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 dicovering poitential 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 thegeen-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 comes with some 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.

```
> data(expression.data)
> data(gene.info)
> data(clinical.info)
```

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 certina that it is used:

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

```
[1] 112   6
```

```
> 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 tial rnak test into a logival 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 inindex 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 = 0.4,
+     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 = 0.4,
+     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 = 0.4, conf = 0.95)
```

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

More genrally, we can create power tables:

```
> biomarkerPowerTable(G = c(10000, 20000, 40000), N1 = 41, N2 = seq(40,
+     100, by = 10), psi = 0.95, conf = 0.95, phi = seq(0.3, 0.5,
+     by = 0.05))

[[1]]
An object of class âĂIJBMPTâĂ
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 âĂIJBMPTâĂ
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 âĂIJBMPTâĂ
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.