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2025-04-07

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#### 0.1 Load libraries

R package mt is used to plot PCA, PLS and LDA plots to assess performance of signal correction implemented in R package qcrlscR. R package tityverse fulfils some data crunch operations and tictoc records the running time, especially for the optimisation of LOESS. All of these packages are available in the CRAN package repository.

```
pkgs <- c("qcrlscR", "mt", "tidyverse", "tictoc")
## install.packages(pkgs)
invisible(lapply(pkgs, library, character.only = TRUE))</pre>
```

#### 0.2 Read data

The data man\_qc in package qcrlscR is a list of two data frames, data and meta.

```
names(man_qc)
#> [1] "data" "meta"
t(sapply(man_qc, dim))
#> [,1] [,2]
#> data 462 656
#> meta 462 2
```

Get meta and data matrix:

```
meta <- man_qc$meta

data <- man_qc$data %>%
  mutate_if(is.character, as.numeric)
```

Extract group information of batch and sample types from meta:

#### 0.3 Missing value filter

Before signal correction, the data should be checked based on the missing values rate and filtered if the rate is higher than the threshold, such as 20%.

Check missing value rates:

```
tail(sort(mv.perc(data)), 20)

#> V1986  V562  V2098  V1602  V348  V1902  V975  V2017  V2020  V163  V1021  V1676  V1540

#> 0.156  0.158  0.160  0.162  0.165  0.167  0.169  0.169  0.169  0.171  0.171  0.171  0.173

#> V1321  V1935  V1079  V610  V1691  V2077  V926

#> 0.182  0.182  0.190  0.197  0.197  0.199
```

Filter data matrix based on missing values rate:

```
filter_qc <- FALSE  # filter on qc missing values or all missing values
thres <- 0.15  # threshold for filtering

if (filter_qc) {  # filter using all missing values
  ret <- mv.filter(data, thres = thres)
} else {  # filter using qc missing values
  ret <- mv.filter.qc(data, cls.qc, thres = thres)
}</pre>
```

Update data matrix after filtering:

```
dat <- ret$dat
```

Missing value imputation is not required in qcrlscR but visualisation of a data matrix, like PCA and LDA plots, does not allow the missing values. Here the missing value filling is used to data screening before and after signal correction.

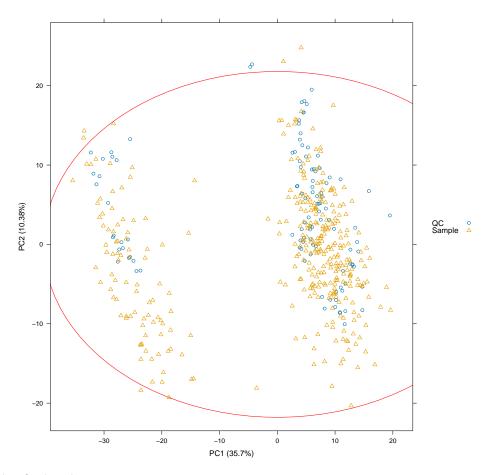
mv.fill in R package mt is used here for missing value imputation. It should be noted that there are a lot of R package available for such purpose in CRAN repository.

```
dat_fill <- dat %>% mv.fill(method = "median", ze_ne = T) %>% as_tibble()
```

Two categories methods, unsupervised method, PCA, and supervised methods, PLS and PCA-LDA, are used for data screening before and after signal correction.

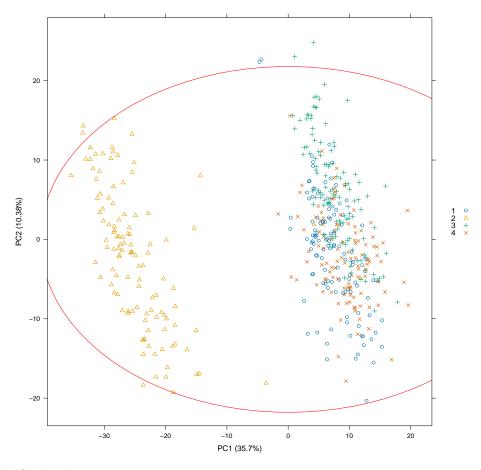
PCA plot for sample types:

```
pcaplot(dat_fill, cls.qc, pcs = c(2, 1), ep = 1)
```



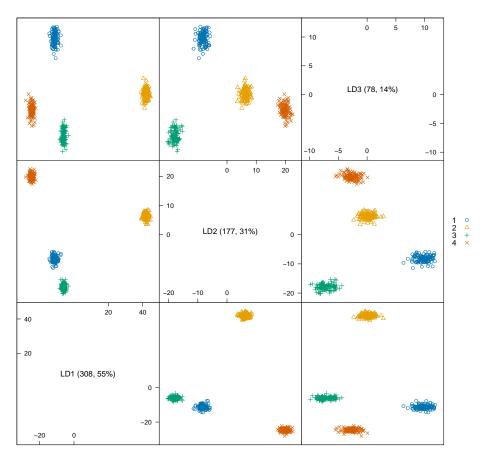
## PCA plot for batches:

 $pcaplot(dat_fill, cls.bl, pcs = c(2, 1), ep = 1)$ 



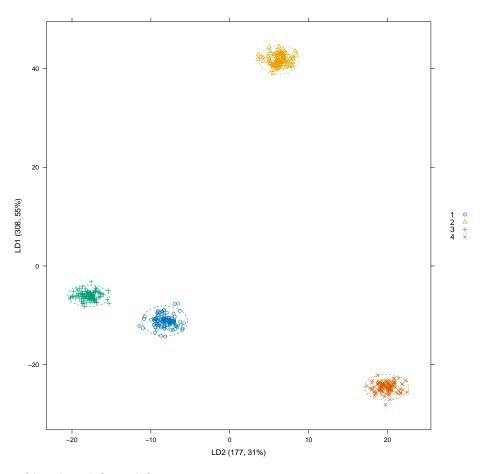
LDA plot for batches:

plot(pcalda(dat\_fill, cls.bl))



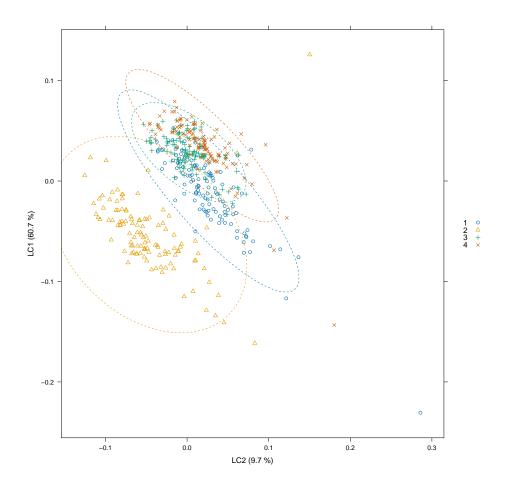
LDA plot of batches: LD1 vs LD2 (only for batch groups larger than 2)

plot(pcalda(dat\_fill, cls.bl), dimen = c(1:2), ep = 2)



PLS plot of batches: LC1 vs LC2

 $plot(plslda(dat_fill, cls.bl), dimen = c(1:2), ep = 2)$ 



# 0.4 Set parameters for QC-RLSC

Some parameters for signal correction:

```
log10 <- T  # log 10 transform data or not
outl <- T  # outlier detect in qc samples or not
intra <- F  # signal correction within batch or not
method <- "subtract" # two methods: "subtract", "divide"
opti <- T  # optimise smooth parameter or not
shift <- T  # batch shift or not</pre>
```

## 0.5 Logarithmic transformation

Log transformation or not:

```
if (log10) {
   dat[dat == 0] <- NA
   dat <- log10(dat)
}</pre>
```

#### 0.6 QC outlier detection

Outlier detection based on QC or not:

```
if (outl) {
    dat \leftarrow sapply(dat, function(x) \{ \#' x \leftarrow dat[, 6, drop = T] \}
        qc_ind <- grepl("qc", cls.qc, ignore.case = TRUE, perl = TRUE)</pre>
       ## get median of qc data
       qc_dat <- x[qc_ind]
        qc_median <- median(qc_dat, na.rm = TRUE)</pre>
        ## assign other data as NA for QC outlier detection
       tmp <- x
       tmp[!qc_ind] <- NA</pre>
       ## QC outlier detection
       out_ind <- outl.det.u(tmp)</pre>
       ## assign outlier as gc median
       x[out_ind] <- qc_median
        return(x)
    }) %>% as_tibble()
}
dat
#> # A tibble: 462 x 620
                                                                                          V25
                         V18 V19
                                                 V20
                                                                 V22
                                                                             V23
                                                                                                      V26
                                                                                                                   V31
                                                                                                                               V33
                                                                                                                                            V34
                                                                                                                                                                     V45
                                                                                                                                                        V39
            <dbl> 
      1 5.94 NA
                                  NA
                                                NA
                                                             NA
                                                                         NA
                                                                                      NA
                                                                                                  NA
                                                                                                               NA
                                                                                                                           NA
                                                                                                                                        NA
                                                                                                                                                                   5.54
      2 6.08 5.74 8.18 5.66 4.97 7.46 4.74 7.28
                                                                                                               4.88
                                                                                                                           6.59 6.88 6.36
      3 5.96 5.70 8.15 5.62 4.96 7.47 NA
                                                                                                     7,28
                                                                                                                4.87
                                                                                                                             6,64
                                                                                                                                         6,90
#> 4 6.04 5.69 8.12 5.60 4.98 7.48 4.75 7.29 4.89 6.61 6.91 6.39
                                                                                                                                                                  5.78
#> 5 5.99 5.68 8.14 5.61 4.92 7.45 4.71 7.27 4.72 6.57 6.91 6.39
                                                                                                                                                                5.75
#> 6 6.04 5.67 8.13 5.60 4.95 7.47 4.74 7.28 4.75 6.56 6.92 6.41 5.76
#> 7 6.05 5.68 8.13 5.60 4.99 7.47 4.75 7.28 4.78 6.56 6.91 6.37 5.76
#> 8 5.95 5.65 8.09 5.57 4.96 7.46 4.73 7.28 4.71 6.56 6.93 6.40 5.73
     9 5.97 5.63 8.10 5.57 4.95 7.47 NA
                                                                                                     7.28 4.93 6.61 6.90 6.37 5.75
#> 10 6.02 5.61 8.08 5.54 4.98 7.47 4.73 7.29 4.97 6.65 6.91 6.39 5.76
#> # i 452 more rows
#> # i 607 more variables: V48 <dbl>, V51 <dbl>, V66 <dbl>, V68 <dbl>, V71 <dbl>,
             V72 <dbl>, V73 <dbl>, V74 <dbl>, V104 <dbl>, V106 <dbl>, V112 <dbl>,
             V115 <dbl>, V116 <dbl>, V121 <dbl>, V122 <dbl>, V123 <dbl>, V124 <dbl>,
             V125 <dbl>, V126 <dbl>, V128 <dbl>, V134 <dbl>, V138 <dbl>, V140 <dbl>,
#> #
             V142 <dbl>, V147 <dbl>, V149 <dbl>, V157 <dbl>, V158 <dbl>, V159 <dbl>,
              V160 <dbl>, V162 <dbl>, V164 <dbl>, V167 <dbl>, V169 <dbl>, V171 <dbl>, ...
```

User can outlier detection methods provided by other R packages. Here qcrlscR only implements a simple univariate method, and detected outliers are replaced with the median values of QC data points.

#### 0.7 QC-RLSC

Perform qc-rlsc within each batch or not (intra batch or inter batch):

```
tic()
if (!intra) {
    res <- qc.rlsc(dat, cls.qc, method = method, opti = opti)
} else { # do signal correction inside each batch
    res <- lapply(levels(cls.bl), function(x) {
        idx <- cls.bl %in% x
        tmp <- qc.rlsc(dat[idx,], cls.qc[idx], method = method, opti = opti)
    })
    res <- bind_rows(res)
}
toc()
#> 15.87 sec elapsed
```

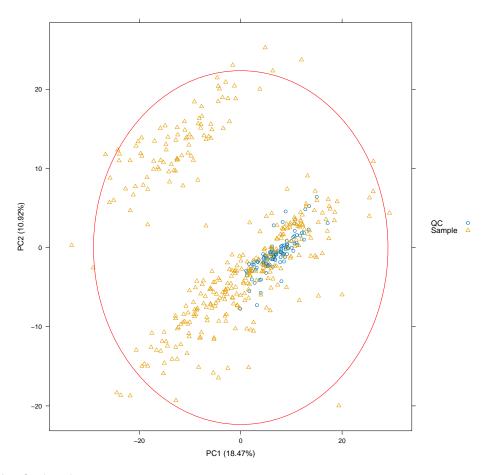
qcrlscR can optimise smoothing span in a range of 0.05 and 0.95, controlled by a binary option opti in function qc.rlsc and qc.rlsc.wrap.

Data visualisation after signal correction:

```
res_fill <- res %>% mv.fill(method = "median", ze_ne = T) %>% as_tibble()
```

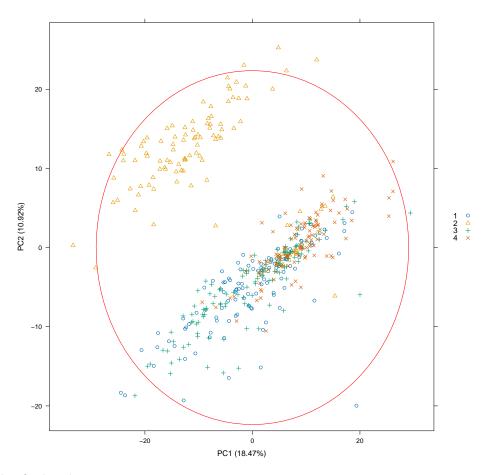
PCA plot for sample types:

```
pcaplot(res_fill, cls.qc, pcs = c(2, 1), ep = 1)
```



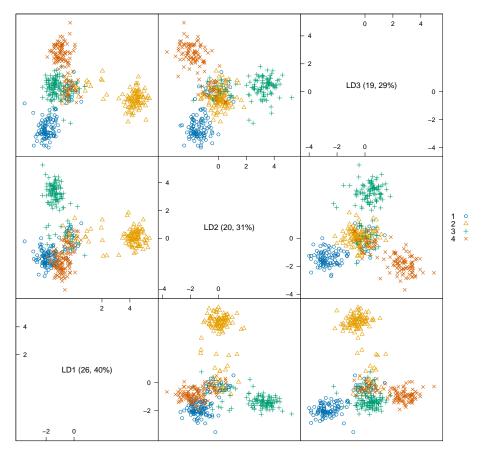
## PCA plot for batches:

 $pcaplot(res_fill, cls.bl, pcs = c(2, 1), ep = 1)$ 



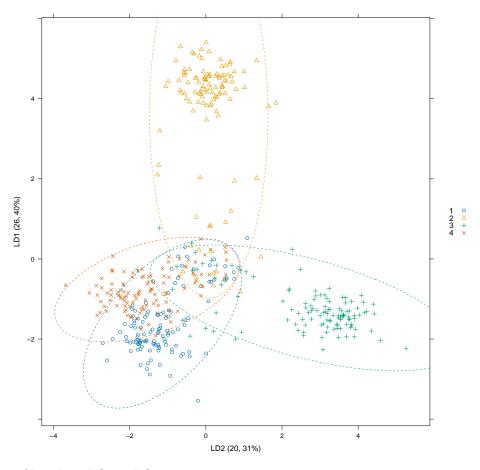
LDA plot for batches:

plot(pcalda(res\_fill, cls.bl))



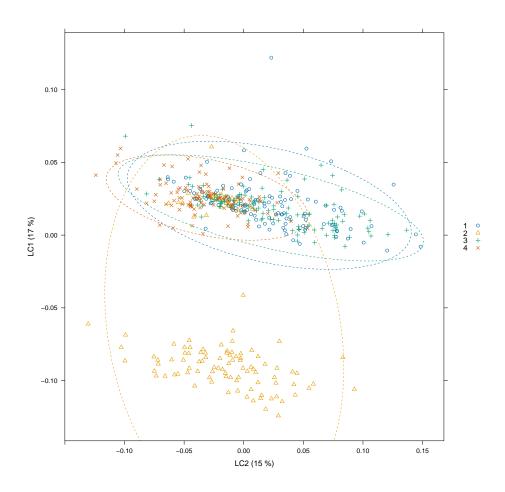
LDA plot of batches: LD1 vs LD2 (only for batch groups larger than 2)

 $plot(pcalda(res_fill, cls.bl), dimen = c(1:2), ep = 2)$ 



PLS plot of batches: LC1 vs LC2

 $plot(plslda(res_fill, cls.bl), dimen = c(1:2), ep = 2)$ 



#### 0.8 Batch shift

If the batch effects are still in the data set, a straightforward batch shifting method can be applied:

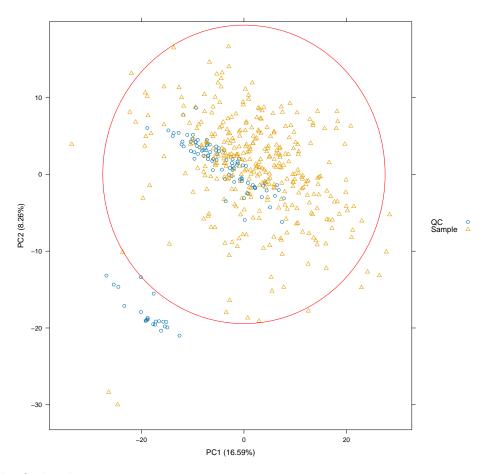
```
if (shift) {
   res <- batch.shift(res, cls.bl, overall_average = T) %>% as_tibble()
}
```

Data visualisation after batch shift:

```
res_fill <- res %>% mv.fill(method = "median", ze_ne = T) %>% as_tibble()
```

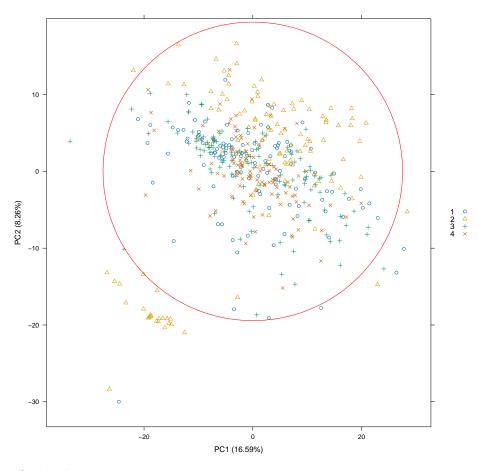
PCA plot for sample types:

```
pcaplot(res_fill, cls.qc, pcs = c(2, 1), ep = 1)
```



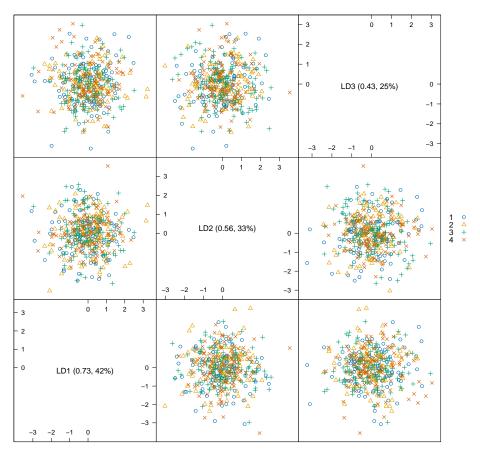
## PCA plot for batches:

 $pcaplot(res_fill, cls.bl, pcs = c(2, 1), ep = 1)$ 



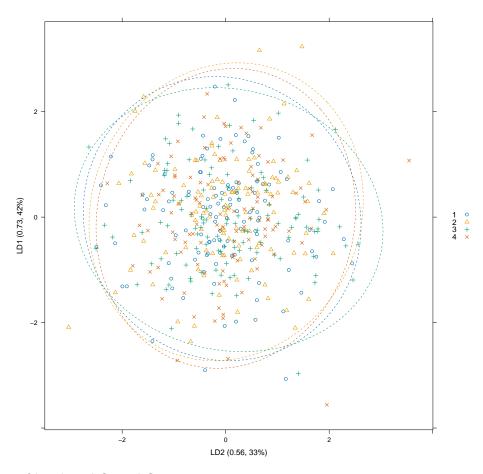
LDA plot for batches:

plot(pcalda(res\_fill, cls.bl))



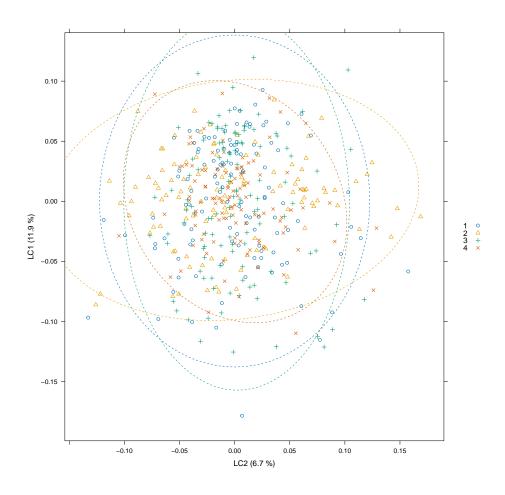
LDA plot of batches: LD1 vs LD2 (only for batch groups larger than 2)

 $plot(pcalda(res_fill, cls.bl), dimen = c(1:2), ep = 2)$ 



PLS plot of batches: LC1 vs LC2

 $plot(plslda(res_fill, cls.bl), dimen = c(1:2), ep = 2)$ 



## 0.9 Save results

Inverse log10 transformation:

# 0.10 QC-RLSC wrapper function

User can use wrapper function qc.rlsc.wrap directly with options of intra or inter batch signal correction, optimisation of span, log transformation and batch shifting.

```
res <- qc.rlsc.wrap(dat, cls.qc, cls.bl, method, intra, opti, log10, outl,
shift) tmp <- list(data = res, meta = meta)
```