# Causal Discovery for Time-Series Data

Luca Castri, PhD, University of Lincoln, UK

# Outline

- **Causal Discovery for Time-series Data**
  - PCMCI algorithm

- Robotics Applications
  - F-PCMCI algorithm
  - CAnDOIT algorithm
  - CausalFlow
  - ROS-Causal

# Causal Discovery for Time-series Data

The PC and FCI causal discovery methods work well with discrete/categorical data.

**example**

non-smoker **0** - smoker **1**
age under 50 **0** - age over 50 **1**
no lung cancer **0** - lung cancer **1**

| Smoker | Age | Lung cancer |
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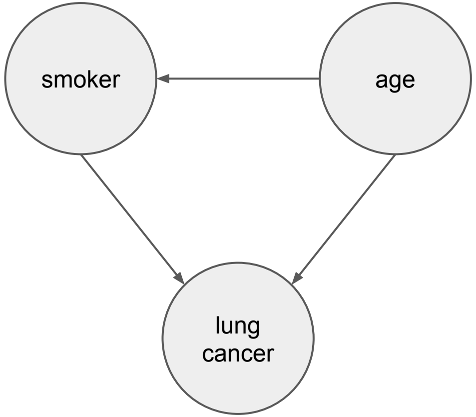

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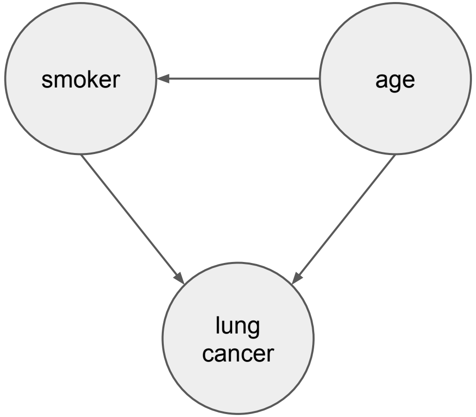

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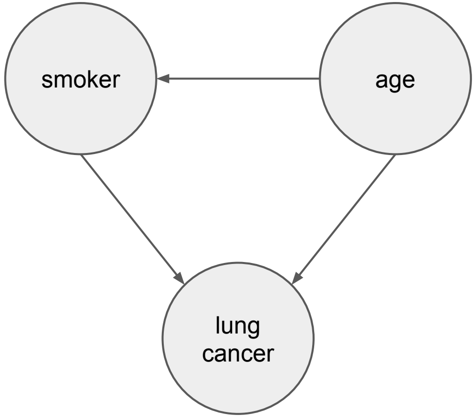

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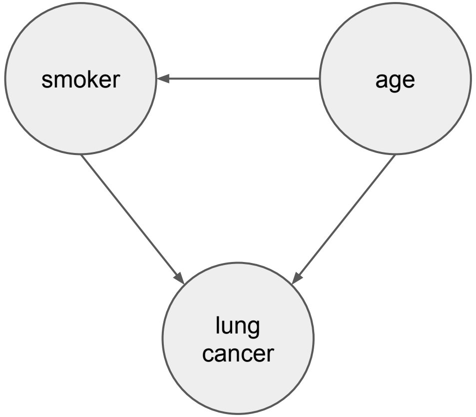

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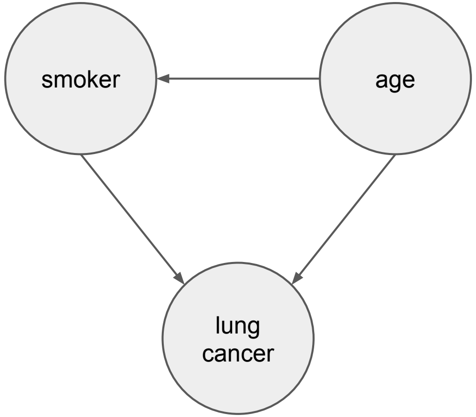

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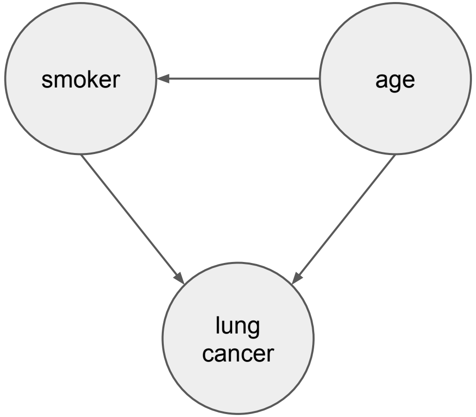


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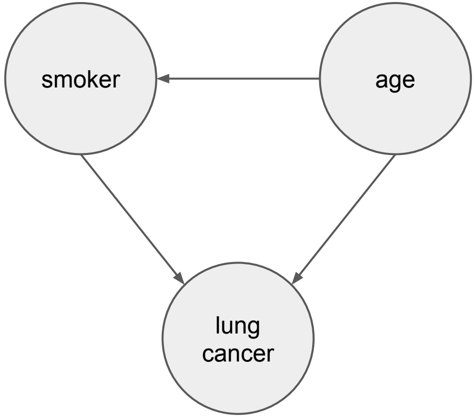


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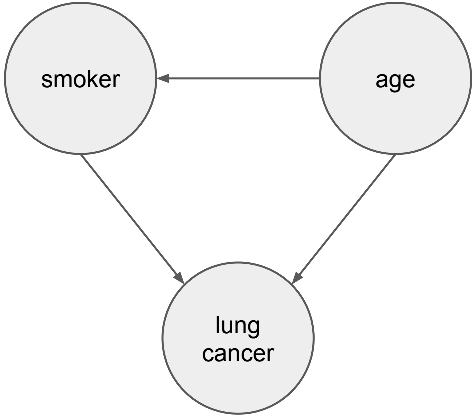


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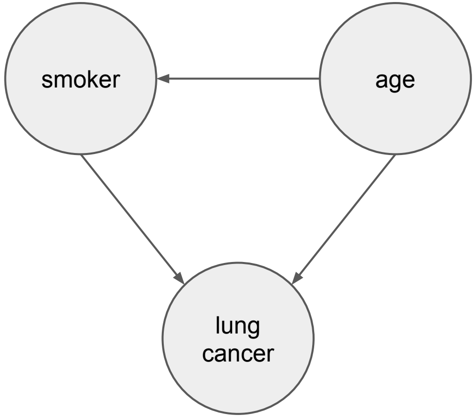


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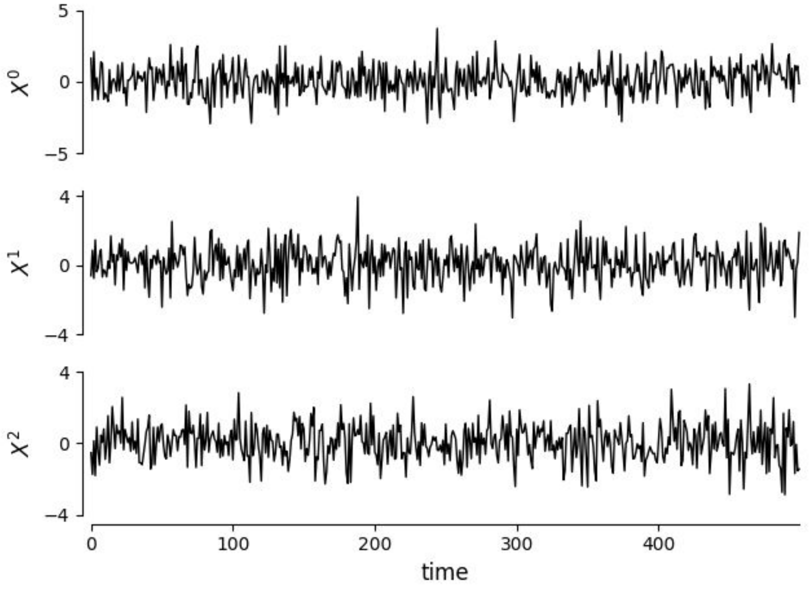
# Causal Discovery for Time-series Data

The PC and FCI causal discovery methods work well with discrete/categorical data.

**What if we deal with time-series data?**
PC/FCI is inappropriate to use with time series data due to:

- time ordering
- lagged dependencies
- high false positive rates due to the autocorrelation.

$$\begin{cases} X_t^0 = 0.2(X_{t-1}^1)^2 + \eta_t^0 \\ X_t^1 = \eta_t^1 \\ X_t^2 = 0.3(X_{t-2}^1)^2 + \eta_t^2 \end{cases}$$



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- **Causal Discovery for Time-series Data**
  - **PCMCI algorithm**

- Robotics Applications
  - F-PCMCI algorithm
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# Causal Discovery for Time-series Data
## PCMCI algorithm

It consists of two main steps:

- **PC algorithm**
  retrieves the causal model structure by considering ONLY lagged dependencies as possible causal relationships between variables

- **MCI test**
  validates the structure found at the previous step by performing a false positive rate optimisation control

$$X^i_{t-\tau} \perp\!\!\!\perp X^j_t | \tilde{P}(X^i_{t-\tau}), \tilde{P}(X^j_t)$$

Key parameter: $\tau$ maximum time delay

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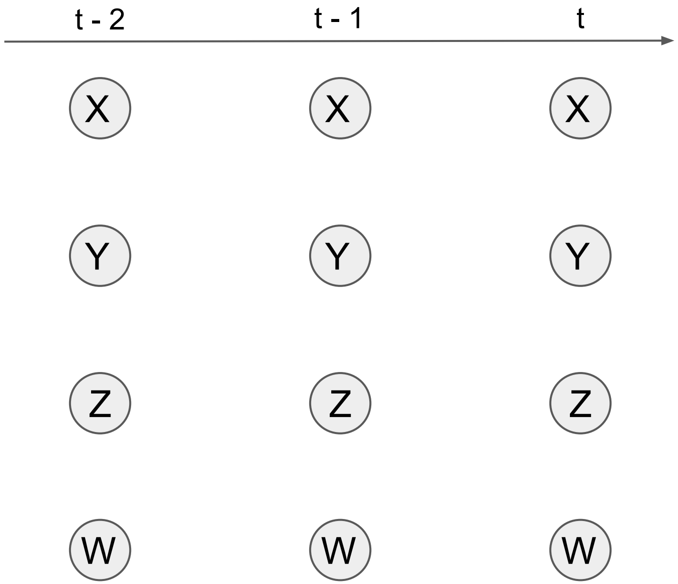

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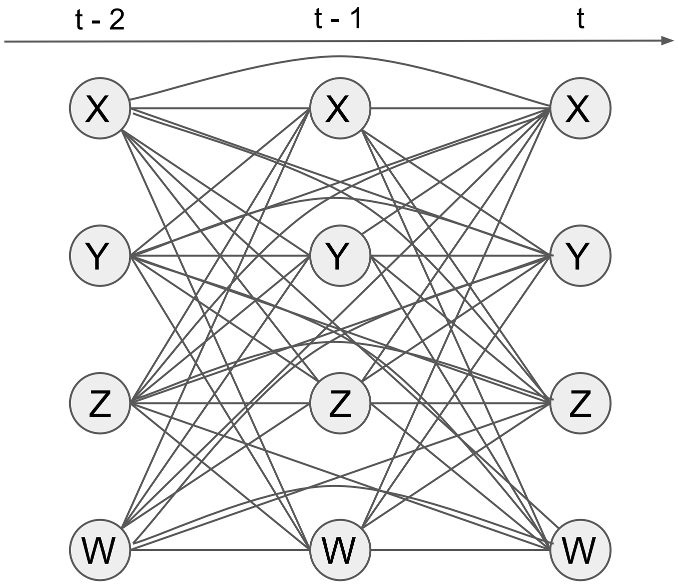

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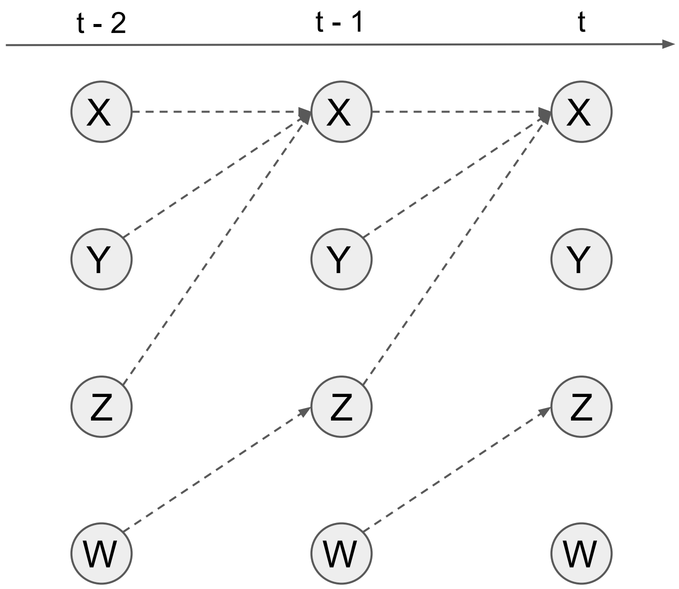

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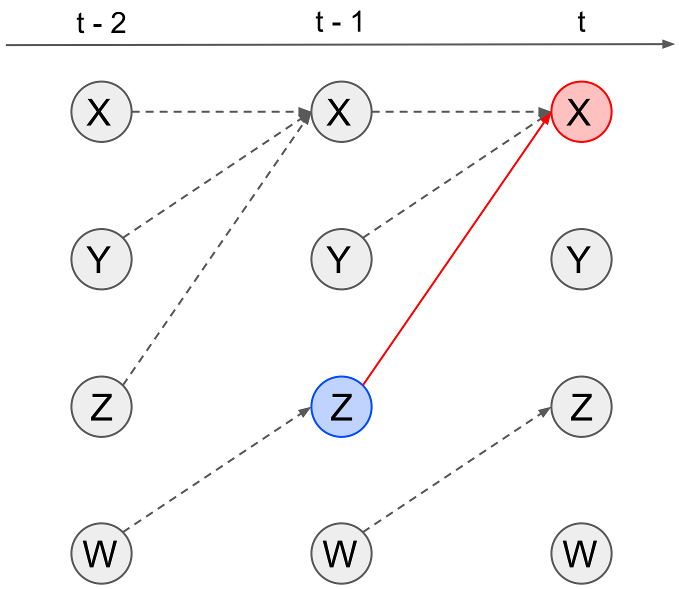

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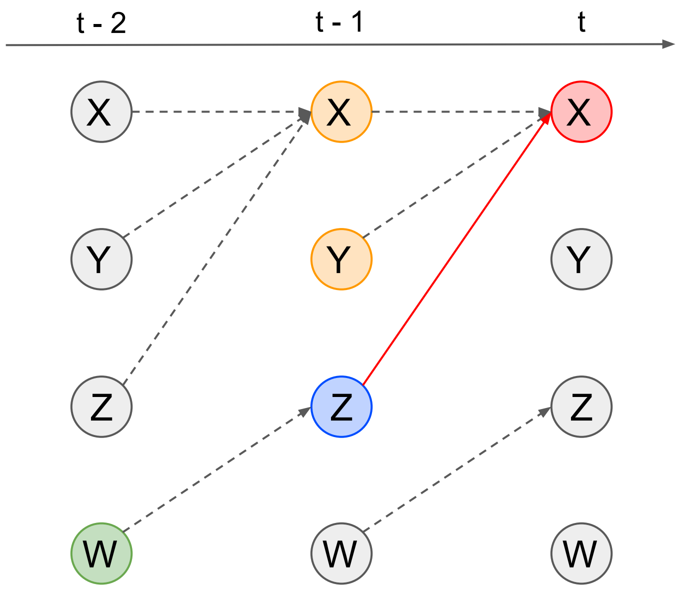

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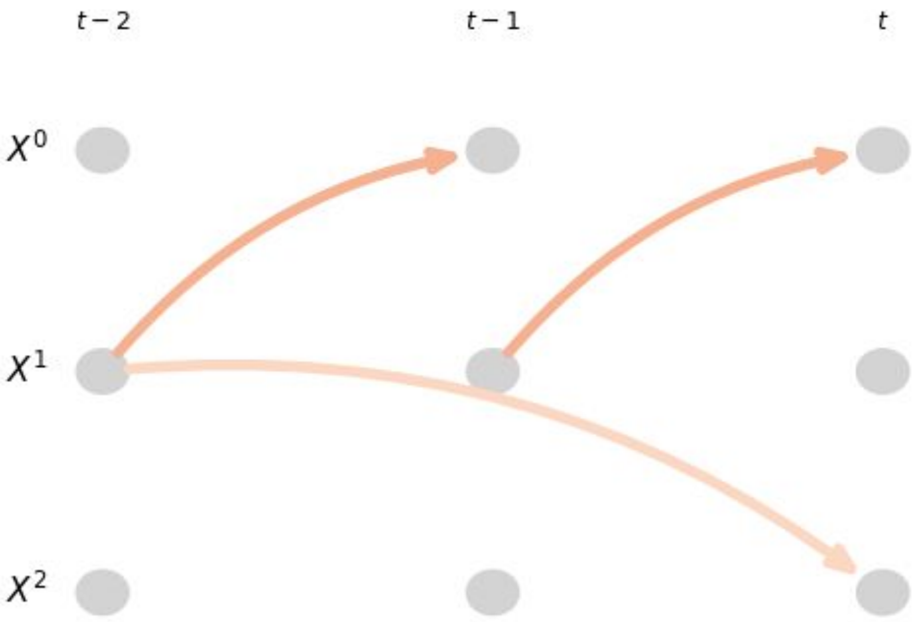

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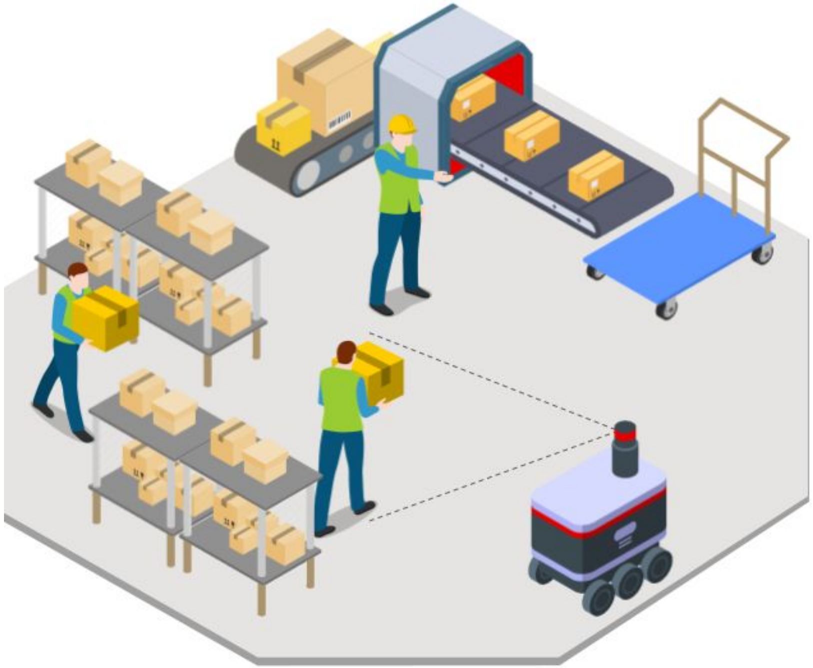
# Robotics Applications

Main challenges in robotics:

- execution time of the causal discovery analysis
- conduct causal discovery using data from observations and interventions
- conduct the causal discovery analysis online



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# Robotics Applications

## F-PCMCI algorithm

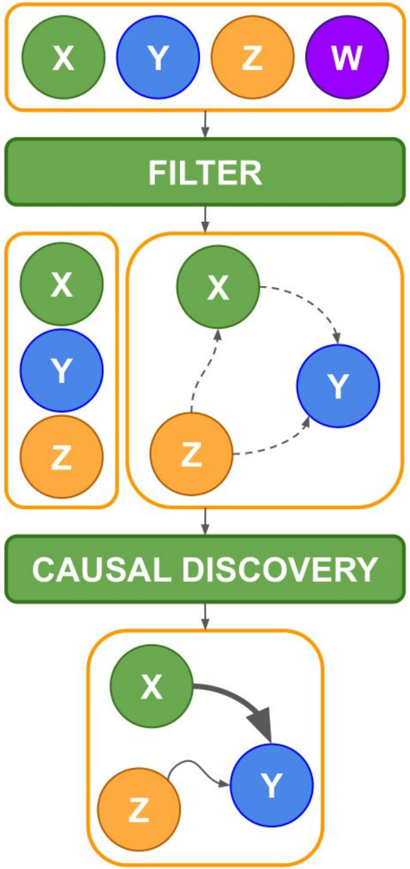
PCMCI computational cost depends on:

- the length of the time-series
- the number of variables

Filtered-PCMCI (**F-PCMCI**) steps:

- takes in input a prefixed set of variables
- the Transfer Entropy-based filter analyses and removes irrelevant variables (e.g., constants or isolated ones). The reduced variable set is used to create a hypothetical causal model
- the hypothetical causal model needs to be validated by a proper causal analysis, which is performed by PCMCI

This strategy enables **faster** and **more accurate** causal discovery




Castri, Luca, et al. "Enhancing Causal Discovery from Robot Sensor Data in Dynamic Scenarios." (2023).

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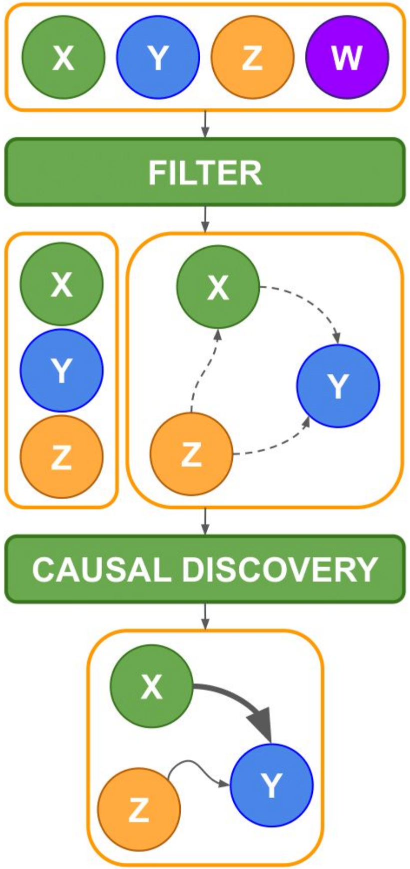


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# Robotics Applications

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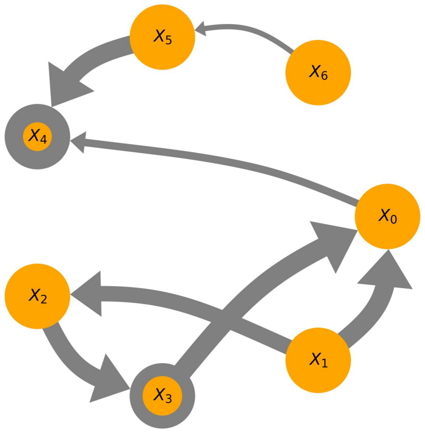
PCMCI

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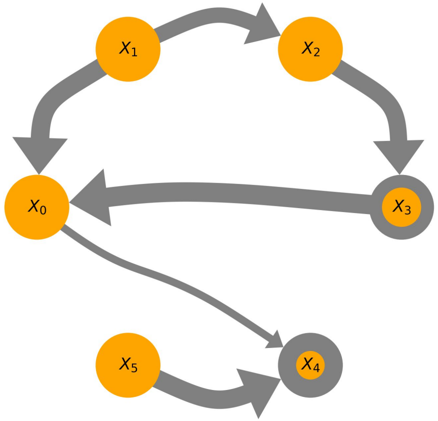


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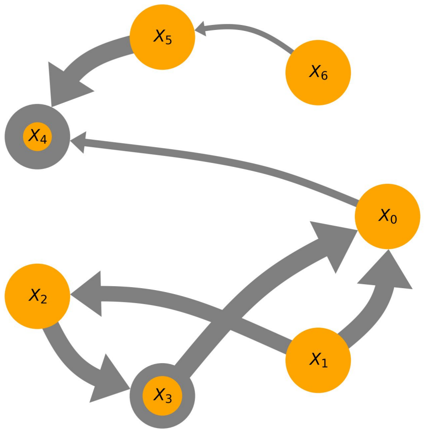


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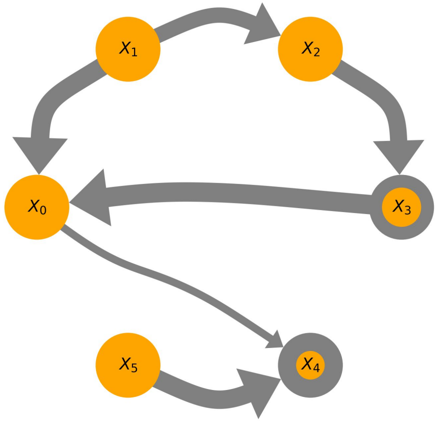


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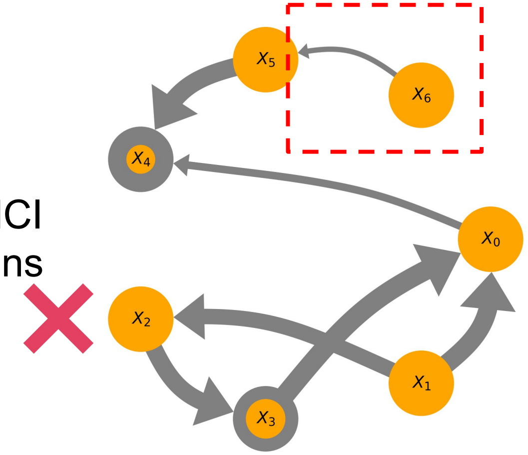
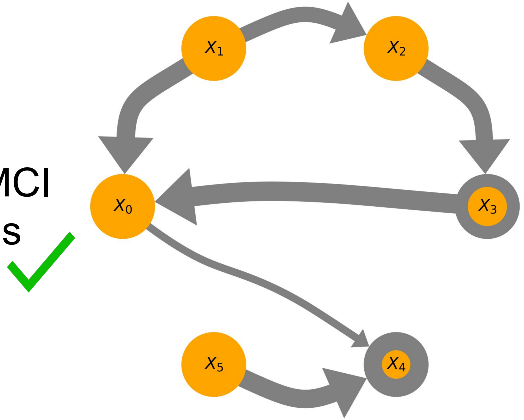
Isolated

PCMCI
~9mins




F-PCMCI
3mins

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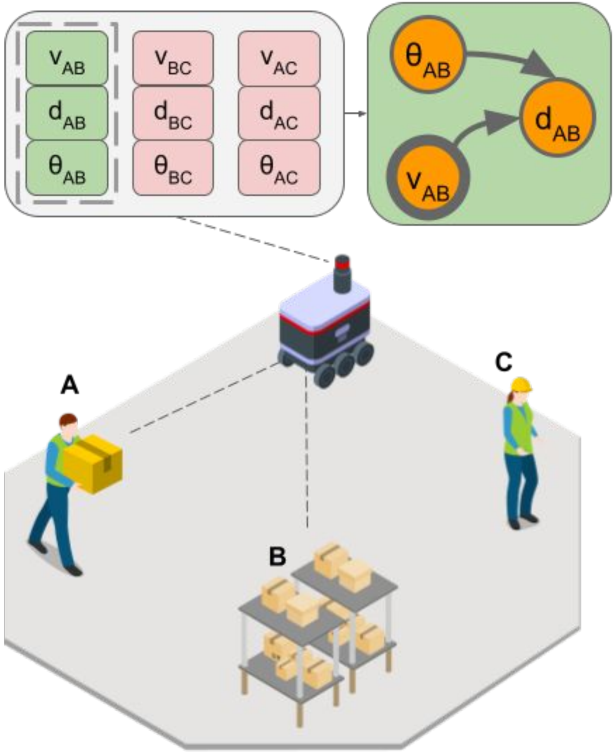
# Robotics Applications

## F-PCMCI algorithm

Considering the interaction scenario modelled by three variables

- $v_{ij}$: relative velocity between agent i and j
- $d_{ij}$: distance between agent i and j
- $theta_{ij}$: angle between agent i and j

**Are all the observable variables useful to understand the observed scenario?**



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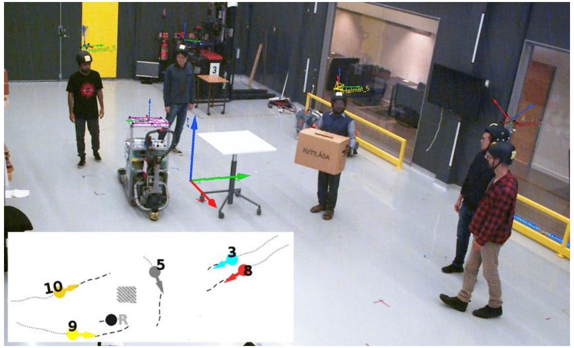


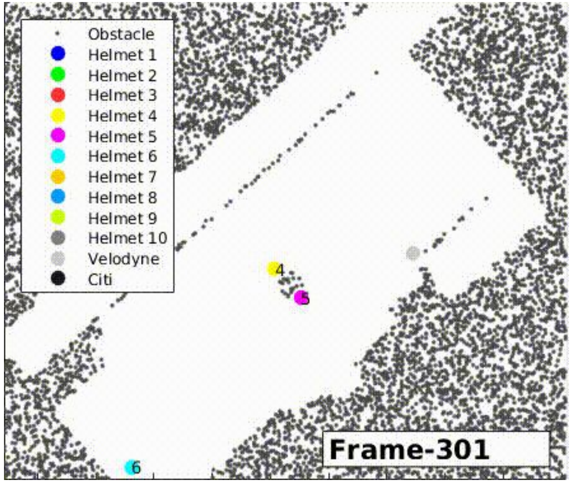


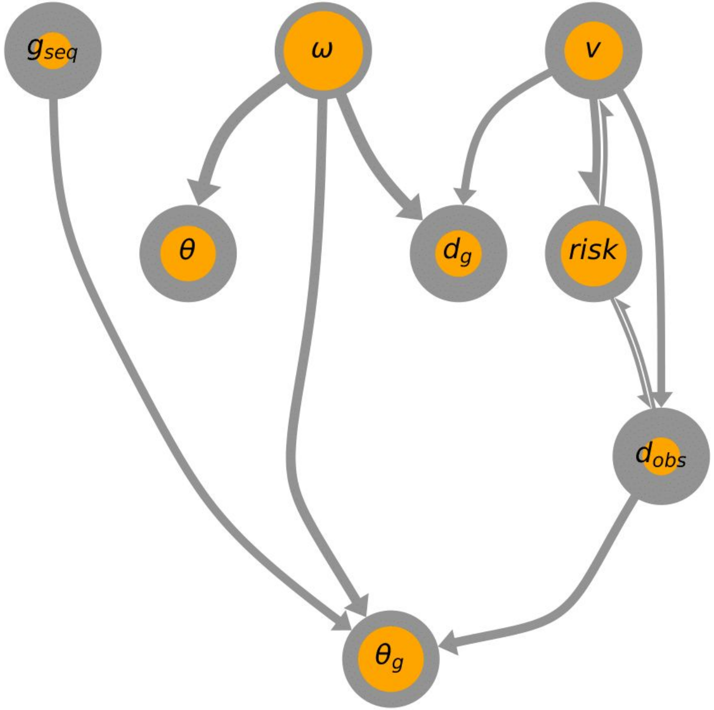


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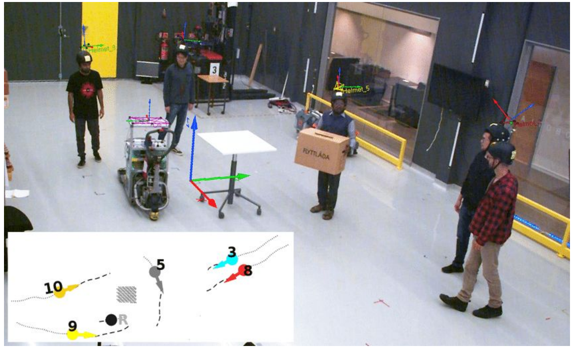
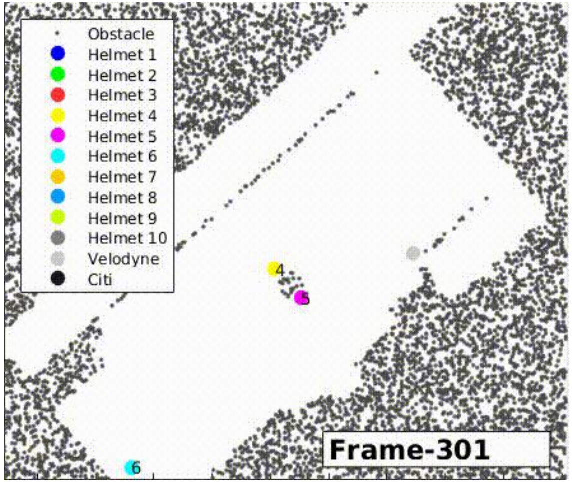
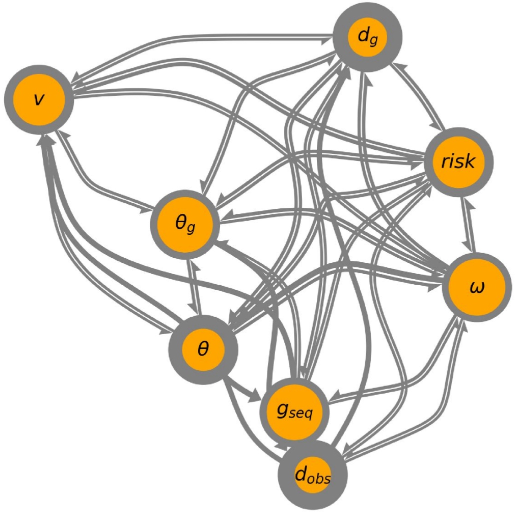
# Robotics Applications

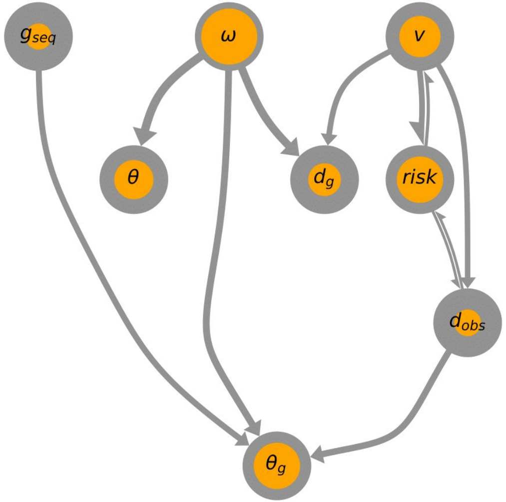
## F-PCMCI algorithm




PCMCI ~80mins




F-PCMCI ~18mins

Castri, Luca, et al. "Enhancing Causal Discovery from Robot Sensor Data in Dynamic Scenarios." (2023).

# Outline

- Causal Discovery for Time-series Data
  - PCMCI algorithm

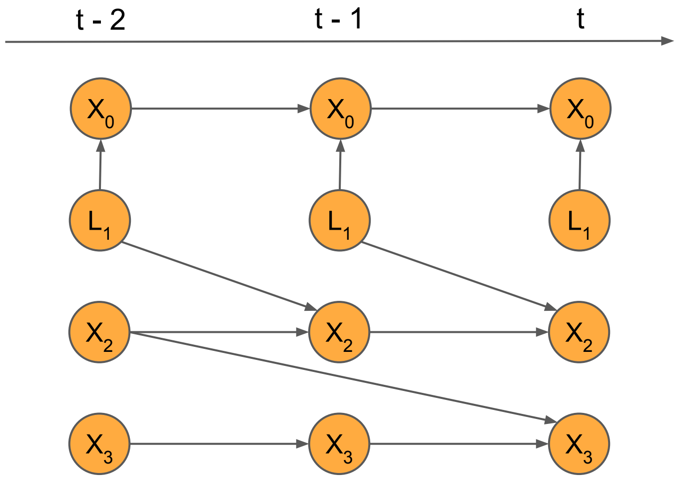
- **Robotics Applications**
  - F-PCMCI algorithm
  - **CAnDOIT algorithm**
  - CausalFlow
  - ROS-Causal

# Robotics Applications

## 🔨 CAnDOIT algorithm

- Observational data alone are often insufficient to accurately identify the correct causal model in complex scenarios where not all variables are observable

$$\begin{cases} X_0(t) = 0.9X_0(t-1) + 0.6X_1(t) + \eta_0 \\ L_1(t) = \eta_1 \\ X_2(t) = 0.9X_2(t-1) + 0.4X_1(t-1) + \eta_2 \\ X_3(t) = 0.9X_3(t-1) - 0.5X_2(t-2) + \eta_3 \end{cases}$$



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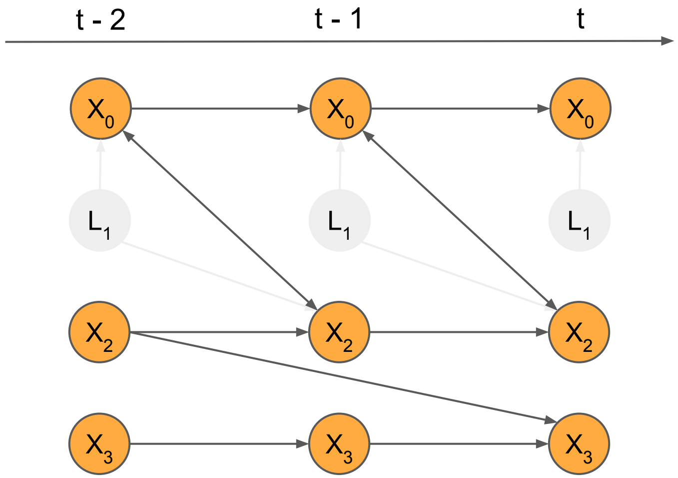

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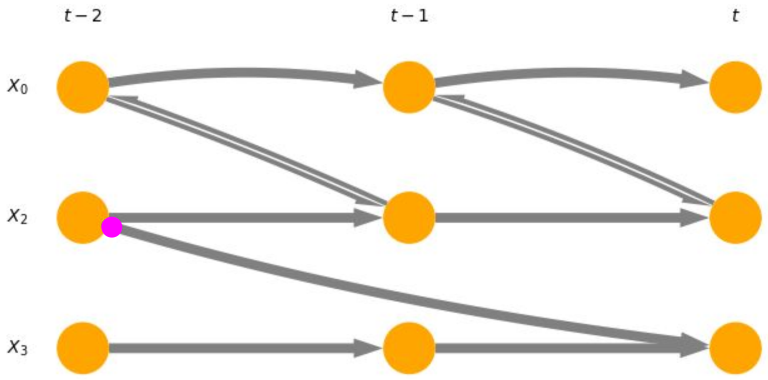
Causal model obtained by using **Latent-PCMCI (LPCMCI)**: version of PCMCI, based on FCI, that handles latent variables



# Robotics Applications

## CAnDOIT algorithm

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$$
\begin{cases}
X_0(t) = 0.9X_0(t-1) + 0.6X_1(t) + \eta_0 \\
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$$

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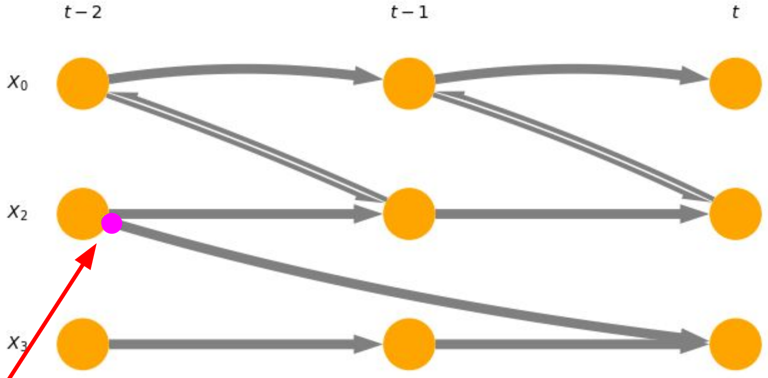


LPCMCI is uncertain about the orientation of this link

$\circ\!\!\rightarrow \; = \; \rightarrow$ or $\leftrightarrow$

# Robotics Applications

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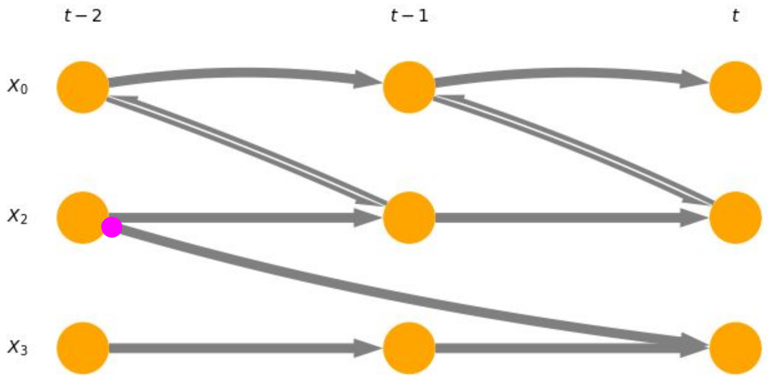
Despite the "simple" toy problem (linear, 4 variables)
- reconstructing the causal model from data is never straightforward
- especially when there are hidden confounders

Causal model obtained by using **Latent-PCMCI (LPCMCI)**: version of PCMCI, based on FCI, that handles latent variables



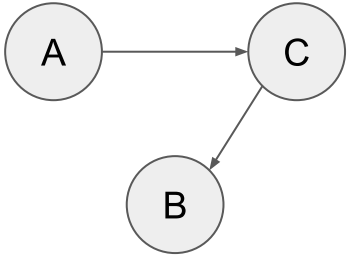

**How can we perform causal discovery using data from observations 👀 and interventions 🔨?**

# Robotics Applications

## 🔨 CAnDOIT algorithm

- Observational data alone are often insufficient to accurately identify the correct causal model in complex scenarios where not all variables are observable
- We need **interventions**

**CAnDOIT: CAusal Discovery with Observational 👀 and Interventional 🔨 data from Time-series**




Castri, Luca, et al. "CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series" (2024).

# Robotics Applications

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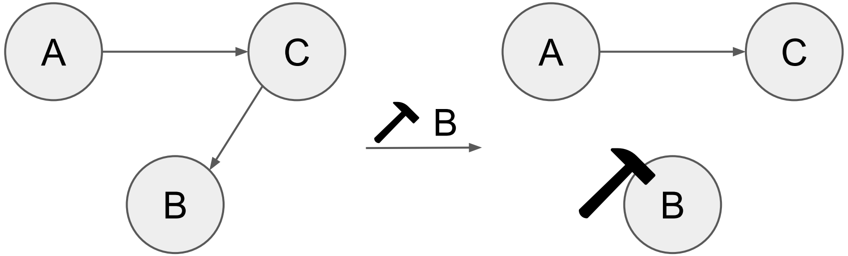


- For the observational case, we need to consider B's parents
- For the interventional case, we need to remove all incoming links to B

**How can we enable a causal discovery method to do this?**

Castri, Luca, et al. "CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series" (2024).

# Robotics Applications

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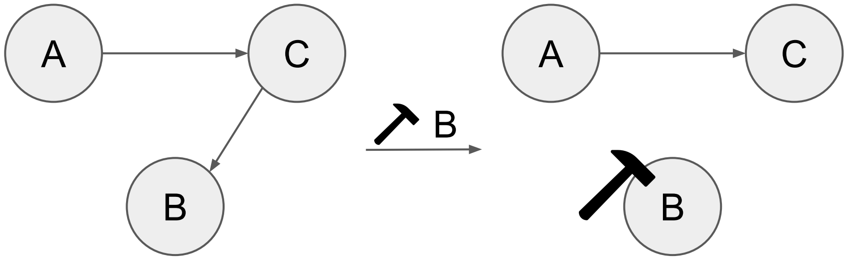
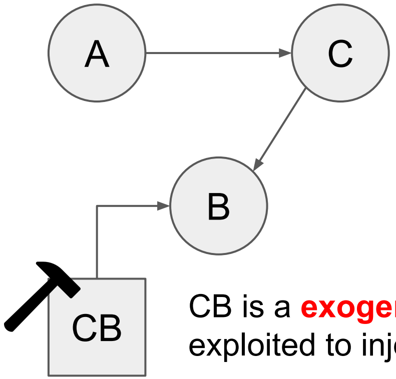



🔨 CAnDOIT uses **context** variables




CB is a **exogenous** dummy variable exploited to inject interventional data

Castri, Luca, et al. "CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series" (2024).

# Robotics Applications

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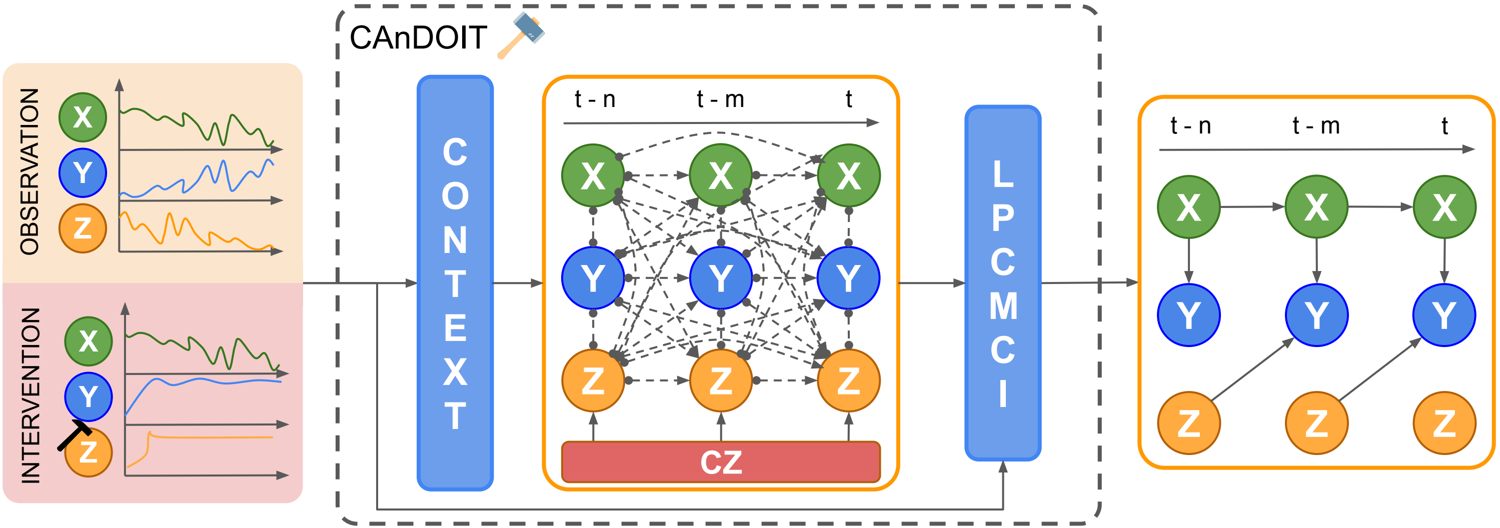


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# Robotics Applications

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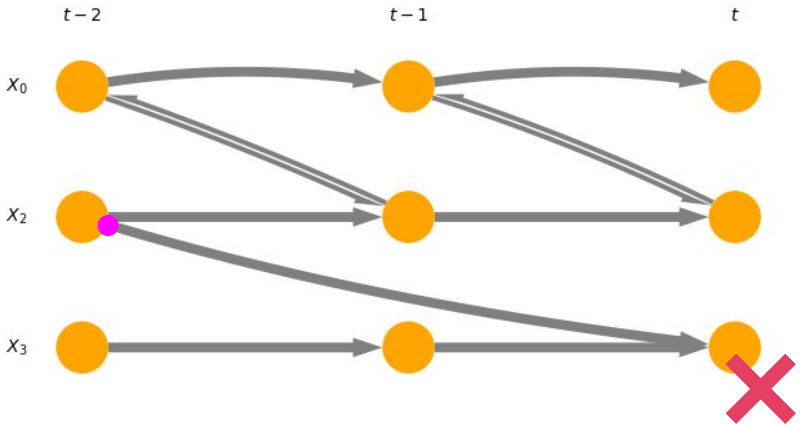
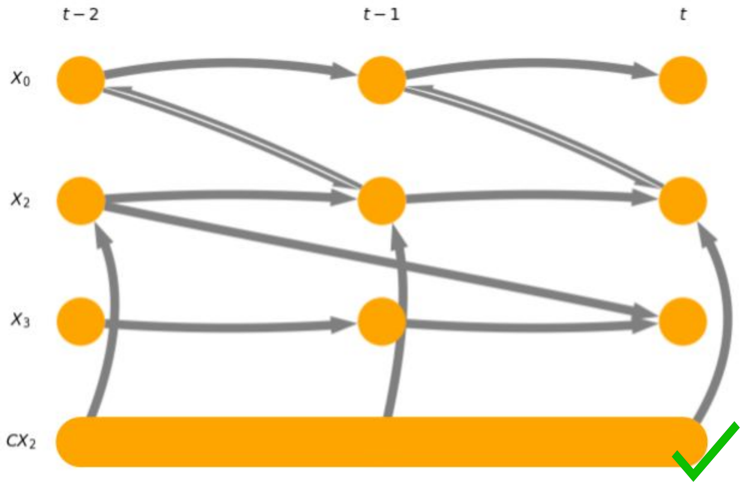


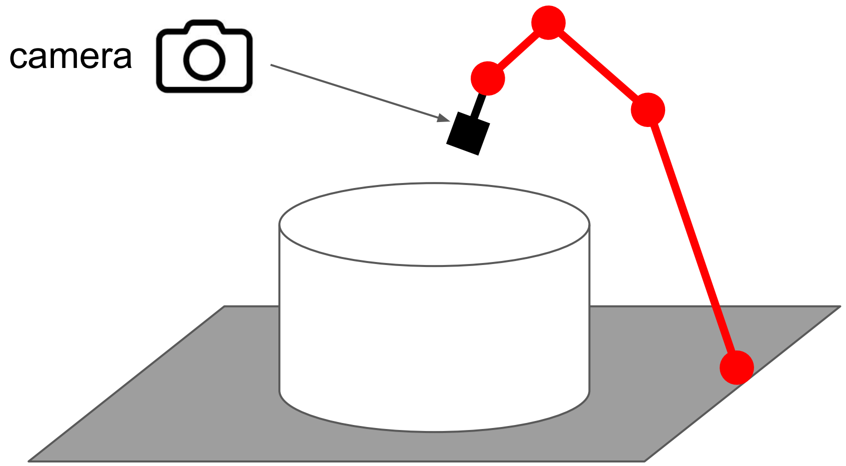

Causal model obtained by using **CAnDOIT**



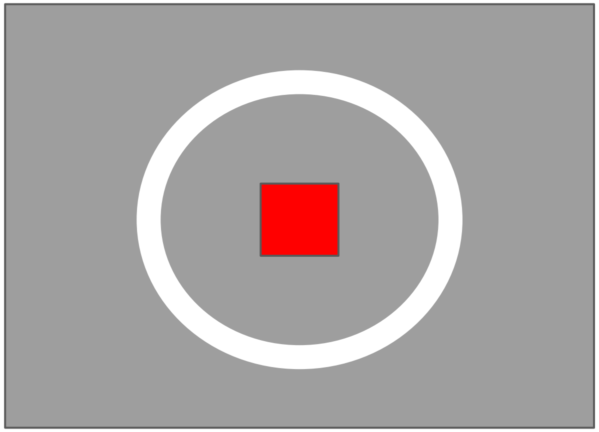
# Robotics Applications

## 🔨 CAnDOIT algorithm

Consider the brightness of the colours of the objects in the cylinder captured by a robot camera




**3D representation**



**2D representation**

Castri, Luca, et al. "CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series" (2024).

# Robotics Applications

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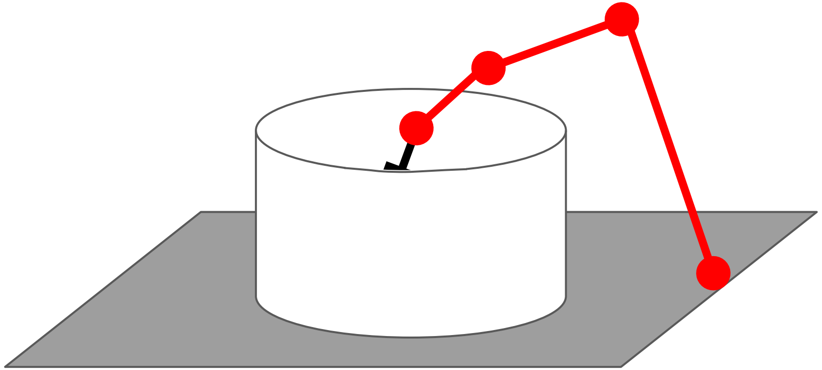

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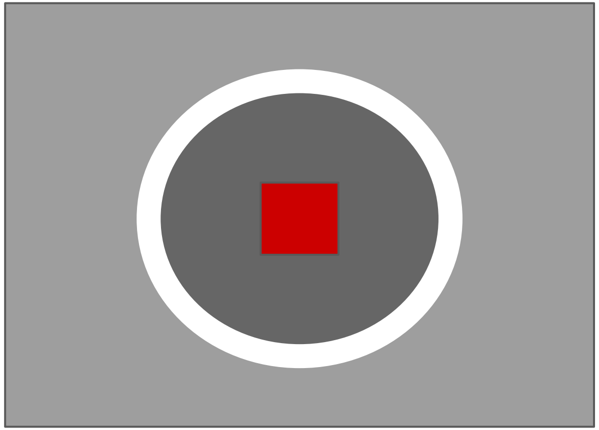

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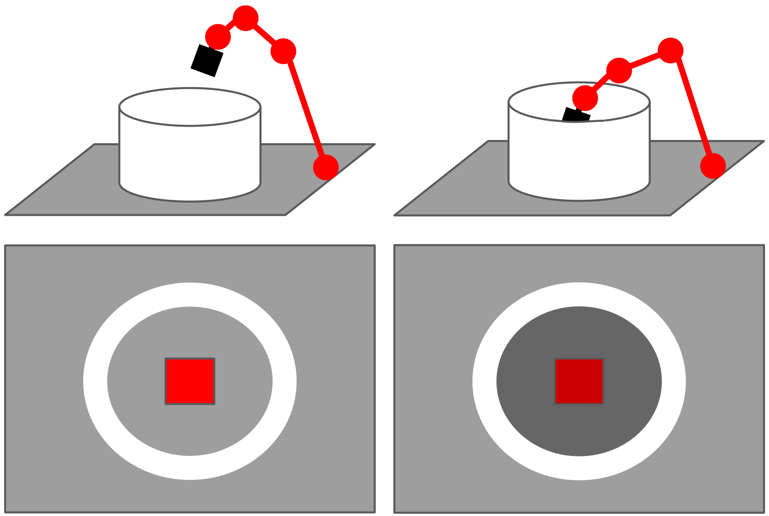
# Robotics Applications

## 🔨 CAnDOIT algorithm

Consider the brightness of the colors of the objects in the cylinder captured by a robot camera

$$\begin{cases} F_c(t) = b(H(t-1)) \\ C_c(t) = b(H(t-1), v(t-1), d_c(t-1)) \end{cases}$$

$$b = K_h \frac{H}{H_{max}} + K_v \left(1 - \frac{v}{v_{max}}\right) + K_d \frac{d_c}{d_{c_{max}}}$$



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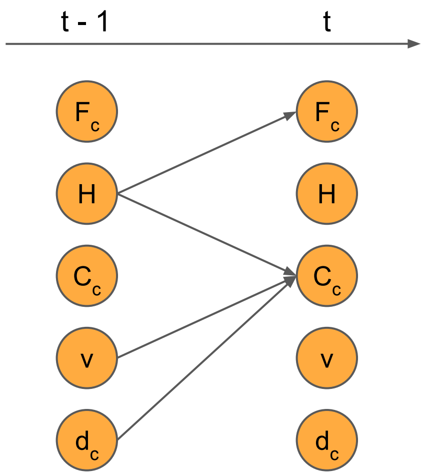
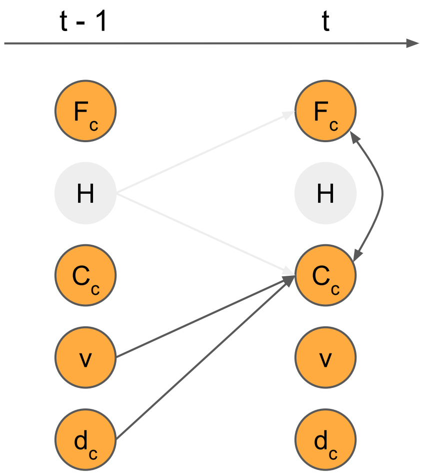
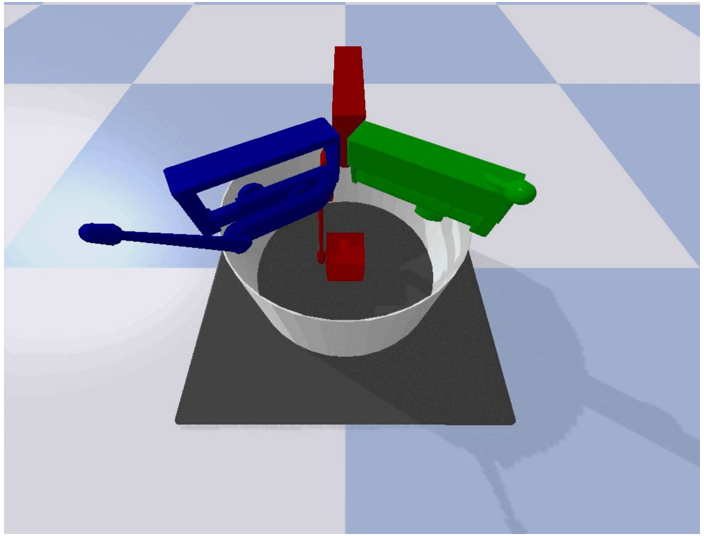
# Robotics Applications

## 🔨 CAnDOIT algorithm



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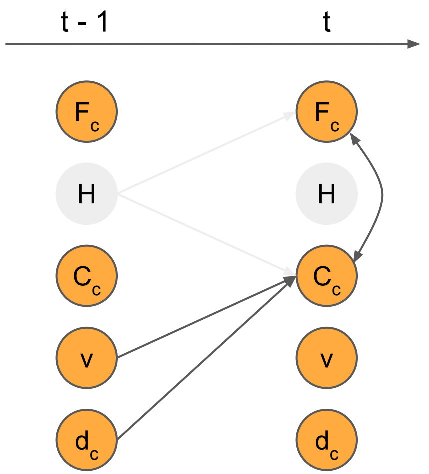
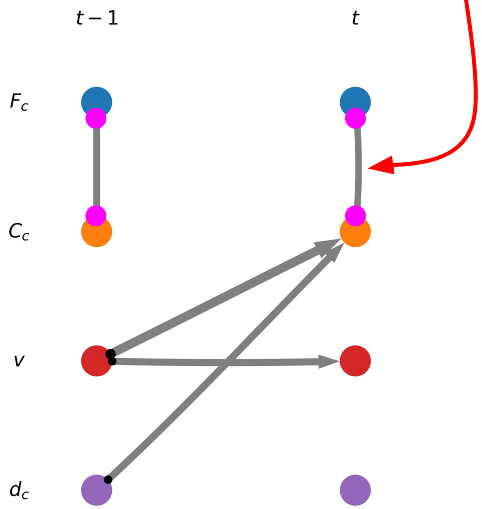
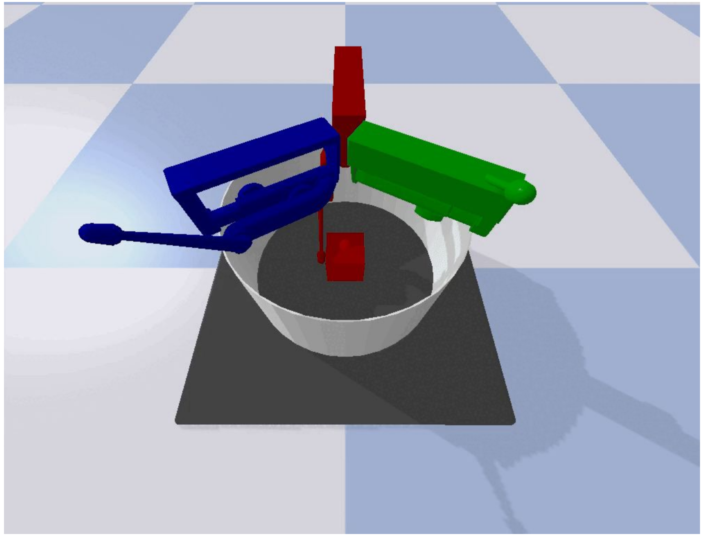
# Robotics Applications

## 🔨 CAnDOIT algorithm

Again, LPCMCI is uncertain about the orientation of this link



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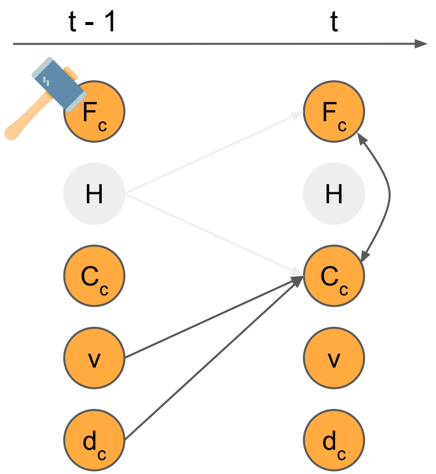
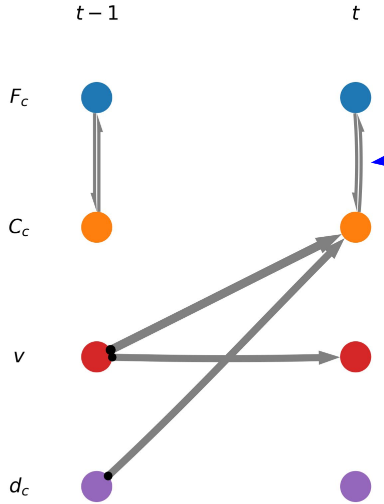
Castri, Luca, et al. "CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series" (2024).

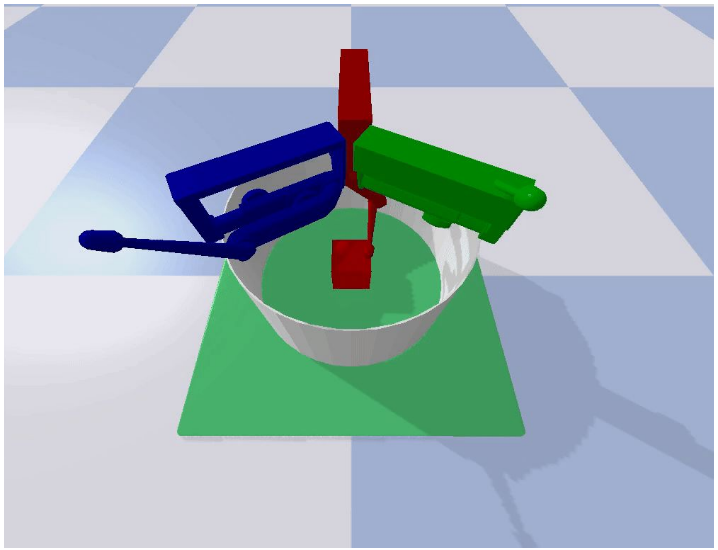
# Robotics Applications

## CAnDOIT algorithm

CAnDOIT using observational and interventional data is able to correctly orient this link



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Castri, Luca, et al. "CAnDOIT: Causal Discovery with Observational and Interventional Data from Time Series" (2024).

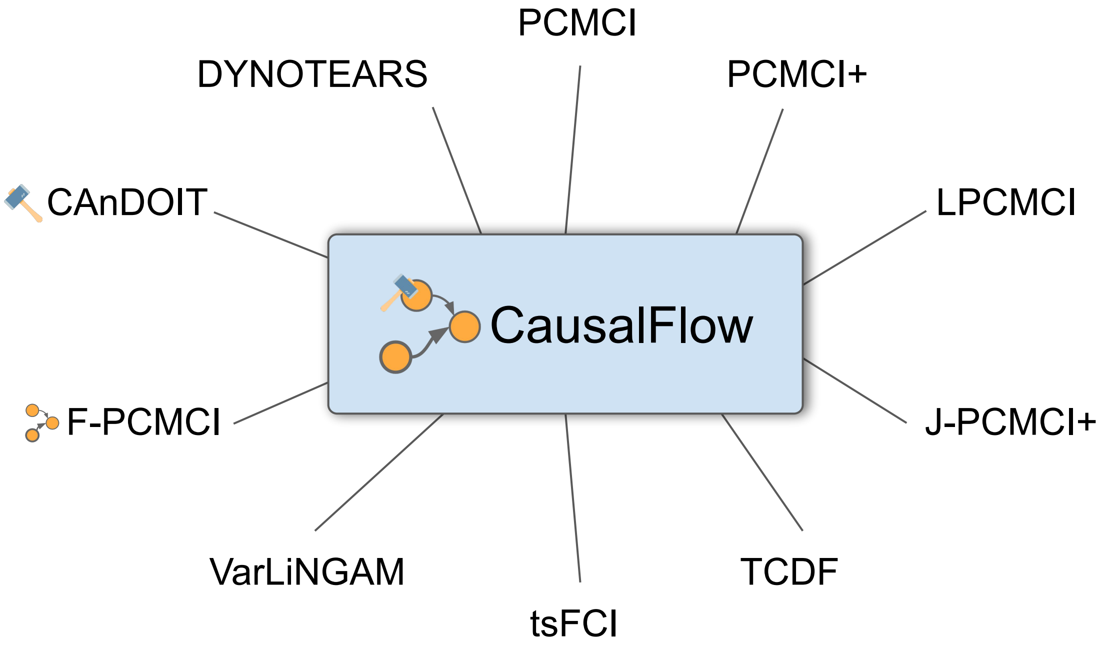
# Outline

- Causal Discovery for Time-series Data
  - PCMCI algorithm

- **Robotics Applications**
  - F-PCMCI algorithm
  - CAnDOIT algorithm
  - **CausalFlow**
  - ROS-Causal

# Robotics Applications

CausalFlow




GitHub

CausalFlow

```
pip install
py-causalflow
```

# Outline

- Causal Discovery for Time-series Data
  - PCMCI algorithm

- **Robotics Applications**
  - F-PCMCI algorithm
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  - **ROS-Causal**

# Robotics Applications

ROS-Causal

## What is Robot Operating System (ROS)?


people tracker


navigation stack


...

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navigation stack


...

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**ROS**




people tracker

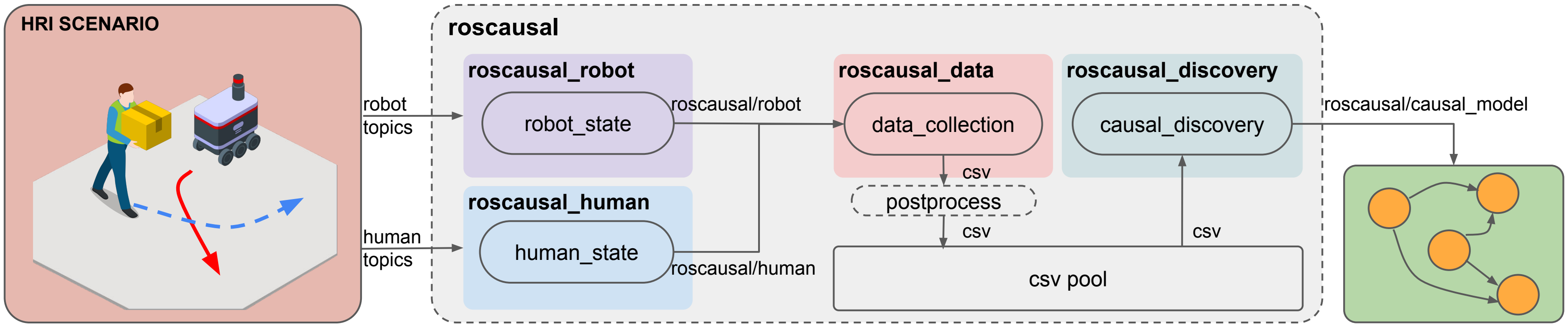
navigation stack

...

## What is Robot Operating System (ROS)?


# Robotics Applications

## ROS-Causal



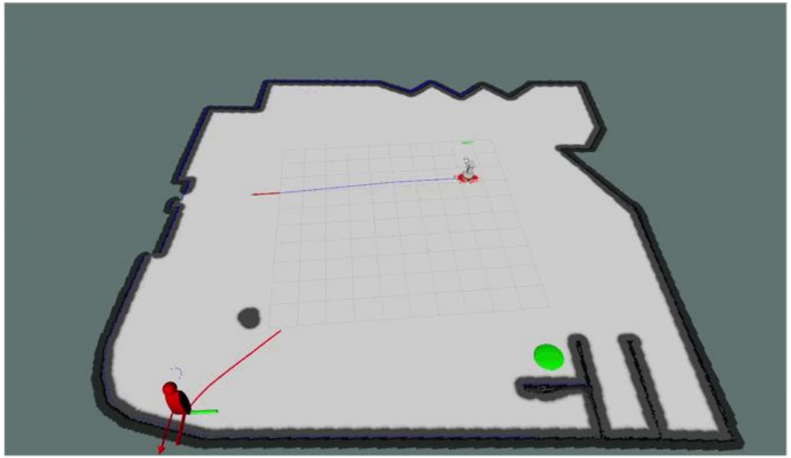

- ROS-Causal extracts and collects data from a HRI scenario, such as agents’ trajectories, and performs causal analysis on the collected data in a batched manner. It is composed by four different rosnodes:
    - roscausal_robot
    - roscausal_human
    - roscausal_data
    - roscausal_discovery

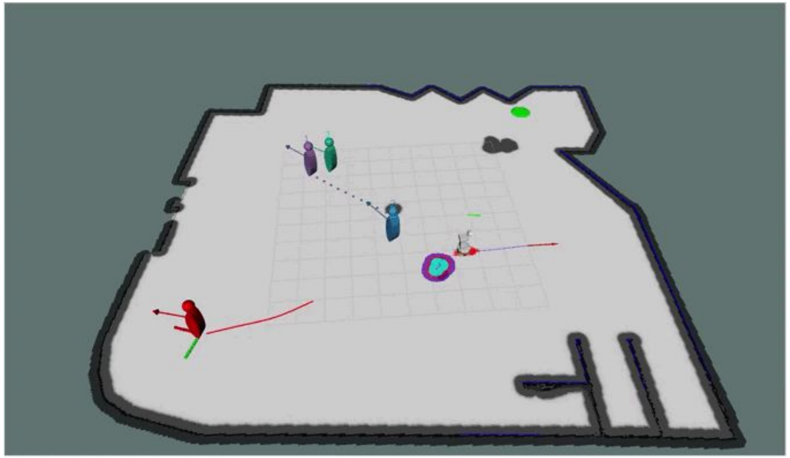
Castri, Luca, et al. "Experimental Evaluation of ROS-Causal in Real-World Human-Robot Spatial Interaction Scenarios" (2024).

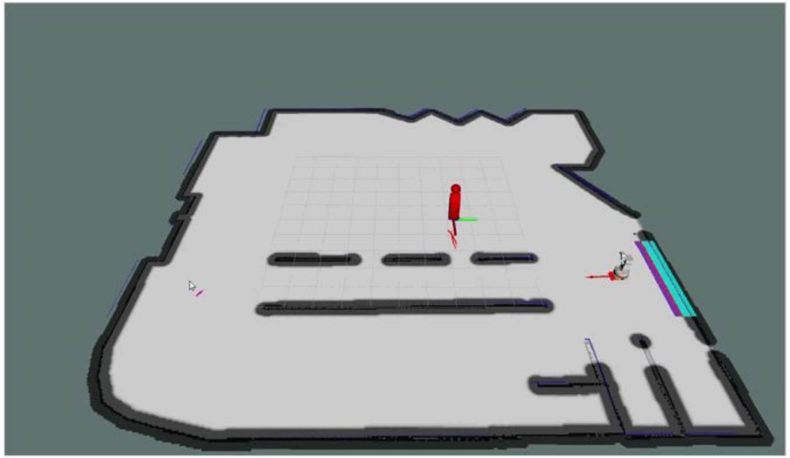
**ROS-Causal_HRISim**

HRI simulator involving:

- TIAGo robot
- pedestrians

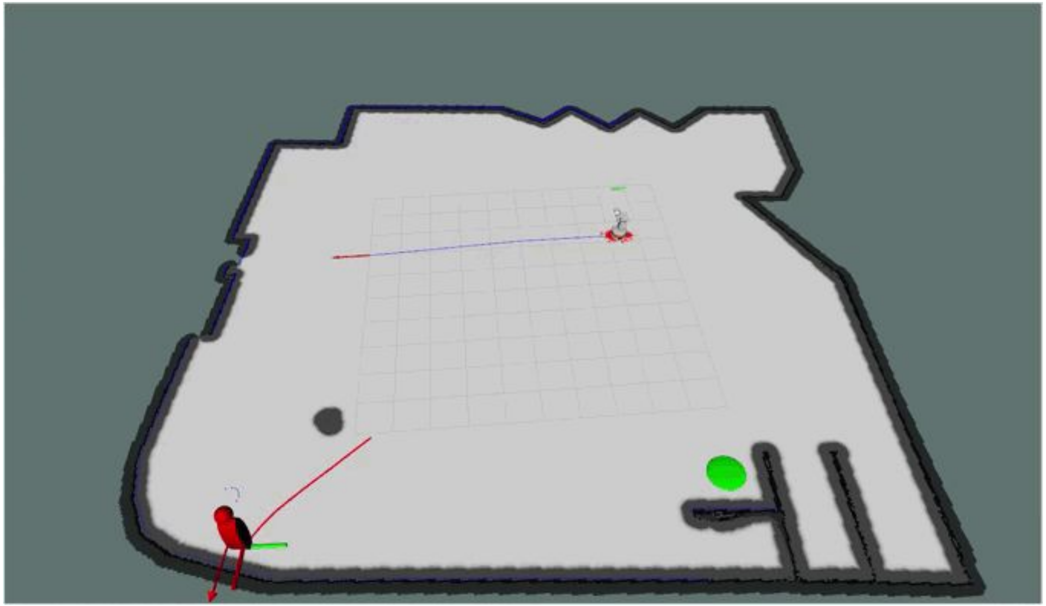


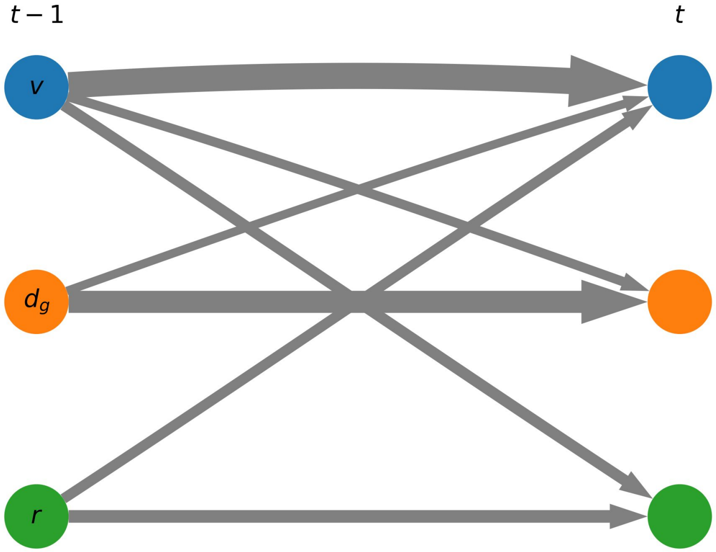




# Robotics Applications

## ROS-Causal



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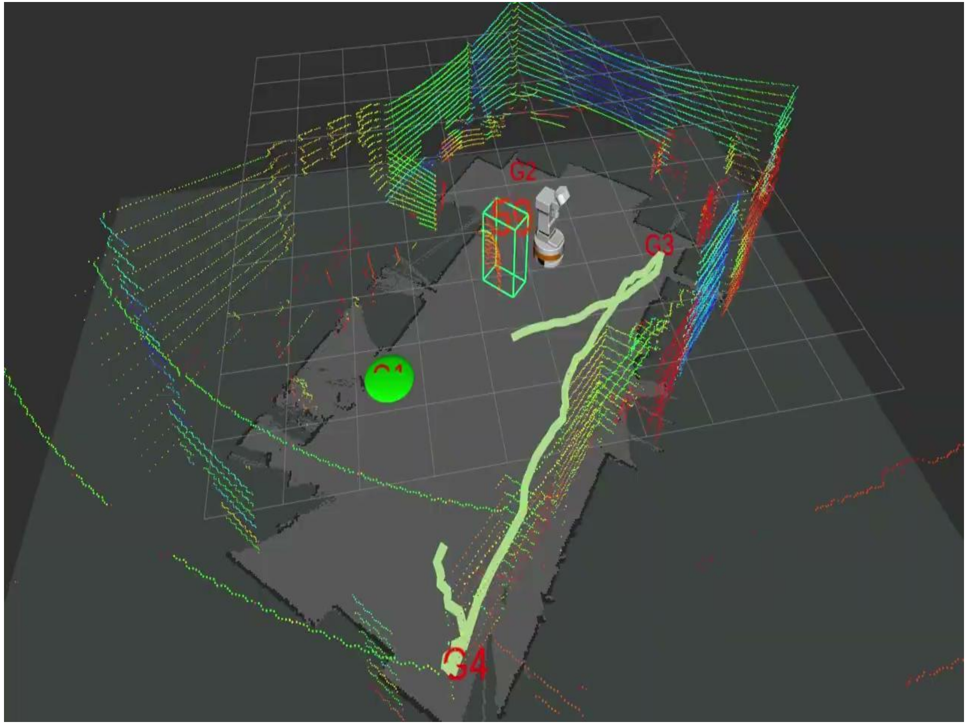
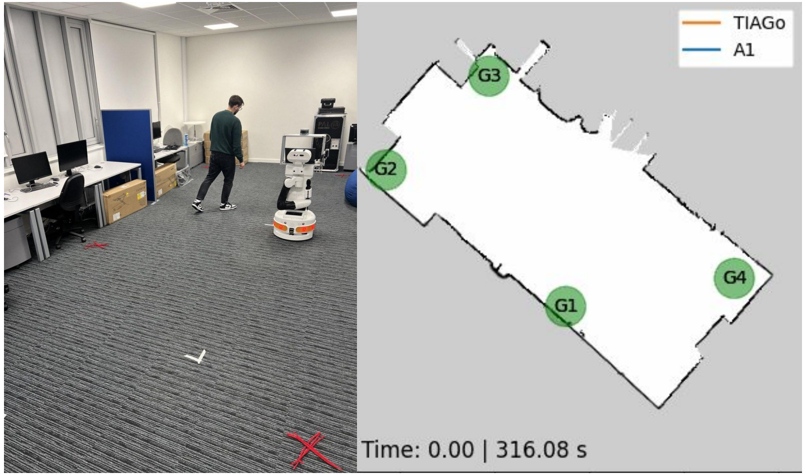
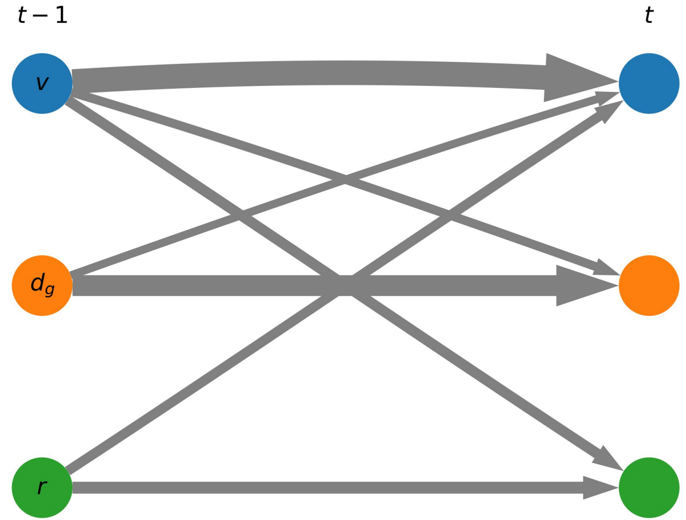
# Robotics Applications

## ROS-Causal





Castri, Luca, et al. "Experimental Evaluation of ROS-Causal in Real-World Human-Robot Spatial Interaction Scenarios" (2024).

# Reference


- Runge, J., Nowack, P., Kretschmer, M., Flaxman, S. and Sejdinovic, D., 2019. Detecting and quantifying causal associations in large nonlinear time series datasets. Science advances, 5(11).
- Castri, L., Mghames, S., Hanheide, M. and Bellotto, N., 2023. Enhancing Causal Discovery from Robot Sensor Data in Dynamic Scenarios. In 2nd Conference on Causal Learning and Reasoning.
- Castri, L., Beraldo, G., Mghames, S., Hanheide M. and Bellotto, N. 2024. Experimental Evaluation of ROS-Causal in Real-World Human-Robot Spatial Interaction Scenarios. In IEEE International Conference on Robot and Human Interactive Communication (RO-MAN).
- Castri, L., Mghames, S., Hanheide M. and Bellotto, N. 2024. CAnDOIT: Causal Discovery with Observational and Interventional Data from Time-Series, Advanced Intelligent Systems.


**CausalFlow**

**ROS-Causal**

Thank you!
questions?