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) and regression credibility models. Furthermore, function simul 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:
3 Hierarchical credibility model

The linear model fitting function of R is named `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 `cn`.

Function `cn` 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) and the regression model of Hachemeister (1975), optionally with the intercept at the barycenter of time (Bühlmann and Gisler, 2005, Section 8.4). The modular design of cm makes it easy to add new models if desired.

This subsection 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). We support 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 contracts are classified into cohorts. In our terminology, this is a two-level hierarchical classification structure. The observations are claim amounts $S_{ijt}$, where index $i = 1, \ldots, I$ identifies the cohort, index $j = 1, \ldots, J_i$ identifies the contract within the cohort and index $t = 1, \ldots, n_{ij}$ 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 contract based on ratios $X_{ijt} = S_{ijt} / w_{ijt}$ is

$$
\hat{\pi}_{ij} = z_{ij}X_{ijw} + (1 - z_{ij})\hat{\pi}_i \tag{1}
$$

with the credibility factors

$$
z_{ij} = \frac{w_{ijw}}{w_{ijw} + s^2/a}, \quad w_{ijw} = \frac{\sum_{t=1}^{n_{ij}} w_{ijt}}{I_i} \quad \text{and} \quad z_{i} = \frac{z_{ij}}{z_{i} + s^2/b}, \quad \sum_{j=1}^{J_i} z_{ij} = 1
$$

and the weighted averages

$$
X_{ijw} = \frac{\sum_{t=1}^{n_{ij}} w_{ijt} X_{ijt}}{w_{ijw}}, \quad X_{i} = \frac{\sum_{j=1}^{J_i} z_{ij} X_{ijw}}{z_{i}}
$$

The estimator of $s^2$ is

$$
s^2 = \frac{1}{\sum_{i=1}^{I} \sum_{j=1}^{J_i} (n_{ij} - 1) \sum_{i=1}^{I} \sum_{j=1}^{J_i} \sum_{t=1}^{n_{ij}} w_{ijt} (X_{ijt} - X_{ijw})^2}. \tag{2}
$$
The three types of estimators for parameters $a$ and $b$ are the following. First, let

\[
A_i = \sum_{j=1}^{J_i} w_{ij} (X_{ijw} - X_{ijw})^2 - (J_i - 1)s^2 \quad c_i = w_{i\xi\Sigma} - \sum_{j=1}^{J_i} \frac{w_{ij}}{w_{i\xi\Sigma}}
\]

\[
B = \sum_{i=1}^{I} z_{iw} (X_{i\xi w} - X_{i\xi w})^2 - (I - 1)a \quad d = z_{\Sigma \xi w} - \sum_{i=1}^{I} \frac{z_{iw}^2}{z_{\Sigma \xi w}}
\]

with

\[
X_{i\xi w} = \sum_{i=1}^{I} \frac{z_{iw}}{z_{\Sigma \xi w}} X_{i\xi w}
\]

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

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

\[
\hat{b} = \max \left( \frac{B}{d}, 0 \right)
\]

the Ohlsson estimators are

\[
\hat{a}' = \frac{\sum_{i=1}^{I} A_i}{\sum_{i=1}^{I} c_i}
\]

\[
\hat{b}' = \frac{B}{d}
\]

and the iterative (pseudo-)estimators are

\[
\bar{a} = \frac{1}{\sum_{i=1}^{I} (J_i - 1)} \sum_{i=1}^{I} \sum_{j=1}^{J_i} z_{ij} (X_{ijw} - X_{ijw})^2
\]

\[
\bar{b} = \frac{1}{I - 1} \sum_{i=1}^{I} z_{i} (X_{i\xi w} - X_{i\xi w})^2
\]

where

\[
X_{i\xi w} = \sum_{i=1}^{I} \frac{z_{i}}{z_{\Sigma \xi w}} X_{i\xi w}
\]

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 $\hat{m} = X_{i\xi w}$.

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 `simul` 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 `NA`s. There can be entities with no experience (complete lines of `NA`s).

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 using the iterative estimators is:

\begin{Sinput}
> 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
\end{Sinput}

\begin{Soutput}
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
\end{Soutput}

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:
\begin{Sinput}
> predict(fit)
\end{Sinput}
\begin{Soutput}
$cohort$
[1] 1949 1543

$state$
[1] 2048 1524 1875 1497 1585
\end{Soutput}

One can also obtain a nicely formatted view of the most important results with a call to \texttt{summary}:
The methods of predict and summary can both report for a subset of the levels by means of an argument levels. For example:
\begin{Sinput}
> summary(fit, levels = "cohort")
\end{Sinput}
\begin{Soutput}
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

<table>
<thead>
<tr>
<th>Level: cohort</th>
<th>Indiv. mean</th>
<th>Weight</th>
<th>Cred. factor</th>
<th>Cred. premium</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1967</td>
<td>1.407</td>
<td>0.9196</td>
<td>1949</td>
</tr>
<tr>
<td>2</td>
<td>1528</td>
<td>1.596</td>
<td>0.9284</td>
<td>1543</td>
</tr>
</tbody>
</table>
\end{Soutput}
\begin{Sinput}
> predict(fit, levels = "cohort")
\end{Sinput}
\begin{Soutput}
$cohort$
[1] 1949 1543
\end{Soutput}

The results above differ from those of Goovaerts and Hoogstad (1987) for the same example because the formulas for the credibility premiums are different.

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

\begin{equation}
\hat{a} = \frac{w_{\Sigma}}{w_{\Sigma}^2 - \sum_{i=1}^I w_i^2} \left( \sum_{i=1}^I w_i (X_{iw} - X_{ww})^2 - (I - 1) \hat{s}^2 \right), \tag{11}
\end{equation}
and the iterative estimator

\[ \tilde{a} = \frac{1}{I-1} \sum_{i=1}^{I} z_i (X_{iw} - X_{ziw})^2 \]  

is better known as the Bichsel–Straub estimator.

To fit the Bühlmann model using \texttt{cm}, one simply does not specify any weights:

\begin{verbatim}
> cm(~state, hachemeister, ratios = ratio.1:ratio.12)
\end{verbatim}

\begin{verbatim}
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
\end{verbatim}

In comparison, the results for the Bühlmann–Straub model using the Bichsel–Straub estimator are:

\begin{verbatim}
> cm(~state, hachemeister, ratios = ratio.1:ratio.12, weights = weight.1:weight.12)
\end{verbatim}

\begin{verbatim}
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
\end{verbatim}
5 Regression model of Hachemeister

The 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). For example, fitting the model

\[ X_t = \beta_0 + \beta_1 t + \epsilon_t, \quad t = 1, \ldots, 12 \]

to the original data set of Hachemeister (1975) is done with

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

Computing the credibility premiums requires to give 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.

\begin{Sinput}
> predict(fit, newdata = data.frame(time = 13))
\end{Sinput}
\begin{Soutput}
[1] 2437 1651 2073 1507 1759
\end{Soutput}

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 at the barycenter of time instead of at time origin (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:
\begin{Sinput}
> 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))
\end{Sinput}
\begin{Soutput}
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

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

  Cred. premium
        2457
        1651
        2071
        1597
        1698
\end{Soutput}
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.

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

References


