Analysis notebook for A Quantitative Systems Pharmacology (QSP) Approach to Repurposing Drugs for Non-Alcoholic Fatty Liver Disease (NAFLD)

Introduction

This code is the analysis portion of the paper. Intermediate data files are stored throughout the notebook as commented out RDS files. These are typically saved when creating the intermediate data is both/or time consuming or used at branch points within the analysis. Some of the code chunks rely on functions from my personal packages which are not on CRAN or BioConductor installed from github.

Installing my packages

```
require(devtools)

# My package(s)
my_pkgs <- c("lefutils", "basicOmics")

if(any(my_pkgs %in% row.names(installed.packages()))){
   devtools::install_github(pasteO("lefeverde/", my_pkgs))
}</pre>
```

Pre-processing pipeline

Creating gene metadata

```
require(tidyverse)
require(biomaRt)
gene_dir <- 'data-raw/DiStefano_raw_data/kallisto/'

# Getting ENS ids from 1st tsv
ens_trans <-
    paste0(gene_dir,list.files(gene_dir)[[1]]) %>%
    read_delim(., "\t") %>%
    pull(target_id) %>%
    str_split(., "\\.") %>%
    map(1) %>%
    unlist

attributes <- c("ensembl_gene_id", "ensembl_transcript_id")</pre>
```

Identifying mis-labeled samples

```
library(matrixStats)
library(edgeR)
library(reshape2)
library(ggplot2)
sex_linked_genes <- c('ENSG00000131002', 'ENSG00000183878', 'ENSG00000067048')</pre>
txi_n192 <- readRDS('DiStefano_txi_and_p_192.rds')</pre>
p192 <- txi_n192[[1]]
txi_n192 <- txi_n192[[2]]</pre>
cnts <- txi_n192$counts</pre>
cnts_per_million <- cnts[rowMedians(cnts) > 1,] %>%
  data.frame(.) %>%
  cpm(., log = FALSE)
plot_data <-
  data.frame(cnts_per_million[sex_linked_genes[1],],
             sex=p192$sex,
             sample_id=p192$dcl_patient_id) %>%
  melt(.) %>%
  dplyr::select( -one_of('variable')) %>%
  arrange(., value)
```

Sex is incorrect for some samples

Since this gene is Y-linked, I expect the males to have much higher expression than the females. I think the non-zero expression in the females can be attributed to multi-mapping reads. Kallisto does mapping a little differently, and so these are not discarded by default like with STAR and HISAT2.

```
female_cutoff <- plot_data %>%
  dplyr::filter(., sex =='Female') %>%
  arrange(., value) %>%
  pull() %>%
  quantile(., probs = .95)

male_cutoff <- plot_data %>%
```

```
dplyr::filter(., sex =='Male') %>%
  arrange(., value) %>%
  pull() %>%
  quantile(., probs = .05)

suspicious_samples <- list(
  dplyr::filter(plot_data[plot_data$sex == 'Male',], value < male_cutoff),
  dplyr::filter(plot_data[plot_data$sex == 'Female',], value > female_cutoff)
) %>%
  lapply(., function(x){
    x$sample_id
}) %>%
  do.call(c, .)
```

Creating new subsetted txi

```
suspicious_samples <-
    c("DLDR_0189","DLDR_0031","DLDR_0022","DLDR_0017","DLDR_0131", "DLDR_0130","DLDR_0140","DLDR_0122","DLDR_0130","DLDR_0140","DLDR_0122","DLDR_0130","DLDR_0140","DLDR_0122","DLDR_0130","DLDR_0140","DLDR_0122","DLDR_0130","DLDR_0140","DLDR_0122","DLDR_0130","DLDR_0140","DLDR_0122","DLDR_0130","DLDR_0140","DLDR_0130","DLDR_0140","DLDR_0130","DLDR_0140","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_0130","DLDR_01
```

DEG analysis

Required packages and setup

```
require(lefutils)
require(basicOmics)
require(edgeR)
require(limma)
require(sva)
```

LIMMA-VOOM w/quantile normalization and SVA

Disease group

```
load('data-raw/gene_annots.RData')
txi_list <- readRDS('DiStefano_txi_and_p_182.rds')</pre>
```

```
p <- txi_list[[1]]</pre>
txi <- txi_list[[2]]</pre>
group_cont <- c('STEATOSIS-NORMAL', 'Lob-NORMAL', 'Lob-STEATOSIS', 'Fibrosis-NORMAL', 'Fibrosis-STEATO
mod <- basicOmics::better_model_matrix(~0 + group, data=p)</pre>
mod0 <- model.matrix(~1, data=p )</pre>
dge <- edgeR::DGEList(counts = txi$counts,</pre>
                        samples = p,
                        genes = gene_annots[row.names(txi$counts),])
dge <- dge[edgeR::filterByExpr(dge, group = dge$samples$diagnosis),]</pre>
dge <- dge[(rowSums(dge$counts > 1) >= .75*dim(dge)[2]),]
dge <- dge[!is.na(dge$genes$entrezgene),]</pre>
v <- voom(dge, mod, normalize.method = 'quantile')</pre>
svobj <- sva(v$E, mod=mod, mod0=mod0)</pre>
# saveRDS(list(v, svobj), 'DiStefano_group_n182_voom_qn_and_svobj.rds')
modSV <- cbind(mod, svobj$sv)</pre>
fit <- make_cont_fit(v, group_cont, modSV)</pre>
# saveRDS(fit, 'DiStefano_group_n182_qn_sva_fit.rds')
res <- get_limma_results(fit, group_cont)</pre>
# saveRDS(res, file = 'DiStefano_group_n182_qn_sva_res.rds')
res$coefficient <- gsub('-', '_vs_', res$coefficient)</pre>
sigsub <- res[res$adj.P.Val < .05,]</pre>
```

Disease stage

```
library(sva)
load('data-raw/gene_annots.RData')
txi_list <- readRDS('DiStefano_txi_and_p_182.rds')</pre>
p <- txi_list[[1]]</pre>
txi <- txi_list[[2]]</pre>
diagnosis_levels <- levels(p$diagnosis)</pre>
# Comparing diagnosis progression
group_cont <-</pre>
  paste0(diagnosis_levels[-1],
         diagnosis_levels[1:(length(diagnosis_levels)- 1)])
# Comparing everything to normal
group_cont <-
  c(group_cont,
    pasteO(diagnosis_levels[-1], '-', 'NORMAL'))
# Comparing fib to lob 1
group_cont <-
  c(group cont,
    paste0(diagnosis_levels[6:8], '-', "Lob_Inflam_1"))
# Comparing to fib to steatosis
group_cont <-
  c(group_cont,
```

```
pasteO(diagnosis_levels[6:8], '-', "STEATOSIS_2"),
    paste0(diagnosis_levels[6:8], '-', "STEATOSIS_3"))
mod <- basicOmics::better_model_matrix(~0 + diagnosis, data=p)</pre>
mod0 <- model.matrix(~1, data=p )</pre>
dge <- edgeR::DGEList(counts = txi$counts,</pre>
                       samples = p,
                       genes = gene_annots[row.names(txi$counts),])
dge <- dge[edgeR::filterByExpr(dge, group = dge$samples$diagnosis),]</pre>
dge <- dge[(rowSums(dge$counts > 1) >= .75*dim(dge)[2]),]
dge <- dge[!is.na(dge$genes$entrezgene),]</pre>
v <- voom(dge, mod, normalize.method = 'quantile')</pre>
svobj <- sva(v$E, mod=mod, mod0=mod0)</pre>
# saveRDS(list(v, svobj), 'DiStefano_diagnosis_n182_voom_qn_and_svobj.rds')
modSV <- cbind(mod, svobj$sv)</pre>
fit <- make_cont_fit(v, group_cont, modSV)</pre>
# saveRDS(fit, 'DiStefano_diagnosis_n182_qn_sva_fit.rds')
res <- get_limma_results(fit, unique(group_cont))</pre>
# saveRDS(res, file = 'DiStefano_diagnosis_n182_qn_sva_res.rds')
sigsub <- res[res$adj.P.Val < .05,]</pre>
```

GSEA pathway analysis

Required packages and setup

```
require(lefutils)
require(basicOmics)
require(clusterProfiler)
```

GSEA with genes ranked by moderated t-statistic

Disease group

```
n_perm <- 10000

gsea_list <- kegg_gsea_by_coef(read_rds('DiStefano_group_n182_qn_sva_res.rds'), nPerm = n_perm)
gsea_df <- lapply(gsea_list, data.frame) %>%
    rbind_named_df_list(., 'coefficient') %>%
    filter(p.adjust < .05)

fn <- paste0('group_kegg_gsea_nperm', n_perm, '_res.rds')
# saveRDS(gsea_df, fn)</pre>
```

Disease stage

```
n_perm <- 10000

gsea_list <- kegg_gsea_by_coef(read_rds('DiStefano_diagnosis_n182_qn_sva_res.rds'), nPerm = n_perm)
gsea_df <- lapply(gsea_list, data.frame) %>%
    rbind_named_df_list(., 'coefficient') %>%
    filter(p.adjust < .05)

fn <- paste0('diagnosis_kegg_gsea_nperm', n_perm, '_res.rds')
saveRDS(gsea_df, fn)</pre>
```

GSVA pathway cluster analysis

Loading KEGG metadata

```
## KEGG Hierchy
pth_data <-
  read rds('../reference files/msigdb v7.0/msigdb v7.0 all tibble.rds') %>%
  filter(SUB_CATEGORY_CODE == "CP:KEGG") %>%
  dplyr::select(STANDARD_NAME,EXACT_SOURCE) %>%
  setNames(., c('name','id'))
hier kegg <-
  read_rds('data-raw/kegg_pathway_hierarchy.rds') %>%
  left_join(pth_data, .) %>%
  arrange(category_level_1)
cp_kegg <-
  '../reference_files/msigdb_v7.0/c2_kegg_entrez_msigdb_v7.0.gmt' %>%
  read.gmt(.) %>%
  filter(ont %in% hier_kegg$name) %>%
  split(., .$ont) %>%
  lapply(., function(x){
    x$gene
  })
kegg_annots <-
  hier_kegg$category_level_1 %>% set_names(., hier_kegg$name)
```

Loading and pre-processing gene expression data

```
load('data-raw/gene_annots.RData')

v <- read_rds('DiStefano_diagnosis_n182_voom_qn_and_svobj.rds')[[1]]
svobj <- read_rds('DiStefano_diagnosis_n182_voom_qn_and_svobj.rds')[[2]]
p <- v$targets</pre>
```

```
e_rm <-
    removeBatchEffect(v, covariates = svobj$sv, design = v$design)
e_rm <-
    uniquefy_by_variance(e_rm, gene_annots, 'entrezgene')
row.names(e_rm) <- gene_annots[row.names(e_rm),]$entrezgene

v_e <- uniquefy_by_variance(v$E, gene_annots, 'entrezgene')
row.names(v_e) <- gene_annots[row.names(v_e),]$entrezgene</pre>
```

Clustering the GSVA data

```
gsva_res_sva <-
   gsva(e_rm, cp_kegg, method='gsva', min.sz=1, max.sz=100000, parallel.sz=3)

tmp_data <- gsva_res_sva[names(kegg_annots),row.names(p)]

# Scaling row wise

tmp_data <-
   t(scale(t(tmp_data)))

tmp_data <- as.data.frame(tmp_data, check.names=FALSE)

col_clust <-
   as.dist(1 - cor(tmp_data, method = 'pearson')) %>%
   hclust(., "ward.D2")
```

Creating new groups based on clustering

Apparently the default cutree will sort the clusters by number of items in each cluster. This is different than ComplexHeatmap. The dendextend version has an option to turn this "feature" off. To do this, set the confusingly named argument order_clusters_as_data to FALSE.

```
coefs_from_clusters <-</pre>
  dendextend::cutree(col_clust, 3, order_clusters_as_data=FALSE) %>%
  enframe %>%
  as.data.frame %>%
  setNames(., c('sample_id', "cluster_idx"))
coefs_from_clusters$cluster_idx <- paste0('c', coefs_from_clusters$cluster_idx)</pre>
coefs_from_clusters$cluster_idx <-</pre>
  factor(coefs_from_clusters$cluster_idx, levels = unique(coefs_from_clusters$cluster_idx))
row.names(coefs_from_clusters) <- coefs_from_clusters$sample_id</pre>
coefs_from_clusters$sample_id <- NULL</pre>
lvls <- levels(coefs_from_clusters$cluster_idx)</pre>
group_cont <-
  lapply(seq along(lvls), function(i){
    x <- lvls[i]
    y <-
      paste(lvls[-i], collapse = '+') %>%
```

```
# paste(lvls, collapse = '+') %>%
paste0("(", ., ")/", length(lvls[-i]))
# paste0("(", ., ")/", length(lvls))
paste0(x, '-', y)
}) %>% unlist
```

Creating gene signatures (GS)

DRP analysis

```
group_cont <- c("c2-c1", "c3-c1", "c3-c2")
mod <-
  better_model_matrix(~0 + cluster_idx, data = coefs_from_clusters)
cont_mod <-
  makeContrasts(contrasts = group_cont, levels=data.frame(mod, check.names = FALSE))
fit <-
  t(scale(t(gsva_res_sva))) %>%
  lmFit(., data.frame(mod)) # Row scaling
fit <- fit %>%
  contrasts.fit(., cont_mod) %>%
  eBayes
res <- get_limma_results(fit, group_cont)</pre>
names(res)[2] <- 'name'</pre>
res <-
  right_join(pth_data, res) %>%
  right_join(hier_kegg, .)
res <- cbind(coefficient=res$coefficient, res[,-7])</pre>
{\it\# saveRDS (res, 'lv\_on\_gsva\_msig\_kegg\_pathways\_from\_row\_scaled\_clusters.rds')}
```

DEG analysis

```
fit <-
   lmFit(v, data.frame(mod)) %>%
   contrasts.fit(., cont_mod) %>%
   eBayes

res <- get_limma_results(fit, group_cont)
# saveRDS(res, "gene_res_from_clusters.rds")</pre>
```

Creating GS

```
cols_to_keep <- c("coefficient", "external_gene_name", "entrezgene", "logFC", "adj.P.Val")
gene_res <- read_rds('gene_res_from_clusters.rds') %>%
```

```
dplyr::select(cols_to_keep) %>%
  distinct
gene_res$entrezgene <- as.character(gene_res$entrezgene)</pre>
sig_pth_res <- read_rds("lv_on_gsva_msig_kegg_pathways_from_row_scaled_clusters.rds") %>%
  filter(adj.P.Val < .05) %>%
  dplyr::select(one_of("coefficient","id","logFC", "adj.P.Val")) %>%
  distinct %>%
  right_join( hier_kegg, .)
sig_gene_res <- gene_res %>%
  filter(adj.P.Val < .05)</pre>
pth_gene_res <-
  inner_join(kegg_df, gene_res)
coefficient <- pth_gene_res$coefficient</pre>
pth_gene_res <- pth_gene_res[,-3]</pre>
pth_gene_res <- cbind(coefficient, pth_gene_res)</pre>
colnames(pth_gene_res)[5:6] <- paste0("gene_", colnames(pth_gene_res)[5:6])</pre>
degs_out_pth <- left_join(fens_pathways, pth_gene_res)</pre>
names(degs_out_pth)[1] <- "Clusters"</pre>
degs_out_pth <- degs_out_pth %>% filter(gene_adj.P.Val < .05)</pre>
# write_csv(degs_out_pth, "degs_from_selected_pathways_20200122.csv")
```