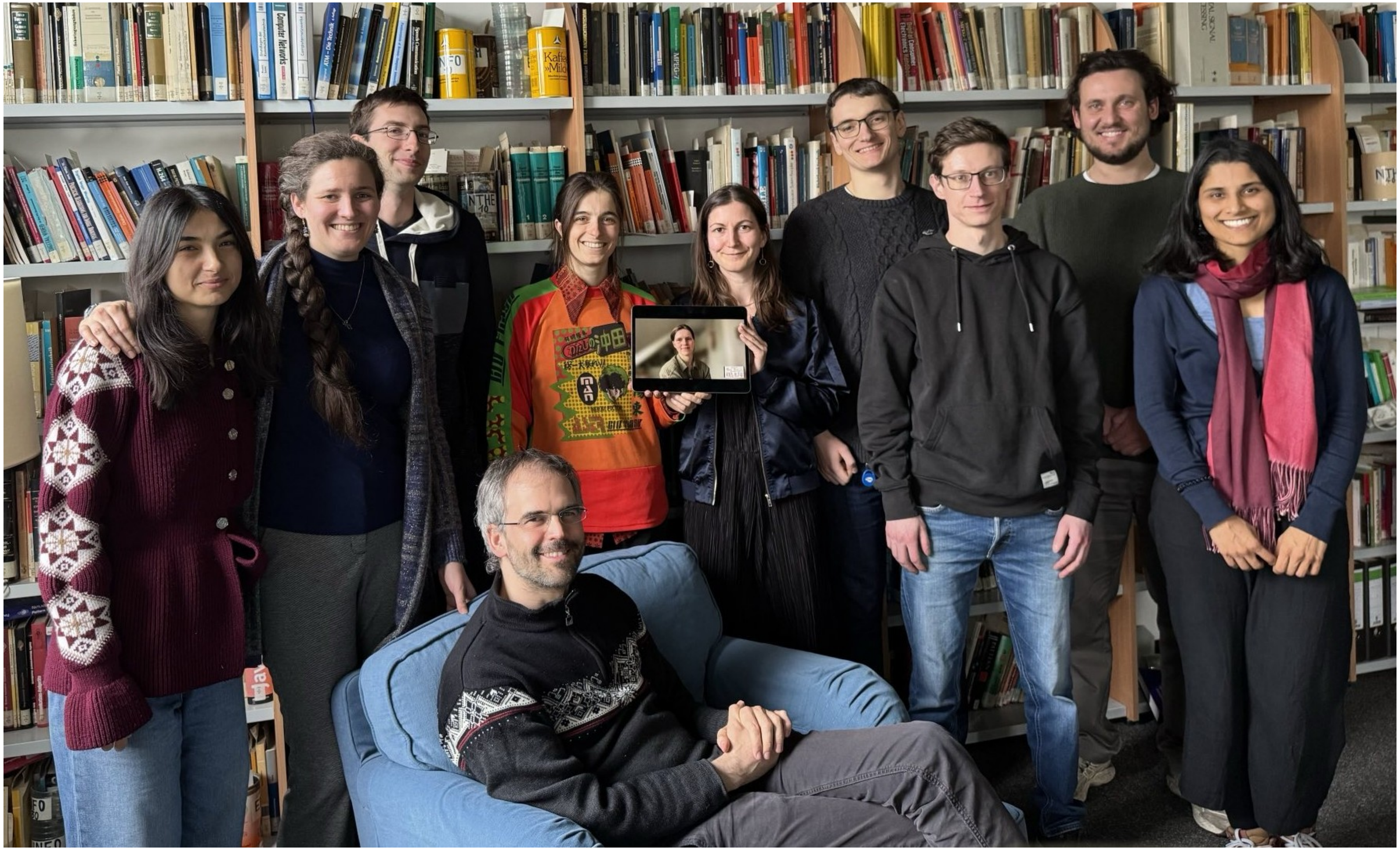
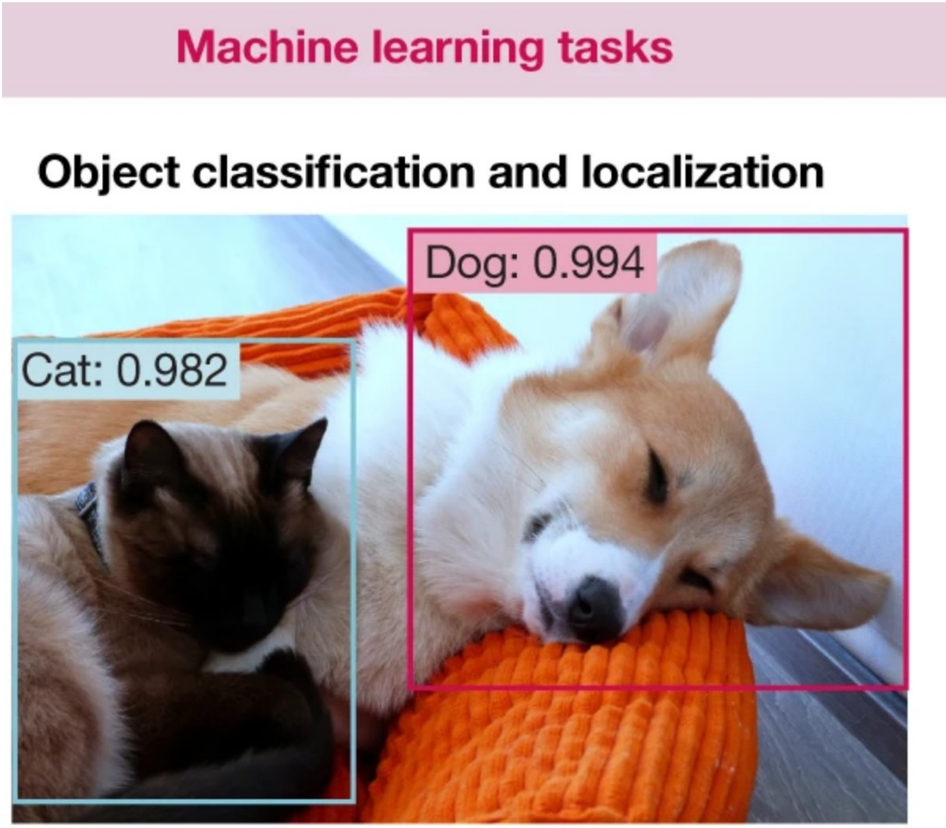
Causal Inference from Time Series Data

Prof. Dr. Jakob Runge
Chair of AI in the Sciences
University of Potsdam

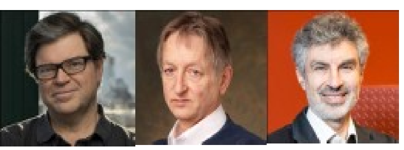
CausalInferenceLab.com
@ UP (and TUB)



Machine learning in science and engineering



Turing-Award 2018
LeCun, Hinton, Bengio

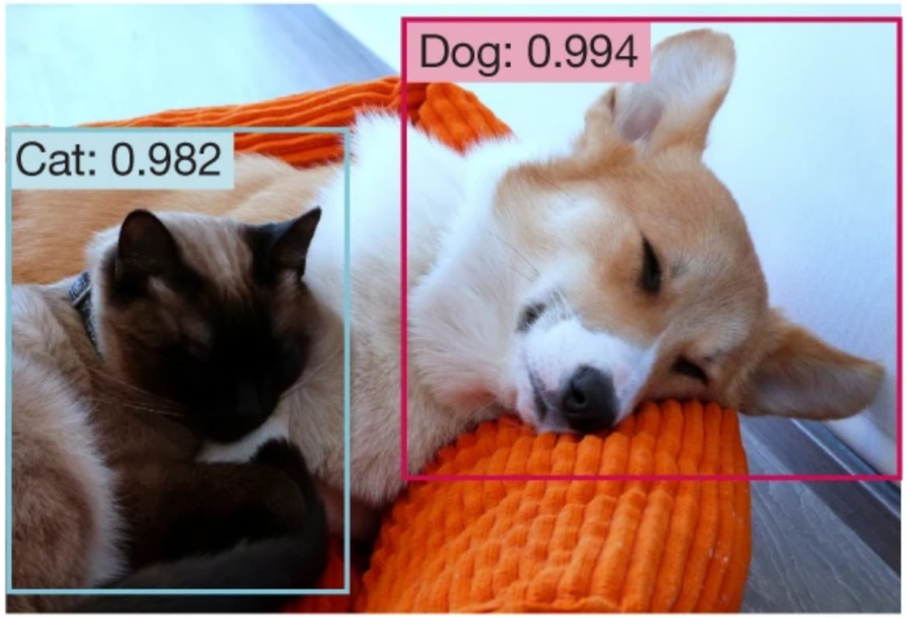


Reichstein et al. 2019

Machine learning in science and engineering

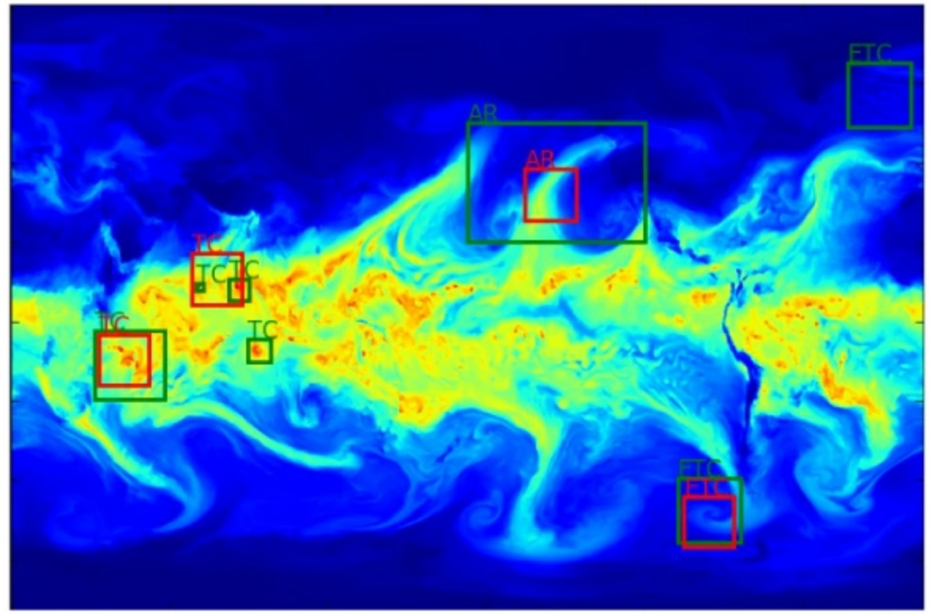
Machine learning tasks

Object classification and localization



Earth science tasks

Pattern classification



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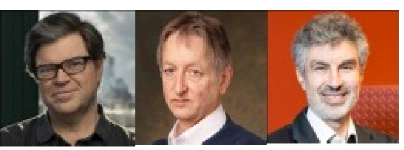

Reichstein et al. 2019

Machine learning in science and engineering

PERSPECTIVE

https://doi.org/10.1038/s41586-019-0912-1

Deep learning and process understanding for data-driven Earth system science

Markus Reichstein[1,2*], Gustau Camps-Valls[3], Bjorn Stevens[4], Martin Jung[1], Joachim Denzler[2,5], Nuno Carvalhais[1,6] & Prabhat[7]

PERSPECTIVE

https://doi.org/10.1038/s43588-022-00264-7

nature computational science

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Enhancing computational fluid dynamics with machine learning

Ricardo Vinuesa[1,2] and Steven L. Brunton[3]

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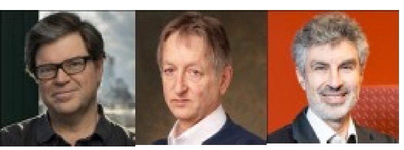

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Deep neural networks for the evaluation and design of photonic devices

Jiaqi Jiang, Mingkun Chen and Jonathan A. Fan ✉

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Machine learning in concrete science: applications, challenges, and best practices

Zhanzhao Li[1] ✉, Jinyoung Yoon[1,2], Rui Zhang[1], Farshad Rajabipour[1], Wil V. Srubar III[3,4], Ismaila Dabo[5] and Aleksandra Radlińska[1]

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PERSPECTIVE

https://doi.org/10.1038/s41467-022-27980-y OPEN

Perspectives in machine learning for wildlife conservation

Devis Tuia[1,17✉], Benjamin Kellenberger[1,17], Sara Beery[2,17],

Machine learning in science and engineering

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Obtaining genetics insights from deep learning via explainable artificial intelligence

Gherman Novakovsky[1,2,7], Nick Dexter[3,4,7], Maxwell W. Libbrecht[4,8], Wyeth W. Wasserman[1,8] and Sara Mostafavi[5,6,8]

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https://doi.org/10.1038/s41593-019-0520-2

Enhancing computational fluid dynamics with machine learning

Ricardo Vinuesa[1,2] and Steven L. Brunton[3]

A deep learning framework for neuroscience

Blake A. Richards[1,2,3,4,42]*, Timothy P. Lillicrap[5,6,42], Philippe Beaudoin[7], Yoshua Bengio[1,4,8],

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Machine learning in science and engineering

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nature medicine

PERSPECTIVE
https://doi.org/10.1038/s41591-019-0548-6

Corrected: Author Correction

Do no harm: a roadmap for responsible machine learning for health care

Jenna Wiens[1,20*], Finale Doshi-Velez[10] Pilar N. Ossorio[16], S

0264-7

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nature neuroscience

A deep learning

Blake A. Richards[1,2,3,4,42*], Timothy P. Lillicrap[5,6,42], P

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AI in health and medicine

Pranav Rajpurkar[1,4], Emma Chen[2,4], Oishi Banerjee[2,4] and Eric J. Topol[3]

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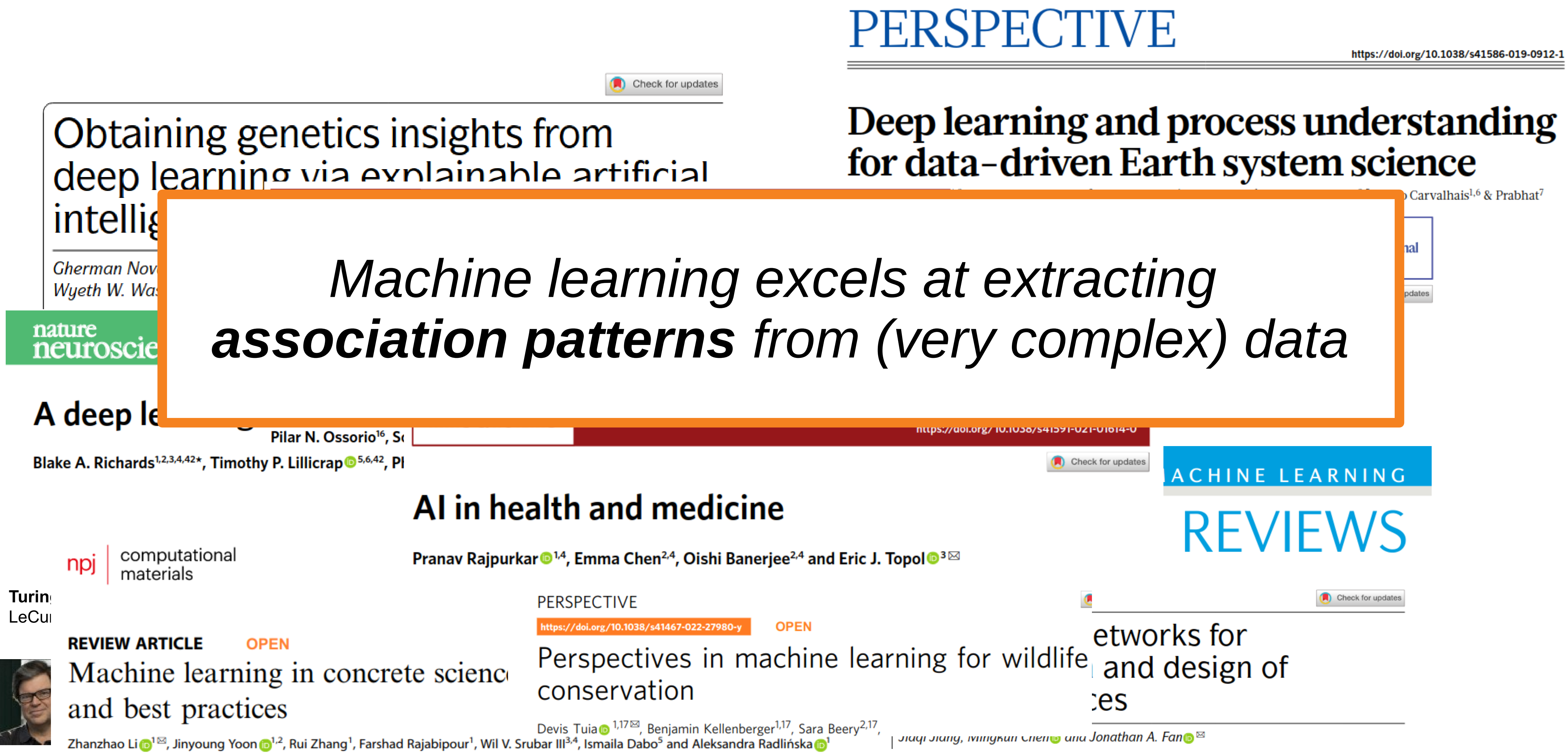
Machine learning in science and engineering

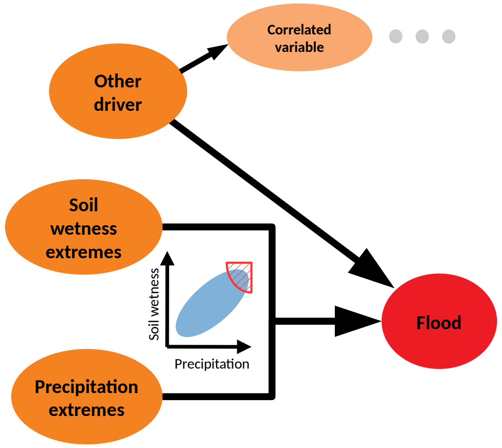


Machine learning excels at extracting ***association patterns*** *from (very complex) data*


However, ...

Causal questions everywhere

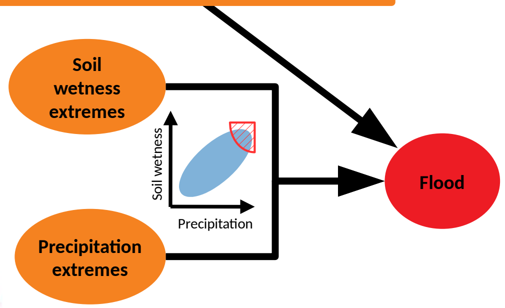
Causal questions everywhere



HELMHOLTZAI XAIDA

Causal questions everywhere

What causes extremes?



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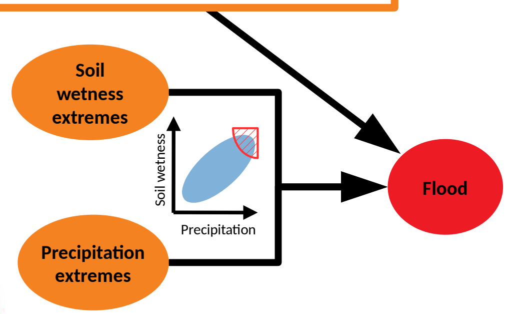

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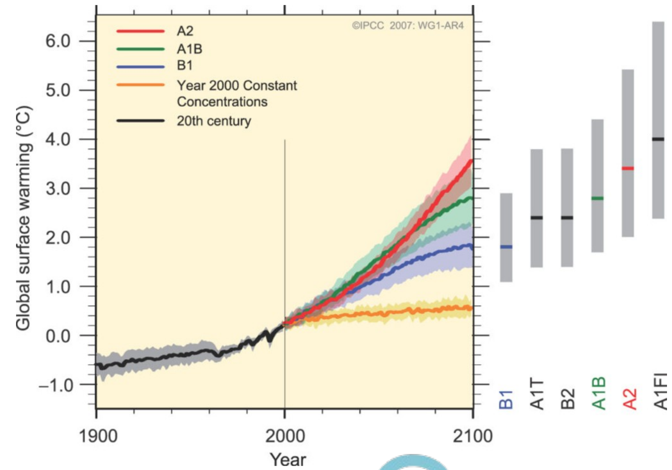

IPCC, Gentine

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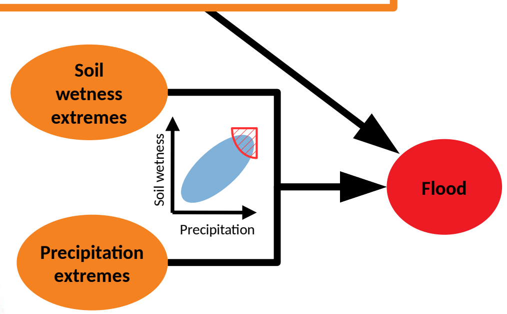

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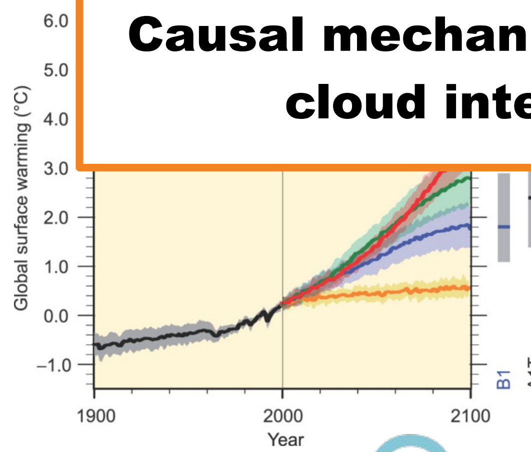
Causal mechanism of aerosol-cloud interactions



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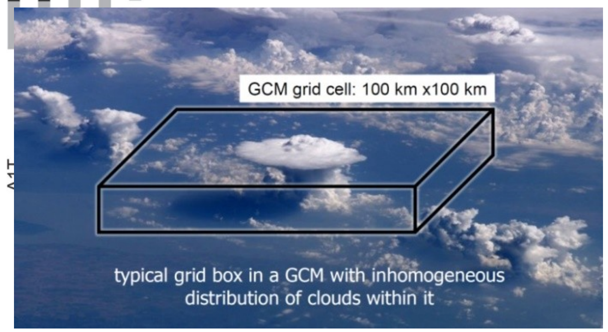

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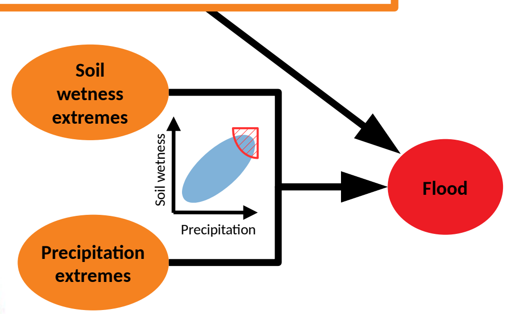

HELMHOLTZ AI XAIDA

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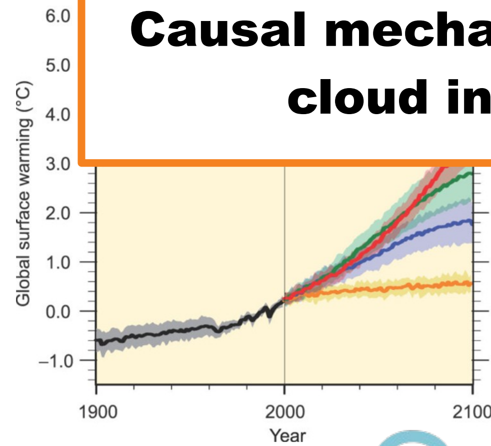

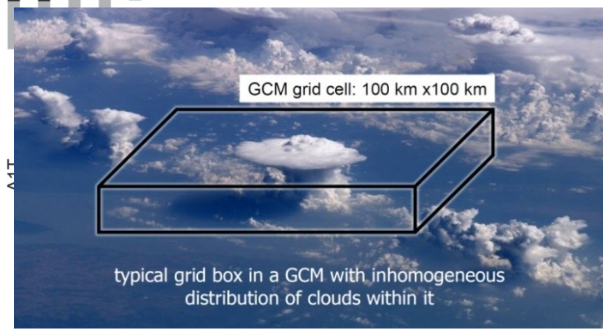

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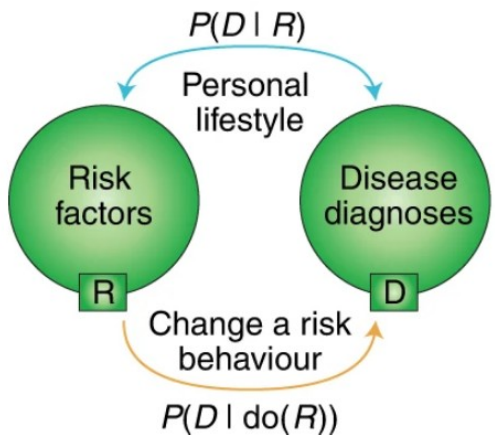

Prosperi *et al.*, 2020

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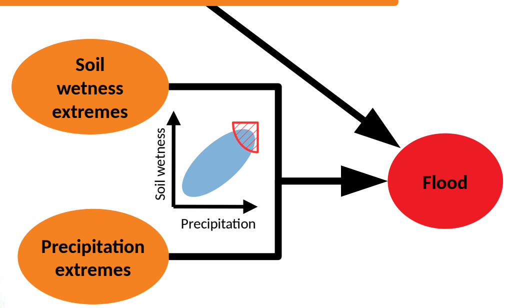

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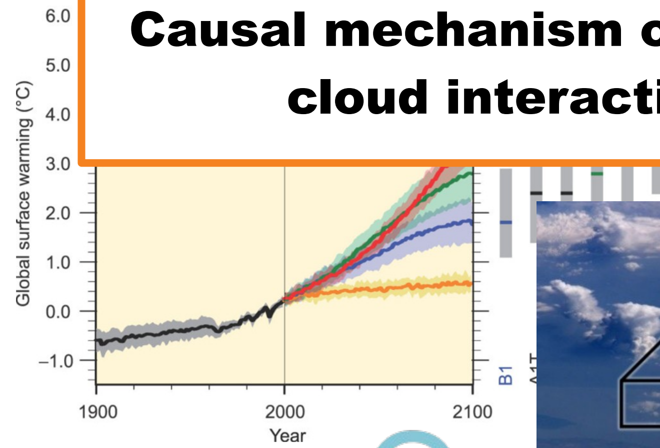

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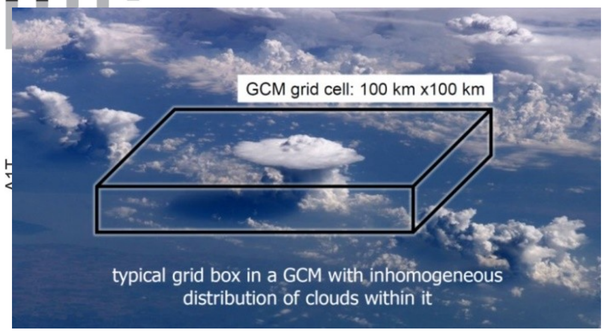
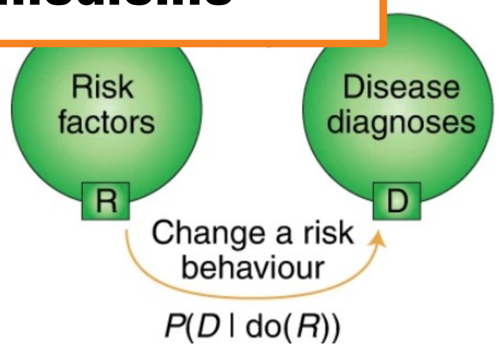


Causes of diseases and personalized medicine



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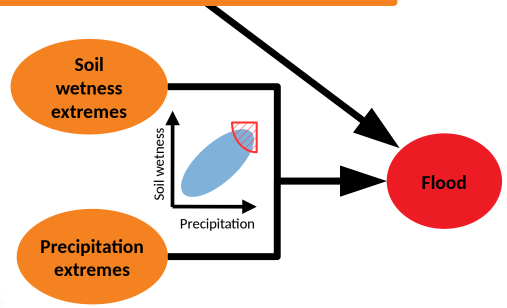

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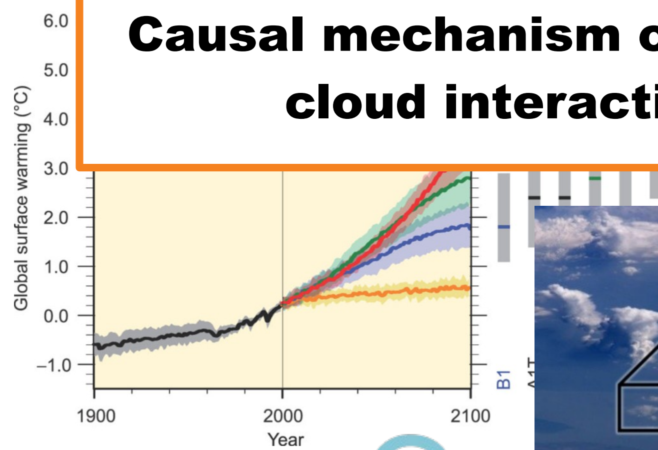

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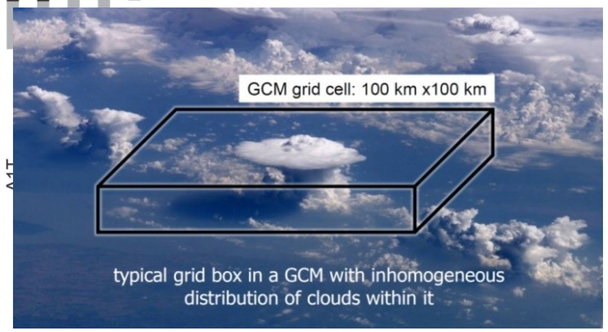

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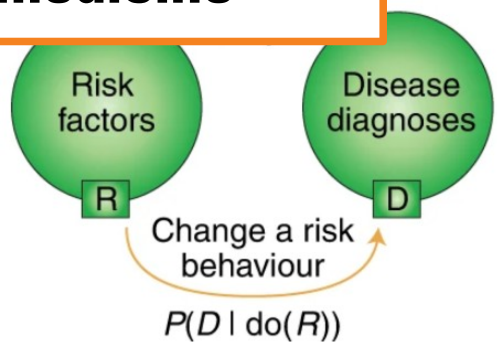

Prosperi *et al.*, 2020

Predict interventions in business / finance / engineering

Causal questions everywhere

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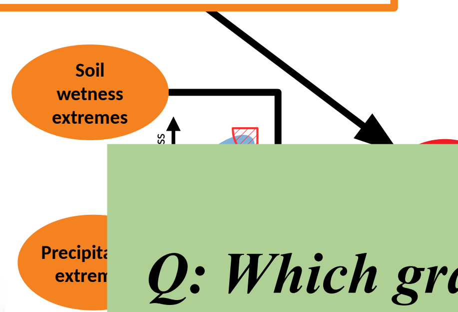

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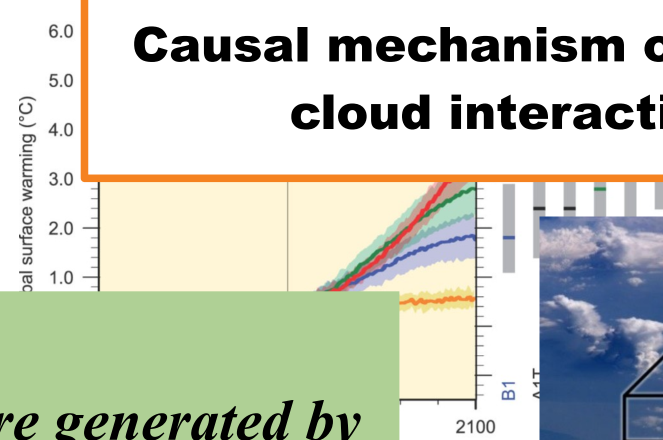
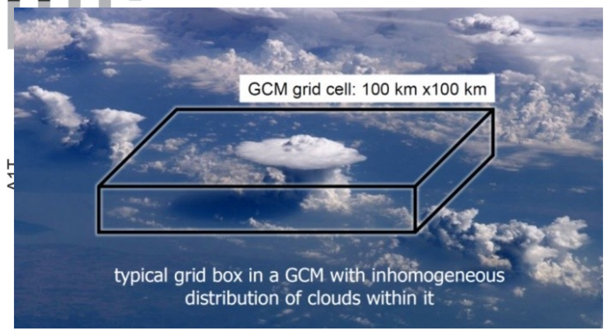
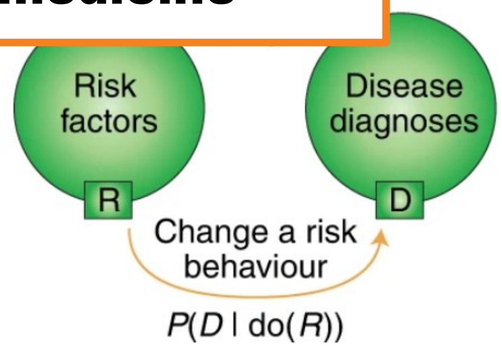




Q: Which graphics were generated by an AI?

Causes of diseases and personalized medicine



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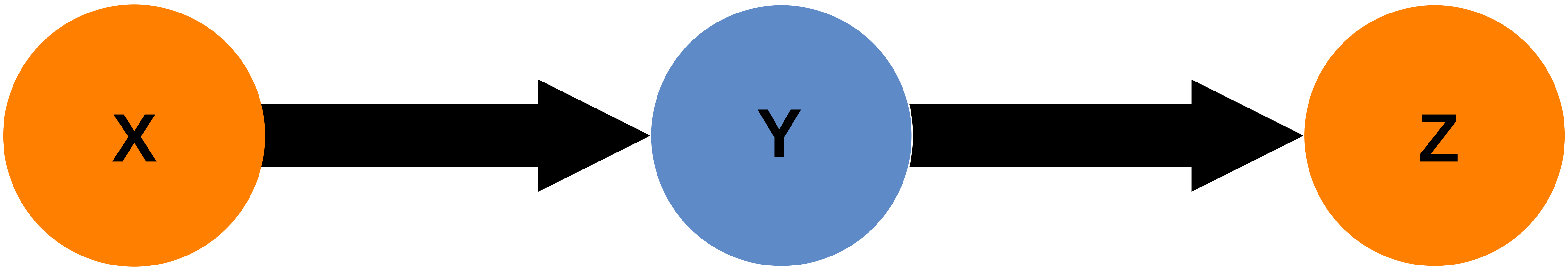
Predict interventions in business / finance / engineering

Group work: Correlation vs Causality



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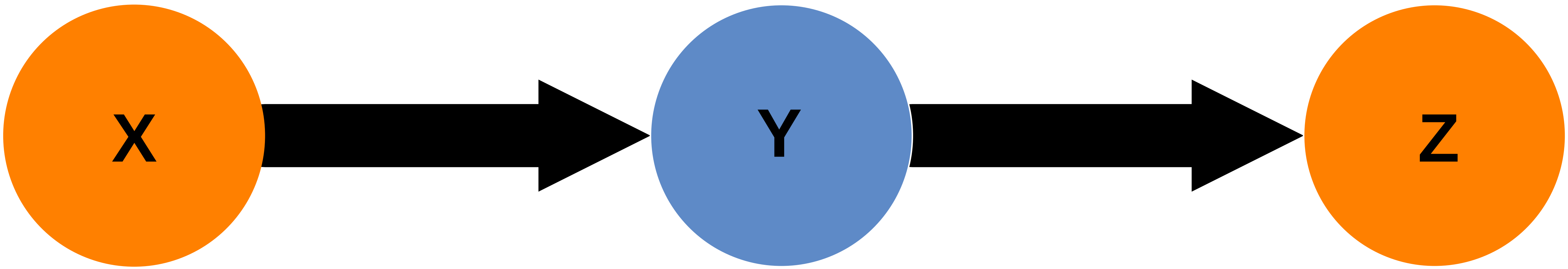

Which model predicts ***Y*** more accurately?

1. $Y = f(X)$ **2.** $Y = f(X,Z)$

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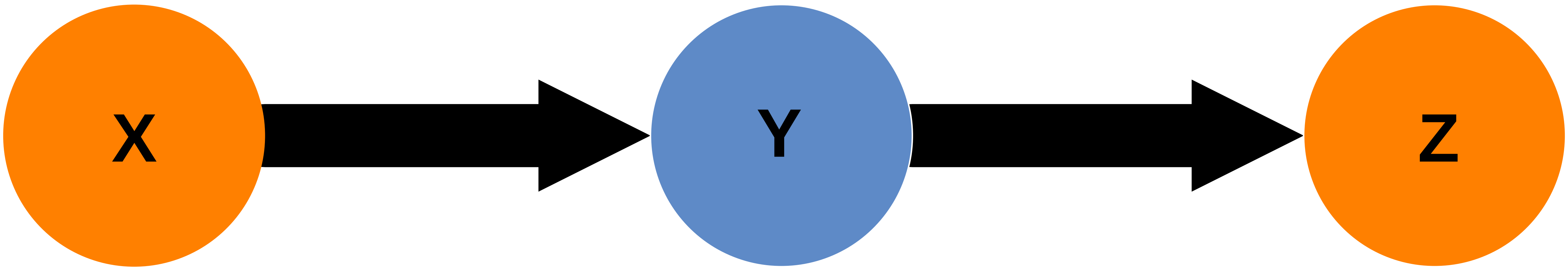

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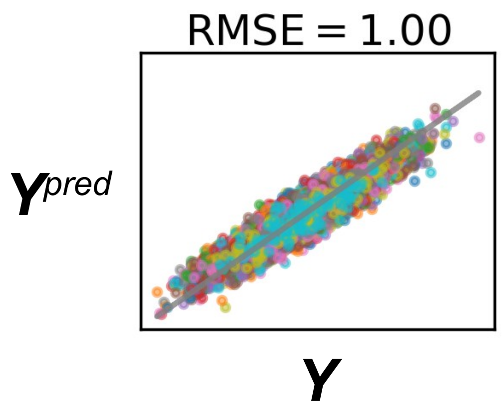

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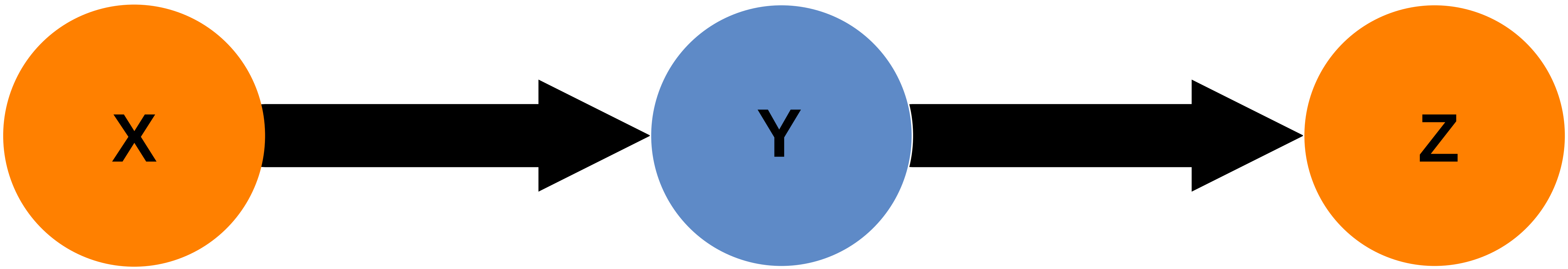

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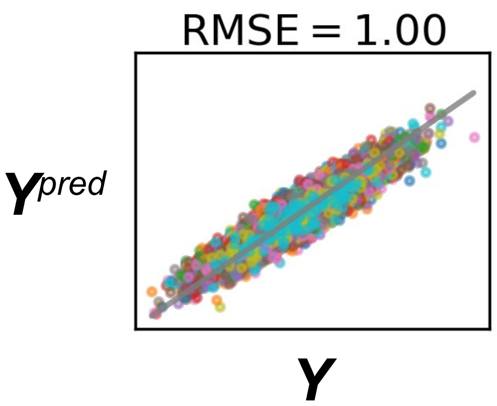

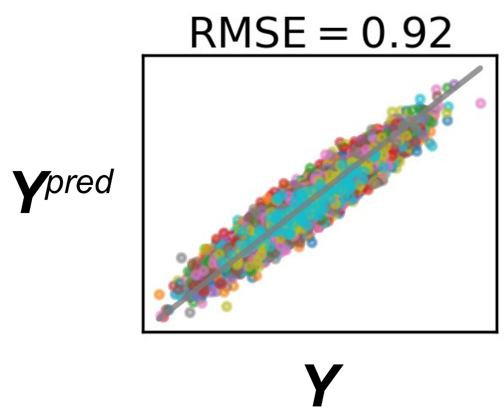

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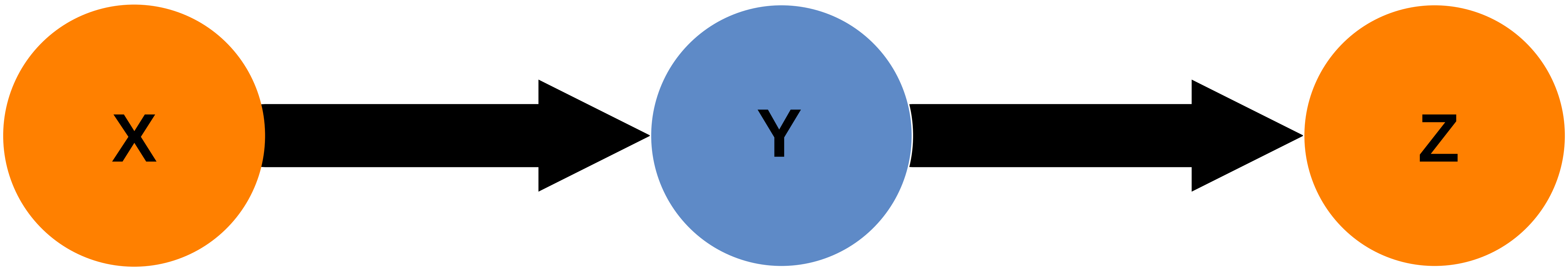

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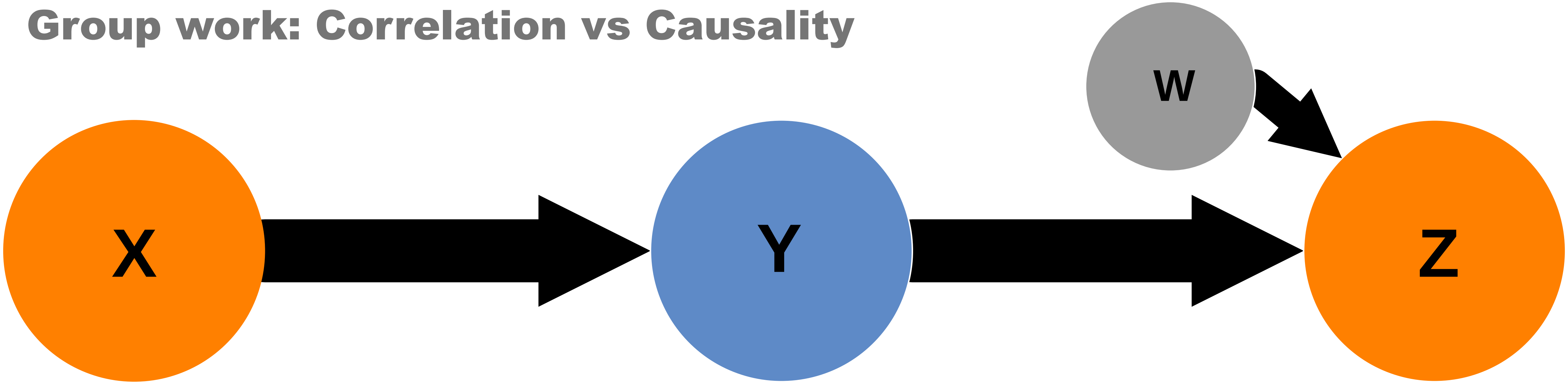

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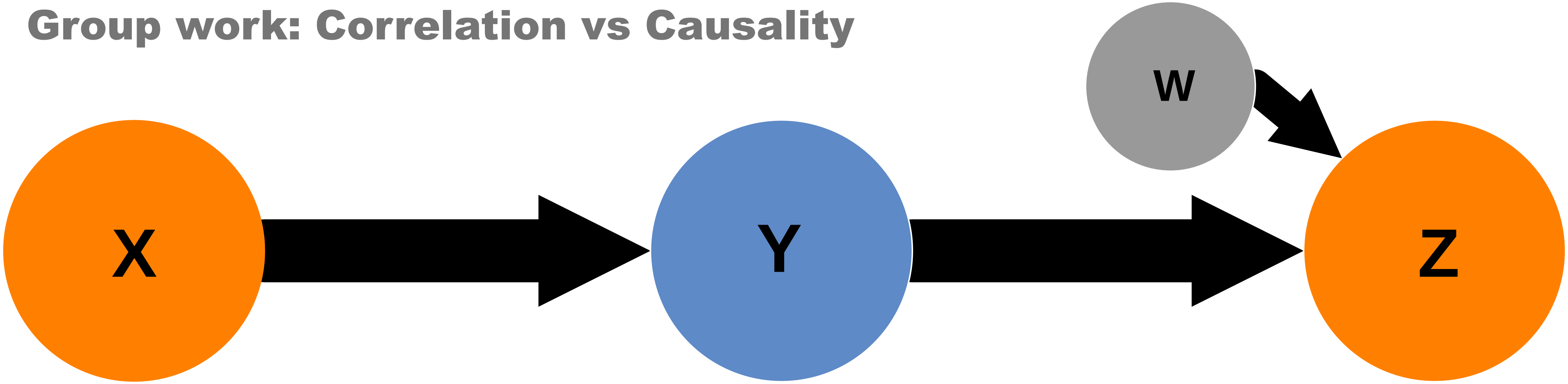

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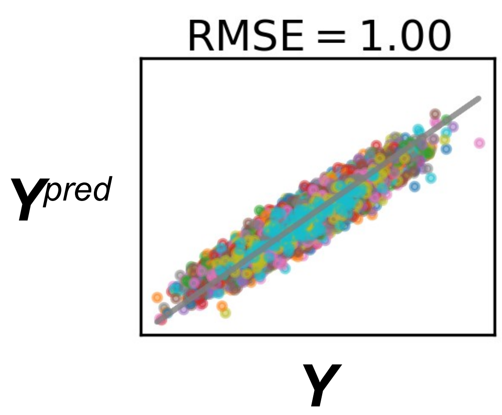

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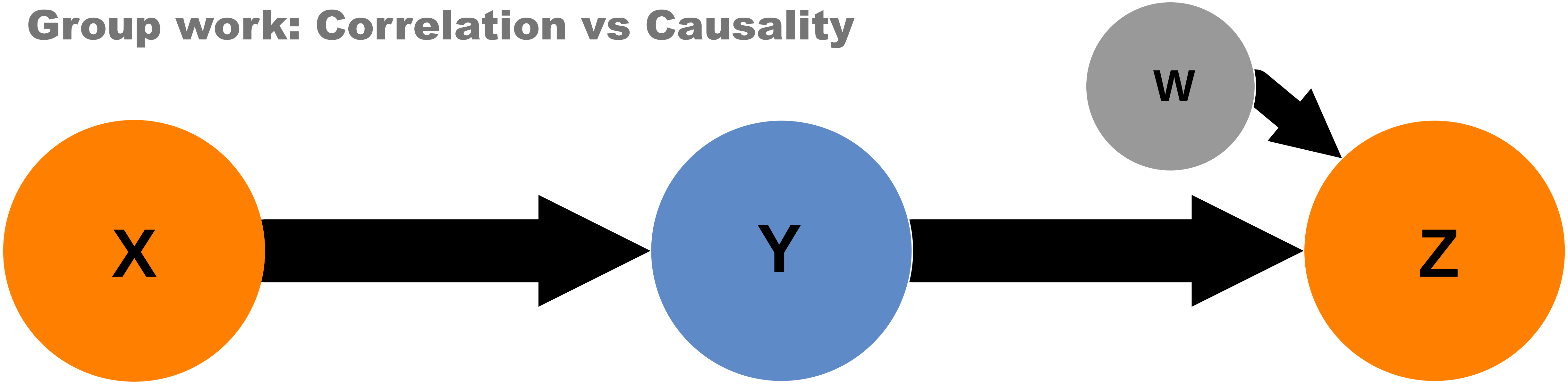

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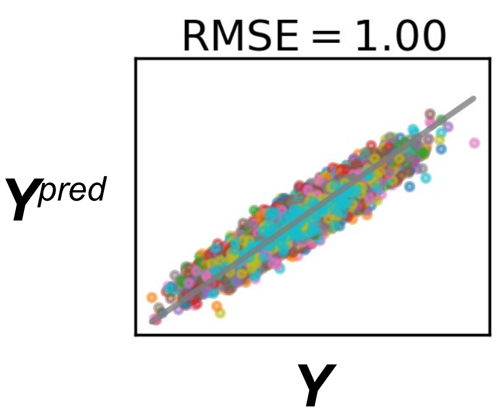
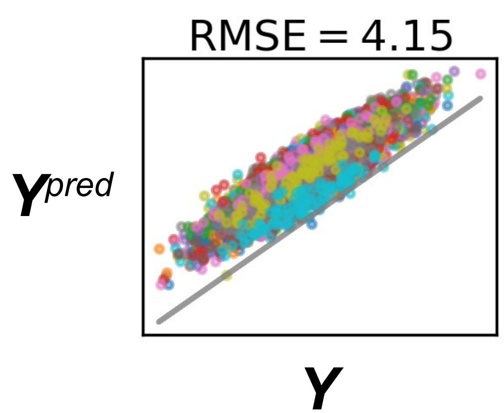
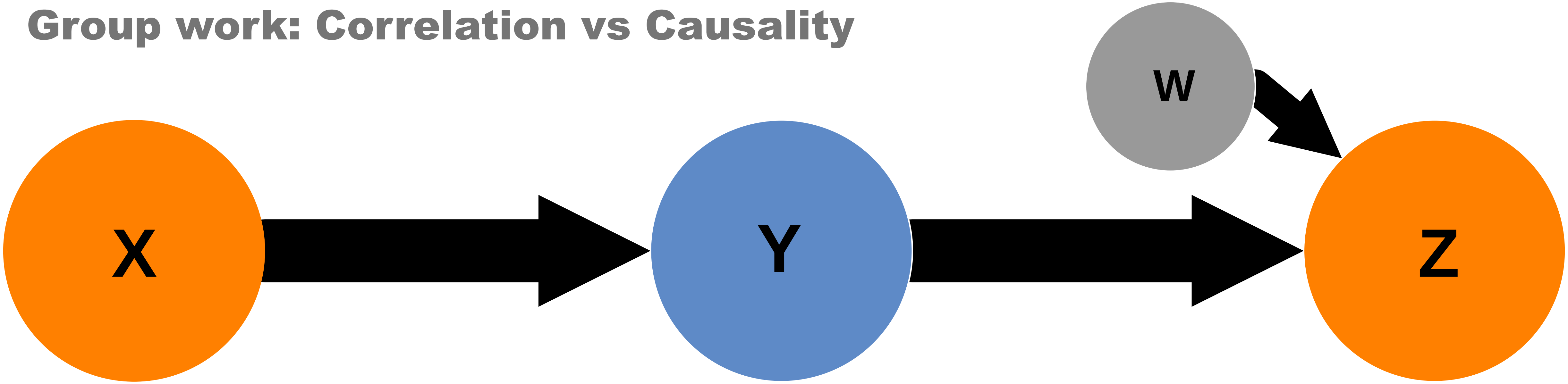


2. *Y* = *f(X,Z)*



Group work: Correlation vs Causality



Which model predicts ***Y*** more accurately if you *train on data from one region* and

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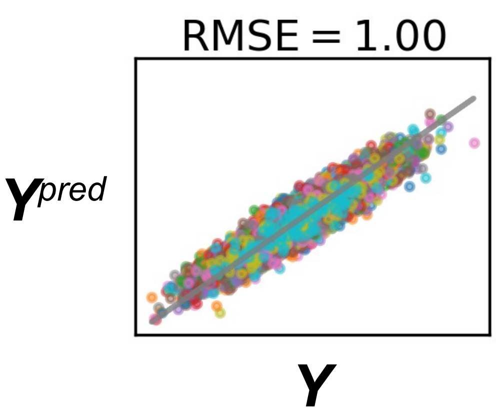
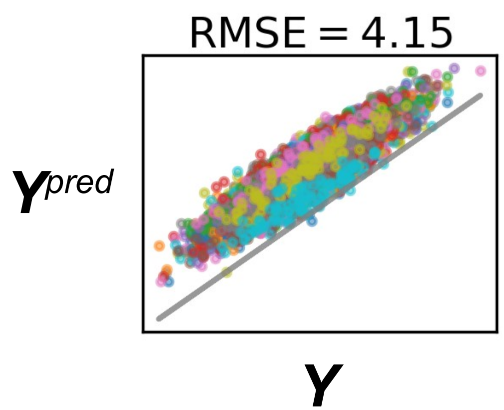
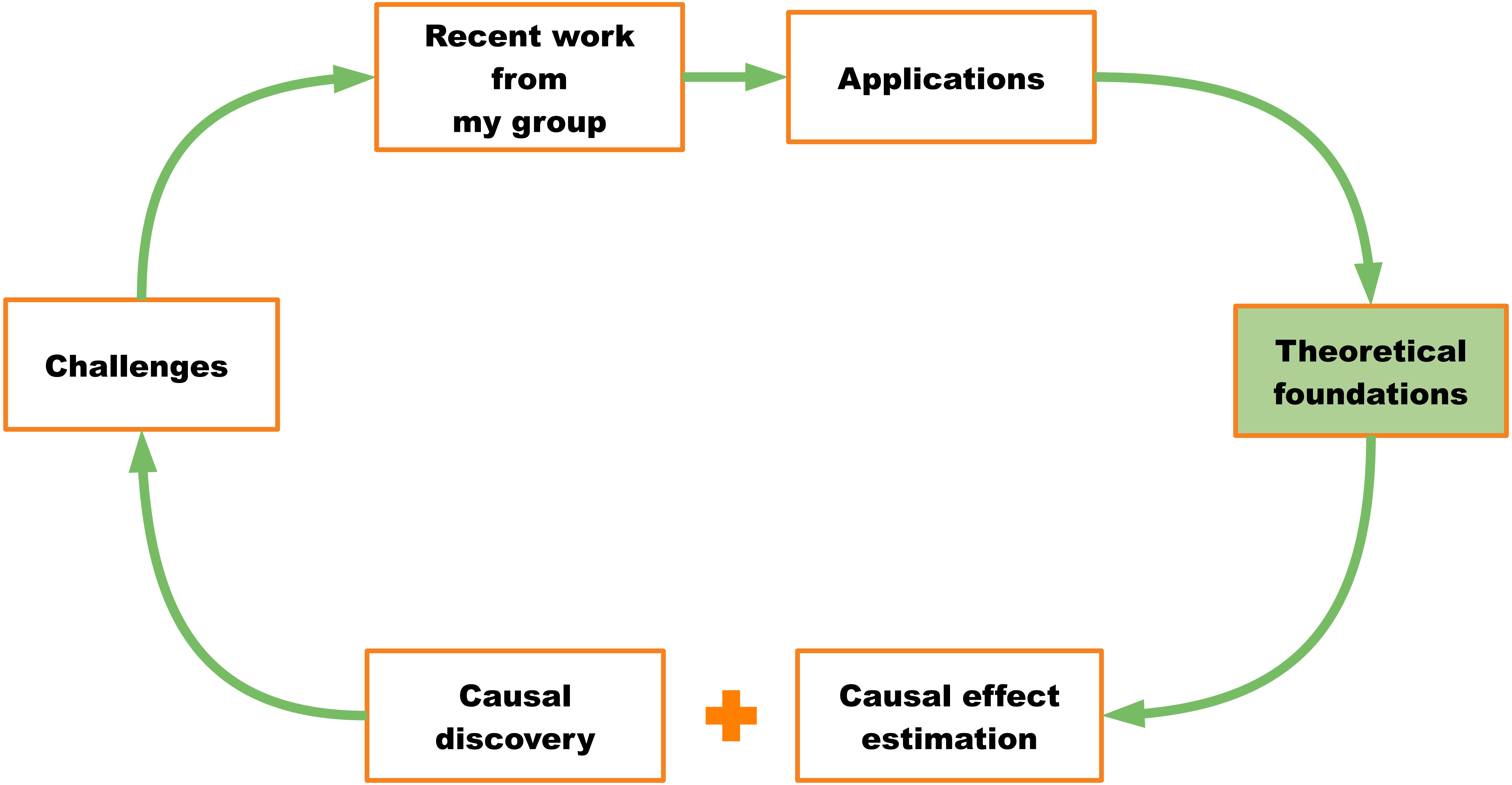
- predict on another region? **(out-of-distribution)**

1. *Y = f(X)* **2. *Y = f(X,Z)***



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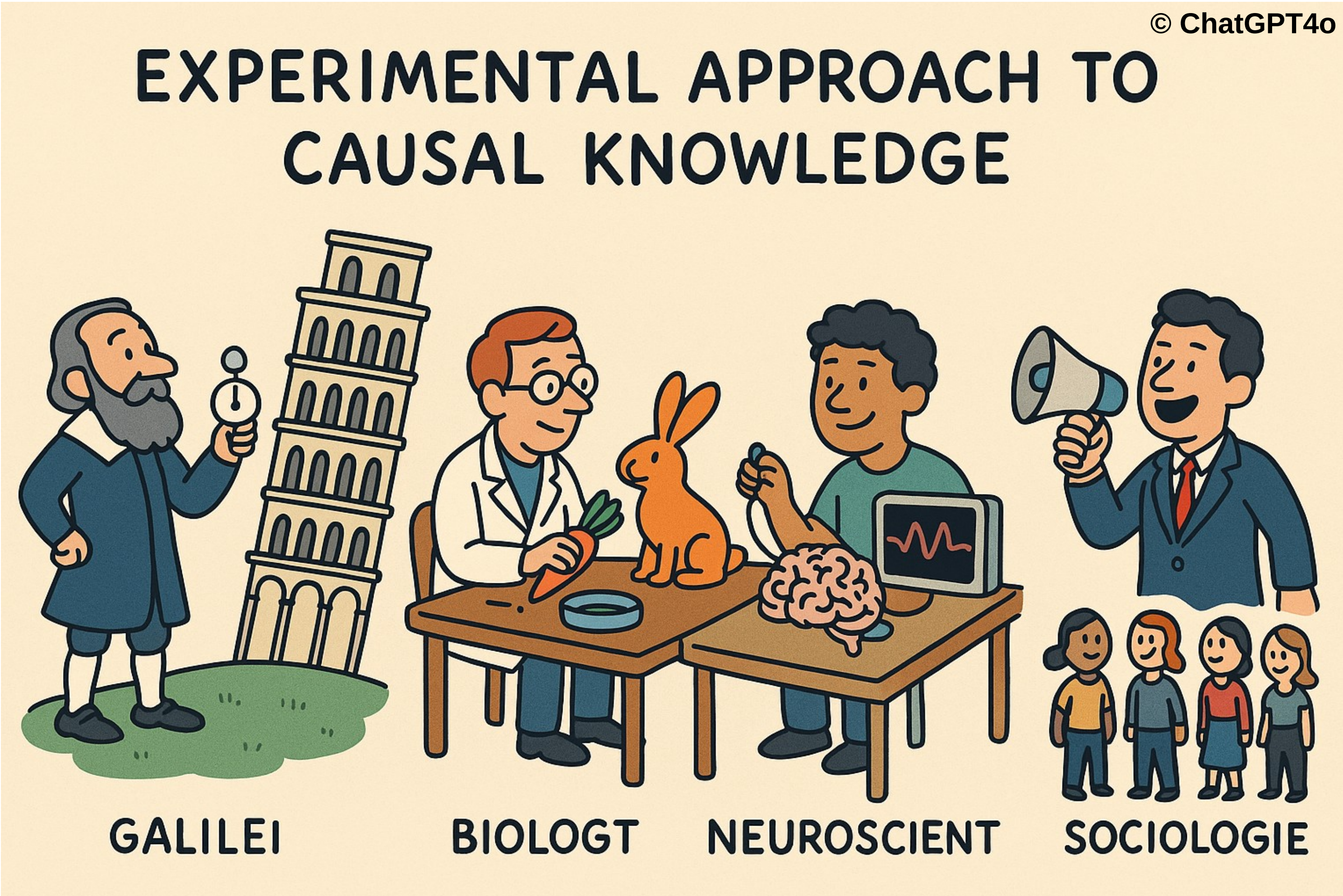
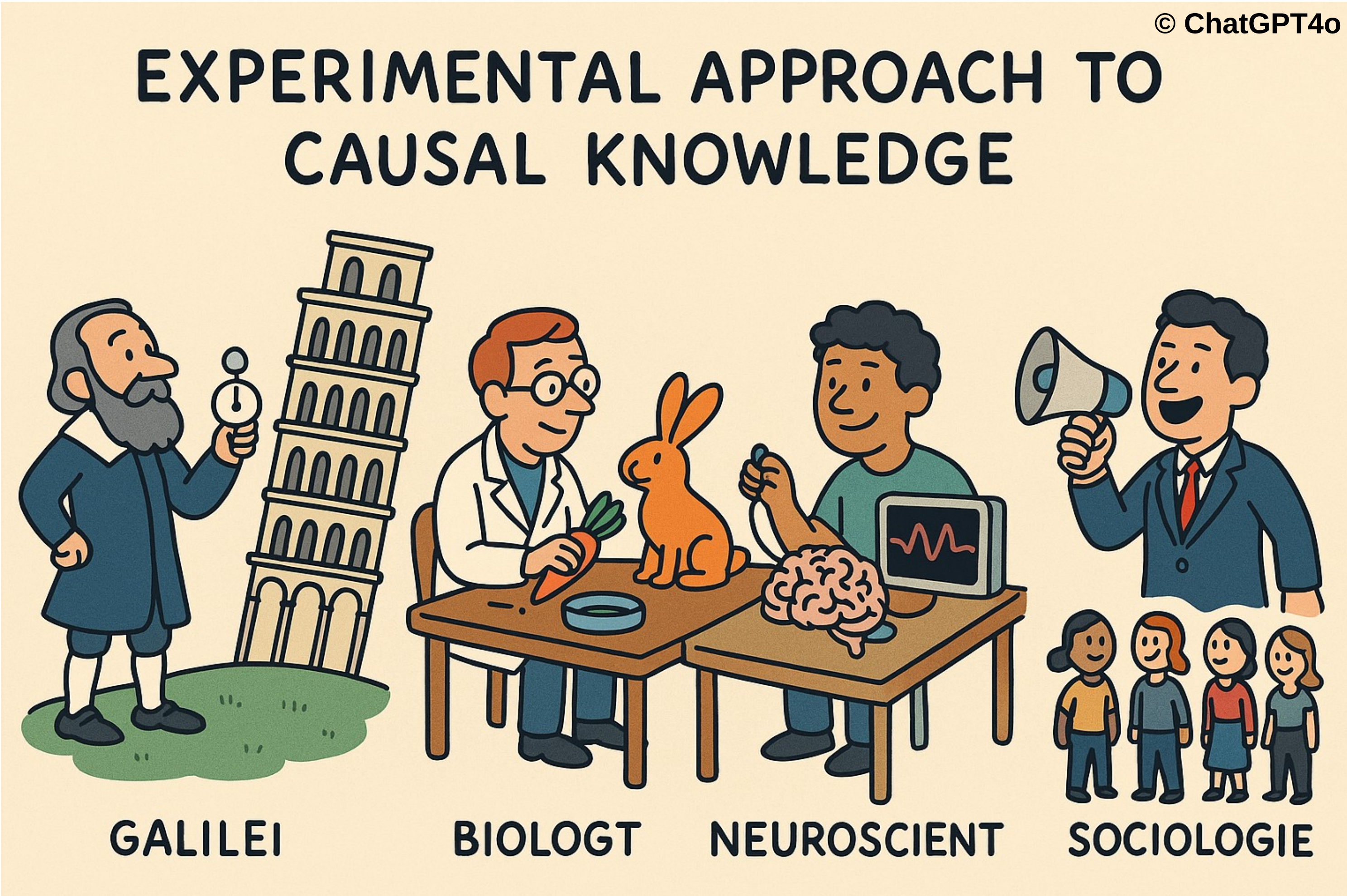
Causal effect estimation
Causal discovery
Challenges

Answering causal questions

Answering causal questions



Answering causal questions



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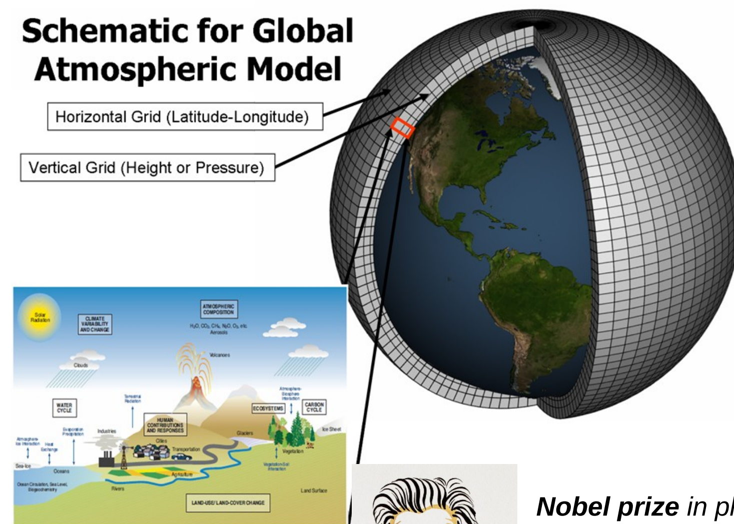

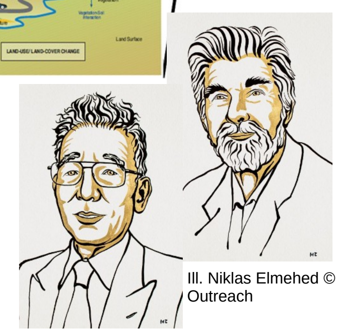

***Nobel prize** in physics 2021 for Klaus Hasselmann and Syukuro Manabe*

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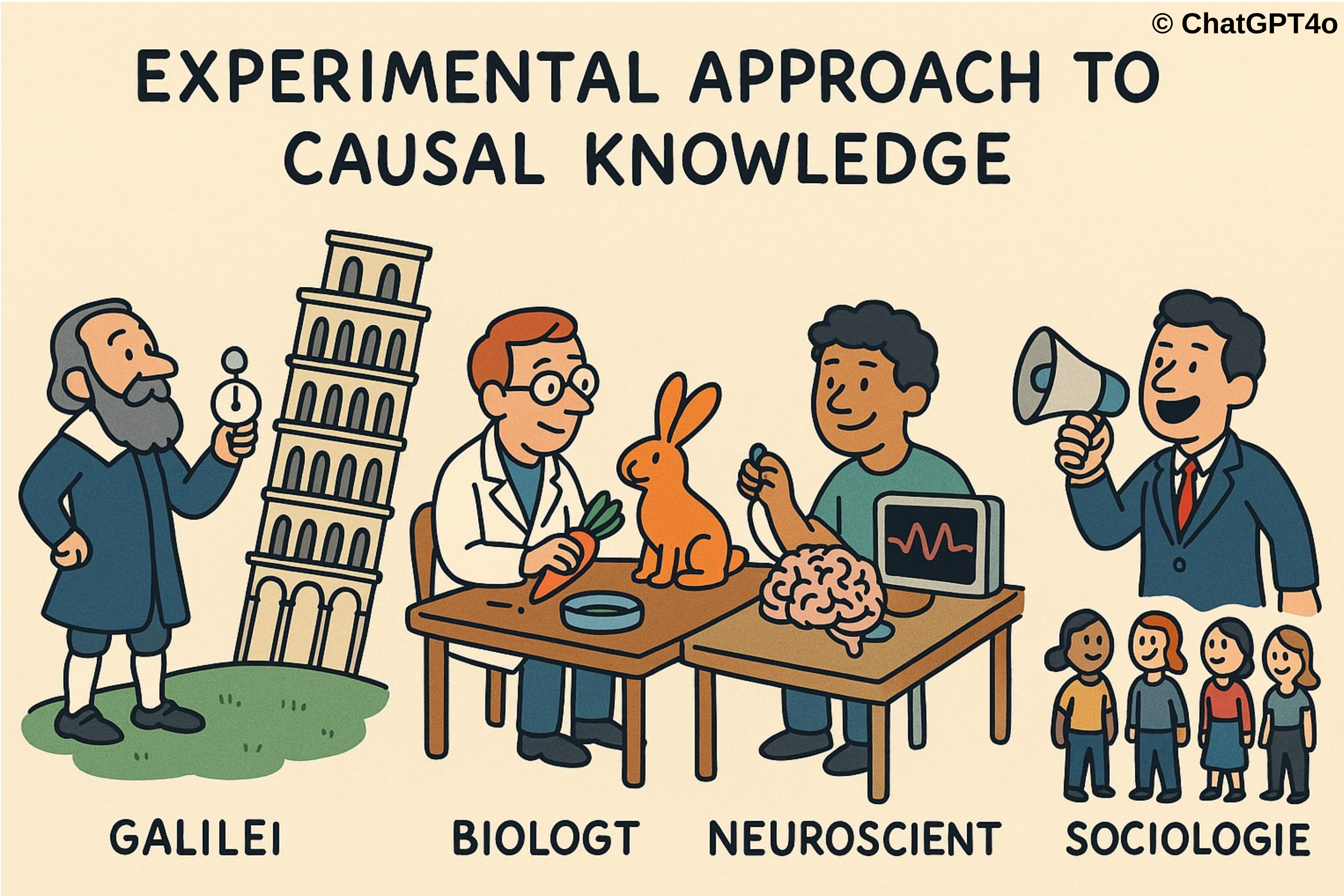
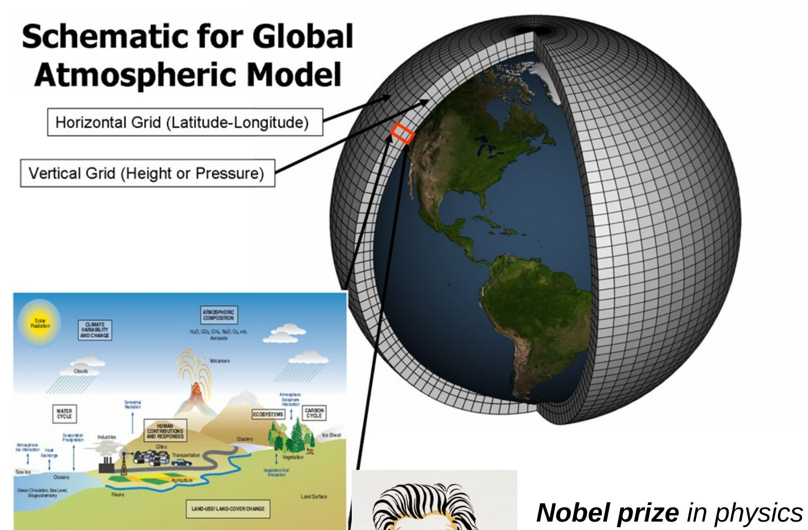
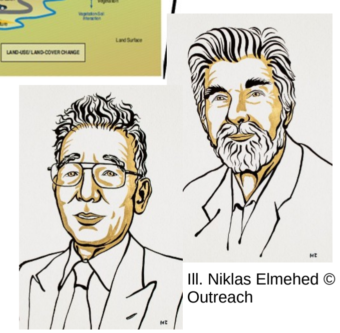
Answering causal questions



Expensive, time consuming, ethical issues, ...





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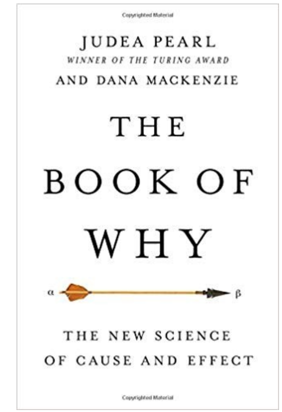
Causal inference



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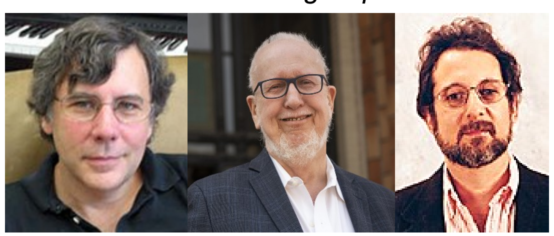

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Glymour,
Scheines

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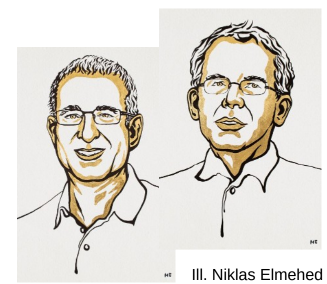
Nobel prize 2021



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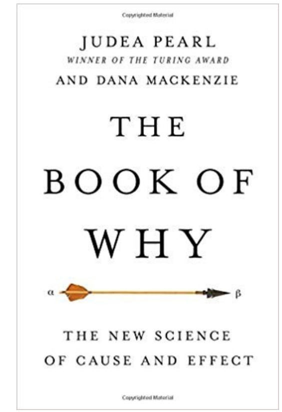
Causal inference

Causal inference enables to utilize domain knowledge to answer causal questions from data.



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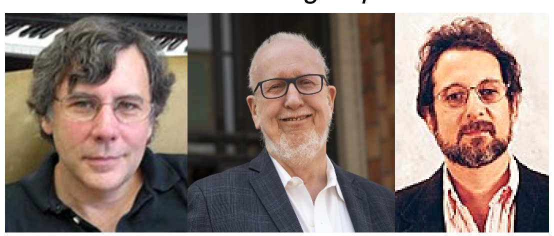

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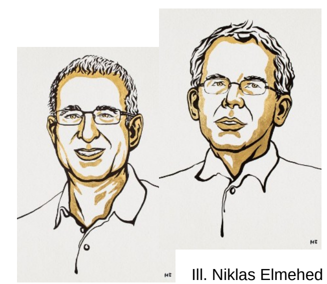

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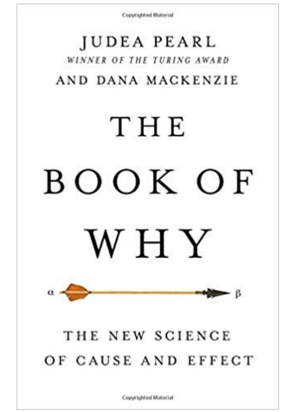

Question

Counter-factual

Causal (interventional)

Non-causal

Underlying system

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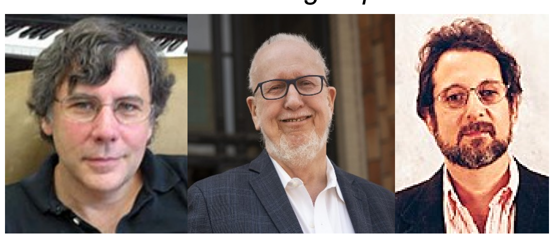

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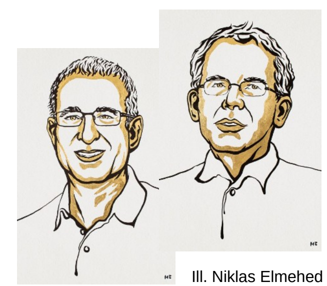

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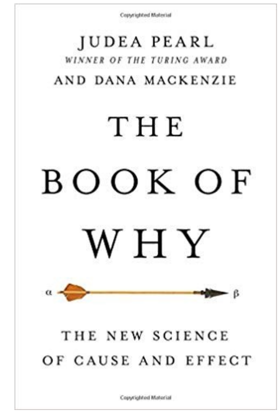
Causal inference



Causal inference enables to utilize domain knowledge to answer causal questions from data.

Question

Counter-factual		
Causal (interventional)		
Non-causal	$p(y\|x)$	Detecting extreme event patterns and correlated variables

Underlying system

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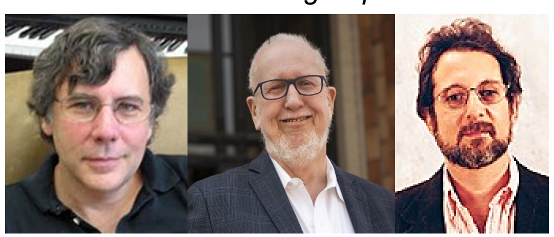

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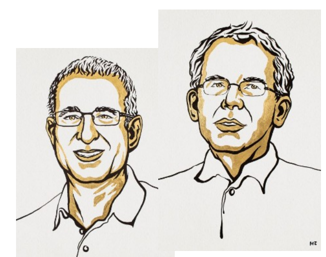

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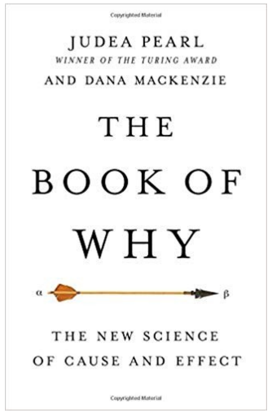
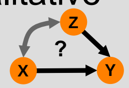
Causal inference



Causal inference enables to utilize domain knowledge to answer causal questions from data.

Question

Counter-factual		
Causal (interventional)	Quantitative $p(y \mid do(x))$ Qualitative G 	Will climate change cause more extreme events in the future?
Non-causal	$p(y \mid x)$	Detecting extreme event patterns and correlated variables

Underlying system

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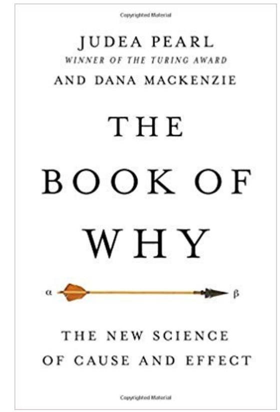
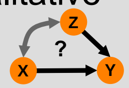


Causal inference enables to utilize domain knowledge to answer causal questions from data.

	Question	
Counter-factual	$p(y'_{x'} \mid y_x)$	What would have been the probability of this extreme event without climate change?
Causal (interventional)	Quantitative $p(y \mid do(x))$ Qualitative G 	Will climate change cause more extreme events in the future?
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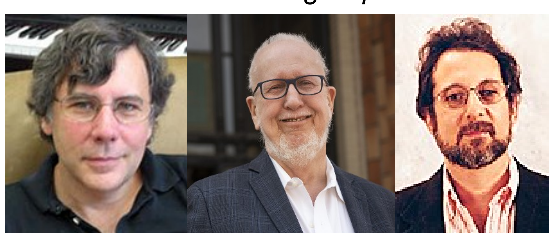

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Underlying system

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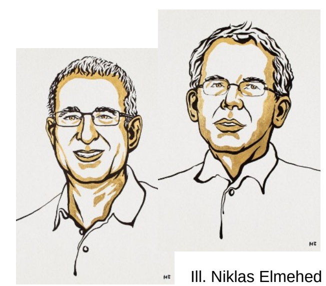

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Causal inference

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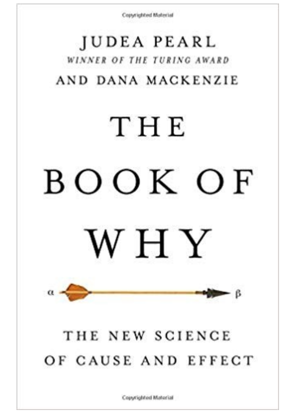
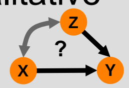


Question			Data
Counter-factual	$p(y'_{x'} \mid y_x)$	What would have been the probability of this extreme event without climate change?	-
Causal (interventional)	Quantitative $p(y \mid do(x))$ Qualitative G 	Will climate change cause more extreme events in the future?	Interventional data
Non-causal	$p(y \mid x)$	Detecting extreme event patterns and correlated variables	Observational data

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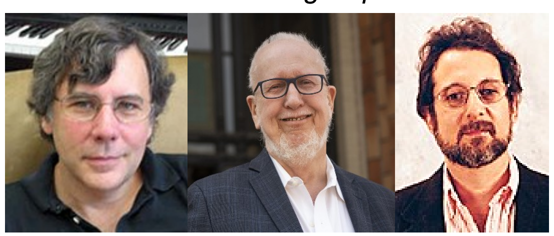

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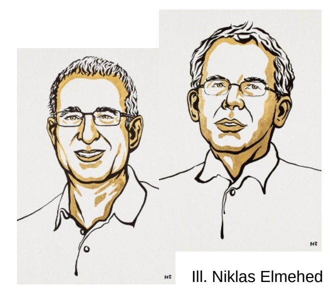

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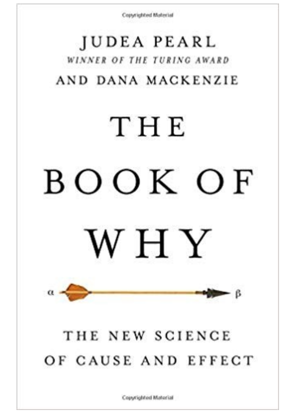

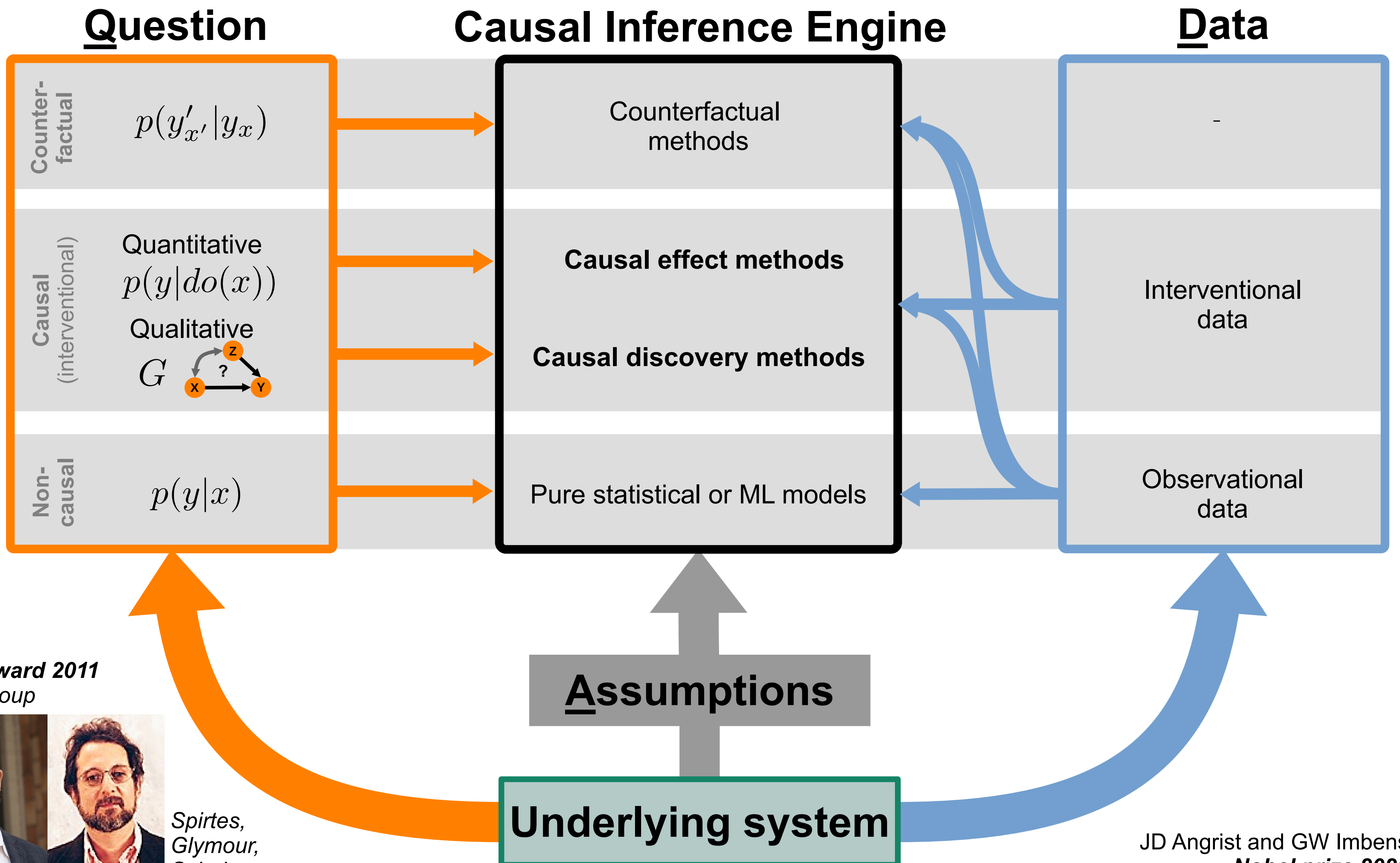

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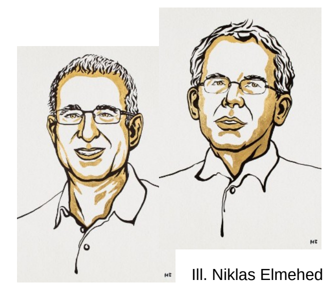

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Causal inference framework

Causal inference framework

Assumes an underlying **observational structural causal model (SCM):**

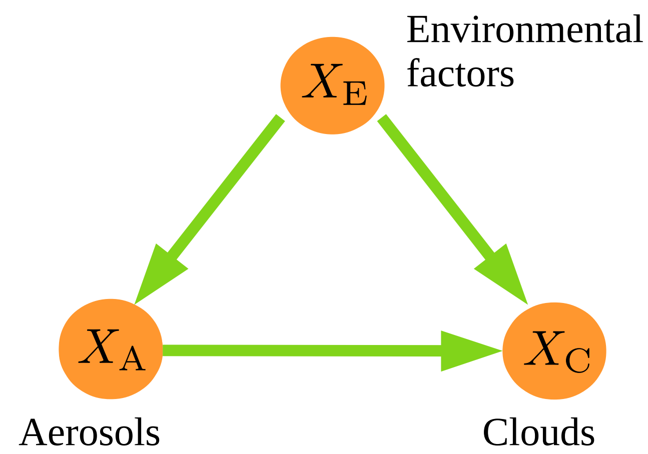
$$X_{\mathrm{A}} := f_{\mathrm{A}}(X_{\mathrm{E}}, \eta_{\mathrm{A}})$$
$$X_{\mathrm{C}} := f_{\mathrm{C}}(X_{\mathrm{A}}, X_{\mathrm{E}}, \eta_{\mathrm{C}})$$
$$X_{\mathrm{E}} := f_{\mathrm{E}}(\eta_{\mathrm{E}})$$

Independent noise terms: $\eta_A,\ \eta_E,\ \eta_C$

Entailed **observational distribution:**

$$p(\mathbf{X}) = p(X_{\mathrm{C}}|X_{\mathrm{A}}, X_{\mathrm{E}}) \cdot p(X_{\mathrm{A}}|X_{\mathrm{E}}) \cdot p(X_{\mathrm{E}})$$

Associated **graph:**



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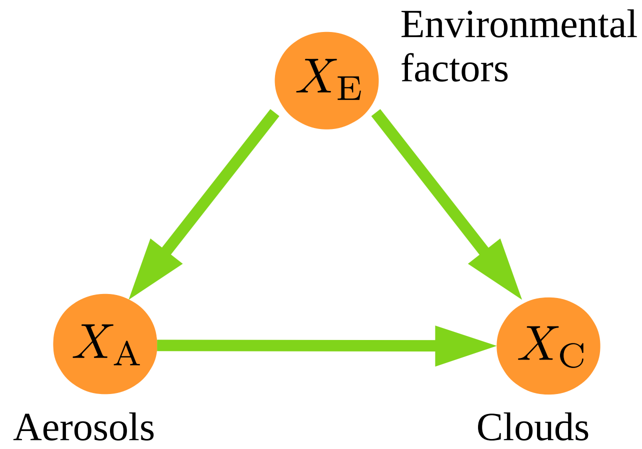


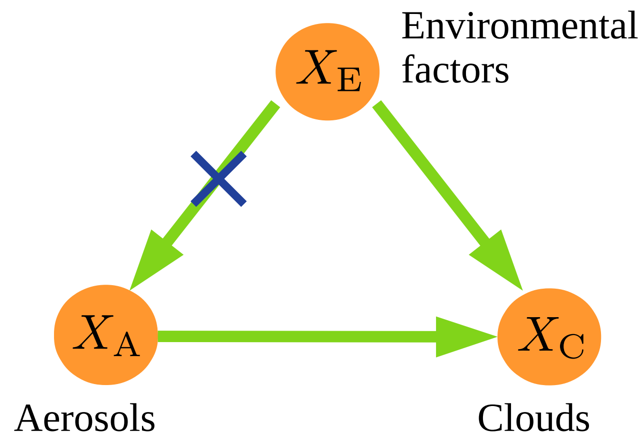
Experiments are represented by **interventional SCM:**

$$X_{\mathrm{A}} \color{red}{:= x'}$$
$$X_{\mathrm{C}} := f_{\mathrm{C}}(X_{\mathrm{A}}, X_{\mathrm{E}}, \eta_{\mathrm{C}})$$
$$X_{\mathrm{E}} := f_{\mathrm{E}}(\eta_{\mathrm{E}})$$

Interventional distribution:

$$p(\mathbf{X} \mid do(X_{\mathrm{A}} = x'))$$

Interventional graph:



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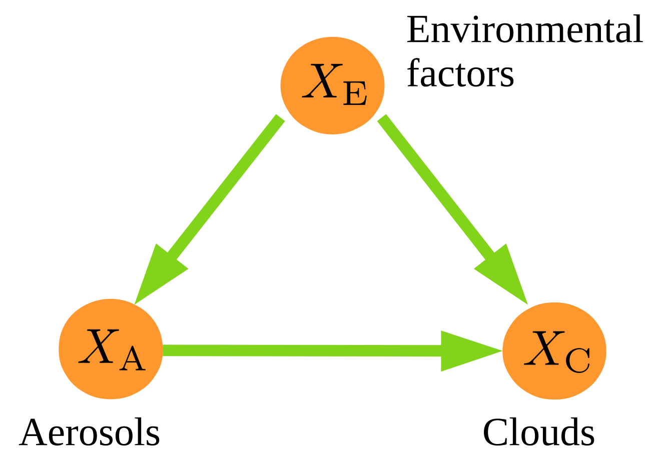
$$p(\mathbf{X}) = p(X_{\mathrm{C}}|X_{\mathrm{A}}, X_{\mathrm{E}}) \cdot p(X_{\mathrm{A}}|X_{\mathrm{E}}) \cdot p(X_{\mathrm{E}})$$

Associated **graph:**



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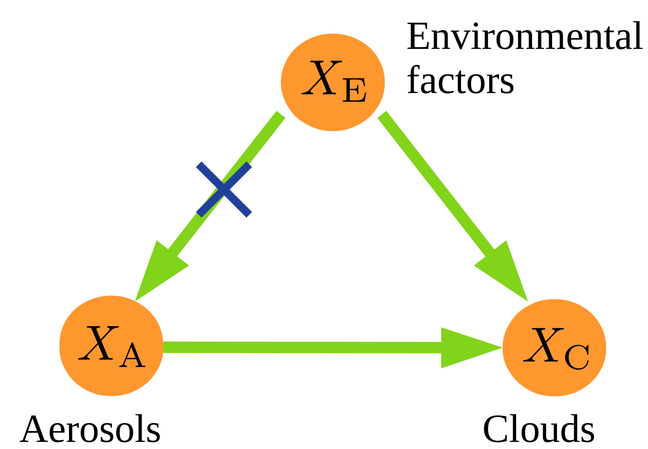
Interventional distribution:

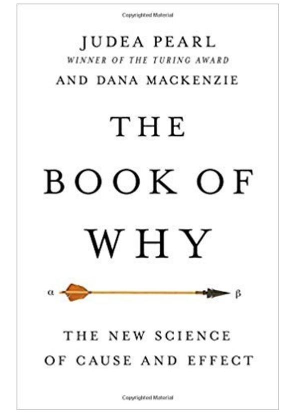
$$p(\mathbf{X} \mid do(X_{\mathrm{A}} = x')) \neq p(\mathbf{X} \mid X_{\mathrm{A}} = x')$$

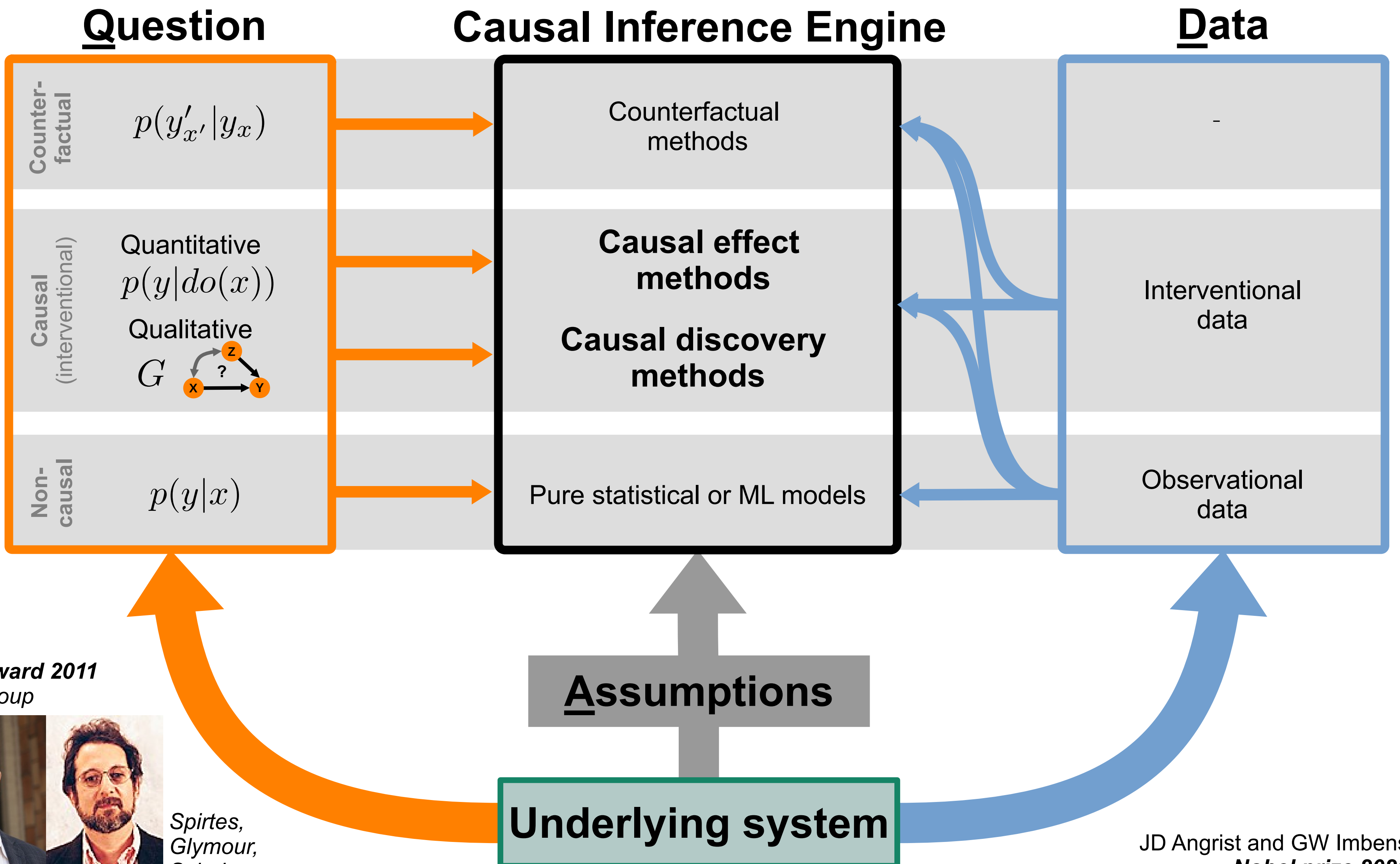
Interventional graph:



Causal inference

Causal inference enables to utilize domain knowledge to answer causal questions from data.





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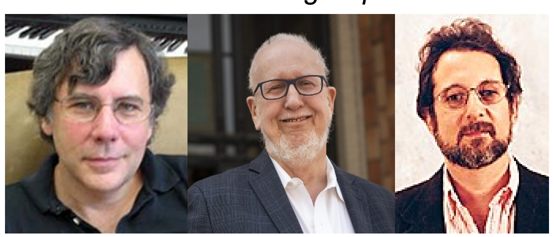

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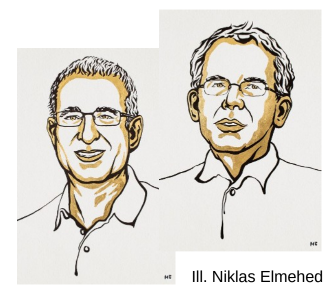

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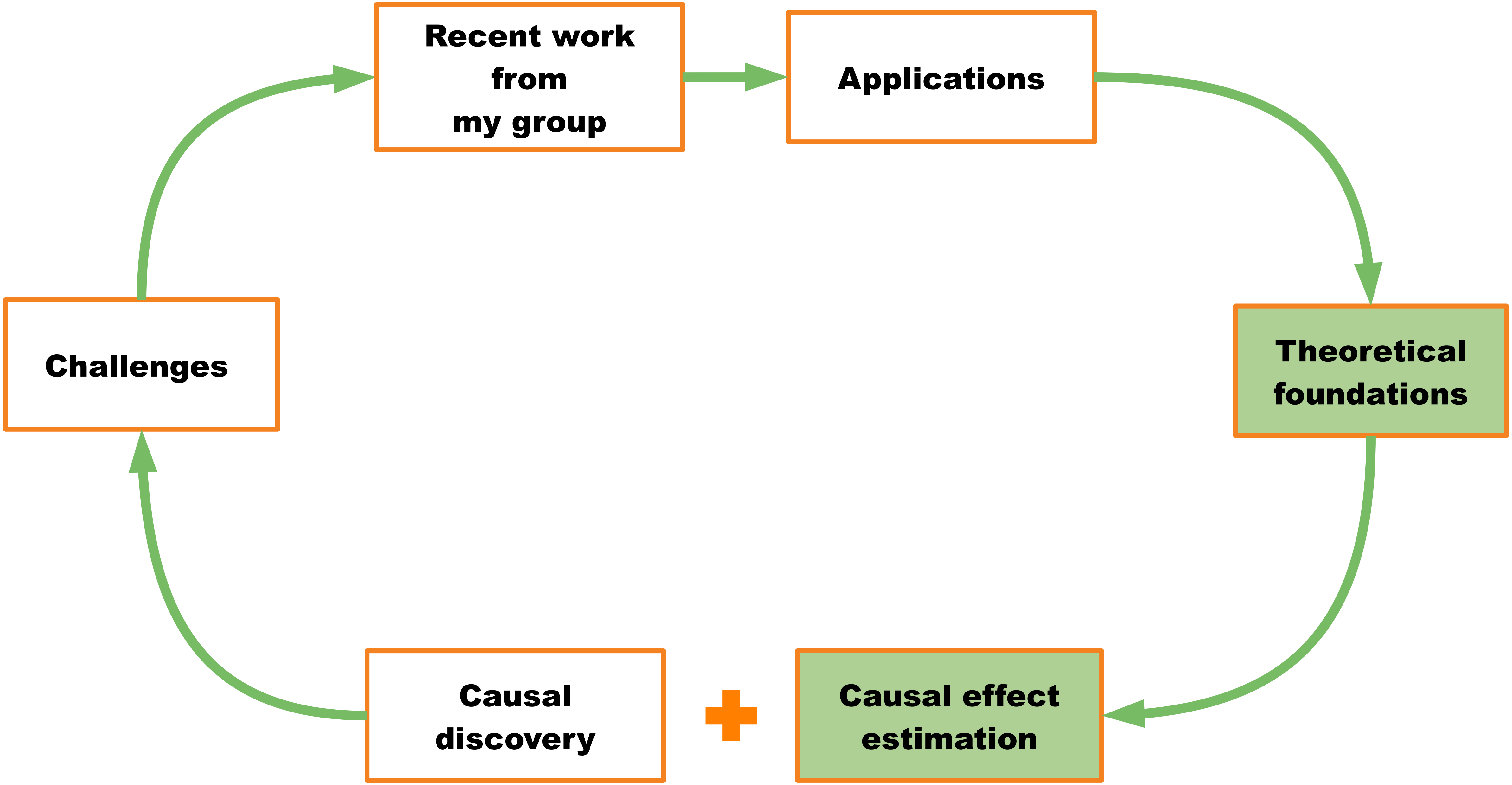
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Applications
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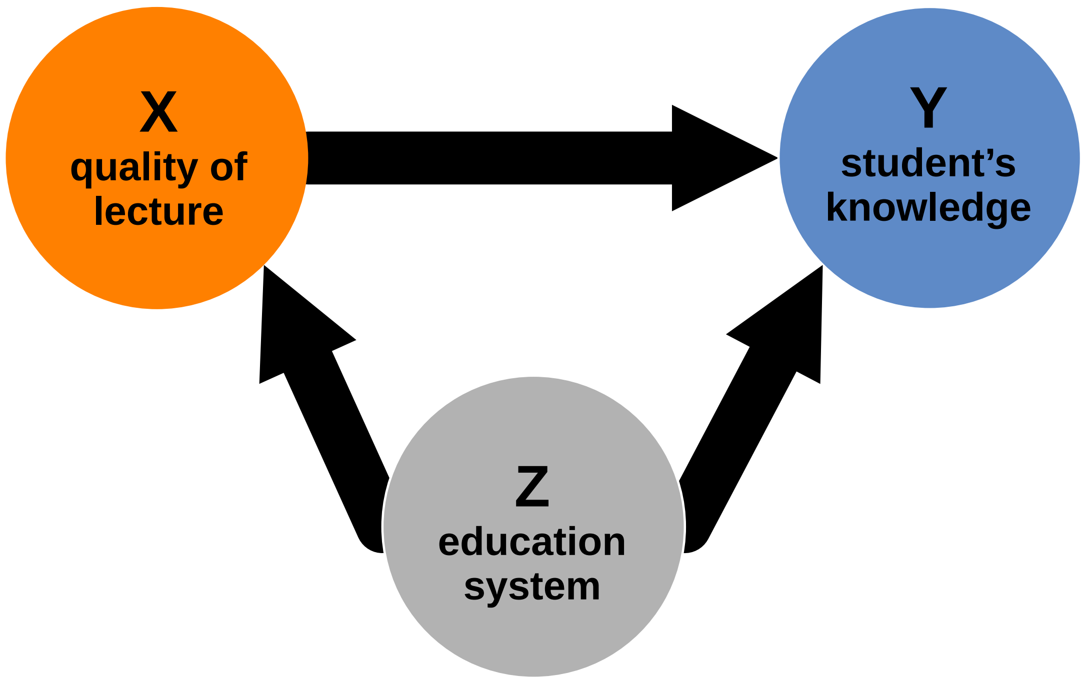
Causal effect estimation
Causal discovery
Challenges

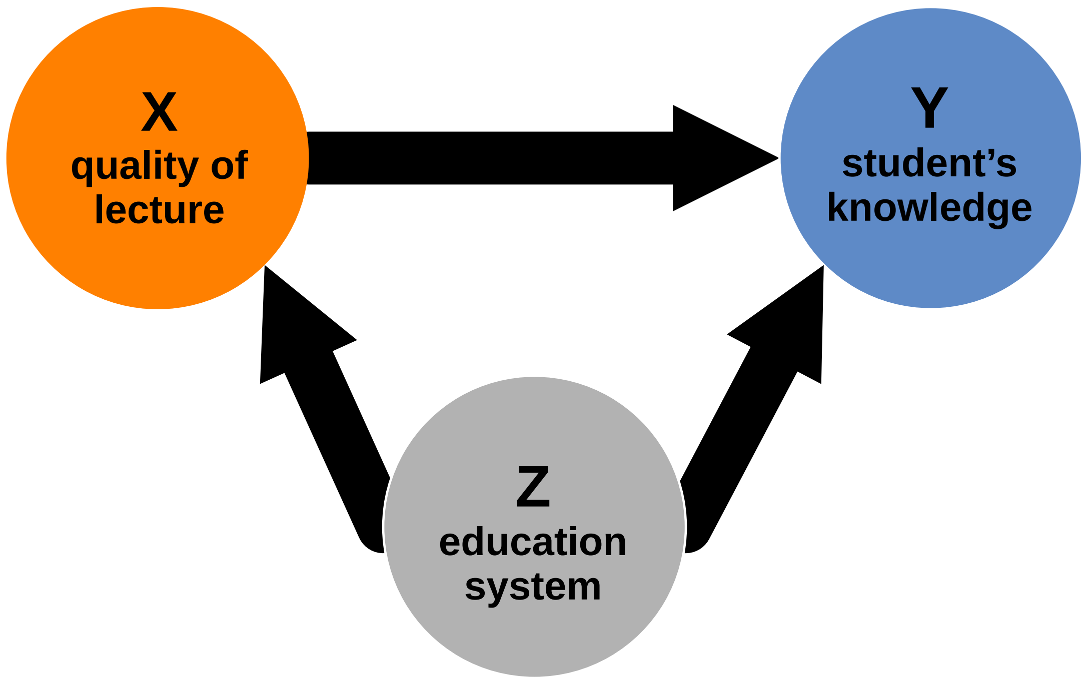
What is a causal effect?



What is a causal effect?

Causal effect is based on the distribution of Y in a system where X was intervened upon:

$$p(y|do(x))$$



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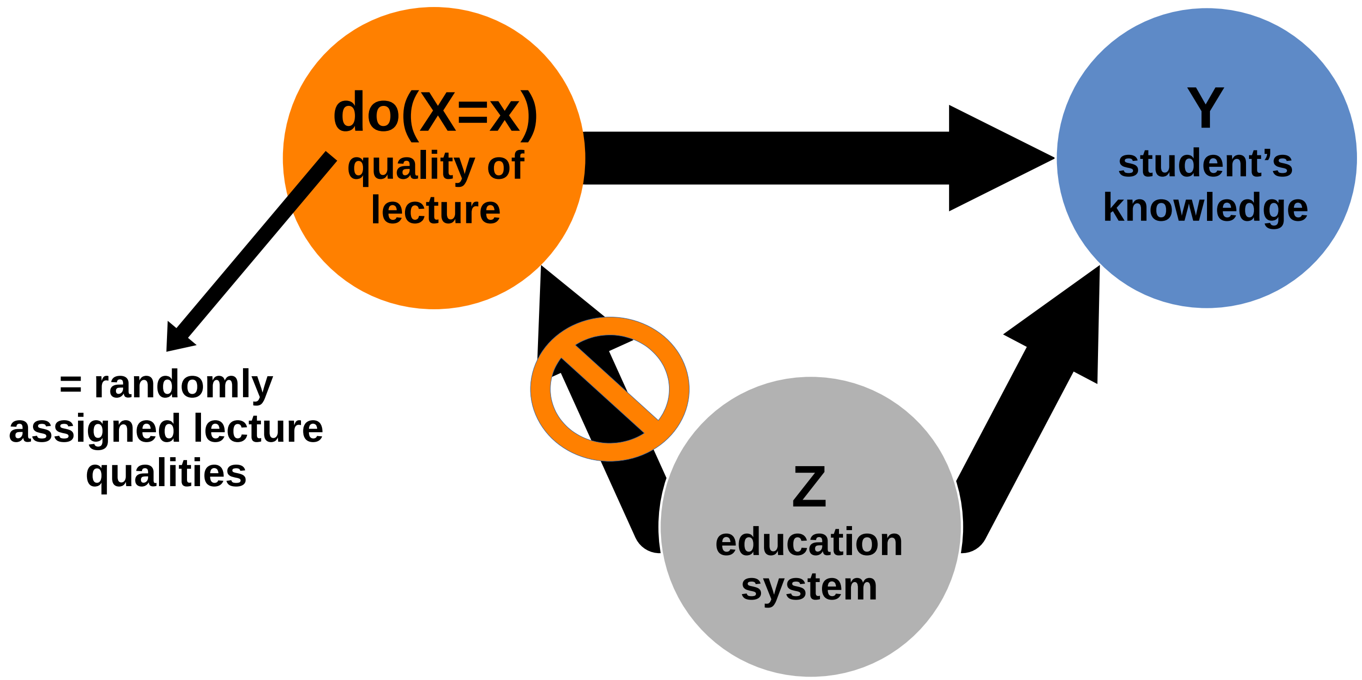

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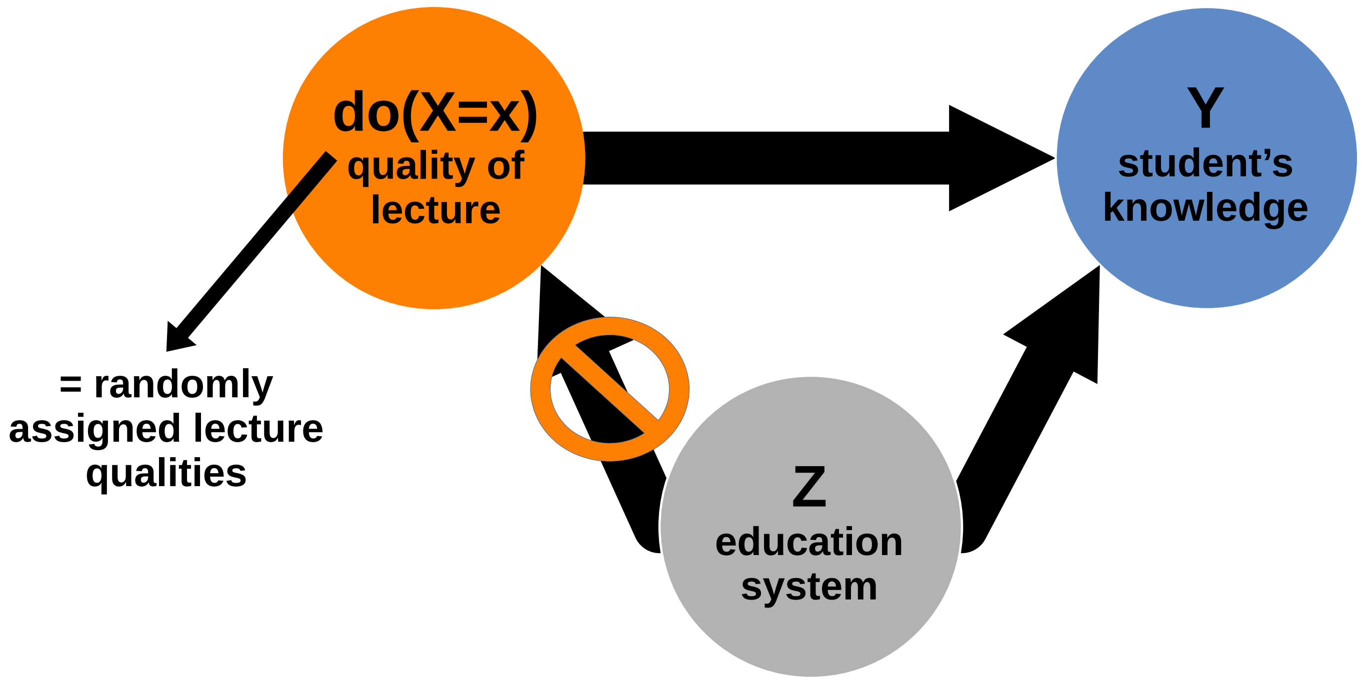
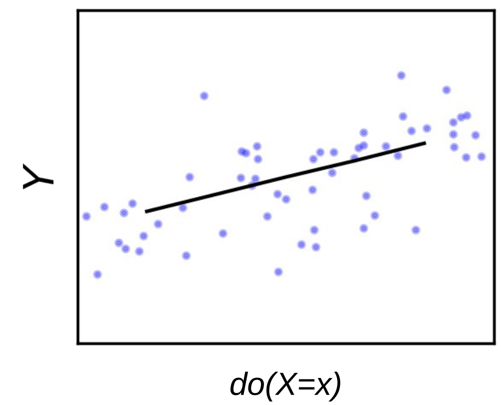


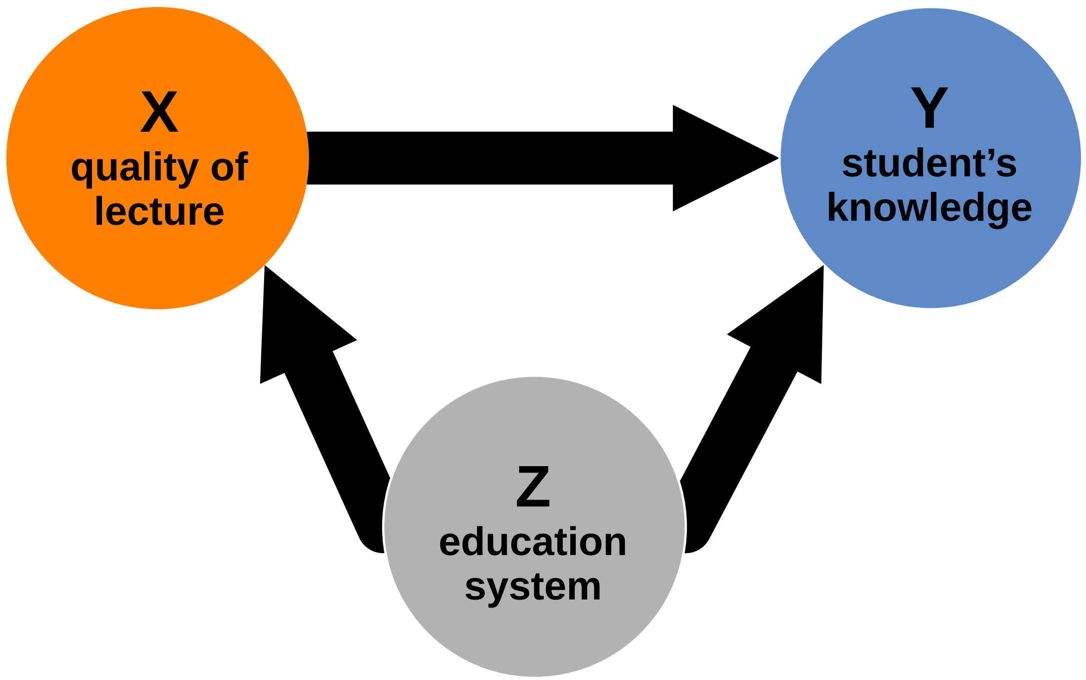


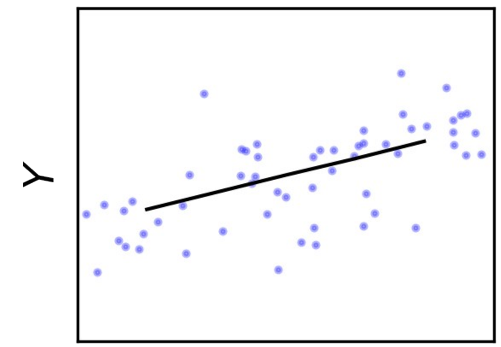
Observational causal effect estimation

Wrong: Correlation regression

$$p(y|x)$$

$$Y = \boxed{\beta_{YX}} X$$





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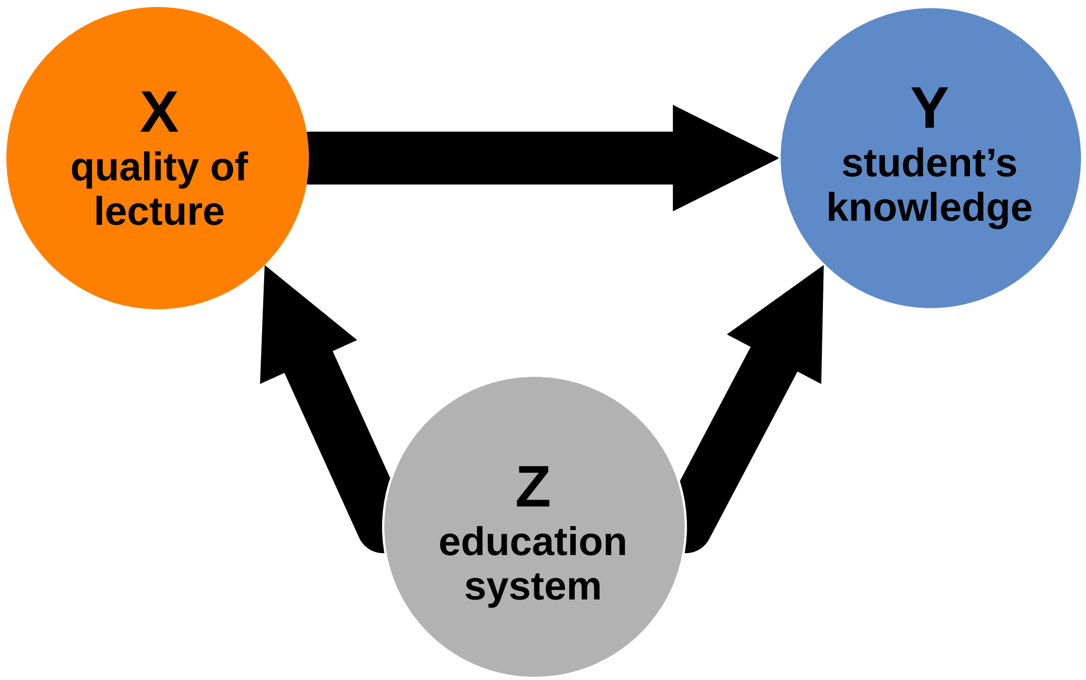
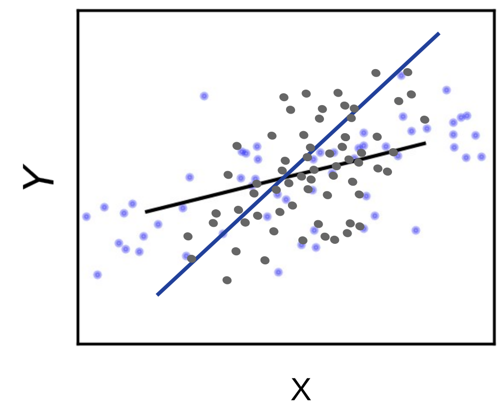
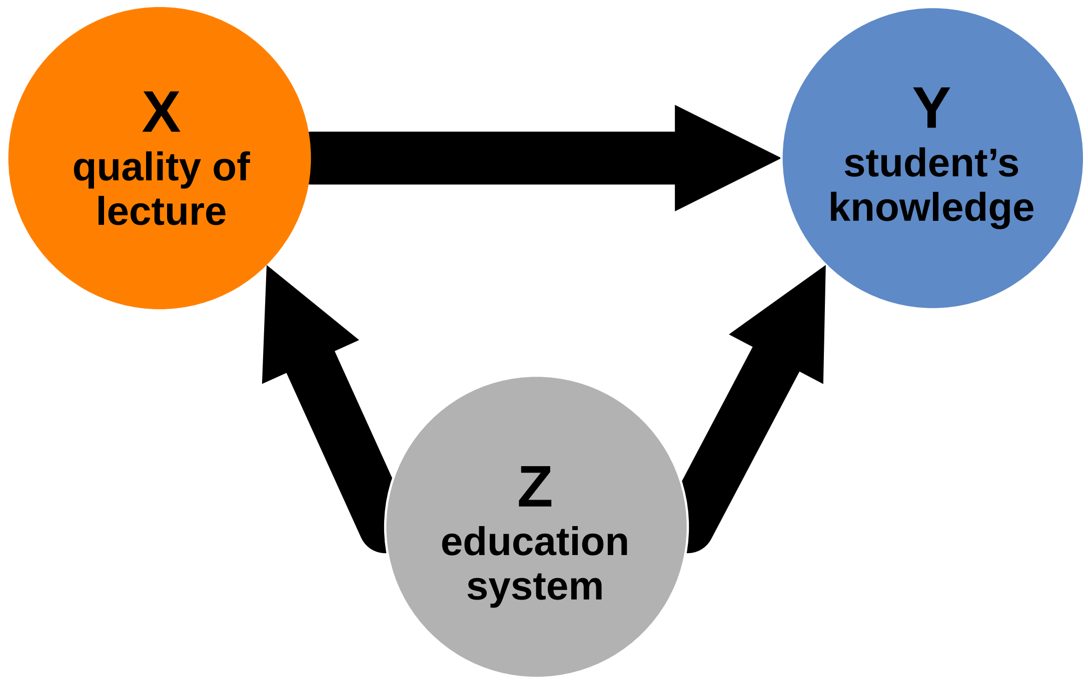




Observational causal effect estimation

Given causal graph and data, *identify* causal effect of intervention from observational distribution

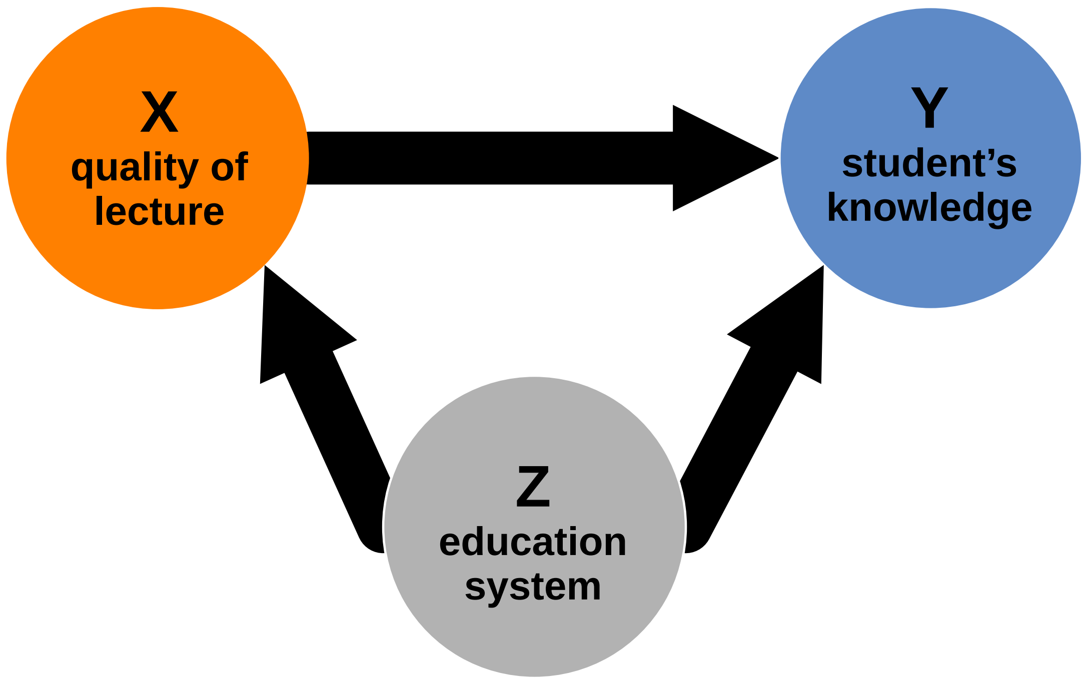
$$p\,(y|do(X{=}x)) = \text{function of observational distribution}$$



Observational causal effect estimation

Given causal graph and data, *identify* causal effect of intervention from observational distribution

$$p\,(y|do(X{=}x)) = \text{function of observational distribution}$$



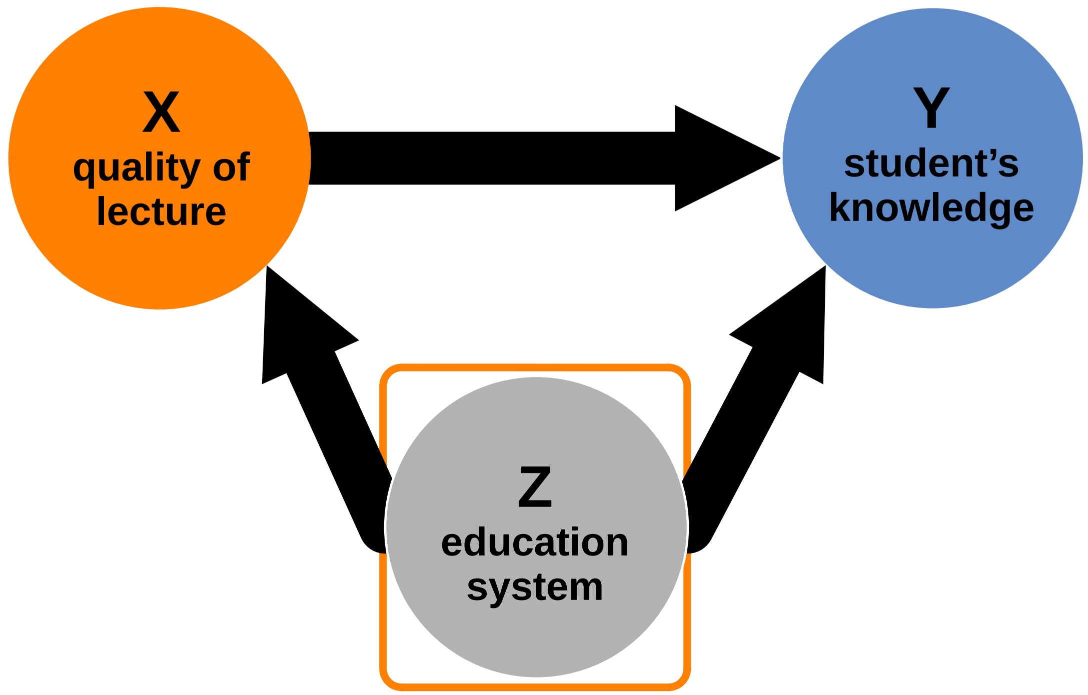
- **(Generalized) backdoor adjustment**
- front-door adjustment
- do-calculus identification

- propensity score matching
- instrumental variables
- difference-in-differences
- regression discontinuity
- ...

Observational causal effect estimation

Given causal graph and data, *identify* causal effect of intervention from observational distribution

$$p\,(y|do(X{=}x)) = \int p(y|x,z)p(z)dz$$ (adjustment identification)



Observational causal effect estimation

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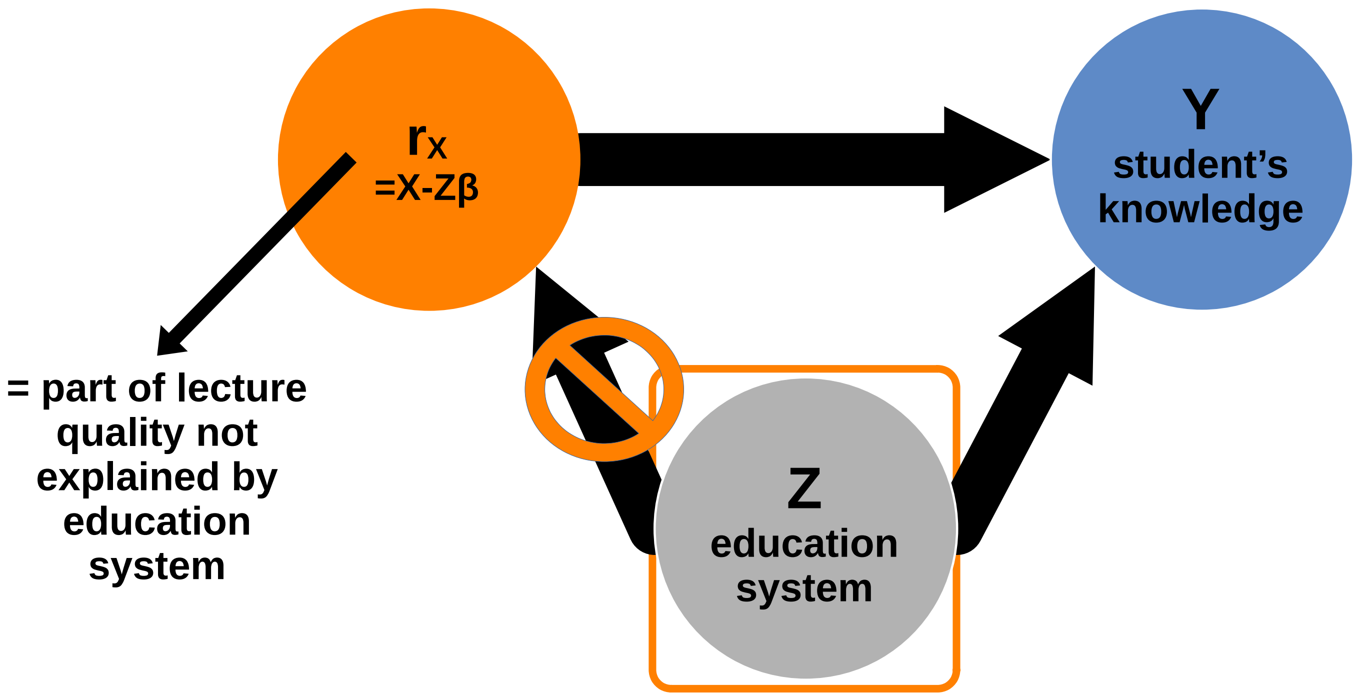
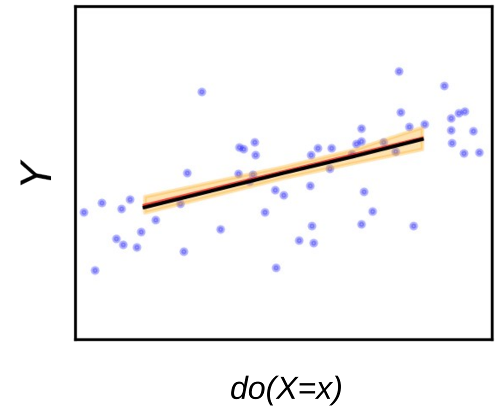
$$Y = \boxed{\beta_{YX\cdot Z}} X + \beta_{YZ\cdot X} Z \qquad \text{(linear adjustment identification)}$$



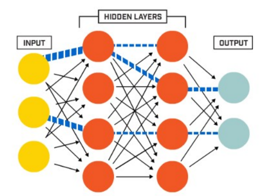


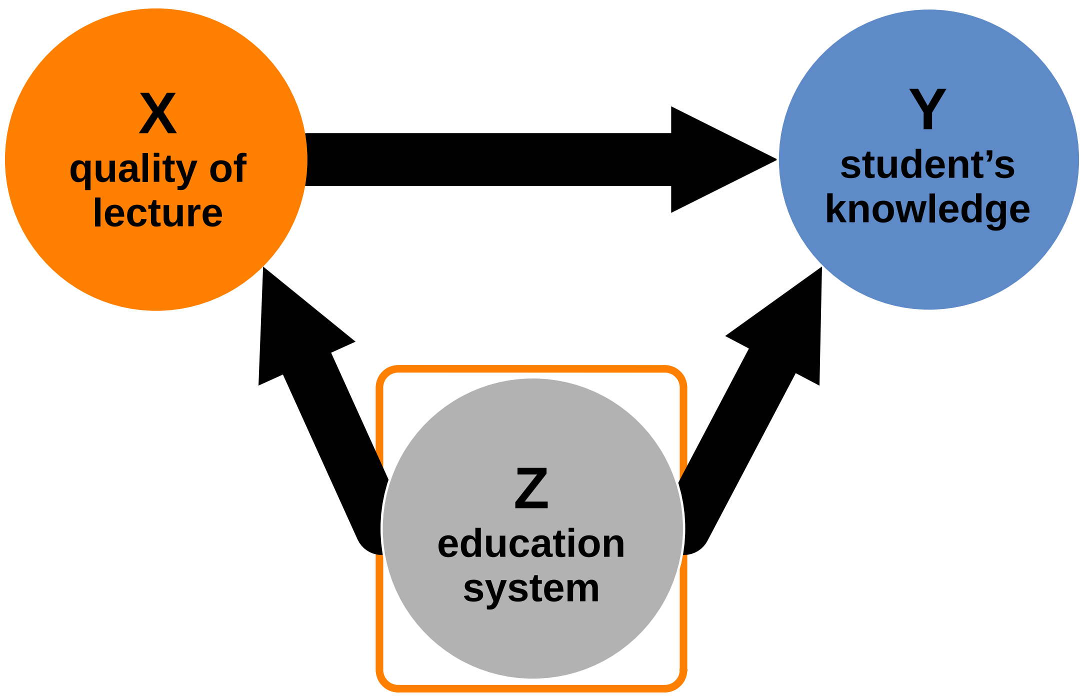
Observational causal effect estimation

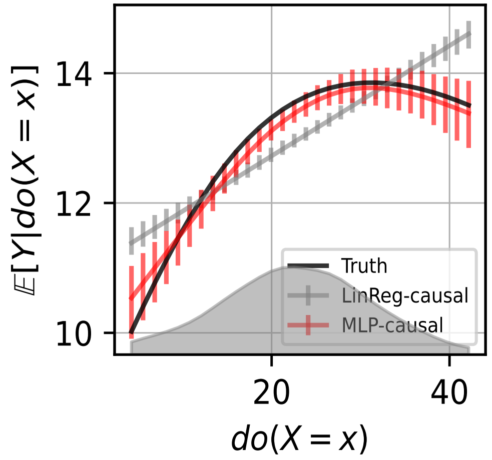
Given causal graph and data, *identify* causal effect of intervention from observational distribution

$$\mathbb{E}\left[y|do(X{=}x)\right] = \int \hat{f}(x,z)p(z)dz$$

(general adjustment identification)







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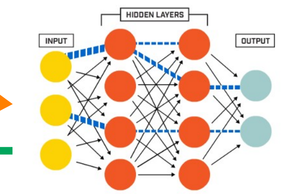
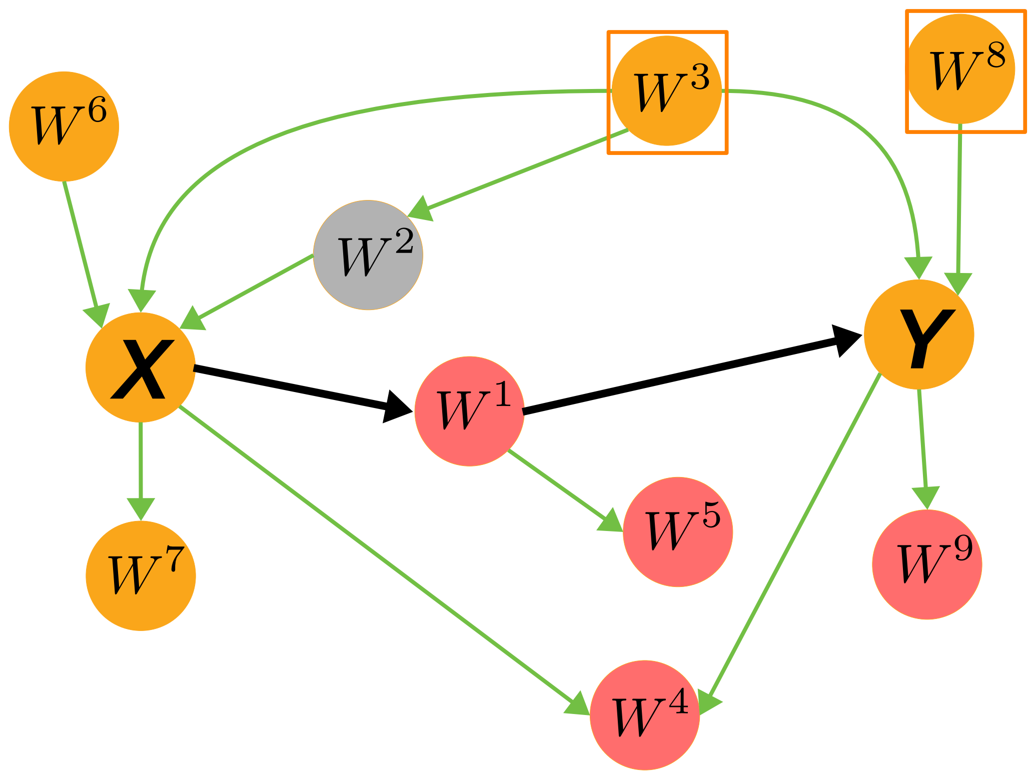




- **(Generalized) backdoor adjustment**
  (Perkovic et al. (2018))

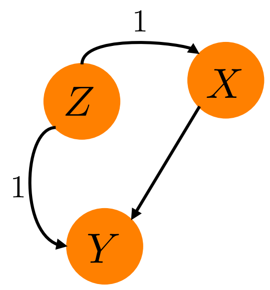
  Z *is a valid adjustment set if:*

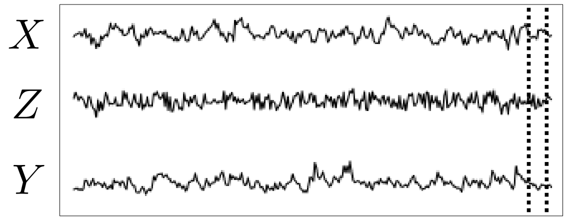
  1) ***Z*** *blocks non-causal paths*
  2) ***Z*** *does not induce collider-bias*

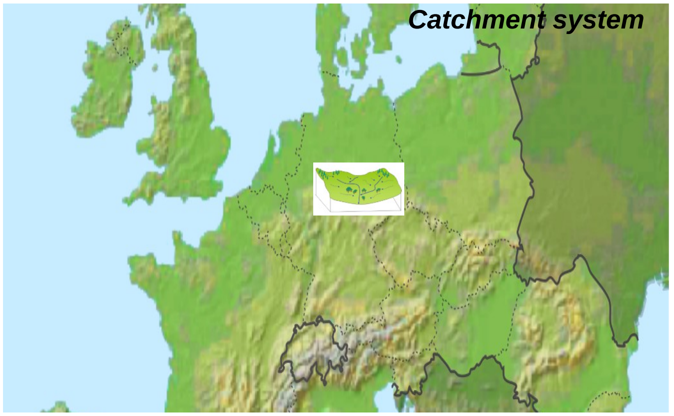
Causal effect estimation for time series

Given causal graph and time series data, *identify* causal effect of intervention from observational distribution

$$p\,(y|do(X{=}x)) = \text{function of observational distribution}$$







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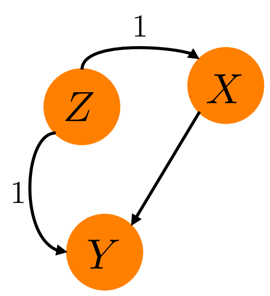

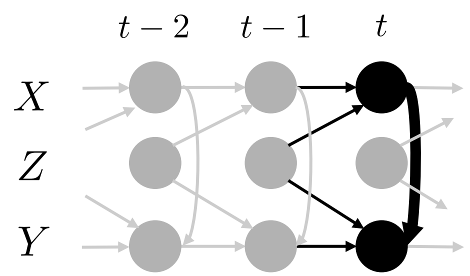

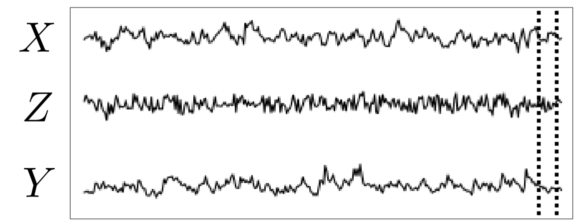

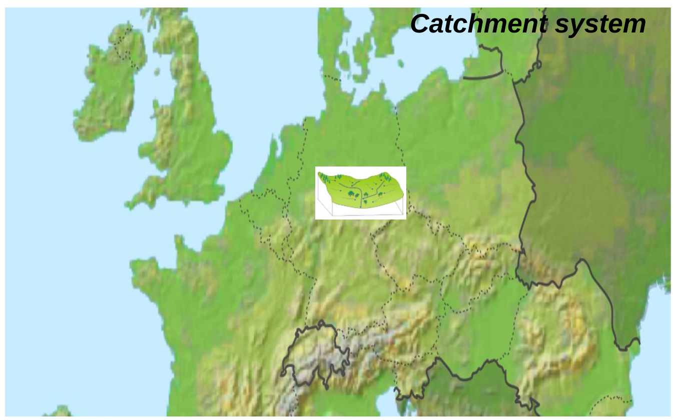

Causal effect estimation for time series from multiple datasets

Given causal graph and multiple datasets of the same system variables, as well as **context data**, *identify* causal effect of intervention from observational distribution

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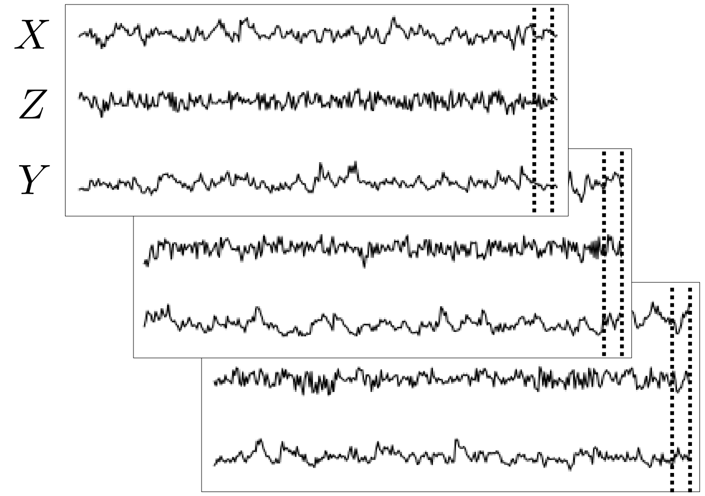

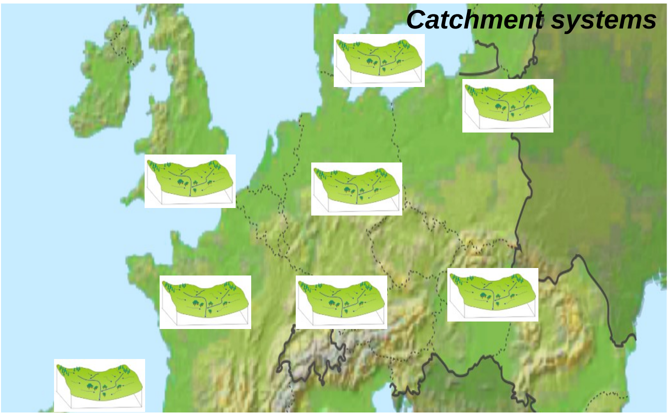

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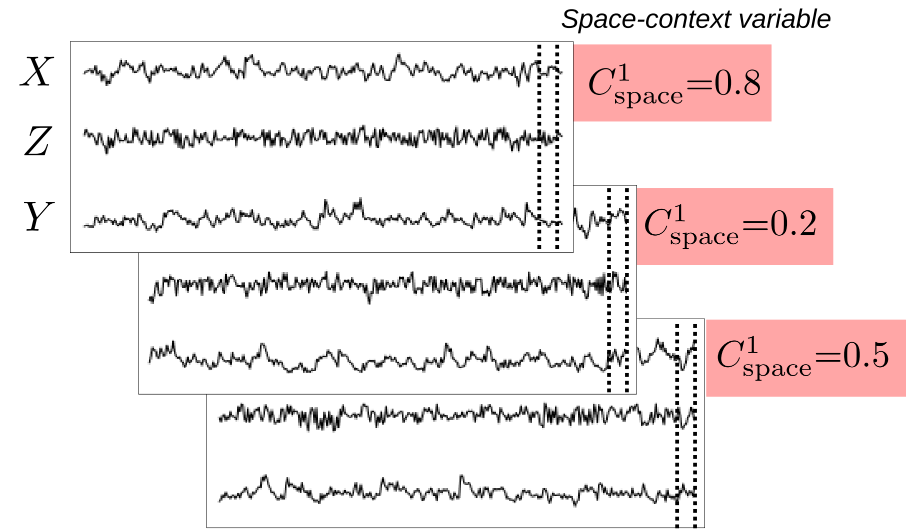

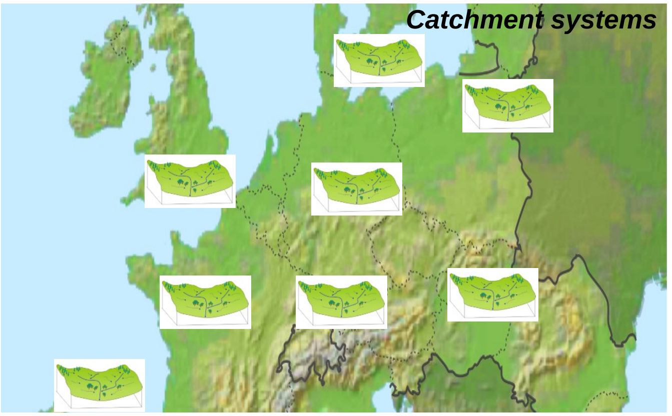

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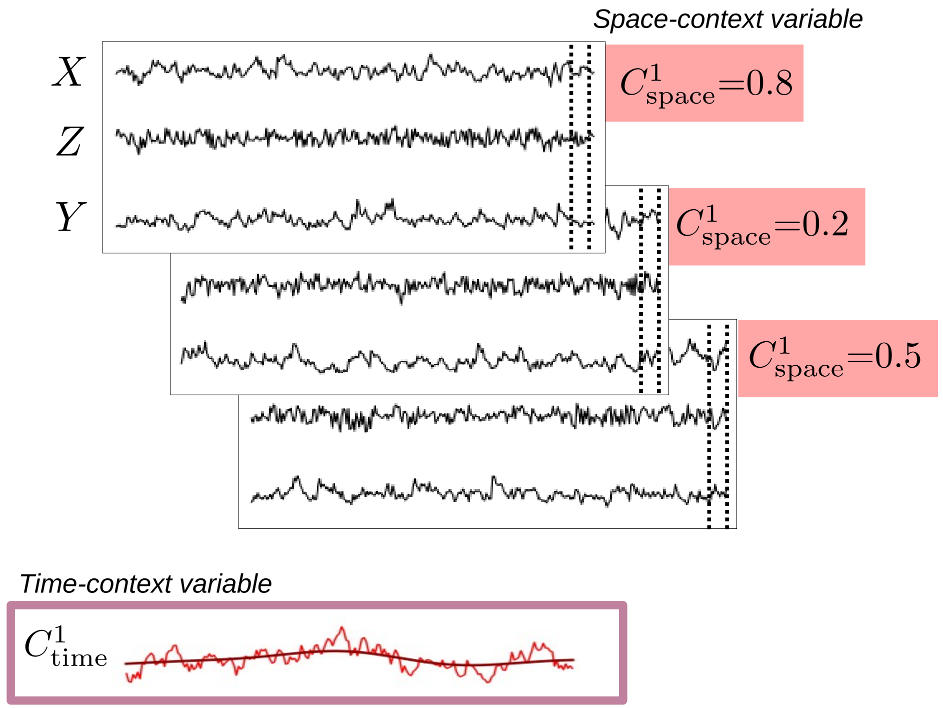

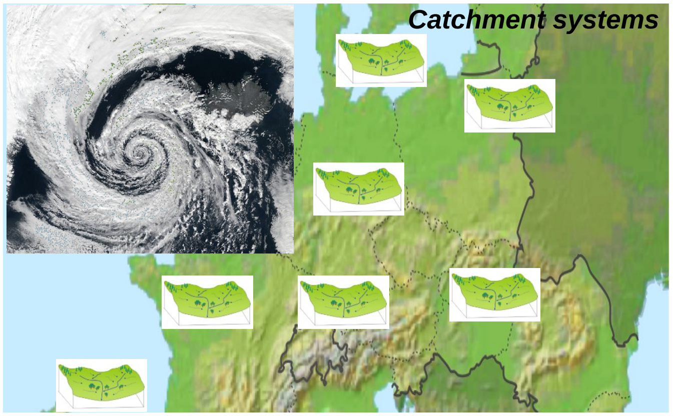

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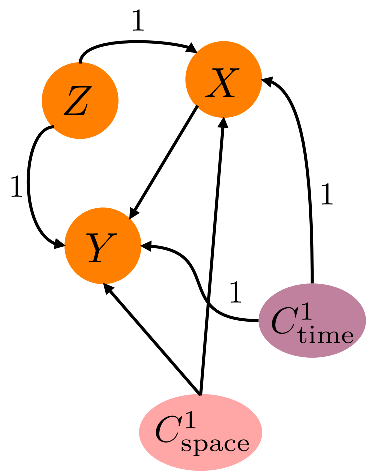

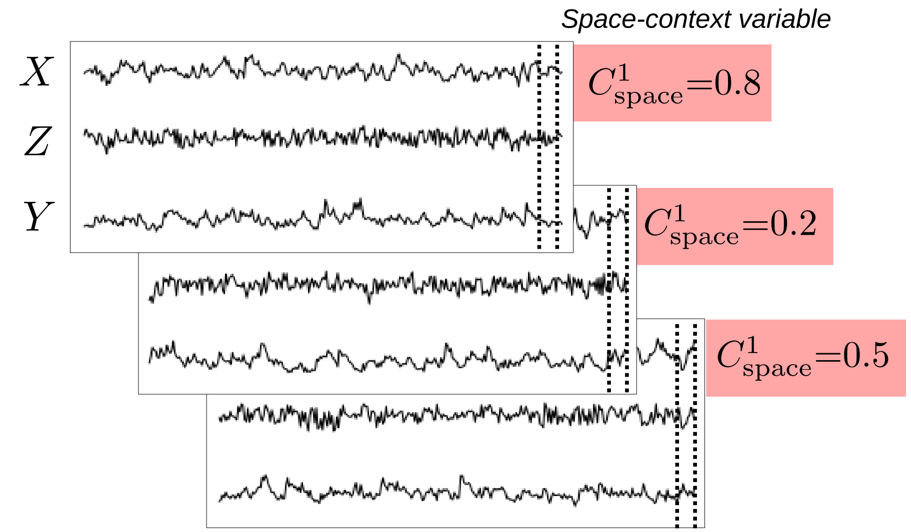

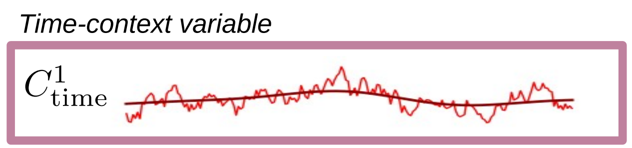

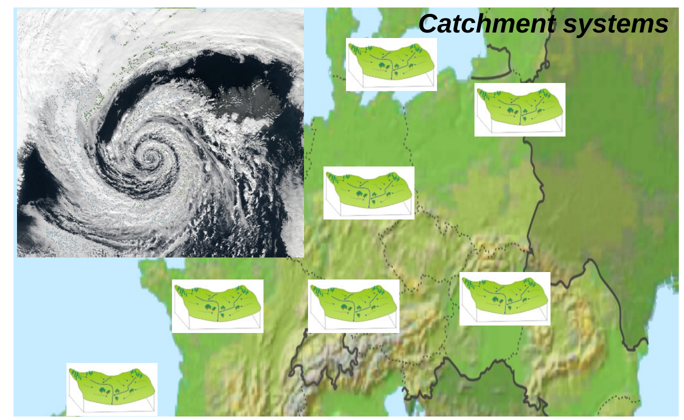

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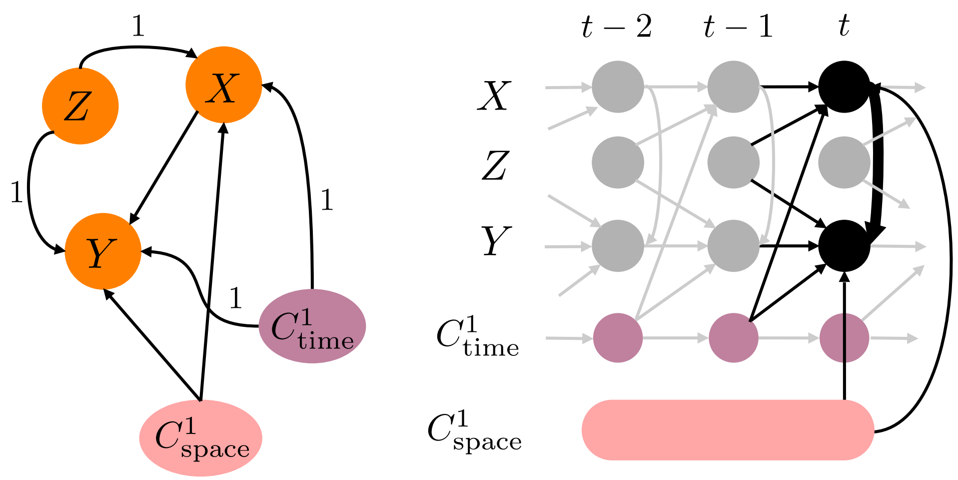

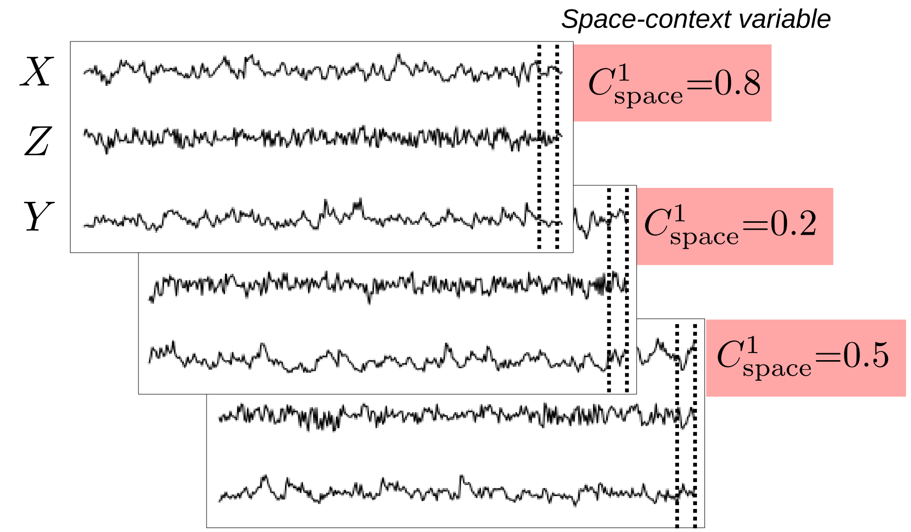

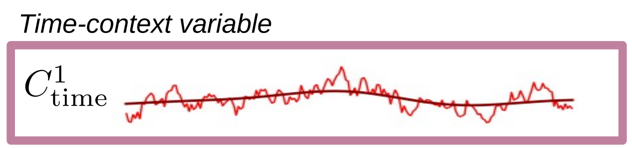

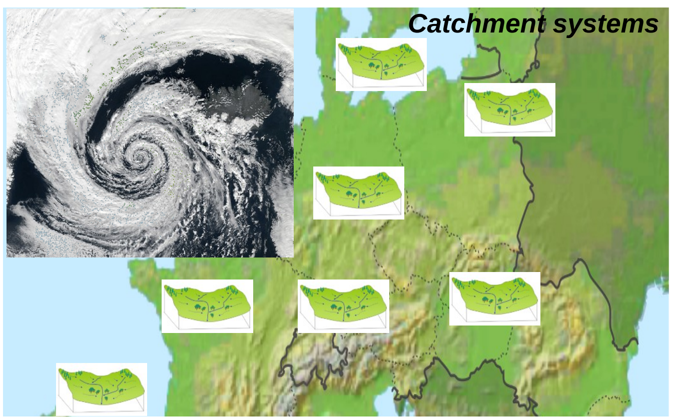

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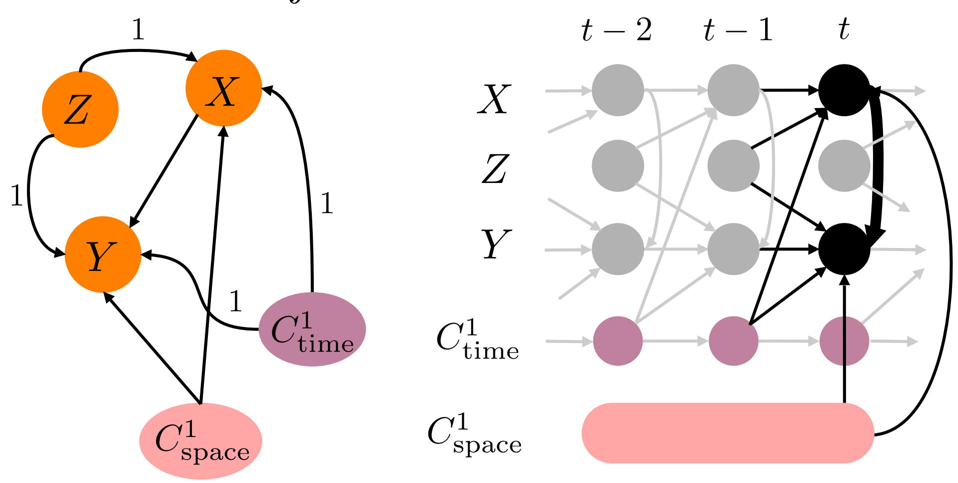
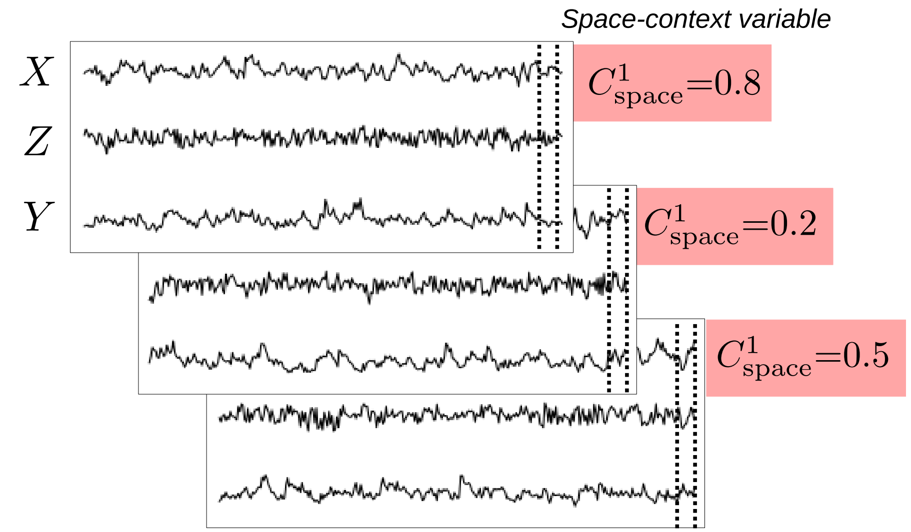
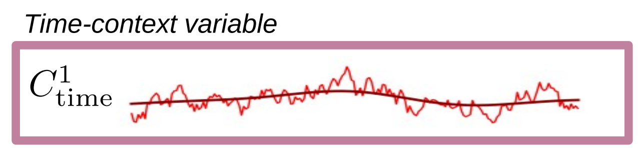
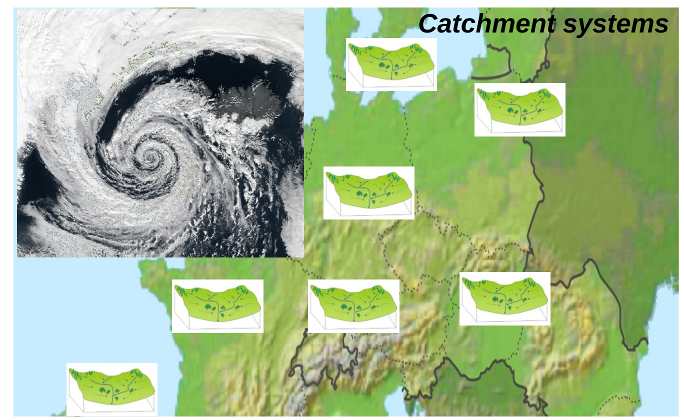
$$\mathbb{E}\left[y|do(X{=}x)\right] = \int \hat{f}(x, z, c^1_{\text{space}}, c^1_{\text{time}})p(z, c^1_{\text{space}}, c^1_{\text{time}})d(\cdots)$$









Causal effect estimation for time series from multiple datasets with hidden context-confounders

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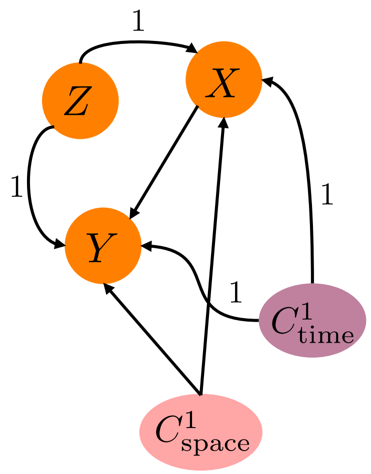
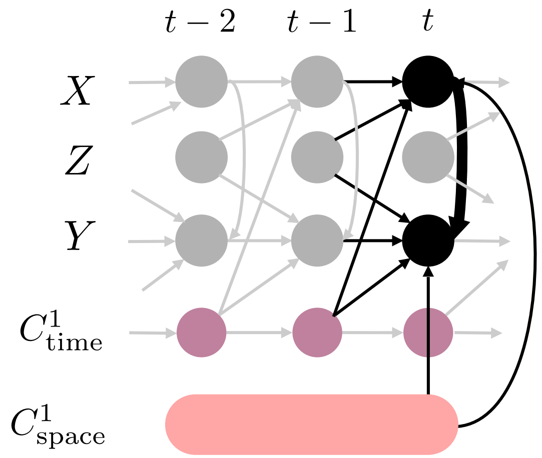
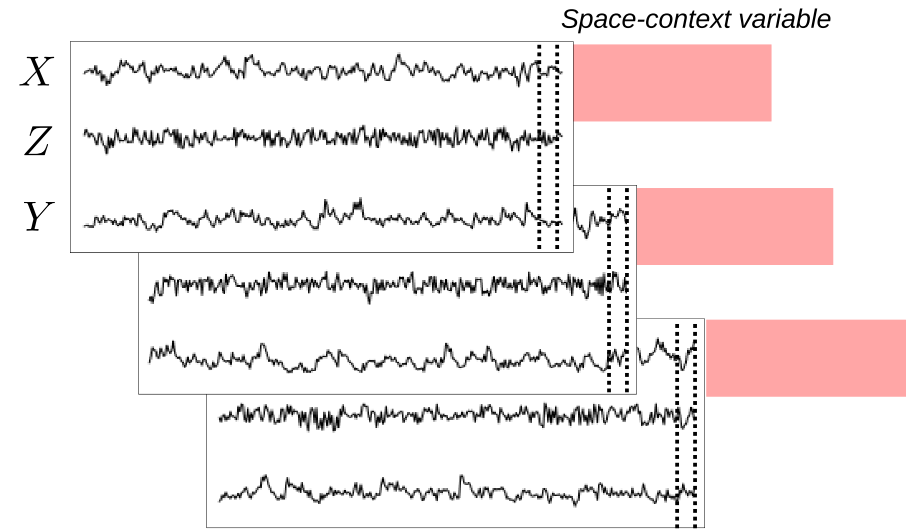
$$\mathbb{E}\left[y|do(X{=}x)\right] = \int \hat{f}(x, z, c^1_{\text{space}}, c^1_{\text{time}})p(z, c^1_{\text{space}}, c^1_{\text{time}})d(\cdots)$$

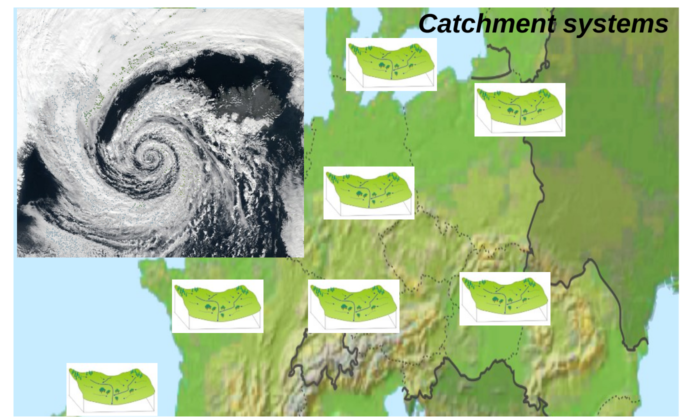






Time-context variable

C^1_{time}



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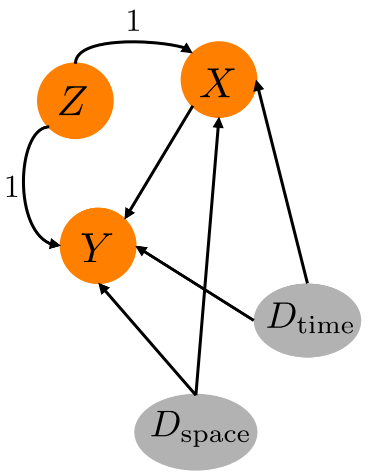
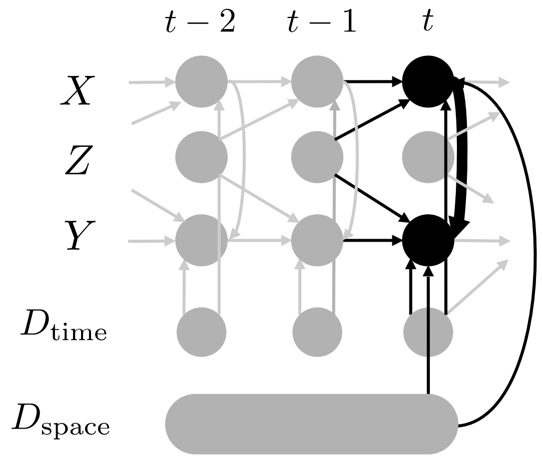
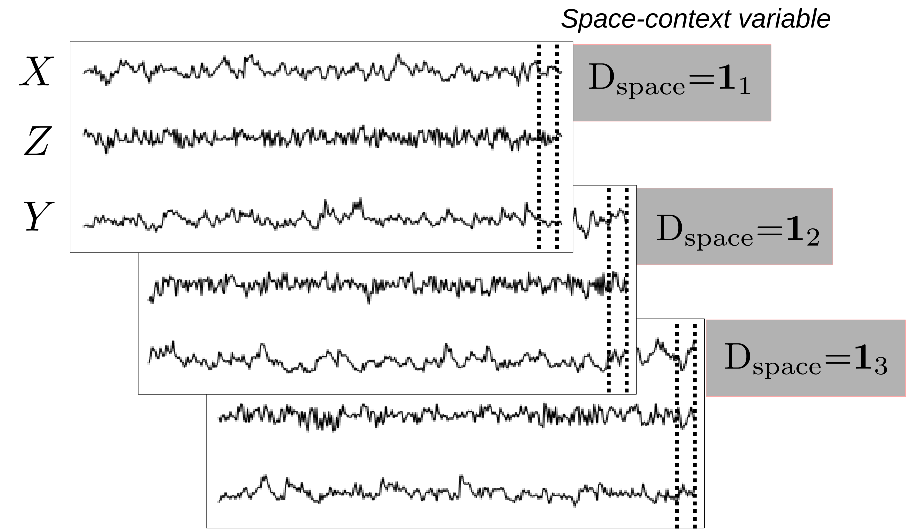
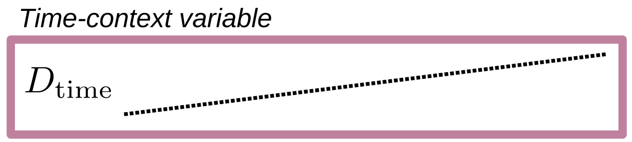
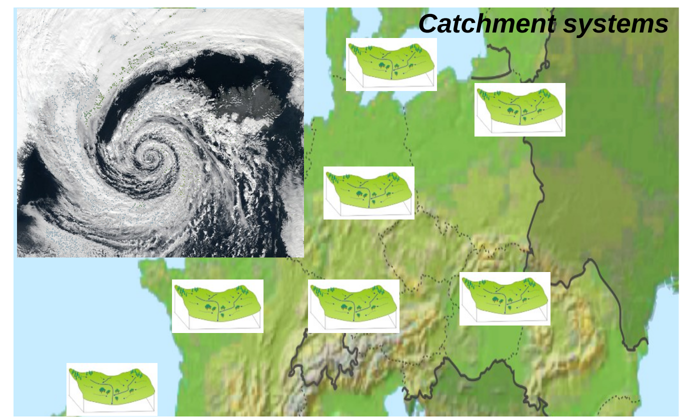


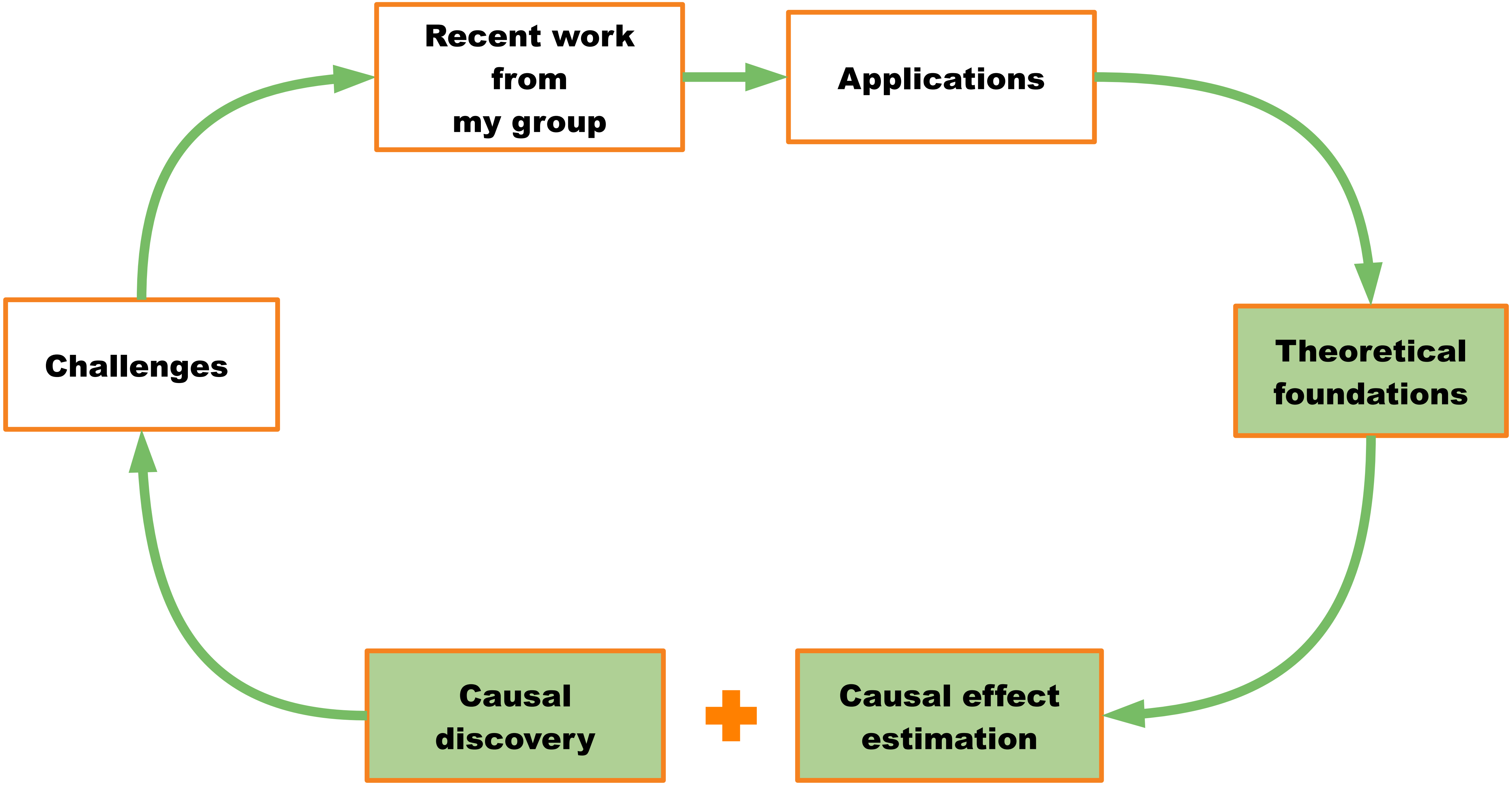






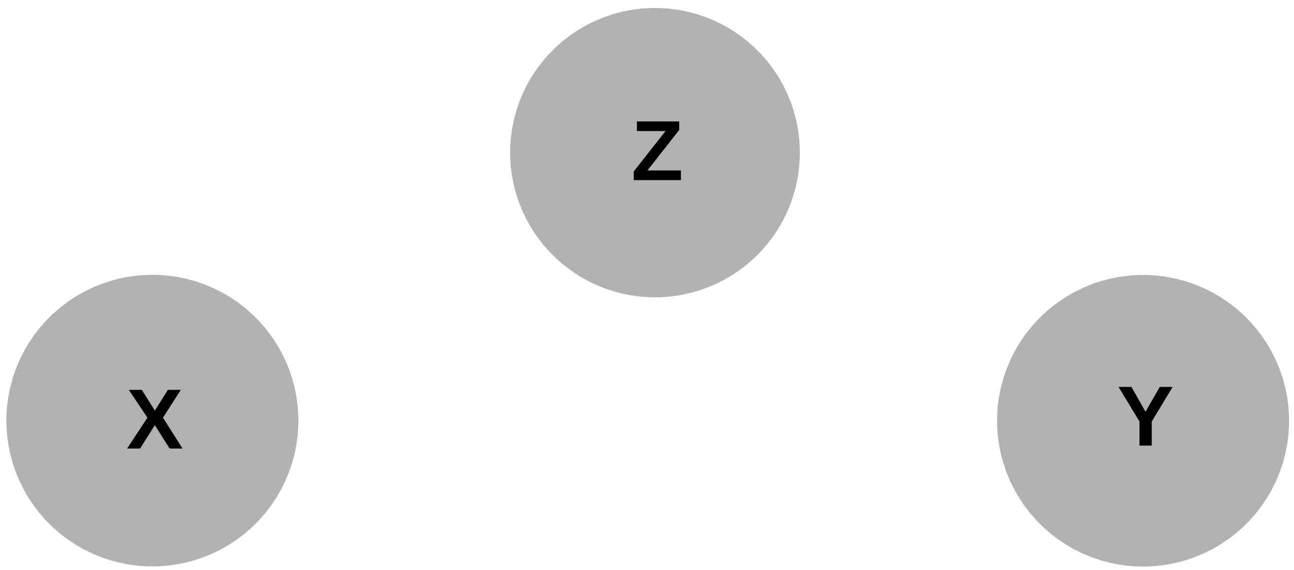


… aka *fixed-effects panel regression (eg Angrist & Pischke, 2009)*


Recent work from my group
Applications
Theoretical foundations
Causal effect estimation
Causal discovery
Challenges

Causal discovery

Given data and *general assumptions*, estimate causal graph from observational distribution



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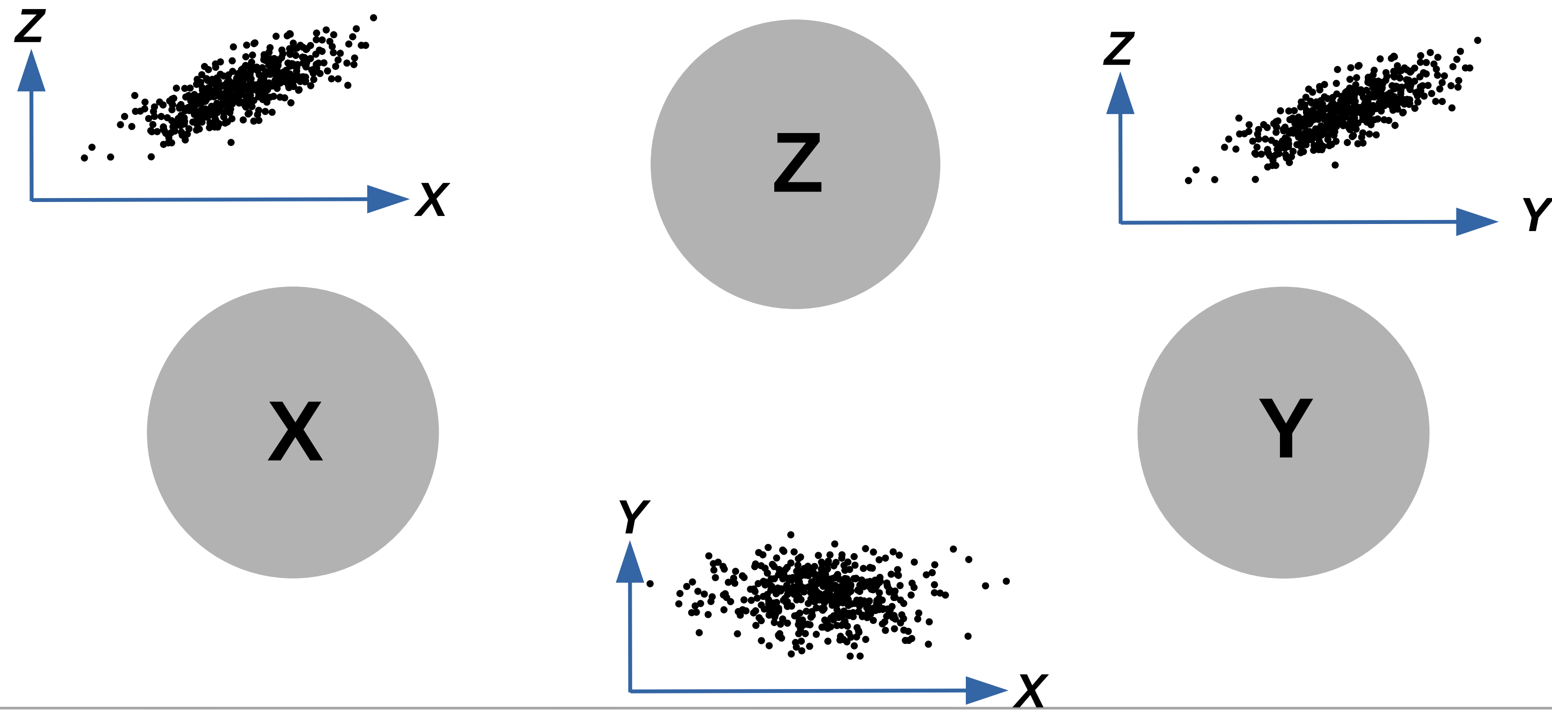
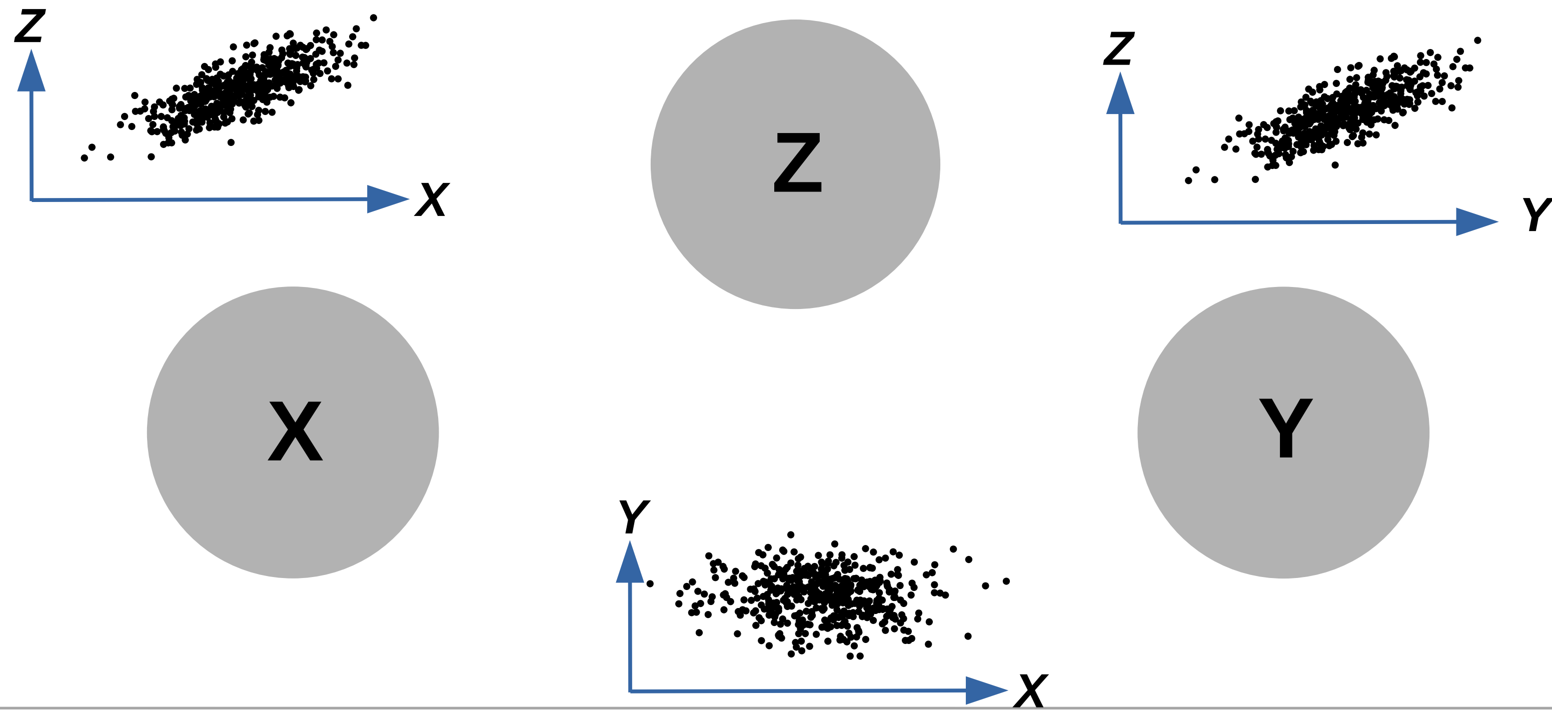


Causal discovery

Given data and *general assumptions*, estimate causal graph from observational distribution

$X \perp\!\!\!\perp Y$ (all others are dependent)



Causal discovery

Given data and *general assumptions*, estimate causal graph from observational distribution

(Conditional) independence in the data distribution

Faithfulness →

← ***Markov***

No open path, whether (in)direct or confounded, in the causal graph

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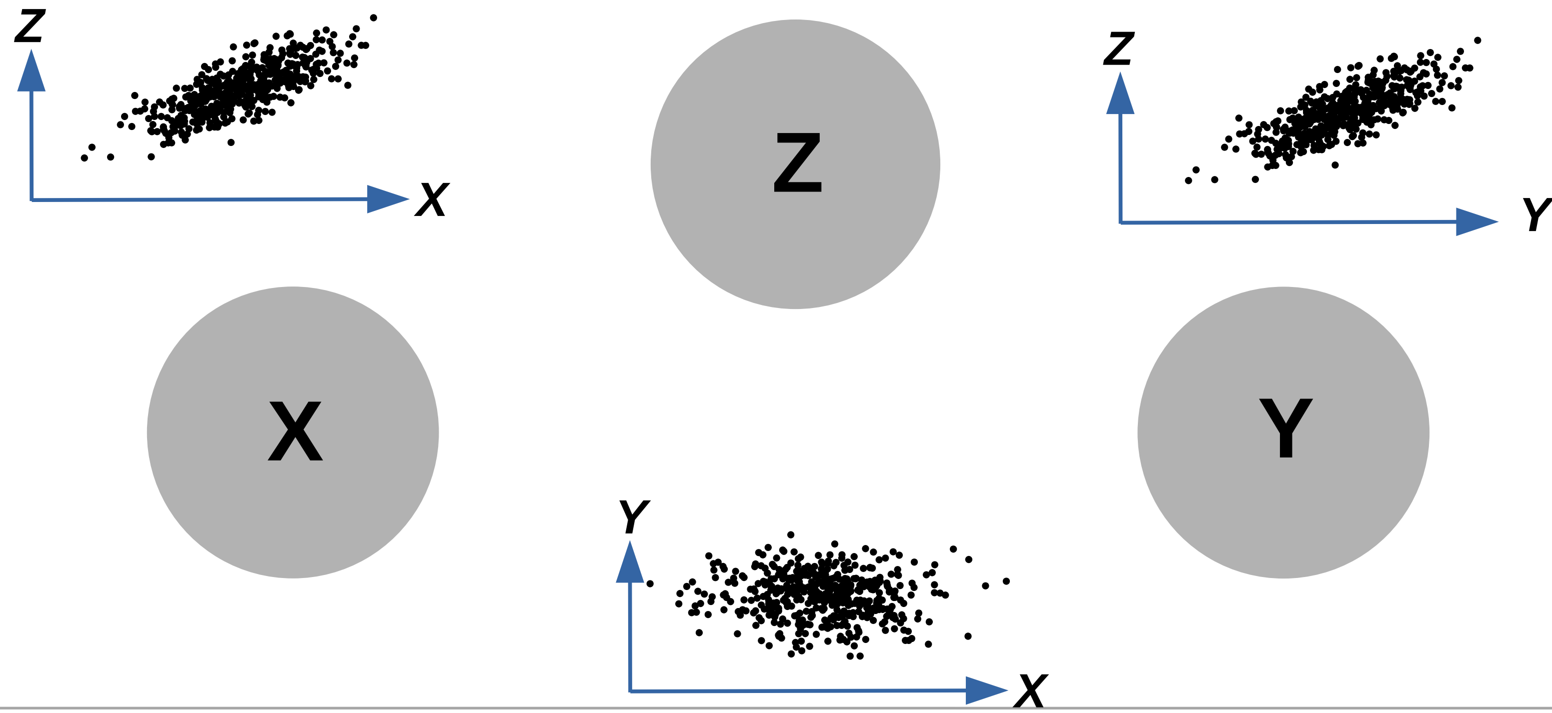

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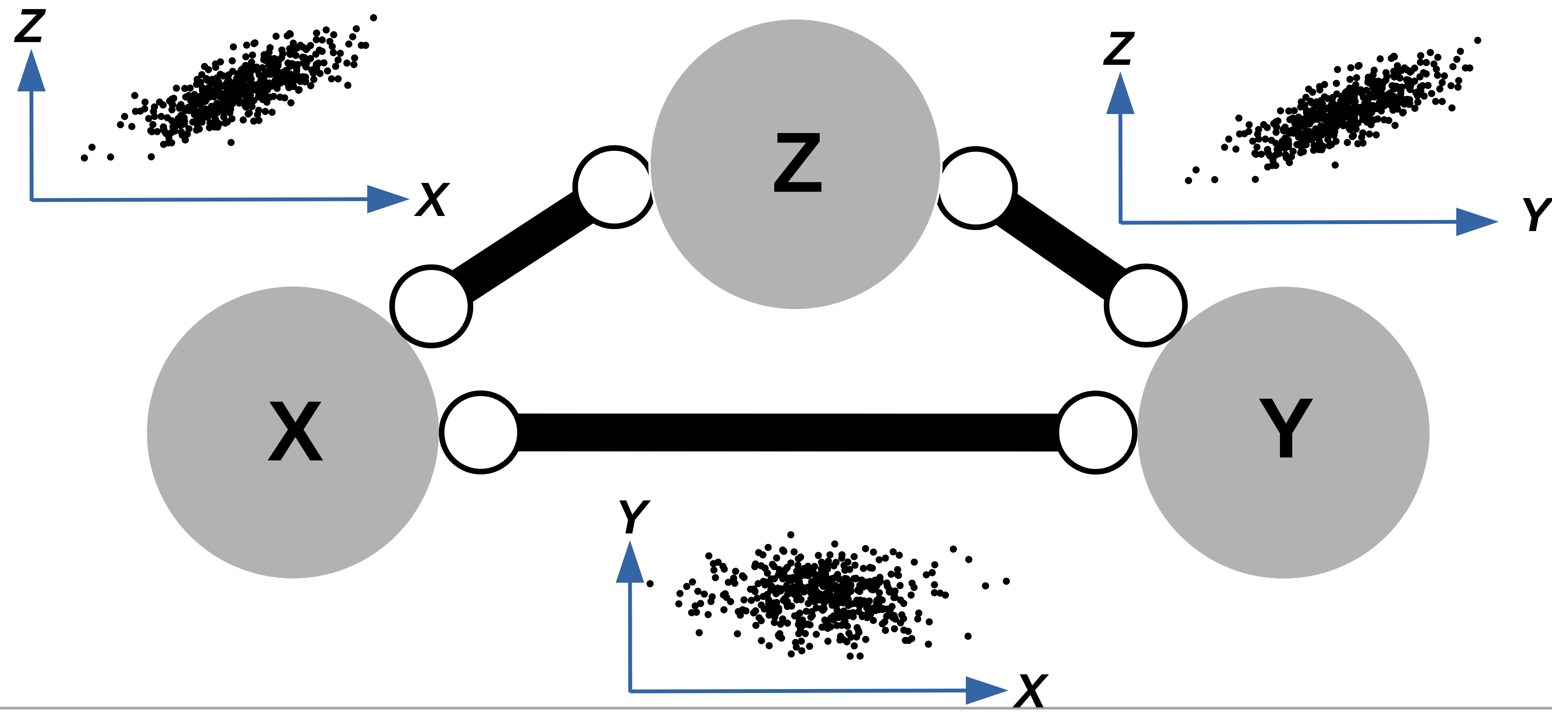

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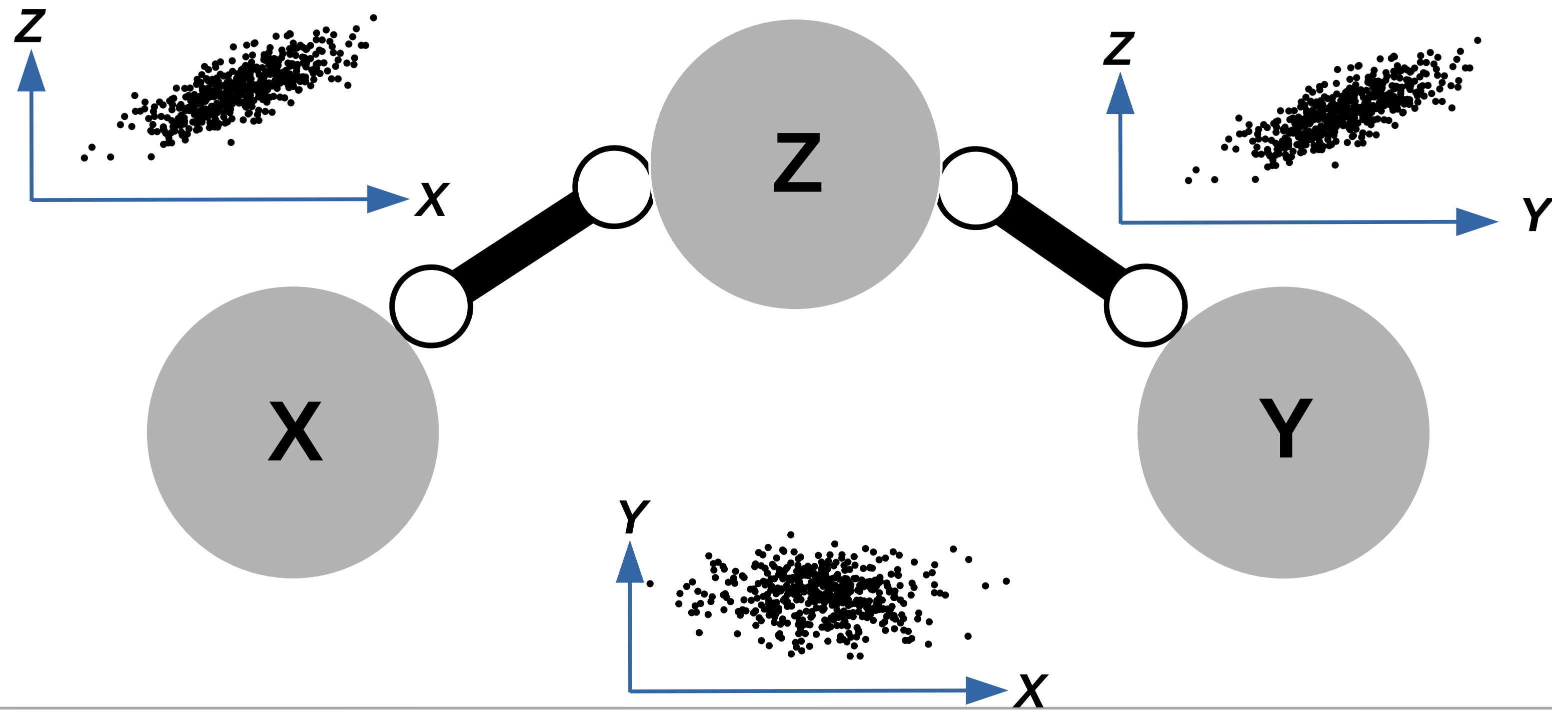

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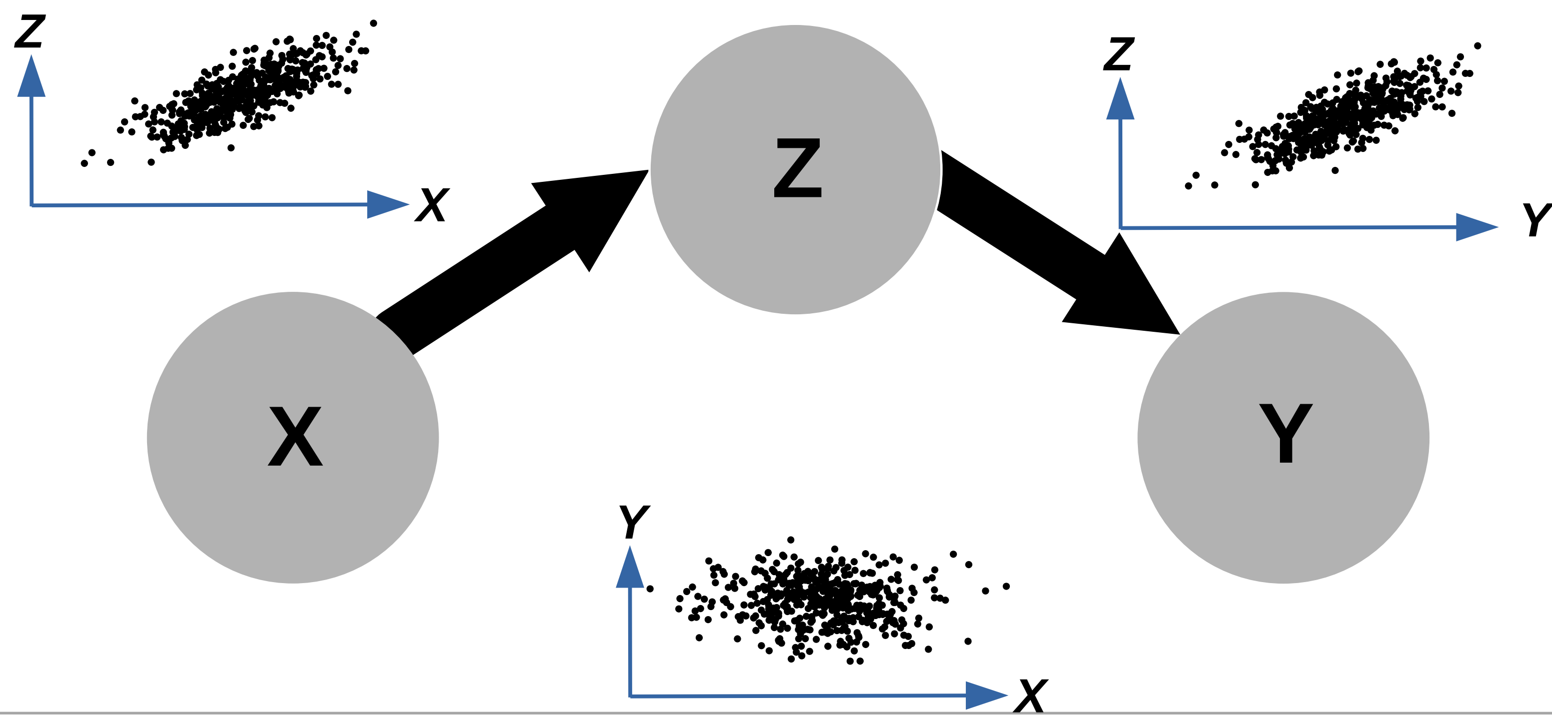

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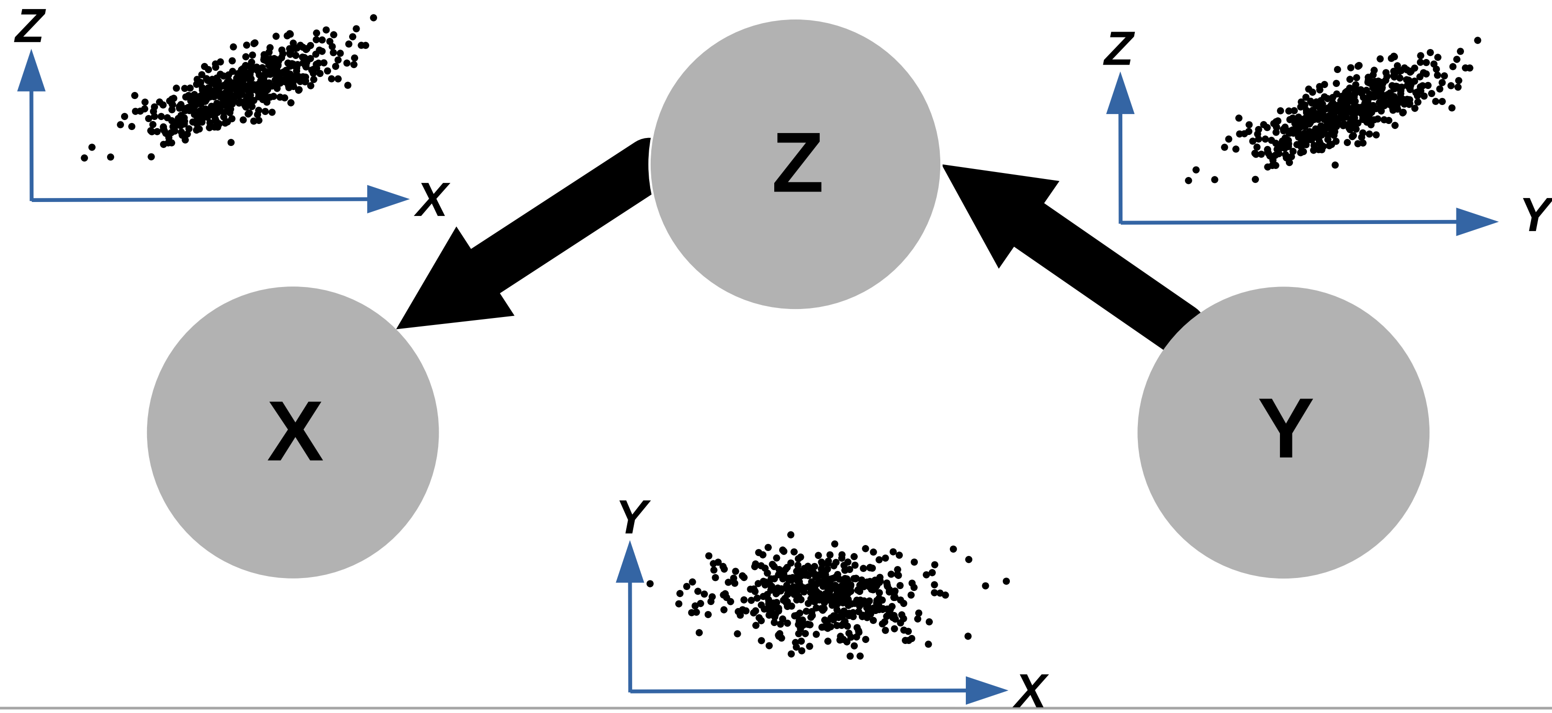

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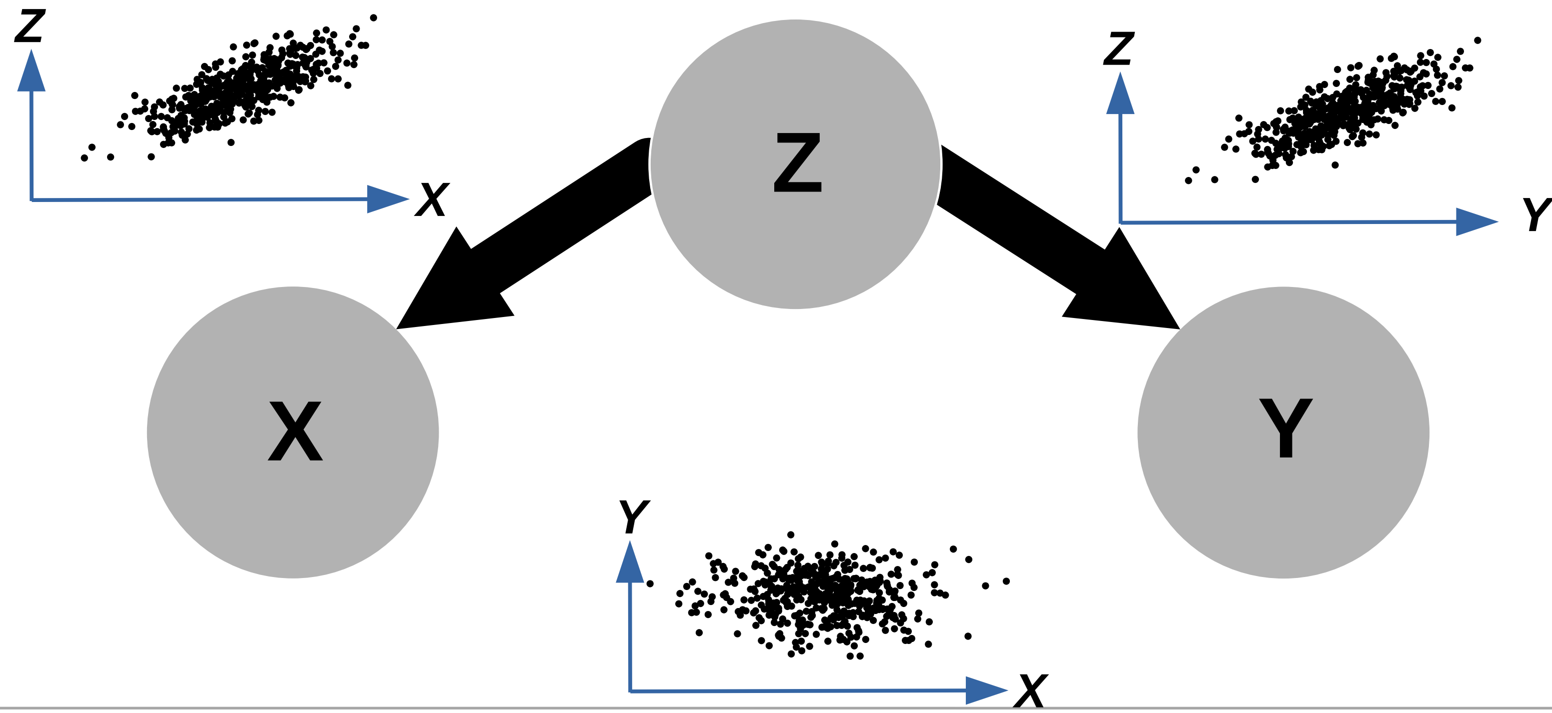

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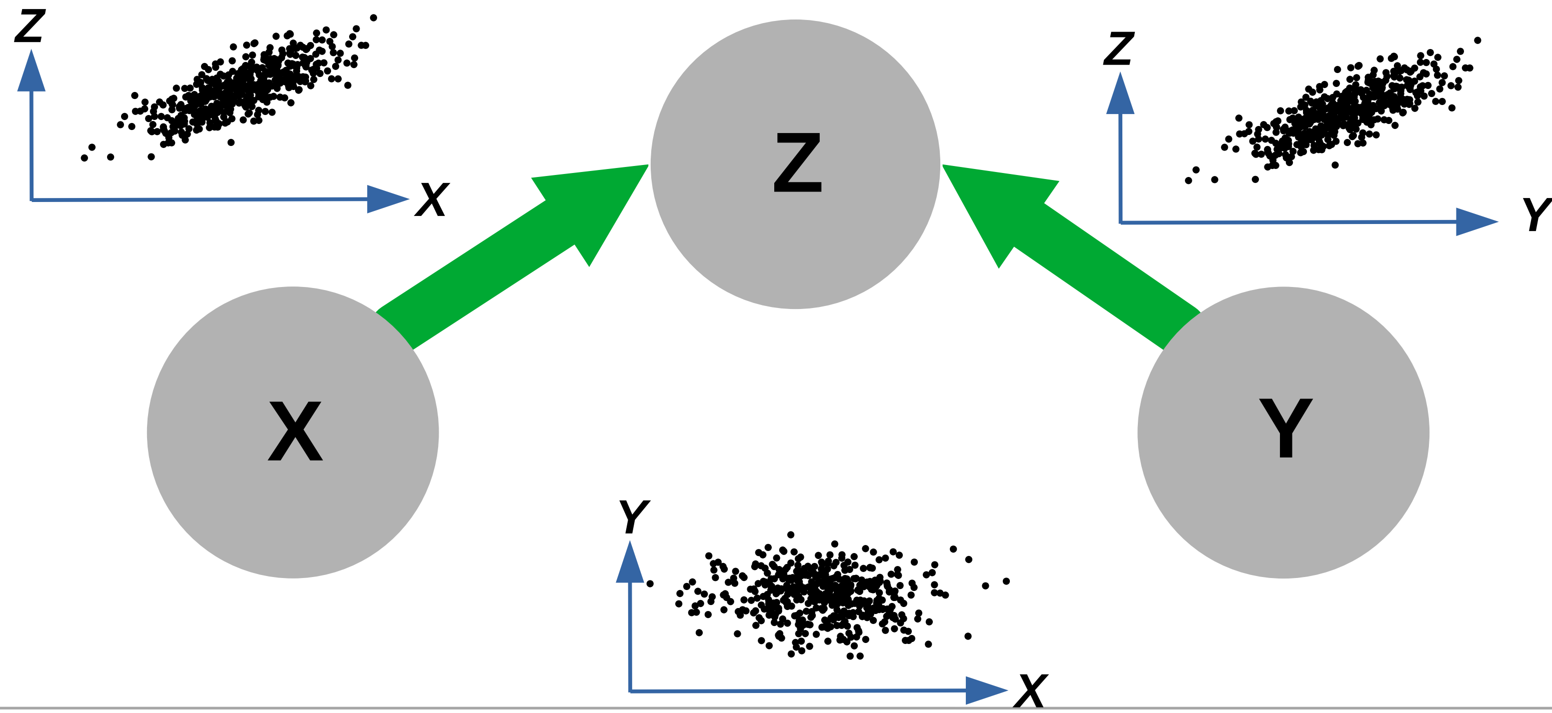


Causal discovery

Given data and *general assumptions*, estimate causal graph from observational distribution

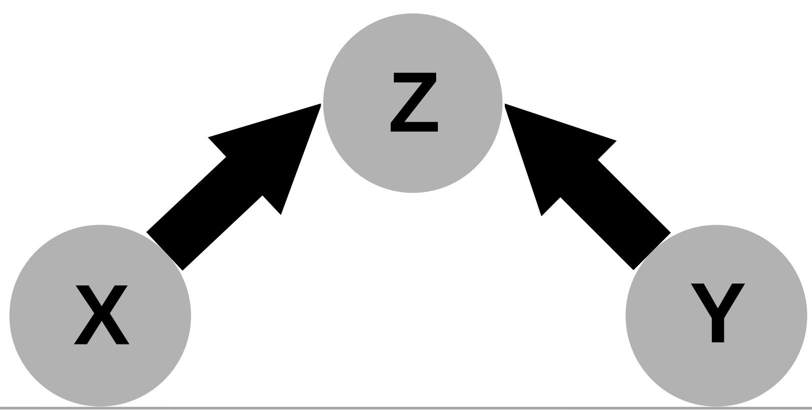
(Conditional) independence in the data distribution

Faithfulness

Markov

No open path, whether (in)direct or confounded, in the causal graph

+ causal sufficiency (no unobserved confounders)



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(Conditional) independence in the data distribution

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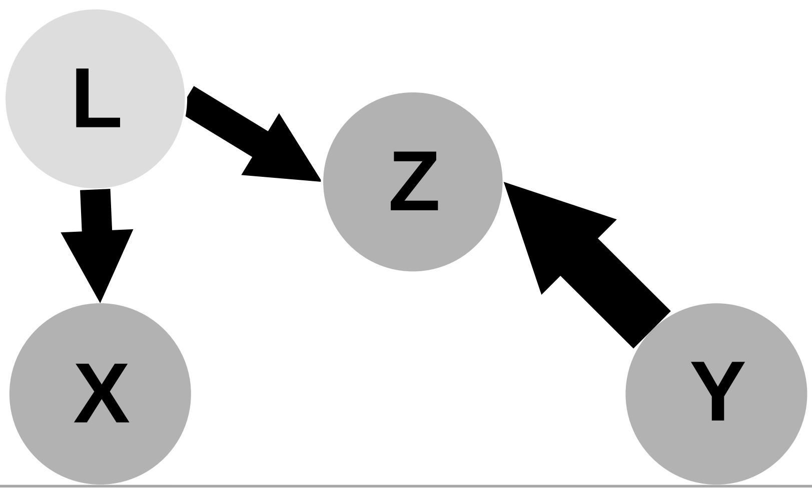
~~+ causal sufficiency~~
~~(no unobserved confounders)~~



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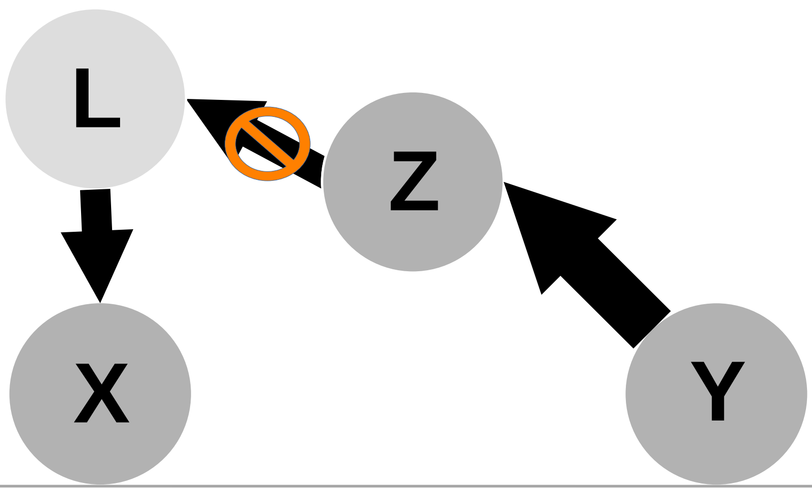

Causal discovery

Given data and *general assumptions*, estimate causal graph from observational distribution

(Conditional) independence in the data distribution

Faithfulness →

← ***Markov***

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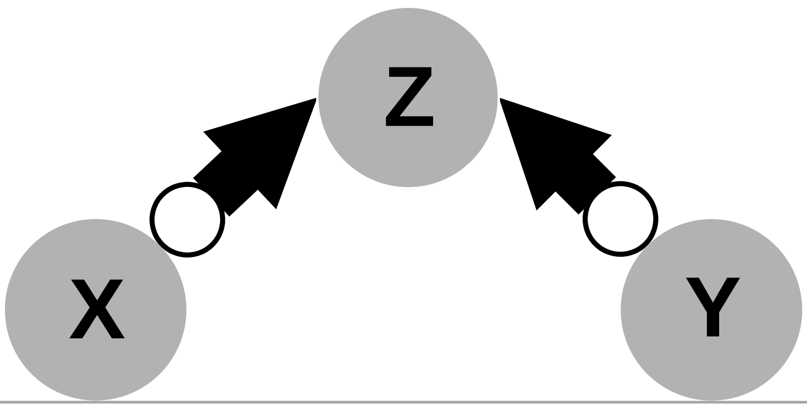

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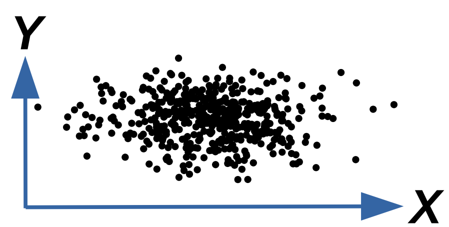

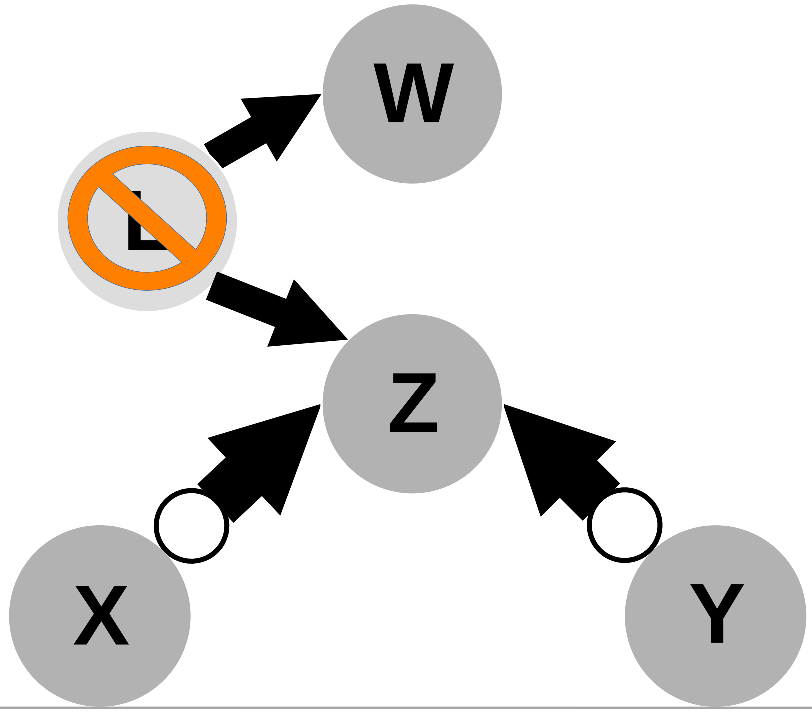

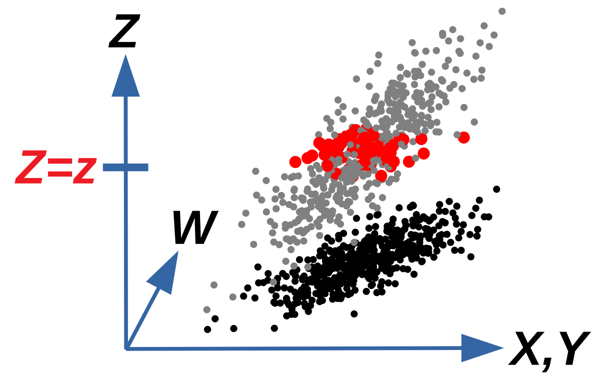

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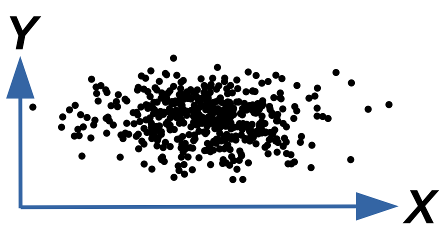
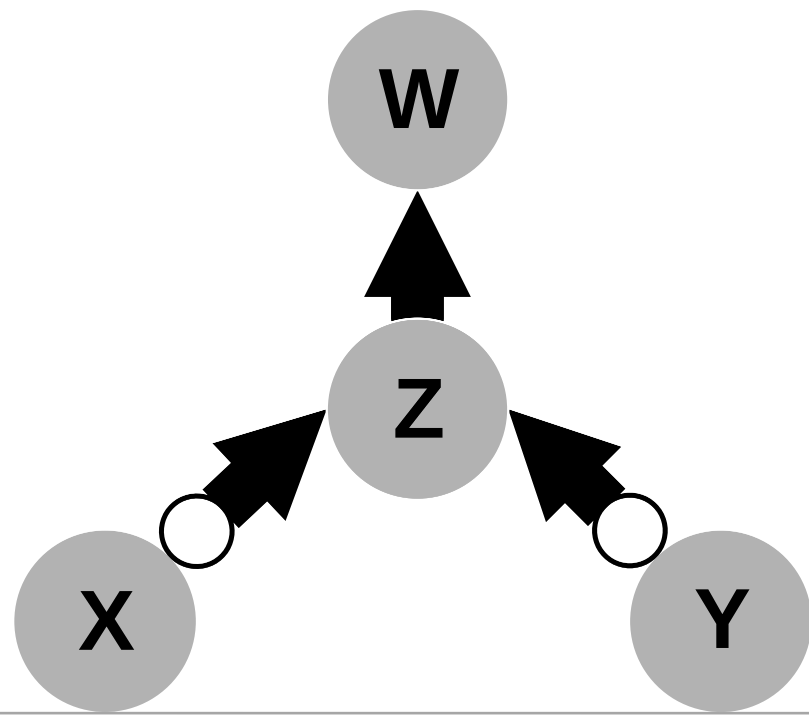
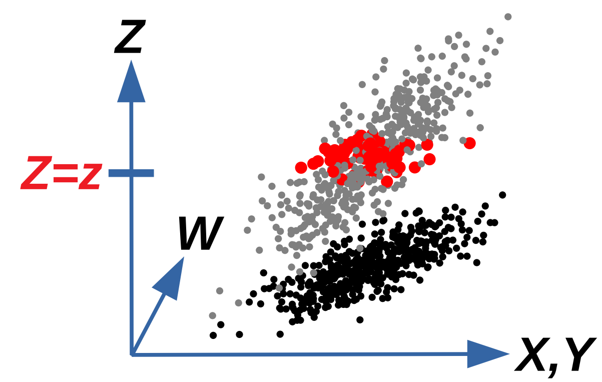






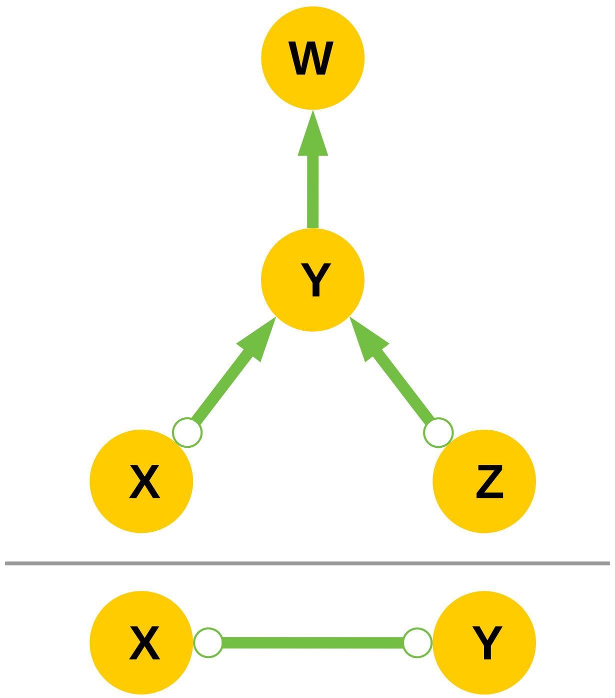
Learning causal graphs

Given data and *general assumptions*, estimate causal graph from observational distribution

Example assumptions:

- Markov & Faithfulness assumption:
  Conditional (in-)dependence in distribution ⇔ (dis-)connection in graph
  ~~Causal sufficiency: No unobserved confounders~~

  → ***Constraint-based causal discovery*** (Spirtes et al. 2000)



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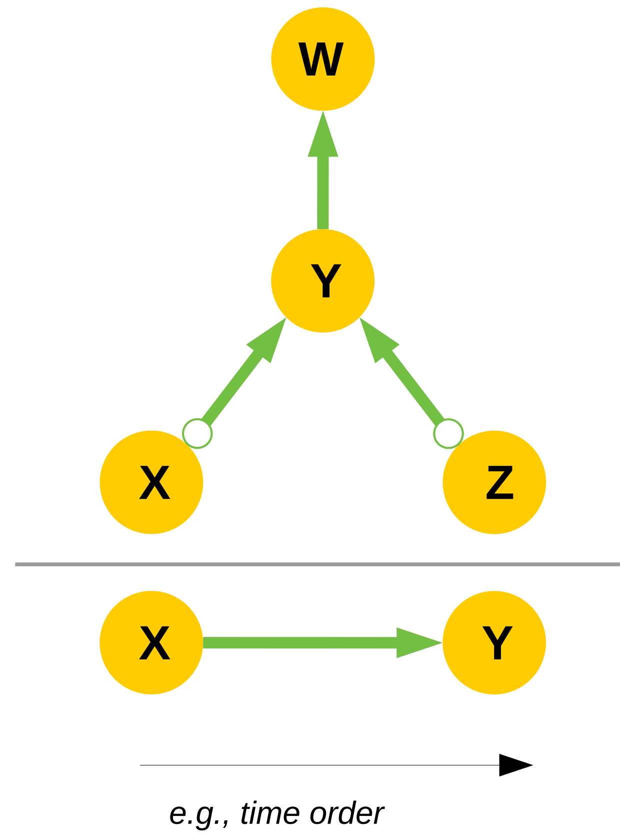
Add domain knowledge...



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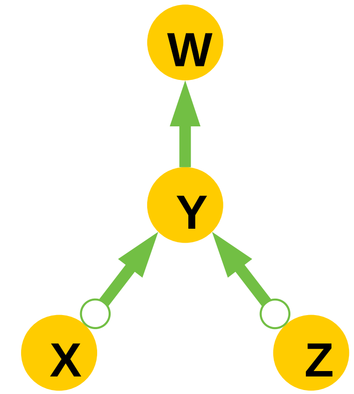

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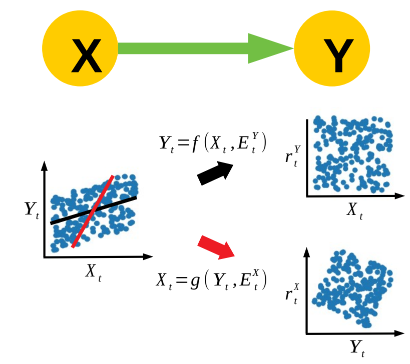
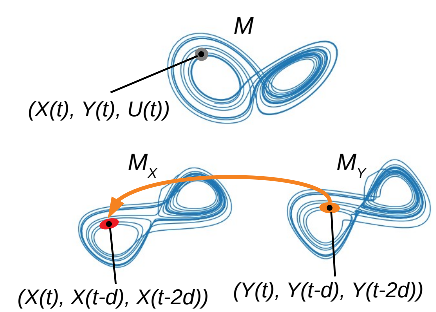


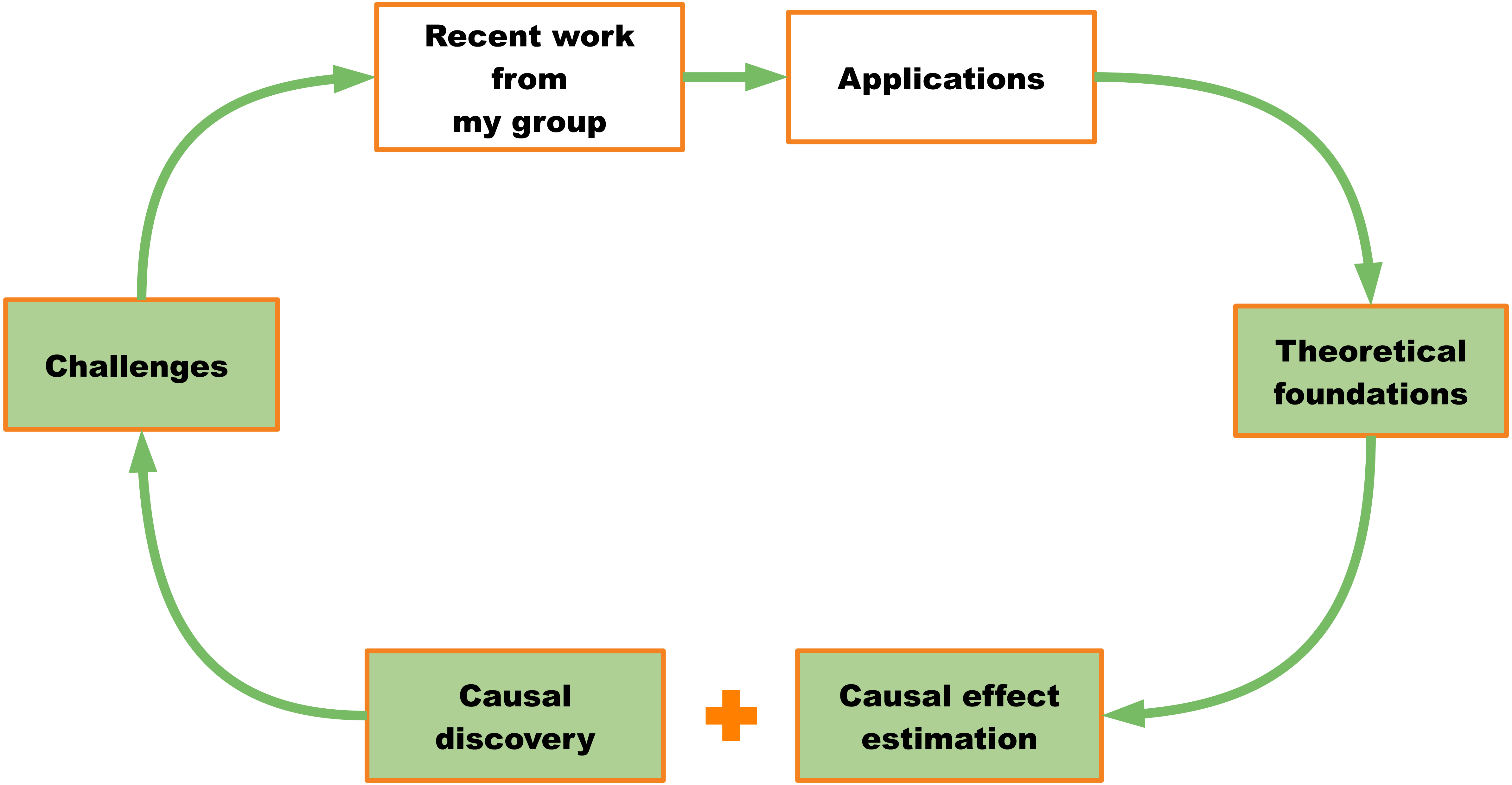
- Assumptions on functional dependencies and noise distributions
  → ***Restricted structural causal modeling*** *(Peters et al. 2018)*

$$\text{Score(Graph; Data)}$$

- Assumptions through likelihood functions and interventional data
  → ***Score-based causal network learning***

- Assumption of an underlying nonlinear dynamical deterministic system
  → ***State-space methods***

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Challenges

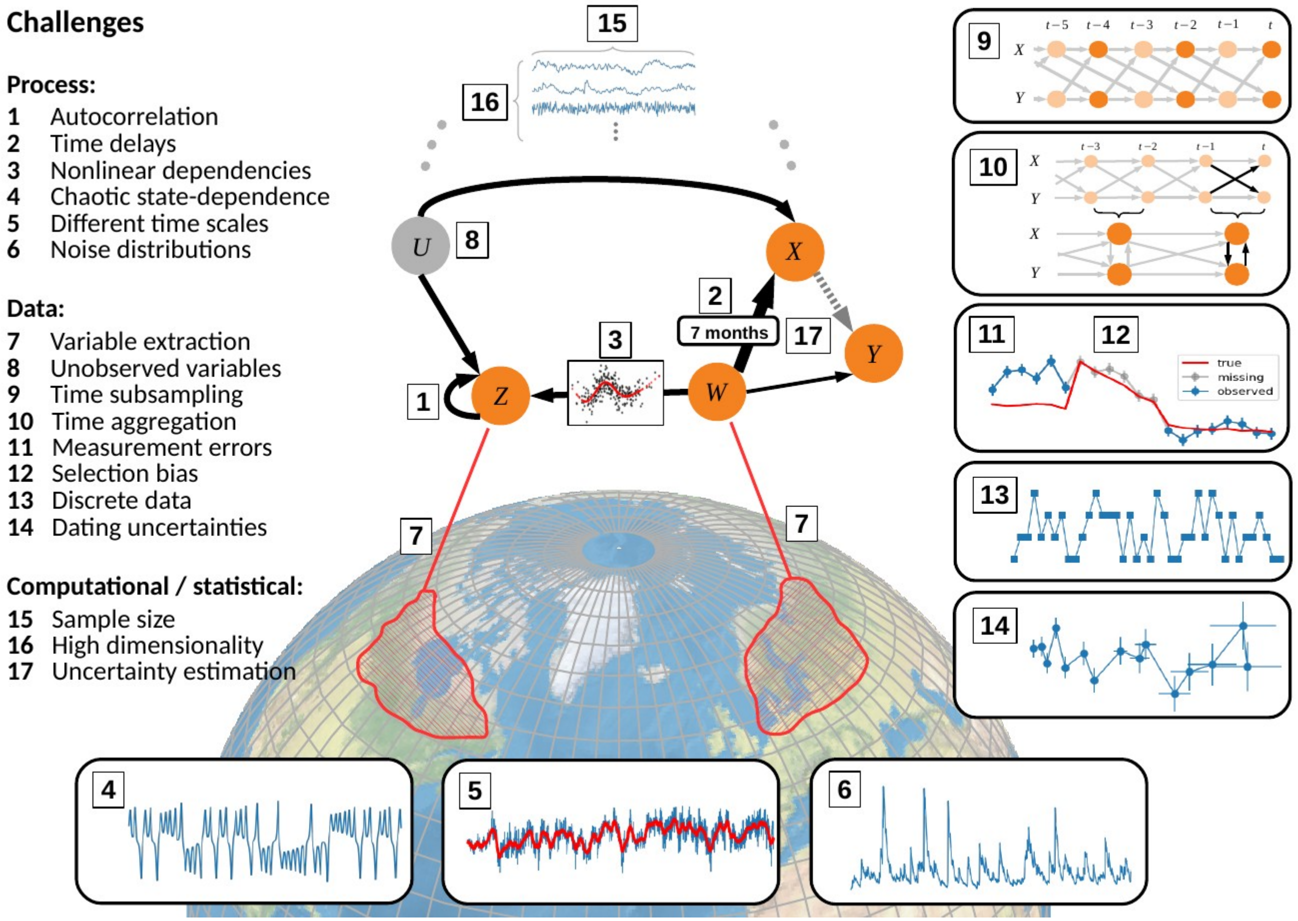
nature COMMUNICATIONS

Runge et al. (2019)

PERSPECTIVE

https://doi.org/10.1038/s41467-019-10105-3 OPEN

Inferring causation from time series in Earth system sciences



Prof. Dr. Jakob Runge
Chair of AI in the Sciences
University of Potsdam

Challenges

Runge et al. (2019)

PERSPECTIVE

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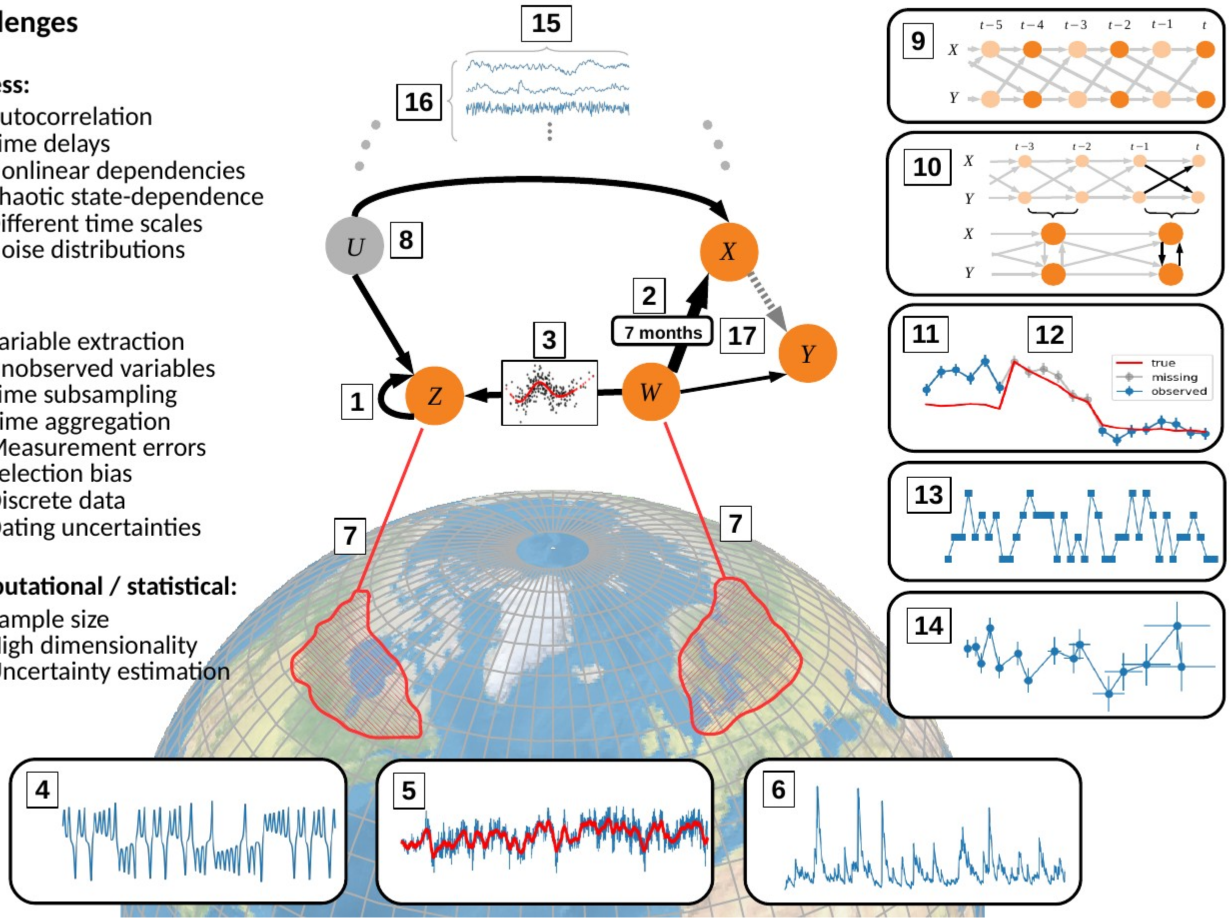
Inferring causation from time series in Earth system sciences

Challenges

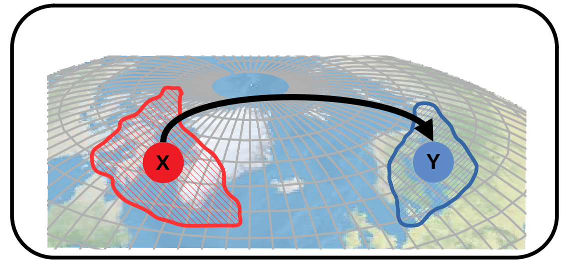
Process:
1 Autocorrelation
2 Time delays
3 Nonlinear dependencies
4 Chaotic state-dependence
5 Different time scales
6 Noise distributions

Data:
7 Variable extraction
8 Unobserved variables
9 Time subsampling
10 Time aggregation
11 Measurement errors
12 Selection bias
13 Discrete data
14 Dating uncertainties

Computational / statistical:
15 Sample size
16 High dimensionality
17 Uncertainty estimation



7 Variables not well-defined



Toward Causal Representation Learning

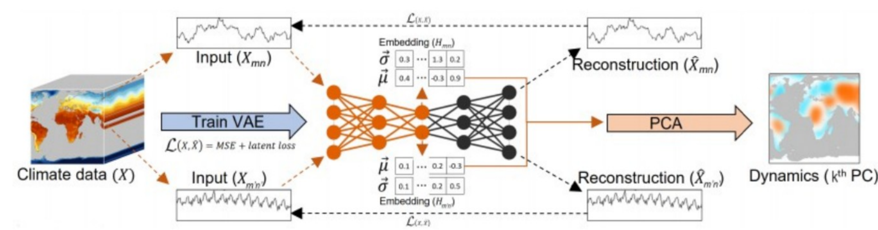
This article reviews fundamental concepts of causal inference and relates them to crucial open problems of machine learning, including transfer learning and generalization, thereby assaying how causality can contribute to modern machine learning research.

By Bernhard Schölkopf, Francesco Locatello, Stefan Bauer, Nan Rosemary Ke, Nal Kalchbrenner, Anirudh Goyal, and Yoshua Bengio

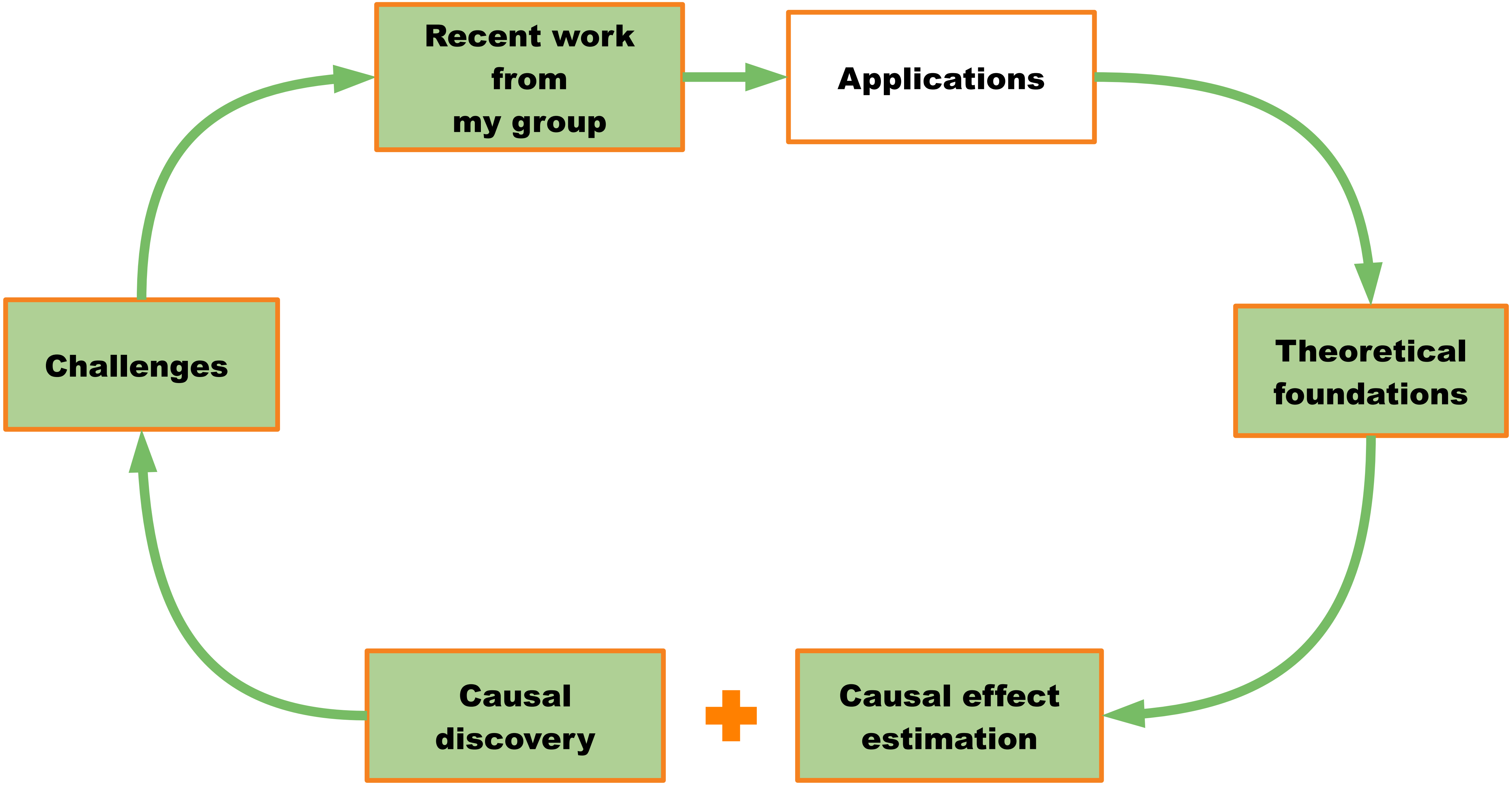
ABSTRACT | The two fields of machine learning and graphical causality arose and are developed separately. However, there is, now, cross-pollination and increasing interest in both fields to benefit from the advances of the other. In this article, we review fundamental concepts of causal inference and relate them to crucial open problems of machine learning, including transfer and generalization, thereby assaying how causality can contribute to modern machine learning research. This also applies in the opposite direction: we note that most work in causality starts from the premise that the causal variables are given. A central problem for AI and causality is, thus, causal representation learning, that is, the discovery of high-level causal variables from low-level observations. Finally, we delineate some implications of causality for machine learning and propose key research areas at the intersection of both communities.

I. INTRODUCTION

If we compare what machine learning can do to what animals accomplish, we observe that the former is rather limited at some crucial feats where natural intelligence excels. These include transfer to new problems and any form of generalization that is not from one data point to the next (sampled from the same distribution), but rather from one problem to the next—both have been termed *generalization*, but the latter is a much harder form thereof, sometimes referred to as *horizontal*, *strong*, or *out-of-distribution* generalization. This shortcoming is not too surprising, given that machine learning often disregards information that animals use heavily: interventions in the world, domain shifts, and temporal structure—by and large, we consider these factors a nuisance and try to engineer them away. In accordance with this, the majority of current successes of machine learning boil down to large-



Tibau *et al.* 2018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My group's work:
Causal inference for time series data

Runge et al. (2019)

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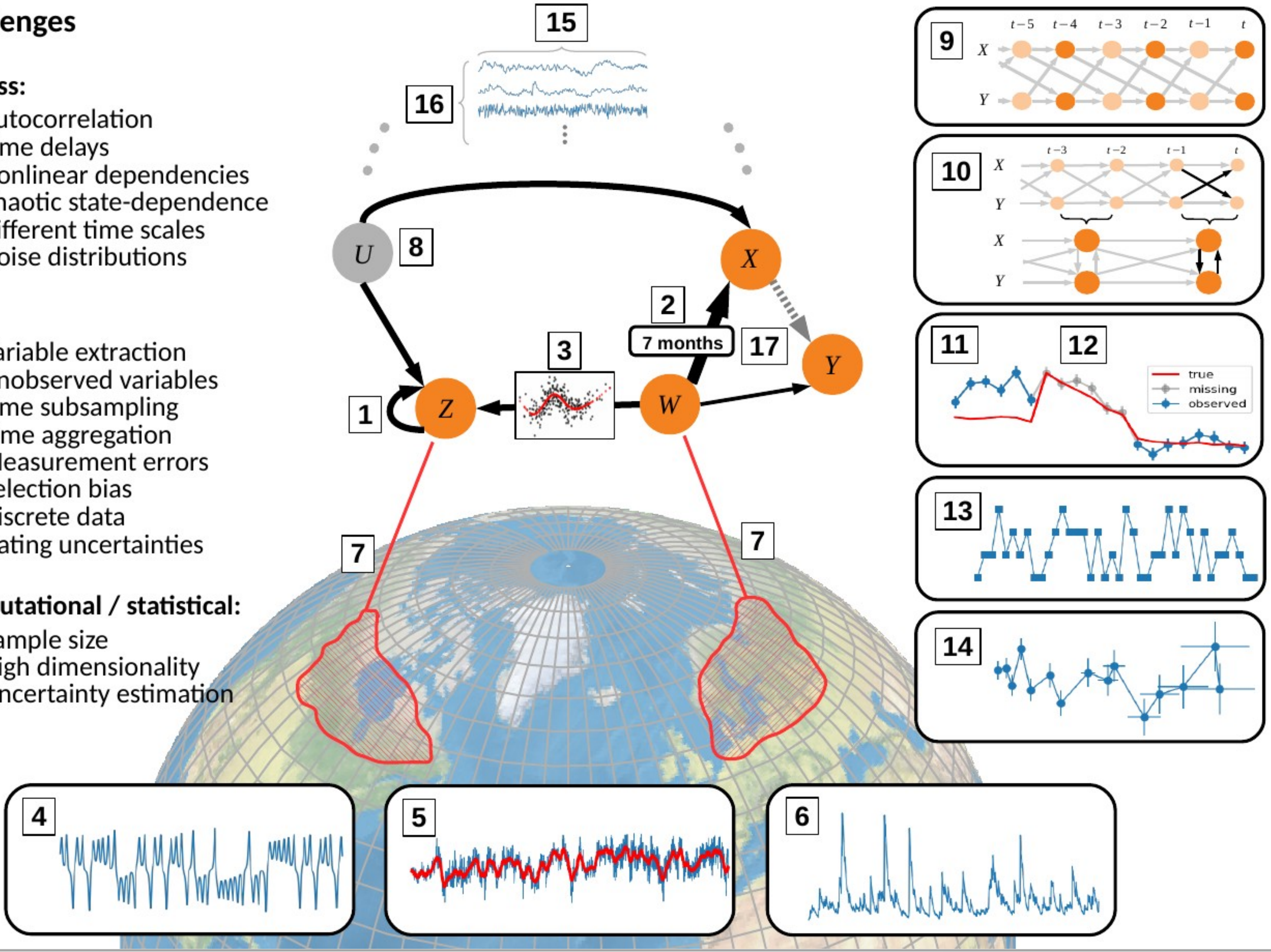
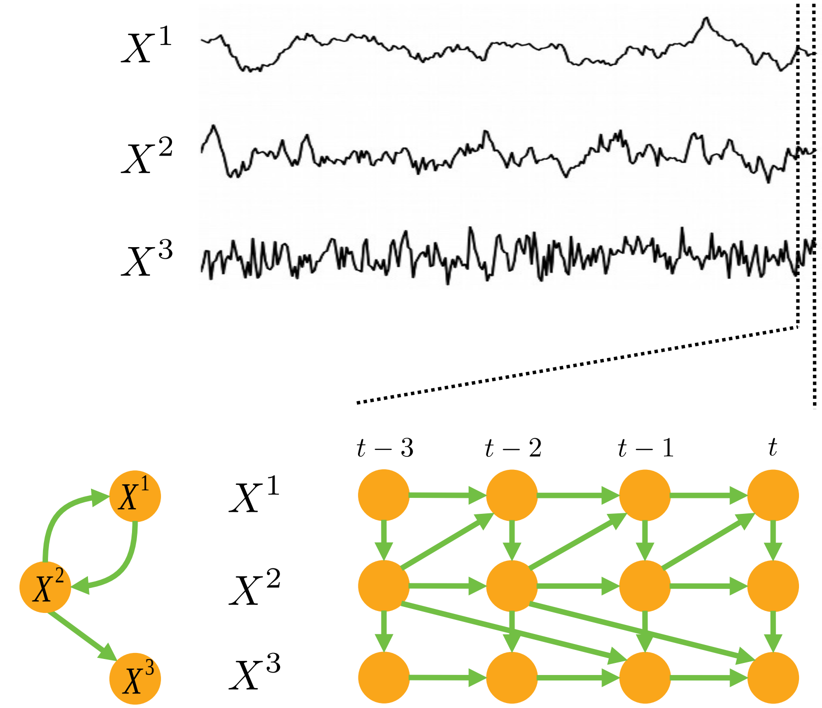


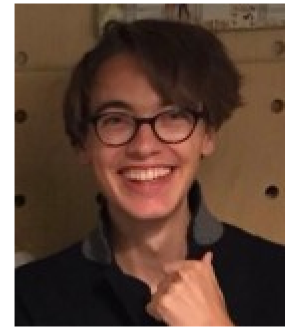


Time series case:
- ***PCMCI causal discovery framework***

	Instantaneous causality	Hidden confounders	Multiple datasets / further aspects
PCMCI[Runge et al 2019]	✘	✘	✔ / -
PCMCI+[Runge 2020]	✔	✘	✔ / -
L-PCMCI[Gerhardus & Runge 2020]	✔	✔	✔ / -
J-PCMCI+[Günther et al. 2023]	✔	✔ (context-related)	✔ / context-links
R-PCMCI[Saggioro et al 2020]	✘	✘	✘ / regimes-learning

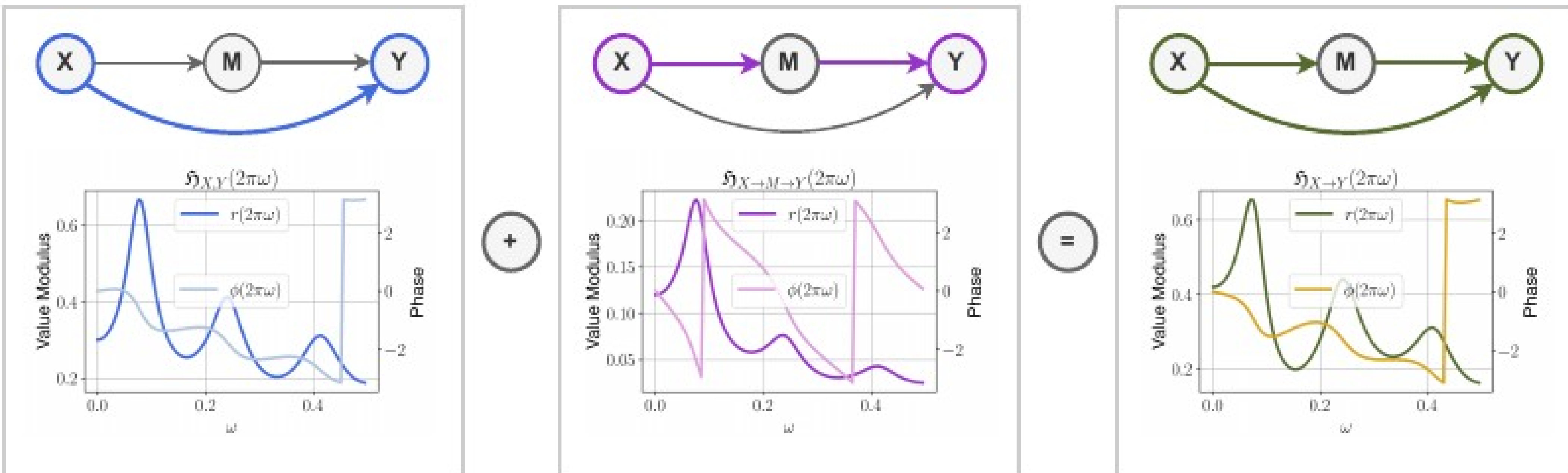
Causal inference in frequency space

Nicolas Reiter



Goal: Develop causal inference foundations at the level of process graphs in frequency space (assuming underlying linear models).

Causal transfer functions



Paper submitted to *Bernoulli*

Learning causal graphs

Given data and *general assumptions*, estimate causal graph from observational distribution

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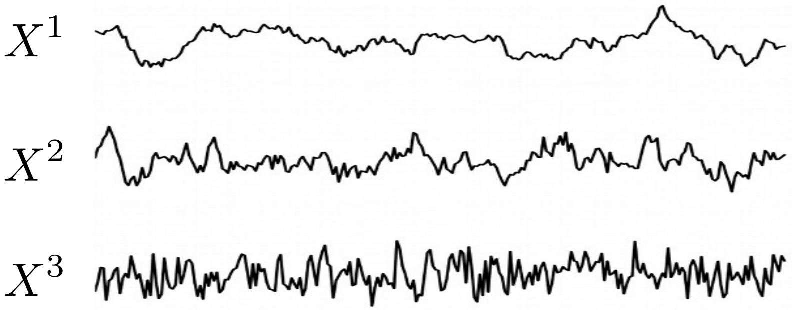

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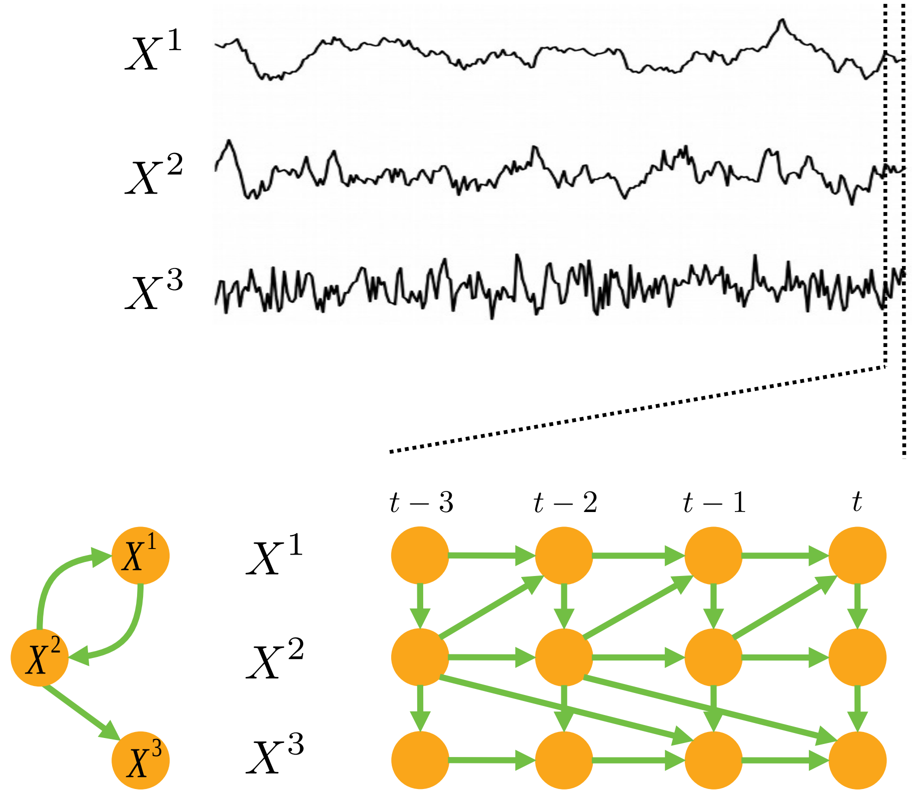

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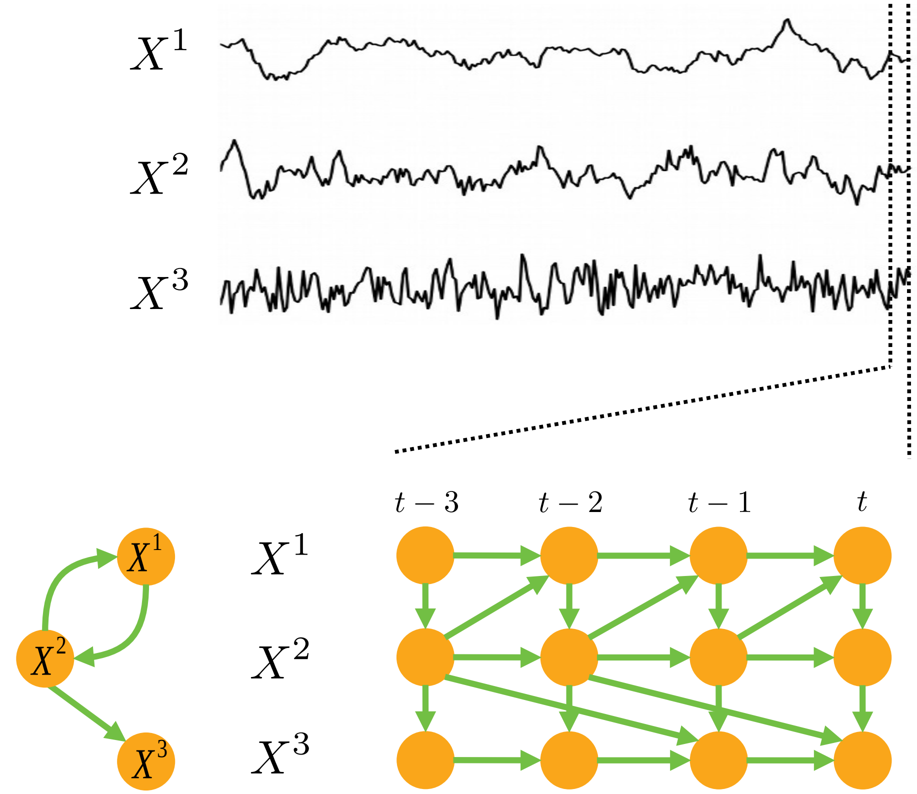
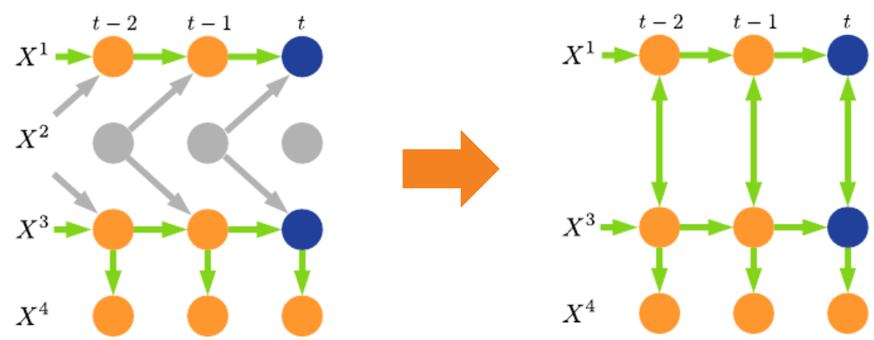
LPCMCI[Gerhardus & Runge 2020]	✔	✔

Basic idea: *include learned parents in cond. indep. tests for increased effect size and well-calibrated tests (Theorem 1 in LPCMCI paper)*





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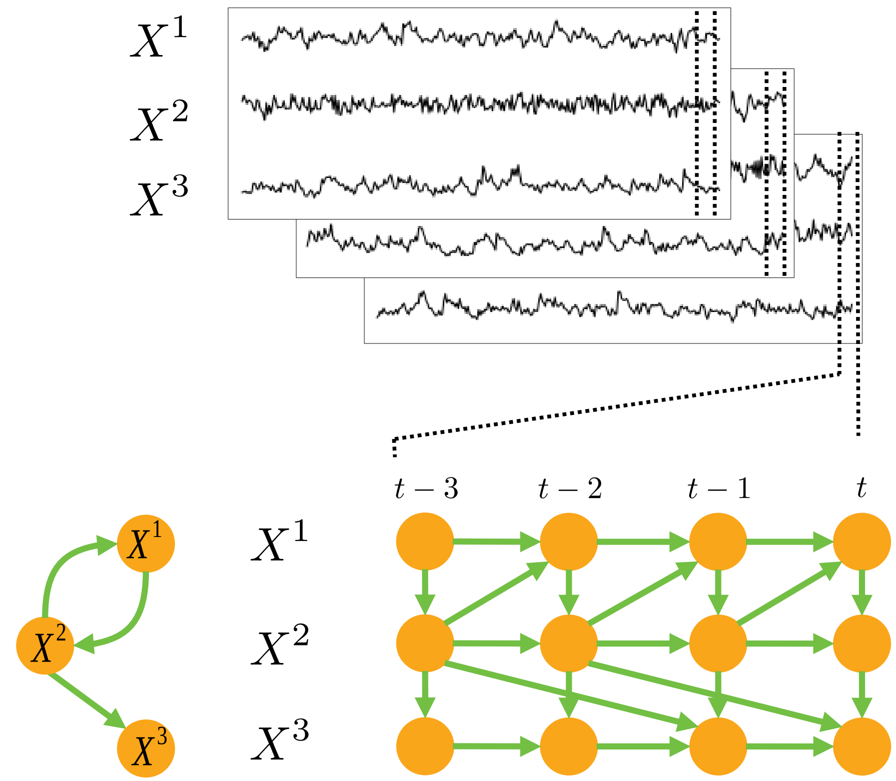

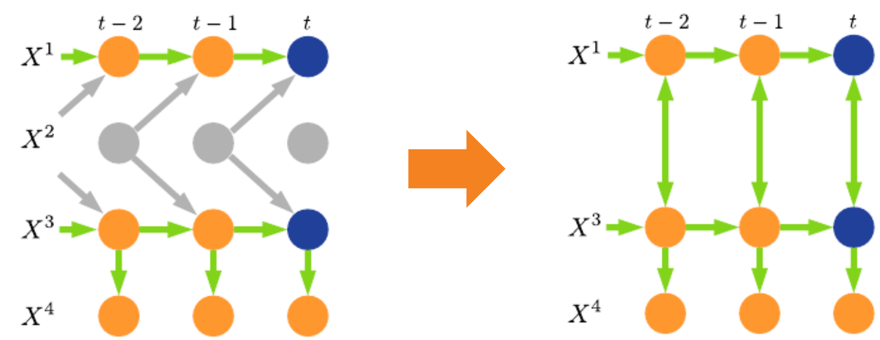

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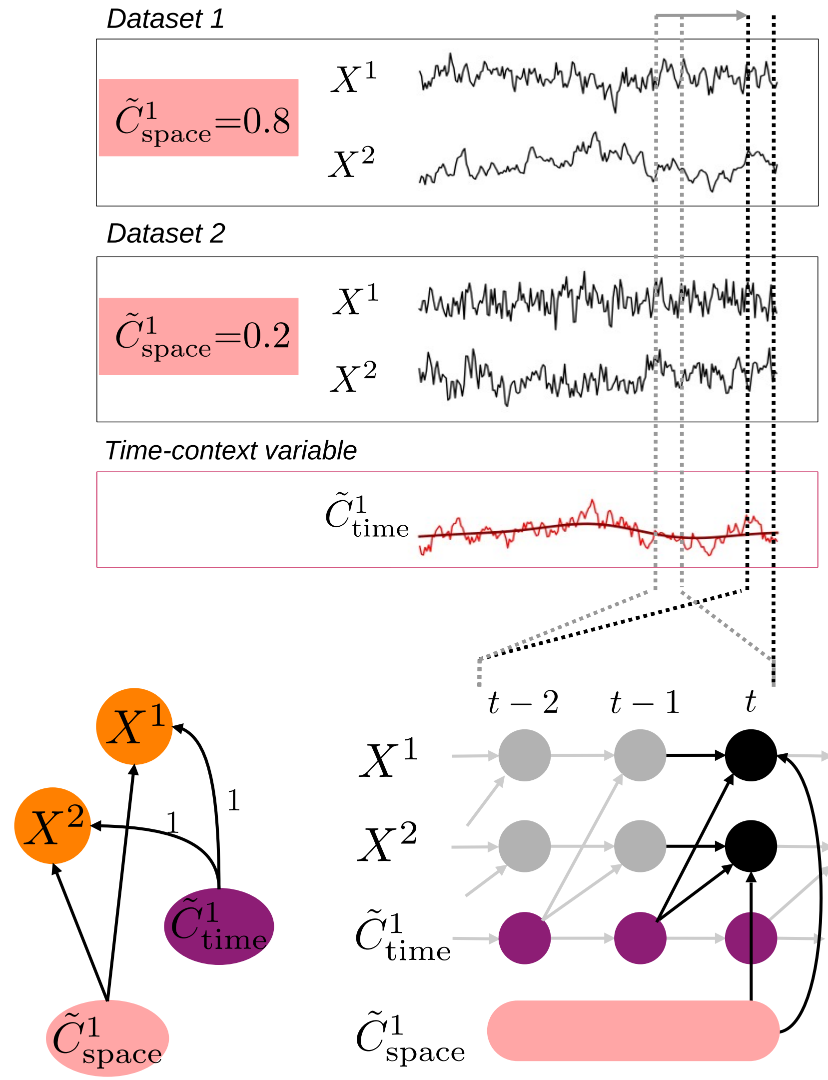
cf. Huang et al (2020), Mooij et al (2020)



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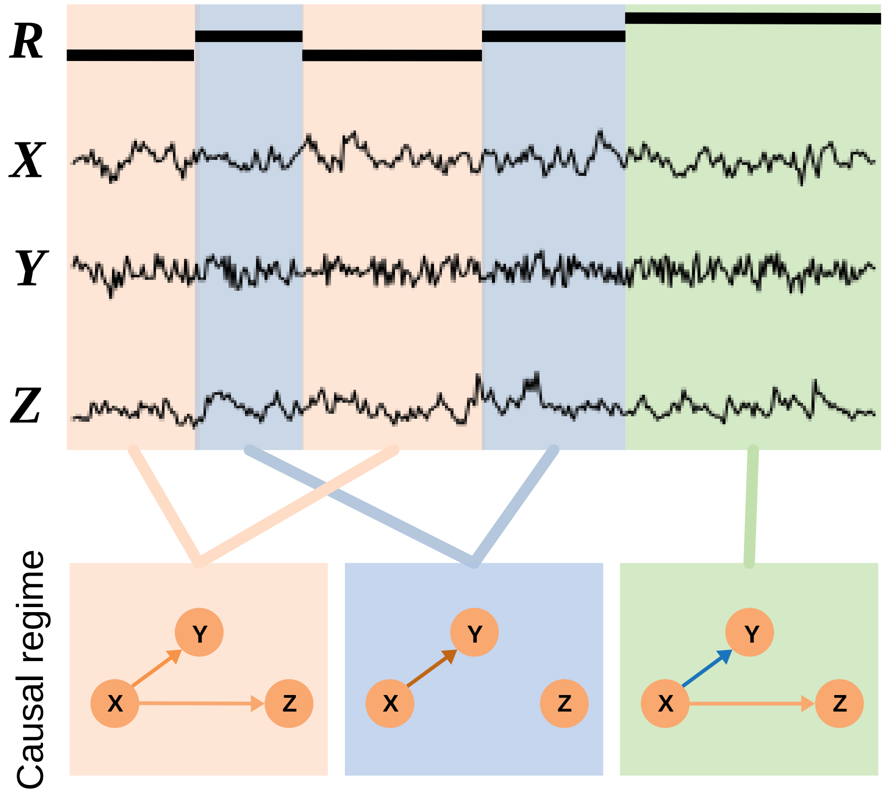

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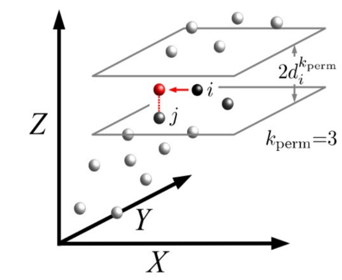
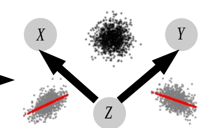
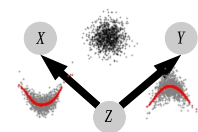
Conditional independence tests $X \perp\!\!\!\perp Y \mid Z$

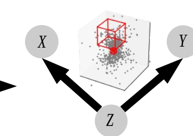
	Nonlinearity / distributions	Variable types	Dimension of X and Y
ParCorr (analytical)	linear gaussian	continuous	univariate
RobustParCorr (analytical)	linear non-gaussian	continuous	univariate
ParCorrWLS[Günther et al.2022] **(analytical)**	linear gaussian, but heteroscedastic	continuous	univariate
GPDC(torch)[Runge et al. 2019] **(permutation-based)**	nonlinear additive	continuous	univariate
CMIknn[Runge 2018] **(permutation-based)**	nonlinear	continuous	multivariate
CMIsymb (permutation-based)	non-parametric	categorical	multivariate
Gsquared (analytical)	non-parametric	categorical	univariate
RegressionCI (analytical)	linear / logistic regression	mixed	univariate

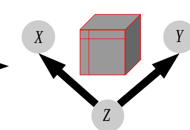
Local permutation shuffle test

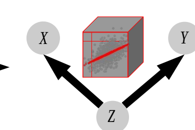


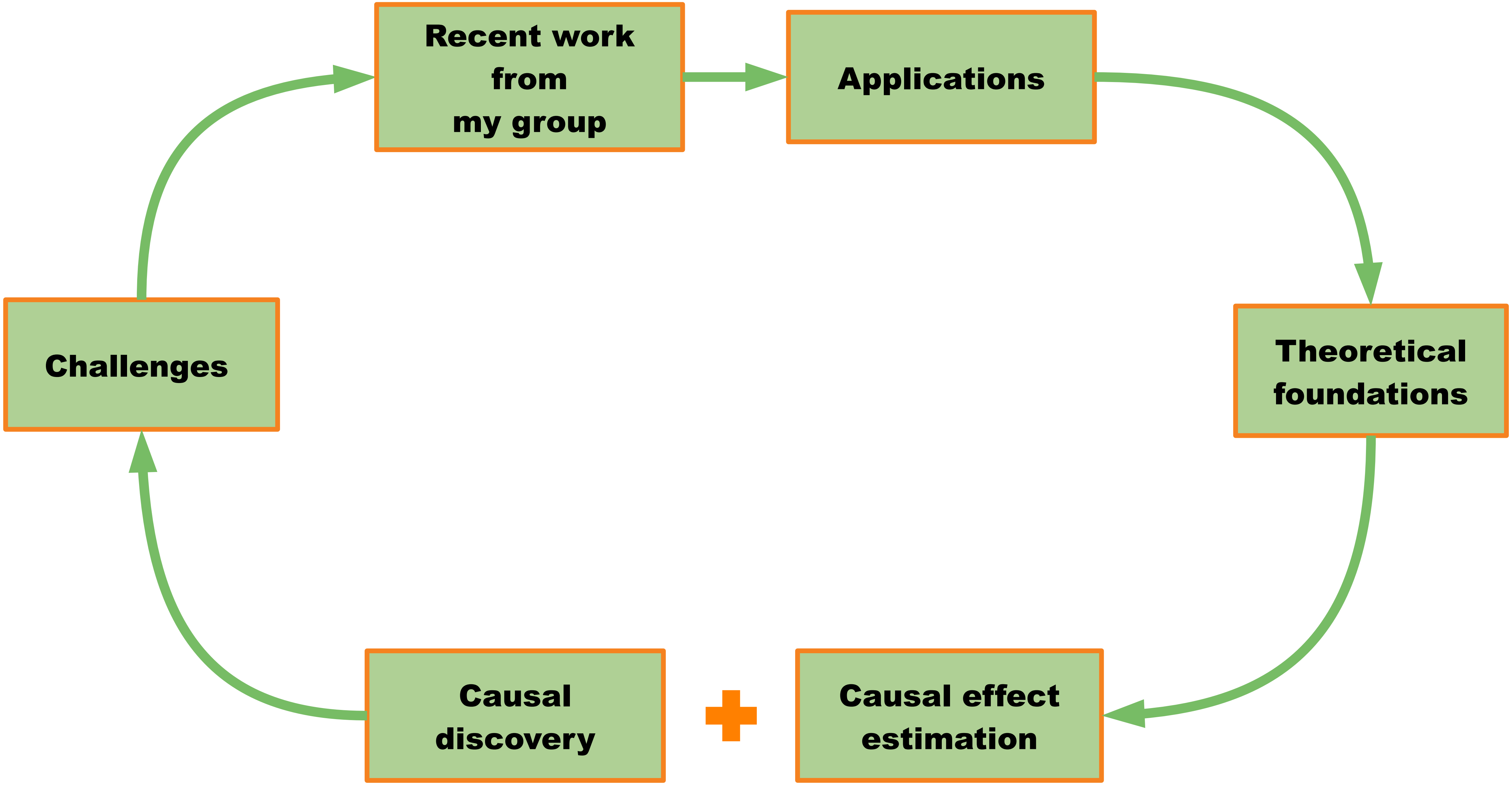








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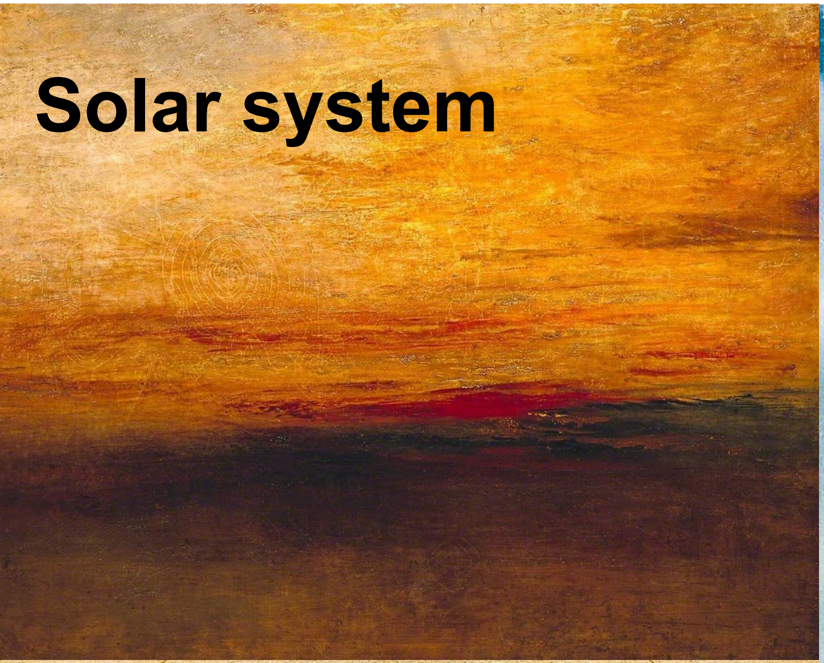
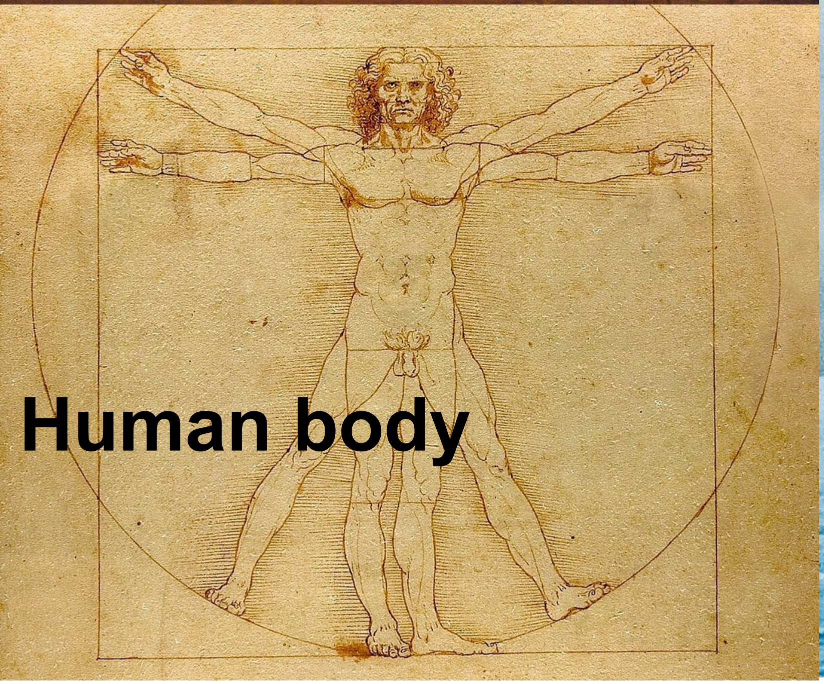
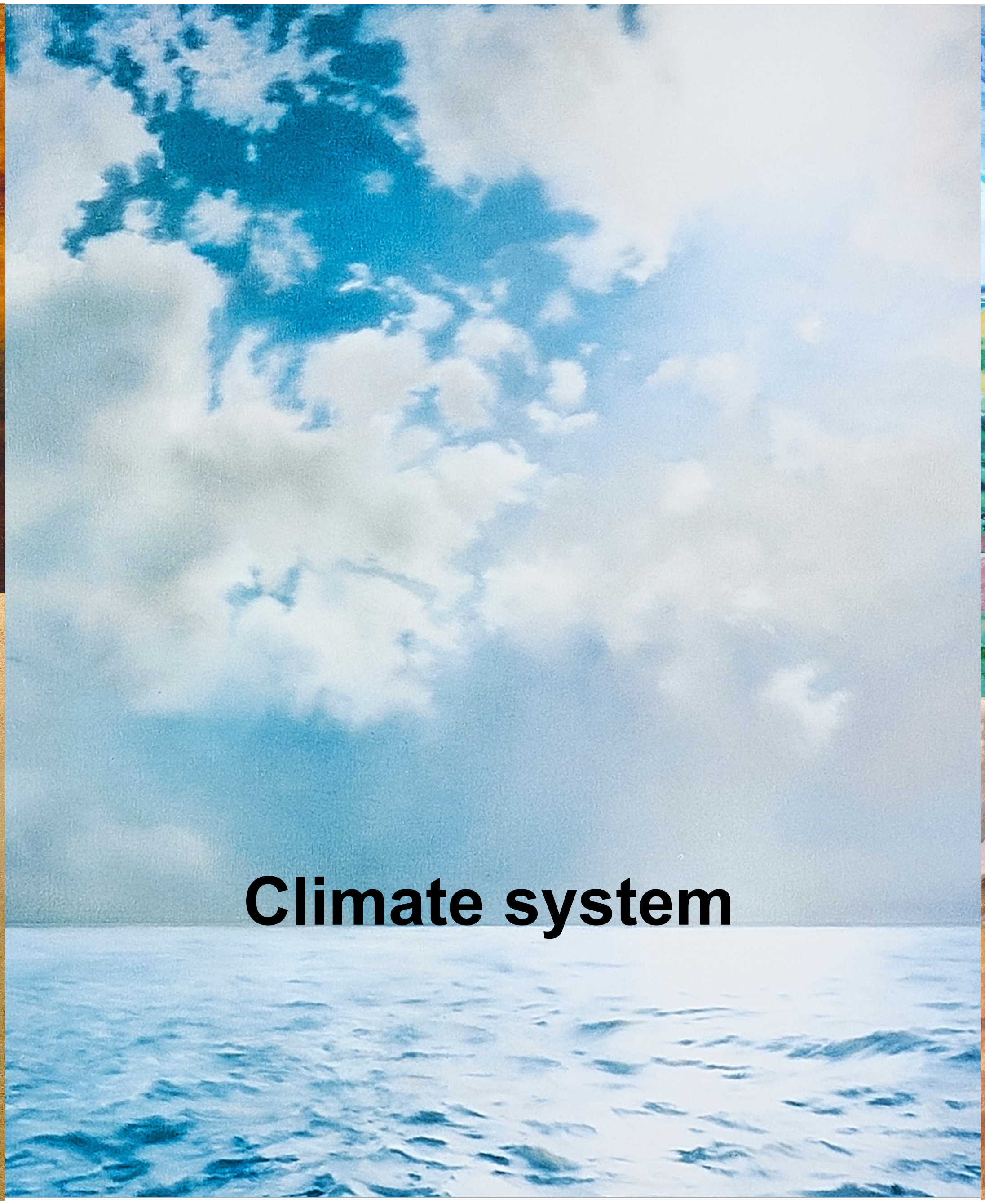
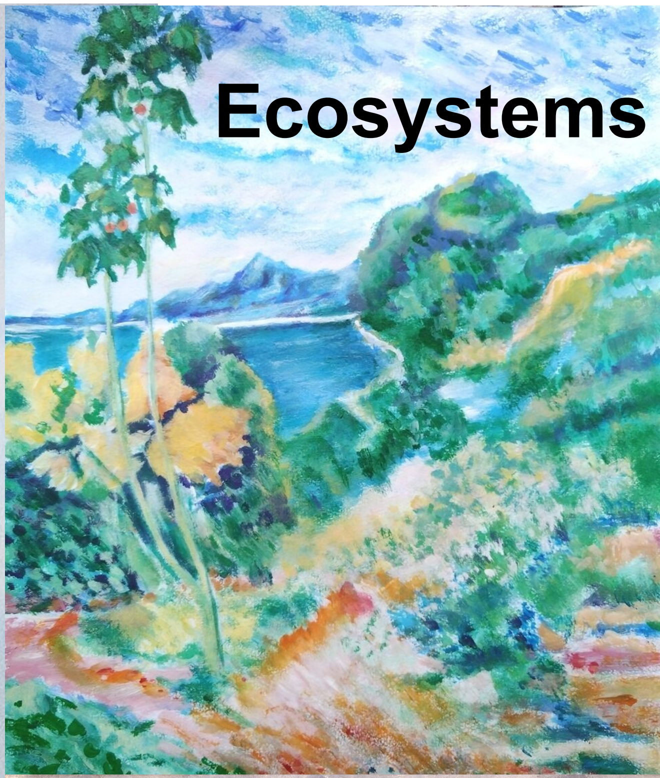
Applications

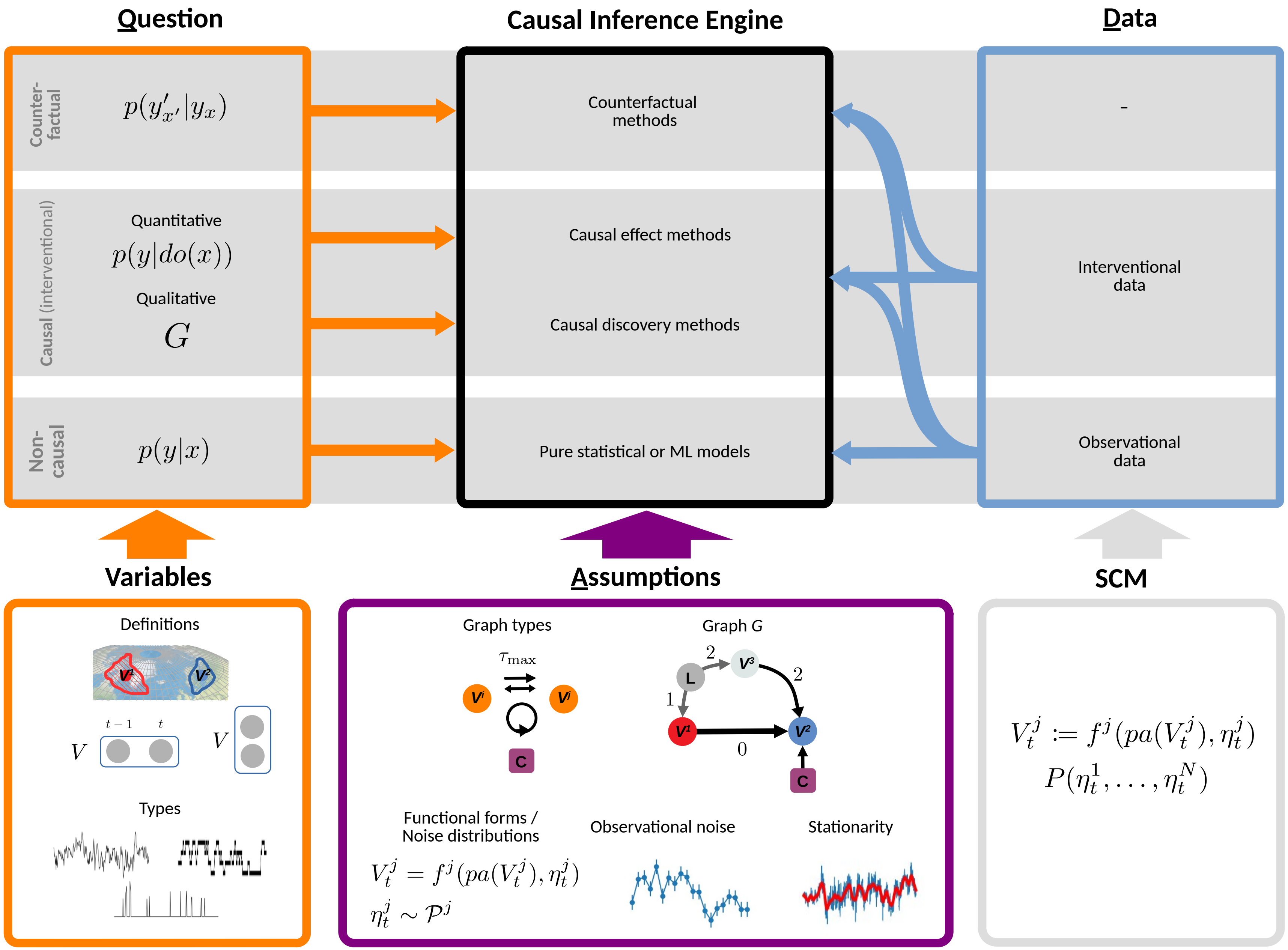






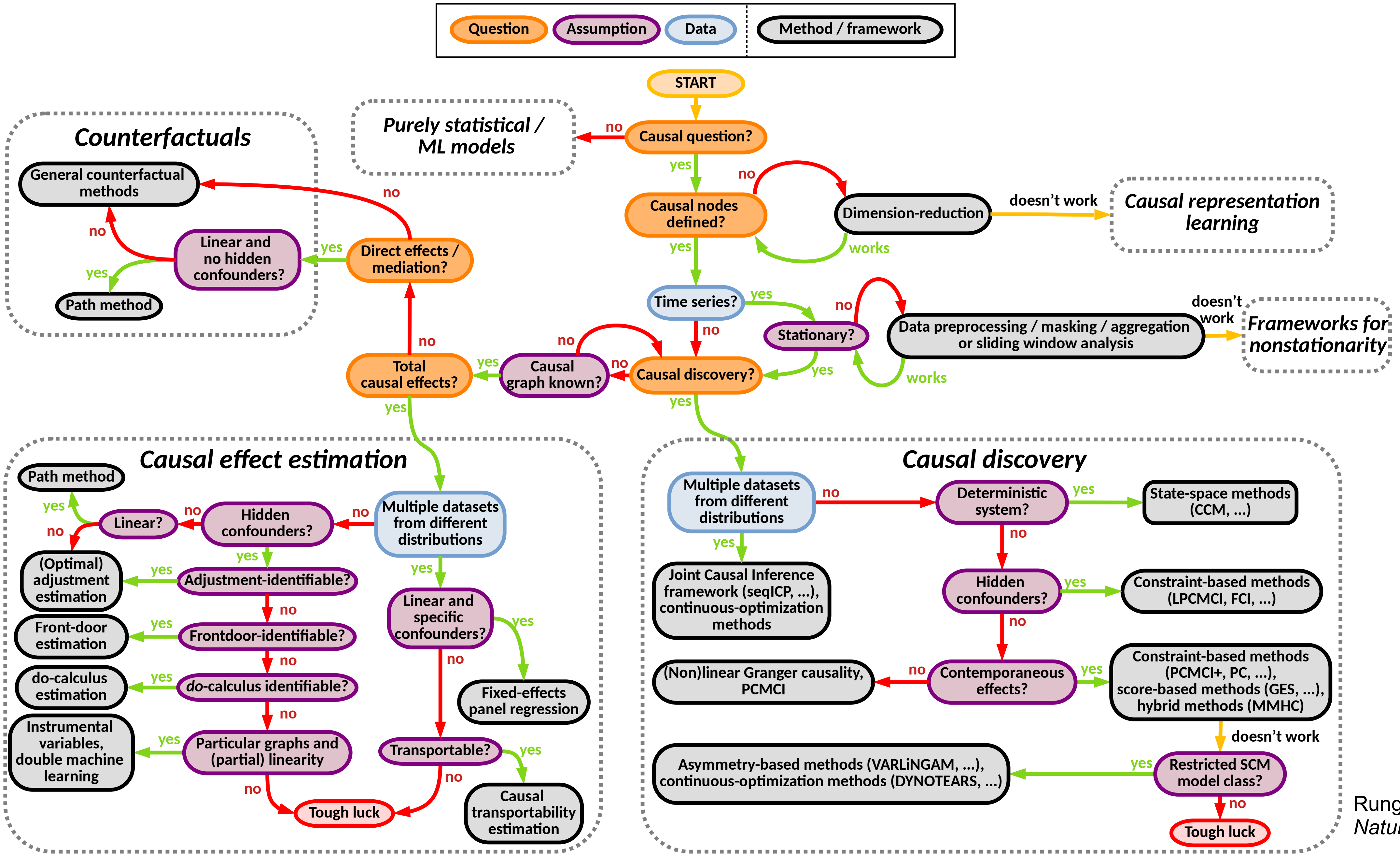


State your problem: Questions – Assumptions – Data



Runge *et al.*,
Nature Rev. EE 2023

QAD-based method selector



Runge *et al.*,
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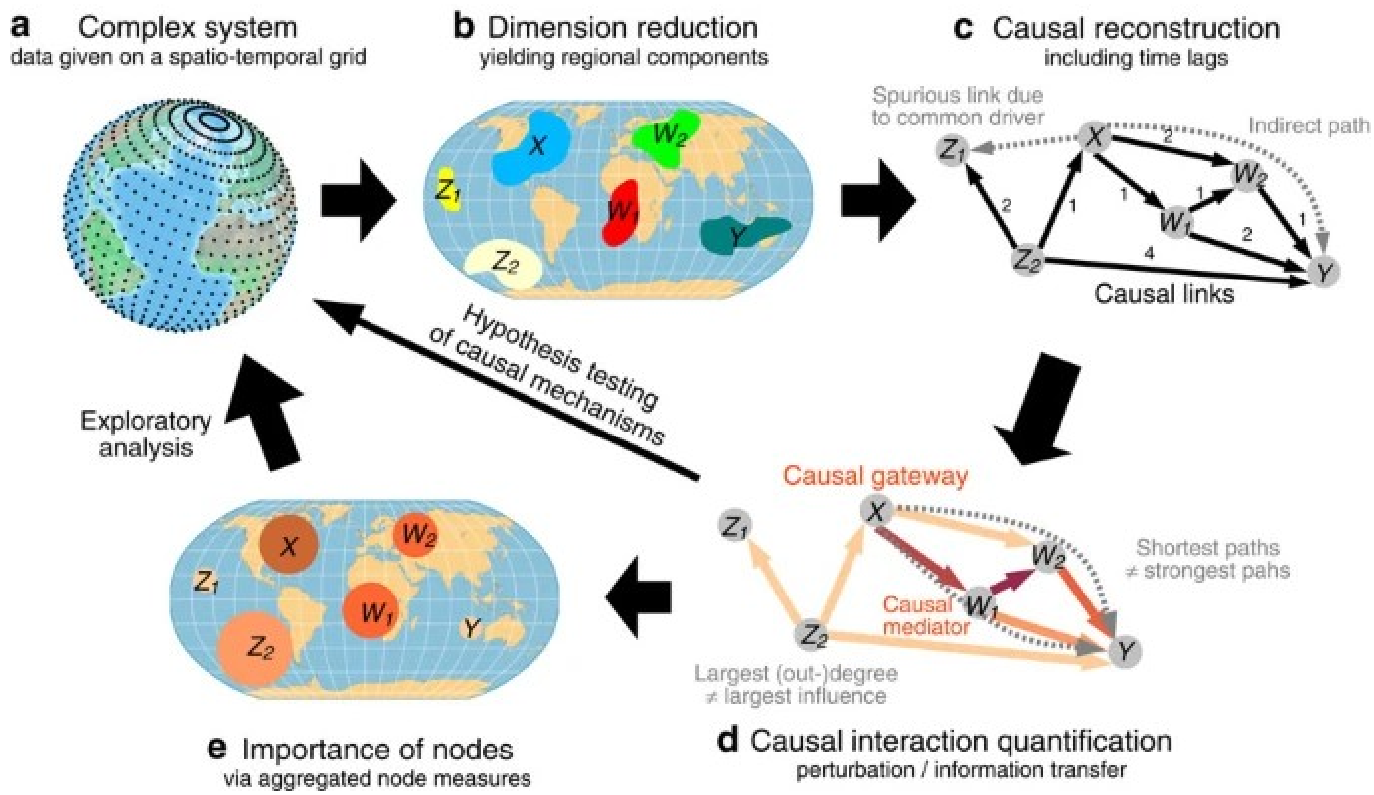
Causal mediation analysis

- Pathway mechanisms between **El Nino** and **Indian monsoon** through sea-level pressure system



Runge et al., NatComm 2015

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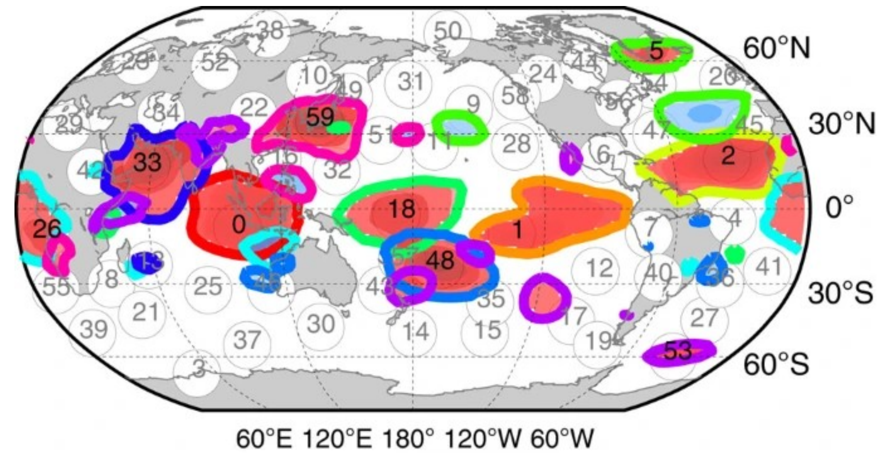

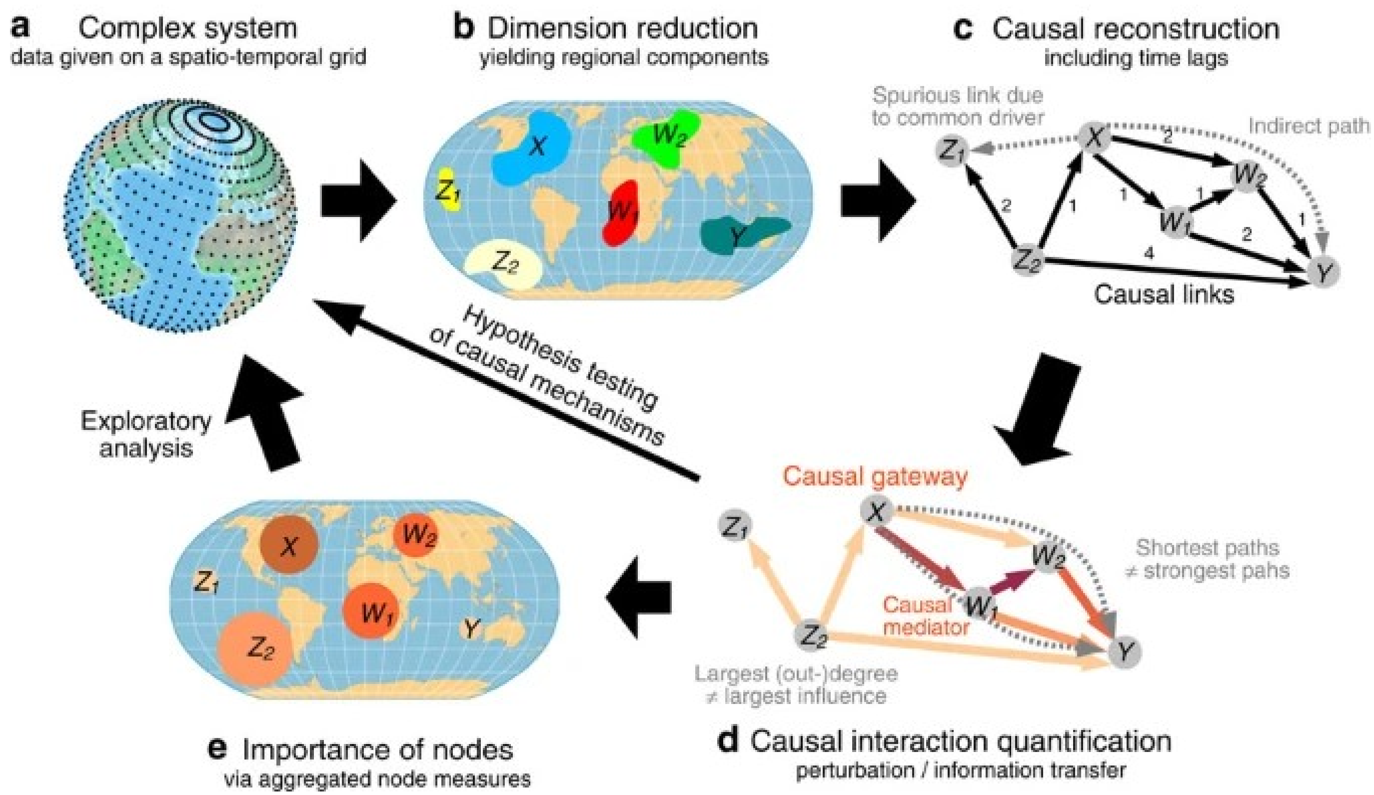

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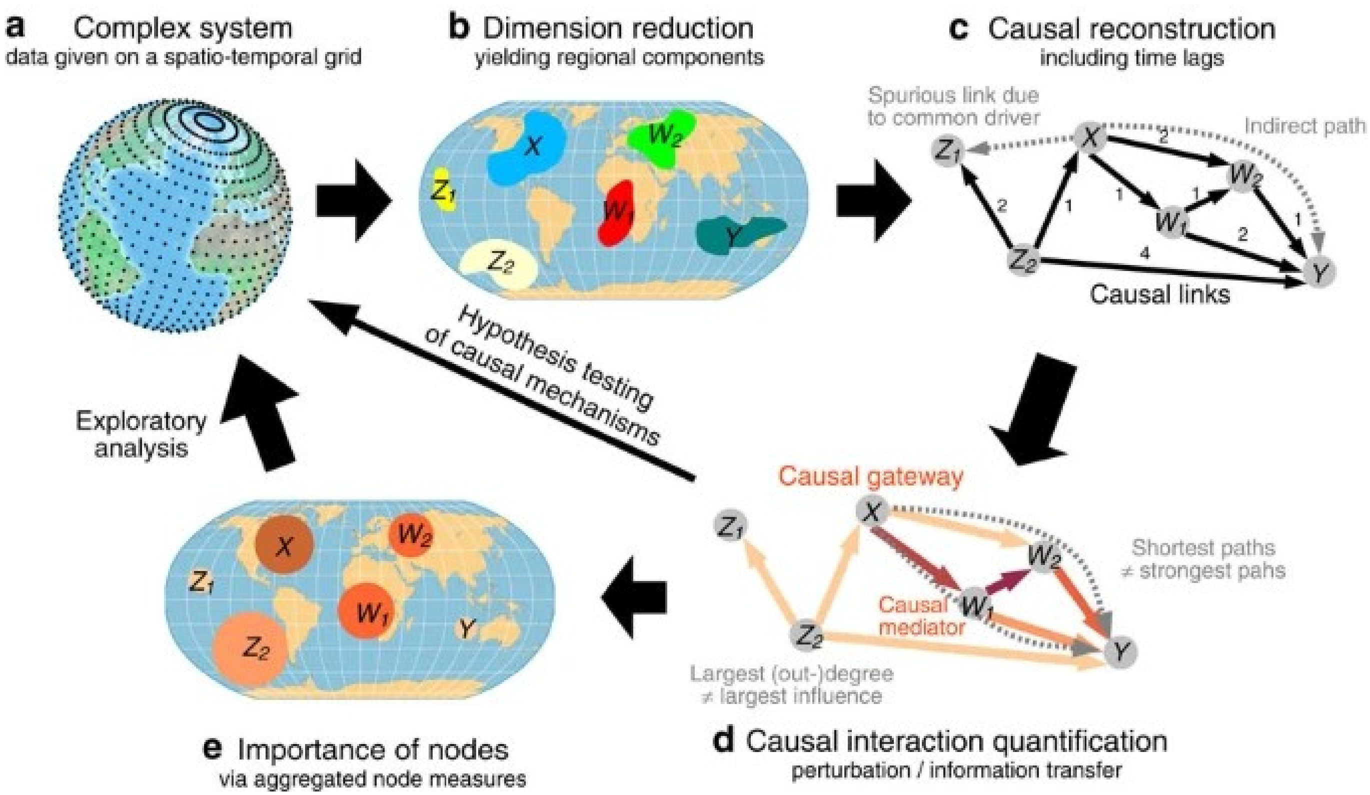

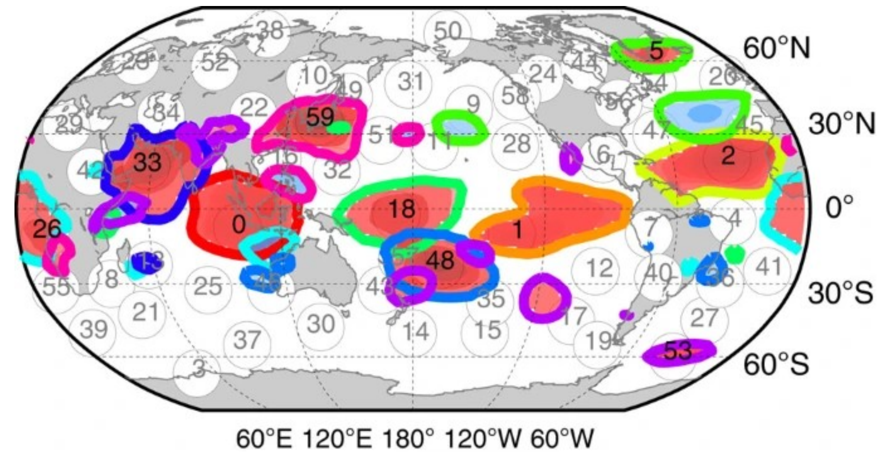

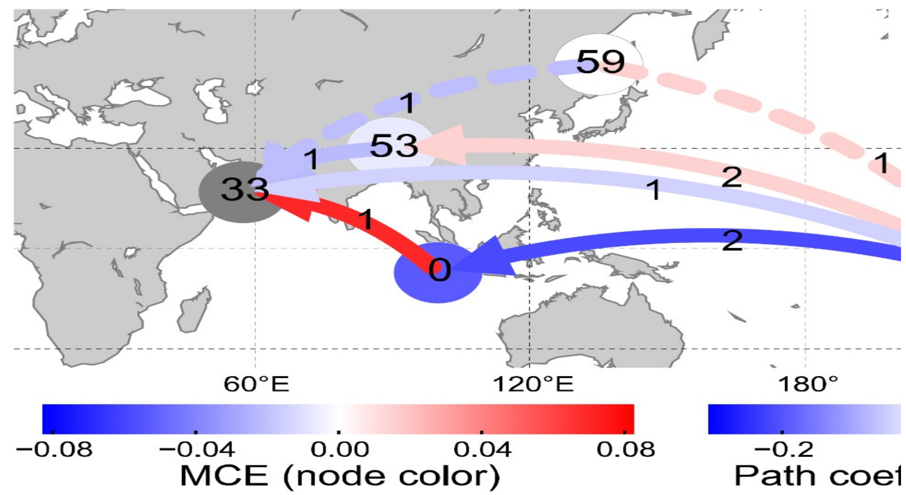

Runge et al., NatComm 2015

Causal relationships between urban form and travel CO2 emissions (Wagner et al., submitted)

- **Context**
  - Car commuting is a major contributor to urban congestion and GHG emissions
  - Built environment (BE) influences car travel distance per capita (VKT)
  - Understanding of how BE affects VKT is required for sustainable urban planning
- **Prior work**
  - ***only correlation based*** - neglecting causal effect mechanisms between BE and VKT
  - ***mostly city specific*** - unclear if relationships hold across various cities around the globe
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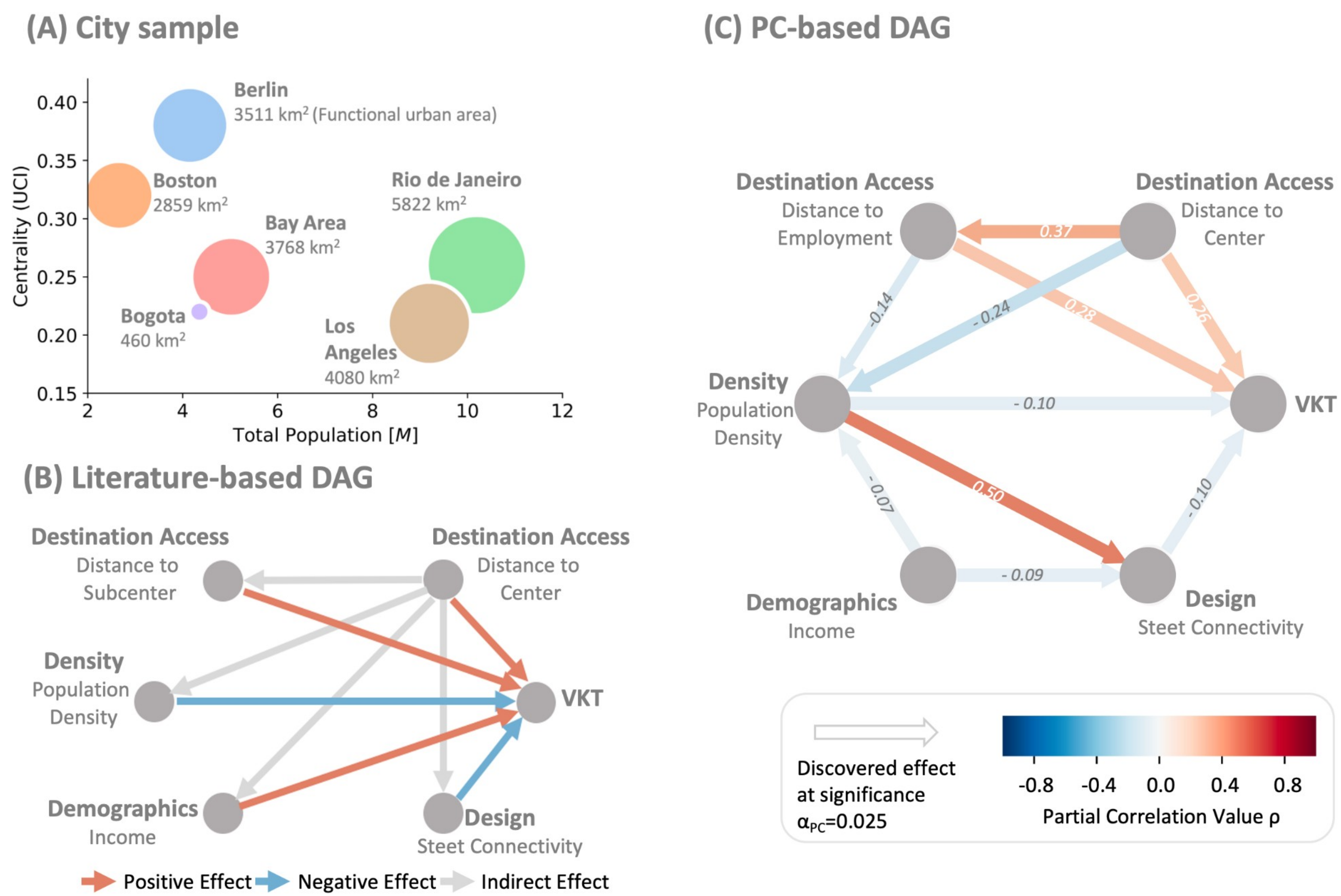
- **Approach**
  1. Gather BE and VKT ***data for six cities*** across 3 continents
  2. Develop BE ***features***, defining:
     1. Distance to center
     2. Distance to jobs
     3. Population density
     4. Street connectivity
     5. Mean household income
  3. Find ***causal graph***, describing relationships between BE Features and VKT
  4. Use graph to ***inform ML model*** and feature importance measure (causal shapley values)
  5. ***Analyse causal effects*** *of BE features* on VKT across all cities and spatially

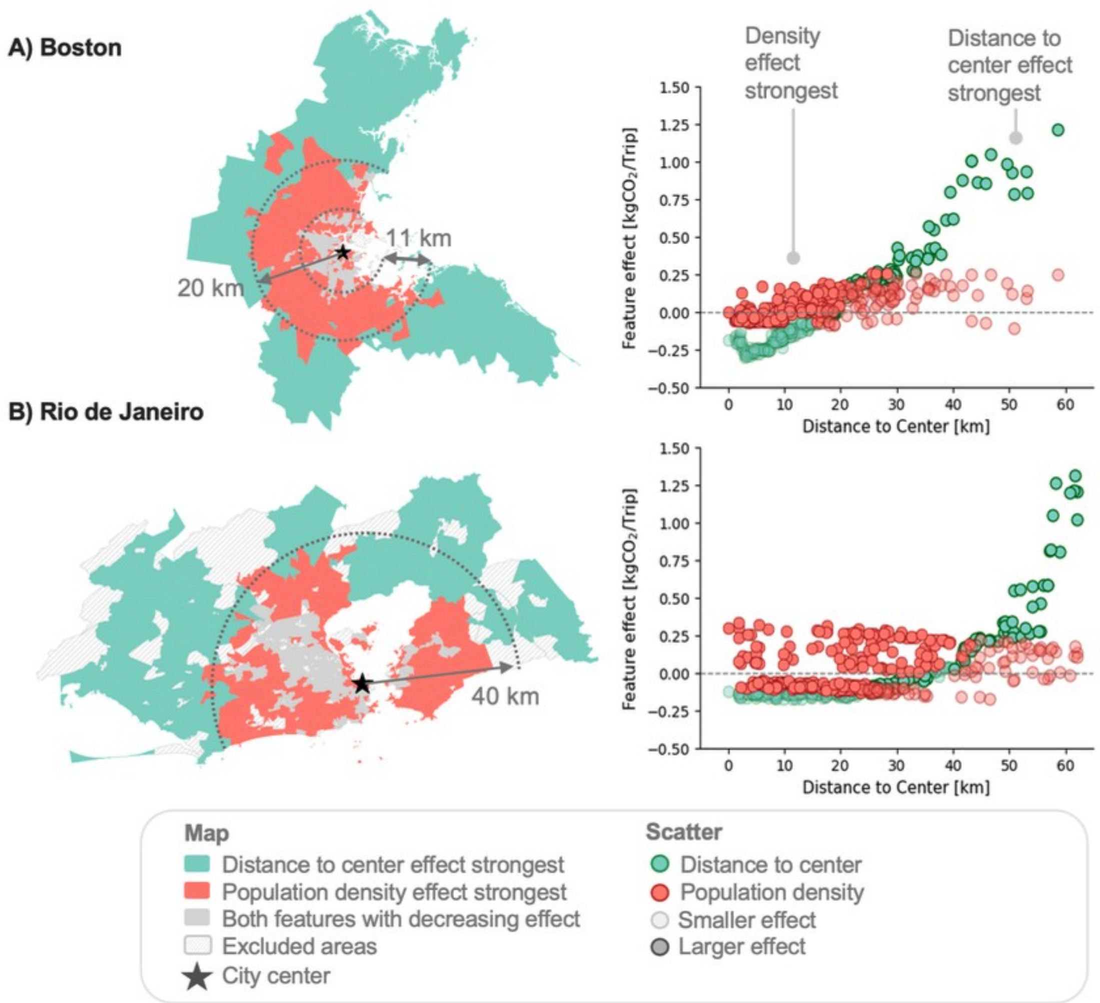
Causal relationships between urban form and travel CO_2 emissions (Wagner et al., submitted)

- **Causal urban form effects partially confirm previous assumptions**



Causal relationships between urban form and travel CO2 emissions (Wagner et al., submitted)

- Which urban form effect matters most depends on specific locations within cities



Take-home message

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- **Causal inference:** Framework to answer causal questions from empirical data


nature reviews earth & environment

https://doi.org/10.1038/s43017-023-00431-y

Technical review

Check for updates

Causal inference for time series

Jakob Runge[1,2], Andreas Gerhardus[1], Gherardo Varando[3], Veronika Eyring[4,5] & Gustau Camps-Valls[3]

CAMBRIDGE UNIVERSITY PRESS

Jakob Runge
Causal Inference for Time Series Data
(release date: 2026)

https://rdcu.be/dfs5X

Take-home message

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- Two settings:
  1) **Assume graphs** and **learn causal effects**
  2) **Learning causal graphs**

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- **Causal inference + AI & ML = Causal AI**

Software and benchmark platform:

- `github.com/jakobrunge/tigramite + causeme.net`
- `pcalg, TETRAD, causalfusion`

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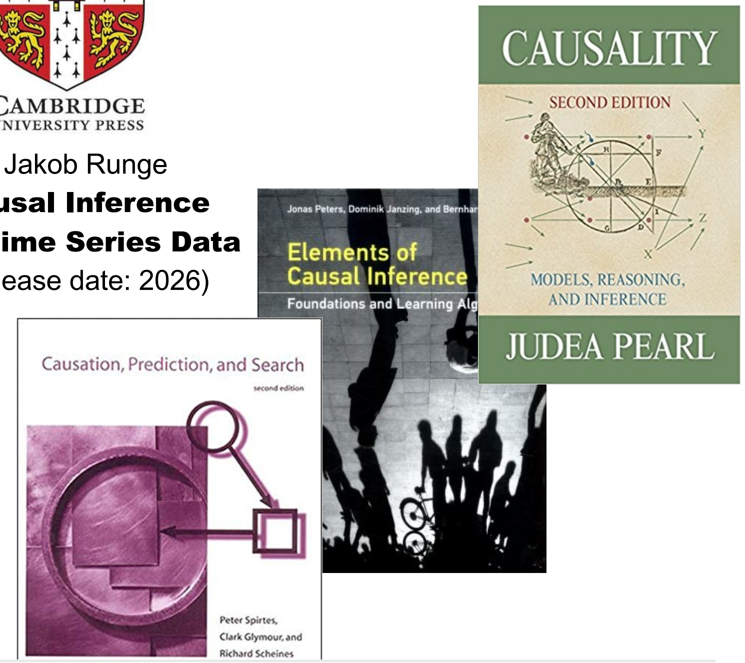

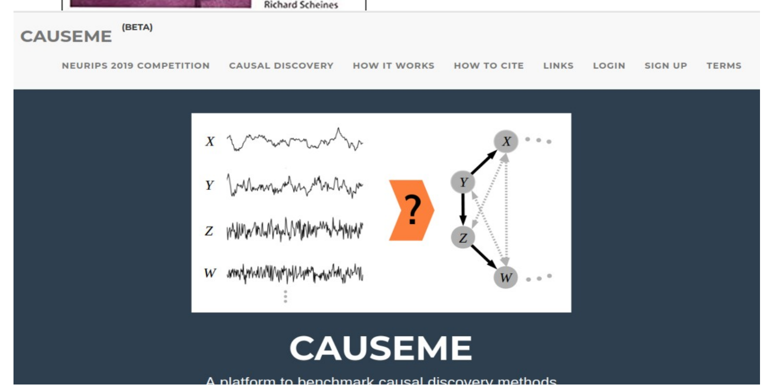

Thank you! Questions?