Definitions of $\psi$-Functions Available in Robustbase

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Preamble

Unless otherwise stated, the following definitions of functions are given by Maronna et al. (2006, p. 31), however our definitions differ sometimes slightly from theirs, as we prefer a different way of standardizing the functions. To avoid confusion, we first define $\psi$- and $\rho$-functions.

Definition 1 A $\psi$-function is a piecewise continuous function $\psi : \mathbb{R} \to \mathbb{R}$ such that

1. $\psi$ is odd, i.e., $\psi(-x) = -\psi(x) \forall x$,

2. $\psi(x) \geq 0$ for $x \geq 0$, and $\psi(x) > 0$ for $0 < x < x_r := \sup\{\tilde{x} : \psi(\tilde{x}) > 0\}$ ($x_r > 0$, possibly $x_r = \infty$).

3* Its slope is 1 at 0, i.e., $\psi'(0) = 1$.

Note that ‘3*’ is not strictly required mathematically, but we use it for standardization in those cases where $\psi$ is continuous at 0. Then, it also follows (from 1.) that $\psi(0) = 0$, and we require $\psi(0) = 0$ also for the case where $\psi$ is discontinuous in 0, as it is, e.g., for the M-estimator defining the median.

Definition 2 A $\rho$-function can be represented by the following integral of a $\psi$-function,

$$\rho(x) = \int_0^x \psi(u)du,$$

which entails that $\rho(0) = 0$ and $\rho$ is an even function.

A $\psi$-function is called redescending if $\psi(x) = 0$ for all $x \geq x_r$ for $x_r < \infty$, and $x_r$ is often called rejection point. Corresponding to a redescending $\psi$-function, we define the function $\tilde{\rho}$, a version of $\rho$ standardized such as to attain maximum value one. Formally,

$$\tilde{\rho}(x) = \rho(x)/\rho(\infty).$$
Note that $\rho(\infty) = \rho(x_r) \equiv \rho(x) \forall |x| \geq x_r$. $\tilde{\rho}$ is a $\rho$-function as defined in Maronna et al. (2006) and has been called $\chi$ function in other contexts. For example, in package robustbase, \texttt{Mchi(x, *)} computes $\tilde{\rho}(x)$, whereas \texttt{Mpsi(x, *, deriv=-1)} ("(-1)-st derivative" is the primitive or antiderivative) computes $\rho(x)$, both according to the above definitions.

**Note:** An alternative slightly more general definition of redescending would only require $\rho(\infty) := \lim_{x \to \infty} \rho(x)$ to be finite. E.g., "Welsh" does not have a finite rejection point, but does have bounded $\rho$, and hence well defined $\rho(\infty)$, and we can use it in \texttt{lmrob}().

### Weakly redescending $\psi$ functions

Note that the above definition does require a finite rejection point $x_r$. Consequently, e.g., the score function $s(x) = -f'(x)/f(x)$ for the Cauchy ($= t_1$) distribution, which is $s(x) = 2x/(1 + x^2)$ and hence non-monotone and "re descends" to 0 for $x \to \pm \infty$, and $\psi_C(x) := s(x)/2$ also fulfills $\psi_C'(0) = 1$, but it has $x_r = \infty$ and hence $\psi_C$ is not a redescending $\psi$-function in our sense. As they appear e.g. in the MLE for $t_\nu$, we call $\psi$-functions fulfilling $\lim_{x \to \infty} \psi(x) = 0$ weakly redescending. Note that they’d naturally fall into two sub categories, namely the one with a finite $\rho$-limit, i.e. $\rho(\infty) := \lim_{x \to \infty} \rho(x)$, and those, as e.g., the $t_\nu$ score functions above, for which $\rho(x)$ is unbounded even though $\rho' = \psi$ tends to zero.

## 1 Monotone $\psi$-Functions

Montone $\psi$-functions lead to convex $\rho$-functions such that the corresponding M-estimators are defined uniquely.

Historically, the “Huber function” has been the first $\psi$-function, proposed by Peter Huber in Huber (1964).

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1 E-mail Oct. 18, 2014 to Manuel and Werner, proposing to change the definition of “redescending”. 
1.1 Huber

The family of Huber functions is defined as,

\[
\rho_k(x) = \begin{cases} 
\frac{1}{2}x^2 & \text{if } |x| \leq k \\
\frac{k(|x| - \frac{k}{2})}{k} & \text{if } |x| > k
\end{cases}
\]

\[
\psi_k(x) = \begin{cases} 
x & \text{if } |x| \leq k \\
k \text{ sign}(x) & \text{if } |x| > k
\end{cases}
\]

The constant \( k \) for 95% efficiency of the regression estimator is 1.345.

> plot(huberPsi, x., ylim=c(-1.4, 5), leg.loc="topright", main=FALSE)

![Figure 1: Huber family of functions using tuning parameter \( k = 1.345 \).](image)

2 Redescenders

For the MM-estimators and their generalizations available via `lmrob()` (and for some methods of `nlrob()`), the \( \psi \)-functions are all redescending, i.e., with finite “rejection point” \( x_r = \sup\{t; \psi(t) > 0\} < \infty \). From `lmrob`, the psi functions are available via `lmrob.control`, or more directly, `.Mpsi.tuning.defaults`.

> names(.Mpsi.tuning.defaults)

[1] "huber"  "bisquare"  "welsh"  "ggw"  "lqq"  "optimal"  "hampel"

and their \( \psi, \rho, \psi' \), and weight function \( w(x) := \psi(x)/x \), are all computed efficiently via C code, and are defined and visualized in the following subsections.
2.1 Bisquare

Tukey’s bisquare (aka “biweight”) family of functions is defined as,

\[
\hat{\rho}_k(x) = \begin{cases} 
1 - \left(1 - \left(\frac{x}{k}\right)^2\right)^3 & \text{if } |x| \leq k \\
1 & \text{if } |x| > k
\end{cases},
\]

with derivative \(\hat{\rho}'_k(x) = 6\psi_k(x)/k^2\) where,

\[
\psi_k(x) = x \left(1 - \left(\frac{x}{k}\right)^2\right)^2 \cdot I_{\{\|x\| \leq k\}}.
\]

The constant \(k\) for 95% efficiency of the regression estimator is 4.685 and the constant for a breakdown point of 0.5 of the S-estimator is 1.548. Note that the exact default tuning constants for M- and MM- estimation in robustbase are available via `.Mpsi.tuning.default()` and `.Mchi.tuning.default()`, respectively, e.g., here,

```r
> print(c(k.M = .Mpsi.tuning.default("bisquare"),
+       k.S = .Mchi.tuning.default("bisquare")), digits = 10)

k.M  k.S
4.685061 1.547640
```

and that the p.psiFun(.) utility is available via

```r
> source(system.file("xtraR/plot-psiFun.R", package = "robustbase", mustWork=TRUE))
> p.psiFun(x., "biweight", par = 4.685)
```

Figure 2: Bisquare family functions using tuning parameter \(k = 4.685\).
2.2 Hampel

The Hampel family of functions (Hampel et al., 1986) is defined as,

\[
\tilde{\rho}_{a,b,r}(x) = \begin{cases} \\
\frac{1}{2}x^2/C & |x| \leq a \\
\left(\frac{1}{2}a^2 + a(|x| - a)\right) / C & a < |x| \leq b \\
\frac{a}{2} \left(2b - a + (|x| - b) \left(1 + \frac{r-|x|}{r-b}\right)\right) / C & b < |x| \leq r \\
1 & r < |x| \\
\end{cases}
\]

\[
\psi_{a,b,r}(x) = \begin{cases} \\
x & |x| \leq a \\
a \text{sign}(x) & a < |x| \leq b \\
a \text{sign}(x) \frac{r-|x|}{r-b} & b < |x| \leq r \\
0 & r < |x| \\
\end{cases}
\]

where \( C := \rho(\infty) = \rho(r) = \frac{a}{2} \left(2b - a + (r - b)\right) = \frac{a}{2} (b - a + r) \).

As per our standardization, \( \psi \) has slope 1 in the center. The slope of the redescending part \((x \in [b, r])\) is \(-a/(r - b)\). If it is set to \(-\frac{1}{2}\), as recommended sometimes, one has

\[
r = 2a + b.
\]

Here however, we restrict ourselves to \(a = 1.5k, b = 3.5k,\) and \(r = 8k\), hence a redescending slope of \(-\frac{1}{3}\), and vary \(k\) to get the desired efficiency or breakdown point.

The constant \(k\) for 95% efficiency of the regression estimator is 0.902 (0.9016085, to be exact) and the one for a breakdown point of 0.5 of the S-estimator is 0.212 (i.e., 0.2119163).

![Image of Hampel family of functions](image.png)

**Figure 3:** Hampel family of functions using tuning parameters 0.902 · (1.5, 3.5, 8).
2.3 GGW

The Generalized Gauss-Weight function, or \textit{ggw} for short, is a generalization of the Welsh \( \psi \)-function (subsection 2.6). In Koller and Stahel (2011) it is defined as,

\[
\psi_{a,b,c}(x) = \begin{cases} 
  x & |x| \leq c \\
  \exp\left(-\frac{1}{2}\frac{(|x|-c)^b}{a}\right) x & |x| > c 
\end{cases}
\]

Our constants, fixing \( b = 1.5 \), and minimal slope at \(-\frac{1}{2}\), for 95% efficiency of the regression estimator are \( a = 1.387 \), \( b = 1.5 \) and \( c = 1.063 \), and those for a breakdown point of 0.5 of the S-estimator are \( a = 0.204 \), \( b = 1.5 \) and \( c = 0.296 \):

```r
> cT <- rbind(cc1 = psi.ggw.findc(ms = -0.5, b = 1.5, eff = 0.95),
+ cc2 = psi.ggw.findc(ms = -0.5, b = 1.5, bp = 0.50)); cT

cc1 0 1.3863620 1.5 1.0628199 4.7773893
cc2 0 0.2036739 1.5 0.2959131 0.3703396
```

Note that above, \( cc[1] = 0 \), \( cc[5] = \rho(\infty) \), and \( cc[2:4] = (a, b, c) \). To get this from \( (a, b, c) \), you could use

```r
> ipsi.ggw <- psi2ipsi("GGW") # = 5
> ccc <- c(0, cT[,2:4], 1)
> integrate(.Mpsi, 0, Inf, ccc=ccc, ipsi=ipsi.ggw)$value # = rho(Inf)

[1] 4.777389
```

```r
> p.psiFun(x, "GGW", par = c(-.5, 1, .95, NA))
```

---

**Figure 4:** GGW family of functions using tuning parameters \( a = 1.387 \), \( b = 1.5 \) and \( c = 1.063 \).
2.4 LQQ

The “linear quadratic quadratic” $\psi$-function, or lqq for short, was proposed by Koller and Stahel (2011). It is defined as,

$$\psi_{b,c,s}(x) = \begin{cases} 
x & |x| \leq c \\
\text{sign}(x) \left( |x| - \frac{s}{2b} (|x| - c)^2 \right) & c < |x| \leq b + c \\
\text{sign}(x) \left( c + b - \frac{bs}{x} + \frac{x}{2} (\frac{x^2}{2} - ax) \right) & b + c < |x| \leq a + b + c \\
0 & \text{otherwise}, \end{cases}$$

where

$$\tilde{x} := |x| - b - c \quad \text{and} \quad a := \frac{2c + 2b - bs}{s - 1}. \quad (3)$$

The parameter $c$ determines the width of the central identity part. The sharpness of the bend is adjusted by $b$ while the maximal rate of descent is controlled by $s$ ($s = 1 - \min_x \psi'(x) > 1$). From (3), the length $a$ of the final descent to 0 is a function of $b$, $c$ and $s$.

If the minimal slope is set to $-\frac{1}{2}$, i.e., $s = 1.5$, and $b/c = 3/2 = 1.5$, the constants for 95% efficiency of the regression estimator are $b = 1.473$, $c = 0.982$ and $s = 1.5$, and those for a breakdown point of 0.5 of the S-estimator are $b = 0.402$, $c = 0.268$ and $s = 1.5$.

> cT <- rbind(cc1 = .psi.lqq.findc(ms= -0.5, b.c = 1.5, eff=0.95, bp=NA ),
+ cc2 = .psi.lqq.findc(ms= -0.5, b.c = 1.5, eff=NA , bp=0.50))
> colnames(cT) <- c("b", "c", "s"); cT

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>b</td>
<td>c</td>
<td>s</td>
</tr>
<tr>
<td>cc1</td>
<td>1.4734061</td>
<td>0.9822707</td>
</tr>
<tr>
<td>cc2</td>
<td>0.4015457</td>
<td>0.2678971</td>
</tr>
</tbody>
</table>

Figure 5: LQQ family of functions using tuning parameters $b = 1.473$, $c = 0.982$ and $s = 1.5$. 
2.5 Optimal

The optimal ψ function as given by Maronna et al. (2006, Section 5.9.1),

\[ \psi_c(x) = \text{sign}(x) \left( -\frac{\varphi'(|x|) + c}{\varphi(|x|)} \right)_+ , \]

where \( \varphi \) is the standard normal density, \( c \) is a constant and \( t_+ := \max(t, 0) \) denotes the positive part of \( t \).

Note that the robustbase implementation uses rational approximations originating from the robust package’s implementation. That approximation also avoids an anomaly for small \( x \) and has a very different meaning of \( c \).

The constant for 95% efficiency of the regression estimator is 1.060 and the constant for a breakdown point of 0.5 of the S-estimator is 0.405.

Figure 6: ‘Optimal’ family of functions using tuning parameter \( c = 1.06 \).
2.6 Welsh

The Welsh $\psi$ function is defined as,

\[
\tilde{\rho}_k(x) = 1 - \exp\left(-\left(\frac{x}{k}\right)^2/2\right)
\]
\[
\psi_k(x) = k^2 \tilde{\rho}_k'(x) = x \exp\left(-\left(\frac{x}{k}\right)^2/2\right)
\]
\[
\psi'_k(x) = (1 - \left(\frac{x}{k}\right)^2) \exp(-\left(\frac{x}{k}\right)^2/2)
\]

The constant $k$ for 95% efficiency of the regression estimator is 2.11 and the constant for a breakdown point of 0.5 of the S-estimator is 0.577.

Note that GGW (subsection 2.3) is a 3-parameter generalization of Welsh, matching for $b = 2$, $c = 0$, and $a = k^2$ (see R code there):

```r
> ccc <- c(0, a = 2.11^2, b = 2, c = 0, 1)
> (ccc[5] <- integrate(.Mpsi, 0, Inf, ccc=ccc, ipsi = 5)$value) # = rho(Inf)
[1] 4.4521
> stopifnot(all.equal(Mpsi(x., ccc, "GGW"), ## psi[ GGW ](x; a=k^2, b=2, c=0) ==
+ Mpsi(x., 2.11, "Welsh")))## psi[Welsh](x; k)
```

Figure 7: Welsh family of functions using tuning parameter $k = 2.11$.

References


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