NOTES 5

Resampling Methods

Acknowledgement: some of the contents are borrowed with or without modification from *An Introduction to Statistical Learning, with applications in R* (Springer, 2013) with permission from the authors: G. James, D. Witten, T. Hastie and R.Tibshirani.

Model Validation

- Training error is different from testing error
- To validate the model performance, hold out a subset of the training observations from the fitting process, and then applying the statistical learning method to those held out observations
- Divide the available set of samples into two parts: a training set and a validation or hold-out set.
- The resulting validation-set error provides an estimate of the test error.

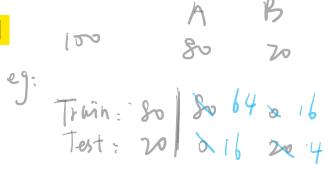
Overfitting

- When a given method yields a small training MSE but a large test MSE, we are said to be *overfitting* the data.
- Mean Square Error (MSE):a measure of the overall model fit

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{f}(x_i))^2,$$

Holdout Procedures

- Common case: data set large but limited
- Problems:
 - Want both sets to be representative
 - Want both sets as large as possible



- Simple check: Are the proportions of classes about the same in each data set?
- Stratified holdout
 - Guarantee that classes are (approximately) proportionally represented
- Repeated holdout
 - Randomly select holdout set several times and average the error rate estimates

Want both sets as large as possible...

- In the validation approach, only a subset of the observations
 — those that are included in the training set rather than in the validation set are used to fit the model.
- The limited size of the training data can also affect the estimation of testing error
- Use K-fold Cross Validation

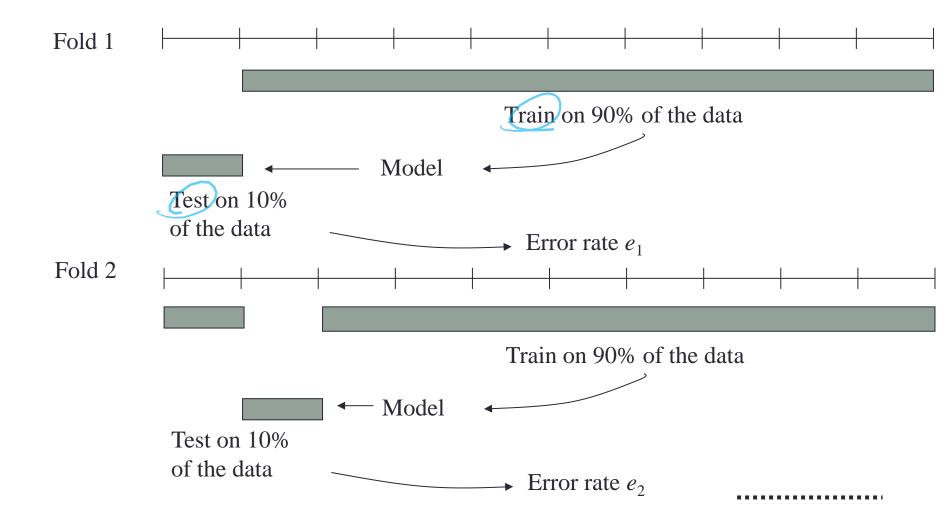
Cross-Validation

- Cross-validation
 - Fixed number of partitions of the data (folds), e.g. 5 and
 10

dride all data into I folds
use 1 of the I for testing

- In turn: each partition used for testing and remaining instances for training
- May use stratification and randomization
- Standard practice:
 - Stratified tenfold cross-validation
 - Instances divided randomly into the ten partitions

Cross Validation



Cross-Validation

Final estimate of error

$$\overline{\mathcal{S}} = \frac{1}{k} \sum_{i=1}^{k} \mathcal{S}_{k}$$

• MSE is used in the case of a quantitative response and misclassification rate in the case of a qualitative response.

Leave-One-Out Holdout

 Setting K = n yields n-fold or leave-one out cross-validation (LOOCV). (n instance set)

- Use all but one instance for training
 - Maximum use of the data
 - High computational cost
 - Non-stratified sample

 LNZ testry data always heby(to 1 (ategory)

Bootstrap when we don't have enough observation for even cross-validation (~ 100 +0 200)

- If the size of the original data set is n, sample it with replacement n times creaf a new dataset with the same
 - · Use as training data 5722 of the original dataset
- How many test instances are there? $\lim_{n\to\infty} \left(1+\frac{x}{n}\right)^n = e^x$ Selected a select for $\left(1-\frac{1}{n}\right)^n \propto e^{-\frac{1}{n}}$ Testing 0.632 Bootstrap

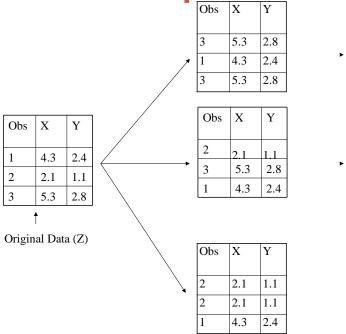
0.632 Bootstrap

- On the average $e^{-1}n = 0.368$ n different instances will be in the test set, where n is the size of the original data set
- Thus, on average we have 63.2% of instance in training set
- Estimate error rate

$$e = 0.632 e_{test} + 0.368 e_{train}$$

on everye, there ill be 63,2% be selented in lesting dataset

Sample With Replacement



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.

What to Do?

- "Large" amounts of data
 - Hold-out 1/3 of data for testing
 - Train a model on 2/3 of data
 - Estimate error (or success) rate and calculate CI
- "Moderate" amounts of data
 - Estimate error rate:
 - Use 10-fold cross-validation with stratification,
 - or use bootstrap.
 - Train model on the entire data set