# Enhancing Human-Robot Spatial Interaction through Causal Inference

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Website: ***https://darko-project.eu***
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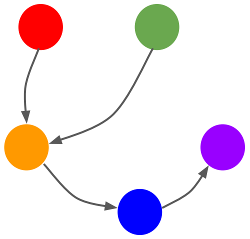
DARKO
Dynamic Agile Production Robots That Learn and Optimise Knowledge and Operations

# Outline



Motivation

Causal Inference overview

Causal Inference in Human-Robot Spatial Interaction

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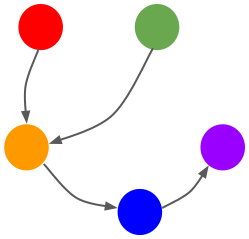


**Motivation**

Causal Inference overview

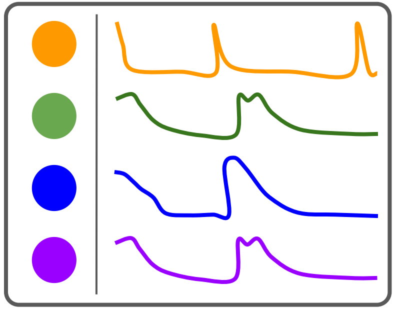
Causal Inference in Human-Robot Spatial Interaction

# Motivation – what is Causal Inference?

- What is it?

  **Science that studies the cause-and-effect relationship between events**
  [Pearl, J., & Mackenzie, D. (2019). The book of why]

- It is divided into two main areas:



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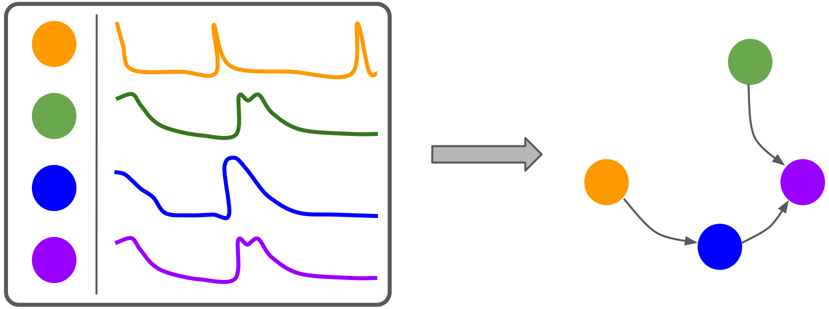

**Causal Discovery**
starting from a set of variables (events) aims to reconstruct the cause-effect model underlying them

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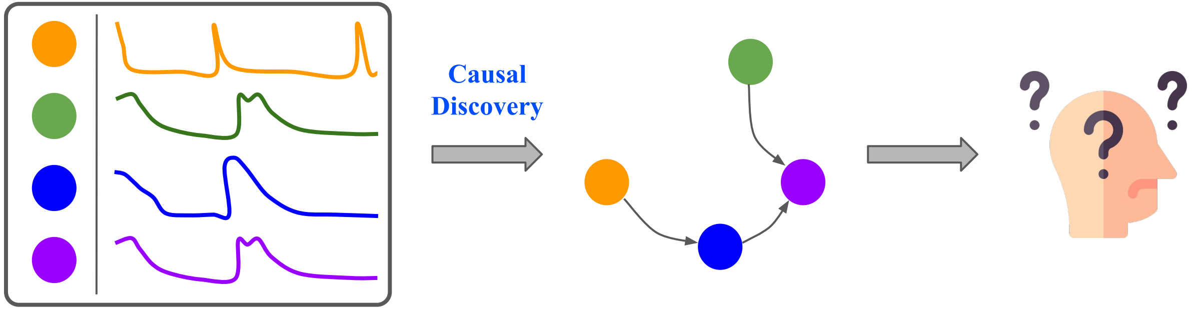


**Causal Reasoning**
reason on the causal model structure and on the cause-effect strength to predict how the observed system evolves

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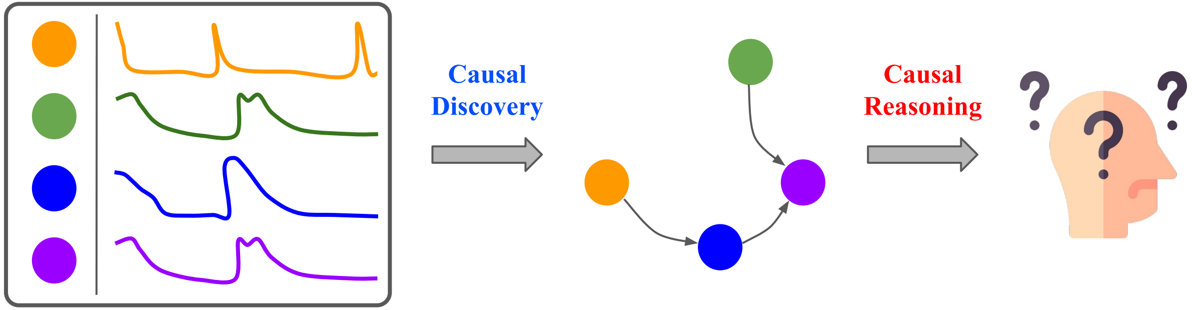

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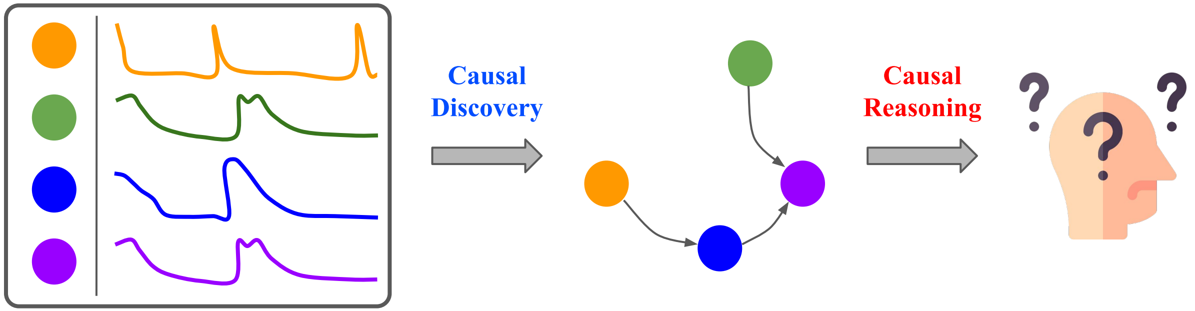
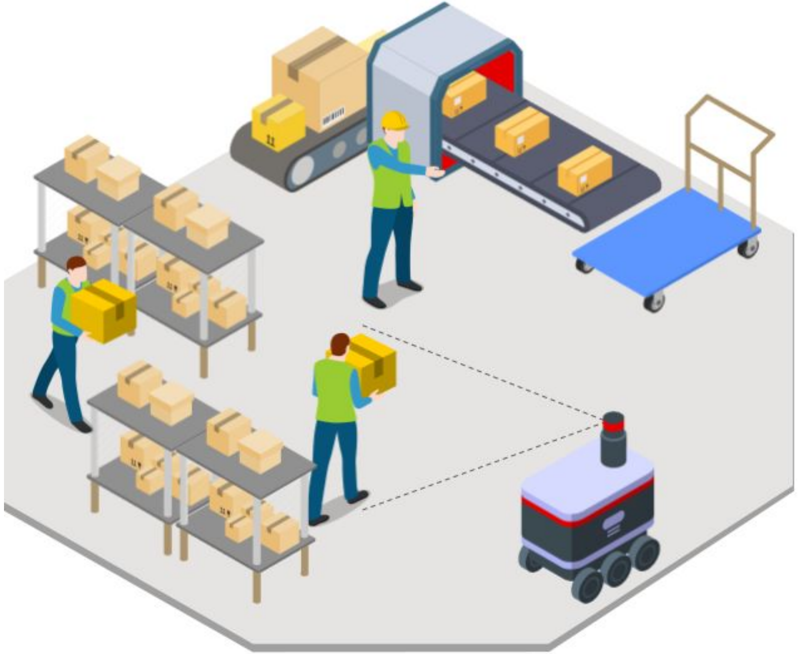



**Can robots benefit from Causal Inference ?**

# Motivation – robotics scenario



DARKO
Dynamic Agile Production Robots That Learn and Optimise Knowledge and Operations

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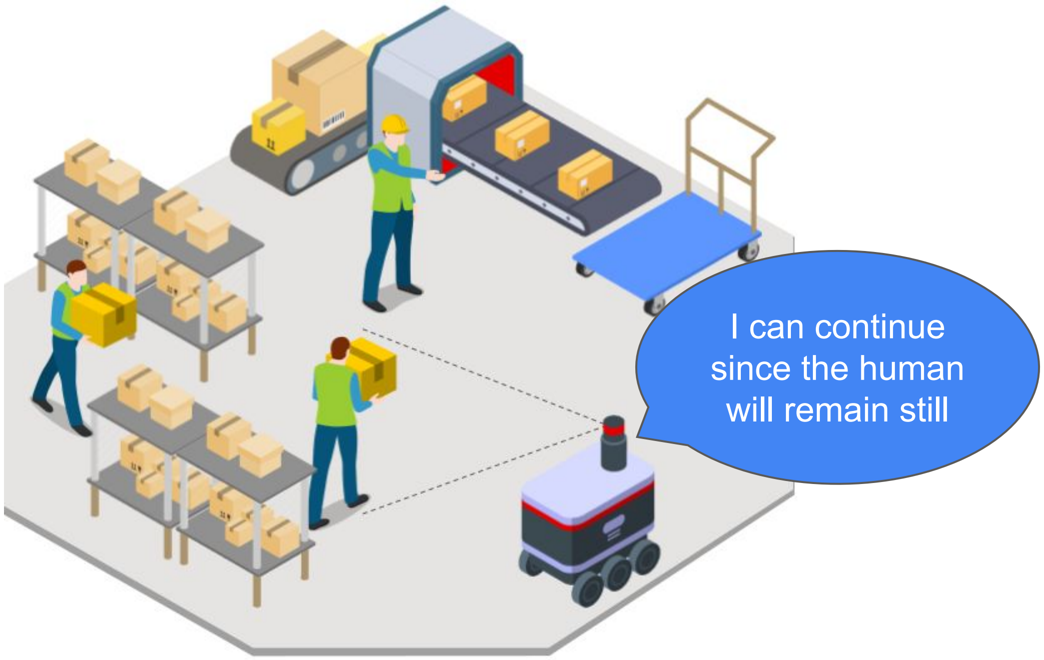

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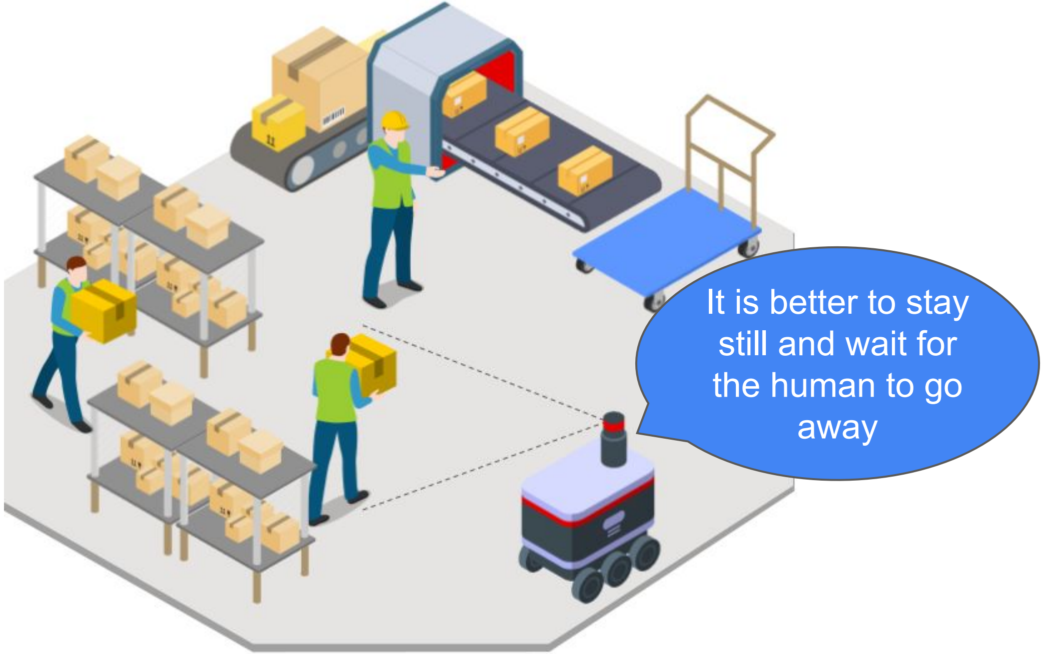
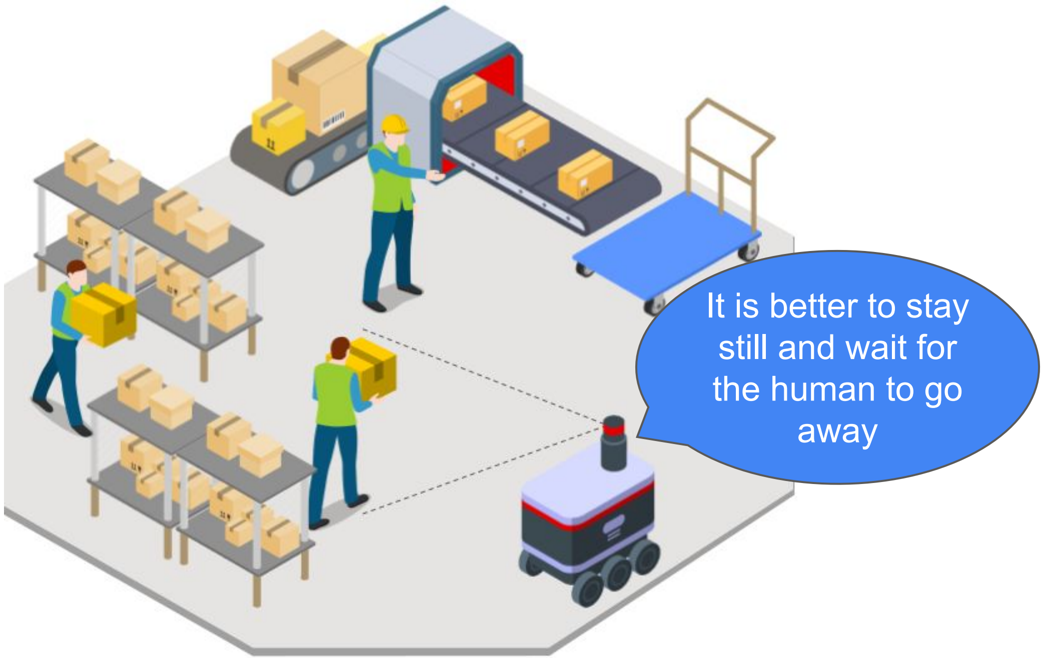


# Motivation – robotics scenario

Discovering the causal model will enable the robot to reason on it and to answer questions like:

- “what happens if I go this way?”
- “what would have happened if I remained still instead of moving?”




Dynamic Agile Production Robots That Learn and Optimise Knowledge and Operations

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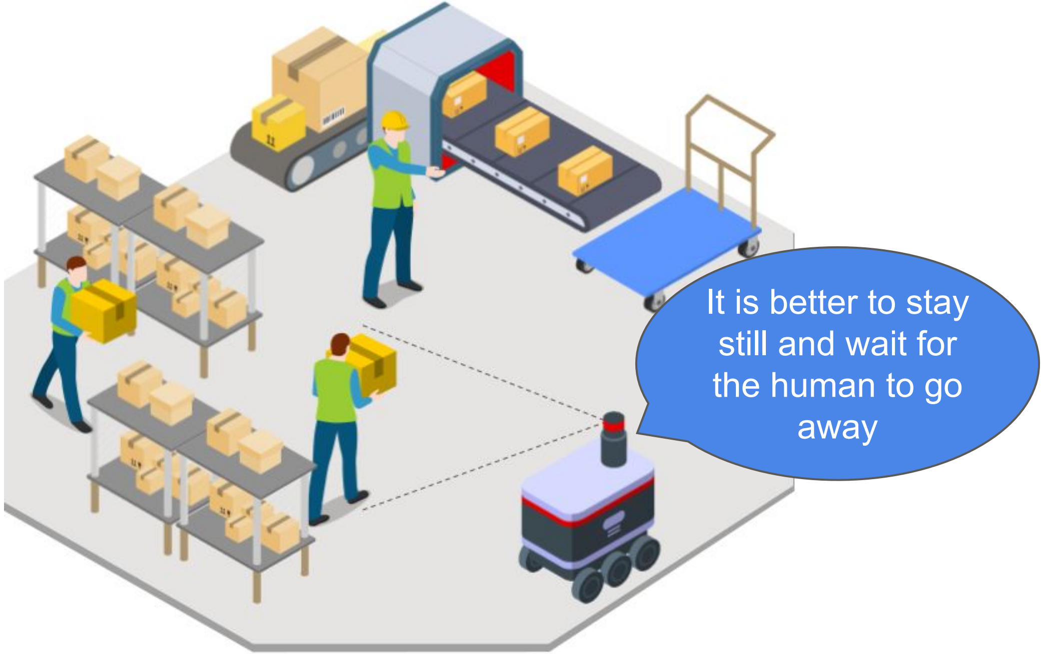
**take the best choice among possible HRSIs**

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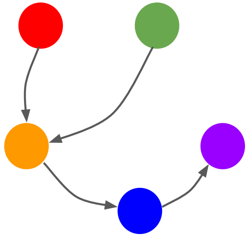


Motivation

**Causal Inference overview**

Causal Inference in Human-Robot Spatial Interaction

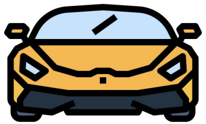
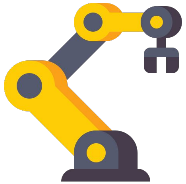
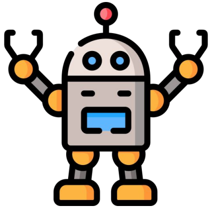
# Causal Inference overview – why is it important?

**Science that studies the cause-and-effect relationship between events**

- **Cause**: I never brush my teeth. **Effect**: I have 5 cavities.
- **Cause**: I've smoked cigarettes daily for 20 years. **Effect**: I have lung cancer.

**Humans reason causally**

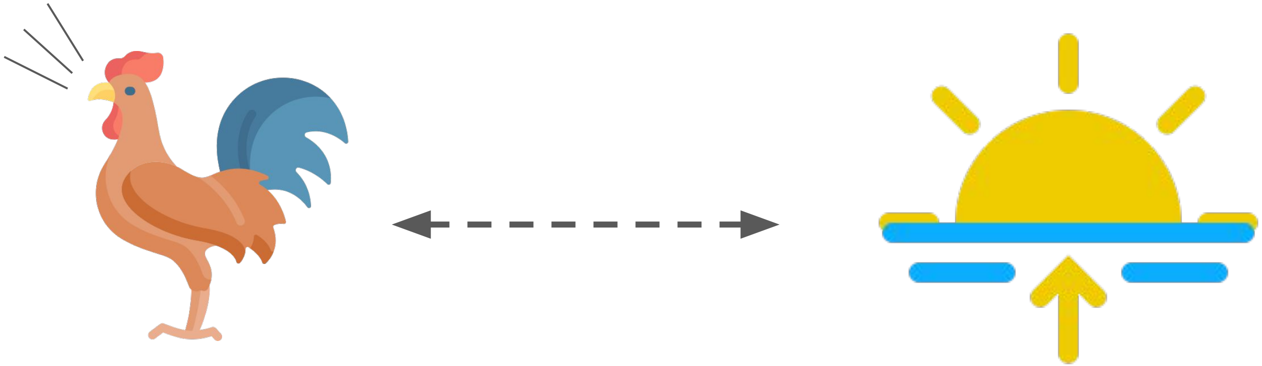
- What about machines? They simply analyse data

- Performing NON-causal analysis on data can lead to wrong relationships

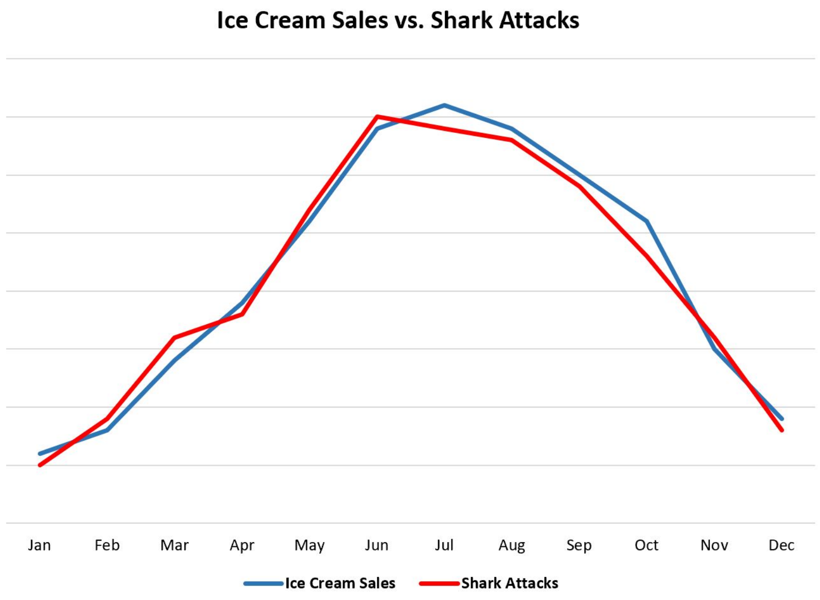
# Causal Inference overview – why is it important?

The cockcrow is **strongly** **associated** with sunrise



# Causal Inference overview – why is it important?

The ice cream sales is **strongly <u>associated</u>** with shark attacks



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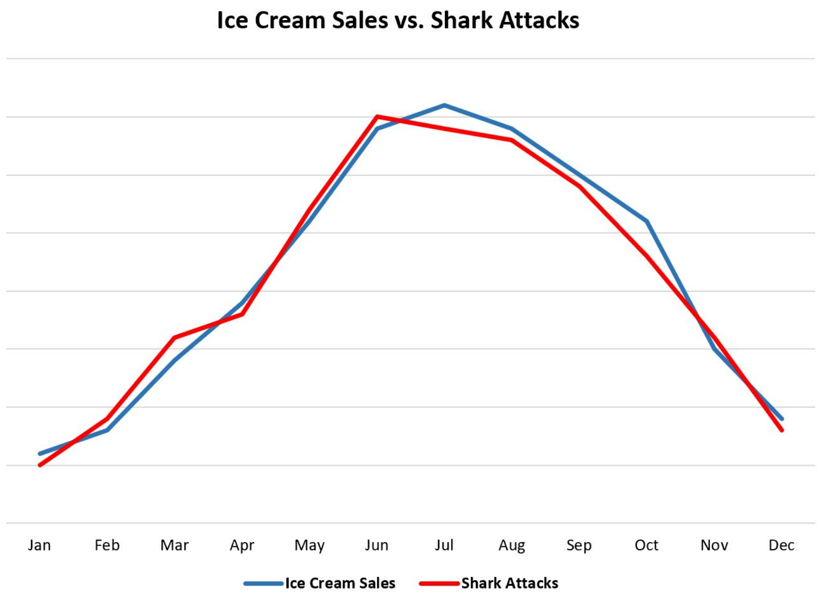


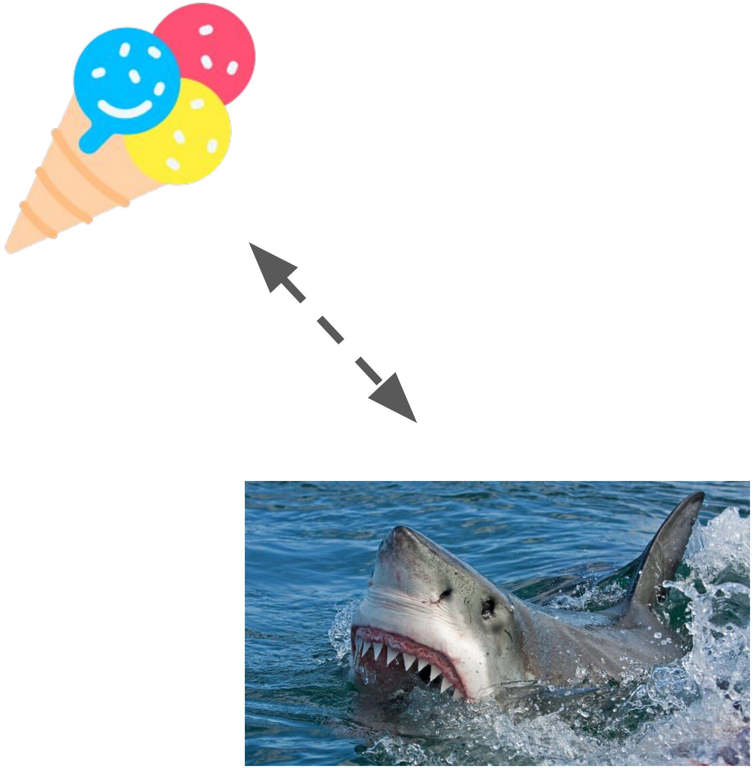

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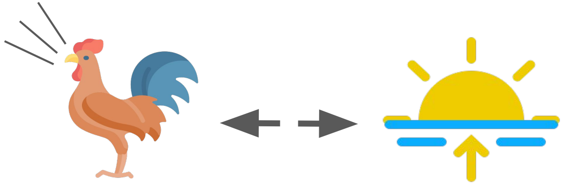
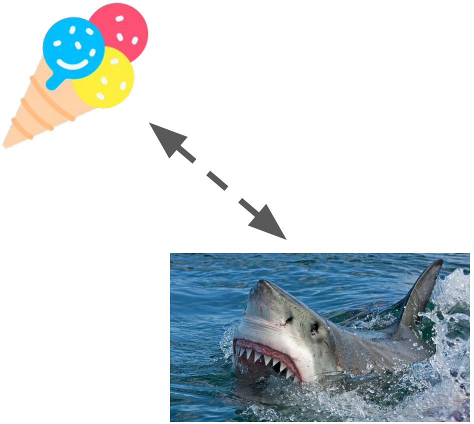


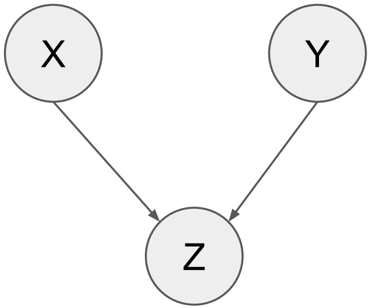
**Correlation**
**is not**
**Causation**



# Causal Inference overview – causal discovery

- What are we trying to discover? A **causal** graph
  data ➡ causal graph

| | X | Y | Z |
|---|---|---|---|
| **0** | 20.000000 | 100.0 | 340.000000 |
| **1** | 20.204082 | 100.0 | 340.408163 |
| **2** | 20.408163 | 100.0 | 340.816327 |
| **3** | 20.612245 | 100.0 | 341.224490 |
| **4** | 20.816327 | 100.0 | 341.632653 |
| **...** | ... | ... | ... |
| **2495** | 29.183673 | 300.0 | 958.367347 |
| **2496** | 29.387755 | 300.0 | 958.775510 |
| **2497** | 29.591837 | 300.0 | 959.183673 |
| **2498** | 29.795918 | 300.0 | 959.591837 |
| **2499** | 30.000000 | 300.0 | 960.000000 |



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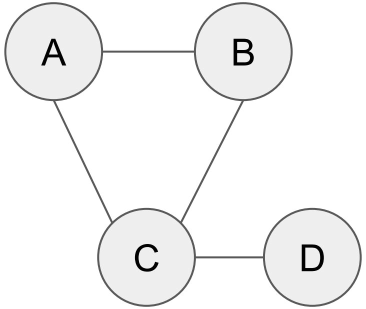
- What are we trying to discover? A **causal** graph
  Let's start from…

Undirected Graph



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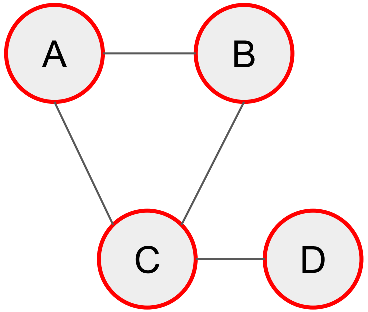


nodes

# Causal Inference overview – causal discovery

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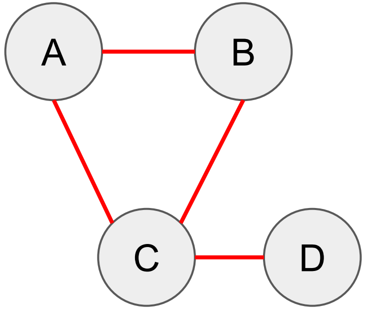


edges

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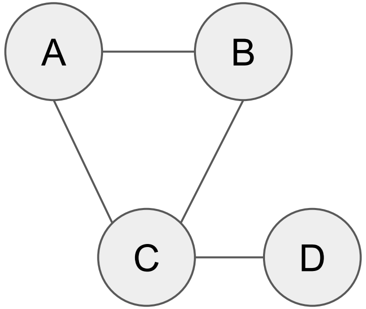


We don’t want this

# Causal Inference overview – causal discovery

- What are we trying to discover? A **causal** graph

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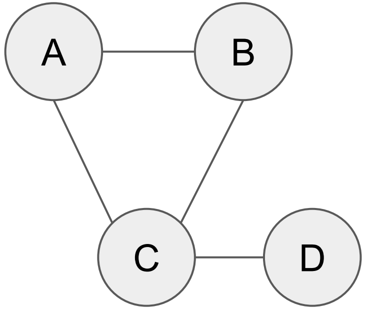
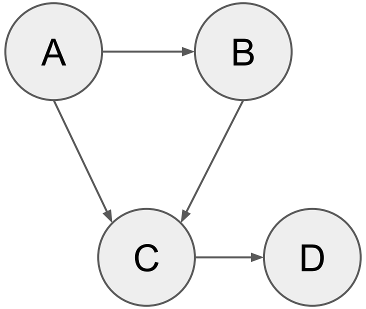



Directed Graph



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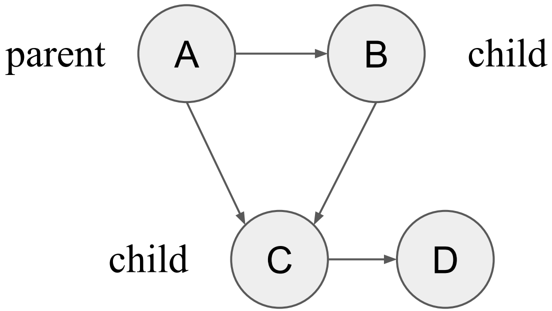

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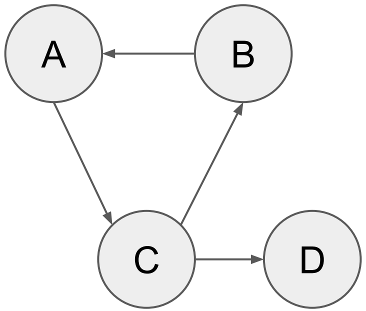
- What are we trying to discover? A **causal** graph

**We do not want cycles**

Directed Graph



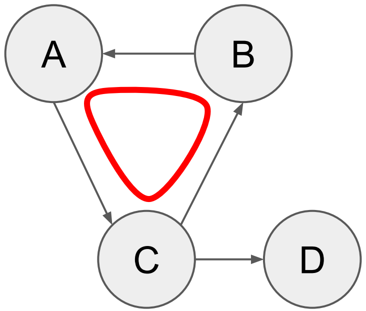
# Causal Inference overview – causal discovery

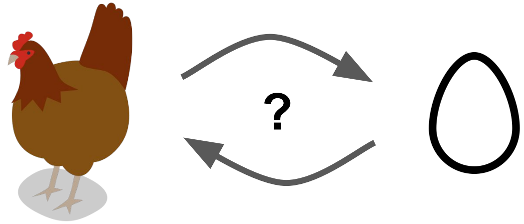
- What are we trying to discover? A **causal** graph

**We do not want cycles**

We need to guarantee the **acyclicity** assumption otherwise we can not distinguish between cause and effect

Directed Graph

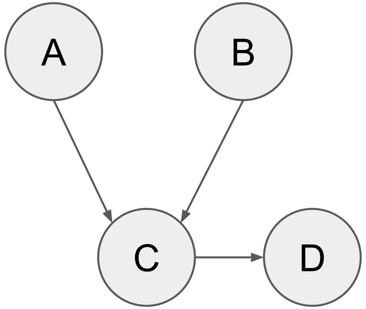


# Causal Inference overview – causal discovery

- What are we trying to discover? A **causal** graph

Directed Acyclic Graph (**DAG**)




- **Why “Direct”?**

  We need oriented edges otherwise they do not represent cause-and-effect relationships

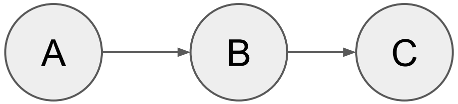
- **Why “Acyclic”?**

  We need to guarantee the **acyclicity** assumption otherwise we can not distinguish between cause and effect

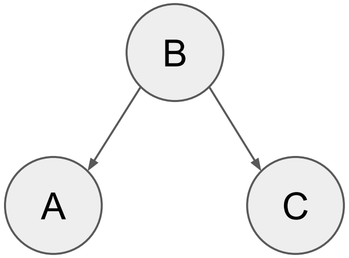
# Causal Inference overview – causal discovery

- DAG configurations

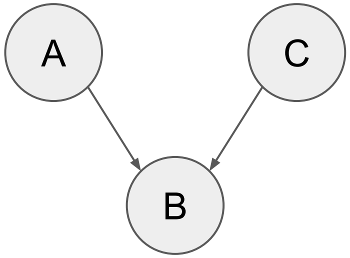
**Chain**




**Fork**




**Collider**



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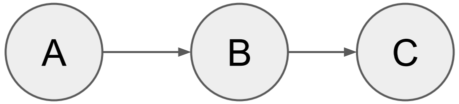


A is a direct cause of B
B is a direct cause of C

**What about A and C?**

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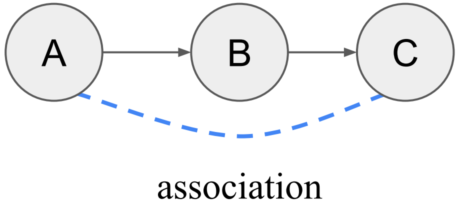


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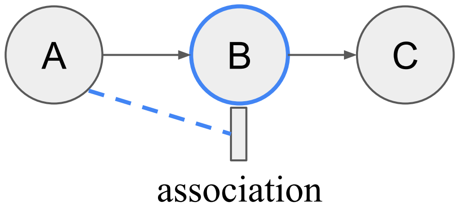


A is a direct cause of B
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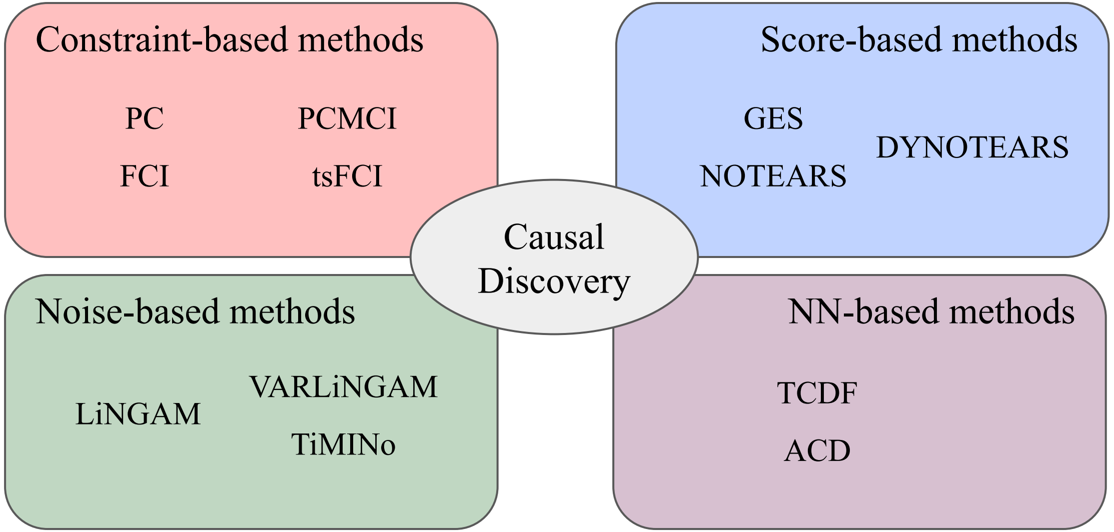
**What about A and C?**
They are associated (statistical dependent) through B

If we condition on B ⇒ A and C are conditionally independent

By conditioning on B, we are creating a **blocked** path. If we do not condition on B, the path from A to C is **unblocked** and the association is free to flow.

# Causal Inference overview – causal discovery

- How can we discover a causal graph from observational data?



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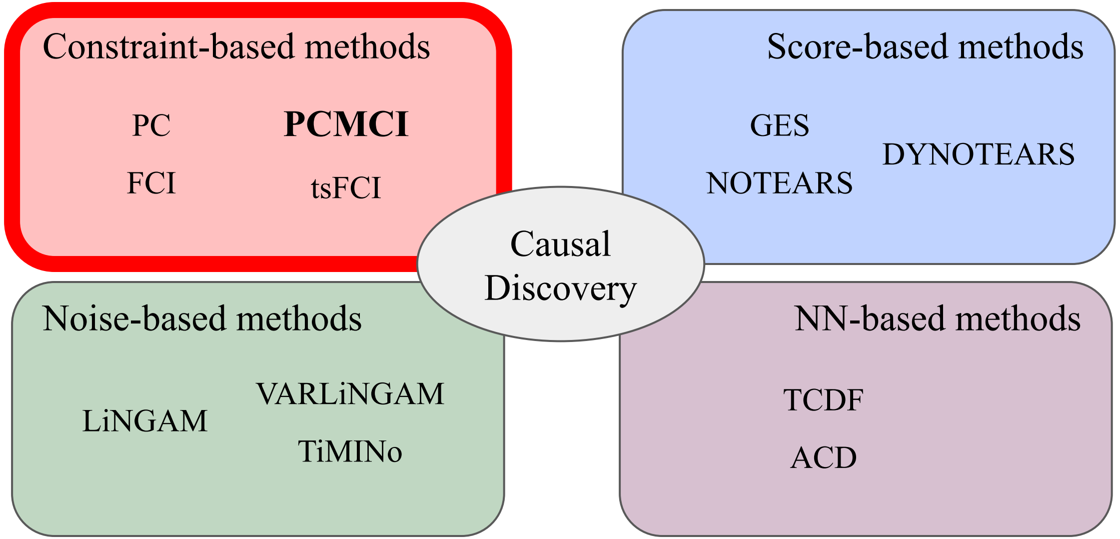

# Causal Inference overview – causal discovery

- 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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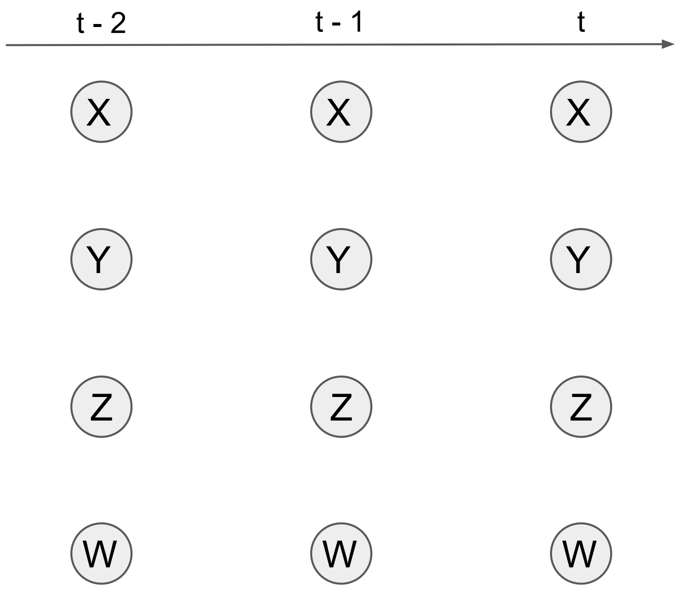

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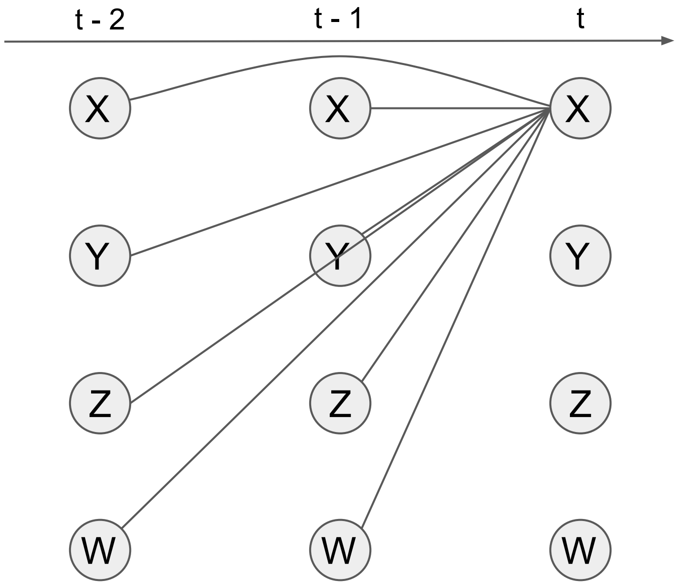

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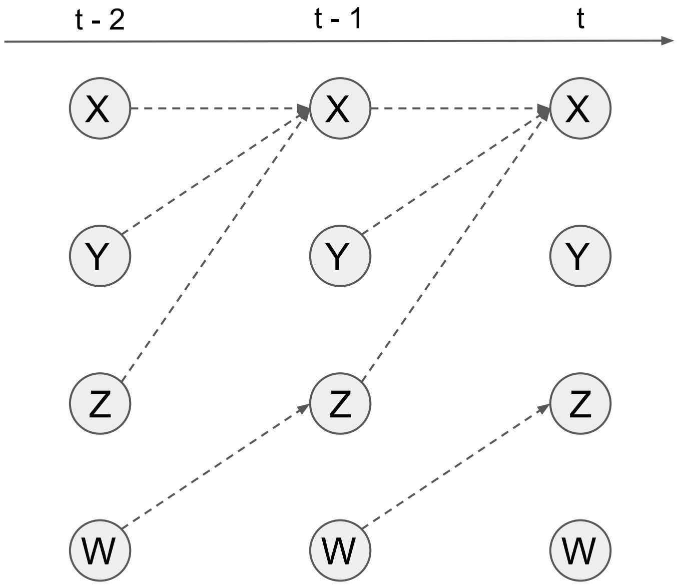

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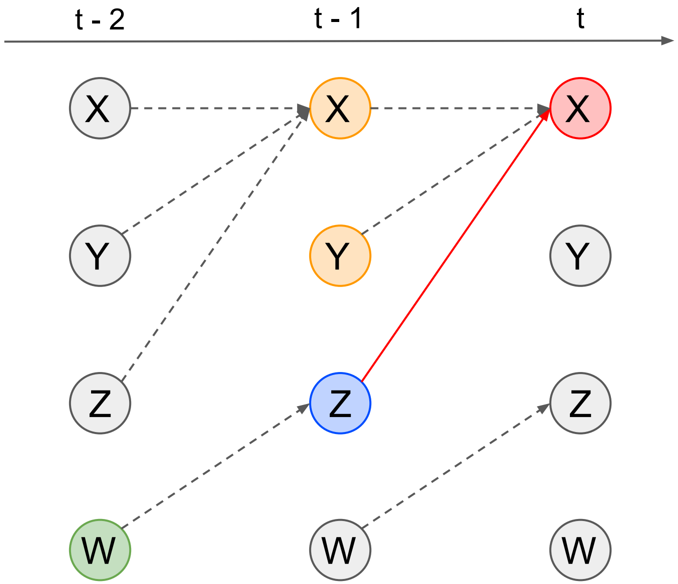

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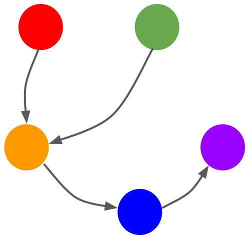

Motivation

Causal Inference overview

**Causal Inference in Human-Robot Spatial Interaction**

# Causal Inference in Human-Robot Spatial Interaction

Reconstructing causal models from time-series data of HRSIs → Can we speed up the causal discovery process? → The need of interventional data → …

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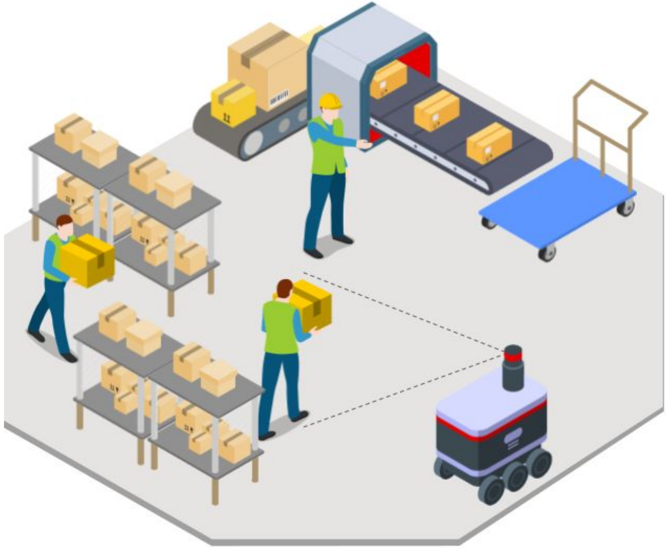
# Causal Inference in Human-Robot Spatial Interaction

## Reconstructing causal models from time-series data of HRSIs

**Aim**

enable the robot to understand human behaviours by discovering the cause-effect relationship between events during a Human-Robot Spatial Interaction (HRSI)



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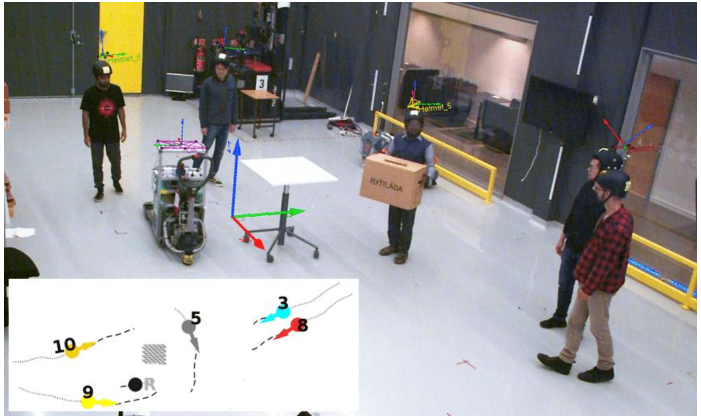
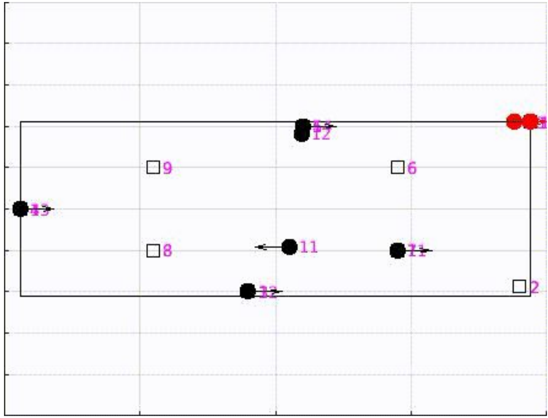
# Causal Inference in Human-Robot Spatial Interaction

## Reconstructing causal models from time-series data of HRSIs



THÖR Dataset [A. Rudenko et al. 2020]



**Single-agent scenario**
system variables:

$$\theta_g, d_g, v$$

expected cause-effect relationships:

$$\theta_g = f(\theta_g, d_g)$$
$$d_g = f(d_g, \theta_g, v)$$
$$v = f(v, \theta_g)$$

**Multi-agent scenario**
system variables:

$$d_g, v, risk$$

expected cause-effect relationships:

$$d_g = f(d_g, v)$$
$$v = f(v, d_g, risk)$$
$$risk = f(risk, v)$$

# Causal Inference in Human-Robot Spatial Interaction

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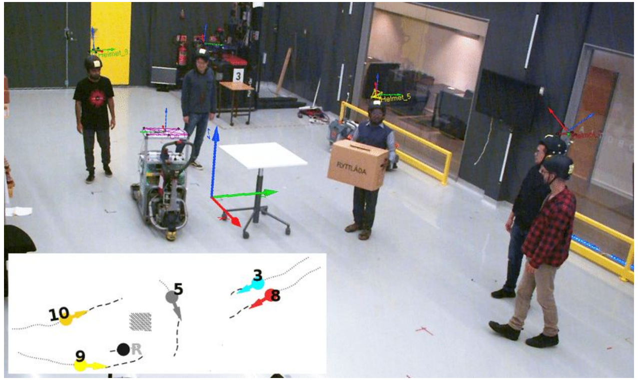
**THÖR**
warehouse-like environment




**ATC**
shopping centre


| SCENARIO | | | |
|---|---|---|---|
| DATASET | | Single-agent | Multi-agent |
| | THÖR | X | X |
| | ATC | X | |

Different scenario observed from the same dataset
➡ different causal models

Same scenario observed from different datasets
➡ same causal models

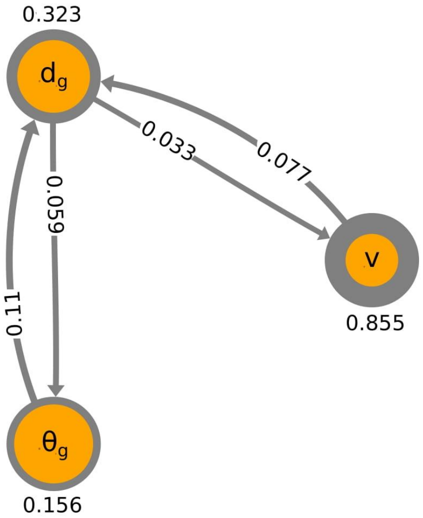
Different scenario observed from different datasets
➡ different causal models

# Causal Inference in Human-Robot Spatial Interaction

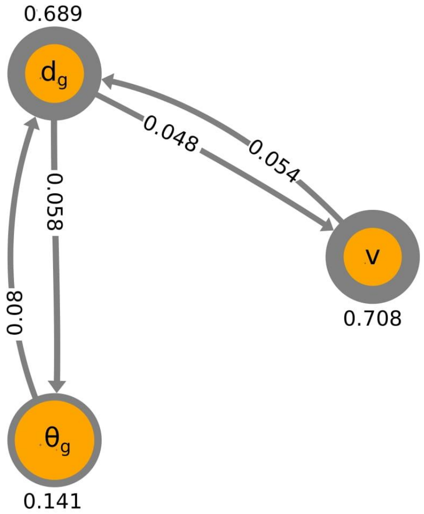
## Reconstructing causal models from time-series data of HRSIs

**τ = 1**

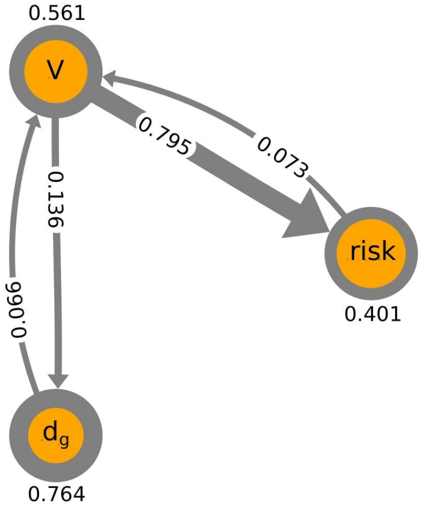
Single-agent
THÖR




Single-agent
ATC




Multi-agent
THÖR



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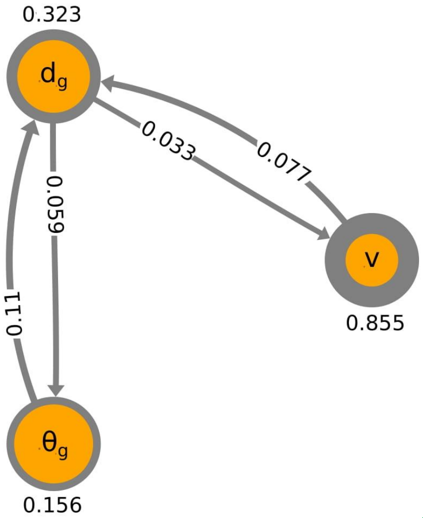
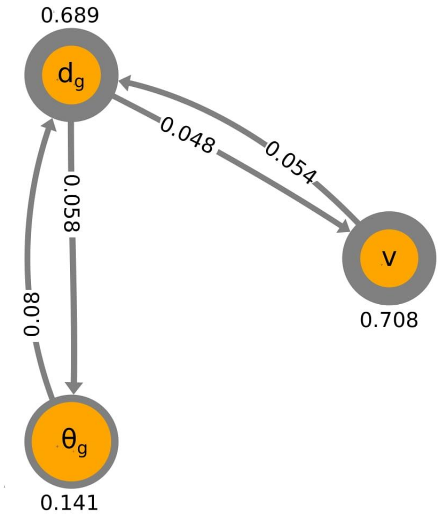
➡ different causal models

**$\tau = 1$**

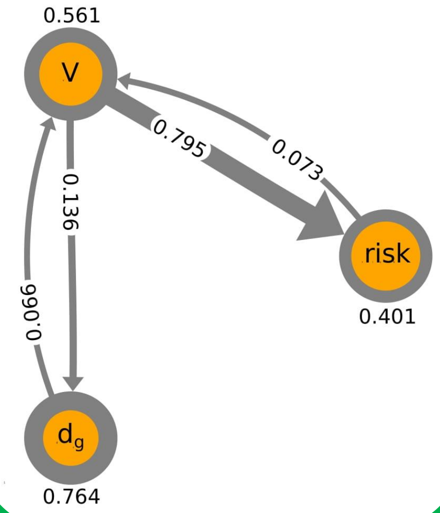
Single-agent THÖR




Single-agent ATC




Multi-agent THÖR



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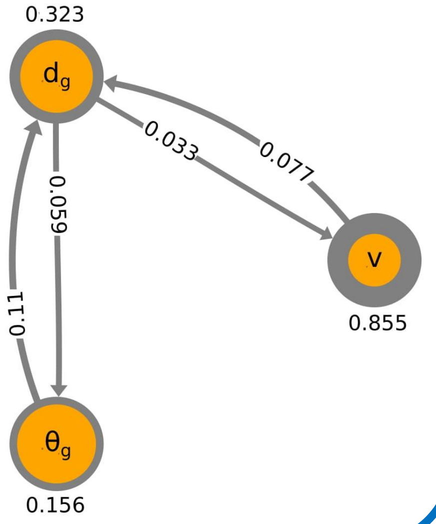
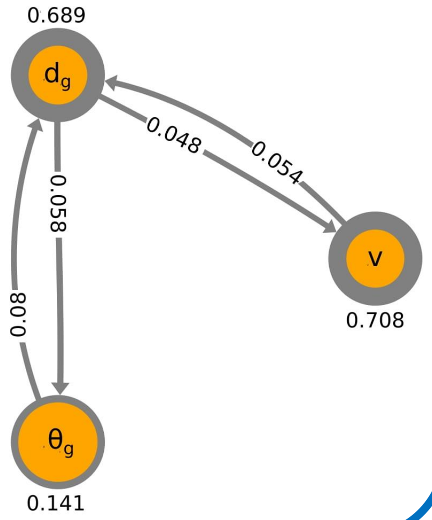
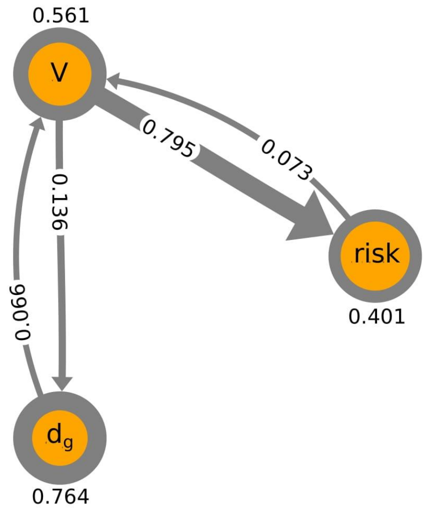



Single-agent ATC




Multi-agent THÖR



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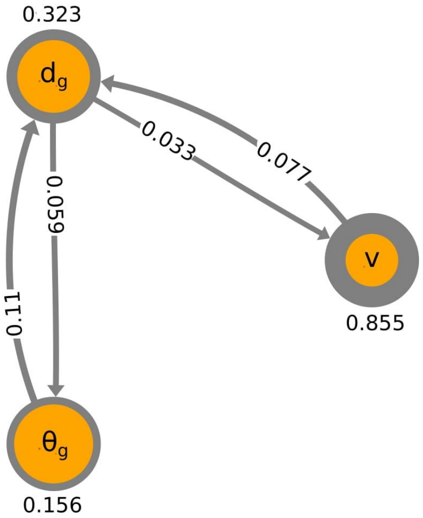
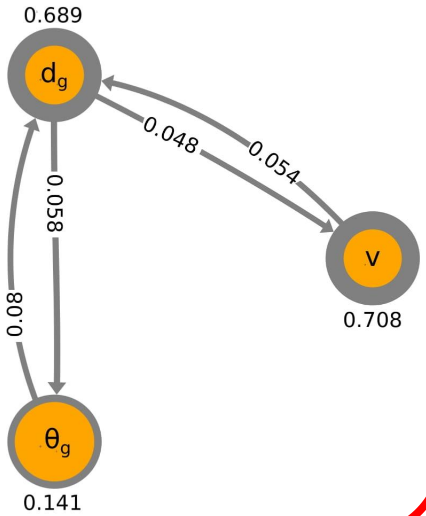
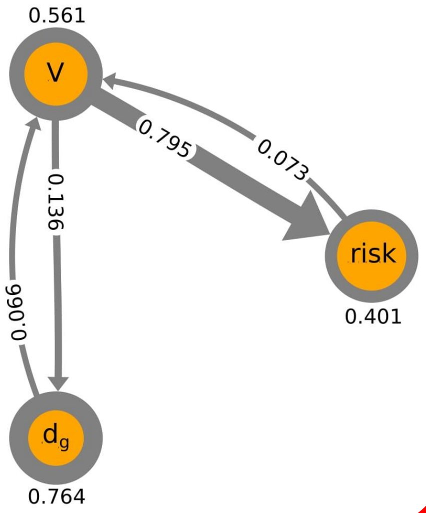



Single-agent
ATC

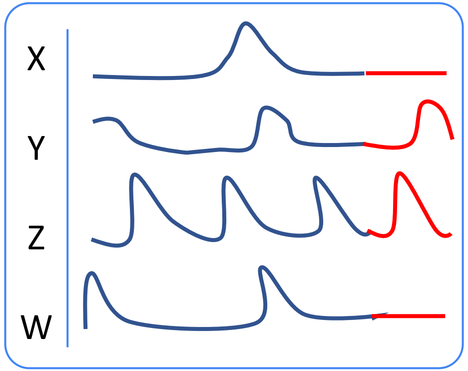



Multi-agent
THÖR



Gaussian Process Regressor:

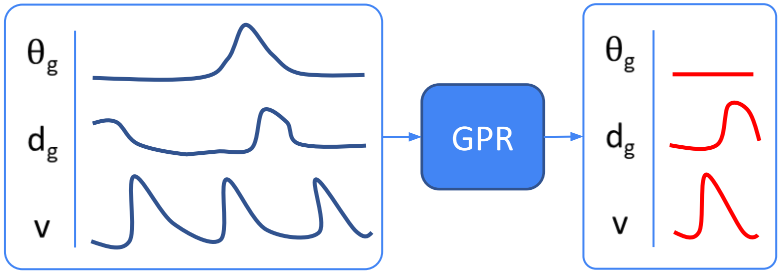
- supervised learning method designed to solve regression and probabilistic classification problems
- widely used for time-series prediction
- embedding the causal structure in the GPR ⇨ **Causal GPR**



# Causal Inference in Human-Robot Spatial Interaction

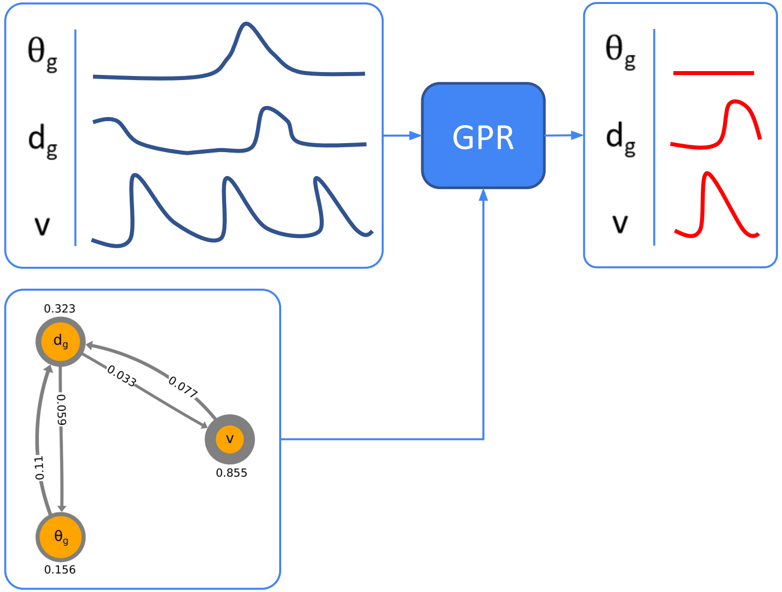
## Reconstructing causal models from time-series data of HRSIs

### Non-causal GPR approach




VS

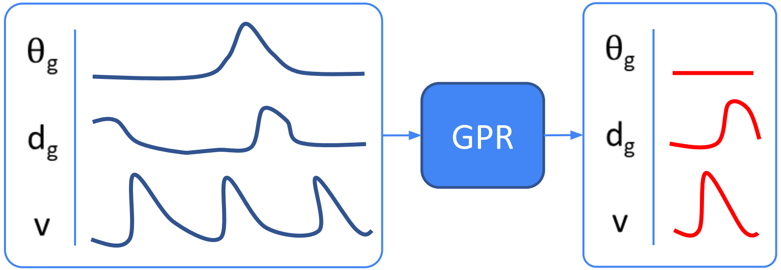
### Causal GPR approach



# Causal Inference in Human-Robot Spatial Interaction

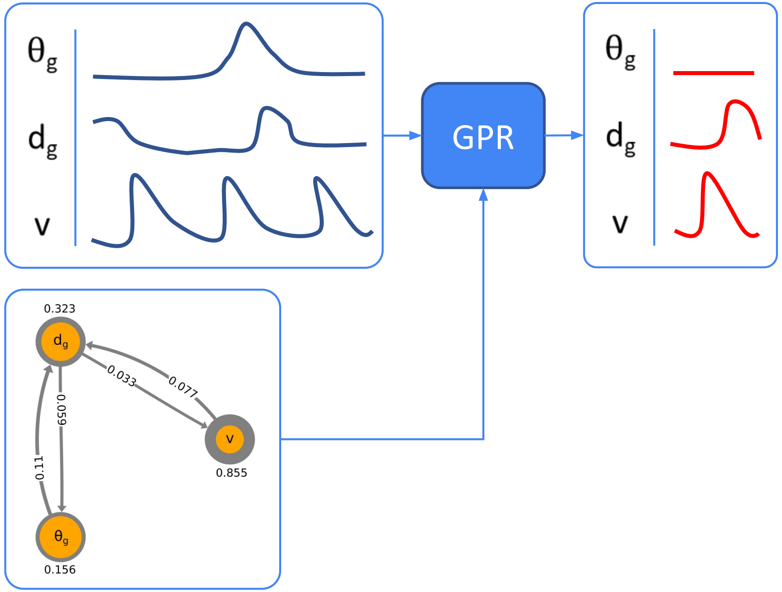
## Reconstructing causal models from time-series data of HRSIs

**Non-causal GPR approach**




VS

**Causal GPR approach**

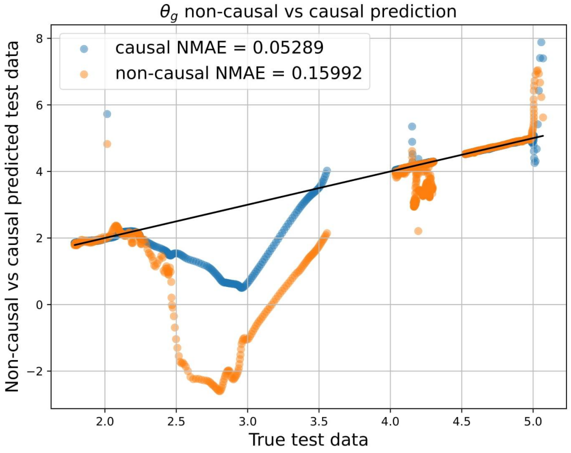


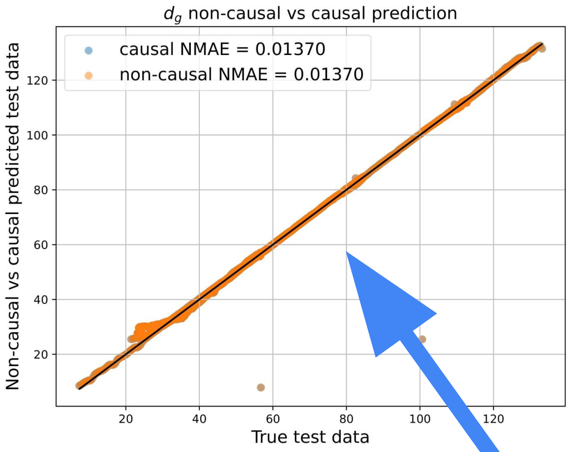

**Evaluation metric**

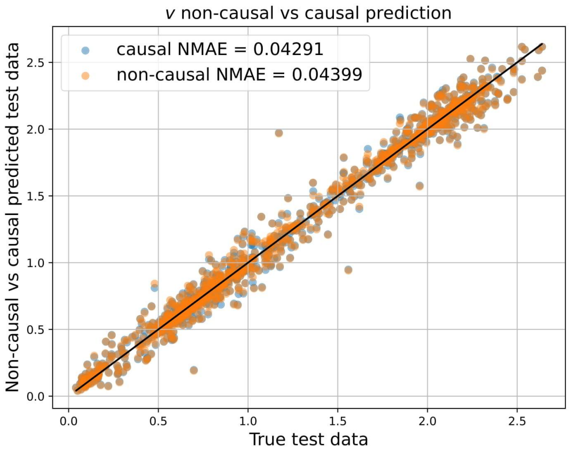
$$NMAE(y, \hat{y}) = \frac{\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{n}}{\frac{1}{n}\sum_{i=1}^{n} y_i}$$

# Causal Inference in Human-Robot Spatial Interaction

## Reconstructing causal models from time-series data of HRSIs

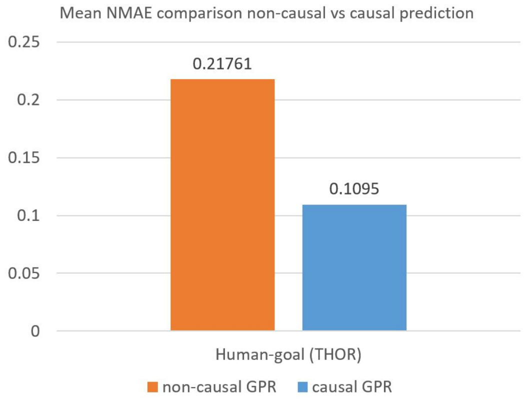



$d_g(t) = f(\theta_g, d_g, v)(t-1)$

→ No difference between non-causal and causal GPR




Mean across the NMAE for each variable

# Causal Inference in Human-Robot Spatial Interaction

## Reconstructing causal models from time-series data of HRSIs

- Non-causal vs causal GPR comparison for the scenarios:
  - Single-agent (THÖR)
  - Single-agent (ATC)
  - Multi-agent (THÖR)

| **Mean NMAE** | **Single-agent** | | **Multi-agent** |
|---|---|---|---|
| | THÖR | ATC | THÖR |
| Non-causal GPR | 0.21761 | 1.61692 | 0.37849 |
| Causal GPR | **0.1095** | **1.54552** | **0.36453** |

# Causal Inference in Human-Robot Spatial Interaction

## Reconstructing causal models from time-series data of HRSIs

- Non-causal vs causal GPR comparison for the scenarios:
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| Non-causal GPR | 0.21761 | 1.61692 | 0.37849 |
| Causal GPR | **0.1095** | **1.54552** | **0.36453** |

~ -50%
prediction error

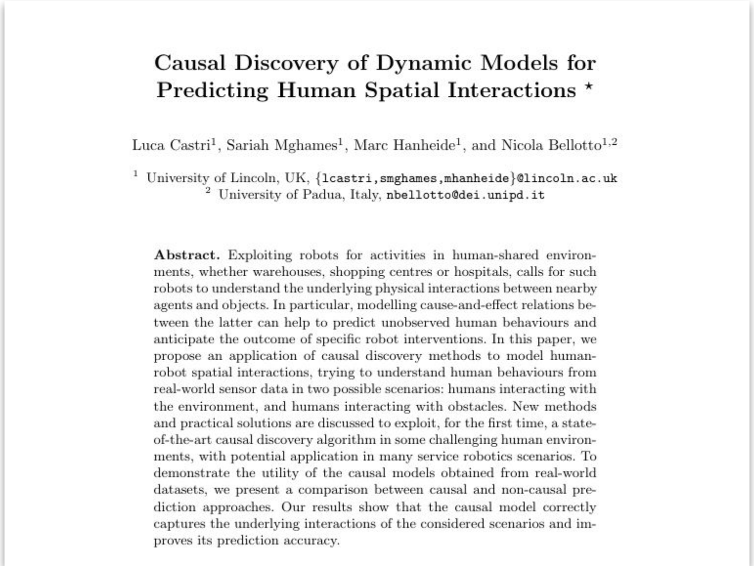
~ -4%
prediction error

## Summing up

- First application of a causal discovery method to real-world sensor data for modelling HRSI
- New causal models from HRSI

## Main limitation

- The PCMCI causal discovery is extremely demanding in terms of computational cost and hardware resources



Causal Discovery of Dynamic Models for Predicting Human Spatial Interactions *

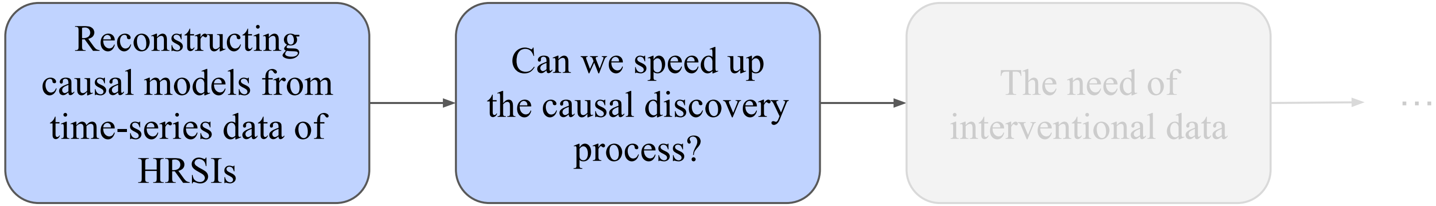
Luca Castri[1], Sariah Mghames[1], Marc Hanheide[1], and Nicola Bellotto[1,2]

[1] University of Lincoln, UK, {lcastri,smghames,mhanheide}@lincoln.ac.uk
[2] University of Padua, Italy, nbellotto@dei.unipd.it

**Abstract.** Exploiting robots for activities in human-shared environments, whether warehouses, shopping centres or hospitals, calls for such robots to understand the underlying physical interactions between nearby agents and objects. In particular, modelling cause-and-effect relations between the latter can help to predict unobserved human behaviours and anticipate the outcome of specific robot interventions. In this paper, we propose an application of causal discovery methods to model human-robot spatial interactions, trying to understand human behaviours from real-world sensor data in two possible scenarios: humans interacting with the environment, and humans interacting with obstacles. New methods and practical solutions are discussed to exploit, for the first time, a state-of-the-art causal discovery algorithm in some challenging human environments, with potential application in many service robotics scenarios. To demonstrate the utility of the causal models obtained from real-world datasets, we present a comparison between causal and non-causal prediction approaches. Our results show that the causal model correctly captures the underlying interactions of the considered scenarios and improves its prediction accuracy.

L. Castri, S. Mghames, M. Hanheide, and N. Bellotto
"Causal discovery of dynamic models for predicting human spatial interactions,"
in International Conference on Social Robotics (ICSR), 2022.

# Causal Inference in Human-Robot Spatial Interaction



# Causal Inference in Human-Robot Spatial Interaction

## Can we speed up the causal discovery process?

**Motivation**

Causal analysis of complex and dynamical systems is extremely demanding in terms of time and hardware resources, making it a challenge for autonomous robotics with limited hardware resources and real-time requirements.

None of the state-of-the-art approaches extracts both the important features representing the system and the causal association between them, while at the same time taking into account the execution time and the computational cost for completing the task.

DARKO
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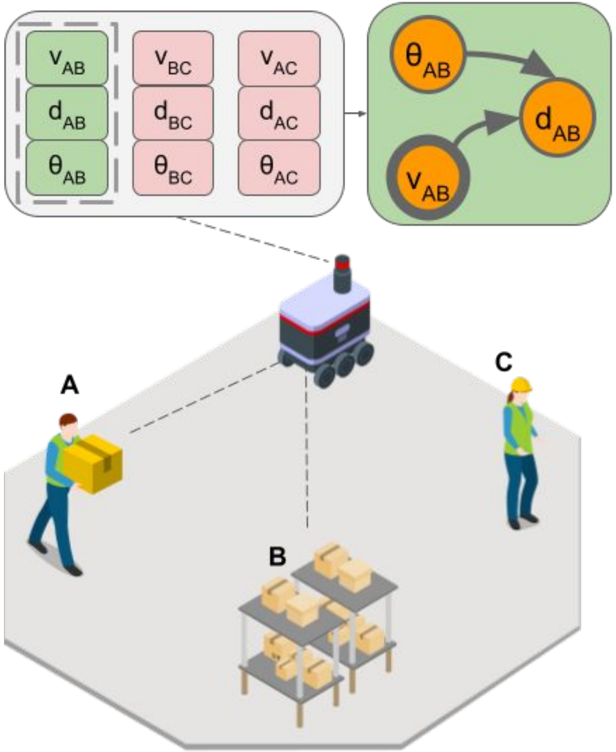
# Causal Inference in Human-Robot Spatial Interaction

## Can we speed up the causal discovery process?

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




DARKO
Dynamic Agile Production Robots That Learn and Optimise Knowledge and Operations

# Causal Inference in Human-Robot Spatial Interaction

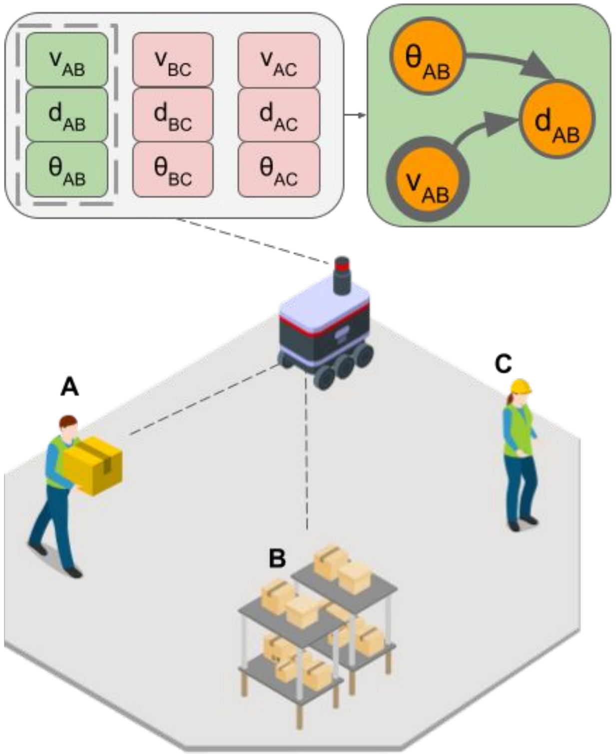
## Can we speed up the causal discovery process?

**Aim**

Create an all-in-one algorithm able to:

- select the most meaningful features from a prefixed set of variables
- build a causal model from such selection

in order to enhance speed and accuracy of the causal discovery and make it more efficient and feasible for robotics applications.




DARKO
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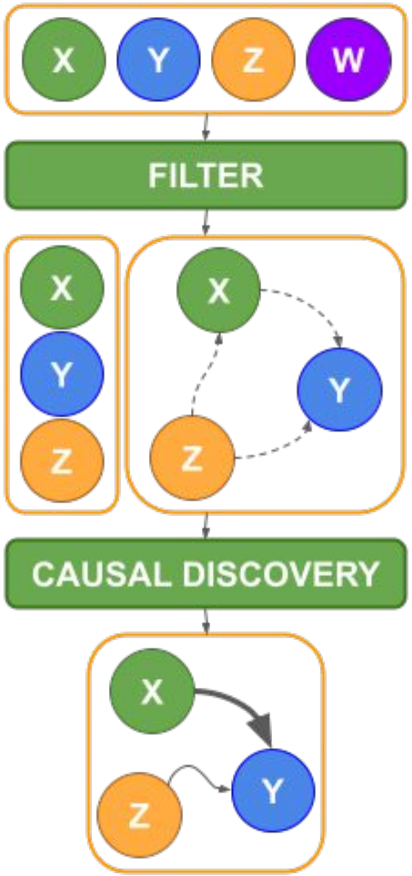
## Can we speed up the causal discovery process?

**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 latter needs to be validated by a proper causal analysis, which is performed by the PCMCI causal discovery algorithm

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



# Causal Inference in Human-Robot Spatial Interaction

## Can we speed up the causal discovery process?

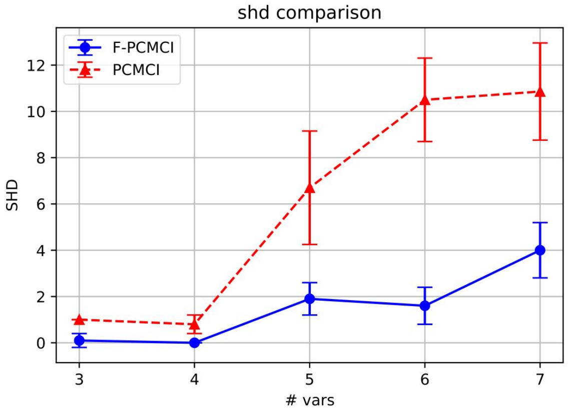
### PCMCI vs F-PCMCI

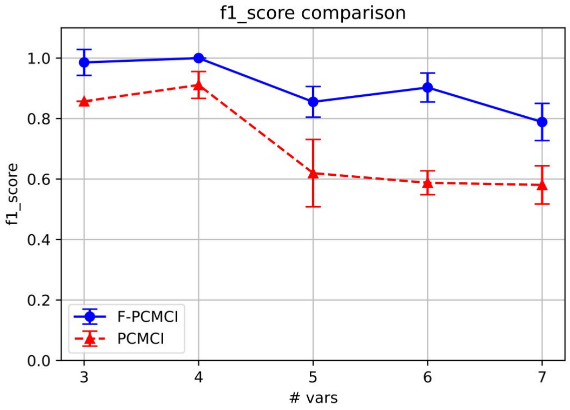
The correctness of our approach was evaluated based on toy problems with known ground-truth causal models. Various types of dependencies:

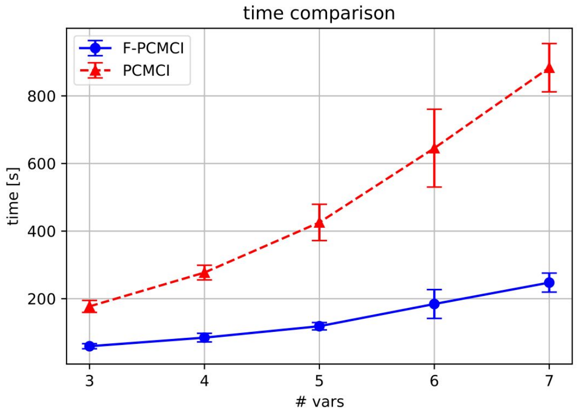
- linear and non-linear cross- and auto-dependency;
- noise-only equations;
- independent and dependent equations;
- different time-lag dependencies.

The analysis was carried out considering a number of system variables varying between 3 and 7. For each configuration, we performed 10 run tests with random system coefficients, using as evaluation metrics the mean over all the tests of:

- Structural Hamming Distance SHD;
- F1-score;
- execution time (in secs).



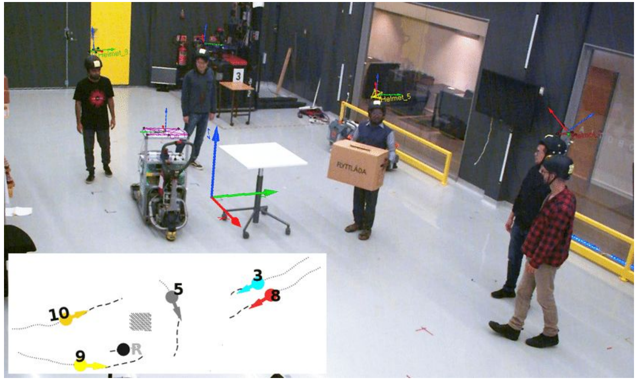
# Causal Inference in Human-Robot Spatial Interaction

## Can we speed up the causal discovery process?

### Modeling Real-world Human Spatial Interactions

We used our approach to model and predict spatial interactions. This application involves three steps:

- extracting time-series of sensor data from human spatial interaction scenarios using the THÖR dataset;
- reconstruct the causal model using F-PCMCI;
- embedding the causal model in a LSTM-based prediction system.



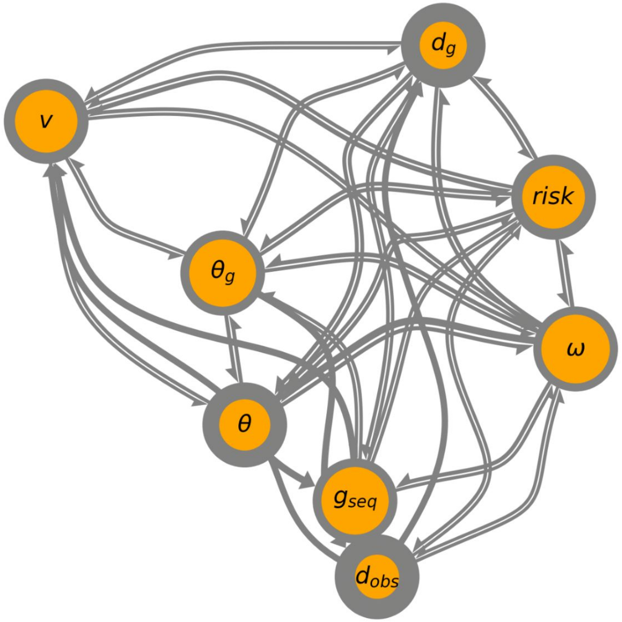

In order to represent human spatial interactions, for each agent we considered 8 variables, which were then used in the causal analysis.

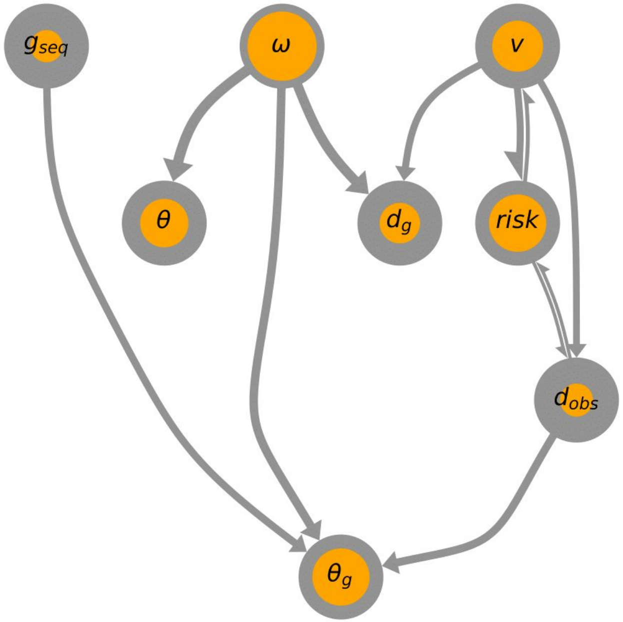
| | | | |
|---|---|---|---|
| $\mathbf{d_g}$ | distance to goal | $\boldsymbol{\theta_g}$ | angle to goal |
| $\mathbf{v}$ | velocity | $\boldsymbol{\omega}$ | angular velocity |
| **risk** | collision risk | $\mathbf{g_{seq}}$ | goal position sequence |
| $\boldsymbol{\theta}$ | orientation | $\mathbf{d_{obs}}$ | distance to closest obstacle |

# Causal Inference in Human-Robot Spatial Interaction

## Can we speed up the causal discovery process?

### Modeling Real-world Human Spatial Interactions




| PCMCI execution time 79’45” | **F-PCMCI execution time 17’33”** |
|---|---|

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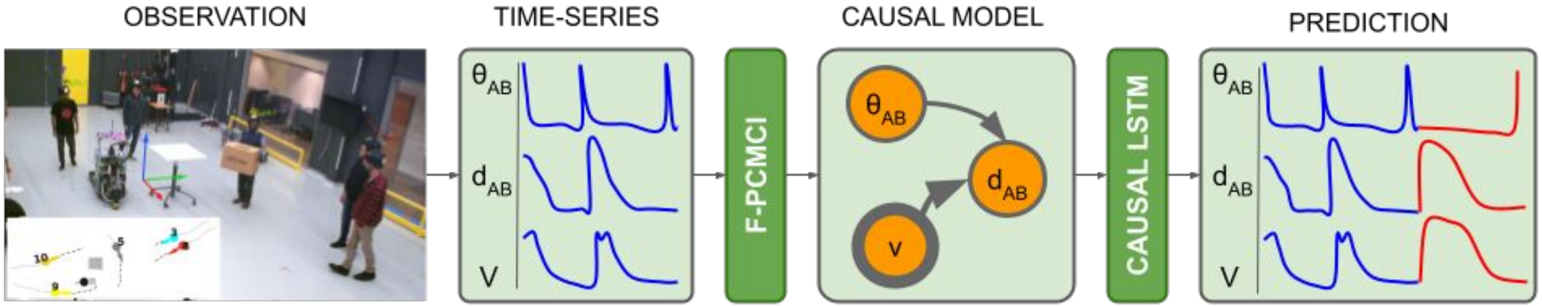
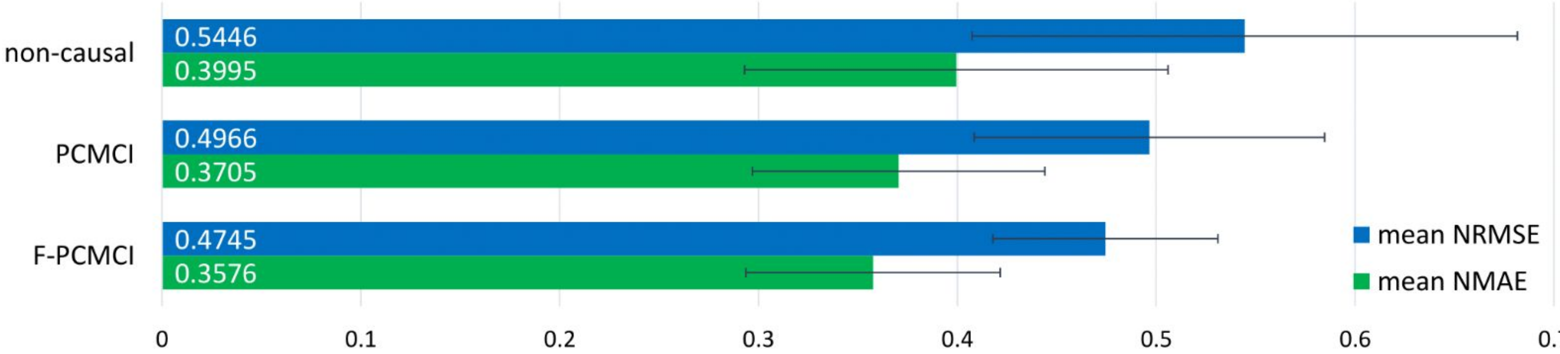
## Can we speed up the causal discovery process?

### Modeling Real-world Human Spatial Interactions



## Can we speed up the causal discovery process?

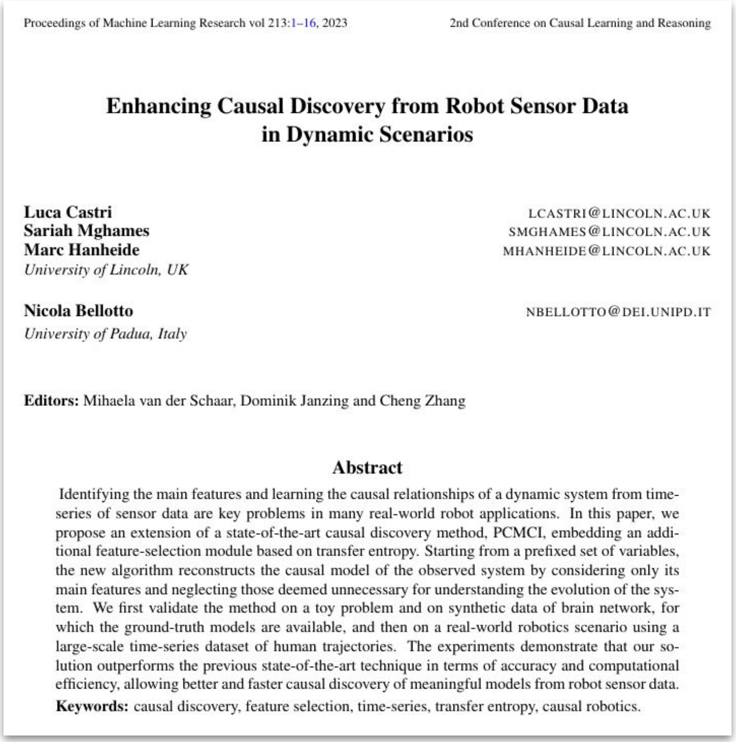
### Summing up

- We extended and improved a state-of-the-art causal discovery algorithm, PCMCI, embedding an additional feature-selection module based on transfer entropy

- **F-PCMCI**
  https://github.com/lcastri/fpcmci
  `pip install fpcmci`

### Main limitation

- We are not exploiting the full power of causal inference: **the intervention**


Proceedings of Machine Learning Research vol 213:1–16, 2023 2nd Conference on Causal Learning and Reasoning

**Enhancing Causal Discovery from Robot Sensor Data in Dynamic Scenarios**

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**Marc Hanheide** MHANHEIDE@LINCOLN.AC.UK
*University of Lincoln, UK*

**Nicola Bellotto** NBELLOTTO@DEI.UNIPD.IT
*University of Padua, Italy*

**Editors:** Mihaela van der Schaar, Dominik Janzing and Cheng Zhang

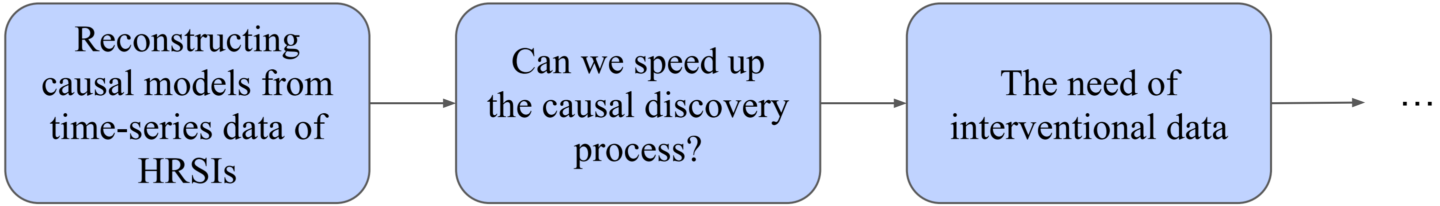
**Abstract**

Identifying the main features and learning the causal relationships of a dynamic system from time-series of sensor data are key problems in many real-world robot applications. In this paper, we propose an extension of a state-of-the-art causal discovery method, PCMCI, embedding an additional feature-selection module based on transfer entropy. Starting from a prefixed set of variables, the new algorithm reconstructs the causal model of the observed system by considering only its main features and neglecting those deemed unnecessary for understanding the evolution of the system. We first validate the method on a toy problem and on synthetic data of brain network, for which the ground-truth models are available, and then on a real-world robotics scenario using a large-scale time-series dataset of human trajectories. The experiments demonstrate that our solution outperforms the previous state-of-the-art technique in terms of accuracy and computational efficiency, allowing better and faster causal discovery of meaningful models from robot sensor data.

**Keywords:** causal discovery, feature selection, time-series, transfer entropy, causal robotics.

L. Castri, S. Mghames, M. Hanheide, and N. Bellotto, "Enhancing causal discovery from robot sensor data in dynamic scenarios," in Conference on Causal Learning and Reasoning, 2023.

# Causal Inference in Human-Robot Spatial Interaction



The need of interventional data

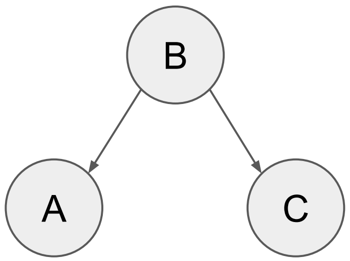
**Motivation**

a primary limitation of the current state-of-the-art algorithms is that they can only handle **observational data**.

The latter are often insufficient to retrieve the correct causal model in complex scenarios where it is impossible to account for all the variables responsible for the system's evolution. In such cases, data from experiments, i.e. **interventional data**, are needed to eliminate spurious links and enhance the quality of the causal model

**Example**

Hidden confounder scenario



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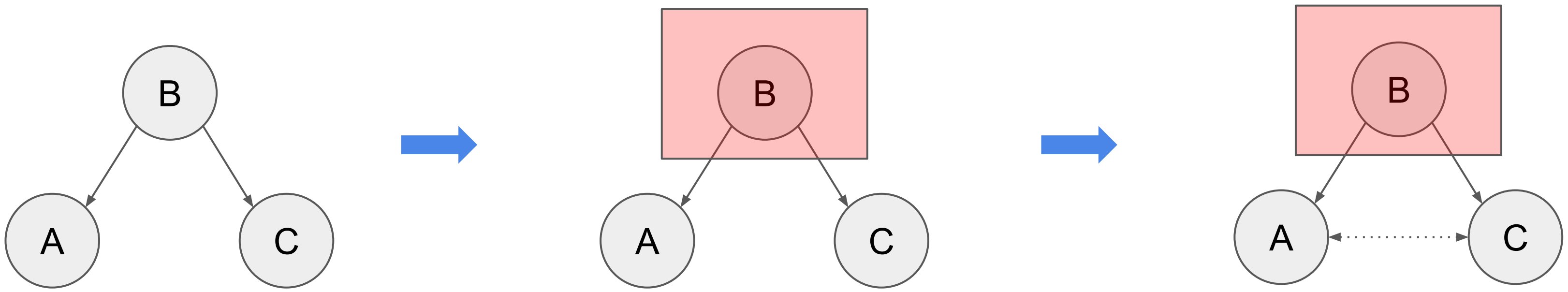

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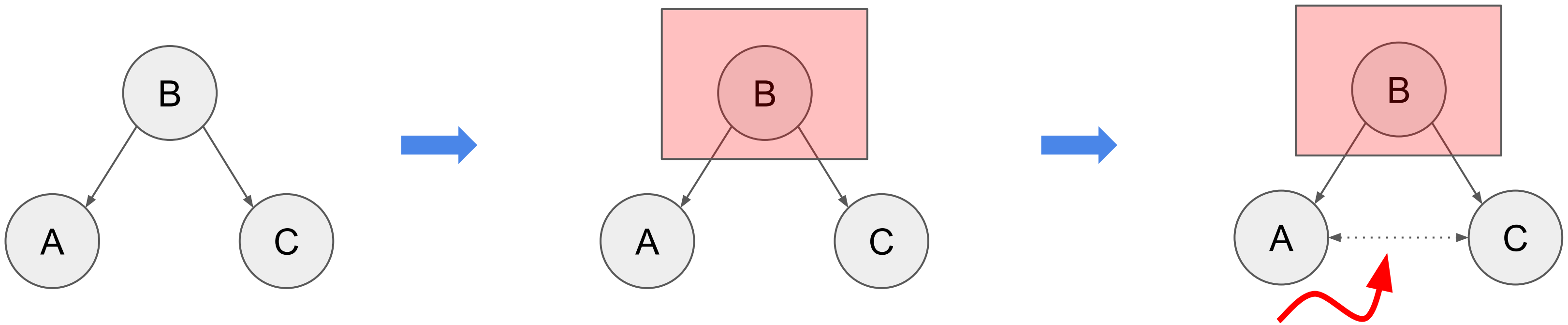


Interventional data are needed to remove spurious links

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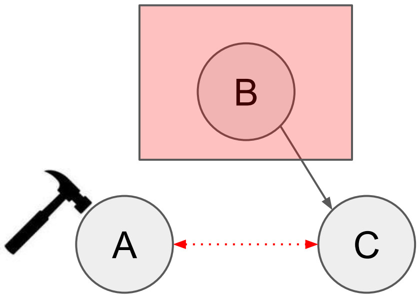
**Motivation**

a primary limitation of the current state-of-the-art algorithms is that they can only handle **observational data**.

The latter are often insufficient to retrieve the correct causal model in complex scenarios where it is impossible to account for all the variables responsible for the system's evolution. In such cases, data from experiments, i.e. **interventional data**, are needed to eliminate spurious links and enhance the quality of the causal model

**Example**

Hidden confounder scenario




Performing an intervention on A, i.e. forcing its value:

- breaks the input links to A
- we can study the effect on C
- If varying A does not lead any change on C → A-C link is spurious

# Thank you

questions?

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