

Training and testing a K-Top-Scoring-Pair (KTSP) classifier with switchBox.

Bahman Afsari and Luigi Marchionni

The Sidney Kimmel Comprehensive Cancer Center,
Johns Hopkins University School of Medicine

Modified: June 20, 2014. Compiled: October 13, 2014

Contents

1	Introduction	2
2	Installing the package	4
3	Data structure	4
3.1	Training set	4
3.2	Testing set	5
4	Training KTSP algorithm	6
4.1	Unrestricted KTSP classifiers	6
4.1.1	Default statistical filtering	6
4.1.2	Alternative filtering methods	8
4.2	Training a Restricted KTSP algorithm	10
5	Calculate and aggregates the TSP votes	12
6	Classify samples and compute the classifier performance	14

6.1	Classifiy training samples	14
6.2	Classifiy validation samples	16
7	Compute the signed TSP scores	17
8	Use of deprecated functions	20
9	System Information	23
10	Literature Cited	23

1 Introduction

The `switchBox` package allows to train and validate a K-Top-Scoring-Pair (KTSP) classifier, as used by Marchionni et al in [1]. KTSP is an extension of the TSP classifier described by Geman and colleagues [2, 3, 4]. The TSP algorithm is a simple binary classifier based on the ordering of two measurements. Basing the prediction solely on the ordering of a small number of features (e.g. gene expressions), known as ranked based methodology, seems a promising approach to build robust classifiers to data normalization and rise to more transparent decision rules. The first and simplest of such methodologies, the Top-Scoring Pair (TSP) classifier, was introduced in [2] and is based on reversal of two features (e.g. the expressions of two genes). Multiple extensions were proposed afterwards, e.g. [3] and many of these extensions have been successfully applied for diagnosis and prognosis of cancer such as recurrence of breast cancer in [1]. A popular successor of TSP classifiers is *kTSP* ([3]), which applies the majority voting among multiple of the the reversal of pairs of features. In addition to being applied by peer scientists, *kTSP* shown its power by wining the ICMLA the challenge for cancer classification in the presence of other competitive methods such as Support Vector Machines ([5]).

KTSP decision is based on k feature (e.g. gene) pairs, say, $\Theta = \{(i_1, j_1), \dots, (i_k, j_k)\}$. If we denote the feature profile with $\underline{X} = (X_1, X_2, \dots)$, the family of rank based classifiers is an aggregation of the comparisons $X_{i_l} < X_{j_l}$. Specifically, the kTSP statistics can be written as:

$$\kappa = \left\{ \sum_{l=1}^k I(X_{i_l} < X_{j_l}) \right\} - \frac{k}{2},$$

where I is the indicator function. The kTSP classification decision can be produced by thresholding the κ , i.e. $\hat{Y} = I\{\kappa > \tau\}$ provided the labels $Y \in \{0, 1\}$. The standard threshold is $\tau = 0$. The only parameters required for calculating κ is the feature pairs. Usually, disjoint feature pairs are desirable because an outlier feature value cannot heavily influence the decision. In the introductory paper to kTSP ([?]), the authors proposed an ad-hoc method for feature selection. This method was based on score for each pair of features which measures how discriminative is a comparison of the feature values. If we denote the score related to the gene i and j by s_{ij} , then the score was defined as

$$s_{ij} = |P(X_i < X_j|Y = 1) - P(X_i < X_j|Y = 0)|.$$

We can sort the pairs of genes by this score. A pair with large score (close to one) indicates that the reversal of the feature value predicts the phenotype accurately.

In [6], an analysis of variance was proposed for gene selection in kTSP and other rank-based classifiers. This method finds the feature pairs which make the distribution of κ under two classes *far apart* in the analysis of variance sense. In mathematical words, we seek the set of feature pairs, Θ^* , that

$$\Theta^* = \arg \max_{\Theta} \frac{E(\kappa(\Theta)|Y = 1) - E(\kappa(\Theta)|Y = 0)}{\sqrt{Var(\kappa(\Theta)|Y = 1) + Var(\kappa(\Theta)|Y = 0)}}.$$

This method automatically chooses the number of genes and hence, it is almost a parameter free method. However, the search for Θ is very intensive search. So, a greedy and approximate search was proposed to find the optimal set of gene pairs. In practice, the only parameter required is a maximum cap for the number pairs, k .

The `switchBox` package contains several utilities enabling to:

1. Filter the features to be used to develop the classifier (*i.e.*, differentially expressed genes);
2. Compute the scores for all available feature pairs to identify the top performing TSPs;
3. Compute the scores for selected feature pairs to identify the top performing TSPs;
4. Identify the number of top pairs, K , to be used in the final classifier;

5. Compute individual TSP votes for one class or the other and aggregate the votes based on various methods;
6. Classify new samples based on the top KTSP based on various methods;

2 Installing the package

Download and install the package `switchBox` from Bioconductor.

```
> source("http://bioconductor.org/biocLite.R")
> biocLite("switchBox")
```

Load the library.

```
> require(switchBox)
```

3 Data structure

3.1 Training set

Load the example training data contained in the `switchBox` package.

```
> ### Load the example data for the TRAINING set
> data(trainingData)
```

The object `matTraining` is a numeric matrix containing gene expression data for the 78 breast cancer patients and the 70 genes used to implement the MammaPrint assay [7]. This data was obtained from the `MammaPrintData` package, as described in [1]. Samples are stored by column and genes by row. Gene annotation is stored as `rownames(matTraining)`.

```
> class(matTraining)
[1] "matrix"
> dim(matTraining)
[1] 70 78
> str(matTraining)
```

```

num [1:70, 1:78] -0.0564 0.0347 -0.0451 -0.1556 0.1394 ...
- attr(*, "dimnames")=List of 2
..$ : chr [1:70] "AA555029_RC_Hs.370457" "AF257175_Hs.15250" "AK000745_Hs.377155" "AKAP2_Hs.516834"
..$ : chr [1:78] "Training1.Bad" "Training2.Bad" "Training3.Good" "Training4.Good" ...

```

The factor `trainingGroup` contains the prognostic information:

```

> ### Show group variable for the TRAINING set
> table(trainingGroup)

trainingGroup
Bad Good
 34   44

```

3.2 Testing set

Load the example testing data contained in the `switchBox` package.

```

> ### Load the example data for the TEST set
> data(testingData)

```

The object `matTesting` is a numeric matrix containing gene expression data for the 307 breast cancer patients and the 70 genes used to validate the MammaPrint assay [8]. This data was obtained from the `MammaPrintData` package, as described in [1]. Also in this case samples are stored by column and genes by row. Gene annotation is stored as `rownames(matTraining)`.

```

> class(matTesting)

[1] "matrix"

> dim(matTesting)

[1] 70 307

> str(matTesting)

num [1:70, 1:307] 0.0035 -0.0599 -0.0678 0.1139 -0.094 ...
- attr(*, "dimnames")=List of 2
..$ : chr [1:70] "AA555029_RC_Hs.370457" "AF257175_Hs.15250" "AK000745_Hs.377155" "AKAP2_Hs.516834"
..$ : chr [1:307] "Test1.Good" "Test2.Good" "Test3.Good" "Test4.Good" ...

```

The factor `testingGroup` contains the prognostic information:

```

> ### Show group variable for the TEST set
> table(testingGroup)

testingGroup
Bad Good
 47  260

```

4 Training KTSP algorithm

4.1 Unrestricted KTSP classifiers

We can train the KTSP algorithm using all possible feature pairs – unrestricted KTSP classifier – with or without statistical feature filtering, using the `SWAP.KTSP.Train` function.

4.1.1 Default statistical filtering

Training an unrestricted KTSP predictor using a statistical feature filtering is the default and it is achieved by using the default parameters, as follows:

```
> ### The arguments to the "SWAP.KTSP.Train" function
> args(SWAP.KTSP.Train)

function (inputMat, phenoGroup, krange = c(3, 5, 7:10), FilterFunc = SWAP.Filter.Wilcoxon,
  RestrictedPairs, ...)
NULL

> ### Train a classifier using default filtering function based on the Wilcoxon test
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup, krange=c(3:15))

Applying filtering function to 'inputMat'...
Computing scores for 70 features.
This will require enough memory for 2415 pairs.
Selecting K...
7 TSP will be used to build the final classifier.

> ### Show the classifier
> classifier

$name
[1] "7TSPs"

$TSPs
      [,1]                [,2]
[1,] "GNAZ_Hs.555870"      "Contig32185_RC_Hs.159422"
[2,] "Contig46223_RC_Hs.22917" "OXCT_Hs.278277"
[3,] "RFC4_Hs.518475"      "L2DTL_Hs.445885"
[4,] "Contig40831_RC_Hs.161160" "CFFM4_Hs.250822"
[5,] "FLJ11354_Hs.523468"    "LOC57110_Hs.36761"
[6,] "Contig55725_RC_Hs.470654" "IGFBP5_Hs.184339"
[7,] "UCH37_Hs.145469"      "SERF1A_Hs.32567"

$score
[1] 0.6029423 0.5467924 0.5347600 0.5280755 0.5267389 0.5200542 0.5133699

$labels
[1] "Bad" "Good"
```

```

> ### Extract the TSP from the classifier
> classifier$TSPs

      [,1]                [,2]
[1,] "GNAZ_Hs.555870"     "Contig32185_RC_Hs.159422"
[2,] "Contig46223_RC_Hs.22917" "OXCT_Hs.278277"
[3,] "RFC4_Hs.518475"      "L2DTL_Hs.445885"
[4,] "Contig40831_RC_Hs.161160" "CFFM4_Hs.250822"
[5,] "FLJ11354_Hs.523468"   "LOC57110_Hs.36761"
[6,] "Contig55725_RC_Hs.470654" "IGFBP5_Hs.184339"
[7,] "UCH37_Hs.145469"     "SERF1A_Hs.32567"

```

Below is shown the way the default feature filtering works. The `SWAP.Filter.Wilcoxon` function takes the phenotype factor, the predictor data, the number of feature to be returned, and a logical value to decide whether to include equal number of featured positively and negatively associated with the phenotype to be predicted.

```

> ### The arguments to the "SWAP.KTSP.Train" function
> args(SWAP.Filter.Wilcoxon)

function (phenoGroup, inputMat, featureNo = 100, UpDown = TRUE)
NULL

> ### Retrieve the top best 4 genes using default Wilcoxon filtering
> ### Note that there are ties
> SWAP.Filter.Wilcoxon(trainingGroup, matTraining, featureNo=4)

[1] "KIAA0175_Hs.184339" "IGFBP5_Hs.184339" "RFC4_Hs.518475"
[4] "FLJ11354_Hs.523468" "GNAZ_Hs.555870"

```

Train a classifier using the `SWAP.Filter.Wilcoxon` filtering function.

```

> ### Train a classifier from the top 4 best genes
> ### according to Wilcoxon filtering function
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup,
                               FilterFunc=SWAP.Filter.Wilcoxon, featureNo=4)

Applying filtering function to 'inputMat'...
Computing scores for 5 features.
This will require enough memory for 10 pairs.
Selecting K...
The required range of k is not available!
The minimum number of available TSP (2) will be used instead.

> ### Show the classifier
> classifier

$name
[1] "2TSPs"

$TSPs
      [,1]                [,2]
[1,] "FLJ11354_Hs.523468" "IGFBP5_Hs.184339"

```

```
[2,] "RFC4_Hs.518475"      "KIAA0175_Hs.184339"
```

```
$score
[1] 0.5173798 0.4826204
```

```
$labels
[1] "Bad" "Good"
```

Train a classifier using all possible features:

```
> ### To use all features "FilterFunc" must be set to NULL
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup, FilterFunc=NULL)
```

```
No feature filtering procedure will be used...
Computing scores for 70 features.
This will require enough memory for 2415 pairs.
Selecting K...
7 TSP will be used to build the final classifier.
```

```
> ### Show the classifier
> classifier
```

```
$name
[1] "7TSPs"
```

```
$TSPs
      [,1]                [,2]
[1,] "GNAZ_Hs.555870"     "Contig32185_RC_Hs.159422"
[2,] "Contig46223_RC_Hs.22917" "OXCT_Hs.278277"
[3,] "RFC4_Hs.518475"     "L2DTL_Hs.445885"
[4,] "Contig40831_RC_Hs.161160" "CFFM4_Hs.250822"
[5,] "FLJ11354_Hs.523468"     "LOC57110_Hs.36761"
[6,] "Contig55725_RC_Hs.470654" "IGFBP5_Hs.184339"
[7,] "UCH37_Hs.145469"       "SERF1A_Hs.32567"
```

```
$score
[1] 0.6029423 0.5467924 0.5347600 0.5280755 0.5267389 0.5200542 0.5133699
```

```
$labels
[1] "Bad" "Good"
```

4.1.2 Alternative filtering methods

Training can also be achieved using alternative filtering methods. These methods can be specified by passing a different filtering function to `SWAP.KTSP.Train`. These functions should use the `phenoGroup`, `inputData` arguments, as well as any other necessary argument (passed using `...`), as shown below.

For instance, we can define an alternative filtering function selecting 10 random features.


```

> ### An alternative filtering function selecting 20 random features
> random10 <- function(situation, data) { sample(rownames(data), 10) }
> random10(trainingGroup, matTraining)

[1] "Contig55377_RC_Hs.463089" "EXT1_Hs.492618" "FGF18_Hs.87191"
[4] "Contig46223_RC_Hs.22917" "AL080059_Hs.173094" "CCNE2_Hs.408658"
[7] "FLJ12443_Hs.368853" "PK428_Hs.516834" "GMP5_Hs.546324"
[10] "ESM1_Hs.129944"

```

Below is a more realistic example of an alternative filtering function. In this case we use the `R t.test` function to select the features with an absolute t-statistics larger than a specified quantile.

```

> ### An alternative filtering function based on a t-test
> topRttest <- function(situation, data, quant = 0.75) {
  out <- apply(data, 1, function(x, ...) t.test(x ~ situation)$statistic )
  names(out[ abs(out) > quantile(abs(out), quant) ])
}
> ### Show the top 5% features using the newly defined filtering function
> topRttest(trainingGroup, matTraining, quant=0.95)

[1] "Contig32185_RC_Hs.159422" "FLJ11354_Hs.523468" "IGFBP5_Hs.184339"
[4] "KIAA0175_Hs.184339"

```

Train a classifier using the alternative filtering function based on the t-test and also define the max number of TSP using `krange`.

```

> ### Train with t-test and krange
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup,
  FilterFunc = topRttest, quant = 0.9, krange=c(15:30) )

Applying filtering function to 'inputMat'...
Computing scores for 7 features.
This will require enough memory for 21 pairs.
Selecting K...
The required range of k is not available!
The minimum number of available TSP (3) will be used instead.

> ### Show the classifier
> classifier

$name
[1] "3TSPs"

$TSPs
  [,1] [,2]
[1,] "GNAZ_Hs.555870" "Contig32185_RC_Hs.159422"
[2,] "FLJ11354_Hs.523468" "IGFBP5_Hs.184339"
[3,] "SERF1A_Hs.32567" "MMP9_Hs.297413"

$score
[1] 0.6029413 0.5173798 0.1631016

$labels
[1] "Bad" "Good"

```

4.2 Training a Restricted KTSP algorithm

The `switchcBox` allows to training a KTSP classifier using a pre-specified set of restricted feature pairs. This can be useful to implement KTSP classifiers restricted to specific TSPs based, for instance, on prior biological information ([9]). To this end, the user must specify a set of candidate pairs by setting `RestrictedPairs` argument.

As an example, we can define a set of candidate pairs by randomly selecting some of the rownames from the `inputMat` matrix and the classifier chooses from this set.

In a real example these pairs would be provided by the user, for instance using prior biological knowledge. The restricted pairs must contain valid feature names, *i.e.* the row names of `inputMat`.

```
> set.seed(123)
> somePairs <- matrix(sample(rownames(matTraining), 6^2, replace=FALSE), ncol=2)
> head(somePairs)

      [,1]                [,2]
[1,] "Contig38288_RC_Hs.144073" "Contig32125_RC_Hs.371395"
[2,] "MP1_Hs.26010"           "KIAA1442_Hs.471955"
[3,] "Contig63649_RC_Hs.72620" "HSA250839_Hs.133062"
[4,] "PK428_Hs.516834"        "SERF1A_Hs.32567"
[5,] "RFC4_Hs.518475"         "DKFZP564D0462_Hs.318894"
[6,] "AK000745_Hs.377155"     "IGFBP5_Hs.511093"

> dim(somePairs)

[1] 18  2
```

Train a classifier using the set of restricted feature pairs and the default filtering:

```
> ### Train
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup,
                               RestrictedPairs = somePairs, krange=3:16)

Applying filtering function to 'inputMat'...
Restricting the analysis to the provided candidate TSPs
Computing scores for 18 available restricted pairs.
This will require enough memory for 18 pairs.
Selecting K...
11 TSP will be used to build the final classifier.

> ### Show the classifier
> classifier
```

```

$name
[1] "11TSPs"

$TSPs
      [,1]                [,2]
[1,] "DKFZP564D0462_Hs.318894" "RFC4_Hs.518475"
[2,] "MP1_Hs.26010"            "KIAA1442_Hs.471955"
[3,] "SERF1A_Hs.32567"         "PK428_Hs.516834"
[4,] "FGF18_Hs.87191"         "Contig46223_RC_Hs.22917"
[5,] "AK000745_Hs.377155"      "IGFBP5_Hs.511093"
[6,] "FLJ22477_Hs.149004"      "FLT1_Hs.507621"
[7,] "KIAA0175_Hs.184339"      "EXT1_Hs.492618"
[8,] "TMEFF1_Hs.336224"        "Contig55377_RC_Hs.463089"
[9,] "ALDH4_Hs.133062"         "Contig55725_RC_Hs.470654"
[10,] "ESM1_Hs.129944"         "FLJ11190_Hs.516834"
[11,] "AA555029_RC_Hs.370457"  "COL4A2_Hs.508716"

$score
[1] 0.4532088 0.3943852 0.3836903 0.3810164 0.3128345 0.2834227 0.2500002 0.2259360
[9] 0.2032088 0.1938504 0.1911766

$labels
[1] "Bad" "Good"

```

Train a classifier using a set of restricted feature pairs, defining the maximum number of TSP using krange and also filtering the features by T-test.

```

> ### Train
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup,
                               RestrictedPairs = somePairs,
                               FilterFunc = topRttest, quant = 0.3,
                               krange=c(3:10) )

```

```

Applying filtering function to 'inputMat'...
Restricting the analysis to the provided candidate TSPs
Computing scores for 10 available restricted pairs.
This will require enough memory for 10 pairs.
Selecting K...
9 TSP will be used to build the final classifier.

```

```

> ### Show the classifier
> classifier

```

```

$name
[1] "9TSPs"

$TSPs
      [,1]                [,2]
[1,] "SERF1A_Hs.32567"     "PK428_Hs.516834"
[2,] "FGF18_Hs.87191"     "Contig46223_RC_Hs.22917"
[3,] "AK000745_Hs.377155" "IGFBP5_Hs.511093"
[4,] "KIAA0175_Hs.184339" "EXT1_Hs.492618"
[5,] "TMEFF1_Hs.336224"   "Contig55377_RC_Hs.463089"
[6,] "ESM1_Hs.129944"     "FLJ11190_Hs.516834"
[7,] "AL137718_Hs.508141" "PECI_Hs.15250"

```

```

[8,] "ECT2_Hs.518299"      "ORC6L_Hs.49760"
[9,] "OXCT_Hs.278277"      "CFFM4_Hs.250822"

$score
[1] 0.38369019 0.38101624 0.31283440 0.25000012 0.22593590 0.19385035 0.17780769
[8] 0.13636374 0.08021399

$labels
[1] "Bad"  "Good"

```

5 Calculate and aggregates the TSP votes

The `SWAP.KTSP.Statistics` function can be used to compute and aggregate the TSP votes using alternative functions to combine the votes. The default method is the count of the signed TSP votes. We can also pass a different function to combine the KTSPs. This function takes an argument `x` – a logical vector corresponding to the TSP votes – of length equal to the number of columns (*e.g.*, the number of cancer patients under analysis) and aggregates the votes of all K TSPs of the classifier identified by the training process (see the `SWAP.KTSP.Train` function).

Here we will use the default parameters (the count of the signed TSP votes)

```

> ### Train a classifier
> classifier <- SWAP.KTSP.Train(matTraining, trainingGroup,
                               FilterFunc = NULL, krange=8)

No feature filtering procedure will be used...
Computing scores for 70 features.
This will require enough memory for 2415 pairs.
Selecting K...
8 TSP will be used to build the final classifier.

> ### Compute the statistics using the default parameters:
> ### counting the signed TSP votes
> ktspStatDefault <- SWAP.KTSP.Statistics(inputMat = matTraining,
                                           classifier = classifier)
> ### Show the components in the output
> names(ktspStatDefault)

[1] "statistics"  "comparisons"

> ### Show some of the votes
> head(ktspStatDefault$comparisons[, 1:2])

GNAZ_Hs.555870>Contig32185_RC_Hs.159422
Training1.Bad      FALSE
Training2.Bad      FALSE
Training3.Good     TRUE

```

```

Training4.Good TRUE
Training5.Bad FALSE
Training6.Bad FALSE
Contig46223_RC_Hs.22917>OXCT_Hs.278277
Training1.Bad FALSE
Training2.Bad FALSE
Training3.Good TRUE
Training4.Good TRUE
Training5.Bad TRUE
Training6.Bad FALSE

> ### Show default statistics
> head(ktspStatDefault$statistics)

Training1.Bad Training2.Bad Training3.Good Training4.Good Training5.Bad
-6 -6 6 6 0
Training6.Bad
-2

```

Here we will use the sum to aggregate the TSP votes

```

> ### Compute
> ktspStatSum <- SWAP.KTSP.Statistics(inputMat = matTraining,
  classifier = classifier, CombineFunc=sum)
> ### Show statistics obtained using the sum
> head(ktspStatSum$statistics)

Training1.Bad Training2.Bad Training3.Good Training4.Good Training5.Bad
1 1 7 7 4
Training6.Bad
3

```

Here, for instance, we will apply a hard threshold equal to 2

```

> ### Compute
> ktspStatThreshold <- SWAP.KTSP.Statistics(inputMat = matTraining,
  classifier = classifier, CombineFunc = function(x) sum(x) > 2 )
> ### Show statistics obtained using the threshold
> head(ktspStatThreshold$statistics)

Training1.Bad Training2.Bad Training3.Good Training4.Good Training5.Bad
FALSE FALSE TRUE TRUE TRUE
Training6.Bad
TRUE

```

We can also make a heatmap showing the individual TSPs votes (see Figure 1 below).

```

> ### Make a heatmap showing the individual TSPs votes
> colorForRows <- as.character(1+as.numeric(trainingGroup))
> heatmap(1*ktspStatThreshold$comparisons, scale="none",
  margins = c(10, 5), cexCol=0.5, cexRow=0.5,
  labRow=trainingGroup, RowSideColors=colorForRows)

```

6 Classify samples and compute the classifier performance

6.1 Classify training samples

The `SWAP.KTSP.Classify` function allows to classify one or more samples using the classifier identified by `SWAP.KTSP.Train`. The **resubstitution** performance in the training set is shown below.

```
> ### Show the classifier
> classifier

$name
[1] "8TSPs"

$TSPs
      [,1]                                [,2]
[1,] "GNAZ_Hs.555870"                    "Contig32185_RC_Hs.159422"
[2,] "Contig46223_RC_Hs.22917"            "OXCT_Hs.278277"
[3,] "RFC4_Hs.518475"                    "L2DTL_Hs.445885"
[4,] "Contig40831_RC_Hs.161160"           "CFFM4_Hs.250822"
[5,] "FLJ11354_Hs.523468"                "LOC57110_Hs.36761"
[6,] "Contig55725_RC_Hs.470654"           "IGFBP5_Hs.184339"
[7,] "UCH37_Hs.145469"                   "SERF1A_Hs.32567"
[8,] "GSTM3_Hs.2006"                     "KIAA0175_Hs.184339"

$score
[1] 0.6029423 0.5467924 0.5347600 0.5280755 0.5267389 0.5200542 0.5133699 0.5080221

$labels
[1] "Bad" "Good"

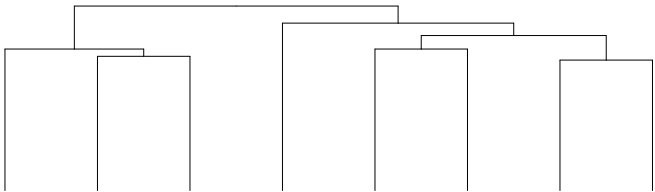
> ### Apply the classifier to the TRAINING set
> trainingPrediction <- SWAP.KTSP.Classify(matTraining, classifier)
> ### Show
> str(trainingPrediction)

Factor w/ 2 levels "Bad","Good": 1 1 2 2 1 1 2 2 1 1 ...
- attr(*, "names")= chr [1:78] "Training1.Bad" "Training2.Bad" "Training3.Good" "Training4.Good" ...

> ### Resubstitution performance in the TRAINING set
> table(trainingPrediction, trainingGroup)

              trainingGroup
trainingPrediction Bad Good
Bad              30    6
Good              4   38
```

We can apply the classifier using a specific decision to combine the K TSP as specified with the `DecideFunc` argument of `SWAP.KTSP.Classify`. This argument is a function working on a logical vector x containing the votes of each



15

TSP. We can for instance count all votes for class one and then classify a patient in one class or the other based on a specific threshold.

```
> ### Usr a CombineFunc based on sum(x) > 5.5
> trainingPrediction <- SWAP.KTSP.Classify(matTraining, classifier,
                                         DecisionFunc = function(x) sum(x) > 5.5 )
> ### Show
> str(trainingPrediction)

Factor w/ 2 levels "Bad","Good": 1 1 2 2 1 1 2 2 1 1 ...
- attr(*, "names")= chr [1:78] "Training1.Bad" "Training2.Bad" "Training3.Good" "Training4.Good" ...

> ### Resubstitution performance in the TRAINING set
> table(trainingPrediction, trainingGroup)

      trainingGroup
trainingPrediction Bad Good
      Bad      34      8
      Good       0     36
```

6.2 Classify validation samples

We can apply the trained classifier to one new sample of the test set:

```
> ### Classify one sample
> testPrediction <- SWAP.KTSP.Classify(matTesting[, 1, drop=FALSE], classifier)
> ### Show
> testPrediction

Test1.Good
      Good
Levels: Bad Good
```

We can apply the trained classifier to a new set of samples, using the default decision rule based on the “majority wins” principle:

```
> ### Apply the classifier to the complete TEST set
> testPrediction <- SWAP.KTSP.Classify(matTesting, classifier)
> ### Show
> table(testPrediction)

testPrediction
      Bad Good
      133  174

> ### Resubstitution performance in the TEST set
> table(testPrediction, testingGroup)
```



```

testingGroup
testPrediction Bad Good
Bad 31 102
Good 16 158

```

We can apply the trained classifier to predict of a new set of samples, using an alternative decision rule specified by `DecideFunc`. For instance, we can classify by thresholding vote counts in favor of one of the classes.

```

> ### Apply the classifier using sum(x) > 5.5
> testPrediction <- SWAP.KTSP.Classify(matTesting, classifier,
                                     DecideFunc = function(x) sum(x) > 5.5 )
> ### Resubstitution performance in the TEST set
> table(testPrediction, testingGroup)

testingGroup
testPrediction Bad Good
Bad 43 138
Good 4 122

```

7 Compute the signed TSP scores

The `switchBox` allows also to compute the individual scores for each TSP of interest. This can be achieved by using the `SWAP.CalculateSignedScore` function as shown below.

Compute the scores using all features for all possible pairs:

```

> ### Compute the scores using all features for all possible pairs
> scores <- SWAP.CalculateSignedScore(matTraining, trainingGroup, FilterFunc=NULL)

No feature filtering procedure will be used...
Computing scores for 70 features.
This will require enough memory for 2415 pairs.

> ### Show scores
> class(scores)

[1] "list"

> dim(scores$score)

[1] 70 70

```

Extract the TSP scores of interest – the absolute value correspond to the scores returned by `SWAP.KTSP.Train`.

```

> ### Get the scores
> scoresOfInterest <- diag(scores$score[ classifier$TSPs[,1] , classifier$TSPs[,2] ])
> ### Their absolute value should correspond to the scores returned by SWAP.KTSP.Train
> all(classifier$score == abs(scoresOfInterest))

[1] TRUE

```

The `SWAP.CalculateSignedScore` function accept the same arguments used by `SWAP.KTSP.Train`. It can compute the scores with or without a filtering function and using or not the restricted pairs, as specified by `FilterFunc` and `RestrictedPairs` respectively.

```

> ### Compute the scores with default filtering function
> scores <- SWAP.CalculateSignedScore(matTraining, trainingGroup, featureNo=20 )

Applying filtering function to 'inputMat'...
Computing scores for 21 features.
This will require enough memory for 210 pairs.

> ### Show scores
> dim(scores$score)

[1] 21 21

> ### Compute the scores without the default filtering function
> ### and using restricted pairs
> scores <- SWAP.CalculateSignedScore(matTraining, trainingGroup,
                                     FilterFunc = NULL, RestrictedPairs = somePairs )

No feature filtering procedure will be used...
Restricting the analysis to the provided candidate TSPs
Computing scores for 18 available restricted pairs.
This will require enough memory for 18 pairs.

> ### Show scores
> class(scores$score)

[1] "numeric"

> length(scores$score)

[1] 18

```

In Figure 2 is shown the histograms for all possible TSP scores.

```

> hist(scores$score, col="salmon", main="TSP scores")

```

```
> hist(scores$score, col="salmon", main="TSP scores")
```

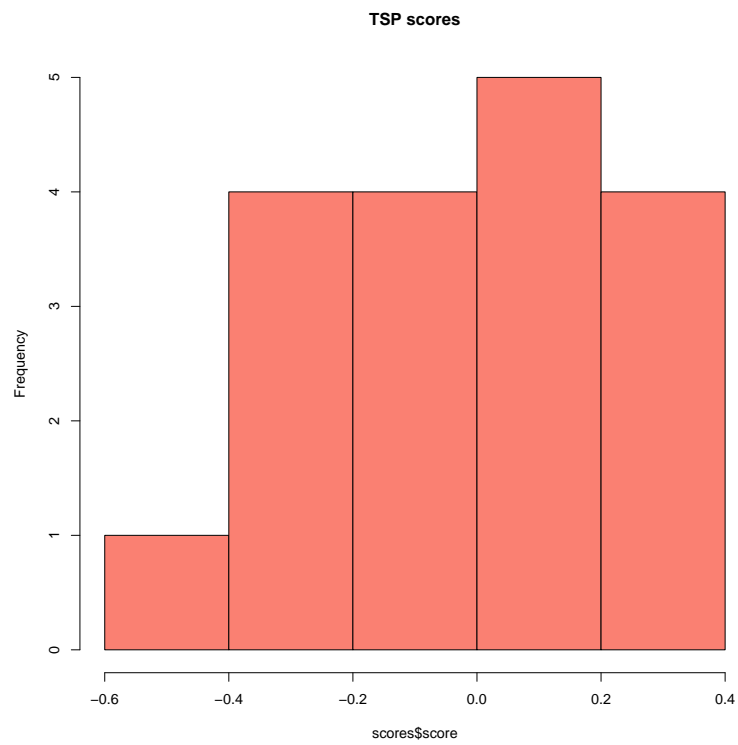


Figure 2: Histograms of all TSP socres.

8 Use of deprecated functions

The two functions `KTSP.Train` and `KTSP.Classify` are deprecated and are included in the package only for backward compatibility. They have been substituted by respectively `SWAP.KTSP.Train` and `SWAP.KTSP.Classify`. These functions were used to train and validate the 8-TSP classifier described by Marchionni et al [1] and are maintained for reproducibility purposes. Example on the way they are used follows.

Preparation of phenotype information (a numeric vector with values equal to 0 or 1) for training the KTSP classifier:

```
> ### Phenotypic group variable for the 78 samples
> table(trainingGroup)

trainingGroup
  Bad Good
   34   44

> levels(trainingGroup)

[1] "Bad" "Good"

> ### Turn into a numeric vector with values equal to 0 and 1
> trainingGroupNum <- as.numeric(trainingGroup) - 1
> ### Show group variable for the TRAINING set
> table(trainingGroupNum)

trainingGroupNum
  0  1
 34 44
```

KTSP classifier training using the deprecated function:

```
> ### Train a classifier using default filtering function based on the Wilcoxon test
> classifier <- KTSP.Train(matTraining, trainingGroupNum, n=8)
> ### Show the classifier
> classifier

$TSPs
      [,1] [,2]
[1,]   42   19
[2,]   24   58
[3,]   63   50
[4,]   22   13
[5,]   37   52
[6,]   27   46
[7,]   69   64
[8,]   43   48

$score
[1] 0.6029417 0.5467919 0.5347597 0.5280752 0.5267384 0.5200538 0.5133694 0.5080218
```

```

$geneNames
      [,1]                                [,2]
[1,] "GNAZ_Hs.555870"                    "Contig32185_RC_Hs.159422"
[2,] "Contig46223_RC_Hs.22917"           "OXCT_Hs.278277"
[3,] "RFC4_Hs.518475"                    "L2DTL_Hs.445885"
[4,] "Contig40831_RC_Hs.161160"           "CFFM4_Hs.250822"
[5,] "FLJ11354_Hs.523468"                "LOC57110_Hs.36761"
[6,] "Contig55725_RC_Hs.470654"           "IGFBP5_Hs.184339"
[7,] "UCH37_Hs.145469"                   "SERF1A_Hs.32567"
[8,] "GSTM3_Hs.2006"                     "KIAA0175_Hs.184339"

```

KTSP classifier performance using the deprecated function:

```

> ### Apply the classifier to one sample of the TEST set using
> ### sum of votes less than 2.5
> trainPrediction <- KTSP.Classify(matTraining, classifier,
                                   combineFunc = function(x) sum(x) < 2.5)

> ### Contingency table
> table(trainPrediction, trainingGroupNum)

      trainingGroupNum
trainPrediction 0  1
               0 34  8
               1  0 36

```

Preparation of phenotype information (a numeric vector with values equal to 0 or 1) for testing the KTSP classifier on new data:

```

> ### Phenotypic group variable for the 307 samples
> table(testingGroup)

testingGroup
Bad Good
 47  260

> levels(testingGroup)

[1] "Bad" "Good"

> ### Turn into a numeric vector with values equal to 0 and 1
> testingGroupNum <- as.numeric(testingGroup) - 1
> ### Show group variable for the TEST set
> table(testingGroupNum)

testingGroupNum
 0  1
47 260

```

Testing on new data and getting KTSP classifier performance using the deprecated function:

```

> ### Apply the classifier to one sample of the TEST set using
> ### sum of votes less than 2.5
> testPrediction <- KTSP.Classify(matTesting, classifier,
    combineFunc = function(x) sum(x) < 2.5)
> ### Show prediction
> table(testPrediction)

testPrediction
  0   1
181 126

> ### Contingency table
> table(testPrediction, testingGroupNum)

      testingGroupNum
testPrediction  0   1
              0  43 138
              1   4 122

```

9 System Information

Session information:

```
> toLatex(sessionInfo())
```

- R version 3.1.1 Patched (2014-09-25 r66681),
x86_64-apple-darwin13.1.0
- Locale:
C/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
- Base packages: base, datasets, grDevices, graphics, methods, stats, utils
- Other packages: switchBox 1.0.0
- Loaded via a namespace (and not attached): tools 3.1.1

10 Literature Cited

References

- [1] Luigi Marchionni, Bahman Afsari, Donald Geman, and Jeffrey T Leek. A simple and reproducible breast cancer prognostic test. *BMC Genomics*, 14:336, 2013.
- [2] Donald Geman, Christian d’Avignon, Daniel Q Naiman, and Raimond L Winslow. Classifying gene expression profiles from pairwise mrna comparisons. *Stat Appl Genet Mol Biol*, 3:Article19, 2004.
- [3] Aik Choon Tan, Daniel Q Naiman, Lei Xu, Raimond L Winslow, and Donald Geman. Simple decision rules for classifying human cancers from gene expression profiles. *Bioinformatics*, 21(20):3896–904, Oct 2005.
- [4] Lei Xu, Aik Choon Tan, Daniel Q Naiman, Donald Geman, and Raimond L Winslow. Robust prostate cancer marker genes emerge from direct integration of inter-study microarray data. *Bioinformatics*, 21(20):3905–11, Oct 2005.

- [5] D. Geman, B. Afsari, and D. Naiman A.C. Tan. Microarray classification from several two-gene expression comparisons. 2008. (Winner, ICMLA Microarray Classification Algorithm Competition).
- [6] Bahman Afsari, Ulisses Braga-Neto, and Donald Geman. Rank discriminants for predicting phenotypes from rna expression. *Annals of Applied Statistics*, to appear.
- [7] Annuska M Glas, Arno Floore, Leonie J M J Delahaye, Anke T Witteveen, Rob C F Pover, Niels Bakx, Jaana S T Lahti-Domenici, Tako J Bruinsma, Marc O Warmoes, René Bernards, Lodewyk F A Wessels, and Laura J Van't Veer. Converting a breast cancer microarray signature into a high-throughput diagnostic test. *BMC Genomics*, 7:278, 2006.
- [8] Marc Buyse, Sherene Loi, Laura van't Veer, Giuseppe Viale, Mauro Delorenzi, Annuska M Glas, Mahasti Saghatchian d'Assignies, Jonas Bergh, Rosette Lidereau, Paul Ellis, Adrian Harris, Jan Bogaerts, Patrick Therasse, Arno Floore, Mohamed Amakrane, Fanny Piette, Emiel Rutgers, Christos Sotiriou, Fatima Cardoso, Martine J Piccart, and TRANSBIG Consortium. Validation and clinical utility of a 70-gene prognostic signature for women with node-negative breast cancer. *J Natl Cancer Inst*, 98(17):1183–92, Sep 2006.
- [9] Relative mRNA Levels of Functionally Interacting Proteins Are Consistent Disease Molecular Signatures. Wang, yuliang and afsari, bahman and geman, donald and price, nathan. *PLOS ONE*, Under revision.