Object Oriented Microarray and Proteomics Analysis (OOMPA)

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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 base package, *oompaBase*. A reitical (but invisible to the user) feature of the *oompaBase* package is that it defines a **class** union allowing you to use "numeric" or "NULL" objects in the design of an S4 class. More intersting user-visibel features include alternative color schemes and vectorized matrix operations to speed the computation of row-by-row mweans, variances, and t-tests.

2 Getting Started

You invoke the package in the usual way:

> library(oompaBase)

3 Color Schemes

To illustrate the various color schemes, we first create a structured matrix:

```
> mat <- matrix(1:1024, ncol = 1)
The following code is used to generate Figure 1.
> opar <- par(mfrow = c(5, 1), mai = c(0.3, 0.5, 0.2, 0.2))
> image(mat, col = redgreen(64), main = "redgreen")
> image(mat, col = jetColors(128), main = "jetColors")
> image(mat, col = blueyellow(32), main = "blueyellow")
> image(mat, col = redscale(64), main = "redscale")
> image(mat, col = bluescale(64), main = "bluescale")
> par(opar)
```

4 Row-by-row Matrix Operations

We now want to illustrate the "matrix operations" that allow for rapid computation of row-by-row means, variances, and t-tests.

We start by creating a slightly more interesting matrix full of random data. First, we make the variance larger in the second half (by column) of the data than in the first half.

```
> ng <- 10000
> ns <- 50
> dat <- matrix(rnorm(ng * ns, 0, rep(c(1, 2), each = 25)), ncol = ns,
      byrow = TRUE)
Next, we shift the mean for te first 500 "genes" (rows).
> dat[1:500, 1:25] <- dat[1:500, 1:25] + 2
In order to compute t-tests, we also assign arbitrary labels separating the "sam-
ple columns" into two groups.
> clas <- factor(rep(c("Good", "Bad"), each = 25))
   Here we compute the row-by-row means.
> a0 <- proc.time()
> myMean <- matrixMean(dat)</pre>
> used0 <- proc.time() - a0
For comparions purposes, we perfor the same computation using apply.
> a1 <- proc.time()
> mm <- apply(dat, 1, mean)</pre>
> used1 <- proc.time() - a1
The results are the same, to within round-off error.
> summary(as.vector(myMean - mm))
```

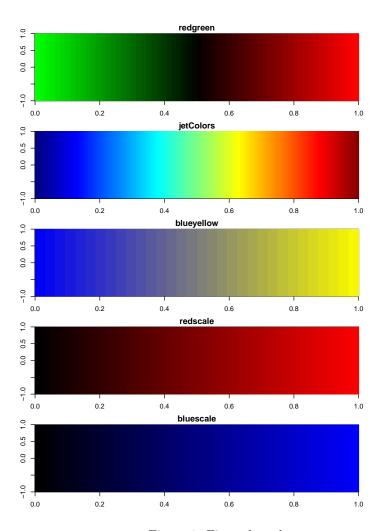


Figure 1: Five color schemes.

```
-1.110e-15 -2.776e-17 0.000e+00 -4.242e-19 2.776e-17 8.882e-16
There is a measurable (although not really user-perceptible) difference in the
time for the two methods.
> used0
   user
         system elapsed
> used1
   user
         system elapsed
   0.20
           0.00
                    0.21
  Here we compute the variances using two different methods.
> a0 <- proc.time()
> myVar <- matrixVar(dat, myMean)</pre>
> a1 <- proc.time()
> vv <- apply(dat, 1, var)
> a2 <- proc.time()
Again, the values are the same:
> summary(as.vector(myVar - vv))
               1st Qu.
                            Median
                                          Mean
                                                   3rd Qu.
-4.441e-15 -4.441e-16 0.000e+00 8.882e-19 4.441e-16 3.997e-15
  However, the time savings is substantially larger.
> a1 - a0
   user system elapsed
> a2 - a1
   user system elapsed
   0.41
           0.00
                    0.41
  Not surprisingly, there is an even bigger time savings when computing (equal
variance) t-statistics.
> t0 <- proc.time()
> myT <- matrixT(dat, clas)</pre>
> t1 <- proc.time()
> tt <- sapply(1:nrow(dat), function(i) {</pre>
      t.test(dat[i, clas == "Bad"], dat[i, clas == "Good"], var.equal = T)$statistic
+ })
```

Mean

3rd Qu.

Max.

Min.

> t2 <- proc.time()

1st Qu.

Median

> summary(as.vector(tt - myT))

> t1 - t0

user system elapsed 0.01 0.02 0.03

> t2 - t1

user system elapsed 4.62 0.00 4.62