

# R3CPET user manual

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## Contents

1	Introduction . . . . .	2
2	Using <i>R3CPET</i> . . . . .	3
2.1	Loading data . . . . .	3
2.2	Creating indexes . . . . .	6
2.3	building networks for DNA regions. . . . .	7
2.4	Inferring chromatin maintainer networks . . . . .	7
2.5	Cluster DNA interactions by enrichment profile . . . . .	10
2.6	Visualization . . . . .	10
2.6.1	Heatmaps. . . . .	11
2.6.2	Enrichment curves . . . . .	11
2.6.3	plot networks . . . . .	12
2.6.4	Networks similarity . . . . .	13
2.6.5	Circos maps. . . . .	14
2.7	Gene enrichment . . . . .	14
2.8	Using the web interface . . . . .	15
2.8.1	Raw data visualization . . . . .	15
2.8.2	Results visualization . . . . .	15
3	Session Info . . . . .	16

# 1 Introduction

**R3CPET** The breakthrough in chromatin conformation study done in the last decade has shed some light on many aspects of gene regulation and revealed that chromatin crosstalk plays an important role in connecting regulatory sequences to their target promoters through loop formation

However, a key limitation of the existing chromatin conformation assays is that they can just give us the genomic coordinates of the interacting DNA fragments but don't tell us on the proteins involved. One used solution is to use *ChIP-Seq* to get the list of the proteins involved at these borders but one limitation is that not all the proteins can be captured and some don't have a specific anti-body.

Thus, computational methods are still useful to give some insight on the protein candidates that can play a role in maintaining these interactions. *R3CPET* comes as a tool to fill this gap and try to infer the loop-maintaining network(s) in a more concise manner.

3CPET is based on the following idea : if we can have the list of the protein networks that maintain all of the DNA-interactions, then we can infer the set the most enriched networks. One of the widely used statistical model in this kind of problems is the HLDA model which is a non-parametric Bayesian that enables us to infer the number of different groups from the data.

In order to apply HLDA, we need to have a corpus of documents and we assign each word to a topic. In our case each document is a network and each word is an edge in that network. To create a network for each interaction we use (i) find the set of the proteins involved a the boundaries of a loop and this by using *ChIP-Seq* peaks or *motifs* data.

In the next step, we use the information in a background PPI to construct the network connecting the two interacting DNA fragments.

The networks are then converted into a *bag* of edges (*i.e* allow repetition) and fed to the HLDA algorithm.

In this model, we suppose that each network  $(j_n)_{n=1}^{\infty}$  is made-up of a mixture of protein complexes each with different a proportion  $\theta_n \sim DP(\alpha, \pi)$ . To infer the number of clusters, the model suppose that we have an infinite number of chromatin maintainer networks distributed according to a certain distribution  $H$ . To enable the sharing the complexes  $(\beta_k)$  across all the networks, an intermediate discrete distribution is introduced  $(\beta_k)_{k=1}^N$  sampled from the base distribution  $H$  using a stick breaking construction  $\pi|\gamma \sim GEM(\gamma)$ .



**Figure 1:** Illustration of the network construction procedure.

Figure 2: HLDA model

## R3CPET user manual 2 Using R3CPET

*R3CPET* package were built to enable the user to upload the data step-by-step and thus giving him a more granular control of the data that he uses. Maybe it sounds like the use needs more labor, but the user can create an [S3](#) wrapper function that encapsulate the workflow functions into one method.

Four main classes are provided by *R3CPET*:

1. `ChiapetExperimentData` - a container for the raw data to use. 3 types of data can be loaded into this class respectively : *ChIA-PET* interactions, *ChIP-Seq* peaks and the background *PPI*.
2. `NetworkCollection` - Holds the list of the build networks for each DNA-interaction and their information.
3. `HLDAResult` - contains the results of the HLDA algorithm.
4. `ChromMaintainers` - contains the final results after processing the HLDA results (*i.e*: list of networks and their nodes).

In addition to these classes additional helper methods for GO enrichment and and gene conversion.

### 2.1 Loading data

Before starting the analysis different kinds of dataset need be loaded. This can be done using a `ChiapetExperimentData` object.

The user can load the data using the `ChiapetExperimentData` constructor. By passing: ChIA-PET interactions data, transcription factors binding site (TFBS) and a protein-protein interaction network. The ChIA-PET interactions can be passed as path to a file or a `GRanges` object. The same is for the TFBS.

```
> library(R3CPET)
> petFile <- file.path(system.file("example", package = "R3CPET"),
+   "HepG2_interactions.txt")
> tfbsFile <- file.path(system.file("example", package = "R3CPET"),
+   "HepG2_TF.txt.gz")
> x <- ChiapetExperimentData(pet = petFile, tfbs = tfbsFile, IsBed = FALSE,
+   ppiType = "HPRD", filter = TRUE)
```

Three types of data can be loaded :

- *ChIA-PET interactions* - which can have two formats: (i) the first type is a file in which the first six columns indicate the left and right interacting parts (generally parsed from the ChIA-PET tool). For example

```
> petPath <- system.file("example", "HepG2_interactions.txt", package = "R3CPET")
> petFile <- read.table(petPath, sep = "\t", header = TRUE)
> head(petFile)

##   chromleft startleft endleft chromright startright
## 1      chr1  1282738 1283678        chr1  1283743
## 2      chr1  1370817 1371926        chr1  1372332
## 3      chr1  2159841 2161268        chr1  2161279
```

```
## 4      chr1    2159841 2161268      chr1    2162130
## 5      chr1    2161279 2162108      chr1    2162130
## 6      chr1    9187131 9188440      chr1    9188469
## endright counts      pvalue  qvalue
## 1  1284926          6 1.075586e-21 8.8e-05
## 2  1373312          8 3.536936e-26 8.8e-05
## 3  2162108         18 5.487730e-57 8.8e-05
## 4  2163908          6 8.048577e-17 8.8e-05
## 5  2163908         17 2.792212e-55 8.8e-05
## 6  9189622          7 2.576820e-28 8.8e-05
```

Here only the 6 first columns are considered. It is up to the user to filter the significant interactions for him.

The second type of files that can be loaded is a four columns file in which the first three columns indicate the genomic location of a DNA region and the forth column indicate if the region is located at the right or left side. The IDs in the fourth column should have the pattern `PET#\d+\.`1 for the left side and `PET#\d+\.`2 for the right side. if the number of the left side interactions is different from the right side an error will be raised.

```
> petPath <- system.file("example", "HepG2_centered.bed", package = "R3CPET")
> petFile <- read.table(petPath, sep = "\t", header = FALSE, comment.char = "+")
>
> head(petFile)

##      V1      V2      V3      V4
## 1 chr1 1241234 1242234 PET#1.1
## 2 chr1 1242724 1243724 PET#1.2
## 3 chr1 1282708 1283708 PET#2.1
## 4 chr1 1283834 1284834 PET#2.2
## 5 chr1 1370871 1371871 PET#3.1
## 6 chr1 1372322 1373322 PET#3.2
```

The method `loadPETs` can be used to load the data

```
> ## if it has 6 columns format IsBed = FALSE
> petPath <- system.file("example", "HepG2_interactions.txt", package = "R3CPET")
> x <- loadPETs(x, petFile = petPath, IsBed = FALSE)

## 304 interacting DNA regions loaded
```

if the file is 4 columns BED file you can set `IsBed = TRUE`

```
> ## loading a 4 columns BED file
> petPath <- system.file("example", "HepG2_centered.bed", package = "R3CPET")
> x <- loadPETs(x, petFile = petPath, IsBed = TRUE, header = FALSE)
```

The `pet(x)` accessor method can be used to read the loaded interactions as *GRanges* object.

- **ChIP-Seq peaks** - All the *ChIP-Seq* peaks of the different TF should be merged into a 4 columns in which the first 3 columns indicate the position of the peak and the last column indicate the associated TF. The `loadTFBS` method can be used to do so.

```
> ## loading a 4 columns BED file
> TFPath <- system.file("example", "HepG2_TF.txt.gz", package = "R3CPET")
```

```

> TF <- read.table(TFPath, sep = "\t", header = FALSE)
> head(TF)

##      V1      V2      V3      V4
## 1 chr8 67804615 67804862 HEY1
## 2 chr15 52200521 52200848 FOSL2
## 3 chr15 70820640 70820932 EP300
## 4 chr13 48775200 48775538 EP300
## 5 chr3 23987219 23988231 FOSL2
## 6 chr6 56263941 56265486 FOSL2

> x <- loadTFBS(x, tfbsFile = TFPath)

## a total of 81414 binding sites for 6 TF were loaded

```

- **Protein interaction** - a background `PPI` is needed to do the networks construction. The package comes with two build in `PPI`: the `HPRD` and the `Biogrid PPI`.

```

> data(HPRD)
> data(Biogrid)
>
> PPI.HPRD

## This graph was created by an old(er) igraph version.
## Call upgrade_graph() on it to use with the current igraph version
## For now we convert it on the fly...

## IGRAPH 84de311 UN-- 9616 39042 --
## + attr: name (v/c)
## + edges from 84de311 (vertex names):
## [1] ALDH1A1--ALDH1A1 ITGA7 --CHRNA1 PPP1R9A--ACTG1
## [4] SRGN --CD44 GRB7 --ERBB2 ERBB2 --PAK1
## [7] ERBB2 --DLG4 ERBB2 --PIK3R2 ERBB2 --PTPN18
## [10] ERBB2 --ERBB2IP SMURF2 --ARHGAP5 ERBB2 --NF2
## [13] ERBB2 --CD82 ERBB2 --ERRFI1 CD44 --MMP7
## [16] ERBB2 --TOB1 ERBB2 --MUC4 ERBB2 --PICK1
## [19] SMURF2 --TXNIP DDX20 --ETV3 TLE1 --FOXG1
## [22] FOXG1 --TLE3 FOXG1 --HDAC1 FOXG1 --SMAD1
## + ... omitted several edges

> PPI.Biogrid

## This graph was created by an old(er) igraph version.
## Call upgrade_graph() on it to use with the current igraph version
## For now we convert it on the fly...

## IGRAPH 2eeef88 UN-- 16227 169166 --
## + attr: name (v/c)
## + edges from 2eeef88 (vertex names):
## [1] MAP2K4--FLNC MYPN --ACTN2 ACVR1 --FNTA
## [4] GATA2 --PML RPA2 --STAT3 ARF1 --GGA3
## [7] ARF3 --ARFIP2 ARF3 --ARFIP1 AKR1A1--EXOSC4
## [10] XRN1 --ALDOA APP --APPBP2 APLP1 --DAB1

```

```
## [13] CITED2--TFAP2A    TFAP2A--EP300    APOB  --MTTP
## [16] ARRB2  --RALGDS    CSF1R  --GRB2    GRB2  --PRRC2A
## [19] LSM1   --NARS     SLC4A1--SLC4A1AP BCL3   --BARD1
## [22] ADRB1  --GIPC1    BRCA1  --ATF1    BRCA1  --MSH2
## + ... omitted several edges
```

The `loadPPI` method can be used to load and filter the `PPI` according to different criteria.

```
> loadPPI(object, type = c("HPRD", "Biogid"), customPPI = NULL,
+         filter = FALSE, term = "GO:0005634", annot = NULL, RPKM = NULL,
+         threshold = 1)
```

if `customPPI` one of the built-in `PPI` will be used otherwise the user can provide a path to an `ncol` formatted graph (two column to indicate interacting nodes) or directly provide an *igraph* object.

The user can also do some filtering to remove proteins that he thinks are not significant. by default the package keeps only the proteins that are located at nucleus (`term = "GO:0005634"`). The user can provide his own annotation to the `annot` parameter. In some cases the user want to keep only the cell specific genes, thus he can filter genes according to their gene expression by providing a two columns gene expression table to the `RPKM` parameter and set the `threshold`.

```
> ## loading the PPI with GO filtering
> x <- loadPPI(x, type = "HPRD", filter = TRUE)

## This graph was created by an old(er) igraph version.
## Call upgrade_graph() on it to use with the current igraph version
## For now we convert it on the fly...

## loading HPRD network, with 9616 nodes
```

## 2.2 Creating indexes

When the user thinks that the data that he loaded is ok, he need to create indexes for processing in the further steps. Indexes can be created by calling the method `createIndexes`.

```
> x <- createIndexes(x)

## [1] "Creating PET table"
## [1] "Sorting Table"
## [1] "Get TF associated with each PETs"
## [1] "Creating Motifs table"
## [1] "Sorting Table"
## [1] "Creating hasMotif table"
## [1] "Sorting Table"

> x

## class: ChiapetExperimentData
## 304 interacting regions
## 6 TF used
## Background PPI:
## nodes: 3447 edges: 14882
## indexes tables have been created
```

## 2.3 building networks for DNA regions

R3CPET user manual

Once all the data are loaded we can go to the next step and build the protein interaction networks for each chromatin loop. The `buildNetworks` is used and a `NetworkCollection` is returned. When the networks are built, the rare and the more frequent edges are removed as they are considered to be not specific. By default, edges that appear in less than 25% or more than 75% of the total networks are removed.

the user can set these values by modifying the `minFreq` and `maxFreq` parameters of the `buildNetworks` method.

```
> nets <- buildNetworks(x, minFreq = 0.1, maxFreq = 0.9)
> nets
```

```
## class NetworkCollection
## 145 network loaded
## 128 different edges has been used
```

The `buildNetworks` uses the *parallel* package to parallelize the processing. If the user has 4 cores, then 4 Rinstances will be launched at the background each running on a core and handling part of the data.

## 2.4 Inferring chromatin maintainer networks

At this step the `InferNetworks` can be used to run the HLDA algorithm and infer the set of the most enriched chromatin maintainer networks. by default, the algorithm do a maximum of 500 iteration or stops after 1 hour.

```
InferNetworks(object, thr = 0.5, max_iter = 500L, max_time = 3600L,
  eta = 0.01, gamma = 1, alpha = 1)
```

To control the behaviour of the algorithm, users can modify the values of the HDP algorithm parameters `eta`, `gamma` and `alpha`. Briefly, `eta` and `alpha` control the sparsity of the edge-to-CMN matrix. In other words, smaller values allow force an edge to belong to a small number of CMNs (ideally one) and larger values (>1) allow them to be uniformly assigned. `gamma` controls the number of CMNs, smaller values leads to less predicted CMNs while larger values leads to more CMNs. Users can check figures S13-S16 of the manuscript.

When the algorithm finishes we get a matrix that indicates the degree of partnership of each edge to the inferred networks (each network is distribution over edges). Thus, to get the top elements in each network, we use the parameter `thr` to select the edges that capture `thr`% of the network. Thus, more general networks tend to have bigger number elements and more specific networks have less elements. At the end a `ChromMaintainers` object is returned.

```
> hlدا <- InferNetworks(nets)
> hlدا
```

```
## class: ChromMaintainers
## HLDA Results:
## -----
## 145 element have been classified into 10 topics
## Number of different words 128
```

The different slots of the `hlدا` object can be accessed using the following accessor methods:

- `topEdges` : to get the list of the top edges in each network.
- `topNodes` : to get the list of the top nodes in each network.

- `networks` : to get a list `igraph` objects.

```
> head(topEdges(hlda))

##      Topic_1      Topic_2      Topic_3
## [1,] "EP300_MYOD1" "ESR1_ESRRA" "FOSL2_JUND"
## [2,] "ARNT_EP300"   "ESR1_NCOA1" "FOSL2_JUN"
## [3,] "GABPA_SP1"   "ESRRA_NCOA1" "JUN_MYOD1"
## [4,] "CREBBP_SMAD3" "NCOA1_PPARGC1A" "JUN_SMAD3"
## [5,] "MYOD1_SP1"   "ESR1_PPARGC1A" "FOSL2_JUNB"
## [6,] "CREBBP_MYOD1" "ESR1_SMAD3"    ""
##      Topic_4      Topic_5      Topic_6      Topic_7
## [1,] "GABPA_SP1"   "ESR1_JUND"    "JUND_SMAD4" "FOSL2_JUND"
## [2,] "MAPK1_SP1"   "EP300_ESR1"   "BRCA1_SMAD4" "EP300_JUN"
## [3,] "MAPK1_SMAD4" "EP300_SMAD4"  "BCL6_EP300"  "FOSL2_JUN"
## [4,] "MAPK1_SMAD3" "ESR1_SMAD4"   "ESR1_SMAD3"  "JUN_SMAD3"
## [5,] "JUND_MAPK1"  "EP300_JDP2"   "BRCA1_SMAD3" ""
## [6,] "BCL6_MAPK1"  ""             ""            ""
##      Topic_8      Topic_9      Topic_10
## [1,] "EP300_GABPA" "EP300_NCOA1" "CREBBP_PROX1"
## [2,] "EP300_SP1"  "GTF2B_NCOA1" "MAPK1_PRKCD"
## [3,] "CREBBP_EP300" "ESRRA_GTF2B" "MAPK1_NCOA3"
## [4,] "ATF1_CREBBP" "ESR1_NCOA3"  "MAPK1_NCOA1"
## [5,] "ATF1_GABPA" "ESRRA_NCOA3" ""
## [6,] "CREBBP_GABPA" "EP300_ESR1"  ""

> head(topNodes(hlda))

##      Topic_1 Topic_2      Topic_3 Topic_4 Topic_5 Topic_6
## [1,] "EP300"  "ESR1"    "FOSL2" "GABPA" "ESR1"  "JUND"
## [2,] "MYOD1"  "ESRRA"   "JUND"  "SP1"   "JUND"  "SMAD4"
## [3,] "ARNT"   "NCOA1"   "JUN"   "MAPK1" "EP300" "BRCA1"
## [4,] "GABPA"  "PPARGC1A" "MYOD1" "SMAD4" "SMAD4" "BCL6"
## [5,] "SP1"    "SMAD3"   "SMAD3" "SMAD3" "JDP2"  "EP300"
## [6,] "CREBBP" "ARNT"    "JUNB"  "JUND"  ""      "ESR1"
##      Topic_7 Topic_8      Topic_9 Topic_10
## [1,] "FOSL2" "EP300"   "EP300" "CREBBP"
## [2,] "JUND"  "GABPA"   "NCOA1" "PROX1"
## [3,] "EP300" "SP1"     "GTF2B" "MAPK1"
## [4,] "JUN"   "CREBBP"  "ESRRA" "PRKCD"
## [5,] "SMAD3" "ATF1"    "ESR1"  "NCOA3"
## [6,] ""      ""        "NCOA3" "NCOA1"
```

The `igraph` networks are not created at the beginning, the `GenerateNetworks` should be used to convert the `topEdges` slot into networks.

```
> hlda <- GenerateNetworks(hlda)
> head(networks(hlda))

## $Network1
## IGRAPH f4f9aa2 UN-B 7 6 --
## + attr: name (v/c), type (v/c)
## + edges from f4f9aa2 (vertex names):
```



```

## [1] EP300 --MYOD1 EP300 --ARNT MYOD1 --SP1
## [4] GABPA --SP1 MYOD1 --CREBBP CREBBP--SMAD3
##
## $Network2
## IGRAPH f4fe87f UN-B 6 9 --
## + attr: name (v/c), type (v/c)
## + edges from f4fe87f (vertex names):
## [1] ESR1 --ESRRA ESR1 --NCOA1 ESRRA--NCOA1
## [4] ESR1 --PPARGC1A ESRRA--PPARGC1A NCOA1--PPARGC1A
## [7] ESR1 --SMAD3 ESR1 --ARNT NCOA1--ARNT
##
## $Network3
## IGRAPH f501818 UN-B 6 5 --
## + attr: name (v/c), type (v/c)
## + edges from f501818 (vertex names):
## [1] FOSL2--JUND FOSL2--JUN JUN --MYOD1 JUN --SMAD3
## [5] FOSL2--JUNB
##
## $Network4
## IGRAPH f5096e6 UN-B 11 15 --
## + attr: name (v/c), type (v/c)
## + edges from f5096e6 (vertex names):
## [1] GABPA--SP1 SP1 --MAPK1 SP1 --SMAD4 MAPK1--SMAD4
## [5] MAPK1--SMAD3 MAPK1--JUND SP1 --BCL6 MAPK1--BCL6
## [9] SP1 --TBP JUND --TBP SP1 --MAPK3 JUND --MAPK3
## [13] SP1 --BRCA1 TBP --ESR1 MAPK3--ESR1
##
## $Network5
## IGRAPH f50c482 UN-B 5 5 --
## + attr: name (v/c), type (v/c)
## + edges from f50c482 (vertex names):
## [1] ESR1 --JUND ESR1 --EP300 ESR1 --SMAD4 EP300--SMAD4
## [5] EP300--JDP2
##
## $Network6
## IGRAPH f50f46f UN-B 7 5 --
## + attr: name (v/c), type (v/c)
## + edges from f50f46f (vertex names):
## [1] JUND --SMAD4 SMAD4--BRCA1 BCL6 --EP300 BRCA1--SMAD3
## [5] ESR1 --SMAD3

```

if the user wants to annotate each protein in the network by its gene expression he can use the `annotateExpression` method. To use this method the user needs to provide a `data.frame` object, that contains the names of the genes in the first column and their expression value in the second.

```

> data(RPKMS)
> hlda <- annotateExpression(hlda, RPKMS)
> networks(hlda)[[1]]

## IGRAPH f4f9aa2 UN-B 7 6 --
## + attr: name (v/c), type (v/c), RPKM (v/n)

```

```
## + edges from f4f9aa2 (vertex names):
## [1] EP300 --MYOD1 EP300 --ARNT MYOD1 --SP1
## [4] GABPA --SP1 MYOD1 --CREBBP CREBBP--SMAD3
```

h3CPET user manual

We can notice that the RPKM attribute was added to the network.

## 2.5 Cluster DNA interactions by enrichment profile

Till the moment we can say ok, we got the list of our networks and we can do further biological examination to check the results, however, it would be nice if we can know which DNA interactions are enriched for same networks. Thus, the package provides a clustering feature to further analysis.

The `clusterInteractions` can be used to do so. The `sota` method of the `clValid` package is used.

The `clusterInteractions` is defined as follow:

```
clusterInteractions(object, method = "sota", nbClus = 20)
```

```
> ## clustering
> hlDa <- clusterInteractions(hlDa, method = "sota", nbClus = 6)

## clusterInteractions : checking
## clusterInteractions : reading args
## using clValid

## DNA interactions have been clustered into 6 cluster
```

## 2.6 Visualization

The package comes with a bunch of visualization plots to enable the exploration of data mainly through the `plot3CPETRes` method.

```
plot3CPETRes(object, path = "", W = 14, H = 7, type = c("heatmap",
  "clusters", "curve", "avgCurve", "netSim", "networks"), byEdge = TRUE,
  layoutfct = layout.kamada.kawai, ...)
```

To get the genomic coordinates of the regions involved in each cluster the methods `getRegionsIncluster` can be used. To use it the initial interaction data should be provided.

```
> getRegionsIncluster(hlDa, x, cluster = 3)

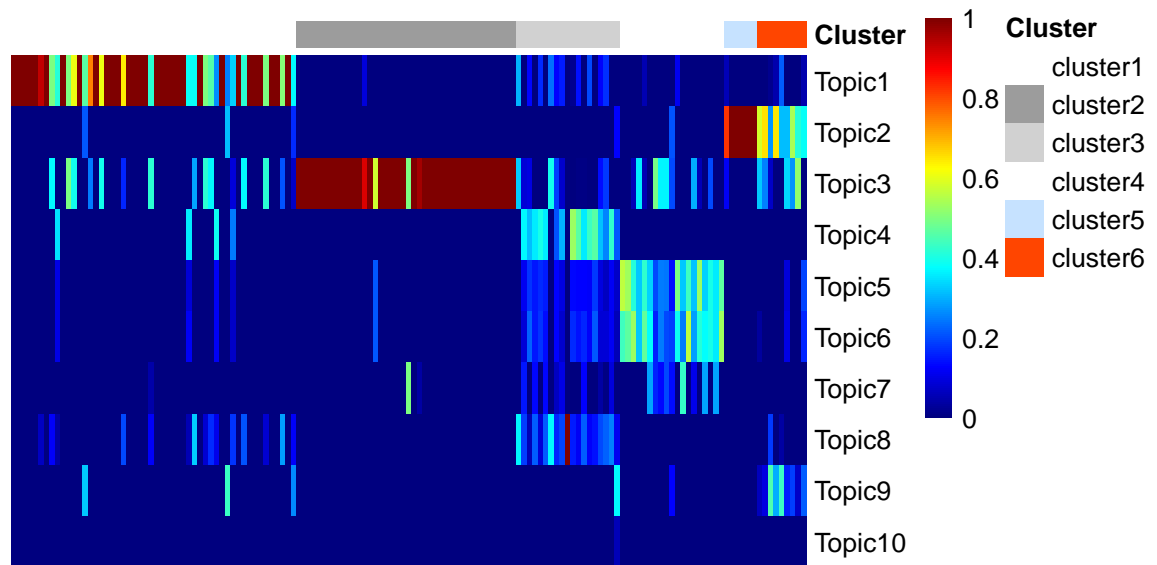
## GRanges object with 38 ranges and 1 metadata column:
##      seqnames      ranges strand |      PET_ID
##      <Rle>         <IRanges> <Rle> | <character>
##      [1]      chr1  20832660-20834660      * |      PET#11.1
##      [2]      chr1  20833954-20835954      * |      PET#11.2
##      [3]      chr1  24116461-24118461      * |      PET#14.1
##      [4]      chr1  24117714-24119714      * |      PET#14.2
##      [5]      chr1  38155583-38157583      * |      PET#26.1
##      ...      ...      ...      ...      ...
##      [34]     chr3 101293007-101295007      * |      PET#222.2
##      [35]     chr3 133378968-133380968      * |      PET#232.1
```

```
## [36] chr3 133380114-133382114 * | PET#232.2
## [37] chr5 110427069-110429069 * | PET#287.1
## [38] chr5 110428082-110430082 * | PET#287.2
## -----
## seqinfo: 6 sequences from an unspecified genome; no seqlengths
```

## 2.6.1 Heatmaps

After clustering the enrichment map can be visualized using the `heatmap` option in the `plot3CPETRes` method. Here each column represent a chromatin-chromatin interaction and each row represents a chromatin maintainer network. The colors indicate the probability that a chromatin-chromatin interaction is maintained by a chromatin maintainer network.

```
> plot3CPETRes(hlda, type = "heatmap")
```

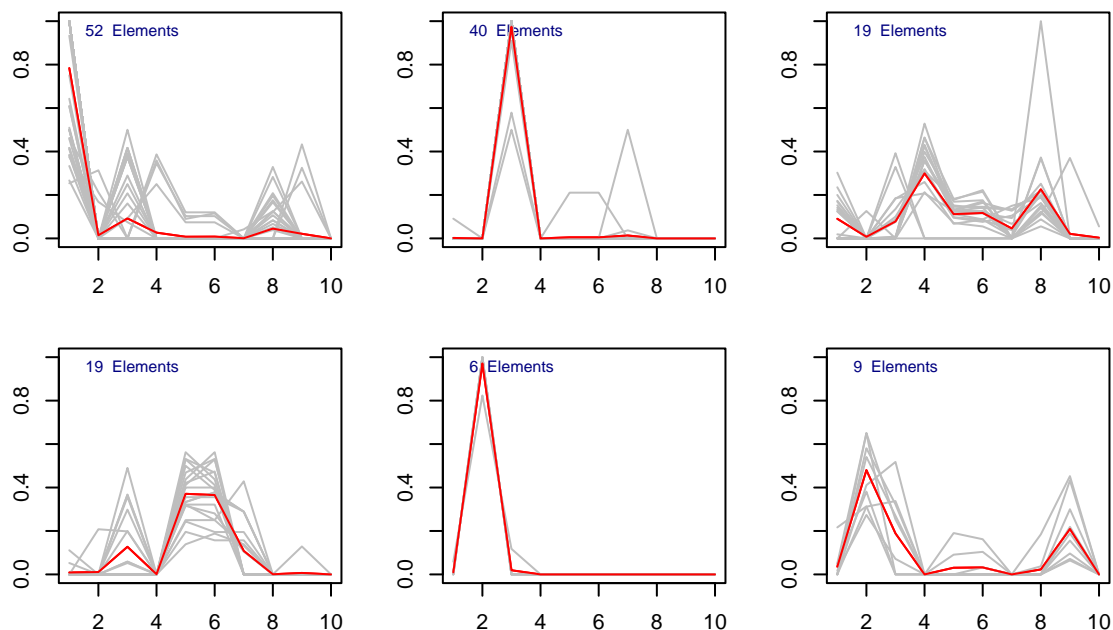


## 2.6.2 Enrichment curves

An other way to check the enrichment of the different chromatin interactions in the different clusters is by plotting the enrichment and average enrichment curves in of the chromatin interactions in each clusters.

if the `type` parameter of the `plot3CPETRes` method is set to `curve` the enrichment profile of all the interactions per cluster is displayed as shown bellow:

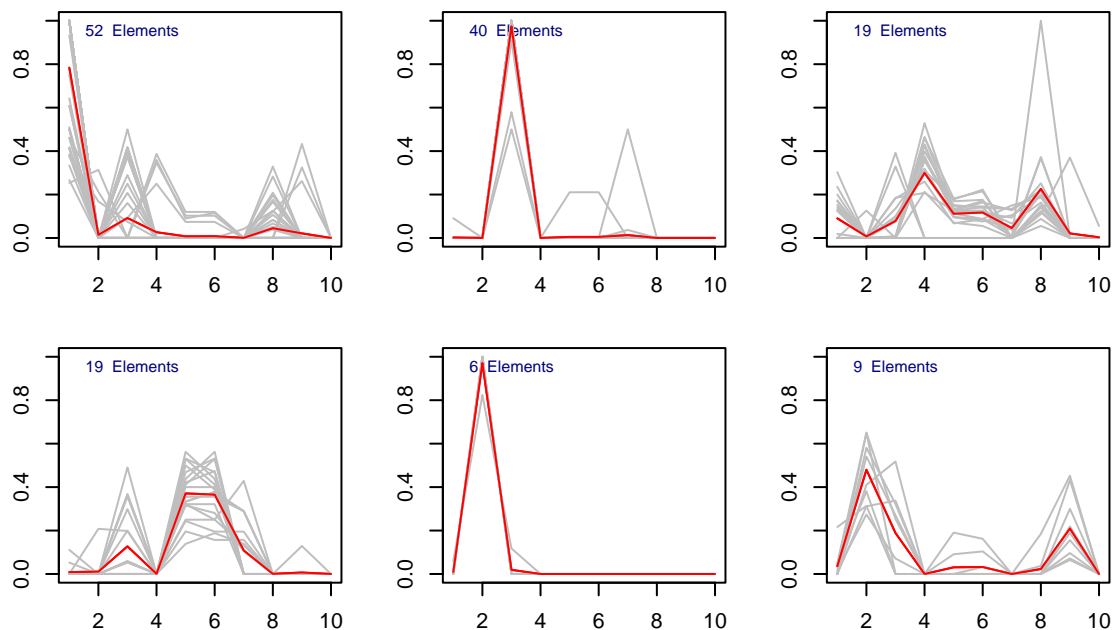
```
> ## plotting curves
> plot3CPETRes(hlda, type = "curve")
```



if `type = "avgCurve"` then the average curves are displayed.

```
> ## plotting Average curves
> plot3CPETRes(hlda, type = "avgCurve")
```

*## curves and avgCurves are only plotted for clues objects. function kept for legacy*

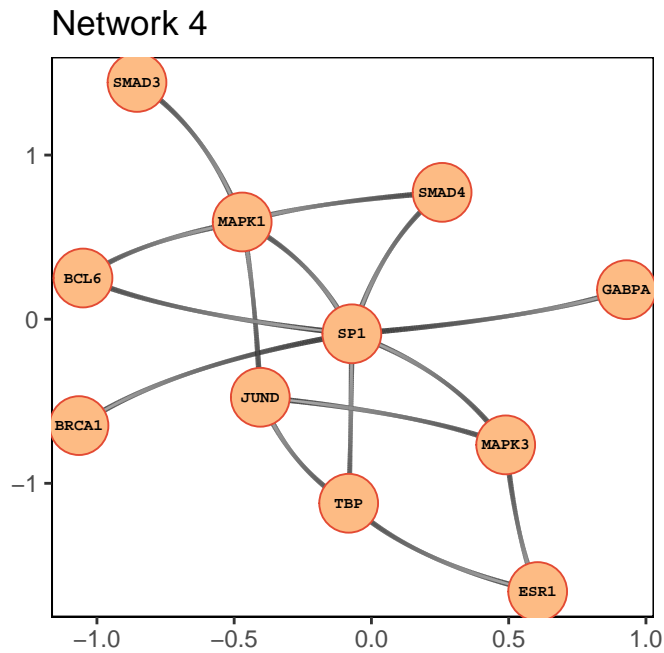


### 2.6.3 plot networks

if `type = "networks"` is used, a pdf file `AllGraphs.pdf` is created and contains one networks per page. This method returns a `ggplot` list (one for each network). By default the `layout.kamada.kawai` from the `igraph` package is used by the user can pass any other function through the `layoutfct` parameter.

```
> nets_plot <- plot3CPETRes(hlda, type = "networks")
> plot(nets_plot[[4]])
```

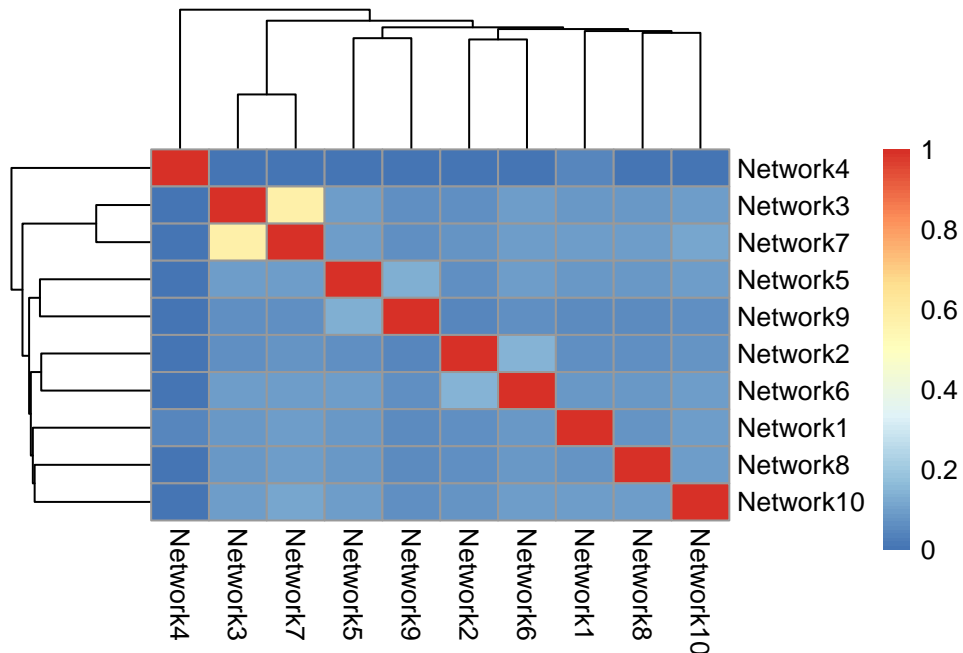
# *R3CPET* user manual



## 2.6.4 Networks similarity

To the degree to which the inferred networks share some common edges we can set `type = "netSim"`. of course, the smaller the similarity the better.

```
> plot3CPETRes(hlda, type = "netSim")
```



## 2.6.5 Circos maps

*R3CPET* also enable the user to plot a basic circos map for a given cluster through the method `visualizeCircos`. The initial data should be passed in the `data` parameter as a `ChiapetExperimentData` object.

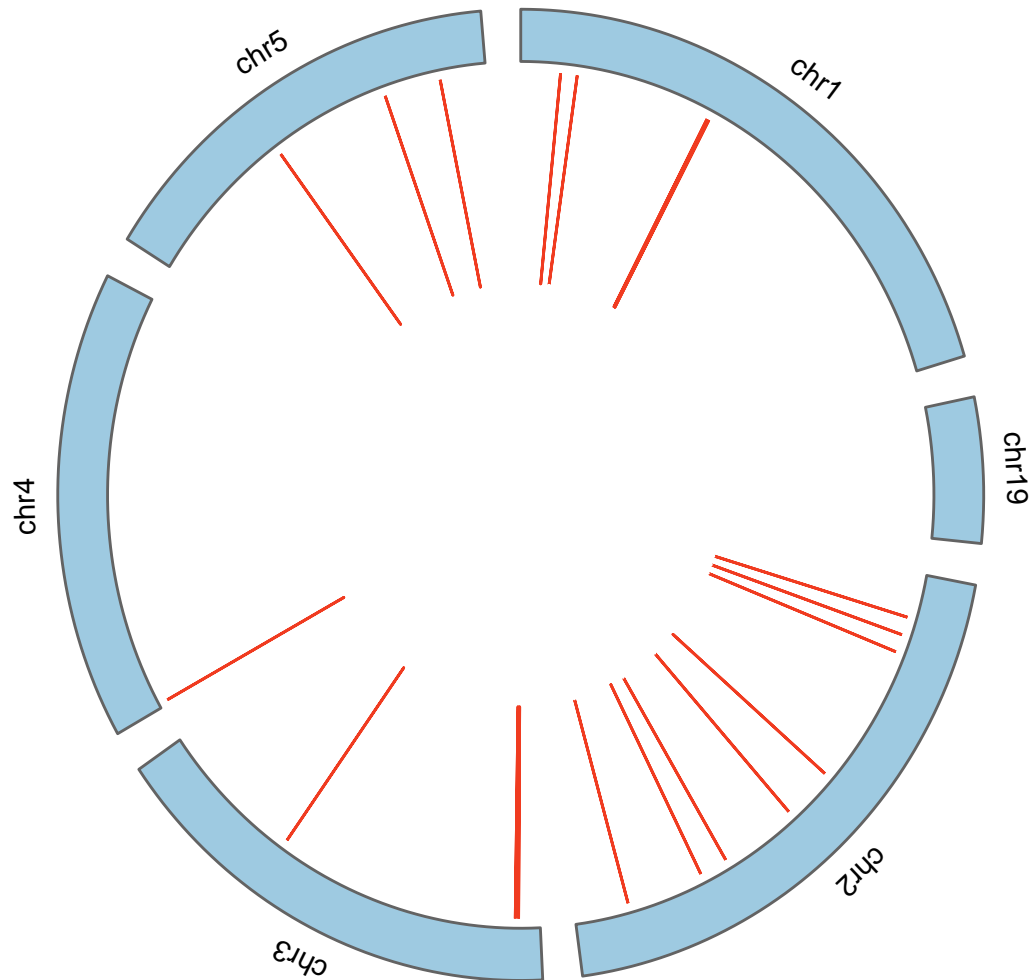
*R3CPET* user manual

```
visualizeCircos(object, data, cluster = 1, chrLenghts = NULL)
```

By default, the human chromosome lengths are used, if the user is using different species he can provide his own chromosome lengths as a two columns `data.frame` that contains the name of the chromosome in the first column and the length in the second one.

```
> visualizeCircos(hlda, x, cluster = 4)
```

### Interactions in cluster 4



## 2.7 Gene enrichment

*R3CPET*enable uses to do a GO analysis using the `DAVID` web service. Two types of enrichment can be done:

- GO enrichment analysis of the proteins of the inferred networks using the `GOEnrich.networks` method.

- GO enrichment of the chromatin interaction clusters using the `GOEnrich.folder` method.

## 2.8 Using the web interface

### R3CPET user manual

After getting all the results (HLDA, clustering, ... etc), the user can display the results using a web browser developed using the *shiny* package. This can be done through the method `createServer`.

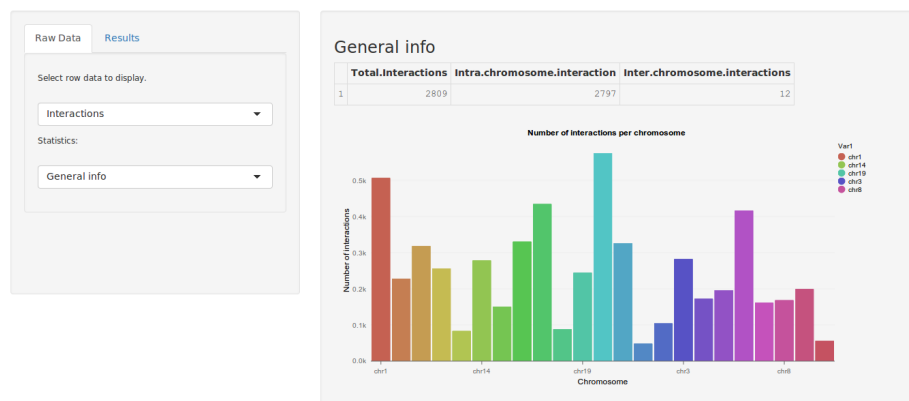
```
createServer(x, nets, hlدا)
```

In the website the user can have some information about the raw data, such as the used TF, how many regions each TF binds, the distribution of interaction per cluster, .... etc. Some of the features are explained in the following points

### 2.8.1 Raw data visualization

Statistics about the 3 types of raw data (chromatin interactions, TFBS, PPI) can be displayed. Two select options are available under the "Raw Data" panel:

Visualize 3CPET results



**Figure 3:** Example showing the histogram of the number of interacting region per chromosome

- data type selection option: in which the user selects the type of data he wants analyze : Interactions, TFBS or PPI.
- statistics selection option : in which the user selects the type of the plot he wants to generate (Figure 4)

### 2.8.2 Results visualization

This panel also enables the user to interactively analyze his results. Two types of results can be analyzed : The concerning the Chromatin maintainer networks, and the other one about the clustered genomic regions. For example, Figure 5. shows a screenshot in which the user selects a Chromatin maintainer network and display it in an interactive manner using the *D3js* javascript library.

## Visualize 3CPET results

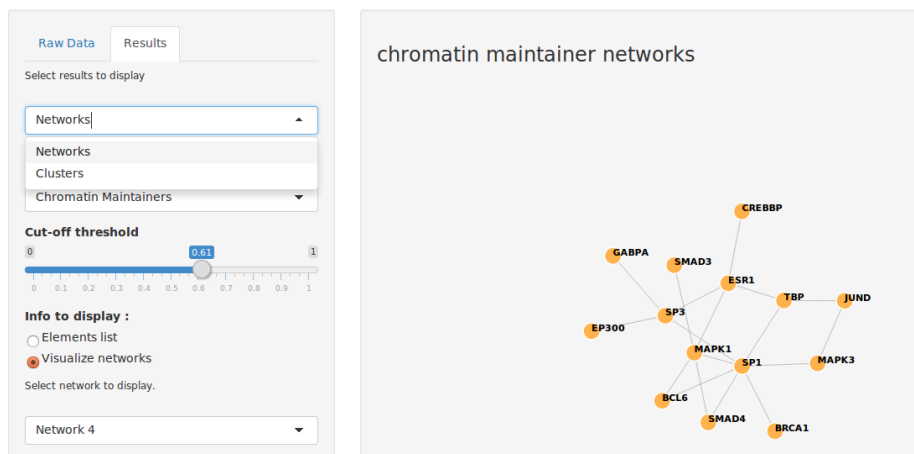


Figure 4: Example of the plots in the web interface

## 3 Session Info

```
sessionInfo()

## R version 4.4.0 RC (2024-04-16 r86468 ucrt)
## Platform: x86_64-w64-mingw32/x64
## Running under: Windows Server 2022 x64 (build 20348)
##
## Matrix products: default
##
## locale:
##  [1] LC_COLLATE=C
##  [2] LC_CTYPE=English_United States.utf8
##  [3] LC_MONETARY=English_United States.utf8
##  [4] LC_NUMERIC=C
##  [5] LC_TIME=English_United States.utf8
##
## time zone: America/New_York
## tzcode source: internal
##
## attached base packages:
## [1] stats4      stats      graphics  grDevices  utils
## [6] datasets   methods    base
##
## other attached packages:
## [1] ggplot2_3.5.1      R3CPET_1.37.0
## [3] Rcpp_1.0.12        igraph_2.0.3
## [5] GenomicRanges_1.57.0 GenomeInfoDb_1.41.0
## [7] IRanges_2.39.0     S4Vectors_0.43.0
## [9] BiocGenerics_0.51.0
##
## loaded via a namespace (and not attached):
```



```
## [1] RColorBrewer_1.1-3
## [2] rstudioapi_0.16.0
## [3] jsonlite_1.8.8
## [4] magrittr_2.0.3
## [5] GenomicFeatures_1.57.0
## [6] farver_2.1.2
## [7] rmarkdown_2.26
## [8] BiocIO_1.15.0
## [9] zlibbioc_1.51.0
## [10] vctrs_0.6.5
## [11] memoise_2.0.1
## [12] Rsamtools_2.21.0
## [13] RCurl_1.98-1.14
## [14] base64enc_0.1-3
## [15] tinytex_0.51
## [16] htmltools_0.5.8.1
## [17] S4Arrays_1.5.0
## [18] progress_1.2.3
## [19] curl_5.2.1
## [20] SparseArray_1.5.4
## [21] Formula_1.2-5
## [22] htmlwidgets_1.6.4
## [23] plyr_1.8.9
## [24] httr2_1.0.1
## [25] cachem_1.0.8
## [26] GenomicAlignments_1.41.0
## [27] lifecycle_1.0.4
## [28] pkgconfig_2.0.3
## [29] Matrix_1.7-0
## [30] R6_2.5.1
## [31] fastmap_1.2.0
## [32] GenomeInfoDbData_1.2.12
## [33] MatrixGenerics_1.17.0
## [34] digest_0.6.35
## [35] colorspace_2.1-0
## [36] GGally_2.2.1
## [37] AnnotationDbi_1.67.0
## [38] OrganismDbi_1.47.0
## [39] Hmisc_5.1-2
## [40] RSQLite_2.3.6
## [41] labeling_0.4.3
## [42] filelock_1.0.3
## [43] fansi_1.0.6
## [44] httr_1.4.7
## [45] abind_1.4-5
## [46] compiler_4.4.0
## [47] withr_3.0.0
## [48] bit64_4.0.5
## [49] htmlTable_2.4.2
## [50] backports_1.4.1
## [51] BiocParallel_1.39.0
```

```
## [52] DBI_1.2.2
## [53] ggstats_0.6.0
## [54] highr_0.10
## [55] biomaRt_2.61.0
## [56] rappdirs_0.3.3
## [57] DelayedArray_0.31.1
## [58] rjson_0.2.21
## [59] tools_4.4.0
## [60] foreign_0.8-86
## [61] nnet_7.3-19
## [62] glue_1.7.0
## [63] restfulr_0.0.15
## [64] grid_4.4.0
## [65] checkmate_2.3.1
## [66] cluster_2.1.6
## [67] reshape2_1.4.4
## [68] generics_0.1.3
## [69] gtable_0.3.5
## [70] BSgenome_1.73.0
## [71] class_7.3-22
## [72] tidyr_1.3.1
## [73] ensemblDb_2.29.0
## [74] data.table_1.15.4
## [75] hms_1.1.3
## [76] xml2_1.3.6
## [77] utf8_1.2.4
## [78] XVector_0.45.0
## [79] pillar_1.9.0
## [80] stringr_1.5.1
## [81] clValid_0.7
## [82] dplyr_1.1.4
## [83] BiocFileCache_2.13.0
## [84] lattice_0.22-6
## [85] rtracklayer_1.65.0
## [86] bit_4.0.5
## [87] biovizBase_1.53.0
## [88] RBGL_1.81.0
## [89] tidyselect_1.2.1
## [90] Biostrings_2.73.0
## [91] knitr_1.46
## [92] gridExtra_2.3
## [93] ggbio_1.53.0
## [94] ProtGenerics_1.37.0
## [95] SummarizedExperiment_1.35.0
## [96] xfun_0.44
## [97] Biobase_2.65.0
## [98] matrixStats_1.3.0
## [99] pheatmap_1.0.12
## [100] stringi_1.8.4
## [101] UCSC.utils_1.1.0
## [102] lazyeval_0.2.2
```

```
## [103] yaml_2.3.8
## [104] evaluate_0.23
## [105] codetools_0.2-20
## [106] tibble_3.2.1
## [107] graph_1.83.0
## [108] BiocManager_1.30.23
## [109] cli_3.6.2
## [110] rpart_4.1.23
## [111] munsell_0.5.1
## [112] dichromat_2.0-0.1
## [113] dbplyr_2.5.0
## [114] png_0.1-8
## [115] XML_3.99-0.16.1
## [116] parallel_4.4.0
## [117] blob_1.2.4
## [118] prettyunits_1.2.0
## [119] AnnotationFilter_1.29.0
## [120] bitops_1.0-7
## [121] txdbmaker_1.1.0
## [122] VariantAnnotation_1.51.0
## [123] scales_1.3.0
## [124] purrr_1.0.2
## [125] crayon_1.5.2
## [126] BiocStyle_2.33.0
## [127] rlang_1.1.3
## [128] KEGGREST_1.45.0
## [129] formatR_1.14
```