

# Bootstrapping

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## Introduction

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- *"to pull oneself up by the bootstraps"*
- A sample is all we have
- Treat the sample as the population

# Why Bootstrap?

- Instances when we have a small sample

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- Instances when we have a small sample
- Assumed distribution can lead to incorrect hypothesis testing

# Bootstrap methods

- Simple bootstrap



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- Methods for time series

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- Confidence Intervals

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$$\tau = \frac{\hat{\theta} - \theta_0}{\hat{s}_\theta}$$

- Percentile t method

$$[\hat{\theta} - \hat{s}_\theta t_{(1-\alpha/2)(B+1)}^*, \hat{\theta} - \hat{s}_\theta t_{(\alpha/2)(B+1)}^*]$$

# Regression

- Resampling Residuals

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- Resampling Cases

# Regression Model

Consider a linear regression model

$$Y = X\beta + \epsilon$$

$Y = (n \times 1)$  vector of values of the dependent variable

$X =$  matrix of  $(n \times k)$  independent variable's data

$\beta = (k \times 1)$  vector of regression coefficients

$\epsilon = (n \times 1)$  errors terms



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Step 2: Using these  $\hat{\beta}$ s and the observed  $Y$  values, we calculate the residuals,

$$\hat{\epsilon}_i = Y_i - \hat{Y}_i.$$

Step 3: Now, we re-sample these residuals with replacement. And create a bootstrapped vector of the independent variable

$$Y_b^* = \hat{Y} + \hat{\epsilon}_b^*$$

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Step 4: These bootstrapped independent variables are then regressed on the previous (fixed), independent variables and a vector of bootstrapped  $\hat{\beta}_b^*$  for this particular re-sample is obtained.

$$\hat{Y}_b^* = X\hat{\beta}_b^* + \hat{\epsilon}$$

Step 3 and 4 are repeated  $B$  times, to obtain a  $(B \times k)$  matrix, with each row representing  $\beta$ s of one re-sample.

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- $(B \times k)$  matrix of bootstrapped regression coefficients

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- If the model has stochastic component
- If the errors are heteroscedastic
- Survey research where independent variables are as random as dependent variable, data resampling works better
- However, most theoretical statisticians suggest, residuals approach



# MATLAB