Robust Regression with Particle Swarm Optimisation and Differential Evolution

Enrico Schumann
es@enricoschumann.net

1   Introduction

We provide a code example for a robust regression problem; for more details, please see Gilli et al. [2011]. (The vignette builds on the script `comparisonLMS.R`.)

2   Data and settings

We start by attaching the NMOF package and fixing a seed. We will use the function `lqs` from the MASS package [Venables and Ripley, 2002], so we attach that package as well.

```
> require("NMOF")
> require("MASS")
> set.seed(11223344)
```

We will use an artificial data set with n observations and p regressors, created with the function `createData`.

```
> createData <- function(n, p, constant = TRUE,
                         sigma = 2, oFrac = 0.1) {
    X <- array(rnorm(n * p), dim = c(n, p))
    if (constant)
        X[ ,1L] <- 1L
    b <- rnorm(p)
    y <- X %*% b + rnorm(n)*0.5
    n0 <- ceiling(oFrac*n)
    when <- sample.int(n, n0)
    X[when, -1L] <- X[when, -1L] + rnorm(n0, sd = sigma)
    list(X = X, y = y, outliers = when)
 }
```

The function also takes arguments `constant` (logical: should the data-generating model contain a constant?); `sigma` (standard deviation of the outliers); and `oFrac` (fraction of outliers). The function evaluates to a list containing the regressors X, the regressand y and a list of the outliers.

We put X and y into the list `Data`. We also add the scalar h, which gives the order statistic of the squared residuals to be minimised. Note that we put `as.vector(y)` into `Data` so that the vector gets 'recycled' in the objective function.

```
> n <- 100L    ## number of observations
> p <- 10L     ## number of regressors
> constant <- TRUE; sigma <- 5; oFrac  <- 0.1
> h <- 75L     ## ... or use something like floor((n+1)/2)
> aux <- createData(n, p, constant, sigma, oFrac)
> X <- aux$X; y <- aux$y
> Data <- list(y = as.vector(y), X = X, h = h)
```

The outliers, added in blue, are often visible.

```
> par(bty = "n", las = 1, tck = 0.01, mar = c(4,4,1,1))
> plot(X[ ,2L], type = "h", ylab = "X values", xlab = "observation")
> lines(aux$outliers, X[aux$outliers ,2L], type = "p", pch = 21,
        col = "blue", bg = "blue")
```
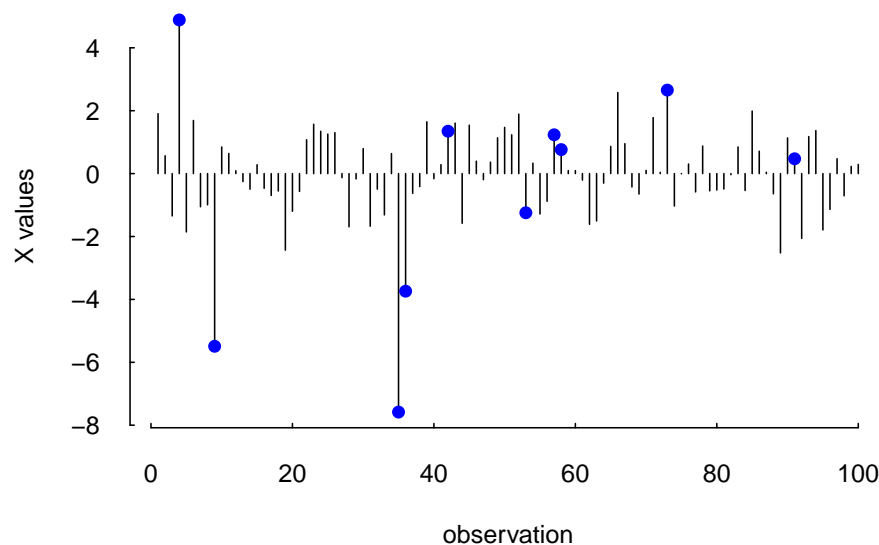
Two example objective functions, Least Trimmed Squares (LTS) and Least Quantile of Squares (LQS). Note that they are identical except for their last line.

```
> OF <- function(param, Data) {
     X <- Data$X; y <- Data$y
     aux <- y - X %*% param
     aux <- aux * aux
     aux <- apply(aux, 2L, sort, partial = Data$h)
     colSums(aux[1:Data$h, ])  ## LTS
 }
> OF <- function(param, Data) {
     X <- Data$X; y <- Data$y
     aux <- y - X %*% param
     aux <- aux * aux
     aux <- apply(aux, 2L, sort, partial = Data$h)
     aux[Data$h, ]  ## LQS
 }
```

Both functions are vectorised. They work with a single solution (`param` would be a vector) or a whole population (`param` would be a matrix; each column would be one solution).

3 Using DE and PSO

We run DE and PSO. We compare the result with `lqs`.

```
> popsize <- 100L; generations <- 500L
> ps <- list(min = rep(-10,p),
             max = rep( 10,p),
             c1 = 0.9,
             c2 = 0.9,
             iner = 0.9,
             initV = 1,
             nP = popsize,
             nG = generations,
             maxV = 5,
             loopOF = FALSE,
             printBar = FALSE,
             printDetail = FALSE)
> de <- list(min = rep(-10,p),
             max = rep( 10,p),
             nP = popsize,
```

2

```
                nG = generations,
                F = 0.7,
                CR = 0.9,
                loopOF = FALSE,
                printBar = FALSE,
                printDetail = FALSE)
> system.time(solPS <- PSopt(OF = OF, algo = ps, Data = Data))
```

```
   user  system elapsed
  1.108   0.008   1.113
```

```
> system.time(solDE <- DEopt(OF = OF, algo = de, Data = Data))
```

```
   user  system elapsed
  1.088   0.000   1.085
```

```
> if (require("MASS", quietly = TRUE)) {
      system.time(test1 <- lqs(y ~ X[ ,-1L], adjust = TRUE,
                               nsamp = 100000L, method = "lqs",
                               quantile = h))
      res1 <- sort((y - X %*% as.matrix(coef(test1)))^2)[h]
 } else
      res1 <- NA
> res2 <- sort((y - X %*% as.matrix(solPS$xbest))^2)[h]
> res3 <- sort((y - X %*% as.matrix(solDE$xbest))^2)[h]
> cat("lqs:   ", res1, "\n",
      "PSopt: ", res2, "\n",
      "DEopt: ", res3, "\n", sep = "")
```

```
lqs:   0.38073
PSopt: 0.25895
DEopt: 0.28958
```

To demonstrate the advantage of a vectorised objective function, we can compare it with looping over the solutions. We first set `loopOF` to TRUE, so we actually loop over the solutions. (We also reduce the number of objective function evaluations since we do not care about the actual solution, only about speed of computation.)

```
> popsize <- 100L; generations <- 20L
> de$nP <- popsize; de$nG <- generations
> ps$nP <- popsize; ps$nG <- generations
> de$loopOF <- TRUE; ps$loopOF <- TRUE
> t1ps <- system.time(solPS <- PSopt(OF = OF, algo = ps, Data = Data))
> t1de <- system.time(solDE <- DEopt(OF = OF, algo = de, Data = Data))
```

To evaluate the objective function in one step, we `loopOF` to FALSE.

```
> de$loopOF <- FALSE; ps$loopOF <- FALSE
> t2ps <- system.time(solPS <- PSopt(OF = OF, algo = ps, Data = Data))
> t2de <- system.time(solDE <- DEopt(OF = OF, algo = de, Data = Data))
```

Speedup:

```
> t1ps[[3L]]/t2ps[[3L]]   ## PS
```

```
[1] 4.1136
```

```
> t1de[[3L]]/t2de[[3L]]   ## DE
```

```
[1] 2.5349
```

References

Manfred Gilli, Dietmar Maringer, and Enrico Schumann. *Numerical Methods and Optimization in Finance*. Elsevier, 2011.

William N. Venables and Brian D. Ripley. *Modern Applied Statistics with S*. Springer, 4th edition, 2002. URL `http://www.stats.ox.ac.uk/pub/MASS4`.