Claims reserving with R: ChainLadder-0.1.5-3 Package Vignette DRAFT

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April 13, 2012

Abstract

The ChainLadder package provides various statistical methods which are typically used for the estimation of outstanding claims reserves in general insurance.

The package has implementations of the Mack-, Munich-, Bootstrap, and multi-variate chain-ladder methods, as well as the loss development factor curve fitting methods of Dave Clark and generalised linear model based reserving models.

This document is still in a draft stage. Any pointers which will help to iron out errors, clarify and make this document more helpful will be much appreciated.

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1 Introduction

1.1 Claims reserving in insurance

Unlike other industries the insurance industry does not sell products as such, but promises. An insurance policy is a promise by the insurer to the policyholder to pay for future claims for an upfront received premium.

As a result insurers don't know the upfront cost of their service, but rely on historical data analysis and judgement to derive a sustainable price for their offering. In General Insurance (or Non-Life Insurance, e.g. motor, property and casualty insurance) most policies run for a period of 12 months. However, the claims payment process can take years or even decades. Therefore often not even the delivery date of their product is known to insurers.

In particular claims arising from casualty insurance can take a long time to settle. Claims can take years to materialise. A complex and costly example are the claims from asbestos liabilities. A research report by a working party of the Institute of Actuaries has estimated that the undiscounted cost of UK mesothelioma-related claims to the UK Insurance Market for the period 2009 to 2050 could be around £10bn [GBB+09]. The cost for aAsbestos related claims in the US for the worldwide insurance industry was estimate to be around $120bn in 2002 [Mic02].

Thus, it should come to no surprise that the biggest item on the liability side of an insurer's balance sheet is often the provision or reserves for future claims payments. Those reserves can be broken down in case reserves (or out-standings claims), which are losses already reported to the insurance company and incurred but not reported (IBNR) claims.

Over the years several methods have been developed to estimate reserves for insurance claims, see [Sch11], [PR02] for an overview. Changes in regulatory requirements, e.g. Solvency II[1] in Europe, have fostered further research into this topic, with a focus on stochastic and statistical techniques.

2 The `ChainLadder` package

2.1 Motivation

The `ChainLadder` [GMZ12] package provides various statistical methods which are typically used for the estimation of outstanding claims reserves in general insurance. The package started out of presentations given by Markus Gesmann at the Stochastic Reserving Seminar at the Institute of Actuaries in 2007 and 2008, followed by talks at Casualty Actuarial Society (CAS) meetings joined by Dan Murphy in 2008 and Wayne Zhang in 2010.

Implementing reserving methods in R has several advantages. R provides:

- a rich language for statistical modelling and data manipulations allowing fast prototyping
- a very active user base, which publishes many extension
- many interfaces to data bases and other applications, such as MS Excel
- an established framework for documentation and testing

[1] See http://ec.europa.eu/internal_market/insurance/solvency/index_en.htm

- workflows with version control systems
- code written in plain text files, allowing effective knowledge transfer
- an effective way to collaborate over the internet
- built in functions to create reproducible research reports[2]
- in combination with other tools such as LaTeX and Sweave easy to set up automated reporting facilities
- access to academic research, which is often first implemented in R

2.2 Brief package overview

This vignette will give the reader a brief overview of the functionallity of the `ChainLadder` package. The functions are discussed and explained in more detail in the respective help files and examples.

The `ChainLadder` package has implementations of the Mack-, Munich- and Bootstrap chain-ladder methods [Mac93a], [Mac99], [QM04], [EV99]. Since version 0.1.3-3 it provides general multivariate chain ladder models by Wayne Zhang [Zha10]. Version 0.1.4-0 introduced new functions on loss development factor (LDF) fitting methods and Cape Cod by Daniel Murphy following a paper by David Clark [Cla03]. Version 0.1.5-0 has added loss reserving models within the generalized linear model framework following a paper by England and Verrall [EV99] implemented by Wayne Zhang.

The package also offers utility functions to convert quickly tables into triangles, triangles into tables, cumulative into incremental and incremental into cumulative triangles.

A set of demos is shipped with the packages and the list of demos is available via:

```
R> demo(package="ChainLadder")
```

and can be executed via

```
R> library(ChainLadder)
R> demo("demo name")
```

Additionally the `ChainLadder` package comes with example files which demonstrates how to the `ChainLadder` functions can be embedded in Excel and Word using the statconn interface[BN07].

For more information and examples see the project web site: http://code.google.com/p/chainladder/

2.3 Installation

We can install `ChainLadder` in the usual way from CRAN, e.g.:

```
R> install.packages('ChainLadder')
```

[2] For an example see the project: Formatted Actuarial Vignettes in R, http://www.favir.net/

For more details about installing packages see [Tea12b]. The installation was successful if the command `library(ChainLadder)` gives you the following message:

```
R> library(ChainLadder)
```

```
ChainLadder version 0.1.5-3 by:
Markus Gesmann <markus.gesmann@gmail.com>
Wayne Zhang <actuary_zhang@hotmail.com>
Daniel Murphy <danielmarkmurphy@gmail.com>

Type library(help='ChainLadder') or ?ChainLadder
to see overall documentation.

Type demo(ChainLadder) to get an idea of the functionality of this package.

See demo(package='ChainLadder') for a list of more demos.

Feel free to send us an email if you would like to be kept informed of
new versions or if you have any feedback, ideas, suggestions or would
like to collaborate.

More information is available on the ChainLadder project web-site:
http://code.google.com/p/chainladder/

To suppress this message use the statement:
suppressPackageStartupMessages(library(ChainLadder))
```


3 Using the `ChainLadder` package

3.1 Working with triangles

Historical insurance data is often presented in form of a triangle structure, showing the development of claims over time for each origin period. An origin period could be the year the policy was sold, or the accident year. Of course the frequency doesn't have to be yearly, e.g. quarterly of monthly origin periods are also often used. Most reserving methods of the `ChainLadder` package expect triangles as input data sets with development periods along the columns and the origin period in rows. The package comes with several example triangles. The following R command will list them all:

```
R> require(ChainLadder)
R> data(package="ChainLadder")
```

Let's look at one example triangle more closely. The following triangle shows data from the Reinsurance Association of America (RAA):

```
R> ## Sample triangle
R> RAA
```

```
      dev
origin    1     2     3     4     5     6     7     8     9    10
  1981 5012  8269 10907 11805 13539 16181 18009 18608 18662 18834
  1982  106  4285  5396 10666 13782 15599 15496 16169 16704    NA
  1983 3410  8992 13873 16141 18735 22214 22863 23466    NA    NA
  1984 5655 11555 15766 21266 23425 26083 27067    NA    NA    NA
  1985 1092  9565 15836 22169 25955 26180    NA    NA    NA    NA
  1986 1513  6445 11702 12935 15852    NA    NA    NA    NA    NA
  1987  557  4020 10946 12314    NA    NA    NA    NA    NA    NA
  1988 1351  6947 13112    NA    NA    NA    NA    NA    NA    NA
  1989 3133  5395    NA    NA    NA    NA    NA    NA    NA    NA
  1990 2063    NA    NA    NA    NA    NA    NA    NA    NA    NA
```

The objective of a reserving exercise is to forecast the future claims development in the bottom right corner of the triangle and potential further developments. Eventually all claims for a given origin period wil be settled, but it is not always obvious to judge how many years or even decades it will take. We speak of long and short tail business depending on the time it takes to pay all claims.

3.1.1 Plotting triangles

The first thing you often want to do is to plot the data to get an overview. For a data set of class `triangle` the `ChainLadder` package provides default plotting methods to give a graphical overview of the data:

```
R> plot(RAA)
```

Setting the argument `lattice=TRUE` will produce individual plots for each origin period[3], see Figure 2.

```
R> plot(RAA, lattice=TRUE)
```

You will notice from the plots in Figures 1 and 2 that the triangle `RAA` presents claims developments for the origin years 1981 to 1990 in a cumulative form. For more information on the triangle plotting functions see the help pages of `plot.triangle`, e.g. via

```
R> ?plot.triangle
```

3.1.2 Transforming triangles between cumulative and incremental representation

The `ChainLadder` packages comes with two helper functions, `cum2incr` and `incr2cum` to transform cumulative triangles into incremental triangles and vice versa:

[3] `ChainLadder` uses the `lattice` package for plotting the development of the origin years in separate panels.

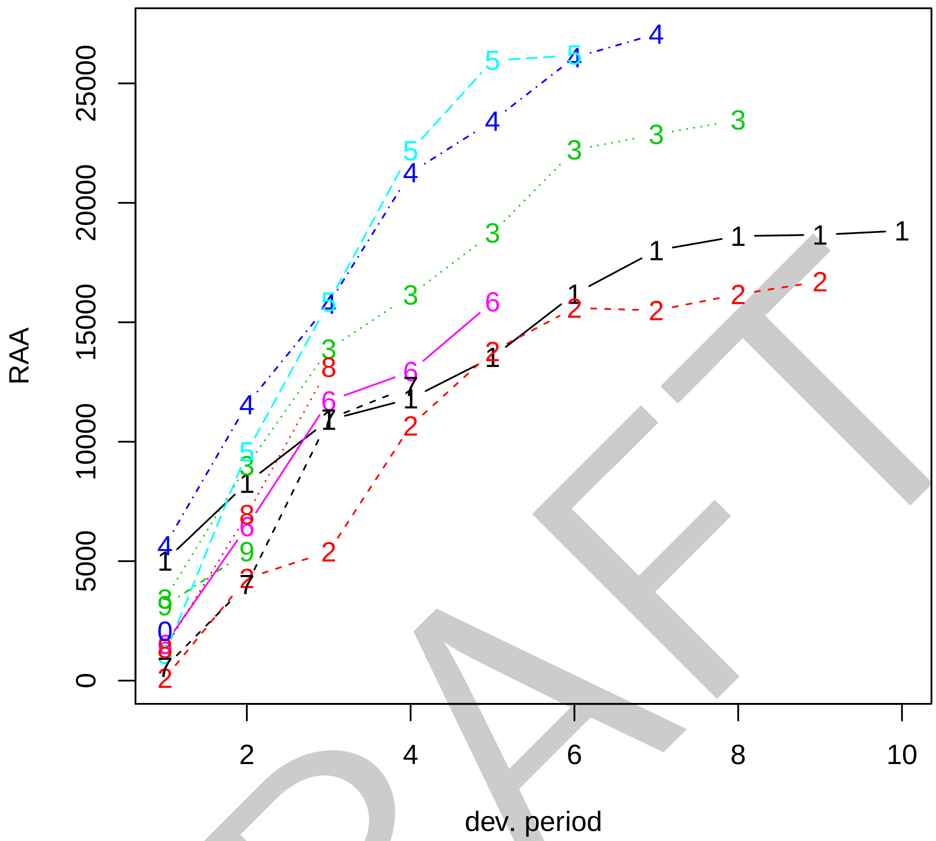


Figure 1: Claims development chart of the `RAA` triangle, with one line per origin period. Output of `plot(RAA)`

```
R> raa.inc <- cum2incr(RAA)
R> ## Show first origin period and its incremental development
R> raa.inc[1,]
```

```
   1    2    3    4    5    6    7    8    9   10
5012 3257 2638  898 1734 2642 1828  599   54  172
```

```
R> raa.cum <- incr2cum(raa.inc)
R> ## Show first origin period and its cumulative development
R> raa.cum[1,]
```

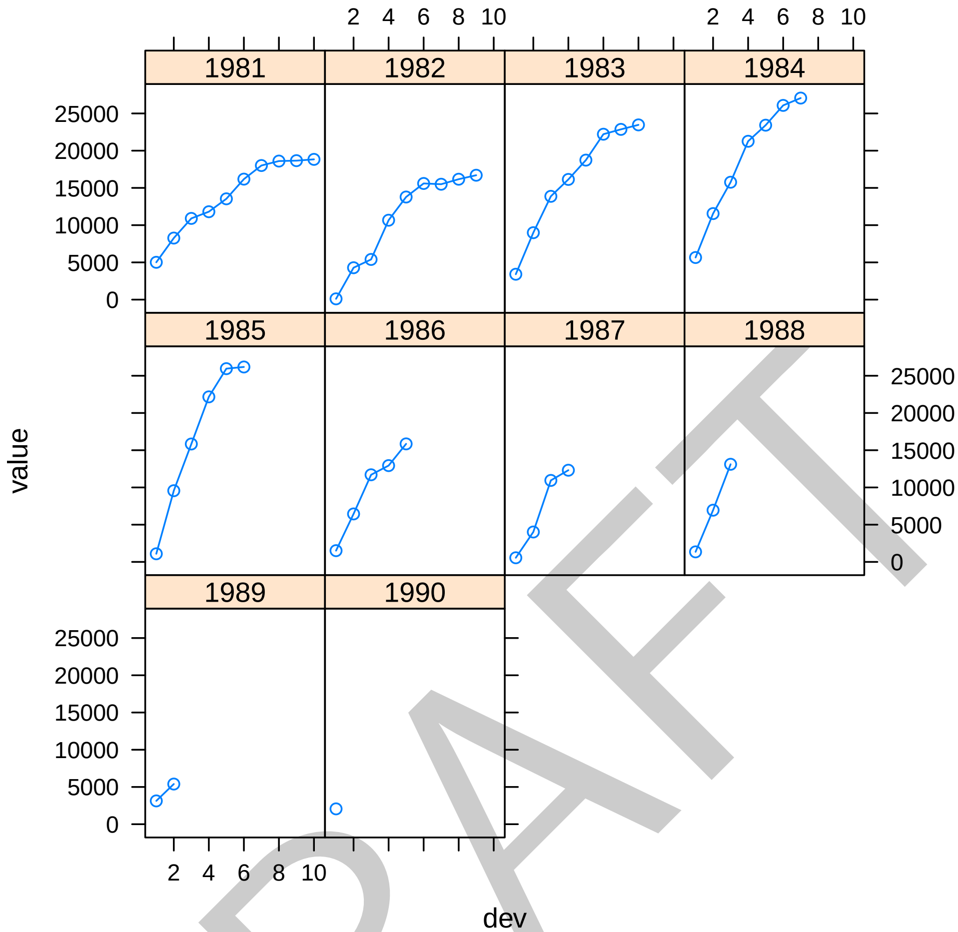


Figure 2: Claims development chart of the `RAA` triangle, with individual panels for each origin period. Output of `plot(RAA, lattice=TRUE)`

```
    1     2     3     4     5     6     7     8     9    10
 5012  8269 10907 11805 13539 16181 18009 18608 18662 18834
```

3.1.3 Importing triangles from external data sources

In most cases you want to analyse your own data, usually stored in data bases. R makes it easy to access data using SQL statements, e.g. via an ODBC connection[4] and the `ChainLadder` packages includes a demo to showcase how data can be imported from a MS Access data base, see:

[4]See the `RODBC` package

```
R> demo(DatabaseExamples)
```

For more details see [Tea12a].

In this section we use data stored in a CSV-file[5] to demonstrate some typical operations you will want to carry out with data stored in data bases. In most cases your triangles will be stored in tables and not in a classical triangle shape. The ChainLadder package contains a CSV-file with sample data in a long table format. We read the data into R's memory with the read.csv command and look at the first couple of rows and summarise it:

```
R> filename <-  file.path(system.file("Database",
+                                     package="ChainLadder"),
+                         "TestData.csv")
R> myData <- read.csv(filename)
R> head(myData)
```

```
  origin dev  value lob
1   1977   1 153638 ABC
2   1978   1 178536 ABC
3   1979   1 210172 ABC
4   1980   1 211448 ABC
5   1981   1 219810 ABC
6   1982   1 205654 ABC
```

```
R> summary(myData)
```

```
     origin          dev             value                          lob
 Min.   :   1   Min.   : 1.00   Min.   : -17657   AutoLiab          :105
 1st Qu.:   3   1st Qu.: 2.00   1st Qu.:  10324   GeneralLiab       :105
 Median :   6   Median : 4.00   Median :  72468   M3IR5             :105
 Mean   : 642   Mean   : 4.61   Mean   : 176632   ABC               : 66
 3rd Qu.:1979   3rd Qu.: 7.00   3rd Qu.: 197716   CommercialAutoPaid: 55
 Max.   :1991   Max.   :14.00   Max.   :3258646   GenIns            : 55
                                                  (Other)           :210
```

Let's focus on one subset of the data. We select the RAA data again:

```
R> raa <- subset(myData, lob %in% "RAA")
R> head(raa)
```

```
   origin dev value lob
67   1981   1  5012 RAA
68   1982   1   106 RAA
69   1983   1  3410 RAA
```

[5]Please ensure that your CSV-file is free from formatting, e.g. characters to separate units of thousands, as those columns will be read as characters or factors rather than numerical values.

```
70   1984   1  5655 RAA
71   1985   1  1092 RAA
72   1986   1  1513 RAA
```

To transform the long table of the RAA data into a triangle we use the function `as.triangle`. The arguments we have to specify are the column names of the origin and development period and further the column which contains the values:

```
R> raa.tri <- as.triangle(raa,
+                         origin="origin",
+                         dev="dev",
+                         value="value")
R> raa.tri

      dev
origin    1    2    3    4    5    6    7   8   9  10
  1981 5012 3257 2638  898 1734 2642 1828 599  54 172
  1982  106 4179 1111 5270 3116 1817 -103 673 535  NA
  1983 3410 5582 4881 2268 2594 3479  649 603  NA  NA
  1984 5655 5900 4211 5500 2159 2658  984  NA  NA  NA
  1985 1092 8473 6271 6333 3786  225   NA  NA  NA  NA
  1986 1513 4932 5257 1233 2917   NA   NA  NA  NA  NA
  1987  557 3463 6926 1368   NA   NA   NA  NA  NA  NA
  1988 1351 5596 6165   NA   NA   NA   NA  NA  NA  NA
  1989 3133 2262   NA   NA   NA   NA   NA  NA  NA  NA
  1990 2063   NA   NA   NA   NA   NA   NA  NA  NA  NA
```

We note that the data has been stored as an incremental data set. As mentioned above, we could now use the function `incr2cum` to transform the triangle into a cumulative format.

We can transform a triangle back into a data frame structure:

```
R> raa.df <- as.data.frame(raa.tri, na.rm=TRUE)
R> head(raa.df)

       origin dev value
1981-1   1981   1  5012
1982-1   1982   1   106
1983-1   1983   1  3410
1984-1   1984   1  5655
1985-1   1985   1  1092
1986-1   1986   1  1513
```

This is particular helpful when you would like to store your results back into data base. Figure 3 gives you an idea of a potential data flow between R and data bases.

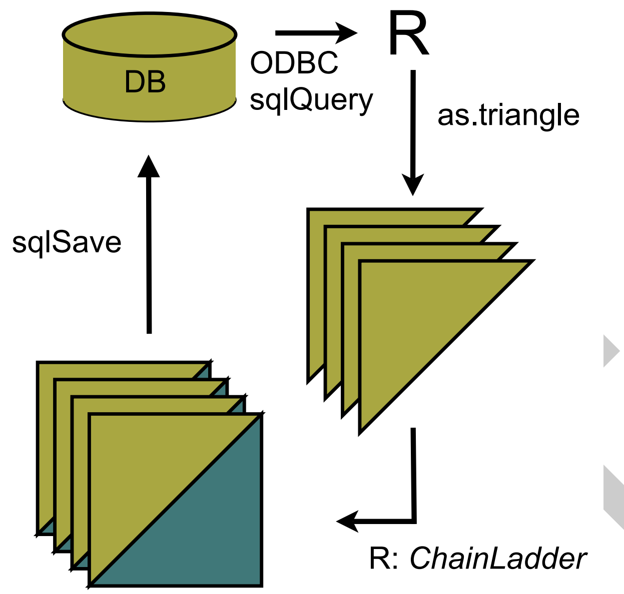


Figure 3: Flow chart of data between R and data bases.

3.1.4 Coping and pasting from MS Excel

Small data sets in Excel can be transfered to R backwards and forwards with via the clipboard under MS Windows.

Copying from Excel to R Select a data set in Excel and copy it into the clipboard, then go to R and type:

```
R> x <- read.table(file="clipboard", sep="\t", na.strings="")
```

Copying from R to Excel Suppose you would like to copy the RAA triangle into Excel, then the following statement would copy the data into the clipboard:

```
R> write.table(RAA, file="clipboard", sep="\t", na="")
```

Now you can paste the content into Excel. Please note that you can't copy lists structures from R to Excel.

3.2 Chain-ladder methods

The classical chain-ladder is a deterministic algorithm to forecast claims based on historical data. It assumes that the proportional developments of claims from one development period to the next are the same for all origin years.

3.2.1 Basic idea

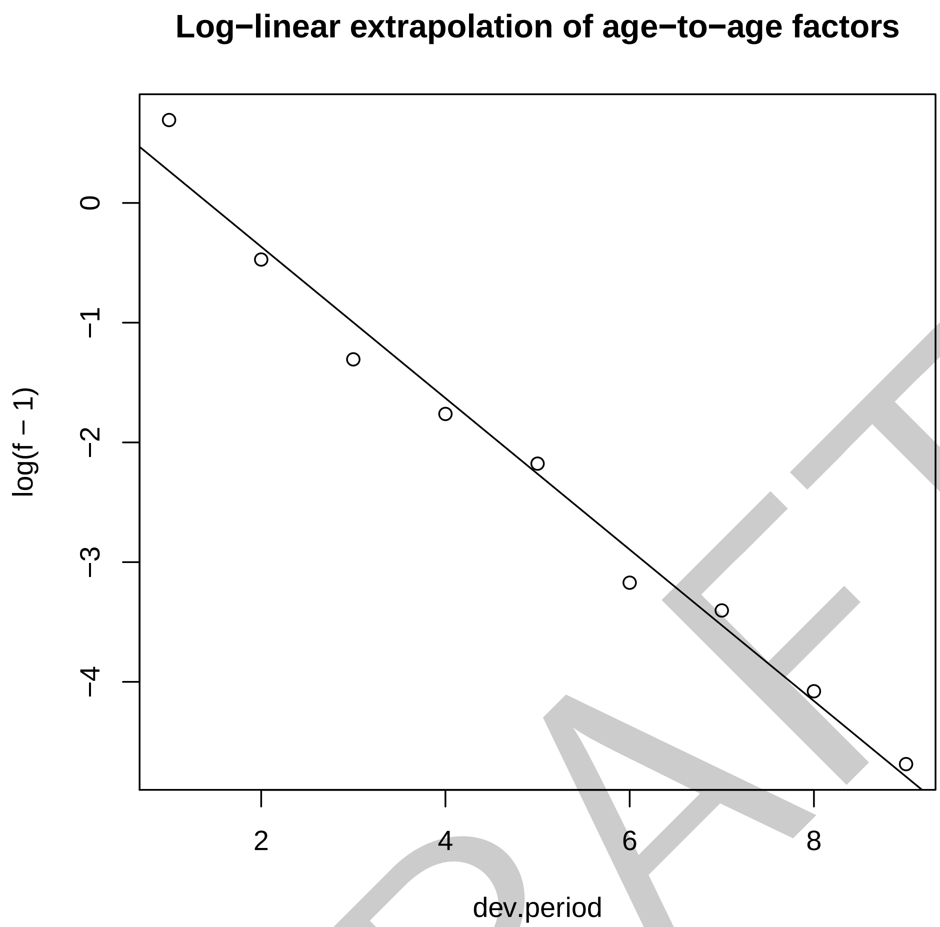
The age-to-age link ratios are calculated as the volume weighted average development ratios of a cumulative loss development triangle from one development period to the next $C_{ik}, i, k = 1, \dots, n$.

$$f_k = \frac{\sum_{i=1}^{n-k} C_{i,k+1}}{\sum_{i=1}^{n-k} C_{i,k}} \tag{1}$$

```
R> n <- 10
R> f <- sapply(1:(n-1),
+             function(i){
+               sum(RAA[c(1:(n-i)),i+1])/sum(RAA[c(1:(n-i)),i])
+             }
+             )
R> f

[1] 2.999 1.624 1.271 1.172 1.113 1.042 1.033 1.017 1.009
```

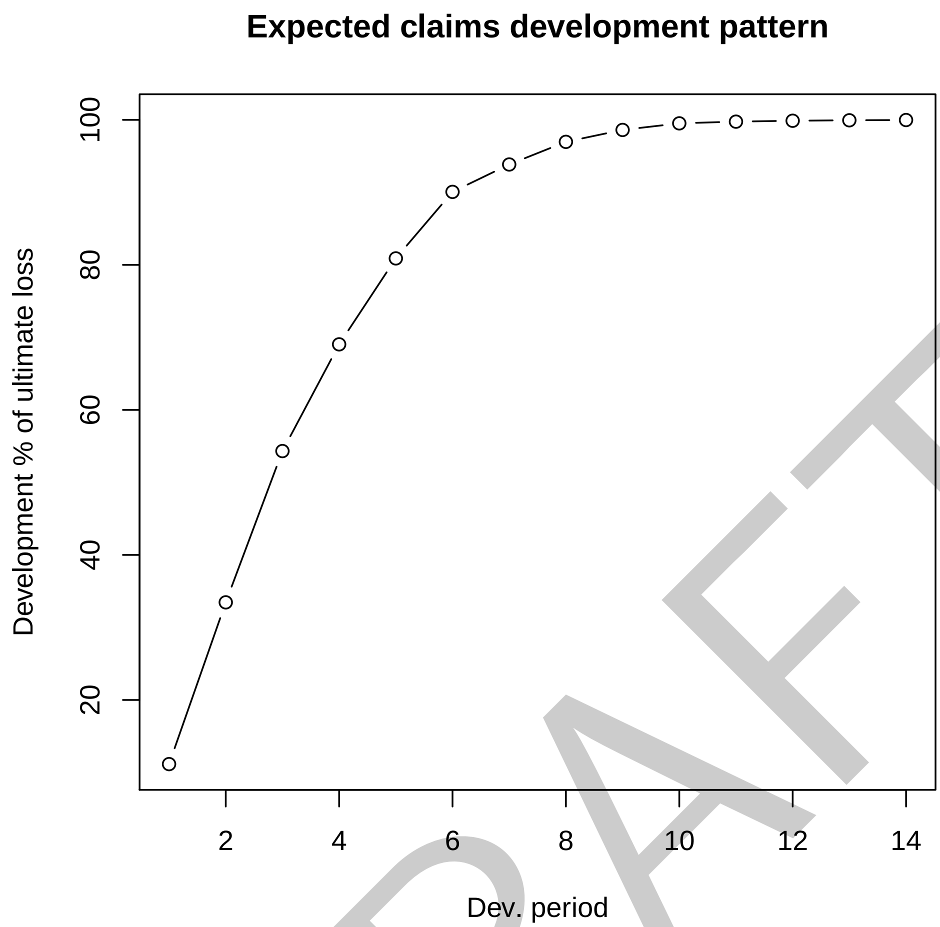
Often it is not suitable to assume that the oldest origin year is fully developed. A typical approach is to extrapolate the development ratios, e.g. assuming a log-linear model.

```
R> dev.period <- 1:(n-1)
R> plot(log(f-1) ~ dev.period, main="Log-linear extrapolation of age-to-age factors")
R> tail.model <- lm(log(f-1) ~ dev.period)
R> abline(tail.model)
R> co <- coef(tail.model)
R> ## extrapolate another 100 dev. period
R> tail <- exp(co[1] + c((n + 1):(n + 100)) * co[2]) + 1
R> f.tail <- prod(tail)
R> f.tail

[1] 1.005
```



The age-to-age factors allow us to plot the expected claims development patterns.

```
R> plot(100*(rev(1/cumprod(rev(c(f, tail[tail>1.0001]))))), t="b",
+      main="Expected claims development pattern",
+      xlab="Dev. period", ylab="Development % of ultimate loss")
```



The link ratios are then applied to the latest know cumulative claims amount to forecast the next development period.

```
R> f <- c(f, f.tail)
R> fullRAA <- RAA
R> for(k in 1:(n-1)){
+   fullRAA[(n-k+1):n, k+1] <- fullRAA[(n-k+1):n,k]*f[k]
+ }
R> fullRAA[,n] <- fullRAA[,n]*f[n]
R> round(fullRAA)
```

```
      dev
origin    1     2     3     4     5     6     7     8     9    10
  1981 5012  8269 10907 11805 13539 16181 18009 18608 18662 18928
```

```
1982  106   4285   5396 10666 13782 15599 15496 16169 16704 16942
1983 3410   8992 13873 16141 18735 22214 22863 23466 23863 24204
1984 5655 11555 15766 21266 23425 26083 27067 27967 28441 28847
1985 1092   9565 15836 22169 25955 26180 27278 28185 28663 29072
1986 1513   6445 11702 12935 15852 17649 18389 19001 19323 19599
1987  557   4020 10946 12314 14428 16064 16738 17294 17587 17838
1988 1351   6947 13112 16664 19525 21738 22650 23403 23800 24139
1989 3133   5395   8759 11132 13043 14521 15130 15634 15898 16125
1990 2063   6188 10046 12767 14959 16655 17353 17931 18234 18495
```

This approach is also called Loss Development Factor (LDF) method.

Since the early 1990s several papers have been published to embed the simple chain-ladder method into a statistical framework. Ben Zehnwirth and Glenn Branett point out in [Zx00] that the age-to-age link ratios can be regarded as the coefficients of a weighted linear regression through the origin, see also [Mur94].

```
R> lmCL <- function(i, Triangle){
+   lm(y~x+0, weights=1/Triangle[,i],
+      data=data.frame(x=Triangle[,i], y=Triangle[,i+1]))
+ }
R> sapply(lapply(c(1:(n-1)), lmCL, RAA), coef)

    x     x     x     x     x     x     x     x     x
2.999 1.624 1.271 1.172 1.113 1.042 1.033 1.017 1.009
```

3.2.2 Mack chain-ladder

Thomas Mack published in 1993 [Mac93b] an article which allows to estimate the standard errors of the chain-ladder forecast without assuming a distribution under certain constrain to the data.

Following Mack [Mac99] let C_{ik} denote the cumulative loss amounts of origin period (e.g. accident year) $i = 1, \ldots, m$, with losses known for development period (e.g. development year) $k \leq n+1-i$.

In order to forecast the amounts C_{ik} for $k > n+1-i$ the Mack chain-ladder-model assumes:

$$\text{CL1: } E[F_{ik}|C_{i1}, C_{i2}, \ldots, C_{ik}] = f_k \text{ with } F_{ik} = \frac{C_{i,k+1}}{C_{ik}} \tag{2}$$

$$\text{CL2: } Var(\frac{C_{i,k+1}}{C_{ik}}|C_{i1}, C_{i2}, \ldots, C_{ik}) = \frac{\sigma_k^2}{w_{ik} C_{ik}^{\alpha}} \tag{3}$$

$$\text{CL3: } \{C_{i1}, \ldots, C_{in}\}, \{C_{j1}, \ldots, C_{jn}\}, \text{ are independent for origin period } i \neq j \tag{4}$$

with $w_{ik} \in [0;1], \alpha \in \{0, 1, 2\}$. If these assumptions are hold, the Mack-chain-ladder-model gives an unbiased estimator for IBNR (Incurred But Not Reported) claims.

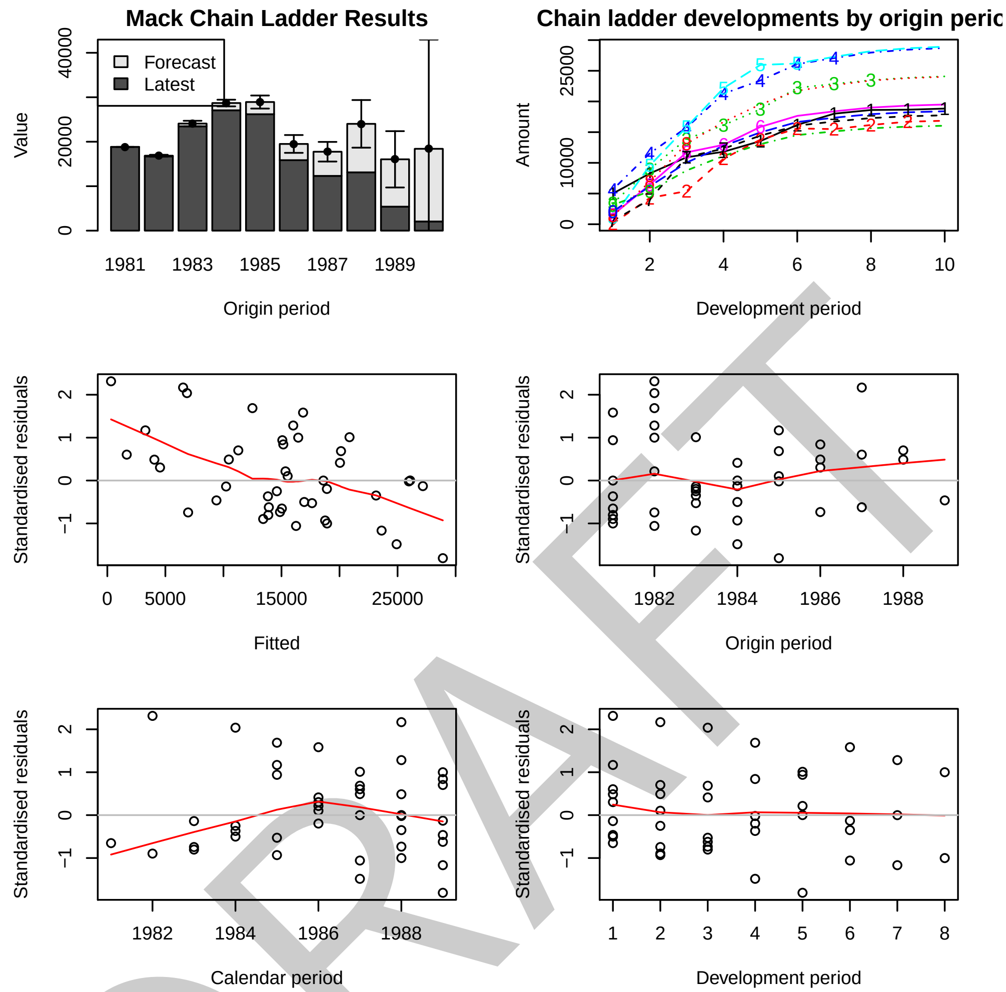
The Mack-chain-ladder model can be regarded as a weighted linear regression through the origin for each development period: `lm(y ~ x  + 0, weights=w/x^(2-alpha))`, where `y` is the vector of claims at development period $k+1$ and `x` is the vector of claims at development period k.

```
R> mack <- MackChainLadder(RAA, est.sigma="Mack")
R> mack

MackChainLadder(Triangle = RAA, est.sigma = "Mack")

     Latest Dev.To.Date Ultimate   IBNR Mack.S.E CV(IBNR)
1981 18,834       1.000   18,834      0        0      NaN
1982 16,704       0.991   16,858    154      206    1.339
1983 23,466       0.974   24,083    617      623    1.010
1984 27,067       0.943   28,703  1,636      747    0.457
1985 26,180       0.905   28,927  2,747    1,469    0.535
1986 15,852       0.813   19,501  3,649    2,002    0.549
1987 12,314       0.694   17,749  5,435    2,209    0.406
1988 13,112       0.546   24,019 10,907    5,358    0.491
1989  5,395       0.336   16,045 10,650    6,333    0.595
1990  2,063       0.112   18,402 16,339   24,566    1.503

              Totals
Latest:    160,987.00
Dev:             0.76
Ultimate:  213,122.23
IBNR:       52,135.23
Mack S.E.:  26,909.01
CV(IBNR):        0.52
```

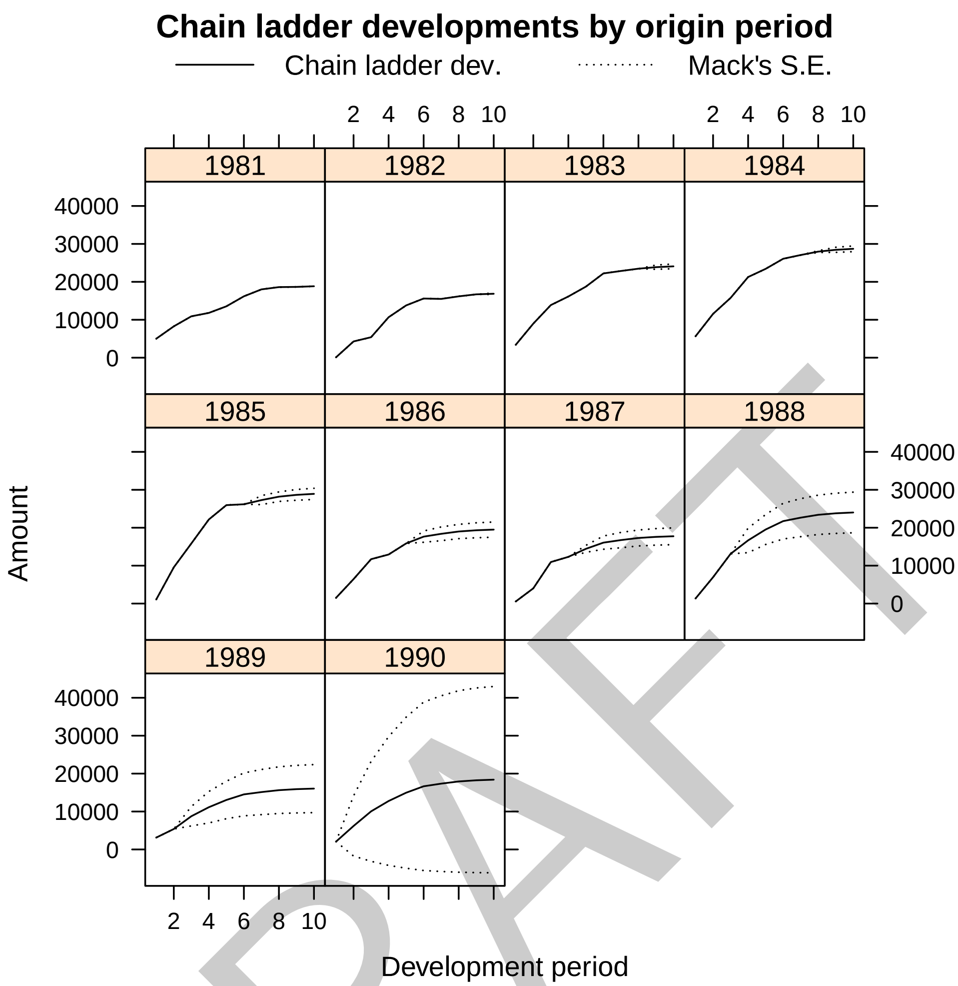
Access the loss development factors and the full triangle

```
R> mack$f

 [1] 2.999 1.624 1.271 1.172 1.113 1.042 1.033 1.017 1.009 1.000

R> mack$FullTriangle

      dev
origin    1     2     3     4     5     6     7     8     9    10
  1981 5012  8269 10907 11805 13539 16181 18009 18608 18662 18834
  1982  106  4285  5396 10666 13782 15599 15496 16169 16704 16858
  1983 3410  8992 13873 16141 18735 22214 22863 23466 23863 24083
  1984 5655 11555 15766 21266 23425 26083 27067 27967 28441 28703
  1985 1092  9565 15836 22169 25955 26180 27278 28185 28663 28927
  1986 1513  6445 11702 12935 15852 17649 18389 19001 19323 19501
  1987  557  4020 10946 12314 14428 16064 16738 17294 17587 17749
  1988 1351  6947 13112 16664 19525 21738 22650 23403 23800 24019
  1989 3133  5395  8759 11132 13043 14521 15130 15634 15898 16045
  1990 2063  6188 10046 12767 14959 16655 17353 17931 18234 18402
```

```
R> plot(mack)
```




```
R> plot(mack, lattice=TRUE)
```



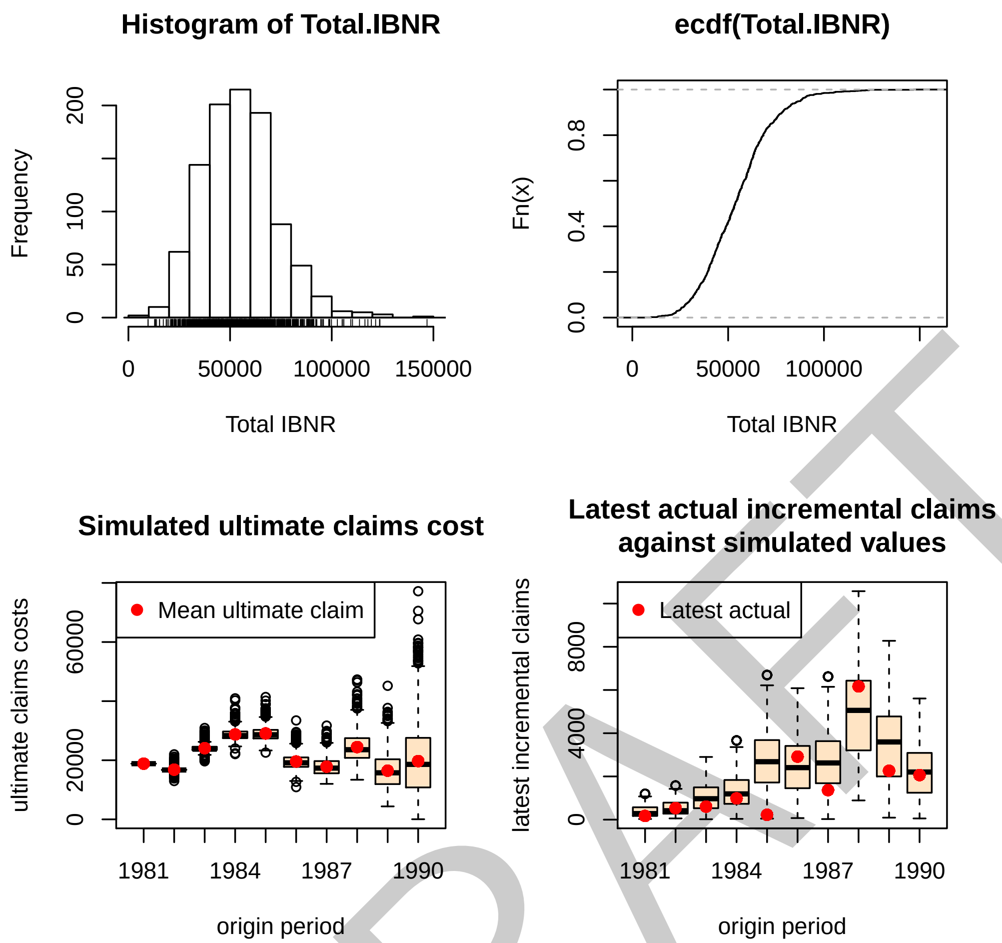
3.2.3 Bootstrap chain-ladder

```
R> # See also the example in section 8 of England & Verrall (2002) on page 55.
R>
R> B <- BootChainLadder(RAA, R=999, process.distr="gamma")
R> B
```

```
BootChainLadder(Triangle = RAA, R = 999, process.distr = "gamma")

     Latest Mean Ultimate Mean IBNR SD IBNR IBNR 75% IBNR 95%
1981 18,834        18,834         0       0        0        0
1982 16,704        16,820       116     662      129    1,254
1983 23,466        24,077       611   1,224    1,106    3,026
```

```
1984 27,067        28,737     1,670   1,935    2,662    5,067
1985 26,180        29,061     2,881   2,385    4,099    7,161
1986 15,852        19,573     3,721   2,567    5,102    8,587
1987 12,314        17,829     5,515   3,080    7,404   11,256
1988 13,112        24,462    11,350   5,194   14,370   21,283
1989  5,395        16,472    11,077   6,132   14,933   22,293
1990  2,063        19,707    17,644  13,159   25,222   41,327

                 Totals
Latest:         160,987
Mean Ultimate:  215,574
Mean IBNR:       54,587
SD IBNR:         18,395
Total IBNR 75%:  64,929
Total IBNR 95%:  87,655

R> plot(B)
R> # Compare to MackChainLadder
R> MackChainLadder(RAA)

MackChainLadder(Triangle = RAA)

     Latest Dev.To.Date Ultimate   IBNR Mack.S.E CV(IBNR)
1981 18,834       1.000   18,834      0        0      NaN
1982 16,704       0.991   16,858    154      143    0.928
1983 23,466       0.974   24,083    617      592    0.959
1984 27,067       0.943   28,703  1,636      713    0.436
1985 26,180       0.905   28,927  2,747    1,452    0.529
1986 15,852       0.813   19,501  3,649    1,995    0.547
1987 12,314       0.694   17,749  5,435    2,204    0.405
1988 13,112       0.546   24,019 10,907    5,354    0.491
1989  5,395       0.336   16,045 10,650    6,332    0.595
1990  2,063       0.112   18,402 16,339   24,566    1.503

               Totals
Latest:    160,987.00
Dev:             0.76
Ultimate:  213,122.23
IBNR:       52,135.23
Mack S.E.:  26,880.74
CV(IBNR):        0.52

R> quantile(B, c(0.75,0.95,0.99, 0.995))

$ByOrigin
     IBNR 75% IBNR 95% IBNR 99% IBNR 99.5%
```

```
1981       0.0       0       0         0
1982     128.8    1254    2810      3481
1983    1105.6    3026    4600      5354
1984    2661.8    5067    7804      8905
1985    4098.9    7161   10165     11113
1986    5101.8    8587   11541     12452
1987    7404.0   11256   14952     16579
1988   14369.7   21283   26130     28868
1989   14932.9   22293   27964     29910
1990   25221.5   41327   56069     57605

$Totals
            Totals
IBNR 75%:    64929
IBNR 95%:    87655
IBNR 99%:   105968
IBNR 99.5%: 117800

R> # fit a distribution to the IBNR
R> library(MASS)
R> plot(ecdf(B$IBNR.Totals))
R> # fit a log-normal distribution
R> fit <- fitdistr(B$IBNR.Totals[B$IBNR.Totals>0], "lognormal")
R> fit

    meanlog      sdlog
  10.847099    0.360747
 ( 0.011414) ( 0.008071)

R> curve(plnorm(x,fit$estimate["meanlog"], fit$estimate["sdlog"]),
+       col="red", add=TRUE)
```

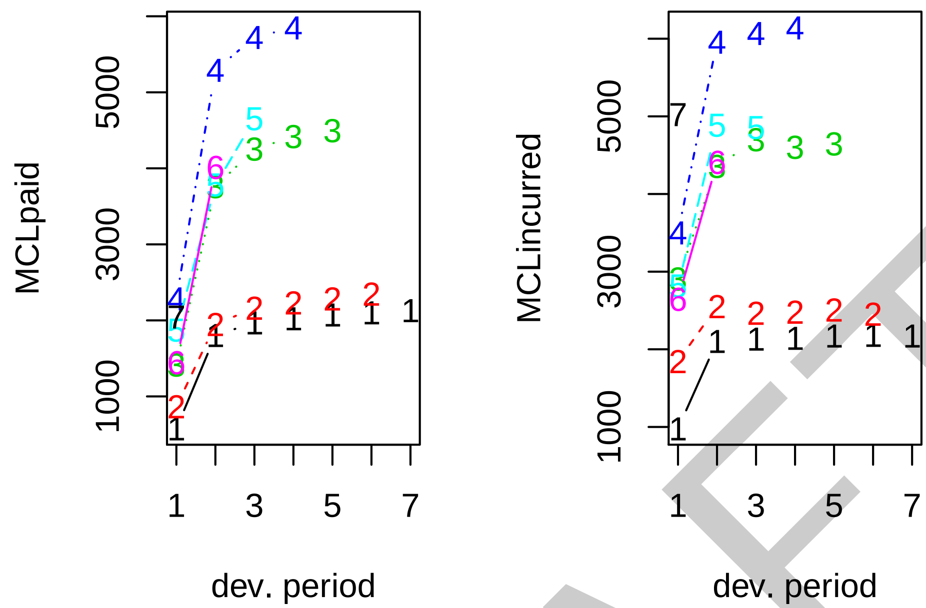


3.2.4 Munich chain-ladder

```
R> MCLpaid
```

```
      dev
origin    1    2    3    4    5    6    7
     1  576 1804 1970 2024 2074 2102 2131
     2  866 1948 2162 2232 2284 2348   NA
     3 1412 3758 4252 4416 4494   NA   NA
     4 2286 5292 5724 5850   NA   NA   NA
     5 1868 3778 4648   NA   NA   NA   NA
     6 1442 4010   NA   NA   NA   NA   NA
     7 2044   NA   NA   NA   NA   NA   NA
```

```
R> MCLincurred

      dev
origin    1    2    3    4    5    6    7
     1  978 2104 2134 2144 2174 2182 2174
     2 1844 2552 2466 2480 2508 2454   NA
     3 2904 4354 4698 4600 4644   NA   NA
     4 3502 5958 6070 6142   NA   NA   NA
     5 2812 4882 4852   NA   NA   NA   NA
     6 2642 4406   NA   NA   NA   NA   NA
     7 5022   NA   NA   NA   NA   NA   NA

R> op <- par(mfrow=c(1,2))
R> plot(MCLpaid)
R> plot(MCLincurred)
R> par(op)
R> # Following the example in Quarg's (2004) paper:
R> MCL <- MunichChainLadder(MCLpaid, MCLincurred, est.sigmaP=0.1, est.sigmaI=0.1)
R> MCL

MunichChainLadder(Paid = MCLpaid, Incurred = MCLincurred, est.sigmaP = 0.1,
    est.sigmaI = 0.1)

  Latest Paid Latest Incurred Latest P/I Ratio Ult. Paid Ult. Incurred
1       2,131           2,174            0.980     2,131         2,174
2       2,348           2,454            0.957     2,383         2,444
3       4,494           4,644            0.968     4,597         4,629
4       5,850           6,142            0.952     6,119         6,176
5       4,648           4,852            0.958     4,937         4,950
6       4,010           4,406            0.910     4,656         4,665
7       2,044           5,022            0.407     7,549         7,650
  Ult. P/I Ratio
1          0.980
2          0.975
3          0.993
4          0.991
5          0.997
6          0.998
7          0.987

Totals
            Paid Incurred P/I Ratio
Latest:   25,525   29,694      0.86
Ultimate: 32,371   32,688      0.99

R> plot(MCL)
```



3.3 Multivariate chain-ladder

The Mack chain ladder technique can be generalized to the multivariate situation where multiple reserving triangles are modeled simultaneuously. The advantage of the multivariate modeling is that correlations among different triangles can be modeled, which will lead to more accurate uncertainty assessment. There has been considerable development in this area, but most of the chain-ladder-based models can be summarized as sequential seemingly unrelated regressions (see Zhang 2010).

Denote $Y_{i,k} = (Y_{i,k}^{(1)}, \cdots, Y_{i,k}^{(N)})$ as an $N \times 1$ vector of cumulative losses at accident year i and development year k where (n) refers to the n-th triangle. Zhang (2010) specifies the model in development period k as:

$$Y_{i,k+1} = A_k + B_k \cdot Y_{i,k} + \epsilon_{i,k}, \tag{5}$$

where A_k is a column of intercepts and B_k is the development matrix for development period k. Assumptions for this model are:

$$E(\epsilon_{i,k}|Y_{i,1}, \cdots, Y_{i,I+1-k}) = 0. \tag{6}$$

$$cov(\epsilon_{i,k}|Y_{i,1}, \cdots, Y_{i,I+1-k}) = D(Y_{i,k}^{-\delta/2})\Sigma_k D(Y_{i,k}^{-\delta/2}). \tag{7}$$

losses of different accident years are independent. (8)

$\epsilon_{i,k}$ are symmetrically distributed. (9)

In the above, D is the diagonal opterator, and δ is a known positive value that controls how the variance depends on the mean (as weights).

The simplest case where $A_k = 0$ and B_k's are diagonal is a naive generalization of the chain ladder, often referred to as the multivariate chain ladder (see Pröhl and Schmidt 2005). The following shows an application of this case using the data set from Merz and Wüthrich (2008):

```
R> data(liab)
R> # this is a list of two triangles
R> length(liab)
```

```
[1] 2
```

```
R> dim(liab[[1]])
```

```
[1] 14 14
```

If we specify `fit.method = "OLS"`, the ordinary least squares will be used in estimating the development factors. As a result, the multivariate model is equivalent to running two Mack chain ladders separately.

```
R> fit1 <- MultiChainLadder(liab, fit.method = "OLS")
R> (s1 <- summary(fit1))
```

```
$`Summary Statistics for Triangle 1`
          Latest Dev.To.Date   Ultimate      IBNR     S.E     CV
1        549,589      1.0000    549,589         0       0 0.0000
2        562,795      0.9966    564,740     1,945   1,743 0.8961
3        602,710      0.9911    608,104     5,394   7,354 1.3633
4        784,632      0.9867    795,248    10,616   9,042 0.8518
5        768,373      0.9806    783,593    15,220  11,181 0.7346
6        811,100      0.9690    837,088    25,988  16,781 0.6457
7        896,728      0.9551    938,861    42,133  19,690 0.4673
8      1,022,241      0.9308  1,098,200    75,959  23,344 0.3073
9      1,019,303      0.8826  1,154,902   135,599  29,585 0.2182
10     1,141,750      0.7976  1,431,409   289,659  37,492 0.1294
11     1,174,196      0.6766  1,735,433   561,237  57,623 0.1027
12     1,032,684      0.4998  2,065,991 1,033,307  89,488 0.0866
13       772,971      0.2905  2,660,561 1,887,590 193,210 0.1024
14       204,325      0.0898  2,274,941 2,070,616 282,960 0.1367
Total 11,343,397      0.6482 17,498,658 6,155,261 427,289 0.0694

$`Summary Statistics for Triangle 2`
         Latest Dev.To.Date  Ultimate      IBNR     S.E      CV
1       391,428       1.000   391,428         0       0  0.0000
2       483,974       1.000   483,839      -135     604 -4.4825
```

```
3       540,742       1.001    540,002       -740   1,436 -1.9416
4       485,016       0.998    486,227      1,211   2,912  2.4043
5       507,752       0.998    508,744        992   3,202  3.2284
6       549,693       0.994    552,825      3,132   5,418  1.7298
7       635,452       0.994    639,113      3,661   6,221  1.6993
8       648,365       0.985    658,410     10,045   7,483  0.7449
9       663,152       0.969    684,719     21,567   9,123  0.4230
10      790,901       0.935    845,543     54,642  16,191  0.2963
11      844,159       0.877    962,734    118,575  26,742  0.2255
12      915,109       0.783  1,169,260    254,151  36,736  0.1445
13      909,066       0.617  1,474,514    565,448  53,398  0.0944
14      394,997       0.277  1,426,060 1,031,063 126,613  0.1228
Total 8,759,806       0.809 10,823,418 2,063,612 162,872  0.0789

$`Summary Statistics for Triangle 1+2`
          Latest Dev.To.Date   Ultimate      IBNR     S.E     CV
1        941,017       1.000    941,017         0       0 0.0000
2      1,046,769       0.998  1,048,579     1,810   1,845 1.0190
3      1,143,452       0.996  1,148,107     4,655   7,493 1.6097
4      1,269,648       0.991  1,281,475    11,827   9,499 0.8032
5      1,276,125       0.988  1,292,337    16,212  11,631 0.7174
6      1,360,793       0.979  1,389,913    29,120  17,634 0.6056
7      1,532,180       0.971  1,577,973    45,793  20,650 0.4509
8      1,670,606       0.951  1,756,610    86,004  24,514 0.2850
9      1,682,455       0.915  1,839,620   157,165  30,960 0.1970
10     1,932,651       0.849  2,276,952   344,301  40,838 0.1186
11     2,018,355       0.748  2,698,167   679,812  63,526 0.0934
12     1,947,793       0.602  3,235,251 1,287,458  96,735 0.0751
13     1,682,037       0.407  4,135,075 2,453,038 200,453 0.0817
14       599,322       0.162  3,701,001 3,101,679 309,995 0.0999
Total 20,103,203       0.710 28,322,077 8,218,874 457,278 0.0556
```

By default, the `summary` produces reserve statistics for all individual triangles, as well as for the portfolio that is assumed to be the sum of the two triangles. This behavior can be changed by supplying the `portfolio` argument. See the documentation for details.

We can verify if this is indeed the same as the univariate Mack chain ladder. For example, we can apply the `MackChainLadder` function on the first triangle:

```
R> fit0 <- MackChainLadder(liab[[1]], est.sigma = "Mack")
R> # just show the total estimates for minimize output
R> t(summary(fit0)$Totals) # the same as the first triangle above

        Latest:   Dev: Ultimate:   IBNR: Mack S.E.: CV(IBNR):
Totals 11343397 0.6482  17498658 6155261     427289   0.06942
```

To allow correlations to be incorporated, we employ the seemingly unrelated regressions that simultaneously model the two triangles in each development period. This is invoked when we specify `fit.method = "SUR"`:

```
R> fit2 <- MultiChainLadder(liab, fit.method = "SUR")
R> s2 <- summary(fit2)
R> print(format(s2$report.summary[[3]], digits = 4, big.mark = ","))
```

```
          Latest Dev.To.Date   Ultimate      IBNR     S.E     CV
1        941,017      1.0000    941,017         0       0 0.0000
2      1,046,769      0.9983  1,048,579     1,810   1,851 1.0221
3      1,143,452      0.9960  1,148,032     4,580   7,859 1.7158
4      1,269,648      0.9909  1,281,370    11,722   9,545 0.8143
5      1,276,125      0.9874  1,292,393    16,268  12,133 0.7458
6      1,360,793      0.9789  1,390,091    29,298  18,913 0.6455
7      1,532,180      0.9704  1,578,868    46,688  22,448 0.4808
8      1,670,606      0.9505  1,757,679    87,073  25,913 0.2976
9      1,682,455      0.9140  1,840,846   158,391  33,294 0.2102
10     1,932,651      0.8482  2,278,572   345,921  45,253 0.1308
11     2,018,355      0.7476  2,699,816   681,461  72,050 0.1057
12     1,947,793      0.6021  3,235,135 1,287,342 112,187 0.0871
13     1,682,037      0.4070  4,132,660 2,450,623 222,927 0.0910
14       599,322      0.1624  3,691,189 3,091,867 342,127 0.1107
Total 20,103,203      0.7100 28,316,248 8,213,045 500,607 0.0610
```

To reduce the output, only the portfolio summary is printed out. We see that the portfolio prediction error is inflated to $500,607$ from $457,278$ in the separate development model ("OLS"). This is because of the positive correlation between the two triangles. The estimated correlation for each development period can be retrieved through the `residCor` function:

```
R> round(unlist(residCor(fit2)), 3)
```

```
 [1]  0.247  0.495  0.682  0.446  0.487  0.451 -0.172  0.805  0.337  0.688
[11] -0.004  1.000  0.021
```

Similarly, most methods that work for linear models such as `coef`, `fitted`, `resid` and so on will also work. Since we have a sequence of models, the retrieved results from these methods are stored in a list. For example, we can retrieve the estimated development factors for each period as

```
R> do.call("rbind", coef(fit2))
```

```
      eq1_x[[1]] eq2_x[[2]]
 [1,]      3.227     2.2224
 [2,]      1.719     1.2688
 [3,]      1.352     1.1200
 [4,]      1.179     1.0665
 [5,]      1.106     1.0356
```

```
 [6,]       1.055     1.0168
 [7,]       1.026     1.0097
 [8,]       1.015     1.0002
 [9,]       1.012     1.0038
[10,]       1.006     0.9994
[11,]       1.005     1.0039
[12,]       1.005     0.9989
[13,]       1.003     0.9997
```

The smaller-than-one developmemt factors from the 10-th period for the second triangle result in the negative IBNR estimates for the first several accident years in the previous output.

The package also offers the `plot` method that produces various summary and diagonostic figures:

```
R> parold <- par(mfrow = c(4, 2), mar = c(4, 4, 2, 1),
+     mgp = c(1.3, 0.3, 0), tck = -0.02)
R> plot(fit2, which.triangle = 1:2, which.plot = 1:4)
R> par(parold)
```

We use the `which.triangle` to suppress the plot for the portfolios, and use the `which.plot` to select the desired types of plots. See the documentation for possible values for these two arguments.

3.4 Clark's methods

3.4.1 Clark's Cap Cod method

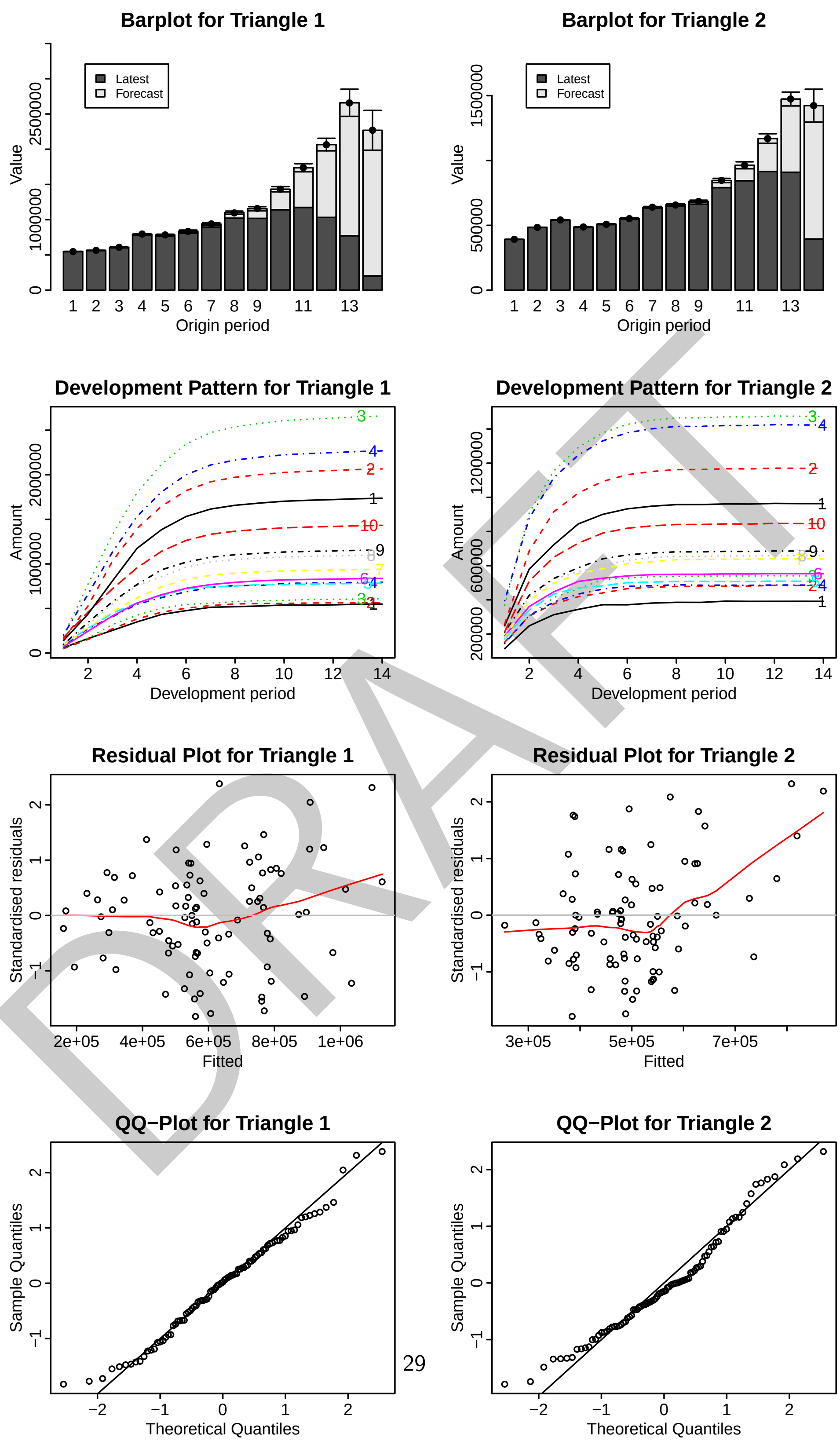
3.4.2 Clark's LDF method

3.5 Generalised linear model methods

Recent years have also seen growing interest in using generalised linear models [GLM] for insurance loss reserving. The use of GLM in insurance loss reserving has many compelling aspects, e.g.,

- when over-dispersed Poisson model is used, it reproduces the estimates from Chain Ladder;
- it provides a more coherent modeling framework than the Mack method;
- all the relevant established statistical theory can be directly applied to perform hypothesis testing and diagnostic checking;

The `glmReserve` function takes an insurance loss triangle, converts it to incremental losses internally if necessary, transforms it to the long format (see as.data.frame) and fits the resulting loss data with a generalised linear model where the mean structure includes both the accident year and the development lag effects. The function also provides both analytical and bootstrapping method to compute the associated prediction errors. The bootstrapping approach also simulates the full predictive distribution, based on which the user can compute other uncertainty measures such as predictive intervals.


Barplot for Triangle 1
Barplot for Triangle 2
Latest
Forecast
Value
Origin period
Development Pattern for Triangle 1
Development Pattern for Triangle 2
Amount
Development period
Residual Plot for Triangle 1
Residual Plot for Triangle 2
Standardised residuals
Fitted
QQ−Plot for Triangle 1
QQ−Plot for Triangle 2
Sample Quantiles
Theoretical Quantiles

Only the Tweedie family of distributions are allowed, that is, the exponential family that admits a power variance function $V(\mu) = \mu^p$. The variance power p is specified in the `var.power` argument, and controls the type of the distribution. When the Tweedie compound Poisson distribution $1 < p < 2$ is to be used, the user has the option to specify `var.power = NULL`, where the variance power p will be estimated from the data using the `cplm` package.

For example, the following fits the over-dispersed Poisson model and spells out the estimated reserve information:

```
R> # load data
R> data(GenIns)
R> GenIns <- GenIns / 1000
R> # fit Poisson GLM
R> (fit1 <- glmReserve(GenIns))

      Latest Dev.To.Date Ultimate  IBNR    S.E     CV
2       5339     0.98252     5434    95  110.1 1.1589
3       4909     0.91263     5379   470  216.0 0.4597
4       4588     0.86599     5298   710  260.9 0.3674
5       3873     0.79725     4858   985  303.6 0.3082
6       3692     0.72235     5111  1419  375.0 0.2643
7       3483     0.61527     5661  2178  495.4 0.2274
8       2864     0.42221     6784  3920  790.0 0.2015
9       1363     0.24162     5642  4279 1046.5 0.2446
10       344     0.06922     4970  4626 1980.1 0.4280
total  30457     0.61982    49138 18681 2945.7 0.1577
```

We can also extract the underlying GLM model by specify `type = "model"` in the `summary` function:

```
R> summary(fit1, type = "model")

Call:
glm(formula = value ~ factor(origin) + factor(dev), family = fam,
    data = ldaFit, offset = offset)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-14.701   -3.913   -0.688    3.675   15.633

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       5.59865    0.17292   32.38  < 2e-16
factor(origin)2   0.33127    0.15354    2.16   0.0377
factor(origin)3   0.32112    0.15772    2.04   0.0492
factor(origin)4   0.30596    0.16074    1.90   0.0650
factor(origin)5   0.21932    0.16797    1.31   0.1999
factor(origin)6   0.27008    0.17076    1.58   0.1225
factor(origin)7   0.37221    0.17445    2.13   0.0398
```

```
factor(origin)8   0.55333    0.18653    2.97   0.0053
factor(origin)9   0.36893    0.23918    1.54   0.1317
factor(origin)10  0.24203    0.42756    0.57   0.5749
factor(dev)2      0.91253    0.14885    6.13  4.7e-07
factor(dev)3      0.95883    0.15257    6.28  2.9e-07
factor(dev)4      1.02600    0.15688    6.54  1.3e-07
factor(dev)5      0.43528    0.18391    2.37   0.0234
factor(dev)6      0.08006    0.21477    0.37   0.7115
factor(dev)7     -0.00638    0.23829   -0.03   0.9788
factor(dev)8     -0.39445    0.31029   -1.27   0.2118
factor(dev)9      0.00938    0.32025    0.03   0.9768
factor(dev)10    -1.37991    0.89669   -1.54   0.1326

(Dispersion parameter for Tweedie family taken to be 52.6)

    Null deviance: 10699  on 54  degrees of freedom
Residual deviance:  1903  on 36  degrees of freedom
AIC: NA

Number of Fisher Scoring iterations: 4
```

Similarly, we can fit the Gamma and a compound Poisson GLM reserving model by changing the `var.power` argument:

```
R> # Gamma GLM
R> (fit2 <- glmReserve(GenIns, var.power = 2))

      Latest Dev.To.Date Ultimate  IBNR     S.E     CV
2       5339     0.98288     5432    93   45.17 0.4857
3       4909     0.91655     5356   447  160.56 0.3592
4       4588     0.88248     5199   611  177.62 0.2907
5       3873     0.79611     4865   992  254.47 0.2565
6       3692     0.71757     5145  1453  351.33 0.2418
7       3483     0.61440     5669  2186  526.29 0.2408
8       2864     0.43870     6529  3665  941.32 0.2568
9       1363     0.24854     5485  4122 1175.95 0.2853
10       344     0.07078     4860  4516 1667.39 0.3692
total  30457     0.62742    48543 18086 2702.71 0.1494

R> # compound Poisson GLM (variance function estimated from the data):
R> (fit3 <- glmReserve(GenIns, var.power = NULL))

      Latest Dev.To.Date Ultimate  IBNR    S.E     CV
2       5339     0.98270     5433    94   91.6 0.9745
3       4909     0.91331     5375   466  186.5 0.4003
```

```
4       4588      0.86780      5287   699   223.7 0.3201
5       3873      0.79709      4859   986   264.8 0.2685
6       3692      0.72164      5116  1424   333.2 0.2340
7       3483      0.61505      5663  2180   452.9 0.2078
8       2864      0.42365      6761  3897   754.6 0.1936
9       1363      0.24231      5626  4263 1019.5 0.2391
10       344      0.06943      4955  4611 1911.0 0.4144
total  30457      0.62058     49078 18621 2831.5 0.1521
```

By default, the formulaic approach is used to compute the prediction errors. We can also carry out bootstrapping simulations by specifying `mse.method = "bootstrap"` (note that this argument supports partial match):

```
R> set.seed(11)
R> (fit5 <- glmReserve(GenIns, mse.method = "boot"))
```

```
      Latest Dev.To.Date Ultimate  IBNR    S.E     CV
2       5339      0.98252     5434    95  105.4 1.1098
3       4909      0.91263     5379   470  216.1 0.4597
4       4588      0.86599     5298   710  266.6 0.3755
5       3873      0.79725     4858   985  307.5 0.3122
6       3692      0.72235     5111  1419  376.3 0.2652
7       3483      0.61527     5661  2178  496.1 0.2278
8       2864      0.42221     6784  3920  812.9 0.2074
9       1363      0.24162     5642  4279 1050.9 0.2456
10       344      0.06922     4970  4626 2004.1 0.4332
total  30457      0.61982    49138 18681 2959.4 0.1584
```

When bootstrapping is used, the resulting object has three additional components - "sims.par", "sims.reserve.mean", and "sims.reserve.pred" that store the simulated parameters, mean values and predicted values of the reserves for each year, respectively.

```
R> names(fit5)
```

```
[1] "call"              "summary"           "Triangle"
[4] "FullTriangle"      "model"             "sims.par"
[7] "sims.reserve.mean" "sims.reserve.pred"
```

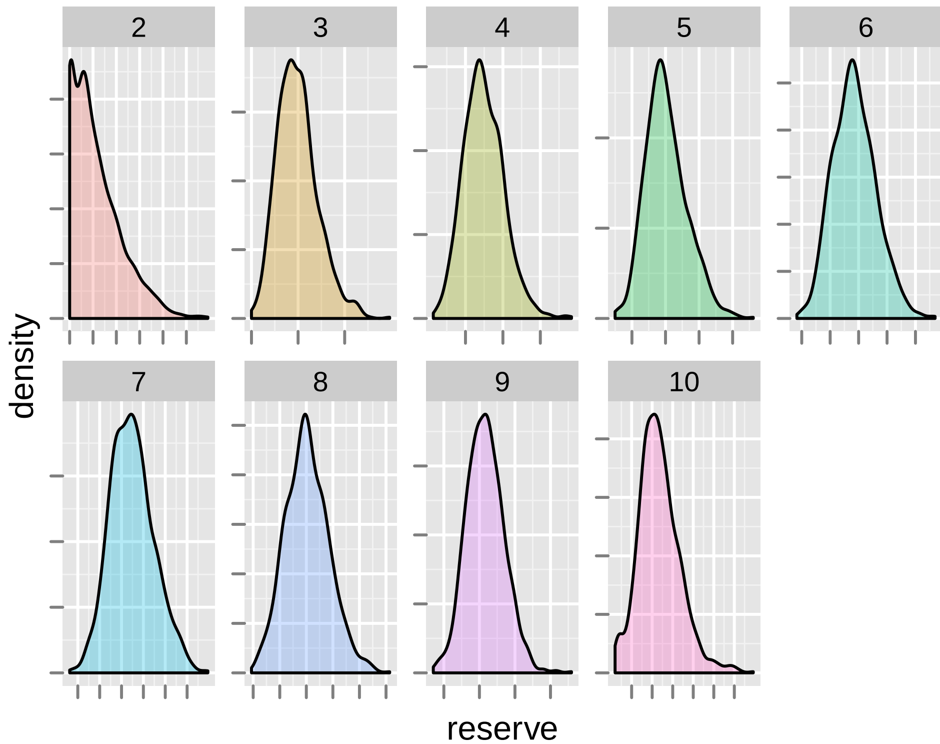
We can thus compute the quantiles of the predictions based on the simulated samples in the "sims.reserve.pred" element as:

```
R> pr <- as.data.frame(fit5$sims.reserve.pred)
R> qv <- c(0.025, 0.25, 0.5, 0.75, 0.975)
R> res.q <- t(apply(pr, 2, quantile, qv))
R> print(format(round(res.q), big.mark = ","), quote = FALSE)
```

```
   2.5%  25%   50%   75%   97.5%
2      0    34    82   170   376
3    136   337   470   615   987
4    279   556   719   917 1,302
5    506   797   972 1,197 1,674
6    774 1,159 1,404 1,666 2,203
7  1,329 1,877 2,210 2,547 3,303
8  2,523 3,463 3,991 4,572 5,713
9  2,364 3,593 4,310 5,013 6,531
10   913 3,354 4,487 5,774 9,165
```

The full predictive distribution of the simulated reserves for each year can be visualized easily:

```
R> library(ggplot2)
R> library(reshape2)
R> prm <- melt(pr)
R> names(prm) <- c("year", "reserve")
R> gg <- ggplot(prm, aes(reserve))
R> gg <- gg + geom_density(aes(fill = year), alpha = 0.3) +
+         facet_wrap(~year, nrow = 2, scales = "free") +
+         opts(axis.text.x = theme_blank(),
+              axis.text.y = theme_blank(),
+              legend.position = "none")
R> print(gg)
```



4 Using ChainLadder with RExcel and SWord

The spreadsheet is located in the Excel folder of the package. The R command

```
R> system.file("Excel", package="ChainLadder")
```

will tell you the exact path to the directory. To use the spreadsheet you will need the RExcel-Add-in [BN07]. The package also provides an example SWord file, demonstrating how the functions of the package can be integrated into a MS Word file via SWord [BN07]. Again you find the Word file via the command:

```
R> system.file("SWord", package="ChainLadder")
```

The package comes with several demos to provide you with an overview of the package functionality, see

```
R> demo(package="ChainLadder")
```

5 Further resources

Other useful documents and resources to get started with R in the context of actuarial work:

- Introduction to R for Actuaries [DS06].
- An Actuarial Toolkit [MSH+06].
- The book *Modern Actuarial Risk Theory – Using R* [KGDD01]
- Actuar package vignettes: `http://cran.r-project.org/web/packages/actuar/index.html`
- Mailing list R-SIG-insurance[6]: Special Interest Group on using R in actuarial science and insurance

5.1 Other insurance related R packages

Below is a list of further R packages in the context of insurance. The list is by no-means complete, and the CRAN Task Views *'Emperical Finance'* and *Probability Distributions* will provide links to additional resources. Please feel free to contact us with items to be added to the list.

- `cplm`: Monte Carlo EM algorithms and Bayesian methods for fitting Tweedie compound Poisson linear models [Zha11].
- `lossDev`: A Bayesian time series loss development model. Features include skewed-t distribution with time-varying scale parameter, Reversible Jump MCMC for determining the functional form of the consumption path, and a structural break in this path [LS11].
- `favir`: Formatted Actuarial Vignettes in R. FAViR lowers the learning curve of the R environment. It is a series of peer-reviewed Sweave papers that use a consistent style [Esc11].
- `actuar`: Loss distributions modelling, risk theory (including ruin theory), simulation of compound hierarchical models and credibility theory [DGP08].
- `fitdistrplus`: Help to fit of a parametric distribution to non-censored or censored data [DMPDD10].
- `mondate`: R packackge to keep track of dates in terms of months [Mur11].
- `lifecontingencies`: Package to perform actuarial evaluation of life contingencies [Spe11].

5.2 Presentations

Over the years the contributors of the `ChainLadder` package have given numerous presentations and most of those are still available online:

- Bayesian Hierarchical Models in Property-Casualty Insurance, Wayne Zhang, 2011

[6] `https://stat.ethz.ch/mailman/listinfo/r-sig-insurance`

- ChainLadder at the Predictive Modelling Seminar, Institute of Actuaries, November 2010, Markus Gesmann, 2011
- Reserve variability calculations, CAS spring meeting, San Diego, Jimmy Curcio Jr., Markus Gesmann and Wayne Zhang, 2010
- The ChainLadder package, working with databases and MS Office interfaces, presentation at the "R you ready?" workshop , Institute of Actuaries, Markus Gesmann, 2009
- The ChainLadder package, London R user group meeting, Markus Gesmann, 2009
- Introduction to R, Loss Reserving with R, Stochastic Reserving and Modelling Seminar, Institute of Actuaries, Markus Gesmann, 2008
- Loss Reserving with R , CAS meeting, Vincent Goulet, Markus Gesmann and Daniel Murphy, 2008
- The ChainLadder package R-user conference Dortmund, Markus Gesmann, 2008

5.3 Further reading

Other papers and presentation which cited `ChainLadder` : [Orr07], [Nic09], [Zha10], [MNNV10], [Sch10], [MNV10], [Esc11], [Spe11]

6 Training and consultancy

Please contact us if you would like to discuss tailored training or consultancy.

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