immunoClust - Automated Pipeline for Population Detection in Flow Cytometry

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Contents

1 Licensing

Under the Artistic License, you are free to use and redistribute this software. However, we ask you to cite the following paper if you use this software for publication.

> Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T.
>
> immunoClust - an automated analysis pipeline for the identification of
>
> immunophenotypic signatures in high-dimensional cytometric datasets.
>
> *Cytometry A* (accepted).

2 Overview

immunoClust presents an automated analysis pipeline for uncompensated fluorescence and mass cytometry data and consists of two parts. First, cell events of each sample are grouped into individual clusters (cell-clustering). Subsequently, a classification algorithm assorts these cell event clusters into populations comparable between different samples (meta-clustering). The clustering of cell events is designed for datasets with large event counts in high dimensions as a global unsupervised method, sensitive to identify rare cell types even when next to large populations. Both parts use model-based clustering with an iterative Expectation Maximization (EM) algorithm and the Integrated Classification Likelihood (ICL) to obtain the clusters.

The cell-clustering process fits a mixture model with t-distributions. Within the clustering process a optimisation of the $asinh$-transformation for the fluorescence parameters is included.

The meta-clustering fits a Gaussian mixture model for the meta-clusters, where adjusted Bhattacharyya-Coefficients give the probability measures between cell- and meta-clusters.

Several plotting routines are available visualising the results of the cell- and meta-clustering process. Additional helper-routines to extract population features are provided.

3 Getting started

The installation on *immunoClust* is normally done within the Bioconductor.

The core functions of *immunoClust* are implemented in C/C++ for optimal utilization of system resources and depend on the GNU Scientific Library (GSL) and Basic Linear Subprogram (BLAS). When installing *immunoClust* form source using Rtools be aware to adjust the GSL library and include pathes in src/Makevars.in or src/Makevars.win (on Windows systems) repectively to the correct installation directory of the GSL-library on the system.

immunoClust relies on the *flowFrame* structure imported from the *flowCore*-package for accessing the measured cell events from a flow cytometer device.

4 Example Illustrating the immunoClust Pipeline

The functionality of the immunoClust pipeline is demonstrated on a dataset of blood cell samples of defined composition that were depleted of particular cell subsets by magnetic cell sorting. Whole blood leukocytes taken from three healthy individuals, which were experimen-

tally modified by the depletion of one particular cell type per sample, including granulocytes (using CD15-MACS-beads), monocytes (using CD14-MACS-beads), T lymphocytes (CD3-MACS-beads), T helper lymphocytes (using CD4-MACS-beads) and B lymphocytes (using CD19-MACS-beads).

The example datasets contain reduced (10.000 cell-events) of the first Flow Cytometry (FC) sample in `dat.fcs` and the *immunoClust* cell-clustering results of all 5 reduced FC samples for the first donor in `dat.exp`. The full sized dataset is published and available under http://flowrepository.org/id/FR-FCM-ZZWB.

4.1 Cell Event Clustering

```
> library(immunoClust)
```

The cell-clustering is performed by the `cell.process` function for each FC sample separately. Its major input are the measured cell-events in a *flowFrame*-object imported from the *flowCore*-package.

```
> data(dat.fcs)
> dat.fcs

flowFrame object '2d36b4cf-da0f-4b8d-9a4c-fc7e4f5fccc8'
with 10000 cells and 7 observables:
               name        desc     range  minRange  maxRange
$P2           FSC-A          NA    262144      0.00    262143
$P5           SSC-A          NA    262144   -111.00    262143
$P8          FITC-A        CD14    262144   -111.00    262143
$P9            PE-A        CD19    262144   -111.00    262143
$P12          APC-A        CD15    262144   -111.00    262143
$P13      APC-Cy7-A         CD4    262144   -111.00    262143
$P14 Pacific Blue-A         CD3    262144    -98.94    262143
171 keywords are stored in the 'description' slot
```

In the `parameters` argument the parameters (named as observables in the `flowFrame`) used for cell-clustering are specified. When omitted all determined parameters are used.

```
> pars=c("FSC-A","SSC-A","FITC-A","PE-A","APC-A","APC-Cy7-A","Pacific Blue-A")
> res.fcs <- cell.process(dat.fcs, parameters=pars)
```

The `summary` method for an *immunoClust*-object gives an overview of the clustering results.

```
> summary(res.fcs)

** Experiment Information **
Experiment name: immunoClust Experiment
Data Filename:   fcs/12443.fcs
Parameters:   FSC-A SSC-A FITC-A PE-A APC-A APC-Cy7-A Pacific Blue-A
Description:  NA NA CD14 CD19 CD15 CD4 CD3

** Data Information **
Number of observations: 10000
Number of parameters:   7
Removed from above:    318 (3.18%)
```

```
Removed from below:    0 (0%)

** Transformation Information **
htrans-A:   0.000000 0.000000 0.010000 0.010000 0.010000 0.010000 0.010000
htrans-B:   0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
htrans-decade:   -1

** Clustering Summary **
ICL bias: 0.30
Number of clusters: 12
Cluster     Proportion  Observations
       1      0.637735          6166
       2      0.015563           149
       3      0.028538           281
       4      0.007352            70
       5      0.038037           374
       6      0.054989           529
       7      0.005142            50
       8      0.114699          1112
       9      0.040364           391
      10      0.033891           330
      11      0.016000           156
      12      0.007691            74

    Min.      0.005142            50
    Max.      0.637735          6166

** Information Criteria **
Log likelihood: -254108.5 -254253.5 -173093
BIC: -254108.5
ICL: -254253.5
```

With the `bias` argument of the `cell.process` function the number of clusters in the final model is controlled.

```
> res2 <- cell.process(dat.fcs, bias=0.25)
> summary(res2)

** Experiment Information **
Experiment name: immunoClust Experiment
Data Filename:   fcs/12443.fcs
Parameters:   FSC-A SSC-A FITC-A PE-A APC-A APC-Cy7-A Pacific Blue-A
Description:  NA NA CD14 CD19 CD15 CD4 CD3

** Data Information **
Number of observations: 10000
Number of parameters:   7
Removed from above:    318 (3.18%)
Removed from below:    0 (0%)

** Transformation Information **
htrans-A:   0.000000 0.000000 0.010000 0.010000 0.010000 0.010000 0.010000
```

```
htrans-B:   0.000000 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
htrans-decade:   -1

** Clustering Summary **
ICL bias: 0.25
Number of clusters: 20
Cluster     Proportion  Observations
       1      0.018608           177
       2      0.009199            84
       3      0.012425           128
       4      0.092283           905
       5      0.035910           353
       6      0.053868           517
       7      0.003634            34
       8      0.350505          3458
       9      0.027906           281
      10      0.285210          2679
      11      0.007287            70
      12      0.005148            50
      13      0.009470            92
      14      0.002119            20
      15      0.024918           230
      16      0.001518            15
      17      0.013363           133
      18      0.023565           226
      19      0.015736           156
      20      0.007328            74

    Min.      0.001518            15
    Max.      0.350505          3458

** Information Criteria **
Log likelihood: -253957.9 -255458.9 -172980.2
BIC: -253957.9
ICL: -255458.9
```

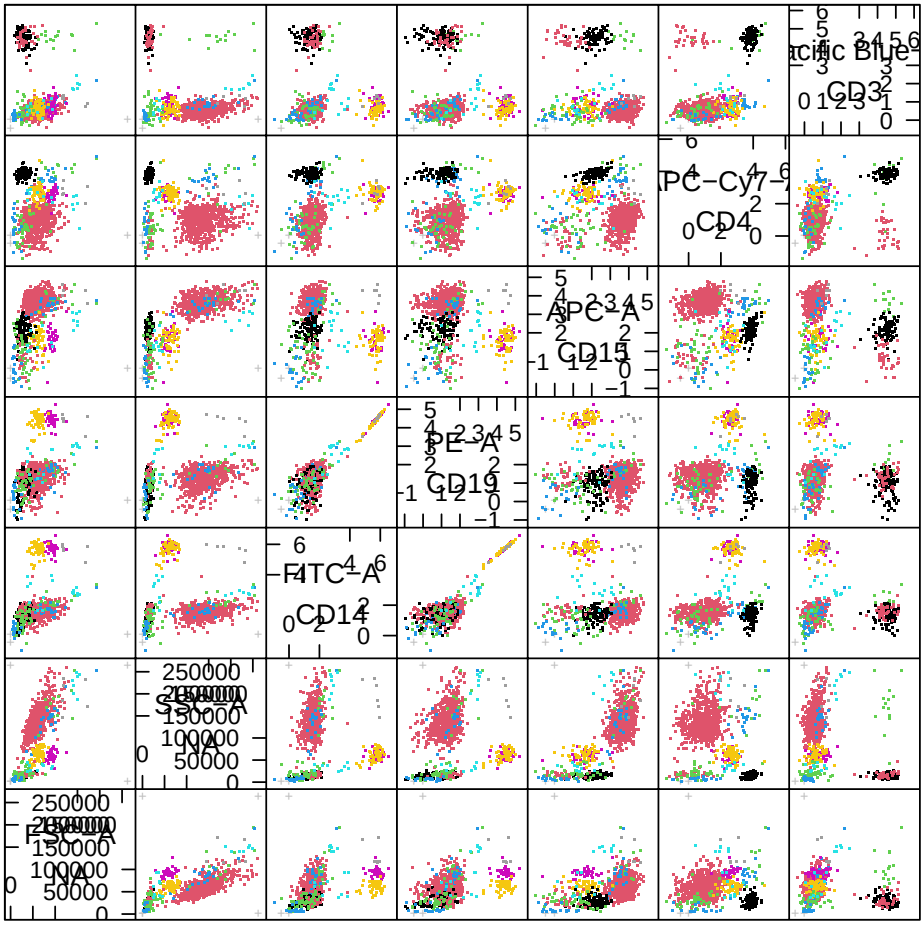
An ICL-bias of 0.3 is reasonable for fluorescence cytometry data based on our experiences, whereas the number of clusters increase dramatically when a `bias` below 0.2 is applied. A principal strategy for the ICL-bias in the whole pipeline is the use of a moderately small `bias` (0.2 - 0.3) for cell-clustering and to optimise the `bias` on meta-clustering level to retrieve the common populations across all samples.

For plotting the clustering results on cell event level, the optimised $asinh$-transformation has to be applied to the raw FC data first.

```
> dat.transformed <- trans.ApplyToData(res.fcs, dat.fcs)
```

A scatter plot matrix of all used parameters for clustering is obtained by the `splom` method.

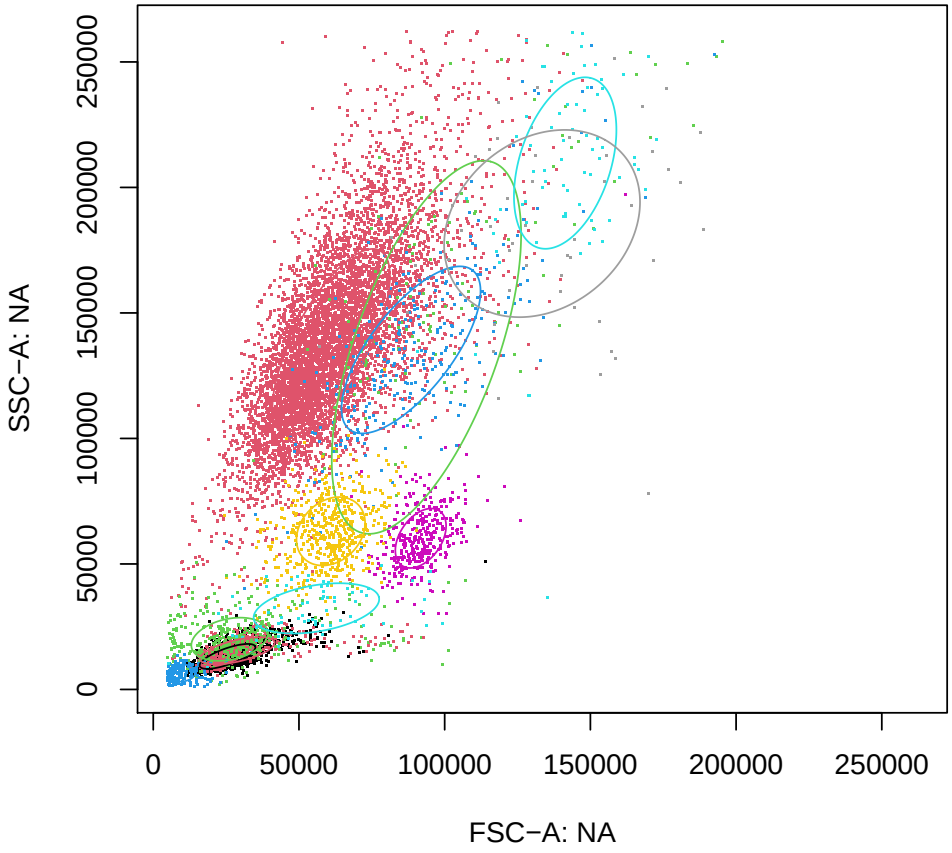
```
> splom(res.fcs, dat.transformed, N=1000)
```



Scatter Plot Matrix

For a scatter plot of 2 particular parameters the `plot` method can be used, where parameters of interest are specified in the `subset` argument.

```
> plot(res.fcs, data=dat.transformed, subset=c(1,2))
```



4.2 Meta Clustering

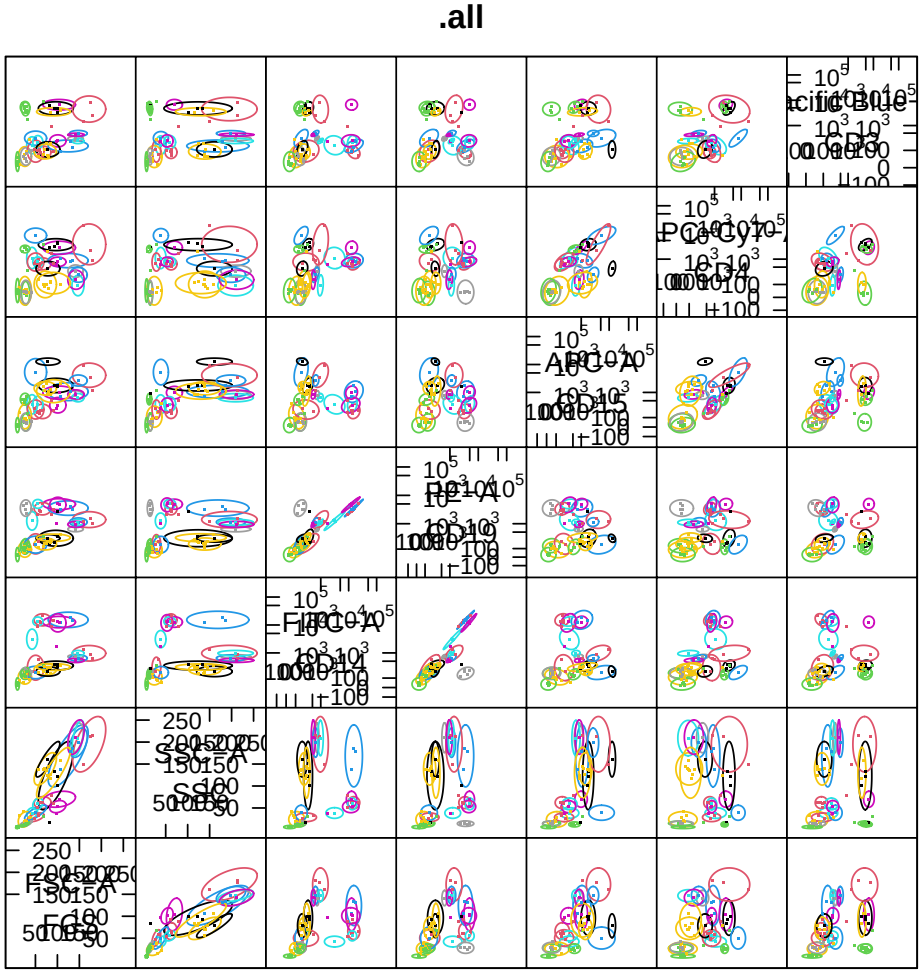
For meta-clustering the cell-clustering results of all FC samples obtained by the `cell.process` function are collected in a `vector` of *immunoClust*-objects and processed by the `meta.process` function.

```
> data(dat.exp)
> meta<-meta.process(dat.exp, meta.bias=0.3)
```

The obtained `immunoMeta`-object contains the meta-clustering result in `$res.clusters`, and the used cell-clusters information in `$dat.clusters`. Additionally, the clusters can be structures manually in a hierarchical mannner using methods of the `immunoMeta`-object.

A scatter plot matrix of the meta-clustering is obtained by the `plot` method.

```
> plot(meta, c())
```



In these scatter plots each cell-cluster is marked by a point of its centre. With the default `plot.ellipse=TRUE` argument the meta-clusters are outlined by ellipses of the 90% quantile.

4.3 Meta Annotation

We take a look on the event numbers of all meta-clusters in each sample

```
> cls <- clusters(meta,c())
> events(meta,cls)

      cls-1 cls-2 cls-3 cls-4 cls-5 cls-6 cls-7 cls-8 cls-9 cls-10 cls-11
exp-1   898   389    50     0     0   344     0   143    71   1107      0
exp-2     0  1079     0   173   102   695   926     8   145   3425    220
exp-3     0   574     0     0     0   780   452   199     0   1585      0
exp-4   761   433    62     0     0   527   331     0     0      0      0
exp-5   950    46    94     0     0   400   325     0     0      0      0
      cls-12 cls-13 cls-14 cls-15 cls-16 cls-17 cls-18 cls-19 cls-20 cls-21
```

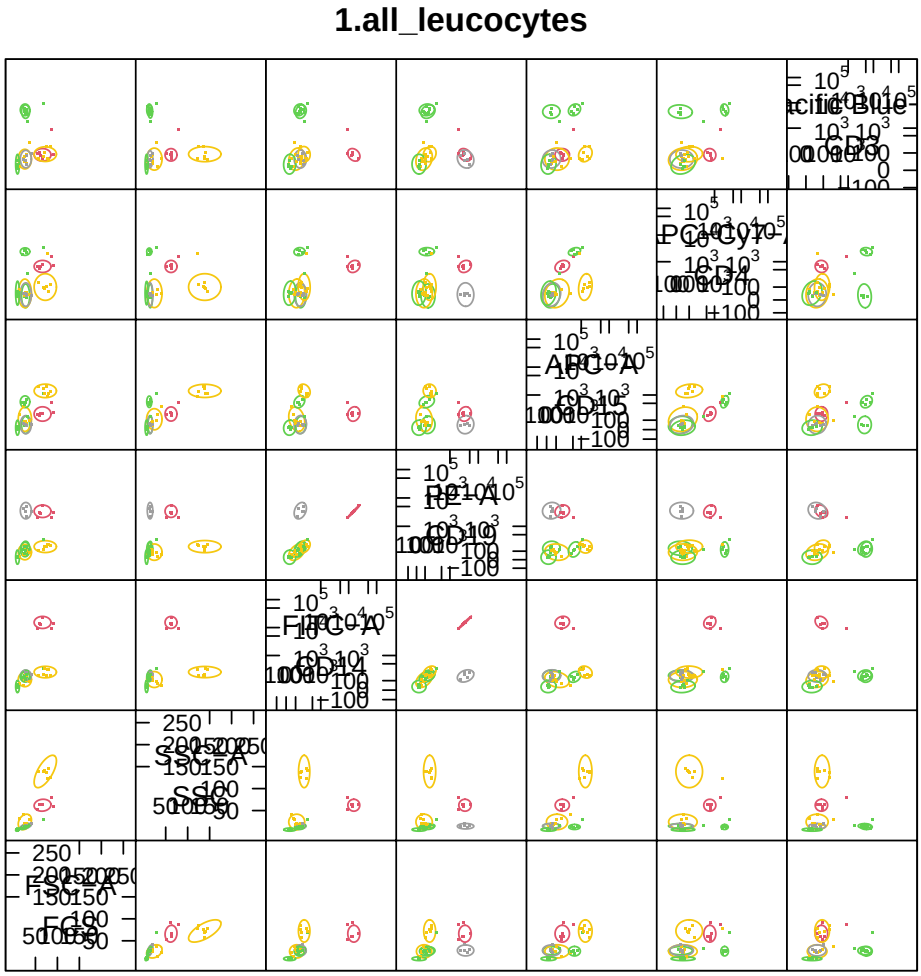
```
       exp-1      0      0   6459     70      0      0    151      0      0      0
       exp-2   1447    923      0      0     24    103    495     77      0      0
       exp-3      0      0   5717      0      0     10    247      0      0    132
       exp-4      0      0   7280      0      0      0    247      0     95      0
       exp-5      0      0   7417      0      0      0    278      0      0      0
             cls-22
       exp-1      0
       exp-2      0
       exp-3     40
       exp-4      0
       exp-5      0
```

and pick the meta-clusters of the five commonly found population, with respect to the technical depletion to collect them in a first annotation level

```
> addLevel(meta,c(1),"leucocytes") <- c(1,2,6,7,10,14,18)
```

In the plot of this level the five major population are seen easily

```
> plot(meta, c(1))
```



and we identify the clusters for the particular populations successivley by their expression levels.

```
> cls <- clusters(meta,c(1))
> sort(mu(meta,cls,7))        ## CD3 expression

[1] 0.5563285 1.0177510 1.0231479 1.4074683 1.4710931 5.3398778 5.5034995

> inc <- mu(meta,cls,7) > 5   ## CD3+ clusters
> cls[inc]

[1]  2 10

> mu(meta,cls[inc],6)         ## CD4 expression

[1] 0.3526607 4.1704618

> addLevel(meta,c(1,1), "CD3+CD4+") <- 10
> addLevel(meta,c(1,2), "CD3+CD4-") <- 2
> cls <- unclassified(meta,c(1))
> sort(mu(meta,cls,5))        ## CD15 expression

[1] 0.1607839 0.4098828 0.8552890 1.2885715 3.1912791
```

```
> inc <- mu(meta,cls,5) > 3
> addLevel(meta,c(1,3), "CD15+") <- cls[inc]
> cls <- unclassified(meta,c(1))
> sort(mu(meta,cls,3))        ## CD14 expression

[1] 0.2970245 0.8748380 1.1685025 5.5770927

> inc <- mu(meta,cls,3) > 5
> addLevel(meta,c(1,4), "CD14+") <- cls[inc]
> cls <- unclassified(meta,c(1))
> sort(mu(meta,cls,4))        ## CD19 expression

[1] 0.2053237 0.6140560 3.9759928

> inc <- mu(meta,cls,4) > 3
> addLevel(meta,c(1,5), "CD19+") <- cls[inc]
```

The whole analysis is performed on uncompensated FC data, thus the high CD19 values on the CD14-population is explained by spillover of FITC into PE.

The event numbers of each meta-cluster and each sample are extracted in a numeric matrix by the `meta.numEvents` function.

```
> tbl <- meta.numEvents(meta, out.all=FALSE)
> tbl[,1:5]

                                    12543 12546 12549 12552 12555
1.1.all_leucocytes_CD3+CD4+.10.green3  1107  3425  1585     0     0
1.2.all_leucocytes_CD3+CD4-.2.green3    389  1079   574   433    46
1.3.all_leucocytes_CD15+.14.yellow     6459     0  5717  7280  7417
1.4.all_leucocytes_CD14+.1.red          898     0     0   761   950
1.5.all_leucocytes_CD19+.7.gray           0   926   452   331   325
1.all_leucocytes.6.yellow               344   695   780   527   400
1.all_leucocytes.18.green3              151   495   247   247   278
.all.3.blue                              50     0     0    62    94
.all.4.cyan                               0   173     0     0     0
.all.5.magenta                            0   102     0     0     0
.all.8.black                            143     8   199     0     0
.all.9.red                               71   145     0     0     0
.all.11.blue                              0   220     0     0     0
.all.12.cyan                              0  1447     0     0     0
.all.13.magenta                           0   923     0     0     0
.all.15.gray                             70     0     0     0     0
.all.16.black                             0    24     0     0     0
.all.17.red                               0   103    10     0     0
.all.19.blue                              0    77     0     0     0
.all.20.cyan                              0     0     0    95     0
.all.21.magenta                           0     0   132     0     0
.all.22.yellow                            0     0    40     0     0
```

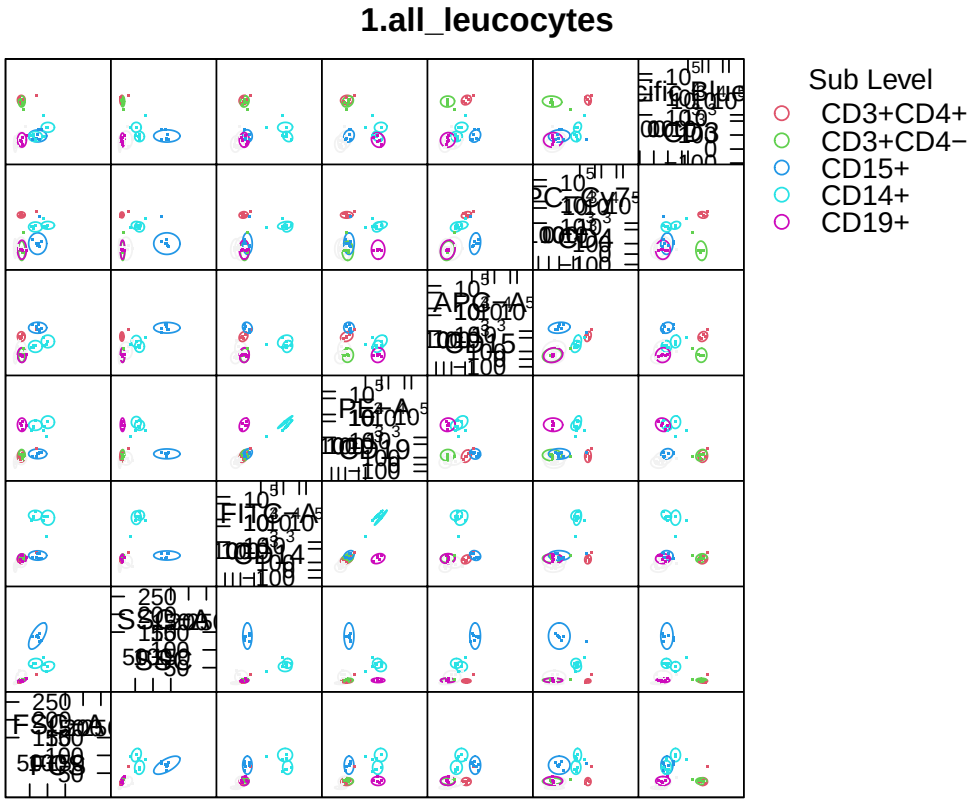
Each row denotes an annotated hierarchical level or/and meta-cluster and each column a data sample used in meta-clustering. The row names give the annotated population name, the meta-cluster index and the default color used in the plot routines for each meta-cluster.

In the last columns additionally the meta-cluster centre values in each parameter are given, which helps to identify the meta-clusters. Further export functions retrieve relative cell event frequencies and sample meta-cluster centre values in a particular parameter.

We see here, that for sample `12546` where the CD15-cells are depleted, the CD14-population is missing. Anyway, this missing cluster could be in the so far unclassified clusters.

```
> move(meta,c(1,4)) <- 13
```

```
> plot(meta, c(1))
```



We see the CD14 population of sample `12546` shifted in FSC and CD3 expression levels, probably due to technical variation in the measurement of the CD15-depleted sample, where the granulocytes are missing which constitute about 60% - 70% of the events in the other samples.

5 Session Info

The documentation and example output was compiled and obtained on the system:

```
> toLatex(sessionInfo())
```

- R version 4.0.3 (2020-10-10), `x86_64-apple-darwin17.0`
- Locale: `C/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8`
- Running under: `macOS Mojave 10.14.6`
- Matrix products: default
- BLAS: `/Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRblas.dylib`
- LAPACK: `/Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRlapack.dylib`
- Base packages: base, datasets, grDevices, graphics, methods, stats, utils
- Other packages: flowCore 2.2.0, immunoClust 1.22.0
- Loaded via a namespace (and not attached): Biobase 2.50.0, BiocGenerics 0.36.0, BiocManager 1.30.10, BiocStyle 2.18.0, RProtoBufLib 2.2.0, Rcpp 1.0.5, RcppParallel 5.0.2, S4Vectors 0.28.0, compiler 4.0.3, cytolib 2.2.0, digest 0.6.27, evaluate 0.14, grid 4.0.3, htmltools 0.5.0, knitr 1.30, lattice 0.20-41, matrixStats 0.57.0, parallel 4.0.3, rlang 0.4.8, rmarkdown 2.5, stats4 4.0.3, tools 4.0.3, xfun 0.18, yaml 2.2.1