

UNIVERSITY OF COPENHAGEN



Introduction to causal discovery

Anne Helby Petersen



Program

- 🗨 Welcome + introduction to DAGs
 - ⚙ Human generated DAG
 - 🗨 Causal discovery: PC algorithm and CPDAGs
 - ⚙ Work with PC in R
 - 🗨 TPC and TPDAGs
 - ⚙ Work with TPC in R
- LUNCH (11.00 - 11.45)



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- ⚙ Human generated DAG with latents
- 🗨 Introduction to PAGs, FCI algorithm and TFCI algorithm
- ⚙ Work with (T)FCI in R
- 🗨 Final remarks + further perspectives



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Manage your own breaks during exercise bits ⚙.



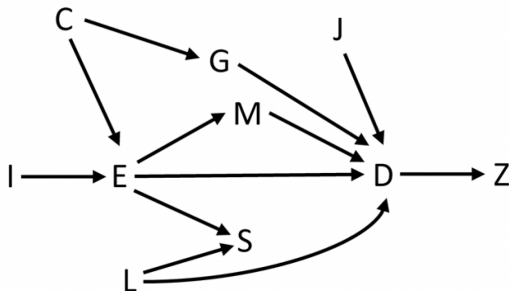
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Directed acyclic graphs (DAGs) 101



- **DAG interpretation:** $X \rightarrow Y$ means that X is a **direct cause** of Y relative to the other variables in the DAG:
 - Cause:** Manipulating X affects Y , but not vice versa
 - Direct cause:** There is no mediator variable M in the DAG such that if M is held constant, Y is no longer affected by changes in X .
- Assumes **no cycles**, i.e., no directed paths $X \rightarrow Y \rightarrow \dots \rightarrow X$.



Why DAGs?

- Tool used for visualizing and summarizing causal assumptions and their implications
- Mathematically neat: A lot of mathematical theory exists, e.g., d-separation, results for equivalence classes, ...
- Useful for guiding causal inference (effect identifiability, adjustment sets)
- But note: (Almost) always a crude simplification of the real world!



Exercise 1: Human generated DAG

Go to the course website and find Exercise: Human Generated DAG.

Follow the instructions to create a DAG individually – we will follow up with a plenary discussion.

