# Package 'scHOTTER'

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Type Package		
<b>Title</b> scHOTTER: Parametric testing for spatially heterogeneous co-expression in single cell data		
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<b>Description</b> scHOTTER is a package that implements kernel-based local correlation analysis for gene pairs and an analytic null for the sample variance of Fisher z correlations across kernels that comprises a parametric alternative to Ghazanfar et al.'s single-cell higher-order testing (scHOT) methodology (Ghazanfar et al., 2020). This pipeline offers improvements in computational efficiency and statistical power, supports both 2D spatial and 1D trajectory (1D) data, and provides a high-level pipeline with access to all intermediate results.		
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 ${\tt approximate\_between\_coefficient\_correlations\_effective}$ 

Approximate correlation between kernel-wise Fisher coefficients

# **Description**

Computes an overlap-based correlation between kernels from a point×kernel weight matrix W. First, columns are normalized to  $A = WD^{-1}$ , where  $D = \operatorname{diag}(\sum_{\ell} w_{k\ell})$ . Then  $\Omega = A^{\top}A$  measures weighted overlap, and we form the cosine-similarity-style correlation

$$C = D_{\Omega}^{-1/2} \Omega D_{\Omega}^{-1/2},$$

where  $D_{\Omega} = \operatorname{diag}(\Omega)$ .

# Usage

approximate\_between\_coefficient\_correlations\_effective(weight\_matrix)

## **Arguments**

weight\_matrix Point × kernel weight matrix (preferably Matrix::dgCMatrix).

# **Details**

Optionally, if effective sample sizes neff are provided, we apply the Fisher-z attenuation factor  $s_k = \sqrt{(n_{\rm eff,k}-3)/(n_{\rm eff,k}-1)}$  (for  $n_{\rm eff,k}>3$ ) by

$$C \leftarrow S C S$$
,  $S = \operatorname{diag}(s_1, \dots, s_K)$ .

The diagonal is set to 1 for kernels with nonzero overlap norm and NA for empty/degenerate kernels.

# Value

A symmetric numeric matrix  $K \times K$  with row/column names equal to kernel names. Diagonal entries are 1 when the kernel has positive norm (nonempty) and NA otherwise.

```
set.seed(1)
coords <- cbind(runif(50), runif(50))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
C1 <- approximate_between_coefficient_correlations_effective(W)
neff <- get_effective_sample_sizes(W)
C2 <- approximate_between_coefficient_correlations_effective(W)
range(C1, na.rm = TRUE)</pre>
```

approximate\_expectation\_effective

Expectation of the sample variance of Fisher z's under dependence

# **Description**

Computes  $\mathbb{E}[S^2]$  for the unbiased sample variance  $S^2 = \frac{1}{n-1} \sum_{i=1}^n (Z_i - \bar{Z})^2$  when the kernel-wise Fisher z vector Z has covariance matrix  $\Sigma$ . The formula used is

$$\mathbb{E}[S^2] = \frac{1}{n-1} \left( \operatorname{tr}(\boldsymbol{H}\boldsymbol{\Sigma}) \right), \quad \boldsymbol{H} = \boldsymbol{I}_n - \frac{1}{n} \boldsymbol{1} \boldsymbol{1}^\top$$

where H is the centreing matrix. For independent components with common variance  $\sigma^2$ , this reduces to  $\mathbb{E}[S^2] = \sigma^2$ .

# Usage

```
approximate_expectation_effective(sigma_matrix)
```

# **Arguments**

sigma\_matrix A symmetric  $n \times n$  covariance matrix for the kernel-wise Fisher z coefficients (e.g., from get\_sigma\_matrix()). May be a base matrix or a **Matrix** object. Rows/columns containing NAs are dropped prior to computation.

#### Value

A single numeric:  $\mathbb{E}[S^2]$ . Returns NA\_real\_ if, after dropping NA rows/cols, fewer than 2 kernels remain.

```
# Sanity check: independent equal-variance case n <- 8; v <- 0.2
Sigma <- diag(rep(v, n))
approximate_expectation_effective(Sigma) # = v
```

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approximate\_variance\_effective

Variance of the sample variance of Fisher z's under dependence

# **Description**

Computes  $\mathrm{Var}(S^2)$  for the unbiased sample variance  $S^2 = \frac{1}{n-1} \sum_{i=1}^n (Z_i - \bar{Z})^2$  when the kernelwise Fisher z vector Z has covariance matrix  $\Sigma$ . The formula used is

$$\operatorname{Var}(S^2) = \frac{2}{(n-1)^2} \left( \operatorname{tr}(\boldsymbol{\Sigma}^2) - \frac{2}{n} \, \boldsymbol{1}^\top \boldsymbol{\Sigma}^2 \boldsymbol{1} + \frac{(\boldsymbol{1}^\top \boldsymbol{\Sigma} \boldsymbol{1})^2}{n^2} \right),$$

which reduces to  $2\sigma^4/(n-1)$  for independent components with common variance  $\sigma^2$ .

# Usage

```
approximate_variance_effective(sigma_matrix)
```

## **Arguments**

sigma\_matrix

A symmetric  $n \times n$  covariance matrix for the kernel-wise Fisher z coefficients (e.g., from get\_sigma\_matrix()). May be a base matrix or a **Matrix** object. Rows/columns containing NAs are dropped prior to computation.

## Value

A single numeric:  $Var(S^2)$ . Returns NA\_real\_ if, after dropping NA rows/cols, fewer than 2 kernels remain.

## **Examples**

```
# Sanity check: independent equal-variance case set.seed(1) n <- 10  
v <- 0.2  
Sigma <- diag(rep(v, n))  
approximate_variance_effective(Sigma) # ~ 2 * v^2 / (n-1)
```

compute\_p\_values

Upper-tail p-values for standardized test statistics

# **Description**

Computes one-sided p-values P(Z>z) assuming the input test statistics are standard normal under the null. This is appropriate when larger values of the statistic (e.g., a standardized sample variance) indicate stronger evidence against the null.

## Usage

```
compute_p_values(test_stats)
```

#### **Arguments**

 $test\_stats \qquad Named \ numeric \ vector \ of \ Z\text{-}scores \ (e.g., from \ compute\_test\_statistics\_standardised\_effection of \ Z\text{-}scores \ (e.g., from \ compute\_test\_statistics\_standardised\_effetion of \ Z\text{-}scores \ (e.g., from \ compute\_test\_statistics\_standardised\_effetion of \ Z$ 

#### Value

A named numeric vector of upper-tail p-values in [0,1]. Non-finite inputs (NA/Inf) return NA\_real\_.

#### **Examples**

```
s2 <- c(a_b = 3, a_c = 5, b_c = 4)
mu <- 4
var <- 1
z <- compute_test_statistics_standardised_effective(var, mu, s2)
p <- compute_p_values(z)
p</pre>
```

compute\_test\_statistics\_standardised\_effective

Standardize sample-variance test statistics into Z-scores

## **Description**

Converts the raw sample variance of local Fisher z correlations (one value per gene pair) into standardized Z-scores using the null mean and variance derived from the kernel dependence structure. The resulting standardised statistic is distributed approximately according to the standard Normal distribution.

# Usage

```
compute_test_statistics_standardised_effective(
  variances,
  expectations,
  vars_of_local_corrs
)
```

### **Arguments**

variances Numeric scalar or vector:  $\mathrm{Var}(S^2)$  under the null. Typically the scalar output

of approximate\_variance\_effective(Sigma). Can also be a named vector

matching vars\_of\_local\_corrs.

expectations — Numeric scalar or vector:  $\mathbb{E}[S^2]$  under the null. Typically the scalar output of

approximate\_expectation\_effective(Sigma). Can also be a named vector matching vars\_of\_local\_corrs.

vars\_of\_local\_corrs

Named numeric vector: observed sample variances (one per gene pair), e.g. from compute\_var\_of\_local\_corrs().

# Value

A named numeric vector of Z-scores aligned with names(vars\_of\_local\_corrs). Entries with non-finite or non-positive variances are returned as NA\_real\_.

```
# Simple algebraic example
s2 <- c(a_b = 3, a_c = 5, b_c = 4)
mu <- 4  # E[S^2]
var <- 1.0  # Var(S^2)
compute_test_statistics_standardised_effective(var, mu, s2)</pre>
```

```
compute_var_of_local_corrs
```

Sample variance of kernel-wise Fisher z per gene pair

## **Description**

Given a matrix of local Fisher z correlations (rows = kernels, columns = gene pairs like "GENE1\_GENE2"), compute the unbiased sample variance  $S^2$  down each column, ignoring NAs. Columns with fewer than two finite values return NA\_real\_.

# Usage

```
compute_var_of_local_corrs(local_corr_matrix)
```

## **Arguments**

```
local_corr_matrix
```

Numeric matrix with rows = kernels and columns = gene-pair labels (e.g., from get\_local\_correlation\_matrix() with fisher\_transform = TRUE).

# Value

A named numeric vector of length ncol(local\_corr\_matrix) containing the sample variance for each gene pair.

```
set.seed(1)
expr <- cbind(a = rnorm(60), b = rnorm(60), c = rnorm(60))
coords <- cbind(runif(60), runif(60))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
Z <- get_local_correlation_matrix(expr, W, fisher_transform = TRUE)
s2 <- compute_var_of_local_corrs(Z)
head(s2)</pre>
```

determine\_overlaps 7

determine\_overlaps

Determine overlapping kernels (share  $\geq 1$  point)

# **Description**

From a binary membership matrix M (points  $\times$  kernels), compute which kernels overlap, where overlap means at least one shared point. Internally uses  $A = M^{\top}M$ ;  $A_{ij} > 0$  indicates that kernels i and j share at least one point. This is an intermediate step required to determine which kernels are "light" and shouldn't be considered in downstream analysis.

# Usage

```
determine_overlaps(membership_matrix)
```

## **Arguments**

```
membership_matrix
```

A 0/1 matrix (preferably Matrix::dgCMatrix) with rows = points and cols = kernels. You can obtain this via generate\_membership\_matrix.

# Value

A named list of length k (number of kernels). Element [[i]] is a character vector of kernel names that overlap with kernel i **including itself**.

# **Examples**

find\_light\_kernels

Identify "light" kernels with too few unique points

# **Description**

Flags kernels that don't have enough assigned points relative to how many other kernels they overlap with. The criterion used is num\_points < num\_overlaps, where num\_points is the column sum of the (0/1) membership matrix and num\_overlaps is the length of the overlap set for that kernel (typically including itself).

#### Usage

```
find_light_kernels(overlapping_list, membership_matrix)
```

#### **Arguments**

```
overlapping_list
```

A named list where each element overlapping\_list[[k]] is a character vector of kernel names that overlap kernel k. See determine\_overlaps.

membership\_matrix

A 0/1 matrix (preferably Matrix::dgCMatrix) of point-kernel memberships with rows = points, cols = kernels.

#### **Details**

This function assumes the overlap list includes each kernel itself (as produced by determine\_overlaps()). If you supply an overlap list that excludes self, the threshold will be one smaller; adjust upstream if needed.

#### Value

A character vector of kernel names deemed "light".

# **Examples**

```
set.seed(1)
coords <- cbind(runif(40), runif(40))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "block")
Memb <- generate_membership_matrix(W)
ovl <- determine_overlaps(Memb)
find_light_kernels(ovl, Memb)</pre>
```

 ${\tt generate\_kernel\_centres\_by\_density}$ 

Generate approximate kernel centres on a grid to hit a target span

# Description

Places kernel centres on a regular grid over the 2D coordinate bounds so that, on average, each kernel would contain roughly span \* n\_points data points (under a uniform-density approximation). This is useful for building spatial kernels whose size scales with the observed point density.

# Usage

```
generate_kernel_centres_by_density(coords, span = NULL)
```

## **Arguments**

coords A numeric matrix or data frame with two columns giving x,y coordinates of

points (rows are points). Column order is c(x, y).

span Optional numeric in (0,1]. Interpreted as the target proportion of data points per

kernel. If NULL, a heuristic default  $13/n_{\text{points}}$  is used (capped at 0.5); a message

is emitted.

#### **Details**

Let n be the number of points and A the area of the bounding box of coords. We approximate point density by n/A and choose a square kernel with side length  $\sqrt{(\mathrm{target\_n})/(n/A)}$  where  $\mathrm{target\_n} = \lceil \mathrm{span} \times n \rceil$ . Grid spacing equals this side length, producing  $n_x \times n_y$  centres that tile the bounding box.

## Value

A numeric matrix with two columns c("x", "y") giving kernel centre coordinates.

# **Examples**

```
set.seed(1)
coords <- cbind(runif(100, 0, 10), runif(100, 0, 5))
centres <- generate_kernel_centres_by_density(coords, span = 0.1)
dim(centres)  # number of centres
head(centres)</pre>
```

```
generate_kernel_centres_by_density_1d

Generate kernel centres for 1D (trajectory) coordinates
```

# Description

For data where exactly one coordinate dimension varies across points (i.e. an effectively 1D trajectory embedded in  $\mathbb{R}^p$ ), place kernel centres along the varying axis so that, on average, each kernel collects about span \* n\_points points (under a uniform-density approximation). Non-varying dimensions are fixed at their column medians.

# Usage

```
generate_kernel_centres_by_density_1d(coords, span = NULL)
```

# **Arguments**

coords Numeric matrix or data frame of coordinates with n rows (points) and p columns

(axes). Exactly one column must have non-zero range; other columns may be constant (or nearly so). The nonzero coordinate may correspond to a pseudo-

timepoint or similar.

span Optional numeric in (0,1]. Target proportion of points per kernel. If NULL, a

heuristic default 13/n is used (capped at 0.5); a message is emitted.

## **Details**

Let L be the range length of the varying axis and n the number of points. We approximate the 1D density by n/L, target the number of points per kernel as  $\lceil \operatorname{span} \cdot n \rceil$ , set the kernel length to  $\operatorname{target_n}/(n/L)$ , and place  $\lceil L/\operatorname{kernel_len} \rceil$  centres evenly over the axis.

#### Value

A numeric matrix with the same columns as coords. The varying axis is filled with an evenly spaced grid over its range; constant axes are filled with their (NA-robust) medians. Row count equals the number of kernel centres.

# **Examples**

generate\_membership\_matrix

Convert a weight matrix to a 0/1 membership matrix

## **Description**

Turns any nonzero weight into 1 and zeros into 0, preserving the sparse structure and dimension names. This is useful for assigning points to kernels based on whether their weight is positive (regardless of magnitude). This is the intermediate step required to generate the list of overlapping kernels.

# Usage

```
generate_membership_matrix(weight_matrix)
```

# **Arguments**

weight\_matrix A numeric matrix or a Matrix::dgCMatrix of weights with rows as points and columns as kernels (e.g., from generate\_weight\_matrix\_euclidean).

# Value

A Matrix::dgCMatrix with the same dimensions and dimnames as weight\_matrix, containing only 0/1 entries.

```
set.seed(1)
coords <- cbind(runif(30), runif(30))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
Mb <- generate_membership_matrix(W)
Matrix::nnzero(Mb)  # number of assigned point-kernel memberships
unique(Mb@x)  # should be c(1) (no stored zeros)</pre>
```

```
generate_weight_matrix_euclidean
```

Build a point-by-kernel weight matrix (Euclidean neighborhoods)

# **Description**

Computes a sparse  $n_{\rm points} \times n_{\rm kernels}$  weight matrix W using Euclidean distance from each kernel centre to each point. Two schemes are supported:

- block: weights are 1 for neighbors within the search radius, 0 otherwise.
- gaussian: weights are  $\exp\{-d^2/(2\sigma^2)\}$ , with  $\sigma = \text{gap}/2$ , where gap is the minimum grid spacing, and d is the distance from the kernel centre to the point of interest.

# Usage

```
generate_weight_matrix_euclidean(
  coords,
  grid_centres,
  span = NULL,
  type = c("block", "gaussian")
)
```

## **Arguments**

coords	Numeric matrix or data frame with two columns $c(x, y)$ giving point coordinates (rows are points).
grid_centres	Numeric matrix or data frame with two columns $c(x, y)$ giving kernel-centre coordinates (e.g., from generate_kernel_centres_by_density).
span	Optional numeric in $(0,1]$ . Target proportion of points to associate with each kernel (used to choose k = ceiling(span * n_points) neighbors). If NULL, defaults to $13/n_{\rm points}$ (capped at 0.5).
type	Character; either "block" or "gaussian".

## **Details**

**Grid spacing (gap).** The search radius is set to the smallest spacing between unique x- or y-coordinates of grid\_centres. If only a single centre exists on an axis, we fall back to a coarse spacing based on the data range.

**Neighbor search.** We query up to  $k = \lceil \operatorname{span} n \rceil$  nearest neighbors per kernel centre using **RANN**. If your **RANN** version does not support radius-restricted search, a standard k-NN query still works; the "block" scheme then effectively selects the returned neighbors.

## Value

A Matrix::dgCMatrix sparse matrix W with rownames taken from coords (if present) and column names " $k_1$ ", ..., " $k_m$ " for m kernels.

# See Also

```
generate_kernel_centres_by_density
```

```
set.seed(1)
coords <- cbind(runif(100, 0, 10), runif(100, 0, 5))
centres <- generate_kernel_centres_by_density(coords, span = 0.1)
Wb <- generate_weight_matrix_euclidean(coords, centres, span = 0.1, type = "block")
Wg <- generate_weight_matrix_euclidean(coords, centres, span = 0.1, type = "gaussian")
dim(Wb); Matrix::nnzero(Wb)</pre>
```

# **Description**

Computes a sparse  $n_{\text{points}} \times n_{\text{kernels}}$  weight matrix using Euclidean distance along the single varying coordinate (pseudotime). Two schemes are supported:

- block: weights are 1 for neighbors within the search radius, 0 otherwise.
- gaussian: weights are  $\exp\{-d^2/(2\sigma^2)\}$ , with  $\sigma=\gcd/2$ , where gap is the kernel spacing (or a fallback radius computed from density) and d is the distance from the kernel centre to the point of interest.

## Usage

```
generate_weight_matrix_euclidean_1d(
  coords,
  grid_centres,
  span = NULL,
  type = c("block", "gaussian")
)
```

## **Arguments**

coords	Numeric matrix/data frame of coordinates. Exactly one column must vary (effective 1D). Other columns may be constant and are ignored for distances.
grid_centres	Numeric matrix/data frame of kernel-centre coordinates (e.g., from generate_kernel_centres_by_
span	Optional numeric in $(0,1]$ . Target proportion of points to associate with each kernel (k = ceiling(span * n_points)). If NULL, defaults to $13/n_{\rm points}$ (capped at 0.5).
type	Character; either "block" or "gaussian".

## Value

```
A Matrix::dgCMatrix with rows = points and columns = kernels ("k_1", ..., "k_m").
```

# See Also

```
generate_kernel_centres_by_density_1d, generate_weight_matrix_euclidean
```

```
set.seed(1)
t <- sort(runif(80, 0, 10))
y0 <- rep(0, 80)
coords <- cbind(t = t, y = y0)
centres <- generate_kernel_centres_by_density_1d(coords, span = 0.2)
Wb <- generate_weight_matrix_euclidean_1d(coords, centres, span = 0.2, type = "block")
Wg <- generate_weight_matrix_euclidean_1d(coords, centres, span = 0.2, type = "gaussian")
dim(Wb); Matrix::nnzero(Wb)</pre>
```

```
get_effective_sample_sizes
```

Effective sample size per kernel (Kish, 1965)

# Description

Computes Kish's effective sample size for each kernel/column of a weight matrix:

$$n_{\text{eff},k} = \frac{(\sum_{\ell} w_{k\ell})^2}{\sum_{\ell} w_{k\ell}^2}.$$

# Usage

```
get_effective_sample_sizes(weight_mat_trimmed, tol = 1e-12)
```

# **Arguments**

weight\_mat\_trimmed

A pointxkernel weight matrix (preferably Matrix::dgCMatrix); can be the output of trim\_weight\_matrix.

Numeric tolerance. Columns with  $\sum w^2 \le$  tol are treated as empty and return 0.

# **Details**

For block weights (0/1),  $n_{\text{eff},k}$  equals the number of positively weighted points in kernel k. For general nonnegative weights,  $n_{\text{eff},k} \leq \sum_{\ell} 1\{w_{k\ell} > 0\}$ .

## Value

A named numeric vector of length k (kernels), giving  $n_{\text{eff}}$  for each kernel (0 for empty kernels).

## References

Kish, L. (1965). Survey Sampling. Wiley.

```
set.seed(1)
coords <- cbind(runif(40), runif(40))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
Wg <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
neff <- get_effective_sample_sizes(Wg)
head(neff)</pre>
```

```
get_local_correlation_matrix
```

Local (kernel-wise) Fisher correlations for all gene pairs

# **Description**

For every unordered gene pair in expr, compute a vector of weighted Pearson correlations  $\hat{r}$ —one per kernel—using weight\_matrix. By default the correlations are Fisher-transformed ( $z = \operatorname{atanh}(\hat{r})$ ). Columns are labeled as "GENE1\_GENE2".

## Usage

```
get_local_correlation_matrix(
  expr,
  weight_matrix,
  fisher_transform = TRUE,
  drop_zero_weight = TRUE
)
```

# **Arguments**

# Value

A numeric matrix with nrow = ncol(weight\_matrix) (kernels) and ncol = choose(p, 2) (gene pairs, where p = ncol(expr)). Row names are kernel names; column names are "GENE1\_GENE2". Entries are Fisher-z if fisher\_transform=TRUE, else raw  $\hat{r}$ .

positive weight for that kernel.

# See Also

```
get_local_correlation_vector_pair
```

```
set.seed(1)
expr <- cbind(g1 = rnorm(60), g2 = rnorm(60), g3 = rnorm(60))
coords <- cbind(runif(60), runif(60))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
Zmat <- get_local_correlation_matrix(expr, W)
dim(Zmat)  # kernels x choose(3,2) = kernels x 3</pre>
```

```
get_local_correlation_vector_pair
```

Local (kernel-wise) weighted correlation for a gene pair

# **Description**

For a gene pair encoded as "GENE1\_GENE2", compute a vector of weighted Pearson correlations  $\hat{r}$ —one per kernel—from a point×kernel weight matrix. By default, correlations are Fisher-transformed  $(z = \operatorname{atanh}(\hat{r}))$ .

## Usage

```
get_local_correlation_vector_pair(
  expr,
  weight_matrix,
  gene_pair,
  fisher_transform = TRUE,
  drop_zero_weight = TRUE
)
```

# **Arguments**

expr Numeric matrix (rows = points/cells, cols = genes) with column names contain-

ing the requested genes.

weight\_matrix A point×kernel weight matrix (preferably Matrix::dgCMatrix) with the same

number of rows as expr.

gene\_pair Character scalar like "GENE1\_GENE2" indicating the two gene column names in

expr.

fisher\_transform

Logical; if TRUE (default), apply the Fisher  $\operatorname{atanh}$  transform to each correlation.

Values with  $|r| \ge 1$  or non-finite are returned as NA\_real\_.

drop\_zero\_weight

Logical; if TRUE (default), restrict each kernel's computation to rows with strictly positive weight for that kernel. If FALSE, all rows are considered (zeros contribute nothing).

## Value

A named numeric vector of length k (number of kernels), where names are the kernel column names in weight\_matrix. Entries are Fisher-z values if fisher\_transform=TRUE, otherwise raw correlations. Kernels with fewer than 2 positively weighted points (or undefined variance) return NA\_real\_.

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#### **Examples**

```
set.seed(1)
expr <- cbind(g1 = rnorm(60), g2 = rnorm(60))
coords <- cbind(runif(60), runif(60))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
zvec <- get_local_correlation_vector_pair(expr, W, "g1_g2")
head(zvec)</pre>
```

get\_sigma\_matrix

Covariance matrix of kernel-wise Fisher z coefficients

# **Description**

Given a kernel-kernel correlation matrix corr (for the Fisher coefficients) and effective sample sizes neff, returns the covariance matrix  $\Sigma = D \operatorname{corr} D$  where  $D = \operatorname{diag}(\sqrt{v})$  and  $v_k = 1/(n_{\mathrm{eff},k} - 3)$  (variance of Fisher z for a correlation).

# Usage

```
get_sigma_matrix(corr, neff)
```

## **Arguments**

A symmetric  $n \times n$  correlation matrix between kernels (e.g., from approximate\_between\_coefficient Preferably a Matrix object; a base matrix is also accepted. **Pass the unattenuated correlation** (call with neff = NULL) so you don't double-apply any scaling.

Numeric vector of length n with effective sample sizes per kernel (e.g., from

get\_effective\_sample\_sizes(W)).

## **Details**

For kernels with  $n_{\rm eff} \leq 3$ , the Fisher z variance is undefined. In that case, we set the corresponding diagonal multiplier to zero while forming  $\boldsymbol{D}$  corr  $\boldsymbol{D}$ , and then mark the affected rows/columns of  $\boldsymbol{\Sigma}$  as NA.

#### Value

A Matrix object of size  $n \times n$  with row/column names taken from corr. Entries corresponding to kernels with  $n_{\rm eff} \leq 3$  are returned as NA\_real\_.

```
set.seed(1)
coords <- cbind(runif(60), runif(60))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
neff <- get_effective_sample_sizes(W)
corr <- approximate_between_coefficient_correlations_effective(W)  # unattenuated
Sigma <- get_sigma_matrix(corr, neff)
Matrix::diag(Sigma)[1:5]</pre>
```

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scHOTTER_pipeline	End-to-end pipeline: local co-expression p-values (stores intermediates)
	ates)

## **Description**

Takes a gene expression matrix whose **rownames encode 2D coordinates** (e.g. "12.3x45.6", "12.3\_45.6", "12.3,45.6", or "12.3 45.6") and returns one-sided upper-tail p-values for the standardized sample-variance statistic of kernel-wise Fisher z correlations, *plus* all intermediate objects.

## Usage

```
scHOTTER_pipeline(
  expr,
  span = NULL,
  kernel_type = c("block", "gaussian"),
  fisher_transform = TRUE,
  drop_zero_weight = TRUE
)
```

# **Arguments**

expr

Numeric matrix (points  $\times$  genes). **Row names must contain** "x y" coordinates separated by x, \_, ,, or whitespace (e.g. "10.2\_5.7"). Column names are gene symbols.

span

Optional numeric in (0,1]; target proportion of points per kernel (passed to kernel generation and weighting). Default uses the package heuristic if NULL.

kernel\_type

"block" or "gaussian"; passed to generate\_weight\_matrix\_euclidean().

fisher\_transform

Logical; Fisher-transform local correlations (atanh). Must be TRUE to match downstream variance formulas (default TRUE).

drop\_zero\_weight

Logical; restrict each kernel's correlation to rows with w>0 for that kernel (default TRUE).

## Value

A list with:

- p\_values: named numeric vector of p-values (one per gene pair).
- summary: data.frame with columns pair, s2, z, p.
- intermediates: a list containing coords, centres, weight\_matrix\_initial, membership, overlaps, light\_kernels, weight\_matrix, local\_corr\_matrix, neff, corr, sigma, expectation, variance, s2, z\_scores, p\_values.
- params: the input parameters actually used.

```
set.seed(1)
n <- 80
coords <- cbind(runif(n, 0, 10), runif(n, 0, 5))
rn <- apply(coords, 1, function(v) paste0(v[1], "_", v[2]))
expr <- cbind(g1 = rnorm(n), g2 = rnorm(n), g3 = rnorm(n))
rownames(expr) <- rn
out <- scHOTTER_pipeline(expr, span = 0.2, kernel_type = "gaussian")
head(out$summary)</pre>
```

scHOTTER\_pipeline\_1d End-to-end pipeline (1D trajectory): local co-expression p-values

# **Description**

A 1D analogue of scHOTTER\_pipeline() for trajectory-like data where *exactly one* coordinate axis varies across points. Row names of expr must encode coordinates (e.g. "xxy", "x\_y", "x,y" or "x y"). The varying axis is used to place kernel centres and compute 1D weights; all subsequent steps (local Fisher z, analytic null, Z, p) are identical to the 2D pipeline.

# Usage

```
scHOTTER_pipeline_1d(
  expr,
  span = NULL,
  kernel_type = c("block", "gaussian"),
  fisher_transform = TRUE,
  drop_zero_weight = TRUE
)
```

# **Arguments**

expr Numeric matrix (points × genes). Row names must encode coordinates. Column

names are gene symbols.

span Optional numeric in (0, 1]; target proportion of points per kernel. If NULL, a

heuristic 13/n capped at 0.5 is used.

kernel\_type "block" or "gaussian"; passed to generate\_weight\_matrix\_euclidean\_1d.

fisher\_transform

Logical; apply Fisher atanh to local correlations (default TRUE). Keep TRUE to

match the null variance model.

drop\_zero\_weight

Logical; restrict each kernel's computation to rows with weight > 0 for that kernel (default TRUE).

## Value

A list with:

- p\_values: named numeric vector of p-values (one per gene pair).
- summary: data.frame with columns pair, s2, z, p.

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• intermediates: a list containing coords, centres, weight\_matrix\_initial, membership, overlaps, light\_kernels, weight\_matrix, local\_corr\_matrix, neff, corr, sigma, expectation, variance, s2, z\_scores, p\_values.

• params: the input parameters actually used.

#### **Examples**

trim\_weight\_matrix

Trim kernels flagged as "light" from a weight matrix

## **Description**

Removes columns (kernels) listed in light\_kernels from a pointxkernel weight matrix. Returns the original matrix if no kernels are specified.

## Usage

```
trim_weight_matrix(weight_matrix, light_kernels)
```

# **Arguments**

# Value

A Matrix::dgCMatrix with the specified columns removed (possibly with zero columns if all kernels are removed).

```
set.seed(1)
coords <- cbind(runif(40), runif(40))
centres <- generate_kernel_centres_by_density(coords, span = 0.2)
W <- generate_weight_matrix_euclidean(coords, centres, span = 0.2, type = "gaussian")
Memb <- generate_membership_matrix(W)
ovl <- determine_overlaps(Memb)
light <- find_light_kernels(ovl, Memb)</pre>
```

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W\_trim <- trim\_weight\_matrix(W, light)
dim(W\_trim)</pre>