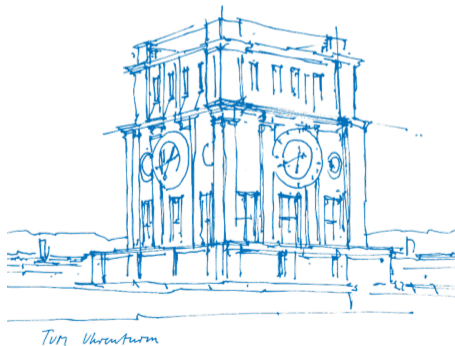


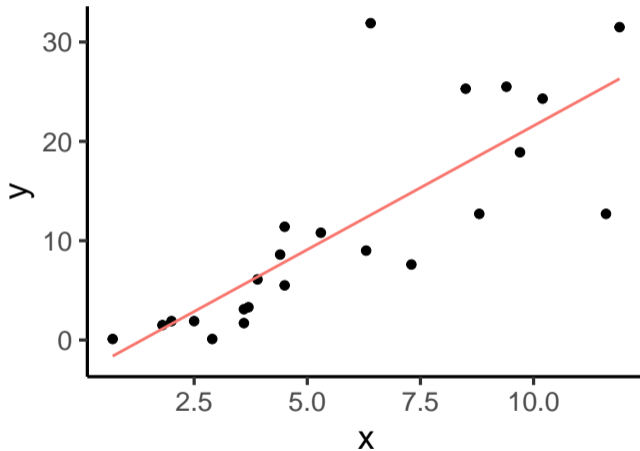
# Confidence in Causal Inference under Structure Uncertainty

**David Strieder (joint work with Mathias Drton)**

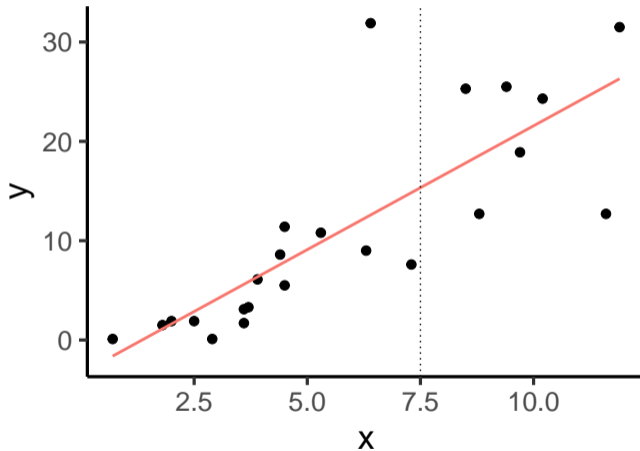
18. Doktorand:innentreffen der Stochastik, Heidelberg  
Aug 21 to Aug 23, 2023



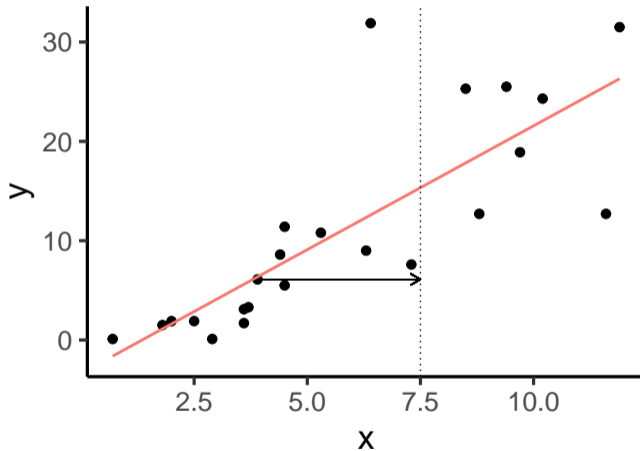
# Motivation



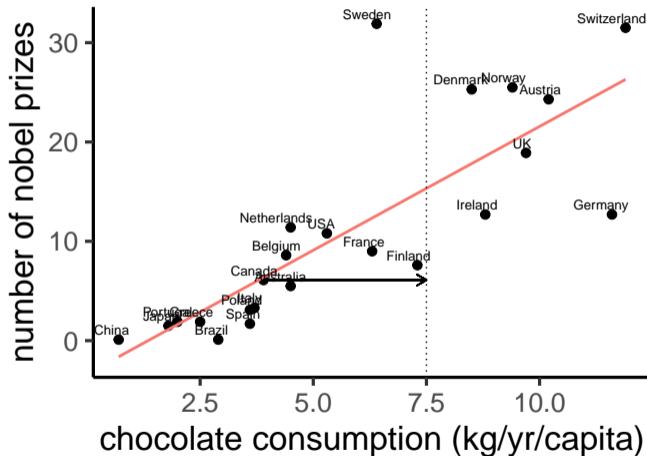
# Motivation



# Motivation



# Motivation



Data from Messerli F., *Chocolate Consumption, Cognitive Function, and Nobel Laureates*, N Engl J Med 2012.

# Structural Equation Models

## Observational Distribution

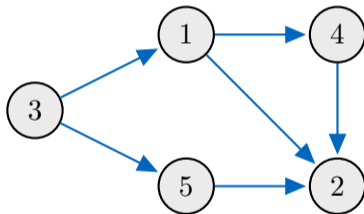
$$X_1 = f_1(X_3, \varepsilon_1)$$

$$X_2 = f_2(X_1, X_4, X_5, \varepsilon_2)$$

$$X_3 = f_3(\varepsilon_3)$$

$$X_4 = f_4(X_1, \varepsilon_4)$$

$$X_5 = f_5(X_3, \varepsilon_5)$$



where  $\varepsilon_j$  mutually independent

# Structural Equation Models

## Interventional Distribution $do(X_1 = x_1)$

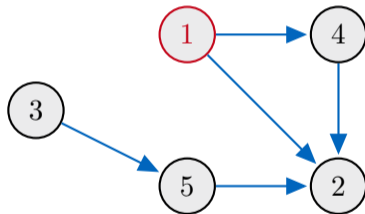
$$X_1 = x_1$$

$$X_2 = f_2(X_1, X_4, X_5, \varepsilon_2)$$

$$X_3 = f_3(\varepsilon_3)$$

$$X_4 = f_4(X_1, \varepsilon_4)$$

$$X_5 = f_5(X_3, \varepsilon_5)$$



where  $\varepsilon_j$  mutually independent

# Structural Equation Models

## Linear SEM with equal variances

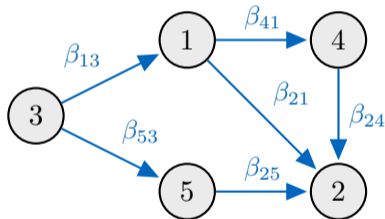
$$X_1 = \beta_{13}X_3 + \varepsilon_1$$

$$X_2 = \beta_{21}X_1 + \beta_{24}X_4 + \beta_{25}X_5 + \varepsilon_2$$

$$X_3 = \varepsilon_3$$

$$X_4 = \beta_{41}X_1 + \varepsilon_4$$

$$X_5 = \beta_{25}X_3 + \varepsilon_5$$

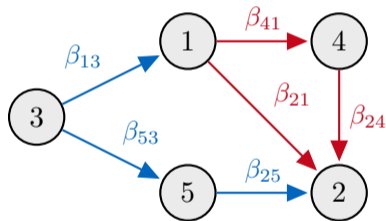


where  $\varepsilon_j \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2)$



- **Interest:** Total causal effect of an intervention on  $X_1$  onto  $X_2$ .

$$\begin{aligned} \mathcal{C}(1 \rightarrow 2) &:= \frac{d}{dx_1} \mathbb{E}[X_2 | \text{do}(X_1 = x_1)] \\ &= \Sigma_{12|p(1)} / \Sigma_{11|p(1)} \end{aligned}$$



$$\mathcal{C}(1 \rightarrow 2) = \beta_{21} + \beta_{41}\beta_{24}$$

- **Idea:** Use test inversion.



- **Goal:** Construct suitable **tests for all**  $\psi \in \mathbb{R}$ .

- **Idea:** Use test inversion.



- **Goal:** Construct suitable **tests for all**  $\psi \in \mathbb{R}$ .
- **Difficulty:** Hypothesis is **union of single hypotheses** over all structures.

$$H_0^{(\psi)} := \bigcup_{G \in \mathcal{G}(d)} H_0^{(\psi)}(G)$$

# Single Hypothesis $H_0^{(\psi)}(G)$

$$H_0^{(\psi)}(G) : \left\{ \Sigma \in \text{PD}(d) : \exists \sigma^2 > 0 \text{ with } \psi \sigma^2 = \Sigma_{1,2|p(1)} \text{ and } \sigma^2 = \Sigma_{k,k|p(k)} \forall k = 1, \dots, d \right\}$$

- **Idea:** Use theory of intersection union test.
- Reject union if we reject each single hypothesis.

- **Idea:** Relax alternative to entire cone of covariance matrices.
- Each single defines hypothesis smooth submanifold.
- Limit distribution is a chi-squared distribution.
- **Result:** Asymptotic  $(1 - \alpha)$ -confidence set for causal effect  $\mathcal{C}(1 \rightarrow 2)$  is

$$\{\psi \in \mathbb{R} : \min_{G \in \mathcal{G}(d) : 1 < G^2} \lambda_n^{(\psi)}(G) \leq \chi_{d,1-\alpha}^2\} \cup \{0 : \min_{G \in \mathcal{G}(d) : 2 < G^1} \lambda_n^{(0)}(G) \leq \chi_{d-1,1-\alpha}^2\}$$

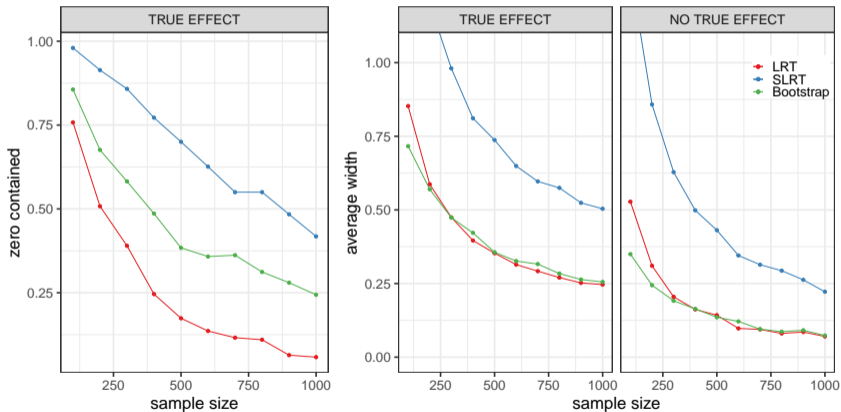
- **Idea:** Split data and use universal critical value.
- Calculate MLE of  $\Sigma$  under alternative based on data part 1.
- Calculate MLE of  $\Sigma$  under hypothesis and likelihoods based on data part 2.
- **Result:**  $(1 - \alpha)$ -confidence set for causal effect  $\mathcal{C}(1 \rightarrow 2)$  is

$$\{\psi \in \mathbb{R} : \min_{G \in \mathcal{G}(d) : 1 <_G 2} \tilde{\lambda}_n^{(\psi)}(G) \leq -2 \log(\alpha)\} \cup \{0 : \min_{G \in \mathcal{G}(d) : 2 <_G 1} \tilde{\lambda}_n^{(0)}(G) \leq -2 \log(\alpha)\}$$

<sup>1</sup>Wasserman L, Ramdas A, Balakrishnan S., *Universal inference*, Proc. Natl. Acad. Sci. USA 2020.

method	$n \setminus \beta$	TRUE EFFECT		
		0.05	0.1	0.5
LRT	100	1.00	0.99	1.00
	500	0.95	0.98	1.00
	1000	0.94	0.97	1.00
SLRT	100	1.00	1.00	1.00
	500	0.98	0.99	1.00
	1000	0.96	0.99	1.00
Bootstrap	100	0.64	0.71	0.97
	500	0.70	0.79	0.98
	1000	0.76	0.83	0.98

Empirical Coverage of 95%-CIs



Zero Contained and Mean Width of 95%-CIs (1000 Random 5-dim. DAGs)