

Analysis of flow cytometry data with R

Training for life scientists

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Outline & Schedule

Day 3

01

Importing data from Excel and arranging plots in a grid

02

Differential state analysis using a paired design

03

Normalization / batch correction

04

Working with gated data in R

Outline & Schedule

Day 4

05

Generate html or PDF reports

Examples and exercises are integrated in the chapters

01

- A. Importing data from Excel**
- B. Arranging plots in grids**

Importing data from an Excel file

Package xlsx

<https://cran.r-project.org/web/packages/xlsx/index.html>

```
> data <- read.xlsx2(file = "excelfile.xlsx",  
sheetName = "Sheet1")
```

	A	B
1	sample	id
2	1	3
3	2	
4		4
5	3	5
6	4	
7		5
8		5
9		

The function *read.xlsx2* considers the empty cells as "" character.

```
> str(data)  
'data.frame': 7 obs. of 2 variables:  
 $ sample: chr  "1" "2" "" "3" ...  
 $ id     : chr  "3" "" "4" "5" ...
```

The function *read.xlsx* considers the empty cells as NA

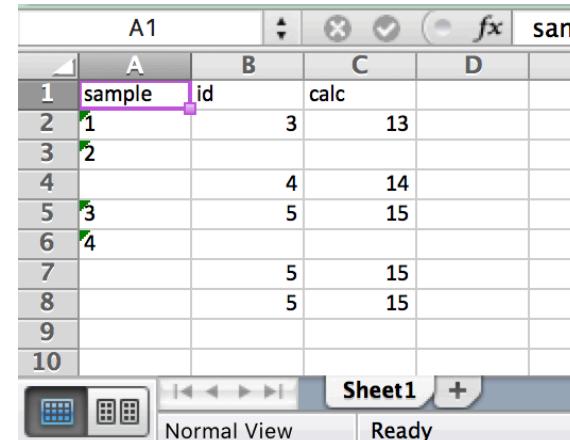
```
> str(data)  
'data.frame': 7 obs. of 2 variables:  
 $ sample: num  1 2 NA 3 4 NA NA  
 $ id     : num  3 NA 4 5 NA 5 5
```

Exporting data to an Excel file

Advantage: no risk of gene name conversion to date like with csv files

Package `xlsx` can be used to export a `data.frame` after manipulating it within R:

```
> data$id<-as.numeric(data$id)  
> data$calc<-data$id+10  
> write.xlsx2(x=data,  
           file = "exclfile2.xlsx",  
           row.names = FALSE,  
           SheetName = "Sheet1")
```



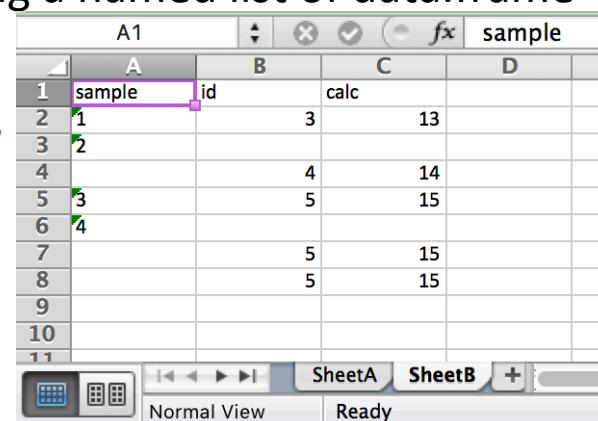
	A1	B	C	D	E
1	sample	id	calc		
2	1		3	13	
3	2			14	
4			4	14	
5	3		5	15	
6	4			15	
7			5	15	
8			5	15	
9					
10					

Another package: `openxlsx`

<https://cran.r-project.org/web/packages/openxlsx/index.html>

Allows to generate several separate sheets providing a named list of `data.frame` objects:

```
> openxlsx::write.xlsx(x = list(SheetA=data[, c(1,2)],  
                           SheetB=data),  
                           file = "exclfile3.xlsx")
```



	A1	B	C	D	E
1	sample	id	calc		
2	1		3	13	
3	2			14	
4			4	14	
5	3		5	15	
6	4			15	
7			5	15	
8			5	15	
9					
10					
11					

Doesn't export rownames by default.

Arranging ggplot2 plots in a grid

Can be useful to compare distribution of values before and after transformation, or to compare a UMAP with cells colored according to different markers.

Package *cowplot*

<https://cran.r-project.org/web/packages/cowplot/index.html>

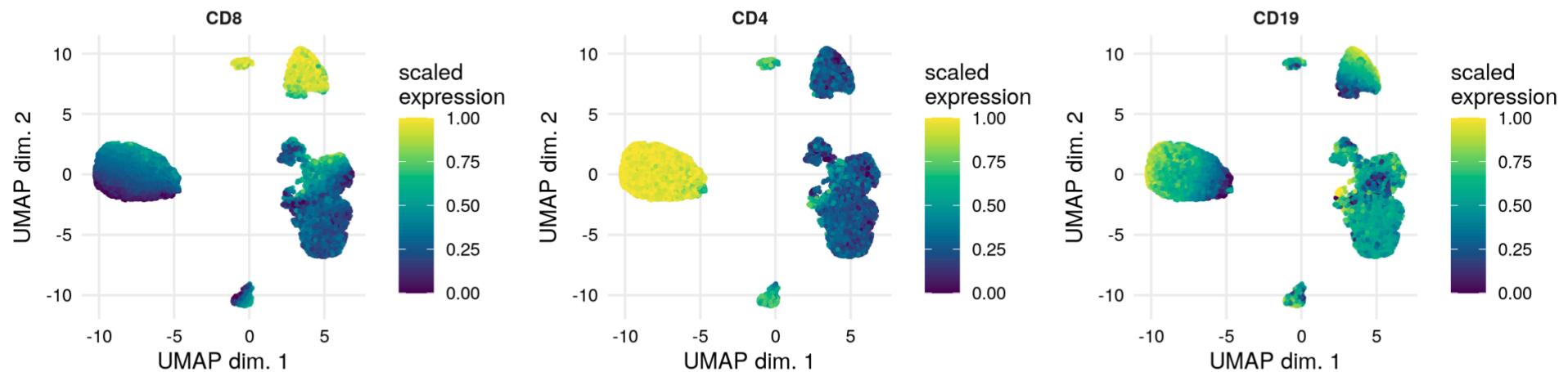
First save each ggplot2 plot to an object:

```
> p1 <- plotDR(sce, dr = "UMAP",
  assay = "exprs", color_by="CD8" )
> p2 <- plotDR(sce, dr = "UMAP",
  assay = "exprs", color_by="CD4")
> p3<-plotDR(sce, dr = "UMAP",
  assay = "exprs", color_by="CD19")
```

Arranging ggplot2 plots in a grid

Use the *plot_grid* function to arrange them in a grid, e.g. all on the same row:

```
> plot_grid(p1, p2, p3, nrow = 1)
```



02

Differential state analysis with a paired design

Differential state (DS) analysis with paired design

Differential expression of cell state markers within clusters

```
> res_DS <- diffcyt(sce_PBMC,  
                      clustering_to_use = "final_annotation",  
                      analysis_type = "DS",  
                      method_DS = "diffcyt-DS-limma",  
                      design = design,  
                      contrast = contrast,  
                      block_id = patient_id)
```

Methods for DS: uses the **limma** package

Vector of patient IDs

How to create a vector of patient IDs from the fcs file names?

```
> ei(sce)$sample_id  
# [1] 0BF51C_0.fcs 0BF51C_14.fcs 0BF51C_7.fcs 0E1F8E_0.fcs 0E1F8E_14.fcs  
# [6] 0E1F8E_7.fcs 180E1A_0.fcs 180E1A_14.fcs 180E1A_7.fcs 1A9B20_0.fcs  
# [11] 1A9B20_14.fcs 1A9B20_7.fcs 61BBAD_0.fcs 61BBAD_14.fcs 61BBAD_7.fcs
```

Using gsub() :

This function replaces all characters having a same pattern with other characters.
We can replace the *_0.fcs*, *_14.fcs* and *_7.fcs* extensions by an empty character:

Create a vector of patient IDs for block design:

```
> patient_id <- ei(sce)$sample_id
```

Use gsub to replace the extensions for the matching elements within the vector:

```
> patient_id <- gsub("_0.fcs", "", patient_id)  
> patient_id <- gsub("_14.fcs", "", patient_id)  
> patient_id <- gsub("_7.fcs", "", patient_id)
```

```
> patient_id
```

```
[1] "0BF51C" "0BF51C" "0BF51C" "0E1F8E" "0E1F8E" "0E1F8E" "180E1A" "180E1A"  
[9] "180E1A" "1A9B20" "1A9B20" "1A9B20" "61BBAD" "61BBAD" "61BBAD"
```

Differential state analysis

Extract results table - same method as for unpaired design:

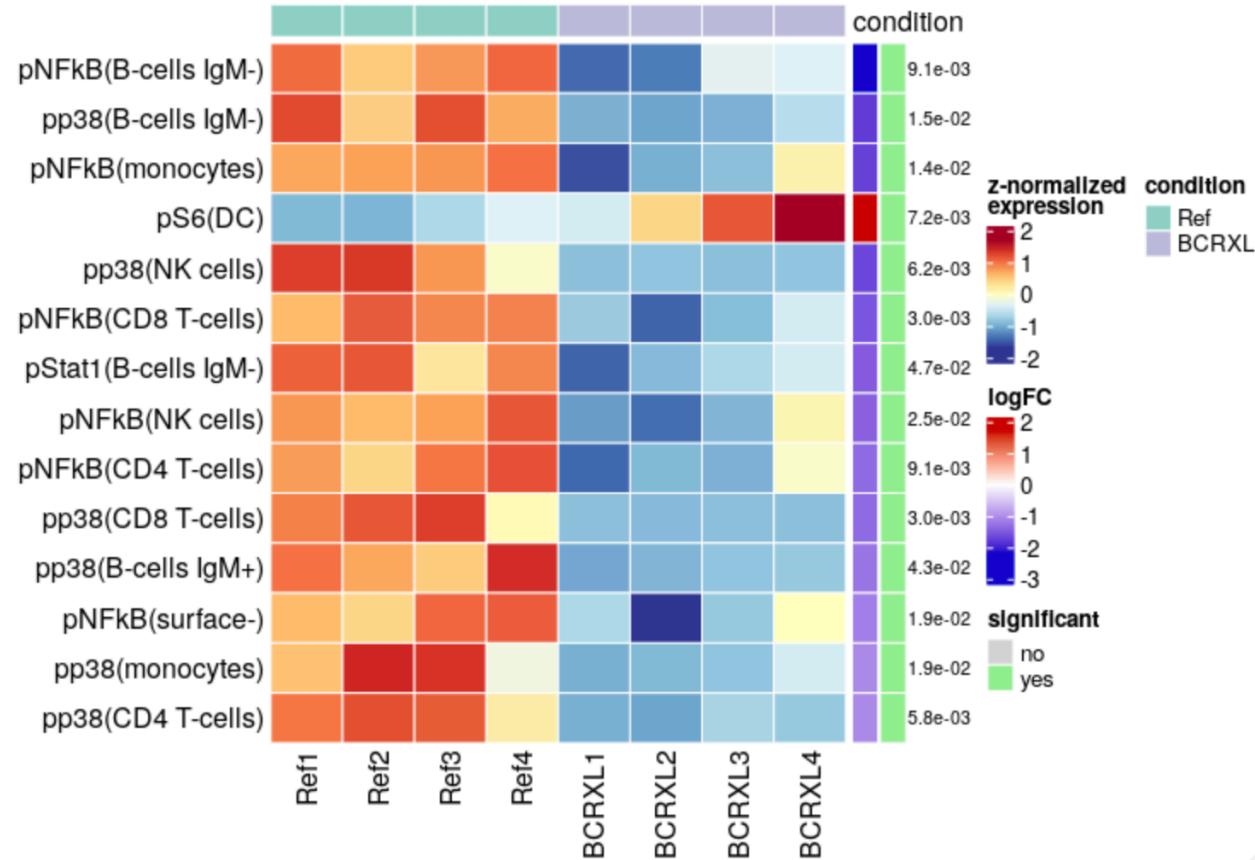
```
> tbl_DS <- rowData(res_DS$res)  
> tbl_DS
```

DataFrame with 20 rows and 4 columns					
		cluster_id	marker_id	p_val	p_adj
		<factor>	<factor>	<numeric>	<numeric>
Other	Other		CD38	0.000883343	0.128085
Other	Other		TCR gd	0.006609759	0.479208
CD4 T cells	CD4 T cells		CD141	0.027918113	0.481051
CD8 T cells	CD8 T cells		CCR5	0.026749683	0.481051
Monocytes	Monocytes		CCR5	0.027850828	0.481051
...
CD4 T cells	CD4 T cells		CD16	0.0703599	0.534035
CD8 T cells	CD8 T cells		CD16	0.0629339	0.534035
Other	Other		CD16	0.0688253	0.534035
CD8 T cells	CD8 T cells		IgD	0.0704875	0.534035
Other	Other		CD161	0.0684019	0.534035
...

Differential state analysis

Plot results for all markers Sorts results by absolute value of logFoldChange

```
> plotDiffHeatmap(sce_PBMC, tbl_DS, all=T , sort_by = "lfc", col_anno ="condition")
```



Let's practice – 7 bis

In this exercise we will test if markers were differentially expressed between two time points (D14 compared to D0), **using a paired design**

Create a new script in which you will

- 1) Load the sce object from exercise number 6 ("sce.annotated.RData").
- 2) Create a vector of patient IDs from the fcs file names using gsub()
- 3) Set up the design and contrast matrices.
- 4) Test for differences in marker expression between D14 and D0, including argument block_id
- 5) View table of results

03

Normalization / batch correction

Spectral flow cytometry analysis workflow

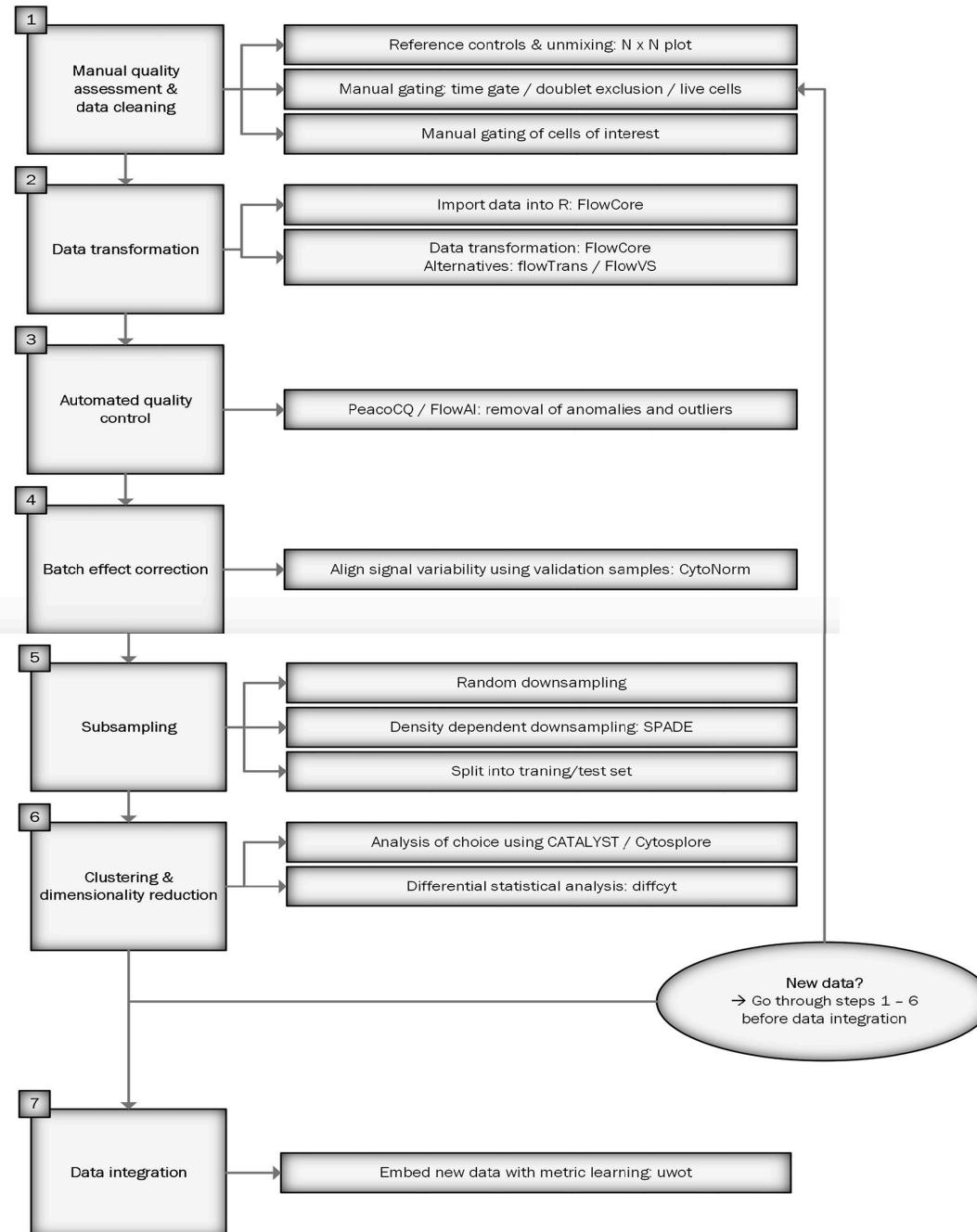
- Workflow based on

The screenshot shows a website layout for a journal article. At the top, there is a navigation bar with the 'frontiers' logo, 'Immunology', and links for 'Sections', 'Articles', 'Research Topics', and 'Editorial Board'. Below the navigation bar, the article title is displayed: 'METHODS article' followed by 'Front. Immunol., 19 November 2021' and 'Sec. Systems Immunology'. The volume information is 'Volume 12 - 2021 | <https://doi.org/10.3389/fimmu.2021.768113>'. To the right of this information, it states 'This article is part of the Research Topic Re-Using Cytometry Datasets in Immunology: "Old Wine into New Wineskins"' and a link 'View all 7 Articles >'. The main title of the article is 'How to Prepare Spectral Flow Cytometry Datasets for High Dimensional Data Analysis: A Practical Workflow'. Below the title, three author names are listed with their corresponding profile icons: Hannah den Braanker^{1,2,3†}, Margot Bongenaar^{1,2†}, and Erik Lubberts^{1,2*}. Below the authors, three footnotes are provided: ¹ Department of Rheumatology, Erasmus University Medical Center, Rotterdam, Netherlands; ² Department of Immunology, Erasmus University Medical Center, Rotterdam, Netherlands; ³ Department of Clinical Immunology and Rheumatology, Maasstad Hospital, Rotterdam, Netherlands. A brief abstract at the bottom states: 'Spectral flow cytometry is an upcoming technique that allows for extensive multicolor panels, enabling simultaneous investigation of a large number of'.

Provide R code to perform the proposed workflow

<https://doi.org/10.3389/fimmu.2021.768113>

Suggested workflow: Figure 1, den Braanker et al



Planning and Preparation

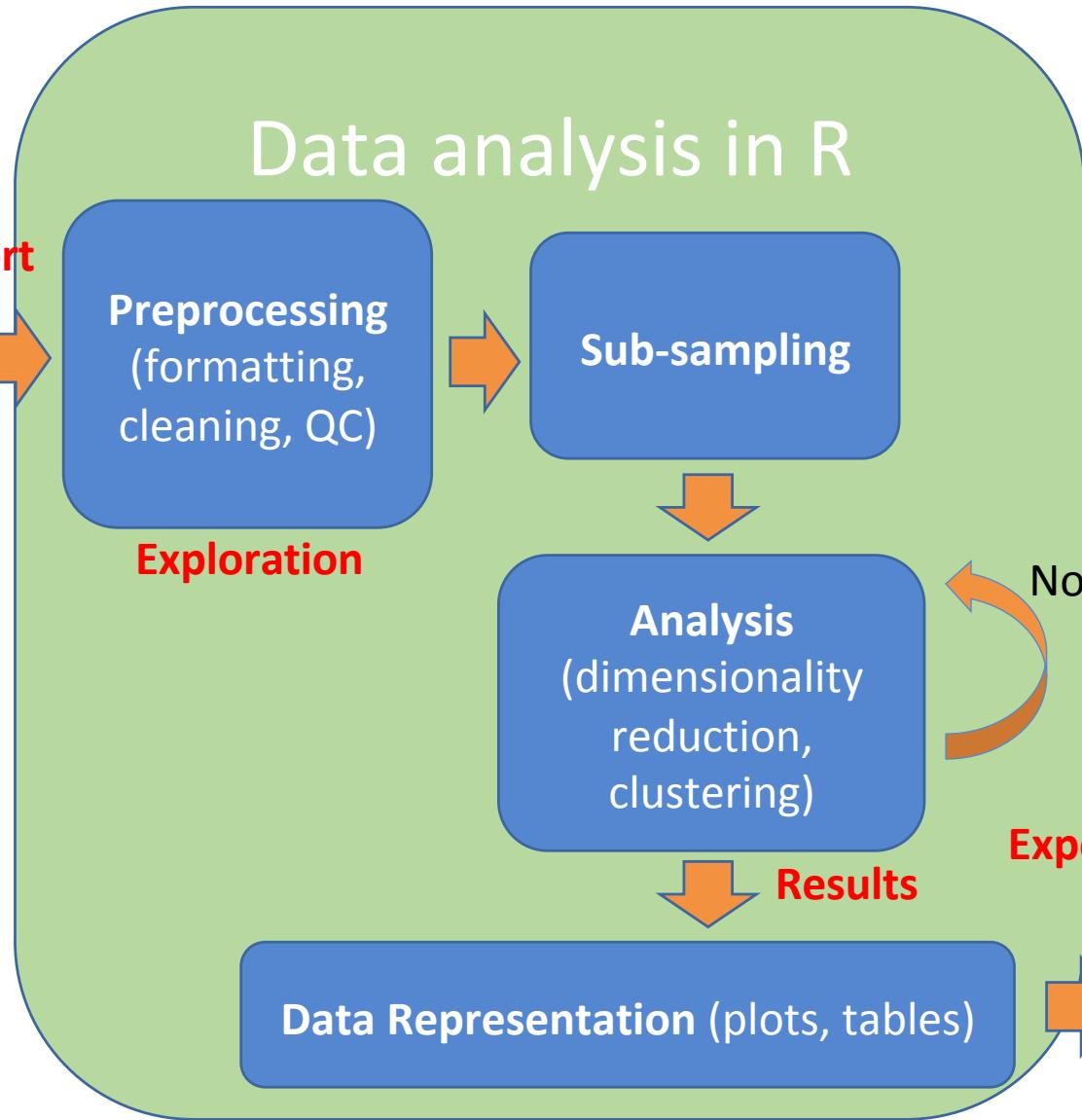


Data acquisition



Manual analysis
(QC, gating)

Import



Simplified workflow presented in day 1 and 2

Communicate (reports)

Spectral flow cytometry analysis workflow

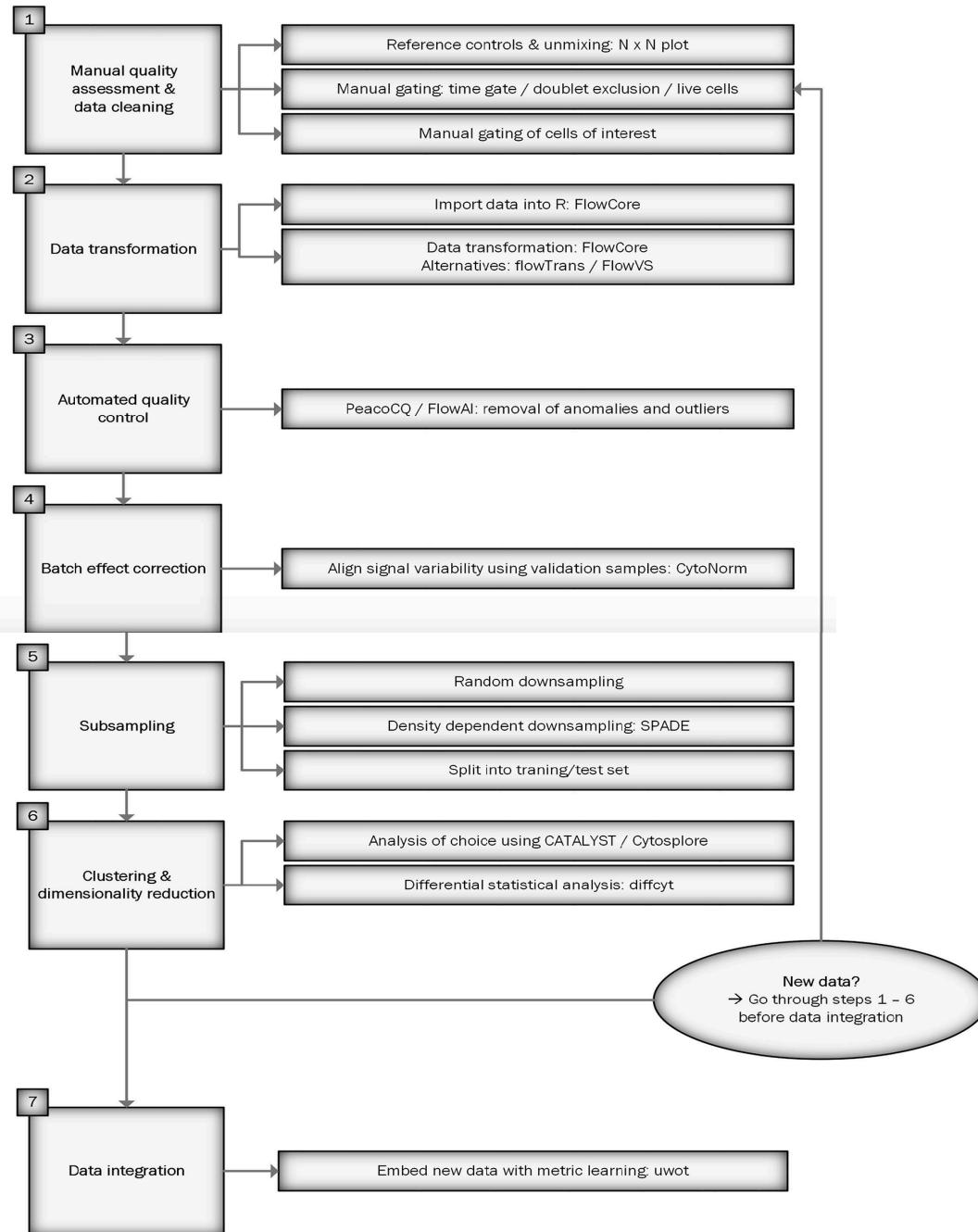
- Workflow based on

The screenshot shows a website layout for a scientific publication. At the top, there is a navigation bar with the 'frontiers' logo, followed by 'Immunology' and other menu items: 'Sections', 'Articles', 'Research Topics', and 'Editorial Board'. Below the navigation bar, the page title is 'METHODS article'. The article details are: 'Front. Immunol., 19 November 2021', 'Sec. Systems Immunology', 'Volume 12 - 2021 | <https://doi.org/10.3389/fimmu.2021.768113>'. To the right, it states 'This article is part of the Research Topic Re-Using Cytometry Datasets in Immunology: "Old Wine into New Wineskins"' and a link 'View all 7 Articles >'. The main title of the article is 'How to Prepare Spectral Flow Cytometry Datasets for High Dimensional Data Analysis: A Practical Workflow'. Below the title, author information is listed: 'Hannah den Braanker^{1,2,3†}', 'Margot Bongenaar^{1,2†}', and 'Erik Lubberts^{1,2*}'. Below the authors, three footnotes are provided: ¹ Department of Rheumatology, Erasmus University Medical Center, Rotterdam, Netherlands; ² Department of Immunology, Erasmus University Medical Center, Rotterdam, Netherlands; ³ Department of Clinical Immunology and Rheumatology, Maasstad Hospital, Rotterdam, Netherlands. A descriptive paragraph at the bottom states: 'Spectral flow cytometry is an upcoming technique that allows for extensive multicolor panels, enabling simultaneous investigation of a large number of'.

Provide R code to perform the proposed workflow

<https://doi.org/10.3389/fimmu.2021.768113>

Suggested workflow: Figure 1, den Braanker et al



<https://doi.org/10.3389/fimmu.2021.768113>

Planning and Preparation



Data acquisition



Manual analysis
(QC, gating)

Import

Data analysis in R

Preprocessing
(formatting,
cleaning, QC)

Exploration

Sub-sampling

Analysis
(dimensionality
reduction,
clustering)

Normalization

Export

Results

Data Representation (plots, tables)

Communicate
(reports)

Simplified workflow
presented in day 1 and 2

CytoNorm

Available on github: <https://github.com/saeyslab/CytoNorm>

van Gassen et al, 2020 <https://onlinelibrary.wiley.com/doi/epdf/10.1002/cyto.a.23904>

Install using devtools package:

```
> library(devtools)
```

```
> install_github('saeyslab/CytoNorm')
```

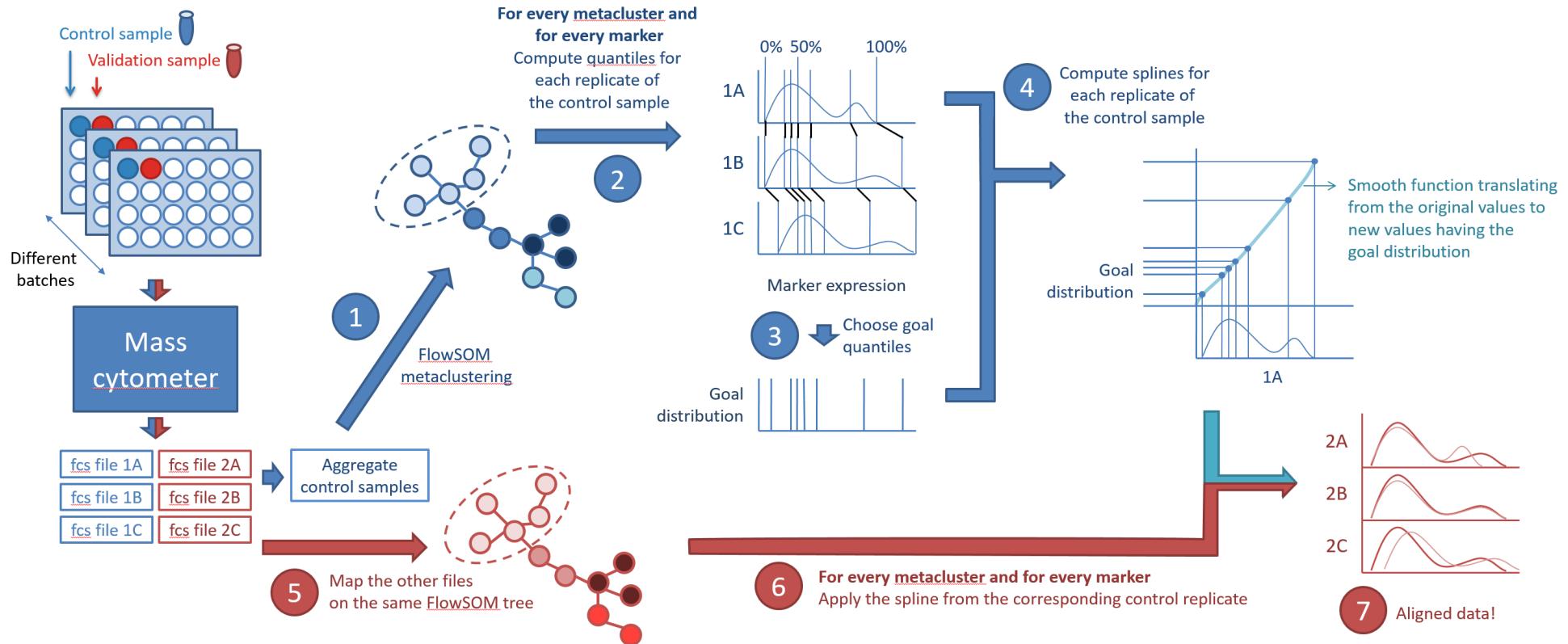
Why do we need to normalize?

Shifts that occur because of batch can have effects on DR for example.

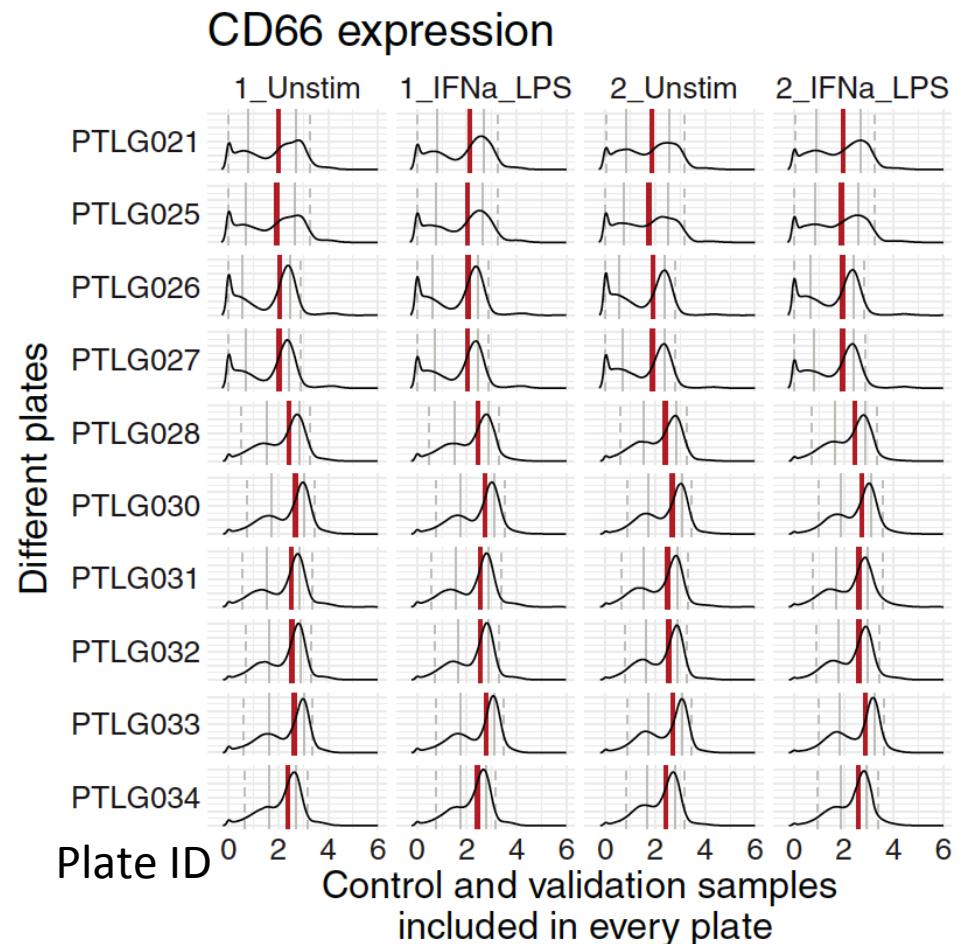
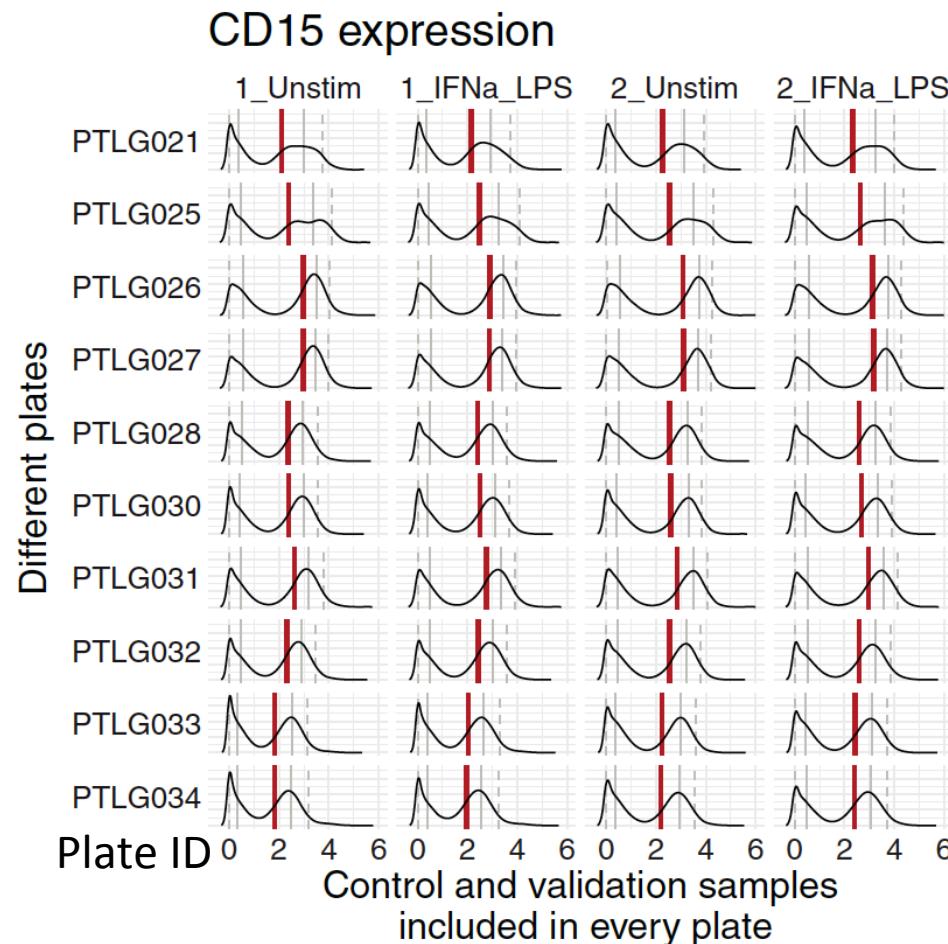
Computational methods can align the distribution of markers across samples.

Normalization methods without a reference sample can hide biologically relevant differences in cell subsets. Different cell types are impacted differently by batch effects (Finak et al, 2014, Cytom. Part A)

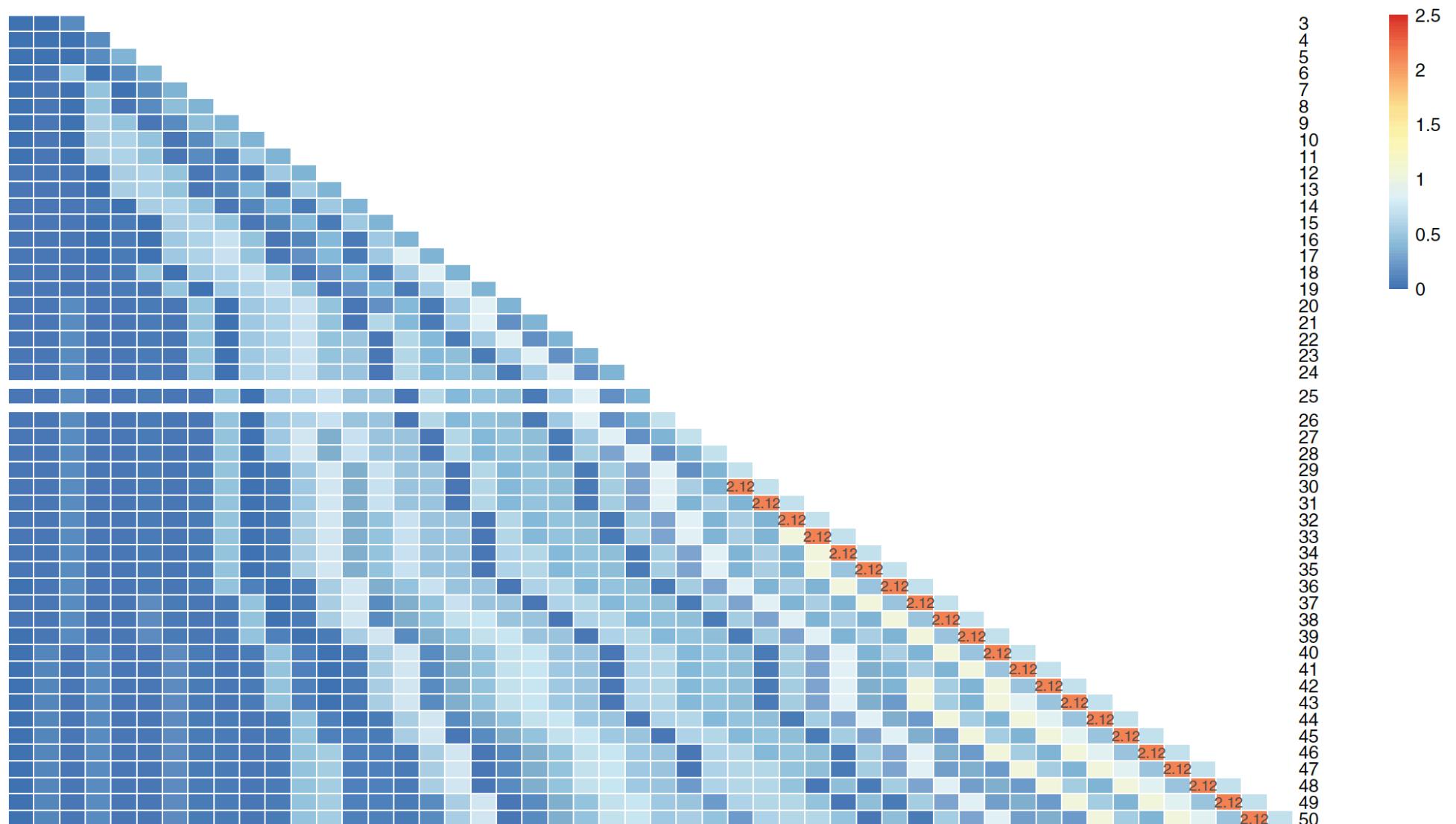
CytoNorm – algorithm overview



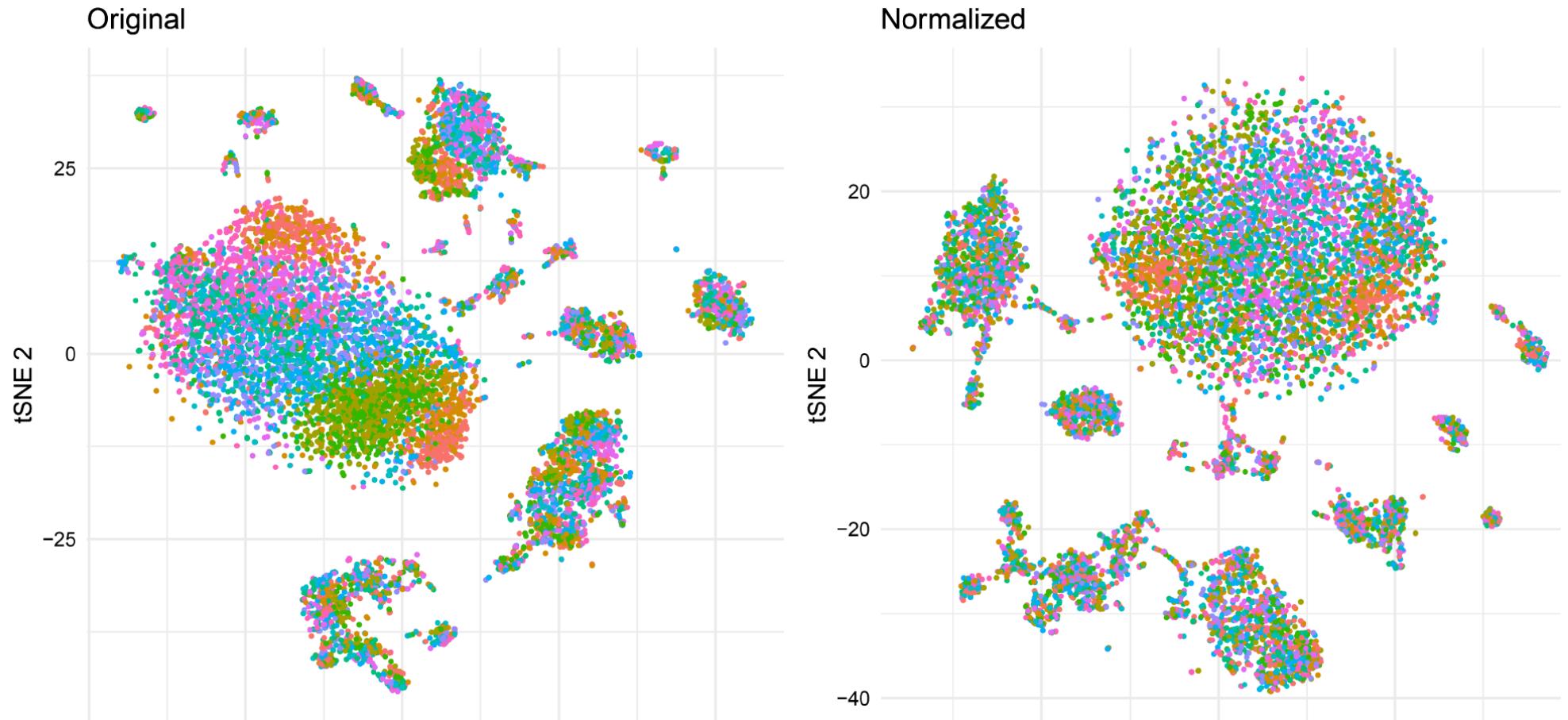
An example of shifts across plates



Assumption: clusters are not affected by batch



Normalization enhances DR plot



1,000 randomly sampled cells for each of 10 samples

Functions of CytoNorm

Functions use flowSet objects containing transformed data (eg arcsinh with fixed cofactor).

Generate pre-clustering with flowSOM:

```
> fsom <- prepareFlowSOM(train_files, ←  
    colsToUse = markerstotransf, ←  
    transformList = NULL,  
    FlowSOM.params = list(xdim=10,  
                          ydim=10,  
                          nClus=20, scale=FALSE)) ←  
    flowSet with technical replicates of a  
    single sample  
    Markers to use for clustering (eg. "type"  
    marker_class)  
    FlowSOM parameters: number of  
    grids and of metaclusters
```

Test for coefficient of variation within clusters:

```
> cvs <- CytoNorm::testCV(fsom, cluster_values = c(5,10,15,20), plot=TRUE)  
> range(cvs$cvs$`20`) # 0.05758965 1.43114512
```

If the clusters are impacted by batch effects, CV values of >1.5 - 2 will occur, then you can choose to put FlowSOM.params to NULL and skip clustering.

Functions of CytoNorm

Train the model, i.e. evaluate quantiles from technical replicates:

```
model <- CytoNorm.train(files = train_files, ← flowSet with technical replicates of a
  labels = labels_train, ← single sample
  channels = markerstotransf, ← Vector of batch ID labels for each technical
  transformList = NULL, ← replicate within the train flowSet
  FlowSOM.params = list(nCells = 6000, ← Markers to use for clustering
    xdim = 10, ← (eg. "type" marker_class)
    ydim = 10, ←
    nClus = 5, ←
    scale = FALSE), ← FlowSOM parameters: number of
                      grids and of metaclusters
  normMethod.train = QuantileNorm.train,
  normParams = list(nQ = 101, ←
    goal = "mean"),
  seed = 1,
  verbose = TRUE)
```

Compute quantiles to describe the distribution of the data, and infer spline functions to equalize these distributions over the files.

Functions of CytoNorm

Normalize the rest of the samples:

```
> CytoNorm.normalize(model = model,  
                      files = validation_files,  
                      labels = label_norm,  
                      transformList = NULL,  
                      transformList.reverse = NULL,  
                      normMethod.normalize = QuantileNorm.normalize,  
                      outputDir = "course_datasets/FR_FCM_Z4KT/Normalized",  
                      prefix = "Norm_",  
                      clean = TRUE,  
                      verbose = TRUE)
```

Model with quantiles obtained using CytoNorm.train()
flowSet with the rest of the samples
Vector of batch ID labels for each sample of the samples to be normalized
Compute quantiles and infer spline functions to equalize these distributions over the files.
Output folder where new fcs files will be created with prefix "Norm_"

Before the exercise: the grep() function

It allows to search for a pattern of characters within a vector:

```
> grep("pattern", myvector)
```

Will return numbers of elements within the vector that correspond to that pattern:

```
> myvector <- c("abc", "xyz", "abcd", "abxyz", "cdy")
> grep("abc", myvector)
# [1] 1 3
```

Use it on flowSet sampleNames to split a flowSet based on sample ID:

```
> train_files <- fcs_transform[grep("REU271", sampleNames(fcs_transform))]
> validation_files <- fcs_transform[-c(grep("REU271", sampleNames(fcs_transform)))]
```

Let's practice – 8

In this exercise we will perform normalization (i.e. batch correction) for fcs files provided in accession **FR_FCM_Z4KT** of the FlowRepository.

Create a new script in which you will:

- 1) Create a flowSet called `fcs_data` of all samples within the `/course_dataset/FR_FCM_Z4KT` folder
- 2) Generate a panel data.frame using `colnames(fcs_data)` antigen names extracted with `pData(parameters(fcs_data[[1]]))$desc`. Create a new column called `marker_class` that will contain the type of markers: all that are not NA should be labeled as "type", except PD-1 which should be labeled as "state". Make sure that the antigen "Zombie UV" is labeled as "none" and not as "type". Save the panel to an Excel file using `write.xlsx2()`.
- 3) Transform the data: extract a vector from the panel data.frame which are the channels to be transformed, which are not labeled with "none". Perform asinh transformation with a cofactor of 3000 for all channels to be transformed, using `transFlowVS()` from the `flowVS` package.
- 4) Split the flowSet resulting from transformation into a *training* flowSet containing all flowFrames from the sample "REU271", and a flowSet with the rest of the flowFrames not corresponding to sample "REU271".

Let's practice – 8

In this exercise we will perform normalization (i.e. batch correction) for fcs files provided in accession **FR_FCM_Z4KT** of the FlowRepository.

Create a new script in which you will:

- 5) Perform pre-clustering with flowSOM with function `prepareFlowSOM()`, providing the flowSet with the training flowFrames, the vector of channels to transform, and `FlowSOM.params = list(xdim=10, ydim=10, nClus=20, scale=FALSE)`
- 6) Test the coefficient of variation within clusters with the `testCV()` function.
- 7) Import the metadata with the batch label of each sample contained in the excel file md.xlsx, using `read.xlsx2()`. Create 2 vectors using the column "batch" in the md.xlsx file. One vector contains the batch labels of the samples that correspond to sample "REU271", and another vector contains the batch labels of the other samples (i.e. not "REU271").
- 8) Estimate quantiles from the training flowSet using `CytoNorm.train()`. Use `FlowSOM.params = list(nCells = 6000, xdim = 10, ydim = 10, nClus = 5, scale = FALSE)`
- 9) Normalize the rest of the samples using `CytoNorm.normalize()`, and using `outputDir = "course_datasets/FR_FCM_Z4KT/Normalized"` Make sure this is a new folder.

04

Working with gated data in R

Gating data in R

- The *GatingSet* class of objects (*flowWorkspace*) for working with gating data in R
- Import a *FlowJo* or *Cytobank* workspace (xml file) with gating data into R
- Manual gating from scratch
 - Using functions from the *flowWorkspace* package
 - Using a graphic-based, interactive tool (*flowGate* package)
- Automated gating methods
 - *FlowClust* package
 - *OpenCyto* package

flowWorkspace

<https://bioconductor.org/packages/release/bioc/html/flowWorkspace.html>

- Provides the *GatingSet* class of objects as an efficient data structure to store, query and visualize gated flow data
- A *GatingSet* (**gs**) stores multiple *GatingHierarchy* (**gh**) objects associated with individual samples

GatingSet ~ *flowSet*

GatingHierarchy ~ *flowFrame*

- Unlike *flowSets*, functions that operate on a *GatingSet* have the potential side-effect of modifying the object (all the modifications are made to the *external pointer*, rather than the R object itself)

flowWorkspaceData

<https://bioconductor.org/packages/release/bioc/html/flowWorkspace.html>

- Contains FCS data files, XML workspaces and GatingSets for testing the flowWorkspace and openCyto packages
- Data from whole blood

Installation

To install this package, start R (version "4.3") and enter:

```
if (!require("BiocManager", quietly = TRUE))
  install.packages("BiocManager")

BiocManager::install("flowWorkspaceData")
```

REMOVE THIS SLIDE?

OR JUST mention we are using the testing data from this package. I will copy the files to the posit, but you can also access the data through this package (AND THEN ADD THE CODE SHOWING HOW ?)

Create a *gatingSet*

Ways to generate a *gatingSet*:

- Imported from workspace XML files from FlowJo, CytoBank or other software using *CytoML* package
- Built from scratch within R (**manual gating**)
- Generated by **automated gating** methods (e.g. *openCyto* package)

Import a workspace using *CytoML*

<https://bioconductor.org/packages/release/bioc/html/CytoML.html>

- Uses platform-specific implementations of the GatingML2.0 standard to exchange gated cytometry data



Published in final edited form as:
Cytometry A. 2015 July ; 87(7): 683–687. doi:10.1002/cyto.a.22690.

ISAC's Gating-ML 2.0 data exchange standard for gating description

Josef Spidlen¹, Wayne Moore², ISAC Data Standards Task Force³, and Ryan R. Brinkman^{†, 1,4}

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²Genetics Department, Stanford University School of Medicine, Stanford, California, United States of America

³Full lists of members and affiliations appear at the end of the paper

⁴Department of Medical Genetics, University of British Columbia, Vancouver, British Columbia, Canada

```
# import workspace from FlowJo
> ws <- open_flowjo_xml("course_datasets/flowWorspaceData/manual.xml")
> gs <- flowjo_to_gatingset(ws, name = "T-cell")
```

Check the name of the function for cytobank

flowWorkspace: basics on *GatingSet* objects

List the samples stored in the GatingSet

```
> sampleNames(gs)
[1] "CytoTrol_CytoTrol_1.fcs_119531" "CytoTrol_CytoTrol_2.fcs_115728"
```

Access metadata

```
> pData(gs)
```

	name	condition
CytoTrol_CytoTrol_1.fcs_119531	CytoTrol_CytoTrol_1.fcs	treatment
CytoTrol_CytoTrol_2.fcs_115728	CytoTrol_CytoTrol_2.fcs	control

Add metadata

```
pData(gs)$condition <- c("treatment","control")
```

Subset a GatingSet by metadata column

```
> subset(gs, subset = treatment == "control")
```

A GatingSet with 1 samples

Retrieve a GatingHierarchical (one sample)

```
> gh <- gs[[1]]
```

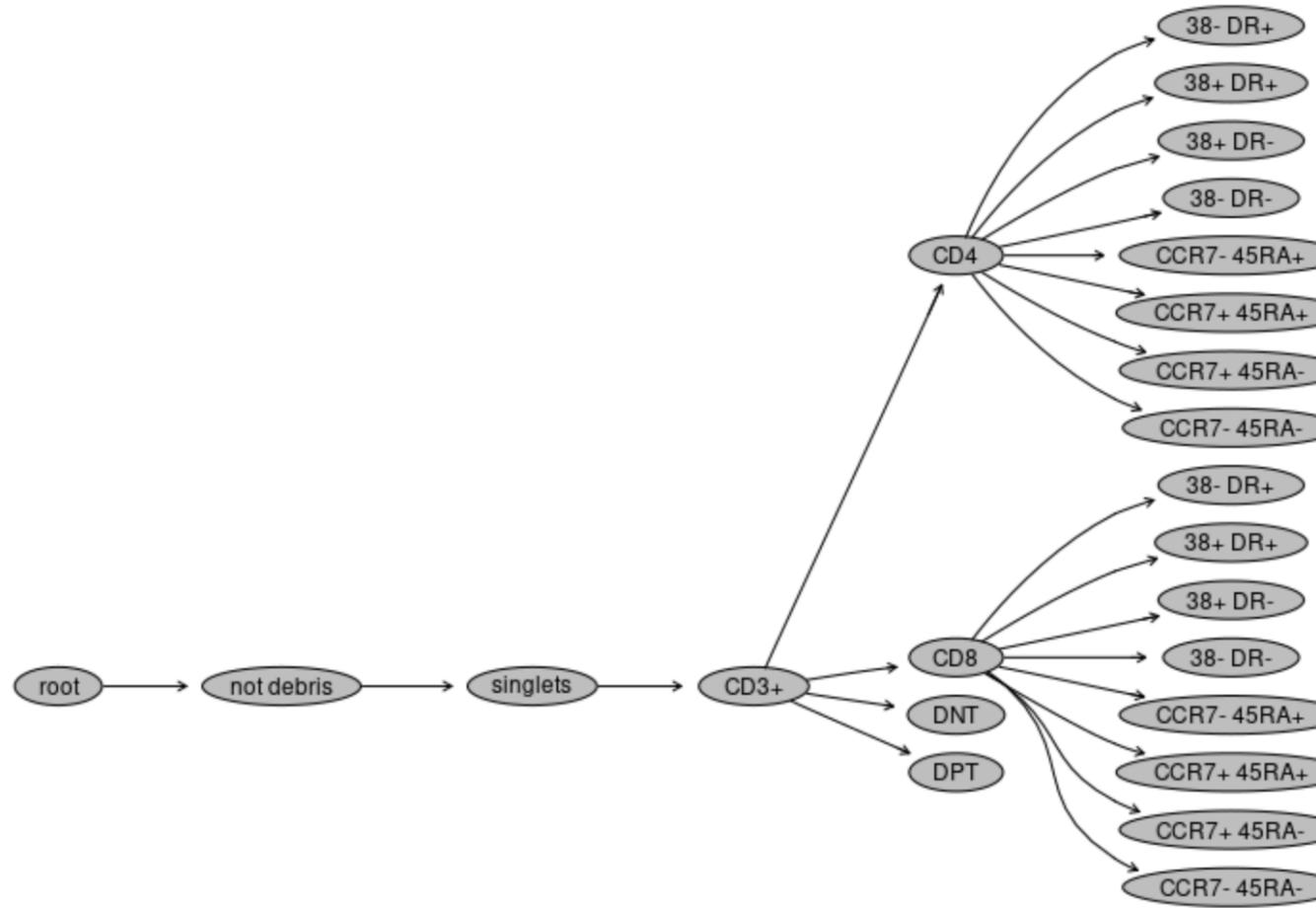
```
> gh
```

Sample:	CytoTrol_CytoTrol_1.fcs_119531
GatingHierarchy	with 24 gates

flowWorkspace: basics on *GatingSet* objects

```
# plot the gating hierarchy (tree)
```

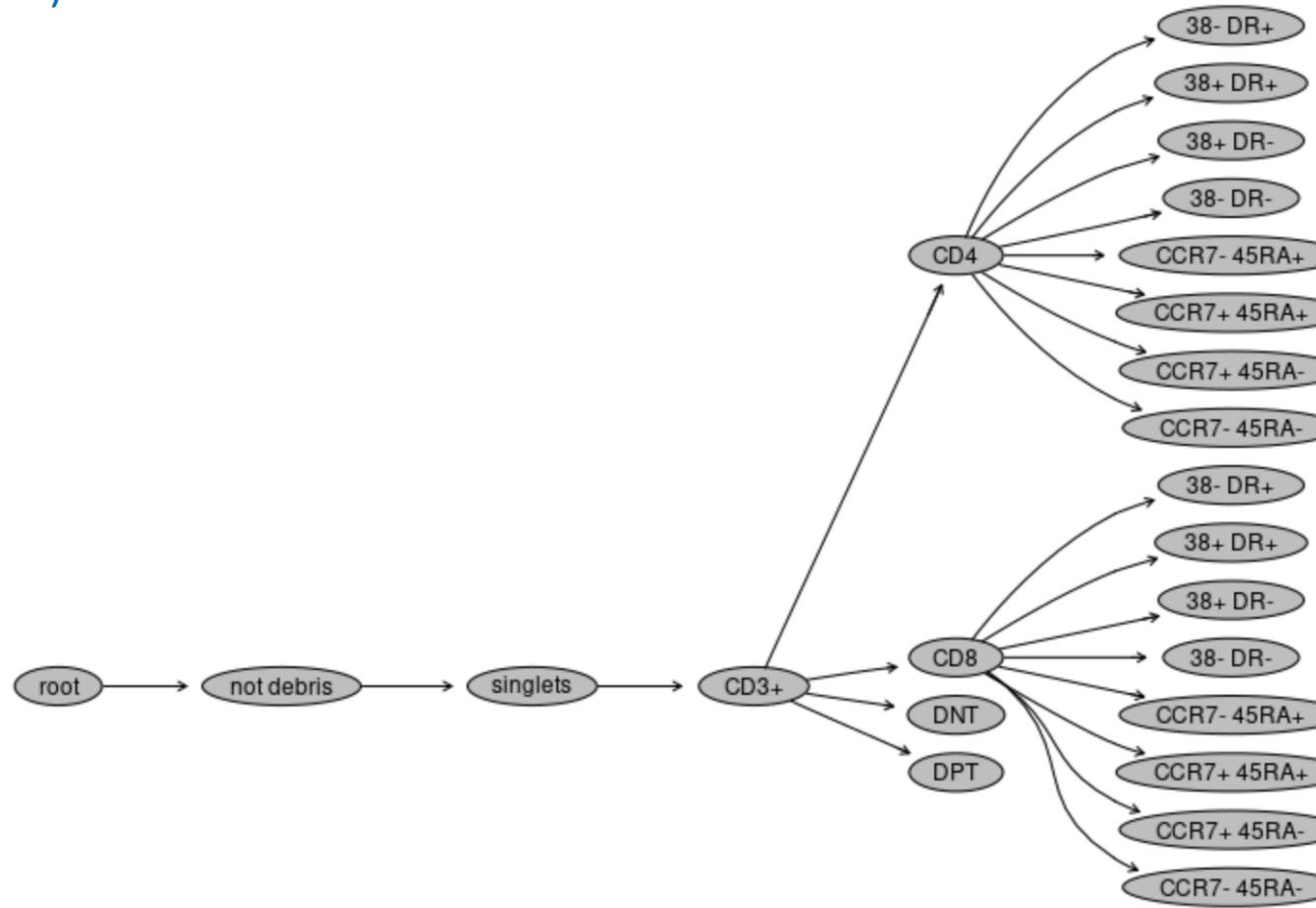
```
> plot(gs)
```



flowWorkspace: basics on *GatingSet* objects

```
# Delete a gate
```

```
> Rm(gs, "DPT")  
> plot(gs)
```



flowWorkspace: basics on *GatingSet* objects

list nodes (cell populations)

```
> gs_get_pop_paths(gs, path = 2)
```

```
[1] "root"                 "not debris"          "not debris/singlets" "singlets/CD3+"      "CD3+/CD4"  
[6] "CD4/38- DR+"        "CD4/38+ DR+"       "CD4/38+ DR-"        "CD4/38- DR-"      "CD4/CCR7- 45RA+"  
[11] "CD4/CCR7+ 45RA+"    "CD4/CCR7+ 45RA-"   "CD4/CCR7- 45RA-"    "CD3+/CD8"        "CD8/38- DR+"  
[16] "CD8/38+ DR+"        "CD8/38+ DR-"       "CD8/38- DR-"        "CD8/CCR7- 45RA+"  "CD8/CCR7+ 45RA+"  
[21] "CD8/CCR7+ 45RA-"    "CD8/CCR7- 45RA-"   "CD3+/DNT"           "CD3+/DPT"
```

```
> gs_get_pop_paths(gs, path = "full")
```

```
[1] "root"                 "/not debris"  
[3] "/not debris/singlets" "/not debris/singlets/CD3+"  
[5] "/not debris/singlets/CD3+/CD4" "/not debris/singlets/CD3+/CD4/38- DR+"
```

The output continues with 17 more entries, each showing a full path from the root node to a specific cell population node.

```
> gs_get_pop_paths(gs, path = "auto")
```

```
[1] "root"                 "not debris"          "singlets"          "CD3+"            "CD4"              "CD4/38- DR+"      "CD4/38+ DR+"  
[8] "CD4/38+ DR-"        "CD4/38- DR-"       "CD4/CCR7- 45RA+"  "CD4/CCR7+ 45RA+"  "CD4/CCR7+ 45RA-" "CD4/CCR7- 45RA-"  "CD8"  
[15] "CD8/38- DR+"        "CD8/38+ DR+"       "CD8/38+ DR-"       "CD8/38- DR-"      "CD8/CCR7- 45RA+"  "CD8/CCR7+ 45RA+"  "CD8/CCR7+ 45RA-"  
[22] "CD8/CCR7- 45RA-"    "DNT"                "DPT"
```

FlowWorkspace: basics on *GatingSet*

```
# retrieve data from all nodes as a cytoset
```

```
> cs <- gs_pop_get_data(gs)
```

```
> class(cs)
```

```
[1] "cytoset"
```

```
attr(,"package")
```

```
[1] "flowWorkspace"
```

```
# convert the cytoset to a flowSet
```

```
> fs <- cytoset_to_flowSet(cs)
```

```
# check the number of cells in the flowSet
```

```
> fsApply(fs, nrow)
```

```
[,1]
```

```
CytoTrol_CytoTrol_1.fcs_119531 119531
```

```
CytoTrol_CytoTrol_2.fcs_115728 115728
```

```
# retrieve data associated to one node (gate)
```

```
> cs <- gs_pop_get_data(gs, "CD4")
```

```
[,1]
```

```
> fs <- cytoset_to_flowSet(cs)
```

```
CytoTrol_CytoTrol_1.fcs_119531 34032
```

```
> fsApply(fs, nrow)
```

```
CytoTrol_CytoTrol_2.fcs_115728 33751
```

FlowWorkspace: basics on *GatingSet* object

```
# Get membership indices with respect to a gate
```

```
> gh_pop_get_indices(gs[[1]], "CD4")
```

```
> table(gh_pop_get_indices(gs[[1]], "CD4"))
```

```
FALSE TRUE
```

```
85499 34032
```

```
# Delete a gate
```

```
> Rm('DPT', gs)
```

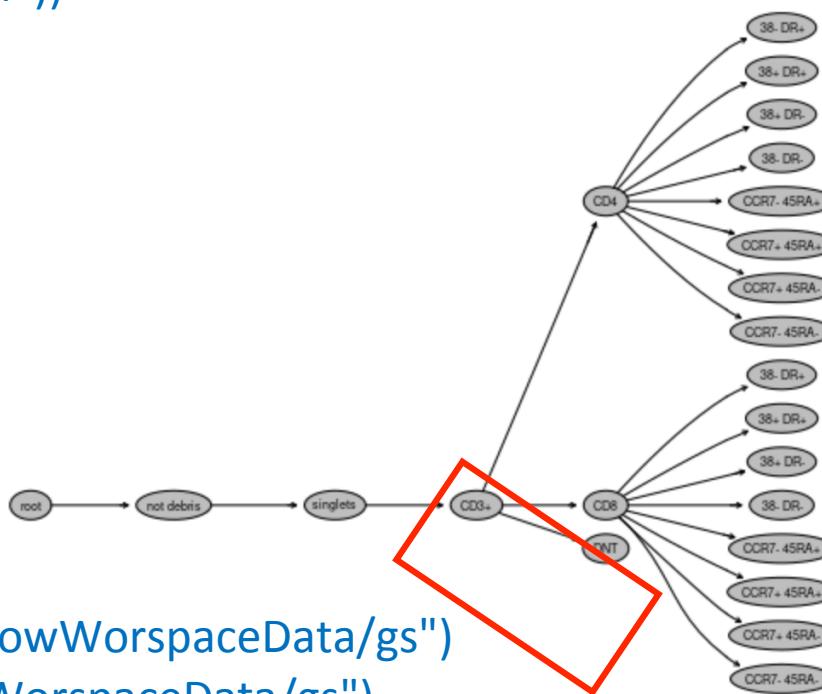
```
> plot(gs)
```

```
# save / load a GatingSet
```

```
> save_gs(gs, path = "course_datasets/flowWorspaceData/gs")
```

```
> gs2 <- load_gs("course_datasets/flowWorspaceData/gs")
```

```
[1] TRUE FALSE FALSE FALSE FALSE TRUE FA  
[16] TRUE FALSE TRUE TRUE TRUE FALSE FA  
[31] FALSE FALSE FALSE FALSE TRUE FALSE FA  
[46] FALSE FALSE FALSE FALSE TRUE TRUE FA
```



The regular R assignment (`<-`) or `save()` routine doesn't work for *GatingSet* objects

FlowWorkspace: build the *GatingSet* from scratch

Start from a *flowSet* (*flowCore*)

```
> load("course_datasets/FR_FCM_Z4KT/fcs_transform.RData") # load the flowSet  
> gs <- GatingSet(fcs_transform) # convert the flowSet to GatingSet
```

Start from a single cell experiment object (CATALYST)

```
> load("course_datasets/FR_FCM_Z4KT/DA_example_sce_PBMC.RData") # load the sce  
> fs <- sce2fcs(sce_PBMC, assay = "exprs") # convert sce to flowSet (CATALYST)  
> gs <- GatingSet(fs) # convert flowSet to GatingSet
```

flowWorkspace: preprocessing functions

Possibility of transforming data (same as with a *flowSet*)

```
# Logicle transformation  
> tf <- estimateLogicle(gs[[1]], channels)  
> gs <- transform(gs, tf)
```

```
# Arcsinh transformation  
> trans.obj <- asinhGml2_trans()  
> channels <- c("", "")  
> transList <- transformerList(channels, trans.obj )  
> gs <- transform(gs, tf)  
> autoplot(...)
```

Other built in functions: `flowjo.biexp_trans`, `flowjo_fasintrans` and
`logicle_trans`

Will test these

FlowWorkspace: transformations

Retrieve the transformations

```
> trans <- gh_get_transformations(gs[[1]])  
> trans[[1]]
```

Could we
also apply
QC
methods ?

FlowWorkspace: basic 1-D gating

THIS PART COMES
FROM THE FLOWCORE
VIGNETTE

Create a basic gate and add to the gs

```
> rg1 <- rectangleGate("FSC-A"=c(50), filterID="NonDebris")  
> gs_pop_add(gs, rg1, parent = "root")
```

Show the
nodes
beforec

Check the nodes (populations)

```
> gs_get_pop_paths(gs)
```

Replace
this with
real code

Gate the data and plot the gate

```
> recompute(gs)  
> autoplot(gs, "NonDebris")
```

Show the nodes
afterwards

Add plots

Get population statistics

```
> gs_pop_get_stats(gs[[]1], "NonDebris") # counts  
> gs_pop_get_stats(gs[[]1], "NonDebris", type = "percent") # proportions
```

Move this
to the end

FlowWorkspace: 2-D gating with polygon

Create a matrix with polygon coordinates

```
> mat <- matrix(c(...), nrow=5)
> colnames(mat) <- c("FSC-A","FSC-H")
```

Create the gate and add to the gs

```
> pg <- polygonGate(mat)
> gs_pop_add(gs, pq, parent = "NonDebris", name = "Singlets")
```

Gate the data

```
> recompute(gs)
> autoplot(gs, "Singlets")
```

Add results

FlowWorkspace: 2-D gating with quadrant gates

A *quadrantGate* results in four sub-populations

```
> qg <- quadGate("B710-A" = 2000, "R780-A" = 3000)  
> gs_pop_add(gs, qg, parent = "CD3", name = c("CD8","DPT","CD4","DNT"))
```

Check the gating hierarchy

```
> gs_pop_get_children(gs[[1]], "CD3")
```

Gate the data

```
> recompute(gs)
```

Add results

I skiped one
gating here,
but it would
be nice to
have a slide
before. See
the
flowCore
vignette

FlowWorkspace: Boolean gates

A *booleanFilter* selects several quadrants

```
> bg <- booleanFilter("CD8-CD4+|CD8-CD4+")
> gs_pop_add(gs, bg, parent = "CD3")
```

Check the gating hierarchy

```
> gs_pop_get_children(gs[[1]], "CD3")
```

Gate the data

```
> recompute(gs)
```

I skiped one
gating here,
but it would
be nice to
have a slide
before. See
the
flowCore
vignette

Add results

Plot the hierarchy

```
> plot(gs)
> plot(gs, bool=TRUE) # with boolean gate
```

THIS WILL HAVE TO
BE SPLIT INTO
SEVERAL SLIDES

Plot the gates

```
> autoplot(gs[[1]])
```

FlowWorkspace: other utilities

Remove nodes from a gating set object

```
> Rm('CD3', gs)  
> gs_get_pop_paths(gs)
```

SHOULD THIS BE
HERE OR WITH THE
BASICS ?

FlowWorkspace: retrieve flow Data and stats

Retrieve the underlying flow data for a gated population

```
> fs_nonDebris <- getData( gs, "NonDebris")
```

THIS IS
DUPLICATED

Get statistics

```
> gs_pop_get_count_fast(gs)
```

Add results

EXERCISE ON GATINGSET

- Import a xml workspace from FlowJo
 - Plot the gating hierarchy
 - Plot the gates
 - Add a gate
 - Statistics
 - Export flow data

flowGate

<https://bioconductor.org/packages/release/bioc/html/flowGate.html>

- Interactive cytometry gating in R
- Based on a shiny app (web application using R)
- Especially geared toward wet-lab cytometerists looking to take advantage of R without having a lot of experience
- Uses `gatingSets`
- You can use transformed data, but `flowGate` was designed to apply desired transformations at the plotting level only

Interactive gating with *FlowGate*

Create a 2-D gate

```
> fs <- read.flowSet(path="course_datasets/FR_FCM_Z3WR/",  
                      pattern = "*.fcs",  
                      transformation = FALSE,  
                      truncate_max_range = FALSE)  
  
> gs <- GatingSet(fs)  
> gs_gate_interactive(gs,  
                      filterId = "Leukocytes",  
                      dims = list("FSC-H", "SSC-H"))
```

type of gate

Draw your gate

Reset Done

Bins

Gate Type:

- Rectangle
- Polygon
- Span
- Quadrant

Enable Manual Coords?

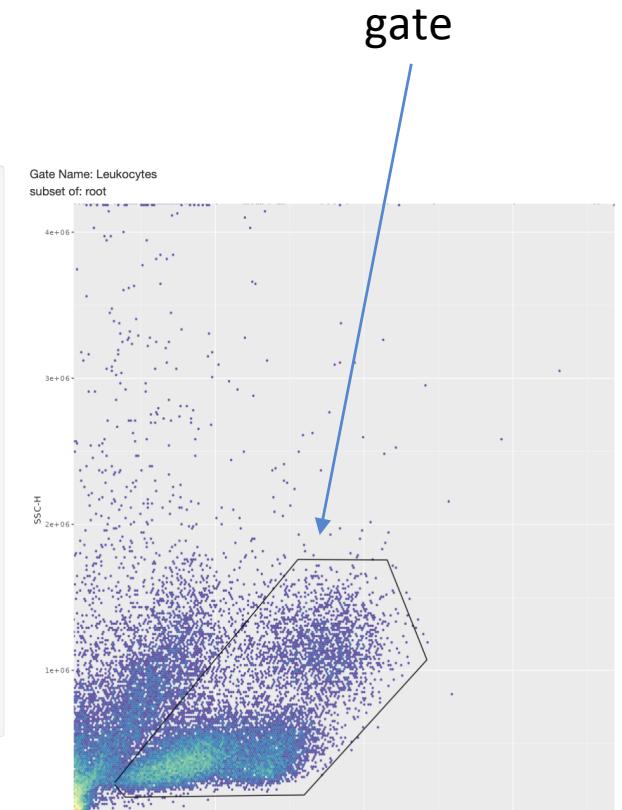
X Minimum: -1000

X Maximum: 50000

Y Minimum: -1000

Y Maximum: 50000

Use FlowJo Biex?



Interactive gating with *FlowGate*

Create a 2-D *polygon* gate

```
> fs <- read.flowSet(path="course_datasets/FR_FCM_Z3WR/",  
                      pattern = "*.fcs",  
                      transformation = FALSE,  
                      truncate_max_range = FALSE)  
  
> gs <- GatingSet(fs)  
> gs_gate_interactive(gs,  
                      filterId = "Leukocytes",  
                      dims = list("FSC-H", "SSC-H"))
```

type of gate

Output message

```
Listening on http://127.0.0.1:5217  
done!  
$Gate  
Polygonal gate 'Leukocytes' with 10 vertices in dimensions FSC-H and SSC-H  
  
$Bins  
[1] 256  
  
$Scaling  
[1] "unused"
```

Draw your gate

Reset Done

Bins: 2 256 2,048

Gate Type:

- Rectangle
- Polygon
- Span
- Quadrant

Enable Manual Coords?

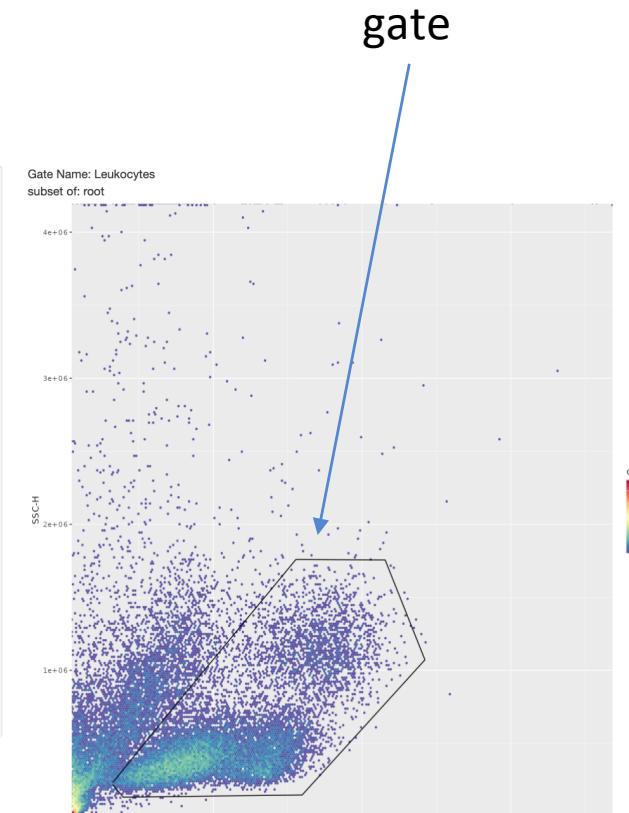
X Minimum: -1000

X Maximum: 50000

Y Minimum: -1000

Y Maximum: 50000

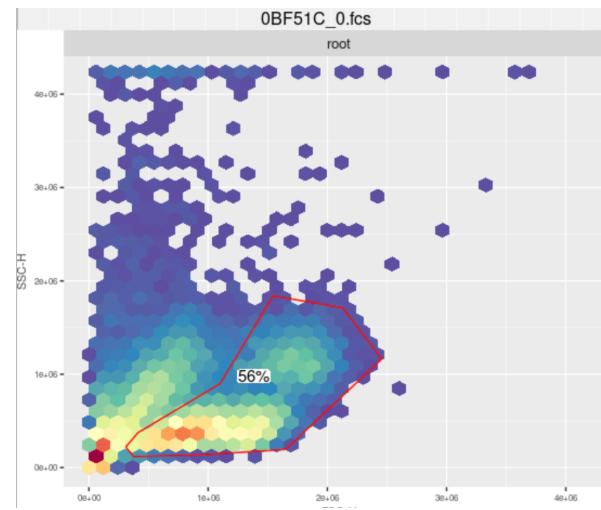
Use FlowJo Biex?



Interactive gating with *FlowGate*

Plot the gate

```
> autoplot(gs[[1]], gate = "Leukocytes")
```



Interactive gating with *FlowGate*

Create a 1-D *span* gate

```
> gs_gate_interactive(gs,  
                      filterId = "CD3",  
                      dims = "BV510-A",  
                      subset = "Leukocytes")
```

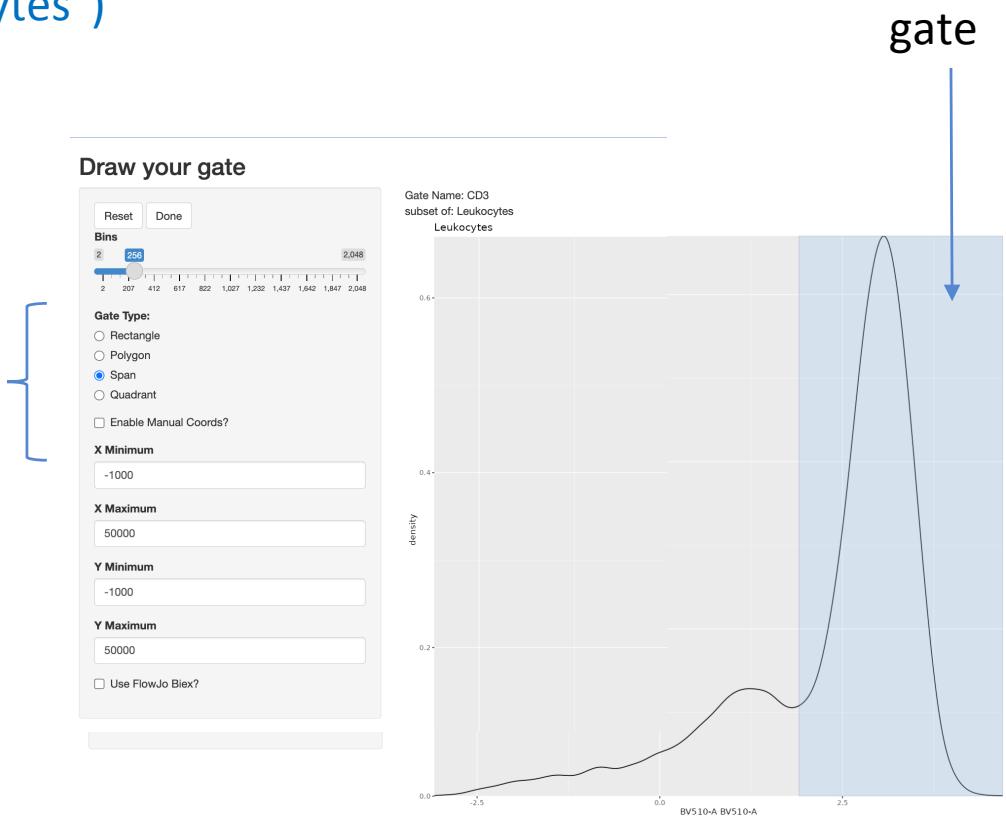
type of gate

Output message

```
Listening on http://127.0.0.1:6815  
done!  
$Gate  
Rectangular gate 'CD3' with dimensions:  
  BV510-A: (1.9068187688965,4.6925115585313)
```

```
$Bins  
[1] 256
```

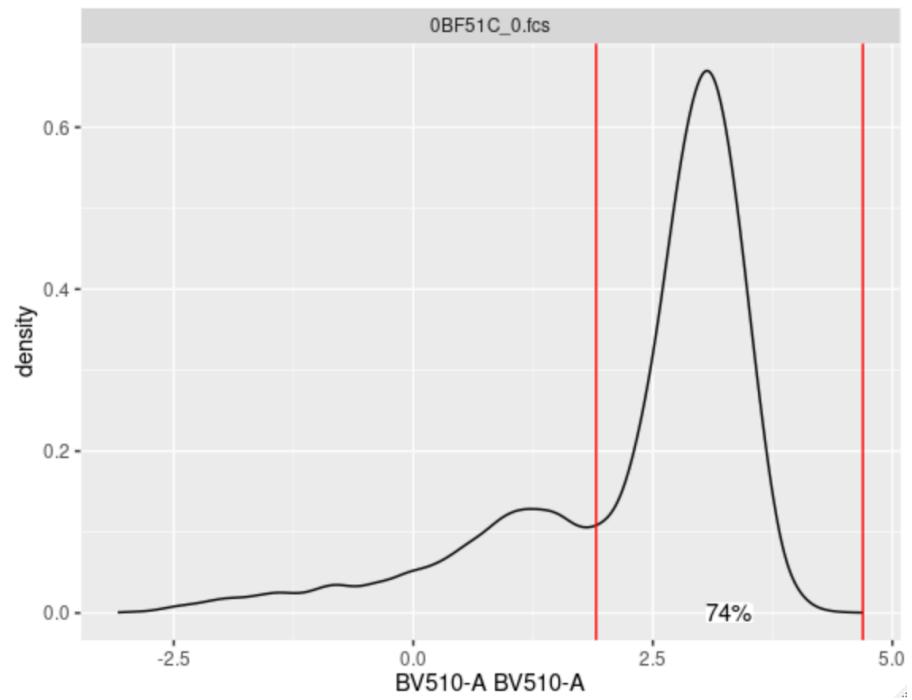
```
$Scaling  
[1] "unused"
```



Interactive gating with *FlowGate*

Plot the 1-D gate

```
> ggcyto(gs[[1]], aes("BV510-A")) +  
  geom_density() +  
  geom_gate("CD3") +  
  geom_stats()
```



Interactive gating with *FlowGate*

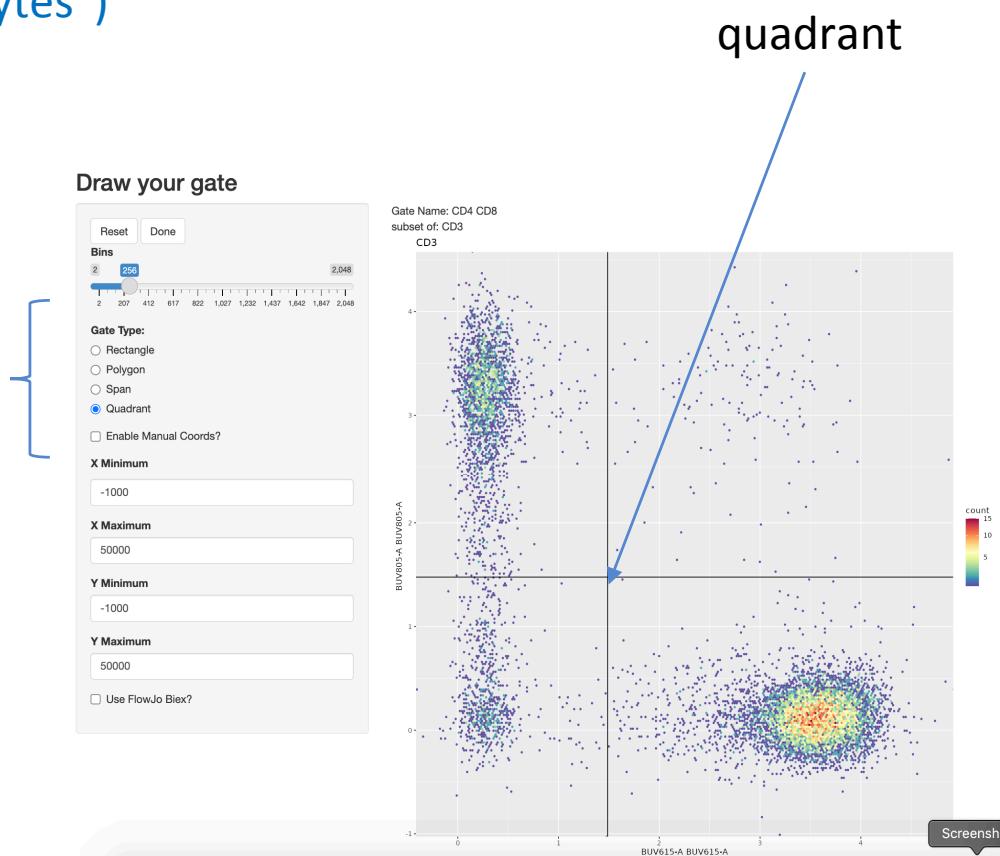
Create a 2-D quadrant gate

```
> gs_gate_interactive(gs,  
                      filterId = "CD4 CD8",  
                      dims = c("BV510-A",),  
                      subset = "Leukocytes")
```

Output message

```
Listening on http://127.0.0.1:6815  
Coordinate system already present. Adding new coordinate system, which will  
replace the existing one.  
done!  
$Gate  
Quadrant gate 'CD4 CD8' with dimensions:  
  BUV615-A: 1.487559  
  BUV805-A: 1.476832  
  
$Bins  
[1] 256  
  
$Scaling  
[1] "unused"
```

type of gate

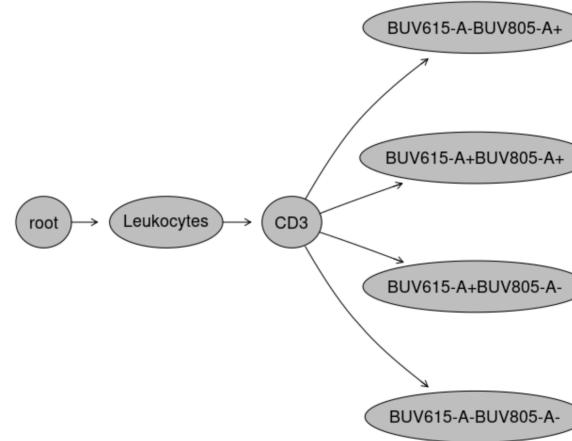


Interactive gating with *FlowGate*

Plot the gating hierarchy

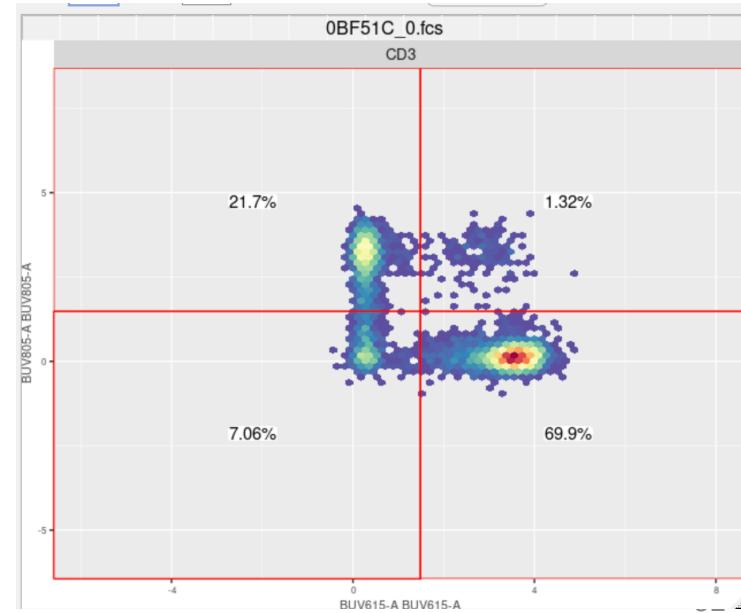
```
> plot(gs)
```

There is no node "CD4 CD8" !



Plot the 2-D quadrant gate

```
> autoplot(gs[[1]],  
          gs_pop_get_children(gs, "CD3"))
```



04

Automated Gating

flowClust

REMOVE
THIS PART

<https://www.bioconductor.org/packages/release/bioc/html/flowClust.html>

- Robust Model-based Clustering of Flow Cytometry Data (Lo et al. 2008)
- Identify cell populations in flow cytometry data
- Based on a multivariate t mixture model with Box-Cox transformation
- ...
- Two options for **estimating the number of clusters when it is unknown**
- **Input are *flowFrames***

Check
paper !

Add some
figures
here !

openCyto

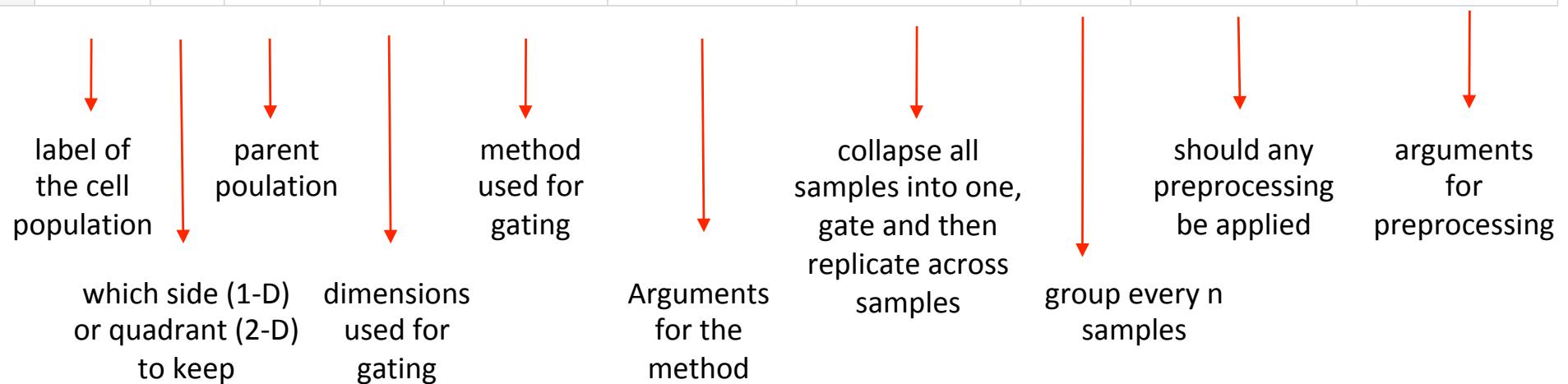
<https://bioconductor.org/packages/release/bioc/html/openCyto.html>

- Hierarchical gating pipeline for flow cytometry data
- Automated gating using a *gatingTemplate* (hierarchical gating scheme)

gatingTemplate

- Prepare a template in a spreadsheet (Excel)

	alias	pop	parent	dims	gating_method	gating_args	collapseDataForGating	groupBy	preprocessing_method	preprocessing_args
1	nonDebris	+	root	FSC-A	gate_mindensity		NA	NA		NA
2	singlets	+	nonDebris	FSC-A,FSC-H	singletGate		NA	NA		NA
3	lymph	+	singlets	FSC-A,SSC-A	flowClust	K=2,target=c(1e5,5e4)	NA	NA	prior_flowClust	NA
4	cd3	+	lymph	CD3	gate_mindensity		TRUE	4		NA
5	*	-/+/-	cd3	cd4,cd8	gate_mindensity	gate_range=c(1,3)	NA	NA		NA
6	activated cd4	++	cd4+cd8-	CD38,HLA	gate_mindensity		NA	NA	standardize_flowset	NA
7	activated cd8	++	cd4-cd8+	CD38,HLA	gate_mindensity		NA	NA	standardize_flowset	NA
8	CD45_neg	-	cd4+cd8-	CD45RA	gate_mindensity	gate_range=c(2,3)	NA	NA		NA
9	CCR7_gate	+	CD45_neg	CCR7	flowClust	neg=1,pos=1	NA	NA		NA
10	*	+/-/-	cd4+cd8-	CCR7,CD45RA	refGate	CD45_neg:CCR7_gate	NA	NA		NA
11	*	+/-/-	cd4-cd8+	CCR7,CD45RA	gate_mindensity		NA	NA		NA



<https://bioconductor.org/packages/release/bioc/vignettes/openCyto/inst/doc/HowToWriteCSVTemplate.html>

gatingTemplate

▲	alias	◆	pop	◆	parent	◆	dims	◆	gating_method	◆	gating_args	◆	collapseDataForGating	◆	groupBy	◆	preprocessing_method	◆	preprocessing_args	◆
1	nonDebris	+			root		FSC-A		gate_mindensity				NA		NA				NA	

- The population name is "nonDebris"
- The parent node is "root"
- Use *mindensity* :
- Generate a 1-D gate on FSC-A and keep the only the positive cells

gatingTemplate

2	singlets	+	nonDebris	FSC-A,FSC-H	singletGate	NA	NA	NA
---	----------	---	-----------	-------------	-------------	----	----	----

- The population name is "singlets"
- The parent node is "nonDebris"
- Use *singletGate* :
- Generate a polygon gate on FSC-A and FSC-H keep the only the singlet cells (singlet+)

gatingTemplate

3	lymph	+	singlets	FSC-A,SSC-A	flowClust	K=2,target=c(1e5,5e4)	NA	NA	prior_flowClust	NA
---	-------	---	----------	-------------	-----------	-----------------------	----	----	-----------------	----

- The population name is "lymph"
- The parent node is "singlets"
- Use *flowClust* :
- Generate a 2-D gate on FSC-A and SSC-A and keep the only the positive cells
- Apply the preprocessing method from *flowClust* (before gating). This is actually an extra argument for *flowClust*

gatingTemplate

5	*	-/+/-	cd3	cd4,cd8	gate_mindensity	gate_range=c(1,3)	NA	NA	NA	NA
---	---	-------	-----	---------	-----------------	-------------------	----	----	----	----

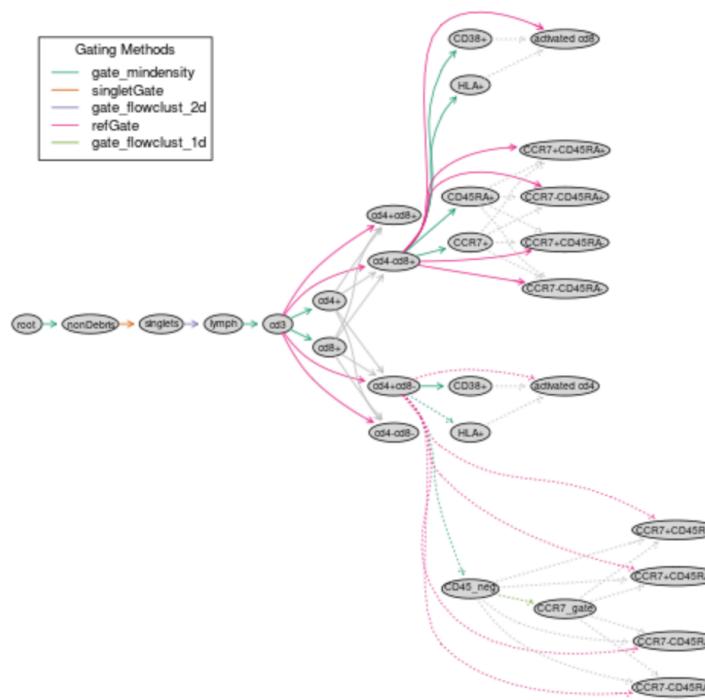
- Specifies that population CD4+/-CD8+/- should be expanded into 6 rows
 - The first two rows are 1-D gates on each dimension
 - The other four rows are rectangle gates that correspond to the four quadrants in the 2-D projection

gatingTemplate

- Export the template in csv format and load it into R

```
# import the gatingTemplate  
> gtFile <- "course_datasets/gating/tcell_gating_template.csv"  
> gt_tcell <- gatingTemplate(gtFile)
```

```
# examine the gating template  
> plot(gt_tcell)
```



openCyto: run the gating pipeline

Load the data and convert to gatingSet

```
# Load the raw data  
> fcsFiles <- list.files(pattern = "CytoTrol", flowDataPath, full = TRUE)  
> fs <- read.flowSet(fcsFiles)
```

```
# Convert to a gatingSet  
> gs <- GatingSet(fs)
```

Preprocess the data using dedicated functions from
flowWorkspace

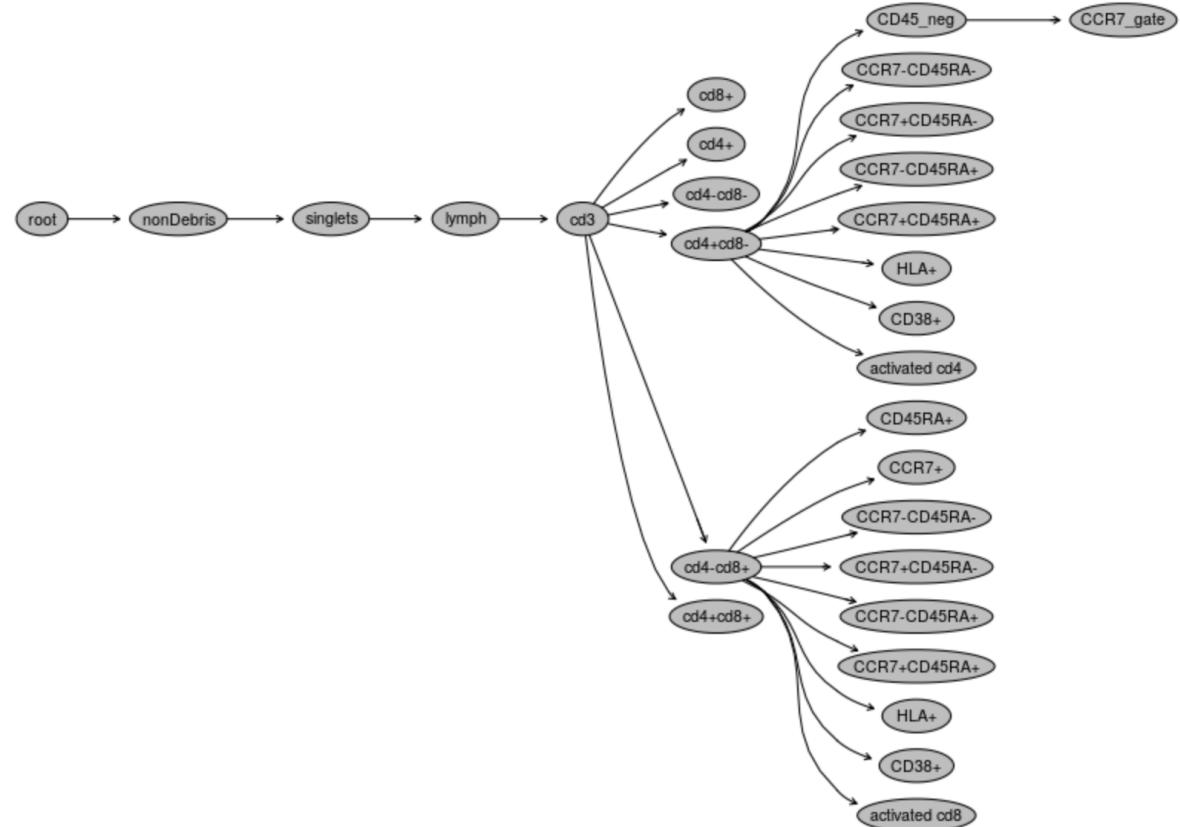
Apply the gating template

```
# Gating  
> gt_gating(gt_tcell, gs)
```

openCyto: run the gating pipeline

Check the gating

```
# Check the gating  
> plot(gs[[1]])
```

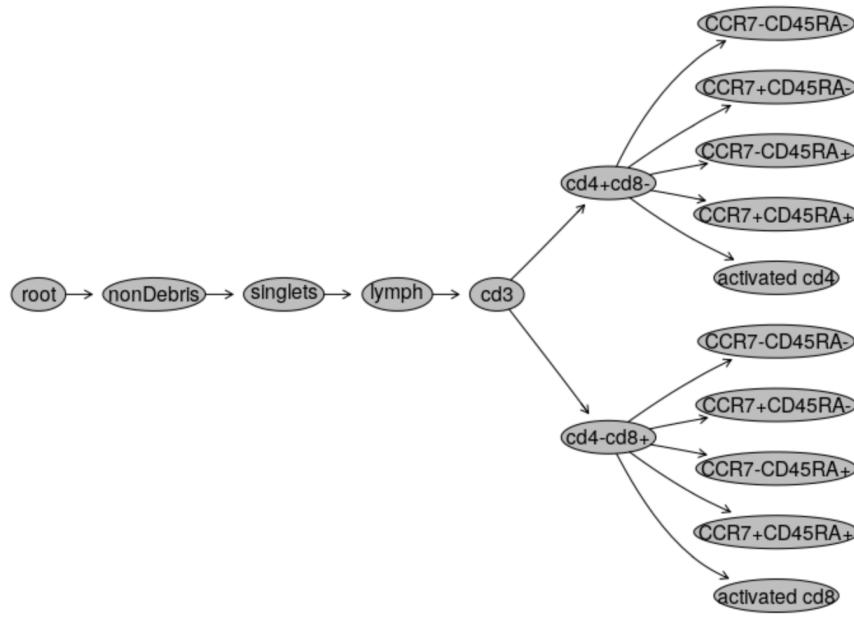


openCyto

Hide populations we are not interested in

```
# Hide populations
```

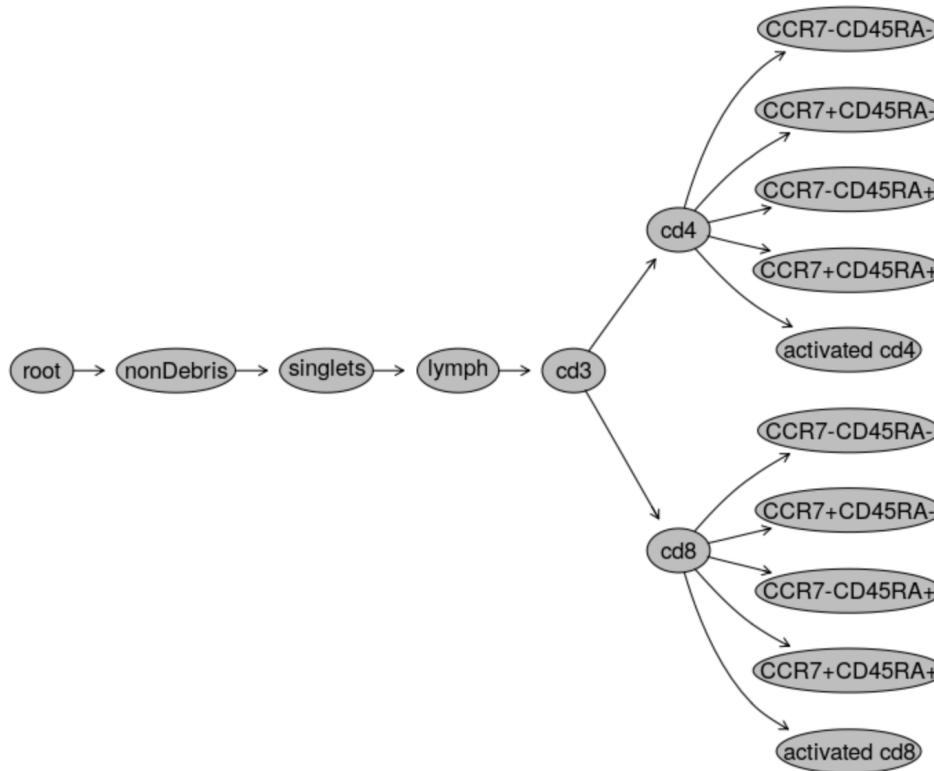
```
> nodesToHide <- c("cd8+", "cd4+", "cd4-cd8", "cd4+cd8+", "cd4+cd8-/HLA+",  
  "cd4+cd8-/CD38+", "cd4-cd8+/HLA+", "cd4-cd8+/CD38+",  
  "CD45_neg/CCR7_gate", "cd4+cd8-/CD45_neg",  
  "cd4-cd8+/CCR7+", "cd4-cd8+/CD45RA+" )  
> lapply(nodesToHide, function(thisNode) gs_pop_set_visibility(gs, thisNode, FALSE))  
> plot(gs[[1]])
```



openCyto

Rename populations

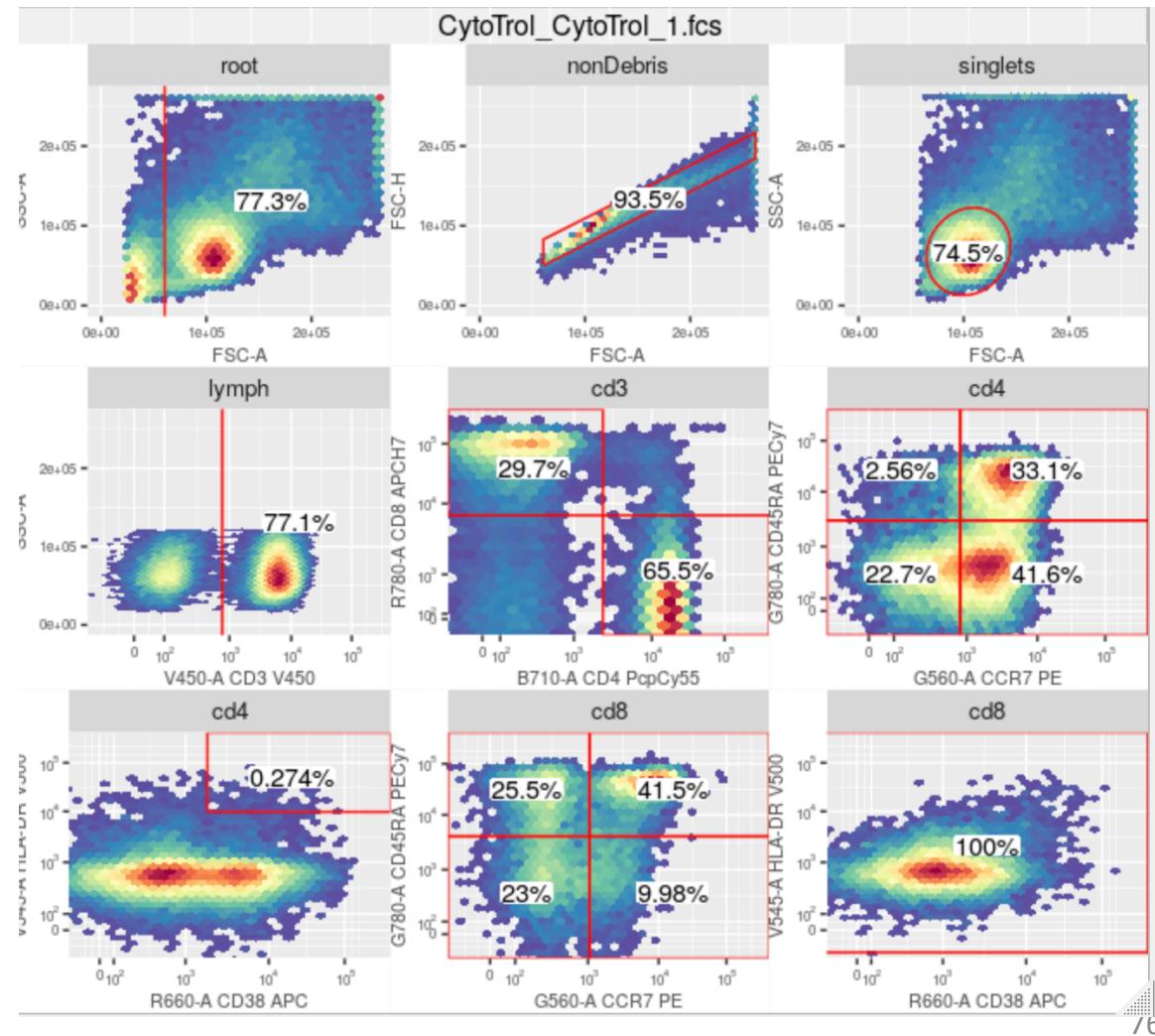
```
# Rename  
> gs_pop_set_name(gs,"cd4+cd8-","cd4")  
> gs_pop_set_name(gs,"cd4-cd8+","cd8")  
> plot(gs[[1]])
```



openCyto

Visualize the gates with *ggcyto*

```
> autoplot(gs[[1]])
```



openCyto: gating without csv template

We can apply each automated gating step using the same fields as in the template

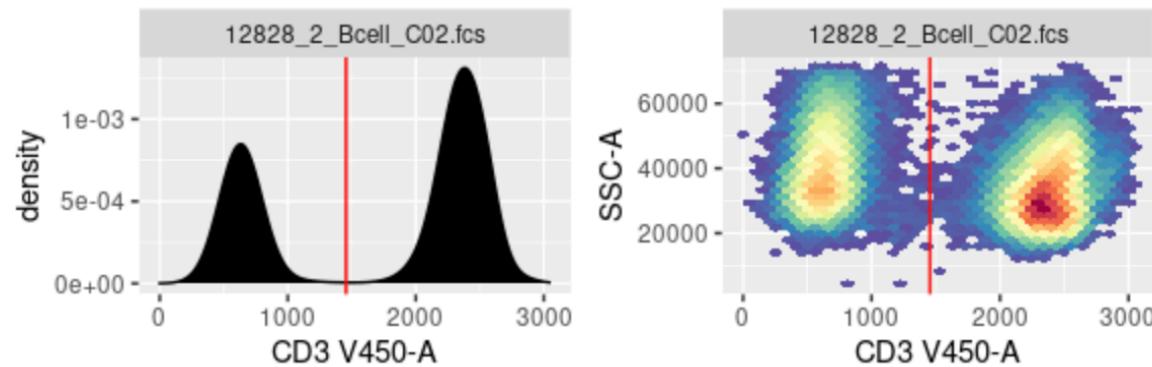
```
> gs_add_gating_method(gs,  
                        alias = "non-activated cd4",  
                        pop = "--",  
                        parent = "cd4",  
                        dims = "CD38,HLA",  
                        gating_method = "tailgate")  
> plot(gs[[1]])
```

openCyto: overview of gating methods

<https://bioconductor.org/packages/release/bioc/vignettes/openCyto/inst/doc/HowToAutoGating.html>

mindensity

Finds the minimum as the cutpoint between positive and negative peaks in a 1-D density plot



- Fast, robust and easy to use
- For markers with a good separation between + and – peaks
- Needs more guidance when there are more than 2 peaks

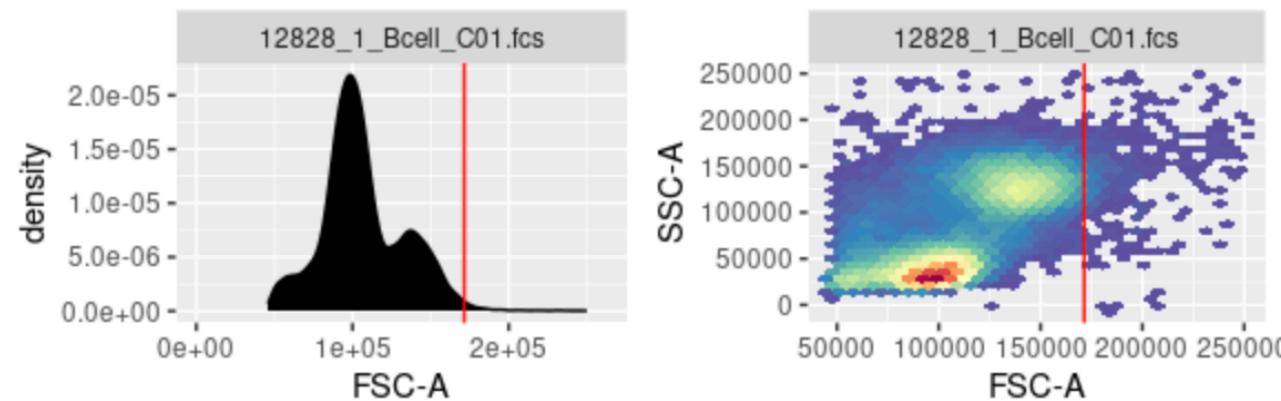
openCyto: overview of gating methods

tailgate

Gates the right side or left side of the 1-D density based on a cutpoint (estimated) in the tail

quantileGate

Alternative to tailgate and it determines the cutpoint by the events quantile

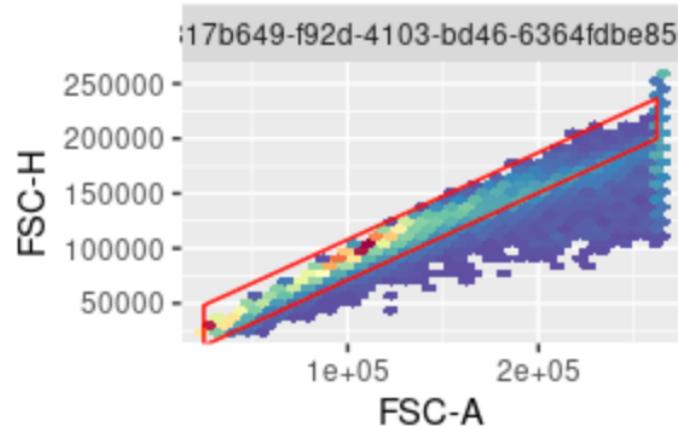


- More commonly used for rare populations (peak is not prominent enough)

openCyto: overview of gating methods

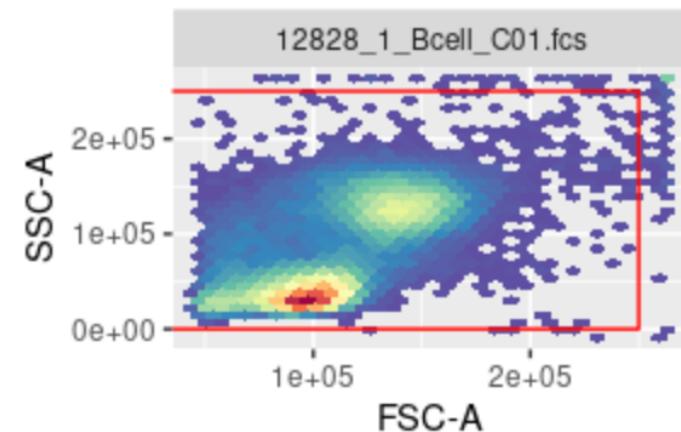
singletGate

Use the area vs height to gate out the singlets



boundary

Constructs a rectangle gate from input range (min and max)

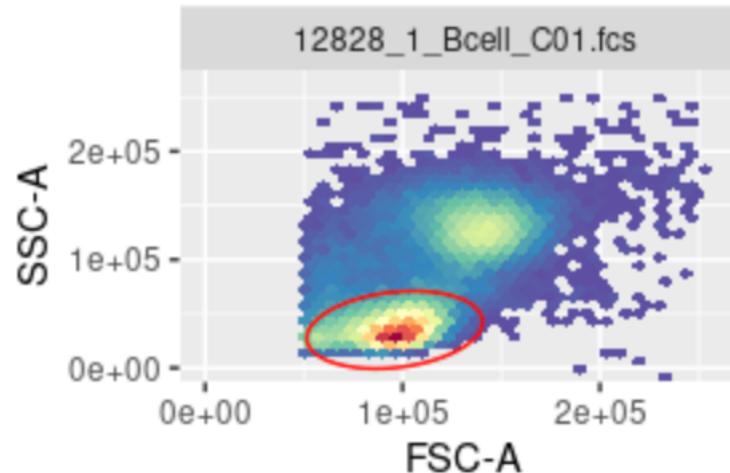


- Used for filtering out very extreme signals at the boundary

openCyto: overview of gating methods

flowClust

1-D or 2-D automated gating methods from flowClust (more details in ?flowClust)



- k = how many cell populations are expected
- $target$ = center of target population (by default the most prominent cluster)
- $quantile$ = how large the ellipse should be

EXERCISE ON AUTOMATED GATING

04

Generate html or PDF reports

Planning and Preparation

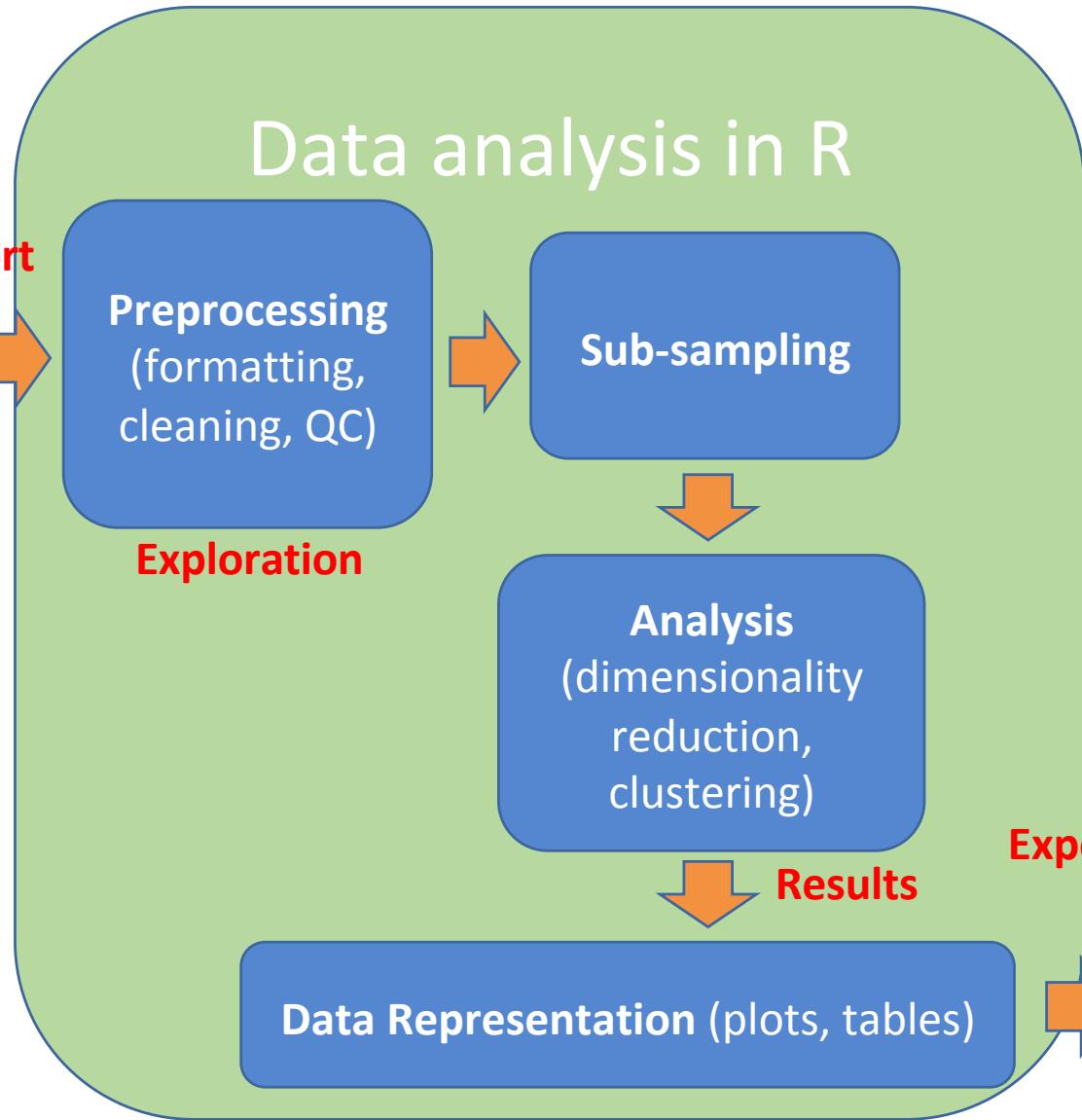


Data acquisition



Manual analysis
(QC, gating)

Import



Communicate
(reports)

Rmarkdown

Thank you for your attention!

<https://agora-cancer.ch/scientific-platforms/translational-data-science-facility/>

Any questions? Contact us !

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