Resampling Methods for Uncertainty Big Data y Machine Learning para Economía Aplicada

Ignacio Sarmiento-Barbieri

Universidad de los Andes

- 1 Uncertainty: Motivation
- 2 What are resampling methods?
- 3 The Bootstrap
 - Example: Elasticity of Demand for Gasoline
- 4 Resampling methods for Out of Sample Prediction

- 1 Uncertainty: Motivation
- 2) What are resampling methods?
- 3 The Bootstrap
 - Example: Elasticity of Demand for Gasoline
- 4 Resampling methods for Out of Sample Prediction

Motivation

- ► The real world is messy.
- ▶ Recognizing this mess will differentiate a sophisticated and useful analysis from one that is hopelessly naive.
- ► This is especially true for highly complicated models, where it becomes tempting to confuse signal with noise and hence "overfit."
- ▶ The ability to deal with this mess and noise is the most important skill you need.

- 1 Uncertainty: Motivation
- 2 What are resampling methods?
- 3 The Bootstrap
 - Example: Elasticity of Demand for Gasoline
- Resampling methods for Out of Sample Prediction

What are resampling methods?

- ➤ Tools that involves repeatedly drawing samples from a training set and refitting a model of interest on each sample in order to obtain more information about the fitted model
 - Parameter Assessment: estimate standard errors
 - ► Model Assessment: estimate test error rates
 - ► They are computationally expensive! But these days we have powerful computers

- Uncertainty: Motivation
- What are resampling methods?
- 3 The Bootstrap
 - Example: Elasticity of Demand for Gasoline
- 4 Resampling methods for Out of Sample Prediction

The Bootstrap

- ► In general terms:
 - $ightharpoonup Y_i$ $i = 1, \ldots, n$
 - \triangleright θ is the magnitude of interest
- ► To calculate it's variance
 - 1 Sample of size *n* with replacement (*bootstrap sample*)
 - 2 Compute $\hat{\theta}_i$ $j = 1, \dots, B$
 - 3 Repeat B times
 - 4 Calculate

$$\hat{V}(\hat{\theta})_B = \frac{1}{B} \sum_{j=1}^B (\hat{\theta}_j - \bar{\theta})^2$$
 (1)

The Bootstrap

- ► There are two key properties of bootstrapping that make this seemingly crazy idea actually work.
 - 1 Each bootstrap sample must be of the same size (N) as the original sample
 - 2 Each bootstrap sample must be taken with replacement from the original sample

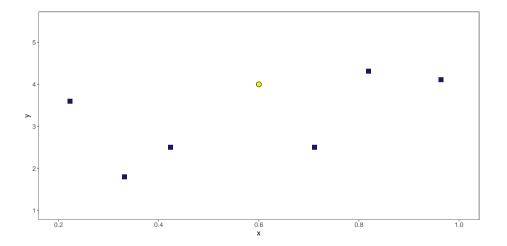
Example: Elasticity of Demand for Gasoline

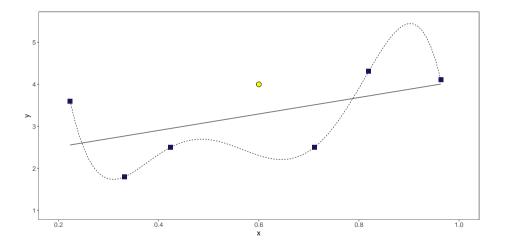


photo from https://www.dailydot.com/parsec/batman-1966-labels-tumblr-twitter-vine/

- Uncertainty: Motivation
- What are resampling methods?
- 3 The Bootstrap
 - Example: Elasticity of Demand for Gasoline
- 4 Resampling methods for Out of Sample Prediction

- ▶ The goal of machine learning is *out of sample* prediction i.e. the ability to predict on new data.
- Overfit: complex models predict well in sample but bad our of sample
- ► How to choose the optimal compelexity level?



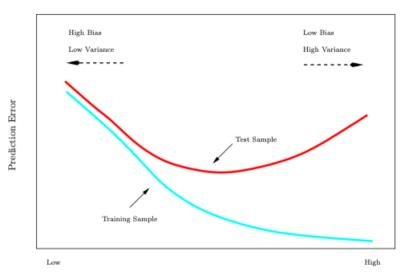


- ► Two concepts
 - ► *Test Prediction Error*: is the prediction error in a test sample

$$Err_{Test} = E[L(Y, \hat{Y}) | Test]$$
 (2)

► *Training Prediction Error*: is the prediction error in the training sample

$$Err_{\mathcal{T}rain} = E[L(Y, \hat{Y})|\mathcal{T}rain]$$
 (3)



Model Complexity

- ► Two concepts
 - ► *Test Prediction Error*: is the prediction error in a test sample

$$Err_{Test} = E[L(Y, \hat{Y}) | Test]$$
 (2)

► *Training Prediction Error*: is the prediction error in the training sample

$$Err_{Train} = E[L(Y, \hat{Y}) | Train]$$
 (3)

► Then how do we estimate the test prediction error?

- ▶ In the absence of a very large designated test set we can use some techinques:
 - 1 Validation Set
 - 2 Loocy
 - 3 K-fold Crossvalidation



photo from https://www.dailydot.com/parsec/batman-1966-labels-tumblr-twitter-vine/