# Building Minimal and Reusable Causal State Abstractions for Reinforcement Learning

(AAAI 2024)

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# Problem Setup

Reinforcement Learning (RL) faces ongoing challenges, particularly in large state spaces

- sample inefficiency
- poor generalization

Solution: causal state abstractions


example task: grasp the pink bottle

# Problem Setup

multiple tasks in the same environment
as *K* Markov decision processes:

$$(S, A, P,\ R^{1,\ldots,K})$$

state space
$S = S^1 \times \cdots \times S^{d_S}$

action
space

unknown
transition

reward functions
for tasks $1, \ldots, K$

# Problem Setup

State abstractions should be…

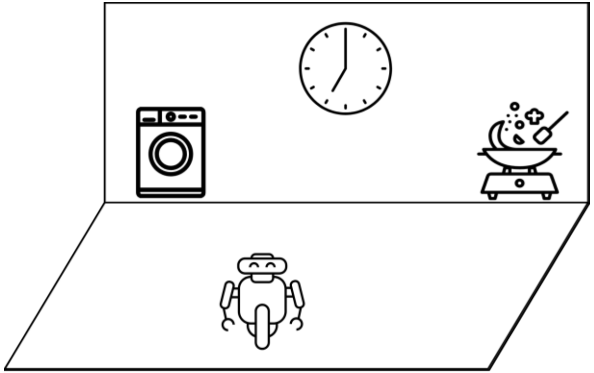
**minimal and sufficient**

- smallest input space for RL to learn a task
- improve sample efficiency & generalization

**reusable**

- enable the agent to learn all tasks in the same environment
- avoid learning each task from scratch

But how?



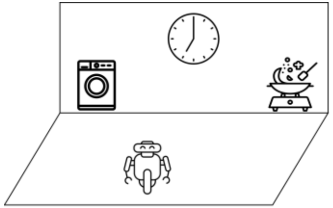
**task 1: wash clothes in**

$R_t^1 := \mathbb{1}[$  **finishes the cycle** $]$

task 2: cook dinner

$R_t^2 := \mathbb{1}[$ finish  at  $]$

# Prior Work 1



*CDL*

Wang et al, "Causal dynamics learning for task-independent state abstraction" ICML 2022.

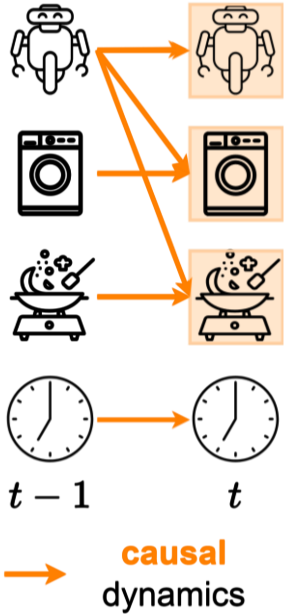
- learns a *causal* dynamics model $f: S_t \times A_t \rightarrow S_{t+1}$
- the state abstraction identifies and keeps all *controllable* state variables

**minimal / sufficient** ×

- includes an extra appliance for each task
- doesn’t include clock

**reusable** ✓

- dynamics (and derived abstraction) are task-independent



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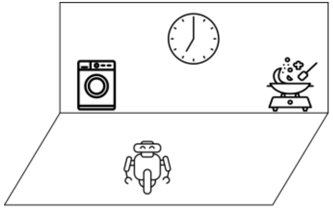
# Prior Work 2



*TIA & Denoised MDPs*

Fu et al, "Learning task informed abstractions" ICML 2021.
Wang et al, "Denoised MDPs: Learning world models better than the world itself" ICML 2022.

(TIA) During task learning:

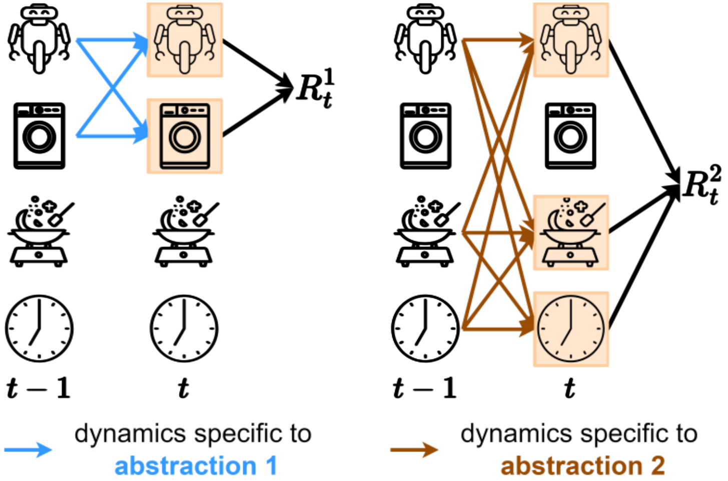
- Identify a minima set of state variables that can predict rewards and the state variables' own dynamics

**minimal/sufficient** ✓

- by analyzing relevance to the reward

**reusable** ×

- dynamics models are specific to reward-relevant state variables



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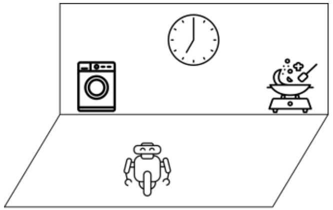
# Causal Bisimulation Model (CBM)



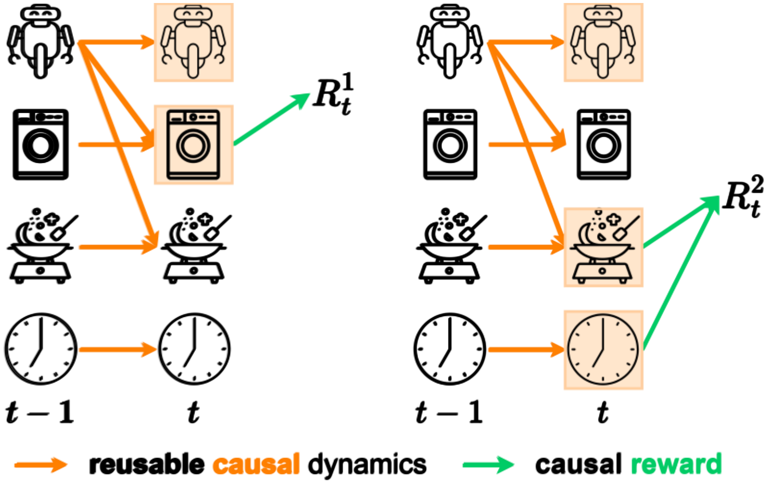
Can we combine the best of both worlds?

**reusable** ✓

– learn a causal dynamics model

**minimal/sufficient** ✓

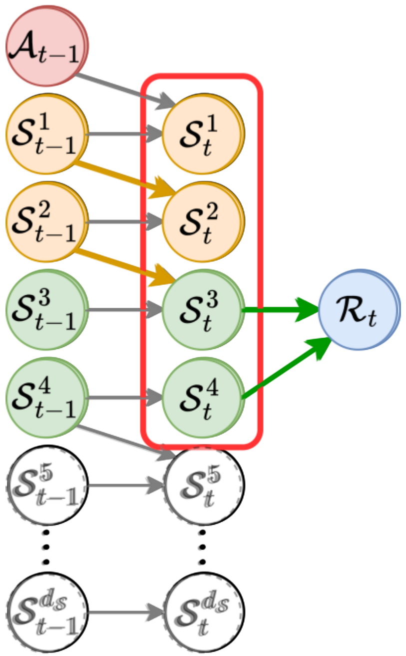
– given a task, learn a causal reward model to remove task-irrelevant state variables and include task-relevant non-controllable variables



# Method (CBM) – causal bisimulation abstraction

Given causal dynamics and reward models, derive the state abstraction as all **ancestors** of the reward:

- parent variables affecting the reward
- ancestor variables affecting the parents via dynamics

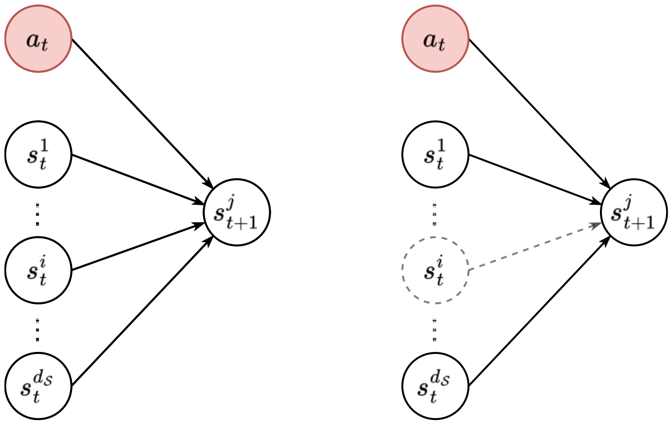


# Method (CBM) – causal dynamics/reward models

Causality **all-but-one** test:

**The dynamics/reward causal edge $s_t^i \to s_{t+1}^j$ or $s_t^i \to r_t^j$ exists**
**if $s_t^i$ is necessary for prediction.**

For example, to determine if a dynamics edge $s_t^i \to s_{t+1}^j$ exists,




$$p\left(s_{t+1}^j \middle| s_t, a_t\right) \overset{?}{\approx} p\left(s_{t+1}^j \middle| \{s_t / s_t^i, a_t\}\right)$$



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Causality **all-but-one** test:

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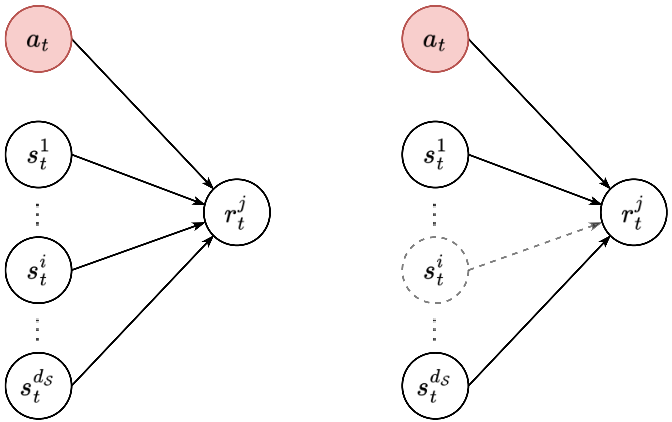
**if $s_t^i$ is necessary for prediction.**

Similarly, to determine if a reward edge $s_t^i \rightarrow r_t^j$ exists,

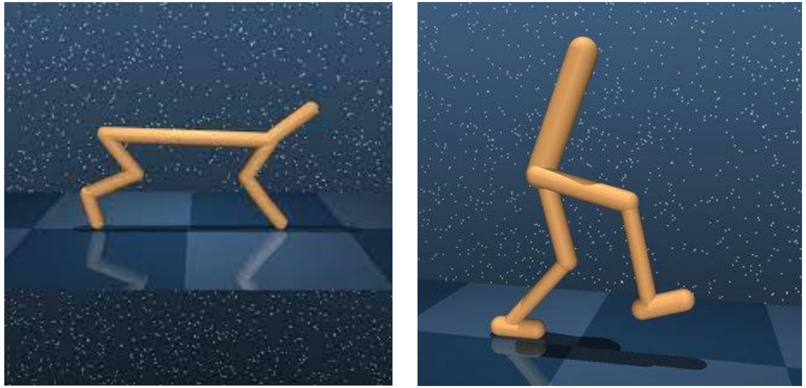



$$p\left(r_t^j \middle| s_t, a_t\right) \overset{?}{\approx} p\left(r_t^j \middle| \{s_t / s_t^i, a_t\}\right)$$

conditional mutual information (CMI)

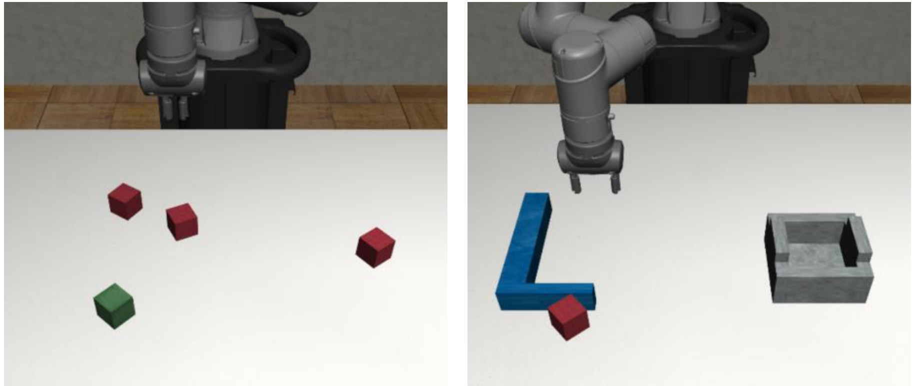
$$\mathrm{CMI} = \mathbb{E}_{s,a,r}\left[\log \frac{p\left(r_t^j \middle| s_t, a_t\right)}{p\left(r_t^j \middle| \{s_t / s_t^i, a_t\}\right)}\right]$$

# Results



DeepMind control suite

Tassa et al. "Deepmind control suite.“ arXiv 2018.



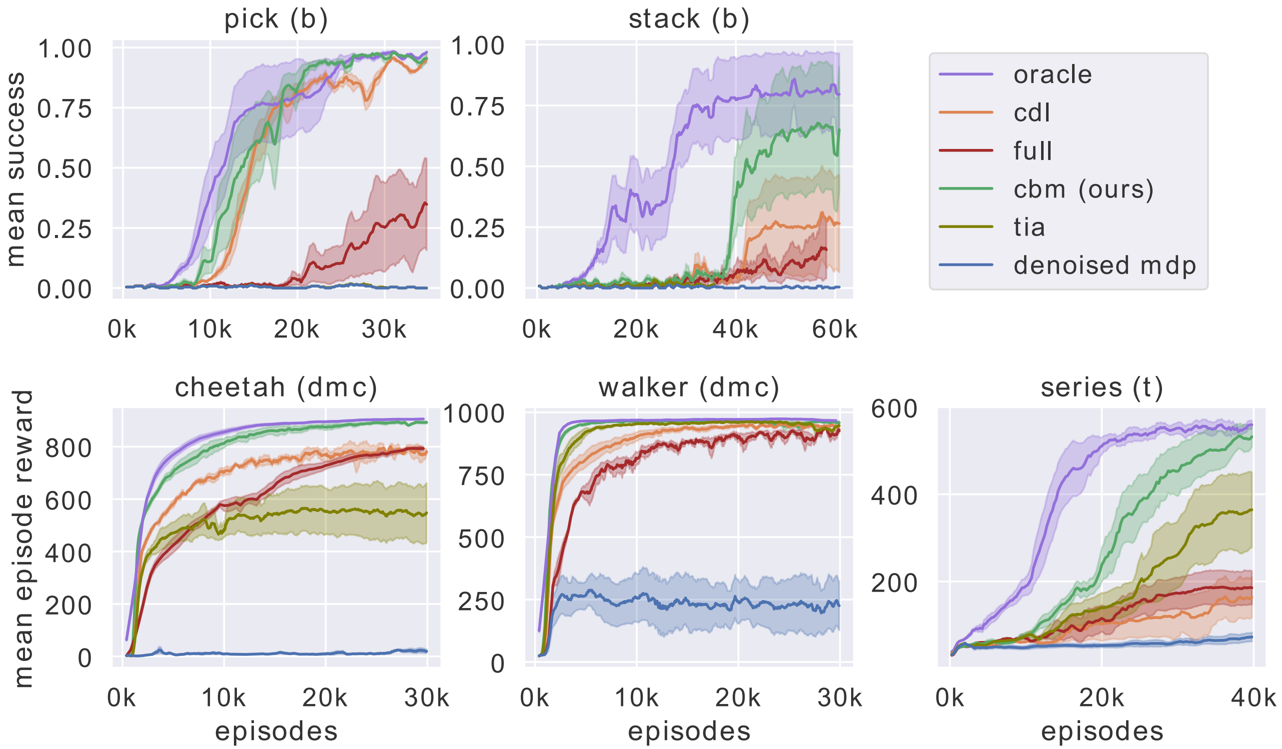
Robosuite table-top manipulation

Zhu et al “Robosuite: A modular simulation framework and benchmark for robot learning." arXiv 2020.

- Tasks: HalfCheetah, Walker
- Uncontrollable (20) and controllable noise variables (20)
- High-dimensional

- Environments: block (b), tool-use (t)
- Tasks: pick (b), stack (b), series (t)
- Pick/stack: moveable and unmovable blocks
- Series: long horizon

# Results - task learning sample efficiency



# Thank you!

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