

# Pathway Analysis - B 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 las células B obtenidos en jVenn.

```
setwd("~/Desktop/ELENA_UOC/TFM")
jVenn_Bcells_vs_GSE22155_02 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Bce
head(jVenn_Bcells_vs_GSE22155_02) # sección de los resultados
```

```
## # A tibble: 6 x 3
##   GSE50509 GSE22155_02 `GSE50509|GSE22155_02`
##   <chr>    <chr>    <chr>
## 1 MXRA7   MS4A1     TLN1
## 2 CDK20   CARD11    CD79A
## 3 HTN1    NIBAN3    NDRG3
## 4 SCN1B   CR2       CD19
## 5 HPN     FCER2     DCTN3
## 6 FGF14-AS2 BANK1    VPRESB3
```

```
jVenn_Bcells_vs_GSE22155_47 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Bcells_vs_GSE22155_47.csv")
jVenn_Bcells_vs_GSE61992 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Bcells_vs_GSE61992.csv")
jVenn_Bcells_vs_GSE91061 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Bcells_vs_GSE91061.csv")
jVenn_Bcells_vs_GSE35640 <- read_csv("DEGs/Venn_diagrams_cell_type_treatments_vs_untreated/jVenn_Bcells_vs_GSE35640.csv")
setwd("~/Desktop/ELENA_UOC/TFM/GOBPs") # Directorio de trabajo
jVenn_Bcells <- read_delim("~/Desktop/ELENA_UOC/TFM/DEGs/Venn_diagrams_cell_type_treatments_comparison/DEGs_Venn_diagrams_cell_type_treatments_comparison.csv",
  delim = ",", escape_double = FALSE, trim_ws = TRUE)
```

## 4 Uncovered

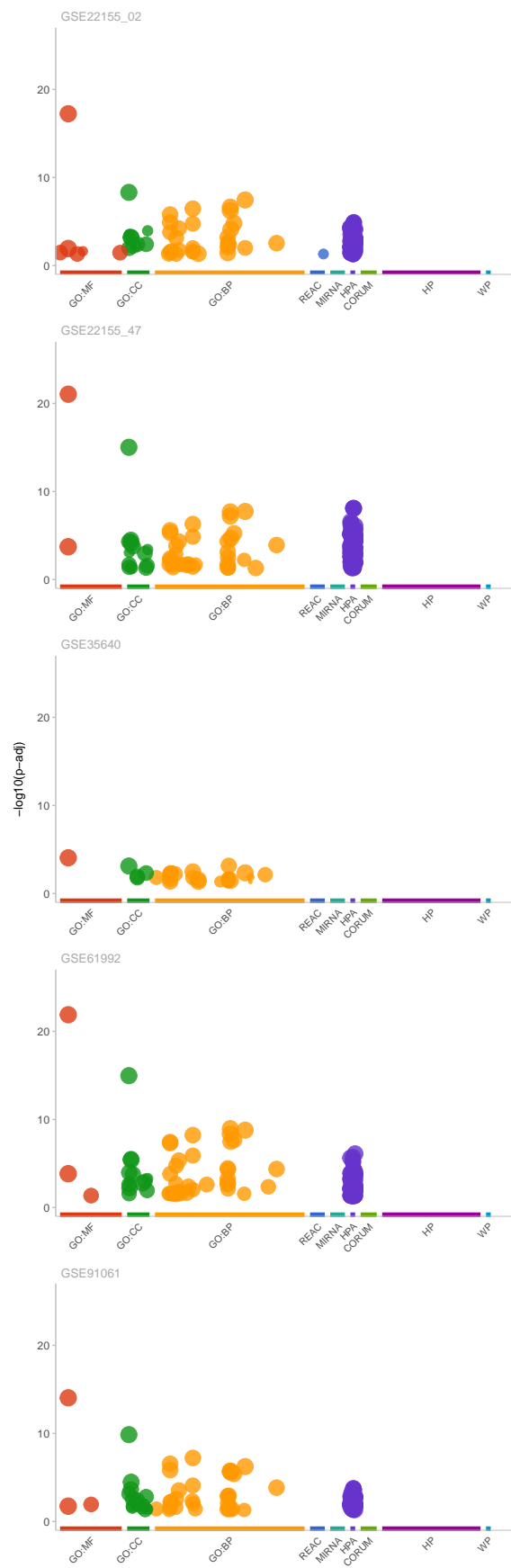
En esta sección contemplo la posibilidad que los DEGs únicos en el dataset con muestras sin tratar se traten de mecanismos que se han sido tratados en la cohorte con inmunoterapia.

Primero realizo el pathway multianálisis:

```
multi_gostres <- gost(query = list("GSE22155_02" = unique(jVenn_Bcells_vs_GSE22155_02$GSE50509[which(is.na(jVenn_Bcells_vs_GSE22155_02$GSE50509) == FALSE)]),
  "GSE22155_47" = jVenn_Bcells_vs_GSE22155_47$GSE50509[which(is.na(jVenn_Bcells_vs_GSE22155_47$GSE50509) == FALSE)],
  "GSE35640" = jVenn_Bcells_vs_GSE35640$GSE50509[which(is.na(jVenn_Bcells_vs_GSE35640$GSE50509) == FALSE)],
  "GSE91061" = jVenn_Bcells_vs_GSE91061$GSE50509[which(is.na(jVenn_Bcells_vs_GSE91061$GSE50509) == FALSE)],
  "GSE61992" = jVenn_Bcells_vs_GSE61992$GSE50509[which(is.na(jVenn_Bcells_vs_GSE61992$GSE50509) == FALSE)]),
  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	3.524736e-08	12680	635	462
## 2	GSE22155_02	TRUE	2.316282e-07	11738	635	432
## 3	GSE22155_02	TRUE	3.462587e-07	6447	635	269
## 4	GSE22155_02	TRUE	5.757019e-07	12287	635	446
## 5	GSE22155_02	TRUE	1.620241e-06	6537	635	269
## 6	GSE22155_02	TRUE	1.259451e-05	5959	635	246
##	precision					
## 1	0.7275591					
## 2	0.6803150					
## 3	0.4236220					
## 4	0.7023622					
## 5	0.4236220					
## 6	0.3874016					

```
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_Bcells_Only_",
        sep = "\t", quote = F, row.names = F))
```

Proporciones de los pathways para cada estudio:

```
df <- as.data.frame(multi_gostres$result[,1:13])
df3 <- table(df$query)
table(df$query)

##
## GSE22155_02 GSE22155_47 GSE35640 GSE61992 GSE91061
## 126 191 27 118 89

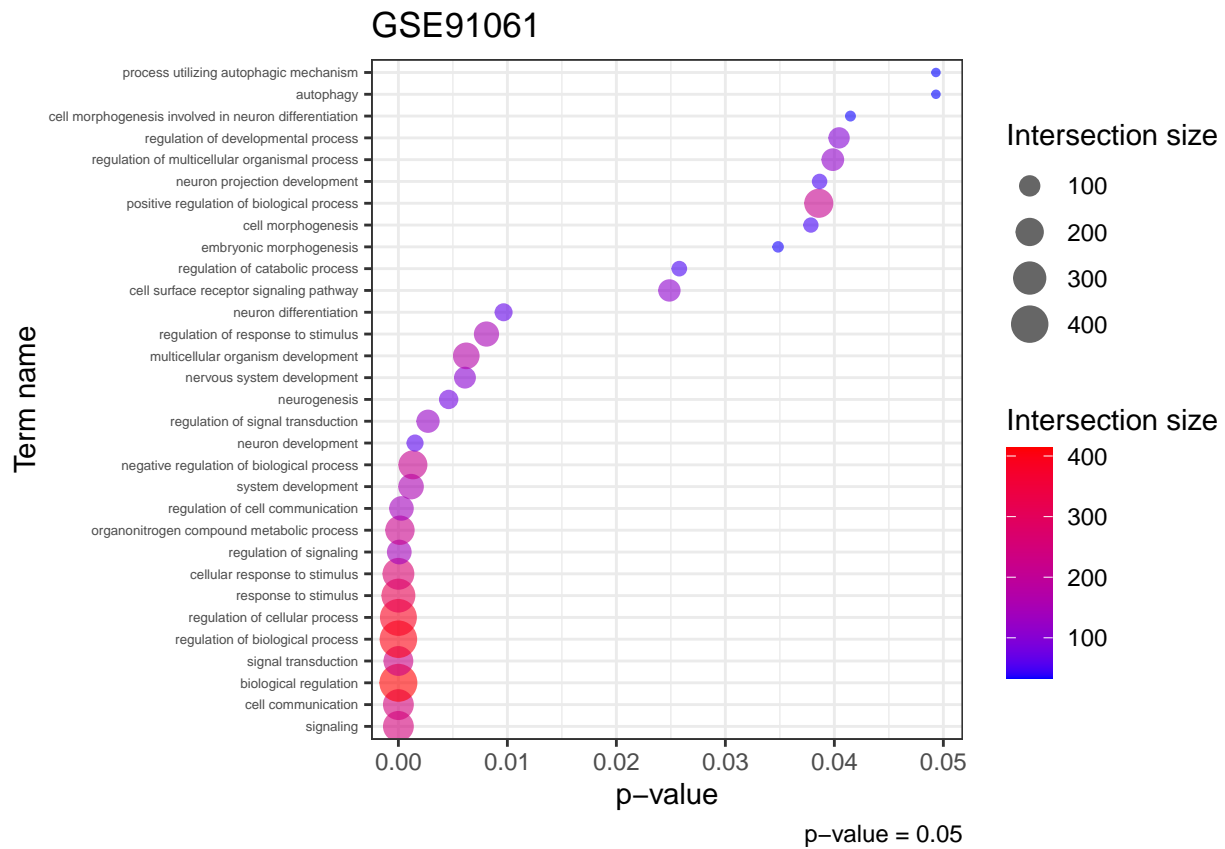
prop.table(table(df$query))*100

##
## GSE22155_02 GSE22155_47 GSE35640 GSE61992 GSE91061
## 22.867514 34.664247 4.900181 21.415608 16.152450

#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/Bcell_GOBPs.txt", sep = "\t",
write.table(df2, file = "./Venn_diagrams_cell_type_treatments_vs_untreated/Bcell_GOBPs_freq.txt", sep =
#rm(jVenn_Bcells_vs_GSE22155_02, jVenn_Bcells_vs_GSE22155_47, jVenn_Bcells_vs_GSE35640, jVenn_Bcells_vs_
```

Barplot of the top GO-BPs:

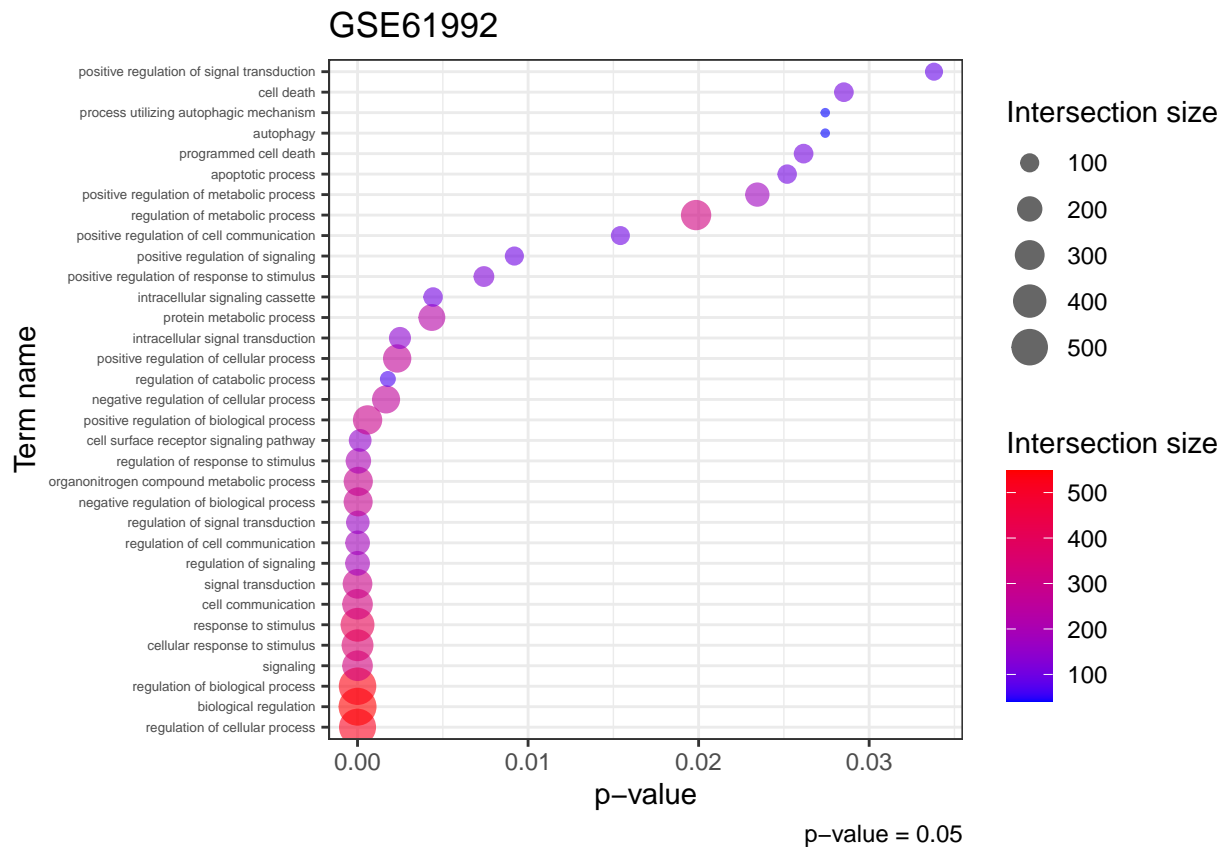
```
df2 <- df[df$source == "GO:BP",]
plot_gobps <- function(study){
df2_GSE91061 <- df2[df2$query == study,]
ggplot(df2_GSE91061, aes(p_value, reorder(term_name,p_value))) + ggtitle(study) +
  geom_point(aes(p_value, reorder(term_name,p_value), colour = intersection_size, size = intersection_size)) +
  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 =
  scale_color_gradient(low="blue", high="red")
}
plot_gobps(study = "GSE91061")
```



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

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

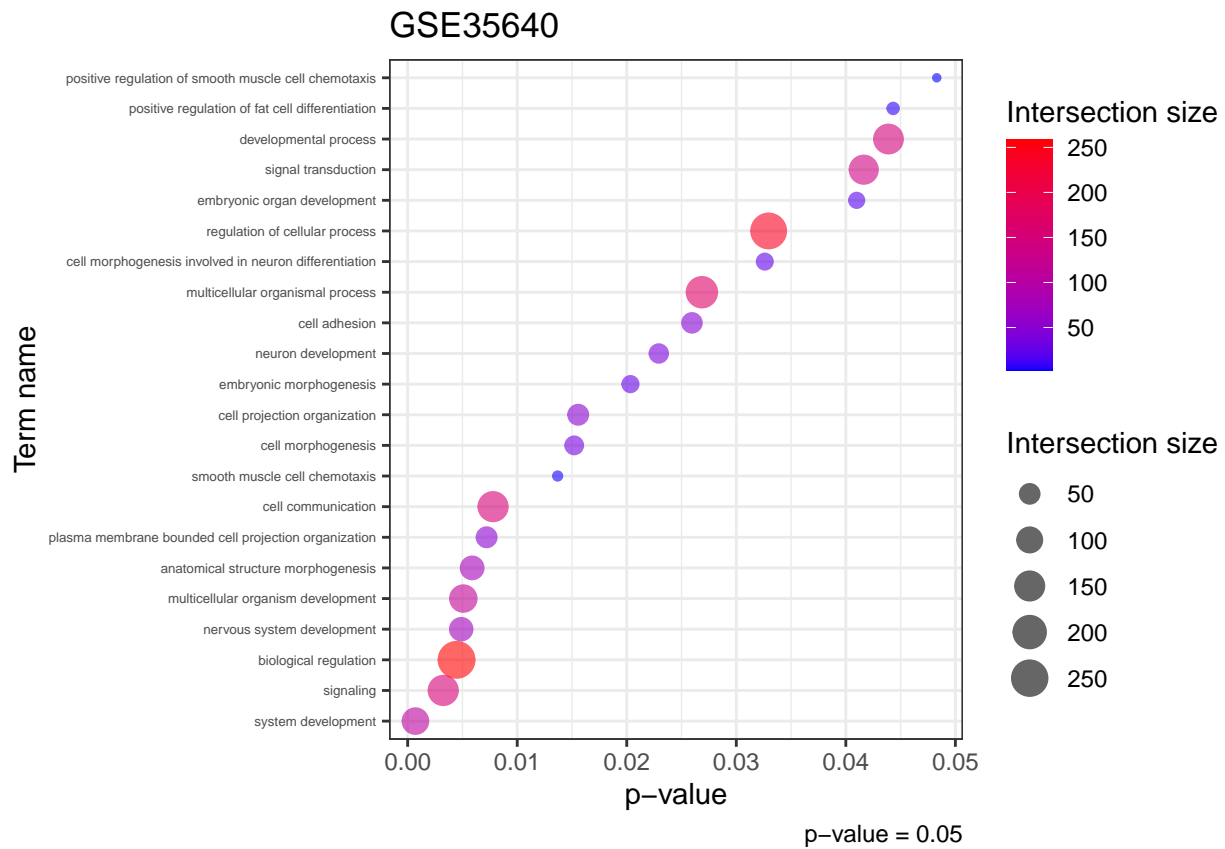
```
plot_gobps(study = "GSE61992")
```



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

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

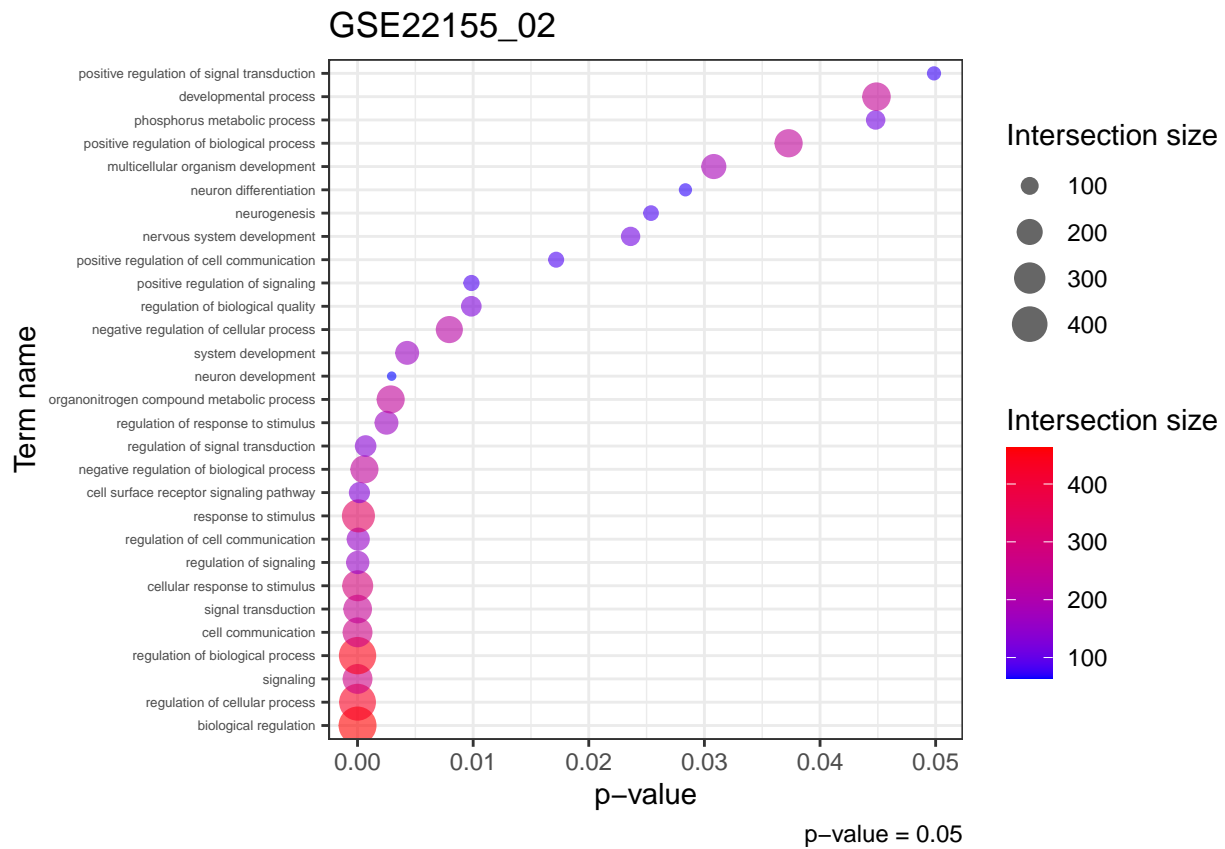
```
plot_gobps(study = "GSE35640")
```



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

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

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

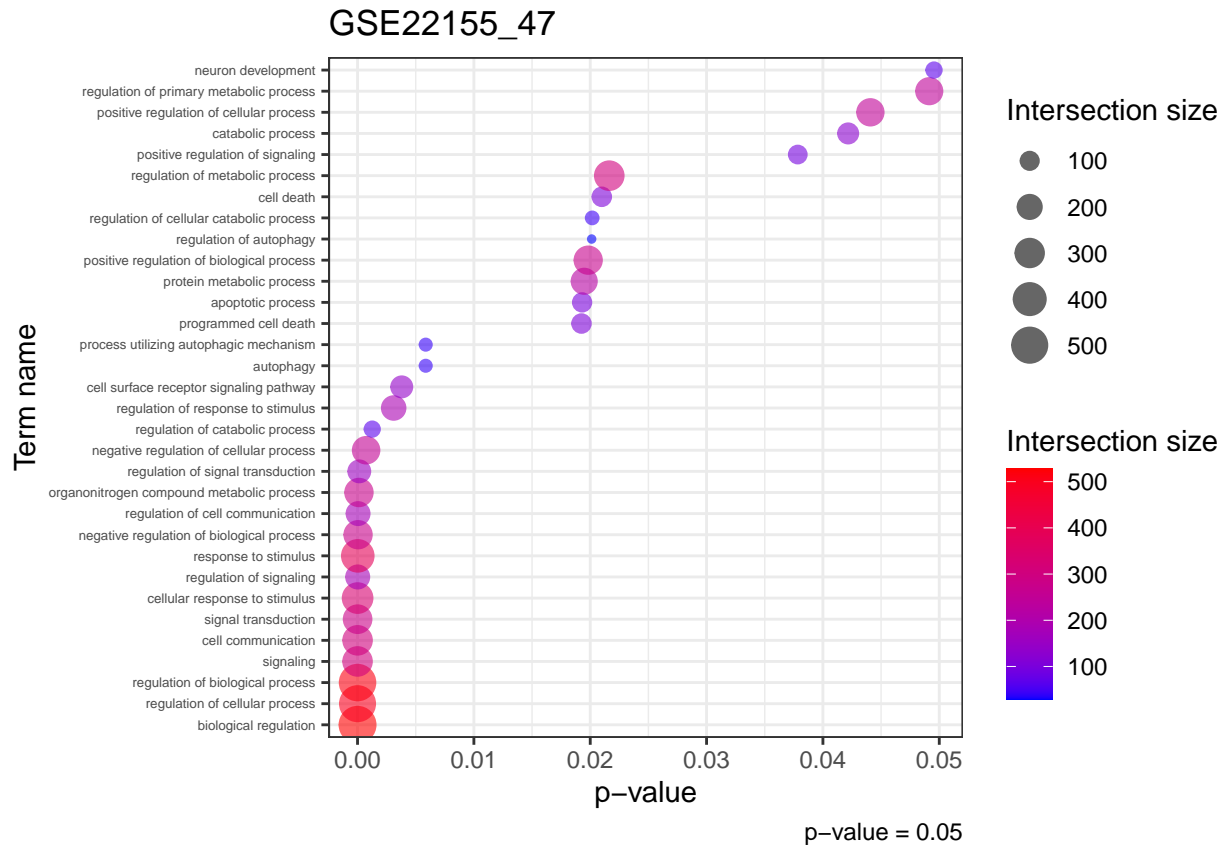


```
print("\n")
```

```
## [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("GSE91061" = jVenn_Bcells$GSE91061[which(is.na(jVenn_Bcells$GSE91061) == F)],
                                   "GSE61992" = jVenn_Bcells$GSE61992[which(is.na(jVenn_Bcells$GSE61992) == F)]),
                      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	1.578067e-03	3855	122	45
## 2	GSE61992	TRUE	2.577132e-11	12345	123	107
## 3	GSE61992	TRUE	7.833757e-07	4777	123	56
## 4	GSE61992	TRUE	1.267838e-04	5487	123	56
## 5	GSE61992	TRUE	1.862430e-04	2055	123	30
## 6	GSE61992	TRUE	2.349428e-04	1521	123	25
##	precision					
## 1	0.3688525					
## 2	0.8699187					
## 3	0.4552846					
## 4	0.4552846					
## 5	0.2439024					

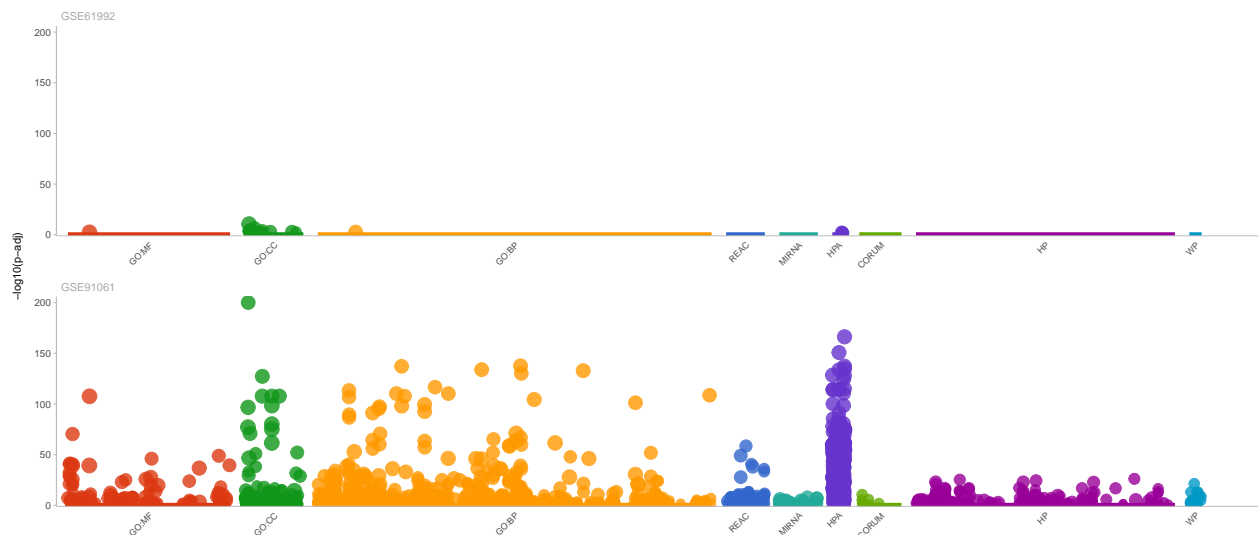
```
## 6 0.2032520
```

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_Bcells_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)

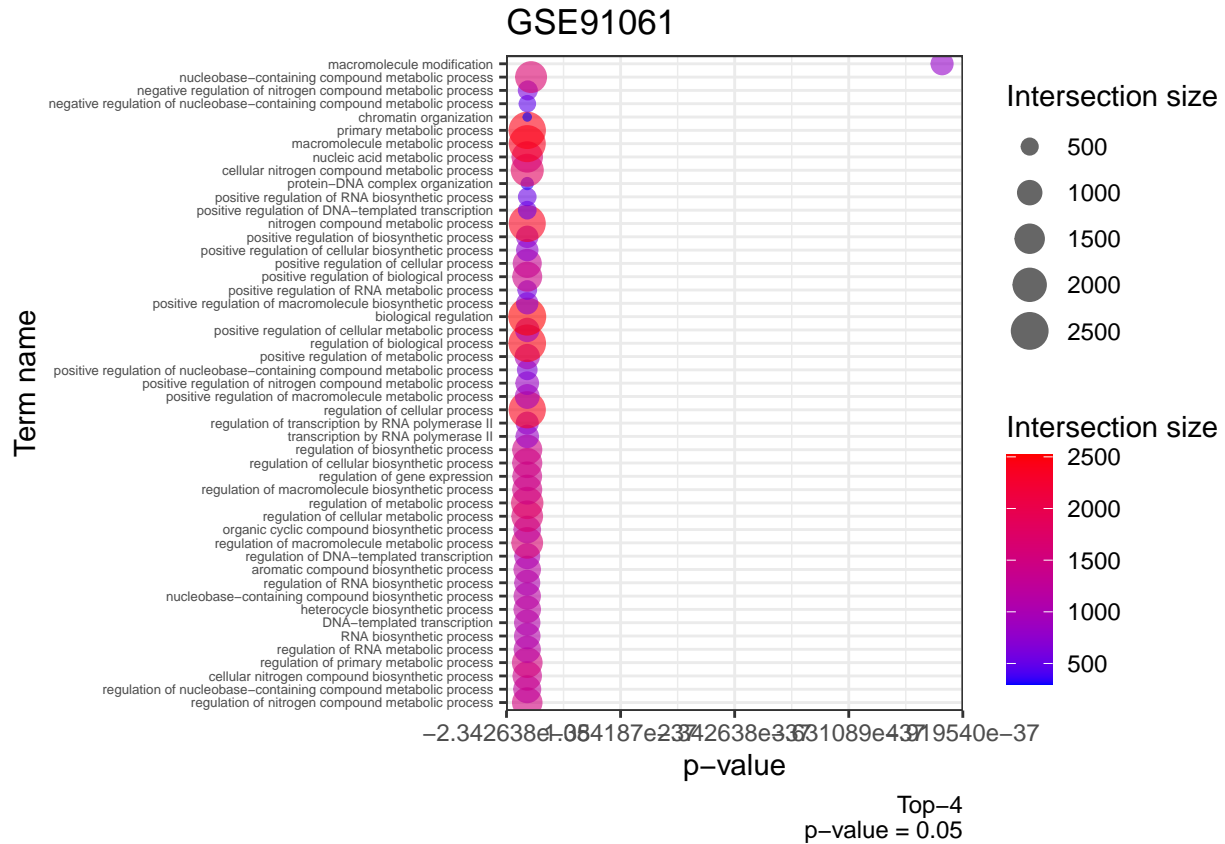
##
## GSE61992 GSE91061
##      17      1571

write.table(gem, file = "./Treatment_comparisons/gProfiler_Bcells_Only_genesets.txt", sep = "\t", quote = F)

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",]
```

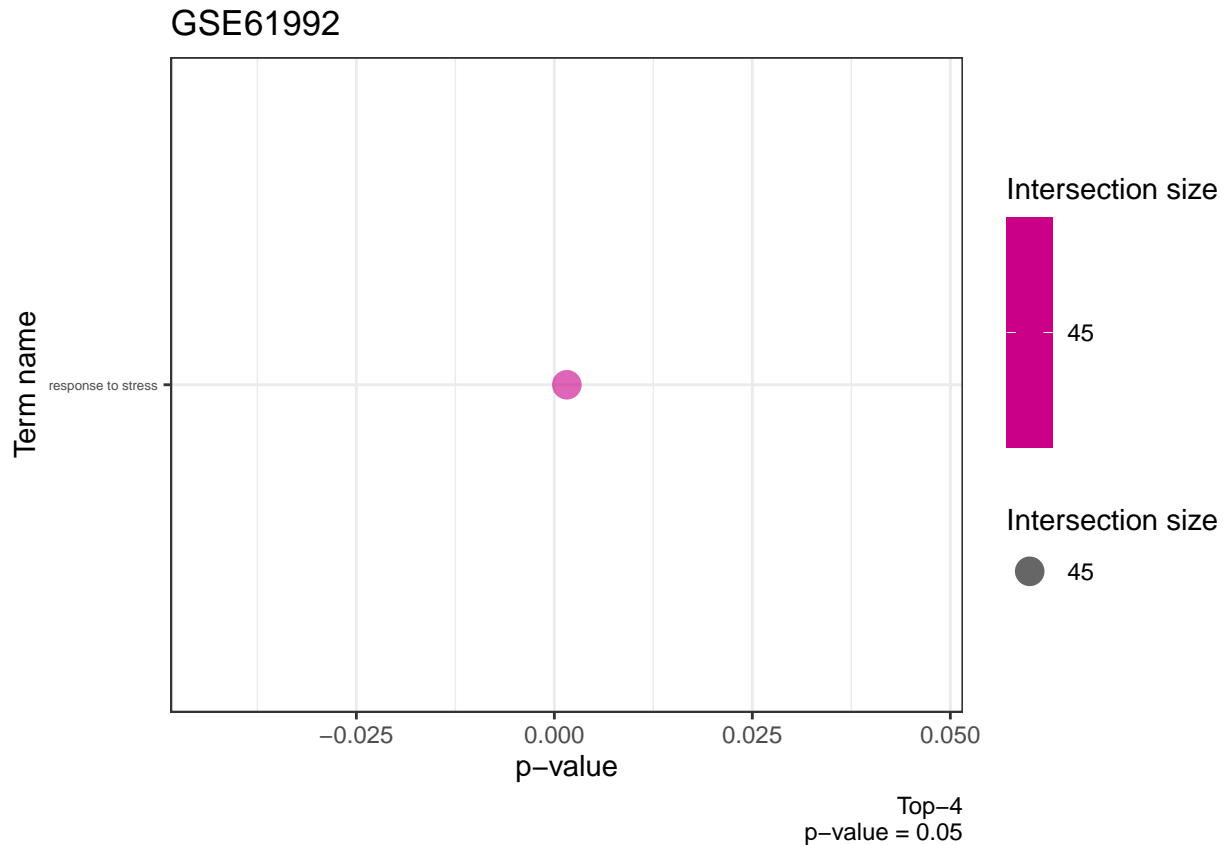
```
df2 <- df2[1:50,]
plot_gobps(study = "GSE91061")
```



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

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

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



## 6 Máximo solapamiento

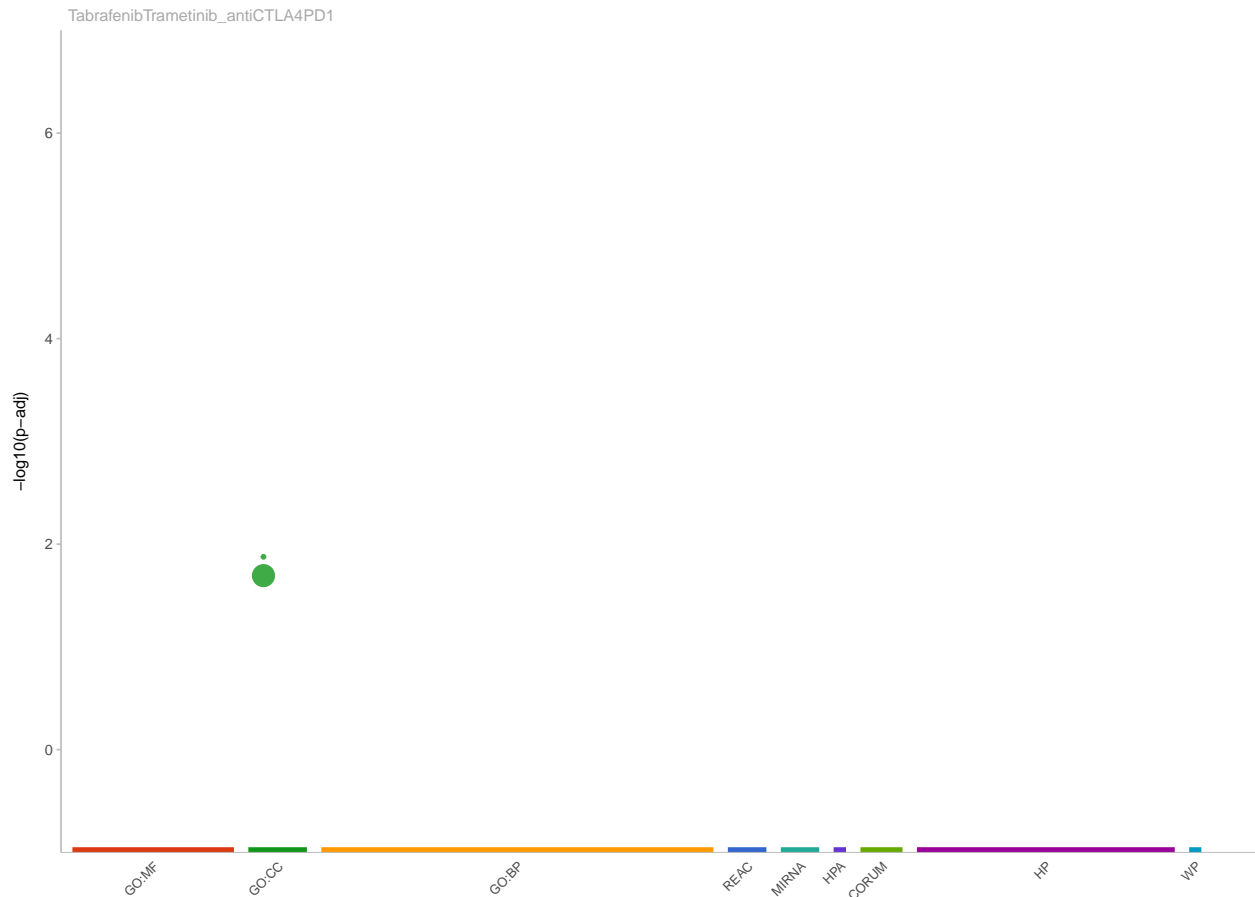
En esta sección analizo los DEGs que más se comparten entre los estudios para observar los mecanismos que pudieran haber en común entre los tratamientos.

Primero realizo el pathway multianálisis:

```
multi_gostres <- gost(query = list(
  "TabrafenibTrametinib_antiCTLA4PD1" =
    jVenn_Bcells$`GSE91061|GSE61992`[which(is.na(jVenn_Bcells$`GSE91061|GSE61992`)==F)]
),
  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
## 1 TabrafenibTrametinib_antiCTLA4PD1      TRUE 0.01328509         9         30
## 2 TabrafenibTrametinib_antiCTLA4PD1      TRUE 0.02026241        11         30
##   intersection_size precision
## 1                   2 0.06666667
## 2                   2 0.06666667
```

```
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("./Treatment_comparisons/gProfiler_Bcells_maxOverlap_geneset_", unique(.y),
        sep = "\t", quote = F, row.names = F))
```

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$query)
gem2 <- gem[grepl("GO", gem$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_Bcells_maxOverlap_geneset_TabrafenibTrametinib_antiCTLA4PD1"))
plot_gobps("TabrafenibTrametinib_antiCTLA4PD1")
dev.off()

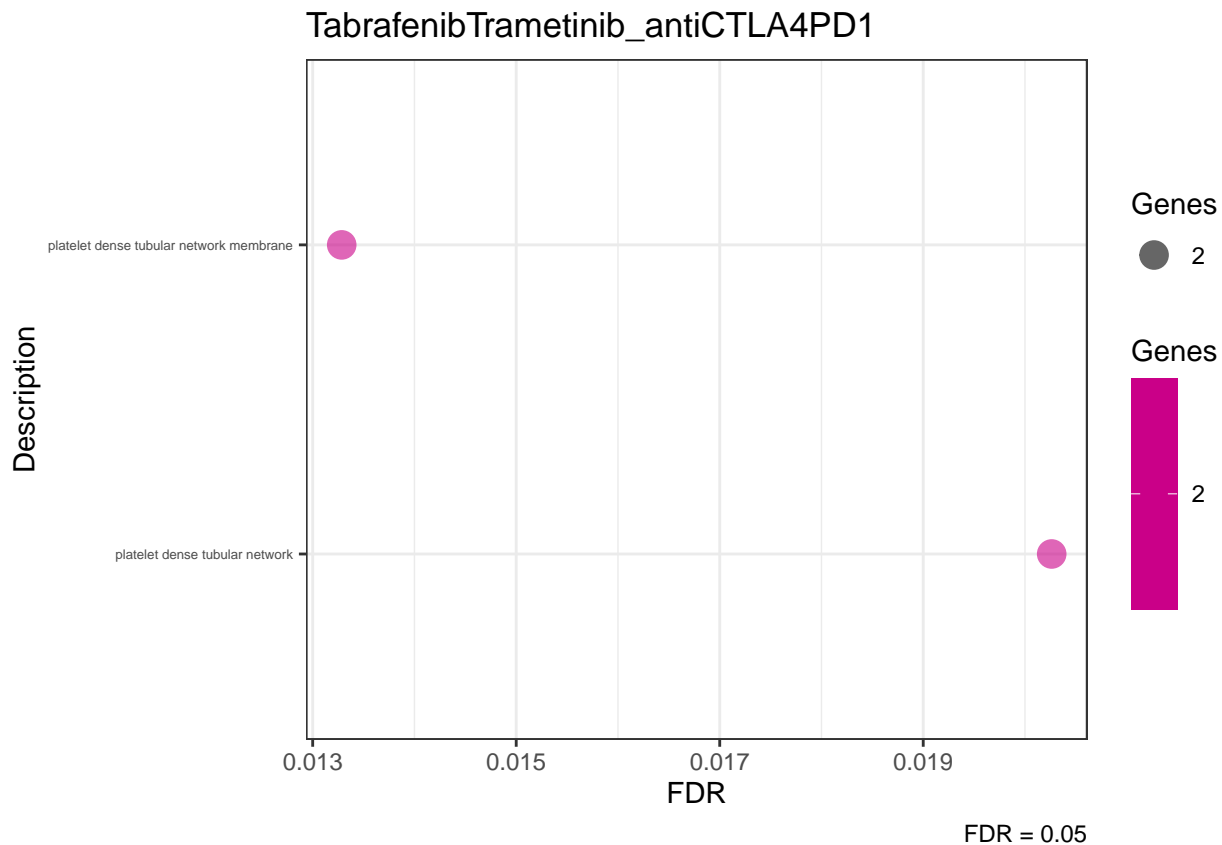
```

```

## pdf
## 2

```

```
plot_gobps("TabrafenibTrametinib_antiCTLA4PD1")
```



```

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_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 = "FDR = 0.05") +
  scale_color_gradient(low="blue", high="red")
}
plot_gobps(study = "TabrafenibTrametinib_antiCTLA4PD1")

```

TabrafenibTrametinib\_antiCTLA4PD1

Term name

p-value

p-value = 0.05