Stochastic Simulation and Power Analysis

Michael Noonan

March 21, 2021

Biol 520C: Statistical modelling for biological data

Table of contents

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- We have an extra lecture at our disposal so I'm going to split the last round of talks up over three lectures so we can have more time for discussion (schedule is on canvas).

Stochastic Simulation and the Monte Carlo Method

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In the past any of these types of projects would require sophisticated analyses but simulations make these accessible to a broader range of biologists (learning sim. methods is easier than learning high level math).

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$$\text{Monte Carlo} = \text{Stochastic Simulation}$$

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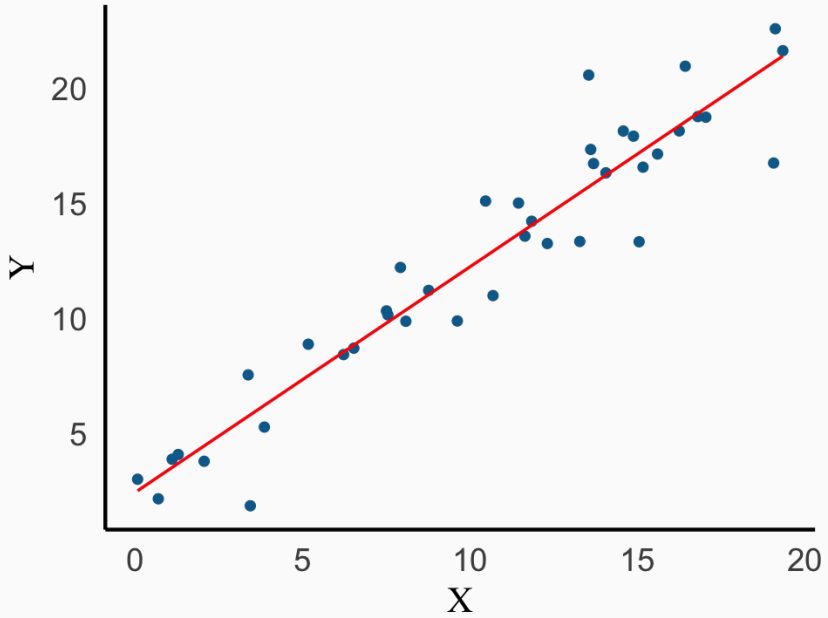
Linear <- function(x) {
  B_0 <- 2
  B_1 <- 1
  mu = B_0 + B_1*x
  rnorm(n = length(x), mean = mu, sd = 2)}

X <- runif(40, 0, 20)
Y <- Linear(X)
```



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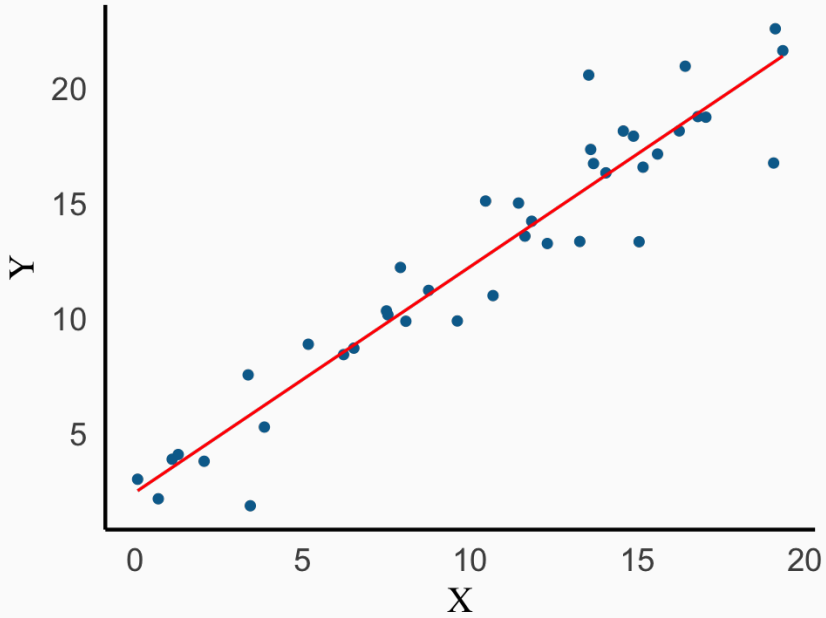


```
Counts <- function(x) {
  B_0 <- 0.01
  B_1 <- 0.15
  eta = exp(B_0 + B_1*x)
  rpois(n = length(x), lambda = eta)}

X <- runif(40, 0, 20)
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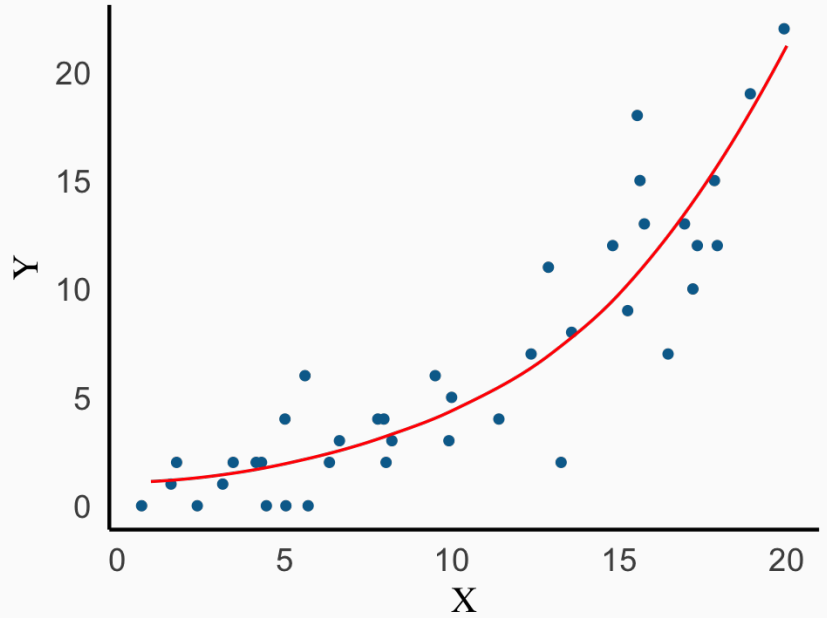

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Linear <- function(x) {
  B_0 <- c(2,0)
  B_1 <- c(1,2)
  mu = B_0[group] + B_1[group]*x
  rnorm(n = length(x), mean = mu, sd = 2)}
X <- runif(50, 0, 20)
Y <- Linear(X)
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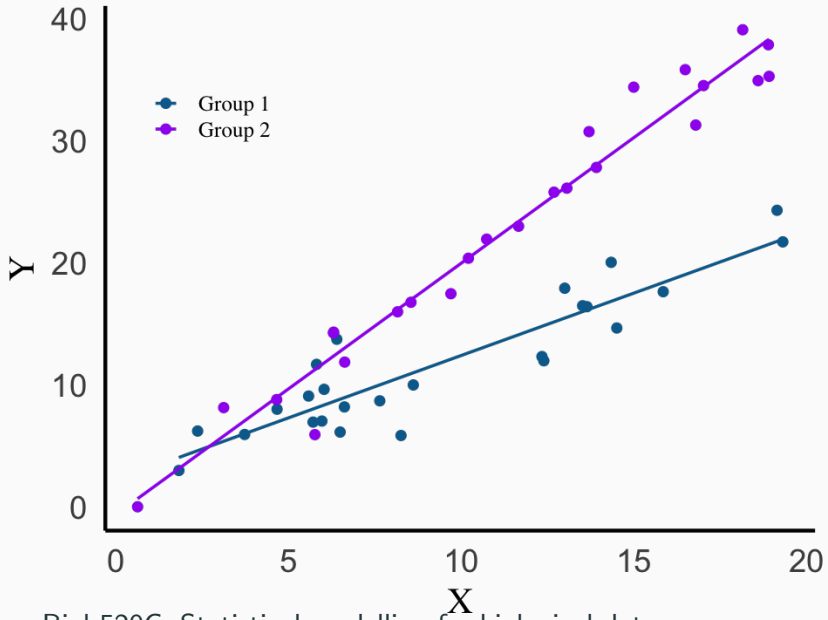

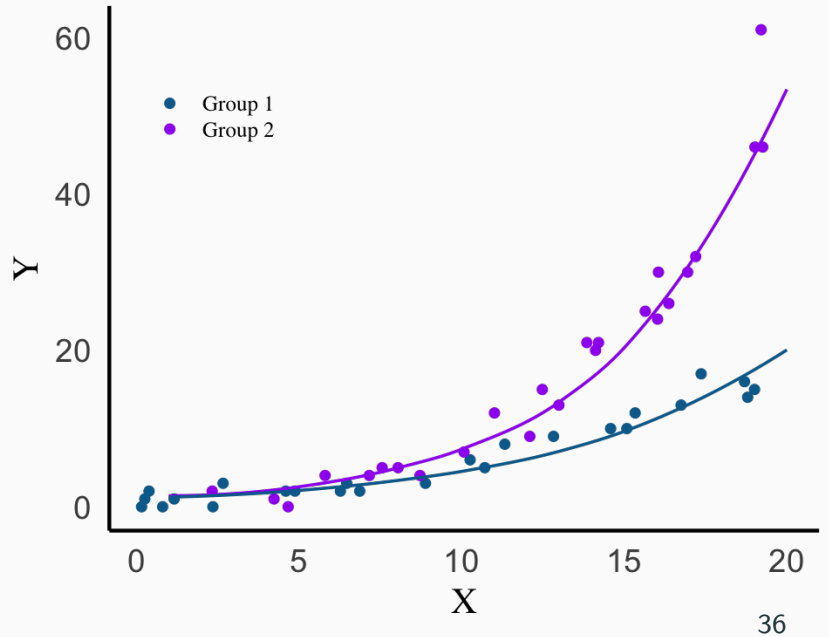

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Imagine a system where traffic volume and temperature influence the number of road killed animals. We can use simulations to explore how climate change might influence road kills.

```
Road_Kills <- function(x, x_2) {
  B_0 <- 0.01
  B_1 <- 0.15
  B_2 <- 0.05
  eta = exp(B_0 + B_1*x + B_2*x_2)
  rpois(n = length(x), lambda = eta)}
```

```
X <- runif(80, 0, 20)

Deaths_15C <- Road_Kills(X, 15)
Deaths_20C <- Road_Kills(X, 20)
Deaths_25C <- Road_Kills(X, 25)
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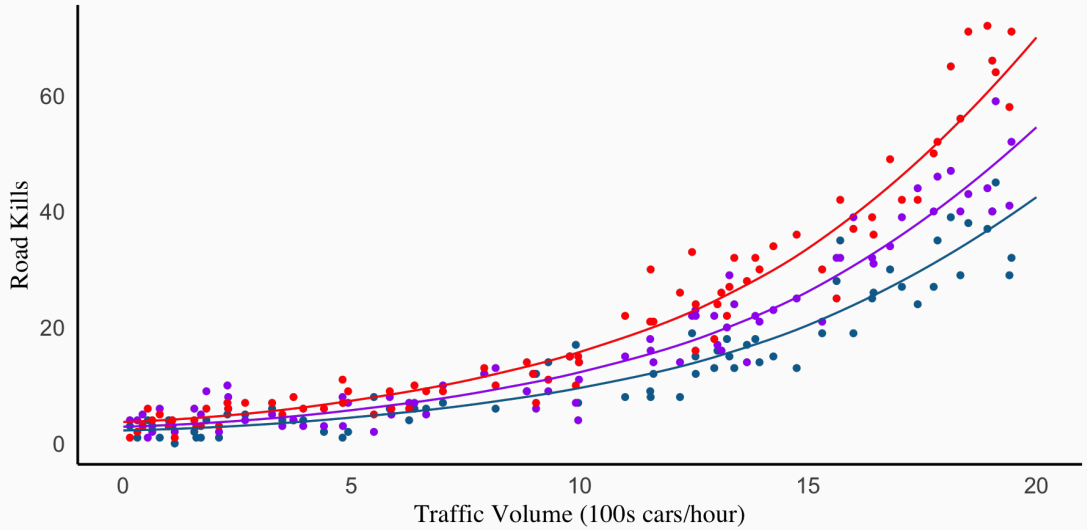

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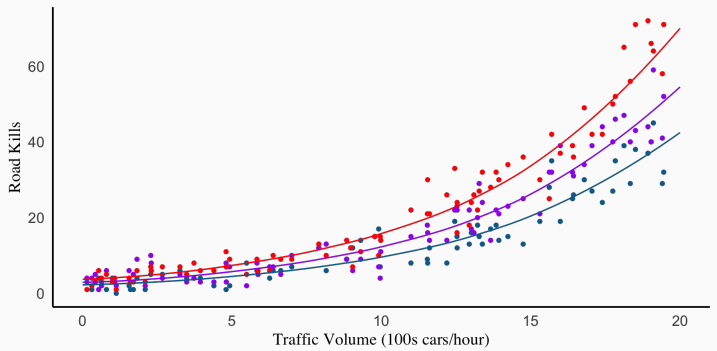

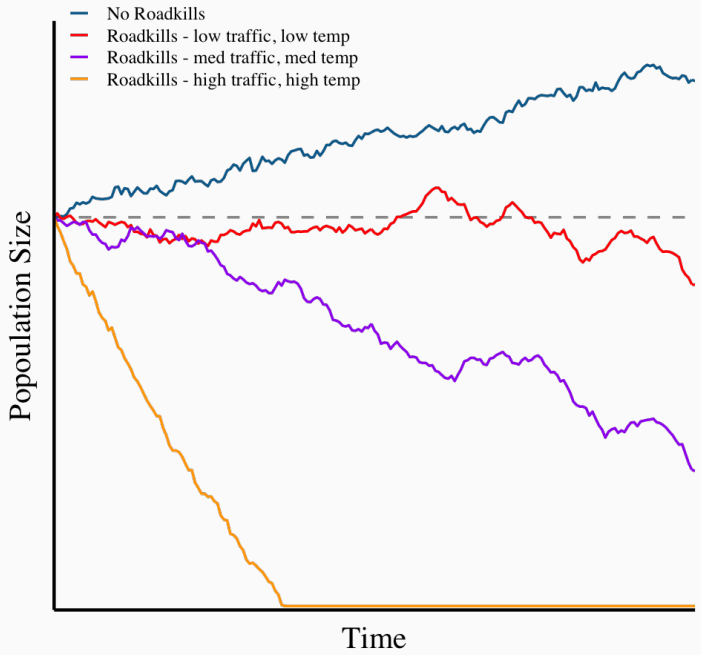

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Always approach simulation studies with care and make sure the computational system you put together matches the biological reality of the system you are trying to study.

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Power analysis in our context involves a special kind of simulation study aimed at exploring how much data you would need in order to get reasonably accurate estimates of your parameters, detect significance of parameters with true effects, and/or detect differences between groups.

Precision and accuracy

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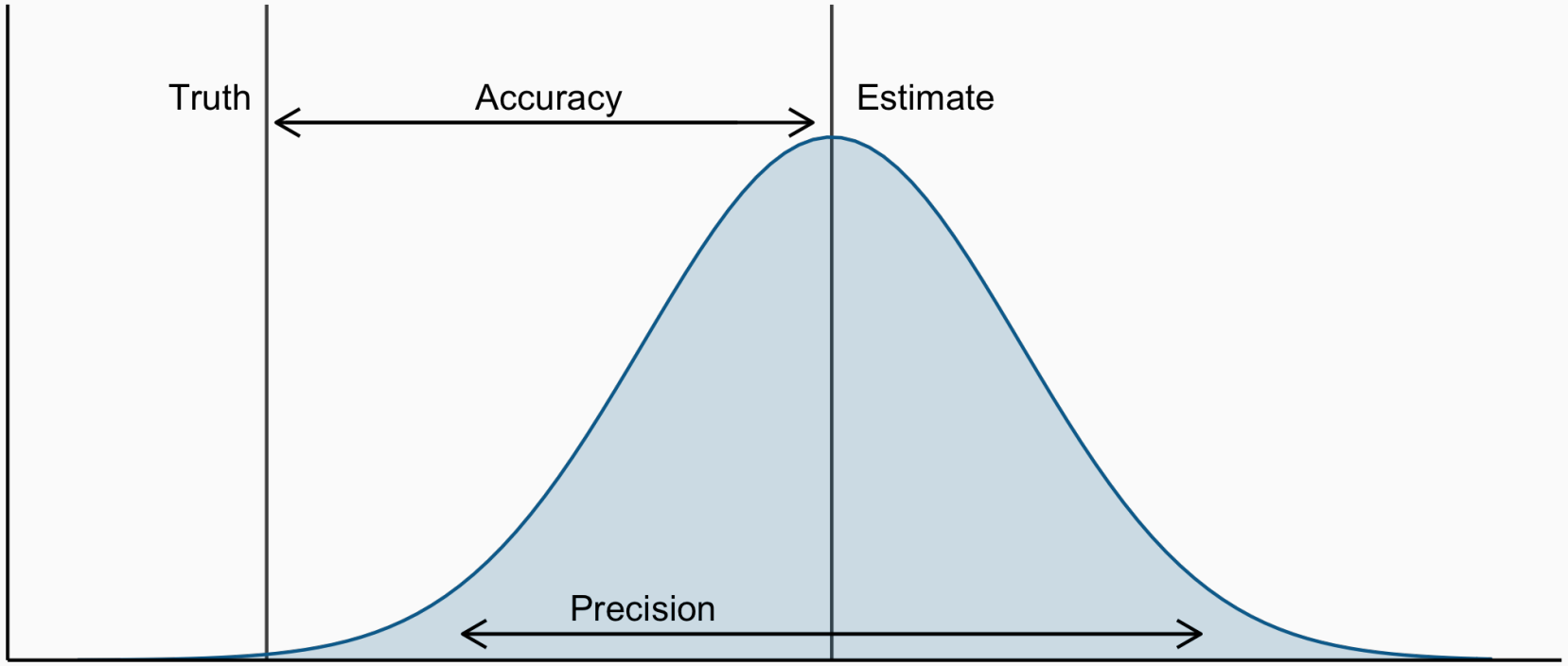
Ultimately, the quality of the inference we can make from our analyses boils down to two main factors, a model's **accuracy** and it's **precision**.



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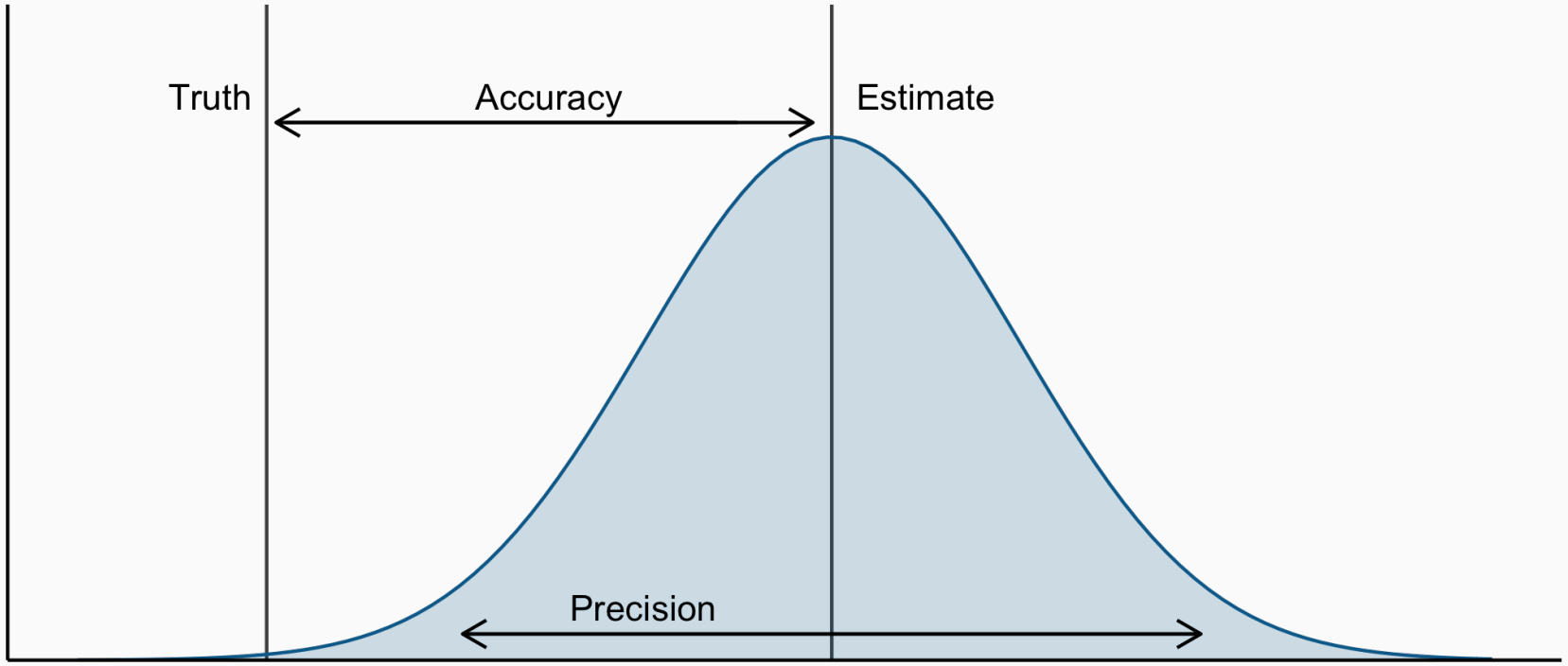

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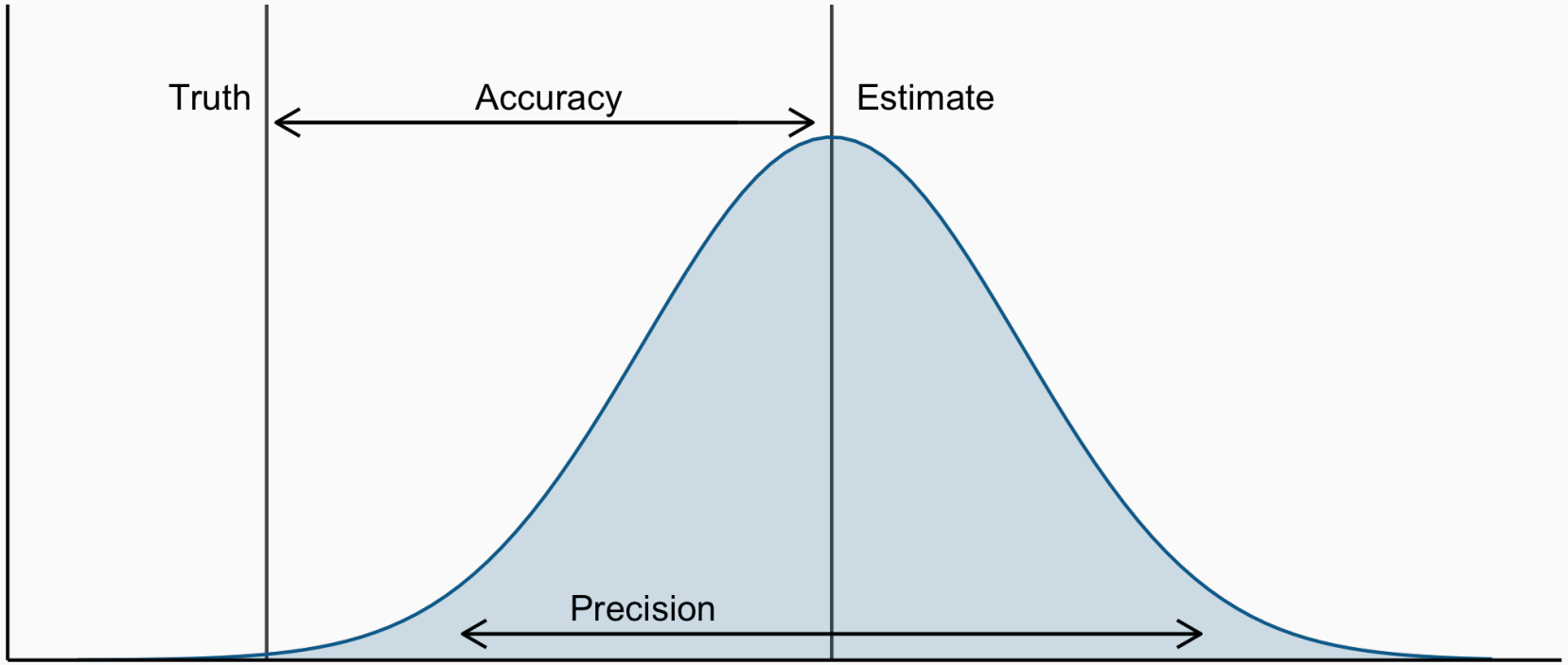
Precision describes variability in the estimates.



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6. Power (precision)

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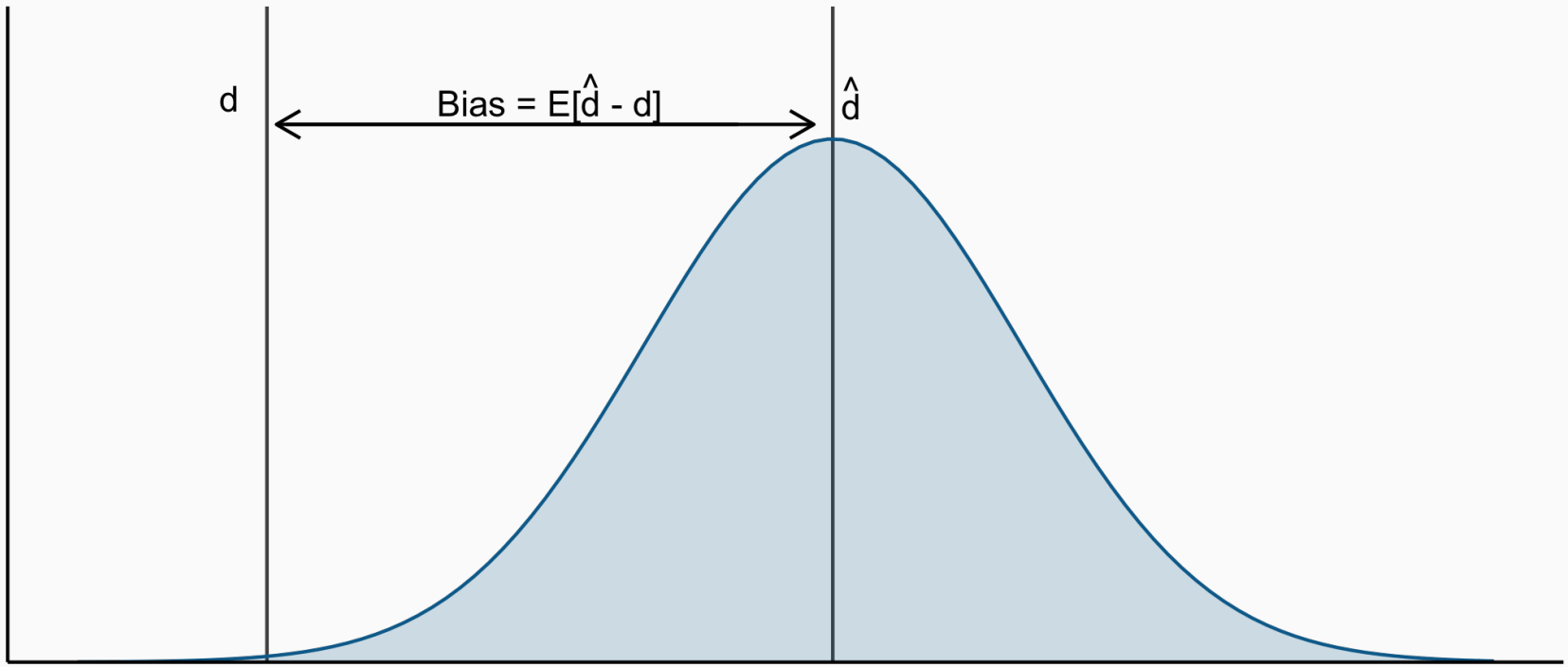

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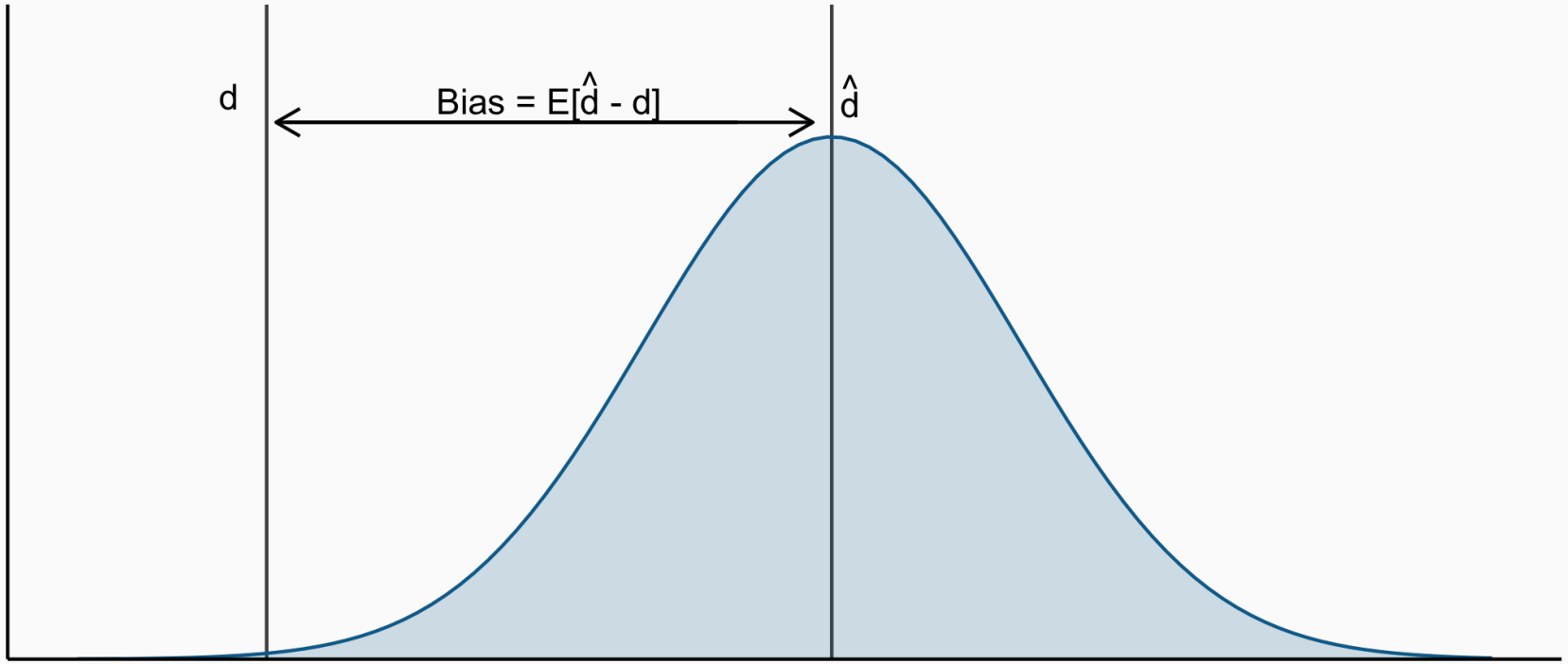
Ideally estimators should be asymptotically unbiased (as $n \to \infty \quad E[\hat{d} - d] \to 0$)



Variance and CI width (precision)

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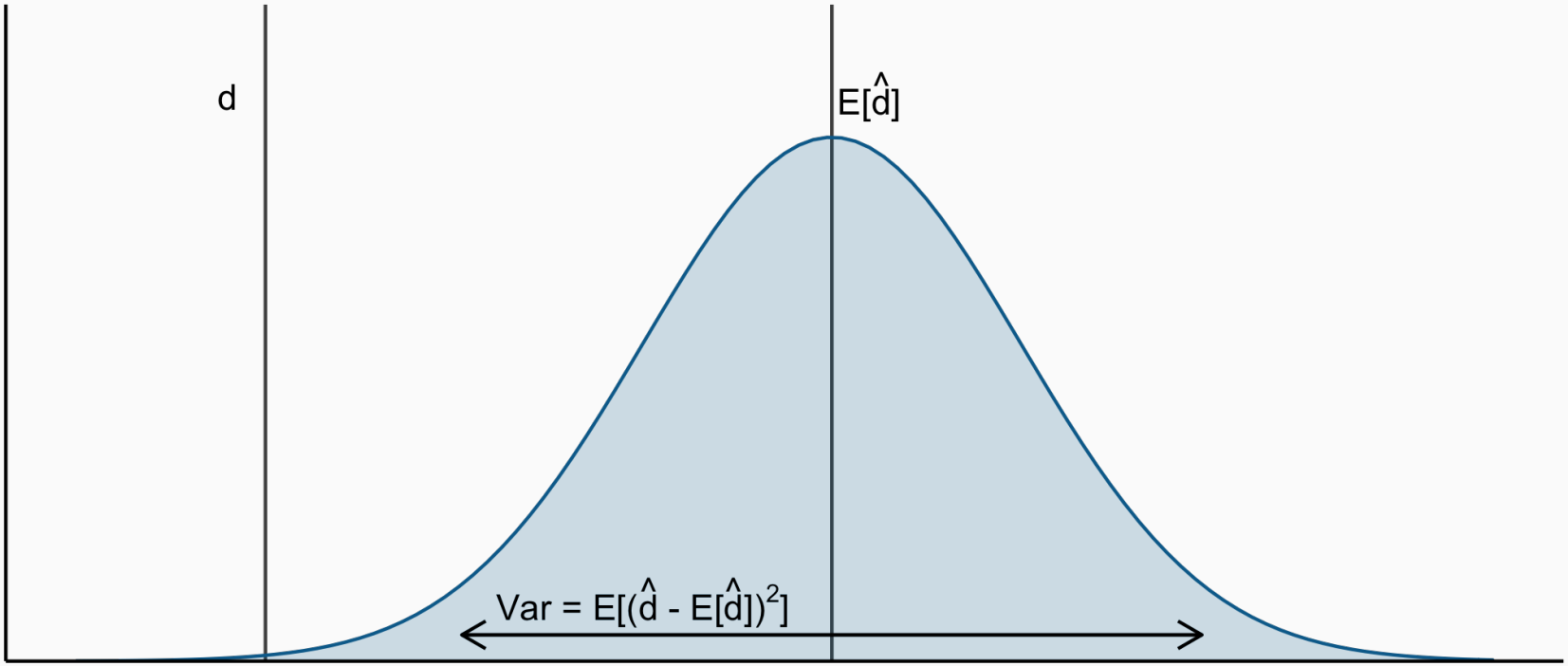

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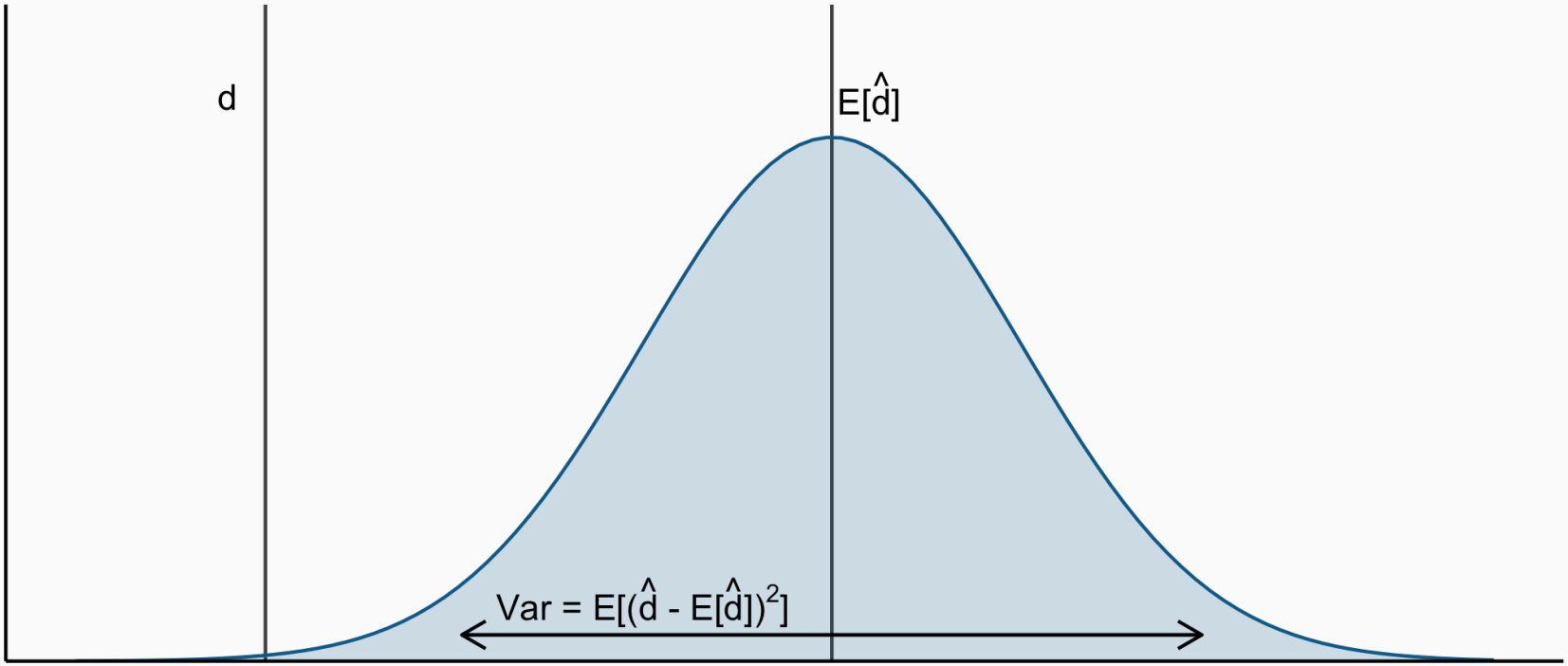
Low variance will give narrow CIs, large variance will give wide CIs



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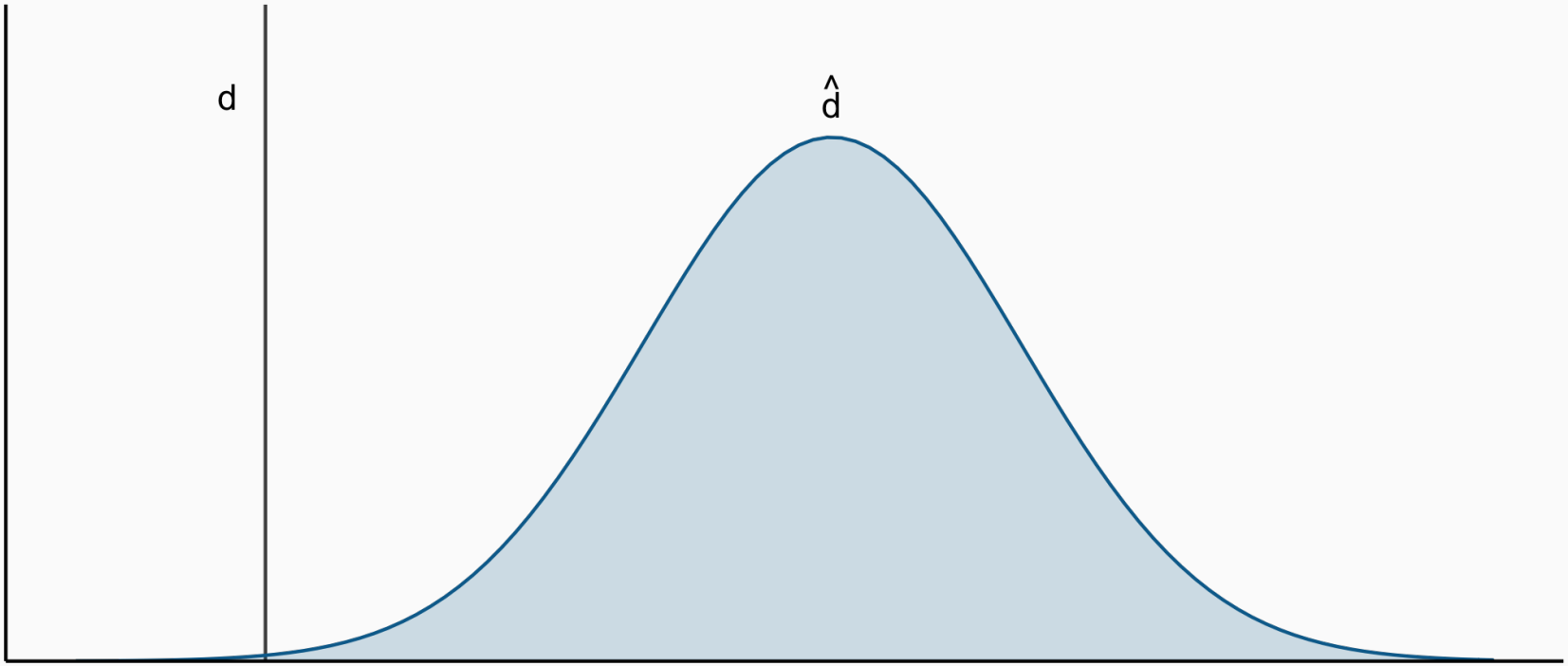

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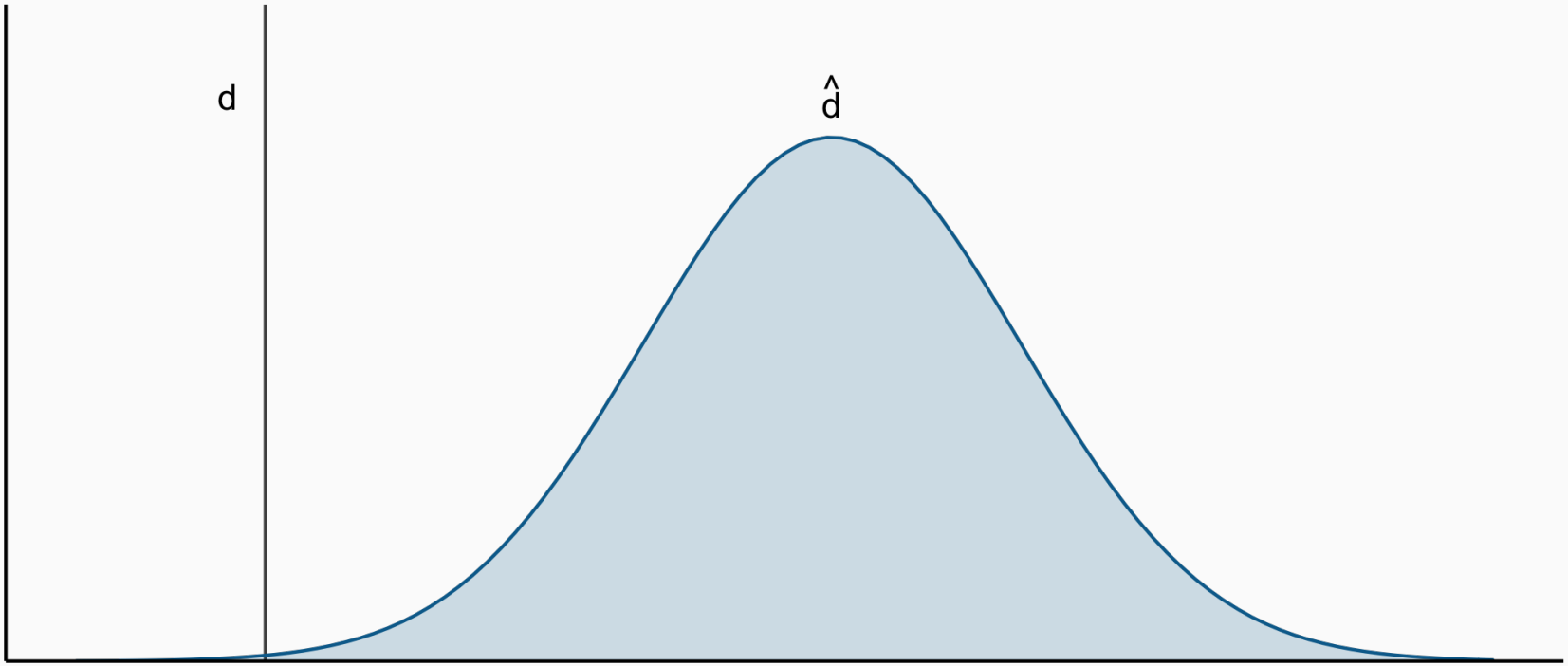
It provides a measure of total variation around the truth.



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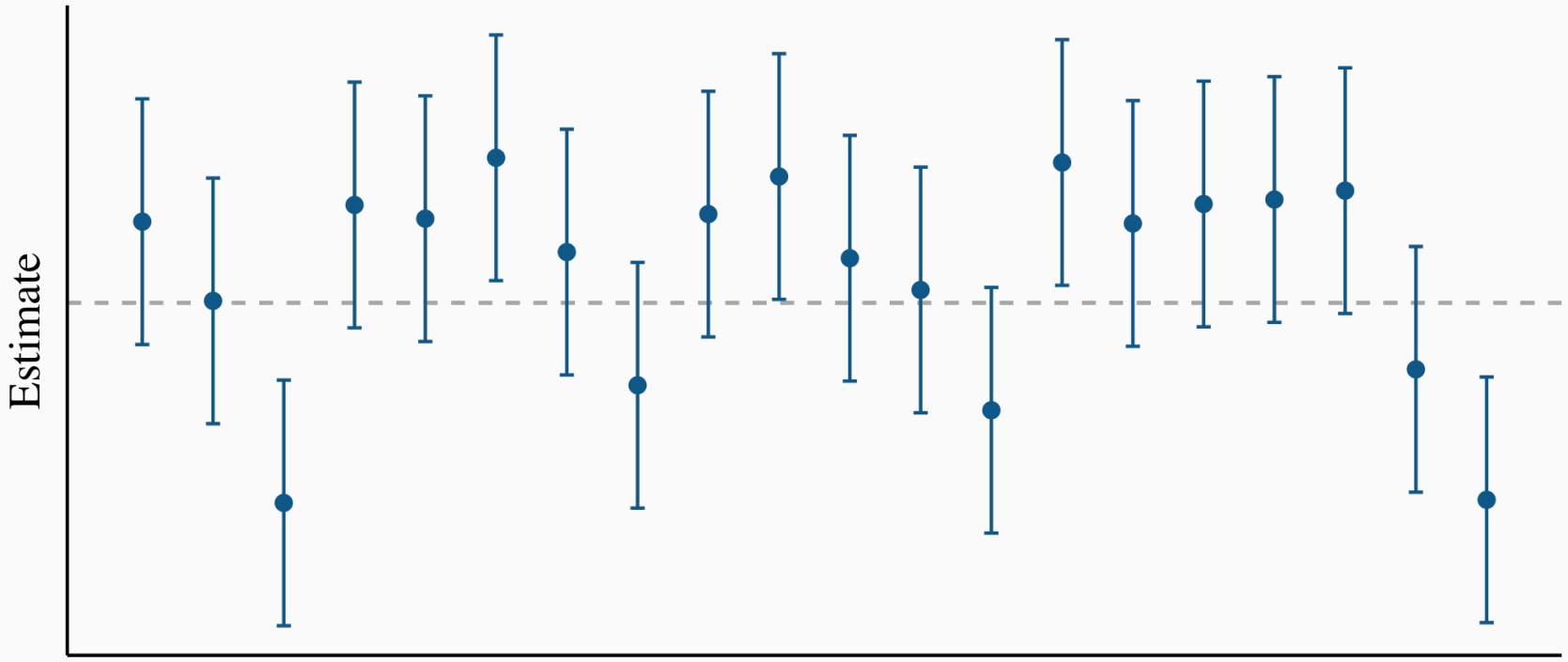

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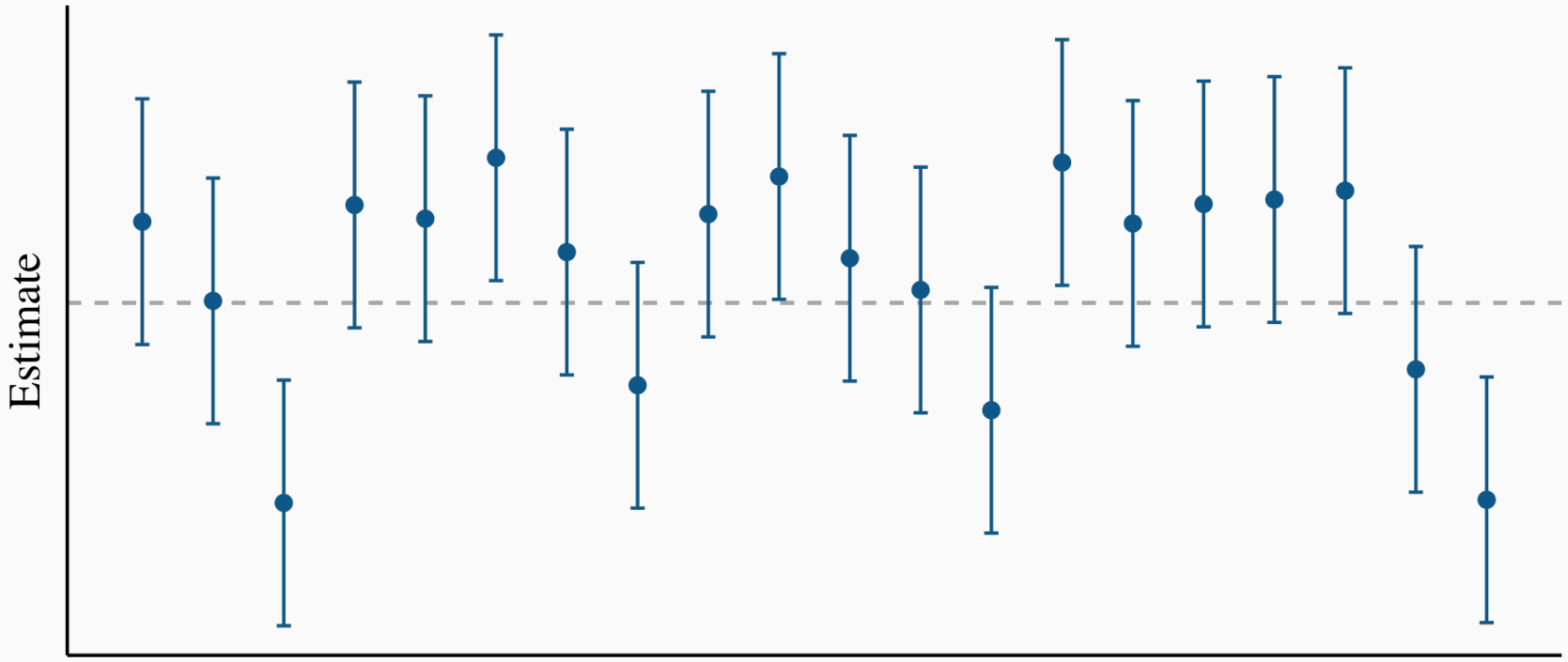
If 95% CIs are behaving like they should, they will include (cover) the truth 95% of the time.



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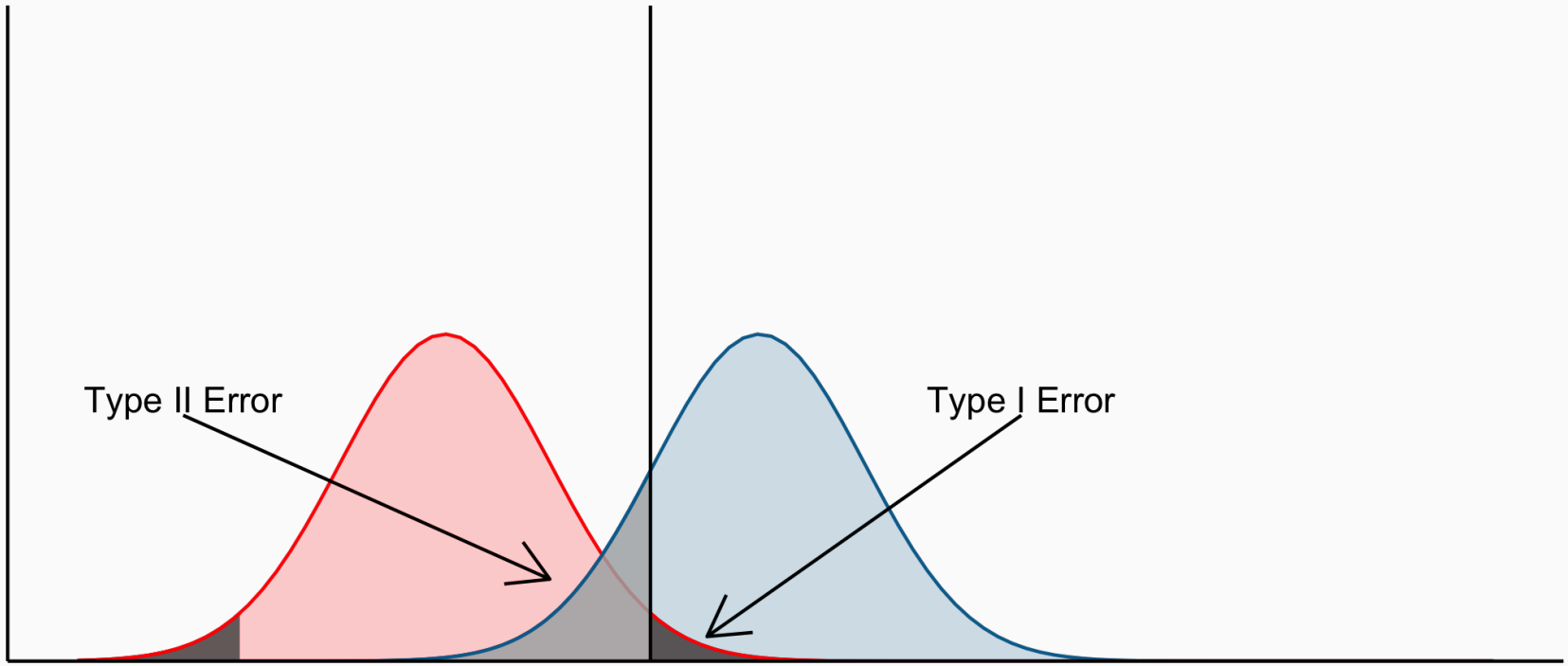

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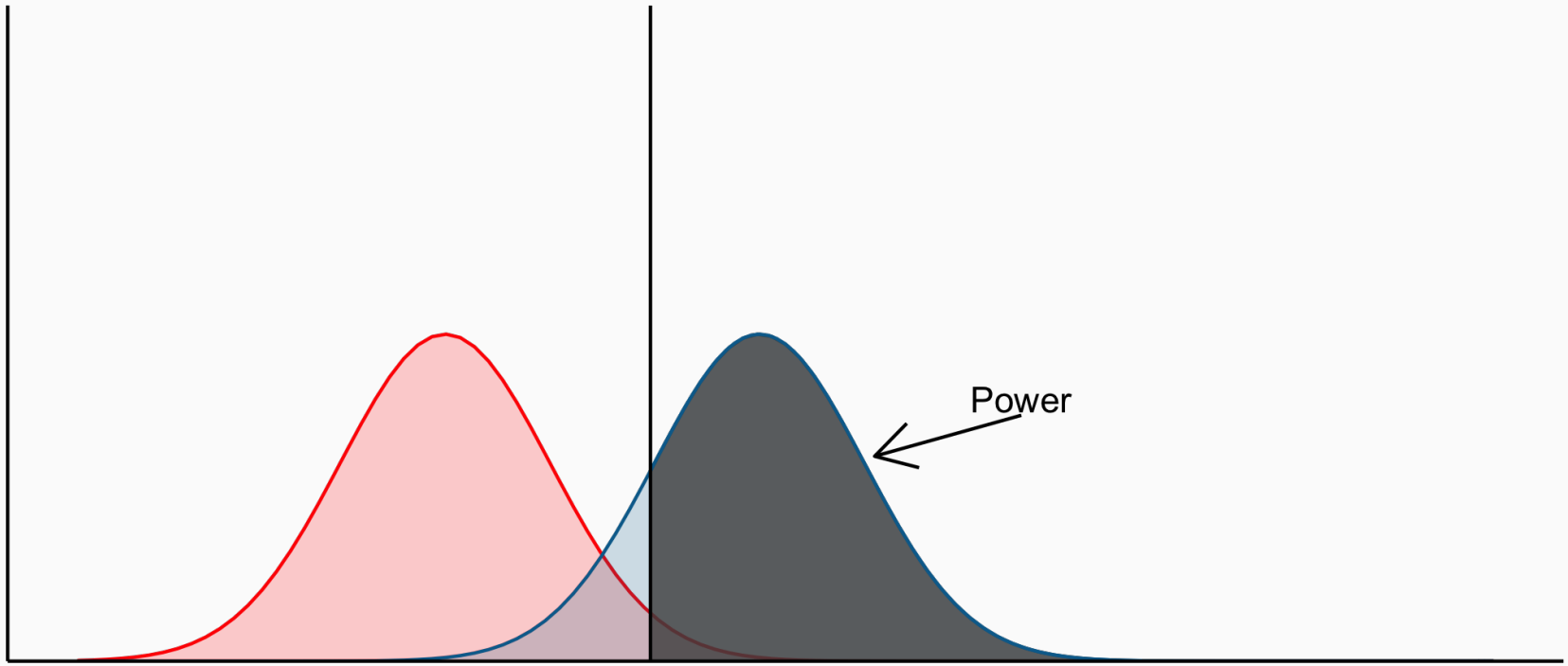

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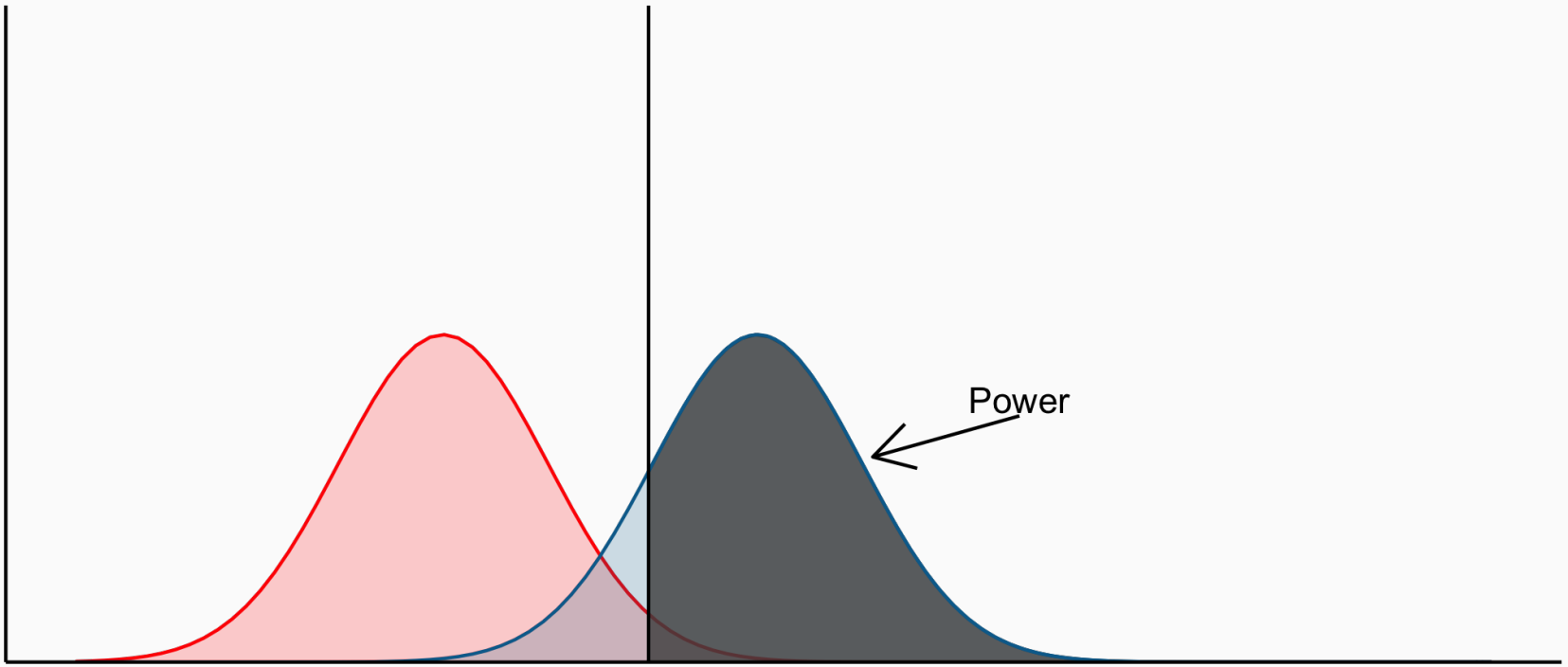

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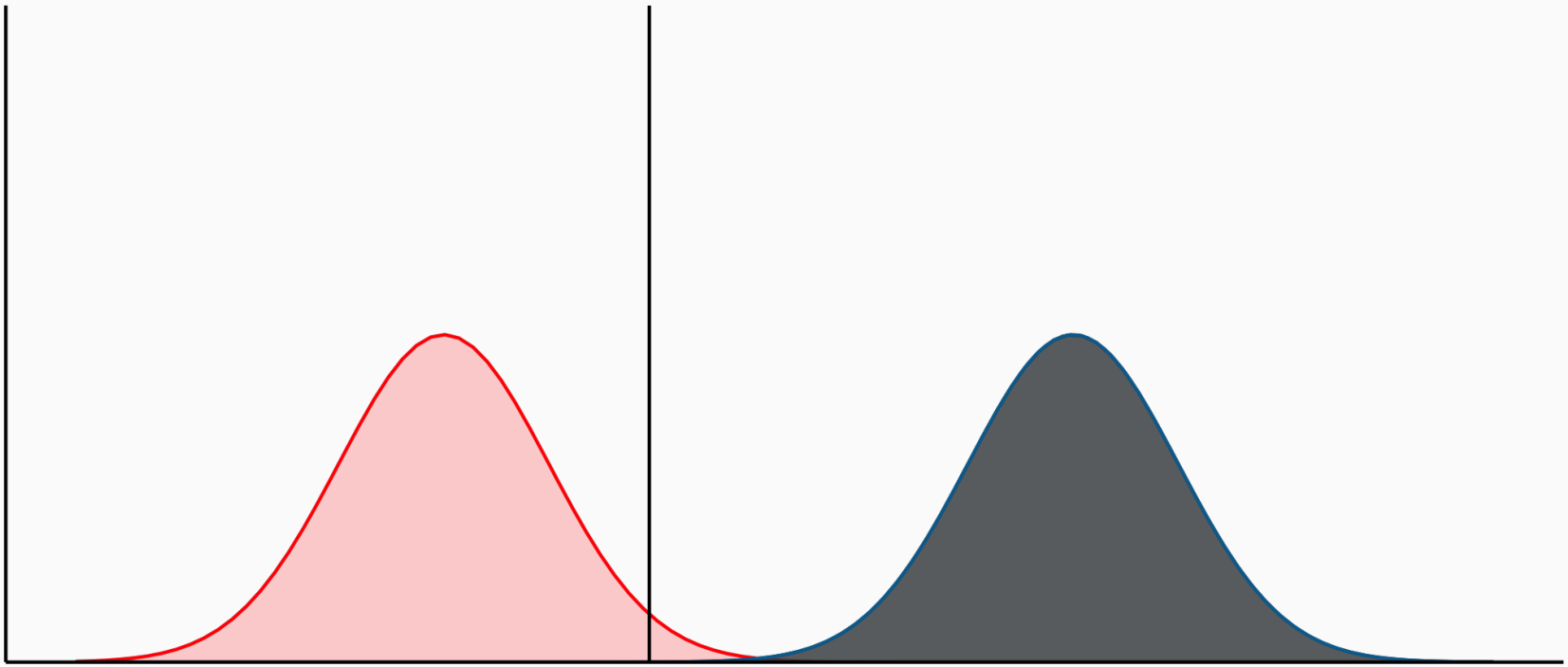

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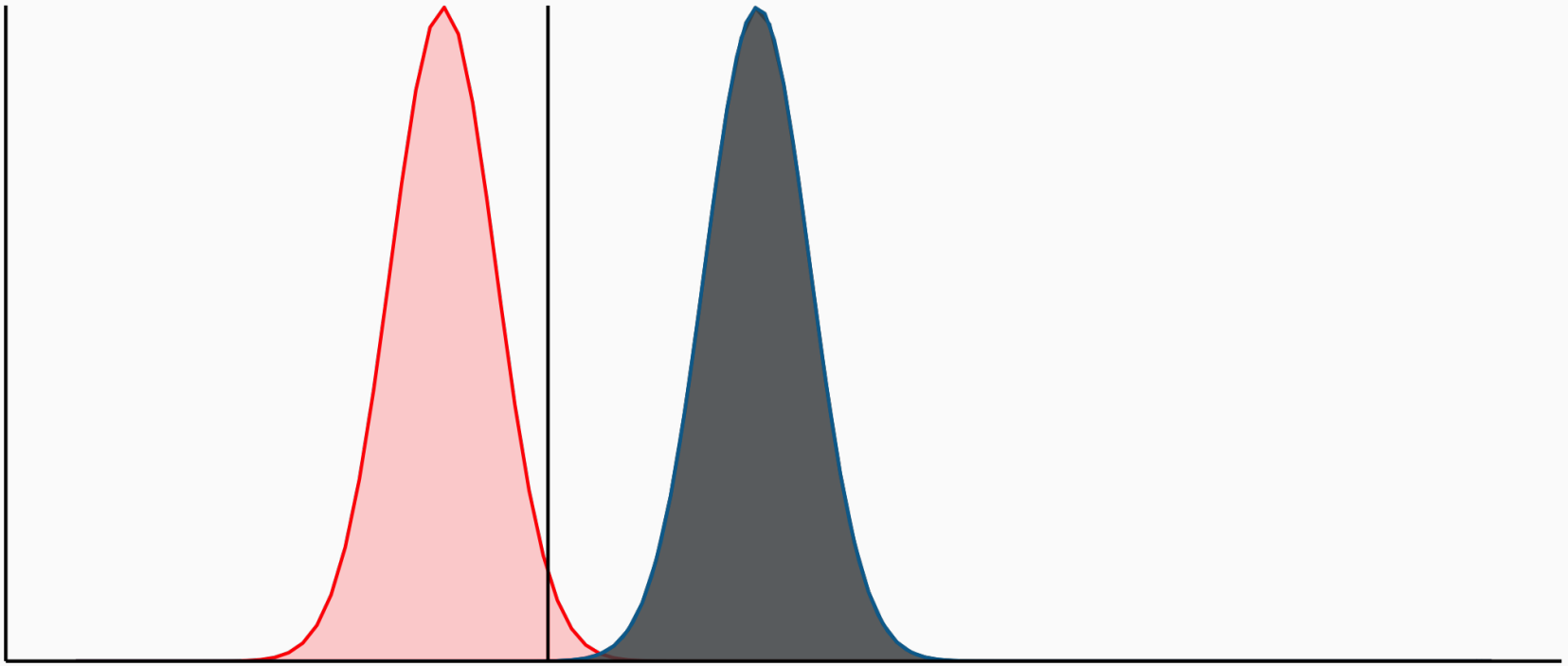
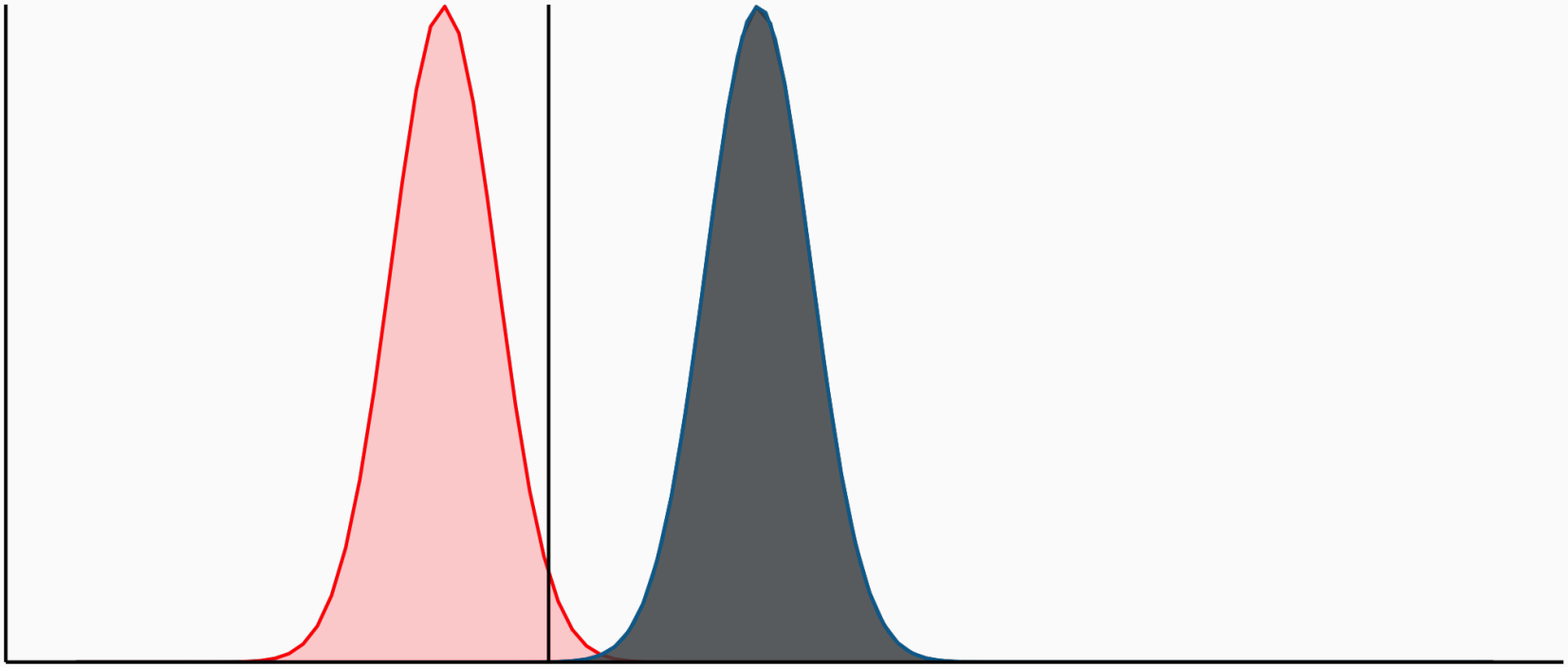
If we want to increase the power of a test there are two options:
1) increase effect size; or 2) make the distributions narrower ($\uparrow N$)



Statistical power (precision)

Some experimental designs can change effects sizes but we usually don't have control over this, so we typically ↑ sample sizes to ↑ power.



Power Analysis in Action

Power Analysis: Linear Regression

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pval <- numeric(nSims)

for(i in 1:nSims){
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Y <- Linear(X)
fit <- lm(Y ~ X)
pval[i] <- coef(summary(fit))["X", "Pr(>|t|)"]}
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sum(pval < 0.05)/nSims
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```

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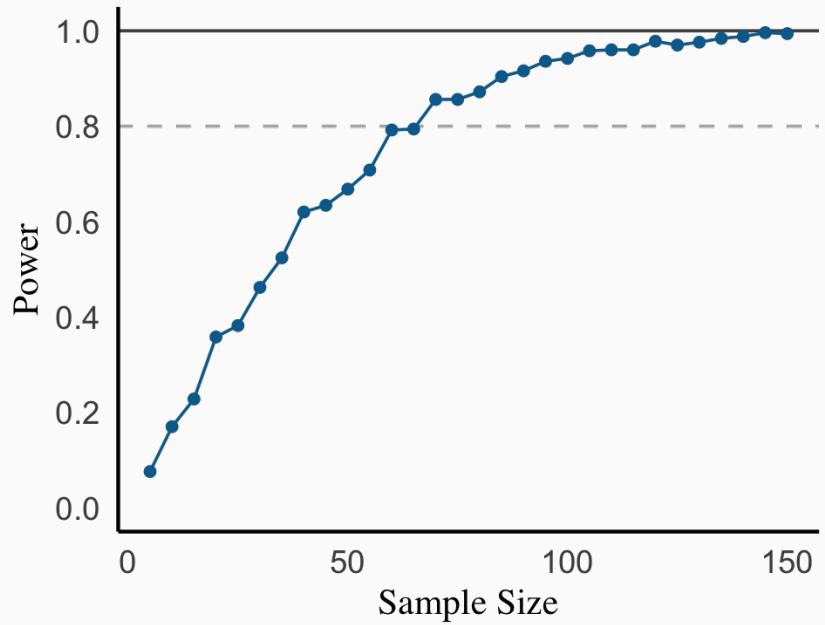

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nSims <- 500
B_1 <- seq(0,2,0.1)
POWER <- numeric(length(B_1))

for(j in 1:length(B_1)){
  pval <- numeric(nSims)
  for(i in 1:nSims){
    X <- runif(20, 0, 20)
    Y <- Linear(X, B_1[j])
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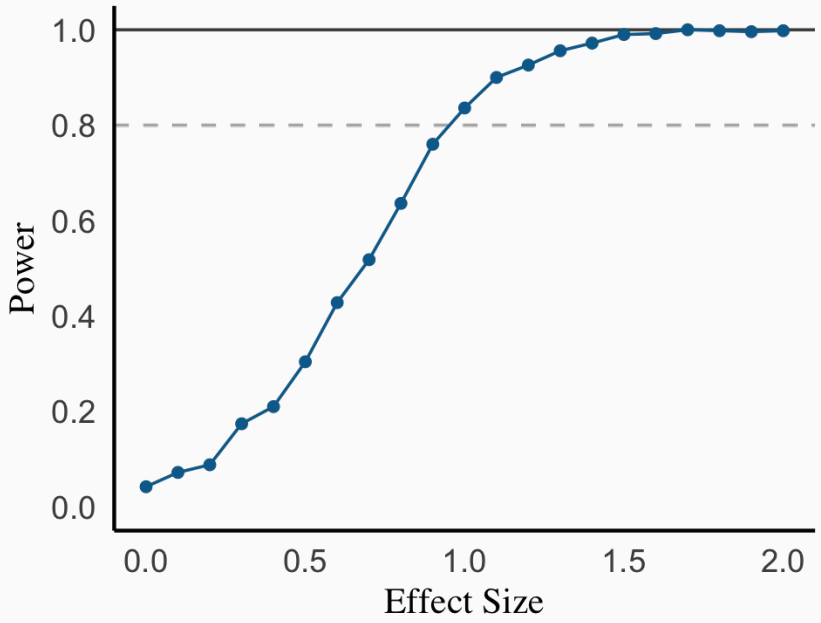

Detecting differences between groups

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  eta = exp(B_0[group] + B_1[group]*x)
  rnbinom(n = length(x), mu = eta, size = 10)
}

nSims <- 500
n <- seq(10,100,10)
POWER <- numeric(length(n))

for(j in 1:length(n)){
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    group <- factor(rep(1:2, each = n[j]/2))
    Y <- Counts(X,group)
    fit <- glm.nb(Y ~ X + group,link = "log")
    pval[i] <- coef(summary(fit))["group2", "Pr
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  }
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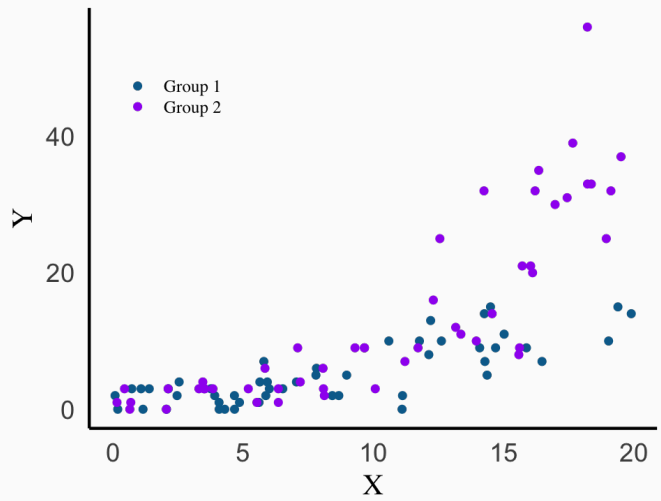
}
```



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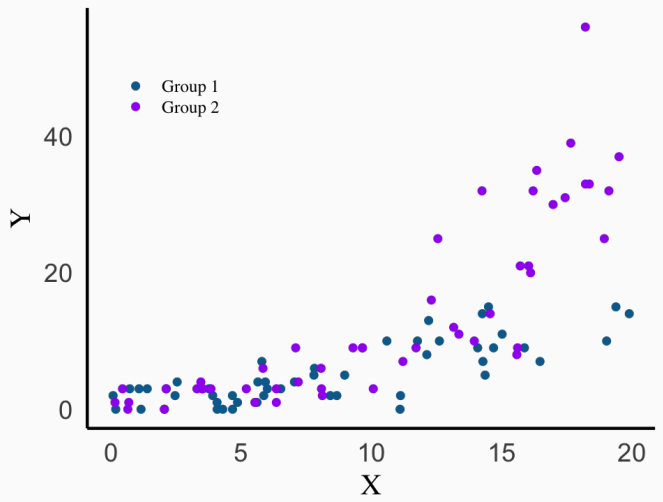
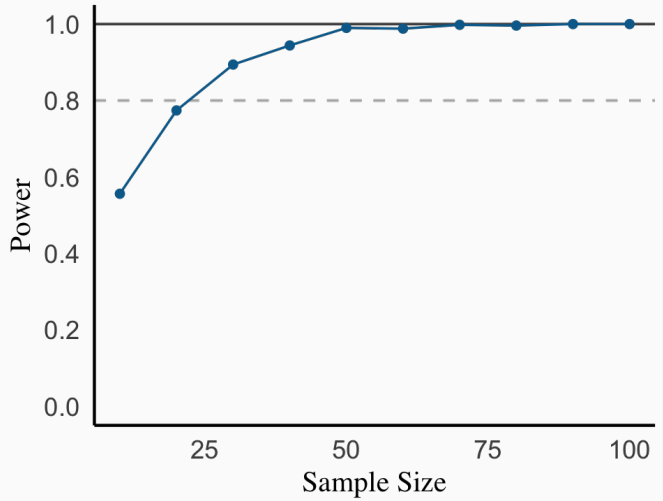
```





Power to detect multiple effects

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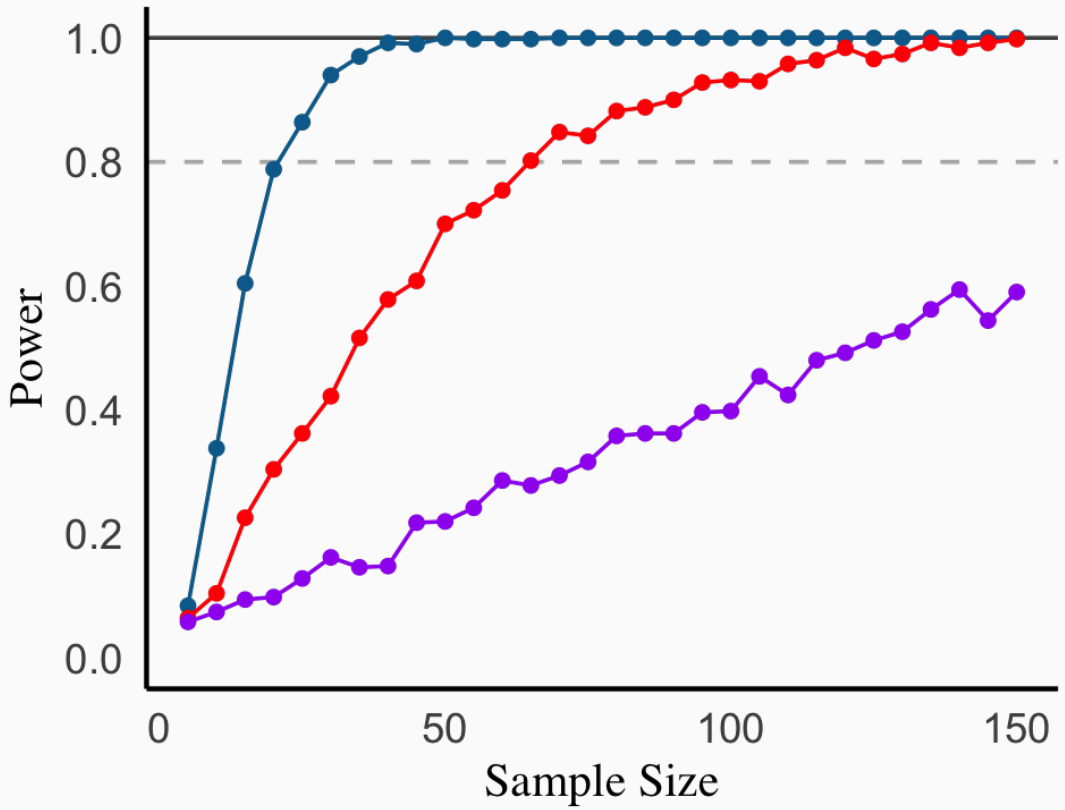
Regression models often contain multiple parameters with different effect sizes and we might be interested in knowing the power for different effects.



Blue: $\beta_1 = 1$; Red: $\beta_2 = 0.5$; Purple: $\beta_3 = .01$

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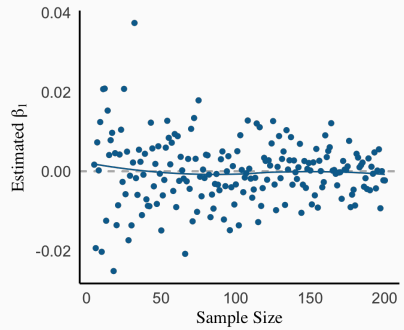
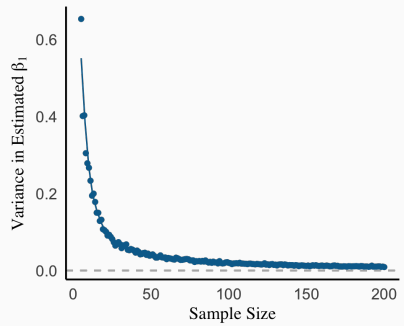
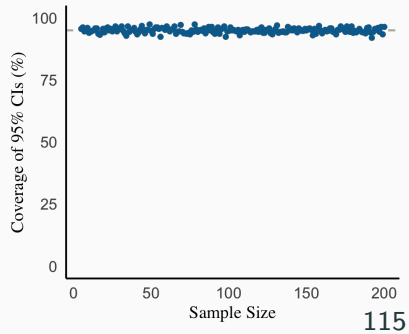
  mu = B_0 + B_1*x
  rnorm(n = length(x), mean = mu, sd = 8)}

nSims <- 500
n <- seq(5,200,1)
BIAS <- numeric(length(n))
VARIANCE <- numeric(length(n))
COVERAGE <- numeric(length(n))
for(j in 1:length(n)){
  bias <- numeric(nSims)
  coverage <- numeric(nSims)
  for(i in 1:nSims){
    X <- runif(n[j], 0, 20)
    Y <- Linear(X)
    fit <- lm(Y ~ X)
    bias[i] <- coef(fit)[2] - 0.5
    coverage[i]<-(0.5<=confint(fit)[2,2]&0.5>= confint(fit)[2,1])
  }
  BIAS[j] <- mean(bias)
  VARIANCE[j] <- var(bias)
  COVERAGE[j] <- sum(coverage)/nSims
}
```







Pseudocode

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A pseudocode can also be translated to another coding language more easily.

Example pseudocode

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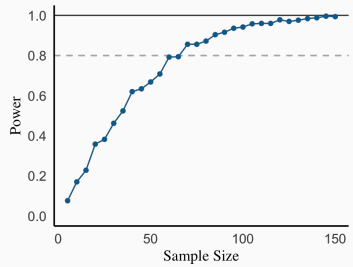
The pseudocode for estimating the statistical power of detecting a linear trend would look like this:



1. Define σ, β_0, β_1, the # of sims, and the sample sizes to test.
2. Build a function for simulating from simple linear model.
3. Build a for loop that simulates data and fits models nSims times.
4. Extract and store the p values from each iteration.
5. Nest this in a for loop that iterates over the different sample sizes.
6. Calculate the power for each sample size and store the results.
7. Plot the results for interpretation.

Pseudocode examples

Pseudocode examples

Hilborn & Mangel (1997) is full of examples of pseudocode if you're interested in seeing what that looks like.

Take home messages

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Simulations can also help us understand the statistical power of our data/model ... but good experimental design is more important than simulation based power analysis (don't overthink it).

References

Hilborn, R. & Mangel, M. (1997). *The ecological detective: confronting models with data*. vol. 28. Princeton University Press.

Bolker, B. M. (2008). Ecological models and data in R. Princeton University Press.