# Package 'bssn'

October 12, 2022

Type Package

Title Birnbaum-Saunders Model				
Version 1.0				
<b>Date</b> 2020-02-12				
Author Luis Benites Sanchez[cre, aut] <pre><lbenitess@pucp.edu.pe>, Rocio Paola Mae- hara[cre, aut] <rp.maeharaa@up.edu.pe> and Paulo Jos<c3><a9> Alejandro Aybar Flo- res[ctb] <a.aybarf@alum.up.edu.pe></a.aybarf@alum.up.edu.pe></a9></c3></rp.maeharaa@up.edu.pe></lbenitess@pucp.edu.pe></pre>				
Maintainer Rocio Paola Maehara <rp.maeharaa@up.edu.pe></rp.maeharaa@up.edu.pe>				
Imports sn, ssmn, mvtnorm, ClusterR				
<b>Description</b> It provides the density, distribution function, quantile function, random number generator, reliability function, failure rate, likelihood function, moments and EM algorithm for Maximum Likelihood estimators, also empirical quantile and generated envelope for a given sample, all this for the three parameter Birnbaum-Saunders model based on Skew-Normal Distribution. Also, it provides the random number generator for the mixture of Birnbaum-Saunders model based on Skew-Normal distribution. Additionally, we incorporate the EM algorithm based on the assumption that the error term follows a finite mixture of Sinh-normal distributions.				
License GPL (>= 2)				
Repository CRAN				
NeedsCompilation no				
<b>Date/Publication</b> 2020-02-13 09:40:03 UTC				
R topics documented:				
bssn-package       2         bssn       3         EMbssn       6         enzyme       8         FMshnReg       9         momentsbssn       11				

2 bssn-package

Index 15

bssn-package Birnbaum-Saunders model

# **Description**

It provides the density, distribution function, quantile function, random number generator, reliability function, failure rate, likelihood function, moments and EM algorithm for Maximum Likelihood estimators, also empirical quantile and generated envelope for a given sample, all this for the three parameter Birnbaum-Saunders model based on Skew-Normal Distribution. Also, it provides the random number generator for the mixture of Birbaum-Saunders model based on Skew-Normal distribution. Additionally, we incorporate the EM algorithm based on the assumption that the error term follows a finite mixture of Sinh-normal distributions.

## **Details**

Package: bssn Type: Package Version: 1.5

Date: 2020-02-12 License: GPL (>=2)

# Author(s)

Rocio Maehara <rmaeharaa@gmail.com> and Luis Benites <lbenitesanchez@gmail.com>

## References

Vilca, Filidor; Santana, L. R.; Leiva, Victor; Balakrishnan, N. (2011). Estimation of extreme percentiles in Birnbaum Saunders distributions. Computational Statistics & Data Analysis (Print), 55, 1665-1678.

Santana, Lucia; Vilca, Filidor; Leiva, Victor (2011). Influence analysis in skew-Birnbaum Saunders regression models and applications. Journal of Applied Statistics, 38, 1633-1649.

## See Also

bssn, EMbssn, momentsbssn, ozone, reliabilitybssn, FMshnReg

# **Examples**

#See examples for the bssnEM function linked above.

bssn 3

bssn

Birnbaum-Saunders model based on Skew-Normal distribution

# **Description**

It provides the density, distribution function, quantile function, random number generator, likelihood function, moments and EM algorithm for Maximum Likelihood estimators for a given sample, all this for the three parameter Birnbaum-Saunders model based on Skew-Normal Distribution. Also, we have the random number generator for the mixture of Birbaum-Saunders model based on Skew-Normal distribution. Finally, the function mmmeth() is used to find the initial values for the parameters alpha and beta using modified-moment method.

## Usage

```
dbssn(ti, alpha=0.5, beta=1, lambda=1.5)
pbssn(q, alpha=0.5, beta=1, lambda=1.5)
qbssn(p, alpha=0.5, beta=1, lambda=1.5)
rbssn(n, alpha=0.5, beta=1, lambda=1.5)
rmixbssn(n,alpha,beta,lambda,pii)
mmmmeth(ti)
```

## **Arguments**

ti	vector of observations.
q	vector of quantiles.
р	vector of probabilities.
n	number of observations.
alpha	shape parameter.
beta	scale parameter.
lambda	skewness parameter.
pii	Are weights adding to 1. Each one of them (alpha, beta and lambda) must be a vector of length g if you want to generate a random numbers from a mixture distribution BSSN.

## **Details**

If alpha, sigma or lambda are not specified they assume the default values of 0.5, 1 and 1.5, respectively, belonging to the Birnbaum-Saunders model based on Skew-Normal distribution denoted by BSSN(0.5,1,1.5).

As discussed in Filidor et. al (2011) we say that a random variable T is distributed as an BSSN with shape parameter  $\alpha > 0$ , scale parameter  $\beta > 0$  and skewness parameter  $\lambda$  in R, if its probability density function (pdf) is given by

$$f(t) = 2\phi(a(t; \alpha, \beta))\Phi(\lambda a(t; \alpha, \beta))A(t; \alpha, \beta), t > 0$$

where  $\phi(.)$  and  $\Phi(.)$  are the standard normal density and cumulative distribution function respectively. Also  $a(t; \alpha, \beta) = (1/\alpha)(\sqrt{t/\beta} - \sqrt{\beta/t})$  and  $A(t; \alpha, \beta) = t^{-3/2}(t+\beta)/(2\alpha\beta^{1/2})$ 

4 bssn

#### Value

dbssn gives the density, pbssn gives the distribution function, qbssn gives the quantile function, rbssn generates a random sample and rmixbssn genrates a mixture random sample.

The length of the result is determined by n for rbssn, and is the maximum of the lengths of the numerical arguments for the other functions dbssn, pbssn and qbssn.

## Author(s)

Rocio Maehara <rmaeharaa@gmail.com> and Luis Benites <lbenitesanchez@gmail.com>

#### References

Vilca, Filidor; Santana, L. R.; Leiva, Victor; Balakrishnan, N. (2011). Estimation of extreme percentiles in Birnbaum Saunders distributions. Computational Statistics & Data Analysis (Print), 55, 1665-1678.

Santana, Lucia; Vilca, Filidor; Leiva, Victor (2011). Influence analysis in skew-Birnbaum Saunders regression models and applications. Journal of Applied Statistics, 38, 1633-1649.

#### See Also

EMbssn, momentsbssn, ozone, reliabilitybssn

```
## Not run:
## Let's plot an Birnbaum-Saunders model based on Skew-Normal distribution!
## Density
sseq < - seq(0,3,0.01)
dens <- dbssn(sseq,alpha=0.2,beta=1,lambda=1.5)</pre>
plot(sseq, dens,type="1", lwd=2,col="red", xlab="x", ylab="f(x)", main="BSSN Density function")
# Differing densities on a graph
# positive values of lambda
y < - seq(0,3,0.01)
f1 < -dbssn(y, 0.2, 1, 1)
f2 <- dbssn(y,0.2,1,2)
f3 < -dbssn(y, 0.2, 1, 3)
f4 < -dbssn(y, 0.2, 1, 4)
den \leftarrow cbind(f1, f2, f3, f4)
matplot(y,den,type="1", col=c("deepskyblue4", "firebrick1", "darkmagenta", "aquamarine4"), ylab
="Density function",xlab="y",lwd=2,sub="(a)")
legend(1.5,2.8,c("BSSN(0.2,1,1)", "BSSN(0.2,1,2)", "BSSN(0.2,1,3)", "BSSN(0.2,1,4)"),
col = c("deepskyblue4", "firebrick1", "darkmagenta", "aquamarine4"), lty=1:4,lwd=2,
seg.len=2,cex=0.8,box.lty=0,bg=NULL)
#negative values of lambda
```

bssn 5

```
y <- seq(0,3,0.01)
 f1 <- dbssn(y, 0.2, 1, -1)
 f2 <- dbssn(y,0.2,1,-2)
 f3 <- dbssn(y,0.2,1,-3)
 f4 < -dbssn(y,0.2,1,-4)
 den \leftarrow cbind(f1, f2, f3, f4)
matplot(y,den,type="1", col=c("deepskyblue4", "firebrick1", "darkmagenta", "aquamarine4"),
ylab ="Density function",xlab="y",lwd=2,sub="(a)")
legend(1.5,2.8,c("BSSN(0.2,1,-1)", "BSSN(0.2,1,-2)", "BSSN(0.2,1,-3)", "BSSN(0.2,1,-4)"),
col=c("deepskyblue4","firebrick1", "darkmagenta", "aquamarine4"), lty=1:4, lwd=2, seg.len=2,
cex=1,box.lty=0,bg=NULL)
## Distribution Function
 sseq <- seq(0.1,6,0.05)
 df <- pbssn(q=sseq,alpha=0.75,beta=1,lambda=3)</pre>
 plot(sseq, df, type = "1", lwd=2, col="blue", xlab="x", ylab="F(x)",
 main = "BSSN Distribution function")
 abline(h=1,lty=2)
#Inverse Distribution Function
prob < seq(0,1,length.out = 1000)
 idf <- qbssn(p=prob,alpha=0.75,beta=1,lambda=3)</pre>
 plot(prob, idf, type="1", lwd=2, col="gray30", xlab="x", ylab =
 expression(F^{-1}^{(x)}), mgp=c(2.3,1,.8))
 title(main="BSSN Inverse Distribution function")
 abline(v=c(0,1),lty=2)
#Random Sample Histogram
 sample <- rbssn(n=10000,alpha=0.75,beta=1,lambda=3)</pre>
 hist(sample,breaks = 70,freq = FALSE,main="")
 title(main="Histogram and True density")
 sseq < - seq(0,8,0.01)
       <- dbssn(sseq,alpha=0.75,beta=1,lambda=3)
 lines(sseq,dens,col="red",lwd=2)
##Random Sample Histogram for Mixture of BSSN
alpha=c(0.55,0.25); beta=c(1,1.5); lambda=c(3,2); pii=c(0.3,0.7)
sample <- rmixbssn(n=1000,alpha,beta,lambda,pii)</pre>
hist(sample$y,breaks = 70,freq = FALSE,main="")
title(main="Histogram and True density")
      <- seq(min(sample$y), max(sample$y), length.out=1000)</pre>
lines(temp, (pii[1]*dbssn(temp, alpha[1], beta[1],lambda[1]))+(pii[2]*dbssn(temp, alpha[2]
, beta[2],lambda[2])), col="red", lty=3, lwd=3) # the theoretical density
lines(temp, pii[1]*dbssn(temp, alpha[1], beta[1],lambda[1]), col="blue", lty=2, lwd=3)
# the first component
lines(temp, pii[2]*dbssn(temp, alpha[2], beta[2],lambda[2]), col="green", lty=2, lwd=3)
# the second component
```

6 EMbssn

## End(Not run)

EM Algorithm Birnbaum-Saunders model based on Skew-Normal dis-

tribution

# Description

Performs the EM algorithm for Birnbaum-Saunders model based on Skew-Normal distribution.

## Usage

```
EMbssn(ti,alpha,beta,delta,initial.values=FALSE, loglik=F,accuracy=1e-8, show.envelope="FALSE",iter.max=500)
```

# **Arguments**

ti Vector of observations.

alpha, beta, delta

Initial values.

initial.values Logical; if TRUE, get the initial values for the parameters.

loglik Logical; if TRUE, showvalue of the log-likelihood.

accuracy The convergence maximum error.

show.envelope Logical; if TRUE, show the simulated envelope for the fitted model.

iter.max The maximum number of iterations of the EM algorithm

## Value

The function returns a list with 11 elements detailed as

iter Number of iterations.

alpha Returns the value of the MLE of the shape parameter.

beta Returns the value of the MLE of the scale parameter.

lambda Returns the value of the MLE of the skewness parameter.

SE Standard Errors of the ML estimates.

table Table containing the ML estimates with the corresponding standard errors.

loglik Log-likelihood.

AIC Akaike information criterion.

BIC Bayesian information criterion.

HQC Hannan-Quinn information criterion.

time processing time.

EMbssn 7

## Author(s)

#### References

Vilca, Filidor; Santana, L. R.; Leiva, Victor; Balakrishnan, N. (2011). Estimation of extreme percentiles in Birnbaum Saunders distributions. Computational Statistics & Data Analysis (Print), 55, 1665-1678.

Santana, Lucia; Vilca, Filidor; Leiva, Victor (2011). Influence analysis in skew-Birnbaum Saunders regression models and applications. Journal of Applied Statistics, 38, 1633-1649.

## See Also

bssn, EMbssn, momentsbssn, ozone, reliabilitybssn

```
## Not run:
#Using the ozone data
data(ozone)
attach(ozone)
#The model
ti
         <- dailyozonelevel
#Initial values for the parameters
initial <- mmmeth(ti)</pre>
        <- initial$alpha0ini
alpha0
beta0
         <- initial$beta0init
lambda0 <- 0
delta0
         <- lambda0/sqrt(1+lambda0^2)
#Estimated parameters of the model (by default)
est_param <- EMbssn(ti,alpha0,beta0,delta0,loglik=T,</pre>
accuracy = 1e-8, show.envelope = "TRUE", iter.max=500)
#ML estimates
alpha <- est_param$res$alpha</pre>
beta
         <- est_param$res$beta
lambda
        <- est_param$res$lambda
#A simple output example
Birnbaum-Saunders model based on Skew-Normal distribution
```

8 enzyme

enzyme

Enzymatic activity in the blood

# Description

These data correspond to representing the metabolism of carcinogenic substances among 245 unrelated individuals.

# Usage

```
data(enzyme)
```

#### **Format**

enzyme is a data frame with 245 cases (rows).

# **Details**

For more information about dataset see Bechtel et al. (1993).

## **Source**

Bechtel, Y., Bonaiti-Pellie, C., Poisson, N., Magnette, J. and Bechtel, P. (1993). A population and family study of n-acetyltransferase using caffeine urinary metabolites. Clinical Pharmacology and Therapeutics, 54, 134-141.

FMshnReg 9

FMshnReg Linear regression models using finite tion	e mixture of Sinh-normal distribu-
---	------------------------------------

# Description

Performs the EM-type algorithm with conditional maximation to perform maximum likelihood inference of the parameters of the proposed model based on the assumption that the error term follows a finite mixture of Sinh-normal distributions.

# Usage

```
FMshnReg(y, x1, alpha = NULL, Abetas = NULL, medj=NULL,
pii = NULL, g = NULL, get.init = TRUE, algorithm = "K-means",
accuracy = 10^-6, show.envelope="FALSE", iter.max = 100)
```

# Arguments

У	the response matrix (dimension nx1).
x1	Matrix or vector of covariates.
alpha	Value of the shape parameter for the EM algorithm. Each of them must be a vector of length g. (the algorithm considers the number of components to be adjusted based on the size of these vectors).
Abetas	Parameters of vector regression dimension $(p+1)$ include intercept.
medj	a list of g arguments of vectors of values (dimension p) for the location parameters.
pii	Value for the EM algorithm. Each of them must be a vector of length g. (the algorithm considers the number of components to be adjusted based on the size of these vectors).
g	The number of cluster to be considered in fitting.
get.init	if TRUE, the initial values are generated via k-means.
algorithm	clustering procedure of a series of vectors according to a criterion. The clustering algorithms may classified in 4 main categories: exclusive, overlapping, hierarchical and probabilistic.
accuracy	The convergence maximum error.
show.envelope	Logical; if TRUE, show the simulated envelope for the fitted model.
iter.max	The maximum number of iterations of the EM algorithm

# Value

The function returns a list with 10 elements detailed as

iter Number of iterations.criteria Attained criteria value.

10 FMshnReg

convergence	Convergence reached or not.
SE	Standard Error estimates, if the output shows NA the function does not provide the standard error for this parameter.
table	Table containing the inference for the estimated parameters.
LK	log-likelihood.
AIC	Akaike information criterion.
BIC	Bayesian information criterion.
EDC	Efficient Determination criterion.
time	Processing time.

## Author(s)

Rocio Maehara <rmaeharaa@gmail.com> and Luis Benites <lbenitesanchez@gmail.com>

## References

Maehara, R. and Benites, L. (2020). Linear regression models using finite mixture of Sinh-normal distribution. In Progress.

Bartolucci, F. and Scaccia, L. (2005). The use of mixtures for dealing with non-normal regression errors, Computational Statistics & Data Analysis 48(4): 821-834.

```
## Not run:
#Using the AIS data
library(FMsmsnReg)
data(ais)
#The model
    <- cbind(1,ais$SSF,ais$Ht)
     <- ais$Bfat
library(ClusterR) #This library is useful for using the k-medoids algorithm.
FMshnReg(y, x1, get.init = TRUE, g=2, algorithm="k-medoids",
accuracy = 10^-6, show.envelope="FALSE", iter.max = 1000)
#A simple output example
Finite Mixture of Sinh Normal Regression Model
Observations = 202
_____
```

momentsbssn 11

```
Estimate
alpha1 0.81346 0.10013
alpha2 3.04894 0.32140
beta0 15.08998 1.70024
beta1 0.17708 0.00242
beta2 -0.07687 0.00934
      -0.25422 0.18069
mu1
       0.37944 0.38802
mu2
       0.59881 0.41006
pii1
Model selection criteria
       Loglik AIC
                         BIC
Value -355.625 721.25 737.791 725.463
Details
-----
Convergence reached? = TRUE
EM iterations = 39 / 1000
Criteria = 6.58e-07
Processing time = 0.725559 secs
## End(Not run)
```

momentsbssn

Estimates

Moments for the Birnbaum-Saunders model based on Skew-Normal distribution

# Description

Mean, variance, skewness and kurtosis for the Birnbaum-Saunders model based on Skew-Normal distribution defined in Filidor et. al (2011).

# Usage

```
meanbssn(alpha=0.5,beta=1,lambda=1.5)
varbssn(alpha=0.5,beta=1,lambda=1.5)
skewbssn(alpha=0.5,beta=1,lambda=1.5)
kurtbssn(alpha=0.5,beta=1,lambda=1.5)
```

12 ozone

# **Arguments**

alpha shape parameter  $\alpha$ . beta scale parameter  $\beta$ . lambda skewness parameter  $\lambda$ .

## Value

meanbssn gives the mean, varbssn gives the variance, skewbssn gives the skewness, kurtbssn gives the kurtosis.

# Author(s)

Rocio Maehara <rmaeharaa@gmail.com> and Luis Benites <lbenitesanchez@gmail.com>

#### References

Vilca, Filidor; Santana, L. R.; Leiva, Victor; Balakrishnan, N. (2011). Estimation of extreme percentiles in Birnbaum Saunders distributions. Computational Statistics & Data Analysis (Print), 55, 1665-1678.

Santana, Lucia; Vilca, Filidor; Leiva, Victor (2011). Influence analysis in skew-Birnbaum Saunders regression models and applications. Journal of Applied Statistics, 38, 1633-1649.

#### See Also

bssn, EMbssn, momentsbssn, ozone, reliabilitybssn

# **Examples**

```
## Let's compute some moments for a Birnbaum-Saunders model based on Skew normal Distribution.
# The well known mean, variance, skewness and kurtosis
meanbssn(alpha=0.5,beta=1,lambda=1.5)
varbssn(alpha=0.5,beta=1,lambda=1.5)
skewbssn(alpha=0.5,beta=1,lambda=1.5)
kurtbssn(alpha=0.5,beta=1,lambda=1.5)
```

ozone

Daily ozone level measurements

# **Description**

These data correspond to daily ozone level measurements (in ppb = ppmx1000) in New York in May-September, 1973, from the New York State Department of Conservation.

# Usage

```
data(ozone)
```

reliabilitybssn 13

## **Format**

ozone is a data frame with 116 cases (rows).

## **Details**

For a complete description of various distributions applied to data concentration of air pollutants see Gokhale and Khare (2004).

#### Source

Leiva, V., Barros, M., Paula, G. e Sanhueza, A. (2007). Generalized BirnbaumSaunders distribution applied to air pollutant concentration. Environmetrics, 19, 235-249.

Nadarajah, S. (2007). A truncated inverted beta distribution with application to air pollution data. Stoch. Environ. Res. Risk. Assess., 22, 285-289.

Gokhale, S. e Khare, M. (2004) A review of deterministic, stochastic and hybrid vehicular exhaust emission models International. J. Transp. Manag., 2, 59-74.

 ${\it Reliability Function for the Birnbaum-Saunders \, model \, based \, on \, Skew-Normal \, distribution}$ 

## **Description**

Two useful descriptors in reliability analysis are the reliability function (rf), and the failure rate (fr) function or hazard function. For a non-negative random variable t with pdf f(t) (and cdf F(t)), its distribution can be characterized equally in terms of the rf, or of the fr, which are respectively defined by R(t) = 1 - F(t), and h(t) = f(t)/R(t), for t > 0, and 0 < R(t) < 1.

# Usage

```
Rebssn(ti,alpha=0.5,beta=1,lambda=1.5)
Fbssn(ti,alpha=0.5,beta=1,lambda=1.5)
```

## **Arguments**

ti dataset.

alpha shape parameter  $\alpha$ . beta scale parameter  $\beta$ . lambda skewness parameter  $\lambda$ .

## Value

Rbssn gives the reliability function, Fbssn gives the failure rate or hazard function.

# Author(s)

14 reliabilitybssn

## References

Leiva, V., Vilca-Labra, F. E., Balakrishnan, N. e Sanhueza, A. (2008). A skewed sinh-normal distribution and its properties and application to air pollution. Comm. Stat. Theoret. Methods. Submetido.

Guiraud, P., Leiva, V., Fierro, R. (2009). A non-central version of the Birnbaum-Saunders distribution for reliability analysis. IEEE Transactions on Reliability 58, 152-160.

## See Also

bssn, EMbssn, momentsbssn, ozone, Rebssn

lty=1:4,lwd=2,seg.len=2,cex=0.9,box.lty=1,bg=NULL)

```
## Let's compute some realiability functions for a Birnbaum-Saunders model based on
## Skew normal Distribution for different values of the shape parameter.
ti <- seq(0,2,0.01)
f1 < - Rebssn(ti, 0.75, 1, 1)
f2 <- Rebssn(ti,1,1,1)
f3 <- Rebssn(ti, 1.5, 1, 1)
f4 <- Rebssn(ti,2,1,1)
den \leftarrow cbind(f1, f2, f3, f4)
matplot(ti,den,type="1", col=c("deepskyblue4","firebrick1","darkmagenta","aquamarine4"),
ylab="S(t)", xlab="t",lwd=2)
legend(1.5,1,c(expression(alpha==0.75), expression(alpha==1), expression(alpha==1.5),
expression(alpha==2)),col= c("deepskyblue4","firebrick1","darkmagenta","aquamarine4"),
lty=1:4, lwd=2, seg.len=2, cex=0.9, box.lty=0, bg=NULL)
## Let's compute some hazard functions for a Birnbaum Saunders model based on
## Skew normal Distribution for different values of the skewness parameter.
ti <- seq(0,2,0.01)
f1 < -Fbssn(ti, 0.5, 1, -1)
f2 < -Fbssn(ti, 0.5, 1, -2)
f3 < -Fbssn(ti, 0.5, 1, -3)
f4 < - Fbssn(ti, 0.5, 1, -4)
den \leftarrow cbind(f1,f2,f3,f4)
matplot(ti,den,type = "1", col = c("deepskyblue4","firebrick1", "darkmagenta", "aquamarine4"),
ylab = "h(t)", xlab="t", lwd=2)
legend(0.1,23, c(expression(lambda==-1), expression(lambda==-2), expression(lambda == -3),
expression(lambda == -4)), col = c("deepskyblue4", "firebrick1", "darkmagenta", "aquamarine4"),
```

# **Index**

* Birnbaum-Saunders Skew-Normal bssn, 3	momentsbssn, 2, 4, 7, 11, 12, 14		
momentsbssn, 11	ozone, 2, 4, 7, 12, 12, 14		
reliabilitybssn, 13 * EM	pbssn (bssn), 3		
EMbssn, 6 FMshnReg, 9	qbssn (bssn), 3		
* FMshn	rbssn (bssn), 3		
FMshnReg, 9	Rebssn, <i>14</i>		
* Moments	Rebssn (reliabilitybssn), 13		
momentsbssn, 11	reliabilitybssn, 2, 4, 7, 12, 13		
* bssn	rmixbssn (bssn), 3		
bssn, 3			
EMbssn, 6 * datasets	skewbssn (momentsbssn), 11		
enzyme, 8	varbssn (momentsbssn), 11		
ozone, 12	var basii (iiioiiicii tabasii), 11		
* failure rate			
reliabilitybssn, 13			
* hazard function			
reliabilitybssn, 13			
* package			
bssn-package, 2			
* reliability function reliabilitybssn, 13			
refrabilitybssii, 13			
bssn, 2, 3, 7, 12, 14 bssn-package, 2			
dbssn (bssn), 3			
EMbssn, 2, 4, 6, 7, 12, 14 enzyme, 8			
Fbssn (reliabilitybssn), 13 FMshnReg, 2, 9			
kurtbssn (momentsbssn), 11			
meanbssn (momentsbssn), 11 mmmeth (bssn), 3			