The Tail Rank Test

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1 Introduction

OOMPA is a suite of object-oriented tools for processing and analyzing large biological data sets, such as those arising from mRNA expression microarrays or mass spectrometry proteomics.

This vignette documents the tail rank test, which provides an alternative method for discovering potential biomarkers in large data sets. The idea is that one starts with a target specificity for a gene as a univariate biomarker, and uses the "normal" or "baseline" samples to estimate a threshold that yields that specificity. Then, for each gene, one counts the number of "cancer" or "experimental" samples that exceed the gene-specific threshold. Significance is determined based on control of the family-wise error rate (FWER).

2 Getting Started

As usual, we start by loading the library.

```
> library(TailRank)
```

The *TailRank* package uses an auxiliary package to supply sample data that we can use to illustrate the methods. The sample data consists of a subset

containing 2000 genes from a prostate cancer study on glass arrays reported by Lapointe and colleagues [1]. The next set of commands loads the data.

```
> library(oompaData)
> data(expression.data)
> data(gene.info)
> data(clinical.info)
> dim(clinical.info)

[1] 112    6
```

There are 112 samples in the study. The `Subgroups` column of the `clinical.info` data frame refers to the subgroups discovered in the original publication by clustering based on the gene expression data. The `ChipType` column identifies the two different generations of glass arrays that were combined in the study. The `Status` column classifies the samples as normal prostate (N), primary prostate tumor (T), or lymph node metastasis (L). Since there is a natural order to this status in terms of the severity of the disease, we are going to make certain that it is used:

```
> clinical.info$Status <- ordered(clinical.info$Status,
+                                 levels=c("N", "T", "L"))
> summary(clinical.info)

     Arrays         Reference        Sample      Status Subgroups ChipType
 p16090 :  1   CRG1    :  1   PL114  :  1   N:41   I  :11    new:86
 p16093 :  1   CRG10   :  1   PL115  :  1   T:62   II :39    old:26
 p16095 :  1   CRG100  :  1   PL116  :  1   L: 9   III:19
 p16097 :  1   CRG101  :  1   PL118.3:  1          N  :41
 p16098 :  1   CRG102  :  1   PL122  :  1          O  : 2
 p16101 :  1   CRG103  :  1   PL129  :  1
 (Other):106   (Other):106   (Other):106
```

3 Performing the Tail Rank Test

The main function in the package is the `TailRankTest`. We start by invoking this function with the default values of the arguments. The summary includes details on the parameters that were used, along with the fact that 49 of the 2000 genes were more highly expressed in non-normal samples than would be expected by chance, based on a 5% FWER.

```
> trt <- TailRankTest(expression.data, clinical.info$Status) #$
> summary(trt)

A tail-rank test object in the up direction.
The test was performed using the bb model.
Specificity: 0.95 computed with tolerance 0.5
```

```
Significance cutoff: 24 based on a family-wise error rate less than 0.05
There are 49 tail-rank statistics that exceed the cutoff
```

In the next example, we increase both the target specificity (from the default of 95% to a desired value of 99%) and the desired confidence limits (to 99% from the default of 95%). With this more stringent criteria, only 25 of the genes remain significant.

```
> trt2 <- TailRankTest(expression.data, clinical.info$Status,
+                     specificity=0.99, confidence=0.99) #$
> summary(trt2)

A tail-rank test object in the up direction.
The test was performed using the bb model.
Specificity: 0.99 computed with tolerance 0.5
Significance cutoff: 19 based on a family-wise error rate less than 0.01
There are 25 tail-rank statistics that exceed the cutoff
```

3.1 Which genes are significant?

After performing an analysis that identifies a gene list like this, it is, of course, natural to want to know which genes were selected. The `as.logical` method converts the results of the tail rank test into a logical vector that selects these significant genes. Using this method, we can verify that the 25 genes selected by the more stringent criteria are a subset of the 49 genes selected using the weaker criteria.

```
> sel <- as.logical(trt)
> sel2 <- as.logical(trt2)
> sum(sel2 & sel)

[1] 25
```

Since this vector serves as index into the `gene.info` database, we can figure out which genes were actually selected.

```
> gene.info[sel2, 3:6]

          Clone.ID Gene.Symbol Cluster.ID Accession
X2180   IMAGE:506669    LOC170394  Hs.157728  AA708916
X23774  IMAGE:244350               Hs.484965    N54811
X5918    IMAGE:26883
X11386  IMAGE:302331          MYL4  Hs.356717  AI668645
X27346  IMAGE:376764          UTRN  Hs.250607  AA046146
X26538  IMAGE:364934         DAPK1  Hs.244318  AA024655
X17798  IMAGE:838829         PLU-1  Hs.143323  AA464869
X7405   IMAGE:814528      TP53INP1   Hs.75497  AA459364
X27228   IMAGE:47475        CYFIP2  Hs.211201    H12043
```

```
X40508   IMAGE:811582              Hs.459841   AA454597
X12648   IMAGE:809421     PCBD     Hs.3192     AA442959
X17040   IMAGE:258175              Hs.23754    N30900
X12642   IMAGE:788667     FAPP2    Hs.233495   AA449847
X39564   IMAGE:306806   FLJ31434   Hs.7988     N91900
X38876   IMAGE:609155     LRRN1    Hs.512663   AA176867
X181     IMAGE:854696    SIAHBP1   Hs.74562    AA630094
X32626   IMAGE:263846    PPP2R1B   Hs.431156   H99771
X13168   IMAGE:129865      STK6    Hs.250822   R11407
X31785   IMAGE:259374      MCCC2   Hs.167531   N31952
X13736  IMAGE:2012757     D2S448   Hs.118893   AI356709
X31836   IMAGE:141815      JAG1    Hs.409202   R70684
X33578   IMAGE:288663      GJB1    Hs.333303   N62394
X10735   IMAGE:882459      PPIC    Hs.110364   AA676404
X5726    IMAGE:447569      RNPC2   Hs.282901   AA702428
X12019   IMAGE:126415              Hs.133130   R06581
```

4   Power Computations

The power depends on the number of genes (G), the number of healthy samples (N1), the number of cancer samples (N2), the target specificity (psi), the confidence (conf = 1 - FWER), and the sensitivity that you want to be able to detect (phi). Here is an example using the sizes from the prostate cancer data set, showing that we have more than 70% power to detect a marker with 40% sensitivity.

```
> tailRankPower(2000, N1=41, N2=71, psi=0.95, phi=0.40, conf=0.95)
```

```
[1] 0.7135006
```

The next example shows that the power decreases to 43% when using the same number of samples with a whole genome array containing 40000 gene probes. (This was the size of the full study from which these 2000 genes were randomly selected.)

```
> tailRankPower(40000, N1=41, N2=71, psi=0.95, phi=0.40, conf=0.95)
```

```
[1] 0.4271892
```

We can determine the power for a variety of cancer sample sizes, keeping everything else the same

```
> tailRankPower(40000, N1=41, N2=seq(40,100,by=10),
+               psi=0.95, phi=0.40, conf=0.95)
```

```
[1] 0.2063922 0.3067931 0.3920020 0.4033145 0.4648195 0.4673351 0.5137604
```

More generally, we can create power tables using the `biomarkerPowerTable`
function. Individual tables have rows labeled by the number of "cancer" samples
and columns labeled by the desired sensitivity; the entries in the table show the
power to detect that level of sensitivity when using that many samples.

```
> biomarkerPowerTable(G=c(10000, 20000, 40000), N1=41,
+                      N2=seq(40, 100, by=10), conf=0.95,
+                      psi=0.95, phi=seq(0.30, 0.50, by=0.05))

[[1]]
An object of class "BMPT"
Slot "G":
[1] 10000

Slot "psi":
[1] 0.95

Slot "conf":
[1] 0.95

Slot "power":
            30         35        40        45        50
40  0.09033665 0.1991811 0.3571932 0.5409076 0.7144119
50  0.12613959 0.2663173 0.4525563 0.6462431 0.8062082
60  0.12068814 0.2640932 0.4577585 0.6584144 0.8203311
70  0.14804875 0.3129456 0.5212980 0.7202351 0.8659786
80  0.17247308 0.3543683 0.5716972 0.7654303 0.8962882
90  0.19413312 0.3895314 0.6121234 0.7992573 0.9171966
100 0.21332331 0.4195350 0.6449771 0.8251594 0.9321230


[[2]]
An object of class "BMPT"
Slot "G":
[1] 20000

Slot "psi":
[1] 0.95

Slot "conf":
[1] 0.95

Slot "power":
            30         35        40        45        50
40  0.05886264 0.1420590 0.2765896 0.4504793 0.6328099
50  0.09058714 0.2069445 0.3772638 0.5720731 0.7487870
```

```
60   0.12068814 0.2640932 0.4577585 0.6584144 0.8203311
70   0.11639120 0.2621789 0.4617095 0.6678071 0.8309751
80   0.14046885 0.3057095 0.5182606 0.7220098 0.8698565
90   0.16239855 0.3434290 0.5642925 0.7629450 0.8967688
100  0.15428558 0.3344203 0.5581562 0.7609404 0.8972354


[[3]]
An object of class "BMPT"
Slot "G":
[1] 40000

Slot "psi":
[1] 0.95

Slot "conf":
[1] 0.95

Slot "power":
               30          35         40         45         50
40   0.03682533 0.09740169 0.2063922 0.3628918 0.5449930
50   0.06324274 0.15651685 0.3067931 0.4956936 0.6837994
60   0.09038819 0.21232817 0.3920020 0.5948291 0.7729542
70   0.09001682 0.21627298 0.4033145 0.6121954 0.7908250
80   0.11292231 0.26053337 0.4648195 0.6752875 0.8392830
90   0.11006564 0.25911220 0.4673351 0.6813917 0.8459462
100  0.12947138 0.29490766 0.5137604 0.7248561 0.8757409
```

5   References

[1] Lapointe J et al. (2004) Gene expression profiling identifies clinically relevant subtypes of prostate cancer. *Proc Natl Acad Sci U S A*, 101, 811–816.