

# An Introduction to LDna package: the basics

## Introduction

This vignette provides a basic tutorial to the **LDna** package.

LDna uses network analyses to find clusters of loci in high linkage disequilibrium (LD) from population genomic data sets. In LD networks vertices represent loci and edges represent LD values above given thresholds. Starting from a high LD threshold value, only a few loci will be connected to each other. As the LD threshold is lowered, more and more edges and loci are added to the network allowing clusters to ‘grow’ with respect to numbers of loci and edges. Distinct clusters that remain separate across large range of LD thresholds indicate subsets of loci that represent different population genetic signals in the data. At sufficiently low LD threshold values all loci will eventually merge (connect by at least one edge) into a single cluster.

**Trees are used to visualise cluster merging** Trees are used to visualise the process of cluster merging with decreasing LD threshold, where branches represent clusters/loci and branch points represent the merger of one or several clusters/loci. This is known as a *single linkage clustering algorithm* (see `?hclust` for details) as only one connection (edge) between clusters is required for them to be considered as ‘merged’. Distance to nodes indicates LD threshold values at which the mergers occur.

**$\lambda$  measures the change in median LD before and after merger** The premise of LDna relies on the notion that ‘interesting’ clusters remain distinct (i.e. separate) across a wide range of LD thresholds and that these clusters are extracted for downstream analyses at an LD threshold value just before they merge. To identify these mergers we record the change in the median LD between all loci in a cluster before and after merger,  $\lambda$ . This is defined as:  $(\tilde{x}_1 - \tilde{x}_2)n$  where  $\tilde{x}_1$  is the median of all pairwise LD values within the focal cluster,  $\tilde{x}_2$  is the median of all pairwise values between loci within the focal cluster and between the loci in the focal cluster and any of the loci it merges with, and  $n$  is the number of loci in the focal cluster. Thus, the addition of individual loci to an existing cluster or the merging of clusters where only one cluster is large (with respect to numbers of loci) will cause small  $\lambda$ -values. In contrast, the merging of at least two large and distinct clusters with highly different LD signals will cause high  $\lambda$ -values for each of the large clusters involved. Clusters with  $\lambda$ -values that comprise outliers (relative to the median of all values in the data set) are then visually explored and subsequently extracted for downstream analyses.

## Pipeline

**Installing** With **devtools** (install from CRAN) LDna can be installed by:

```
devtools::install_github("petrikemppainen/LDna")
```

This downloads the source directly from **github** and builds the vignettes and thus requires LaTeX to be installed on your computer.

Alternatively, download the source file from [the LDna github repository](#) and install by:

```
install.packages("/path_to/source_file", repos = NULL, type = "source")
```

and then load the package:

```
library(LDna)
```

**About estimating LD** The only input data for LDna is a matrix of all pairwise LD values between loci from a population genomics data set. This is the primary bottleneck of LDna analyses as the number of pairwise comparisons increase by  $n * (n - 1) / 2$  where  $n$  is the number of loci in the data set. Although not the fastest method, LD can be estimated by the function `LD` from the **genetics** package (see `?genetics::LD` for details). The squared correlation coefficient between pairs of loci,  $R^2$ , is strongly recommended as it takes into account the heterozygosity of the loci (which other common estimates of LD, such as  $D$  or  $D'$ , do not). Note that  $R^2$  can only be calculated for bi-allelic markers.

**Sample data set** Although LDna analyses are meant to deal with large population genomic data sets, here we show the principles of LDna using an LD matrix with only eight loci.

```
LDmat <- structure(c(NA, 0.84, 0.64, 0.24, 0.2, 0.16, 0.44, 0.44, NA, NA, 0.8,
  0.28, 0.4, 0.36, 0.36, 0.24, NA, NA, NA, 0.48, 0.32, 0.2, 0.36, 0.2, NA,
  NA, NA, NA, 0.76, 0.56, 0.6, 0.2, NA, NA, NA, NA, NA, 0.72, 0.68, 0.24,
  NA, NA, NA, NA, NA, NA, 0.44, 0.24, NA, NA, NA, NA, NA, NA, NA, 0.2, NA,
  NA, NA, NA, NA, NA, NA, NA), .Dim = c(8L, 8L), .Dimnames = list(paste("L",
  1:8, sep = ""), paste("L", 1:8, sep = "")))
LDmat
```

	L1	L2	L3	L4	L5	L6	L7	L8
L1	NA	NA	NA	NA	NA	NA	NA	NA
L2	0.84	NA	NA	NA	NA	NA	NA	NA
L3	0.64	0.80	NA	NA	NA	NA	NA	NA
L4	0.24	0.28	0.48	NA	NA	NA	NA	NA
L5	0.20	0.40	0.32	0.76	NA	NA	NA	NA
L6	0.16	0.36	0.20	0.56	0.72	NA	NA	NA
L7	0.44	0.36	0.36	0.60	0.68	0.44	NA	NA
L8	0.44	0.24	0.20	0.20	0.24	0.24	0.2	NA

**Produce raw data for LDna** The first step in LDna is to build a *single linkage clustering* tree from an LD matrix and acquire summary data for each of the clusters identified by this tree. This is achieved by the function `LDnaRaw` which takes a lower diagonal LD matrix and outputs a list with two objects. The first, `ldna$clusterfile`, is a matrix with all unique clusters as columns and the loci as rows, where TRUE indicates the presence of a locus in a specific cluster (else FALSE is given). The second, `ldna$stats`, is a data frame that gives all edges for the above tree along with summary information, including  $\lambda$ . By default all LD values are rounded to the nearest hundred as this significantly reduces computation time and has little affect on the analyses as a whole.

```
ldna <- LDnaRaw(LDmat)
```

As seen from the object `ldna$clusterfile` this data set includes seven unique clusters of which cluster “7\_0.44” includes all loci. The number after the underscore for each cluster-name indicates the highest LD threshold at which it is present.

```
ldna$clusterfile
```

	7_0.44	6_0.48	2_0.8	5_0.68	4_0.72	3_0.76	1_0.84
L1	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE

L2	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE
L3	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE
L4	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE
L5	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE
L6	TRUE	TRUE	FALSE	TRUE	TRUE	FALSE	FALSE
L7	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE
L8	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

In the object `ldna$stats` each row represents a tree-edge with the following information for each cluster: name for the focal cluster, name for the parent cluster (cluster after merger), edge length (in units of LD), the number of edges,  $nE$ , number of vertices (loci),  $nV$ , and  $\lambda$ .

`ldna$stats`

	cluster	parent_cluster	edge.length	nV	nE	Lambda
1	7_0.44	root	0.44	8	12	0.00
2	6_0.48	7_0.44	0.04	7	9	0.56
3	5_0.68	6_0.48	0.2	4	3	1.04
4	4_0.72	5_0.68	0.04	3	2	0.24
5	2_0.8	6_0.48	0.32	3	2	1.32
6	3_0.76	4_0.72	0.04	2	1	0.08
7	1_0.84	2_0.8	0.04	2	1	0.08
8	L5	3_0.76	0.24	1	0	0.00
9	L4	3_0.76	0.24	1	0	0.00
10	L6	4_0.72	0.28	1	0	0.00
11	L7	5_0.68	0.32	1	0	0.00
12	L2	1_0.84	0.16	1	0	0.00
13	L1	1_0.84	0.16	1	0	0.00
14	L3	2_0.8	0.2	1	0	0.00
15	L8	7_0.44	0.56	1	0	0.00

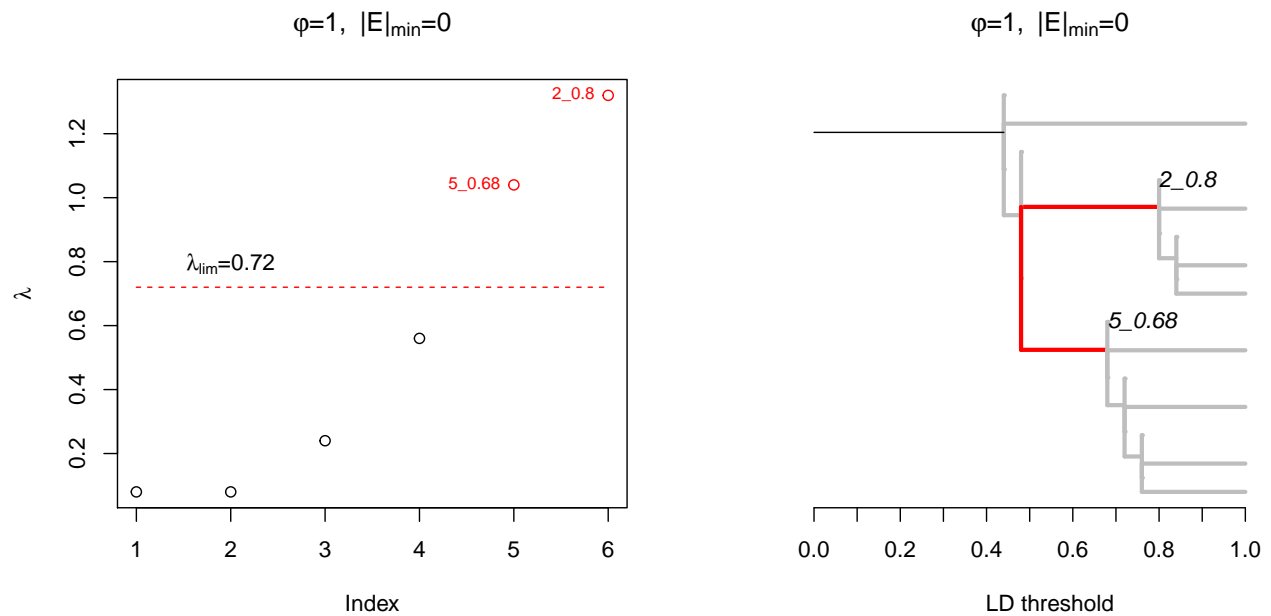
**Identify and extract clusters** Next we proceed with studying the tree and extracting clusters using the function `extractClusters`. In this process we need to decide which clusters are consider as outliers with respect to their  $\lambda$ -values. An outlier cluster (OC) is defined as any cluster with a  $\lambda$ -value higher than

$$\lambda_{lim(\varphi)} = median + mad * \varphi$$

where *mad* is the *median absolute deviation* (see `?mad` for details) across all  $\lambda$ -values, and  $\varphi$  is a user defined factor (in reality the argument `constant` for the `mad` function). Thus,  $\varphi$  (controlled by the argument *phi*) determines how stringent LDna is with respect to considering a cluster an *OC*. This makes the absolute values of  $\lambda$  irrelevant as each value is assessed in relation to all other values in the data set/tree. It is also possible to define the minimum number of edges,  $|E|_{min}$  (specified by the argument `min.edges`), to restrict which branches are shown in the tree (this is necessary for larger data sets and will be covered in more detaied in the advanced tutorial). In order to simplify this process, a tip with zero edge length is added for each node/cluster. Here we set `min.edges=0` in order to visualise the entire tree, including branches representing individual loci. We set `phi=1`, but note that any value between 0 and 2 will give identical result.

By default, the function `extractClusters` prints two figures. The first shows all  $\lambda$ -values in increasing order, where the red dashed line indicates  $\lambda_{lim}$  above which any value is considered as an outlier (indicated in red). In this analysis two clusters: `2_08` and `5_58`, are outliers. The second figure shows the tree that visualises the cluster merging process. Only tip labels for the two internal branches that comprise *OCs* are shown and the branches leading to these nodes are colored red. Note also the extra tips with zero branch lengths associated with every node as mentioned above.

```
par(mfcol=c(1,2))
clusters <- extractClusters(ldna, min.edges = 0, phi = 1)
```



`extractClusters` outputs a list with all OCs and their loci.

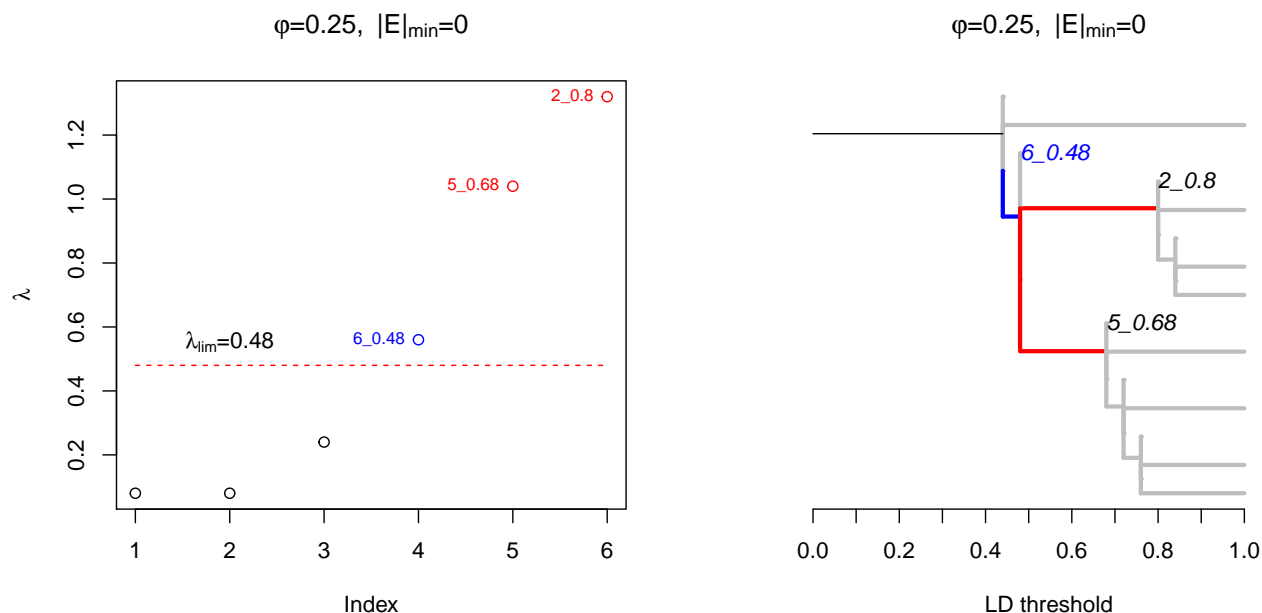
```
clusters
```

```
$`2_0.8`
[1] "L1" "L2" "L3"
```

```
$`5_0.68`
[1] "L4" "L5" "L6" "L7"
```

If  $\phi$  is lowered to 0.25 one additional cluster,  $6_{0.48}$ , becomes an outlier.

```
par(mfcol=c(1,2))
clusters <- extractClusters(ldna, min.edges = 0, phi = 0.25, rm.COCs=FALSE)
```



```
clusters
```

```
$`2_0.8`
[1] "L1" "L2" "L3"

$`5_0.68`
[1] "L4" "L5" "L6" "L7"

$`6_0.48`
[1] "L1" "L2" "L3" "L4" "L5" "L6" "L7"
```

As seen above, *OC 6\_0.48* represents the merging of the two previous *OCs* (*2\_0.8* and *5\_0.68*). To distinguish that an *OC* contains loci from those extracted at an higher LD threshold than itself we denote it as a “*compound outlier cluster*”, “*COC*”, as opposed to a “*single outlier cluster*”, “*SOC*”. Typically we are mainly interested in *SOCs* and thus by default only *SOCs* are considered. However, as in the example above, when `rm.COCs=FALSE` all *OCs* are shown in the figures (and extracted) and any *COCs* are colored blue.

**summaryLDna** Based on the outfiles produced above (*ldna*, *clusters* and *LDmat*), information of the *OCs* can be further summarizes by the function **summaryLDna**. In addition to the information already available from the *ldna* file above, **summaryLDna** outputs a data frame with the following information for each extracted cluster: “*Type*”, which indicates whether an *OC* is a *SOC* or a *COC* (for the given settings for *min.edges* and *phi*); “*Merge.at*”, which indicates at which LD threshold the clusters merge and; “*Mean.LD*” which gives the mean of all pairwise LD values within the *OC*.

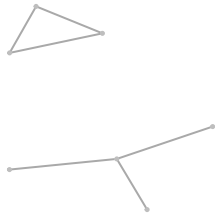
```
summary <- summaryLDna(ldna, clusters, LDmat)
summary
```

	Type	Merge.at	nLoci	nE	Lambda	Mean.LD	Mean.LD.SE
2_0.8	SOC	0.48	3	2	1.32	0.760	0.0611
5_0.68	SOC	0.48	4	3	1.04	0.627	0.0481
6_0.48	COC	0.44	7	9	0.56	0.469	0.0460

**plotLDnetworks** Lastly the function `plotLDcluster` is used to visually inspect the extracted clusters. This function is based on functions from the package **igraph** and always needs the original LD matrix as an input. First we can plot the full network at a given threshold by setting `option=1` and specifying the threshold. As this can be done without any additional information besides the LD matrix, this should be the first thing to do with the data as it gives an instant impression of how much clustering exists (see the advanced tutorial for details). At LD `threshold=0.6` the two *OCs* (corresponding to *2\_0.08* and *5\_0.68*) are still separate, i.e. not connect by any edge.

```
plotLDnetwork(LDmat=LDmat, option=1, threshold=0.6)
```

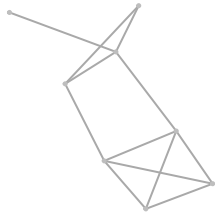
**@0.6**



At LD `threshold=0.4` all loci are connected to a single cluster by at least one edge. If the LD threshold is lowered even further more edges will be added to the network but the loci will remain the same (a cluster is defined by its unique set of loci not its set of edges).

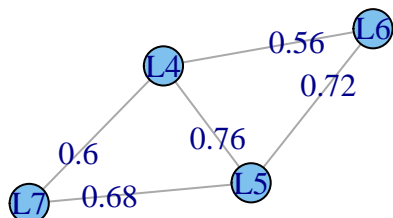
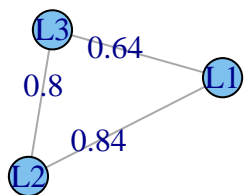
```
plotLDnetwork(LDmat=LDmat, option=1, threshold=0.40)
```

**@0.4**



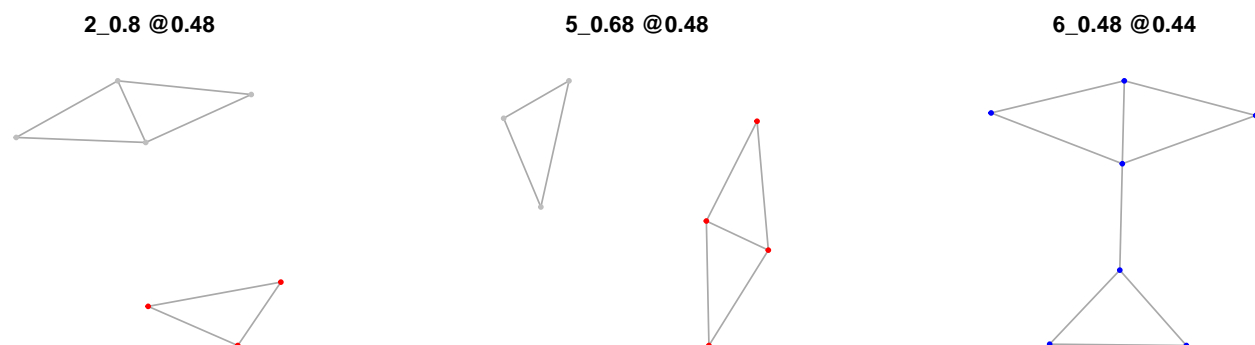
At the core `extractClusters` lies two functions from the package **igraph**: `graph.adjacency` and `plot.igraph`. The below example is used to show how these functions can be used to for instance show all vertex names (i.e locus names) and all LD values for the edges. Igraph is highly flexible and for custom networks and `?igraph` is a good place to start.

```
# Creates a 'weighted' graph object from our lower diagonal LD matrix
g <- graph.adjacency(LDmat, mode="lower", diag=FALSE, weighted=T)
# Removes edges with weights (LD values) below 0.5
g <- delete.edges(g, which(E(g)$weight<=0.5))
# Removes 'unconnected' vertices (loci)
g <- delete.vertices(g, which(degree(g) < 1))
# plots graph, 'edge.label' is used to add the LD values for each edge
plot.igraph(g, edge.label=E(g)$weight)
```



With `option=2`, by default `plotLDnetwork` plots a network for each *OC* at an LD threshold just before it merges. For this the outputs from `LDnaRaw` and `extractClusters` and `summaryLDna` also need to be included. The title gives the cluster name in question and the LD threshold at which the network is drawn and any loci from the OC in question is indicated in red (*SOC*) or blue (*COC*).

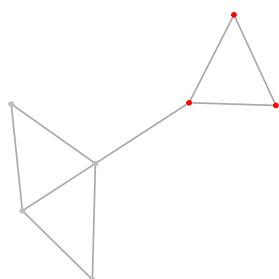
```
par(mfcol=c(1,3))
plotLDnetwork(ldna, LDmat, option=2, clusters=clusters, summary=summary)
```



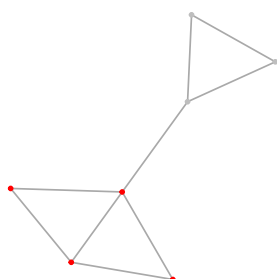
By setting the argument `after.merger` to `TRUE`, the network is printed at an LD threshold just after merger. Note thus that the networks are plotted at different LD thresholds compared to above. Overall `extractClusters` is a highly customizable functions which will be further demonstrated in the advanced tutorial.

```
par(mfcol=c(1,3))
plotLDnetwork(ldna, LDmat, option=2, clusters=clusters, summary=summary, after.merger=TRUE)
```

**2\_0.8 @0.44**



**5\_0.68 @0.44**



**6\_0.48 @0.43**

