

Pathway Analysis - Treg cells

Input data: DEGs

Elena Eyre Sánchez, PhD

2025-01-04

Contents

1	Introducción y Objetivo	1
2	Paquetes y datos	1
3	Datos	1
4	Uncovered	2
5	Exclusive	9
6	Máximo solapamiento	13

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 Treg obtenidas en jVenn.

```
setwd("~/Desktop/ELENA_UOC/TFM")
jVenn_Tregcells_vs_GSE22155_02 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_")
head(jVenn_Tregcells_vs_GSE22155_02) # sección de los resultados
```

```
## # A tibble: 6 x 3
##   GSE50509 GSE22155_02 `GSE50509|GSE22155_02`
##   <chr>      <chr>      <chr>
## 1 H3C4      RPS16      LINC01091
## 2 H2BC6     POLR2I     CTLA4
## 3 OR10K2    RNPS1      CYP27B1
## 4 CEMIP     RPS29      CLDND1
## 5 JSRP1     RPL10      VMA21
## 6 PIM2      HCFC1      OGT
```

```
jVenn_Tregcells_vs_GSE22155_47 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Tre
jVenn_Tregcells_vs_GSE91061 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Tre
jVenn_Tregcells_vs_GSE35640 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Tre
jVenn_Tregcells_vs_GSE61992 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Tre
setwd("~/Desktop/ELENA_UOC/TFM/GOBPs") # Directorio de trabajo
jVenn_Tregcells <- read_delim("~/Desktop/ELENA_UOC/TFM/DEGs/Venn_diagrams_cell_type_treatments_comparis
  delim = ",", escape_double = FALSE, trim_ws = TRUE)
```

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:

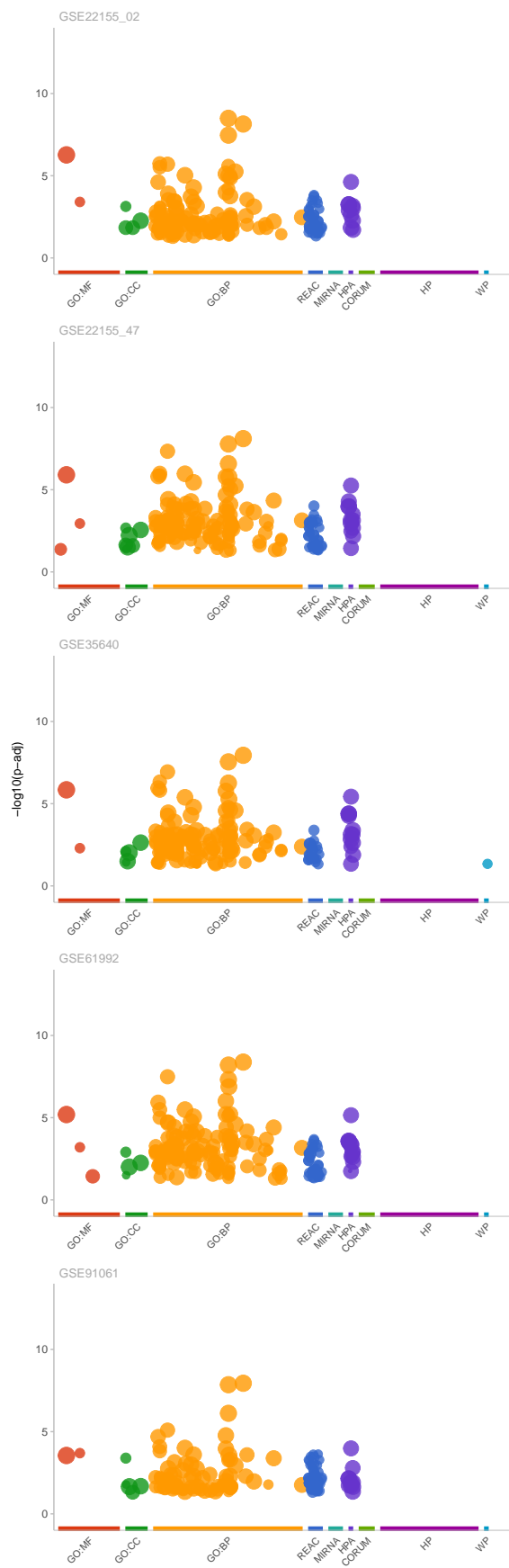
En esta sección contemplo la posibilidad que los DEGs únicos en el dataset sin tratar se traten de mecanismos que se escapan al tratamiento pero que igualmente se ven afectados por la enfermedad.

Primero realizo el pathway multianálisis:

```
multi_gostres <- gost(query = list("GSE22155_02" = unique(jVenn_Tregcells_vs_GSE22155_02$GSE50509[which
  "GSE22155_47" = jVenn_Tregcells_vs_GSE22155_47$GSE50509[which(is.na(jVenn_Tre
  "GSE35640" = jVenn_Tregcells_vs_GSE35640$GSE50509[which(is.na(jVenn_Tregce
  "GSE91061" = jVenn_Tregcells_vs_GSE91061$GSE50509[which(is.na(jVenn_Tregce
  "GSE61992" = jVenn_Tregcells_vs_GSE61992$GSE50509[which(is.na(jVenn_Tregce
  )),
  evcodes = TRUE, multi_query = FALSE,
  sources = c("GO", "REAC", "MIRNA", "CORUM", "HP", "HPA", "WP"))
head(multi_gostres$result[,1:7])
```

##	query	significant	p_value	term_size	query_size	intersection_size
## 1	GSE22155_02	TRUE	3.202117e-09	12287	479	353
## 2	GSE22155_02	TRUE	7.158934e-09	12680	479	360
## 3	GSE22155_02	TRUE	3.399091e-08	11738	479	338
## 4	GSE22155_02	TRUE	1.828431e-06	1512	479	73
## 5	GSE22155_02	TRUE	1.985401e-06	1988	479	88
## 6	GSE22155_02	TRUE	2.498789e-06	881	479	51
##	precision					
## 1	0.7369520					
## 2	0.7515658					
## 3	0.7056367					
## 4	0.1524008					
## 5	0.1837161					
## 6	0.1064718					

```
p <- gostplot(multi_gostres, capped = FALSE, interactive = F)
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$result[,c("query", "term_id", "term_name", "p_value", "intersection_size")]
colnames(gem) <- c("query", "GO.ID", "Description", "p.Val", "Genes")
gem$FDR <- gem$p.Val
gem$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_Tregcells_Onl",
        sep = "\t", quote = F, row.names = F))
```

Proporciones de los pathways para cada estudio:

```
df <- as.data.frame(multi_gostres$result[,1:13])
table(df$query)

##
## GSE22155_02 GSE22155_47 GSE35640 GSE61992 GSE91061
## 169 178 169 181 131

prop.table(table(df$query))*100

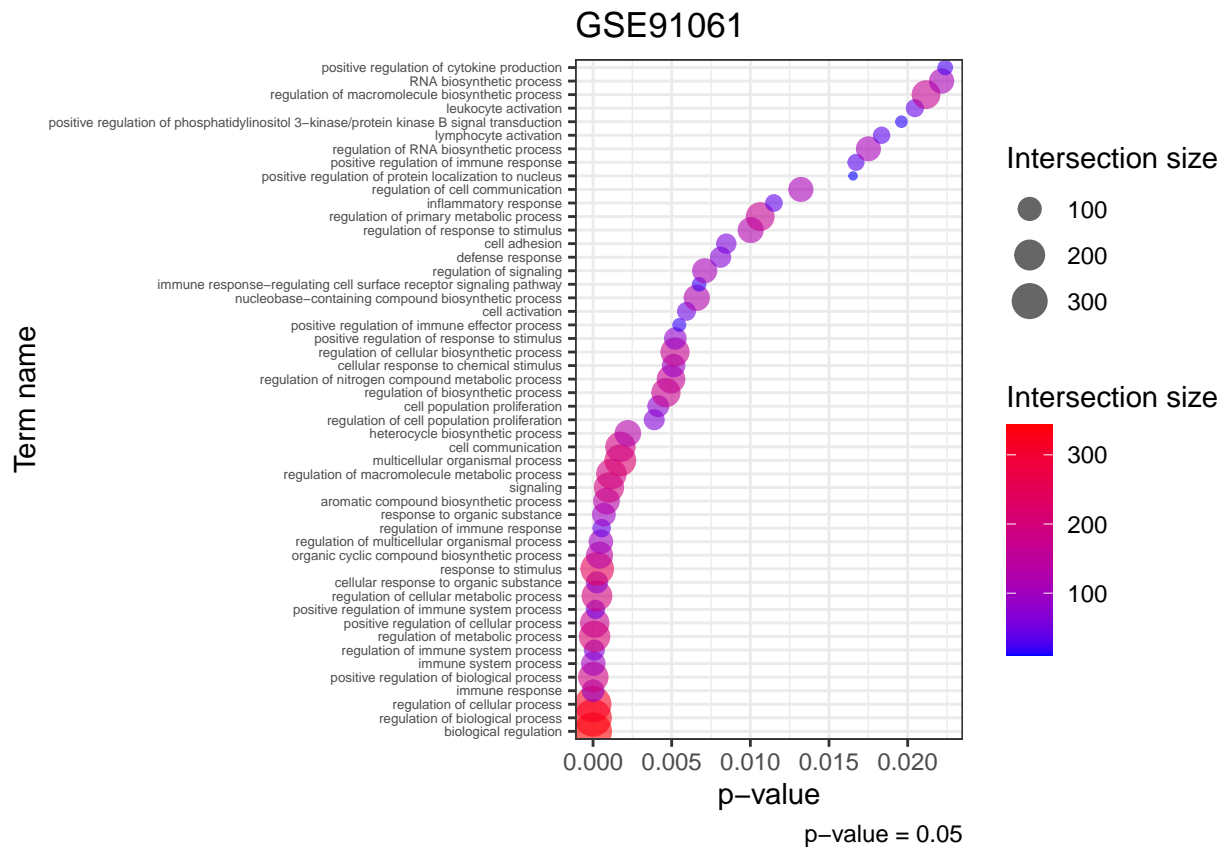
##
## GSE22155_02 GSE22155_47 GSE35640 GSE61992 GSE91061
## 20.41063 21.49758 20.41063 21.85990 15.82126

#table(df$term_name)
#prop.table(table(df$term_name))*100
df2 <- as.data.frame(table(df$term_name, df$query))
#length(unique(df2$Var1))
write.table(df, file = "./Venn_diagrams_cell_type_treatments_vs_untreated/Tregcells_GOBP.txt", sep = "\t",
write.table(df2, file = "./Venn_diagrams_cell_type_treatments_vs_untreated/Tregcells_GOBP_freq.txt", sep = "\t",
#rm(jVenn_Tregcells_vs_GSE22155_02, jVenn_Tregcells_vs_GSE22155_47, jVenn_Tregcells_vs_GSE35640, jVenn_Tregcells_vs_GSE61992, jVenn_Tregcells_vs_GSE91061)
```

Barplot of the top GO-BPs:

```
plot_gobps <- function(study, n = 50){
df2 <- df[df$source == "GO:BP",]
df2_GSE91061 <- df2[df2$query == study,]
df2_GSE91061 <- df2_GSE91061[1:n,]
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_size)) +
  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 = "Intersection size")
  scale_color_gradient(low="blue", high="red")
}

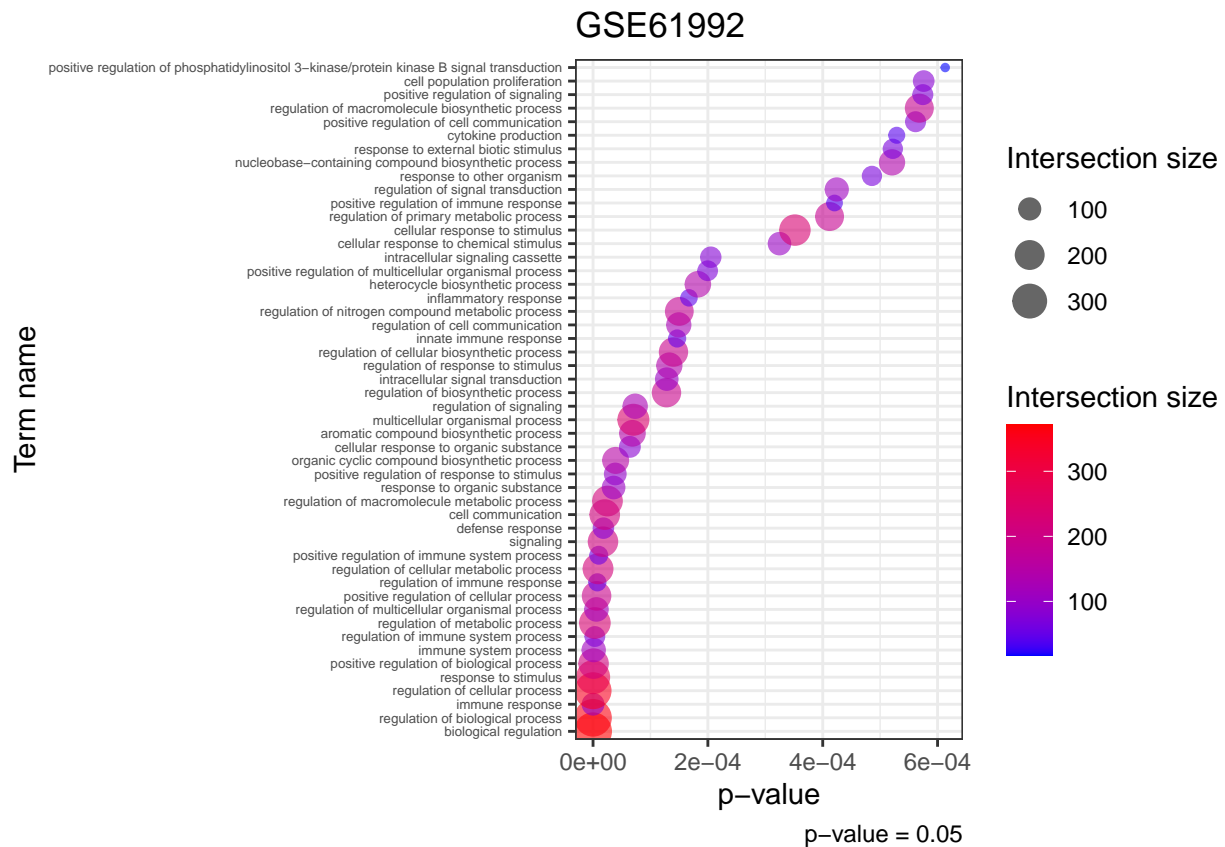
plot_gobps(study = "GSE91061")
```



```
print("\n")
```

```
## [1] "\n"
```

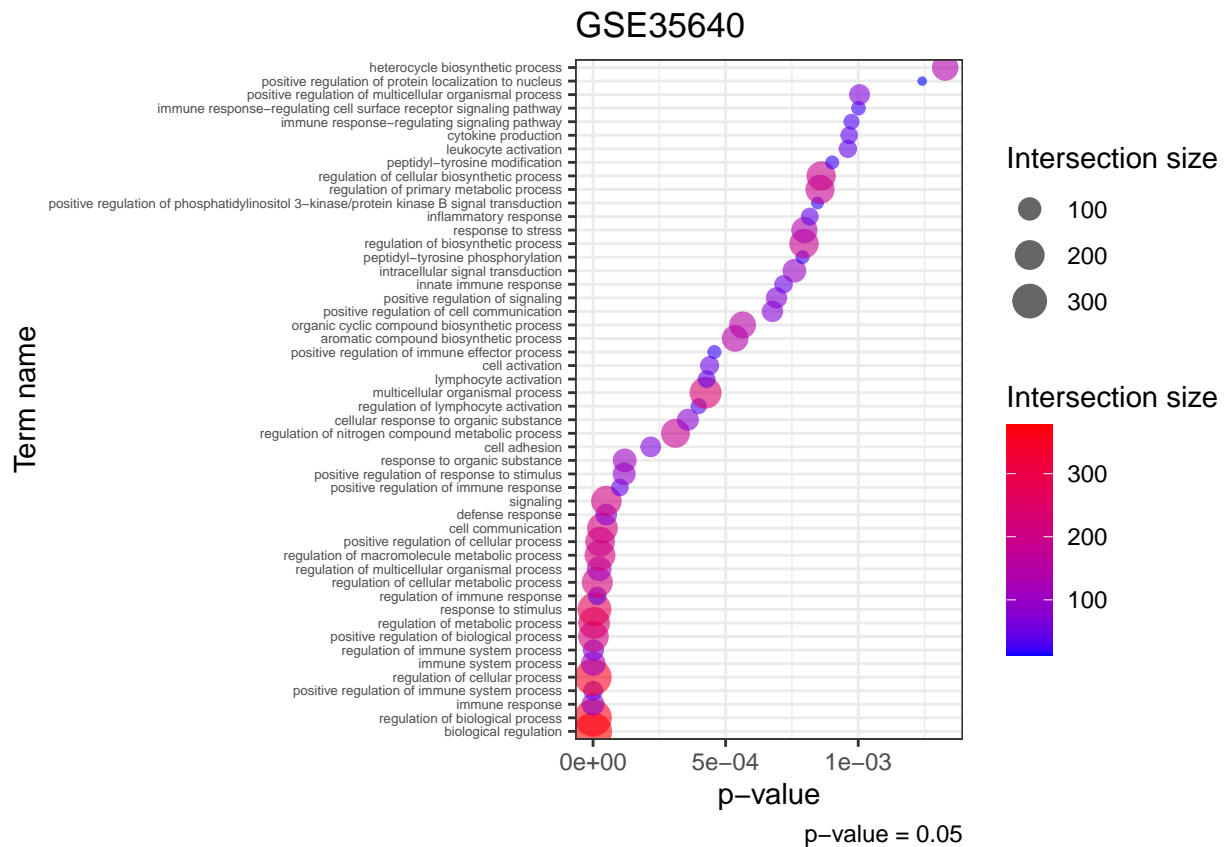
```
plot_gobps(study = "GSE61992")
```



```
print("\n")
```

```
## [1] "\n"
```

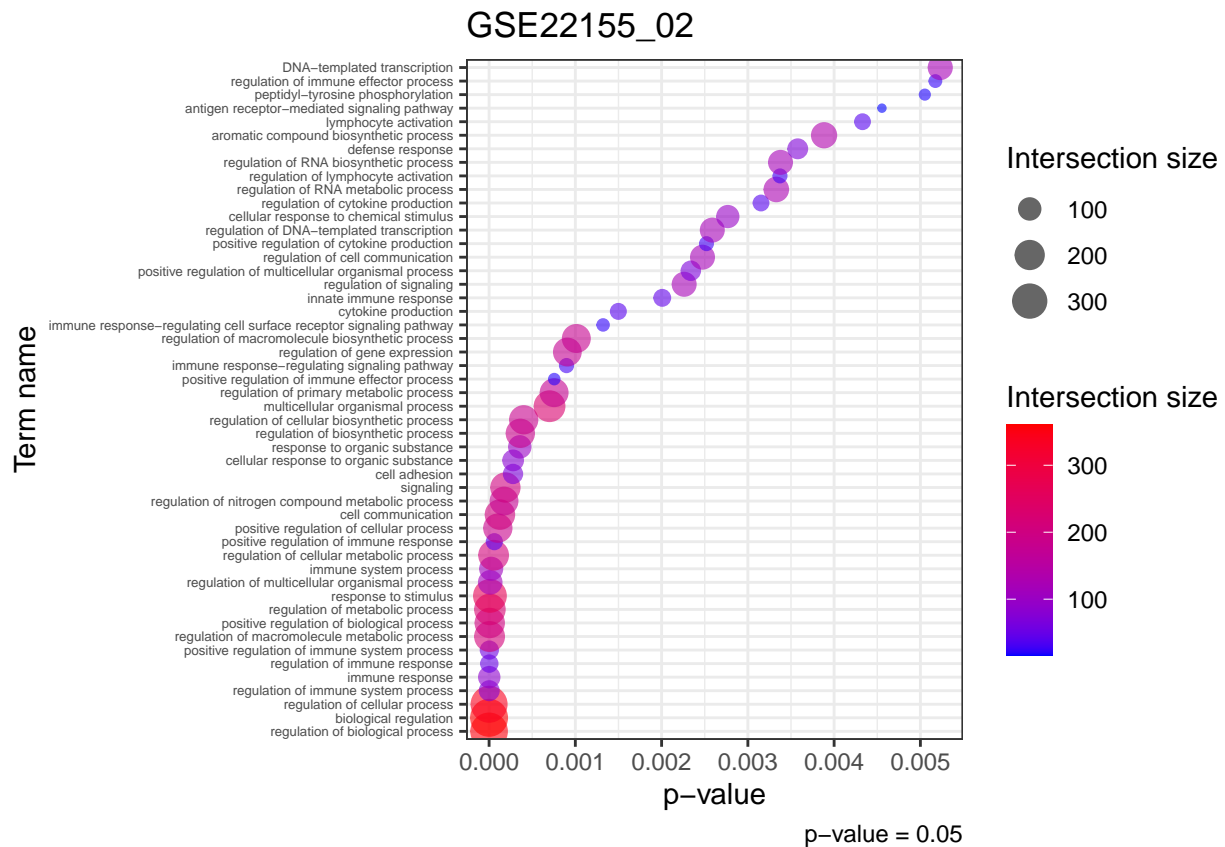
```
plot_gobps(study = "GSE35640")
```



```
print("\n")
```

```
## [1] "\n"
```

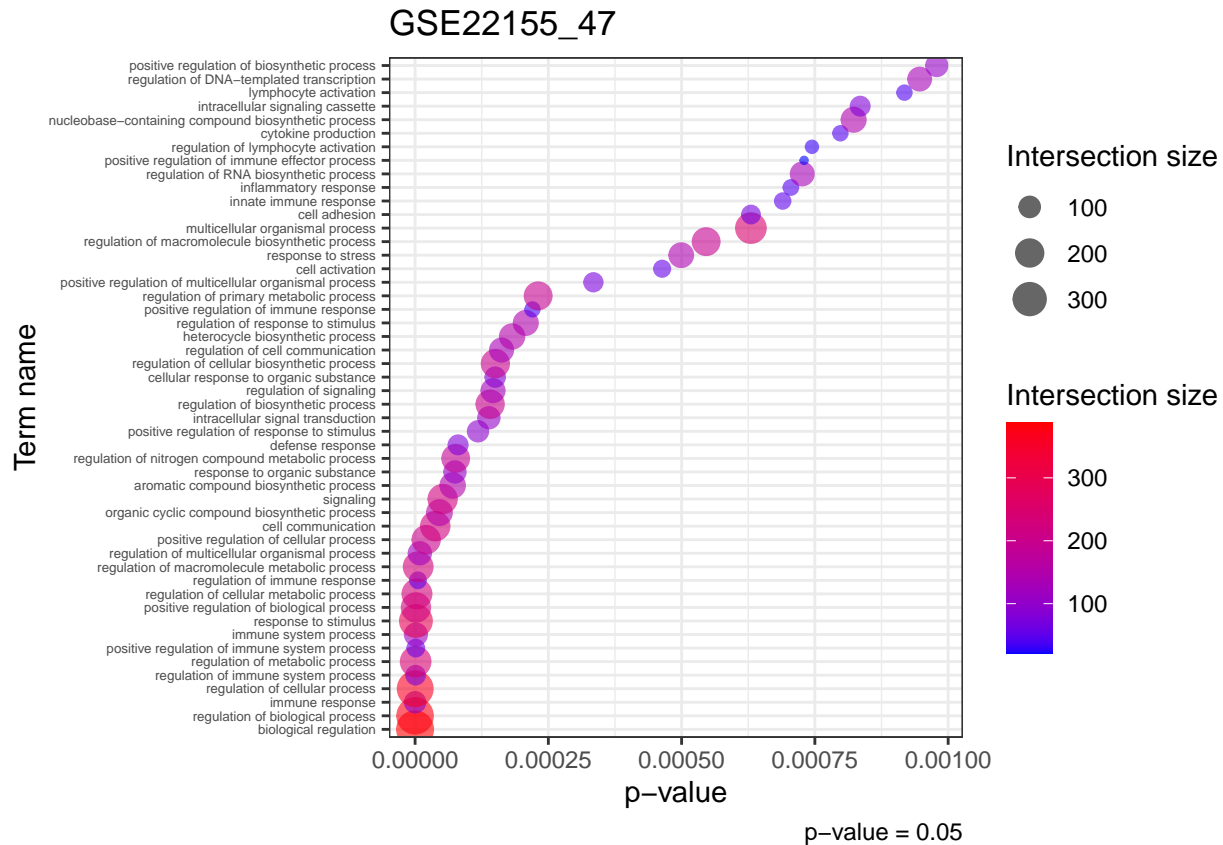
```
plot_gobps(study = "GSE22155_02")
```



```
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_Tregcells$GSE61992[which(is.na(jVenn_Tregcells$GSE61992))],
                                "GSE91061" = jVenn_Tregcells$GSE91061[which(is.na(jVenn_Tregcells$GSE91061))]),
                    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	0.008324058	2	16	2
## 2	GSE61992	TRUE	0.024903238	3	16	2
## 3	GSE61992	TRUE	0.008105184	2637	54	20
## 4	GSE61992	TRUE	0.009362157	13	54	3
## 5	GSE61992	TRUE	0.013481220	2	54	2
## 6	GSE61992	TRUE	0.013481220	2	54	2
##	precision					
## 1	0.12500000					
## 2	0.12500000					
## 3	0.37037037					
## 4	0.05555556					
## 5	0.03703704					

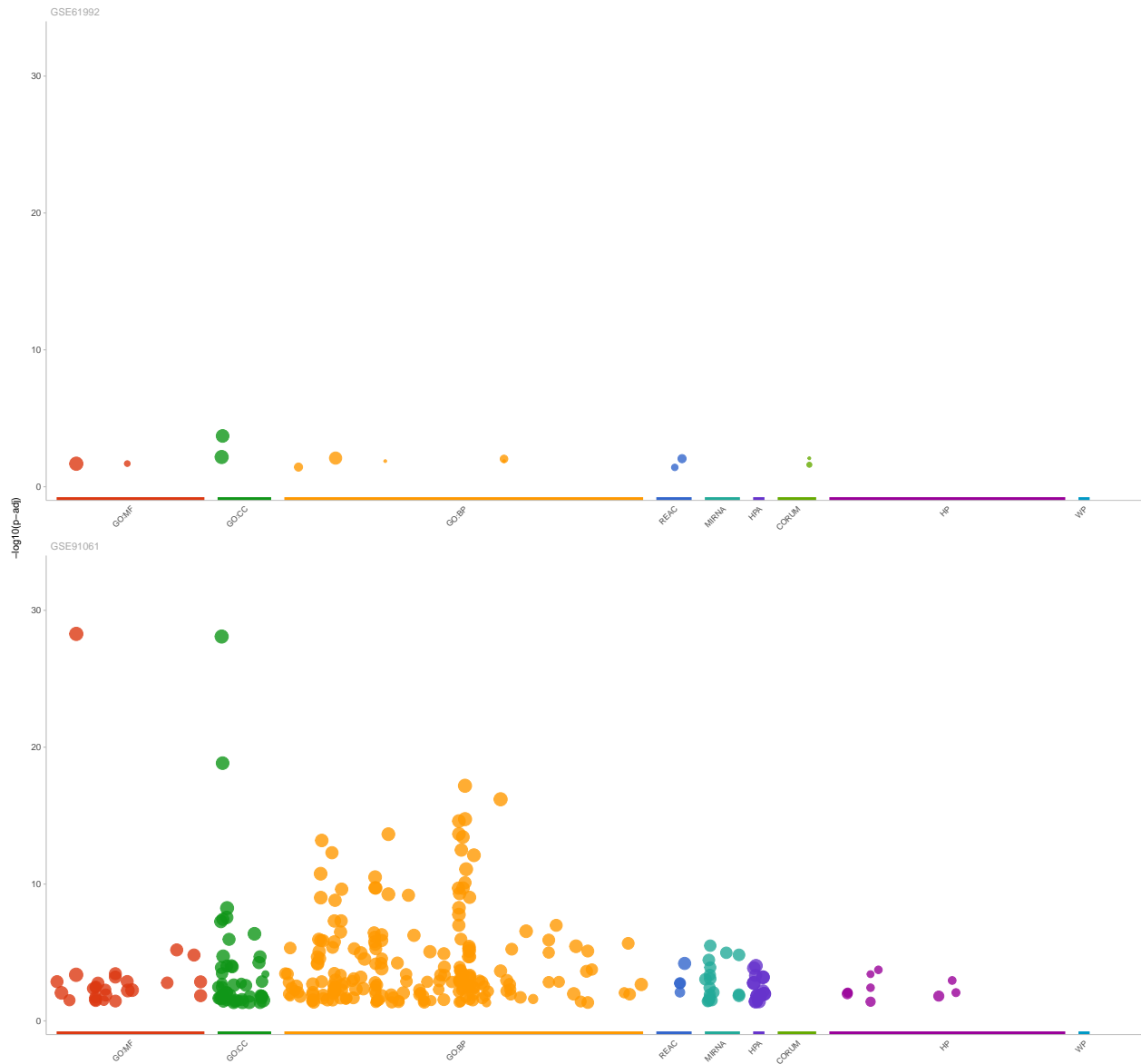
```
## 6 0.03703704
```

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$result[,c("query", "term_id", "term_name", "p_value", "intersection_size")]
colnames(gem) <- c("query", "GO.ID", "Description", "p.Val", "Genes")
gem$FDR <- gem$p.Val
gem$Phenotype = "+1"

gem %>% group_by(query) %>%
  group_walk(~
    write.table(data.frame(.x[,c("GO.ID", "Description", "p.Val", "FDR", "Phenotype", "Genes")]),
      file = paste0("./Treatment_comparisons/gProfiler_Tregcells_Only_geneset_", unique(.y$query)),
      sep = "\t", quote = F, row.names = F))

p <- gostplot(multi_gostres, capped = FALSE, interactive = F)
p
```



Proporciones de los pathways para cada estudio:

```
df <- as.data.frame(multi_gostres$result[,1:13])
table(df$query)
```

```
##
## GSE61992 GSE91061
##      13      325
```

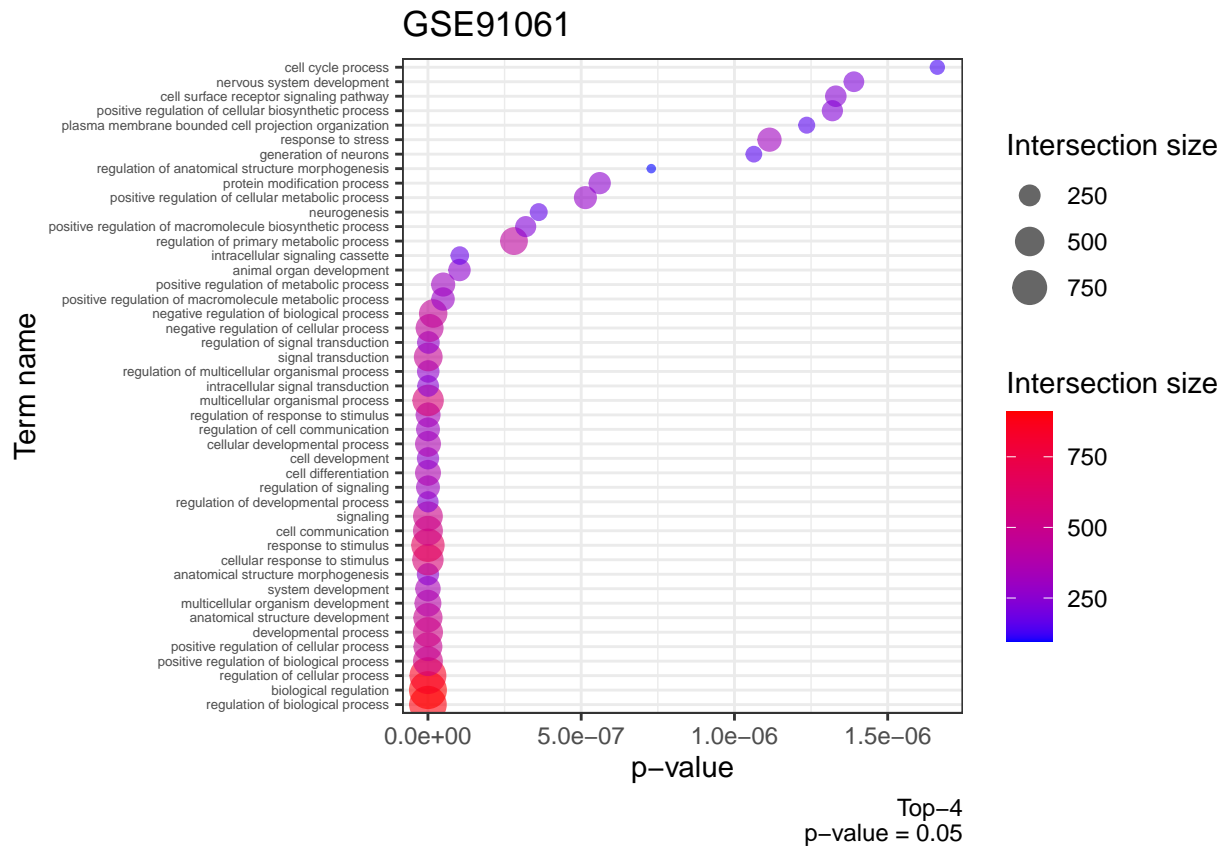
```
write.table(gem, file = "./Treatment_comparisons/gProfiler_Tregcells_Only_genesets.txt", sep = "\t", quote = FALSE)
```

```
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_size)) +
  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 = "Intersection size")
  scale_color_gradient(low="blue", high="red")
}
```

```

}
df2 <- df[df$source == "GO:BP",]
df2 <- df2[1:50,]
plot_gobps(study = "GSE91061")

```



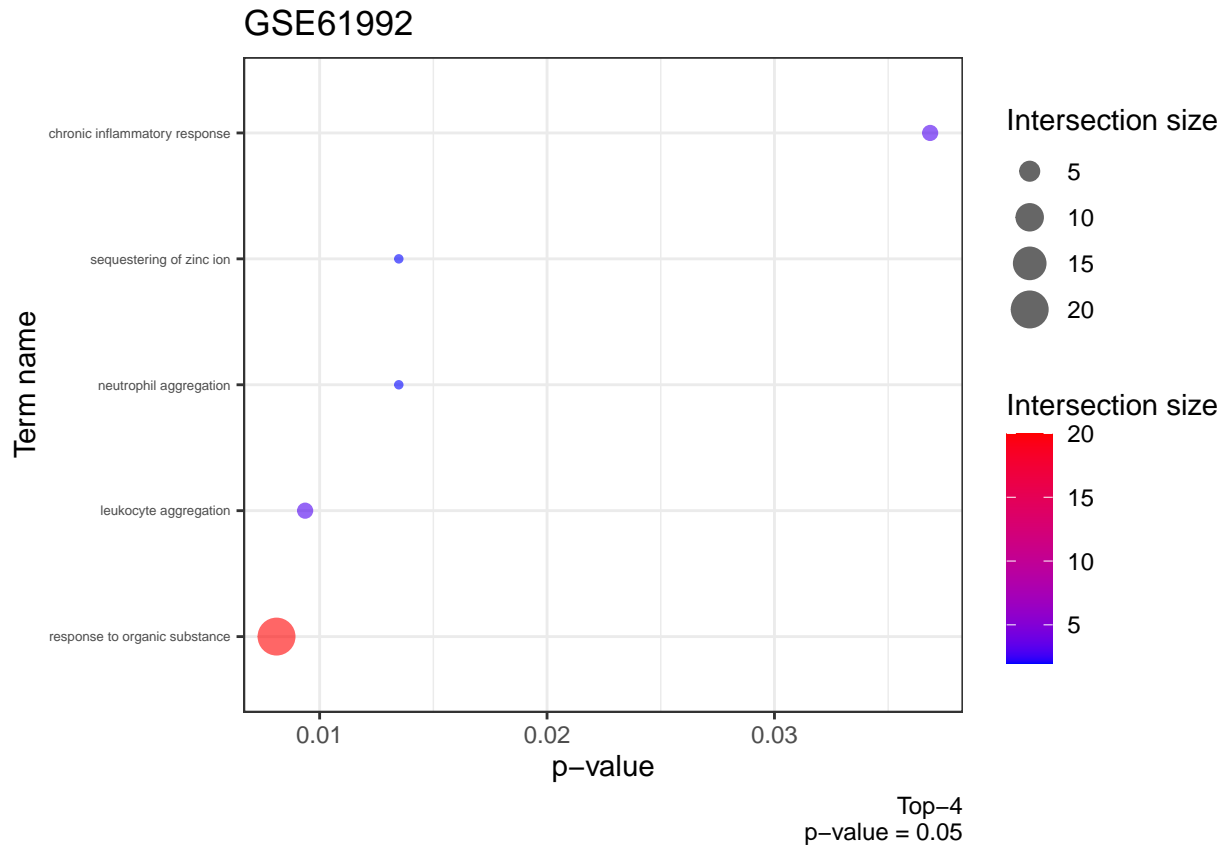
```
print("\n")
```

```
## [1] "\n"
```

```

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

```



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, pero no se obtiene resultado: “Empty query. Please double check your input.” Sólo hay 5 genes, lo que debe impedir obtener un resultado.

```
#multi_gostres <- gost(query = list("TabrafenibTrametinib_antiCTLA4PD1" = jVenn_Tregcells$`GSE91061|GSE
#`),
#                               evcodes = TRUE, multi_query = FALSE,
#                               sources = c("GO", "REAC", "MIRNA", "CORUM", "HP", "HPA", "WP"))
#head(multi_gostres$result[,1:7])
```