

Description

Data from a conjoint experiment in which two partial profiles of credit cards were presented to 946 respondents. The variable `bank$choiceAtt$choice` indicates which profile was chosen. The profiles are coded as the difference in attribute levels. Thus, a "-1" means the profile coded as a choice of "0" has the attribute. A value of 0 means that the attribute was not present in the comparison.

data on age, income and gender (female=1) are also recorded in `bank$demo`

Usage

```
data(bank)
```

Format

This R object is a list of two data frames, `list(choiceAtt,demo)`.

List of 2

\$ choiceAtt: 'data.frame': 14799 obs. of 16 variables:

```
...$ id : int [1:14799] 1 1 1 1 1 1 1 1 1 1
...$ choice : int [1:14799] 1 1 1 1 1 1 1 1 0 1
...$ Med_FInt : int [1:14799] 1 1 1 0 0 0 0 0 0 0
...$ Low_FInt : int [1:14799] 0 0 0 0 0 0 0 0 0 0
...$ Med_VInt : int [1:14799] 0 0 0 0 0 0 0 0 0 0
...$ Rewrd_2 : int [1:14799] -1 1 0 0 0 0 0 1 -1 0
...$ Rewrd_3 : int [1:14799] 0 -1 1 0 0 0 0 0 1 -1
...$ Rewrd_4 : int [1:14799] 0 0 -1 0 0 0 0 0 0 1
...$ Med_Fee : int [1:14799] 0 0 0 1 1 -1 -1 0 0 0
...$ Low_Fee : int [1:14799] 0 0 0 0 0 1 1 0 0 0
...$ Bank_B : int [1:14799] 0 0 0 -1 1 -1 1 0 0 0
...$ Out_State : int [1:14799] 0 0 0 0 -1 0 -1 0 0 0
...$ Med_Rebate : int [1:14799] 0 0 0 0 0 0 0 0 0 0
...$ High_Rebate : int [1:14799] 0 0 0 0 0 0 0 0 0 0
...$ High_CredLine: int [1:14799] 0 0 0 0 0 0 0 -1 -1 -1
...$ Long_Grace : int [1:14799] 0 0 0 0 0 0 0 0 0 0
```

\$ demo : 'data.frame': 946 obs. of 4 variables:

```
...$ id : int [1:946] 1 2 3 4 6 7 8 9 10 11
...$ age : int [1:946] 60 40 75 40 30 30 50 50 50 40
...$ income: int [1:946] 20 40 30 40 30 60 50 100 50 40
...$ gender: int [1:946] 1 1 0 0 0 0 1 0 0 0
```

Details

Each respondent was presented with between 13 and 17 paired comparisons. Thus, this dataset has a panel structure.

Source

Allenby and Ginter (1995), "Using Extremes to Design Products and Segment Markets," *JMR*, 392-403.

References

Appendix A, *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
data(bank)
cat(" table of Binary Dep Var", fill=TRUE)
print(table(bank$choiceAtt[,2]))
cat(" table of Attribute Variables", fill=TRUE)
mat=apply(as.matrix(bank$choiceAtt[,3:16]),2,table)
print(mat)
cat(" means of Demographic Variables", fill=TRUE)
mat=apply(as.matrix(bank$demo[,2:3]),2,mean)
print(mat)

## example of processing for use with rhierBinLogit
##
if(0)
{
choiceAtt=bank$choiceAtt
Z=bank$demo

## center demo data so that mean of random-effects
## distribution can be interpreted as the average respondent

Z[,1]=rep(1,nrow(Z))
Z[,2]=Z[,2]-mean(Z[,2])
Z[,3]=Z[,3]-mean(Z[,3])
Z[,4]=Z[,4]-mean(Z[,4])
Z=as.matrix(Z)

hh=levels(factor(choiceAtt$id))
nhh=length(hh)
lgtdata=NULL
for (i in 1:nhh) {
  y=choiceAtt[choiceAtt[,1]==hh[i],2]
  nobs=length(y)
  X=as.matrix(choiceAtt[choiceAtt[,1]==hh[i],c(3:16)])
  lgtdata[[i]]=list(y=y,X=X)
}
```

```

cat("Finished Reading data",fill=TRUE)
fsh()

Data=list(lgtdata=lgtdata,Z=Z)
Mcmc=list(R=10000,sbeta=0.2,keep=20)
set.seed(66)
out=rhierBinLogit(Data=Data,Mcmc=Mcmc)

begin=5000/20
end=10000/20

summary(out$Deltadraw,burnin=begin)
summary(out$Vbetadraw,burnin=begin)

if(0){
## plotting examples

## plot grand means of random effects distribution (first row of Delta)
index=4*c(0:13)+1
matplot(out$Deltadraw[,index],type="l",xlab="Iterations/20",ylab="",
main="Average Respondent Part-Worths")

## plot hierarchical coefs
plot(out$betadraw)

## plot log-likelihood
plot(out$llike,type="l",xlab="Iterations/20",ylab="",main="Log Likelihood")

}
}

```

breg	<i>Posterior Draws from a Univariate Regression with Unit Error Variance</i>
-------------	--

Description

breg makes one draw from the posterior of a univariate regression (scalar dependent variable) given the error variance = 1.0. A natural conjugate, normal prior is used.

Usage

```
breg(y, X, betabar, A)
```

Arguments

y	vector of values of dep variable.
X	n (length(y)) x k Design matrix.
betabar	k x 1 vector. Prior mean of regression coefficients.
A	Prior precision matrix.

Details

model: $y = x'\beta + e$. $e \sim N(0, 1)$.

prior: $\beta \sim N(\text{betabar}, A^{-1})$.

Value

k x 1 vector containing a draw from the posterior distribution.

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

In particular, X must be a matrix. If you have a vector for X, coerce it into a matrix with one column

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##

if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=1000} else {R=10}

## simulate data
set.seed(66)
n=100
X=cbind(rep(1,n),runif(n)); beta=c(1,2)
y=X%*%beta+rnorm(n)
##
## set prior
A=diag(c(.05,.05)); betabar=c(0,0)
##
## make draws from posterior
betadraw=matrix(double(R*2),ncol=2)
for (rep in 1:R) {betadraw[rep,]=breg(y,X,betabar,A)}
##
## summarize draws
mat=apply(betadraw,2,quantile,probs=c(.01,.05,.5,.95,.99))
mat=rbind(beta,mat); rownames(mat)[1]="beta"; print(mat)
```

Description

`cgetC` obtains a list of censoring points, or cut-offs, used in the ordinal multivariate probit model of Rossi et al (2001). This approach uses a quadratic parameterization of the cut-offs. The model is useful for modeling correlated ordinal data on a scale from 1, ..., k with different scale usage patterns.

Usage

```
cgetC(e, k)
```

Arguments

<code>e</code>	quadratic parameter (>0 and less than 1)
<code>k</code>	items are on a scale from 1, ..., k

Value

A vector of $k+1$ cut-offs.

Warning

This is a utility function which implements **no** error-checking.

Author(s)

Rob McCulloch and Peter Rossi, Graduate School of Business, University of Chicago.
(Peter.Rossi@ChicagoGsb.edu).

References

Rossi et al (2001), "Overcoming Scale Usage Heterogeneity," *JASA*96, 20-31.

See Also

[rscaleUsage](#)

Examples

```
##  
cgetC(.1,10)
```

cheese

Sliced Cheese Data

Description

Panel data with sales volume for a package of Borden Sliced Cheese as well as a measure of display activity and price. Weekly data aggregated to the "key" account or retailer/market level.

Usage

```
data(cheese)
```

Format

A data frame with 5555 observations on the following 4 variables.

RETAILER a list of 88 retailers

VOLUME unit sales

DISP a measure of display activity – per cent ACV on display

PRICE in \$

Source

Boatwright et al (1999), "Account-Level Modeling for Trade Promotion," *JASA* 94, 1063-1073.

References

Chapter 3, *Bayesian Statistics and Marketing* by Rossi et al.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
data(cheese)
cat(" Quantiles of the Variables ",fill=TRUE)
mat=apply(as.matrix(cheese[,2:4]),2,quantile)
print(mat)

##
## example of processing for use with rhierLinearModel
##
if(0)
{

retailer=levels(cheese$RETAILER)
nreg=length(retailer)
nvar=3
regdata=NULL
```

```

for (reg in 1:nreg) {
  y=log(cheese$VOLUME[cheese$RETAILER==retailer[reg]])
  iota=c(rep(1,length(y)))
  X=cbind(iota,cheese$DISP[cheese$RETAILER==retailer[reg]],
          log(cheese$PRICE[cheese$RETAILER==retailer[reg]]))
  regdata[[reg]]=list(y=y,X=X)
}
Z=matrix(c(rep(1,nreg)),ncol=1)
nz=ncol(Z)
##
## run each individual regression and store results
##
lscoef=matrix(double(nreg*nvar),ncol=nvar)
for (reg in 1:nreg) {
  coef=lsfit(regdata[[reg]]$X,regdata[[reg]]$y,intercept=FALSE)$coef
  if (var(regdata[[reg]]$X[,2])==0) { lscoef[reg,1]=coef[1]; lscoef[reg,3]=coef[2]}
  else {lscoef[reg,]=coef }
}

R=2000
Data=list(regdata=regdata,Z=Z)
Mcmc=list(R=R,keep=1)

set.seed(66)
out=rhierLinearModel(Data=Data,Mcmc=Mcmc)

cat("Summary of Delta Draws",fill=TRUE)
summary(out$Deltadraw)
cat("Summary of Vbeta Draws",fill=TRUE)
summary(out$Vbetadraw)

if(0){
#
# plot hier coefs
plot(out$betadraw)
}

}

```

clusterMix

Cluster Observations Based on Indicator MCMC Draws

Description

clusterMix uses MCMC draws of indicator variables from a normal component mixture model to cluster observations based on a similarity matrix.

Usage

```
clusterMix(zdraw, cutoff = 0.9, SILENT = FALSE)
```

Arguments

<code>zdraw</code>	R x nobs array of draws of indicators
<code>cutoff</code>	cutoff probability for similarity (def=.9)
<code>SILENT</code>	logical flag for silent operation (def= FALSE)

Details

define a similarity matrix, `Sim`, `Sim[i,j]`=1 if observations `i` and `j` are in same component. Compute the posterior mean of `Sim` over indicator draws.

clustering is achieved by two means:

Method A: Find the indicator draw whose similarity matrix minimizes, $\text{loss}(E[\text{Sim}] - \text{Sim}(z))$, where loss is absolute deviation.

Method B: Define a Similarity matrix by setting any element of $E[\text{Sim}] = 1$ if $E[\text{Sim}] > \text{cutoff}$. Compute the clustering scheme associated with this "windsorized" Similarity matrix.

Value

<code>clustera</code>	indicator function for clustering based on method A above
<code>clusterb</code>	indicator function for clustering based on method B above

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rnmixGibbs](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0)
{
  ## simulate data from mixture of normals
  n=500
  pvec=c(.5,.5)
  mu1=c(2,2)
  mu2=c(-2,-2)
```



```

Sigma1=matrix(c(1,.5,.5,1),ncol=2)
Sigma2=matrix(c(1,.5,.5,1),ncol=2)
comps=NULL
comps[[1]]=list(mu1,backsolve(chol(Sigma1),diag(2)))
comps[[2]]=list(mu2,backsolve(chol(Sigma2),diag(2)))
dm=rmmixture(n,pvec,comps)
## run MCMC on normal mixture
R=2000
Data=list(y=dm$x)
ncomp=2
Prior=list(ncomp=ncomp,a=c(rep(100,ncomp)))
Mcmc=list(R=R,keep=1)
out=rmmixGibbs(Data=Data,Prior=Prior,Mcmc=Mcmc)
begin=500
end=R
## find clusters
outclusterMix=clusterMix(out$zdraw[begin:end,])
##
## check on clustering versus "truth"
## note: there could be switched labels
##
table(outclusterMix$clustera,dm$z)
table(outclusterMix$clusterb,dm$z)
}
##

```

condMom	<i>Computes Conditional Mean/Var of One Element of MVN given All Others</i>
---------	---

Description

condMom compute moments of conditional distribution of ith element of normal given all others.

Usage

```
condMom(x, mu, sigi, i)
```

Arguments

x	vector of values to condition on - ith element not used
mu	length(x) mean vector
sigi	length(x)-dim covariance matrix
i	conditional distribution of ith element

Details

$x \sim MVN(\mu, \Sigma)$.

condMom computes moments of x_i given x_{-i} .

Value

a list containing:

<code>cmean</code>	cond mean
<code>cvar</code>	cond variance

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##
sig=matrix(c(1,.5,.5,.5,1,.5,.5,.5,1),ncol=3)
sigi=chol2inv(chol(sig))
mu=c(1,2,3)
x=c(1,1,1)
condMom(x,mu,sigi,2)
```

<code>createX</code>	<i>Create X Matrix for Use in Multinomial Logit and Probit Routines</i>
----------------------	---

Description

`createX` makes up an X matrix in the form expected by Multinomial Logit ([rmnlIndepMetrop](#) and [rhierMnlRwMixture](#)) and Probit ([rmnpGibbs](#) and [rmvpGibbs](#)) routines. Requires an array of alternative specific variables and/or an array of "demographics" or variables constant across alternatives which may vary across choice occasions.

Usage

```
createX(p, na, nd, Xa, Xd, INT = TRUE, DIFF = FALSE, base = p)
```

Arguments

<code>p</code>	integer - number of choice alternatives
<code>na</code>	integer - number of alternative-specific vars in <code>Xa</code>
<code>nd</code>	integer - number of non-alternative specific vars
<code>Xa</code>	$n \times p \times na$ matrix of alternative-specific vars
<code>Xd</code>	$n \times nd$ matrix of non-alternative specific vars
<code>INT</code>	logical flag for inclusion of intercepts
<code>DIFF</code>	logical flag for differencing wrt to base alternative
<code>base</code>	integer - index of base choice alternative

note: `na,nd,Xa,Xd` can be `NULL` to indicate lack of `Xa` or `Xd` variables.

Value

X matrix – $n \times (p - DIFF) \times [(INT + nd) \times (p - 1) + na]$ matrix.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmnlIndepMetrop](#), [rmnpGibbs](#)

Examples

```
na=2; nd=1; p=3
vec=c(1,1.5,.5,2,3,1,3,4.5,1.5)
Xa=matrix(vec,byrow=TRUE,ncol=3)
Xa=cbind(Xa,-Xa)
Xd=matrix(c(-1,-2,-3),ncol=1)
createX(p=p,na=na,nd=nd,Xa=Xa,Xd=Xd)
createX(p=p,na=na,nd=nd,Xa=Xa,Xd=Xd,base=1)
createX(p=p,na=na,nd=nd,Xa=Xa,Xd=Xd,DIFF=TRUE)
createX(p=p,na=na,nd=nd,Xa=Xa,Xd=Xd,DIFF=TRUE,base=2)
createX(p=p,na=na,nd=NULL,Xa=Xa,Xd=NULL)
createX(p=p,na=NULL,nd=nd,Xa=NULL,Xd=Xd)
```

customerSat

Customer Satisfaction Data

Description

Responses to a satisfaction survey for a Yellow Pages advertising product. All responses are on a 10 point scale from 1 to 10 (10 is "Excellent" and 1 is "Poor")

Usage

```
data(customerSat)
```

Format

A data frame with 1811 observations on the following 10 variables.

- q1 Overall Satisfaction
- q2 Setting Competitive Prices
- q3 Holding Price Increase to a Minimum
- q4 Appropriate Pricing given Volume
- q5 Demonstrating Effectiveness of Purchase
- q6 Reach a Large # of Customers
- q7 Reach of Advertising
- q8 Long-term Exposure
- q9 Distribution
- q10 Distribution to Right Geographic Areas

Source

Rossi et al (2001), "Overcoming Scale Usage Heterogeneity," *JASA* 96, 20-31.

References

Case Study 3, *Bayesian Statistics and Marketing* by Rossi et al.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
data(customerSat)
apply(as.matrix(customerSat),2,table)
```

Description

Monthly data on detailing (sales calls) on 1000 physicians. 23 mos of data for each Physician. Includes physician covariates. Dependent Variable (**scripts**) is the number of new prescriptions ordered by the physician for the drug detailed.

Usage

```
data(detailing)
```

Format

This R object is a list of two data frames, list(counts,demo).

List of 2:

\$ counts:'data.frame': 23000 obs. of 4 variables:

...\$ id : int [1:23000] 1 1 1 1 1 1 1 1 1 1

...\$ scripts : int [1:23000] 3 12 3 6 5 2 5 1 5 3

...\$ detailing : int [1:23000] 1 1 1 2 1 0 2 2 1 1

...\$ lagged_scripts: int [1:23000] 4 3 12 3 6 5 2 5 1 5

\$ demo :'data.frame': 1000 obs. of 4 variables:

...\$ id : int [1:1000] 1 2 3 4 5 6 7 8 9 10

...\$ generalphys : int [1:1000] 1 0 1 1 0 1 1 1 1 1

...\$ specialist: int [1:1000] 0 1 0 0 1 0 0 0 0 0

...\$ mean_samples: num [1:1000] 0.722 0.491 0.339 3.196 0.348

Details

generalphys is dummy for if doctor is a "general practitioner," specialist is dummy for if the physician is a specialist in the therapeutic class for which the drug is intended, mean_samples is the mean number of free drug samples given the doctor over the sample.

Source

Manchanda, P., P. K. Chintagunta and P. E. Rossi (2004), "Response Modeling with Non-Random Marketing Mix Variables," *Journal of Marketing Research* 41, 467-478.

Examples

```
data(detailing)
cat(" table of Counts Dep Var", fill=TRUE)
print(table(detailing$counts[,2]))
cat(" means of Demographic Variables",fill=TRUE)
mat=apply(as.matrix(detailing$demo[,2:4]),2,mean)
print(mat)
```

```

##
## example of processing for use with rhierNegbinRw
##
if(0)
{
data(detailing)
counts = detailing$counts
Z = detailing$demo

# Construct the Z matrix
Z[,1] = 1
Z[,2]=Z[,2]-mean(Z[,2])
Z[,3]=Z[,3]-mean(Z[,3])
Z[,4]=Z[,4]-mean(Z[,4])
Z=as.matrix(Z)
id=levels(factor(counts$id))
nreg=length(id)
nobs = nrow(counts$id)

regdata=NULL
for (i in 1:nreg) {
  X = counts[counts[,1] == id[i],c(3:4)]
  X = cbind(rep(1,nrow(X)),X)
  y = counts[counts[,1] == id[i],2]
  X = as.matrix(X)
  regdata[[i]]=list(X=X, y=y)
}
nvar=ncol(X)          # Number of X variables
nz=ncol(Z)            # Number of Z variables
rm(detailing,counts)
cat("Finished Reading data",fill=TRUE)
fsh()

Data = list(regdata=regdata, Z=Z)
deltabar = matrix(rep(0,nvar*nz),nrow=nz)
Vdelta = 0.01 * diag(nz)
nu = nvar+3
V = 0.01*diag(nvar)
a = 0.5
b = 0.1
Prior = list(deltabar=deltabar, Vdelta=Vdelta, nu=nu, V=V, a=a, b=b)

R = 10000
keep =1
s_beta=2.93/sqrt(nvar)
s_alpha=2.93
c=2
Mcmc = list(R=R, keep = keep, s_beta=s_beta, s_alpha=s_alpha, c=c)
out = rhierNegbinRw(Data, Prior, Mcmc)

# Unit level mean beta parameters
Mbeta = matrix(rep(0,nreg*nvar),nrow=nreg)

```

```

ndraws = length(out$alphadraw)
for (i in 1:nreg) { Mbeta[i,] = rowSums(out$Betadraw[i, , ])/ndraws }

cat(" Deltadraws ",fill=TRUE)
summary(out$Deltadraw)
cat(" Vbetadraws ",fill=TRUE)
summary(out$Vbetadraw)
cat(" alphadraws ",fill=TRUE)
summary(out$alphadraw)

if(0){
## plotting examples
plot(out$betadraw)
plot(out$alphadraw)
plot(out$Deltadraw)
}
}

```

eMixMargDen

Compute Marginal Densities of A Normal Mixture Averaged over MCMC Draws

Description

eMixMargDen assumes that a multivariate mixture of normals has been fitted via MCMC (using **rnmixGibbs**). For each MCMC draw, the marginal densities for each component in the multivariate mixture are computed on a user-supplied grid and then averaged over draws.

Usage

```
eMixMargDen(grid, probdraw, compdraw)
```

Arguments

grid	array of grid points, grid[i,] are ordinates for ith component
probdraw	array - each row of which contains a draw of probabilities of mixture comp
compdraw	list of lists of draws of mixture comp moments

Details

length(compdraw) is number of MCMC draws.
 compdraw[[i]] is a list draws of mu and inv Chol root for each of mixture components.
 compdraw[[i]][[j]] is jth component. compdraw[[i]][[j]]\$mu is mean vector; compdraw[[i]][[j]]\$rooti is the UL decomp of Σ^{-1} .

Value

an array of the same dimension as grid with density values.

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type. To avoid errors, call with output from [rnmixGibbs](#).

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rnmixGibbs](#)

fsh

Flush Console Buffer

Description

Flush contents of console buffer. This function only has an effect on the Windows GUI.

Usage

`fsh()`

Value

No value is returned.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

Description

ghkvec computes the GHK approximation to the integral of a multivariate normal density over a half plane defined by a set of truncation points.

Usage

```
ghkvec(L, trunpt, above, r)
```

Arguments

L	lower triangular Cholesky root of Covariance matrix
trunpt	vector of truncation points
above	vector of indicators for truncation above(1) or below(0)
r	number of draws to use in GHK

Value

approximation to integral

Note

ghkvec can accept a vector of truncations and compute more than one integral. That is, length(trunpt)/length(above) number of different integrals, each with the same Sigma and mean 0 but different truncation points. See example below for an example with two integrals at different truncation points.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##  
  
Sigma=matrix(c(1,.5,.5,1),ncol=2)  
L=t(chol(Sigma))  
trunpt=c(0,0,1,1)  
above=c(1,1)  
ghkvec(L,trunpt,above,100)
```

Description

llmnl evaluates log-likelihood for the multinomial logit model.

Usage

```
llmnl(beta, y, X)
```

Arguments

beta	k x 1 coefficient vector
y	n x 1 vector of obs on y (1, ..., p)
X	n*p x k Design matrix (use <code>createX</code> to make)

Details

Let $\mu_{i,j} = X_i\beta$, then $Pr(y_i = j) = \exp(\mu_{i,j}) / \sum_k \exp(\mu_{i,k})$.
 X_i is the submatrix of X corresponding to the ith observation. X has n*p rows.
Use `createX` to create X.

Value

value of log-likelihood (sum of log prob of observed multinomial outcomes).

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

`createX`, `rmnlIndepMetrop`

Examples

```
##  
## Not run: ll=llmnl(beta,y,X)
```

llmnp

Evaluate Log Likelihood for Multinomial Probit Model

Description

llmnp evaluates the log-likelihood for the multinomial probit model.

Usage

```
llmnp(beta, Sigma, X, y, r)
```

Arguments

beta	k x 1 vector of coefficients
Sigma	(p-1) x (p-1) Covariance matrix of errors
X	X is n*(p-1) x k array. X is from differenced system.
y	y is vector of n indicators of multinomial response (1, ..., p).
r	number of draws used in GHK

Details

X is (p-1)*n x k matrix. Use `createX` with `DIFF=TRUE` to create X.

Model for each obs: $w = X\beta + e$. $e \sim N(0, \text{Sigma})$.

censoring mechanism:

if $y = j (j < p)$, $w_j > \max(w_{-j})$ and $w_j > 0$
if $y = p$, $w < 0$

To use GHK, we must transform so that these are rectangular regions e.g. if $y = 1$, $w_1 > 0$ and $w_1 - w_{-1} > 0$.

Define A_j such that if $j=1, \dots, p-1$, $A_j w = A_j \mu + A_j e > 0$ is equivalent to $y = j$. Thus, if $y=j$, we have $A_j e > -A_j \mu$. Lower truncation is $-A_j \mu$ and $cov = A_j \text{Sigma}(A_j)$. For $j = p$, $e < -\mu$.

Value

value of log-likelihood (sum of log prob of observed multinomial outcomes).

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapters 2 and 4.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[createX](#), [rmnpGibbs](#)

Examples

```
##  
## Not run: ll=llmnp(beta,Sigma,X,y,r)
```

llnhlogit

Evaluate Log Likelihood for non-homothetic Logit Model

Description

llmnp evaluates log-likelihood for the Non-homothetic Logit model.

Usage

```
llnhlogit(theta, choice, lnprices, Xexpend)
```

Arguments

theta	parameter vector (see details section)
choice	n x 1 vector of choice (1, ..., p)
lnprices	n x p array of log-prices
Xexpend	n x d array of vars predicting expenditure

Details

Non-homothetic logit model with: $\ln(\psi_i(U)) = \alpha_i - e^{k_i}U$

Structure of theta vector

alpha: (p x 1) vector of utility intercepts.

k: (p x 1) vector of utility rotation parms.

gamma: (k x 1) – expenditure variable coefs.

tau: (1 x 1) – logit scale parameter.

Value

value of log-likelihood (sum of log prob of observed multinomial outcomes).

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 4.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[simnhlogit](#)

Examples

```
##  
## Not run: ll=llnhlogit(theta,choice,lnprices,Xexpend)
```

lndIChisq

Compute Log of Inverted Chi-Squared Density

Description

lndIChisq computes the log of an Inverted Chi-Squared Density.

Usage

```
lndIChisq(nu, ssq, x)
```

Arguments

nu	d.f. parameter
ssq	scale parameter
x	ordinate for density evaluation

Details

$Z = \nu * ssq / \chi^2_\nu$, $Z \sim$ Inverted Chi-Squared.

lndIChisq computes the complete log-density, including normalizing constants.

Value

log density value

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[dchisq](#)

Examples

```
##  
lndIChisq(3,1,2)
```

`lndIWishart`

Compute Log of Inverted Wishart Density

Description

`lndIWishart` computes the log of an Inverted Wishart density.

Usage

```
lndIWishart(nu, V, IW)
```

Arguments

<code>nu</code>	d.f. parameter
<code>V</code>	"location" parameter
<code>IW</code>	ordinate for density evaluation

Details

$Z \sim \text{Inverted Wishart}(\text{nu}, V)$.

in this parameterization, $E[Z] = 1/(\text{nu} - k - 1)V$, V is a $k \times k$ matrix `lndIWishart` computes the complete log-density, including normalizing constants.

Value

log density value

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rwishart](#)

Examples

```
##  
lndIWishart(5,diag(3),(diag(3)+.5))
```

lndMvn

Compute Log of Multivariate Normal Density

Description

lndMvn computes the log of a Multivariate Normal Density.

Usage

```
lndMvn(x, mu, rooti)
```

Arguments

x	density ordinate
mu	mu vector
rooti	inv of Upper Triangular Cholesky root of Sigma

Details

$z \sim N(\mu, \Sigma)$

Value

log density value

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[lndMvst](#)

Examples

```
##  
Sigma=matrix(c(1,.5,.5,1),ncol=2)  
lndMvn(x=c(rep(0,2)),mu=c(rep(0,2)),rooti=backsolve(chol(Sigma),diag(2)))
```

lndMvst

Compute Log of Multivariate Student-t Density

Description

lndMvst computes the log of a Multivariate Student-t Density.

Usage

```
lndMvst(x, nu, mu, rooti,NORMC)
```

Arguments

x	density ordinate
nu	d.f. parameter
mu	mu vector
rooti	inv of Cholesky root of Sigma
NORMC	include normalizing constant, def: FALSE

Details

$$z \sim MVst(mu, nu, \Sigma)$$

Value

log density value

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[lndMvn](#)

Examples

```
##  
Sigma=matrix(c(1,.5,.5,1),ncol=2)  
lndMvst(x=c(rep(0,2)),nu=4,mu=c(rep(0,2)),rooti=backsolve(chol(Sigma),diag(2)))
```

logMargDenNR

Compute Log Marginal Density Using Newton-Raftery Approx

Description

logMargDenNR computes log marginal density using the Newton-Raftery approximation. Note: this approximation can be influenced by outliers in the vector of log-likelihoods. Use with **care** .

Usage

```
logMargDenNR(ll)
```

Arguments

ll vector of log-likelihoods evaluated at length(ll) MCMC draws

Value

approximation to log marginal density value.

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 6.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

margarine

Household Panel Data on Margarine Purchases

Description

Panel data on purchases of margarine by 516 households. Demographic variables are included.

Usage

```
data(margarine)
```

Format

This is an R object that is a list of two data frames, `list(choicePrice,demos)`

List of 2

\$ choicePrice:'data.frame': 4470 obs. of 12 variables:

...\$ hhid : int [1:4470] 2100016 2100016 2100016 2100016

...\$ choice : num [1:4470] 1 1 1 1 1 4 1 1 4 1

...\$ PPK_Stk : num [1:4470] 0.66 0.63 0.29 0.62 0.5 0.58 0.29

...\$ PBB_Stk : num [1:4470] 0.67 0.67 0.5 0.61 0.58 0.45 0.51

...\$ PFL_Stk : num [1:4470] 1.09 0.99 0.99 0.99 0.99 0.99 0.99

...\$ PHse_Stk: num [1:4470] 0.57 0.57 0.57 0.57 0.45 0.45 0.29

...\$ PGen_Stk: num [1:4470] 0.36 0.36 0.36 0.36 0.33 0.33 0.33

...\$ PImp_Stk: num [1:4470] 0.93 1.03 0.69 0.75 0.72 0.72 0.72

...\$ PSS_Tub : num [1:4470] 0.85 0.85 0.79 0.85 0.85 0.85 0.85

...\$ PPK_Tub : num [1:4470] 1.09 1.09 1.09 1.09 1.07 1.07 1.07

...\$ PFL_Tub : num [1:4470] 1.19 1.19 1.19 1.19 1.19 1.19 1.19

...\$ PHse_Tub: num [1:4470] 0.33 0.37 0.59 0.59 0.59 0.59 0.59

Pk is Parkay; BB is BlueBonnett, Fl is Fleischmanns, Hse is house, Gen is generic, Imp is Imperial, SS is Shed Spread. _Stk indicates stick, _Tub indicates Tub form.

\$ demos : 'data.frame': 516 obs. of 8 variables:

```
...$ hhid : num [1:516] 2100016 2100024 2100495 2100560
...$ Income : num [1:516] 32.5 17.5 37.5 17.5 87.5 12.5
...$ Fs3_4 : int [1:516] 0 1 0 0 0 0 0 0 0
...$ Fs5 : int [1:516] 0 0 0 0 0 0 0 1 0
...$ Fam_Size : int [1:516] 2 3 2 1 1 2 2 5 2
...$ college : int [1:516] 1 1 0 0 1 0 1 0 1
...$ whtcollar: int [1:516] 0 1 0 1 1 0 0 0 1
...$ retired : int [1:516] 1 1 1 0 0 1 0 1 0
```

Fs3_4 is dummy (family size 3-4). Fs5 is dummy for family size ≥ 5 . college, whtcollar, retired are dummies reflecting these statuses.

Details

choice is a multinomial indicator of one of the 10 brands (in order listed under format). All prices are in \$.

Source

Allenby and Rossi (1991), "Quality Perceptions and Asymmetric Switching Between Brands," *Marketing Science* 10, 185-205.

References

Chapter 5, *Bayesian Statistics and Marketing* by Rossi et al.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
data(margarine)
cat(" Table of Choice Variable ",fill=TRUE)
print(table(margarine$choicePrice[,2]))
cat(" Means of Prices",fill=TRUE)
mat=apply(as.matrix(margarine$choicePrice[,3:12]),2,mean)
print(mat)
cat(" Quantiles of Demographic Variables",fill=TRUE)
mat=apply(as.matrix(margarine$demos[,2:8]),2,quantile)
print(mat)

##
## example of processing for use with rhierMnlRwMixture
##
if(0)
{
  select= c(1:5,7) ## select brands
  chPr=as.matrix(margarine$choicePrice)
  ## make sure to log prices
  chPr=cbind(chPr[,1],chPr[,2],log(chPr[,2+select]))
}
```

```

demos=as.matrix(margarine$demos[,c(1,2,5)])

## remove obs for other alts
chPr=chPr[chPr[,2] <= 7,]
chPr=chPr[chPr[,2] != 6,]

## recode choice
chPr[chPr[,2] == 7,2]=6

hhid1=levels(as.factor(chPr[,1]))
lgtdata=NULL
nlgt=length(hhid1)
p=length(select) ## number of choice alts
ind=1
for (i in 1:nlgt) {
  nobs=sum(chPr[,1]==hhid1[i])
  if(nobs >=5) {
    data=chPr[chPr[,1]==hhid1[i],]
    y=data[,2]
    names(y)=NULL
    X=createX(p=p,na=1,Xa=data[,3:8],nd=NULL,Xd=NULL,INT=TRUE,base=1)
    lgtdata[[ind]]=list(y=y,X=X,hhid=hhid1[i]); ind=ind+1
  }
}
nlgt=length(lgtdata)
##
## now extract demos corresponding to hhs in lgtdata
##
Z=NULL
nlgt=length(lgtdata)
for(i in 1:nlgt){
  Z=rbind(Z,demos[demos[,1]==lgtdata[[i]]$hhid,2:3])
}
##
## take log of income and family size and demean
##
Z=log(Z)
Z[,1]=Z[,1]-mean(Z[,1])
Z[,2]=Z[,2]-mean(Z[,2])

keep=5
R=20000
mcmc1=list(keep=keep,R=R)
out=rhierMnlRwMixture(Data=list(p=p,lgtdata=lgtdata,Z=Z),Prior=list(ncomp=1),Mcmc=mcmc1)

summary(out$Deltadraw)
summary(out$nmix)

if(0){
## plotting examples
plot(out$nmix)
plot(out$Deltadraw)}
}

```

`mixDen`

Compute Marginal Density for Multivariate Normal Mixture

Description

`mixDen` computes the marginal density for each component of a normal mixture at each of the points on a user-specified grid.

Usage

```
mixDen(x, pvec, comps)
```

Arguments

<code>x</code>	array - <i>ith</i> column gives grid points for <i>ith</i> variable
<code>pvec</code>	vector of mixture component probabilities
<code>comps</code>	list of lists of components for normal mixture

Details

`length(comps)` is the number of mixture components. `comps[[j]]` is a list of parameters of the *j*th component. `comps[[j]]$mu` is mean vector; `comps[[j]]$rooti` is the UL decomp of Σ^{-1} .

Value

an array of the same dimension as grid with density values.

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rnmixGibbs](#)

Examples

```
## Not run:
##
## see examples in rnmixGibbs documentation
##
## End(Not run)
```

`mixDenBi`

Compute Bivariate Marginal Density for a Normal Mixture

Description

`mixDenBi` computes the implied bivariate marginal density from a mixture of normals with specified mixture probabilities and component parameters.

Usage

```
mixDenBi(i, j, xi, xj, pvec, comps)
```

Arguments

<code>i</code>	index of first variable
<code>j</code>	index of second variable
<code>xi</code>	grid of values of first variable
<code>xj</code>	grid of values of second variable
<code>pvec</code>	normal mixture probabilities
<code>comps</code>	list of lists of components

Details

`length(comps)` is the number of mixture components. `comps[[j]]` is a list of parameters of the j th component. `comps[[j]]$mu` is mean vector; `comps[[j]]$rooti` is the UL decomp of Σ^{-1} .

Value

an array (`length(xi)=length(xj) x 2`) with density value

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rnmixGibbs](#), [mixDen](#)

Examples

```
## Not run:
##
## see examples in rnmixGibbs documentation
##
## End(Not run)
```

`mnlHess`

Computes -Expected Hessian for Multinomial Logit

Description

`mnlHess` computes -Expected[Hessian] for Multinomial Logit Model

Usage

```
mnlHess(beta,y, X)
```

Arguments

<code>beta</code>	k x 1 vector of coefficients
<code>y</code>	n x 1 vector of choices, (1, ..., p)
<code>X</code>	n*p x k Design matrix

Details

See [llmnl](#) for information on structure of X array. Use [createX](#) to make X.

Value

k x k matrix

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[llmnl](#), [createX](#), [rmnlIndepMetrop](#)

Examples

```
##  
## Not run: mnlHess(beta,y,X)
```

<code>mnpProb</code>	<i>Compute MNP Probabilities</i>
----------------------	----------------------------------

Description

`mnpProb` computes MNP probabilities for a given X matrix corresponding to one observation. This function can be used with output from `rmnpGibbs` to simulate the posterior distribution of market shares or fitted probabilities.

Usage

```
mnpProb(beta, Sigma, X, r)
```

Arguments

<code>beta</code>	MNP coefficients
<code>Sigma</code>	Covariance matrix of latents
<code>X</code>	X array for one observation – use <code>createX</code> to make
<code>r</code>	number of draws used in GHK (def: 100)

Details

see [rmnpGibbs](#) for definition of the model and the interpretation of the beta, Sigma parameters. Uses the GHK method to compute choice probabilities. To simulate a distribution of probabilities, loop over the beta, Sigma draws from `rmnpGibbs` output.

Value

p x 1 vector of choice probabilities

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapters 2 and 4.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmnpGibbs](#), [createX](#)

Examples

```
##
## example of computing MNP probabilities
## here I'm thinking of Xa as having the prices of each of the 3 alternatives
Xa=matrix(c(1,.5,1.5),nrow=1)
X=createX(p=3,na=1,nd=NULL,Xa=Xa,Xd=NULL,DIFF=TRUE)
beta=c(1,-1,-2) ## beta contains two intercepts and the price coefficient
Sigma=matrix(c(1,.5,.5,1),ncol=2)
mnpProb(beta,Sigma,X)
```

momMix	<i>Compute Posterior Expectation of Normal Mixture Model Moments</i>
--------	--

Description

momMix averages the moments of a normal mixture model over MCMC draws.

Usage

```
momMix(probdraw, compdraw)
```

Arguments

probdraw	R x ncomp list of draws of mixture probs
compdraw	list of length R of draws of mixture component moments

Details

R is the number of MCMC draws in argument list above.

ncomp is the number of mixture components fitted.

compdraw is a list of lists of lists with mixture components.

compdraw[[i]] is ith draw.

compdraw[[i]][[j]][[1]] is the mean parameter vector for the jth component, ith MCMC draw.

compdraw[[i]][[j]][[2]] is the UL decomposition of Σ^{-1} for the jth component, ith MCMC draw.

Value

a list of the following items ...

<code>mu</code>	Posterior Expectation of Mean
<code>sigma</code>	Posterior Expection of Covariance Matrix
<code>sd</code>	Posterior Expectation of Vector of Standard Deviations
<code>corr</code>	Posterior Expectation of Correlation Matrix

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmixGibbs](#)

<code>nmat</code>	<i>Convert Covariance Matrix to a Correlation Matrix</i>
-------------------	--

Description

`nmat` converts a covariance matrix (stored as a vector, col by col) to a correlation matrix (also stored as a vector).

Usage

```
nmat(vec)
```

Arguments

`vec` k x k Cov matrix stored as a k*k x 1 vector (col by col)

Details

This routine is often used with `apply` to convert an R x (k*k) array of covariance MCMC draws to correlations. As in `corrdraws=apply(vardraws,1,nmat)`

Value

$k \times k$ x 1 vector with correlation matrix

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

Examples

```
##
set.seed(66)
X=matrix(rnorm(200,4),ncol=2)
Varmat=var(X)
nmat(as.vector(Varmat))
```

numEff	<i>Compute Numerical Standard Error and Relative Numerical Efficiency</i>
--------	---

Description

`numEff` computes the numerical standard error for the mean of a vector of draws as well as the relative numerical efficiency (ratio of variance of mean of this time series process relative to iid sequence).

Usage

```
numEff(x, m = as.integer(min(length(x), (100/sqrt(5000)) * sqrt(length(x)))))
```

Arguments

<code>x</code>	R x 1 vector of draws
<code>m</code>	number of lags for autocorrelations

Details

default for number of lags is chosen so that if $R = 5000$, $m = 100$ and increases as the \sqrt{R} .

Value

<code>stderr</code>	standard error of the mean of x
<code>f</code>	variance ratio (relative numerical efficiency)

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
numEff(rnorm(1000),m=20)
numEff(rnorm(1000))
```

orangeJuice

Store-level Panel Data on Orange Juice Sales

Description

yx, weekly sales of refrigerated orange juice at 83 stores.
storedemo, contains demographic information on those stores.

Usage

```
data(orangeJuice)
```

Format

This R object is a list of two data frames, list(yx,storedemo).

List of 2

\$ yx : 'data.frame': 106139 obs. of 19 variables:

...\$ store : int [1:106139] 2 2 2 2 2 2 2 2 2 2

...\$ brand : int [1:106139] 1 1 1 1 1 1 1 1 1 1

...\$ week : int [1:106139] 40 46 47 48 50 51 52 53 54 57

...\$ logmove : num [1:106139] 9.02 8.72 8.25 8.99 9.09

...\$ constant: int [1:106139] 1 1 1 1 1 1 1 1 1 1

...\$ price1 : num [1:106139] 0.0605 0.0605 0.0605 0.0605 0.0605

...\$ price2 : num [1:106139] 0.0605 0.0603 0.0603 0.0603 0.0603

...\$ price3 : num [1:106139] 0.0420 0.0452 0.0452 0.0498 0.0436

...\$ price4 : num [1:106139] 0.0295 0.0467 0.0467 0.0373 0.0311

...\$ price5 : num [1:106139] 0.0495 0.0495 0.0373 0.0495 0.0495

```
...$ price6 : num [1:106139] 0.0530 0.0478 0.0530 0.0530 0.0530
...$ price7 : num [1:106139] 0.0389 0.0458 0.0458 0.0458 0.0466
...$ price8 : num [1:106139] 0.0414 0.0280 0.0414 0.0414 0.0414
...$ price9 : num [1:106139] 0.0289 0.0430 0.0481 0.0423 0.0423
...$ price10 : num [1:106139] 0.0248 0.0420 0.0327 0.0327 0.0327
...$ price11 : num [1:106139] 0.0390 0.0390 0.0390 0.0390 0.0382
...$ deal : int [1:106139] 1 0 0 0 0 0 1 1 1 1
...$ feat : num [1:106139] 0 0 0 0 0 0 0 0 0 0
...$ profit : num [1:106139] 38.0 30.1 30.0 29.9 29.9
```

1 Tropicana Premium 64 oz; 2 Tropicana Premium 96 oz; 3 Florida's Natural 64 oz;
 4 Tropicana 64 oz; 5 Minute Maid 64 oz; 6 Minute Maid 96 oz;
 7 Citrus Hill 64 oz; 8 Tree Fresh 64 oz; 9 Florida Gold 64 oz;
 10 Dominicks 64 oz; 11 Dominicks 128 oz.

```
$ storedemo:'data.frame': 83 obs. of 12 variables:
...$ STORE : int [1:83] 2 5 8 9 12 14 18 21 28 32
...$ AGE60 : num [1:83] 0.233 0.117 0.252 0.269 0.178
...$ EDUC : num [1:83] 0.2489 0.3212 0.0952 0.2222 0.2534
...$ ETHNIC : num [1:83] 0.1143 0.0539 0.0352 0.0326 0.3807
...$ INCOME : num [1:83] 10.6 10.9 10.6 10.8 10.0
...$ HHLARGE : num [1:83] 0.1040 0.1031 0.1317 0.0968 0.0572
...$ WORKWOM : num [1:83] 0.304 0.411 0.283 0.359 0.391
...$ HVAL150 : num [1:83] 0.4639 0.5359 0.0542 0.5057 0.3866
...$ SSTRDIST: num [1:83] 2.11 3.80 2.64 1.10 9.20
...$ SSTRVOL : num [1:83] 1.143 0.682 1.500 0.667 1.111
...$ CPDIST5 : num [1:83] 1.93 1.60 2.91 1.82 0.84
...$ CPWVOL5 : num [1:83] 0.377 0.736 0.641 0.441 0.106
```

Details

store store number

brand brand indicator

week week number

logmove log of the number of units sold

constant a vector of 1

price1 price of brand 1

deal in-store coupon activity

feature feature advertisement

STORE store number

AGE60 percentage of the population that is aged 60 or older

EDUC percentage of the population that has a college degree

ETHNIC percent of the population that is black or Hispanic

INCOME median income

HHLARGE percentage of households with 5 or more persons
 WORKWOM percentage of women with full-time jobs
 HVAL150 percentage of households worth more than \$150,000
 SSTRDIST distance to the nearest warehouse store
 SSTRVOL ratio of sales of this store to the nearest warehouse store
 CPDIST5 average distance in miles to the nearest 5 supermarkets
 CPWVOL5 ratio of sales of this store to the average of the nearest five stores

Source

Alan L. Montgomery (1997), "Creating Micro-Marketing Pricing Strategies Using Supermarket Scanner Data," *Marketing Science* 16(4) 315-337.

References

Chapter 5, *Bayesian Statistics and Marketing* by Rossi et al.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```

## Example
## load data
data(orangeJuice)

## print some quantiles of yx data
cat("Quantiles of the Variables in yx data",fill=TRUE)
mat=apply(as.matrix(orangeJuice$yx),2,quantile)
print(mat)

## print some quantiles of storedemo data
cat("Quantiles of the Variables in storedemo data",fill=TRUE)
mat=apply(as.matrix(orangeJuice$storedemo),2,quantile)
print(mat)

## Example 2 processing for use with rhierLinearModel
##
##
if(0)
{

## select brand 1 for analysis
brand1=orangeJuice$yx[(orangeJuice$yx$brand==1),]

store = sort(unique(brand1$store))
nreg = length(store)
nvar=14

regdata=NULL
for (reg in 1:nreg) {

```

```

y=brand1$logmove[brand1$store==store[reg]]
iota=c(rep(1,length(y)))
X=cbind(iota,log(brand1$price1[brand1$store==store[reg]]),
        log(brand1$price2[brand1$store==store[reg]]),
        log(brand1$price3[brand1$store==store[reg]]),
        log(brand1$price4[brand1$store==store[reg]]),
        log(brand1$price5[brand1$store==store[reg]]),
        log(brand1$price6[brand1$store==store[reg]]),
        log(brand1$price7[brand1$store==store[reg]]),
        log(brand1$price8[brand1$store==store[reg]]),
        log(brand1$price9[brand1$store==store[reg]]),
        log(brand1$price10[brand1$store==store[reg]]),
        log(brand1$price11[brand1$store==store[reg]]),
        brand1$deal[brand1$store==store[reg]],
        brand1$feat[brand1$store==store[reg]])
regdata[[reg]]=list(y=y,X=X)
}

## storedemo is standardized to zero mean.

Z=as.matrix(orangeJuice$storedemo[,2:12])
dmean=apply(Z,2,mean)
for (s in 1:nreg){
  Z[s,]=Z[s,]-dmean
}
iotaz=c(rep(1,nrow(Z)))
Z=cbind(iotaz,Z)
nz=ncol(Z)

Data=list(regdata=regdata,Z=Z)
Mcmc=list(R=R,keep=1)

out=rhierLinearModel(Data=Data,Mcmc=Mcmc)

summary(out$Deltadraw)
summary(out$Vbetadraw)

if(0){
## plotting examples
plot(out$betadraw)
}
}

```

`plot.bayesm.hcoef` *Plot Method for Hierarchical Model Coefs*

Description

`plot.bayesm.hcoef` is an S3 method to plot 3 dim arrays of hierarchical coefficients. Arrays are of class `bayesm.hcoef` with dimensions: cross-sectional unit x coef x MCMC draw.

Usage

```
## S3 method for class 'bayesm.hcoef':  
plot(x,burnin,...)
```

Arguments

x	An object of S3 class, bayesm.hcoef
burnin	no draws to burnin, def: .1*R
...	standard graphics parameters

Details

Typically, `plot.bayesm.hcoef` will be invoked by a call to the generic plot function as in `plot(object)` where object is of class bayesm.hcoef. All of the **bayesm** hierarchical routines return draws of hierarchical coefficients in this class (see example below). One can also simply invoke `plot.bayesm.hcoef` on any valid 3-dim array as in `plot.bayesm.hcoef(betadraws)`

`plot.bayesm.hcoef` is also exported for use as a standard function, as in `plot.bayesm.hcoef(array)`.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

See Also

[rhierMnlRwMixture](#), [rhierLinearModel](#), [rhierLinearMixture](#), [rhierNegbinRw](#)

Examples

```
##  
## not run  
# out=rhierLinearModel(Data,Prior,Mcmc)  
# plot(out$betadraws)  
#
```

<code>plot.bayesm.mat</code>	<i>Plot Method for Arrays of MCMC Draws</i>
------------------------------	---

Description

`plot.bayesm.mat` is an S3 method to plot arrays of MCMC draws. The columns in the array correspond to parameters and the rows to MCMC draws.

Usage

```
## S3 method for class 'bayesm.mat':  
plot(x,names,burnin,tvalues,TRACEPLOT,DEN,INT,CHECK_NDRAWS, ...)
```


Arguments

<code>x</code>	An object of either S3 class, <code>bayesm.mat</code> , or S3 class, <code>mcmc</code>
<code>names</code>	optional character vector of names for coefficients
<code>burnin</code>	number of draws to discard for burn-in, def: <code>.1*nrow(X)</code>
<code>tvalues</code>	vector of true values
<code>TRACEPLOT</code>	logical, TRUE provide sequence plots of draws and acfs, def: TRUE
<code>DEN</code>	logical, TRUE use density scale on histograms, def: TRUE
<code>INT</code>	logical, TRUE put various intervals and points on graph, def: TRUE
<code>CHECK_NDRAWS</code>	logical, TRUE check that there are at least 100 draws, def: TRUE
<code>...</code>	standard graphics parameters

Details

Typically, `plot.bayesm.mat` will be invoked by a call to the generic plot function as in `plot(object)` where `object` is of class `bayesm.mat`. All of the `bayesm` MCMC routines return draws in this class (see example below). One can also simply invoke `plot.bayesm.mat` on any valid 2-dim array as in `plot.bayesm.mat(betadraws)`.

`plot.bayesm.mat` paints (by default) on the histogram:

green "`|`" delimiting 95% Bayesian Credibility Interval
yellow "`()`" showing ± 2 numerical standard errors
red "`|`" showing posterior mean

`plot.bayesm.mat` is also exported for use as a standard function, as in `plot.bayesm.mat(matrix)`

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, Peter.Rossi@ChicagoGsb.edu.

Examples

```
##
## not run
# out=runiregGibbs(Data,Prior,Mcmc)
# plot(out$betadraw)
#
```

<code>plot.bayesm.nmix</code>	<i>Plot Method for MCMC Draws of Normal Mixtures</i>
-------------------------------	--

Description

`plot.bayesm.nmix` is an S3 method to plot aspects of the fitted density from a list of MCMC draws of normal mixture components. Plots of marginal univariate and bivariate densities are produced.

Usage

```
## S3 method for class 'bayesm.nmix':  
plot(x,names,burnin,Grid,bi.sel,nstd,marg,Data,ngrid,ndraw, ...)
```

Arguments

<code>x</code>	An object of S3 class bayesm.nmix
<code>names</code>	optional character vector of names for each of the dimensions
<code>burnin</code>	number of draws to discard for burn-in, def: <code>.1*nrow(X)</code>
<code>Grid</code>	matrix of grid points for densities, def: mean +/- nstd std deviations (if Data no supplied), range of Data if supplied)
<code>bi.sel</code>	list of vectors, each giving pairs for bivariate distributions, def: <code>list(c(1,2))</code>
<code>nstd</code>	number of standard deviations for default Grid, def: 2
<code>marg</code>	logical, if TRUE display marginals, def: TRUE
<code>Data</code>	matrix of data points, used to paint histograms on marginals and for grid
<code>ngrid</code>	number of grid points for density estimates, def:50
<code>ndraw</code>	number of draws to average Mcmc estimates over, def:200
<code>...</code>	standard graphics parameters

Details

Typically, `plot.bayesm.nmix` will be invoked by a call to the generic plot function as in `plot(object)` where object is of class bayesm.nmix. These objects are lists of three components. The first component is an array of draws of mixture component probabilities. The second component is not used. The third is a lists of lists of lists with draws of each of the normal components.

`plot.bayesm.nmix` can also be used as a standard function, as in `plot.bayesm.nmix(list)`.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

See Also

[rnmixGibbs](#), [rhierMnlRwMixture](#), [rhierLinearMixture](#), [rDPGibbs](#)

Examples

```
##  
## not run  
# out=rnmixGibbs(Data,Prior,Mcmc)  
# plot(out,bi.sel=list(c(1,2),c(3,4),c(1,3)))  
#       # plot bivariate distributions for dimension 1,2; 3,4; and 1,3  
#
```

Description

`rbiNormGibbs` implements a Gibbs Sampler for the bivariate normal distribution. Intermediate moves are shown and the output is contrasted with the iid sampler. ⁱ This function is designed for illustrative/teaching purposes.

Usage

```
rbiNormGibbs(initx = 2, inity = -2, rho, burnin = 100, R = 500)
```

Arguments

<code>initx</code>	initial value of parameter on x axis (def: 2)
<code>inity</code>	initial value of parameter on y axis (def: -2)
<code>rho</code>	correlation for bivariate normals
<code>burnin</code>	burn-in number of draws (def:100)
<code>R</code>	number of MCMC draws (def:500)

Details

(theta1,theta2) $N((0,0), \text{Sigma}=\text{matrix}(c(1,\text{rho},\text{rho},1),\text{ncol}=2))$

Value

R x 2 array of draws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapters 2 and 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##  
## Not run:  out=rbiNormGibbs(rho=.95)
```

Description

rbprobitGibbs implements the Albert and Chib Gibbs Sampler for the binary probit model.

Usage

```
rbprobitGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(X,y)
Prior	list(betabar,A)
Mcmc	list(R,keep)

Details

Model: $z = X\beta + e$. $e \sim N(0, I)$. $y=1$, if $z > 0$.

Prior: $\beta \sim N(\text{betabar}, A^{-1})$.

List arguments contain

X Design Matrix

y n x 1 vector of observations, (0 or 1)

betabar k x 1 prior mean (def: 0)

A k x k prior precision matrix (def: .01I)

R number of MCMC draws

keep thinning parameter - keep every keepth draw (def: 1)

Value

betadraw R/keep x k array of betadraws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmnpGibbs](#)

Examples

```
##
## rbprobitGibbs example
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
simbprobit=
function(X,beta) {
  ## function to simulate from binary probit including x variable
  y=ifelse((X%*%beta+rnorm(nrow(X)))<0,0,1)
  list(X=X,y=y,beta=beta)
}

nobs=200
X=cbind(rep(1,nobs),runif(nobs),runif(nobs))
beta=c(0,1,-1)
nvar=ncol(X)
simout=simbprobit(X,beta)

Data1=list(X=simout$X,y=simout$y)
Mcmc1=list(R=R,keep=1)

out=rbprobitGibbs(Data=Data1,Mcmc=Mcmc1)

summary(out$betadraw,tvalues=beta)

if(0){
  ## plotting example
  plot(out$betadraw,tvalues=beta)
}
```

rdirichlet

Draw From Dirichlet Distribution

Description

rdirichlet draws from Dirichlet

Usage

```
rdirichlet(alpha)
```

Arguments

alpha vector of Dirichlet parms (must be > 0)

Value

Vector of draws from Dirichlet

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##  
set.seed(66)  
rdirichlet(c(rep(3,5)))
```

rDPGibbs

Density Estimation with Dirichlet Process Prior and Normal Base

Description

rDPGibbs implements a Gibbs Sampler to draw from the posterior for a normal mixture problem with a Dirichlet Process prior. A natural conjugate base prior is used along with priors on the hyper parameters of this distribution. One interpretation of this model is as a normal mixture with a random number of components that can grow with the sample size.

Usage

```
rDPGibbs(Prior, Data, Mcmc)
```

Arguments

Prior	list(Prioralpha,lambda.hyper)
Data	list(y)
Mcmc	list(R,keep,maxuniq,SCALE,gridsize)

Details

Model:

$$y_i \sim N(\mu_i, \text{Sigma}_i).$$

Priors:

$$\theta_i = (\mu_i, \text{Sigma}_i) \sim DP(G_0(\text{lambda}), \alpha)$$

$$G_0(\text{lambda}) :$$

$$\mu_i | \text{Sigma}_i \sim N(0, \text{Sigma}_i(x) a^{-1})$$

$$\text{Sigma}_i \sim IW(\nu, \nu * v * I)$$

$$\text{lambda}(a, \nu, v) :$$

$$a \sim \text{uniform on grid}[\text{alim}[1], \text{alim}[2]]$$

$$\nu \sim \text{uniform on grid}[\dim(\text{data})-1 + \exp(\text{nulim}[1]), \dim(\text{data})-1 + \exp(\text{nulim}[2])]$$

$$v \sim \text{uniform on grid}[\text{vlim}[1], \text{vlim}[2]]$$

$$\alpha \sim (1 - (\alpha - \text{alphamin}) / (\text{alphamax} - \text{alphamin}))^{\text{power}}$$

alpha= alphamin then expected number of components = Istarmin

alpha= alphamax then expected number of components = Istarmax

list arguments

Data:

y N x k matrix of observations on k dimensional data

Prioralpha:

Istarmin expected number of components at lower bound of support of alpha

Istarmax expected number of components at upper bound of support of alpha

power power parameter for alpha prior

lambda_hyper:

alim defines support of a distribution, def: c(.01,2)

nulim defines support of nu distribution, def: c(.01,3)

vlim defines support of v distribution, def: c(.1,4)

Mcmc:

R number of mcmc draws

keep thinning parm, keep every keepth draw

maxuniq storage constraint on the number of unique components

SCALE should data be scaled by mean, std deviation before posterior draws, def: TRUE

gridsize number of discrete points for hyperparameter priors, def: 20

output:

the basic output are draws from the predictive distribution of the data in the object, **nmix**. The average of these draws is the Bayesian analogue of a density estimate.

nmix:

probdraw R/keep x 1 matrix of 1s

zdraw R/keep x N matrix of draws of indicators of which component each obs is assigned to

compdraw R/keep list of draws of normals

Output of the components is in the form of a list of lists.

compdraw[[i]] is ith draw – list of lists.

compdraw[[i]][[1]] is list of parms for a draw from predictive.

compdraw[[i]][1][[1]] is the mean vector. **compdraw**[[i]][1][[2]] is the inverse of Cholesky root. $\text{Sigma} = \text{t}(\text{R}) \% * \% \text{R}$, $R^{-1} = \text{compdraw}[[i]][1][[2]]$.

Value

nmix	a list containing: probdraw , zdraw , compdraw
alphadraw	vector of draws of DP process tightness parameter
nudraw	vector of draws of base prior hyperparameter
adraw	vector of draws of base prior hyperparameter
vdraw	vector of draws of base prior hyperparameter

Note

we parameterize the prior on Sigma_i such that $\text{mode}(\text{Sigma}) = \text{nu}/(\text{nu} + 2)vI$. The support of nu enforces valid IW density; $\text{nulim}[1] > 0$

We use the structure for **nmix** that is compatible with the **bayesm** routines for finite mixtures of normals. This allows us to use the same summary and plotting methods.

The default choices of **alim**, **nulim**, and **vlim** determine the location and approximate size of candidate "atoms" or possible normal components. The defaults are sensible given that we scale the data. Without scaling, you want to insure that **alim** is set for a wide enough range of values (remember **a** is a precision parameter) and the **v** is big enough to propose **Sigma** matrices wide enough to cover the data range.

A careful analyst should look at the posterior distribution of **a**, **nu**, **v** to make sure that the support is set correctly in **alim**, **nulim**, **vlim**. In other words, if we see the posterior bunched up at one end of these support ranges, we should widen the range and rerun.

If you want to force the procedure to use many small atoms, then set **nulim** to consider only large values and set **vlim** to consider only small scaling constants. Set **Istarmax** to a large number. This will create a very "lumpy" density estimate somewhat like the classical Kernel density estimates. Of course, this is not advised if you have a prior belief that densities are relatively smooth.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

See Also

[rnmixGibbs](#), [rmixture](#), [rmixGibbs](#) , [eMixMargDen](#), [momMix](#), [mixDen](#), [mixDenBi](#)

Examples

```
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

## simulate univariate data from Chi-Sq

set.seed(66)
N=200
chisqdf=8; y1=as.matrix(rchisq(N,df=chisqdf))

## set arguments for rDPGibbs

Data1=list(y=y1)
Prioralpha=list(Istarmin=1,Istarmax=10,power=.8)
Prior1=list(Prioralpha=Prioralpha)

Mcmc=list(R=R,keep=1,maxuniq=200)

out1=rDPGibbs(Prior=Prior1,Data=Data1,Mcmc)

if(0){
## plotting examples
rgi=c(0,20); grid=matrix(seq(from=rgi[1],to=rgi[2],length.out=50),ncol=1)
deltax=(rgi[2]-rgi[1])/nrow(grid)
plot(out1$nmix,Grid=grid,Data=y1)
## plot true density with histogram
plot(range(grid[,1]),1.5*range(dchisq(grid[,1],df=chisqdf)),type="n",xlab=paste("Chisq ; ",N," obs",sep=""))
hist(y1,xlim=rgi,freq=FALSE,col="yellow",breaks=20,add=TRUE)
lines(grid[,1],dchisq(grid[,1],df=chisqdf)/(sum(dchisq(grid[,1],df=chisqdf))*deltax),col="blue",lwd=2)
}

## simulate bivariate data from the "Banana" distribution (Meng and Barnard)
banana=function(A,B,C1,C2,N,keep=10,init=10)
{ R=init*keep+N*keep
  x1=x2=0
  bimat=matrix(double(2*N),ncol=2)
  for (r in 1:R)
  { x1=rnorm(1,mean=(B*x2+C1)/(A*(x2^2)+1),sd=sqrt(1/(A*(x2^2)+1)))
    x2=rnorm(1,mean=(B*x2+C2)/(A*(x1^2)+1),sd=sqrt(1/(A*(x1^2)+1)))
    if (r>init*keep && r%%keep==0) {mkeep=r/keep; bimat[mkeep-init,]=c(x1,x2)} }
  return(bimat)
}

set.seed(66)
nvar2=2
A=0.5; B=0; C1=C2=3
y2=banana(A=A,B=B,C1=C1,C2=C2,1000)

Data2=list(y=y2)
```

```

Prioralpha=list(Istarmin=1,Istarmax=10,power=.8)
Prior2=list(Prioralpha=Prioralpha)
Mcmc=list(R=R,keep=1,maxuniq=200)

out2=rDPGibbs(Prior=Prior2,Data=Data2,Mcmc)

if(0){
## plotting examples

rx1=range(y2[,1]); rx2=range(y2[,2])
x1=seq(from=rx1[1],to=rx1[2],length.out=50)
x2=seq(from=rx2[1],to=rx2[2],length.out=50)
grid=cbind(x1,x2)

plot(out2$nmix,Grid=grid,Data=y2)

## plot true bivariate density
tden=matrix(double(50*50),ncol=50)
for (i in 1:50){ for (j in 1:50)
  {tden[i,j]=exp(-0.5*(A*(x1[i]^2)*(x2[j]^2)+(x1[i]^2)+(x2[j]^2)-2*B*x1[i]*x2[j]-2*C1*x1[i]-2*C2*x2[j]
}
tden=tden/sum(tden)
image(x1,x2,tden,col=terrain.colors(100),xlab="",ylab="")
contour(x1,x2,tden,add=TRUE,drawlabels=FALSE)
title("True Density")
}

```

rhierBinLogit

MCMC Algorithm for Hierarchical Binary Logit

Description

rhierBinLogit implements an MCMC algorithm for hierarchical binary logits with a normal heterogeneity distribution. This is a hybrid sampler with a RW Metropolis step for unit-level logit parameters.

rhierBinLogit is designed for use on choice-based conjoint data with partial profiles. The Design matrix is based on differences of characteristics between two alternatives. See Appendix A of *Bayesian Statistics and Marketing* for details.

Usage

```
rhierBinLogit(Data, Prior, Mcmc)
```

Arguments

Data	list(lgtdata,Z) (note: Z is optional)
Prior	list(Deltabar,ADelta,nu,V) (note: all are optional)
Mcmc	list(sbeta,R,keep) (note: all but R are optional)

Details

Model:

$y_{hi} = 1$ with $pr = \exp(x'_{hi}\beta_{hi}) / (1 + \exp(x'_{hi}\beta_{hi}))$. β_{hi} is $nvar \times 1$.
 $h=1, \dots, \text{length}(\text{lgtdata})$ units or "respondents" for survey data.

$\beta_{hi} = Z\Delta[h,] + u_h$.

Note: here $Z\Delta$ refers to $Z\%*\Delta$, $Z\Delta[h,]$ is h th row of this product.
 Δ is an $n_z \times nvar$ array.

$u_h \sim N(0, V_{\beta_{hi}})$.

Priors:

$\Delta = \text{vec}(\Delta) \sim N(\text{vec}(\Delta_{prior}), V_{\beta_{hi}}(x)A\Delta^{-1})$

$V_{\beta_{hi}} \sim IW(\nu, V)$

Lists contain:

lgtdata list of lists with each cross-section unit MNL data

lgtdata[[h]]\$y n_h vector of binary outcomes (0,1)

lgtdata[[h]]\$X n_h by $nvar$ design matrix for h th unit

Delta $n_z \times nvar$ matrix of prior means (def: 0)

A prior prec matrix (def: .01I)

nu d.f. parm for IW prior on norm comp Sigma (def: $nvar+3$)

V pds location parm for IW prior on norm comp Sigma (def: null)

sbeta scaling parm for RW Metropolis (def: .2)

R number of MCMC draws

keep MCMC thinning parm: keep every **keepth** draw (def: 1)

Value

a list containing:

Deltadraw $R/\text{keep} \times n_z \times nvar$ matrix of draws of Δ

betadraw $n_{lgt} \times nvar \times R/\text{keep}$ array of draws of β_{hi}

Vbetadraw $R/\text{keep} \times nvar \times nvar$ matrix of draws of $V_{\beta_{hi}}$

llike R/keep vector of log-like values

reject R/keep vector of reject rates over n_{lgt} units

Note

Some experimentation with the Metropolis scaling parameter (**sbeta**) may be required.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rhierMnlRwMixture](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=10000} else {R=10}

set.seed(66)
nvar=5                      ## number of coefficients
nlgt=1000                   ## number of cross-sectional units
nobs=10                     ## number of observations per unit
nz=2                        ## number of regressors in mixing distribution

## set hyper-parameters
##      B=ZDelta + U

Z=matrix(c(rep(1,nlgt),runif(nlgt,min=-1,max=1)),nrow=nlgt,ncol=nz)
Delta=matrix(c(-2,-1,0,1,2,-1,1,-.5,.5,0),nrow=nz,ncol=nvar)
iota=matrix(1,nrow=nvar,ncol=1)
Vbeta=diag(nvar)+.5*iota%*%t(iota)

## simulate data
lgtdata=NULL

for (i in 1:nlgt)
{ beta=t(Delta)%*%Z[i,]+as.vector(t(chol(Vbeta))%*%rnorm(nvar))
  X=matrix(runif(nobs*nvar),nrow=nobs,ncol=nvar)
  prob=exp(X%*%beta)/(1+exp(X%*%beta))
  unif=runif(nobs,0,1)
  y=ifelse(unif<prob,1,0)
  lgtdata[[i]]=list(y=y,X=X,beta=beta)
}

out=rhierBinLogit(Data=list(lgtdata=lgtdata,Z=Z),Mcmc=list(R=R))

cat("Summary of Delta draws",fill=TRUE)
summary(out$Deltadraw,tvalues=as.vector(Delta))
cat("Summary of Vbeta draws",fill=TRUE)
summary(out$Vbetadraw,tvalues=as.vector(Vbeta[upper.tri(Vbeta,diag=TRUE)]))

if(0){
## plotting examples
plot(out$Deltadraw,tvalues=as.vector(Delta))
plot(out$betadraw)
plot(out$Vbetadraw,tvalues=as.vector(Vbeta[upper.tri(Vbeta,diag=TRUE)]))
}
```

}

rhierLinearMixture *Gibbs Sampler for Hierarchical Linear Model*

Description

rhierLinearMixture implements a Gibbs Sampler for hierarchical linear models with a mixture of normals prior.

Usage

```
rhierLinearMixture(Data, Prior, Mcmc)
```

Arguments

Data	list(regdata,Z) (Z optional).
Prior	list(deltabar,Ad,mubar,Amu,nu,V,nu.e,ssq,ncomp) (all but ncomp are optional).
Mcmc	list(R,keep) (R required).

Details

Model: $\text{length}(\text{regdata})$ regression equations.
 $y_i = X_i \beta_i + e_i$. $e_i \sim N(0, \tau_{u_i})$. nvar X vars in each equation.

Priors:
 $\tau_{u_i} \sim \text{nu.e} * \text{ssq}_i / \chi^2_{\text{nu.e}}$. τ_{u_i} is the variance of e_i .

$\beta_i = \text{ZDelta}[i,] + u_i$.

Note: here ZDelta refers to $\text{Z} \% \% \text{D}$, ZDelta[i,] is ith row of this product.
Delta is an nz x nvar array.

$u_i \sim N(\mu_{ind}, \text{Sigma}_{ind})$. $ind \sim \text{multinomial}(\text{pvec})$.

$\text{pvec} \sim \text{dirichlet}(\text{a})$
 $\text{delta} = \text{vec}(\text{Delta}) \sim N(\text{deltabar}, A_d^{-1})$
 $\mu_j \sim N(\text{mubar}, \text{Sigma}_j(x) A_{\mu}^{-1})$
 $\text{Sigma}_j \sim \text{IW}(\text{nu}, V)$

List arguments contain:

regdata list of lists with X,y matrices for each of $\text{length}(\text{regdata})$ regressions

regdata[[i]]\$X X matrix for equation i

regdata[[i]]\$y y vector for equation i

deltabar nz*nvar vector of prior means (def: 0)

Ad prior prec matrix for $\text{vec}(\Delta)$ (def: $.01I$)
mubar $nvar \times 1$ prior mean vector for normal comp mean (def: 0)
Amu prior precision for normal comp mean (def: $.01I$)
nu d.f. parm for IW prior on norm comp Sigma (def: $nvar+3$)
V pds location parm for IW prior on norm comp Sigma (def: nuI)
nu.e d.f. parm for regression error variance prior (def: 3)
ssq scale parm for regression error var prior (def: $\text{var}(y_i)$)
ncomp number of components used in normal mixture
R number of MCMC draws
keep MCMC thinning parm: keep every keepth draw (def: 1)

Value

a list containing

taudraw	$R/\text{keep} \times n\text{reg}$ array of error variance draws
betadraw	$n\text{reg} \times nvar \times R/\text{keep}$ array of individual regression coef draws
Deltadraw	$R/\text{keep} \times nz \times nvar$ array of Deltadraws
nmix	list of three elements, (probdraw, NULL, compdraw)

Note

More on **probdraw** component of nmix return value list:
 this is an R/keep by $ncomp$ array of draws of mixture component probs (pvec)
 More on **compdraw** component of nmix return value list:

$\text{compdraw}[[i]]$ the i th draw of components for mixtures

$\text{compdraw}[[i]][[j]]$ i th draw of the j th normal mixture comp

$\text{compdraw}[[i]][[j]][[1]]$ i th draw of j th normal mixture comp mean vector

$\text{compdraw}[[i]][[j]][[2]]$ i th draw of j th normal mixture cov parm (rooti)

Note: Z should **not** include an intercept and should be centered for ease of interpretation.

Be careful in assessing prior parameter, Amu. .01 can be too small for some applications.
 See Rossi et al, chapter 5 for full discussion.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rhierLinearModel](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
nreg=300; nobs=500; nvar=3; nz=2

Z=matrix(runif(nreg*nz),ncol=nz)
Z=t(t(Z)-apply(Z,2,mean))
Delta=matrix(c(1,-1,2,0,1,0),ncol=nz)
tau0=.1
iota=c(rep(1,nobs))

## create arguments for rmixture

tcomps=NULL
a=matrix(c(1,0,0,0.5773503,1.1547005,0,-0.4082483,0.4082483,1.2247449),ncol=3)
tcomps[[1]]=list(mu=c(0,-1,-2),rooti=a)
tcomps[[2]]=list(mu=c(0,-1,-2)*2,rooti=a)
tcomps[[3]]=list(mu=c(0,-1,-2)*4,rooti=a)
tpvec=c(.4,.2,.4)

regdata=NULL                                     # simulated data with Z
betas=matrix(double(nreg*nvar),ncol=nvar)
tind=double(nreg)

for (reg in 1:nreg) {
  tempout=rmixture(1,tpvec,tcomps)
  betas[reg,]=Delta%*%Z[reg,]+as.vector(tempout$x)
  tind[reg]=tempout$z
  X=cbind(iota,matrix(runif(nobs*(nvar-1)),ncol=(nvar-1)))
  tau=tau0*runif(1,min=0.5,max=1)
  y=X%*%betas[reg,]+sqrt(tau)*rnorm(nobs)
  regdata[[reg]]=list(y=y,X=X,beta=betas[reg,],tau=tau)
}

## run rhierLinearMixture

Data1=list(regdata=regdata,Z=Z)
Prior1=list(ncomp=3)
Mcmc1=list(R=R,keep=1)
```

```

out1=rhierLinearMixture(Data=Data1,Prior=Prior1,Mcmc=Mcmc1)

cat("Summary of Delta draws",fill=TRUE)
summary(out1$Deltadraw,tvalues=as.vector(Delta))
cat("Summary of Normal Mixture Distribution",fill=TRUE)
summary(out1$nmix)

if(0){
## plotting examples
plot(out1$betadraw)
plot(out1$nmix)
plot(out1$Deltadraw)
}

```

rhierLinearModel	<i>Gibbs Sampler for Hierarchical Linear Model</i>
------------------	--

Description

rhierLinearModel implements a Gibbs Sampler for hierarchical linear models with a normal prior.

Usage

```
rhierLinearModel(Data, Prior, Mcmc)
```

Arguments

Data	list(regdata,Z) (Z optional).
Prior	list(Deltabar,A,nu.e,ssq,nu,V) (optional).
Mcmc	list(R,keep) (R required).

Details

Model: $\text{length}(\text{regdata})$ regression equations.

$y_i = X_i \beta_i + e_i$. $e_i \sim N(0, \tau_i)$. nvar X vars in each equation.

Priors:

$\tau_i \sim \text{nu.e} * \text{ssq}_i / \chi^2_{\text{nu.e}}$. τ_i is the variance of e_i .

$\beta_i \sim N(\text{ZDelta}[i,], V_{\beta_i})$.

Note: ZDelta is the matrix $Z * \text{Delta}$; [i,] refers to ith row of this product.

$\text{vec}(\text{Delta})$ given $V_{\beta_i} \sim N(\text{vec}(\text{Deltabar}), V_{\beta_i}(x)A^{-1})$.

$V_{\beta_i} \sim IW(\text{nu}, V)$.

$\text{Delta}, \text{Deltabar}$ are nvar x nvar. A is nvar x nvar. V_{β_i} is nvar x nvar.

Note: if you don't have any z vars, set $Z = \text{iota}(\text{nreg} \times 1)$.

List arguments contain:

regdata list of lists with X,y matrices for each of length(regdata) regressions
regdata[[i]]\$X X matrix for equation i
regdata[[i]]\$y y vector for equation i
Deltabar nz x nvar matrix of prior means (def: 0)
A nz x nz matrix for prior precision (def: .01I)
nu.e d.f. parm for regression error variance prior (def: 3)
ssq scale parm for regression error var prior (def: var(y_i))
nu d.f. parm for Vbeta prior (def: nvar+3)
V Scale location matrix for Vbeta prior (def: nu*I)
R number of MCMC draws
keep MCMC thinning parm: keep every keepth draw (def: 1)

Value

a list containing
betadraw nreg x nvar x R/keep array of individual regression coef draws
taudraw R/keep x nreg array of error variance draws
Deltadraw R/keep x nz x nvar array of Deltadraws
Vbetadraw R/keep x nvar*nvar array of Vbeta draws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rhierLinearMixture](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

nreg=100; nobs=100; nvar=3
Vbeta=matrix(c(1,.5,0,.5,2,.7,0,.7,1),ncol=3)
Z=cbind(c(rep(1,nreg)),3*runif(nreg)); Z[,2]=Z[,2]-mean(Z[,2])
nz=ncol(Z)
Delta=matrix(c(1,-1,2,0,1,0),ncol=2)
Delta=t(Delta) # first row of Delta is means of betas
Beta=matrix(rnorm(nreg*nvar),nrow=nreg)%*%chol(Vbeta)+Z%*%Delta
```

```

tau=.1
iota=c(rep(1,nobs))
regdata=NULL
for (reg in 1:nreg) { X=cbind(iota,matrix(runif(nobs*(nvar-1)),ncol=(nvar-1)))
  y=X%*%Beta[reg,]+sqrt(tau)*rnorm(nobs); regdata[[reg]]=list(y=y,X=X) }

Data1=list(regdata=regdata,Z=Z)
Mcmc1=list(R=R,keep=1)
out=rhierLinearModel(Data=Data1,Mcmc=Mcmc1)

cat("Summary of Delta draws",fill=TRUE)
summary(out$Deltadraw,tvalues=as.vector(Delta))
cat("Summary of Vbeta draws",fill=TRUE)
summary(out$Vbetadraw,tvalues=as.vector(Vbeta[upper.tri(Vbeta,diag=TRUE)]))

if(0){
## plotting examples
plot(out$betadraw)
plot(out$Deltadraw)
}

```

rhierMnLDP

*MCMC Algorithm for Hierarchical Multinomial Logit with
Dirichlet Process Prior Heterogeneity*

Description

rhierMnLDP is a MCMC algorithm for a hierarchical multinomial logit with a Dirichlet Process Prior for the distribution of heterogeneity. A base normal model is used so that the DP can be interpreted as allowing for a mixture of normals with as many components as there are panel units. This is a hybrid Gibbs Sampler with a RW Metropolis step for the MNL coefficients for each panel unit. This procedure can be interpreted as a Bayesian semi-parametric method in the sense that the DP prior can accommodate heterogeneity of an unknown form.

Usage

```
rhierMnLDP(Data, Prior, Mcmc)
```

Arguments

Data	list(p,lgtdata,Z) (Z is optional)
Prior	list(deltabar,Ad,Prioralpha,lambda_hyper) (all are optional)
Mcmc	list(s,w,R,keep) (R required)

Details

Model:

$y_i \sim MNL(X_i, \beta_{\theta_i})$. $i=1, \dots, \text{length}(\text{lgtdata})$. θ_{θ_i} is $\text{nvar} \times 1$.

$\beta_{\theta_i} = Z\Delta[i,] + u_i$.

Note: here $Z\Delta$ refers to $Z\%*\%D$, $Z\Delta[i,]$ is i th row of this product.
 Δ is an $\text{nz} \times \text{nvar}$ array.

$\beta_{\theta_i} \sim N(\mu_i, \Sigma_{\theta_i})$.

Priors:

$\theta_{\theta_i} = (\mu_i, \Sigma_{\theta_i}) \sim DP(G_0(\lambda), \alpha)$

$G_0(\lambda) :$

$\mu_i | \Sigma_{\theta_i} \sim N(0, \Sigma_{\theta_i}(x)a^{-1})$

$\Sigma_{\theta_i} \sim IW(\nu, \nu * v * I)$

$\lambda(a, \nu, v) :$

$a \sim \text{uniform}[\text{alim}[1], \text{alimb}[2]]$

$\nu \sim \text{dim}(\text{data}) - 1 + \exp(z)$

$z \sim \text{uniform}[\text{dim}(\text{data}) - 1 + \text{nulim}[1], \text{nulim}[2]]$

$v \sim \text{uniform}[\text{vlim}[1], \text{vlim}[2]]$

$\alpha \sim (1 - (\alpha - \alpha_{\text{amin}})/(\alpha_{\text{amax}} - \alpha_{\text{amin}}))^{\text{power}}$

$\alpha = \alpha_{\text{amin}}$ then expected number of components = Istarmin

$\alpha = \alpha_{\text{amax}}$ then expected number of components = Istarmax

Lists contain:

Data:

p p is number of choice alternatives

lgtdata list of lists with each cross-section unit MNL data

lgtdata[[i]]\$y n_i vector of multinomial outcomes (1, ..., m)

lgtdata[[i]]\$X n_i by nvar design matrix for i th unit

Prior:

deltabar $\text{nz} * \text{nvar}$ vector of prior means (def: 0)

Ad prior prec matrix for $\text{vec}(\Delta)$ (def: .01I)

Prioralpha:

Istarmin expected number of components at lower bound of support of α def(1)

Istarmax expected number of components at upper bound of support of α (def: $\min(50, .1 * \text{nlgt})$)

power power parameter for α prior (def: .8)

lambda_hyper:

alim defines support of a distribution, def:c(.01,2)
nulim defines support of nu distribution, def:c(.01,3)
vlim defines support of v distribution, def:c(.1,4)

Mcmc:

R number of mcmc draws
keep thinning parm, keep every keepth draw
maxuniq storage constraint on the number of unique components
gridsize number of discrete points for hyperparameter priors, def: 20

Value

a list containing:

Deltadraw	R/keep x nz*nvar matrix of draws of Delta, first row is initial value
betadraw	nlgt x nvar x R/keep array of draws of betas
nmix	list of 3 components, probdraw, NULL, compdraw
adraw	R/keep draws of hyperparm a
vdraw	R/keep draws of hyperparm v
nudraw	R/keep draws of hyperparm nu
Istardraw	R/keep draws of number of unique components
alphadraw	R/keep draws of number of DP tightness parameter
loglike	R/keep draws of log-likelihood

Note

As is well known, Bayesian density estimation involves computing the predictive distribution of a "new" unit parameter, θ_{n+1} (here "n"=nlgt). This is done by averaging the normal base distribution over draws from the distribution of θ_{n+1} given $\theta_1, \dots, \theta_n, \alpha, \lambda, \text{Data}$. To facilitate this, we store those draws from the predictive distribution of θ_{n+1} in a list structure compatible with other **bayesm** routines that implement a finite mixture of normals.

More on **nmix** list:

contains the draws from the predictive distribution of a "new" observations parameters. These are simply the parameters of one normal distribution. We enforce compatibility with a mixture of k components in order to utilize generic summary plotting functions.

Therefore, **probdraw** is a vector of ones. **zdraw** (indicator draws) is omitted as it is not necessary for density estimation. **compdraw** contains the draws of the θ_{n+1} as a list of list of lists.

More on **compdraw** component of return value list:

compdraw[[i]] ith draw of components for mixtures

compdraw[[i][[1]]] ith draw of the θ_{n+1}

compdraw[[i][[1]][[1]]] ith draw of mean vector

compdraw[[i][[1]][[2]]] ith draw of parm (rooti)

We parameterize the prior on Σ_i such that $\text{mode}(\Sigma) = \nu/(\nu + 2)vI$. The support of ν enforces a non-degenerate IW density; $\text{nulim}[1] > 0$.

The default choices of `alim`, `nulim`, and `vlim` determine the location and approximate size of candidate "atoms" or possible normal components. The defaults are sensible given a reasonable scaling of the X variables. You want to insure that `alim` is set for a wide enough range of values (remember `a` is a precision parameter) and the `v` is big enough to propose Σ matrices wide enough to cover the data range.

A careful analyst should look at the posterior distribution of `a`, `nu`, `v` to make sure that the support is set correctly in `alim`, `nulim`, `vlim`. In other words, if we see the posterior bunched up at one end of these support ranges, we should widen the range and rerun.

If you want to force the procedure to use many small atoms, then set `nulim` to consider only large values and set `vlim` to consider only small scaling constants. Set `alphamax` to a large number. This will create a very "lumpy" density estimate somewhat like the classical Kernel density estimates. Of course, this is not advised if you have a prior belief that densities are relatively smooth.

Note: `Z` should **not** include an intercept and is centered for ease of interpretation.

Large R values may be required (>20,000).

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rhierMnlRwMixture](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=20000} else {R=10}

set.seed(66)
p=3                                # num of choice alterns
ncoef=3
nlgt=300                           # num of cross sectional units
nz=2
Z=matrix(runif(nz*nlgt),ncol=nz)
Z=t(t(Z)-apply(Z,2,mean))          # demean Z
ncomp=3                             # no of mixture components
```

```

Delta=matrix(c(1,0,1,0,1,2),ncol=2)
comps=NULL
comps[[1]]=list(mu=c(0,-1,-2),rooti=diag(rep(2,3)))
comps[[2]]=list(mu=c(0,-1,-2)*2,rooti=diag(rep(2,3)))
comps[[3]]=list(mu=c(0,-1,-2)*4,rooti=diag(rep(2,3)))
pvec=c(.4,.2,.4)

simnmlwX= function(n,X,beta) {
  ## simulate from MNL model conditional on X matrix
  k=length(beta)
  Xbeta=X%*%beta
  j=nrow(Xbeta)/n
  Xbeta=matrix(Xbeta,byrow=TRUE,ncol=j)
  Prob=exp(Xbeta)
  iota=c(rep(1,j))
  denom=Prob%*%iota
  Prob=Prob/as.vector(denom)
  y=vector("double",n)
  ind=1:j
  for (i in 1:n)
    {yvec=rmultinom(1,1,Prob[i,]); y[i]=ind%*%yvec}
  return(list(y=y,X=X,beta=beta,prob=Prob))
}

## simulate data with a mixture of 3 normals
simlgtdata=NULL
ni=rep(50,300)
for (i in 1:nlgt)
{
  betai=Delta%*%Z[i,]+as.vector(rmixture(1,pvec,comps)$x)
  Xa=matrix(runif(ni[i]*p,min=-1.5,max=0),ncol=p)
  X=createX(p,na=1,nd=NULL,Xa=Xa,Xd=NULL,base=1)
  outa=simnmlwX(ni[i],X,betai)
  simlgtdata[[i]]=list(y=outa$y,X=X,beta=betai)
}

## plot betas
if(1){
  ## set if(1) above to produce plots
  bmat=matrix(0,nlgt,ncoef)
  for(i in 1:nlgt) {bmat[i,]=simlgtdata[[i]]$beta}
  par(mfrow=c(ncoef,1))
  for(i in 1:ncoef) hist(bmat[,i],breaks=30,col="magenta")
}

## set Data and Mcmc lists
keep=5
Mcmc1=list(R=R,keep=keep)
Data1=list(p=p,lgtdata=simlgtdata,Z=Z)

out=rhierMnlDP(Data=Data1,Mcmc=Mcmc1)

cat("Summary of Delta draws",fill=TRUE)
summary(out$Deltadraw,tvalues=as.vector(Delta))

```

```

if(0) {
## plotting examples
plot(out$betadraw)
plot(out$nmix)
}

```

rhierMnlRwMixture	<i>MCMC Algorithm for Hierarchical Multinomial Logit with Mixture of Normals Heterogeneity</i>
--------------------------	--

Description

rhierMnlRwMixture is a MCMC algorithm for a hierarchical multinomial logit with a mixture of normals heterogeneity distribution. This is a hybrid Gibbs Sampler with a RW Metropolis step for the MNL coefficients for each panel unit.

Usage

```
rhierMnlRwMixture(Data, Prior, Mcmc)
```

Arguments

Data	list(p,lgtdata,Z) (Z is optional)
Prior	list(a,deltabar,Ad,mubar,Amu,nu,V,ncomp) (all but ncomp are optional)
Mcmc	list(s,w,R,keep) (R required)

Details

Model:

$y_i \sim MNL(X_i, \beta_{\theta_i})$. $i=1, \dots, \text{length}(\text{lgtdata})$. θ_{θ_i} is nvar x 1.

$\beta_{\theta_i} = Z\Delta[i,] + u_i$.

Note: here ZDelta refers to $Z \%*\% D$, ZDelta[i,] is ith row of this product.

Delta is an nz x nvar array.

$u_i \sim N(\mu_{ind}, \Sigma_{ind})$. $ind \sim \text{multinomial}(\text{pvec})$.

Priors:

$\text{pvec} \sim \text{dirichlet}(a)$

$\Delta = \text{vec}(\Delta) \sim N(\text{deltabar}, A_d^{-1})$

$\mu_j \sim N(\text{mubar}, \Sigma_j(x) A_{\mu}^{-1})$

$\Sigma_j \sim \text{IW}(\text{nu}, V)$

Lists contain:

p p is number of choice alternatives

lgtdata list of lists with each cross-section unit MNL data
lgtdata[[i]]\$y n_i vector of multinomial outcomes (1,...,m)
lgtdata[[i]]\$X n_i by nvar design matrix for ith unit
a vector of length ncomp of Dirichlet prior parms (def: rep(5,ncomp))
deltabar nz*nvar vector of prior means (def: 0)
Ad prior prec matrix for vec(D) (def: .01I)
mubar nvar x 1 prior mean vector for normal comp mean (def: 0)
Amu prior precision for normal comp mean (def: .01I)
nu d.f. parm for IW prior on norm comp Sigma (def: nvar+3)
V pds location parm for IW prior on norm comp Sigma (def: nuI)
ncomp number of components used in normal mixture
s scaling parm for RW Metropolis (def: 2.93/sqrt(nvar))
w fractional likelihood weighting parm (def: .1)
R number of MCMC draws
keep MCMC thinning parm: keep every keepth draw (def: 1)

Value

a list containing:

Deltadraw	R/keep x nz*nvar matrix of draws of Delta, first row is initial value
betadraw	nlgt x nvar x R/keep array of draws of betas
nmix	list of 3 components, probdraw, NULL, compdraw
loglike	log-likelihood for each kept draw (length R/keep)

Note

More on **probdraw** component of nmix list:
 R/keep x ncomp matrix of draws of probs of mixture components (pvec)
 More on **compdraw** component of return value list:

compdraw[[i]] the ith draw of components for mixtures
compdraw[[i][[j]]] ith draw of the jth normal mixture comp
compdraw[[i][[j]][[1]]] ith draw of jth normal mixture comp mean vector
compdraw[[i][[j]][[2]]] ith draw of jth normal mixture cov parm (rooti)

Note: Z should **not** include an intercept and is centered for ease of interpretation.

Be careful in assessing prior parameter, Amu. .01 is too small for many applications. See Rossi et al, chapter 5 for full discussion.

Note: as of version 2.0-2 of **bayesm**, the fractional weight parameter has been changed to a weight between 0 and 1. w is the fractional weight on the normalized pooled likelihood. This differs from what is in Rossi et al chapter 5, i.e.

$$like_i(1 - w)xlike_{pooled}(n_i/N) * w$$

Large R values may be required (>20,000).

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmnlIndepMetrop](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=10000} else {R=10}

set.seed(66)
p=3                                # num of choice alterns
ncoef=3
nlgt=300                           # num of cross sectional units
nz=2
Z=matrix(runif(nz*nlgt),ncol=nz)
Z=t(t(Z)-apply(Z,2,mean))          # demean Z
ncomp=3                             # no of mixture components
Delta=matrix(c(1,0,1,0,1,2),ncol=2)
comps=NULL
comps[[1]]=list(mu=c(0,-1,-2),rooti=diag(rep(1,3)))
comps[[2]]=list(mu=c(0,-1,-2)*2,rooti=diag(rep(1,3)))
comps[[3]]=list(mu=c(0,-1,-2)*4,rooti=diag(rep(1,3)))
pvec=c(.4,.2,.4)

simnmnlw= function(n,X,beta) {
  ## simulate from MNL model conditional on X matrix
  k=length(beta)
  Xbeta=X%*%beta
  j=nrow(Xbeta)/n
  Xbeta=matrix(Xbeta,byrow=TRUE,ncol=j)
  Prob=exp(Xbeta)
  iota=c(rep(1,j))
  denom=Prob%*%iota
  Prob=Prob/as.vector(denom)
  y=vector("double",n)
```

```

    ind=1:j
    for (i in 1:n)
      {yvec=rmultinom(1,1,Prob[i,]); y[i]=ind%*%yvec}
    return(list(y=y,X=X,beta=beta,prob=Prob))
  }

## simulate data
simlgtdata=NULL
ni=rep(50,300)
for (i in 1:nlgt)
{
  betai=Delta%*%Z[i,]+as.vector(rmixture(1,pvec,comps)$x)
  Xa=matrix(runif(ni[i]*p,min=-1.5,max=0),ncol=p)
  X=createX(p,na=1,nd=NULL,Xa=Xa,Xd=NULL,base=1)
  outa=simmlwX(ni[i],X,betai)
  simlgtdata[[i]]=list(y=outa$y,X=X,beta=betai)
}

## plot betas
if(0){
  ## set if(1) above to produce plots
  bmat=matrix(0,nlgt,ncoef)
  for(i in 1:nlgt) {bmat[i,]=simlgtdata[[i]]$beta}
  par(mfrow=c(ncoef,1))
  for(i in 1:ncoef) hist(bmat[,i],breaks=30,col="magenta")
}

## set parms for priors and Z
Prior1=list(ncomp=5)

keep=5
Mcmc1=list(R=R,keep=keep)
Data1=list(p=p,lgtdata=simlgtdata,Z=Z)

out=rhierMnlRwMixture(Data=Data1,Prior=Prior1,Mcmc=Mcmc1)

cat("Summary of Delta draws",fill=TRUE)
summary(out$Deltadraw,tvalues=as.vector(Delta))
cat("Summary of Normal Mixture Distribution",fill=TRUE)
summary(out$nmix)

if(0) {
  ## plotting examples
  plot(out$betadraw)
  plot(out$nmix)
}

```

Description

`rhierNegbinRw` implements an MCMC strategy for the hierarchical Negative Binomial (NBD) regression model. Metropolis steps for each unit level set of regression parameters are automatically tuned by optimization. Over-dispersion parameter (α) is common across units.

Usage

```
rhierNegbinRw(Data, Prior, Mcmc)
```

Arguments

Data	list(regdata,Z)
Prior	list(Deltabar,Adelta,nu,V,a,b)
Mcmc	list(R,keep,s_beta,s_alpha,c,Vbeta0,Delta0)

Details

Model: $y_i \sim \text{NBD}(\text{mean}=\lambda, \text{over-dispersion}=\alpha)$.

$\lambda = \exp(X_i \beta_i)$

Prior: $\beta_i \sim N(\Delta' z_i, V\beta)$.

$\text{vec}(\Delta | V\beta) \sim N(\text{vec}(\Delta_{\text{bar}}), V\beta(x) \Delta)$.

$V\beta \sim \text{IW}(\nu, V)$.

$\alpha \sim \text{Gamma}(a, b)$.

note: prior mean of $\alpha = a/b$, variance = $a/(b^2)$

list arguments contain:

regdata list of lists with data on each of nreg units

regdata[[i]]\$X nobs.i x nvar matrix of X variables

regdata[[i]]\$y nobs.i x 1 vector of count responses

Z nreg x nz mat of unit chars (def: vector of ones)

Deltabar nz x nvar prior mean matrix (def: 0)

Adelta nz x nz pds prior prec matrix (def: .01I)

nu d.f. parm for IWishart (def: nvar+3)

V location matrix of IWishart prior (def: nuI)

a Gamma prior parm (def: .5)

b Gamma prior parm (def: .1)

R number of MCMC draws

keep MCMC thinning parm: keep every keepth draw (def: 1)

s_beta scaling for beta | alpha RW inc cov (def: 2.93/sqrt(nvar))

s_alpha scaling for alpha | beta RW inc cov (def: 2.93)

c fractional likelihood weighting parm (def:2)

Vbeta0 starting value for Vbeta (def: I)

Delta0 starting value for Delta (def: 0)

Value

a list containing:

<code>llike</code>	R/keep vector of values of log-likelihood
<code>betadraw</code>	<code>nreg x nvar x R</code> /keep array of beta draws
<code>alphadraw</code>	R/keep vector of alpha draws
<code>acceptrbeta</code>	acceptance rate of the beta draws
<code>acceptralpha</code>	acceptance rate of the alpha draws

Note

The NBD regression encompasses Poisson regression in the sense that as alpha goes to infinity the NBD distribution tends to the Poisson.

For "small" values of alpha, the dependent variable can be extremely variable so that a large number of observations may be required to obtain precise inferences.

For ease of interpretation, we recommend demeaning Z variables.

Author(s)

Sridhar Narayanam & Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rnegbinRw](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}
##
set.seed(66)
simnegbin =
function(X, beta, alpha) {
# Simulate from the Negative Binomial Regression
lambda = exp(X %*% beta)
y=NULL
for (j in 1:length(lambda))
y = c(y,rnbinom(1,mu = lambda[j],size = alpha))
return(y)
}

nreg = 100          # Number of cross sectional units
T = 50              # Number of observations per unit
```

```

nobs = nreg*T
nvar=2          # Number of X variables
nz=2           # Number of Z variables

# Construct the Z matrix
Z = cbind(rep(1,nreg),rnorm(nreg,mean=1,sd=0.125))

Delta = cbind(c(4,2), c(0.1,-1))
alpha = 5
Vbeta = rbind(c(2,1),c(1,2))

# Construct the regdata (containing X)
simnegbindata = NULL
for (i in 1:nreg) {
  betai = as.vector(Z[i,]*%Delta) + chol(Vbeta)%*%rnorm(nvar)
  X = cbind(rep(1,T),rnorm(T,mean=2,sd=0.25))
  simnegbindata[[i]] = list(y=simnegbin(X,betai,alpha), X=X,beta=betai)
}

Beta = NULL
for (i in 1:nreg) {Beta=rbind(Beta,matrix(simnegbindata[[i]]$beta,nrow=1))}

Data1 = list(regdata=simnegbindata, Z=Z)
Mcmc1 = list(R=R)

out = rhierNegbinRw(Data=Data1, Mcmc=Mcmc1)

cat("Summary of Delta draws",fill=TRUE)
summary(out$Deltadraw,tvalues=as.vector(Delta))
cat("Summary of Vbeta draws",fill=TRUE)
summary(out$Vbetadraw,tvalues=as.vector(Vbeta[upper.tri(Vbeta,diag=TRUE)]))
cat("Summary of alpha draws",fill=TRUE)
summary(out$alpha,tvalues=alpha)

if(0){
## plotting examples
plot(out$betadraw)
plot(out$alpha,tvalues=alpha)
plot(out$Deltadraw,tvalues=as.vector(Delta))
}

```

rivDP

Linear "IV" Model with DP Process Prior for Errors

Description

rivDP is a Gibbs Sampler for a linear structural equation with an arbitrary number of instruments. **rivDP** uses a mixture of normals for the structural and reduced form equation implemented with a Dirichlet Process Prior.

Usage

`rivDP(Data, Prior, Mcmc)`

Arguments

Data	<code>list(z,w,x,y)</code>
Prior	<code>list(md,Ad,mbg,Abg,lambda,Prioralpha)</code> (optional)
Mcmc	<code>list(R,keep,SCALE)</code> (R required)

Details

Model:

$$x = z'\delta + e1.$$

$$y = \beta x + w'\gamma + e2.$$

$$e1, e2 \sim N(\theta_i). \theta_i \text{ represents } \mu_i, \Sigma_i$$

Note: Error terms have non-zero means. DO NOT include intercepts in the z or w matrices. This is different from `rivGibbs` which requires intercepts to be included explicitly.

Priors:

$$\delta \sim N(md, Ad^{-1}). \text{vec}(\beta, \gamma) \sim N(mbg, Abg^{-1})$$

$$\theta_i \sim G$$

$$G \sim DP(\alpha, G_0)$$

G_0 is the natural conjugate prior for (μ, Σ) :

$$\Sigma \sim IW(\nu, \nu I) \text{ and } \mu | \Sigma \sim N(0, 1/\alpha \Sigma)$$

These parameters are collected together in the list `lambda`. It is highly recommended that you use the default settings for these hyper-parameters.

$$\alpha \sim (1 - (\alpha - \alpha_{min})/(\alpha_{max} - \alpha_{min}))^{power}$$

where α_{min} and α_{max} are set using the arguments in the reference below. It is highly recommended that you use the default values for the hyperparameters of the prior on alpha

List arguments contain:

- `z` matrix of obs on instruments
- `y` vector of obs on lhs var in structural equation
- `x` "endogenous" var in structural eqn
- `w` matrix of obs on "exogenous" vars in the structural eqn
- `md` prior mean of delta (def: 0)
- `Ad` pds prior prec for prior on delta (def: .01I)
- `mbg` prior mean vector for prior on beta,gamma (def: 0)
- `Abg` pds prior prec for prior on beta,gamma (def: .01I)
- `lambda` list of hyperparameters for theta prior- use default settings

Prior **alpha** list of hyperparameters for theta prior- use default settings

R number of MCMC draws

keep MCMC thinning parm: keep every keepth draw (def: 1)

SCALE scale data, def: TRUE

gridsize gridsize parm for alpha draws (def: 20)

output includes object **nmix** of class "bayesm.nmix" which contains draws of predictive distribution of errors (a Bayesian analogue of a density estimate for the error terms).

nmix:

probdraw not used

zdraw not used

compdraw list R/keep of draws from bivariate predictive for the errors

note: in compdraw list, there is only one component per draw

Value

a list containing:

deltadraw R/keep x dim(delta) array of delta draws

betadraw R/keep x 1 vector of beta draws

gammadraw R/keep x dim(gamma) array of gamma draws

Istardraw R/keep x 1 array of draws of the number of unique normal components

alphadraw R/keep x 1 array of draws of Dirichlet Process tightness parameter

nmix R/keep x list of draws for predictive distribution of errors

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see "A Semi-Parametric Bayesian Approach to the Instrumental Variable Problem," by Conley, Hansen, McCulloch and Rossi, Journal of Econometrics (2008).

See Also

rivGibbs

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

##
## simulate scaled log-normal errors and run
##
set.seed(66)
k=10
delta=1.5
Sigma=matrix(c(1,.6,.6,1),ncol=2)
N=1000
tbeta=4
set.seed(66)
scalefactor=.6
root=chol(scalefactor*Sigma)
mu=c(1,1)
##
## compute interquartile ranges
##
ninterq=qnorm(.75)-qnorm(.25)
error=matrix(rnorm(100000*2),ncol=2)
error=t(t(error)+mu)
Err=t(t(exp(error))-exp(mu+.5*scalefactor*diag(Sigma)))
lnNinterq=quantile(Err[,1],prob=.75)-quantile(Err[,1],prob=.25)
##
## simulate data
##
error=matrix(rnorm(N*2),ncol=2)%*%root
error=t(t(error)+mu)
Err=t(t(exp(error))-exp(mu+.5*scalefactor*diag(Sigma)))
#
# scale appropriately
Err[,1]=Err[,1]*ninterq/lnNinterq
Err[,2]=Err[,2]*ninterq/lnNinterq
z=matrix(runif(k*N),ncol=k)
x=z*%(delta*c(rep(1,k)))+Err[,1]
y=x*tbeta+Err[,2]

# set initial values for MCMC
Data = list(); Mcmc=list()
Data$z = z; Data$x=x; Data$y=y

# start MCMC and keep results
Mcmc$maxuniq=100
Mcmc$R=R
end=Mcmc$R
begin=100

out=rivDP(Data=Data,Mcmc=Mcmc)

cat("Summary of Beta draws",fill=TRUE)
```



```
summary(out$betadraw,tvalues=tbeta)

if(0){
## plotting examples
plot(out$betadraw,tvalues=tbeta)
plot(out$nmix) ## plot "fitted" density of the errors
##

}
```

rivGibbs

Gibbs Sampler for Linear "IV" Model

Description

rivGibbs is a Gibbs Sampler for a linear structural equation with an arbitrary number of instruments.

Usage

```
rivGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(z,w,x,y)
Prior	list(md,Ad,mbg,Abg,nu,V) (optional)
Mcmc	list(R,keep) (R required)

Details

Model:

$$x = z'\delta + e1.$$

$$y = \beta x + w'\gamma + e2.$$

$$e1, e2 \sim N(0, \textit{Sigma}).$$

Note: if intercepts are desired in either equation, include vector of ones in z or w

Priors:

$$\delta \sim N(md, Ad^{-1}). \textit{vec}(\beta, \gamma) \sim N(mbg, Abg^{-1})$$

$$\textit{Sigma} \sim \textit{IW}(\textit{nu}, V)$$

List arguments contain:

z matrix of obs on instruments

y vector of obs on lhs var in structural equation

x "endogenous" var in structural eqn

w matrix of obs on "exogenous" vars in the structural eqn

md prior mean of delta (def: 0)

Ad pds prior prec for prior on delta (def: .01I)

mbg prior mean vector for prior on beta,gamma (def: 0)
 Abg pds prior prec for prior on beta,gamma (def: .01I)
 nu d.f. parm for IW prior on Sigma (def: 5)
 V pds location matrix for IW prior on Sigma (def: nuI)
 R number of MCMC draws
 keep MCMC thinning parm: keep every keepth draw (def: 1)

Value

a list containing:

deltadraw R/keep x dim(delta) array of delta draws
 betadraw R/keep x 1 vector of beta draws
 gammadraw R/keep x dim(gamma) array of gamma draws
 Sigmadraw R/keep x 4 array of Sigma draws

Author(s)

Rob McCulloch and Peter Rossi, Graduate School of Business, University of Chicago,
 <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
simIV = function(delta,beta,Sigma,n,z,w,gamma) {
  eps = matrix(rnorm(2*n),ncol=2) %*% chol(Sigma)
  x = z %*% delta + eps[,1]; y = beta*x + eps[,2] + w%*%gamma
  list(x=as.vector(x),y=as.vector(y)) }
n = 200 ; p=1 # number of instruments
z = cbind(rep(1,n),matrix(runif(n*p),ncol=p))
w = matrix(1,n,1)
rho=.8
Sigma = matrix(c(1,rho,rho,1),ncol=2)
delta = c(1,4); beta = .5; gamma = c(1)
simiv = simIV(delta,beta,Sigma,n,z,w,gamma)

Mcmc1=list(); Data1 = list()
Data1$z = z; Data1$w=w; Data1$x=simiv$x; Data1$y=simiv$y
Mcmc1$R = R
Mcmc1$keep=1
```

```

out=rivGibbs(Data=Data1,Mcmc=Mcmc1)

cat("Summary of Beta draws",fill=TRUE)
summary(out$betadraw,tvalues=beta)
cat("Summary of Sigma draws",fill=TRUE)
summary(out$Sigmadraw,tvalues=as.vector(Sigma[upper.tri(Sigma,diag=TRUE)]))

if(0){
## plotting examples
plot(out$betadraw)
}

```

rmixGibbs

Gibbs Sampler for Normal Mixtures w/o Error Checking

Description

rmixGibbs makes one draw using the Gibbs Sampler for a mixture of multivariate normals.

Usage

```
rmixGibbs(y, Bbar, A, nu, V, a, p, z, comps)
```

Arguments

y	data array - rows are obs
Bbar	prior mean for mean vector of each norm comp
A	prior precision parameter
nu	prior d.f. parm
V	prior location matrix for covariance priro
a	Dirichlet prior parms
p	prior prob of each mixture component
z	component identities for each observation – "indicators"
comps	list of components for the normal mixture

Details

rmixGibbs is not designed to be called directly. Instead, use **rnmixGibbs** wrapper function.

Value

a list containing:

p	draw mixture probabilities
z	draw of indicators of each component
comps	new draw of normal component parameters

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Rob McCulloch and Peter Rossi, Graduate School of Business, University of Chicago, <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Allenby, McCulloch, and Rossi, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rnmixGibbs](#)

rmixture

Draw from Mixture of Normals

Description

rmixture simulates iid draws from a Multivariate Mixture of Normals

Usage

```
rmixture(n, pvec, comps)
```

Arguments

n	number of observations
pvec	ncomp x 1 vector of prior probabilities for each mixture component
comps	list of mixture component parameters

Details

comps is a list of length, `ncomp = length(pvec)`. `comps[[j]][[1]]` is mean vector for the *j*th component. `comps[[j]][[2]]` is the inverse of the cholesky root of Sigma for that component

Value

A list containing ...

x	An <i>n</i> x <code>length(comps[[1]][[1]])</code> array of iid draws
z	A <i>n</i> x 1 vector of indicators of which component each draw is taken from

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

See Also

[rnmixGibbs](#)

`rmnlIndepMetrop`

MCMC Algorithm for Multinomial Logit Model

Description

`rmnlIndepMetrop` implements Independence Metropolis for the MNL.

Usage

```
rmnlIndepMetrop(Data, Prior, Mcmc)
```

Arguments

<code>Data</code>	<code>list(p,y,X)</code>
<code>Prior</code>	<code>list(A,betabar)</code> optional
<code>Mcmc</code>	<code>list(R,keep,nu)</code>

Details

Model: $y \sim \text{MNL}(X, \beta)$. $Pr(y = j) = \exp(x'_j \beta) / \sum_k \exp(x'_k \beta)$.

Prior: $\beta \sim N(\text{betabar}, A^{-1})$

list arguments contain:

- `p` number of alternatives
- `y` nobs vector of multinomial outcomes (1, ..., p)
- `X` nobs*p x nvar matrix
- `A` nvar x nvar pds prior prec matrix (def: .01I)
- `betabar` nvar x 1 prior mean (def: 0)
- `R` number of MCMC draws
- `keep` MCMC thinning parm: keep every keepth draw (def: 1)
- `nu` degrees of freedom parameter for independence t density (def: 6)

Value

a list containing:

<code>betadraw</code>	R/keep x nvar array of beta draws
<code>loglike</code>	R/keep vector of loglike values for each draw
<code>acceptr</code>	acceptance rate of Metropolis draws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 5.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rhierMnlRwMixture](#)

Examples

```
##

if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
n=200; p=3; beta=c(1,-1,1.5,.5)

simmnl= function(p,n,beta) {
  # note: create X array with 2 alt.spec vars
  k=length(beta)
  X1=matrix(runif(n*p,min=-1,max=1),ncol=p)
  X2=matrix(runif(n*p,min=-1,max=1),ncol=p)
  X=createX(p,na=2,nd=NULL,Xd=NULL,Xa=cbind(X1,X2),base=1)
  Xbeta=X%*%beta # now do probs
  p=nrow(Xbeta)/n
  Xbeta=matrix(Xbeta,byrow=TRUE,ncol=p)
  Prob=exp(Xbeta)
  iota=c(rep(1,p))
  denom=Prob%*%iota
  Prob=Prob/as.vector(denom)
  # draw y
  y=vector("double",n)
  ind=1:p
  for (i in 1:n)
    { yvec=rmultinom(1,1,Prob[i,]); y[i]=ind%*%yvec }
  return(list(y=y,X=X,beta=beta,prob=Prob))
}
```

```

simout=simnnl(p,n,beta)

Data1=list(y=simout$y,X=simout$X,p=p); Mcmc1=list(R=R,keep=1)
out=rmnlIndepMetrop(Data=Data1,Mcmc=Mcmc1)

cat("Summary of beta draws",fill=TRUE)
summary(out$betadraw,tvalues=beta)

if(0){
## plotting examples
plot(out$betadraw)
}

```

rmnpGibbs

Gibbs Sampler for Multinomial Probit

Description

rmnpGibbs implements the McCulloch/Rossi Gibbs Sampler for the multinomial probit model.

Usage

```
rmnpGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(p, y, X)
Prior	list(betabar,A,nu,V) (optional)
Mcmc	list(beta0,sigma0,R,keep) (R required)

Details

model:

$w_i = X_i\beta + e$. $e \sim N(0, \textit{Sigma})$. note: w_i, e are $(p-1) \times 1$.

$y_i = j$, if $w_{ij} > \max(0, w_{i,-j})$ $j=1, \dots, p-1$. $w_{i,-j}$ means elements of w_i other than the j th.

$y_i = p$, if all $w_i < 0$.

priors:

$\beta \sim N(\textit{betabar}, A^{-1})$

$\textit{Sigma} \sim \textit{IW}(\textit{nu}, V)$

to make up X matrix use [createX](#) with DIFF=TRUE.

List arguments contain

p number of choices or possible multinomial outcomes

`y` $n \times 1$ vector of multinomial outcomes
`X` $n \times (p-1) \times k$ Design Matrix
`betabar` $k \times 1$ prior mean (def: 0)
`A` $k \times k$ prior precision matrix (def: $.01I$)
`nu` d.f. parm for IWishart prior (def: $(p-1) + 3$)
`V` pds location parm for IWishart prior (def: $nu \cdot I$)
`beta0` initial value for beta
`sigma0` initial value for sigma
`R` number of MCMC draws
`keep` thinning parameter - keep every keepth draw (def: 1)

Value

a list containing:

`betadraw` $R/keep \times k$ array of betadraws
`sigmadraw` $R/keep \times (p-1) \times (p-1)$ array of sigma draws – each row is in vector form

Note

beta is not identified. $\beta/\sqrt{\sigma_{11}}$ and Σ/σ_{11} are. See Allenby et al or example below for details.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 4.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmvpGibbs](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
p=3
n=500
beta=c(-1,1,1,2)
Sigma=matrix(c(1,.5,.5,1),ncol=2)
k=length(beta)
```



```

X1=matrix(runif(n*p,min=0,max=2),ncol=p); X2=matrix(runif(n*p,min=0,max=2),ncol=p)
X=createX(p,na=2,nd=NULL,Xa=cbind(X1,X2),Xd=NULL,DIFF=TRUE,base=p)

simmnp= function(X,p,n,beta,sigma) {
  indmax=function(x) {which(max(x)==x)}
  Xbeta=X%*%beta
  w=as.vector(crossprod(chol(sigma),matrix(rnorm((p-1)*n),ncol=n)))+ Xbeta
  w=matrix(w,ncol=(p-1),byrow=TRUE)
  maxw=apply(w,1,max)
  y=apply(w,1,indmax)
  y=ifelse(maxw < 0,p,y)
  return(list(y=y,X=X,beta=beta,sigma=sigma))
}

simout=simmnp(X,p,500,beta,Sigma)

Data1=list(p=p,y=simout$y,X=simout$X)
Mcmc1=list(R=R,keep=1)

out=rmnpGibbs(Data=Data1,Mcmc=Mcmc1)

cat(" Summary of Betadraws ",fill=TRUE)
betatilde=out$betadraw/sqrt(out$sigmadraw[,1])
attributes(betatilde)$class="bayesm.mat"
summary(betatilde,tvalues=beta)

cat(" Summary of Sigmadraws ",fill=TRUE)
sigmadraw=out$sigmadraw/out$sigmadraw[,1]
attributes(sigmadraw)$class="bayesm.var"
summary(sigmadraw,tvalues=as.vector(Sigma[upper.tri(Sigma,diag=TRUE)]))

if(0){
## plotting examples
plot(betatilde,tvalues=beta)
}

```

rmultireg

Draw from the Posterior of a Multivariate Regression

Description

rmultireg draws from the posterior of a Multivariate Regression model with a natural conjugate prior.

Usage

```
rmultireg(Y, X, Bbar, A, nu, V)
```

Arguments

Y	n x m matrix of observations on m dep vars
X	n x k matrix of observations on indep vars (supply intercept)
Bbar	k x m matrix of prior mean of regression coefficients
A	k x k Prior precision matrix
nu	d.f. parameter for Sigma
V	m x m pdf location parameter for prior on Sigma

Details

Model: $Y = XB + U$. $cov(u_i) = Sigma$. B is k x m matrix of coefficients. $Sigma$ is m x m covariance.

Priors: $beta$ given $Sigma \sim N(betabar, Sigma(x)A^{-1})$. $betabar = vec(Bbar)$; $beta = vec(B)$
 $Sigma \sim IW(nu, V)$.

Value

A list of the components of a draw from the posterior

B	draw of regression coefficient matrix
Sigma	draw of Sigma

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
n=200
m=2
X=cbind(rep(1,n),runif(n))
k=ncol(X)
B=matrix(c(1,2,-1,3),ncol=m)
```

```

Sigma=matrix(c(1,.5,.5,1),ncol=m); RSigma=chol(Sigma)
Y=X%*%B+matrix(rnorm(m*n),ncol=m)%*%RSigma

betabar=rep(0,k*m);Bbar=matrix(betabar,ncol=m)
A=diag(rep(.01,k))
nu=3; V=nu*diag(m)

betadraw=matrix(double(R*k*m),ncol=k*m)
Sigmadraw=matrix(double(R*m*m),ncol=m*m)
for (rep in 1:R)
  {out=rmultireg(Y,X,Bbar,A,nu,V);betadraw[rep,]=out$B
   Sigmadraw[rep,]=out$Sigma}

cat(" Betadraws ",fill=TRUE)
mat=apply(betadraw,2,quantile,probs=c(.01,.05,.5,.95,.99))
mat=rbind(as.vector(B),mat); rownames(mat)[1]="beta"
print(mat)
cat(" Sigma draws",fill=TRUE)
mat=apply(Sigmadraw,2,quantile,probs=c(.01,.05,.5,.95,.99))
mat=rbind(as.vector(Sigma),mat); rownames(mat)[1]="Sigma"
print(mat)

```

rmvpGibbs

Gibbs Sampler for Multivariate Probit

Description

rmvpGibbs implements the Edwards/Allenby Gibbs Sampler for the multivariate probit model.

Usage

```
rmvpGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(p,y,X)
Prior	list(betabar,A,nu,V) (optional)
Mcmc	list(beta0,sigma0,R,keep) (R required)

Details

model:

$w_i = X_i \beta + e$. $e \sim N(0, \Sigma)$. note: w_i is $p \times 1$.
 $y_{ij} = 1$, if $w_{ij} > 0$, else $y_i = 0$. $j=1, \dots, p$.

priors:

$\beta \sim N(\text{betabar}, A^{-1})$

$Sigma \sim IW(nu, V)$

to make up X matrix use `createX`

List arguments contain

`p` dimension of multivariate probit

`X` $n \times p \times k$ Design Matrix

`y` $n \times p \times 1$ vector of 0,1 outcomes

`betabar` $k \times 1$ prior mean (def: 0)

`A` $k \times k$ prior precision matrix (def: $.01I$)

`nu` d.f. parm for IWishart prior (def: $(p-1) + 3$)

`V` pds location parm for IWishart prior (def: $nu \times I$)

`beta0` initial value for beta

`sigma0` initial value for sigma

`R` number of MCMC draws

`keep` thinning parameter - keep every keepth draw (def: 1)

Value

a list containing:

`betadraw` $R/keep \times k$ array of betadraws

`sigmadraw` $R/keep \times p \times p$ array of sigma draws – each row is in vector form

Note

beta and Sigma are not identified. Correlation matrix and the betas divided by the appropriate standard deviation are. See Allenby et al for details or example below.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 4.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmnpGibbs](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
p=3
n=500
beta=c(-2,0,2)
Sigma=matrix(c(1,.5,.5,.5,1,.5,.5,.5,1),ncol=3)
k=length(beta)
I2=diag(rep(1,p)); xadd=rbind(I2)
for(i in 2:n) { xadd=rbind(xadd,I2)}; X=xadd

simmvp= function(X,p,n,beta,sigma) {
  w=as.vector(crossprod(chol(sigma),matrix(rnorm(p*n),ncol=n)))+ X%*%beta
  y=ifelse(w<0,0,1)
  return(list(y=y,X=X,beta=beta,sigma=sigma))
}

simout=simmvp(X,p,500,beta,Sigma)

Data1=list(p=p,y=simout$y,X=simout$X)
Mcmc1=list(R=R,keep=1)
out=rmvpGibbs(Data=Data1,Mcmc=Mcmc1)

ind=seq(from=0,by=p,length=k)
inda=1:3
ind=ind+inda
cat(" Betadraws ",fill=TRUE)
betatilde=out$betadraw/sqrt(out$sigmadraw[,ind])
attributes(betatilde)$class="bayesm.mat"
summary(betatilde,tvalues=beta/sqrt(diag(Sigma)))

rdraw=matrix(double((R)*p*p),ncol=p*p)
rdraw=t(apply(out$sigmadraw,1,nmat))
attributes(rdraw)$class="bayesm.var"
tvalue=nmat(as.vector(Sigma))
dim(tvalue)=c(p,p)
tvalue=as.vector(tvalue[upper.tri(tvalue,diag=TRUE)])
cat(" Draws of Correlation Matrix ",fill=TRUE)
summary(rdraw,tvalues=tvalue)

if(0){
plot(betatilde,tvalues=beta/sqrt(diag(Sigma)))
}
```

Description

`rmvst` draws from a Multivariate student-t distribution.

Usage

```
rmvst(nu, mu, root)
```

Arguments

<code>nu</code>	d.f. parameter
<code>mu</code>	mean vector
<code>root</code>	Upper Tri Cholesky Root of Sigma

Value

`length(mu)` draw vector

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[lndMvst](#)

Examples

```
##  
set.seed(66)  
rmvst(nu=5,mu=c(rep(0,2)),root=chol(matrix(c(2,1,1,2),ncol=2)))
```

Description

rnegbinRw implements a Random Walk Metropolis Algorithm for the Negative Binomial (NBD) regression model. $\text{beta} \mid \text{alpha}$ and $\text{alpha} \mid \text{beta}$ are drawn with two different random walks.

Usage

```
rnegbinRw(Data, Prior, Mcmc)
```

Arguments

Data	list(y,X)
Prior	list(betabar,A,a,b)
Mcmc	list(R,keep,s_beta,s_alpha,beta0)

Details

Model: $y \sim NBD(\text{mean} = \text{lambda}, \text{over} - \text{dispersion} = \text{alpha})$.
 $\text{lambda} = \exp(x'\text{beta})$

Prior: $\text{beta} \sim N(\text{betabar}, A^{-1})$

$\text{alpha} \sim \text{Gamma}(a, b)$.

note: prior mean of $\text{alpha} = a/b$, $\text{variance} = a/(b^2)$

list arguments contain:

y nobs vector of counts (0,1,2,...)

X nobs x nvar matrix

betabar nvar x 1 prior mean (def: 0)

A nvar x nvar pds prior prec matrix (def: .01I)

a Gamma prior parm (def: .5)

b Gamma prior parm (def: .1)

R number of MCMC draws

keep MCMC thinning parm: keep every keepth draw (def: 1)

s_beta scaling for $\text{beta} \mid \text{alpha}$ RW inc cov matrix (def: $2.93/\sqrt{\text{nvar}}$)

s_alpha scaling for $\text{alpha} \mid \text{beta}$ RW inc cov matrix (def: 2.93)

Value

a list containing:

<code>betadraw</code>	R/keep x nvar array of beta draws
<code>alphadraw</code>	R/keep vector of alpha draws
<code>llike</code>	R/keep vector of log-likelihood values evaluated at each draw
<code>acceptrbeta</code>	acceptance rate of the beta draws
<code>acceptralpha</code>	acceptance rate of the alpha draws

Note

The NBD regression encompasses Poisson regression in the sense that as alpha goes to infinity the NBD distribution tends toward the Poisson.

For "small" values of alpha, the dependent variable can be extremely variable so that a large number of observations may be required to obtain precise inferences.

Author(s)

Sridhar Narayanam & Peter Rossi, Graduate School of Business, University of Chicago, <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby, McCulloch. <http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rhierNegbinRw](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=1000} else {R=10}

set.seed(66)
simnegbin =
function(X, beta, alpha) {
# Simulate from the Negative Binomial Regression
lambda = exp(X %*% beta)
y=NULL
for (j in 1:length(lambda))
  y = c(y,rnbinom(1,mu = lambda[j],size = alpha))
return(y)
}

nobs = 500
nvar=2          # Number of X variables
alpha = 5
Vbeta = diag(nvar)*0.01
```



```

# Construct the regdata (containing X)
simnegbindata = NULL
beta = c(0.6,0.2)
X = cbind(rep(1,nobs),rnorm(nobs,mean=2,sd=0.5))
simnegbindata = list(y=simnegbin(X,beta,alpha), X=X, beta=beta)

Data1 = simnegbindata
Mcmc1 = list(R=R)

out = rnegbinRw(Data=Data1,Mcmc=Mcmc1)

cat("Summary of alpha/beta draw",fill=TRUE)
summary(out$alphadraw,tvalues=alpha)
summary(out$betadraw,tvalues=beta)

if(0){
## plotting examples
plot(out$betadraw)
}

```

rnmixGibbs

Gibbs Sampler for Normal Mixtures

Description

rnmixGibbs implements a Gibbs Sampler for normal mixtures.

Usage

```
rnmixGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(y)
Prior	list(Mubar,A,nu,V,a,ncomp) (only ncomp required)
Mcmc	list(R,keep) (R required)

Details

Model:

$y_i \sim N(\mu_{ind_i}, \Sigma_{ind_i})$.

ind \sim iid multinomial(p). p is a ncomp x 1 vector of probs.

Priors:

$\mu_j \sim N(\text{mubar}, \Sigma_j(x)A^{-1})$. $\text{mubar} = \text{vec}(Mubar)$.

$\Sigma_j \sim \text{IW}(\text{nu}, V)$.

note: this is the natural conjugate prior – a special case of multivariate regression.

$p \sim \text{Dirchlet}(a)$.

Output of the components is in the form of a list of lists.
`compsdraw[[i]]` is ith draw – list of ncomp lists.
`compsdraw[[i]][[j]]` is list of parms for jth normal component.
`jcomp=compsdraw[[i]][j]`. Then j th comp $\sim N(jcomp[[1]], Sigma)$, $Sigma = t(R) \%* \% R$,
 $R^{-1} = jcomp[[2]]$.

List arguments contain:

- y n x k array of data (rows are obs)
- Mubar 1 x k array with prior mean of normal comp means (def: 0)
- A 1 x 1 precision parameter for prior on mean of normal comp (def: .01)
- nu d.f. parameter for prior on Sigma (normal comp cov matrix) (def: k+3)
- V k x k location matrix of IW prior on Sigma (def: nul)
- a ncomp x 1 vector of Dirichlet prior parms (def: rep(5,ncomp))
- ncomp number of normal components to be included
- R number of MCMC draws
- keep MCMC thinning parm: keep every keepth draw (def: 1)

Value

`nmix`
a list containing: `probdraw`, `zdraw`, `compdraw`

Note

more details on contents of `nmix`:

`probdraw` R/keep x ncomp array of mixture prob draws

`zdraw` R/keep x nobs array of indicators of mixture comp identity for each obs

`compdraw` R/keep lists of lists of comp parm draws

In this model, the component normal parameters are not-identified due to label-switching. However, the fitted mixture of normals density is identified as it is invariant to label-switching. See Allenby et al, chapter 5 for details. Use `eMixMargDen` or `momMix` to compute posterior expectation or distribution of various identified parameters.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, <Peter.Rossi@ChicagoGsb.edu>.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmixture](#), [rmixGibbs](#), [eMixMargDen](#), [momMix](#), [mixDen](#), [mixDenBi](#)

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

set.seed(66)
dim=5; k=3 # dimension of simulated data and number of "true" components
sigma = matrix(rep(0.5,dim^2),nrow=dim);diag(sigma)=1
sigfac = c(1,1,1);mufac=c(1,2,3); compsmv=list()
for(i in 1:k) compsmv[[i]] = list(mu=mufac[i]*1:dim,sigma=sigfac[i]*sigma)
comps = list() # change to "rooti" scale
for(i in 1:k) comps[[i]] = list(mu=compsmv[[i]][[1]],rooti=solve(chol(compsmv[[i]][[2]])))
pvec=(1:k)/sum(1:k)

nobs=500
dm = rmixture(nobs,pvec,comps)

Data1=list(y=dm$x)
ncomp=9
Prior1=list(ncomp=ncomp)
Mcmc1=list(R=R,keep=1)
out=rnmixGibbs(Data=Data1,Prior=Prior1,Mcmc=Mcmc1)

cat("Summary of Normal Mixture Distribution",fill=TRUE)
summary(out)
tmom=momMix(matrix(pvec,nrow=1),list(comps))
mat=rbind(tmom$mu,tmom$sd)
cat(" True Mean/Std Dev",fill=TRUE)
print(mat)

if(0){
##
## plotting examples
##
plot(out,Data=dm$x)
}
```

rordprobitGibbs

Gibbs Sampler for Ordered Probit

Description

rordprobitGibbs implements a Gibbs Sampler for the ordered probit model.

Usage

```
rordprobitGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(X, y, k)
Prior	list(betabar, A, dstarbar, Ad)
Mcmc	list(R, keep, s, change, draw)

Details

Model: $z = X\beta + e$. $e \sim N(0, I)$. $y=1,...,k$. $\text{cutoff}=c(c [1] ,...c [k+1])$.
 $y=k$, if $c [k] \leq z < c [k+1]$.

Prior: $\beta \sim N(\text{betabar}, A^{-1})$. $\text{dstar} \sim N(\text{dstarbar}, Ad^{-1})$.

List arguments contain

X n x nvar Design Matrix

y n x 1 vector of observations, (1,...,k)

k the largest possible value of y

betabar nvar x 1 prior mean (def: 0)

A nvar x nvar prior precision matrix (def: .01I)

dstarbar ndstar x 1 prior mean, ndstar=k-2 (def: 0)

Ad ndstar x ndstar prior precision matrix (def:I)

s scaling parm for RW Metropolis (def: 2.93/sqrt(nvar))

R number of MCMC draws

keep thinning parameter - keep every keepth draw (def: 1)

Value

betadraw	R/keep x k matrix of betadraws
cutdraw	R/keep x (k-1) matrix of cutdraws
dstardraw	R/keep x (k-2) matrix of dstardraws
accept	a value of acceptance rate in RW Metropolis

Note

set $c[1]=-100$. $c[k+1]=100$. $c[2]$ is set to 0 for identification.

The relationship between cut-offs and dstar is

$c[3] = \exp(\text{dstar}[1])$, $c[4]=c[3]+\exp(\text{dstar}[2])$,..., $c[k] = c[k-1] + \exp(\text{dstar}[k-2])$

Be careful in assessing prior parameter, Ad. .1 is too small for many applications.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, <Peter.Rossi@ChicagoGsb.edu>.

References

Bayesian Statistics and Marketing by Rossi, Allenby and McCulloch
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rbprobitGibbs](#)

Examples

```
##
## rordprobitGibbs example
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}

## simulate data for ordered probit model

simordprobit=function(X, betas, cutoff){
  z = X*betas + rnorm(nobs)
  y = cut(z, br = cutoff, right=TRUE, include.lowest = TRUE, labels = FALSE)
  return(list(y = y, X = X, k=(length(cutoff)-1), betas= betas, cutoff=cutoff ))
}

set.seed(66)
nobs=300
X=cbind(rep(1,nobs),runif(nobs, min=0, max=5),runif(nobs,min=0, max=5))
k=5
betas=c(0.5, 1, -0.5)
cutoff=c(-100, 0, 1.0, 1.8, 3.2, 100)
simout=simordprobit(X, betas, cutoff)
Data=list(X=simout$X,y=simout$y, k=k)

## set Mcmc for ordered probit model

Mcmc=list(R=R)
out=rordprobitGibbs(Data=Data,Mcmc=Mcmc)

cat(" ", fill=TRUE)
cat("acceptance rate= ",accept=out$accept,fill=TRUE)

## outputs of betadraw and cut-off draws

cat(" Summary of betadraws",fill=TRUE)
summary(out$betadraw,tvalues=betas)
cat(" Summary of cut-off draws",fill=TRUE)
summary(out$cutdraw,tvalues=cutoff[2:k])

if(0){
## plotting examples
plot(out$cutdraw)
}
```

rscaleUsage	<i>MCMC Algorithm for Multivariate Ordinal Data with Scale Usage Heterogeneity.</i>
--------------------	---

Description

rscaleUsage implements an MCMC algorithm for multivariate ordinal data with scale usage heterogeneity.

Usage

```
rscaleUsage(Data,Prior, Mcmc)
```

Arguments

Data	list(k,x)
Prior	list(nu,V,mubar,Am,gsigma,gl11,gl22,gl12,Lambdanu,LambdaV,ge) (optional)
Mcmc	list(R,keep,ndghk,printevery,e,y,mu,Sigma,sigma,tau,Lambda) (optional)

Details

Model: $n=nrow(x)$ individuals respond to $m=ncol(x)$ questions. all questions are on a scale $1, \dots, k$. for respondent i and question j ,
 $x_{ij} = d$, if $c_{d-1} \leq y_{ij} \leq c_d$.
 $d=1, \dots, k$. $c_d = a + bd + ed^2$.

$$y_i = \mu + \tau_i * \iota + \sigma_i * z_i. \quad z_i \sim N(0, \Sigma).$$

Priors:

$$(\tau_i, \ln(\sigma_i)) \sim N(\phi, \Lambda). \quad \phi = (0, \lambda_{22}).$$

$$\mu \sim N(\bar{m}, A^{-1}).$$

$$\Sigma \sim IW(nu, V).$$

$$\Lambda \sim IW(\Lambda_{nu}, \Lambda V).$$

$$e \sim \text{unif on a grid}.$$

Value

a list containing:

Sigmadraw	R/keep x m*m array of Sigma draws
mudraw	R/keep x m array of mu draws
taudraw	R/keep x n array of tau draws
sigmadraw	R/keep x n array of sigma draws
Lambdadraw	R/keep x 4 array of Lamda draws
edraw	R/keep x 1 array of e draws

Warning

τ_{τ_i} , σ_{σ_i} are identified from the scale usage patterns in the m questions asked per respondent (# cols of x). Do not attempt to use this on data sets with only a small number of total questions!

Note

It is **highly** recommended that the user choose the default settings. This means not specifying the argument `Prior` and setting `R` in `Mcmc` and `Data` only. If you wish to change prior settings and/or the grids used, please read the case study in Allenby et al carefully.

Author(s)

Rob McCulloch and Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby, and McCulloch, Case Study on Scale Usage Heterogeneity.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=1000} else {R=1}
{
  data(customerSat)
  surveydat = list(k=10,x=as.matrix(customerSat))

  Mcmc1 = list(R=R)
  set.seed(66)
  out=rscaleUsage(Data=surveydat,Mcmc=Mcmc1)

  summary(out$mudraw)
}
```

rsurGibbs

Gibbs Sampler for Seemingly Unrelated Regressions (SUR)

Description

`rsurGibbs` implements a Gibbs Sampler to draw from the posterior of the Seemingly Unrelated Regression (SUR) Model of Zellner

Usage

```
rsurGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(regdata)
Prior	list(betabar,A, nu, V)
Mcmc	list(R,keep)

Details

Model: $y_i = X_i \beta_i + e_i$. $i=1, \dots, m$. m regressions.
 $(e(1,k), \dots, e(m,k)) \sim N(0, \text{Sigma})$. $k=1, \dots, \text{nobs}$.

We can also write as the stacked model:

$y = X\beta + e$ where y is a $\text{nobs} \times m$ long vector and $k = \text{length}(\beta) = \sum(\text{length}(\beta_i))$.

Note: we must have the same number of observations in each equation but we can have different numbers of X variables

Priors: $\beta \sim N(\text{betabar}, A^{-1})$. $\text{Sigma} \sim IW(\text{nu}, V)$.

List arguments contain

regdata list of lists, `regdata[[i]] = list(y=yi, X=Xi)`

betabar $k \times 1$ prior mean (def: 0)

A $k \times k$ prior precision matrix (def: $.01I$)

nu d.f. parm for Inverted Wishart prior (def: $m+3$)

V scale parm for Inverted Wishart prior (def: $\text{nu} \times I$)

R number of MCMC draws

keep thinning parameter - keep every `keepth` draw

Value

list of MCMC draws

betadraw $R \times k$ array of betadraws

Sigmadraw $R \times (m \times m)$ array of Sigma draws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[rmultireg](#)

Examples

```
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=1000} else {R=10}
##
## simulate data from SUR
set.seed(66)
beta1=c(1,2)
beta2=c(1,-1,-2)
nobs=100
nreg=2
iota=c(rep(1,nobs))
X1=cbind(iota,runif(nobs))
X2=cbind(iota,runif(nobs),runif(nobs))
Sigma=matrix(c(.5,.2,.2,.5),ncol=2)
U=chol(Sigma)
E=matrix(rnorm(2*nobs),ncol=2)
y1=X1%*%beta1+E[,1]
y2=X2%*%beta2+E[,2]
##
## run Gibbs Sampler
regdata=NULL
regdata[[1]]=list(y=y1,X=X1)
regdata[[2]]=list(y=y2,X=X2)

Mcmc1=list(R=R)

out=rsurGibbs(Data=list(regdata=regdata),Mcmc=Mcmc1)

cat("Summary of beta draws",fill=TRUE)
summary(out$betadraw,tvalues=c(beta1,beta2))
cat("Summary of Sigmadraws",fill=TRUE)
summary(out$Sigmadraw,tvalues=as.vector(Sigma[upper.tri(Sigma,diag=TRUE)]))

if(0){
plot(out$betadraw,tvalues=c(beta1,beta2))
}
```

rtrun

Draw from Truncated Univariate Normal

Description

rtrun draws from a truncated univariate normal distribution

Usage

```
rtrun(mu, sigma, a, b)
```

Arguments

<code>mu</code>	mean
<code>sigma</code>	sd
<code>a</code>	lower bound
<code>b</code>	upper bound

Details

Note that due to the vectorization of the `rnorm`, `qnorm` commands in R, all arguments can be vectors of equal length. This makes the inverse CDF method the most efficient to use in R.

Value

draw (possibly a vector)

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##
set.seed(66)
rtrun(mu=c(rep(0,10)),sigma=c(rep(1,10)),a=c(rep(0,10)),b=c(rep(2,10)))
```

`runireg`

IID Sampler for Univariate Regression

Description

`runireg` implements an iid sampler to draw from the posterior of a univariate regression with a conjugate prior.

Usage

```
runireg(Data, Prior, Mcmc)
```

Arguments

Data	<code>list(y,X)</code>
Prior	<code>list(betabar,A, nu, ssq)</code>
Mcmc	<code>list(R,keep)</code>

Details

Model: $y = X\beta + e$. $e \sim N(0, \sigma^2)$.

Priors: $\beta \sim N(\text{betabar}, \sigma^2 A^{-1})$. $\sigma^2 \sim (nu * ssq) / \chi^2_{nu}$. List arguments contain

X n x k Design Matrix
y n x 1 vector of observations
betabar k x 1 prior mean (def: 0)
A k x k prior precision matrix (def: .01I)
nu d.f. parm for Inverted Chi-square prior (def: 3)
ssq scale parm for Inverted Chi-square prior (def: var(y))
R number of draws
keep thinning parameter - keep every keepth draw

Value

list of iid draws
betadraw R x k array of betadraws
sigmasqdraw R vector of sigma-sq draws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[runiregGibbs](#)

Examples

```
if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=2000} else {R=10}
set.seed(66)
n=200
X=cbind(rep(1,n),runif(n)); beta=c(1,2); sigsq=.25
y=X%*%beta+rnorm(n,sd=sqrt(sigsq))

out=runireg(Data=list(y=y,X=X),Mcmc=list(R=R))

cat("Summary of beta/sigma-sq draws",fill=TRUE)
summary(out$betadraw,tvalues=beta)
summary(out$sigmasqdraw,tvalues=sigsq)

if(0){
## plotting examples
plot(out$betadraw)
}
```

runiregGibbs

Gibbs Sampler for Univariate Regression

Description

runiregGibbs implements a Gibbs Sampler to draw from posterior of a univariate regression with a conditionally conjugate prior.

Usage

```
runiregGibbs(Data, Prior, Mcmc)
```

Arguments

Data	list(y,X)
Prior	list(betabar,A, nu, ssq)
Mcmc	list(sigmasq,R,keep)

Details

Model: $y = X\beta + e$. $e \sim N(0, \text{sigmasq})$.

Priors: $\beta \sim N(\text{betabar}, A^{-1})$. $\text{sigmasq} \sim (nu * \text{ssq}) / \text{chisq}_{nu}$. List arguments contain

X n x k Design Matrix

y n x 1 vector of observations

betabar k x 1 prior mean (def: 0)

A k x k prior precision matrix (def: .01I)

nu d.f. parm for Inverted Chi-square prior (def: 3)
 ssq scale parm for Inverted Chi-square prior (def:var(y))
 R number of MCMC draws
 keep thinning parameter - keep every keepth draw

Value

list of MCMC draws

 betadraw R x k array of betadraws
 sigmasqdraw R vector of sigma-sq draws

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 3.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[runireg](#)

Examples

```

if(nchar(Sys.getenv("LONG_TEST")) != 0) {R=1000} else {R=10}
set.seed(66)
n=100
X=cbind(rep(1,n),runif(n)); beta=c(1,2); sigsq=.25
y=X%*%beta+rnorm(n,sd=sqrt(sigsq))

Data1=list(y=y,X=X); Mcmc1=list(R=R)

out=runiregGibbs(Data=Data1,Mcmc=Mcmc1)

cat("Summary of beta and Sigma draws",fill=TRUE)
summary(out$betadraw,tvalues=beta)
summary(out$sigmasqdraw,tvalues=sigsq)

if(0){
## plotting examples
plot(out$betadraw)
}

```

Description

`rwishart` draws from the Wishart and Inverted Wishart distributions.

Usage

```
rwishart(nu, V)
```

Arguments

<code>nu</code>	d.f. parameter
<code>V</code>	pds location matrix

Details

In the parameterization used here, $W \sim W(nu, V)$, $E[W] = nuV$.

If you want to use an Inverted Wishart prior, you *must invert the location matrix* before calling `rwishart`, e.g.

$Sigma \sim IW(nu, V)$; $Sigma^{-1} \sim W(nu, V^{-1})$.

Value

<code>W</code>	Wishart draw
<code>IW</code>	Inverted Wishart draw
<code>C</code>	Upper tri root of W
<code>CI</code>	$\text{inv}(C)$, $W^{-1} = CICI'$

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, Peter.Rossi@ChicagoGsb.edu.

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 2.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
##  
set.seed(66)  
rwishart(5,diag(3))$IW
```

Scotch

Survey Data on Brands of Scotch Consumed

Description

from Simmons Survey. Brands used in last year for those respondents who report consuming scotch.

Usage

```
data(Scotch)
```

Format

A data frame with 2218 observations on the following 21 variables. All variables are coded 1 if consumed in last year, 0 if not.

Chivas.Regal a numeric vector
Dewar.s.White.Label a numeric vector
Johnnie.Walker.Black.Label a numeric vector
J...B a numeric vector
Johnnie.Walker.Red.Label a numeric vector
Other.Brands a numeric vector
Glenlivet a numeric vector
Cutty.Sark a numeric vector
Glenfiddich a numeric vector
Pinch..Haig. a numeric vector
Clan.MacGregor a numeric vector
Ballantine a numeric vector
Macallan a numeric vector
Passport a numeric vector
Black...White a numeric vector
Scoresby.Rare a numeric vector
Grants a numeric vector
Ushers a numeric vector
White.Horse a numeric vector
Knockando a numeric vector
the.Singleton a numeric vector

Source

Edwards, Y. and G. Allenby (2003), "Multivariate Analysis of Multiple Response Data," *JMR* 40, 321-334.

References

Chapter 4, *Bayesian Statistics and Marketing* by Rossi et al.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
data(Scotch)
cat(" Frequencies of Brands", fill=TRUE)
mat=apply(as.matrix(Scotch),2,mean)
print(mat)
##
## use Scotch data to run Multivariate Probit Model
##
if(0){
##

y=as.matrix(Scotch)
p=ncol(y); n=nrow(y)
dimnames(y)=NULL
y=as.vector(t(y))
y=as.integer(y)
I_p=diag(p)
X=rep(I_p,n)
X=matrix(X,nrow=p)
X=t(X)

R=2000
Data=list(p=p,X=X,y=y)
Mcmc=list(R=R)
set.seed(66)
out=rmvpGibbs(Data=Data,Mcmc=Mcmc)

ind=(0:(p-1))*p + (1:p)
cat(" Betadraws ",fill=TRUE)
mat=apply(out$betadraw/sqrt(out$sigmadraw[,ind]),2,quantile,probs=c(.01,.05,.5,.95,.99))
attributes(mat)$class="bayesm.mat"
summary(mat)
rdraw=matrix(double((R)*p*p),ncol=p*p)
rdraw=t(apply(out$sigmadraw,1,nmat))
attributes(rdraw)$class="bayesm.var"
cat(" Draws of Correlation Matrix ",fill=TRUE)
summary(rdraw)

}
```

`simnhlogit`

Simulate from Non-homothetic Logit Model

Description

`simnhlogit` simulates from the non-homothetic logit model

Usage

```
simnhlogit(theta, lnprices, Xexpend)
```

Arguments

<code>theta</code>	coefficient vector
<code>lnprices</code>	n x p array of prices
<code>Xexpend</code>	n x k array of values of expenditure variables

Details

For detail on parameterization, see `llnhlogit`.

Value

a list containing:

<code>y</code>	n x 1 vector of multinomial outcomes (1, ..., p)
<code>Xexpend</code>	expenditure variables
<code>lnprices</code>	price array
<code>theta</code>	coefficients
<code>prob</code>	n x p array of choice probabilities

Warning

This routine is a utility routine that does **not** check the input arguments for proper dimensions and type.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

References

For further discussion, see *Bayesian Statistics and Marketing* by Rossi, Allenby and McCulloch, Chapter 4.

<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

See Also

[llnhlogit](#)

<code>summary.bayesm.mat</code>	<i>Summarize Mcmc Parameter Draws</i>
---------------------------------	---------------------------------------

Description

`summary.bayesm.mat` is an S3 method to summarize marginal distributions given an array of draws

Usage

```
## S3 method for class 'bayesm.mat':  
summary(object, names, burnin = trunc(0.1 * nrow(X)), tvalues, QUANTILES = TRUE, TRAILER = TRUE)
```

Arguments

<code>object</code>	<code>object</code> (hereafter <code>X</code>) is an array of draws, usually an object of class "bayesm.mat"
<code>names</code>	optional character vector of names for the columns of <code>X</code>
<code>burnin</code>	number of draws to burn-in, def: <code>.1*nrow(X)</code>
<code>tvalues</code>	optional vector of "true" values for use in simulation examples
<code>QUANTILES</code>	logical for should quantiles be displayed, def: <code>TRUE</code>
<code>TRAILER</code>	logical for should a trailer be displayed, def: <code>TRUE</code>
<code>...</code>	optional arguments for generic function

Details

Typically, `summary.bayesm.nmix` will be invoked by a call to the generic summary function as in `summary(object)` where `object` is of class `bayesm.mat`. Mean, Std Dev, Numerical Standard error (of estimate of posterior mean), relative numerical efficiency (see `numEff`) and effective sample size are displayed. If `QUANTILES=TRUE`, quantiles of marginal distributions in the columns of `X` are displayed.

`summary.bayesm.mat` is also exported for direct use as a standard function, as in `summary.bayesm.mat(matrix)`.

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

See Also

[summary.bayesm.var](#), [summary.bayesm.nmix](#)

Examples

```
##
## not run
# out=rmpGibbs(Data,Prior,Mcmc)
# summary(out$betadraw)
#
```

<code>summary.bayesm.nmix</code>	<i>Summarize Draws of Normal Mixture Components</i>
----------------------------------	---

Description

`summary.bayesm.nmix` is an S3 method to display summaries of the distribution implied by draws of Normal Mixture Components. Posterior means and Variance-Covariance matrices are displayed.

Note: 1st and 2nd moments may not be very interpretable for mixtures of normals. This summary function can take a minute or so. The current implementation is not efficient.

Usage

```
## S3 method for class 'bayesm.nmix':
summary(object, names, burnin = trunc(0.1 * nrow(probdraw)), ...)
```

Arguments

<code>object</code>	an object of class "bayesm.nmix" – a list of lists of draws
<code>names</code>	optional character vector of names fo reach dimension of the density
<code>burnin</code>	number of draws to burn-in, def: <code>.1*nrow(probdraw)</code>
<code>...</code>	parms to send to summary

Details

an object of class "bayesm.nmix" is a list of three components:

`probdraw` a matrix of R/keep rows by dim of normal mix of mixture prob draws

`second comp` not used

`compdraw` list of list of lists with draws of mixture comp parms

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, Peter.Rossi@ChicagoGsb.edu.

See Also

[summary.bayesm.mat](#), [summary.bayesm.var](#)

Examples

```
##
## not run
# out=rnmix(Data,Prior,Mcmc)
# summary(out)
#
```

<code>summary.bayesm.var</code>	<i>Summarize Draws of Var-Cov Matrices</i>
---------------------------------	--

Description

`summary.bayesm.var` is an S3 method to summarize marginal distributions given an array of draws

Usage

```
## S3 method for class 'bayesm.var':
summary(object, names, burnin = trunc(0.1 * nrow(Vard)), tvalues, QUANTILES = FALSE , ...)
```

Arguments

<code>object</code>	<code>object</code> (hereafter, <code>Vard</code>) is an array of draws of a covariance matrix
<code>names</code>	optional character vector of names for the columns of <code>Vard</code>
<code>burnin</code>	number of draws to burn-in, def: <code>.1*nrow(Vard)</code>
<code>tvalues</code>	optional vector of "true" values for use in simulation examples
<code>QUANTILES</code>	logical for should quantiles be displayed, def: <code>TRUE</code>
<code>...</code>	optional arguments for generic function

Details

Typically, `summary.bayesm.var` will be invoked by a call to the generic summary function as in `summary(object)` where `object` is of class `bayesm.var`. Mean, Std Dev, Numerical Standard error (of estimate of posterior mean), relative numerical efficiency (see `numEff`) and effective sample size are displayed. If `QUANTILES=TRUE`, quantiles of marginal distributions in the columns of `Vard` are displayed.

`Vard` is an array of draws of a covariance matrix stored as vectors. Each row is a different draw.

The posterior mean of the vector of standard deviations and the correlation matrix are also displayed

Author(s)

Peter Rossi, Graduate School of Business, University of Chicago, (Peter.Rossi@ChicagoGsb.edu).

See Also

[summary.bayesm.mat](#), [summary.bayesm.nmix](#)

Examples

```
##  
## not run  
# out=rmpGibbs(Data,Prior,Mcmc)  
# summary(out$sigmadraw)  
#
```

tuna

Data on Canned Tuna Sales

Description

Volume of canned tuna sales as well as a measure of display activity, log price and log wholesale price. Weekly data aggregated to the chain level. This data is extracted from the Dominick's Finer Foods database maintained by the University of Chicago <http://http://research.chicagogsb.edu/marketing/databases/dominicks/dataset.aspx>. Brands are seven of the top 10 UPCs in the canned tuna product category.

Usage

```
data(tuna)
```

Format

A data frame with 338 observations on the following 30 variables.

WEEK a numeric vector

MOVE1 unit sales of Star Kist 6 oz.

MOVE2 unit sales of Chicken of the Sea 6 oz.

MOVE3 unit sales of Bumble Bee Solid 6.12 oz.

MOVE4 unit sales of Bumble Bee Chunk 6.12 oz.

MOVE5 unit sales of Geisha 6 oz.

MOVE6 unit sales of Bumble Bee Large Cans.

MOVE7 unit sales of HH Chunk Lite 6.5 oz.

NSALE1 a measure of display activity of Star Kist 6 oz.

NSALE2 a measure of display activity of Chicken of the Sea 6 oz.

NSALE3 a measure of display activity of Bumble Bee Solid 6.12 oz.

NSALE4 a measure of display activity of Bumble Bee Chunk 6.12 oz.

NSALE5 a measure of display activity of Geisha 6 oz.

NSALE6 a measure of display activity of Bumble Bee Large Cans.
 NSALE7 a measure of display activity of HH Chunk Lite 6.5 oz.
 LPRICE1 log of price of Star Kist 6 oz.
 LPRICE2 log of price of Chicken of the Sea 6 oz.
 LPRICE3 log of price of Bumble Bee Solid 6.12 oz.
 LPRICE4 log of price of Bumble Bee Chunk 6.12 oz.
 LPRICE5 log of price of Geisha 6 oz.
 LPRICE6 log of price of Bumble Bee Large Cans.
 LPRICE7 log of price of HH Chunk Lite 6.5 oz.
 LWHPRIC1 log of wholesale price of Star Kist 6 oz.
 LWHPRIC2 log of wholesale price of Chicken of the Sea 6 oz.
 LWHPRIC3 log of wholesale price of Bumble Bee Solid 6.12 oz.
 LWHPRIC4 log of wholesale price of Bumble Bee Chunk 6.12 oz.
 LWHPRIC5 log of wholesale price of Geisha 6 oz.
 LWHPRIC6 log of wholesale price of Bumble Bee Large Cans.
 LWHPRIC7 log of wholesale price of HH Chunk Lite 6.5 oz.
 FULLCUST total customers visits

Source

Chevalier, A. Judith, Anil K. Kashyap and Peter E. Rossi (2003), "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data," *The American Economic Review* , 93(1), 15-37.

References

Chapter 7, *Bayesian Statistics and Marketing* by Rossi et al.
<http://faculty.chicagogsb.edu/peter.rossi/research/bsm.html>

Examples

```
data(tuna)
cat(" Quantiles of sales",fill=TRUE)
mat=apply(as.matrix(tuna[,2:5]),2,quantile)
print(mat)

##
## example of processing for use with rivGibbs
##
if(0)
{
  data(tuna)
  t = dim(tuna)[1]
  customers = tuna[,30]
  sales = tuna[,2:8]
  lnprice = tuna[,16:22]
```

```

lnwhPrice= tuna[,23:29]
share=sales/mean(customers)
shareout=as.vector(1-rowSums(share))
lnprob=log(share/shareout)

# create w matrix

I1=as.matrix(rep(1, t))
I0=as.matrix(rep(0, t))
intercept=rep(I1, 4)
brand1=rbind(I1, I0, I0, I0)
brand2=rbind(I0, I1, I0, I0)
brand3=rbind(I0, I0, I1, I0)
w=cbind(intercept, brand1, brand2, brand3)

## choose brand 1 to 4

y=as.vector(as.matrix(lnprob[,1:4]))
X=as.vector(as.matrix(lnprice[,1:4]))
lnwhPrice=as.vector(as.matrix (lnwhPrice[1:4]))
z=cbind(w, lnwhPrice)

Data=list(z=z, w=w, x=X, y=y)
Mcmc=list(R=R, keep=1)
set.seed(66)
out=rivGibbs(Data=Data,Mcmc=Mcmc)

cat(" betadraws ",fill=TRUE)
summary(out$betadraw)

if(0){
## plotting examples
plot(out$betadraw)
}
}

```