

APPLICATIONS

1. Matrix computation for Google's PageRank algorithm

How to solve the matrix equation and obtain Google solution for the textbook example

(Elements of Statistical Learning, pp. 576-578)



```
> x=c(0,1,1,0,0,0,1,0,1,0,0,0,0,0,1,0)
> L = matrix(x,4,4)      # Define a 4x4 matrix L showing linkage among web pages
> L                      # R reads a matrix column by column
     [,1] [,2] [,3] [,4]
[1,]  0  0  1  0
[2,]  1  0  0  0
[3,]  1  1  0  1
[4,]  0  0  0  0

> e = matrix( rep(1,4), 4, 1 )  # Vector of 1s
> e
     [,1]
[1,]  1
[2,]  1
[3,]  1
[4,]  1

> C = diag( colSums(L) )      # Diagonal matrix C showing the number
> C                          # of outgoing links from each web page
     [,1] [,2] [,3] [,4]
[1,]  2  0  0  0
[2,]  0  1  0  0
[3,]  0  0  1  0
[4,]  0  0  0  1

# Matrix multiplication is %*%
# Inverse matrix is solve(C)
# Transpose matrix is t(e)

> A = 0.15*(e%*%t(e))/4 + 0.85*L%*%solve(C)
> A
     [,1] [,2] [,3] [,4]
[1,] 0.0375 0.0375 0.8875 0.0375
[2,] 0.4625 0.0375 0.0375 0.0375
```

```
[3,] 0.4625 0.8875 0.0375 0.8875
[4,] 0.0375 0.0375 0.0375 0.0375
```

```
> eigen(A)                # Computes eigenvalues and eigenvectors of A
$values
```

```
[1] 1.000000e+00+0.00e+00i -4.250000e-01+4.25e-01i
[3] -4.250000e-01-4.25e-01i  5.477659e-18+0.00e+00i
```

```
$vectors
```

```
      [,1]      [,2]
[1,] -0.64470397+0i  7.071068e-01+0.000000e+00i
[2,] -0.33889759+0i -3.535534e-01-3.535534e-01i
[3,] -0.68212419+0i -3.535534e-01+3.535534e-01i
[4,] -0.06489841+0i -2.175463e-17-4.017163e-18i
      [,3]      [,4]
[1,]  7.071068e-01+0.000000e+00i -9.941546e-16+0i
[2,] -3.535534e-01+3.535534e-01i -7.071068e-01+0i
[3,] -3.535534e-01-3.535534e-01i -1.968623e-16+0i
[4,] -2.175463e-17+4.017163e-18i  7.071068e-01+0i
```

```
> install.packages("expm")    # This package contains matrix powers
> library(expm)              # "Exponentiation of a matrix"
> A100 = A%^%100              # Large power of matrix A
> A100                        # (a simple but not an optimal method)
```

```
      [,1] [,2] [,3] [,4]
[1,] 0.3725269 0.3725269 0.3725269 0.3725269
[2,] 0.1958239 0.1958239 0.1958239 0.1958239
[3,] 0.3941492 0.3941492 0.3941492 0.3941492
[4,] 0.0375000 0.0375000 0.0375000 0.0375000
      # "Converged"! All columns are the same
      # Take one column of  $A^{100}$ 
```

```
> p = A100[,1]
> p
[1] 0.3725269 0.1958239 0.3941492 0.0375000
> p=t(t(p))                # Now R understands it as a column
> p
```

```
      [,1]
[1,] 0.3725269
[2,] 0.1958239
[3,] 0.3941492
[4,] 0.0375000
```

```
      # Verify that it is a solution of  $p = Ap$ 
```

```
> A%*%p
      [,1]
[1,] 0.3725269
[2,] 0.1958239
[3,] 0.3941492
[4,] 0.0375000
```

```
> t(e)%*%p                # p is not properly normalized yet, we need  $e'p = N = 4$ 
                        # but we have the sum of  $p[i] = 1$ 
```

```

      [,1]
[1,] 1

> p*4      # This is the solution. Ranked by importance, we have
      [,1]      # web pages ordered as 3, 1, 2, 1
[1,] 1.4901074
[2,] 0.7832956
[3,] 1.5765969
[4,] 0.1500000

```

Another way is by iterations (standard method of solving fixed-point equations):

```

> p = matrix(c(1,0,0,0),4,1)  # The initial vector is kind of arbitrary
> p
      [,1]
[1,] 1
[2,] 0
[3,] 0
[4,] 0

> for (n in (1:100)){ p = A%*%p }  # Iterate p[next] = A*p[current]
> 4*p      # Same result
      [,1]
[1,] 1.4901074
[2,] 0.7832956
[3,] 1.5765969
[4,] 0.1500000

```

2. Spam detection

The Spam data with description are in <https://archive.ics.uci.edu/ml/datasets/Spambase>

We can also get its formatted version from a package “kernlab”

```

> library(kernlab)
> data(spam)
> dim(spam)
[1] 4601 58
> names(spam)
 [1] "make"           "address"         "all"             "num3d"
 [5] "our"            "over"            "remove"          "internet"
 [9] "order"          "mail"            "receive"         "will"
[13] "people"         "report"          "addresses"       "free"
[17] "business"       "email"           "you"             "credit"
[21] "your"           "font"            "num000"          "money"
[25] "hp"             "hpl"             "george"          "num650"
[29] "lab"            "labs"            "telnet"          "num857"
[33] "data"           "num415"          "num85"           "technology"
[37] "num1999"        "parts"           "pm"              "direct"
[41] "cs"             "meeting"         "original"        "project"
[45] "re"             "edu"             "table"           "conference"
[49] "charSemicolon" "charRoundbracket" "charSquarebracket" "charExclamation"
[53] "charDollar"     "charHash"        "capitalAve"      "capitalLong"

```

```
[57] "capitalTotal"      "type"
```

```
> table(type)
type
nonspam  spam
 2788   1813
```

LOGISTIC REGRESSION

```
> logreg = glm( type ~ ., data=spam, family = "binomial" )
> prob.spam = fitted.values(logreg)
> class.spam = ifelse( prob.spam > 0.5, "spam", "nonspam" )
> table(class.spam, type)
      type
class.spam nonspam  spam
  nonspam    2666   194
   spam      122 1619

> mean( type == class.spam )
[1] 0.9313193      # Correct classification rate = 93% (better be validated by CV)
```

What are error rates among spam and benign emails?

```
> sum( type=="nonspam" & class.spam=="spam" ) / sum( type=="nonspam" )
[1] 0.04375897
> sum( type=="spam" & class.spam=="nonspam" ) / sum( type=="spam" )
[1] 0.107005
```

Reducing the error rate for nonspam emails, with loss function $L(1,0)=1$, $L(0,1)=10$

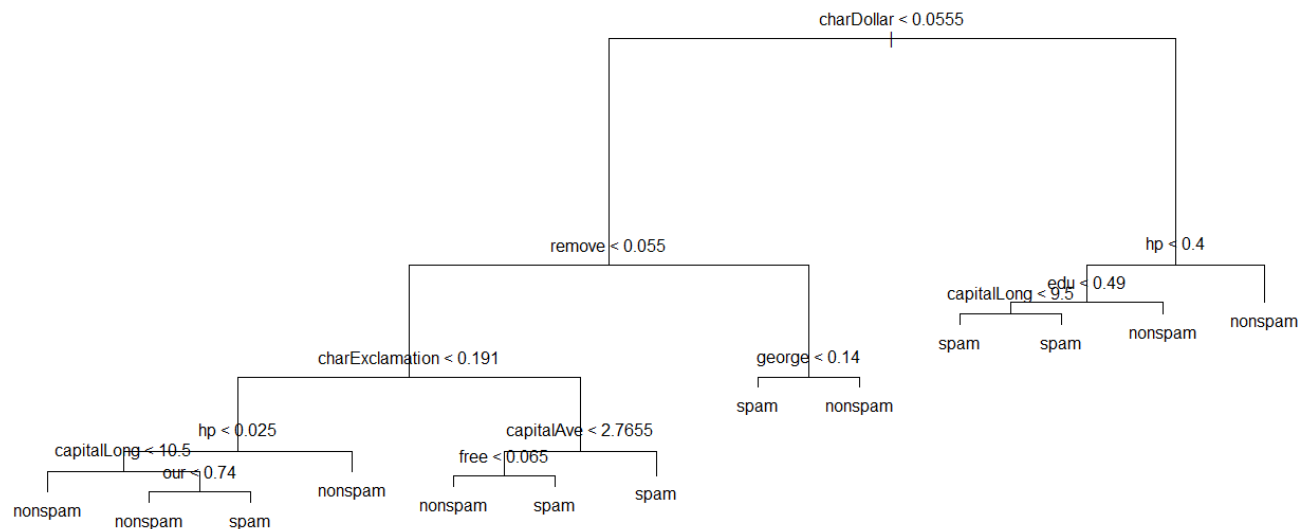
```
> class.spam = ifelse( prob.spam > 10/11, "spam", "nonspam" )
> table(class.spam, type)
      type
class.spam nonspam  spam
  nonspam    2759   674
   spam       29 1139

> mean( type == class.spam )
[1] 0.8472071
> sum( type=="nonspam" & class.spam=="spam" ) / sum( type=="nonspam" )
[1] 0.01040172
> sum( type=="spam" & class.spam=="nonspam" ) / sum( type=="spam" )
[1] 0.3717595
```

The overall error rate increased, and the error rate of misclassifying spam emails as nonspam increased substantially, but the error rate for benign emails is only 1% now.

DECISION TREES

```
> tr = tree( type ~ ., data=spam )
> plot(tr); text(tr);
```



```
> summary(tr)
```

Misclassification error rate: 0.08259 = 380 / 4601

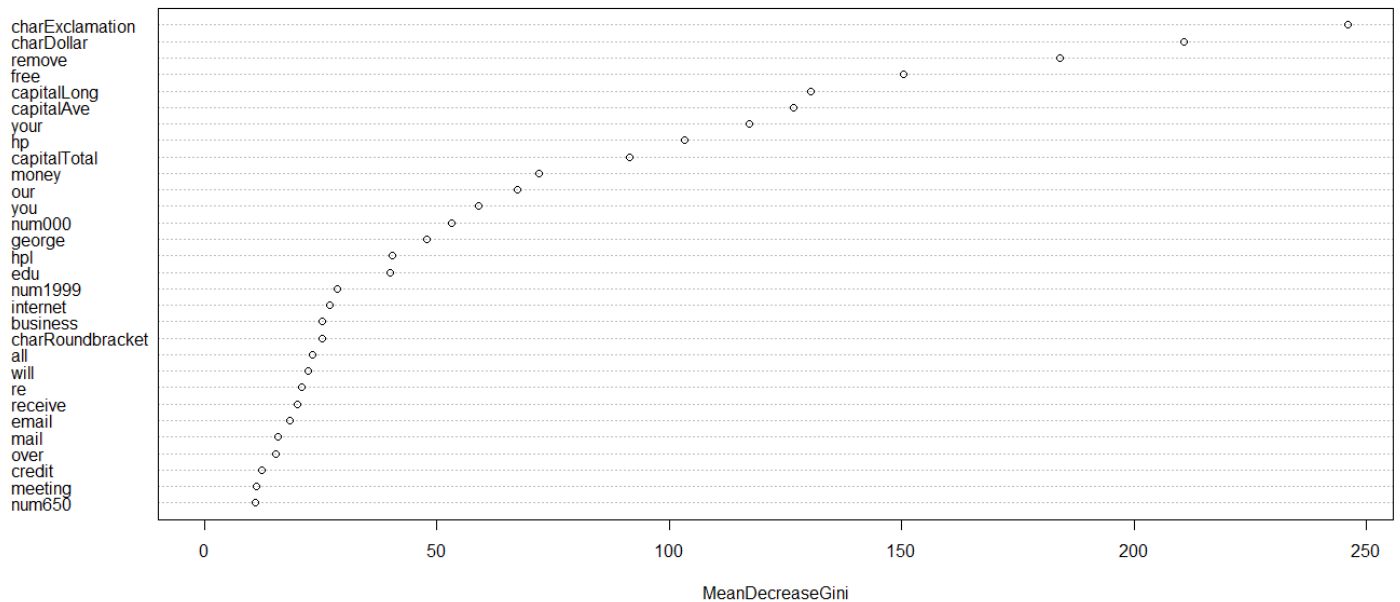
Optimization – random forests

```
> library(randomForest)
```

```
> rf = randomForest( type ~ ., data=spam )
```

```
> varImpPlot(rf)
```

To see which variables are most significant in a tree based classification



```
> rf
```

Number of trees: 500

No. of variables tried at each split: 7

That's approx. square root of the number of X-variables

OOB estimate of error rate: 4.52%

The lowest classification rate we could get so far

Confusion matrix:

	nonspam	spam	class.error
nonspam	2710	78	0.02797704
spam	130	1683	0.07170436

DISCRIMINANT ANALYSIS

```
> library(MASS)
> LDA = lda( type ~ ., data=spam, CV=TRUE )
> table( type, LDA$class )
type      nonspam spam
nonspam    2656  132
spam       394 1419
> mean( type != LDA$class )
[1] 0.114323          # This error rate is higher

> QDA = qda( type ~ ., data=spam, CV=TRUE )
> table( type, QDA$class )
type      nonspam spam
nonspam    2090  691
spam        87 1722
> mean( type != QDA$class )
[1] NA
> summary(QDA$class)
nonspam spam NA's
 2177 2413  11          # There are missing values, predictions not computed by QDA
                        # We'll remove these points

> mean( type != QDA$class, na.rm=TRUE )
[1] 0.1694989          # No improvement with QDA; linear models are ok
```

SUPPORT VECTOR MACHINES

```
> library(e1071)
> SVM = svm( type ~ ., data=spam, kernel="linear" )
> summary(SVM)
Number of Support Vectors: 940
( 456 484 )          # 940 support vectors (not cleanly classified) out of 4601 data points
> dim(spam)
[1] 4601 58

> class = predict(SVM)
> table(class,type)
      type
class nonspam spam
nonspam  2663  185
spam     125 1628
> mean( class != type )
[1] 0.06737666          # Best rate so far?
```