Causal Discovery of Dynamic Models for Predicting Human Spatial Interactions

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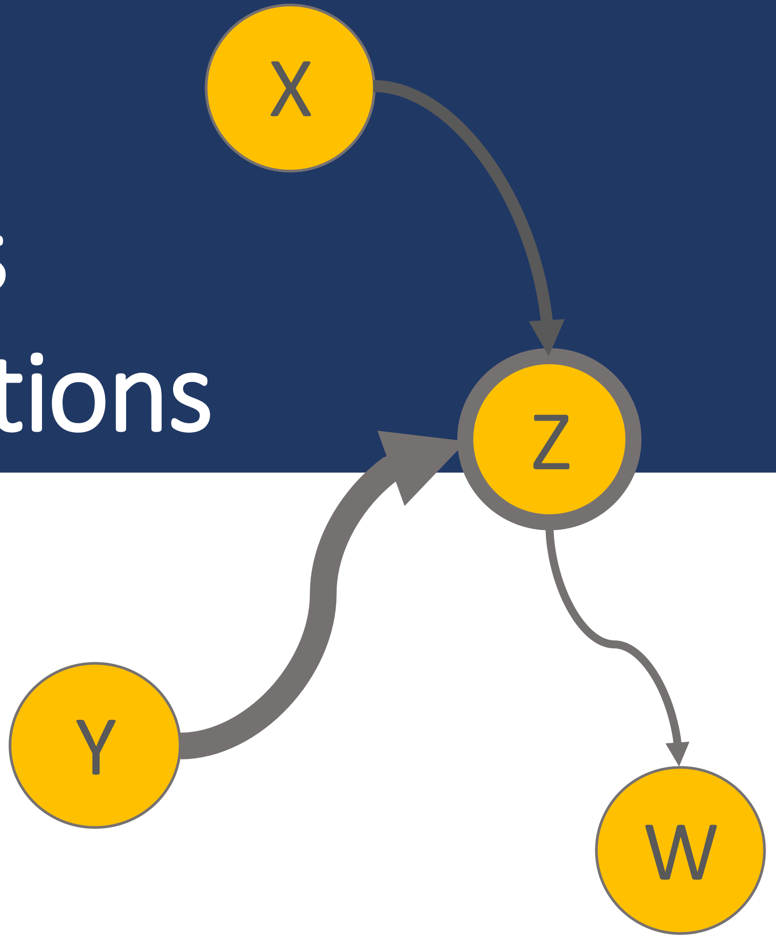
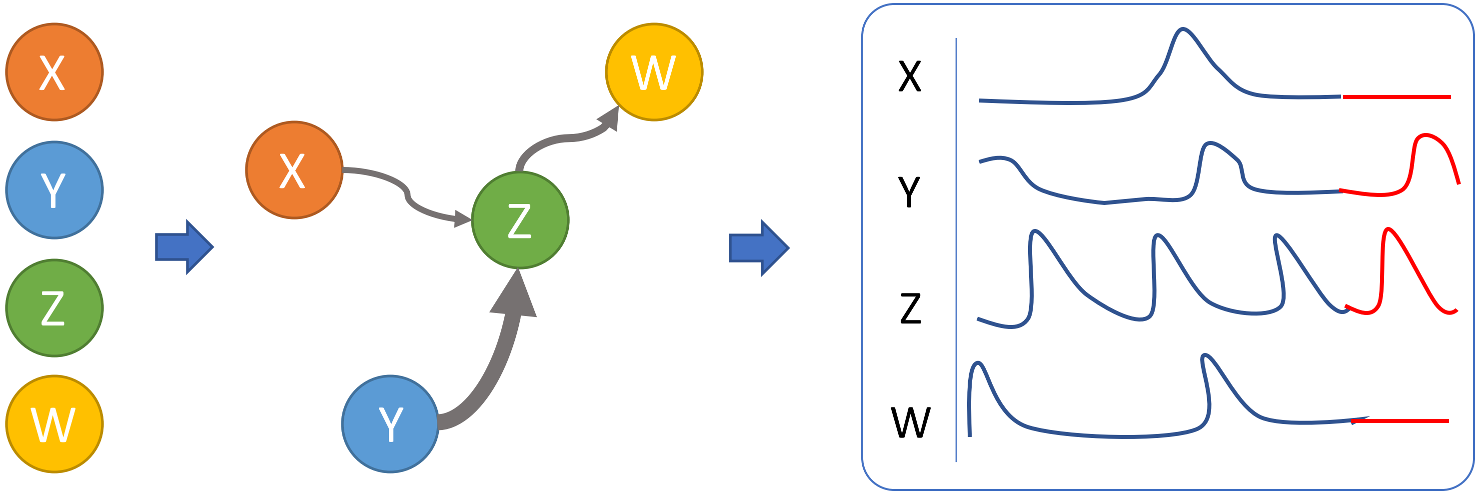


Causal inference and Robotics

Science which studies the cause-effect relationship between events [1]

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

Causal Reasoning
reason on the causal model to predict how the observed system evolves



[1] Pearl, J., & Mackenzie, D. (2019). The book of why

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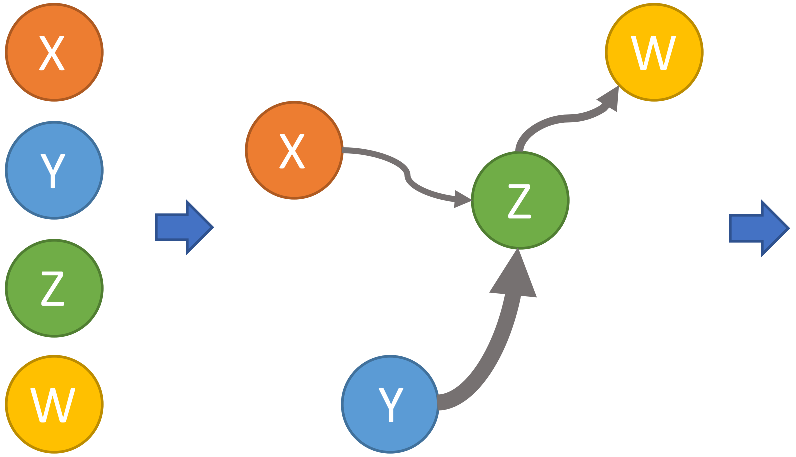
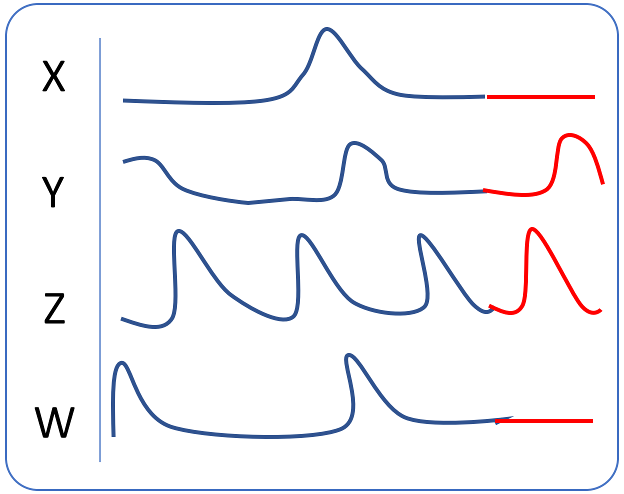


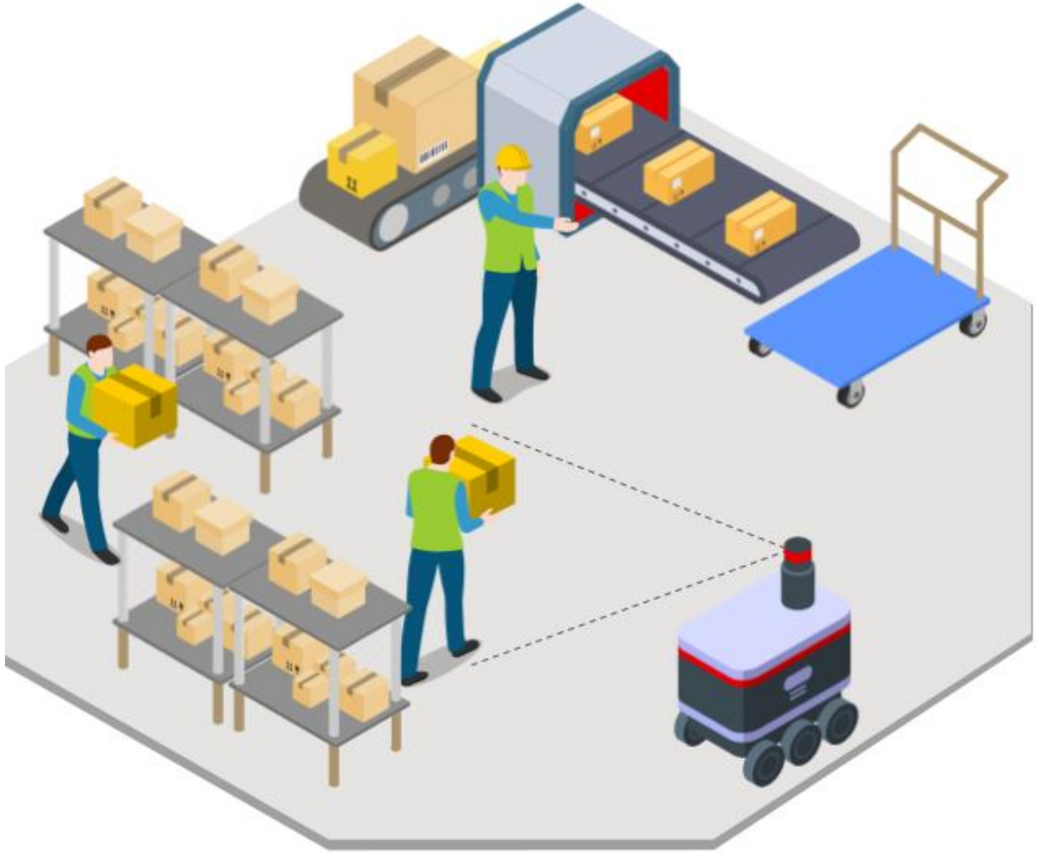


Can robots benefit from causal inference ?

[1] Pearl, J., & Mackenzie, D. (2019). The book of why

General idea

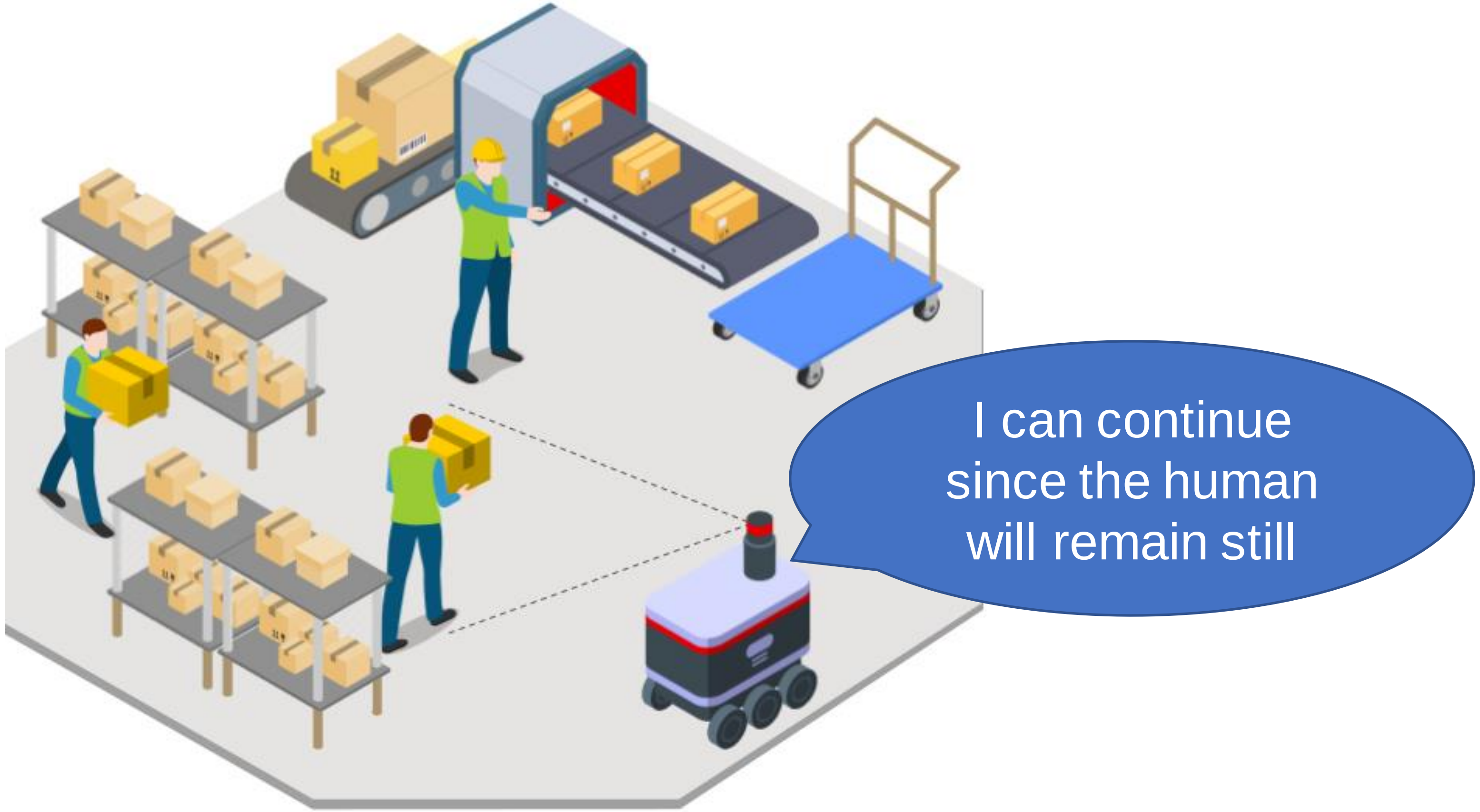
Enable the robot to understand human behaviours by discovering the cause-effect relationship between events during a Human-Robot Spatial Interaction (HRSI)



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

General idea

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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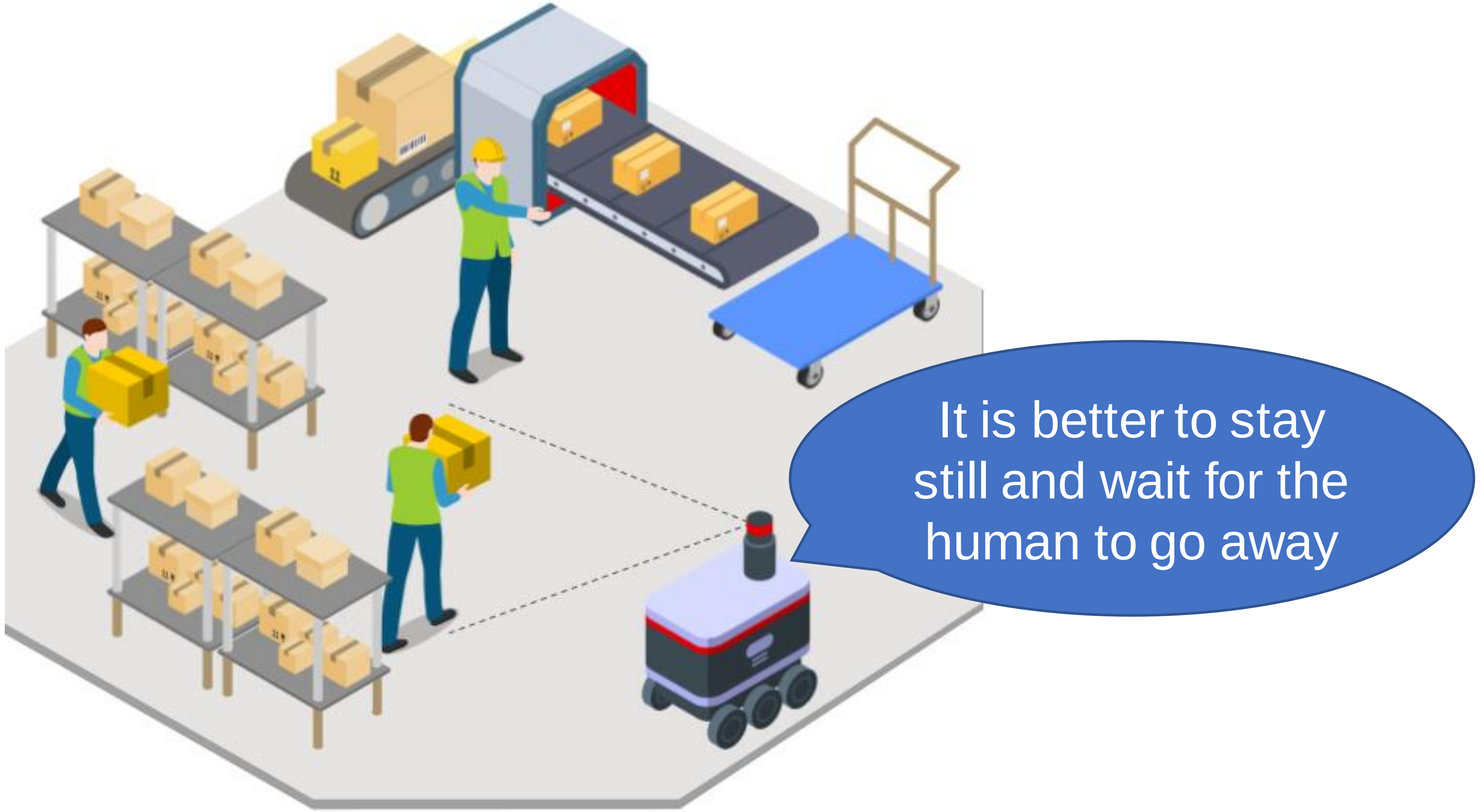


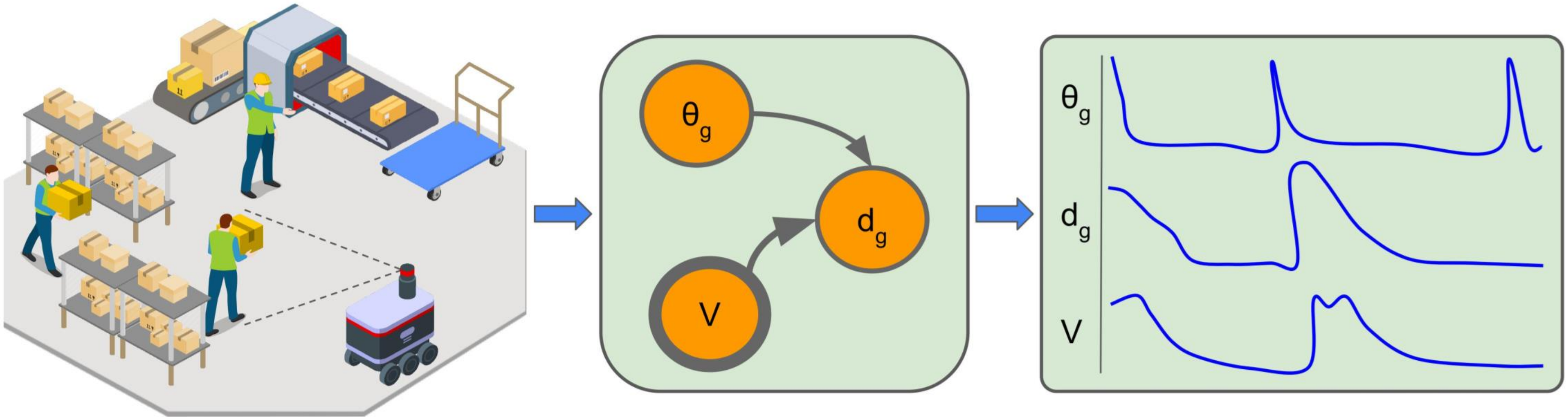
Dynamic Agile Production Robots That Learn and Optimise Knowledge and Operations

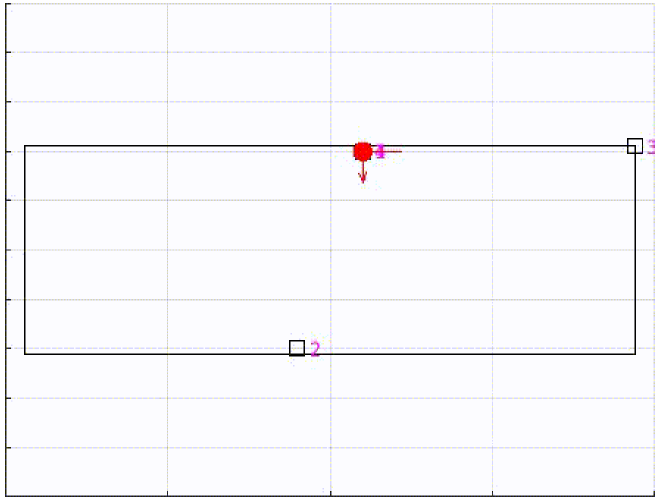
General idea

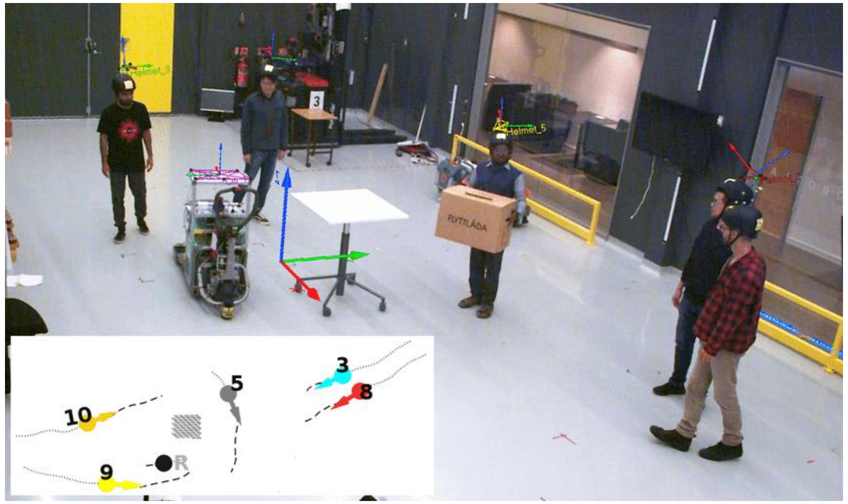
Discovering the causal model will enable the robot to reason on it and to answer questions like:

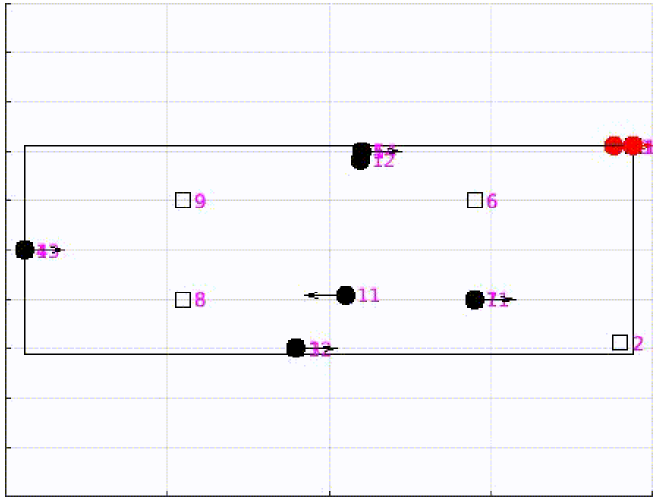
- “what happens if I go this way?”
- “what would have happened if I remained still instead of moving?”

→ **take the best choice among possible HRSIs**









Single-agent scenario

- system variables:
  θ_g, d_g, v

- expected cause-effect relationships
  - $\theta_g = f(\theta_g, d_g)$
  - $d_g = f(d_g, \theta_g, v)$
  - $v = f(v, d_g)$

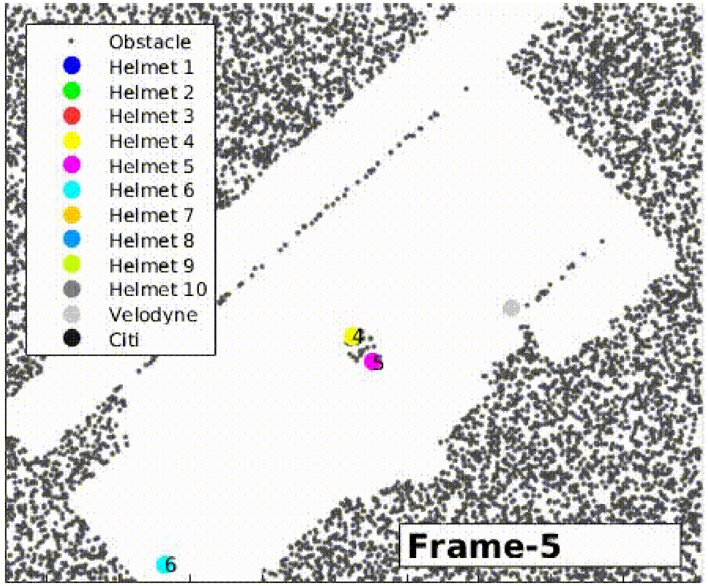
Multi-agent scenario

- system variables:
  $d_g, v, risk$

- expected cause-effect relationships
  - $d_g = f(d_g, v)$
  - $v = f(v, d_g, risk)$
  - $risk = f(risk,\ v)$

Real-world dataset and evaluation methodology

THÖR
warehouse-like environment



ATC
shopping centre environment

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

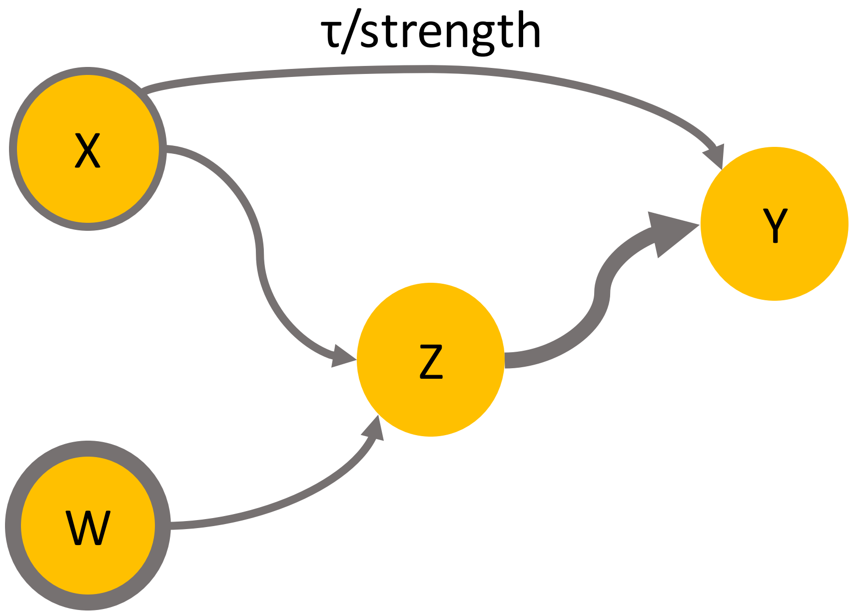
Different scenario observed from the same dataset
➔ different causal models

Same scenario observed from different datasets
➔ same causal models

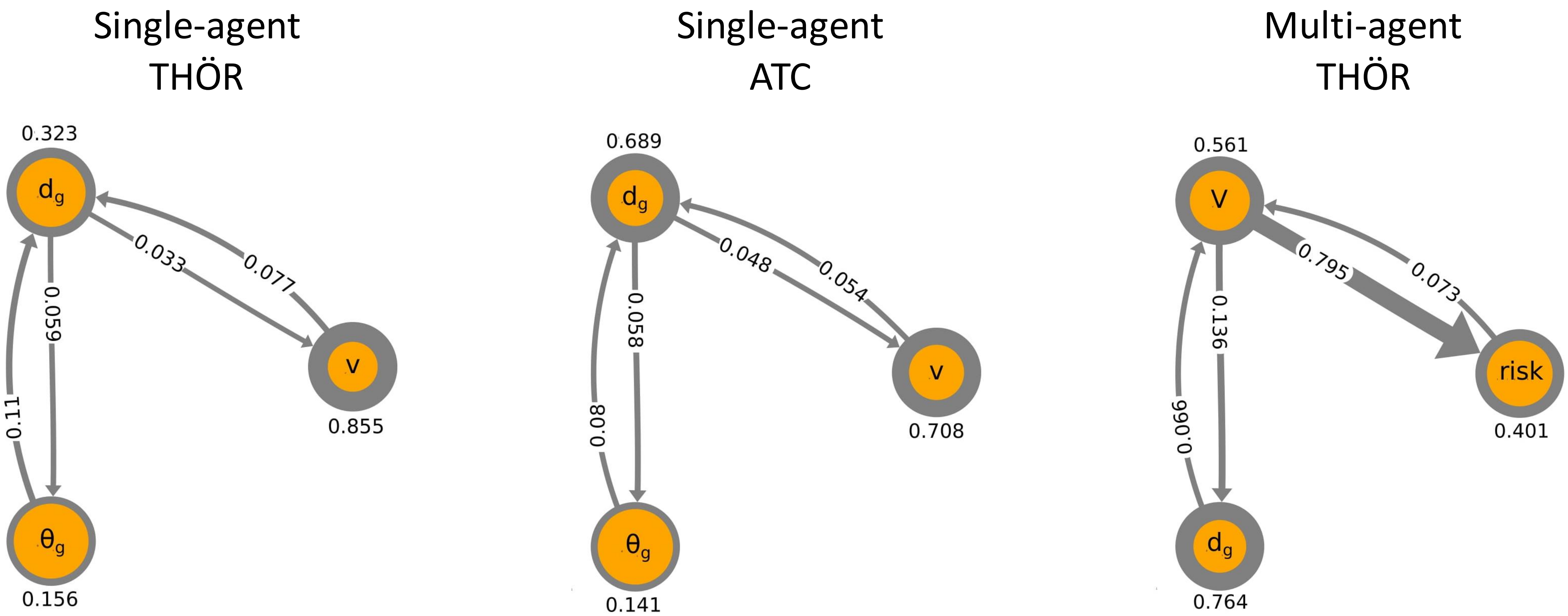
Different scenario observed from different datasets
➔ different causal models

PCMCI algorithm:

- PC algorithm +
  false-positive rate control optimization (MCI)
- key parameters:
  - τ maximum time delay
  - α confidence level
    (false-positive rate threshold)

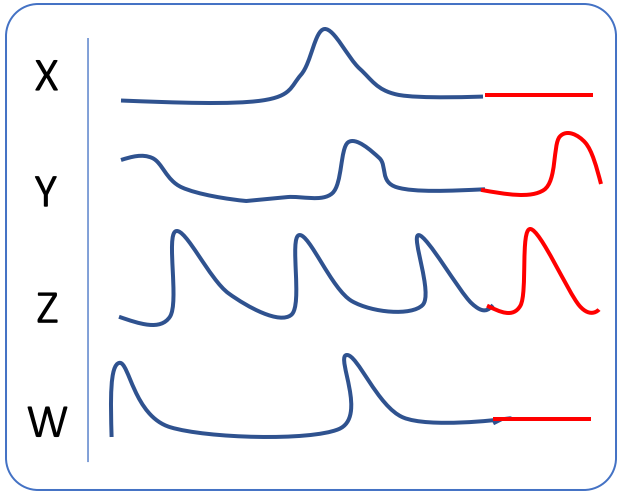


τ = 1


Single-agent
THÖR
0.323
d_g
0.033
0.077
0.059
0.11
v
0.855
θ_g
0.156
Single-agent
ATC
0.689
d_g
0.048
0.054
0.058
0.08
v
0.708
θ_g
0.141
Multi-agent
THÖR
0.561
V
0.795
0.073
0.136
0.066
risk
0.401
d_g
0.764

Gaussian Process Regressor:

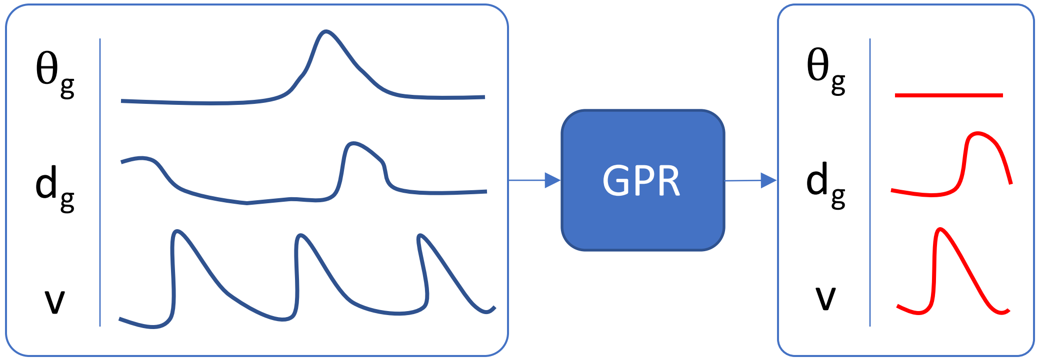
- supervised learning method designed to solve regression and probabilistic classification problems
- widely used for time-series prediction [2]
- embedding the causal structure in the GPR → **Causal GPR**



[2] Roberts, Stephen, et al. "Gaussian processes for time-series modelling."
Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences (2013)

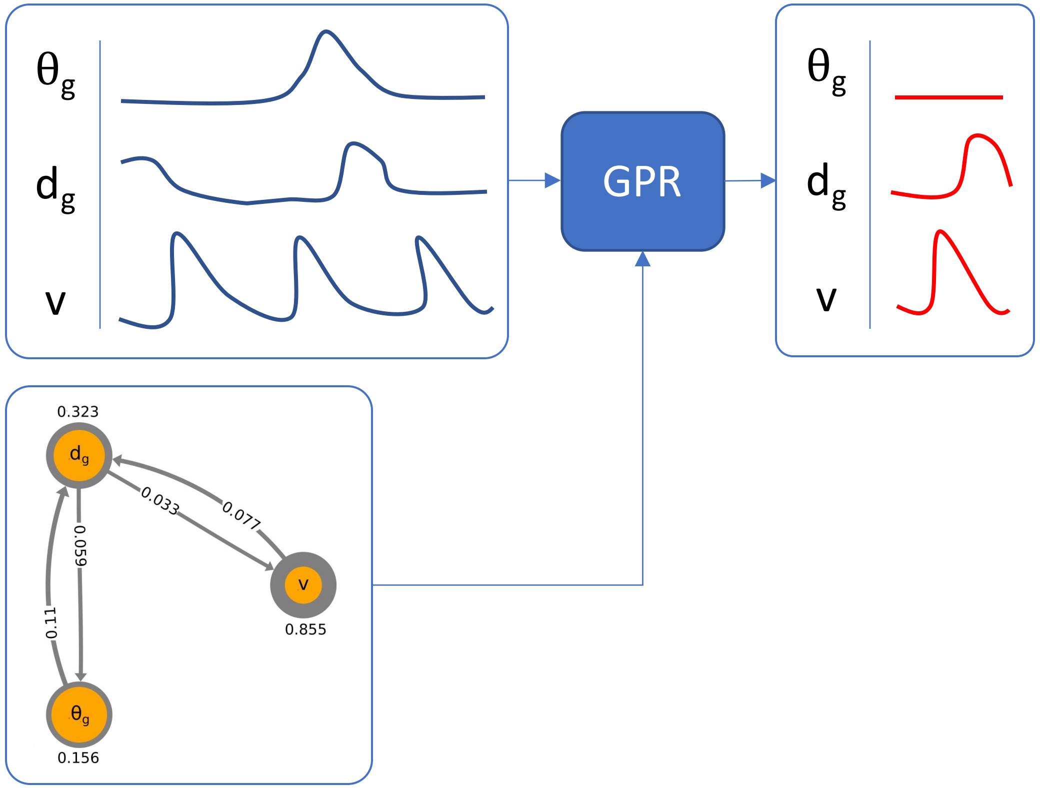
Results: non-causal GPR vs causal GPR

Non-causal GPR approach



VS

Causal GPR approach



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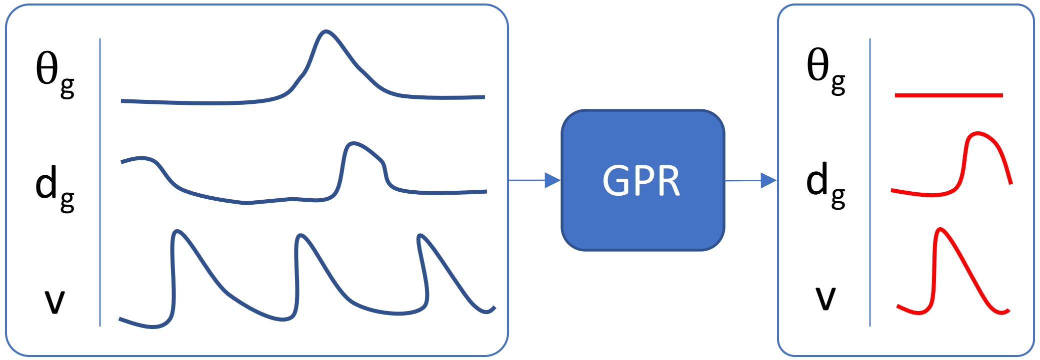
Non-causal GPR approach



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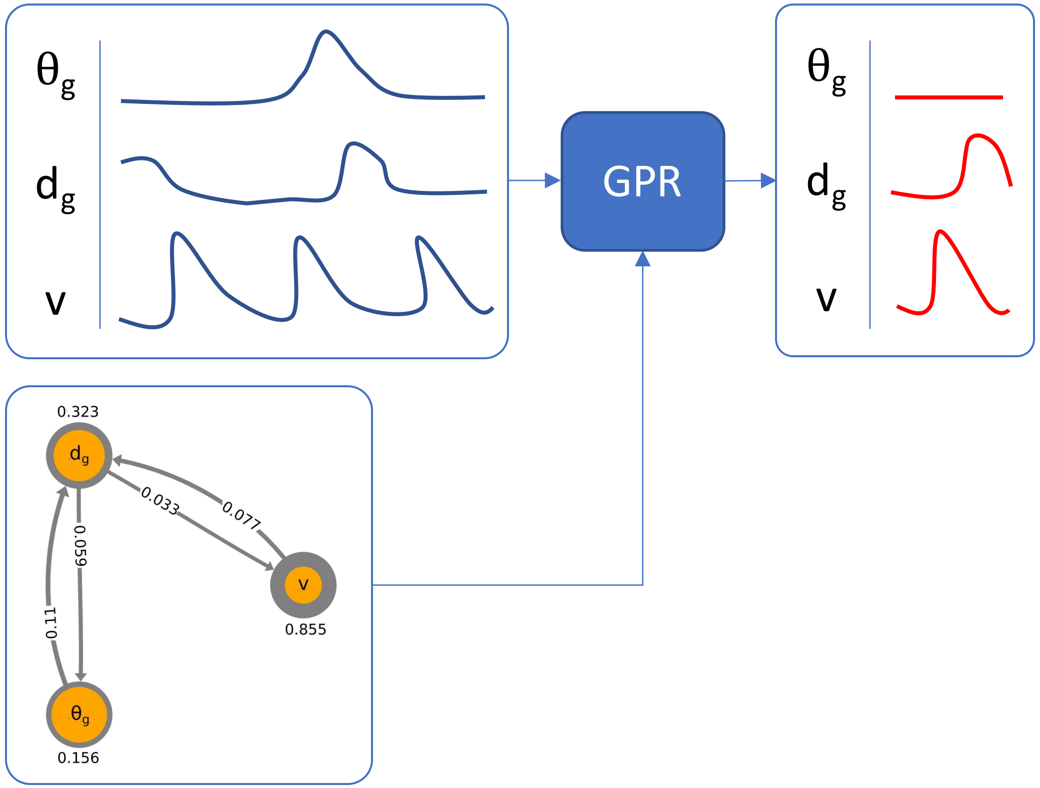
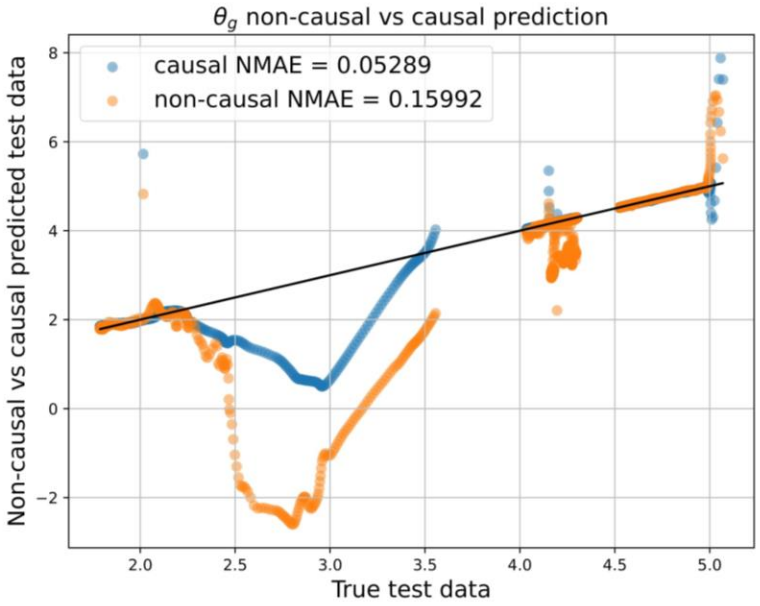
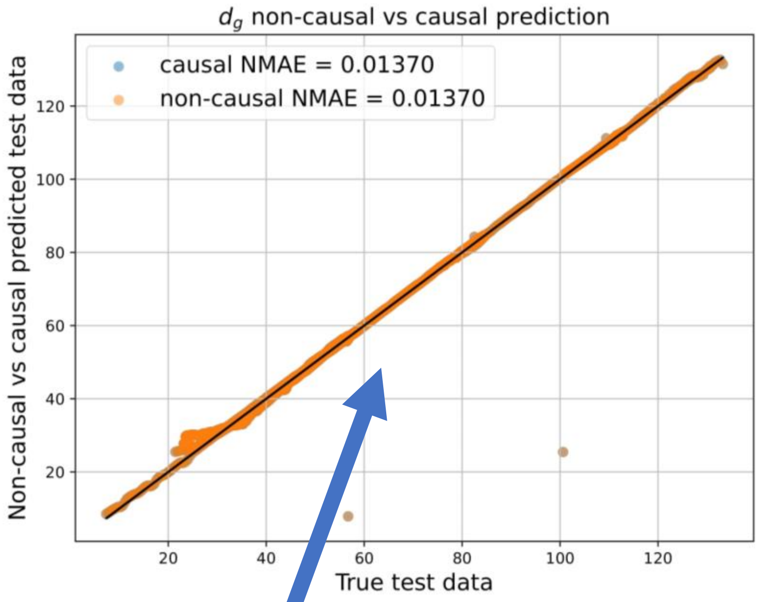


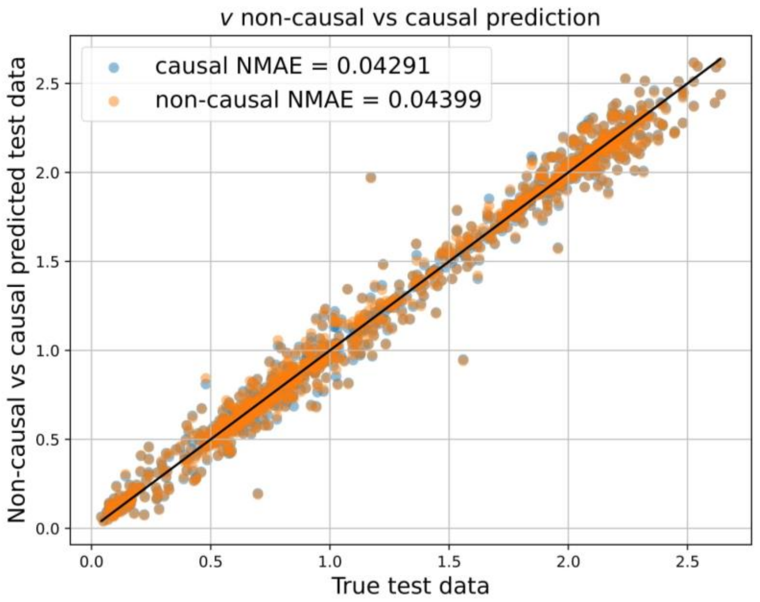
Evaluation metric

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

Results: non-causal GPR vs causal GPR – Single-agent scenario (THÖR)

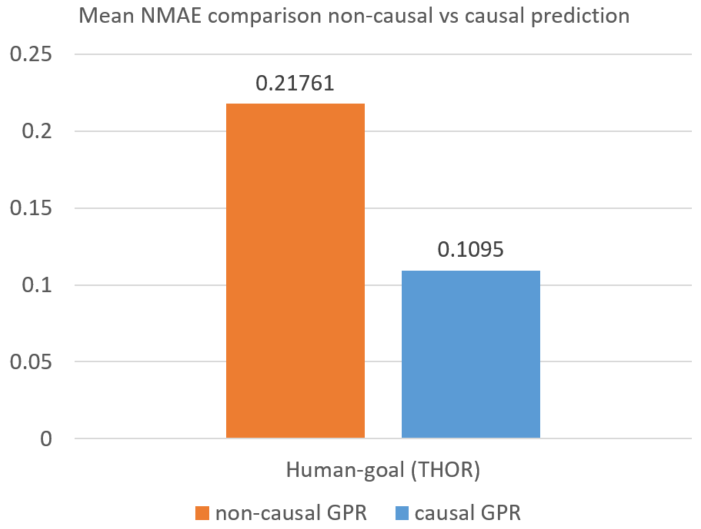






$d_g(t) = f(\theta_g, d_g, v)(t-1)$

→ No difference between non-causal and causal GPR



Mean across the NMAE for each variable

Results: non-causal GPR vs causal GPR - Overall

- 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**

Results: non-causal GPR vs causal GPR - Overall

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~ -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

Future work

- Automatically learn the most important features for modelling HRSI
- Causal analysis on observational and interventional data
- Data collected by on-board robot sensor data

Thank you

DARKO

Dynamic Agile Production Robots That Learn and Optimise Knowledge and Operations

DARKO link - https://darko-project.eu/

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