

# Package ‘EbayesThresh’

July 21, 2025

**Encoding** UTF-8

**Type** Package

**Title** Empirical Bayes Thresholding and Related Methods

**Version** 1.4-12

**Date** 2017-07-29

**URL** <https://github.com/stephenslab/EbayesThresh>

**BugReports** <https://github.com/stephenslab/EbayesThresh/issues>

**Description** Empirical Bayes thresholding using the methods developed by I. M. Johnstone and B. W. Silverman. The basic problem is to estimate a mean vector given a vector of observations of the mean vector plus white noise, taking advantage of possible sparsity in the mean vector. Within a Bayesian formulation, the elements of the mean vector are modelled as having, independently, a distribution that is a mixture of an atom of probability at zero and a suitable heavy-tailed distribution. The mixing parameter can be estimated by a marginal maximum likelihood approach. This leads to an adaptive thresholding approach on the original data. Extensions of the basic method, in particular to wavelet thresholding, are also implemented within the package.

**Imports** stats, wavethresh

**Suggests** testthat, knitr, rmarkdown, dplyr, ggplot2

**NeedsCompilation** no

**License** GPL (>= 2)

**VignetteBuilder** knitr

**Author** Bernard W. Silverman [aut],  
Ludger Evers [aut],  
Kan Xu [aut],  
Peter Carbonetto [aut, cre],  
Matthew Stephens [aut]

**Maintainer** Peter Carbonetto <peter.carbonetto@gmail.com>

**Repository** CRAN

**Date/Publication** 2017-08-08 04:02:13 UTC

Contents

beta.cauchy . . . . .	2
beta.laplace . . . . .	3
ebayesthresh . . . . .	4
ebayesthresh.wavelet . . . . .	7
postmean . . . . .	9
postmed . . . . .	10
tfromw . . . . .	11
tfromx . . . . .	13
threshld . . . . .	14
wandafromx . . . . .	15
wfromt . . . . .	16
wfromx . . . . .	17
wmonfromx . . . . .	18
zetafromx . . . . .	19
<b>Index</b>	<b>21</b>

---

beta.cauchy	<i>Function beta for the quasi-Cauchy prior</i>
-------------	---

---

Description

Given a value or vector  $x$  of values, find the value(s) of the function  $\beta(x) = g(x)/\phi(x) - 1$ , where  $g$  is the convolution of the quasi-Cauchy with the normal density  $\phi(x)$ .

Usage

beta.cauchy(x)

Arguments

x                      a real value or vector

Value

A vector the same length as  $x$ , containing the value(s)  $\beta(x)$ .

Author(s)

Bernard Silverman

References

See ebayesthresh and <http://www.bernardsilverman.com>

See Also

[beta.laplace](#)

**Examples**

```
beta.cauchy(c(-2,1,0,-4,8,50))
```

---

beta.laplace

*Function beta for the Laplace prior*


---

**Description**

Given a single value or a vector of  $x$  and  $s$ , find the value(s) of the function  $\beta(x; s, a) = g(x; s, a) / f_n(x; 0, s) - 1$ , where  $f_n(x; 0, s)$  is the normal density with mean 0 and standard deviation  $s$ , and  $g$  is the convolution of the Laplace density with scale parameter  $a$ ,  $\gamma_a(\mu)$ , with the normal density  $f_n(x; \mu, s)$  with mean  $\mu$  and standard deviation  $s$ .

**Usage**

```
beta.laplace(x, s = 1, a = 0.5)
```

**Arguments**

<code>x</code>	the value or vector of data values
<code>s</code>	the value or vector of standard deviations; if vector, must have the same length as <code>x</code>
<code>a</code>	the scale parameter of the Laplace distribution

**Value**

A vector of the same length as `x` is returned, containing the value(s)  $\beta(x)$ .

**Note**

The Laplace density is given by  $\gamma(u; a) = \frac{1}{2}ae^{-a|u|}$  and is also known as the double exponential density.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[beta.cauchy](#)

**Examples**

```
beta.laplace(c(-2,1,0,-4,8,50), s=1)
beta.laplace(c(-2,1,0,-4,8,50), s=1:6, a=1)
```

---

ebayesthresh

*Empirical Bayes thresholding on a sequence*


---

## Description

Given a sequence of data, performs Empirical Bayes thresholding, as discussed in Johnstone and Silverman (2004).

## Usage

```
ebayesthresh(x, prior = "laplace", a = 0.5, bayesfac = FALSE,
sdev = NA, verbose = FALSE, threshrule = "median", universalthresh = TRUE,
stabadjustment)
```

## Arguments

x	Vector of data values.
prior	Specification of prior to be used conditional on the mean being nonzero; can be "cauchy" or "laplace".
a	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used. If, on entry, a = NA and prior = "laplace", then the scale parameter will also be estimated by marginal maximum likelihood. If a is not specified then the default value 0.5 will be used.
bayesfac	If bayesfac = TRUE, then whenever a threshold is explicitly calculated, the Bayes factor threshold will be used.
sdev	The sampling standard deviation of the data x. If, on entry, sdev = NA, then the standard deviation will be estimated using the median absolute deviation from zero, as mad(x, center = 0). If a single value is passed to sdev, sampling standard deviation will be the same for all observations. A vector of the same length as data sequence can be passed to allow heterogeneous standard deviation, currently only for Laplace prior.
verbose	Controls the level of output. See below.
threshrule	Specifies the thresholding rule to be applied to the data. Possible values are "median" (use the posterior median); "mean" (use the posterior mean); "hard" (carry out hard thresholding); "soft" (carry out soft thresholding); "none" (find various parameters, but do not carry out any thresholding).
universalthresh	If universalthresh = TRUE, the thresholds will be upper bounded by universal threshold; otherwise, the thresholds can take any non-negative values.
stabadjustment	If stabadjustment = TRUE, the vectors of standard deviations and data values will be divided by the mean of standard deviations in case of inefficiency caused by large value of standard deviation. For heterogeneous sampling standard deviation only; ignored if standard deviation is homogeneous.

## Details

It is assumed that the data vector  $(x_1, \dots, x_n)$  is such that each  $x_i$  is drawn independently from a normal distribution with mean  $\theta_i$  and variance  $\sigma_i^2$  ( $\sigma_i$  is the same in the homogeneous case). The prior distribution of each  $\theta_i$  is a mixture with probability  $1 - w$  of zero and probability  $w$  of a given symmetric heavy-tailed distribution. The mixing weight, and possibly a scale factor in the symmetric distribution, are estimated by marginal maximum likelihood. The resulting values are used as the hyperparameters in the prior.

The true effects  $\theta_i$  can be estimated as the posterior median or the posterior mean given the data, or by hard or soft thresholding using the posterior median threshold. If hard or soft thresholding is chosen, then there is the additional choice of using the Bayes factor threshold, which is the value such that the posterior probability of zero is exactly half if the data value is equal to the threshold.

## Value

If verbose = FALSE, a vector giving the values of the estimates of the underlying mean vector.

If verbose = TRUE, a list with the following elements:

muhat	the estimated mean vector (omitted if threshrule = "none")
x	the data vector as supplied
threshold.sdevscale	the threshold as a multiple of the standard deviation sdev
threshold.origscale	the threshold measured on the original scale of the data
prior	the prior that was used
w	the mixing weight as estimated by marginal maximum likelihood
a	(only present if Laplace prior used) the scale factor as supplied or estimated
bayesfac	the value of the parameter bayesfac, determining whether Bayes factor or posterior median thresholds are used
sdev	the standard deviations of the data as supplied or estimated
threshrule	the thresholding rule used, as specified above

## Author(s)

Bernard Silverman

## References

- Johnstone, I. M. and Silverman, B. W. (2004) Needles and straw in haystacks: Empirical Bayes estimates of possibly sparse sequences. *Annals of Statistics*, **32**, 1594–1649.
- Johnstone, I. M. and Silverman, B. W. (2004) EbayesThresh: R software for Empirical Bayes thresholding. *Journal of Statistical Software*, **12**.
- Johnstone, I. M. (2004) ‘Function Estimation and Classical Normal Theory’ ‘The Threshold Selection Problem’. The Wald Lectures I and II, 2004. Available from <http://www-stat.stanford.edu/~imj>.

Johnstone, I. M. and Silverman, B. W. (2005) Empirical Bayes selection of wavelet thresholds. *Annals of Statistics*, **33**, 1700–1752.

The papers by Johnstone and Silverman are available from <http://www.bernardsilverman.com>.

See also <http://www-stat.stanford.edu/~imj> for further references, including the draft of a monograph by I. M. Johnstone.

## See Also

[tfromx](#), [threshld](#)

## Examples

```
# Data with homogeneous sampling standard deviation using
# Cauchy prior.
eb1 <- ebayesthresh(x = rnorm(100, c(rep(0,90),rep(5,10))),
                    prior = "cauchy", sdev = NA)

# Data with homogeneous sampling standard deviation using
# Laplace prior.
eb2 <- ebayesthresh(x = rnorm(100, c(rep(0,90), rep(5,10))),
                    prior = "laplace", sdev = 1)

# Data with heterogeneous sampling standard deviation using
# Laplace prior.
set.seed(123)
mu <- c(rep(0,90), rep(5,10))
sd <- c(rep(1, 40), rep(3, 60))
x <- mu + rnorm(100, sd = sd)

# With constraints on thresholds.
eb3 <- ebayesthresh(x = x, prior = "laplace", a = NA, sdev = sd)

# Without constraints on thresholds. Observe that the estimates with
# constraints on thresholds have fewer zeroes than the estimates without
# constraints.
eb4 <- ebayesthresh(x = x, prior = "laplace", a = NA, sdev = sd,
                    universalthresh = FALSE)
print(sum(eb3 == 0))
print(sum(eb4 == 0))

# Data with heterogeneous sampling standard deviation using Laplace
# prior.
set.seed(123)
mu <- c(rep(0,90), rep(5,10))
sd <- c(rep(1, 40), rep(5,40), rep(15, 20))
x <- mu + rnorm(100, sd = sd)

# In this example, infinity is returned as estimate when some of the
# sampling standard deviations are extremely large. However, this can
# be solved by stabilizing the data sequence before the analysis.
eb5 <- ebayesthresh(x = x, prior = "laplace", a = NA, sdev = sd)
```

```
# With stabilization.
eb6 <- ebayesthresh(x = x, prior = "laplace", a = NA, sdev = sd,
  stabadjustment = TRUE)
```

---

ebayesthresh.wavelet    *Empirical Bayes thresholding on the levels of a wavelet transform.*

---

## Description

Apply an Empirical Bayes thresholding approach level by level to the detail coefficients in a wavelet transform.

## Usage

```
ebayesthresh.wavelet(xtr, vscale = "independent", smooth.levels = Inf,
  prior = "laplace", a = 0.5, bayesfac = FALSE,
  threshrule = "median")

ebayesthresh.wavelet.dwt(x.dwt, vscale = "independent", smooth.levels = Inf,
  prior = "laplace", a = 0.5, bayesfac = FALSE,
  threshrule = "median")

ebayesthresh.wavelet.wd(x.wd, vscale = "independent", smooth.levels = Inf,
  prior = "laplace", a = 0.5, bayesfac = FALSE,
  threshrule = "median")

ebayesthresh.wavelet.splus(x.dwt, vscale = "independent", smooth.levels = Inf,
  prior = "laplace", a = 0.5, bayesfac = FALSE,
  threshrule = "median")
```

## Arguments

xtr	The wavelet transform of a vector of data. The transform is obtained using one of the wavelet transform routines in R or in S+WAVELETS. Any choice of wavelet, boundary condition, etc provided by these routines can be used.
x.dwt	Wavelet transform input for ebayesthresh.wavelet.dwt.
x.wd	Wavelet transform input for ebayesthresh.wavelet.wd.
vscale	Controls the scale used at different levels of the transform. If vscale is a scalar quantity, then it will be assumed that the wavelet coefficients at every level have this standard deviation. If vscale = "independent", the standard deviation will be estimated from the highest level of the wavelet transform and will then be used for all levels processed. If vscale="level", then the standard deviation will be estimated separately for each level processed, allowing standard deviation that is level-dependent.
smooth.levels	The number of levels to be processed, if less than the number of levels of detail calculated by the wavelet transform.

prior	Specification of prior to be used for the coefficients at each level, conditional on their mean being nonzero; can be cauchy or laplace.
a	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used. If, on entry, a=NA and prior="laplace", then the scale parameter will also be estimated at each level by marginal maximum likelihood. If a is not specified then the default value 0.5 will be used.
bayesfac	If bayesfac=TRUE, then whenever a threshold is explicitly calculated, the Bayes factor threshold will be used.
threshrule	Specifies the thresholding rule to be applied to the coefficients. Possible values are median (use the posterior median); mean (use the posterior mean); hard (carry out hard thresholding); soft (carry out soft thresholding).

### Details

The routine `ebayesthresh.wavelet` can process a wavelet transform obtained using the routine `wd` in the `WaveThresh R` package, the routines `dwt` or `modwt` in the `waveslim R` package, or one of the routines (either `dwt` or `nd.dwt`) in `S+WAVELETS`.

Note that the wavelet transform must be calculated before the routine `ebayesthresh.wavelet` is called; the choice of wavelet, boundary conditions, decimated vs nondecimated wavelet, and so on, are made when the wavelet transform is calculated.

Apart from some housekeeping to estimate the standard deviation if necessary, and to determine the number of levels to be processed, the main part of the routine is a call, for each level, to the smoothing routine [ebayesthresh](#).

The basic notion of processing each level of detail coefficients is easily transferred to transforms constructed using other wavelet software. Similarly, it is straightforward to modify the routine to give other details of the wavelet transform, if necessary using the option `verbose = TRUE` in the calls to [ebayesthresh](#).

The main routine `ebayesthresh.wavelet` calls the relevant one of the routines `ebayesthresh.wavelet.wd` (for a transform obtained from `WaveThresh`), `ebayesthresh.wavelet.dwt` (for transforms obtained from either `dwt` or `modwt` in `waveslim`) or `ebayesthresh.wavelet.splus` (for transforms obtained from `S+WAVELETS`).

### Value

The wavelet transform (in the same format as that supplied to the routine) of the values of the estimated regression function underlying the original data.

### Author(s)

Bernard Silverman

### References

Johnstone, I. M. and Silverman, B. W. (2005) Empirical Bayes selection of wavelet thresholds. *Annals of Statistics*, **33**, 1700–1752.

See also the other references given for [ebayesthresh](#) and at <http://www.bernardsilverman.com>.



**See Also**[ebayesthresh](#)


---

postmean	<i>Posterior mean estimator</i>
----------	---------------------------------

---

**Description**

Given a single value or a vector of data and sampling standard deviations (sd equals 1 for Cauchy prior), find the corresponding posterior mean estimate(s) of the underlying signal value(s).

**Usage**

```
postmean(x, s, w = 0.5, prior = "laplace", a = 0.5)
postmean.laplace(x, s = 1, w = 0.5, a = 0.5)
postmean.cauchy(x, w)
```

**Arguments**

x	A data value or a vector of data.
s	A single value or a vector of standard deviations if the Laplace prior is used. If a vector, must have the same length as x. Ignored if Cauchy prior is used.
w	The value of the prior probability that the signal is nonzero.
prior	Family of the nonzero part of the prior; can be "cauchy" or "laplace".
a	The scale parameter of the nonzero part of the prior if the Laplace prior is used.

**Value**

If  $x$  is a scalar, the posterior mean  $E(\theta|x)$  where  $\theta$  is the mean of the distribution from which  $x$  is drawn. If  $x$  is a vector with elements  $x_1, \dots, x_n$  and  $s$  is a vector with elements  $s_1, \dots, s_n$  ( $s_i$  is 1 for Cauchy prior), then the vector returned has elements  $E(\theta_i|x_i, s_i)$ , where each  $x_i$  has mean  $\theta_i$  and standard deviation  $s_i$ , all with the given prior.

**Note**

If the quasicauchy prior is used, the argument  $a$  and  $s$  are ignored.

If  $\text{prior} = \text{"laplace"}$ , the routine calls `postmean.laplace`, which finds the posterior mean explicitly, as the product of the posterior probability that the parameter is nonzero and the posterior mean conditional on not being zero.

If  $\text{prior} = \text{"cauchy"}$ , the routine calls `postmean.cauchy`; in that case the posterior mean is found by expressing the quasi-Cauchy prior as a mixture: The mean conditional on the mixing parameter is found and is then averaged over the posterior distribution of the mixing parameter, including the atom of probability at zero variance.

**Author(s)**

Bernard Silverman

**References**See [ebayesthresh](#) and <http://www.bernardsilverman.com>**See Also**[postmed](#)**Examples**

```
postmean(c(-2,1,0,-4,8,50), w = 0.05, prior = "cauchy")
postmean(c(-2,1,0,-4,8,50), s = 1:6, w = 0.2, prior = "laplace", a = 0.3)
```

---

postmed

---

*Posterior median estimator*


---

**Description**

Given a single value or a vector of data and sampling standard deviations (sd is 1 for Cauchy prior), find the corresponding posterior median estimate(s) of the underlying signal value(s).

**Usage**

```
postmed(x, s, w = 0.5, prior = "laplace", a = 0.5)
postmed.laplace(x, s = 1, w = 0.5, a = 0.5)
postmed.cauchy(x, w)
cauchy.medzero(x, z, w)
```

**Arguments**

x	A data value or a vector of data.
s	A single value or a vector of standard deviations if the Laplace prior is used. If a vector, must have the same length as x. Ignored if Cauchy prior is used.
w	The value of the prior probability that the signal is nonzero.
prior	Family of the nonzero part of the prior; can be "cauchy" or "laplace".
a	The scale parameter of the nonzero part of the prior if the Laplace prior is used.
z	The data vector (or scalar) provided as input to <code>cauchy.medzero</code> .

**Details**

The routine calls the relevant one of the routines `postmed.laplace` or `postmed.cauchy`. In the Laplace case, the posterior median is found explicitly, without any need for the numerical solution of an equation. In the quasi-Cauchy case, the posterior median is found by finding the zero, component by component, of the vector function `cauchy.medzero`.

**Value**

If  $x$  is a scalar, the posterior median  $\text{med}(\theta|x)$  where  $\theta$  is the mean of the distribution from which  $x$  is drawn. If  $x$  is a vector with elements  $x_1, \dots, x_n$  and  $s$  is a vector with elements  $s_1, \dots, s_n$  ( $s_i$  is 1 for Cauchy prior), then the vector returned has elements  $\text{med}(\theta_i|x_i, s_i)$ , where each  $x_i$  has mean  $\theta_i$  and standard deviation  $s_i$ , all with the given prior.

**Note**

If the quasicauchy prior is used, the argument  $a$  and  $s$  are ignored. The routine calls the appropriate one of `postmed.laplace` or `postmed.cauchy`.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[postmean](#)

**Examples**

```
postmed(c(-2,1,0,-4,8,50), w = 0.05, prior = "cauchy")
postmed(c(-2,1,0,-4,8,50), s = 1:6, w = 0.2, prior = "laplace", a = 0.3)
```

---

tfromw

*Find threshold from mixing weight*


---

**Description**

Given a single value or a vector of weights (i.e. prior probabilities that the parameter is nonzero) and sampling standard deviations (sd equals 1 for Cauchy prior), find the corresponding threshold(s) under the specified prior.

**Usage**

```
tfromw(w, s = 1, prior = "laplace", bayesfac = FALSE, a = 0.5)

laplace.threshzero(x, s = 1, w = 0.5, a = 0.5)

cauchy.threshzero(z, w)
```

**Arguments**

x	Parameter value passed to <code>laplace.threshzero</code> objective function.
w	Prior weight or vector of weights.
s	A single value or a vector of standard deviations if the Laplace prior is used. If w is a vector, must have the same length as w. Ignored if Cauchy prior is used.
prior	Specification of prior to be used; can be "cauchy" or "laplace".
bayesfac	Specifies whether Bayes factor threshold should be used instead of posterior median threshold.
a	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used.
z	The putative threshold vector for <code>cauchy.threshzero</code> .

**Details**

The Bayes factor method uses a threshold such that the posterior probability of zero is exactly half if the data value is equal to the threshold. If `bayesfac` is set to FALSE (the default) then the threshold is that of the posterior median function given the data value.

The routine carries out a binary search over each component of an appropriate vector function, using the routine [vecbinsolv](#).

For the posterior median threshold, the function to be zeroed is `laplace.threshzero` or `cauchy.threshzero`.

For the Bayes factor threshold, the corresponding functions are [beta.laplace](#) or [beta.cauchy](#).

**Value**

The value or vector of values of the estimated threshold(s).

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[wfromx](#), [tfromx](#), [wandafromx](#)

**Examples**

```
tfromw(c(0.05, 0.1), s = 1)
tfromw(c(0.05, 0.1), prior = "cauchy", bayesfac = TRUE)
```

---

tfromx	<i>Find thresholds from data</i>
--------	----------------------------------

---

### Description

Given a vector of data and standard deviations (sd equals 1 for Cauchy prior), find the value or vector (heterogeneous sampling standard deviation with Laplace prior) of thresholds corresponding to the marginal maximum likelihood choice of weight.

### Usage

```
tfromx(x, s = 1, prior = "laplace", bayesfac = FALSE, a = 0.5,
       universalthresh = TRUE)
```

### Arguments

x	Vector of data.
s	A single value or a vector of standard deviations if the Laplace prior is used. If a vector, must have the same length as x. Ignored if Cauchy prior is used.
prior	Specification of prior to be used; can be "cauchy" or "laplace".
bayesfac	Specifies whether Bayes factor threshold should be used instead of posterior median threshold.
a	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used.
universalthresh	If universalthresh = TRUE, the thresholds will be upper bounded by universal threshold; otherwise, the thresholds can take any non-negative values.

### Details

First, the routine [wfromx](#) is called to find the estimated weight. Then the routine [tfromw](#) is used to find the threshold. See the documentation for these routines for more details.

### Value

The numerical value or vector of the estimated thresholds is returned.

### Author(s)

Bernard Silverman

### References

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

### See Also

[tfromw](#), [wfromx](#)

**Examples**

```
tfromx(x = rnorm(100, c(rep(0,90),rep(5,10))), prior = "cauchy")
```

---

**threshld***Threshold data with hard or soft thresholding*

---

**Description**

Given a data value or a vector of data, threshold the data at a specified value, using hard or soft thresholding.

**Usage**

```
threshld(x, t, hard = TRUE)
```

**Arguments**

x	a data value or a vector of data
t	value of threshold to be used
hard	specifies whether hard or soft thresholding is applied

**Value**

A value or vector of values the same length as x, containing the result of the relevant thresholding rule applied to x.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[ebayesthresh](#)

**Examples**

```
threshld(-5:5, 1.4, FALSE)
```

wandafromx

*Find weight and scale factor from data if Laplace prior is used.***Description**

Given a vector of data and a single value or vector of sampling standard deviations, find the marginal maximum likelihood choice of both weight and scale factor under the Laplace prior.

**Usage**

```
wandafromx(x, s = 1, universalthresh = TRUE)
negloglik.laplace(xpar, xx, ss, tlo, thi)
```

**Arguments**

x	A vector of data.
s	A single value or a vector of standard deviations. If vector, must have the same length as x.
universalthresh	If universalthresh = TRUE, the thresholds will be upper bounded by universal threshold; otherwise, the thresholds can take any non-negative values.
xx	A vector of data.
xpar	Vector of two parameters: xpar[1] : a value between 0 and 1, which will be adjusted to range of w; xpar[2], scale factor "a".
ss	Vector of standard deviations.
tlo	Lower bound of thresholds.
thi	Upper bound of thresholds.

**Details**

The parameters are found by marginal maximum likelihood.

The search is over weights corresponding to threshold  $t_i$  in the range  $[0, s_i \sqrt{2 \log n}]$  if universalthresh=TRUE, where  $n$  is the length of the data vector and  $(s_1, \dots, s_n)$  is the vector of sampling standard deviation of data  $(x_1, \dots, x_n)$ ; otherwise, the search is over  $[0, 1]$ .

The search uses a nonlinear optimization routine ([optim](#) in R) to minimize the negative log likelihood function `negloglik.laplace`. The range over which the scale factor is searched is (0.04, 3). For reasons of numerical stability within the optimization, the prior is parametrized internally by the threshold and the scale parameter.

**Value**

A list with values:

w	The estimated weight.
a	The estimated scale factor.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[wfromx](#), [tfromw](#)

**Examples**

```
wandafromx(rnorm(100, c(rep(0,90),rep(5,10))), s = 1)
```

---

wfromt

---

*Mixing weight from posterior median threshold*


---

**Description**

Given a value or vector of thresholds and sampling standard deviations (sd equals 1 for Cauchy prior), find the mixing weight for which this is(these are) the threshold(s) of the posterior median estimator. If a vector of threshold values is provided, the vector of corresponding weights is returned.

**Usage**

```
wfromt(tt, s = 1, prior = "laplace", a = 0.5)
```

**Arguments**

tt	Threshold value or vector of values.
s	A single value or a vector of standard deviations if the Laplace prior is used. If a vector, must have the same length as tt. Ignored if Cauchy prior is used.
prior	Specification of prior to be used; can be "cauchy" or "laplace".
a	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used.

**Value**

The numerical value or vector of values of the corresponding weight is returned.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>



**See Also**[tfromw](#)**Examples**

```
wfromt(c(2,3,5), prior = "cauchy" )
```

wfromx

*Find Empirical Bayes weight from data***Description**

Suppose the vector  $(x_1, \dots, x_n)$  is such that  $x_i$  is drawn independently from a normal distribution with mean  $\theta_i$  and standard deviation  $s_i$  ( $s_i$  equals 1 for Cauchy prior). The prior distribution of the  $\theta_i$  is a mixture with probability  $1 - w$  of zero and probability  $w$  of a given symmetric heavy-tailed distribution. This routine finds the marginal maximum likelihood estimate of the parameter  $w$ .

**Usage**

```
wfromx(x, s = 1, prior = "laplace", a = 0.5, universalthresh = TRUE)
```

**Arguments**

x	Vector of data.
s	A single value or a vector of standard deviations if the Laplace prior is used. If a vector, must have the same length as x. Ignored if Cauchy prior is used.
prior	Specification of prior to be used; can be "cauchy" or "laplace".
a	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used.
universalthresh	If universalthresh = TRUE, the thresholds will be upper bounded by universal threshold; otherwise, the thresholds can take any non-negative values.

**Details**

The weight is found by marginal maximum likelihood.

The search is over weights corresponding to threshold  $t_i$  in the range  $[0, s_i \sqrt{2 \log n}]$  if universalthresh=TRUE, where  $n$  is the length of the data vector and  $(s_1, \dots, s_n)$  ( $s_i$  is 1 for Cauchy prior) is the vector of sampling standard deviation of data  $(x_1, \dots, x_n)$ ; otherwise, the search is over  $[0, 1]$ .

The search is by binary search for a solution to the equation  $S(w) = 0$ , where  $S$  is the derivative of the log likelihood. The binary search is on a logarithmic scale in  $w$ .

If the Laplace prior is used, the scale parameter is fixed at the value given for a, and defaults to 0.5 if no value is provided. To estimate a as well as w by marginal maximum likelihood, use the routine [wandafromx](#).

**Value**

The numerical value of the estimated weight.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[wandafromx](#), [tfromx](#), [tfromw](#), [wfromt](#)

**Examples**

```
wfromx(x = rnorm(100, s = c(rep(0,90),rep(5,10))), prior = "cauchy")
```

---

wmonfromx

*Find monotone Empirical Bayes weights from data.*

---

**Description**

Given a vector of data, find the marginal maximum likelihood choice of weight sequence subject to the constraints that the weights are monotone decreasing.

**Usage**

```
wmonfromx(xd, prior = "laplace", a = 0.5, tol = 1e-08, maxits = 20)
```

**Arguments**

xd	A vector of data.
prior	Specification of the prior to be used; can be cauchy or laplace.
a	Scale parameter in prior if prior="laplace". Ignored if prior="cauchy".
tol	Absolute tolerance to within which estimates are calculated.
maxits	Maximum number of weighted least squares iterations within the calculation.

**Details**

The weights is found by marginal maximum likelihood. The search is over weights corresponding to thresholds in the range  $[0, \sqrt{2 \log n}]$ , where  $n$  is the length of the data vector.

An iterated least squares monotone regression algorithm is used to maximize the log likelihood. The weighted least squares monotone regression routine [isotone](#) is used.

To turn the weights into thresholds, use the routine [tfromw](#); to process the data with these thresholds, use the routine [threshld](#).

**Value**

The vector of estimated weights is returned.

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[wfromx](#), [isotone](#)

---

zetafromx	<i>Estimation of a parameter in the prior weight sequence in the EbayesThresh paradigm.</i>
-----------	---

---

**Description**

Suppose a sequence of data has underlying mean vector with elements  $\theta_i$ . Given the sequence of data, and a vector of scale factors `cs` and a lower limit `pilo`, this routine finds the marginal maximum likelihood estimate of the parameter `zeta` such that the prior probability of  $\theta_i$  being nonzero is of the form `median(pilo, zeta*cs, 1)`.

**Usage**

```
zetafromx(xd, cs, pilo = NA, prior = "laplace", a = 0.5)
```

**Arguments**

<code>xd</code>	A vector of data.
<code>cs</code>	A vector of scale factors, of the same length as <code>xd</code> .
<code>pilo</code>	The lower limit for the estimated weights. If <code>pilo=NA</code> it is calculated according to the sample size to be the weight corresponding to the universal threshold $\sqrt{2 \log n}$ .
<code>prior</code>	Specification of prior to be used conditional on the mean being nonzero; can be <code>cauchy</code> or <code>laplace</code> .
<code>a</code>	Scale factor if Laplace prior is used. Ignored if Cauchy prior is used. If, on entry, <code>a=NA</code> and <code>prior="laplace"</code> , then the scale parameter will also be estimated by marginal maximum likelihood. If <code>a</code> is not specified then the default value 0.5 will be used.

**Details**

An exact algorithm is used, based on splitting the range up for zeta into subintervals over which no element of  $\text{zeta} * \text{cs}$  crosses either `pilo` or 1.

Within each of these subintervals, the log likelihood is concave and its maximum can be found to arbitrary accuracy; first the derivatives at each end of the interval are checked to see if there is an internal maximum at all, and if there is this can be found by a binary search for a zero of the derivative.

Finally, the maximum of all the local maxima over these subintervals is found.

**Value**

A list with the following elements:

<code>zeta</code>	The value of zeta that yields the marginal maximum likelihood.
<code>w</code>	The weights (prior probabilities of nonzero) yielded by this value of zeta.
<code>cs</code>	The factors as supplied to the program.
<code>pilo</code>	The lower bound on the weight, either as supplied or as calculated internally.

**Note**

Once the maximizing zeta and corresponding weights have been found, the thresholds can be found using the program [tfromw](#), and these can be used to process the original data using the routine [threshld](#).

**Author(s)**

Bernard Silverman

**References**

See [ebayesthresh](#) and <http://www.bernardsilverman.com>

**See Also**

[tfromw](#), [threshld](#), [wmonfromx](#), [wfromx](#)

# Index

## \* nonparametric

- beta.cauchy, [2](#)
  - beta.laplace, [3](#)
  - ebayesthresh, [4](#)
  - ebayesthresh.wavelet, [7](#)
  - postmean, [9](#)
  - postmed, [10](#)
  - tfromw, [11](#)
  - tfromx, [13](#)
  - threshld, [14](#)
  - wandafromx, [15](#)
  - wfromt, [16](#)
  - wfromx, [17](#)
  - wmonfromx, [18](#)
  - zetafromx, [19](#)
- beta.cauchy, [2](#), [3](#), [12](#)
- beta.laplace, [2](#), [3](#), [12](#)
- cauchy.medzero (postmed), [10](#)
- cauchy.threshzero (tfromw), [11](#)
- ebayesthresh, [2](#), [3](#), [4](#), [8–14](#), [16](#), [18–20](#)
- ebayesthresh.wavelet, [7](#)
- isotone, [18](#), [19](#)
- laplace.threshzero (tfromw), [11](#)
- negloglik.laplace (wandafromx), [15](#)
- optim, [15](#)
- postmean, [9](#), [11](#)
- postmed, [10](#), [10](#)
- tfromw, [11](#), [13](#), [16–18](#), [20](#)
- tfromx, [6](#), [12](#), [13](#), [18](#)
- threshld, [6](#), [14](#), [18](#), [20](#)
- vecbinsolv, [12](#)
- wandafromx, [12](#), [15](#), [17](#), [18](#)
- wfromt, [16](#), [18](#)
- wfromx, [12](#), [13](#), [16](#), [17](#), [19](#), [20](#)
- wmonfromx, [18](#), [20](#)
- zetafromx, [19](#)