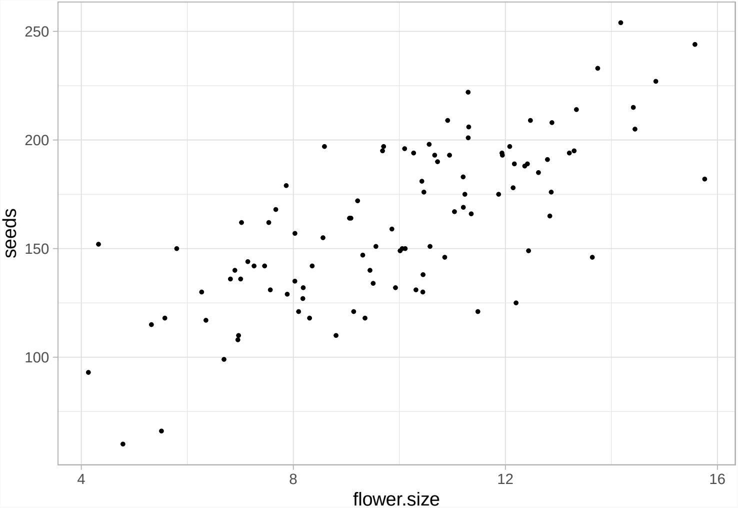
From causal salads to causal inference

Francisco Rodríguez-Sánchez

https://frodriguezsanchez.net

Self-learnt stuff ahead

Larger flowers produce more seeds



Larger flowers produce more seeds

```
lm(seeds ~ flower.size)
```

Variable	*Beta*	*SE*	*p.value*
(Intercept)	57	10.1	<0.001
flower.size	**11**	**0.978**	**<0.001**

Does flower size

really **cause**

increased seed production?

Shall we select plants with large flowers

to increase seed production?

Shall we select plants with large flowers

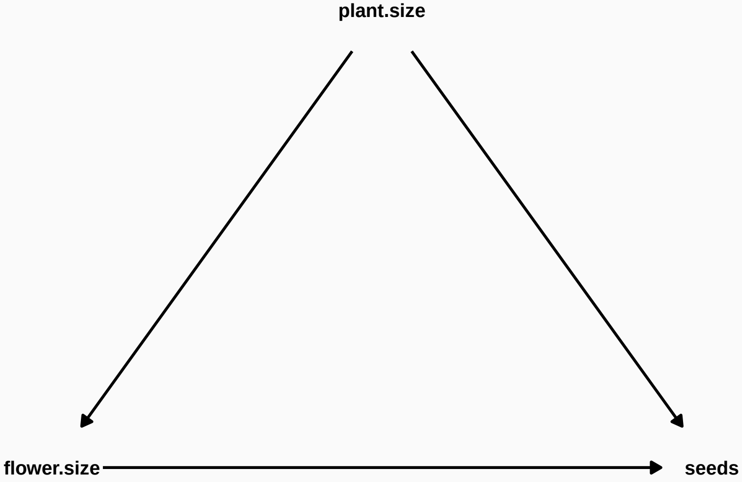
to increase seed production?

We tried but didn't get the expected benefits

Maybe large plants (e.g. growing on better soil)

have large flowers AND produce more seeds?

Maybe plant size is a CONFOUNDER?



Adjusting for plant size (confounding)

```
lm(seeds ~ flower.size + plant.size)
```

Variable	*Beta*	*SE*	*p.value*
(Intercept)	12	12.9	0.4
flower.size	**6.6**	**1.18**	**<0.001**
plant.size	0.82	0.168	<0.001

Including pollinators (bees)

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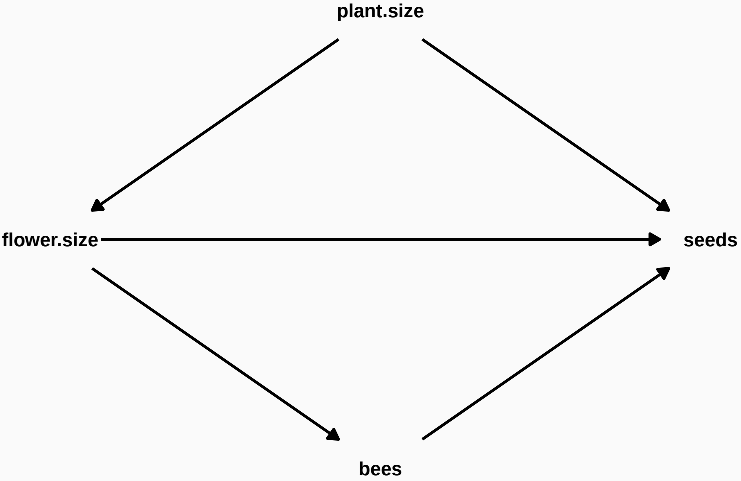
```
lm(seeds ~ flower.size + plant.size + bees)
```

Variable	*Beta*	*SE*	*p.value*
(Intercept)	5.2	12.1	0.7
flower.size	**2.1**	**1.56**	**0.2**
plant.size	0.90	0.157	<0.001
bees	8.8	2.14	<0.001

Pollinators are a MEDIATOR



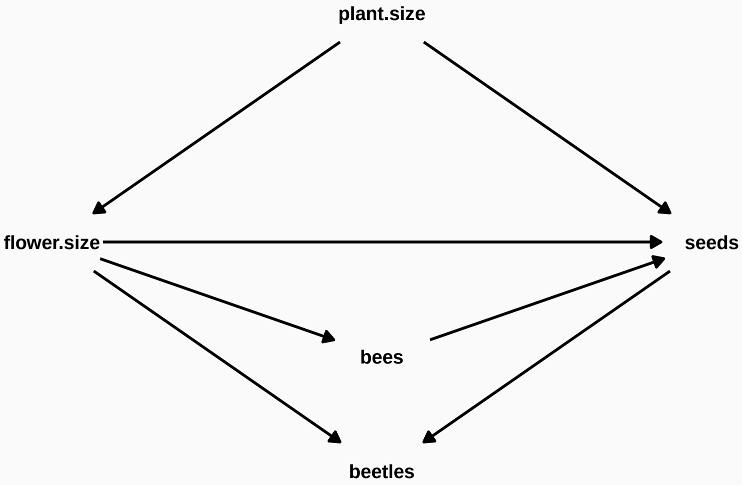
Including beetles (pollen & seed predators)

```
lm(seeds ~ flower.size + plant.size + bees +
beetles)
```

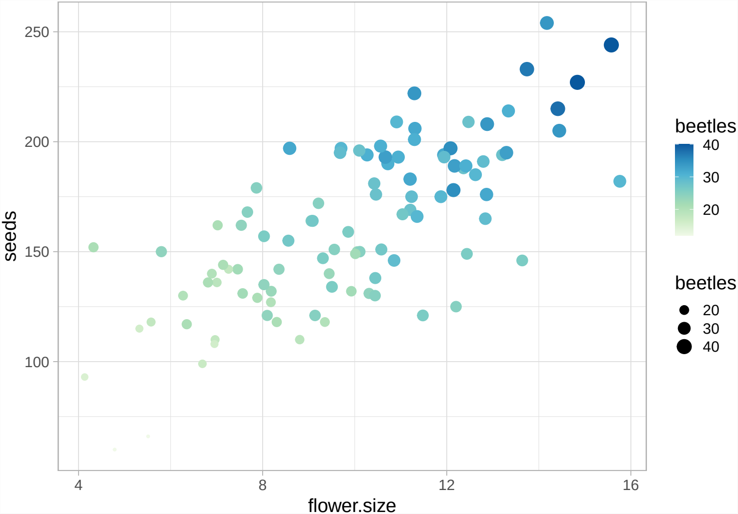
Variable	*Beta*	*SE*	*p.value*
(Intercept)	-11	8.67	0.2
flower.size	**-3.8**	**1.25**	**0.003**
plant.size	0.47	0.118	<0.001
bees	4.8	1.56	0.003
beetles	5.2	0.529	<0.001

Now flower.size has negative coefficient!!

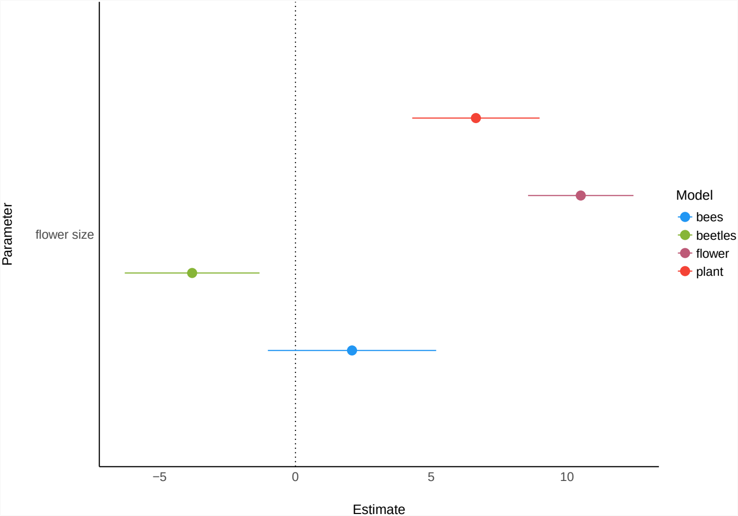
Beetles are a COLLIDER



Colliders induce negative relation between treatment (flower.size) and outcome (seeds)



What is the real causal effect of flower size?



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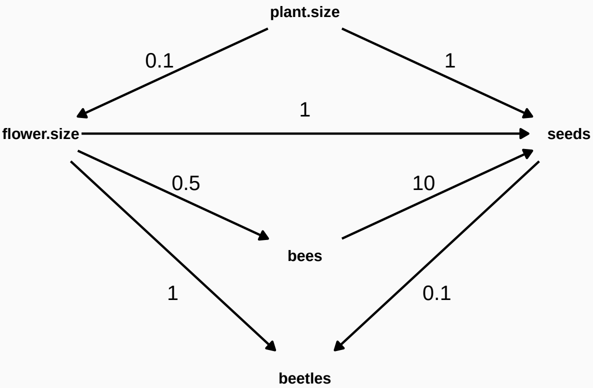

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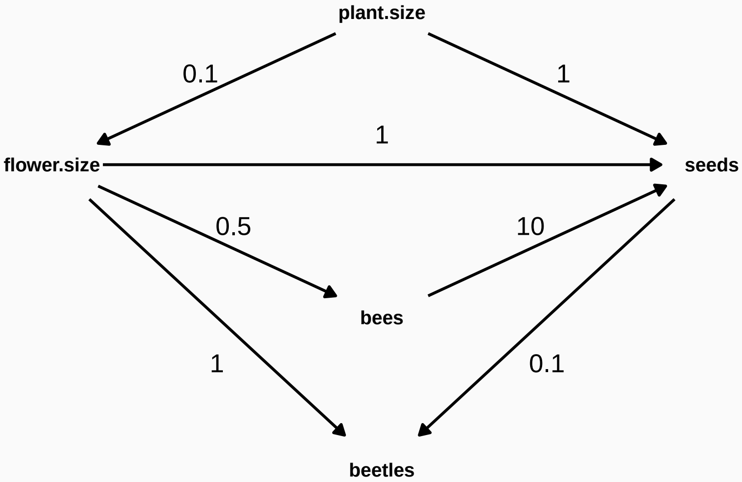
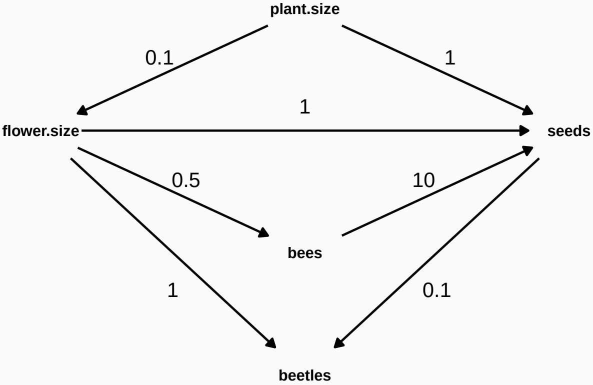


AVOID **COLLIDERS!**

What is the real causal effect of flower size?



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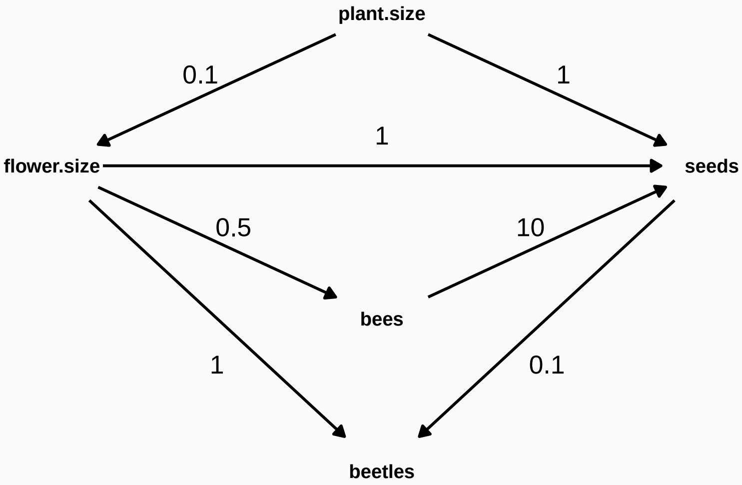
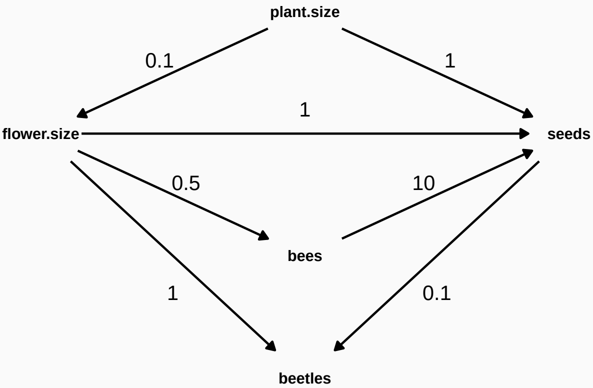


MEDIATORS split **total effect** into **direct** and **indirect** effects

What is the real causal effect of flower size?



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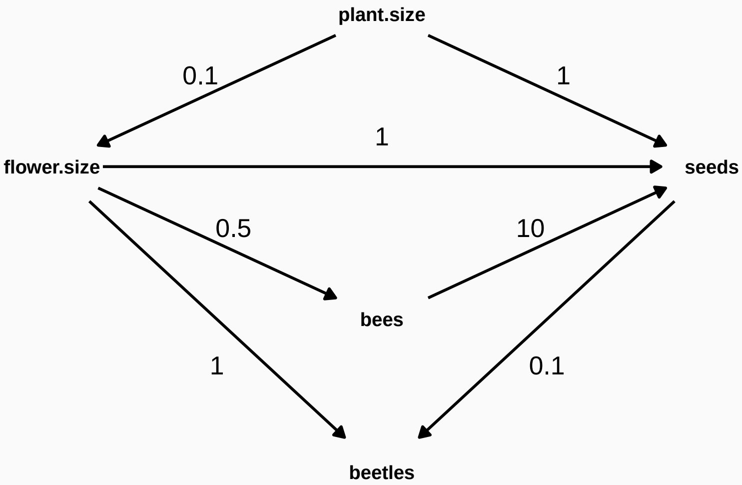
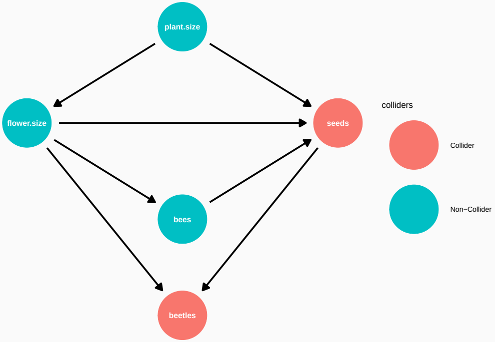


Include CONFOUNDERS to avoid bias (backdoor criterion)

Tools to identify correct causal structure

```
dagify(
  seeds ~ plant.size + flower.size + bees,
  flower.size ~ plant.size,
  bees ~ flower.size,
  beetles ~ flower.size + seeds,
  coords = coords
) |>
  ggdag_collider(size = 2) + theme_dag_blank()
```



Causal salads

Causal salads

You put everything into a regression equation, toss with some creative story-telling, and hope the reviewers eat it

R. McElreath

Jerry Pank

Causal salads

Throwing predictor variables into a statistical model

hoping this will improve the analysis is a dreadful idea

Jan Vanhove

Predictive criteria don’t help for causal inference

Predictive criteria don’t help to choose correct causal model

Making good predictions doesn’t require accurate causal model

Model	AIC	R2
m.flower	933.3	0.5
m.flower.plant	913.2	0.6
m.flower.plant.bees	899.1	0.7
m.flower.plant.bees.beetles	829.9	0.8

“Best model” (based on AIC or R2) not good for causal inference

Simpler (best) model provides biased causal estimates

Simulate response depending on two correlated variables (Hartig 2022)

```
x1 = runif(100)
x2 = 0.8*x1 + 0.2*runif(100)
y = x1 + x2 + rnorm(100)
```

y	x1	x2
-0.1	0.3	0.4
1.7	0.8	0.7
0.6	0.4	0.4
1.4	0.9	0.9
0.8	0.9	0.8
0.2	0.0	0.2

Simpler (best) model provides biased causal estimates

Simulate response depending on two correlated variables (Hartig 2022)

```r
fullmodel = lm(y ~ x1 + x2)
```

```
Call:
lm(formula = y ~ x1 + x2)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.8994 -0.6821 -0.1086  0.5749  3.3663 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -0.1408     0.2862  -0.492    0.624
x1            1.2158     1.5037   0.809    0.421
x2            0.8518     1.8674   0.456    0.649

Residual standard error: 0.9765 on 97 degrees of freedom
Multiple R-squared:  0.237, Adjusted R-squared:  0.2212 
F-statistic: 15.06 on 2 and 97 DF,  p-value: 2.009e-06
```

Simpler (best) model provides biased causal estimates

```r
simplemodel = MASS::stepAIC(fullmodel, trace = 0)
```

```

Call:
lm(formula = y ~ x1)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.9047 -0.6292 -0.1019  0.6077  3.3394 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.04633    0.19670  -0.236    0.814    
x1           1.88350    0.34295   5.492 3.13e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9725 on 98 degrees of freedom
Multiple R-squared:  0.2353,    Adjusted R-squared:  0.2275 
F-statistic: 30.16 on 1 and 98 DF,  p-value: 3.134e-07
```

Automated model selection (dredge)

Simulating data with 10 random predictors

```r
dat <- data.frame(y = rnorm(100),
                  x = matrix(runif(1000), ncol = 10))
```

y	x.1	x.2	x.3	x.4	x.5	x.6	x.7	x.8	x.9	x.10
-0.1	0.6	0.6	0.3	0.8	0.2	0.0	0.4	0.4	0.3	0.2
0.8	0.4	0.4	0.9	0.2	0.5	0.1	0.6	0.2	0.0	0.0
-0.5	0.0	0.3	0.4	0.3	0.1	0.1	0.9	0.9	0.5	0.8
-0.6	0.7	0.7	0.4	0.5	0.2	0.7	0.7	0.8	0.5	0.3
0.7	0.0	0.6	0.9	0.1	0.2	0.4	0.8	0.6	0.6	0.1
-0.1	0.4	0.2	0.9	0.4	0.6	0.5	0.9	0.1	0.8	0.8

Automated model selection

Running `MuMIn::dredge` with 10 random predictors

```
full.model <- lm(y ~ ., data = dat)
dd <- MuMIn::dredge(full.model)
```

Best model:

Parameter	Coefficient	SE	p
(Intercept)	-1.50	0.36	0.00
x.2	0.78	0.36	0.03
x.5	0.59	0.32	0.07
x.6	0.61	0.35	0.09
x.9	0.87	0.34	0.01

Extract from `dredge` help

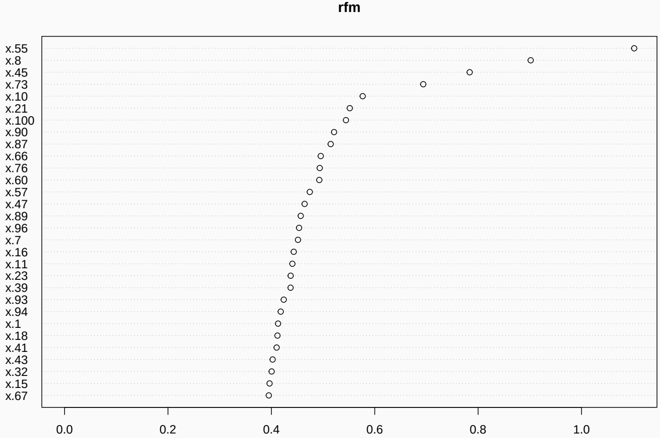
"Let the computer find out" is a poor strategy and usually reflects the fact that the researcher did not bother to think clearly about the problem of interest and its scientific setting

Burnham and Anderson 2002

Variable importance in machine learning

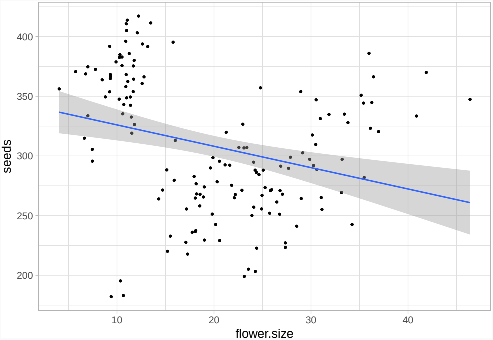
Random forest on **100 random predictors**

```r
dat <- data.frame(x = matrix(runif(50000), ncol = 100), y = runif(500))
rfm <- randomForest::randomForest(y ~ ., data = dat)
varImpPlot(rfm)
```



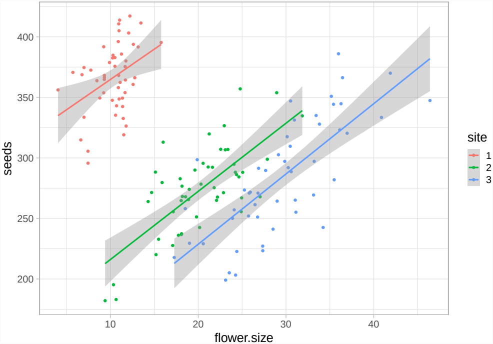
Simpson's paradox as a causal problem

Simpson's paradox



Variable	*Beta*	*SE*	*p.value*
(Intercept)	344	10.7	<0.001
flower.size	**-1.8**	**0.486**	**<0.001**

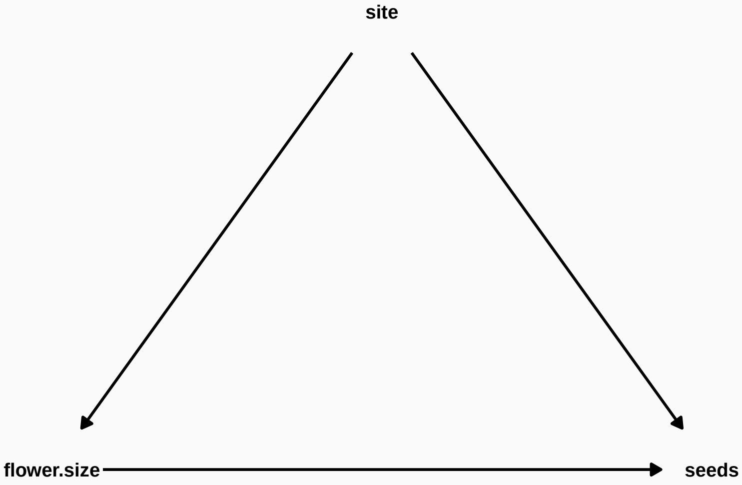
Simpson’s paradox



Variable	*Beta*	*SE*	*p.value*
(Intercept)	308	6.50	<0.001
flower.size	**5.7**	**0.500**	**<0.001**
site			
1	—	—	

Simpson's paradox

Site is a confounder!



From causal salads to causal inference

Causal interpretation requires **external knowledge**

To estimate causal effects accurately we require more information than can be gleaned from statistical tools alone

D'Agostino et al

Causal interpretation requires

external knowledge

To estimate causal effects accurately we require more information than can be gleaned from statistical tools alone

D'Agostino et al

No amount of data reliably turns salad into sense

R. McElreath

From causal salad to causal inference

- Draw the **causal graph** (DAG) beforehand

From causal salad to causal inference

- Draw the **causal graph** (DAG) beforehand
- Control for **confounders**

From causal salad to causal inference

- Draw the causal graph (DAG) beforehand
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- Avoid conditioning on post-treatment variables

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    - Treatment -> Covariate -> Outcome

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- Draw the **causal graph** (DAG) beforehand
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- Beware of **collider bias**

From causal salad to causal inference

- Draw the **causal graph** (DAG) beforehand
- Control for **confounders**
- Avoid conditioning on **post-treatment variables**
    - Treatment -> Covariate -> Outcome
- Beware of **collider bias**
- **Predictive criteria** not fit for causal inference

To learn more

Suchinta Arif's papers

McElreath's workshop on causal inference

`https://www.r-causal.org`

`https://theeffectbook.net`