# Causal Dynamics Learning for Task-Independent State Abstraction

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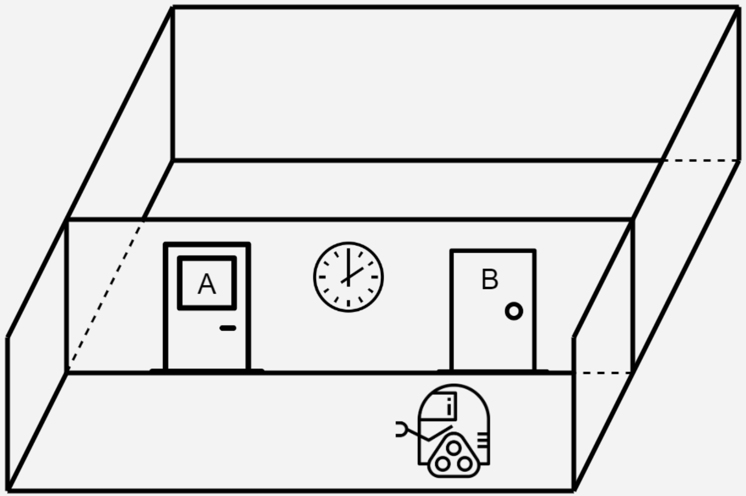
Sony AI

# 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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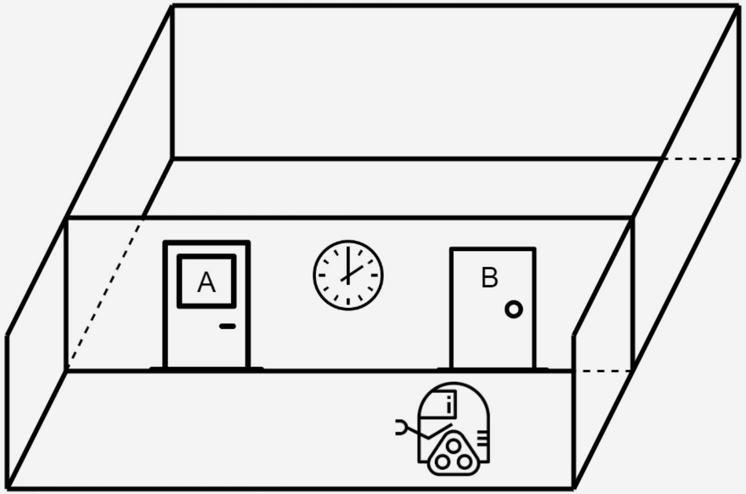


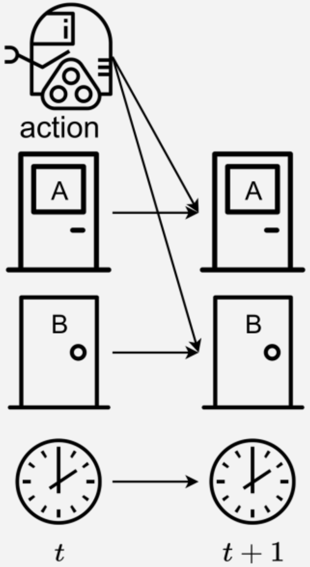


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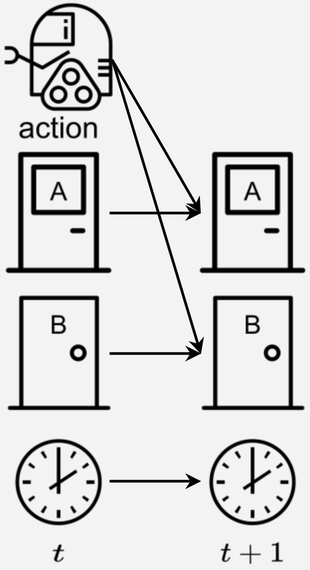
But most model-based RL work uses dense dynamics models (fully-connected networks).

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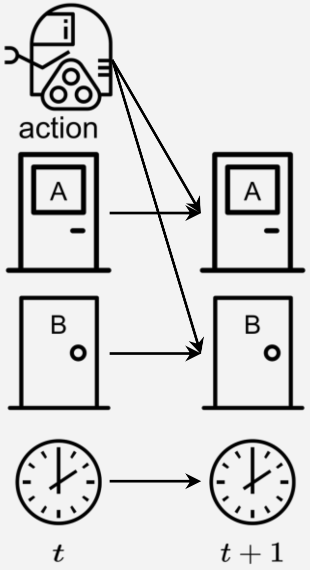


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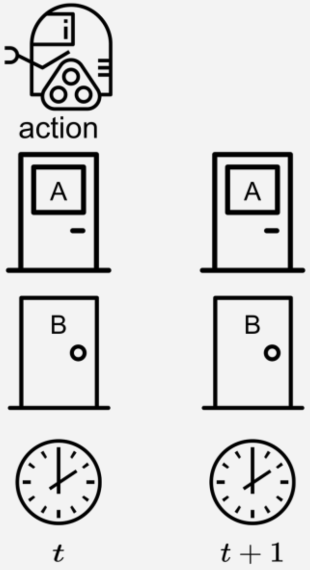


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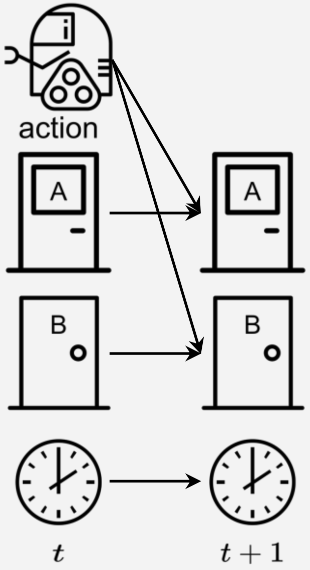


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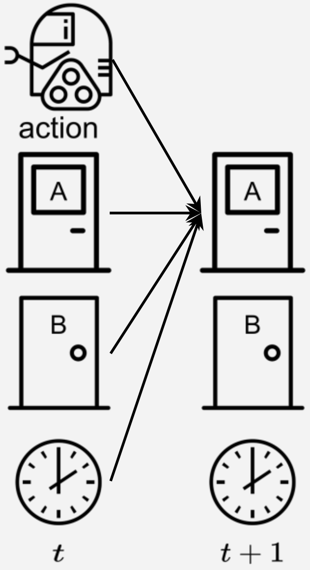


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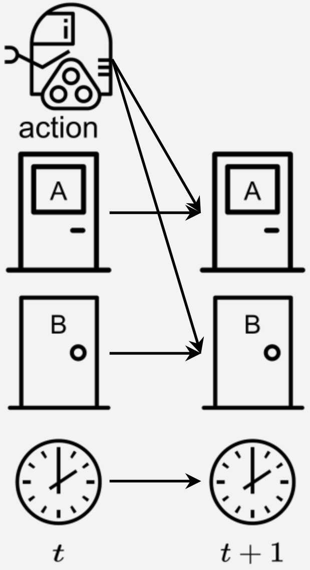


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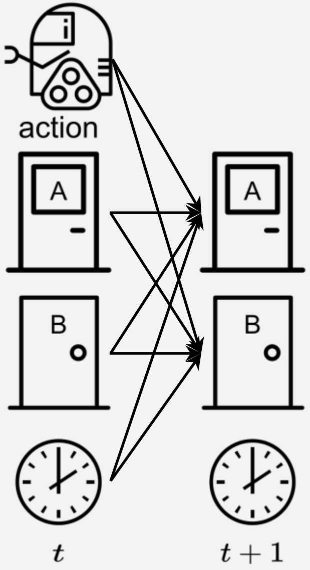


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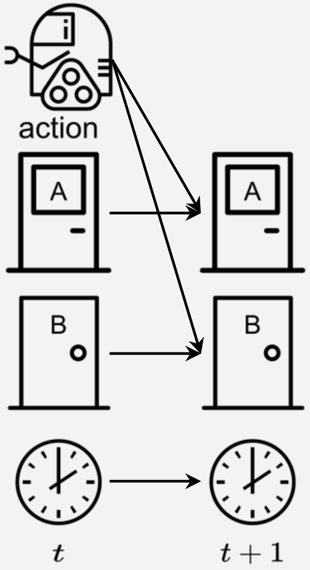


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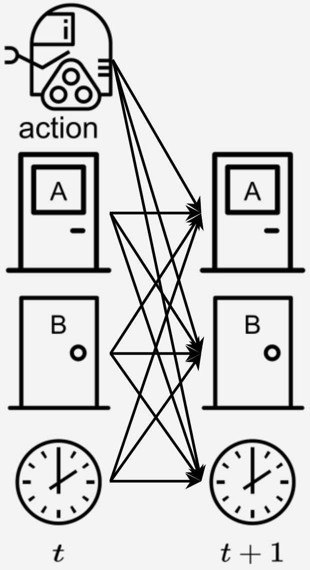


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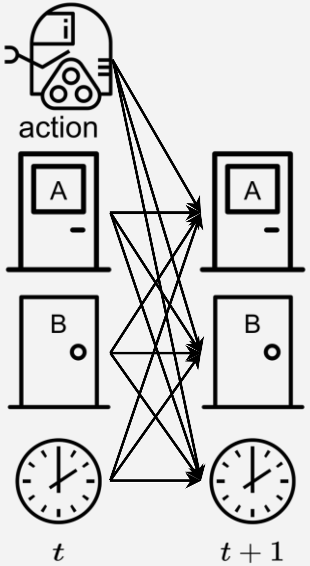


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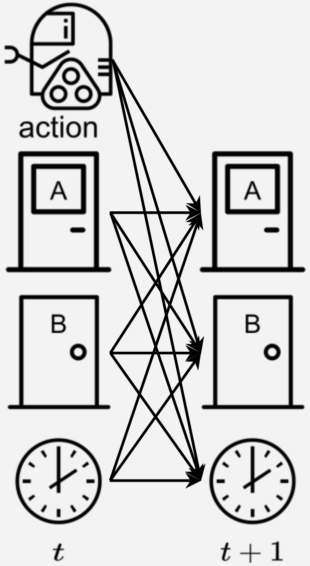


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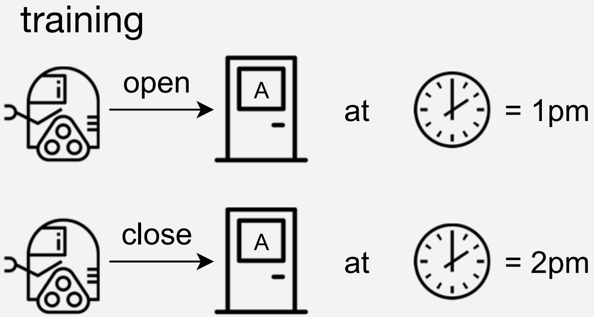


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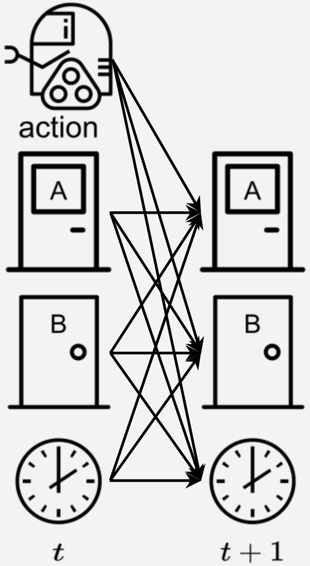


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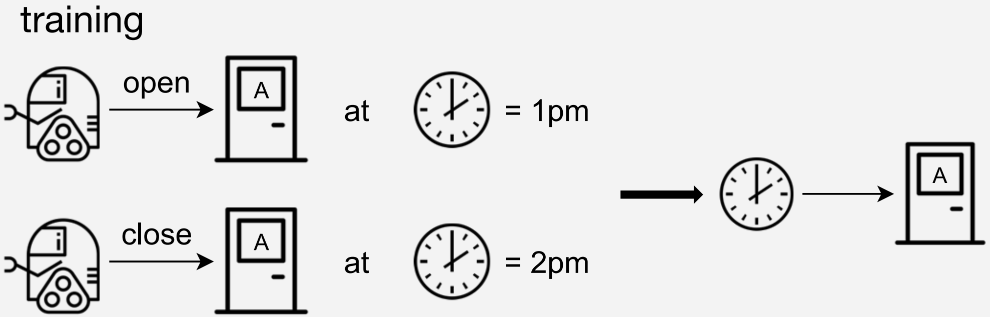


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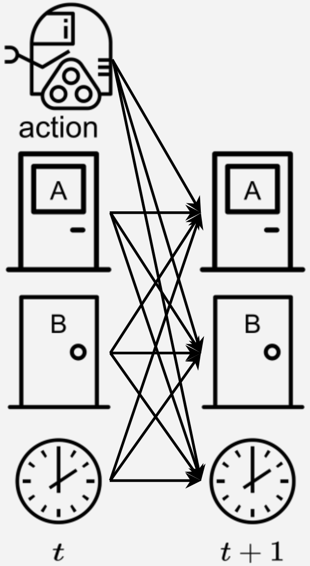


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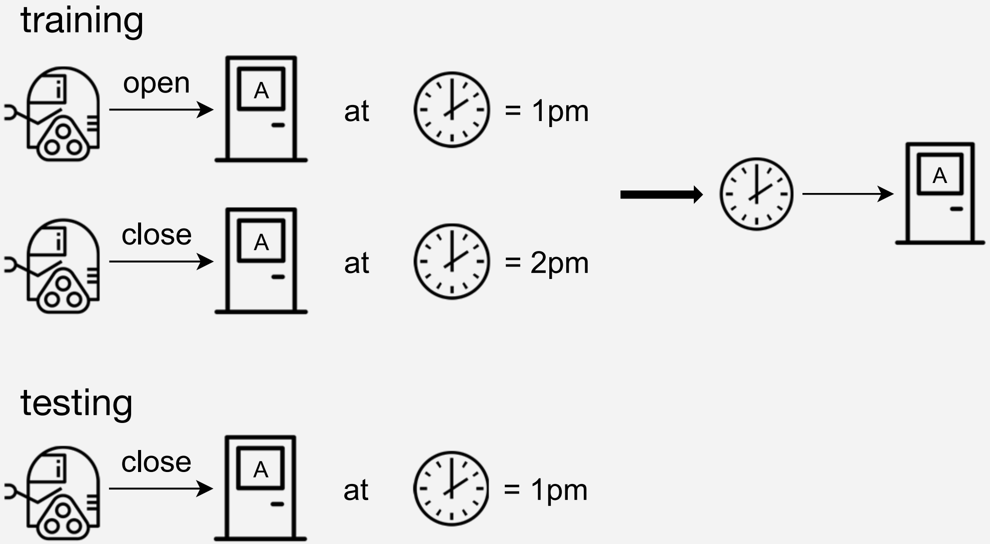


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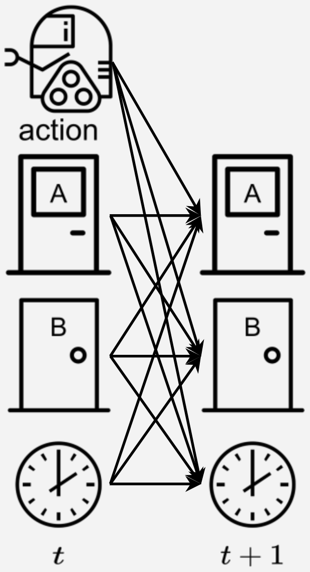


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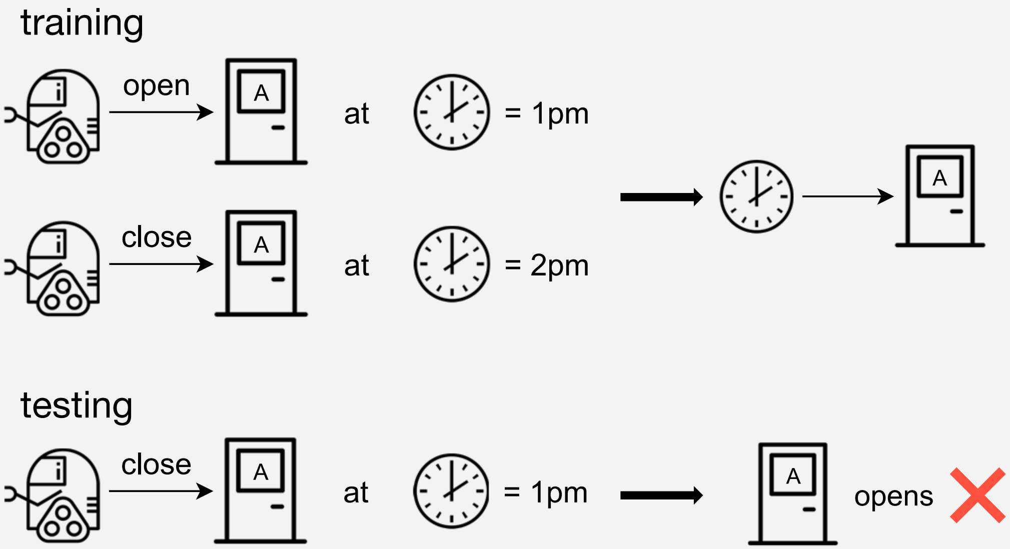


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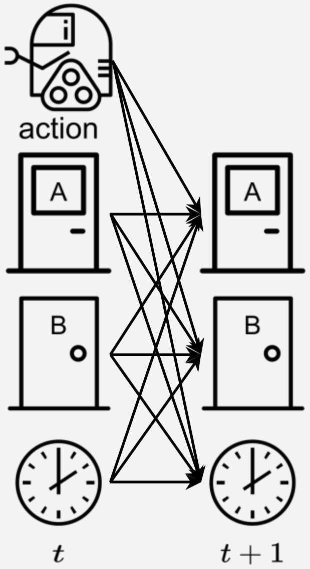


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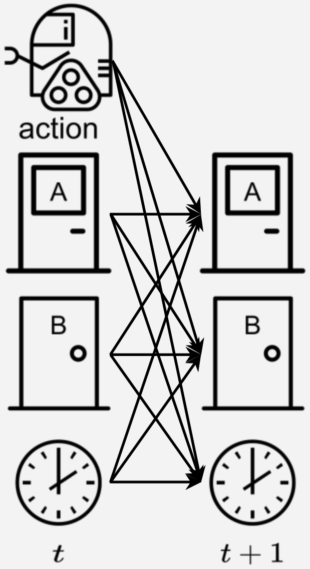


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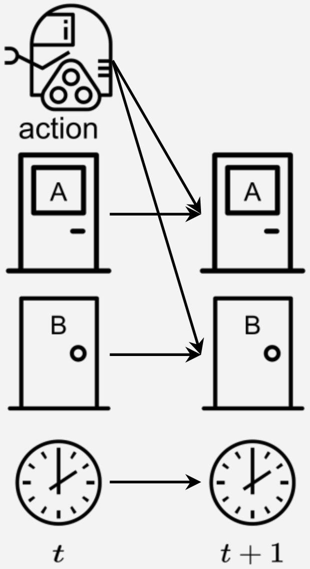


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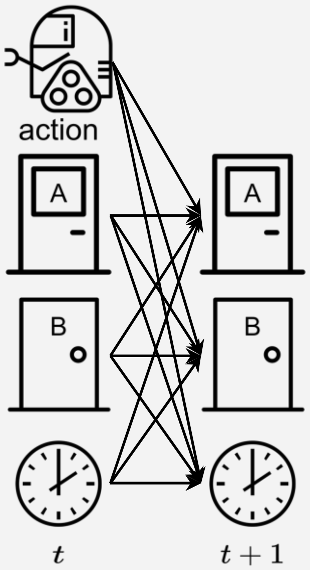


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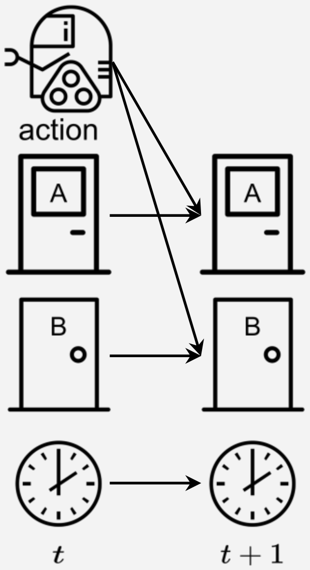



only keep causal edges, robust to outliers,
e.g., clock outliers won't affect door A & B prediction

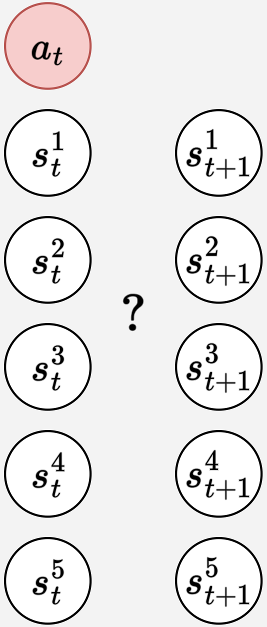
# Problem Setup

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

**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)



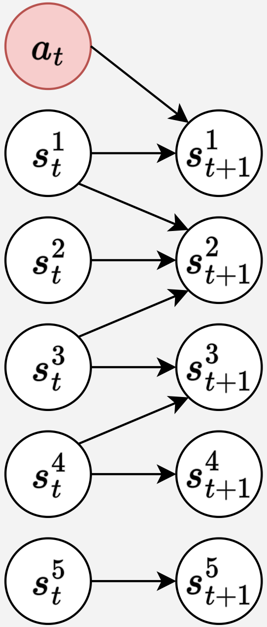
# Problem Setup

Goals

1. Learn a causal dynamics model from transition data

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

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



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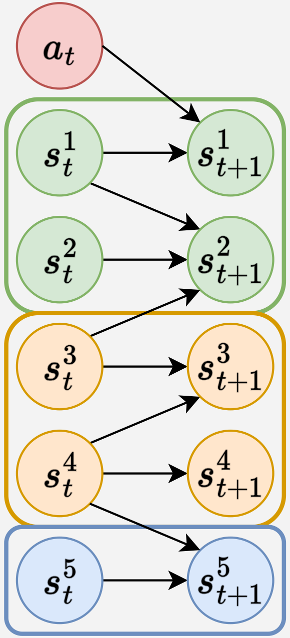
1. Learn a causal dynamics model from transition data
2. Split state variables into three categories

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

$S^c$: 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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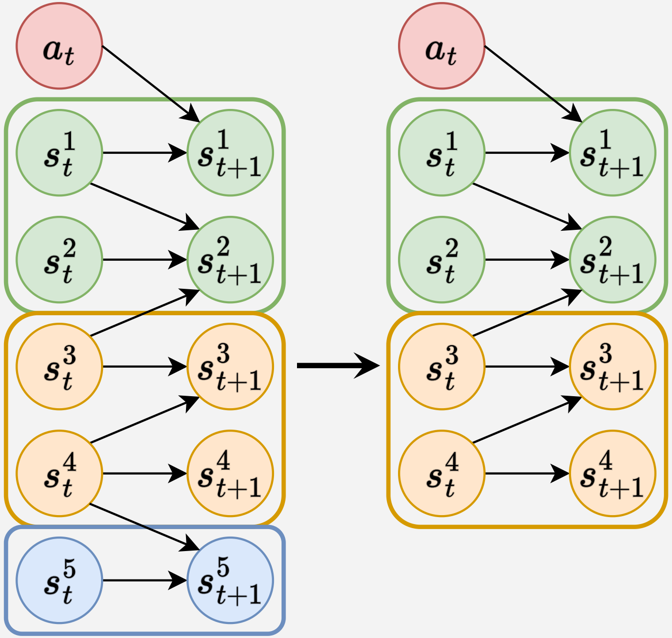
2. Split state variables into three categories
3. Derive a state abstraction by omitting action-irrelevant state variables



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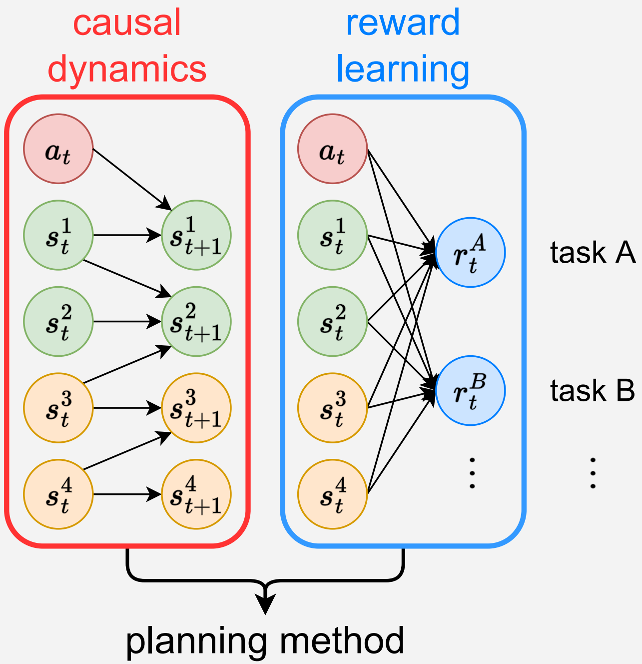
4. Use the abstracted causal dynamics to learn (many) downstream tasks



# Related Work

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

$$R(x, a) = R(x', a),$$

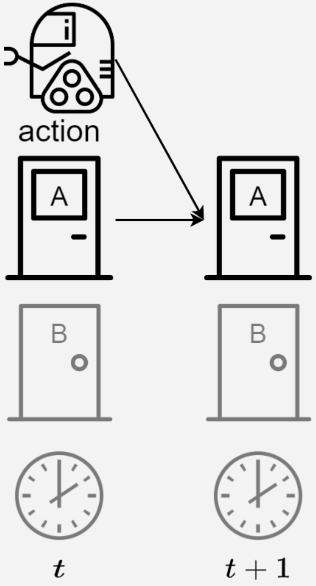
$$\sum_{x'' \in \phi^{-1}(s)} P(x''|x, a) = \sum_{x'' \in \phi^{-1}(s)} P(x''|x', a)$$

[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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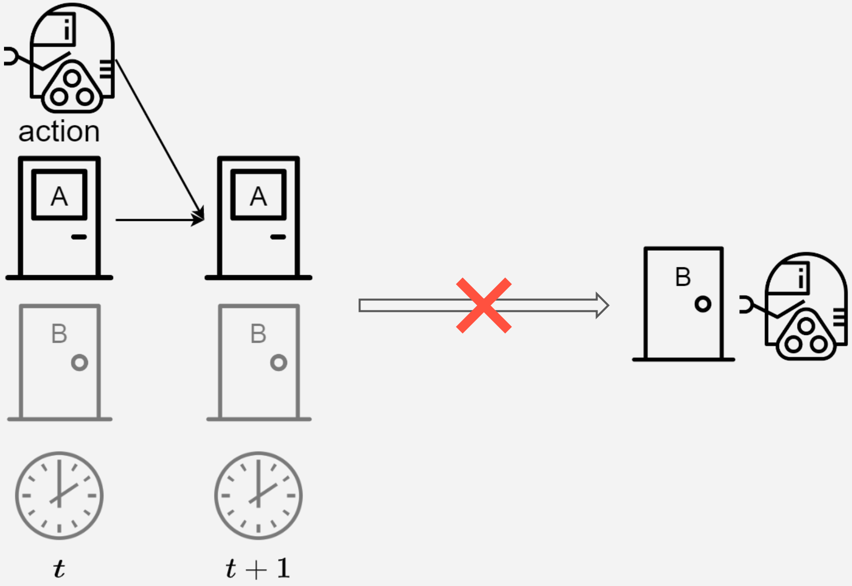

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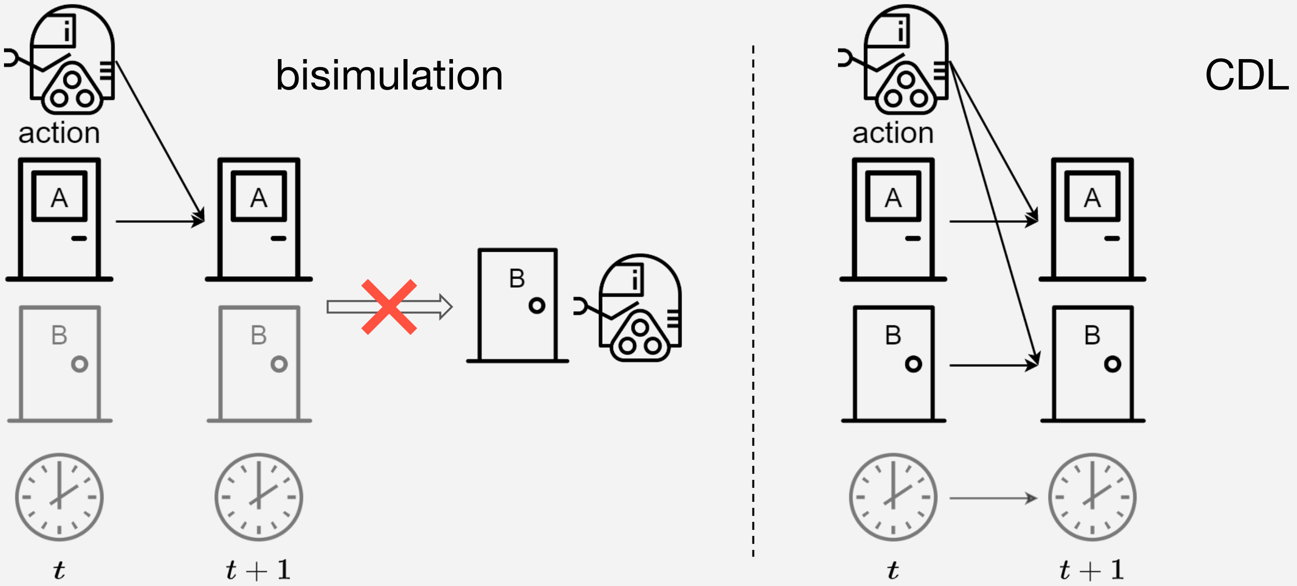
  In contrast, CDL's abstraction can be applied to a larger range of tasks.



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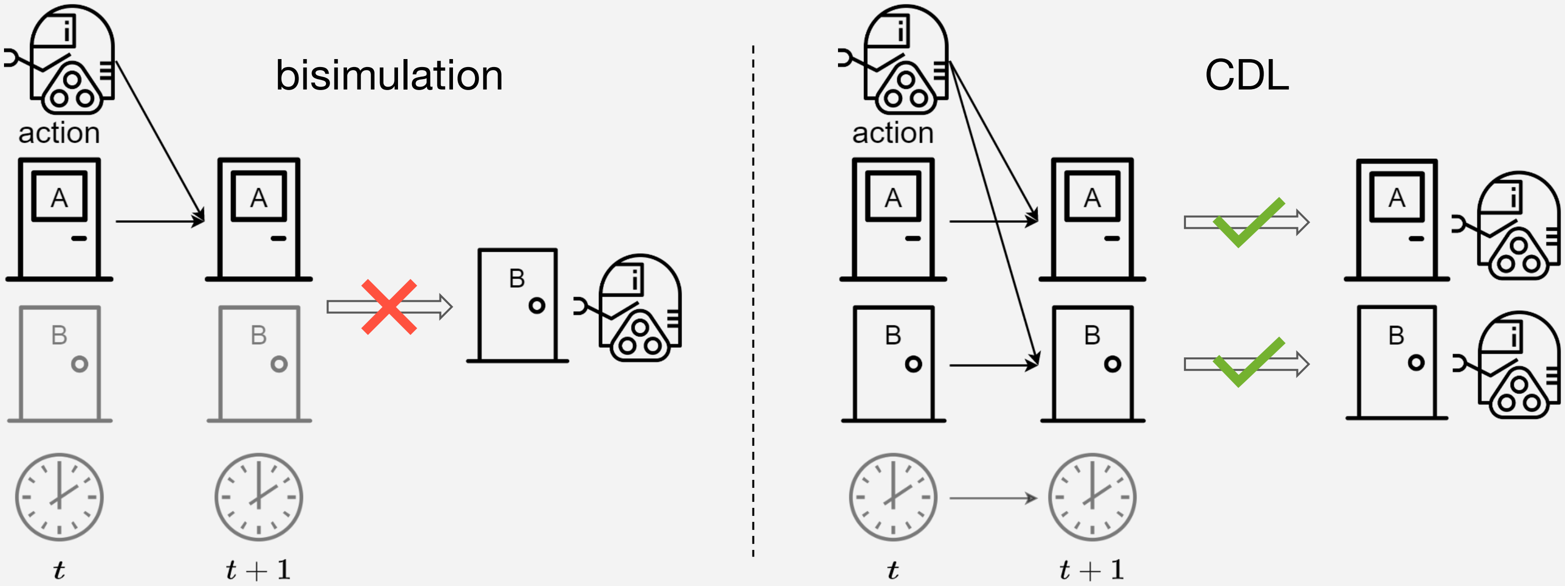

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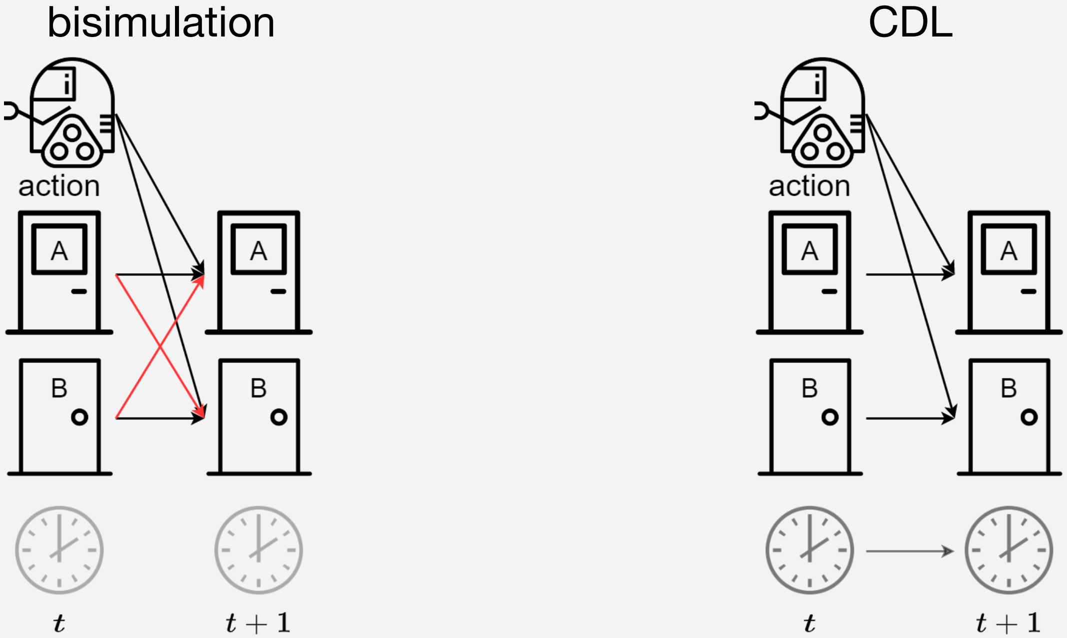
- Most bisimulation work still uses dense dynamics, leading to poor generalization.



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So far, the key of CDL is to learn a causal dynamics model.

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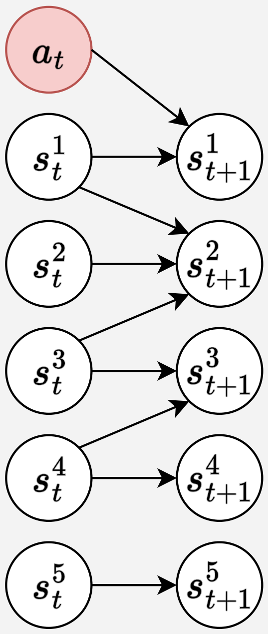

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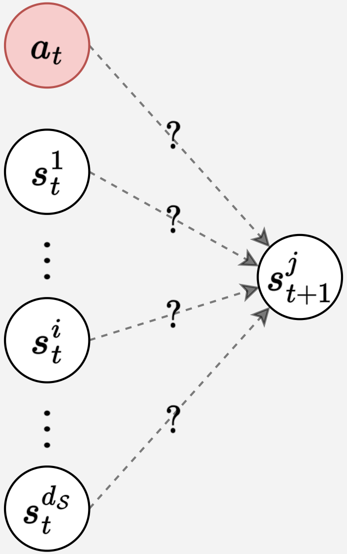
Specifically, for each state variable $\boldsymbol{s}^j$, how to determine if a state variable $\boldsymbol{s}^i$ is one of its parents?



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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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Skipping assumptions and proofs,

**Theorem 1**

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

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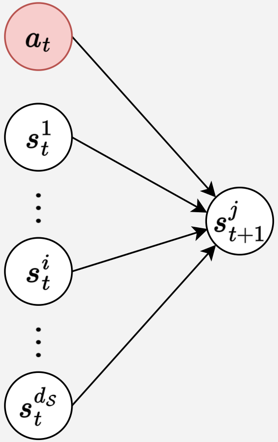

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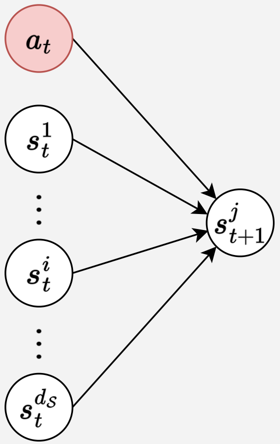


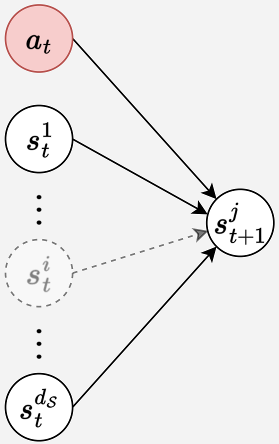

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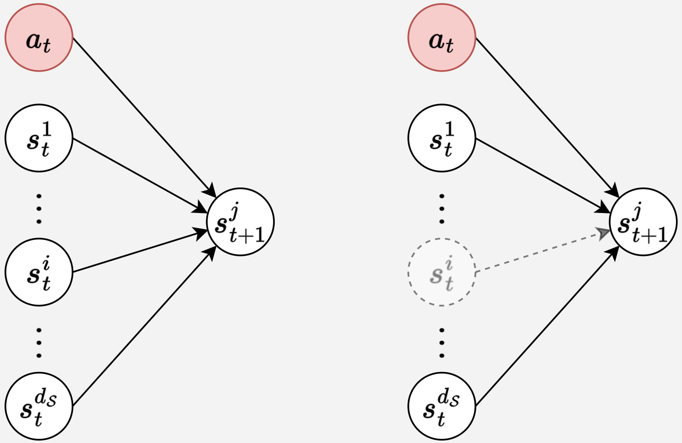


$$p(s_{t+1}^j | s_t, a_t) \stackrel{?}{=} p(s_{t+1}^j | \{s_t / s_t^i, a_t\})$$

# Method

Learn and predict $p(s_{t+1}^j|s_t, a_t)$ & $p(s_{t+1}^j|\{s/s^i\}_t, a_t)$ using generative models, but there will be $d_S^2$ 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 $p(s^j_{t+1}|\cdot)$ .

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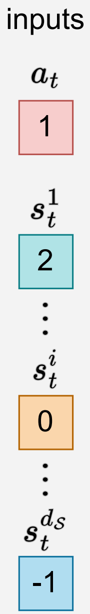

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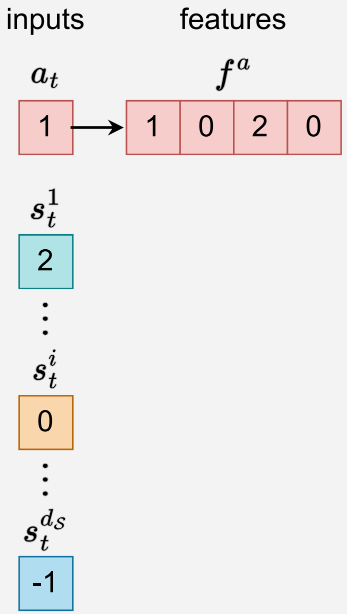

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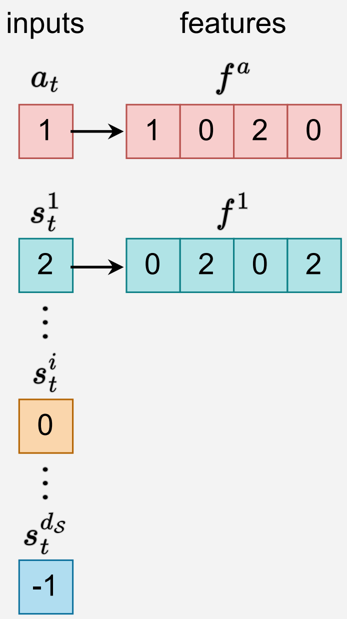

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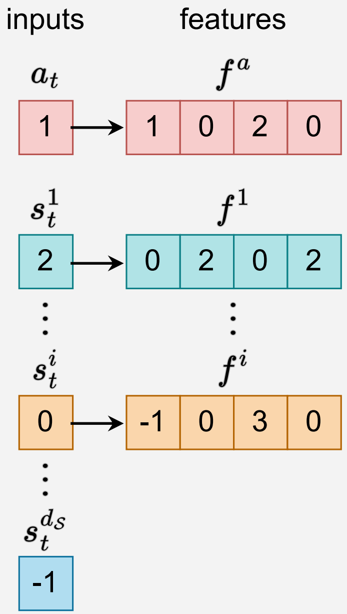

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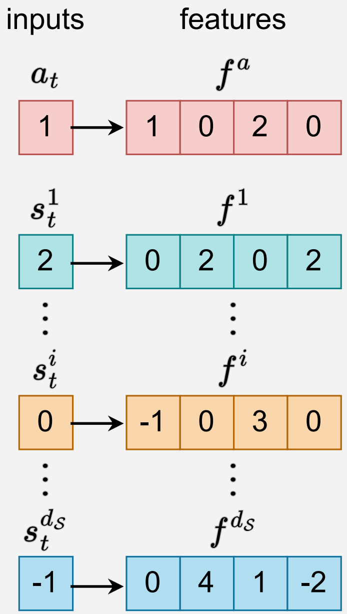

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With $M_j$ and an element-wise maximum module, one network can represent all models.
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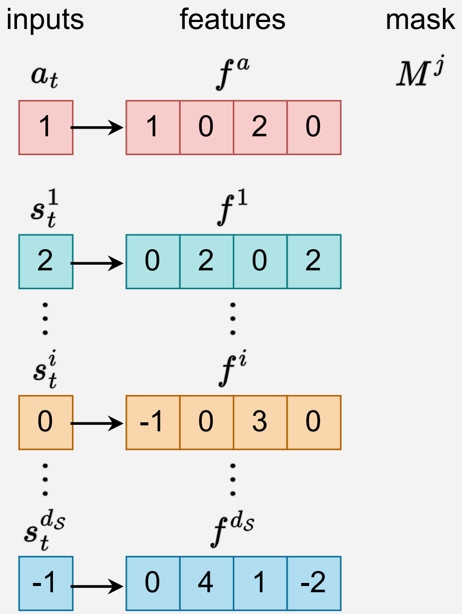

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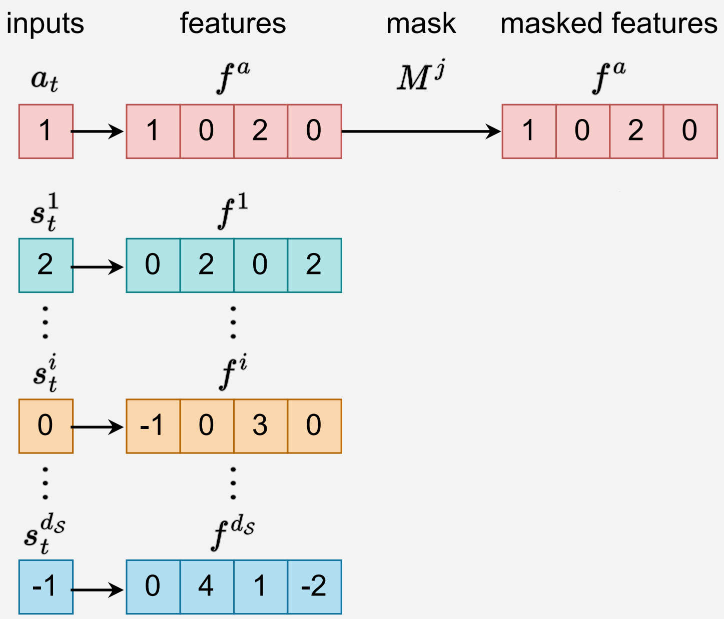

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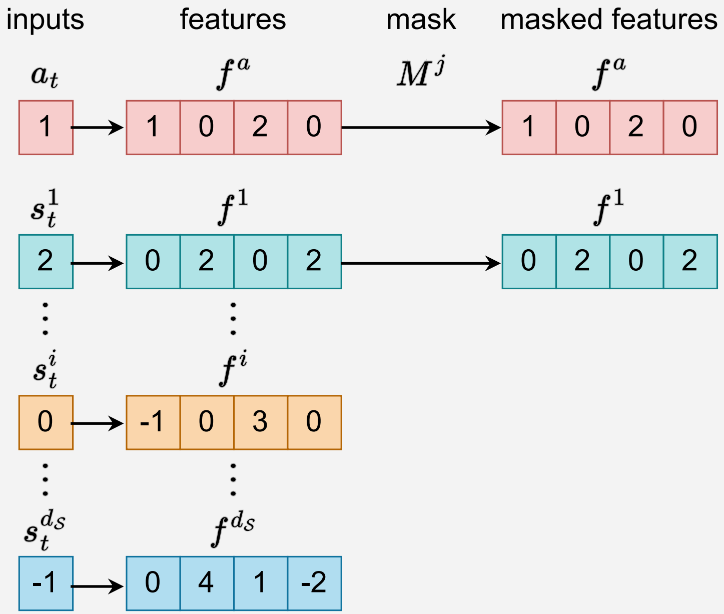

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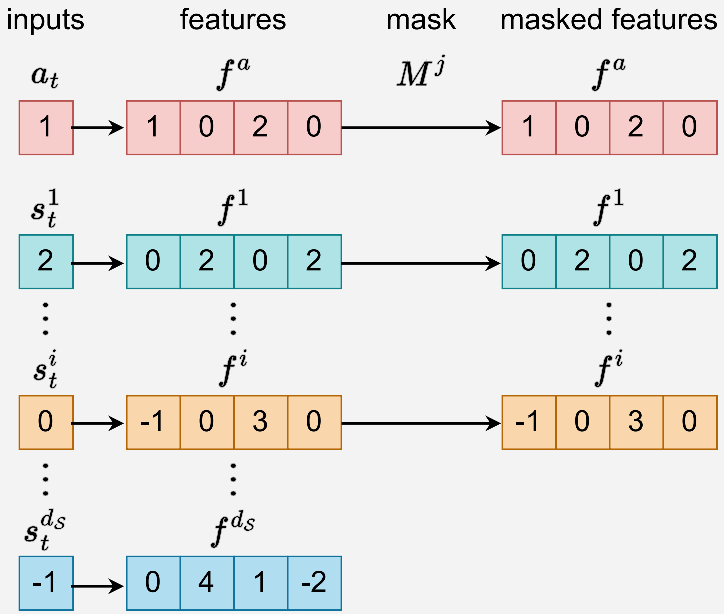

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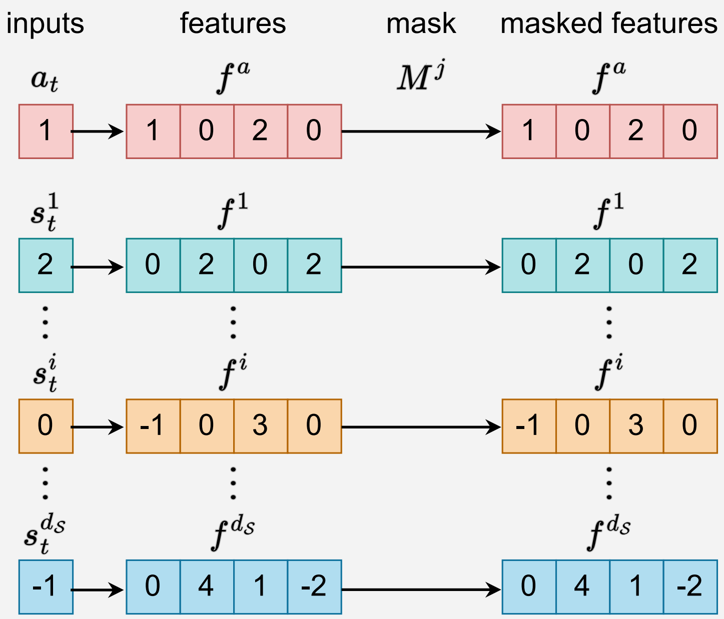

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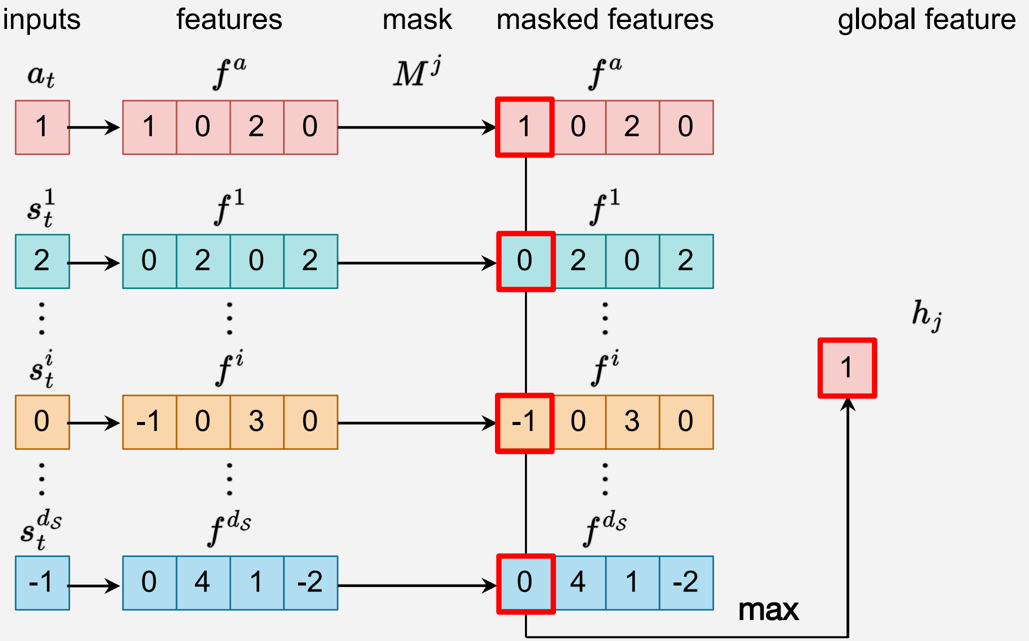

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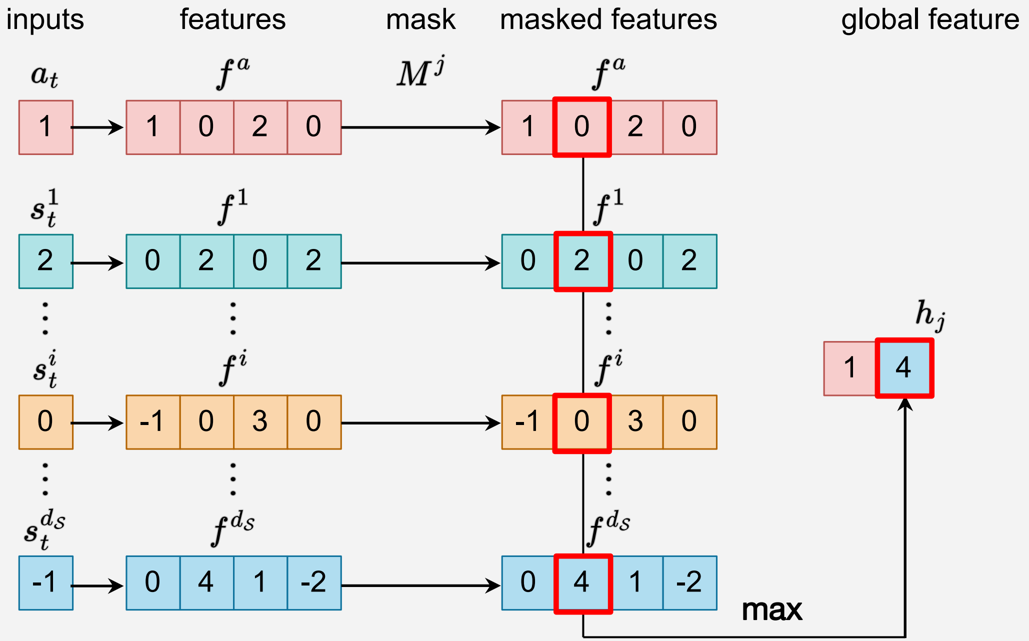

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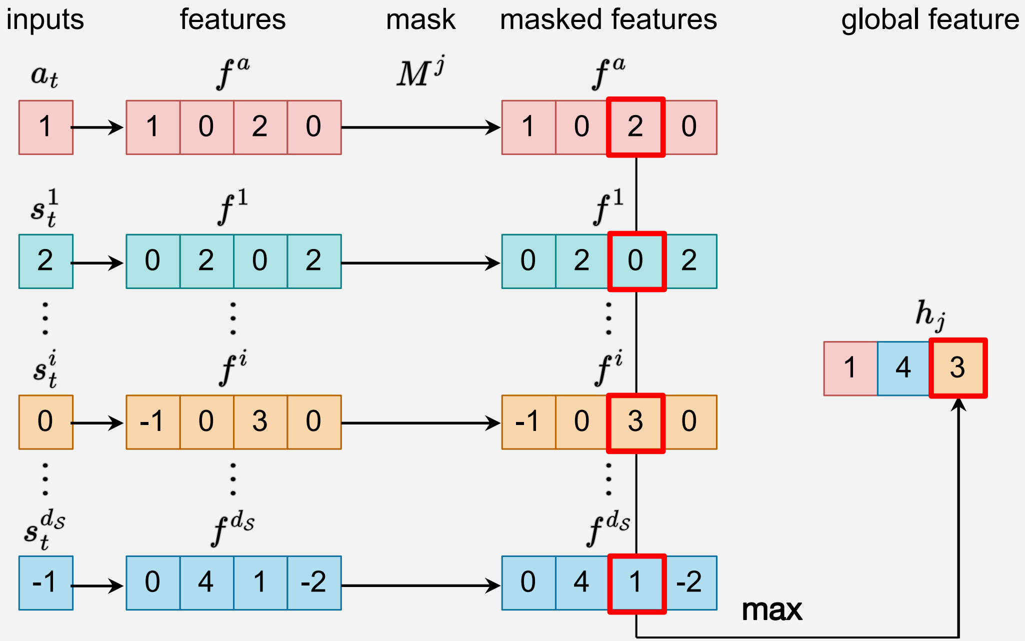

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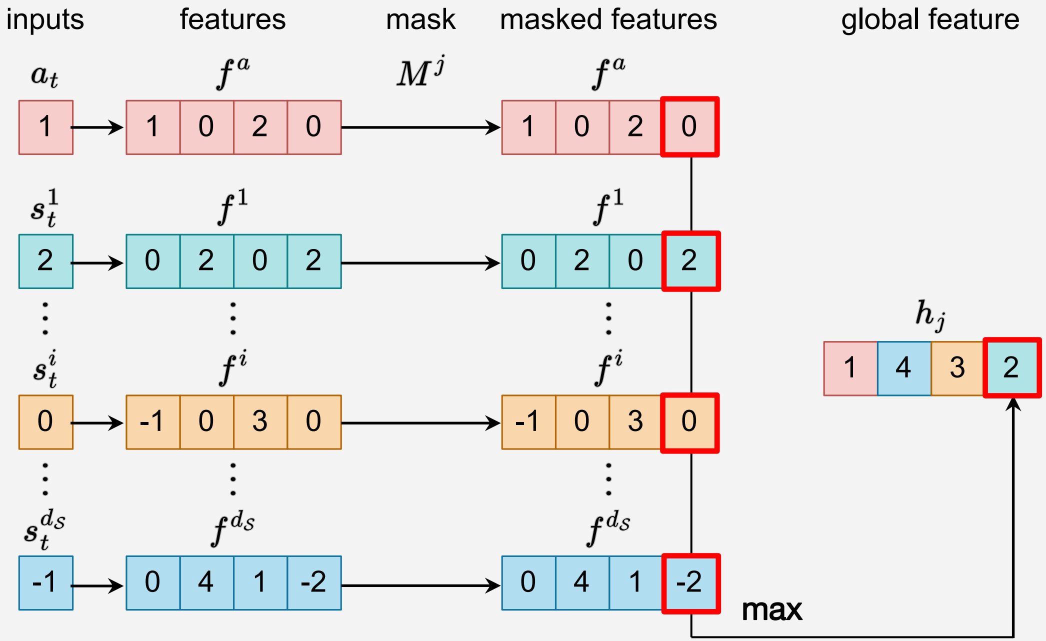

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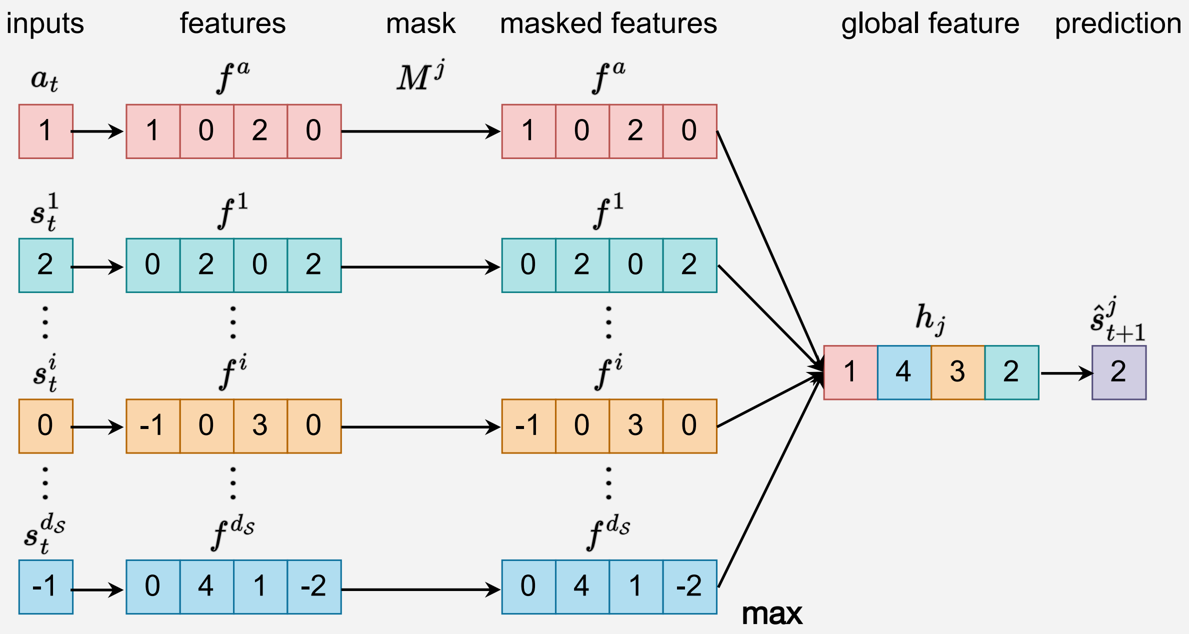

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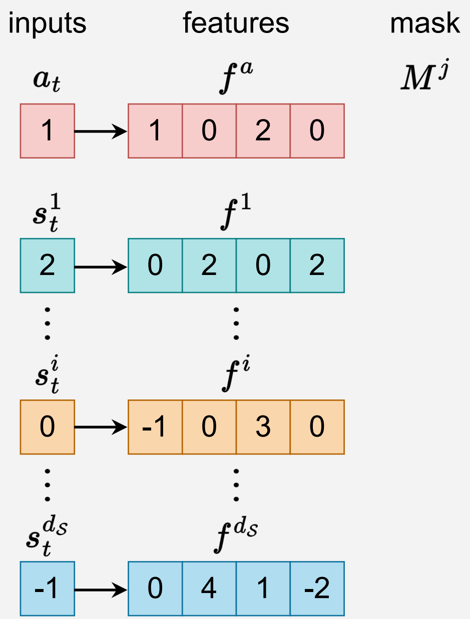

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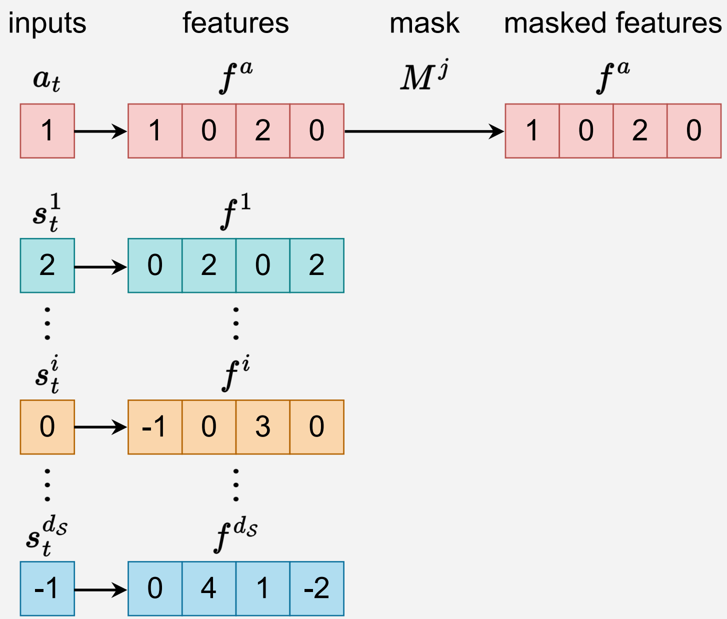

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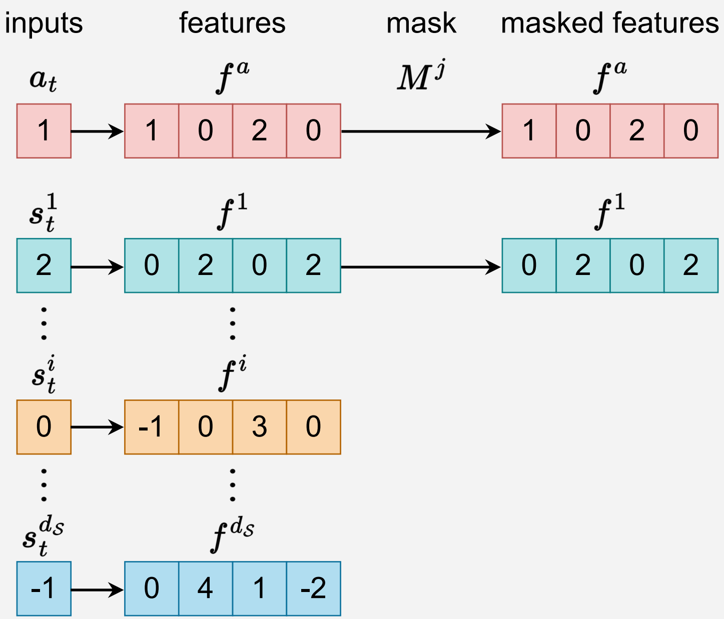

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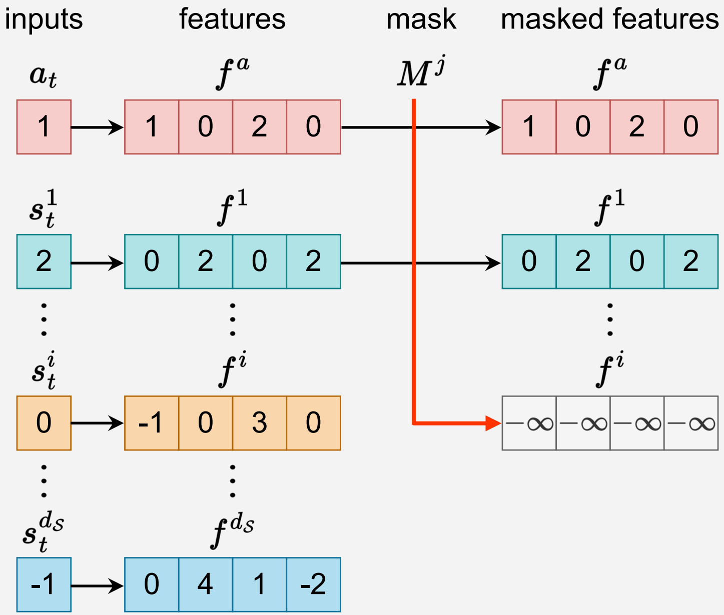

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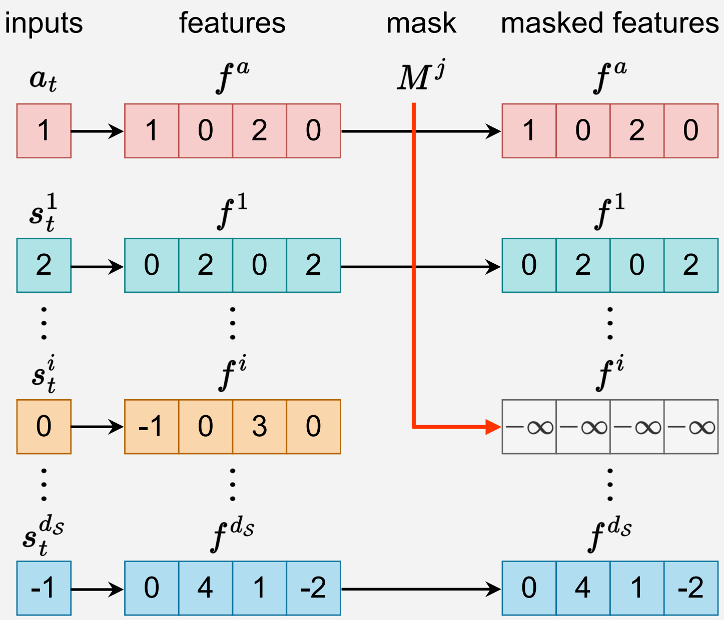

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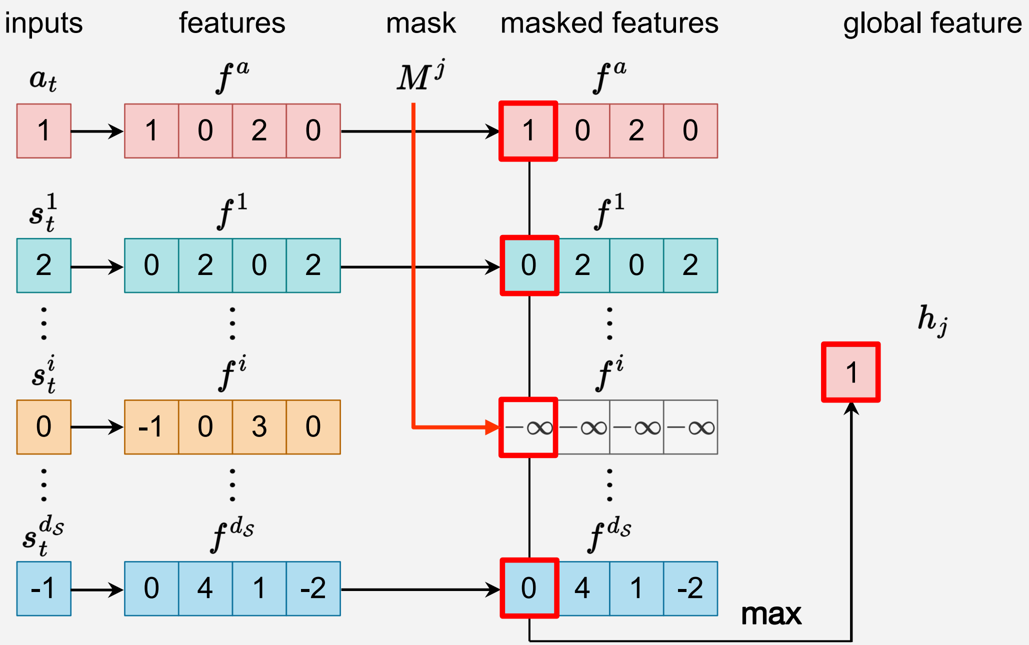

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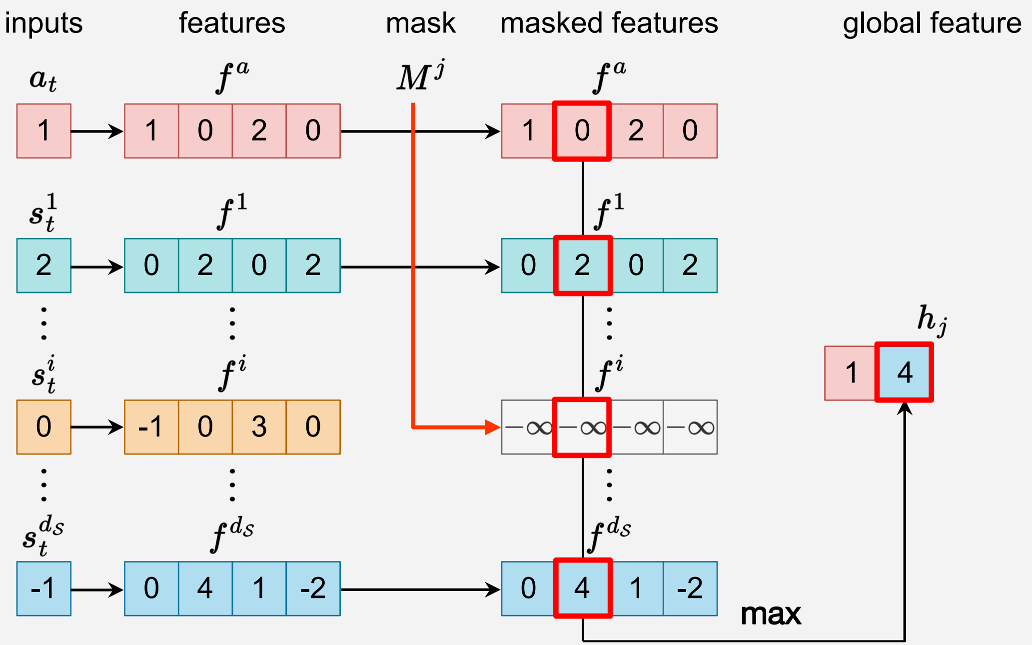

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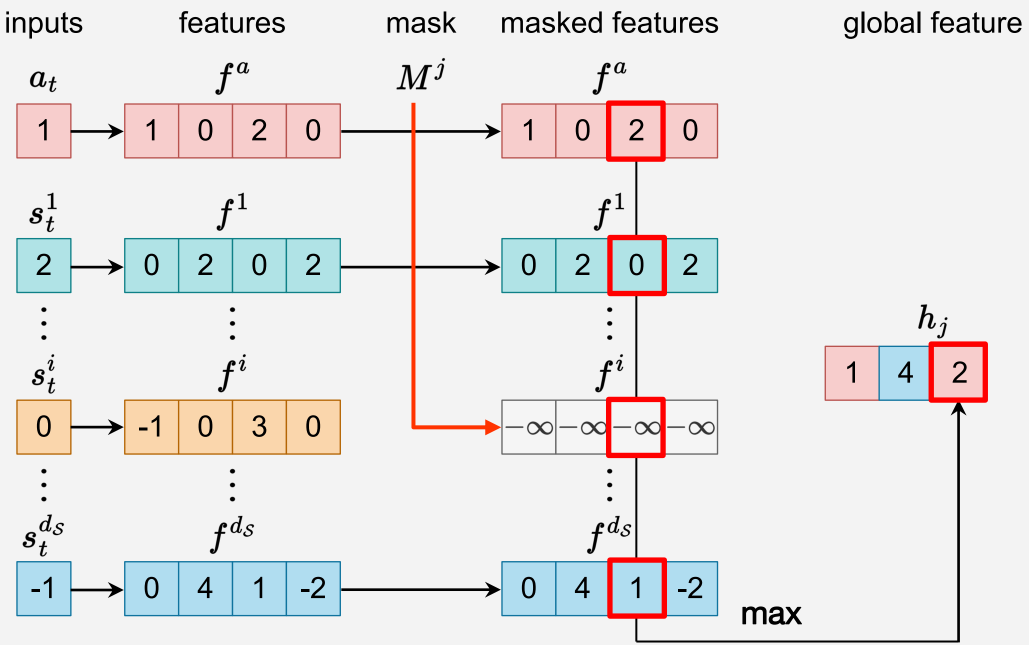

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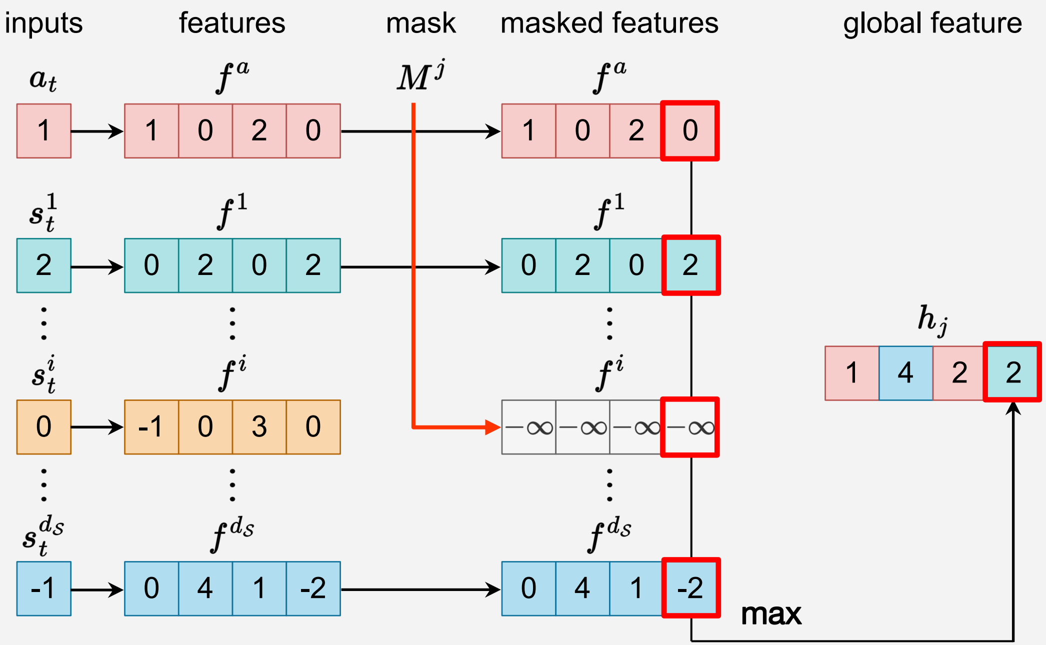

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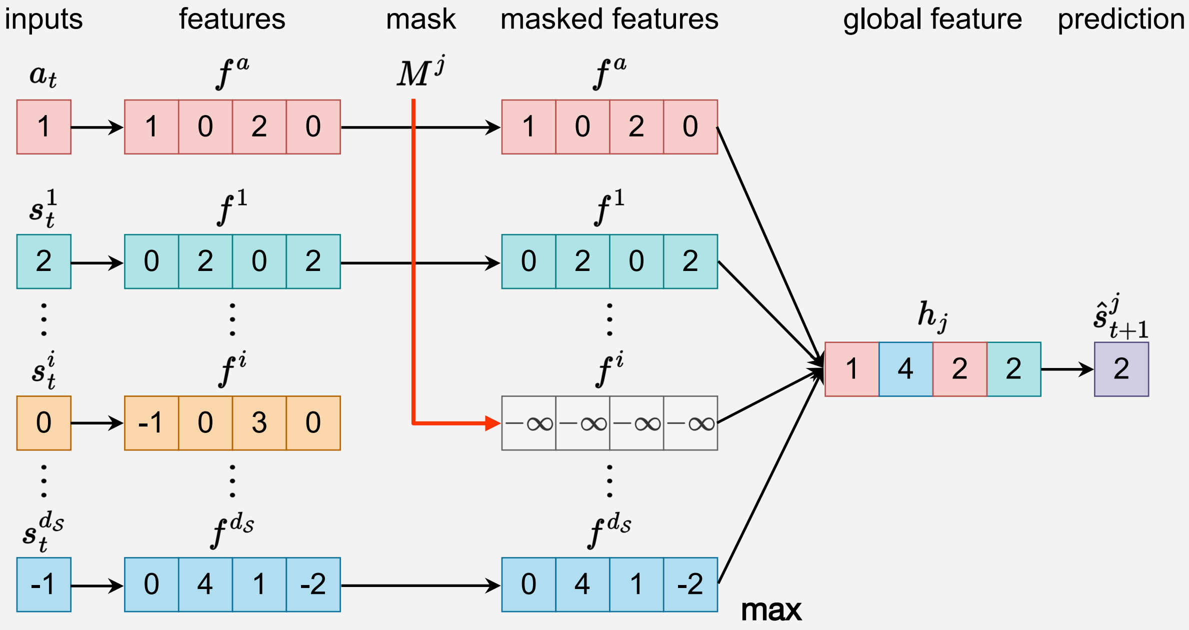
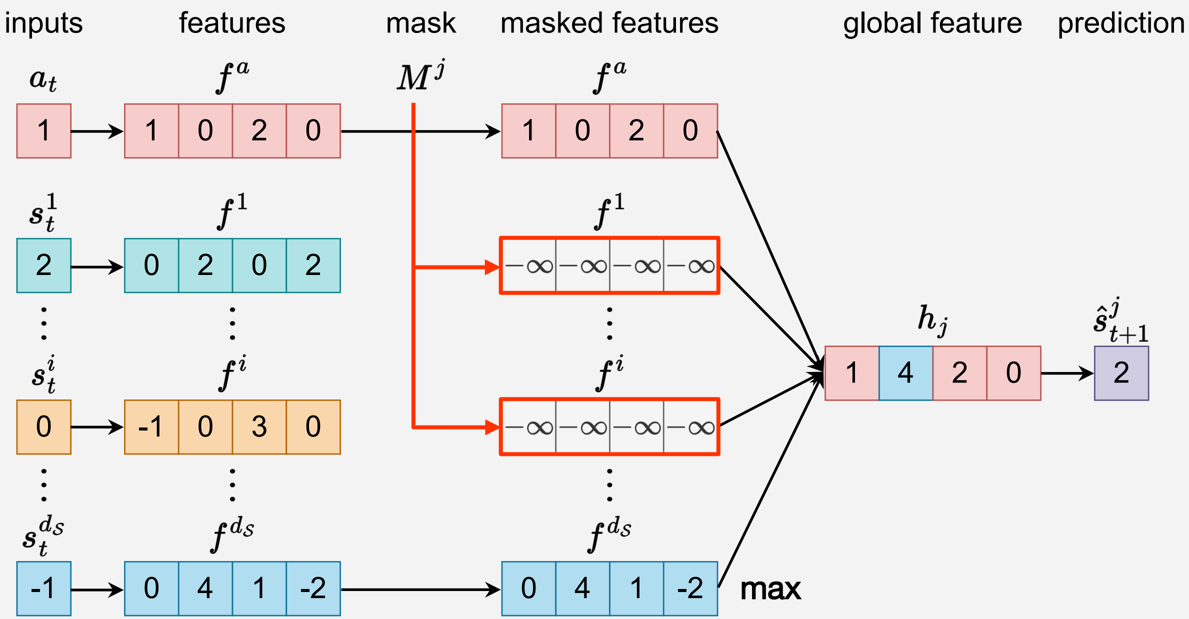
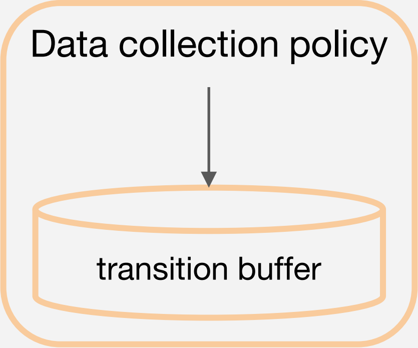


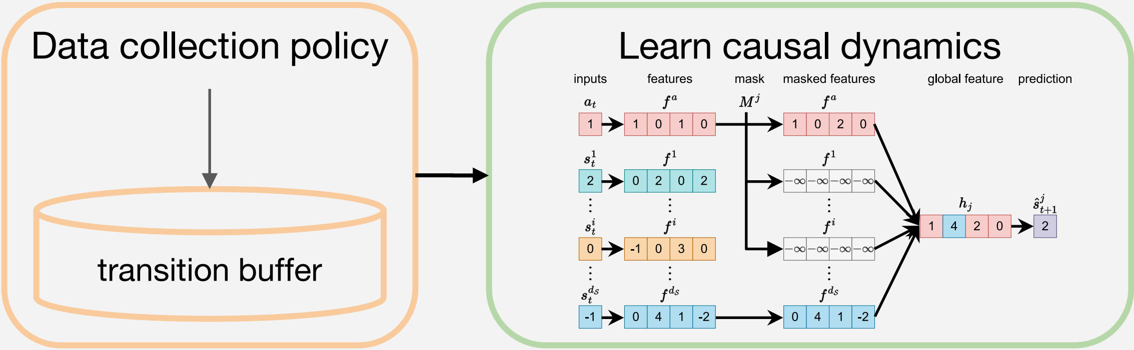
# Method

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






# Causal Dynamics Learning (CDL)

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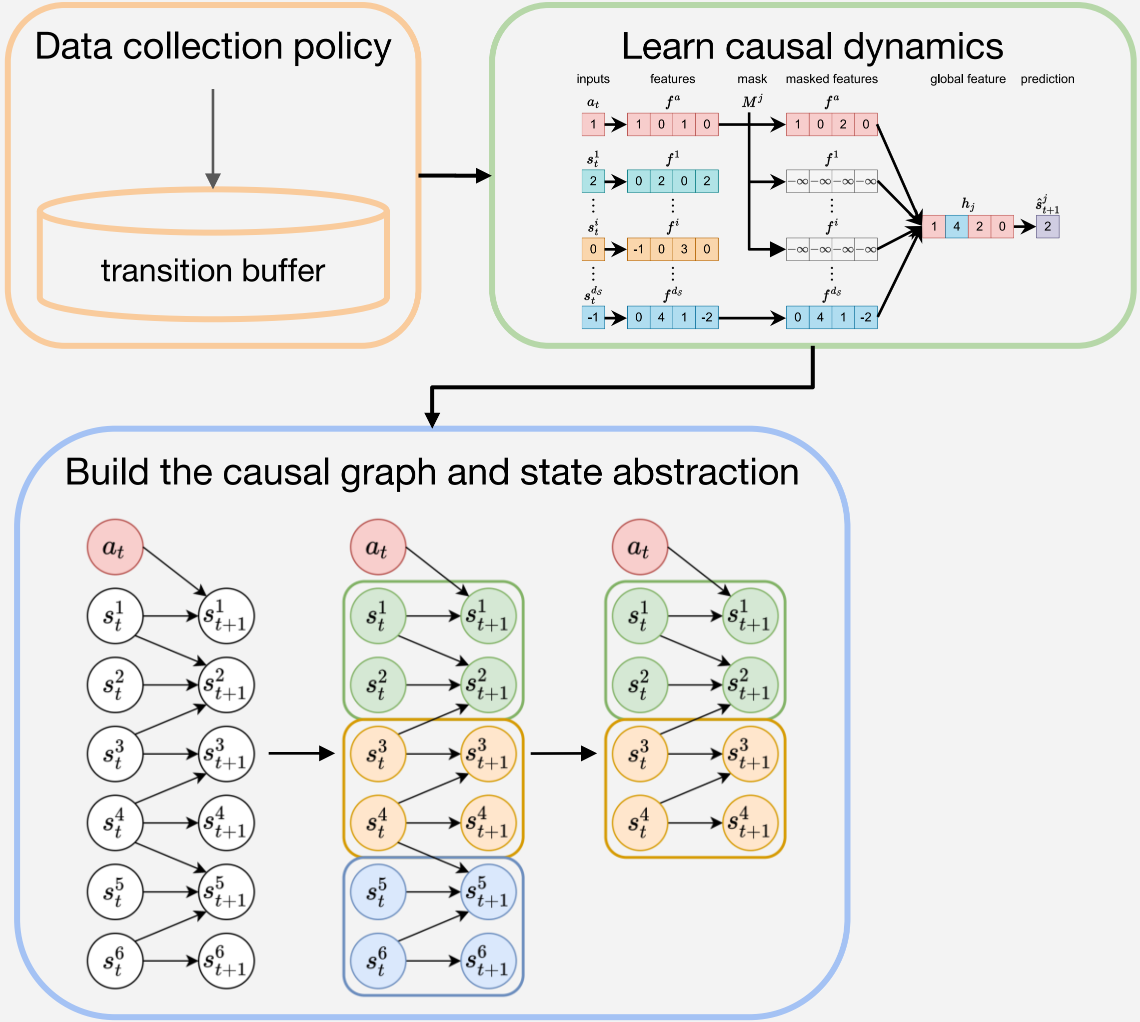


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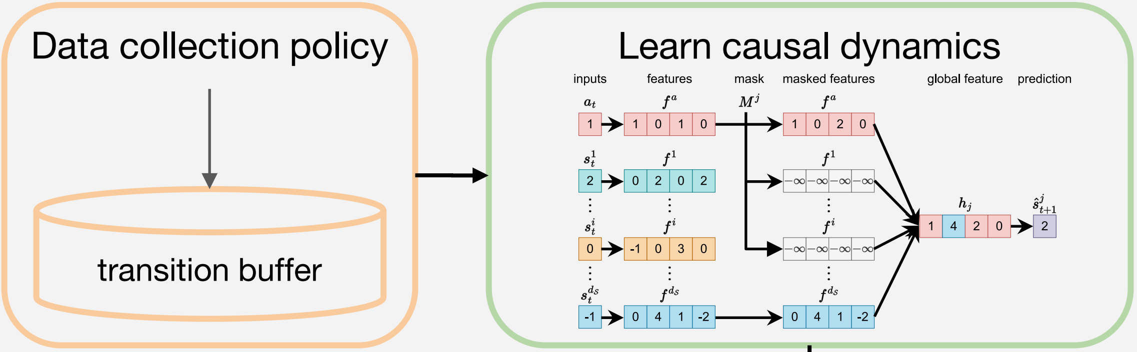
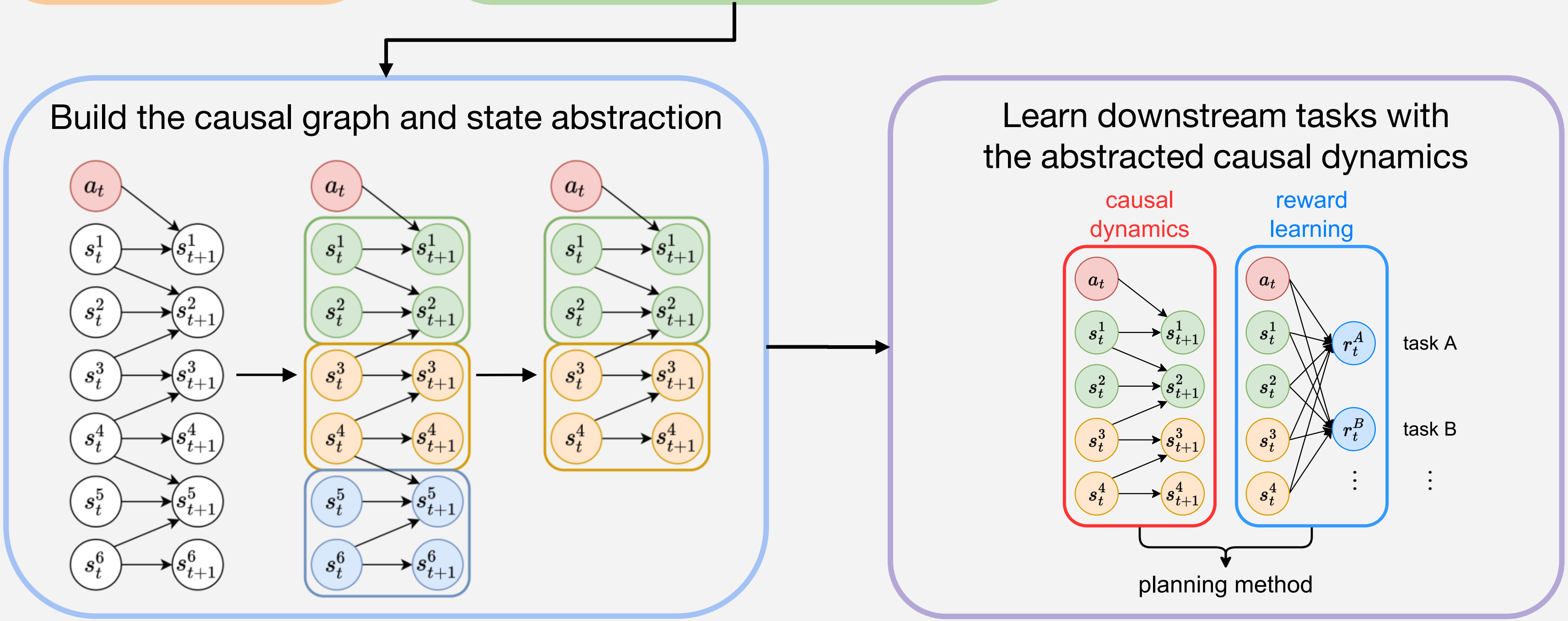
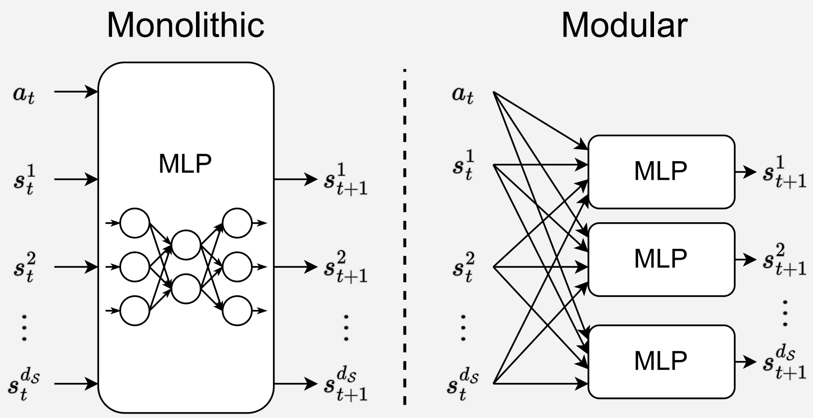


# Experiments

## Baselines



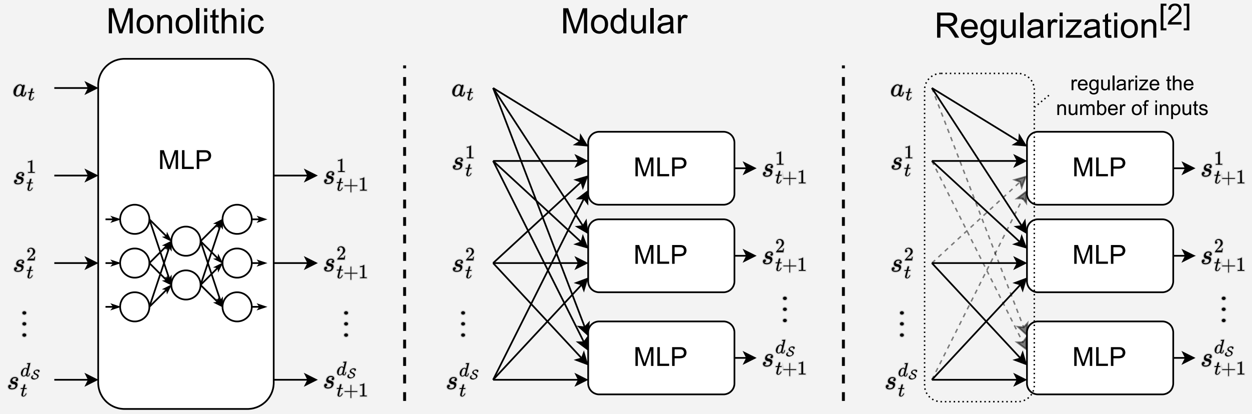

MLP: multi-layer perceptron



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

# Experiments

## Baselines

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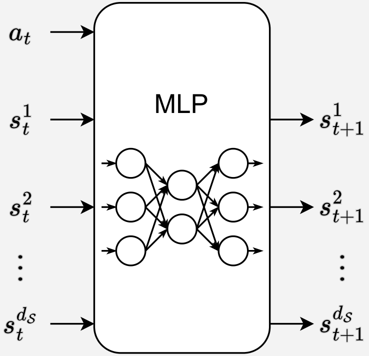
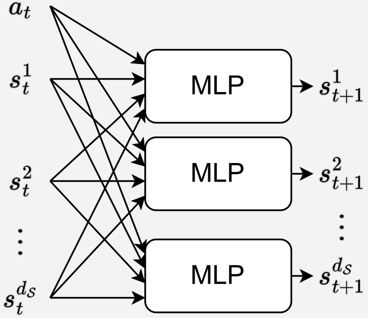
# Experiments

## Baselines

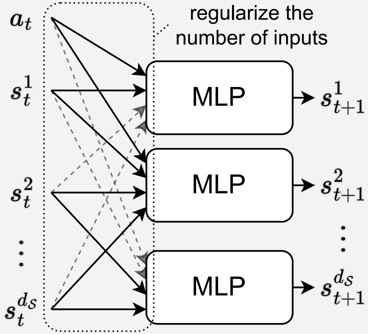
### Monolithic



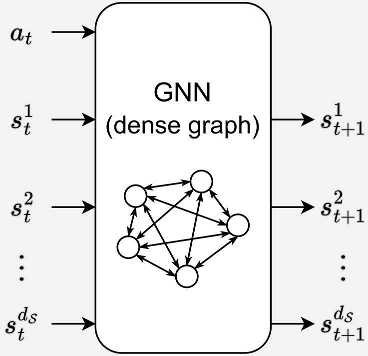

### Modular




### Regularization[2]




### Graph Neural Network[3]




MLP: multi-layer perceptron



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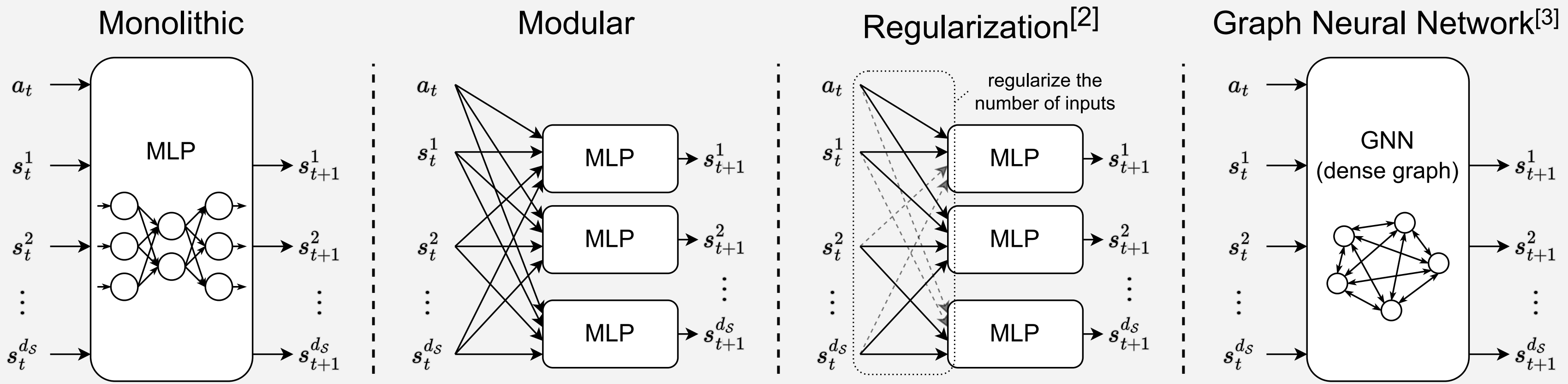
# Experiments

## Baselines




MLP: multi-layer perceptron

Does each baseline learn a causal model?

✗ ✗ ✓ ✗

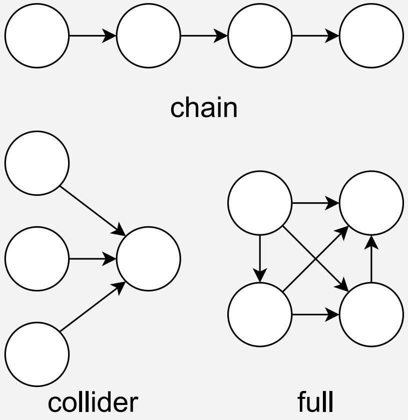


[2] Wang et al., Neurips 2021. [3] Kipf et al., ICLR 2020

# Experiments

## Chemical Environment[4]

Synthesized environment
– with different underlying graphs



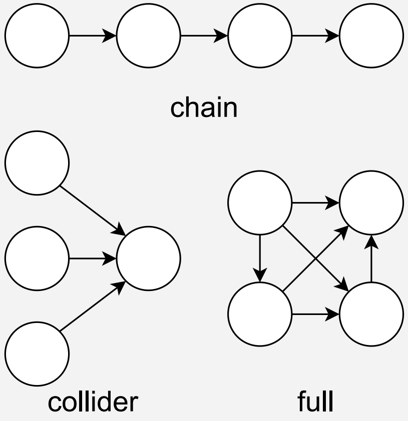


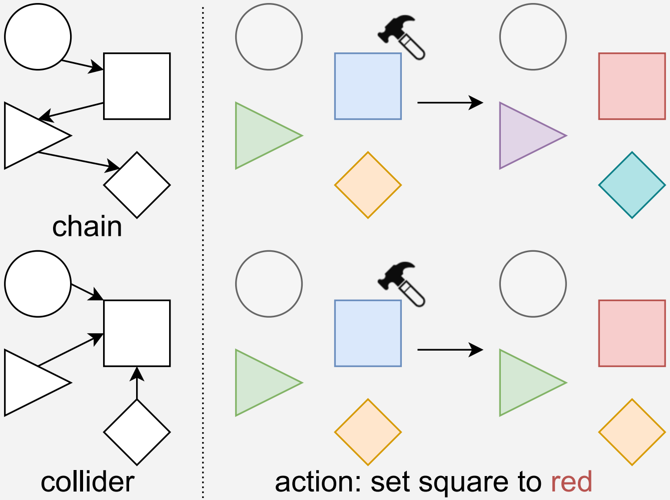

[4] Ke et al., Neurips 2021.

# 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.




[4] Ke et al., Neurips 2021.

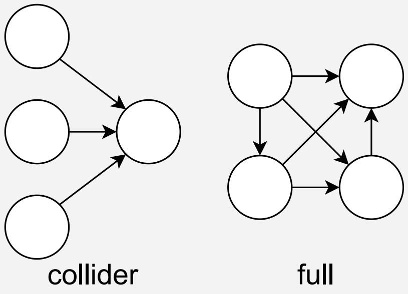
# Experiments

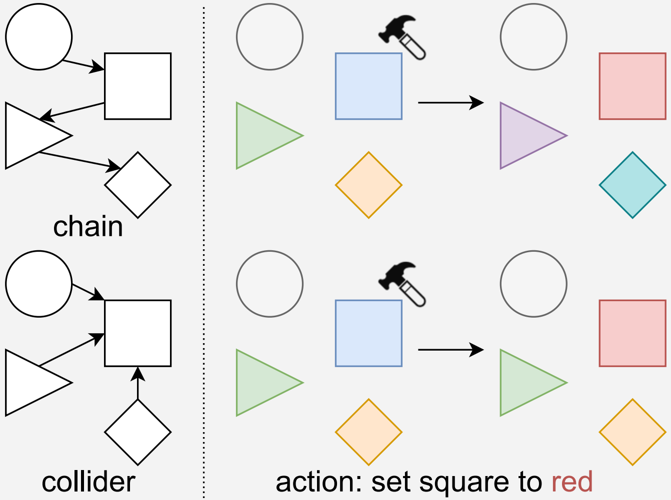
## Chemical Environment[4]

Synthesized environment

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

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



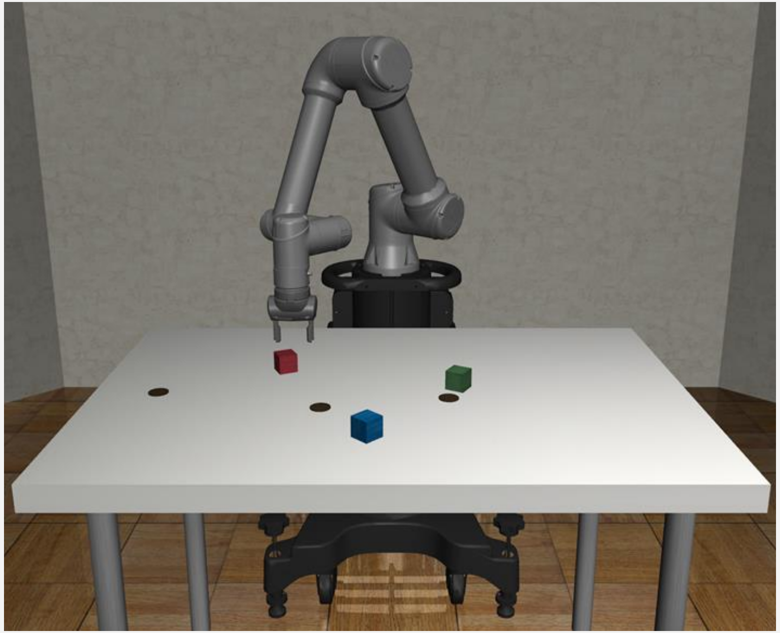




[4] Ke et al., Neurips 2021.

# Experiments

## Manipulation Environment

State Variables:



# Experiments

## Manipulation Environment

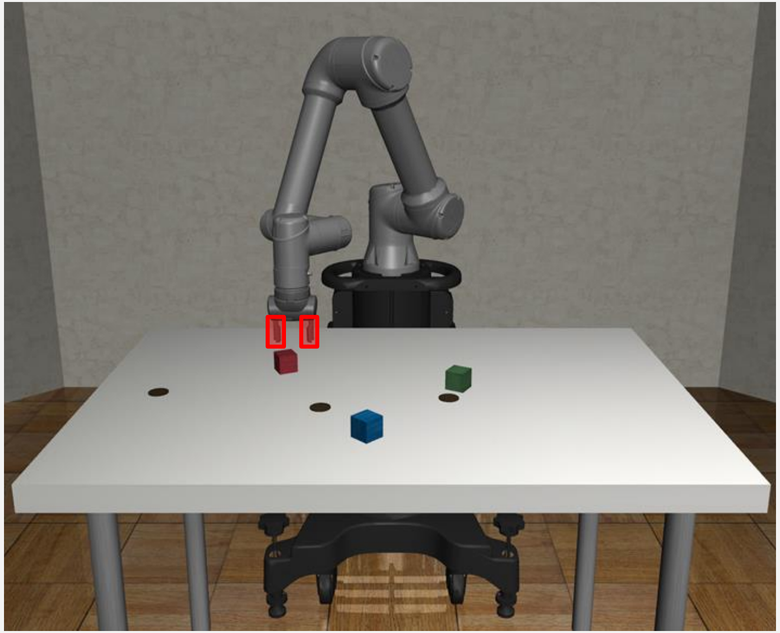
State Variables:
- end-effector (eef)

# Experiments

## Manipulation Environment

State Variables:

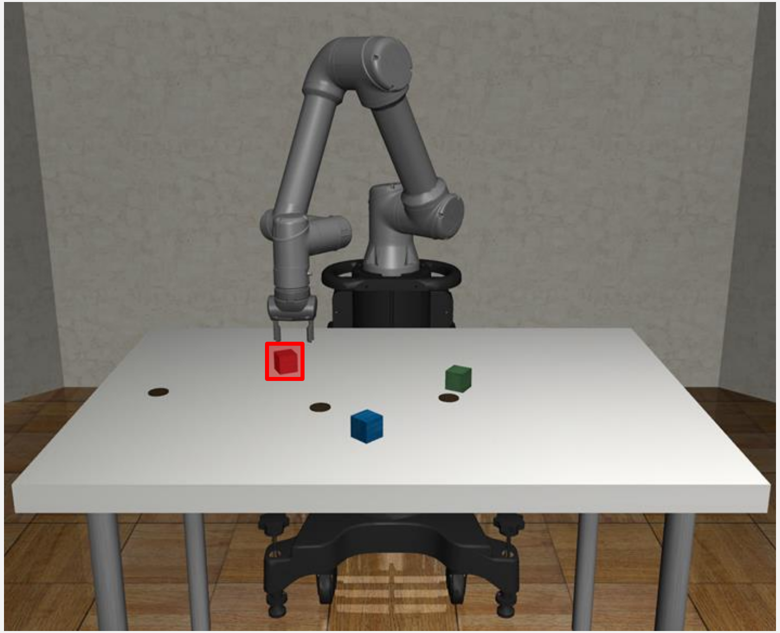
- end-effector (eef)
- gripper (grp)



# Experiments

## Manipulation Environment

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

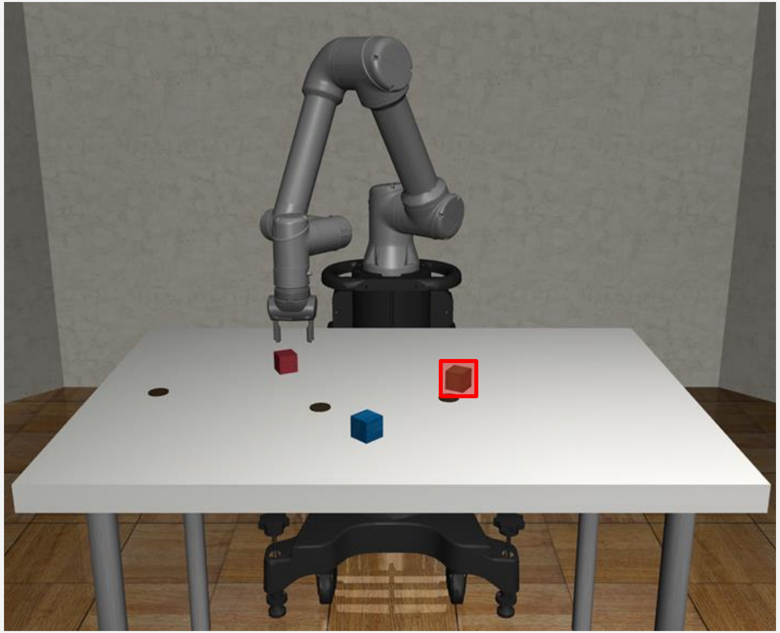


# Experiments

## Manipulation Environment

State Variables:

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

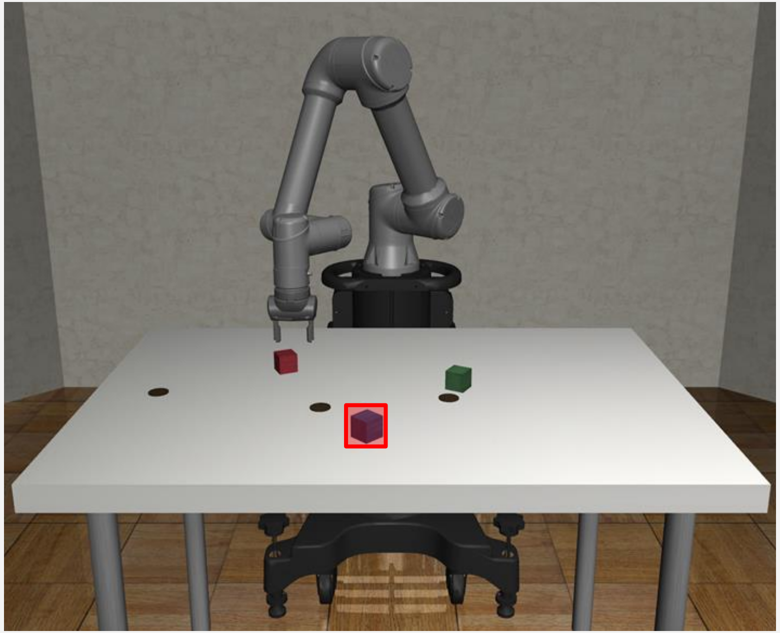


# Experiments

## Manipulation Environment

State Variables:

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



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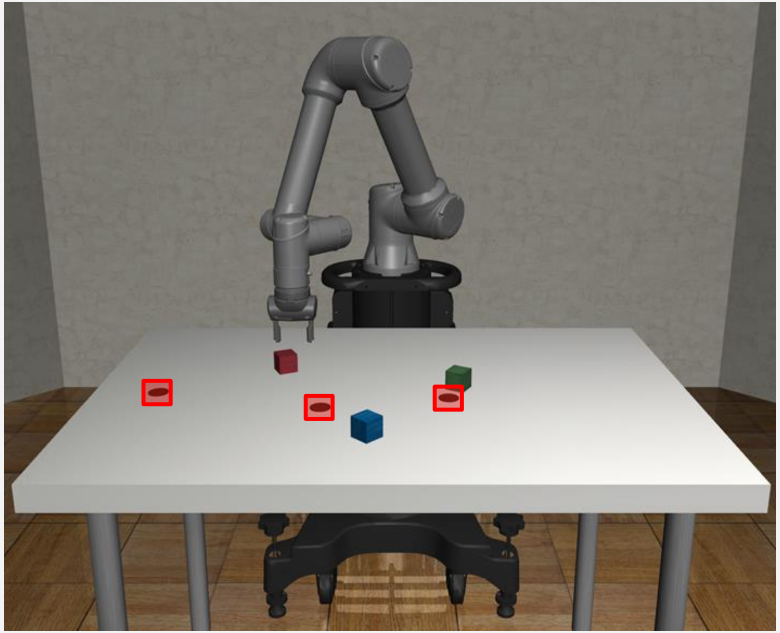
State Variables:

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



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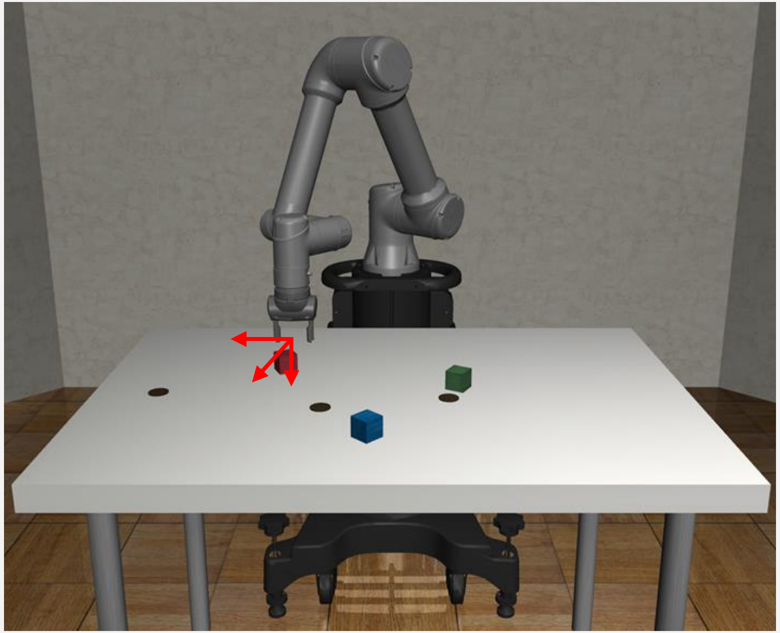
- non-interactable markers (mkr$^{1\text{-}3}$)

Action dimensions:

- end-effector target



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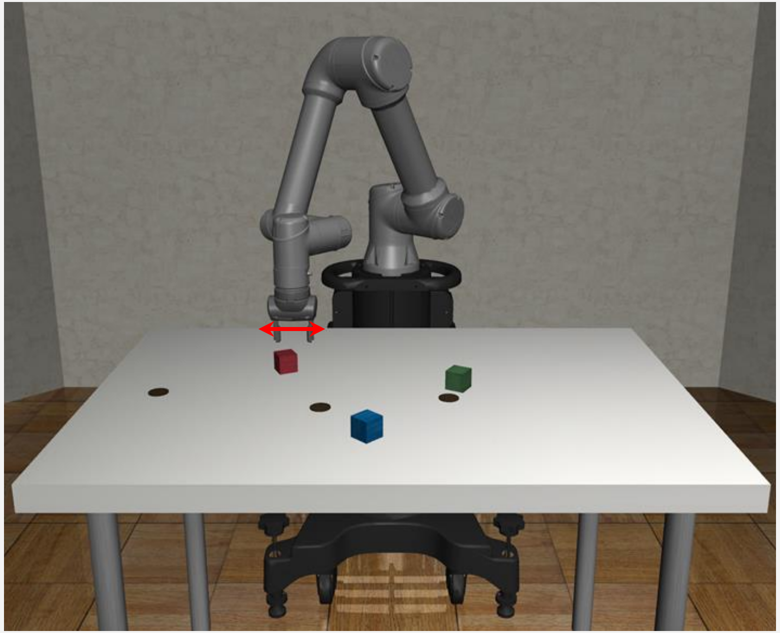
State Variables:
- end-effector (eef)
- gripper (grp)
- the movable object (mov)
- the unmovable object (unm)
- the randomly moving object (rand)
- non-interactable markers ($mkr^{1\text{-}3}$)

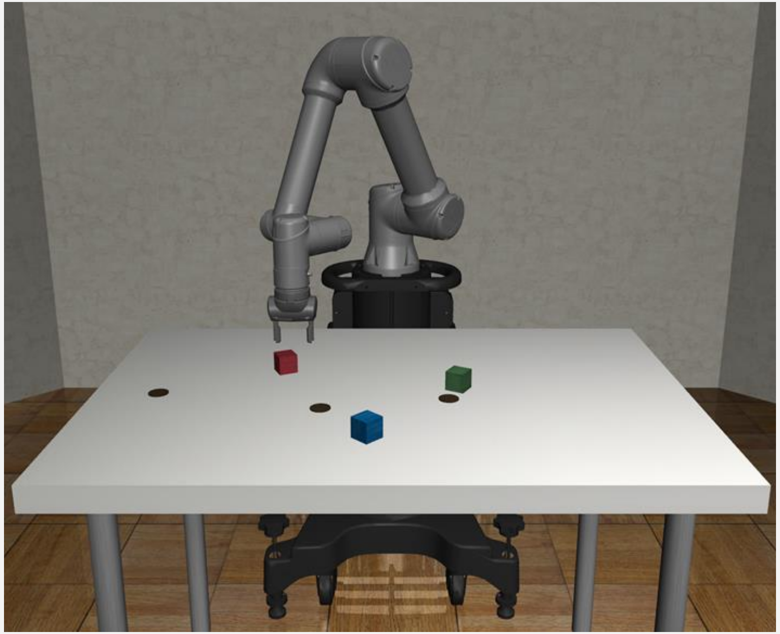
Action dimensions:
- end-effector target
- gripper open/close

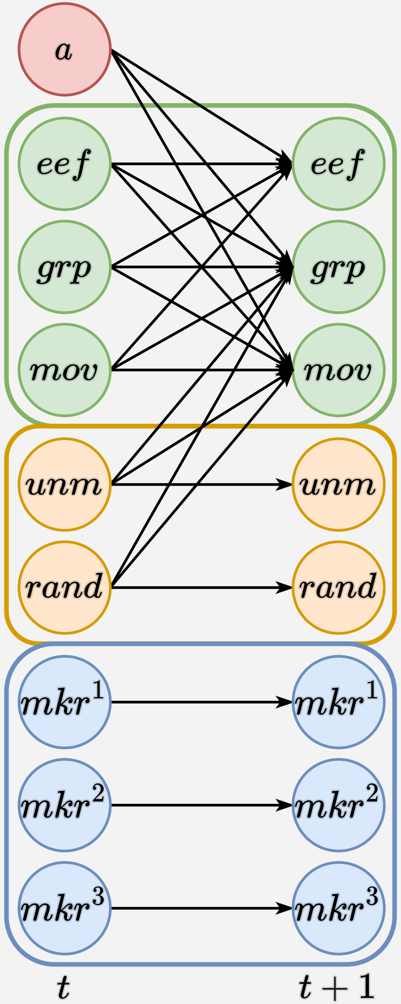


# Results

## 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.

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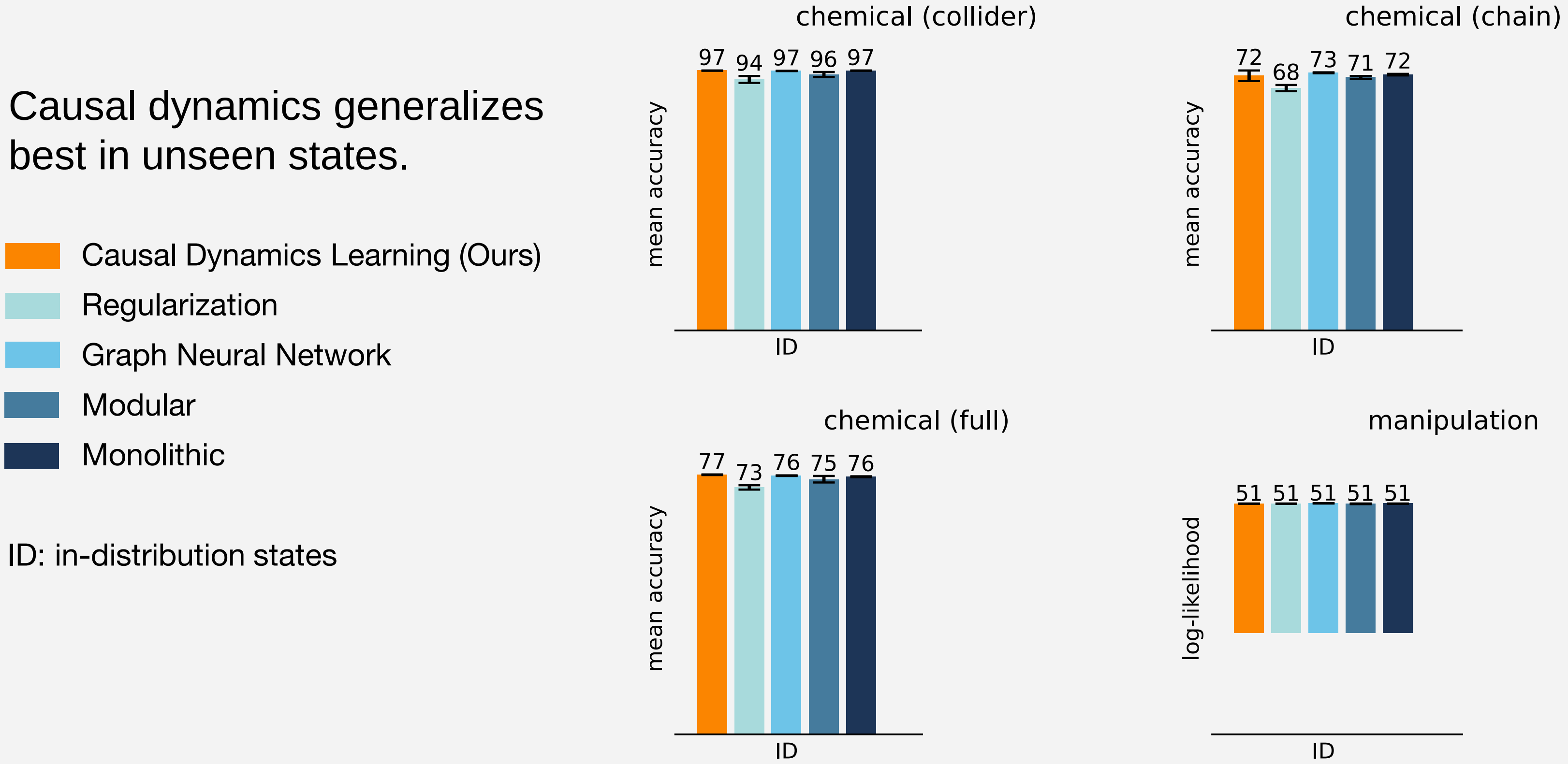
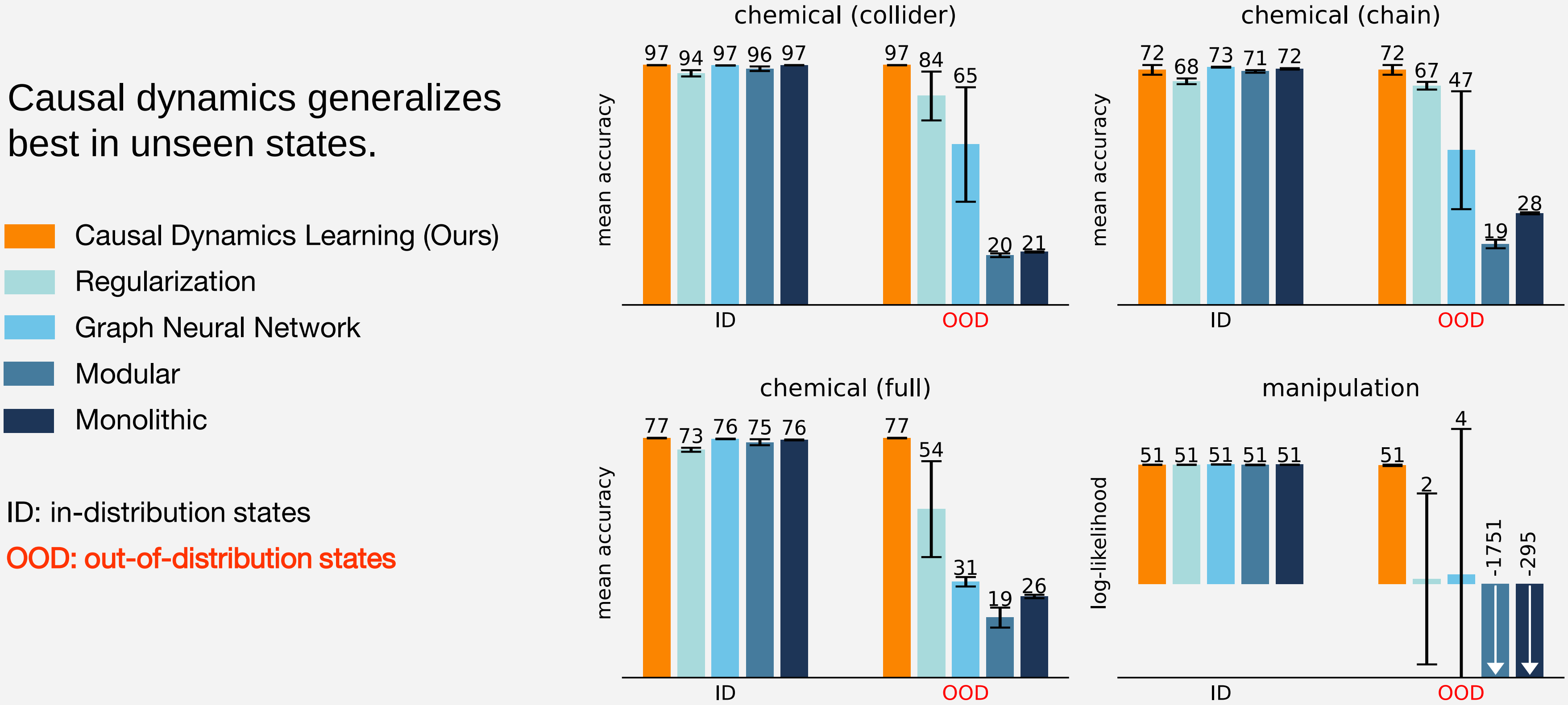



ID: in-distribution states

# Results

## Dynamics Generalization

Causal dynamics generalizes best in unseen states.



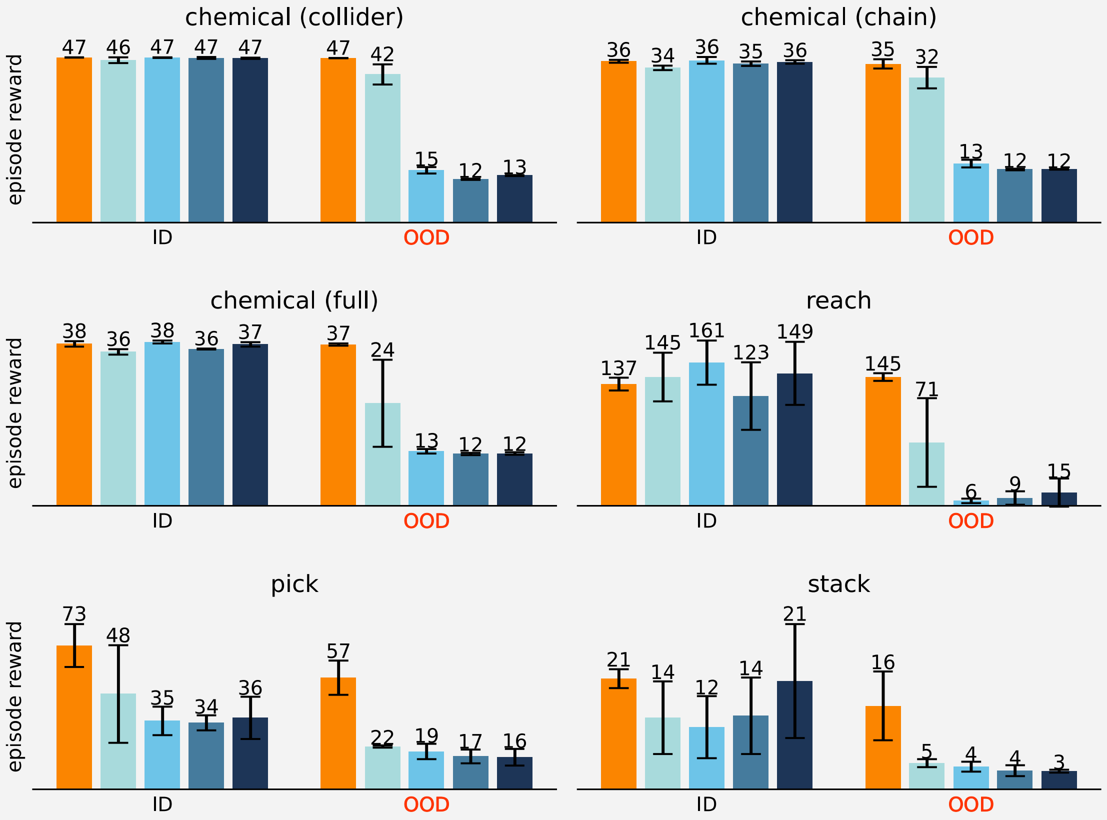

ID: in-distribution states

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





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

Scan to read the paper

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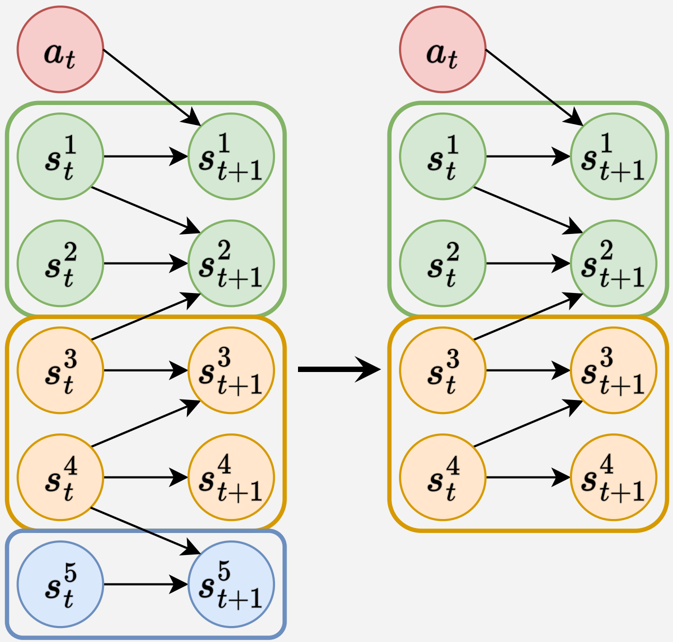
# Problem Setup

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.

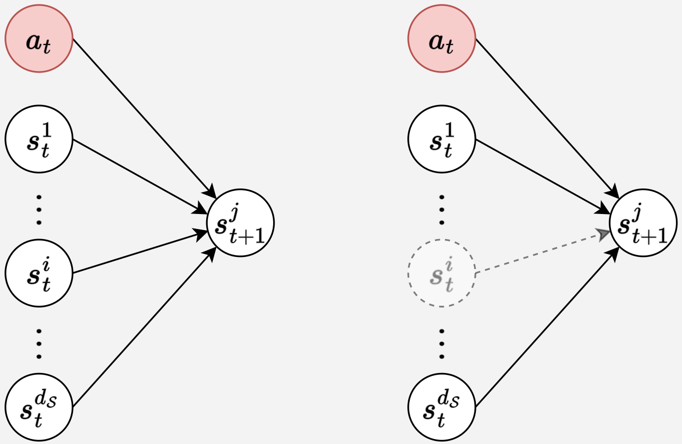


# Method

Key idea: determine if the causal edge $s_t^i \to s_{t+1}^j$ 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 $s_t^i \to s_{t+1}^j$.

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




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

$$\Updownarrow$$

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