

# SIMULATION

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# TABLE OF CONTENTS

- Introduction
- Basics
- Linear Regression
- Logistic Regression
- Confounding
- Selection Bias
- Generalized Linear Models

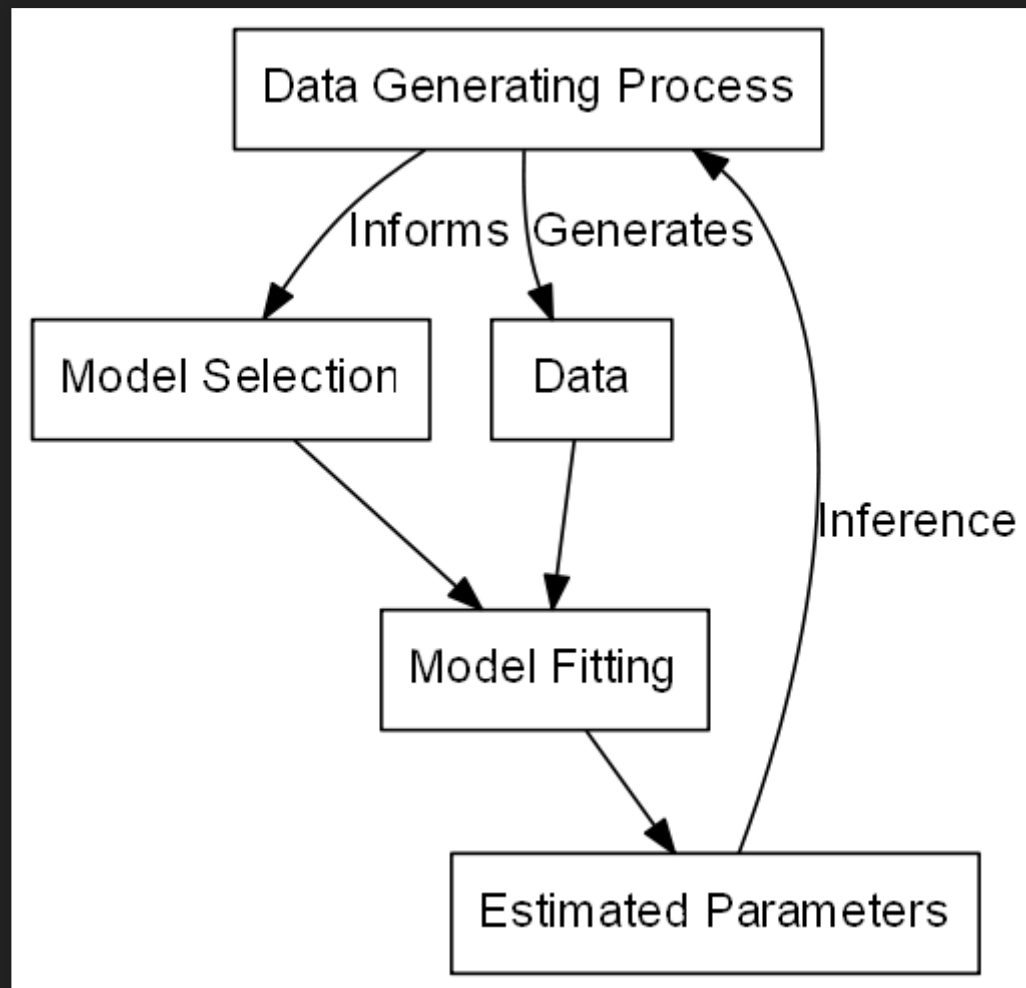
# INTRODUCTION

*Simulation is the imitation of the operation of a real-world process or system – Wikipedia*

# OUR TYPICAL SITUATION

We want to know more about a biological process for which we have measured some data

- An biological process generates data
- We measure and collect this data
- Invent model how we **think** data was generated
- Fit the model to our data
- Giving us the parameters for the model
- Inferences about the data-generating process

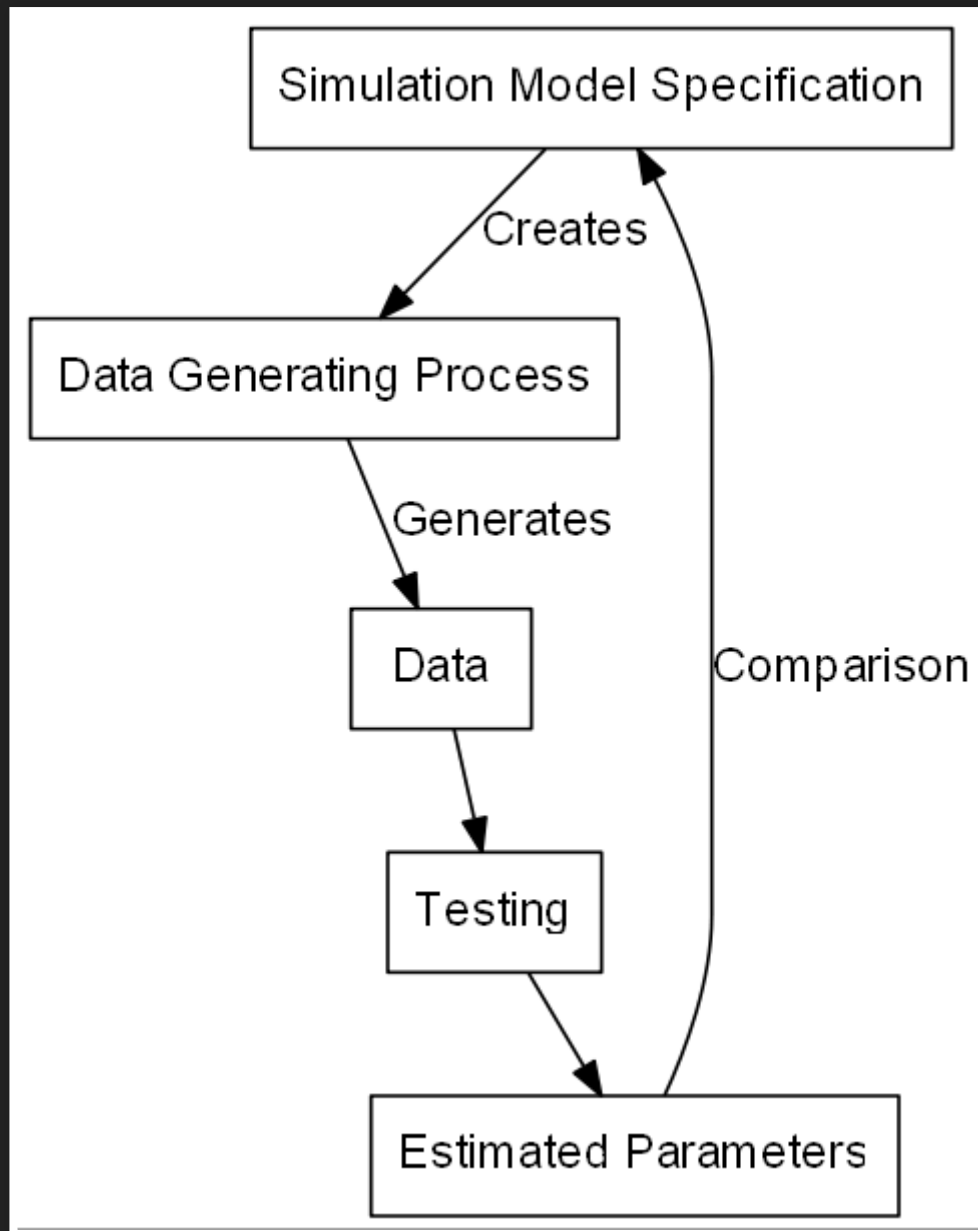


# THE SIMULATION SITUATION

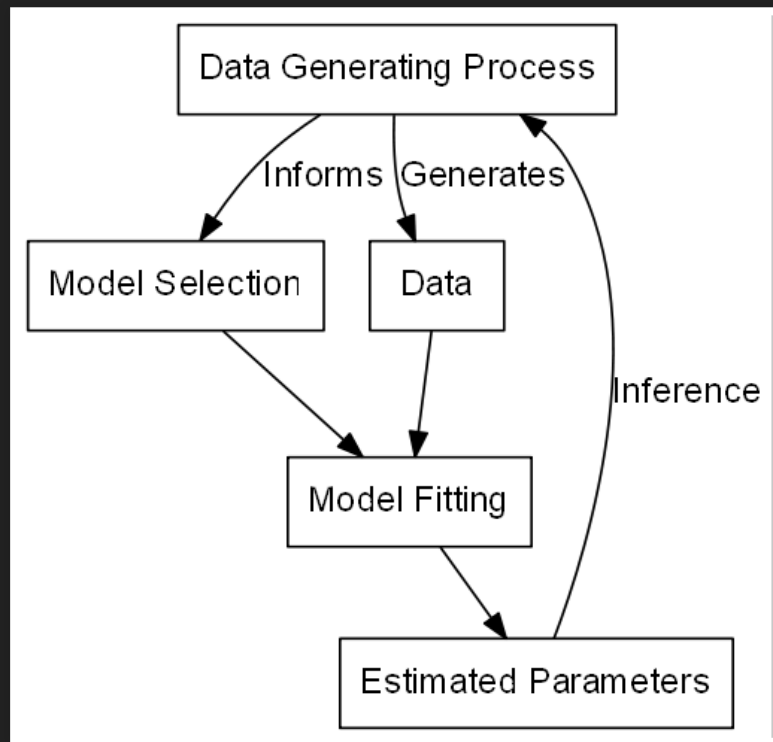
We want to know more about how something behaves, given data of specific type



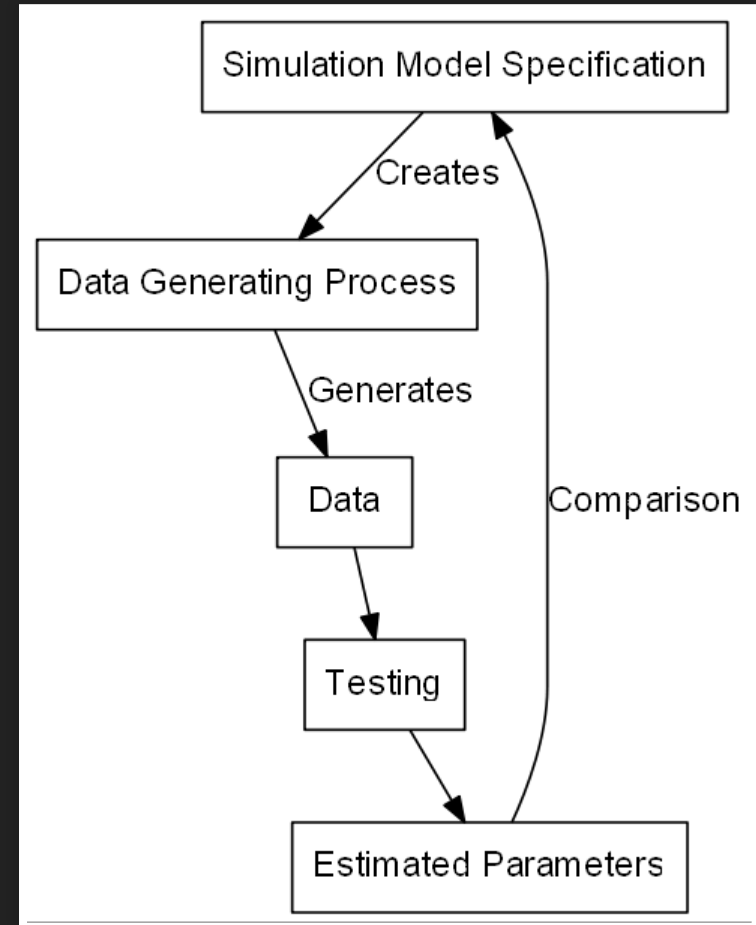
- Specify a model for the simulated data
- Including model parameters
- **Generate data using this model**
- Test something given our data
- Compare the result to our "true" model



# Typical situation



# Simulation situation



# BASICS

# LINEAR REGRESSION

# WHEN DO WE USE IT?

- Continuous dependent variable ( $y$ )
  - Cont./discrete independent variables ( $x_1, \dots, x_p$ )
  - Error normally distributed
- 

- $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + \epsilon$
- $\epsilon \sim \text{normal}(0, \sigma)$

# IN GLM NOTATION

- Dependent variable from normal distribution ( $y$ )
  - Cont./discrete independent variables ( $x_1, \dots, x_p$ )
- 

- $E(y) = \mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p$
- $y \sim \text{normal}(\mu, \sigma)$

# LOGISTIC REGRESSION



# WHEN DO WE USE IT?

- Binary dependent variable ( $y$ )
  - Cont./discrete independent variables ( $x_1, \dots, x_p$ )
  - No common error distribution independent of predictor values
- 

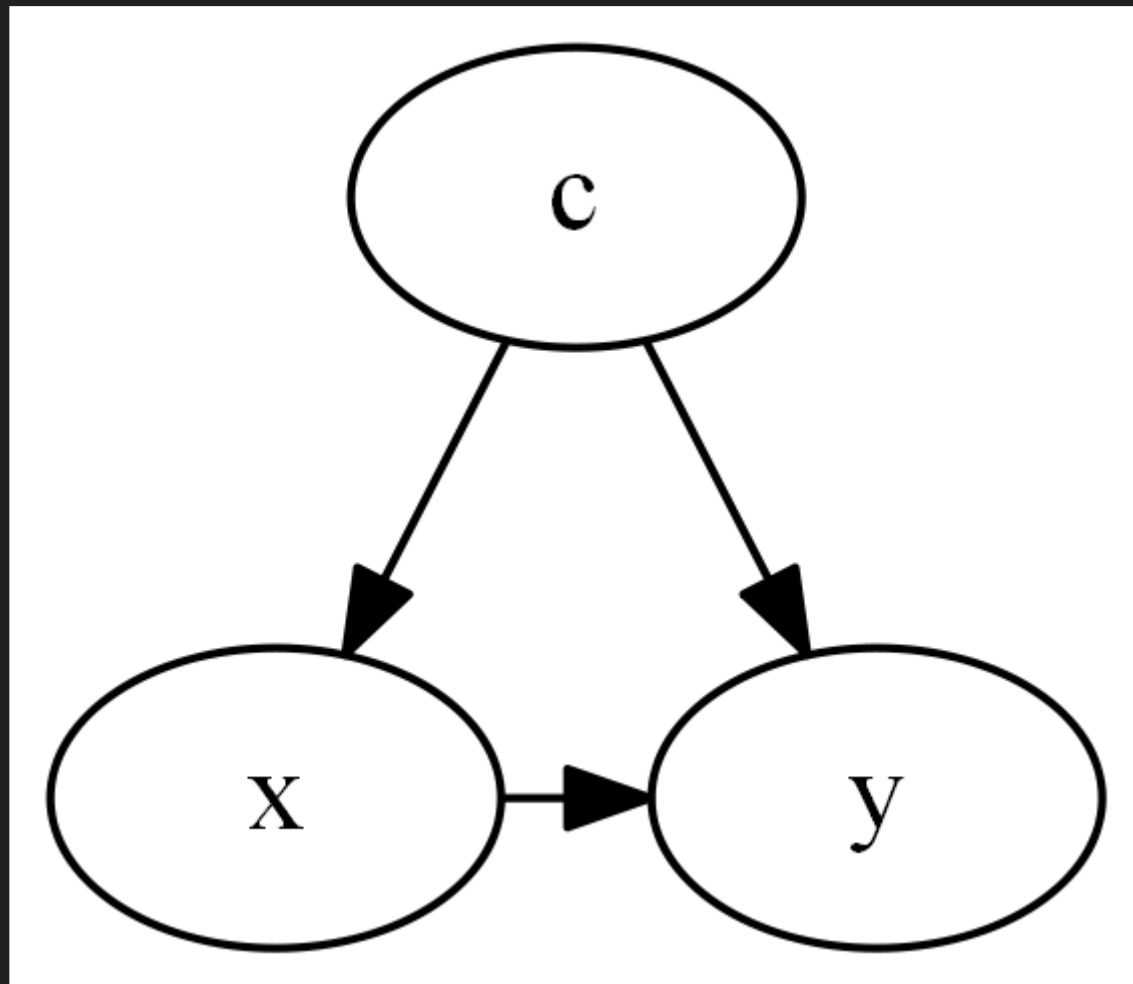
- $\text{logit}(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + \epsilon$
- $\text{logit}(y) = \log\left(\frac{y}{1-y}\right)$
- $\epsilon$  has no independent distribution

# IN GLM NOTATION

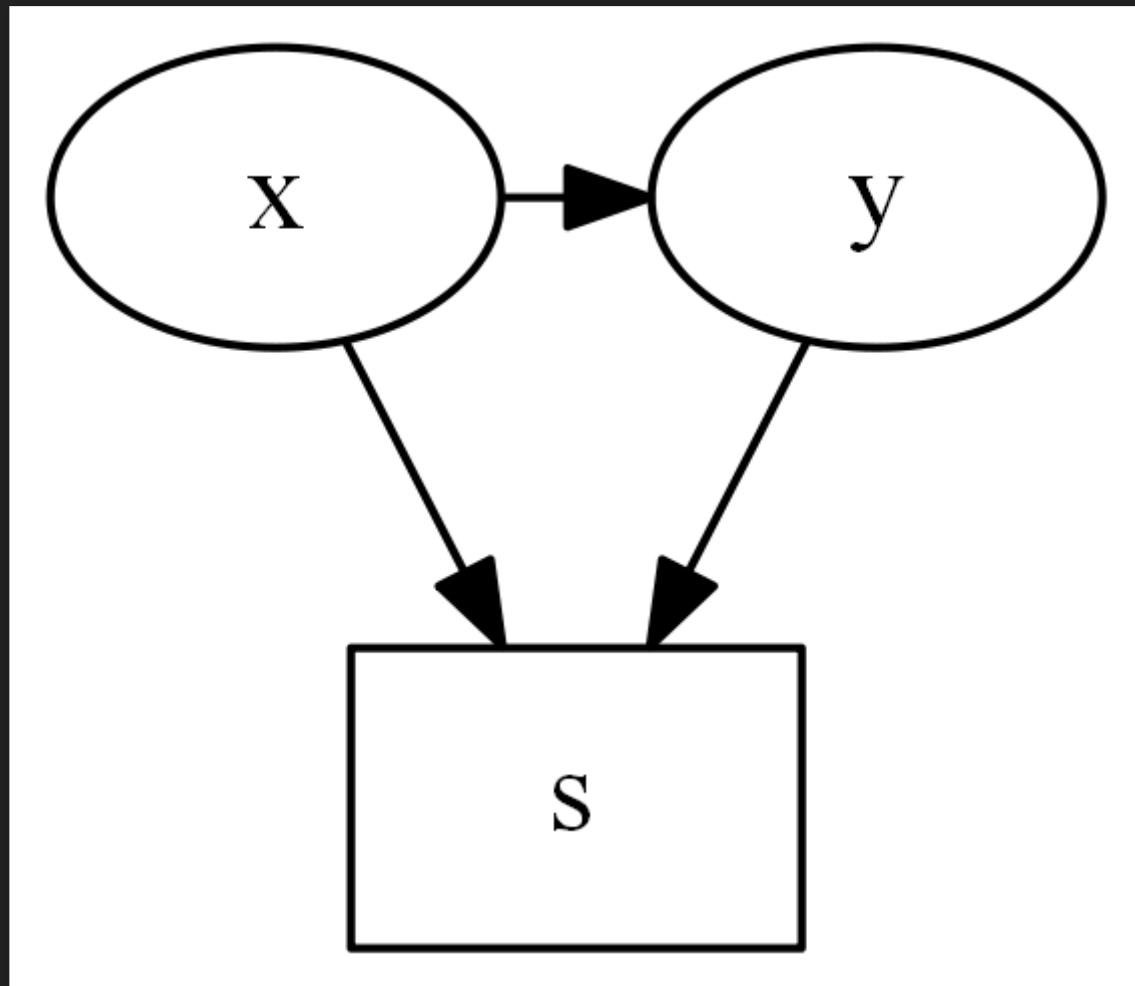
- Dep. var. from binomial distr. with 1 trial ( $y$ )
  - Cont./discrete independent variables ( $x_1, \dots, x_p$ )
- 

- $E(y) = \mu = \text{logit}^{-1}(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p)$
- $\text{logit}^{-1}(x) = \frac{e^x}{1+e^x}$
- $y \sim \text{binomial}(1, \mu)$

# CONFOUNDING



# SELECTION BIAS



# GENERALIZED LINEAR MODELS

- $E(y) = \mu = g^{-1}(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p)$
  - $y \sim \text{distribution}(\mu)$
- 

- $E(y) = \mu = g^{-1}(\mathbf{X}\boldsymbol{\beta})$
- $y \sim \text{distribution}(\mu)$