

Package: demu (via r-universe)

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Description Implements the Determinantal point process (DPP) based optimal design emulator described in Pratola, Lin and Craigmile (2018) <[arXiv:1804.02089](https://arxiv.org/abs/1804.02089)> for Gaussian process regression models. See <<http://www.matthewpratola.com/software>> for more information and examples.

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demu-package	<i>demu is an open-source R package implementing a Gaussian process optimal design emulator based on Determinantal point processes.</i>
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Description

demu implements a determinantal point process emulator for probabilistically sampling optimal designs for Gaussian process (GP) regression models. Currently, demu is a proof of concept implementation that implements basic DPP sampling, conditional DPP sampling for drawing designs of fixed size n , sequential DPP sampling to build designs iteratively and a faster C++ implementation of the conditional DPP sampler using sparse matrices. The package supports popular stationary correlation functions commonly used in GP regression models, including the Gaussian and Wendland correlation functions.

Details

The main model fitting functions in the package include `sim.dpp.modal()` for dense correlation matrices and `sim.dpp.modal.fast()` for sparse correlation matrices. These functions use a grid-based approximation to sample from the relevant DPP model.

Author(s)

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References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

See Also

[sim.dpp.modal](#), [sim.dpp.modal.fast](#), [sim.dpp.modal.seq](#), [sim.dpp.modal.fast.seq](#)

generalized.wendland *Calculate the correlation matrix according to the generalized Wendland model.*

Description

generalized.wendland() is a helper function that constructs a correlation matrix according to the generalized Wendland model with lengthscales given by the parameter vector theta. When kap=0 the correlation model corresponds to the Askey correlation model. The design must have been already formatted in distlist format using the function makedistlist().

Usage

```
generalized.wendland(l.d, theta, kap)
```

Arguments

l.d	Current design distance matrices in distlist format
theta	A vector of range parameters
kap	A non-negative scalar parameter

Value

A list containing the constructed correlation matrix.

See Also

[demu-package](#) [rhomat](#) [matern32](#) [matern52](#) [wendland1](#) [wendland2](#)

Examples

```
library(demu)

design=matrix(runif(10,0,1),ncol=2,nrow=5)
theta=0.3
kap=3
l.d=makedistlist(design)
R=generalized.wendland(l.d,theta,kap)$R
R
```

getranges	<i>Get variable ranges from a design matrix.</i>
-----------	--

Description

getranges() is a helper function to get the lower/upper bounds of variables in a design matrix, used for rescaling the inputs to the $[0, 1]$ hypercube.

Usage

```
getranges(design)
```

Arguments

design	An $n \times p$ matrix of input settings
--------	--

Value

A $p \times 2$ matrix with the lower and upper bounds (rounded to nearest integer value) of all p variables in the design matrix.

Examples

```
library(demu)

design=matrix(runif(10,1,5),ncol=2,nrow=5)
getranges(design)
```

makedistlist	<i>Make list of distance matrices for calculating GP correlation matrices.</i>
--------------	--

Description

makedistlist() is a helper function used to setup the difference matrices that are used by the DPP models.

Usage

```
makedistlist(design)
```

Arguments

design	An $n \times p$ matrix of input settings
--------	--

Value

A list of p matrices, each of dimension $n \times n$ that contain the outer subtractions of each variable in the design matrix.

See Also

[getranges](#) [scaledesign](#)

Examples

```
library(demu)

design=matrix(runif(10,1,5),ncol=2,nrow=5)
r=getranges(design)
design=scaledesign(design,r)
l.v=makedistlist(design)
```

matern32	<i>Calculate the correlation matrix according to the Matern model with $\nu = 3/2$.</i>
----------	--

Description

`matern32()` is a helper function that constructs a correlation matrix according to the Matern model with parameter $\nu = 3/2$ and lengthscales given by the parameter vector `theta`. The design must have been already formatted in `distlist` format using the function `makedistlist()`.

Usage

```
matern32(l.d, theta)
```

Arguments

<code>l.d</code>	Current design distance matrices in <code>distlist</code> format
<code>theta</code>	A vector of range parameters

Value

A list containing the constructed correlation matrix.

See Also

[demu-package](#) [rhomat](#) [matern52](#) [wendland1](#) [wendland2](#) [generalized.wendland](#)

Examples

```
library(demu)

design=matrix(runif(10,0,1),ncol=2,nrow=5)
theta=rep(0.2,2)
l.d=makedistlist(design)
R=matern32(l.d,theta)$R
R
```

matern52

Calculate the correlation matrix according to the Matern model with $\nu = 5/2$.

Description

matern52() is a helper function that constructs a correlation matrix according to the Matern model with parameter $\nu = 5/2$ and lengthscales given by the parameter vector theta. The design must have been already formatted in distlist format using the function makedistlist().

Usage

```
matern52(l.d, theta)
```

Arguments

l.d	Current design distance matrices in distlist format
theta	A vector of range parameters

Value

A list containing the constructed correlation matrix.

See Also

[demu-package](#) [rhomat](#) [matern32](#) [wendland1](#) [wendland2](#) [generalized.wendland](#)

Examples

```
library(demu)

design=matrix(runif(10,0,1),ncol=2,nrow=5)
theta=rep(0.2,2)
l.d=makedistlist(design)
R=matern52(l.d,theta)$R
R
```

remove.projections	<i>Identify candidate points making up all marginal subprojections of an existing design.</i>
--------------------	---

Description

remove.projections() is a helper function to identify all lower-dimensional marginal projection points of the existing design points indexed by curpts. This function can be used to remove a subset of points from the *candidate set* in order to enforce non-collapsingness of when sequentially adding design points.

Usage

```
remove.projections(curpts,X)
```

Arguments

curpts	Indices of points currently in the design
X	An n x p matrix of all candidate points

Value

A list containing the vector curpts, the vector projpts which contains the identified projection points of the current design, and allpts.

See Also

[demu-package sim.dpp.modal.seq](#)

Examples

```
library(demu)

n1=3
n2=3
n3=3
rho=rep(1e-10,2)
ngrid=10

x=seq(0,1,length=ngrid)
X=as.matrix(expand.grid(x,x))
l.d=makedistlist(X)

# Initial design
R=rhomat(l.d,rho)$R
pts.1=sim.dpp.modal(R,n1)
pts.1.proj=remove.projections(pts.1,X)

# Plot - design points in black, design+projection points in grey.
```

```
#plot(X,xlim=c(0,1),ylim=c(0,1))
#points(X[pts.1.proj$projpts,],pch=20,cex=2,col="grey")
#points(X[pts.1,],pch=20,cex=2)
```

rhomat	<i>Calculate the correlation matrix according to the squared exponential family of models.</i>
--------	--

Description

rhomat() is a helper function that constructs a correlation matrix according to the squared exponential model with parameterized by correlation parameters rho taking values in [0,1) and the exponent parameter alpha. The default of alpha=2 results in the Gaussian correlation while selecting alpha=1 corresponds to the Exponential correlation model. The design must have been already formatted in distlist format using the function makedistlist().

Usage

```
rhomat(l.d,rho,alpha=2)
```

Arguments

l.d	Current design distance matrices in distlist format
rho	A vector of correlation parameters taking on values in [0,1)
alpha	Exponent parameter

Value

A list containing the constructed correlation matrix.

See Also

[demu-package](#) [matern52](#) [wendland1](#) [wendland2](#) [generalized.wendland](#)

Examples

```
library(demu)

design=matrix(runif(10,0,1),ncol=2,nrow=5)
rho=rep(0.01,2)
l.d=makedistlist(design)
R=rhomat(l.d,rho)$R
R
```

scaledesign	<i>Rescale a design matrix to the [0,1] hypercube.</i>
-------------	--

Description

scaledesign() is a helper function to rescale a design to the $[0, 1]$ hypercube using variable ranges previously extracted by a call to getranges().

Usage

```
scaledesign(design,r)
```

Arguments

design	An $n \times p$ matrix of input settings
r	An $p \times 2$ matrix of variable ranges extracted from getranges()

Value

A $n \times p$ design matrix rescaled to the $[0, 1]$ hypercube.

See Also

[unscalemat](#)

Examples

```
library(demu)

design=matrix(runif(10,1,5),ncol=2,nrow=5)
r=getranges(design)
scaledesign(design,r)
```

sim.dpp.modal	<i>Draw samples from the conditional DPP design emulator.</i>
---------------	---

Description

sim.dpp.modal() uses the DPP-based design emulator of Pratola et al. (2018) to draw a sample of the n-run optimal design for a Gaussian process regression model with stationary correlation function $r(x, x')$, where the entries of R are formed by evaluating $r(x, x')$ over a grid of candidate locations.

Usage

```
sim.dpp.modal(R,n=0,eigs=NULL)
```

Arguments

R	A correlation matrix evaluated over a grid of candidate design sites.
n	Size of the design to sample.
eigs	One can alternatively pass the pre-computed eigendecomposition of the correlation matrix instead of R.

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A vector of indices to the sampled design sites.

References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

See Also

[demu-package](#) [sim.dpp.modal.fast](#) [sim.dpp.modal.seq](#)

Examples

```
library(demu)

# candidate grid
ngrid=20
x=seq(0,1,length=ngrid)
X=as.matrix(expand.grid(x,x))
l.d=makedistlist(X)

# draw design from DPP mode
n=21
rho=0.01
R=rhomat(l.d,rep(rho,2))$R
pts=sim.dpp.modal(R,n)

# Could plot the result:
# plot(X,xlim=c(0,1),ylim=c(0,1))
# points(X[pts,],pch=20)
```

sim.dpp.modal.fast *Draw samples from the conditional DPP design emulator.*

Description

sim.dpp.modal.fast() is similar to sim.dpp.modal but is a C++ codepath that makes use of SPAM's sparse matrices to enable faster computation. It implements the DPP-based design emulator of Pratola et al. (2018) to draw a sample of the n-run optimal design for a Gaussian process regression model with compact correlation function $r(x, x')$, where the entries of R are formed by evaluating $r(x, x')$ over a grid of candidate locations.

Usage

```
sim.dpp.modal.fast(R,n)
```

Arguments

R	A sparse correlation matrix evaluated over a grid of candidate design sites. The sparse matrix should be of type dgCMatrix (see package spam).
n	Size of the design to sample.

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A vector of indices to the sampled design sites.

References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

See Also

[demu-package sim.dpp.modal](#) [sim.dpp.modal.seq](#)

Examples

```
library(demu)
library(fields)
library(spam)
library(Matrix)
library(Rcpp)

# candidate grid
```

```

ngrid=20
x=seq(0,1,length=ngrid)
X=as.matrix(expand.grid(x,x))

# draw design from DPP mode
n=21
theta=0.39
R.spam=wendland.cov(X,X,theta=theta,k=3)
R=as.dgCMatrix.spam(R.spam)
rm(R.spam)
pts=sim.dpp.modal.fast(R,n)

# Could plot the result:
# plot(X,xlim=c(0,1),ylim=c(0,1))
# points(X[pts,],pch=20)

```

```
sim.dpp.modal.fast.seq
```

Draw sequential samples from the conditional DPP given previously sampled points already in the design.

Description

`sim.dpp.modal.fast.seq()` is similar to `sim.dpp.modal.fast` but sequentially selects n additional points to add to the design given that the points in `curpts` are already in the design from previous sequential iterations. It uses the C++ codepath that makes use of SPAM's sparse matrices to enable faster computation. It implements the DPP-based design emulator of Pratola et al. (2018) to draw a sequential sample of the n -run additional optimal design points for a Gaussian process regression model with compact correlation function $r(x, x')$, where the entries of R are formed by evaluating $r(x, x')$ over a grid of candidate locations.

Usage

```
sim.dpp.modal.fast.seq(curpts, R, n)
```

Arguments

<code>curpts</code>	A vector of indices to the candidate points that already appear in the design.
<code>R</code>	A sparse correlation matrix evaluated over a grid of candidate design sites. The sparse matrix should be of type <code>dgCMatrix</code> (see package spam).
<code>n</code>	Size of the design to sample.

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A vector of indices to the sampled design sites.

References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

See Also

[demu-package](#) [sim.dpp.modal.fast](#) [sim.dpp.modal](#)

Examples

```
library(demu)
library(fields)
library(spam)
library(Matrix)

n1=3
n2=3
n3=3
rho=0.2
ngrid=10

x=seq(0,1,length=ngrid)
X=as.matrix(expand.grid(x,x))
l.d=makedistlist(X)

# Initial design
R.spam=wendland.cov(X,X,theta=rho,k=3)
R=as.dgCMatrix.spam(R.spam)
pts.1=sim.dpp.modal.fast(R,n1)
pts.1.proj=remove.projections(pts.1,X)

# Next sequential step, removing projections
pts.2=sim.dpp.modal.fast.seq(pts.1.proj$allpts,R,n2)
design=c(pts.1,pts.2$pts.new)
pts.2.proj=remove.projections(design,X)

# Next sequential step, removing projections
pts.3=sim.dpp.modal.fast.seq(pts.2.proj$allpts,R,n3)
design=c(design,pts.3$pts.new)

# Or, starting with the initial design, don't remove projections
pts.2=sim.dpp.modal.fast.seq(pts.1,R,n2)
designB=c(pts.1,pts.2$pts.new)

pts.3=sim.dpp.modal.fast.seq(designB,R,n3)
designB=c(designB,pts.3$pts.new)
```

```

# Plot the result:
#par(mfrow=c(1,3))
#plot(X,xlim=c(0,1),ylim=c(0,1),main="Initial Design")
#points(X[pts.1,],pch=20,cex=2)
#
#plot(X,xlim=c(0,1),ylim=c(0,1),main="+3x2 remove projections")
#points(X[design,],pch=20,cex=2)
#
#plot(X,xlim=c(0,1),ylim=c(0,1),main="+3x2 not removing projections")
#points(X[designB,],pch=20,cex=2)

```

sim.dpp.modal.np	<i>Draw samples from the conditional DPP design emulator using a kmeans-based Nystrom approximation.</i>
------------------	--

Description

sim.dpp.modal.np() uses sim.dpp.modal.nystrom.kmeans() to draw a design of n points in p dimensions using the kmeans-based Nystrom approximation of Zhang and Kwok (2010) and the DPP-based design emulator of Pratola et al. (2018). The design constructed assumes a Gaussian process regression model with stationary correlation function $r(x, x')$, where the entries of R are formed by evaluating $r(x, x')$ over a set of landmarks chosen by the kmeans algorithm, and the resulting eigenvectors are projected into the higher dimensional space using the Nystrom approximation. Additional options for sim.dpp.modal.nystrom.kmeans() can be passed to alter the construction of the landmark set.

Usage

```
sim.dpp.modal.np(n,p,N,rho,m=max(ceiling(N*0.1),n),...)
```

Arguments

n	Size of the desired design.
p	Dimension of the desired design.
N	Number of kernel approximation points drawn uniformly from the p -dimensional design space.
rho	The $p \times 1$ parameter vector for the Gaussian correlation model.
m	Number of landmark points to use in constructing the kmeans-based Nystrom approximation.
...	Additional options to pass to sim.dpp.modal.nystrom.kmeans() for drawing the design.

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A list containing a matrix which is the union of the $N \times p$ uniformly sampled kernel approximation points and the m selected landmark sites, and the indices into this matrix of the selected design sites.

References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

Zhang, Kai and Kwok, James T. (2010) Clustered Nystrom method for large scale manifold learning and dimension reduction. *IEEE Transactions on Neural Networks*, **21.10**, 1576–1587. doi: [10.1109/TNN.2010.2064786](https://doi.org/10.1109/TNN.2010.2064786)

See Also

[demu-package sim.dpp.modal](#) [sim.dpp.modal.nystrom.kmeans](#)

Examples

```
library(demu)

n=50
p=5
N=500
rho=rep(0.01,5)
samp=sim.dpp.modal.np(n,p,N,rho)

# Could plot the result:
# pchvec=rep(1,nrow(samp$X))
# pchvec[samp$pts]=20
# cexvec=rep(0.1,nrow(samp$X))
# cexvec[samp$pts]=1
# colvec=rep("black",nrow(samp$X))
# colvec[samp$pts]="red"
# pairs(samp$X,pch=pchvec,cex=cexvec,col=colvec,xlim=c(0,1),ylim=c(0,1))
```

sim.dpp.modal.nystrom *Draw samples from the conditional DPP design emulator using grid-based Nystrom approximation.*

Description

sim.dpp.modal.nystrom() uses the DPP-based design emulator of Pratola et al. (2018) to draw a sample of the n -run optimal design for a Gaussian process regression model with stationary correlation function $r(x, x')$, where the entries of R are formed by evaluating $r(x, x')$ over a grid of candidate locations. This function uses a grid-based Nystrom approximation based on the passed matrix X to avoid constructing a large correlation matrix if dimension n_{grid}^p and its subsequent eigendecomposition.

Usage

```
sim.dpp.modal.nystrom(Xin, rho, n=0, ngrid=NULL, method="Nystrom")
```

Arguments

Xin	A initial $n \times p$ matrix of points.
rho	The $p \times 1$ parameter vector for the Gaussian correlation model.
n	Size of the design to sample from the candidate grid.
ngrid	Size of the candidate grid will be $ngrid^p$.
method	Type of approximation to use. Currently only supports "Nystrom".

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A list containing the candidate points constructed and the points selected as the design sites from this candidate set as well as their indices.

References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

See Also

[demu-package](#) [sim.dpp.modal](#) [sim.dpp.modal.nystrom.kmeans](#)

Examples

```
library(demu)

# Starting design
X=matrix(runif(10*2),ncol=2)
rho=rep(0.01,2)
n=10
ngrid=11
samp=sim.dpp.modal.nystrom(X,rho,n,ngrid)
samp$design

# Could plot the result:
# plot(samp$X,xlim=c(0,1),ylim=c(0,1))
# points(samp$X[samp$pts,],pch=20)
```

 sim.dpp.modal.nystrom.kmeans

Subsample an observational dataset using the conditional DPP design emulator with a kmeans-based Nystrom approximation.

Description

sim.dpp.modal.nystrom.kmeans() uses the kmeans-based Nystrom approximation of Zhang and Kwok (2010) to select n design sites from the observational dataset X_{in} using the DPP-based design emulator of Pratola et al. (2018). The design constructed assumes a Gaussian process regression model with stationary correlation function $r(x, x')$, where the entries of R are formed by evaluating $r(x, x')$ over a set of landmarks chosen by the kmeans algorithm, and the resulting eigenvectors are projected into the higher dimensional space using the Nystrom approximation. Additional options for the MiniBatchKmeans() algorithm from package ClusterR can be passed to alter the construction of the landmark set.

Usage

```
sim.dpp.modal.nystrom.kmeans(Xin, rho=rep(0.01, ncol(Xin)),
  n, m=max(ceiling(nrow(Xin)*0.1), n), method="KmeansNystrom",
  initializer="kmeans++", ...)
```

Arguments

Xin	An $n \times p$ dataset of observations from which we want to draw subsamples.
n	Size of the designed subsample to draw from X_{all} .
rho	The $p \times 1$ parameter vector for the Gaussian correlation model.
m	Number of landmark points to use in constructing the kmeans-based Nystrom approximation.
method	Type of approximation to use. Currently only supports "KmeansNystrom".
initializer	Initialization to use in the Kmeans algorithm, default is "kmeans++".
...	Additional options to pass to MiniBatchKmeans() for selecting the landmark points.

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A list containing a matrix which is the union of the observation matrix X_{in} and selected landmark sites, the indices into this matrix of the selected design sites as well as matrix of the design sites.

References

- Pratola, Matthew T., Lin, C. Devon, and Craigmille, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.
- Zhang, Kai and Kwok, James T. (2010) Clustered Nystrom method for large scale manifold learning and dimension reduction. *IEEE Transactions on Neural Networks*, **21.10**, 1576–1587. doi: [10.1109/TNN.2010.2064786](https://doi.org/10.1109/TNN.2010.2064786)

See Also

[demu-package](#) [sim.dpp.modal](#) [sim.dpp.modal.nystrom](#)

Examples

```
library(demu)

# Fake dataset in 5 dimensions
X=matrix(runif(500*5),ncol=5)
rho=rep(0.01,5)
n=50
samp=sim.dpp.modal.nystrom.kmeans(X,rho,n)
samp$design

# Could plot the result:
# pchvec=rep(1,nrow(samp$X))
# pchvec[samp$pts]=20
# cexvec=rep(0.1,nrow(samp$X))
# cexvec[samp$pts]=1
# colvec=rep("black",nrow(samp$X))
# colvec[samp$pts]="red"
# pairs(samp$X,pch=pchvec,cex=cexvec,col=colvec,xlim=c(0,1),ylim=c(0,1))
```

sim.dpp.modal.seq	<i>Draw sequential samples from the conditional DPP given previously sampled points already in the design.</i>
-------------------	--

Description

`sim.dpp.modal.seq()` is similar to `sim.dpp.modal` but sequentially selects `n` additional points to add to the design given that the points in `curpts` are already in the design from previous sequential iterations. It implements the DPP-based design emulator of Pratola et al. (2018) to draw a sequential sample of `n`-run additional optimal design points for a Gaussian process regression model with correlation function $r(x, x')$, where the entries of `R` are formed by evaluating $r(x, x')$ over a grid of candidate locations. As is typical, `R` is formed based on *all* of the candidate grid points.

Usage

```
sim.dpp.modal.seq(curpts, R, n)
```

Arguments

curpts	A vector of indices to the candidate points that already appear in the design.
R	A correlation matrix evaluated over a grid of candidate design sites.
n	Size of the design to sample.

Details

For more details on the method, see Pratola et al. (2018). Detailed examples demonstrating the method are available at <http://www.matthewpratola.com/software>.

Value

A vector of indices to add to the existing design sites.

References

Pratola, Matthew T., Lin, C. Devon, and Craigmile, Peter. (2018) Optimal Design Emulators: A Point Process Approach. *arXiv:1804.02089*.

See Also

[demu-package](#) [sim.dpp.modal](#) [sim.dpp.modal.fast](#)

Examples

```
library(demu)

n1=3
n2=3
n3=3
rho=rep(1e-10,2)
ngrid=10

x=seq(0,1,length=ngrid)
X=as.matrix(expand.grid(x,x))
l.d=makedistlist(X)

# Initial design
R=rhomat(l.d,rho)$R
pts.1=sim.dpp.modal(R,n1)
pts.1.proj=remove.projections(pts.1,X)

# Next sequential step, removing projections
pts.2=sim.dpp.modal.seq(pts.1.proj$allpts,R,n2)
design=c(pts.1,pts.2$pts.new)
pts.2.proj=remove.projections(design,X)

# Next sequential step, removing projections
pts.3=sim.dpp.modal.seq(pts.2.proj$allpts,R,n3)
design=c(design,pts.3$pts.new)
```

```

# Or, starting with the initial design, don't remove projections
pts.2=sim.dpp.modal.seq(pts.1,R,n2)
designB=c(pts.1,pts.2$pts.new)

pts.3=sim.dpp.modal.seq(designB,R,n3)
designB=c(designB,pts.3$pts.new)

# Plot the result:
#par(mfrow=c(1,3))
#plot(X,xlim=c(0,1),ylim=c(0,1),main="Initial Design")
#points(X[pts.1,],pch=20,cex=2)
#
#plot(X,xlim=c(0,1),ylim=c(0,1),main="+3x2 remove projections")
#points(X[design,],pch=20,cex=2)
#
#plot(X,xlim=c(0,1),ylim=c(0,1),main="+3x2 not removing projections")
#points(X[designB,],pch=20,cex=2)

```

unscalemat

Unscale a matrix back to its original ranges.

Description

unscalemat() is a helper function to rescale a matrix back to its original ranges. Typically this is used to rescale the posterior samples of the parameters back to their original scale.

Usage

```
unscalemat(mat,r)
```

Arguments

mat	An $n \times p$ matrix of numbers scaled to the $[0, 1]$ hypercube
r	An $p \times 2$ matrix of the original ranges of the variables

Value

A $n \times p$ matrix with variables rescaled back to their original ranges, as specified by ranges.

See Also

[getranges scaledesign](#)

Examples

```
library(demu)

design=matrix(runif(10,1,5),ncol=2,nrow=5)
r=getranges(design)
design=scaledesign(design,r)
unscalemat(design,r)
```

wendland1

Calculate the correlation matrix according to the Wendland1 model.

Description

wendland1() is a helper function that constructs a correlation matrix according to the Wendland 1 model with lengthscales given by the parameter vector `theta`. The design must have been already formatted in `distlist` format using the function `makedistlist()`.

Usage

```
wendland1(l.d, theta)
```

Arguments

<code>l.d</code>	Current design distance matrices in <code>distlist</code> format
<code>theta</code>	A vector of range parameters

Value

A list containing the constructed correlation matrix.

See Also

[demu-package](#) [rhomat](#) [matern32](#) [matern52](#) [wendland2](#) [generalized.wendland](#)

Examples

```
library(demu)

design=matrix(runif(10,0,1),ncol=2,nrow=5)
theta=rep(0.3,2)
l.d=makedistlist(design)
R=wendland1(l.d, theta)$R
R
```

`wendland2`*Calculate the correlation matrix according to the Wendland2 model.*

Description

`wendland2()` is a helper function that constructs a correlation matrix according to the Wendland 2 model with lengthscales given by the parameter vector `theta`. The design must have been already formatted in `distlist` format using the function `makedistlist()`.

Usage

```
wendland2(l.d, theta)
```

Arguments

<code>l.d</code>	Current design distance matrices in <code>distlist</code> format
<code>theta</code>	A vector of range parameters

Value

A list containing the constructed correlation matrix.

See Also

[demu-package](#) [rhomat](#) [matern32](#) [matern52](#) [wendland1](#) [generalized.wendland](#)

Examples

```
library(demu)

design=matrix(runif(10,0,1),ncol=2,nrow=5)
theta=rep(0.3,2)
l.d=makedistlist(design)
R=wendland2(l.d,theta)$R
R
```

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