

Preprocessing And clustering

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Loading packages

```
suppressMessages(library(dplyr))
suppressMessages(library(Seurat))
suppressMessages(library(patchwork))
suppressMessages(library(ggplot2))
suppressMessages(library(dittoSeq))
suppressMessages(library(formatR))
```

Loading data

```
# Importing myeloid cells
path <- "../1-Preprocessing_workflow"
myeloid_cells <- readRDS(paste0(path, "/Myeloid_cells_Part1.rds"))

# Importing IM_cells
IMcells.data <- Read10X(data.dir = paste("barcode_j0", sep = ""))
IMcells <- CreateSeuratObject(counts = IMcells.data, project = "IM_cells", min.cells = 3,
  min.features = 200)

# QC on IM_cells
IMcells[["percent.mt"]] <- PercentageFeatureSet(IMcells, pattern = "^mt-")
IMcells <- subset(IMcells, subset = nFeature_RNA > 1000 & nFeature_RNA < 4000 &
  nCount_RNA <
    20000 & percent.mt < 10)
```

Integretion workflow

```
seurat_list <- list(myeloid_cells, IMcells)

seurat_list <- lapply(X = seurat_list, FUN = function(x) {
  x <- NormalizeData(x)
  x <- FindVariableFeatures(x, selection.method = "vst", nfeatures = 2000)
})

features <- SelectIntegrationFeatures(object.list = seurat_list)

cells.anchors <- FindIntegrationAnchors(object.list = seurat_list, anchor.features =
  features)
```

```
cells.combined <- IntegrateData(anchorset = cells.anchors)
```

```
cells.combined <- ScaleData(cells.combined, verbose = FALSE)
```

```
cells.combined <- RunPCA(cells.combined, npcs = 30, verbose = FALSE)
```

```
cells.combined <- RunUMAP(cells.combined, reduction = "pca", dims = 1:16)
```

```
## Warning: The default method for RunUMAP has changed from calling Python UMAP via reticulate to the R  
## To use Python UMAP via reticulate, set umap.method to 'umap-learn' and metric to 'correlation'  
## This message will be shown once per session
```

```
cells.combined <- FindNeighbors(cells.combined, reduction = "pca", dims = 1:16)
```

```
cells.combined <- FindClusters(cells.combined, resolution = 0.7)
```

```
## Modularity Optimizer version 1.3.0 by Ludo Waltman and Nees Jan van Eck
```

```
##
```

```
## Number of nodes: 6311
```

```
## Number of edges: 226798
```

```
##
```

```
## Running Louvain algorithm...
```

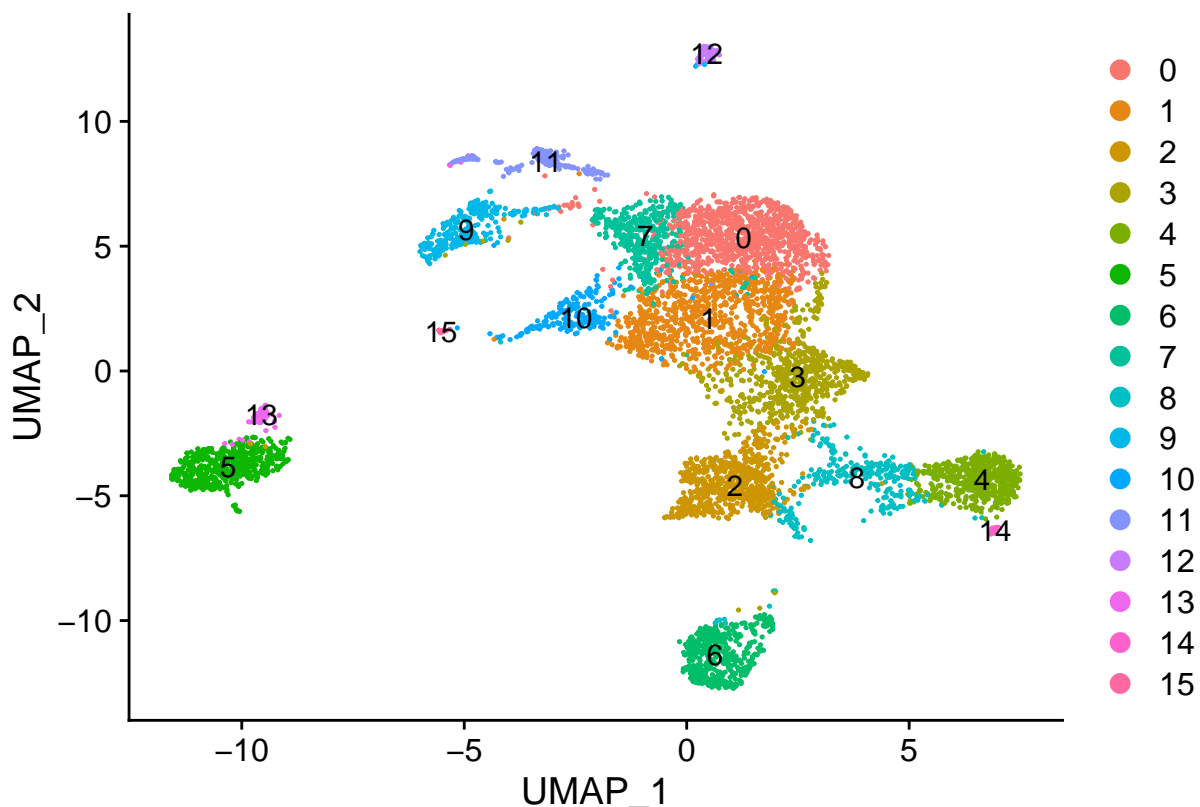
```
## Maximum modularity in 10 random starts: 0.8713
```

```
## Number of communities: 16
```

```
## Elapsed time: 0 seconds
```

Visualizing all clusters

```
DimPlot(cells.combined, reduction = "umap", label = T)
```



The clusters 12, 14, 15 were identified as contamination and had to be removed.

```
# Selecting the clusters we want to keep
myeloid_cells_filtered <- subset(cells.combined, seurat_clusters %in% c(0, 1, 2,
  3, 4, 5, 6, 7, 8, 9, 10, 11, 13))

# Re-running the linear reduction step
myeloid_cells_filtered <- FindVariableFeatures(myeloid_cells_filtered, selection.method =
"vst",
  nfeatures = 2000)
all.genes <- rownames(myeloid_cells_filtered)
myeloid_cells_filtered <- ScaleData(myeloid_cells_filtered, features = all.genes)
myeloid_cells_filtered <- RunPCA(myeloid_cells_filtered, features =
VariableFeatures(object = myeloid_cells_filtered))
plot1 <- DimPlot(myeloid_cells_filtered, reduction = "pca")

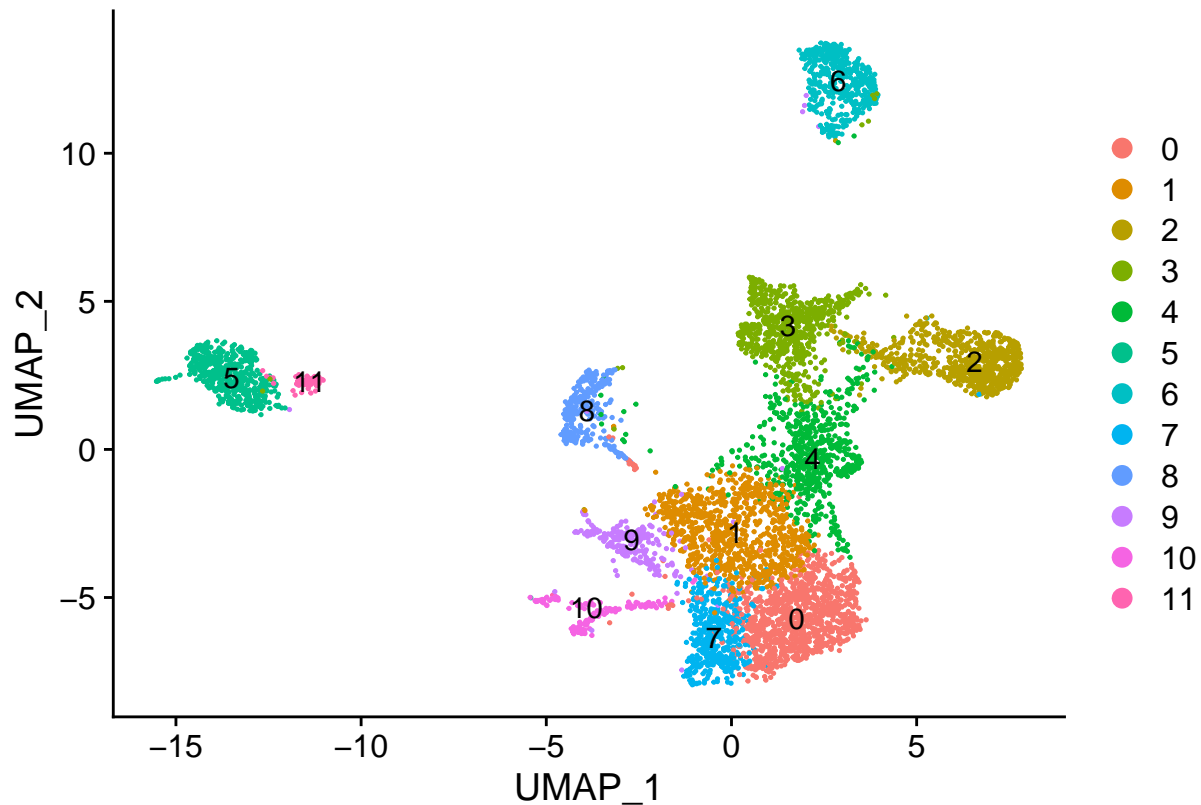
myeloid_cells_filtered <- JackStraw(myeloid_cells_filtered, num.replicate = 100)
myeloid_cells_filtered <- ScoreJackStraw(myeloid_cells_filtered, dims = 1:20)
plot2 <- JackStrawPlot(myeloid_cells_filtered, dims = 1:20)
plot3 <- ElbowPlot(myeloid_cells_filtered)

# Re running the clustering step
myeloid_cells_filtered <- RunUMAP(myeloid_cells_filtered, dims = 1:15)
myeloid_cells_filtered <- FindNeighbors(myeloid_cells_filtered, dims = 1:15)
myeloid_cells_filtered <- FindClusters(myeloid_cells_filtered, resolution = 0.7) # the
resolution has been chosen based on trial and error, and 0.7 appear to be the most
relevant
```

Reversing umap coordiante for consistency

```
myeloid_cells_filtered@reductions$umap@cell.embeddings[, 2] <-
-myeloid_cells_filtered@reductions$umap@cell.embeddings[,
  2]

DimPlot(myeloid_cells_filtered, reduction = "umap", label = T)
```



Saving the results for further analysis

```
saveRDS(myeloid_cells_filtered, "Myeloid_cells_Part2.rds")
```

```
sessionInfo()
```

```
## R version 4.0.3 (2020-10-10)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu 20.04.6 LTS
##
## Matrix products: default
## BLAS: /usr/lib/x86_64-linux-gnu/openblas-pthread/libblas.so.3
## LAPACK: /usr/lib/x86_64-linux-gnu/openblas-pthread/liblapack.so.3
##
## locale:
##  [1] LC_CTYPE=en_US.UTF-8      LC_NUMERIC=C
##  [3] LC_TIME=fr_BE.UTF-8      LC_COLLATE=en_US.UTF-8
##  [5] LC_MONETARY=fr_BE.UTF-8  LC_MESSAGES=en_US.UTF-8
##  [7] LC_PAPER=fr_BE.UTF-8     LC_NAME=C
##  [9] LC_ADDRESS=C             LC_TELEPHONE=C
## [11] LC_MEASUREMENT=fr_BE.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
## other attached packages:
## [1] formatR_1.14      dittoSeq_1.2.6    ggplot2_3.4.0     patchwork_1.1.2
```

```

## [5] SeuratObject_4.1.3 Seurat_4.3.0      dplyr_1.0.10
##
## loaded via a namespace (and not attached):
## [1] plyr_1.8.8      igraph_1.4.1
## [3] lazyeval_0.2.2  sp_1.6-0
## [5] splines_4.0.3   listenv_0.9.0
## [7] scattermore_0.8 GenomeInfoDb_1.26.7
## [9] digest_0.6.31   htmltools_0.5.4
## [11] fansi_1.0.4     magrittr_2.0.3
## [13] tensor_1.5       cluster_2.1.0
## [15] ROCR_1.0-11      limma_3.46.0
## [17] globals_0.16.2  matrixStats_0.63.0
## [19] R.utils_2.12.2  spatstat.sparse_3.0-0
## [21] colorspace_2.1-0 ggrepel_0.9.2
## [23] xfun_0.37        crayon_1.5.2
## [25] RCurl_1.98-1.10 jsonlite_1.8.4
## [27] progressr_0.13.0 spatstat.data_3.0-0
## [29] survival_3.2-7   zoo_1.8-11
## [31] glue_1.6.2       polyclip_1.10-4
## [33] gtable_0.3.1     zlibbioc_1.36.0
## [35] XVector_0.30.0   leiden_0.4.3
## [37] DelayedArray_0.16.3 future.apply_1.10.0
## [39] SingleCellExperiment_1.12.0 BiocGenerics_0.36.1
## [41] abind_1.4-5       scales_1.2.1
## [43] pheatmap_1.0.12  DBI_1.1.3
## [45] edgeR_3.32.1     spatstat.random_3.1-3
## [47] miniUI_0.1.1.1   Rcpp_1.0.10
## [49] viridisLite_0.4.1 xtable_1.8-4
## [51] reticulate_1.27  stats4_4.0.3
## [53] htmlwidgets_1.6.1 httr_1.4.5
## [55] RColorBrewer_1.1-3 ellipsis_0.3.2
## [57] ica_1.0-3         farver_2.1.1
## [59] pkgconfig_2.0.3  R.methodsS3_1.8.2
## [61] uwot_0.1.14      deldir_1.0-6
## [63] locfit_1.5-9.4   utf8_1.2.3
## [65] labeling_0.4.2    tidyselect_1.2.0
## [67] rlang_1.0.6       reshape2_1.4.4
## [69] later_1.3.0       munsell_0.5.0
## [71] tools_4.0.3       cli_3.6.0
## [73] generics_0.1.3    ggribes_0.5.4
## [75] evaluate_0.20     stringr_1.5.0
## [77] fastmap_1.1.1     yaml_2.3.7
## [79] goftest_1.2-3     knitr_1.42
## [81] fitdistrplus_1.1-8 purrr_1.0.1
## [83] RANN_2.6.1        pbapply_1.7-0
## [85] future_1.32.0     nlme_3.1-162
## [87] mime_0.12         R.oo_1.25.0
## [89] compiler_4.0.3    rstudioapi_0.14
## [91] plotly_4.10.1     png_0.1-8
## [93] spatstat.utils_3.0-1 tibble_3.1.8
## [95] stringi_1.7.12    highr_0.10
## [97] lattice_0.20-41   Matrix_1.5-3
## [99] vctrs_0.5.2       pillar_1.8.1
## [101] lifecycle_1.0.3  spatstat.geom_3.0-6

```

## [103] lmtest_0.9-40	RcppAnnoy_0.0.20
## [105] data.table_1.14.8	cowplot_1.1.1
## [107] bitops_1.0-7	irlba_2.3.5.1
## [109] httpuv_1.6.9	GenomicRanges_1.42.0
## [111] R6_2.5.1	promises_1.2.0.1
## [113] KernSmooth_2.23-20	gridExtra_2.3
## [115] IRanges_2.24.1	parallelly_1.34.0
## [117] codetools_0.2-19	MASS_7.3-53
## [119] assertthat_0.2.1	SummarizedExperiment_1.20.0
## [121] withr_2.5.0	sctransform_0.3.5
## [123] S4Vectors_0.28.1	GenomeInfoDbData_1.2.4
## [125] parallel_4.0.3	grid_4.0.3
## [127] tidyr_1.2.1	rmarkdown_2.19
## [129] MatrixGenerics_1.2.1	Rtsne_0.16
## [131] spatstat.explore_3.0-5	Biobase_2.50.0
## [133] shiny_1.7.4	