

PAPER TITLE TO BE DEFINED (in common.yaml)

10-DE genes across pseudotime

2021-12-09 14:07:55 +0100

Abstract

Lung interstitium macrophages (IMs) are non-alveolar resident tissue macrophages which contribute to the lung homeostasis. These cells were reported to be heterogeneous by our group and other teams, which contains two main distinct subpopulations: CD206+ IMs and CD206- IMs. However, the exact origin of IMs and the transcriptional programs that control IM differentiation remains unclear. In recent report, we analyzed the refilled IMs in the course of time after induced IM depletion with single-cell RNA sequencing (10X Genomics Chromium) and bulk RNA sequencing.

Contents

1	Description	2
2	Prepare data	2
3	DE gene expression across IM-differentiation	2
3.1	Annotate the cells associated to either differentiation of CD206+ IMs or CD206- IMs	5
4	TradeSeq analysis for the differentiation of monocytes to either of IM subsets	5
4.1	Construct sce object for TradeSeq	5
4.2	Clustering using RSEC, clusterExperiment	7
5	Show gene expression pattern calculated by TradeSeq in heatmap	9
5.1	Data preparation	9
5.2	Draw heatmap	9
5.3	Annotate DE genes as CD206+/CD206- IM differentiation specific or common genes	10
5.4	Daw heatmap with expression patterns of unchanged/common genes in the order of pseudotime	13
5.5	Make with changed/specific genes	15
6	Functionality analysis of DE genes across pseudotime (common genes)	16
6.1	Manually classify genes by expression timing peak	17
6.2	GO/KEGG enrichment analysis with 3 classes of common genes	17
7	Show gene expression pattern with TradeSeq results	22
7.1	Class 1 common genes	22
7.2	Class 2 common genes	23
7.3	Class 3 common genes	25
8	Session information	26
9	References	28

1 Description

2 Prepare data

```
suppressMessages(  
{  
  library(Seurat)  
  library(ComplexHeatmap)  
  library(ggplot2)  
  library(dplyr)  
  library(RColorBrewer)  
  library(circlize)  
  library(monocle3)  
})  
  
mo <- readRDS(file = "../9-Monocle_analysis_and_pseudotime_estimation/Mono  
_to_IM.cds")
```

3 DE gene expression across IM-differentiation

DE genes across pseudotime of IM differentiation ## Across pseudotime of IM differentiation

Prepare matrix with z-scores, smoothened and scaled data across pseudotime for heatmap.

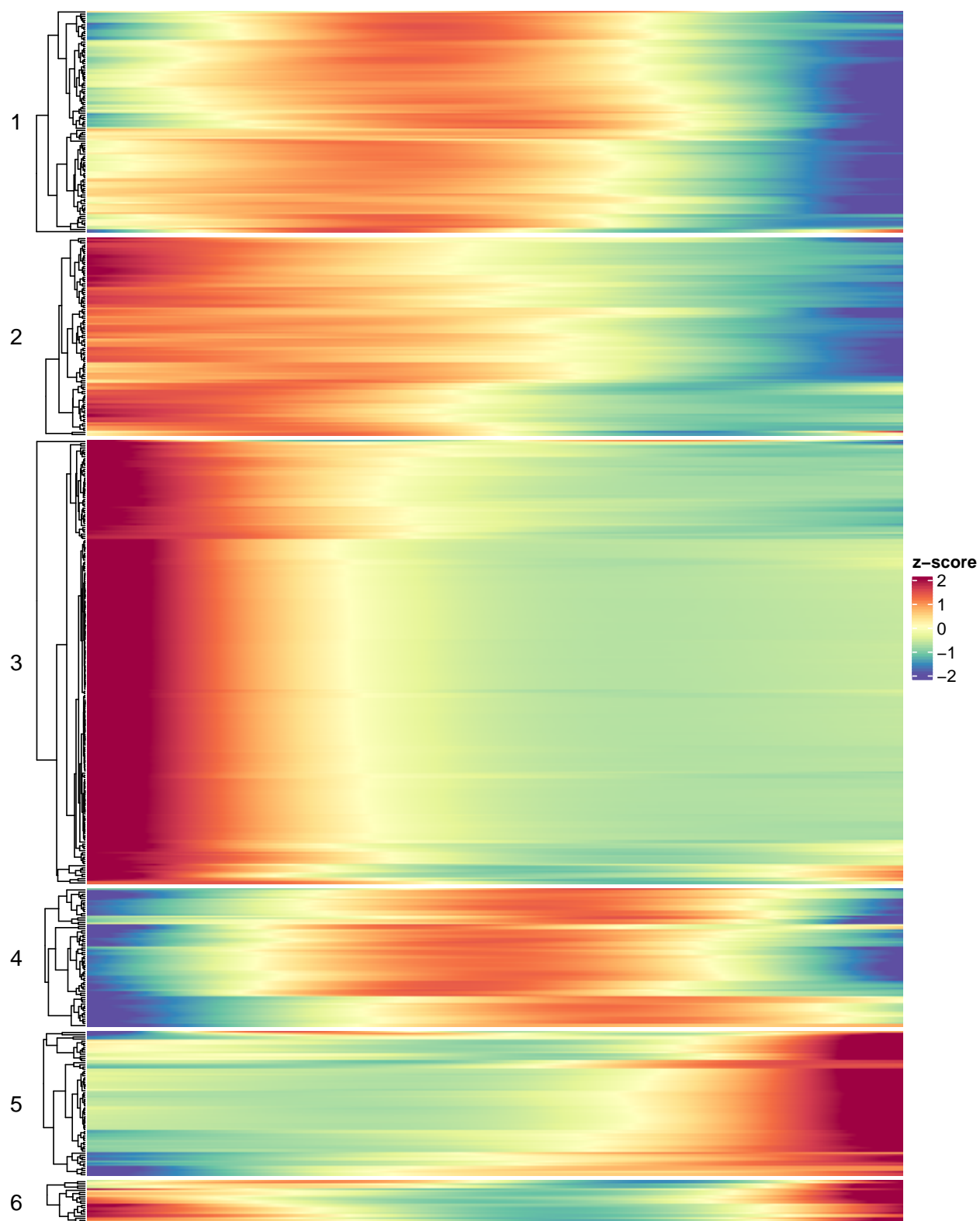
```
pt.matrix <- exprs(mo)[match(genes, rownames(rowData(mo))), order(pseudotime  
(mo))]  
cellnames <- colnames(pt.matrix)  
#Can also use "normalized_counts" instead of "exprs" to use various  
normalization methods, for example:  
#normalized_counts(cds, norm_method = "log")  
  
pt.matrix <- t(apply(pt.matrix, 1, function(x){smooth.spline(x, df=3)$y}))  
pt.matrix <- t(apply(pt.matrix, 1, function(x){(x-mean(x))/sd(x)}))  
rownames(pt.matrix) <- genes  
colnames(pt.matrix) <- cellnames
```

Show DE genes in unsupervised heatmap.

```
#K means with 6 groups  
htkm <- Heatmap(  
  pt.matrix,  
  # use_raster = FALSE, # use FALSE to export to vector image.  
  name = "z-score",  
  col = colorRamp2(seq(from=-2, to=2, length=11),  
    rev(brewer.pal(11, "Spectral"))),  
  show_row_names = FALSE,  
  show_column_names = FALSE,  
  row_names_gp = gpar(fontsize = 3),  
  row_km = 6,  
  row_km_repeats = 31,  
  row_dend_reorder = TRUE,  
  row_title_rot = 0,  
  cluster_rows = TRUE,  
  cluster_row_slices = FALSE,
```

```
    cluster_columns      = FALSE,  
  )  
  htkm <- draw(htkm)
```

16
17
18
19



In this heatmap, the x axis is pseudotime, which represents differentiation state from monocytes (left) to IMs (right).

3.1 Annotate the cells associated to either differentiation of CD206+ IMs or CD206- IMs

```

library(magrittr)
# Get the closest vertice for every cell
y_to_cells <- mo@principal_graph_aux$UMAP$pr_graph_cell_proj_closest_
  vertex%>%as.data.frame()

y_to_cells$cells <- rownames(y_to_cells)
y_to_cells$Y <- y_to_cells$V1

# Get the root vertices
# It is the same node as above
root <- mo@principal_graph_aux$UMAP$root_pr_nodes

principalgraph <- mo@principal_graph$UMAP

# Get the other endpoints
endpoints <- names(which(igraph::degree(principalgraph) == 1))
endpoints <- endpoints[!endpoints %in% root]

# For each endpoint
cellWeights <- lapply(endpoints, function(endpoint) {
  # We find the path between the endpoint and the root
  path <- igraph::shortest_paths(principalgraph, root, endpoint)$vpath
  [[1]]
  path <- as.character(path)
  # We find the cells that map along that path
  df <- y_to_cells[y_to_cells$Y %in% path, ]
  df <- data.frame(weights = as.numeric(colnames(mo) %in% df$cells))
  colnames(df) <- endpoint
  return(df)
}) %>% do.call(what = 'cbind', args = .) %>%
  as.matrix()
rownames(cellWeights) <- colnames(mo)
colnames(cellWeights) <- c("CD206_IM_branch", "MHCII_IM_branch")
pseudotime <- matrix(mo@principal_graph_aux$UMAP$pseudotime, ncol = ncol(
  cellWeights),
  nrow = ncol(mo), byrow = FALSE)
rownames(pseudotime) <- colnames(mo)

```

4 TradeSeq analysis for the differentiation of monocytes to either of IM subsets

4.1 Construct sce object for TradeSeq

```

suppressMessages(library(tradeSeq))

# this step is VERY time consuming
sce <- fitGAM(counts = mo@assays@data$counts,
  pseudotime = pseudotime,
  cellWeights = cellWeights)

```

```
saveRDS(sce, file = "./sce.4339cells.newversion.Rds")
```

Between-lineage comparisons (CD206+ IM vs CD206- IM differentiation) ## Between-lineage comparisons (CD206+ IM vs CD206- IM differentiation)

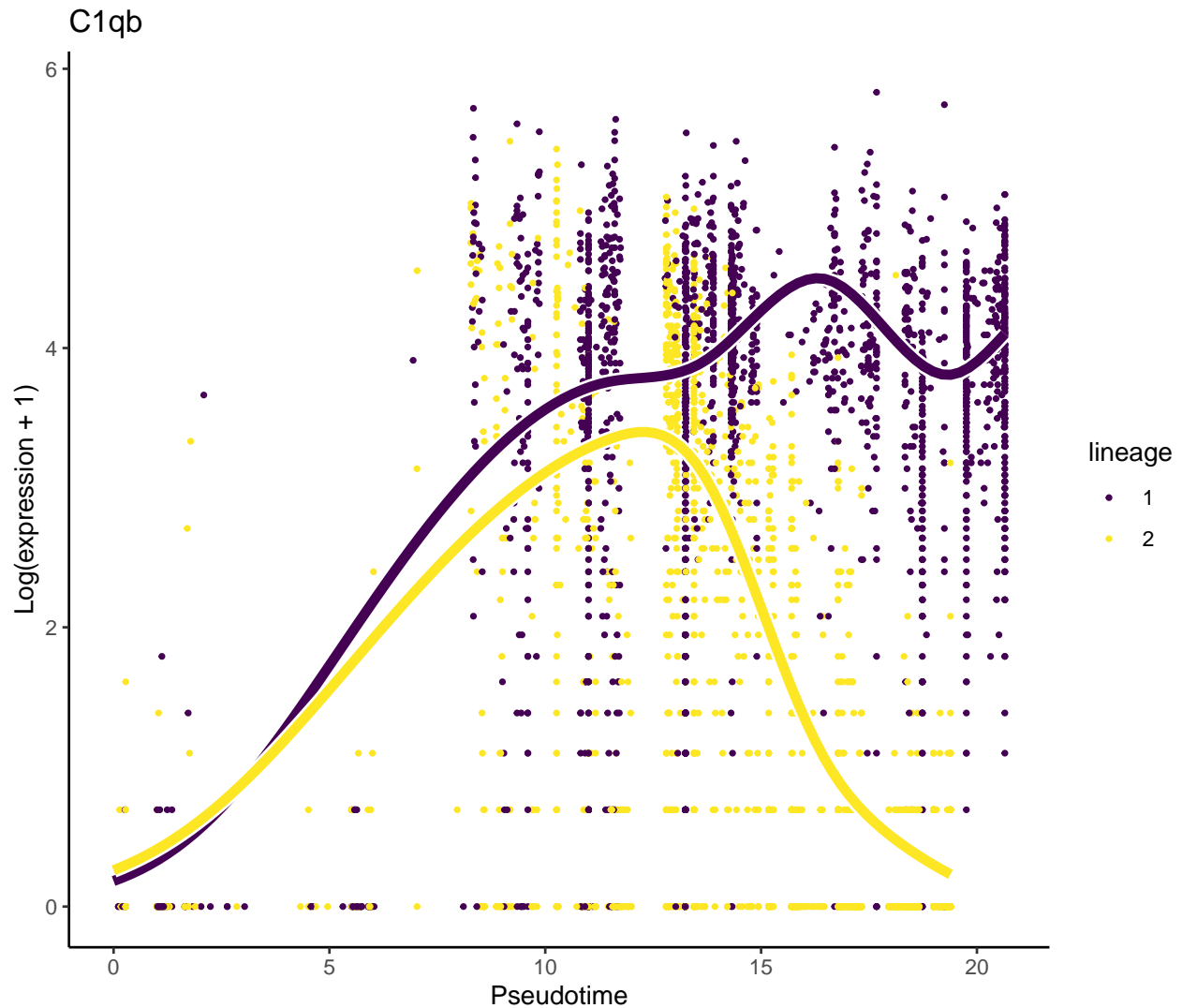
Association of gene expression with pseudotime (find significant DE genes along pseudotime).

```
assoRes <- associationTest(sce)
endRes <- diffEndTest(sce)
head(assoRes)
```

```
## # A tibble: 6 x 4
##   waldStat    df      pvalue meanLogFC
##   <dbl> <dbl>      <dbl>      <dbl>
## 1    210.     9  0.000000000000000000  0.222
## 2    28.4     9  0.000815000000000000  0.113
## 3     NA     NA NA 0.000000000000000000  0.121
## 4    41.8     9  0.000003600000000000  0.0958
## 5    36.4     9  0.000033000000000000  0.163
## 6    45.1     9  0.000008800000000000  0.160
```

Plot the most sig gene:

```
library(ggplot2)
o <- order(endRes$waldStat, decreasing = TRUE)
sigGene <- names(sce)[o[1]]
plotSmoother(sce, counts = counts(sce), gene = sigGene
             #, curvesCol = c("#33A02C", "#B2DF8A")
             ) + ggtitle(sigGene)
```



What's the top genes?

```
names(sce)[o[1:20]]
```

##	[1]	"C1qb"	"Ctsb"	"C1qa"	"Selenop"	"Csfr1r"	"Timp2"	"Pf4"	1
##	[8]	"C1qc"	"Serinc3"	"Cd209a"	"Lsp1"	"Lgmn"	"ApoE"	"Blvrb"	2
##	[15]	"Olfm1"	"Tnip3"	"Rpl13"	"Ninj1"	"Rpl28"	"H2-DMb1"		3

4.2 Clustering using RSEC, clusterExperiment

tradeSeq provides the functionality to cluster genes according to their expression pattern along the lineages with the `clusterExpressionPatterns` function. A number of equally spaced points for every lineage are selected to perform the clustering, and the number of points can be selected with the `nPoints` argument. (from `vignette("tradeSeq")`)

```
library(clusterExperiment)
nPointsClus <- 20 # The number of points to use for clustering the
  expression patterns..
clusPat <- clusterExpressionPatterns(sce,
```

```

nPoints = nPointsClus,
genes = genes,
random.seed = 43,
beta = 0.2
)

## 36 parameter combinations, 36 use sequential method, 36 use subsampling
method
## Running Clustering on Parameter Combinations...
## done.

clusterLabels <- primaryCluster(clusPat$rsec)

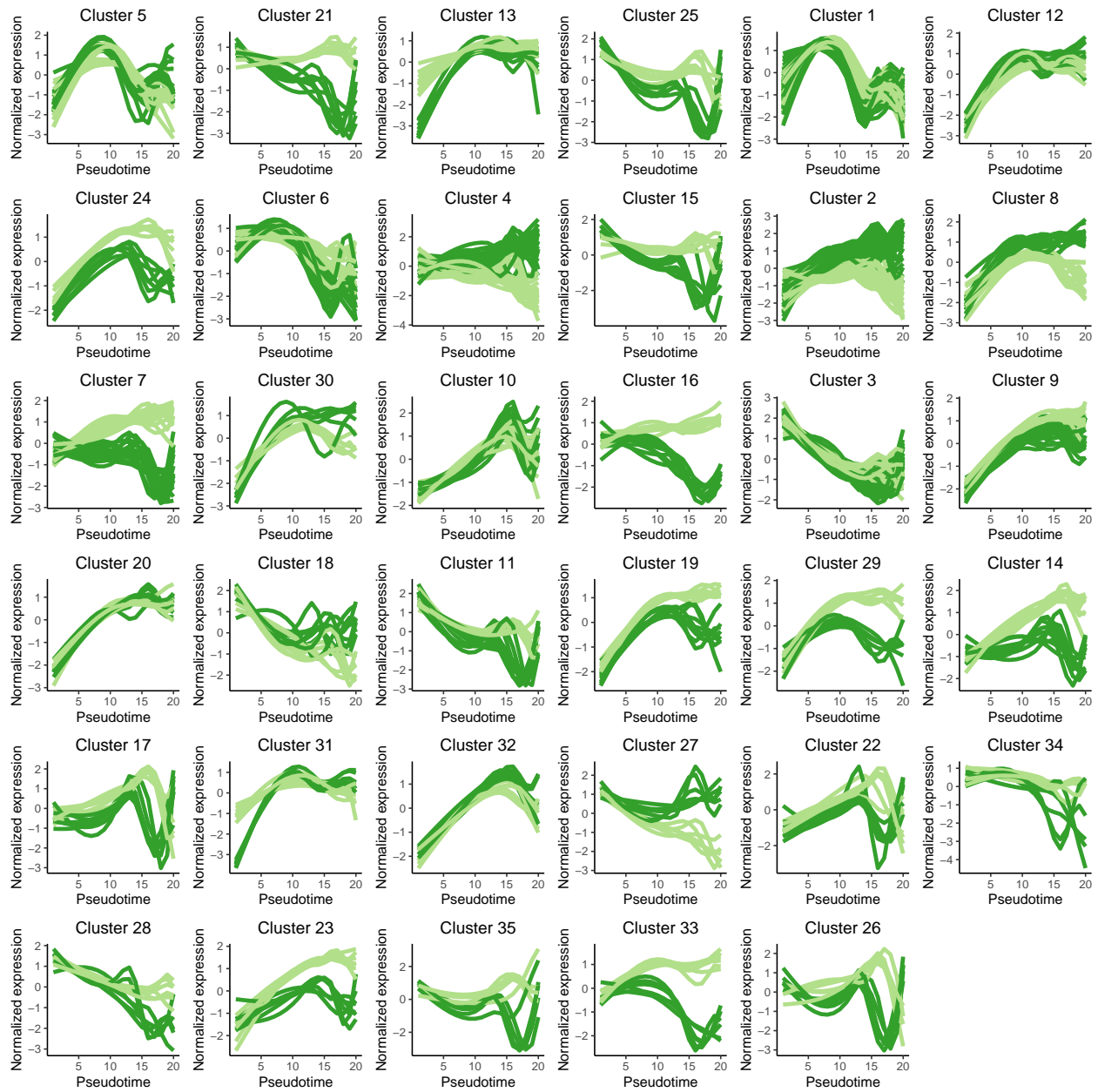
cUniq <- unique(clusterLabels) #
cUniq <- cUniq[!cUniq == -1] # remove unclustered genes

# cUniq <- cUniq[cUniq == -1]
# Any samples not found as part of a homogenous set of clusters at that
point will be classified as unclustered (given a value of -1)

# beta: value between 0 and 1 to decide how stable clustership membership
has to be before 'finding' and removing the cluster.
if (exists("p.total")) { rm(p.total)}

for (xx in cUniq) {
  cId <- which(clusterLabels == xx)
  p <- ggplot(data = data.frame(x = 1:nPointsClus,
                                y = rep(range(clusPat$yhatScaled[cId, ]),
                                          nPointsClus / 2)),
              aes(x = x, y = y)) +
    geom_point(alpha = 0) +
    labs(title = paste0("Cluster_", xx), x = "Pseudotime", y = "
      Normalized_expression") +
    theme_classic() +
    theme(plot.title = element_text(hjust = 0.5))
  for (ii in 1:length(cId)) {
    geneId <- rownames(clusPat$yhatScaled)[cId[ii]]
    p <- p +
      geom_line(data = data.frame(x = rep(1:nPointsClus, 2),
                                      y = clusPat$yhatScaled[geneId, ],
                                      lineage = rep(0:1, each = nPointsClus)),
                aes(col = as.character(lineage), group = lineage), lwd =
                  1.5)
  }
  p <- p + guides(color = "none") +
    scale_color_manual(values = c("#33A02C", "#B2DF8A"),
                       breaks = c("0", "1"))
  if (exists("p.total")) { p.total <- p.total + p } else {p.total <- p}
}
print(p.total)

```

5 Show gene expression pattern calculated by TradeSeq in heatmap

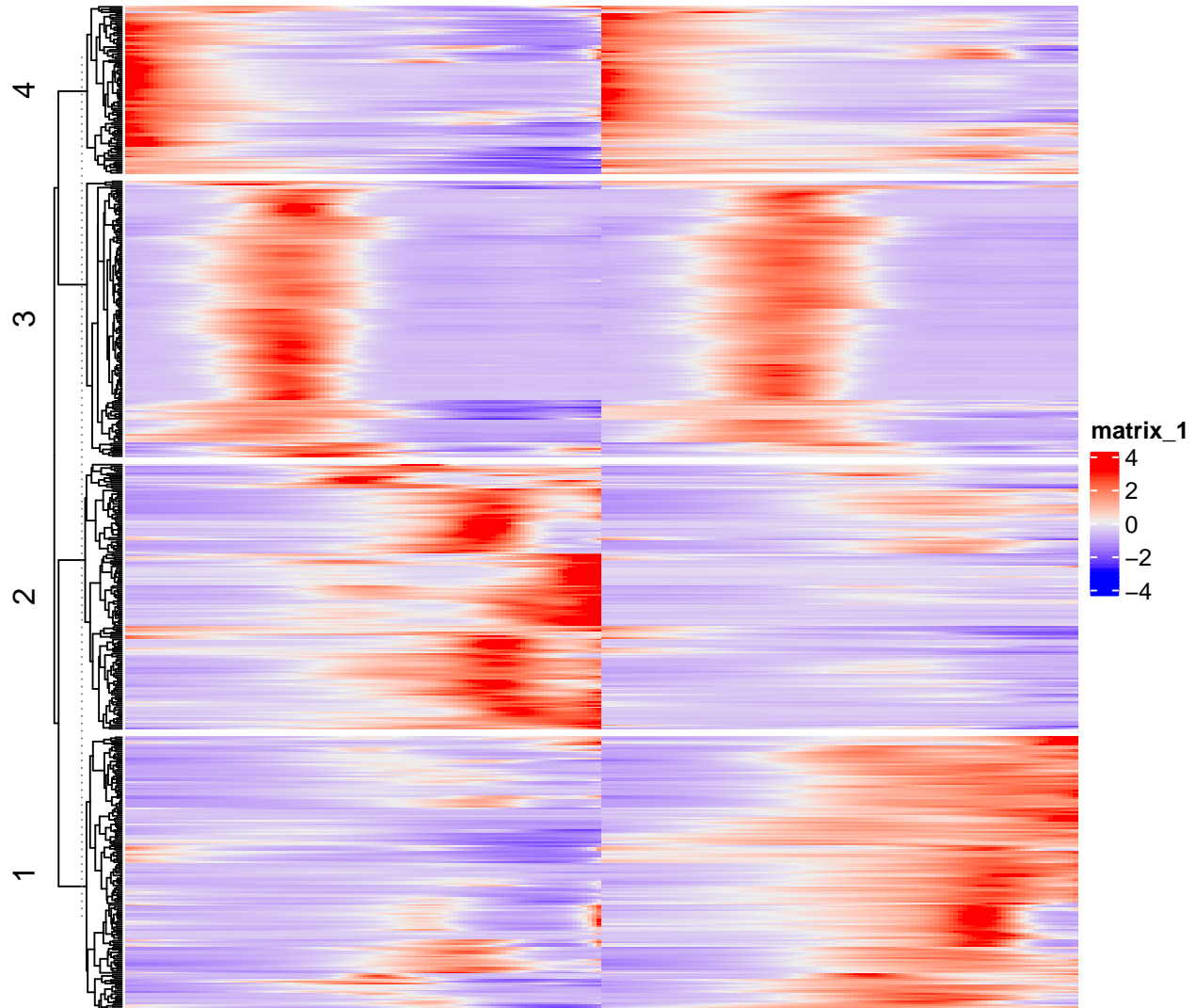
5.1 Data preparation

Here we use the DE genes calculated in DE genes across pseudotime of IM differentiation.

```
yhatSmooth <- predictSmooth(sce, gene = genes, nPoints = 100, tidy = FALSE) 1
yhatSmoothScaled <- t(scale(t(yhatSmooth))) 2
```

5.2 Draw heatmap

```
heatSmooth <- Heatmap(yhatSmoothScaled, cluster_columns = FALSE, show_row_ 1
  names = FALSE, show_column_names = FALSE, row_km = 4)
heatSmooth <- draw(heatSmooth) 2
```



Two IM differentiation show similar patterns but some genes (especially cluster 2 and 1) are different in CD206+ and CD206-.

5.3 Annotate DE genes as CD206+/CD206- IM differentiation specific or common genes

According to the heatmap above, some of DE genes should remain unchanged (common) and half of them are specific to one of two IM differentiation.

We use wald statistic calculated in diffEndTest to annotate the “common” genes and “specific” genes. (in Between-lineage comparisons (CD206+ IM vs CD206- IM differentiation))

```
endRes.DE <- endRes[rownames(yhatSmooth), ] 1
summary(endRes.DE$waldStat) 2
```

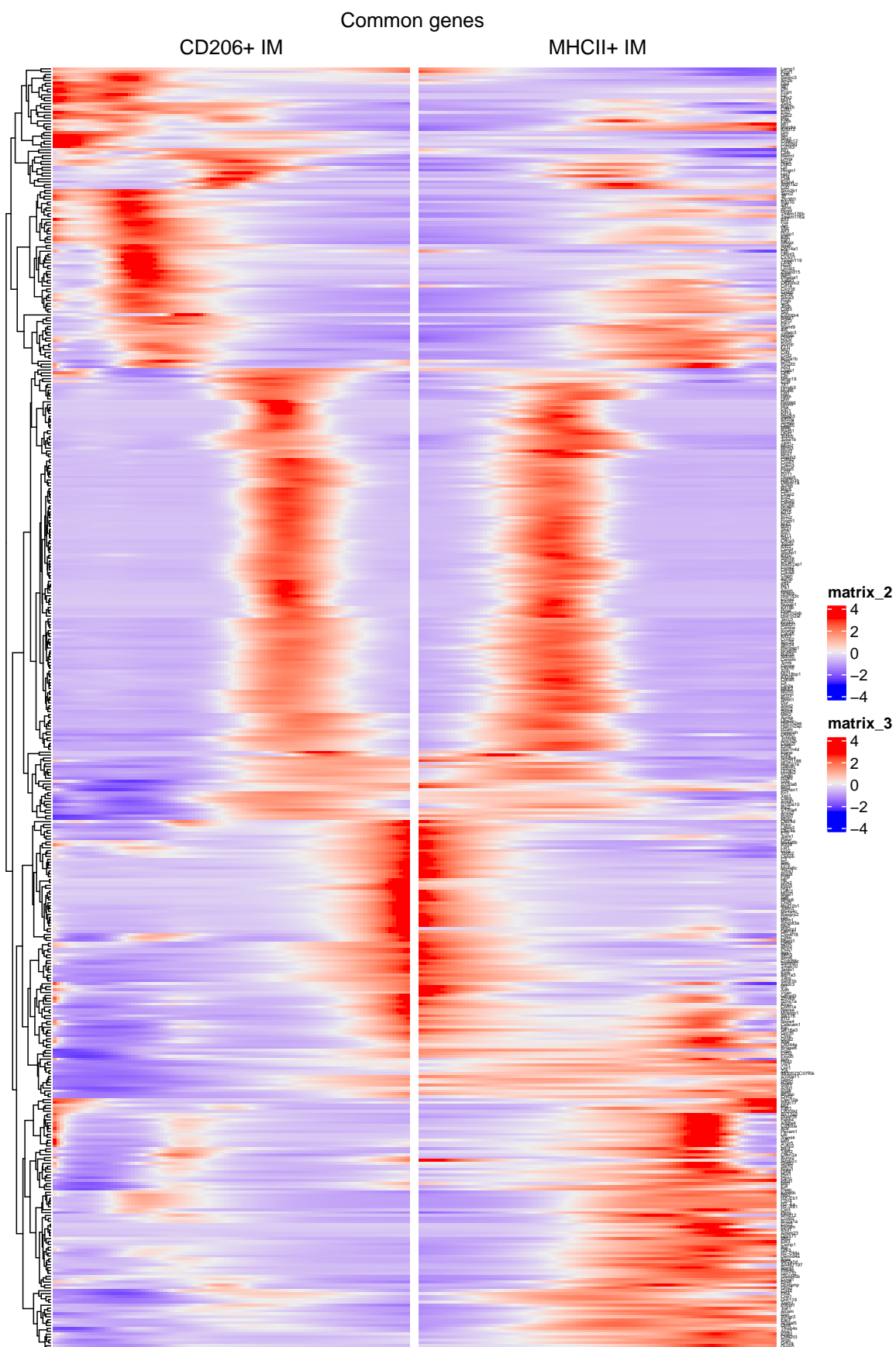
##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	1
##	0.0027	3.8599	41.4571	123.7353	168.7434	1263.9587	2

Let's use $\text{waldStat} > 40$ and $\log\text{FC} > 2$ as cut threshold.

```
genes.changed <- rownames(filter(endRes.DE, waldStat > 70 & (logFC1_2 > 2
| logFC1_2 < -2) ))
genes.noChange <- setdiff(rownames(endRes.DE) , genes.changed)
```

Make heatmap with unchanged/common genes.

```
heatSmooth_cd206.unchanged <- Heatmap(yhatSmoothScaled[genes.noChange,
100:1], cluster_columns = FALSE, show_row_names = FALSE, show_column_
names = FALSE, column_title = "CD206+IM")
heatSmooth_mhcii.unchanged <- Heatmap(yhatSmoothScaled[genes.noChange,
101:200], cluster_columns = FALSE, show_row_names = TRUE, row_names_gp
= gpar(fontsize = 3), show_column_names = FALSE, column_title = "MHCII
+IM")
heatSmooth_combined.unchanged <- draw ( heatSmooth_cd206.unchanged +
heatSmooth_mhcii.unchanged, column_title = "CommonIMgenes", auto_adjust
= FALSE)
```



5.4 Daw heatmap with expression patterns of unchanged/common genes in the order of pseudotime

Let's find the expression peak of each gene:

```
orderByExpressionPeak <- function(x, # matrix
                                     decreasing = FALSE,
                                     output.position = FALSE # if true, give
                                                                relative position 0 - 1, or output
                                                                order.
                                     ) {
  indx.peak <- apply(x, 1 , which.max)

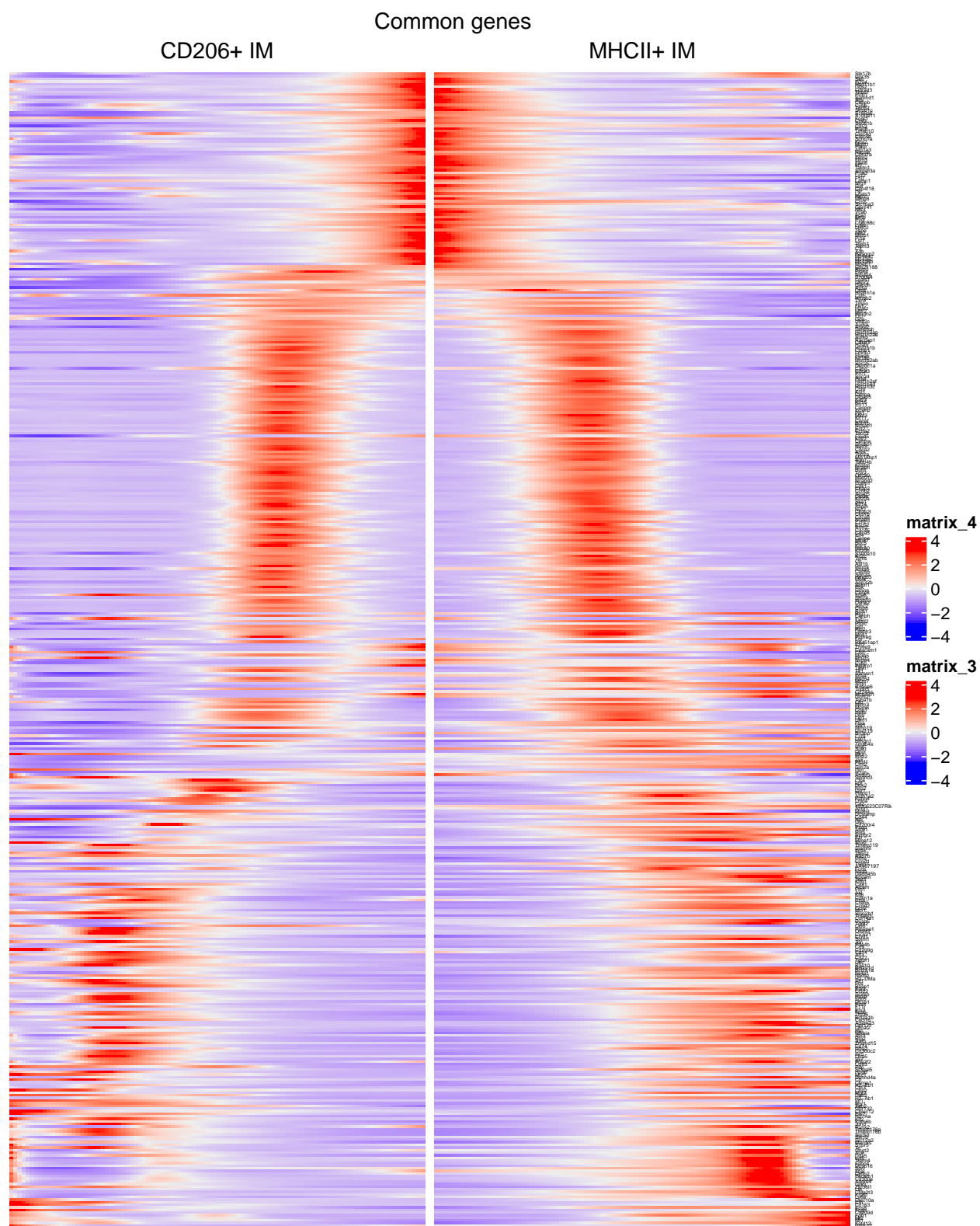
  if(output.position) {
    po <- indx.peak/nrow(x)
    if (! length(rownames(x)) == 0) {names(po) <- rownames(x)}
    return(po)
  } else {
    o <- order(indx.peak)
    if (! length(rownames(x)) == 0) {names(o) <- rownames(x)[o]}
    return (o)}
}
```

Make average peak pseudotime peak for each gene:

```
po.cd206 <- orderByExpressionPeak(yhatSmoothScaled[genes.noChange, 1:100],
                                  output.position = TRUE)
po.mhcii <- orderByExpressionPeak(yhatSmoothScaled[genes.noChange,
                                                    101:200], output.position = TRUE)
order.mean <- order ( ( po.cd206 + po.mhcii ) /2)

heatSmooth_cd206.unchanged.ordered <- Heatmap(yhatSmoothScaled[genes.
  noChange, 100:1], cluster_columns = FALSE, show_row_names = FALSE,
  show_column_names = FALSE, row_order = order.mean, column_title = "
  CD206+IM")

heatSmooth_combined.unchanged.ordered <- draw ( heatSmooth_cd206.unchanged
  .ordered + heatSmooth_mhcii.unchanged, column_title = "Common_genes",
  auto_adjust = FALSE)
```



```
pdf(file = "../Figures/Heatmap_common_genes_IMs_diff_across_pseudotime.pdf", width = 8, height = 10)
heatSmooth_combined.unchanged.ordered
dev.off()
```

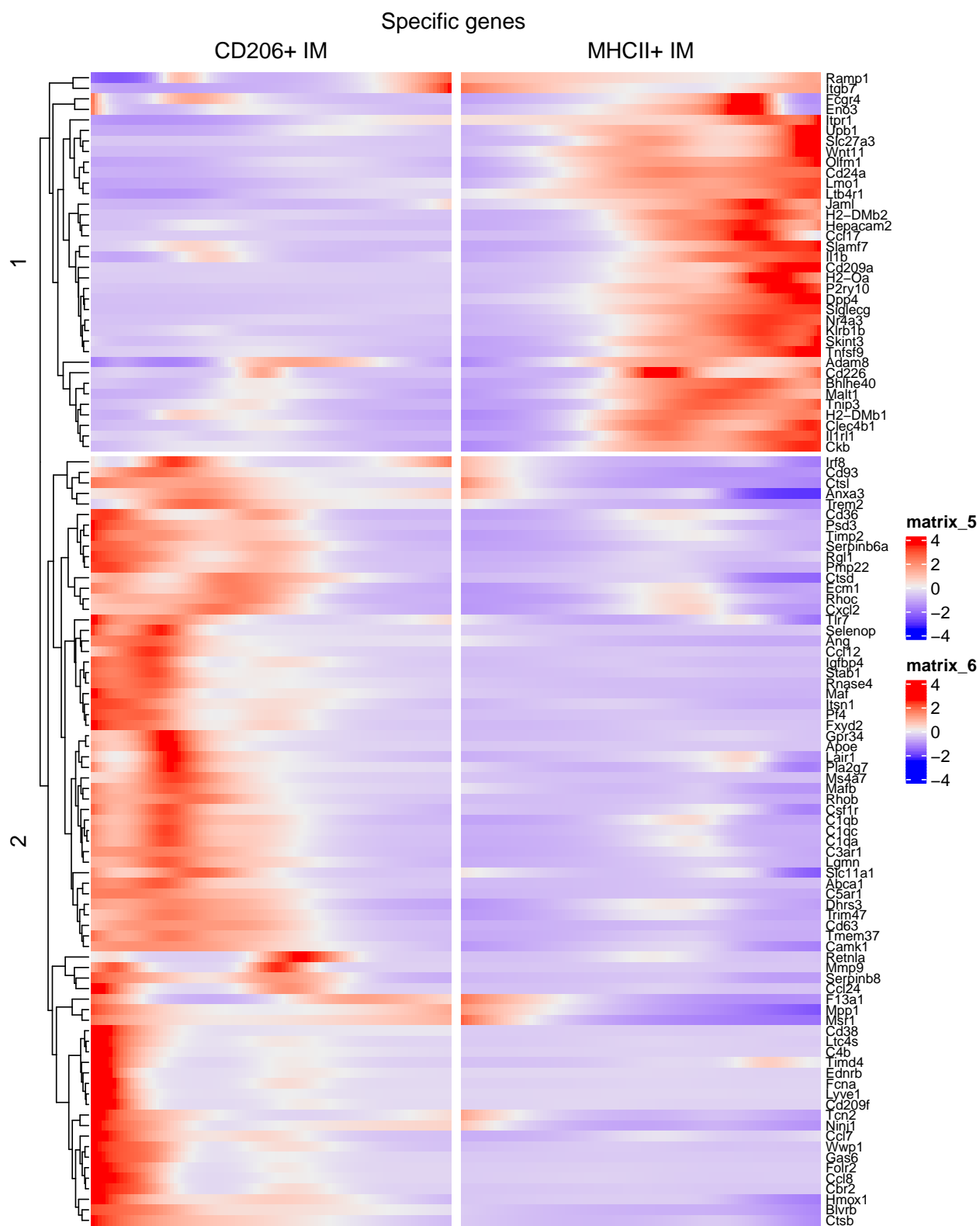
```
## pdf
## 2
```

1
2

5.5 Make with changed/specific genes

```
heatSmooth_cd206.changed <- Heatmap(yhatSmoothScaled[genes.changed,  
  100:1], cluster_columns = FALSE, show_row_names = FALSE, cluster_rows  
  = hclust(dist(yhatSmoothScaled[genes.changed, ])), show_column_names =  
  FALSE, column_title = "CD206+IM")  
  
heatSmooth_mhcii.changed <- Heatmap(yhatSmoothScaled[genes.changed,  
  101:200], cluster_columns = FALSE, show_row_names = TRUE, row_names_gp  
  = gpar(fontsize = 8), show_column_names = FALSE, column_title = "MHCII+  
  IM")  
  
heatSmooth_combined.changed <- draw ( heatSmooth_cd206.changed +  
  heatSmooth_mhcii.changed, column_title = "Specific genes", split = 2)
```

1
2
3
4
5



6 Functionality analysis of DE genes across pseudotime (common genes)


```
common.genes <- heatSmooth_cd206.unchanged.ordered@row_names_param$labels[ 1
  heatSmooth_cd206.unchanged.ordered@row_order]
```

6.1 Manually classify genes by expression timing peak

Class-1 genes are the genes expressed in monocytes but turned off in the very early phase:

```
genes.class1 <- common.genes[1:which(common.genes == "Gm21188")] 1
length(genes.class1) 2
```

```
## [1] 75 1
```

Class-2 genes are the genes up-regulated in early phase of differentiation and turned off during transit phase.

```
genes.class2 <- common.genes[(which(common.genes == "Gm21188")+1) : which( 1
  common.genes == "Diaph3")] 1
length(genes.class2) 2
```

```
## [1] 140 1
```

Class-3 genes are the late upregulated genes during IM differentiation.

```
genes.class3 <- common.genes[(which(common.genes == "Diaph3")+1) : length( 1
  common.genes)] 1
length(genes.class3) 2
```

```
## [1] 228 1
```

Save gene lists:

```
write.csv(genes.class1, file = "./common_genes_class1.csv", quote = FALSE) 1
write.csv(genes.class2, file = "./common_genes_class2.csv", quote = FALSE) 2
write.csv(genes.class3, file = "./common_genes_class3.csv", quote = FALSE) 3
```

6.2 GO/KEGG enrichment analysis with 3 classes of common genes

```
suppressMessages(library(clusterProfiler)) 1
source("../R/entrez2symbol.R") 2
source("../R/replaceEntrezID.R") 3
```

6.2.1 KEGG enrichment for common genes class 1

```
symb <- genes.class1 1
de_entrez <- bitr( geneID = symb, fromType = "SYMBOL", toType = "ENTREZID" 2
  , OrgDb = "org.Mm.eg.db", drop = TRUE ) $ ENTREZID
result.enrichKEGG <- enrichKEGG(de_entrez, organism = "mmu", keyType = " 3
  ncbi-geneid")
result.enrichKEGG <- replaceEntrezID(result.enrichKEGG, organism = "mmu") 4
write.csv(result.enrichKEGG@result, file = "./Results_enrichment/ 5
  enrichKEGG_common_genes_class1.csv")
result.enrichKEGG@result 6
```

```
## # A tibble: 149 x 9
##   ID      Description  GeneRatio BgRatio  pvalue p.adjust  qvalue
##   geneID Count
##   <chr>   <chr>      <chr>      <chr>      <dbl>    <dbl>    <dbl> <
##   chr>   <int>
##  1 mmu04145 Phagosome    7/36      182/89~ 6.53e-6 0.000973 9.00e-4
##    Thbs1~      7
##  2 mmu05152 Tuberculosis 6/36      180/89~ 7.21e-5 0.00537 4.97e-3
##    Cebpb~      6
##  3 mmu05140 Leishmanias~ 3/36      70/8943 2.73e-3 0.119    1.10e-1
##    Cybb/~      3
##  4 mmu04918 Thyroid hor~ 3/36      74/8943 3.19e-3 0.119    1.10e-1
##    Plcb1~      3
##  5 mmu04970 Salivary se~ 3/36      86/8943 4.88e-3 0.145    1.34e-1
##    Plcb1~      3
##  6 mmu04610 Complement ~ 3/36      93/8943 6.07e-3 0.151    1.39e-1
##    Plaur~      3
##  7 mmu04613 Neutrophil ~ 4/36      207/89~ 9.20e-3 0.167    1.55e-1
##    Plcb1~      4
##  8 mmu04621 NOD-like re~ 4/36      211/89~ 9.82e-3 0.167    1.55e-1
##    Ifi20~      4
##  9 mmu04960 Aldosterone~ 2/36      38/8943 1.01e-2 0.167    1.55e-1
##    Scnn1~      2
## 10 mmu04973 Carbohydrat~ 2/36      48/8943 1.58e-2 0.236    2.18e-1
##    Plcb1~      2
## # ... with 139 more rows
```

6.2.2 GO enrichment for common genes class 1

```
result.enrichGO <- enrichGO(de_entrez, OrgDb = "org.Mm.eg.db", ont = "BP")
result.enrichGO <- replaceEntrezID(result.enrichGO, organism = "mmu")
write.csv(result.enrichGO@result, file = "./Results_enrichment/enrichGO_
common_genes_class1.csv")
result.enrichGO@result
```

```
## # A tibble: 1,740 x 9
##   ID      Description  GeneRatio BgRatio  pvalue p.adjust  qvalue
##   geneID Count
##   <chr>   <chr>      <chr>      <chr>      <dbl>    <dbl>    <dbl> <chr>
##   <int>
##  1 G0:00~ myeloid leu~ 10/72      219/23~ 1.40e-9 2.16e-6 1.65e-6 Gpr35
##    /S~      10
##  2 G0:00~ cellular ex~ 7/72      72/233~ 2.48e-9 2.16e-6 1.65e-6 Sell/
##    Pl~      7
##  3 G0:00~ leukocyte m~ 11/72      360/23~ 1.32e-8 7.68e-6 5.86e-6 Gpr35
##    /S~      11
##  4 G0:00~ leukocyte c~ 9/72      219/23~ 2.45e-8 1.07e-5 8.14e-6 Gpr35
##    /S~      9
##  5 G0:00~ positive re~ 11/72      418/23~ 6.08e-8 2.12e-5 1.61e-5 Sell/
##    If~      11
##  6 G0:00~ type I inte~ 5/72      40/233~ 1.47e-7 3.64e-5 2.78e-5
##    Samhd1/~    5
```

```
## 7 G0:00~ cellular re~ 5/72      40/233~ 1.47e-7  3.64e-5  2.78e-5
  Samhd1/~      5
## 8 G0:00~ defense res~ 11/72     464/23~ 1.74e-7  3.64e-5  2.78e-5 Slpi/
  Ce~      11
## 9 G0:00~ positive re~ 9/72      278/23~ 1.88e-7  3.64e-5  2.78e-5
  Ifi204/~      9
## 10 G0:00~ response to~ 5/72     45/233~ 2.70e-7  4.70e-5  3.59e-5
  Samhd1/~      5
## # ... with 1,730 more rows
```

6.2.3 KEGG enrichment for common genes class 2

```
symb <- genes.class2
de_entrez <- bitr( geneID = symb, fromType = "SYMBOL", toType = "ENTREZID"
  , OrgDb = "org.Mm.eg.db", drop = TRUE ) $ ENTREZID
result.enrichKEGG <- enrichKEGG(de_entrez, organism = "mmu", keyType = "
  ncbi-geneid")
result.enrichKEGG <- replaceEntrezID(result.enrichKEGG, organism = "mmu")
write.csv(result.enrichKEGG@result, file = "./Results_enrichment/
  enrichKEGG_common_genes_class2.csv")
result.enrichKEGG@result
```

```
## # A tibble: 88 x 9
##   ID      Description GeneRatio BgRatio  pvalue p.adjust  qvalue
##   <chr>      <chr>      <chr>      <chr>      <dbl>      <dbl>      <dbl> <
##   chr> <int>
## 1 mmu04114 Oocyte mei~ 11/50      121/89~ 4.20e-11  2.64e-9  2.28e-9
  Aurka~      11
## 2 mmu04110 Cell cycle 11/50      125/89~ 6.01e-11  2.64e-9  2.28e-9
  Ccnb1~      11
## 3 mmu04914 Progester~ 9/50      92/8943 1.54e- 9  4.51e-8  3.88e-8
  Aurka~      9
## 4 mmu04115 p53 signal~ 5/50      72/8943 4.70e- 5  1.03e-3  8.90e-4
  Ccnb1~      5
## 5 mmu00240 Pyrimidine~ 4/50      58/8943 2.94e- 4  5.17e-3  4.45e-3
  Rrm2/~      4
## 6 mmu04218 Cellular s~ 6/50      184/89~ 5.24e- 4  7.68e-3  6.62e-3
  Ccnb1~      6
## 7 mmu05222 Small cell~ 4/50      93/8943 1.75e- 3  2.20e-2  1.90e-2 Fn1
  /C~      4
## 8 mmu05166 Human T-ce~ 6/50      250/89~ 2.55e- 3  2.64e-2  2.28e-2
  Bub1b~      6
## 9 mmu05132 Salmonella~ 6/50      253/89~ 2.70e- 3  2.64e-2  2.28e-2
  Gapdh~      6
## 10 mmu04512 ECM-recept~ 3/50      88/8943 1.29e- 2  1.14e-1  9.80e-2 Fn1
  /H~      3
## # ... with 78 more rows
```

6.2.4 GO enrichment for common genes class 2

```
result.enrichGO <- enrichGO(de_entrez, OrgDb = "org.Mm.eg.db", ont = "BP")
```

```

result.enrichGO <- replaceEntrezID(result.enrichGO, organism = "mmu")
write.csv(result.enrichGO@result, file = "./Results_enrichment/enrichGO_
  common_genes_class2.csv")
result.enrichGO@result

```

```

## # A tibble: 1,780 x 9
##   ID      Description GeneRatio BgRatio   pvalue p.adjust   qvalue
##   <chr>    <chr>      <chr>    <chr>    <dbl>    <dbl>    <dbl> <chr>
##   <int>
## 1 G0:00~ chromosome~ 50/127    324/23~ 7.39e-60 1.32e-56 1.08e-56
##   Ube2c/~ 50
## 2 G0:00~ nuclear ch~ 43/127    262/23~ 2.75e-52 1.75e-49 1.44e-49
##   Ube2c/~ 43
## 3 G0:00~ sister chr~ 39/127    181/23~ 2.95e-52 1.75e-49 1.44e-49
##   Ube2c/~ 39
## 4 G0:01~ mitotic nu~ 43/127    268/23~ 7.78e-52 2.91e-49 2.39e-49
##   Ube2c/~ 43
## 5 G0:00~ mitotic si~ 37/127    151/23~ 8.18e-52 2.91e-49 2.39e-49
##   Ube2c/~ 37
## 6 G0:00~ nuclear di~ 46/127    418/23~ 9.43e-48 2.80e-45 2.30e-45
##   Ube2c/~ 46
## 7 G0:00~ organelle ~ 47/127    472/23~ 9.12e-47 2.32e-44 1.91e-44
##   Mtf2/~ 47
## 8 G0:00~ spindle or~ 27/127    179/23~ 1.59e-31 3.54e-29 2.91e-29
##   Aurka/~ 27
## 9 G0:19~ microtubul~ 24/127    142/23~ 2.56e-29 5.06e-27 4.16e-27
##   Aurka/~ 24
## 10 G0:00~ regulation~ 21/127    103/23~ 1.42e-27 2.53e-25 2.08e-25
##   Ube2c/~ 21
## # ... with 1,770 more rows

```

6.2.5 KEGG enrichment for common genes class 3

```

symb <- genes.class3
de_entrez <- bitr( geneID = symb, fromType = "SYMBOL", toType = "ENTREZID"
  , OrgDb = "org.Mm.eg.db", drop = TRUE ) $ ENTREZID
result.enrichKEGG <- enrichKEGG(de_entrez, organism = "mmu", keyType = "
  ncbi-geneid")
result.enrichKEGG <- replaceEntrezID(result.enrichKEGG, organism = "mmu")
write.csv(result.enrichKEGG@result, file = "./Results_enrichment/
  enrichKEGG_common_genes_class3.csv")
result.enrichKEGG@result

```

```

## # A tibble: 228 x 9
##   ID      Description GeneRatio BgRatio   pvalue p.adjust   qvalue
##   <chr>    <chr>      <chr>    <chr>    <dbl>    <dbl>    <dbl> <chr>
##   <int>
## 1 mmu04210 Apoptosis    15/141    136/89~ 2.97e-9   6.77e-7 4.69e-7
##   Ctsc/~ 15
## 2 mmu04145 Phagosome    15/141    182/89~ 1.56e-7   1.78e-5 1.23e-5
##   Tubb5~ 15

```

```
## 3 mmu05166 Human T-cel~ 17/141 250/89~ 3.62e-7 2.27e-5 1.57e-5 6
  Il1r2~ 17
## 4 mmu05202 Transcripti~ 16/141 223/89~ 3.97e-7 2.27e-5 1.57e-5 7
  Il1r2~ 16
## 5 mmu04640 Hematopoiet~ 10/141 94/8943 2.02e-6 9.20e-5 6.37e-5 8
  Il1r2~ 10
## 6 mmu04380 Osteoclast ~ 11/141 128/89~ 5.10e-6 1.94e-4 1.34e-4 9
  Fosl2~ 11
## 7 mmu05323 Rheumatoid ~ 9/141 87/8943 8.42e-6 2.74e-4 1.90e-4 10
  Ctsk/~ 9
## 8 mmu05140 Leishmanias~ 8/141 70/8943 1.30e-5 3.69e-4 2.56e-4 11
  Itga4~ 8
## 9 mmu05152 Tuberculosis 12/141 180/89~ 2.55e-5 6.46e-4 4.48e-4 12
  Lsp1/~ 12
## 10 mmu04064 NF-kappa B ~ 9/141 105/89~ 3.88e-5 8.85e-4 6.13e-4 13
  Gadd4~ 9
## # ... with 218 more rows 14
```

6.2.6 GO enrichment for common genes class 3

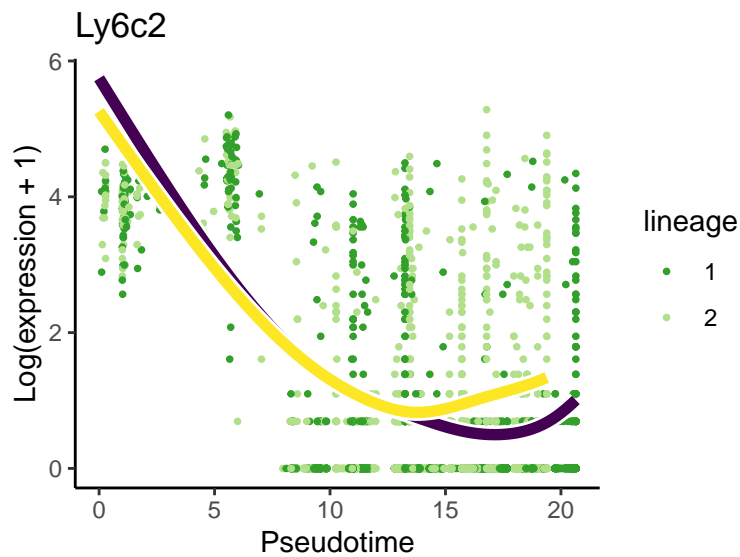
```
result.enrichGO <- enrichGO(de_entrez, OrgDb = "org.Mm.eg.db", ont = "BP") 1
result.enrichGO <- replaceEntrezID(result.enrichGO, organism = "mmu") 2
write.csv(result.enrichGO@result, file = "./Results_enrichment/enrichGO_ 3
  common_genes_class3.csv")
result.enrichGO@result 4
```

```
## # A tibble: 3,419 x 9 1
## ID Description GeneRatio BgRatio pvalue p.adjust qvalue 2
  geneID Count
## <chr> <chr> <chr> <chr> <dbl> <dbl> <dbl> <chr> 3
  > <int>
## 1 G0:00~ regulation ~ 23/224 372/23~ 1.72e-12 5.89e-9 4.30e-9 4
  Il1r2/~ 23
## 2 G0:00~ negative re~ 22/224 462/23~ 8.04e-10 7.67e-7 5.61e-7 Fgr/ 5
  Ce~ 22
## 3 G0:00~ positive re~ 17/224 265/23~ 8.72e-10 7.67e-7 5.61e-7 6
  Ceacam~ 17
## 4 G0:19~ regulation ~ 21/224 424/23~ 9.85e-10 7.67e-7 5.61e-7 7
  Ceacam~ 21
## 5 G0:00~ leukocyte c~ 19/224 345/23~ 1.12e- 9 7.67e-7 5.61e-7 8
  Ceacam~ 19
## 6 G0:00~ leukocyte m~ 19/224 360/23~ 2.27e- 9 1.29e-6 9.44e-7 9
  Itga4/~ 19
## 7 G0:00~ regulation ~ 19/224 372/23~ 3.88e- 9 1.75e-6 1.28e-6 10
  Ceacam~ 19
## 8 G0:19~ positive re~ 15/224 221/23~ 4.10e- 9 1.75e-6 1.28e-6 11
  Ceacam~ 15
## 9 G0:00~ lymphocyte ~ 11/224 103/23~ 4.60e- 9 1.75e-6 1.28e-6 12
  Itga4/~ 11
## 10 G0:00~ antigen pro~ 6/224 16/233~ 5.42e- 9 1.85e-6 1.35e-6 Ctss 13
  /H~ 6
## # ... with 3,409 more rows 14
```

7 Show gene expression pattern with TradeSeq results

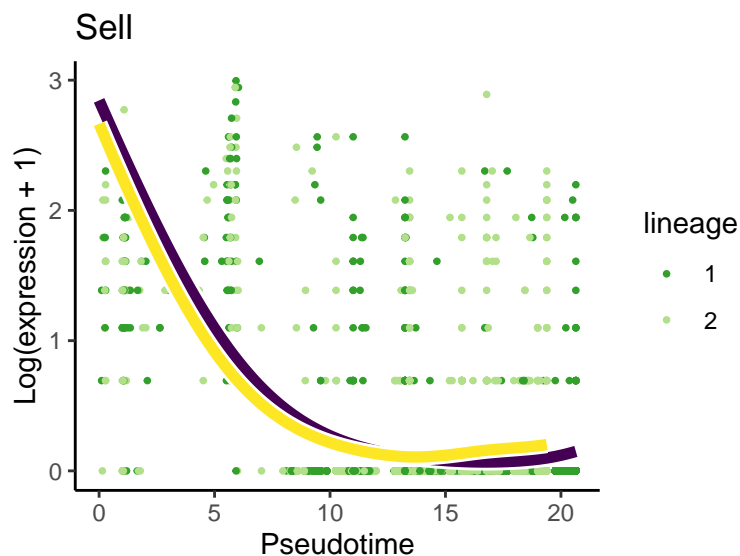
7.1 Class 1 common genes

```
require(ggplot2)
sigGene <- "Ly6c2"
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene) +
  scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```

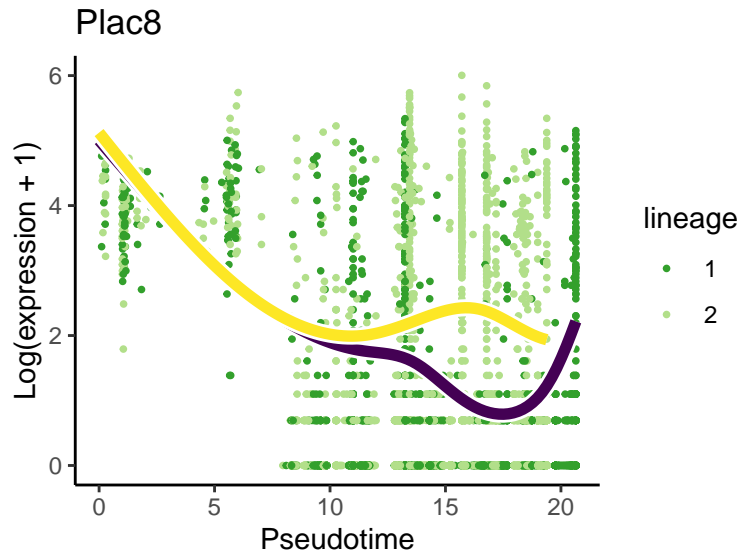


```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,
  ".pdf"),
  width = 4, height = 3)
```

```
sigGene <- "Sell"
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene) +
  scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



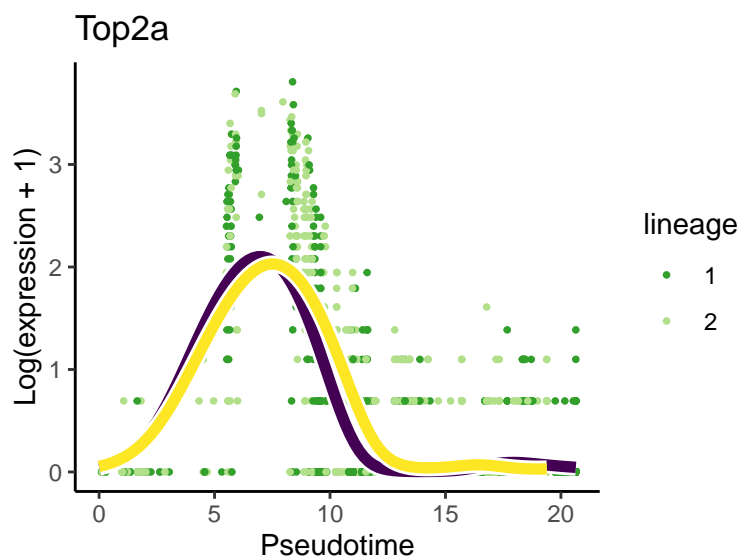
```
sigGene <- "Plac8"
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene) +
  scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,
  ".pdf"),
  width = 4, height = 3)
```

7.2 Class 2 common genes

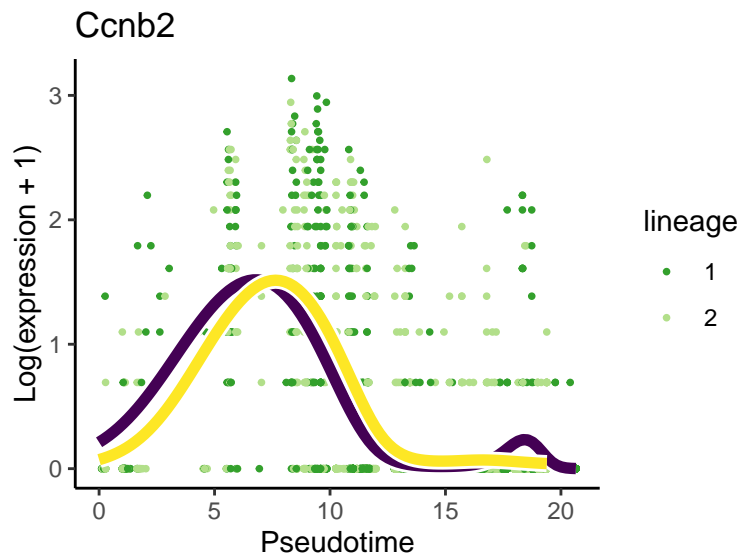
```
sigGene <- "Top2a"
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene) +
  scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,
  ".pdf"),
```

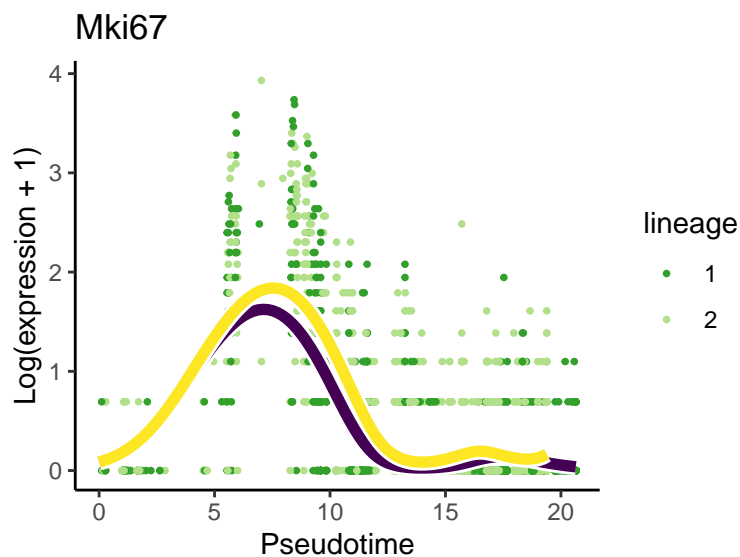
```
width = 4, height = 3)
```

```
sigGene <- "Ccnb2"  
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene  
  ) + scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,  
  ".pdf"),  
  width = 4, height = 3)
```

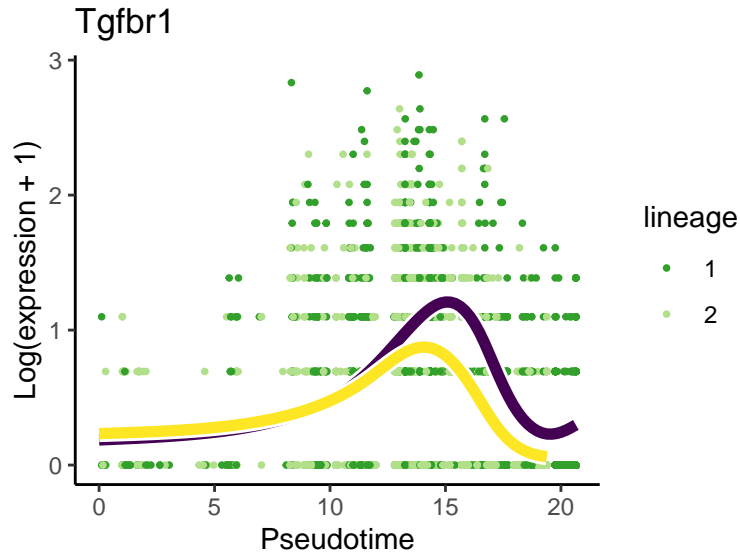
```
sigGene <- "Mki67"  
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene  
  ) + scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,  
  ".pdf"),  
  width = 4, height = 3)
```

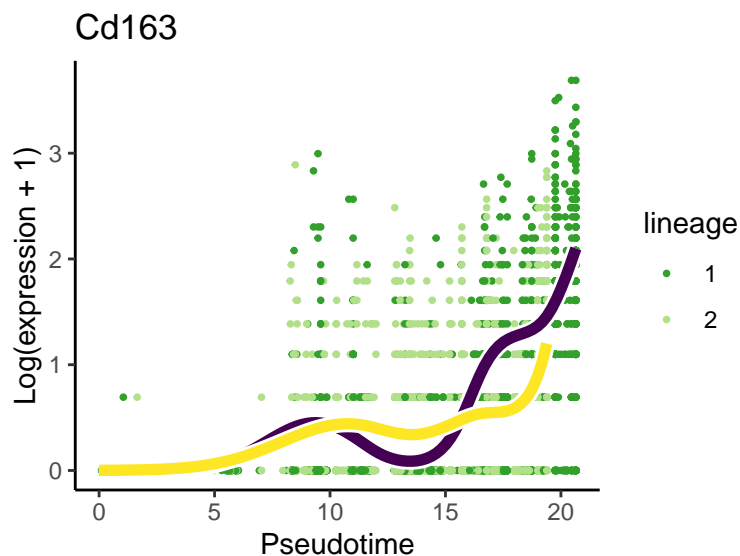

7.3 Class 3 common genes

```
sigGene <- "Tgfb1"
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene) +
  scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



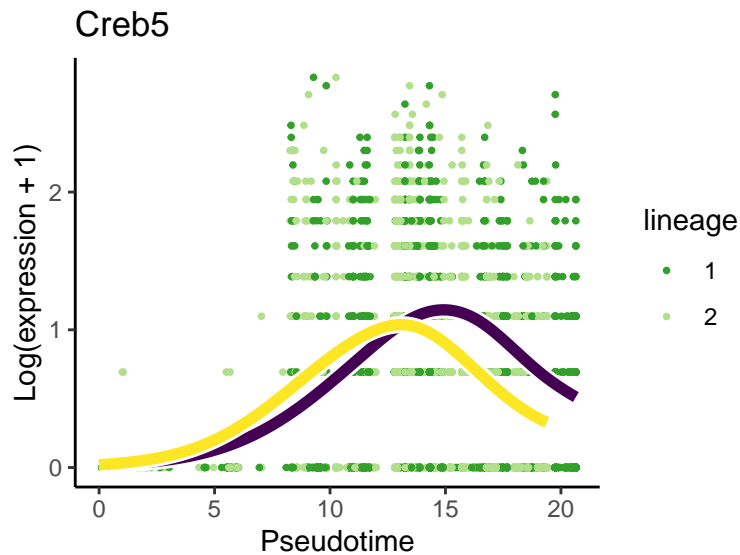
```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,
  ".pdf"),
  width = 4, height = 3)
```

```
sigGene <- "Cd163"
plotSmoother(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene) +
  scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,
  ".pdf"),
  width = 4, height = 3)
```

```
sigGene <- "Creb5"
plotSmothers(sce, counts = counts(sce), gene = sigGene) + ggtitle(sigGene)
  ) + scale_color_manual(values = c("#33A02C", "#B2DF8A"))
```



```
ggsave(filename = paste("../Figures/TradeSeq_plot_IM_lineages_", sigGene,
  ".pdf"),
  width = 4, height = 3)
```

8 Session information

R session:

```
sessionInfo()
```

```
## R version 4.0.3 (2020-10-10)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu 20.04.3 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=en_GB.UTF-8       LC_COLLATE=en_US.UTF-8
##  [5] LC_MONETARY=en_GB.UTF-8   LC_MESSAGES=en_US.UTF-8
##  [7] LC_PAPER=en_GB.UTF-8      LC_NAME=C
##  [9] LC_ADDRESS=C              LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_GB.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
##  [1] stats4    parallel  grid       stats      graphics  grDevices  utils
##  [8] datasets  methods   base
##
```

```

## other attached packages:
## [1] org.Mm.eg.db_3.12.0          AnnotationDbi_1.52.0
## [3] clusterProfiler_3.18.1      clusterExperiment_2.11.2
## [5] tradeSeq_1.4.0              magrittr_2.0.1
## [7] monocle3_1.0.0              SingleCellExperiment_1.12.0
## [9] SummarizedExperiment_1.20.0 GenomicRanges_1.42.0
## [11] GenomeInfoDb_1.26.7         IRanges_2.24.1
## [13] S4Vectors_0.28.1           MatrixGenerics_1.2.1
## [15] matrixStats_0.61.0          Biobase_2.50.0
## [17] BiocGenerics_0.36.1         circlize_0.4.13
## [19] RColorBrewer_1.1-2          dplyr_1.0.7
## [21] ggplot2_3.3.5               ComplexHeatmap_2.6.2
## [23] SeuratObject_4.0.4          Seurat_4.0.5
##
## loaded via a namespace (and not attached):
## [1] rsvd_1.0.5                   ica_1.0-2                zinbwave_1.12.0
## [4] class_7.3-17                 foreach_1.5.1            lmtest_0.9-39
## [7] crayon_1.4.2                 spatstat.core_2.3-2      MASS_7.3-53
## [10] rhdf5filters_1.2.1           nlme_3.1-153             qlcMatrix_0.9.7
## [13] GOSemSim_2.16.1             rlang_0.4.12             XVector_0.30.0
## [16] ROCR_1.0-11                 irlba_2.3.5              limma_3.46.0
## [19] phylobase_0.8.10            BiocParallel_1.24.1      rjson_0.2.20
## [22] bit64_4.0.5                 glue_1.5.1               pheatmap_1.0.12
## [25] rngtools_1.5.2              sctransform_0.3.2        spatstat.sparse_2
## [28] classInt_0.4-3              DOSE_3.16.0              spatstat.geom_2.3-0
## [31] VGAM_1.1-5                  tidyselect_1.1.1         fitdistrplus_1.1-6
## [34] XML_3.99-0.8                tidyr_1.1.4              zoo_1.8-9
## [37] sf_1.0-4                    xtable_1.8-4             spData_2.0.1
## [40] evaluate_0.14               cli_3.1.0                zlibbioc_1.36.0
## [43] rstudioapi_0.13            miniUI_0.1.1.1           sp_1.4-6
## [46] rpart_4.1-15                fastmatch_1.1-3          pbmcapply_1.5.0
## [49] locfdr_1.1-8                shiny_1.7.1              BiocSingular_1.6.0
## [52] xfun_0.28                   clue_0.3-60              cluster_2.1.0
## [55] tidygraph_1.2.0            tibble_3.1.6             expm_0.999-6
## [58] ggrepel_0.9.1              ape_5.5                  listenv_0.8.0
## [61] png_0.1-7                   future_1.23.0            withr_2.4.3
## [64] bitops_1.0-7                slam_0.1-49              ggforce_0.3.3
## [67] plyr_1.8.6                  sparsesvd_0.2            e1071_1.7-9
## [70] coda_0.19-4                 pillar_1.6.4             GlobalOptions_0.1.2
## [73] cachem_1.0.6                kernlab_0.9-29           raster_3.5-2
## [76] GetoptLong_1.0.5            gmodels_2.18.1           vctr_0.3.8
## [79] ellipsis_0.3.2              generics_0.1.1           NMF_0.23.0
## [82] tools_4.0.3                 rncl_0.8.4               munsell_0.5.0
## [85] tweenr_1.0.2                fgsea_1.16.0             proxy_0.4-26
## [88] DelayedArray_0.16.3         fastmap_1.1.0            HSMMSingleCell_1
## [91] compiler_4.0.3              abind_1.4-5              httpuv_1.6.3
## [94] pkgmaker_0.32.2             plotly_4.10.0            GenomeInfoDbData_1
## [97] gridExtra_2.3               edgeR_3.32.1             lattice_0.20-41
## [100] deldir_1.0-6                utf8_1.2.2               later_1.3.0
## [103] wk_0.5.0                    jsonlite_1.7.2           scales_1.1.1
## [106] prncurve_2.1.6              docopt_0.7.1             pbapply_1.5-0

```

## [109]	genefilter_1.72.1	lazyeval_0.2.2	LearnBayes_2.15.1	72
## [112]	promises_1.2.0.1	doParallel_1.0.16	goftest_1.2-3	73
## [115]	spatstat.utils_2.2-0	reticulate_1.22	rmarkdown_2.11	74
## [118]	cowplot_1.1.1	textshaping_0.3.6	Rtsne_0.15	75
## [121]	downloader_0.4	softImpute_1.4-1	uwot_0.1.11	76
## [124]	igraph_1.2.9	HDF5Array_1.18.1	survival_3.2-7	77
## [127]	yaml_2.2.1	systemfonts_1.0.3	DDRTree_0.1.5	78
## [130]	htmltools_0.5.2	memoise_2.0.1	locfit_1.5-9.4	79
## [133]	graphlayouts_0.7.2	viridisLite_0.4.0	digest_0.6.29	80
## [136]	assertthat_0.2.1	mime_0.12	densityClust_0.3	81
## [139]	registry_0.5-1	units_0.7-2	RSQLite_2.2.9	82
## [142]	yulab.utils_0.0.4	future.apply_1.8.1	data.table_1.14.2	83
## [145]	blob_1.2.2	RNeXML_2.4.5	ragg_1.2.1	84
## [148]	fastICA_1.2-3	splines_4.0.3	labeling_0.4.2	85
## [151]	Rhdf5lib_1.12.1	Cairo_1.5-12.2	RCurl_1.98-1.5	86
## [154]	monocle_2.18.0	hms_1.1.1	rhdf5_2.34.0	87
## [157]	colorspace_2.0-2	BiocManager_1.30.16	shape_1.4.6	88
## [160]	Rcpp_1.0.7	RANN_2.6.1	enrichplot_1.10.2	89
## [163]	fansi_0.5.0	parallelly_1.29.0	R6_2.5.1	90
## [166]	ggribes_0.5.3	lifecycle_1.0.1	gdata_2.18.0	91
## [169]	leiden_0.3.9	DO.db_2.9	Matrix_1.3-4	92
## [172]	howmany_0.3-1	qvalue_2.22.0	RcppAnnoy_0.0.19	93
## [175]	iterators_1.0.13	stringr_1.4.0	htmlwidgets_1.5.4	94
## [178]	beachmat_2.6.4	polyclip_1.10-0	purrr_0.3.4	95
## [181]	shadowtext_0.0.9	terra_1.4-22	mgcv_1.8-33	96
## [184]	globals_0.14.0	patchwork_1.1.1	slingshot_1.8.0	97
## [187]	codetools_0.2-18	GO.db_3.12.1	FNN_1.1.3	98
## [190]	gtools_3.9.2	prettyunits_1.1.1	gridBase_0.4-7	99
## [193]	gtable_0.3.0	DBI_1.1.1	ggfun_0.0.4	100
## [196]	tensor_1.5	httr_1.4.2	highr_0.9	101
## [199]	KernSmooth_2.23-20	stringi_1.7.6	progress_1.2.2	102
## [202]	reshape2_1.4.4	farver_2.1.0	uuid_1.0-3	103
## [205]	spdep_1.1-12	annotate_1.68.0	viridis_0.6.2	104
## [208]	magick_2.7.3	xml2_1.3.3	combinat_0.0-8	105
## [211]	rvcheck_0.2.1	boot_1.3-25	s2_1.0.7	106
## [214]	ade4_1.7-18	scattermore_0.7	bit_4.0.4	107
## [217]	scatterpie_0.1.7	spatstat.data_2.1-0	ggraph_2.0.5	108
## [220]	pkgconfig_2.0.3	knitr_1.36		109

9 References