



UNIVERSITY OF  
SAN FRANCISCO

Master of Science  
in Analytics

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# Resampling Methods

Machine Learning 1

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# Model assessment & selection

- How do you know whether a model is good?
  - ... in a computationally tractable way?
  - ... for regression and classification?
- To build a good model, how flexible should it be?
  - What settings should the hyperparameters have?



# Is the model good?

- Performance on test material is lower than on train
  - \* Almost always...
  - Why?
- Estimate test performance using training material
  - Randomly-generated portion, *validation set*, not used for training



- What is the problem with this technique?



# Cross-validation

- Types

- Leave-One-Out Cross-Validation (LOOCV)



- k-Fold Cross-Validation

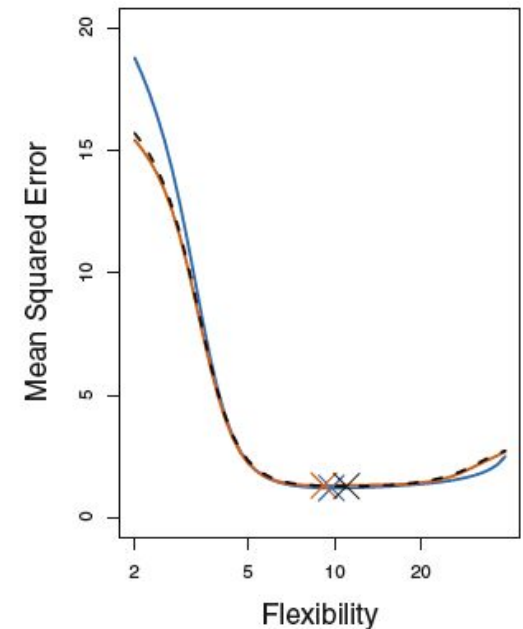
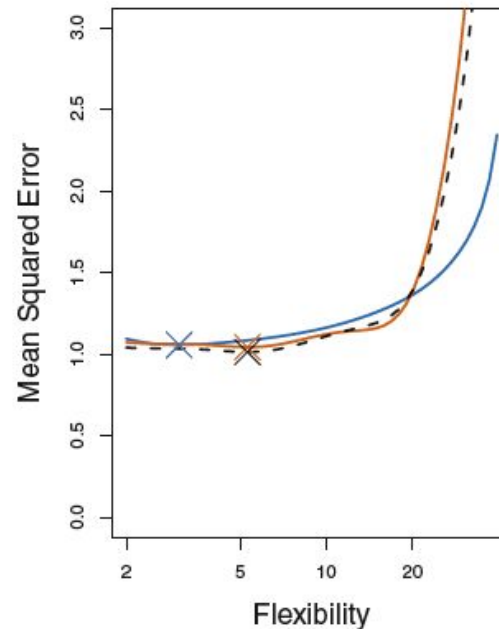
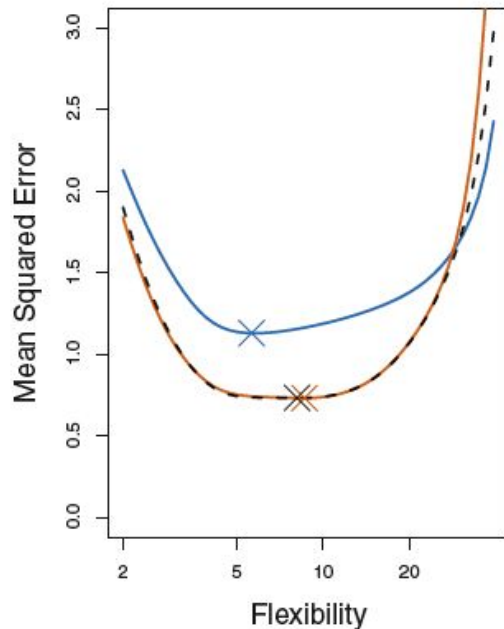
- Results (regression)

$$CV_{(k)} = \frac{1}{k} \sum_{i=1}^k MSE_i$$



# Train vs. test

- Problem: what is the true [read: test] MSE?
  - Examples: LOOCV, k-fold CV and test MSE



- Curves are similar but suggest different (incorrect) flexibility points
- Can the uncertainty be quantified?



# The bootstrap

- Objective: quantify uncertainty

- Sub-objective: decrease variability ("risk")

$$\alpha = \frac{\sigma_Y^2 - \sigma_{XY}}{\sigma_X^2 + \sigma_Y^2 - 2\sigma_{XY}}$$

- Since all  $\sigma$  terms above are unknown, we estimate from data
- Curves are similar but suggest different (incorrect) flexibility points

- Algorithm:

- Choose some (large) value, B (eg. 1000)
- Create B sets from training by sampling with replacement
- Compute average (or majority) and SE performance estimates:

$$\bar{\alpha} = \frac{1}{1,000} \sum_{r=1}^{1,000} \hat{\alpha}_r \quad \text{SE}_B(\hat{\alpha}) = \sqrt{\frac{1}{B-1} \sum_{r=1}^B \left( \hat{\alpha}^{*r} - \frac{1}{B} \sum_{r'=1}^B \hat{\alpha}^{*r'} \right)^2}$$



# Example

