Statistical Rethinking
Winter 2019

Lecture 06 / Week 3

The Haunted DAG & The Causal Terror

Index variable

R code 5.36

```
d$sex <- ifelse( d$male==1 , 2 , 1 )
str( d$sex )
```

```
 num [1:544] 2 1 1 2 1 2 1 2 1 2 ...
```

$$h_i \sim \text{Normal}(\mu_i, \sigma)$$
$$\mu_i = \alpha_{\text{SEX}[i]}$$
$$\alpha_j \sim \text{Normal}(178, 20) \quad , \text{for } j = 1..2$$
$$\sigma \sim \text{Uniform}(0, 50)$$

Index variable

```
m5.8 <- quap(
    alist(
        height ~ dnorm( mu , sigma ) ,
        mu <- a[sex] ,
        a[sex] ~ dnorm( 178 , 20 ) ,
        sigma ~ dunif( 0 , 50 )
    ) , data=d )
precis( m5.8 , depth=2 )
```

R code 5.37

```
        mean   sd   5.5%  94.5%
a[1]  134.91 1.61 132.34 137.48
a[2]  142.58 1.70 139.86 145.29
sigma  27.31 0.83  25.98  28.63
```

Differences

```
post <- extract.samples(m5.8)
post$diff_fm <- post$a[,1] - post$a[,2]
precis( post , depth=2 )
```

R code 5.38

```
quap posterior: 10000 samples from m5.8
          mean   sd   5.5%  94.5%     histogram
sigma    27.29 0.84  25.95  28.63 ▁▁▁▂▅▅▅▃▂▁▁▁
a[1]    134.91 1.59 132.37 137.42 ▁▁▂▅▅▅▃▁▁▁▁▁
a[2]    142.60 1.71 139.90 145.35     ▁▁▃▅▅▃▁▁
diff_fm  -7.70 2.33 -11.41  -3.97   ▁▁▁▂▅▅▃▁▁▁
```

Female hurricanes are deadlier than male hurricanes

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Edited* by Susan T. Fiske, Princeton University, Princeton, NJ, and approved May 14, 2014 (received for review February 13, 2014)

Do people judge hurricane risks in the context of gender-based expectations? We use more than six decades of death rates from US hurricanes to show that feminine-named hurricanes cause significantly more deaths than do masculine-named hurricanes. Laboratory experiments indicate that this is because hurricane names lead to gender-based expectations about severity and this, in turn, guides respondents' preparedness to take protective action. This finding indicates an unfortunate and unintended consequence of the gendered naming of hurricanes, with important implications for policymakers, media practitioners, and the general public concerning hurricane communication and preparedness.

gender stereotypes | implicit bias | risk perception | natural hazard communication | bounded rationality

violence and destruction (23, 24). We extend these findings to hypothesize that the anticipated severity of a hurricane with a masculine name (Victor) will be greater than that of a hurricane with a feminine name (Victoria). This expectation, in turn, will affect the protective actions that people take. As a result, a hurricane with a feminine vs. masculine name will lead to less protective action and more fatalities.

Archival Study

To test this hypothesis, we used archival data on actual fatalities caused by hurricanes in the United States (1950–2012). Ninety-four Atlantic hurricanes made landfall in the United States during this period (25). Nine independent coders who were blind to the hypothesis rated the masculinity vs. femininity of historical hurricane names on two items (1 = very masculine, 11 = very

Female hurricanes are not deadlier than male hurricanes

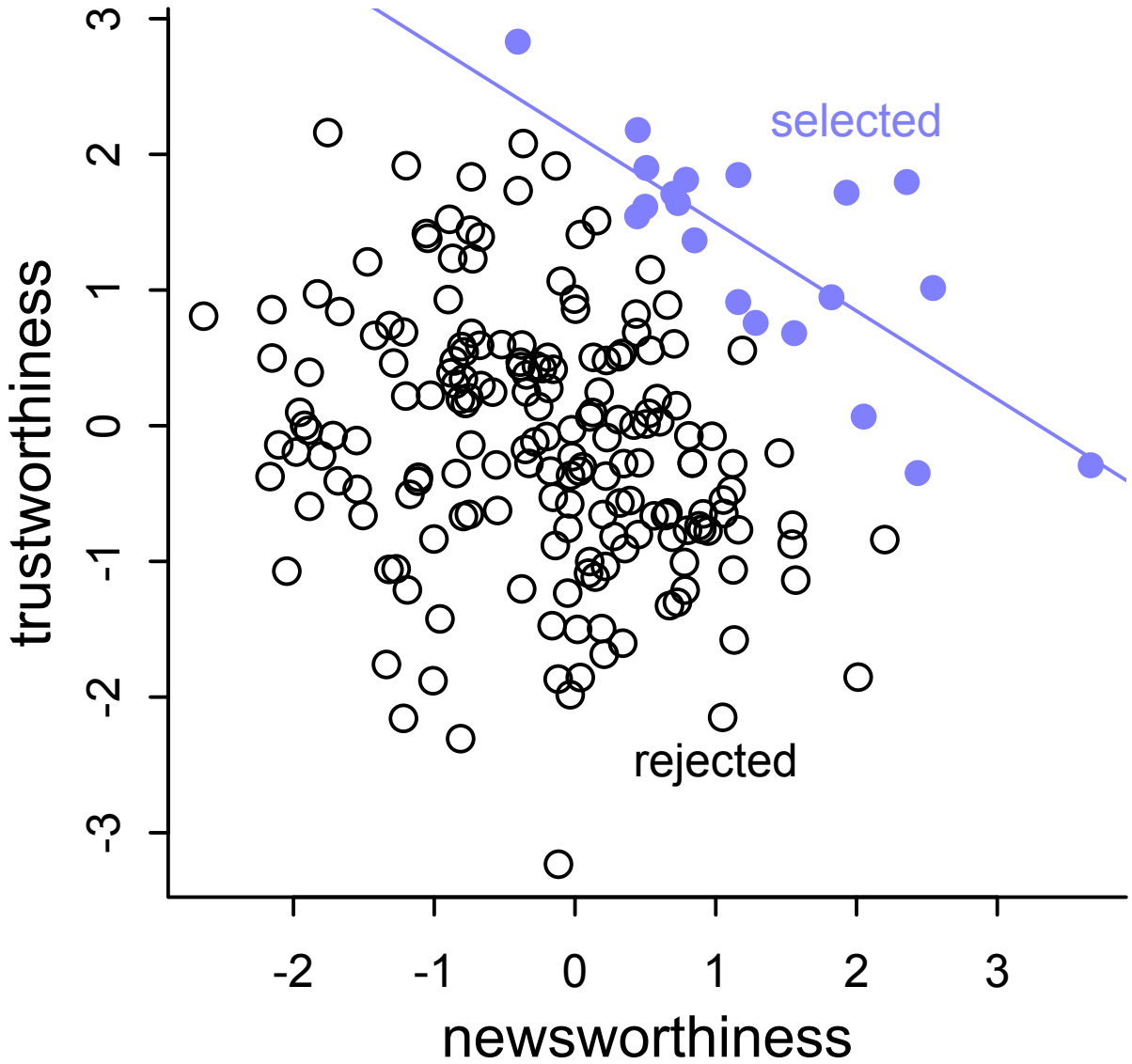
Jung et al. (1) assert that hurricanes that made landfall in the United States killed more people when they had female names rather than male names. The article has stirred much controversy. Criticisms range from the tolls had smaller death tolls when the hurricanes were strong (lower pressure), but higher death tolls when the hurricanes were weak (higher pressure). The latter result is driven by the pre-1978 sample (model 5). In safety infrastructures and more reflective of other characteristics for weaker storms and after 1978. Even though a lower importance of safety infrastructures during weaker storms and an overall improvement in or a con-

```
data(Hurricanes)
```

Why aren't surprising things true?

Dr Felisa Wolfe-Simon at Mono Lake

Selection-distortion effect



Regression as a wicked oracle

- Regression automatically focuses on the most informative cases
- Cases that don't help are automatically ignored
- But not kind — ask carefully

Why not just add everything?

- Could just add all available predictors to model
  - "We controlled for..."

- Almost always a bad idea
  - Adding variables *creates* confounds
  - Residual confounding
  - Overfitting

Ye Olde Causal Alchemy

The Four Elemental Confounds

The Fork

$$X \leftarrow Z \rightarrow Y$$

The Pipe

$$X \rightarrow Z \rightarrow Y$$

The Collider

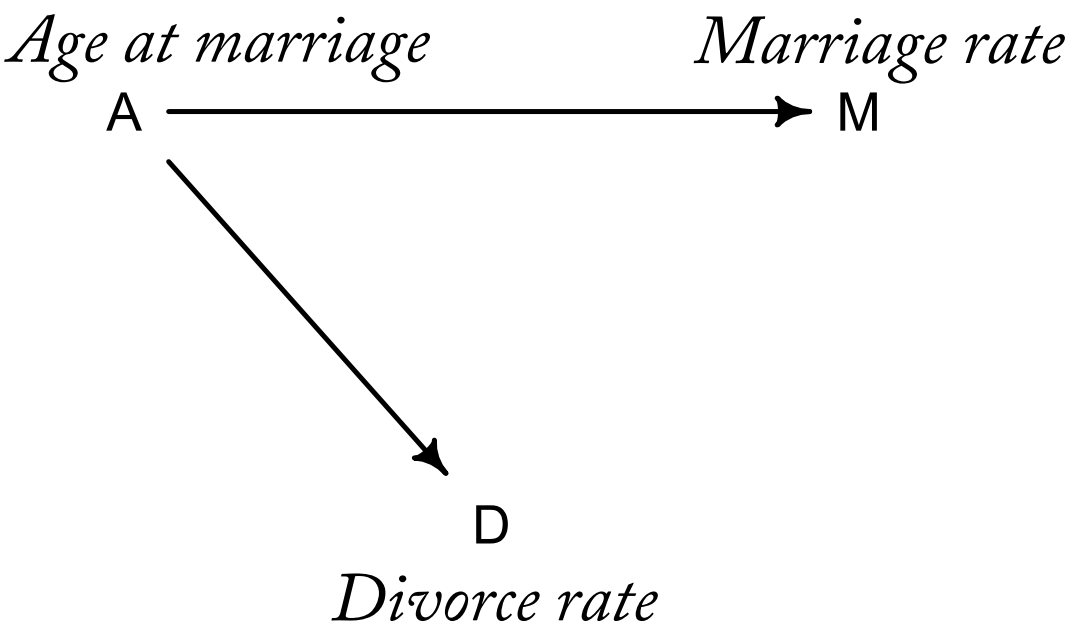
$$X \rightarrow Z \leftarrow Y$$

The Descendant

$$\begin{tikzcd} X \arrow[r] & Z \arrow[r] \arrow[d] & Y \\ & A & \end{tikzcd}$$

The Confounding Fork

$$X \leftarrow Z \rightarrow Y$$



Z is a common cause of X and Y

DE-confounding!

conditioning on Z removes dependency between X and Y

$$X \perp\!\!\!\perp Y \mid Z$$

The Perplexing Pipe

$X \rightarrow Z \rightarrow Y$

X causes Z causes Y

Z mediates association between X and Y

conditioning on Z removes dependency between X and Y:

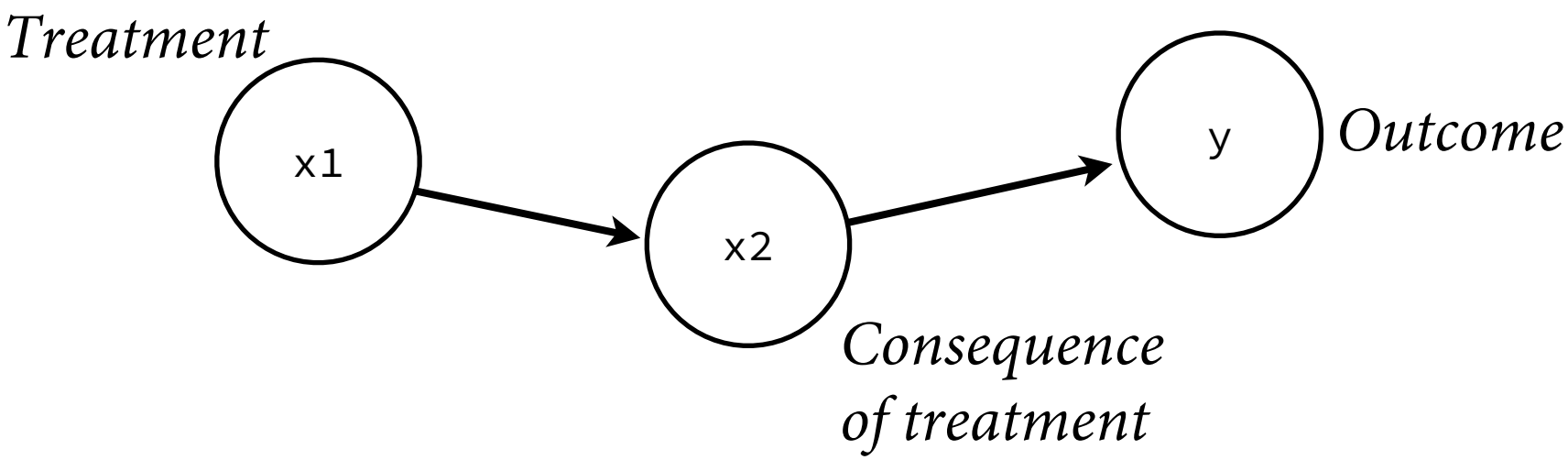
$X \perp\!\!\!\perp Y \mid Z$

data do not distinguish from fork!

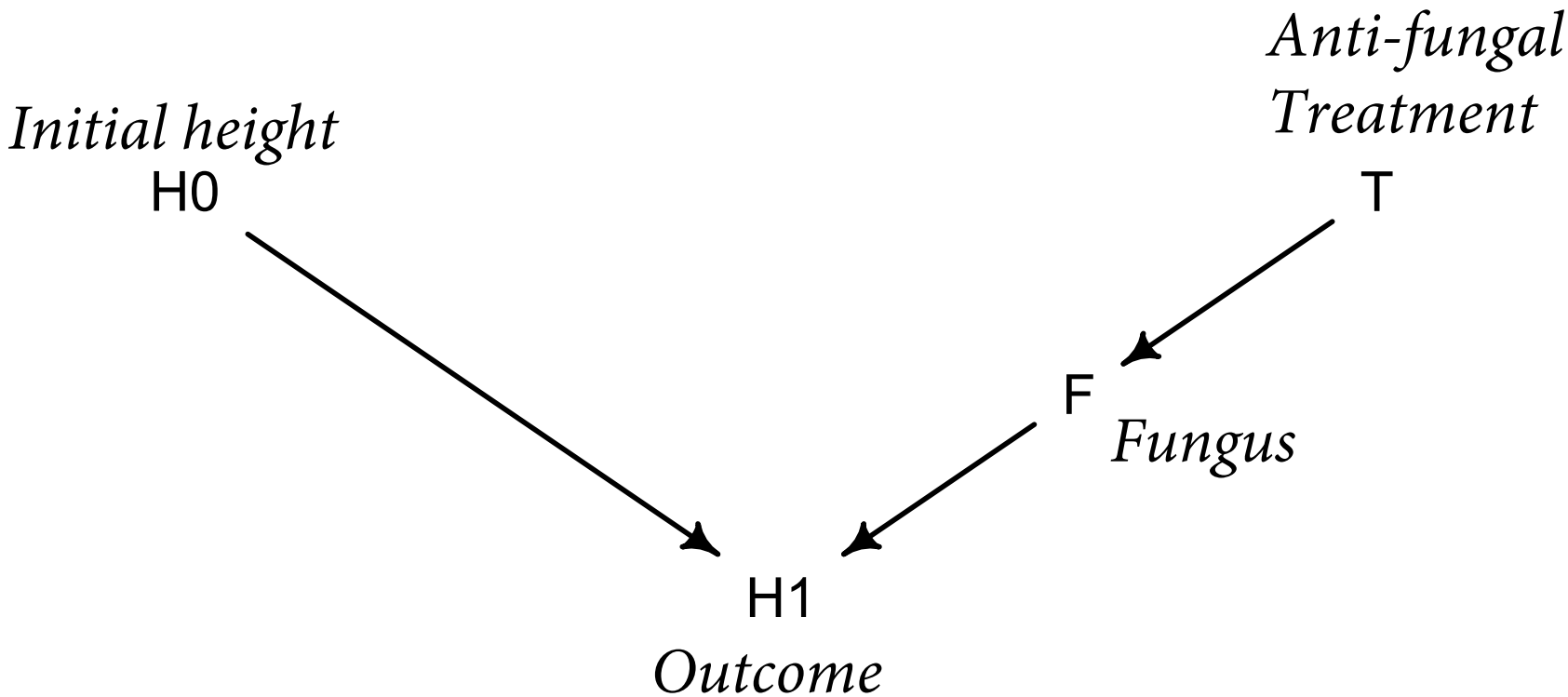
$X \perp\!\!\!\perp Y \mid Z$ in both

Post-treatment bias

- The pipe confounds when we ignore it
- *Post-treatment bias:* Controlling for consequence of treatment statistically knocks out treatment



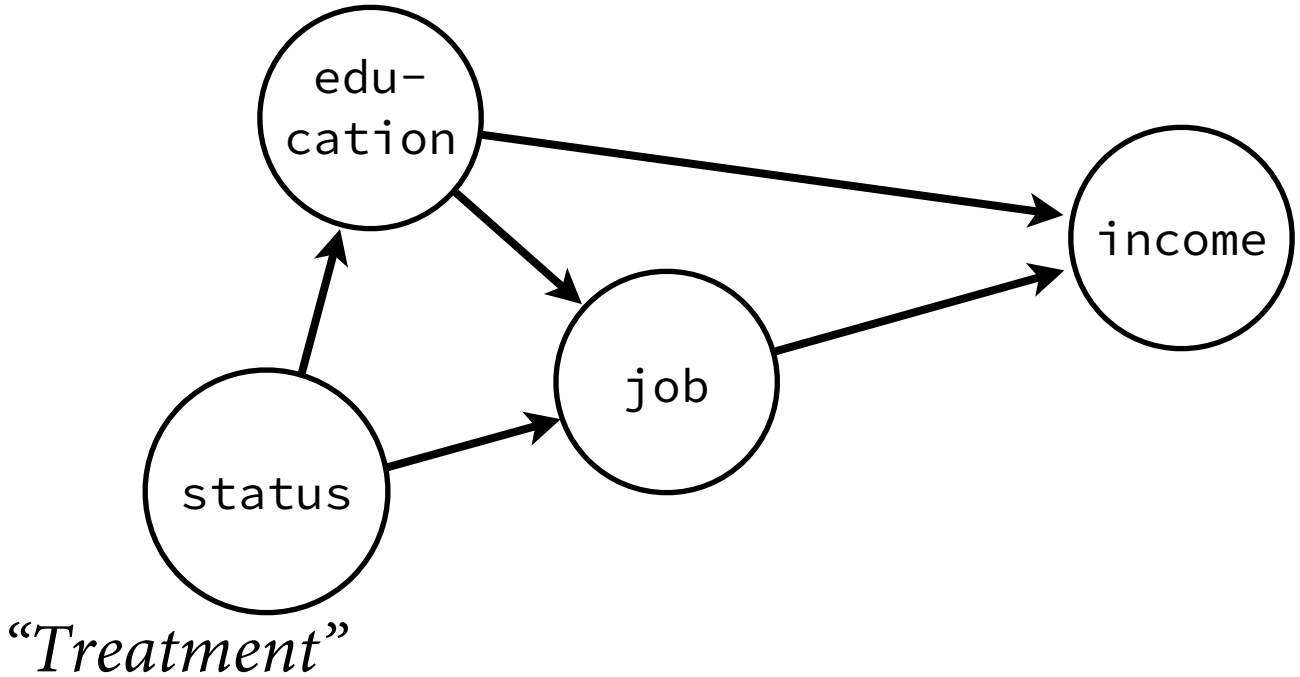
Post-treatment bias



Section 6.2

Post-treatment bias

Observational studies harder



Controlling for every available variable likely to block a pipe someplace.

The Explosive Collider

$$X \longrightarrow Z \longleftarrow Y$$

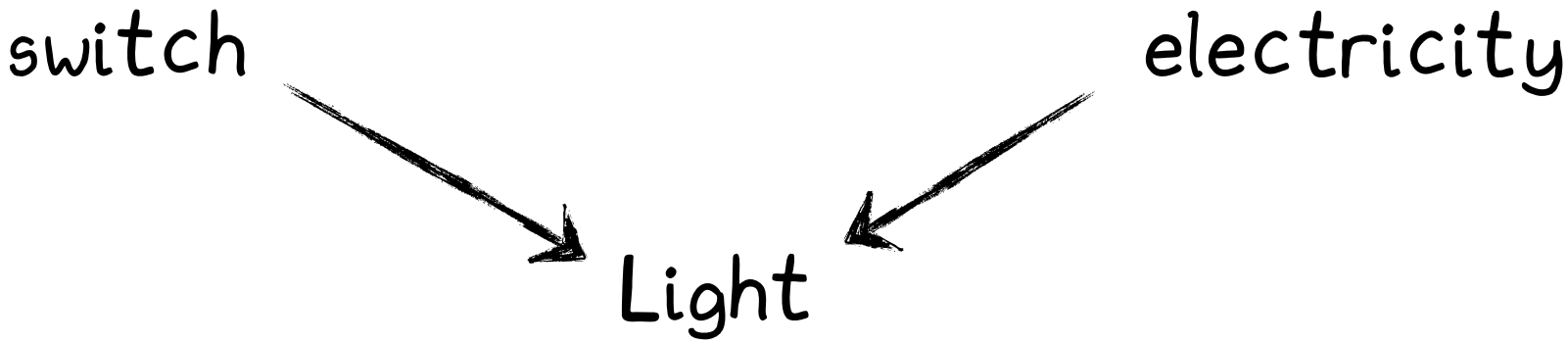
X and Y jointly cause Z

X and Y independent

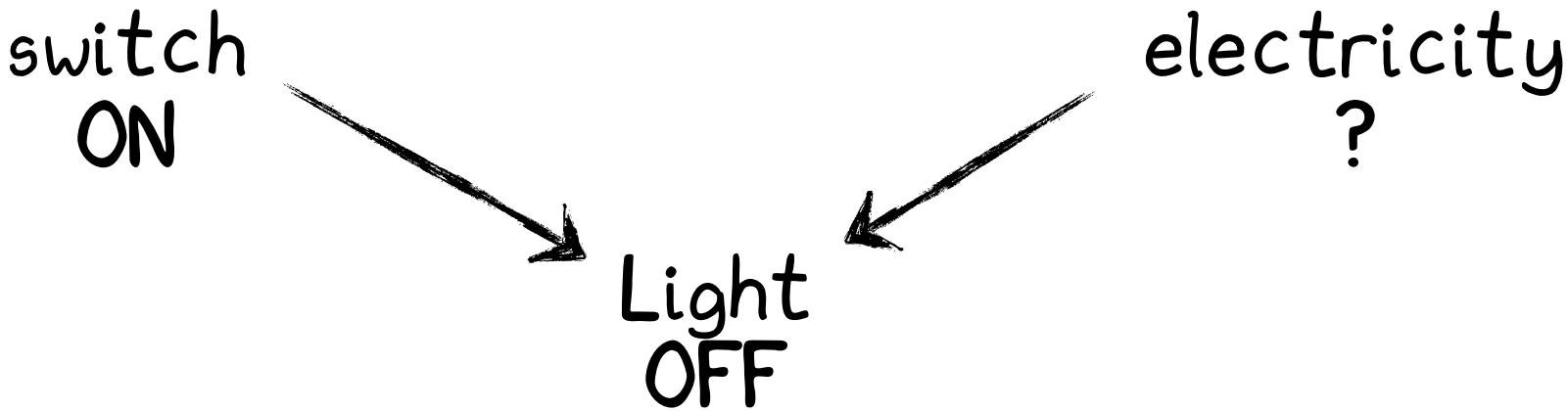
conditioning on Z
creates dependency
between X and Y

learning X and Z reveals Y

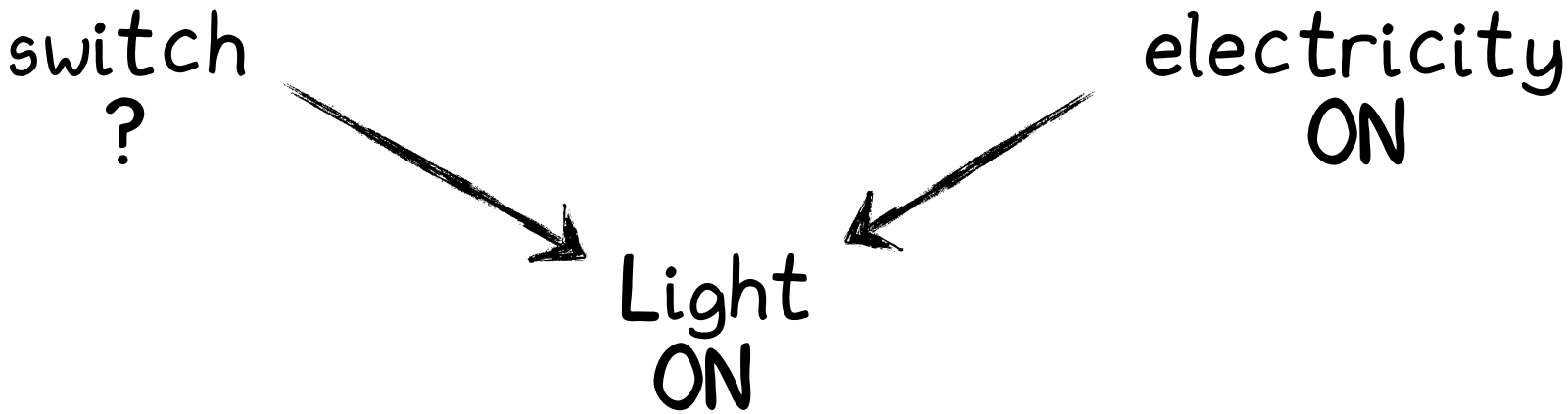
Conditioning on a Collider



Conditioning on a Collider



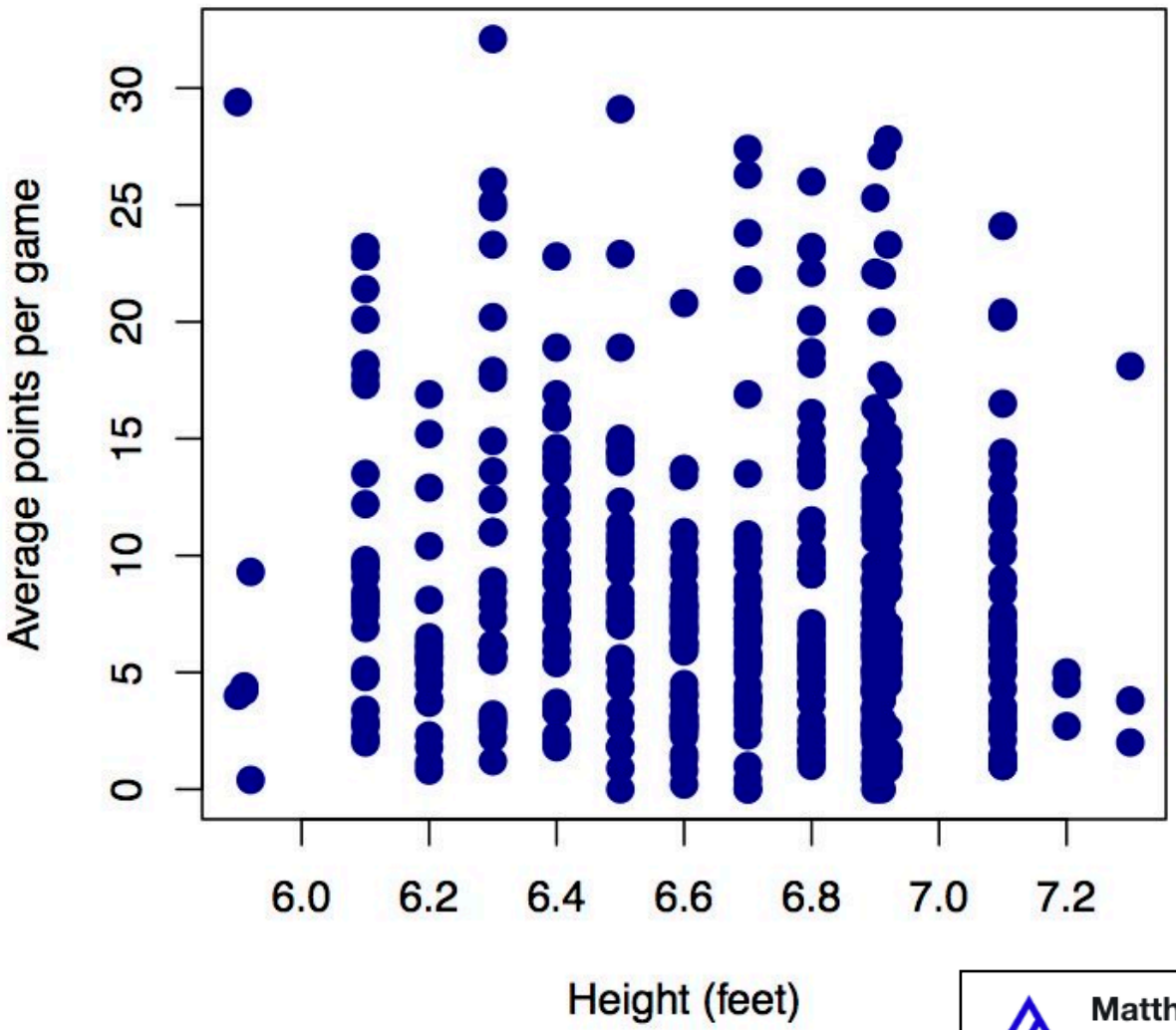
Conditioning on a Collider



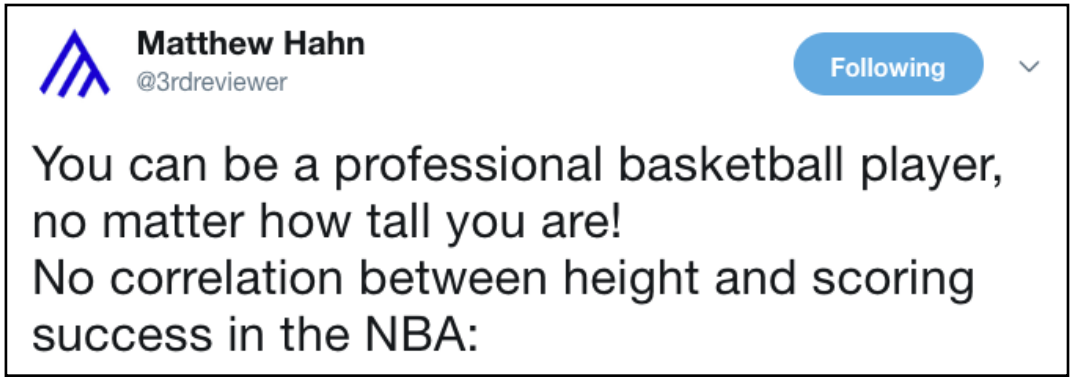
Conditioning on a Collider

Conditioning on a Collider

Are taller people better at basketball?



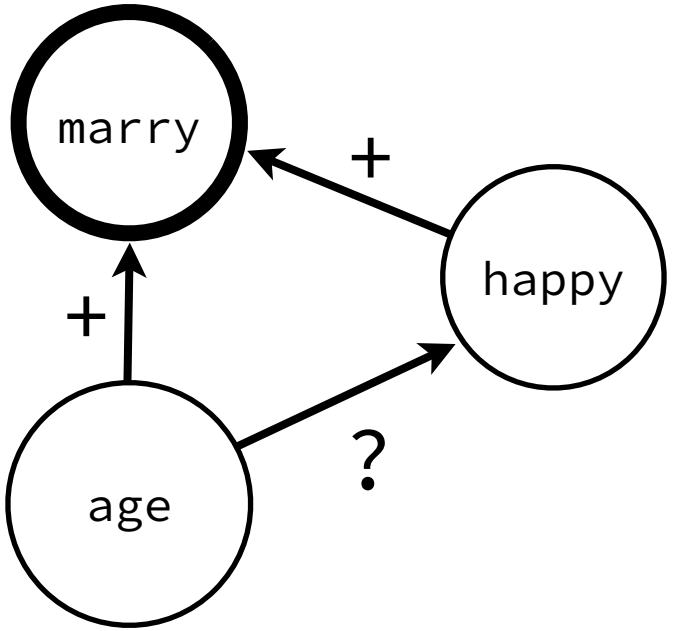
473 NBA players, 2016-2017 season



Collider confounding

Conditioning on collider is like selecting on sub-population.

Are older people less happy? Should we control for marriage status?



Collider simulation

- Assumptions:
  - 20 people born each year
  - Uniform happiness at birth, never changes
  - At 18 years old, eligible to marry. Probability of marriage in each year proportional to happiness.
  - Married people remain married until death.
  - At age 65, move to south coast of Spain.

R code 6.22

```
library(rethinking)
d <- sim_happiness( seed=1977 , N_years=1000 )
precis(d)
```

```
'data.frame': 1300 obs. of 3 variables:
          mean    sd  5.5% 94.5%     histogram
age       33.0 18.77  4.00 62.00 ▇▇▇▇▇▇▇▇▇▇▇▇
married    0.3  0.46  0.00  1.00    ▇_____▂
happiness  0.0  1.21 -1.79  1.79      ▅▅▅▅▅▅
```

Collider of sorrow

R code 6.24

```
d2$mid <- d2$married + 1
m6.9 <- quap(
    alist(
        happiness ~ dnorm( mu , sigma ),
        mu <- a[mid] + bA*A,
        a[mid] ~ dnorm( 0 , 1 ),
        bA ~ dnorm( 0 , 2 ),
        sigma ~ dexp(1)
    ) , data=d2 )
precis(m6.9,depth=2)
```

single

married

```
        mean   sd  5.5% 94.5%
a[1]   -0.23 0.06 -0.34 -0.13
a[2]    1.26 0.08  1.12  1.40
bA     -0.75 0.11 -0.93 -0.57
sigma   0.99 0.02  0.95  1.03
```

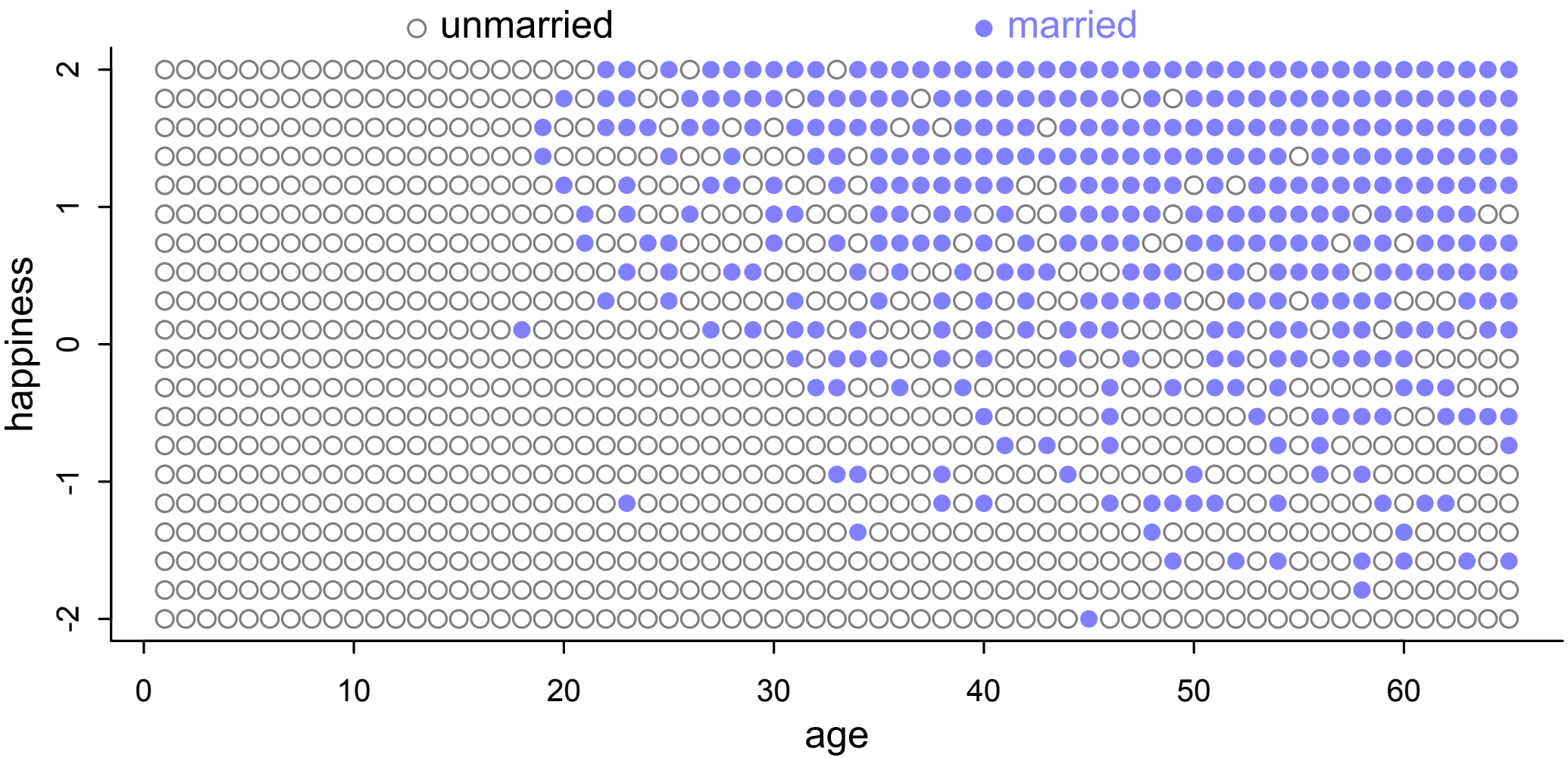


Figure 6.5

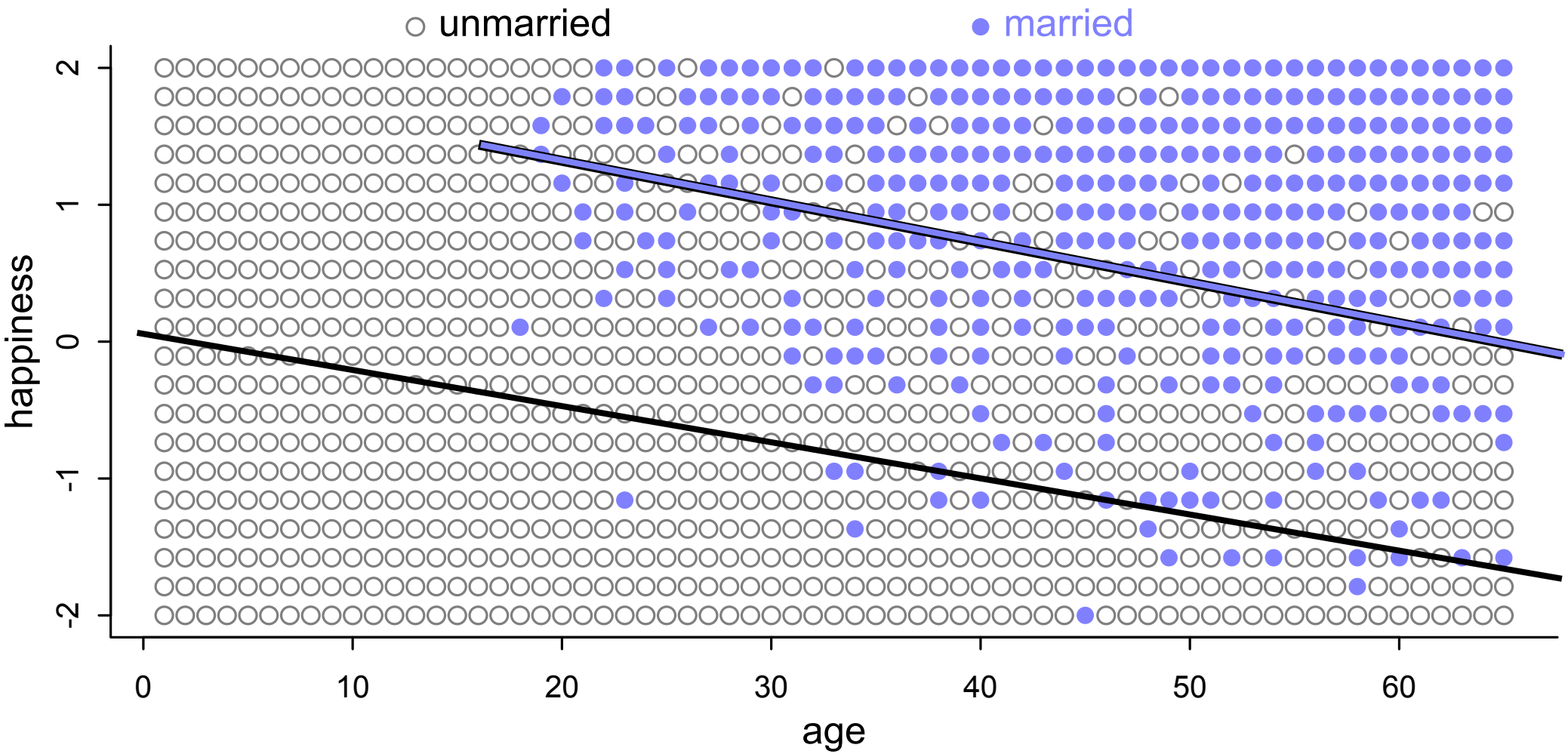
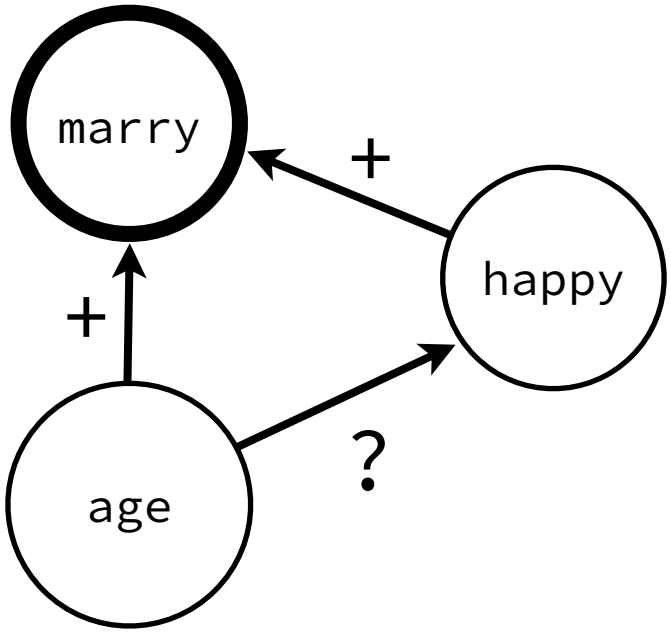


Figure 6.5

Collider confounding

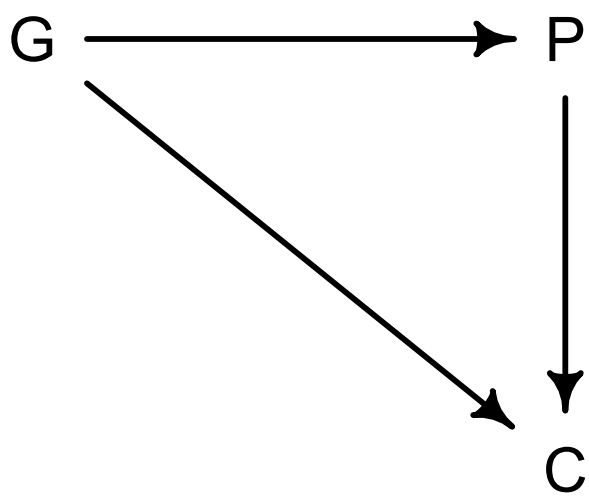
Are older people less happy? Controlling for marriage status creates a confound.

Cannot know whether to control for some variable, without a causal model.



The Haunted DAG

- Unmeasured variables can also create colliders
- Example: Influence of grandparents (G) and parents (P) on education of children (C)



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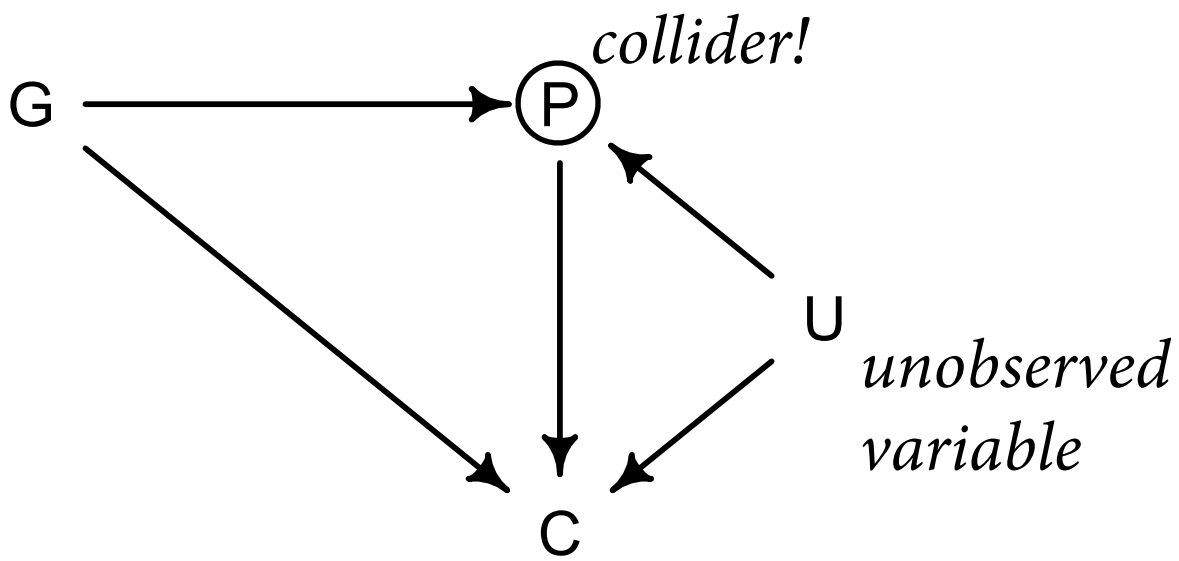


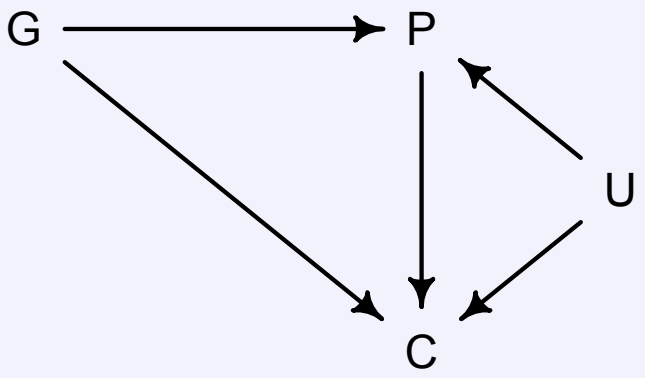
Simulated haunting

R code 6.26

```
N <- 200  # number of 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
```

R code 6.27

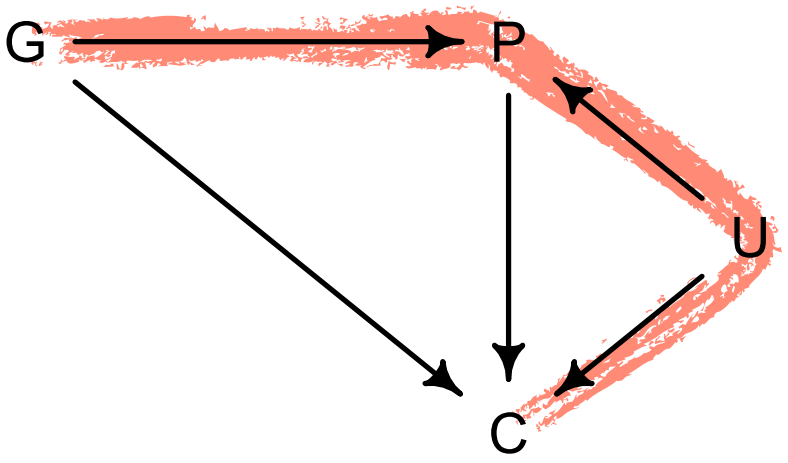
```
set.seed(1)
U <- 2*rbern( N , 0.5 ) - 1
G <- rnorm( N )
P <- rnorm( N , b_GP*G + b_U*U )
C <- rnorm( N , b_PC*P + b_GC*G + b_U*U )
d <- data.frame( C=C , P=P , G=G , U=U )
```



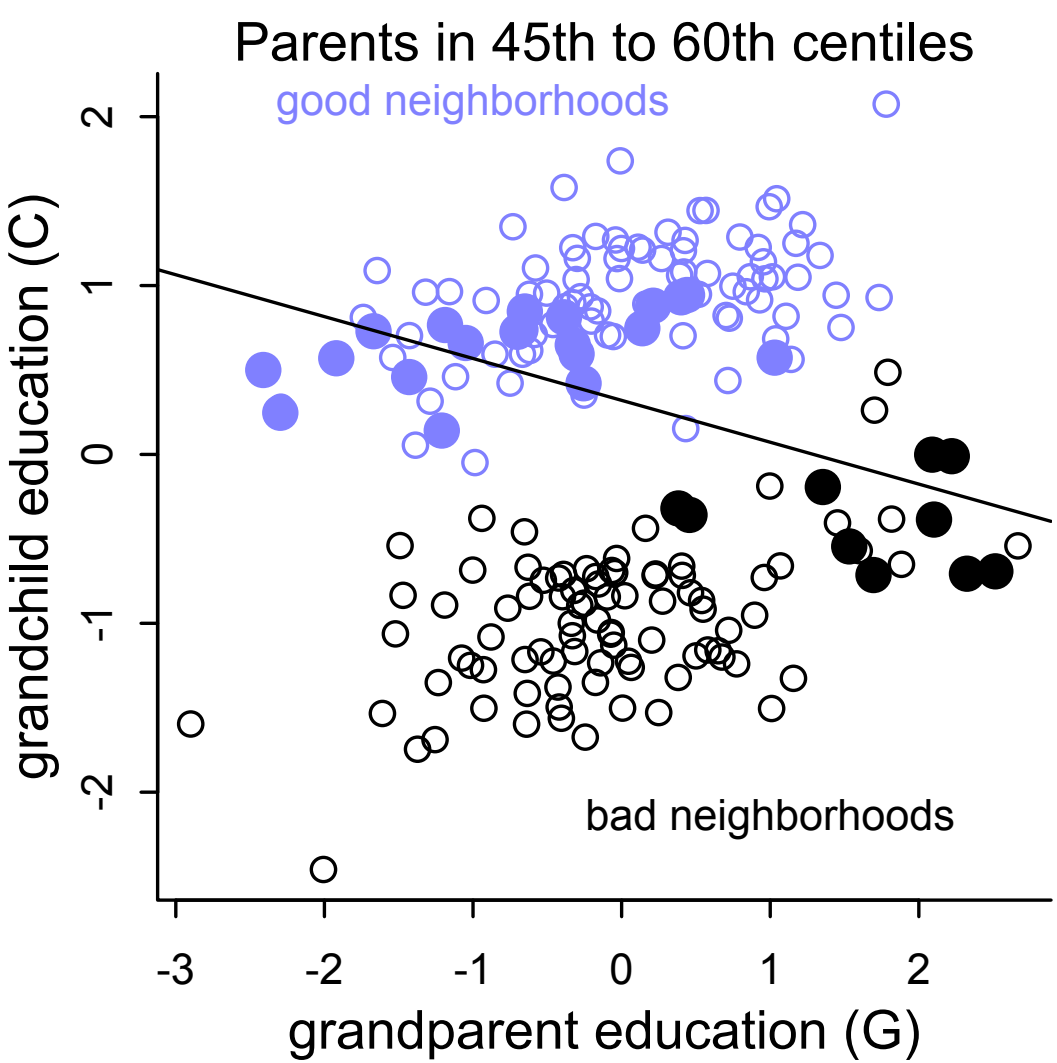
Simulated haunting

- Conditioning on parents distorts inference about grandparents
- Reason: Opens a "backdoor" through U to C

```
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 )
precis(m6.11)
```




```
       mean   sd  5.5% 94.5%
a     -0.12 0.10 -0.28  0.04
b_PC   1.79 0.04  1.72  1.86
b_GC  -0.84 0.11 -1.01 -0.67
sigma  1.41 0.07  1.30  1.52
```



Consider those P in 45-60th centile of education.

P in good neighborhoods must have had *less* educated G.

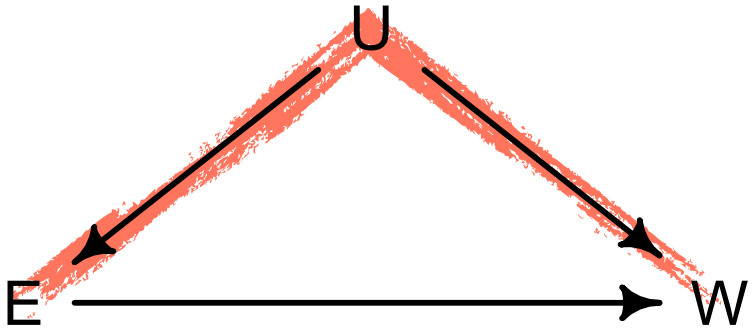
P in bad neighborhoods must have had *more* educated G.

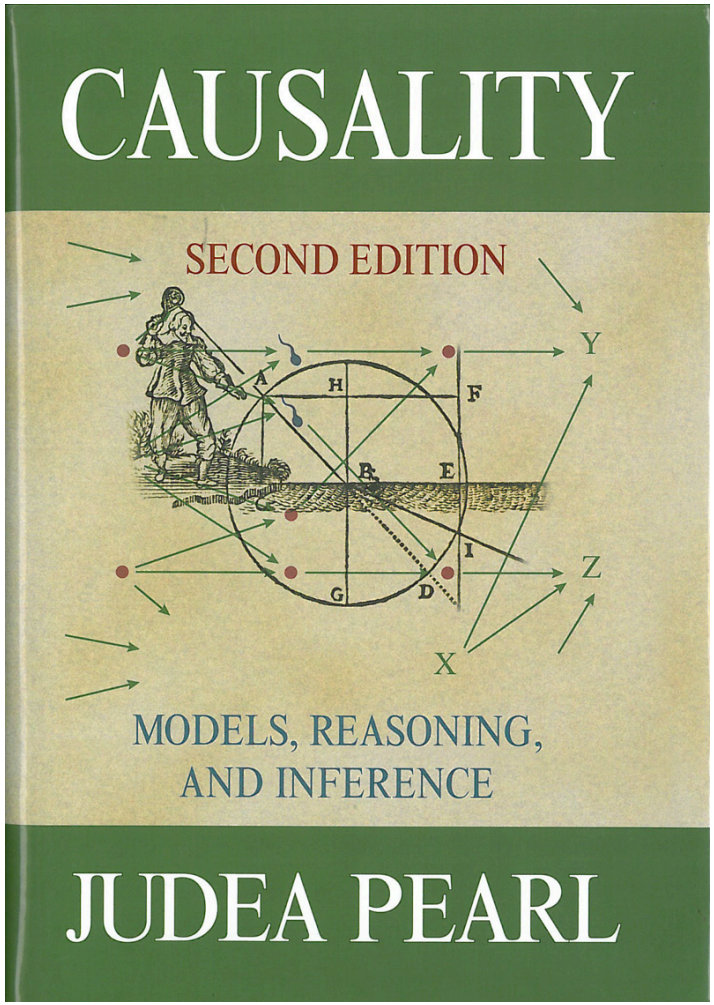
Otherwise they wouldn't all be in same quantile.

Figure 6.6

Shutting the back door

- What ties these examples together:
- The **back-door criterion**: Confounding caused by existence of open back door paths from X to Y
- If you know your elements, you know how to open/close each of them





Ye Olde Causal Alchemy

The Four Elemental Confounds

The Fork

$$X \leftarrow Z \rightarrow Y$$

The Pipe

$$X \rightarrow Z \rightarrow Y$$

The Collider

$$X \rightarrow Z \leftarrow Y$$

The Descendant

$$\begin{tikzcd} X \arrow[r] & Z \arrow[r] \arrow[d] & Y \\ & A & \end{tikzcd}$$

The Fork

$$X \leftarrow Z \rightarrow Y$$

Open unless you condition on Z

The Pipe

$$X \rightarrow Z \rightarrow Y$$

Open unless you condition on Z

The Collider

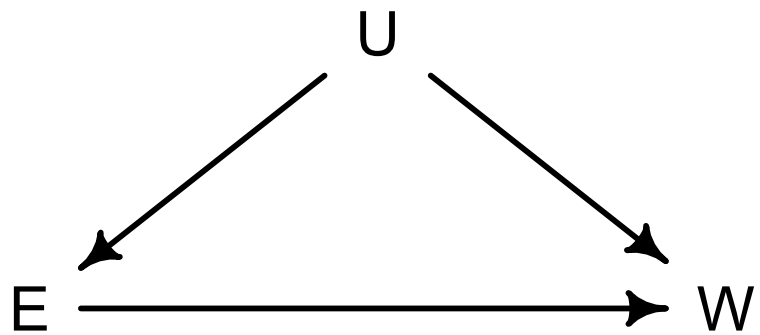
$$X \rightarrow Z \leftarrow Y$$

Closed until you condition on Z

The Descendant

$$\begin{tikzcd} X \arrow[r] & Z \arrow[r] \arrow[d] & Y \\ & A & \end{tikzcd}$$

Conditioning on A is like conditioning on Z



Two paths from E to W:

(1) E → W

(2) E ← U → W

Close 2nd path by conditioning on U, closing the pipe.

$$\begin{tikzcd}
G \arrow[r] \arrow[dr] & P \arrow[d] & \\
& C & U \arrow[l] \arrow[ul] \arrow[u]
\end{tikzcd}$$

3 paths from G to C:

(1) G → C

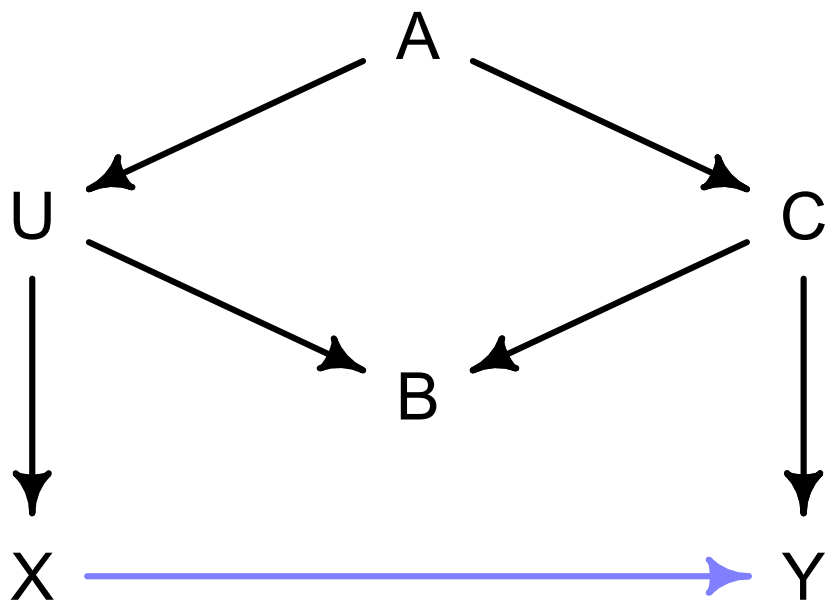
(2) G → P → C

(3) G → P ← U → C

Condition on P:
Closes (2) but opens (3)

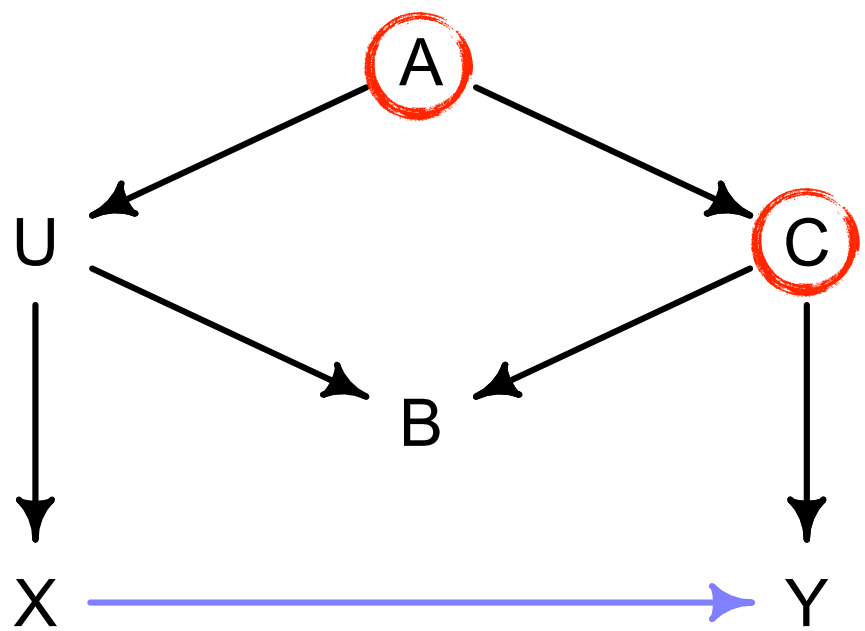
Something more interesting

- Which variables, if any, should you condition on to infer X → Y?
- Procedure: (1) Find all paths. (2) Open/close as necessary.



Something more interesting

- Which variables, if any, should you condition on to infer X → Y?
- Condition on A or C. Do not condition on B.



(1) $X \leftarrow U \leftarrow A \rightarrow C \rightarrow Y$

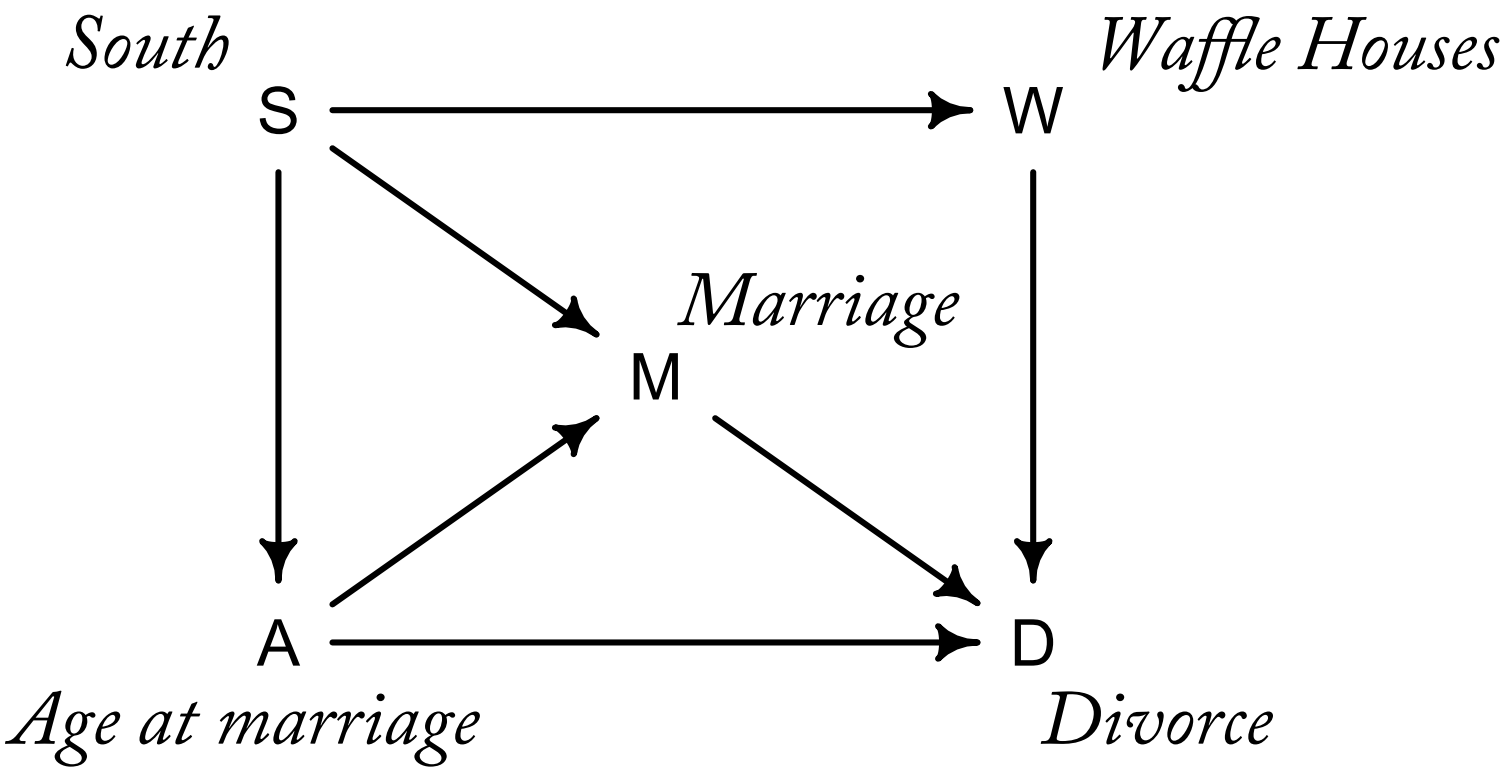
This path is open.

(2) $X \leftarrow U \rightarrow B \leftarrow C \rightarrow Y$

This path is closed.

Waffles Requiem

- Remember the waffles.
- Which to control to infer W → D?



Waffles Requiem

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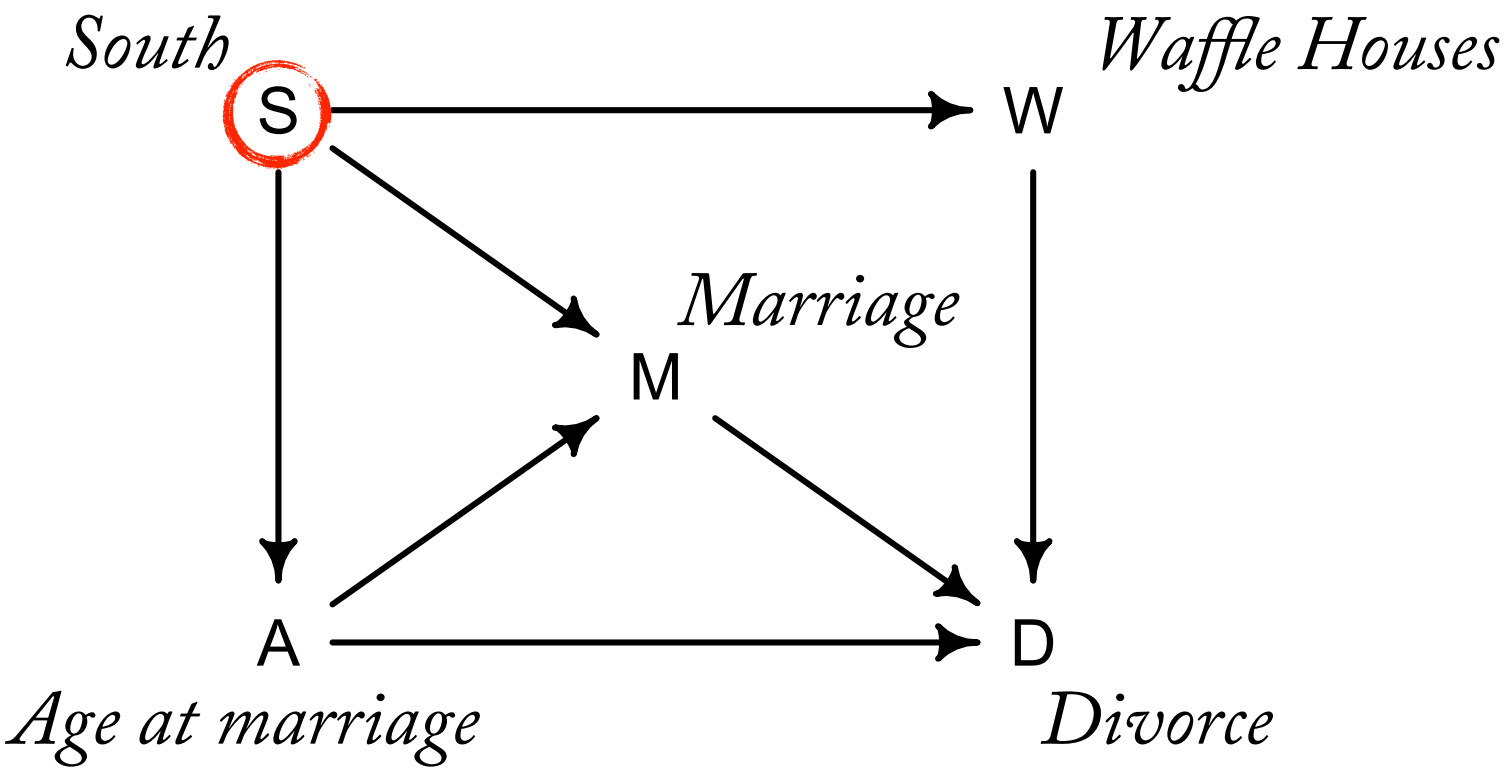


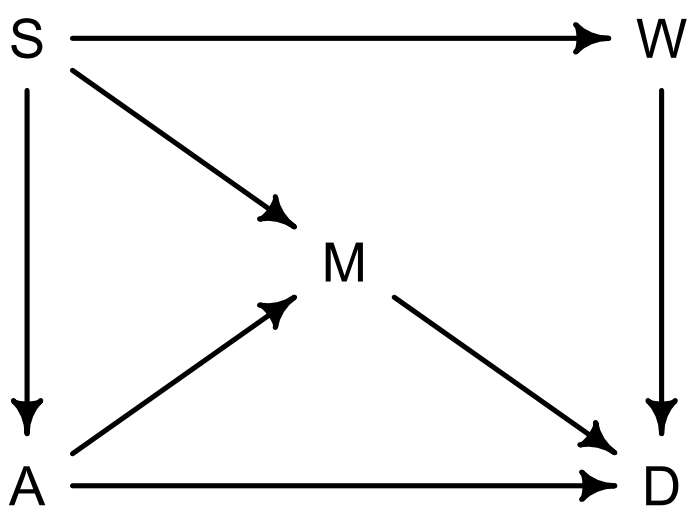
Implied conditional independence

- Given DAG, can test some implications

```
impliedConditionalIndependencies( dag_6.2 )
```

R code 6.36

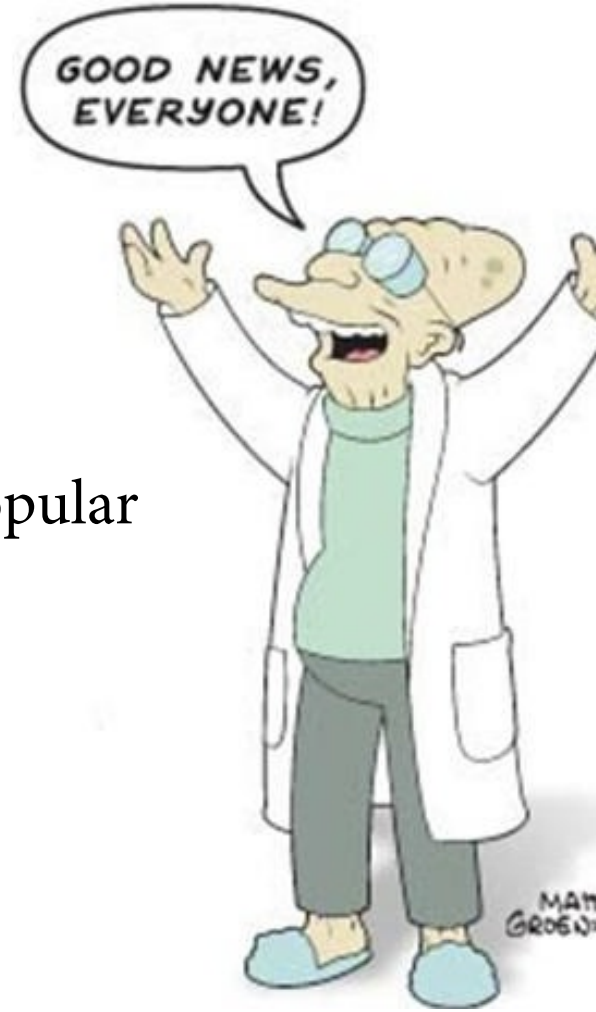
```
A _||_ W | S
D _||_ S | A, M, W
M _||_ W | S
```



(1) A and W independent, conditioning on S
(2) D and S independent, conditioning on A, M, & W
(3) M and W independent, conditioning on S

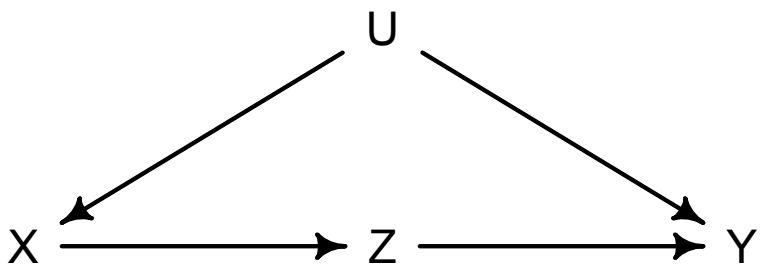
Causal inference hard but possible

- Demonstrate capable of inferring cause
- Experiments not required!
- Experiments not always practical & ethical
  - Disease, evolution, development, dynamics of popular music, global climate, war
- Experiments must choose an intervention
  - Interventions influence many variables at once
  - Experimentally manipulate obesity?

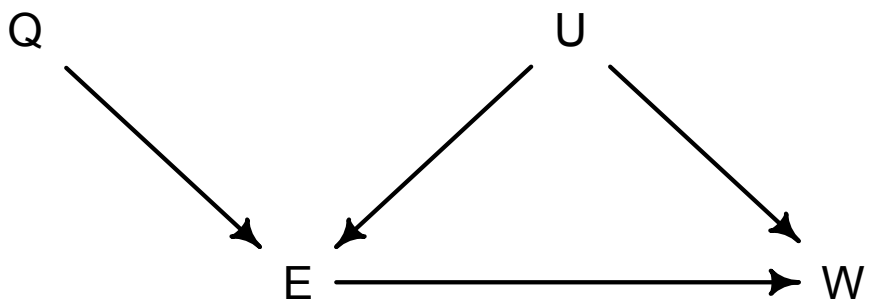


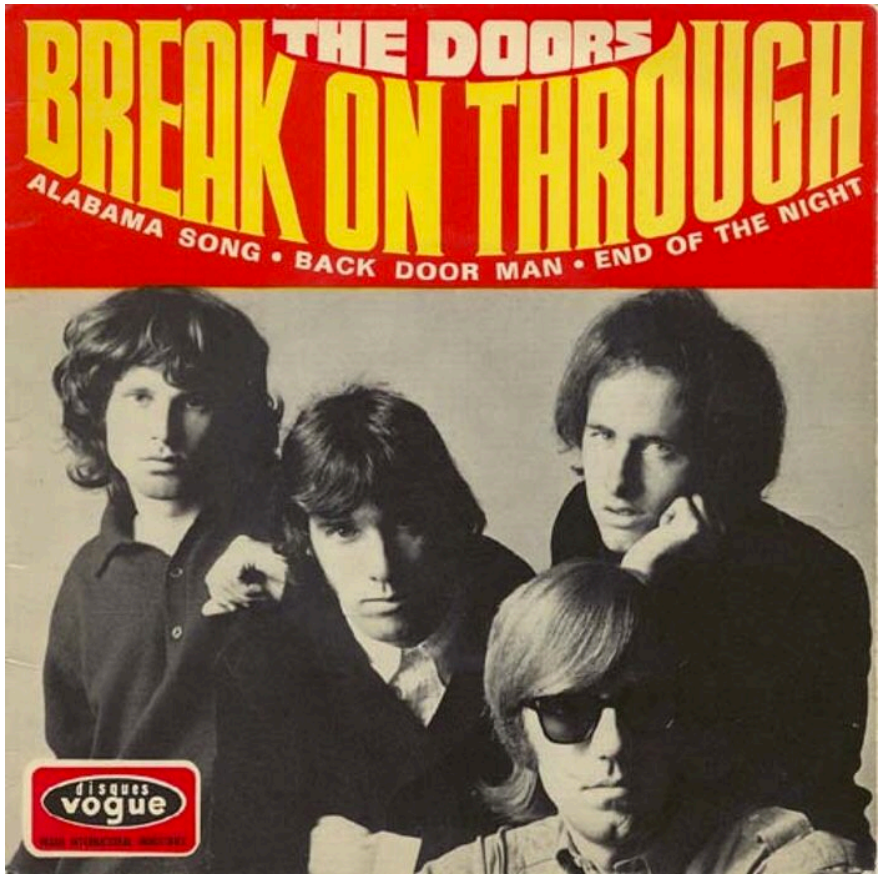
More than the Back Door

- Closing back doors is not the only option
- Front-door criterion



- Instrumental variables

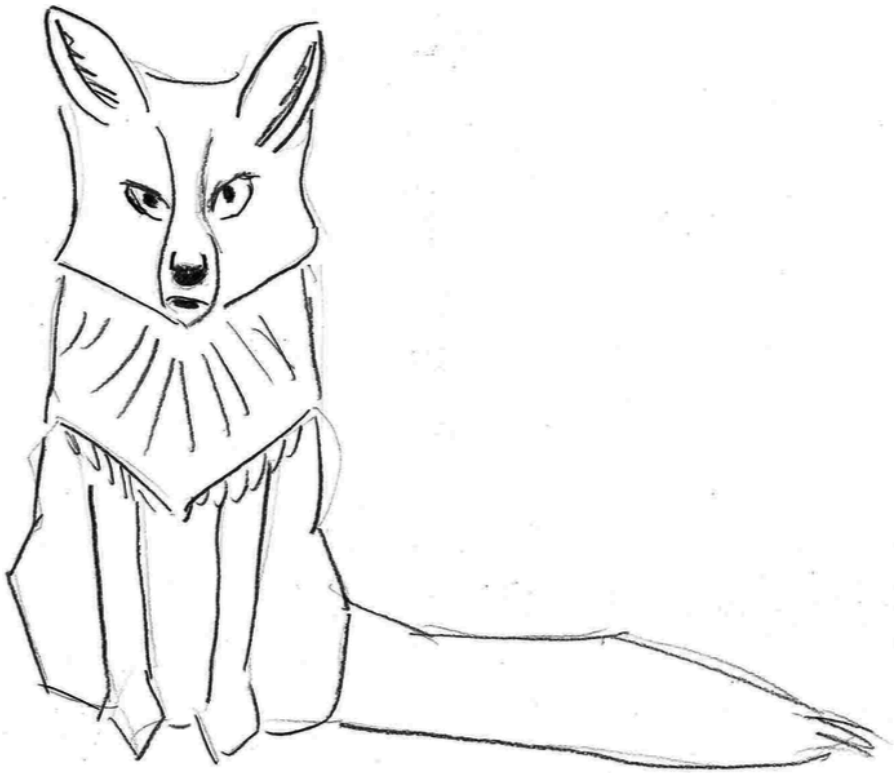




Directed Acyclic Gaffes

- Don't get cocky
- DAGs are small world constructs
- Residual confounding:
  - Misclassification
  - Measurement error
  - Missingness
- DAGs can accommodate these problems, but maybe tell us there are no solutions
- Eventually need *real* models of the system

Moving forward



- Homework: DAG practice

- Next week, Chapter 7
  - Sailing between
    (1) the whirlpool of *underfitting*
    (2) the many-headed monster of *overfitting*