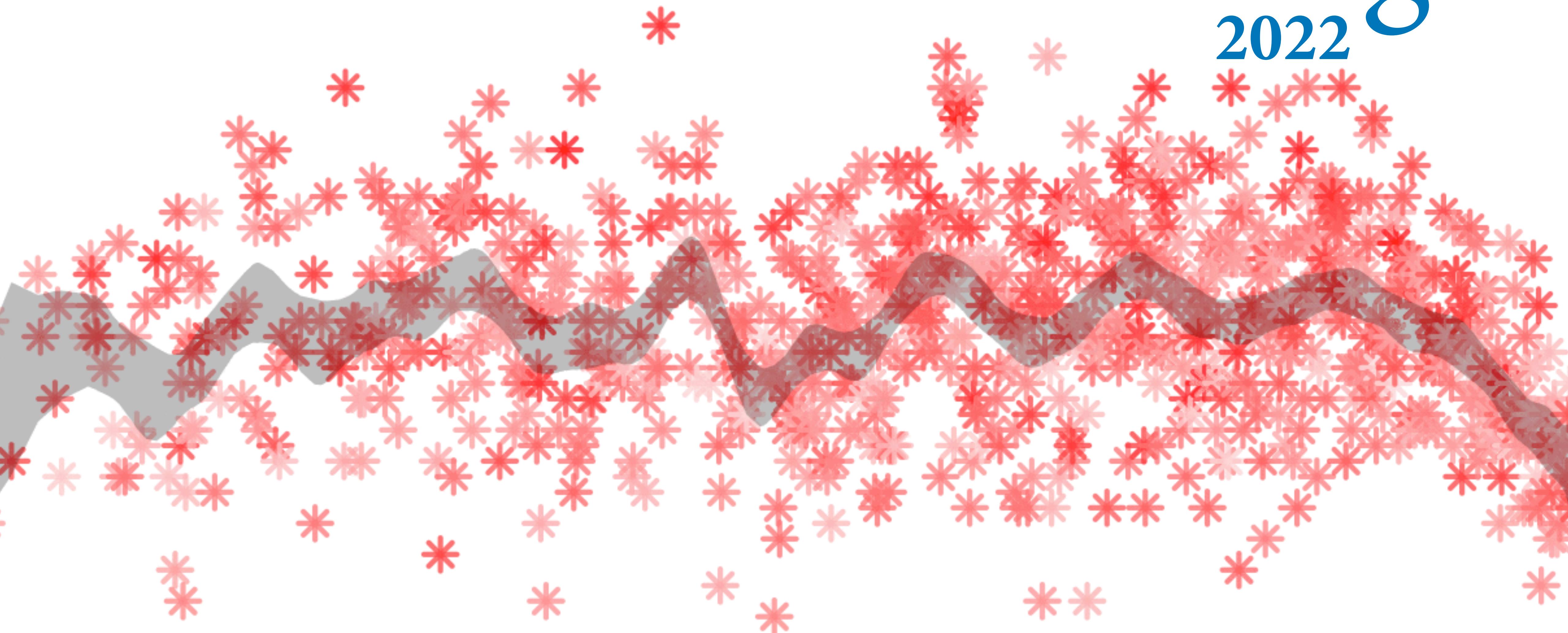


# Statistical Rethinking

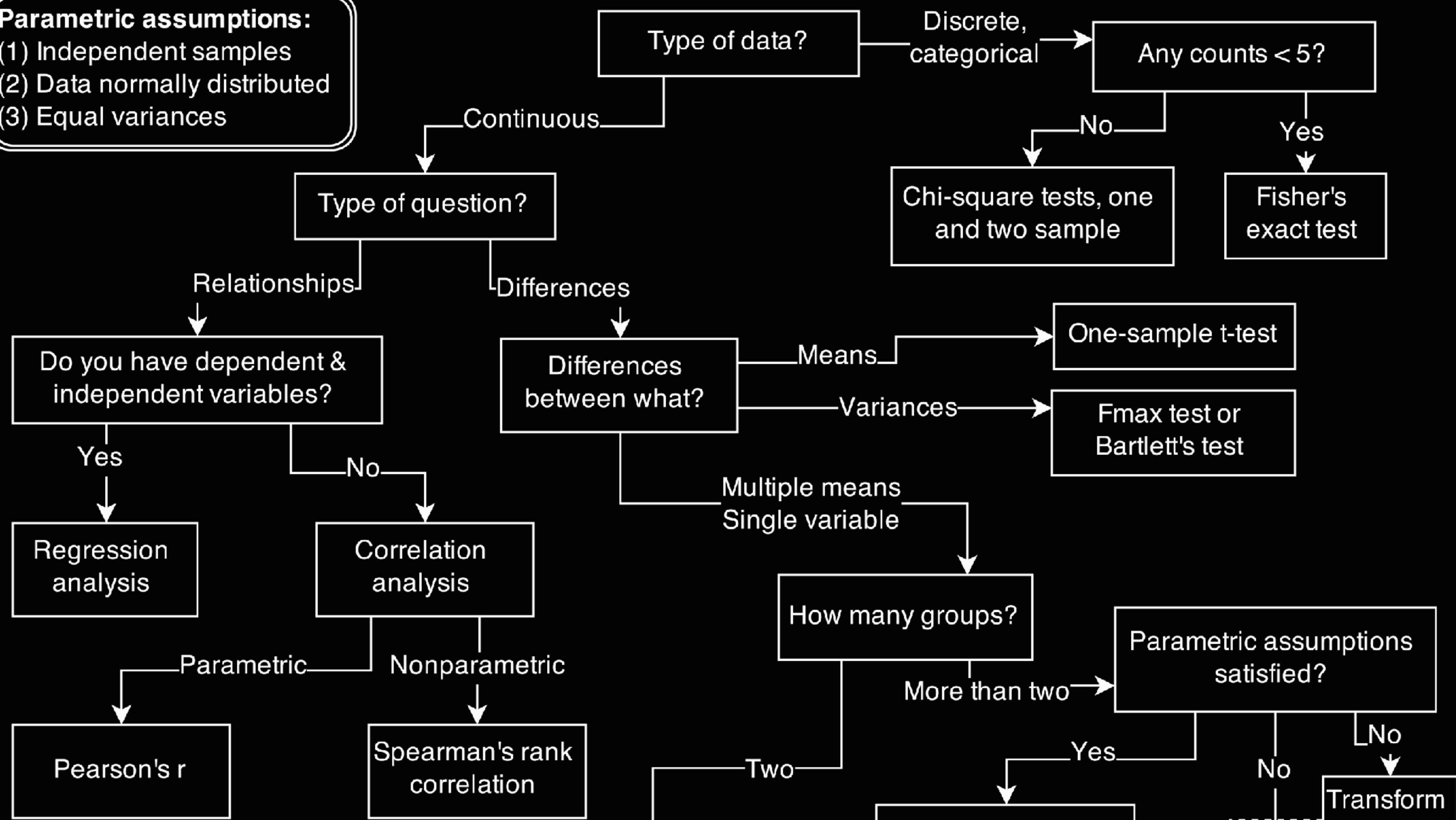
2022



(1) The Golem of Prague

## Parametric assumptions:

- (1) Independent samples
- (2) Data normally distributed
- (3) Equal variances



Second  
Edition

Texts in Statistical Science

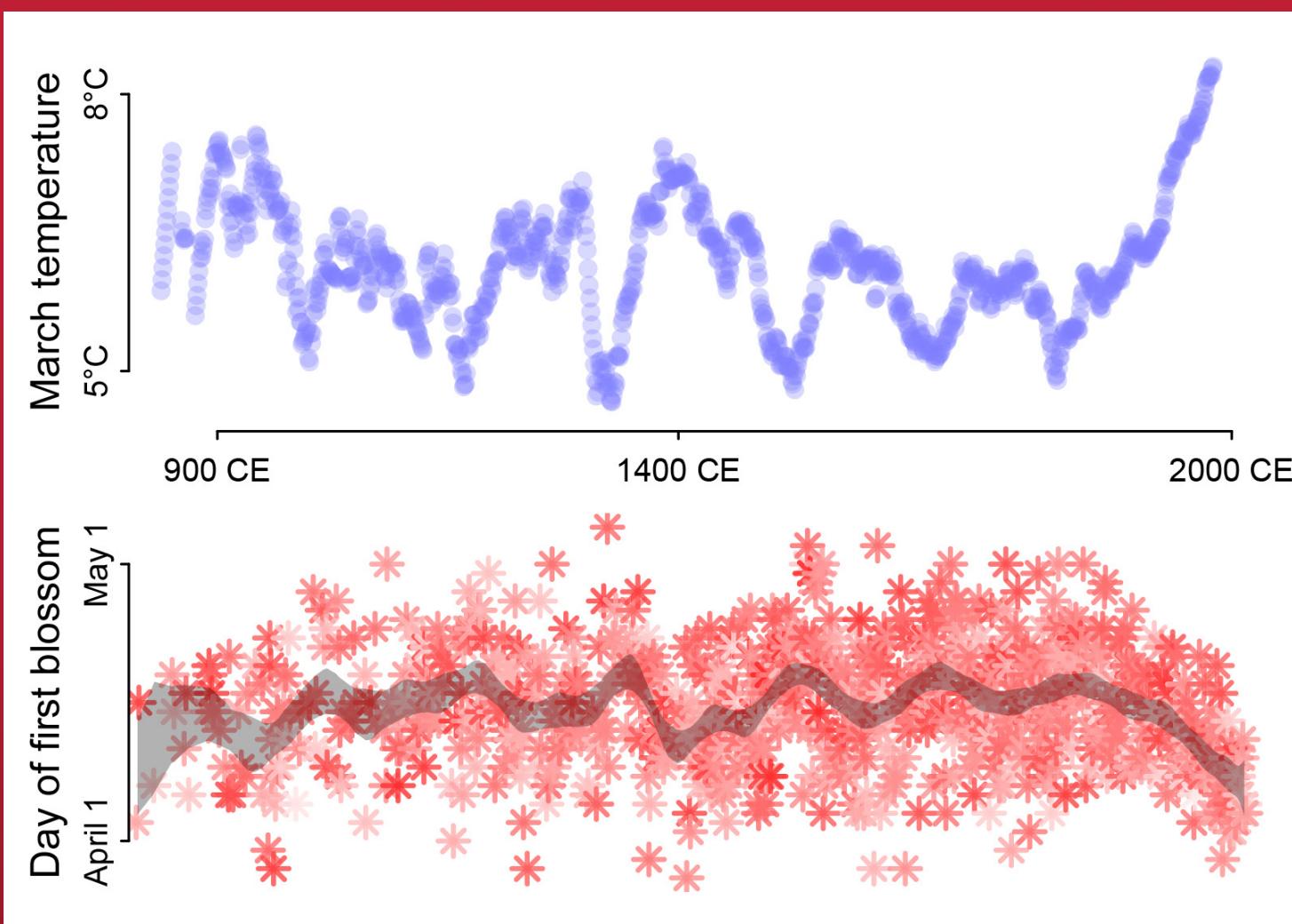
# Statistical Rethinking

McElreath



# Statistical Rethinking

A Bayesian Course  
with Examples in R and Stan  
**SECOND EDITION**



Richard McElreath

CRC Press  
Taylor & Francis Group

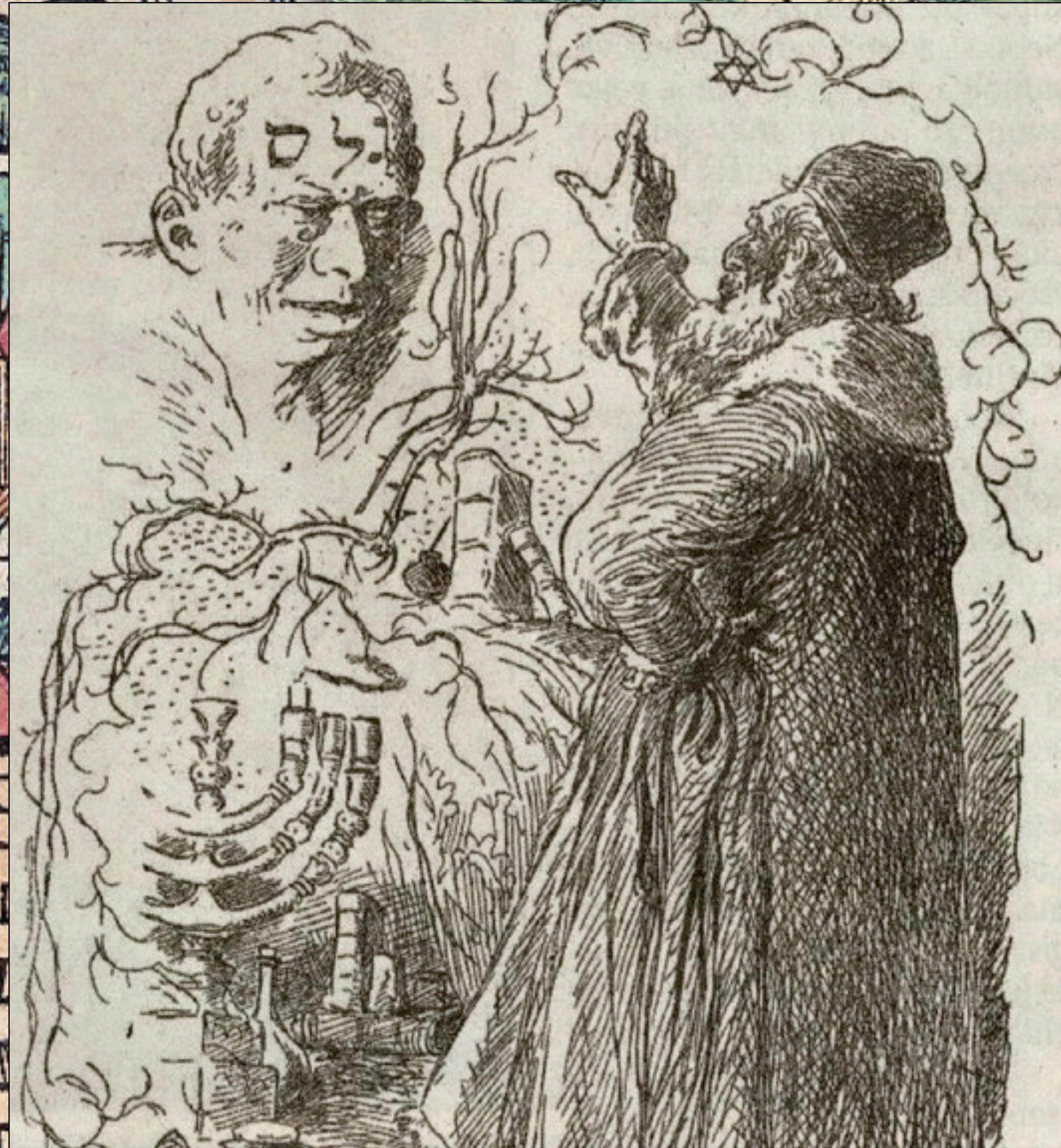
A CHAPMAN & HALL BOOK

Rethinking  
the role of  
statistical  
analysis in  
research  
20 lectures

GOLEMS  
OWLS  
DAGS

PRAGA

Prague 16th century





Art from: “Breath of Bones: A Tale of the Golem” (2014)

# Golems

Clay robots

Powerful

No wisdom or foresight

Dangerous



“Breath of Bones: A Tale of the Golem” (2014)

# Statistical Models

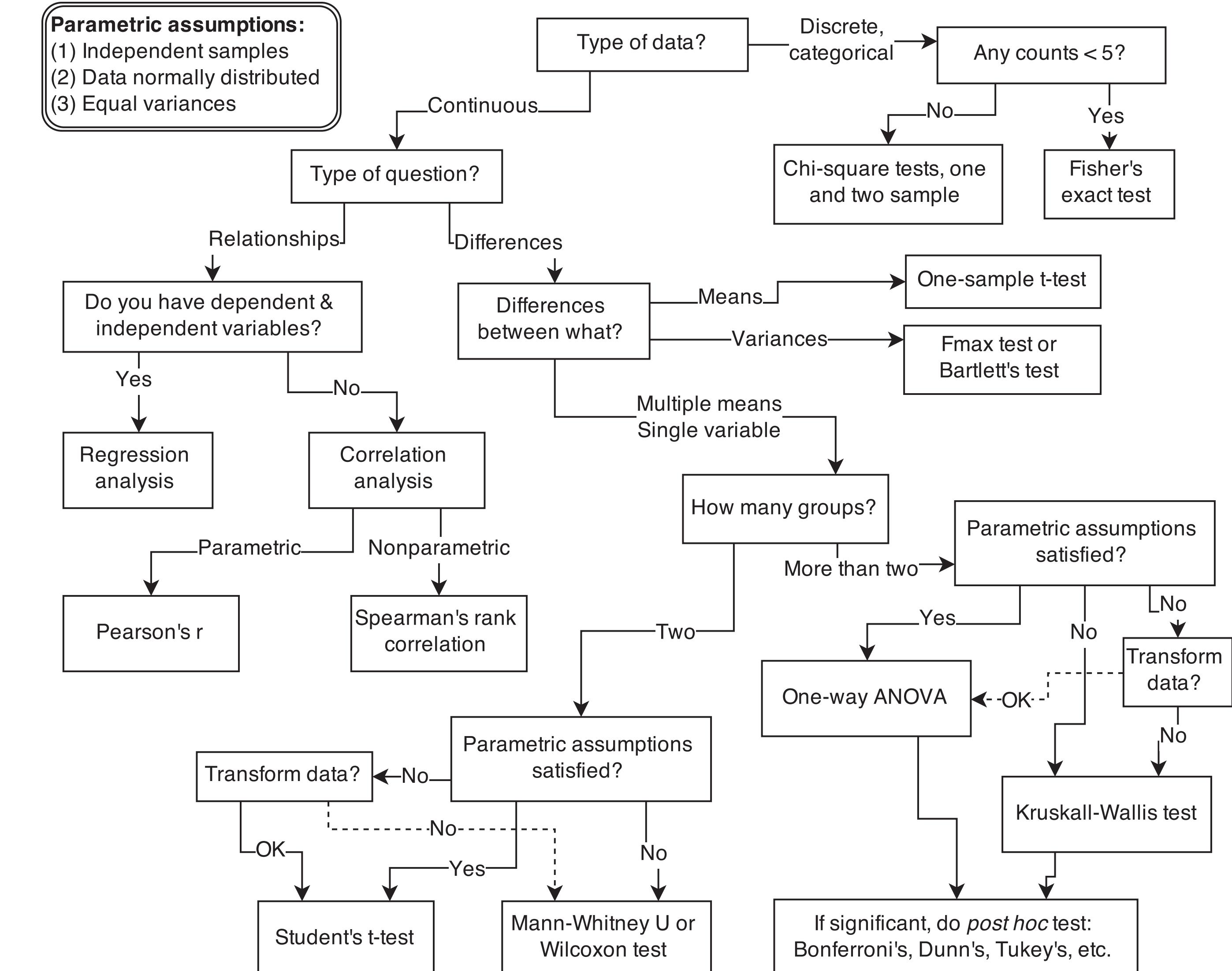
Clay robots

Powerful

No wisdom or foresight

Dangerous

Like Golems



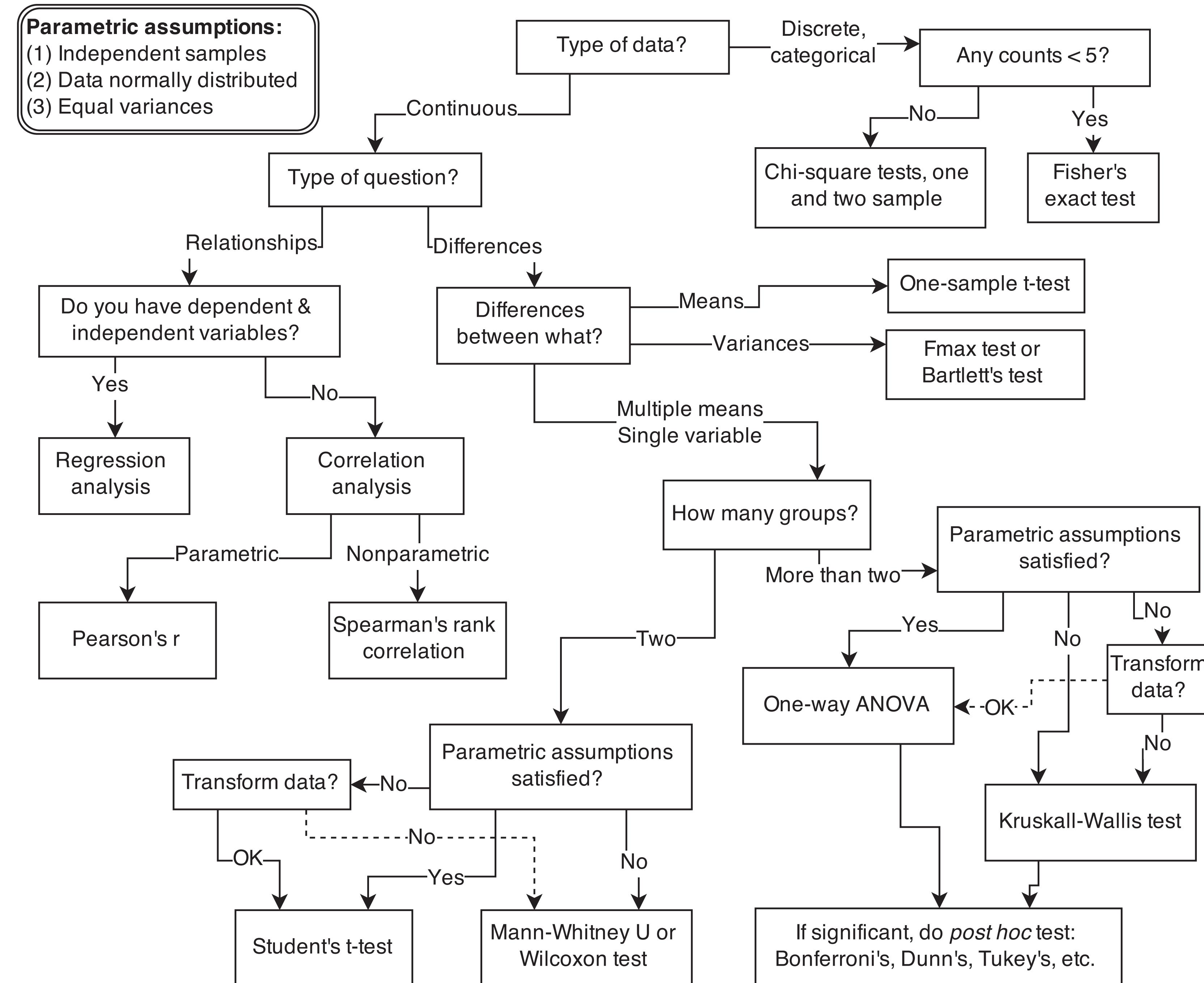


Figure 1.1

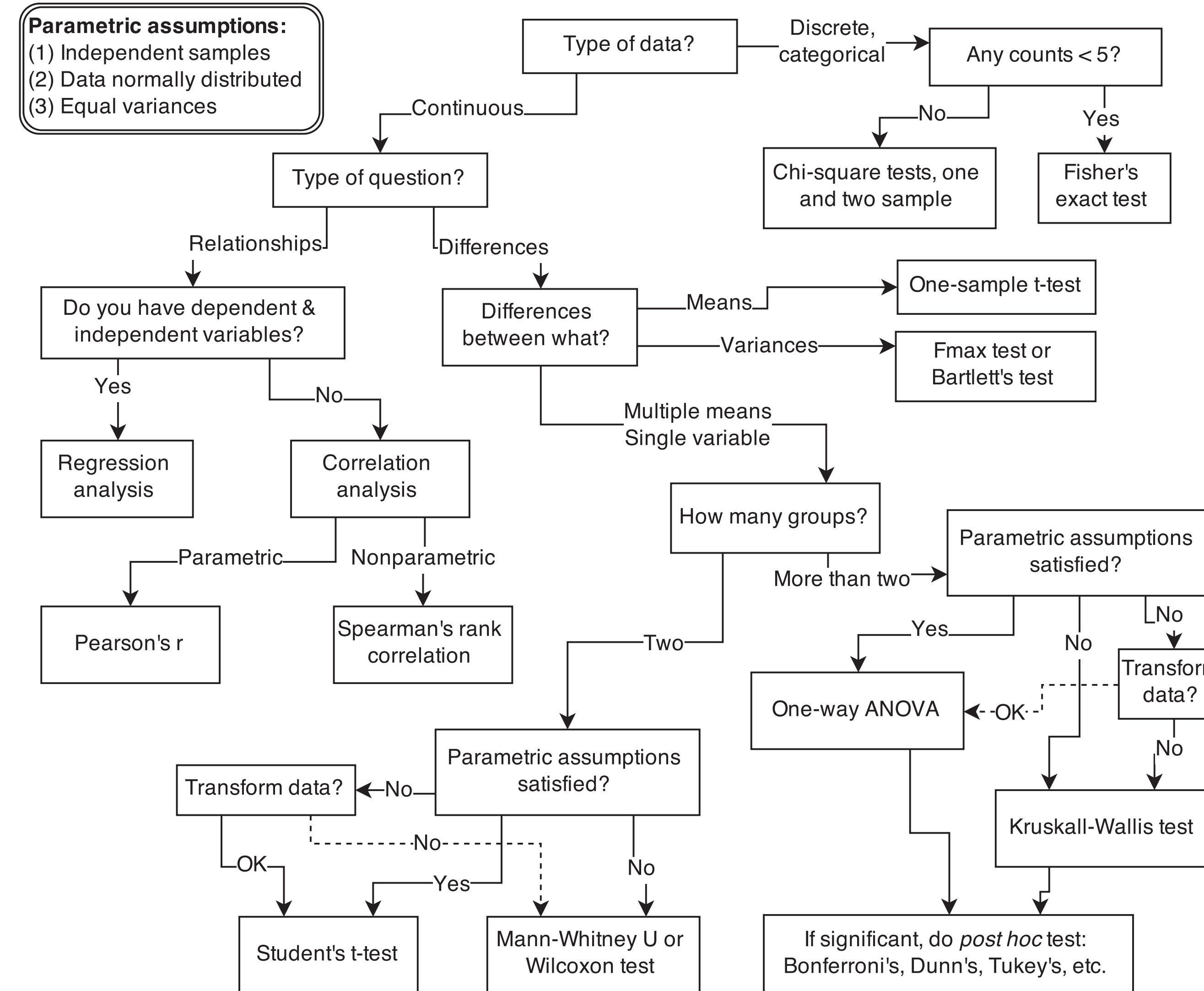
# Statistical Models

# Incredibly limiting

Focus on rejecting null  
hypotheses instead of research  
hypotheses

Relationship between hypothesis and test not clear

# Industrial framework



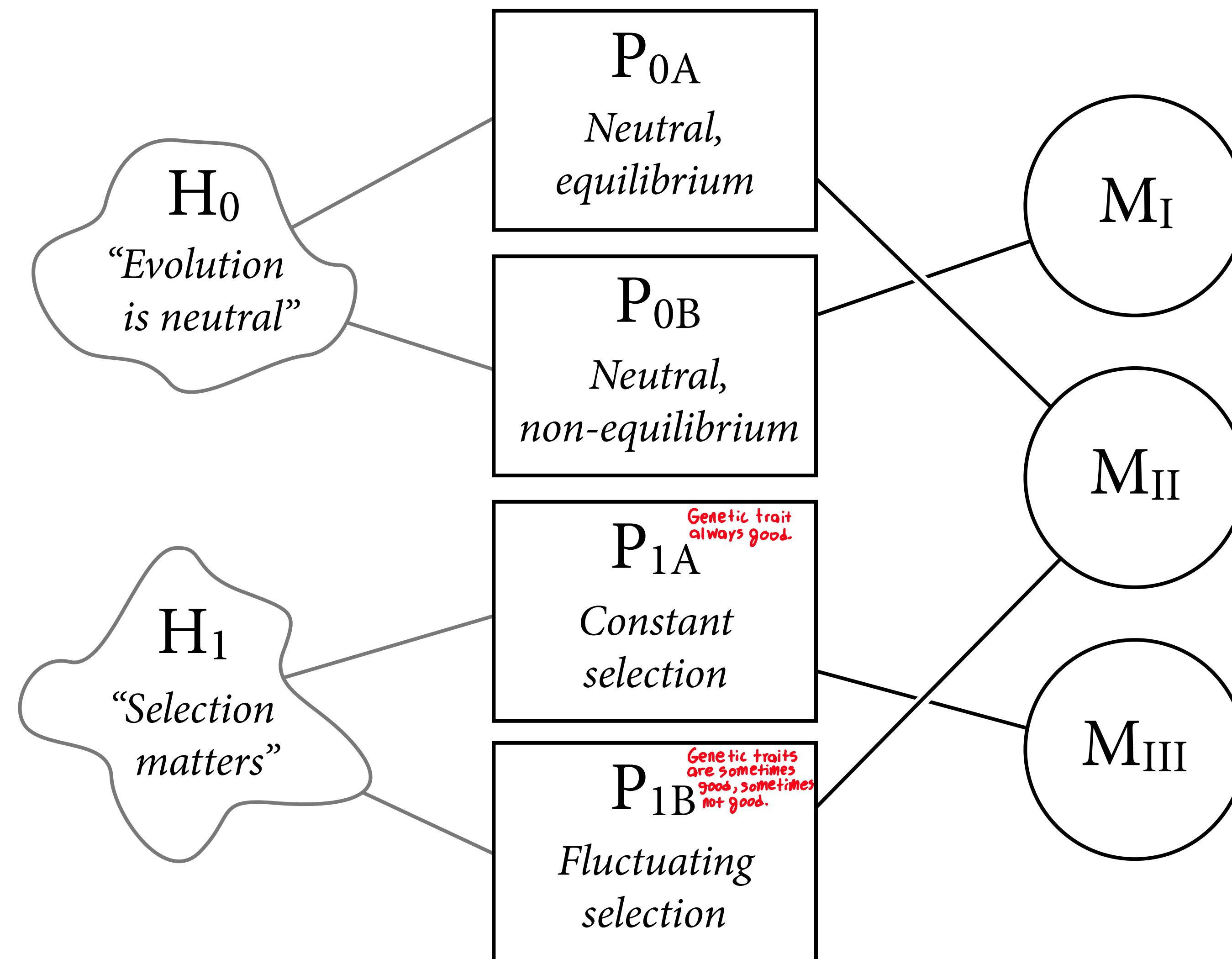
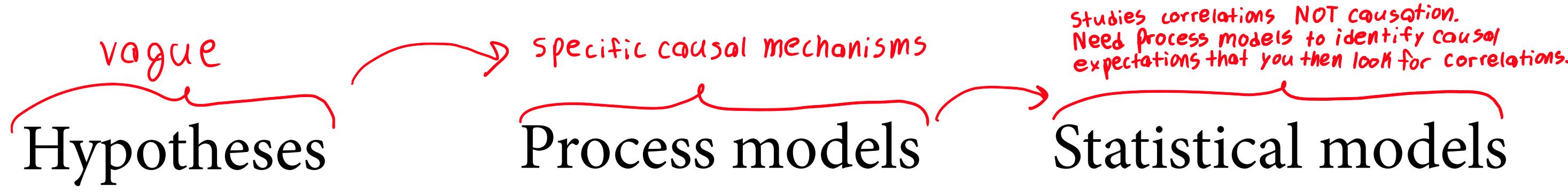


Figure 1.2

# Null Models Rarely Unique

Null phylogeny?

No such "null"  
hypothesis to  
randomize to

Null ecological community?

Null social network?



# Hypotheses and Models

Research requires more than tiny null robots

Also requires:

Precise process model(s)

Statistical model (procedure, golem) justified by implications of process model(s) and question (estimand)

**OWLS**

# HOW TO DRAW AN OWL

(Joke)



1. Draw some circles

# HOW TO DRAW AN OWL

(Joke)

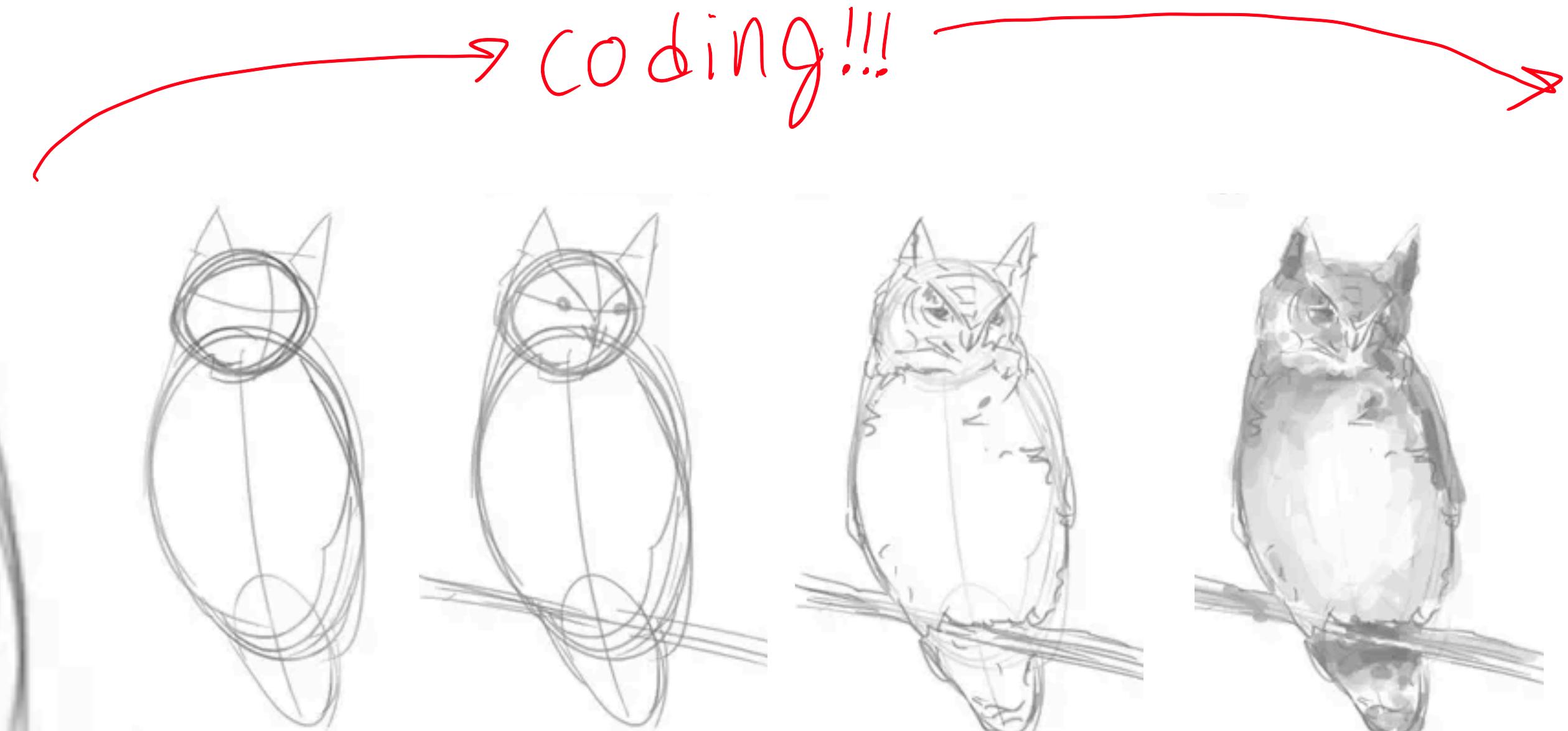


1. Draw some circles



2. Draw the rest of the owl

# HOW TO DRAW AN OWL

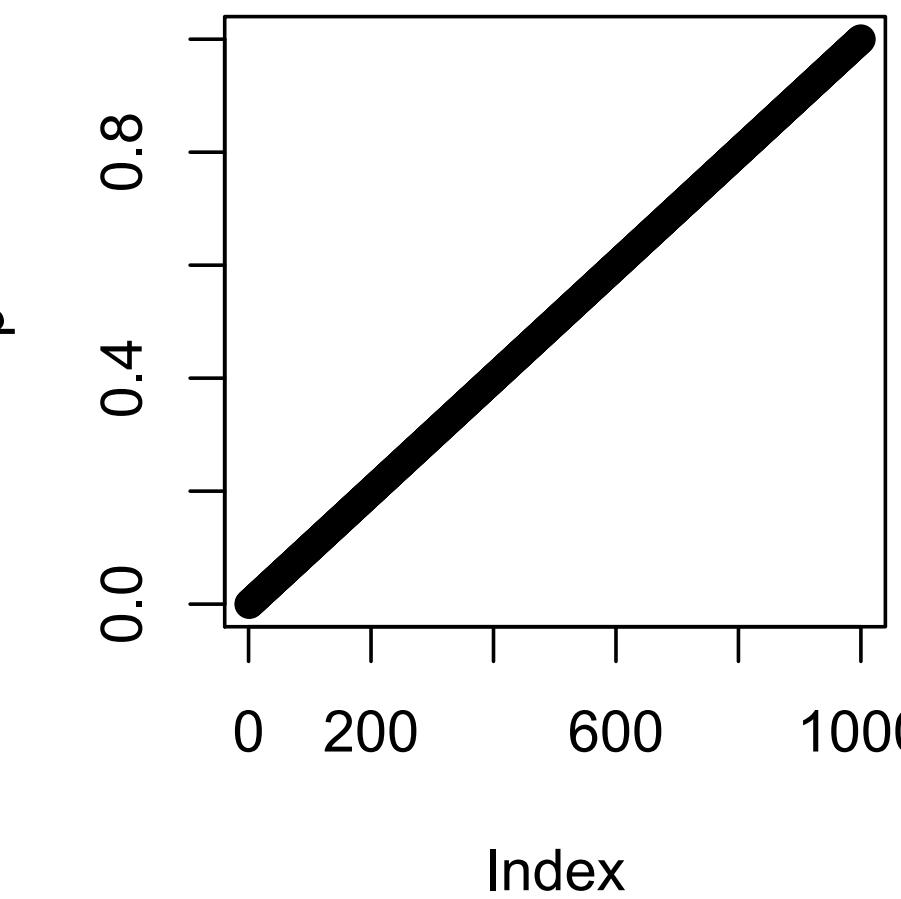


Coding!!!

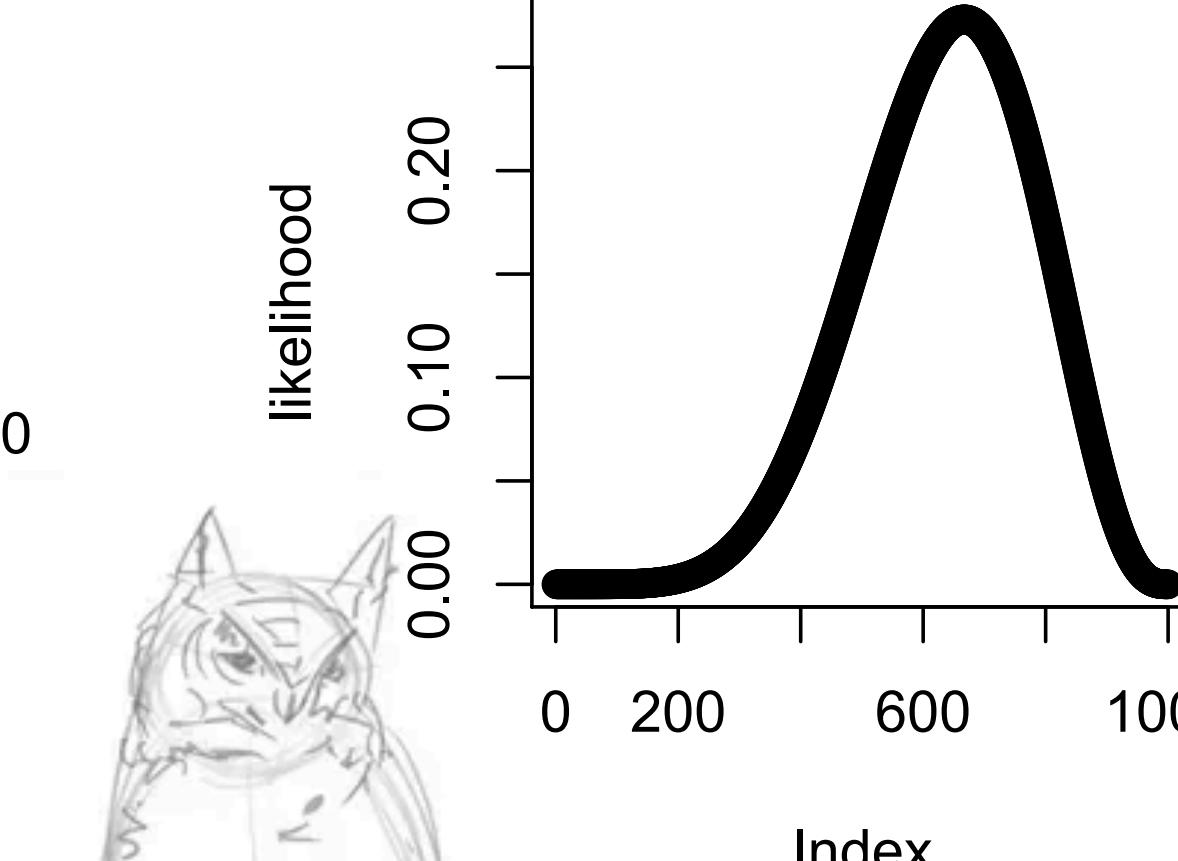
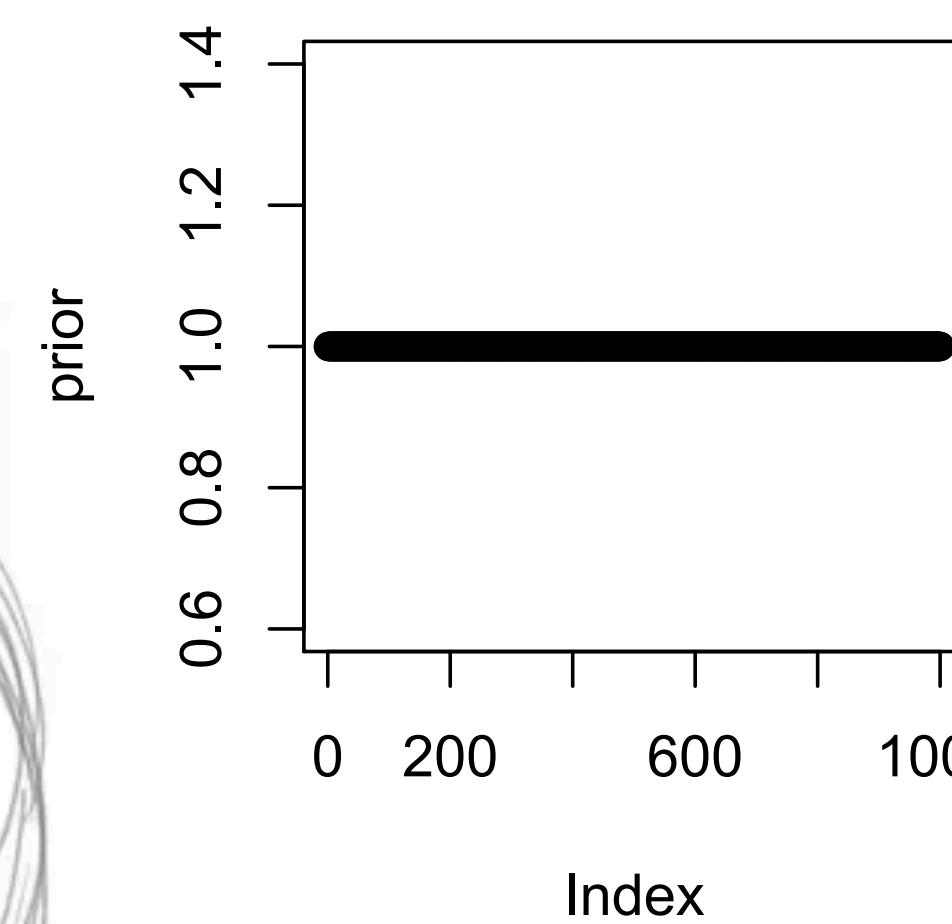


1. Draw some circles

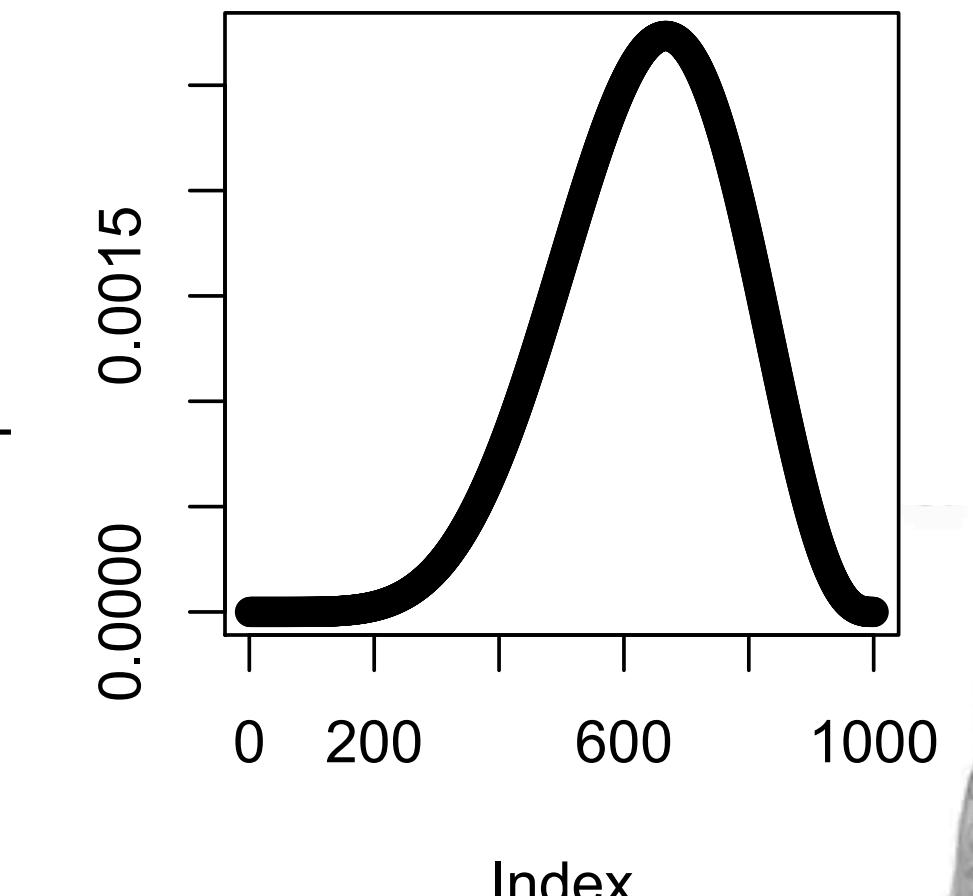
2. Draw the rest of the owl



```
p_grid <- seq( from=0 , to=1 , length.out=1000 )
prob_p <- rep( 1 , 1000 )
prob_data <- dbinom( 6 , size=9 , prob=p_grid )
posterior <- prob_data * prob_p
posterior <- posterior / sum(posterior)
```



posterior



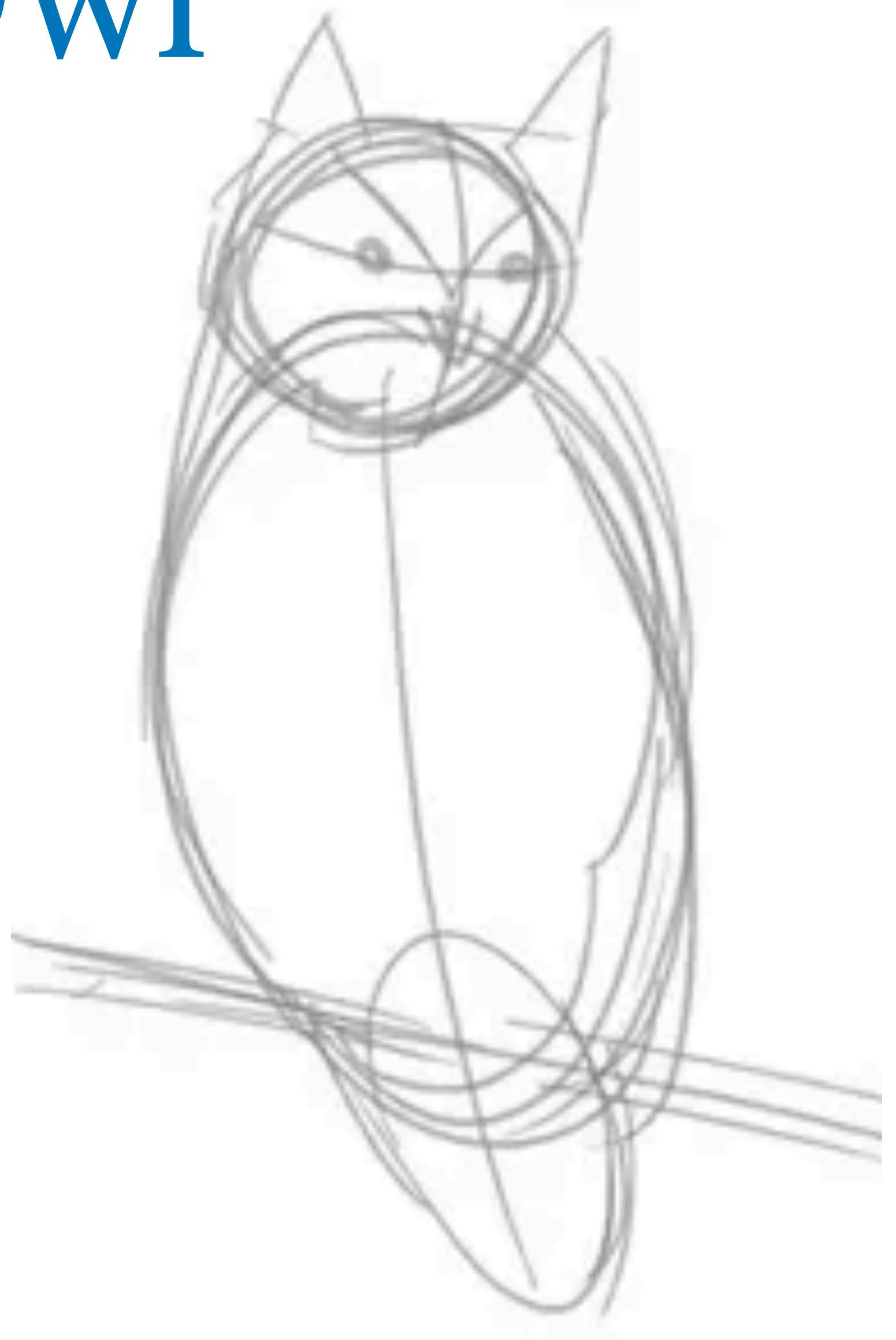
# Drawing the Bayesian Owl

Three modes:

Understand what you are doing

Document your work, reduce error

Respectable scientific workflow



# Drawing the Bayesian Owl

1. Theoretical estimand
2. Scientific (causal) model(s)
3. Use 1 & 2 to build statistical model(s)
4. Simulate from 2 to validate 3 yields 1
5. Analyze real data



**Saturn, Galileo 1610**



# Drawing the Bayesian Owl

Bayesian approach is permissive, flexible

Express uncertainty at all levels

Direct solutions for measurement error,  
missing data

Focus on scientific modeling



DAGS

**BAYES**

**FREQUENTISM**





# Science Before Statistics

For **statistical models** to produce scientific insight, they require additional **scientific (causal) models**

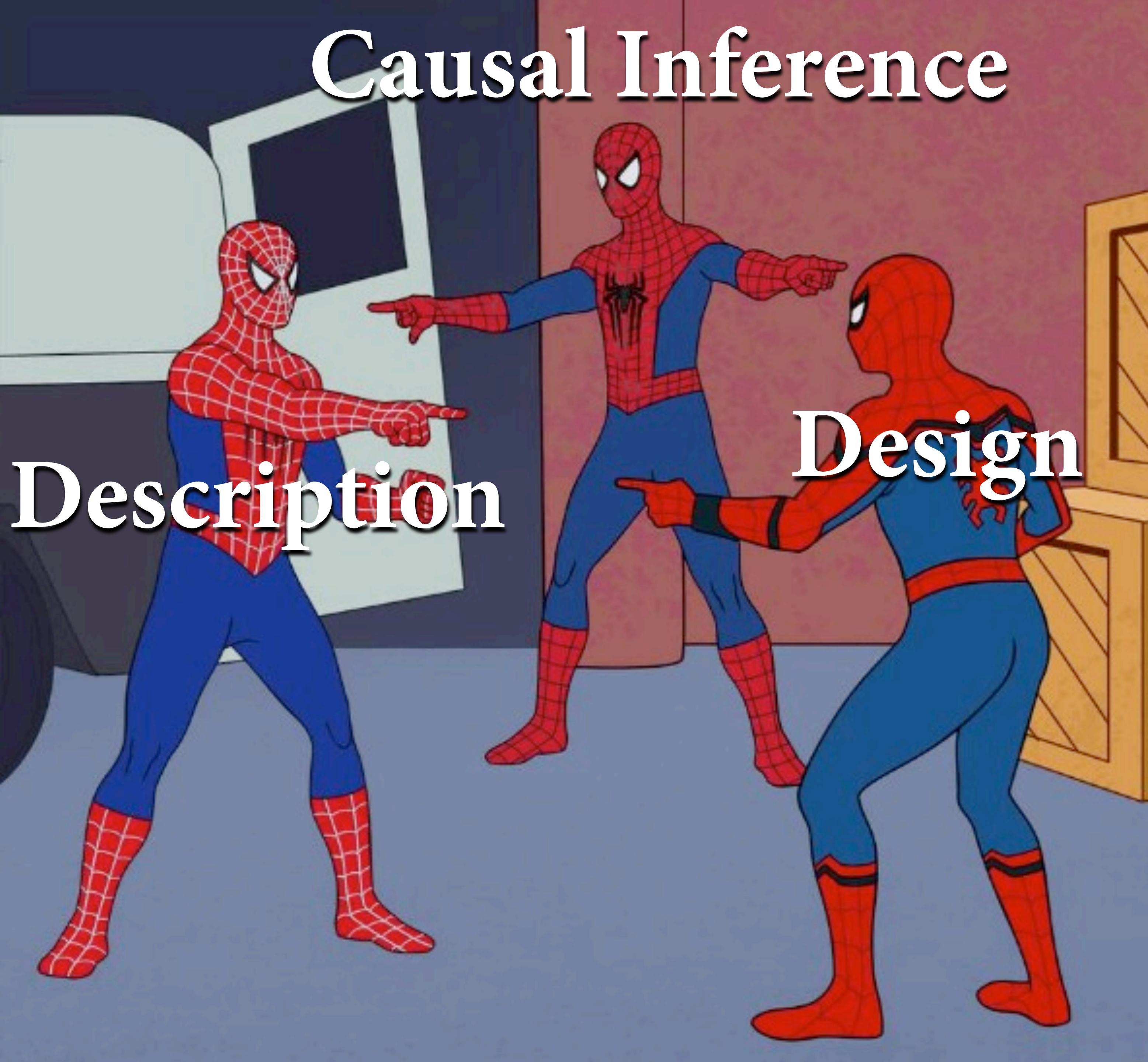
The **reasons** for a statistical analysis are not found in the data themselves, but rather in the **causes** of the data

The **causes** of the data cannot be extracted from the data alone. No causes in; no causes out.

# Causal Inference

Description

Design

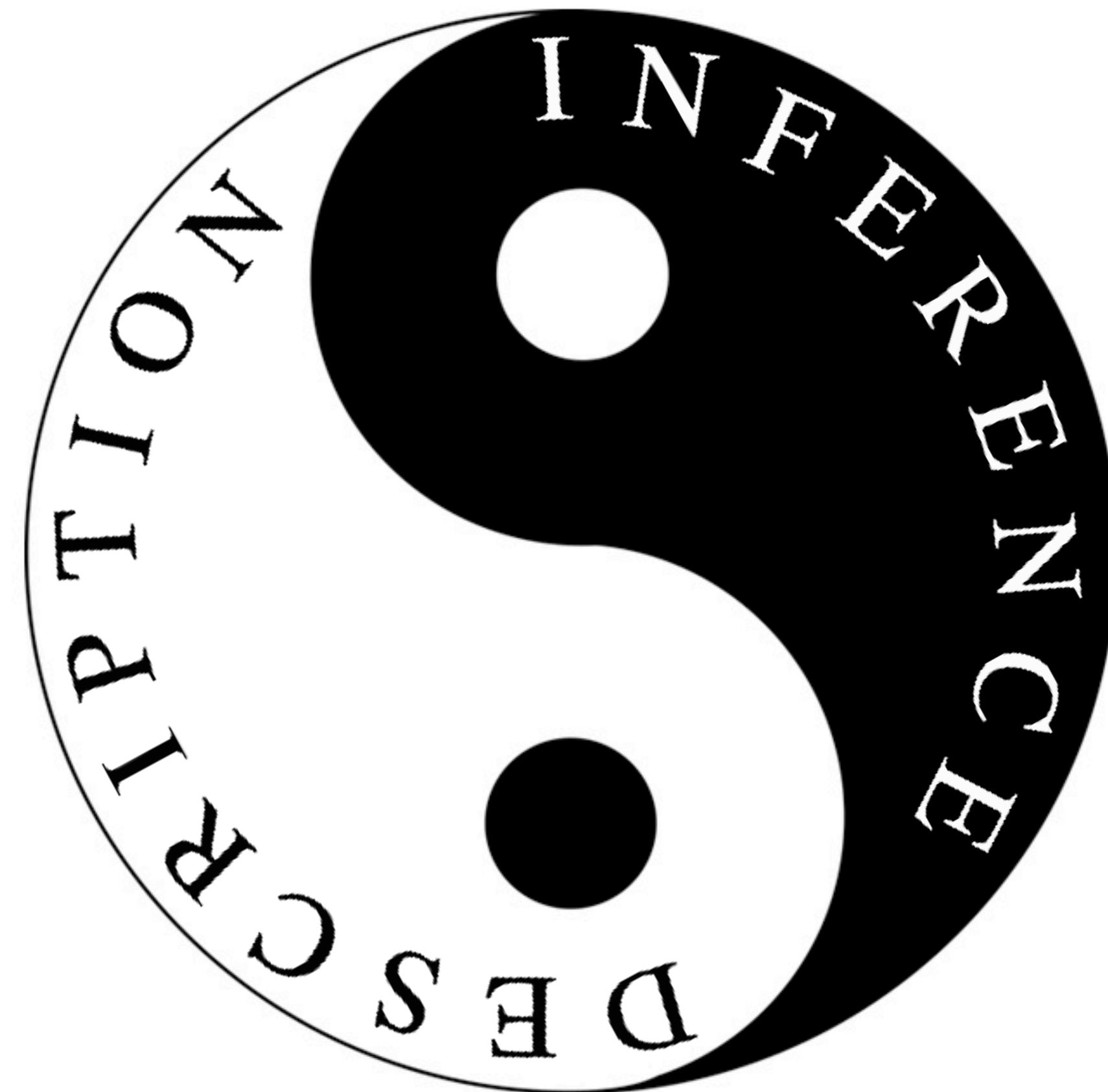


# Causes Are Not Optional

---

Even when goal is **descriptive**, need causal model

The **sample** differs from the **population**; describing the population requires causal thinking



# What is Causal Inference?

More than **association** between variables

Causal inference is <sup>special kind of</sup> **prediction** of intervention

Causal inference is **imputation** of missing observations

counterfactual imagining of  
Something that might have happened.

**CORRELATION  
IMPLIES  
CAUSATION**

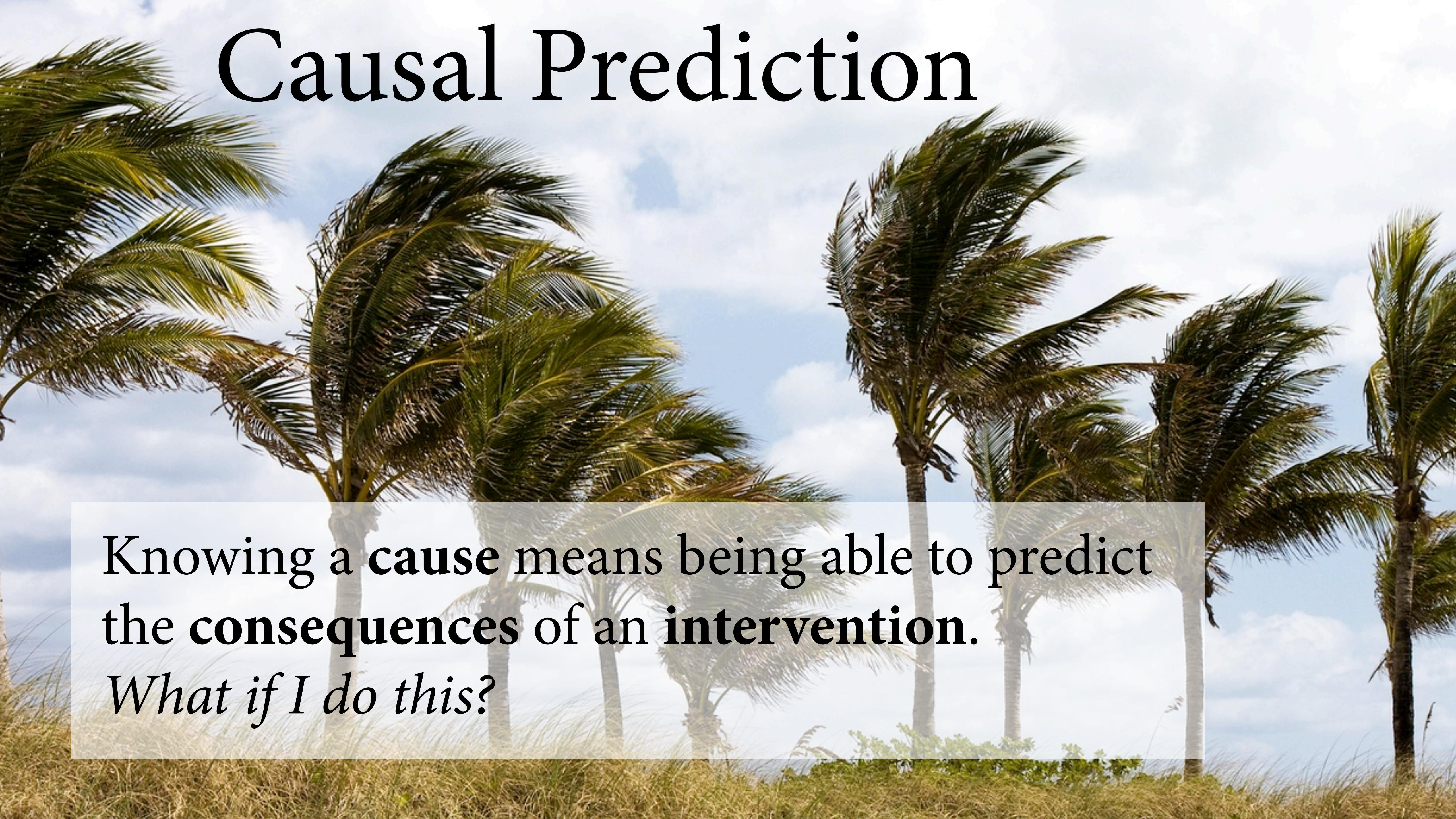
**CORRELATION  
DOES NOT  
IMPLY CAUSATION**

**CAUSATION  
DOES NOT  
IMPLY CORRELATION**

**REALITY IS  
A SIMULATION**



# Causal Prediction

A photograph of several tall palm trees standing in a row. The trees are leaning slightly to the left, suggesting a strong wind from the right. The background is a bright, cloudy sky. The foreground is filled with the tops of tall, dry grasses.

Knowing a **cause** means being able to predict  
the **consequences** of an **intervention**.  
*What if I do this?*

# Causal Imputation



Knowing a **cause** means being able to construct unobserved **counterfactual outcomes**.

*What if I had done something else?*

↳ Then causal inference means that you know what would have happened

# DAGs

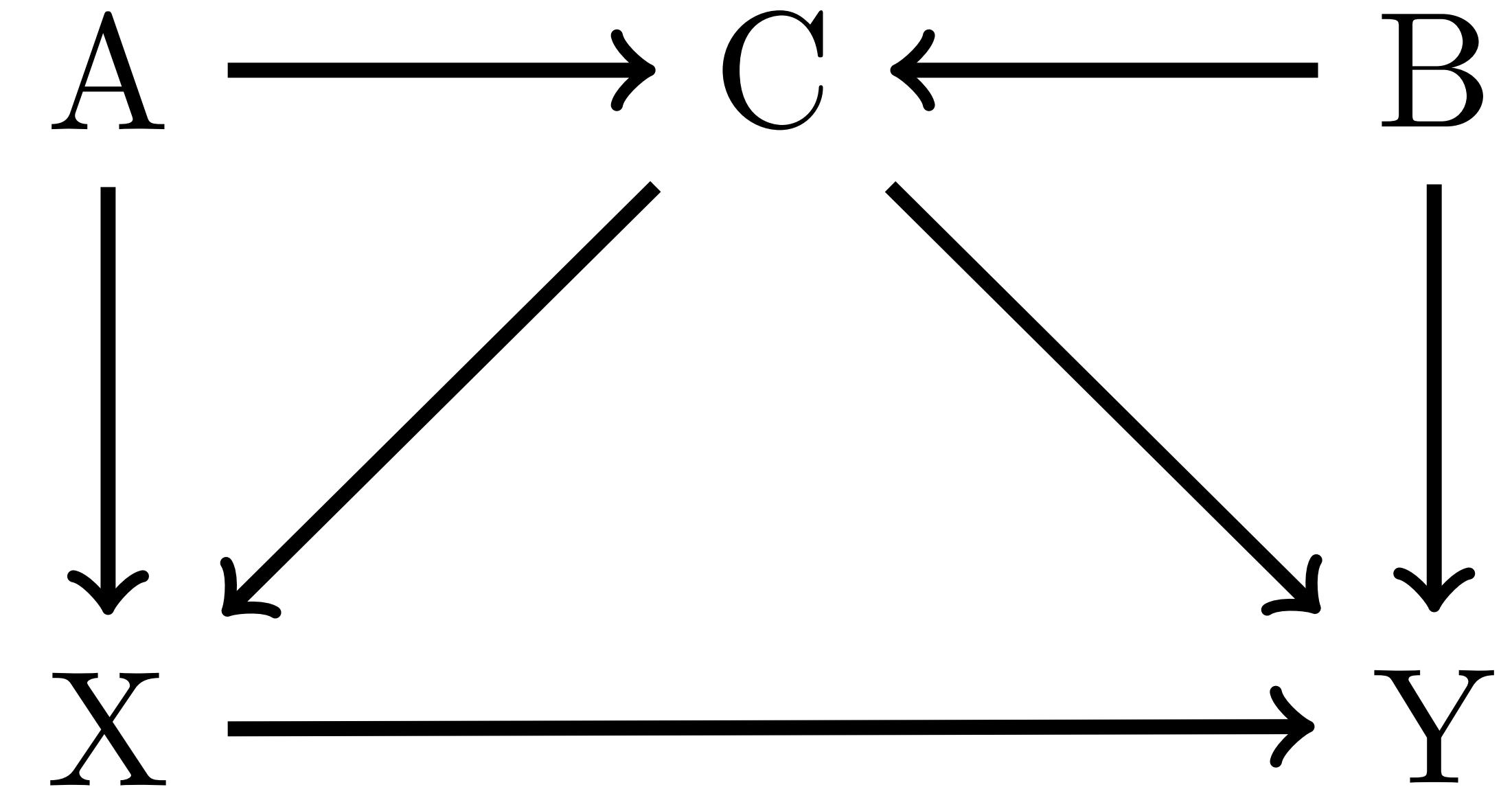
Directed Acyclic Graphs (DAG)

Heuristic causal models

Clarify scientific thinking

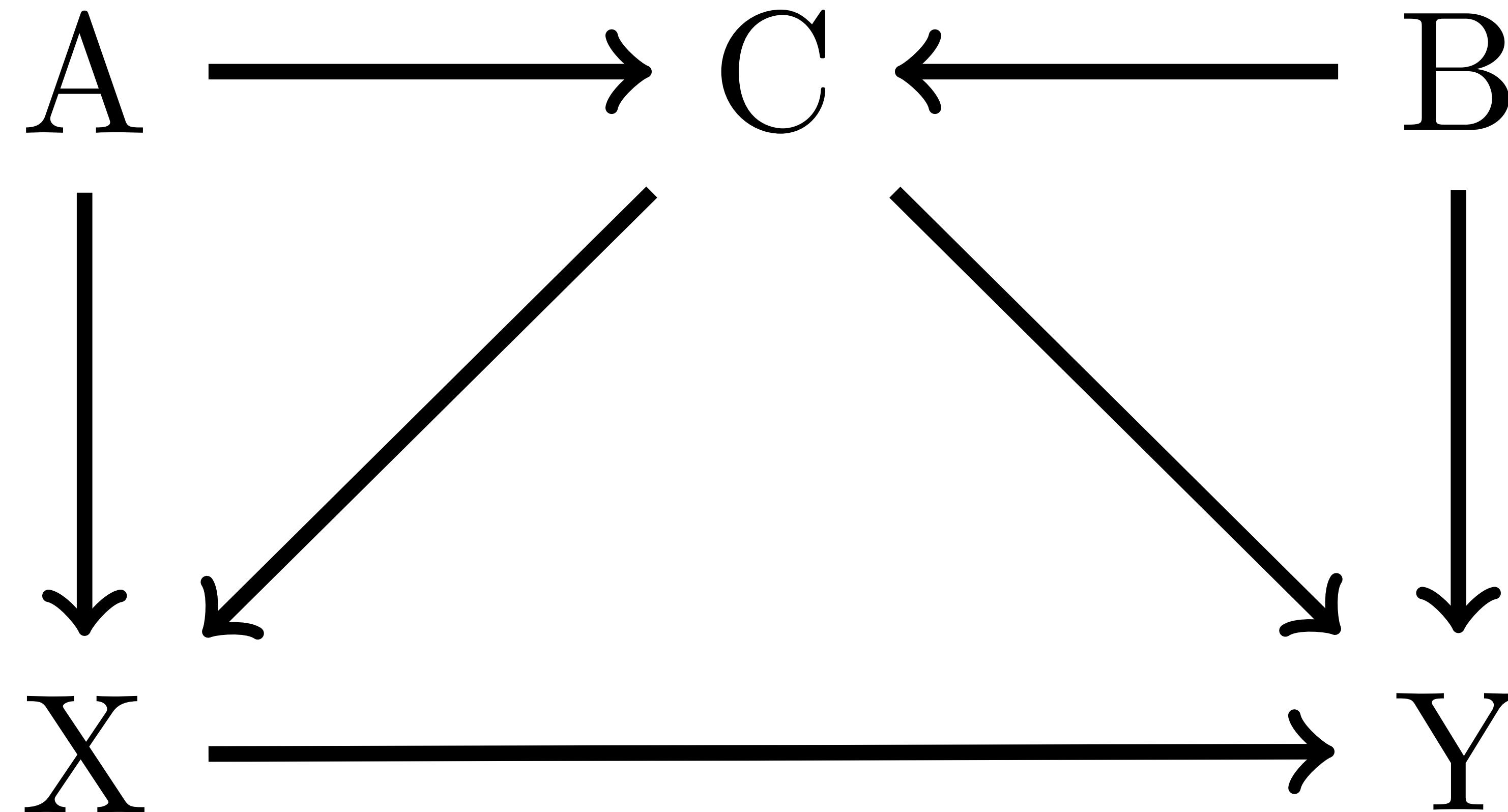
Analyze to deduce appropriate statistical models

Much more as the course develops

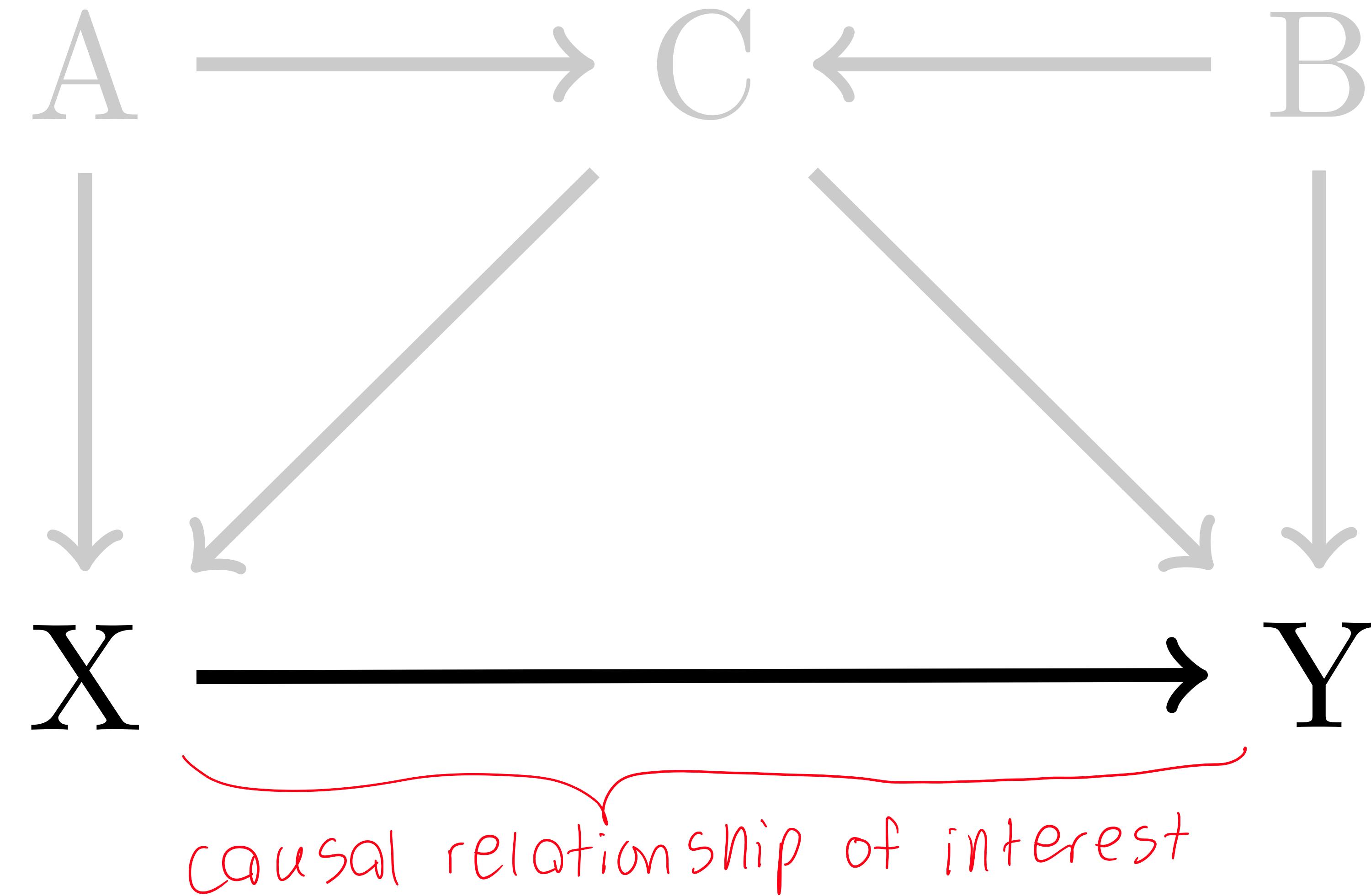


# DAGs

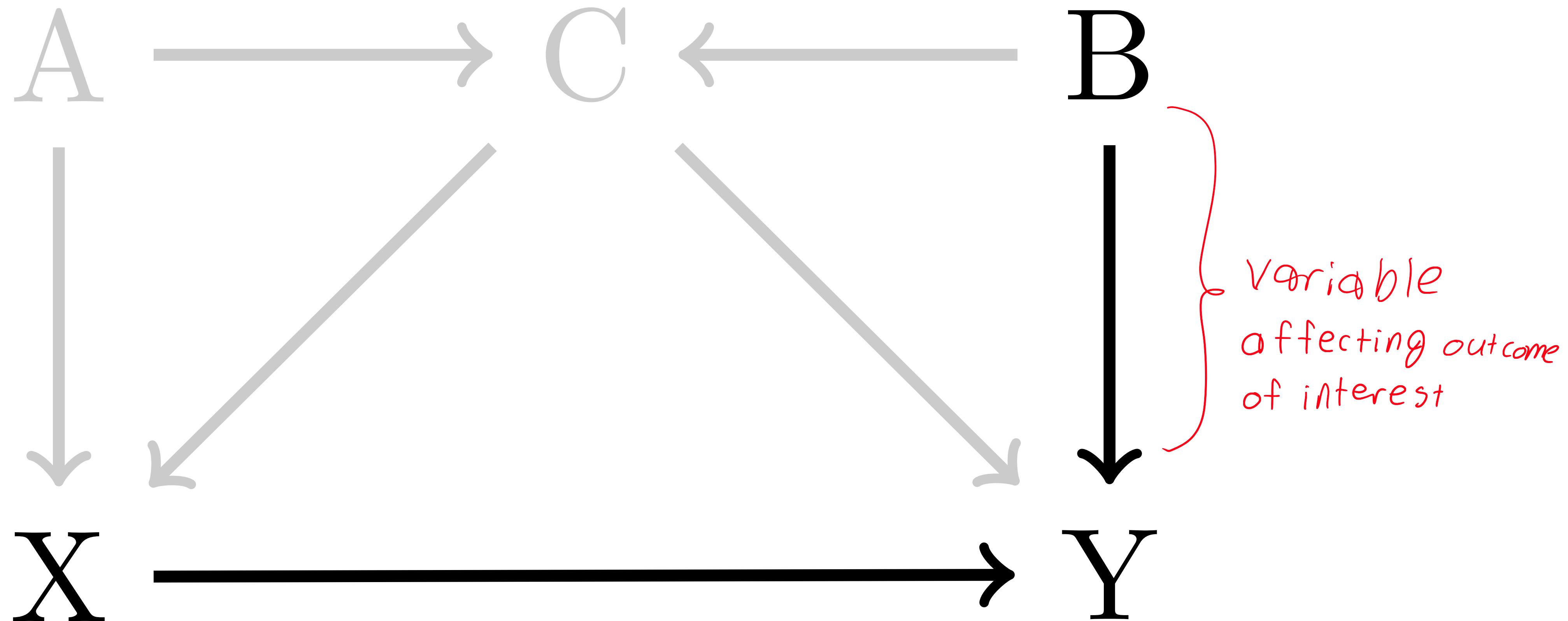
Each letter = variable  
Each arrow = causal relationships



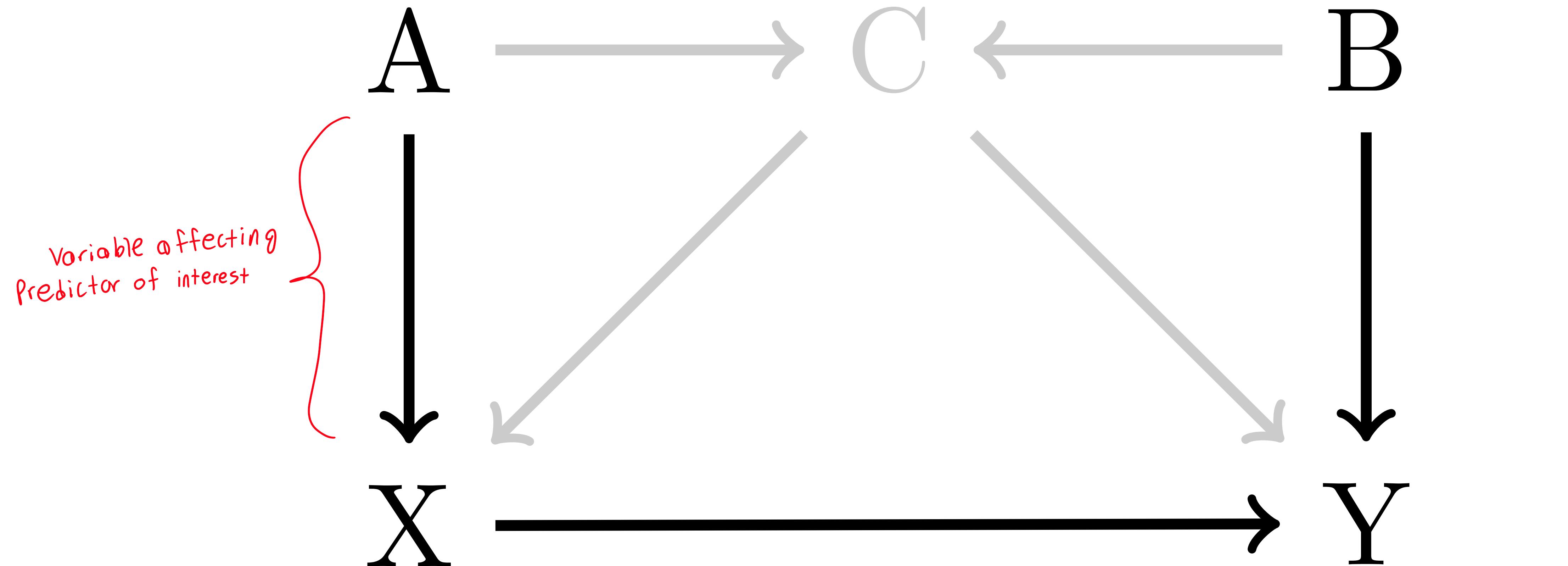
# DAGs



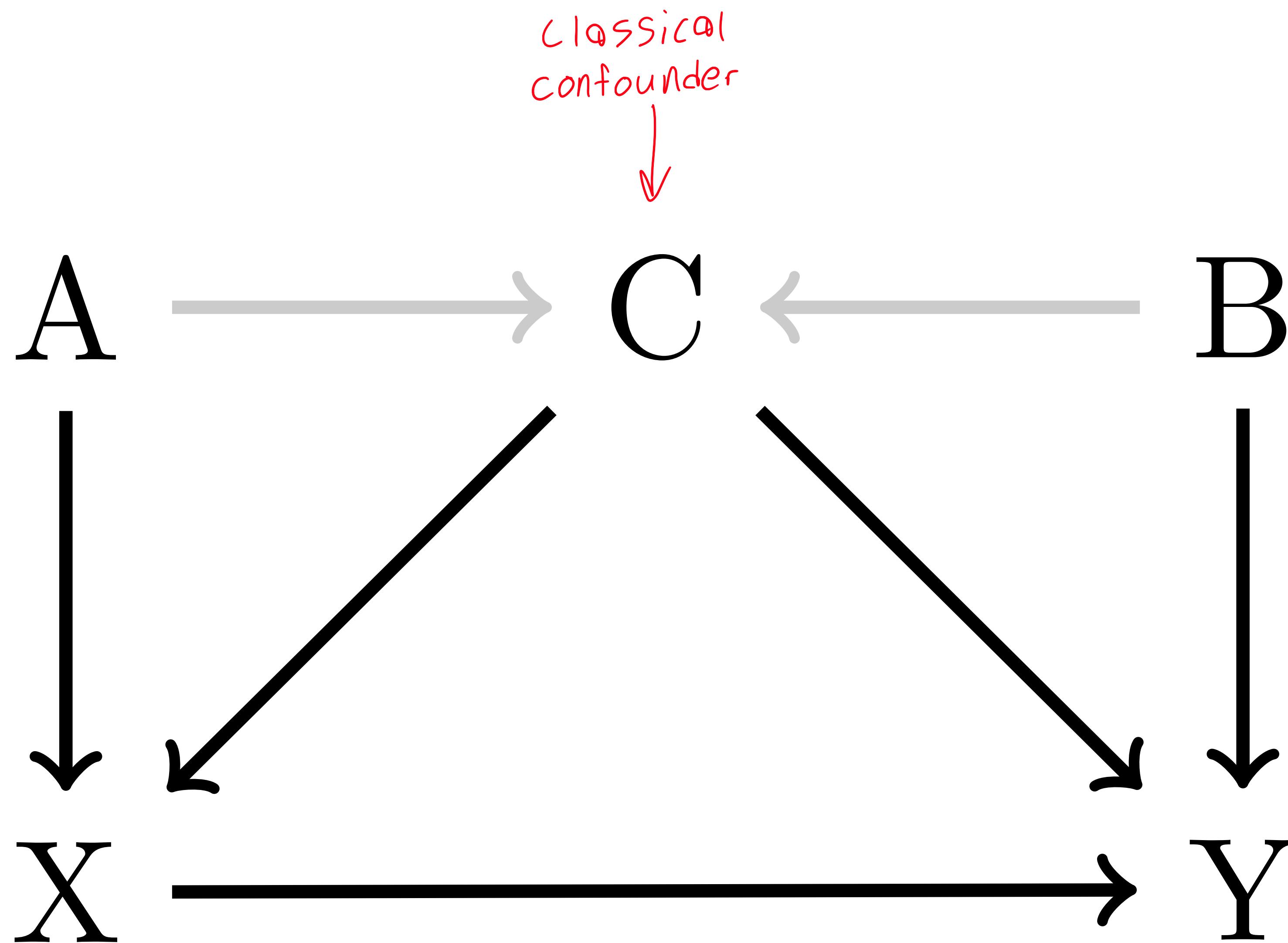
# DAGs



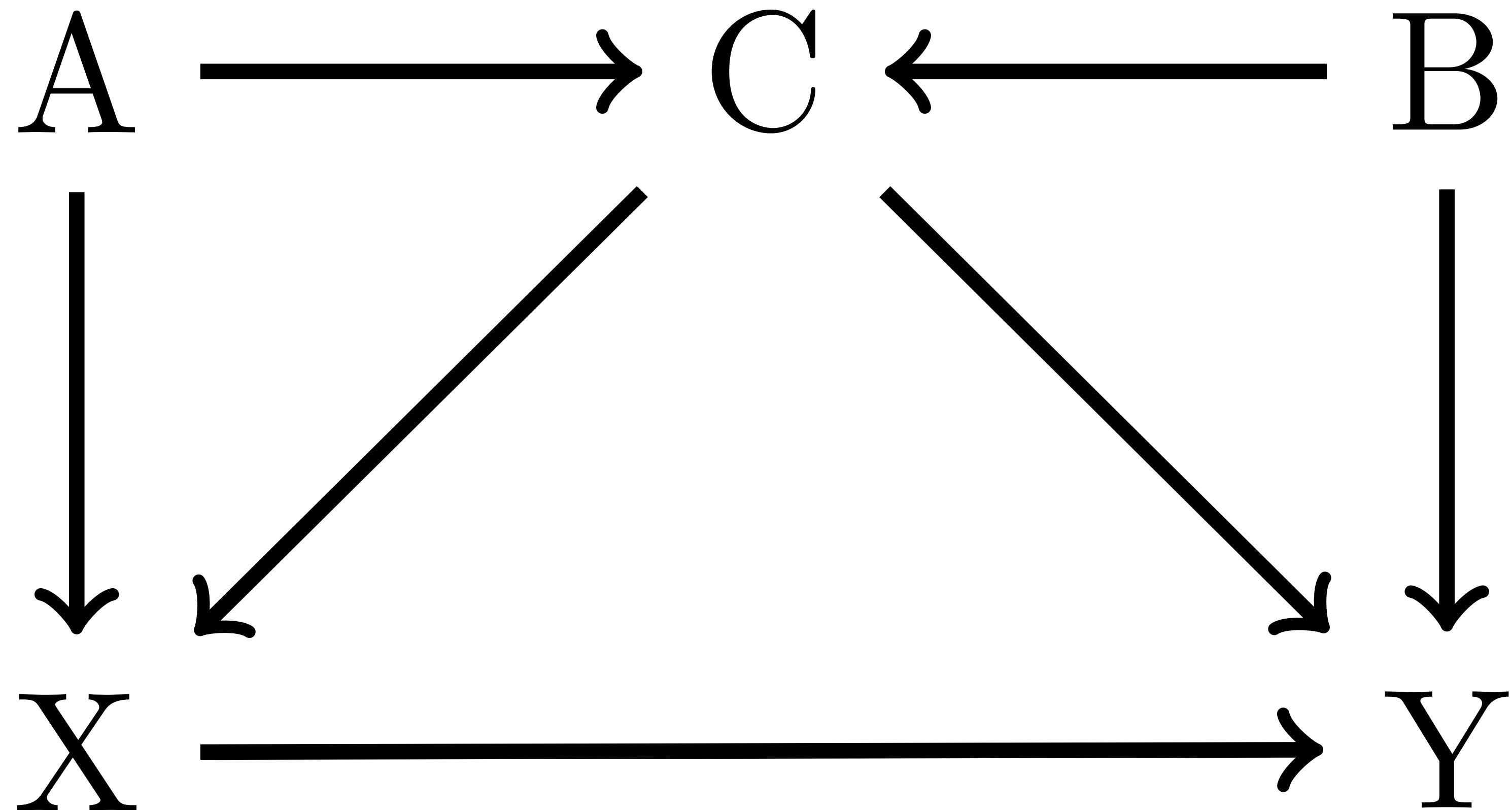
# DAGs



# DAGs



# DAGs



# DAGs

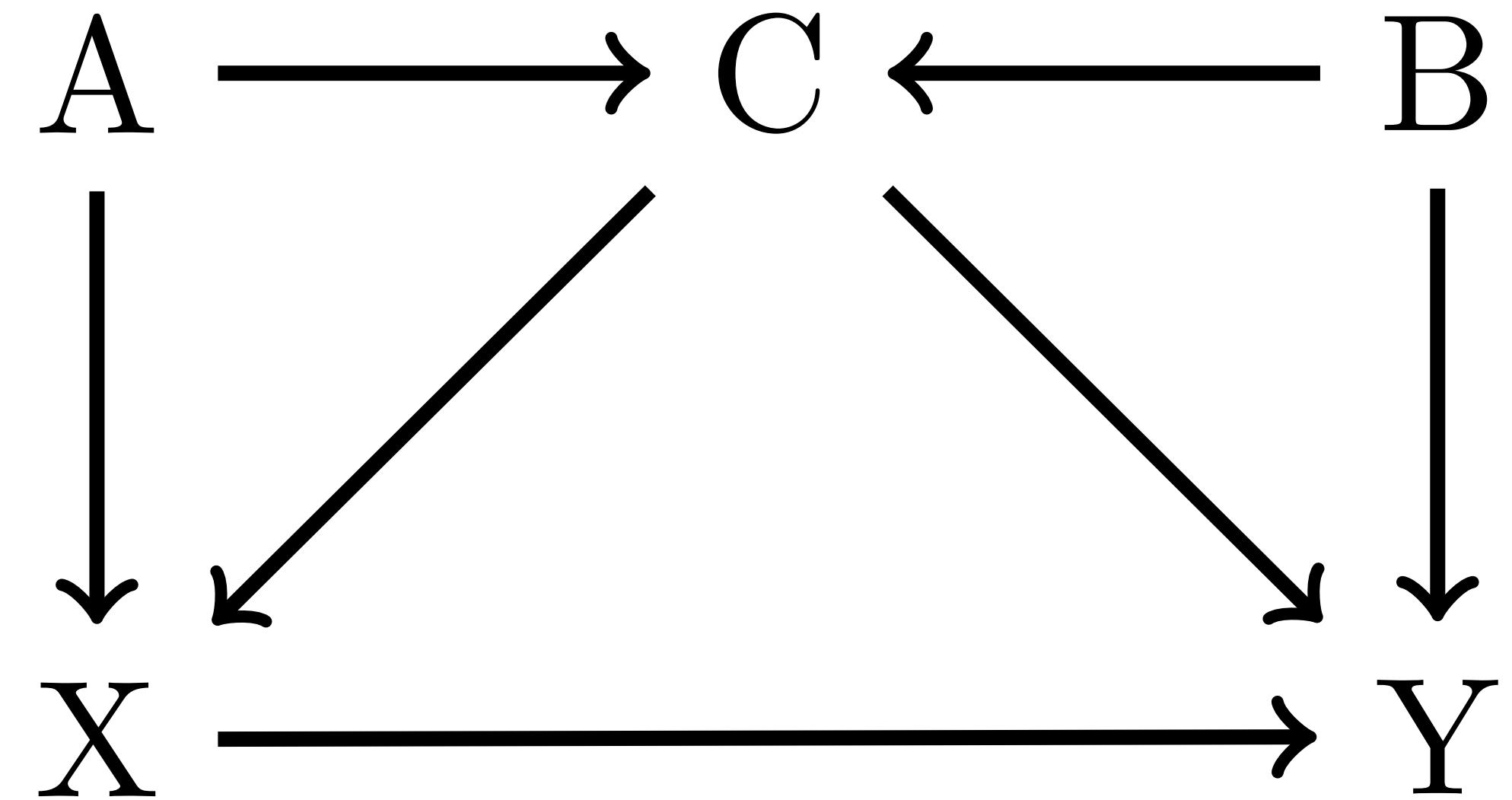
Different queries, different models

Which control variables?

Absolute not safe to add everything — **bad controls**

How to test the causal model?

With more scientific knowledge, can do more



# Golems, Owls, DAGs

**Golems:** Brainless, powerful statistical models

**Owls:** Documented, objective procedures

**DAGs:** Transparent scientific assumptions to  
**justify** scientific effort  
**expose** it to useful critique  
**connect** theories to golems

# Course Schedule

Week 1	Bayesian inference	Chapters 1, 2, 3
Week 2	Linear models & Causal Inference	Chapter 4
Week 3	Causes, Confounds & Colliders	Chapters 5 & 6
Week 4	Overfitting / Interactions	Chapters 7 & 8
Week 5	MCMC & Generalized Linear Models	Chapters 9, 10, 11
Week 6	Integers & Other Monsters	Chapters 11 & 12
Week 7	Multilevel models I	Chapter 13
Week 8	Multilevel models II	Chapter 14
Week 9	Measurement & Missingness	Chapter 15
Week 10	Generalized Linear Madness	Chapter 16

[https://github.com/rmcelreath/statrethinking\\_2022](https://github.com/rmcelreath/statrethinking_2022)