Credibility theory features of **actuar**

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1 Introduction

Credibility models are actuarial tools to distribute premiums fairly among a heterogeneous group of policyholders (henceforth called *entities*). More generally, they can be seen as prediction methods applicable in any setting where repeated measures are made for subjects with different risk levels.

The credibility theory features of **actuar** consist of matrix `hachemeister` containing the famous data set of Hachemeister (1975) and function `cm` to fit hierarchical (including Bühlmann, Bühlmann-Straub), regression and linear Bayes credibility models. Furthermore, function `rcomphierarc` can simulate portfolios of data satisfying the assumptions of the aforementioned credibility models; see the `"simulation"` vignette for details.

2 Hachemeister data set

The data set of Hachemeister (1975) consists of private passenger bodily injury insurance average claim amounts, and the corresponding number of claims, for five U.S. states over 12 quarters between July 1970 and June 1973. The data set is included in the package in the form of a matrix with 5 rows and 25 columns. The first column contains a state index, columns 2–13 contain the claim averages and columns 14–25 contain the claim numbers:

```
> data(hachemeister)
> hachemeister
     state ratio.1 ratio.2 ratio.3 ratio.4 ratio.5
[1,]     1    1738    1642    1794    2051    2079
[2,]     2    1364    1408    1597    1444    1342
[3,]     3    1759    1685    1479    1763    1674
[4,]     4    1223    1146    1010    1257    1426
[5,]     5    1456    1499    1609    1741    1482
     ratio.6 ratio.7 ratio.8 ratio.9 ratio.10 ratio.11
[1,]    2234    2032    2035    2115     2262     2267
[2,]    1675    1470    1448    1464     1831     1612
[3,]    2103    1502    1622    1828     2155     2233
[4,]    1532    1953    1123    1343     1243     1762
[5,]    1572    1606    1735    1607     1573     1613
     ratio.12 weight.1 weight.2 weight.3 weight.4
[1,]     2517     7861     9251     8706     8575
[2,]     1471     1622     1742     1523     1515
[3,]     2059     1147     1357     1329     1204
[4,]     1306      407      396      348      341
[5,]     1690     2902     3172     3046     3068
     weight.5 weight.6 weight.7 weight.8 weight.9
[1,]     7917     8263     9456     8003     7365
[2,]     1622     1602     1964     1515     1527
[3,]      998     1077     1277     1218      896
[4,]      315      328      352      331      287
[5,]     2693     2910     3275     2697     2663
     weight.10 weight.11 weight.12
[1,]      7832      7849      9077
[2,]      1748      1654      1861
[3,]      1003      1108      1121
[4,]       384       321       342
[5,]      3017      3242      3425
```

3 Hierarchical credibility model

The linear model fitting function of R is `lm`. Since credibility models are very close in many respects to linear models, and since the credibility model fitting function of **actuar** borrows much of its interface from `lm`, we named the credibility function `cm`.

Function `cm` acts as a unified interface for all credibility models supported by the package. Currently, these are: the unidimensional models of Bühlmann (1969) and Bühlmann and Straub (1970); the hierarchical model of Jewell (1975) (of which the first two are special cases); the regression model of Hachemeister (1975), optionally with the intercept at the barycenter of time

(Bühlmann and Gisler, 2005, Section 8.4); linear Bayes models. The modular design of cm makes it easy to add new models if desired.

This section concentrates on usage of cm for hierarchical models.

There are some variations in the formulas of the hierarchical model in the literature. We compute the credibility premiums as given in Bühlmann and Jewell (1987) or Bühlmann and Gisler (2005), supporting three types of estimators of the between variance structure parameters: the unbiased estimators of Bühlmann and Gisler (2005) (the default), the slightly different version of Ohlsson (2005) and the iterative pseudo-estimators as found in Goovaerts and Hoogstad (1987) or Goulet (1998).

Consider an insurance portfolio where *entities* are classified into *cohorts*. In our terminology, this is a two-level hierarchical classification structure. The observations are claim amounts S_{ijt}, where index $i = 1, \dots, I$ identifies the cohort, index $j = 1, \dots, J_i$ identifies the entity within the cohort and index $t = 1, \dots, n_{ij}$ identifies the period (usually a year). To each data point corresponds a weight — or volume — w_{ijt}. Then, the best linear prediction for the next period outcome of a entity based on ratios $X_{ijt} = S_{ijt}/w_{ijt}$ is

$$\begin{aligned} \hat{\pi}_{ij} &= z_{ij} X_{ijw} + (1 - z_{ij}) \hat{\pi}_i \\ \hat{\pi}_i &= z_i X_{izw} + (1 - z_i) m, \end{aligned} \tag{1}$$

with the credibility factors

$$z_{ij} = \frac{w_{ij\Sigma}}{w_{ij\Sigma} + s^2/a}, \qquad w_{ij\Sigma} = \sum_{t=1}^{n_{ij}} w_{ijt}$$

$$z_i = \frac{z_{i\Sigma}}{z_{i\Sigma} + a/b}, \qquad z_{i\Sigma} = \sum_{j=1}^{J_i} z_{ij}$$

and the weighted averages

$$\begin{aligned} X_{ijw} &= \sum_{t=1}^{n_{ij}} \frac{w_{ijt}}{w_{ij\Sigma}} X_{ijt} \\ X_{izw} &= \sum_{j=1}^{J_i} \frac{z_{ij}}{z_{i\Sigma}} X_{ijw}. \end{aligned}$$

The estimator of s^2 is

$$\hat{s}^2 = \frac{1}{\sum_{i=1}^{I} \sum_{j=1}^{J_i} (n_{ij} - 1)} \sum_{i=1}^{I} \sum_{j=1}^{J_i} \sum_{t=1}^{n_{ij}} w_{ijt} (X_{ijt} - X_{ijw})^2. \tag{2}$$

The three types of estimators for the variance components a and b are the following. First, let

$$A_i = \sum_{j=1}^{J_i} w_{ij\Sigma}(X_{ijw} - X_{iww})^2 - (J_i - 1)s^2 \qquad c_i = w_{i\Sigma\Sigma} - \sum_{j=1}^{J_i} \frac{w_{ij\Sigma}^2}{w_{i\Sigma\Sigma}}$$

$$B = \sum_{i=1}^{I} z_{i\Sigma}(X_{izw} - \bar{X}_{zzw})^2 - (I-1)a \qquad d = z_{\Sigma\Sigma} - \sum_{i=1}^{I} \frac{z_{i\Sigma}^2}{z_{\Sigma\Sigma}},$$

with

$$\bar{X}_{zzw} = \sum_{i=1}^{I} \frac{z_{i\Sigma}}{z_{\Sigma\Sigma}} X_{izw}. \tag{3}$$

(Hence, $\mathrm{E}[A_i] = c_i a$ and $\mathrm{E}[B] = db$.) Then, the Bühlmann–Gisler estimators are

$$\hat{a} = \frac{1}{I} \sum_{i=1}^{I} \max\left(\frac{A_i}{c_i}, 0\right) \tag{4}$$

$$\hat{b} = \max\left(\frac{B}{d}, 0\right), \tag{5}$$

the Ohlsson estimators are

$$\hat{a}' = \frac{\sum_{i=1}^{I} A_i}{\sum_{i=1}^{I} c_i} \tag{6}$$

$$\hat{b}' = \frac{B}{d} \tag{7}$$

and the iterative (pseudo-)estimators are

$$\tilde{a} = \frac{1}{\sum_{i=1}^{I}(J_i - 1)} \sum_{i=1}^{I} \sum_{j=1}^{J_i} z_{ij}(X_{ijw} - X_{izw})^2 \tag{8}$$

$$\tilde{b} = \frac{1}{I-1} \sum_{i=1}^{I} z_i(X_{izw} - X_{zzw})^2, \tag{9}$$

where

$$X_{zzw} = \sum_{i=1}^{I} \frac{z_i}{z_\Sigma} X_{izw}. \tag{10}$$

Note the difference between the two weighted averages (3) and (10). See Belhadj et al. (2009) for further discussion on this topic.

Finally, the estimator of the collective mean m is $\hat{m} = X_{zzw}$.

The credibility modeling function `cm` assumes that data is available in the format most practical applications would use, namely a rectangular array (matrix or data frame) with entity observations in the rows and with one or more classification index columns (numeric or character). One will recognize the output format of `rcomphierarc` and its summary methods.

Then, function cm works much the same as lm. It takes in argument: a formula of the form ~ terms describing the hierarchical interactions in a data set; the data set containing the variables referenced in the formula; the names of the columns where the ratios and the weights are to be found in the data set. The latter should contain at least two nodes in each level and more than one period of experience for at least one entity. Missing values are represented by NAs. There can be entities with no experience (complete lines of NAs).

In order to give an easily reproducible example, we group states 1 and 3 of the Hachemeister data set into one cohort and states 2, 4 and 5 into another. This shows that data does not have to be sorted by level. The fitted model below uses the iterative estimators of the variance components.

```
> X <- cbind(cohort = c(1, 2, 1, 2, 2), hachemeister)
> fit <- cm(~cohort + cohort:state, data = X,
+           ratios = ratio.1:ratio.12,
+           weights = weight.1:weight.12,
+           method = "iterative")
> fit
Call:
cm(formula = ~cohort + cohort:state, data = X, ratios = ratio.1:ratio.12,
    weights = weight.1:weight.12, method = "iterative")

Structure Parameters Estimators

  Collective premium: 1746

  Between cohort variance: 88981
  Within cohort/Between state variance: 10952
  Within state variance: 139120026
```

The function returns a fitted model object of class "cm" containing the estimators of the structure parameters. To compute the credibility premiums, one calls a method of predict for this class.

```
> predict(fit)
$cohort
[1] 1949 1543

$state
[1] 2048 1524 1875 1497 1585
```

One can also obtain a nicely formatted view of the most important results with a call to summary.

```
> summary(fit)
Call:
cm(formula = ~cohort + cohort:state, data = X, ratios = ratio.1:ratio.12,
    weights = weight.1:weight.12, method = "iterative")
```

```
Structure Parameters Estimators

  Collective premium: 1746

  Between cohort variance: 88981
  Within cohort/Between state variance: 10952
  Within state variance: 139120026

Detailed premiums

  Level: cohort
    cohort Indiv. mean Weight Cred. factor Cred. premium
    1      1967        1.407  0.9196       1949
    2      1528        1.596  0.9284       1543

  Level: state
    cohort state Indiv. mean Weight Cred. factor
    1      1     2061        100155 0.8874
    2      2     1511         19895 0.6103
    1      3     1806         13735 0.5195
    2      4     1353          4152 0.2463
    2      5     1600         36110 0.7398
    Cred. premium
    2048
    1524
    1875
    1497
    1585
```

The methods of `predict` and `summary` can both report for a subset of the levels by means of an argument `levels`.

```
> summary(fit, levels = "cohort")
Call:
cm(formula = ~cohort + cohort:state, data = X, ratios = ratio.1:ratio.12,
    weights = weight.1:weight.12, method = "iterative")

Structure Parameters Estimators

  Collective premium: 1746

  Between cohort variance: 88981
  Within cohort variance: 10952

Detailed premiums
```

```
    cohort Indiv. mean Weight Cred. factor Cred. premium
    1      1967        1.407  0.9196       1949
    2      1528        1.596  0.9284       1543
> predict(fit, levels = "cohort")
$cohort
[1] 1949 1543
```

4 Bühlmann and Bühlmann–Straub models

As mentioned above, the Bühlmann and Bühlmann–Straub models are simply one-level hierarchical models. In this case, the Bühlmann–Gisler and Ohlsson estimators of the between variance parameters are both identical to the usual Bühlmann and Straub (1970) estimator

$$\hat{a} = \frac{w_{\Sigma\Sigma}}{w_{\Sigma\Sigma}^2 - \sum_{i=1}^{I} w_{i\Sigma}^2} \left(\sum_{i=1}^{I} w_{i\Sigma}(X_{iw} - X_{ww})^2 - (I-1)\hat{s}^2 \right), \tag{11}$$

and the iterative estimator

$$\tilde{a} = \frac{1}{I-1} \sum_{i=1}^{I} z_i (X_{iw} - X_{zw})^2 \tag{12}$$

is better known as the Bichsel–Straub estimator.

To fit the Bühlmann model using cm, one simply does not specify any weights.

```
> cm(~state, hachemeister, ratios = ratio.1:ratio.12)
Call:
cm(formula = ~state, data = hachemeister, ratios = ratio.1:ratio.12)

Structure Parameters Estimators

  Collective premium: 1671

  Between state variance: 72310
  Within state variance: 46040
```

When weights are specified together with a one-level model, cm automatically fits the Bühlmann–Straub model to the data. In the example below, we use the Bichsel–Straub estimator for the between variance.

```
> cm(~state, hachemeister, ratios = ratio.1:ratio.12,
+    weights = weight.1:weight.12)
Call:
cm(formula = ~state, data = hachemeister, ratios = ratio.1:ratio.12,
    weights = weight.1:weight.12)
```

```
Structure Parameters Estimators

  Collective premium: 1684

  Between state variance: 89639
  Within state variance: 139120026
```

5 Regression model of Hachemeister

The credibility regression model of Hachemeister (1975) is a generalization of the Bühlmann–Straub model. If data shows a systematic trend, the latter model will typically under- or over-estimate the true premium of an entity. The idea of Hachemeister was to fit to the data a regression model where the parameters are a credibility weighted average of an entity's regression parameters and the group's parameters.

In order to use `cm` to fit a credibility regression model to a data set, one simply has to supply as additional arguments `regformula` and `regdata`. The first one is a formula of the form `~ terms` describing the regression model, and the second is a data frame of regressors. That is, arguments `regformula` and `regdata` are in every respect equivalent to arguments `formula` and `data` of `lm`, with the minor difference that `regformula` does not need to have a left hand side (and is ignored if present). Below, we fit the model

$$X_{it} = \beta_0 + \beta_1 t + \varepsilon_t, \quad t = 1, \dots, 12$$

to the original data set of Hachemeister (1975).

```
> fit <- cm(~state, hachemeister, regformula = ~ time,
+           regdata = data.frame(time = 1:12),
+           ratios = ratio.1:ratio.12,
+           weights = weight.1:weight.12)
> fit
Call:
cm(formula = ~state, data = hachemeister, ratios = ratio.1:ratio.12,
    weights = weight.1:weight.12, regformula = ~time, regdata = data.frame(time = 1:12))

Structure Parameters Estimators

  Collective premium: 1469 32.05

  Between state variance:  24154 2700.0
                            2700  301.8
  Within state variance: 49870187
```

To compute the credibility premiums, one has to provide the "future" values of the regressors as in `predict.lm`.

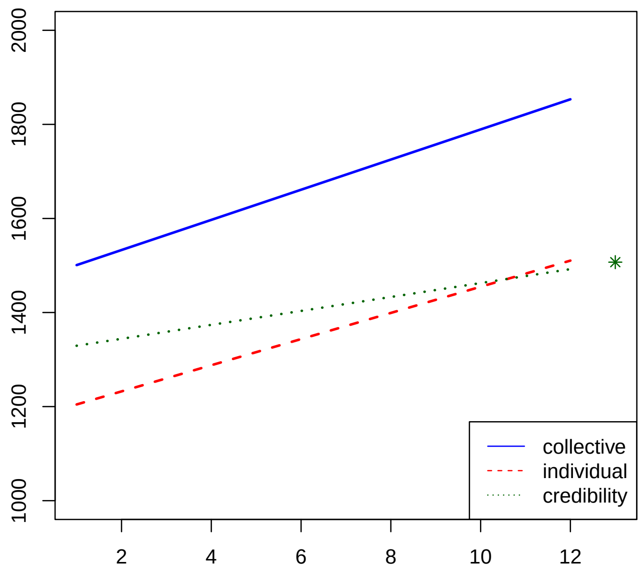

Figure 1: Collective, individual and credibility regression lines for State 4 of the Hachemeister data set. The point indicates the credibility premium.

```
> predict(fit, newdata = data.frame(time = 13))
[1] 2437 1651 2073 1507 1759
```

It is well known that the basic regression model has a major drawback: there is no guarantee that the credibility regression line will lie between the collective and individual ones. This may lead to grossly inadequate premiums, as Figure 1 shows.

The solution proposed by Bühlmann and Gisler (1997) is simply to position the intercept not at time origin, but instead at the barycenter of time (see also Bühlmann and Gisler, 2005, Section 8.4). In mathematical terms, this essentially amounts to using an orthogonal design matrix. By setting the argument `adj.intercept` to `TRUE` in the call, `cm` will automatically fit the credibility regression model with the intercept at the barycenter of time. The resulting regression coefficients have little meaning, but the predictions are sensible.

```
> fit2 <- cm(~state, hachemeister, regformula = ~ time,
+            regdata = data.frame(time = 1:12),
+            adj.intercept = TRUE,
```

```
+            ratios = ratio.1:ratio.12,
+            weights = weight.1:weight.12)
> summary(fit2, newdata = data.frame(time = 13))
Call:
cm(formula = ~state, data = hachemeister, ratios = ratio.1:ratio.12,
    weights = weight.1:weight.12, regformula = ~time, regdata = data.frame(time = 1:12),
    adj.intercept = TRUE)

Structure Parameters Estimators

  Collective premium: -1675 117.1

  Between state variance:  93783    0
                               0 8046
  Within state variance: 49870187

Detailed premiums

    state Indiv. coef. Cred. matrix  Adj. coef.
    1     -2062.46     0.9947 0.0000 -2060.41
            216.97     0.0000 0.9413   211.10
    2     -1509.28     0.9740 0.0000 -1513.59
             59.60     0.0000 0.7630    73.23
    3     -1813.41     0.9627 0.0000 -1808.25
            150.60     0.0000 0.6885   140.16
    4     -1356.75     0.8865 0.0000 -1392.88
             96.70     0.0000 0.4080   108.77
    5     -1598.79     0.9855 0.0000 -1599.89
             41.29     0.0000 0.8559    52.22
    Cred. premium
    2457

    1651

    2071

    1597

    1698
```

Figure 2 shows the beneficient effect of the intercept adjustment on the premium of State 4.

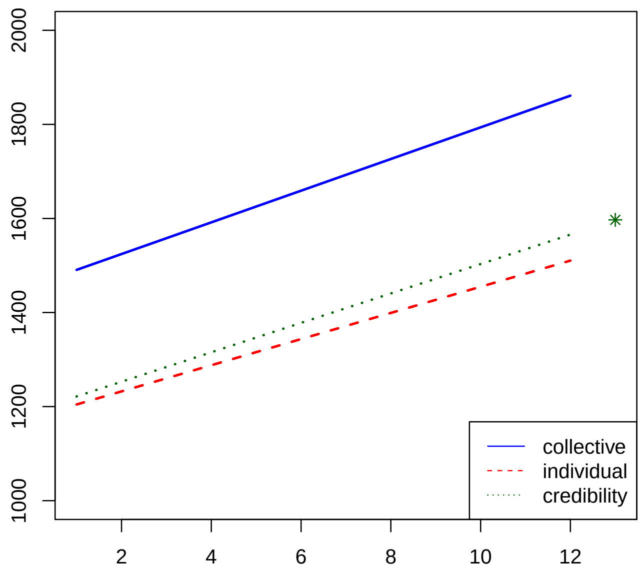

Figure 2: Collective, individual and credibility regression lines for State 4 of the Hachemeister data set when the intercept is positioned at the barycenter of time. The point indicates the credibility premium.

6 Linear Bayes model

In the pure bayesian approach to the ratemaking problem, we assume that the observations X_t, $t = 1, \dots, n$, of an entity depend on its risk level θ, and that this risk level is a realization of an unobservable random variable Θ. The best (in the mean square sense) approximation to the unknown risk premium $\mu(\theta) = \mathrm{E}[X_t|\Theta = \theta]$ based on observations $X_1, \dots, X_n$ is the Bayesian premium

$$B_{n+1} = \mathrm{E}[\mu(\Theta)|X_1, \dots, X_n].$$

It is then well known (Bühlmann and Gisler, 2005; Klugman et al., 2012) that for some combinaisons of distributions, the Bayesian premium is linear and can written as a credibility premium

$$B_{n+1} = z\bar{X} + (1 - z)m,$$

where $m = \mathrm{E}[\mu(\Theta)]$ and $z = n/(n + K)$ for some constant K.

The combinations of distributions yielding a linear Bayes premium involve members of the univariate exponential family for the distribution of $X|\Theta = \theta$ and their natural conjugate for the distribution of Θ:

- $X|\Theta = \theta \sim \text{Poisson}(\theta)$, $\Theta \sim \text{Gamma}(\alpha, \lambda)$;
- $X|\Theta = \theta \sim \text{Exponential}(\theta)$, $\Theta \sim \text{Gamma}(\alpha, \lambda)$;
- $X|\Theta = \theta \sim \text{Normal}(\theta, \sigma_2^2)$, $\Theta \sim \text{Normal}(\mu, \sigma_1^2)$;
- $X|\Theta = \theta \sim \text{Bernoulli}(\theta)$, $\Theta \sim \text{Beta}(a, b)$;
- $X|\Theta = \theta \sim \text{Geometric}(\theta)$, $\Theta \sim \text{Beta}(a, b)$;

and the convolutions

- $X|\Theta = \theta \sim \text{Gamma}(\tau, \theta)$, $\Theta \sim \text{Gamma}(\alpha, \lambda)$;
- $X|\Theta = \theta \sim \text{Binomial}(\nu, \theta)$, $\Theta \sim \text{Beta}(a, b)$;
- $X|\Theta = \theta \sim \text{Negative Binomial}(r, \theta)$ and $\Theta \sim \text{Beta}(a, b)$.

Appendix A provides the complete formulas for the above combinations of distributions.

In addition, Bühlmann and Gisler (2005, section 2.6) show that if $X|\Theta = \theta \sim \text{Single Parameter Pareto}(\theta, x_0)$ and $\Theta \sim \text{Gamma}(\alpha, \lambda)$, then the Bayesian estimator of parameter θ — not of the risk premium! — is

$$\hat{\Theta} = \eta \hat{\theta}^{\text{MLE}} + (1 - \eta) \frac{\alpha}{\lambda},$$

where

$$\hat{\theta}^{\text{MLE}} = \frac{n}{\sum_{i=1}^{n} \ln(X_i / x_0)}$$

is the maximum likelihood estimator of θ and

$$\eta = \frac{\sum_{i=1}^{n} \ln(X_i / x_0)}{\lambda + \sum_{i=1}^{n} \ln(X_i / x_0)}$$

is a weight not restricted to $(0, 1)$. (See the `"distributions"` package vignette for details on the Single Parameter Pareto distribution.)

When argument `formula` is `"bayes"`, function `cm` computes pure Bayesian premiums — or estimator in the Pareto/Gamma case — for the combinations of distributions above. We identify which by means of argument `likelihood` that must be one of `"poisson"`, `"exponential"`, `"gamma"`, `"normal"`, `"bernoulli"`, `"binomial"`, `"geometric"`, `"negative binomial"` or `"pareto"`. The parameters of the distribution of $X|\Theta = \theta$, if any, and those of the distribution of Θ are specified using the argument names (and default values) of `dgamma`, `dnorm`, `dbeta`, `dbinom`, `dnbinom` or `dpareto1`, as appropriate.

Consider the case where

$$\begin{aligned} X|\Theta = \theta &\sim \text{Poisson}(\theta) \\ \Theta &\sim \text{Gamma}(\alpha, \lambda). \end{aligned}$$

The posterior distribution of Θ is

$$\Theta | X_1, \dots, X_n \sim \text{Gamma}\left(\alpha + \sum_{t=1}^{n} X_t, \lambda + n\right).$$

Therefore, the Bayesian premium is

$$\begin{aligned}
B_{n+1} &= \mathrm{E}[\mu(\Theta)|X_1, \dots, X_n] \\
&= \mathrm{E}[\Theta|X_1, \dots, X_n] \\
&= \frac{\alpha + \sum_{t=1}^{n} X_t}{\lambda + n} \\
&= \frac{n}{n+\lambda}\,\bar{X} + \frac{\lambda}{n+\lambda}\frac{\alpha}{\lambda} \\
&= z\bar{X} + (1-z)m,
\end{aligned}$$

with $m = \mathrm{E}[\mu(\Theta)] = \mathrm{E}[\Theta] = \alpha/\lambda$ and

$$z = \frac{n}{n+K}, \quad K = \lambda.$$

One may easily check that if $\alpha = \lambda = 3$ and $X_1 = 5, X_2 = 3, X_3 = 0, X_4 = 1, X_5 = 1$, then $B_6 = 1.625$. We obtain the same result using `cm`.

```
> x <- c(5, 3, 0, 1, 1)
> fit <- cm("bayes", x, likelihood = "poisson",
+             shape = 3, rate = 3)
> fit
Call:
cm(formula = "bayes", data = x, likelihood = "poisson", shape = 3,
    rate = 3)

Structure Parameters Estimators

  Collective premium: 1

  Between variance: 0.3333
  Within variance: 1
> predict(fit)
[1] 1.625
> summary(fit)
Call:
cm(formula = "bayes", data = x, likelihood = "poisson", shape = 3,
    rate = 3)

Structure Parameters Estimators
```

```
  Collective premium: 1

  Between variance: 0.3333
  Within variance: 1

Detailed premiums

    Indiv. mean Weight Cred. factor Bayes premium
    2           5      0.625        1.625
```

A Linear Bayes formulas

This appendix provides the main linear Bayes credibility results for combinations of a likelihood function member of the univariate exponential family with its natural conjugate. For each combination, we provide, other than the names of the distributions of $X|\Theta = \theta$ and Θ:

- the posterior distribution $\Theta|X_1 = x_1, \dots, X_n = x_n$, always of the same type as the prior, only with updated parameters;
- the risk premium $\mu(\theta) = \mathrm{E}[X|\Theta = \theta]$;
- the collective premium $m = \mathrm{E}[\mu(\Theta)]$;
- the Bayesian premium $B_{n+1} = \mathrm{E}[\mu(\Theta)|X_1, \dots, X_n]$, always equal to the collective premium evaluated at the parameters of the posterior distribution;
- the credibility factor when the Bayesian premium is expressed as a credibility premium.

A.1 Bernoulli/beta case

$X|\Theta = \theta \sim \text{Bernoulli}(\theta)$
$\Theta \sim \text{Beta}(a, b)$
$\Theta|X_1 = x_1, \dots, X_n = x_n \sim \text{Beta}(\tilde{a}, \tilde{b})$

$$\tilde{a} = a + \sum_{t=1}^{n} x_t$$
$$\tilde{b} = b + n - \sum_{t=1}^{n} x_t$$

Risk premium

$$\mu(\theta) = \theta$$

Collective premium

$$m = \frac{a}{a+b}$$

Bayesian premium

$$B_{n+1} = \frac{a + \sum_{t=1}^{n} X_t}{a+b+n}$$

Credibility factor

$$z = \frac{n}{n+a+b}$$

A.2 Binomial/beta case

$X|\Theta = \theta \sim \text{Binomial}(\nu, \theta)$
$\Theta \sim \text{Beta}(a, b)$
$\Theta|X_1 = x_1, \ldots, X_n = x_n \sim \text{Beta}(\tilde{a}, \tilde{b})$

$$\tilde{a} = a + \sum_{t=1}^{n} x_t$$

$$\tilde{b} = b + n\nu - \sum_{t=1}^{n} x_t$$

Risk premium

$$\mu(\theta) = \nu\theta$$

Collective premium

$$m = \frac{\nu a}{a+b}$$

Bayesian premium

$$B_{n+1} = \frac{\nu(a + \sum_{t=1}^{n} X_t)}{a+b+n\nu}$$

Credibility factor

$$z = \frac{n}{n + (a+b)/\nu}$$

A.3 Geometric/Beta case

$X|\Theta = \theta \sim \text{Geometric}(\theta)$
$\Theta \sim \text{Beta}(a, b)$
$\Theta|X_1 = x_1, \ldots, X_n = x_n \sim \text{Beta}(\tilde{a}, \tilde{b})$

$$\tilde{a} = a + n$$

$$\tilde{b} = b + \sum_{t=1}^{n} x_t$$

Risk premium

$$\mu(\theta) = \frac{1-\theta}{\theta}$$

Collective premium

$$m = \frac{b}{a-1}$$

Bayesian premium

$$B_{n+1} = \frac{b + \sum_{t=1}^{n} X_t}{a + n - 1}$$

Credibility factor

$$z = \frac{n}{n + a - 1}$$

A.4 Negative binomial/Beta case

$X|\Theta = \theta \sim$ Negative binomial(r, θ)
$\Theta \sim$ Beta(a, b)
$\Theta|X_1 = x_1, \ldots, X_n = x_n \sim$ Beta$(\tilde{a}, \tilde{b})$

$$\tilde{a} = a + nr$$
$$\tilde{b} = b + \sum_{t=1}^{n} x_t$$

Risk premium

$$\mu(\theta) = \frac{r(1-\theta)}{\theta}$$

Collective premium

$$m = \frac{rb}{a-1}$$

Bayesian premium

$$B_{n+1} = \frac{r(b + \sum_{t=1}^{n} X_t)}{a + nr - 1}$$

Credibility factor

$$z = \frac{n}{n + (a-1)/r}$$

A.5 Poisson/Gamma case

$X|\Theta = \theta \sim$ Poisson(θ)
$\Theta \sim$ Gamma(α, λ)
$\Theta|X_1 = x_1, \ldots, X_n = x_n \sim$ Gamma$(\tilde{\alpha}, \tilde{\lambda})$

$$\tilde{\alpha} = \alpha + \sum_{t=1}^{n} x_t$$
$$\tilde{\lambda} = \lambda + n$$

Risk premium

$$\mu(\theta) = \theta$$

Collective premium

$$m = \frac{\alpha}{\lambda}$$

Bayesian premium

$$B_{n+1} = \frac{\alpha + \sum_{t=1}^{n} X_t}{\lambda + n}$$

Credibility factor

$$z = \frac{n}{n + \lambda}$$

A.6 Exponential/Gamma case

$X|\Theta = \theta \sim \text{Exponential}(\theta)$
$\Theta \sim \text{Gamma}(\alpha, \lambda)$
$\Theta|X_1 = x_1, \ldots, X_n = x_n \sim \text{Gamma}(\tilde{\alpha}, \tilde{\lambda})$

$$\tilde{\alpha} = \alpha + n$$

$$\tilde{\lambda} = \lambda + \sum_{t=1}^{n} x_t$$

Risk premium

$$\mu(\theta) = \frac{1}{\theta}$$

Collective premium

$$m = \frac{\lambda}{\alpha - 1}$$

Bayesian premium

$$B_{n+1} = \frac{\lambda + \sum_{t=1}^{n} X_t}{\alpha + n - 1}$$

Credibility factor

$$z = \frac{n}{n + \alpha - 1}$$

A.7 Gamma/Gamma case

$X|\Theta = \theta \sim \text{Gamma}(\tau, \theta)$
$\Theta \sim \text{Gamma}(\alpha, \lambda)$
$\Theta|X_1 = x_1, \ldots, X_n = x_n \sim \text{Gamma}(\tilde{\alpha}, \tilde{\lambda})$

$$\tilde{\alpha} = \alpha + n\tau$$

$$\tilde{\lambda} = \lambda + \sum_{t=1}^{n} x_t$$

Risk premium

$$\mu(\theta) = \frac{\tau}{\theta}$$

Collective premium

$$m = \frac{\tau\lambda}{\alpha - 1}$$

Bayesian premium

$$B_{n+1} = \frac{\tau(\lambda + \sum_{t=1}^{n} X_t)}{\alpha + n\tau - 1}$$

Credibility factor

$$z = \frac{n}{n + (\alpha - 1)/\tau}$$

A.8 Normal/Normal case

$X|\Theta = \theta \sim \text{Normal}(\theta, \sigma_2^2)$
$\Theta \sim \text{Normal}(\mu, \sigma_1^2)$
$\Theta|X_1 = x_1, \dots, X_n = x_n \sim \text{Normal}(\tilde{\mu}, \tilde{\sigma}_1^2)$

$$\tilde{\mu} = \frac{\sigma_1^2 \sum_{t=1}^{n} x_t + \sigma_2^2 \mu}{n\sigma_1^2 + \sigma_2^2}$$
$$\tilde{\sigma}_1^2 = \frac{\sigma_1^2 \sigma_2^2}{n\sigma_1^2 + \sigma_2^2}$$

Risk premium

$$\mu(\theta) = \theta$$

Collective premium

$$m = \mu$$

Bayesian premium

$$B_{n+1} = \frac{\sigma_1^2 \sum_{t=1}^{n} X_t + \sigma_2^2 \mu}{n\sigma_1^2 + \sigma_2^2}$$

Credibility factor

$$z = \frac{n}{n + \sigma_2^2/\sigma_1^2}$$

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