

# Package ‘sorocs’

May 9, 2026

**Version** 0.1.0

**Title** A Bayesian Semiparametric Approach to Correlated ROC Surfaces

**Description** A Bayesian semiparametric Dirichlet process mixtures to estimate correlated receiver operating characteristic (ROC) surfaces and the associated volume under the surface (VUS) with stochastic order constraints. The reference paper is: Zhen Chen, Beom Seuk Hwang, (2018) "A Bayesian semiparametric approach to correlated ROC surfaces with stochastic order constraints". *Biometrics*, 75, 539-550. <[doi:10.1111/biom.12997](https://doi.org/10.1111/biom.12997)>.

**License** GPL-3

**Imports** MASS, MCMCpack, mvtnorm

**Encoding** UTF-8

**LazyData** TRUE

**RoxygenNote** 7.0.2

**URL** <http://github.com/wzhang17/sorocs.git>

**BugReports** <http://github.com/wzhang17/sorocs/issues>

**Suggests** knitr, rmarkdown

**VignetteBuilder** knitr

**NeedsCompilation** no

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### Description

The example data is meant to represent the dataset supplied by the Physician Reliability Study (PRS), which is explored in Section 5 of the paper. The 'sampledata' file contains the following variables:

### Usage

asrm

### Format

A data frame with 129 rows and following variables:

**STUDYID** Subject id

**logREscoremean1** log value of mean of four Regional Experts' scores at setting 1

**logREscoremean2** log value of mean of four Regional Experts' scores at setting 2

**TN1** sum of the IE(International Experts)'s diagnoses for positive disease at setting 1

**TN2** sum of the IE(International Experts)'s diagnoses for positive disease at setting 2

**TN12** TN1+TN2

**JN1** number of non-missing IE's diagnoses for positive disease at setting 1

**JN2** number of non-missing IE's diagnoses for positive disease at setting 2

**JN12** JN1+JN2

**TNN1** sum of the IE's diagnoses for severe disease at setting 1

**TNN2** sum of the IE's diagnoses for severe disease at setting 2

**TNN12** TNN1+TNN2

**JNN1** number of non-missing IE's diagnoses for severe disease at setting 1

**JNN2** number of non-missing IE's diagnoses for severe disease at setting 2

**JNN12** JNN1+JNN2

### Source

<https://doi.org/10.1111/biom.12997>

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 sorocs

*A Bayesian Semiparametric Dirichlet Process Mixtures to Estimate Correlated ROC Surfaces with Stochastic Order Constraints*

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## Description

A Bayesian nonparametric Dirichlet process mixtures to estimate the receiver operating characteristic (ROC) surfaces and the associated volume under the surface (VUS), a summary measure similar to the area under the curve measure for ROC curves. To model distributions flexibly, including their skewness and multi-modality characteristics a Bayesian nonparametric Dirichlet process mixtures was used. Between-setting correlations is handled by dependent Dirichlet process mixtures that have bivariate distributions with nonzero correlations as their bases. To accommodate ordering constraints, the stochastic ordering in the context of mixture distributions was adopted.

## Usage

```
sorocs(
  nsim = 4,
  nburn = 2,
  Yvariable1,
  Yvariable2,
  gridY = seq(0, 5, by = 0.05),
  Xvariable1,
  Xvariable2,
  gam0 = -4.6,
  gam1 = 9.2,
  lamb0 = -4.6,
  lamb1 = 9.2,
  H = 30,
  L = 30,
  alpha1 = 1,
  alpha2 = 1,
  alpha3 = 1,
  lambda1 = 1,
  lambda2 = 1,
  mu1 = matrix(c(0.5, 0.5), 2, 1),
  mu2 = matrix(c(1, 1), 2, 1),
  mu3 = matrix(c(3, 3), 2, 1),
  m1 = c(0, 0),
  m2 = c(0, 0),
  m3 = c(0, 0),
  A1 = 10 * diag(2),
  A2 = 10 * diag(2),
  A3 = 10 * diag(2),
  Sig1 = matrix(c(1, 0.5, 0.5, 1), 2, 2),
  Sig2 = matrix(c(1, 0.5, 0.5, 1), 2, 2),
  Sig3 = matrix(c(1, 0.5, 0.5, 1), 2, 2),
```

```

nu = 6,
C0 = 10 * diag(2),
a1 = 2,
a2 = 2,
b1 = 0.1,
b2 = 0.1
)

```

### Arguments

nsim	Number of simulations
nburn	Burn in number
Yvariable1	Dependent variable at setting 1
Yvariable2	Dependent variable at setting 2
gridY	a regular sequence spanning the range of Y variable
Xvariable1	independent variable at setting 1
Xvariable2	independent variable at setting 2
gam0	Initial value for the test score distributions (e.g., a priori information between different disease populations for a single test or between multiple correlated tests)
gam1	Initial value for the test score distributions
lamb0	Initial value for the test score distributions
lamb1	Initial value for the test score distributions
H	truncation level number for Dirichlet process prior truncation approximation
L	truncation level number for Dirichlet process prior truncation approximation
alpha1	fixed values of the precision parameters of the Dirichlet process
alpha2	fixed values of the precision parameters of the Dirichlet process
alpha3	fixed values of the precision parameters of the Dirichlet process
lambda1	fixed values of the precision parameters of the Dirichlet process
lambda2	fixed values of the precision parameters of the Dirichlet process
mu1	fixed values of the bivariate normal parameters of the Dirichlet process
mu2	fixed values of the bivariate normal parameters of the Dirichlet process
mu3	fixed values of the bivariate normal parameters of the Dirichlet process
m1	fixed values of the bivariate normal parameters of the Dirichlet process
m2	fixed values of the bivariate normal parameters of the Dirichlet process
m3	fixed values of the bivariate normal parameters of the Dirichlet process
A1	Initial values of the bivariate normal parameters of the Dirichlet process
A2	Initial values of the bivariate normal parameters of the Dirichlet process
A3	Initial values of the bivariate normal parameters of the Dirichlet process
Sig1	Initial values of the inverse Wishart distribution parameters of the Dirichlet process

Sig2	Initial values of the inverse Wishart distribution parameters of the Dirichlet process
Sig3	Initial values of the inverse Wishart distribution parameters of the Dirichlet process
nu	Initial values of the inverse Wishart distribution parameters of the Dirichlet process
C0	Initial values of the inverse Wishart distribution parameters of the Dirichlet process
a1	Initial shape values of the inverse-gamma base distributions for the Dirichlet process
a2	Initial shape values of the inverse-gamma base distributions for the Dirichlet process
b1	Initial scale values of the inverse-gamma base distributions for the Dirichlet process
b2	Initial scale values of the inverse-gamma base distributions for the Dirichlet process

### Value

A list of posterior estimates

### References

Zhen Chen, Beom Seuk Hwang. (2018) *A Bayesian semiparametric approach to correlated ROC surfaces with stochastic order constraints*. *Biometrics*, 75, 539-550. <https://doi.org/10.1111/biom.12997>

### Examples

```
library(MASS)
library(MCMCpack)
library(mvtnorm)
data(asrm)
Y1 <- asrm$logREscoremean2[1:10]
Y2 <- asrm$logREscoremean1[1:10]
X1 <- asrm$TN12[1:20]/asrm$JN12[1:10]
X2 <- asrm$TNN12[1:20]/asrm$JNN12[1:10]
try1 <- sorocs::sorocs( H = 12, L = 12, Yvariable1 =Y1, Yvariable2= Y2,
                       gridY=seq(0,5,by=1), Xvariable1= X1, Xvariable2 =X2)
```

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