Recent outlier detection methods with illustrations in loss reserving

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Context

Reserving
Robustness and Outliers

Robust Statistical Techniques
Robustness criteria
Heuristic Tools
Robust M-estimation
Outlier Detection Techniques

Robust Reserving
Overview
Illustration - Robust Bivariate Chain Ladder
Robust N-Dimensional Chain-Ladder

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The Reserving Problem

<table>
<thead>
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<td>( X_{I,1} )</td>
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</table>

**Figure:** Aggregate claims run-off triangle

- Complete the square (or rectangle)
- Also - multivariate extensions.
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Common Reserving Techniques

- Deterministic Chain-Ladder
- Stochastic Chain-Ladder (Hachmeister and Stanard, 1975; England and Verrall, 2002)
- Mack’s Model (Mack, 1993)
- GLMs (Wright, 1990)
- Regression - e.g. Taylor and Ashe (1983); Taylor (1988); Kremer (1997)
- Bornhuetter-Ferguson technique (Bornhuetter and Ferguson, 1972)
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One of the (many) challenges for practitioners

Imagine one of the observations in the triangle is fairly large (or small)—larger (smaller) than you would generally expect *(really?)*. What do you do?

- Even one data point may have a major impact on the outcome—either positive or negative (refer to our previous GIS presentation, and associated paper Avanzi, Lavender, Taylor, and Wong, 2016)
- on the one hand, to adjust it too much will lead to an under-(over-)estimation of the reserve
- on the other hand, to leave it may lead to an over-(under-)estimation of the reserve

How can we determine in a rigorous way whether this is an outlier? How can we best allow for this / adjust the observation?
Outliers in Reserving (Van Wouwe et al., 2009)

- One or more observations differ from majority
- Can be due to
  - Exceptional circumstances
  - Mistakes
- Outliers are present in real data (Verdonck, Van Wouwe, and Dhaene, 2009; Van Wouwe, Verdonck, and Van Rompay, 2009; Verdonck and Van Wouwe, 2011)
- Existence of such outliers can potentially have significant impact on the reserves and also the Standard Error of the reserve estimate.
Robustness: Definition

Ability of model or estimation procedure to not be overtly influenced by outliers and/or deviations from assumptions.

Why Make Something Robust?

- More closely reflect reality $\rightarrow$ Enhanced accuracy & reliability
- Guard against oversimplification for mathematical convenience
- Identify and further inspect aberrations in the data

What are the trade-offs?

- Bias $(data\ is\ manipulated)$
- Efficiency $(precisely\ wrong\ vs\ approximatively\ right)$
  - A tale of two extremes
- Complexity $(should\ we\ bother?)$
Illustration - Efficiency Trade-Off

Standard Error of Reserves are

- Marginally increased when no outliers are present
- Always decreased when one outlier present. Often significantly (e.g. $X_{1,9}$ and $X_{2,4}$)

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(Verdonck, Van Wouwe, and Dhaene, 2009)
Robustness in Reserving Models

- Deterministic chain-ladder:
  - Development factors are essentially means, and means are non-robust.

- Stochastic chain-ladder:
  - Maximum or quasi-likelihood estimation of parameters is non-robust (Pregibon, 1982; Künsch, Stefanski, and Carroll, 1989; Verdonck and Debruyne, 2011)

  (applies also to other parametric reserving techniques)
Robustness in Reserving - Additional complications

Motivation for our work:

- Claims data is **often skewed** → not fully accounted for in existing robust reserving (see, e.g. Verdonck and Van Wouwe, 2011).
- General insurers often operate across multiple lines of business → robust **multivariate technique** required
Summary of problem

Loss reserving techniques are based on simplifying assumptions. Not all observations will conform to these assumptions.

Challenges

- Identifying outliers in a statistically rigorous manner, including observations that violate the dependence structure of multiple data sets
  - Misclassification risk
  - Particularly when skewness is present
- Adjusting detected outliers appropriately
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Three fundamental features (Huber and Ronchetti, 2009):

1. **Efficiency**: Optimal or nearly optimal efficiency at the assumed model
2. **Stability**: Small divergences should only have a minor effect on performance
3. **Breakdown**: Moderately greater divergences should not lead to a disaster
Robust Statistical Techniques

- Heuristic Tools - Facilitate understanding of the robustness of the procedure
- Robust M-estimation - ensure parameters are estimated in a robust fashion
- Outlier Detection - Identify aberrant observations
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Heuristic Tools

- Influence Functions (Huber and Ronchetti, 2009; Hampel, 1968)

\[ \text{IF}(x, F, T) = \lim_{h \to 0} \frac{T((1 - h)F + h\delta_x) - T(F)}{h} \]

- Verdonck and Debruyne (2011): Influence functions for estimates of \( \alpha_i, \beta_j \), future claims & reserves in Poisson GLM CL unbounded.
Heuristic Tools

- Impact Functions (Venter and Tampubolon, 2008; Avanzi, Lavender, Taylor, and Wong, 2016)

\[ IF_{k,j}(T) = \frac{\partial T}{\partial X_{k,j}} \]

- Highlight sensitivity of statistics to individual observations
- Venter and Tampubolon (2008): Calculate impact functions and GDFs (Ye, 1998) for a range of models.

- Gross Error Sensitivity
- Breakdown Point
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M-estimators

\[ \sum m(x_i; T_n) = \min! \]

Where \( T_n \) is the estimate

OR implicitly

\[ \sum \psi(x_i; T_n) = 0 \]

where \( \psi \) represents the derivative of \( m \)

Not necessarily robust in their own right (Pregibon, 1982; Künsch, Stefanski, and Carroll, 1989; Stefanski, Carroll, and Ruppert, 1986) → depends how observations are weighted

Verdonck and Debruyne (2011) provide a robust GLM reserving methodology by utilising a Huber Function.
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Common Outlier Detection Techniques

- Boxplots (Tukey, 1977; Hubert and Vandervieren, 2008)
- Bagplots (Rousseeuw, Ruts, and Tukey, 1999)
- *bagdistance* (Hubert, Rousseeuw, and Segaert, 2016)
- Adjusted Outlyingness (Hubert and Van der Veeken, 2008)
- MCD (Rousseeuw, 1984) Mahalanobis Distance
BoxPlot

- Univariate data: $x_1, x_2, ..., x_n$
- $Q_1$: First quartile
- $Q_3$: Third quartile
- IQR: $Q_3 - Q_1$
- Non-outlying observations: $[Q_1 - 1.5*IQR, Q_3 + 1.5*IQR]$
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- Robust Statistical Techniques
- Outlier Detection Techniques
Adjusted Boxplot

- $\text{med}_n$: median of the data
- $h(x_i, x_j) = \frac{(x_j - \text{med}_n) - (\text{med}_n - x_i)}{x_j - x_i}$, $x_i < \text{med}_n < x_j$
- $MC(X_n) = \text{med}_{x_i < \text{med}_n < x_j} h(x_i, x_j)$
- Adjusted boxplot:
  
  $[Q1 - 1.5e^{-4MC}IQR, Q3 + 1.5e^{3MC}IQR]$, $MC > 0$
  
  $[Q1 - 1.5e^{3MC}IQR, Q3 + 1.5e^{4MC}IQR]$, $MC < 0$
Boxplot and Adjusted Boxplot

Classical
(Tukey, 1977)

\[ [Q1 - 1.5IQR, Q3 + 1.5IQR] \]

Skew-Adjusted
(Hubert and Van der Veeken, 2008)

\[ [Q1 - h_l(MC)IQR, Q3 + h_u(MC)IQR] \]
Boxplots in Robust Reserving Literature

Deterministic Robust Chain-Ladder of Verdonck, Van Wouwe, and Dhaene (2009):

- Applies classical boxplot on residuals after testing for normality of data at two stages in methodology
- Recommends utilising Skew-Adjusted boxplot if normality rejected
Minimum Covariance Determinant (MCD)

\[ MD(x_i) = \sqrt{(x_i - \hat{\mu}_0)'\Sigma_0^{-1}(x_i - \hat{\mu}_0)} \]

(Rousseeuw, 1984)

Adjust outliers by bringing them back to the tolerance ellipse given by the 95th percentile of \( \chi^2 \) distribution.
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Robust Statistical Techniques

Outlier Detection Techniques

**Halfspace Depth (Tukey, 1975)**

- Bounded Influence Function (Romanazzi, 2001)
- Tukey Median has high Breakdown Point (up to \( \frac{1}{3} \)) (Donoho and Gasko, 1992)
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Bagplot
Adjusted Outlyingness

- Adjustment of Stahel-Donoho Outlyingness (Donoho, 1982) to account for skewness

- Adjusted Outlyingness:

\[ AO_i = AO^{(1)}(x_i, X_n) = \begin{cases} 
\frac{x_i - \text{med}(X_n)}{w_2 - \text{med}(X_n)}, & \text{if } x_i > \text{med}(X_n) \\
\frac{\text{med}(X_n) - x_i}{\text{med}(X_n) - w_1}, & \text{if } x_i < \text{med}(X_n) 
\end{cases} \]
- $x_1$ and $x_2$ are the same distance to the median
- But the scales are different
- $x_1$ is an outlier, $x_2$ is not

(Hubert and Van der Veeken, 2008)
Multivariate Data - Adjusted Outlyingness

- Project the data in the direction $a$ to maximize the univariate outlyingness measure
- If large AO in one direction then observation may be an outlier
- Adjusted Outlyingness:

$$AO_i = AO(x_i, X_n) = \sup_{a \in \mathbb{R}^p} AO^{(1)}(a^T x_i, X_n a)$$

- Plot Adjusted Boxplot for all $AO_i$
- Cutoff value: $Q_3 + 1.5 e^{3MC} IQR$
AO-Based Bagplot
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**bagdistance**
Recent Developments

mrfDepth Package

- Previously, bagplot fence factor was chosen to be 3.
- Hubert, Rousseeuw, and Segaert (2015) derived distribution of \( \text{bagdistance} \) when underlying data is elliptical.
- As a result Segaert, Hubert, Rousseeuw, Raymaekers, and Vakili (2017) have developed a new fence factor given by 
  \[ \sqrt{\chi^2_{\{99,N\}}} \]
- This new cut-off has more rigorous foundations.
- A new cutoff value for Adjusted Outlyingness given by 
  \[ \sqrt{\chi^2_{\{99,N\}}} \cdot \text{median}(AO) \]
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Robust Bivariate Chain-Ladder

**General Approach**

1. Perform robust GLM chain-ladder on each triangle separately
2. Store residuals as bivariate data set
3. Detect bivariate outliers
4. Treat outliers
5. Perform multivariate time series chain-ladder
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Existing Robust Bivariate Chain-Ladder

Shortcomings of Current Techniques

- MCD Mahalanobis Distance
  - Does not incorporate skewness at all
    → FALSE or MISSED detections
- Bagplot
  - Does not provide unique measure of outlyingness
    → limits communicability and potential treatment options
  - Only can handle mild skewness
  - Computationally expensive
    → $O(n^2(\log n)^2)$. 
New Robust Bivariate Chain-Ladder

New Approaches

- Adjusted Outlyingness
  - Explicitly incorporates robust measure of skewness
  - Suitable for more extreme levels of skewness
  - Provides unique measure of outlyingness
  - Less computationally expensive than bagplot ($O(mnp \log n)$)
  - Important for extensions to higher dimensions

- bagdistance
  - Derived from bagplot
  - Provides unique measure of outlyingness
  - Can determine how outlying observations are
  - More treatment options become available
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Robust Bivariate Chain-Ladder Example

- Real data over 10 years from Shi, Basu, and Meyers (2012)
- Personal and Commercial Auto Insurance Lines
- 55 observations
- Bivariate Skewness = 7.21
MCD Mahalanobis Distance

**Figure:** Initial Tolerance Ellipses

**Figure:** Tolerance Ellipses After Adjustment
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Illustration - Robust Bivariate Chain Ladder

Bagplot

**Figure:** Bagplot without fence

**Figure:** Bagplot with fence drawn in green
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Adjusted Outlyingness

**Figure:** Adjusted Outlyingness bagplot without fence

**Figure:** Adjusted Outlyingness bagplot with fence drawn in green
Adjusted Outlyingness using alternative mrfDepth cut-off value

Figure: Adjusted-Outlyingness bagplot using mrfDepth cut-off

Figure: Bagplot
Outlier Detection Results

<table>
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<tr>
<th>Outliers</th>
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<th>MCD</th>
<th>AO*</th>
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Table: Outlier Detection Results

*All were detected only when using traditional AO cut-off value.

**Using cut-off distance of $\sqrt{\chi_{0.99,2}^2}$. 
Weighting adjustment of outliers based on bagdistance

**Figure:** bagdistance adjustment mechanism with no limit

**Figure:** bagdistance adjustment mechanism with limit
## Final Reserves and rmse

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**Table: Bivariate Example Reserves and rmse**

- Modest adjustment in reserves
- Significant reduction in rmse of reserves
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Extension of Robust Bivariate Chain-Ladder including techniques based on
- Adjusted Outlyingness
- Halfspace Depth
Adjusted Outlyingness Approach

Figure: Trivariate Residuals with 3D AO-based Bag

Figure: Trivariate Residuals with 3D AO-based Bag and Loop
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Adjust residuals back to relevant convex polyhedron using parametric line-clipping algorithm (Cyrus and Beck, 1978; Liang and Barsky, 1984)
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References
Some remarks

- We put forward extensions to robust chain ladder techniques
- We do not recommend that these methodologies should necessarily replace existing methodologies.
- Rather, we recommend this analysis is done in addition to existing analysis as a diagnostic tool so as to gain further insights about possible outliers.
- This should then inform how to proceed with existing techniques, and may prompt the actuary to make some additional investigations about the data.
Summary

In this presentation we

▶ Reviewed outlier detection techniques, and the (scant) literature in robust reserving
▶ Implemented and explored recent developments in cut-off values for the bagplot and Adjusted-Outlyingness techniques
▶ Provided novel alternative adjustment mechanisms based on bagdistance and Adjusted Outliness
▶ Explained how to extend the robust bivariate chain-ladder to an N-dimensional framework
Conclusions

- Claims data are often skewed and contain outliers
- Using our techniques, such features can be more reliably identified in multivariate settings
- This should inform the reserving process, and ultimately lead to more reliable reserves
Recent outlier detection methods with illustrations loss reserving

References

Context
  Reserving
  Robustness and Outliers

Robust Statistical Techniques
  Robustness criteria
  Heuristic Tools
  Robust M-estimation
  Outlier Detection Techniques

Robust Reserving
  Overview
  Illustration - Robust Bivariate Chain Ladder
  Robust N-Dimensional Chain-Ladder

Summary and Conclusions

References
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References IV


URL https://cran.r-project.org/web/packages/mrfDepth/mrfDepth.pdf


References V


