Chib, Shin and Simoni (2018): R package betel

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Introduction

This package does the Bayesian estimation and comparison of moment condition models as developed in Chib, Shin, and Simoni (2018).

The models estimated in this package are specified through moment restrictions of the type $\mathbb{E}^P[\boldsymbol{g}(\boldsymbol{X}, \boldsymbol{\theta})] = \mathbf{0}$, where $\boldsymbol{g}(\boldsymbol{X}, \boldsymbol{\theta})$ is a known vector-valued function of a random vector $\boldsymbol{X}$ and an unknown parameter vector $\boldsymbol{\theta}$, and P is the unknown data distribution.

This package conducts the prior-posterior analysis of these models by a one block tailored MCMC method. For further details see Chib and Greenberg (1995) and Chib, Shin, and Simoni (2018). The marginal likelihood of the model is calculated by the method of Chib (1995), as extended to M-H samplers by Chib and Jeliazkov (2001).

Installing the package

The package zip file (for windows) or tar file (for the mac) can be downloaded from https://apps.olin.wustl.edu/faculty/chib/czzg/. The downloaded package can be installed from Rstudio -> Tools -> Install Package -> and changing the Install from option to Package Archive file. Then, scroll to the location where the downloaded package was saved (typically the download files folder), and select the file.

Example Run

Once the package has been installed, you can run the following code that estimates the IV regression example discussed in the source paper.

The model of interest is

$$y = \alpha + x\beta + w\delta + \varepsilon, \qquad \mathbb{E}^P[\varepsilon] = 0$$

where

$$\boldsymbol{\theta} = (\alpha, \beta, \delta)$$

and the covariate x is correlated with the error. To learn about the causal effect parameter β, we suppose that two instruments, z_1 and z_2, are available. We also suppose that w is uncorrelated with ε.

The overidentified moment restrictions in this example are

$$\begin{aligned}
\mathbb{E}^P\left[(y_i - \alpha - x_i\beta - w_i\delta)\right] &= 0 \\
\mathbb{E}^P\left[(y_i - \alpha - x_i\beta - w_i\delta)\, z_{1i}\right] &= 0 \\
\mathbb{E}^P\left[(y_i - \alpha - x_i\beta - w_i\delta)\, z_{2i}\right] &= 0 \\
\mathbb{E}^P\left[(y_i - \alpha - x_i\beta - w_i\delta)\, w_i\right] &= 0, \qquad (i \le n)
\end{aligned}$$

For the purpose of this package, one can view these moments in the following way. Let $\boldsymbol{\varepsilon}(\boldsymbol{\theta}) = (\varepsilon_1(\boldsymbol{\theta}), ..., \varepsilon_n(\boldsymbol{\theta}))$ denote the n vector of errors, where $\varepsilon_i(\boldsymbol{\theta}) = y_i - \alpha - x_i\beta - w_i\delta$. Let $\boldsymbol{Z} = (\mathbf{1}, \boldsymbol{w}, \boldsymbol{z}_1, \boldsymbol{z}_2)$ denote the $n \times 4$ matrix of data. Then, the moments for all n observations take the form

$$\mathbb{E}^P\left[\boldsymbol{\varepsilon}(\boldsymbol{\theta}) \circ \mathbf{1}, \boldsymbol{\varepsilon}(\boldsymbol{\theta}) \circ \boldsymbol{w}, \boldsymbol{\varepsilon}(\boldsymbol{\theta}) \circ \boldsymbol{z}_1, \boldsymbol{\varepsilon}(\boldsymbol{\theta}) \circ \boldsymbol{z}_2\right] = 0$$

where $\circ$ is the Hadamard (element by element multiplication) operator. The package requires that the $n \times 4$ matrix within square brackets is coded in a function that is passed as the argument gfunc into the function **betel::bayesetel** that does the estimation.

```
rm(list = ls())
library(czzg)
library(betel)
library(nor1mix);

# GENERATE DATA

set.seed(100)
n = 200;

Sigma = matrix(c(1,.7,.7,1),nr = 2)
```

```r
Cp = t(chol(Sigma));
E = matrix(0,nr = 2,nc = n);

# parameters of the error components
mue1 = 1/2;
mue2 = -1/2;
sig1 = 0.5;
sig2 = 1.118;
q1 = 0.5;

a = norMix(mu = c(mue1,mue2),
           sigma = c(sig1,sig2),
           w = c(q1,1-q1));
for (i in 1:n) {
    ei = Cp%*%rnorm(2);
    u = pnorm(ei[1]);
    v = pnorm(ei[2]);
    e1i = qnorMix(u,a);
    e2i = qnorm(v);
    E[,i] = c(e1i,e2i);
}
z1 = 0.5 + rnorm(n);
z2 = 0.5 + rnorm(n);
w = runif(n);
e2 = E[2,];
e1 = E[1,]

beta = .5;
x = z1 + z2 + w + e2;
y = 1 + x*beta + .7*w + e1;
dat = cbind(rep(1,n),x,w,z1,z2);


# SET UP MOMENTS
# returns a n*d matrix
# the moments must be expressed in terms of psi,y and dat
# what is in psi, y and dat will vary from problem to problem
```

```r
gfunc = function(psi = psi,
                 y = y,
                 dat = dat) {
    X = dat[,1:3];
    e = y - X %*% psi;
    E = e %*% rep(1,4);
    Z = dat[,c(1,3:5)];
    G = E * Z;
    return(G);
}

k = 3;     # number of parameters
d = 4;     # number of moments
nt = 40;   # training sample size for prior

psi0 = lm(y[1:nt]~x[1:nt]+w[1:nt])$coefficients;
names(psi0) = c("alpha","beta","delta");
psi0_ = as.matrix(psi0);
Psi0_ = 5*rep(1,k);

lam0 = .5*rnorm(d);
nu = 2.5;

# MCMC ESTIMATION BY THE CSS (2018) method

psim = betel::bayesetel(gfunc = gfunc,
                        y = y[-(1:nt)],
                        dat = dat[-(1:nt),],
                        psi0 = psi0,
                        lam0 = lam0,
                        psi0_ = psi0_,
                        Psi0_ = Psi0_,
                        nu = 2.5,
                        nuprop = 15,
                        controlpsi = list(maxiterpsi = 50,
                                          mingrpsi = 1.0e-8),
                        controllam = list(maxiterlam = 50,
                                          mingrlam = 1.0e-7))
```

```
## this is psi0 0.9579335 0.5446932 0.05974696
## tailoring to find the proposal has started ...
## $muprop
##     alpha      beta     delta
## 0.7626357 0.4457489 1.1615118
##
## $Pprop
##           [,1]     [,2]      [,3]
## [1,] 170.84950 232.5167  85.72942
## [2,] 232.51666 866.7771 148.46776
## [3,]  85.72942 148.4678  59.97333
##
## $value
## [1] 820.5057
##
## $grad
## [1] -6.584796e-05 -1.979328e-04 -3.479257e-05
##
## this is g 2000
## this is psi1 0.8162699 0.3838563 1.195132
## this is counter/g 0.8305
## this is g 4000
## this is psi1 0.6889423 0.4925472 1.268583
## this is counter/g 0.82175
## this is g 6000
## this is psi1 0.9109545 0.4655859 0.9017836
## this is counter/g 0.8173333
## this is g 8000
## this is psi1 0.8252601 0.4358501 1.225811
## this is counter/g 0.817875
## this is g 10000
## this is psi1 0.7569381 0.4256043 1.1964
## this is counter/g 0.8172
## this is g in numerator of C-J 2000
## this is g in numerator of C-J 4000
## this is g in numerator of C-J 6000
## this is g in numerator of C-J 8000
## this is g in numerator of C-J 10000
## this is g in denominator of C-J 2000
```

```
## this is g in denominator of C-J 4000
## this is g in denominator of C-J 6000
## this is g in denominator of C-J 8000
## this is g in denominator of C-J 10000
```

```
summarymcmc(psim)
```

```
## Bayesian Moment Condition Model
## Estimation by the Chib, Shin and Simoni (2018) method
## sample size is  160
## MCMC sample size is  10000
##        postmean     postsd postmedian     lower     upper    ineff
## alpha 0.7596687 0.15243823  0.7628591 0.4348581 1.0533112 1.501278
## beta  0.4379033 0.04717905  0.4402567 0.3361522 0.5243891 1.506400
## delta 1.1560973 0.26580856  1.1557320 0.6255279 1.6919343 1.468270
## log marg likelihood by Chib (1995) and Chib Jeliazkov (2001): -824.8789
```

References

Chib, Siddhartha. 1995. "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association* 90 (432): 1313–21.

Chib, Siddhartha, and Edward Greenberg. 1995. "Understanding the Metropolis-Hastings algorithm." *The American Statistician* 49 (4): 327–35.

Chib, Siddhartha, and Ivan Jeliazkov. 2001. "Marginal likelihood from the Metropolis-Hastings output." *Journal of the American Statistical Association* 96 (453): 270–81.

Chib, Siddhartha, Minchul Shin, and Anna Simoni. 2018. "Bayesian Estimation and Comparison of Moment Condition Models." *Journal of the American Statistical Association* 113 (524): 1656–68.