KPMG

Actuarial Modernization: Expedited Approaches for Reserving, Pricing, and Financial Reporting

Actuarial analysis in the digital age

NAIC Predictive Analytics Book Club

December 4, 2018

Agenda

Topic

Reserve Modernization – Refresh

Industry Overview – Current Pilots and Uses

Applications of Reserve Modernization

Case Studies

Results Interpretation & Visualization

The components are interconnected and build on each other

	Robotic process automation	Cognitive Analysis	Results Presentation	Enterprise Response
Description	— Automation of repetitive tasks — Use of “bots” – a kind of super macro that operates across systems	— Machine learning techniques applied to claims valuation — Results allocated at a granular claim level	— New techniques to tailor and present results — Enhanced ad hoc analytics	— Operating model to translate new insights into action — Mobilization across core departments – pricing, underwriting, claims, finance
Approach	— Review existing process flows, identify automation points — Develop and test ‘bot’ macros	— Leverages new statistical software — Uses structured and unstructured data, including individual claim characteristics	— Applies new visualization tools to the granular data — Combination of standard, tailored, and ad hoc reports	— Identifies processes, structure, roles, and governance to communicate, interpret, and respond to insights/trends
Benefits	— Shorter cycle times and faster close process — Less resources needed – deploy to other priorities or eliminate to save costs	— Faster identification of trends — Results at granular claim level allows for deeper root cause analysis	— Better, user-friendly reports with more granular insights — Stronger engagement by business-side consumer of the information	— Common view of issues — Coordinated cross-unit action — Effective, timely response to issues

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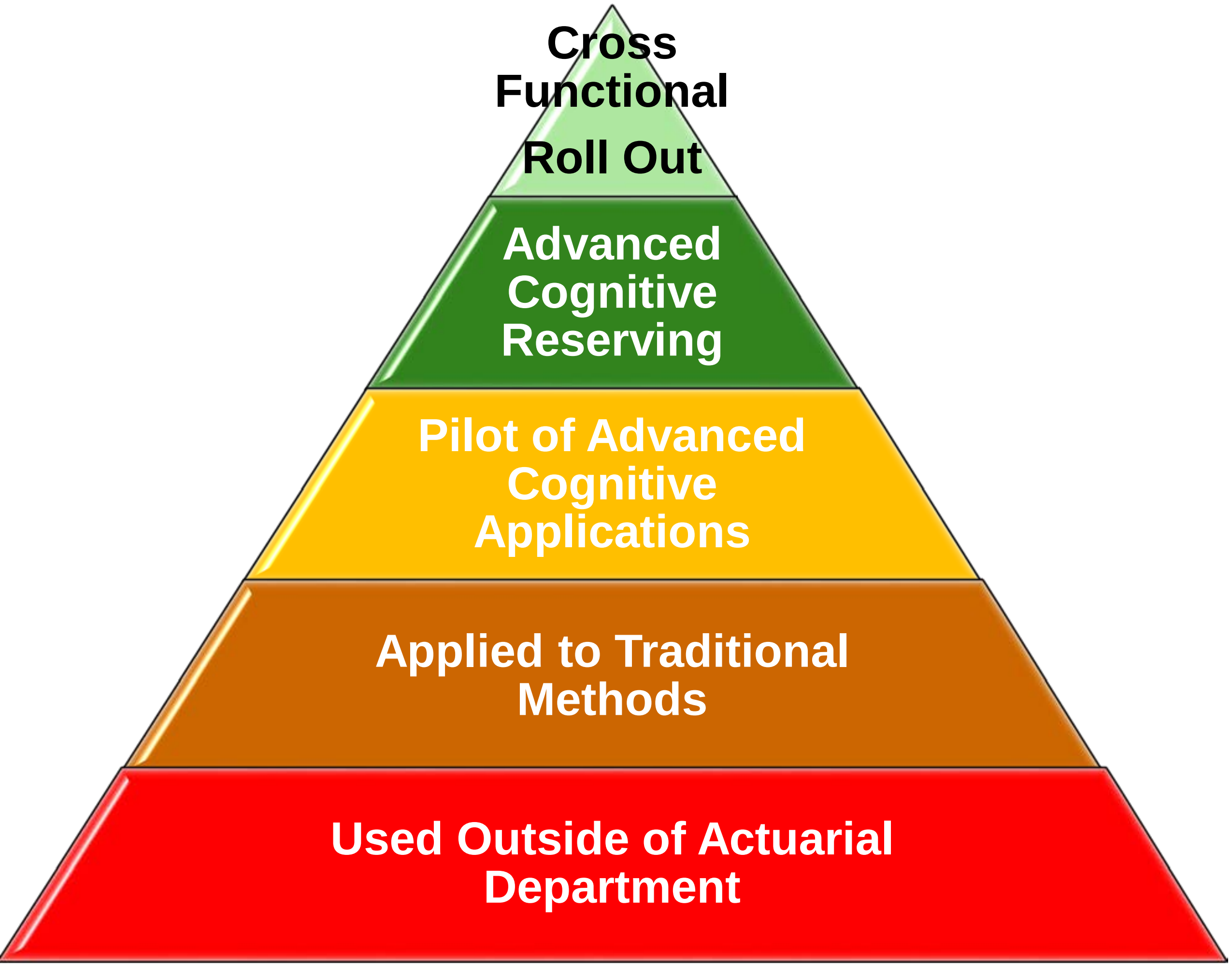
State of the Industry



Commentary

- Market Leading - One global P&C insurer is currently rolling out cognitive reserving across multiple Segments
  - By perhaps 1-2 years ahead of other leading adopters
- Several more sophisticated Companies are piloting claims level reserving approaches
  - Often technical exercises on troubled segments
- Some have taken the approach that these tools should be used to enhance traditional methods
- Many companies are using Cognitive approaches outside the reserving function

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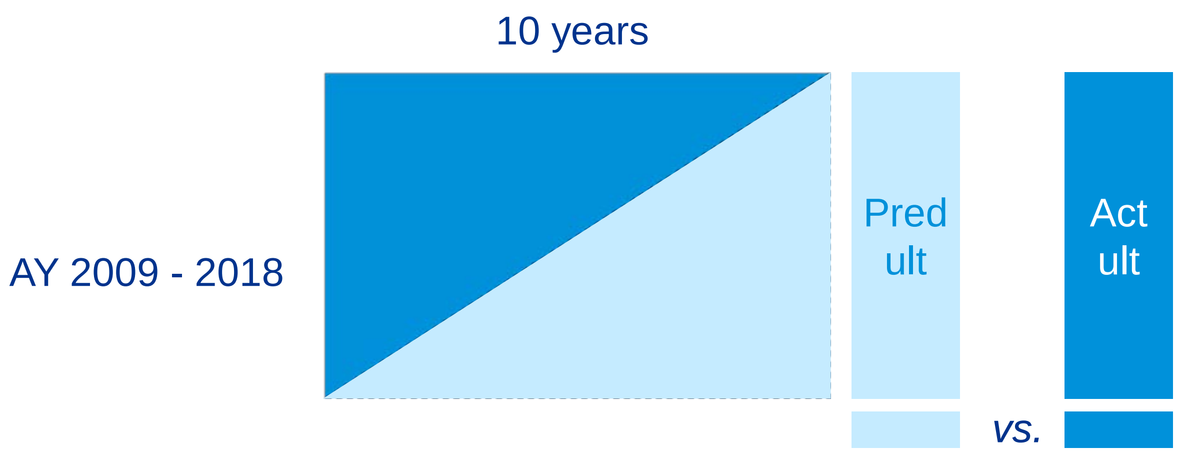
A Range of Applications are being Considered

- Traditional Methods
- Pricing
- Financial Reporting
- Distribution Channel Evaluation
- Target Markets
- Claims Handling Enhancement
- IFRS 17

Automation of Traditional Methods

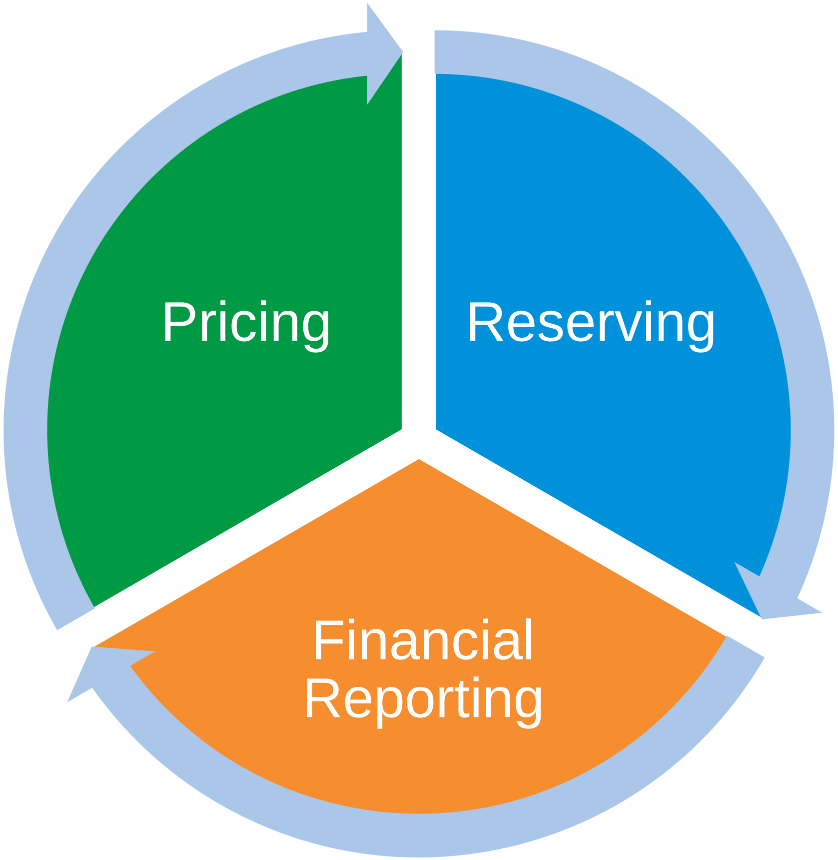
Squaring the triangle



Predict the unpaid losses to calculate ultimate losses and compare to actual ultimates

Pricing

Application of Cognitive Analytics allows for more granular results that can yield significant results in pricing as well as reserving

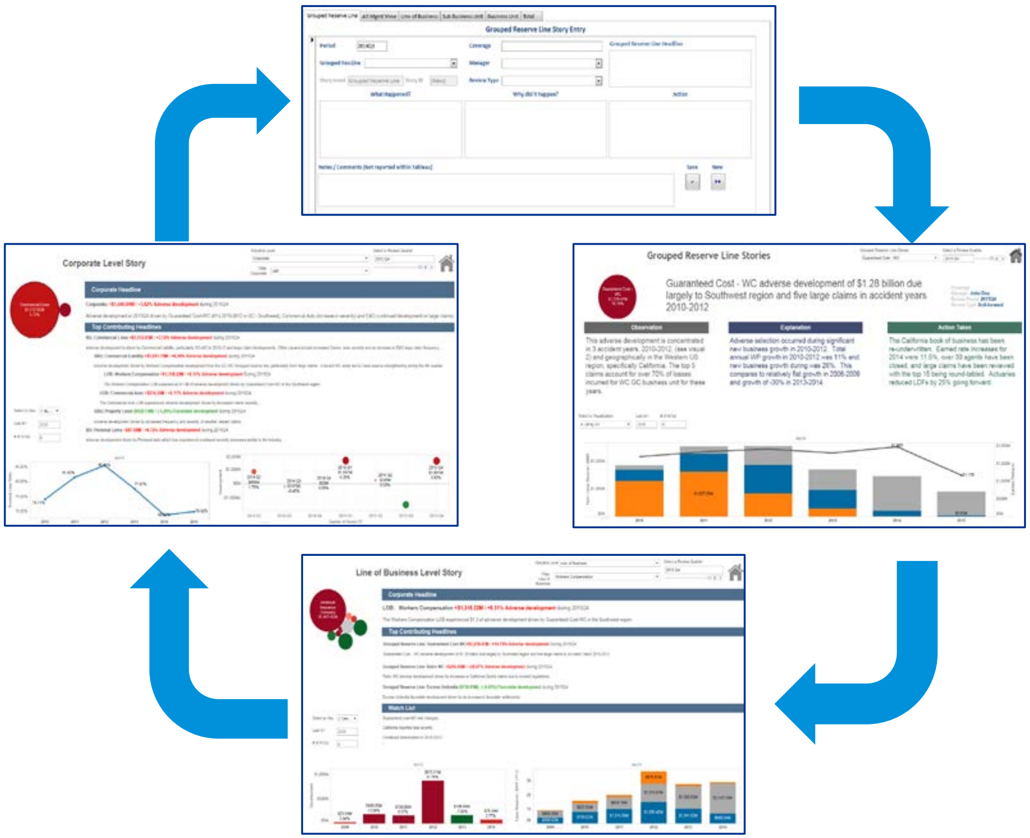


Commentary

- Granular evaluation of loss experience can be applied across many company functions
- The granularity of calculations will help close the feedback loop between core actuarial functions
- Numerous applications in areas that are now siloed such as:
  - Relativities
  - Risk Classification
  - Establishment of tiers
  - Expense loading and allocation

Financial and Profitability Reporting

The results of Cognitive tools have numerous applications to financial reporting and planning as well



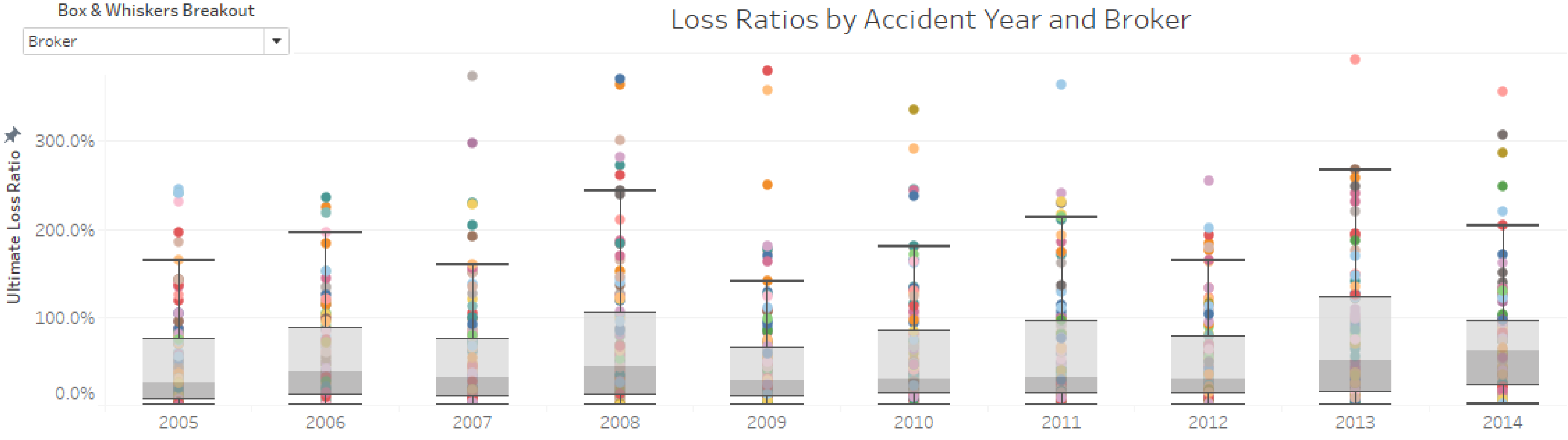
Commentary

- Cognitive methods provide detailed future cash flows
- Drillable profitability data by profit center and book of business
- More accurate capital allocation
- Partial automation of financial reporting packets

Reserve Modernization - Applications

Underwriter & Broker Evaluation

Examine the performance of distribution channels in an intuitive and systematic manner

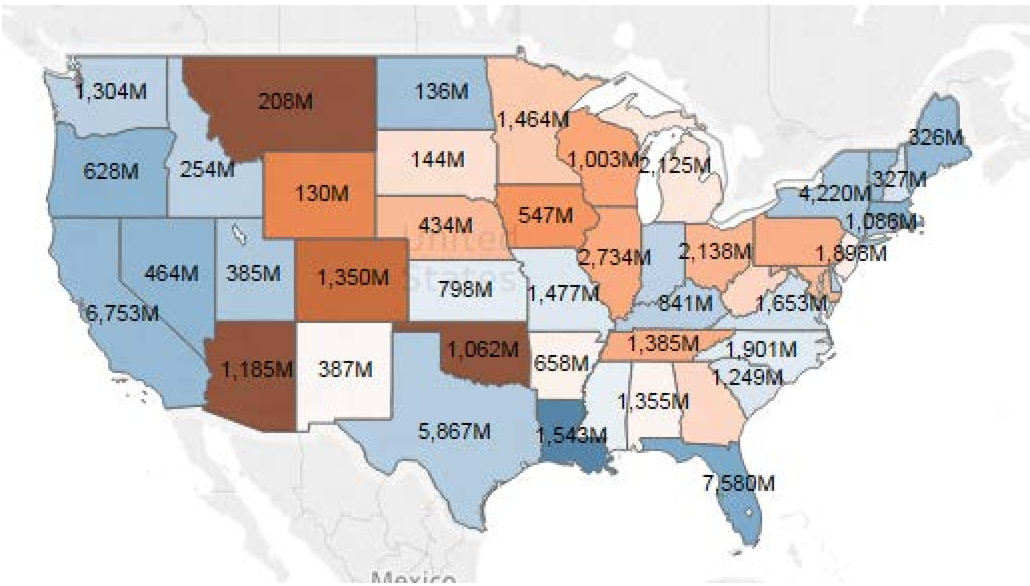


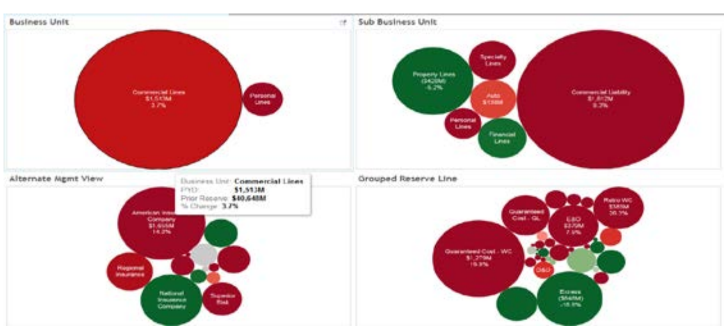
Commentary

- Evaluate performance on a loss cost basis of longer periods of time
- Consider variation of results
- Layer in other key evaluation metrics such as retention and production

Target Market Evaluation

Evaluate profitability along numerous metrics to identify areas to grow and segments to avoid



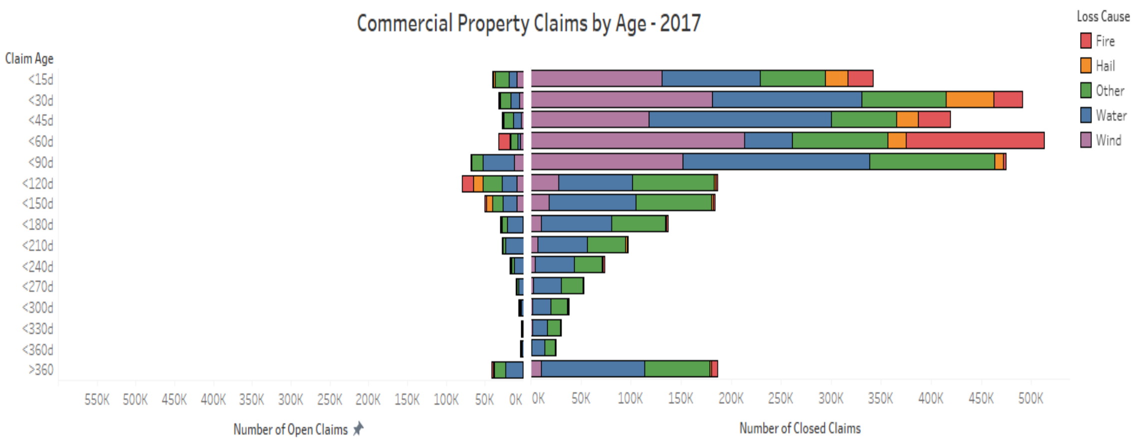


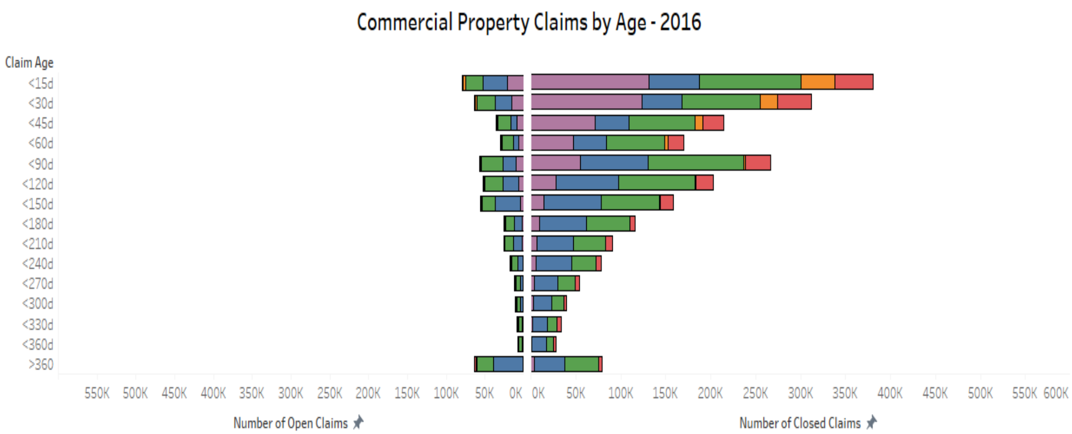
Commentary

- Target segments
- Target regions
- Target business units
- Target distribution channels

Claims Function Enhancement

Cognitive methods have the potential to help insurers with many aspects of claims handling





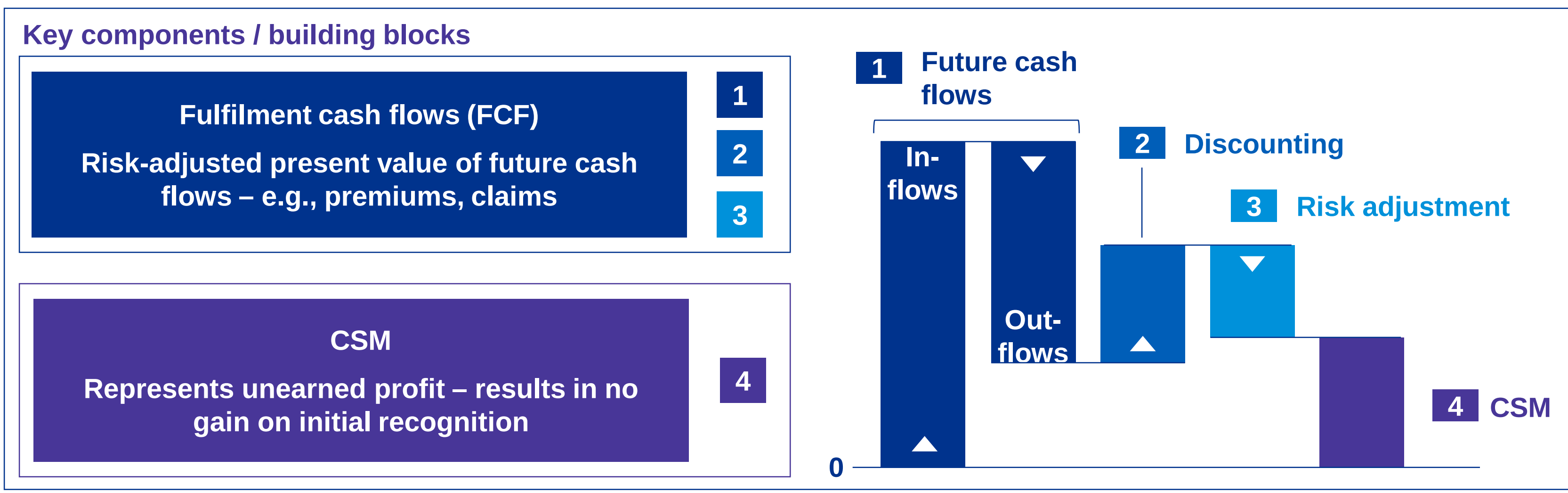
Commentary

- Setting more accurate case reserves
- Reserve strength & claim closure rates
- Claims triage
- Automation potential with RPA
- Reinsurance recoveries

IFRS 17

Claim level IBNR and projected cash flows provide a solution to related issues under IFRS 17:

- **Cash flows at a granular level may be required for discounting and risk margin calculations**
- **Onerous contract testing can be required in various segments**
- **For segments under the General Measurement Model, establishment of the CSM can require evaluation of various segmentations**
- **The flexibility of experience at a granular level can provide critical input into IFRS calculations**



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Results Interpretation & Visualization

Case studies

Use Case 1 – U.S. Life Operation of Global Multi-Line Insurer – Cognitive Reserving Solution using a Random Forest Model to predict state changes impacting universal life cash flows

Use Case 2 – Multiple Cognitive Reserving Solutions leveraging Gradient Boosting and Random Forest Models to proactively identify deterioration of problematic business segments:

- Client A - U.S. Operation of Global P&C Insurer – Commercial Auto Reserving Model
- Client B – E&S Operation of a Top 5 US Insurer – Binding Casualty Policy Profitability Model

Prediction of state change

- Existing method for predicting state change was performing poorly
  - Cognitive analysis used to predict the probability of state changes
  - Response variable is probability of state change

- Possible policyholder states:
  - Stable
  - Near lapse
  - Lapsed with payment plan
  - No payment expected

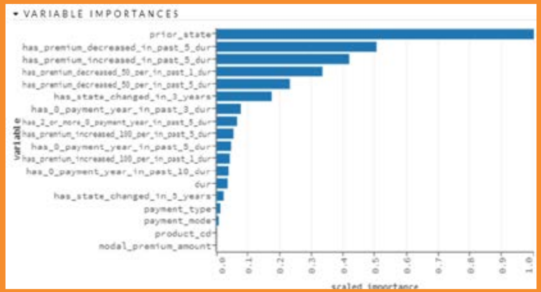
Case 1

Model build considerations

- Parameter selection based on one way analysis

- Hyper parameter selection based on a grid search

- Data storage – simplified through K mean clustering analysis

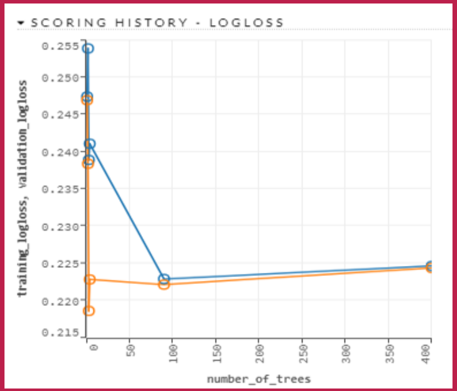


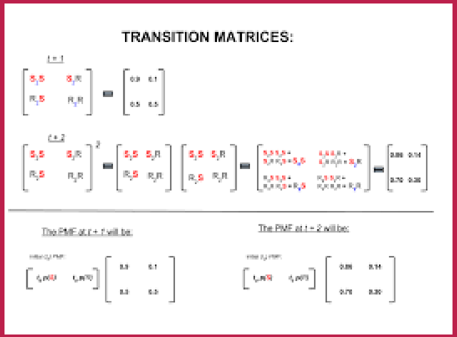
Model implementation

— Results of random forest model fed into markov chain matrix

— Markov chain monte carlo method applied recursively to obtain 80 years of cash flows

— Results summarized in 10 buckets determined by K means analysis

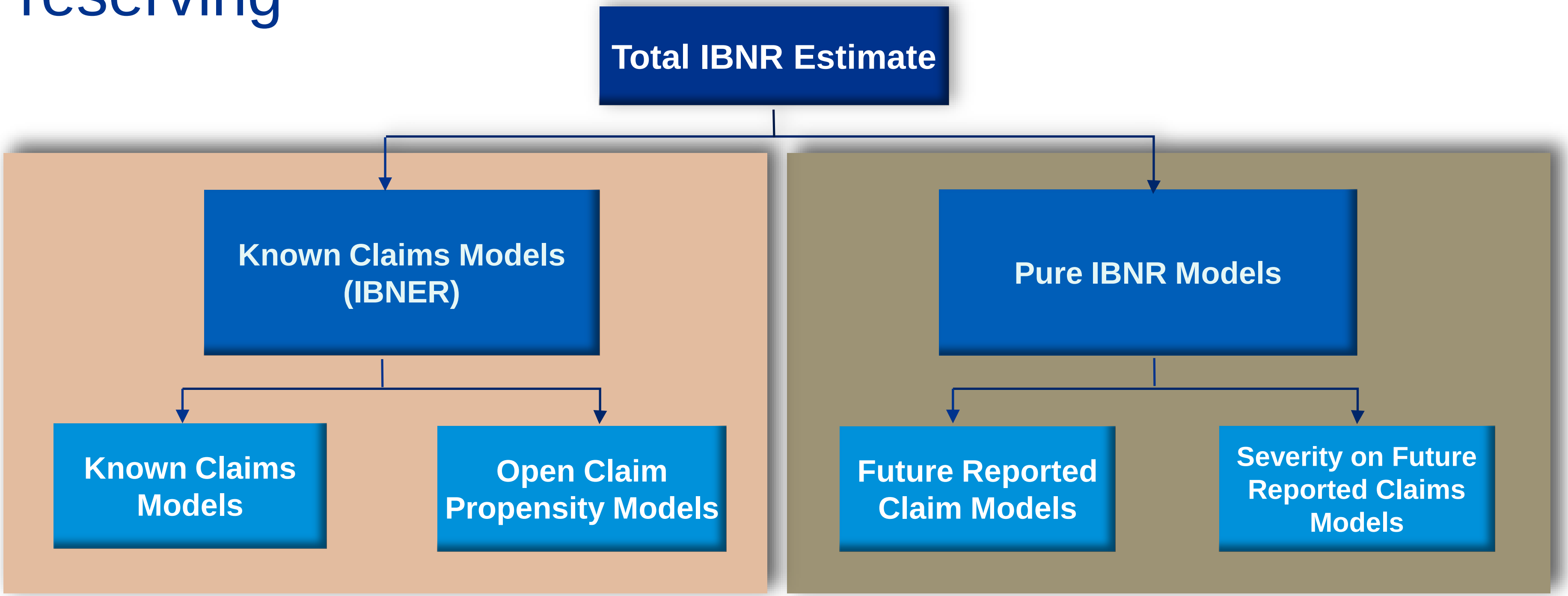




Case 2 – Client A

Model Overview

Generalized machine learning framework for cognitive reserving



Claim coverage level

Portfolio level

15

Case 2 – Client A

IBNER Approach

Calculation is performed at low level of granularity (e.g. Claim) – leveraging granular data assets

IBNER

	Actual Experience			Future Predicted Experience			
Period	**1**	**2**	**3**	**4(F)**	**5(F)**	**6(F)**	**7(F)**
Actual Incremental Paid Losses	2500	0	3000	NA	NA	NA	NA
Known Claims Model Estimate	NA	NA	NA	3000	4000	7000	7500
Open Claim Propensity Estimate	NA	NA	NA	25%	21%	18%	15%
Conditional Probability of Open Estimate[1]	NA	NA	NA	100%	84%	72%	60%
Estimated IBNER[2]	NA	NA	NA	3000	3360	5040	4500

Example – not derived from any company sources

[1]Conditional probability of claim open at the beginning of each future period given that the claim is open at the beginning of period 4. (e.g. Conditional Probability of Open for Period 5 = 0.21 / 0.25 = 0.84) 17

*[2]Estimated IBNER = Known Claims Model Estimate * Conditional Probability of Open*

Case 2 – Client A

Using Generalized Approach for Pure IBNR Estimation

Pure IBNR

Calculation is performed at portfolio level (can be allocated to policy)

	Actual Experience			Future Predicted Experience			
Period	**1**	**2**	**3**	**4(F)**	**5(F)**	**6(F)**	**7(F)**
Actual Newly Reported Claims	**1000**	**300**	**100**	NA	NA	NA	NA
Future Reported Claims Model Estimate	NA	NA	NA	30	20	12	5
Severity on Future Reported Claims Model Estimate	NA	NA	NA	35,000	38,000	42,000	47,000
Estimated Pure IBNR	NA	NA	NA	**1.05M**	**760k**	**504k**	**235k**

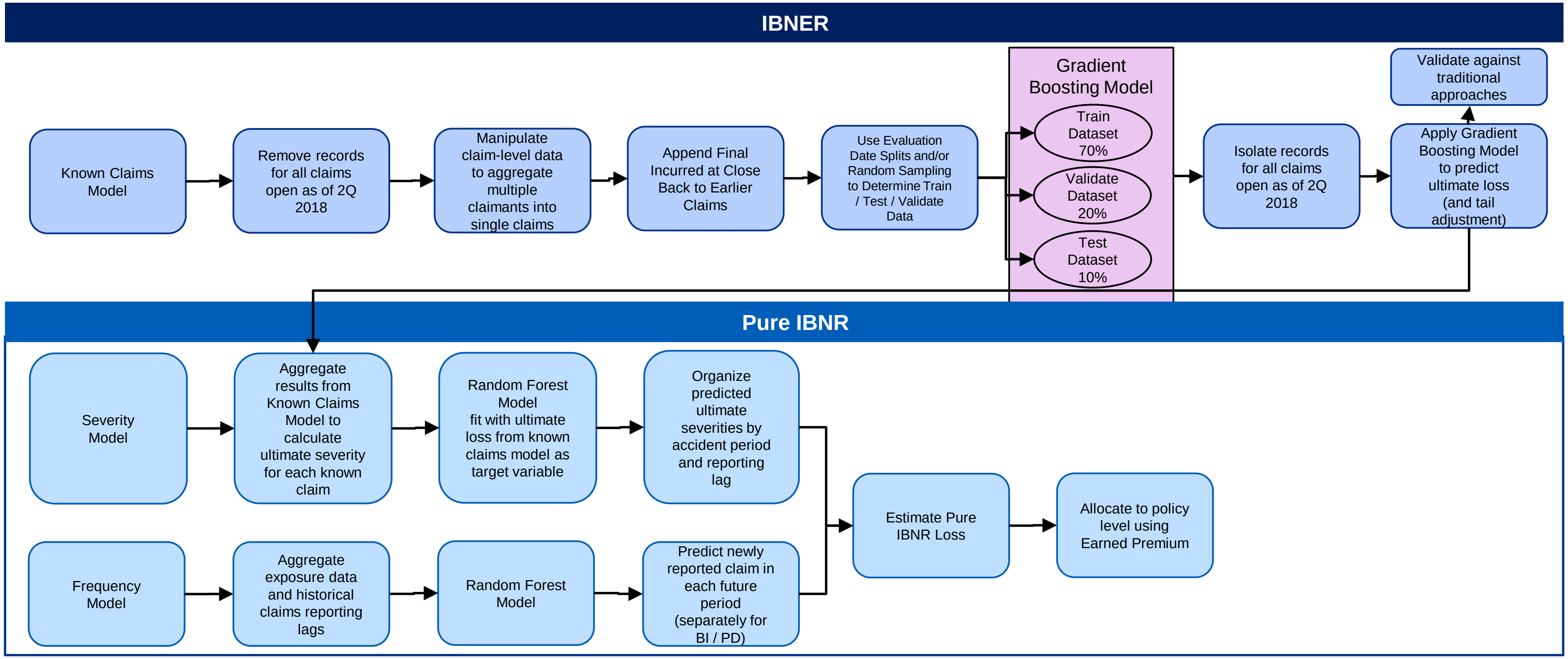
Total IBNR = IBNER + Pure IBNR

Example – not derived from any company sources

Case 2 – Client B

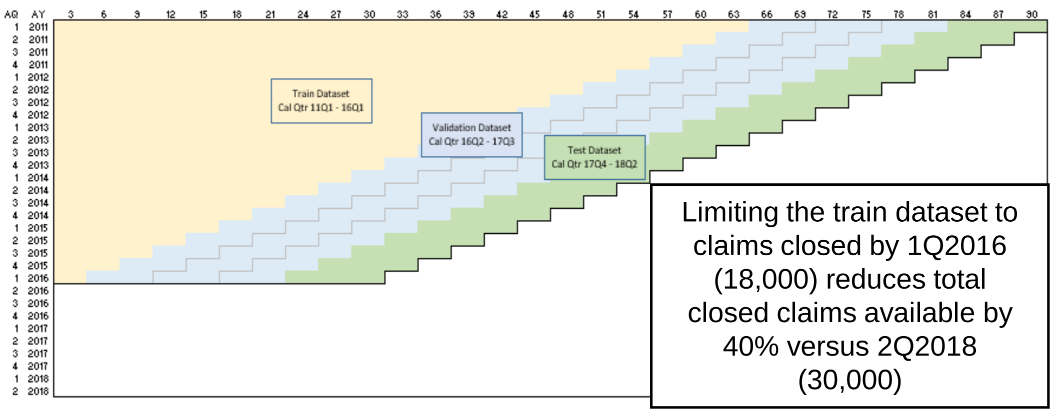
Detailed Plan for Profitability Analysis

As currently envisioned, we will create a Known Claims Model to estimate IBNER at a granular level and conduct an analysis of Frequency and Severity to estimate pure IBNR:

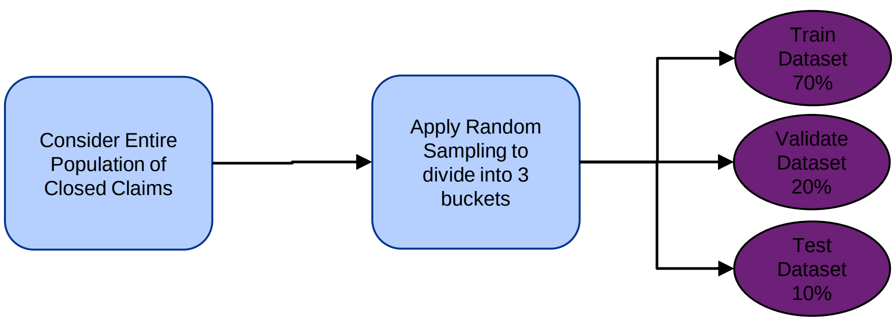


Test and Validation Approaches

Approach #1: Longitudinal Holdout



Approach #2: Based on Expected Distribution of Closed Claims



Validation approach used for selections of

- Model methods
- Hyper parameters
- Predictive variables

Test approach used to evaluate the model performance

- Do the selected methods with hyper parameters and variables generalize well in different time periods?

Two approaches test

- Actual vs predicted claim emergence / ultimate at close
    - Using data test set
- Model predicted IBNER / Pure IBNR vs. traditional methods indications

Case 2

Granular Results = Flexible Insights

Levels with largest paid deviations from expected

Commercial auto liability

Illustrative

Variable	Level	Actual – expected paid losses	Primary driver	Secondary driver
State	Texas	$32,000,000	Closed claim count (Higher than expected)	Paid severity (Higher than expected)
Segment	Construction large account	$20,000,000	Paid severity (Higher than expected)	Closed claim count (Higher than expected)
…	…	…	…	…
Vehicle weight	Heavy weight truck	- $19,000,000	Paid severity (Lower than expected)	N/a
Unbundled indicator	TPA Handled	- $55,000,000	Newly reported claim count (lower than expected)	Paid severity (Lower than expected)

Is TPA data properly in our systems?

This Cognitive Actual vs. Expected tool will also provide fast insights about trends which benefit risk selection, pricing, claim handling, etc.

Case 2 – Client B

Tiering – Illustrative Example of Segmentation

Profitable Classes

"A" Classes

Accident Year	Earned Premium	Ultimate Loss Ratio
2011	37,006,340	34.3%
2012	36,407,096	32.0%
2013	39,034,261	39.2%
2014	40,261,749	42.3%
2015	41,718,413	26.9%
2016	42,087,124	22.8%
2017	42,267,347	27.0%
Total	278,782,331	30.7%
2011-13	112,447,698	34.3%
2014-17	166,334,633	28.2%

Consists of Derived Program Codes for:

- Selected Mercantile
- Alarm Installation
- Landowners
- Offices
- Welding
- Landscapers
- Home Health Care
- Exercise and Health

8.4% decline in already low loss ratios from older years to more recent

Unprofitable Classes

"C" Classes

Accident Year	Earned Premium	Ultimate Loss Ratio
2011	18,434,129	100.9%
2012	19,897,639	109.9%
2013	22,863,494	103.7%
2014	28,277,897	130.1%
2015	31,133,767	138.1%
2016	32,026,072	127.2%
2017	33,078,866	154.9%
Total	185,711,865	127.1%
2011-13	61,195,262	105.1%
2014-17	124,516,603	137.9%

Consists of the following business, by Derived Program Code & noted features:

- Condo Associations in NY and FL
- Apartments in CA
- Motels
- Bars and Taverns
- Class 040006 (Adult Day Care) in TX, CA, NY & FL
- Artisan Contractors (excluding NYLL) in subcontracted Classes (091585 & 091583)

Remaining Classes

"B" Classes

Accident Year	Earned Premium	Ultimate Loss Ratio
2011	217,759,676	48.9%
2012	226,605,359	48.0%
2013	246,685,981	48.3%
2014	276,321,007	56.4%
2015	293,284,212	54.2%
2016	302,186,749	56.9%
2017	308,008,582	58.6%
Total	1,870,851,567	53.6%
2011-13	691,051,017	48.4%
2014-17	1,179,800,550	56.6%

- Consists of all other business excluding New York Labor Law (NYLL). NYLL classes were excluded as Nationwide E&S has exited that business
- Increased 7.1% in more recent years
- There likely remains significant opportunity to further segment this business

New York Contractors

NY Contractors

Accident Year	Earned Premium	Ultimate Loss Ratio
2011	13,745,120	105.2%
2012	14,482,344	117.6%
2013	16,956,029	106.3%
2014	22,427,473	141.6%
2015	29,477,192	108.9%
2016	19,630,336	74.6%
2017	9,162,464	25.6%
Total	125,880,958	103.5%
2011-13	45,183,493	109.6%
2014-17	80,697,465	100.2%

- Defined as the combination of labor law exposure and the NY insured state
- An exclusion was introduced in 2015 to address the issues with labor law. This exclusion made the product unattractive in the market
- Resulting shifts in the business could distort Tiering indications without adjustment
- Note in a runoff contractor book, audit premiums tend to artificially lower the runoff year loss ratios

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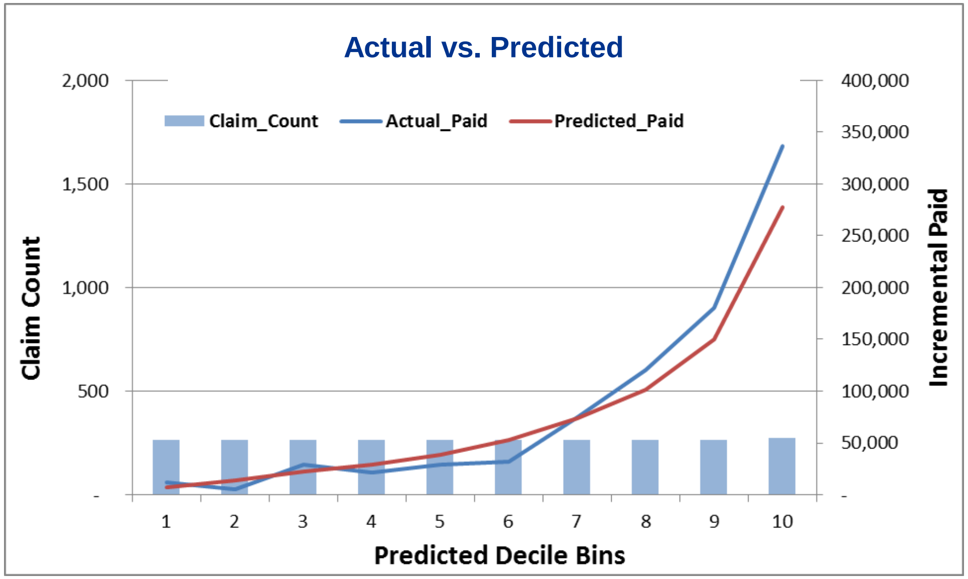
Model lift

Coverage one incremental paid loss model



Lift charts show the performance of the model on the test dataset (14Q1 – 16Q4).

- Predictions are binned from low to high into deciles.
- The red line (Predicted) tracks well with the blue line (Actual), except for some under fitting.

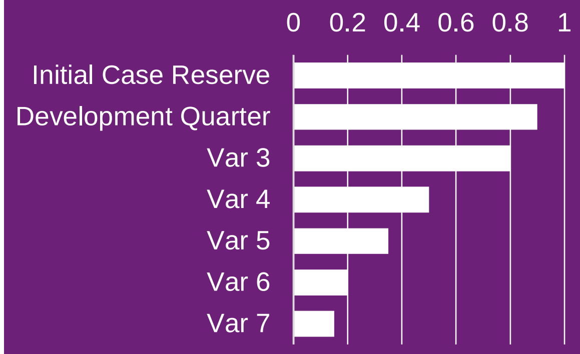
Relative variable importance

— Method of ranking the variables in the model in terms of their "importance"

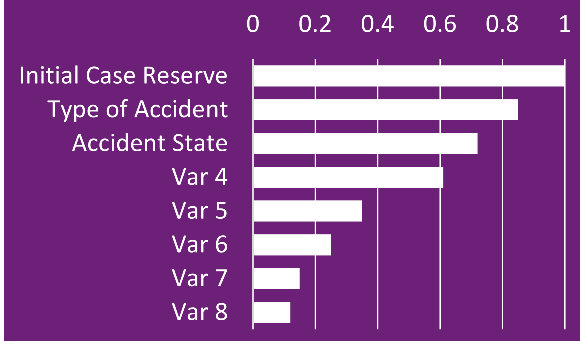
— Importance of a variable calculated by crediting it with the reduction in the sum of squares

— Scaling done so that the variable with the largest reduction in sum of squares is one

Coverage 1 model – relative importance



Coverage 2 model – relative importance



Example – not derived from any company sources

Partial dependency plots

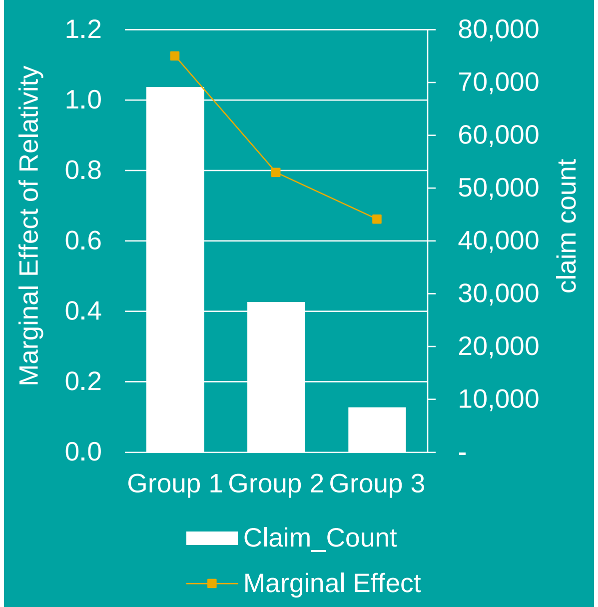
— Tool for visualizing the relationship of variables with target variable.

— Helpful with machine learning methods to provide more insight into the models

— Partial dependence represents the effect of a predictor(s) on target variable after accounting for the average effects of the other predictors.

— Use caution if the variable whose partial dependence you are calculating has interactions with the remaining variables

Example



Note:

All else being equal, Group 1 has 70% greater incremental payments per quarter than Group 3

Example – not derived from any company sources

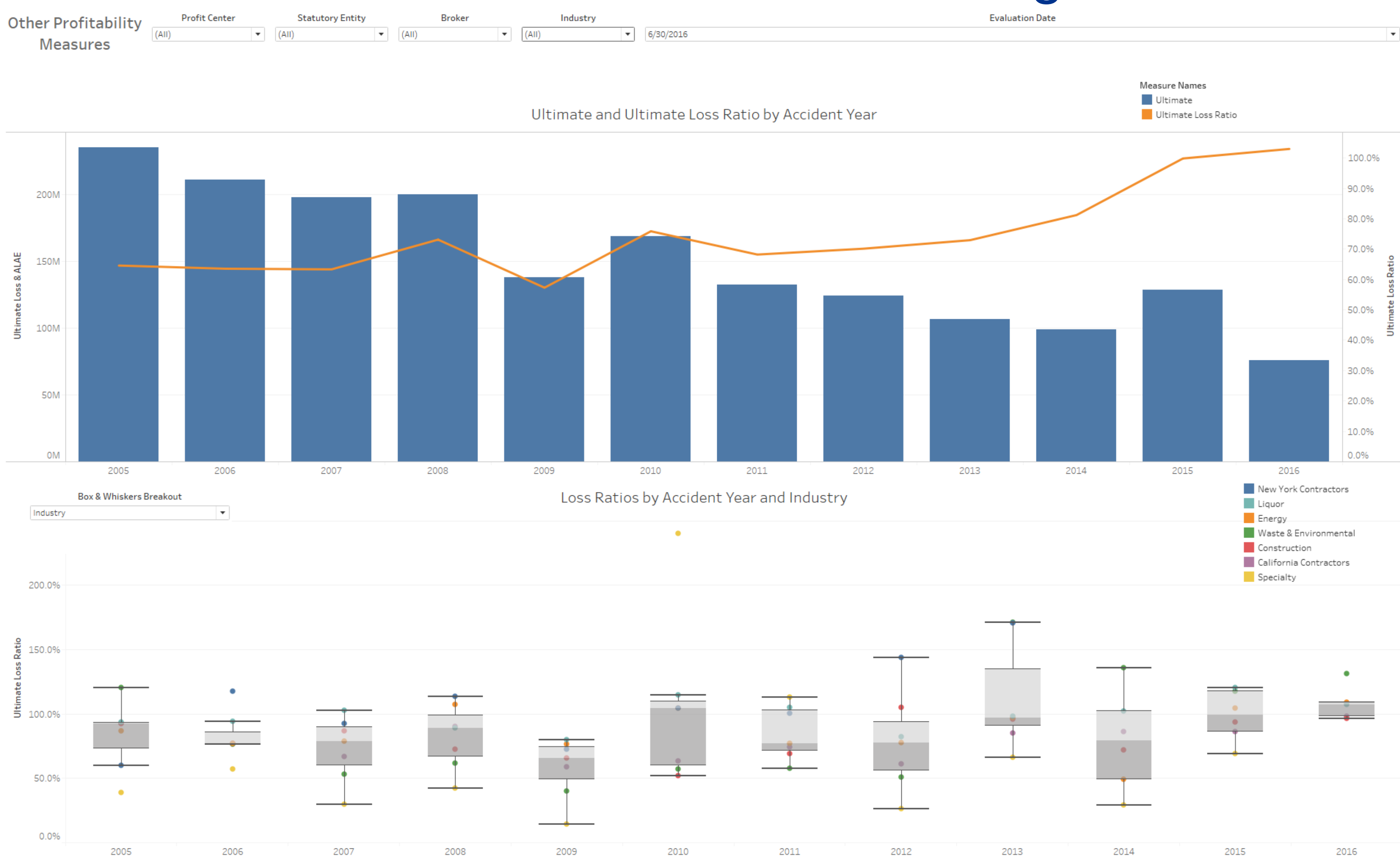
POJO review

- Final tree structure can be viewed in "Plain Old Java Object" format
- Interpretation of variable usage in tree structure
  - Variable type
  - Tree split points

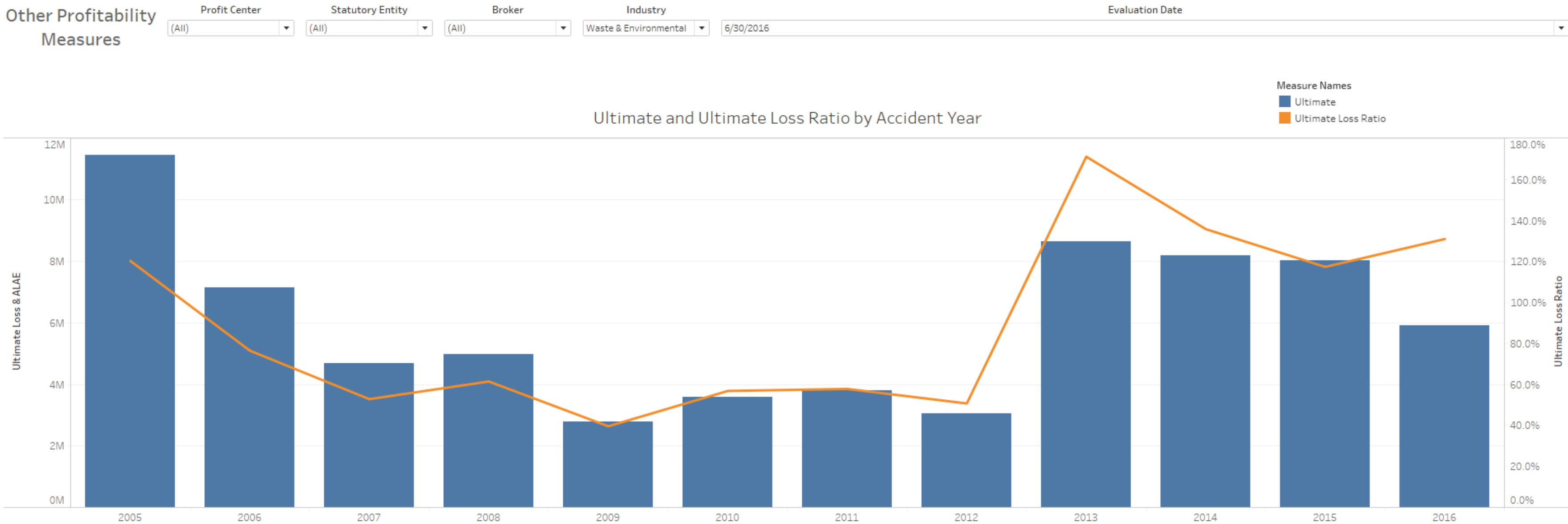
```
// Column domains. The last array contains domain of response column.
public static final String[][] DOMAINS = new String[][] {
  /* ClaimType */ model_gbm_validation_ColInfo_0.VALUES,
  /* ClaimDescriptionCode */ model_gbm_validation_ColInfo_1.VALUES,
  /* ClaimState */ model_gbm_validation_ColInfo_2.VALUES,
  /* DevelopmentMonth */ null,
  /* ClaimMonth */ null,
  /* TPAIndicator */ model_gbm_validation_ColInfo_5.VALUES,
  /* StatutoryCo */ model_gbm_validation_ColInfo_6.VALUES,
  /* CededIndicator */ null,
  /* UnderwritingOffice */ model_gbm_validation_ColInfo_8.VALUES,
  /* ClassGrouping */ model_gbm_validation_ColInfo_9.VALUES,
  /* InitialExpectedLoss */ null,
};
```

```
class model_gbm_validation_Tree_0_class_0 {
  static final double score0(double[] data) {
    double pred =      (Double.isNaN(data[8]) || data[8 /* UnderwritingOffice */] <20.5f ?
         (data[7 /* CededIndicator */] <1.0002446f ?
             (Double.isNaN(data[10]) || data[10 /* InitialExpectedLoss */] <14186.336f ?
                78.54965f :
                25125.646f) :
             (data[10 /* InitialExpectedLoss */] <-12199.999f ?
                -21045.748f :
                -1463.4309f)) :
         (Double.isNaN(data[10]) || data[10 /* InitialExpectedLoss */] <120323.08f ?
             (!Double.isNaN(data[0 /* ClaimType */]) && (GenModel.bitSetIsInRange(GRPSPLIT0, 0, data[0]) && !GenModel.bitSetContains(GRPSPLIT0, 0, data[0])) ?
                -878.5838f :
                771.9814f) :
            22522.334f));
    return pred;
  } // constant pool size = 31B, number of visited nodes = 6, static init size = 30B
  // {01000100 00101010 10000000 00011100}
  public static final byte[] GRPSPLIT0 = new byte[] {34, 84, 1, 56};
}
```

Data Visualization – Granular Investigation



Data Visualization – Granular Investigation



Thank you

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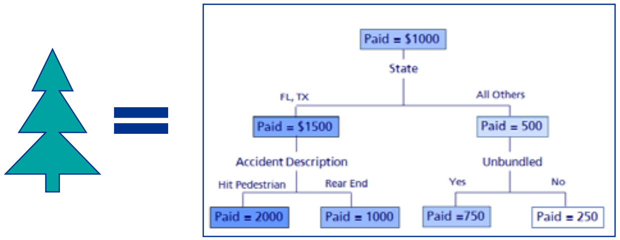
Appendix:

Machine Learning Basics

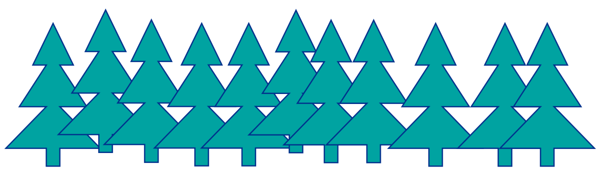
Model types



Example – not derived from any company sources

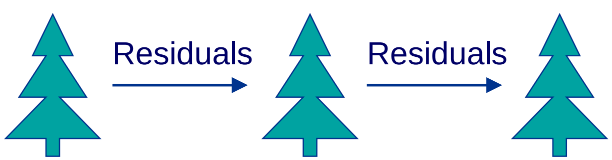
- A tree is a simple set of splitting rules on the data, what we call a “weak learner”
- A group of “weak learners” can come together to form a “strong learner”

Random Forest



Random Forest is a collection of “weak learners” (trees) built using bootstrap sample of training data. The prediction is a combination of predictions over the individual trees.

Gradient Boosting



Gradient Boosting is a collection of “weak learners” (trees) used sequentially, with each tree focused on improving the prediction of the previous tree. In each step a bootstrap sample of data is taken. A tree is fit to the “current residuals” and the residuals are updated for the next step.

Gradient Boosted Regression Trees

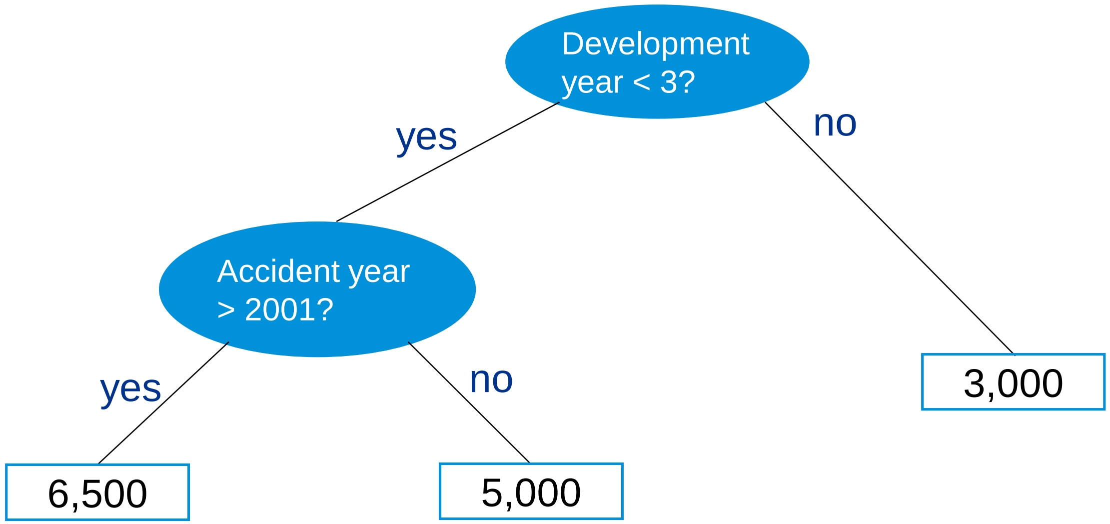
What's in a name?

Gradient Boosting	Regression Tree
• Machine learning technique that combines many weak models into a stronger model (ensembling)	• Predictive model that can be represented using a tree

First described by Friedman (2001).

Some Heuristics*

One decision tree

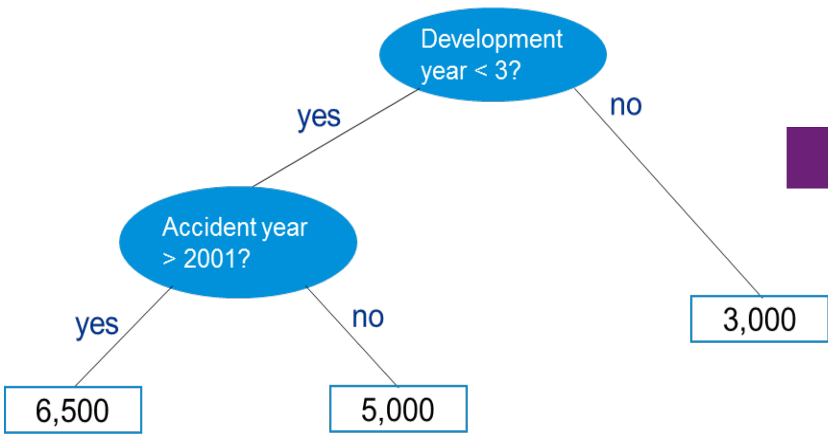


**via a very simplified illustrative example*

Some Heuristics

One decision tree

Not so great performance

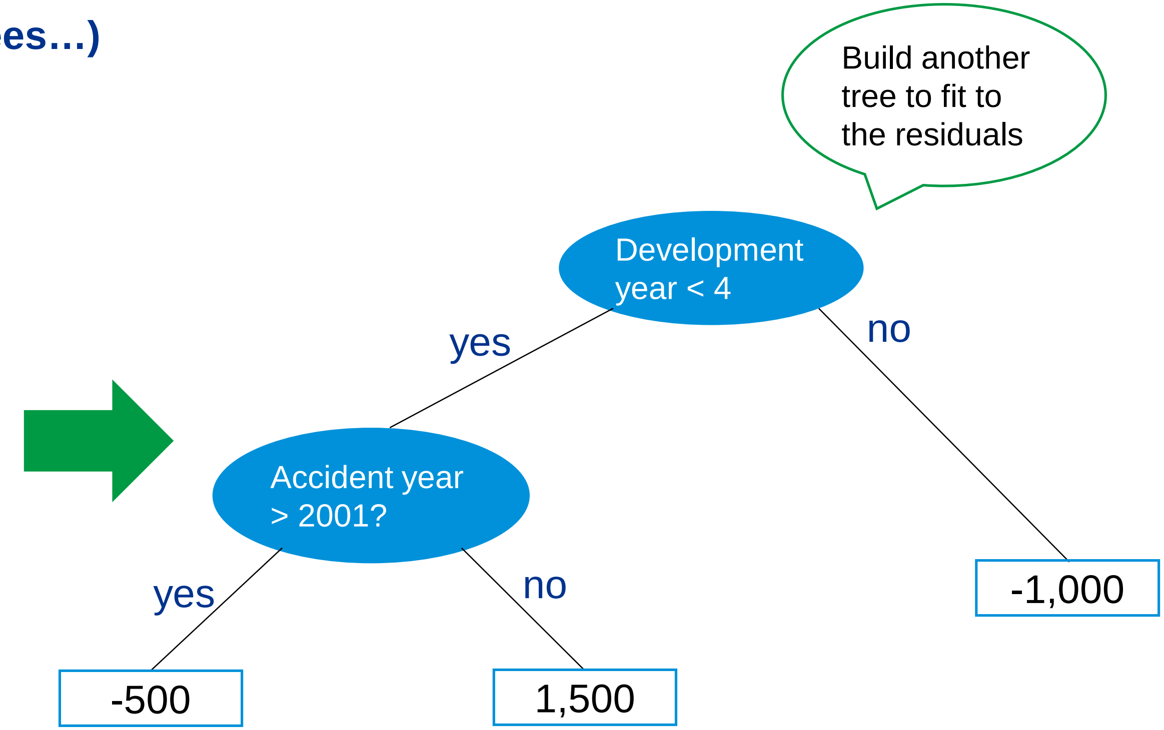


AY	Dev	Increm loss	Predicted	Residual
2000	1	5,000	5,000	0
2000	2	7,000	5,000	2,000
2000	3	4,000	3,000	1,000
2000	4	2,000	3,000	-1,000
2001	1	4,500	5,000	-500
2001	2	6,500	5,000	1,500
2001	3	3,500	3,000	500
2002	1	5,500	6,500	-1,000
2002	2	7,500	6,500	1,000
2003	1	6,000	6,500	-500

Some Heuristics

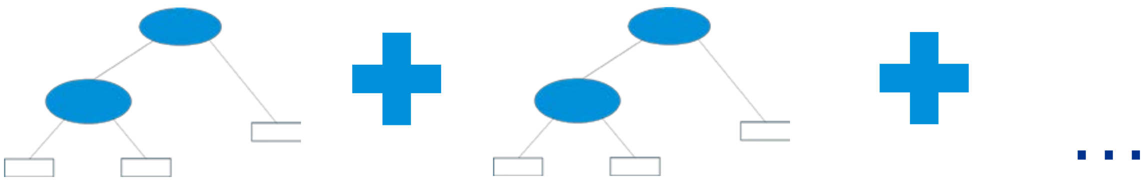
Boosting (more decision trees…)

AY	Dev	Residual
2000	1	0
2000	2	2,000
2000	3	1,000
2000	4	-1,000
2001	1	-500
2001	2	1,500
2001	3	500
2002	1	-1,000
2002	2	1,000
2003	1	-500



Some Heuristics

Boosting (more decision trees…)



AY	Dev	Residual (1^{st} tree)	Prediction (2^{nd} tree)	Residual (2^{nd} tree)	…
2000	1	0	1,500	-1,500	…
2000	2	2,000	1,500	500	…
2000	3	1,000	1,500	-500	…
2000	4	-1,000	-1000	0	…
2001	1	-500	1,500	-2,000	…
2001	2	1,500	1,500	0	…
2001	3	500	1,500	-1,000	…
2002	1	-1,000	-500	-500	…
2002	2	1,000	-500	1,500	
2003	1	-500	-500	0	

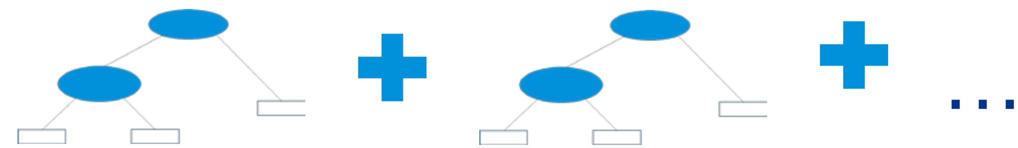
$$2{,}000 - 1{,}500 = 500$$

Each tree tries to correct the error of the previous trees. By constructing a sequence of many trees we'll have ourselves a decent model.

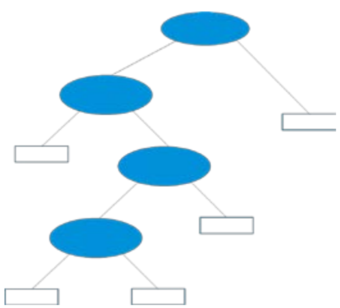
Hyperparameters & Tuning

There are many ways to specify a GBM algorithm; as examples,

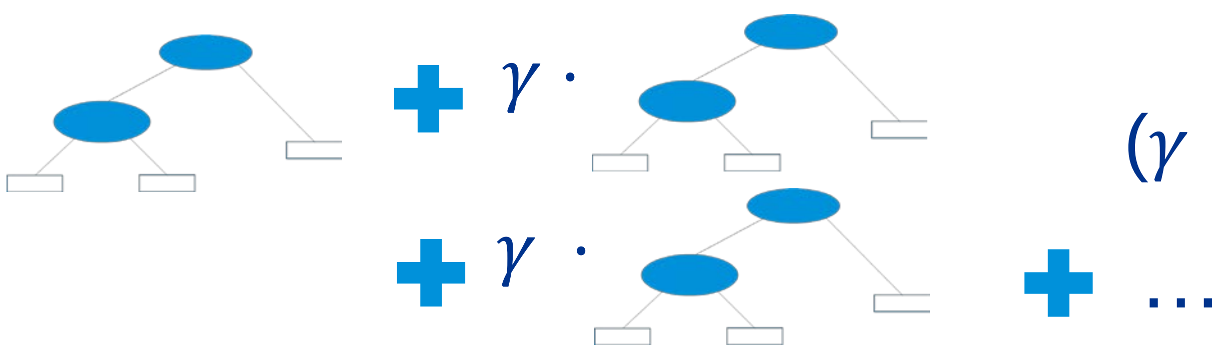
- Number of trees



- Depth of trees



- Learning rate



$(\gamma < 1)$

Hyperparameters & Tuning

There are many ways to specify a GBM algorithm

- Number of trees
- Depth of trees
- Learning rate
- Sampling rate of training data
- Sampling rate of predictors
- …

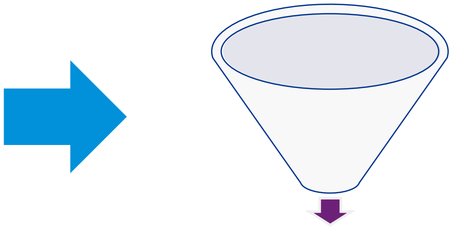
- 50, 100, 200
- 1, 5, 20
- 0.01, 0.1
- 0.5, 0.8
- 0.5, 0.8
- …

Hyperparameters & Tuning

How do we pick the best one(s)?

• Number of trees	• 50, 100, 200
• Depth of trees	• 1, 5, 20
• Learning rate	• 0.01, 0.1
• Sampling rate of training data	• 0.5, 0.8
• Sampling rate of predictors	• 0.5, 0.8
• …	• …

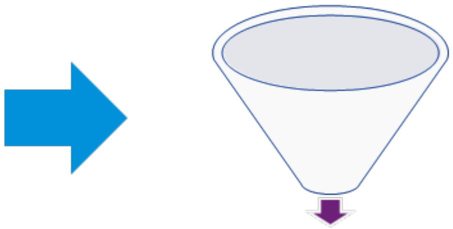
$3(3)(2)(2)(2) = 72$ combinations!



Hyperparameters & Tuning

"Autopilot"

$3(3)(2)(2)(2) = 72$ combinations!



- Models are fit using each of the 72 combinations and are compared using cross-validation, the combination of hyperparameters with the lowest MSE is then fit to the total data set.

Hyperparameters & Tuning

“Autopilot”

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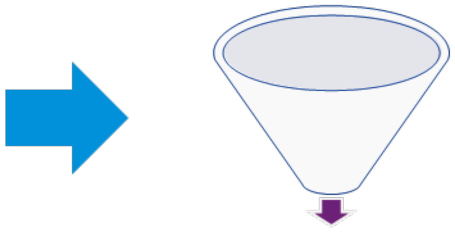

- Models are fit using each of the 72 combinations and are compared using cross-validation, the combination of hyperparameters with the lowest MSE is then fit to the total data set.
- We can feed into our funnel more than one type of algorithm. In other words, we can simultaneously test GBM, GLM, and other techniques such as Random Forests or Neural Networks, much like actuaries considering Chain Ladder and Bornhuetter-Ferguson

Hyperparameters & Tuning

“Autopilot”

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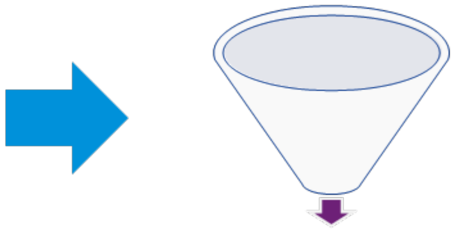

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- We can feed into our funnel more than one type of algorithm. In other words, we can simultaneously test GBM, GLM, and other techniques such as Random Forests or Neural Networks, much like actuaries considering Chain Ladder and Bornhuetter-Ferguson.
- Instead of building one model, we build a pipeline which generates a model on its own for subsequent review dates.

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