Actuaries Club of the Southwest

Spring 2019 Meeting

Anticipating Events: Using member-level predictive models to calculate IBNR reserves

Anders Larson, FSA, MAAA
Jack Leemhuis, ASA, MAAA

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Limitations

- The views expressed in this presentation are those of the presenters, and not those of Milliman. Nothing in this presentation is intended to represent a professional opinion or be an interpretation of actuarial standards of practice.

Agenda

IBNR primer

Why use member-level predictive models?

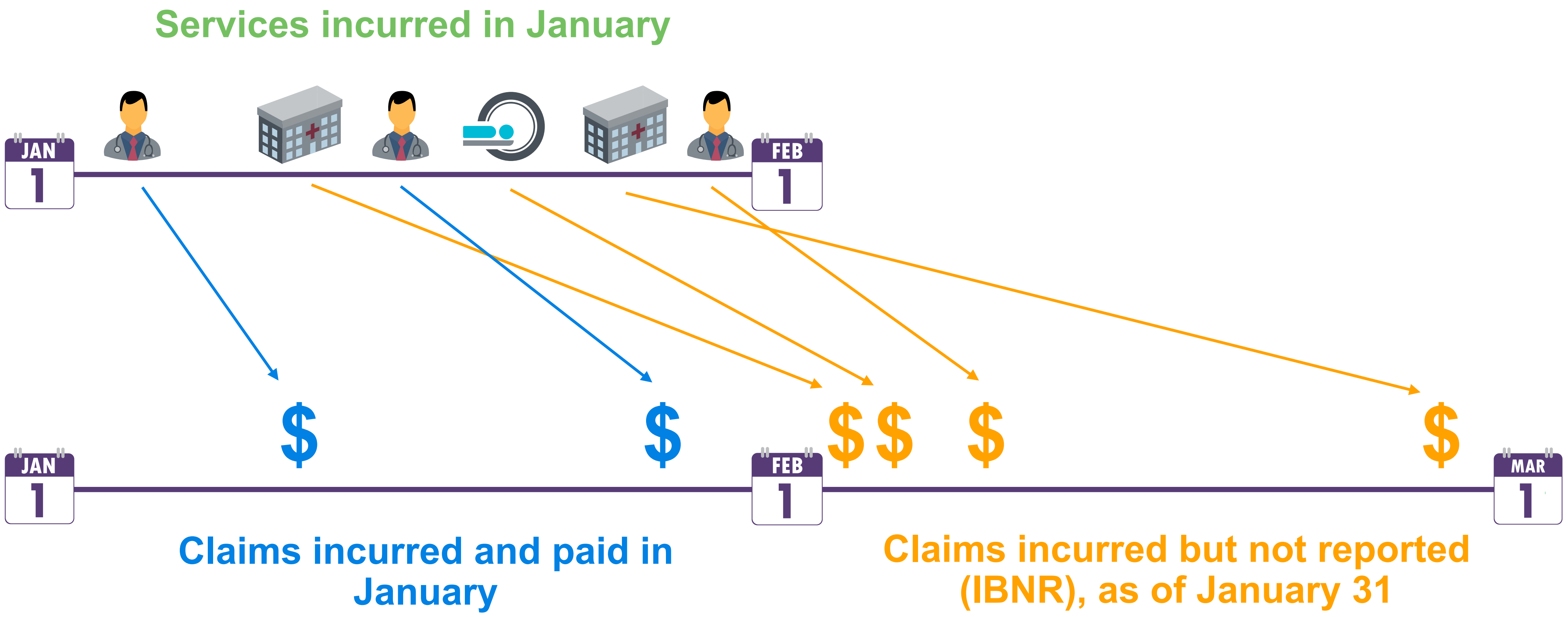
How we built our model

What we found

Conclusion

IBNR primer

What is IBNR?


Services incurred in January
JAN 1
FEB 1
$
$
$ $
$
$
JAN 1
FEB 1
MAR 1
Claims incurred and paid in January
Claims incurred but not reported (IBNR), as of January 31

Traditional methods – completion factor

- Estimate the percentage of incurred claims that are believed to have been reported already in a given incurred month, based on historical claims data and runout patterns
- Take the sum of all incurred claims that have been reported in that month, and divide by this percentage to get the total estimated amount of incurred claims for a given incurred month
  - The IBNR is the difference between the estimated total and the claims that are known to have been reported already

Application of Completion Factor Method to Estimate IBNR				
	A	B	C = A / B	D = C–A
Incurred Month	Claims Reported to Date	Assumed Completion Factor	Estimated Final Incurred Claims	IBNR
December 2017	$1,000,000	40.0%	$2,500,000	$1,500,000
November 2017	$1,200,000	60.0%	$2,000,000	$800,000
October 2017	$900,000	90.0%	$1,000,000	$100,000
September 2017	$1,000,000	100.0%	$1,000,000	$0

Traditional methods – projection method

- Pull claims from a time period far enough in the past that it can be reasonably assumed that all claims for this time period are complete
- Calculate the average total incurred claim cost per member
  - Often these values are adjusted for trend, seasonality or other known changes since the historical time period
- Then take the difference between this estimate and the average amount of reported claims per member for a given incurred month in the present – this is the IBNR on a per-member basis
  - The total IBNR for a given month for an entire pool is this per-member IBNR, multiplied by the total number of members in the pool for that month
  - Does not consider the amount of claims already reported in these recent months

Differences between traditional methods

- Completion factor method
  - Best used for incurred months where claim payments are assumed to be more mature
  - Assumes historical payment timing is predictive of recent payment patterns

- Projection method
  - Best used for very recent months
  - Assumes claims reported to date in these recent months are not generally a good predictor of total incurred claims
  - Assumes historical per member costs are predictive of recent per member costs

Why use member-level predictive models?

Potential for improved accuracy

- Versus traditional methods, predictive models can better handle high-dimensional data sets
  - Can more accurately attribute risk to different segments of these data sets
- Predictive models also better handle complex relationships between predictions and the variables in the data used to make them
  - It is also more transparent in predictive models what variables (“features”) have a greater impact on predictions
  - This helps us improve the predictive models, and thus make better predictions
- Because IBNR can fluctuate wildly, traditional methods may lead to less accurate IBNR predictions
  - This is especially true for small groups of members or payers with unstable payment patterns
  - Better accuracy of these IBNR estimates is the biggest potential gain of using predictive models

Reasonable results for subpopulations

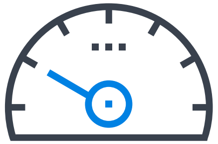
- Traditional methods rely upon aggregate completion patterns
  - Therefore, estimating IBNR at the member level is not reasonable
  - Predictive models allow us to reasonably estimate IBNR for individual members
  - These member-level IBNR predictions can be summed together to create an aggregate IBNR estimate for an entire employer group or pool of business
- Predictive models also allow us to make more accurate predictions for different subpopulations
  - This is hard to do for traditional methods – either lose the credibility of the entire pool, or do not pick up on the underlying payment pattern for a specific subpopulation
  - With predictive models however, we can leverage the credibility of an entire pool of members, while, at the same time, accurately reflect the specific risk characteristics for the specific subpopulation

Drawbacks of member-level approach

- While the applications and benefits of member-level predictive models are obvious, there are some drawbacks that need to be considered
  - More data elements are required to make predictions at the member level

Demographics

Geography



Risk Scores, etc

    - These extra data elements, along with having to view each individual claim for a given member, leads to larger data sets and increased data processing time
  - Modeling software that is capable of making these types of predictions require input data to be in a very specific format
    - Therefore you must manipulate the aforementioned larger data sets into these specific formats
  - Unlike traditional methods, which generally require a common spreadsheet application (e.g. Microsoft Excel), you must have access to a sophisticated platform that is capable of making predictions using a predictive model

How we built our model

High-level overview of our process

- Collect data incurred over several years
  - Limit all data to claims paid within 6 months of incurred date
- Claims incurred in latest year held out for testing
- Train model using data incurred in previous years
  - Model designed to predict IBNR in a given incurred month
    - One model for predicting most recent incurred month (which has 0 months run-out)
    - Separate models to predict two preceding incurred months (which have 1 and 2 months run-out, respectively)
    - In theory, additional models could be built to predict older months as well
- Gather member-level data as of various paid dates in the past to understand the relationship between various features known at the time and the IBNR that ultimately materialized

From lag triangles to training data

Lag Month	July 2019	August 2019	September 2019	October 2019	November 2019	December 2019
0	447,835	526,177	545,758	934,279	674,097	627,608
1	1,562,170	2,121,764	1,380,255	1,186,437	1,130,330	
2	260,090	899,707	158,255	255,746		
3	25,748	21,772	4,623			
4	(862)	25,884				
5	249					

From lag triangles to training data

Lag Month	July 2019	August 2019	September 2019	October 2019	November 2019	December 2019
0	245	0	0	0	0	245
1	0	12,022	802	0	1,200	
2	0	(503)	8,233	0		
3	0	0	75			
4	0	0				
5	0					

Limit data to one member at a time

From lag triangles to training data

Lag Month	July 2018	August 2018	September 2018	October 2018	November 2018	December 2018
0	0	0	503	0	0	650
1	190	0	802	0	920	1,203
2	0	0	(88)	12,922	0	0
3	0	0	79	330	0	0
4	0	0	71	0	0	620
5	0	0	30	0	0	0

Build training data as of an older paid date

From lag triangles to training data

Lag Month	July 2018	August 2018	September 2018	October 2018	November 2018	December 2018
0	0	0	503	0	0	650
1	190	0	802	0	920	1,203
2	0	0	(88)	12,922	0	0
3	0	0	79	330	0	0
4	0	0	71	0	0	620
5	0	0	30	0	0	0

Train model to predict the total IBNR in a given incurred month

From lag triangles to training data

Lag Month	July 2018	August 2018	September 2018	October 2018	November 2018	December 2018
0	0	0	503	0	0	650
1	190	0	802	0	920	1,203
2	0	0	(88)	12,922	0	0
3	0	0	79	330	0	0
4	0	0	71	0	0	620
5	0	0	30	0	0	0

One set of features is based on average claims paid in various lag months

From lag triangles to training data

Lag Month	July 2018	August 2018	September 2018	October 2018	November 2018	December 2018
0	0	0	503	0	0	650
1	190	0	802	0	920	1,203
2	0	0	(88)	12,922	0	0
3	0	0	79	330	0	0
4	0	0	71	0	0	620
5	0	0	30	0	0	0

Another set of features is based on total claims incurred in recent months

From lag triangles to training data

Lag Month	June 2018	July 2018	August 2018	September 2018	October 2018	November 2018
0	88	0	0	503	0	0
1	2,333	190	0	802	0	920
2	0	0	0	(88)	12,922	0
3	190	0	0	79	330	0
4	0	0	0	71	0	0
5	0	0	0	30	0	0

Repeat process as of older paid dates to build further training data

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Other features

In addition to the historical payment information represented in the lag triangles discussed in the previous slide, other important features were included to train the models

- Demographic information: age and gender
- Clinical information: HHS-HCC risk score
- Leading indicator features: missing IP indicator, missing OP indicator
  - Helped the model identify potential large IP and OP claims that had been incurred but not reported
  - During hospital visits, there is an accompanying physician (professional) bill that is often processed more quickly and much less expensive than the facility bill
  - When only a professional bill is reported, there is a strong chance that a large, expensive IP or OP facility claim is yet to be reported

Later in this presentation, we show the effect of these various features on the model's prediction of the total IBNR estimate

Potential features we did not include

- There were some features that were not included in our case study, largely due to time constraints in this “proof of concept” analysis
- Some features that we did not include but could be considered in future models include:

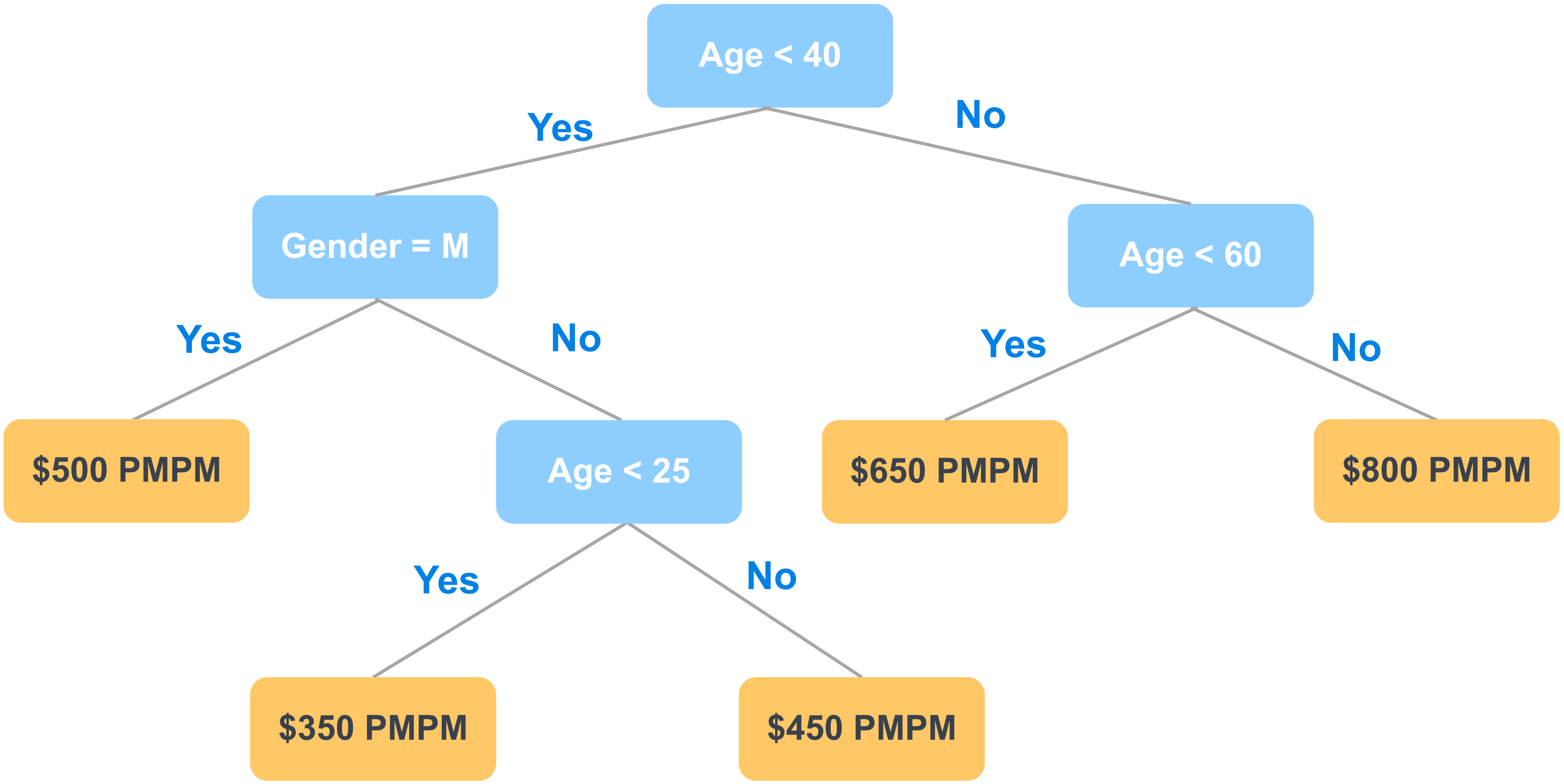
HCC conditions

Geographic level factors (e.g. locality factors)

Plan level features (e.g. the type of plan design a member uses)

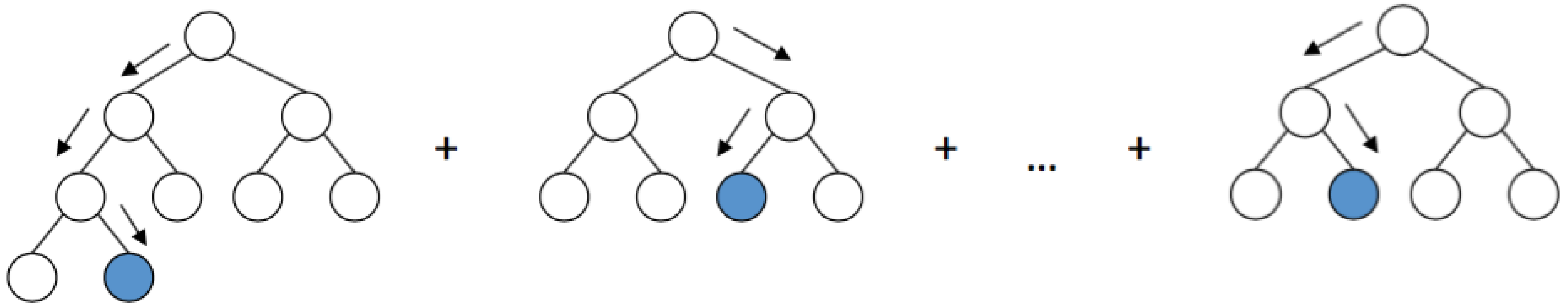
Prescriptions that a member is taking

What is a gradient boosting machine (GBM)?



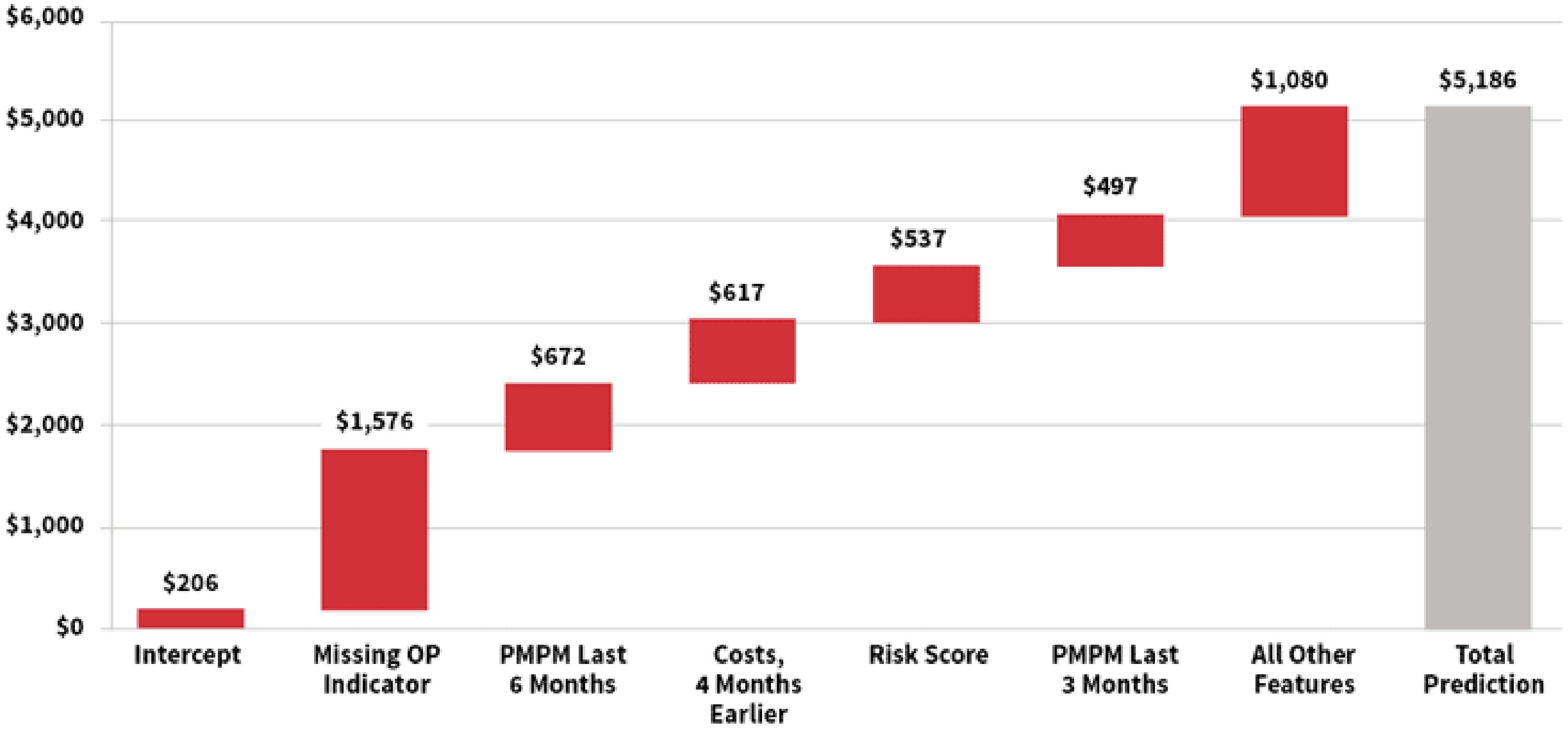
What is a gradient boosting machine (GBM)?

- Learns complex variables interactions and non-linear relationships automatically
- Less interpretable than regression models but more predictive
- How it works
  - Collection of many decision trees
  - Each tree improves upon prediction of prior tree



What we found

What drives the predictions for a member?



Relationships between features

- Which variables ("features") to include when building a predictive model is very important
  - Better, more carefully considered features lead to the highest increases in predictive power
  - Some common and important health care features include age, gender, plan design, and the geography of the member
  - The timing of when claims are incurred and when claims are reported is extremely influential when predicting IBNR
- Predictive models help us identify important relationships between features and predictions; we can utilize these relationships to fine tune our model and in return get more accurate predictions
- The two tables on the next slide show us the relationships between variables and their impact on the IBNR

Relationships between features (continued)

Average IBNR in Lag 0 by Certain Key Features		
	Missing IP Indicator	
Prior Year's Claims PMPM	Yes	No
$0–$200	$12,612	$92
$200–$400	$10,152	$316
$400–$600	$15,103	$391
$600–$800	$14,302	$473
$800–$1,000	$17,017	$530
$1,000–$10,000,000	$19,831	$1,545

	Risk Score			
Claims Paid in L0	0–0.5	0.5–1.0	1.0–2.0	2.0+
$0–$1,000	$98	$157	$217	$757
$1,000–$2,500	$1,591	$1,595	$2,408	$5,374
$2,500–$10,000	$2,170	$2,492	$2,029	$8,361
$10,000–$10,000,000	$2,231	$2,934	$4,954	$16,225

Accuracy compared to traditional models

- To evaluate accuracy, we compared the 10 group-level models for each predictive model to the two traditional methods discussed earlier
  - Then compared predictions to the known actual IBNR for each model; the aggregate error across all 10 groups was then calculated
- The table below shows that the GBM model and penalized regression more accurately predicted the overall IBNR, and had less variation in these predictions

Error Metrics for Traditional Methods and Predictive Models			
Traditional Methods	**Aggregate Percentage Error**	**Average Absolute Percentage Error**	**Standard Deviation**
Completion Factor	**–3.6%**	**42.8%**	**72%**
Projection Method	**8.3%**	**43.2%**	**47%**
Predictive Models			
Gradient Boosting Machine	**1.4%**	**24.8%**	**29%**
Penalized Regression	**–0.1%**	**27.1%**	**34%**

Conclusion

Practical considerations

Practical Considerations Before Using Predictive Models for IBNR
▪ How will you define success for the endeavor? ▪ What kind and quality of data do you have? ▪ Will you need access to new data fields not currently used in the reserving process? ▪ Do you have access to modeling software? ▪ Do you have the expertise to create and deploy a predictive model? ▪ Can you obtain the data and generate predictions fast enough to meet valuation timelines? ▪ Can the results be explained to auditors and key stakeholders?

Original article

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Thank you

Anders.Larson@milliman.com

Jack.Leemhuis@milliman.com