

From causal salads to causal inference

Francisco Rodríguez-Sánchez

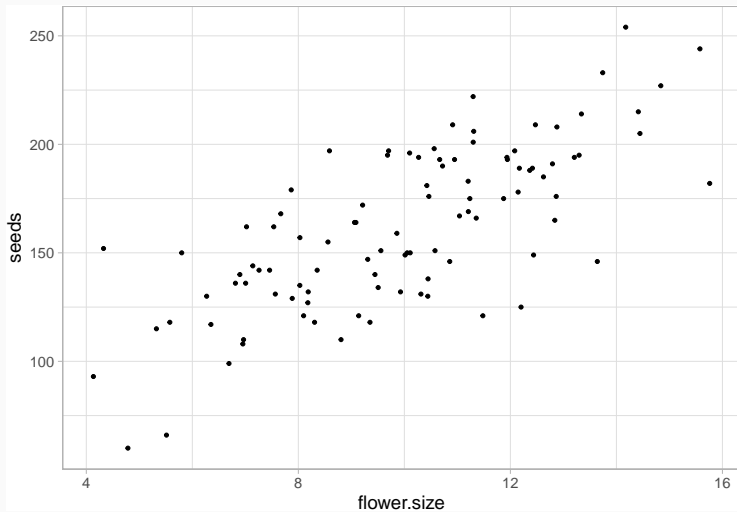
<https://frodriguezsanchez.net>



Self-learnt stuff ahead



Larger flowers produce more seeds



Larger flowers produce more seeds

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

<i>Variable</i>	<i>Beta</i>	<i>SE</i>	<i>p.value</i>
(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?

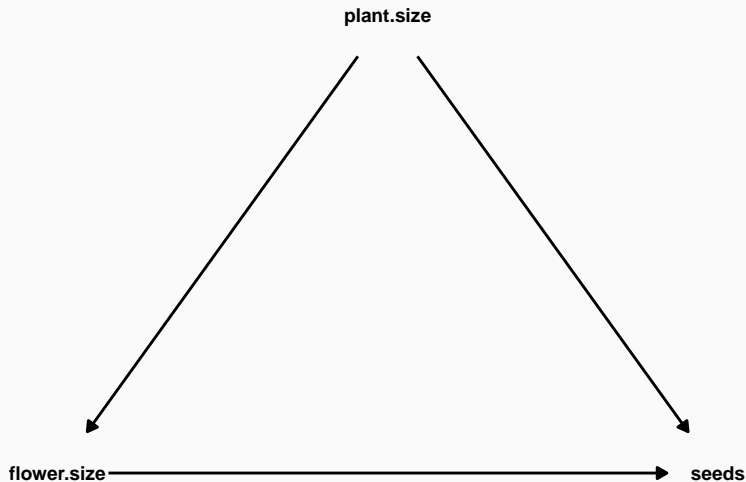
Shall we select plants with large flowers
to increase seed production?

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)
```

<i>Variable</i>	<i>Beta</i>	<i>SE</i>	<i>p.value</i>
(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)

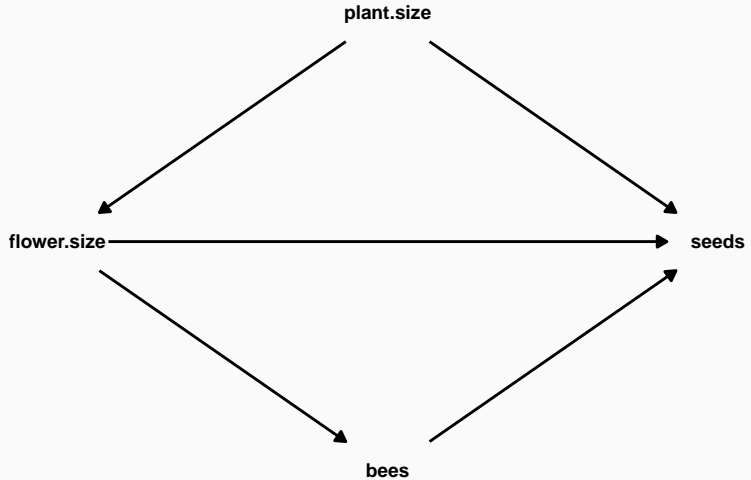


Including pollinators (bees)

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

<i>Variable</i>	<i>Beta</i>	<i>SE</i>	<i>p.value</i>
(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**



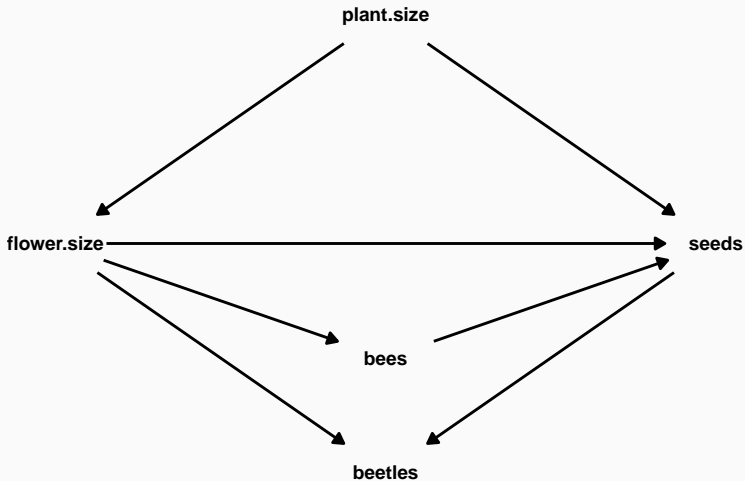
Including beetles (pollen & seed predators)

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

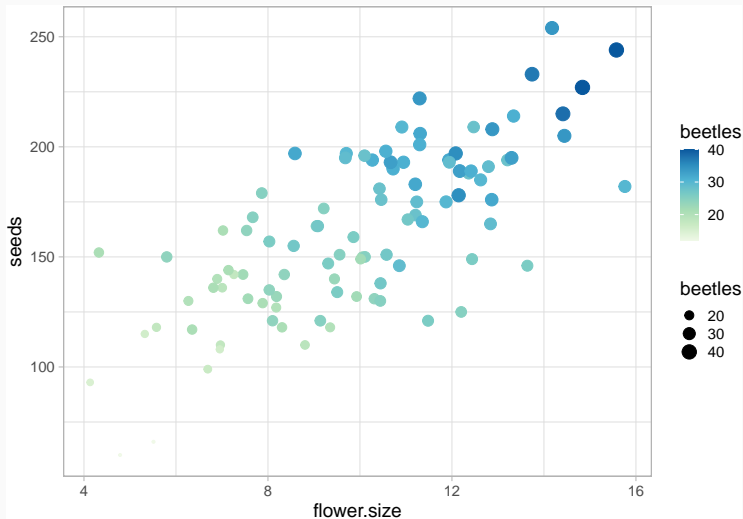
<i>Variable</i>	<i>Beta</i>	<i>SE</i>	<i>p.value</i>
(Intercept)	-11	8.67	0.2
flower.size	-3.8	1.25	0.003
plant.size	0.47	0.118	<0.001
bees	4.8	1.56	0.003
beetles	5.2	0.529	<0.001

Now flower.size has negative coefficient!!

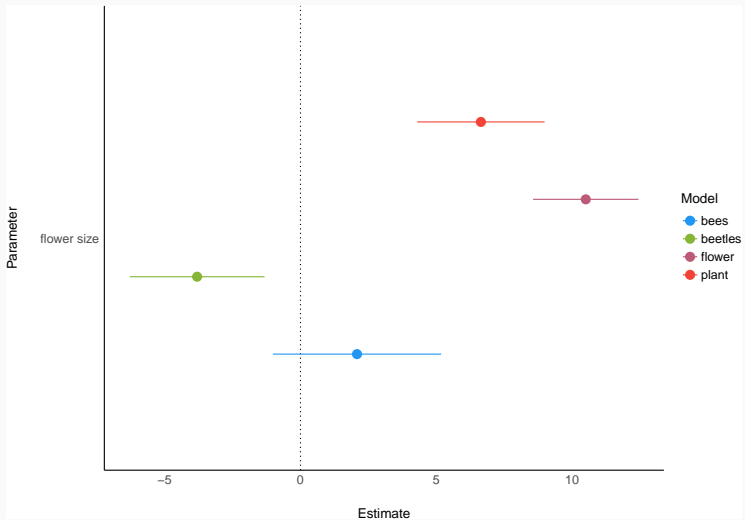
Beetles are a COLLIDER



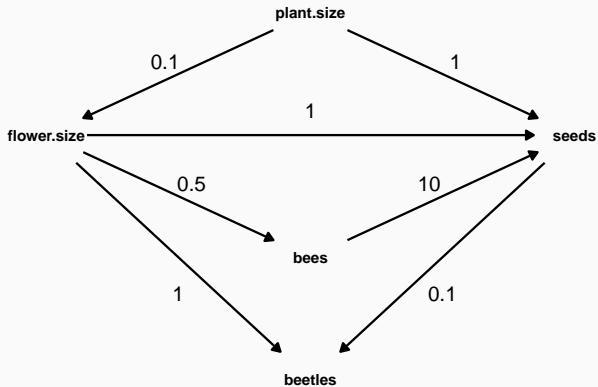
Colliders induce negative relation between treatment (flower.size) and outcome (seeds)



What is the real causal effect of flower size?

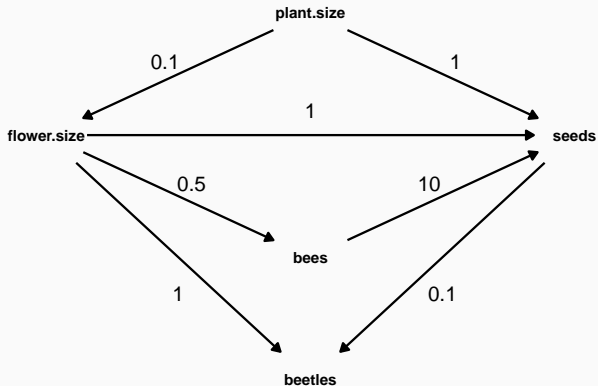


What is the real causal effect of flower size?



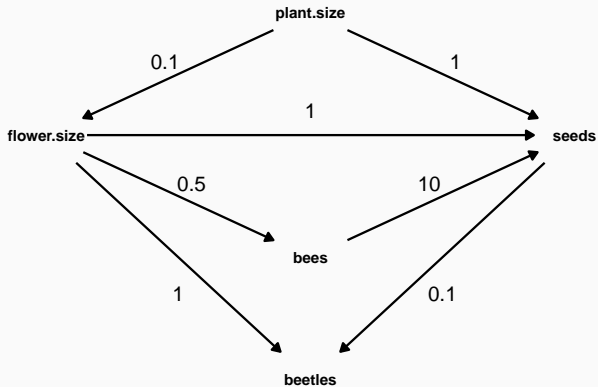
Variable	Beta	SE	p.value
(Intercept)	-11	8.67	0.2
flower.size	-3.8	1.25	0.003
plant.size	0.47	0.118	<0.001
bees	4.8	1.56	0.003
beetles	5.2	0.529	<0.001

What is the real causal effect of flower size?



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

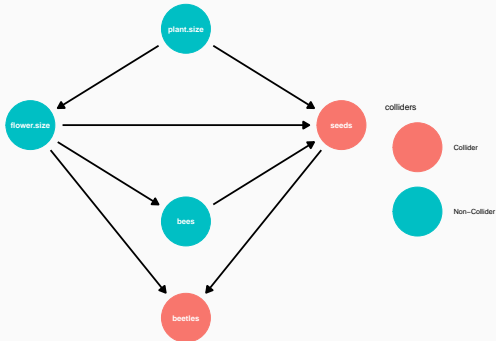
What is the real causal effect of flower size?



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

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

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

R. McElreath



*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)
```

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

Simpler (best) model provides biased causal estimates

```
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

Running `MuMIn::dredge` with 10 random predictors

```
dat <- data.frame(x = matrix(runif(1000), ncol = 10), y = rnorm(100))  
full.model <- lm(y ~ ., data = dat)  
dd <- MuMIn::dredge(full.model)
```

Best model:

Parameter	Coefficient	SE	p
(Intercept)	-0.83	0.30	0.01
x.1	0.85	0.34	0.01
x.3	0.66	0.32	0.04
x.6	0.64	0.37	0.09
x.7	-0.80	0.31	0.01

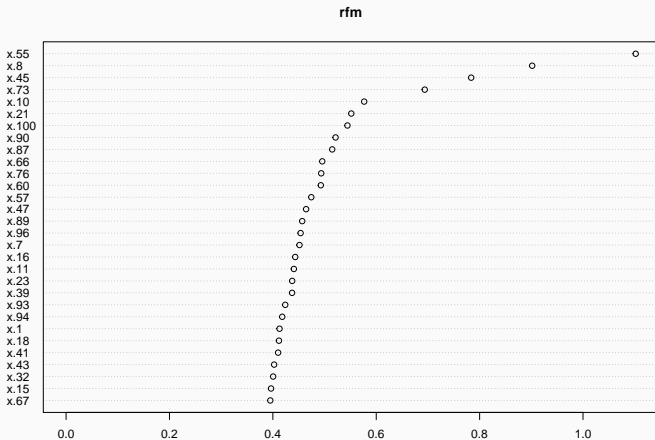
“Let the computer find out” is a poor strategy and usually reflects the fact that the researcher did not bother to think clearly about the problem of interest and its scientific setting

Burnham and Anderson 2002

Variable importance in machine learning

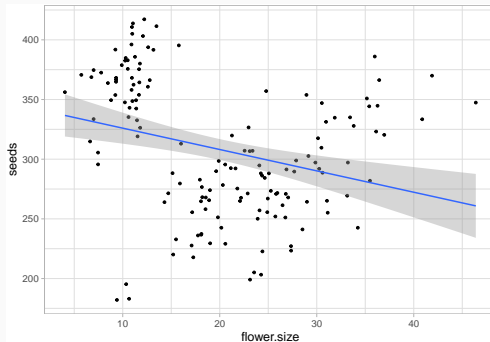
Random forest on 100 random predictors

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



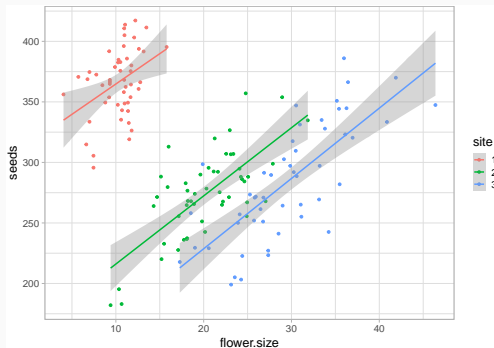
Simpson's paradox as a causal problem

Simpson paradox



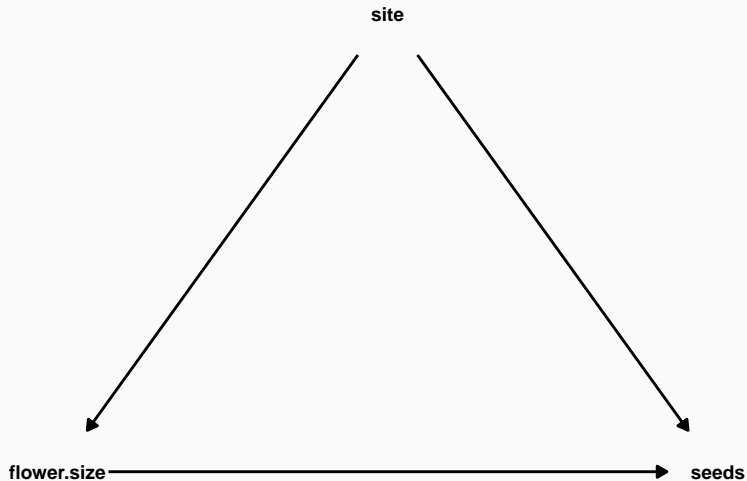
<i>Variable</i>	<i>Beta</i>	<i>SE</i>	<i>p.value</i>
(Intercept)	344	10.7	<0.001
flower.size	-1.8	0.486	<0.001

Simpson paradox



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

Simpson paradox



Key messages

Causal interpretation requires external knowledge

No amount of data reliably turns salad into sense

R. McElreath

Causal interpretation requires external knowledge

No amount of data reliably turns salad into sense

R. McElreath

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

D'Agostino et al

From causal salad to causal inference

- Draw generative model (causal graph) beforehand

From causal salad to causal inference

- Draw generative model (causal graph) beforehand
- Control for confounders

From causal salad to causal inference

- Draw generative model (causal graph) beforehand
- Control for confounders
- Avoid conditioning on post-treatment variables

From causal salad to causal inference

- Draw generative model (causal graph) beforehand
- Control for confounders
- Avoid conditioning on post-treatment variables
- Beware of collider bias

From causal salad to causal inference

- Draw generative model (causal graph) beforehand
- Control for confounders
- Avoid conditioning on post-treatment variables
- 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>