

Package: ridgetorus (via r-universe)

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Title PCA on the Torus via Density Ridges

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Description Implementation of a Principal Component Analysis (PCA) in the torus via density ridge estimation. The main function, `ridge_pca()`, obtains the relevant density ridge for bivariate sine von Mises and bivariate wrapped Cauchy distribution models and provides the associated scores and variance decomposition. Auxiliary functions for evaluating, fitting, and sampling these models are also provided. The package provides replicability to García-Portugués and Prieto-Tirado (2023) [doi:10.1007/s11222-023-10273-9](https://doi.org/10.1007/s11222-023-10273-9).

License GPL-3

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URL <https://github.com/egarpor/ridgetorus>

BugReports <https://github.com/egarpor/ridgetorus>

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ridgetorus-package	ridgetorus: <i>PCA on the Torus via Density Ridges</i>
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Description

Implementation of a Principal Component Analysis (PCA) in the torus via density ridge estimation. The main function, `ridge_pca()`, obtains the relevant density ridge for bivariate sine von Mises and bivariate wrapped Cauchy distribution models and provides the associated scores and variance decomposition. Auxiliary functions for evaluating, fitting, and sampling these models are also provided. The package provides replicability to García-Portugués and Prieto-Tirado (2023) <doi:10.1007/s11222-023-10273-9>.

Author(s)

Eduardo García-Portugués and Arturo Prieto-Tirado.

References

García-Portugués, E. and Prieto-Tirado, A. (2023). Toroidal PCA via density ridges. *Statistics and Computing*, 33(5):107. doi:10.1007/s11222023102739

biv_lrt	<i>Tests of homogeneity and independence in bivariate sine von Mises and wrapped Cauchy distributions</i>
---------	---

Description

Performs the following likelihood ratio tests for the concentrations in bivariate sine von Mises and wrapped Cauchy distributions: (1) *homogeneity*: $H_0 : \kappa_1 = \kappa_2$ vs. $H_1 : \kappa_1 \neq \kappa_2$, and $H_0 : \xi_1 = \xi_2$ vs. $H_1 : \xi_1 \neq \xi_2$, respectively; (2) *independence*: $H_0 : \lambda = 0$ vs. $H_1 : \lambda \neq 0$, and $H_0 : \rho = 0$ vs. $H_1 : \rho \neq 0$. The tests (1) and (2) can be performed simultaneously.

Usage

```
biv_lrt(x, hom = FALSE, indep = FALSE, fit_mle = NULL, type, ...)
```

Arguments

x	matrix of dimension $c(n, 2)$ containing the n observations of the pair of angles.
hom	test the homogeneity hypothesis? Defaults to FALSE.
indep	test the independence hypothesis? Defaults to FALSE.
fit_mle	output of <code>fit_bvm_mle</code> or <code>fit_bwc_mle</code> with <code>hom = FALSE</code> . Computed internally if not provided.
type	either "bvm" (bivariate sine von Mises) or "bwc" (bivariate wrapped Cauchy).
...	optional parameters passed to <code>fit_bvm_mle</code> and <code>fit_bwc_mle</code> , such as <code>start</code> , <code>lower</code> , or <code>upper</code> .

Value

A list with class `htest`:

statistic	the value of the likelihood ratio test statistic.
p.value	the p -value of the test (computed using the asymptotic distribution).
alternative	a character string describing the alternative hypothesis.
method	description of the type of test performed.
df	degrees of freedom.
data.name	a character string giving the name of theta.
fit_mle	maximum likelihood fit.
fit_null	maximum likelihood fit under the null hypothesis.

References

Kato, S. and Pewsey, A. (2015). A Möbius transformation-induced distribution on the torus. *Biometrika*, 102(2):359–370. doi:[10.1093/biomet/asv003](https://doi.org/10.1093/biomet/asv003)

Singh, H., Hnizdo, V., and Demchuk, E. (2002). Probabilistic model for two dependent circular variables. *Biometrika*, 89(3):719–723. doi:[10.1093/biomet/89.3.719](https://doi.org/10.1093/biomet/89.3.719)

Examples

```

## Bivariate sine von Mises

# Homogeneity
n <- 200
mu <- c(0, 0)
kappa_0 <- c(1, 1, 0.5)
kappa_1 <- c(0.7, 0.1, 0.25)
samp_0 <- r_bvm(n = n, mu = mu, kappa = kappa_0)
samp_1 <- r_bvm(n = n, mu = mu, kappa = kappa_1)
biv_lrt(x = samp_0, hom = TRUE, type = "bvm")
biv_lrt(x = samp_1, hom = TRUE, type = "bvm")

# Independence
kappa_0 <- c(0, 1, 0)
kappa_1 <- c(1, 0, 1)
samp_0 <- r_bvm(n = n, mu = mu, kappa = kappa_0)
samp_1 <- r_bvm(n = n, mu = mu, kappa = kappa_1)
biv_lrt(x = samp_0, indep = TRUE, type = "bvm")
biv_lrt(x = samp_1, indep = TRUE, type = "bvm")

# Independence and homogeneity
kappa_0 <- c(3, 3, 0)
kappa_1 <- c(3, 1, 0)
samp_0 <- r_bvm(n = n, mu = mu, kappa = kappa_0)
samp_1 <- r_bvm(n = n, mu = mu, kappa = kappa_1)
biv_lrt(x = samp_0, indep = TRUE, hom = TRUE, type = "bvm")
biv_lrt(x = samp_1, indep = TRUE, hom = TRUE, type = "bvm")

## Bivariate wrapped Cauchy

# Homogeneity
xi_0 <- c(0.5, 0.5, 0.25)
xi_1 <- c(0.7, 0.1, 0.5)
samp_0 <- r_bwc(n = n, mu = mu, xi = xi_0)
samp_1 <- r_bwc(n = n, mu = mu, xi = xi_1)
biv_lrt(x = samp_0, hom = TRUE, type = "bwc")
biv_lrt(x = samp_1, hom = TRUE, type = "bwc")

# Independence
xi_0 <- c(0.1, 0.5, 0)
xi_1 <- c(0.3, 0.5, 0.2)
samp_0 <- r_bwc(n = n, mu = mu, xi = xi_0)
samp_1 <- r_bwc(n = n, mu = mu, xi = xi_1)
biv_lrt(x = samp_0, indep = TRUE, type = "bwc")
biv_lrt(x = samp_1, indep = TRUE, type = "bwc")

# Independence and homogeneity
xi_0 <- c(0.2, 0.2, 0)
xi_1 <- c(0.1, 0.2, 0.1)
samp_0 <- r_bwc(n = n, mu = mu, xi = xi_0)
samp_1 <- r_bwc(n = n, mu = mu, xi = xi_1)

```

```
biv_lrt(x = samp_0, indep = TRUE, hom = TRUE, type = "bwc")
biv_lrt(x = samp_1, indep = TRUE, hom = TRUE, type = "bwc")
```

bvm	<i>Density evaluation, sampling, and parameter estimation of the bivariate sine von Mises distribution</i>
-----	--

Description

Computation of the density and normalizing constant $T(\kappa_1, \kappa_2, \lambda)$ of the bivariate sine von Mises

$$f(\theta_1, \theta_2) = T(\kappa_1, \kappa_2, \lambda) \exp\{\kappa_1 \cos(\theta_1 - \mu_1) + \kappa_2 \cos(\theta_2 - \mu_2) + \lambda \sin(\theta_1 - \mu_1) \sin(\theta_2 - \mu_2)\}.$$

Simulation of samples from a bivariate sine von Mises.

Maximum likelihood and method of moments estimation of the parameters $(\mu_1, \mu_2, \kappa_1, \kappa_2, \lambda)$.

Usage

```
d_bvm(x, mu, kappa, log_const = NULL)
```

```
const_bvm(kappa, M = 25, MC = 10000)
```

```
r_bvm(n, mu, kappa)
```

```
fit_bvm_mm(
  x,
  lower = c(0, 0, -30),
  upper = c(30, 30, 30),
  start = NULL,
  M = 25,
  hom = FALSE,
  indep = FALSE,
  ...
)

fit_bvm_mle(
  x,
  start = NULL,
  M = 25,
  lower = c(-pi, -pi, 0, 0, -30),
  upper = c(pi, pi, 30, 30, 30),
  hom = FALSE,
  indep = FALSE,
  ...
)
```

Arguments

<code>x</code>	matrix of size $c(n_x, 2)$ with the angles on which the density is evaluated.
<code>mu</code>	circular means of the density, a vector of length 2.
<code>kappa</code>	vector of length 3 with the concentrations (κ_1, κ_2) and the dependence parameter λ of the density.
<code>log_const</code>	logarithm of the normalizing constant. Computed internally if NULL (default).
<code>M</code>	truncation of the series expansion for computing the normalizing constant. Defaults to 25.
<code>MC</code>	Monte Carlo replicates for computing the normalizing constant when there is no series expansion. Defaults to $1e4$.
<code>n</code>	sample size.
<code>lower, upper</code>	vectors of length 5 with the bounds for the likelihood optimizer. Default to $c(-\pi, -\pi, 0, -30)$ and $c(\pi, \pi, 30, 30)$.
<code>start</code>	a vector of length 5 with the initial values for the maximum likelihood optimizer. The first two entries are disregarded in <code>fit_bvm_mm</code> . If NULL (default), the starting values are taken from the estimation of marginal von Mises in <code>fit_bvm_mm</code> . In <code>fit_bvm_mle</code> , the method of moments estimates are employed.
<code>hom</code>	assume a homogeneous distribution with equal marginal concentrations? Defaults to FALSE.
<code>indep</code>	set the dependence parameter to zero? Defaults to FALSE.
<code>...</code>	further parameters passed to <code>mleOptimWrapper</code> .

Value

- `d_bvm`: a vector of length n_x with the density evaluated at `x`.
- `const_bvm`: the value of the normalizing constant $T(\kappa_1, \kappa_2, \lambda)$.
- `r_bvm`: a matrix of size $c(n, 2)$ with the random sample.
- `fit_mme_bvm`, `fit_mle_bvm`: a list with the estimated parameters $(\mu_1, \mu_2, \kappa_1, \kappa_2, \lambda)$ and the object `opt` containing the optimization summary.

References

- Mardia, K. V., Hughes, G., Taylor, C. C., and Singh, H. (2008). A multivariate von Mises with applications to bioinformatics. *Canadian Journal of Statistics*, 36(1):99–109. doi:10.1002/cjs.5550360110
- Singh, H., Hnizdo, V., and Demchuk, E. (2002). Probabilistic model for two dependent circular variables. *Biometrika*, 89(3):719–723. doi:10.1093/biomet/89.3.719

Examples

```
## Density evaluation

mu <- c(0, 0)
kappa <- 3:1
nth <- 50
```

```

th <- seq(-pi, pi, l = nth)
x <- as.matrix(expand.grid(th, th))
const <- const_bvm(kappa = kappa)
d <- d_bvm(x = x, mu = mu, kappa = kappa, log_const = log(const))
filled.contour(th, th, matrix(d, nth, nth), col = viridisLite::viridis(31),
               levels = seq(0, max(d), l = 30))

## Sampling and estimation

n <- 100
samp <- r_bvm(n = n, mu = mu, kappa = kappa)
(param_mm <- fit_bvm_mm(samp)$par)
(param_mle <- fit_bvm_mle(samp)$par)

```

bwc

Density evaluation, sampling, and parameter estimation of the bivariate wrapped Cauchy distribution

Description

Computation of the density of a bivariate wrapped Cauchy:

$$f(\theta_1, \theta_2) = c(\xi_1, \xi_2, \rho) \{c_0(\xi_1, \xi_2, \rho) - c_1(\xi_1, \xi_2, \rho) \cos(\theta_1 - \mu_1) - c_2(\xi_1, \xi_2, \rho) \cos(\theta_2 - \mu_2) - c_3(\xi_1, \xi_2, \rho) \cos(\theta_1 - \mu_1) \cos(\theta_2 - \mu_2)\}$$

Simulation of samples from a bivariate wrapped Cauchy.

Maximum likelihood and method of moments estimation of the parameters $(\mu_1, \mu_2, \xi_1, \xi_2, \rho)$.

Usage

```

d_bwc(x, mu, xi)

r_bwc(n, mu, xi)

fit_bwc_mm(x, hom = FALSE, indep = FALSE)

fit_bwc_mle(
  x,
  start = NULL,
  lower = c(-pi, -pi, 0, 0, -1 + 0.001),
  upper = c(pi, pi, 1 - 0.001, 1 - 0.001, 1 - 0.001),
  hom = FALSE,
  indep = FALSE,
  ...
)

```

Arguments

<code>x</code>	matrix of size $c(n_x, 2)$ with the angles on which the density is evaluated.
<code>mu</code>	circular means of the density, a vector of length 2.
<code>xi</code>	a vector of length 3 with the marginal concentrations (ξ_1, ξ_2) , and the dependence parameter ρ .
<code>n</code>	sample size.
<code>hom</code>	assume a homogeneous distribution with equal marginal concentrations? Defaults to FALSE.
<code>indep</code>	set the dependence parameter to zero? Defaults to FALSE.
<code>start</code>	a vector of length 5 with the initial values for the maximum likelihood optimizer. If NULL (default), the method of moments estimates are employed.
<code>lower, upper</code>	vectors of length 5 with the bounds for the likelihood optimizer. Default to $c(-\pi, -\pi, 0, 0, -1 + 1e-3)$ and $c(\pi, \pi, 1 - 1e-3, 1 - 1e-3, 1 - 1e-3)$.
<code>...</code>	further parameters passed to <code>mleOptimWrapper</code> .

Value

- `d_bwc`: a vector of length n_x with the density evaluated at `x`.
- `r_bwc`: a matrix of size $c(n, 2)$ with the random sample.
- `fit_mme_bwc`, `fit_mle_bwc`: a list with the parameters $(\mu_1, \mu_2, \xi_1, \xi_2, \rho)$ and the object `opt` containing the optimization summary.

Author(s)

The original code for `r_bwc` was supplied by Arthur Pewsey.

References

Kato, S. and Pewsey, A. (2015). A Möbius transformation-induced distribution on the torus. *Biometrika*, 102(2):359–370. doi:[10.1093/biomet/asv003](https://doi.org/10.1093/biomet/asv003)

Examples

```
## Density evaluation

mu <- c(0, 0)
xi <- c(0.3, 0.5, 0.4)
nth <- 50
th <- seq(-pi, pi, l = nth)
x <- as.matrix(expand.grid(th, th))
d <- d_bwc(x = x, mu = mu, xi = xi)
filled.contour(th, th, matrix(d, nth, nth), col = viridisLite::viridis(20),
               levels = seq(0, max(d), l = 20))

## Sampling and estimation

n <- 100
```



```
samp <- r_bwn(n = n, mu = mu, xi = xi)
(param_mm <- fit_bwn_mm(samp)$par)
(param_mle <- fit_bwn_mle(samp)$par)
```

bwn	<i>Density evaluation, sampling, and parameter estimation of the bivariate wrapped normal distribution</i>
-----	--

Description

Computation of the density of the bivariate wrapped normal.
 Simulation of pairs of samples from a bivariate wrapped normal.
 Maximum likelihood estimation of the parameters (μ, Σ) .

Usage

```
d_bwn(x, mu, Sigma, kmax = 2)

r_bwn(n, mu, Sigma)

fit_bwn_mle(
  x,
  kmax = 2,
  lower = c(-pi, -pi, 0.001, 0.001, -1),
  upper = c(pi, pi, 20, 20, 1),
  ...
)
```

Arguments

x	matrix of size $c(n_x, 2)$ with the angles on which the density is evaluated.
mu	circular means of the density, a vector of length 2.
Sigma	covariance matrix of size $c(2, 2)$.
kmax	integer number up to truncate the wrapped normal series in $-kmax:kmax$. Defaults to 2.
n	sample size.
lower, upper	vector of length 5 with the bounds of the parameters for the maximum likelihood optimizer.
...	further parameters passed to mleOptimWrapper .

Value

- `d_bwn`: a vector of length n_x with the density evaluated at x .
- `r_bwn`: a matrix of size $c(n, 2)$ with the random sample.
- `fit_bwn_mle`: a list with the parameters (μ, Σ) and the object `opt` containing the optimization summary.

Examples

```
## Density evaluation

mu <- c(0, 0)
Sigma <- 3 * matrix(c(1.5, 0.75, 0.75, 1), nrow = 2, ncol = 2)
nth <- 50
th <- seq(-pi, pi, l = nth)
x <- as.matrix(expand.grid(th, th))
d <- d_bwn(x = x, mu = mu, Sigma = Sigma)
filled.contour(th, th, matrix(d, nth, nth), col = viridisLite::viridis(31),
               levels = seq(0, max(d), l = 30))

## Sampling and estimation

n <- 100
samp <- r_bwn(n = 100, mu = mu, Sigma = Sigma)
(param_mle <- fit_bwn_mle(samp)$par)
```

earthquakes

Japanese earthquakes dataset

Description

Pre-earthquake direction of steepest descent and the direction of lateral ground movement before and after, respectively, an earthquake in Noshiro (Japan) in 1983.

Usage

earthquakes

Format

A data frame with 678 rows and 2 variables:

theta1 Direction of steepest descent.

theta2 Direction of lateral ground movement.

Details

The direction is measured in radians in $[0, 2\pi)$ with $0 / \frac{\pi}{2} / \pi / \frac{3\pi}{2} / 2\pi$ representing the East / North / West / South / East directions.

References

Hamada, M. and O'Rourke, T. (1992). Case Studies of Liquefaction & Lifeline Performance During Past Earthquake. Volume 1: Japanese Case Studies. Technical Report NCEER-92-0001. National Center for Earthquake Engineering Research, University at Buffalo. [doi:10.1016/0886-7798\(93\)90146m](https://doi.org/10.1016/0886-7798(93)90146m)

Jones, M. C., Pewsey, A., and Kato, S. (2015). On a class of circulas: copulas for circular distributions. *Annals of the Institute of Statistical Mathematics*, 67(5):843–862. doi:10.1007/s10463014-04936

Rivest, L.-P. (1997). A decentred predictor for circular-circular regression. *Biometrika*, 84(3):717–726. doi:10.1093/biomet/84.3.717

Examples

```
# Load data
data("earthquakes")

# Transform the data into [-pi, pi)
earthquakes <- sdetorus::toPiInt(earthquakes)
plot(earthquakes, xlab = expression(theta[1]), ylab = expression(theta[2]),
     xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE)
sdetorus::torusAxis()

# Perform TR-PCA
fit <- ridge_pca(x = earthquakes)
show_ridge_pca(fit)
```

frechet

Fréchet statistics on the torus

Description

Computes the Fréchet mean, variance, and standard deviation of a sample on the d -torus $[-l, l]^d$, $d \geq 1$, with $-l \equiv l$ identified.

Usage

```
frechet_mean(x, l = pi, N = 500, draw_plot = FALSE)
```

```
frechet_ss(x, l = pi, N = 500, draw_plot = FALSE)
```

Arguments

<code>x</code>	sample of angles on $[-l, l)$, a vector or a matrix.
<code>l</code>	half-period of the circular data. Can be a vector of length <code>ncol(x)</code> if <code>x</code> is a matrix. Defaults to <code>pi</code> .
<code>N</code>	size of the grid in $[-l, l)$ for the exhaustive search of the mean. Defaults to <code>5e2</code> .
<code>draw_plot</code>	draw a diagnostic plot showing the Fréchet loss function? Defaults to <code>FALSE</code> .

Value

- `frechet_mean`: a list with the marginal Fréchet means (`mu`), variances (`var`), and standard deviations (`sd`).
- `frechet_ss`: a list with the Fréchet variances (`var`) and the cumulative proportion of total variance explained (`var_exp`).

Examples

```
## Circular data

# Sample from a wrapped normal
x <- sdetorus::toPiInt(rnorm(n = 5e2, mean = 2, sd = 1))
frechet_mean(x = x)

# Sample from a bimodal distribution
x <- sdetorus::toPiInt(rnorm(n = 5e2, mean = c(1, -2), sd = c(0.5, 0.75)))
frechet_mean(x = x)

# Periodic data in [-2, 2)
x <- sdetorus::toInt(rnorm(n = 5e2, mean = c(-2, 1), sd = 2:1),
                    a = -2, b = 2)
frechet_mean(x = x, l = 2)

## Toroidal data

# Sample from a multivariate wrapped normal
n <- 50
S <- rbind(c(2.5, -0.2, 0.5),
           c(-0.2, 1.5, -0.5),
           c(0.5, -0.5, 0.75))
x <- sdetorus::toPiInt(mvtnorm::rmvnorm(n, mean = c(0, 1.5, -2), sigma = S))
(f <- frechet_mean(x = x))

# Total Fréchet variance is sum of marginal variances
sum(torus_dist(x, y = f$mu, squared = TRUE)) / n
sum(f$var)

# Cumulative proportion of variances
frechet_ss(x)
```

ridge_curve

Fourier-fitted ridge curve and related utilities

Description

Given the angles θ in $[-\pi, \pi)$, `ridge_curve` computes the Fourier-fitted ridge curve $(\theta, r_1(\theta))$ or $(r_2(\theta), \theta)$, where

$$r_j(\theta) := \text{atan2}(S_m(\theta), C_m(\theta))$$

with $C_m(x) := a_0/2 + \sum_{k=1}^m a_k \cos(kx)$ and $S_m(x) := \sum_{k=1}^m b_k \sin(kx)$ for $j = 1, 2$. `der_ridge_curve` and `dist_ridge_curve` compute the derivatives of and the distances along these curves, respectively. `alpha_ridge_curve` provides a uniform grid of the ridge curve using the arc-length parametrization. `proj_ridge_curve` gives the ridge's θ for which the curve is closer to any point on $[-\pi, \pi]^2$.

Usage

```
ridge_curve(
  theta,
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
  at2 = TRUE
)
```

```
der_ridge_curve(
  theta,
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
  norm = NULL,
  at2 = TRUE
)
```

```
dist_ridge_curve(
  alpha,
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
  N = 500,
  der = TRUE,
  shortest = TRUE,
  at2 = TRUE
)
```

```
arclength_ridge_curve(
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
  N = 500,
  L = 500,
  at2 = TRUE
)
```

```
proj_ridge_curve(
  x,
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
)
```

```

N = 500,
ridge_curve_grid = NULL,
arclength = FALSE,
at2 = TRUE
)

```

Arguments

theta	vector θ of size nth.
mu	a vector of size 2 giving (μ_1, μ_2) . Defaults to $c(\theta, \theta)$.
coefs	list of coefficients \cos_a (a_k) and \sin_b (b_k) giving the Fourier fit of the ridge curve. Defaults to <code>list(cos_a = c(θ, θ), sin_b = θ)</code> . See examples.
ind_var	index j of the variable that parametrizes the ridge. Defaults to 1.
at2	do the atan2 fit instead of the sine fit (only using S_m)? Defaults to TRUE. at2 = FALSE is not recommended to use.
norm	normalize tangent vectors? If different from NULL (the default), the vectors are normalized to have the given norm.
alpha	a vector of size 2.
N	number of discretization points for approximating curve lengths. Defaults to 5e2.
der	use derivatives to approximate curve lengths? Defaults to TRUE.
shortest	return the shortest possible distance? Defaults to TRUE.
L	number of discretization points for computing the arc-length parametrization curve lengths. Defaults to 5e2.
x	a matrix of size $c(n_x, 2)$ with angular coordinates.
ridge_curve_grid	if provided, the ridge_curve evaluated at a grid of size N. If not provided, it is computed internally. Useful for saving computations.
arclength	use the arc-length parametrization to compute the projections? This yields a more uniform grid for searching the projections. Defaults to TRUE.

Value

- ridge_curve: a matrix of size $c(n_{th}, 2)$ with the ridge curve evaluated at theta.
- der_ridge_curve: a matrix of size $c(n_{th}, 2)$ with the derivatives of the ridge curve evaluated at theta.
- dist_ridge_curve: the distance between two points along the ridge curve, a non-negative scalar.
- proj_ridge_curve: a list with (1) the theta's that give the points in the ridge curve that are the closest (in the flat torus distance) to x (a matrix of size $c(n_x, 2)$); (2) the indexes of ridge_curve_grid in which those theta's were obtained.
- arclength_ridge_curve: a vector of size N giving the theta angles that yield a uniform-length grid of the ridge curve.

Examples

```

mu <- c(-0.5, 1.65)
th <- seq(-pi, pi, l = 200)
K <- 5
coefs <- list(cos_a = 1 / (1:(K + 1))^3, sin_b = 1 / (1:K)^3)
rid1 <- ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = 1)
rid2 <- ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = 2)
plot(mu[1], mu[2], xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE,
     xlab = expression(theta[1]), ylab = expression(theta[2]),
     pch = "*", col = 5, cex = 3)
sdetorus::linesTorus(rid1[, 1], rid1[, 2], col = 1)
sdetorus::linesTorus(rid2[, 1], rid2[, 2], col = 2)
abline(v = mu[1], lty = 3, col = 5)
abline(h = mu[2], lty = 3, col = 5)
points(ridge_curve(theta = mu[1], mu = mu, coefs = coefs, ind_var = 1),
       col = 1)
points(ridge_curve(theta = mu[2], mu = mu, coefs = coefs, ind_var = 2),
       col = 2)
sdetorus::torusAxis()

## der_ridge_curve

th <- seq(-pi, pi, l = 10)
mu <- c(0.5, 1.5)
K <- 5
coefs <- list(cos_a = 1 / (1:(K + 1))^3, sin_b = 1 / (1:K)^3)
rid1 <- ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = 1)
rid2 <- ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = 2)
v1 <- der_ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = 1,
                     norm = 0.5)
v2 <- der_ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = 2,
                     norm = 0.5)
points(rid1, pch = 16, col = 1)
points(rid2, pch = 16, col = 2)
arrows(x0 = rid1[, 1], y0 = rid1[, 2],
       x1 = (rid1 + v1)[, 1], y1 = (rid1 + v1)[, 2],
       col = 3, angle = 5, length = 0.1)
arrows(x0 = rid2[, 1], y0 = rid2[, 2],
       x1 = (rid2 + v2)[, 1], y1 = (rid2 + v2)[, 2],
       col = 4, angle = 5, length = 0.1)

## dist_ridge_curve

# Distances accuracy
a <- c(-pi / 2, pi)
mu <- c(-pi / 2, pi / 2)
dist_ridge_curve(alpha = a, mu = mu, coefs = coefs, der = TRUE, N = 1e6)
dist_ridge_curve(alpha = a, mu = mu, coefs = coefs, der = FALSE, N = 1e6)
dist_ridge_curve(alpha = a, mu = mu, coefs = coefs, der = TRUE, N = 1e2)
dist_ridge_curve(alpha = a, mu = mu, coefs = coefs, der = FALSE, N = 1e2)

## arclength_ridge_curve

```

```

mu <- c(-pi / 2, pi / 2)
alpha <- arclength_ridge_curve(mu = mu, coefs = coefs, ind_var = 1, N = 25)
alpha <- sdetorus::toPiInt(c(alpha, alpha[1]))
rid <- ridge_curve(theta = alpha, mu = mu, coefs = coefs, ind_var = 1)
plot(mu[1], mu[2], pch = "*", col = 5, cex = 3, xlim = c(-pi, pi),
      ylim = c(-pi, pi), axes = FALSE, xlab = expression(theta[1]),
      ylab = expression(theta[2]))
sdetorus::linesTorus(rid[, 1], rid[, 2], col = 1, pch = 16)
points(rid[, 1], rid[, 2], pch = 16, col = 1)
abline(v = mu[1], lty = 3, col = 5)
abline(h = mu[2], lty = 3, col = 5)
sdetorus::torusAxis()

## proj_ridge_curve

mu <- c(0, 0)
n <- 25
x <- matrix(runif(2 * n, -pi, pi), nrow = n, ncol = 2)
col <- rainbow(n)
th <- seq(-pi, pi, l = 100)
old_par <- par(no.readonly = TRUE)
par(mfrow = c(1, 2))
for (j in 1:2) {

  plot(x, xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE,
        xlab = expression(theta[1]), ylab = expression(theta[2]), col = col)
  rid <- ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = j)
  sdetorus::linesTorus(x = rid[, 1], y = rid[, 2], lwd = 2)
  abline(v = mu[1], lty = 3)
  abline(h = mu[2], lty = 3)
  points(mu[1], mu[2], pch = "*", cex = 3)
  sdetorus::torusAxis()
  theta_projs <- proj_ridge_curve(x = x, mu = mu, coefs = coefs, ind_var = j,
                                ridge_curve_grid = rid)$theta_proj
  projs <- ridge_curve(theta = theta_projs, mu = mu, coefs = coefs,
                       ind_var = j)
  points(projs, col = col, pch = 3)
  for (i in 1:n) {

    sdetorus::linesTorus(x = c(x[i, 1], projs[i, 1]),
                        y = c(x[i, 2], projs[i, 2]), col = col[i], lty = 3)

  }

}
par(old_par)

```


Description

Computation of the connected component of the density ridge of in a given set of points or, if not specified, in a regular grid on $[-\pi, \pi)$.

Usage

```
ridge_bvm(mu, kappa, eval_points, subint_1, subint_2)
```

```
ridge_bwc(mu, xi, eval_points, subint_1, subint_2)
```

```
ridge_bwn(mu, Sigma, kmax = 2, eval_points, subint_1, subint_2)
```

Arguments

mu	circular means of the density, a vector of length 2.
kappa	vector of length 3 with the concentrations (κ_1, κ_2) and the dependence parameter λ of the density.
eval_points	evaluation points for the ridge.
subint_1	number of points for θ_1 .
subint_2	number of points for θ_2 at each θ_1 .
xi	a vector of length 3 with the marginal concentrations (ξ_1, ξ_2) , and the dependence parameter ρ .
Sigma	covariance matrix of size $c(2, 2)$.
kmax	integer number up to truncate the wrapped normal series in $-kmax:kmax$. Defaults to 2.

Value

A matrix of size $c(\text{subint}_1, 2)$ containing the points of the connected component of the ridge.

References

Ozertem, U. and Erdogmus, D. (2011). Locally defined principal curves and surfaces. *Journal of Machine Learning Research*, 12(34):1249–1286. [doi:10.6083/M4ZG6Q60](https://doi.org/10.6083/M4ZG6Q60)

Examples

```
# Bivariate von Mises
mu <- c(0, 0)
kappa <- c(0.3, 0.5, 0.4)
nth <- 100
th <- seq(-pi, pi, l = nth)
x <- as.matrix(expand.grid(th, th))
d <- d_bvm(x = x, mu = mu, kappa = kappa)
image(th, th, matrix(d, nth, nth), col = viridisLite::viridis(20))
ridge <- ridge_bvm(mu = mu, kappa = kappa, subint_1 = 5e2,
                  subint_2 = 5e2)
points(ridge)
```

```

# Bivariate wrapped Cauchy
mu <- c(0, 0)
xi <- c(0.3, 0.6, 0.25)
nth <- 100
th <- seq(-pi, pi, l = nth)
x <- as.matrix(expand.grid(th, th))
d <- d_bwc(x = x, mu = mu, xi = xi)
image(th, th, matrix(d, nth, nth), col = viridisLite::viridis(20))
ridge <- ridge_bwc(mu = mu, xi = xi, subint_1 = 5e2, subint_2 = 5e2)
points(ridge)

# Bivariate wrapped normal
mu <- c(0, 0)
Sigma <- matrix(c(10, 3, 3, 5), nrow = 2)
nth <- 100
th <- seq(-pi, pi, l = nth)
x <- as.matrix(expand.grid(th, th))
d <- d_bwn(x = x, mu = mu, Sigma = Sigma)
image(th, th, matrix(d, nth, nth), col = viridisLite::viridis(20))
ridge <- ridge_bwn(mu = mu, Sigma = Sigma, subint_1 = 5e2,
                  subint_2 = 5e2)
points(ridge)

```

ridge_fourier_fit *Fourier expansion of a given curve*

Description

Computation of the Fourier expansion coefficients of a given curve.

Usage

```
ridge_fourier_fit(curve, K = 15, norm_prop = 1, N = 1280, at2 = TRUE)
```

Arguments

curve	points of the curve.
K	number of terms in the Fourier expansion. Defaults to 15.
norm_prop	percentage of explained norm. Defaults to 1.
N	number of Gaussian quadrature points, passed to Gauss_Legen_nodes . Defaults to 1280.
at2	do the atan2 fit instead of the sine fit (only using S_m)? Defaults to TRUE. at2 = FALSE is not recommended to use.

Value

The coefficients of the fit (see [ridge_curve](#)). A list with entries:

cos_a contains a_0, a_1, \dots, a_m .
 sin_b contains b_1, \dots, b_m .

Examples

```
# Zero mean
ridge0 <- ridge_bvm(mu = c(0, 0), kappa = c(1, 2, -5), subint_1 = 5e2,
                   subint_2 = 5e2)
coefs <- ridge_fourier_fit(ridge0)
th <- seq(-pi, pi, l = 500)
plot(ridge0, xlim = c(-pi, pi), ylim = c(-pi, pi))
points(ridge_curve(th, mu = c(0, 0), coefs = coefs, at2 = TRUE), col = 3,
       cex = 0.5)

# Non-zero mean from a zero-mean ridge
mu <- c(1.4, 2)
ridge1 <- ridge_bvm(mu = mu, kappa = c(1, 2, -5), subint_1 = 5e2,
                   subint_2 = 5e2) # Just for plot
plot(ridge1, xlim = c(-pi, pi), ylim = c(-pi, pi))
points(mu[1], mu[2], col = 4, pch = "*", cex = 5)
points(ridge_curve(th, mu = mu, coefs = coefs), col = 3, cex = 0.5)

# Other zero-mean example
mu <- c(0, 0)
ridge <- ridge_bwc(mu = mu, xi = c(0.3, 0.5, 0.7), subint_1 = 5e2,
                  subint_2 = 5e2)
plot(ridge, xlim = c(-pi, pi), ylim = c(-pi, pi))
coefs <- ridge_fourier_fit(ridge)
points(ridge_curve(th, mu = mu, coefs = coefs), col = 4, cex = 0.5)

# Another zero-mean example
mu <- c(0, 0)
ridge <- ridge_bwc(mu = mu, xi = c(0.8, 0.1, 0.75), subint_1 = 5e2,
                  subint_2 = 5e2)
plot(ridge, xlim = c(-pi, pi), ylim = c(-pi, pi))
coefs <- ridge_fourier_fit(ridge)
points(ridge_curve(th, mu = mu, coefs = coefs), col = 4, cex = 0.5)
```

 ridge_pca

Toroidal PCA via density ridges

Description

This function computes the whole process of toroidal PCA via density ridges on a given sample: parameter estimation of the underlying distribution, estimation of the connected component of the ridge, and determination of its Fourier expansion from which to obtain the first and second scores.

Usage

```
ridge_pca(
  x,
  type = c("auto", "bvm", "bwc")[1],
  N = 500,
  K = 15,
  scale = TRUE,
  lrts = TRUE,
  alpha = 0.05,
  at2 = TRUE,
  ...
)
```

Arguments

x	matrix of dimension $c(n, 2)$ containing the n observations of the pair of angles.
type	either "bvm" (bivariate sine von Mises), "bwc" (bivariate wrapped Cauchy), or "auto" (default). "auto" performs both fits and uses the one with lowest BIC.
N	number of discretization points for approximating curve lengths. Defaults to $5e2$.
K	number of terms in the Fourier expansion. Defaults to 15.
scale	scale the resulting scores to $[-\pi, \pi]^2$? Defaults to TRUE.
lrts	run <code>biv_lrt</code> to check the null hypothesis of homogeneous concentration parameters using likelihood ratio tests? If TRUE (default), enforces the special horizontal/vertical/diagonal cases to become "sticky" fits.
alpha	significance level for the homogeneity test.
at2	do the <code>atan2</code> fit instead of the sine fit (only using S_m)? Defaults to TRUE. <code>at2 = FALSE</code> is not recommended to use.
...	optional parameters passed to <code>fit_bvm_mle</code> and <code>fit_bwc_mle</code> , such as <code>start</code> , <code>lower</code> , or <code>upper</code> .

Value

A list with:

mu_hat	estimated circular means of the sample.
coefs_hat	estimated Fourier coefficients.
ind_var	indexing variable.
scores	scores for each of the sample points.
var_exp	percentage of explained variance.
fit_mle	maximum likelihood fit.
bic_fit	BIC of the fit.
data	original sample.
scales	vector of length 2 with the scale limits for the axes.

type	type of fit performed.
p_hom	p -value of the homogeneity test.
p_indep	p -value of the independence test.

Examples

```
## Bivariate von Mises

n <- 100
x <- r_bvm(n = n, mu = c(1, 2), kappa = c(0.4, 0.4, 0.5))
fit <- ridge_pca(x = x, type = "bvm")
show_ridge_pca(fit = fit, col_data = "red")

x <- r_bvm(n = n, mu = c(2, 1), kappa = c(1, 2, 0))
fit <- ridge_pca(x = x, type = "bvm")
show_ridge_pca(fit = fit, col_data = "red")

x <- r_bvm(n = n, mu = c(2, 1), kappa = c(3, 2, 0))
fit <- ridge_pca(x = x, type = "bvm")
show_ridge_pca(fit = fit, col_data = "red")

## Bivariate wrapped Cauchy

x <- r_bwc(n = n, mu = c(1, 2), xi = c(0.2, 0.2, 0.5))
fit <- ridge_pca(x = x, type = "bwc")
show_ridge_pca(fit = fit, col_data = "red")

x <- r_bwc(n = n, mu = c(1, 2), xi = c(0.2, 0.8, 0))
fit <- ridge_pca(x = x, type = "bwc")
show_ridge_pca(fit = fit, col_data = "red")

x <- r_bwc(n = n, mu = c(1, 2), xi = c(0.5, 0.2, 0))
fit <- ridge_pca(x = x, type = "bwc")
show_ridge_pca(fit = fit, col_data = "red")
```

ridge_scores

Scores and scales for Fourier-fitted ridge curves

Description

Computation of PCA scores for [Fourier-fitted ridge curves](#). The scores are defined as follows:

- First scores: signed distances along the ridge curve of the data projections to μ .
- Second scores: signed toroidal distances from the data points to their ridge projections.

The scores can be scaled to $(-\pi, \pi)$ or remain as $(l/2, m_2)$, where l is the length of the curve and m_2 is the maximal absolute second score.

Usage

```

ridge_scores(
  x,
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
  N = 500,
  scale = TRUE,
  at2 = TRUE
)

max_score_2(
  mu = c(0, 0),
  coefs = list(cos_a = c(0, 0), sin_b = 0),
  ind_var = 1,
  L = 25,
  f = 2,
  at2 = TRUE
)

```

Arguments

x	a matrix of size $c(n_x, 2)$ with angular coordinates.
mu	a vector of size 2 giving (μ_1, μ_2) . Defaults to $c(0, 0)$.
coefs	list of coefficients \cos_a (a_k) and \sin_b (b_k) giving the Fourier fit of the ridge curve. Defaults to $\text{list}(\cos_a = c(0, 0), \sin_b = 0)$. See examples.
ind_var	index j of the variable that parametrizes the ridge. Defaults to 1.
N	number of discretization points for approximating curve lengths. Defaults to $5e2$.
scale	scale the resulting scores to $[-\pi, \pi]^2$? Defaults to TRUE.
at2	do the atan2 fit instead of the sine fit (only using S_m)? Defaults to TRUE. $\text{at2} = \text{FALSE}$ is not recommended to use.
L	grid along the variable ind_var used for searching the maximum allowed second score. Defaults to 25.
f	factor for shrinking the grid on the variable that is different to ind_var . Defaults to 2.

Details

The mean μ corresponds to the first score being null.

Value

ridge_scores returns a list with:

scores	a matrix of size $c(n_x, 2)$ with the ridge scores.
--------	---

scales a vector of length 2 with the scale limits for the axes.

max_score_2 computes the maximum allowed second score to rescale if scale = TRUE.

Examples

```
mu <- c(-0.5, 1.65)
th <- seq(-pi, pi, l = 200)
K <- 5
coefs <- list(cos_a = 1 / (1:(K + 1))^3, sin_b = 1 / (1:K)^3)
n <- 10
col <- rainbow(n)

set.seed(13213)
old_par <- par(no.readonly = TRUE)
par(mfrow = c(2, 2))
for (j in 1:2) {

  # Simulate synthetic data close to the ridge curve
  rid <- ridge_curve(theta = th, mu = mu, coefs = coefs, ind_var = j)
  ind <- sort(sample(length(th), size = n))
  eps <- 0.25 * matrix(runif(2 * n, -1, 1), nrow = n, ncol = 2)
  x <- sdetorus::toPiInt(rid[ind, ] + eps)

  # Plot ridge and synthetic data, with signs from the second scores
  s <- ridge_scores(x, mu = mu, coefs = coefs, ind_var = j)$scores
  plot(x, xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE,
       xlab = expression(theta[1]), ylab = expression(theta[2]), col = col,
       pch = ifelse(sign(s[, 2]) == 1, "+", "-"), cex = 1.25)
  sdetorus::linesTorus(rid[, 1], rid[, 2], lwd = 2)
  abline(v = mu[1], lty = 3)
  abline(h = mu[2], lty = 3)
  points(mu[1], mu[2], pch = "*", cex = 3)
  sdetorus::torusAxis()

  # Projections
  theta_projs <- proj_ridge_curve(x = x, mu = mu, coefs = coefs,
                                ind_var = j, ridge_curve_grid = rid,
                                )$theta_proj
  projs <- ridge_curve(theta = theta_projs, mu = mu, coefs = coefs,
                       ind_var = j)
  for (i in 1:n) {

    sdetorus::linesTorus(x = c(x[i, 1], projs[i, 1]),
                        y = c(x[i, 2], projs[i, 2]),
                        col = col[i], lty = 3)

  }

  # Scores plot
  plot(s, xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE,
       xlab = "Score 1", ylab = "Score 2", col = col,
       pch = ifelse(sign(s[, 2]) == 1, "+", "-"))
}
```

```
sdetorus::torusAxis()
abline(v = 0, lty = 3)
abline(h = 0, lty = 3)
points(0, 0, pch = "*", cex = 3)

}
par(old_par)
```

santabarbara

Santa Barbara currents

Description

The Santa Barbara Channel is a coastal area in California. This dataset contains the sea currents in the four areas present in the data application in García-Portugués and Prieto-Tirado (2022). Precisely, it contains the 24-hour speed-weighted mean of the currents' direction in each of the four areas downloaded from the [NOAA High Frequency Radar National Server](#).

Usage

santabarbara

Format

A data frame with 1092 rows and 4 variables:

- A** Sea current direction at zone A.
- B** Sea current direction at zone B.
- C** Sea current direction at zone C.
- D** Sea current direction at zone D.

Details

The selection of these four areas is motivated by previous studies on the Santa Barbara currents, like Auad et al. (1998). The direction is measured in radians in $[-\pi, \pi]$ with $-\pi / -\frac{\pi}{2} / 0 / \frac{\pi}{2} / \pi$ representing the East / South / West / North / East directions. The script performing the data preprocessing is available at [data-acquisition.R](#). The data was retrieved on 2022-10-21.

References

- Auad, G., Hendershott, M. C., and Winant, C. D. (1998). Wind-induced currents and bottom-trapped waves in the Santa Barbara Channel. *Journal of Physical Oceanography*, 28(1):85–102. [doi:10.1175/15200485\(1998\)028<0085:WICABT>2.0.CO;2](https://doi.org/10.1175/15200485(1998)028<0085:WICABT>2.0.CO;2)
- García-Portugués, E. and Prieto-Tirado, A. (2023). Toroidal PCA via density ridges. *Statistics and Computing*, 33(5):107. [doi:10.1007/s11222023102739](https://doi.org/10.1007/s11222023102739)

Examples

```
# Load data
data("santabarbara")
AB_zone <- santabarbara[c("A","B")]

# Perform TR-PCA
fit <- ridge_pca(x = AB_zone)
show_ridge_pca(fit)
```

show_ridge_pca

Illustration of toroidal PCA via density ridges

Description

Shows the scores computation for PCA via density ridges on $[-\pi, \pi)^2$.

Usage

```
show_ridge_pca(
  fit,
  n_max = 500,
  projs = TRUE,
  projs_lines = TRUE,
  signs = TRUE,
  col_data = 1,
  col_projs = c(3, 4),
  main = "",
  N = 500,
  at2 = TRUE
)
```

Arguments

fit	the output of <code>ridge_pca</code> .
n_max	maximum number of data points to draw. These are sampled from the data provided. Defaults to 500.
projs	draw projections? Defaults to TRUE.
projs_lines	draw projection lines? Defaults to TRUE.
signs	plot the original data points with + and - facets depending on the signs of the second scores? Defaults to TRUE.
col_data	color(s) for the data points. Defaults to 1.
col_projs	a vector of size 2 giving the colors for the curve-projected data and the ridge curve, respectively. Defaults to c(3, 4).
main	caption of the plot. Empty by default.

N	number of discretization points for approximating curve lengths. Defaults to 5e2.
at2	do the atan2 fit instead of the sine fit (only using S_m)? Defaults to TRUE. at2 = FALSE is not recommended to use.

Value

Nothing, the functions are called to produce plots.

Examples

```
# Generate data
set.seed(987654321)
n <- 50
S1 <- rbind(c(1, -0.7), c(-0.7, 1))
S2 <- rbind(c(1, 0.5), c(0.5, 1))
x <- rbind(mvtnorm::rmvnorm(n, mean = c(0, pi / 2), sigma = S1),
           mvtnorm::rmvnorm(n, mean = c(pi, -pi / 2), sigma = S2))
x <- sdetorus::toPiInt(x)
col <- rainbow(2)[rep(1:2, each = n)]

# ridge_pca and its visualization
fit <- ridge_pca(x = x, at2 = FALSE)
show_ridge_pca(fit = fit, col_data = col, at2 = FALSE)
fit2 <- ridge_pca(x = x, at2 = TRUE)
show_ridge_pca(fit = fit2, col_data = col, at2 = TRUE)
```

torus_dist	<i>Toroidal distances</i>
------------	---------------------------

Description

Computation of distances on $[-\pi, \pi]^d$, $d \geq 1$, between two sets of observations.

Usage

```
torus_dist(x, y, squared = FALSE)
```

Arguments

x	a matrix of size $c(nx, d)$ with angles on $[-\pi, \pi)$.
y	either a matrix with the same size as x or a vector of size nx.
squared	return the squared distance? Defaults to FALSE.

Details

The maximal distance on $[-\pi, \pi]^d$ is $\sqrt{d}\pi$.

Value

A vector of size $n \times n$ with the distances between the observations of x and y .

Examples

```
# Illustration of torus distances
n <- 10
x <- matrix(runif(2 * n, -pi, pi), nrow = n, ncol = 2)
y <- c(pi / 2, pi / 3)
col <- rainbow(n)
plot(x, xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE, col = col,
      xlab = expression(theta[1]), ylab = expression(theta[2]), pch = 16)
sdetorus::torusAxis()
points(y[1], y[2], col = 1, pch = 17)
for (i in 1:n) {
  sdetorus::linesTorus(x = c(x[i, 1], y[1]),
                      y = c(x[i, 2], y[2]), lty = 2, col = col[i])
}
text(x = x, labels = sprintf("%.2f", torus_dist(x, y)), col = col, pos = 1)
```

torus_pairs

*Toroidal pairs plot***Description**

Pairs plots for data on $[-\pi, \pi]^d$, $d \geq 2$. The diagonal panels contain kernel density estimates tailored to circular data.

Usage

```
torus_pairs(
  x,
  max_dim = 10,
  columns = NULL,
  col_data = 1,
  ylim_dens = c(0, 1.5),
  bwd = "ROT",
  scales = rep(pi, ncol(x))
)
```

Arguments

x a matrix of size $c(n \times d)$ with angles on $[-\pi, \pi]$.

max_dim the maximum number of scores to produce the scores plot. Defaults to 10.

columns if specified, the variables to be plotted. If NULL (the default), the first **max_dim** variables are plotted.

col_data	color(s) for the data points. Defaults to 1.
ylim_dens	common ylim for the diagonal plots. Defaults to $c(0, 1)$.
bwd	type of bandwidth selector used in the kernel density plots. Either "ROT", "EMI", "AMI", "LSCV", or "LCV". See <code>bw_dir_pi</code> and <code>bw_dir_cv</code> . Defaults to "ROT".
scales	scales of the torus. Defaults to <code>rep(pi, ncol(x))</code> .

Details

The default bandwidth selector is the Rule-Of-Thumb (ROT) selector in García-Portugués (2013). It is fast, yet it may oversmooth non-unimodal densities. The EMI selector gives more flexible fits.

Value

A `ggplot`. The density plots show the [Fréchet means](#) (red bars) and the Fréchet standard deviations (gray text).

References

García-Portugués, E. (2013). Exact risk improvement of bandwidth selectors for kernel density estimation with directional data. *Electronic Journal of Statistics*, 7:1655–1685. [doi:10.1214/13-ejs821](https://doi.org/10.1214/13-ejs821)

Examples

```
# Generate data
n <- 50
set.seed(123456)
x <- sdetorus::toPiInt(rbind(
  mvtnorm::rmvnorm(n = n, mean = c(-pi, -pi) / 2,
    sigma = diag(0.1, nrow = 2)),
  mvtnorm::rmvnorm(n = n, mean = c(-3 * pi / 2, 0) / 2,
    sigma = diag(0.1, nrow = 2)),
  mvtnorm::rmvnorm(n = n, mean = c(0, pi / 2),
    sigma = diag(0.1, nrow = 2))
))
col <- rainbow(3)[rep(1:3, each = n)]

# Torus pairs
torus_pairs(x, col_data = col)

fit <- ridge_pca(x = x)
torus_pairs(fit$scores, col_data = col)
```

wind	<i>Texas wind dataset</i>
------	---------------------------

Description

Wind direction at 6:00 and 7:00 from June 1, 2003 to June 30, 2003, in radians, measured at a weather station in Texas coded as C28-1.

Usage

```
wind
```

Format

A data frame with 30 rows and 2 variables:

theta1 Direction at 6:00 am.

theta2 Direction at 12:00 noon.

Details

The direction is measured in radians in $[-\pi, \pi)$ with $-\pi/2$, 0 , $\pi/2$ representing the East/South/West/North/East directions.

References

Johnson, R. A. and Wehrly, T. (1977). Measures and models for angular correlation and angular-linear correlation. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(2):222–229. <https://www.jstor.org/stable/2984799>

Examples

```
# Load data
data("wind")
plot(wind, xlab = expression(theta[1]), ylab = expression(theta[2]),
      xlim = c(-pi, pi), ylim = c(-pi, pi), axes = FALSE)
sdetorus::torusAxis()

# Perform TR-PCA
fit <- ridge_pca(x = wind)
show_ridge_pca(fit)
```

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