UNIVERSITY OF COPENHAGEN

Causal Inference

Sebastian Weichwald
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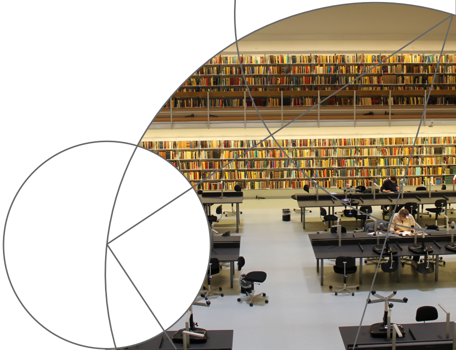
Lviv Data Science Summer School Online
2020-07-20

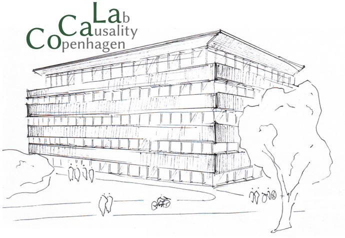


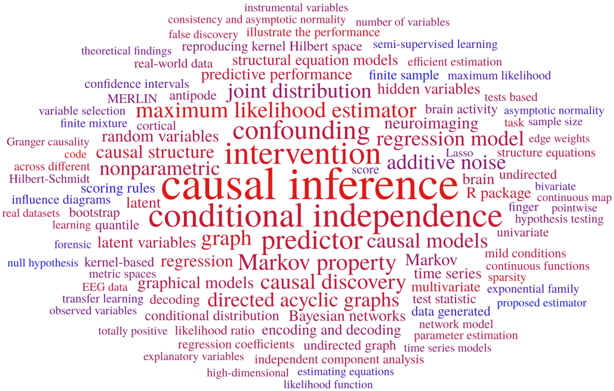
Learn more on Causality at Lviv Summer School 2020

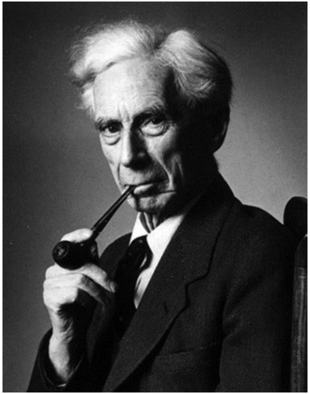
- Fundamentals of Causal Learning
- Wednesday, July 22
- 8:00–12:30 UTC
- Marharyta Aleksandrova

More online lectures on Causality

- 4 lectures on causality by J Peters (8 h)
  MIT Statistics and Data Science Center, 2017 `stat.mit.edu/news/four-lectures-causality`
- causality tutorial by D Janzing and S Weichwald (4 h)
  Conference on Cognitive Computational Neuroscience 2019 `sweichwald.de/ccn2019`
- course on causality by S Bauer and B Schölkopf (3 h)
  Machine Learning Summer School 2020 `youtube.com/watch?v=btmJtThWmhA`
- course on causality by D Janzing and B Schölkopf (3 h)
  Machine Learning Summer School 2013 `mlss.tuebingen.mpg.de/2013/speakers.html`


CoCaLab
Copenhagen Causality Lab


instrumental variables
consistency and asymptotic normality
number of variables
false discovery
illustrate the performance
theoretical findings
reproducing kernel Hilbert space
semi-supervised learning
real-world data
structural equation models
efficient estimation
confidence intervals
predictive performance
finite sample
maximum likelihood
MERLIN
antipode
joint distribution
hidden variables
tests based
variable selection
maximum likelihood estimator
brain activity
asymptotic normality
finite mixture
cortical
neuroimaging
task
sample size
Granger causality
random variables
confounding
regression model
edge weights
code
causal structure
intervention
Lasso
structure equations
across different
nonparametric
additive noise
score
Hilbert-Schmidt
causal inference
brain
undirected
scoring rules
R package
bivariate
influence diagrams
latent
continuous map
finger
pointwise
real datasets
bootstrap
conditional independence
hypothesis testing
learning
quantile
univariate
forensic
latent variables
graph
predictor
causal models
mild conditions
null hypothesis
kernel-based
regression
Markov property
Markov
continuous functions
metric spaces
time series
sparsity
EEG data
graphical models
causal discovery
multivariate
exponential family
transfer learning
decoding
directed acyclic graphs
test statistic
proposed estimator
observed variables
conditional distribution
Bayesian networks
data generated
network model
totally positive
likelihood ratio
encoding and decoding
parameter estimation
regression coefficients
undirected graph
time series models
explanatory variables
independent component analysis
high-dimensional
estimating equations
likelihood function



"All philosophers, of every school, imagine that causation is one of the fundamental axioms or postulates of science, yet, oddly enough, in advanced sciences such as gravitational astronomy, the word "cause" never occurs. [...] To me, it seems that [...] the reason why physics has ceased to look for causes is that, in fact, there are no such things. The law of causality, I believe, like much that passes muster among philosophers, is a relic of a bygone age, surviving, like the monarchy, only because it is erroneously supposed to do no harm."

— B Russell (1913), On the Notion of Cause

Image from theeconplayground.com.

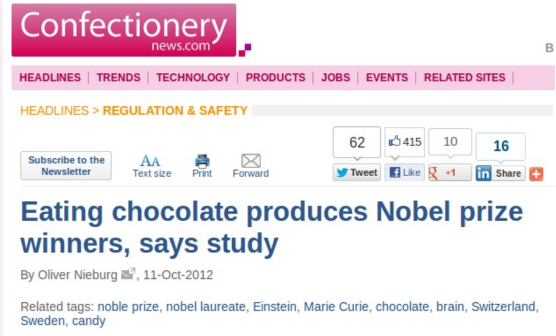
"Fortunately, very few physicists paid attention to Russell's enigma. They continued to write equations in the office and talk cause–effect in the cafeteria; with astonishing success they smashed the atom, invented the transistor and the laser.

The same is true for engineering."

— J Pearl (2009), Causality

Image from baye.cs.ucla.edu.

↯ Causal questions require causal answers.



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Eating chocolate produces Nobel prize winners, says study

By Oliver Nieburg, 11-Oct-2012

Related tags: noble prize, nobel laureate, Einstein, Marie Curie, chocolate, brain, Switzerland, Sweden, candy

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Chocolate And Nobel Prizes In Study

4 comments, 2 called-out + Comment Now + Follow Comments

You don't have to be a genius to like chocolate, but geniuses are more likely to eat lots of chocolate, at least according to a new paper published in the August *New England Journal of Medicine*. Franz Messerli reports a highly

Messerli duly points out that correlation does not prove causation, but, he writes, "since chocolate consumption has been documented to improve cognitive function, it seems most likely that in a dose-dependent way, chocolate intake provides the abundant fertile ground needed for the sprouting of Nobel laureates. Obviously, these findings are hypothesis-generating only and will have to be tested in a prospective, randomized trial."

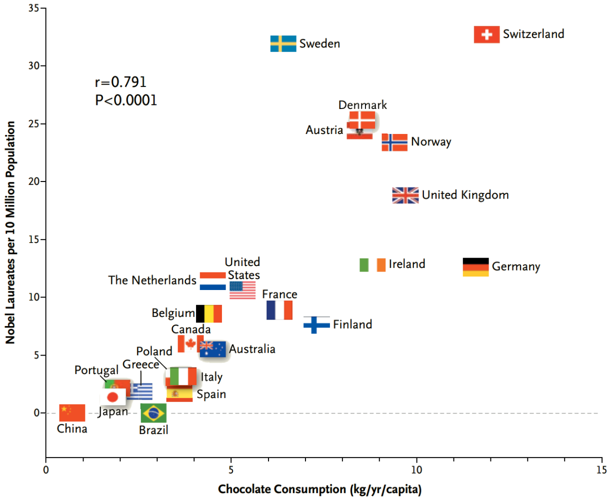
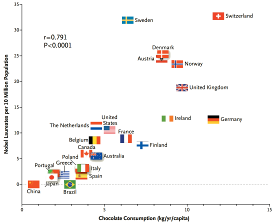


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.



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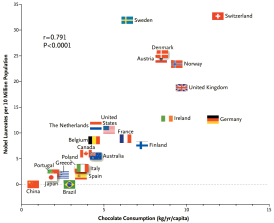

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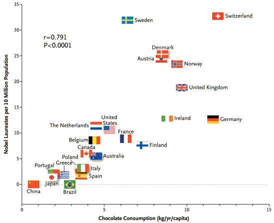
Kim goes on a cruise to another country..



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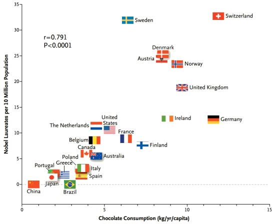
SEEING: ..and reports back that year's chocolate consumption.



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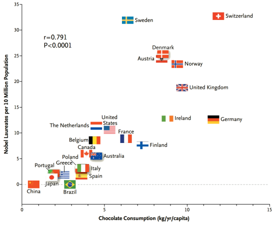

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SEEING: ..and reports back that year's chocolate consumption.

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⇝ Can we predict #country's Nobel Laureates?

↯ Causal questions require causal answers.

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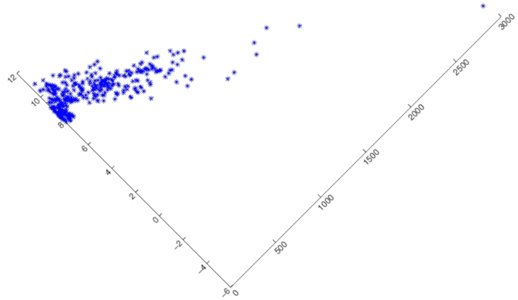
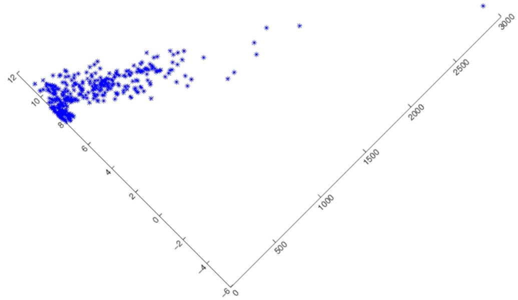
SEEING VS DOING

What's the cause and what's the effect?



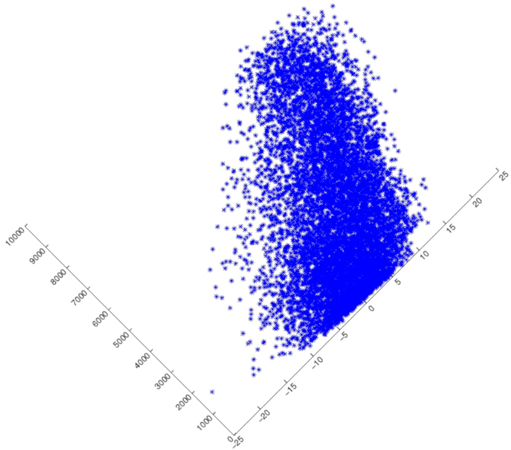
Z Y

What's the cause and what's the effect?



Temperature $Z \quad \leftarrow \quad Y$ Altitude

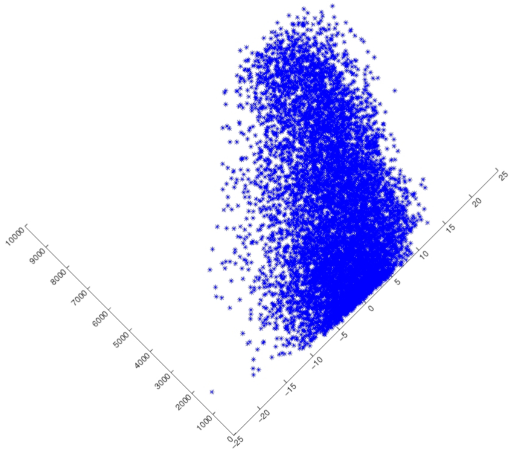
What's the cause and what's the effect?



W *Q*

Mooij, Janzing, Zscheischler, and Schölkopf (2014). *CauseEffectPairs repository* at webdav.tuebingen.mpg.de/cause-effect/.

What's the cause and what's the effect?



Solar Radiation W $\longrightarrow$ Q Temperature

Mooij, Janzing, Zscheischler, and Schölkopf (2014). *CauseEffectPairs repository* at webdav.tuebingen.mpg.de/cause-effect/.

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SEEING VS DOING

- ⚡ Causal questions require causal answers.
- ☹ "Correlation does not imply causation."
- ☺ Correlation(s) may tell us something about causation.

SEEING VS DOING

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SEEING VS DOING

☺ Correlation(s) may tell us something about causation.

⇝ **Causal Inference:** assumptions, data, explicit, algorithmic

CAUSATION AS A PROGRAMMER'S NIGHTMARE

Input:

1. "If the grass is wet, then it rained"
2. "If we break this bottle, the grass will get wet"

Output: "If we break this bottle, then it rained"

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Pearl (2009). Causality: Models, Reasoning, and Inference.

NEEDED: ALGEBRA OF DOING

Available: algebra of **seeing**

e.g., What is the chance it rained if we **see** the grass wet?

$$P\,(rain \mid wet) = ? \qquad \left\{= P\,(wet \mid rain)\frac{P(rain)}{P(wet)}\right\}$$

Needed: algebra of **doing**

e.g., What is the chance it rained if we **make** the grass wet?

$$P\,(rain \mid do(wet)) = ? \quad \{= P\,(rain)\}$$

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Pearl (2009). Causality: Models, Reasoning, and Inference.

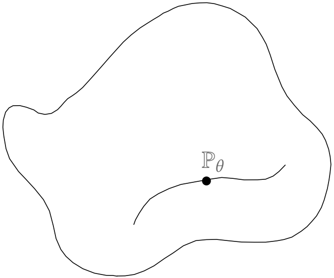
Formalizing the difference between seeing and doing

- **observational probabilities:**
  $p(y|x)$ probability for $Y = y$, given that we observed $X = x$
- **interventional probabilities:**
  $p(y|\operatorname{do}(x))$ probability for $Y = y$, given that we have set X to x

Confusing $p(y|x)$ with $p(y|\operatorname{do}(x))$ is the reason for most of the common misconceptions about causality!

"Normal" Probabilistic Model:

$\mathcal{M}_X : \theta \mapsto \mathbb{P}_\theta$



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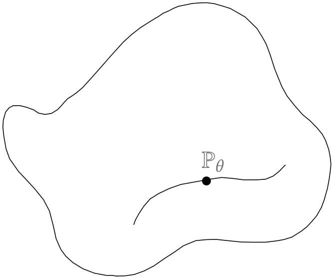
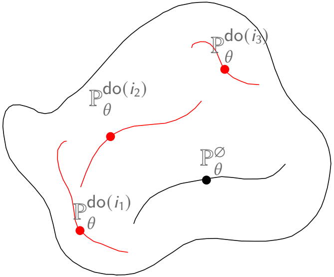


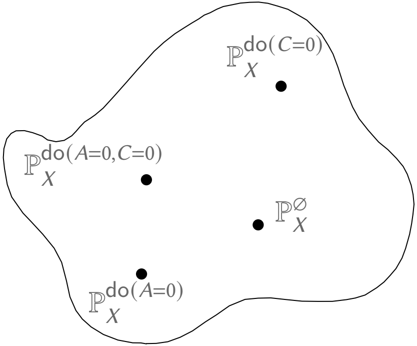
Causal Model:

$$\mathcal{M}_X : \theta \mapsto \{\mathbb{P}_\theta^{\mathrm{do}(i)} \; : \; i \in \mathcal{I}_X\}$$

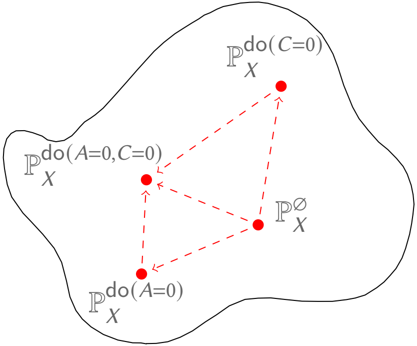
$\mathcal{I}_X$ is set of interventions.



Causal Models

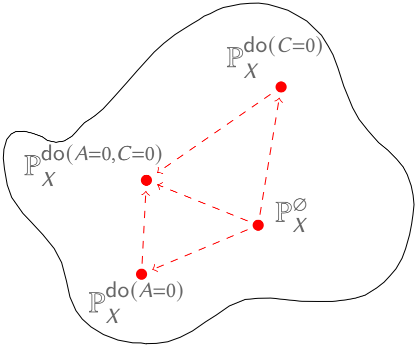


Causal Models



$\mathcal{I}_X$ has partial ordering structure

Causal Models



$\mathcal{I}_X$ has partial ordering structure

$\mathcal{M}_X$ implies the poset of distributions $\mathcal{P}_X := \left(\left\{\mathbb{P}_X^{\mathrm{do}(i)} \;:\; i \in \mathcal{I}_X\right\}, \leq_X\right)$

Structural Causal Models

$$\mathcal{M}_X = (\mathcal{S}_X, \mathcal{I}_X, \mathbb{P}_{E_X})$$

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- $\mathcal{S}_X = \begin{cases} X_1 = E_1 \\ X_2 = X_1 + E_2 \end{cases}$

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- $\mathcal{S}_X = \begin{cases} X_1 = E_1 \\ X_2 = X_1 + E_2 \end{cases}$
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observational

$$\mathbb{P}^{\emptyset}_{X_1} \sim \mathcal{N}(0, 1)$$

$$\mathbb{P}^{\emptyset}_{X_2} \sim \mathcal{N}(0, 2)$$

Structural Causal Models

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- $\mathcal{S}_X = \begin{cases} X_1 = E_1 \\ X_2 = X_1 + E_2 \end{cases}$
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- $E \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

observational	intervention on X_1
$\mathbb{P}^{\varnothing}_{X_1} \sim \mathcal{N}(0,1)$	$\mathbb{P}^{\mathrm{do}(X_1=5)}_{X_1} \equiv 5$
$\mathbb{P}^{\varnothing}_{X_2} \sim \mathcal{N}(0,2)$	$\mathbb{P}^{\mathrm{do}(X_1=5)}_{X_2} \sim \mathcal{N}(5,1)$

Structural Causal Models

$$\mathcal{M}_X = (\mathcal{S}_X, \mathcal{I}_X, \mathbb{P}_{E_X})$$

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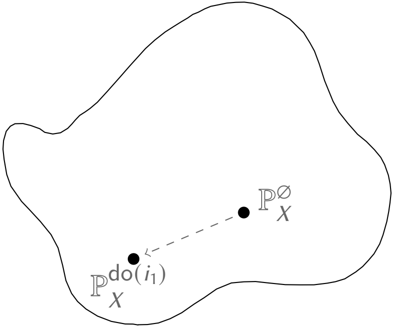
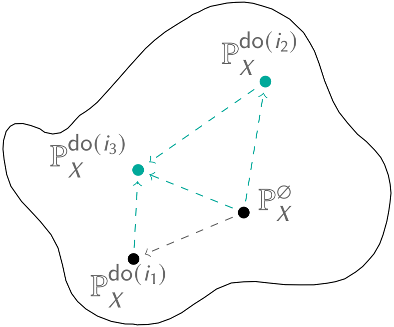
observational	intervention on X_1	intervention on X_2
$\mathbb{P}^{\varnothing}_{X_1} \sim \mathcal{N}(0,1)$	$\mathbb{P}^{\mathrm{do}(X_1=5)}_{X_1} \equiv 5$	$\mathbb{P}^{\mathrm{do}(X_2=3)}_{X_1} \sim \mathcal{N}(0,1)$
$\mathbb{P}^{\varnothing}_{X_2} \sim \mathcal{N}(0,2)$	$\mathbb{P}^{\mathrm{do}(X_1=5)}_{X_2} \sim \mathcal{N}(5,1)$	$\mathbb{P}^{\mathrm{do}(X_2=3)}_{X_2} \equiv 3$

causal discovery?

observations → causal model





$$\left\{\mathbb{P}_X^{\mathrm{do}(i)} \;:\; i \in \mathcal{I}_{\mathrm{sub}} \subsetneq \mathcal{I}_X\right\}$$

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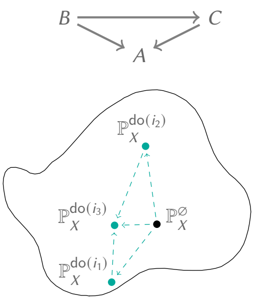
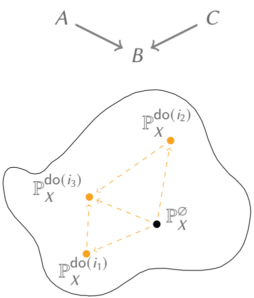
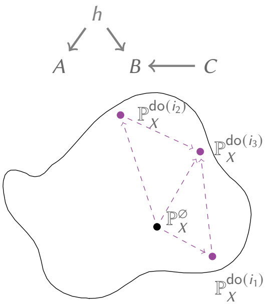


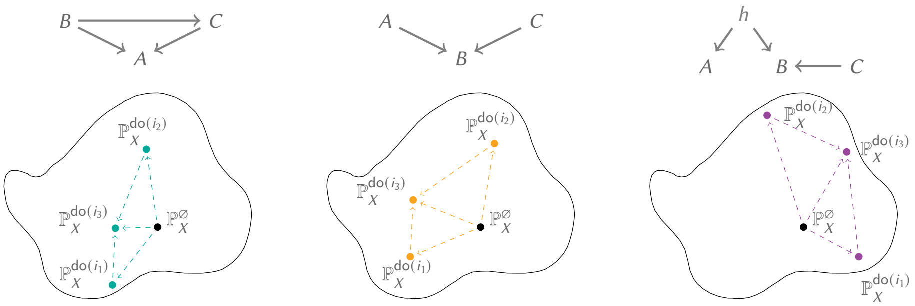
$$
\begin{aligned}
A &= \tfrac{1}{2}B - \tfrac{1}{2}C + \sqrt{3/2}\,N_A \\
B &= \sqrt{3}\,N_B \\
C &= \tfrac{1}{3}B + \sqrt{2/3}\,N_C
\end{aligned}
$$



$$
\begin{aligned}
A &= \sqrt{2}\,N_A \\
B &= \tfrac{1}{2}A + C + \sqrt{3/2}\,N_B \\
C &= N_C
\end{aligned}
$$



$$
\begin{aligned}
A &= h + N_A \\
B &= h + C + N_B \\
C &= N_C
\end{aligned}
$$



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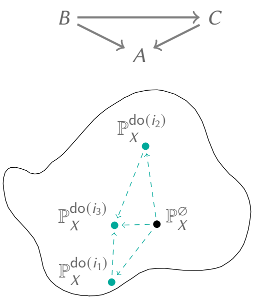
⇝ 3 models inducing the same observational yet different interventional distributions



$$A = {}^1\!/\!_2 B - {}^1\!/\!_2 C + \sqrt{{}^3\!/\!_2}\,N_A$$
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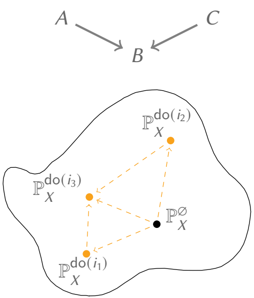

$$A = \sqrt{2}\,N_A$$
$$B = {}^1\!/\!_2 A + C + \sqrt{{}^3\!/\!_2}\,N_B$$
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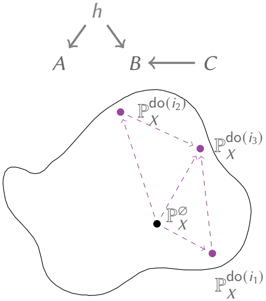

$$A = h + N_A$$
$$B = h + C + N_B$$
$$C = N_C$$

⇝ 3 models inducing the same observational yet different interventional distributions

↯ fitting observational data well is not enough ↯

Reichenbach's principle of common cause (1956)

If two variables X and Y are statistically dependent then either

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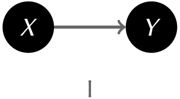

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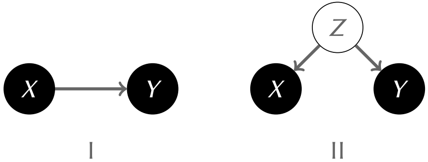

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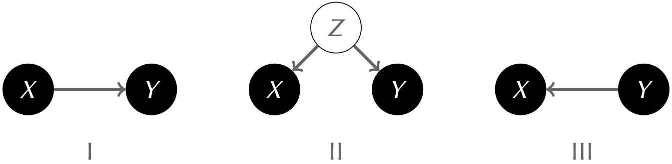

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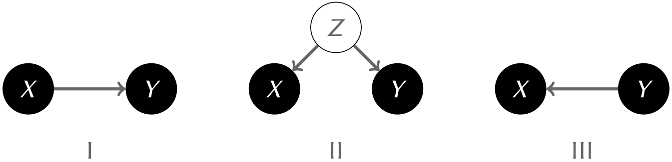
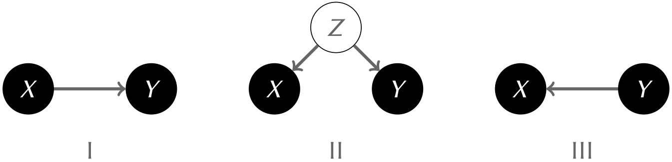


- every statistical dependence is due to a causal relation

Reichenbach's principle of common cause (1956)

If two variables X and Y are statistically dependent then either



- every statistical dependence is due to a causal relation
- cases I, II, and III can also occur simultaneously

Reichenbach's principle of common cause (1956)

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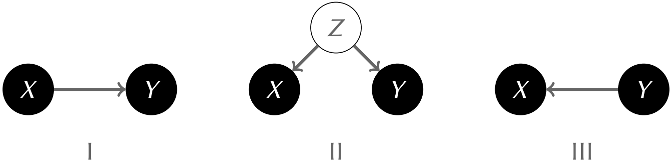
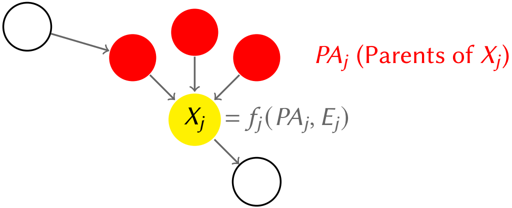


- every statistical dependence is due to a causal relation
- cases I, II, and III can also occur simultaneously
- distinction between the 3 cases is a key problem in scientific reasoning

Functional model of causality Pearl and Spirtes, Glymour, Scheines

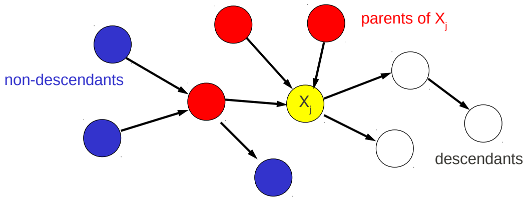
- every node X_j is a function of its parents and an unobserved noise term E_j



- all noise terms E_j are statistically independent (causal sufficiency)
- which properties of $P(X_1, \ldots, X_n)$ follow?

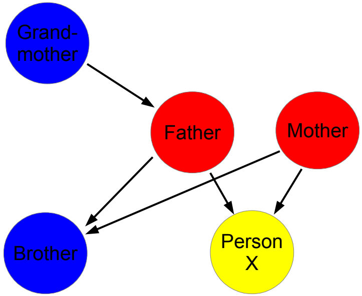
Causal Markov condition (4 equivalent statements)

- **existence of a functional model**
- **local Markov condition:** every node is conditionally independent of its non-descendants, given its parents



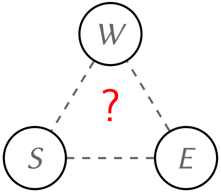
- **global Markov condition:** describes all independences via d-separation
- **Markov factorization:** $P(X_1, \ldots, X_n) = \prod_j P(X_j | PA_j)$

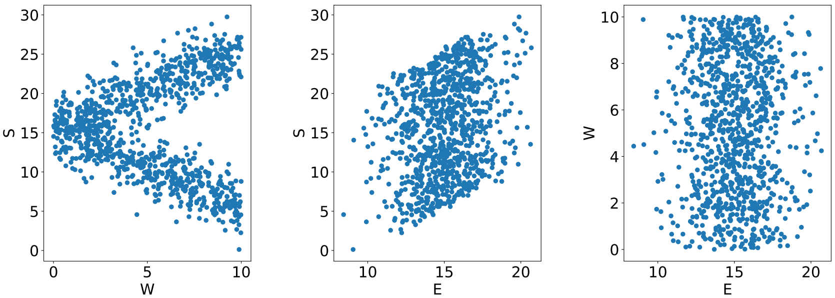
Metaphor for the local Markov condition



If someone knows the genes of X's parents, neither the genes of the grandmother nor the genes of the brother contain additional information about X.

Given observations of W, E, and S (🚲), what is the causal structure?





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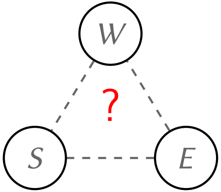
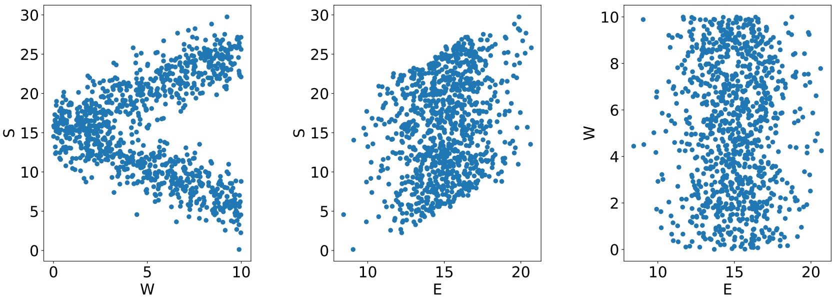


- Which variable pairs are (in)dependent? (All dependent given the 3rd.)



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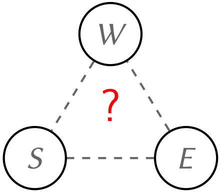
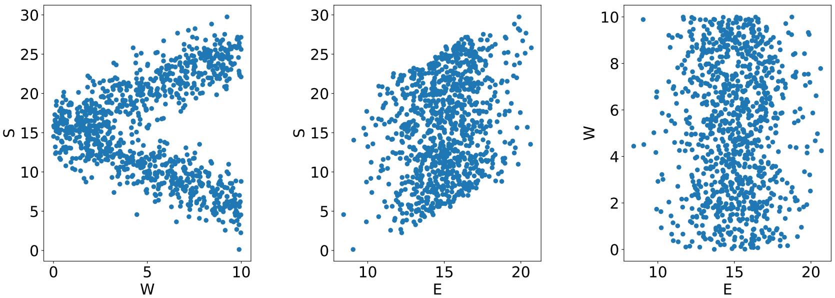


- Which variable pairs are (in)dependent? (All dependent given the 3rd.)
- Assume existence of a functional model.



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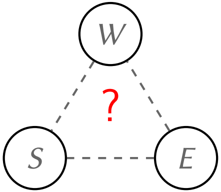

- Which variable pairs are (in)dependent? (All dependent given the 3rd.)
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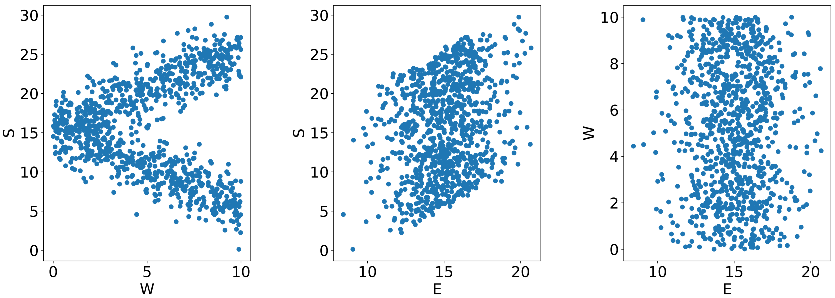

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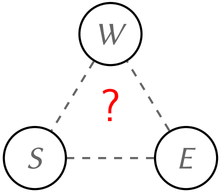
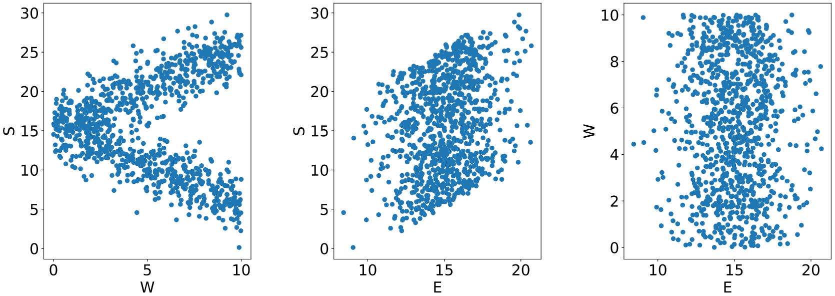
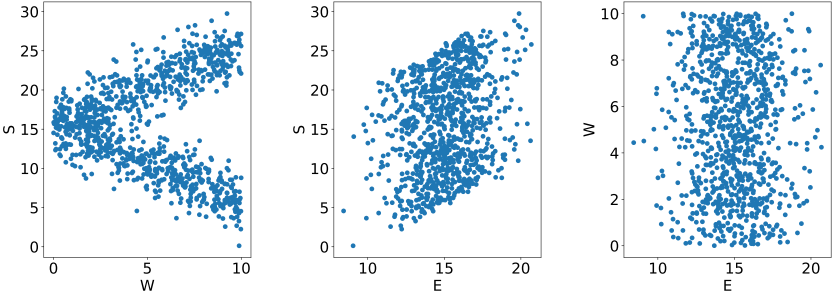


- Which variable pairs are (in)dependent? (All dependent given the 3rd.)
- Assume existence of a functional model.
- Which causal structures are possible? (7)
- Further assumption to narrow it down?

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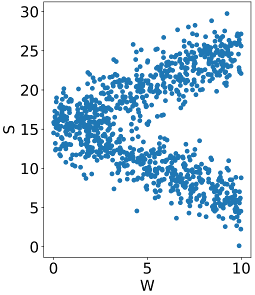
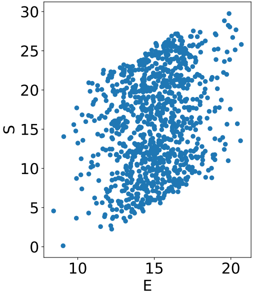


dependent



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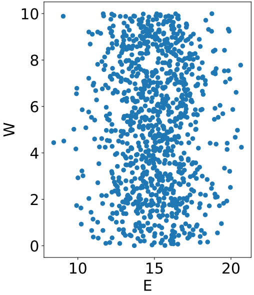
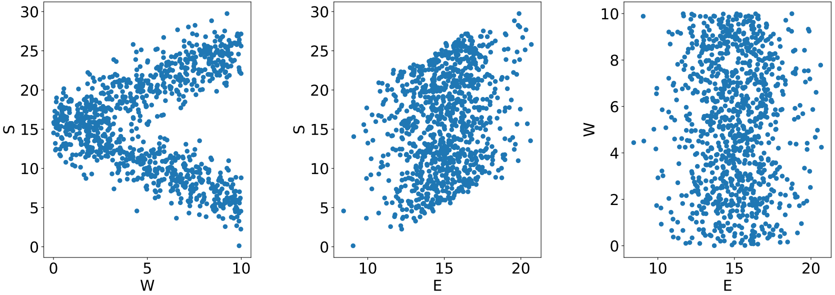
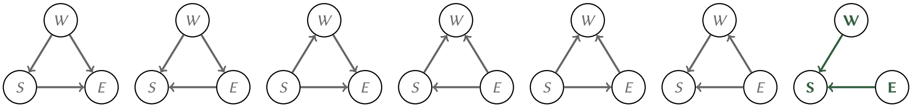
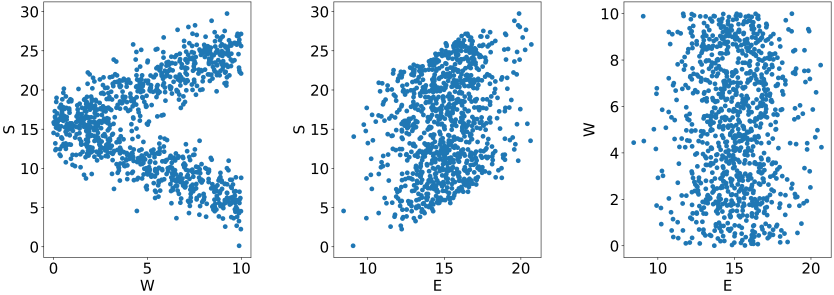


independent

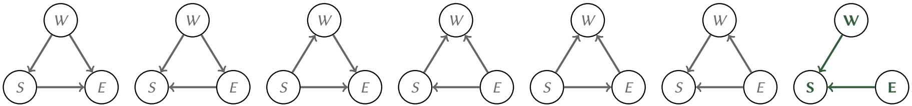


dependent dependent independent





dependent dependent independent



Assume existence of a functional model (causal sufficiency) & faithfulness.

Pearl's do-operator

How to compute $p(x_1, \ldots, x_n | \operatorname{do}(x_i^*))$:

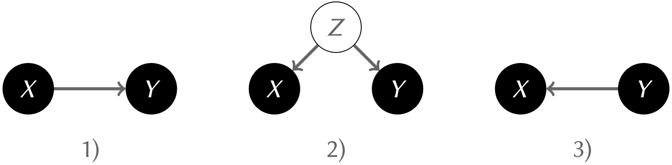
- Write $p(x_1, \ldots, x_n)$ as

$$\prod_{k=1}^{n} p(x_k | \operatorname{parents}(x_k))$$

- and replace $p(x_i | \operatorname{parents}(x_i))$ with δ_{x_i, x_i^*}

$$p(x_1, \ldots, x_n | \operatorname{do}(x_i^*)) = \delta_{x_i, x_i^*} \prod_{k \neq i} p(x_k | \operatorname{parents}(x_k))$$

Examples



1. interventional and observational probabilities coincide (seeing = doing)

$$p(y|\operatorname{do}(x)) = p(y|x)$$

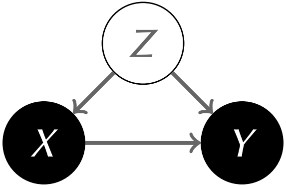
2. intervening on x does not change y

$$p(y|\operatorname{do}(x)) = p(y) \neq p(y|x)$$

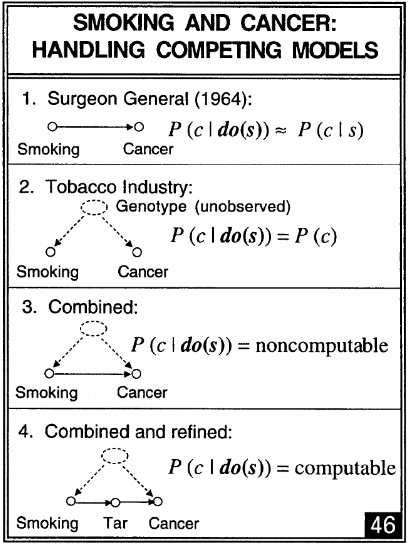
3. intervening on x does not change y

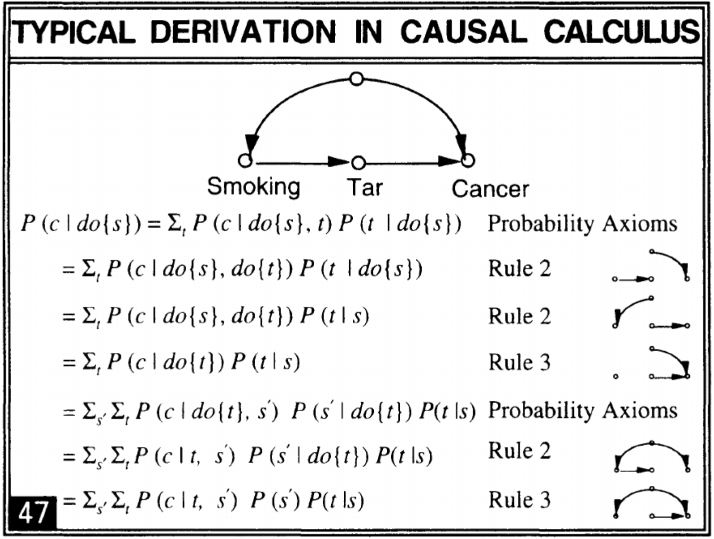
$$p(y|\operatorname{do}(x)) = p(y) \neq p(y|x)$$

Confounder correction



$$p(y|\,\mathrm{do}(x)) = \sum_z p(y|x,z)\color{blue}{p(z)} \neq \sum_z p(y|x,z)\color{blue}{p(z|x)} = p(y|x)$$


SMOKING AND CANCER: HANDLING COMPETING MODELS
1. Surgeon General (1964):
Smoking
Cancer
$P(c \mid do(s)) \approx P(c \mid s)$
2. Tobacco Industry:
Genotype (unobserved)
Smoking
Cancer
$P(c \mid do(s)) = P(c)$
3. Combined:
Smoking
Cancer
$P(c \mid do(s)) =$ noncomputable
4. Combined and refined:
Smoking
Tar
Cancer
$P(c \mid do(s)) =$ computable
46


TYPICAL DERIVATION IN CAUSAL CALCULUS
Smoking
Tar
Cancer
$P(c \mid do\{s\}) = \Sigma_t P(c \mid do\{s\}, t)\, P(t \mid do\{s\})$ Probability Axioms
$= \Sigma_t P(c \mid do\{s\}, do\{t\})\, P(t \mid do\{s\})$ Rule 2
$= \Sigma_t P(c \mid do\{s\}, do\{t\})\, P(t \mid s)$ Rule 2
$= \Sigma_t P(c \mid do\{t\})\, P(t \mid s)$ Rule 3
$= \Sigma_{s'} \Sigma_t P(c \mid do\{t\}, s')\, P(s' \mid do\{t\})\, P(t \mid s)$ Probability Axioms
$= \Sigma_{s'} \Sigma_t P(c \mid t, s')\, P(s' \mid do\{t\})\, P(t \mid s)$ Rule 2
$= \Sigma_{s'} \Sigma_t P(c \mid t, s')\, P(s')\, P(t \mid s)$ Rule 3
47

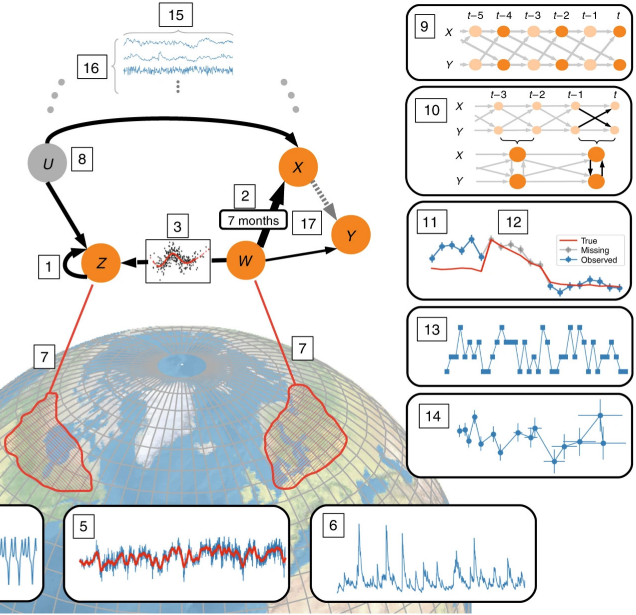
Level (Symbol)	Typical Activity	Typical Questions	Examples
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in$Y$?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. Intervention $P(y\|do(x), z)$	Doing Intervening	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? Would Kennedy be alive had Oswald not shot him? What if I had not been smoking the past 2 years?

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



↯ Causal questions require causal answers.

- ↯ Causal questions require causal answers.
- ☹ "Correlation does not imply causation."

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☹ "Correlation does not imply causation."

SEEING VS DOING

↯ Causal questions require causal answers.

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SEEING VS DOING

☺ Correlation(s) may tell us something about causation.

↯ Causal questions require causal answers.

☹ "Correlation does not imply causation." SEEING VS DOING

☺ Correlation(s) may tell us something about causation.

⇝ **Causal Inference:** assumptions, data, explicit, algorithmic

Causal Inference: assumptions, data, explicit, algorithmic

CoCaLab Copenhagen Causality

@sweichwald

Causal Inference: assumptions, data, explicit, algorithmic

- 4 lectures on causality by J Peters (8 h)
  MIT Statistics and Data Science Center, 2017 `stat.mit.edu/news/four-lectures-causality`
- causality tutorial by D Janzing and S Weichwald (4 h)
  Conference on Cognitive Computational Neuroscience 2019 `sweichwald.de/ccn2019`
- course on causality by S Bauer and B Schölkopf (3 h)
  Machine Learning Summer School 2020 `youtube.com/watch?v=btmJtThWmhA`
- course on causality by D Janzing and B Schölkopf (3 h)
  Machine Learning Summer School 2013 `mlss.tuebingen.mpg.de/2013/speakers.html`

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