Software for Distributions in R

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Outline



2 Distributions in Base R

3 Design for Distribution Implementation

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Distributions

- Distributions are how we model uncertainty
- There is well-established theory concerning distributions
- There are standard approaches for fitting distributions
- There are many distributions which have been found to be of interest
- Software implementation of distributions is a well-defined subject in comparision to say modelling of time-series

Introduction

- In base R there are 20 distributions implemented, at least in part
- All univariate—consider univariate distributions only
- Numerous other distributions have been implemented in R
 - CRAN packages solely devoted to one or more distributions
 - CRAN packages which implement distributions incidentally (e.g. VGAM)
 - implementations of distributions not on CRAN
 - See the task view

http://cran.r-project.org/web/views/Distributions.html

Introduction

- $\bullet\,$ There are overlaps in coverage of distributions in ${\bf R}\,$
- \bullet Implementations of distributions in ${\bf R}$ are inconsistent
 - naming of objects
 - parameterizations
 - function arguments
 - functionality
 - return structures
- It is useful to discuss some standardization of implementation of software for distributions



2 Distributions in Base R

3 Design for Distribution Implementation

Distributions in Base R

- Implementation in **R** is essentially the provision of *dpqr* functions: the density (or probability) function, distribution function, quantile or inverse distribution function and random number generation
- The distributions are the binomial (binom), geometric (geom), hypergeometric (hyper), negative binomial (nbinom), Poisson (pois), Wilcoxon signed rank statistic (signrank), Wilcoxon rank sum statistic (wilcox), beta (beta), Cauchy (Cauchy), non-central chi-squared (chisq), exponential (exp), F (f), gamma (gamma), log-normal (lnorm), logistic (logis), normal (norm), t (t), uniform (unif), Weibull (weibull), and Tukey studentized range (tukey) for which only the p and q functions are implemented

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dpqr Functions

- Any experienced R user will be aware of the naming conventions for the density, cumulative distribution, quantile and random number generation functions for the base R distributions
- The argument lists for the dpqr functions are standard
- First argument is x, p, q and n for respectively a vector of quantiles, a vector of quantiles, a vector of probabilities, and the sample size
- rwilcox is an exception using nn because n is a parameter
- Subsequent arguments give the parameters
- The gamma distribution is unusual, with argument list shape, rate =1, scale = 1/rate
- This mechanism allows the user to specify the second parameter as either the scale or the rate

dpqr Functions

- Other arguments differ among the dpqr functions
- The d functions take the argument log, the p and q functions the argument log.p
- These allow the extension of the range of accurate computation for these quantities
- The p and q functions have the argument lower.tail
- The dpqr functions are coded in C and may be found in the source software tree at /src/math/
- They are in large part due to Ross Ihaka and Catherine Loader
- Martin Mächler is now responsible for on-going maintenance

Testing and Validation

- The algorithms used in the dpqr functions are well-established algorithms taken from a substantial scientific literature
- There are also tests performed, found in the directory tests in two files d-p-q-r-tests.R and p-r-random-tests.R
- Tests in d-p-q-r-tests.R are "inversion tests" which check that qdist(pdist(x))=x for values x generated by rdist
- There are tests relying on special distribution relationships, and tests using extreme values of parameters or arguments
- For discrete distributions equality of cumsum(ddist(.))=pdist(.)

Testing and Validation

• Tests in p-r-random-tests.R are based on an inequality of Massart:

$$\Pr\left(\sup_{x}|\hat{F}_{n}(x)-F(x)|>\lambda\right)\leq 2\exp(-2n\lambda^{2})$$

where \hat{F}_n is the empirical distribution function for a

- This is a version of the Dvoretsky-Kiefer-Wolfowitz inequality with the best possible constant, namely the leading 2 in the right hand side of the inequality
- $\bullet\,$ The inequality above is true for all distribution functions, for all n and $\lambda\,$
- Distributions are tested by generating a sample of size 10,000 and comparing the difference between the empirical distribution function and distribution function

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Outline Introduction Distributions Design

What Should be Provided?

- Besides the obvious dpqr functions, what else is needed?
 - moments, at least low order ones
 - the mode for unimodal distributions
 - moment generating function and characteristic function
 - functions for changing parameterisations
 - functions for fitting of distributions and fit diagnostics
 - goodness-of-fit tests
 - methods associated with fit results: print, plot, summary, print.summary and coef

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 for maximum likelihood fits, methods such as logLik and profile

Fitting Diagnostics

- To assess the fit of a distribution, diagnostic plots should be provided
- Some useful plots are
 - a histogram or empirical density with fitted density
 - a log-histogram with fitted log-density
 - a QQ-plot with optional fitted line
 - a PP-plot with optional fitted line
- For maximum likelihood estimation, contour plots and perspective plots for pairs of parameters, and likelihood profile plots

Fitting

- Some generic fitting routines are currently available
- mle from stats4 can be used to fit distributions but the log likelihood and starting values must be supplied
- fitdistr from MASS will automatically fit most of the distributions from base **R**
- Other distributions can be fitted using mle by supplying the density and started values
- In designing fitting functions, the structure of the object returned and the methods available are vital aspects
- mle returns an S4 object of class mle
- fitdistr produces and S3 object of class fitdistr

Fitting

• The methods available for an object of class mle are:

Method	Action
confint	Confidence intervals from likelihood profiles
logLik	Extract maximized log-likelihood
profile	Likelihood profile generation
show	Display object briefly
summary	Generate object summary
update	Update fit
vcov	Extract variance-covariance matrix

- For fitdistr the methods are print, coef, and logLik
- Neither function returns the data, so a plot method which produces suitable diagnostic plots is not possible
- Ideally a fit should return and object of class distFit say, and the mle class should extend that

Some Principles

- Some principles are
 - $\bullet\,$ the major guide to the design should be what exists in base ${\bf R}\,$
 - the design should be logical with as few special cases as possible
 - the design should minimize the possibility of programming mistakes by users and developers
 - the design should simplify as much as possible the provision of the range of facilities needed to implement a distribution
- A naming scheme for functions is an important part of a standard

A Possible Naming Scheme

Function Name	Description
ddist	Density function or probability function
pdist	Cumulative distribution function
qdist	Quantile function
rdist	Random number generator
<i>dist</i> Mean	Theoretical mean
<i>dist</i> Var	Theoretical variance
$dist { m Skew}$	Theoretical skewness
<i>dist</i> Kurt	Theoretical kurtosis
<i>dist</i> Mode	Mode of the density
<i>dist</i> Moments	Theoretical moments (and mode)
<i>dist</i> MGF	Moment generating function
<i>dist</i> ChFn	Characteristic function
<i>dist</i> ChangePars	Change parameterization of the distribution
<i>dist</i> Fit	Result of fitting the distribution to data
<i>dist</i> Test	Test the distribution

Some Alternatives

- Use dots: hyperb.mean, usually deprecated because of confusion with S3 methods
- Use initial letters: mhyperb, but what about the mgf, multivariate distributions?

Function Arguments

- Specification of parameters could allow for the parameters to be specified as a vector
- This is helpful for maximum likelihood estimation
- The approach used for the gamma distribution can be used to allow for both single parameter specification and vector parameter specification
- Separate parameters should be in the order of location, scale, skewness, kurtosis

Classes

- I don't have a view on whether S3 or S4 classes should be used, but probably S4 classes should be aimed for
- For a fit from a distribution, the class could be called distfit
- A fit for a particular distribution would add the distribution name: hyperbfit, distfit with S3 methods
- For S4 methods the class distfit would be extended
- Similar ideas would be used for tests: a Kolomogorov-Smirnov test would have class kstest, htest with S3 methods

Testing

- Testing is vital to quality of software and developers should provide test data and code
- Firstly test parameter sets should be provided, which cover the range of the parameter set
- Unit tests should be provided for all functions: the RUnit package supports this
- The distributions in Rmetrics have tests of this type, although further development seems warranted
- The Massart inequality seems ideal to use in testing

Final Thoughts

- The distr package is an object-oriented implementation of distributions
- It facilitates operations on distributions such as convolutions
- It uses sampling for calculation of moments and distribution functions
- The package VarianceGamma has been designed and implemented using these ideas
- Implementing the logarithm options of the dpq functions is quite difficult for the distributions in which we are interested