# Analysis of Singh et al. (2002) Prostate Cancer Data

Requires "sda" in version 1.3.2 (January 2014) or later

## Load "sda" package and Singh et al. (2002) data set

```
library("sda")

## Loading required package: entropy
## Loading required package: corpcor
## Loading required package: fdrtool

Singh et al. (2002) gene expression data for prostate cancer:

data(singh2002)

Xtrain = singh2002$x
Ytrain = singh2002$y

dim(Xtrain)  # 102 6033

## [1] 102 6033

length(Ytrain)  # 102

## [1] 102

levels(Ytrain)

## [1] "cancer" "healthy"
```

#### Feature ranking with t-scores

Corresponds to assuming a diagonal covariance matrix (DDA).

Compute ranking:

```
ranking.DDA = sda.ranking(Xtrain, Ytrain, diagonal=TRUE)

## Computing t-scores (centroid vs. pooled mean) for feature ranking

##
## Number of variables: 6033

## Number of observations: 102

## Number of classes: 2

##
## Estimating optimal shrinkage intensity lambda.freq (frequencies): 1

## Estimating variances (pooled across classes)

## Estimating optimal shrinkage intensity lambda.var (variance vector): 0.205

##
##
## Computing false discovery rates and higher cricitism scores for each feature

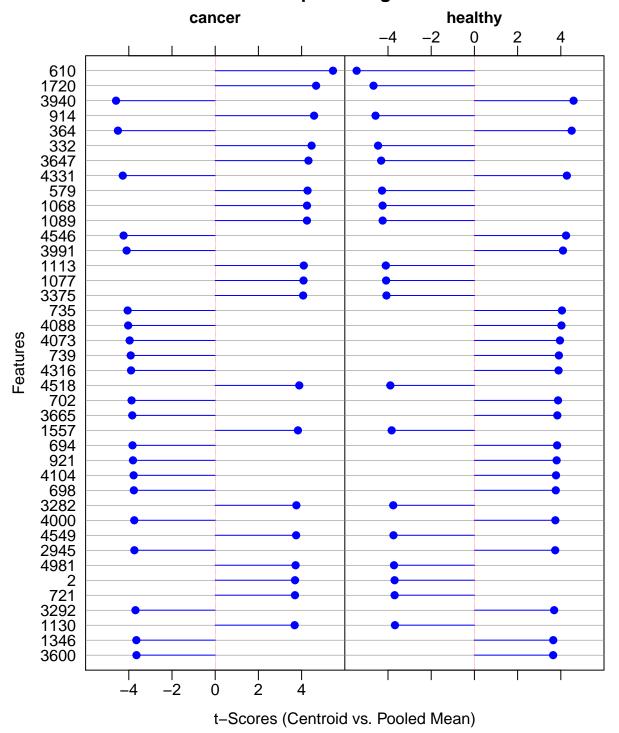
ranking.DDA[1:10,]

## idx score t.cancer t.healthy lfdr HC
```

Plot t-scores for the top 40 genes:

```
plot(ranking.DDA, top=40)
```

The 40 Top Ranking Features



Number of features with local FDR < 0.8 (i.e. features useful for prediction):

```
sum(ranking.DDA[,"lfdr"] < 0.8) # 166</pre>
```

## [1] 166

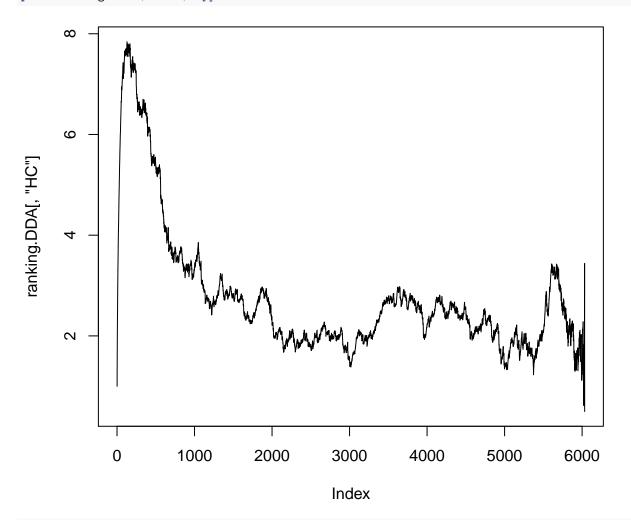
Number of features with local FDR < 0.2 (i.e. significant non-null features):

```
sum(ranking.DDA[,"lfdr"] < 0.2) # 53</pre>
```

## [1] 53

Optimal number of features according to Higher Criticism:

plot(ranking.DDA[,"HC"], type="1")



which.max( ranking.DDA[1:1000,"HC"] ) #129

## [1] 129

### Feature ranking with correlation-adjusted t-scores (CAT scores)

Corresponds to assuming a full covariance matrix (LDA).

Compute ranking:

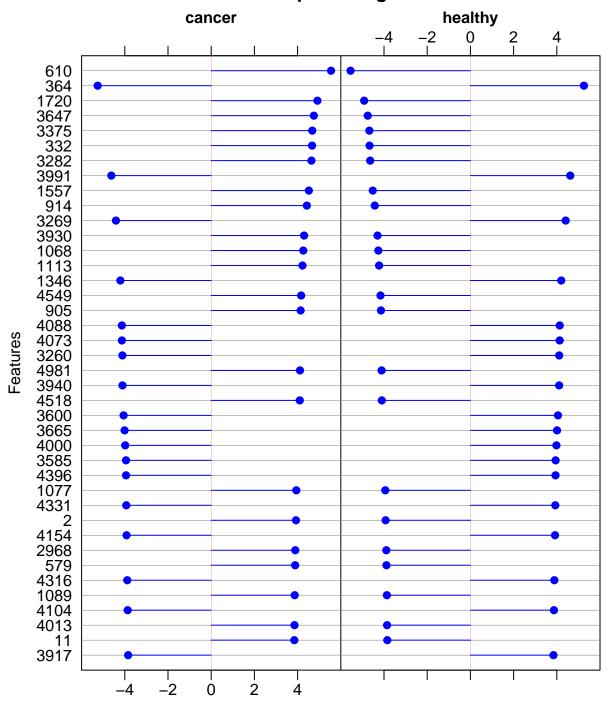
```
## Computing cat scores (centroid vs. pooled mean) for feature ranking
##
## Number of variables: 6033
## Number of observations: 102
## Number of classes: 2
##
## Estimating optimal shrinkage intensity lambda.freq (frequencies): 1
## Estimating variances (pooled across classes)
## Estimating optimal shrinkage intensity lambda.var (variance vector): 0.205
##
## Computing the square root of the inverse pooled correlation matrix
## Estimating optimal shrinkage intensity lambda (correlation matrix): 0.8924
##
## Computing false discovery rates and higher cricitism scores for each feature
ranking.LDA[1:10,]
```

```
score cat.cancer cat.healthy
##
        idx
                                             lfdr
##
  [1,] 610 30.79055 5.548923 -5.548923 0.001534840 0.9996617
## [2,] 364 27.61803 -5.255285
                              5.255285 0.006636026 1.4130468
   [3,] 1720 24.18723 4.918052
                              -4.918052 0.006636026 1.7263343
## [5,] 3375 21.88957 4.678629
                              -4.678629 0.006636026 2.2222410
## [6,] 332 21.81020
                    4.670139
                              -4.670139 0.006636026 2.4367013
   [7,] 3282 21.53894
                    4.641007
                              -4.641007 0.006636026 2.6324612
## [8,] 3991 21.37747 -4.623578
                               4.623578 0.022021468 2.8152840
## [9,] 1557 20.42711 4.519636
                              -4.519636 0.022021468 2.9795916
## [10,] 914 19.60042
                     4.427237
                              -4.427237 0.022021468 3.1325509
```

Plot cat scores for the top 40 genes:

```
plot(ranking.LDA, top=40)
```

The 40 Top Ranking Features



Correlation-Adjusted t-Scores (Centroid vs. Pooled Mean)

Number of features with local FDR < 0.8 (i.e. features useful for prediction):

```
sum(ranking.LDA[,"lfdr"] < 0.8) # 131</pre>
```

## [1] 131

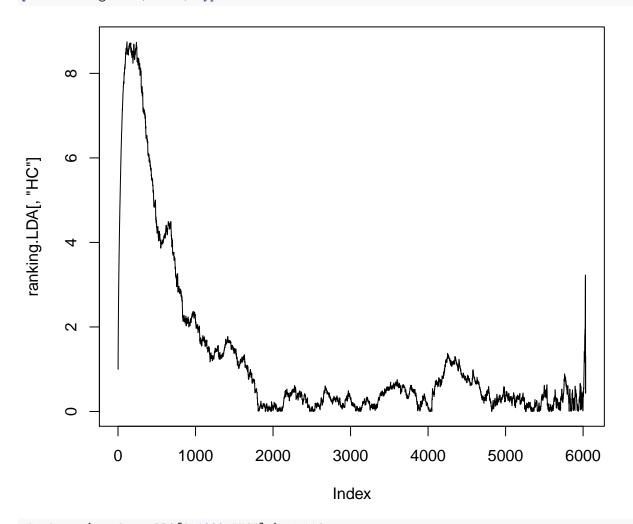
Number of features with local FDR < 0.2 (i.e. significant non-null features):

```
sum(ranking.LDA[,"lfdr"] < 0.2) # 62</pre>
```

## [1] 62

Optimal number of features according to Higher Criticism:

plot(ranking.LDA[,"HC"], type="1")



which.max( ranking.LDA[1:1000,"HC"] ) # 116

## [1] 116

#### Estimate prediction accuracy using crossvalidation

```
library("crossval")
```

Setup prediction function: estimate the accuracy of a predictor with a fixed number of predictors (note this takes into account the uncertainty in estimating the variable ordering).

```
predfun = function(Xtrain, Ytrain, Xtest, Ytest, numVars, diagonal=FALSE)
{
    # estimate ranking and determine the best numVars variables
    ra = sda.ranking(Xtrain, Ytrain, verbose=FALSE, diagonal=diagonal, fdr=FALSE)
    selVars = ra[,"idx"][1:numVars]

# fit and predict
sda.out = sda(Xtrain[, selVars, drop=FALSE], Ytrain, diagonal=diagonal, verbose=FALSE)
    ynew = predict(sda.out, Xtest[, selVars, drop=FALSE], verbose=FALSE)$class

# count false and true positives/negatives
negative = levels(Ytrain)[2] # "healthy"
    cm = confusionMatrix(Ytest, ynew, negative=negative)

return(cm)
}
```

Our setup for crossvalidation:

FP

TP

## 0.170 4.715 4.830 0.485

TN

FN

```
K = 10 # number of folds
B = 20 # number of repetitions
```

Estimate accuracy of LDA using the top 120 features ranked by CAT scores:

```
set.seed(12345)
cv.lda120 = crossval(predfun, Xtrain, Ytrain, K=K, B=B, numVars=120, diagonal=FALSE, verbose=FALSE)
cv.lda120$stat
      FP
            TP
                  TN
## 0.110 4.725 4.890 0.475
diagnosticErrors(cv.lda120$stat)
##
         acc
                  sens
                             spec
                                        ppv
                                                   npv
                                                             lor
## 0.9426471 0.9086538 0.9780000 0.9772492 0.9114632 6.0917753
Estimate accuracy of DDA using the top 120 features ranked by t scores:
set.seed(12345)
cv.dda120 = crossval(predfun, Xtrain, Ytrain, K=K, B=B, numVars=120, diagonal=TRUE, verbose=FALSE)
cv.dda120$stat
```

```
diagnosticErrors(cv.dda120$stat)
```

diagnosticErrors(cv.dda10\$stat)

```
## acc sens spec ppv npv lor
## 0.9357843 0.9067308 0.9660000 0.9651996 0.9087488 5.6211586
```

Same as before but using only the top 10 features:

```
set.seed(12345)
cv.dda10 = crossval(predfun, Xtrain, Ytrain, K=K, B=B, numVars=10, diagonal=TRUE, verbose=FALSE)
cv.dda10$stat

## FP TP TN FN
## 1.370 3.355 3.630 1.845
```

```
## acc sens spec ppv npv lor
## 0.6848039 0.6451923 0.7260000 0.7100529 0.6630137 1.5723944
```