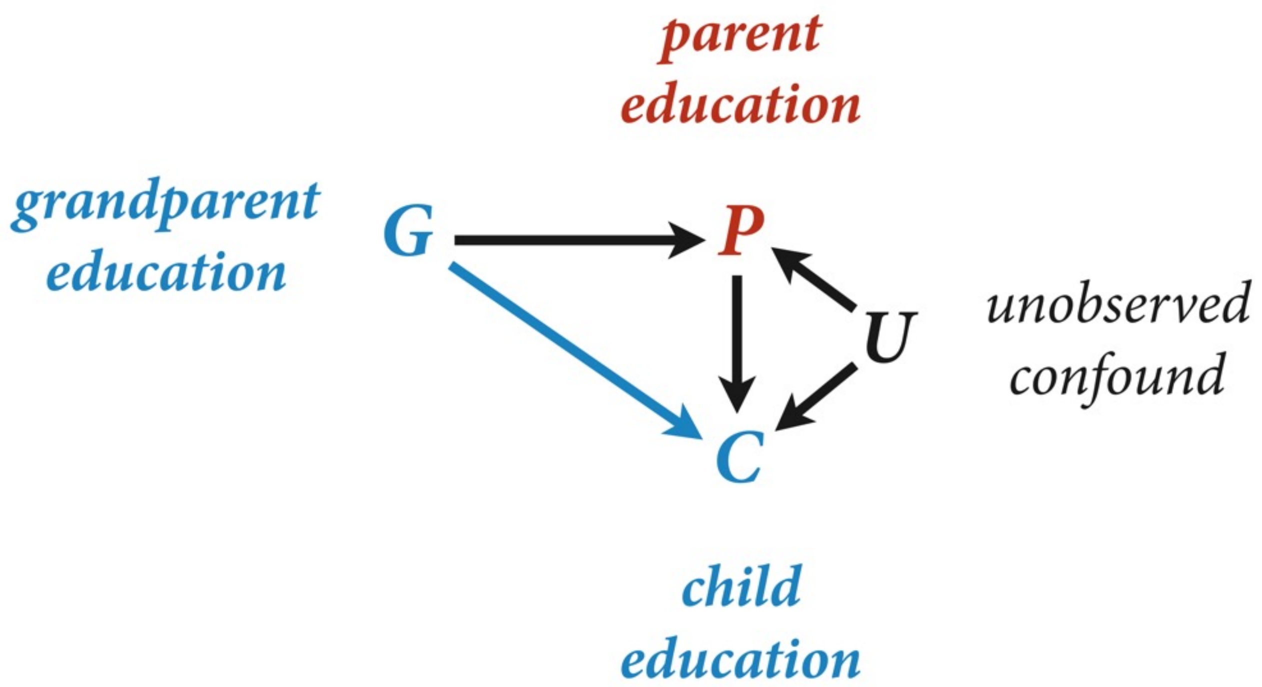
Methods 4 - 6

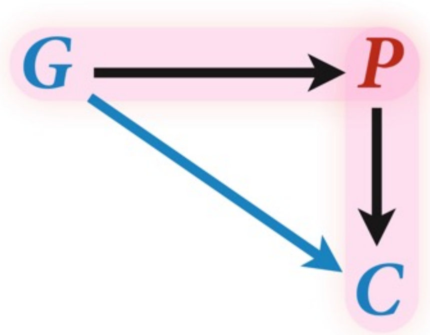
Chris Mathys

BSc Programme in Cognitive Science

Spring 2022

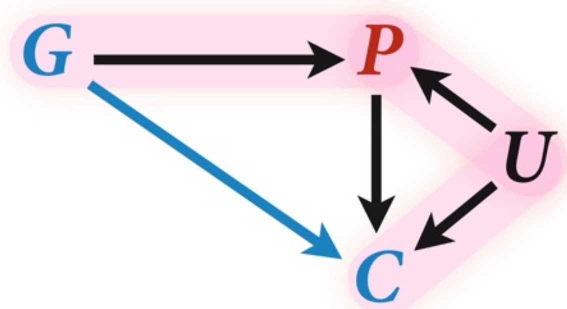


Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022



P is a mediator

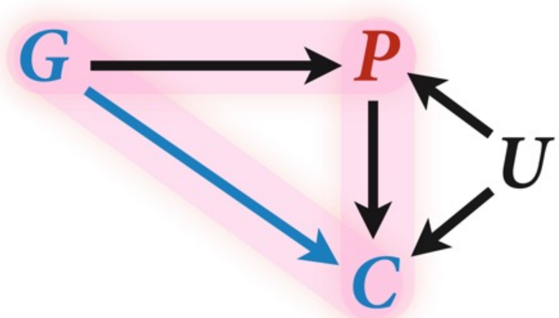
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



P is a collider

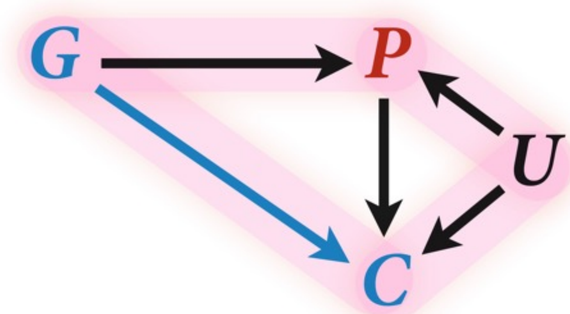
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Can estimate **total** effect of G on C



$$C_i \sim \text{Normal}(\mu_i, \sigma)$$
$$\mu_i = \alpha + \beta_G G_i$$

Cannot estimate **direct** effect



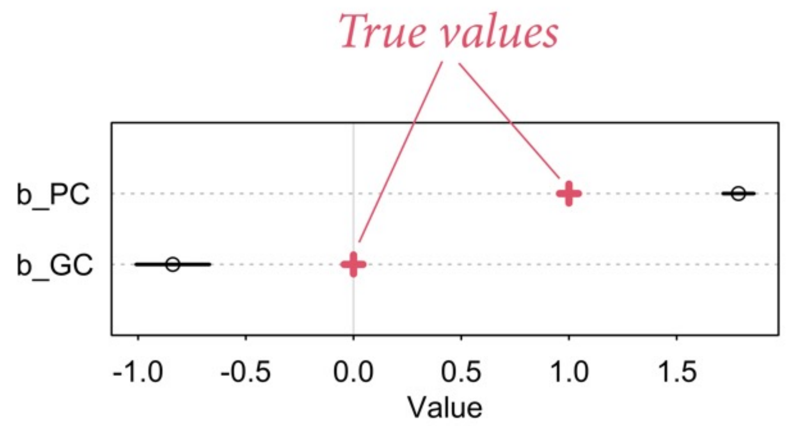
$$C_i \sim \text{Normal}(\mu_i, \sigma)$$
$$\mu_i = \alpha + \beta_G G_i + \beta_P P_i$$

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

```
N <- 200  # num grandparent-parent-child triads
b_GP <- 1 # direct effect of G on P
b_GC <- 0 # direct effect of G on C
b_PC <- 1 # direct effect of P on C
b_U <- 2 #direct effect of U on P and C

set.seed(1)
U <- 2*rbern( N , 0.5 ) - 1
G <- rnorm( N )
P <- rnorm( N , b_GP*G + b_U*U )
C <- rnorm( N , b_PC*P + b_GC*G + b_U*U )
d <- data.frame( C=C , P=P , G=G , U=U )

m6.11 <- quap(
    alist(
        C ~ dnorm( mu , sigma ),
        mu <- a + b_PC*P + b_GC*G,
        a ~ dnorm( 0 , 1 ),
        c(b_PC,b_GC) ~ dnorm( 0 , 1 ),
        sigma ~ dexp( 1 )
    ), data=d )
```



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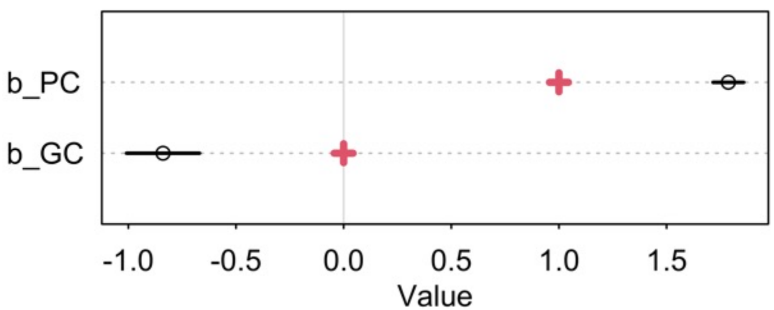
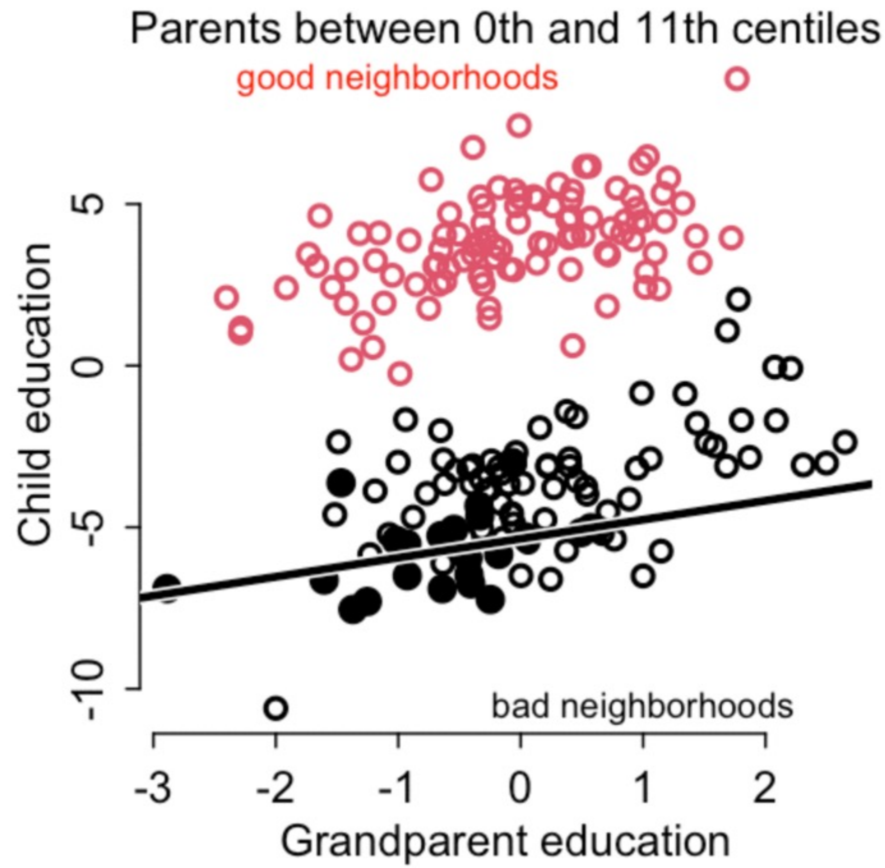
Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022

Stratify by parent centile (collider)

Two ways for parents to attain their education: from *G* or from *U*





Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

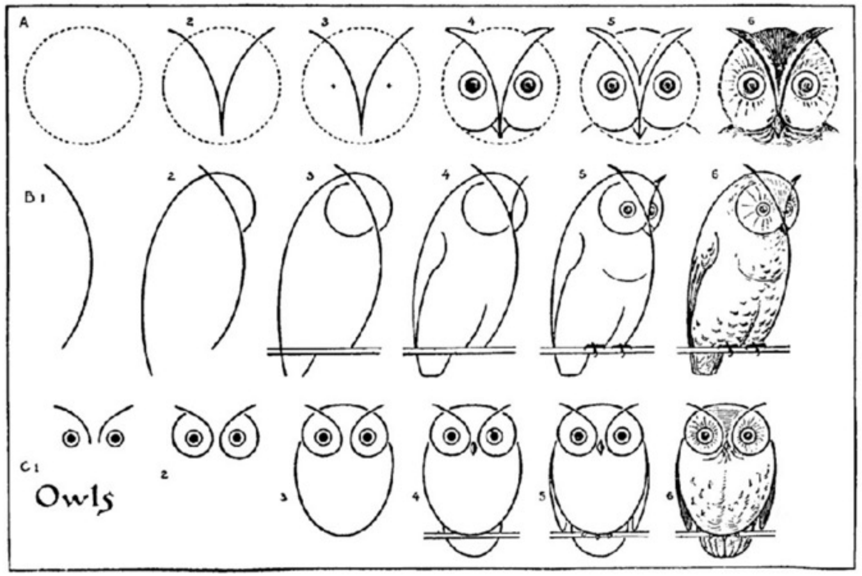
From Theory to Estimate

Our job is to

(1) Clearly state assumptions

(2) Deduce implications

(3) Test implications



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Avoid Being Clever At All Costs

Being clever is neither reliable nor transparent

Now what?

Given a causal model, can use logic to derive implications

Others can use same logic to verify/challenge your work

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

The Fork

$$X \leftarrow Z \rightarrow Y$$

X and *Y* associated
unless stratify by *Z*

The Pipe

$$X \rightarrow Z \rightarrow Y$$

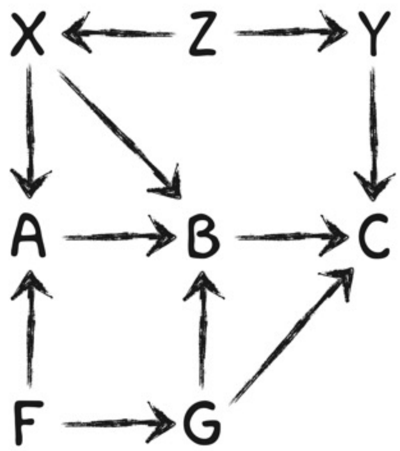
X and *Y* associated
unless stratify by *Z*

The Collider

$$X \rightarrow Z \leftarrow Y$$

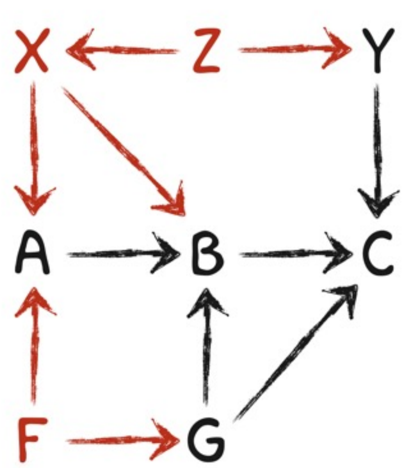
X and *Y* not associated
unless stratify by *Z*

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

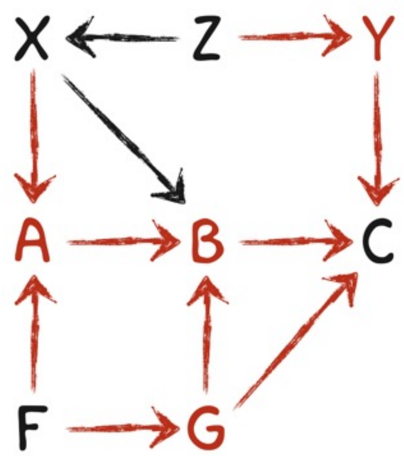
Forks



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Forks

Pipes



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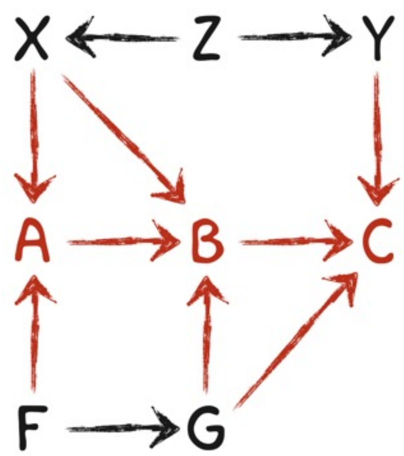
Forks

Pipes

Colliders



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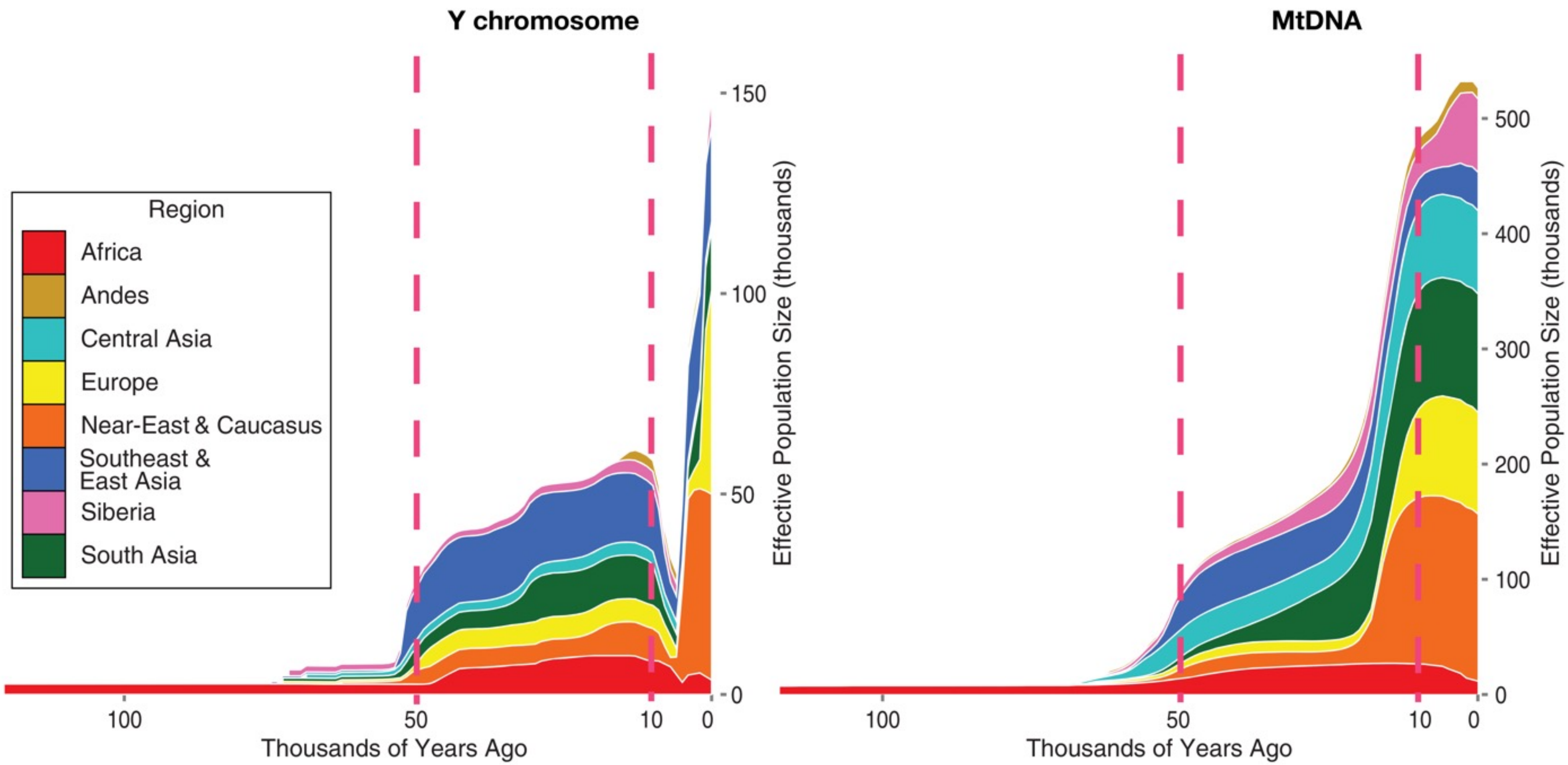


Karmin, M., (+100) et al., A recent bottleneck of Y chromosome diversity coincides with a global change in culture, *Genome research* 2015, DOI:10.1101/gr.186684.114

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

DAG Thinking

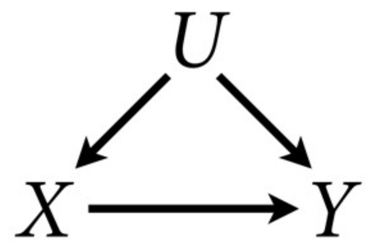
In an experiment, we cut causes of the treatment

We ***randomize*** (hopefully)

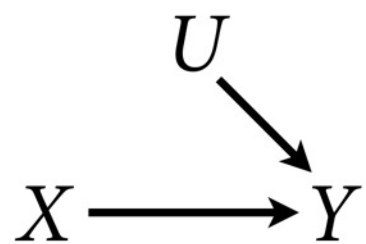
So how does causal inference without randomization ever work?

Is there a statistical procedure that mimics randomization?

Without randomization



With randomization



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

DAG Thinking

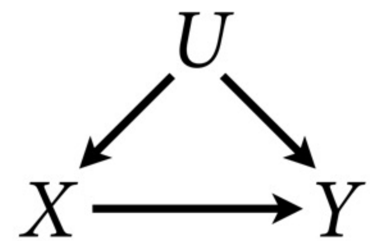
Is there a statistical procedure that mimics randomization?

$$P(Y \mid \mathrm{do}(X)) = P(Y \mid ?)$$

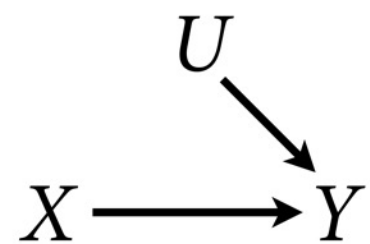
do(X) means intervene on X

Can analyze causal model to find answer (if it exists)

Without randomization



With randomization



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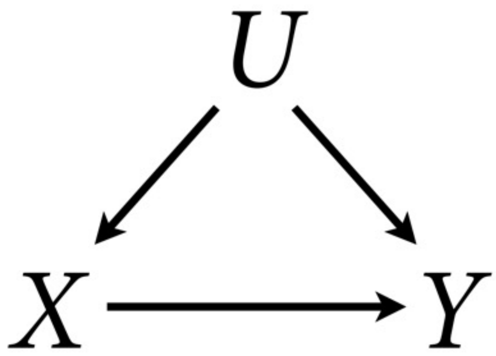
Example: Simple Confound



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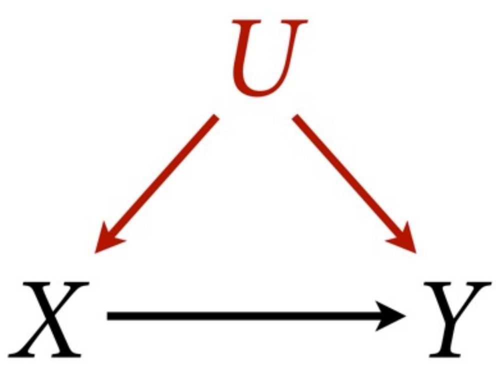
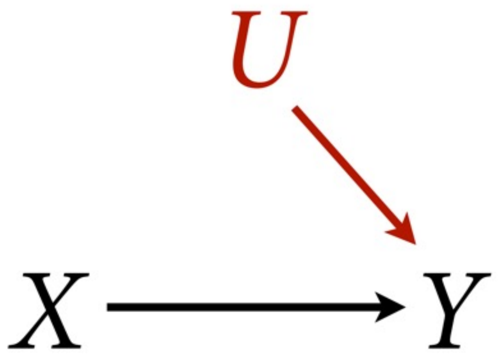


Non-causal path
X <– U –> Y

Close the fork!
Condition on U

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Example: Simple Confound



Non-causal path
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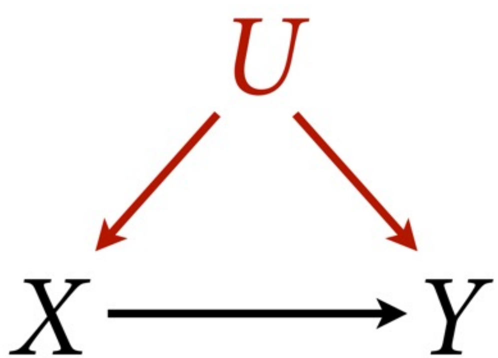


Non-causal path
X <– U –> Y

Close the fork!
Condition on U

$$P(Y \mid \mathrm{do}(X)) = \sum_U P(Y \mid X, U)P(U) = \mathrm{E}_U P(Y \mid X, U)$$

"The distribution of Y, stratified by X and U, averaged over the distribution of U."

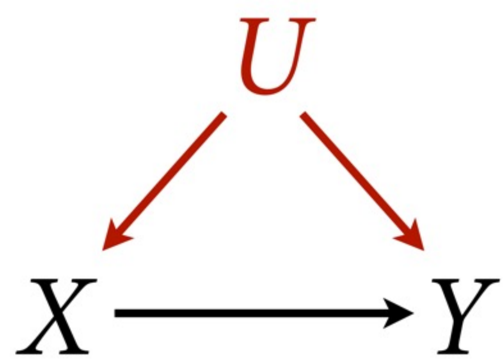
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

$$P(Y \mid \mathrm{do}(X)) = \sum_U P(Y \mid X, U)P(U) = \mathrm{E}_U P(Y \mid X, U)$$

"The distribution of Y, stratified by X and U, averaged over the distribution of U."

The causal effect of X on Y is **not** (in general) the **coefficient** relating X to Y

It is the distribution of Y when we change X, **averaged** over the distributions of the control variables (here U)



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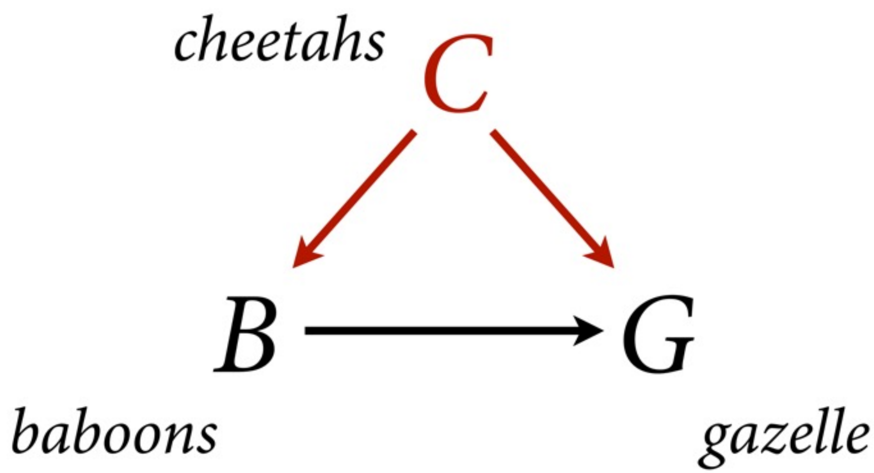
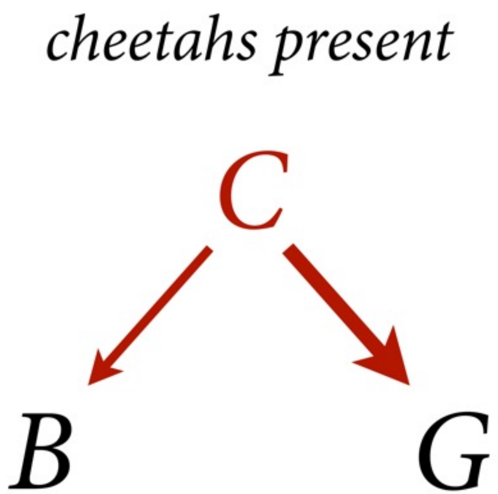
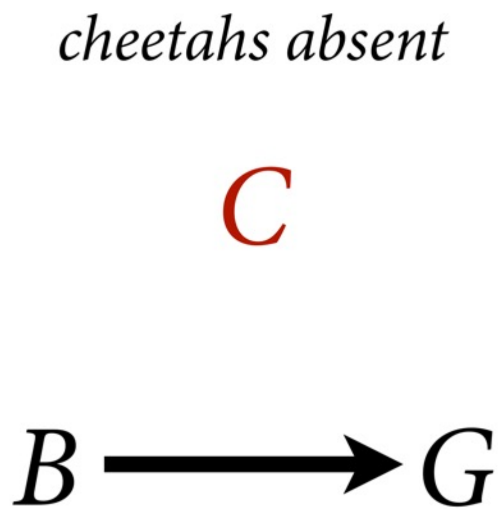
Marginal Effects Example



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Marginal Effects Example





Causal effect of baboons depends upon distribution of cheetahs

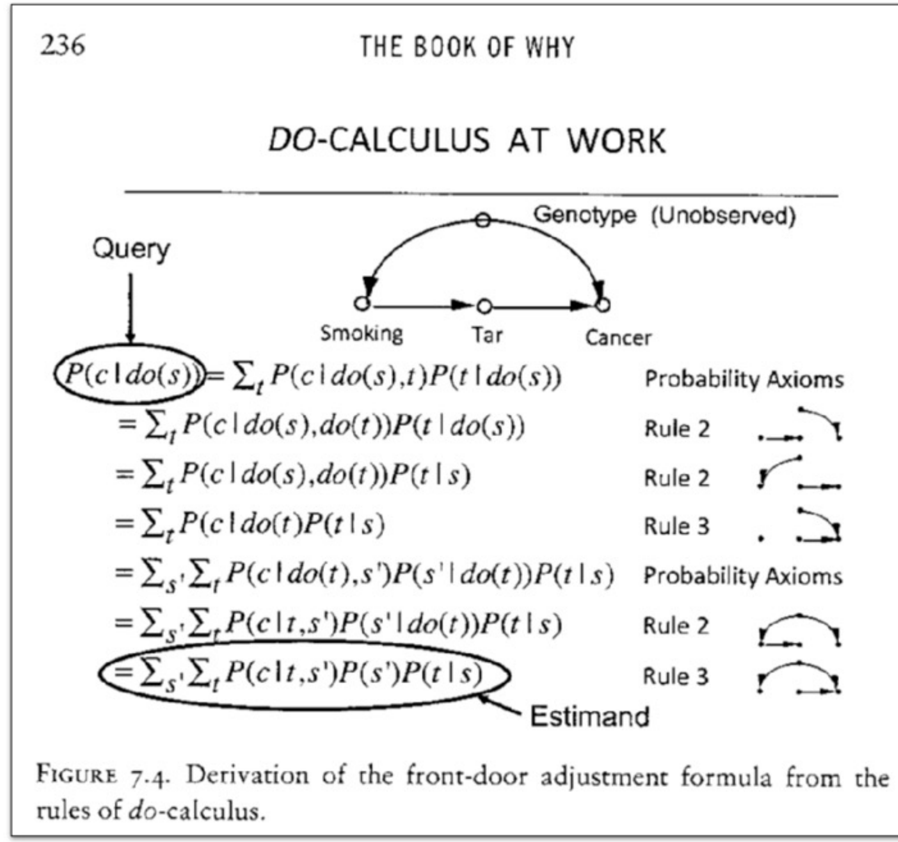
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

do-calculus

For DAGs, rules for finding $P(Y|\text{do}(X))$ known as **do-calculus**

do-calculus says what is possible to say **before** picking functions

Additional assumptions yield additional implications



DO-CALCULUS AT WORK

$P(c \mid do(s)) = \sum_t P(c \mid do(s), t) P(t \mid do(s))$	Probability Axioms
$= \sum_t P(c \mid do(s), do(t)) P(t \mid do(s))$	Rule 2
$= \sum_t P(c \mid do(s), do(t)) P(t \mid s)$	Rule 2
$= \sum_t P(c \mid do(t) P(t \mid s)$	Rule 3
$= \sum_{s'} \sum_t P(c \mid do(t), s') P(s' \mid do(t)) P(t \mid s)$	Probability Axioms
$= \sum_{s'} \sum_t P(c \mid t, s') P(s' \mid do(t)) P(t \mid s)$	Rule 2
$= \sum_{s'} \sum_t P(c \mid t, s') P(s') P(t \mid s)$	Rule 3

FIGURE 7.4. Derivation of the front-door adjustment formula from the rules of *do*-calculus.

Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022

do-calculus

do-calculus is **worst case**:
additional assumptions often allow stronger inference

do-calculus is **best case**:
if inference possible by do-calculus, does not depend on special assumptions

Judea Pearl, father of do-calculus, in 1966

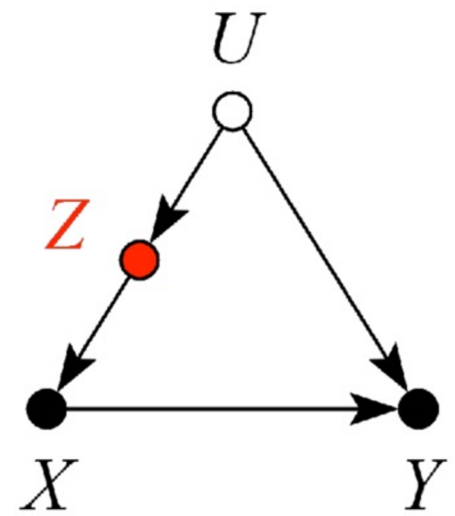
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Backdoor Criterion

Very useful implication of do-calculus is the **Backdoor Criterion**

Backdoor Criterion is a shortcut to applying rules of do-calculus

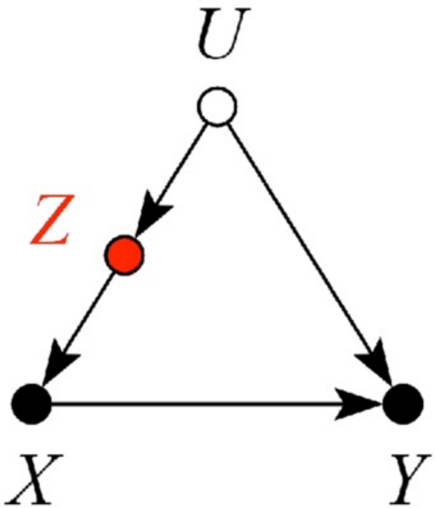
Also inspires **strategies** for research design that yield valid estimates



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Backdoor Criterion

Backdoor Criterion: Rule to find a set of variables to stratify (condition) by to yield $P(Y|\mathrm{do}(X))$



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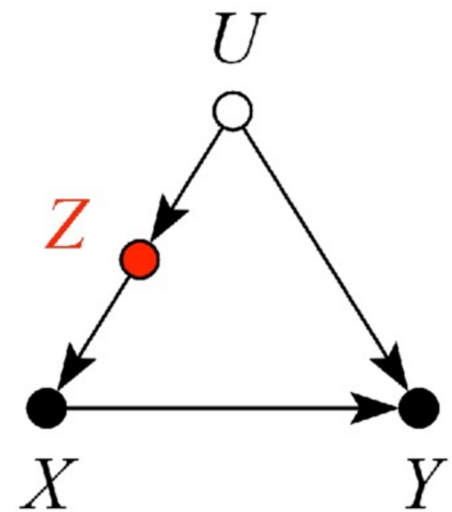
Backdoor Criterion

Backdoor Criterion: Rule to find a set of variables to stratify (condition) by to yield $P(Y|\mathrm{do}(X))$

(1) Identify all **paths** connection the treatment (X) to the outcome (Y)



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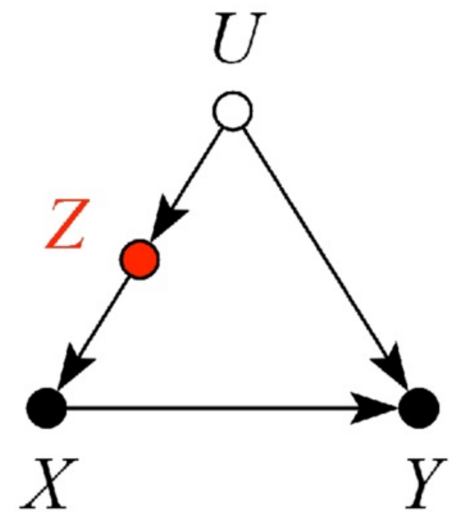
(1) Identify all **paths** connection the treatment (X) to the outcome (Y)

(2) Paths with arrows **entering** X are backdoor paths (non-causal paths)



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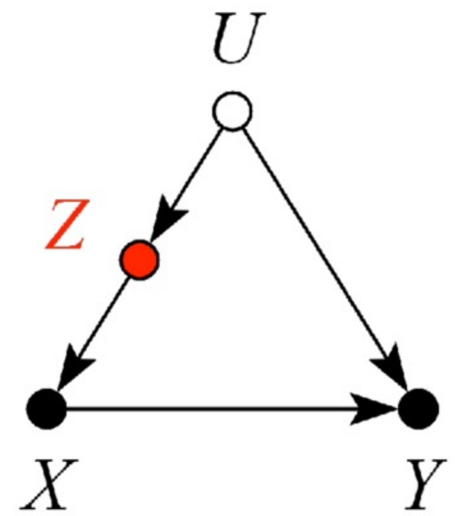
(1) Identify all **paths** connection the treatment (X) to the outcome (Y)

(2) Paths with arrows **entering** X are backdoor paths (non-causal paths)

(3) Find adjustment set that closes/blocks all backdoor paths



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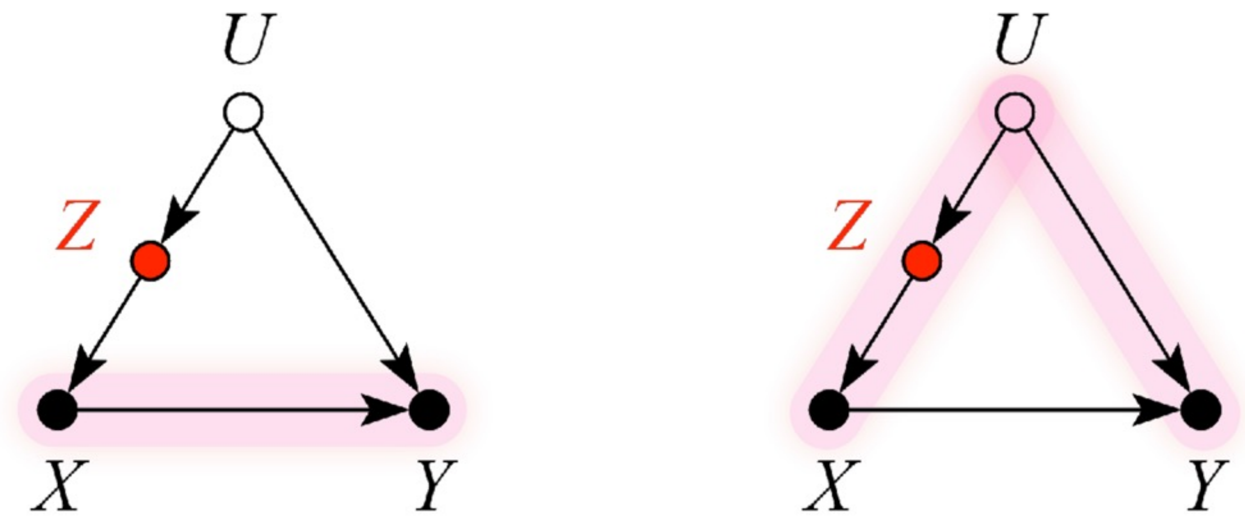

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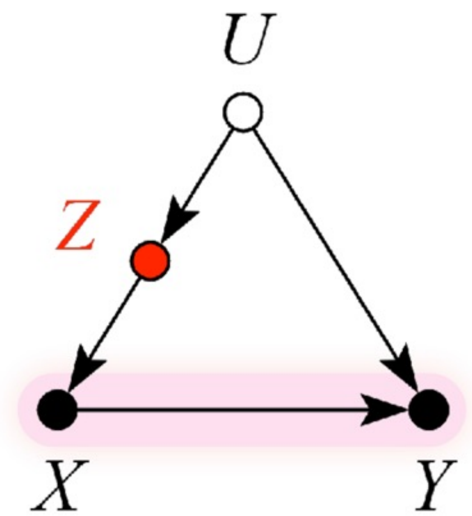
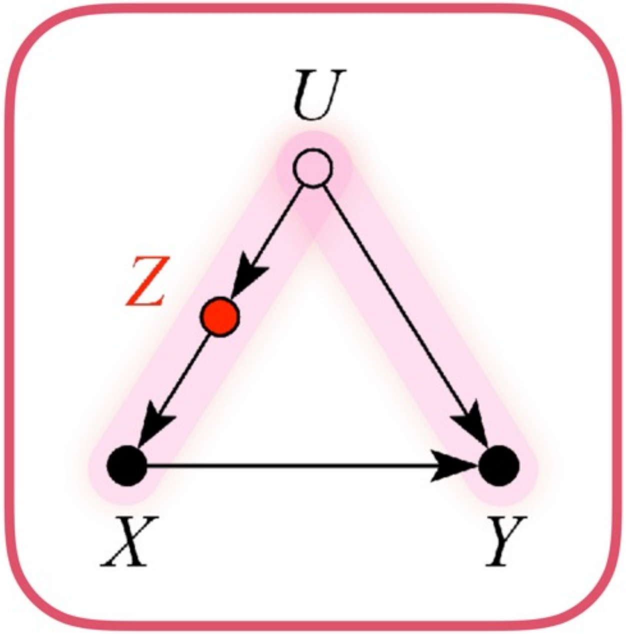
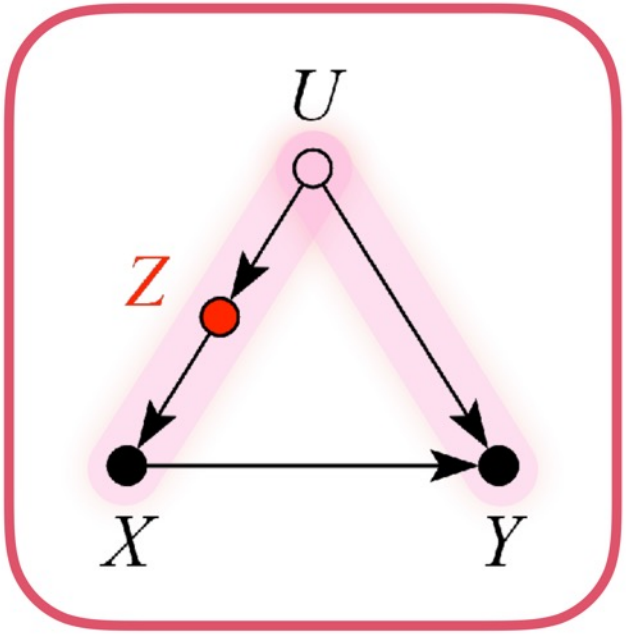




Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

(3) Find a set of control variables that close/block all backdoor paths

Block the pipe: $X \perp\!\!\!\perp U \mid Z$



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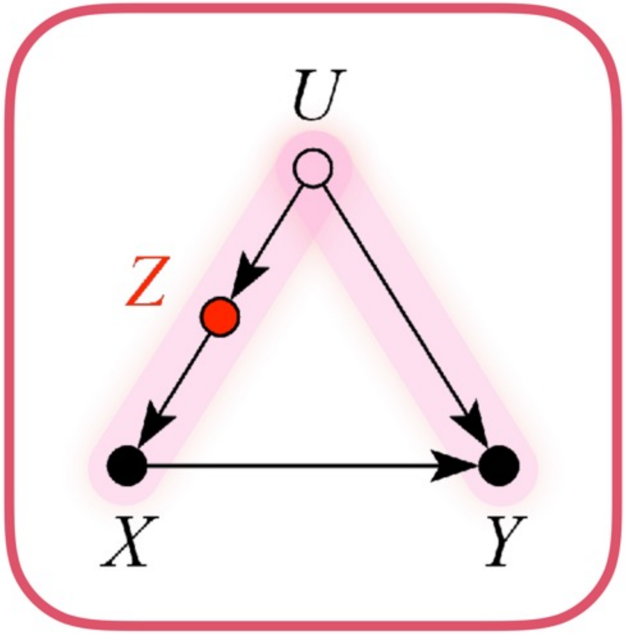
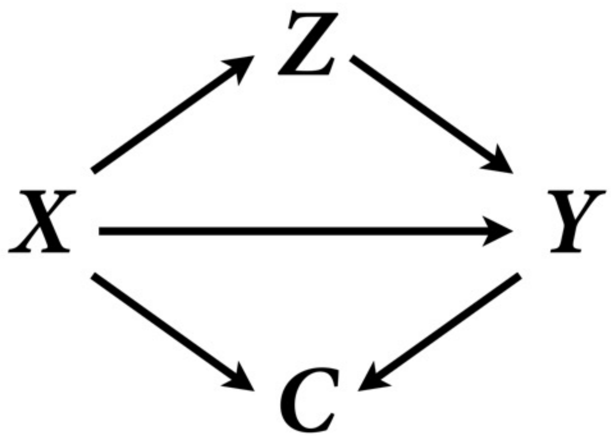
$$P(Y \mid \mathrm{do}(X)) = \sum_{U} P(Y \mid X, Z) P(Z)$$

$$Y_i \sim \mathrm{Normal}(\mu_i, \sigma)$$
$$\mu_i = \alpha + \beta_X X_i + \beta_Z Z_i$$



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

List all the paths connecting **X** and **Y**. Which need to be closed to estimate effect of **X** on **Y**?



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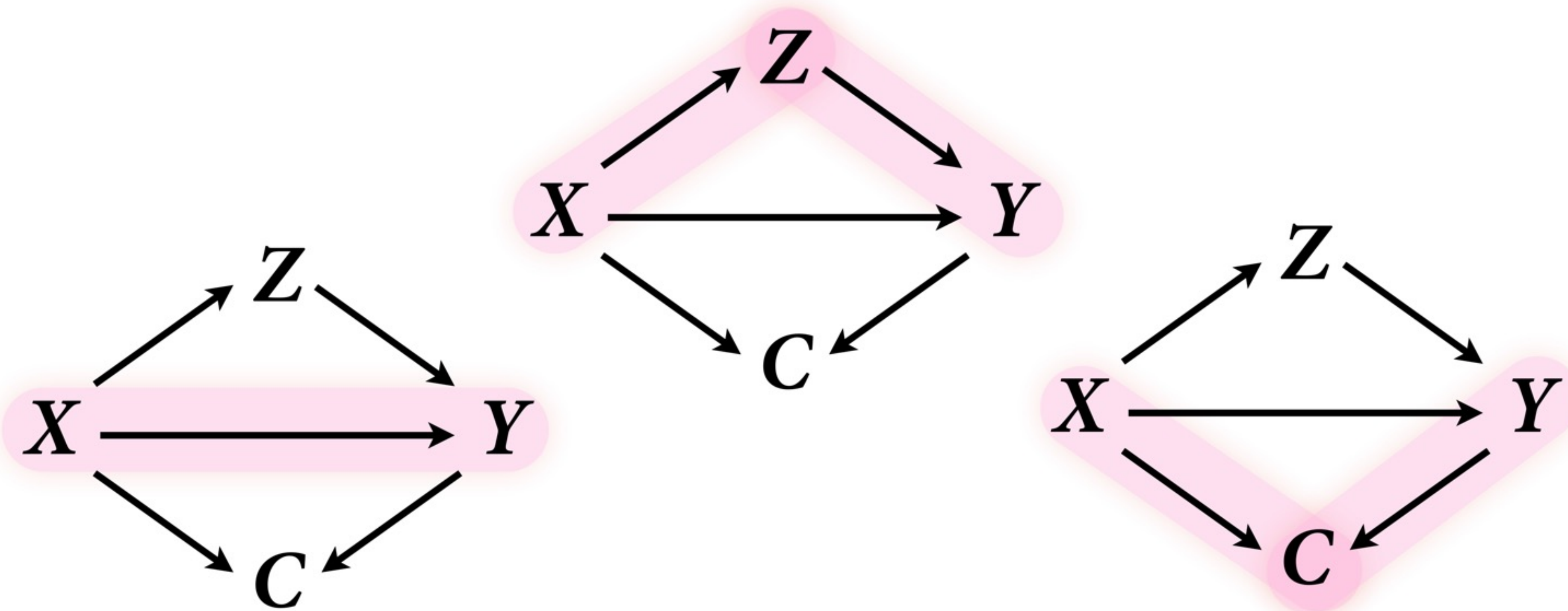

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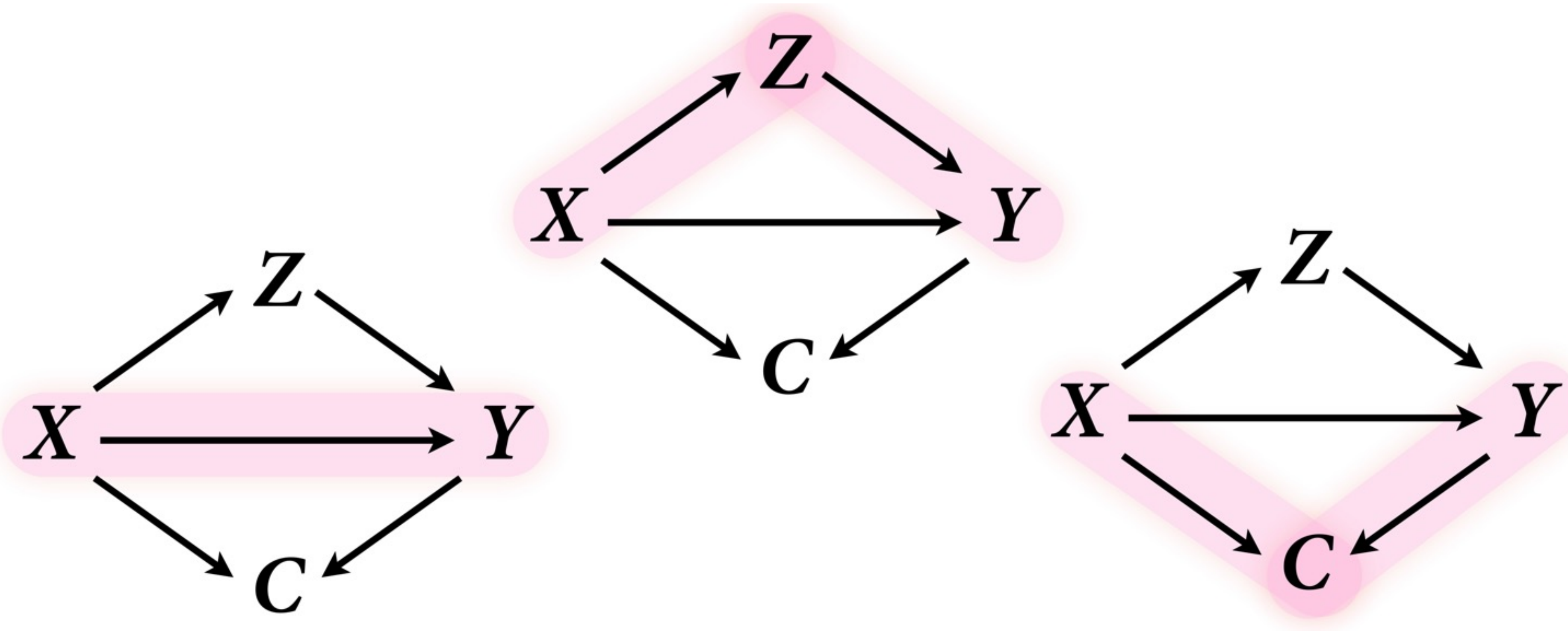

Adjustment set: *nothing!*

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

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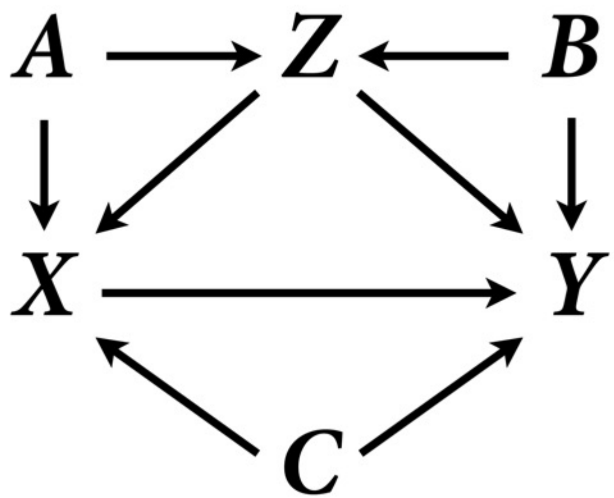

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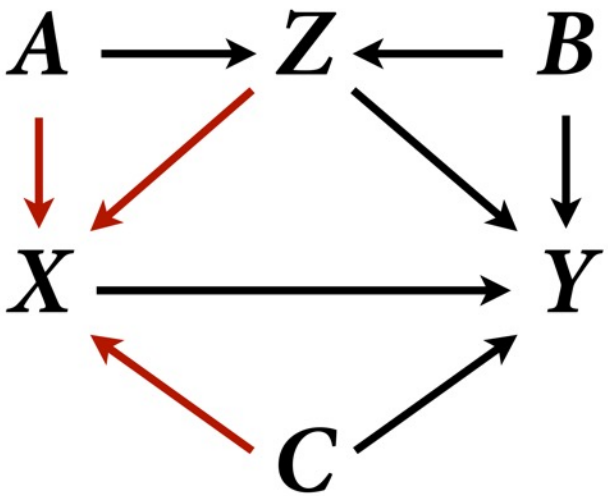
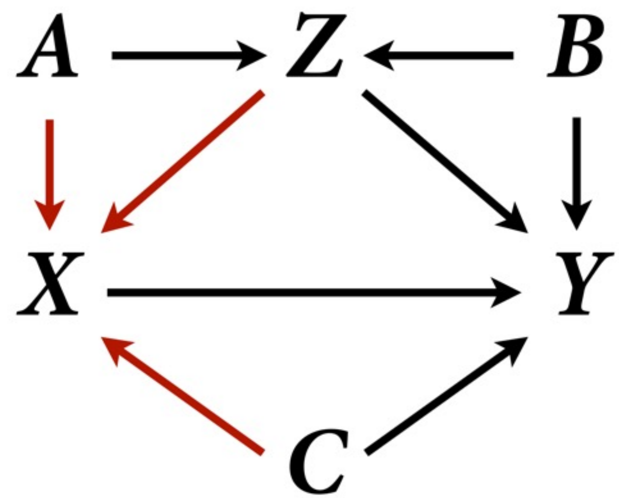
$$P(Y|\text{do}(X))$$





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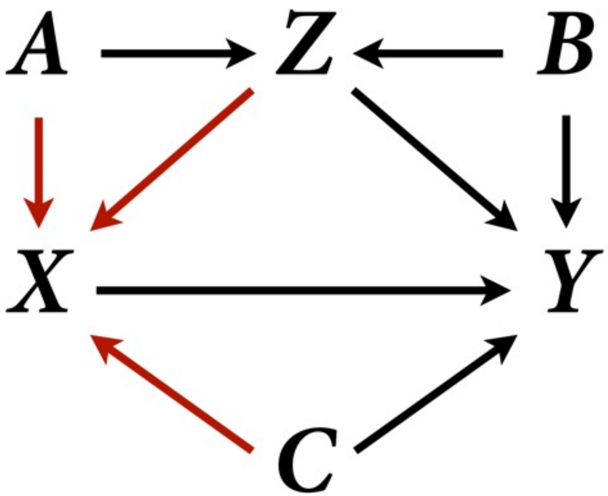

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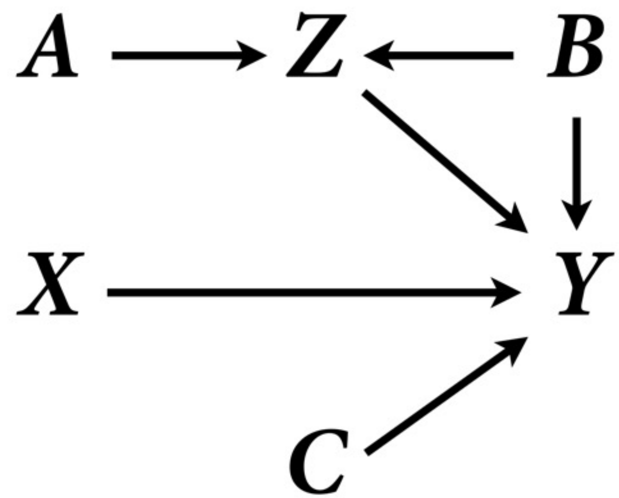

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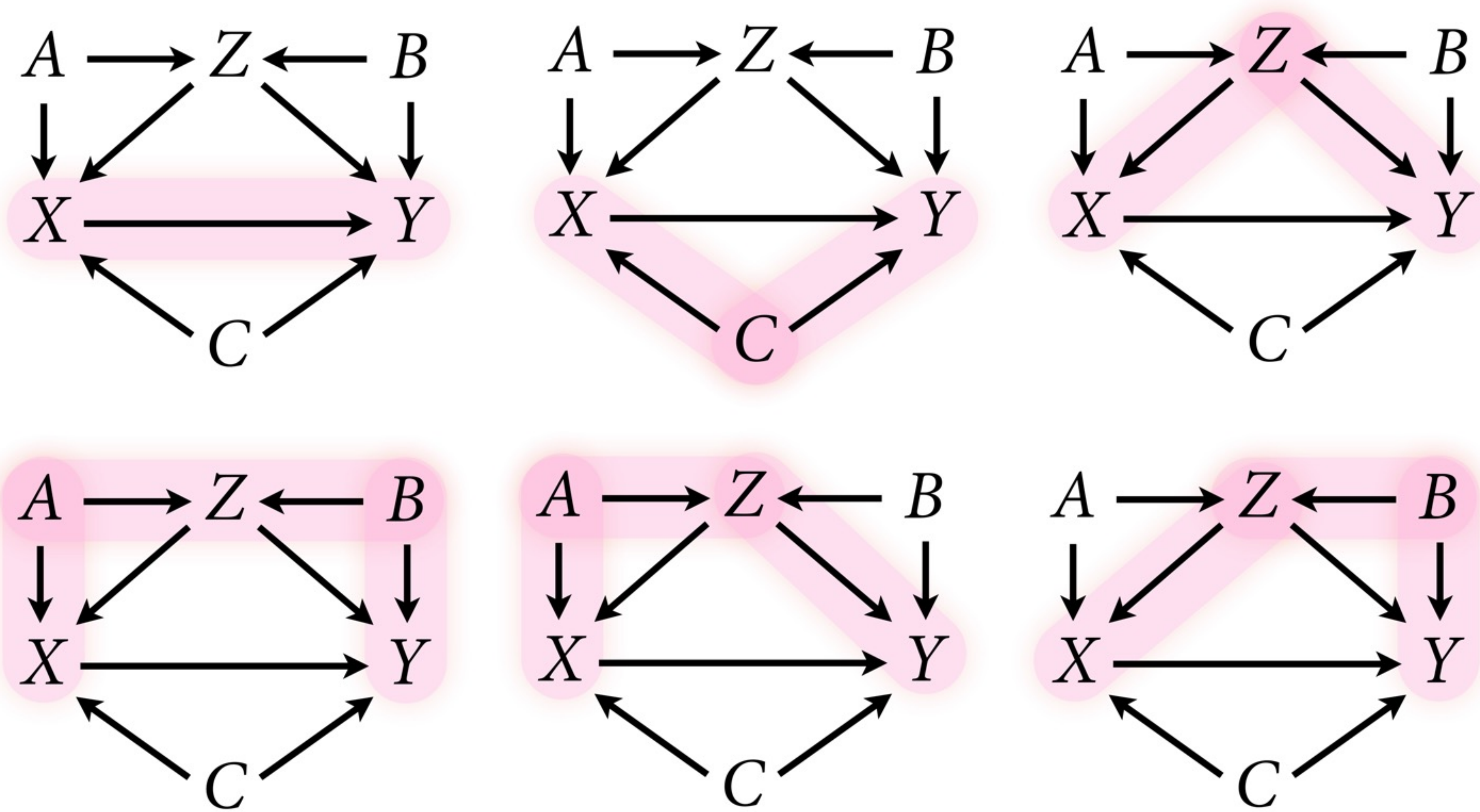
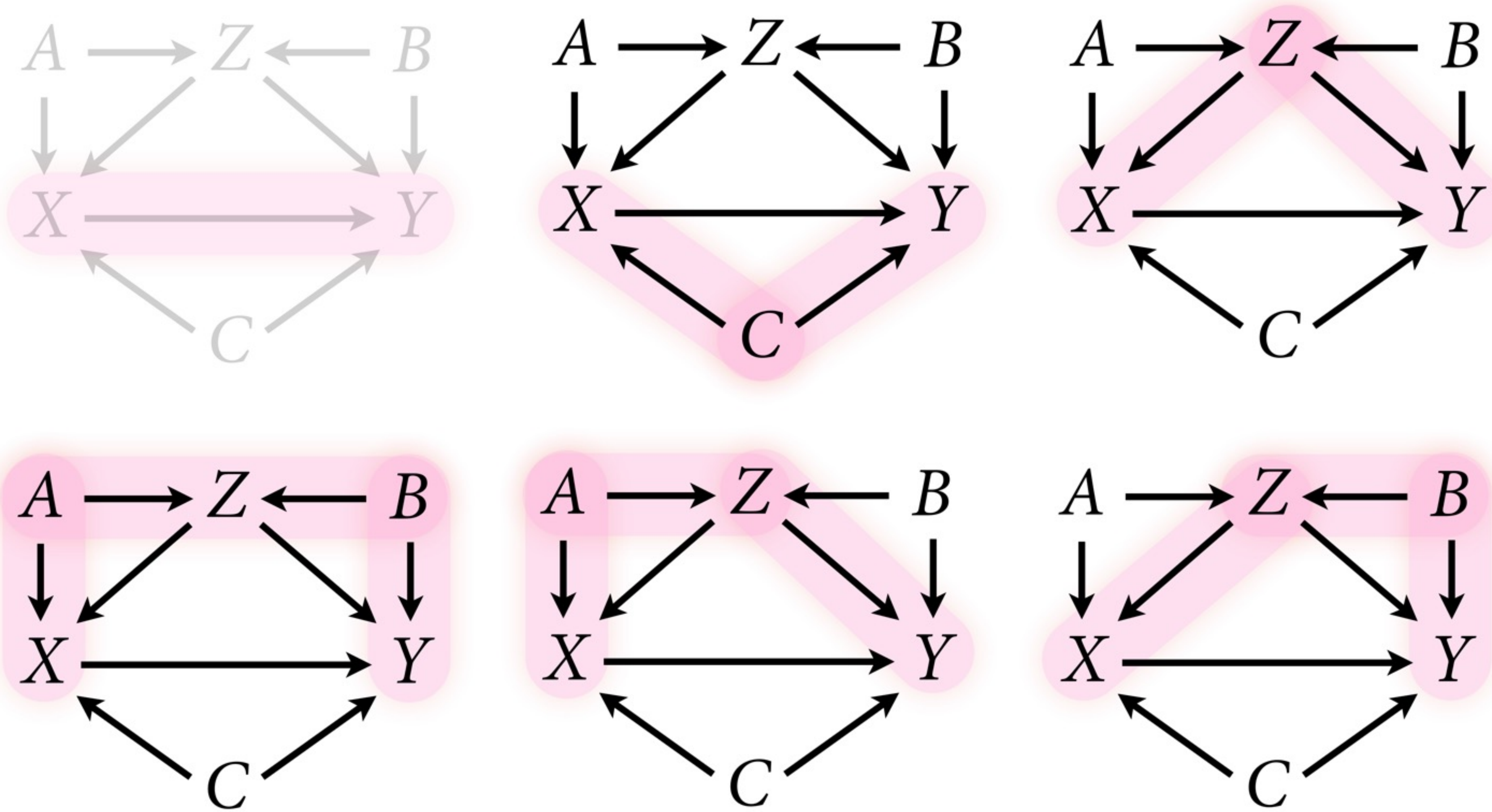
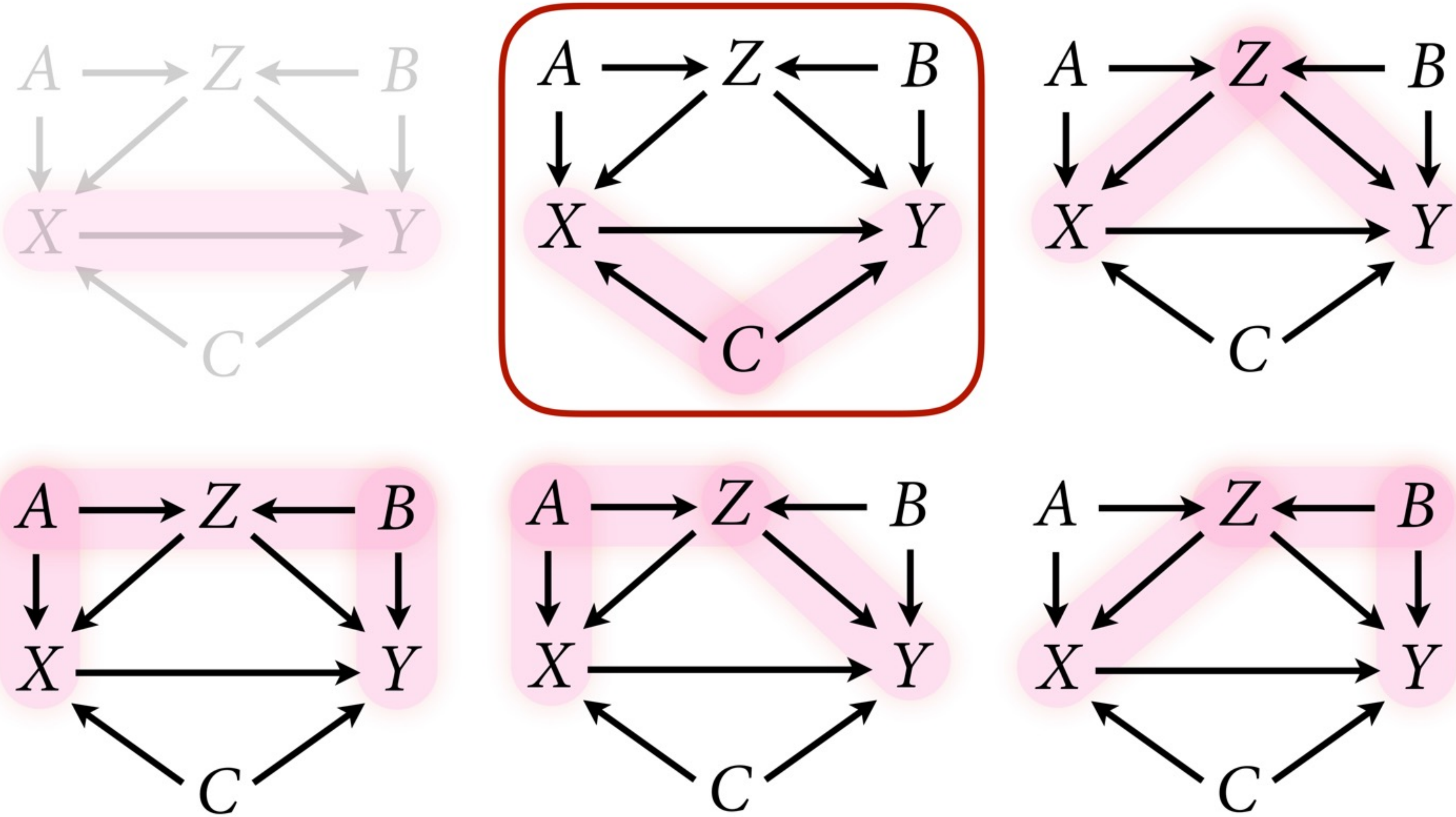


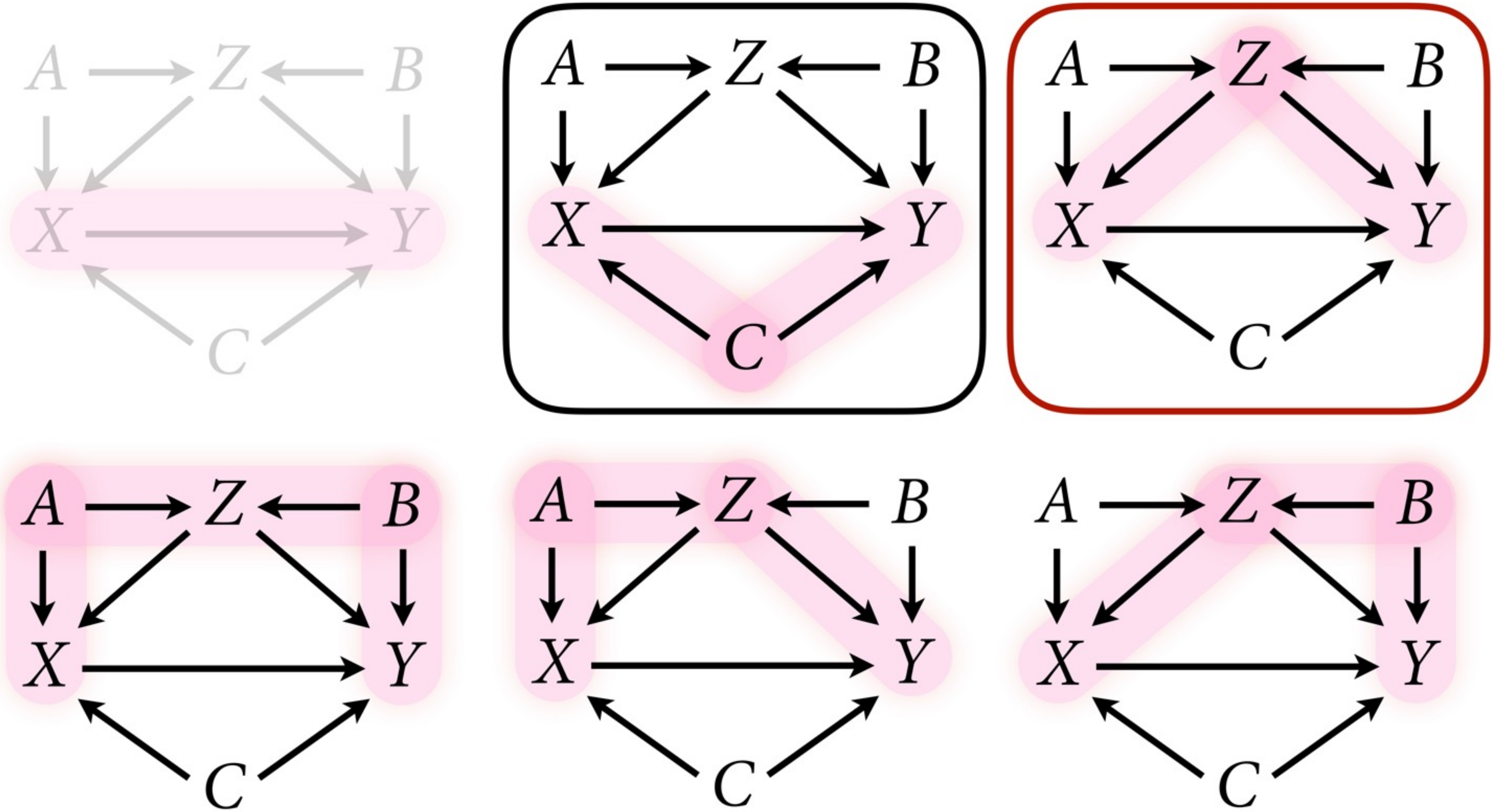
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



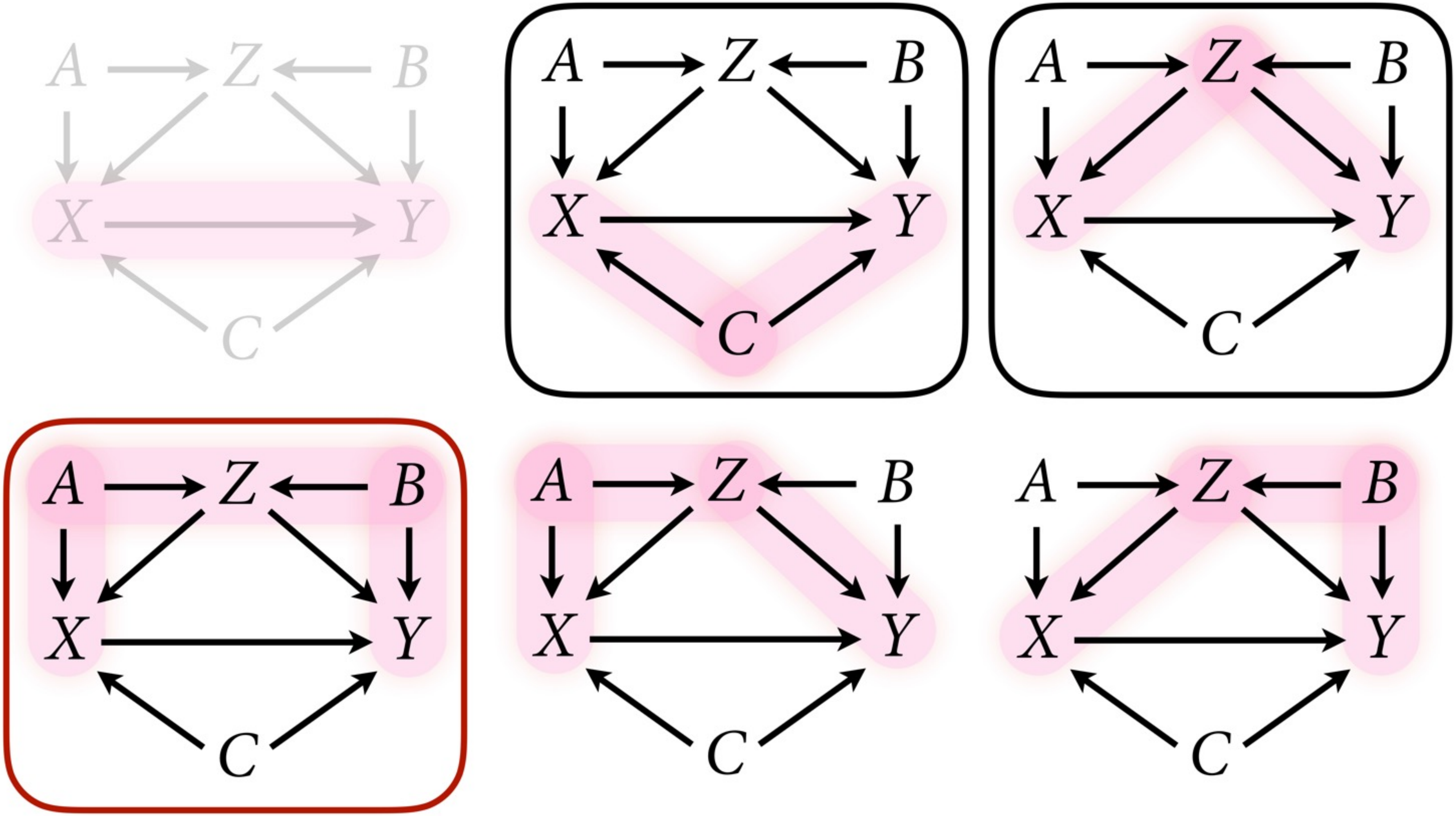
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



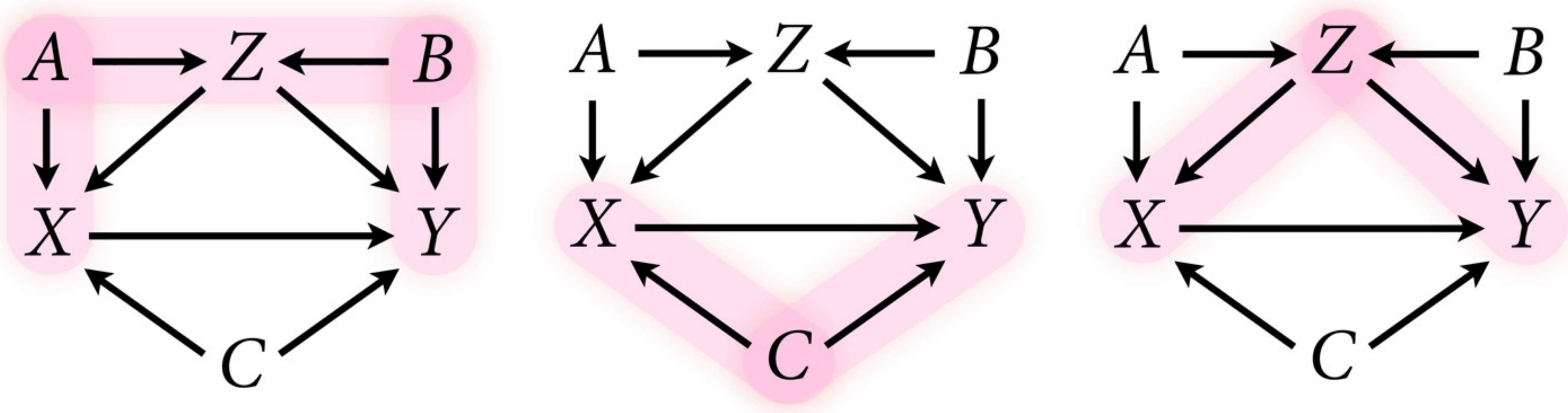
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

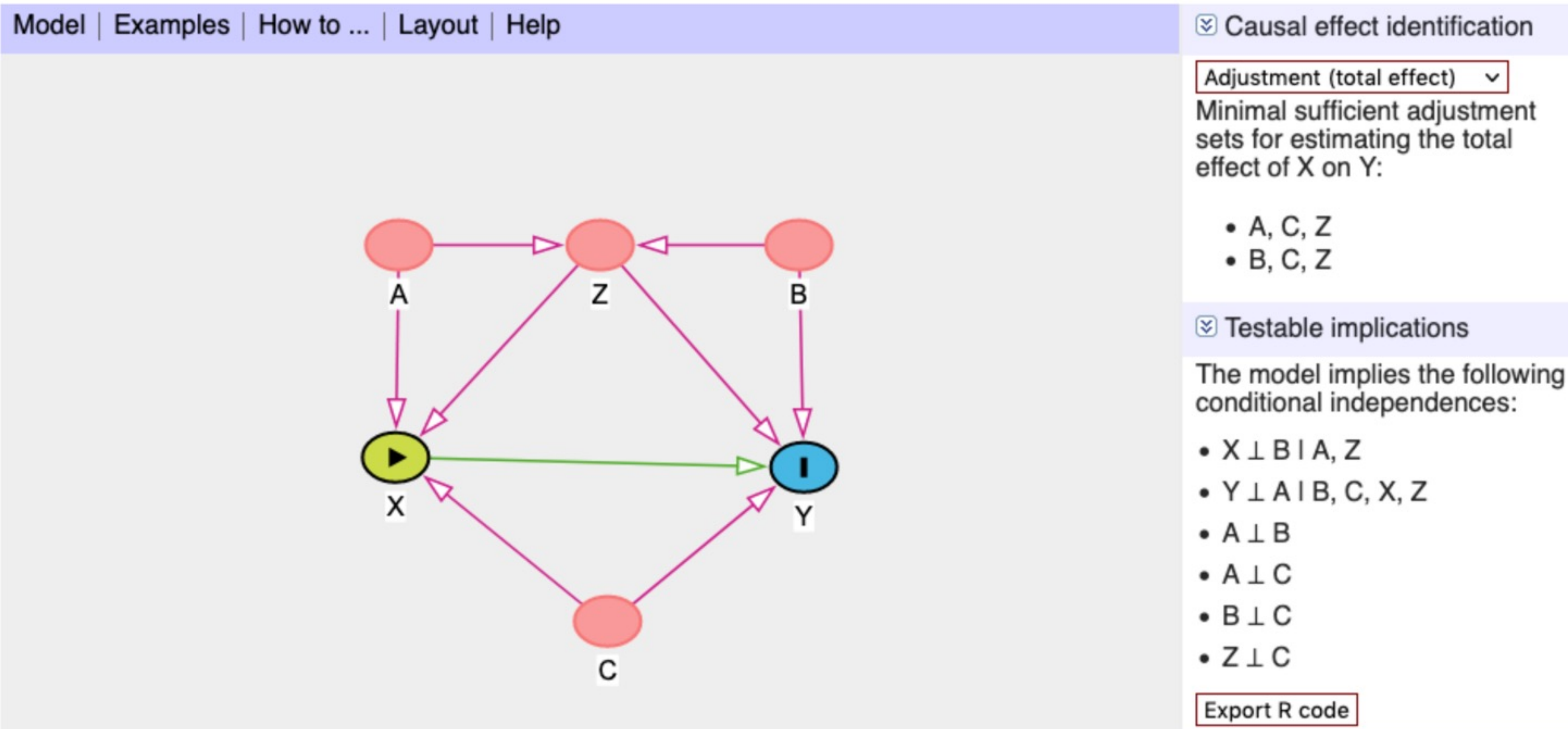


Adjustment set: C, Z, *and either* A *or* B

(B is better choice)

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

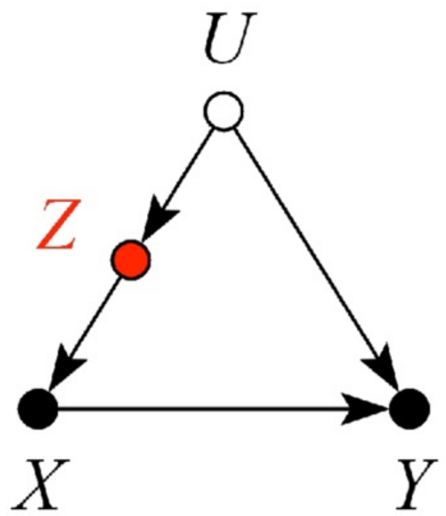
www.dagitty.net



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Backdoor Criterion

Backdoor Criterion: Rule to find adjustment set to yield $P(Y|\mathrm{do}(X))$

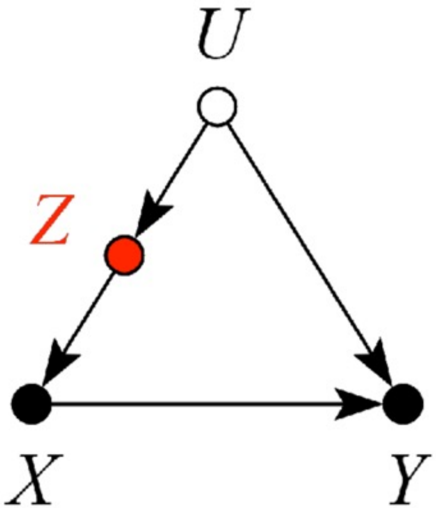


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Backdoor Criterion

Backdoor Criterion: Rule to find adjustment set to yield $P(Y|\mathrm{do}(X))$

Beware non-causal paths that you open while closing other paths!



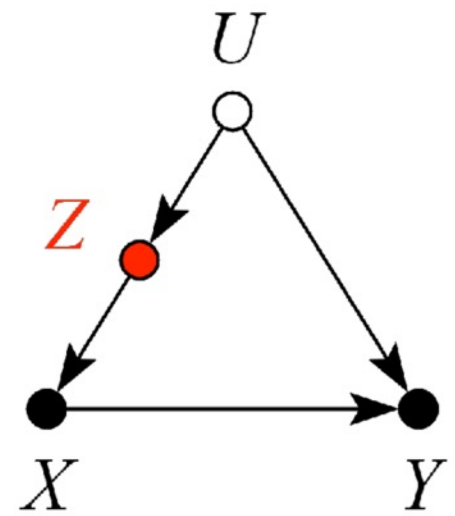
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Backdoor Criterion

Backdoor Criterion: Rule to find adjustment set to yield $P(Y|\mathrm{do}(X))$

Beware non-causal paths that you open while closing other paths!

More than backdoors:



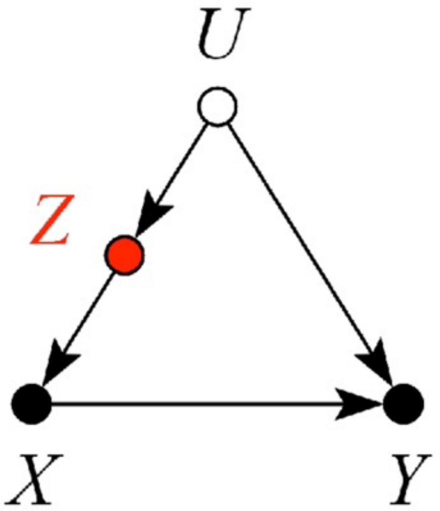
Backdoor Criterion

Backdoor Criterion: Rule to find adjustment set to yield $P(Y|\mathrm{do}(X))$

Beware non-causal paths that you open while closing other paths!

More than backdoors:

Also solutions with simultaneous equations (instrumental variables e.g.)



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Backdoor Criterion

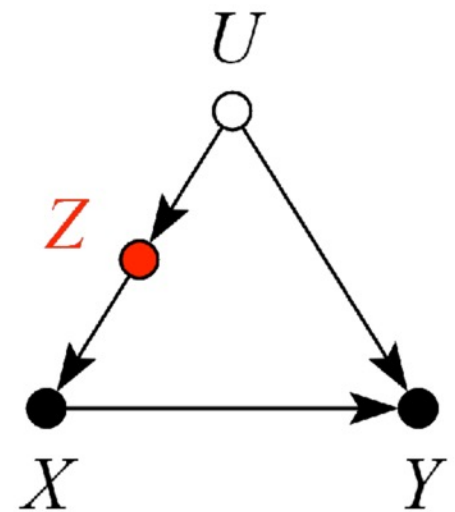
Backdoor Criterion: Rule to find adjustment set to yield $P(Y|\mathrm{do}(X))$

Beware non-causal paths that you open while closing other paths!

More than backdoors:

Also solutions with simultaneous equations (instrumental variables e.g.)

Full Luxury Bayes: use all variables, but in separate sub-models instead of single regression



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Good & Bad Controls

"Control" variable: Variable introduced to an analysis so that a causal estimate is possible

Common **wrong** heuristics for choosing control variables

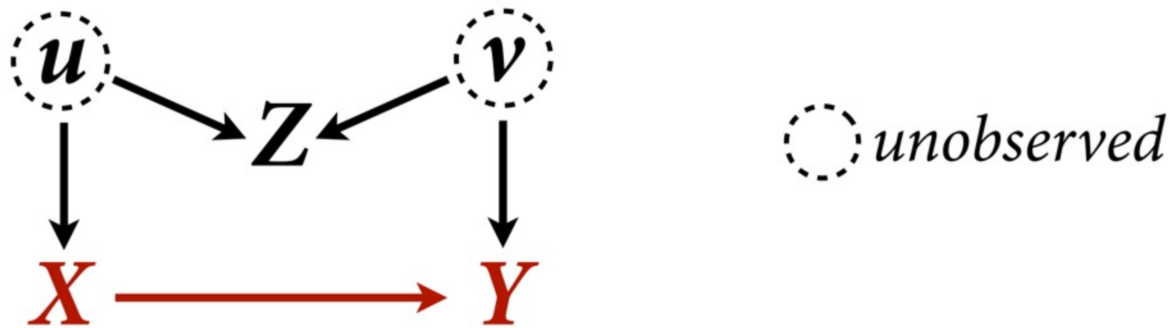
- Anything in the spreadsheet **YOLO**!
- Any variables not highly **collinear**
- Any **pre-treatment** measurement (baseline)

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

$$X \longrightarrow Y$$

Cinelli, Forney, Pearl 2021 A Crash Course in Good and Bad Controls

Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022



Cinelli, Forney, Pearl 2021 A Crash Course in Good and Bad Controls

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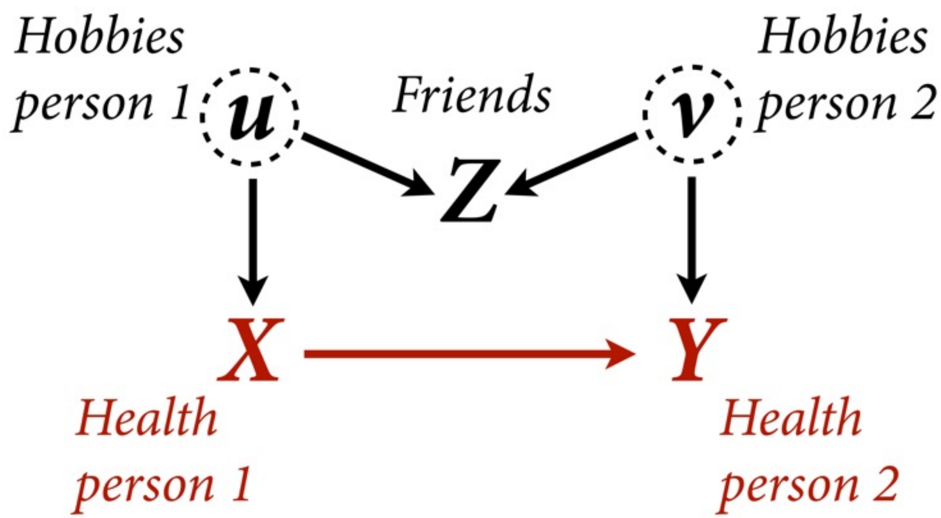
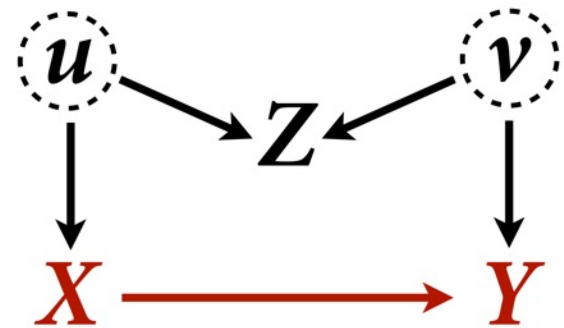


Cinelli, Forney, Pearl 2021 A Crash Course in Good and Bad Controls

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

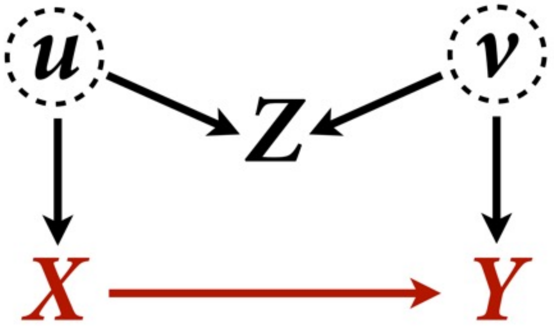
(1) List the paths



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

(1) List the paths

$X \rightarrow Y$

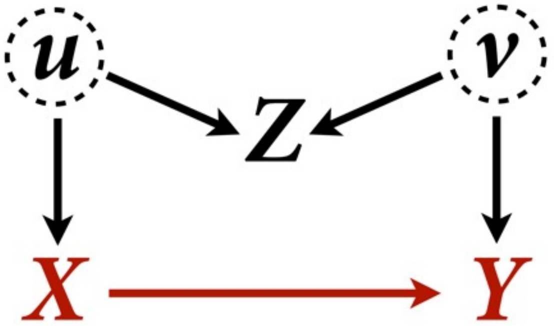


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

(1) List the paths

$$X \rightarrow Y$$

$$X \leftarrow u \rightarrow Z \leftarrow v \rightarrow Y$$



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

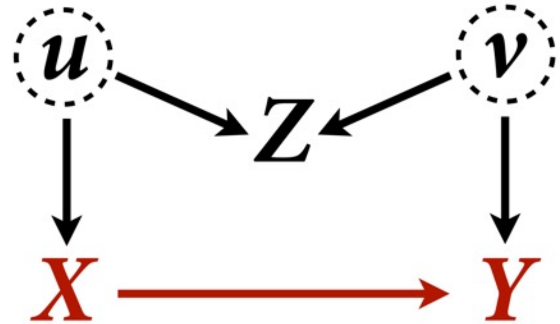
(1) List the paths (2) Find backdoors

$$X \to Y$$

frontdoor & open

$$X \leftarrow u \to Z \leftarrow v \to Y$$

backdoor & closed



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

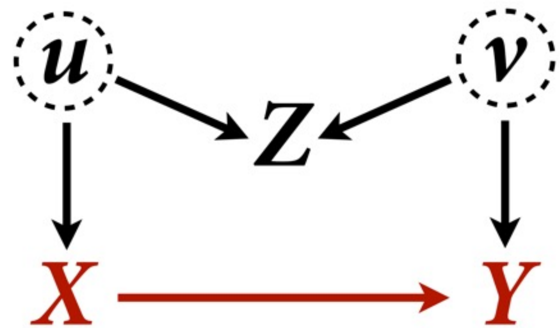
(1) List the paths (2) Find backdoors

$$X \rightarrow Y$$

frontdoor & open

$$X \leftarrow u \rightarrow Z \leftarrow v \rightarrow Y$$

backdoor & closed



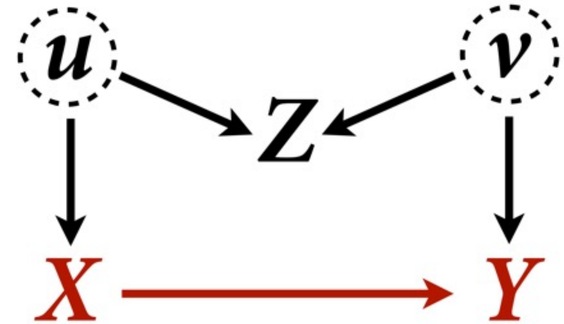
(1) List the paths (2) Find backdoors (3) Close backdoors

$X \rightarrow Y$

frontdoor & open

$X \leftarrow u \rightarrow Z \leftarrow v \rightarrow Y$

backdoor & closed



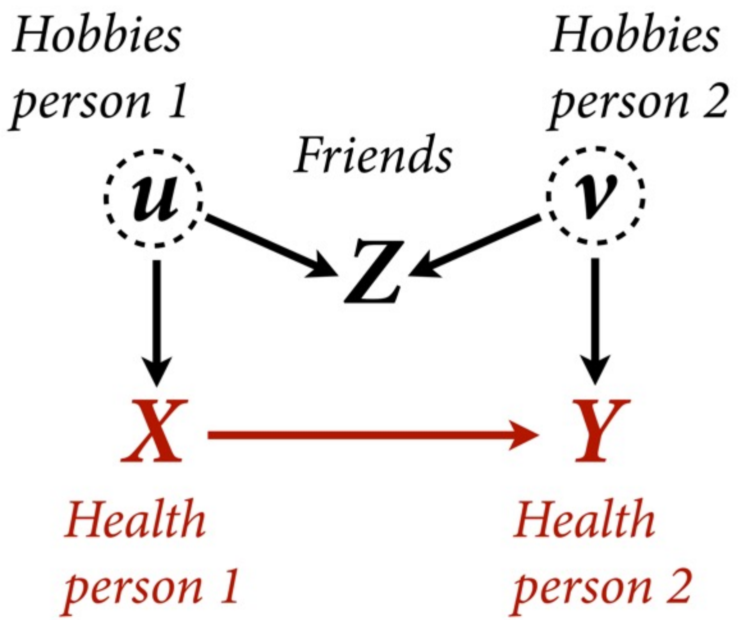
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

What happens if you stratify by *Z*?

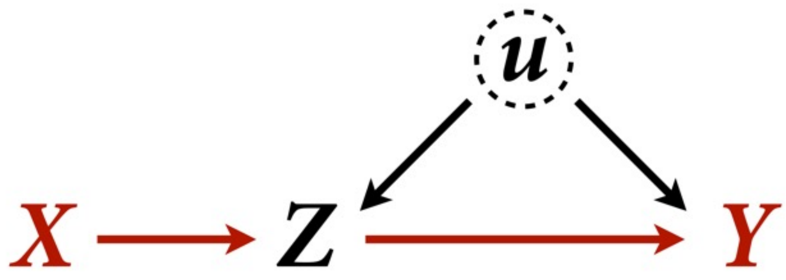
Opens the backdoor path

Z could be a **pre-treatment** variable

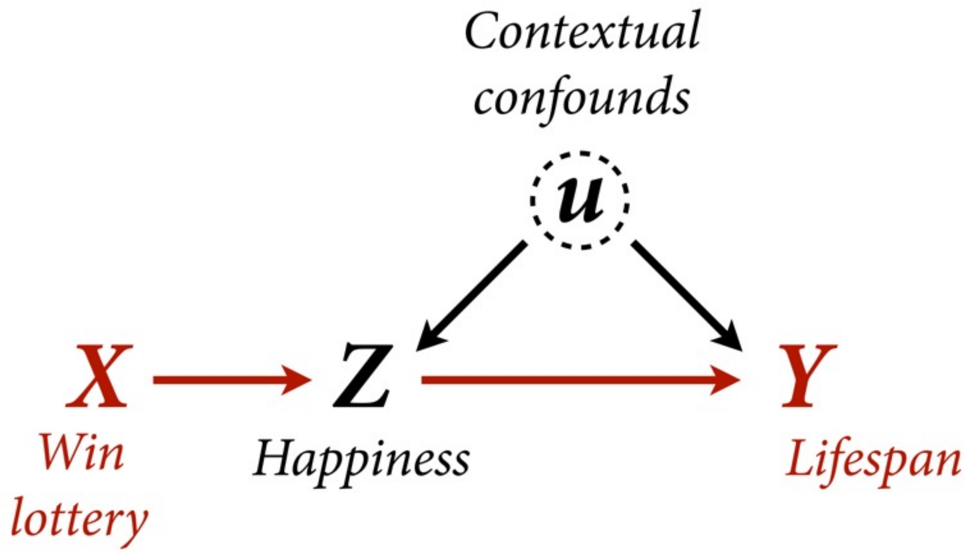
Not safe to always control pre-treatment measurements



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

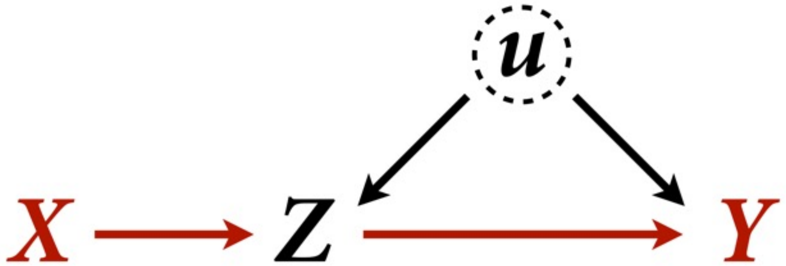


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

$$X \to Z \to Y$$

$$X \to Z \leftarrow u \to Y$$

No backdoor, no need to control for Z

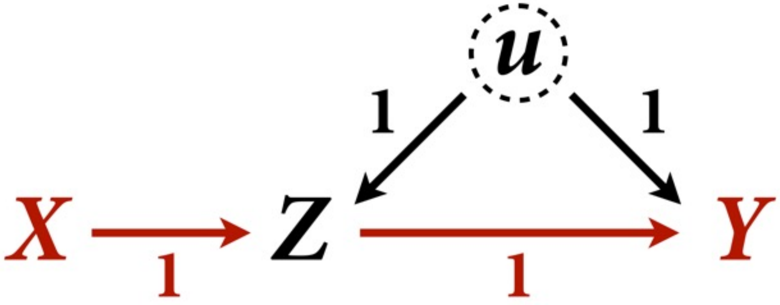


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

```
f <- function(n=100,bXZ=1,bZY=1) {
    X <- rnorm(n)
    u <- rnorm(n)
    Z <- rnorm(n, bXZ*X + u)
    Y <- rnorm(n, bZY*Z + u )
    bX <- coef( lm(Y ~ X) )['X']
    bXZ <- coef( lm(Y ~ X + Z) )['X']
    return( c(bX,bXZ) )
}

sim <- mcreplicate( 1e4 , f() , mc.cores=8 )

dens( sim[1,] , lwd=3 , xlab="posterior mean" )
dens( sim[2,] , lwd=3 , col=2 , add=TRUE )
```



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

```r
f <- function(n=100,bXZ=1,bZY=1) {
    X <- rnorm(n)
    u <- rnorm(n)
    Z <- rnorm(n, bXZ*X + u)
    Y <- rnorm(n, bZY*Z + u )
    bX <- coef( lm(Y ~ X) )['X']
    bXZ <- coef( lm(Y ~ X + Z) )['X']
    return( c(bX,bXZ) )
}

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dens( sim[1,] , lwd=3 , xlab="posterior mean" )
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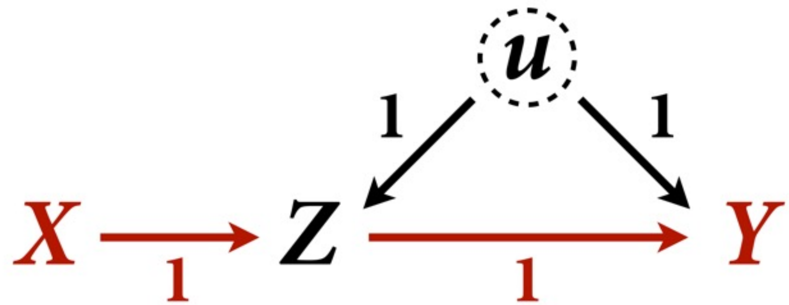
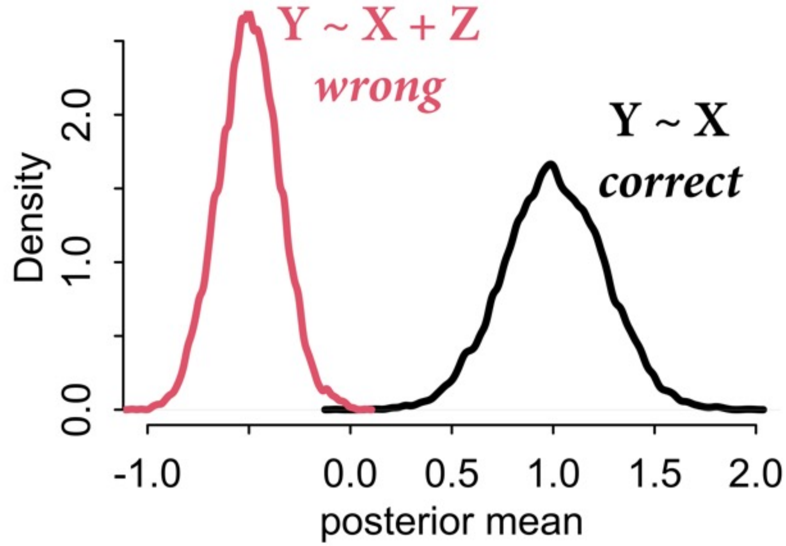




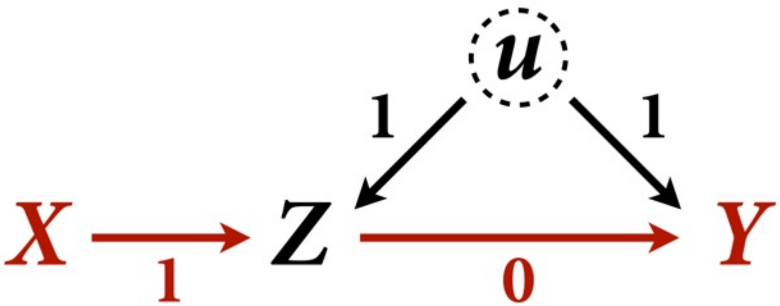
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

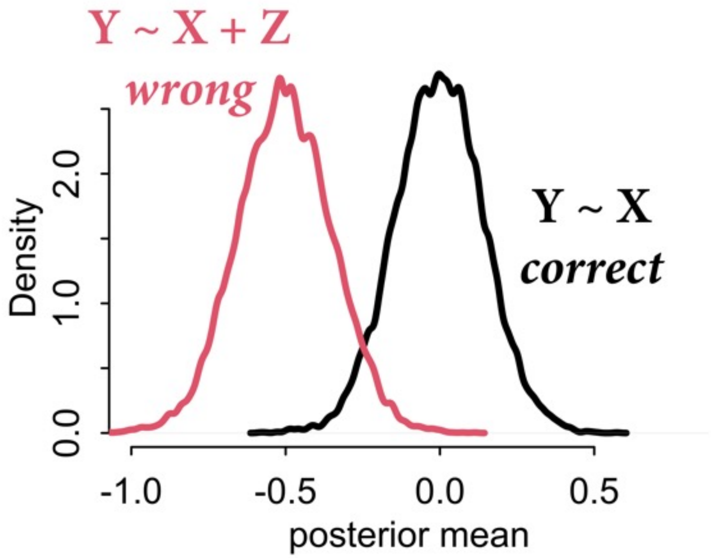
Change bZY to zero

```r
f <- function(n=100,bXZ=1,bZY=1) {
    X <- rnorm(n)
    u <- rnorm(n)
    Z <- rnorm(n, bXZ*X + u)
    Y <- rnorm(n, bZY*Z + u )
    bX <- coef( lm(Y ~ X) )['X']
    bXZ <- coef( lm(Y ~ X + Z) )['X']
    return( c(bX,bXZ) )
}

sim <- mcreplicate( 1e4 , f(bZY=0) , mc.cores=8 )

dens( sim[1,] , lwd=3 , xlab="posterior mean" )
dens( sim[2,] , lwd=3 , col=2 , add=TRUE )
```





Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

$X \to Z \to Y$

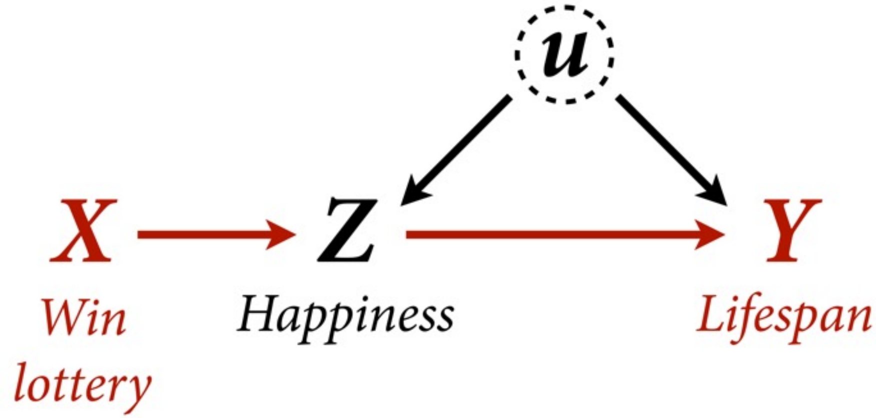
$X \to Z \leftarrow u \to Y$

No backdoor, no need to control for Z

Controlling for Z biases treatment estimate X

Controlling for Z opens biasing path through u

Can estimate effect of X; Cannot estimate mediation effect Z



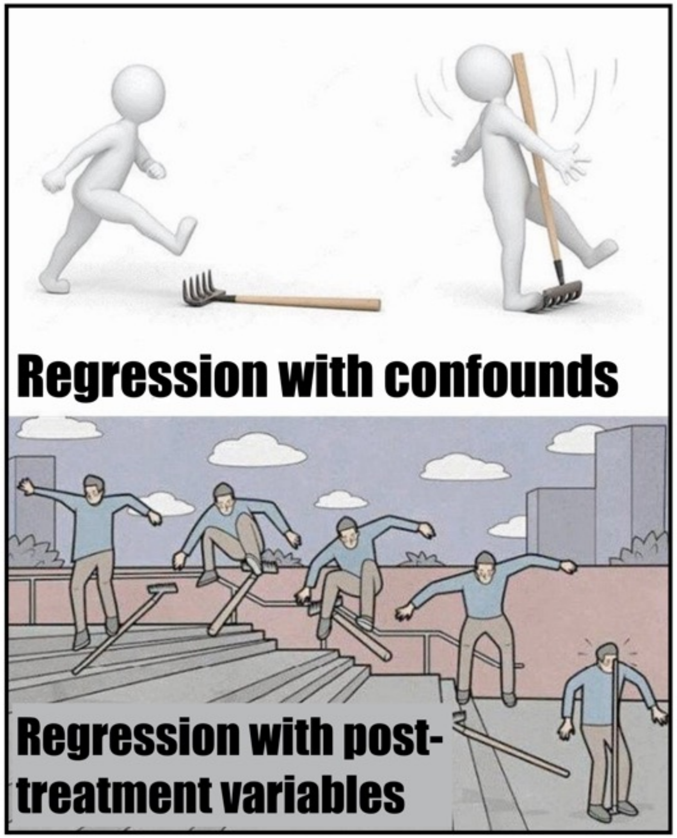
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Post-treatment bias is common

Table 1 Posttreatment Conditioning in Experimental Studies

Category	Prevalence
Engages in posttreatment conditioning	46.7%
Controls for/interacts with a posttreatment variable	21.3%
Drops cases based on posttreatment criteria	14.7%
Both types of posttreatment conditioning present	10.7%
No conditioning on posttreatment variables	52.0%
Insufficient information to code	1.3%

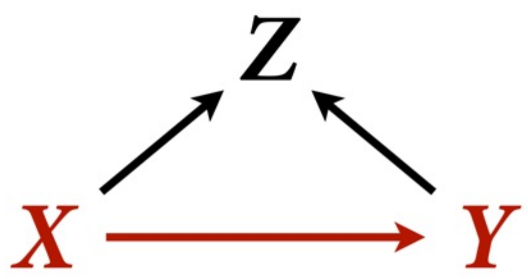
Note: The sample consists of 2012–14 articles in the *American Political Science Review*, the *American Journal of Political Science*, and the *Journal of Politics* including a survey, field, laboratory, or lab-in-the-field experiment (n = 75).



Montgomery et al 2018 How Conditioning on Posttreatment Variables Can Ruin Your Experiment

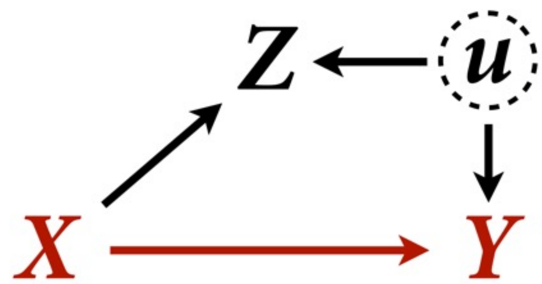
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Do not touch the collider!



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Colliders not always so obvious



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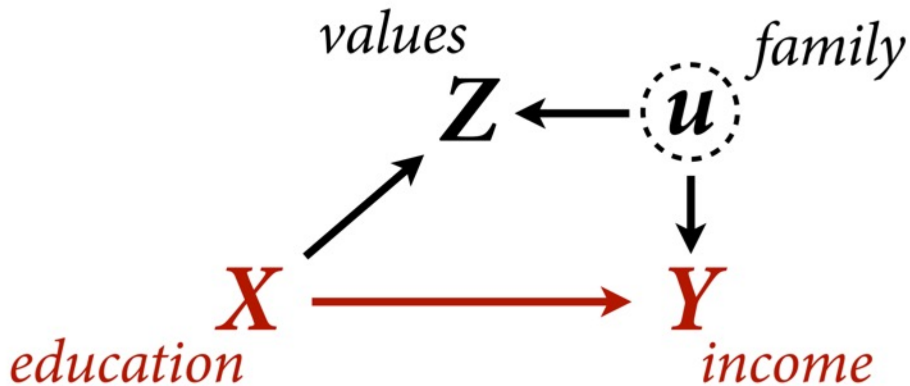
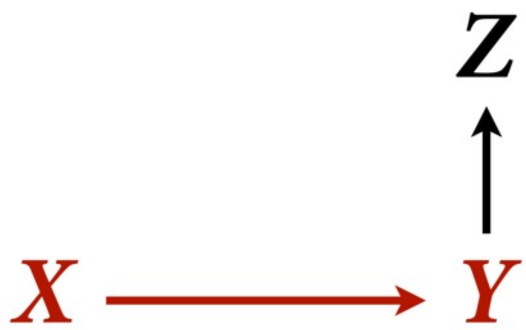


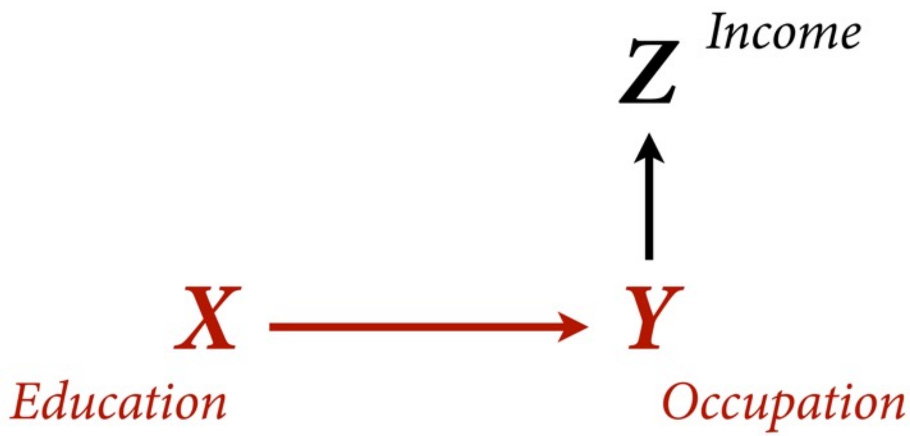
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

“Case-control bias”



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

“Case-control bias”



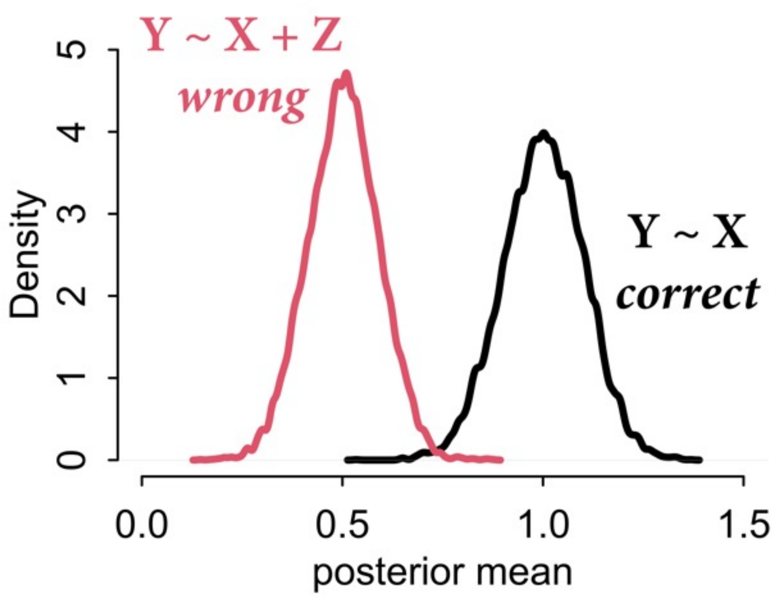
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

“Case-control bias”

```
f <- function(n=100,bXY=1,bYZ=1) {
    X <- rnorm(n)
    Y <- rnorm(n, bXY*X )
    Z <- rnorm(n, bYZ*Y )
    bX <- coef( lm(Y ~ X) )['X']
    bXZ <- coef( lm(Y ~ X + Z) )['X']
    return( c(bX,bXZ) )
}

sim <- mcreplicate( 1e4 , f() , mc.cores=8 )

dens( sim[1,] , lwd=3 , xlab="posterior mean" )
dens( sim[2,] , lwd=3 , col=2 , add=TRUE )
```

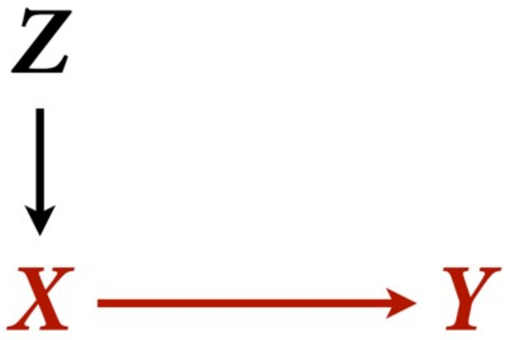


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

“Precision parasite”

No backdoors

But still not good to condition on *Z*



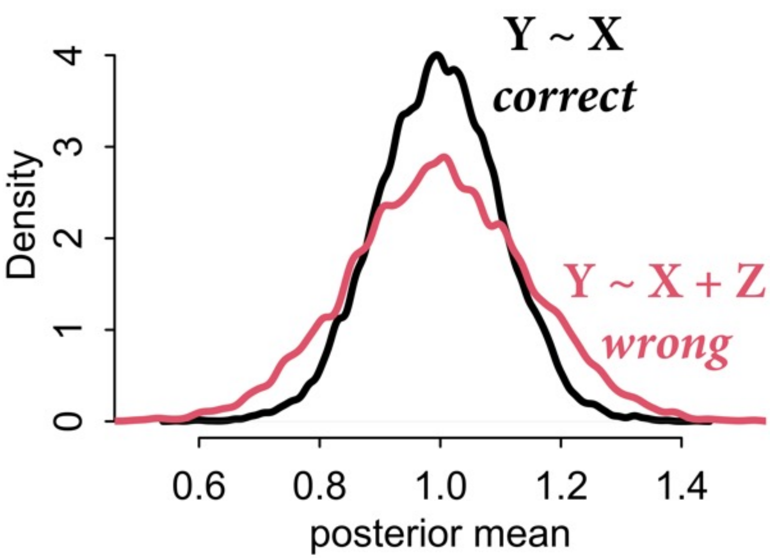
“Precision parasite”

$$Z \longrightarrow X \longrightarrow Y$$

```r
f <- function(n=100,bZX=1,bXY=1) {
    Z <- rnorm(n)
    X <- rnorm(n, bZX*Z )
    Y <- rnorm(n, bXY*X )
    bX <- coef( lm(Y ~ X) )['X']
    bXZ <- coef( lm(Y ~ X + Z) )['X']
    return( c(bX,bXZ) )
}

sim <- mcreplicate( 1e4 , f(n=50) , mc.cores=8 )

dens( sim[1,] , lwd=3 , xlab="posterior mean" )
dens( sim[2,] , lwd=3 , col=2 , add=TRUE )
```

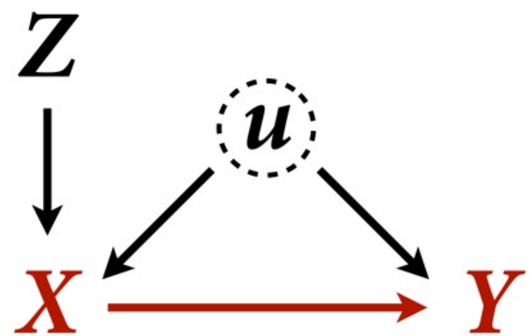


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

"Bias amplification"

X and ***Y*** confounded by ***u***

Something **truly awful** happens when we add ***Z***

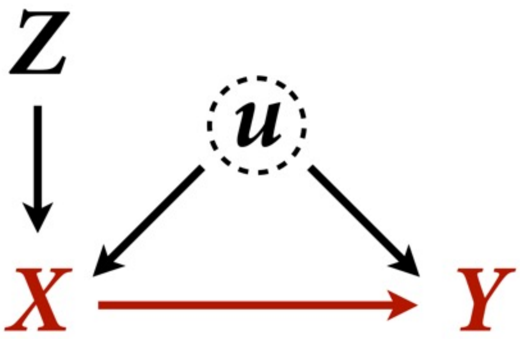


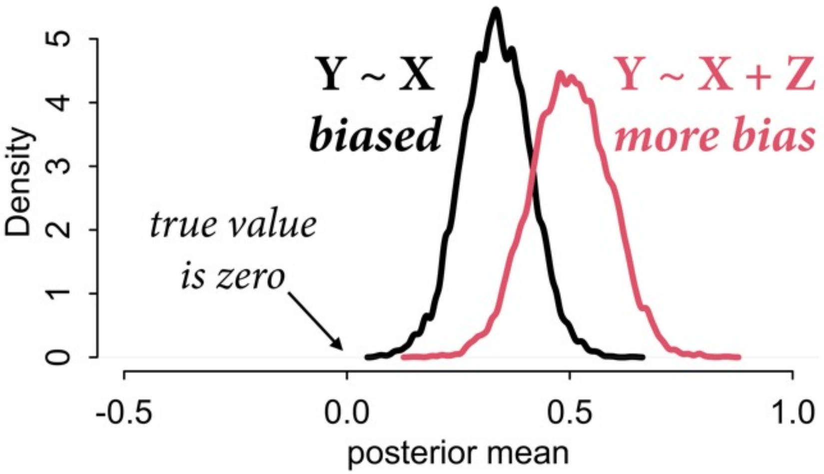
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

```r
f <- function(n=100,bZX=1,bXY=1) {
    Z <- rnorm(n)
    u <- rnorm(n)
    X <- rnorm(n, bZX*Z + u )
    Y <- rnorm(n, bXY*X + u )
    bX <- coef( lm(Y ~ X) )['X']
    bXZ <- coef( lm(Y ~ X + Z) )['X']
    return( c(bX,bXZ) )
}

sim <- mcreplicate( 1e4 , f(bXY=0) , mc.cores=8 )

dens( sim[1,] , lwd=3 , xlab="posterior mean" )
dens( sim[2,] , lwd=3 , col=2 , add=TRUE )
```





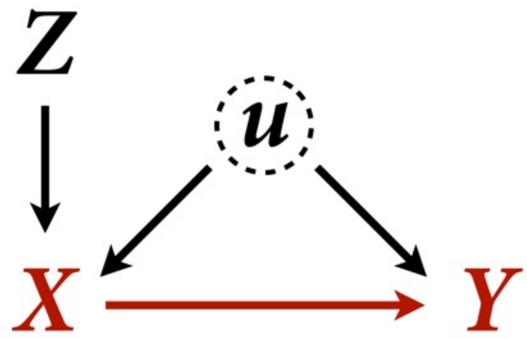
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

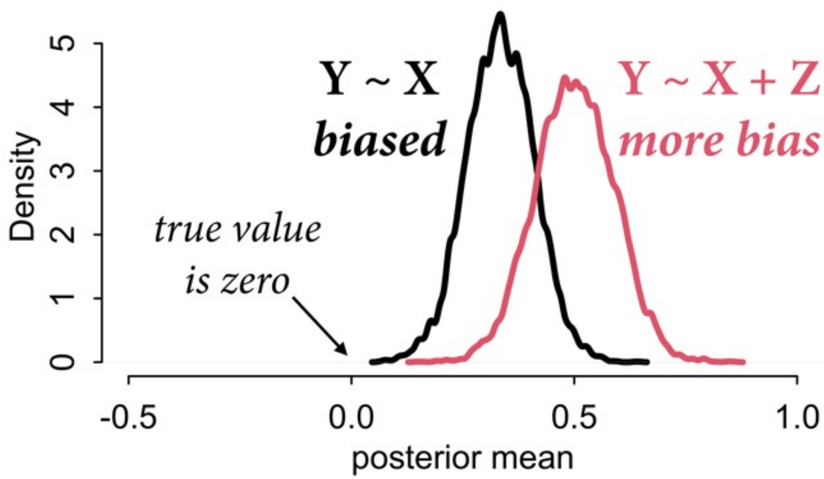
WHY?

Covariation ***X*** & ***Y*** requires variation in their causes

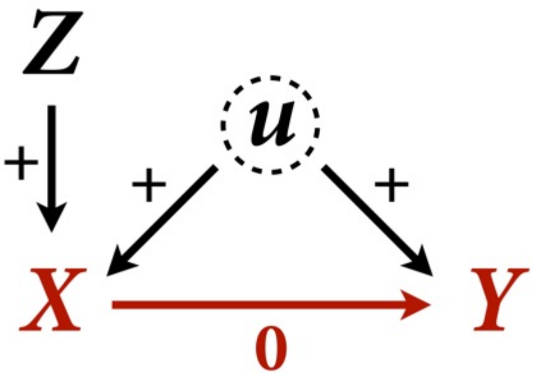
Within each level of ***Z***, less variation in ***X***

Confound ***u*** relatively more important within each ***Z***

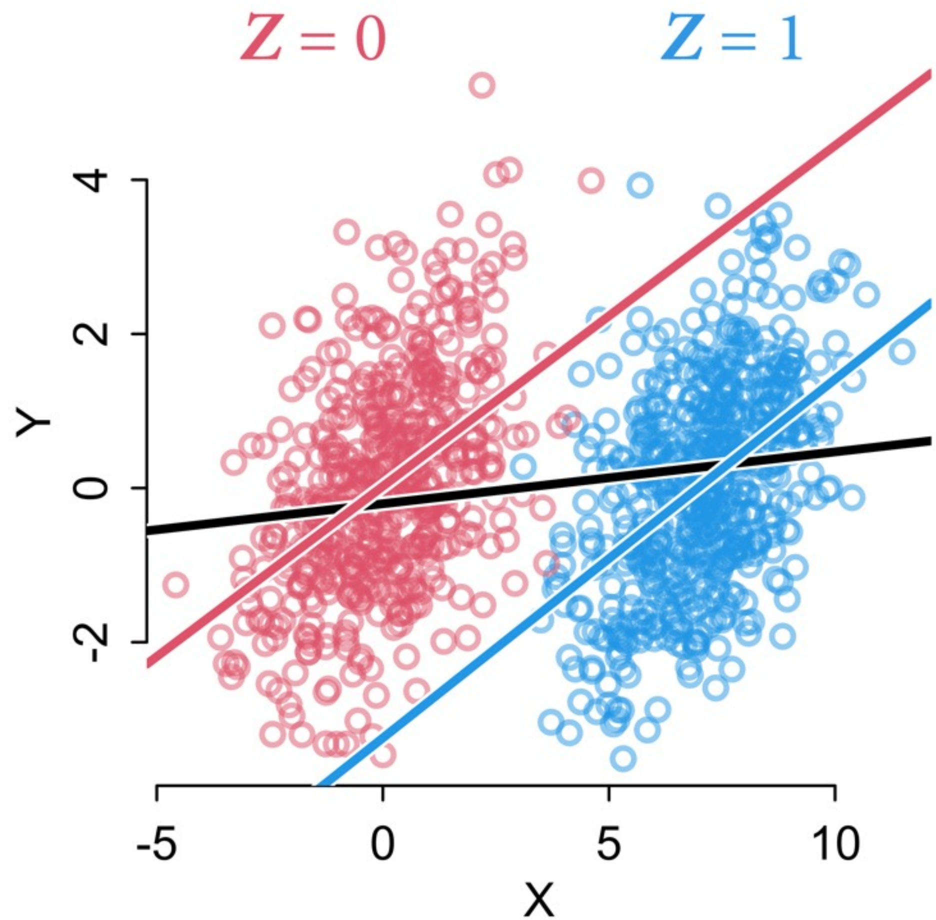




Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022




```
n <- 1000
Z <- rbern(n)
u <- rnorm(n)
X <- rnorm(n, 7*Z + u )
Y <- rnorm(n, 0*X + u )
```



Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022

Good & Bad Controls

"Control" variable: Variable introduced to an analysis so that a causal estimate is possible

Heuristics fail — adding control variables can be worse than omitting

Make assumptions explicit

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Table 2 Fallacy

Not all coefficients are causal effects

Statistical model designed to identify ***X*** –> ***Y*** will not also identify effects of control variables

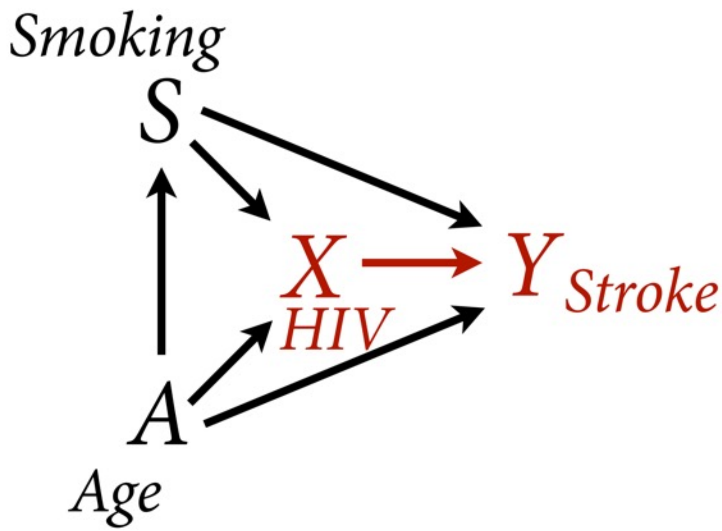
Table 2 is dangerous

TABLE 2—ESTIMATED PROBIT MODELS FOR THE USE OF A SCREEN

	Preliminaries blind		Finals blind
	(1)	(2)	(3)
(Proportion female)$_{t-1}$	2.744	3.120	0.490
	(3.265)	(3.271)	(1.163)
	[0.006]	[0.004]	[0.011]
(Proportion of orchestra personnel with <6 years tenure)$_{t-1}$	−26.46	−28.13	−9.467
	(7.314)	(8.459)	(2.787)
	[−0.058]	[−0.039]	[−0.207]
"Big Five" orchestra		0.367	
		(0.452)	
		[0.001]	
pseudo R^2	0.178	0.193	0.050
Number of observations	294	294	434

Westreich & Greenland 2013 The Table 2 Fallacy

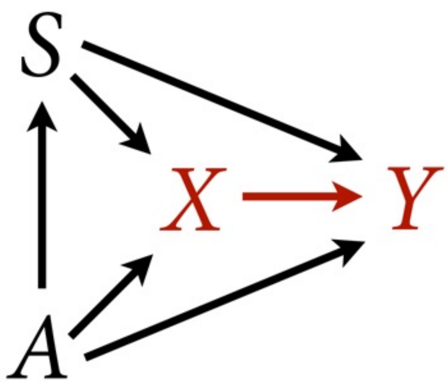
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



Westreich & Greenland 2013 The Table 2 Fallacy

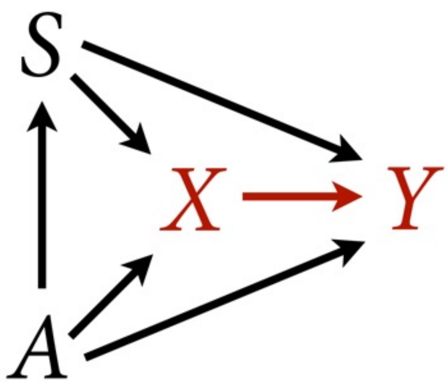
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Use Backdoor Criterion



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

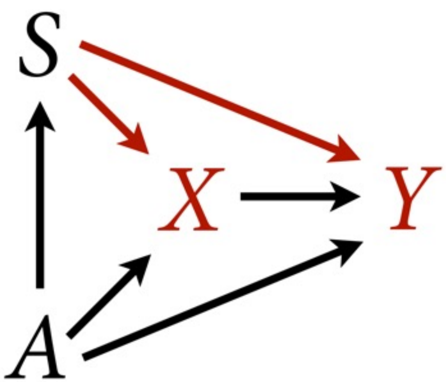
Use Backdoor Criterion

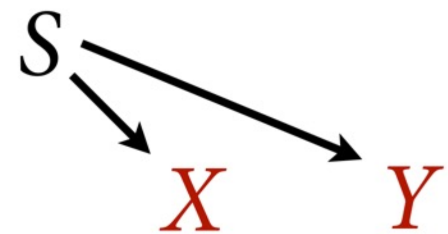


$X \longrightarrow Y$

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

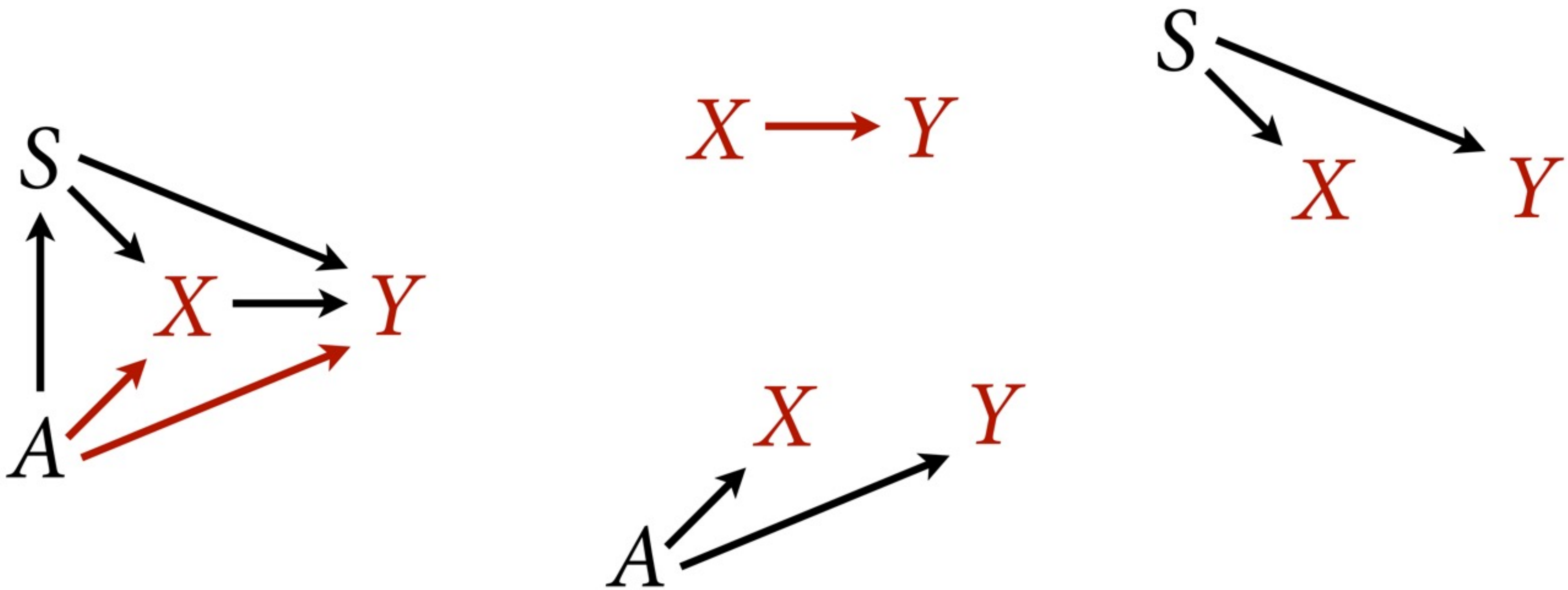
Use Backdoor Criterion





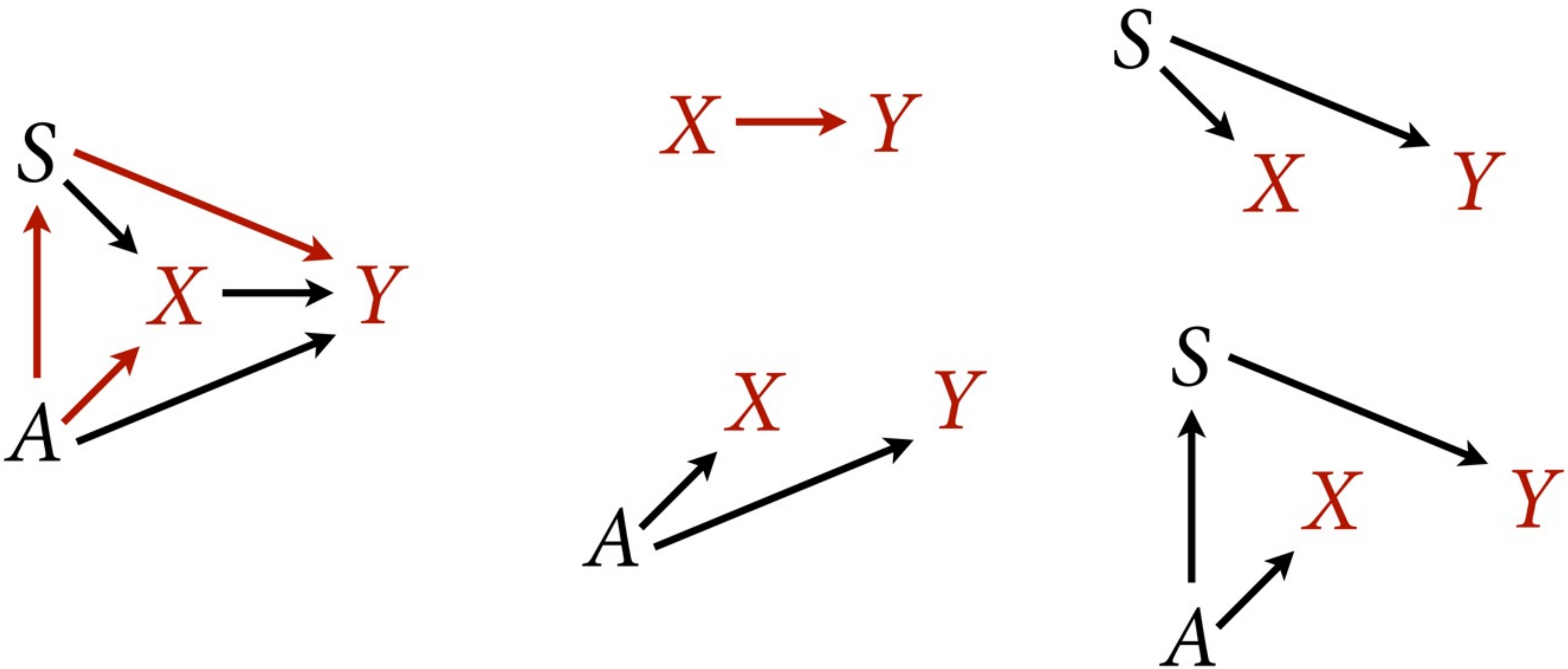
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Use Backdoor Criterion



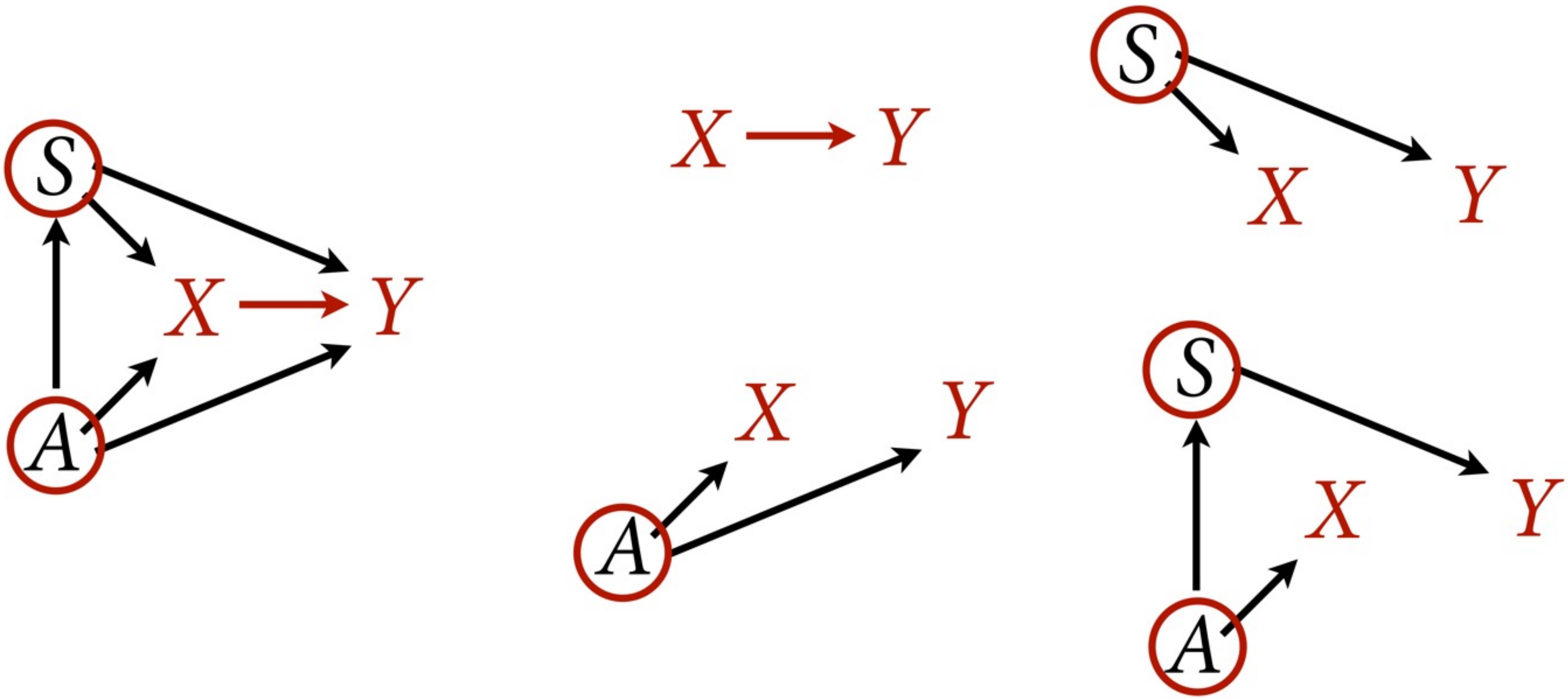
Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Use Backdoor Criterion

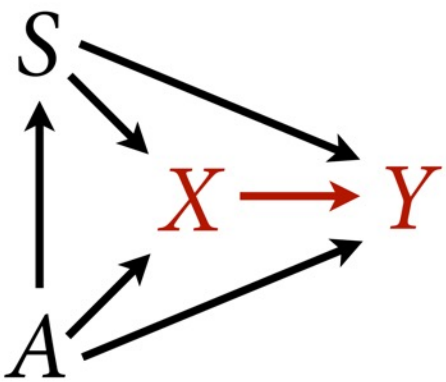


Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Use Backdoor Criterion



Source: Richard McElreath, https://github.com/rmcelreath/stat_rethinking_2022

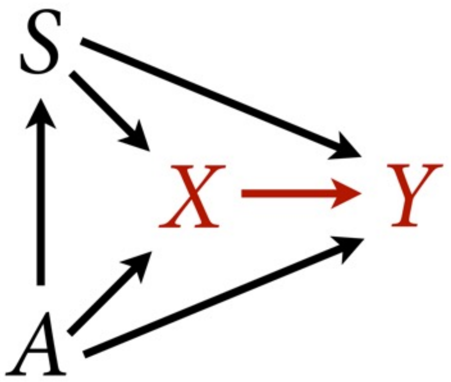


$$Y_i \sim \text{Normal}(\mu_i, \sigma)$$
$$\mu_i = \alpha + \beta_X X_i + \beta_S S_i + \beta_A A_i$$

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

X

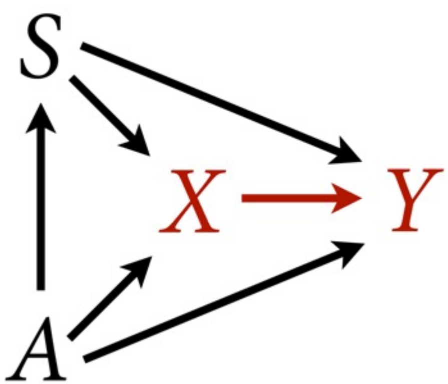
Unconditional



Confounded by A and S

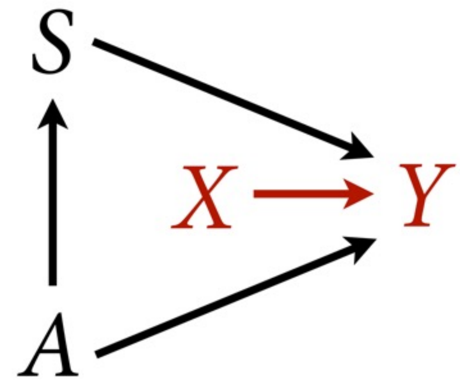
X

Unconditional



Confounded by *A* and *S*

Conditional on A and S

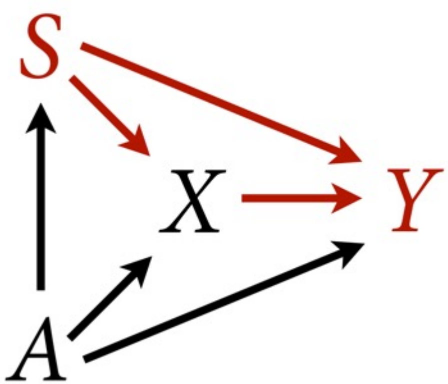


Coefficient for ***X***:
Effect of *X* on *Y*
(still must marginalize!)

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

S

Unconditional

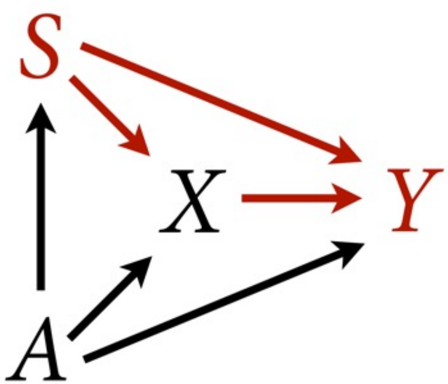


Effect of S
confounded by A

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

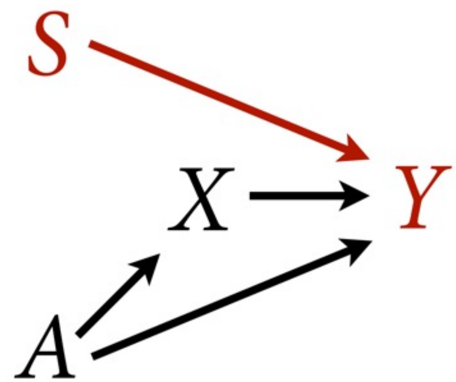
S

Unconditional



Effect of S
confounded by A

Conditional on A and X

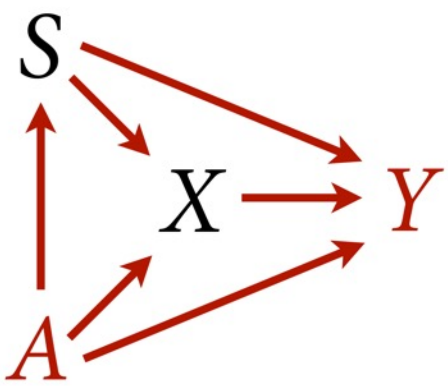


Coefficient for **S**:
Direct effect of S on Y

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

A

Unconditional

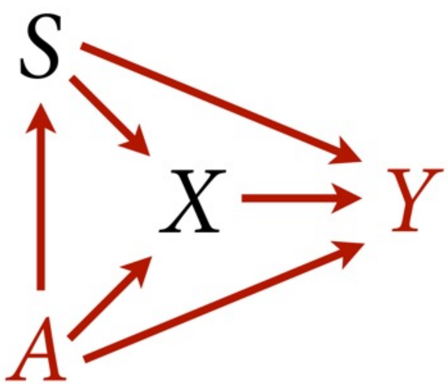


Total causal effect of *A* on *Y* flows through all paths

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

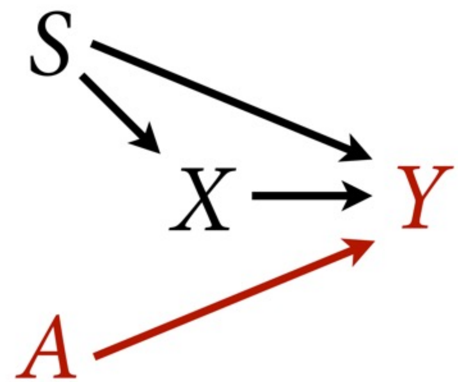
A

Unconditional



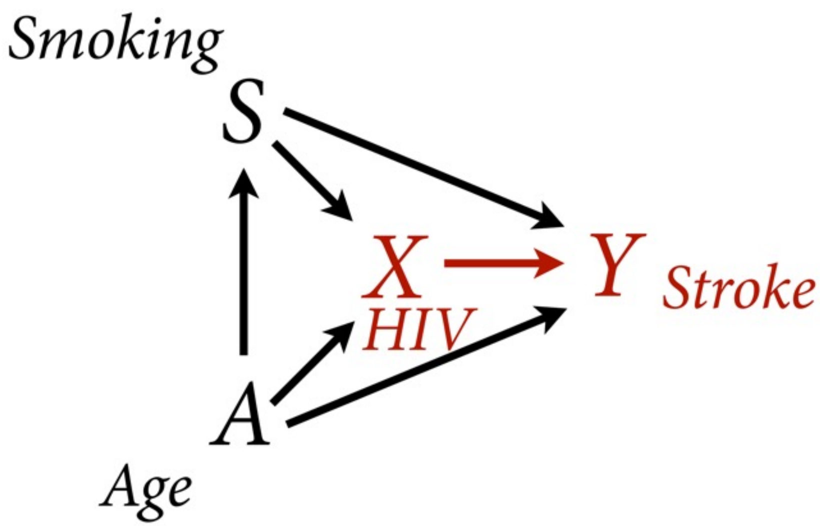
Total causal effect of *A* on *Y* flows through all paths

Conditional on X and S

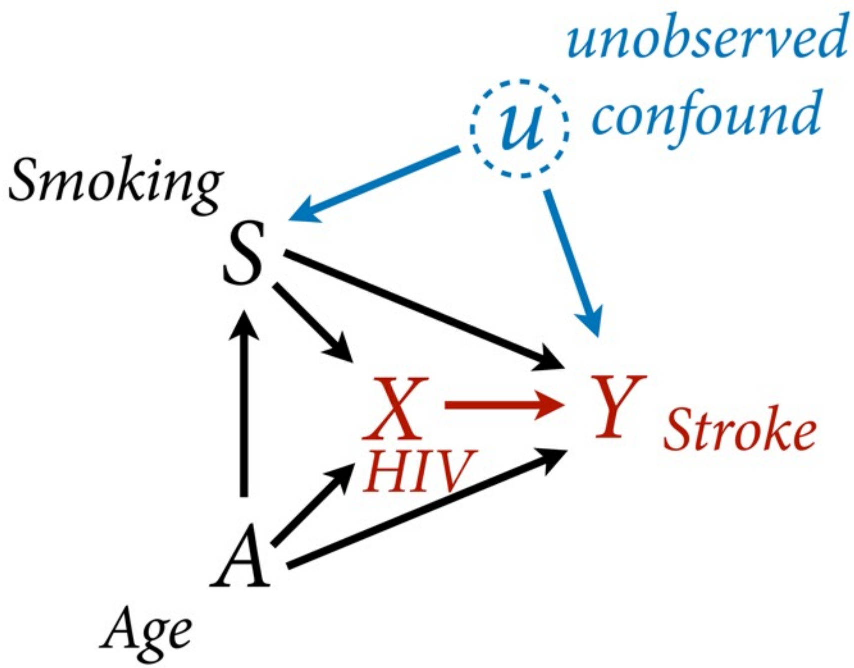


Coefficient for **A**:
Direct effect of *A* on *Y*

Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Table 2 Fallacy

Not all coefficients created equal

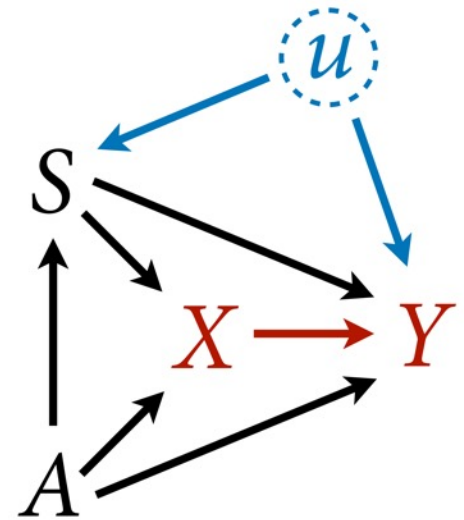
So do not present them as equal

Options:

Do not present control coefficients

Give explicit interpretation of each

No causal model, no interpretation



Source: Richard McElraeth, https://github.com/rmcelreath/stat_rethinking_2022

Imagine Confounding

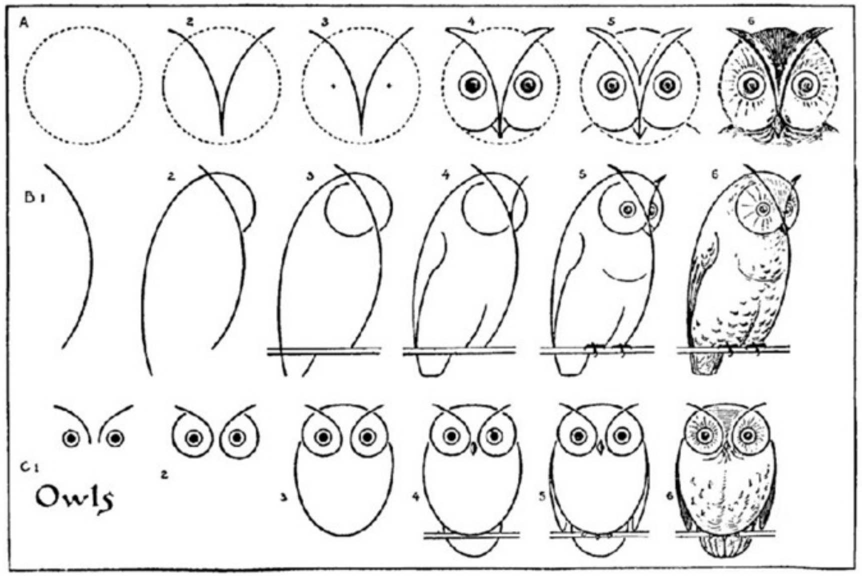
Often we cannot credibly adjust for all confounding

Do not give up!

Biased estimate can be better than no estimate

Sensitivity analysis: draw the implications of what you don't know

Find natural experiment or design one



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