Introduction to Statistical Learning

INF 552, Machine Learning for Data Informatics

University of Southern California

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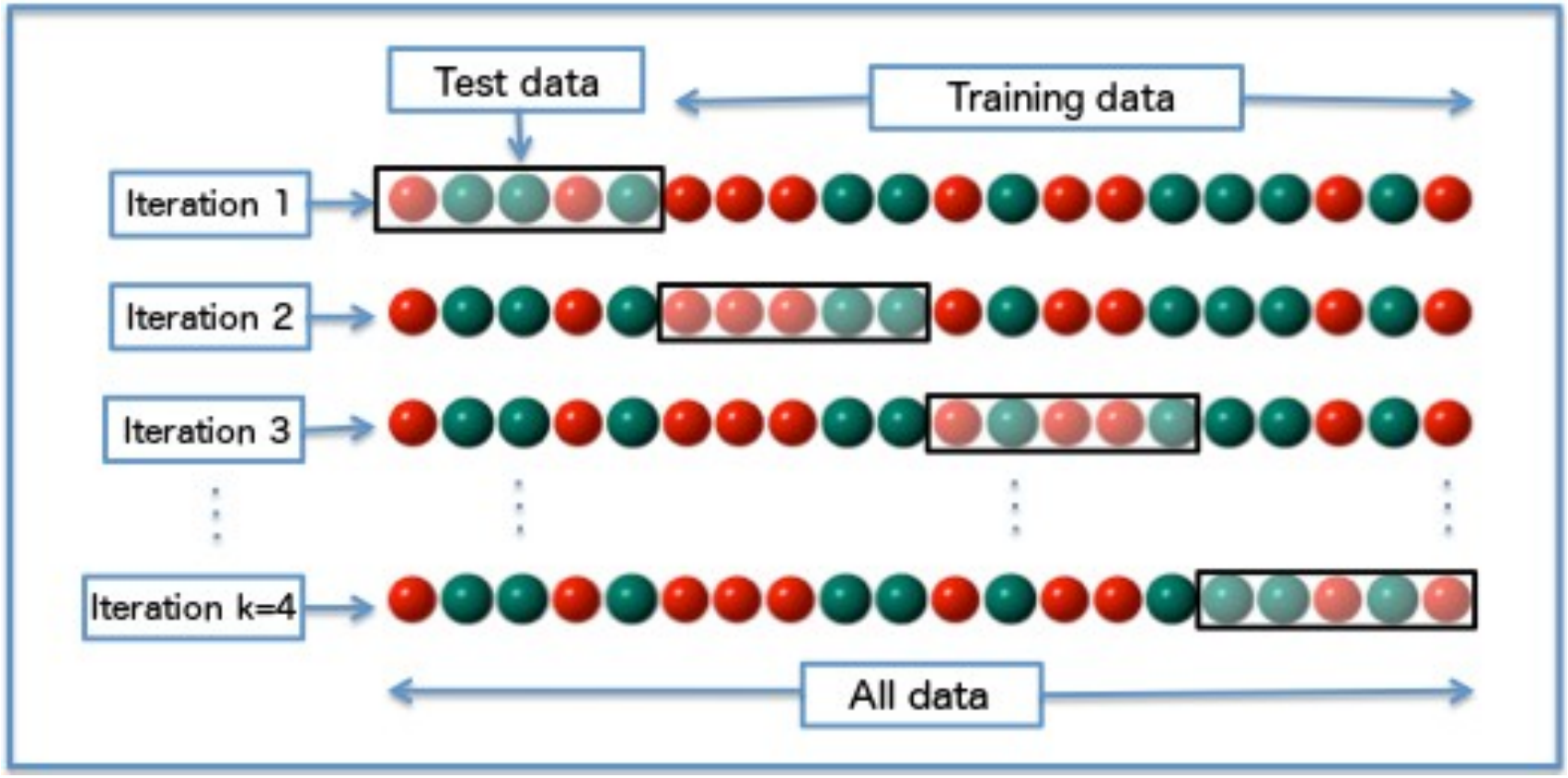
Lesson 4
Resampling



Resampling Methods

- Repeatedly drawing samples from a training set and refitting a model on each sample to obtain more information about the fitted model.

- Example: Estimate the variability of a linear regression fit by repeatedly drawing different samples from the training data, fitting a regression model to each new sample, and then examining the extent to which the resulting fits differ.

Resampling Methods

- Model Assessment: having chosen a final model, estimating its prediction error on new data.
- Model Selection: estimating the performance of different models in order to choose the best one.

Resampling Methods (cont.)

Cross-Validation

Used to estimate test set prediction error rates associated with a given machine learning method to evaluate its performance, or to select the appropriate level of model flexibility.

Bootstrap

Used most commonly to provide a measure of accuracy of a parameter estimate or of a given machine learning method.

Model Assessment

The *generalization* performance of a machine learning method relates to its prediction capability on independent test sets.

Assessment of this performance is extremely important in practice, since it guides the choice of the machine learning method or model.

Further, this gives us a measure of the quality of the ultimately chosen model.

Model Assessment (cont.)

Test Error

The average prediction error of a machine learning method on new observations.

The prediction error over an independent test sample.

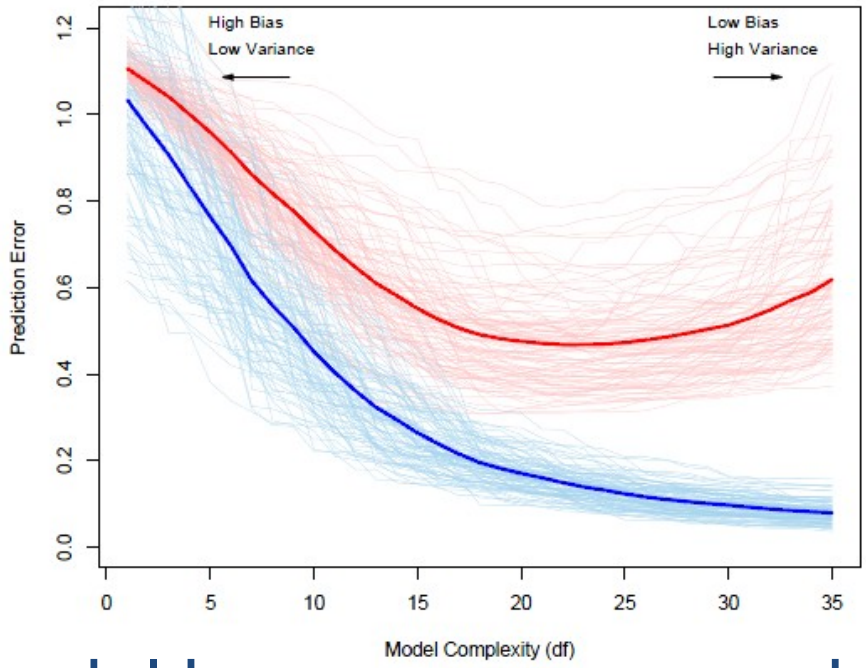
Training Error

The average loss over the training sample:

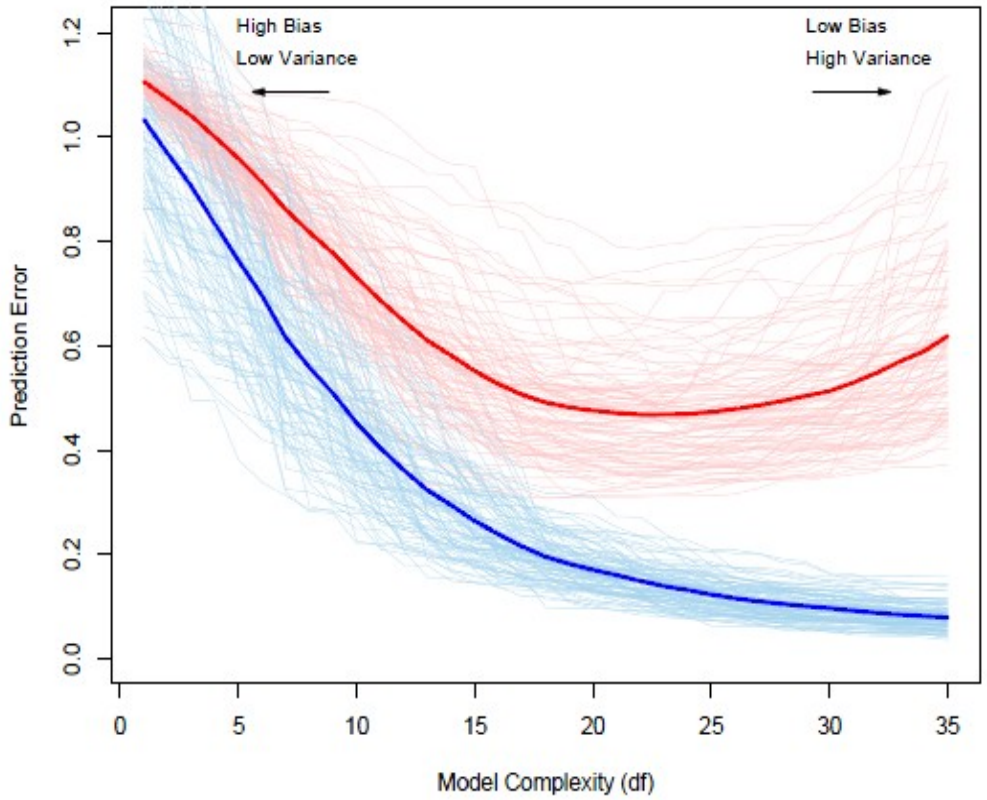
$$\overline{\text{err}} = \frac{1}{N}\sum_{i=1}^{N} L(y_i, \hat{f}(x_i))$$

Note: The training error rate can dramatically *underestimate* the test error rate

Model Assessment (cont.)



- As the model becomes more and more complex, it uses the training data more and is able to adapt to more complicated underlying structures.
- Hence, there is a decrease in bias but an increase in variance.
- However, training error is not a good estimate of the test error.



- Training error consistently decreases with model complexity.
- A model with zero training error is overfit to the training data and will typically generalize poorly.

Model Assessment (cont.)

- If we are in a data-rich situation, the best approach for both *model selection* and *model assessment* is to randomly divide the dataset into three parts: training set, validation set, and test set.

Model Assessment (cont.)

- The *training set* is used to fit the models. The *validation set* is used to estimate prediction error for model selection. The *test set* is used for assessment of the prediction error of the final chosen model.

- A typical split might by 50% for training, and 25% each for validation and testing.

Model Assessment (cont.)

Best solution: use a large designated test set, which is often not available. For the methods presented here, there is insufficient data to split it into three parts.

There are some methods to make mathematical adjustments to the training error rate in order to estimate the test error rate:

Cp statistic, AIC, BIC (we will discuss these next)

Model Assessment (cont.)

Here, we consider cross-validation (CV) methods that estimate the test error by *holding out* a subset of the training observations from the fitting process, and then applying the machine learning method to those held out observations.

Overview: Model Selection

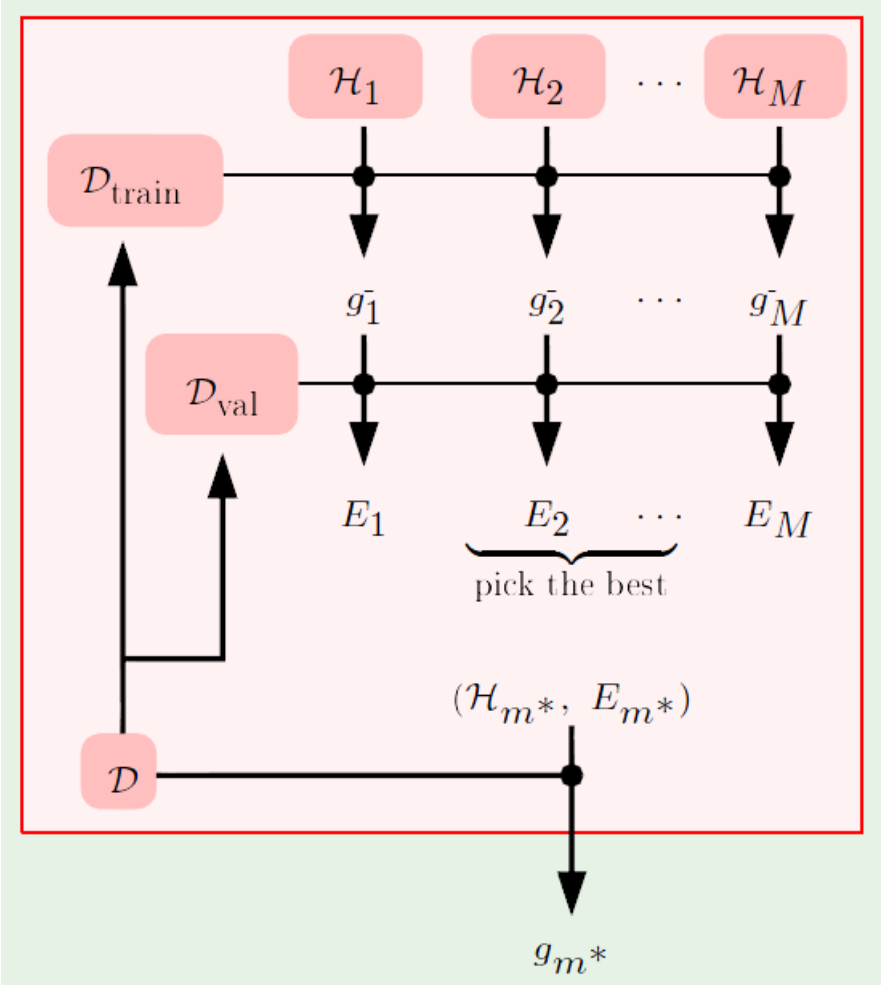
- The most important use of validation is for *model selection*
- In almost every learning situation, there are some choices to be made and we need a principled way of making these choices.
- The leap is to realize that *validation* can be used to estimate the out-of-sample error for more than one model.

Overview: Model Selection (cont.)

Suppose we have M models; validation can be used to select one of these models.

We use the training data to fit the model, and we evaluate each model on the validation set to obtain the validation errors.

It is now a simple matter to select the model with the lowest validation error.

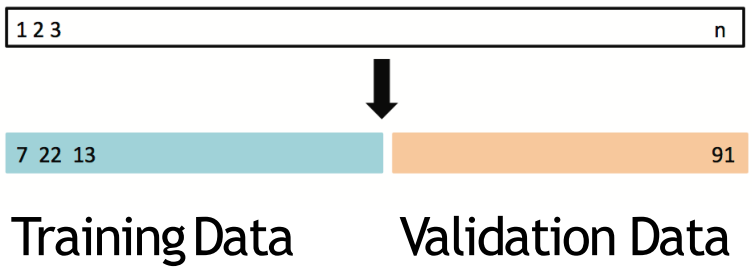


Validation Set Approach

We wish to find a set of variables that give the lowest *validation error rate* (an estimate of the *test error rate*).

If we have a large data set, we can randomly split the data into separate training and validation data sets.

Then, we use the training data set to build each possible model and select the model that gives the lowest error rate when applied to the validation data set.



Validation Set Approach: Example

Example: we want to predict *mpg* from *horsepower*

Two models:

mpg ~ horsepower

mpg ~ horsepower + horspower^2

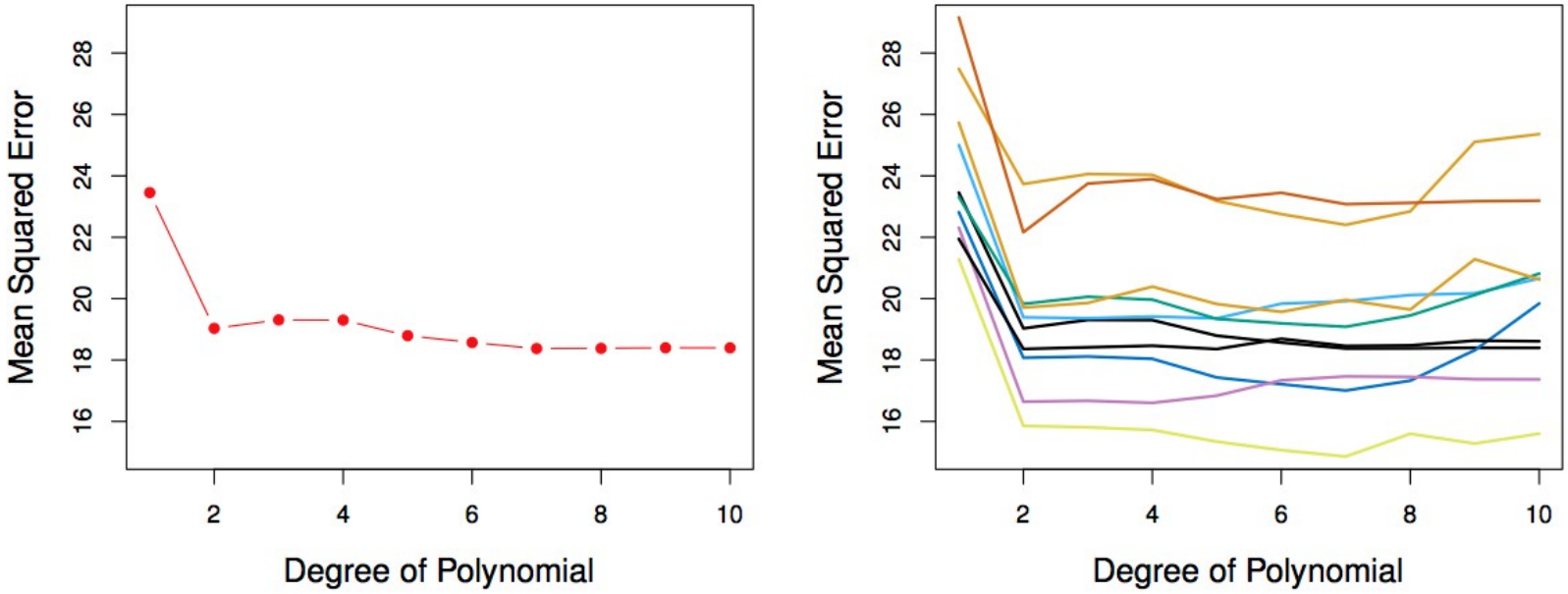
Which model gives a better fit?

We randomly split (50/50) *392 observations* into training and validation data sets, and we fit both models using the training data.

Next, we evaluate both models using the validation data set.

Winner = model with the *lowest* validation (testing) MSE

Validation Set Approach: Example Results



Left Panel: Validation error estimates for a single split into training and validation data sets.

Right Panel: Validation error estimates for multiple splits; shows the test error rate is highly variable.

Validation Set Approach: Review

Advantages:

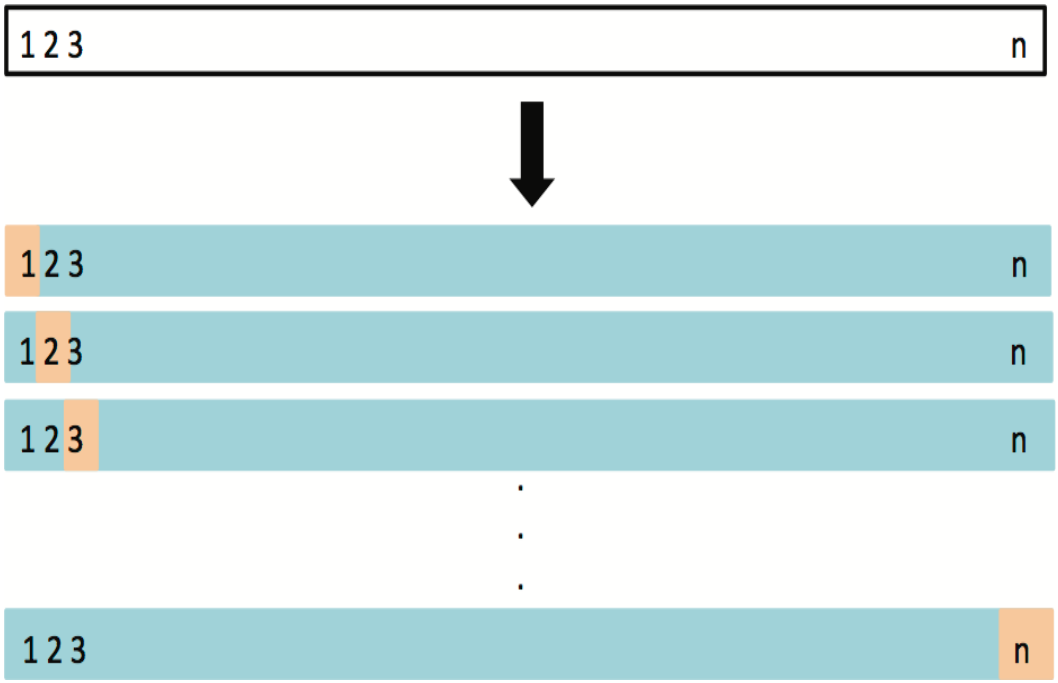
- Conceptually simple and easy implementation.

Drawbacks:

- The validation set error rate (MSE) can be highly variable.
- Only a subset of the observations (those in the training set) are used to fit the model.
- Machine learning methods tend to perform worse when trained on fewer observations.
- Thus, the validation set error rate may tend to *overestimate* the test error rate for the model fit on the entire data set.

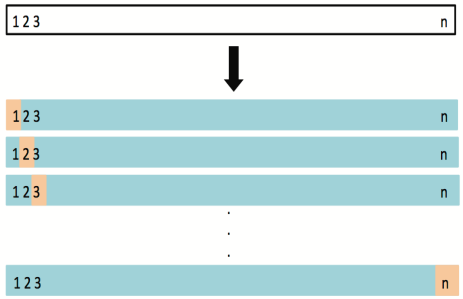
Leave-One-Out Cross-Validation

Instead of two subsets of comparable size, a single observation is used for the validation set and the remaining observations (n – 1) make up the training set.



Leave-One-Out Cross-Validation

- **LOOCV Algorithm:**
  - Split the entire data set of size *n* into:
    - Blue = training data set
    - Beige = validation data set



  - Fit the model using the training data set
  - Evaluate the model using validation set and compute the corresponding MSE.
  - Repeat this process *n* times, producing *n* squared errors. The average of these *n* squared errors estimates the test MSE.

$$\mathrm{CV}_{(n)} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{MSE}_i$$

Validation Set Approach vs. LOOCV

LOOCV has far less bias and, therefore, tends not to overestimate the test error rate.

Performing LOOCV multiple times always yields the same results because there is no randomness in the training/validation set splits.

LOOCV is computationally intensive because the model has to be fit *n* times.

K-Fold Cross-Validation

- The simplest and most widely used method for estimating prediction error.

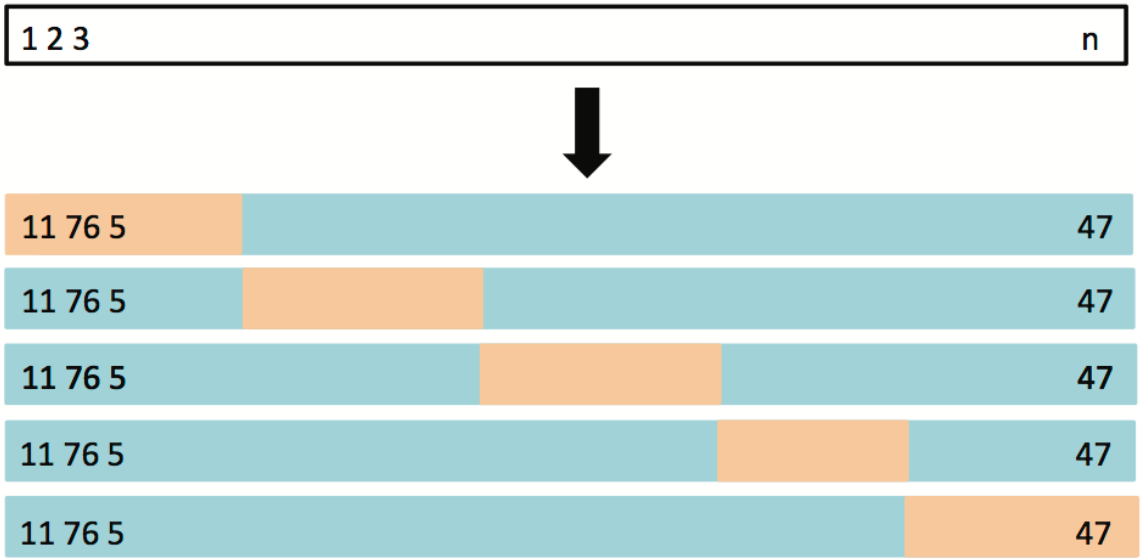
- Directly estimates the average prediction error when the model is applied to an independent test sample.

K-Fold Cross-Validation

- Had we enough data, we would use a validation set to assess the performance of the model.

- To finesse the problem, *K*-fold cross-validation uses part of the available data to fit the model, and a different part to test it.

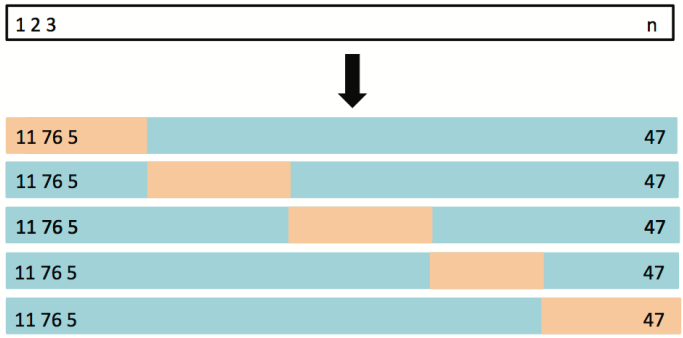
K-Fold Cross-Validation (cont.)



We use this method because LOOCV is computationally intensive.

We randomly divide the data set of into *K* folds (typically *K* = 5 or 10).

K-Fold Cross-Validation (cont.)



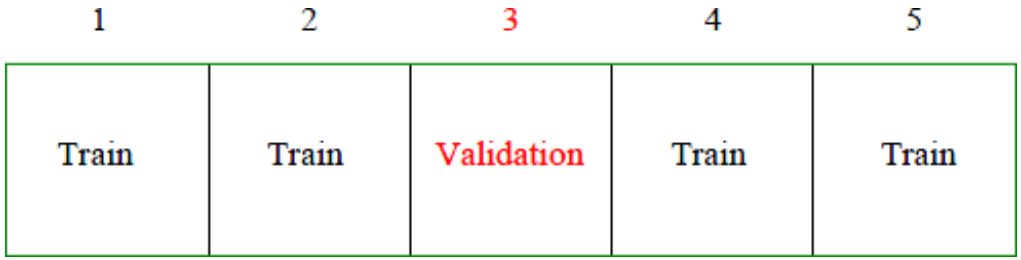
- The first fold is treated as a validation set, and the method is fit on the remaining $K - 1$ folds. The MSE is computed on the observations in the *held-out* fold. The process is repeated K times, taking out a different part each time.
- By averaging the K estimates of the test error, we get an estimated validation (test) error rate for new observations.

K-Fold Cross-Validation (cont.)

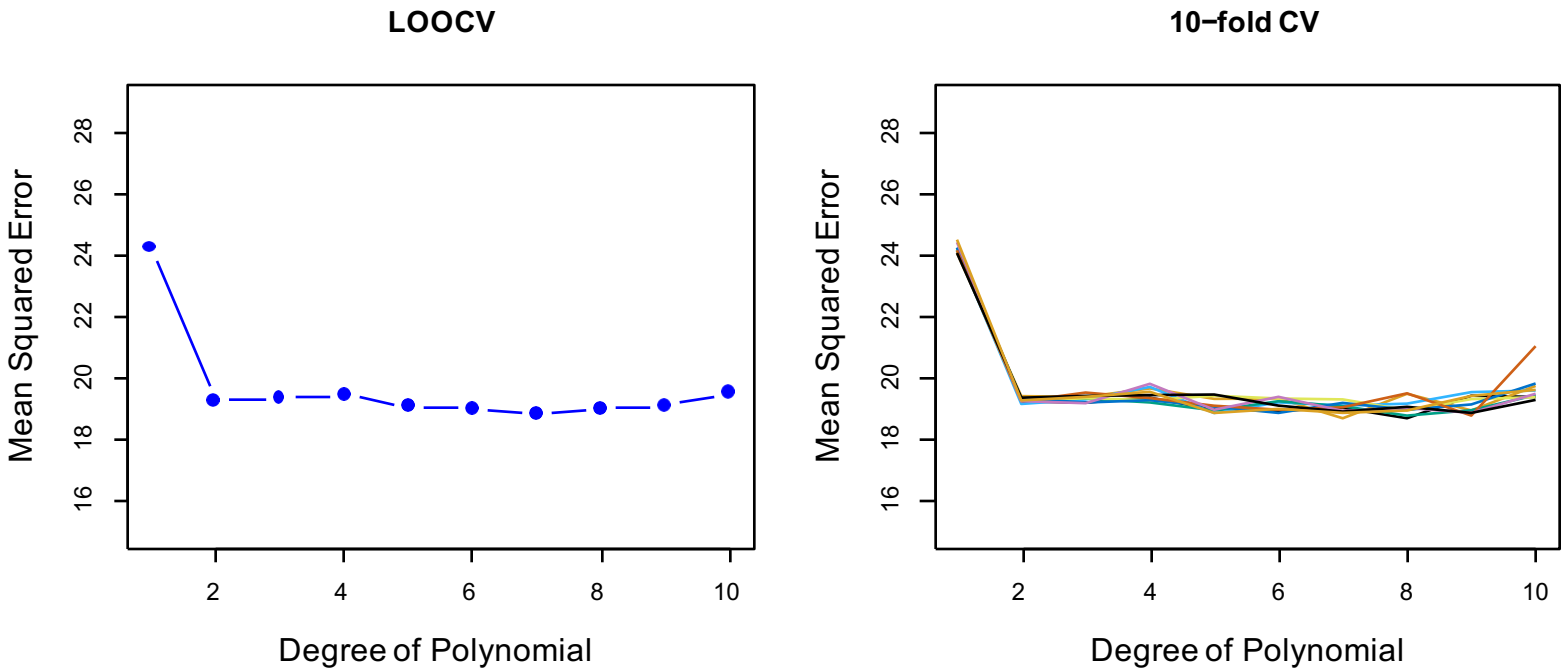
Let the *K* folds be $F_1, \ldots, F_K$, where F_k denotes the indices of the observations in fold *k*. There are n_k observations in fold *k*: if *N* is a multiple of *K*, then $n_k = n / K$.

Compute: $$\mathrm{CV}_{(K)} = \sum_{k=1}^{K} \frac{n_k}{n} \mathrm{MSE}_k$$

where $\mathrm{MSE}_k = \sum_{i \in C_k} (y_i - \hat{y}_i)^2 / n_k$ and $\hat{y}_i$ is the fitted value for observation *i*, obtained from the data with fold *k* removed.



K-Fold Cross-Validation vs. LOOCV



Left Panel: LOOCV Error Curve

Right Panel: *10*-fold CV run nine separate times, each with a different random split of the data into ten parts.

Note: LOOCV is a special case of *K*-fold, where $K = n$

Bias-Variance Trade-off for *K*-Fold Cross-Validation

Which is better, LOOCV or *K*-fold CV?

- LOOCV is more computationally intensive
- LOOCV has less bias than *K*-fold CV (when $K < n$) :
  - Each training set is $(K-1)/K$ as big as the original training set, so the estimates of prediction error will typically be biased upward. *Why?*

Bias-Variance Trade-off for *K*-Fold Cross-Validation

Which is better, LOOCV or *K*-fold CV?

- However, LOOCV has higher variance than *K*-fold CV (when $K < n$):
- It doesn't *shake up* the data enough. The estimates from each fold are highly correlated and hence their average can have high variance.
- Thus, we see the bias-variance trade-off between the two resampling methods

Bias-Variance Trade-off for *K*-Fold Cross-Validation

K-fold CV with $K = 5$ or $K = 10$ are commonly used, as these values have been shown empirically to yield test error rate estimates that suffer neither from excessively high bias nor from very high variance

Cross-Validation on Classification Problems

We will cover classification problems in more detail later in the course, but we briefly show how CV can be used when Y is qualitative (categorical) as opposed to quantitative. Here, rather than use MSE to quantify test error, we instead use the number of misclassified observation.

Cross-Validation on Classification Problems

LOOCV Error Rate:

$$\mathrm{CV}_{(n)} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{Err}_i \text{ , where } \mathrm{Err}_i = I(Y_i \neq \hat{Y}_i)$$

We use CV as follows:

- Divide data into *K* folds; hold-out one part and fit using the rest (compute error rate on hold-out data); repeat *K* times.
- CV Error Rate: average over the *K* errors we have computed

Cross-validation: right and wrong

- Consider a simple classifier applied to some two-class data:
  1. Starting with 5000 predictors and 50 samples, find the 100 predictors having the largest correlation with the class labels.
  2. We then apply a classifier such as logistic regression, using only these 100 predictors.

  How do we estimate the test set performance of this classifier?

  Can we apply cross-validation in step 2, forgetting about step 1?

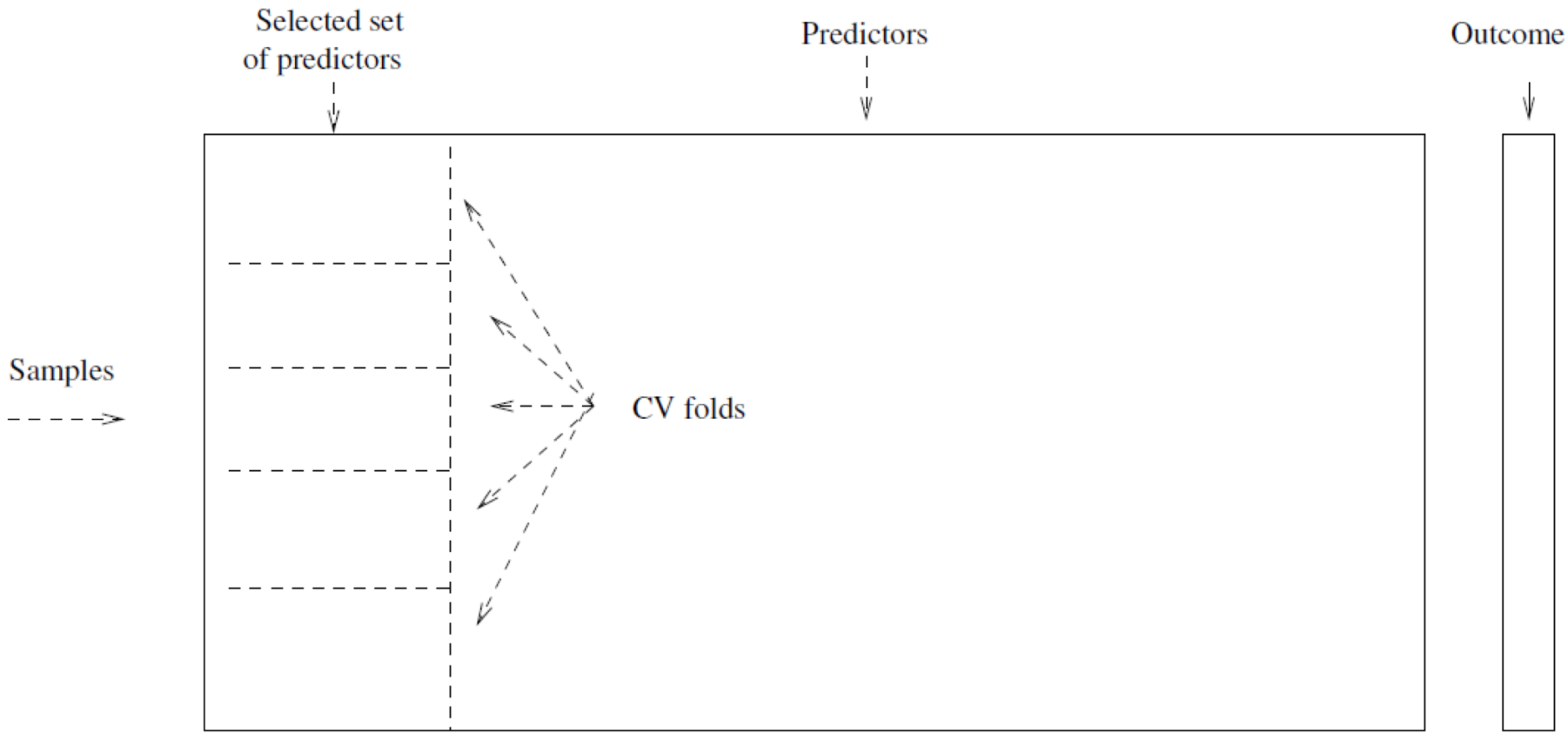
NO!

- This would ignore the fact that in Step 1, the procedure *has already seen the labels of the training data*, and made use of them. This is a form of training and must be included in the validation process.

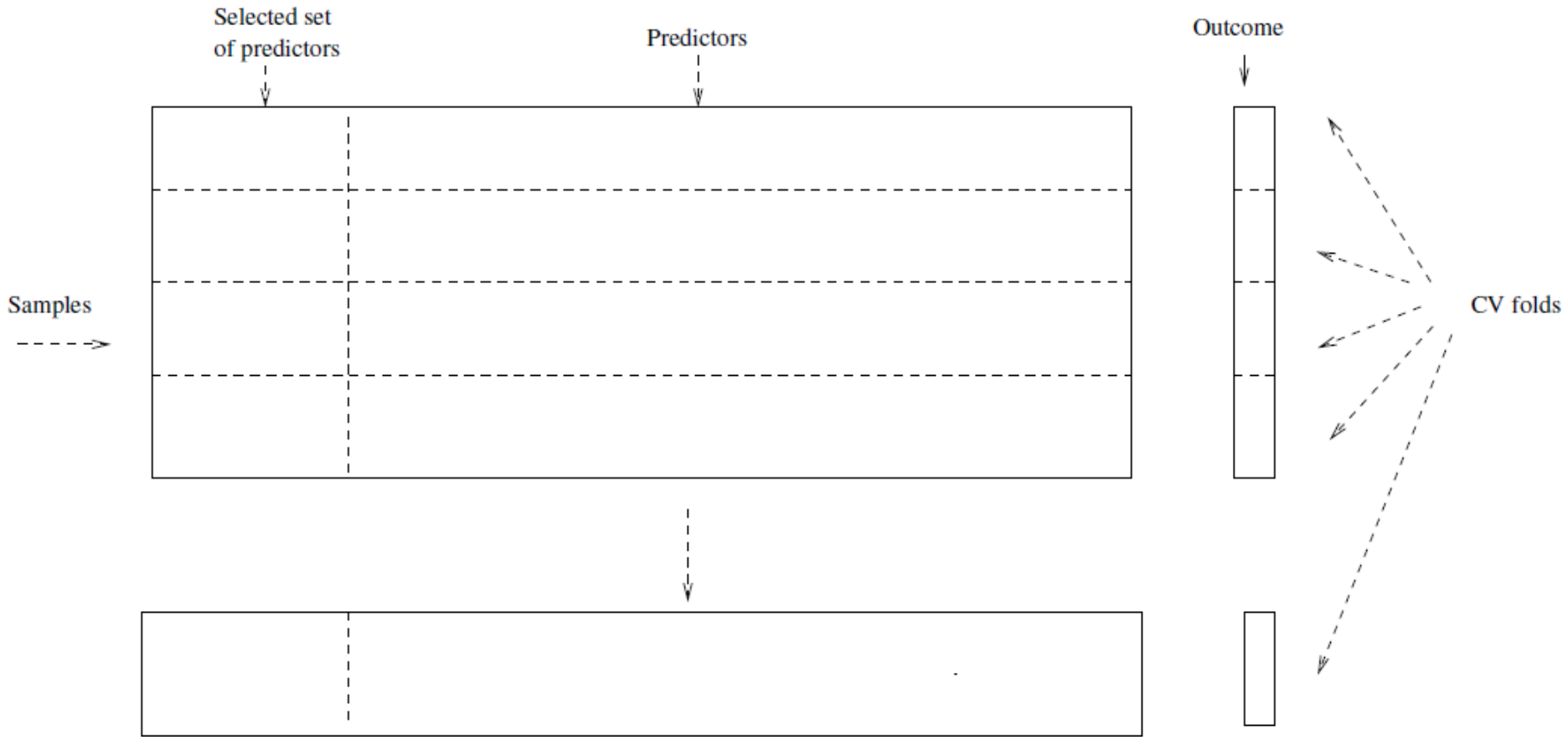
The Wrong and Right Way

- *Wrong:* Apply cross-validation in step 2.
- *Right:* Apply cross-validation to steps 1 and 2.

Cross-Validation: Wrong Way



Cross-Validation: Right Way



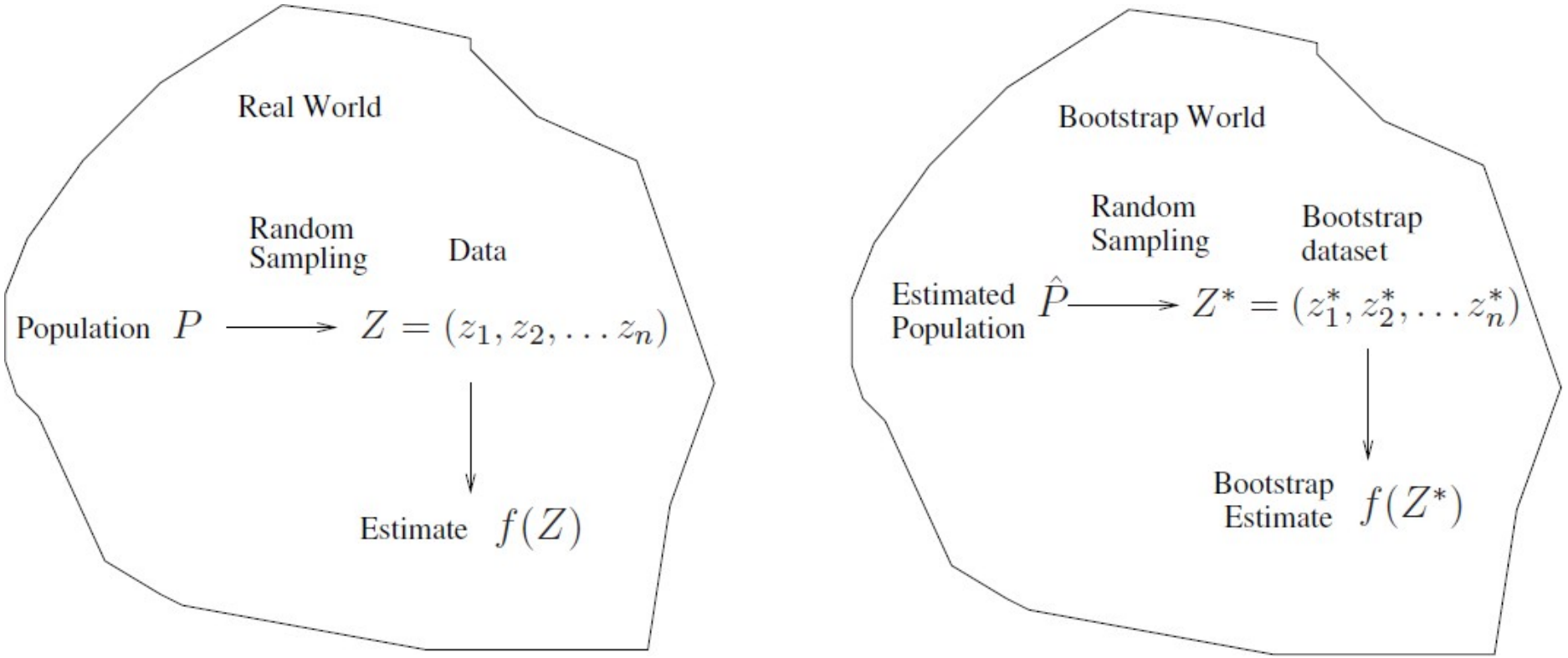
The Bootstrap

- The *bootstrap* is used to quantify uncertainty associated with a given estimator or machine learning method; it is a general tool for assessing statistical accuracy.

The Bootstrap

- As an example, it can be used to estimate the standard errors of the coefficients from a linear regression fit, or a confidence interval for that coefficient.
- The use of the term bootstrap derives from the phrase “to pull oneself up by one’s bootstraps.”

The Bootstrap: Overview



The Bootstrap: Overview (cont.)

Suppose we have a model fit to a set of training data. We denote the training set by $\mathbf{Z} = (z_1, z_2, \ldots, z_N)$ where $z_i = (x_i, y_i)$.

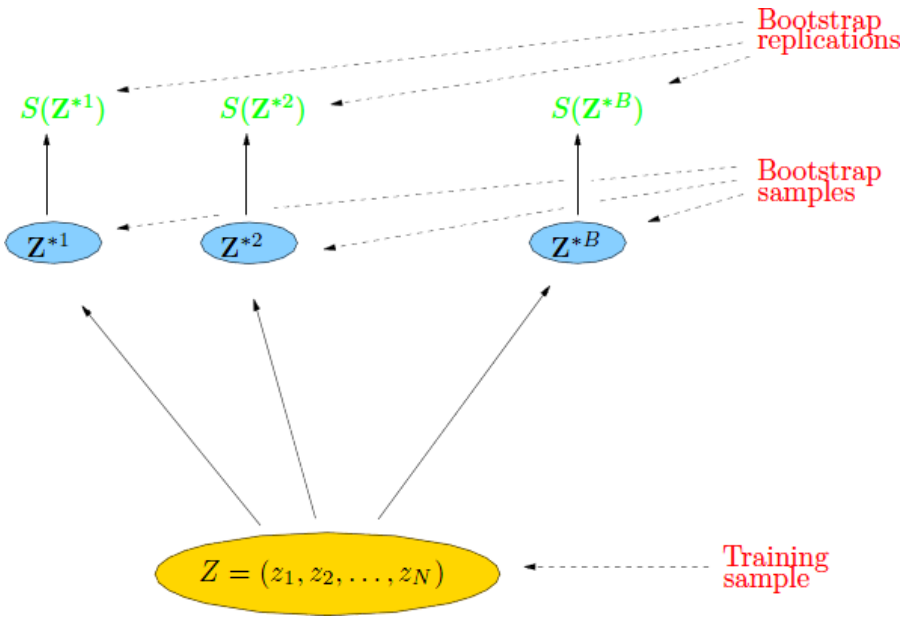
The basic idea is to randomly draw datasets **with replacement** from the training data, each sample the same size as the original training set.

This is done B times, producing B bootstrap datasets. Then we refit the model to each of the bootstrap datasets, and examine the behavior of the fits over the B replications.

The Bootstrap: Overview (cont.)

$S(\mathbf{Z})$ is any quantity computed from the data $\mathbf{Z}$, for example, the prediction at some input point.

From the bootstrap sampling we can estimate any aspect of the distribution of $S(\mathbf{Z})$, for example, its variance:



$$\widehat{\mathrm{Var}}[S(\mathbf{Z})] = \frac{1}{B-1}\sum_{b=1}^{B}(S(\mathbf{Z}^{*b}) - \bar{S}^*)^2$$

$$\bar{S}^* = \sum_b S(\mathbf{Z}^{*b})/B$$

The Bootstrap: Overview (cont.)

$$\widehat{\mathrm{Var}}[S(\mathbf{Z})] = \frac{1}{B-1}\sum_{b=1}^{B}(S(\mathbf{Z}^{*b}) - \bar{S}^*)^2$$

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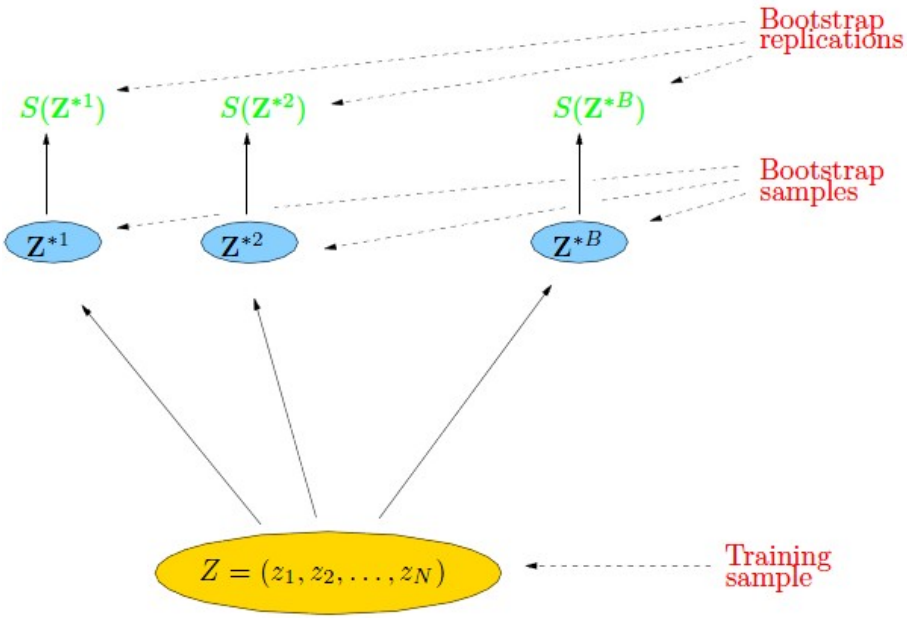


Note that this estimated variance can be thought of as a Monte-Carlo estimate of the variance of $S(\mathbf{Z})$ under sampling from the empirical distribution function.

The Bootstrap: An Example

Suppose that we wish to invest a fixed sum of money in two financial assets that yield returns X and Y; note that X and Y are random quantities.

We will invest a fraction α of our money in X, and will invest the remaining $1 - \alpha$ in Y.

Goal: Since there is variability associated with the returns on these two assets, we wish to choose α to minimize the total risk, or variance, of our investment.

The Bootstrap: An Example (cont.)

In other words, we wish to minimize $\text{Var}(\alpha X + (1 - \alpha)Y)$

The value that minimizes the risk, in this examples, is:

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

where

$$\sigma_X^2 = \text{Var}(X), \sigma_Y^2 = \text{Var}(Y), \text{ and } \sigma_{XY} = \text{Cov}(X, Y)$$

The Bootstrap: An Example (cont.)

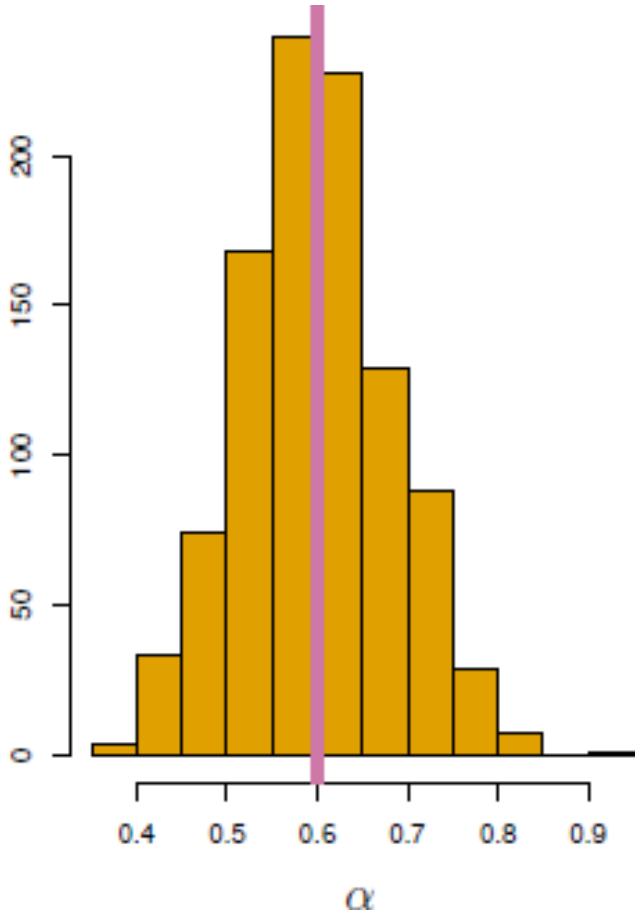
In reality, the quantities, σ_X^2, σ_Y^2 and σ_{XY} are unknown, so we can compute estimates for these quantities using a data set that contains past measurements for *X* and *Y*. We can then estimate the value of *α* that minimizes risk using:

$$\hat{\alpha} = \frac{\hat{\sigma}_Y^2 - \hat{\sigma}_{XY}}{\hat{\sigma}_X^2 + \hat{\sigma}_Y^2 - 2\hat{\sigma}_{XY}}$$

The Bootstrap: An Example (cont.)

We can use this approach for estimating α on a simulated data set, where 100 pairs of returns for the investments X and Y are simulated.

In order to quantify the accuracy of our estimate of α, we also estimate the standard deviation of $\hat{\alpha}$

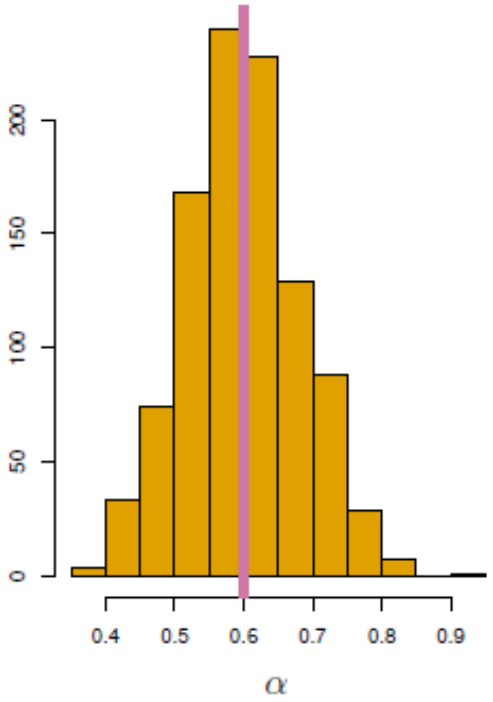


The Bootstrap: An Example (cont.)

To do so, the process of simulating 100 paired observations of *X* and *Y* is repeated 1,000 times; now we have 1,000 estimates for *α.*

The mean over all 1,000 estimates for *α* → $\bar{\alpha} = \frac{1}{1000} \sum_{r=1}^{1000} \hat{\alpha}_r = 0.5996$

The standard deviation of the estimates → $\sqrt{\frac{1}{1000-1} \sum_{r=1}^{1000} (\hat{\alpha}_r - \bar{\alpha})^2} = 0.083$



The Bootstrap: An Example (cont.)

In rough terms, for a random sample from the population, we would expect $\hat{\alpha}$ to differ from α by approximately 0.08, on average.

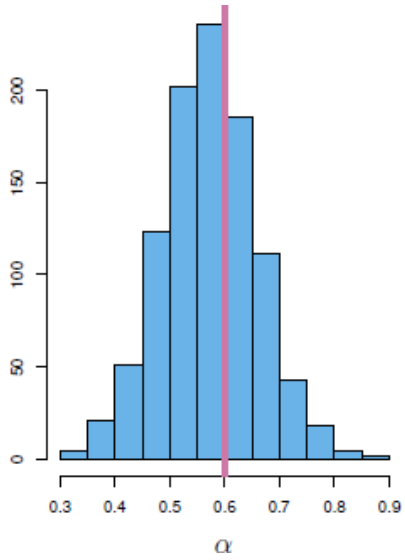
In the real world, this procedure **cannot be applied** because for real data we cannot generate new samples from the original population.

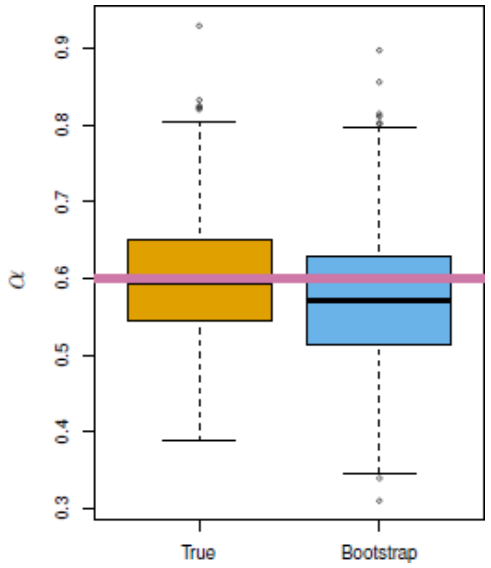
The Bootstrap: An Example (cont.)

The **bootstrap** approach, however, allows us to use a computer to mimic the process of obtaining new data sets; this enables use to estimate the variability of our estimate without generating additional samples.

The Bootstrap: An Example (cont.)

Rather than repeatedly obtaining independent data sets from the population, we instead obtain distinct data sets by repeatedly sampling observations from the original data set **with replacement**.

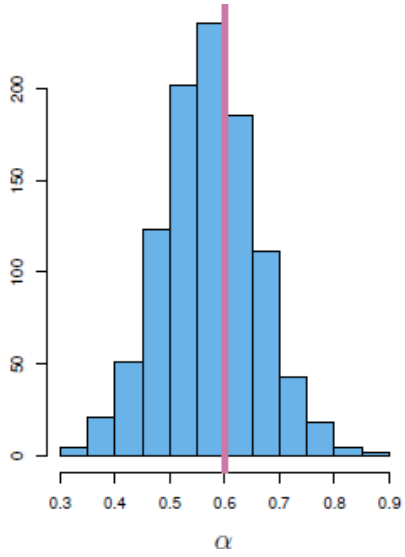


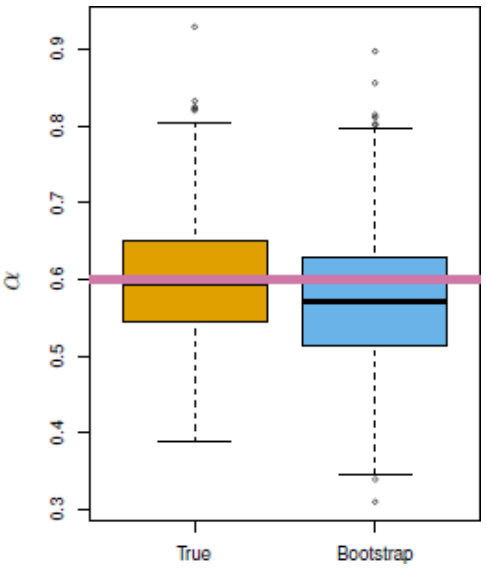


The Bootstrap: An Example (cont.)

Each of these *bootstrap data sets* is created by sampling *with replacement*, and is the *same size* as the original data set.

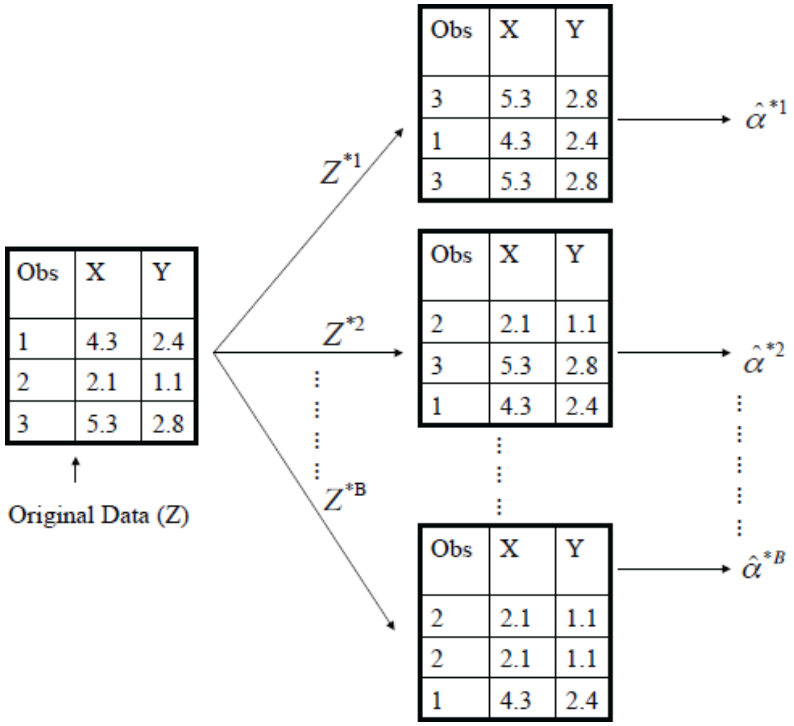
As a result, some observations may appear more than once in a given bootstrap data set and some not at all.





The Bootstrap: An Example (cont.)

A graphical illustration of the bootstrap approach on a small sample containing $n = 3$ observations.



Each bootstrap data set contains n observations, sampled **with replacement** from the original data set.

Each bootstrap data set is used to obtain an estimate of α.

The Bootstrap: An Example (cont.)

Denoting the first bootstrap data set by Z^{*1}, we can use Z^{*1} to produce a new bootstrap estimate for α, which we call $\hat{\alpha}^{*1}$

This procedure is repeated *B* times for some large value of *B* (say 100 or 1000), in order to produce *B* different bootstrap data sets, Z^{*1}, Z^{*2},…, Z^{*B}, and *B* corresponding α estimates, $\hat{\alpha}^{*1}, \hat{\alpha}^{*2}, ..., \hat{\alpha}^{*B}$.

The Bootstrap: An Example (cont.)

We compute the standard error of these bootstrap estimates using:

$$\mathrm{SE}_B(\hat{\alpha}) = \sqrt{\frac{1}{B-1}\sum_{r=1}^{B}\left(\hat{\alpha}^{*r} - \bar{\hat{\alpha}}^{*}\right)^2}$$

This serves as an estimate of the standard error of $\hat{\alpha}$ estimated from the original data set.

The Bootstrap: More Details

In more complex data situations, figuring out the appropriate way to generate bootstrap samples can require some thoughts.

For example, if the data is a time series, we cannot simply sample the observations with replacement.

The Bootstrap: More Details

However, we can instead create blocks of consecutive observations, and sample those with replacement. Then, we paste together sampled blocks to obtain a bootstrap dataset.

The Bootstrap: More Details (cont.)

Although the bootstrap is used primarily to obtain standard errors of an estimate, it can also provide approximate confidence intervals for a population parameters.

One approach is known as *Bootstrap Percentile* confidence interval.

Bootstrap Percentile Confidence Interval: Example

Assume the sample data is
30, 37, 36, 43, 42, 43, 43, 46, 41, 42

Problem: Estimate the mean μ of the underlying distribution and give an 80% bootstrap confidence interval.

Bootstrap Percentile Confidence Interval: Example

The sample mean is $\overline{x}$ = 40.3, which is an estimate of the true mean μ of the underlying distribution.

To construct the confidence interval we need to know how much the distribution of $\overline{x}$ varies around μ. That is, we'd like to know the distribution of

$$\delta = \overline{x} - \mu.$$

If we knew this distribution we could find $\delta_{0.1}$ and $\delta_{0.9}$, the 0.1 and 0.9 critical values of δ.

Bootstrap Percentile Confidence Interval: Example

If we knew the distribution of $\delta = \overline{x} - \mu$. we could find $\delta_{0.1}$ and $\delta_{0.9}$, the 0.1 and 0.9 critical values of δ, for which

$$P(\delta_{.9} \leq \overline{x} - \mu \leq \delta_{.1} \,|\, \mu) = 0.8 \;\Leftrightarrow$$

which gives an 80% confidence interval of

Bootstrap Percentile Confidence Interval: Example

The bootstrap principle offers a practical approach to estimating the distribution of $\delta = \overline{x} - \mu$.

It says that we can approximate it by the distribution of

$$\delta^* = \overline{x}^* - \overline{x}$$

where $\overline{x}^*$ is the mean of an empirical bootstrap sample and δ* is the statistic calculated from a bootstrap sample.

Bootstrap Percentile Confidence Interval: Example

20 bootstrap samples were generated, each of size 10. Each of the 20 columns in the following array is one bootstrap sample.

43	36	46	30	43	43	43	37	42	42	43	37	36	42	43	43	42	43	42	43
43	41	37	37	43	43	46	36	41	43	43	42	41	43	46	36	43	43	43	42
42	43	37	43	46	37	36	41	36	43	41	36	37	30	46	46	42	36	36	43
37	42	43	41	41	42	36	42	42	43	42	43	41	43	36	43	43	41	42	46
42	36	43	43	42	37	42	42	42	46	30	43	36	43	43	42	37	36	42	30
36	36	42	42	36	36	43	41	30	42	37	43	41	41	43	43	42	46	43	37
43	37	41	43	41	42	43	46	46	36	43	42	43	30	41	46	43	46	30	43
41	42	30	42	37	43	43	42	43	43	46	43	30	42	30	42	30	43	43	42
46	42	42	43	41	42	30	37	30	42	43	42	43	37	37	37	42	43	43	46
42	43	43	41	42	36	43	30	37	43	42	43	41	36	37	41	43	42	43	43

Bootstrap Percentile Confidence Interval: Example

Next we compute $\delta^* = \overline{x}^* - \overline{x}$ for each bootstrap sample (i.e. each column) and sort them from smallest to biggest:

43	36	46	30	43	43	43	37	42	42	43	37	36	42	43	43	42	43	42	43
43	41	37	37	43	43	46	36	41	43	43	42	41	43	46	36	43	43	43	42
42	43	37	43	46	37	36	41	36	43	41	36	37	30	46	46	42	36	36	43
37	42	43	41	41	42	36	42	42	43	42	43	41	43	36	43	43	41	42	46
42	36	43	43	42	37	42	42	42	46	30	43	36	43	43	42	37	36	42	30
36	36	42	42	36	36	43	41	30	42	37	43	41	41	43	43	42	46	43	37
43	37	41	43	41	42	43	46	46	36	43	42	43	30	41	46	43	46	30	43
41	42	30	42	37	43	43	42	43	43	46	43	30	42	30	42	30	43	43	42
46	42	42	43	41	42	30	37	30	42	43	42	43	37	37	37	42	43	43	46
42	43	43	41	42	36	43	30	37	43	42	43	41	36	37	41	43	42	43	43

-1.6, -1.4, -1.4, -0.9, -0.5, -0.2, -0.1, 0.1, 0.2, 0.2, 0.4, 0.4, 0.7, 0.9, 1.1, 1.2, 1.2, 1.6, 1.6, 2.0

Bootstrap Percentile Confidence Interval: Example

The critical values $\delta_{0.1}$ and $\delta_{0.9}$ by $\delta^*_{0.1}$ and $\delta^*_{0.9}$.

$\delta^*_{0.1}$ is at the 90th percentile, i.e. the 18th element in the list, 1.6.

Likewise, $\delta^*_{0.9}$ is at the 10th percentile, i.e. the 2nd element in the list, -1.4.

$$[\overline{x} - \delta^*_{.1},\ \overline{x} - \delta^*_{.9}] \ = \ [40.3 - 1.6,\ 40.3 + 1.4] \ = \ [38.7,\ 41.7]$$

The Bootstrap: More Details (cont.)

In cross-validation, each of the K validation folds is distinct from the other $K - 1$ folds used for training (i.e. there is no overlap).

To estimate the prediction error using the bootstrap, one approach would be to fit the model in question on a set of bootstrap samples, and then keep track of how well it predicts the original training set.

The Bootstrap: More Details (cont.)

If $\hat{f}^{*b}(x_i)$ is the predicted value at x_i, from the model fitted to the b^{th} bootstrap dataset, our estimate is:

$$\widehat{\text{Err}}_{\text{boot}} = \frac{1}{B}\frac{1}{N}\sum_{b=1}^{B}\sum_{i=1}^{N} L(y_i, \hat{f}^{*b}(x_i))$$

The Bootstrap: More Details (cont.)

This estimate does not provide a good estimate in general because the bootstrap datasets are acting as the training samples, while the original training set is acting as the test sample, and these two samples have observations in common.

- Each bootstrap sample has significant overlap with the original data.

The Bootstrap: More Details (cont.)

- Note that about 2/3 of the original N data points appear in each bootstrap sample:

$$\Pr\{\text{Observation } i \in \text{bootstrap sample } b\}$$
$$= 1 - \Pr\{\text{Observation } i \notin \text{bootstrap sample } b\}$$

- One the other hand

$$\Pr\{\text{Observation } i \notin \text{bootstrap sample } b\}$$
$$= \Pr\{\text{Observation } i \text{ is not any of the } N \text{ members of the bootstrap sample } b\}$$

The Bootstrap: More Details (cont.)

- One the other hand

$$\Pr\{\text{Observation } i \notin \text{ bootstrap sample } b\}$$
$$= \Pr\{\text{Observation } i \text{ is not any of the } N \text{ members of the bootstrap sample } b\}$$
$$= \Pr\{\text{Each of the } N \text{ members of the bootsrap sample } b \text{ is one of the } N\text{-1 observations other than } i \ \}$$

- Therefore

$$\Pr\{\text{Observation } i \notin \text{ bootstrap sample } b\} = (1 - 1/N)^N$$

when N is large, this is equal to e^{-1}

- So

$$\Pr\{\text{Observation } i \in \text{ bootstrap sample } b\} \approx 1 - e^{-1} \approx 0.632$$

The Bootstrap: More Details (cont.)

This overlap can make overfit predictions like unrealistically good, and is the reason that cross-validation explicitly uses non-overlapping data for the training and test samples.

In other words, this will cause the bootstrap to seriously *underestimate* the true prediction error.

By mimicking cross-validation, a better bootstrap estimate can be obtained.

The Bootstrap: More Details (cont.)

For each observation, we only keep track of prediction from bootstrap samples not containing that observation.
The leave-one-out bootstrap estimate of prediction error is defined by:

$$\widehat{\mathrm{Err}}^{(1)} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{|C^{-i}|}\sum_{b\in C^{-i}} L(y_i, \hat{f}^{*b}(x_i))$$

Here C^{-i} is the set of indices of the bootstrap samples b that do *not* contain observation I, and $|C^{-i}|$ is the number of such samples.

The Bootstrap: More Details (cont.)

Note that the leave-one-out bootstrap solves the problem of overfitting, but has a training-set-size bias.

- The ".632 estimator" is designed to alleviate this bias.

Summary

Resampling methods for machine learning model selection and assessment.

The validation set approach, leave-one-out cross-validation, and *K*-fold cross-validation.

The bootstrap method for assessing statistical accuracy.