

Flexible Regression and Smoothing

The `gamlss.family` Distributions

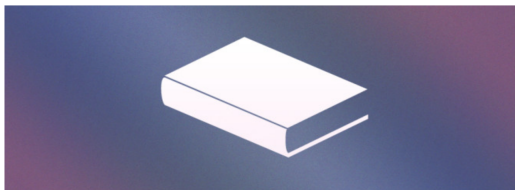
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Information

Books & Vignettes



The GAMLSS Books

One book on GAMLSS is published and two others are in preparation

- * `'Flexible Regression and Smoothing: Using GAMLSS in R'` was published in April 2017. See [here](#) for an old [draft version](#).
- * `'Distributions for Location Scale and Shape: Using GAMLSS in R'`, is in preparation. See [here](#) for the November 2017 [draft version](#) of the book.
- * `'Generalised Additive Models for Location Scale and Shape: A Distributional Regression Approach'` is in preparation. A draft version will appear in the summer 2018.

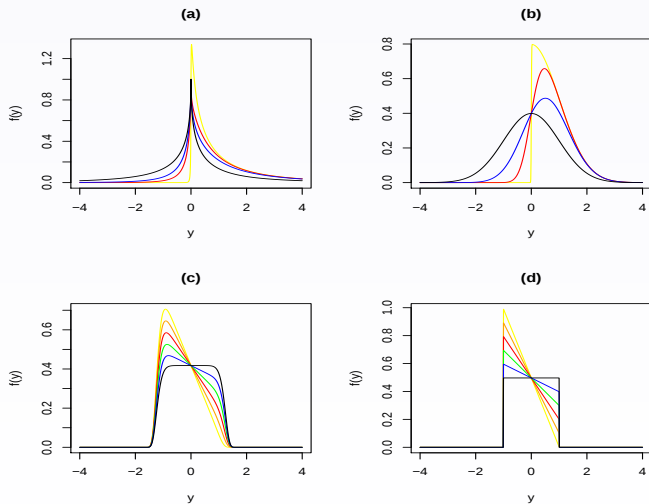
Different types of distribution in GAMLSS

- ① *continuous distributions*: $f_Y(y|\theta)$, are usually defined on $(-\infty, +\infty)$, $(0, +\infty)$ or $(0, 1)$.
- ② *discrete distributions*: $P(Y = y|\theta)$ are defined on $y = 0, 1, 2, \dots, n$, where n is a known finite value or n is infinite, i.e. usually discrete (count) values.
- ③ *mixed distributions*: (finite mixture distributions) are mixtures of continuous and discrete distributions, i.e. continuous distributions where the range of Y has been expanded to include some discrete values with non-zero probabilities.

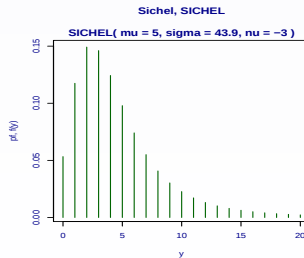
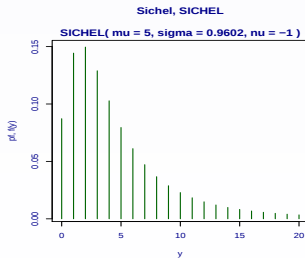
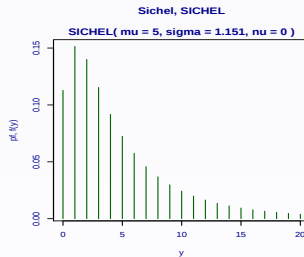
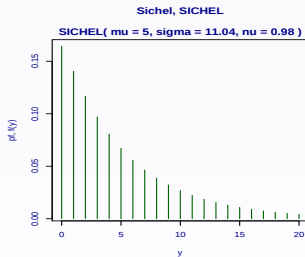
Different types of distribution: demos

- 1 demo.GA()
- 2 demo.PO()
- 3 demo.BI()
- 4 demo.BE()
- 5 demo.BEINF()

Example of continuous distribution: SEP1

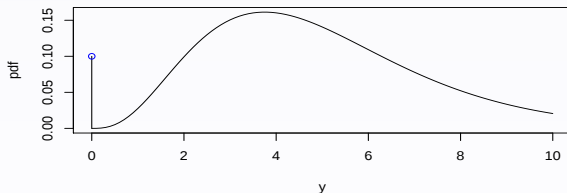


Example of discrete distribution: Sichel

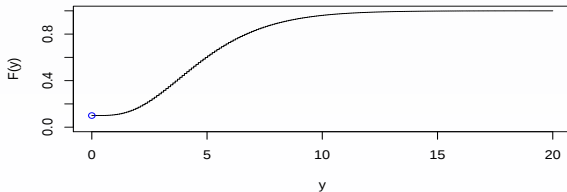


Example of mixed distribution distributions: ZAGA

Zero adjusted GA



Zero adjusted Gamma c.d.f.



Skewness and kurtosis

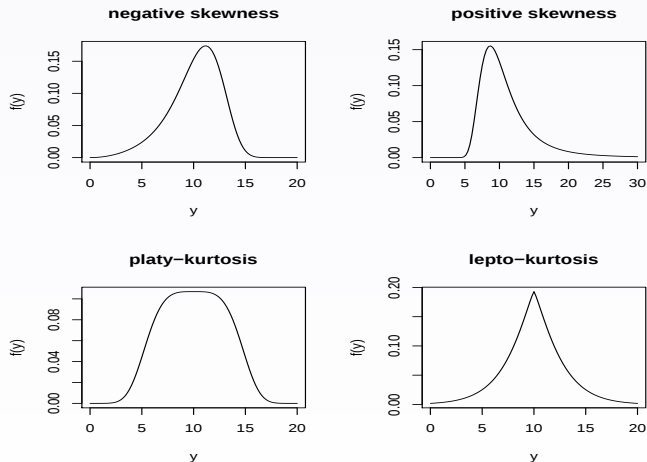


Figure: Showing different types of continuous distributions  gamlss

Types of continuous distributions

$(-\infty, \infty)$: real line $\mathbb{R}$

$(0, \infty)$: positive real line $\mathbb{R}^+$

$(0, 1)$ real line on interval $\mathbb{R}_{(0,1)}$ (not containing zero or one)

Location and scale family

For these distributions, if

$$Y \sim \mathcal{D}(\mu, \sigma, \nu, \tau)$$

then

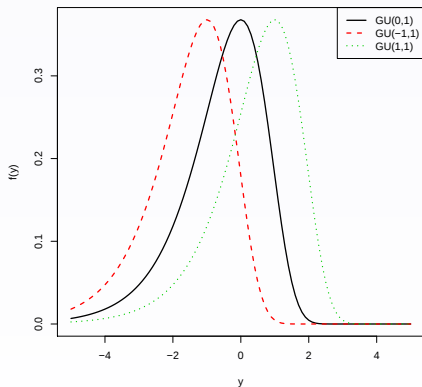
$$\varepsilon = (Y - \mu)/\sigma \sim \mathcal{D}(0, 1, \nu, \tau),$$

i.e. $Y = \mu + \sigma\varepsilon$, so Y is a scaled and shifted version of the random variable ε .

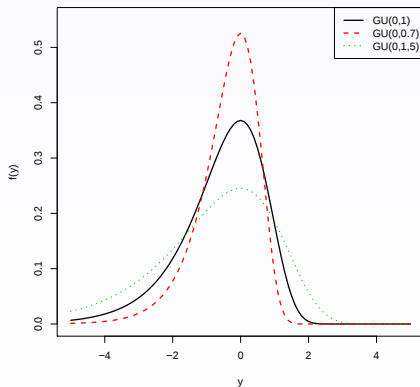
All $(-\infty, \infty)$ distributions in GAMLSS except `exGAUS`(μ, σ, τ) are *location-scale* families

Location-scale family

(a) changing the location parameter



(b) changing the scale parameter



Two parameter on $\mathcal{R}$

Two parameter distributions on $(-\infty, \infty)$

Gumbel $GU(\mu, \sigma)$ left skew

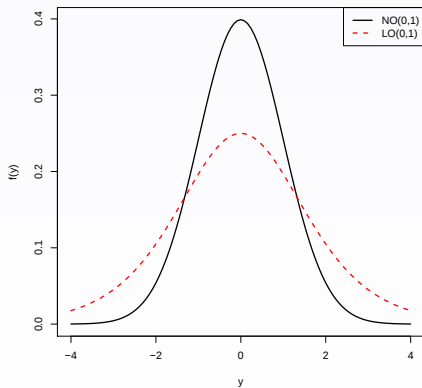
Logistic $LO(\mu, \sigma)$ leptokurtic

Normal $NO(\mu, \sigma)$ and $NO2(\mu, \sigma)$

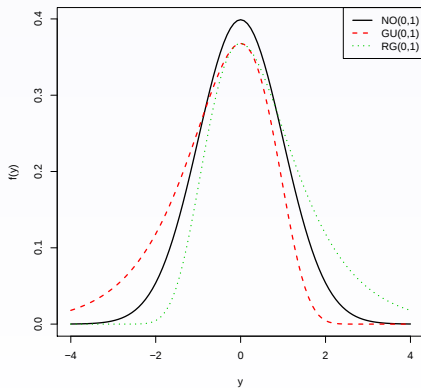
Reverse Gumbel $RG(\mu, \sigma)$ right skew

Two parameter on $\mathcal{R}$

(a) NO and LO distributions



(b) NO, GU, and RG distributions



Three parameter on $\mathfrak{R}$

exponential Gaussian : $\text{exGAUS}(\mu, \sigma, \nu)$ for modelling right skew data,

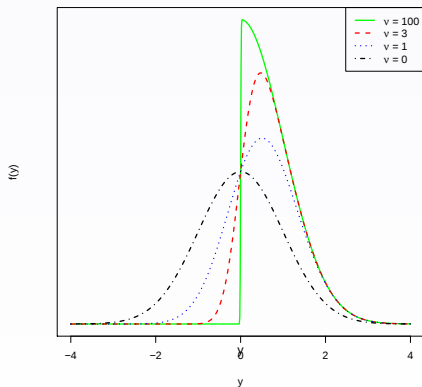
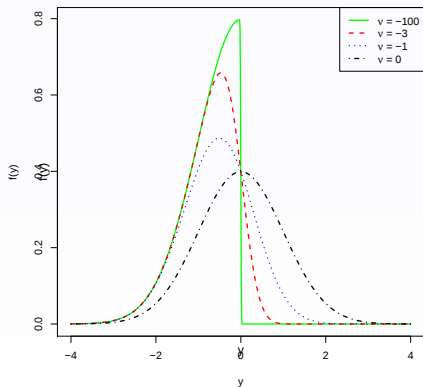
normal family: $\text{NOF}(\mu, \sigma, \nu)$ for modelling mean and variance relationships following the power law;

power exponential: $\text{PE}(\mu, \sigma, \nu)$ and $\text{PE2}(\mu, \sigma, \nu)$ for modelling leptokurtotic and platykurtotic data;

t family: $\text{TF}(\mu, \sigma, \nu)$ and $\text{TF2}(\mu, \sigma, \nu)$ for modelling leptokurtotic data;

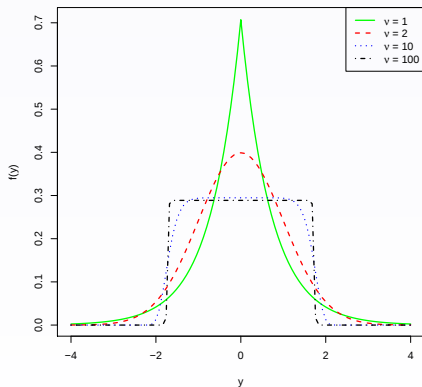
skew normal: $\text{SN1}(\mu, \sigma, \nu)$ and $\text{SK2}(\mu, \sigma, \nu)$ for modelling skewness in data.

Three parameter on $\mathfrak{R}$: skew normal type 1

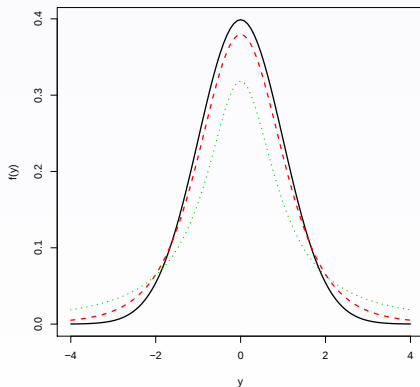


Three parameter on $\mathfrak{R}$: PE and TF distributions

(a) power exponential



(b) the t-family



Four parameter on $\mathfrak{R}$

exponential generalised beta type 2: $\text{EGB2}(\mu, \sigma, \nu, \tau)$ skewness and leptokurtosis;

generalised t : $\text{GT}(\mu, \sigma, \nu, \tau)$ kurtosis;

Johnson's SU: $\text{JSU}(\mu, \sigma, \nu, \tau)$ and $\text{JSUo}(\mu, \sigma, \nu, \tau)$ skewness and leptokurtosis;

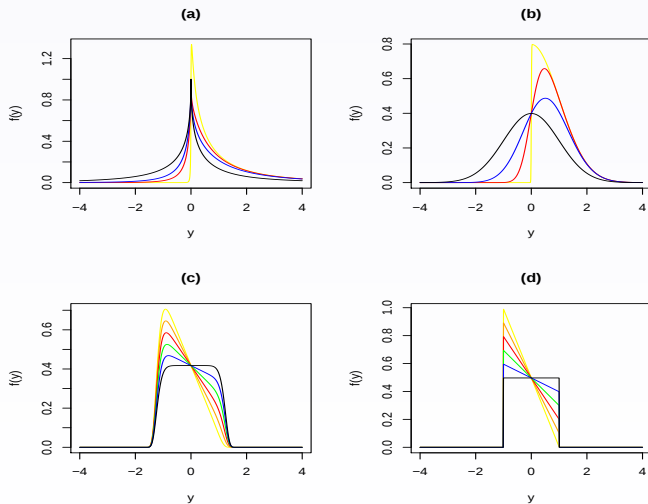
normal-exponential- t : $\text{NET}(\mu, \sigma, \nu, \tau)$, robustly location and scale;

skew exponential power: $\text{SEP1}(\mu, \sigma, \nu, \tau)$, $\text{SEP2}(\mu, \sigma, \nu, \tau)$, $\text{SEP3}(\mu, \sigma, \nu, \tau)$ and $\text{SEP4}(\mu, \sigma, \nu, \tau)$ skewness and leptokurtosis;

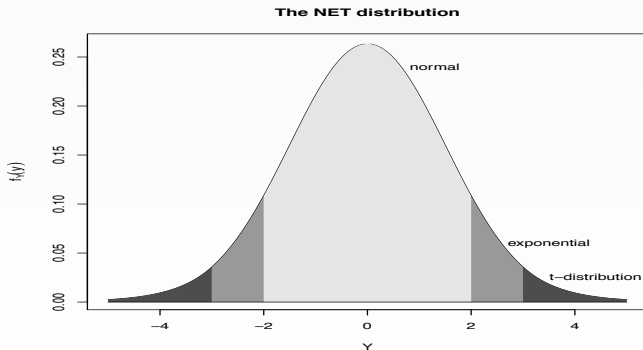
sinh-arcsinh: $\text{SHASH}(\mu, \sigma, \nu, \tau)$, $\text{SHASHo}(\mu, \sigma, \nu, \tau)$ and $\text{SHASHo2}(\mu, \sigma, \nu, \tau)$ skewness and leptokurtosis;

skew t : $\text{ST1}(\mu, \sigma, \nu, \tau)$, $\text{ST2}(\mu, \sigma, \nu, \tau)$, $\text{ST3}(\mu, \sigma, \nu, \tau)$, $\text{ST4}(\mu, \sigma, \nu, \tau)$, $\text{ST5}(\mu, \sigma, \nu, \tau)$ and $\text{SST}(\mu, \sigma, \nu, \tau)$ skewness and leptokurtosis.

Example of four parameter on $\mathcal{R}$: SEP1



The NET distribution



Summary of GAMLSS family distributions defined on $(-\infty, +\infty)$

Distributions	family	no par.	skewness	kurtosis
Exp. Gaussian	exGAUS	3	positive	-
Exp.G. beta 2	EGB2	4	both	lepto
Gen. t	GT	4	(symmetric)	lepto
Gumbel	GU	2	(negative)	-
Johnson's SU	JSU, JSUo	4	both	lepto
Logistic	LO	2	(symmetric)	(lepto)
Normal-Expon.- t	NET	2,(2)	(symmetric)	lepto
Normal	NO-NO2	2	(symmetric)	
Normal Family	NOF	3	(symmetric)	(meso)

Summary of GAMLSS family distributions defined on $(-\infty, +\infty)$

Power Expon.	PE-PE2	3	(symmetric)	both
Reverse Gumbel	RG	2	positive	
Sinh Arcsinh	SHASH,	4	both	both
Skew Exp. Power	SEP1-SEP4	4	both	both
Skew t	ST1-ST5, SST	4	both	lepto
t Family	TF	3	(symmetric)	lepto

Continuous distribution on $\mathfrak{R}^+$: scale family

If a random variable is distributed as

$$Y \sim \mathcal{D}(\mu, \sigma, \nu, \tau)$$

and

$$\varepsilon = (Y/\mu) \sim \mathcal{D}(1, \sigma, \nu, \tau)$$

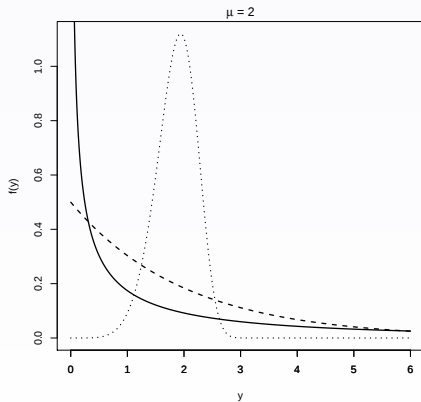
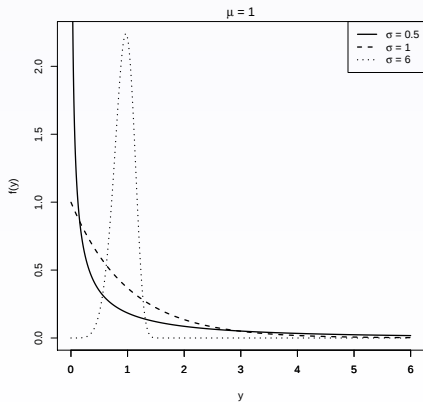
then Y has a scale family and the random variable

$$Y = \mu\varepsilon$$

is a scaled version of the random variable ε .

μ does not effect the shape.

Continuous distribution on $\mathbb{R}^+$: Weibull pdf



Continuous distribution on $\mathbb{R}^+$: one and two parameters

exponential $\text{EXP}(\mu, \sigma)$

gamma: $\text{GA}(\mu, \sigma)$ member of the exponential family;

inverse gamma: $\text{IGAMMA}(\mu, \sigma)$;

inverse Gaussian: $\text{IG}(\mu, \sigma)$ a member of the exponential family;

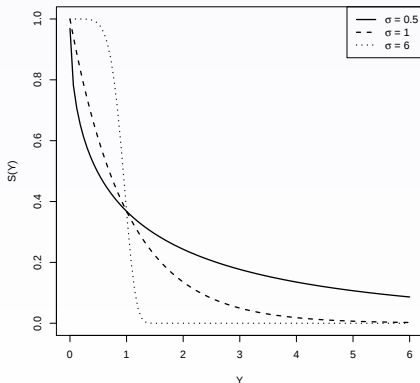
log-normal: $\text{LOGNO}(\mu, \sigma)$ and $\text{LOGNO2}(\mu, \sigma)$.

Pareto: $\text{PARETO}(\mu, \sigma)$, $\text{PARETO2o}(\mu, \sigma)$ and $\text{GP}(\mu, \sigma)$ for heavy tail;

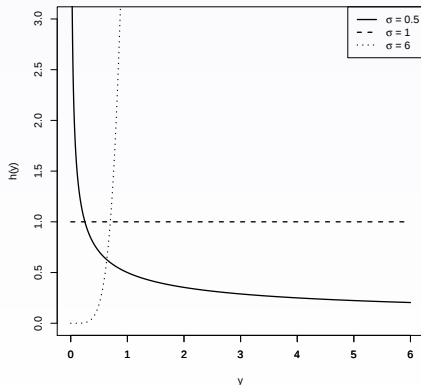
Weibull: $\text{WEI}(\mu, \sigma)$, $\text{WEI2}(\mu, \sigma)$ and $\text{WEI3}(\mu, \sigma)$ used in survival analysis.

Continuous distribution on $\mathbb{R}^+$: Weibull survival and hazard functions

(a) survival function



(b) hazard function



Continuous distribution on $\mathbb{R}^+$: three parameters

Box-Cox Cole and Green $\text{BCCG}(\mu, \sigma, \nu)$ known also as the LMS method in centile estimation.

generalised gamma $\text{GG}(\mu, \sigma, \nu)$

generalised inverse Gaussian $\text{GIG}(\mu, \sigma, \nu)$

log-normal family $\text{LNO}(\mu, \sigma, \nu)$ based on the standard Box-Cox transformation

$$Z = \begin{cases} \frac{(Y^\nu - 1)}{\nu} & \text{if } \nu \neq 0 \\ \log(Y) & \text{if } \nu = 0 \end{cases} \quad (1)$$

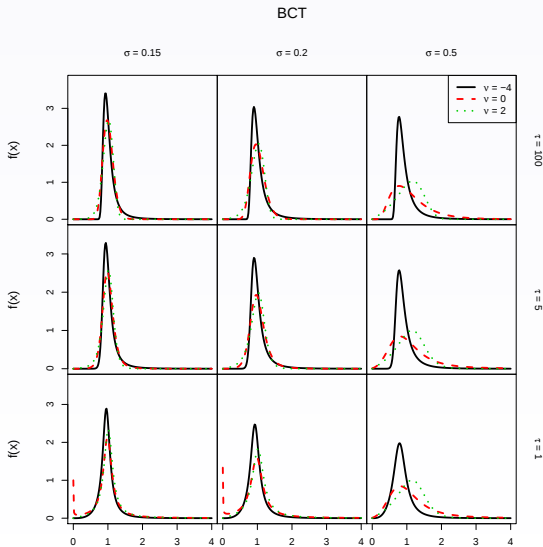
Continuous distribution on $\mathfrak{R}^+$: four parameters

Box-Cox power exponential BCPE(μ, σ, ν, τ) and BCPEo(μ, σ, ν, τ)
skewness and platy-lepto;

Box-Cox t BCT(μ, σ, ν, τ) and BCTo(μ, σ, ν, τ) skewness and
leptokurtosis;

generalised beta type 2 GB2(μ, σ, ν, τ) skewness and platy-lepto.

Continuous distribution on $\mathcal{R}^+$: four parameters, BCT



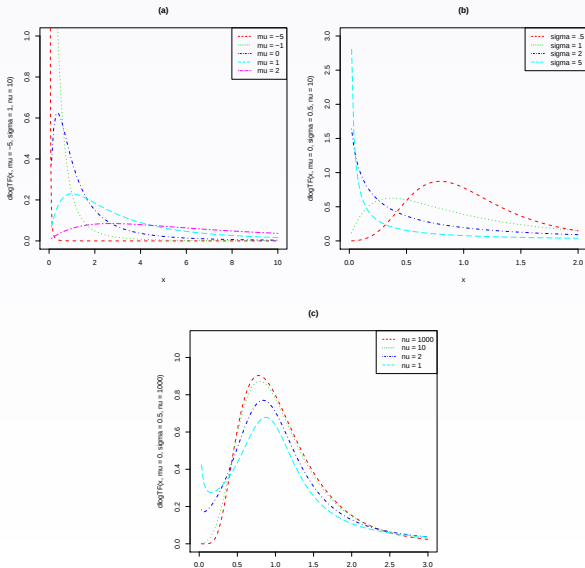
Continuous GAMLSS family distributions defined on $(0, +\infty)$

Distributions	family	no par.	skewness	kurtosis
BCCG	BCCG	3	both	
BCPE	BCPE	4	both	both
BCT	BCT	4	both	lepto
Exponential	EXP	1	(positive)	-
Gamma	GA	2	(positive)	-
Gen. Beta type 2	GB2	4	both	both
Gen. Gamma	GG-GG2	3	positive	-
Gen. Inv. Gaussian	GIG	3	positive	-
Inv. Gaussian	IG	2	(positive)	-
Log Normal	LOGNO	2	(positive)	-
Log Normal family	LNO	2,(1)	positive	
Reverse Gen. Extreme	RGE	3	positive	-
Weibull	WEI-WEI3	2	(positive)	-

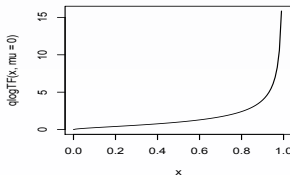
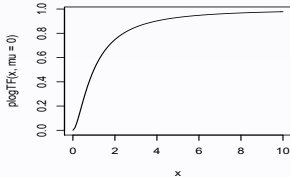
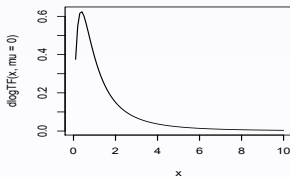
Transformation from $(-\infty, \infty)$ to $(0, +\infty)$

- Any distribution for Z on $(-\infty, \infty)$ can be transformed to a corresponding distribution for $Y = \exp(Z)$ on $(0, +\infty)$
- For example: from t distribution to $\log t$ distribution
- `gen.Family("TF", type="log")`

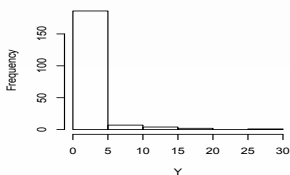
Positive response: log T distribution



Positive response: log T distribution



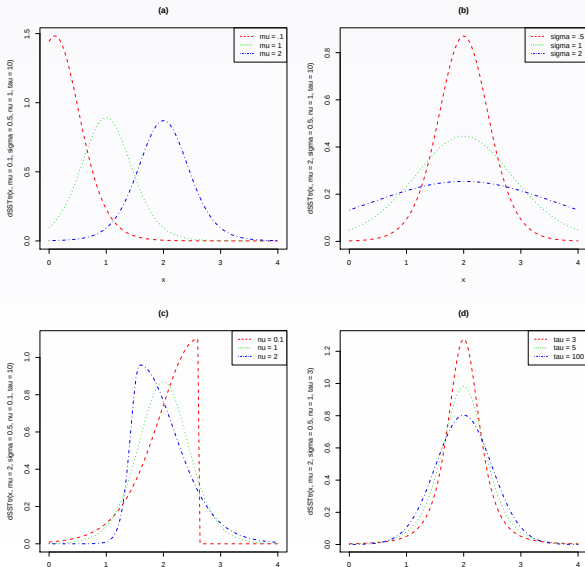
Histogram of Y



Truncating from $(-\infty, \infty)$ to $(0, +\infty)$

- Any distribution for Z on $(-\infty, \infty)$ can be truncated to a corresponding distribution for Y on $(0, +\infty)$
- For example: from $\text{SST}(\mu, \sigma, \nu, \tau)$ distribution to $\text{flipped-SST}(\mu, \sigma, \nu, \tau)$ distribution
- `gen.trun(0, "SST", type="left")`

Truncating from $(-\infty, \infty)$ to $(0, +\infty)$



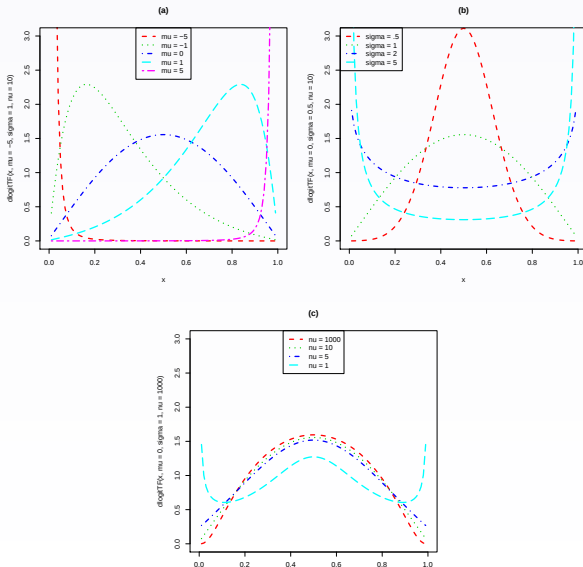
Continuous GAMLSS family distributions defined on $(0, 1)$

Distributions	family	no par.	skewness	kurtosis
Beta	BE	2	(both)	-
Beta original	BEo	2	(both)	-
Logit normal	LOGITNO	2	(both)	-
Generalized beta type 1	GB1	4	(both)	(both)

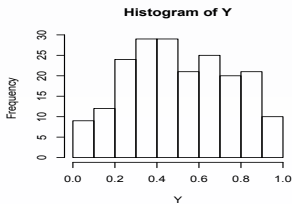
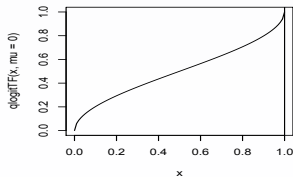
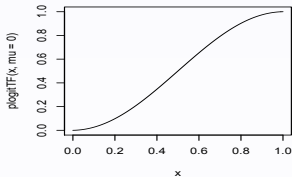
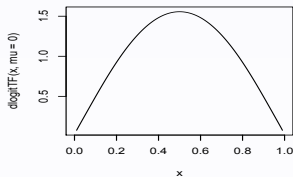
Transformation from $(-\infty, \infty)$ to $(0, 1)$

- Any distribution for Z on $(-\infty, \infty)$ can be transformed to a corresponding distribution for $Y = \frac{1}{1+e^{-Z}}$ on $(0, 1)$
- For example: from t distribution to *logit* t distribution
- `gen.Family("TF", "logit")`

logit T distribution

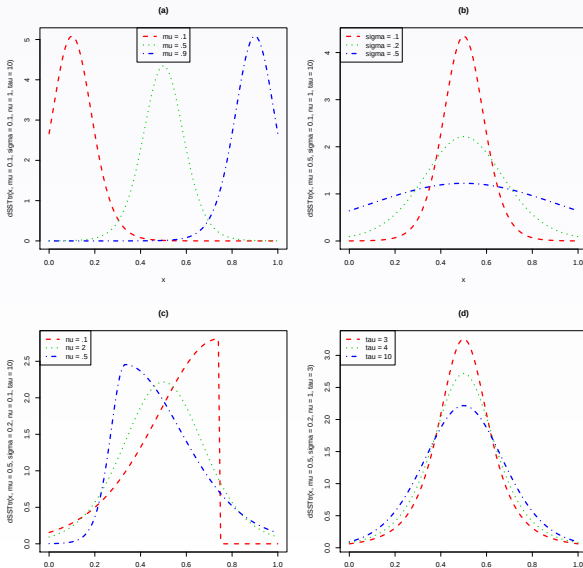


logit T distribution



Truncating from $(-\infty, \infty)$ to $(0, 1)$

- Any distribution for Z on $(-\infty, \infty)$ can be truncated to a corresponding distribution for Y on $(0, 1)$
- For example: from $\text{SST}(\mu, \sigma, \nu, \tau)$ distribution to $\text{trun-SST}(\mu, \sigma, \nu, \tau)$ distribution
- `gen.trun(c(0,1), "SST", type="both")`

Truncated SST on $(0, 1)$ 

Summary of methods of generating distributions

- ① univariate transformation from a single random variable (LOGNO, BCCG, BCPE, BCT, EGB2, SHASHo, inverse log and logic transformations ...)
- ② transformation from two or more random variables (TF, ST2, exGAUS)
- ③ truncation distributions
- ④ a (continuous or finite) mixture of distributions (TF, GT, GB2, EGB2)
- ⑤ Azzalini type methods (SN1, SEP1, SEP2, ST1, ST2)
- ⑥ splicing distributions (SN2, SEP3, SEP4, ST3, ST4, NET)
- ⑦ stopped sums
- ⑧ systems of distributions

Comparison of properties of distributions

- 1 Explicit pdf cdf and inverse cdf
- 2 Explicit centiles and centile based measures (e.g median)
- 3 Explicit moment based measures (e.g. mean)
- 4 Explicit mode(s)
- 5 Continuity of the pdf and its derivatives with respect to y
- 6 Continuity of the pdf with respect to μ , σ , ν and τ
- 7 Flexibility in modelling skewness and kurtosis
- 8 Range of Y

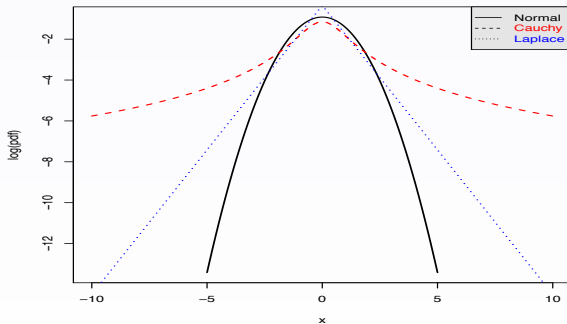
Theoretical comparison of distributions

- OK we have a lot of distributions in GAMLSS.
Do we need any more?
- Do we need all of them or some of them are redundant?

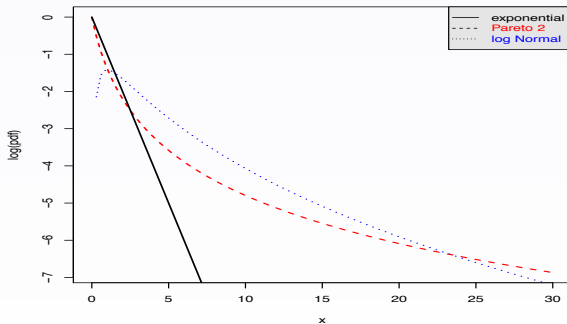
Is there any way to compare them theoretically?

- We can compare the **tail** behaviour in of the distributions
- Since most of then are location-scale we can compare their flexibility in terms of **skewness and kurtosis**

Comparing tails: real line



Comparing tails: positive real line



Types of tails

There are three main forms for $\log f_Y(y)$ for a tail of Y

Type I: $-k_2 (\log |y|)^{k_1},$

Type II: $-k_4 |y|^{k_3},$

Type III: $-k_6 e^{k_5 |y|},$

decreasing k 's results in a heavier tail,

Types of tails: classification (real line)

Value of k_1-k_6	Distribution name	Distribution
$k_1 = 1$	Cauchy	CA(μ, σ)
	Generalized t	GT(μ, σ, ν, τ)
	Skew t type 3	ST3(μ, σ, ν, τ)
	Skew t type 4	ST4(μ, σ, ν, τ)
	Stable t	SB(μ, σ, ν, τ) TF(μ, σ, ν)
$k_1 = 2$	Johnson's SU	JSU(μ, σ, ν, τ)
	Johnson's SU original	JSUo(μ, σ, ν, τ)
$0 < k_3 < \infty$	Power exponential	PE(μ, σ, ν)
	Power exponential type 2	PE2(μ, σ, ν)
	Sinh-arcsinh original	SHASHo(μ, σ, ν, τ)
	Sinh-arcsinh	SHASH(μ, σ, ν, τ)
	Skew exponential power type 3	SEP3(μ, σ, ν, τ)
	Skew exponential power type 4	SEP4(μ, σ, ν, τ)
$k_3 = 1$	Exponential generalized beta type 2	EGB2(μ, σ, ν, τ)
	Gumbel	GU(μ, σ)
	Laplace	LA(μ, σ)
	Logistic	LG(μ, σ)
	Reverse Gumbel	RG(μ, σ)
$k_3 = 2$	Normal	NO(μ, σ)
$0 < k_5 < \infty$	Gumbel	GU(μ, σ)
	Reverse Gumbel	RG(μ, σ)

Types of tails: classification (positive real line)

Value of k_1-k_6	Distribution name	Distribution
$k_1 = 1$	Box-Cox Cole-Green	BCCG(μ, σ, ν)
	Box-Cox power exponential	BCPE(μ, σ, ν, τ)
	Box-Cox t	BCT(μ, σ, ν, τ)
	Generalized beta type 2	GB2(μ, σ, ν, τ)
	Generalized gamma	GG(μ, σ, ν)
	Inverse gamma	IGA(μ, σ)
	log t	LOGT(μ, σ, ν)
$k_1 = 2$	Pareto Type 2	PA2o(μ, σ)
	Box-Cox Cole-Green	BCCG(μ, σ, ν)
	Lognormal	LOGNO(μ, σ)
	Log Weibull	LOGWEI(μ, σ)
$1 \leq k_1 < \infty$	Box-Cox power exponential	BCPE(μ, σ, ν, τ)
$0 < k_3 < \infty$	Box-Cox Cole-Green	BCCG(μ, σ, ν)
	Box-Cox power exponential	BCPE(μ, σ, ν, τ)
	Generalized gamma	GG(μ, σ, ν)
	Weibull	WEI(μ, σ)
$k_3 = 1$	Exponential	EX(μ)
	Gamma	GA(μ, σ)
	Generalized inverse Gaussian	GIG(μ, σ, ν)
	Inverse Gaussian	IG(μ, σ)

How to fit distributions in R

`optim()` or `mle()` requires initial parameter values

`gamlssML()` mle a using variation of the `mle()` function

`gamlss()`: mle using RS or CG or mixed algorithms,

`histDist()` mle using RS or CG or mixed algorithms, for a univariate sample only, and plots a histogram of the data with the fitted distribution

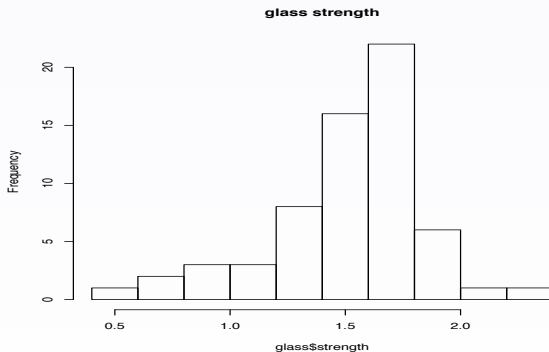
`fitDist()` fits a set of distributions and chooses the one with the smallest GAIC

Strength of glass fibres data

Data summary:

- R data file:** glass in package `gamlss.data` of dimensions 63×1
 - source:** Smith and Naylor (1987)
 - strength:** the strength of glass fibres (the unit of measurement are not given).
 - purpose:** to demonstrate the fitting of a parametric distribution to the data.
- conclusion:** a SEP4 distribution fits adequately

Strength of glass fibres data: SBC



Strength of glass fibres data: creating truncated distribution

```
data(glass)
library(gamlss.tr)
gen.trun(par = 0, family = TF)
```

A truncated family of distributions from TF
has been generated
and saved under the names:
dTFtr pTFtr qTFtr rTFtr TFtr

The type of truncation is left and the
truncation parameter is 0

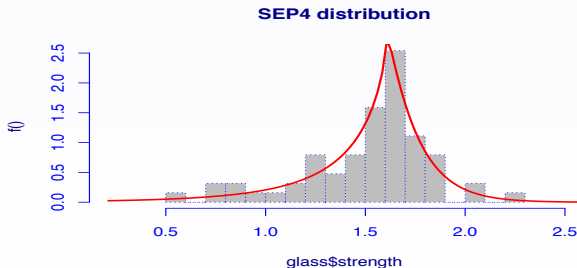
Strength of glass fibres data: fitting the models

```
> m1<-fitDist(strength, data=glass, k=2, extra="TFtr")
# AIC
> m2<-fitDist(strength, data=glass, k=log(length(strength)),
extra="TFtr") # SBC
> m1$fit[1:8]
SEP4 SEP3 SHASHo EGB2 JSU BCPEo ST2 BCTo
27.68790 27.98191 28.01800 28.38691 30.41380 31.17693 31.40101 31.47677
> m2$fit[1:8]
SEP4 SEP3 SHASHo EGB2 GU WEI3 JSU PE
36.26044 36.55444 36.59054 36.95945 38.19839 38.69995 38.98634 39.00792
```

Strength of glass fibres data: Results

```
histDist(glass$strength, SEP4, nbins = 13,  
  main = "SEP4 distribution",  
  method = mixed(20, 50))
```

Strength of glass fibres data: SBC



Strength of glass fibres data: summary

```
Call:  gamlss(formula = y~1, family = FA)
```

```
Mu Coefficients:
```

```
(Intercept)
```

```
1.581
```

```
Sigma Coefficients:
```

```
(Intercept)
```

```
-1.437
```

```
Nu Coefficients:
```

```
(Intercept)
```

```
-0.1280
```

```
Tau Coefficients:
```

```
(Intercept)
```

```
0.3183
```

```
Degrees of Freedom for the fit: 4 Residual Deg. of Freedom 59
```

```
Global Deviance: 19.8111
```

```
AIC: 27.8111
```

```
SBC: 36.3836
```

END

for more information see

www.gamlss.org