Pathway Analysis - Dendríticas cells Input data: DEGs

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1 Introducción y Objetivo

En este script realizo un pathways análisis con los DEGs obtenidos de los Venn Diagrams, y preparo el resultado en archivos gem para extraer un gráfico posteriormente en Cytoscape (https://cran.r-project.org/web/packages/gprofiler2/vignettes/gprofiler2.html).

2 Paquetes y datos

3 Datos

Cargo inicialmente los listados de células Dendríticas obtenidas en jVenn.

```
setwd("~/Desktop/ELENA_UOC/TFM")
jVenn_DendriticCells_vs_GSE22155_02 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/j
head(jVenn_DendriticCells_vs_GSE22155_02) # sección de los resultados</pre>
```

```
## # A tibble: 6 x 3
               GSE22155_02 `GSE50509|GSE22155_02`
##
     GSE50509
##
     <chr>>
               <chr>
                            <chr>>
## 1 LINCO1091 MYOZ3
                            Clorf52
## 2 CEMIP
               LEFTY1
                            ZMYM3
## 3 CCDC51
               FLNA
                            SYT13
## 4 NSMCE2
               PASD1
                            CDK4
## 5 PCGF2
               PKP4
                            HYAL3
## 6 C8orf76
                            TRIM65
               CARD9
```

```
jVenn_DendriticCells_vs_GSE22155_47 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/j
jVenn_DendriticCells_vs_GSE91061 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVen.
jVenn_DendriticCells_vs_GSE35640 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVen.
jVenn_DendriticCells_vs_GSE61992 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVen.
setwd("~/Desktop/ELENA_UOC/TFM/GOBPs") # Directorio de trabajo
jVenn_DendriticCells <- read_delim("~/Desktop/ELENA_UOC/TFM/DEGs/Venn_diagrams_cell_type_treatments_com.
delim = ",", escape_double = FALSE, trim_ws = TRUE)</pre>
```

4 Uncovered

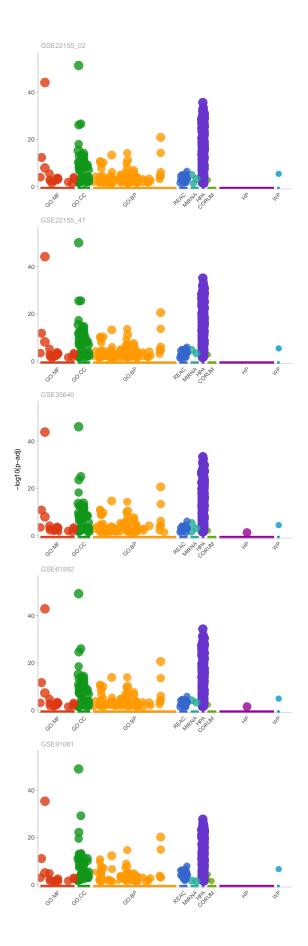
En esta sección contemplo la posibilidad que los DEGs únicos en el dataset sin tratar se traten de mecanismos que se escapan al tratamiento pero que igualmente se ven afectados por la enfermedad.

Primero realizo el pathway multianálisis:

En esta sección contemplo la posibilidad que los DEGs únicos en el dataset sin tratar se traten de mecanismos que se escapan al tratamiento pero que igualmente se ven afectados por la enfermedad.

Primero realizo el pathway multianálisis:

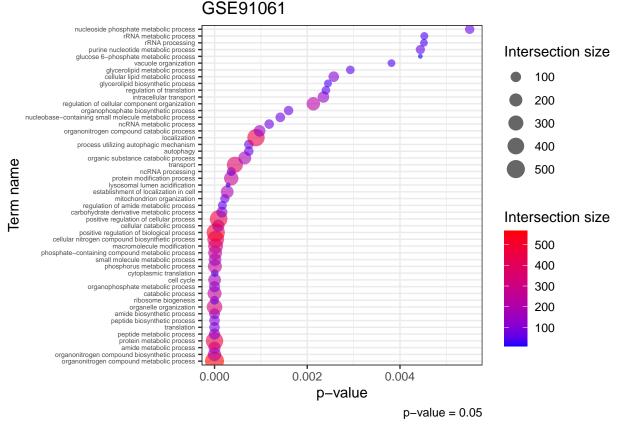
```
multi_gostres <- gost(query = list("GSE22155_02" = unique(jVenn_DendriticCells_vs_GSE22155_02$GSE50509[
                              "GSE22155_47" = jVenn_DendriticCells_vs_GSE22155_47$GSE50509[which(is.na(j
                              "GSE35640" = jVenn_DendriticCells_vs_GSE35640$GSE50509[which(is.na(jVenn_D
                              "GSE91061" = jVenn_DendriticCells_vs_GSE91061$GSE50509[which(is.na(jVenn_D
                              "GSE61992" = jVenn_DendriticCells_vs_GSE61992$GSE50509[which(is.na(jVenn_D
                              ),
                      evcodes = TRUE, multi_query = FALSE,
                      sources = c("GO", "REAC", "MIRNA", "CORUM", "HP", "HPA", "WP"))
head(multi_gostres$result[,1:7])
##
           query significant
                                   p_value term_size query_size intersection_size
## 1 GSE22155 02
                        TRUE 1.713402e-03
                                                  74
                                                             400
                                                                                23
## 2 GSE22155_02
                        TRUE 1.440922e-21
                                                5986
                                                            1567
                                                                               628
## 3 GSE22155_02
                        TRUE 5.337948e-15
                                                1761
                                                                               231
                                                            1567
## 4 GSE22155 02
                        TRUE 5.978821e-15
                                                1194
                                                            1567
                                                                               174
## 5 GSE22155_02
                        TRUE 4.207302e-14
                                                4912
                                                            1567
                                                                               507
                        TRUE 7.206663e-12
## 6 GSE22155 02
                                                4836
                                                            1567
                                                                               490
##
     precision
## 1 0.0575000
## 2 0.4007658
## 3 0.1474154
## 4 0.1110402
## 5 0.3235482
## 6 0.3126994
p <- gostplot(multi_gostres, capped = FALSE, interactive = F)</pre>
p
```



Estos resultados son los que utilizo para generar los archivos gem que archivo para usar más tarde en Cytoscape.

format to GEM

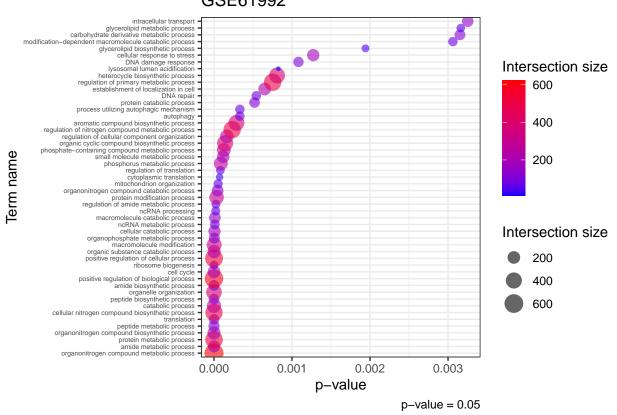
```
gem <- multi_gostres$result[,c("query", "term_id", "term_name", "p_value", "intersection_size")]</pre>
colnames(gem) <- c("query", "GO.ID", "Description", "p.Val", "Genes")</pre>
gem$FDR <- gem$p.Val</pre>
gem$Phenotype = "+1"
gem %>% group_by(query) %>%
    group_walk(~
        write.table(data.frame(.x[,c("GO.ID", "Description", "p.Val", "FDR", "Phenotype", "Genes")]),
                                  file = paste0("./Venn_diagrams_cell_type_treatments_vs_untreated/gProfiler_DendriticCel
                                  sep = "\t", quote = F, row.names = F))
Proporciones de los pathways para cada estudio:
df <- as.data.frame(multi_gostres$result[,1:13])</pre>
table(df$query)
##
## GSE22155 02 GSE22155 47
                                                                GSE35640
                                                                                          GSE61992
                                                                                                                   GSE91061
##
                       439
                                                 438
                                                                          409
                                                                                                    419
                                                                                                                              413
prop.table(table(df$query))*100
##
## GSE22155_02 GSE22155_47
                                                                GSE35640
                                                                                          GSE61992
                                                                                                                   GSE91061
##
            20.72710
                                      20.67989
                                                                19.31067
                                                                                          19.78281
                                                                                                                   19.49953
#table(df$term_name)
#prop.table(table(df$term_name))*100
df2 <- as.data.frame(table(df$term_name, df$query))</pre>
#length(unique(df2$Var1))
write.table(df, file = "./Venn_diagrams_cell_type_treatments_vs_untreated/DendriticCells_GOBPs.txt", se
write.table(df2, file = "./Venn_diagrams_cell_type_treatments_vs_untreated/DendriticCells_GOBPs_freq.tx
rm(jVenn_DendriticCells_vs_GSE22155_02, jVenn_DendriticCells_vs_GSE22155_47, jVenn_DendriticCells_vs_GSE22155_57, jVenn_DendriticCells_vs_GSE22155_57, jVenn_DendriticCells_vs_GSE22155_57, jVenn_De
plot_gobps <- function(study, n = 50){</pre>
df2 <- df[df$source == "GO:BP",]</pre>
df2_GSE91061 \leftarrow df2[df2$query == study,]
df2_GSE91061 <- df2_GSE91061[1:n,]</pre>
ggplot(df2_GSE91061, aes(p_value, reorder(term_name,p_value))) + ggtitle(study) +
    geom_point(aes(p_value, reorder(term_name,p_value), colour = intersection_size, size = intersection_s
    theme_bw() + theme(axis.text.y.left = element_text(size = 5)) +
   labs(x= "p-value", y="Term name", colour = "Intersection size", size = "Intersection size", caption =
    scale_color_gradient(low="blue", high="red")
plot_gobps(study = "GSE91061")
```



print("\n")

[1] "\n"

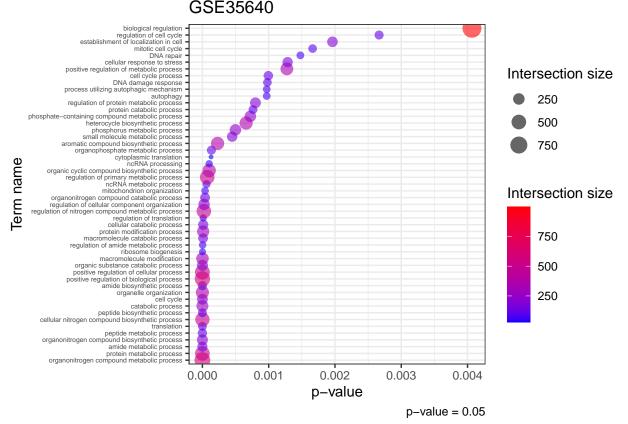
plot_gobps(study = "GSE61992")



print("\n")

[1] "\n"

plot_gobps(study = "GSE35640")

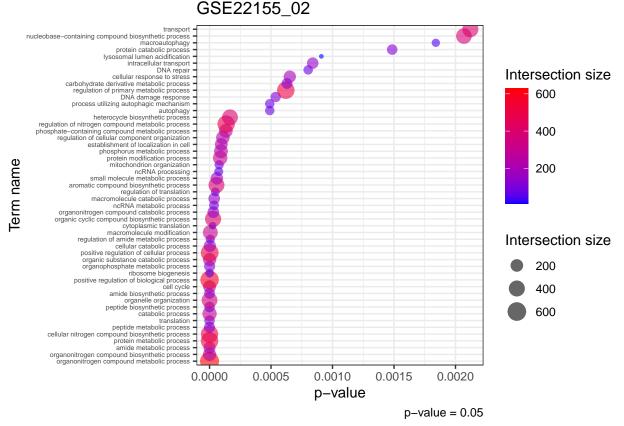


print("\n")

[1] "\n"

plot_gobps(study = "GSE22155_02")

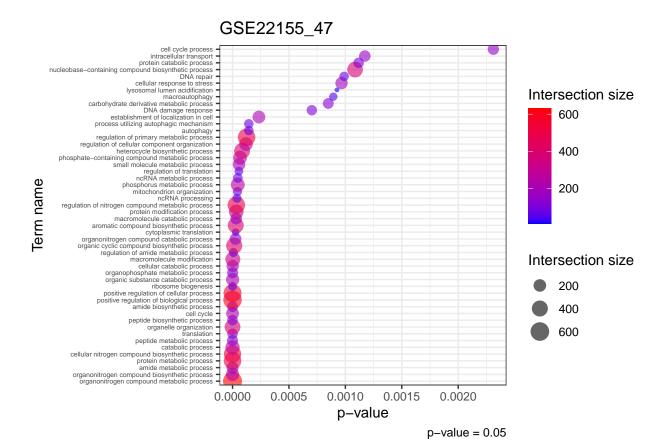
GSE22155_02



print("\n")

[1] "\n"

plot_gobps(study = "GSE22155_47")



5 Exclusive

En esta sección analizo los DEGs exclusivos para cada estudio, y realizo un multi-análisis para cada estudio. Los resultados los guardo como archivos gem específicos para usar en Cytoscape.

Primero realizo el pathway multianálisis:

```
multi_gostres <- gost(query = list("GSE61992" = jVenn_DendriticCells$GSE61992[which(is.na(jVenn_Dendrit
                              "GSE91061" = jVenn DendriticCells$GSE91061[which(is.na(jVenn DendriticCell
                              ),
                      evcodes = TRUE, multi_query = FALSE,
                      sources = c("GO", "REAC", "MIRNA", "CORUM", "HP", "HPA", "WP"))
head(multi_gostres$result[,1:7])
##
        query significant
                                p_value term_size query_size intersection_size
## 1 GSE61992
                     TRUE 7.923024e-05
                                            12345
                                                           81
## 2 GSE61992
                     TRUE 1.870319e-04
                                             2203
                                                                              24
## 3 GSE61992
                     TRUE 1.286308e-03
                                             5487
                                                           81
                                                                             39
## 4 GSE61992
                     TRUE 7.012270e-03
                                             1194
                                                           81
                                                                             15
                                                           81
## 5 GSE61992
                     TRUE 7.432560e-03
                                             1200
                                                                             15
                     TRUE 8.370056e-03
## 6 GSE61992
                                             1521
                                                           81
                                                                             17
     precision
##
## 1 0.8271605
## 2 0.2962963
## 3 0.4814815
## 4 0.1851852
## 5 0.1851852
```

6 0.2098765

Estos resultados son los que utilizo para generar los archivos gem que archivo para usar más tarde en Cytoscape.

```
Proporciones de los pathways para cada estudio:
df <- as.data.frame(multi_gostres$result[,1:13])</pre>
table(df$query)
##
## GSE61992 GSE91061
##
         25
                 1409
write.table(gem, file = "./Treatment_comparisons/gProfiler_DendriticCells_Only_genesets.txt", sep = "\t
plot_gobps <- function(study){</pre>
df2_GSE91061 \leftarrow df2[df2$query == study,]
ggplot(df2_GSE91061, aes(p_value, reorder(term_name,p_value))) + ggtitle(study) +
```

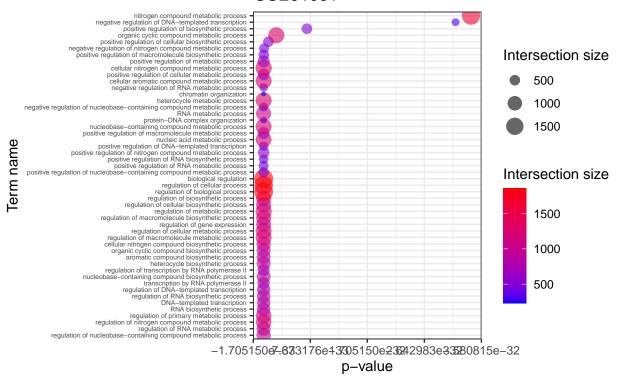
theme_bw() + theme(axis.text.y.left = element_text(size = 5)) +

scale_color_gradient(low="blue", high="red")

geom_point(aes(p_value, reorder(term_name,p_value), colour = intersection_size, size = intersection_s

labs(x= "p-value", y="Term name", colour = "Intersection size", size = "Intersection size", caption =

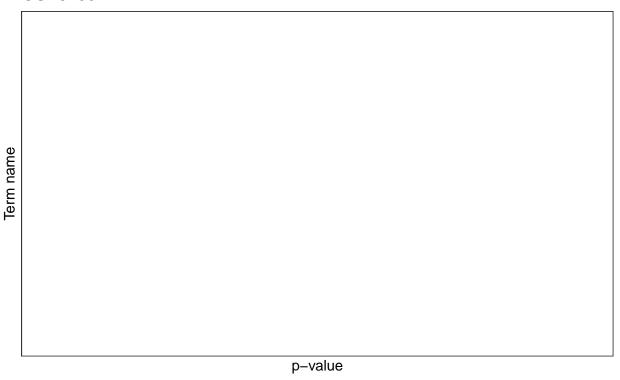
```
}
df2 <- df[df$source == "G0:BP",]
df2 <- df2[1:50,]
plot_gobps(study = "GSE91061")</pre>
```



Top-4 p-value = 0.05

```
print("\n")
## [1] "\n"

df2 <- df[df$source == "GO:BP",]
plot_gobps(study = "GSE61992")</pre>
```



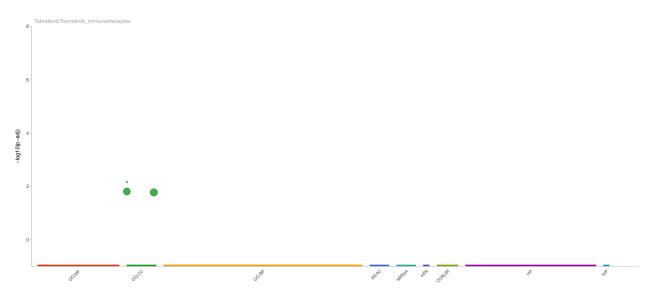
Top-4 p-value = 0.05

6 Máximo solapamiento

En esta sección analizo los DEGs que más se comparten entre los estudios para observar los mecanismos que pudieran haber en común entre los tratamientos.

Primero realizo el pathway multianálisis:

```
multi_gostres <- gost(query = list("TabrafenibTrametinib_Immunotherapies" = jVenn_DendriticCells$`GSE91</pre>
),
                       evcodes = TRUE, multi_query = FALSE,
                       sources = c("GO", "REAC", "MIRNA", "CORUM", "HP", "HPA", "WP"))
head(multi_gostres$result[,1:7])
##
                                     query significant
                                                            p_value term_size
## 1 TabrafenibTrametinib_Immunotherapies
                                                   TRUE 0.006753903
                                                                            16
## 2 TabrafenibTrametinib_Immunotherapies
                                                   TRUE 0.015485312
                                                                            24
## 3 TabrafenibTrametinib_Immunotherapies
                                                   TRUE 0.016825261
                                                                            25
##
     query_size intersection_size precision
## 1
             15
                                 2 0.1333333
## 2
             15
                                 2 0.1333333
## 3
             15
                                 2 0.1333333
p <- gostplot(multi_gostres, capped = FALSE, interactive = F)</pre>
р
```



Estos resultados son los que utilizo para generar los archivos gem que archivo para usar más tarde en Cytoscape.

Al mirar los procesos por cada comparación salieron demasiados para poder visualizarlos bien, por lo que decidí restringir a los procesos GO-BPs únicamente y guardarlos en pdf.

```
#unique(gem$query)
gem2 <- gem[grep("GO",gem$GO.ID),]
plot_gobps <- function(query, cutoff = 0.05) {
    gem2 <- gem2[gem2$FDR <= cutoff,]
    gem2_1 <- gem2[gem2$query == query, ]
    ggplot(gem2_1, aes(FDR, Description)) + ggtitle(query) +
        geom_point(aes(FDR, Description, colour = Genes, size = Genes), alpha = 0.6)+
        theme_bw() + theme(axis.text.y.left = element_text(size = 5)) +
        labs(caption = paste0("FDR = ",cutoff))+
        scale_color_gradient(low="blue", high="red")
}

pdf(file = paste0("./Treatment_comparisons/gProfiler_DendriticCells_maxOverlap_TabrafenibTrametinib_Imm
        plot_gobps("TabrafenibTrametinib_Immunotherapies")
        dev.off()

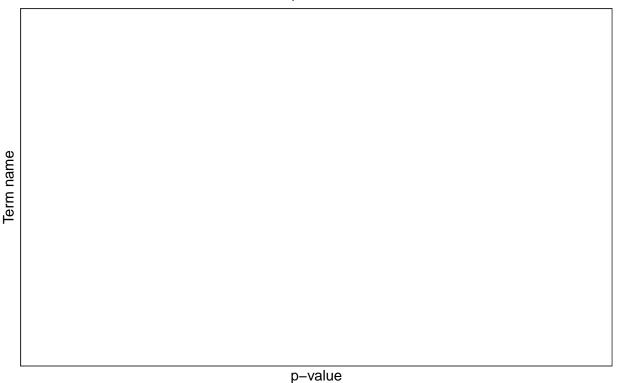
## pdf</pre>
```

##

2

```
df <- as.data.frame(multi_gostres$result[,1:13])
df2 <- df[df$source == "GO:BP",]
plot_gobps <- function(study){
    df2_GSE91061 <- df2[df2$query == study,]
    ggplot(df2_GSE91061, aes(p_value, reorder(term_name,p_value))) + ggtitle(study) +
        geom_point(aes(p_value, reorder(term_name,p_value), colour = intersection_size, size = intersection_s
        theme_bw() + theme(axis.text.y.left = element_text(size = 5)) +
        labs(x= "p-value", y="Term name", colour = "Intersection size", size = "Intersection size", caption =
        scale_color_gradient(low="blue", high="red")
}
plot_gobps(study = "TabrafenibTrametinib_Immunotherapies")</pre>
```

TabrafenibTrametinib_Immunotherapies



p-value = 0.05