Causality
Solving for Why

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Algorithmic Causality

The goals of the mini-course

- providing a gentle introduction to causal inference,
- presenting recent achievements in algorithmic causality, and
- describing new research directions, applications, new techniques, and challenging open problems.

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- providing a gentle introduction to causal inference,
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The major contributors to the field

- Judea Pearl (Turing Award, 2011)
- Peter Spirtes
- Clark Glymour
- Donald Rubin
- Jamie Robins
- Peter Bühlman
- Elias Bareinboim
- Joshua D. Angrist, Guido W. Imbens (Nobel in Economic Sciences, 2021)
- and many others...

Discovering of causal relationships

What causal relationships can be established? In ...

... economy?

[wikipedia]

... health?

[wikipedia]

... AI-based systems?

Predict effect of

... the tax increase on economic growth

... a new drug have on the recovery

... the decision of an autonomous vehicle

What is Causality?

it rains

lawn is wet

What is Causality?

it rains

?!

$\longleftarrow$

lawn is wet

What is Causality?

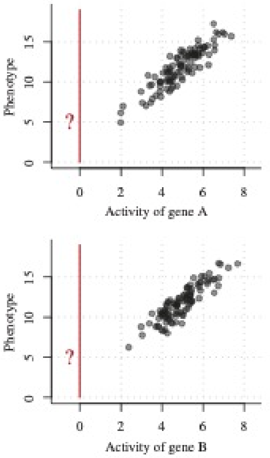
it rains

lawn is wet

correlation is not causation

What is Causality?

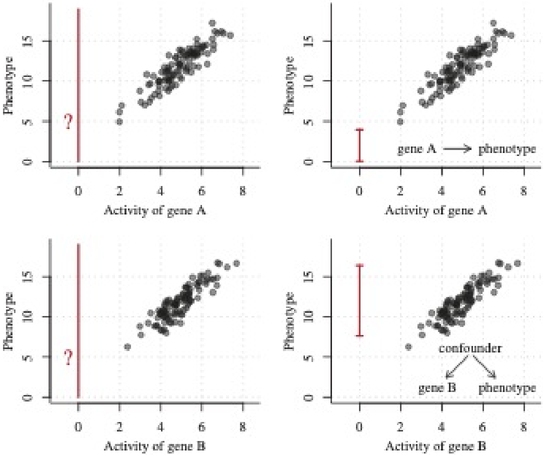
Example: Gene Perturbation[1]



[1] J. Peters, D. Janzing, and B. Schölkopf. Elements of causal inference: foundations and learning algorithms. MIT press, 2017

What is Causality?

Example: Gene Perturbation[1]



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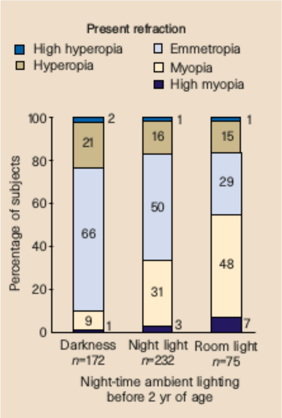
Central Problems

1. Useful graphical representations for causal models
2. Learning causal structure from data
3. How to compute interventions?
4. How can we deal with the problem of hidden variables?
5. Can we test counterfactual statements?
6. Is causality useful?

Motivating Example 1

Myopia and ambient lighting at night



Motivating Example 1

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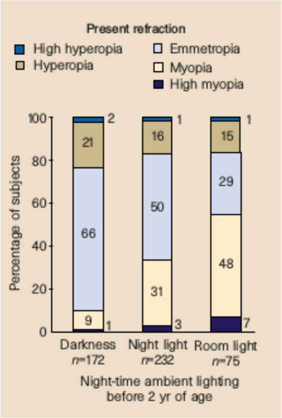


" ... the strength of the association ... does suggest that the absence of a daily period of darkness during childhood is a potential precipitating factor in the development of myopia"

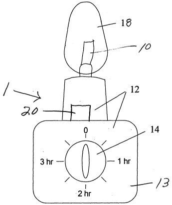
Quinn, Shin, Maguire, Stone: Myopia and ambient lighting at night, Nature 1999

Motivating Example 1

Myopia and ambient lighting at night

Patents
Night light with sleep timer US20050007889A1, United States

Abstract *A timer a light and an optional music source is located on or in a housing of a nightlight assembly. When this assembly is plugged into a source of electric power, the timer is set to a selected time for the light and optional music to remain on. After this selected time has elapsed, the light and music automatically turns off, allowing for sleep in appropriate darkness and silence.*



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II BACKGROUND OF THE INVENTION: Many young children prefer the comfort of a nightlight when they go to bed, but their caregivers would prefer them to sleep in darkness. A University of Pennsylvania study, Quinn, G. E., Shin, C. H., Maguire, M. G. and Stone, R. A. Myopia and ambient lighting at night. Nature, 399: 113-114, 1999 (May 13,1999), has shown that children who sleep with a light on may have a higher risk of developing nearsightedness as they get older.

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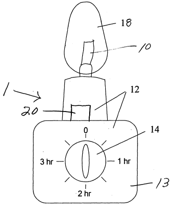

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Q: Does the night light with sleep timer decreases the risk of myopia?

Motivating Example 2

Kidney stone treatments

- Effectiveness of kidney stone treatments
- Relevant factors: Treatment (A or B), Recovery (Y or N)

Stones	Treatment A	Treatment B
Overall	$\frac{273}{350} = 0.780$	$\frac{289}{350} = 0.826$

[Charig et al. British Medical Journal, 1986]

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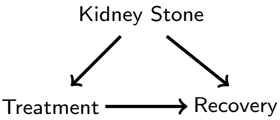
ground truth



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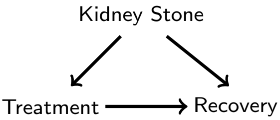

Q: What is the expected recovery if all get treatment B, independently on size?

Motivating Example 3

Smoking

Richard Doll and A. Bradford Hill, *Smoking and Carcinoma of the Lung*, Br Med J. 1950 Sep 30; 2(4682): 739–748

TABLE VII.—*Estimate of Total Amount of Tobacco Ever Consumed by Smokers; Lung-carcinoma Patients and Control Patients with Diseases Other Than Cancer*

Disease Group	No. Who have Smoked Altogether					Probability Test
	365 Cigs.–	50,000 Cigs.–	150,000 Cigs.–	250,000 Cigs.–	500,000 Cigs. +	
Males: Lung-carcinoma patients (647)	19 (2·9%)	145 (22·4%)	183 (28·3%)	225 (34·8%)	75 (11·6%)	$\chi^2 = 30 \cdot 60$; $n = 4$; $P < 0 \cdot 001$
Control patients with diseases other than cancer (622)..	36 (5·8%)	190 (30·5%)	182 (29·3%)	179 (28·9%)	35 (5·6%)	
Females: Lung-carcinoma patients (41)..	10 (24·4%)	19 (46·3%)	5 (12·2%)	7 (17·1%)	0 (0·0%)	$\chi^2 = 12 \cdot 97$; $n = 2$; $0 \cdot 001 < P < 0 \cdot 01$ (Women smoking 15 or more cigarettes a day grouped together)
Control patients with diseases other than cancer (28) ..	19 (67·9%)	5 (17·9%)	3 (10·7%)	1 (3·6%)	0 (0·0%)	

Discovering of causal relationships

Complex systems

- Causal relationships in complex systems:
  - Does smoking cause lung cancer?
  - Did drug X cure the patient?
  - Predict effect of the tax increase on economic growth
  - Predict effect of the decision of an autonomous vehicle

Discovering of causal relationships

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- Causal relationships in complex systems:
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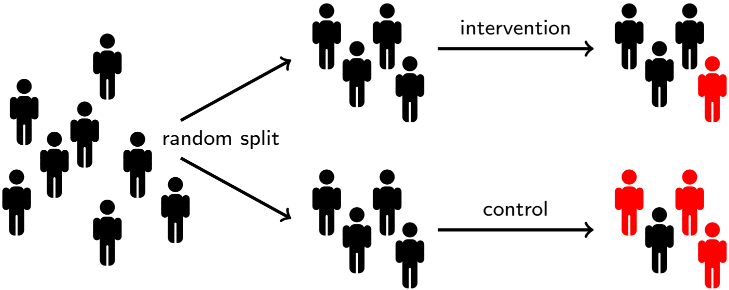
- Direct experimentation



Discovering of causal relationships

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  - ethically problematic
  - expensive
  - impossible

Discovering of causal relationships

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  - Predict effect of the decision of an autonomous vehicle
- Direct experimentation
  - ethically problematic
  - expensive
  - impossible
- On the other hand, there are often available large amounts of observed data that can provide relevant information about these issues

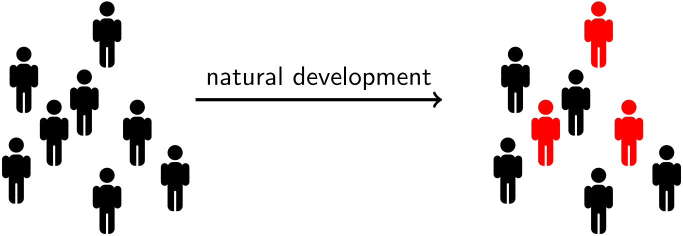
	16	23	26	30	33	41	45	53	55	58	66	75	77	78	81	86	87	89	90	...
L77V	6,1	4	7,5	5,4	3	5,5	8,7	1,7	1,4	8,7	14	8,3	141,4	100,9	22,3	14,8	25,3	42,4	6,5	...
M81L	3,3	2,6	10,8	8,2	7,5	7,4	2,6	7,8	15,4	12,8	19,5	4,3	144,5	54,8	383,9	13,8	33,9	17,6	17,9	...
M109L	7,1	6,7	11,9	10,6	5,1	9,1	5,2	8,7	17	8,7	7,4	10,1	7,9	25	8,4	0	31,5	117	0	...
M112L	12,5	5,2	5,3	4,1	14,2	18,7	17,9	31,1	4,8	3	2,4	4	18,8	13,9	17,5	12,6	39	16,1	1,1	...
L116V	8,8	5,1	3,4	7	4,8	8,6	6,9	10,4	3,4	2,5	5,6	2,8	11,7	13,8	15,6	3,8	4,8	15,7	1,9	...
M120L	7,2	3,5	5,3	0,6	4,3	0,4	1,1	8,5	0	0,9	5,8	1,3	10,7	8,1	10,9	4,9	1,5	5,1	2,7	...
M137L	3,5	2,2	3,2	3,4	4,2	9,7	6,9	9,6	1,5	3,3	3,9	4,2	42,2	13,8	36,4	2,4	3	11,8	8,4	...
I150L	6	4,1	2,8	7,2	5,7	7,3	5,1	5,7	4,8	5,1	19,8	5,2	48,1	11,6	53,3	3,1	8,4	10,7	5	...
L159V	4,1	4,9	1,9	4,7	0,8	8,4	10,3	7,6	3,8	3,6	7,7	2,5	19,7	12,8	24,7	1,9	13,7	12,1	5,3	...
L167V	4,9	4,2	5,1	5,3	7,2	4,2	11,2	8,9	4,7	2,1	11,7	0,6	4,5	4,8	4	3,3	1,4	9	8,9	...
L174V	7,8	3,3	6,1	6,6	4,7	9,2	10,3	3,3	4,8	14,4	12,5	1,1	93	39,4	134,8	26,7	20,4	15,8	18,5	...
V186A	2,1	3,8	1,3	1,5	0,9	4,1	5,7	1,2	3,3	1,1	10,1	2	15	7,6	13,9	3,6	3,8	6	5,3	...
V187A	7,6	3,7	3,2	6,9	3	7,4	11,4	4,6	5,3	5,9	7,5	4,3	15,8	9,8	5,5	11,9	5,3	6	6,6	...
L198V	5	4,2	1,8	10,7	6,2	5,2	6,8	5	1,2	2,6	3,5	4,2	9,9	5,1	6,6	1,8	7,7	5,6	9,4	...
M216L	1,9	1,4	1,6	3,5	5,8	10	6,2	7,6	5,3	3,5	4,4	1,4	7,7	4,7	5,3	0,8	4,6	5,9	4,4	...
L225V	4	8,1	1,8	3,4	3,6	4,2	7	2,8	3,5	1,6	8,9	1,5	5,5	4,2	4,1	4,5	6,8	4,1	4	...
...																				

[Aoto *et al.*, Scientific reports 6 (2016)]

Discovering of causal relationships

Complex systems

- Causal relationships in complex systems:
  - Does smoking cause lung cancer?
  - Did drug X cure the patient?
  - Predict effect of the tax increase on economic growth
  - Predict effect of the decision of an autonomous vehicle
- Direct experimentation
  - ethically problematic
  - expensive
  - impossible
- Discovering of causal effects from observed data



Structural Causal Model (SCM)

Structural Equations with Noise Distribution

- SCMs model observational distributions over $X_1, \ldots, X_n$

$$
\begin{aligned}
X_1 &:= F_1(N_1)\\
X_2 &:= F_2(X_1, N_2)\\
X_3 &:= F_3(X_1, N_3)\\
X_4 &:= F_4(X_2, X_3, N_4)
\end{aligned}
$$

N_i jointly independent
Graph is a DAG

$$
\begin{tikzcd}
 & X_1 \arrow[dl] \arrow[dr] & \\
X_2 \arrow[dr] & & X_3 \arrow[dl] \\
 & X_4 &
\end{tikzcd}
$$

Structural Causal Model (SCM)

Structural Equations with Noise Distribution

- SCMs can model interventions, as e.g.

$$
\begin{aligned}
X_1 &:= F_1(N_1)\\
X_2 &:= 1\\
X_3 &:= F_3(X_1, N_3)\\
X_4 &:= F_4(X_2, X_3, N_4)
\end{aligned}
$$

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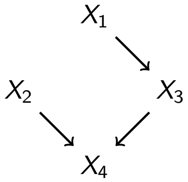

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Structural Equations with Noise Distribution

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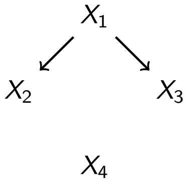
$$X_1 := F_1(N_1)$$
$$X_2 := F_2(X_1, N_2)$$
$$X_3 := F_3(X_1, N_3)$$
$$X_4 := 11$$

N_i jointly independent
Graph is a DAG



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Structural Equations with Noise Distribution

- SCMs model observational distributions over $X_1, \ldots, X_n$, denote them P

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$$
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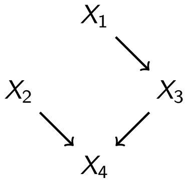

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Structural Equations with Noise Distribution

- Note that in general, $P(\ldots \mid X_4 = 11) \neq P_{do(X_4:=11)}(\ldots)$

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Structural Causal Model (SCM)

Identification of Causal Effects From Observed Data: Kidney Stones

Stones	Treatment A	Treatment B
Overall	$\frac{273}{350} = 0.780$	$\frac{289}{350} = 0.826$
Small $\left(\frac{357}{700} = 0.51\right)$	$\frac{81}{87} = 0.931$	$\frac{234}{270} = 0.867$
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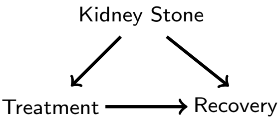
ground truth



Q: What is the expected recovery if all get treatment B, independently on stone size?

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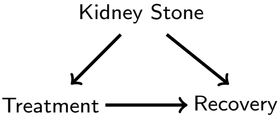

Q: What is the expected recovery if all get treatment B, independently on stone size?

- SCM models observational distributions P over S, T, R

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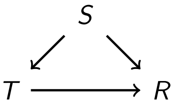
$$R := F_3(S, T, N_3)$$

N_i jointly independent
Graph is a DAG



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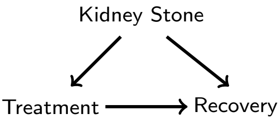

Q: What is the expected recovery if all get treatment B, independently on stone size?

- Task: compute interventional distribution $P_{do(T:=B)}(R = 1)$

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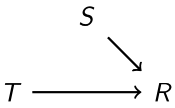
$$T := B$$
$$R := F_3(S, T, N_3)$$

N_i jointly independent
Graph is a DAG



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Identification of Causal Effects From Observed Data: Kidney Stones

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$$
\begin{tikzcd}
 & S \arrow[dr] & \\
T \arrow[rr] & & R
\end{tikzcd}
$$

$$
\begin{aligned}
&P_{do(T:=B)}(R = 1)\\
&\quad = \quad \textstyle\sum_s P_{do(T:=B)}(R = 1, S = s, T = B)\\
&\quad = \quad \textstyle\sum_s P_{do(T:=B)}(R = 1 \mid S = s, T = B) P_{do(T:=B)}(S = s, T = B)\\
&\quad = \quad \textstyle\sum_s P_{do(T:=B)}(R = 1 \mid S = s, T = B) P_{do(T:=B)}(S = s)\\
&\quad = \quad \textstyle\sum_s P(R = 1 \mid S = s, T = B) P(S = s)\\
&\quad = \quad 0.782\\
&\quad < \quad 0.832\\
&\quad = \quad \ldots\\
&P_{do(T:=A)}(R = 1)
\end{aligned}
$$

Structural Causal Model (SCM)

Identification of Causal Effects From Observed Data: Smoking

- Does smoking (S) cause lung cancer (C)?
- Assume that the variables are binary, taking on true (1) or false (0) values
- Moreover, assume the following (hypothetical) data set from a study on the relations among cancer and cigarette smoking

	Group Type	% of Population	% of Cancer cases
$S = 0$	Nonsmokers	50	9.75
$S = 1$	Smokers	50	85.25

- Task: compute the causal effects $P_{do(S:=1)}(C = 1)$ from data in this model

Structural Causal Model (SCM)

Identification of Causal Effects From Observed Data: Smoking

- Does smoking (S) cause lung cancer (C)?
- Assume that the variables are binary, taking on true (1) or false (0) values
- Moreover, assume the following (hypothetical) data set from a study on the relations among cancer and cigarette smoking

	Group Type	% of Population	% of Cancer cases
$S = 0$	Nonsmokers	50	9.75
$S = 1$	Smokers	50	85.25

- Task: compute the causal effects $P_{do(S:=1)}(C = 1)$ from data in this model

$$S \longrightarrow C$$

Smoking Cancer

$$P_{do(S:=s)}(C = c) = P(c \mid s)$$

- $P_{do(S:=0)}(C = 1) \; = \; 0.0975$
- $P_{do(S:=1)}(C = 1) \; = \; 0.8525$

Structural Causal Model (SCM)

Identification of Causal Effects From Observed Data: Smoking

- Does smoking (S) cause lung cancer (C)?
- Assume, to forestall antismoking legislation, the tobacco industry has argued that the observed correlation between smoking and lung cancer could be explained by some sort of carcinogenic genotype that involves inborn craving for nicotine
- Thus, consider in our model the relevant factor: Genotype (G)
- Unfortunately, the feature is not measurable (called also unobserved)
- Can the causal effects $P_{do(S:=1)}(C = 1)$ be estimated from data in this model?

	Group Type	% of Population	% of Cancer cases
$S = 0$	Nonsmokers	50	9.75
$S = 1$	Smokers	50	85.25

Genotype (unobserved)

$$
\begin{tikzcd}
 & G \arrow[dl] \arrow[dr] & \\
S \arrow[rr] & & C
\end{tikzcd}
$$

Smoking   Cancer

Structural Causal Model (SCM)

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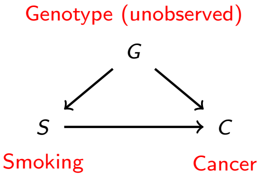


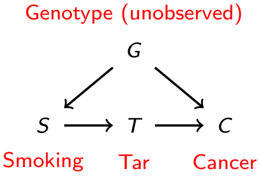
$P_{do(S:=s)}(C = c)$ non-computable :(

Structural Causal Model (SCM)

Identification of Causal Effects From Observed Data: Smoking

- Task: compute the causal effects $P_{do(S:=s)}(C = 1)$ from data:

		Group Type	$P(s,t)$ % of Population	$P(C=1 \mid s,t)$ % of Cancer cases
$S = 0$	$T = 0$	Nonsmokers, No tar	47.5	10
$S = 1$	$T = 0$	Smokers, No tar	2.5	90
$S = 0$	$T = 1$	Nonsmokers, Tar	2.5	5
$S = 1$	$T = 1$	Smokers, Tar	47.5	85



Structural Causal Model (SCM)

Identification of Causal Effects From Observed Data: Smoking

- Task: compute the causal effects $P(C = 1 \mid do(s))$ from data:

		Group Type	$P(s,t)$ % of Population	$P(C = 1 \mid s, t)$ % of Cancer cases
$S = 0$	$T = 0$	Nonsmokers, No tar	47.5	10
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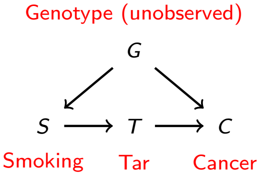


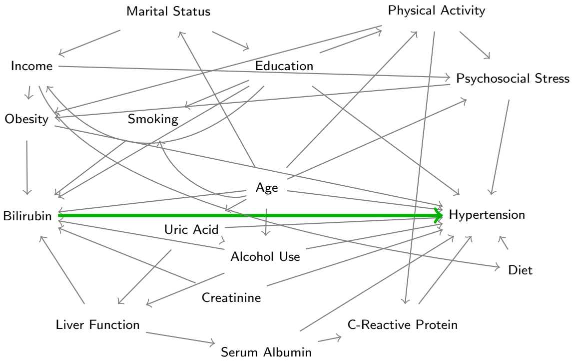
In our course we will show that the following formula can be used:

$$P_{do(s)}(c) = \sum_t P(t \mid s) \sum_{s'} P(c \mid s', t) P(s')$$

- $$\begin{aligned} P_{do(S:=0)}(C=1) &= .95(.10 \times .50 + .90 \times .50) + .05(.05 \times .50 + .85 \times .50) \\ &= .95 \times .50 + .05 \times .45 \;=\; .4975 \end{aligned}$$
- $$\begin{aligned} P_{do(S:=1)}(C=1) &= .05(.10 \times .50 + .90 \times .50) + .95(.05 \times .50 + .85 \times .50) \\ &= .05 \times .50 + .95 \times .45 \;=\; .4525 \end{aligned}$$

Causal inference

Serum bilirubin and the risk of hypertension analysis with *dagitty*



Conclusions: High serum bilirubin may decrease the risk of hypertension

[Wang et al., Int J Epidemiol 2015]

Causal inference

More motivations

- AI-controlled robots need to know the effects of their actions before they act.
- Autonomous vehicles can be trained faster and more effectively if they distinguish cause and effect instead of acting randomly.
- Exploratory scientific studies try to derive the causes of effects from observations.

Causal inference

Challenging problems

- Estimation of causal effects
- Identification problem
- Learning causal structures
- ...

Algorithmic Causality with Applications

- **Backgrounds**
  conditional independence, marginalization, covariance, regression
- **Causal structures, causal models**
  DAGs, d-separation, d-paths, colliders, CI and d-separation, Markov equivalence, latent / hidden variables
- **Causal effects: direct and total effects Intervention**
  modelling of controlled experiments, do-operator, do-calculus: calculus of intervention, Simpson's paradox
- **Estimation of causal effects**
  covariate adjustment, Pearl's back door criterion, complete back door criterion, front-door criterion classes of Markov equivalent structures (CPDAGS, PAGS, chain graphs, etc.)
- **Causal structural learning**
  learning from lists of CIs (Verma/Pearl, Meek's), learning from CI tests (IC algorithm, PC algorithm, FCI,...
- **Structural equations, linear structural equation models (SEMs)**
  inference in linear systems, parameter identification, estimation of causal effects in SEMs
- **Counterfactual inference**