# Package 'ICV'

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Title Indirect cross-validation (ICV) for kernel density estimation
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Description Functions for computing the global and local Gaussian density estimates based on the ICV bandwidth. See the article of Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. Journal of the American Statistical Association, 105(489), 415-423.
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C\_ICV

C\_ICV

The ICV rescaling constant.

# **Description**

Computing the ICV rescaling constant defined by expression (3) of Savchuk, Hart, and Sheather (2010).

# Usage

```
C_ICV(alpha, sigma)
```

# **Arguments**

alpha first parameter of the selection kernel, sigma second parameter of the selection kernel.

## **Details**

Calculation of the ICV rescaling constant C defined by (3) in Savchuk, Hart, and Sheather (2010). The constant is a function of the parameters  $(\alpha, \sigma)$  of the selection kernel L\_ICV defined by expression (4) in the same article. The Gaussian kernel is to be used for computing the ultimate density estimate.

# Value

The ICV rescaling constant C.

# References

Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.

## See Also

```
ICV, h_ICV, L_ICV, MISE_mixnorm, KDE_ICV, LocICV.
```

```
\# ICV rescaling constant for the selection kernel with (alpha,sigma)=(2.42,5.06). C_ICV(2.42,5.06)
```

h\_ICV

h\_ICV

The ICV bandwidth.

# **Description**

Calculation of the ICV bandwidth for the Gaussian density estimator corresponding to expression (12) of Savchuk, Hart, and Sheather (2010).

#### Usage

 $h_{ICV}(x)$ 

## **Arguments**

Х

numerical vector of data.

# **Details**

Computing the ICV bandwidth for a univariate numerical data set of size n < 12,058. The ICV bandwidth is consistent for the MISE optimal bandwidth (see Wand and Jones (1995)). The Gaussian kernel is used for computing the ultimate density estimate. The following values of the paramaters of the selection kernel L\_ICV are used:  $(\alpha,\sigma)=(2.42,5.06)$ . The ICV bandwidth does not exceed the oversmoothed bandwidth of Terrell (1990). See expression (12) of Savchuk et al. (2010).

# Value

The ICV bandwidth.

## References

- Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.
- Wand, M.P. and Jones, M.C. (1995). Kernel Smoothing. Chapman and Hall, London.
- Terrel, G. (1990). The maximum smoothing principle in density estimation. *Journal of the American Statistical Association*, 85, 470-477.

## See Also

```
ICV, C_ICV, L_ICV, MISE_mixnorm, KDE_ICV, LocICV.
```

```
# ICV bandwidth for a random sample of size n=100 from a N(0,1) density. 
 h_{LCV(rnorm(100))}
```

4 h\_isemixnorm

h_isemixnorm	The ISE-optimal bandwidth in the case when the true density is the
	specified mixture of normal distributions.

# **Description**

Computing the ISE-optimal bandwidth in the case when the true density is the specified mixture of normal distributions and the Gaussian kernel is used to compute the ultimate density estimate.

# Usage

```
h_isemixnorm(x, w, mu, sdev)
```

# **Arguments**

x numerical vector of data,

w vector of weighs (positive numbers between 0 and 1 that add up to one),

mu vector of means,

sdev vector of standard deviations.

#### **Details**

Computing the ISE-optimal bandwidth (i.e. the minimizer of the ISE function) in the case when the true density is the mixture of normal distributions defined by the vector of weights w, the vector of means  $\mu$ , and the vector of standard deviations  $\sigma$ . See expression (2.3) of Marron and Wand (1992). It is assumed that the normals are defined as parsimonious as possible. The normal distributions in the mixture should be ordered such that the means in  $\mu$  are sorted in a nondecreasing order. The Gaussian kernel is used for computing the ultimate density estimate.

# Value

The ISE-optimal bandwidth.

## References

Marron, J.S., Wand, M.P. (1992). Exact Mean Integrated Squared Error. *The Annals of Statistics*, 20(2), 712-736.

## See Also

```
mixnorm, ISE_mixnorm, MISE_mixnorm.
```

# **Examples**

```
# ISE optimal bandwidth for a random sample of size n=100 generated from a normal mixture defined by \# w=c(1/5,1/5,3/5), \# u=(0,1/2,13/12), \# u=(0,1/2
```

```
\mbox{\#} This corresponds to the skewed unimodal density of Marron and Wand (1992).
```

 $h_{isemixnorm(rnorm(100),c(1/5,1/5,3/5),c(0,1/2,13/12),c(1,2/3,5/9))}$ 

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ICV

The ICV function.

## **Description**

Computing ICV(h), the value of the ICV function, at a given bandwidth h (vector) for a data set x of size n < 12,058. See Savchuk, Hart, and Sheather (2010).

## Usage

```
ICV(h, x)
```

## **Arguments**

h numerical vector of bandwidth values (in the final scale),

x numerical vecror of data.

#### **Details**

Computation of ICV(h) for given h (bandwidth vector) and x (data vector). The sample size n<12,058. The Gaussian kernel is to be used for computing the ultimate kernel density estimate. The parameters of the selection kernel are  $(\alpha,\sigma)=(2.42,5.06)$ . The ICV bandwidth h\_ICV is the minimizer of the ICV function.

#### Value

The value of ICV(h) for given h and data (x).

## References

Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.

## See Also

```
h_ICV, C_ICV, L_ICV, MISE_mixnorm, KDE_ICV, LocICV.
```

```
#Example 1. Computation of ICV(h) at h=0.4 for a random sample of size n=100 from a N(0,1) distribution.
ICV(0.4,rnorm(100))

#Example 2. (Calculations for a random sample of size n=250 from the separated bimodal density).
w=c(1/2,1/2)
mu=c(-3/2,3/2)
sdev=c(1/2,1/2)

# Generating a sample of size n=250 from the separated bimodal density of Marron and Wand (1992).
dat=mixnorm(250,w,mu,sdev)
h_OS=(243/(35*length(dat)*2*sqrt(pi)))^0.2*sd(dat) # Computing the oversmoothed bandwidth.
h_opt=round(h_ICV(dat),digits=4)
harg=seq(0.1,3,len=100)
X11()
plot(harg,ICV(harg,x=dat),'1',lwd=3,xlab="h",ylab="ICV",cex.lab=1.7,cex.axis=1.7)
```

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```
title(main="ICV(h)",cex.main=1.7)
lines(c(h_OS,h_OS),c(-0.5,0.5),lty="dashed",lwd=3)
legend(0.75,-0.05,legend="Vertical line shows the oversmothed bandwidth")
legend(1.35,0.1,legend=paste("h_ICV=",h_opt),cex=2,bty="n")
# Notice that the scale of the ICV function is such that its minimizer is the ICV bandwidth h_ICV.
# Thus, no additional rescaling of the ICV function's minimizer is needed to obtain the ICV bandwidth.
X11()
dens=density(dat,bw=h_opt)
plot(dens,main="",cex.lab=1.7,cex.axis=1.7,lwd=3,xlab=paste("n=250, ","h=h_ICV=",h_opt),ylim=c(0,0.45))
title(main="KDE based on h_ICV",cex.main=1.7)
arg=seq(-3.5,3.5,len=1000)
lines(arg,w[1]*dnorm(arg,mu[1],sd=sdev[1])+w[2]*dnorm(arg,mu[2],sd=sdev[2]),lwd=3,lty="dashed")
legend(-1,0.45,lty=c("solid","dashed"),lwd=c(3,3),legend=c("ICV estimate","True density"),bty="n")
```

ISE mixnorm

The ISE function in the case when the underlying density is the specified mixture of normal distributions.

## **Description**

Computing ISE(h) for given h in the case when the underlying density is the specified mixture of normal distributions and the Gaussian kernel is used to compute the ultimate density estimate.

## Usage

```
ISE_mixnorm(h, x, w, mu, sdev)
```

# Arguments

h numerical vector of bandwidth values,

x numerical vector of data,

w vector of weighs (positive numbers between 0 and 1 that add up to one),

mu vector of means,

sdev vector of standard deviations.

#### **Details**

Computing ISE(h) in the case when the true density is the mixture of normal distributions defined by the vector of weights w, the vector of means  $\mu$ , and the vector of standard deviations  $\sigma$ . See expression (2.3) of Marron and Wand (1992). It is assumed that the normals are defined as parsimonious as possible. The normal distributions in the mixture should be ordered such that the means in  $\mu$  are arranged in a nondecreasing order. The Gaussian kernel is to be used for computing the ultimate density estimate.

#### Value

The vector of ISE values corresponding to the specifies values of h.

# References

Marron, J.S., Wand, M.P. (1992). Exact Mean Integrated Squared Error. *The Annals of Statistics*, 20(2), 712-736.

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#### See Also

```
mixnorm, h_isemixnorm, MISE_mixnorm.
```

## **Examples**

```
harg=seq(0.01,1,len=100)
w=c(3/4,1/4)
mu=c(0,3/2)
sdev=c(1,1/3)
# The vectors w, mu, and sdev define the skewed bimodal density of Marron and Wand (1992).
dat=mixnorm(300,w,mu,sdev)
h_ISE=round(h_isemixnorm(dat,w,mu,sdev),digits=4)
ISEarray=ISE_mixnorm(harg,dat,w,mu,sdev)
X11()
plot(harg,ISEarray,'l',lwd=3,xlab="h, n=300",ylab="ISE",cex.lab=1.7,cex.axis=1.7,main="")
title(main="ISE(h)",cex.main=1.7)
legend(0.2,0.08,legend=paste("h_ISE=",h_ISE),cex=2)
```

KDE\_ICV

Computing the kernel density estimate based on the ICV bandwidth.

## **Description**

Computing the Gaussian density estimate based on h\_ICV.

## Usage

```
KDE_ICV(x)
```

# **Arguments**

х

numerical vector of data.

## **Details**

Computing the Gaussian density estimate based on h\_ICV. The ICV selection kernel L\_ICV is based on  $(\alpha, \sigma) = (2.42, 5.06)$ .

### Value

A list containing the following components:

arg vector of sorted values of the argument at which the density estmate is computed, y vector of density estimates at the corresponding values of the argument.

The function also produces a graph of the resulting ICV kernel density estimate.

# References

- Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.
- Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2009). An empirical study of indirect cross-validation. Nonparametric Statistics and Mixture Models: A Festschrift in Honor of Thomas P. Hettmansperger. World Scientific Publishing, 288-308.

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#### See Also

```
ICV, h_ICV, L_ICV, LocICV, C_ICV.
```

## **Examples**

```
\label{lem:example} \begin{tabular}{ll} \tt \#Example & (Density estimate for eruption duration of the Old Faithful Geyser). \\ \tt data=faithful[[1]] \\ \tt dens=KDE\_ICV(data) \end{tabular}
```

LocICV

The local ICV function.

## **Description**

Computing the local ICV function at the given estimation point, as explained in Section 6 of Savchuk, Hart, and Sheather (2010).

# Usage

```
LocICV(h, xest, x, eta, alpha, sigma)
```

## **Arguments**

h	bandwidth (scalar) in the final scale,
xest	estimation point (scalar),
x	numerical vector of data,
eta	smoothing parameter,
alpha	first parameter of the selection kernel,
sigma	second parameter of the selection kernel.

# Details

Calculation of the local ICV function at the given estimation point xest. The Gaussian kernel is used for local weighting. The ultimate kernel density estimate is computed based on the Gaussian kernel. The parameters of the selection kernel L\_ICV are  $\alpha$  and  $\sigma$ . The minimizer of the local ICV function is to be used in computing the ultimate density estimate without additional rescaling. Parameter  $\eta$  is a smoothing parameter that determines the degree to which the cross-validation is local. A suggested value of  $\eta$  is  $\eta = R/20$ , where R is the range of data.

# Value

The value of the local ICV function at the fixed estimation point and for the specified value of the bandwidth (see Section 6 of Savchuk, Hart, and Sheather (2010)).

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#### References

- Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.
- Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2009). An empirical study of indirect cross-validation. Nonparametric Statistics and Mixture Models: A Festschrift in Honor of Thomas P. Hettmansperger. World Scientific Publishing, 288-308.
- Hall, P., and Schukany, W. R. (1989). A local cross-validation algorithm. *Statistics and Probability Letters*, 8, 109-117.

#### See Also

```
h_ICV, C_ICV, L_ICV, MISE_mixnorm, ICV, KDE_ICV.
```

## **Examples**

```
# Local ICV function for a random sample of size n=150 from the kurtotic density of Marron and Wand (1992).
dat=mixnorm(150,c(2/3,1/3),c(0,0),c(1,1/10))
a=2.42 # alpha
s=5.06 # sigma
harg=seq(0.025,1,len=100)
Xest=0.1
                                   # estimation point
LocICV_Xest=numeric(length(harg))
for(i in 1:length(harg))
      LocICV_Xest[i]=LocICV(harg[i], Xest, dat, 0.2, a, s)
h\_Xest=optimize(LocICV,c(0.001,0.2),tol=0.001,xest=Xest,eta=0.2,x=dat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=Xest,eta=0.2,xedat,alpha=a,sigma=s)\\ \$minimum=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xest=0.001,xe
h_Xest=round(h_Xest,digits=4)
X11()
plot(harg,LocICV_Xest,'l',lwd=3,xlab="harg",ylab="LocICV_Xest",main="",cex.lab=1.7, cex.axis=1.7)
title(main=paste("Local ICV function at x=",Xest),cex.main=1.7)
legend(0.1,max(LocICV_Xest),legend=paste("h_x=",h_Xest),cex=1.7)
legend(0.2,max(LocICV_Xest)-0.15,legend="Note: first local minimizer is used", cex=1.5,bty="n")
```

L\_ICV

The ICV selection kernel.

# **Description**

The ICV selection kernel L defined by expression (4) of Savchuk, Hart, and Sheather (2010).

# Usage

```
L_ICV(u, alpha, sigma)
```

## Arguments

u numerical argument of the selection kernel,
alpha first parameter of the selection kernel,
sigma second parameter of the selection kernel.

#### **Details**

The ICV selection kernel  $L(u; \alpha, \sigma) = (1 + \alpha)\phi(u) - \alpha\phi(u/\sigma)/\sigma$ , where  $\phi$  denotes the Gaussian kernel.

## Value

```
The value of L(u; \alpha, \sigma).
```

#### References

Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.

#### See Also

```
ICV, h_ICV, C_ICV, MISE_mixnorm, KDE_ICV, LocICV.
```

## **Examples**

```
# Graph of the ICV selection kernel with (alpha,sigma)=(2.42,5.06).
u=seq(-10,10,len=1000)
kern=L_ICV(u,2.42,5.06)
X11()
plot(u,kern,'l',lwd=2,ylim=c(-0.2,1.2),ylab="kernel",cex.lab=1.7,cex.axis=1.7,main="")
lines(u,dnorm(u),lwd=3,lty="dashed")
title(main="Selection kernel with (alpha,sigma)=(2.42,5.06)",cex.main=1.6)
legend(-11, 1.2, legend=c("ICV kernel","Gaussian kernel"),lwd=c(3,3),lty=c(1,2),bty="n",cex=1.3)
```

MISE\_mixnorm

The MISE function in the case when the true density is the specified mixture of normal distributions and the selection kernel L\_ICV is used in the cross-validation stage.

# **Description**

Computing MISE(h) for given h in the case when the true density is the specified mixture of normal distributions and the kernel is L\_ICV defined by expression (4) of Savchuk, Hart, and Sheather (2010).

# Usage

```
MISE_mixnorm(h, n, alpha, sigma, w, mu, sdev)
```

#### **Arguments**

h	numerical vector of bandwidth values,
n	sample size,
alpha	first parameter of the selection kernel,
sigma	second parameter of the selection kernel,
W	vector of weighs (positive numbers between 0 and 1 that add up to one),
mu	vector of means,
sdev	vector of standard deviations.

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#### **Details**

Calculation of MISE(h) in the case when the true density is the mixture of normal distributions defined by the vector of weights w, the vector of means  $\mu$ , and the vector of standard deviations  $\sigma$ . See expression (2.3) of Marron and Wand (1992). It is assumed that the normals are defined as parsimonious as possible. The normal distributions in the mixture should be ordered such that the means in  $\mu$  are arranged in a nondecreasing order. The MISE function is based on the selection kernel L\_ICV defined by expression (4) of Savchuk, Hart, and Sheather (2010). Notice that the Gaussian kernel  $\phi$  is the special case of L\_ICV given that (Case 1)  $\alpha=0$ ,  $\sigma>0$  or (Case 2)  $\sigma=1$ ,  $-\infty<\alpha<\infty$ .

#### Value

The vector of MISE values corresponding to the specified values of h.

#### References

- Savchuk, O.Y., Hart, J.D., Sheather, S.J. (2010). Indirect cross-validation for density estimation. *Journal of the American Statistical Association*, 105(489), 415-423.
- Marron, J.S., Wand, M.P. (1992). Exact Mean Integrated Squared Error. The Annals of Statistics, 20(2), 712-736.

#### See Also

```
mixnorm, ISE_mixnorm, h_isemixnorm, L_ICV, ICV, h_ICV, C_ICV.
```

```
# Example 1. MISE for the separated bimodal density of Marron and Wand (1992).
# in the case (alpha, sigma) = (2.42, 5.06), n=100.
harray=seq(0.05,1,len=1000)
w=c(1/2,1/2)
m=c(-3/2,3/2)
s=c(1/2,1/2)
MISEarray=MISE_mixnorm(harray, 100, 2.42, 5.06, w, m, s)
hopt=round(optimize(MISE_mixnorm,c(0.01,1),n=100,alpha=2.42,sigma=5.06,w=w,mu=m,sdev=s)$minimum,digits=4)
X11()
plot(harray, MISEarray, 'l', lwd=3, xlab="h", ylab="MISE", cex.lab=1.7, cex.axis=1.7, main="")
title(main="MISE(h) for the separated bimodal density",cex.main=1.5)
legend(0.45,0.45,legend=c(paste("h_MISE=",hopt),"n=100"),bty="n",cex=1.7)
# Example 2. MISE for the N(0,1) density in the case of the Gaussian kernel and n=500.
harray=seq(0.03,1,len=1000)
MISEarray=MISE_mixnorm(harray,500,1,1,1,0,1)
hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ \$minimum, digits=4) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, w=1, mu=0, sdev=1) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sigma=1, sdev=1) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1, sdev=1) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1) \\ hopt=round (optimize (MISE\_mixnorm, c(0.01,1), n=500, alpha=1) \\ hopt=round (optimixe (MISE\_mixnorm, c(0.01,1), n=500, alpha=1) \\ hopt=round (optimixe (MISE\_mixe (MISE\_mixe
X11()
plot(harray, MISEarray, 'l', lwd=3, xlab="h", ylab="MISE", cex.lab=1.7, cex.axis=1.7, main="")
title(main="MISE(h) for the standard normal density",cex.main=1.7)
legend(0.2,0.02,legend=c(paste("h_MISE=",hopt),"n=500"),bty="n",cex=1.7)
```

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mixnorm	Generating a random sample from the specified mixture of normal distributions.

# **Description**

Generating a random sample of size n from the normal mixture defined by expression (2.3) of Marron and Wand (1992).

## Usage

```
mixnorm(n, w, mu, sdev)
```

### **Arguments**

n desired sample size,

w vector of weighs (positive numbers between 0 and 1 that add up to one),

mu vector of means,

sdev vector of standard deviations.

#### **Details**

Producing a random sample of size n from the normal mixture defined by the vector of weights w, the vector of means  $\mu$ , and the vector of standard deviations  $\sigma$ . See Marron and Wand (1992). It is assumed that the normals are defined as parsimonious as possible. The normal distributions in the mixture should be ordered such that the means in  $\mu$  are arranged in a nondecreasing order.

#### Value

A random sample of size n from the specified mixture of normals.

### References

Marron, J.S., Wand, M.P. (1992). Exact Mean Integrated Squared Error. *The Annals of Statistics*, 20(2), 712-736.

# See Also

ISE\_mixnorm, h\_isemixnorm, MISE\_mixnorm.

```
# Generating a sample of size n=300 from the separated bimodal density of Marron and Wand (1992).  w=c(0.5,0.5) \\ m=c(-3/2,3/2) \\ sdev=c(1/2,1/2) \\ dat=mixnorm(300,w,mu,sdev) # generated data vector \\ arg=seq(-4,4,len=1000) # argument \\ f=w[1]*dnorm(arg,mu[1],sd=sdev[1])+w[2]*dnorm(arg,mu[2],sd=sdev[2]) # true density X11() \\ hist(dat,freq=F,ylab="",main="",cex.lab=1.7,cex.axis=1.7,xlim=c(-4,4),lwd=2,ylim=c(0,0.45),col='grey') \\ title(main="Separated bimodal density",cex.main=1.7)
```

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```
legend(-5,0.4,legend="n=300",cex=2,bty="n")
lines(arg,f,lwd=3,'1')
```

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