Addendum to RFP

Loss Reserve Modeling in Actuarial Literature

We should point out that transforming a loss triangle into the form of a longitudinal data set is not new. When Zehnwirth published his paper “Best Estimate for Reserves” in the *Proceedings of the Casualty Actuarial Society*, he put loss triangles into a longitudinal data set form to feed into his analytical routines. What is new is to explicitly recognize that our loss reserving problem can be put into a generic format that is familiar to a wide range of research and data science practitioners.

Linking Loss Triangles to Longitudinal Data Sets

Typically, actuaries arrange the data sets they use to estimate future loss payments in a tabular format called a loss triangle. One can readily convert the data set displayed in a loss triangle format to a longitudinal data set using the dates employed in constructing a loss triangle which has the characteristic that the history is right censored with the time at which it is censored depending on the exposure period. An example is shown below where the first row of the loss triangle is put into the start of a longitudinal data set. Only the first row of the loss triangle is shown in the longitudinal data set example in the interest of space, but all of the values for the triangle cells that are not in the “NA” category would be included in the longitudinal data set. The Accident Period (in this example the time period is a year) is a time period used to group claims by the incident date for the event that triggers coverage under a policy sold by a Property and Casualty Insurance Company and those groups form the subjects for the study. Companies will commonly create sets of triangles by coverage for the policies they sell and may elect to further subdivide those groups by business unit or state in which policies coverage has effect. The history of claim activity by subject is captured in regular increments which is the hallmark of a longitudinal data set. The “NA” in a cell below indicates a future time period for the Accident Period and filling in those “NA” values with forecasts is the goal of the analysis. Please note that there will be other values furnished within the data sets besides incremental payments.

Incremental Paid Loss Triangle Example as of 12/31/2023

Accident Period	Development Year									
	1	2	3	4	5	6	7	8	9	10
2014	1.5	2.53	8.34	25.87	7.94	4.22	2.74	1.75	0.95	0.72
2015	1.21	1.73	6.55	23.03	7.45	4.02	2.34	1.46	1.35	NA
2016	1.17	1.92	6.75	17.27	7.45	4.22	2.68	1.94	NA	NA
2017	2.38	2.36	6.76	19.61	7.38	4.17	2.57	NA	NA	NA
2018	1.39	1.78	6.1	19	7.57	4.62	NA	NA	NA	NA
2019	1.42	1.92	7.31	19.52	6.7	NA	NA	NA	NA	NA
2020	1.28	3.11	6.93	19.63	NA	NA	NA	NA	NA	NA
2021	1.22	2.46	8.1	NA	NA	NA	NA	NA	NA	NA
2022	1.06	1.67	NA	NA	NA	NA	NA	NA	NA	NA
2023	1.59	NA	NA	NA	NA	NA	NA	NA	NA	NA

Translation to Longitudinal Data Set Example

Accident_Period	Calendar_Year	Development_Year	Value
2014	2014	1	1.5
2014	2015	2	2.53
2014	2016	3	8.34
2014	2017	4	25.87
2014	2018	5	7.94
2014	2019	6	4.22
2014	2020	7	2.74
2014	2021	8	1.75
2014	2022	9	0.95
2014	2023	10	0.72