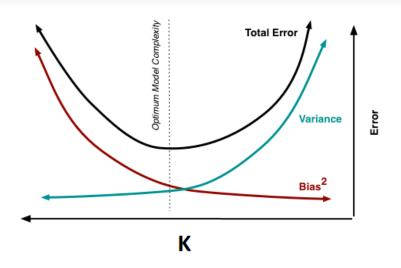
# Introduction to Data Science

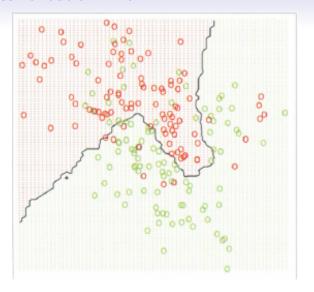
DSA1101

Semester 1, 2018/2019 Week 6

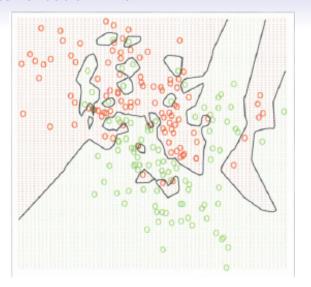
- This week, we will continue to explore n-fold cross validation in R
- We will also examine the R code in more detail



Bias-variance tradeoff. Source: http://scott.fortmann-roe.com



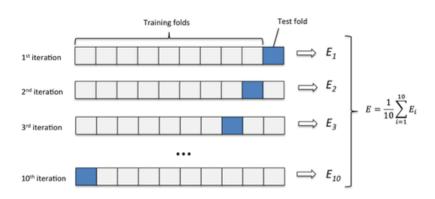
Prediction by majority vote with 15 nearest neighbors. Source: *The Elements of Statistical Learning*, Hastie et al.



Prediction by majority vote with one nearest neighbor. Source: *The Elements of Statistical Learning*, Hastie et al.

- The entire dataset is randomly split into N datasets of approximately equal size.
- N-1 of these datasets are treated as the training dataset, while the remaining one is the test dataset. A measure of the model error is obtained.
- This process is repeated across the various combinations of N datasets taken N-1 at a time.
- ullet The observed N models errors are averaged across the N folds.

# Diagnostics of Classifiers



- We will illustrate how to implement n-fold cross-validation in R to evaluate the performance of the k-nearest neighbor classifier
- In particular, we will attempt to estimate the optimal value of k (or the optimal model complexity) that will give the best classification performance

- We will illustrate n-fold cross validation using the famous Iris
  Flower Dataset which was first introduced in 1936 by the
  famous statistician Ronald Fisher and consists of 50
  observations from each of three species of Iris (Iris setosa, Iris
  virginica and Iris versicolor).
- Four features (x) were measured from each sample: the length and the width of the sepals and petals.



Source: http://suruchifialoke.com

- The dataset has been posted to IVLE as 'iris.csv'
- Also available at https://archive.ics.uci.edu/ml/datasets/Iris
- 150 data points with the following attribute information:
- (1) sepal length in cm
- (2) sepal width in cm
- (3) petal length in cm
- (4) petal width in cm
- (5) class: Iris Setosa, Iris Versicolour or Iris Virginica

 Read in the dataset. Note that variable names are not found in the CSV file

• We can rename the attributes more meaningfully

```
> names(iris)
2 [1] "V1" "V2" "V3" "V4" "V5"
3 > names(iris) = c("X1", "X2", "X3", "X4", "Y")
4 > names(iris)
5 [1] "X1" "X2" "X3" "X4" "Y"
6 > head(iris)
     X1 X2 X3 X4
8 1 5.1 3.5 1.4 0.2 Iris-setosa
9 2 4.9 3.0 1.4 0.2 Iris-setosa
10 3 4.7 3.2 1.3 0.2 Iris-setosa
11 4 4.6 3.1 1.5 0.2 Iris-setosa
12 5 5.0 3.6 1.4 0.2 Iris-setosa
13 6 5.4 3.9 1.7 0.4 Iris-setosa
```

- Using the same dataset as both the training and testing data can give misleading results
- For example, when k = 1, we use each single data point to predict itself:

```
> set.seed(1)
> library(class)
> X=iris[,c("X1","X2","X3","X4")]
> Y=iris[,c("Y")]
> pred <- knn(train=X, test=X, cl=Y, k=1)
> mean(Y != pred)
[1] 0
> mean(Y == pred)
[1] 1
```

• Therefore there is a need for more principled methods to evaluate classifier performance, e.g. *n*-fold cross validation

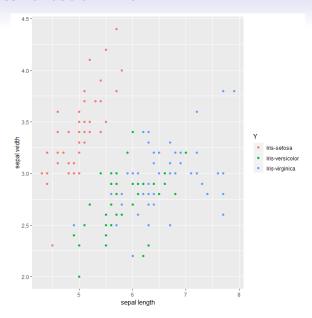
- Note that the code mean(Y!=pred) computes the proportion of data points which label is predicted incorrectly
- A small example:

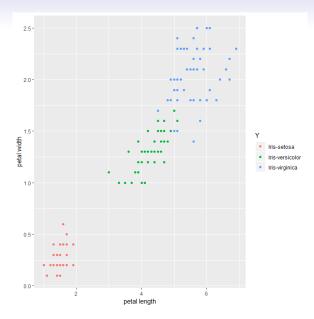
```
> Predicted= c(1,1,0,0,1,1)
> Actual= c(1,1,1,0,0,1)
> Predicted != Actual
4 [1] FALSE FALSE TRUE FALSE TRUE FALSE
5 > mean(Predicted != Actual)
6 [1] 0.3333333
7 > Predicted == Actual
8 [1] TRUE TRUE FALSE TRUE FALSE TRUE
9 > mean(Predicted == Actual)
10 [1] 0.66666667
```

 Similarly, the code mean(Y==pred) computes the proportion of data points which label is predicted correctly

 Before running n-fold cross validation, we can try to visualize the label and feature patterns

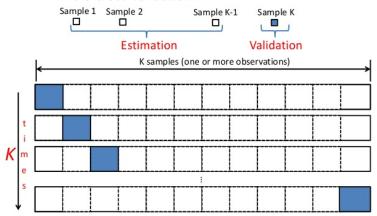
```
library(ggplot2)
2 library(magrittr)
3 # sepal width vs. sepal length
  ggplot(aes(x=X[,1], y=X[,2], color=Y)) +
5 geom_point()+
  labs(x = "sepal length")+ labs(y = "sepal width"
7 # petal width vs. petal length
   ggplot(aes(x=X[,3], y=X[,4], color=Y)) +
  geom_point()+
   labs(x = "petal length")+ labs(y = "petal width"
10
```





# Cross-validation: How it works?

K-fold cross-validation:



 We will perform 10-fold cross validation; first randomly split the 150 data points into 10 sets:

```
1 > n_folds=10
2 > folds_i <- sample(rep(1:n_folds, length.out = 150))
3 > table(folds_i)
4 folds_i
5 1 2 3 4 5 6 7 8 9 10
6 15 15 15 15 15 15 15 15 15 15
```

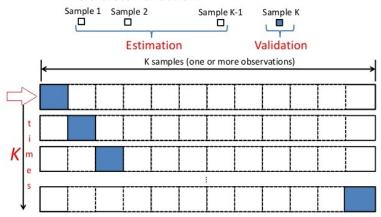
- We illustrate how the 150 data points is randomly divided into 10 sets using the previous code
- A simple example involves 3-fold, 12 data points

 In this case, sample(index) generates a random permutation of the elements of index

- Now, we are ready to run *n*-fold cross validation in R
- We will first set k = 1 for the k-nearest neighbors classifier

# **Cross-validation: How it works?**

K-fold cross-validation:



• We start with k=1, and observe first iteration: using the first dataset as our test data and the remaining 9 datasets as training data

Note that the command test\_j<-which(folds\_j==1)
generates the indices corresponding to data points in the first
data set:</li>

```
1  > folds_j[1:20]
2  [1] 4 9 8 4 7 7 1 10 1 1 6 3
3  [13] 8 1 7 9 5 7 4 3
4 > which(folds_j == 1)
5  [1] 7 9 10 14 22 23 26 37 43
6  [10] 98 107 118 130 132 146
```

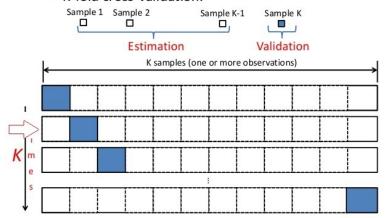
- The command X[-test\_j,] removes the data points from first data set from the feature dataframe, keeping the data points from the remaining nine data sets
- Similarly, the command Y[-test\_j] removes the data points from first data set from the label vector, keeping the data points from the remaining nine data sets
- The command X[test\_j,] keeps the data points only from first data set from the feature dataframe

 Therefore, the following command takes only the first data set as the test data, and the remaining nin data sets as the training data

```
pred <- knn(train=X[ -test_j, ], test=X[test_j,
], cl=Y[-test_j], k=1)</pre>
```

# **Cross-validation: How it works?**

K-fold cross-validation:



 Now we perform the second iteration: using the second dataset as our test data and the remaining 9 datasets as training data

- We need to run the same code for j = 3, 4, 5, ..., 10.
- The for loop in R allows us to write compact code for this

```
> for (j in 1:10) {
   print(j)
4 [1] 1
5 [1] 2
6 [1] 3
  [1] 4
  [1] 5
  [1]
  [1]
10
  [1]
11
  [1]
12
```

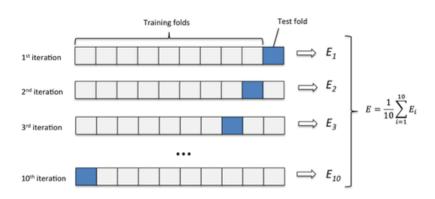
Putting it altogether in a for loop in R:

```
> err=numeric(10)
 > acc=numeric(10)
4 > for (j in 1:10) {
6 + test_j <- which(folds_j == j)
7 + pred <- knn(train=X[ -test_j, ], test=X[test_j,
     ], cl=Y[-test_j], k=1)
9 + err[j]=mean(Y[test_j] != pred)
10 + acc[j]=mean(Y[test_j] == pred)
11 + }
12
13 > err
   [1] 0.06666667 0.06666667 0.06666667
14
   [4] 0.06666667 0.00000000 0.06666667
15
16
   [7] 0.06666667 0.00000000 0.00000000
  [10] 0.00000000
17
```

- Here, err=numeric(10) declares a numeric vector of length
   10
- Therefore, the error rate from each iteration of the 10-fold cross-validation can be saved to the vector err
- Similarly, the accuracy from each iteration of the 10-fold cross-validation can be saved to the vector acc

```
1 > test=numeric(10)
2 > test
3 [1] 0 0 0 0 0 0 0 0 0
```

# Diagnostics of Classifiers



- For the k-nearest neighbor classifier with k=1, the final estimated error rate is the average of the ten error rates across the 10-fold iterations.
- Similarly, the final estimated accuracy is the average of the ten accuracies across the 10-fold iterations.

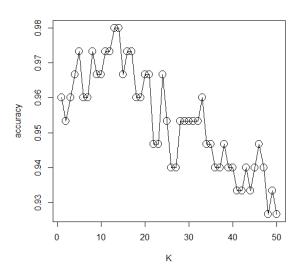
```
1 > error=mean(err)
2 > accur=mean(acc)
3 > error
4 [1] 0.04
5 > accur
6 [1] 0.96
```

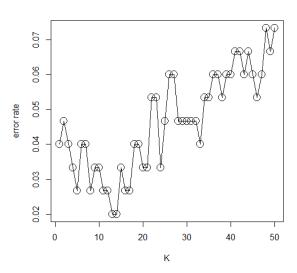
- However, to plot the accuracy (or error rate) against different values of k, we need to repeat the 10-fold cross validation procedure at different values of k
- ullet This suggest another for loop structure, indexed by k
- In this example, we will perform 10-fold cross validation for k = 1, 2, ..., 50.

```
error differentK=numeric(50)
2 accur_differentK=numeric(50)
3
4 for (K in 1:50) {
5
6 error=numeric(10)
7 accur=numeric(10)
8 for (j in 1:10) {
    test_j <- which(folds_j == j)</pre>
9
   pred <- knn(train=X[ -test_j, ], test=X[test_j,</pre>
10
        ], cl=Y[-test_j], k=K)
    error[j]=mean(Y[test_j] != pred)
11
    accur[j]=mean(Y[test_j] == pred)
12
13 }
14 error_differentK[K]=mean(error)
15 accur_differentK[K]=mean(accur)
16 }
```

• Then, we can plot the accuracy (or error rate) against different values of k, to determine the optimal k.

```
plot(1:50, accur_differentK, type="o", ylab="
accuracy", xlab="K", cex.axis=1, cex=2)
plot(1:50, error_differentK, type="o", ylab="error
rate", xlab="K", cex.axis=1, cex=2)
```





• Recall the confusion matrix

		Predicted Class	
		Positive	Negative
Actual Class		\ /	False Negatives (FN)
	Negative	False Positives (FP)	True Negatives (TN)

Recall the confusion matrix

		Predicted Class		
		Positive	Negative	
Actual Class	Positive	True Positives (TP)	False Negatives (FN)	
	Negative	False Positives (FP)	True Negatives (TN)	

• accuracy = 
$$\frac{TP+TN}{TP+FN+FP+TN}$$

• error rate = 
$$\frac{TP+TN}{TP+FN+FP+TN}$$

 $\bullet \ \, {\sf Therefore} \,\, {\sf accuracy} = 1 - {\sf error} \,\, {\sf rate} \,\,$ 

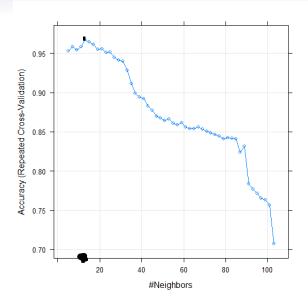
- To illustrate the n-fold cross validation procedure, we have written our own code in R to implement it
- There are many data analytics packages in R that offers ready-made solutions which make our jobs much easier
- We will use one such package, 'caret', as an example
- library(caret)

• We will perform 10-fold cross-validation for the *k*-nearest neighbor classifier:

```
fitControl <- trainControl(## 10-fold CV
                               method = "repeatedcv",
                               number = 10,
3
                               ## repeated ten times
4
                               repeats = 10)
5
 set.seed(2)
  knnFit1 <- train(Y ..., data = iris,
                    method = "knn",
8
                    trControl = fitControl,
9
                    preProcess = c("center", "scale")
10
                    tuneLength=50)
11
```

• We will perform 10-fold cross-validation for the *k*-nearest neighbor classifier:

```
> knnFit1
2 k-Nearest Neighbors
3
4 Resampling results across tuning parameters:
5
   k Accuracy Kappa
6
      5 0.9526667 0.929
      7 0.9586667 0.938
8
      9 0.9540000 0.931
9
10
11 Accuracy was used to select the optimal model
     using the largest value.
12 The final value used for the model was k = 13.
13
14 plot (knnFit1)
```





- Wines were grown in the same region in Italy but derived from 3 different cultivars.
- The task is to predict wine origin based on 13 attributes having continuous values

- The 13 features (X) of the dataset are:
- 1 Alcohol
- 2 Malic acid
- 3 Ash
- 4 Alkalinity of ash
- 5 Magnesium
- 6 Total phenols
- 7 Flavanoids
- 8 Nonflavonoids phenols
- 9 Proanthocyanins
- 10 Color intensity
- 11 Hue
- 12 OD280/OD315 of diluted wines
- 13 Proline

- The data set is available from https://archive.ics.uci. edu/ml/machine-learning-databases/wine/wine.data
- Task is to predict label Y of origin: 1,2 or 3

```
dataurl <- "https://archive.ics.uci.edu/ml/machine
    -learning-databases/wine/wine.data"

download.file(url = dataurl, destfile = "wine.data")

wine_df <- read.csv("wine.data", header = FALSE)</pre>
```

```
head(wine_df)
2
               VЗ
                   ٧4
                         ٧5
                             ٧6
                                        ٧8
       14.23 1.71 2.43 15.6 127 2.80
     1 13.20 1.78 2.14 11.2 100 2.65
     1 13.16 2.36 2.67 18.6 101 2.80
     1 14.37 1.95 2.50 16.8 113 3.85 3.49
    1 13.24 2.59 2.87
                        21.0
                            118 2.80
     1 14.20 1.76 2.45
                        15.2 112 3.27
      V9
         V10
                          V13
              V 1 1
                    V12
    0.28 2.29 5.64
                   1.04 3.92
 2 0.26 1.28 4.38 1.05 3.40
                              1050
 3 0.30 2.81 5.68
                   1.03 3.17
13 4 0.24 2.18 7.80
                   0.86 3.45
                              1480
14 5 0.39 1.82 4.32
                   1.04 2.93
                              735
15 6 0.34 1.97 6.75 1.05 2.85
                             1450
```

• First column 'V1' contains the wine origin labels

• We will perform 10-fold cross validation for the *k*-nearest neighbors classifier on the wine data set:

```
wine_df$V1=factor(wine_df$V1)
trctrl <- trainControl(method = "repeatedcv",
    number = 10, repeats = 10)
set.seed(3)
knn_fit <- train(V1 ~ ., data = wine_df, method = "
knn",
trControl=trctrl,
preProcess = c("center", "scale")
tuneLength = 20)
plot(knn_fit)</pre>
```

• We will perform 10-fold cross validation for the *k*-nearest neighbors classifier on the wine data set:

```
> knn fit
2 k-Nearest Neighbors
3
  178 samples
   13 predictor
    3 classes: '1', '2', '3'
6
7
    k Accuracy
8
     5 0.9718920
                    0.9577857
q
     7 0.9689800 0.9534599
10
     9 0.9713657 0.9570151
11
    11 0.9657086 0.9486180
12
13
   Accuracy was used to select the optimal model
14
      using
   the largest value.
16 The final value used for the model was k = 35.
```

