## Fabricio Almeida-Silva

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```
library(here)
## here() starts at /home/faalm/Dropbox/Working_from_home/polyploid_GRNs
library(magrene)
library(tidyverse)
## -- Attaching packages ------ tidyverse 1.3.1 --
## v ggplot2 3.3.6 v purrr 0.3.4
## v tibble 3.1.7 v dplyr 1.0.9
## v tidyr 1.2.0 v stringr 1.4.0
## v readr 2.1.2 v forcats 0.5.1
## -- Conflicts ------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
library(BioNERO)
##
## Attaching package: 'BioNERO'
## The following object is masked from 'package:tidyr':
     replace_na
library(ComplexHeatmap)
## Loading required package: grid
## ==========
## ComplexHeatmap version 2.12.0
## Bioconductor page: http://bioconductor.org/packages/ComplexHeatmap/
## Github page: https://github.com/jokergoo/ComplexHeatmap
## Documentation: http://jokergoo.github.io/ComplexHeatmap-reference
## If you use it in published research, please cite:
## Gu, Z. Complex heatmaps reveal patterns and correlations in multidimensional
## genomic data. Bioinformatics 2016.
## The new InteractiveComplexHeatmap package can directly export static
## complex heatmaps into an interactive Shiny app with zero effort. Have a try!
## This message can be suppressed by:
## suppressPackageStartupMessages(library(ComplexHeatmap))
set.seed(123)
dup_palette <- c(SSD = "#1984c5", WGD = "#ffb400")
```

## 1 Overview

Here, we will describe the code to perform enrichment analyses to go deeper into the functions of genes in motifs. We will target motifs types differently:

- V and bifan motifs: enrichment for TF families using all TFs in the GRN as background;
- Lambda, delta, and bifan motifs: functional enrichment (GO and InterPro terms) using all targets in the GRN as background.

## 2 Enrichment analysis

Let's start by loading the required data.

```
# Load annotation
load(here("data", "functional_annotation.rda"))
# Load TFs
load(here("data", "tfs.rda"))
# Load GRN
load(here("products", "result_files", "grns.rda"))
## Create a list of TFs and targets for each GRN to use as
## background
bg_tfs <- lapply(grns, function(x) {</pre>
    return(unique(x$Node1))
bg_targets <- lapply(grns, function(x) {</pre>
    return(unique(x$Node2))
})
rm(grns)
# Load motifs
species <- names(functional_annotation)</pre>
files <- here("products", "result_files", "motifs", paste0("motifs_",</pre>
    tolower(species), ".rda"))
for (s in files) {
    load(s)
}
# Combine motifs for each species in a single object
motifs <- list(Athaliana = motifs_athaliana, Gmax = motifs_gmax,</pre>
    Ptrichocarpa = motifs_ptrichocarpa, Slycopersicum = motifs_slycopersicum,
    Vvinifera = motifs_vvinifera, Osativa = motifs_osativa, Zmays = motifs_zmays)
rm(motifs_athaliana)
rm(motifs_gmax)
rm(motifs_ptrichocarpa)
rm(motifs_slycopersicum)
rm(motifs_vvinifera)
rm(motifs_osativa)
rm(motifs_zmays)
```

To make it easier, let's define wrapper functions around BioNERO::enrichment\_analysis() that perform the enrichment analysis for each species and peak.

```
# Perform SEA and add columns with info on class, mode,
# motif, and peak
enrichment <- function(genes, background, annot, mode = NULL,
    motif = NULL, peak = NULL) {</pre>
```

```
if (is(annot, "data.frame")) {
        class <- names(annot)[2]</pre>
        enrich <- BioNERO::enrichment_analysis(genes, background,</pre>
             annot, column = class)
        if (!is.null(enrich)) {
             enrich$Class <- class</pre>
             enrich$Mode <- mode
             enrich$Motif <- motif</pre>
             if (!is.null(peak)) {
                 enrich$Peak <- peak
             }
        }
    } else {
        classes <- c("GOBP", "GOMF", "InterPro")</pre>
        enrich <- lapply(classes, function(x) {</pre>
             annot_df <- annot[[x]]</pre>
             col <- names(annot_df)[2]</pre>
             res <- BioNERO::enrichment_analysis(genes, background,</pre>
                 annot_df, column = col)
             if (!is.null(res)) {
                 res$Class <- x
                 res$Mode <- mode
                 res$Motif <- motif
                 if (!is.null(peak)) {
                   res$Peak <- peak
                 }
             }
             return(res)
        })
        enrich <- Reduce(rbind, enrich)</pre>
    return(enrich)
}
# Perform SEA for each species, by peak and mode
sea <- function(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    species) {
    # Iterate through each species
    enrichment_res <- Reduce(rbind, lapply(species, function(x) {</pre>
        message("Working on species ", x)
        # Functional annotation and TFs
        annot <- annot_list[[x]]</pre>
        tf <- tf_list[[x]]</pre>
        # Background genes
        background_targets <- bg_targets[[x]]</pre>
        background_tfs <- bg_tfs[[x]]</pre>
```

```
peaks <- names(motifs[[x]])</pre>
# Iterate through each peak
bypeak <- Reduce(rbind, lapply(peaks, function(y) {</pre>
    message("Peak: ", y)
    events <- c("WGD", "SSD")</pre>
    byevent <- Reduce(rbind, lapply(events, function(z) {</pre>
        message("Mode: ", z)
        \# legend: x = species; y = peak; z = mode
        motif_vec <- motifs[[x]][[y]][[z]]</pre>
        # V motifs
        v_genes <- unique(gsub("->.*", "", gsub(".*<-",</pre>
          "", motif_vec$V)))
        v_sea <- enrichment(v_genes, background_tfs,</pre>
          tf, z, "V", y)
        # Bifan motifs - TF
        bifan_tf <- gsub("->.*", "", motif_vec$bifan)
        bifan_tf <- unique(unlist(strsplit(bifan_tf,
          ",")))
        bifan_sea_tf <- NULL
        if (length(bifan_tf) != 0) {
          bifan_sea_tf <- enrichment(bifan_tf, background_tfs,
            tf, z, "bifan", y)
        }
        # Bifan motifs - target
        bifan_genes <- gsub(".*->", "", motif_vec$bifan)
        bifan_genes <- unique(unlist(strsplit(bifan_genes,</pre>
          ",")))
        bifan_sea_tar <- NULL</pre>
        if (length(bifan_genes) != 0) {
          bifan_sea_tar <- enrichment(bifan_genes, background_targets,</pre>
            annot, z, "bifan", y)
        }
        # Lambda
        lambda_genes <- gsub("<-.*->", ",", motif_vec$lambda)
        lambda_genes <- unique(unlist(strsplit(lambda_genes,</pre>
          ",")))
        lambda_sea <- NULL</pre>
        if (length(lambda_genes) != 0) {
          lambda_sea <- enrichment(lambda_genes, background_targets,</pre>
            annot, z, "lambda", y)
        }
        # Delta
        delta_genes <- gsub("<-.*->", ",", motif_vec$delta)
        delta_genes <- unique(unlist(strsplit(delta_genes,</pre>
          ",")))
```

```
delta_sea <- NULL
                 if (length(delta_genes) != 0) {
                   delta_sea <- enrichment(delta_genes, background_targets,</pre>
                     annot, z, "delta", y)
                 }
                 # Combine results in a single data frame
                 sea_final <- rbind(v_sea, bifan_sea_tf, bifan_sea_tar)</pre>
                 return(sea_final)
            }))
             return(byevent)
        }))
        if (!is.null(bypeak)) {
             bypeak$Species <- x
        }
         return(bypeak)
    }))
    return(enrichment_res)
}
# Broader SEA, not filtered by peak
sea_global <- function(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, species) {
    # Iterate through each species
    enrichment_res <- Reduce(rbind, lapply(species, function(x) {</pre>
        message("Working on species ", x)
        # Functional annotation and TFs
        annot <- annot_list[[x]]</pre>
        tf <- tf_list[[x]]
        # Background genes
        background_targets <- bg_targets[[x]]</pre>
        background_tfs <- bg_tfs[[x]]</pre>
        # Create a list of motifs by mode (WGD and SSD),
        # combining peaks
        peaks <- names(motifs[[x]])</pre>
        genes_wgd <- unlist(lapply(peaks, function(y) {</pre>
            motif_vec <- motifs[[x]][[y]]$WGD</pre>
             return(motif_vec)
        }), recursive = FALSE)
        genes_wgd <- sapply(unique(names(genes_wgd)), function(x) {</pre>
             return(unname(unlist(genes_wgd[names(genes_wgd) ==
                 x])))
        }, simplify = FALSE)
        genes_ssd <- unlist(lapply(peaks, function(y) {</pre>
            motif_vec <- motifs[[x]][[y]]$SSD</pre>
             return(motif_vec)
```

```
}), recursive = FALSE)
genes_ssd <- sapply(unique(names(genes_ssd)), function(x) {</pre>
    return(unname(unlist(genes_ssd[names(genes_ssd) ==
        x])))
}, simplify = FALSE)
mlist <- list(WGD = genes_wgd, SSD = genes_ssd)</pre>
# Iterate through `mlist` and perform SEA by mode
events <- c("WGD", "SSD")</pre>
byevent <- Reduce(rbind, lapply(events, function(z) {</pre>
    message("Mode: ", z)
    motif_vec <- mlist[[z]]</pre>
    # V motifs
    v_genes <- unique(gsub("->.*", "", gsub(".*<-", "",</pre>
        motif_vec$V)))
    v_sea <- enrichment(v_genes, background_tfs, tf,</pre>
        z, "V", y)
    # Bifan motifs - TF
    bifan_tf <- gsub("->.*", "", motif_vec$bifan)
    bifan_tf <- unique(unlist(strsplit(bifan_tf, ",")))</pre>
    bifan_sea_tf <- NULL
    if (length(bifan_tf) != 0) {
        bifan_sea_tf <- enrichment(bifan_tf, background_tfs,</pre>
          tf, z, "bifan", y)
    }
    # Bifan motifs - target
    bifan_genes <- gsub(".*->", "", motif_vec$bifan)
    bifan_genes <- unique(unlist(strsplit(bifan_genes,</pre>
        ",")))
    bifan_sea_tar <- NULL
    if (length(bifan_genes) != 0) {
        bifan_sea_tar <- enrichment(bifan_genes, background_targets,</pre>
           annot, z, "bifan", y)
    }
    # Lambda
    lambda_genes <- gsub("<-.*->", ",", motif_vec$lambda)
    lambda_genes <- unique(unlist(strsplit(lambda_genes,</pre>
        ",")))
    lambda_sea <- NULL</pre>
    if (length(lambda_genes) != 0) {
        lambda_sea <- enrichment(lambda_genes, background_targets,</pre>
           annot, z, "lambda", y)
    }
    # Delta
    delta_genes <- gsub("<-.*->", ",", motif_vec$delta)
    delta_genes <- unique(unlist(strsplit(delta_genes,</pre>
```

```
",")))
            delta_sea <- NULL
            if (length(delta_genes) != 0) {
                 delta_sea <- enrichment(delta_genes, background_targets,</pre>
                   annot, z, "delta", y)
            }
            # Combine results in a single data frame
            sea_final <- rbind(v_sea, bifan_sea_tf, bifan_sea_tar)</pre>
            return(sea_final)
        }))
        return(byevent)
    }))
    if (!is.null(enrichment_res)) {
        enrichment_res$Species <- x
    return(enrichment_res)
}
```

Now, let's perform the SEA for each species.

```
annot_list <- functional_annotation
tf_list <- tfs
# Performing SEA for each species
sea_ath <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    "Athaliana")
sea_gma <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
sea_ptr <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    "Ptrichocarpa")
sea_sly <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    "Slycopersicum")
sea_vvi <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    "Vvinifera")
sea_osa <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    "Osativa")
sea_zma <- sea(motifs, annot_list, tf_list, bg_targets, bg_tfs,</pre>
    "Zmays")
sea_by_peak <- rbind(sea_ath, sea_gma, sea_sly, sea_vvi, sea_osa,</pre>
    sea_zma)
sea_by_peak$GeneID <- NULL</pre>
readr::write_tsv(sea_by_peak, file = here("products", "tables",
    "motif_functional_enrichment_by_peak.tsv"))
```

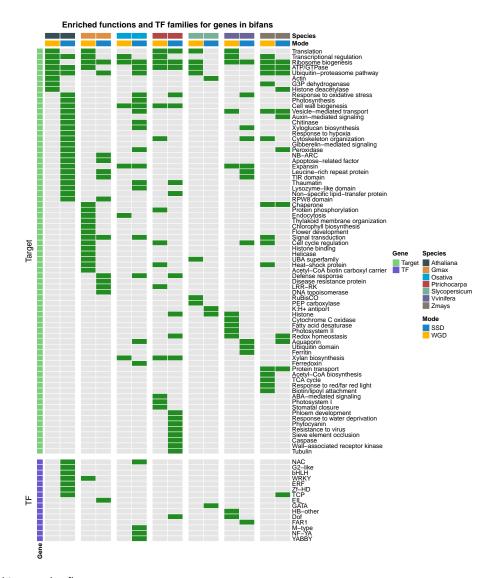
To conclude, let's perform another SEA, but not by peak. Here, we will only perform the SEA for WGD- and SSD- derived gene pairs in motifs.

```
# Perform global SEA
seag_ath <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, "Athaliana")
seag_gma <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bq_tfs, "Gmax")
seag_ptr <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, "Ptrichocarpa")
seag_sly <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, "Slycopersicum")
seag_vvi <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, "Vvinifera")
seag_osa <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, "Osativa")
seag_zma <- sea_global(motifs, annot_list, tf_list, bg_targets,</pre>
    bg_tfs, "Zmays")
# Combine results into a single data frame
sea_combined <- rbind(seag_ath %>%
    mutate(Species = "Athaliana"), seag_gma %>%
    mutate(Species = "Gmax"), seag_sly %>%
    mutate(Species = "Slycopersicum"), seag_vvi %>%
    mutate(Species = "Vvinifera"), seag_osa %>%
    mutate(Species = "Osativa"), seag_zma %>%
    mutate(Species = "Zmays"), seag_ptr %>%
    mutate(Species = "Ptrichocarpa"))
sea_combined$GeneID <- NULL</pre>
sea_combined$Peak <- NULL</pre>
readr::write_tsv(sea_combined, file = here("products", "tables",
    "motif_functional_enrichment_by_mode.tsv"))
```

After manual inspection of the enrichment results, I created the table *summa-rized\_functional\_enrichment\_of\_motifs.csv*, which contains summarized enrichment results for visual exploration. One important thing to observe is that the only class of motifs with enriched functions/TF families was bifans.

To conclude, let's visualize enrichment results as a presence/absence heatmap.

```
# colors Column annotation: species, mode
annotation_col <- data.frame(row.names = colnames(pav), Mode = gsub(".*_",
    "", colnames(pav)), Species = gsub("_.*", "", colnames(pav)))
## Row annotation: gene type (TF or target)
c <- sum_enrich %>%
    dplyr::select(Class, Motif) %>%
    distinct() %>%
    as.data.frame()
annotation_row <- data.frame(row.names = c$Class, Gene = c$Motif)
annotation_row$Gene <- gsub("Targets", "Target", annotation_row$Gene)</pre>
## Annotation colors
annotation_colors <- list(Mode = dup_palette, Species = c(Athaliana = "#374E55FF",
    Gmax = "#DF8F44FF", Osativa = "#00A1D5FF", Ptrichocarpa = "#B24745FF",
    Slycopersicum = "#79AF97FF", Vvinifera = "#6A6599FF", Zmays = "#80796BFF"),
    Gene = c(TF = "slateblue3", Target = "palegreen3"))
# Plot heatmap
p_heatmap <- ComplexHeatmap::pheatmap(pav, name = "Presence/absence",</pre>
    main = "Enriched functions and TF families for genes in bifans",
    cluster_rows = FALSE, cluster_cols = FALSE, annotation_col = annotation_col,
    annotation_row = annotation_row, labels_col = rep("", ncol(pav)),
    annotation_colors = annotation_colors, column_split = annotation_col$Species,
    row_split = annotation_row$Gene, row_gap = unit(3, "mm"),
    column_gap = unit(3, "mm"), color = c("grey90", "forestgreen"),
    border_color = "white", legend = FALSE)
p_heatmap
```



By looking at the figure, we can see some patterns:

- SSD-derived genes in bifans are enriched in stress-related genes. These include genes involved in response to oxidative stress, response to hypoxia, and different classes of pathogenesis-related proteins, such as chitinases and lysozymes, peroxidases, and thaumatins. There are also leucine-rich repeat receptor kinases, TIR domains, and wall-associated kinases.
- Overall, only SSD-derived genes were enriched in particular TF families. Although WGD-derived tend to be retained more often than SSD-derived genes, WGD-derived genes in bifans were not enriched in any specific TF family.
- SSD-derived genes are enriched in stress-related transcription factor families, such as NAC, G2-like, bHLH, WRKY, and ERF. This is in line with previous observations that stress-related TFs tend to be duplicated by tandem duplications. This mechanism is likely adaptive, as genes in tandem tend to be co-regulated. Then, keeping stressrelated genes in tandem arrays would ensure that they are coordinately activated.

WGD-derived genes in bifans are enriched in processes such as translation, flower development, transcriptional regulation, histone modifications, photosynthesis-related processes (e.g., chlorophyll biosynthesis, thylakoid membrane organization, RuBisCO, and photosystem I formation), cell cycle regulation, and carbohydrate and lipid metabolism.

```
# Save heatmap as PDF
pdf(file = here("products", "plots", "heatmap_motif_functional_enrichment.pdf"),
    width = 10, height = 12)
p_heatmap
dev.off()
```

## Session info

This document was created under the following conditions:

```
sessioninfo::session_info()
## - Session info -----
## setting value
## version R version 4.2.1 (2022-06-23)
## os Ubuntu 20.04.4 LTS
## system x86_64, linux-qnu
## ui X11
   language (EN)
## collate en_US.UTF-8
## ctype en_US.UTF-8
## tz Europe/Brussels
## date 2022-08-12
## pandoc 2.18 @ /usr/lib/rstudio/bin/quarto/bin/tools/ (via rmarkdown)
##
## package * version date (UTC) lib source
2022-06-15 [1] Github (Bioconductor/BiocStyle@7150c28)
## BioNERO
                      * 1.4.0 2022-04-26 [1] Bioconductor
                    2.64.0 2022-04-26 [1] Bioconductor
4.0.4 2020-08-04 [1] CRAN (R 4.2.0)
4.0.5 2020-08-30 [1] CRAN (R 4.2.0)
1.0-7 2021-04-24 [1] CRAN (R 4.2.0)
1.2.3 2022-04-10 [1] CRAN (R 4.2.0)
0.27 2022-06-14 [1] CRAN (R 4.2.0)
0.8.0 2022-04-13 [1] CRAN (R 4.2.0)
## Biostrings
## bit
## bit64
## bitops
## blob
## bookdown
## broom
```

##	cachem		1.0.6	2021-08-19	[1]	CRAN (R 4.2.0)
##	car		3.1-0	2022-06-15	[1]	CRAN (R 4.2.0)
##	carData		3.0-5	2022-01-06	[1]	CRAN (R 4.2.0)
##	cellranger		1.1.0	2016-07-27	[1]	CRAN (R 4.2.0)
##	checkmate		2.1.0	2022-04-21	[1]	CRAN (R 4.2.0)
##	circlize		0.4.15	2022-05-10	[1]	CRAN (R 4.2.0)
##	cli		3.3.0	2022-04-25	[1]	CRAN (R 4.2.0)
##	clue		0.3-61	2022-05-30	[1]	CRAN (R 4.2.0)
##	cluster		2.1.3	2022-03-28	[1]	CRAN (R 4.2.0)
##	coda		0.19-4	2020-09-30	[1]	CRAN (R 4.2.0)
##	codetools		0.2-18	2020-11-04	[1]	CRAN (R 4.2.0)
##	colorspace		2.0-3	2022-02-21	[1]	CRAN (R 4.2.0)
##	ComplexHeatmap	*	2.12.0	2022-04-26	[1]	Bioconductor
##	crayon		1.5.1	2022-03-26	[1]	CRAN (R 4.2.0)
##	data.table		1.14.2	2021-09-27	[1]	CRAN (R 4.2.0)
##	DBI		1.1.3	2022-06-18	[1]	CRAN (R 4.2.0)
##	dbplyr		2.2.1	2022-06-27	[1]	CRAN (R 4.2.1)
##	DelayedArray		0.22.0	2022-04-26	[1]	Bioconductor
##	DESeq2		1.36.0	2022-04-26	[1]	Bioconductor
##	digest		0.6.29	2021-12-01	[1]	CRAN (R 4.2.0)
##	doParallel		1.0.17	2022-02-07	[1]	CRAN (R 4.2.0)
##	dplyr	*	1.0.9	2022-04-28	[1]	CRAN (R 4.2.0)
##	dynamicTreeCut		1.63-1	2016-03-11	[1]	CRAN (R 4.2.0)
##	edgeR		3.38.1	2022-05-15	[1]	Bioconductor
##	ellipsis		0.3.2	2021-04-29	[1]	CRAN (R 4.2.0)
##	evaluate		0.15	2022-02-18	[1]	CRAN (R 4.2.0)
##	fansi		1.0.3	2022-03-24	[1]	CRAN (R 4.2.0)
##	fastcluster		1.2.3	2021-05-24	[1]	CRAN (R 4.2.0)
##	fastmap		1.1.0	2021-01-25	[1]	CRAN (R 4.2.0)
##			0.5.1	2021-01-27	[1]	CRAN (R 4.2.0)
##	foreach		1.5.2	2022-02-02	[1]	CRAN (R 4.2.0)
##	foreign		0.8-82	2022-01-13	[1]	CRAN (R 4.2.0)
##	formatR		1.12			CRAN (R 4.2.0)
##	Formula		1.2-4			CRAN (R 4.2.0)
##	fs		1.5.2			CRAN (R 4.2.0)
##	genefilter		1.78.0	2022-04-26	[1]	Bioconductor
##	geneplotter		1.74.0			Bioconductor
##	generics		0.1.2			CRAN (R 4.2.0)
##	GENIE3		1.18.0			Bioconductor
##	GenomeInfoDb		1.32.2			Bioconductor
##	GenomeInfoDbData		1.2.8			Bioconductor
##	GenomicRanges		1.48.0			Bioconductor
##	GetoptLong		1.0.5			CRAN (R 4.2.0)
##	ggnetwork		0.5.10			CRAN (R 4.2.0)
##	ggnewscale		0.4.7			CRAN (R 4.2.0)
##	331		3.3.6			CRAN (R 4.2.0)
##	ggpubr		0.4.0			CRAN (R 4.2.0)
##	ggsignif		0.6.3			CRAN (R 4.2.0)
##	GlobalOptions		0.1.2			CRAN (R 4.2.0)
##	glue		1.6.2			CRAN (R 4.2.0)
##	GO.db		3.15.0	2022-05-06	[1]	Bioconductor

##	gridExtra		2.3	2017-09-09	[1]	CRAN (R 4.2.0)
##	gtable		0.3.0	2019-03-25	[1]	CRAN (R 4.2.0)
##	haven		2.5.0	2022-04-15	[1]	CRAN (R 4.2.0)
##	here	*	1.0.1	2020-12-13	[1]	CRAN (R 4.2.0)
##	Hmisc		4.7-0	2022-04-19	[1]	CRAN (R 4.2.0)
##	hms		1.1.1	2021-09-26	[1]	CRAN (R 4.2.0)
##	htmlTable		2.4.0	2022-01-04	[1]	CRAN (R 4.2.0)
##	htmltools		0.5.2	2021-08-25	[1]	CRAN (R 4.2.0)
##	htmlwidgets		1.5.4	2021-09-08	[1]	CRAN (R 4.2.0)
##	httr		1.4.3	2022-05-04	[1]	CRAN (R 4.2.0)
##	igraph		1.3.2	2022-06-13	[1]	CRAN (R 4.2.0)
##	impute		1.70.0	2022-04-26	[1]	Bioconductor
##	intergraph		2.0-2	2016-12-05	[1]	CRAN (R 4.2.0)
##	IRanges		2.30.0	2022-04-26	[1]	Bioconductor
##	iterators		1.0.14	2022-02-05	[1]	CRAN (R 4.2.0)
##	jpeg		0.1-9	2021-07-24	[1]	CRAN (R 4.2.0)
##	jsonlite		1.8.0	2022-02-22	[1]	CRAN (R 4.2.0)
##	KEGGREST		1.36.2	2022-06-09	[1]	Bioconductor
##	knitr		1.39	2022-04-26	[1]	CRAN (R 4.2.0)
##	lattice		0.20-45	2021-09-22	[1]	CRAN (R 4.2.0)
##	latticeExtra		0.6-29	2019-12-19	[1]	CRAN (R 4.2.0)
##	lifecycle		1.0.1	2021-09-24	[1]	CRAN (R 4.2.0)
##	limma		3.52.2	2022-06-19	[1]	Bioconductor
##	locfit		1.5-9.5	2022-03-03	[1]	CRAN (R 4.2.0)
##	lubridate		1.8.0	2021-10-07	[1]	CRAN (R 4.2.0)
##	magick		2.7.3	2021-08-18	[1]	CRAN (R 4.2.0)
##	magrene	*	0.99.0	2022-07-27	[1]	Bioconductor
##	magrittr		2.0.3	2022-03-30	[1]	CRAN (R 4.2.0)
##	Matrix		1.4-1	2022-03-23	[1]	CRAN (R 4.2.0)
##	MatrixGenerics		1.8.1	2022-06-26	[1]	Bioconductor
##	matrixStats		0.62.0	2022-04-19	[1]	CRAN (R 4.2.0)
##	memoise		2.0.1	2021-11-26	[1]	CRAN (R 4.2.0)
##	mgcv		1.8-40	2022-03-29	[1]	CRAN (R 4.2.0)
##	minet		3.54.0	2022-04-26	[1]	Bioconductor
##	modelr		0.1.8	2020-05-19	[1]	CRAN (R 4.2.0)
##	munsell		0.5.0	2018-06-12	[1]	CRAN (R 4.2.0)
##	NetRep		1.2.4	2020-10-07	[1]	CRAN (R 4.2.0)
##	network		1.17.2	2022-05-21	[1]	CRAN (R 4.2.0)
##	networkD3				[1]	CRAN (R 4.2.0)
##	nlme		3.1-158	2022-06-15	[1]	CRAN (R 4.2.0)
##	nnet		7.3-17	2022-01-13	[1]	CRAN (R 4.2.0)
##	pillar		1.7.0	2022-02-01	[1]	CRAN (R 4.2.0)
##	pkgconfig		2.0.3			CRAN (R 4.2.0)
##	plyr		1.8.7	2022-03-24	[1]	CRAN (R 4.2.0)
##	png		0.1-7	2013-12-03	[1]	CRAN (R 4.2.0)
##	preprocessCore		1.58.0	2022-04-26	[1]	Bioconductor
##	purrr		0.3.4	2020-04-17	[1]	CRAN (R 4.2.0)
##	R6		2.5.1	2021-08-19	[1]	CRAN (R 4.2.0)
##	RColorBrewer		1.1-3			CRAN (R 4.2.0)
##	Rcpp					CRAN (R 4.2.0)
##	RCurl		1.98-1.7	2022-06-09	[1]	CRAN (R 4.2.0)

```
* 2.1.2 2022-01-30 [1] CRAN (R 4.2.0)
1.4.0 2022-03-28 [1] CRAN (R 4.2.0)
2.0.1 2021-08-05 [1] CRAN (R 4.2.0)
1.4.4 2020-04-09 [1] CRAN (R 4.2.0)
 ## readr
 ## readxl
 ## reprex
 ## reshape2
 ## RhpcBLASctl
                                             0.21-247.1 2021-11-05 [1] CRAN (R 4.2.0)
                                            0.2.21 2022-01-09 [1] CRAN (R 4.2.0)
1.0.3 2022-06-27 [1] CRAN (R 4.2.1)
2.14 2022-04-25 [1] CRAN (R 4.2.0)
 ## rjson
 ## rlang
 ## rmarkdown
                                         2.14 2022-04-25 [1] CRAN (R 4.2.0)
4.1.16 2022-01-24 [1] CRAN (R 4.2.0)
2.0.3 2022-04-02 [1] CRAN (R 4.2.0)
2.2.14 2022-05-07 [1] CRAN (R 4.2.0)
0.7.0 2021-02-13 [1] CRAN (R 4.2.0)
0.13 2020-11-12 [1] CRAN (R 4.2.0)
1.0.2 2021-10-16 [1] CRAN (R 4.2.0)
0.34.0 2022-04-26 [1] Bioconductor
 ## rpart
## rprojroot
 ## RSQLite
 ## rstatix
## rstudioapi
 ## rvest
 ## S4Vectors
## scales 1.2.0 2022-04-13 [1] CRAN (R 4.2.0)
## sessioninfo 1.2.2 2021-12-06 [1] CRAN (R 4.2.0)
## shape 1.4.6 2021-05-19 [1] CRAN (R 4.2.0)
## statmod 1.4.36 2021-05-10 [1] CRAN (R 4.2.0)
## statnet.common 4.6.0 2022-05-02 [1] CRAN (R 4.2.0)
## stringi 1.7.6 2021-11-29 [1] CRAN (R 4.2.0)
## stringr * 1.4.0 2019-02-10 [1] CRAN (R 4.2.0)
## SummarizedExperiment 1.26.1 2022-04-29 [1] Bioconductor
## survival 3.3-1 2022-03-03 [1] CRAN (R 4.2.0)
## sva 3.44.0 2022-04-26 [1] Bioconductor
                                         3.3-1 2022-03-03 [1] CRAN (R 4.2.0)
3.44.0 2022-04-26 [1] Bioconductor

* 3.1.7 2022-05-03 [1] CRAN (R 4.2.0)

* 1.2.0 2022-02-01 [1] CRAN (R 4.2.0)

1.1.2 2022-02-21 [1] CRAN (R 4.2.0)

* 1.3.1 2021-04-15 [1] CRAN (R 4.2.0)

0.3.0 2022-03-28 [1] CRAN (R 4.2.0)

1.2.2 2021-07-24 [1] CRAN (R 4.2.0)

0.4.1 2022-04-13 [1] CRAN (R 4.2.0)

1.5.7 2021-11-30 [1] CRAN (R 4.2.0)

1.71 2022-04-22 [1] CRAN (R 4.2.0)

2.5.0 2022-03-03 [1] CRAN (R 4.2.0)

0.31 2022-05-10 [1] CRAN (R 4.2.0)

3.99-0.10 2022-06-09 [1] CRAN (R 4.2.0)

1.3.3 2021-11-30 [1] CRAN (R 4.2.0)

1.8-4 2019-04-21 [1] CRAN (R 4.2.0)
 ## sva
 ## tibble
 ## tibble
## tidyr
 ## tidyselect
## tidyverse
 ## tzdb
 ## utf8
 ## vctrs
 ## vroom
 ## WGCNA
 ## withr
 ## xfun
 ## XML
 ## xml2
                                                   1.8-4 2019-04-21 [1] CRAN (R 4.2.0)
 ## xtable
                                         0.36.0 2022-04-26 [1] Bioconductor
2.3.5 2022-02-21 [1] CRAN (R 4.2.0)
 ## XVector
 ## yaml
                                  1.42.0 2022-04-26 [1] Bioconductor
 ## zlibbioc
 ##
 ## [1] /home/faalm/R/x86_64-pc-linux-gnu-library/4.2
 ## [2] /usr/local/lib/R/site-library
 ## [3] /usr/lib/R/site-library
 ## [4] /usr/lib/R/library
 ##
 ## ------
```