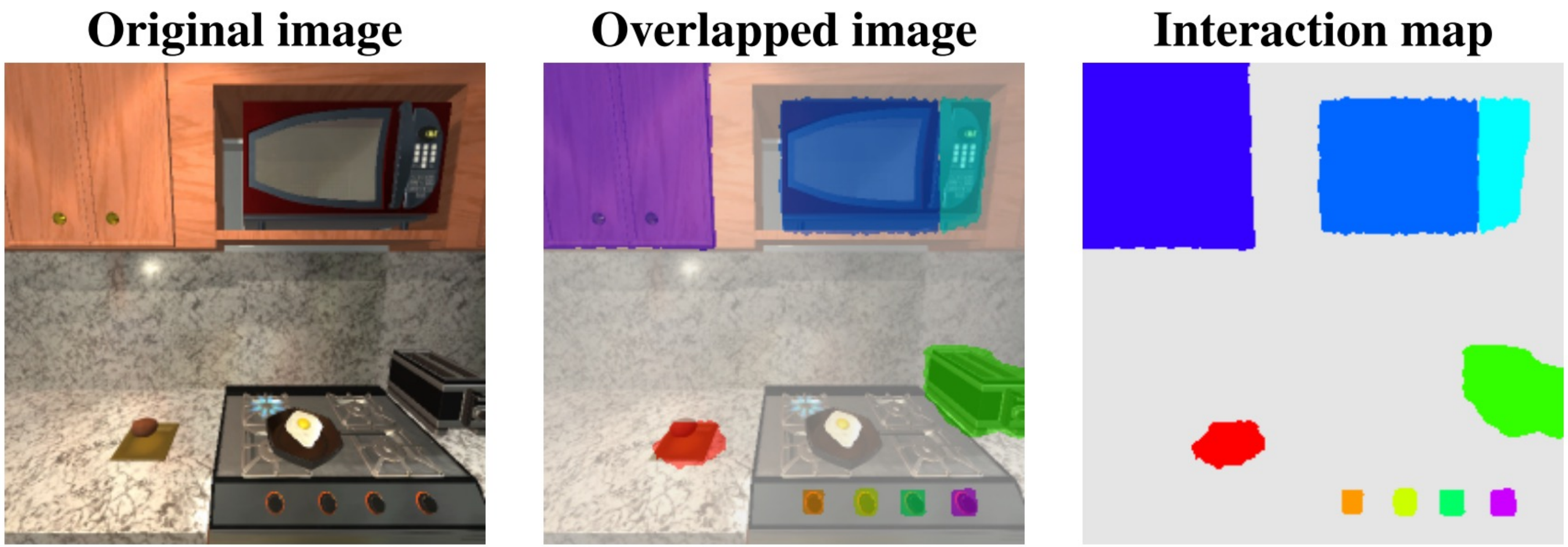
iTHOR

- Kitchen environment with 10 causal variables
  - Cabinet (open/closed)
  - Microwave (open/closed)
  - Microwave (on/off)
  - Egg (position, broken, cooked)
  - Plate/potato (position)
  - 4x Stove burner (on/off, burning)
  - Toaster (on/off)
- Actions represented as x-y coordinate of a randomly sampled object pixel

Models	iTHOR
iVAE (Khemakhem et al., 2020a)	0.48 / 0.35
LEAP (Yao et al., 2022b)	0.63 / 0.45
DMS (Lachapelle et al., 2022b)	0.61 / 0.40
BISCUIT-NF (Ours)	**0.96 / 0.15**

iTHOR – Interaction Maps

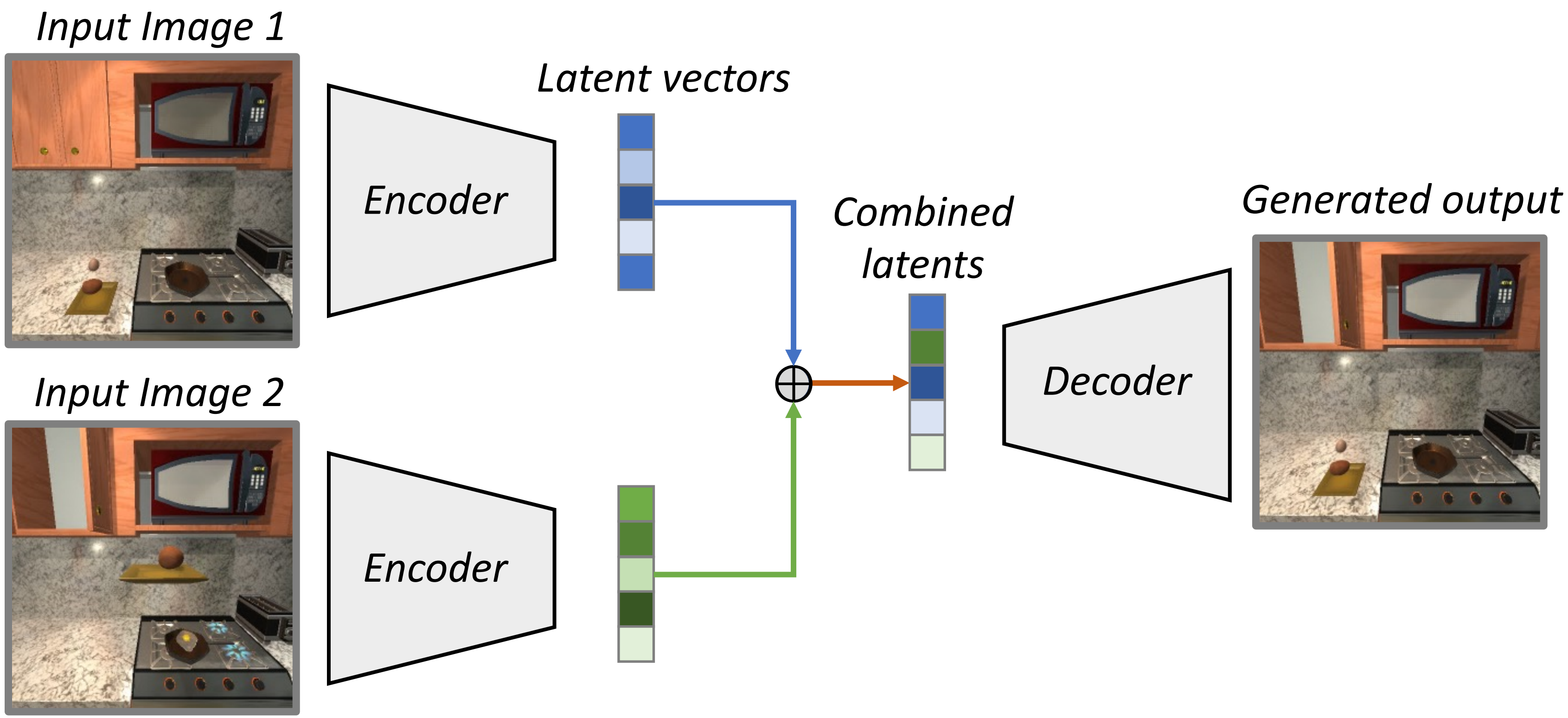
- Visualize learned interaction variables by the x-y locations they are active
- Each causal variable shown in different color



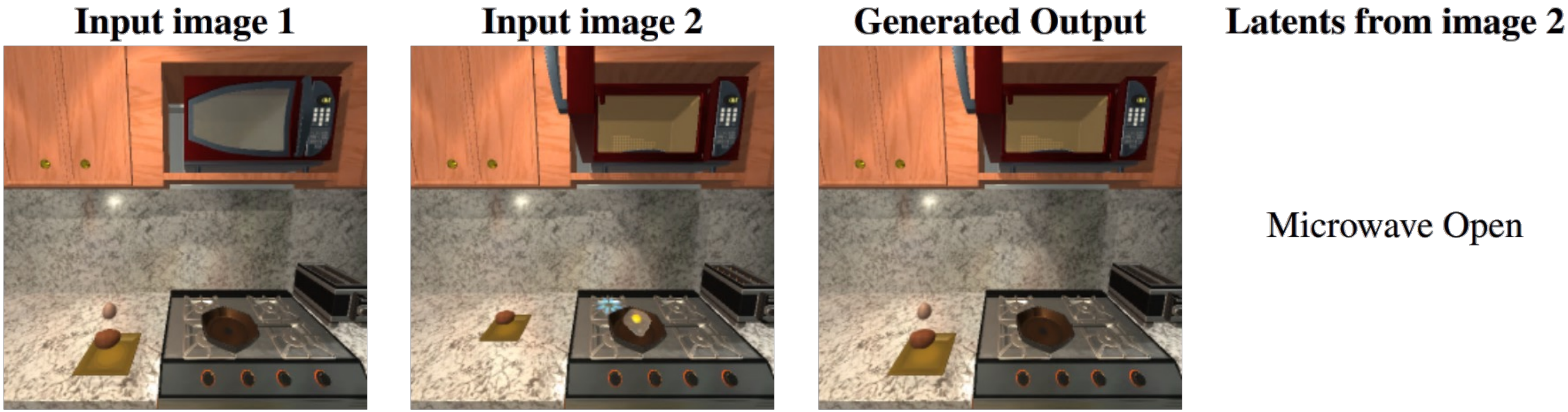
iTHOR – Triplet Evaluation

- Test compositional generation ability of latent space
- Suitable across various identifiability classes

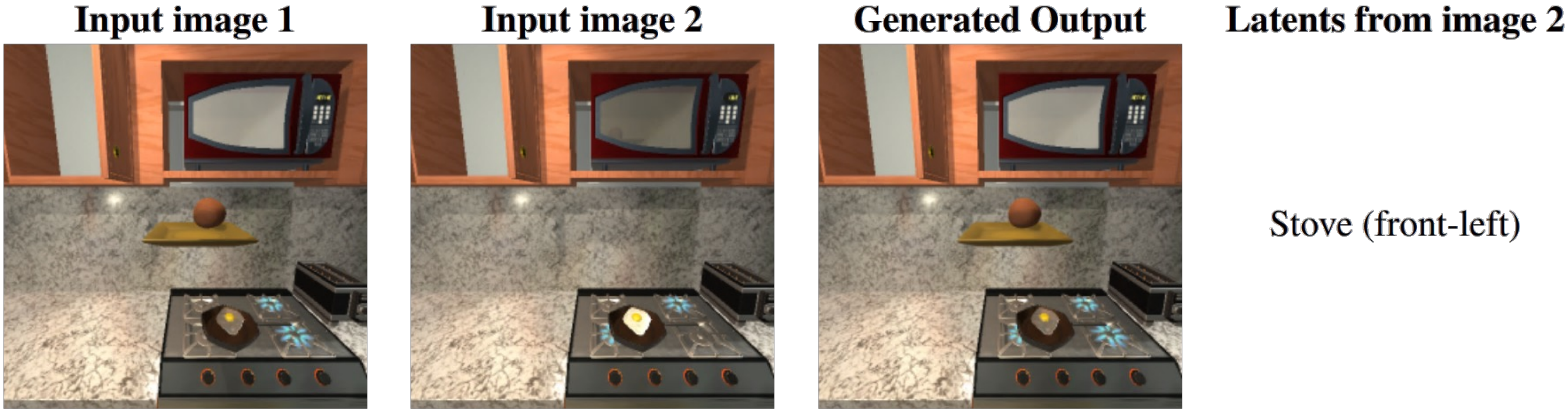
Goal
Open Cabinet
Turn on Microwave
Keep other variables fixed



iTHOR – Triplet Evaluation



iTHOR – Triplet Evaluation



iTHOR – BISCUIT Demo

Demo: https://colab.research.google.com/github/phlippe/BISCUIT/blob/main/demo.ipynb

Conclusion

- BISCUIT identifies causal variables from interactive environments
- Key assumption: binary interaction variables describe agent-causal variable interactions
- Applicable to a variety of robotic and embodied AI environments
- Ability to ‘imagine’ by performing latent interventions
- Identifies actions to perform interventions

Project website and demo: phlippe.github.io/BISCUIT/

Collaborators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References

[Lippe et al., 2023b] Lippe P, Magliacane S, Löwe S, Asano YM, Cohen T, Gavves E. BISCUIT: Causal Representation Learning from Binary Interactions. In 39th Conference on Uncertainty in Artificial Intelligence, 2023. Project page https://phlippe.github.io/BISCUIT/.

[Ahuja et al., 2022] Ahuja K, Hartford J, Bengio Y. Properties from mechanisms: an equivariance perspective on identifiable representation learning. In International Conference on Learning Representations 2022.

[Khemakhem et al., 2020] Khemakhem, I., Kingma, D., Monti, R., and Hyvarinen, A. Variational Autoencoders and Nonlinear ICA: A Unifying Framework. In *Proceedings of the Twenty Third Inter- national Conference on Artificial Intelligence and Statistics*, volume 108 of *Proceedings of Machine Learning Research*. PMLR, 2020.

[Lachapelle et al., 2022] Lachapelle, S., Rodriguez, P., Le, R., Sharma, Y., Everett, K. E., Lacoste, A., and Lacoste-Julien, S. Disentanglement via Mechanism Sparsity Regularization: A New Principle for Nonlinear ICA. In First Conference on Causal Learning and Reasoning, 2022.

[Lippe et al., 2022] Lippe, P., Magliacane, S., Löwe, S., Asano, Y. M., Cohen, T., and Gavves, E. CITRIS: Causal Identifiability from Temporal Intervened Sequences. In Proceedings of the 39th International Conference on Machine Learning, ICML, 2022.

[Lippe et al., 2023a] Lippe, P., Magliacane, S., Löwe, S., Asano, Y. M., Cohen, T., and Gavves, E. Causal representation learning for instantaneous and temporal effects in interactive systems. In The Eleventh International Conference on Learning Representations, 2023.

[Yao et al., 2022a] Yao, W., Chen, G., and Zhang, K. Temporally Disentangled Representation Learning. In Advances in Neural Information Processing Systems 35, NeurIPS, 2022.

[Yao et al., 2022b] Yao, W., Sun, Y., Ho, A., Sun, C., and Zhang, K. Learning Temporally Causal Latent Processes from General Temporal Data. In International Conference on Learning Representations, 2022.