Functional-based claims reserving with `ProfileLadder`

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Motivation

1. **Flexible non-parametric (functional-based) claims reserving methods**
   (Research in Teams in BIRS, Banff, summer 2014)
2. **Empirical validation, testing, real actuarial data applications**
   (three competitive functional-based reserving algorithms, summer 2020)
3. **Automated, data-driven software implementation**
   (deploying a software package available on CRAN... 2024/2025)

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ProfileLadder

CRAN 0.2.2 | downloads 2273 | release v0.2.2

Functional claims reserving methods based on aggregated chain-ladder data, also known as a run-off triangle, implemented in three nonparametric algorithms (PARALLAX, REACT, and MACRAME) proposed in Maciak, Mizera, and Pešta (2022). [DOI: 10.1017/asb.2022.4]

ProfileLadder: Main ideas behind...

The aim: to provide an overall framework for a very general, theoretically non-restrictive, and practically easily applicable risk assessment/forecasting based on aggregated data...

In non-life insurance in particular, it accounts for a stochastic prediction of the overall loss reserves that are required by some regulator to be kept to cover possible (future) claims...

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- **Standard actuarial R package ChainLadder** `install.packages("ChainLadder")`
  - implements all common and typically used reserving methods – utilizing parametric statistical techniques based on aggregated data structured in the run-off triangles (e.g., the Mack model, over-dispersed Poisson model, Tweedie model, ...)

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  - implements all common and typically used reserving methods – utilizing parametric statistical techniques based on aggregated data structured in the run-off triangles (e.g., the Mack model, over-dispersed Poisson model, Tweedie model, ...)
- **Newly deployed R package ProfileLadder** `install.packages("ProfileLadder")`
  - non-restrictive, non-parametric, and functional-based, reserve prediction methods proposed and theoretically justified in M., Mizera, and Pešta (2022) (e.g., parallel approximation model and Markov chain based prediction, ...)

Run-off triangles: Incremental or cumulative data

Accident year i	Development year j				
	1	2	$\cdots$	$n-1$	n
1	$Y_{1,1}$	$Y_{1,2}$	$\cdots$	$Y_{1,n-1}$	$Y_{1,n}$
2	$Y_{2,1}$	$Y_{2,2}$	$\cdots$	$Y_{2,n-1}$	
			$\ddots$		
$\vdots$	$\vdots$	$\vdots$	$Y_{i,n+1-i}$		
$n-1$	$Y_{n-1,1}$	$Y_{n-1,2}$			
n	$Y_{n,1}$				

Table: Run-off triangle with the observed cumulative claim amounts $Y_{i,j}$ for $i+j \leq n+1$.

Sometimes also represented in terms of incremental payments, $X_{i,j} = Y_{i,j} - Y_{i,j-1}$, for $Y_{i,0} = 0$.

Run-off triangles: Incomplete development profiles

Accid.	Development year j									
year i	1	2	3	4	5	6	7	8	9	10
1	5244	9228	10823	11352	11791	12082	12120	12199	12215	12215
2	5984	9939	11725	12346	12746	12909	13034	13109	13113	13115
3	7452	12421	14171	14752	15066	15354	15637	15720	15744	15786
4	7115	11117	12488	13274	13662	13859	13872	13935	13973	13972
5	5753	8969	9917	10697	11135	11282	11255	11331	11332	11354
6	3937	6524	7989	8543	8757	8901	9013	9012	9046	9164
7	5127	8212	8976	9325	9718	9795	9833	9885	9816	9815
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9	5129	8202	9185	9681	9951	10033	10133	10182	10182	10183
10	3689	6043	6789	7089	7164	7197	7253	7267	7266	7266

(a) Complete portfolio 1

Accid.	Development year j									
year i	1	2	3	4	5	6	7	8	9	10
1	794	1277	1848	2080	2352	2441	2442	2452	2452	2452
2	847	1427	1796	2084	2322	2331	2367	2393	2393	2459
3	701	1317	1912	2147	2196	2285	2290	2291	2359	2359
4	808	1423	1844	1993	2091	2093	2110	2122	2142	2142
5	756	1465	1819	1993	2096	2160	2206	2216	2219	2217
6	771	1266	1489	1685	1822	1836	1857	1910	1919	1918
7	723	1562	1895	2115	2266	2314	2314	2313	2313	2313
8	862	1397	1679	1775	1858	1858	1859	1863	1863	1863
9	930	1523	1971	2150	2197	2224	2292	2332	2341	2341
10	825	1312	1556	1724	1825	1854	1872	1872	1872	1872

(b) Complete portfolio 2

Run-off triangles: Incomplete development profiles

Accid. year i	Development year j: 1	2	3	4	5	6	7	8	9	10
1	5244	9228	10823	11352	11791	12082	12120	12199	12215	12215
2	5984	9939	11725	12346	12746	12909	13034	13109	13113	13115
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(e) Complete portfolio 1

Accid. year i	Development year j: 1	2	3	4	5	6	7	8	9	10
1	794	1277	1848	2080	2352	2441	2442	2452	2452	2452
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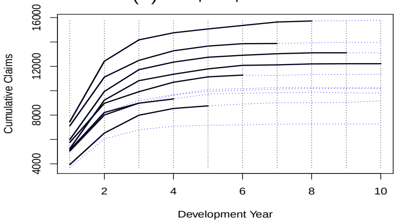
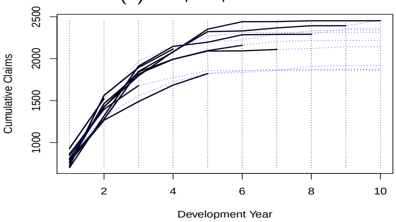
(f) Complete portfolio 2



(g) Development profies for portfolio 1



(h) Development profies for portfolio 2

PARALLAX/REACT/MACRAME

- The building block of all of the proposed methods are so-called functional development profiles, respectively the "patterns of loss emergence" (Clark, 2003)
- The overall reserves are modeled in non-parametric ways with no practical limitations for the underlying data under rigorous theoretical guarantees (Maciak, Mizera, Pešta, 2022)
- Complex software toolbox in the R package ProfileLadder including exploratory and confirmatory statistical tools (Maciak, Matúš, Mizera, and Pešta, 2025?)

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❑ **PARALLAX** – parallel approximation by missing fragments

```
R> parallelReserve(chainladder)
```

❑ **REACT** – approximation by the most recent segment

```
R> parallelReserve(chainladder, method = "react")
```

❑ **MACRAME** – Markov Chain based approximation of missing fragments

```
R> mcReserve(chainladder)
```

PARALLAX: Parallel approximation of missing fragments

- Observed triangle $Y_{i,j}$, for $i = 1, \ldots, n$ and $j = 1, \ldots, n+1-i$
- Set the observed as the predicted $\widehat{Y}_{i,j} = Y_{i,j}$ for $i = 1, \ldots, n$ and $j = 1, \ldots, n+1-i$

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- Set the observed as the predicted $\widehat{Y}_{i,j} = Y_{i,j}$ for $i = 1, \dots, n$ and $j = 1, \dots, n+1-i$

- Find the most similar development profile

$$\widehat{\ell}_{i,j} = \arg \min_{\ell \in \{1,\dots,n-j\}} \left| \widehat{Y}_{i,j} - Y_{\ell,j} \right| \qquad (1)$$

- Predict the unobserved (future) value $Y_{i,j+1}$ such that

$$\widehat{Y}_{i,j+1} = \widehat{Y}_{i,j} + \left(Y_{\widehat{\ell}_{i,j},j+1} - Y_{\widehat{\ell}_{i,j},j} \right) \qquad (2)$$

REACT: Approximation by the most recent accident year

- Observed triangle $Y_{i,j}$, for $i = 1, \dots, n$ and $j = 1, \dots, n + 1 - i$
- Set the observed as the predicted $\widehat{Y}_{i,j} = Y_{i,j}$ for $i = 1, \dots, n$ and $j = 1, \dots, n + 1 - i$

REACT: Approximation by the most recent accident year

- Observed triangle $Y_{i,j}$, for $i = 1, \ldots, n$ and $j = 1, \ldots, n+1-i$
- Set the observed as the predicted $\widehat{Y}_{i,j} = Y_{i,j}$ for $i = 1, \ldots, n$ and $j = 1, \ldots, n+1-i$
- Predict the unobserved (future) value $Y_{i,j+1}$ such that

$$\widehat{Y}_{i,j+1} = \widehat{Y}_{i,j} + (\widehat{Y}_{i-1,j+1} - \widehat{Y}_{i-1,j}) \tag{3}$$

Run-off triangles vs. development profiles

Accid. year i	Development year j									
	1	2	3	4	5	6	7	8	9	10
1	**5244**	9228	10823	11352	11791	12082	12120	12199	12215	12215
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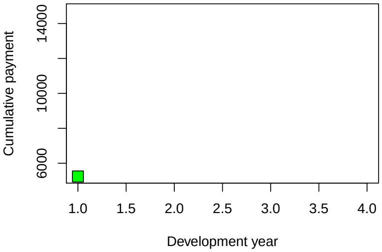

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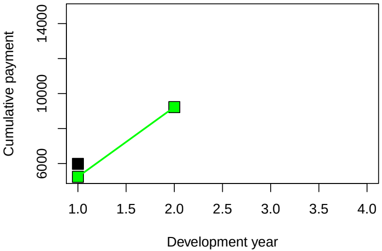

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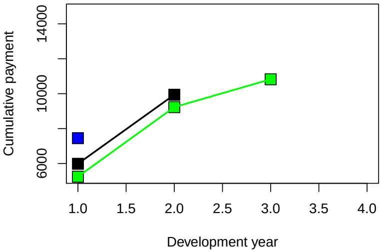

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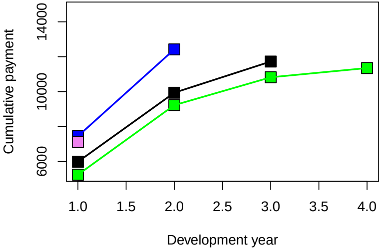

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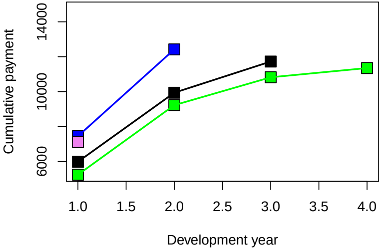
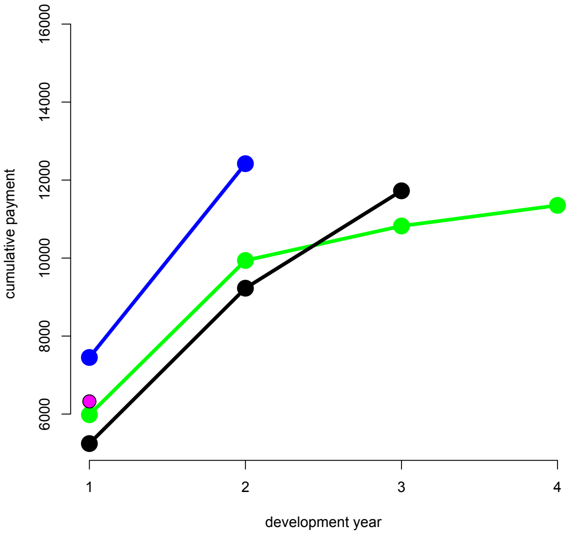


And so on ...

PARALLAX illustration

`parallelReserve(...)`



PARALLAX illustration

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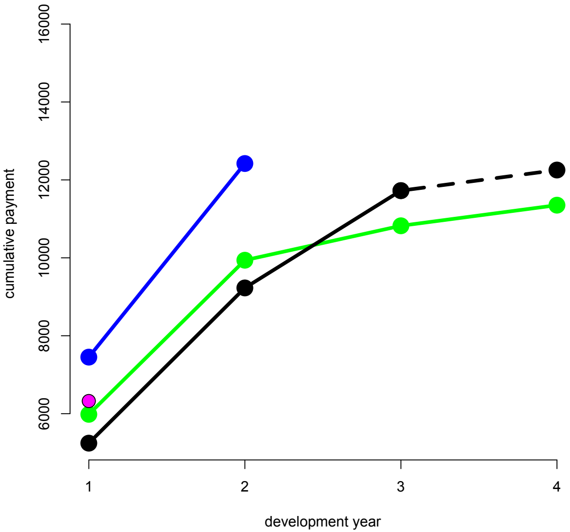

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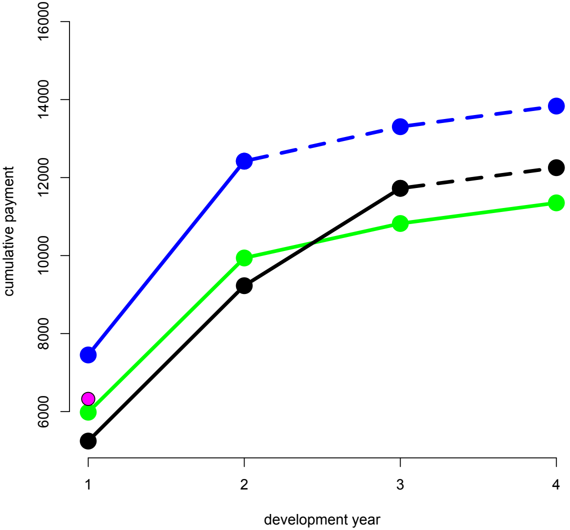

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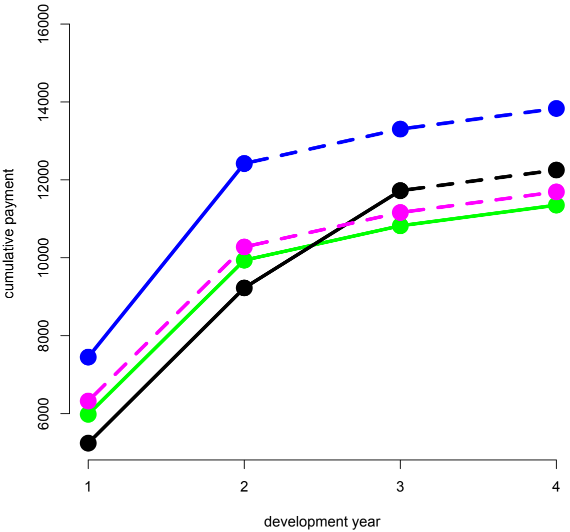
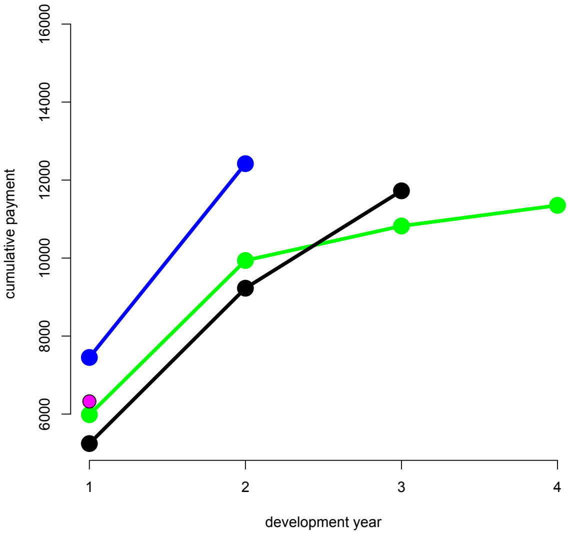


REACT illustration

`parallelReserve(..., method = "react")`



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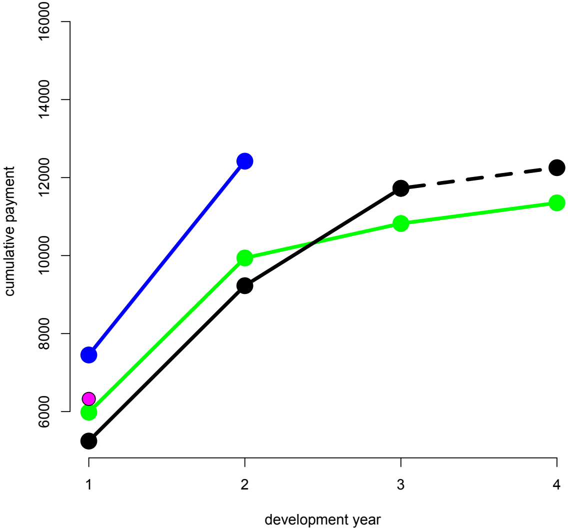

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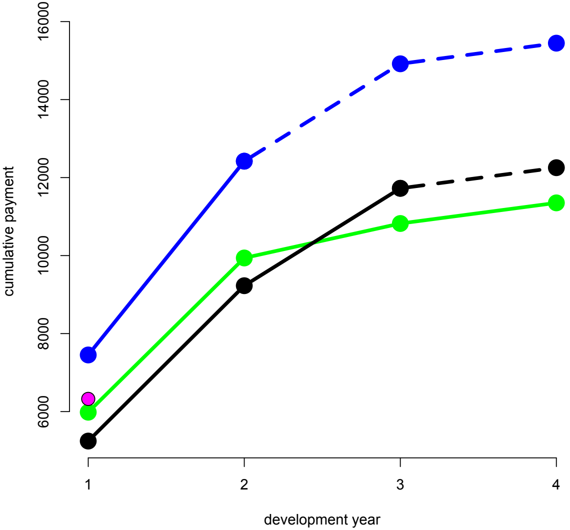

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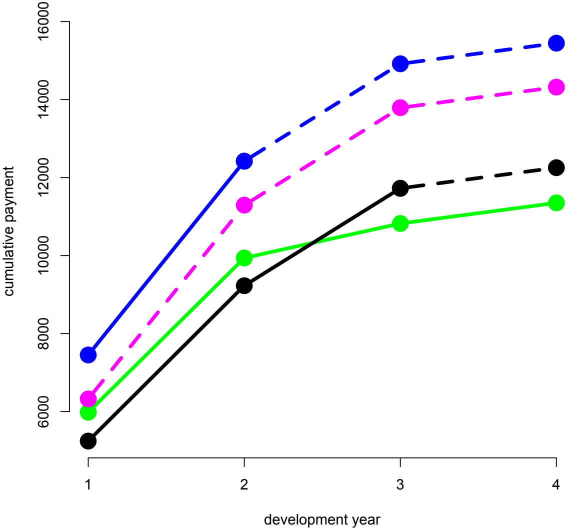

Markov chain driven profile completion `mcReserve(...)`

- relatively complex stochastic model (govern by a homogeneous Markov Chain) that drives the overall prediction (allows for user-based modifications)
- additional triangle exploratory needed to make appropriate user-based decisions (determining the set of Markov states, estimating transition matrix, etc.)

Markov chain driven profile completion `mcReserve(...)`

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- additional triangle exploratory needed to make appropriate user-based decisions (determining the set of Markov states, estimating transition matrix, etc.)

- The best results (so far) still obtained with the proposed data-driven approach (the algorithm originaly proposed and proved in Maciak, Mizera, and Pešta, 2022)
- Additional adjustments and improvements of the R code – package version 0.2.2 (available from CRAN, Maciak, Matúš, Mizera, and Pešta, 2025)

Standard parametric approaches vs. nonparametric

- **ODP Model** – standard (benchmark) model from the `ChainLadder` package

```
R> glmReserve(chainladder)

      First Latest  Dev.To.Date Ultimate IBNR          S.E        CV
2           13113    1.0000000    13113    0   0.01035287       Inf
3           15720    0.9992372    15732   12  29.38975320 2.4491461
4           13872    0.9934116    13964   92  73.46098788 0.7984890
5           11282    0.9850694    11453  171  96.26787355 0.5629700
6            8757    0.9688019     9039  282 120.58781735 0.4276164
7            9325    0.9397360     9923  598 177.57019068 0.2969401
8            8984    0.8905630    10088 1104 246.00693847 0.2228324
9            8202    0.7789914    10529 2327 379.54811405 0.1631062
10           3689    0.4788422     7704 4015 622.22022041 0.1549739
total       92944    0.9152986   101545 8601 880.66723938 0.1023913
```

Three estimation algorithms embeded in two R functions

- **PARALLAX** – parallel approximation by missing fragments (`ProfileLadder` package)

```
R> parallelReserve(chainladder)

      First Latest Dev.To.Date Ultimate IBNR
2      5984  13113   1.0000000    13113    0
3      7452  15720   0.9997456    15724    4
4      7115  13872   0.9943373    13951   79
5      5753  11282   0.9883487    11415  133
6      3937   8757   0.9690163     9037  280
7      5127   9325   0.9496894     9819  494
8      5046   8984   0.9142159     9827  843
9      5129   8202   0.8361709     9809 1607
10     3689   3689   0.4197292     8789 5100
total 49232  92944   0.9158488   101484 8540
```

Permutation bootstrap extension

```
R> permuteReserve(parallelReserve(chainladder))

      First Latest Dev.To.Date Ultimate IBNR        S.E        CV
2      5984  13113   1.0000000    13113    0   0.000000       NaN
3      7452  15720   0.9997456    15724    4   8.383726 2.0959316
4      7115  13872   0.9943373    13951   79  25.711837 0.3254663
5      5753  11282   0.9883487    11415  133  48.488393 0.3645744
6      3937   8757   0.9690163     9037  280  69.136437 0.2469158
7      5127   9325   0.9496894     9819  494  90.724193 0.1836522
8      5046   8984   0.9142159     9827  843 205.792826 0.2441196
9      5129   8202   0.8361709     9809 1607 526.256553 0.3274776
10     3689   3689   0.4197292     8789 5100 644.562513 0.1263848
total 49232  92944   0.9158488   101484 8540 826.267197 0.0967526

Overall reserve distribution
     Boot.Mean        Std.Er.        BootCov%     BootVar.995
   9012.544548     826.267197        9.167968        1.219966

The PARALLAX predicted reserve represents the 32.53% quantile of the reserve distribution
Bootstrap simulated reserves beyond 2sigma rule: 15 (out of 500)
```

Bootstrap resampled reserves

Instead of the point prediction the regulator/company is typicaly interested in the overall distributional prediction of the reserve (typically the 0.995 quantile of the reserve distribution)...

$\Longrightarrow$ imposing some distributional assumptions or using resamplng methods...

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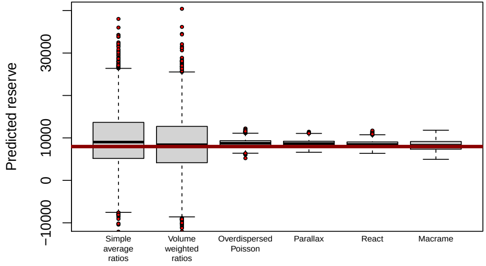

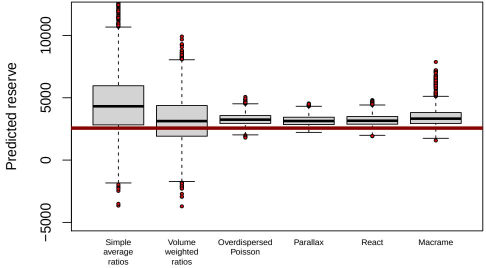

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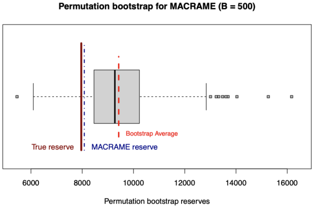
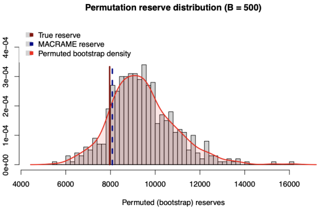
Prediction method	Point prediction	Permutation bootstrap	Residual bootstrap
PARALLAX	0.03s. (0.006)	15.01s. (0.341)	✗
REACT	0.01s. (0.001)	9.04s. (0.116)	✗
MACRAME	0.04s. (0.012)	48.75s. (11.51)	✗
Chainladder	0.03s. (0.008)	31.70s. (0.276)	✗
Mack model	0.04s. (0.002)	42.10s. (0.650)	✗
ODP model	3.86s. (0.043)	63.37m. (0.148)	∞ m. (NA*)
Tweedie formula	0.24s. (0.026)	4.19m. (0.307)	3.69m. (0.252)

ProfileLadder package: Permutation bootstrap

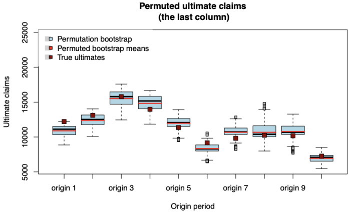
```
R> permuteReserve(...)
```



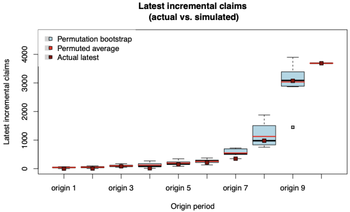
(a) Boxplot of $\{\widehat{\mathcal{R}}^{(b)}\}_{b=1}^{100}$ values



(b) Histogram and the estimated density



(c) Simulated ultimate claims



(d) Simulated run-off diagonals

Core functions of the R package `ProfileLadder`

- **Point predictions** – three functional-based reserve prediction algorithms
  - **PARALLAX** – **Parallel approximation** by missing fragments
    ```
    R> parallelReserve(data)     ## parallelReserve.R | 230 lines / 80 documentation
    ```
  - **REACT** – Approximation by the most **recent accident** segment
    ```
    R> parallelReserve(data, method = "react")
    ```
  - **MACRAME** – **Markov chain fragment** approximation
    ```
    R> mcReserve(data)           ## mcReserve.R | 405 lines / 110 documentation
    ```
- **Distributional prediction** – performed in terms of permutation bootstrap resampling
  - **Permutation bootstrap** – applicable to all nonparametric and also classical parametric methods
    ```
    R> permuteReserve(...)       ## permuteReserve.R | 320 lines / 120 documentation
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  ```
- **Additional utility/design functions** – for an easy integration with other packages
  ```
  R> as.profileLadder(); observed(); set.fancy.print(); zzz(); ...
  ```

It is the era of data... big data actually

- **Reproducibility data for testing purposes and comparisons**
  - real data from Mayers and Shi (2011) used in the theoretical paper (10×10) *(although, provided in a different structure in the `raw` package)*

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  - real run-off triangles not made available in any other public sources yet (17×17) *(provided by Generali-Česká Pojištovna, a.s.)*

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Empirical comparisons and validation using real data

- 518 run-off triangles from the National Association of Insurance Commissioners (NAIC) database – available in the R package `raw` (Meyers and Shi, 2011)
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(*i*) 130 run-off triangles that were ODP compliant (with non-negative increments only, but profiles being entirely zero not allowed)

(*ii*) 299 not ODP compliant triangles (negative increments exists, but still no entirely zero profiles)

(*iii*) 89 remaining triangles that could be considered "rather atypical", but are still not uncommon in the actuarial practice

Out-of-sample bootstrap performance measures

Reserve% gives an absolute relative difference of the predicted reserve and the true reserve defined for each triangle as $100 \times \left| \frac{\text{predicted reserve}}{\text{true reserve}} - 1 \right|$ and averaged over all triangles in the given scenario (smaller values are better);

BootCoV% expresses a coefficient of variation for the bootstrapped reserve distribution relative to the bootstrap mean $100 \times \frac{\text{Std.Dev(bootstrapped reserves)}}{\text{Avg(bootstrapped reserves)}}$ averaged, again, over all triangles in the given scenario (smaller values are better);

BootVaR$_{.995}$ denotes the 99.5% quantile of the bootstrap distribution relative to the bootstrapped mean $\frac{\text{Quantile}_{0.995}\text{(bootstrapped reserves)}}{\text{Avg(bootstrapped reserves)}}$ and averaged over all triangles in the given scenario (smaller values are better);

BootQnt$_{.950}$ provides a percentage proportion of the triangles in the given scenario for which the true reserve is dominated by the 95% quantile of the bootstrapped distribution (values closest to 95% are preferred).

Claims reserves evaluation

Method	`Reserve%`		`BootCoV%`		`BootVaR`$_{.995}$		`BootQnt`$_{.950}$
Average	58.79	*(186.00)*	79.46	*(144.67)*	3.67	*(3.57)*	100.00%
Weighted	47.13	*(130.91)*	53.60	*(61.46)*	2.63	*(1.81)*	98.46%
ODP Model	47.10	*(130.89)*	**16.98**	*(10.16)*	**1.54**	*(0.39)*	86.92%
PARALLAX	57.85	*(125.45)*	**22.34**	*(16.13)*	**1.59**	*(0.46)*	**96.92%**
REACT	**43.19**	*(78.28)*	24.08	*(18.03)*	1.64	*(0.51)*	97.69%
MACRAME	**45.32**	*(76.43)*	23.93	*(12.65)*	1.73	*(0.42)*	**95.38%**

Table: Overall empirical performance of six claims reserving techniques when applied to the group (i), 130 ODP compliant run-off triangles from Meyers and Shi (2011). The corresponding standard deviations are given in parentheses; two best results are indicated by bold typeface.

Claims reserves evaluation II

Method	Reserve%		BootCoV%		BootVaR$_{.995}$		BootQnt$_{.950}$
Average	215.95	*(1128.77)*	4045.61	*(4.0e+04)*	43.14	*(461.41)*	99.67%
Weighted	541.33	*(6135.24)*	−3e+03	*(2.3e+04)*	−7.43	*(132.37)*	97.99%
Chainladder	541.33	*(6135.24)*	**29.78**	*(212.59)*	**1.97**	*(7.58)*	83.28%
PARALLAX	**68.83**	*(132.40)*	**9.53**	*(628.55)*	**1.70**	*(11.04)*	**92.98%**
REACT	97.85	*(334.97)*	66.60	*(182.67)*	2.92	*(4.99)*	**94.31%**
MACRAME	**68.38**	*(93.76)*	51.26	*(36.96)*	2.75	*(1.59)*	91.97%

Table: Empirical performance of six claims reserving techniques applied to the group (ii), 299 "rather typical" but ODP non-compliant run-off triangles from Meyers and Shi (2011). The corresponding standard deviations are given in parentheses; two best results are indicated by bold typeface.

Some conclusions

Three unsupervised loss reserving techniques based on non-parametric and distribution free approaches offering the following advantages:

(i) they are simple, straightforward, and easily applicable;

(ii) they require neither distributional nor parametric assumptions and apply to all kinds of run-off triangles, including those with negative incremental cells or zero cumulative claim amounts over some development periods;

(iii) various stochastic model assumptions can be postulated in order to derive desirable statistical properties serving as the methods' justifications;

(iv) it is straightforward to obtain also the overall reserve distributions via bootstrapping techniques;

(v) and the proposed methods are also robust against outliers.

ProfileLadder package on CRAN (Verson 0.2.2)

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