Pertusis challenge 3.2

Slim Fourati

2024-01-12

```
suppressPackageStartupMessages(library(package = "knitr"))
suppressPackageStartupMessages(library(package = "glmnet"))
suppressPackageStartupMessages(library(package = "edgeR"))
suppressPackageStartupMessages(library(package = "biomaRt"))
suppressPackageStartupMessages(library(package = "GSVA"))
suppressPackageStartupMessages(library(package = "agua"))
suppressPackageStartupMessages(library(package = "tidyverse"))
workDir <- "/Users/iew5629/Desktop/Projects/20231013_Pertussis/Workspace"
options(readr.show_col_types = FALSE)
agua::h2o_start()
# 2020
pts2020DF <- read_tsv(file</pre>
                                      = file.path(workDir, "documents/2020LD_subject.tsv"))
sample2020DF <- read_tsv(file</pre>
                                         = file.path(workDir, "documents/2020LD_specimen.tsv"))
fcm2020DF <- read_tsv(file = file.path(workDir, "documents/2020LD_pbmc_cell_frequency.tsv"))</pre>
ab2020DF <- read_tsv(file = file.path(workDir, "documents/2020LD_plasma_ab_titer.tsv"))
olink2020DF <- read_tsv(file = file.path(workDir, "documents/2020LD_plasma_cytokine_concentration.tsv")</pre>
ge2020DF <- read_tsv(file = file.path(workDir, "documents/2020LD_pbmc_gene_expression.tsv"))</pre>
# 2021
pts2021DF <- read_tsv(file = file.path(workDir, "documents/2021LD_subject.tsv"))</pre>
sample2021DF <- read_tsv(file = file.path(workDir, "documents/2021LD_specimen.tsv"))</pre>
fcm2021DF <- read_tsv(file = file.path(workDir, "documents/2021LD_pbmc_cell_frequency.tsv"))</pre>
ab2021DF <- read_tsv(file = file.path(workDir, "documents/2021LD_plasma_ab_titer.tsv"))
olink2021DF <- read_tsv(file = file.path(workDir, "documents/2021LD_plasma_cytokine_concentration.tsv")
ge2021DF <- read_tsv(file = file.path(workDir, "documents/2021LD_pbmc_gene_expression.tsv"))</pre>
# 2022
pts2022DF <- read_tsv(file = file.path(workDir, "documents/2022BD_subject.tsv"))</pre>
sample2022DF <- read_tsv(file = file.path(workDir, "documents/2022BD_specimen.tsv"))</pre>
ge2022DF <- read_tsv(file = file.path(workDir, "documents/2022BD_pbmc_gene_expression.tsv"))</pre>
```

Challenge3.2

```
yDF <- ge2020DF %>%
filter(versioned_ensembl_gene_id %in% "ENSG00000277632.1") %>%
merge(y = sample2020DF, by = "specimen_id", all.x = TRUE) %>%
merge(y = pts2020DF, by = "subject_id", all.x = TRUE) %>%
filter(planned_day_relative_to_boost %in% c(0, 3)) %>%
select(subject_id, planned_day_relative_to_boost, tpm) %>%
pivot_wider(names_from = planned_day_relative_to_boost, values_from = tpm, names_prefix = "tpm_") %>%
```

pts info

```
xDF <- pts2020DF %>%
  dplyr::select(-dataset) %>%
  column_to_rownames(var = "subject_id") %>%
  mutate_if(is.character, as.factor) %>%
  mutate_if(is.Date, as.factor) %>%
  slice(match(yDF$subject_id, table = rownames(.)))
xDF <- sapply(xDF, as.numeric) %>%
  scale() %>%
  as.matrix()
fit <- cv.glmnet(x = xDF,</pre>
                 y = yDF$tpm_FC,
                 nfolds = nrow(xDF),
                 grouped = FALSE)
plot(fit)
coef(fit, s = fit$lambda.min) %>%
  as.matrix() %>%
  as.data.frame() %>%
 rownames_to_column() %>%
  filter(s1 != 0) %>%
  kable()
x2DF <- pts2021DF %>%
  dplyr::select(-dataset) %>%
  column_to_rownames(var = "subject_id") %>%
  mutate_if(is.character, as.factor) %>%
  mutate_if(is.Date, as.factor) %>%
  slice(match(y2DF$subject_id, table = rownames(.)))
x2DF <- sapply(x2DF, as.numeric) %>%
  scale() %>%
  as.matrix()
yhat <- predict(fit, newx = as.matrix(x2DF), s = fit$lambda.min, type = "response")</pre>
plot(rank(-1 * yhat), rank(-1 * y2DF$tpm_FC))
cor.test(rank(-1 * yhat), rank(-1 * y2DF$tpm_FC))
```

BL ab

```
xDF <- ab2020DF %>%
  merge(y = sample2020DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2020DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0 &
           grepl(pattern = "IgG", isotype)) %>%
  mutate(cname = paste0(isotype, "_", antigen),
         cname = make.names(cname)) %>%
  dplyr::select(subject_id, cname, MFI_normalised) %>%
  distinct() %>%
  pivot_wider(names_from = cname, values_from = MFI_normalised) %>%
  column to rownames(var = "subject id") %>%
  slice(match(yDF$subject_id, table = rownames(.)))
x2DF <- ab2021DF %>%
  merge(y = sample2021DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2021DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
  mutate(cname = paste0(isotype, "_", antigen),
         cname = make.names(cname)) %>%
  dplyr::select(subject_id, cname, MFI_normalised) %>%
  distinct() %>%
  pivot_wider(names_from = cname, values_from = MFI_normalised) %>%
  column_to_rownames(var = "subject_id") %>%
  slice(match(y2DF$subject_id, table = rownames(.)))
xDF <- xDF[, intersect(colnames(xDF), colnames(x2DF))]</pre>
x2DF <- x2DF[, colnames(xDF)]</pre>
xDF <- scale(xDF)</pre>
x2DF <- scale(x2DF)</pre>
fit <- cv.glmnet(x = as.matrix(xDF),</pre>
                 y = yDF$tpm_FC,
                 nfolds = nrow(xDF),
                 grouped = FALSE)
plot(fit)
```

FCM

```
xDF <- fcm2020DF %>%
  mutate(cell_type_name = make.names(cell_type_name)) %>%
  merge(y = sample2020DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2020DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
  dplyr::select(subject_id, cell_type_name, percent_live_cell) %>%
  pivot_wider(names_from = cell_type_name, values_from = percent_live_cell) %>%
  column_to_rownames(var = "subject_id") %>%
  slice(match(yDF$subject_id, table = rownames(.)))
xDF[is.na(xDF)] <- 0</pre>
```

```
merge(y = sample2021DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2021DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
  dplyr::select(subject_id, cell_type_name, percent_live_cell) %>%
  pivot_wider(names_from = cell_type_name, values_from = percent_live_cell) %>%
  column_to_rownames(var = "subject_id") %>%
  slice(match(y2DF$subject_id, table = rownames(.))) %>%
  setNames(nm = make.names(names(.))) %>%
  setNames(nm = make.unique(names(.)))
x2DF[is.na(x2DF)] <- 0</pre>
xDF <- xDF[, intersect(colnames(xDF), colnames(x2DF))]</pre>
x2DF <- x2DF[, colnames(xDF)]</pre>
xDF <- scale(xDF)</pre>
x2DF <- scale(x2DF)</pre>
fit <- cv.glmnet(x = as.matrix(xDF),</pre>
                 y = yDF$tpm_FC[match(rownames(xDF), table = yDF$subject_id)],
                 nfolds = nrow(xDF),
                 grouped = FALSE)
plot(fit)
coef(fit, s = fit$lambda.min) %>%
 as.matrix() %>%
  as.data.frame() %>%
 rownames to column() %>%
 filter(s1 != 0) %>%
 kable()
yhat <- predict(fit, newx = as.matrix(x2DF), s = fit$lambda.min, type = "response")</pre>
plot(yhat[, "s1"], y2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_id)])
cor.test(yhat[, "s1"], y2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_id)])
plot(rank(-1 * yhat[, "s1"]), rank(-1 * y2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_id)]))
cor.test(rank(-1 * yhat[, "s1"]), rank(-1 * y2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_id)]
```

Olink

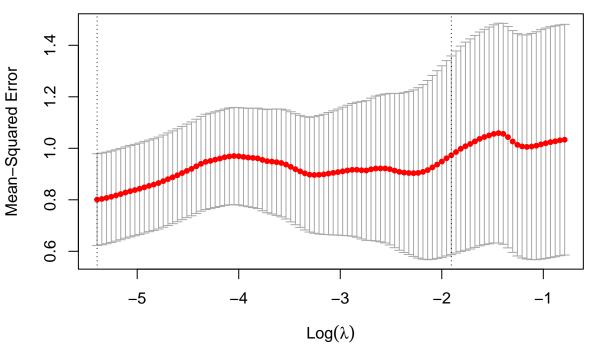
```
xDF <- olink2020DF %>%
  merge(y = sample2020DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2020DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
  dplyr::select(subject_id, protein_id, protein_expression) %>%
  pivot_wider(names_from = protein_id, values_from = protein_expression) %>%
  column_to_rownames(var = "subject_id") %>%
  slice(match(yDF$subject_id, table = rownames(.)))

x2DF <- olink2021DF %>%
  merge(y = sample2021DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2021DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
  dplyr::select(subject_id, protein_id, protein_expression) %>%
```

GE

```
# extract dO GE
dORawMat <- ge2020DF %>%
  merge(y = sample2020DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2020DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
 mutate(ensembl_gene_id = gsub(pattern = "\\.[0-9]+$", replacement = "", versioned_ensembl_gene_id)) %
  dplyr::select(subject_id, ensembl_gene_id, raw_count) %>%
  pivot_wider(names_from = subject_id, values_from = raw_count) %>%
  column_to_rownames(var = "ensembl_gene_id")
# TMM normalization
dge <- DGEList(counts = dORawMat,</pre>
              remove.zeros = TRUE)
## Removing 17632 rows with all zero counts
dge <- calcNormFactors(object = dge, method = "TMM")</pre>
normalizedCounts <- cpm(dge, normalized.lib.sizes = TRUE, log = TRUE)
# convert ensembl_qene_id to qene_symbol
human <- useMart("ensembl", dataset = "hsapiens_gene_ensembl")</pre>
id2symbol <- getBM(attributes = c("ensembl_gene_id", "hgnc_symbol"),</pre>
                   filters = "ensembl_gene_id",
                             = rownames(normalizedCounts),
                   values
                               = human)
                   mart.
geneDOMat <- normalizedCounts %>%
  as.data.frame() %>%
  rownames_to_column(var = "ensembl_gene_id") %>%
 merge(y = id2symbol, by = "ensembl_gene_id") %>%
  select(-ensembl_gene_id) %>%
  slice(order(apply(select(., -hgnc_symbol), MARGIN = 1, FUN = var), decreasing = TRUE)) %>%
  filter(!duplicated(hgnc_symbol) & hgnc_symbol != "") %>%
  column_to_rownames(var = "hgnc_symbol") %>%
```

```
as.matrix()
# GSVA with BTM
load(file = "/Users/iew5629/Desktop/Projects/20231013_Pertussis/Workspace/documents/GeneSets.rda")
BTM.geneSets <- BTM.geneSets[!grepl(pattern = "TBA", names(BTM.geneSets))]
names(BTM.geneSets) <- make.names(names(BTM.geneSets))</pre>
flag <- BTM.geneSets %>%
  stack() %>%
  filter(values %in% rownames(geneDOMat)) %>%
  group_by(ind) %>%
  summarize(n = n()) %>%
  arrange(desc(n)) %>%
  filter(n >= 15)
gsDOMat <- gsva(expr = geneDOMat, gset.idx.list = BTM.geneSets[flag$ind], verbose = FALSE)
## Warning: Calling gsva(expr=., gset.idx.list=., method=., ...) is deprecated;
## use a method-specific parameter object (see '?gsva').
# prediction
xDF <- t(gsDOMat)</pre>
xDF <- xDF[intersect(yDF$subject_id, rownames(xDF)), ]</pre>
fit <- cv.glmnet(x = as.matrix(xDF),</pre>
                 y = yDF$tpm_FC[match(rownames(xDF), table = yDF$subject_id)],
                 nfolds = nrow(xDF),
                 grouped = FALSE)
plot(fit)
                          29 28 29 22 21
                                                  18 16
                                                           14
            33
                33 31
                                                                 10
                                                                      9 2
                                                                            1 0
     4
```

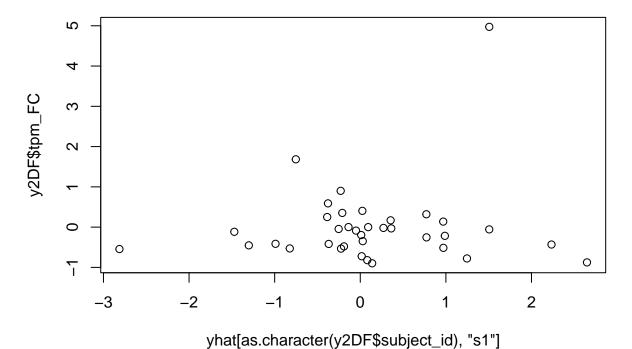


```
as.data.frame() %>%
rownames_to_column() %>%
filter(s1 != 0) %>%
kable()
```

rowname	s1
(Intercept)	0.0779051
regulation.of.antigen.presentation.and.immune.responseM5.0.	-1.3207204
DC.surface.signatureS5.	2.1841579
leukocyte.migrationM88.0.	3.2259302
extracellular.matrixIIM2.1.	-0.1290229
ActivatedLPSdendritic.cell.surface.signatureS11.	-1.4536757
collagenTGFB.family.et.alM77.	0.8294259
Memory.B.cell.surface.signatureS9.	-2.1451839
extracellular.matrixcollagenM210.	-1.5811316
plasma.cellsB.cellsimmunoglobulinsM156.0.	0.1833736
E2F1.targetsQ3M10.0.	-0.3990246
extracellular.matrixIM2.0.	1.6860579
T.cell.activationII $M7.3$.	-0.2143592
mitotic.cell.divisionM6.	0.9791532
mismatch.repairIM22.0.	0.0245695
amino.acid.metabolishm.and.transportM154.0.	0.1956264
plasma.cellsimmunoglobulinsM156.1.	0.2581210
Plasma.cell.surface.signatureS3.	2.3222467
mitotic.cell.cycleM4.7.	-0.7667907
E2F1.targetsQ4M10.1.	-0.7004611
DNA.repairM76.	0.0911635
$cell.movement Adhesion.\dots Platelet.activation M30.$	0.0751056
enriched.in.membrane.proteinsM124.	-0.4041152
chemokines.and.inflammatory.molecules.in.myeloid.cellsM86.0.	1.0183543
plasma.membranecell.junctionM162.0.	-0.9430751
transmembrane.transportIIM191.	0.1597762
$complement.activationI.\dots M112.0.$	0.1242818
T.cell.differentiation Th $2M19$.	0.2585772
KLF12.targets.networkM32.3.	-0.1389076
enriched.in.NK.cellsIIM61.0.	0.1178695
leukocyte.differentiationM160.	-1.3409812
platelet.activationactin.bindingM196.	-0.4106829
extracellular.region.clusterGOM189.	-0.7031621
mitochondrial.clusterM235.	0.0631323

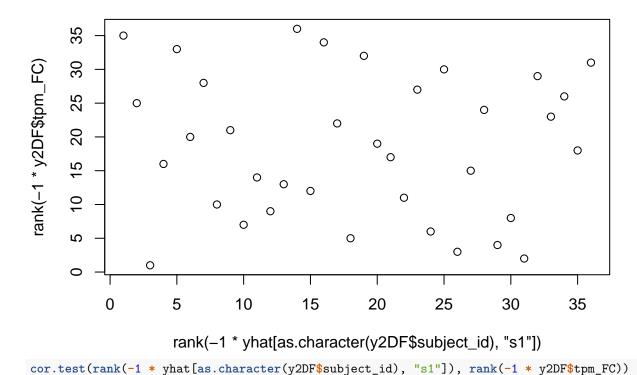
```
# extract d0 GE of 2021
d0RawMat <- ge2021DF %>%
  merge(y = sample2021DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2021DF, by = "subject_id", all.x = TRUE) %>%
  filter(planned_day_relative_to_boost %in% 0) %>%
  mutate(ensembl_gene_id = gsub(pattern = "\\.[0-9]+$", replacement = "", versioned_ensembl_gene_id)) %
  dplyr::select(subject_id, ensembl_gene_id, raw_count) %>%
  pivot_wider(names_from = subject_id, values_from = raw_count) %>%
  column_to_rownames(var = "ensembl_gene_id")
# TMM normalization
```

```
dge <- DGEList(counts = dORawMat,</pre>
               remove.zeros = TRUE)
## Removing 18536 rows with all zero counts
dge <- calcNormFactors(object = dge, method = "TMM")</pre>
normalizedCounts <- cpm(dge, normalized.lib.sizes = TRUE, log = TRUE)
# convert ensembl_qene_id to qene_symbol
id2symbol <- getBM(attributes = c("ensembl_gene_id", "hgnc_symbol"),</pre>
                   filters = "ensembl_gene_id",
                             = rownames(normalizedCounts),
                   values
                             = human)
                   mart
geneDOMat <- normalizedCounts %>%
 as.data.frame() %>%
 rownames_to_column(var = "ensembl_gene_id") %>%
 merge(y = id2symbol, by = "ensembl_gene_id") %>%
  select(-ensembl_gene_id) %>%
  slice(order(apply(select(., -hgnc_symbol), MARGIN = 1, FUN = var), decreasing = TRUE)) %>%
  filter(!duplicated(hgnc_symbol) & hgnc_symbol != "") %>%
  column_to_rownames(var = "hgnc_symbol") %>%
  as.matrix()
# GSVA with BTM
gsDOMat <- gsva(expr = geneDOMat, gset.idx.list = BTM.geneSets[flag$ind], verbose = FALSE)
## Warning: Calling gsva(expr=., gset.idx.list=., method=., ...) is deprecated;
## use a method-specific parameter object (see '?gsva').
# prediction
x2DF <- t(gsD0Mat)</pre>
yhat <- predict(fit, newx = as.matrix(x2DF), s = fit$lambda.min, type = "response")</pre>
plot(yhat[as.character(y2DF$subject_id), "s1"], y2DF$tpm_FC)
```

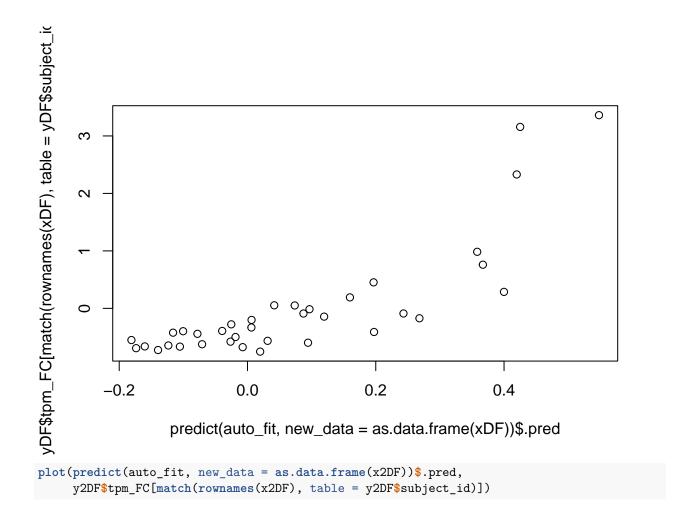


cor.test(yhat[as.character(y2DF\$subject_id), "s1"], y2DF\$tpm_FC)

```
##
## Pearson's product-moment correlation
##
## data: yhat[as.character(y2DF$subject_id), "s1"] and y2DF$tpm_FC
## t = 0.67419, df = 34, p-value = 0.5047
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.2220577 0.4272701
## sample estimates:
## cor
## 0.1148573
plot(rank(-1 * yhat[as.character(y2DF$subject_id), "s1"]), rank(-1 * y2DF$tpm_FC))
```



```
##
##
   Pearson's product-moment correlation
##
## data: rank(-1 * yhat[as.character(y2DF$subject_id), "s1"]) and rank(-1 * y2DF$tpm_FC)
## t = -0.35185, df = 34, p-value = 0.7271
\#\# alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
   -0.3812236 0.2737205
## sample estimates:
##
           cor
## -0.06023166
set.seed(seed= 3)
trainDF <- xDF %>%
  as.data.frame() %>%
  mutate(tpm_FC = yDF$tpm_FC[match(rownames(xDF), table = yDF$subject_id)])
auto_fit <- auto_ml() %>%
     set_engine("h2o", max_runtime_secs = 5) %>%
     set_mode("regression") %>%
     fit(tpm_FC ~ ., data = trainDF)
plot(predict(auto_fit, new_data = as.data.frame(xDF))$.pred,
     yDF$tpm_FC[match(rownames(xDF), table = yDF$subject_id)])
```



```
2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_
      2
                                                                        0
      4
      \mathfrak{C}
      ^{\circ}
                                               0
                                 0
      0
                                                                           ത
                        0
                                   0 0
                                                                                      0
                          0
                                    00
                             0
                                                                          0
             0
                                            00
                    0
                            0
                                                         0
      7
                        -0.2
                                         0.0
                                                         0.2
                                                                          0.4
                    predict(auto_fit, new_data = as.data.frame(x2DF))$.pred
cor.test(predict(auto_fit, new_data = as.data.frame(x2DF))$.pred,
     y2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_id)])
##
##
    Pearson's product-moment correlation
##
## data: predict(auto_fit, new_data = as.data.frame(x2DF))$.pred and y2DF$tpm_FC[match(rownames(x2DF),
## t = 1.8097, df = 34, p-value = 0.07919
\#\# alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
    -0.03558416 0.56949335
## sample estimates:
##
         cor
## 0.2964169
cor.test(rank(-1 * predict(auto_fit, new_data = as.data.frame(x2DF))$.pred),
     rank(-1 * y2DF$tpm_FC[match(rownames(x2DF), table = y2DF$subject_id)]))
##
##
    Pearson's product-moment correlation
##
## data: rank(-1 * predict(auto_fit, new_data = as.data.frame(x2DF))$.pred) and rank(-1 * y2DF$tpm_FC[
## t = 2.4617, df = 34, p-value = 0.01906
\#\# alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.0692439 0.6361780
## sample estimates:
```

```
## cor
## 0.3889318
```

2022 test set

```
set.seed(seed= 3)
# train on 2020 and 2021 baseline ab only
dORawMat <- ge2022DF %>%
  merge(y = sample2022DF, by = "specimen_id", all.x = TRUE) %>%
  merge(y = pts2022DF, by = "subject_id", all.x = TRUE) %>%
 filter(planned_day_relative_to_boost %in% 0) %>%
  mutate(ensembl_gene_id = gsub(pattern = "\\.[0-9]+$", replacement = "", versioned_ensembl_gene_id)) %
  dplyr::select(subject_id, ensembl_gene_id, raw_count) %>%
  pivot wider(names from = subject id, values from = raw count) %>%
  column_to_rownames(var = "ensembl_gene_id")
# TMM normalization
dge <- DGEList(counts</pre>
                            = dORawMat,
               remove.zeros = TRUE)
## Removing 22646 rows with all zero counts
dge <- calcNormFactors(object = dge, method = "TMM")</pre>
normalizedCounts <- cpm(dge, normalized.lib.sizes = TRUE, log = TRUE)
# convert ensembl_gene_id to gene_symbol
id2symbol <- getBM(attributes = c("ensembl_gene_id", "hgnc_symbol"),</pre>
                   filters = "ensembl_gene_id",
                              = rownames(normalizedCounts),
                   mart
                               = human)
geneDOMat <- normalizedCounts %>%
  as.data.frame() %>%
 rownames_to_column(var = "ensembl_gene_id") %>%
  merge(y = id2symbol, by = "ensembl_gene_id") %>%
  select(-ensembl_gene_id) %>%
  slice(order(apply(select(., -hgnc_symbol), MARGIN = 1, FUN = var), decreasing = TRUE)) %>%
  filter(!duplicated(hgnc_symbol) & hgnc_symbol != "") %>%
  column_to_rownames(var = "hgnc_symbol") %>%
  as.matrix()
# GSVA with BTM
gsDOMat <- gsva(expr = geneDOMat, gset.idx.list = BTM.geneSets[flag$ind], verbose = FALSE)</pre>
## Warning: Calling gsva(expr=., gset.idx.list=., method=., ...) is deprecated;
## use a method-specific parameter object (see '?gsva').
# prediction
x3DF <- t(gsD0Mat)</pre>
xDF <- xDF[, intersect(colnames(xDF), colnames(x2DF))]</pre>
x2DF <- x2DF[, colnames(xDF)]</pre>
x3DF <- x3DF[, colnames(xDF)]</pre>
trainDF <- rbind(xDF, x2DF) %>%
```

```
as.data.frame() %>%
  mutate(tpm_FC = c(yDF$tpm_FC, y2DF$tpm_FC))
auto_fit <- auto_ml() %>%
     set_engine("h2o", max_runtime_secs = 5) %>%
     set_mode("regression") %>%
     fit(tpm_FC ~ ., data = trainDF)
yhat <- predict(auto_fit, new_data = x3DF)$.pred</pre>
rhat <- rank(-1 * yhat)</pre>
print(cbind(rownames(x3DF), rhat))
               rhat
    [1,] "97"
               "9"
##
  [2,] "98"
               "13"
##
  [3,] "99" "3"
## [4,] "100" "16"
## [5,] "101" "11"
## [6,] "102" "17"
## [7,] "103" "21"
## [8,] "104" "2"
## [9,] "105" "18"
## [10,] "106" "19"
## [11,] "107" "6"
## [12,] "108" "15"
## [13,] "109" "12"
## [14,] "110" "5"
## [15,] "111" "7"
## [16,] "112" "8"
## [17,] "114" "1"
## [18,] "115" "10"
## [19,] "116" "14"
## [20,] "117" "20"
## [21,] "118" "4"
agua::h2o_end()
sessionInfo()
## R version 4.3.2 (2023-10-31)
## Platform: aarch64-apple-darwin23.0.0 (64-bit)
## Running under: macOS Sonoma 14.2.1
## Matrix products: default
         /opt/homebrew/Cellar/openblas/0.3.25/lib/libopenblasp-r0.3.25.dylib
## LAPACK: /opt/homebrew/Cellar/r/4.3.2/lib/R/lib/libRlapack.dylib; LAPACK version 3.11.0
##
## locale:
## [1] en US.UTF-8/en US.UTF-8/en US.UTF-8/C/en US.UTF-8/en US.UTF-8
## time zone: America/Chicago
## tzcode source: internal
## attached base packages:
## [1] stats
                graphics grDevices utils
                                               datasets methods
                                                                    base
```

```
##
## other attached packages:
   [1] lubridate 1.9.3 forcats 1.0.0
                                        stringr_1.5.1
                                                        dplyr 1.1.4
  [5] purrr_1.0.2
                        readr_2.1.5
                                                        tibble_3.2.1
##
                                        tidyr_1.3.0
                                                        parsnip_1.1.1
##
   [9] ggplot2_3.4.4
                        tidyverse_2.0.0 agua_0.1.3
                                                        limma 3.58.1
## [13] GSVA 1.50.0
                        biomaRt 2.58.0
                                        edgeR 4.0.6
                        Matrix 1.6-5
## [17] glmnet 4.1-8
                                        knitr 1.45
##
## loaded via a namespace (and not attached):
##
     [1] jsonlite_1.8.8
                                     rstudioapi_0.15.0
##
     [3] shape_1.4.6
                                     magrittr_2.0.3
##
                                     zlibbioc_1.48.0
     [5] rmarkdown_2.25
##
     [7] vctrs_0.6.5
                                     memoise_2.0.1
##
     [9] DelayedMatrixStats_1.24.0
                                     RCurl_1.98-1.14
##
  [11] htmltools_0.5.7
                                     S4Arrays_1.2.0
##
   [13] dials_1.2.0
                                     progress_1.2.3
##
  [15] curl_5.2.0
                                     Rhdf5lib_1.24.1
  [17] SparseArray_1.2.3
                                     rhdf5_2.46.1
  [19] parallelly_1.36.0
                                     cachem_1.0.8
   [21] lifecycle_1.0.4
                                     iterators 1.0.14
## [23] pkgconfig_2.0.3
                                     rsvd_1.0.5
## [25] R6_2.5.1
                                     fastmap_1.1.1
## [27] future_1.33.1
                                     GenomeInfoDbData_1.2.11
## [29] MatrixGenerics 1.14.0
                                     tune 1.1.2
## [31] digest_0.6.34
                                     colorspace 2.1-0
## [33] furrr_0.3.1
                                     AnnotationDbi_1.64.1
## [35] S4Vectors_0.40.2
                                     irlba_2.3.5.1
## [37] GenomicRanges_1.54.1
                                     RSQLite_2.3.4
## [39] beachmat_2.18.0
                                     filelock_1.0.3
                                     timechange_0.2.0
## [41] yardstick_1.2.0
## [43] fansi_1.0.6
                                     httr_1.4.7
## [45] abind_1.4-5
                                     compiler_4.3.2
  [47] bit64_4.0.5
                                     withr_2.5.2
  [49] BiocParallel_1.36.0
                                     DBI_1.2.1
##
   [51] highr_0.10
                                     HDF5Array_1.30.0
## [53] lava_1.7.3
                                     MASS_7.3-60
## [55] rappdirs_0.3.3
                                     DelayedArray 0.28.0
## [57] tools_4.3.2
                                     future.apply_1.11.1
##
   [59] nnet_7.3-19
                                     glue_1.7.0
## [61] h2o_3.44.0.3
                                     rhdf5filters_1.14.1
## [63] grid_4.3.2
                                     generics 0.1.3
## [65] recipes_1.0.9
                                     gtable_0.3.4
##
   [67] tzdb 0.4.0
                                     class_7.3-22
##
                                     data.table_1.14.10
  [69] rsample_1.2.0
  [71] hms_1.1.3
                                     BiocSingular_1.18.0
##
                                     xm12_1.3.6
  [73] ScaledMatrix_1.10.0
##
   [75] utf8_1.2.4
                                     XVector_0.42.0
##
  [77] BiocGenerics_0.48.1
                                     foreach_1.5.2
  [79] pillar_1.9.0
                                     vroom_1.6.5
## [81] splines_4.3.2
                                     lhs_1.1.6
## [83] BiocFileCache_2.10.1
                                     lattice_0.22-5
## [85] survival 3.5-7
                                     bit_4.0.5
## [87] annotate_1.80.0
                                     tidyselect_1.2.0
## [89] SingleCellExperiment_1.24.0 locfit_1.5-9.8
```

```
## [91] Biostrings_2.70.1
                                     IRanges_2.36.0
## [93] SummarizedExperiment_1.32.0 stats4_4.3.2
## [95] xfun_0.41
                                     Biobase_2.62.0
## [97] statmod_1.5.0
                                     hardhat_1.3.0
## [99] timeDate_4032.109
                                     matrixStats_1.2.0
## [101] stringi_1.8.3
                                     DiceDesign_1.10
## [103] yaml 2.3.8
                                     workflows 1.1.3
## [105] evaluate_0.23
                                     codetools_0.2-19
## [107] graph_1.80.0
                                     cli_3.6.2
## [109] rpart_4.1.23
                                     xtable_1.8-4
## [111] munsell_0.5.0
                                     Rcpp_1.0.12
## [113] GenomeInfoDb_1.38.5
                                     globals_0.16.2
## [115] dbplyr_2.4.0
                                     png_0.1-8
## [117] XML_3.99-0.16
                                     parallel_4.3.2
## [119] gower_1.0.1
                                     blob_1.2.4
## [121] prettyunits_1.2.0
                                     sparseMatrixStats_1.14.0
## [123] bitops_1.0-7
                                     listenv_0.9.0
## [125] GPfit_1.0-8
                                     GSEABase 1.64.0
## [127] ipred_0.9-14
                                     prodlim_2023.08.28
## [129] scales_1.3.0
                                     crayon 1.5.2
                                     KEGGREST_1.42.0
## [131] rlang_1.1.3
```