

ON CAUSAL AND ANTICAUSAL LEARNING

RICHARD SCHÖLKOPF, DOMINIK JANZING, JONAS PETERS, ELENI SGOURITSA, KUN ZHANG, JORIS M



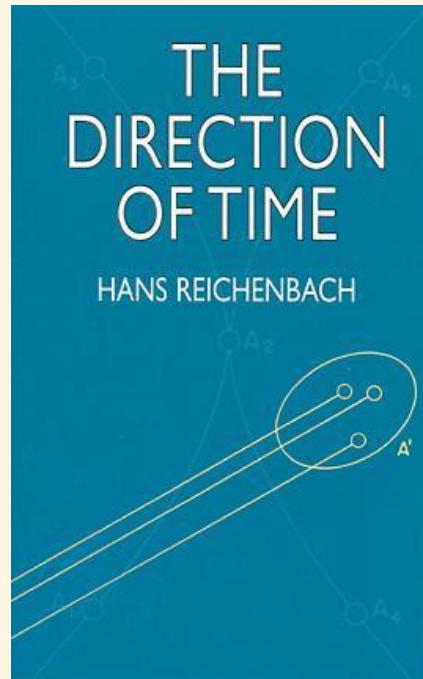
INTERNATIONAL CONFERENCE ON MACHINE LEARNING (ICML) 2012

TEST OF TIME HONORABLE MENTION: ICML 2022

THE DIRECTION OF TIME

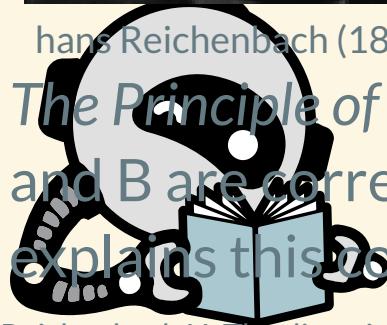


hans Reichenbach (1891 - 1953)

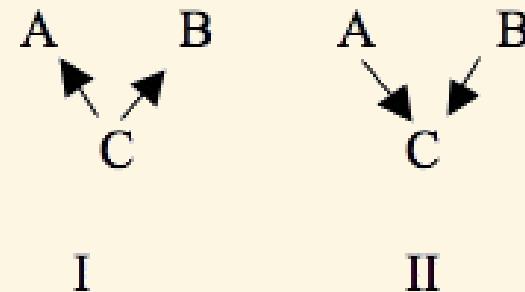


1956

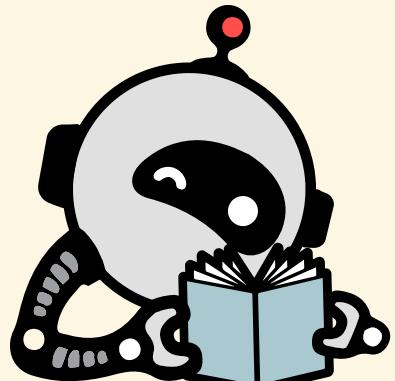
The *Principle of the Common Cause* states that if two events or variables A and B are correlated (i.e., associated), there must be a common cause that explains this correlation.



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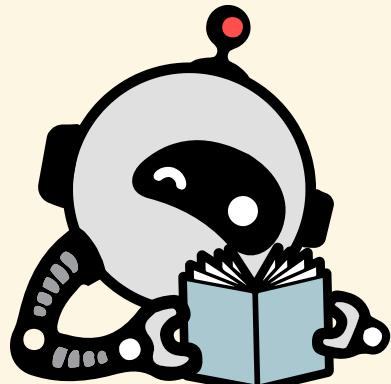
STATISTICAL VS CAUSAL POINT OF VIEW



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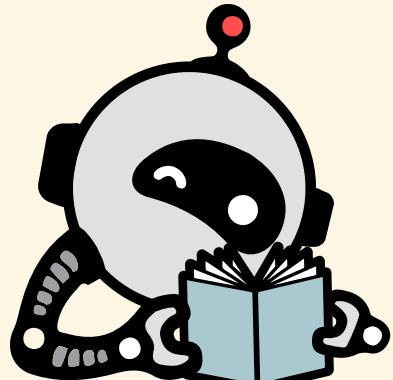
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Would fewer people smoke if cigarettes were more socially stigmatized?

BUT HOW TO GO FROM DATA TO CAUSAL GRAPH?



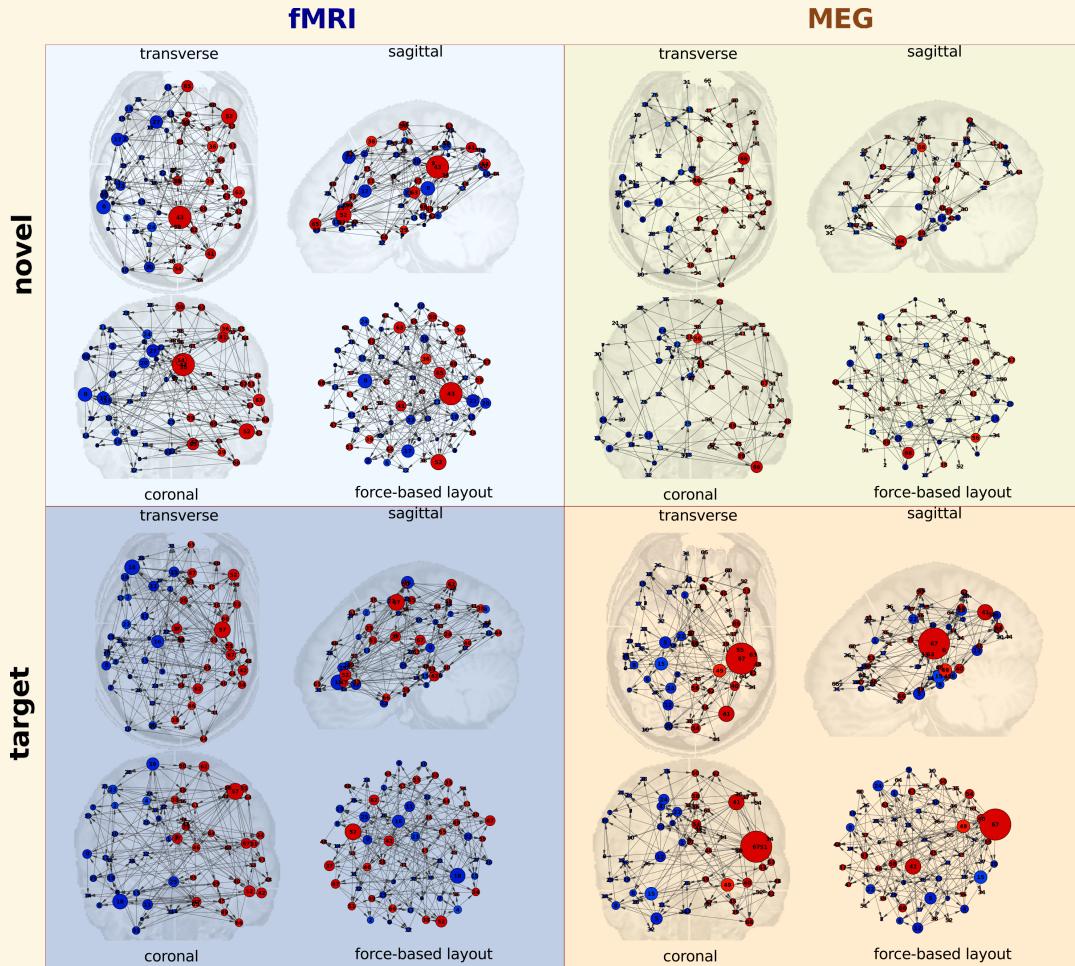
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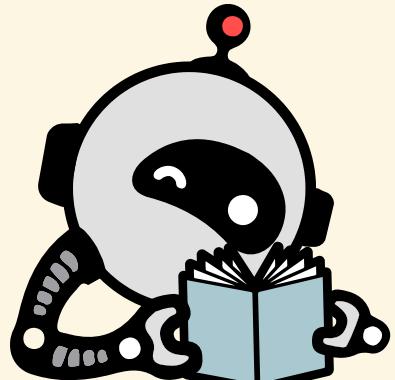


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NEED A FEW ASSUMPTIONS

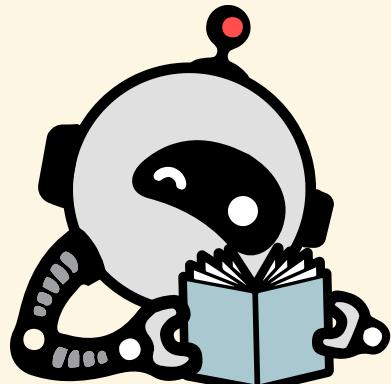


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- **THE (CAUSAL) MARKOV ASSUMPTION**

Given a causal graph, each variable is conditionally independent of its non-descendants, given its direct causes (parents).

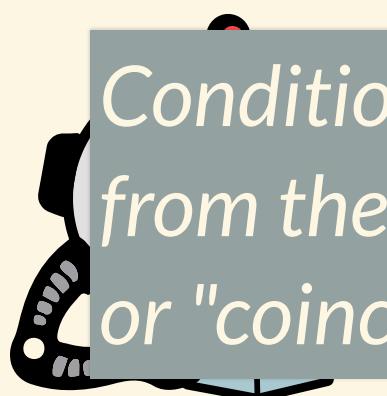


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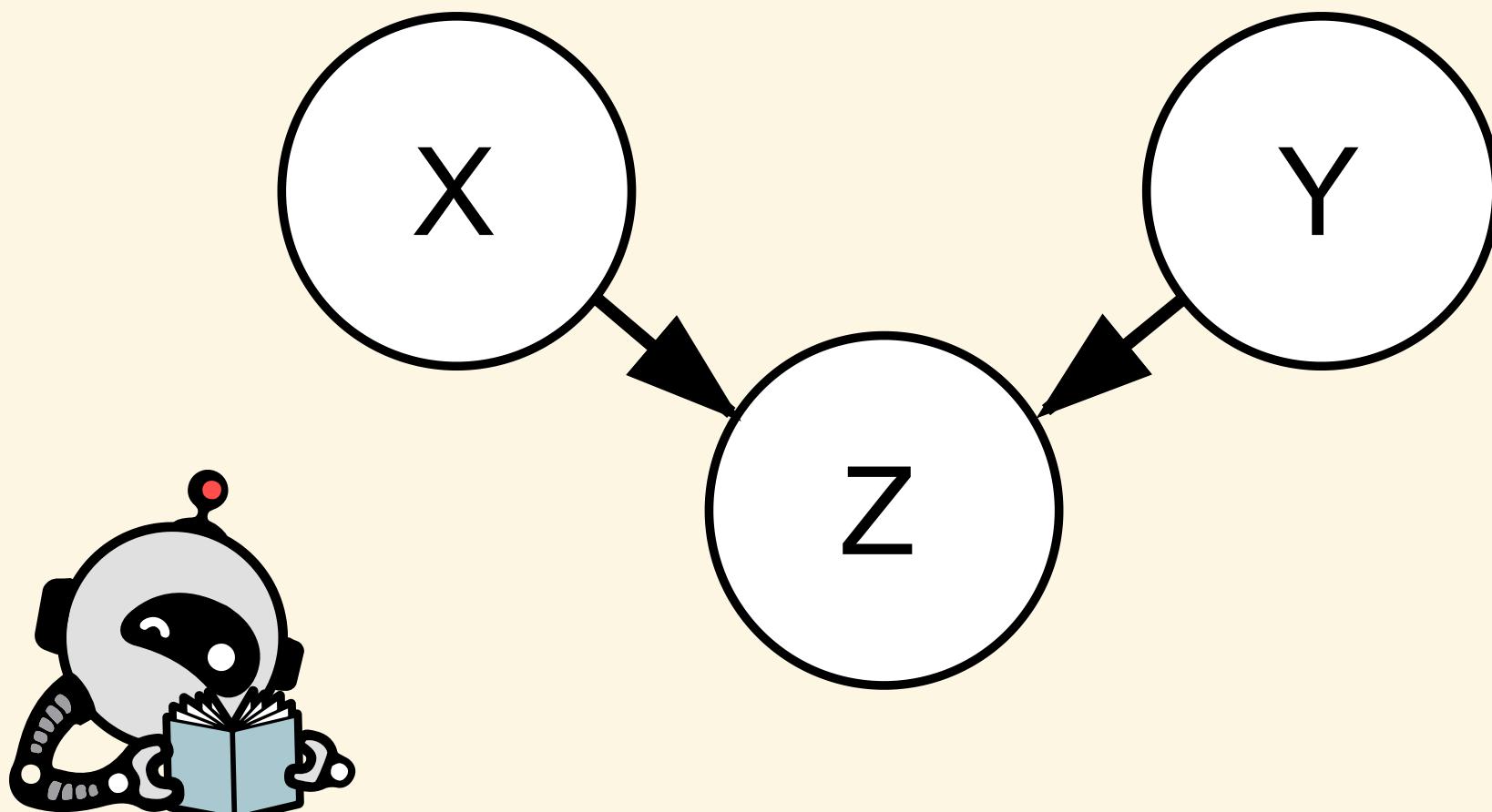
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- **THE FAITHFULNESS ASSUMPTION**

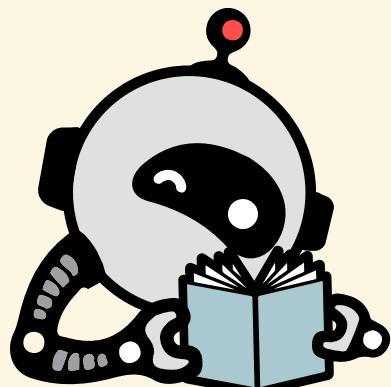
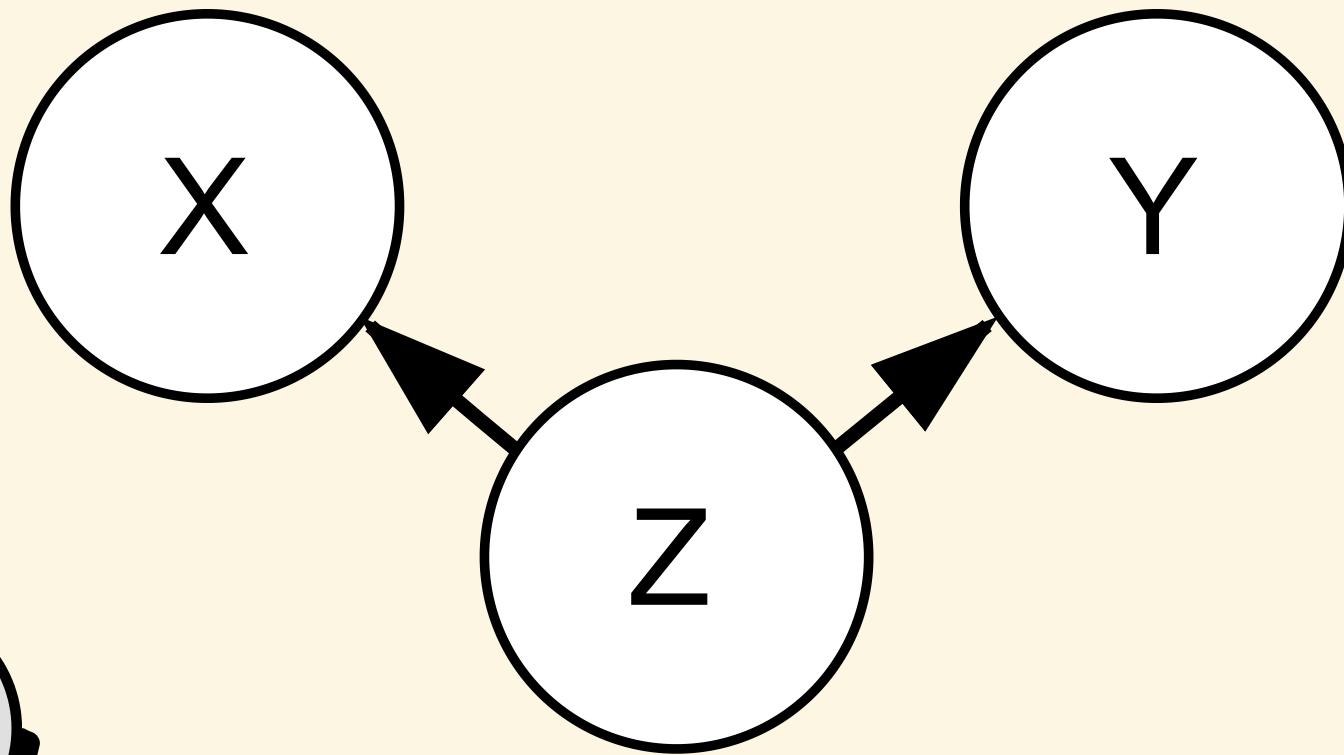


Conditional independencies in the data result only from the underlying causal structure (no "fine-tuning" or "coincidental cancellations").

THE COLLIDER

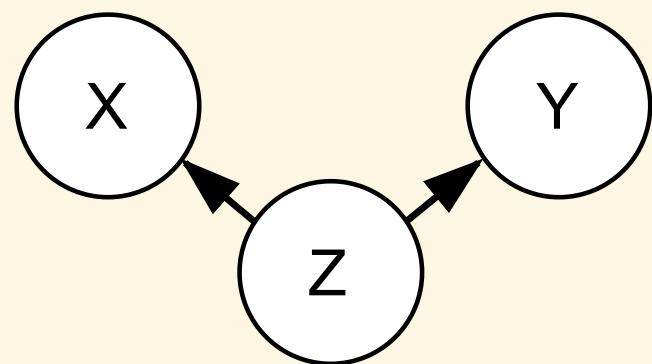
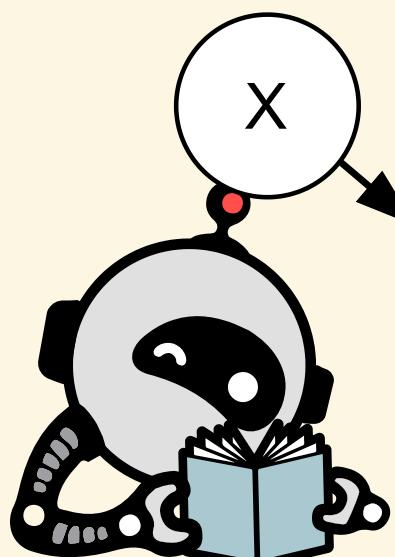


THE COMMON CAUSE

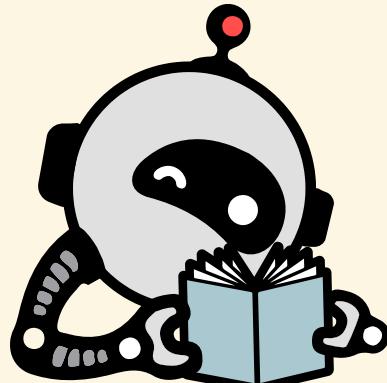
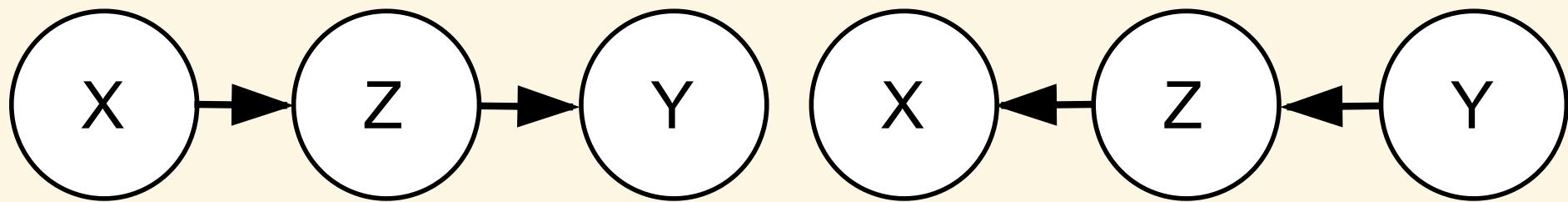


CAN BE RESOLVED BASED ON INDEPENDENCE TESTS

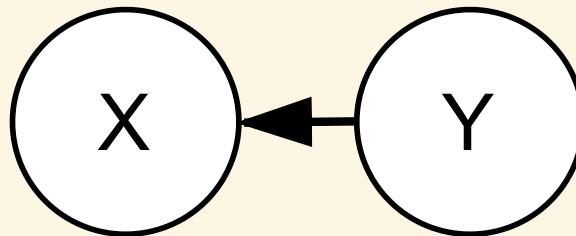
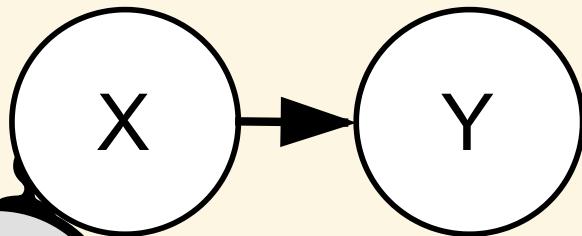
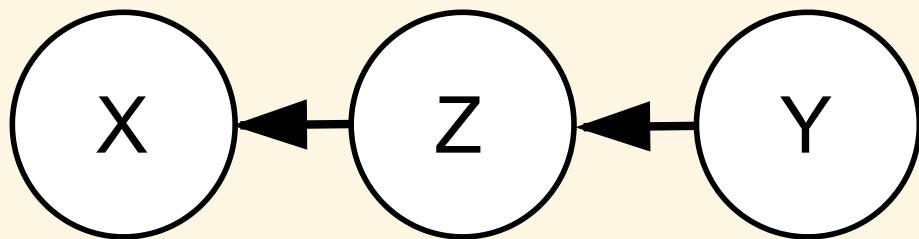
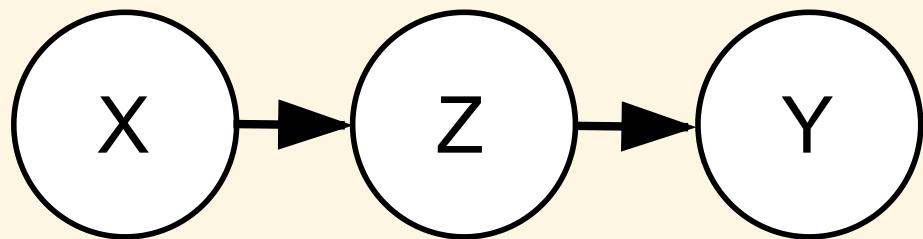
$$\begin{aligned} X &\parallel Y \\ X &\parallel Y|Z \end{aligned}$$



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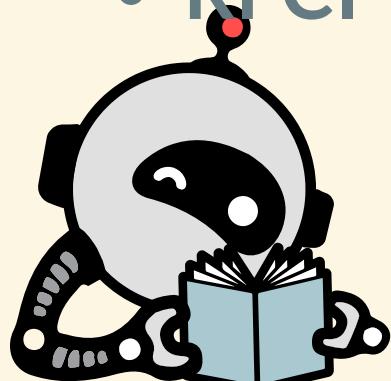


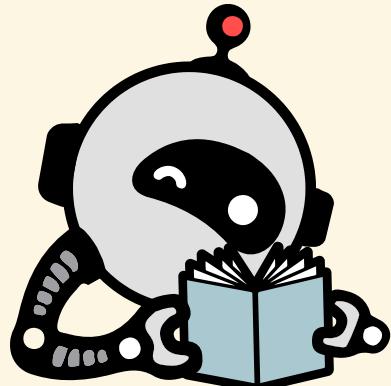
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TEST-BASED CAUSAL DISCOVERY ALGORITHMS

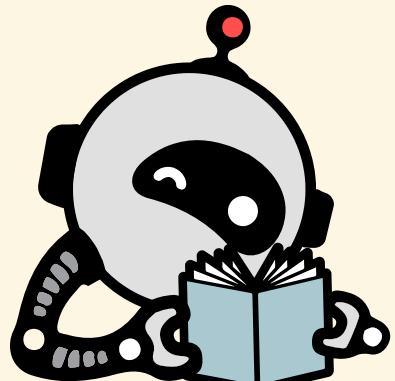
- PC algorithm (Peter Spirtes and Clark Glymour)
- FCI - Fast Causal Inference
- TPDA - Three-Phase Dependency Analysis
- RFCI - Really Fast Causal Inference





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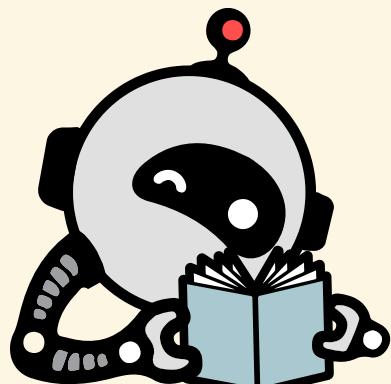
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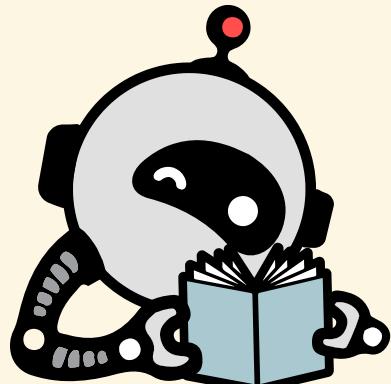
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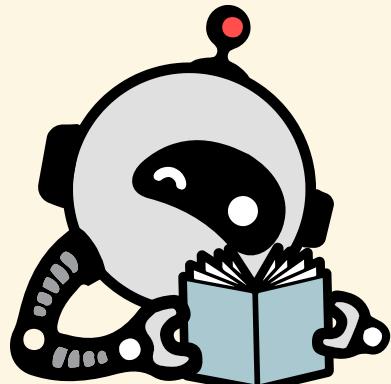
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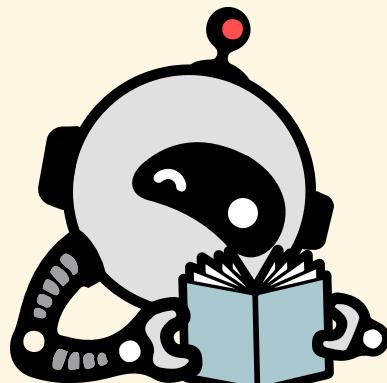
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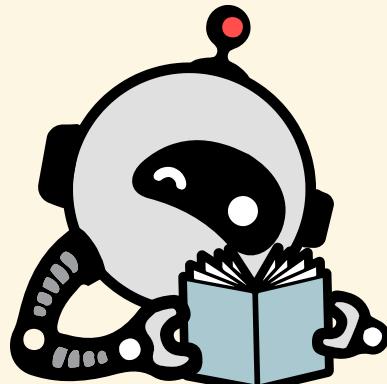
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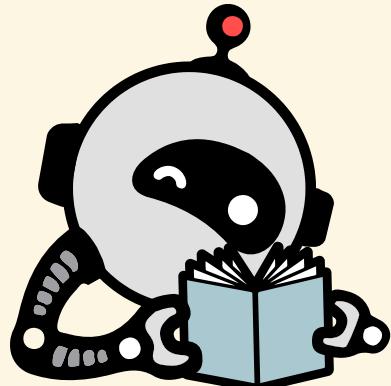
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- Additive noise models and algorithms such as PC, FCI, and LiNGAM for causal discovery.
- The underlying causal structure is important for successful machine learning applications.



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