Today

- Questions from homework
- Frequentist inference algorithms
 - linear model sampling distribution
 - classical confidence intervals
 - bootstrap

Frequentist inference algorithms

- All frequentist inferences are based on the sampling distribution
- The sampling distribution is the frequentist approach to considering all the ways data could have happened (i.e. looking back)

Main concepts from HW videos

- Sampling distribution algorithm (4 lines)
- Sampling distribution imagined but true
- Confidence interval covers true value, x%
 - reliability of procedure
- Plug in principle
- Coverage algorithm, adds line:
 - calculate the interval for the sample statistic

Frequentist inference recipe

- 1) Make a model (biologically informed)
- 2) Which quantity of the model corresponds to the science? (map model to question)
 - parameters?
 - f(parameters)? e.g. predictions of y
- 3) Train the model
- 4) Get quantity from the trained model (sample statistic)
- 5) Derive an inference (e.g. 95% CI) from the sampling distribution of the sample statistic
- 6) Plug in an estimate of the sampling distribution

Linear model parameters

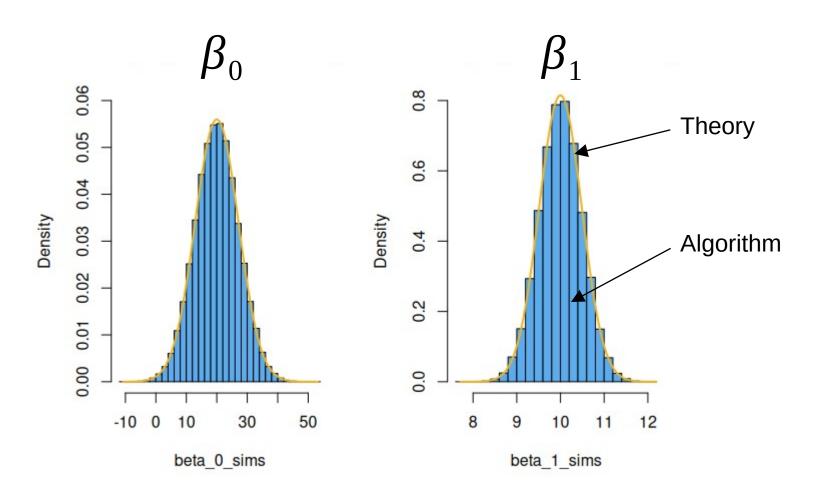
$$y_i = \beta_0 + \beta_1 x_i + e_i$$
$$e_i \sim \text{Normal}(0, \sigma^2)$$

Sampling distribution algorithm

repeat very many times
sample data from the population
train the linear model to estimate the parameters
plot sampling distributions (histograms) of the parameter estimates

Code: linear_model_sampling_distribution.md

Sampling distributions



Confidence interval (95%)

$$\beta_0 \pm t_{95} \sigma_0$$

Contain 95% of true sampling distribution

$$\beta_1 \pm t_{95} \sigma_1$$

$$t_{95} \approx 2.0$$

Plug in

$$\hat{\beta}_0 \pm t_{95} \hat{\sigma}_0$$

$$\hat{\sigma}_0 = \operatorname{fn}(\hat{\sigma}_e) \quad \hat{\sigma}_e = \operatorname{fn}(\operatorname{SSQ})$$

$$\hat{eta}_1\!\pm\!t_{95}\hat{\sigma}_1$$

$$\hat{\beta}_1 \pm t_{95} \hat{\sigma}_1$$
 $\hat{\sigma}_1 = \operatorname{fn}(\hat{\sigma}_e)$

Bootstrap

Sampling distribution algorithm

```
repeat very many times
sample data from the population
fit the model
estimate the parameters
plot sampling distribution (histogram) of the parameter estimates
```

Bootstrap algorithm

```
repeat very many times

generate data based on the sample 
fit the model
estimate the parameters
plot sampling distribution (histogram) of the parameter estimates
```

Bootstrap algorithms

- Non-parametric bootstrap
 - resample the data
- Empirical bootstrap
 - resample the residuals
- Parametric bootstrap
 - generate data from a distribution
 - use estimated parameters of the distribution

Huge advantage

 Can obtain uncertainty for any quantity that can be calculated from any fitted model

Code (e.g. empirical bootstrap)

```
( i in 1:10000 ) {
     e boot <- sample(e fit, replace=TRUE)</pre>
     df booty \leftarrow coef(fit)[1] + coef(fit)[2]*df boot<math>x + e boot
     fit boot <-lm(y \sim x, data=df boot)
     boot beta0[i] <- coef(fit boot)[1]</pre>
     boot beta1[i] <- coef(fit boot)[2]</pre>
                Bootstrap distribution beta 0
                                         Bootstrap distribution beta 1
               0.05
                                  95%
               9.0
plug in
               0.03
                                                                 Pseudocode
            Density
                                      Density
                                         <u>4</u>.
                                                                 For many times
               0.02
                                                                   Resample errors from model fit (with
                                                                 replacement)
               0.0
                                                                   Create new y-values at original x values
                                                                   Fit the model
               8
                                                                   Keep parameter estimates
                      20
                                           80
                                                90
                                                     10.0
                         30
                             40
                                                          110
```

boot beta1

boot beta0

Bootstrapped CI

- Learning goals
 - Understand how bootstrap algorithms mimic the sampling distribution algorithm
 - Gain intuition for the plug in principle by using it directly
 - Using simulation, understand how the sampling distribution is the basis for frequentist inference
 - Develop algorithms from first principles that can be applied to any model

Code a bootstrapped CI

- Use your linear data
- CI for β_0 , β_1
- CI for y|x (aka the line)

- Use empirical bootstrap
- Use percentile method

Bootstrap: further reading

Brief exposition:

James G, Witten D, Hastie T, Tibshirani R (2021). An Introduction to Statistical Learning: With Applications in R, Second edition. Springer, New York. Chapter 5.2.

Definitive references:

Davison AC, Hinkley DV (1997). Bootstrap Methods and Their Application. Cambridge University Press, Cambridge; New York, NY, USA.

Efron B, Tibshirani R (1993). An Introduction to the Bootstrap. Chapman & Hall, New York.