Timing Rayleigh Quotient minimization in R

by John C. Nash

Abstract This vignette is simply to record the methods and results for timing various Rayleigh Quotient minimizations with R using different functions and different ways of running the computations, in particular trying Fortran subroutines and the R byte compiler. It has been updated from a 2012 document to reflect changes in R and its packages that make it awkward to reprocess the original document on newer computers.

The computational task

The maximal and minimal eigensolutions of a symmetric matrix A are extrema of the Rayleigh Quotient

$$R(x) = (x'Ax)/(x'x)$$

We could also deal with generalized eigenproblems of the form

$$Ax = eBx$$

where B is symmetric and positive definite by using the Rayleigh Quotient (RQ)

$$R_g(x) = (x'Ax)/(x'Bx)$$

In this document, *B* will always be an identity matrix, but some programs we test assume that it is present.

Note that the objective is scaled by the parameters, in fact by by their sum of squares. Alternatively, we may think of requiring the **normalized** eigensolution, which is given as

$$x_{normalized} = x/sqrt(x'x)$$

Timings and speedups

In R, execution times can be measured by the function system. time, and in particular the third element of the object this function returns. However, various factors influence computing times in a modern computational system, so we generally want to run replications of the times. The R packages **rbenchmark** and **microbenchmark** can be used for this. I have a preference for the latter. However, to keep the time to prepare this vignette with **Sweave** or **knitR** reasonable, many of the timings will be done with only system.time.

There are some ways to speed up R computations.

- The code can be modified to use more efficient language structures. We show some of these below, in particular, to use vector operations.
- We can use the R byte code compiler by Luke Tierney, which has been part of the R distribution since version 2.14.
- We can use compiled code in other languages. Here we show how Fortran subroutines can be used.

Our example matrix

We will use a matrix called the Moler matrix (Nash, 1979, Appendix 1). This is a positive definite symmetric matrix with one small eigenvalue. We will show a couple of examples of computing the small eigenvalue solution, but will mainly perform timings using the maximal eigenvalue solution, which we will find by minimizing the RQ of (-1) times the matrix. (The eigenvalue of this matrix is the negative of the maximal eigenvalue of the original, but the eigenvectors are equivalent to within a scaling factor for non-degenerate eigenvalues.)

Here is the code for generating the Moler matrix.

However, since R is more efficient with vectorized code, the following routine by Ravi Varadhan should do much better.

```
molerfast <- function(n) {
# A fast version of `molermat'
    A <- matrix(0, nrow = n, ncol = n)
    j <- 1:n
    for (i in 1:n) {
        A[i, 1:i] <- pmin(i, 1:i) - 2
    }
    A <- A + t(A)
    diag(A) <- 1:n
    A
}</pre>
```

Time to build the matrix

Let us see how long it takes to build the Moler matrix of different sizes. In 2012 we used the byte-code compiler, but that now seems to be active by default and NOT to give worthwhile improvements. We also include times for the eigen() function that computes the full set of eigensolutions very quickly.

#> Loading required package: microbenchmark

```
#>
                 osize eigentime bfast
       n buildi
                                  789
#> 1
         2869
                 20216
                           887
      50
           6077
                 80216
                            2061
                                   615
#> 2 100
#> 3 150 10268 180216
                            4191 1124
     200 16498 320216
                            5611 1358
#> 4
     250 25040 500216
#> 5
                            8564 1862
     300 35453 720216
#> 6
                           11370 2430
     350 47422 980216
                           14715 3029
#> 7
#> 8 400 60907 1280216
                           19330 3801
#> 9 450 79044 1620216
                           25121 4342
#> 10 500 93532 2000216
                           30489 7914
#> buildi - interpreted build time
#> osize - matrix size in bytes; eigentime - all eigensolutions time
#> bfast - interpreted vectorized build time
#> Times converted to milliseconds
```

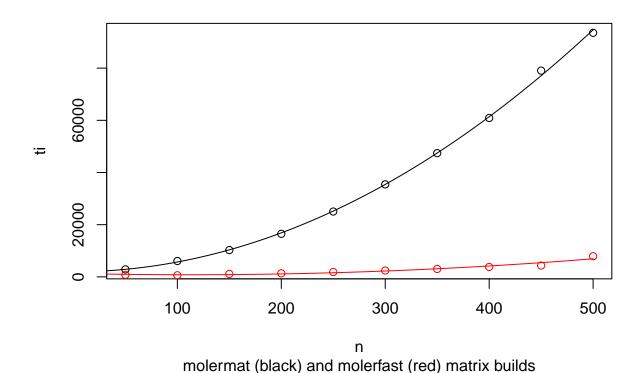
It does not appear that the compiler has much effect, or else it is being automatically invoked.

We can graph the times. The code, which is not echoed here, also models the times and the object size created as almost perfect quadratic models in n. However, the vectorized code is much, much faster, and the byte code compiler does not appear to help.

```
#>
#> Call:
#> lm(formula = ti ~ n + n2)
```

```
#>
#> Residuals:
#>
       Min
                 1Q
                      Median
                                    3Q
                                            Max
#> -1161.39 -325.49
                      -72.59
                                16.32 1937.35
#>
#> Coefficients:
#>
               Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 1.919e+03 1.056e+03
                                    1.818
              8.919e-01 8.818e+00 0.101
              3.693e-01 1.562e-02 23.637 6.16e-08 ***
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 897.6 on 7 degrees of freedom
#> Multiple R-squared: 0.9994, Adjusted R-squared: 0.9992
#> F-statistic: 5607 on 2 and 7 DF, p-value: 6.063e-12
#> Call:
\# lm(formula = tf ~ n + n2)
#>
#> Residuals:
#>
       Min
                 1Q
                      Median
                                    3Q
                                            Max
#> -1107.88 -197.61
                       54.16
                                         988.21
                                250.24
#>
#> Coefficients:
#>
                Estimate Std. Error t value Pr(>|t|)
#> (Intercept) 1326.82833 725.00458
                                     1.830 0.10993
                                    -1.513 0.17404
#> n
                 -9.16263
                             6.05585
#> n2
                 0.04072
                             0.01073
                                     3.795 0.00676 **
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 616.4 on 7 degrees of freedom
#> Multiple R-squared: 0.9399, Adjusted R-squared: 0.9227
#> F-statistic: 54.73 on 2 and 7 DF, p-value: 5.324e-05
```

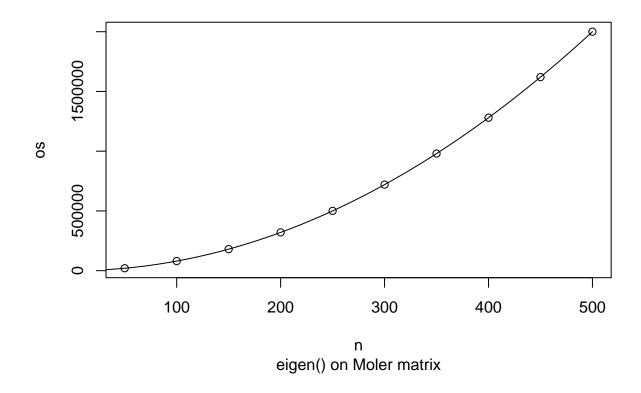
Execution time vs matrix size



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```
#> Warning in summary.lm(osize): essentially perfect fit: summary may be
#> unreliable
#>
#> Call:
\# lm(formula = os ~ n + n2)
#>
#> Residuals:
#>
                     1Q
                            Median
                                                      Max
         Min
#> -2.654e-12 -1.314e-13 3.293e-13 7.262e-13 1.211e-12
#>
#> Coefficients:
#>
               Estimate Std. Error
                                     t value Pr(>|t|)
#> (Intercept) 2.160e+02 1.617e-12 1.336e+14 < 2e-16 ***
#> n
              5.127e-13 1.351e-14 3.795e+01 2.29e-09 ***
#> n2
              8.000e+00 2.394e-17 3.342e+17 < 2e-16 ***
#> ---
#> Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Residual standard error: 1.375e-12 on 7 degrees of freedom
                          1, Adjusted R-squared:
#> Multiple R-squared:
#> F-statistic: 1.112e+36 on 2 and 7 DF, p-value: < 2.2e-16
```

Execution time vs matrix size



Computing the Rayleigh Quotient

The Rayleigh Quotient requires the quadratic form x'Ax divided by the inner product x'x. R lets us form this in several ways.

```
rqdir<-function(x, AA){
  rq<-0.0
  n<-length(x) # assume x, AA conformable
  for (i in 1:n) {
    for (j in 1:n) {
      rq<-rq+x[i]*AA[[i,j]]*x[j] # Note - sign
  }</pre>
```

```
}
rq
}
Somewhat better (as we shall show below) is

ray1<-function(x, AA){
   rq<- t(x)%*%AA%*%x
}
and (believed) better still is

ray2<-function(x, AA){
   rq<- as.numeric(crossprod(x, crossprod(AA,x)))
}</pre>
```

Note that we could implicitly include the minus sign in these routines to allow for finding the maximal eigenvalue by minimizing the Rayleigh Quotient of -A. However, such shortcuts often rebound when the implicit negation is overlooked.

If we already have the inner product $A \times a$ as vector ax from some other computation, then we can simply use

```
ray3<-function(x, AA, ax=axftn){
    # ax is a function to form AA%*%x
    rq<- - as.numeric(crossprod(x, ax(x, AA)))
}</pre>
```

1 References

Bibliography

J. C. Nash. *Compact Numerical Methods for Computers: Linear Algebra and Function Minimisation*. Adam Hilger, Bristol, 1979. Second Edition, 1990, Bristol: Institute of Physics Publications. [p1]

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