Causal Inference

PSYC 573

University of Southern California
March 29, 2022

Causation

> Data are profoundly dumb about causal relationships

--- Pearl & Mackenzie (2018)

Materials based on chapters 5 and 6 of McElreath (2020)

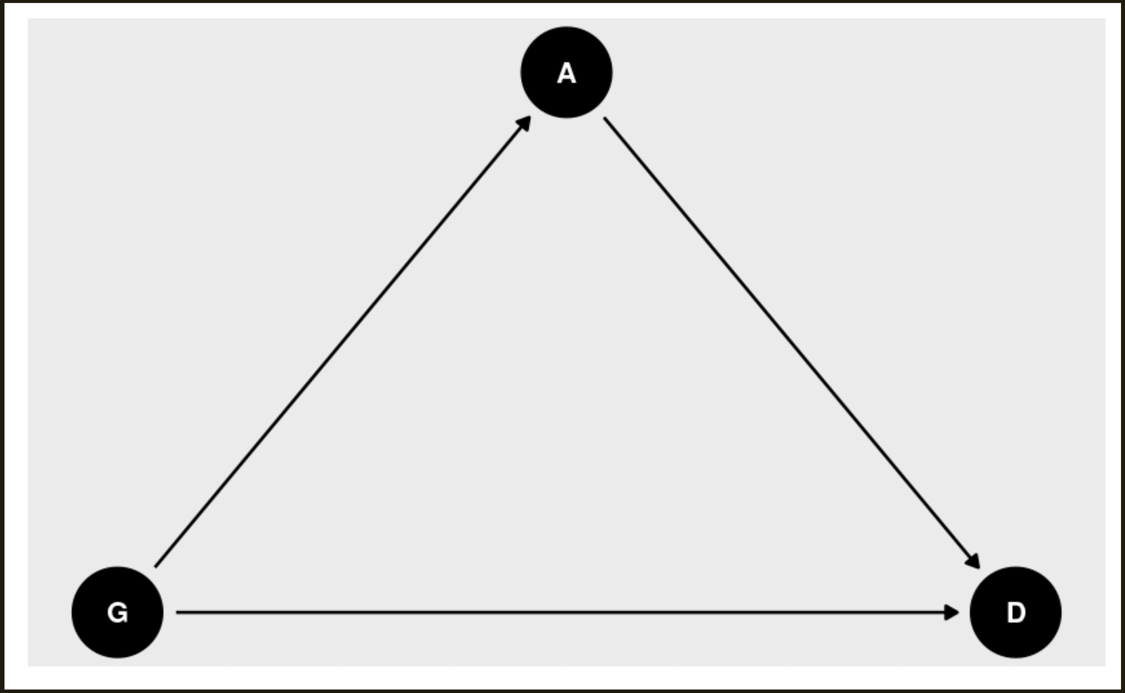
Causal Inference

Obtaining an estimate of the causal effect of one variable on another

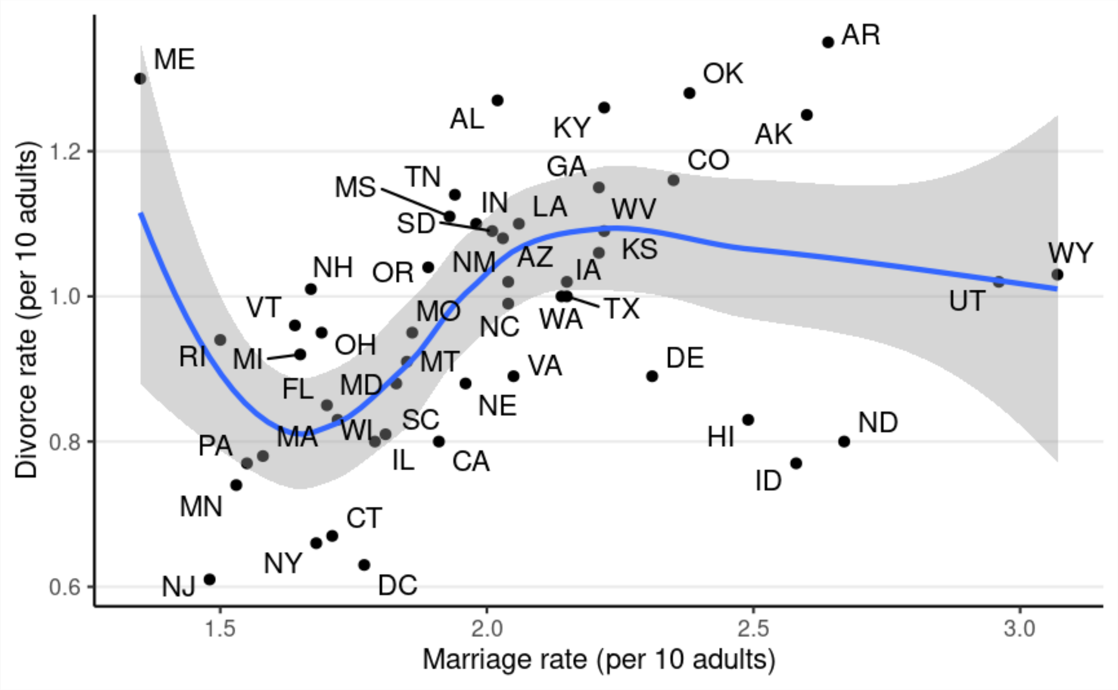
> an hour more exercise per day causes an increase in happiness by 0.1 to 0.2 points

- Intervention: if I exercise one hour more, my happiness will increase by 0.1 to 0.2 points
- Counterfactual: had I exercised one less hour, my happiness would have been 0.1 to 0.2 points less

Directed Acyclic Graph

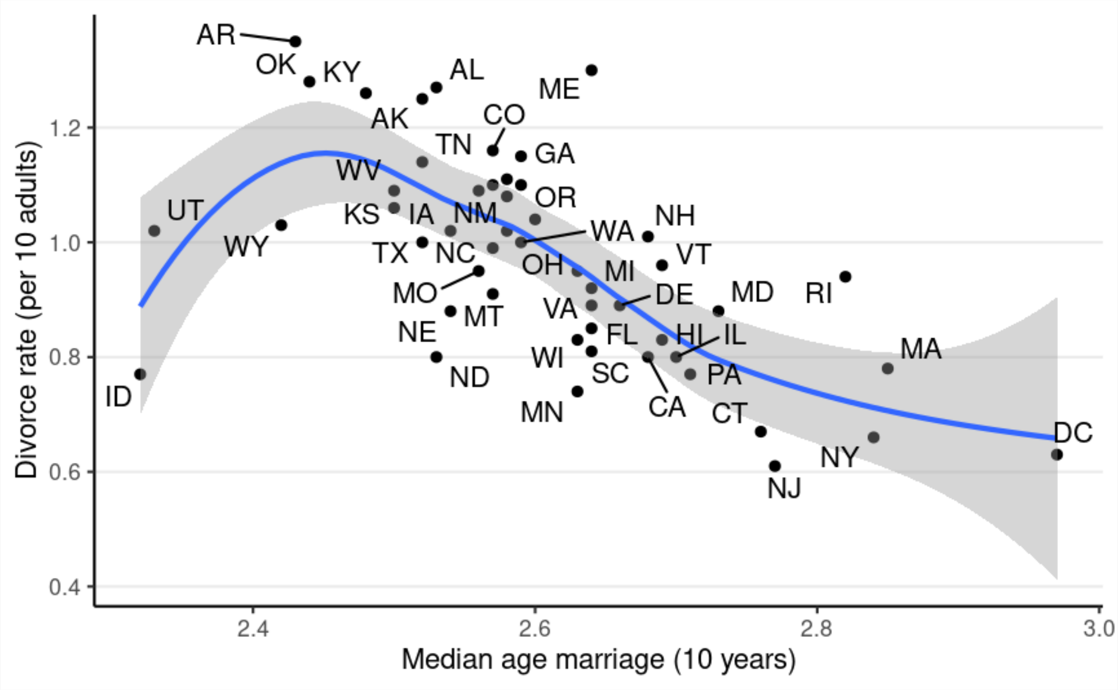


Data from the 2009 American Community Survey (ACS)



Does marriage **cause** divorce? (pay attention to the unit of analysis)

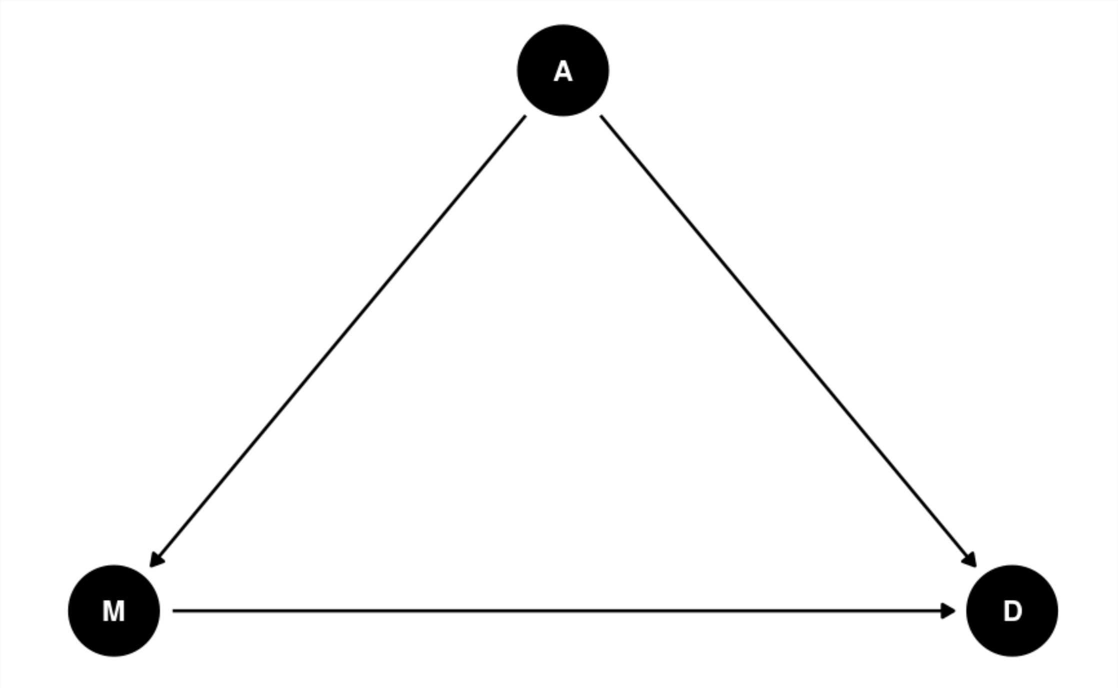
Age at marriage?

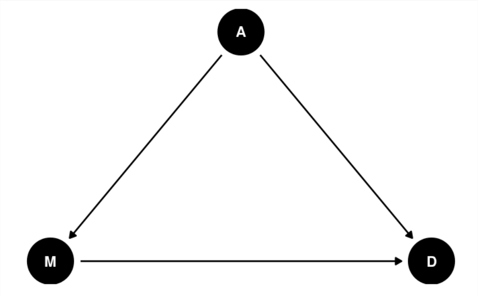


Directed Acyclic Graph (DAG)

Allows researchers to encode **causal assumptions** of the data

- Based on knowledge of the *data* and the *variables*





"Weak" assumptions

- A *may* directly influence M
- A *may* directly influence D
- M *may* directly influence D

"Strong" assumptions: things not shown in the graph

- E.g., M does not directly influence A
- E.g., A is the only relevant variable in the causal pathway M $\rightarrow$ D

Basic Types of Junctions

Fork: $A \leftarrow B \rightarrow C$

Chain/Pipe: $A \rightarrow B \rightarrow C$

Collider: $A \rightarrow B \leftarrow C$

Fork

aka Classic confounding

- *Confound*: something that misleads us about a causal influence

M $\leftarrow$ A $\rightarrow$ D

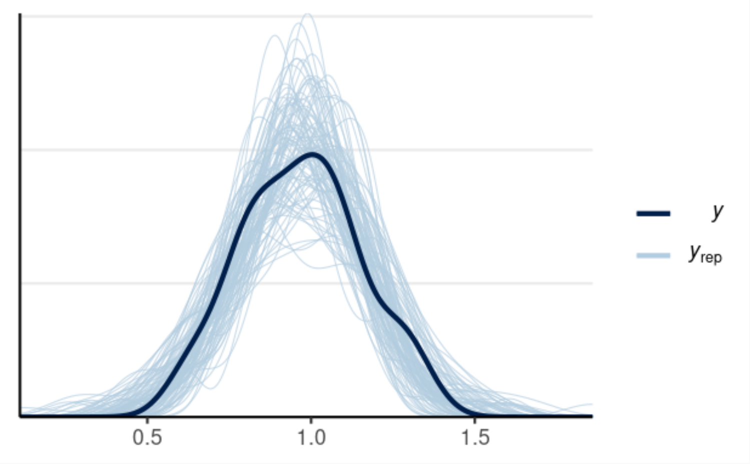
Assuming the DAG is correct,

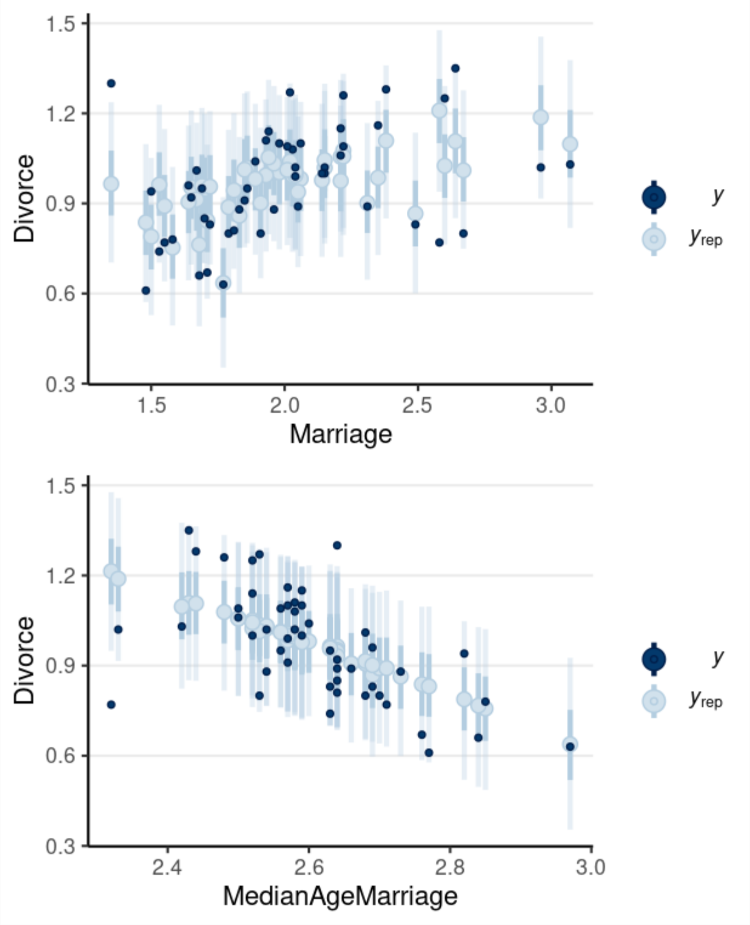
- the causal effect of M $\rightarrow$ D can be obtained by holding constant A
    - stratifying by A; "controlling" for A

Model brms Results

$$
\begin{aligned}
D_i &\sim N(\mu_i, \sigma) \\
\mu_i &= \beta_0 + \beta_1 A_i + \beta_2 M_i \\
\beta_0 &\sim N(0, 5) \\
\beta_1 &\sim N(0, 1) \\
\beta_2 &\sim N(0, 1) \\
\sigma &\sim t_4^{+}(0, 3)
\end{aligned}
$$

Posterior predictive checks





Pedicting an Intervention

> What would happen to the divorce rate if we encourage more people to get married, so that marriage rate increases by 1 per 10 adults?

Based on our DAG, this should not change the median marriage age

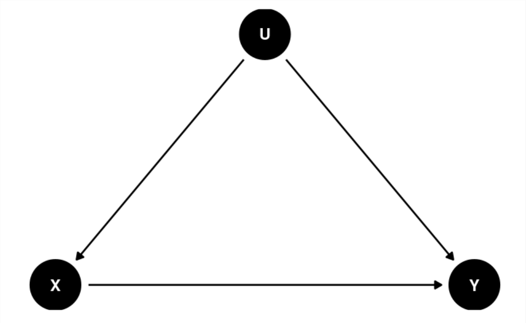
Marriage	MedianAgeMarriage	Estimate	Est.Error	Q2.5	Q97.5
2	2.5	1.07	0.034	0.999	1.14
3	2.5	1.03	0.068	0.894	1.16

Randomization

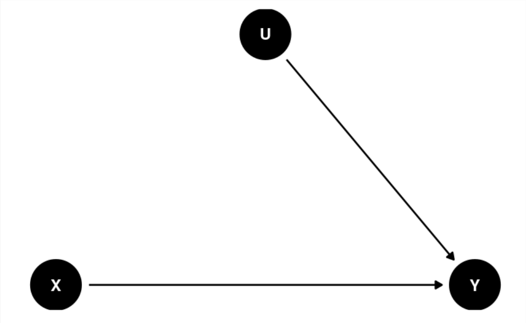
Framing Experiment

- X: exposure to a negatively framed news story about immigrants
- Y: anti-immigration political action

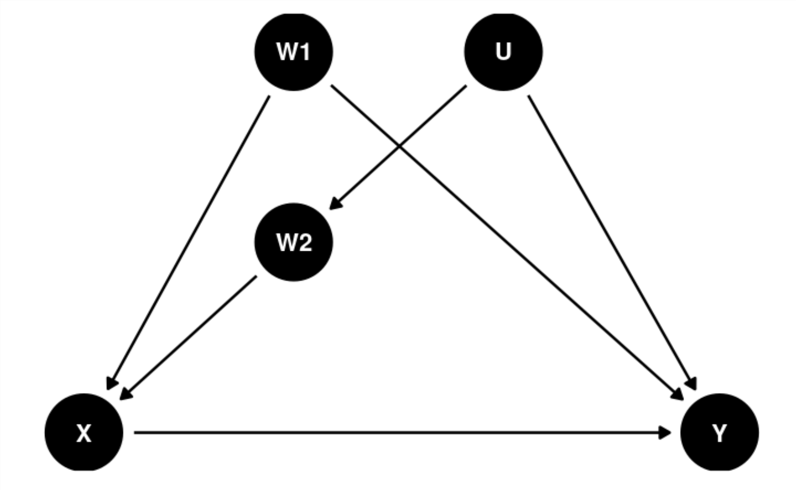
No Randomization



Randomization



Back-Door Criterion



The causal effect of X $\rightarrow$ Y can be obtained by blocking all the backdoor paths that do not involve descendants of X

- Randomization: (when done successfully) eliminates all paths entering X
- Conditioning (holding constant)

Dagitty

```r
library(dagitty)
dag4 <- dagitty("dag{
  X -> Y; W1 -> X; U -> W2; W2 -> X; W1 -> Y; U -> Y
}")
latents(dag4) <- "U"
adjustmentSets(dag4, exposure = "X", outcome = "Y",
               effect = "direct")
```

```
>#  { W1, W2 }
```

```r
impliedConditionalIndependencies(dag4)
```

```
>#  W1 _||_ W2
```

Post-Treatment Bias

Data for Framing Experiment

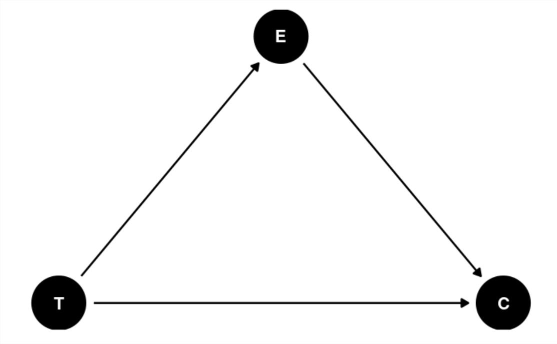
- `cong_mesg`: binary variable indicating whether or not the participant agreed to send a letter about immigration policy to his or her member of Congress
- `emo`: post-test anxiety about increased immigration (0-9)
- `tone`: framing of news story (0 = positive, 1 = negative)

Results

	No adjustment	**Adjusting for feeling**
b_Intercept	−0.81 [−1.18, −0.45]	−2.01 [−2.60, −1.40]
b_tone	0.22 [−0.29, 0.74]	−0.14 [−0.71, 0.42]
b_emo		0.32 [0.21, 0.43]

Which one estimates the causal effect?

Mediation



In the DAG, E is a post-treatment variable potentially influenced by T

- E is a potential **mediator**

> A mediator is very different from a confounder

Mediation Analysis

Model Code Output

$$
\begin{aligned}
\text{emo}_i &\sim N(\mu_i^{\text{e}}, \sigma) \\
\mu_i^{\text{e}} &= \beta_0^{\text{e}} + \beta_1 \text{tone}_i \\
\text{cong\_mesg}_i &\sim \text{Bern}(\mu_i^{\text{c}}, \sigma^c) \\
\text{logit}(\mu_i^{\text{c}}) &= \eta_i \\
\eta_i &= \beta_0^{\text{c}} + \beta_2 \text{tone}_i + \beta_3 \text{emo}_i \\
\beta_0^{\text{e}}, \beta_0^{\text{c}} &\sim N(0, 5) \\
\beta_1, \beta_2, \beta_3 &\sim N(0, 1) \\
\sigma &\sim t_4^+(0, 3)
\end{aligned}
$$

Direct Effect

Causal effect when holding mediator at a specific level

```r
cond_df <- data.frame(tone = c(0, 1, 0, 1),
                      emo = c(0, 0, 9, 9))
cond_df %>%
  bind_cols(
    fitted(m_med, newdata = cond_df)[ , , "congmesg"]
  ) %>%
  knitr::kable()
```

tone	emo	Estimate	Est.Error	Q2.5	Q97.5
0	0	0.122	0.032	0.069	0.195
1	0	0.108	0.033	0.054	0.183
0	9	0.699	0.071	0.549	0.826
1	9	0.669	0.063	0.539	0.786

Indirect Effect

Change in Y of the control group if their mediator level changes to what the treatment group *would have obtained*

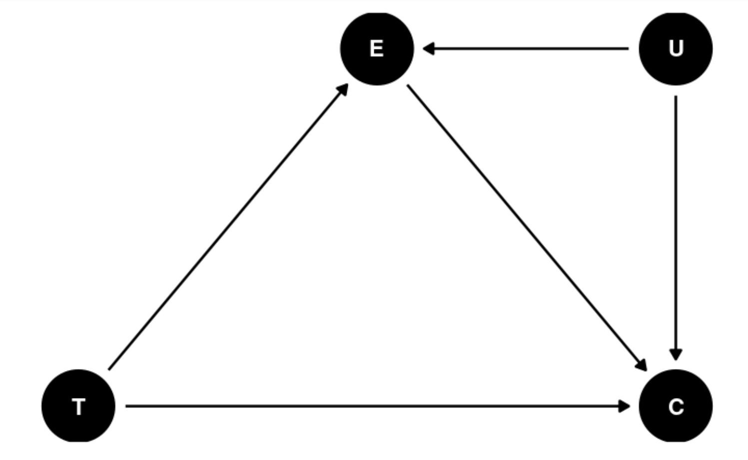
Quick Demo using posterior means[1]

- T = 0, E(M) = 3.39
- T = 1, E(M) = 3.39 + 1.14 = 4.53

tone	emo	Estimate	Est.Error	Q2.5	Q97.5
0	3.39	0.286	0.042	0.208	0.372
0	4.53	0.365	0.048	0.275	0.462

[1]: Fully Bayesian analyses in the note

Potential Confounding



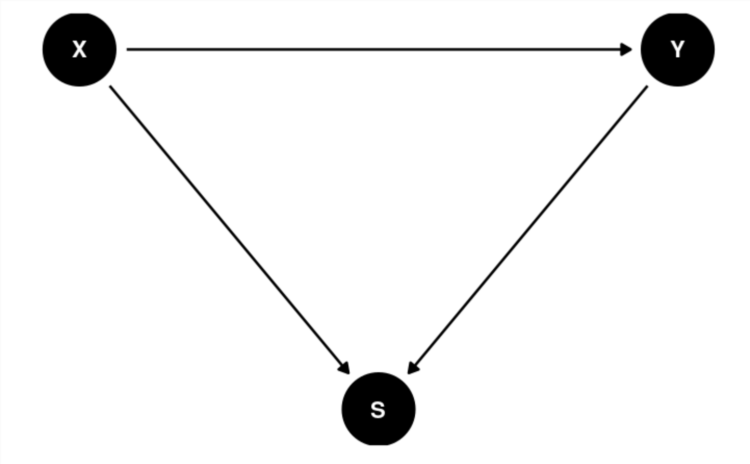
Maybe age is related to both `emo` and `cong_mesg`?

```
m_med2 <- brm(
  # Two equations for two outcomes
  bf(cong_mesg ~ tone + emo + age) +
    bf(emo ~ tone + age) +
    set_rescor(FALSE),
  data = framing,
  seed = 1338,
  iter = 4000,
  family = list(bernoulli("logit"),
                gaussian("identity"))
)
```

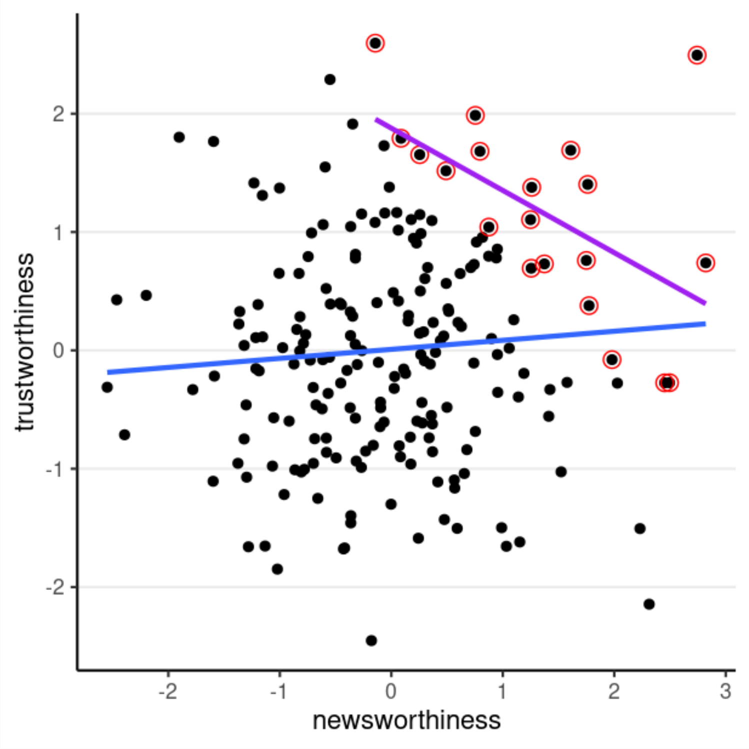
Unobserved Confounding

Can be incorporated by assigning priors to the unobserved confounding paths

Collider Bias



E.g., Is the most newsworthy research the least trustworthy?



Conditioning on a collider creates spurious associations

- nice person → date ← good-looking person
- impulsivity → high-risk youth ← delinquency
- healthcare worker → COVID-19 testing ← COVID-19 severity[2]
- standardized test → admission ← research skills
- maternal smoking → birth weight → birth defect ← mortality

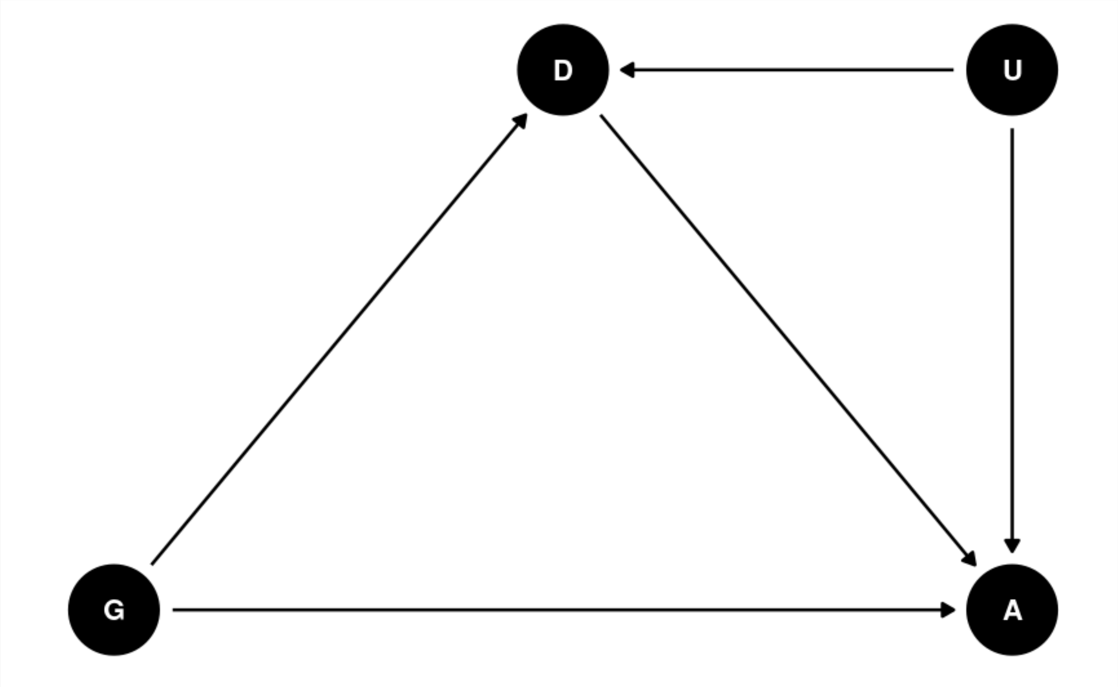
[2]: See https://www.nature.com/articles/s41467-020-19478-2

Final Example

Student Admissions at UC Berkeley

Dept	App_Male	Admit_Male	Percent_Male	App_Female	Admit_Female	Percent_Female
A	825	512	62.1	108	89	82.41
B	560	353	63.0	25	17	68.00
C	325	120	36.9	593	202	34.06
D	417	138	33.1	375	131	34.93
E	191	53	27.7	393	94	23.92
F	373	22	5.9	341	24	7.04
Total	2691	1198	44.5	1835	557	30.35

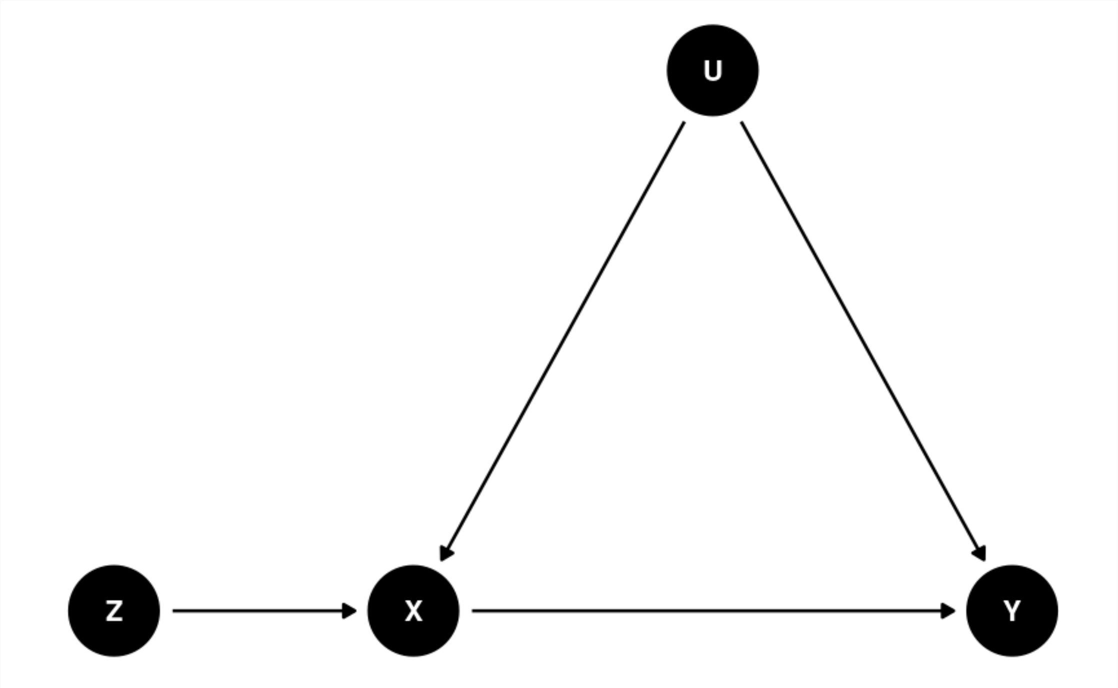
Causal Thinking



What do we mean by the causal effect of gender?

What do we mean by gender bias?

Instrumental Variables



See more in the note

Remarks

- Causal inference requires **causal assumptions**
  - You need a DAG
- Blindly adjusting for covariates does not give better results
  - post-treatment bias, collider bias, etc
- Think carefully about what causal quantity is of interest
  - E.g., direct, indirect, total
- Causal inferences are possible with both experimental and non-experimental data