The Actuary and IBNR Techniques

A Machine Learning Approach

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Beyond the horizon. Together.

AGENDA

Traditional IBNR Reserving

ML Approach to IBNR Reserving

Case Study

Conclusion

Beyond the horizon. Together.

TRADITIONAL IBNR RESERVING

BASED ON JUDGEMENT AND HEURISTICS

- Traditionally used subjective expert judgement and heuristics to select a reserving method and parameters of the method (Loss Ratios/LDFs, etc)
- How scientific is the reserving process?
    - e.g. Can we measure the impact of subjective choices on how well we predict future claims payments?
    - Note that some selections not part of statistical models of IBNR e.g. subjective exclusion of LDFs
- Examine performance next year or quarter with AvE
- Often focus on ensuring reserves are enough
- Limited guidance on which techniques to choose and what parameters to select beyond “rules of thumb”

MODERN REQUIREMENTS FOR RESERVING

BEST ESTIMATE RESERVES

- Need to determine a best estimate reserve—but what does this mean?
- Solvency II says:
  - best estimate shall correspond to the probability weighted average of future cash flows, taking account of the time value of money

$$\hat{R}_x = \sum_{i \in \Omega} E_x \, q_x^i \, P(q_x = q_x^i)$$

- Our suggestion: find scientific basis on which to ensure that the expected value of the AvE over time is as close to 0 as possible => more focus on accuracy, less dependence on judgement and "rules of thumb"
- Focus on ensuring that our choices are correct over time!

PERSPECTIVES ON RESERVING

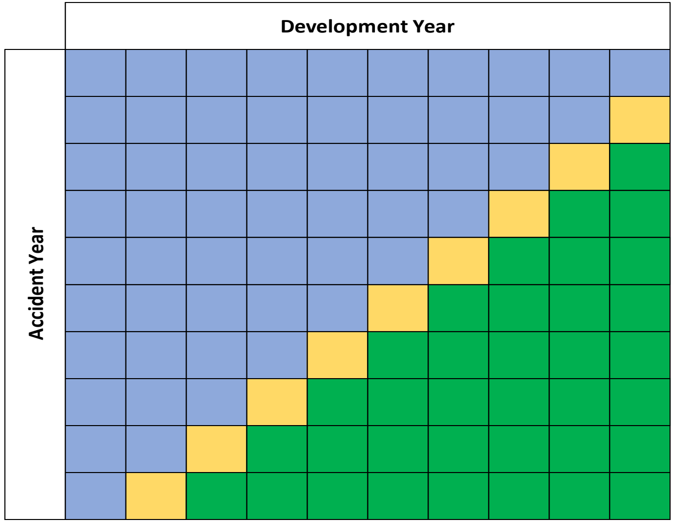
STATIC VS DYNAMIC

- Often reserve techniques presented at point in time – static perspective
- Actuaries must re-estimate reserves on a regular basis (e.g. monthly/quarterly)
- What are ideal techniques to meet goals of reserving process? E.g:
  - minimize AvE differences
  - stabilize ultimate loss ratios
  - reduce P&L impact as much as possible etc
- Dynamic perspective received less attention
- Our focus – select reserving models that have good properties in the dynamic perspective

SETUP

METHOD AND METRICS

- Restricted our analysis to traditional techniques:
  - Chain Ladder/Bornhuetter-Ferguson/Generalized Cape Cod
- How to judge a reserving analysis: Actual versus expected (AvE)/Claims development result (CDR)
- Upper triangle is known
- AvE:
  - next diagonal of actual incremental payments vs predicted
- CDR:
- AvE plus
  - IBNR held for green triangle at time t+1
  - Less IBNR held for green triangle at time t
  - SAM Reserve risk calibrated using variance of CDR



THE MACHINE LEARNING APPROACH TO IBNR RESERVING

ML APPROACH TO SELECTING METHOD AND PARAMETERS

- Partition data into “training” and “testing” subsets
- Determine ability of each model and parameter set to predict unseen data using the “test” subset
- Choose the model and parameter set that results in the best predictive performance on the unseen “test” subset

THE MACHINE LEARNING APPROACH TO IBNR RESERVING

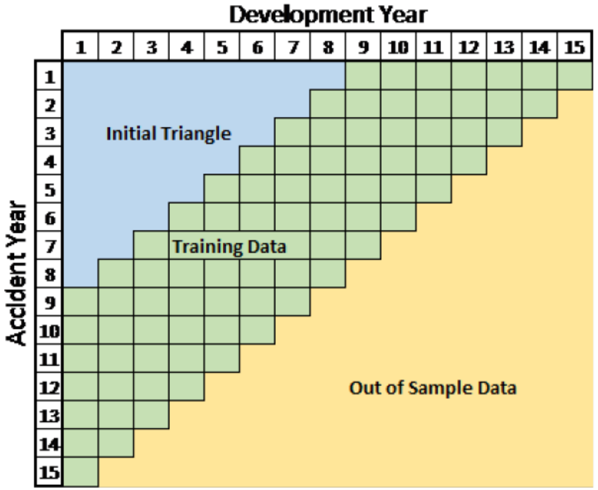
APPLY THIS TO TRADITIONAL IBNR RESERVING

1. Define a set of IBNR calculation methodologies (such as CL, BF, CC with varying parameters)
2. Fit these methodologies on sub-triangles starting from a small initial triangle, and then increasing the triangle by one calendar year until the end of the available data
3. At each sub-triangle, calculate the performance of the methodology using some performance metric (AvE/CDR)
4. Select the methodology that results in the best score across all sub triangles

THE MACHINE LEARNING APPROACH TO IBNR RESERVING

DEMONSTRATING THE PROCESS VISUALLY

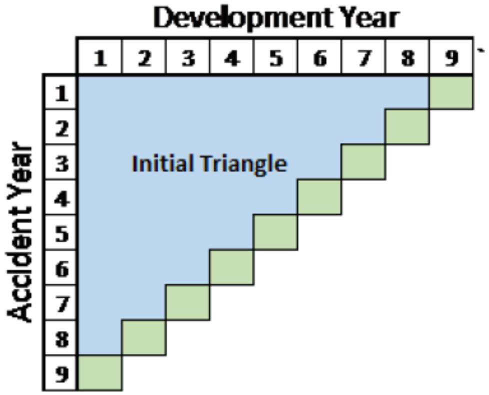
- Subset the triangle into an **initial triangle**, **training diagonals**, and **out of sample data**



THE MACHINE LEARNING APPROACH TO IBNR RESERVING

DEMONSTRATING THE PROCESS VISUALLY

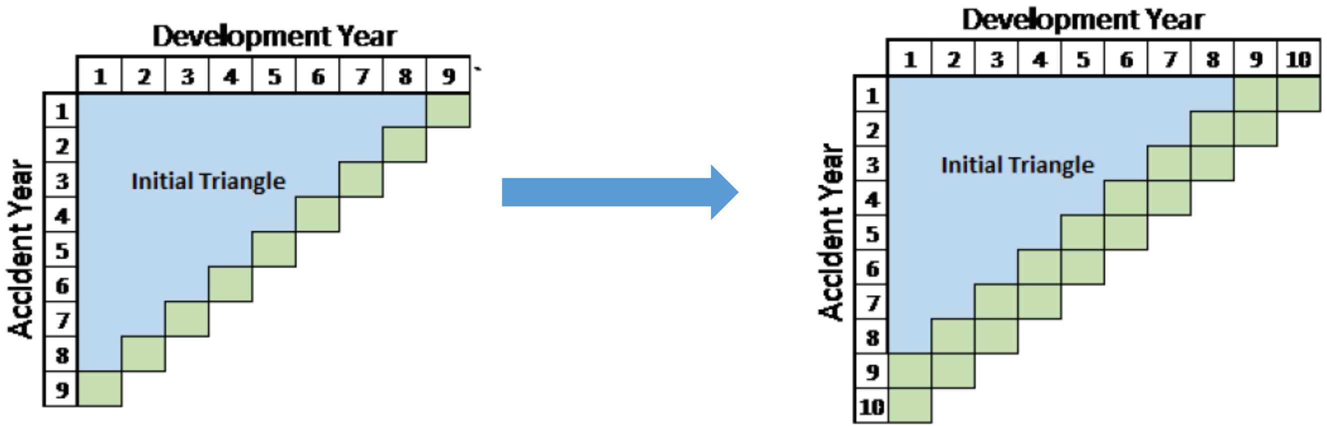
- Apply the chosen IBNR methodology to the **initial triangle**, and calculate the performance metric on the **latest training diagonal**



THE MACHINE LEARNING APPROACH TO IBNR RESERVING

DEMONSTRATING THE PROCESS VISUALLY

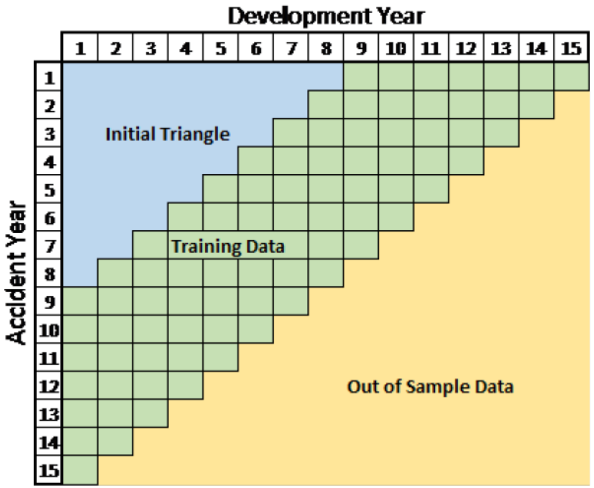
- Increase by another calendar year, fit on the initial triangle plus the calendar year previously assessed, test the performance on the next calendar year



THE MACHINE LEARNING APPROACH TO IBNR RESERVING

DEMONSTRATING THE PROCESS VISUALLY

- Perform this across the full training data, and select the methodology that minimises the performance score



THE MACHINE LEARNING APPROACH TO IBNR RESERVING

BRINGING IT ALL TOGETHER

1. Select a reasonably sized **initial triangle**
2. Select several of the most recent calendar periods as the **training set**
3. For each reserving methodology, **M**, from a collection of possible methodologies:
   a. Apply the reserving methodology to the **initial triangle**
   b. Calculate the performance metric on the ***first*** diagonal of the **training set**
   c. Include the ***first*** diagonal of the **training set** in the **initial triangle** and apply ***M***
   d. Calculate the performance metric against the ***second*** diagonal of the **training set**
   e. Repeat until all diagonals of the **training set** are exhausted
   f. Calculate the average performance metric for **M** across all diagonals in the **training set**
4. Select **M** that achieves the best performance metric

THE MACHINE LEARNING APPROACH TO IBNR RESERVING

SO WHAT PERFORMANCE METRIC TO USE?

- The initial thought is the actual claims minus our expected claims (AvE)
- **This ensures predictive accuracy is maximised**
- But this can cause instability in our reserves over time—we need consistency too

WE PROPOSE THE CLAIMS DEVELOPMENT RESULT

- CDR = AvE + ΔIBNR
- That is, we add the change in the IBNR from one calendar period to the next as a penalty
- **This ensures predictive accuracy is maximised, and reserve stability is achieved**
- This is equivalent to minimising the change in ultimate claims over calendar periods

CASE STUDIES: PARAMETER SPACE

WE SELECT FROM THE FOLLOWING PARAMETER SPACE

Method	Parameter	Choice Set	Description
CL, BF, CC	drop_high	[True, False]	Whether to drop the highest individual development factors in all development periods
CL, BF, CC	drop_low	[True, False]	Whether to drop the lowest individual development factors in all development periods
CL, BF, CC	n_periods	$k \in [5..21]$	Number of accident years over which to calculate development factors
BF	apriori	$\alpha \in \{0.40, 0.41, \ldots, 0.59, 0.60\}$	Apriori loss ratio for the BF method
CC	decay	$\gamma \in \{0.00, 0.05, \ldots, 0.95, 1.00\}$	Decay parameter for the CC method

CASE STUDY 1: SWISS TRIANGLE

	12	24	36	48	60	72	84	96	108	120	132	144	156	168	180	192	204	216	228	240
1979	3 670	5 817	6 462	6 671	6 775	7 002	7 034	7 096	7 204	7 326	7 395	7 438	7 468	7 541	7 580	7 677	7 794	7 919	8 047	8 051
1980	4 827	7 600	8 274	8 412	9 059	9 197	9 230	9 277	9 331	9 435	9 864	9 621	9 654	9 704	9 743	9 745	9 745	9 748	9 749	9 749
1981	7 130	10 852	11 422	12 024	12 320	12 346	12 379	12 426	12 460	12 500	12 508	12 547	12 557	12 624	12 639	12 644	12 647	12 666	12 711	12 713
1982	9 244	13 340	13 758	13 853	13 894	13 942	13 980	14 001	14 012	14 070	14 085	14 098	14 111	14 118	14 120	14 133	14 141	14 145	14 166	14 167
1983	10 019	14 223	15 403	15 579	15 732	15 921	16 187	16 420	16 531	16 559	16 568	16 585	16 597	16 614	16 617	16 619	16 681	16 681	16 687	16 711
1984	9 966	14 599	15 181	15 431	15 506	15 538	15 906	16 014	16 537	16 833	16 951	17 038	17 040	17 195	17 298	17 307	17 308	17 308	17 309	17 310
1985	10 441	15 043	15 577	15 784	15 926	16 054	16 087	16 107	16 311	16 366	16 396	16 414	16 419	16 426	16 480	16 480	16 480	16 480	16 482	16 482
1986	10 578	15 657	16 352	16 714	17 048	17 289	17 632	17 646	17 662	17 678	17 693	17 700	17 706	17 706	17 712	17 713	17 718	17 719	17 719	17 719
1987	11 214	16 482	17 197	17 518	18 345	18 480	18 505	18 520	18 578	18 633	18 671	18 689	18 746	18 772	18 774	18 804	18 804	18 804	18 806	18 806
1988	11 442	17 621	18 465	18 693	18 882	18 965	20 464	20 522	20 558	20 607	20 611	21 250	21 257	22 505	22 509	22 516	22 518	22 522	22 523	22 527
1989	11 720	17 779	18 655	18 940	19 098	19 368	19 970	20 162	20 195	20 415	20 510	20 594	20 657	20 752	20 823	20 899	20 983	21 124	21 622	21 627
1990	13 293	20 689	21 696	22 439	22 798	23 054	23 394	23 554	23 888	24 061	24 096	24 301	24 356	24 389	24 391	24 784	24 784	24 794	24 894	24 900
1991	15 063	22 917	23 543	24 032	24 156	24 232	24 360	24 410	24 884	24 896	24 968	25 031	25 172	25 459	25 460	25 470	25 734	25 774	25 877	25 883
1992	16 986	23 958	25 090	25 392	25 546	26 099	26 129	26 149	26 166	26 231	26 328	26 743	27 023	27 048	27 075	27 168	27 234	27 276	27 386	27 392
1993	16 681	24 867	25 871	26 463	26 941	27 120	27 164	27 183	27 250	27 490	27 497	27 561	27 565	27 582	27 706	27 787	27 855	27 898	28 010	28 017
1994	17 595	25 152	26 140	27 090	27 568	27 637	27 805	28 003	28 223	28 240	28 245	28 250	28 257	28 297	28 347	28 430	28 499	28 543	28 658	28 665
1995	16 547	25 396	26 506	27 043	27 866	27 882	27 903	27 933	28 492	28 545	28 564	28 686	28 695	28 897	28 948	29 033	29 104	29 149	29 266	29 273
1996	15 449	22 702	23 909	24 690	26 083	26 525	26 567	26 640	26 695	26 801	26 814	27 018	27 078	27 269	27 317	27 397	27 463	27 506	27 616	27 623
1997	18 043	26 918	28 256	28 569	28 964	29 268	29 344	29 393	30 159	30 936	30 966	31 122	31 190	31 410	31 466	31 558	31 635	31 684	31 811	31 819

	EP
1979	17 684
1980	18 762
1981	22 056
1982	25 489
1983	24 819
1984	26 887
1985	31 782
1986	32 585
1987	32 726
1988	36 372
1989	36 873
1990	38 938
1991	42 109
1992	40 818
1993	43 180
1994	47 061
1995	48 428
1996	52 565
1997	52 728

CASE STUDY 1: SWISS TRIANGLE

OPTIMAL PARAMETERS FOUND (CHAIN LADDER)

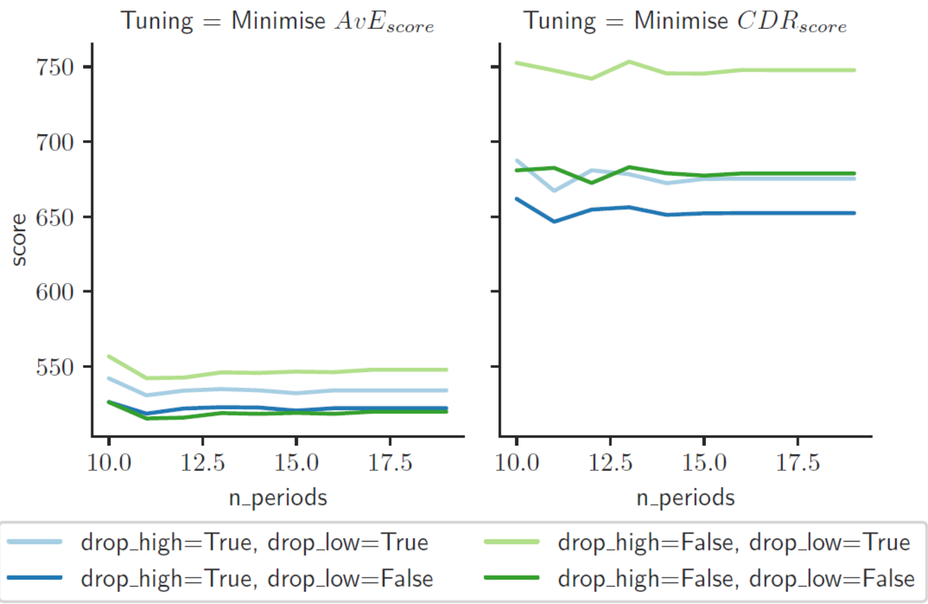
PARAMETER	BASIC CL	MINIMISE AvE	MINIMISE CDR
drop_high	False	False	True
drop_low	False	False	False
n_periods	19	11	11
apriori	n/a	n/a	n/a
decay	n/a	n/a	n/a

Scores

MODEL	RMSE	DELTA	RANK
Basic CL	669.69	-	23 out of 40
Minimise AvE	675.38	+0.9%	27 out of 40
Minimise CDR	617.81	-7.8%	12 out of 40

CASE STUDY 1: SWISS TRIANGLE

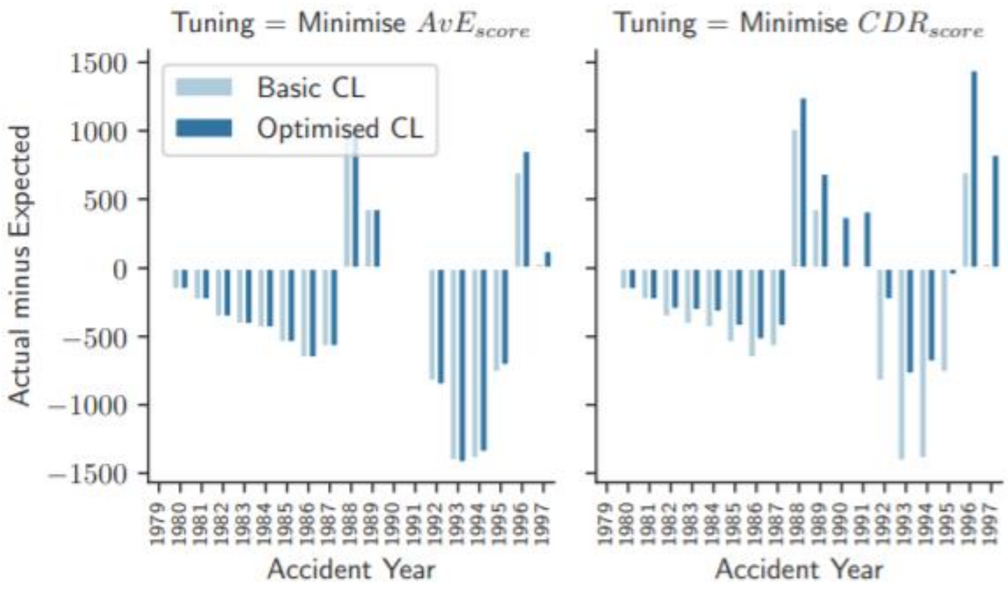
FUNCTION PLOT OF PARAMETERS (CHAIN LADDER)



The model performance is much more sensitive to the choice of which development factors to drop than the number of periods of claims experience to include in the calculation of the development factors

CASE STUDY 1: SWISS TRIANGLE

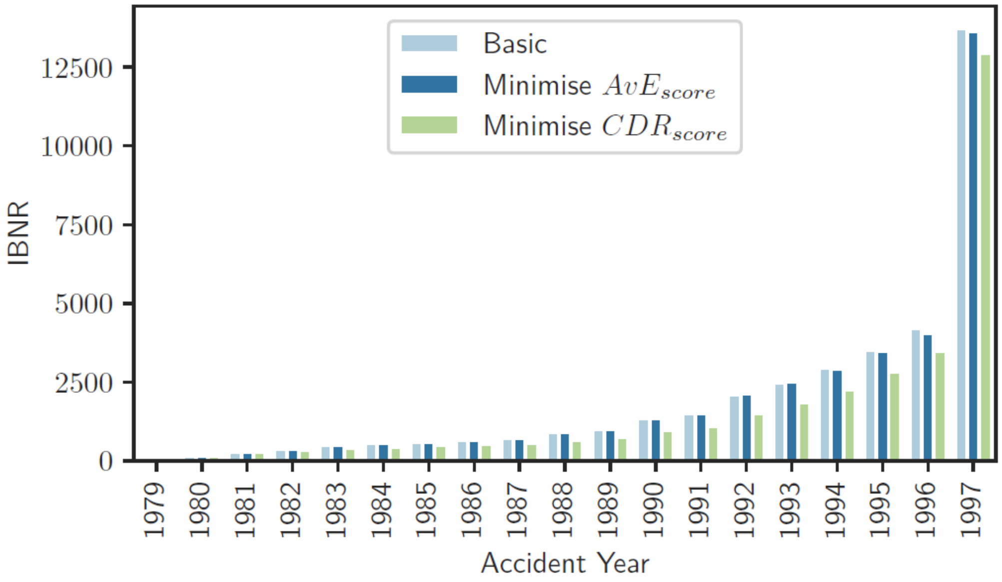
COMPARISON OF SCORES (CHAIN LADDER)

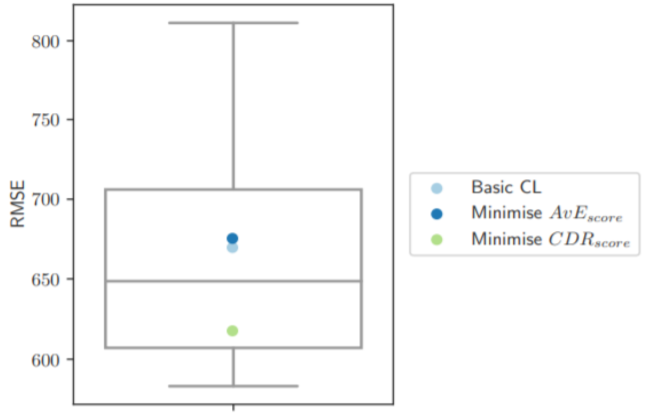


- Using a lower number of periods to calculate the development factors has minimal impact until the most recent accident years
- Minimising the CDR_{score} reduces overestimation in these years at the expense of underestimating claims on the most recent accident years
- On average the estimates of the ultimate claims are closer to the actual ultimate claims than both the basic CL and the model found by minimising the AvE_{score}.

CASE STUDY 1: SWISS TRIANGLE

COMPARISON OF IBNR (CHAIN LADDER)





MODEL	TOTAL IBNR	DELTA
Basic CL	37 727	-
Minimise AvE	37 417	-0.8%
Minimise CDR	31 595	-16.3%

CASE STUDY 2: LONG-TAIL LIABILITY

	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45	48	51	54	57	60	63
2010Q1	2 014	3 925	6 027	6 477	5 624	5 159	5 214	6 241	6 705	6 716	7 373	7 696	9 011	9 230	8 409	8 448	8 824	9 202	9 388	9 350	9 456
2010Q2	2 531	4 102	3 675	3 868	4 796	6 866	6 072	6 014	5 986	5 788	5 951	5 958	6 048	6 065	5 877	5 969	5 987	5 997	5 767	5 808	5 803
2010Q3	2 373	4 426	7 274	6 514	6 699	7 063	7 603	7 727	7 130	7 655	7 949	8 587	9 113	7 730	7 925	8 276	8 180	7 821	7 822	7 821	8 156
2010Q4	3 665	6 028	5 679	5 793	5 158	5 203	4 824	4 749	5 152	5 240	5 261	5 361	5 262	5 606	5 473	5 359	6 051	5 921	6 166	6 196	6 026
2011Q1	3 685	6 009	6 655	5 535	6 292	6 972	6 793	6 362	6 510	6 457	6 734	6 836	7 817	8 117	8 602	8 508	8 709	9 368	9 671	10 319	10 079
2011Q2	5 624	9 330	8 640	7 676	7 066	6 535	7 004	6 965	7 007	7 244	7 124	7 119	7 294	7 251	6 981	7 051	6 988	7 025	7 182	6 672	6 676
2011Q3	6 360	8 485	9 147	6 628	6 883	6 990	7 417	7 768	8 117	7 775	7 908	7 946	7 905	7 504	8 561	8 369	8 323	8 495	8 286	8 255	8 536
2011Q4	3 655	4 338	4 000	4 568	6 659	6 571	6 599	6 949	7 303	7 384	8 192	8 635	8 644	9 207	9 792	9 953	10 002	9 407	9 452	8 273	8 371
2012Q1	1 203	2 897	3 289	2 418	2 197	3 144	3 153	3 073	3 109	2 367	1 992	2 083	2 505	2 678	2 594	2 648	2 661	2 521	2 529	2 370	2 370
2012Q2	1 110	2 111	3 328	5 474	5 593	5 660	4 710	4 874	4 569	4 547	4 601	4 720	5 137	5 208	5 589	6 254	6 507	6 507	6 593	6 604	6 659
2012Q3	776	3 290	6 315	7 099	7 206	6 951	6 911	6 848	6 906	6 826	7 025	7 046	7 394	10 204	9 915	9 643	9 929	10 269	10 221	10 808	10 913
2012Q4	1 858	3 064	3 965	3 906	4 058	4 270	4 019	3 867	5 107	4 984	4 972	5 328	5 752	5 802	5 554	6 083	6 530	6 523	6 565	6 570	6 520
2013Q1	1 608	4 000	4 989	4 800	4 795	5 482	4 778	4 847	4 767	5 147	5 977	5 955	6 004	6 077	6 228	6 502	6 590	6 603	7 607	7 754	7 754
2013Q2	3 120	3 906	7 002	9 182	9 680	7 916	10 125	10 614	11 271	11 901	11 493	11 493	11 778	11 796	11 238	11 358	11 099	11 107	11 450	11 413	11 607
2013Q3	1 187	1 949	3 062	4 515	4 628	4 755	4 882	4 970	4 877	5 969	6 023	6 168	6 384	7 815	7 804	7 262	8 047	8 042	8 288	8 340	8 330
2013Q4	508	1 844	4 445	6 456	7 419	7 357	7 118	7 671	7 984	8 776	9 575	9 615	9 884	9 908	7 871	8 005	7 982	7 898	7 900	7 894	7 732
2014Q1	632	1 951	2 235	4 025	5 071	5 654	6 389	7 468	7 458	7 303	7 230	7 366	7 498	8 081	8 313	8 779	8 854	9 396	9 567	10 067	10 908
2014Q2	576	3 531	8 148	10 026	10 225	10 713	11 674	11 833	11 639	12 485	12 279	12 327	11 754	11 809	11 776	11 854	11 687	11 709	11 365	11 469	10 940
2014Q3	1 549	4 807	6 178	8 651	10 214	11 283	11 203	11 552	12 697	12 468	12 828	14 163	13 962	14 114	14 932	16 581	16 279	15 668	15 625	17 347	17 165
2014Q4	1 877	4 342	4 787	6 310	7 943	8 482	8 670	8 747	9 150	9 374	9 823	10 712	11 522	11 242	12 279	13 806	13 721	13 858	14 244	16 558	16 406

	EP
2010Q1	25 728
2010Q2	25 975
2010Q3	24 954
2010Q4	24 478
2011Q1	23 899
2011Q2	21 730
2011Q3	15 232
2011Q4	11 990
2012Q1	11 731
2012Q2	11 503
2012Q3	13 317
2012Q4	14 270
2013Q1	15 193
2013Q2	15 077
2013Q3	18 804
2013Q4	17 930
2014Q1	18 825
2014Q2	20 181
2014Q3	20 891
2014Q4	23 654

CASE STUDY 2: LONG-TAIL LIABILITY

OPTIMAL PARAMETERS FOUND

PARAMETER	BASIC CC	MINIMISE AvE	MINIMISE CDR
drop_high	False	False	False
drop_low	False	False	False
n_periods	21	10	11
apriori	n/a	0.46	0.41
decay	0.75	n/a	n/a

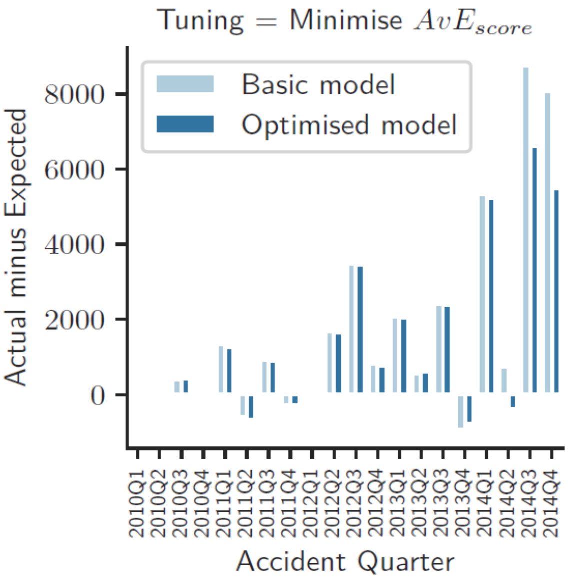
Scores

MODEL	RMSE	DELTA	RANK
Basic CC	3 170.88	-	1 073 out of 1 848
Minimise AvE	2 552.39	-19.5%	461 out of 1 848
Minimise CDR	2 893.23	-8.8%	832 out of 1 848

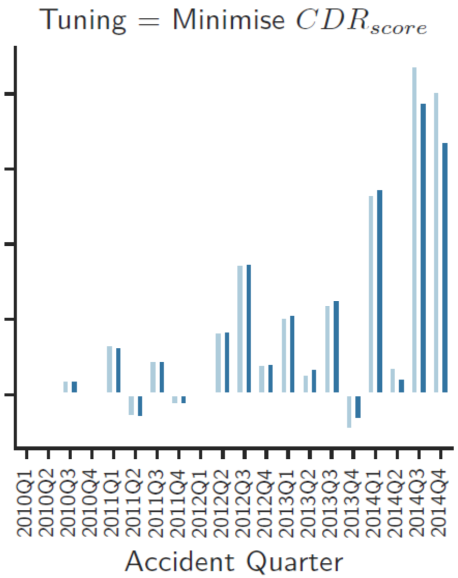
CASE STUDY 2: LONG-TAIL LIABILITY

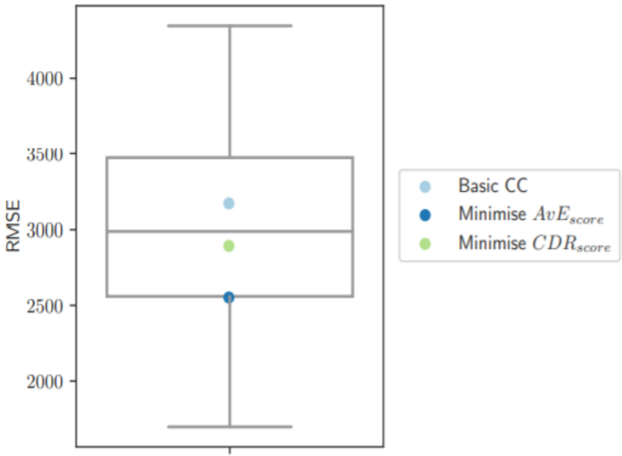
COMPARISON OF SCORES

BF Model



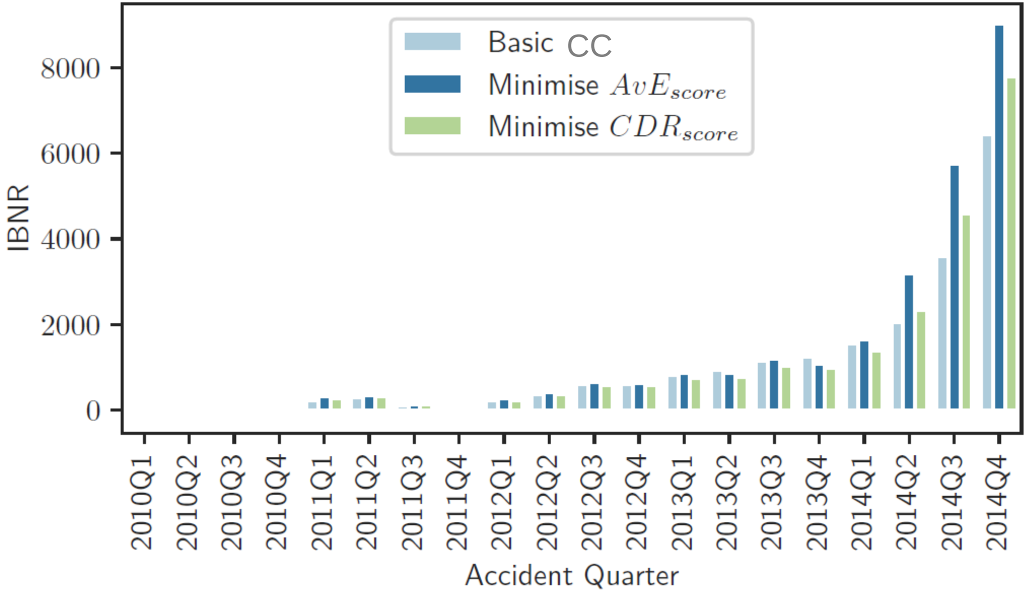
BF Model





CASE STUDY 2: LONG-TAIL LIABILITY

COMPARISON OF IBNR



MODEL	TOTAL IBNR	DELTA
Basic CC	20 859	-
Minimise AvE	44 731	114%
Minimise CDR	37 155	78%

CONCLUDING REMARKS

WHAT WE DID

- We presented a framework for selecting reserving models that are expected to perform well in predicting out of sample claims development experience
- We demonstrated that, on two example triangles, our proposal performs relatively well
- Thus, we conclude that scoring reserving models based on historic claims development data provides a useful way of determining which models are likely to predict future development well
- Finally, our framework provides an objective way to select methods that produce best estimate IBNR reserves

CONCLUDING REMARKS

UNDERSTANDING WHAT WORKED

- Found that:
  - CDR was a good metric for Swiss Triangle
  - AvE was a good metric for long tail triangles
- What is the difference?
  - CDR ensures that change in IBNR is minimized
  - Only makes sense if confident in estimate of IBNR
- Can measure our confidence using Mack MSE:
  - Swiss Triangle: CoV = 13.5%
  - Long tail: CoV = 67%
- => CoV can help us choose the correct metric

CONCLUDING REMARKS

HOW OUR PAPER CAN BE USEFUL

- The results can be used as a benchmark to test traditional approaches to IBNR reserving. By reconciling between models, extra insight into the claim's development experience can be generated
- When reserving triangles for the first time, applying the framework can enable the actuary to produce a quick baseline set of reserve estimates
- Finally, by selecting reserving models that are expected to minimize the AvE or CDR metrics, the amount of effort necessary to explain the reserve movements or adverse development should be reduced
- Aim to release open-source Python package in 1Q20.

PAPER & ACKNOWLEDGMENTS

- Joint work with Caesar Balona
- Paper:
- https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3697256
- Many thanks to Prof Mario Wüthrich and Lisa Pines

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