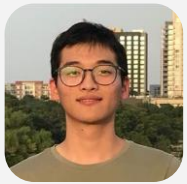
Causal Dynamics Learning for Task-Independent State Abstraction

Zizhao Wang, Xuesu Xiao, Zifan Xu, Yuke Zhu, and Peter Stone





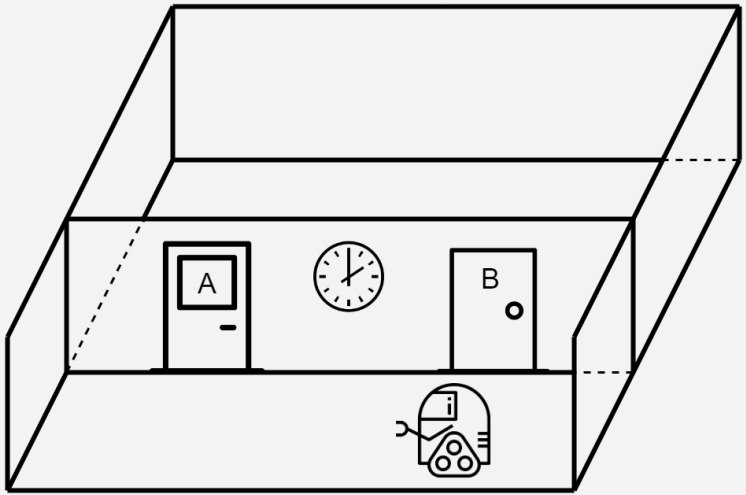
LARG Learning Agents Research Group The University of Texas at Austin | RPL UT Robot Perception & Learning Lab | Sony AI

Motivation

Real-world dynamics are usually ***sparse***.

- The transition of each state variable only depends on a few state variables.

For example, for an environment with a robot, two doors and a clock on the wall:



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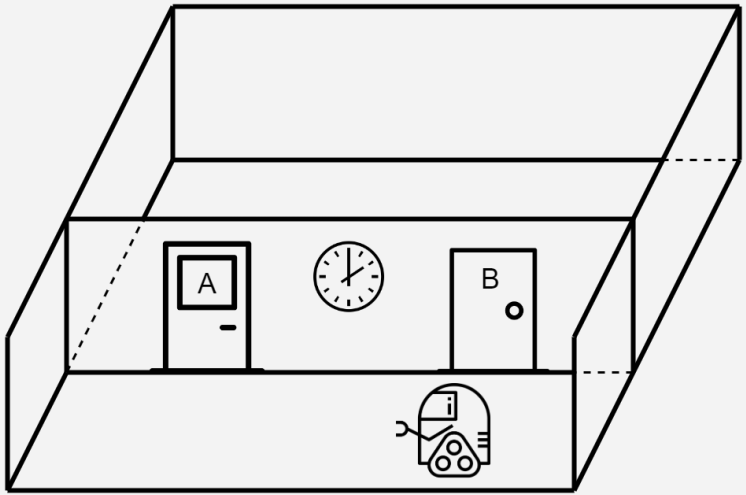

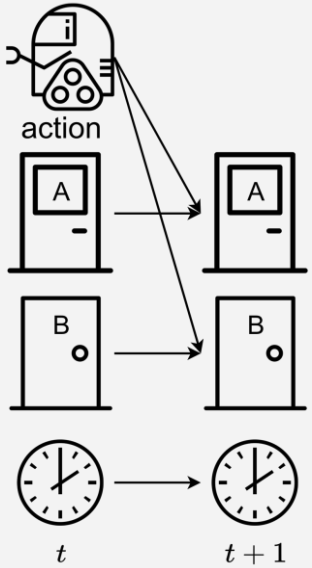

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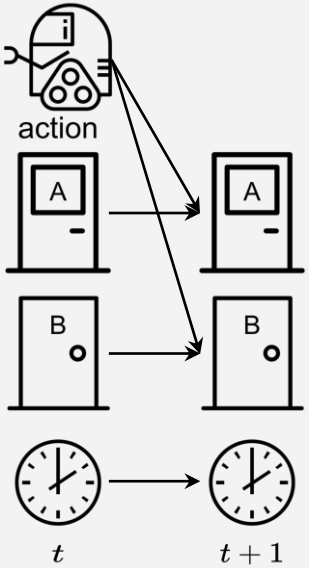
But most model-based RL work uses dense dynamics models (fully-connected networks).



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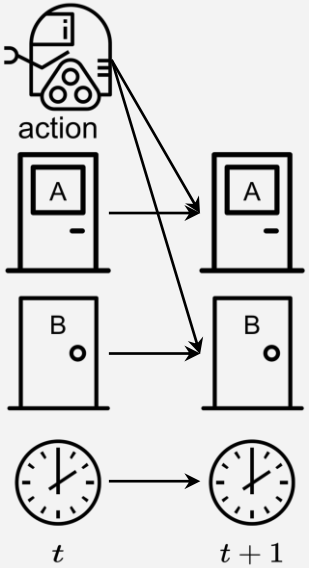

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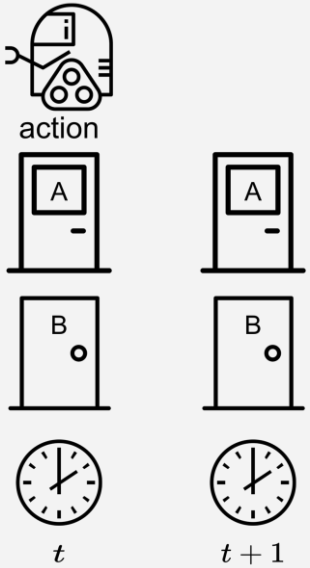

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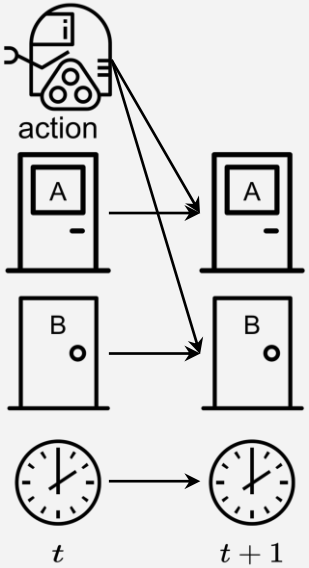

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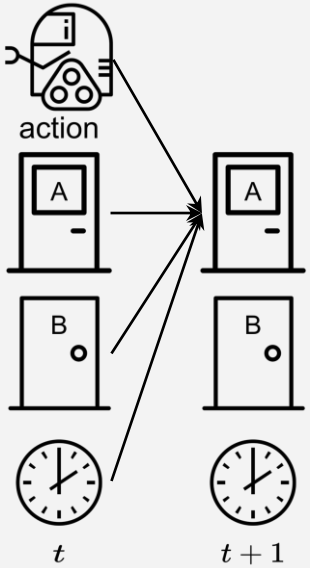

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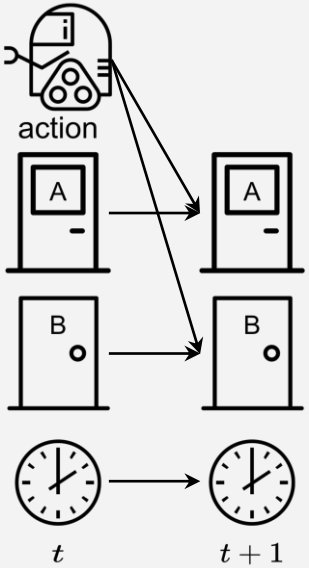

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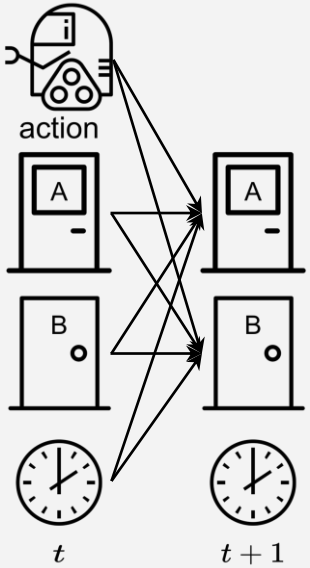

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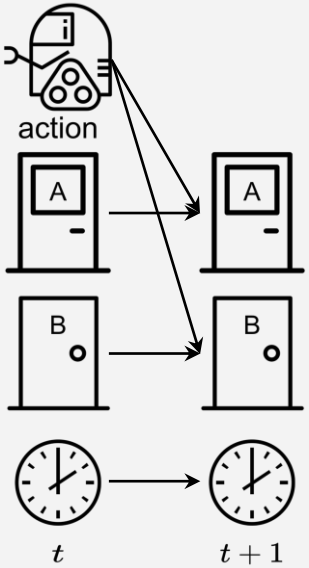

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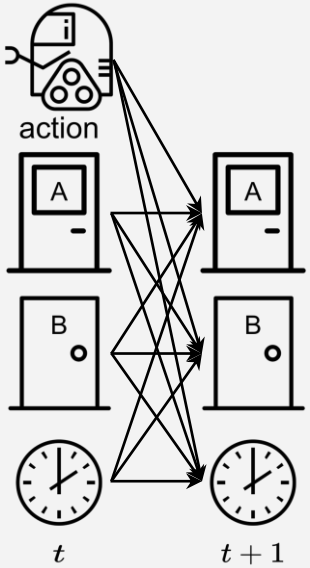

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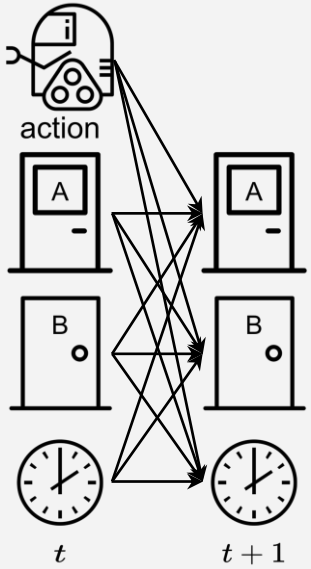

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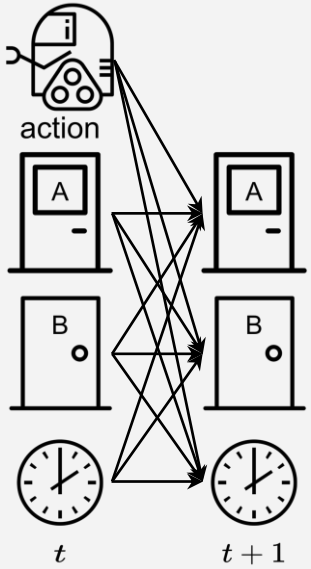

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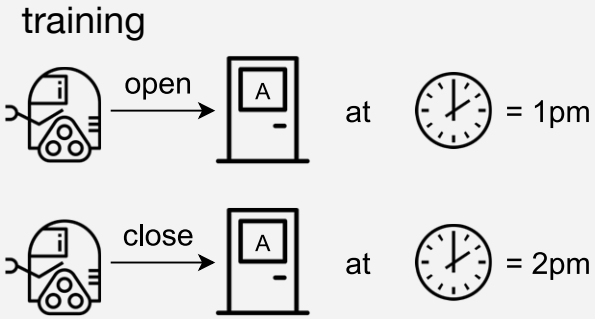

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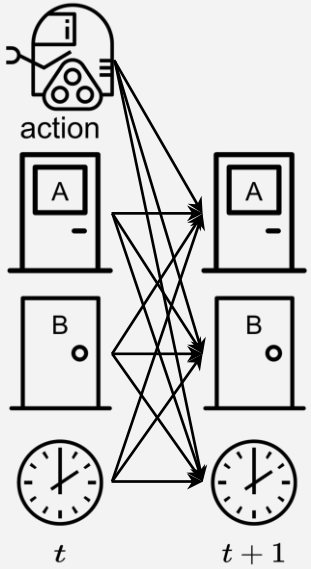

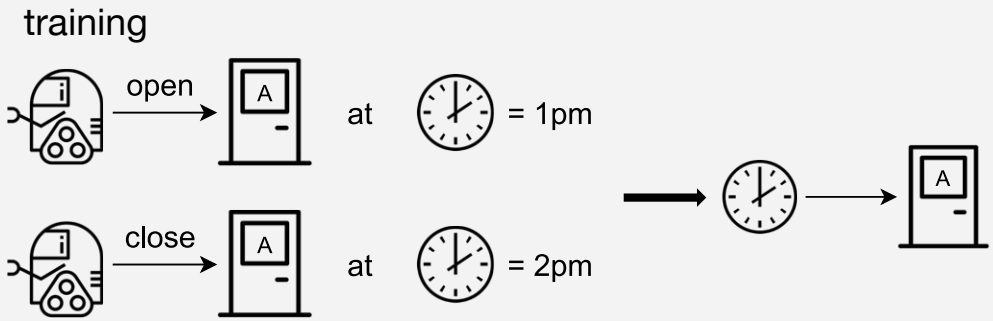

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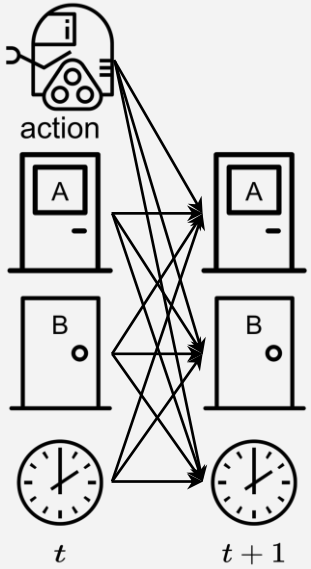

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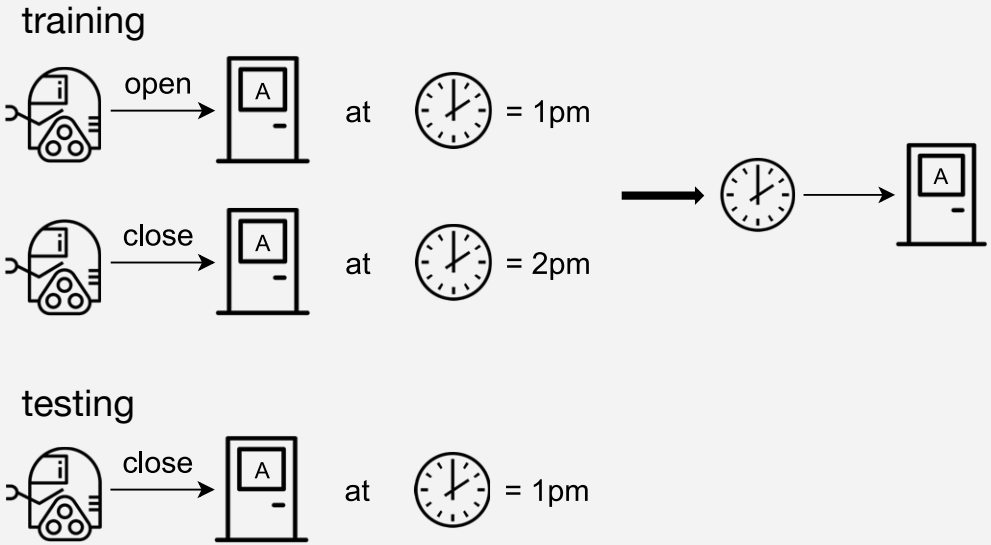

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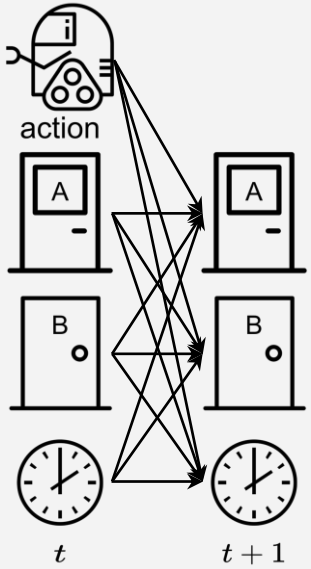

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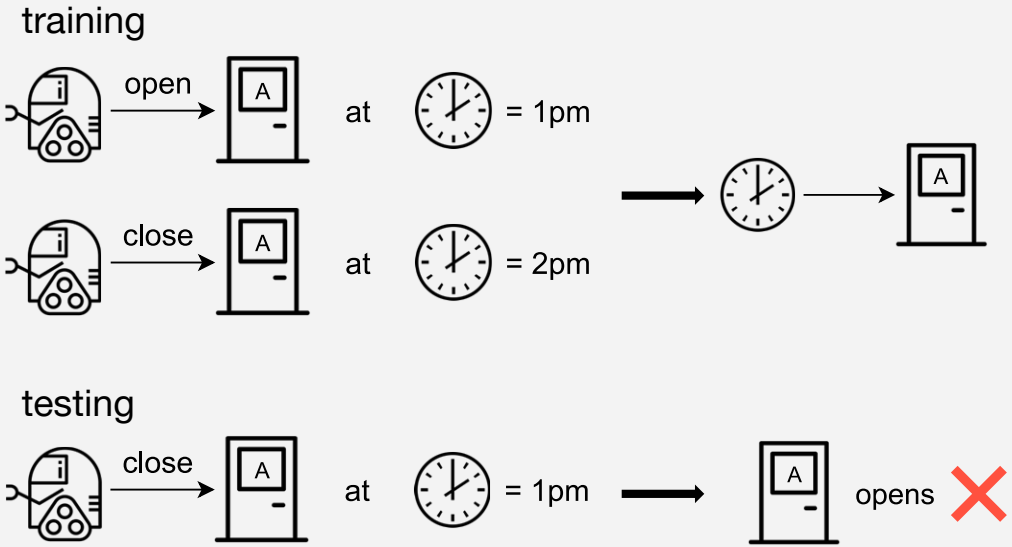

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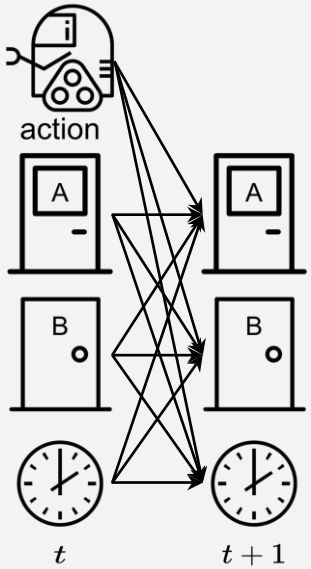

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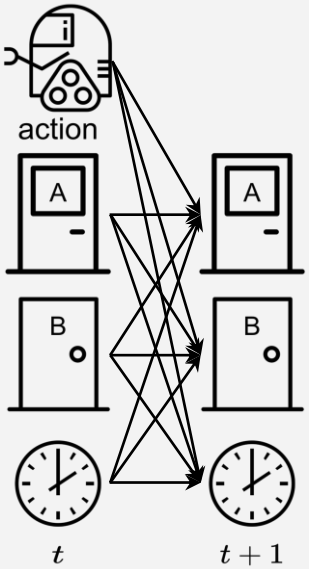

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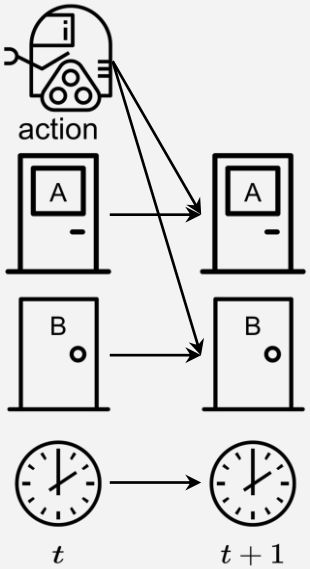

only keep causal edges, robust to outliers,

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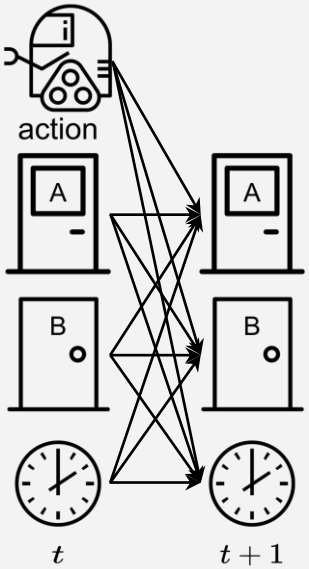

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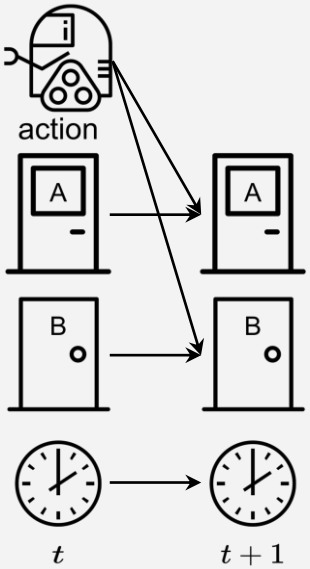


only keep causal edges, robust to outliers,
e.g., clock outliers won't affect door A & B prediction

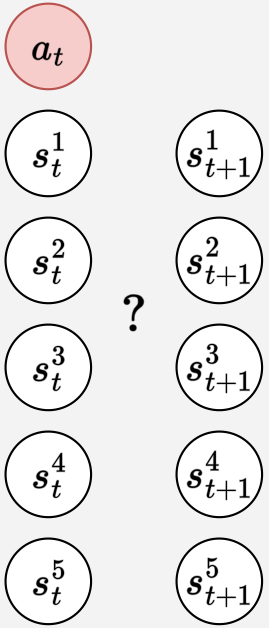
Problem Setup

$$< \mathcal{S}, \mathcal{A}, \mathcal{P} >$$

S: state space (known, *high-level* variables are given)
We leave handling low-level, partially-observable state space (e.g., images) as future work.

A: action space (known)

P: transition probability (not known)



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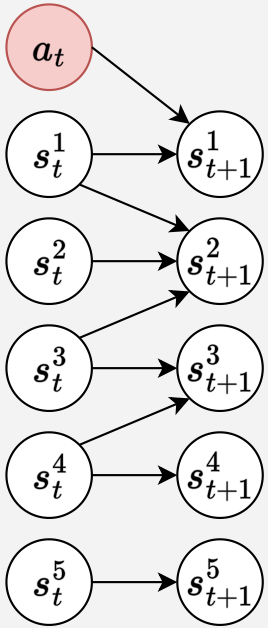
1. Learn a causal dynamics model from transition data

$$\mathcal{P}(s_{t+1}|s_t, a_t) = \prod_{i=1}^{d_\mathcal{S}} \mathcal{P}(s^i_{t+1}|\mathbf{PA}_{s^i})$$

$\mathbf{PA}_{s^i}$ are parents of s^i during the data generation process.



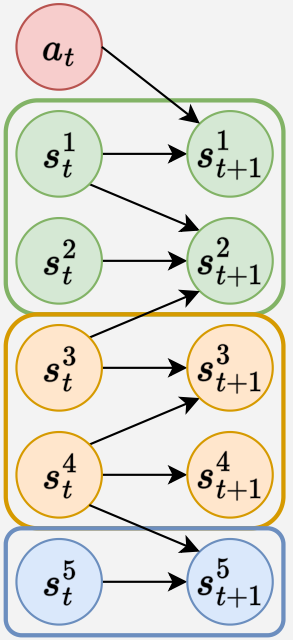
Problem Setup

Goals

1. Learn a causal dynamics model from transition data
2. Split state variables into three categories

$$\mathcal{S} = \mathcal{S}^c \times \mathcal{S}^c \times \mathcal{S}^i$$

S^c: space of controllable state variables
S^r: space of action-relevant state variables
S^i: space of action-irrelevant state variables



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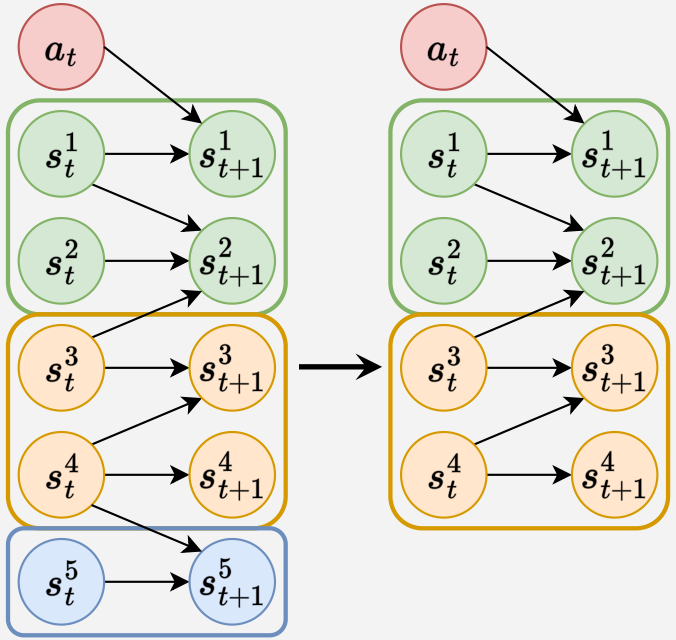
2. Split state variables into three categories
3. Derive a state abstraction by omitting action-irrelevant state variables



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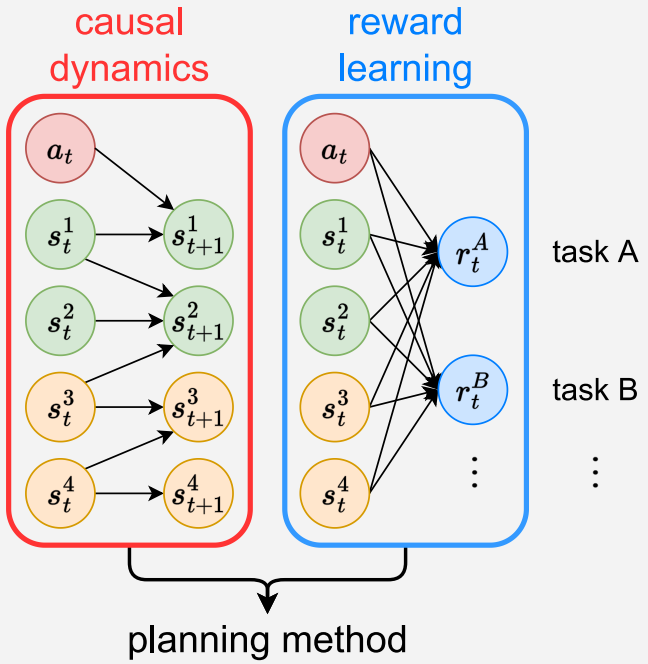
3. Derive a state abstraction by omitting action-irrelevant state variables
4. Use the abstracted causal dynamics to learn (many) downstream tasks



Related Work

Bisimulation[1] ϕ: bisimulation considers two states the same $\phi(x) = \phi(x')$ if

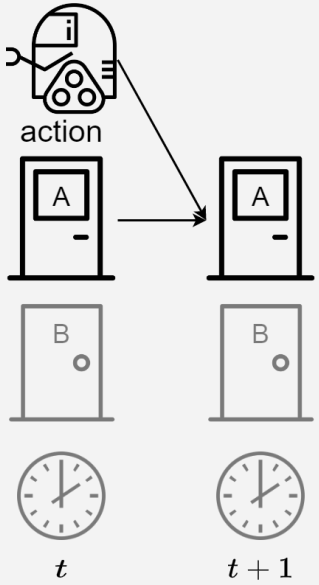
$$R(x, a) = R(x', a),$$
$$\sum_{x'' \in \phi^{-1}(s)} P(x''|x, a) = \sum_{x'' \in \phi^{-1}(s)} P(x''|x', a)$$

[1] Ravindran, B., 2004; Li, L., 2009

Related Work

Compared to CDL,

- Bisimulation is reward-specific (applicable to limited tasks).
  e.g., the bisimulation abstraction learned from “opening door A” can’t be used for “opening door B”.



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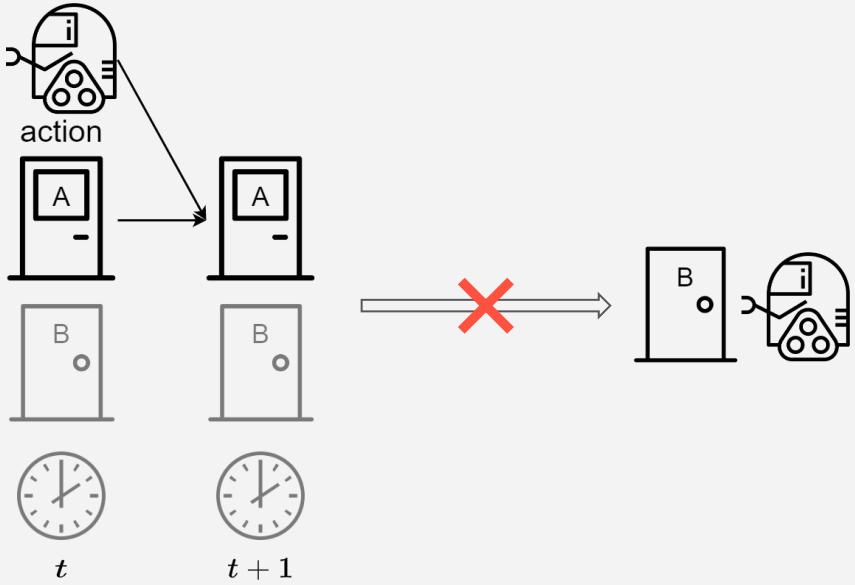

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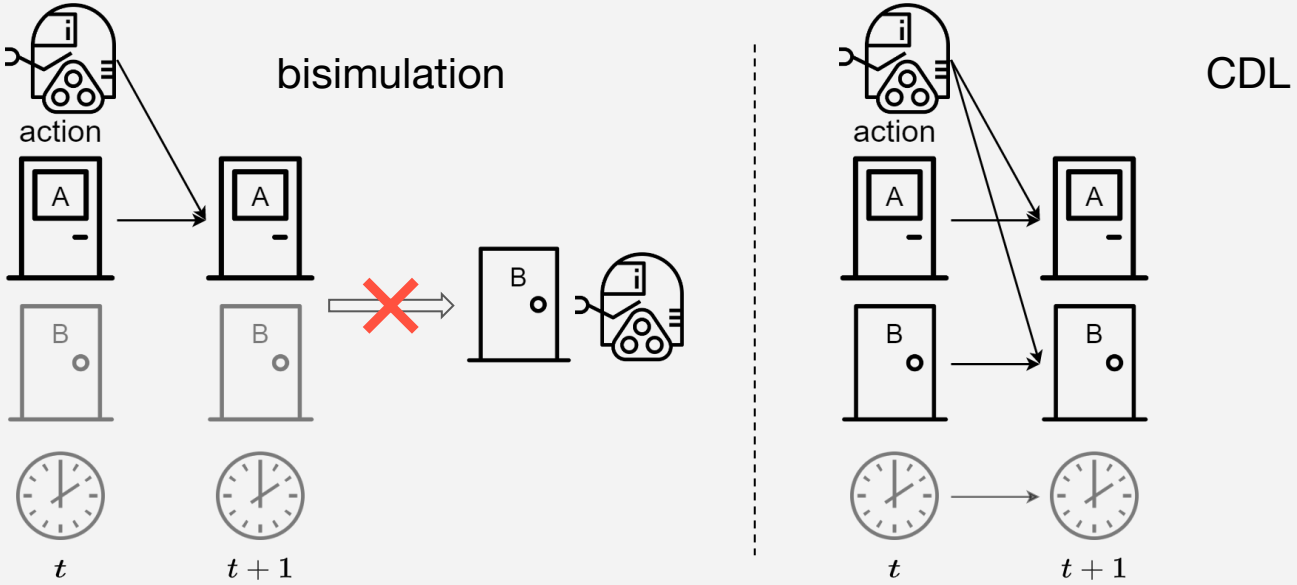

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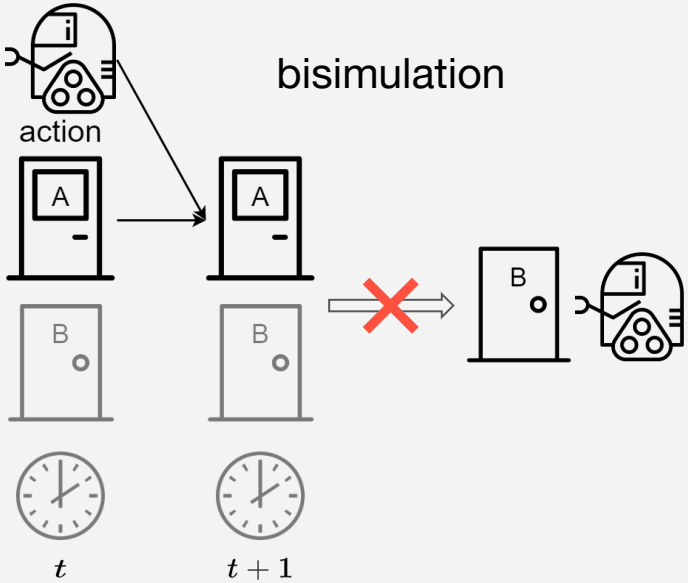
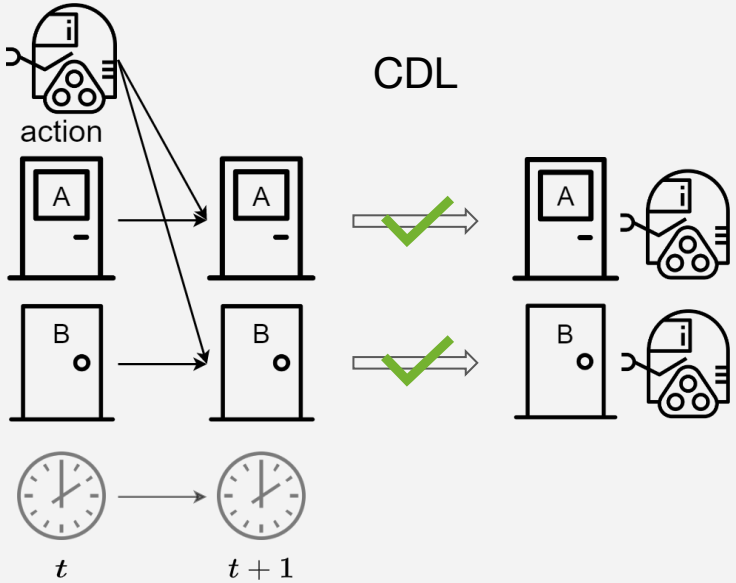
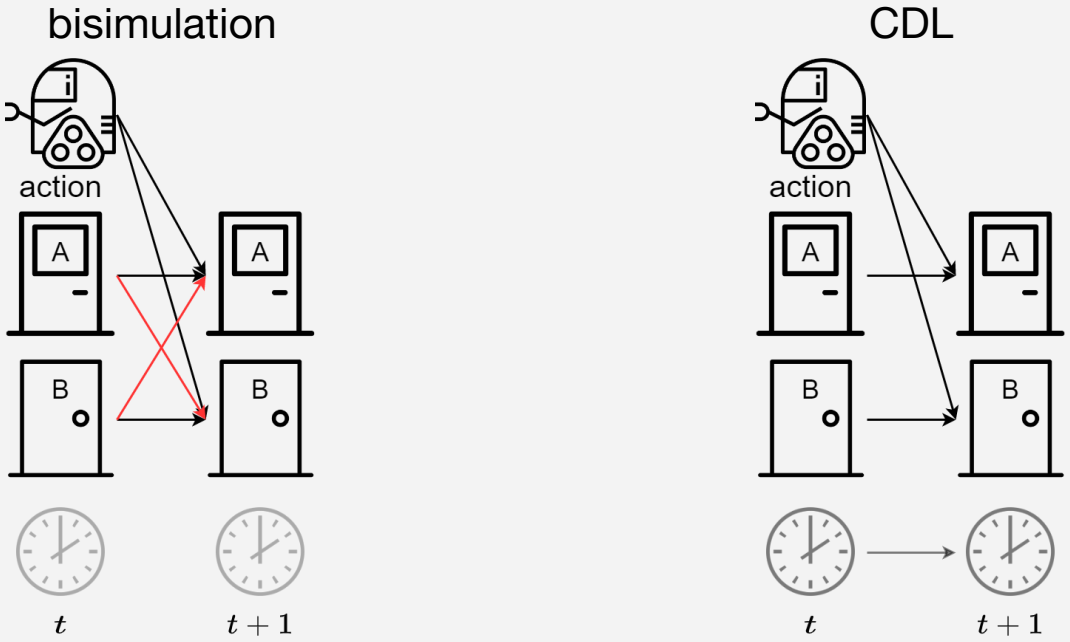




Related Work

Compared to CDL,

- Bisimulation is reward-specific and thus applicable to **limited** tasks.
- Most bisimulation work still uses dense dynamics, leading to poor generalization.



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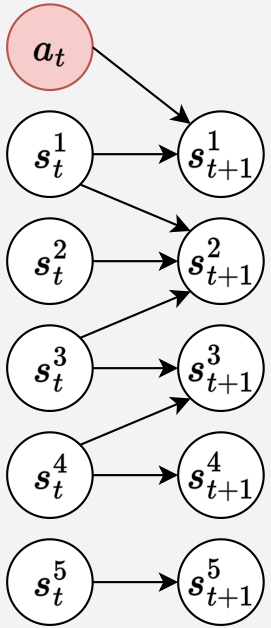

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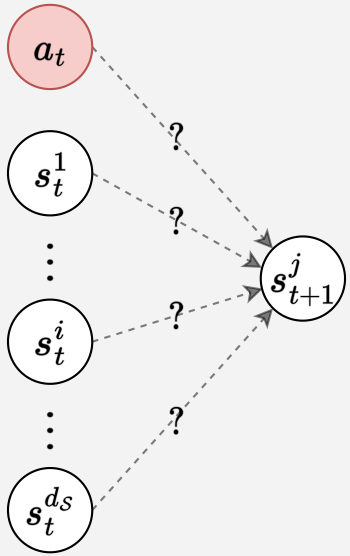
Specifically, for each state variable s^j, how to determine if a state variable s^i is one of its parents?



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Key idea: determine if the causal edge $s_t^i \rightarrow s_{t+1}^j$ exists with a conditional independence test.

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Theorem 1

If $s_t^i \not\perp\!\!\!\perp s_{t+1}^j | \{s_t / s_t^i, a_t\}$, then $s_t^i \rightarrow s_{t+1}^j$.

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In other words, is s_t^i needed to predict s_{t+1}^j?

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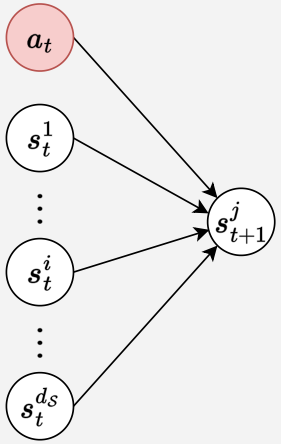

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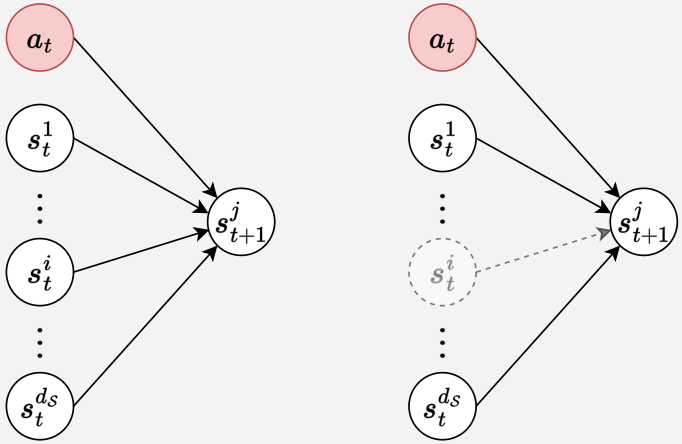

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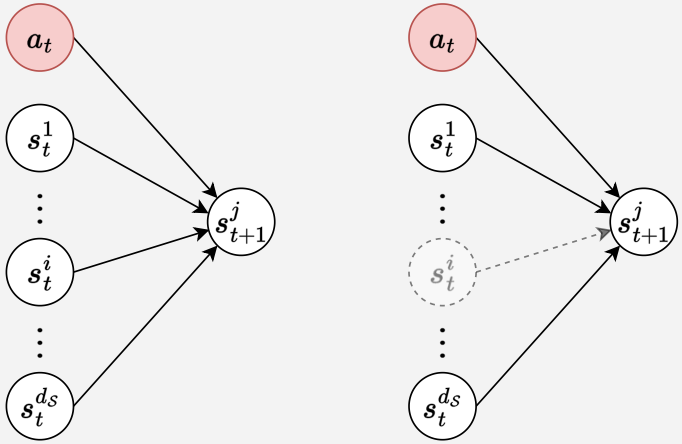

$$p(s_{t+1}^j | s_t, a_t) \stackrel{?}{=} p(s_{t+1}^j | \{s_t / s_t^i, a_t\})$$

Method

Learn and predict $p(s^j_{t+1}|s_t, a_t)$ & $p(s^j_{t+1}|\{s/s^i\}_t, a_t)$ using generative models, but there will be $d^2_{\mathcal{S}}$ models to train...

Method

Learning $p(s^j_{t+1}|s_t, a_t)$ & $p(s^j_{t+1}|\{s/s^i\}_t, a_t)$ needs to train $d^2_{\mathcal{S}}$ models.
With a mask M_j and an element-wise maximum module, one network can represent all generative models in the form of $p(s^j_{t+1}|\cdot)$.

Method

Learning $p(s^j_{t+1}|s_t, a_t)$ & $p(s^j_{t+1}|\{s/s^i\}_t, a_t)$ needs to train d_S^2 models.
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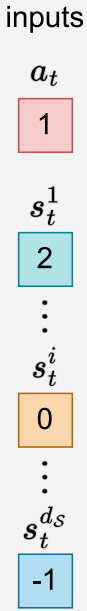

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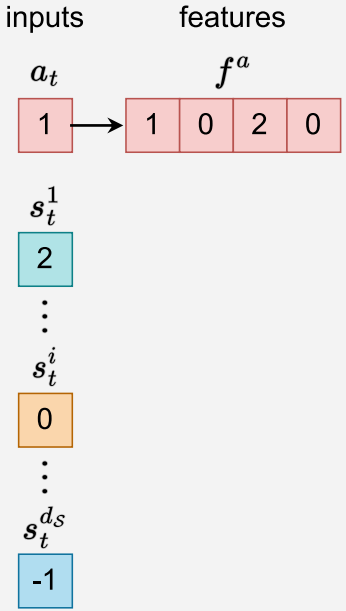

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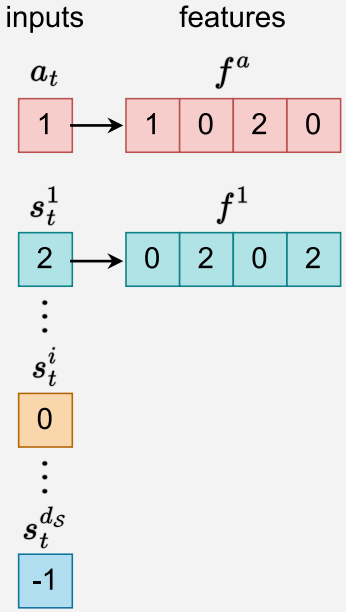

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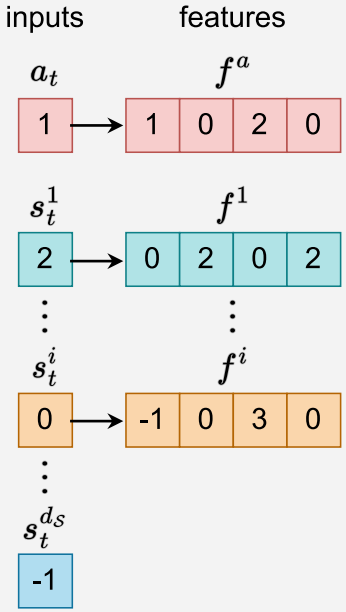

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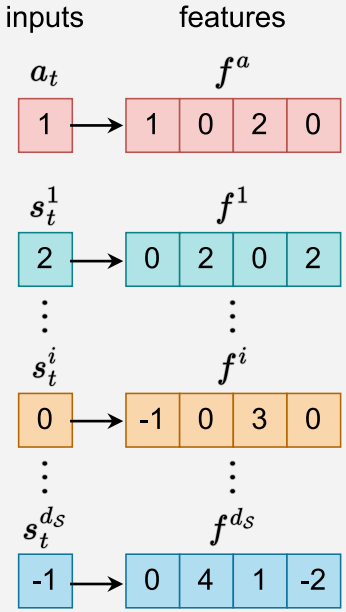

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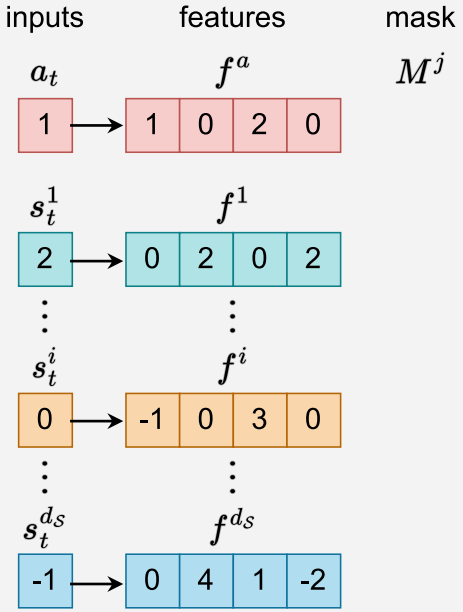

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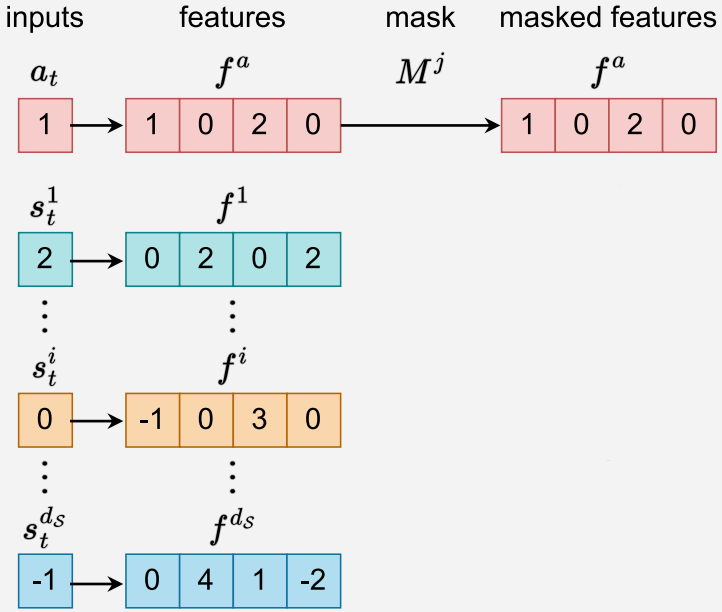

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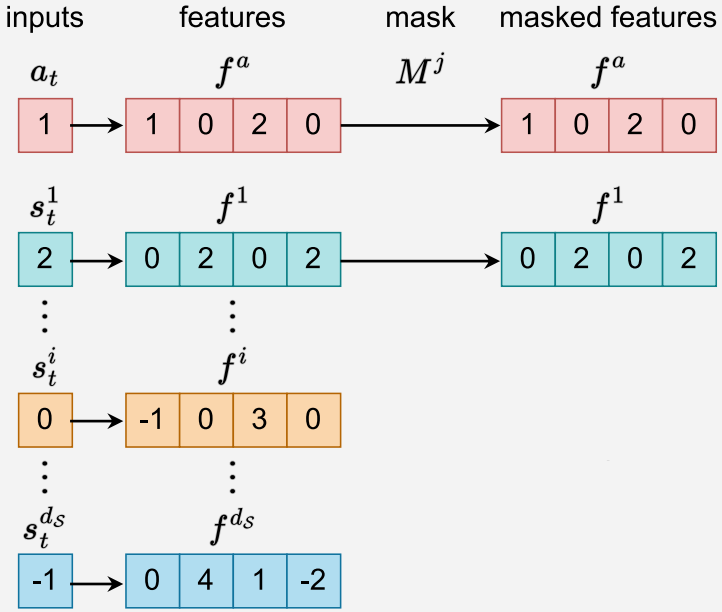

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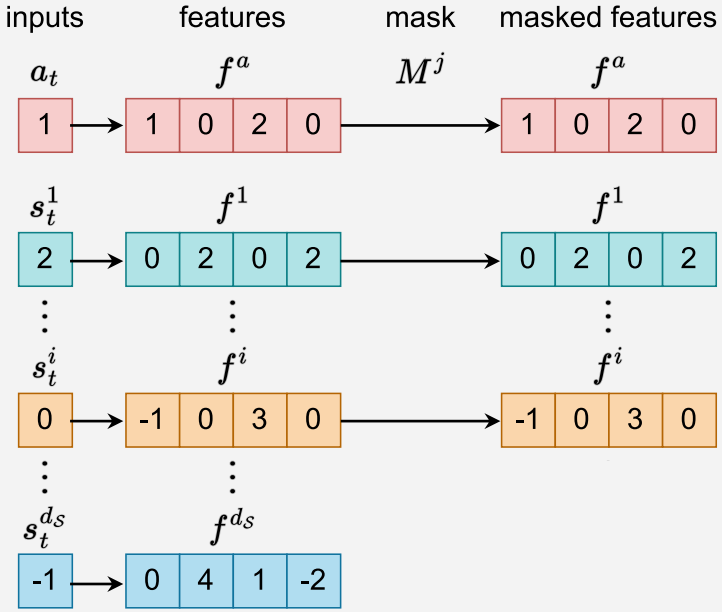

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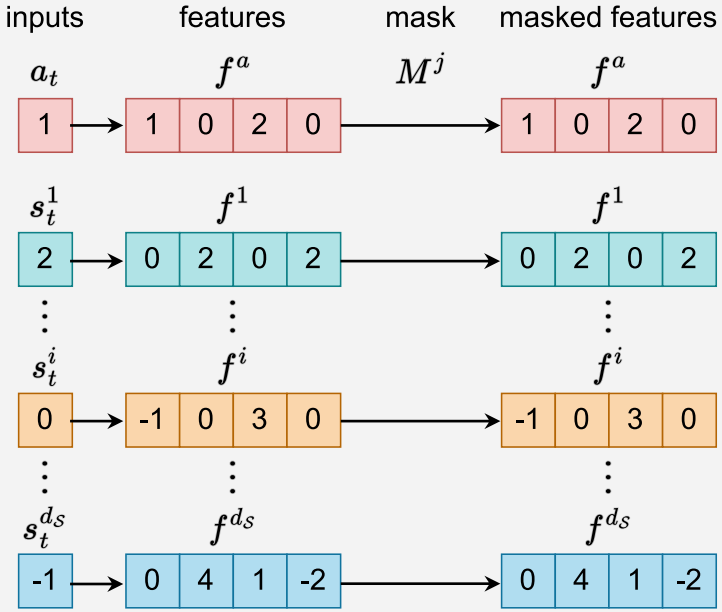

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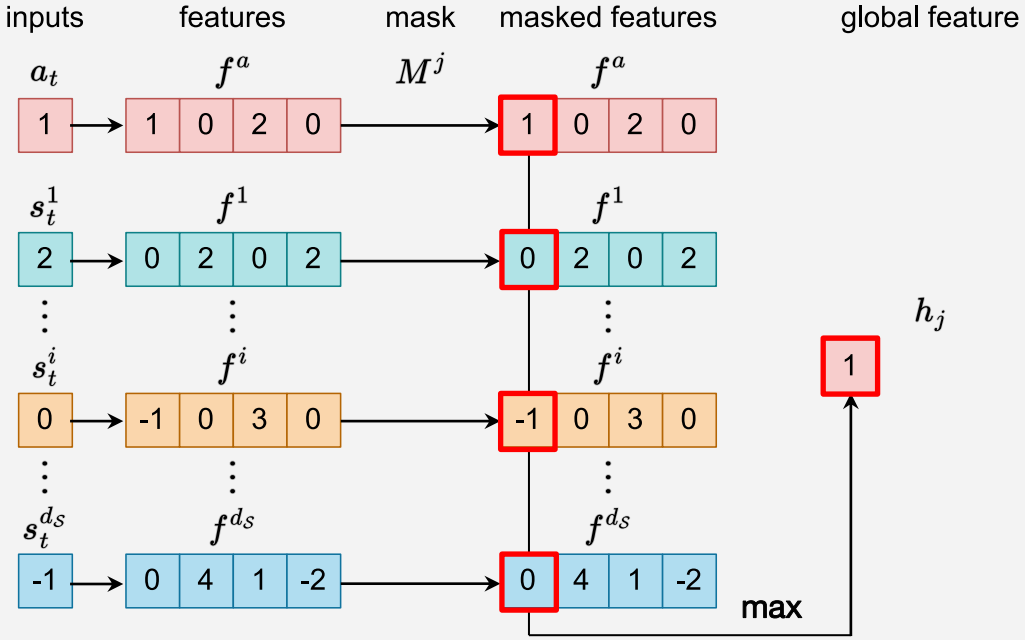

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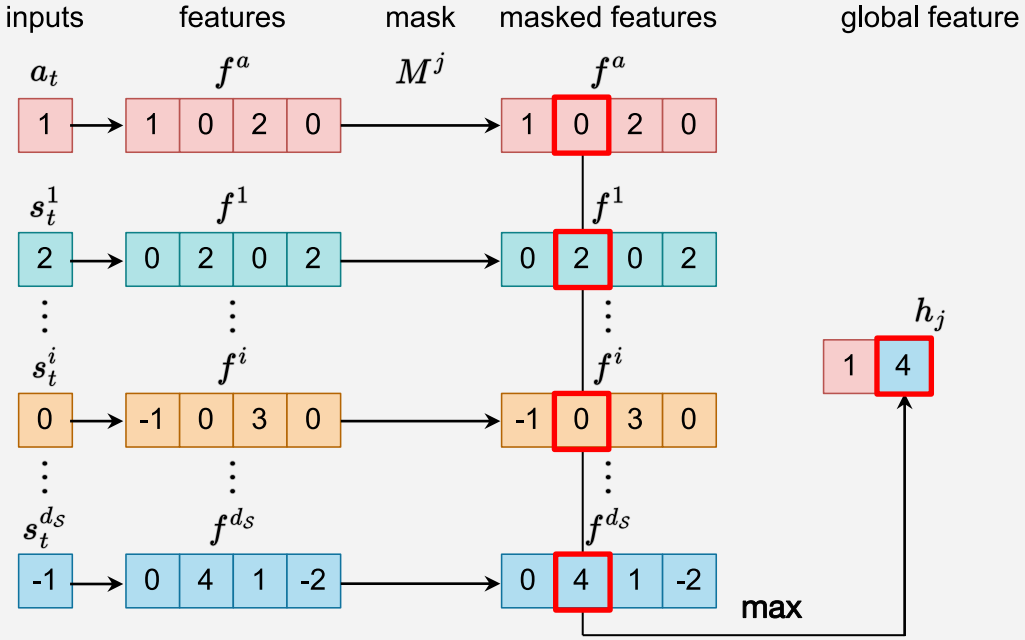

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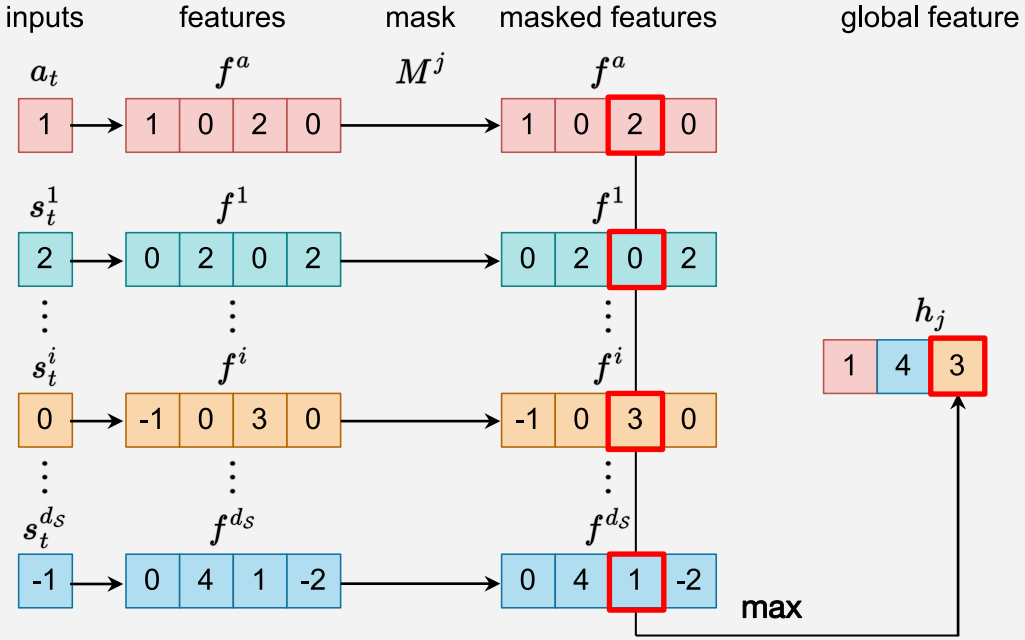

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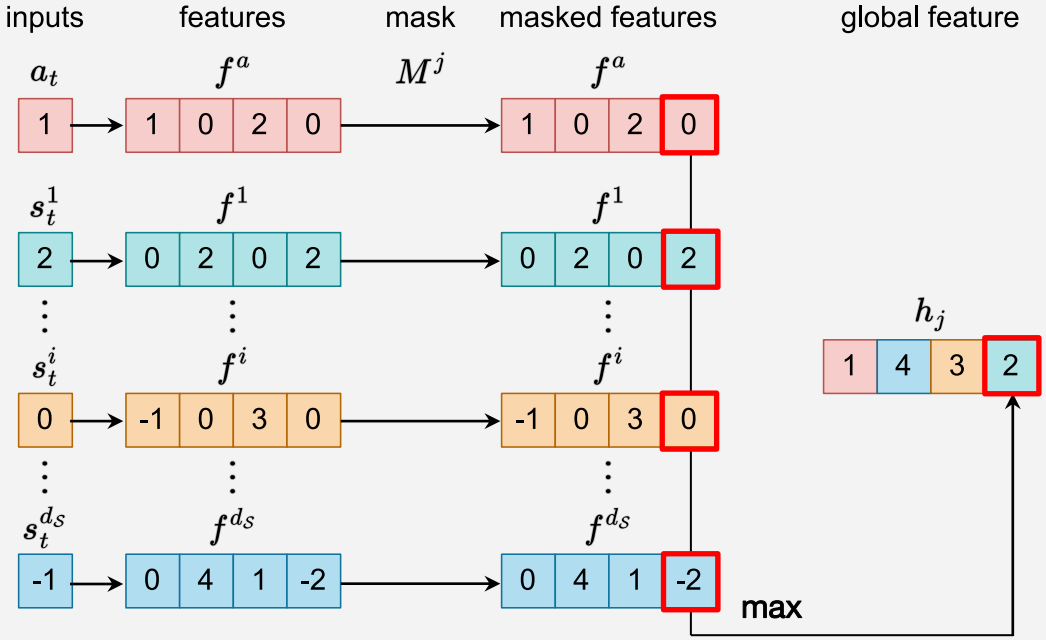

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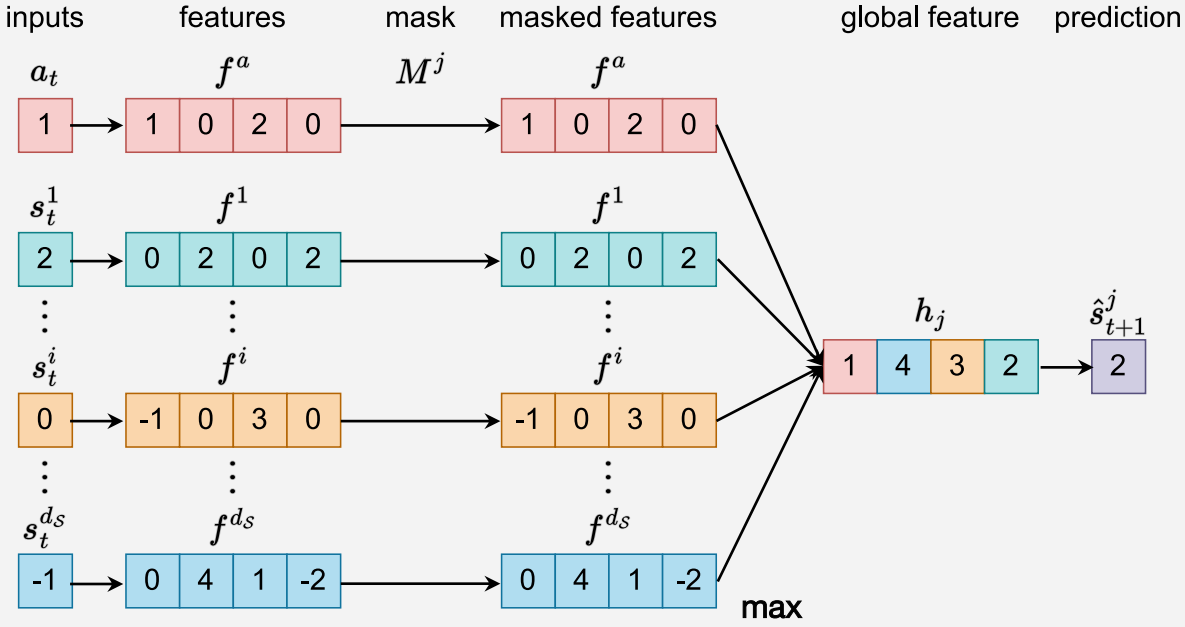

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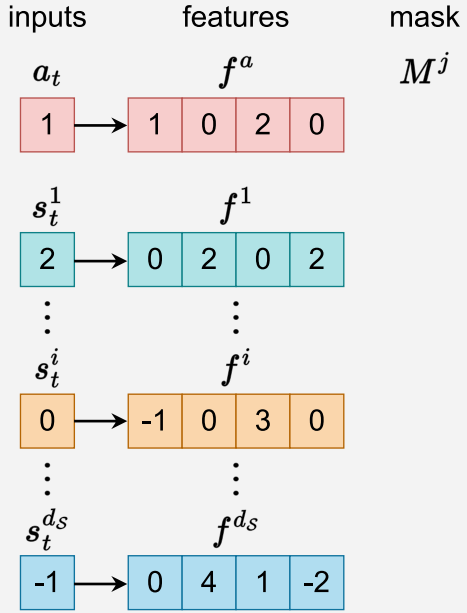

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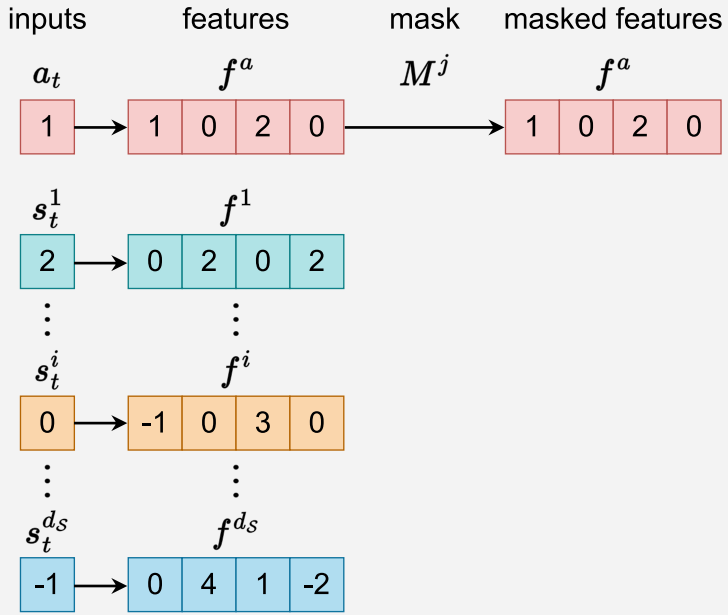

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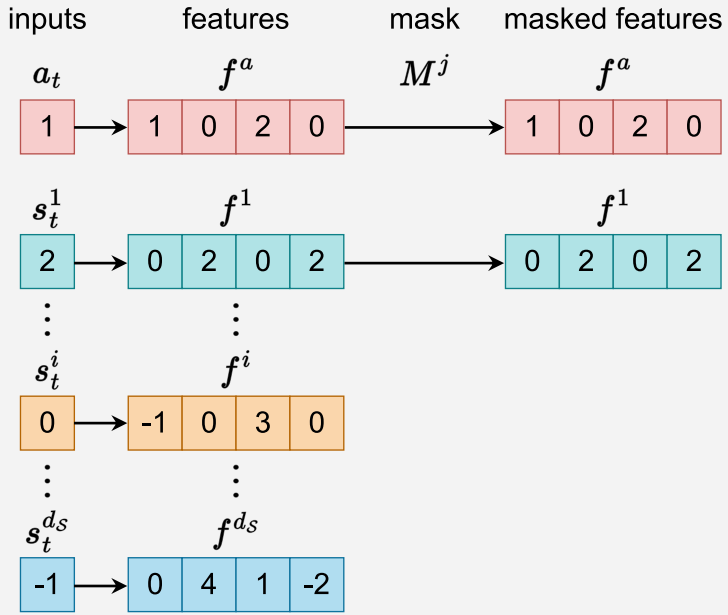

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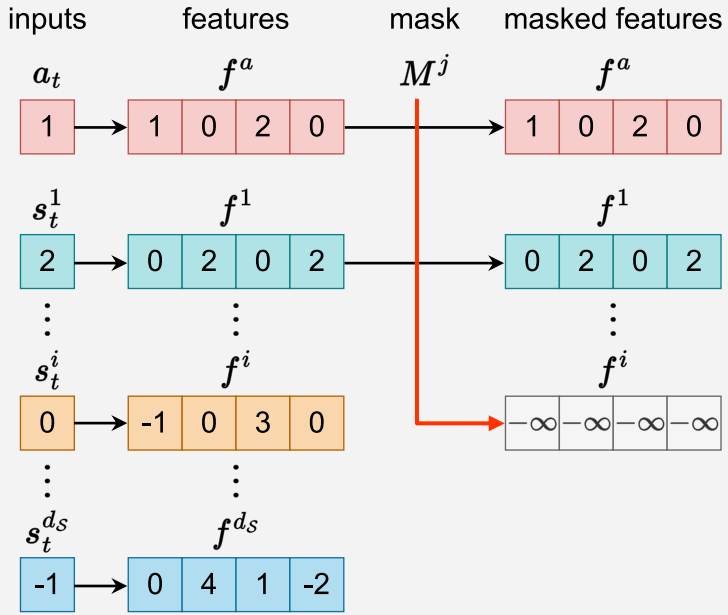

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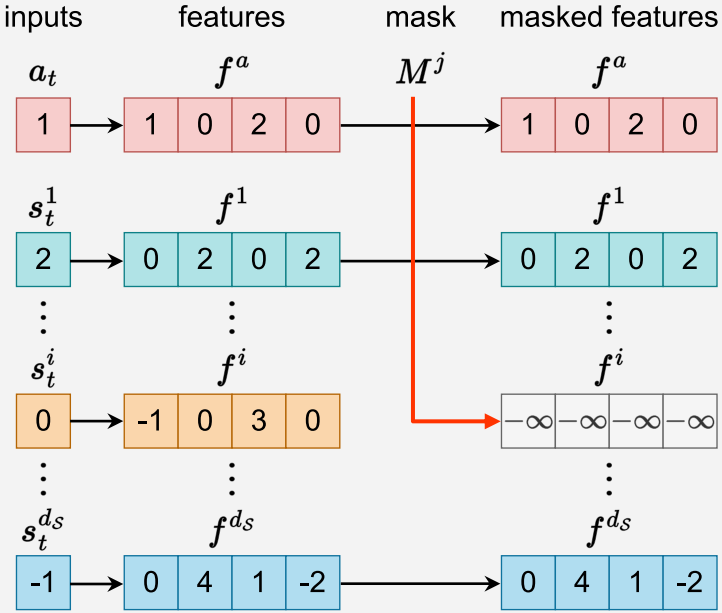

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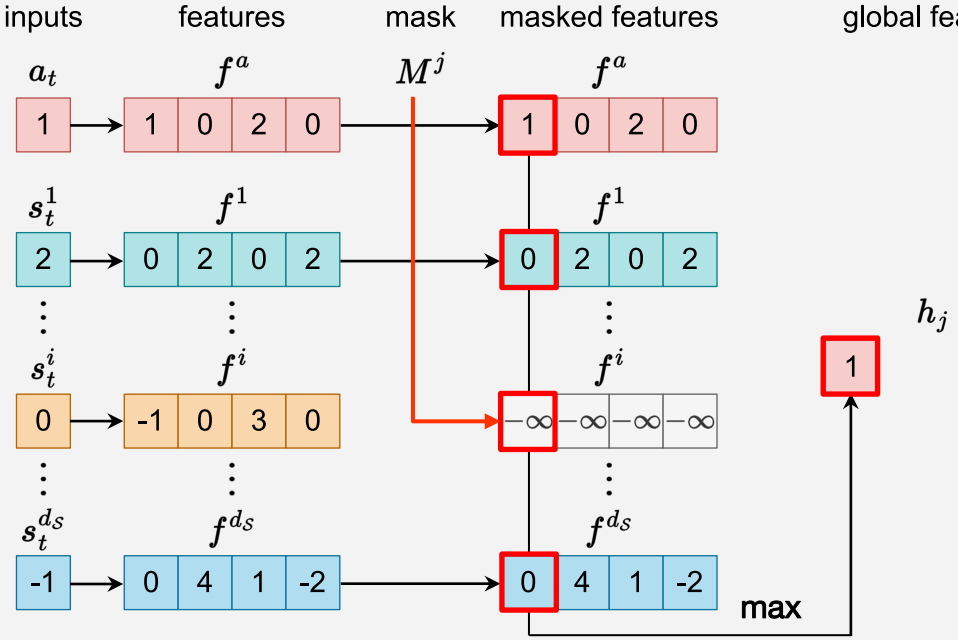

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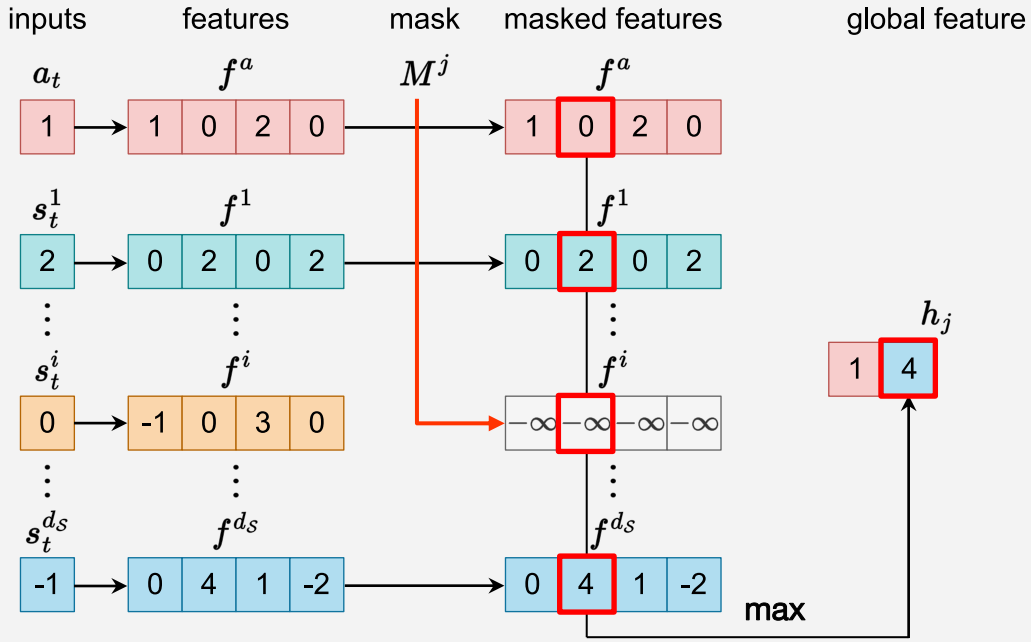

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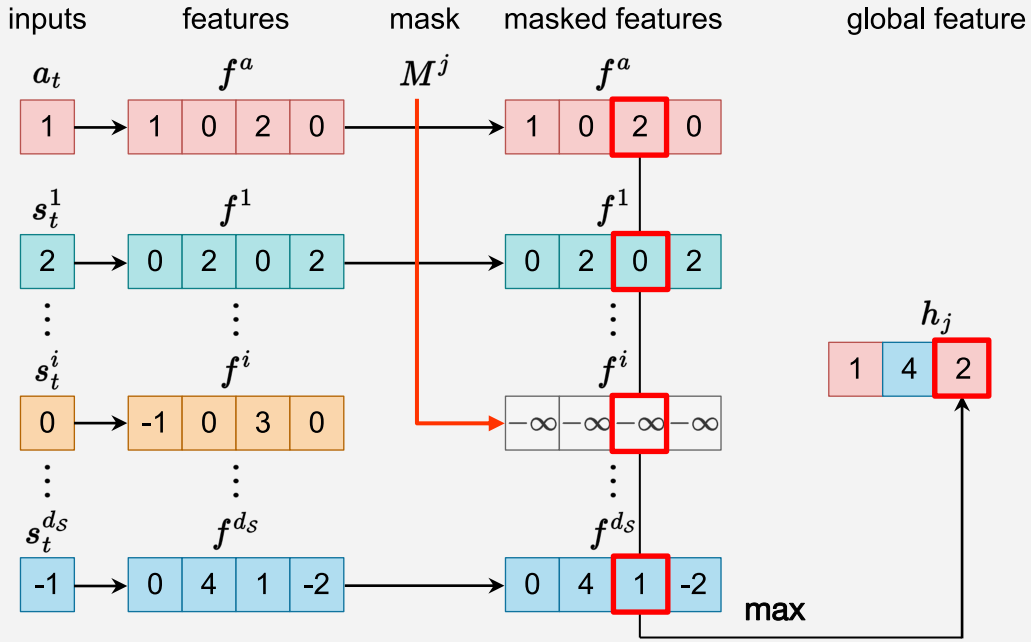

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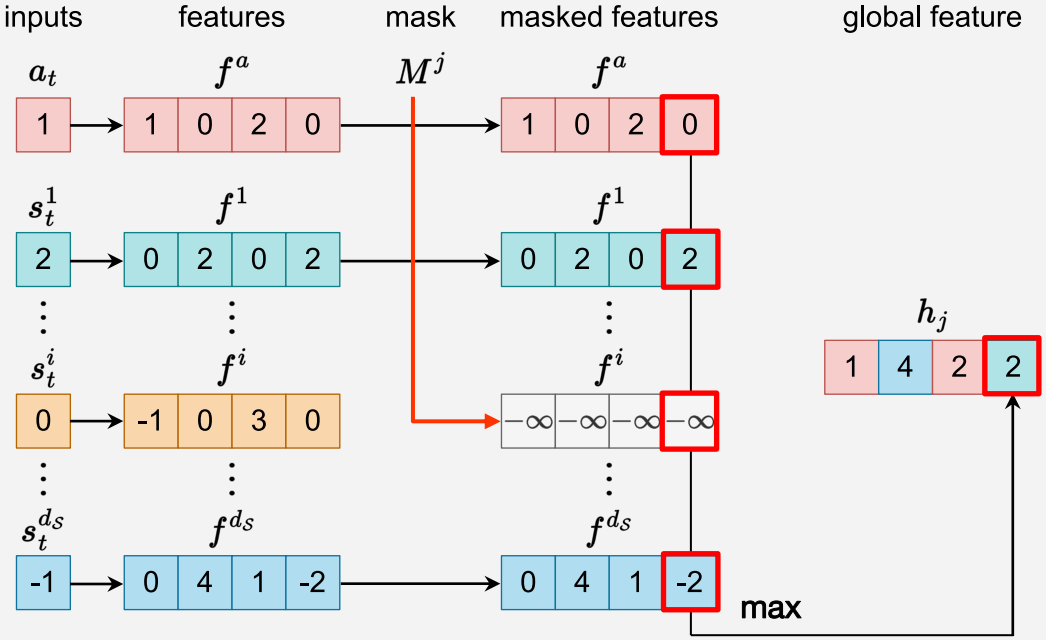

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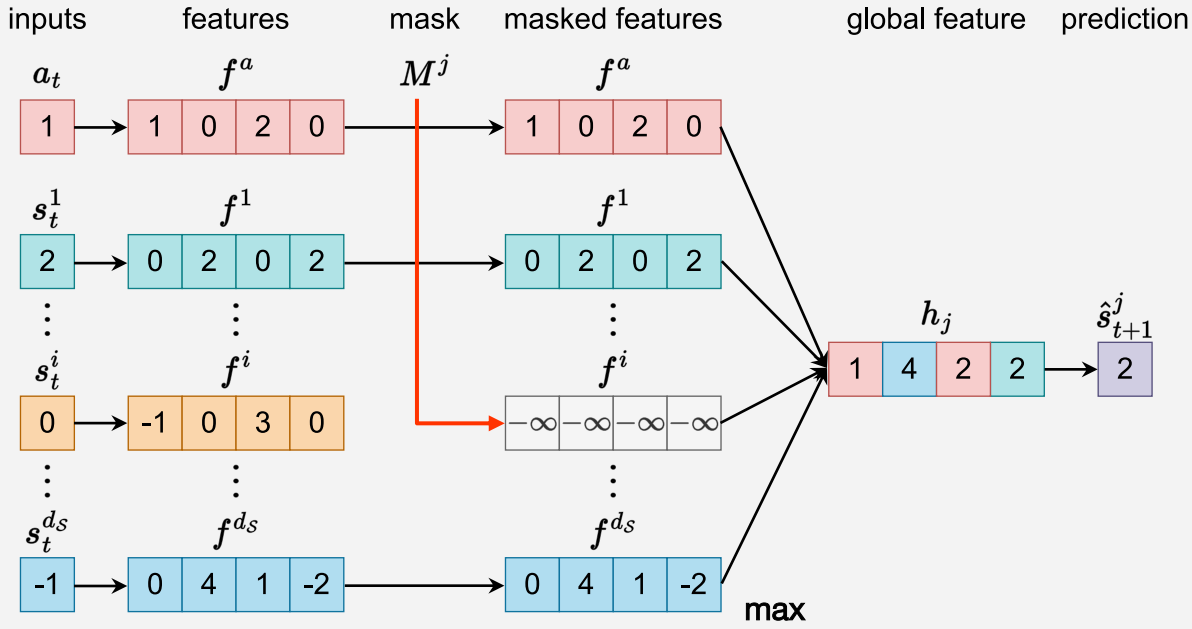
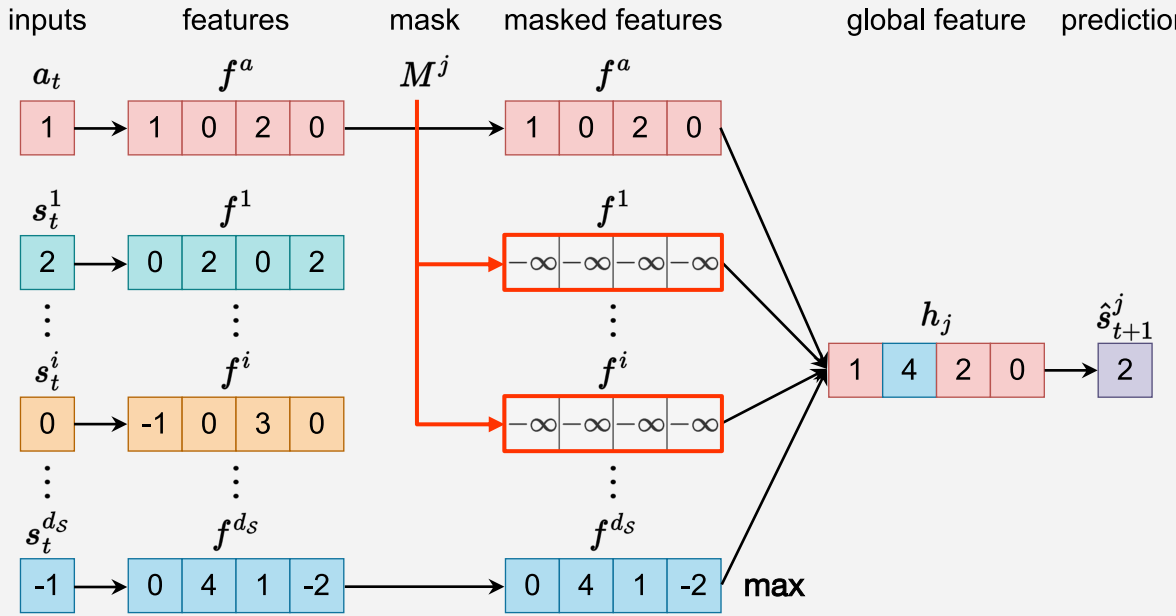
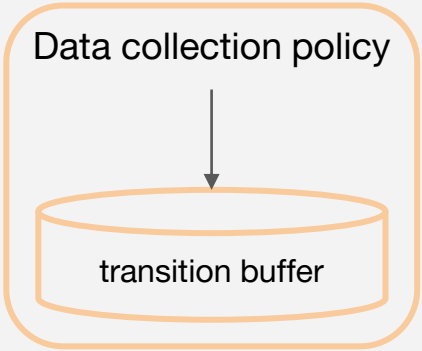


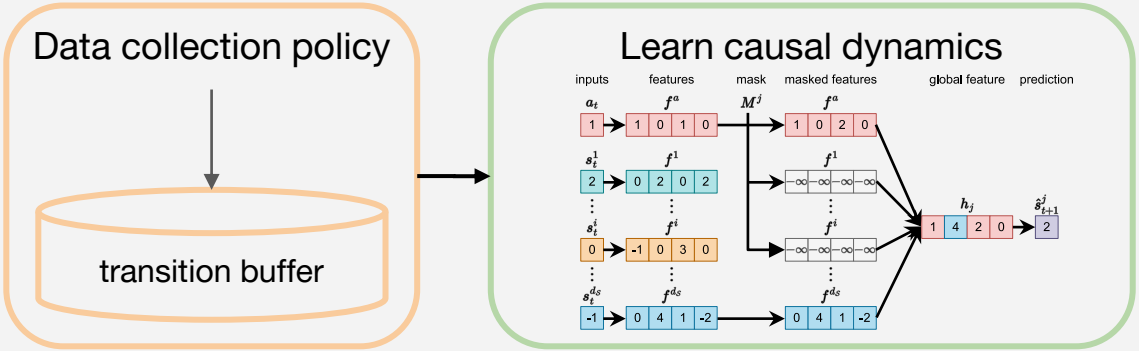
Method

After training, to represent the causal model $p(s_{t+1}^j | \mathbf{PA}_t^j)$, we can adjust the mask to select causal parents of s^j only.





Causal Dynamics Learning (CDL)



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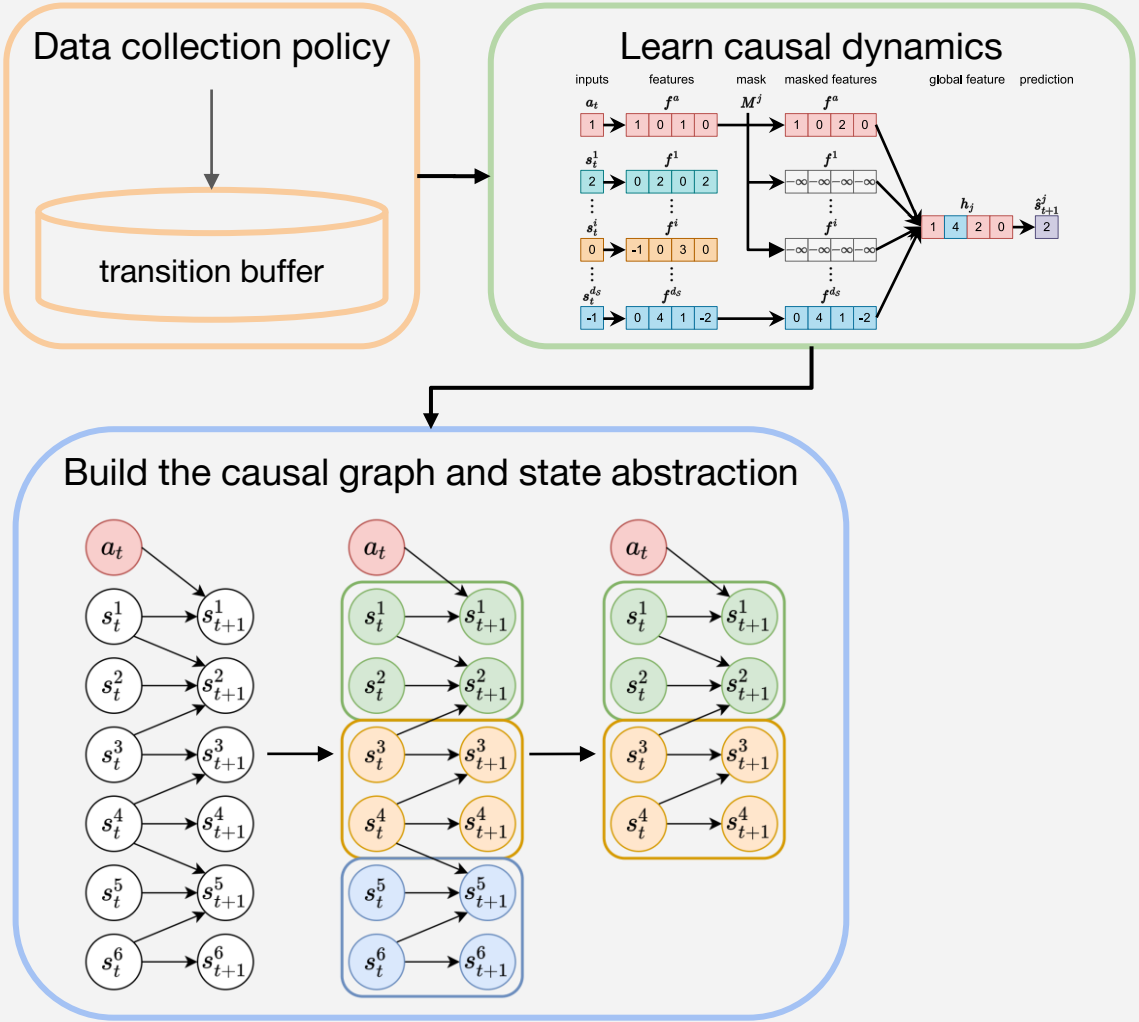

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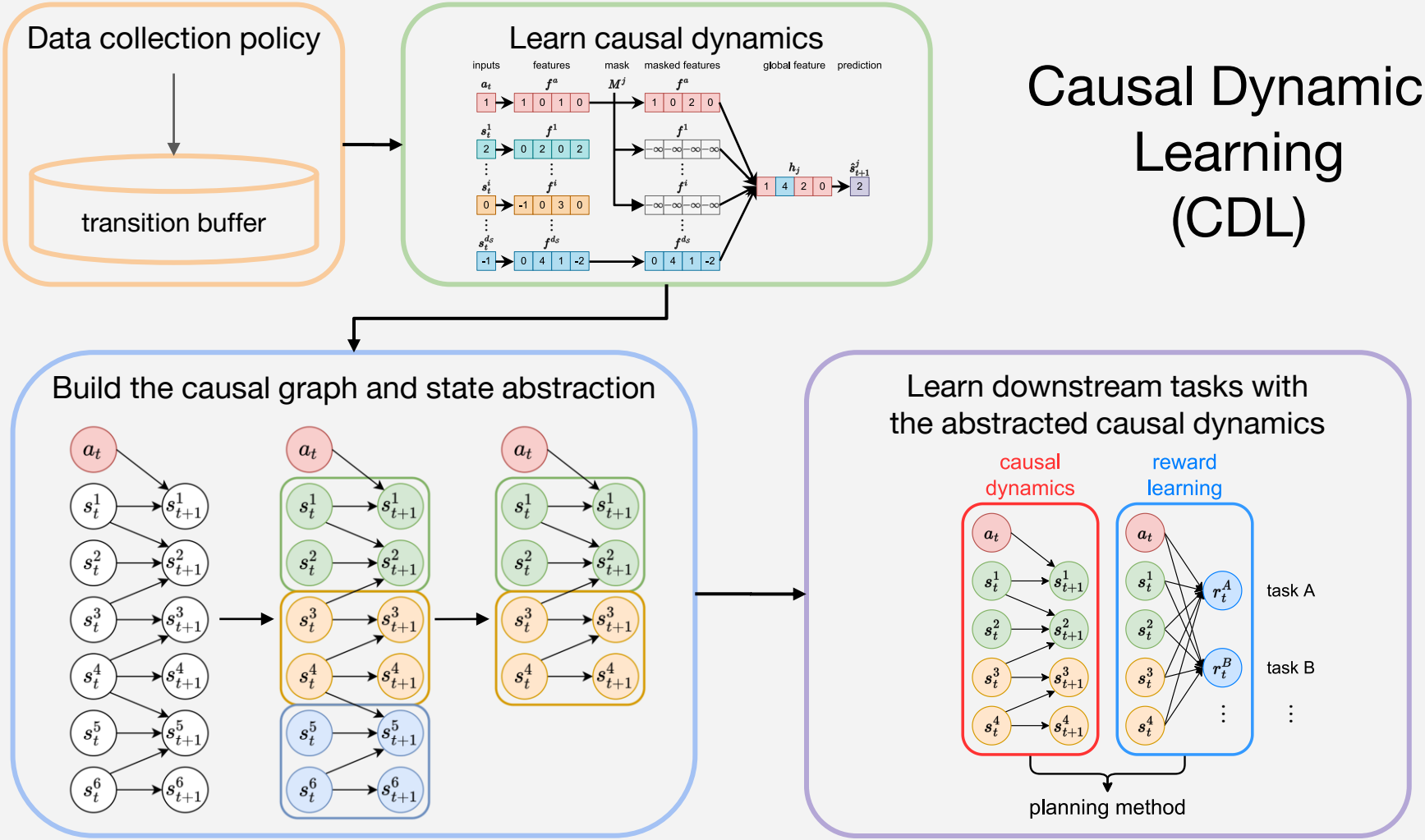
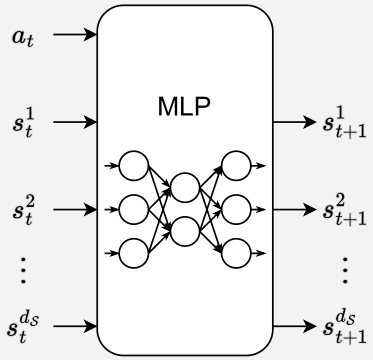


Experiments

Baselines

Monolithic



MLP: multi-layer perceptron

[2] Wang et al., Neurips 2021. [3] Kipf et al., ICLR 2020

Experiments

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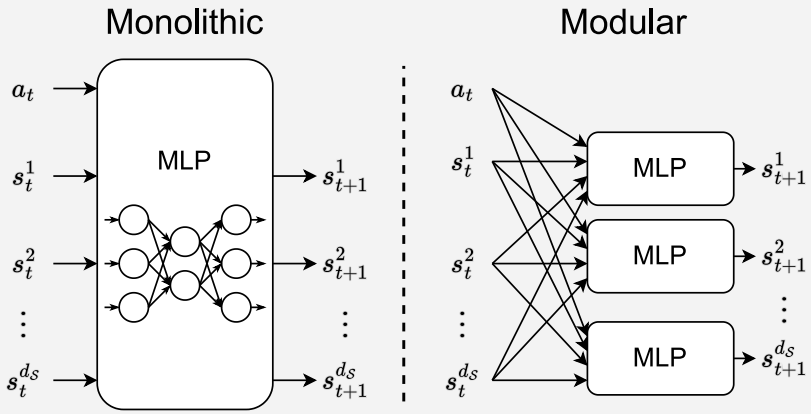

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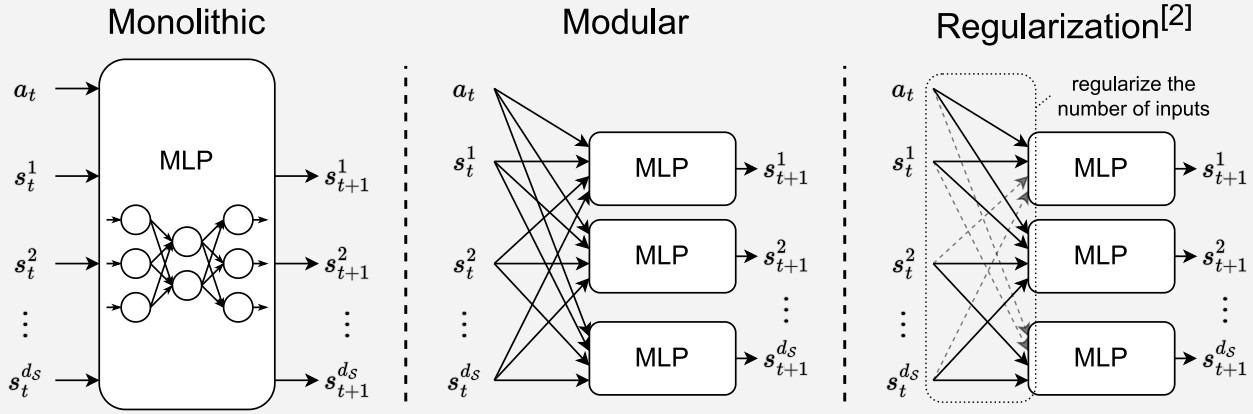

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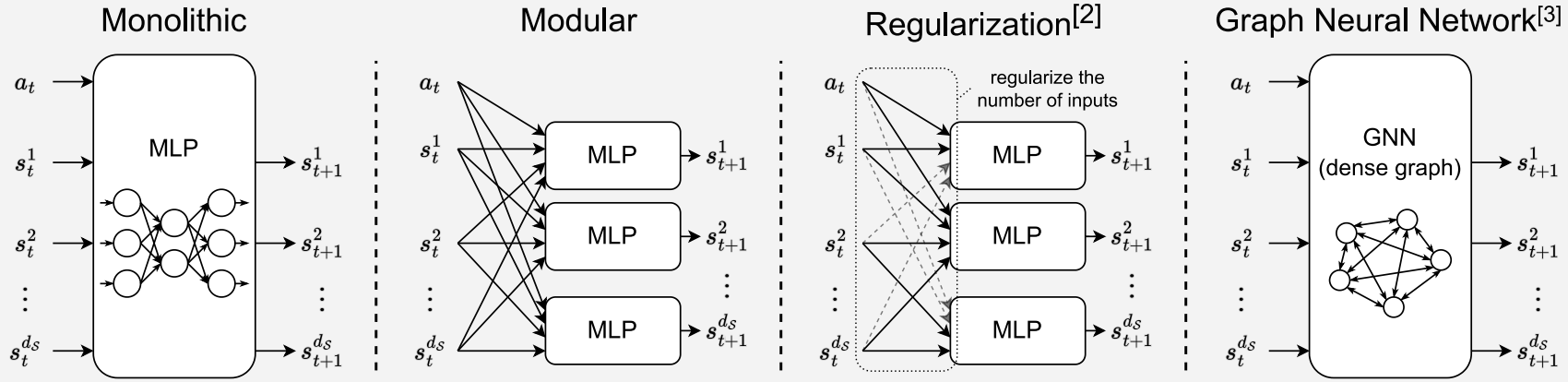

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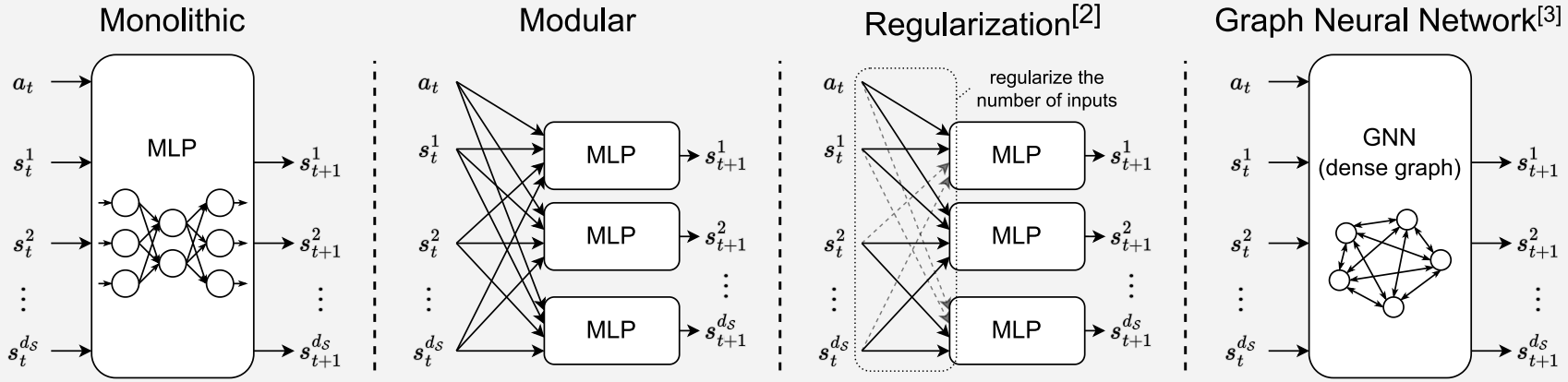

MLP: multi-layer perceptron

Does each baseline learn a causal model?

✗ ✗ ✓ ✗

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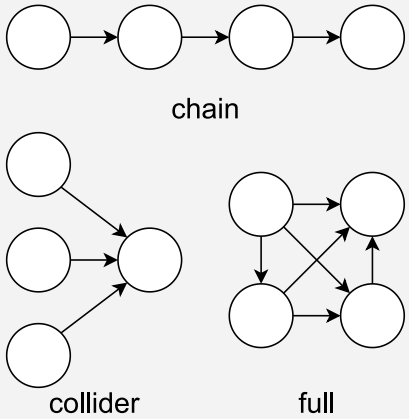
Experiments

Chemical Environment[4]

Synthesized environment
– with different underlying graphs



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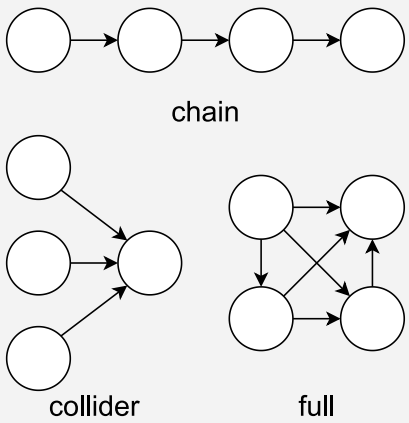
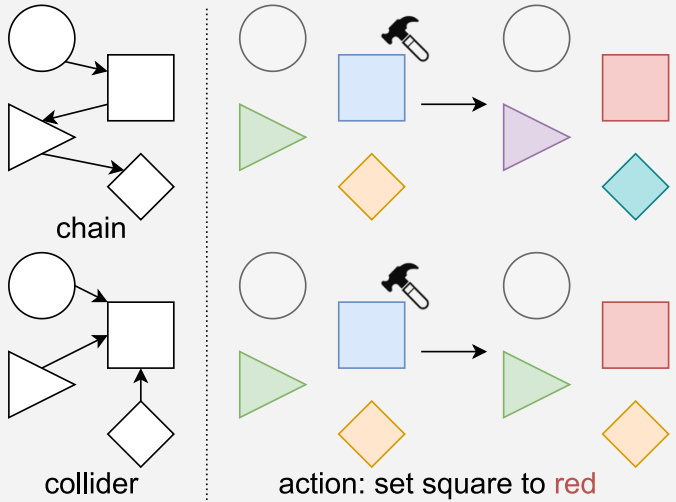
Experiments

Chemical Environment[4]

Synthesized environment
- with different underlying graphs
- as action changes the color of one node, colors of all its descendants will also change.





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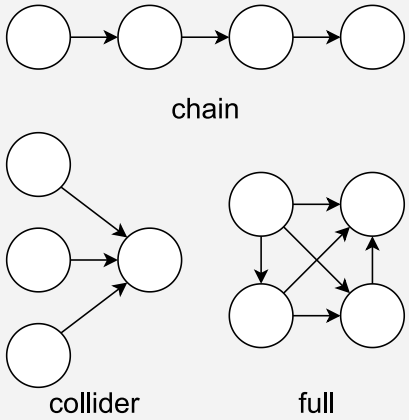
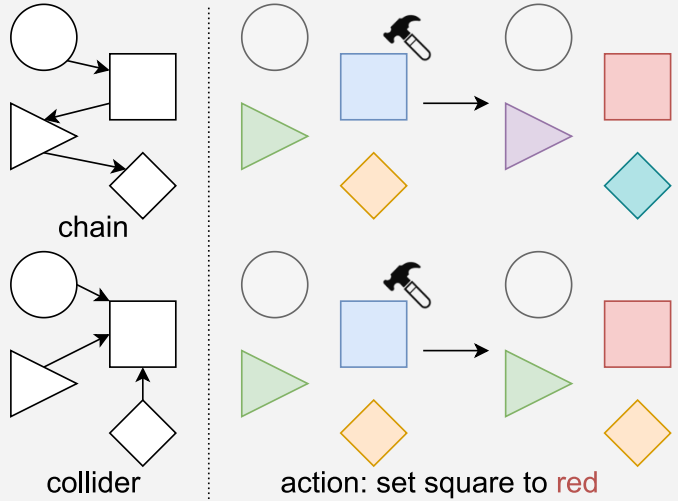
- with different underlying graphs
- as action changes the color of one node, colors of all its descendants will also change.

Action-irrelevant variables: positions sampled from $N(0, 0.01)$.



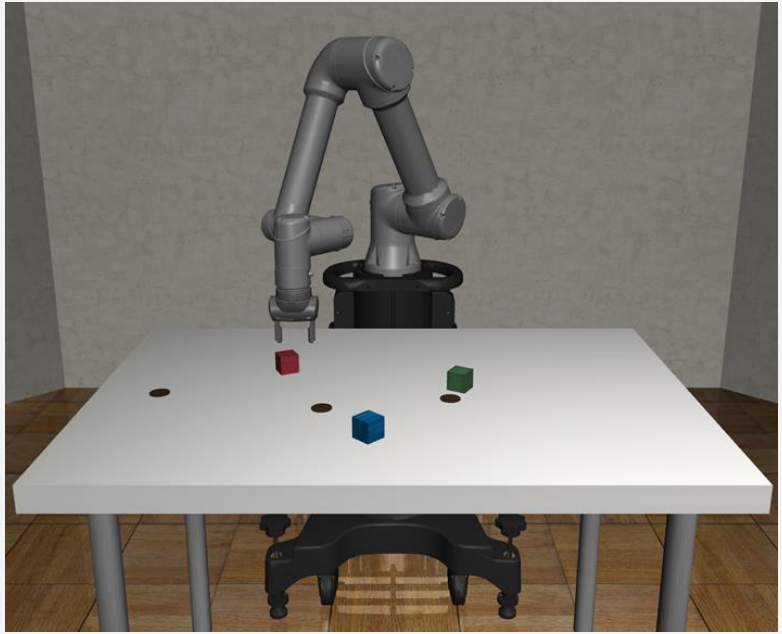


[4] Ke et al., Neurips 2021.

Experiments

Manipulation Environment

State Variables:



Experiments

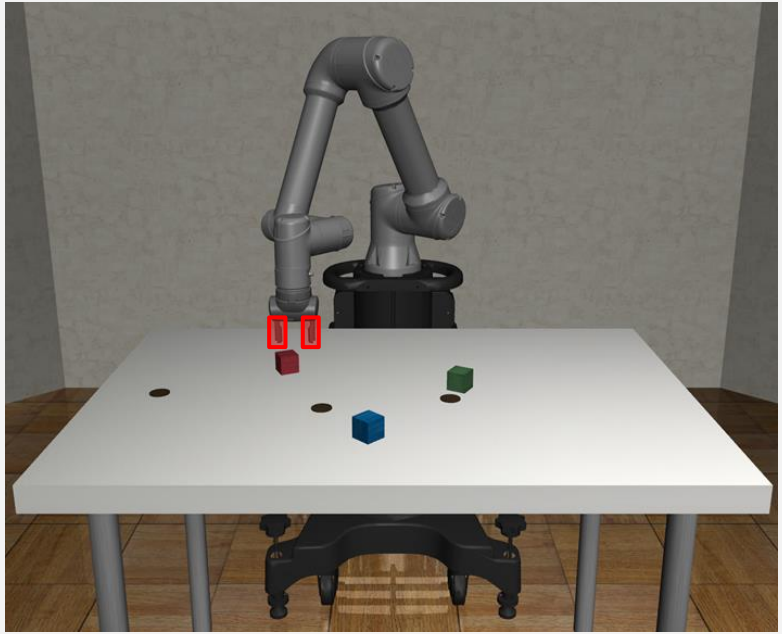
Manipulation Environment

State Variables:
- end-effector (eef)

Experiments

Manipulation Environment

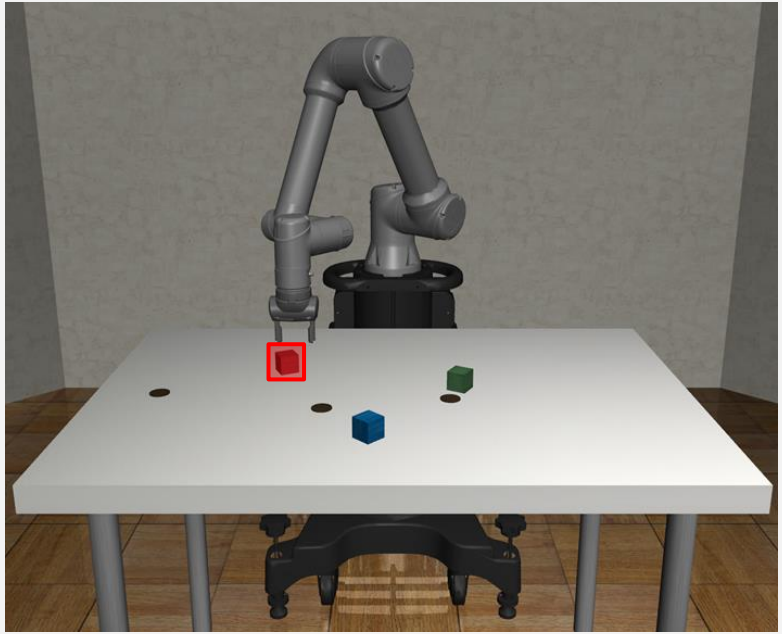
State Variables:
- end-effector (eef)
- gripper (grp)



Experiments

Manipulation Environment

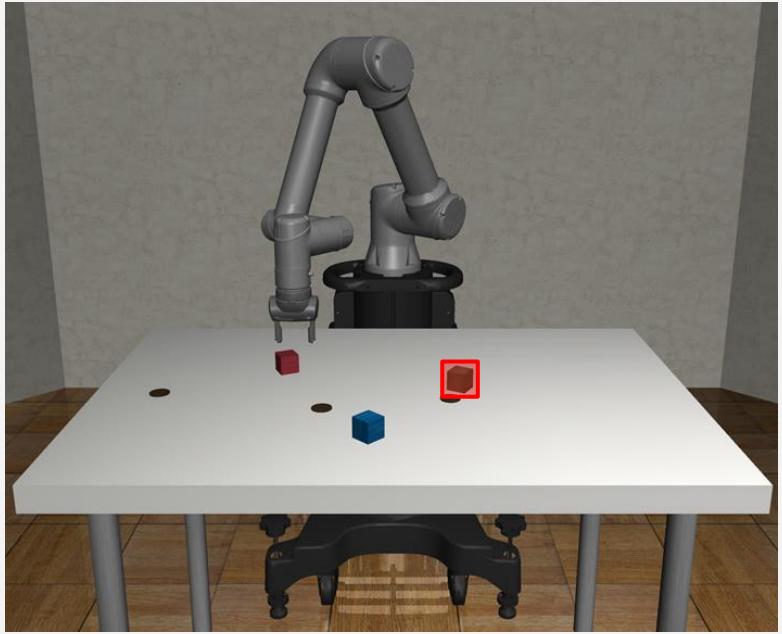
State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)



Experiments

Manipulation Environment

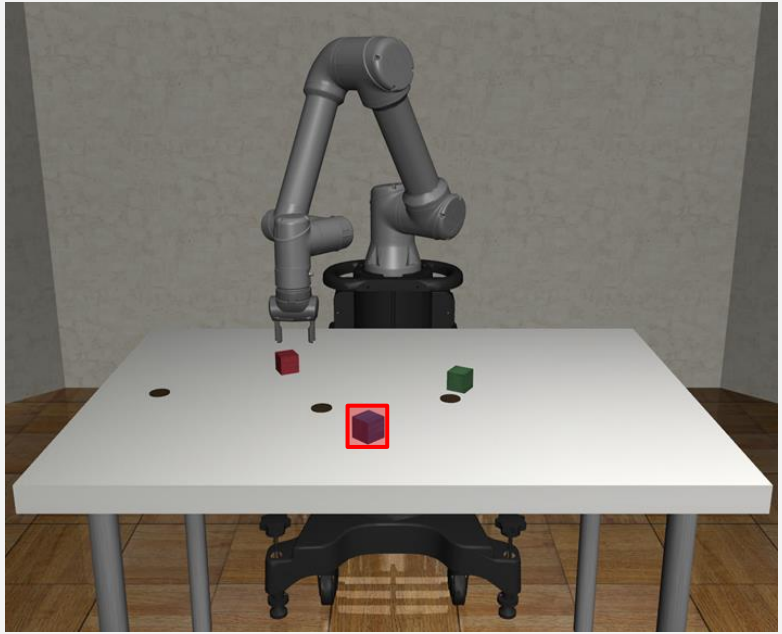
State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)
- the unmovable object (unm)



Experiments

Manipulation Environment

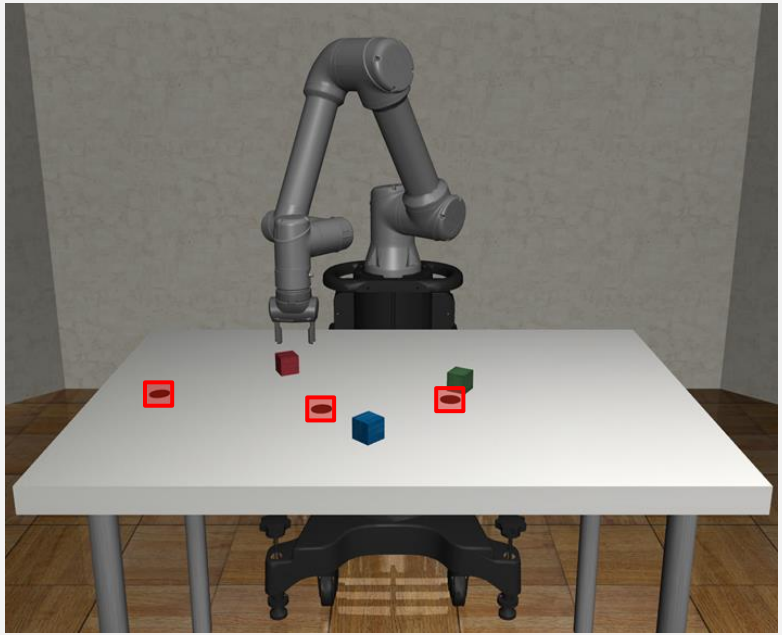
State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)
- the unmovable object (unm)
- the randomly moving object (rand)



Experiments

Manipulation Environment

State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)
- the unmovable object (unm)
- the randomly moving object (rand)
- non-interactable markers (mkr^{1-3})

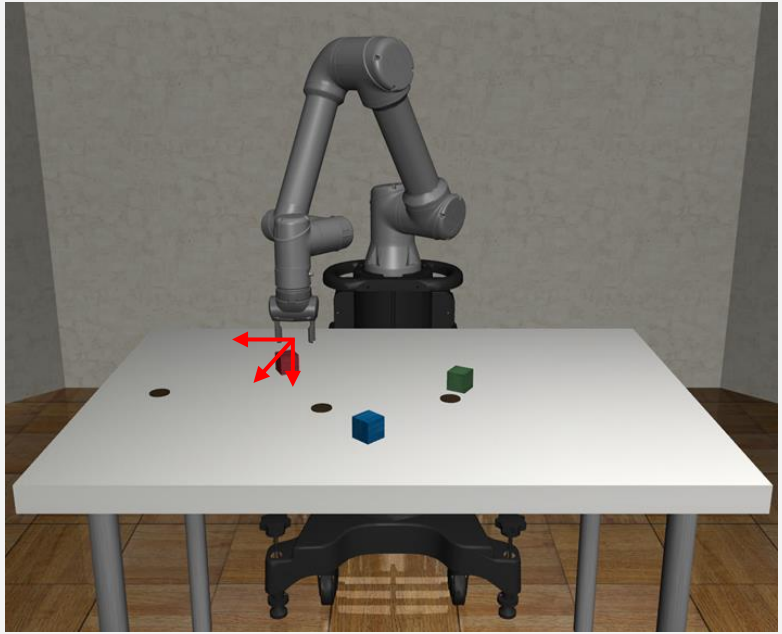


Experiments

Manipulation Environment

State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)
- the unmovable object (unm)
- the randomly moving object (rand)
- non-interactable markers (mkr^{1-3})

Action dimensions:
- end-effector target

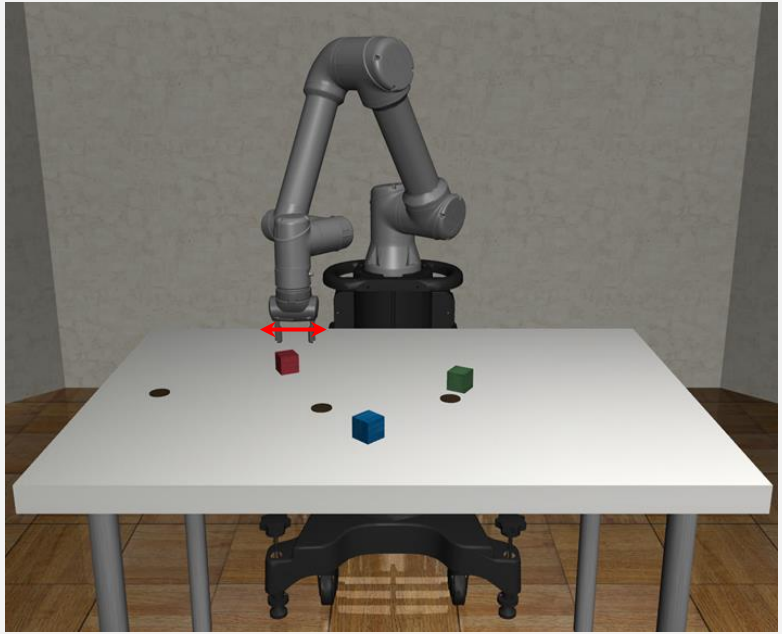


Experiments

Manipulation Environment

State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)
- the unmovable object (unm)
- the randomly moving object (rand)
- non-interactable markers (mkr^{1-3})

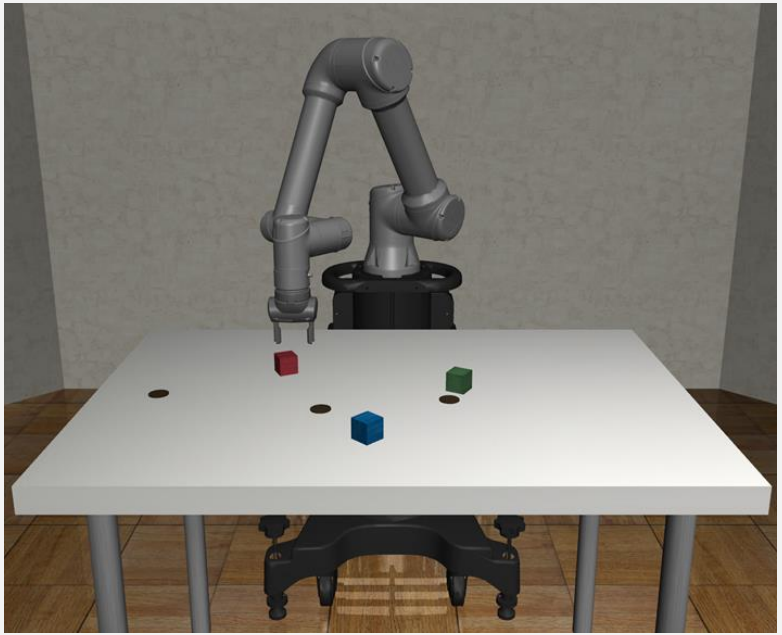
Action dimensions:
- end-effector target
- gripper open/close

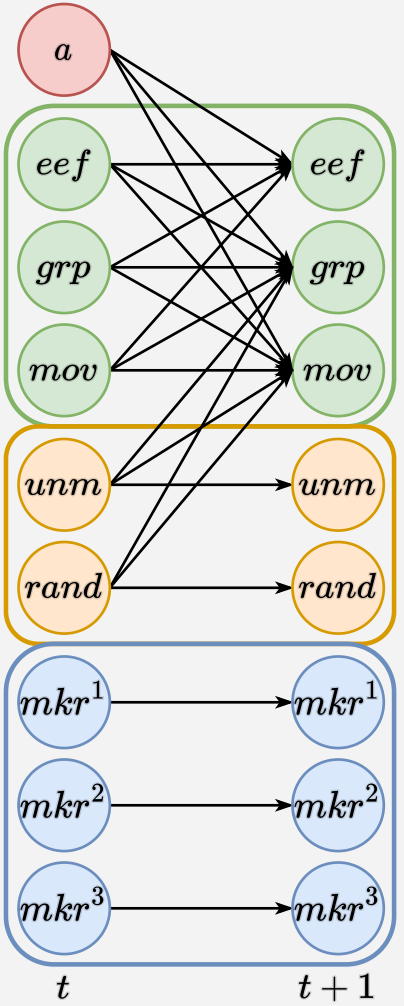


Results

Causal Graph Accuracy

At the object level, the learned dependence is (subjectively) reasonable.





Results

Causal Graph Accuracy

Table 1. Causal Graph Accuracy (in %) for CDL and Reg

Environment	**CDL** (Ours)	**Reg**
Chemical (Collider)	**100.0** $\pm$ 0.0	99.4 $\pm$ 0.4
Chemical (Chain)	**100.0** $\pm$ 0.1	99.7 $\pm$ 0.1
Chemical (Full)	**99.1** $\pm$ 0.1	97.7 $\pm$ 0.4
Manipulation	**90.2** $\pm$ 0.3	84.4 $\pm$ 0.5

Results

Dynamics Generalization

Causal dynamics generalizes best in unseen states.

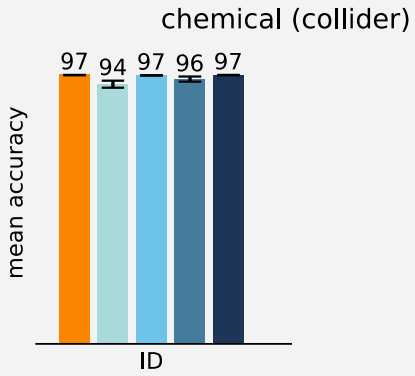
Results

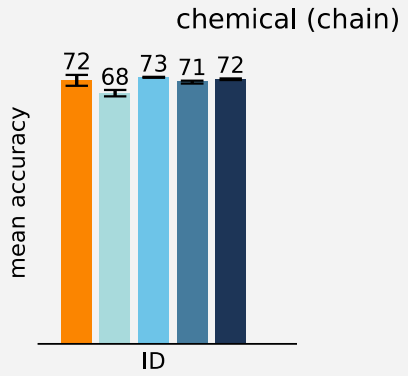
Dynamics Generalization

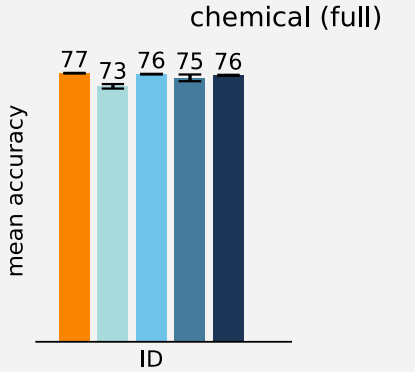
Causal dynamics generalizes best in unseen states.

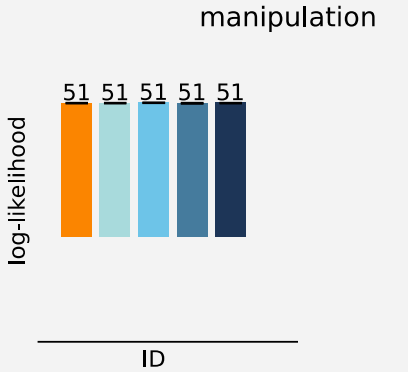
- Causal Dynamics Learning (Ours)
- Regularization
- Graph Neural Network
- Modular
- Monolithic

ID: in-distribution states









Results

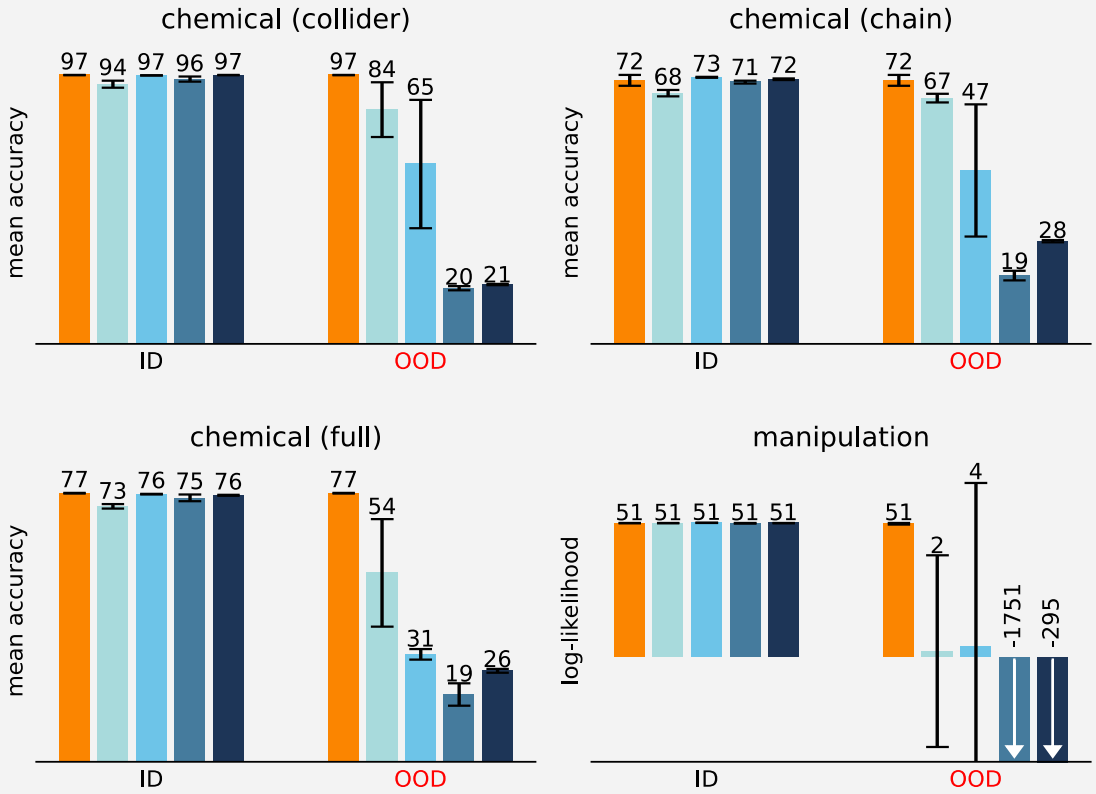
Dynamics Generalization

Causal dynamics generalizes best in unseen states.

- Causal Dynamics Learning (Ours)
- Regularization
- Graph Neural Network
- Modular
- Monolithic

ID: in-distribution states

OOD: out-of-distribution states



Results

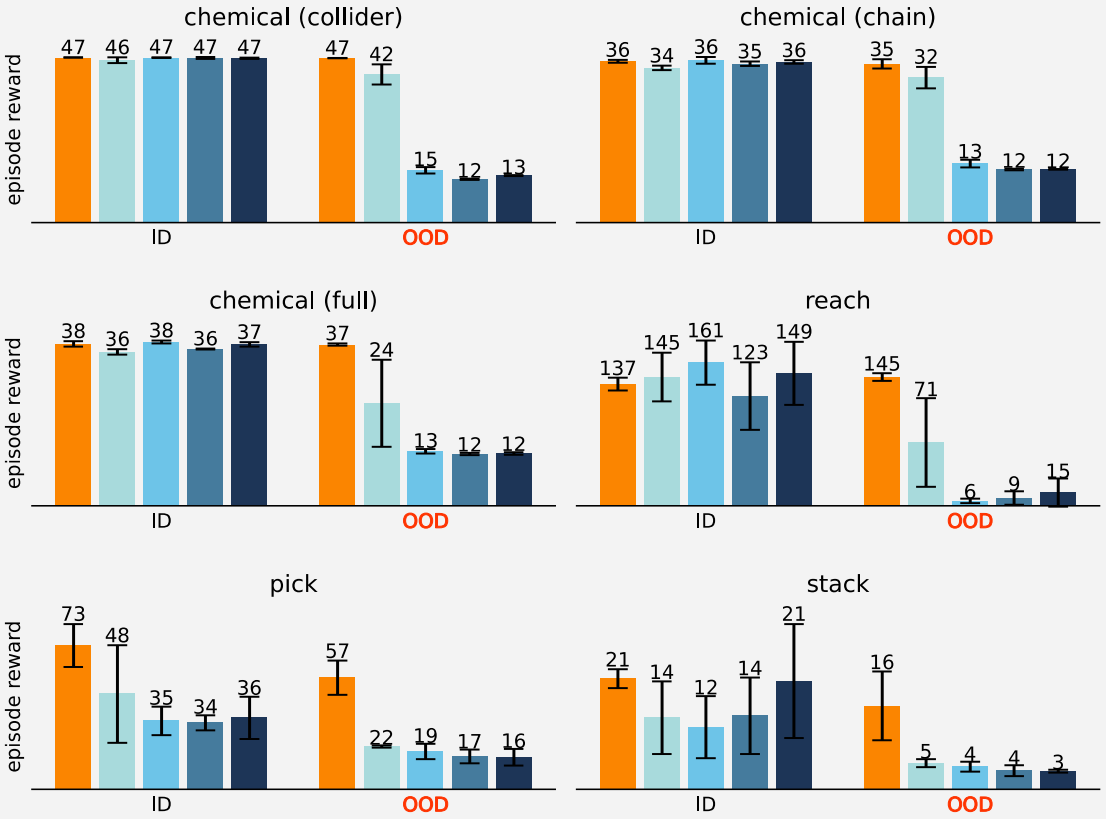
Task Generalization

Causal dynamics generalizes best in unseen states.

- Causal Dynamics Learning (Ours)
- Regularization
- Graph Neural Network
- Modular
- Monolithic

ID: in-distribution states

OOD: out-of-distribution states



Limitations and Future Directions

Scale to high-dimensional observations (e.g. images)?

- Learn disentangled representations, then learn dynamics in the representation space

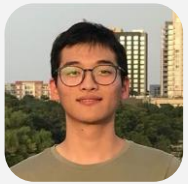
Causal dependencies are learned globally only.

- Learning local independencies to further sparsify the dynamics.

Causal Dynamics Learning for Task-Independent State Abstraction

Zizhao Wang, Xuesu Xiao, Zifan Xu, Yuke Zhu, and Peter Stone





Contact Information:
Zizhao Wang: zizhao.wang@utexas.edu

Link to the Paper: https://arxiv.org/pdf/2206.13452.pdf

Scan to read the paper

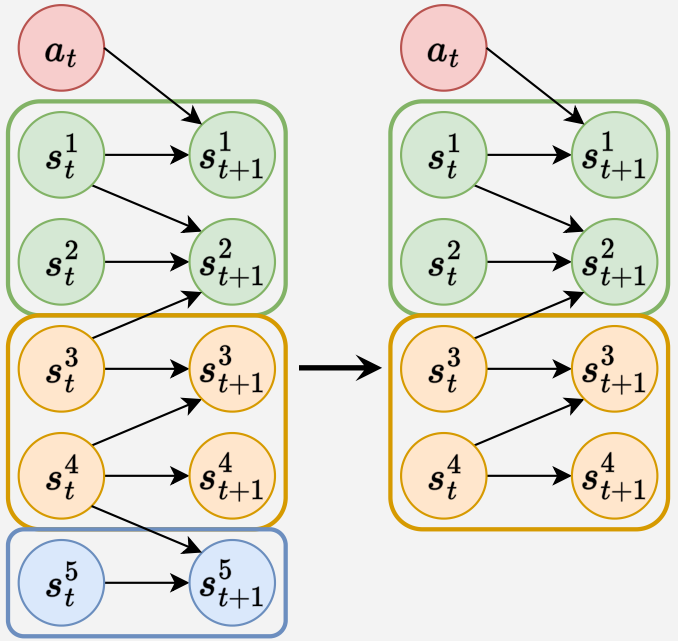
LARG Learning Agents Research Group The University of Texas at Austin | RPL UT Robot Perception & Learning Lab | Sony AI

Problem Setup

CDL's **state abstraction** omits action-irrelevant variables.
What tasks can this state abstraction solve?

- ✓ Tasks whose rewards are defined by controllable and action-relevant state variables
- ✗ Tasks with rewards involving action-irrelevant state variables

Solving any task (learning any reward) means no abstraction.

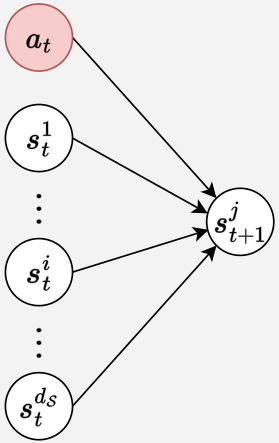


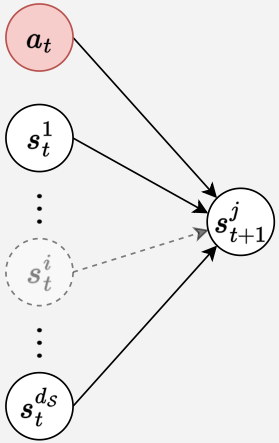
Method

Key idea: determine if the causal edge $s_t^i \rightarrow s_{t+1}^j$ exists with a conditional independence test.

Theorem 1 If $s_t^i \not\perp\!\!\!\perp s_{t+1}^j | \{s_t / s_t^i, a_t\}$, then $s_t^i \rightarrow s_{t+1}^j$.

In other words, is s_t^i needed to predict s_{t+1}^j?





$$p(s_{t+1}^j | s_t, a_t) \stackrel{?}{=} p(s_{t+1}^j | \{s_t / s_t^i, a_t\})$$

$$\Updownarrow$$

$$\text{CMI}^{ij} = \mathbb{E}[\log \frac{p(s_{t+1}^j | s_t, a_t)}{p(s_{t+1}^j | \{s / s^i\}_t, a_t)}] \geq \epsilon$$