

Package: fcfdr (via r-universe)

September 5, 2024

Title Flexible cFDR

Version 1.0.0

Description Provides functions to implement the Flexible cFDR (Hutchinson et al. (2021) <[doi:10.1371/journal.pgen.1009853](https://doi.org/10.1371/journal.pgen.1009853)>) and Binary cFDR (Hutchinson et al. (2021) <[doi:10.1101/2021.10.21.465274](https://doi.org/10.1101/2021.10.21.465274)>) methodologies to leverage auxiliary data from arbitrary distributions, for example functional genomic data, with GWAS p-values to generate re-weighted p-values.

Imports locfdr, MASS, ggplot2, cowplot, fields, dplyr, spatstat.geom, polyCub, hexbin, bigsplines, data.table, grDevices, Hmisc

Suggests stats, knitr, rmarkdown, digest, testthat (>= 3.0.0)

License MIT + file LICENSE

Encoding UTF-8

LazyData true

Roxygen list(markdown = TRUE)

RoxygenNote 7.1.2

VignetteBuilder knitr

Depends R (>= 3.5.0)

Config/testthat/edition 3

NeedsCompilation no

Author Anna Hutchinson [aut, cre] (<<https://orcid.org/0000-0002-9224-4410>>), Chris Wallace [aut], Thomas Willis [ctb, aut], James Liley [ctb]

Maintainer Anna Hutchinson <annahutchinson1995@gmail.com>

Repository <https://annahutch.r-universe.dev>

RemoteUrl <https://github.com/annahutch/fcfdr>

RemoteRef HEAD

RemoteSha c2e73698a179726dadf2b28b07b121a4cdc6aa40

Contents

binary_cfdr	2
corr_plot	3
flexible_cfdr	4
log10pv_plot	6
match_ind_maf	7
parameters_in_locfdr	7
pv_plot	9
stratified_qqplot	10
T1D_application_data	11

Index	12
--------------	-----------

binary_cfdr	<i>Perform cFDR leveraging binary auxiliary covariates</i>
--------------------	--

Description

Perform cFDR leveraging binary auxiliary covariates

Usage

```
binary_cfdr(p, q, group)
```

Arguments

p	p-values for principal trait (vector of length n)
q	binary auxiliary data values (vector of length n)
group	group membership of each SNP for leave-one-out procedure (vector of length n) (e.g. chromosome number or LD block)

Value

data.frame of p, q and v values

Examples

```
# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing functional genomic data).
# We use the parameters_in_locfdr() function to extract the parameters estimated by
# the locfdr function.
```

```
# generate p
set.seed(2)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))
p <- 2*pnorm(-abs(zp))
```

```
# generate q
q <- rbinom(n, 1, 0.1)

group <- c(rep("A", n/2), rep("B", n/2))

binary_cfdr(p, q, group)
```

corr_plot*Violin plot of p-values for quantiles of q***Description**

Violin plot of p-values for quantiles of q

Usage

```
corr_plot(p, q, ylim = c(0, 1.5))
```

Arguments

p	p values for principal trait (vector of length n)
q	auxiliary data values (vector of length n)
ylim	y-axis limits (-log10)

Details

Can be used to investigate the relationship between p and q

If this shows a non-monotonic relationship then the cFDR framework should not be used
(because e.g. cFDR cannot simultaneously shrink v-values for high p and low p)

Value

ggplot object

Examples

```
# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing functional genomic data).
# We use the corr_plot() function to visualise the relationship between p and q.
```

```
# generate p
set.seed(1)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))
p <- 2*pnorm(-abs(zp))
```

```
# generate q
mixture_comp1 <- function(x) rnorm(x, mean = -0.5, sd = 0.5)
mixture_comp2 <- function(x) rnorm(x, mean = 2, sd = 1)
q <- c(mixture_comp1(n1p), mixture_comp2(n-n1p))

corr_plot(p, q)
```

flexible_cfdr *Perform Flexible cFDR*

Description

Performs Flexible cFDR for continuous auxiliary covariates

Usage

```
flexible_cfdr(
  p,
  q,
  indep_index,
  res_p = 300,
  res_q = 500,
  nxbin = 1000,
  gridp = 50,
  splinecorr = TRUE,
  dist_thr = 0.5,
  locfdr_df = 10,
  plot = TRUE,
  maf = NULL,
  check_indep_cor = TRUE,
  enforce_p_q_cor = TRUE
)
```

Arguments

p	p-values for principal trait (vector of length n)
q	continuous auxiliary data values (vector of length n)
indep_index	indices of independent SNPs
res_p	number of grid points in x-direction (p) for KDE estimation
res_q	number of grid points in y-direction (q) for KDE estimation
nxbin	number of bins in x-direction (p) for hex-binning
gridp	number of data points required in a KDE grid point for left-censoring
splinecorr	logical value for whether spline correction should be implemented

dist_thr	distance threshold for spline correction
locfdr_df	df parameter in locfdr function
plot	logical value for whether to produce plots to assess KDE fit
maf	minor allele frequencies for SNPs to which p and q relate (optional and used to perform MAF matching)
check_indep_cor	check that sign of the correlation between p and q is the same in the independent subset as in the whole
enforce_p_q_cor	if p and q are negatively correlated, flip the sign on q values

Details

If maf is specified, then the independent SNPs will be down-sampled to match the minor allele frequency distribution.

Value

List of length two: (1) data.frame of p-values, q-values and v-values (2) data.frame of auxiliary data (q_low used for left censoring, how many data-points were left censored and/or spline corrected)

Examples

```
# this is a long running example

# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing functional genomic data).
# We use the flexible_cfdr() function to generate v-values using default parameter values.

# generate p
set.seed(1)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))
p <- 2*pnorm(-abs(zp))

# generate q
mixture_comp1 <- function(x) rnorm(x, mean = -0.5, sd = 0.5)
mixture_comp2 <- function(x) rnorm(x, mean = 2, sd = 1)
q <- c(mixture_comp1(n1p), mixture_comp2(n-n1p))

n_indep <- n

flexible_cfdr(p, q, indep_index = 1:n_indep)
```

log10pv_plot*Plot -log10(p) against -log10(v) and colour by q***Description**

Plot -log10(p) against -log10(v) and colour by q

Usage`log10pv_plot(p, q, v, axis_lim = c(0, 20))`**Arguments**

<code>p</code>	p values for principal trait (vector of length n)
<code>q</code>	auxiliary data values (vector of length n)
<code>v</code>	v values from cFDR
<code>axis_lim</code>	Optional axis limits

Details

Can be used to visualise the results from Flexible cFDR

Value

ggplot object

Examples

```
# this is a long running example

# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing functional genomic data).
# We use the flexible_cfdr() function to generate v-values and then the log10pv_plot() function
# to visualise the results.

# generate p
set.seed(1)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))
p <- 2*pnorm(-abs(zp))

# generate q
mixture_comp1 <- function(x) rnorm(x, mean = -0.5, sd = 0.5)
mixture_comp2 <- function(x) rnorm(x, mean = 2, sd = 1)
q <- c(mixture_comp1(n1p), mixture_comp2(n-n1p))

n_indep <- n
```

```
res <- flexible_cfdr(p, q, indep_index = 1:n_indep)
log10pv_plot(p = res[[1]]$p, q = res[[1]]$q, v = res[[1]]$v)
```

match_ind_maf

Function to downsample independent SNPs to match MAF distribution of whole set.

Description

Matches MAF distribution of independent set of SNPs to MAF distribution of whole set of SNPs to avoid MAF-based confounding.

Usage

```
match_ind_maf(maf, indep_index)
```

Arguments

maf	minor allele frequencies of (all) SNPs
indep_index	indices of independent SNPs

Details

Must supply maf values from the whole data set, not just the independent SNPs.

Value

indices of independent SNP in chosen in sample

parameters_in_locfdr *parameters_in_locfdr*

Description

parameters_in_locfdr

Usage

```
parameters_in_locfdr(
  p,
  q,
  indep_index,
  res_p = 300,
  res_q = 500,
  maf = NULL,
  check_indep_cor = TRUE,
  enforce_p_q_cor = TRUE
)
```

Arguments

<code>p</code>	<code>p</code> values for principal trait (vector of length <code>n</code>)
<code>q</code>	continuous auxiliary data values (vector of length <code>n</code>)
<code>indep_index</code>	indices of independent SNPs
<code>res_p</code>	resolution for <code>p</code>
<code>res_q</code>	resolution for <code>q</code>
<code>maf</code>	minor allele frequencies for SNPs to which <code>p</code> and <code>q</code> relate (optional and used to perform MAF matching)
<code>check_indep_cor</code>	check that sign of the correlation between <code>p</code> and <code>q</code> is the same in the independent subset as in the whole
<code>enforce_p_q_cor</code>	if <code>p</code> and <code>q</code> are negatively correlated, flip the sign on <code>q</code> values

Value

list of values used as input into `locfdr::locfdr` function intrinsically in `flexible_cfdr`

Examples

```
# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing functional genomic data).
# We use the parameters_in_locfdr() function to extract the parameters estimated by
# the locfdr function.

# generate p
set.seed(1)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))
p <- 2*pnorm(-abs(zp))

# generate q
mixture_comp1 <- function(x) rnorm(x, mean = -0.5, sd = 0.5)
mixture_comp2 <- function(x) rnorm(x, mean = 2, sd = 1)
```

```

q <- c(mixture_comp1(n1p), mixture_comp2(n-n1p))

n_indep <- n

parameters_in_locfdr(p, q, indep_index = 1:n_indep)

```

pv_plot*Plot p against v and colour by q***Description**

Plot p against v and colour by q

Usage

```
pv_plot(p, q, v, axis_lim = c(0, 1))
```

Arguments

p	p values for principal trait (vector of length n)
q	auxiliary data values (vector of length n)
v	v values from cFDR
axis_lim	Optional axis limits

Details

Can be used to visualise the results from Flexible cFDR

Value

ggplot object

Examples

```

# this is a long running example

# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing functional genomic data).
# We use the flexible_cfdr() function to generate v-values and then the pv_plot() function
# to visualise the results.

# generate p
set.seed(1)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))

```

```

p <- 2*pnorm(-abs(zp))

# generate q
mixture_comp1 <- function(x) rnorm(x, mean = -0.5, sd = 0.5)
mixture_comp2 <- function(x) rnorm(x, mean = 2, sd = 1)
q <- c(mixture_comp1(n1p), mixture_comp2(n-n1p))

n_indep <- n

res <- flexible_cfdr(p, q, indep_index = 1:n_indep)

pv_plot(p = res[[1]]$p, q = res[[1]]$q, v = res[[1]]$v)

```

stratified_qqplot *Stratified Q-Q plot.*

Description

Stratified Q-Q plot.

Usage

```

stratified_qqplot(
  data_frame,
  prin_value_label,
  cond_value_label = NULL,
  thresholds = c(1, 0.1, 0.01, 0.001, 1e-04)
)

```

Arguments

data_frame	data.frame containing p-values and auxiliary data values
prin_value_label	label of principal p-value column in data_frame
cond_value_label	label of conditional trait column in data_frame
thresholds	threshold values to define strata

Details

Can be used to investigate the relationship between p and q

Note that this function does not do the heavy lifting of styling the plot's aesthetics.

Value

ggplot object

Examples

```
# In this example, we generate some p-values (representing GWAS p-values)
# and some arbitrary auxiliary data values (e.g. representing GWAS p-values for a related trait).
# We use the stratified_qqplot() function to examine the relationship between p and q

# generate p
set.seed(1)
n <- 1000
n1p <- 50
zp <- c(rnorm(n1p, sd=5), rnorm(n-n1p, sd=1))
p <- 2*pnorm(-abs(zp))

# generate q
zq <- c(rnorm(n1p, sd=4), rnorm(n-n1p, sd=1.2))
q <- 2*pnorm(-abs(zq))

df <- data.frame(p, q)

stratified_qqplot(data_frame = df, prin_value_label = "p", cond_value_label = "q")
```

T1D_application_data *Data for T1D application*

Description

A data.frame containing the rsID, chromosome (CHR19) and base pair position (BP19) in hg19, reference allele (REF), alternative allele (ALLT), type 1 diabetes GWAS p-value (T1D_pval), minor allele frequency (MAF), LDAK weight (LDAK_weight), rheumatoid arthritis GWAS p-value (RA_pval), binary regulatory factor binding site overlap (DGF), average H3K27ac fold change value in T1D-relevant cell types (H3K27ac) for 113,543 SNPs in the T1D GWAS (<https://www.nature.com/articles/ng.3245>)

Usage

`T1D_application_data`

Format

A data frame with 113543 rows and 11 variables:

Details

Minor allele frequencies estimated from the CEU sub-population samples in the 1000 Genomes Project Phase 3 data set. Missing values were replaced by drawing samples from the empirical distribution of MAFs

Index

* **datasets**
 T1D_application_data, 11

binary_cfdr, 2

corr_plot, 3

flexible_cfdr, 4

log10pv_plot, 6

match_ind_maf, 7

parameters_in_locfdr, 7
pv_plot, 9

stratified_qqplot, 10

T1D_application_data, 11