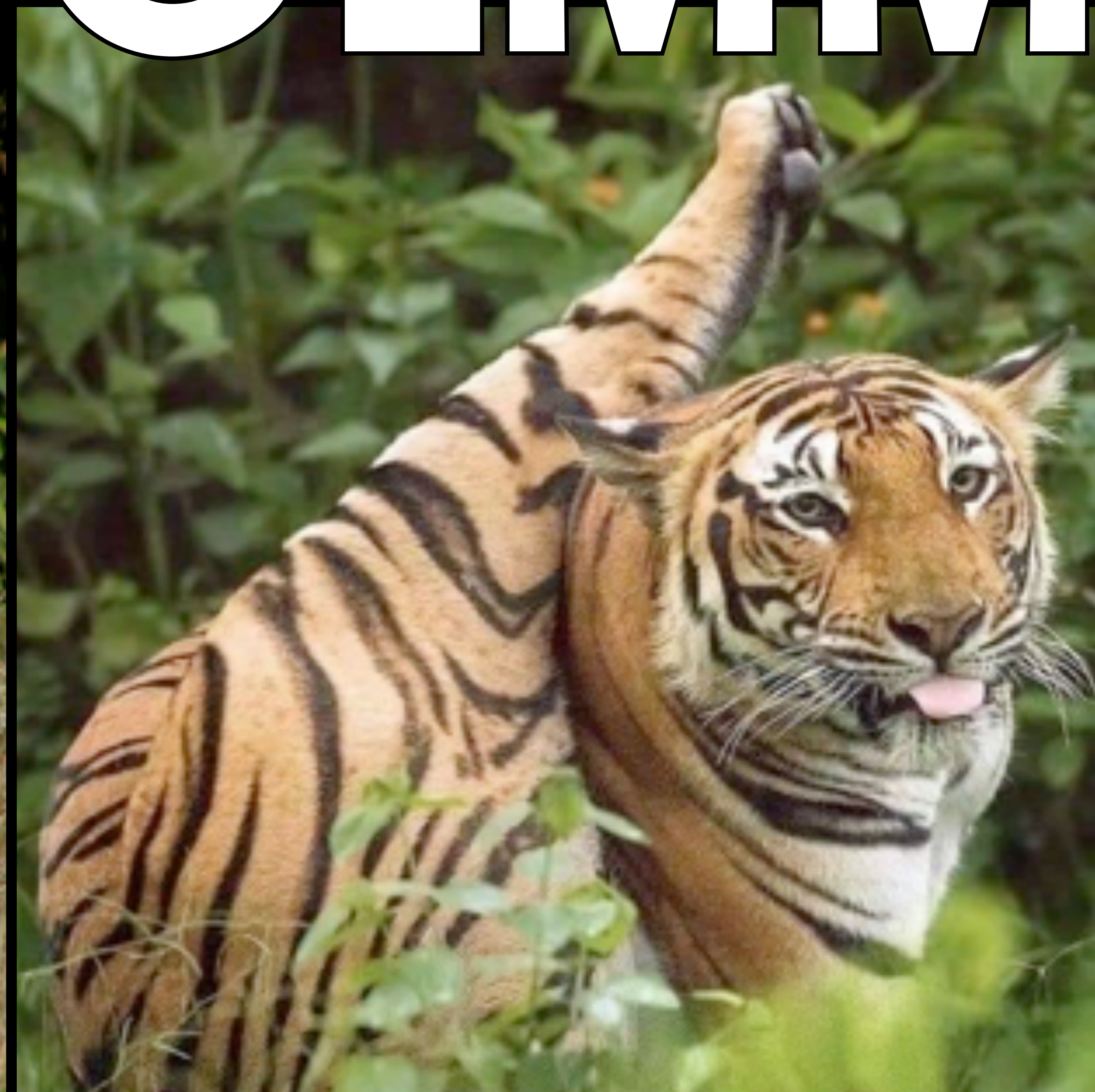
GLM

GLMM



More than regression

- Sometimes the causal model implies you need a regression model
- But this is not true in general
- Need a general approach for estimating arbitrary causal models

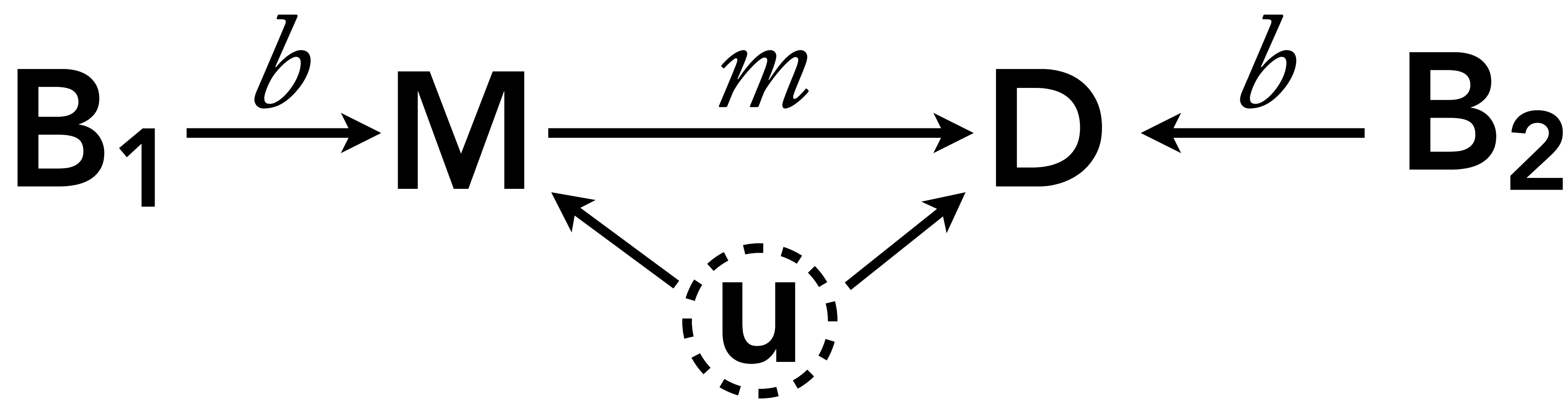
Bayesian Inference

- Bayesian inference is just probability theory
- Given a generative model, Bayesian inference can extract information from data
- If there is no information in the data, it will show
- The generative model is neither Bayesian nor anything else

Bayesian Causal Inference

- It can be hard to analyze an arbitrary causal model
- Full Luxury Bayesian Inference™
  - Program the structural causal model as a Bayesian network
  - Let probability theory analyze the model for you
- "Luxury" is not free: Computation can be challenging; analyzing the model yourself explains things that Bayes will not speak

Bayesian Moms



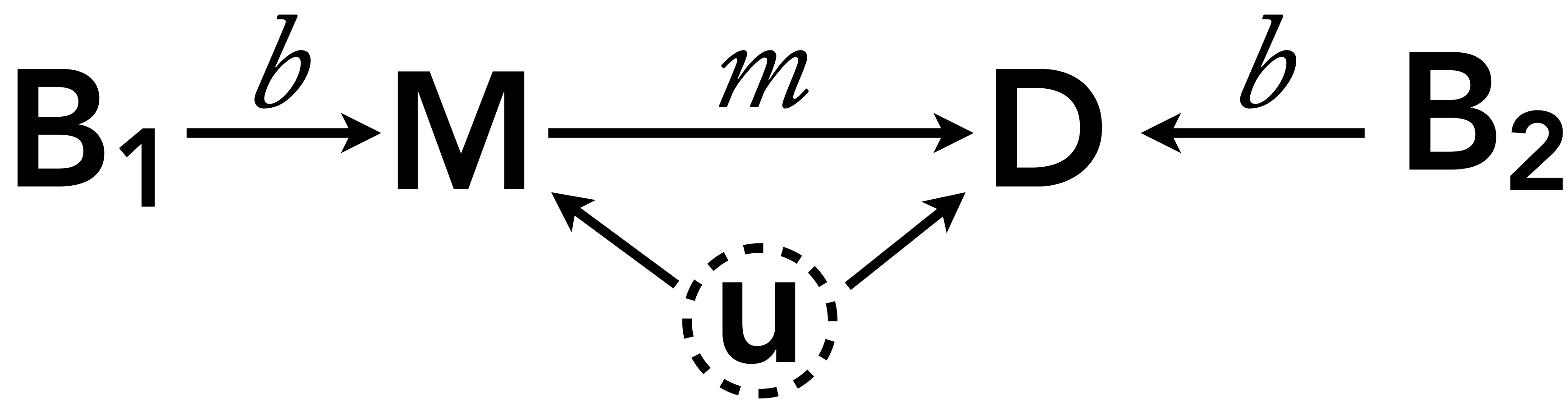
$$M \sim f_M(B_1, u)$$

$$D \sim f_D(M, B_2, u)$$

$$B_1, B_2 \sim f_B(.)$$

$$u \sim f_u(.)$$

Bayesian Moms




```
# mom model
    M ~ normal( mu , sigma ),
    mu <- a1 + b*B1 + k*U[i],
# daughter model
    D ~ normal( nu , tau ),
    nu <- a2 + b*B2 + m*M + k*U[i],
# B1 and B2
    B1 ~ bernoulli(p),
    B2 ~ bernoulli(p),
# unmeasured confound
    vector[N]:U ~ normal(0,1),
# priors
    c(a1,a2,b,m) ~ normal( 0 , 0.5 ),
    c(k,sigma,tau) ~ exponential( 1 ),
    p ~ beta(2,2)
```

$$M \sim f_M(B_1, u)$$

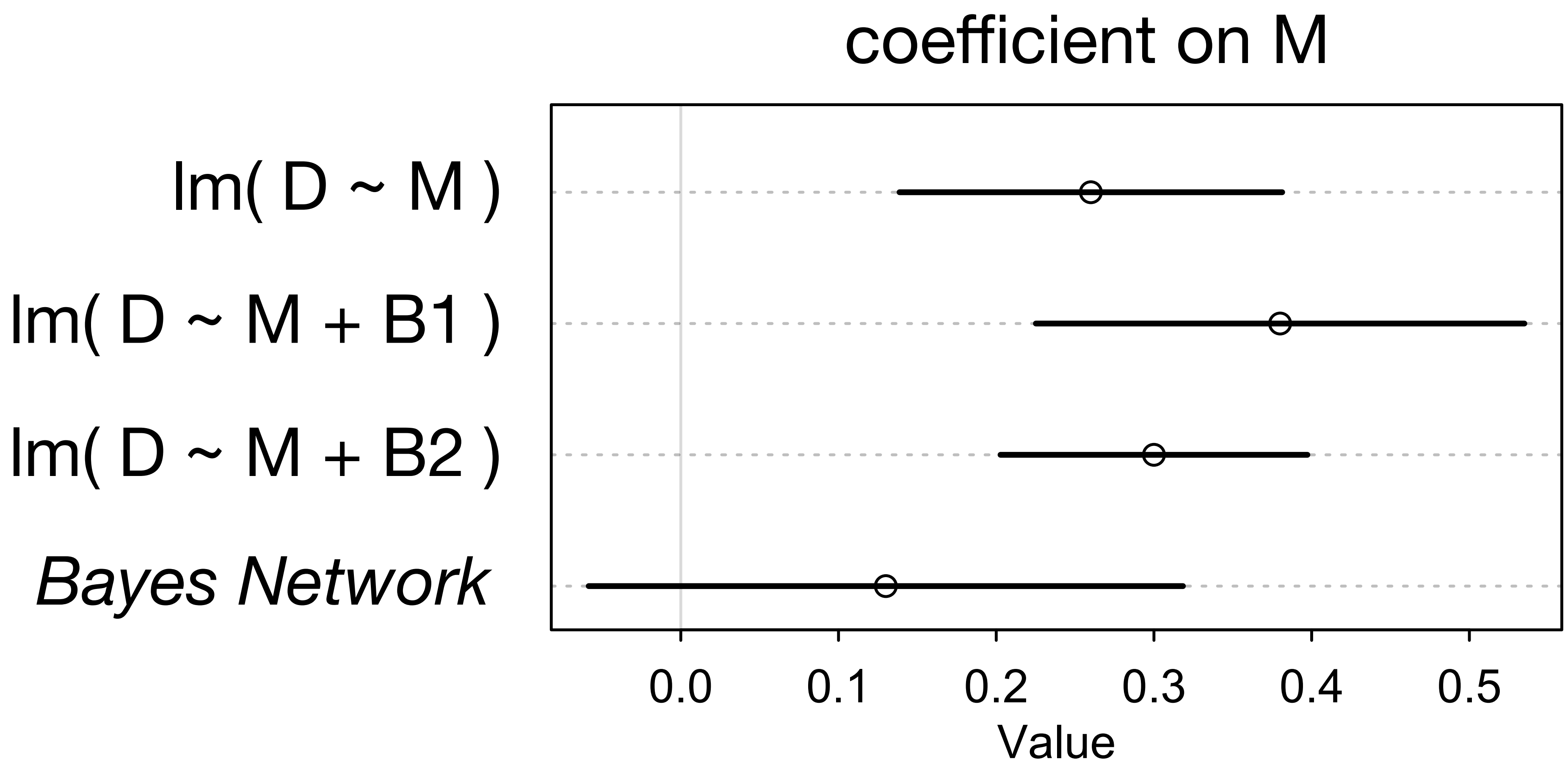
$$D \sim f_D(M, B_2, u)$$

$$B_1, B_2 \sim f_B(.)$$

$$u \sim f_u(.)$$

Code for examples: github.com/rmcelreath/causal_salad_2021

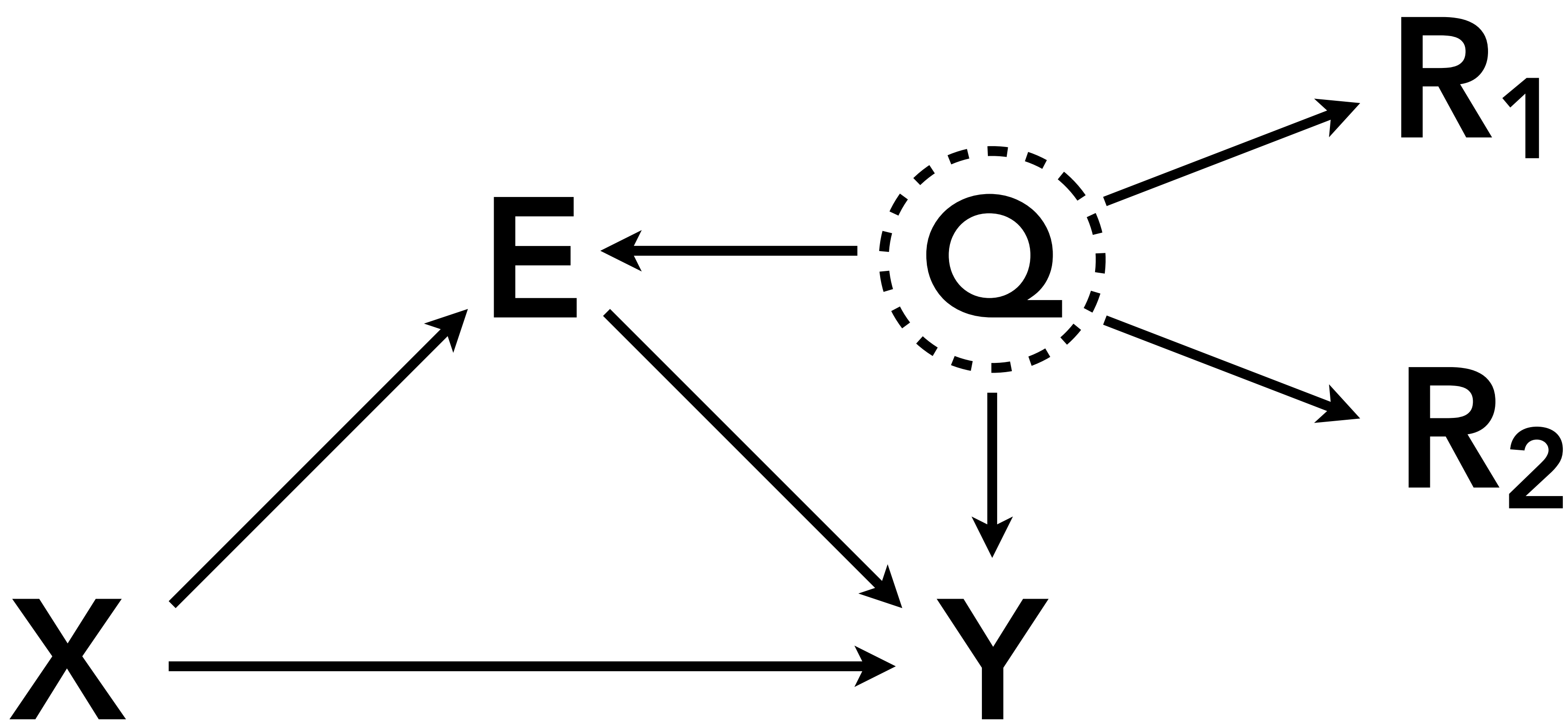
Bayesian Moms

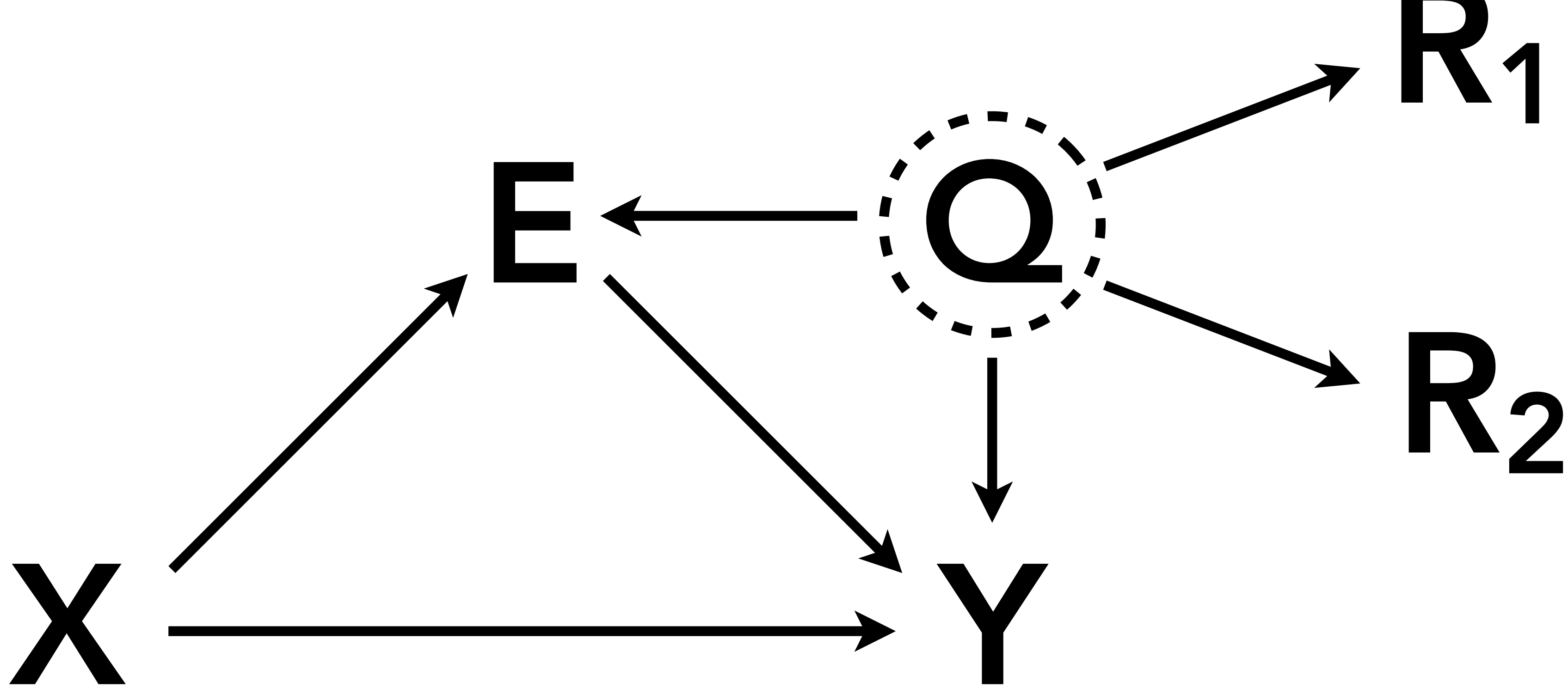


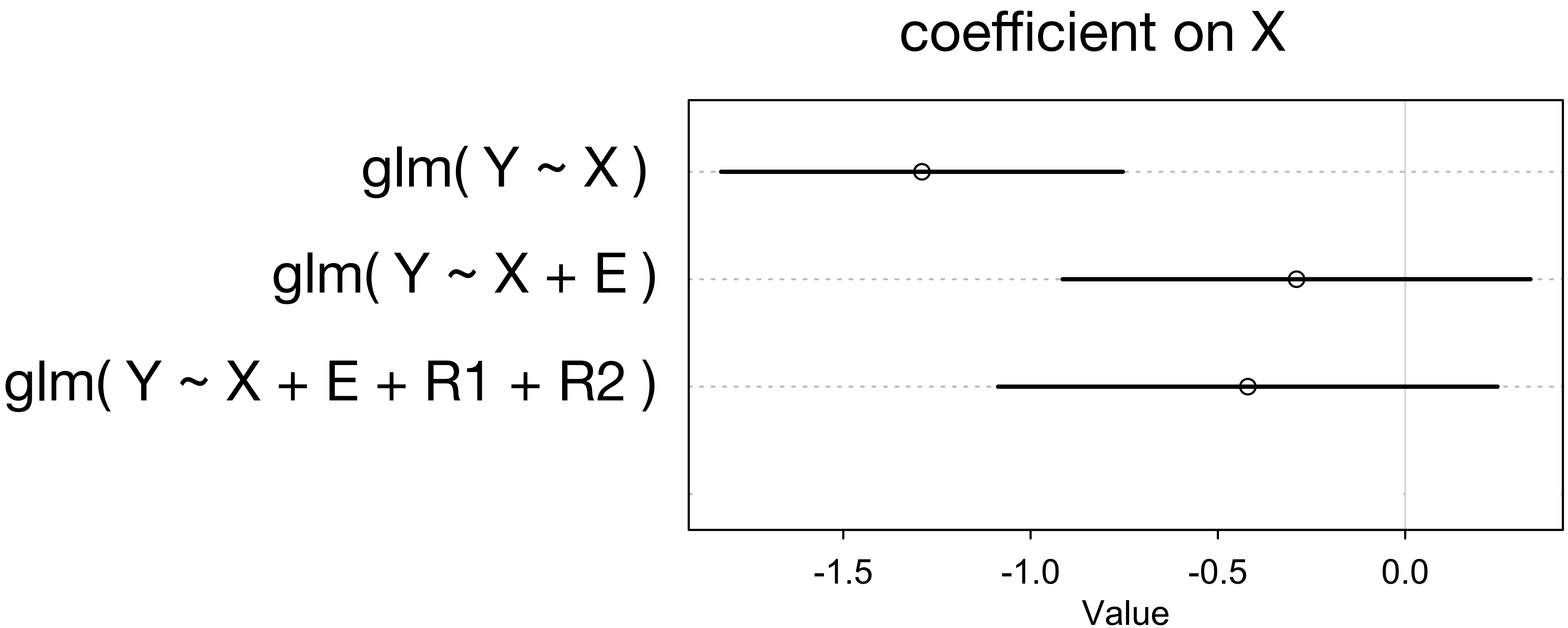
Code for examples: github.com/rmcelreath/causal_salad_2021

Peer Bias

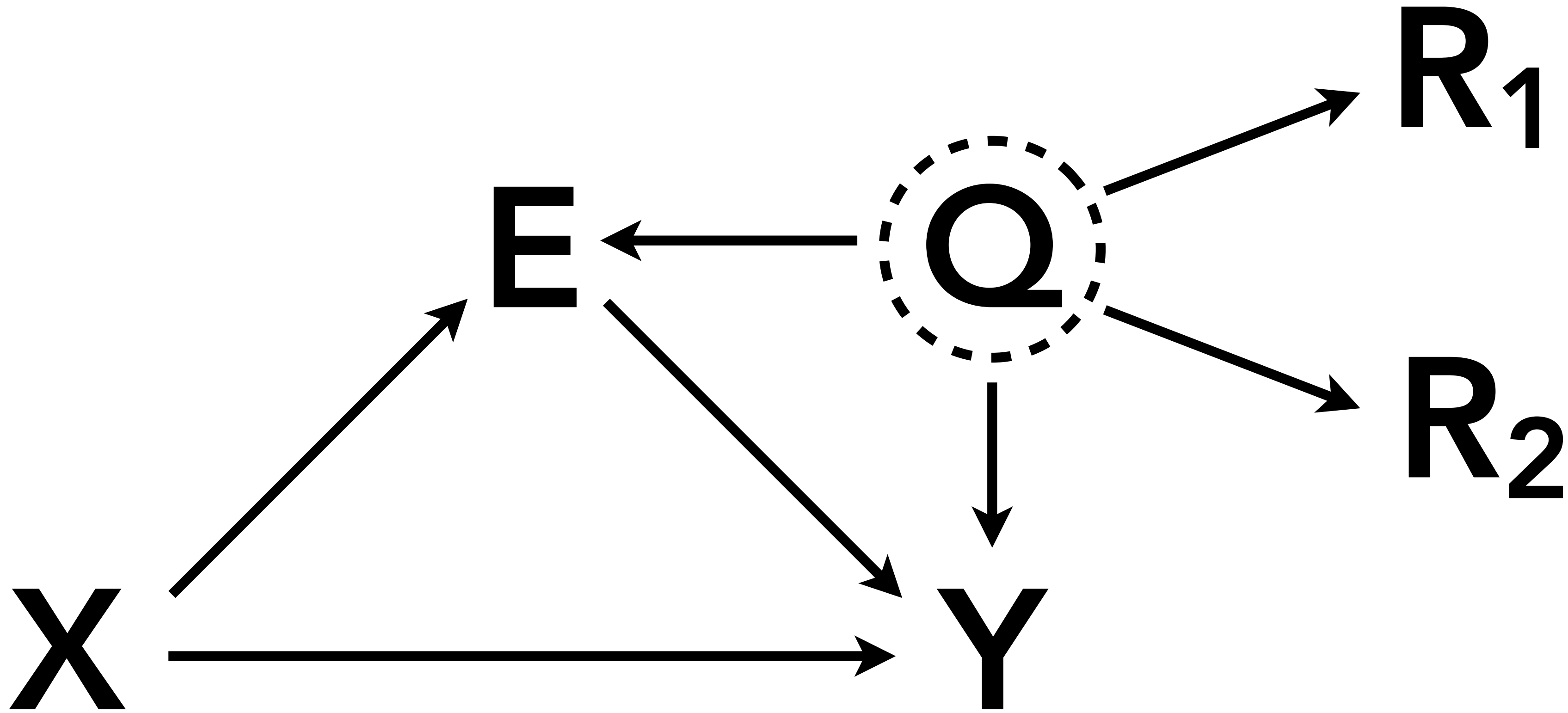
- We don't know **Q**, but what if we have some proxies of it?





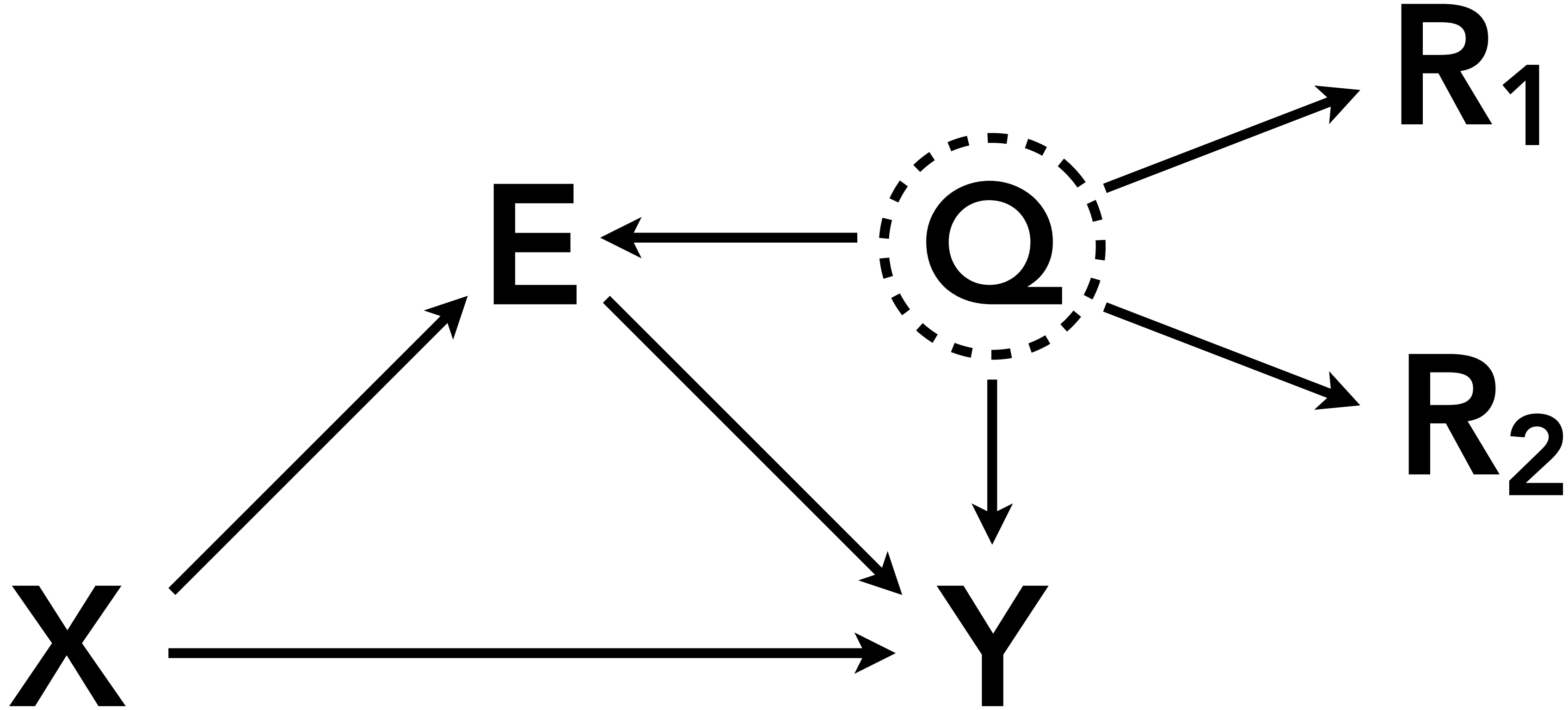


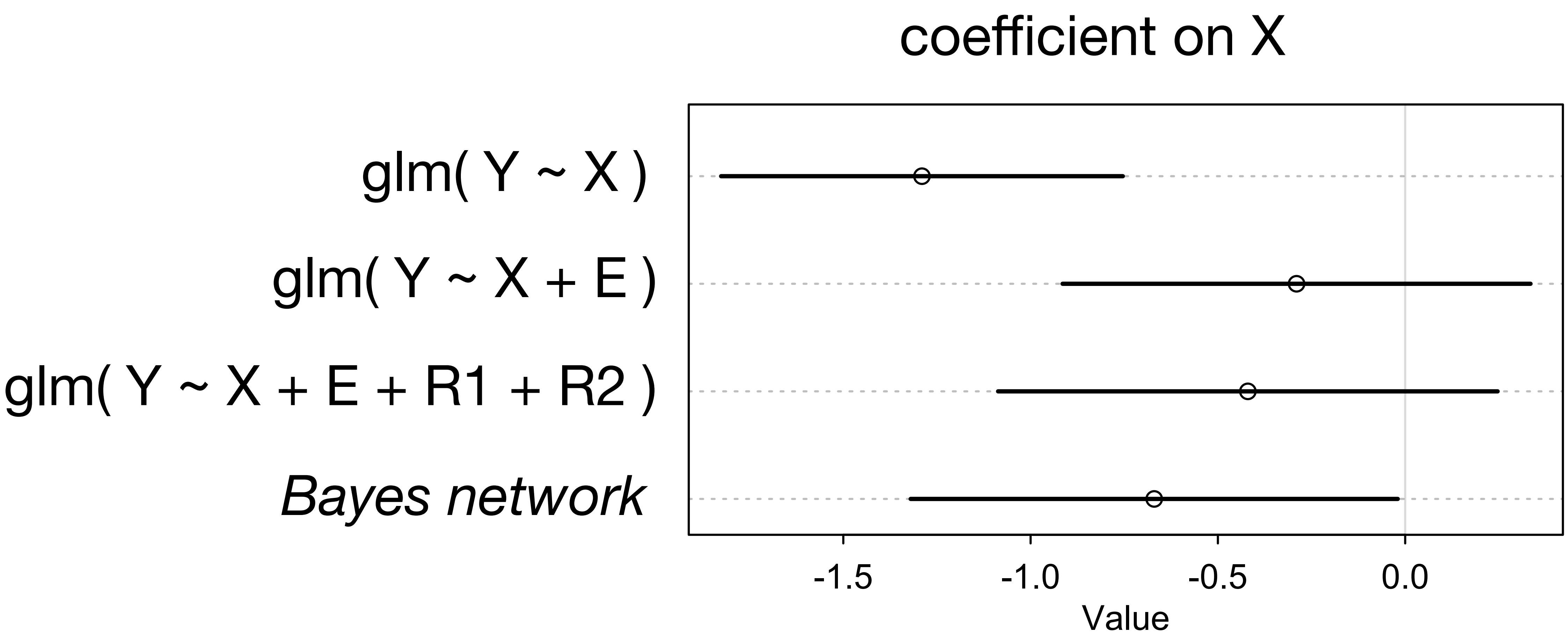
Code for examples: github.com/rmcelreath/causal_salad_2021




```
# Y model
Y ~ bernoulli(p),
logit(p) <- a[E] + X*XX + h*Q[id],
a[E] ~ normal(0,1),
X ~ normal(0,1),
h ~ half_normal(0,1),
# Q model
vector[id]:Q ~ normal(0,1),
R1 ~ normal(Q,1),
R2 ~ normal(Q,1)
```

Code for examples: github.com/rmcelreath/causal_salad_2021





Code for examples: github.com/rmcelreath/causal_salad_2021

Not Magic

- Bayesian inference is only as good as
  - The generative model fed into it
  - The sample fed into it
  - The numerical algorithm
- But conditional on the model, you cannot do better
- Provides ways to handle missing data, measurement error — **add cause** of missingness and error to model
- Things like **social networks** & **phylogenies** are never "observed". Must be **inferred** from often bad data. Need a causal model of observations.

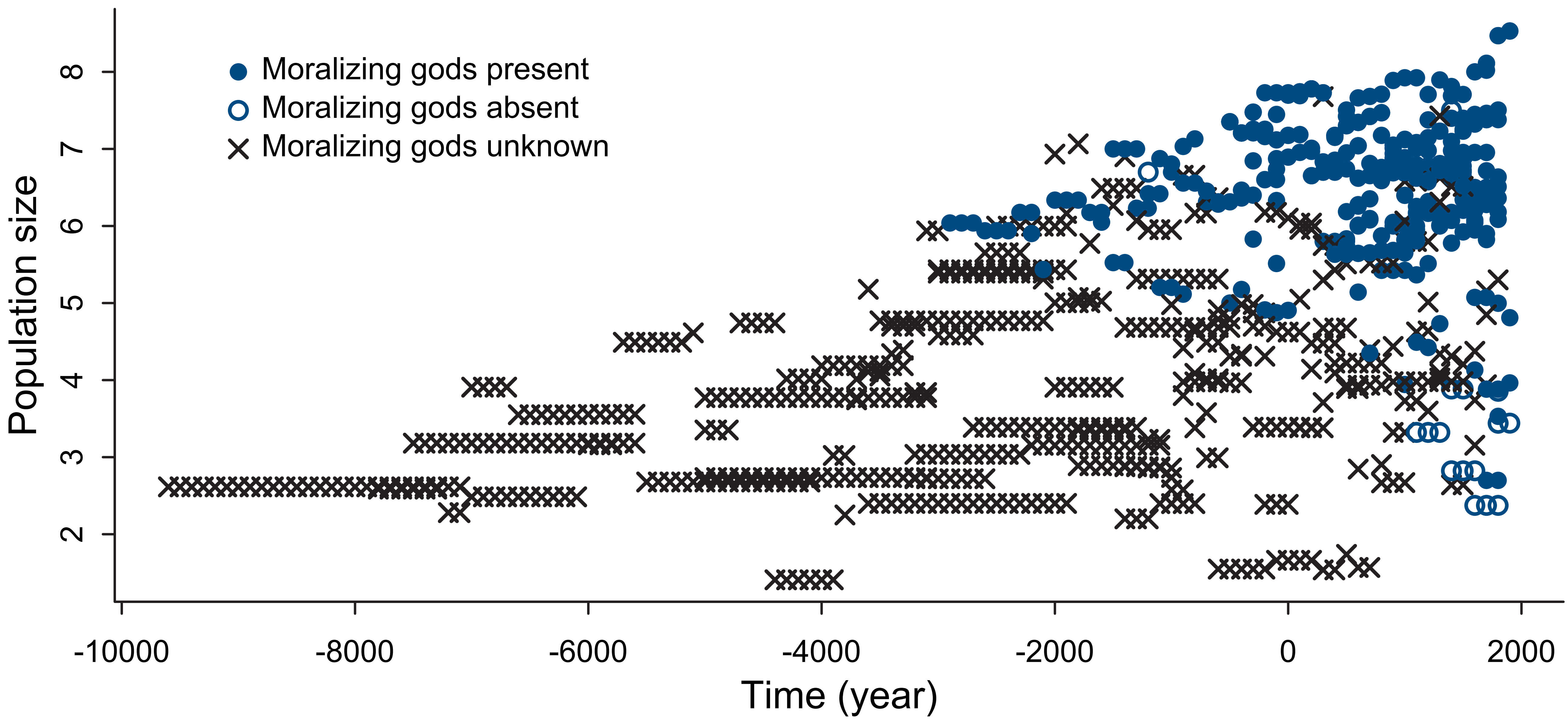


FIGURE 15.7. Missing values in the `Moralizing_gods` data. The blue points, both open and filled, are observed values for the presence of beliefs about moralizing gods. The x symbols are unknowns, the missing values.

McElreath 2020 *Statistical Rethinking*, page 514


Science Before Statistics
CAUSAL
INFERENCE

Science Before Statistics

- Causal inference requires
  - A causal model distinct from any statistical models
  - Analysis of the implications of the causal model for (1) research design (2) testing (3) estimation strategy
  - Some way to perform estimation
- Descriptive and experimental research no exceptions

Much much more

- Computation of treatment effects: not a single parameter
- Post-stratification: effect for the population, not the sample
- Partial-identification: confounded but learning
- Research design

Full Luxury Causal Workflow

1. Derive candidate causal model using “science”

2. Program model as a generative simulation

3. Design research & validate statistical analysis using (2)

4. Confront model with data; celebrate wins and losses equally

5. Revise and repeat

Full Sadness Non-Causal Workflow

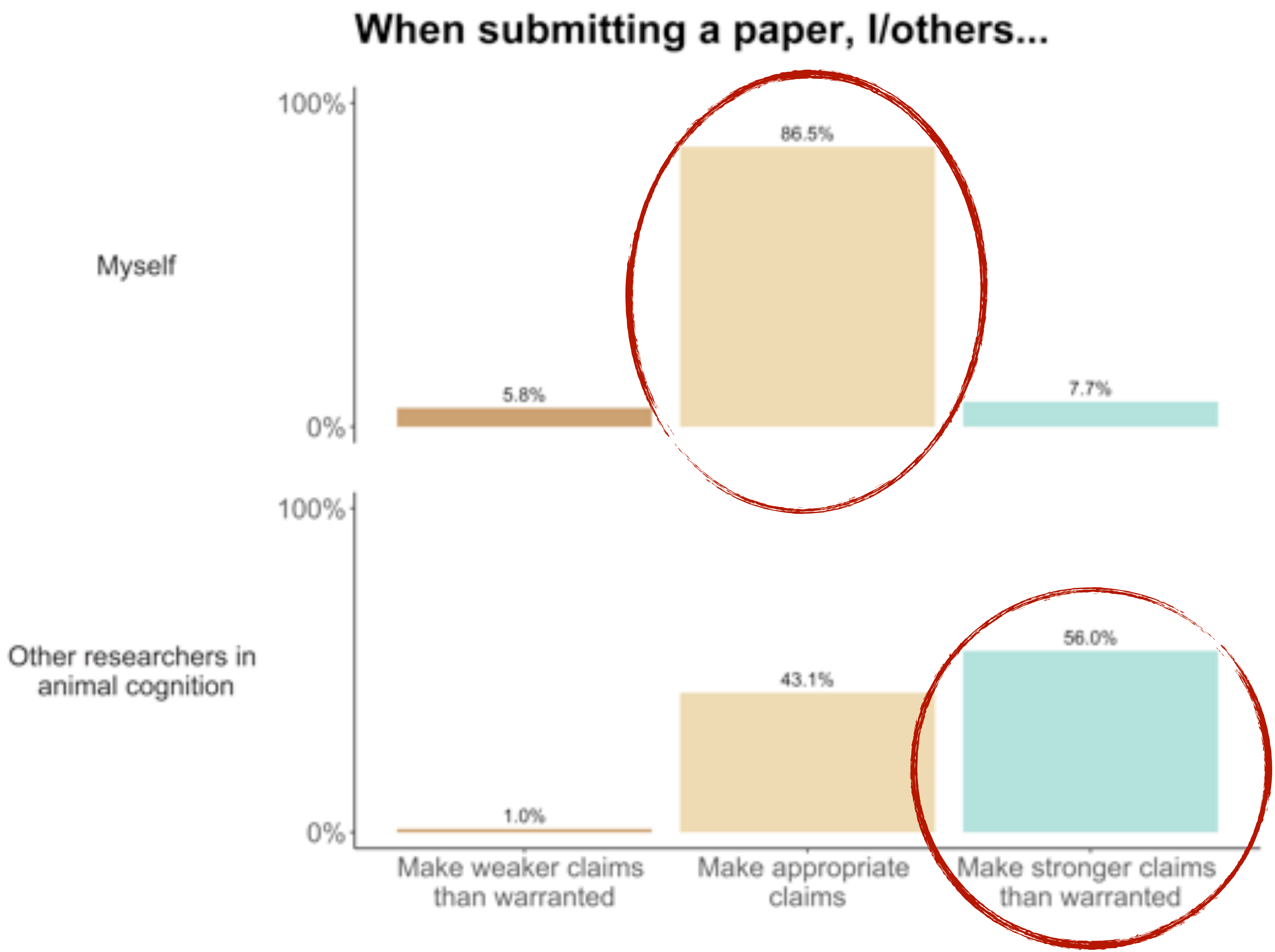
1. Find or collect some variables that are **conceptually**, but not **logically**, relevant to phenomenon

2. Probe the data anyway you can to reveal **asterisks**

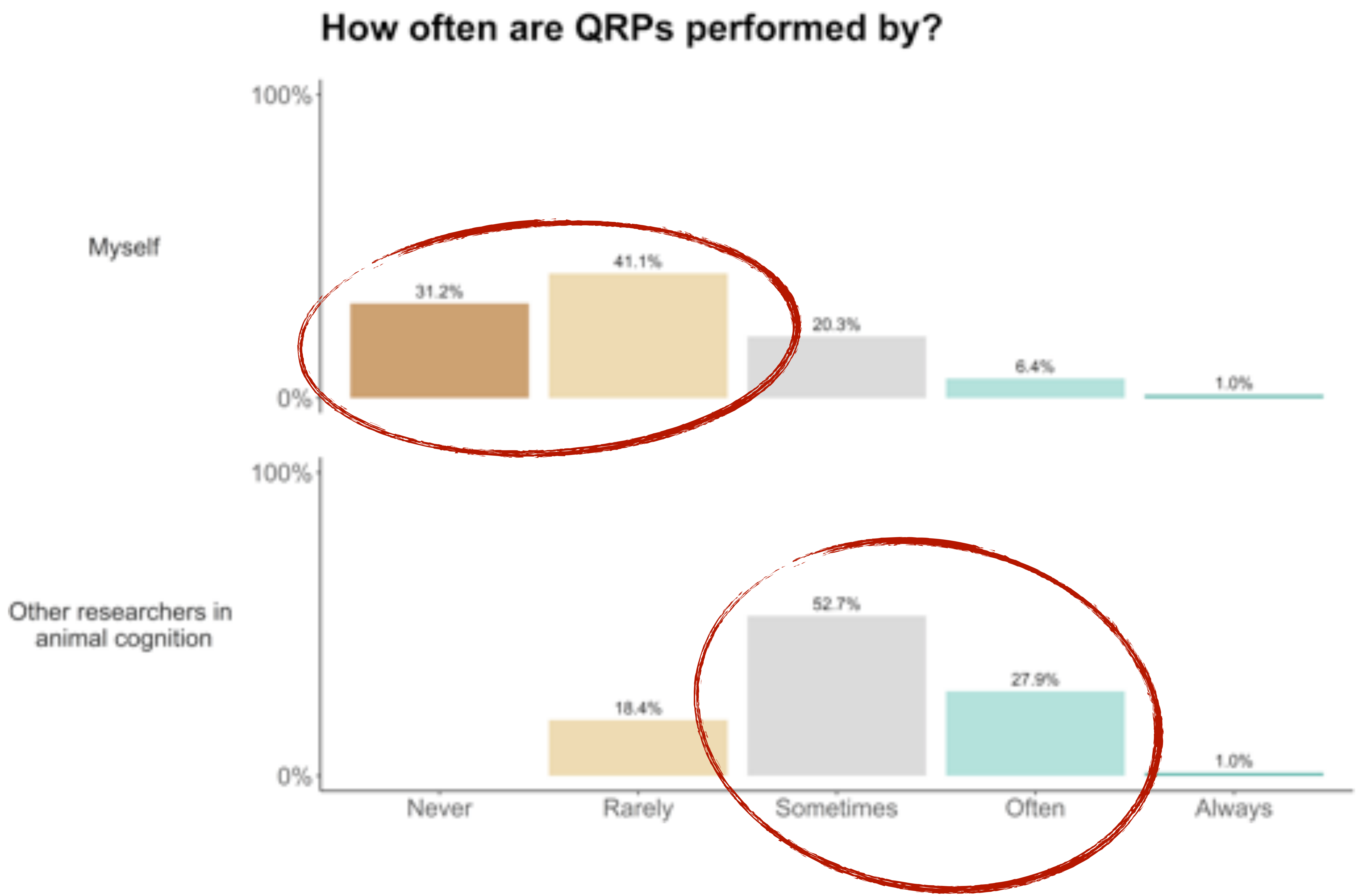
3. Tell a hopeful, **causal story** about what these asterisks exist

4. Never state the **assumptions** that license your story

5. Revel in your magnificent h-index



Farrar, Ostojić, Clayton 2021 The hidden side of animal cognition research



Farrar, Ostojić, Clayton 2021 The hidden side of animal cognition research

Much much more