

#### **Module 5: Resampling Methods**

Lecture 11 Feb 8th, 2023 Ch 5.1.3-4:



### Recap

LOOCV 
$$CV_{(n)} = \frac{1}{n} \sum_{i=1}^{n} MSE_{i}$$
• Leverage out  $\int_{CV_{(K)}} CV_{(K)} = \sum_{k=1}^{K} \frac{n_{k}}{n} MSE_{k}$ 

### *K*-fold Cross-validation

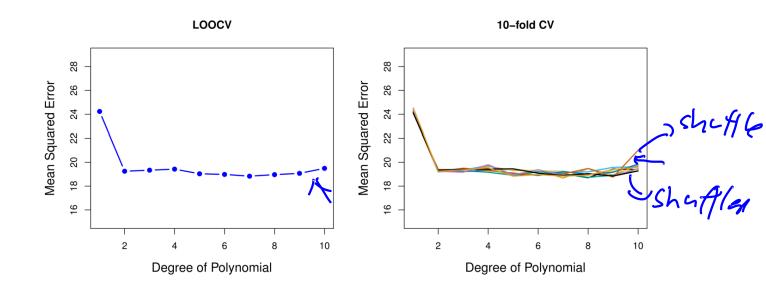


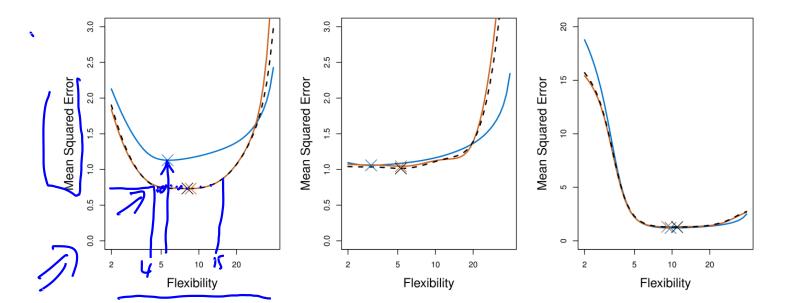
Hybrid between validation set and LOOCV

$$CV_{(K)} = \sum_{k=1}^{K} \frac{n_k}{n} MSE_k$$

# Coding – Building k-fold CV







Blue True error

Dashed LOOCV estimate

Orange 10-fold CV

We divide the data into K roughly equal-sized parts

Compute

$$CV_K = \sum_{k=1}^K \frac{n_k}{n} Err_k$$

where 
$$\operatorname{Err}_k = \sum_{i \in C_k} I(y_i \neq \hat{y}_i) / n_k$$
.

## Example: GWAS

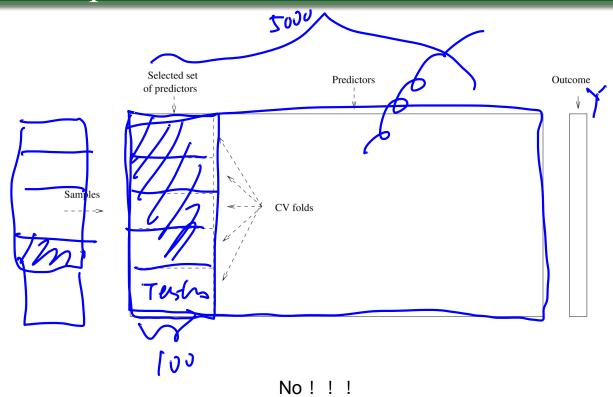
MICHIGAN STATE

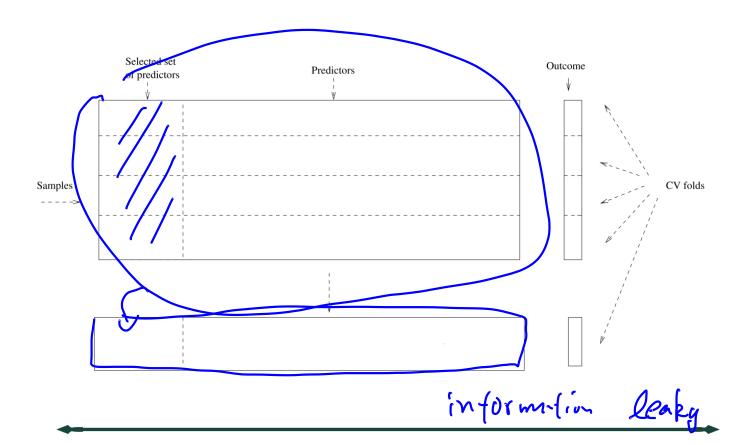
5000 >> 50

- Sample size n = 50, number of predictors (SNPs) p = 5000; Predictor heart attach after age of 60.
- Step 1: Select the top 100 predictors having the largest torn of the correlation with the class labels

  An Turis
- Step2: We then apply a classifier (logistic regression) using only these 100 predictors

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





### Bootstrap





• Bootstrap is used to quantify the uncertainty associated with an estimator or machine learning method.

It can provide an estimate of the standard error of a coefficient. Then we can dp hypothesis test and confidence interval.

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# Bootstrap: Finance Example



- To invest two stocks that yield return of X and Y, where X and Y are random.
- We will invest a fraction  $\alpha$  of our money in X and the rest in Y.
- Assume both stock have the same average return over the years. What criteria should we use for allocate the

investment?

E(X)= ECY)

d Vn(X) >> Un(Y)

### Bootstrap: Finance Example



• We want to minimize the total risk or variance of our investment.

$$\rightarrow Var(\alpha X + (1 - \alpha)Y).$$

• The solution is

$$lpha = rac{\sigma_Y^2 - \sigma_{XY}}{\sigma_X^2 + \sigma_Y^2 - 2\sigma_{XY}}$$
  $\forall w(2X) = 2^2 V_{tr}(X)$ 

where  $\sigma_X^2 = \operatorname{Var}(X)$ ,  $\sigma_Y^2 = \overline{\operatorname{Var}(Y)}$ , and  $\sigma_{XY} = \operatorname{Cov}(X, Y)$ .

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$$= (1) \bigvee (x) (x, y)$$

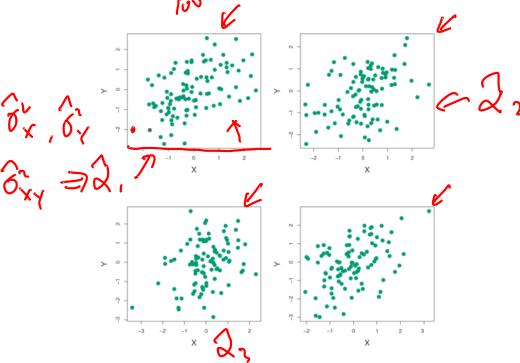
= Var(X) + Var(Y) + 2 (ar(X, Y)

# Finance Example: Simulations



- But the values of  $\sigma_X^2$ ,  $\sigma_Y^2$ , and  $\sigma_{XY}$  are unknown.
- We can compute estimates for these quantities,  $\hat{\sigma}_X^2$ ,  $\hat{\sigma}_Y^2$ , and  $\hat{\sigma}_{XY}$ , using a data set that contains measurements for X and Y.
- We can then estimate the value of  $\alpha$  that minimizes the variance of our investment using

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



**FIGURE 5.9.** Each panel displays 100 simulated returns for investments X and Y. From left to right and top to bottom, the resulting estimates for  $\alpha$  are 0.576, 0.532, 0.657, and 0.651.

# Finance Example: Simulations



- To estimate the standard deviation of  $\hat{\alpha}$ , we repeated the process of simulating 100 paired observations of X and Y, and estimating  $\alpha$  1,000 times.
- We thereby obtained 1,000 estimates for  $\alpha$ , which we can call  $\hat{\alpha}_1, \hat{\alpha}_2, \dots, \hat{\alpha}_{1000}$ .
  - For these simulations the parameters were set to  $\sigma_X^2 = 1, \sigma_Y^2 = 1.25$ , and  $\sigma_{XY} = 0.5$ , and so we know that the true value of  $\alpha$  is 0.6 (indicated by the red line).

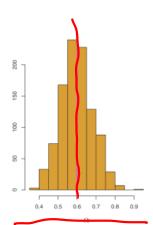
• The mean over all 1,000 estimates for  $\alpha$  is

$$\bar{\alpha} = \frac{1}{1000} \sum_{r=1}^{1000} \hat{\alpha}_r = 0.5996,$$

very close to  $\alpha = 0.6$ , and the standard deviation of the estimates is

$$\sqrt{\frac{1}{1000 - 1} \sum_{r=1}^{1000} (\hat{\alpha}_r - \bar{\alpha})^2} = 0.083.$$

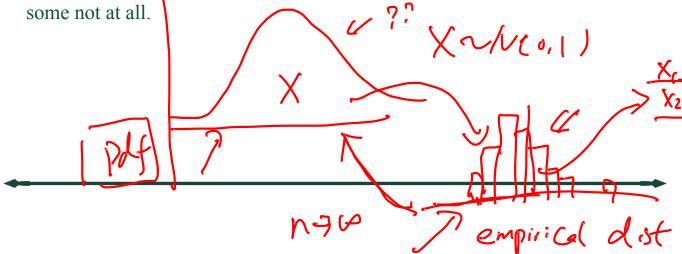
• This gives us a very good idea of the accuracy of  $\hat{\alpha}$ :  $SE(\hat{\alpha}) \approx 0.083$ .



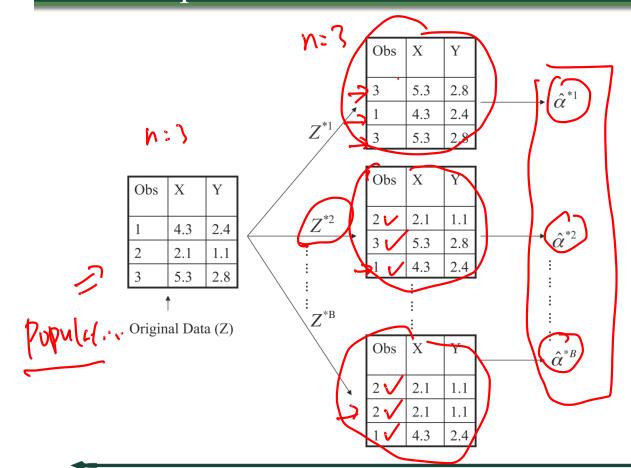
### Finance Example: Reality

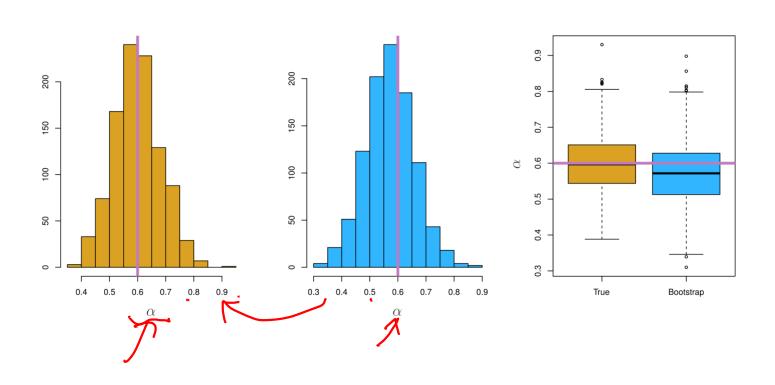


- The procedure outlined above cannot be applied, because for real data we cannot generate new samples from the original population.
- The bootstrap approach allows us to use a computer to mimic the process of obtaining new data sets.
- Rather than repeatedly sampling from the population, we instead obtain distinct data sets by repeatedly sampling observations from the original data set with replacement.
- Each of these "bootstrap data sets" is created by sampling with replacement, and is the same size as our original dataset. Some observations may appear more than once in a given bootstrap data set and



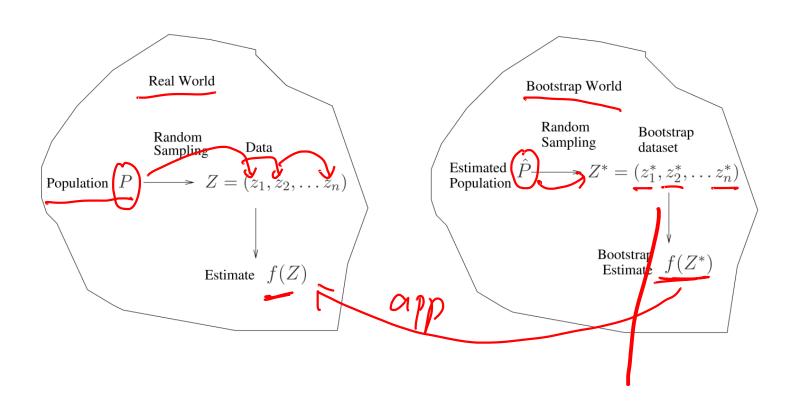
### Boostrap Illustration





### A General Picture for the Bootstrap



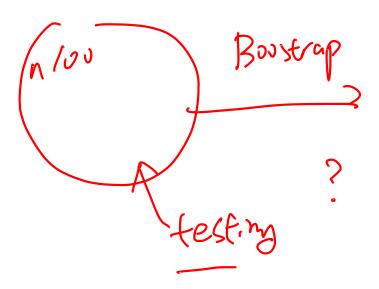


## Boostrap for Prediction Error?



# Bonus Quiz

• Can we use one boostrap dataset as training and the original data set as test set?





### Bonus Quiz 13

(20 pts) For a classification problem with K = 2 ( $Y \in \{0, 1, 6\}$ ), we know the oracle classifier is

$$C(x) = j$$
, if  $p_j(x) = \max\{p_0(x), p_1(x)\}\$ ,

which is based on the loss with equal weight for Type I and II error. If we know Type I error will cost \$1000 while Type II error will cost \$3000. Derive the new oracle classifier which minimizes this cost.

classification

logistic regression

### Bonus Quiz 15



• When sample size n is large, we know a bootstrap dataset will contain 1 - e - 1 = 63.2% of original data. Write a code to demonstrate it using n = 1000000

Supervised (asstication of Linear raped Classification of white Ownservised) There the best

Final Various trade-of.

SE(B)? CI, H
inference inference.

X of qualitation, interaction terms