Causality

for Decision Making

Mengyue Yang

University College London

Email: mengyue.yang.20@ucl.ac.uk

Website: https://ymy4323460.github.io/

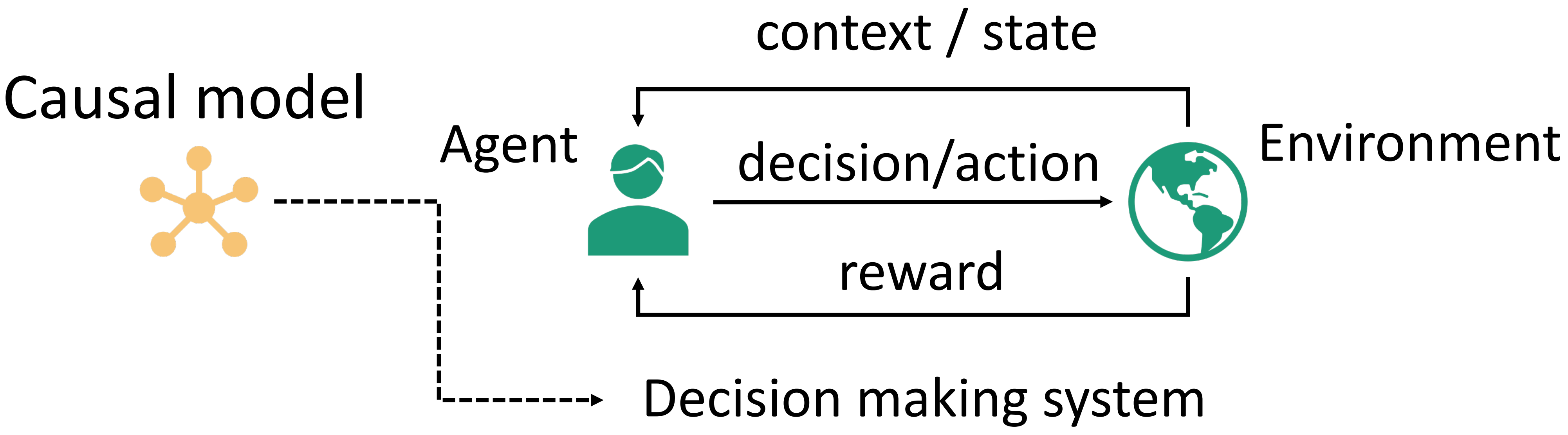
What’s causal decision making

- Causal inference is the process of understanding the cause-and-effect relationships between variables or events.
- A decision-making system is an approach used to make informed choices in various contexts.

Causal decision-making system usually apply causal inference technics to make a better decision to meet the needs of the requirements of explanation, generalization or safety etc. .

Causality and Decision Making

- Reasoning: Understanding the factors in the system
- Making decision: Learning how to take actions



Advantages of causal decision making

- Clarifying Causal Relations: Identify the key factors and avoid being misled by spurious correlations.

- Enhancing Decision Accuracy and Effectiveness: predict the outcomes make the wisest choices.

- Reducing Decision Risks: Identify potential bad effects and avoid risks of generalization.

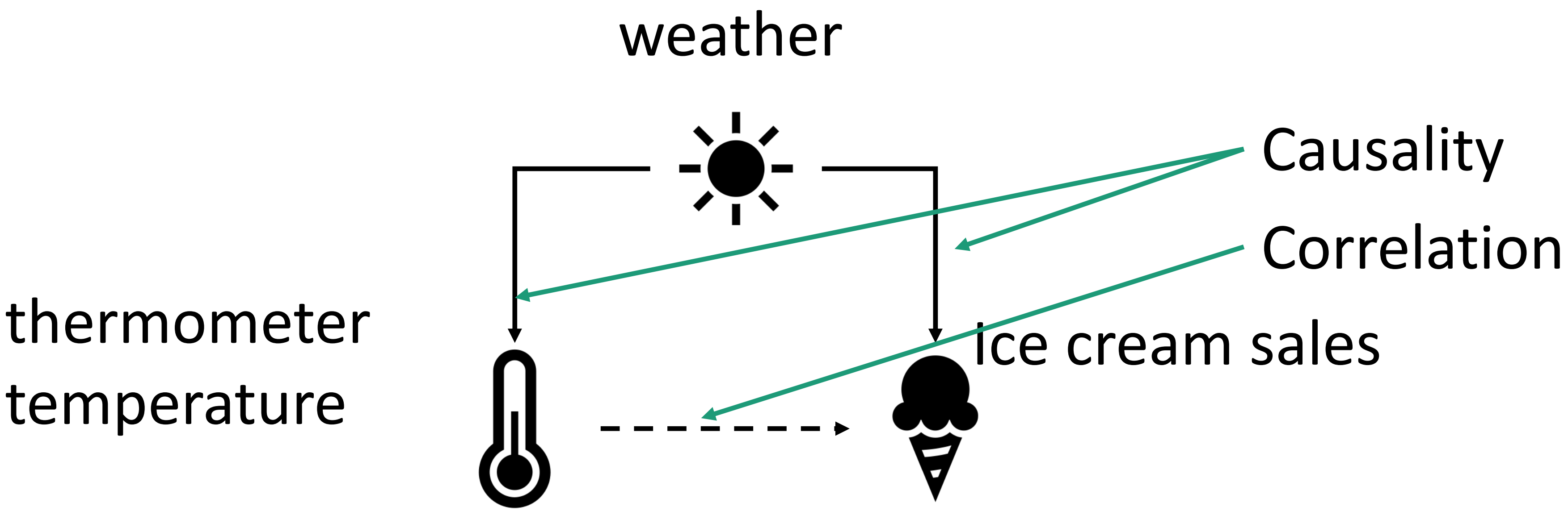
Outline

- Backgrounds
  - Intro to causality and decision-making system.
- Current causal decision-making method
  - Causality in Static and Dynamic system, including environment understanding, learning to intervene, counterfactual reasoning
- Advanced topic
  - Challenges about causality in LLM agents

The technical details please refer to the related papers

Background:
Causal Inference
The Pearl’s Hierarchy

Correlation doesn’t mean causality



Causal information rather than commonly used association has more generalization ability in prediction task.

The philosophy of Causality

• Descartes ascribed cause to eternal truth.

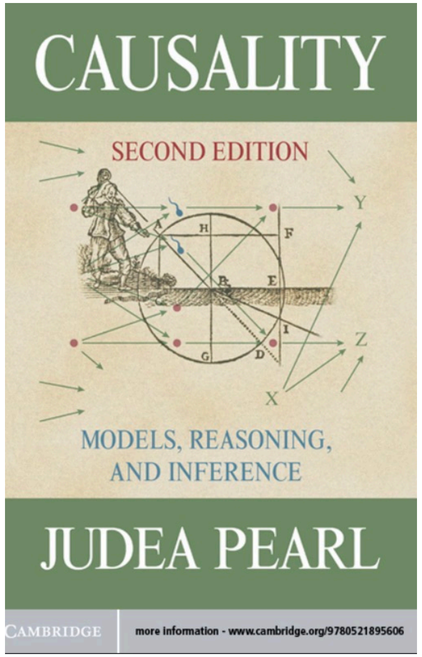
The truth of the world

→

The truth of the world in our head

→

Imagine what will happen -------- Consciousness

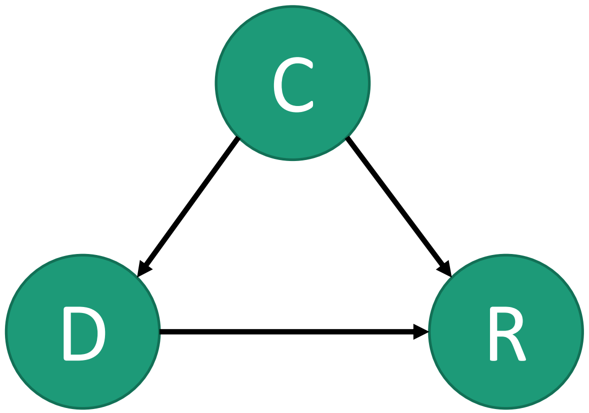


Judea Pearl. Causality

Causal Diagram

- Causal Model

$G =$ Context



Decision Reward

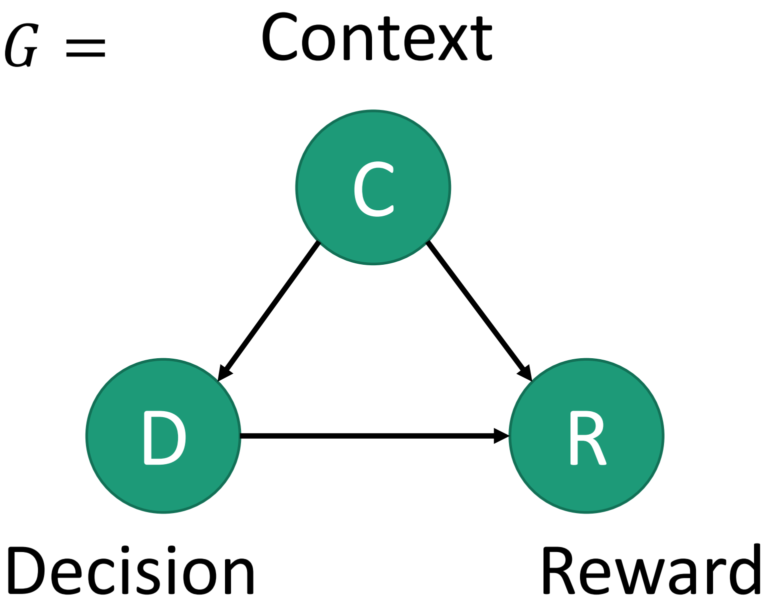
$\mathrm{D} = f(C, \epsilon_D)$ $P(C, D, R)$

$R = f(D, C, \epsilon_R)$ $P(R|D)$ Decision effect

Causal Diagram

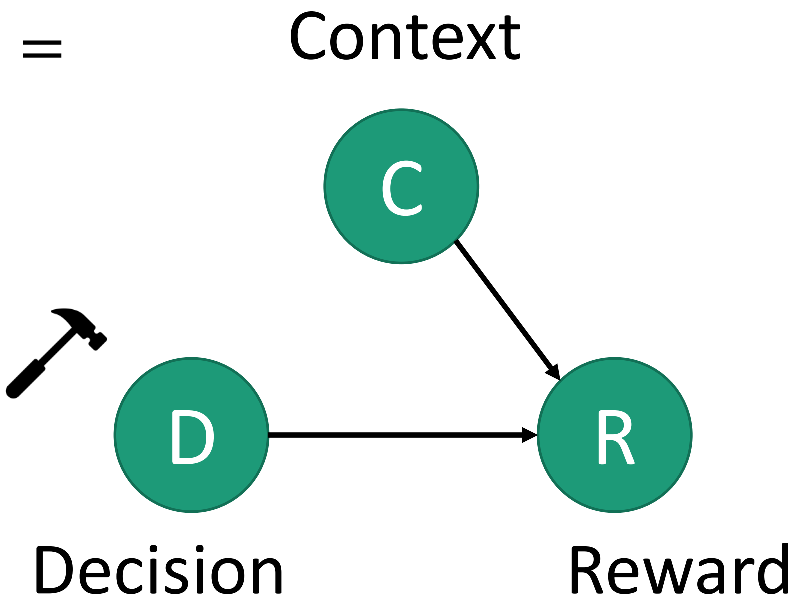
- Causal Model

$G =$



- Intervention

$G_{do(D)} =$



$P(R|D = d)$

Observational

$D = d$

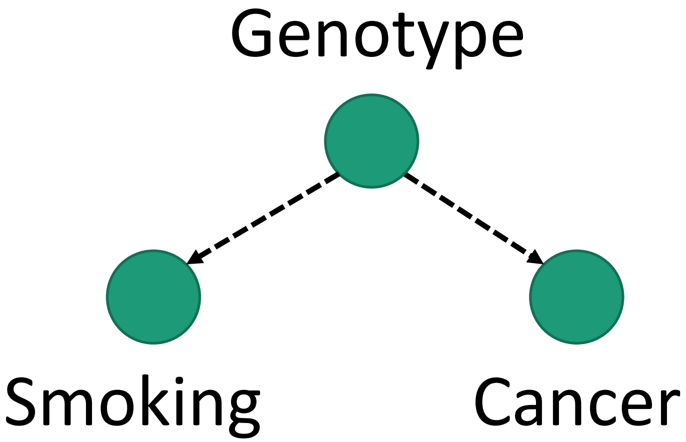
$R = f(C, D, \epsilon_R)$

$P(R|do(D = d))$

Interventional

Intervention and correlation probability

$$P(C|do(S)) = P(C|S)$$

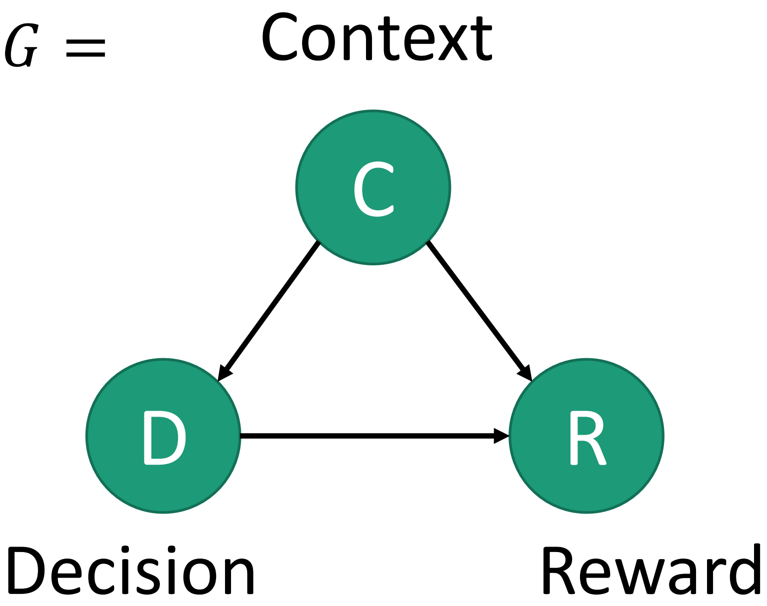


$$P(C|do(S)) = P(C)$$

Causal Diagram

- Causal Model

$G =$

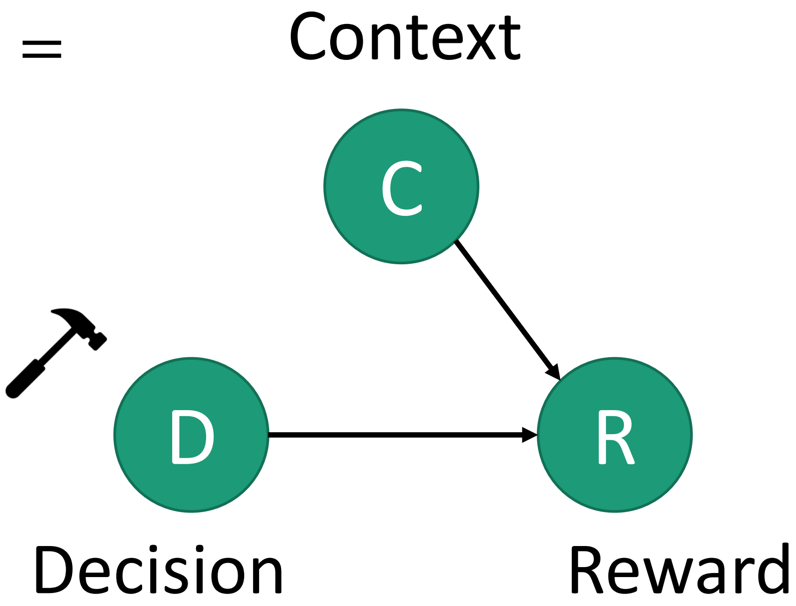


$\mathrm{D} = d'$

$R = f(D, C, \epsilon_R)$

- Counterfactual

$G_{do(D)} =$

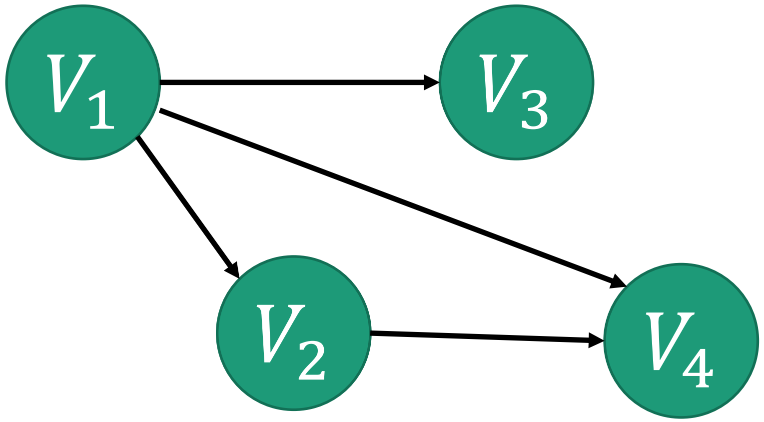


$P(R_{D=d'} | D = d, R = r)$

Counterfactual

Structure Causal Model

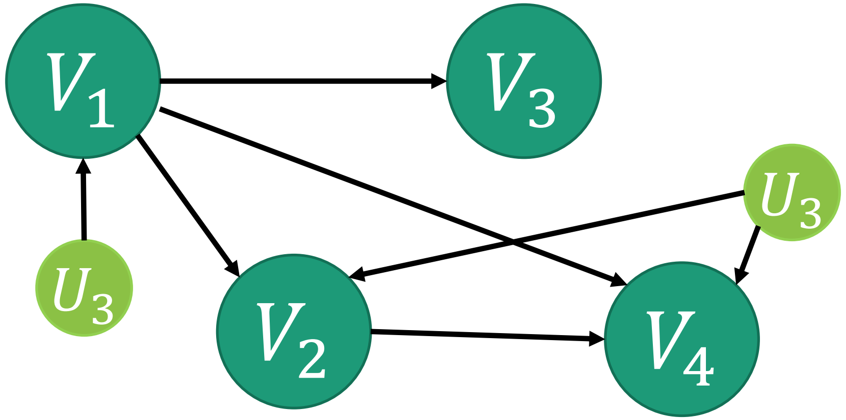
- Endogenous Variables: $V = \{V_1, .., V_n\}$, the variables in the system



A structure causal model M is a tuple of factors $\{V, U, F, P(u)\}$

Structure Causal Model

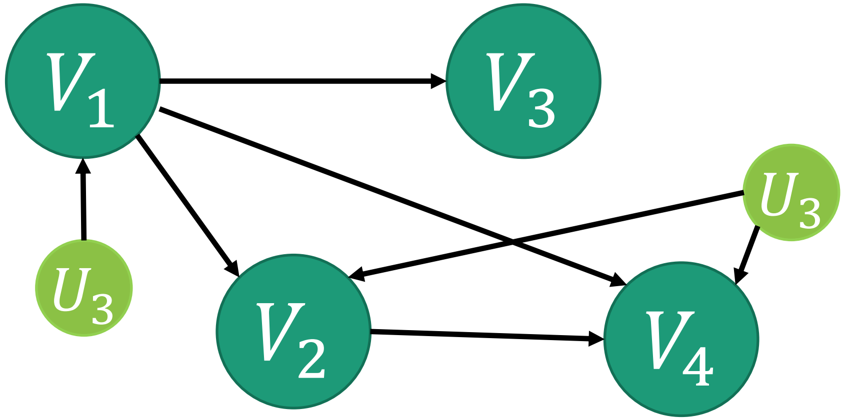
- Exogenous Variables: U $= \{U_1, .., U_m\}$, the variables out of the system, but have causal effect in system



A structure causal model M is a tuple of factors $\{V, U, F, P(u)\}$

Structure Causal Model

- Confounder: the variable U_i is a confounder if and only if it influence both cause and effect



The confounder will influence the causal estimation, the method doesn't consider confounder may lead to the estimation error which called the Simpson's Paradox.

Simpson's Paradox

	All		Men		Women	
	Applicants	Admitted	Applicants	Admitted	Applicants	Admitted
Total	12,763	41%	8,442	44%	4,321	35%

Department	All		Men		Women	
	Applicants	Admitted	Applicants	Admitted	Applicants	Admitted
A	933	64%	**825**	62%	108	82%
B	585	63%	**560**	63%	25	68%
C	918	35%	325	37%	**593**	34%
D	792	34%	417	33%	375	35%
E	584	25%	191	28%	**393**	24%
F	714	6%	373	6%	341	7%
Total	**4526**	**39%**	**2691**	**45%**	**1835**	**30%**

Legend:

greater percentage of successful applicants than the other gender

greater number of applicants than the other gender

bold – the two 'most applied for' departments for each gender

SIMPSON'S PARADOX

(Pearson et al. 1899; Yule 1903; Simpson 1951)

- Any statistical relationship between two variables may be **reversed** by including additional factors in the analysis.

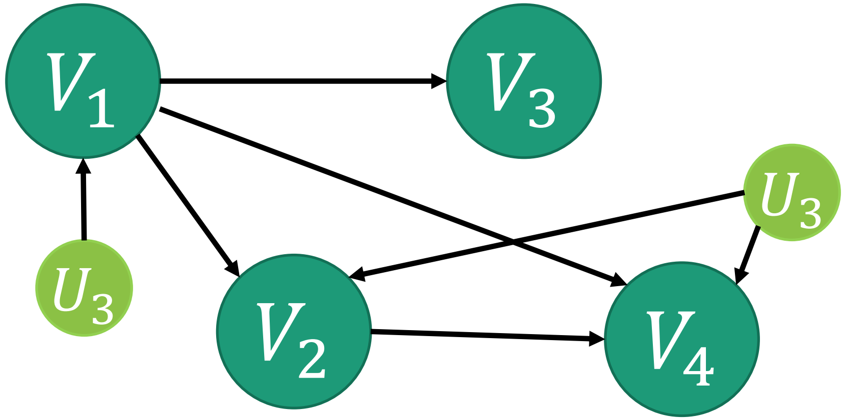
Application: The adjustment problem

- Which factors **should** be included in the analysis.

48

Structure Causal Model

- Functions: $\mathrm{F} = \{f_1, .., f_n\}$, the generative function determine endogenous variables $V_i = f_i(pa_i, U_i)$, where $pa_i \subset V, U_i \subset U$.



A structure causal model M is a tuple of factors $\{V, U, F, P(u)\}$

Pearl's Causal Hierarchy

Association

Question:
What is?

What does the smoking tell us about the lung cancer.

Seeing

Intervention

Question:
What if?

What will happen if someone keep smoking

Doing

Counterfactual

Question:
Was it?

Will the lung cancer get worse if someone smoking.

Imagination

Pearl's Causal Hierarchy

Association

Question:
What is?

(Un)Supervised Learning

Seeing

Intervention

Question:
What if?

Reinforcement Learning

Doing

Counterfactual

Question:
What if?

Retrospective Model-based RL

Imagination

Pearl's Causal Hierarchy

Association

Question:
What is?

$P(X, Y)$

Probabilistic Modeling

Seeing

Intervention

Question:
What if?

$P(Y \mid do(X))$

Causal Modeling

Doing

Counterfactual

Question:
What if?

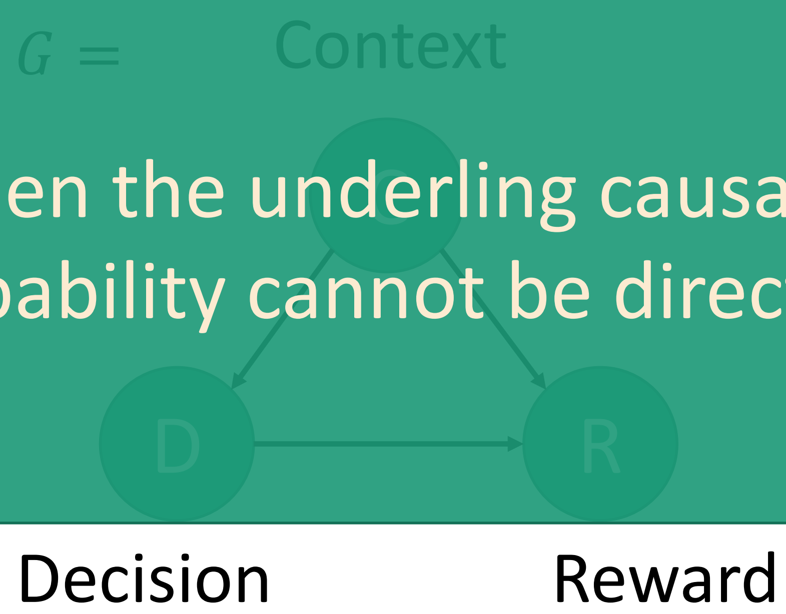
$P(Y_{X=x'} \mid X = x, Y = y)$

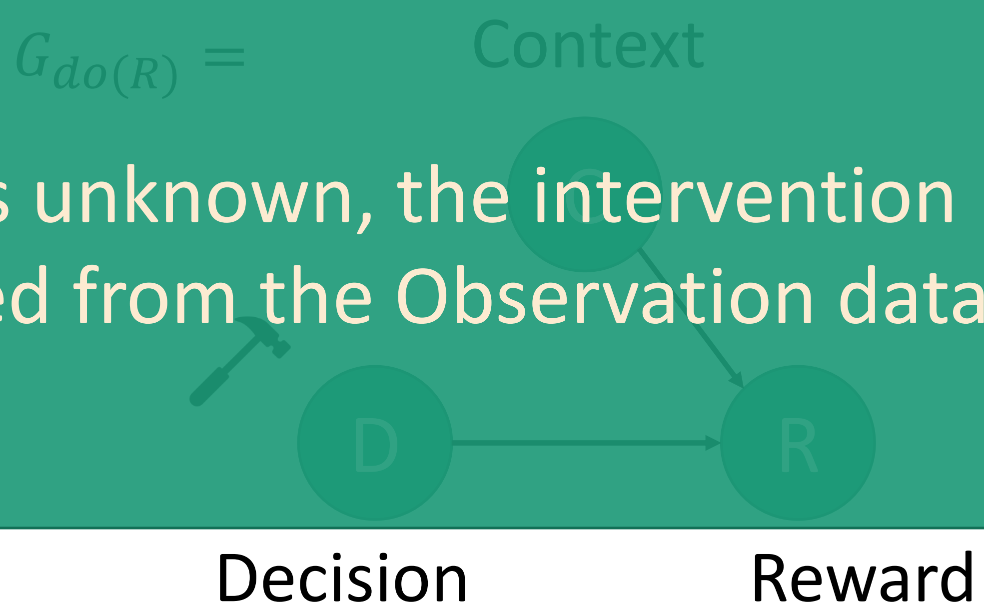
Causal Modeling

Imagination

Causal Diagram

- Causal Model
- Intervention





When the underling causal model is unknown, the intervention probability cannot be directly inferred from the Observation data

$P(R|D = d)$

$D = d$

$P(R|do(D = d))$

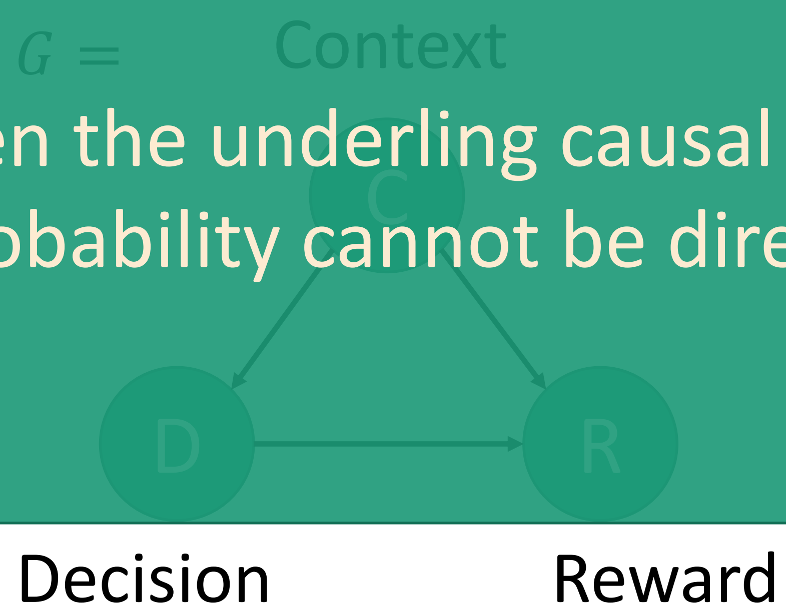
Observational

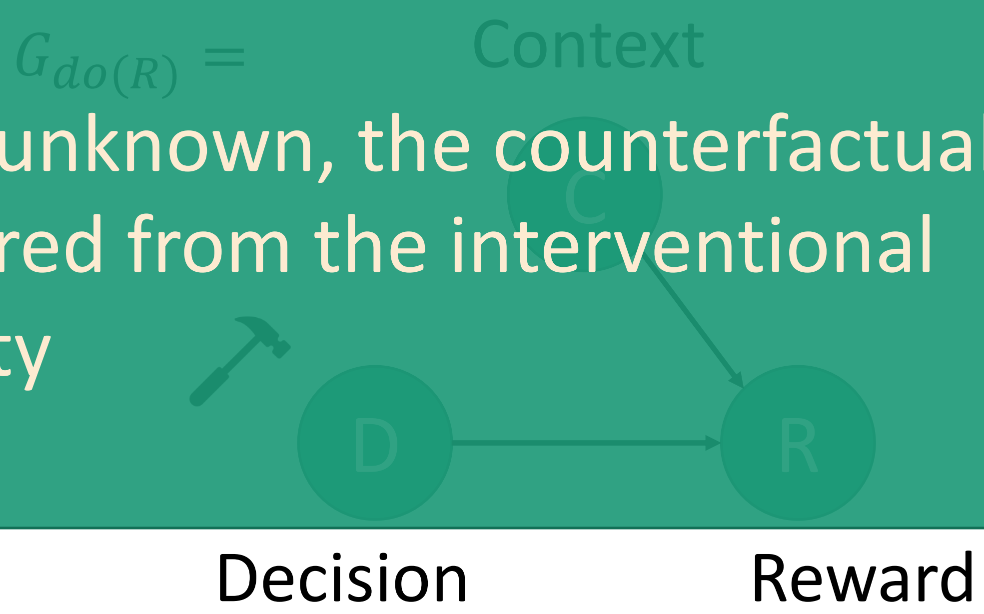
$R = f(C, D, \epsilon_R)$

Interventional

Causal Diagram

- Causal Model
- Counterfactual





When the underling causal model is unknown, the counterfactual probability cannot be directly inferred from the interventional probability

$\mathrm{D} = d'$

$R = f(D, C, \epsilon_R)$

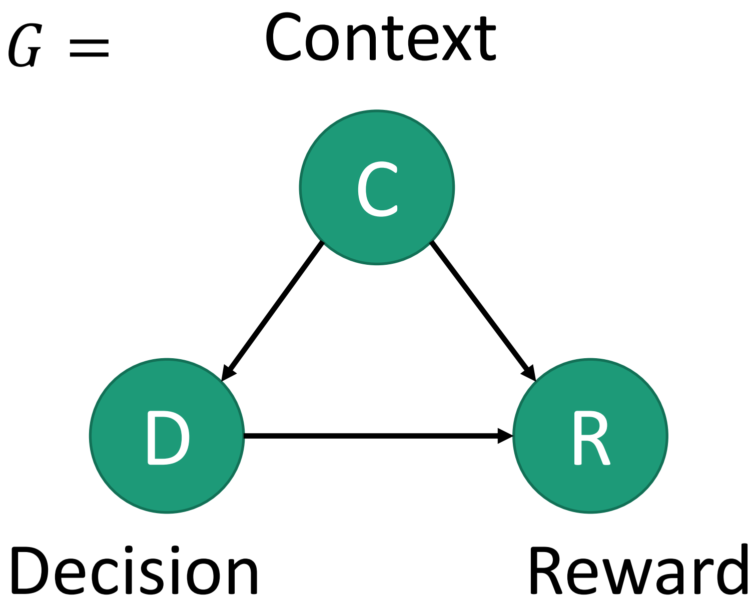
$P(R_{D=d'} | D = d, R = r)$

Counterfactual

Causal Diagram

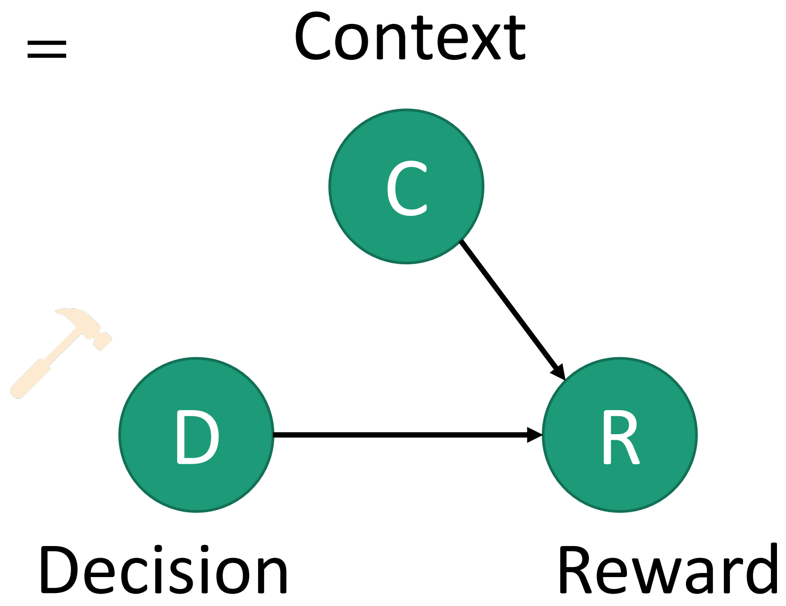
- Causal Model

$G =$



- Intervention

$G_{do(D)} =$

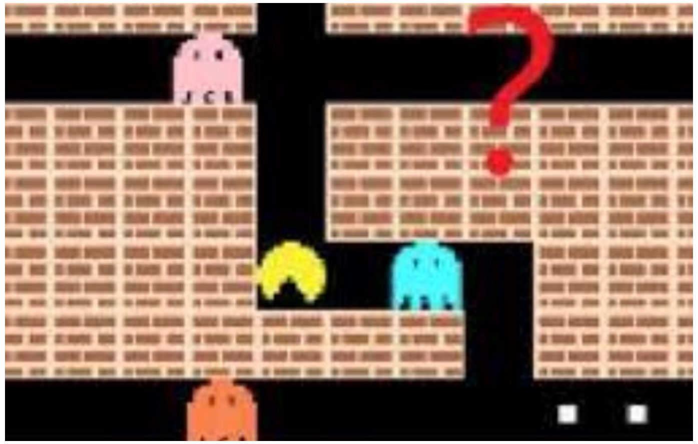


Understanding the underling SCMs is a prerequisite for inferring intervention and counterfactual

Background:
Causal Inference from Observation data

The scenario where ideal intervention distribution is hard to get

Observation from the world



Observation is the Mixture of factors
Unknown causal relations

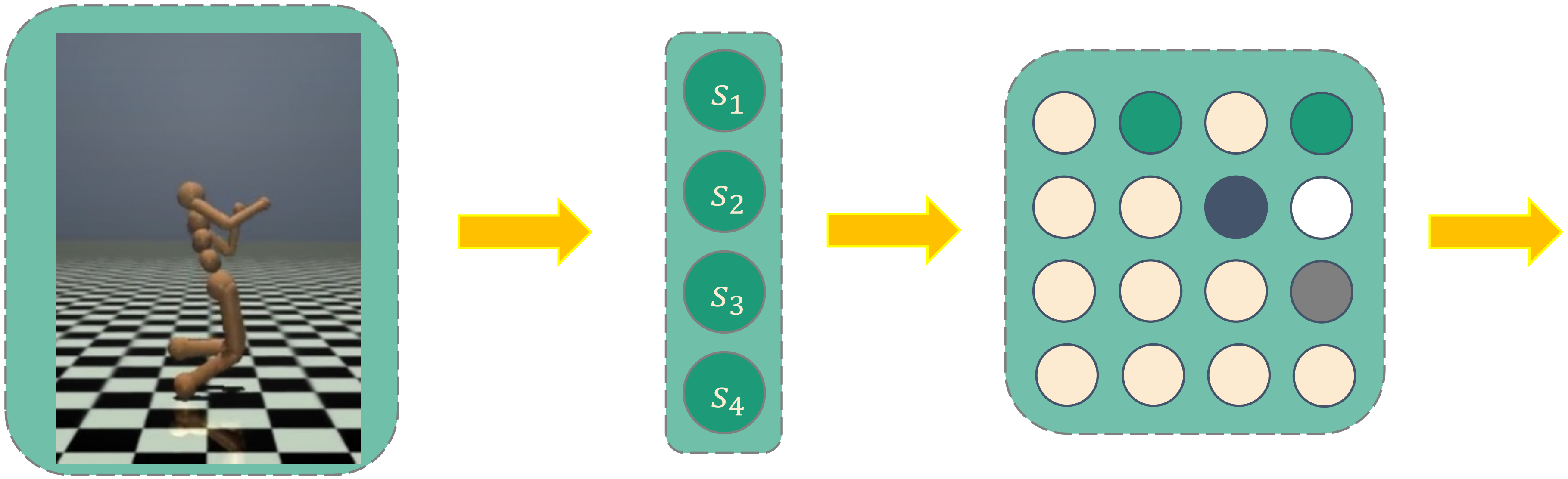
Understanding the world

- How to identify the causal structure, causal effect from the pure observations?
  - It was decided by the property of data and the form of model function but not related to the way we train the model.

Definition 3.2.3 (Identifiability)
Let $Q(M)$ be any computable quantity of a model M. We say that Q is identifiable *in a class* $\boldsymbol{M}$ *of models if, for any pairs of models M_1 and M_2 from* $\boldsymbol{M}$, $Q(M_1) = Q(M_2)$ *whenever* $P_{M_1}(v) = P_{M_2}(v)$. *If our observations are limited and permit only a partial set F_M of features (of $P_M(v)$) to be estimated, we define Q to be* identifiable from F_M *if* $Q(M_1) = Q(M_2)$ *whenever* $F_{M1} = F_{M2}$.

Understanding the world

- Causal Disentangle
- Causal Discovery



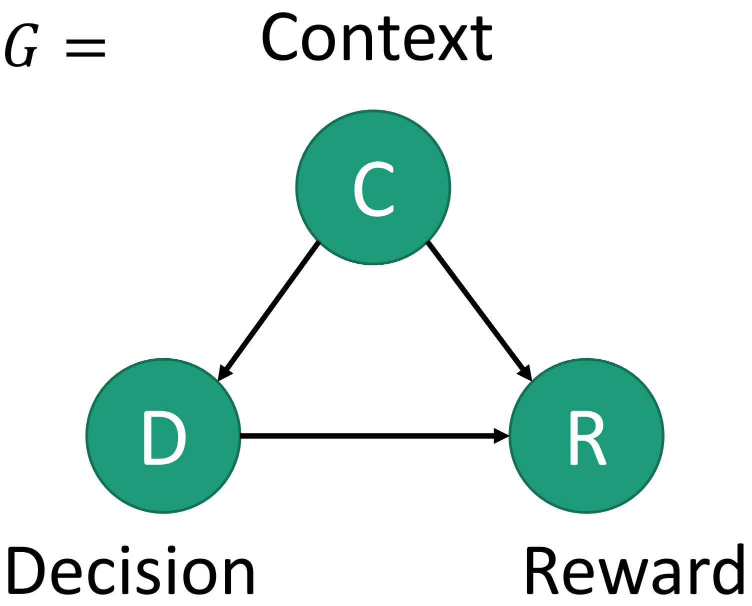
$$V_i = f_i(pa_i, U_i)$$

Observation State/Representation Causal Graph Structure Causal Models

Understanding the world

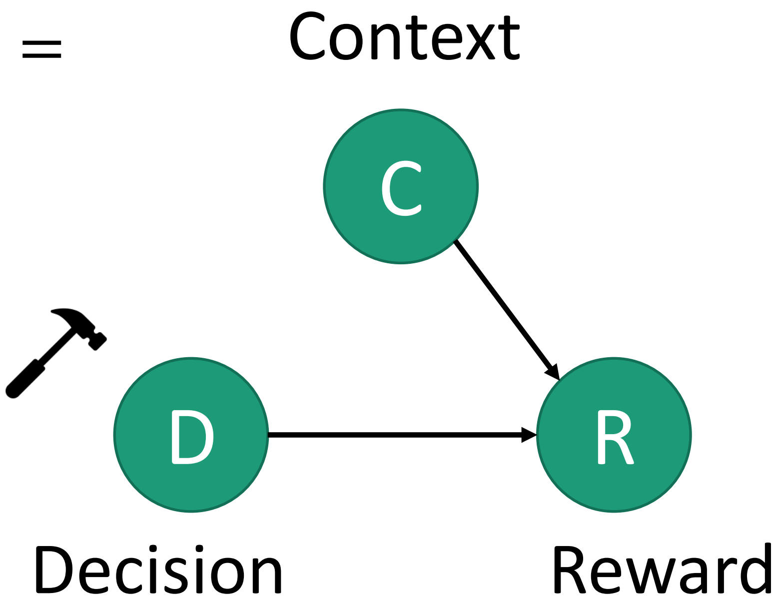
- Intervention identification

$G =$



$P(R|D)$

$G_{do(D)} =$

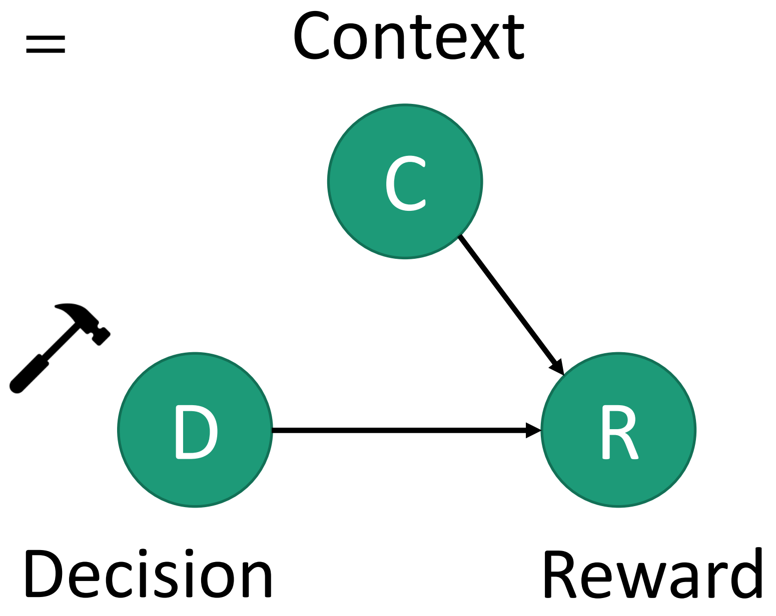


$P(R|do(D = d))$

Understanding the world

- Counterfactual estimation

$G_{do(D)} =$



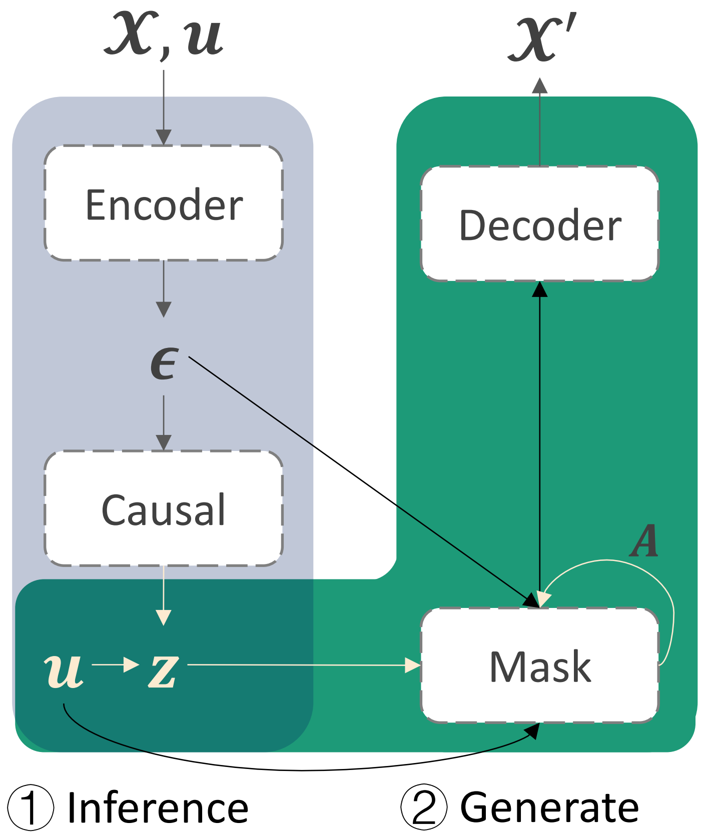
$P(R|do(D = d))$

$P(C_{D=d'}, S_{D=d'} | C = c, D = d, R = r)$

Causal Disentangle

- Causal disentangle aims at finding the causal factors from observation data. [Yang et al., Suter et al., Besserve et al.]

- The causal factors might have the causal relationships.



$$z = A^T z + \epsilon = \left(I - A^T\right)^{-1} \epsilon$$

Identifiability in Disentanglement

- Identifiability

Uniquely determine the representation of each factor from observed data. [Khemakhem et al. 1, Khemakhem et al. 2]

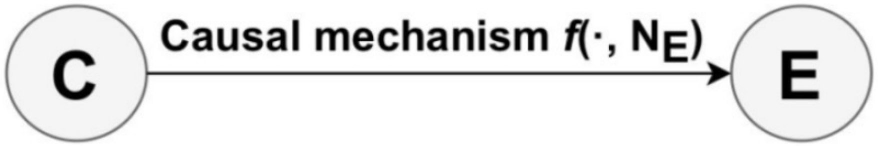
$$p_\theta(x, z|u) = p(x|z)p(z|u)$$

Representation contains all the information of the underling factors.

$$(\mathbf{f}, \mathbf{T}, \boldsymbol{\lambda}) \sim (\tilde{\mathbf{f}}, \tilde{\mathbf{T}}, \tilde{\boldsymbol{\lambda}}) \Leftrightarrow$$
$$\exists A, \mathbf{c} \mid \mathbf{T}(\mathbf{f}^{-1}(\mathbf{x})) = A\tilde{\mathbf{T}}(\tilde{\mathbf{f}}^{-1}(\mathbf{x})) + \mathbf{c}, \forall \mathbf{x} \in \mathcal{X}$$

Causal Direction Discovery

- Independent causal mechanism

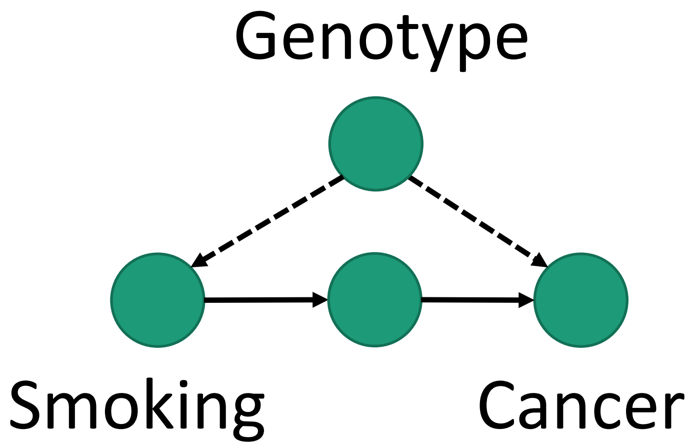


- D-Separation

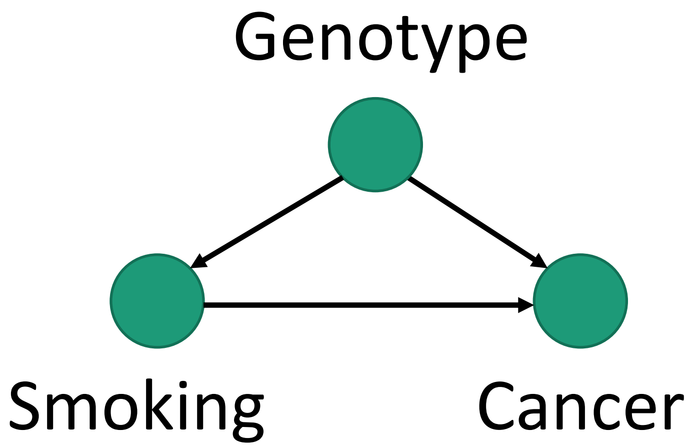
A fork $A \leftarrow B \rightarrow C$ or a chain $A \rightarrow B \rightarrow C$ such that the middle vertex B is in Z, or a collider $A \rightarrow B \leftarrow C$ such that middle vertex B, or any descendant of it, is not in Z.

Intervention Identification

- Front door criterion

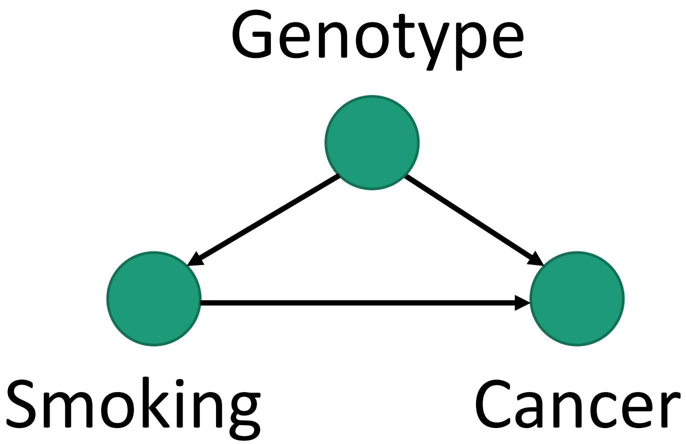


- Back door criterion



Intervention Identification

- Back door criterion



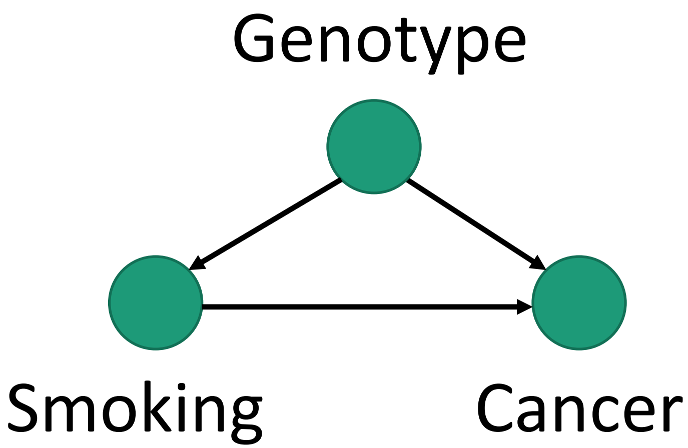
Definition 3.3.1 (Back-Door)
A set of variables Z satisfies the back-door *criterion relative to an ordered pair of variables* (X_i, X_j) *in a DAG G if:*

(i) *no node in Z is a descendant of* X_i; *and*

(ii) *Z blocks every path between* X_i *and* X_j *that contains an arrow into* X_i.

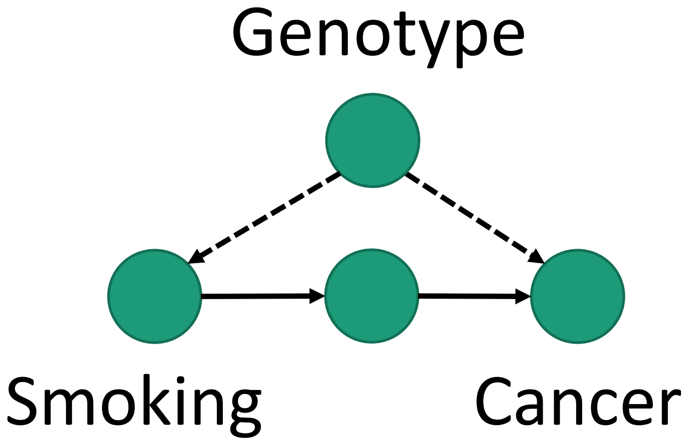
Intervention Identification

- Back door criterion



$$P(y \mid \hat{x}) = \sum_{z} P(y \mid x, z) P(z).$$

Front door criterion



- Front door criterion

Definition 3.3.3 (Front-Door)
A set of variables Z is said to satisfy the front-door *criterion relative to an ordered pair of variables* (X, Y) *if:*

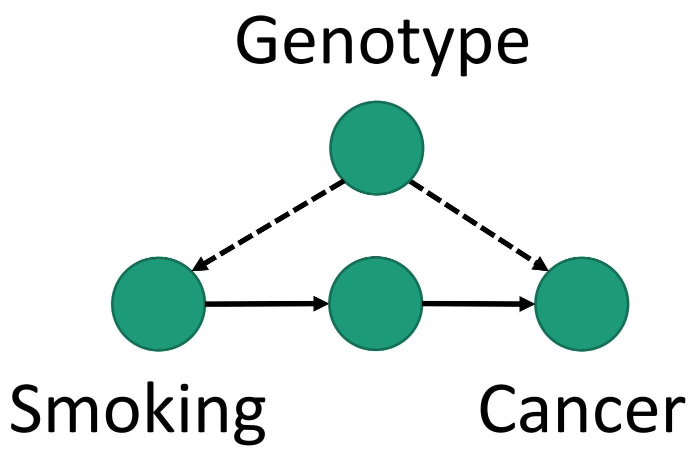
(i) *Z intercepts all directed paths from X to Y;*

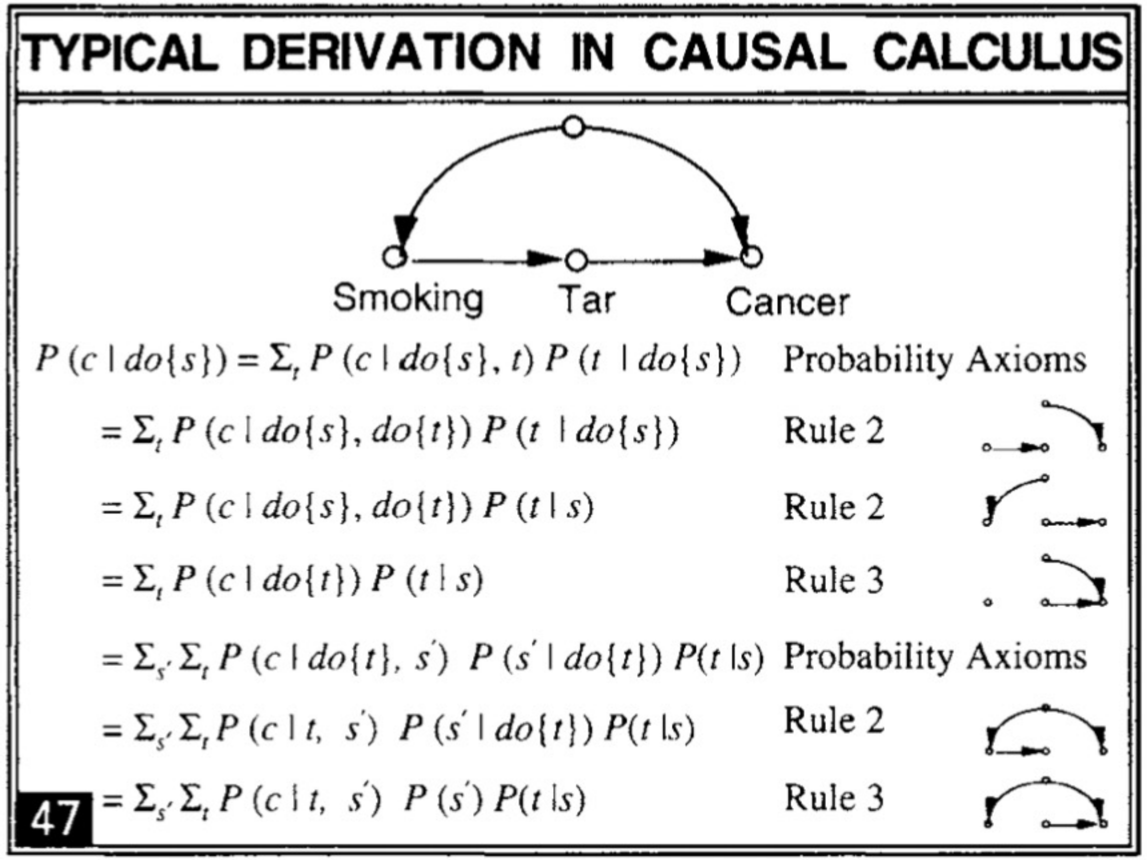
(ii) *there is no unblocked back-door path from X to Z; and*

(iii) *all back-door paths from Z to Y are blocked by X.*

Front door criterion

- Front door criterion





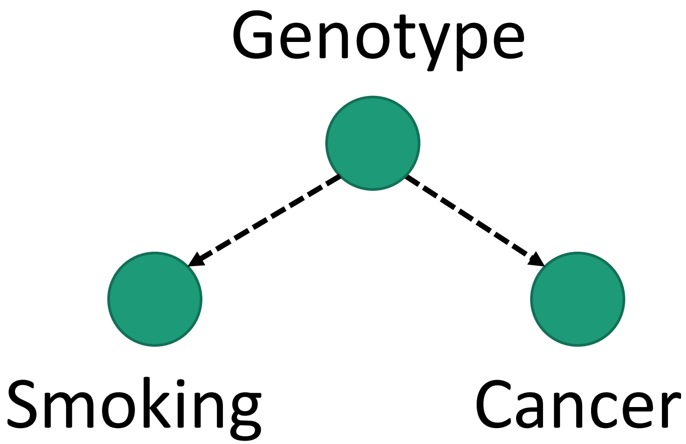
TYPICAL DERIVATION IN CAUSAL CALCULUS

$P(c \mid do\{s\}) = \Sigma_t P(c \mid do\{s\}, t)\, P(t \mid do\{s\})$	Probability Axioms
$= \Sigma_t P(c \mid do\{s\}, do\{t\})\, P(t \mid do\{s\})$	Rule 2
$= \Sigma_t P(c \mid do\{s\}, do\{t\})\, P(t \mid s)$	Rule 2
$= \Sigma_t P(c \mid do\{t\})\, P(t \mid s)$	Rule 3
$= \Sigma_{s'} \Sigma_t P(c \mid do\{t\}, s')\, P(s' \mid do\{t\})\, P(t \mid s)$	Probability Axioms
$= \Sigma_{s'} \Sigma_t P(c \mid t, s')\, P(s' \mid do\{t\})\, P(t \mid s)$	Rule 2
$= \Sigma_{s'} \Sigma_t P(c \mid t, s')\, P(s')\, P(t \mid s)$	Rule 3

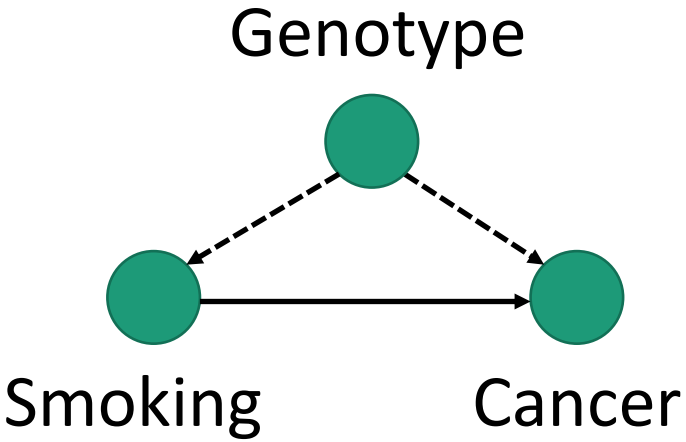
47

Causal Diagram

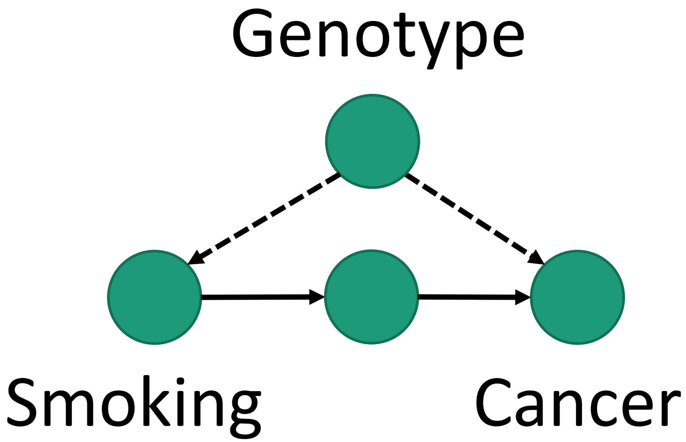
$$P(C|do(S)) = P(C|S)$$



$$P(C|do(S)) = P(C)$$



$$P(C|do(S)) = \text{noncomputable}$$



$$P(C|do(S)) = \text{computable}$$

Counterfactual Estimation

Abduction-action-prediction

- Abduction: deriving the posterior of the exogenous variables $P(U|Z = z')$
- Action: modifying causal graph G by removing the edges going into Z and set $Z = z$ (intervention) to derive $P(\mathrm{y}|Z = z, U)$
- Prediction: computing the distribution $P\left(y^M_{Z=z}(z')\right) = \int_U P(y|Z = z)p(U|Z = z')dU$

Conclusion of Causal Inference so far

- Basic Concept
  - Association, intervention and counterfactual and estimation
- Models
  - Structure Causal models

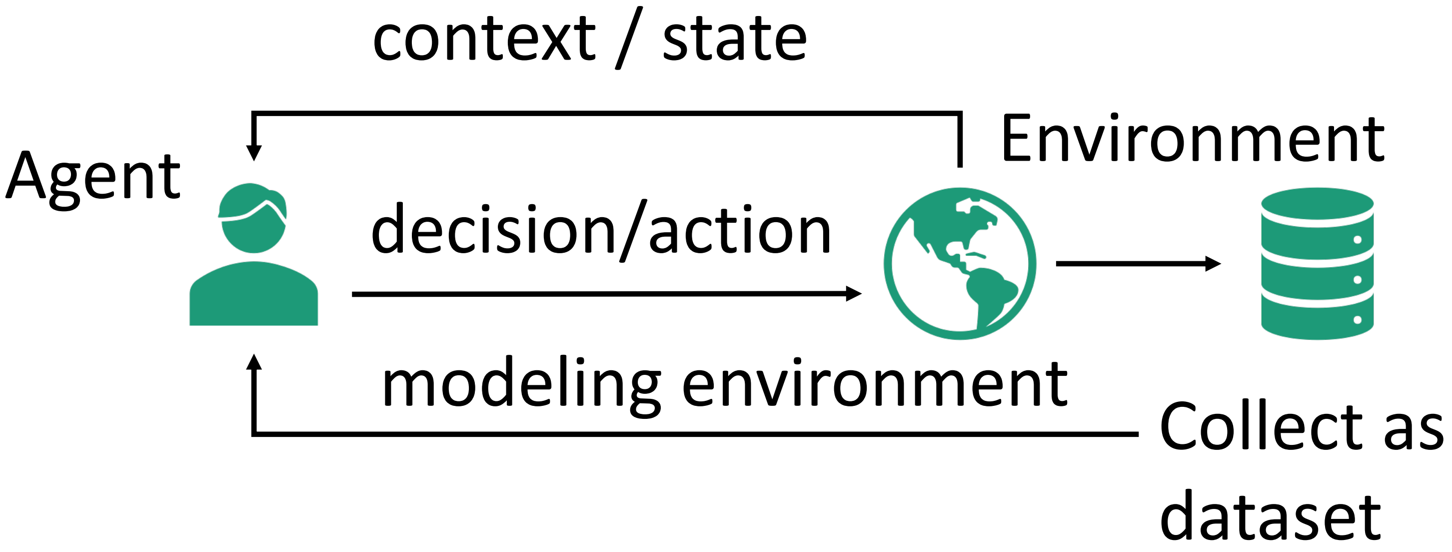
Background:
Decision Making System

Static decision making

- Goal oriented: making decision by modeling the environment.
- Doesn't care about long-term interaction

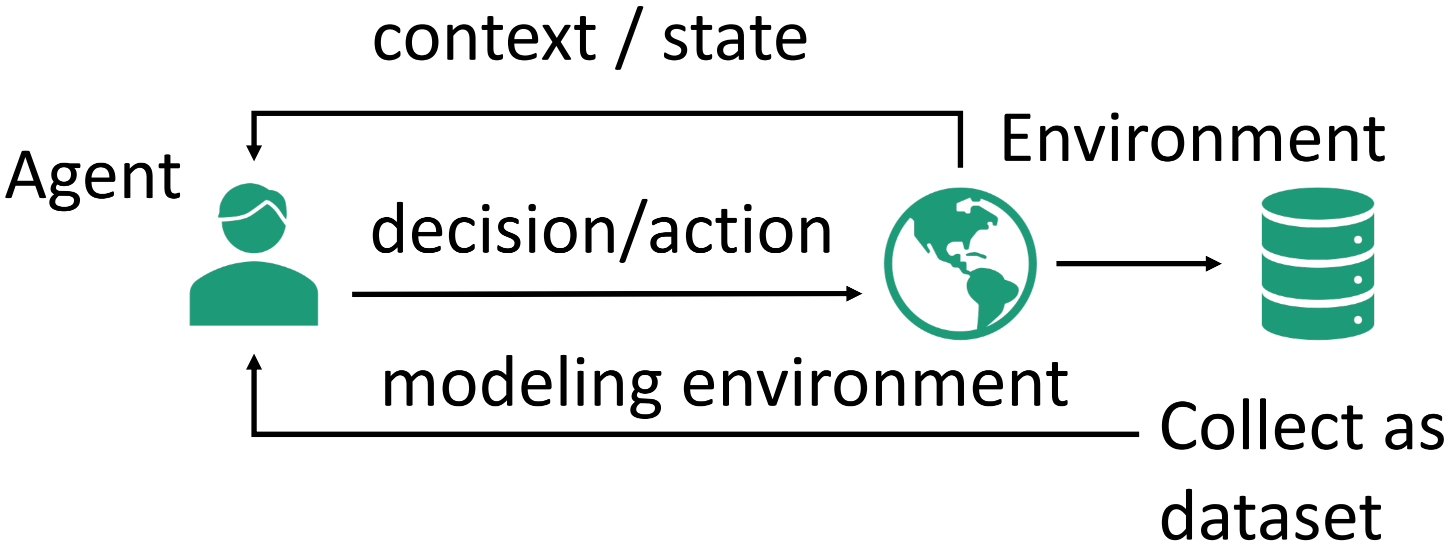
Online advertising, auction, recommendation, healthcare…

Big Picture



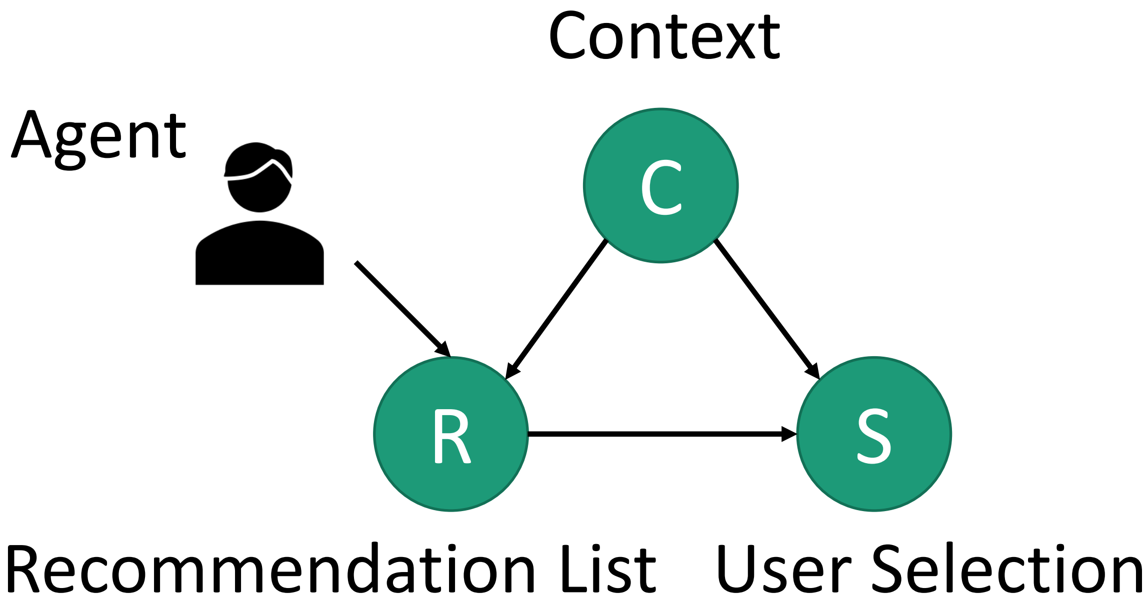
- Making decision by maximizing the short-term reward (user feedback …) or just by the rules.
- The method relies on modeling the environment.

Big Picture



- The decision based on the domain knowledge, prior rules or the model learned from historical data.
- Learning to make decision without directly interaction with environment like planning and MBRL.

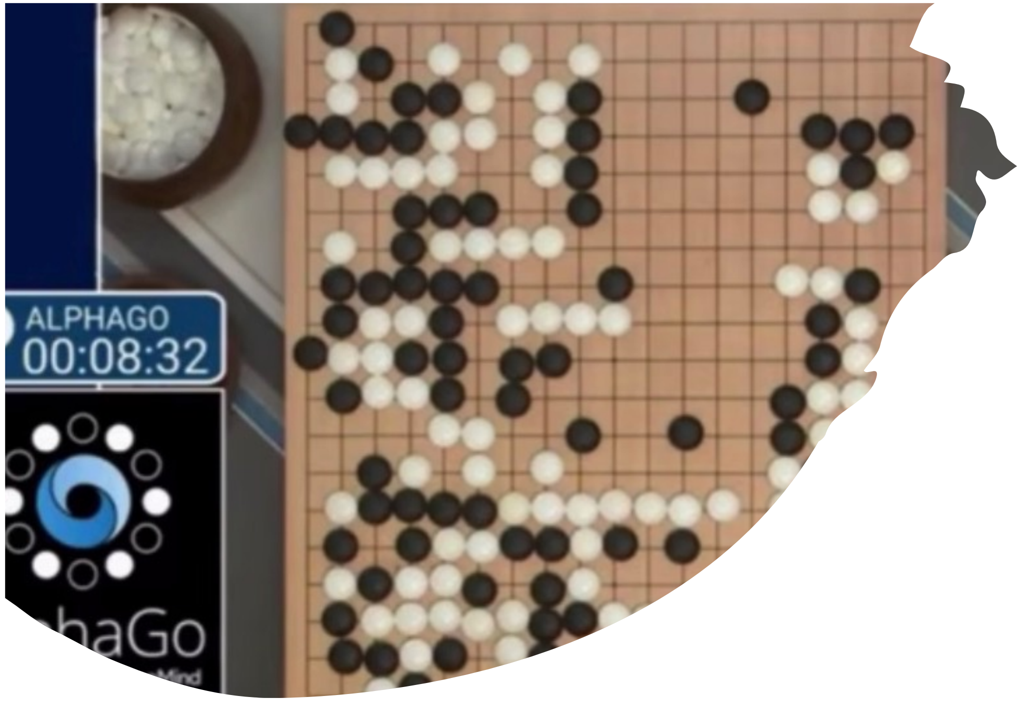
An example

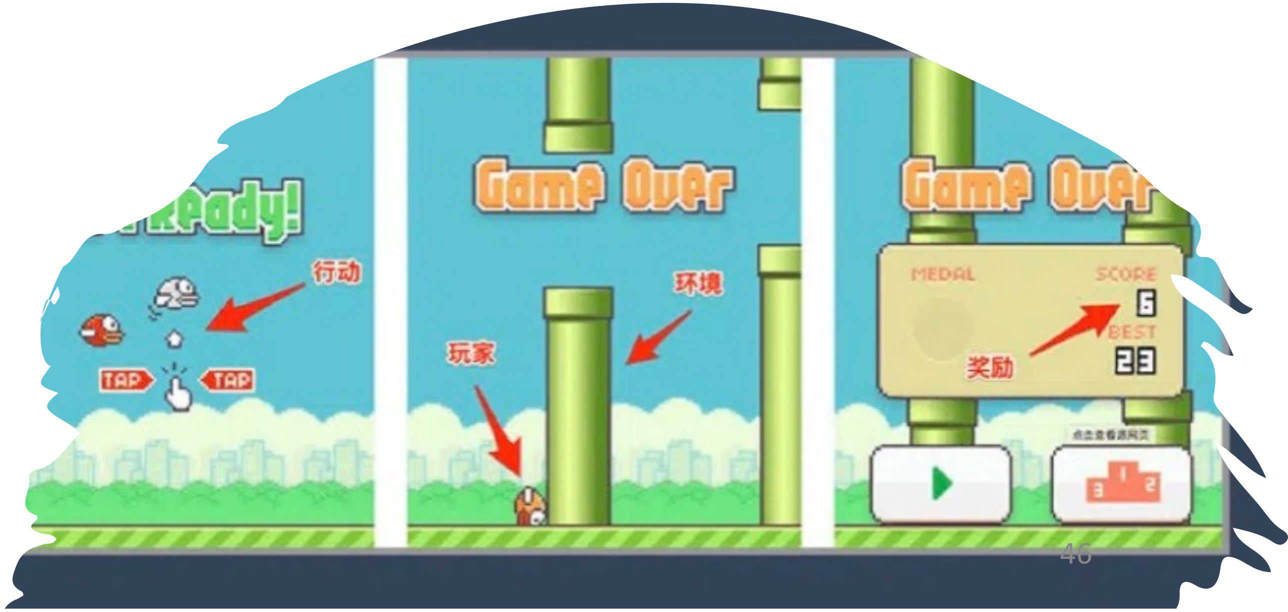


- Agent (the system) making decision (provide impression list) based on context.
- The decision aim to get well user selection.

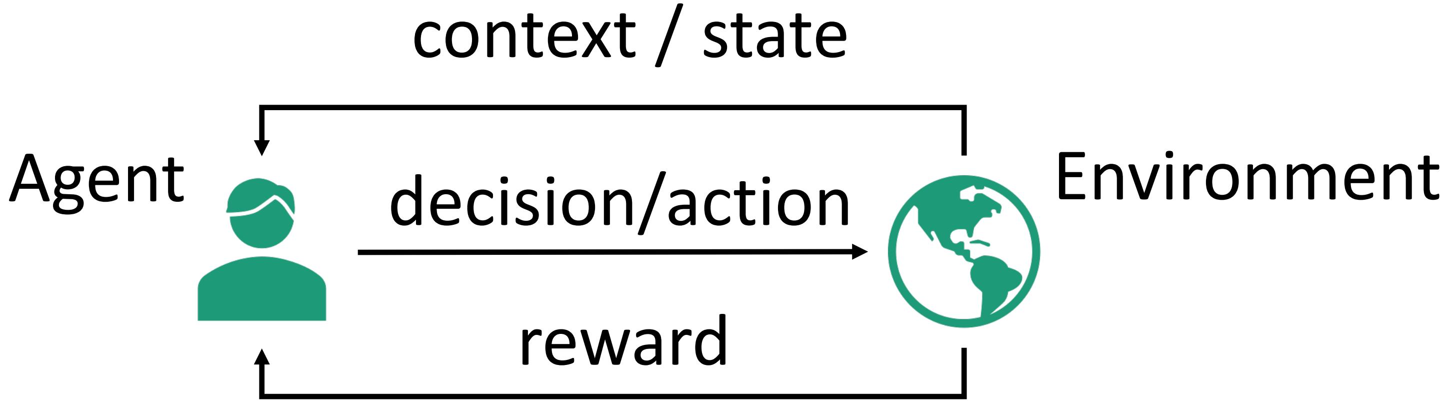
Dynamic decision making

- Goal oriented: making decision to maximize long-term reward.
- The decision based on the interaction with environment.



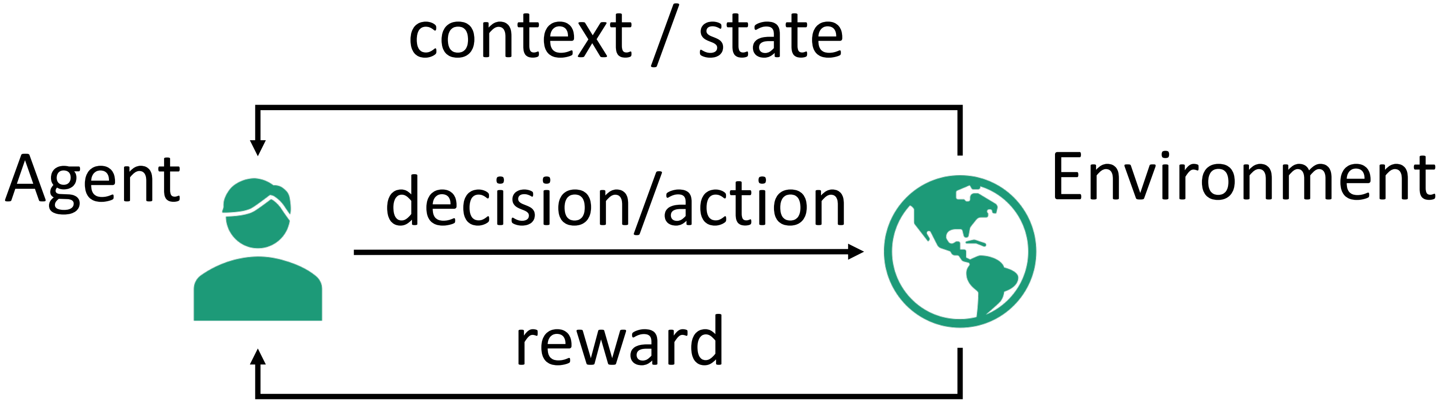


The dynamic decision making system



- Making decision to maximize environment reward.
- Making decision by interaction with environment.

The dynamic decision making system



- General approach using reinforcement learning (RL)/online learning.

Factors in RL

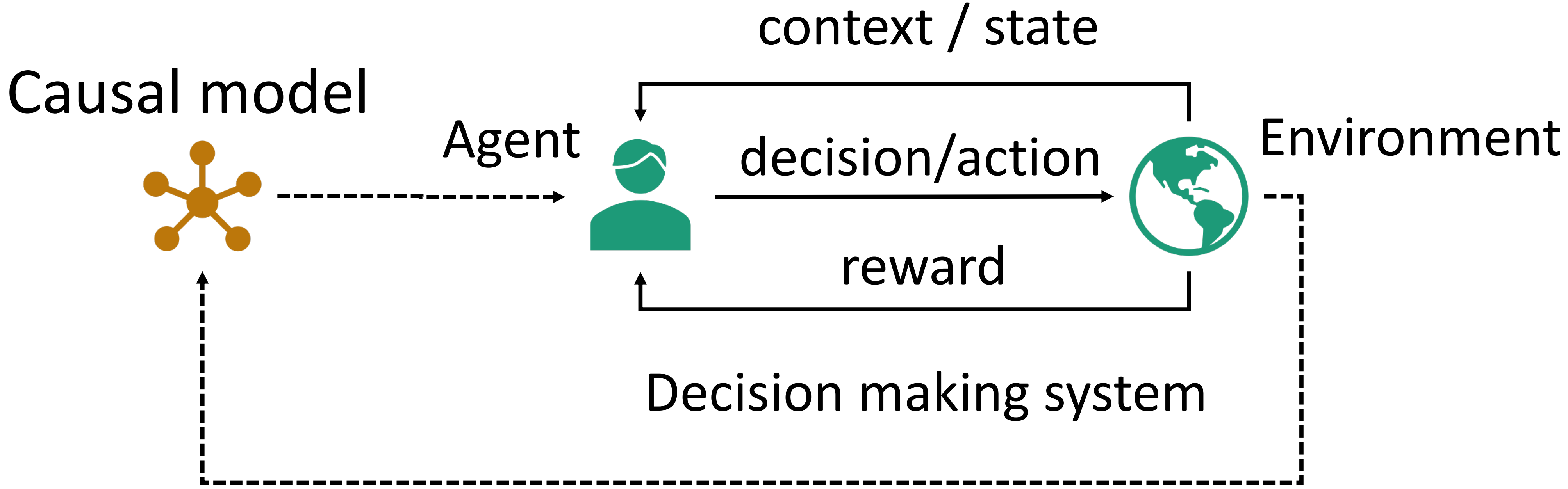
- Observation (O) : The observation from environment
- State (S) : the feature to describe current state of environment and agent
- Action (A) : Agent takes action to interact with environment.
- Reward(R): the environment feedbacks regarding action in current state.
- Policy (π): the probability to take action $a_t = \pi(s_t)$
- Transition: The probability of next state $p(s_{t+1}|s_t, a_t)$

Static & Dynamic

	Interaction	Policy
Static	No interaction	The policy based on maximizing the potential reward based on model or just prior rules.
Dynamic	Interaction with environment	Maximizing the long-time reward.

Causality for Decision Making

Big Picture of Causal Decision Making



- Reasoning environment
- Making better decision

Causal Decision Making

- Understanding the world/environment
- What to intervene
- What's the counterfactual results

- Better explanation / reasoning ability
- Decision for generalization, robustness and sample efficiency

Tasks for Causal Decision Making

Understanding causal variable	Understanding causal model	Where to intervene	Understanding Counterfactual
Scenario: POMDP, Static DM	Scenario: RL, Static DM	Scenario: RL, Static DM	Scenario: Static DM
Tasks: Causal disentangle	Tasks: Causal discovery	Tasks: Intervention identification	Tasks: Counterfactual estimation

Reasoning

Decision Making

General process

Understanding the world
- Causal disentangle
- Environment estimation

Reasoning

What to intervene
- Find the action worth to take

Decision Making

Counterfactual inference
- Enhance the imagination

Decision Making

Causal Decision Making Tasks

- Causal disentangle in RL [Sontakke et al.].
- Environment estimation: [Li et al. 1, Zholus et al, Ding et al., Liu et al.].

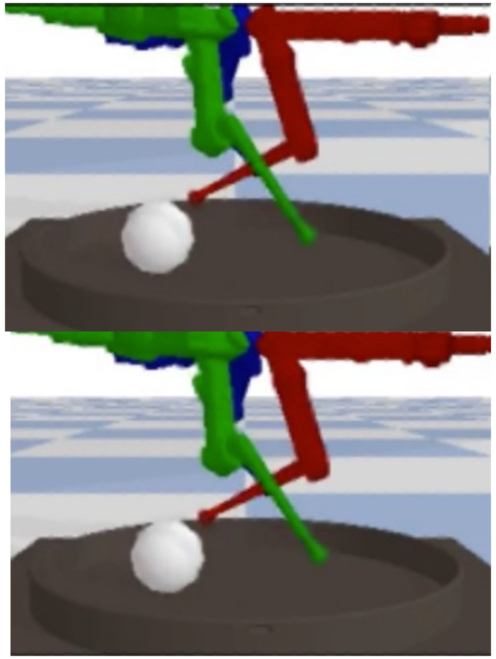
- Where to intervene: [Wang et al 1, Huang et al.,]
- Counterfactual imagination: [Li et al., Yang et al. 2, Pitis et al.]

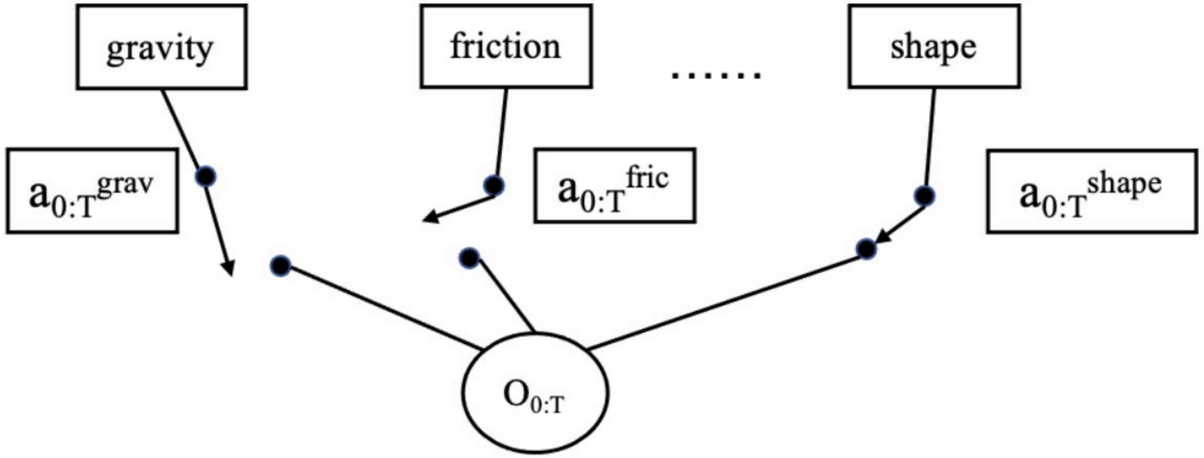
Causality for Decision Making

Understanding the world by using causality

Causal Curiosity

- Understanding the causal world [Sontakke et al.].





Causal Curiosity

- Classical POMDP: $(O, S, A, \varphi, \theta, r)$
  - observation space O, state space S, action space A, the transition function φ, emission function θ, and the reward function r.
- Causal POMDP
  - The state are divided into the controllable state s^c and the uncontrollable state s^u

Causal Curiosity

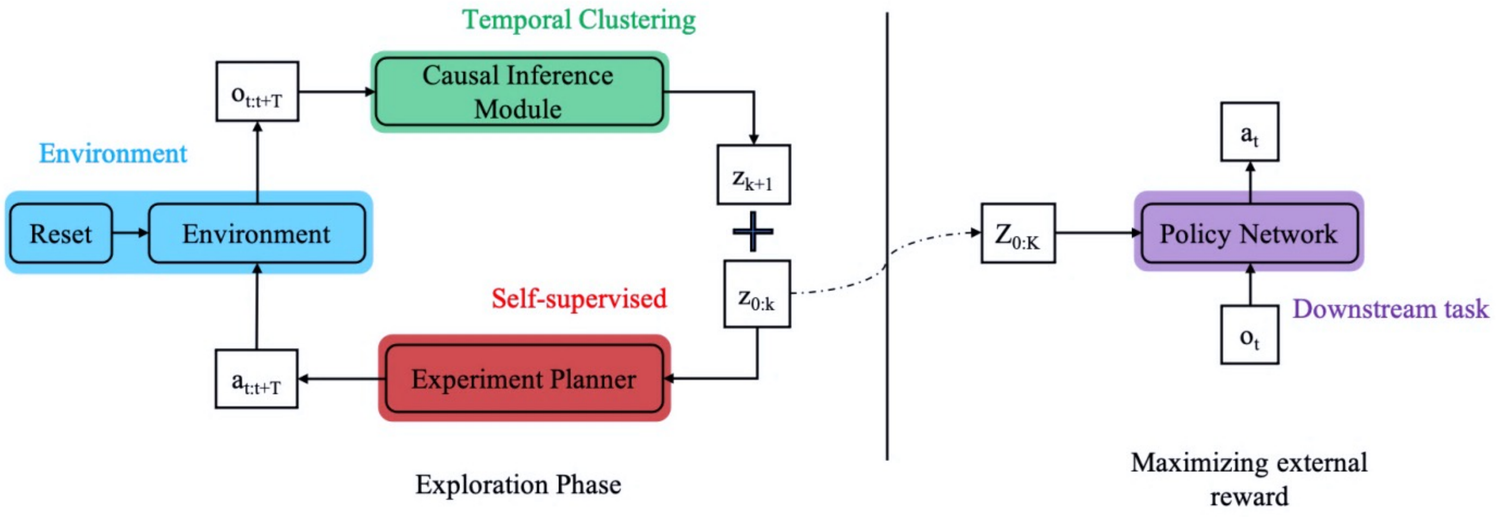
- Causal POMDP
  - The transition function $\phi(\mathbf{s}^c_{t+1}|\mathbf{s}^c_t, f_{sel}(\mathcal{H}, \mathbf{s}^c_t, \mathbf{a}_t), \mathbf{a}_t)$

if a body on the ground (i.e., state s^c_t) is thrown upwards (i.e., action a_t), the outcome s_{t+1} is caused by the causal factor gravity (i.e., $f_{sel}(H, s^c_t, a_t) = \{gravity\}$),

  - The Observation $\mathbf{o}_{t+1} = \theta(\mathbf{s}^c_t, f_{sel}(\mathcal{H}, \mathbf{s}^c_t, \mathbf{a}_t), \mathbf{a}_t)$

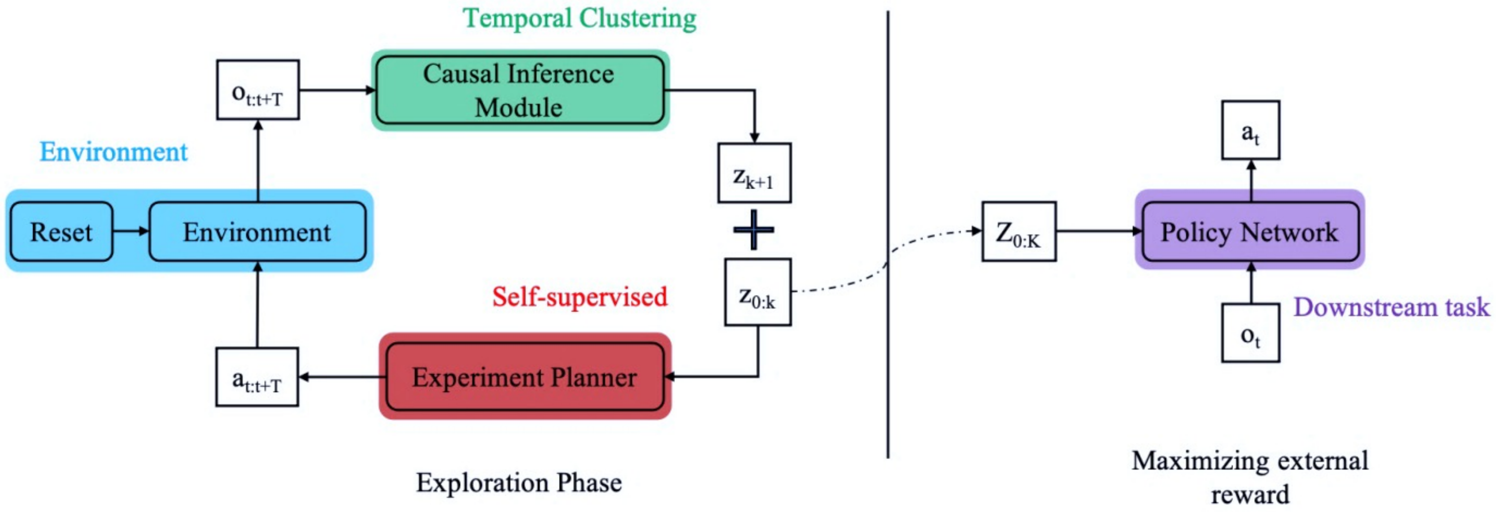
Causal Curiosity

- The Experiment Planner: allow the agent to discover action sequences such that the resultant observation trajectory is caused by a single causal factor $\mathbf{a}^*_{0:T} = \underset{\mathbf{a}_{0:T}}{\arg\min}(L(\mathbf{M}) + L(\mathbf{O}|\mathbf{M}))$



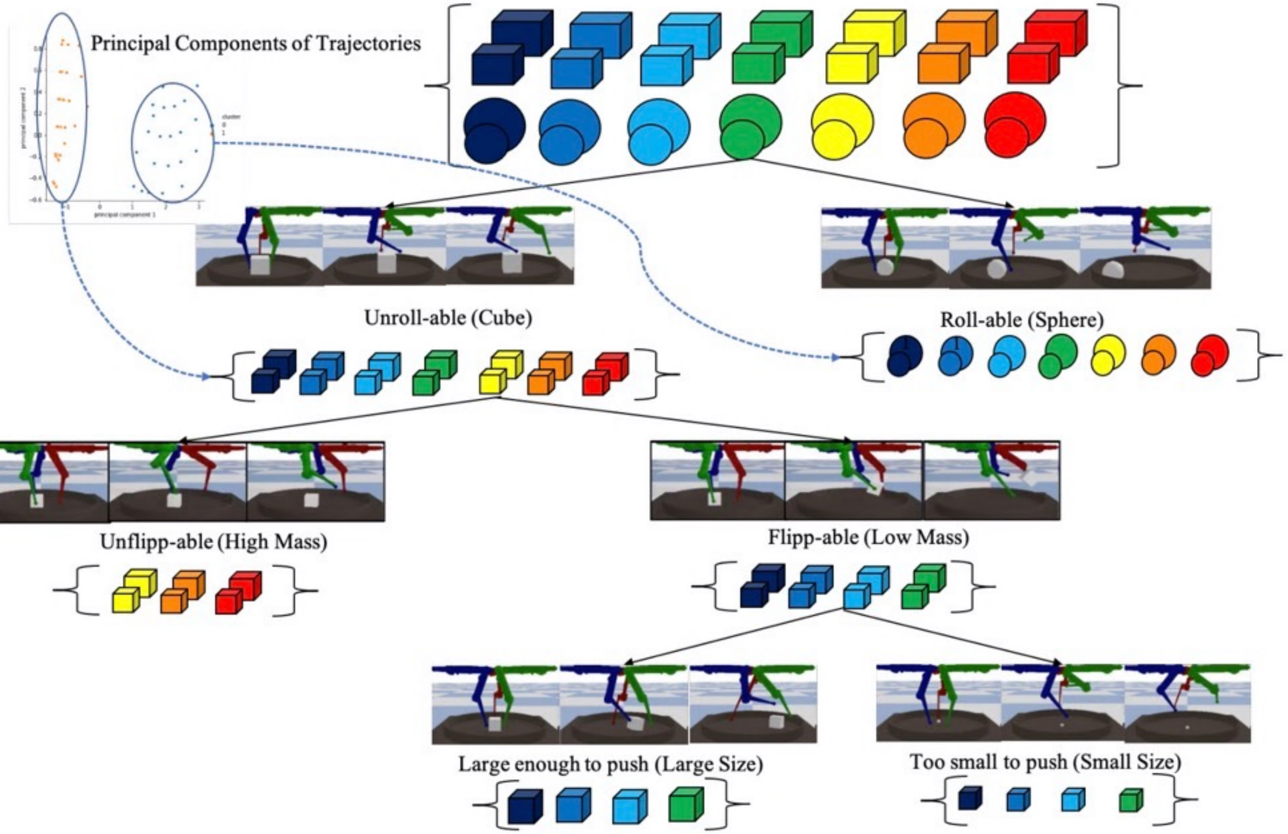
Causal Curiosity

- Causal Inference Module: Inferring the related representation by observational data.



Causal Curiosity

- Interventions on beliefs: recursively intervene the environment by generated actions



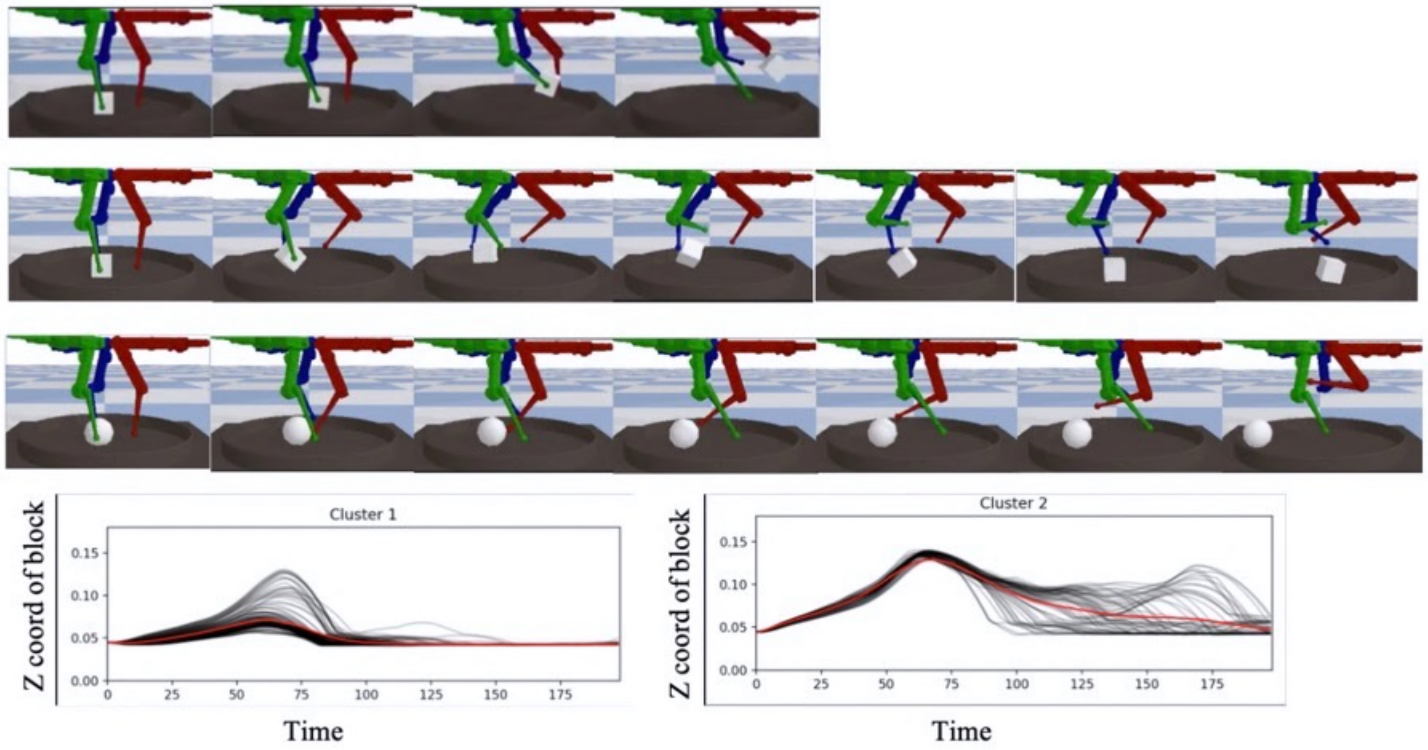
Causal Curiosity

A

B

C

D

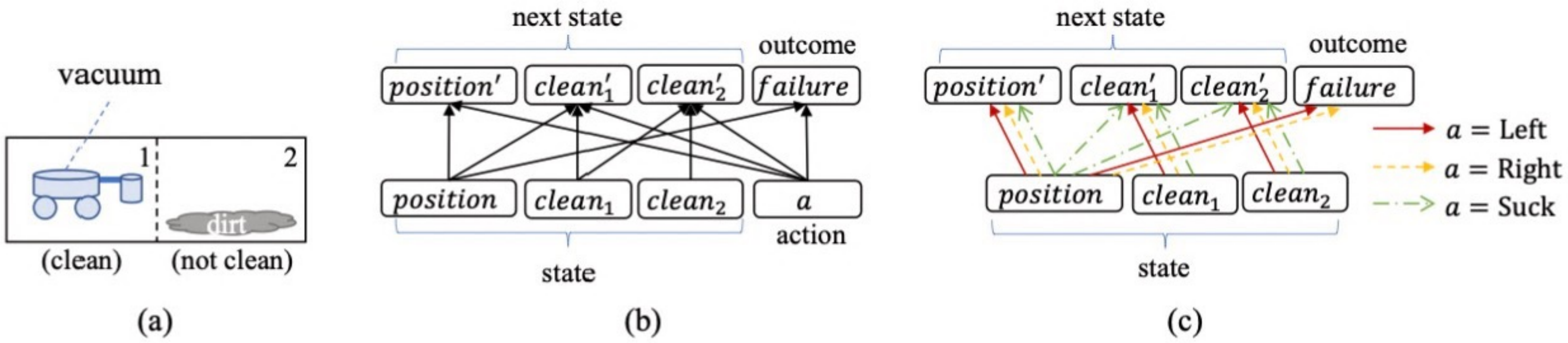


Explain the World [Yu et al.]

- Learning the causal model to explain the world
- Factorized MDP: $\langle S, A, O, R, P, T, \gamma \rangle$. Each state is factorized into n state variables.
- SCMs: The structure causal model
- AIMs: The action influence model
- SCM to explain the world that can be converted to an AIM based on specially-designed structural equations

Explain the World

- SCM: The model formalizes the causal relationships between multiple variables.
- AIM: a causal model for RL, to generate explanations about why the agent take some actions.

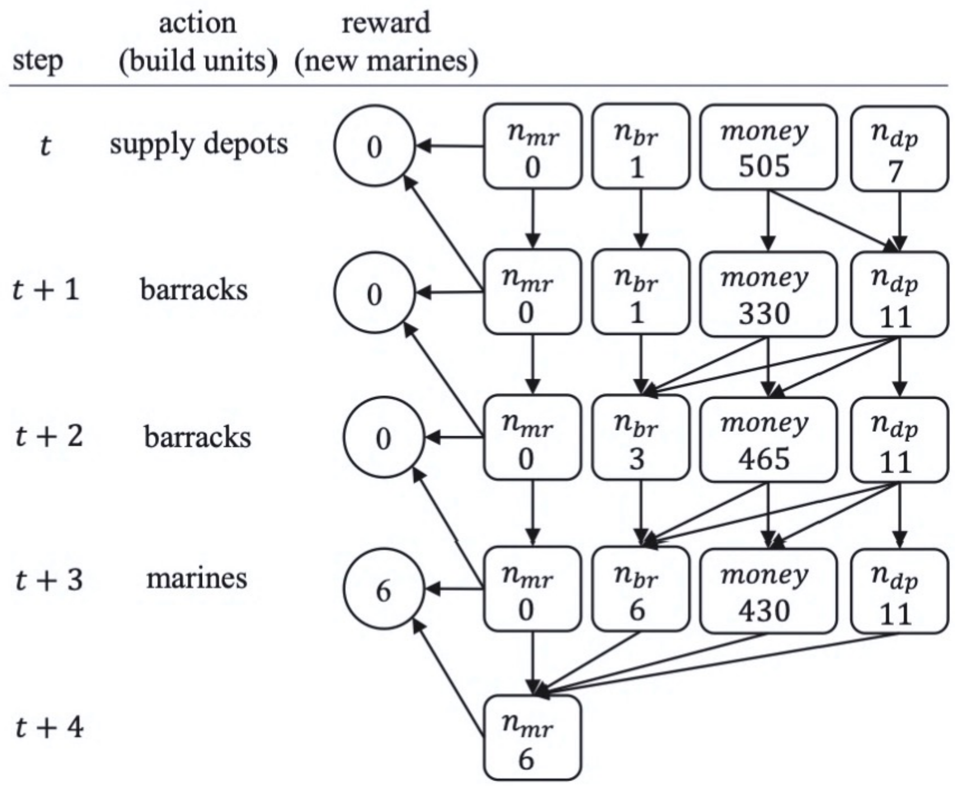


Explain the World

- Causal Discovery, between current step $u := (s, a)$ and next step $v := (s', o)$
$$u_i \in PA(v_j) \iff (u_i \not\perp\!\!\!\perp v_j \mid u_{-i}),$$
- Causal Influence network (AIM)
$$Pr(v_j \mid PA(v_j))$$
- Connection between SCMs and AIM

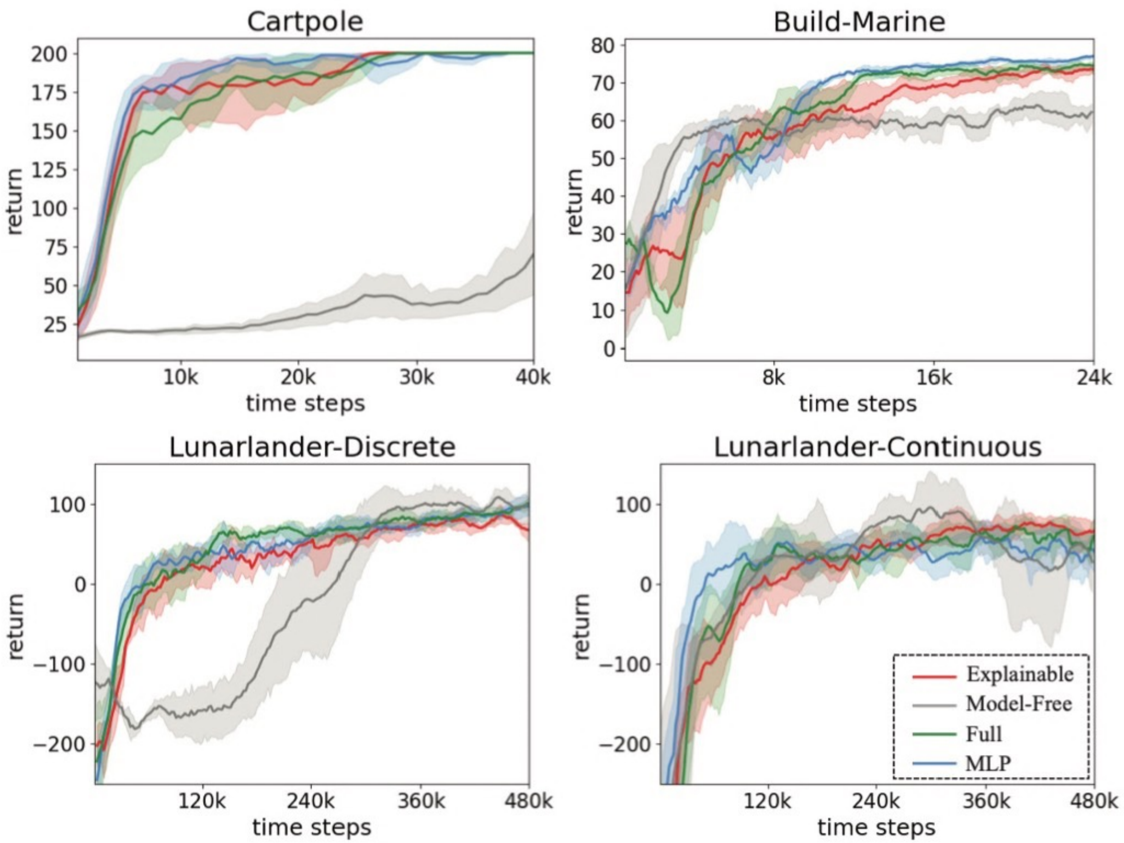
$$f_{\boldsymbol{a}}^j(PA_{\boldsymbol{a}}(v_j)) = D^j\Big(\sum_{s_i \in PA_{\boldsymbol{a}}(v_j)} \alpha_i^j \cdot \boldsymbol{c}_i^j(s_i) + \alpha_a^j \cdot \boldsymbol{c}_a^j\Big).$$

Explain the World



Explain the World

- The causal model might decline the efficiency of RL and planning



Explanation and Planning

- Goal Orientation: Considering the causal explanation and the goal of the task, simontanously.

When and Where to intervene/take action for a better performance?

Causality for Decision Making

What to intervene

Causal Enhanced Decision

- Rarely in control of the object of interest
- Physical contacts are hard to model
- Objects are enabling manipulation towards further goals.

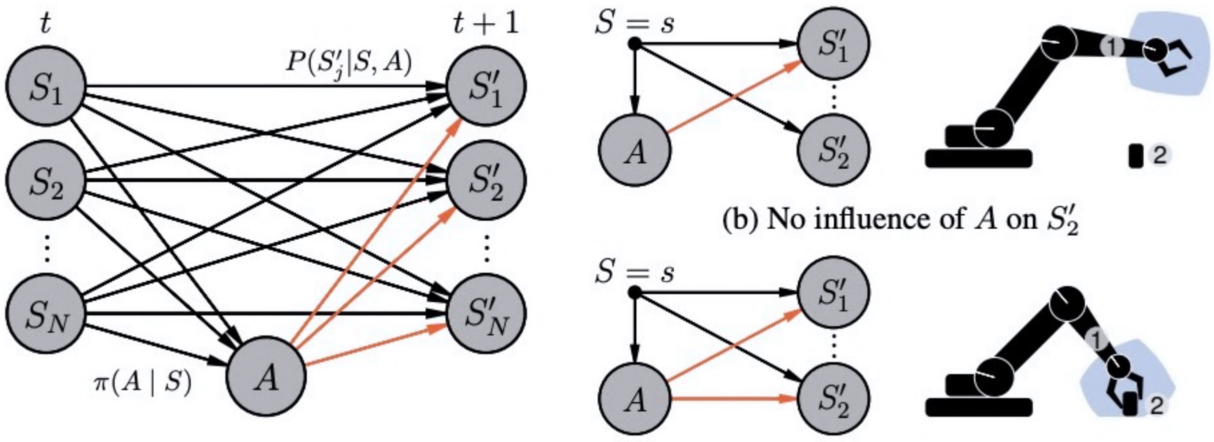
Knowing when and what the agent can influence with its actions [Seitzer et al.]

Causal Enhanced Decision

- Agents can be rewarded with a bonus for visiting states of causal influence.
- Such a bonus leads the agent to quickly discover useful behavior even in the absence of task-specific rewards.

Causal Enhanced Decision

- Modeling the environment
  - Independent Causal Mechanism



(a) Causal Graph $\mathcal{G}$

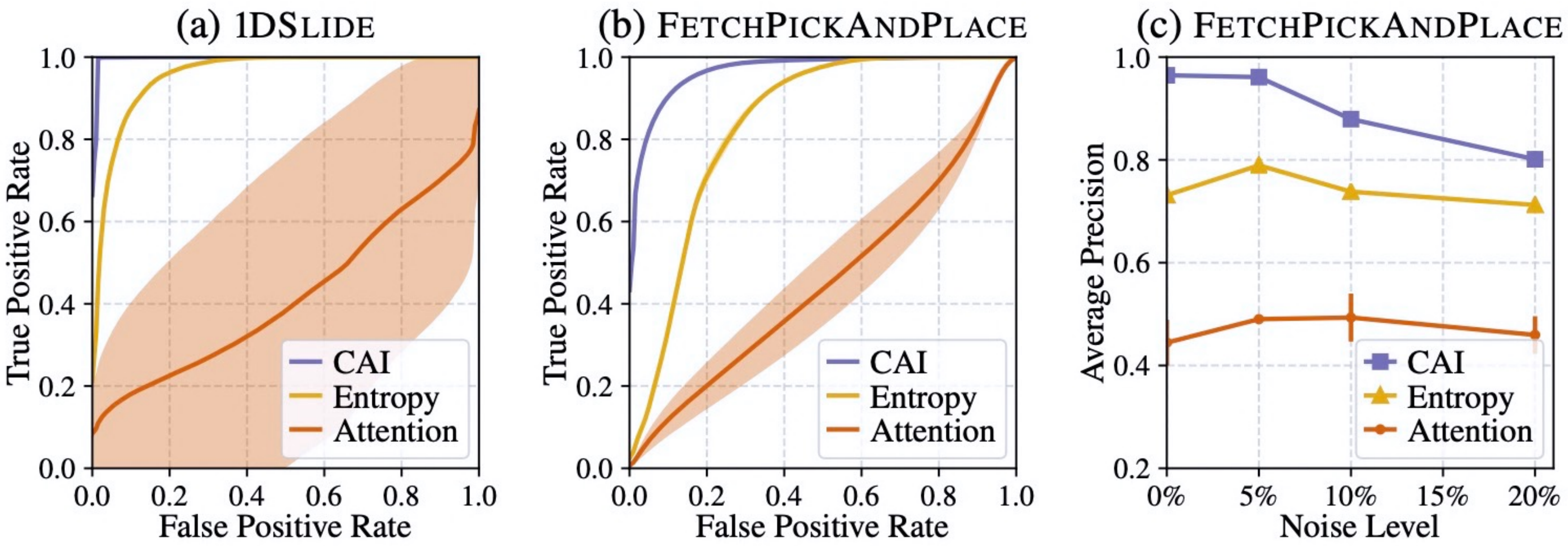
(b) No influence of A on S'_2

(c) Influence of A on S'_1 and S'_2

Proposition 1. *Let $\mathcal{G}_{S=s}$ be the graph of the local CGM induced by $S = s$. There is an edge $A \rightarrow S'_j$ in $\mathcal{G}_{S=s}$ under the intervention* $\mathrm{do}(A := \pi(a|s))$ *if and only if $S'_j \not\perp\!\!\!\perp A \mid S = s$.*

Causal Enhanced Decision

- Empirical Evaluation of Causal Influence Detection



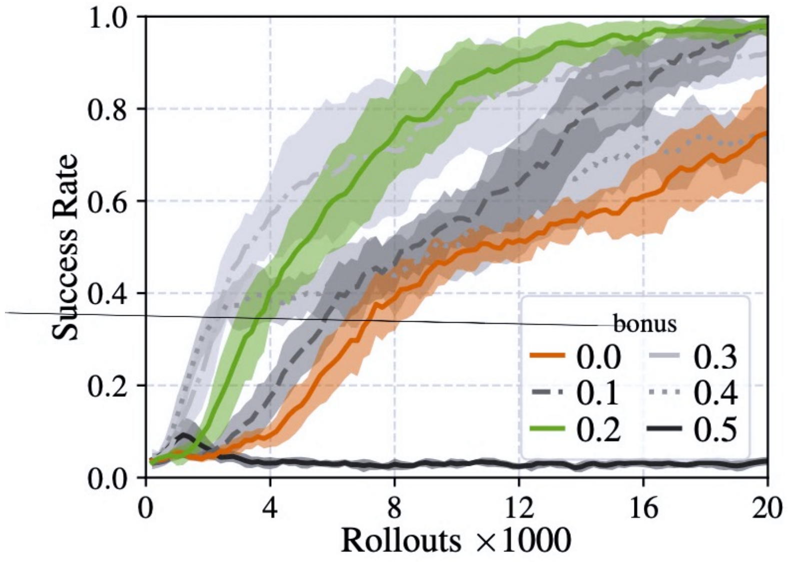
Causal Enhanced Decision

- Improving Efficiency in Reinforcement Learning
  - Better state exploration through an exploration bonus.
  - Causal action exploration.
  - Prioritizing experiences with causal influence during training.

Causal Enhanced Decision

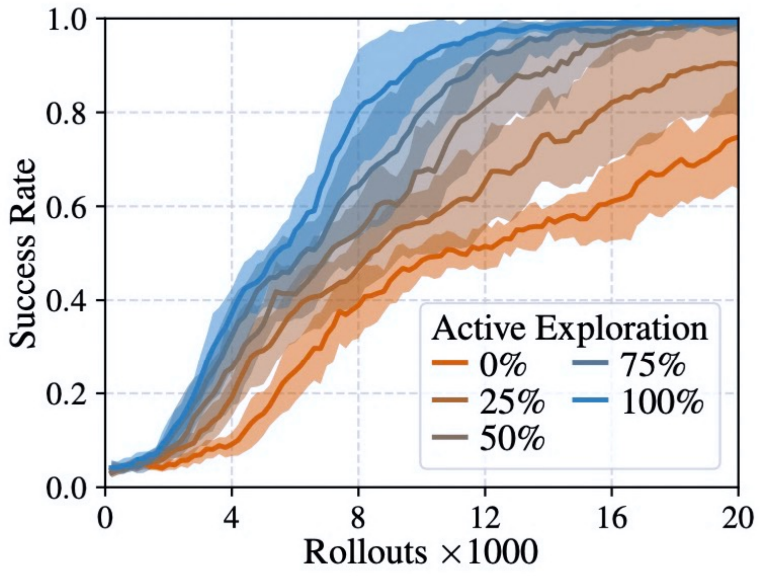
- Causal Action Influence as Reward Bonus.

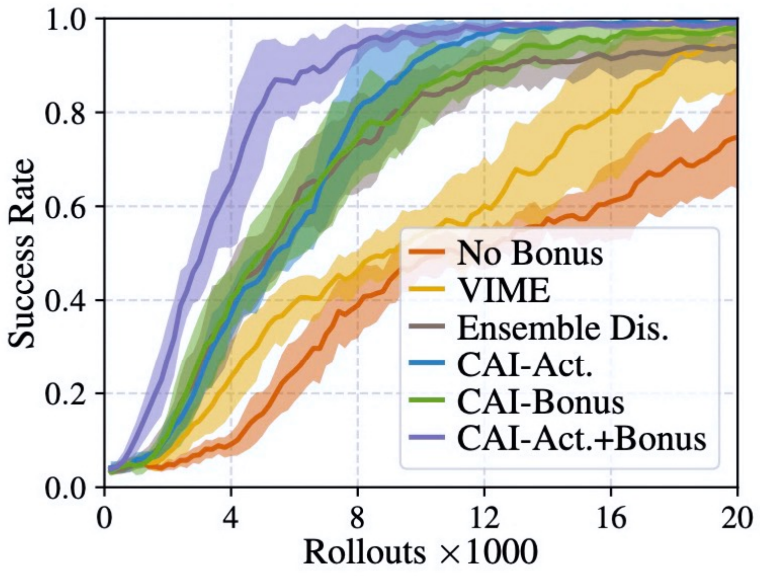
Reward of the goal + Reward of the satisfaction of causal influence detection



Causal Enhanced Decision

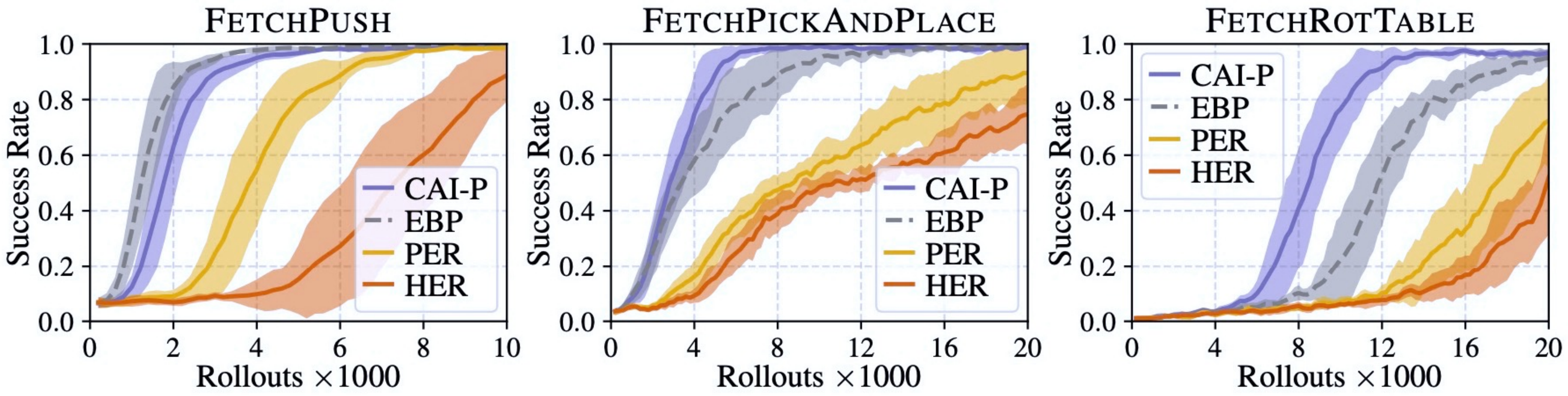
- Following Actions with the Most Causal Influence.





Causal Enhanced Decision

- Causal Influence-based Experience Replay
  - Prioritizing According to Causal Influence.
  - influence-based prioritization (CAI-P), hindsight experience replay (HER)…



Effectiveness of causality

- Sample Efficiency [Seitzer et al.]
- Generalization [Ding et al.]
- Explanation [Yu et al.]

Causality for Decision Making

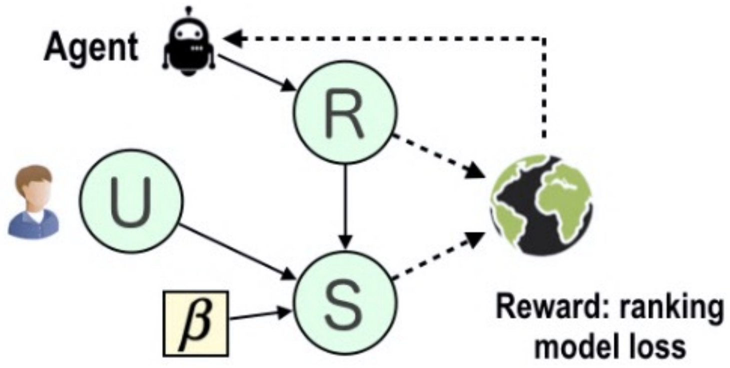
The Wings of Counterfactual Imagination

Counterfactual estimation in decision making

- General Process
  - Learning functions in SCMs
  - -> Abduction: find exogenous variables
  - -> Action: generating new training samples
  - -> Prediction: different generate policy: random, learning based
  - Producing better samples, help to get better decisions.

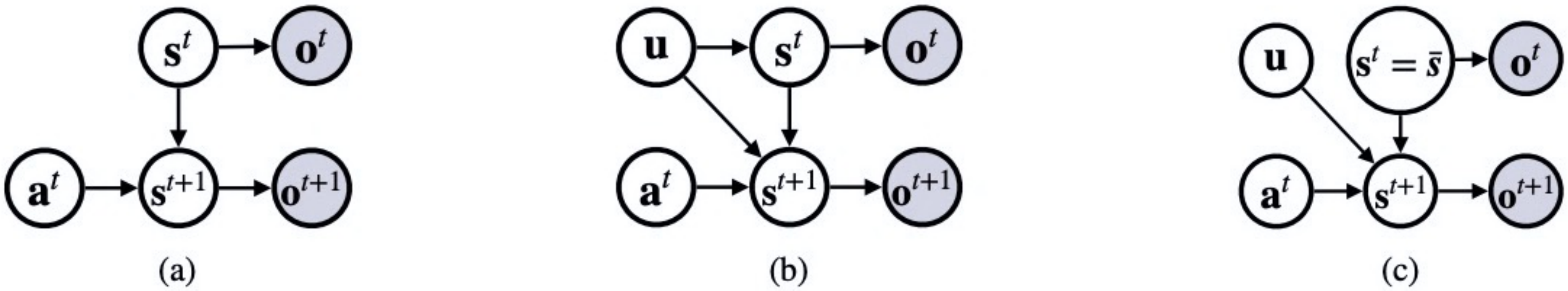
Counterfactual estimation in decision making

- Generate counterfactual data.[Yang et al. 2]
  - Randomly augmented samples : debias from historical policy
  - Goal oriented augmented samples: better rewards.



Counterfactual estimation in decision making

- Counterfactual estimation in World Models [Li et al.]



Counterfactual estimation in decision making

- Counterfactual estimation in World Models

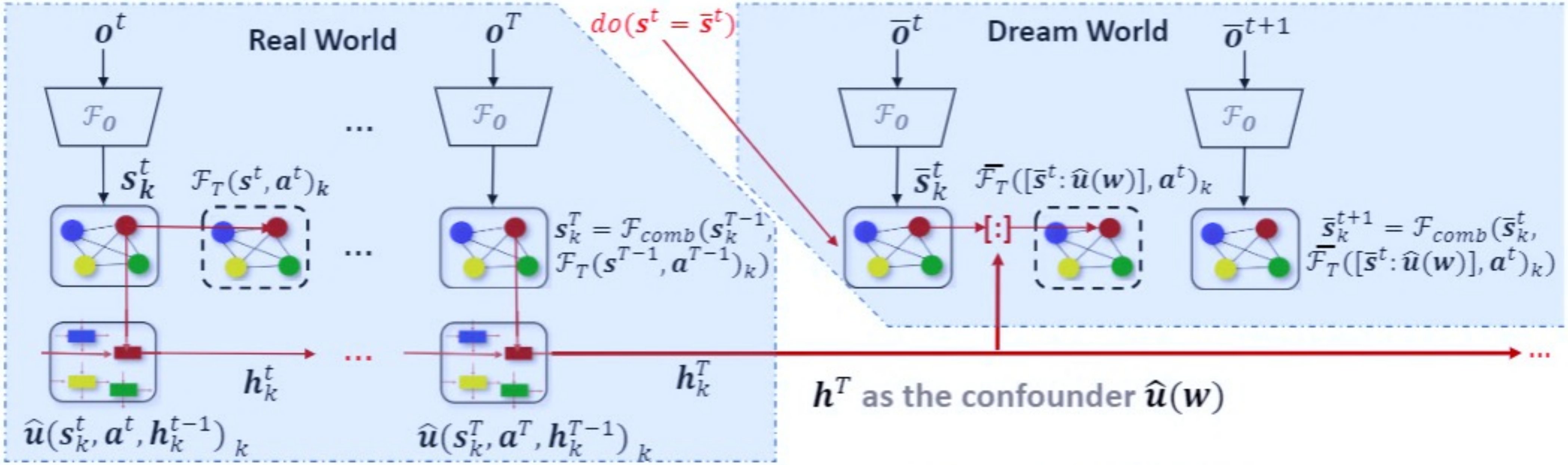
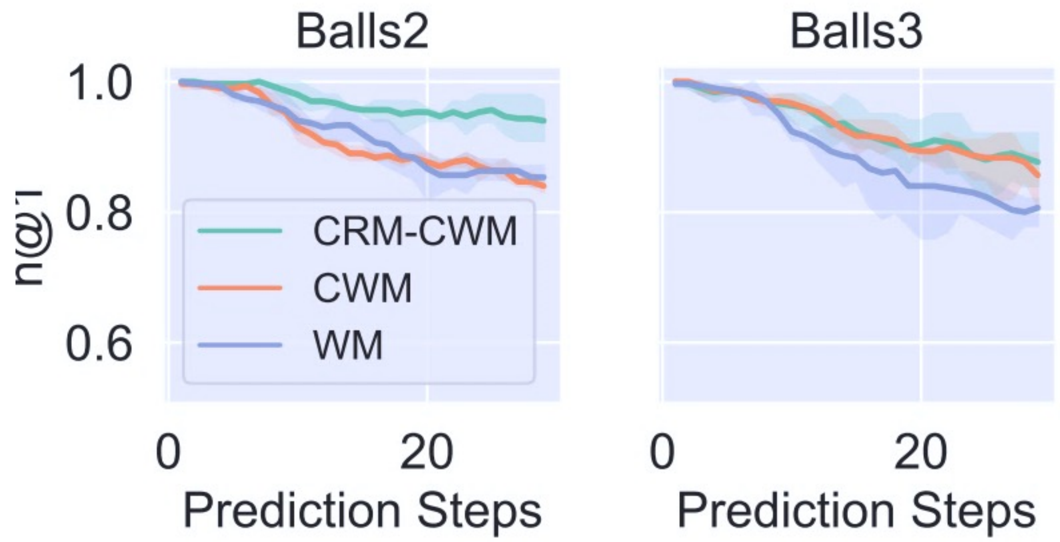
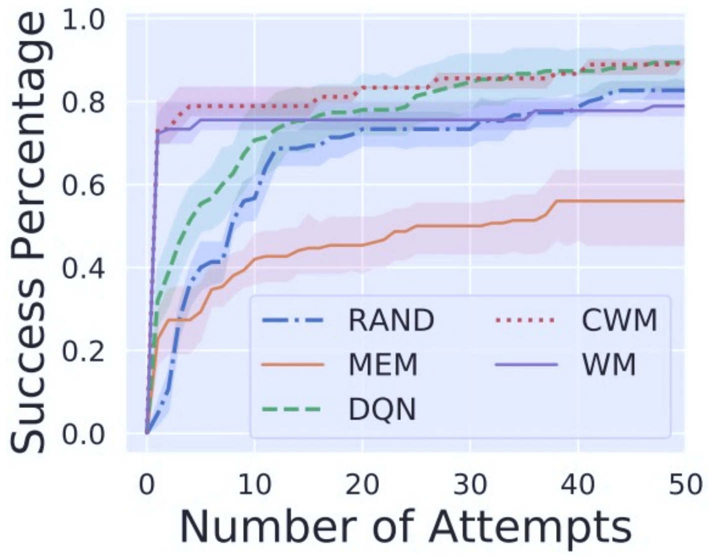


Figure 2: An illustration of the proposed Causal World Models.

Counterfactual estimation in decision making

- Counterfactual performance and efficiency





Advanced Topic: Challenges in Reasoning and Decision Making of Causal LLM

LLM basics

- Training and Fine-tuning
  - Supervised fine-tuning (SFT).
  - Reward model (RM): reinforcement learning via proximal policy optimization (PPO) on this reward model.
- In-context Learning
  - Directly inference by providing prompts

Can LLM tell causal rather than association?

- Problem 1: Unstable.
    - Fail to determine implicit causal but it can tell the explicit causal relationships.[Gao et al.]
    - It can only find causal under specific prompt.[Zečević et al. , Hobbhahn et al.]
    - Fail to find causality under very complex sentence which contains lot of factors.[Gao et al.]

Can LLM tell causal rather than association?

- Problem 2: AI Hallucinations .
  - From the bias between factual and counterfactual observations (data level)
  - From the training and fine-tuning policy like RLHF (training level)
  - From the advanced technology like CoT and in context learning (inference level)

Can LLM tell causal rather than association?

Question: "What is heavier: A kilogram of metal or a kilogram of feathers?”
Answer: A kilogram of metal is heavier than a kilogram of feathers.

Question: "A kilogram of metal is heavier than a kilogram of feathers”
Answer: They weigh the same.

The boundary of LLM's causal ability [Zhang]

Type 1: Identifying causal relationships using domain knowledge

Example 1: Patient: Will my minor spine injury cause numbness in my shoulder?

Example 2: Person: I am balancing a glass of water on my head. Suppose I take a quick step to the right. What will happen to the glass?

Type 2: Discovering new knowledge from data

Example 1: Scientist: In a new scientific experiment. I observe two variables A and B which were A causes B or B causes A.

Example 2: Marketing specialist: I plan to launch a new membership program different from our competitors X and Y. There are two ways to design the benefit as members. The first is "buy four and get a fifth one for free," and the other is "get 20 dollar cash return for every 100 dollar spend". Which one should I choose?

The boundary of LLM’s causal ability [Zhang]

Type 3: Quantitative estimating of the consequences of actions

Example 1: Sales manager: I have 1000 dealers with the following information about them [...]. I can only give membership to 100 of them next year. I want the membership program provides the highest revenue growth. Which 100 dealers should I choose?

Example 2: Medical doctor: This is the third time that this patient has returned with lumbago. The epidural steroid injections helped him before, but not for long. I injected 12mn betamethasone the last two times. What is the dose that I should use this time?

Why LLM can not tell causality stably?

- Bias in training/ inference data: lack of counterfactual data.
- Lack of explainable explicit identifiable causal relationships/representation in model designing.
- Lack of causal/counterfactual learning form like learning strategy or objectives. It will produce bias.
- The inference process not include causal restrictions.

Future work: what we could do?

Let LLM get the ability of understanding the causal mechanism

- Data Level
  - The counterfactual data collection
- Model Level
  - Explicit and Implicit causal model
- Method Level
  - Causal constraints
- In-context learning
  - Better Instruction

Thank You!

More question feel free to reach me at

mengyue.yang.20@ucl.ac.uk

Reference

- Suter et al. Robustly disentangled causal mechanisms: Validating deep representations for interventional robustness.
- Besserve et al. Counterfactuals uncover the modular structure of deep generative models.
- Yang et al. 1 Causalvae: Disentangled representation learning via neural structural causal models.
- Khemakhem et al. 1 Variational Autoencoders and Nonlinear ICA: A Unifying Framework.
- Khemakhem et al. 2 Ice-beem: Identifiable conditional energy-based deep models based on nonlinear ica

Reference

- Sontakke et al. Causal Curiosity: RL Agents Discovering Self-supervised Experiments for Causal Representation Learning
- Yang et al. 2 Top-N Recommendation with Counterfactual User Preference Simulation.
- Li et al. Causal World Models by Unsupervised Deconfounding of Physical Dynamics.
- Zholus et al. Factorized World Models for Learning Causal Relationships.
- Ding et al. Generalizing Goal-Conditioned Reinforcement Learning with Variational Causal Reasoning

Reference

- Wang et al. 1 Causal Dynamics Learning for Task-Independent State Abstraction.
- Yu et al. 2 Explainable Reinforcement Learning via a Causal World Model.
- Huang et al. Action-Sufficient State Representation Learning for Control with Structural Constraints
- Liu et al. Learning World Models with Identifiable Factorization.
- Pitis et al. MOCODA: Model-based Counterfactual Data Augmentation.

Reference

- Lee et al. Characterizing Optimal Mixed Policies: Where to Intervene, What to Observe
- Seitzer et al. Causal Influence Detection for Improving Efficiency in Reinforcement Learning
- Gao et al. Is ChatGPT a Good Causal Reasoner? A Comprehensive Evaluation
- Zečević et al. Causal Parrots: Large Language Models May Talk Causality But Are Not Causal
- Hobbhahn et al. Investigating causal understanding in LLMs

Reference

- Zhang et al. Understanding Causality with Large Language Models: Feasibility and Opportunities
- Hammond et al. Reasoning about Causality in Games
- Pearl. Causality.