

DE analysis

Sergey Naumenko

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Contents

Overview	2
Checking to see that the transcript to gene mapping is correct	2
Sanity check that metadata matches your expression	2
Run DESeq2	3
Wald test	3
DEGreport QC	4
Size factor QC - samples 1-15	4
Size factor QC - samples 16-30	5
Size factor QC - samples 31-40 (44)	6
Mean-Variance QC plots	7
treatment	7
response	8
ER	9
tumor_percentage_high	10
Covariates effect on count data	11
Covariates correlation with metrics	13
Sample-level QC analysis	18
PCA - treatment	18
PCA - response	19
PCA - ER	20
PCA - tumor_percentage	21
PCA - tumor_percentage_high	22
PCA - date_of	22
Inter-correlation analysis	24
Without study_id	24
Without study_id = top 1000 variable genes	26
Without study_id = top 500 variable genes	28
With study_id	31
Treatment Post vs Pre - see Table3	33
Response pCR vs non-pCR - see Table4	33

ER : Positive vs Negative - Table 5	33
tumor_percentage_high : High vs Low - Table 6	33
date_of: 20180323 vs 20180228 - Table 7	33
Visualization	34
Heatmaps	40
Prepare files for GSEA	50
GSEA day-wise	50
R session	50

Overview

- Principal Investigator: Beth Overmoyer
- Experiment: RNAseq_analysis_of_inflammatory_breast_cancer_hbc04141
- study 6 was excluded because of low read depth in 3373-3
- <https://www.bioconductor.org/packages/release/bioc/vignettes/DEGreport/inst/doc/DEGreport.html>
- AnnotationHub. We use ensembl version matching bcbio pipeline - v94.
- HBC materials
- HBC materials - functional analysis
- <http://bioconductor.org/packages/release/bioc/vignettes/DESeq2/inst/doc/DESeq2.html>

Checking to see that the transcript to gene mapping is correct

When you have annotations that are from a different source from your reference you can run into problems (i.e lose genes). Some checks you can do before proceeding:

1. Look at the dimensions of your count matrix. Do you have ~20k genes present? `dim(txi$counts)`
2. When running `tximport()` you will get a message in your console. If you see something like `transcripts missing from tx2gene` start troubleshooting.

```
dim(txi$counts)
```

```
## [1] 58735    44
```

Sanity check that metadata matches your expression

It is always a good idea to check if: 1. Do you have expression data for all samples listed in your metadata?
2. Are the samples in your expression data in the same order as your metadata?

```
### Check that sample names match in both files
all(colnames(txi$counts) %in% rownames(meta))
```

```
## [1] TRUE
```

```
### Check that sample names match in both files
all(colnames(txi$counts) %in% rownames(meta))
```

```
## [1] TRUE
```

```
### Check that all samples are in the same order
meta <- meta[colnames(txi$counts),]
all(colnames(txi$counts) == rownames(meta))
```

```
## [1] TRUE
```

Run DESeq2

estimating size factors
estimating dispersions
gene-wise dispersion estimates
mean-dispersion relationship
final dispersion estimates
fitting model and testing

- Estimating size factors and count normalization
- Gene-wise dispersions
- Mean-dispersion(variance) relationship and the Negative Binomial Model
- Model fitting and hypothesis testing

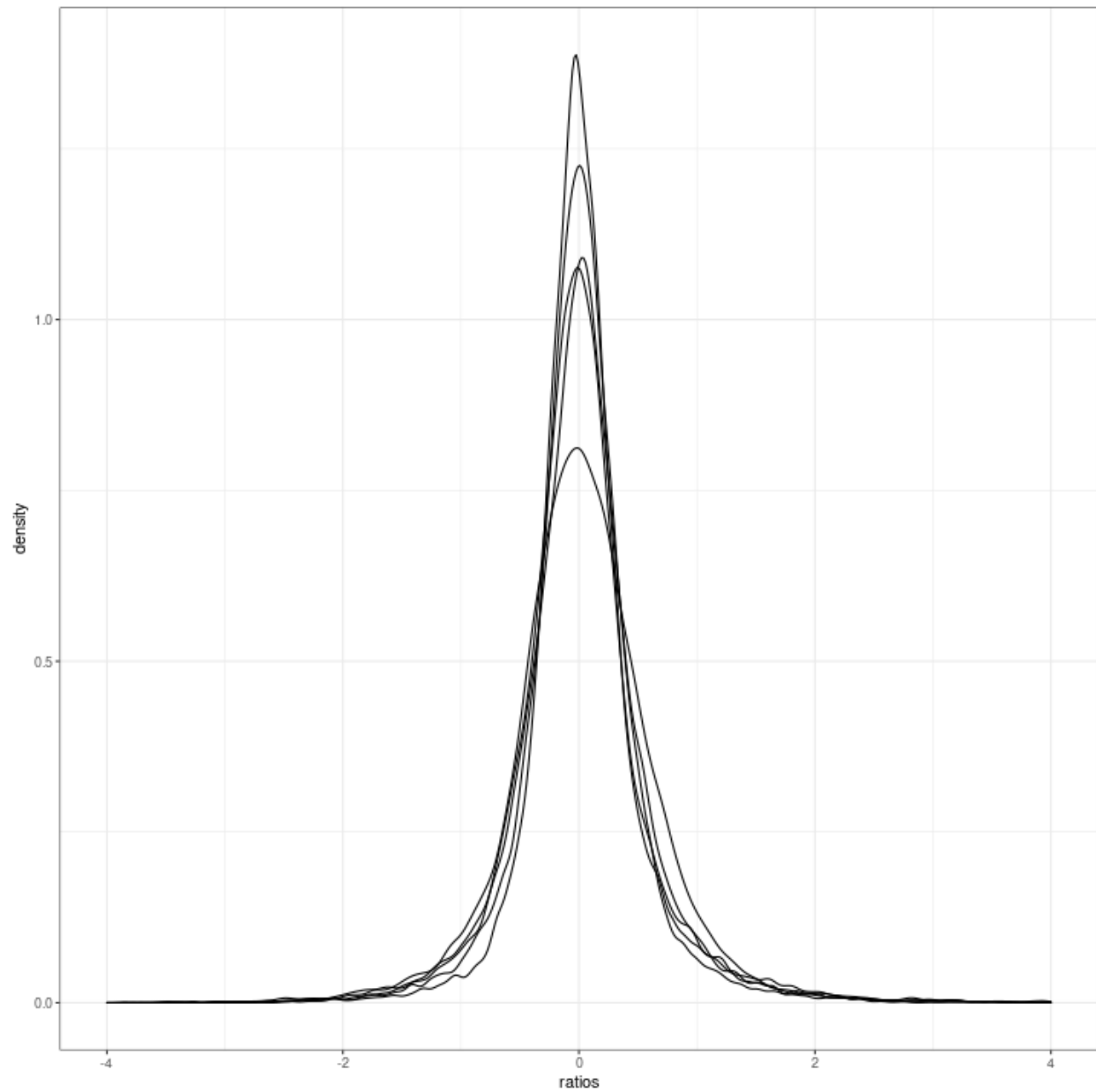
Wald test

Here we subset protein coding genes.

DEGreport QC

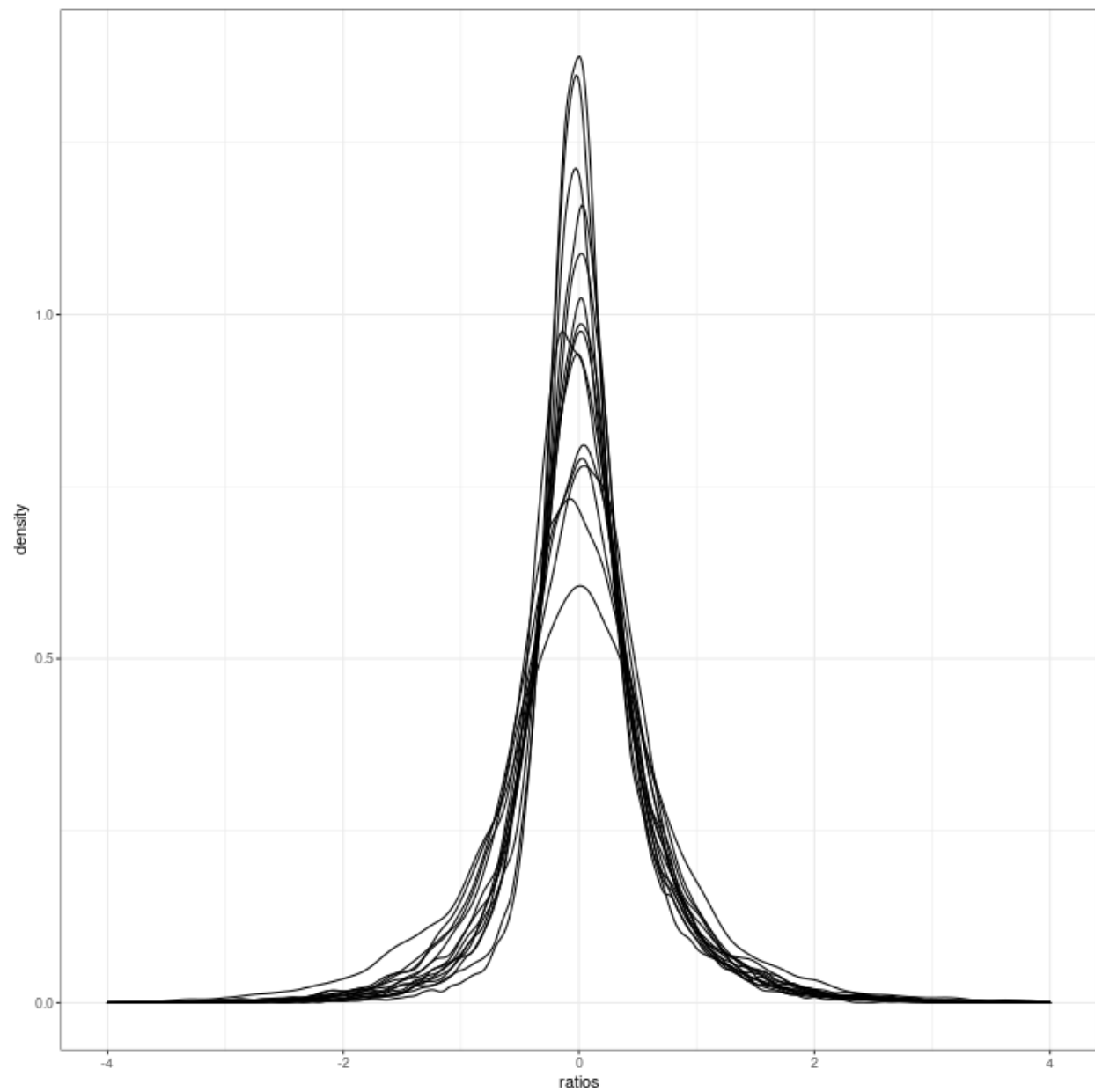
Size factor QC - samples 1-15

```
counts <- counts(dds, normalized = TRUE)
design <- as.data.frame(colData(dds))
degCheckFactors(counts[, 1:5])
```



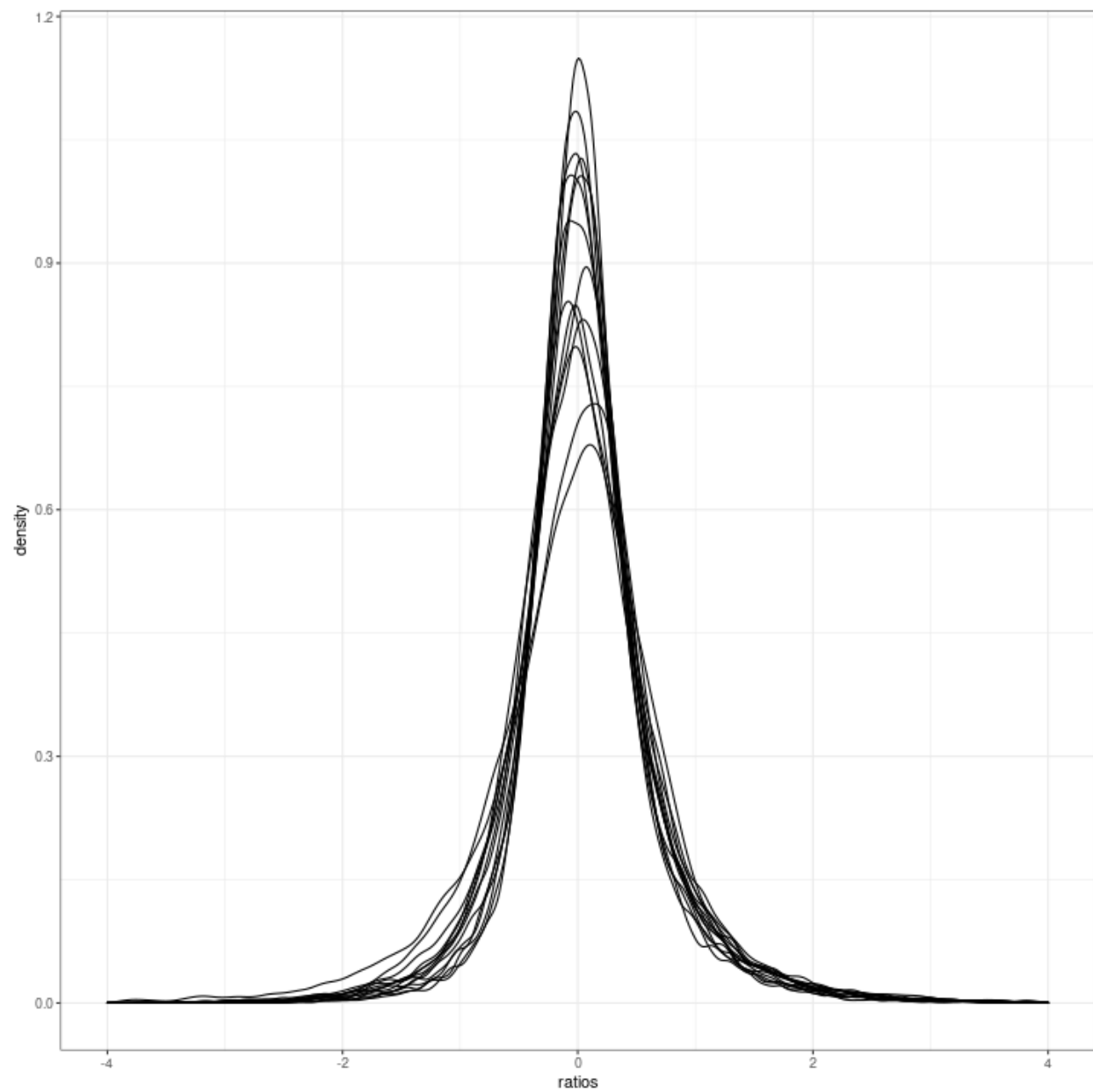
Size factor QC - samples 16-30

```
degCheckFactors(counts[, 16:30])
```



Size factor QC - samples 31-40 (44)

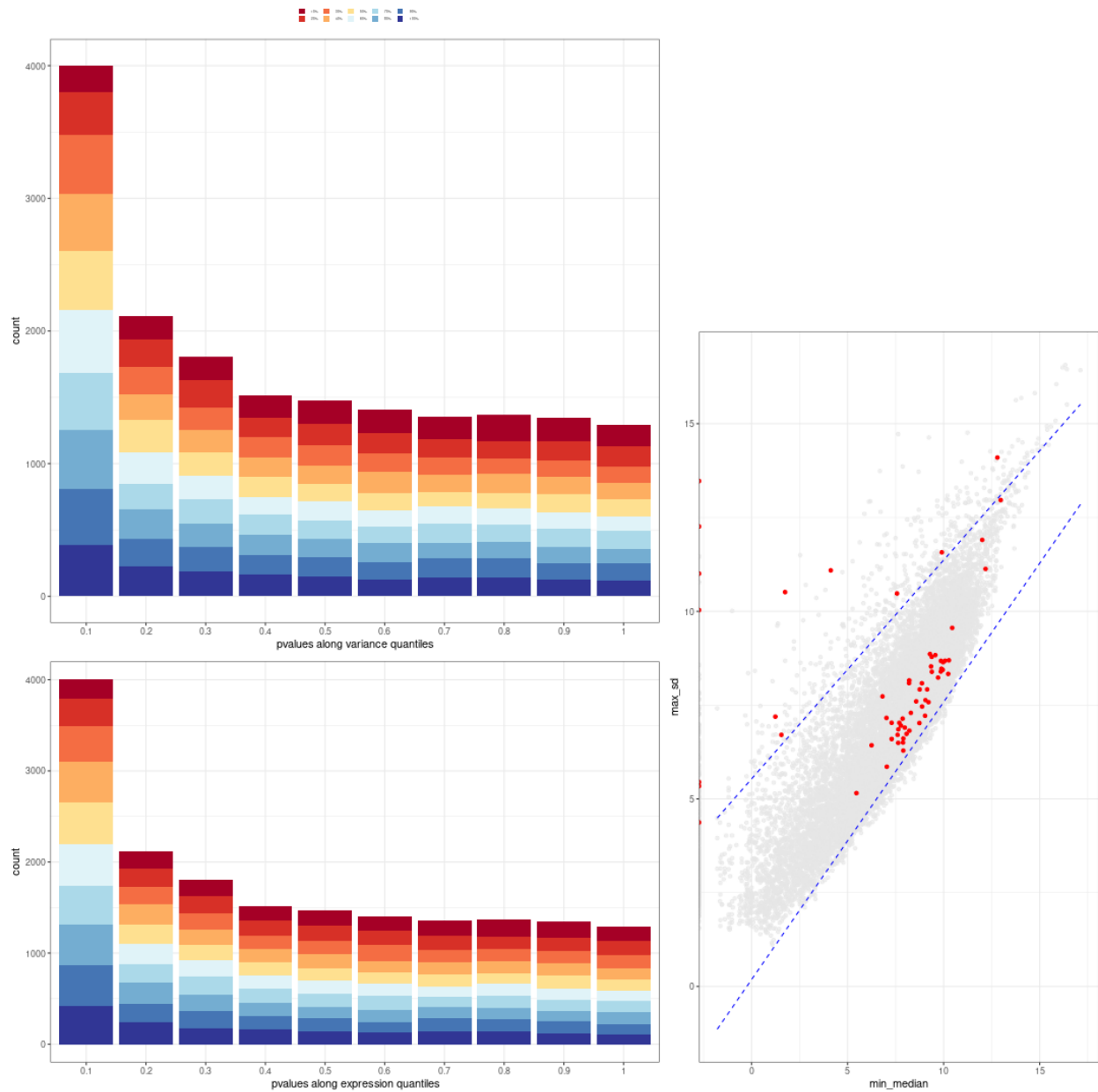
```
degCheckFactors(counts[, 31:ncol(counts)])
```



Mean-Variance QC plots

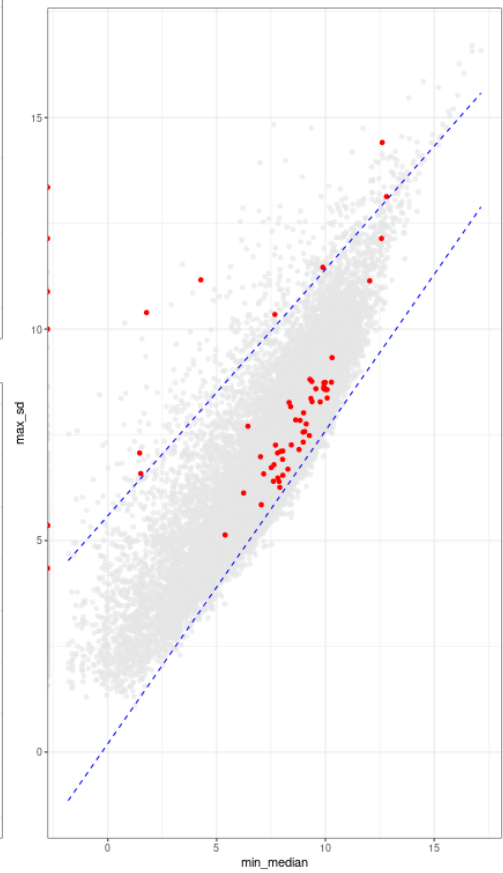
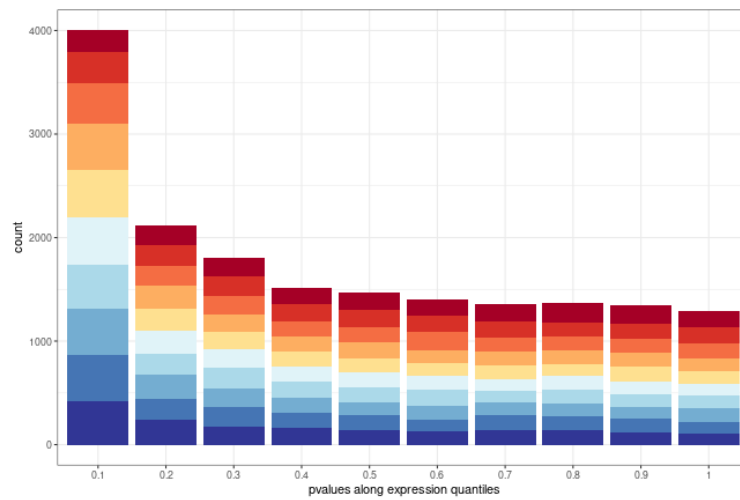
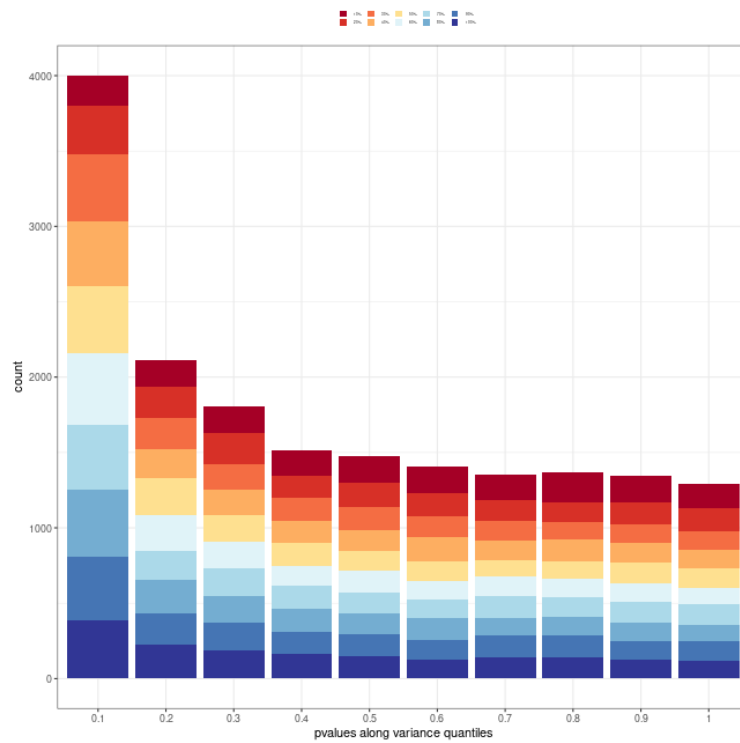
treatment

```
res <- results(dds)
degQC(counts, design[["treatment"]], pvalue = res[["pvalue"]])
```



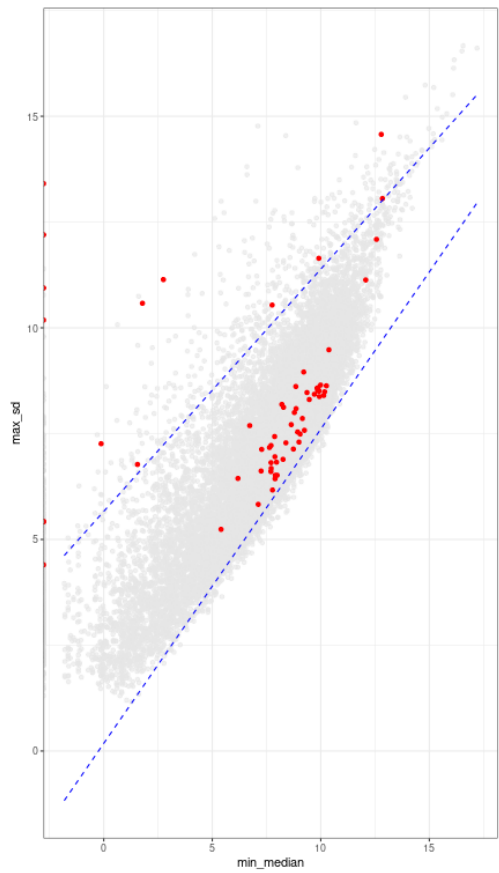
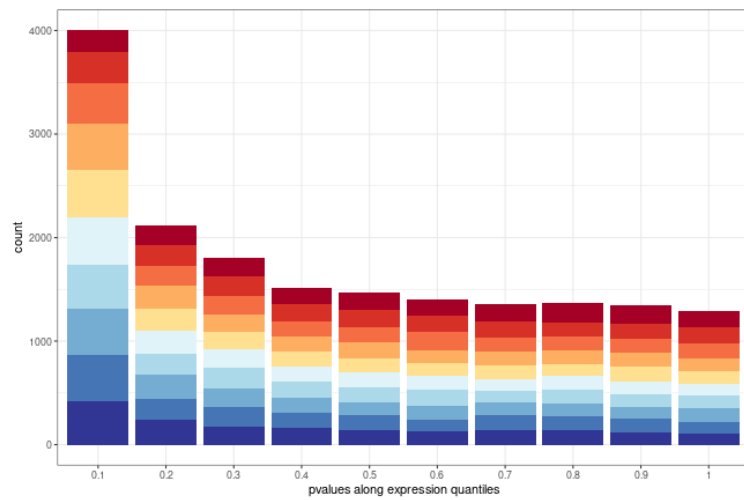
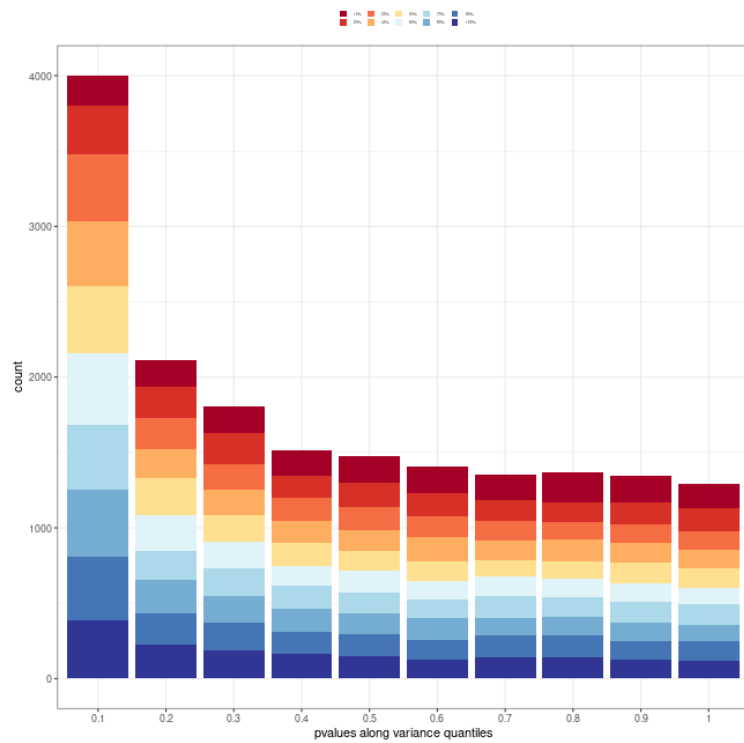
response

```
degQC(counts, design[["response"]], pvalue = res[["pvalue"]])
```



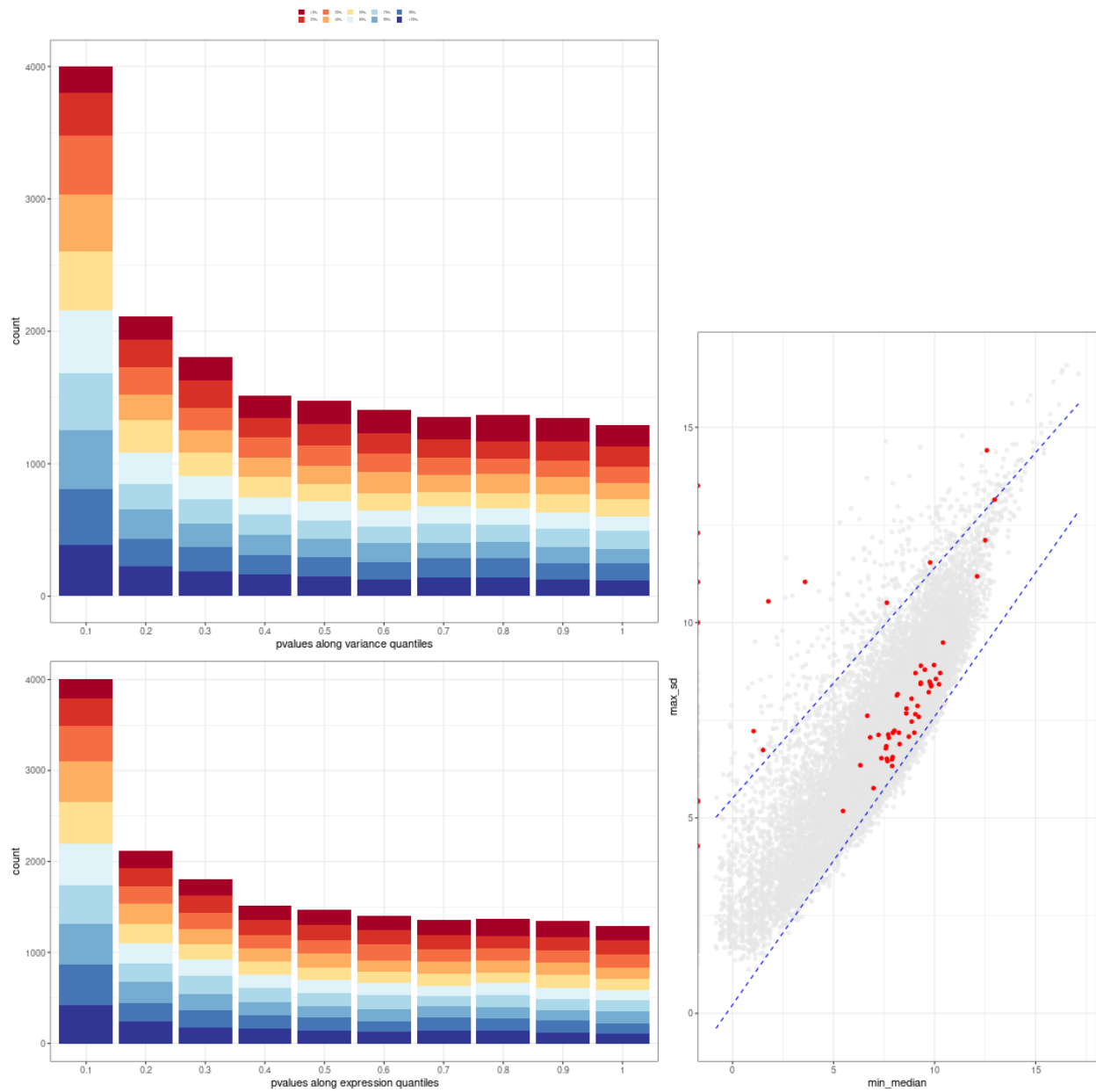
ER

```
degQC(counts, design[["er"]], pvalue = res[["pvalue"]])
```



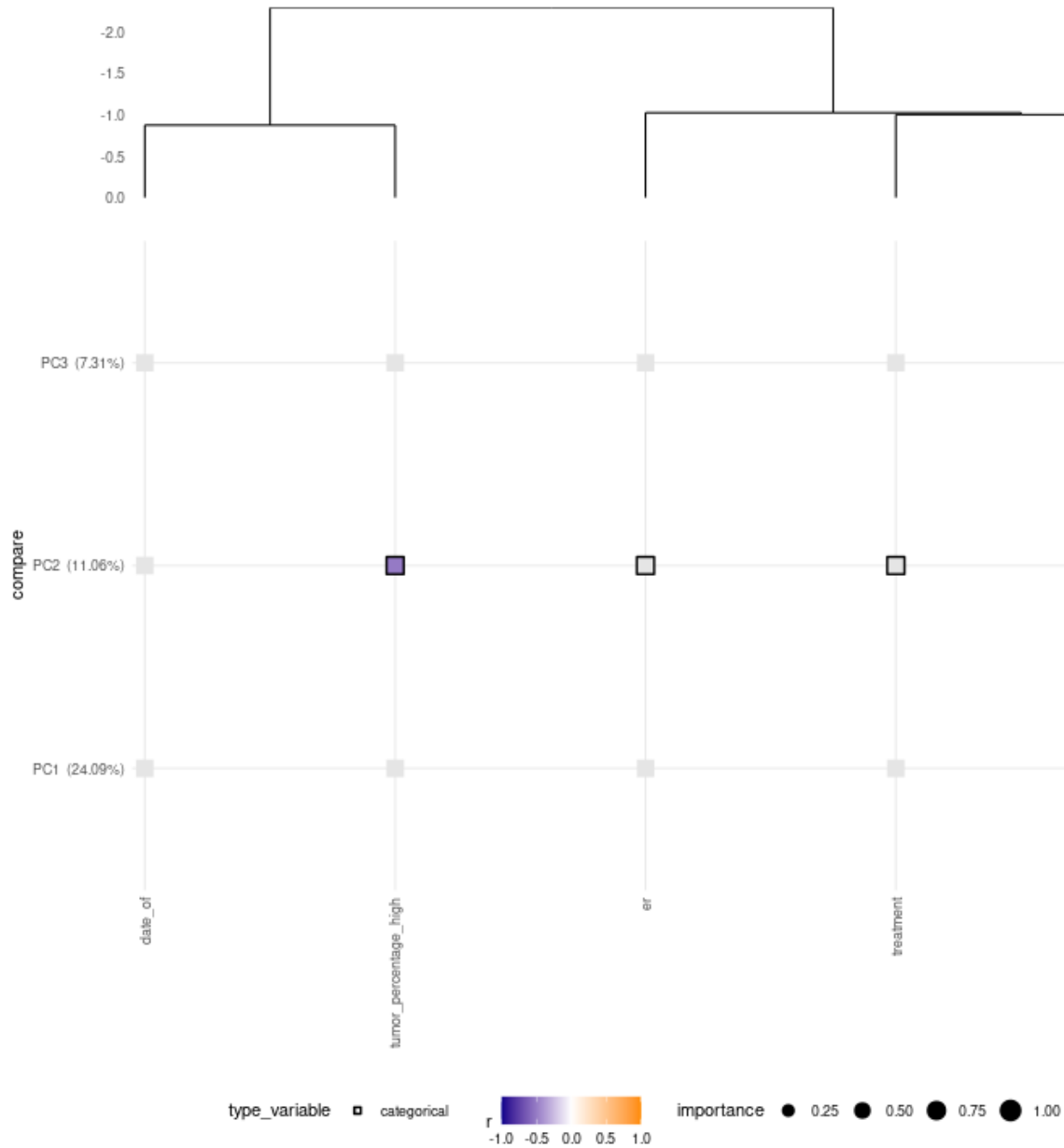
tumor_percentage_high

```
degQC(counts, design[["tumor_percentage_high"]], pvalue = res[["pvalue"]])
```

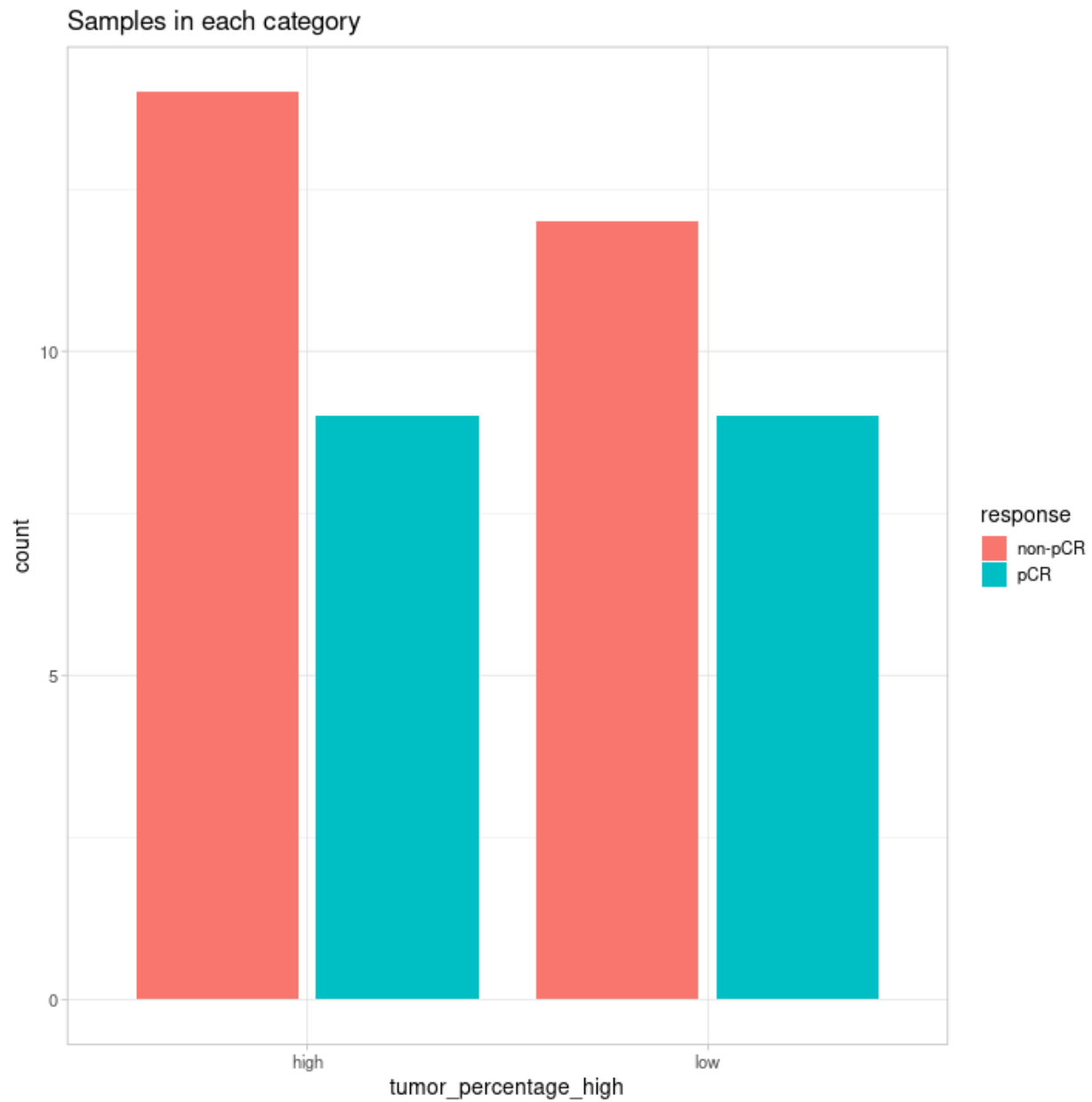


Covariates effect on count data

```
mdata <- colData(dds) %>% as.data.frame() %>%  
  dplyr::select(treatment, response, er, date_of, tumor_percentage_high)  
resCov <- degCovariates(log2(counts(dds)+0.5), mdata)
```



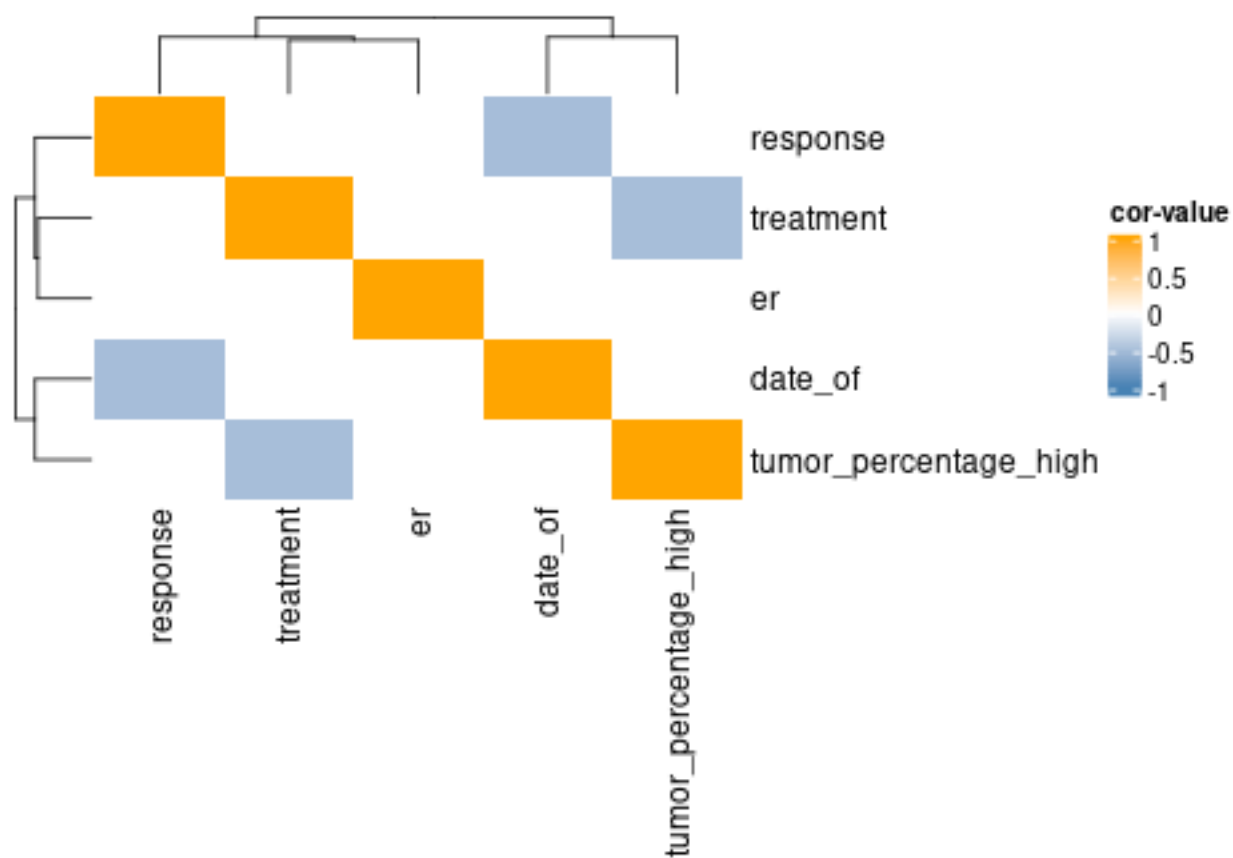
```
mdata %>% ggplot(aes(tumor_percentage_high, fill = response)) +  
  geom_bar(position = "dodge2") +  
  ggtitle("Samples in each category")
```



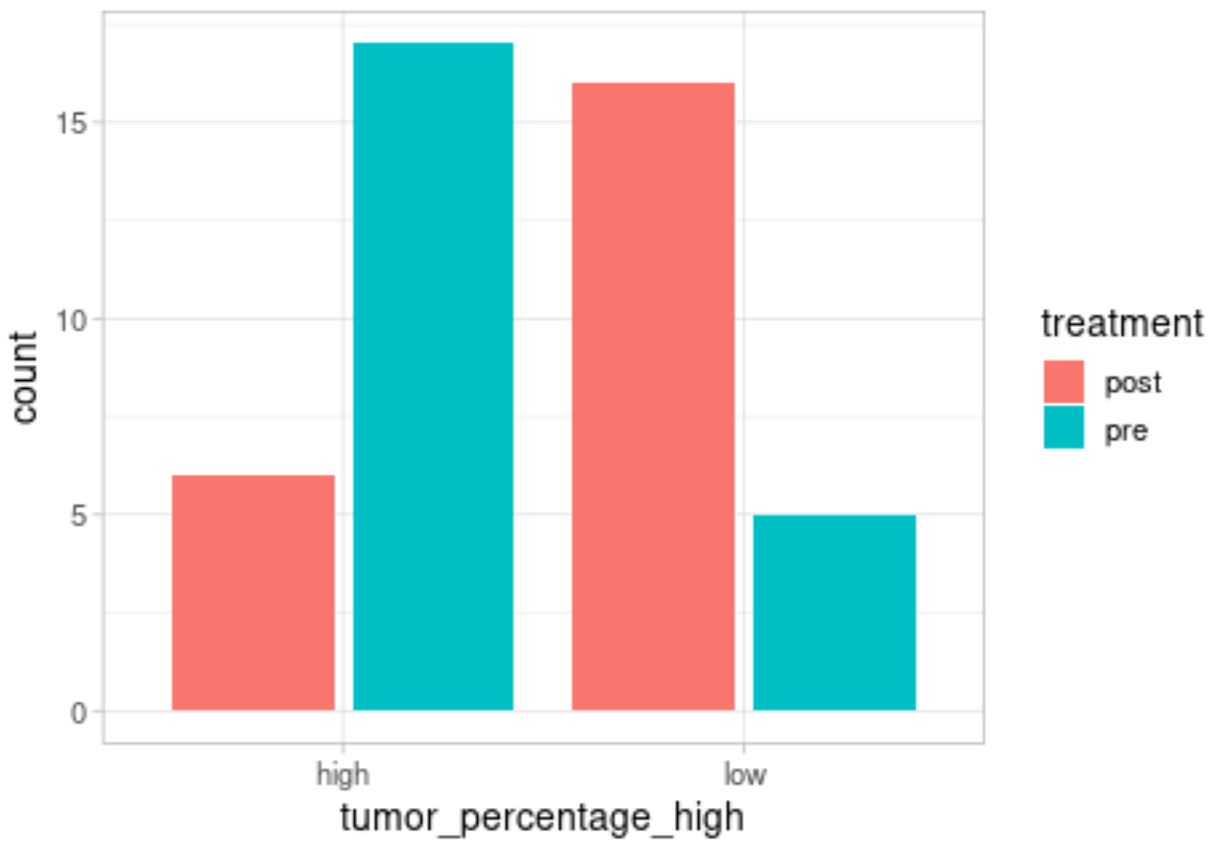
Samples split equally between tumor_percentage_high for both response types. That allows to control for tumor_percentage_high batch effectively.

Covariates correlation with metrics

```
cor <- degCorCov(mdata)
```



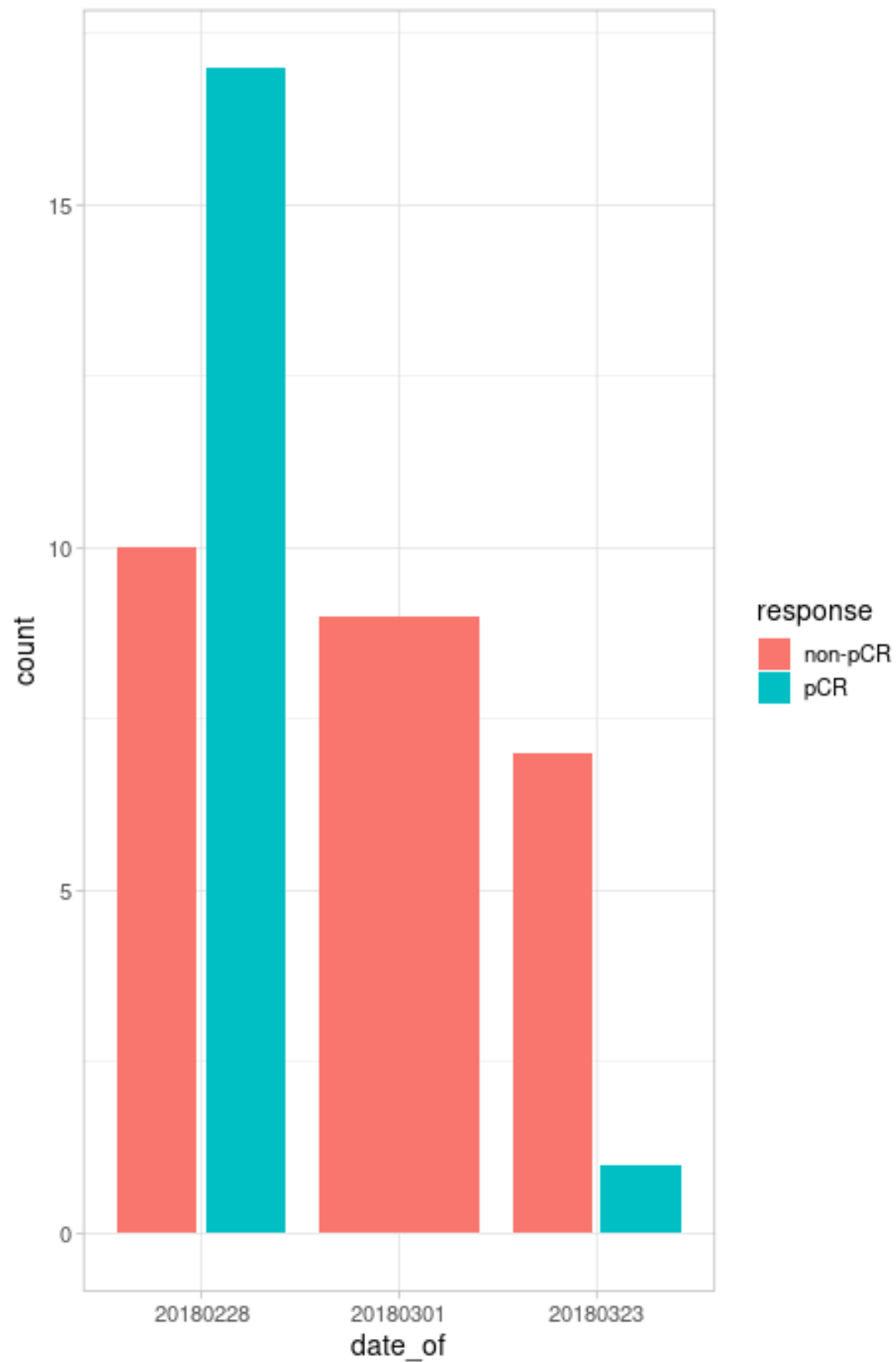
```
mdata %>% ggplot(aes(tumor_percentage_high, fill = treatment)) + geom_bar(position = "dodge2")
```



pre-treatment samples have a larger proportion of higher tumor_percentage - tumor content decreases after treatment, it is harder to sample high purity tumors.

```
mdata %>% ggplot(aes(date_of, fill = response)) +  
  geom_bar(position = "dodge2") +  
  ggtitle("Distribution of samples across dates of sequencing")
```

Distribution of samples across dates of sequencing

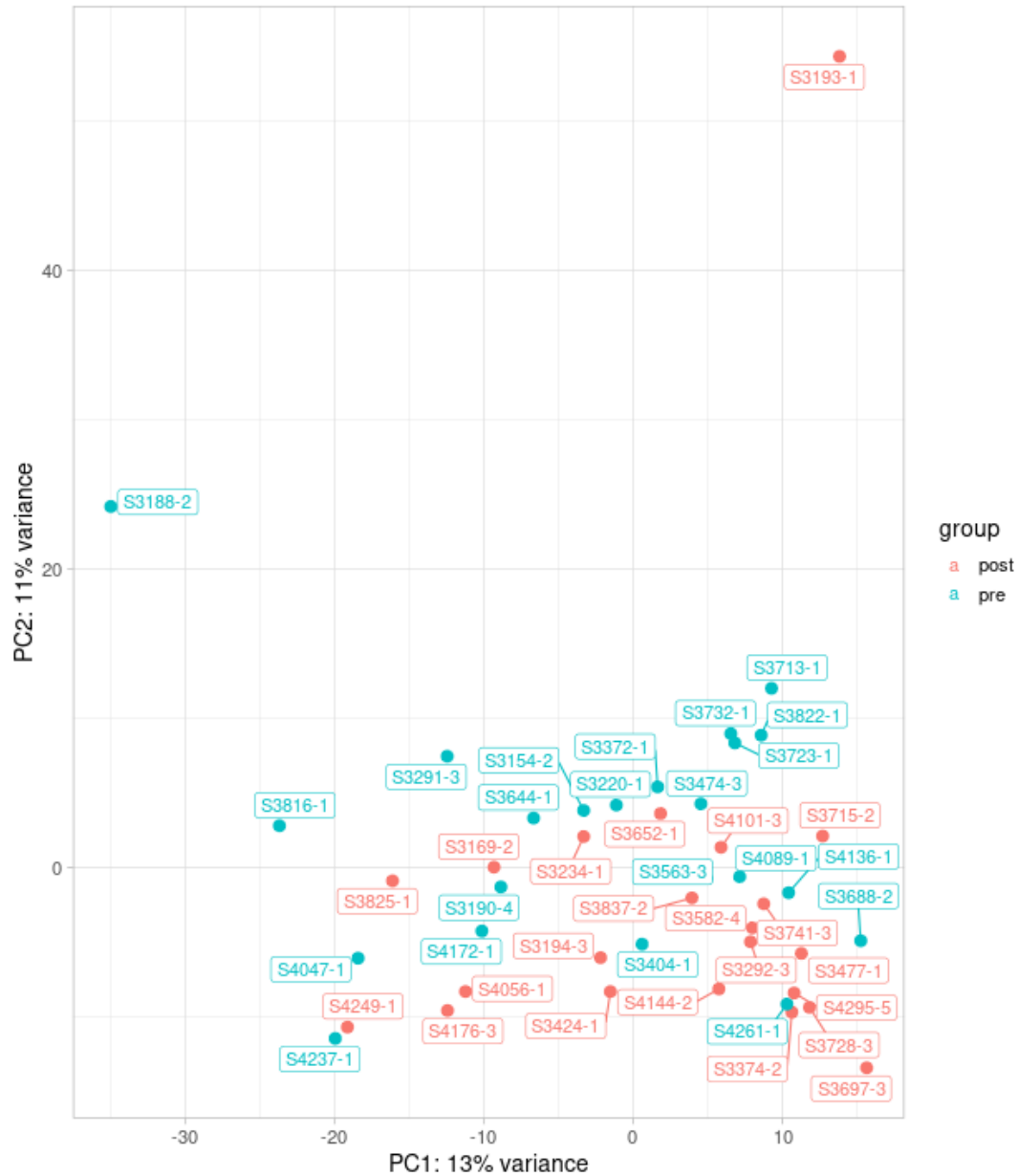


Most pCR samples were sequenced on 20180228 and non-pCR on two other dates. It is important to check the magnitude of DE signal between dates.

Sample-level QC analysis

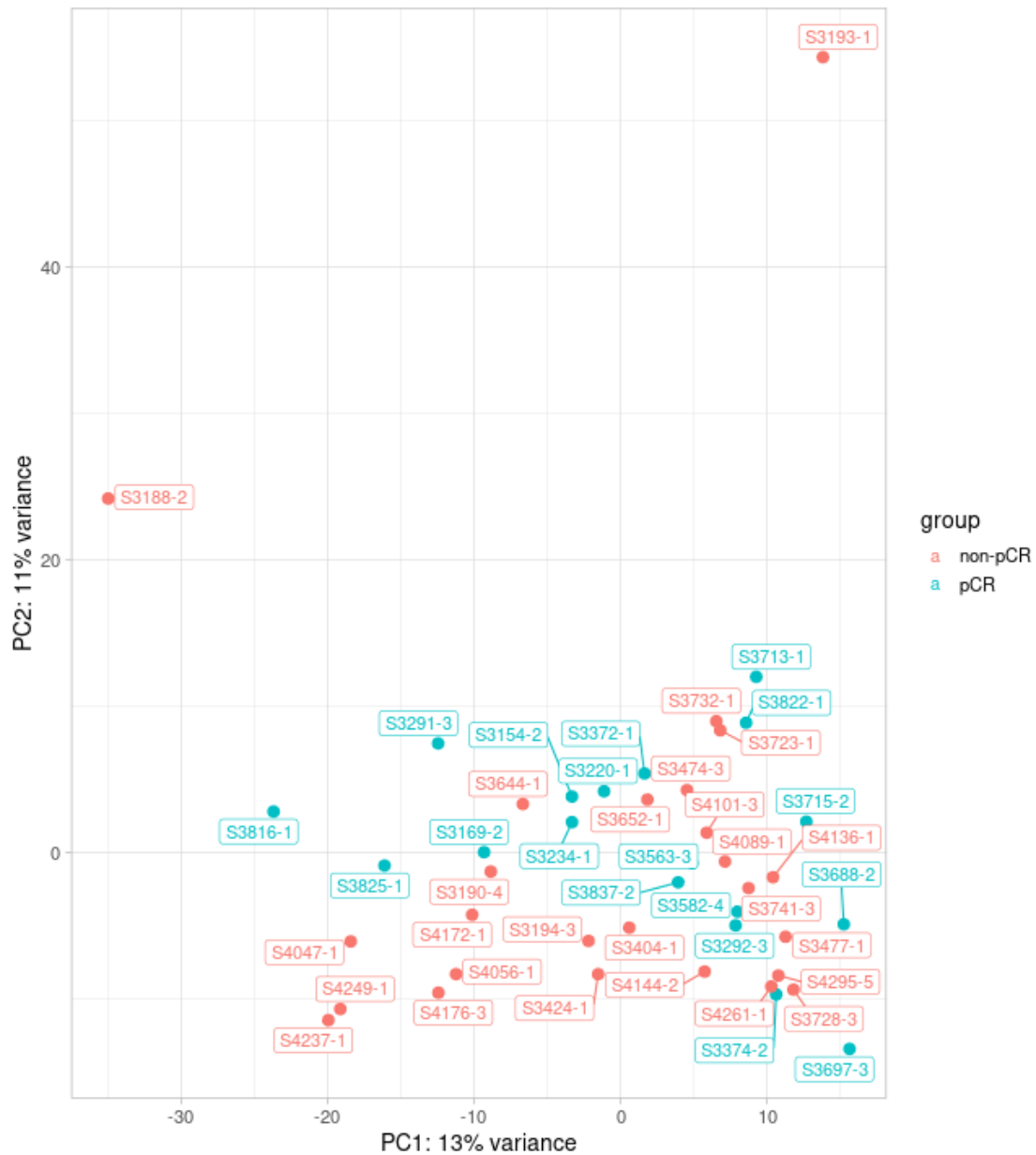
PCA - treatment

```
# Use the DESeq2 function  
plotPCA(rld, intgroup = c("treatment")) + geom_label_repel(aes(label = name))
```



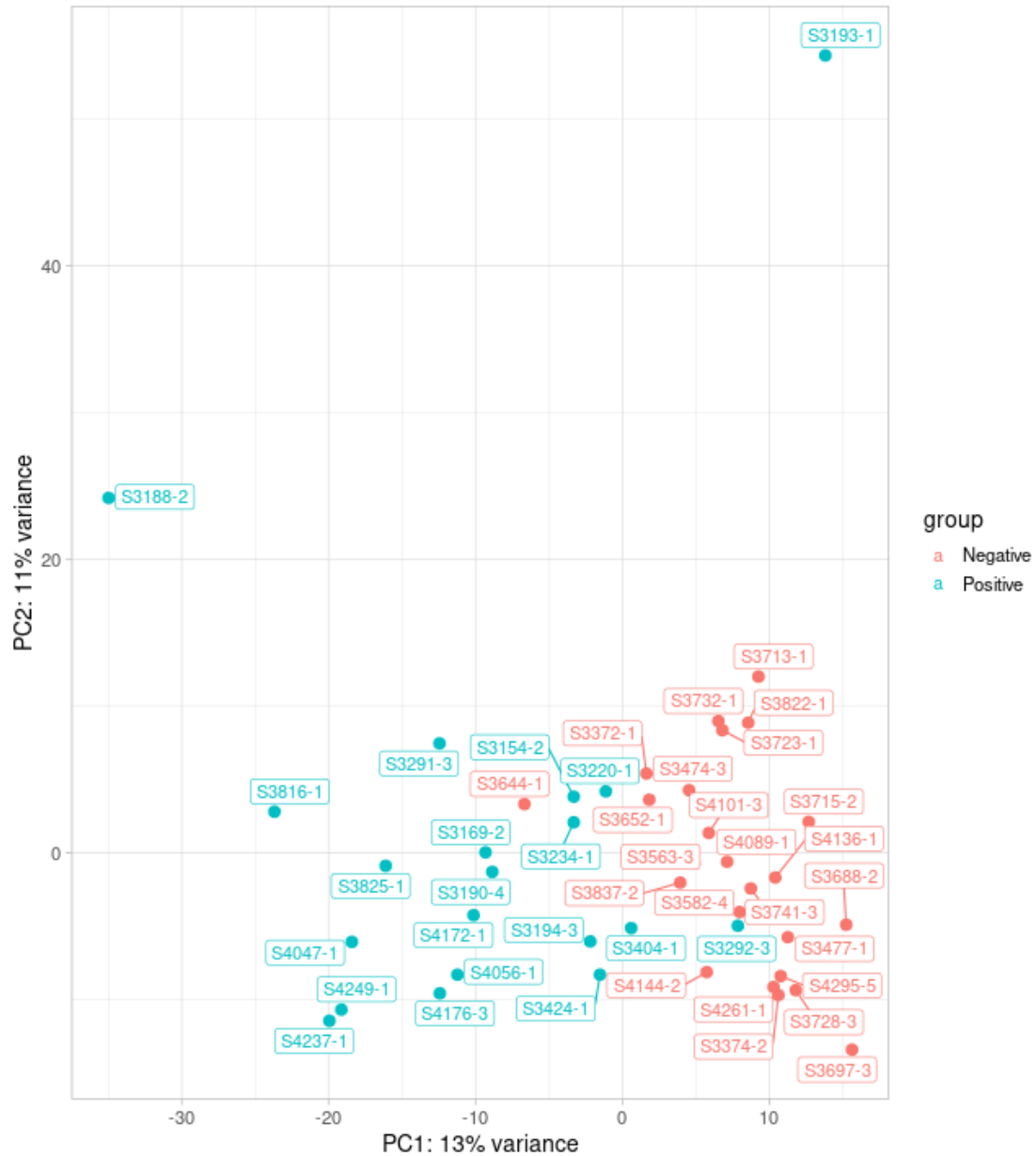
PCA - response

```
# Use the DESeq2 function  
plotPCA(rld, intgroup = c("response")) + geom_label_repel(aes(label = name))
```



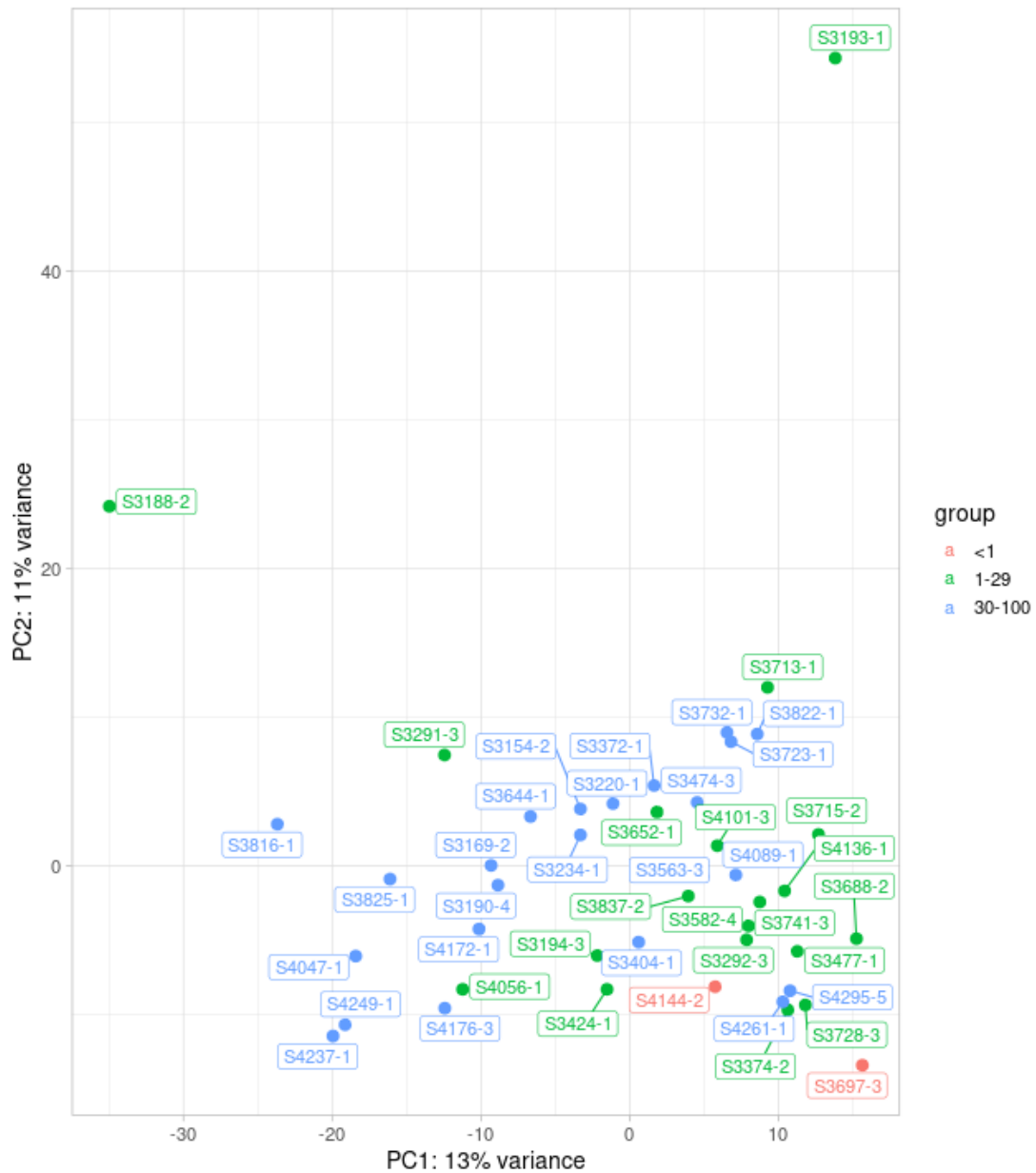
PCA - ER

```
# Use the DESeq2 function  
plotPCA(rld, intgroup = c("er")) + geom_label_repel(aes(label = name))
```



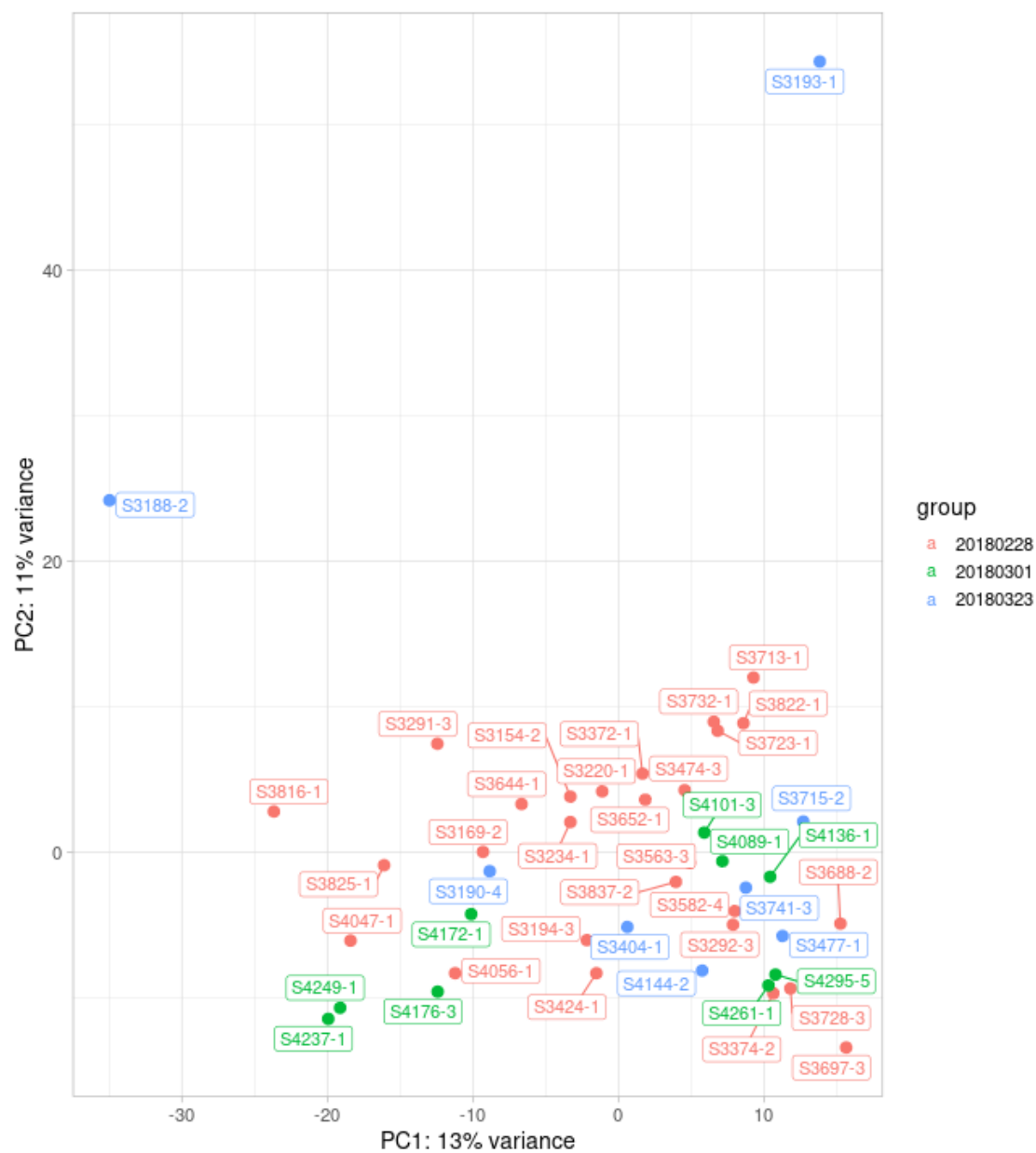
PCA - tumor_percentage

```
# Use the DESeq2 function  
plotPCA(rld, intgroup = c("tumor_percentage")) + geom_label_repel(aes(label = name))
```



```
# Use the DESeq2 function
plotPCA(rld, intgroup = c("tumor_percentage_high")) + geom_label_repel(aes(label = name))
```





Inter-correlation analysis

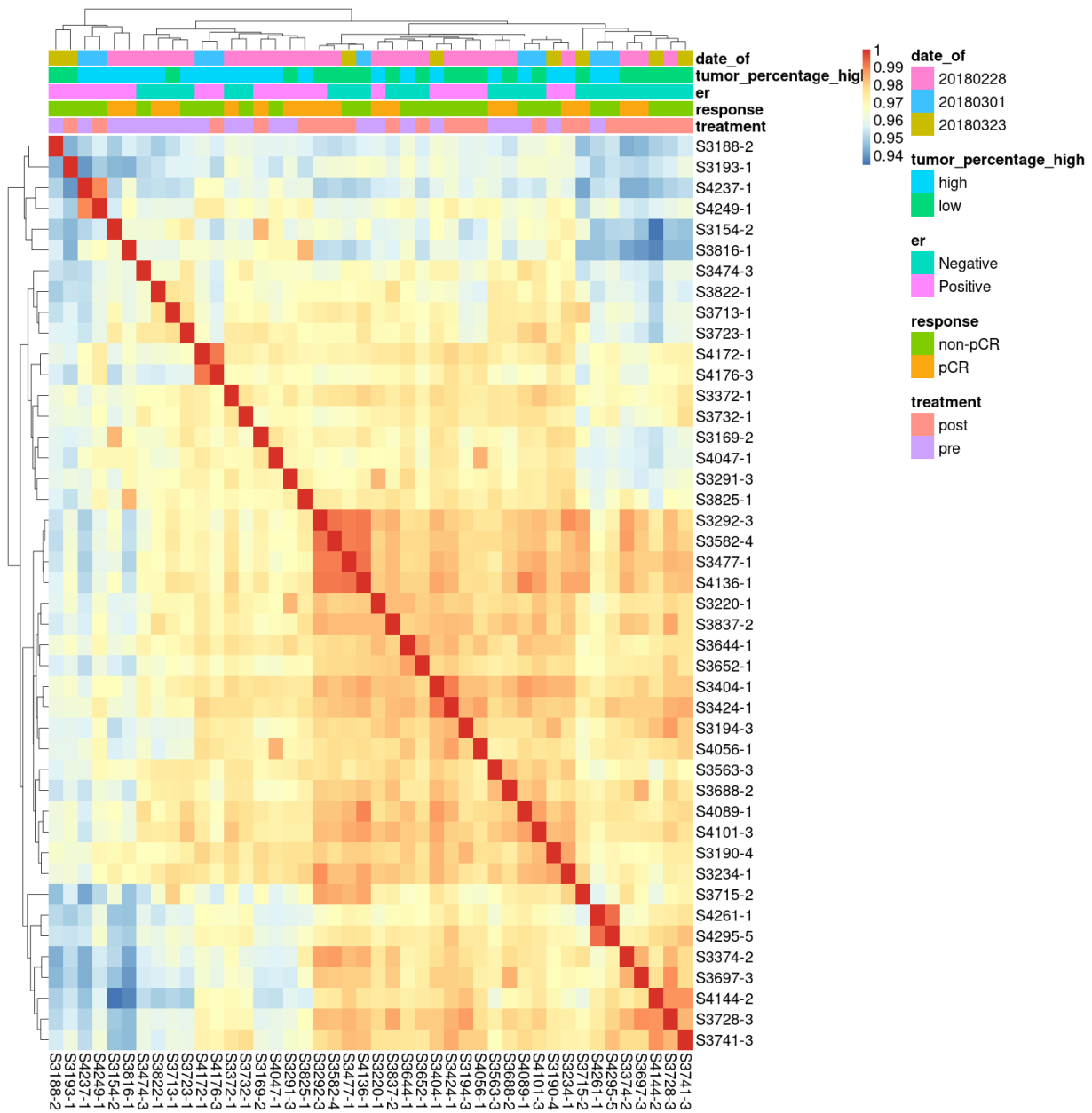
Without study_id

```
# Correlation matrix
rld_cor <- cor(rld_mat)

meta$study_id <- as.factor(meta$study_id)
# Create annotation file for samples
annotation <- meta[, c("treatment", "response", "er", "tumor_percentage_high", "date_of")]

# Change colors
heat.colors <- brewer.pal(6, "Blues")

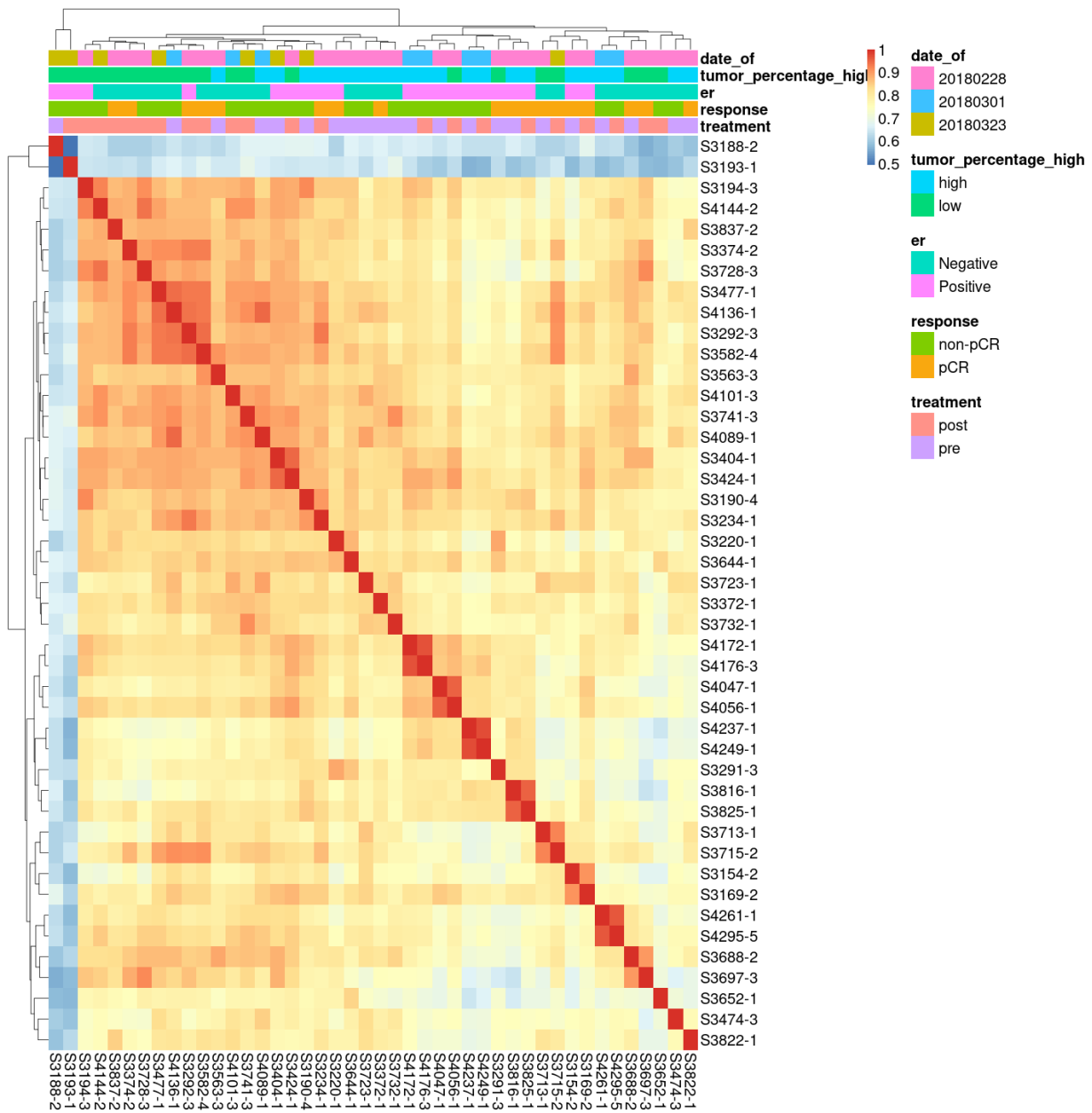
# Plot heatmap
pheatmap(rld_cor,
          annotation = annotation,
          border = NA,
          fontsize = 20)
```

Without study_id = top 1000 variable genes

```
rv <- rowVars(rld_mat)
rv <- order(rv, decreasing = TRUE) %>% head(1000)
rld_mat_1000 <- rld_mat[rv,]
annotation <- meta[, c("treatment", "response", "er", "tumor_percentage_high", "date_of")]

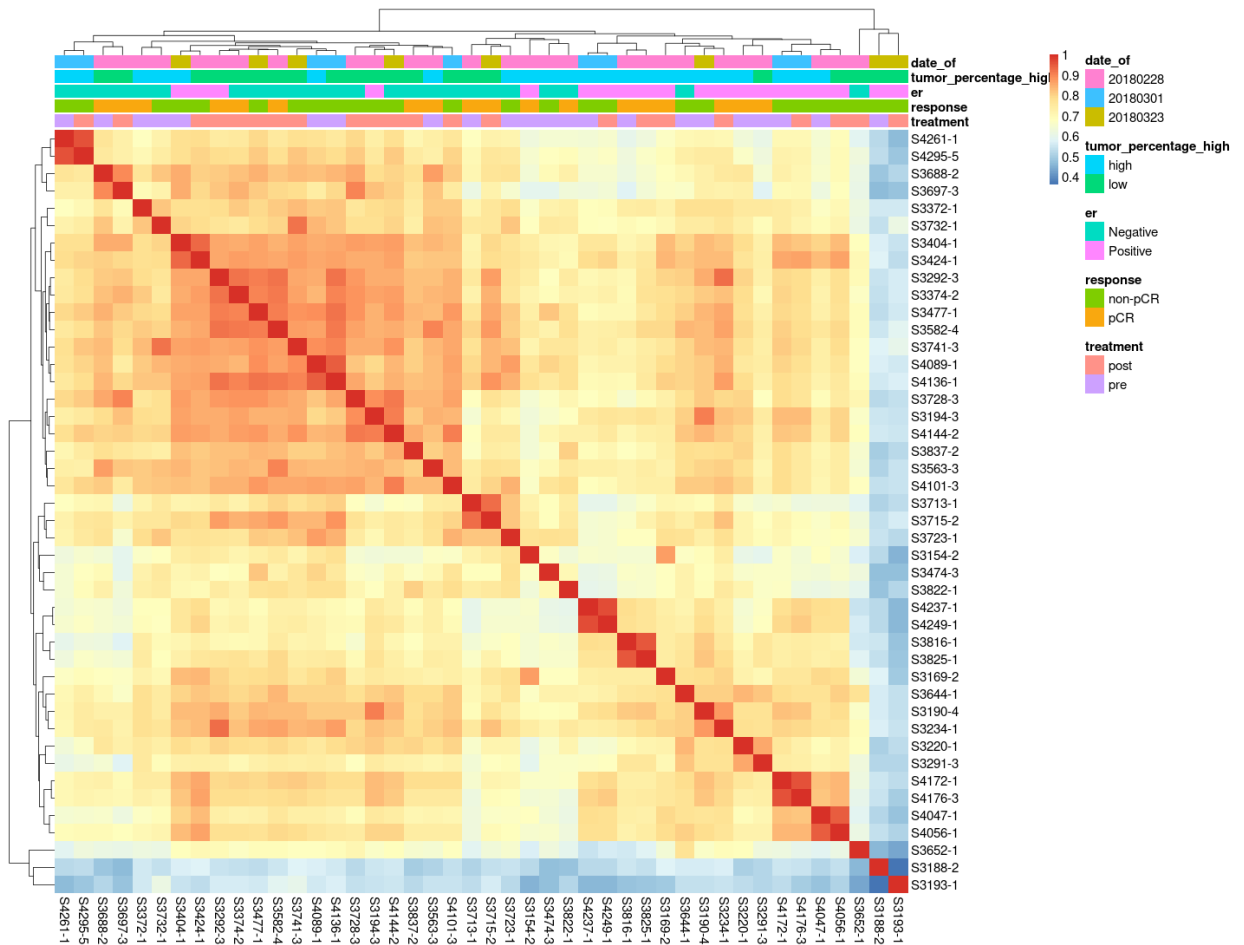
# Change colors
heat.colors <- brewer.pal(6, "Blues")
rld_cor <- cor(rld_mat_1000)
# Plot heatmap
pheatmap(rld_cor,
          annotation = annotation,
          border = NA,
          fontsize = 20)
```



Without study_id = top 500 variable genes

```
rv <- rowVars(rld_mat)
rv <- order(rv, decreasing = TRUE) %>% head(500)
rld_mat_500 <- rld_mat[rv,]
annotation <- meta[, c("treatment", "response", "er", "tumor_percentage_high", "date_of")]

# Change colors
heat.colors <- brewer.pal(6, "Blues")
rld_cor <- cor(rld_mat_500)
# Plot heatmap
fig3a <- as.ggplot(pheatmap(rld_cor,
  annotation = annotation,
  border = NA,
  fontsize = 15,
  cellheight = 20))
```



```
saveRDS(fig3a, "data/fig3a.RDS")
pheatmap(rld_cor,
  annotation = annotation,
  border = NA,
  fontsize = 20)
```



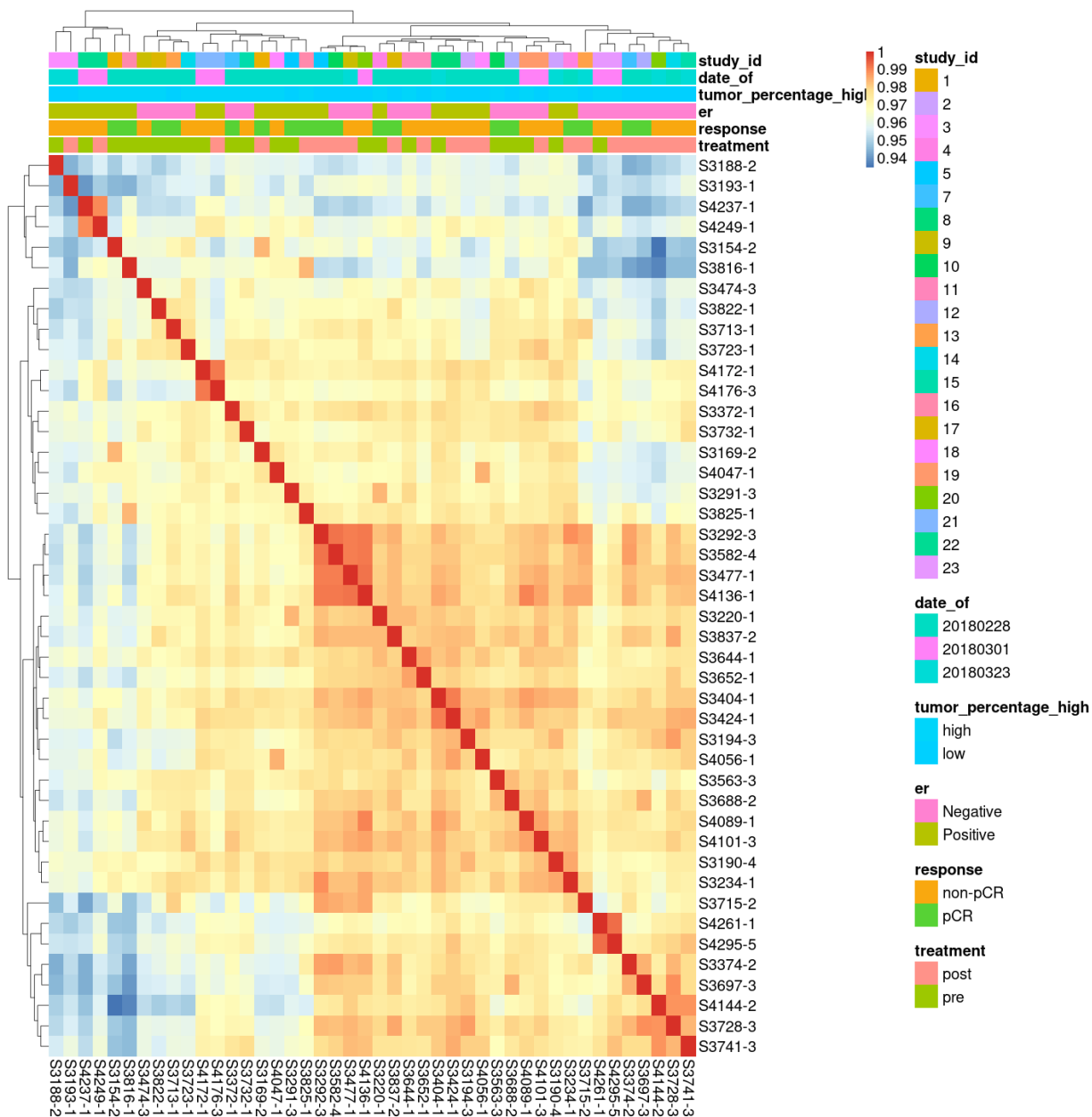
With study_id

```
# Correlation matrix
rld_cor <- cor(rld_mat)

meta$study_id <- as.factor(meta$study_id)
# Create annotation file for samples
annotation <- meta[, c("treatment", "response", "er", "tumor_percentage_high", "date_of", "study_id")]

# Change colors
heat.colors <- brewer.pal(6, "Blues")

# Plot heatmap
pheatmap(rld_cor,
          annotation = annotation,
          border = NA,
          fontsize = 20)
```



Treatment Post vs Pre - see Table3

Response pCR vs non-pCR - see Table4

ER : Positive vs Negative - Table 5

tumor__percentage__high : High vs Low - Table 6

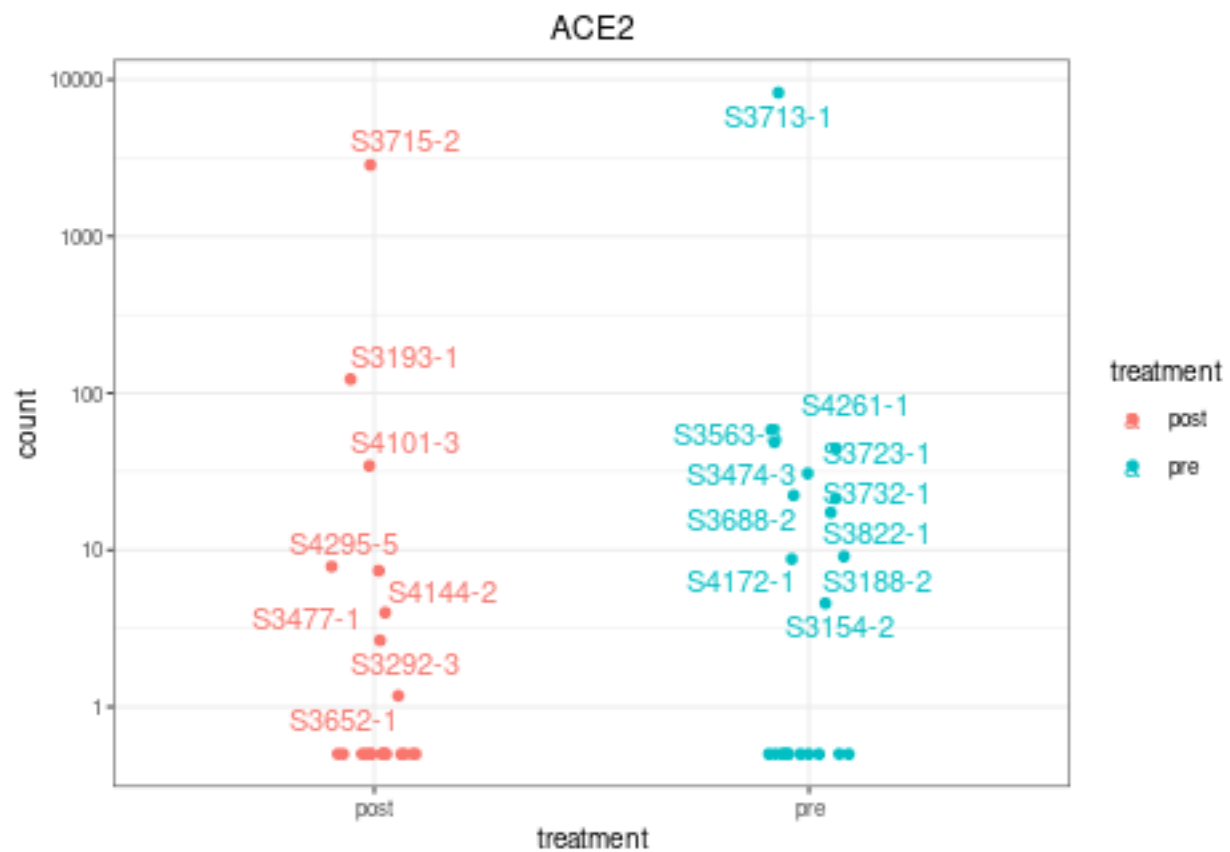
date__of: 20180323 vs 20180228 - Table 7

Visualization

Gene example

```
d <- plotCounts(dds,
  gene = "ENSG00000130234",
  intgroup = "treatment",
  returnData = TRUE)

ggplot(d, aes(x = treatment, y = count, color = treatment)) +
  geom_point(position = position_jitter(w = 0.1, h = 0)) +
  geom_text_repel(aes(label = rownames(d))) +
  theme_bw(base_size = 10) +
  ggtitle("ACE2") +
  theme(plot.title = element_text(hjust = 0.5)) +
  scale_y_log10()
```

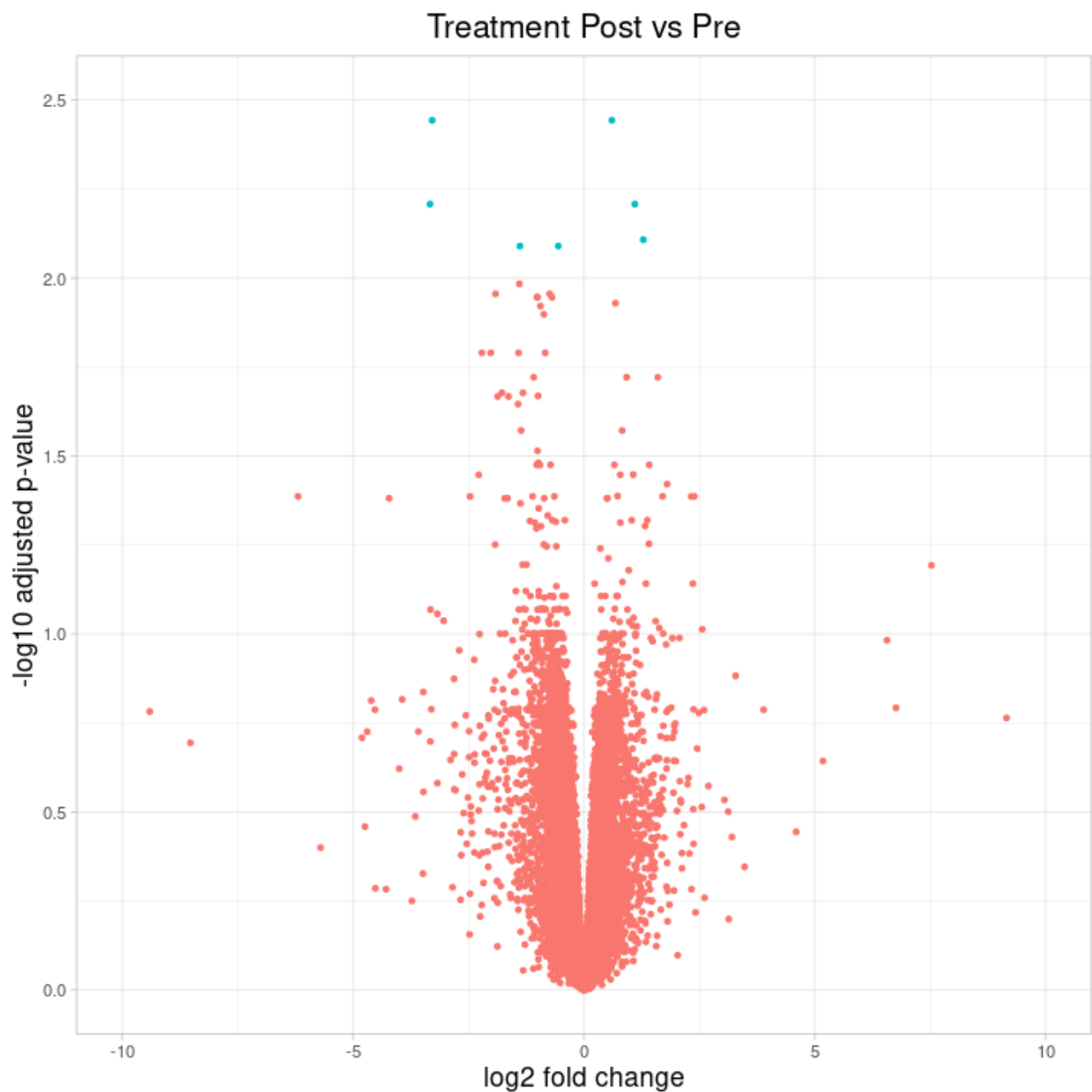


```

# Add a column for significant genes
resTreatment_tb <- resTreatment_tb %>% mutate(threshold = padj < 0.01)

## Volcano plot
ggplot(resTreatment_tb) +
  geom_point(aes(x = log2FoldChange, y = -log10(padj), colour = threshold)) +
  ggtitle("Treatment Post vs Pre") +
  xlab("log2 fold change") +
  ylab("-log10 adjusted p-value") +
  scale_x_continuous(limits = c(-10,10)) +
  scale_y_continuous(limits = c(0, 2.5)) +
  theme(legend.position = "none",
        plot.title = element_text(size = rel(1.5), hjust = 0.5),
        axis.title = element_text(size = rel(1.25)))

```

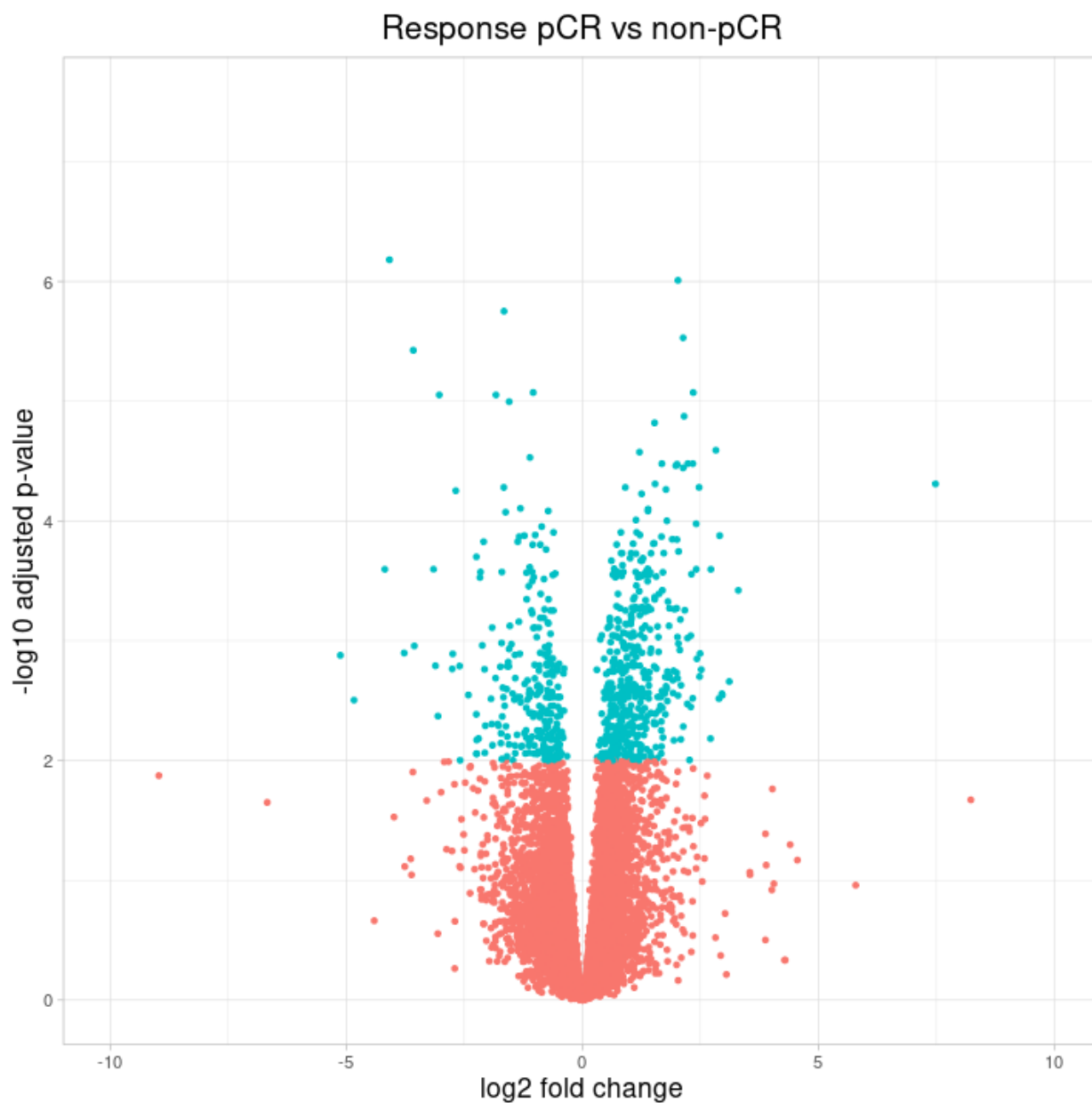


```

# Add a column for significant genes
resResponse_tb <- resResponse_tb %>% mutate(threshold = padj < 0.01)

ggplot(resResponse_tb) +
  geom_point(aes(x = log2FoldChange, y = -log10(padj), colour = threshold)) +
  ggtitle("Response pCR vs non-pCR") +
  xlab("log2 fold change") +
  ylab("-log10 adjusted p-value") +
  scale_x_continuous(limits = c(-10,10)) +
  scale_y_continuous(limits = c(0, 7.5))+
  theme(legend.position = "none",
        plot.title = element_text(size = rel(1.5), hjust = 0.5),
        axis.title = element_text(size = rel(1.25)))

```

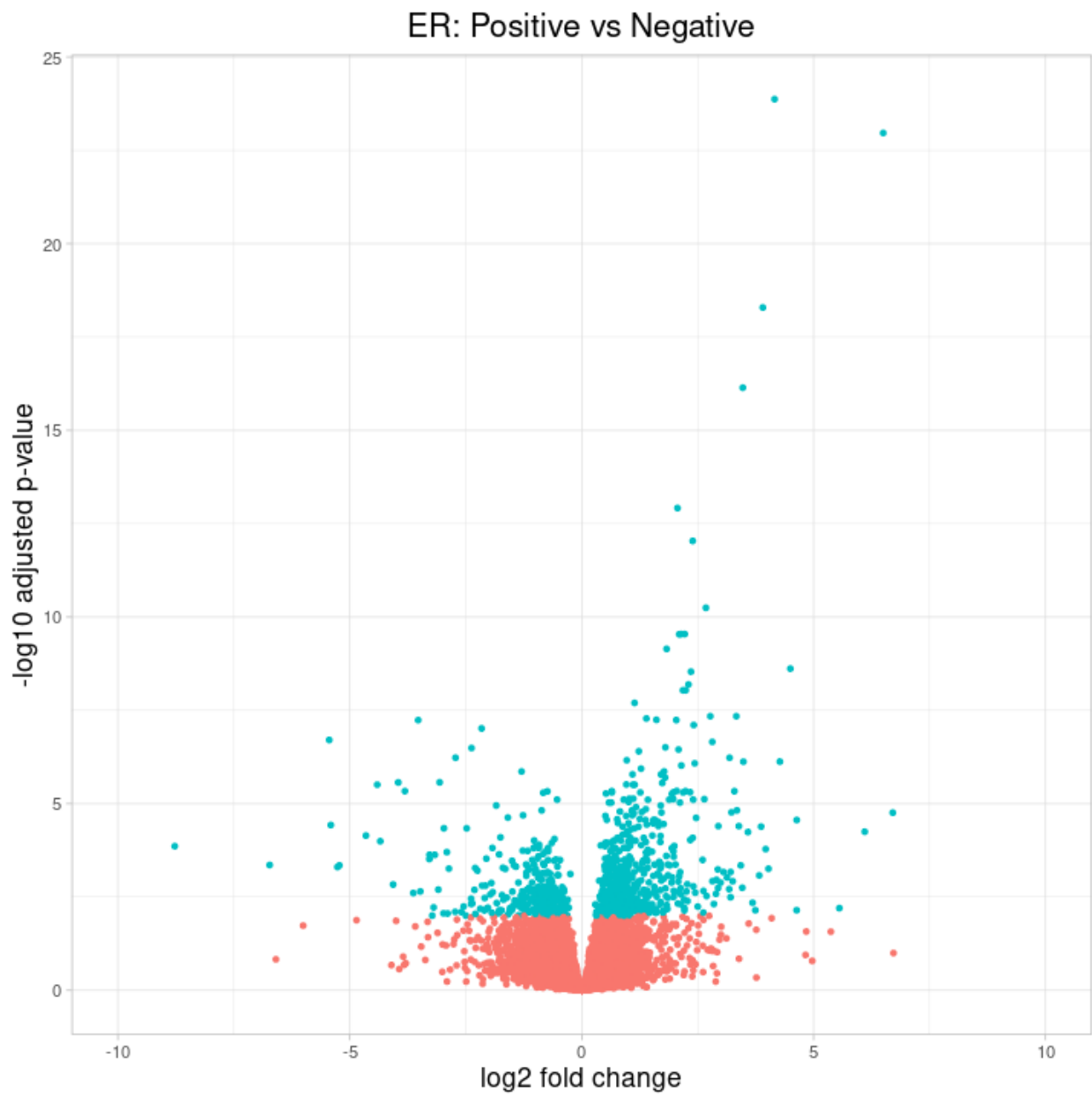


```

# Add a column for significant genes
resER_tb <- resER_tb %>% mutate(threshold = padj < 0.01)

ggplot(resER_tb) +
  geom_point(aes(x = log2FoldChange, y = -log10(padj), colour = threshold)) +
  ggtitle("ER: Positive vs Negative") +
  xlab("log2 fold change") +
  ylab("-log10 adjusted p-value") +
  scale_x_continuous(limits = c(-10,10)) +
  theme(legend.position = "none",
        plot.title = element_text(size = rel(1.5), hjust = 0.5),
        axis.title = element_text(size = rel(1.25)))

```

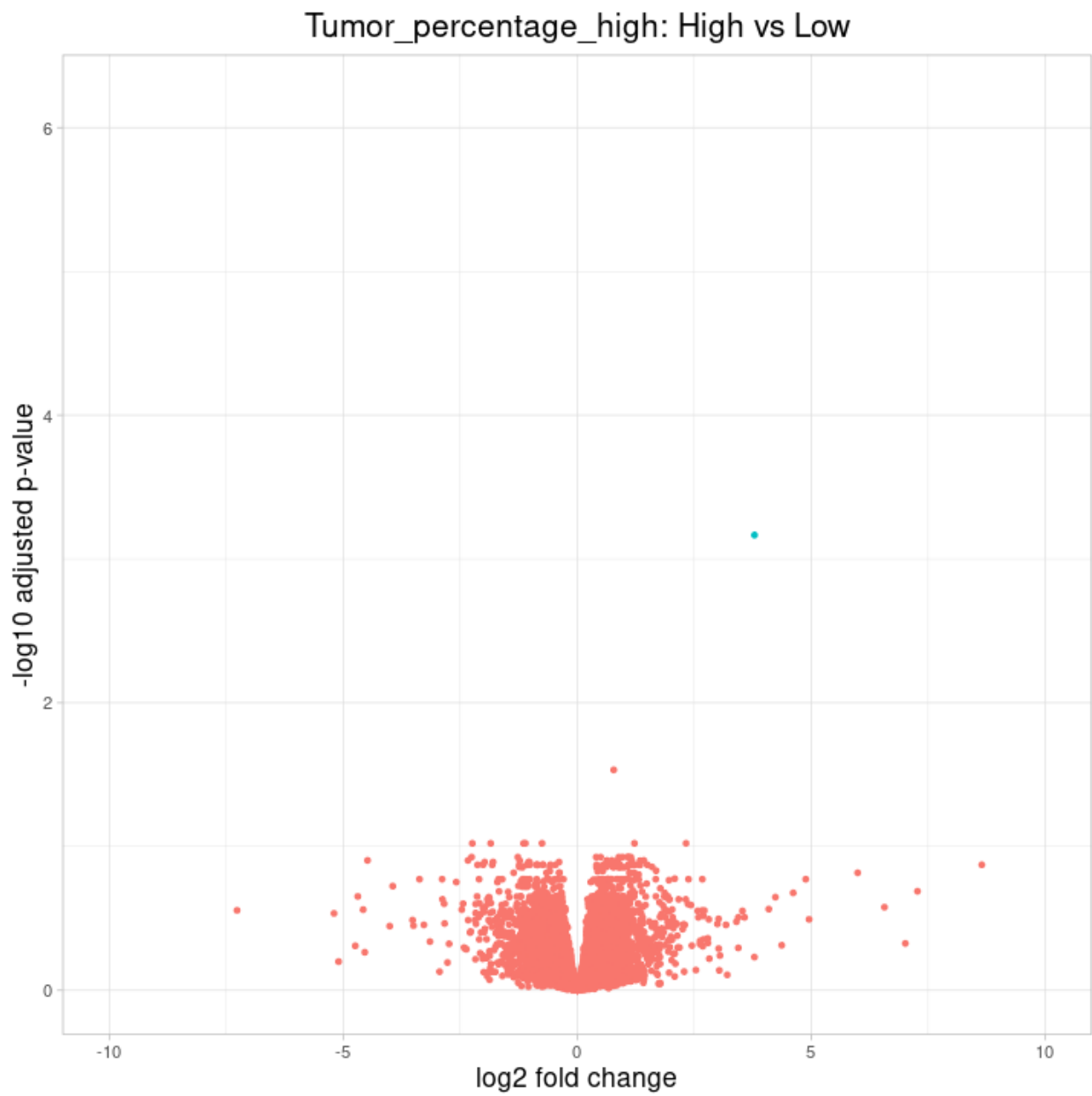


```

# Add a column for significant genes
resTP_tb <- resTP_tb %>% mutate(threshold = padj < 0.01)

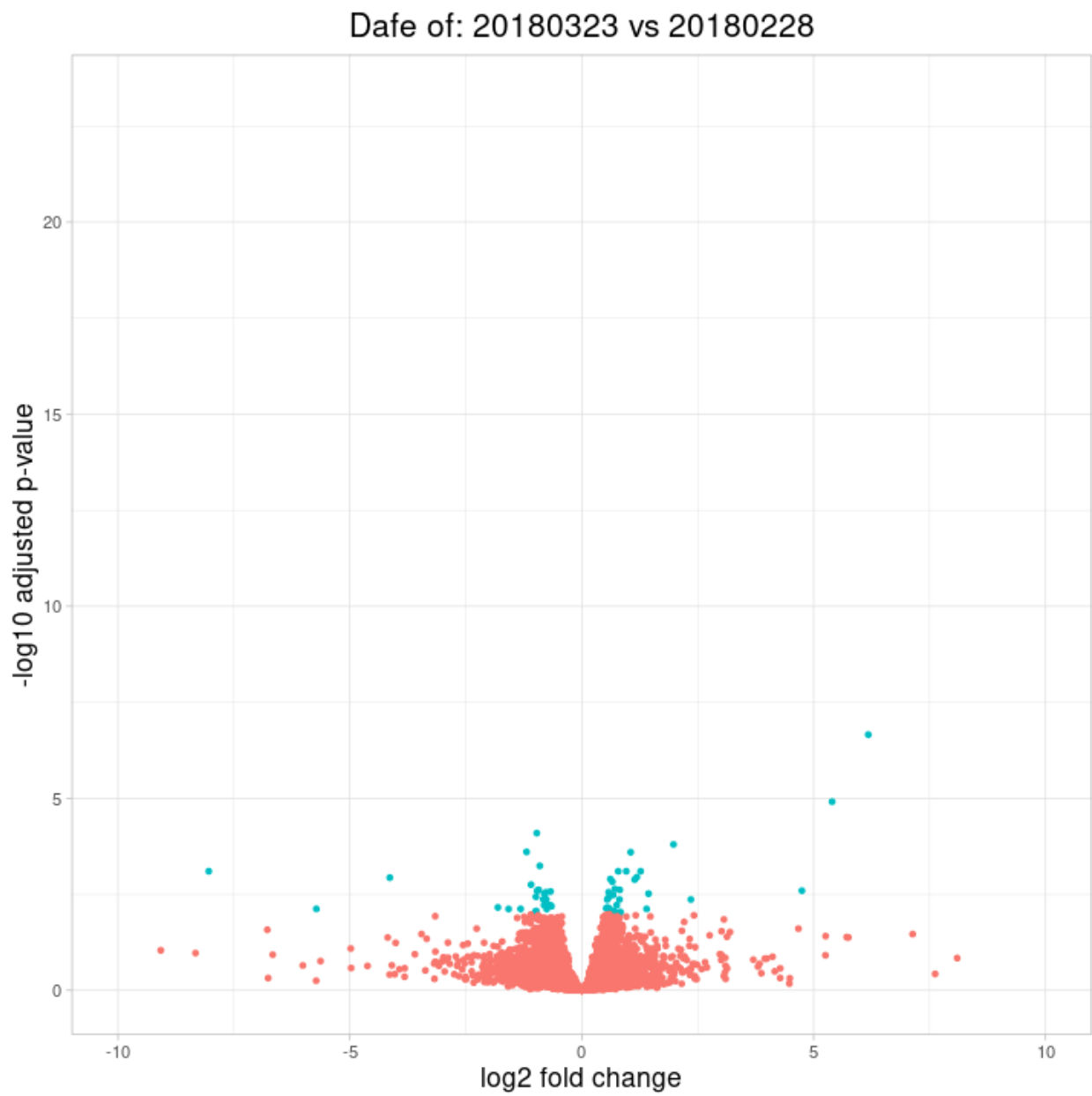
ggplot(resTP_tb) +
  geom_point(aes(x = log2FoldChange, y = -log10(padj), colour = threshold)) +
  ggtitle("Tumor_percentage_high: High vs Low") +
  xlab("log2 fold change") +
  ylab("-log10 adjusted p-value") +
  scale_x_continuous(limits = c(-10,10)) +
  theme(legend.position = "none",
        plot.title = element_text(size = rel(1.5), hjust = 0.5),
        axis.title = element_text(size = rel(1.25)))

```



```
# Add a column for significant genes
resD0_tb <- resD0_tb %>% mutate(threshold = padj < 0.01)

ggplot(resD0_tb) +
  geom_point(aes(x = log2FoldChange, y = -log10(padj), colour = threshold)) +
  ggtitle("Date of: 20180323 vs 20180228") +
  xlab("log2 fold change") +
  ylab("-log10 adjusted p-value") +
  scale_x_continuous(limits = c(-10,10)) +
  theme(legend.position = "none",
        plot.title = element_text(size = rel(1.5), hjust = 0.5),
        axis.title = element_text(size = rel(1.25)))
```



Heatmaps

```
# Create a matrix of normalized expression
sig_up <- resTreatment_tb_significant %>% arrange(-log2FoldChange) %>% head(50) %>% pull(gene)
sig_down <- resTreatment_tb_significant %>% arrange(log2FoldChange) %>% head(50) %>% pull(gene)
sig <- c(sig_up, sig_down)

row_annotation <- gene_symbol %>%
  as_tibble() %>%
  dplyr::filter(gene_id %in% sig)

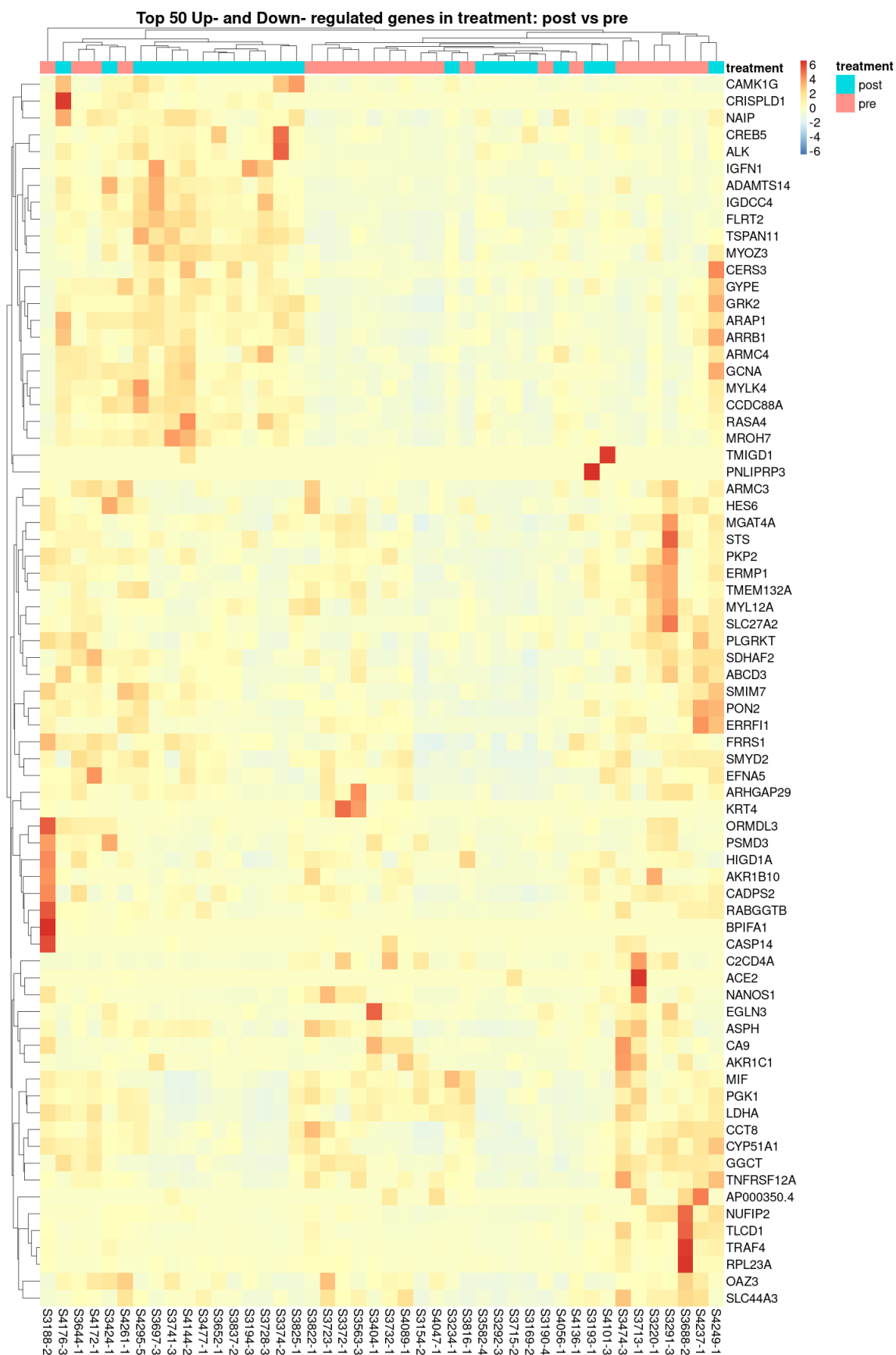
plotmat <- txi$abundance[c(sig_up, sig_down),] %>% as.data.frame() %>%
  rownames_to_column(var = "ensembl_gene_id") %>%
  left_join(gene_symbol, by = c("ensembl_gene_id" = "gene_id")) %>%
  drop_na(symbol)

plotmat$ensembl_gene_id <- NULL

plotmat <- plotmat %>% column_to_rownames(var = "symbol") %>% as.matrix()

# Color palette
heat.colors <- brewer.pal(6, "YlOrRd")

# Plot heatmap
# color = heat.colors,
pheatmap(plotmat, scale = "row",
  show_rownames = TRUE,
  border = FALSE,
  annotation = meta[, c("treatment"), drop = FALSE],
  main = "Top 50 Up- and Down- regulated genes in treatment: post vs pre",
  fontsize = 20)
```

```

# Create a matrix of normalized expression
sig_up <- resResponse_tb_significant %>% arrange(-log2FoldChange) %>% head(50) %>% pull(gene)
sig_down <- resResponse_tb_significant %>% arrange(log2FoldChange) %>% head(50) %>% pull(gene)
sig <- c(sig_up, sig_down)

row_annotation <- gene_symbol %>%
  as_tibble() %>%
  dplyr::filter(gene_id %in% sig)

plotmat <- txi$abundance[c(sig_up, sig_down),] %>% as.data.frame() %>%
  rownames_to_column(var = "ensembl_gene_id") %>%
  left_join(gene_symbol, by = c("ensembl_gene_id" = "gene_id")) %>%
  drop_na(symbol)

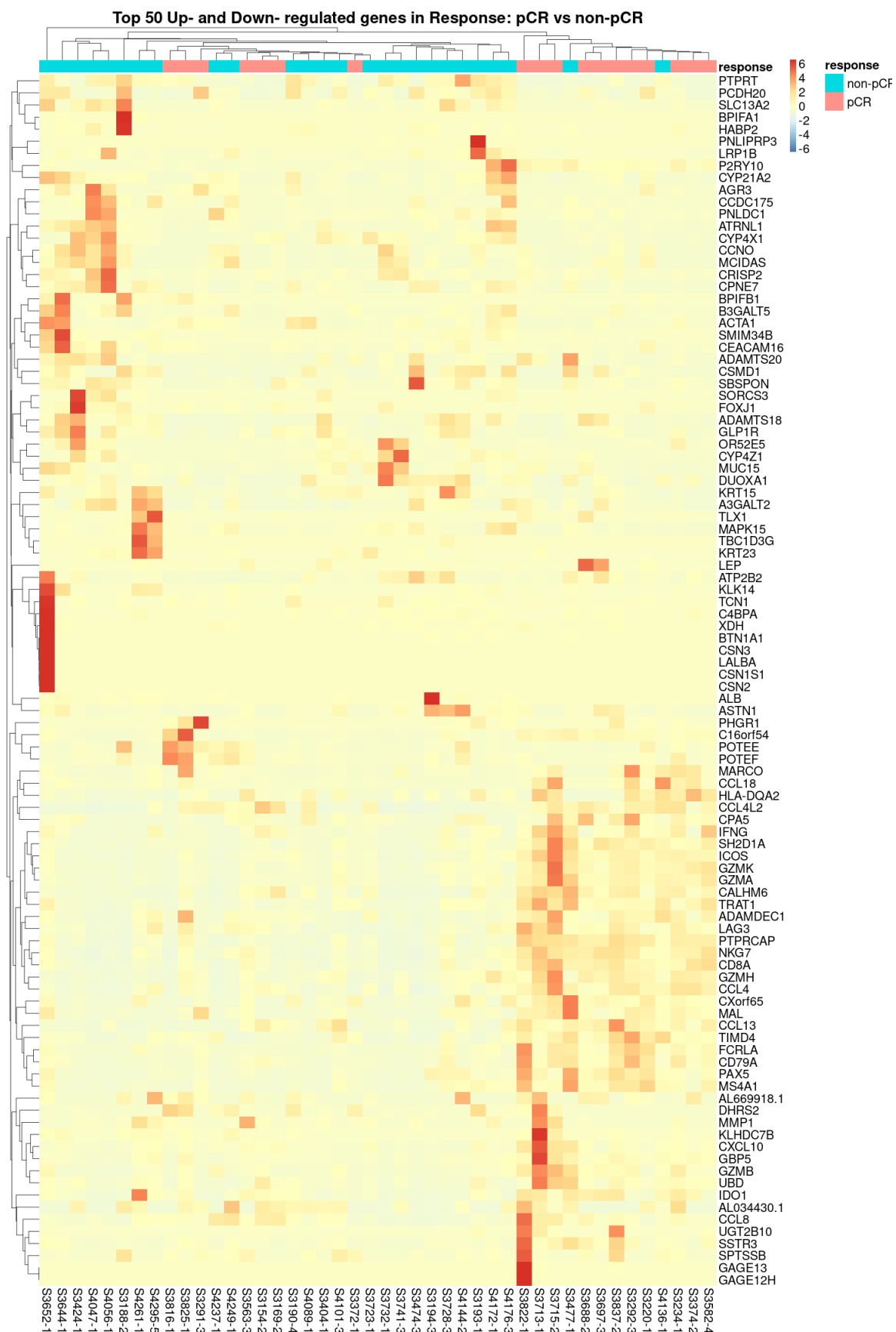
plotmat$ensembl_gene_id <- NULL

plotmat <- plotmat %>% column_to_rownames(var = "symbol") %>% as.matrix()

# Color palette
heat.colors <- brewer.pal(6, "YlOrRd")

# Plot heatmap
pheatmap(plotmat,
  scale = "row",
  show_rownames = TRUE,
  border = FALSE,
  annotation = meta[, c("response"), drop = FALSE],
  main = "Top 50 Up- and Down- regulated genes in Response: pCR vs non-pCR",
  fontsize = 20)

```



```

# Create a matrix of normalized expression
sig_up <- resER_tb_significant %>% arrange(-log2FoldChange) %>% head(50) %>% pull(gene)
sig_down <- resER_tb_significant %>% arrange(log2FoldChange) %>% head(50) %>% pull(gene)
sig <- c(sig_up, sig_down)

row_annotation <- gene_symbol %>%
  as_tibble() %>%
  dplyr::filter(gene_id %in% sig)

plotmat <- txi$abundance[c(sig_up, sig_down),] %>% as.data.frame() %>%
  rownames_to_column(var = "ensembl_gene_id") %>%
  left_join(gene_symbol, by = c("ensembl_gene_id" = "gene_id")) %>%
  drop_na(symbol)

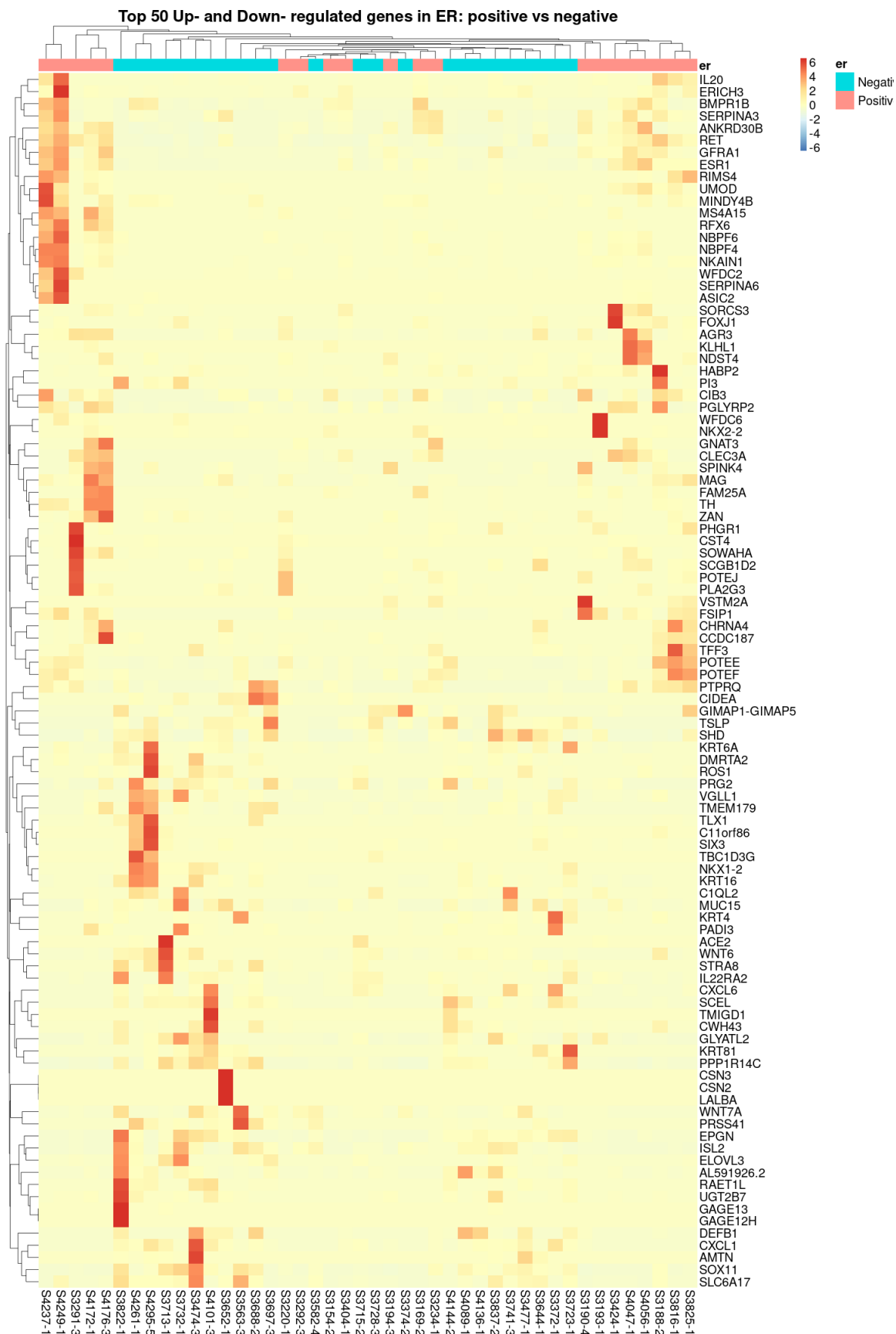
plotmat$ensembl_gene_id <- NULL

plotmat <- plotmat %>% column_to_rownames(var = "symbol") %>% as.matrix()

# Color palette
heat.colors <- brewer.pal(6, "YlOrRd")

# Plot heatmap
pheatmap(plotmat,
  scale = "row",
  show_rownames = TRUE,
  border = FALSE,
  annotation = meta[, c("er"), drop = FALSE],
  main = "Top 50 Up- and Down- regulated genes in ER: positive vs negative",
  fontsize = 20)

```



```

# Create a matrix of normalized expression
sig_up <- resTP_tb_significant %>% arrange(-log2FoldChange) %>% head(50) %>% pull(gene)
sig_down <- resTP_tb_significant %>% arrange(log2FoldChange) %>% head(50) %>% pull(gene)
sig <- c(sig_up, sig_down)

row_annotation <- gene_symbol %>%
  as_tibble() %>%
  dplyr::filter(gene_id %in% sig)

plotmat <- txi$abundance[c(sig_up, sig_down),] %>% as.data.frame() %>%
  rownames_to_column(var = "ensembl_gene_id") %>%
  left_join(gene_symbol, by = c("ensembl_gene_id" = "gene_id")) %>%
  drop_na(symbol)

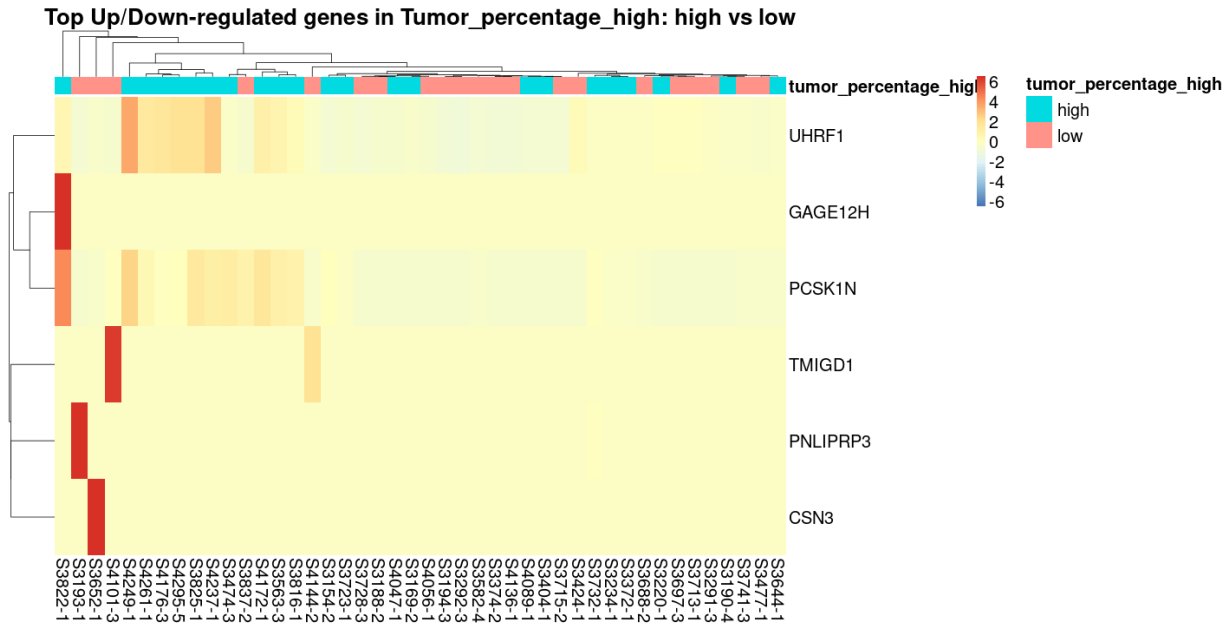
plotmat$ensembl_gene_id <- NULL

plotmat <- plotmat %>% column_to_rownames(var = "symbol") %>% as.matrix()

# Color palette
heat.colors <- brewer.pal(6, "YlOrRd")

```

```
# Plot heatmap
pheatmap(plotmat,
  scale = "row",
  show_rownames = TRUE,
  border = FALSE,
  annotation = meta[, c("tumor_percentage_high"), drop = FALSE],
  main = "Top Up/Down-regulated genes in Tumor_percentage_high: high vs low",
  fontsize = 20)
```



```

# Create a matrix of normalized expression
sig_up <- resD0_tb_significant %>% arrange(-log2FoldChange) %>% head(50) %>% pull(gene)
sig_down <- resD0_tb_significant %>% arrange(log2FoldChange) %>% head(50) %>% pull(gene)
sig <- c(sig_up, sig_down)

row_annotation <- gene_symbol %>%
  as_tibble() %>%
  dplyr::filter(gene_id %in% sig)

plotmat <- txi$abundance[c(sig_up, sig_down),] %>% as.data.frame() %>%
  rownames_to_column(var = "ensembl_gene_id") %>%
  left_join(gene_symbol, by = c("ensembl_gene_id" = "gene_id")) %>%
  drop_na(symbol)

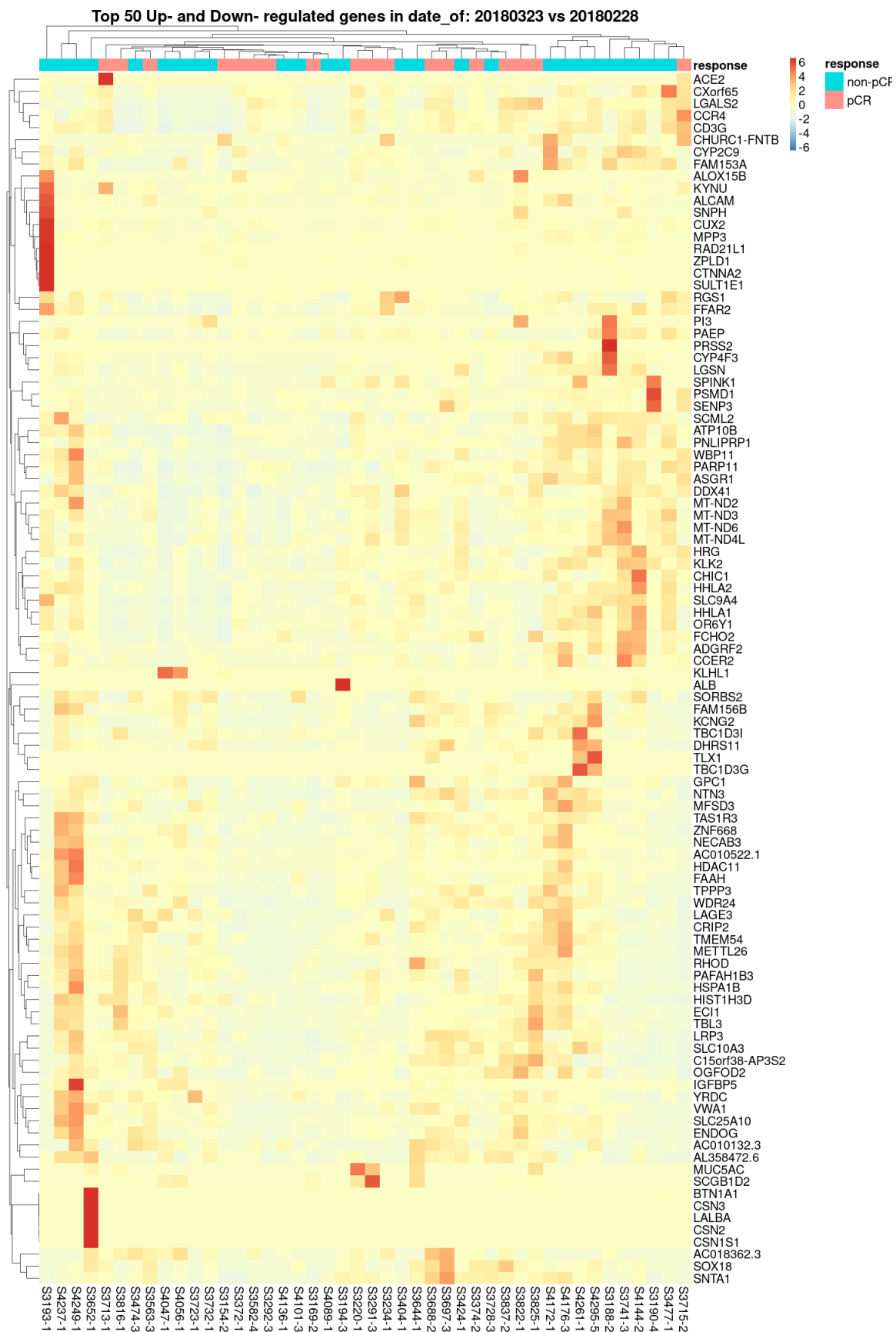
plotmat$ensembl_gene_id <- NULL

plotmat <- plotmat %>% column_to_rownames(var = "symbol") %>% as.matrix()

# Color palette
heat.colors <- brewer.pal(6, "YlOrRd")

# Plot heatmap
pheatmap(plotmat,
  scale = "row",
  show_rownames = TRUE,
  border = FALSE,
  annotation = meta[, c("response"), drop = FALSE],
  main = "Top 50 Up- and Down- regulated genes in date_of: 20180323 vs 20180228",
  fontsize = 20)

```

Prepare files for GSEA

GSEA day-wise

```
result_file <- paste0("tables/all_samples.4gsea.day_wise.txt")

samples_post <- meta %>% dplyr::filter(treatment == "post") %>% row.names()
samples_pre <- meta %>% dplyr::filter(treatment == "pre") %>% row.names()

counts_gsea <- counts_gsea[,c("NAME", "DESCRIPTION", samples_post, samples_pre)]
# gsea now supports ENSEMBL_IDs
write_tsv(counts_gsea, result_file)

treatment_vector <- c(rep("post", length(samples_post)), rep("pre", length(samples_pre)))
treatment_str <- paste(treatment_vector, collapse = " ")

file_conn <- file("tables/all_samples.4gsea.day_wise.cls")
writeLines(c("44 2 1",
            "# post pre",
            treatment_str),
            file_conn)
close(file_conn)
```

R session

```
sessionInfo()

## R version 4.0.3 (2020-10-10)
## Platform: x86_64-redhat-linux-gnu (64-bit)
## Running under: Fedora 32 (Workstation Edition)
##
## Matrix products: default
## BLAS/LAPACK: /usr/lib64/libopenblas-r0.3.12.so
##
## locale:
##  [1] LC_CTYPE=en_CA.UTF-8      LC_NUMERIC=C
##  [3] LC_TIME=en_CA.UTF-8      LC_COLLATE=en_CA.UTF-8
##  [5] LC_MONETARY=en_CA.UTF-8  LC_MESSAGES=en_CA.UTF-8
##  [7] LC_PAPER=en_CA.UTF-8     LC_NAME=C
##  [9] LC_ADDRESS=C             LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_CA.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] parallel stats4      stats      graphics  grDevices  utils      datasets
## [8] methods   base
##
## other attached packages:
##  [1] ggplotify_0.0.6          ensemblDb_2.14.1
##  [3] AnnotationFilter_1.14.0  GenomicFeatures_1.42.3
##  [5] AnnotationDbi_1.52.0     AnnotationHub_2.22.1
##  [7] BiocFileCache_1.14.0     dbplyr_2.1.1
```

```

## [9] knitr_1.30 ggrepel_0.9.1
## [11] tximport_1.18.0 DEGreport_1.26.0
## [13] pheatmap_1.0.12 RColorBrewer_1.1-2
## [15] forcats_0.5.1 stringr_1.4.0
## [17] dplyr_1.0.5 purrr_0.3.4
## [19] readr_1.4.0 tidyr_1.1.3
## [21] tibble_3.1.1 ggplot2_3.3.3
## [23] tidyverse_1.3.1 DESeq2_1.30.1
## [25] SummarizedExperiment_1.20.0 Biobase_2.50.0
## [27] MatrixGenerics_1.2.1 matrixStats_0.58.0
## [29] GenomicRanges_1.42.0 GenomeInfoDb_1.26.7
## [31] IRanges_2.24.1 S4Vectors_0.28.1
## [33] BiocGenerics_0.36.1
##
## loaded via a namespace (and not attached):
## [1] readxl_1.3.1 backports_1.2.1
## [3] circlize_0.4.12 plyr_1.8.6
## [5] lazyeval_0.2.2 ConsensusClusterPlus_1.54.0
## [7] splines_4.0.3 BiocParallel_1.24.1
## [9] digest_0.6.27 htmltools_0.5.1.1
## [11] fansi_0.4.2 magrittr_2.0.1
## [13] memoise_2.0.0 cluster_2.1.0
## [15] limma_3.46.0 ComplexHeatmap_2.6.2
## [17] Biostrings_2.58.0 annotate_1.68.0
## [19] Nozzle.R1_1.1-1 modelr_0.1.8
## [21] askpass_1.1 prettyunits_1.1.1
## [23] colorspace_2.0-0 blob_1.2.1
## [25] rvest_1.0.0 rappdirs_0.3.3
## [27] haven_2.4.1 xfun_0.19
## [29] crayon_1.4.1 RCurl_1.98-1.3
## [31] jsonlite_1.7.2 genefilter_1.72.1
## [33] survival_3.2-7 glue_1.4.2
## [35] gtable_0.3.0 zlibbioc_1.36.0
## [37] XVector_0.30.0 MatrixModels_0.5-0
## [39] GetoptLong_1.0.5 DelayedArray_0.16.3
## [41] shape_1.4.5 SparseM_1.81
## [43] scales_1.1.1 DBI_1.1.1
## [45] edgeR_3.32.1 Rcpp_1.0.6
## [47] progress_1.2.2 xtable_1.8-4
## [49] lasso2_1.2-21.1 tmvnsim_1.0-2
## [51] clue_0.3-59 gridGraphics_0.5-1
## [53] bit_4.0.4 httr_1.4.2
## [55] ellipsis_0.3.1 farver_2.1.0
## [57] pkgconfig_2.0.3 reshape_0.8.8
## [59] XML_3.99-0.6 locfit_1.5-9.4
## [61] utf8_1.2.1 labeling_0.4.2
## [63] tidyselect_1.1.0 rlang_0.4.10
## [65] later_1.2.0 munsell_0.5.0
## [67] BiocVersion_3.12.0 cellranger_1.1.0
## [69] tools_4.0.3 cachem_1.0.4
## [71] cli_2.5.0 generics_0.1.0
## [73] RSQLite_2.2.7 broom_0.7.6
## [75] evaluate_0.14 fastmap_1.1.0
## [77] ggdendro_0.1.22 yaml_2.2.1

```

## [79] bit64_4.0.5	fs_1.5.0
## [81] nlme_3.1-149	quantreg_5.85
## [83] mime_0.9	xml2_1.3.2
## [85] biomaRt_2.46.3	compiler_4.0.3
## [87] rstudioapi_0.13	curl_4.3
## [89] png_0.1-7	interactiveDisplayBase_1.28.0
## [91] reprex_2.0.0	geneplotter_1.68.0
## [93] stringi_1.5.3	lattice_0.20-41
## [95] ProtGenerics_1.22.0	Matrix_1.2-18
## [97] psych_2.1.3	vctrs_0.3.7
## [99] pillar_1.6.0	lifecycle_1.0.0
## [101] BiocManager_1.30.12	GlobalOptions_0.1.2
## [103] conquer_1.0.2	cowplot_1.1.1
## [105] bitops_1.0-7	rtracklayer_1.50.0
## [107] httpuv_1.6.0	R6_2.5.0
## [109] promises_1.2.0.1	MASS_7.3-53
## [111] assertthat_0.2.1	openssl_1.4.3
## [113] rjson_0.2.20	withr_2.4.2
## [115] GenomicAlignments_1.26.0	Rsamtools_2.6.0
## [117] mnormt_2.0.2	GenomeInfoDbData_1.2.4
## [119] hms_1.0.0	grid_4.0.3
## [121] rvcheck_0.1.8	rmarkdown_2.5
## [123] Cairo_1.5-12.2	logging_0.10-108
## [125] shiny_1.6.0	lubridate_1.7.10