From the Chain Ladder to Individual Claims Reserving using Machine Learning techniques

Alessandro Carrato, ISOA FIA
alessandro.carrato@gmail.com

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Content Topics

BRIDGING ACTUARIES´AND DATA SCIENTISTS´WORLDS

TRADITIONAL ACTUARIES

Aggregated actuarial methods based on triangles

Interpretability	Straightforward
Data required	Paid/Incurred Triangles
Aggregation	Along LoBs
Projection	Triangles methods on aggregated level

OUR PROJECT

Gradual introduction of machine learning techniques into traditional reserving methods

Interpretability	Very high
Data required	Data underlying the triangles
Aggregation	Clustering techniques
Projection	(Constrained) regression on individual level

DATA SCIENTISTS

Individual claims reserving with gradient boosting and neural networks

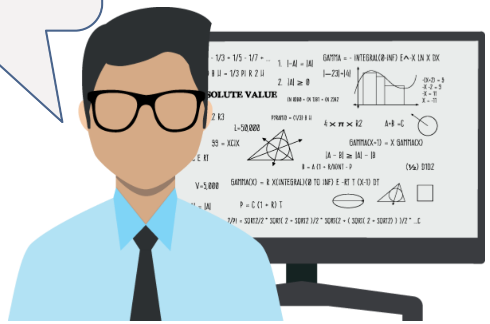
Interpretability	Sometimes very complex to understand
Data required	Complex merging of different data sources
Aggregation	Implicit with black box methods
Projection	Black box methods on individual level

CLASSIC VS MACHINE LEARNING APPROACH

We want **to predict** well and **to understand** what‘s going on

„My model fits the data perfectly, but I do not know how well it predicts…“

„I do not know how my model works, but it predicts well“



Traditional statistics

*The focus is mainly on **„fitting well“ the data***

- The models minimize the in-sample error
- There is no explicit consideration of prediction accuracy

Our approach

*We focus on **prediction power while retaining some interpretability***

- We choose the best model using traditional loss functions
- Asymptotically equivalent to cross validation

Machine Learning

*The focus is on prediction power, **interpretability is not important***

- The best model is the one that minimizes the out-of-sample error
- Cross-validation criterion

AZ AI RESERVING: TWO STEPS APPROACH

Aggregating homogeneous claims

- We make use of clustering techniques to **identify claims which are similar**, considering their **paid and incurred histories** (and other factors, eg. AY)
- Ideally, by clustering you can obtain different triangles for which the traditional methods' **assumptions of homogeneity hold true**

Projection of the ultimate cost

1. Chain-ladder can be seen as a **constrained linear regression**; we proved(*) that this holds true also **on an individual claim basis**
2. The idea is that **one can gradually extend the model,** by removing constraints or adding more features, to improve **prediction power**

The algorithm automatically selects the best combination of clusters and parameters to predict the ultimate cost claim by claim

The model can be extended even further using popular/recent ML techniques(**), but this will result in a lack of model interpretability

Remark: the above can be applied only to **reported** claims, ie. to derive the **IBNER** component of the reserve. The **IBNYR** component is automatically estimated via a traditional approach

(*) *Carrato, Visintin (2018) - „From Chain Ladder to Individual Claims Reserving with Machine Learning“* (to be published)

(**) Traditional Machine Learning approach defines $C_j = f(\mathbf{X_{j-1}}) + \varepsilon_{j-1}$, where *f* is found via **gradient boosting** or **neural networks**

AZ AI RESERVING: SWOT ANALYSIS

S

- (Extremely) Fast and scalable
- IBN(E)R automatically allocated at individual claim level
- Not expensive

W

- Uncertainty on reserves impossible to assess directly
- Partial lack of interpretation / understanding of model results

Internal

O

- Avoid cumbersome data requirements (as minimum requirement)
- Easy to explain to stakeholders (eg. regulators, top management, etc.)

T

- Heavily relies on data quality (“garbage in, garbage out”)
- Needs still human supervision to ensure results are reasonable

External

Positive

Negative

Strengths
Scalable and efficient tool

Weaknesses
Difficult to assess uncertainty

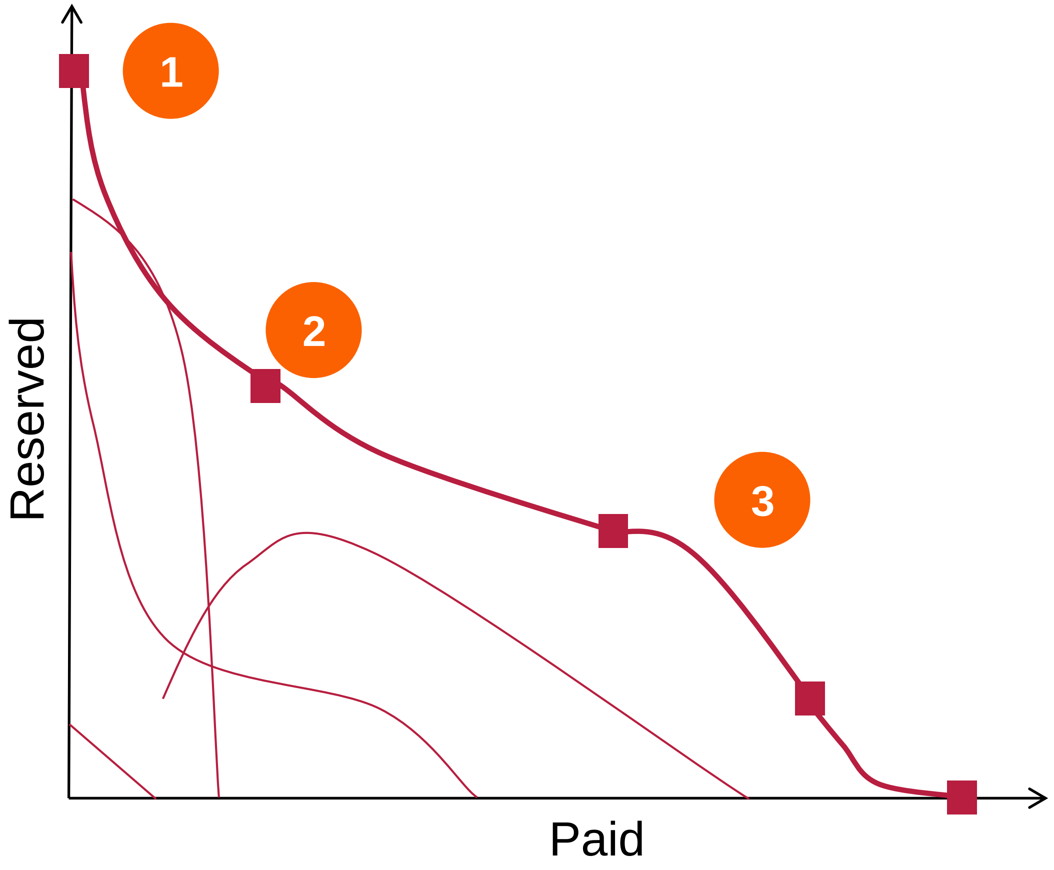
Opportunities
No significant IT investment (or cumbersome data requirements)

Threats
Cannot predict market environment changes (eg. legislation)

CONTENT TOPICS

THE PAID-RESERVED TRAJECTORY

Following Mack(*), we consider (in the basic setup) the paid-reserved trajectory of each claim. **The joint modeling of paid and incurred data can greatly improve the prediction accuracy of the model** by, for example, letting us identify large losses.



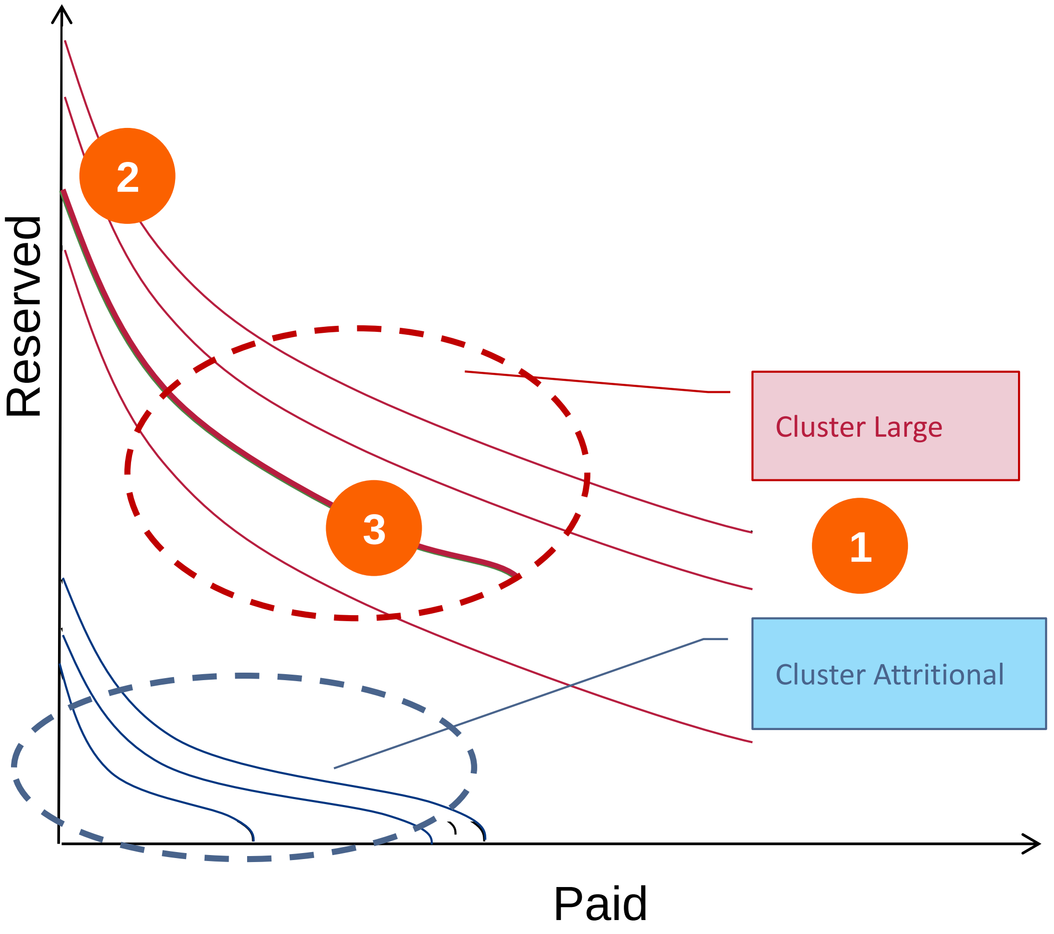
1. After its occurence, a claim is reported and a case reserve is allocated
2. Subsequently, a certain amount is paid and the case reserve decreases accordingly
3. The claim continues its developing until is definitively closed

There can be differente kinds of trajectories. Our aim is to spot patterns in the trajectories to aggregate claims with similar developments.

(*) *Mack (2002) – "Schadenversicherungsmathematik", Section 3.4.5*

STEP 1 - CLUSTERING THE CLAIMS

With clustering techniques, **we are able to identify and aggregate claims with similar trajectories (*)** up to a fixed development period



1. With the k-means algorithm, we are able to spot a certain number (in this case, two) of clusters of similar claims. In practice, the number of clusters is chosen minimazing the loss function of the predictive model.

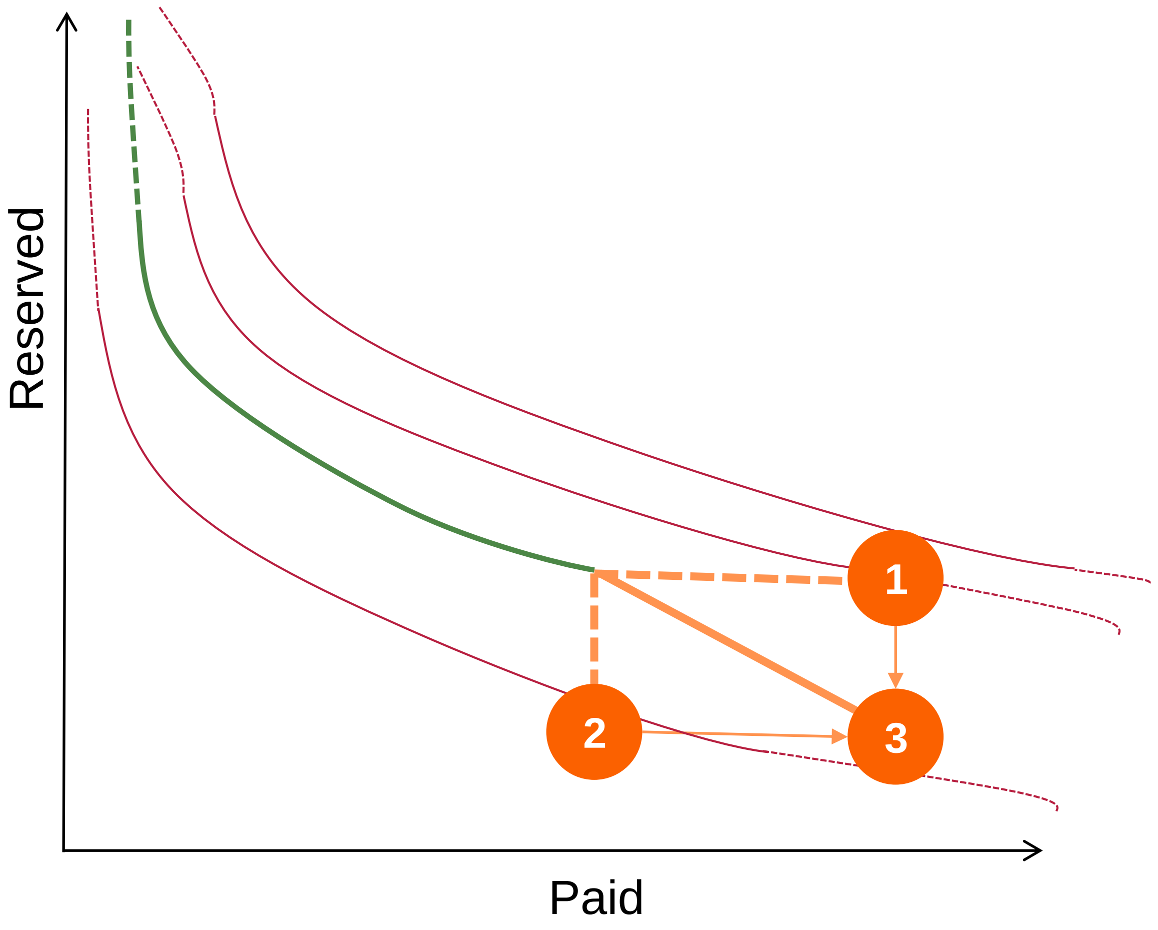
2. We now consider a claim (the one in green) less developed than the ones considered before. **We aim at predicting its next point in the trajectory using its similarity to the more developed claims.**

3. Due to its past trajectory, the green claim is classified as a member of «Cluster Large»

(*) Please note that Chain Ladder uses only the latest information („Markovian“ assumption) instead of the full trajectory. To this extent, the AZ AI Reserving model is a step further.

STEP 2 - PREDICTING THE NEXT POINT OF THE TRAJECTORY

In the previous step, we have determined that the green claim belongs to the ”red” cluster ...
.. the **next step** is to **predict the next point of its paid-reserved trajectory**



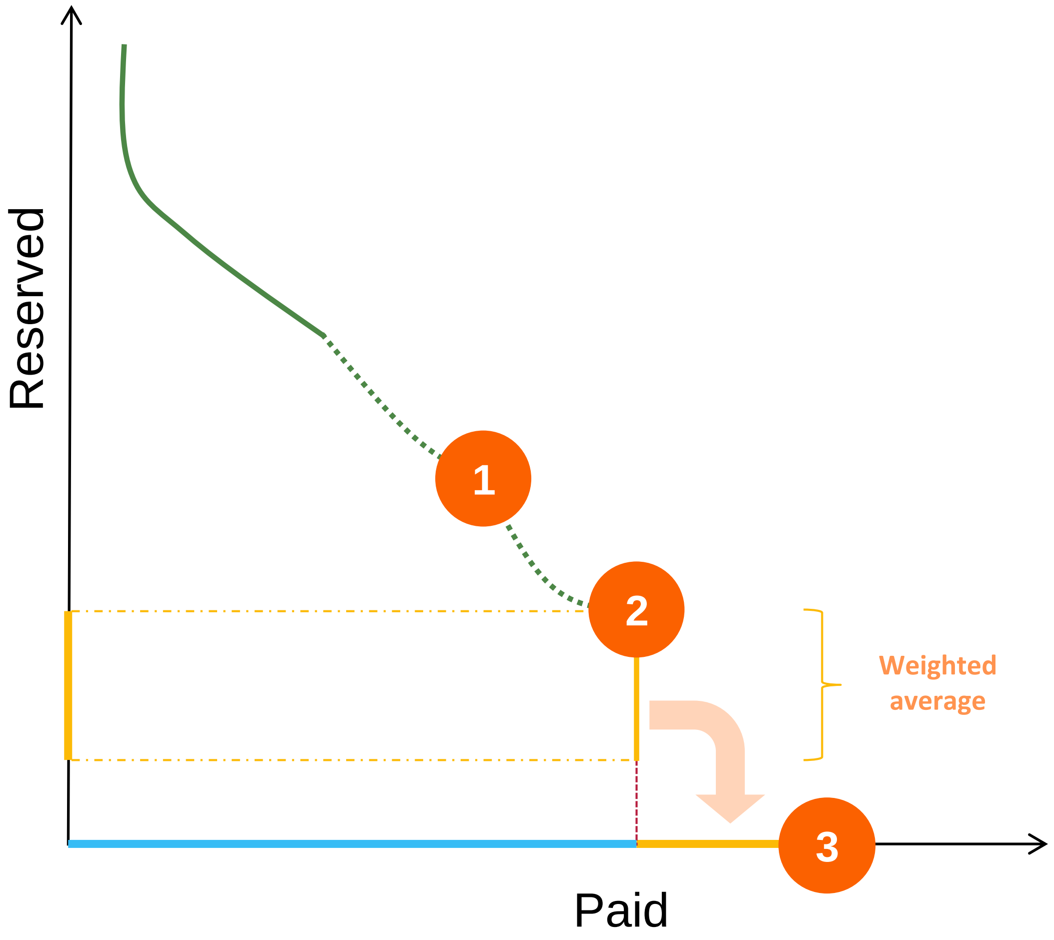
1. **We model the cumulative paid amount with a linear regression**, we fit it on the known (the red ones) claims and we predict the next paid amount for the green claim (usually higher, if there are not S&S ...)

2. Similarly, we model the incurred amount, so that we obtain the new reserved amount (usually lower)

3. Therefore, the projected point has coordinates defined by (1) and (2)

STEP 3 - PREDICTING THE ULTIMATE COST

In the previous step, we were able to predict the following point of the trajectory...
... we now describe **how to predict the ultimate cost of a claim**



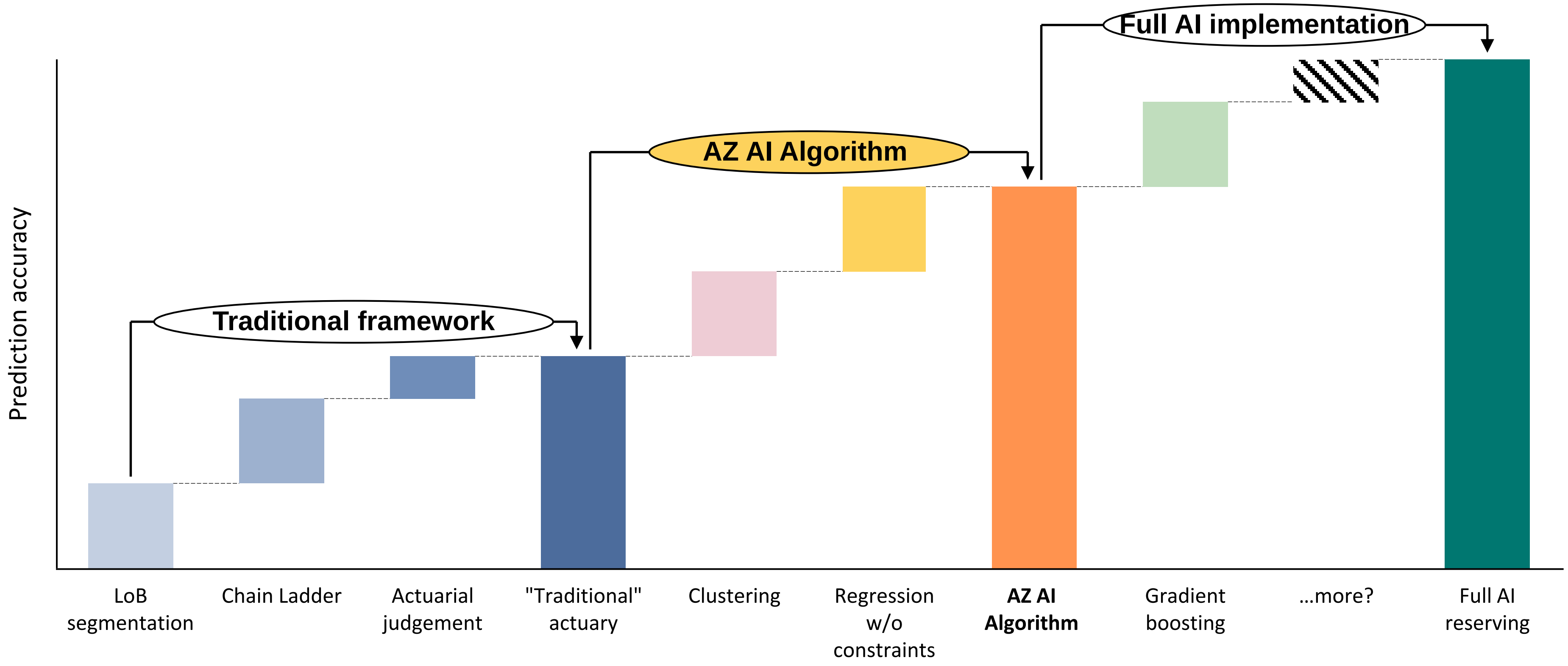
1. The precedures described at Steps 1 and 2 is iterated until a claim reaches its maximum development;

2. At the last development, we obtain an ultimate paid and (usually) a not nil case reserve;

3. To take into account the incurred information, **we consider the weighted average** (*) **between paid and incurred ultimates.**

(*) The reason to consider the weighted average and not another statistics is justified by *decision theory*, as method to minimize the expected loss (or error)

THE LONG ROAD OF AI RESERVING …



AZ AI Algorithm already provides strong foundations to improve existing reserving processes, whilst full AI implementation (w/o human supervision) still in development as results are not robust enough

CONTENT TOPICS

OUTPUT EXAMPLE

Accident_Year	N_Claims	Latest_Paid	Latest_Incurred	Ultimate_Paid W/o_Tails	Ultimate_Paid_With_Tails	Ultimate_Incurred	Selected_Ultimate	Outstandings	Reserve	IBNR	IBNR/Outstandings	Unreported_Claims	Unreported_Claims_Reserve	Total Reserve
2002	11905	22,493,303.00	23,187,210.00	22,493,303.00	23,658,386.00	23,187,210.00	23,644,286.00	693,907.00	1,150,983.00	457,076.00	65.87	0	0	1,150,983.00
2003	12615	20,208,059.00	20,584,786.00	20,211,477.00	20,553,239.00	20,562,424.00	20,553,407.00	376,728.00	345,349.00	-31,379.00	-8.33	0	0	345,349.00
2004	12151	16,525,782.00	16,741,494.00	16,537,007.00	16,665,702.00	16,423,151.00	16,662,576.00	215,712.00	136,795.00	-78,917.00	-36.58	0	0	136,795.00
2005	12130	16,583,467.00	17,801,160.00	16,608,008.00	16,792,195.00	17,072,954.00	16,811,401.00	1,217,693.00	227,934.00	-989,760.00	-81.28	0	0	227,934.00
2006	13204	19,396,872.00	20,134,375.00	19,504,298.00	19,697,421.00	19,251,456.00	19,681,086.00	737,503.00	284,213.00	-453,290.00	-61.46	0	0	284,213.00
2007	14227	19,137,938.00	20,265,641.00	19,233,072.00	19,252,752.00	18,841,782.00	19,229,883.00	1,127,702.00	91,945.00	-1,035,757.00	-91.85	0	0	91,945.00
2008	16171	18,127,178.00	19,212,155.00	18,305,117.00	18,320,781.00	17,544,742.00	18,276,955.00	1,084,976.00	149,777.00	-935,199.00	-86.2	0	0	149,777.00
2009	22401	23,386,624.00	27,528,517.00	24,199,842.00	24,220,109.00	23,919,386.00	24,174,863.00	4,141,893.00	788,239.00	-3,353,654.00	-80.97	0	0	788,239.00
2010	31127	24,976,205.00	29,546,505.00	25,894,963.00	25,915,474.00	25,451,906.00	25,843,769.00	4,570,300.00	867,564.00	-3,702,736.00	-81.02	1	830	868,394.00
2011	33043	26,364,172.00	35,415,927.00	27,946,178.00	27,957,922.00	28,307,974.00	28,047,390.00	9,051,754.00	1,683,218.00	-7,368,537.00	-81.4	1	849	1,684,067.00
2012	30341	20,938,095.00	27,970,885.00	22,787,422.00	22,821,528.00	19,937,780.00	22,096,460.00	7,032,790.00	1,158,365.00	-5,874,425.00	-83.53	2	1,457.00	1,159,822.00
2013	33183	20,821,489.00	35,884,413.00	23,780,638.00	23,828,377.00	23,320,914.00	23,615,363.00	15,062,924.00	2,793,874.00	-12,269,050.00	-81.45	11	7,828.00	2,801,702.00
2014	34834	21,478,074.00	40,081,678.00	25,783,903.00	25,813,778.00	25,436,353.00	25,638,599.00	18,603,604.00	4,160,525.00	-14,443,079.00	-77.64	18	13,248.00	4,173,773.00
2015	34448	18,983,171.00	46,367,602.00	23,676,851.00	23,688,430.00	28,820,462.00	26,719,378.00	27,384,431.00	7,736,207.00	-19,648,224.00	-71.75	34	26,372.00	7,762,579.00
2016	32096	17,134,951.00	40,424,375.00	23,013,255.00	23,035,757.00	25,111,228.00	24,231,484.00	23,289,425.00	7,096,534.00	-16,192,891.00	-69.53	83	62,662.00	7,159,196.00
2017	28679	10,444,773.00	33,513,436.00	22,506,961.00	22,518,749.00	21,720,192.00	21,969,070.00	23,068,663.00	11,524,297.00	-11,544,366.00	-50.04	1649	1,263,189.00	12,787,486.00
Total	372555	317,000,153.00	454,660,159.00	352,482,295.00	354,740,600.00	354,909,914.00	357,195,970.00	137,660,005.00	40,195,819.00	-97,464,188.00	-0.70800657	1799	1,376,435.00	41,572,254.00

We obtain, automatically, a results summary similar to the one in ResQ. **This can be used to compare the algorithm with traditional actuarial methods and for diagnostics purpose.**

DIAGNOSTICS EXAMPLE (FOR A DEVELOPMENT PERIOD)

Attritional claims of recent AYs

Cluster of medium-sized claims

The model automatically decides wheter to include an intercept: incurred data typicallx are fit well with a simple chain-ladder

B	C	D	E	F	G	H	I	J	K	L	M	N
Cluster_ID	Number_of_Claims	Beta_Paid	Intercept_Paid	Beta_Incurred	Intercept_Incurred	Mean_Paid	Mean_Incurred	Std_Paid	Std_Incurred	Std_Res_Paid	Std_Res_Incurred	Weighted_AY_Average
1	164,170	1.002771862	10.39479057	0.977778068	0	509	814	1,025.00	1,912.00	12	46	2010.759701
2	1,852	1.030763881	1192.52397	0.990106326	0	19,895.00	36,352.00	18,885.00	43,292.00	1,896.00	559	2007.702246
3	46	1.054085761	0	1.024635221	0	301,938.00	338,908.00	104,015.00	150,371.00	17,252.00	9,118.00	2006.216627
4	230	1.583768924	0.00033214	0.989338072	0	57,465.00	304,666.00	83,364.00	128,727.00	59,020.00	3,525.00	2008.124556
5	75,974	1.014200023	9.21910958	0.987082649	0	779	1,164.00	1,455.00	2,752.00	29	39	2004.749927

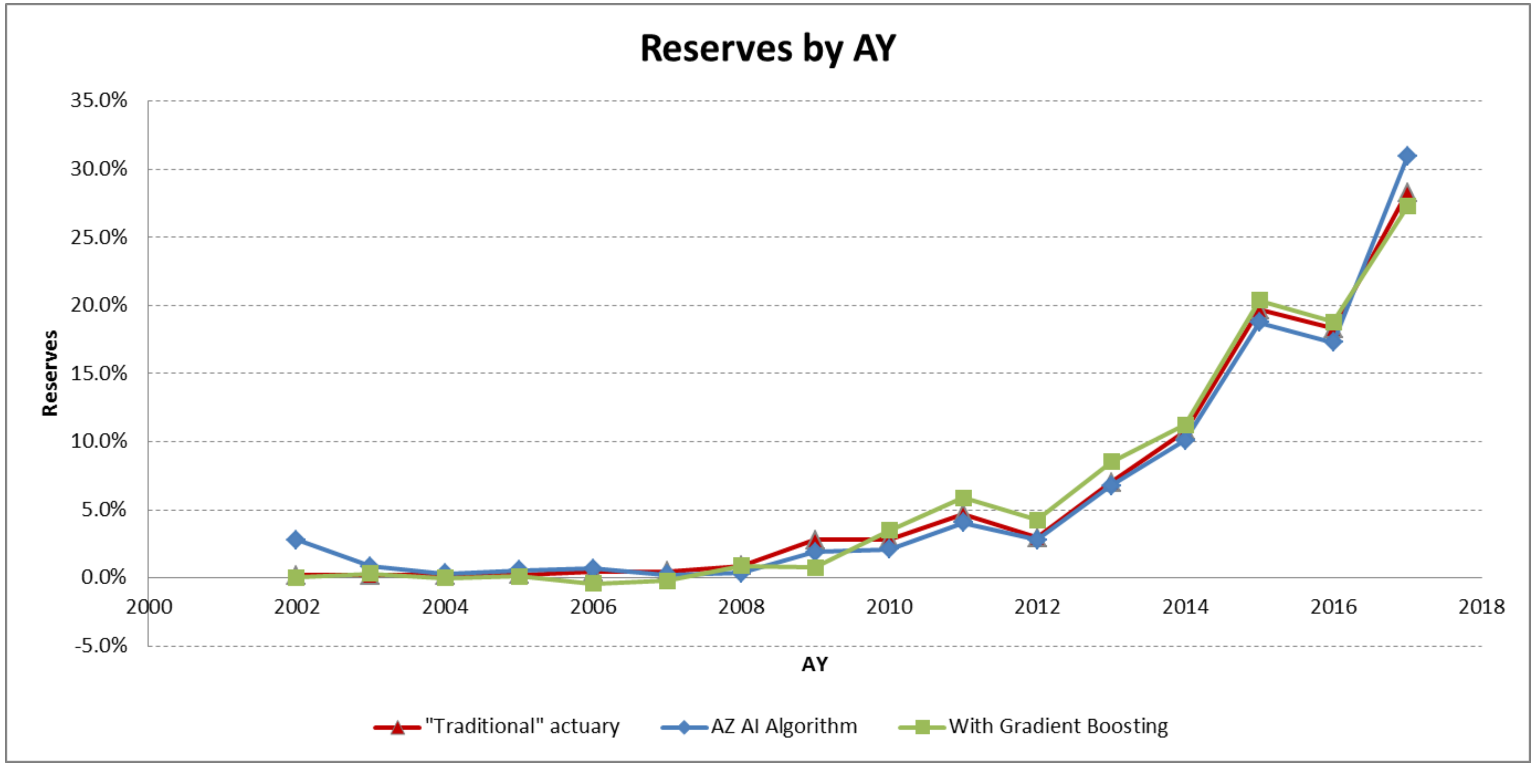
Two clusters of large claims, but at very different stages of development (huge differences in the paid development factors).

Attritional claims of older AYs: different dev. patterns

Many automatic insights on data to help actuaries also on traditional reserving process ...

COMPARISON OF RESULTS: MTPL TYPE LOB

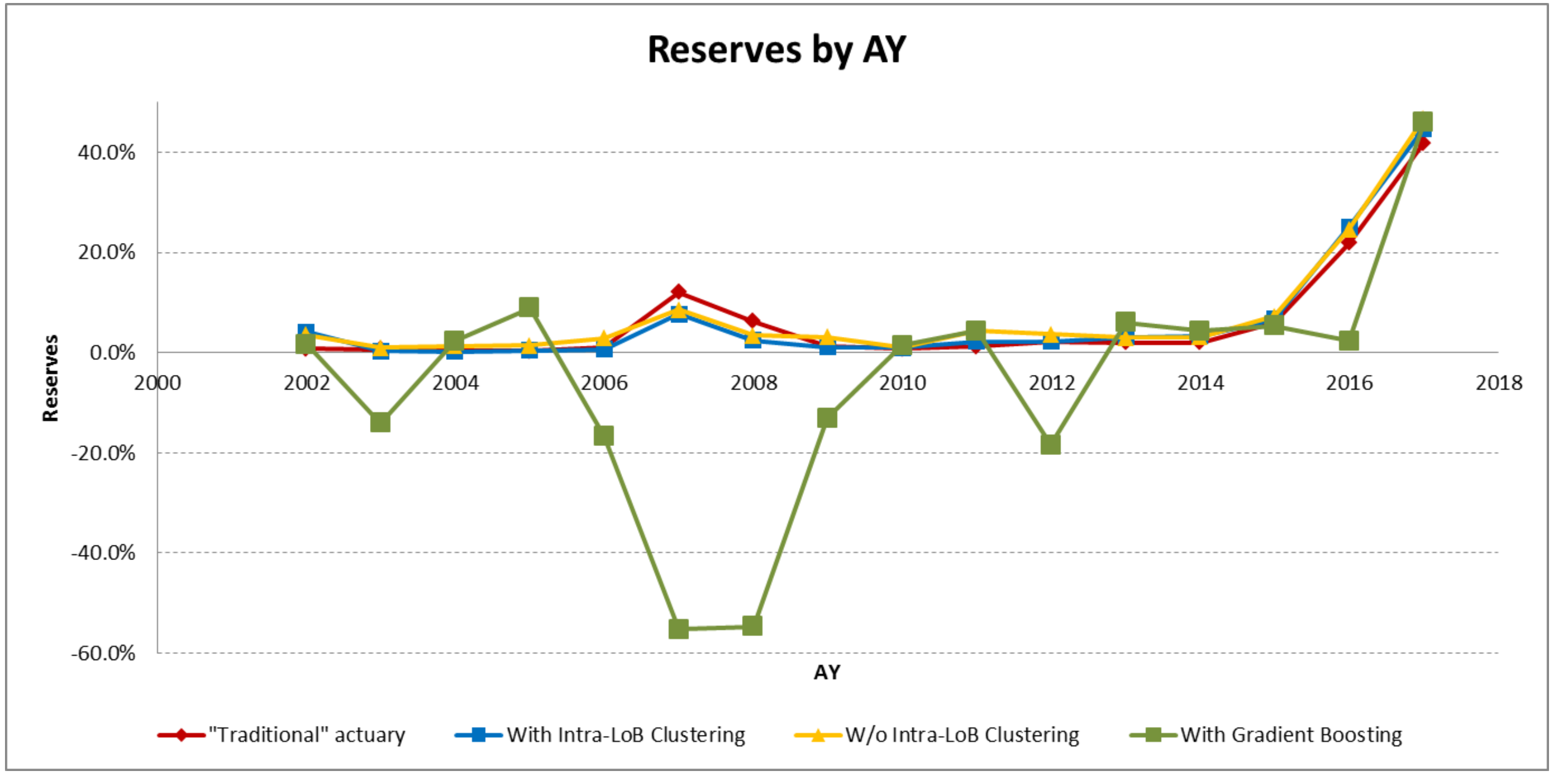
AY	AZ AI Algorithm	"Traditional" actuary	With Gradient Boosting
2002	2.8%	0.2%	0.1%
2003	0.8%	0.2%	0.3%
2004	0.3%	0.2%	0.0%
2005	0.6%	0.2%	0.1%
2006	0.7%	0.5%	-0.4%
2007	0.2%	0.5%	-0.2%
2008	0.4%	0.9%	0.9%
2009	1.9%	2.8%	0.8%
2010	2.1%	2.8%	3.5%
2011	4.1%	4.7%	5.9%
2012	2.8%	3.0%	4.2%
2013	6.8%	7.0%	8.5%
2014	10.1%	10.8%	11.3%
2015	18.8%	19.7%	20.4%
2016	17.3%	18.3%	18.8%
2017	30.9%	28.3%	27.3%
Total	**100.5%**	**100.0%**	**101.3%**



For LoBs with significant amount of data, gradient boosting can be run and results look reasonable …

COMPARISON OF RESULTS: PROPERTY TYPE LOB

AY	With Intra-LoB Clustering	"Traditional" actuary	W/o Intra-LoB Clustering	Gradient Boosting
2002	4.1%	0.8%	3.6%	1.7%
2003	0.3%	0.6%	1.0%	-14.2%
2004	0.2%	0.3%	1.3%	2.3%
2005	0.4%	0.2%	1.4%	8.9%
2006	0.6%	0.9%	2.9%	-16.7%
2007	7.6%	12.1%	8.6%	-55.3%
2008	2.5%	6.2%	3.5%	-54.8%
2009	1.1%	1.2%	3.1%	-13.1%
2010	0.9%	0.7%	1.0%	1.5%
2011	2.2%	1.2%	4.3%	4.3%
2012	2.2%	2.1%	3.7%	-18.5%
2013	3.1%	2.0%	3.0%	6.0%
2014	3.4%	2.0%	3.1%	4.3%
2015	6.6%	6.0%	7.2%	5.3%
2016	25.1%	21.8%	24.6%	2.3%
2017	44.7%	41.9%	46.7%	45.9%
Total	**105.0%**	**100.0%**	**118.9%**	**-90.0%**



For small LoBs, where not much data is available, Gradient Boosting can provide erratic results while AZ AI Algorithm still performs reasonably well

MANY THANKS FOR YOUR ATTENTION

AUTHOR

QR contact details:

Alessandro is a qualified actuary, currently working as Regional Chief Actuary for Iberia & LatAm in Allianz SE, Munich. During his career, he has been presented and speaker at several actuarial conferences, focusing mainly in P&C Risk Management and Stochastic Reserving. Since 2012, he is also an author of the R *ChainLadder* package, freely available online. In the recent years his main interest is around bridging the actuarial world to the modern data scientist techniques

Acknowledgement: most of the work presented has been realised thanks to the hard work and commitment of **Michele Visintin**, a MSc student of the University of Trieste at the time of writing. I would really like to reiterate my thanks to him, who really gave a great contribution to this visionary project.

FAQ

(1) What you do is not really “individual claims reserving”, as eventually you work on aggregated data

To the extent we define as “individual pricing tariffs” GLMs on individual data, I don’t see why this shouldn’t be an “individual claim reserving”. As per pricing, we need to group the claims into “similar” pockets, to be able to assign to a new claim a “behaviour” similar to one observed in the past. Of course, the IBNR at claim level are still “on average” (for the given cluster), but it doesn’t really matter as eventually this allows results to be aggregated to any segmentation (eg. portfolio or regulatory LoBs)

(2) Your algorithm cannot do IBNYR

Absolutely true: IBNYR are done as per traditional techniques (see remark in slide 6)

(3) Is your algorithm stable?

Compared to gradient boosting or neural networks, it definitively is. And – thanks to the clustering seed – it’s possible to replicate all the results for a third (independent) party

(4) How do you measure uncertainty?

In a nutshell: “stochastic uncertainty” is not possible. This is a general issue anyway of newer data science techniques. To communicate with the business, I prefer to give a range using the fork on Incurred and Paid projections rather than using (tons of) actuarial judgement with copulas at claim level or whatsoever …

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