

Package ‘SBSA’

February 19, 2015

Type Package

Title Simplified Bayesian Sensitivity Analysis

Version 0.2.3

Date 31 January 2014

Author Davor Cubranic and Paul Gustafson

Maintainer Davor Cubranic <cubranic@stat.ubc.ca>

Description Simplified Bayesian Sensitivity Analysis

URL <http://sbsa.r-forge.r-project.org/>

License GPL (>= 3)

LazyLoad yes

Depends R (>= 3.0.2)

Imports Rcpp (>= 0.8.6)

Suggests MASS, xtable

LinkingTo Rcpp (>= 0.8.6), RcppArmadillo (>= 0.2.6)

SystemRequirements GNU make

NeedsCompilation yes

Repository CRAN

Date/Publication 2014-01-31 21:47:18

R topics documented:

SBSA-package	2
fitSBSA	2

Index	6
--------------	----------

 SBSA-package

Simplified Bayesian Sensitivity Analysis

Description

Simplified Bayesian sensitivity analysis of models with partially observed confounders.

Details

The SBSA package is an implementation of algorithms for simplified Bayesian sensitivity analysis described in *Gustafson et al (2010)*. It has one entry function, `fitSBSA`. For more details refer to the relevant help files.

Author(s)

Davor Cubranic <cubranic@stat.ubc.ca> and Paul Gustafson <gustaf@stat.ubc.ca>

Maintainer: Davor Cubranic <cubranic@stat.ubc.ca>

References

Gustafson, P., L. C. McCandless, A. R. Levy, and S. Richardson. (2010) ‘Simplified Bayesian Sensitivity Analysis for Mismeasured and Unobserved Confounders.’ *Biometrics*, 66(4):1129-1137. DOI: 10.1111/j.1541-0420.2009.01377.x

See Also

[fitSBSA](#)

Examples

```
## see examples for fitSBSA
```

 fitSBSA

Fitting Simplified Bayesian Sensitivity Models

Description

Conducts sensitivity analysis over a model involving unobserved and poorly measured covariates.

Usage

```
fitSBSA(y, x, w, a, b, k2=NULL, e12=NULL,
        cor.alpha=0, sd.alpha=1e+06, nrep=5000,
        sampler.jump=c(alpha=.15, beta.z=.1, sigma.sq=.5, tau.sq=.05,
                       beta.u.gamma.x=.3, gamma.z=.15),
        q.steps=25, family=c("continuous", "binary"))
```

Arguments

<code>y</code>	a vector of outcomes
<code>x</code>	a (standardized) vector of exposures
<code>w</code>	a (standardized) matrix of noisy measurements
<code>a</code>	parameter of the prior for magnitude of measurement error on confounder Z_j
<code>b</code>	parameter of the prior for magnitude of measurement error on confounder Z_j
<code>k2</code>	(optional) magnitude of prior uncertainty about $(U X, Z)$ regression coefficients
<code>e12</code>	(optional) residual variance for $(U X, Z)$
<code>cor.alpha</code>	(optional) value of the ρ parameter of the bivariate normal prior for α
<code>sd.alpha</code>	(optional) value of the σ parameter of the bivariate normal prior for α
<code>nrep</code>	number of MCMC steps
<code>sampler.jump</code>	named vector of standard deviation of <ul style="list-style-type: none"> • <code>alpha.jump</code> for block reparametrizing α • <code>beta.z.jump</code> for block reparametrizing β_z • <code>sigma.sq</code> (continuous case only) jump for block reparametrizing σ^2 • <code>tau.sq</code> jump for block reparametrizing τ^2 • <code>beta.u.gamma.x</code> jump for block reparametrizing β_u and γ_z • <code>gamma.z</code> jump for block reparametrizing γ_z
<code>q.steps</code>	number of steps in numeric integration of likelihood (only used for binary outcome variables)
<code>family</code>	a character string indicating the assumed distribution of the outcome. Valid values are "continuous", the default, or "binary".

Details

The function uses a simplified Bayesian sensitivity analysis algorithm that models the outcome variable Y in terms of exposure X and confounders $Z = (Z_1, \dots, Z_p)$ and $U = (U_1, \dots, U_q)$, where U s are unobserved, and Z s are measured imprecisely as W s. (I.e., the observed data is (Y, X, W) .) Parameters of the model are then estimated using MCMC with reparametrizing block-sampling. The estimated parameters are as follows:

- $\tau: (W|Y, U, Z, X) \sim N_p(Z, \text{diag}(\tau^2))$
- $\gamma_x, \gamma_z: (U|X, Z) \sim N(\gamma_x X + \gamma_z' Z)$
- $\alpha, \beta_u, \beta_z, \sigma: (Y|U, Z, X) \sim N(\alpha_0 + \alpha_x X + \beta_u U + \beta_z' Z, \sigma^2)$

Value

a list with the following elements:

<code>acc</code>	a vector of counts of how many times each block sampler successfully made a jump. Vector elements are named by their block, as in the <code>sampler.jump</code> argument.
<code>alpha</code>	a $nrep \times 2$ matrix of the value of α parameter at each MCMC step

beta.z a $nrep \times p$ matrix of the value of β_z parameter at each MCMC step
 gamma.z a $nrep \times p$ matrix of the value of γ_z parameter at each MCMC step
 tau.sq a $nrep \times p$ matrix of the value of τ^2 parameter at each MCMC step
 gamma.x a vector of the value of γ_x parameter at each MCMC step
 beta.u a vector of the value of β_u parameter at each MCMC step
 sigma.sq a vector of the value of σ^2 parameter at each MCMC step

References

Gustafson, P. and McCandless, L. C and Levy, A. R. and Richardson, S. (2010) *Simplified Bayesian Sensitivity Analysis for Mismeasured and Unobserved Confounders*. *Biometrics*, 66(4):1129–1137. DOI: 10.1111/j.1541-0420.2009.01377.x

Examples

```
### simulated data example
n <- 1000

### exposure and true confounders equi-correlated with corr=.6
tmp <- sqrt(.6)*matrix(rnorm(n),n,5) +
      sqrt(1-.6)*matrix(rnorm(n*5),n,5)
x <- tmp[,1]
z <- tmp[,2:5]

### true outcome relationship
y <- rnorm(n, x + z%%rep(.5,4), .5)

### first two confounders are poorly measured, ICC=.7, .85
### third is correctly measured, fourth is unobserved
w <- z[,1:3]
w[,1] <- w[,1] + rnorm(n, sd=sqrt(1/.7-1))
w[,2] <- w[,2] + rnorm(n, sd=sqrt(1/.85-1))

### fitSBSA expects standardized exposure, noisy confounders
x.sdz <- (x-mean(x))/sqrt(var(x))
w.sdz <- apply(w, 2, function(x) {(x-mean(x)) / sqrt(var(x))})

### prior information: ICC very likely above .6, mode at .8
### via Beta(5,21) distribution
fit <- fitSBSA(y, x.sdz, w.sdz, a=5, b=21, nrep=10000,
              sampler.jump=c(alpha=.02, beta.z=.03,
                              sigma.sq=.05, tau.sq=.004,
                              beta.u.gamma.x=.4, gamma.z=.5))

### check MCMC behaviour
print(fit$acc)
plot(fit$alpha[,2], pch=20)

### inference on target parameter in original scale
```

fitSBSA

5

```
trgt <- fit$alpha[1001:10000,2]/sqrt(var(x))  
print(c(mean(trgt), sqrt(var(trgt))))
```

Index

- *Topic **Bayesian inference**
 - SBSA-package, [2](#)
 - *Topic **Measurement error**
 - SBSA-package, [2](#)
 - *Topic **Sensitivity analysis**
 - SBSA-package, [2](#)
 - *Topic **TODO**
 - fitSBSA, [2](#)
 - *Topic **Unobserved confounder**
 - SBSA-package, [2](#)
- fitSBSA, [2](#), [2](#)
- SBSA (SBSA-package), [2](#)
- SBSA-package, [2](#)