

Back-door and front-door criteria

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Identifiability in Markovian models

The back-door criterion

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Preliminaries

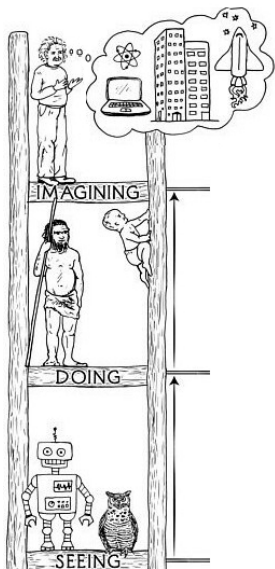
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Conclusion

Causal reasoning (1/2)

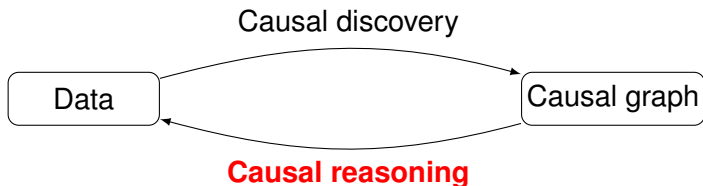


Counterfactuals

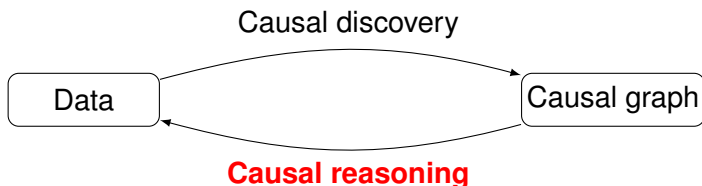
Interventions

Associations

Causal reasoning (2/2)

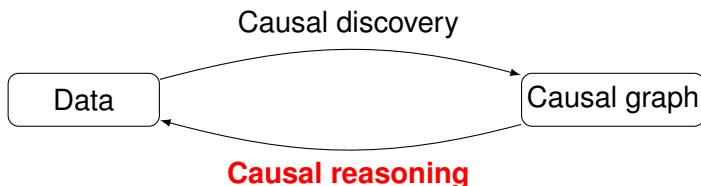


Causal reasoning (2/2)



Goal: Estimate the causal effect or effect of an intervention.

Causal reasoning (2/2)



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It is not always possible.

Recap about causal graphical models (1/4)

Active and blocked paths A path is said to be *blocked* by a set of vertices $\mathcal{Z} \subseteq \mathcal{V}$ if:

- ▶ it contains a chain $A \rightarrow B \rightarrow C$ or a fork $A \leftarrow B \rightarrow C$ and $B \in \mathcal{Z}$, or
- ▶ it contains a collider $A \rightarrow B \leftarrow C$ such that no descendant of B is in \mathcal{Z} .

d-separation Given disjoint sets $\mathcal{X}, \mathcal{Y}, \mathcal{Z} \subseteq \mathcal{V}$, we say that \mathcal{X} and \mathcal{Y} are *d-separated* by \mathcal{Z} if every path between a node in \mathcal{X} and a node in \mathcal{Y} is blocked by \mathcal{Z} and we write $\mathcal{X} \perp\!\!\!\perp_G \mathcal{Y} \mid \mathcal{Z}$.

Recap about causal graphical models (1/4)

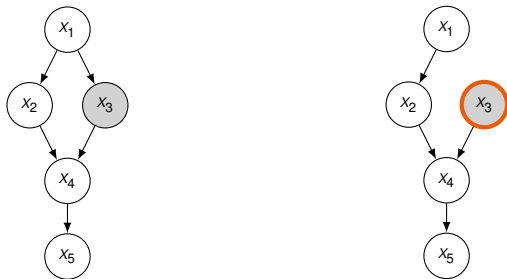
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Recap about causal graphical models (2/4)

Conditioning vs intervention



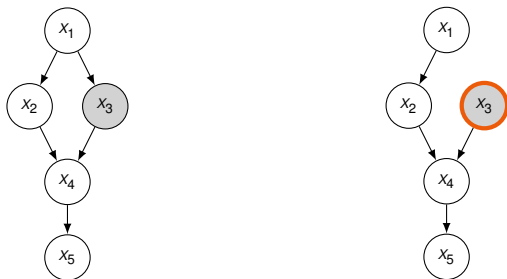
$$\Pr(X_1, X_2, X_4, X_5 | X_3 = \text{off}) \text{ vs } \Pr_{X_3=\text{off}}(X_1, X_2, X_4, X_5)$$

$$\Pr(X_1, X_2, X_4, X_5 | X_3 = \text{off}) \text{ vs } \Pr(X_1, X_2, X_4, X_5 | \text{do}(X_3 = \text{off}))$$

The $\text{do}()$ operator allows to represent interventions in equations.

Recap about causal graphical models (2/4)

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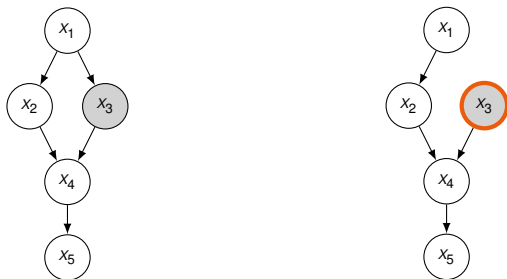
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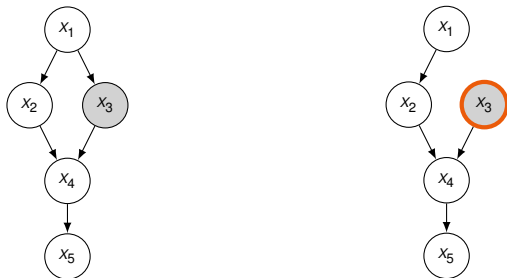
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The $\text{do}()$ operator allows to represent interventions in equations.

Recap about causal graphical models (3/4)

Bayesian network factorization:

$$\Pr(V_1 = v_1, \dots, V_d = v_d) = \prod_i \Pr(V_i = v_i \mid \text{Parents}(V_i))$$

Truncated factorization: if we intervene on a subset $S \subset \mathbf{V}$, then

$$\Pr(V_1 = v_1, \dots, V_d = v_d \mid \text{do}(S = s)) = \prod_{i \notin S} \Pr(V_i = v_i \mid \text{Parents}(V_i))$$

if v_1, \dots, v_d are values consistent with the intervention, else,

$$\Pr(V_1 = v_1, \dots, V_d = v_d \mid \text{do}(S = s)) = 0$$

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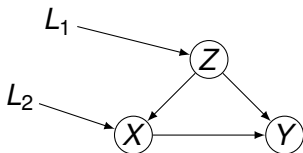
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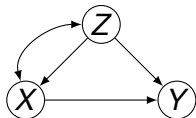
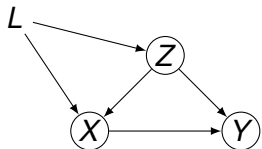
$$\Pr(v_1, \dots, v_d \mid \text{do}(s)) = 0$$

Recap about causal graphical models (4/4)

Markovian models: A model M is Markovian if the graph induced by M contains no bidirected edges (the graph is a DAG).



Semi-Markovian models: A model M is semi-Markovian if the graph induced by M contains bidirected edges (the graph is a ADMG).



Causal effect identifiability

The causal effect $\Pr(y \mid do(x))$ from a causal graph \mathcal{G} is identifiable if $\Pr(y \mid do(x))$ can be computed uniquely from observational data.

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Identifiability in Markovian models

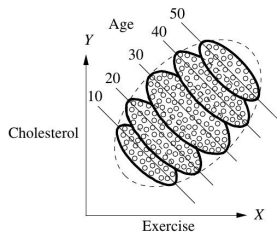
The back-door criterion

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Conclusion

Simpson paradox 1

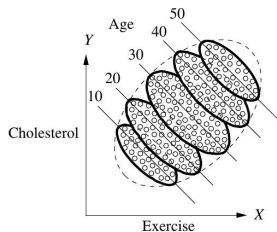
In a study, we measure weekly exercise and cholesterol levels for various age groups.



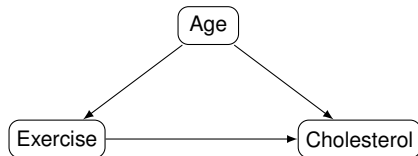
What is the effect of exercise on cholesterol $\Pr(c \mid do(e))$?

Simpson paradox 1

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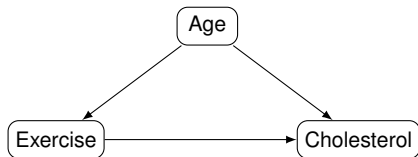


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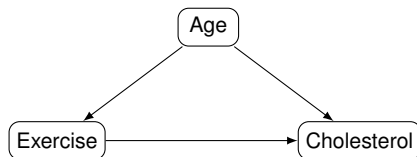
Simpson paradox 1: a simple solution

$\Pr(c \mid do(e))?$



Simpson paradox 1: a simple solution

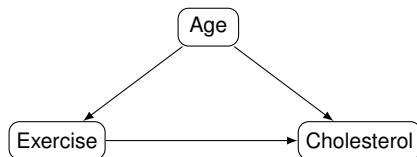
$\Pr(c \mid do(e))?$



$$\Pr(a, e, c) = \Pr(a) \Pr(e \mid a) \Pr(c \mid a, e) \quad (\text{BN fact.})$$

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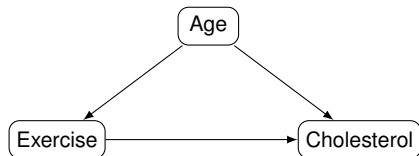
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(Truncated fact.)

Simpson paradox 1: a simple solution

$\Pr(c \mid do(e))?$



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(BN fact.)

$$\Pr(a, c \mid do(e)) = \Pr(a) \Pr(c \mid a, e)$$

(Truncated fact.)

$$\Pr(c \mid do(e)) = \sum_a \Pr(a) \Pr(c \mid a, e)$$

(marginalizing)

Identifiability in Markovian models

Theorem (identifiability in Markovian models): Given a causal graph \mathcal{G} of any Markovian model in which a subset \mathcal{V} of variables are measured, the causal effect $\Pr(y \mid do(x))$ is identifiable whenever $\{X \cup Y \cup Parents(X)\} \subseteq \mathcal{V}$, and is given by the direct causes adjustment:

$$\Pr(y \mid do(x)) = \sum_{z \in Parents(x)} \Pr(y \mid x, z) \Pr(z)$$

(proof on board)

Limitations of the direct causes adjustment

- ▶ In Markovian models, is it possible to find a smaller adjustment set?

- ▶ What about semi-Markovian models?

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Back-door criterion

The **back-door criterion**: Consider a causal graph \mathcal{G} and a causal effect $P(y \mid do(x))$. A set of variables \mathcal{Z} satisfies the back-door criterion iff:

- ▶ no node in \mathcal{Z} is a descendant of X ;
- ▶ \mathcal{Z} blocks every path between X and Y that contains an arrow into X .

Back-door adjustment

Theorem (back-door adjustment): If Z satisfies the back-door criterion relative to (X, Y) and if $\Pr(x, z) > 0$, then the causal effect of X on Y is identifiable and is given by

$$\Pr(y \mid do(x)) = \sum_z \Pr(y \mid x, z) \Pr(z).$$

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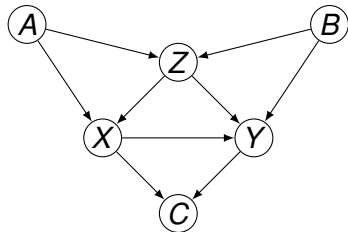
(proof on board)

Property (back-door in Markovian models): The causal effect in Markovian models is always identifiable using the back-door criterion and is given by the back-door adjustment.

proof as an exercise

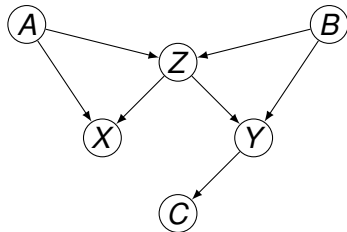
Back-door criterion: using d-separation

Causal graph \mathcal{G}



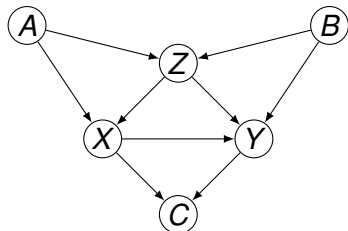
$\Pr(y \mid do(x))$

Mutilated graph \mathcal{G}_m



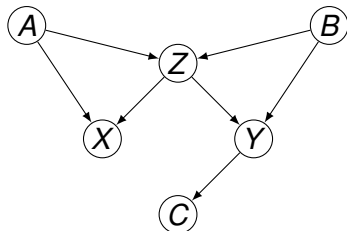
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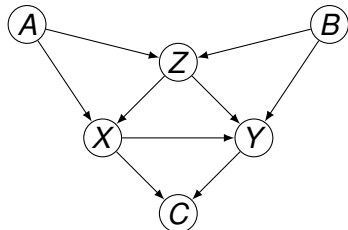
Mutilated graph \mathcal{G}_m



$X \perp\!\!\!\perp Y \mid Z$ in \mathcal{G}_m ?

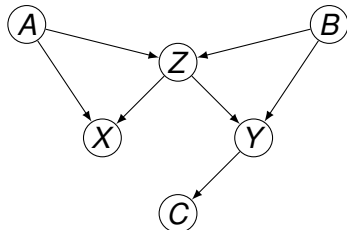
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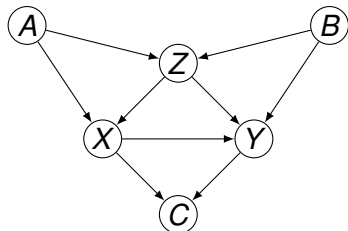
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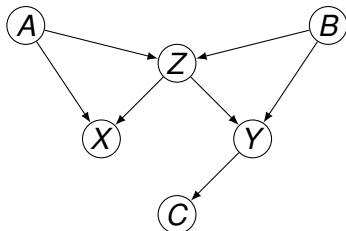
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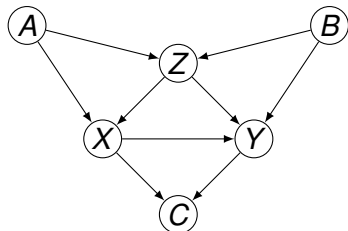


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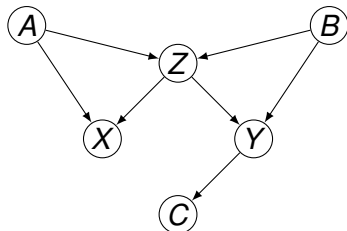
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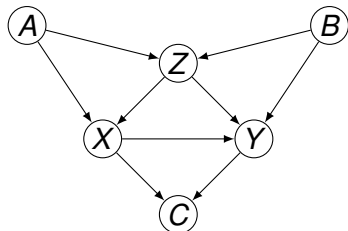


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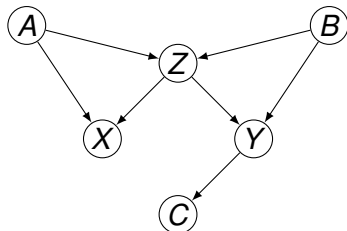
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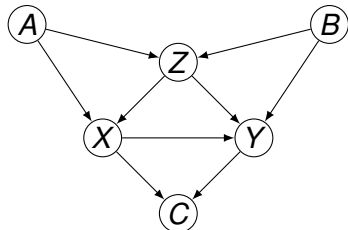
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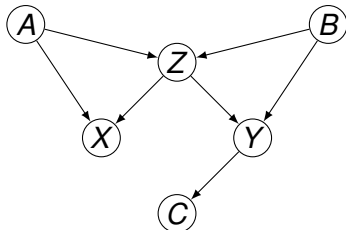
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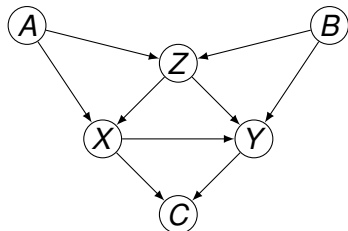
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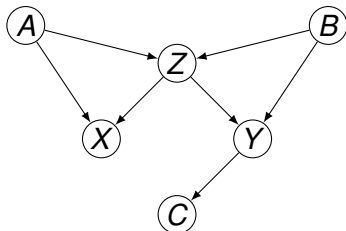
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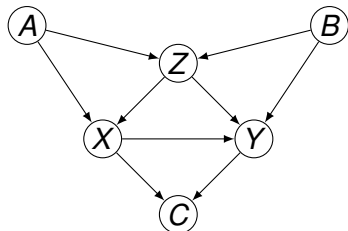
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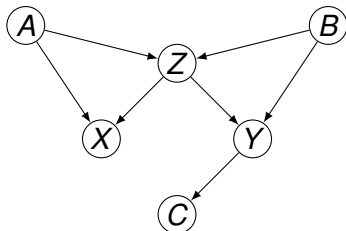
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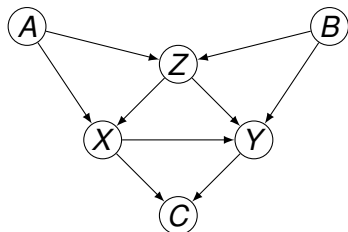
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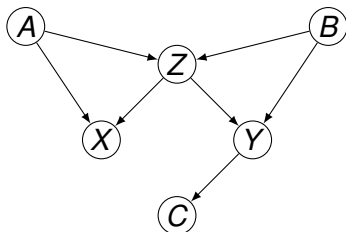
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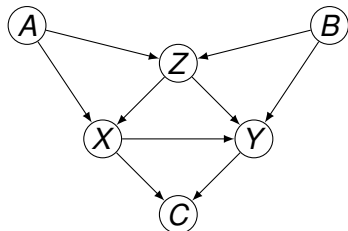
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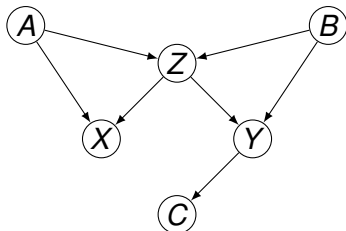
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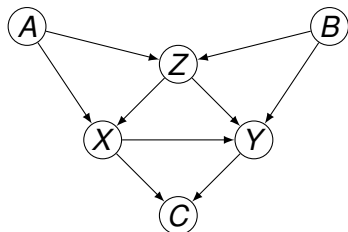
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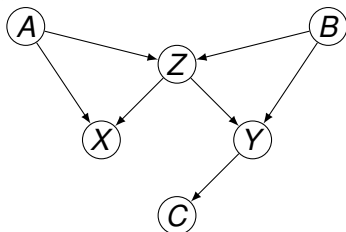
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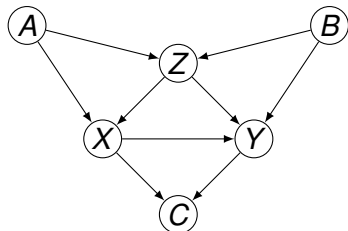
$X \perp\!\!\!\perp_G Y \mid C$ in \mathcal{G}_m ? **No**

$X \perp\!\!\!\perp_G Y \mid A, B$ in \mathcal{G}_m ? **No**

$X \perp\!\!\!\perp_G Y \mid Z, A$ in \mathcal{G}_m ?

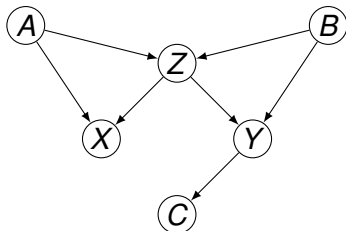
Back-door criterion: using d-separation

Causal graph \mathcal{G}



$\Pr(y \mid do(x))$

Mutilated graph \mathcal{G}_m



$X \perp\!\!\!\perp_G Y \mid Z$ in \mathcal{G}_m ? **No**

$X \perp\!\!\!\perp_G Y \mid A$ in \mathcal{G}_m ? **No**

$X \perp\!\!\!\perp_G Y \mid B$ in \mathcal{G}_m ? **No**

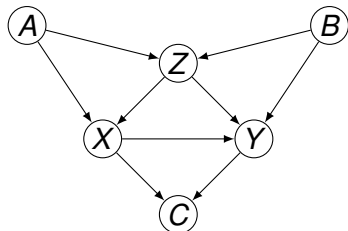
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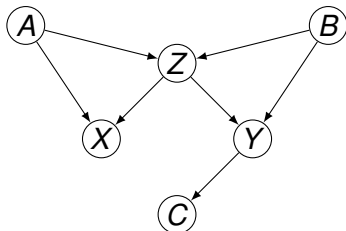
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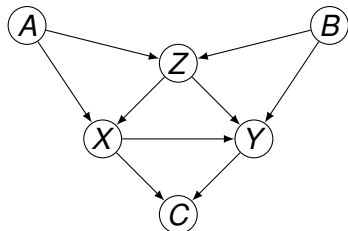
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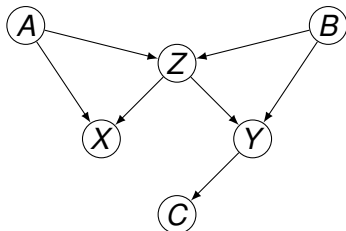
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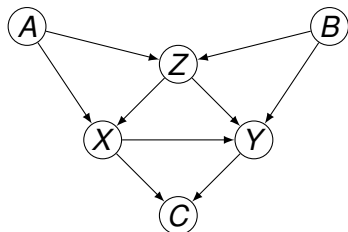
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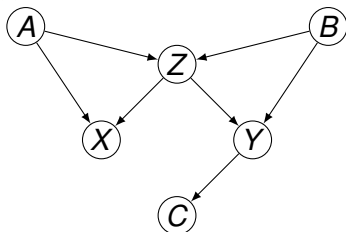
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$\Pr(y | do(x))$

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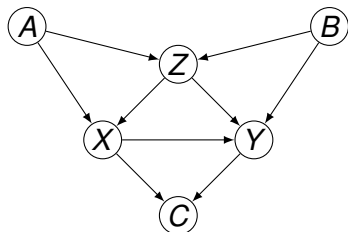
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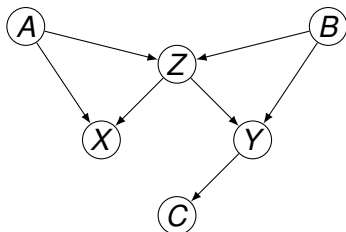
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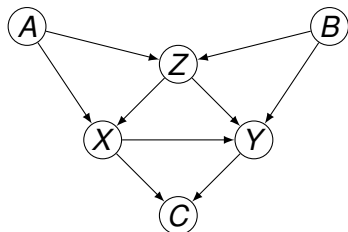
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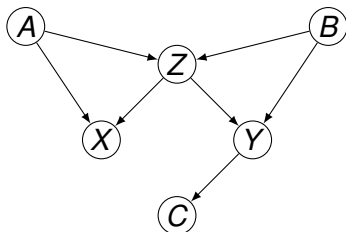
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$X \perp\!\!\!\perp_G Y \mid Z, A, B$ in \mathcal{G}_m ? **Yes**

Back-door sets:

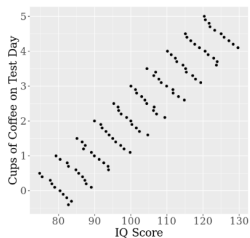
$\{Z, A\}$

$\{Z, B\}$

$\{Z, A, B\}$

Simpson paradox 2 and the back-door in action

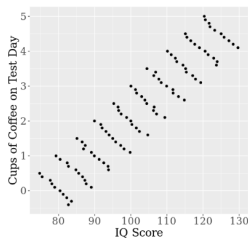
In a study, we measure the number of coffee intake, IQ score for a sample of a population with various education level.



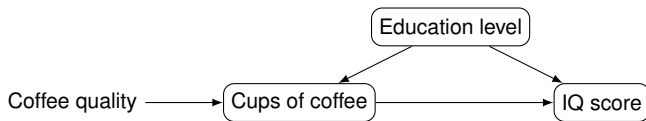
What is the effect of the nb cups of coffee on IQ score $\Pr(i | do(c))$?

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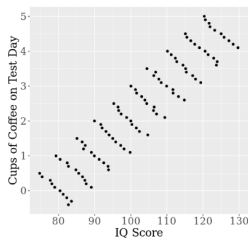


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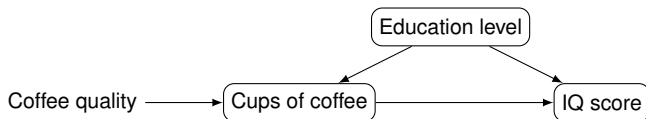


Simpson paradox 2 and the back-door in action

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$$\Pr(i | do(c)) = \sum \Pr(i | c, e) \Pr(e)$$

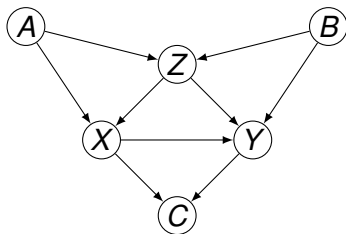
Incompleteness of the back-door criterion

- ▶ If there exists a set that satisfy the back-door criterion for $\Pr(y \mid do(x))$, then $\Pr(y \mid do(x))$ is identifiable;

- ▶ If there exists a no set that satisfy the back-door criterion for $\Pr(y \mid do(x))$, then $\Pr(y \mid do(x))$ is not necessarily not identifiable.

Exercise 1

- ▶ Consider the following causal graph. List all *minimal* sets of variables that satisfy the back-door criterion for $\Pr(y \mid \text{do}(x))$;
- ▶ Repeat for $\Pr(y \mid \text{do}(x, b))$.



Minimal set: any set of variables such that if you remove any of the variables from the set, it will no longer meet the criterion.

Table of content

Preliminaries

Identifiability in Markovian models

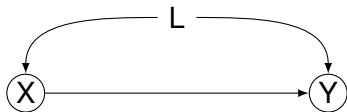
The back-door criterion

The front-door criterion

Conclusion

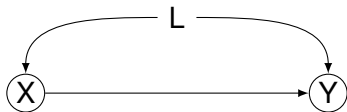
Going beyond the back-door (1/2)

Consider the following semi-Markovian model. Is $\Pr(y \mid do(x))$ identifiable using the backdoor criterion?



Going beyond the back-door (1/2)

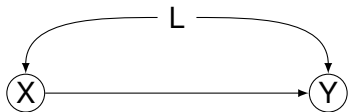
Consider the following semi-Markovian model. Is $\Pr(y \mid do(x))$ identifiable using the backdoor criterion?



No and it cannot be identified by any other criterion.

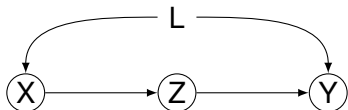
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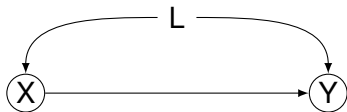
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What about the following semi-Markovian model?



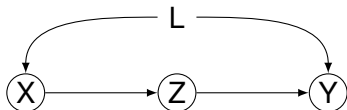
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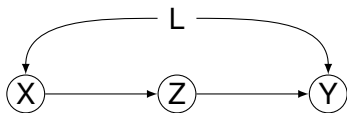
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What about the following semi-Markovian model?

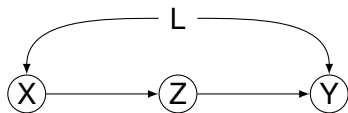


No but it can be identified by some other criterion.

Going beyond the back-door (2/2)



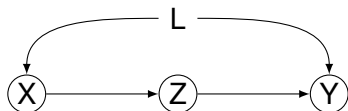
Going beyond the back-door (2/2)



▶ $\Pr(z \mid do(x)) = \Pr(z \mid x)$

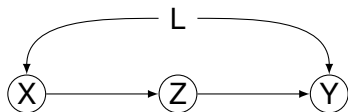
(No back-door)

Going beyond the back-door (2/2)



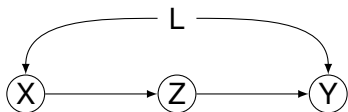
- ▶ $\Pr(z \mid do(x)) = \Pr(z \mid x)$ (No back-door)
- ▶ $\Pr(y \mid do(z)) = \sum_x \Pr(y \mid z, x) \Pr(x)$ (X blocks the back-door)

Going beyond the back-door (2/2)



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$$\Pr(y \mid do(x)) = \sum_z \Pr(z \mid x) \sum_{x'} \Pr(y \mid z, x') \Pr(x')$$

Front-door criterion

Front-door criterion: Consider a causal graph \mathcal{G} and a causal effect $\Pr(y \mid do(x))$. A set of variables \mathcal{Z} satisfies the front-door criterion iff:

- ▶ \mathcal{Z} intercepts all directed paths from X to Y ;
- ▶ There is no back-door path from X to \mathcal{Z} ;
- ▶ All back-door paths from \mathcal{Z} to Y are blocked by X .

Front-door adjustment

Theorem (front-door adjustment): if Z satisfies the front-door criterion relative to (X, Y) and if $\Pr(x, z) > 0$, then the causal effect of X on Y is identifiable and is given by

$$\Pr(y \mid \mathit{do}(X = x)) = \sum_z \Pr(z \mid x) \sum_{x'} \Pr(y \mid x', z) \Pr(x').$$

(proof on slide 25)

Simpson paradox 3 and the front-door in action

In a study, we measure the tar and the % of cancer among smokers and non smokers in a randomly selected sample of the population.

Smokers	Tar	% of cancer
No	No	10
No	Yes	5
Yes	No	90
Yes	Yes	85



What is the effect of smoking on cancer $\Pr(c | do(s))$?

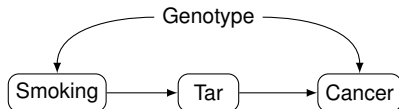
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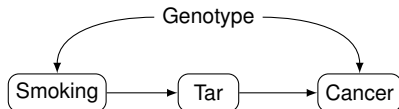
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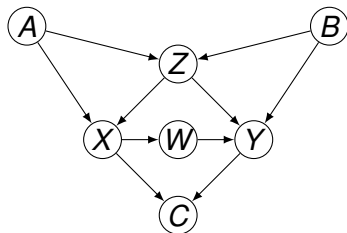
Incompleteness of the front-door criterion

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- ▶ If there exists a no set that satisfy the fack-door criterion for $\Pr(y \mid do(x))$, then $\Pr(y \mid do(x))$ is not necesarly not identifiable.

The combination of the back-door and front door criterions are also incomplete.

Exercise 2

Consider that in the following causal graph, only X and Y , and one additional variable can be measured. Which variable would allow the identification of $\Pr(y \mid do(x))$?

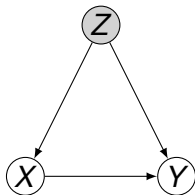


Exercise 3

Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?

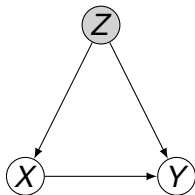
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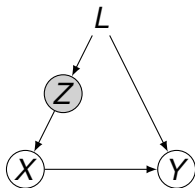
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- ▶ Z blocks a back-door path
 $\implies Z$ is a good control.

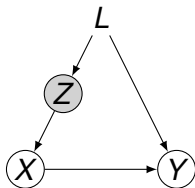
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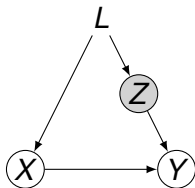
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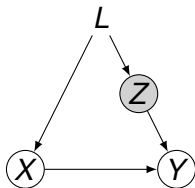
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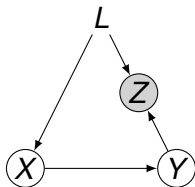
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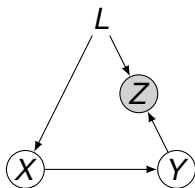
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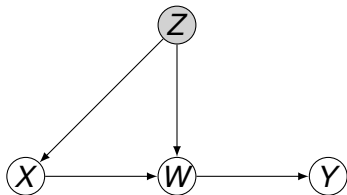
Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?



- ▶ Z activates a back-door path
 $\implies Z$ is a bad control.

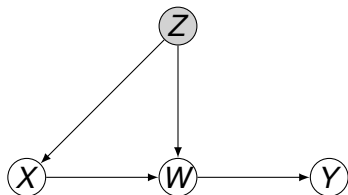
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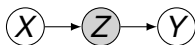
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Exercise 3

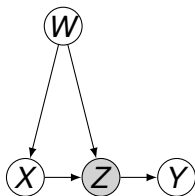
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- ▶ Z d-separates X from Y
 $\implies Z$ is a bad control.

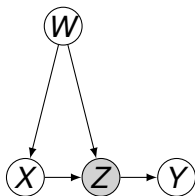
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Exercise 3

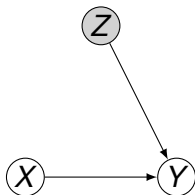
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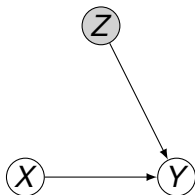
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Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?



Exercise 3

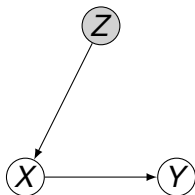
Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?



- ▶ Z does not open any backdoor paths from X to Y
 $\implies Z$ is a neutral control;
- ▶ Controlling for Z can reduce the variation of Y , and helps improve the precision of the estimate in finite samples.

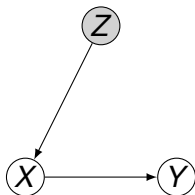
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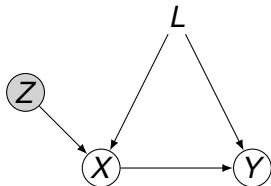
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- ▶ Z does not open any backdoor paths from X to Y
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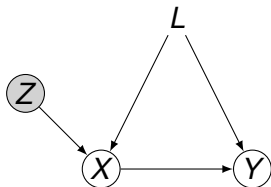
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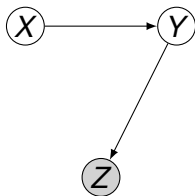
Is Z a good, bad or neutral control for $\Pr(y | do(x))$?



- ▶ Z does not block existing backdoor path from X to Y
 $\implies Z$ is a bad control;
- ▶ In linear models, controlling for Z amplify any existing bias.

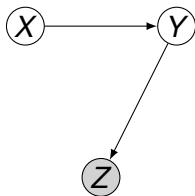
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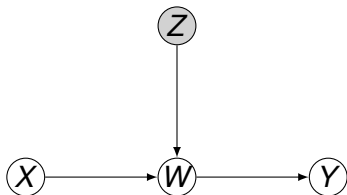
Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?



- ▶ Selection bias
 $\implies Z$ is a bad control.

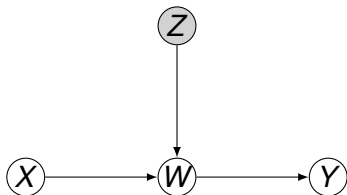
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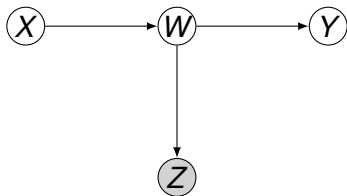
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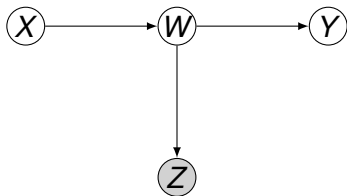
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Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?



Exercise 3

Is Z a good, bad or neutral control for $\Pr(y \mid do(x))$?



- ▶ Z is a descendant of X
 $\implies Z$ is a bad control.

Table of content

Preliminaries

Identifiability in Markovian models

The back-door criterion

The front-door criterion

Conclusion

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- ▶ Semi Markovian models are not always identifiable;
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- ▶ The front-door adjustment can identify some causal effects in semi Markovian models;
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References (1/2)

Direct inspirations

1. *Causality*, J. Pearl. Cambridge University Press, 2nd edition, 2009
2. *Causal inference in statistics: A Primer*, J. Pearl, M. Glymour, N. P. Jewell. Wiley, 2019
3. *The book of why*, J. Pearl, D. Mackenzie. Basic Books, 2018

Additional readings

1. *A Crash Course in Good and Bad Control*, C. Cinelli, A. Forney, J. Pearl. Sociological Methods and Research, 2022
2. *Simpson's paradox in psychological science: A practical guide*, R. Kievit, W. Frankenhuis, L. Waldorp, D. Borsboom. Frontiers in Psychology, 2013