

# Supplementary Text S5: Runtime benchmark

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# 1 Introduction

---

Here, we will perform a runtime benchmark for functions related to duplicate classification and substitution rates calculation using model organisms.

To start, let's load the required data and packages.

```
set.seed(123) # for reproducibility

# Load required packages
library(doubletrouble)
library(here)
## here() starts at /home/faalm/Dropbox/package_benchmarks/doubletrouble_paper
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr   1.5.1
## v ggplot2    3.5.1      v tibble    3.2.1
## v lubridate  1.9.3      v tidyr     1.3.1
## v purrr      1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
library(patchwork)

source(here("code", "utils.R"))

# Load sample metadata for Ensembl instances
load(here("products", "result_files", "metadata_all.rda"))
```

## 2 Benchmark 1: `classify_gene_pairs()`

---

Here, we will benchmark the performance of `classify_gene_pairs()` with model organisms.

First, let's get the genome and annotation data.

```
# Create a data frame with names of model species and their Ensembl instances
model_species <- data.frame(
  species = c(
    "arabidopsis_thaliana", "caenorhabditis_elegans",
    "homo_sapiens", "saccharomyces_cerevisiae",
    "drosophila_melanogaster", "danio_rerio"
  ),
  instance = c(
    "plants", "metazoa", "ensembl", "fungi", "metazoa", "ensembl"
  )
)

# For each organism, download data, and identify and classify duplicates
model_duplicates <- lapply(seq_len(nrow(model_species)), function(x) {
```

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```
species <- model_species$species[x]
instance <- model_species$instance[x]

# Get annotation
annot <- get_annotation(model_species[x, ], instance)

# Get proteome and keep only primary transcripts
seq <- get_proteomes(model_species[x, ], instance)
seq <- filter_sequences(seq, annot)

# Process data
pdata <- syntenet::process_input(seq, annot, filter_annotation = TRUE)

# Perform DIAMOND search
outdir <- file.path(tempdir(), paste0(species, "_intra"))
diamond <- syntenet::run_diamond(
  seq = pdata$seq,
  compare = "intraspecies",
  outdir = outdir,
  threads = 4,
  ... = "--sensitive"
)

fs::dir_delete(outdir)

# Classify duplicates - standard mode
start <- Sys.time()
duplicate_pairs <- classify_gene_pairs(
  blast_list = diamond,
  annotation = pdata$annotation,
  scheme = "standard"
)[[1]]
end <- Sys.time()
runtime <- end - start

return(runtime)
})
names(model_duplicates) <- gsub("_", " ", str_to_title(model_species$species))

# Summarize results in a table
benchmark_classification <- data.frame(
  species = names(model_duplicates),
  time_seconds = as.numeric(unlist(model_duplicates))
)

# Save results
save(
  benchmark_classification, compress = "xz",
  file = here("products", "result_files", "benchmark_classification.rda")
)
```

### 3 Benchmark 2: `pairs2kaks()`

Next, we will benchmark the performance of `pairs2kaks()` for duplicate pairs in the *Saccharomyces cerevisiae* genome. We will do it using a single thread, and using parallelization (with 4 and 8 threads).

First of all, let's get the required data for `pairs2kaks()`.

```
# Load duplicate pairs for S. cerevisiae
load(here("products", "result_files", "fungi_duplicates.rda"))
scerevisiae_pairs <- fungi_duplicates["saccharomyces_cerevisiae"]

# Get CDS for S. cerevisiae
scerevisiae_cds <- get_cds_ensembl("saccharomyces_cerevisiae", "fungi")
```

Now, we can do the benchmark.

```
# 1 thread
start <- Sys.time()
kaks <- pairs2kaks(
  scerevisiae_pairs,
  scerevisiae_cds,
  threads = 1
)
end <- Sys.time()
runtime1 <- end - start

# 4 threads
start <- Sys.time()
kaks <- pairs2kaks(
  scerevisiae_pairs,
  scerevisiae_cds,
  threads = 4
)
end <- Sys.time()
runtime4 <- end - start

# 8 threads
start <- Sys.time()
kaks <- pairs2kaks(
  scerevisiae_pairs,
  scerevisiae_cds,
  threads = 8
)
end <- Sys.time()
runtime8 <- end - start

# Summarize results in a table
benchmark_kaks <- data.frame(
  Threads = factor(c(1, 4, 8)),
  Time_minutes = as.numeric(c(runtime1, runtime4, runtime8))
) |>
```

```
dplyr::mutate(
  Pairs_per_minute = nrow(scerevisiae_pairs[[1]]) / Time_minutes,
  Pairs_per_second = nrow(scerevisiae_pairs[[1]]) / (Time_minutes * 60)
)
save(
  benchmark_kaks, compress = "xz",
  file = here("products", "result_files", "benchmark_kaks.rda")
)
```

## 4 Benchmark 3: doubletrouble vs DupGen\_finder

Here, we will classify duplicate pairs in the *A. thaliana* genome using **doubletrouble** and DupGen\_finder to assess if they produce the same results, and compare their runtimes.

First, let's get all data we need (proteomes, annotation, and DIAMOND tables).

```
# Get annotation
smeta <- data.frame(
  species = c("arabidopsis_thaliana", "amborella_trichopoda"),
  instance = "plants"
)
annot <- get_annotation(smeta, "plants")

# Get proteome and keep only primary transcripts
seq <- get_proteomes(smeta, "plants")
seq <- filter_sequences(seq, annot)

# Process data
pdata <- syntenet::process_input(seq, annot, filter_annotation = TRUE)

# Run intraspecies DIAMOND search
outdir <- file.path(tempdir(), "benchmark3_intra")
diamond_intra <- syntenet::run_diamond(
  seq = pdata$seq,
  compare = "intraspecies",
  outdir = outdir,
  threads = 4,
  ... = "--sensitive"
)
fs::dir_delete(outdir)

# Run interspecies DIAMOND search
outdir2 <- file.path(tempdir(), "benchmark3_inter")
compare_df <- data.frame(
  query = "arabidopsis.thaliana", target = "amborella.trichopoda"
)

diamond_inter <- syntenet::run_diamond(
  seq = pdata$seq,
  compare = compare_df,
```

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```
outdir = outdir2,
threads = 4,
... = "--sensitive"
)
fs::dir_delete(outdir2)
```

Now, let's classify duplicates with **doubletrouble**.

```
# Classify duplicates with doubletrouble
start1 <- Sys.time()
dups1 <- classify_gene_pairs(
  blast_list = diamond_intra[2],
  annotation = pdata$annotation,
  blast_inter = diamond_inter,
  scheme = "extended",
  collinearity_dir = here("products")
)
end1 <- Sys.time()
runtime1 <- end1 - start1
```

Next, we will classify duplicates with DupGen\_finder. For that, we will first export input data in the required format.

```
# Export data
## .blast files
b1 <- diamond_intra$arabidopsis.thaliana_arabidopsis.thaliana |>
  mutate(
    query = str_replace_all(query, "^ara_", ""),
    db = str_replace_all(db, "^ara_", "")
  )

b2 <- diamond_inter$arabidopsis.thaliana_amborella.trichopoda |>
  mutate(
    query = str_replace_all(query, "^ara_", ""),
    db = str_replace_all(db, "^amb_", "")
  )

write_tsv(b1, file = file.path(tempdir(), "Ath.blast"), col_names = FALSE)
write_tsv(b2, file = file.path(tempdir(), "Ath_Atr.blast"), col_names = FALSE)

## .gff files
gff1 <- pdata$annotation$arabidopsis.thaliana |>
  as.data.frame() |>
  mutate(gene = str_replace_all(gene, "^ara_", "")) |>
  mutate(seqnames = str_replace_all(seqnames, "ara_", "ara-")) |>
  dplyr::select(seqnames, gene, start, end)

gff2 <- pdata$annotation$amborella.trichopoda |>
  as.data.frame() |>
  mutate(gene = str_replace_all(gene, "^amb_", "")) |>
  mutate(seqnames = str_replace_all(seqnames, "^amb_", "amb-")) |>
  dplyr::select(seqnames, gene, start, end)
```

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```
gff2 <- bind_rows(gff1, gff2)

write_tsv(gff1, file = file.path(tempdir(), "Ath.gff"), col_names = FALSE)
write_tsv(gff2, file = file.path(tempdir(), "Ath_Atr.gff"), col_names = FALSE)

# Classify duplicates with DupGen_finder
args = c(
  "-i", tempdir(), "-t Ath -c Atr",
  "-o", file.path(tempdir(), "results"),
  "-e 1e-10"
)

start2 <- Sys.time()
system2("DupGen_finder.pl", args = args)
end2 <- Sys.time()
runtime2 <- end2 - start2
```

Now, let's compare both algorithms in terms of runtime and results.

```
# Load `DupGen_finder.pl` results
files <- c(
  "Ath.wgd.pairs", "Ath.tandem.pairs", "Ath.proximal.pairs",
  "Ath.transposed.pairs", "Ath.dispersed.pairs"
)
files <- file.path(tempdir(), "results", files)
names(files) <- c("SD", "TD", "PD", "TRD", "DD")
dups2 <- Reduce(rbind, lapply(seq_along(files), function(x) {
  d <- read_tsv(files[x], show_col_types = FALSE) |>
    mutate(type = names(files)[x]) |>
    select(1, 3, type) |>
    as.data.frame()

  names(d)[c(1,2)] <- c("dup1", "dup2")

  return(d)
}))

# Compare runtime
comp_runtime <- data.frame(doubletrouble = runtime1, DupGen_finder = runtime2)

# Compare number of gene pairs per category
comp_results <- inner_join(
  count(dups1$arabidopsis.thaliana, type) |>
    dplyr::rename(n_doubletrouble = n),
  count(dups2, type) |>
    dplyr::rename(n_DupGen_finder = n),
  by = "type"
)
comp_results <- bind_rows(
  comp_results,
  data.frame(
```

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```
    type = "Total",
    n_doubletrouble = sum(comp_results$n_doubletrouble),
    n_DupGen_finder = sum(comp_results$n_DupGen_finder)
  )
)
```

```
list(runtime = comp_runtime, results = comp_results)
## $runtime
##   doubletrouble DupGen_finder
## 1  3.71474 secs 3.373682 secs
##
## $results
##   type n_doubletrouble n_DupGen_finder
## 1   SD           4329           4355
## 2   TD           2075           2131
## 3   PD           2789            896
## 4  TRD           6703           5941
## 5   DD          31589          17834
## 6 Total          47485          31157
```

Overall, results are similar, but there are important differences. In terms of runtime, there is no significant difference (this is the runtime of a single run, so there's some stochasticity). In terms of results, the numbers of SD, TD, and TRD pairs are similar, but there are more pronounced differences for PD and DD pairs. In particular, the total number of paralogous pairs differs between algorithms. When we remove rows from the DIAMOND output based on the E-value threshold and remove self (e.g., "gene1-gene1") and redundant hits (e.g., "gene1-gene2" and "gene2-gene1"), we get the following total number of pairs:

```
# Get total number of paralog pairs from DIAMOND output
evaluate <- 1e-10
dmd <- diamond_intra$arabidopsis.thaliana-arabidopsis.thaliana

all_paralogs <- lapply(list(dmd), function(x) {
  fpair <- x[x$evaluate <= evaluate, c(1, 2)]
  fpair <- fpair[fpair[, 1] != fpair[, 2], ]
  fpair <- fpair[!duplicated(t(apply(fpair, 1, sort))), ]
  names(fpair) <- c("dup1", "dup2")
  return(fpair)
}][[1]]

nrow(all_paralogs)
## [1] 47485
```

The total number of paralogous pairs in the DIAMOND output is the same as sum of classes for **doubletrouble**, but greater than the sum of classes for **DupGen\_finder**, indicating that the latter probably does some additional (undocumented) filtering before classifying gene pairs, or it could be a bug.

Finally, since the number of PD pairs identified by **doubletrouble** is much greater than the number of PD pairs identified by **DupGen\_finder**, we will explore a few of these PD pairs so check whether **doubletrouble** misclassified them.



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```
pd1 <- dups1$arabidopsis.thaliana |>
  filter(type == "PD")

pd2 <- dups2 |>
  filter(type == "PD")

# Get all pairs in `pd1` and `pd2`
p1 <- t(apply(pd1[, 1:2], 1, sort)) |>
  as.data.frame() |>
  mutate(V1 = str_replace_all(V1, "^ara_", "")) |>
  mutate(V2 = str_replace_all(V2, "^ara_", "")) |>
  mutate(pair_string = str_c(V1, V2, sep = "-")) |>
  pull(pair_string)

p2 <- t(apply(pd2[, 1:2], 1, sort)) |>
  as.data.frame() |>
  mutate(pair_string = str_c(V1, V2, sep = "-")) |>
  pull(pair_string)

# Sample PD pairs from doubletrouble that are not PD pairs in DupGen_finder
examples <- p1[!p1 %in% p2] |> head(n = 5)

# Check whether they are PD pairs or not
ath_annot <- pdata$annotation$arabidopsis.thaliana
range_examples <- lapply(examples, function(x) {
  g1 <- paste0("ara_", strsplit(x, "-")[[1]][1])
  g2 <- paste0("ara_", strsplit(x, "-")[[1]][2])
  ranges <- ath_annot[ath_annot$gene %in% c(g1, g2)]
  return(ranges)
})
```

```
range_examples
## [[1]]
## GRanges object with 2 ranges and 1 metadata column:
##      seqnames      ranges strand |      gene
##      <Rle>        <IRanges> <Rle> | <character>
## 128 ara_1 428650-430720      - | ara_AT1G02220
## 130 ara_1 437860-439559      - | ara_AT1G02250
## -----
## seqinfo: 7 sequences from an unspecified genome; no seqlengths
##
## [[2]]
## GRanges object with 2 ranges and 1 metadata column:
##      seqnames      ranges strand |      gene
##      <Rle>        <IRanges> <Rle> | <character>
## 127 ara_1 427548-427811      - | ara_AT1G02210
## 130 ara_1 437860-439559      - | ara_AT1G02250
## -----
## seqinfo: 7 sequences from an unspecified genome; no seqlengths
##
## [[3]]
```

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```
## GRanges object with 2 ranges and 1 metadata column:
##      seqnames      ranges strand |      gene
##      <Rle>        <IRanges> <Rle> | <character>
## 17117 ara_4 656407-659178      - | ara_AT4G01520
## 17120 ara_4 673862-676445      - | ara_AT4G01550
## -----
## seqinfo: 7 sequences from an unspecified genome; no seqlengths
##
## [[4]]
## GRanges object with 2 ranges and 1 metadata column:
##      seqnames      ranges strand |      gene
##      <Rle>        <IRanges> <Rle> | <character>
## 15329 ara_3 17882465-17884515    + | ara_AT3G48290
## 15332 ara_3 17887996-17889942    + | ara_AT3G48310
## -----
## seqinfo: 7 sequences from an unspecified genome; no seqlengths
##
## [[5]]
## GRanges object with 2 ranges and 1 metadata column:
##      seqnames      ranges strand |      gene
##      <Rle>        <IRanges> <Rle> | <character>
## 25845 ara_5 21378702-21379744    + | ara_AT5G52720
## 25847 ara_5 21382482-21383432    + | ara_AT5G52740
## -----
## seqinfo: 7 sequences from an unspecified genome; no seqlengths
```

In these first five examples of pairs that are classified as PD pairs by **doubletrouble**, but not by **DupGen\_finder**, we can see based on the numbers in row names that they are indeed very close, separated by only a few genes (<10). Thus, they are true PD pairs that **DupGen\_finder** failed to classify as PD pairs, or removed in their undocumented filtering (described above).

## Session info

This document was created under the following conditions:

```
## - Session info -----
## setting value
## version R version 4.4.1 (2024-06-14)
## os      Ubuntu 22.04.4 LTS
## system  x86_64, linux-gnu
## ui      X11
## language (EN)
## collate en_US.UTF-8
## ctype   en_US.UTF-8
## tz      Europe/Brussels
## date    2024-07-26
## pandoc  3.1.1 @ /usr/lib/rstudio/resources/app/bin/quarto/bin/tools/ (via rmarkdown)
##
## - Packages -----
```

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##	package	* version	date (UTC)	lib	source
##	abind	1.4-5	2016-07-21	[1]	CRAN (R 4.4.1)
##	ade4	1.7-22	2023-02-06	[1]	CRAN (R 4.4.1)
##	AnnotationDbi	1.66.0	2024-05-01	[1]	Bioconductor 3.19 (R 4.4.1)
##	ape	5.8	2024-04-11	[1]	CRAN (R 4.4.1)
##	Biobase	2.64.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
##	BiocGenerics	0.50.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
##	BiocIO	1.14.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
##	BiocManager	1.30.23	2024-05-04	[1]	CRAN (R 4.4.1)
##	BiocParallel	1.38.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
##	BiocStyle	* 2.32.1	2024-06-16	[1]	Bioconductor 3.19 (R 4.4.1)
##	Biostrings	2.72.1	2024-06-02	[1]	Bioconductor 3.19 (R 4.4.1)
##	bit	4.0.5	2022-11-15	[1]	CRAN (R 4.4.1)
##	bit64	4.0.5	2020-08-30	[1]	CRAN (R 4.4.1)
##	bitops	1.0-7	2021-04-24	[1]	CRAN (R 4.4.1)
##	blob	1.2.4	2023-03-17	[1]	CRAN (R 4.4.1)
##	bookdown	0.40	2024-07-02	[1]	CRAN (R 4.4.1)
##	cachem	1.1.0	2024-05-16	[1]	CRAN (R 4.4.1)
##	cli	3.6.3	2024-06-21	[1]	CRAN (R 4.4.1)
##	coda	0.19-4.1	2024-01-31	[1]	CRAN (R 4.4.1)
##	codetools	0.2-20	2024-03-31	[1]	CRAN (R 4.4.1)
##	colorspace	2.1-0	2023-01-23	[1]	CRAN (R 4.4.1)
##	crayon	1.5.3	2024-06-20	[1]	CRAN (R 4.4.1)
##	curl	5.2.1	2024-03-01	[1]	CRAN (R 4.4.1)
##	DBI	1.2.3	2024-06-02	[1]	CRAN (R 4.4.1)
##	DelayedArray	0.30.1	2024-05-07	[1]	Bioconductor 3.19 (R 4.4.1)
##	digest	0.6.36	2024-06-23	[1]	CRAN (R 4.4.1)
##	doParallel	1.0.17	2022-02-07	[1]	CRAN (R 4.4.1)
##	doubletrouble	* 1.4.1	2024-07-25	[1]	Bioconductor
##	dplyr	* 1.1.4	2023-11-17	[1]	CRAN (R 4.4.1)
##	evaluate	0.24.0	2024-06-10	[1]	CRAN (R 4.4.1)
##	fansi	1.0.6	2023-12-08	[1]	CRAN (R 4.4.1)
##	fastmap	1.2.0	2024-05-15	[1]	CRAN (R 4.4.1)
##	forcats	* 1.0.0	2023-01-29	[1]	CRAN (R 4.4.1)
##	foreach	1.5.2	2022-02-02	[1]	CRAN (R 4.4.1)
##	generics	0.1.3	2022-07-05	[1]	CRAN (R 4.4.1)
##	GenomeInfoDb	1.40.1	2024-05-24	[1]	Bioconductor 3.19 (R 4.4.1)
##	GenomeInfoDbData	1.2.12	2024-07-24	[1]	Bioconductor
##	GenomicAlignments	1.40.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
##	GenomicFeatures	1.56.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
##	GenomicRanges	1.56.1	2024-06-12	[1]	Bioconductor 3.19 (R 4.4.1)
##	ggnetwork	0.5.13	2024-02-14	[1]	CRAN (R 4.4.1)
##	ggplot2	* 3.5.1	2024-04-23	[1]	CRAN (R 4.4.1)
##	glue	1.7.0	2024-01-09	[1]	CRAN (R 4.4.1)
##	gtable	0.3.5	2024-04-22	[1]	CRAN (R 4.4.1)
##	here	* 1.0.1	2020-12-13	[1]	CRAN (R 4.4.1)
##	hms	1.1.3	2023-03-21	[1]	CRAN (R 4.4.1)
##	htmltools	0.5.8.1	2024-04-04	[1]	CRAN (R 4.4.1)
##	htmlwidgets	1.6.4	2023-12-06	[1]	CRAN (R 4.4.1)
##	httr	1.4.7	2023-08-15	[1]	CRAN (R 4.4.1)
##	igraph	2.0.3	2024-03-13	[1]	CRAN (R 4.4.1)

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## intergraph	2.0-4	2024-02-01	[1]	CRAN (R 4.4.1)
## IRanges	2.38.1	2024-07-03	[1]	Bioconductor 3.19 (R 4.4.1)
## iterators	1.0.14	2022-02-05	[1]	CRAN (R 4.4.1)
## jsonlite	1.8.8	2023-12-04	[1]	CRAN (R 4.4.1)
## KEGGREST	1.44.1	2024-06-19	[1]	Bioconductor 3.19 (R 4.4.1)
## knitr	1.48	2024-07-07	[1]	CRAN (R 4.4.1)
## lattice	0.22-6	2024-03-20	[1]	CRAN (R 4.4.1)
## lifecycle	1.0.4	2023-11-07	[1]	CRAN (R 4.4.1)
## lubridate	* 1.9.3	2023-09-27	[1]	CRAN (R 4.4.1)
## magrittr	2.0.3	2022-03-30	[1]	CRAN (R 4.4.1)
## MASS	7.3-61	2024-06-13	[1]	CRAN (R 4.4.1)
## Matrix	1.7-0	2024-04-26	[1]	CRAN (R 4.4.1)
## MatrixGenerics	1.16.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
## matrixStats	1.3.0	2024-04-11	[1]	CRAN (R 4.4.1)
## mclust	6.1.1	2024-04-29	[1]	CRAN (R 4.4.1)
## memoise	2.0.1	2021-11-26	[1]	CRAN (R 4.4.1)
## MSA2dist	1.8.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
## munsell	0.5.1	2024-04-01	[1]	CRAN (R 4.4.1)
## network	1.18.2	2023-12-05	[1]	CRAN (R 4.4.1)
## networkD3	0.4	2017-03-18	[1]	CRAN (R 4.4.1)
## nlme	3.1-165	2024-06-06	[1]	CRAN (R 4.4.1)
## patchwork	* 1.2.0	2024-01-08	[1]	CRAN (R 4.4.1)
## pheatmap	1.0.12	2019-01-04	[1]	CRAN (R 4.4.1)
## pillar	1.9.0	2023-03-22	[1]	CRAN (R 4.4.1)
## pkgconfig	2.0.3	2019-09-22	[1]	CRAN (R 4.4.1)
## png	0.1-8	2022-11-29	[1]	CRAN (R 4.4.1)
## purrr	* 1.0.2	2023-08-10	[1]	CRAN (R 4.4.1)
## pwalgn	1.0.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
## R6	2.5.1	2021-08-19	[1]	CRAN (R 4.4.1)
## RColorBrewer	1.1-3	2022-04-03	[1]	CRAN (R 4.4.1)
## Rcpp	1.0.13	2024-07-17	[1]	CRAN (R 4.4.1)
## RCurl	1.98-1.16	2024-07-11	[1]	CRAN (R 4.4.1)
## readr	* 2.1.5	2024-01-10	[1]	CRAN (R 4.4.1)
## restfulr	0.0.15	2022-06-16	[1]	CRAN (R 4.4.1)
## rjson	0.2.21	2022-01-09	[1]	CRAN (R 4.4.1)
## rlang	1.1.4	2024-06-04	[1]	CRAN (R 4.4.1)
## rmarkdown	2.27	2024-05-17	[1]	CRAN (R 4.4.1)
## rprojroot	2.0.4	2023-11-05	[1]	CRAN (R 4.4.1)
## Rsamtools	2.20.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
## RSQLite	2.3.7	2024-05-27	[1]	CRAN (R 4.4.1)
## rstudioapi	0.16.0	2024-03-24	[1]	CRAN (R 4.4.1)
## rtracklayer	1.64.0	2024-04-30	[1]	Bioconductor 3.19 (R 4.4.1)
## S4Arrays	1.4.1	2024-05-20	[1]	Bioconductor 3.19 (R 4.4.1)
## S4Vectors	0.42.1	2024-07-03	[1]	Bioconductor 3.19 (R 4.4.1)
## scales	1.3.0	2023-11-28	[1]	CRAN (R 4.4.1)
## seqinr	4.2-36	2023-12-08	[1]	CRAN (R 4.4.1)
## sessioninfo	1.2.2	2021-12-06	[1]	CRAN (R 4.4.1)
## SparseArray	1.4.8	2024-05-24	[1]	Bioconductor 3.19 (R 4.4.1)
## statnet.common	4.9.0	2023-05-24	[1]	CRAN (R 4.4.1)
## stringi	1.8.4	2024-05-06	[1]	CRAN (R 4.4.1)
## stringr	* 1.5.1	2023-11-14	[1]	CRAN (R 4.4.1)

## Supplementary Text S5: Runtime benchmark

```
## SummarizedExperiment 1.34.0 2024-05-01 [1] Bioconductor 3.19 (R 4.4.1)
## syntenet 1.6.0 2024-05-01 [1] Bioconductor 3.19 (R 4.4.1)
## tibble * 3.2.1 2023-03-20 [1] CRAN (R 4.4.1)
## tidyr * 1.3.1 2024-01-24 [1] CRAN (R 4.4.1)
## tidyselect 1.2.1 2024-03-11 [1] CRAN (R 4.4.1)
## tidyverse * 2.0.0 2023-02-22 [1] CRAN (R 4.4.1)
## timechange 0.3.0 2024-01-18 [1] CRAN (R 4.4.1)
## tzdb 0.4.0 2023-05-12 [1] CRAN (R 4.4.1)
## UCSC.utils 1.0.0 2024-04-30 [1] Bioconductor 3.19 (R 4.4.1)
## utf8 1.2.4 2023-10-22 [1] CRAN (R 4.4.1)
## vctrs 0.6.5 2023-12-01 [1] CRAN (R 4.4.1)
## withr 3.0.0 2024-01-16 [1] CRAN (R 4.4.1)
## xfun 0.46 2024-07-18 [1] CRAN (R 4.4.1)
## XML 3.99-0.17 2024-06-25 [1] CRAN (R 4.4.1)
## XVector 0.44.0 2024-04-30 [1] Bioconductor 3.19 (R 4.4.1)
## yaml 2.3.9 2024-07-05 [1] CRAN (R 4.4.1)
## zlibbioc 1.50.0 2024-04-30 [1] Bioconductor 3.19 (R 4.4.1)
##
## [1] /home/faalm/R/x86_64-pc-linux-gnu-library/4.4
## [2] /usr/local/lib/R/site-library
## [3] /usr/lib/R/site-library
## [4] /usr/lib/R/library
##
## -----
```