



Artificial Intelligence: Reserving in a Digital Age

Actuarial analysis in the digital age
Singapore Actuarial Society –
10th General Insurance Conference
May 31, 2018



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Agenda

Topic

Insurance modernization – A new vision to drive enterprise performance

Introduction to artificial intelligence applications in actuarial analysis

Robotic process automation

Introduction to cognitive methods and applications

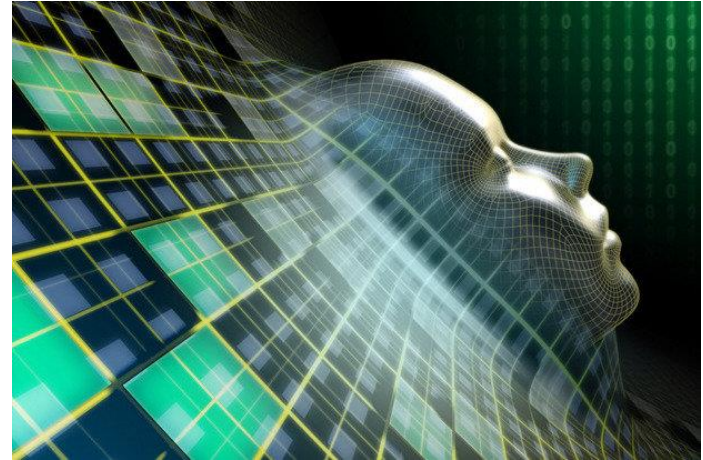
Interpretation and explanation of results

Enterprise response



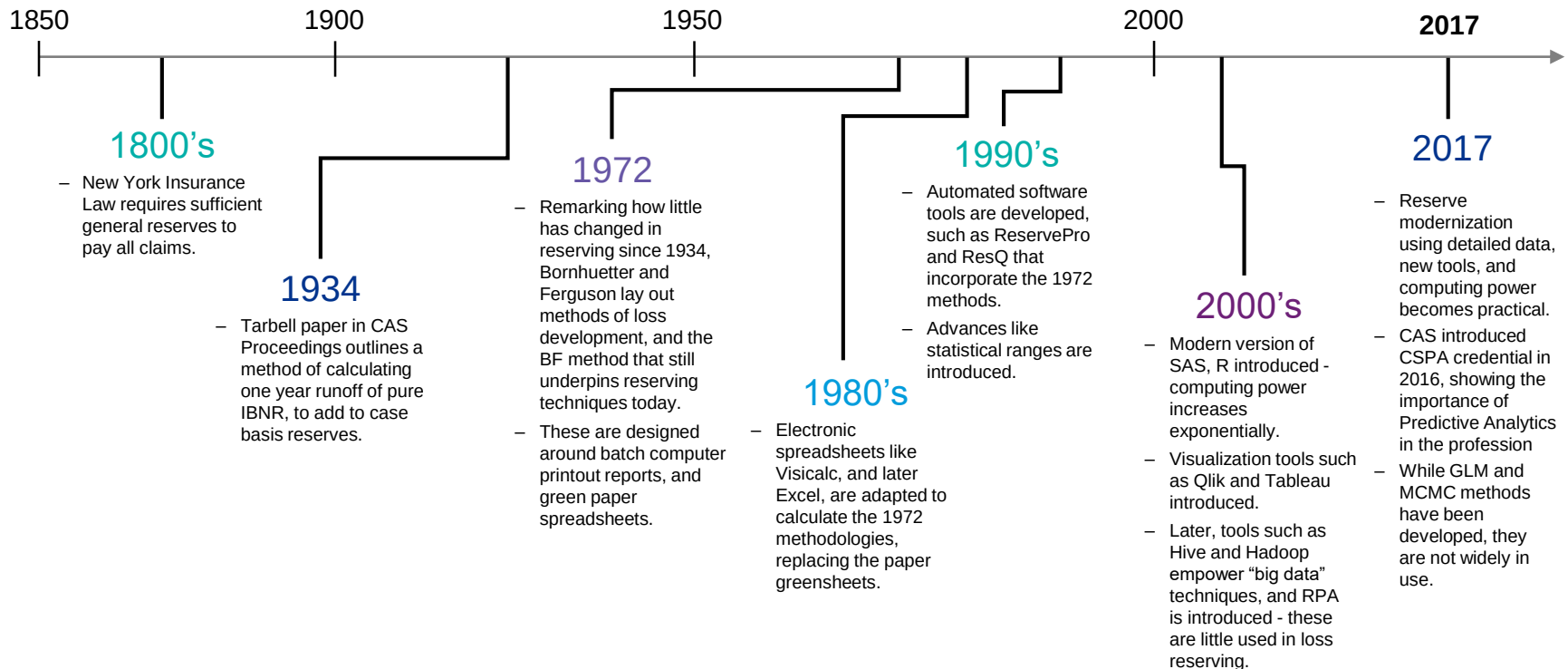
Motivation

- Many new technological innovations are available today
- Recent changes
 - Underwriting
 - Claim handling
- How actuarial reserve analysis is performed has changed little over the last century



Decades of the same approach

How reserves are established has changed little over the last century.



Illustrative packages

The emergence of new technology, coupled with enhanced computing power, has the potential to radically disrupt this historic approach.

Data preparation

**R, HIVE, python,
Hadoop, sas**

Cognitive –
machine learning

sas, R, python

Visualization

tableau, Qlik

Robotic process
automation

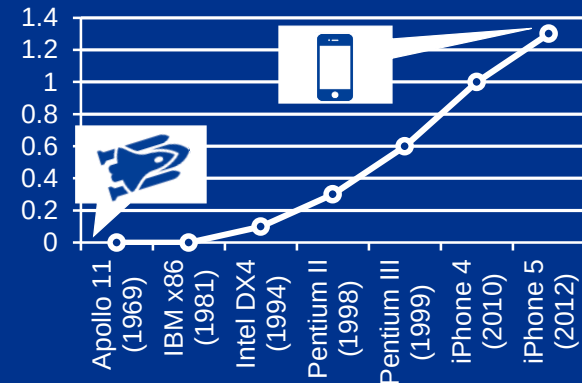
**AUTOMATION ANYWHERE,
blueprism**

Computing power has increased significantly over time

We have seen a 1 trillion-fold increase in computer processing capabilities over the past 60 years⁽¹⁾

Today's smartphone has more computing power than the Apollo 11 Guidance Computer

CPU speed in GHz ⁽²⁾



Source: ⁽¹⁾Experts Exchange, "Processing Power Compared"

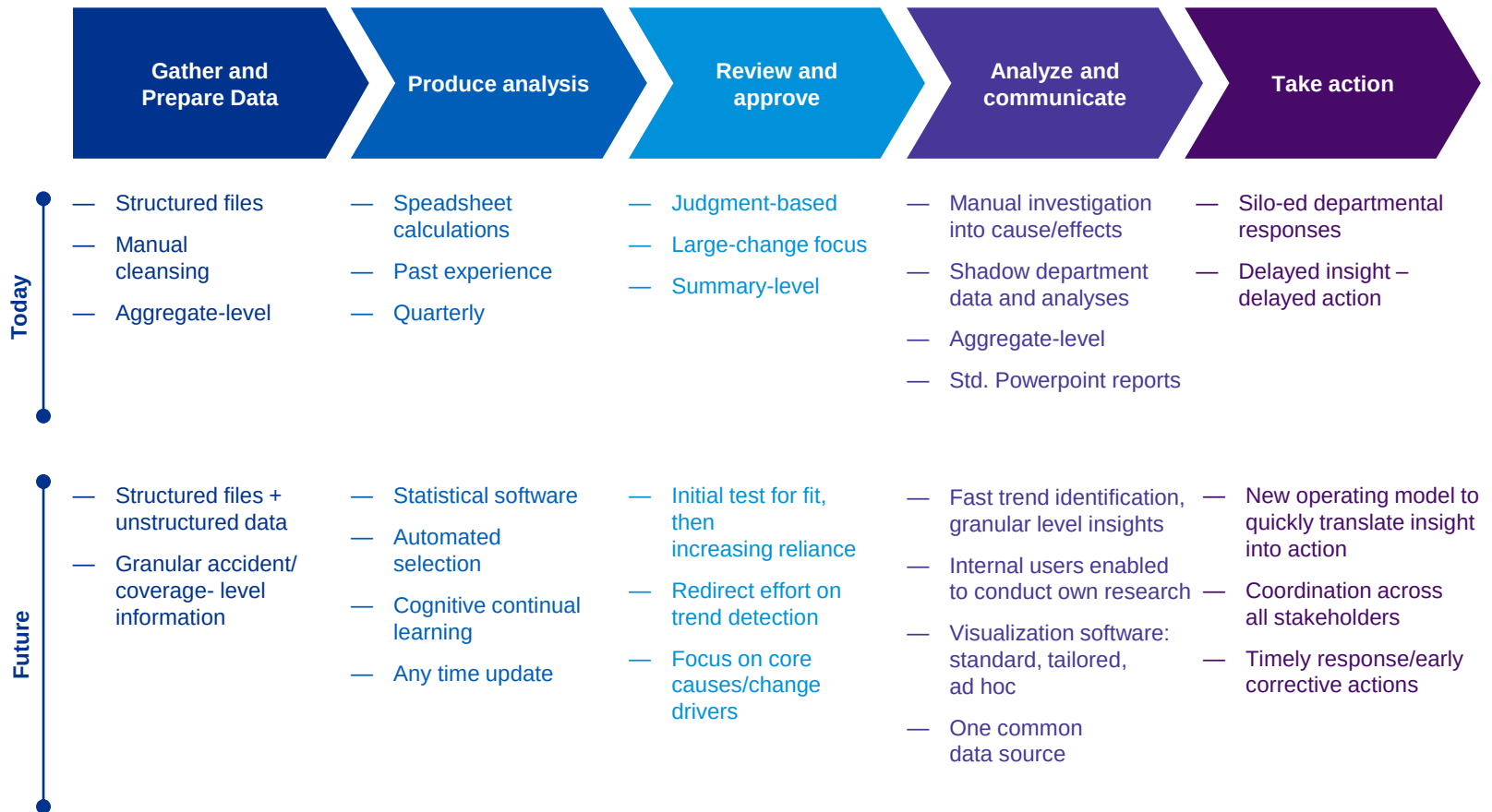
Source: ⁽²⁾Frost & Sullivan, "Addressing Mobile Cybersecurity"



A new vision

Insight driven performance

We envision a new way of doing actuarial work: broader more granular data feed sophisticated actuarial software that automatically determines correlations and predicts for future. It enables flexible real-time analyses to identify trends faster and take coordinated actions sooner across all key departments to strengthen performance.



Granular, flexible, fast, actionable

- 1  Granular data
 - Information captured at accident/coverage level
 - Combination of structured and unstructured data
 - Flexibility to aggregate and analyze as desired
- 2  Deeper and quicker insight
 - A more precise analysis production processes
 - Ability to identify trends and other business insight faster
 - Selections based on innate risk and claims characteristics
 - Analysis reflect the detailed risks
- 3  Faster reaction
 - Realize changes in the environment more quickly, and react
 - Techniques that respond as claims are reported
 - Analysis re-parameterized regularly using machine learning techniques
- 4  Frequency of review
 - Run actuarial analyses at any valuation date for which data is available (e.g., automatically run weekly)
 - For example, an analysis could easily be run a few weeks before close
- 5  Increased efficiency
 - Robotic process automation can lead to increased speed to close
 - Actuarial analysts are freed up to digest the trends and communicate them to the organization, for timely actions
- 6  Seamless communication
 - A modern reserving process produces an output ready made for deriving insights using visualization tools
 - Others can be given views of the data appropriate to their access requirements, to derive their own insights for their business segments



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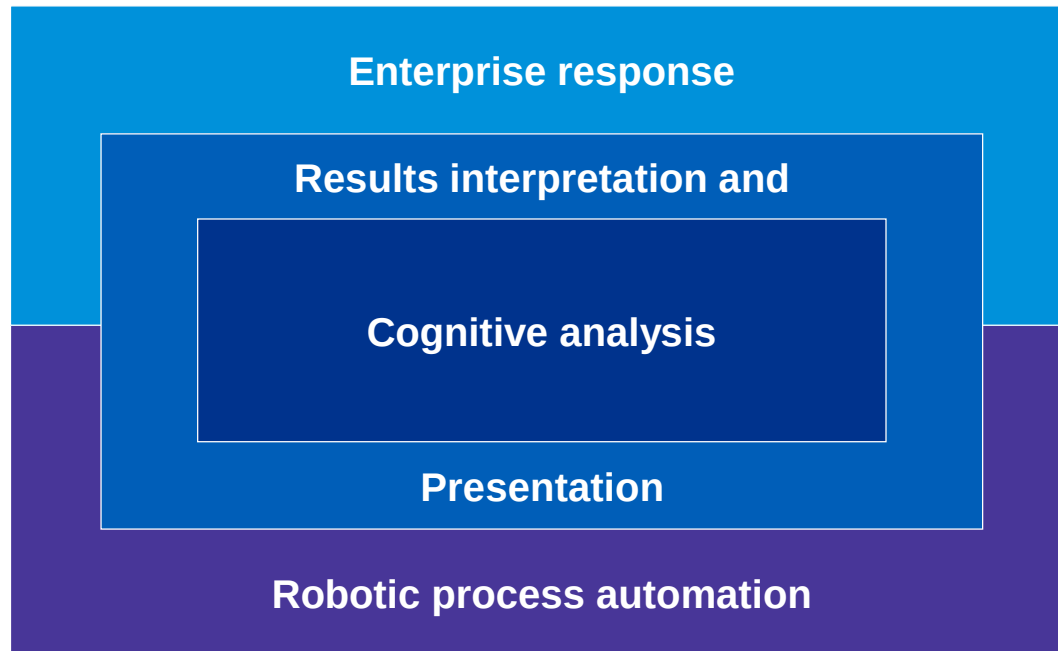
Interpretation and explanation of results

Enterprise response



Four core components

With cognitive analysis at the core, results interpretation and presentation surround this automated analytical engine to enable easy and fast consumption of claim insights. The enterprise response component coordinates and mobilizes actions across the stakeholder departments, while RPA ultimately aims to further streamline the underlying processes.



The components are interconnected and build on each other

	Robotic process automation	Cognitive Analysis	Results Presentation	Enterprise Response
Description	<ul style="list-style-type: none"> Automation of repetitive tasks Use of “bots” – a kind of super macro that operates across systems 	<ul style="list-style-type: none"> Machine learning techniques applied to claims valuation Results allocated at a granular claim level 	<ul style="list-style-type: none"> New techniques to tailor and present results Enhanced ad hoc analytics 	<ul style="list-style-type: none"> Operating model to translate new insights into action Mobilization across core departments – pricing, underwriting, claims, finance
Approach	<ul style="list-style-type: none"> Review existing process flows, identify automation points Develop and test ‘bot’ macros 	<ul style="list-style-type: none"> Leverages new statistical software Uses structured and unstructured data, including individual claim characteristics 	<ul style="list-style-type: none"> Applies new visualization tools to the granular data Combination of standard, tailored, and ad hoc reports 	<ul style="list-style-type: none"> Identifies processes, structure, roles, and governance to communicate, interpret, and respond to insights/trends
Benefits	<ul style="list-style-type: none"> Shorter cycle times and faster close process Less resources needed – deploy to other priorities or eliminate to save costs 	<ul style="list-style-type: none"> Faster identification of trends Results at granular claim level allows for deeper root cause analysis 	<ul style="list-style-type: none"> Better, user-friendly reports with more granular insights Stronger engagement by business-side consumer of the information 	<ul style="list-style-type: none"> Common view of issues Coordinated cross-unit action Effective, timely response to issues



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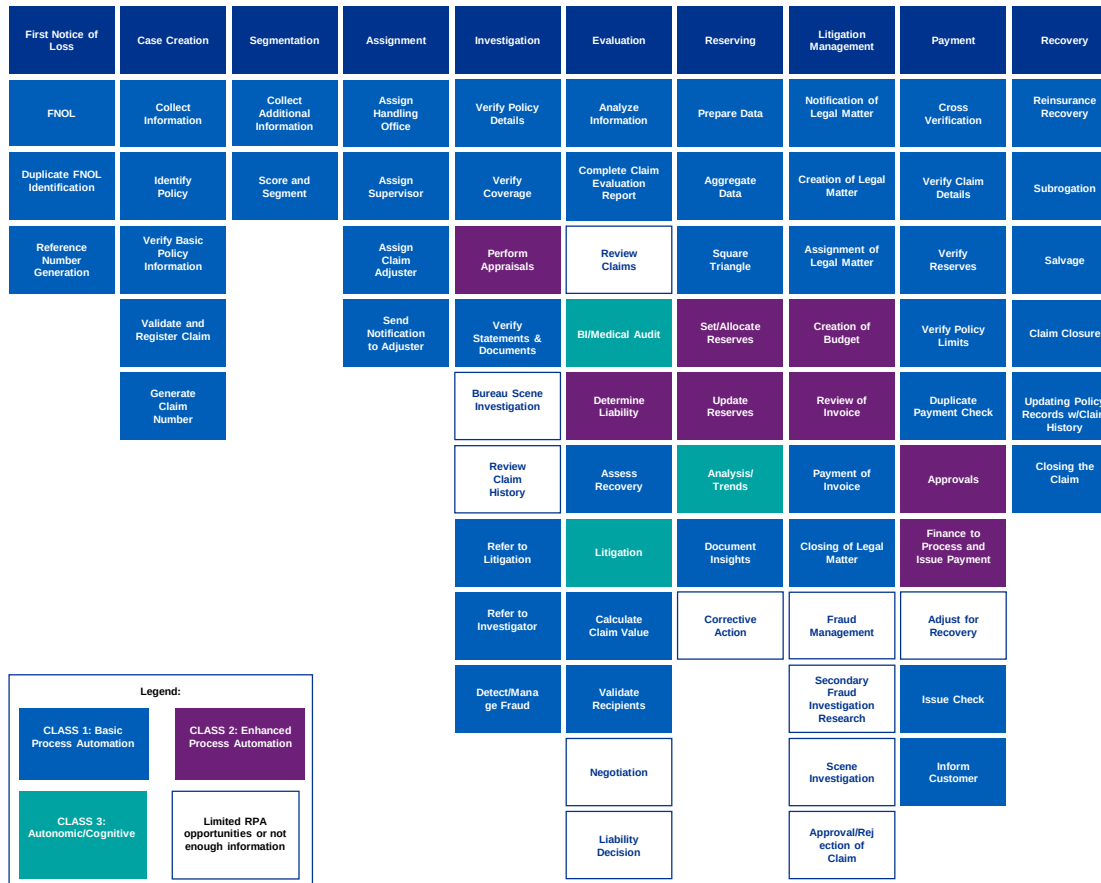
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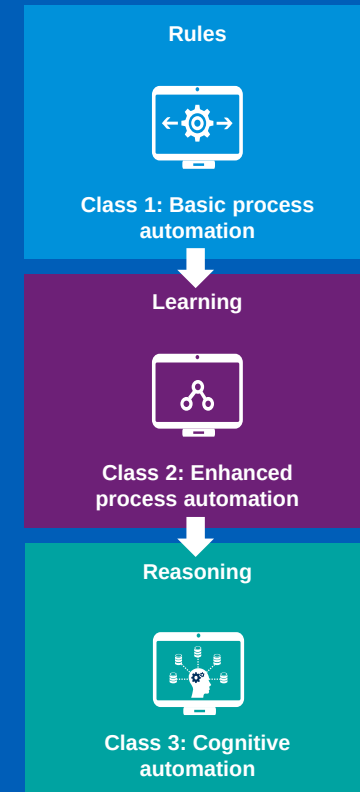


RPA – Reserving as part of broader claim play

Robotic process automation has the ability to improve operational efficiencies across the entire claims operation. The reserving process is particularly ripe for automation.



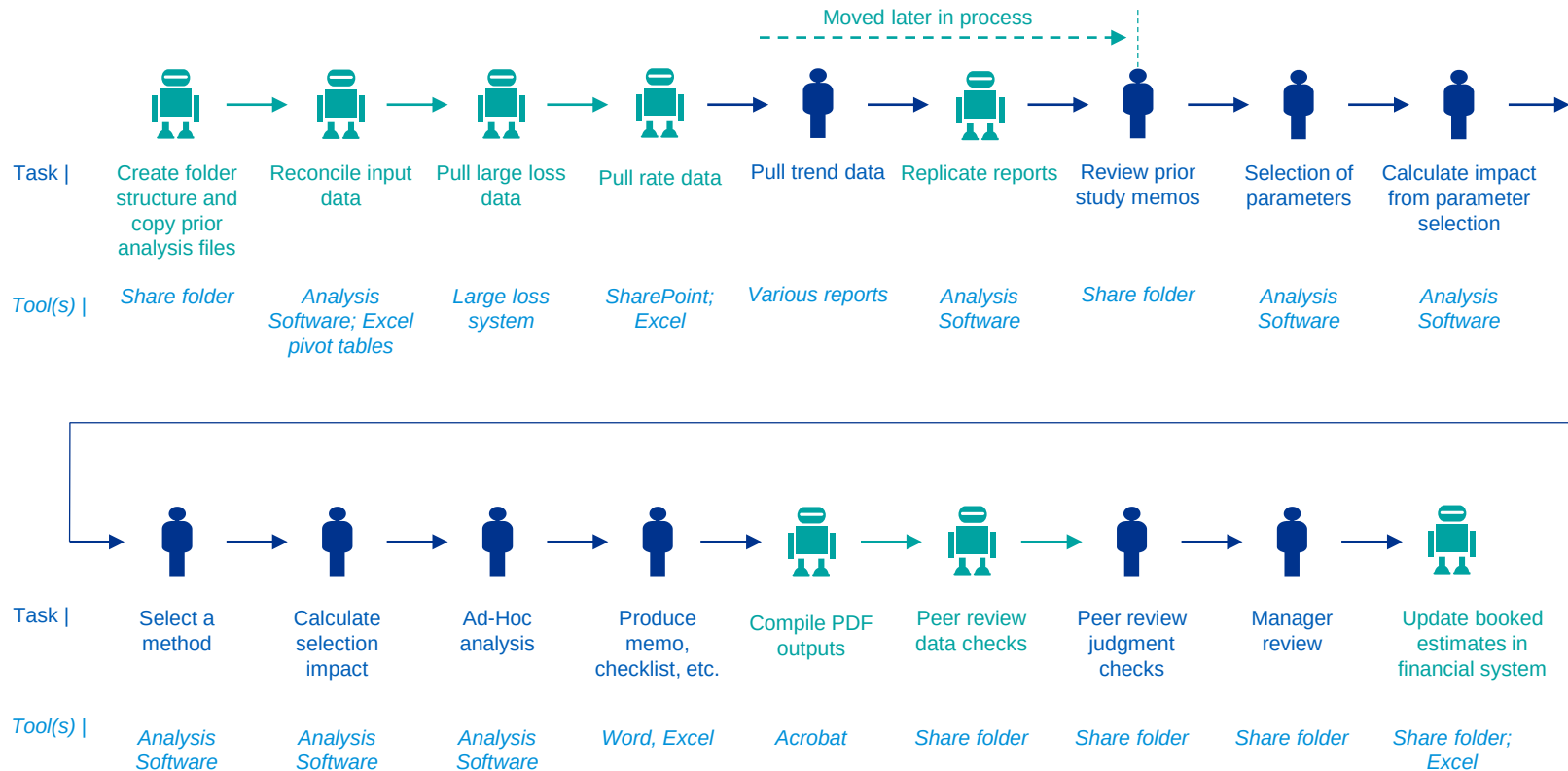
The path to cognitive automation



Use case

RPA for analysis

Using RPA bot process automation, we have configured a bot to complete 8 of the 18 high-level manual tasks in the analyst's analysis process.



— In 10 weeks, we automated 18% of analyst effort in analysis

— We also identified process re-engineering opportunities (incl. RPA) that are expected to reduce analyst effort approximately 50%



Task executed by an RPA bot with analyst interaction for exception handling only



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Cognitive computing/analysis

Cognitive computing – Systems which mimic the functioning of the human brain such as the ability to learn, understand, reason, and interact.¹

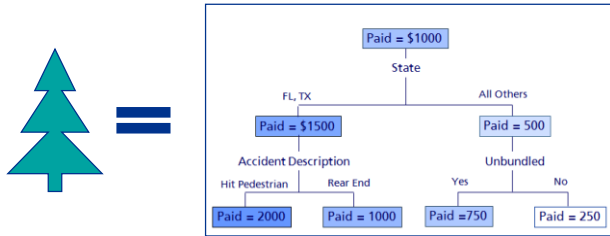
Cognitive analysis – refers to leveraging cognitive computing to make the actuarial analysis more efficient and more insightful.

¹“Computing, cognition and the future of knowing – How humans and machines are forging a new age of understanding”, John Kelly, IBM Research and Solutions Portfolio

https://researchweb.watson.ibm.com/software/IBMResearch/multimedia/Computing_Cognition_WhitePaper.pdf



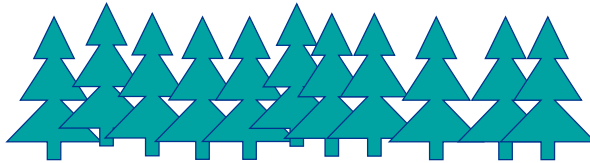
Model types



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

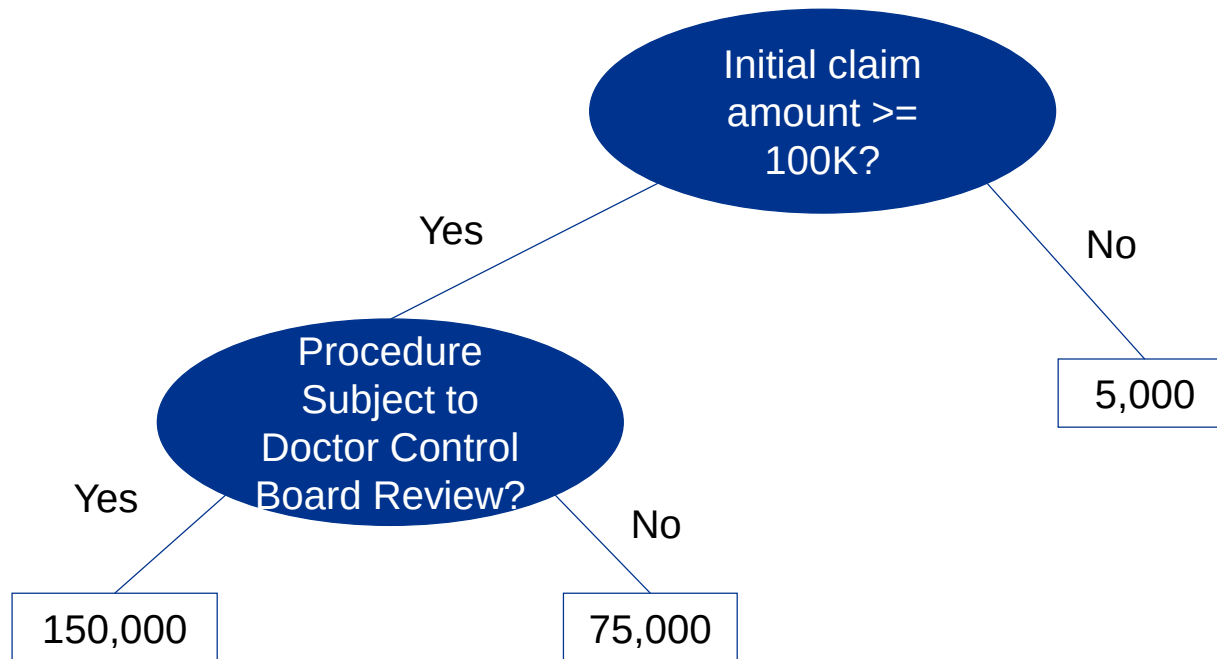


Gradient Boosting is a collection of “weak learners” (trees) used sequentially, with each tree focused on improving the prediction of the previous tree. In each step a bootstrap sample of data is taken. A tree is fit to the “current residuals” and the residuals are updated for the next step.



Decision tree heuristics

One decision tree

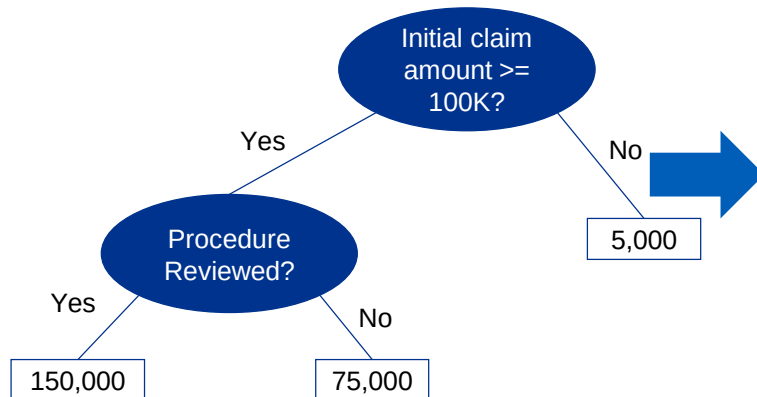


**via a very simplified illustrative example*



Decision tree heuristics (continued)

One decision tree



Not so great performance

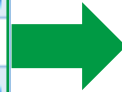
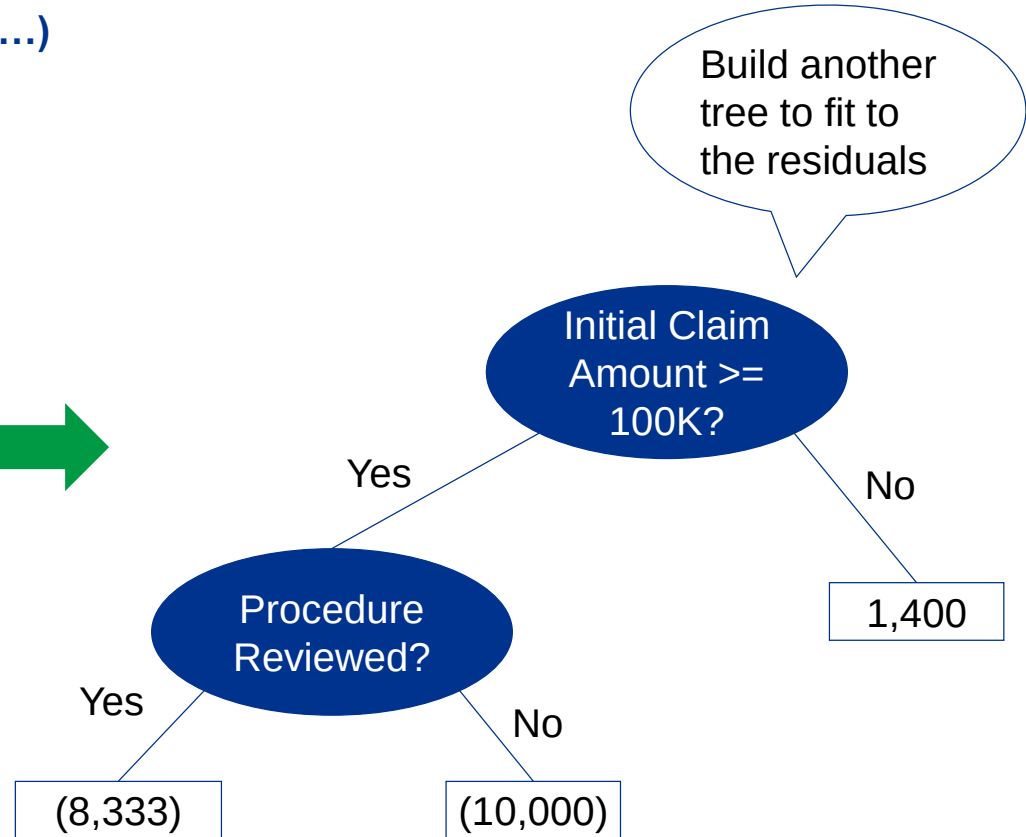
Initial Claim Amount	Procedure Reviewed?	Incremental Loss	Predicted	Residual
150,000	Yes	100,000	150,000	(50,000)
10,000	No	15,000	5,000	10,000
5,000	Yes	3,000	5,000	(2,000)
200,000	Yes	200,000	150,000	50,000
100,000	No	10,000	5,000	5,000
125,000	No	50,000	75,000	(25,000)
50,000	No	8,000	5,000	3,000
1,000	No	2,000	5,000	(3,000)
250,000	Yes	125,000	150,000	(25,000)
25,000	Yes	4,000	5,000	(1,000)



Decision tree heuristics (continued)

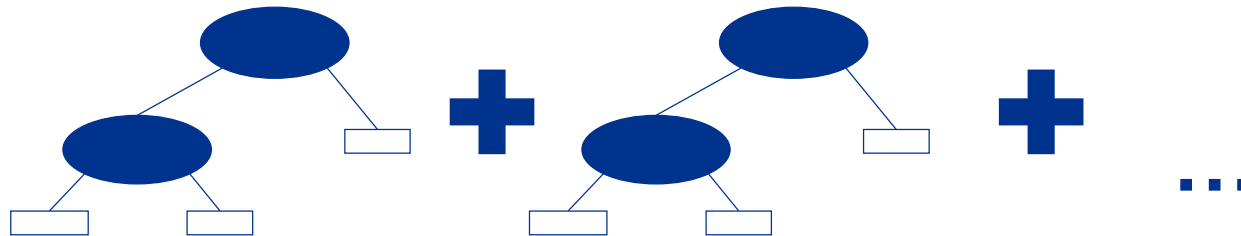
Boosting (more decision trees...)

Initial Claim Amount	Procedure Reviewed?	Residual
150,000	Yes	(50,000)
10,000	No	10,000
5,000	Yes	(2,000)
200,000	Yes	50,000
100,000	No	5,000
125,000	No	(25,000)
50,000	No	3,000
1,000	No	(3,000)
250,000	Yes	(25,000)
25,000	Yes	(1,000)



Decision tree heuristics (continued)

Boosting (more decision trees...)



Initial Claim Amount	Procedure Reviewed?	Residual (1 st tree)	Prediction (2 nd tree)	Residual (2 nd tree)
150,000	Yes	(50,000)	(8,333)	(41,667)
10,000	No	10,000	1,400	8,600
5,000	Yes	(2,000)	1,400	(3,400)
200,000	Yes	50,000	(8,333)	58,333
100,000	No	5,000	1,400	3,600
125,000	No	(25,000)	(10,000)	(15,000)
50,000	No	3,000	1,400	1,600
1,000	No	(3,000)	1,400	(4,400)
250,000	Yes	(25,000)	(8,333)	(16,667)
25,000	Yes	(1,000)	1,400	(2,400)

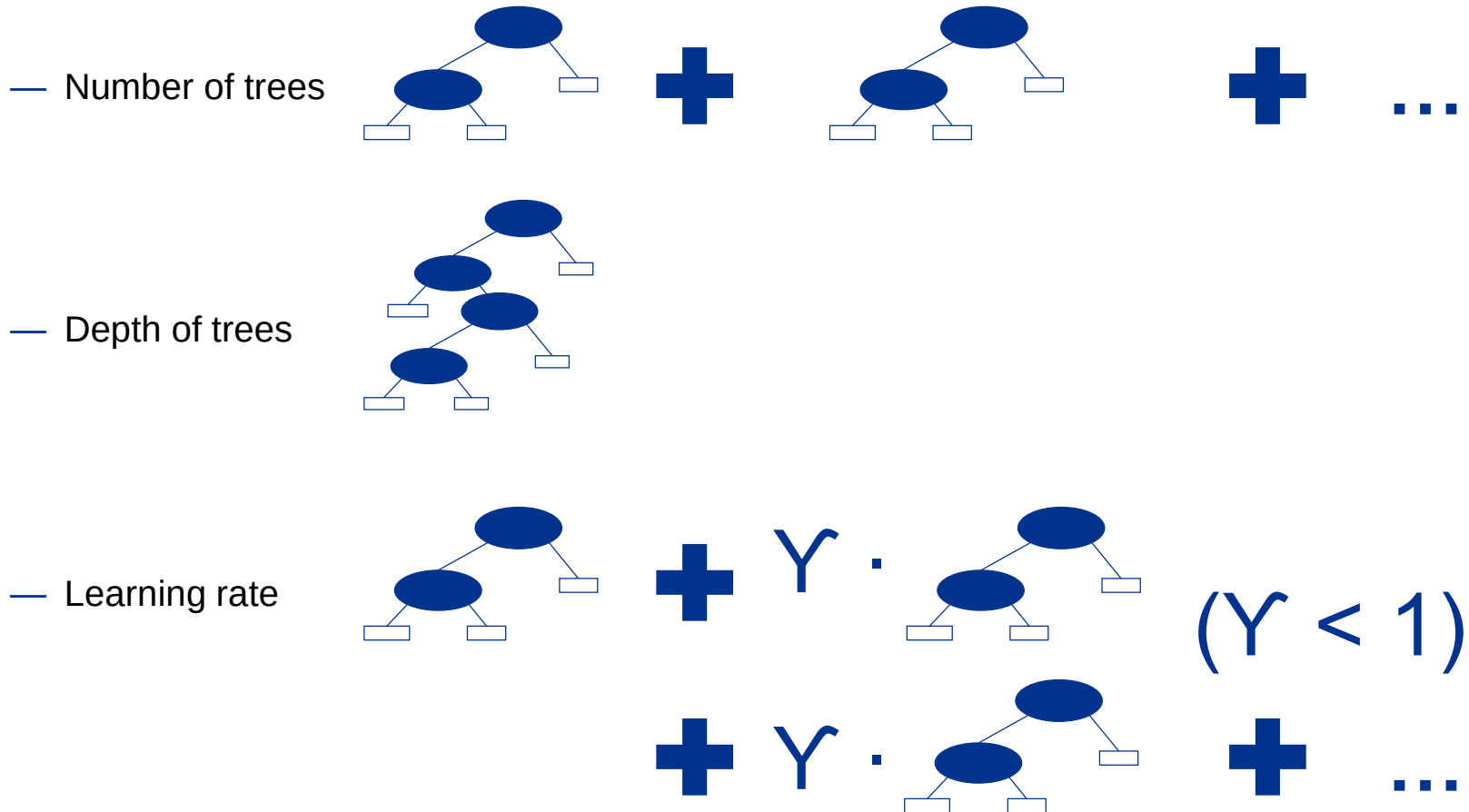
$$10,000 - 1,400 = 8,600$$

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



Decision tree hyperparameters

There are many ways to specify a decision tree algorithm; for example:



Pros and cons

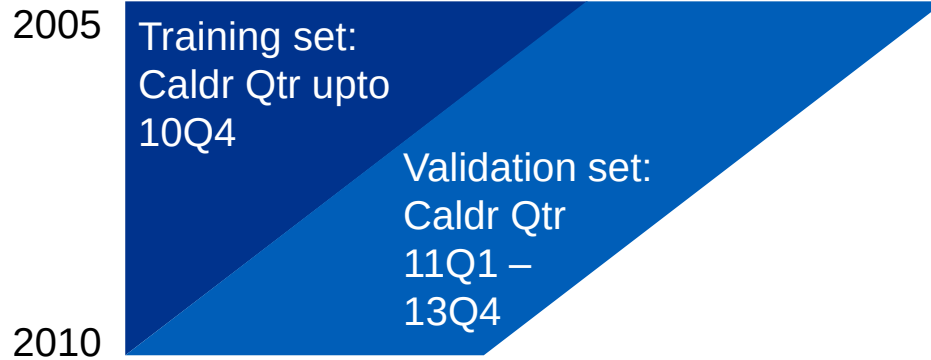
	Pros	Cons
Random Forest	<ul style="list-style-type: none">— Modeling non-linear and complex relationships— Fast algorithms – can leverage parallel computing	<ul style="list-style-type: none">— Can be difficult to explain— Often “beat” by well-tuned GBMs
Gradient Boosting Machine (GBM)	<ul style="list-style-type: none">— Modeling non-linear and complex relationships— Algorithm has more “levers” in terms of hyperparameters	<ul style="list-style-type: none">— Can be difficult to explain— Can be difficult to tune due to large number of hyperparameters
Generalized Linear Models (GLM)	<ul style="list-style-type: none">— Easy to explain— Well established in Actuarial community	<ul style="list-style-type: none">— Need to be more explicit about interactions and non-linear relationships



Model Training & Validation

Model dataset (AY 2005 – 2013)

Accident
period



Validation approach used for the selections of

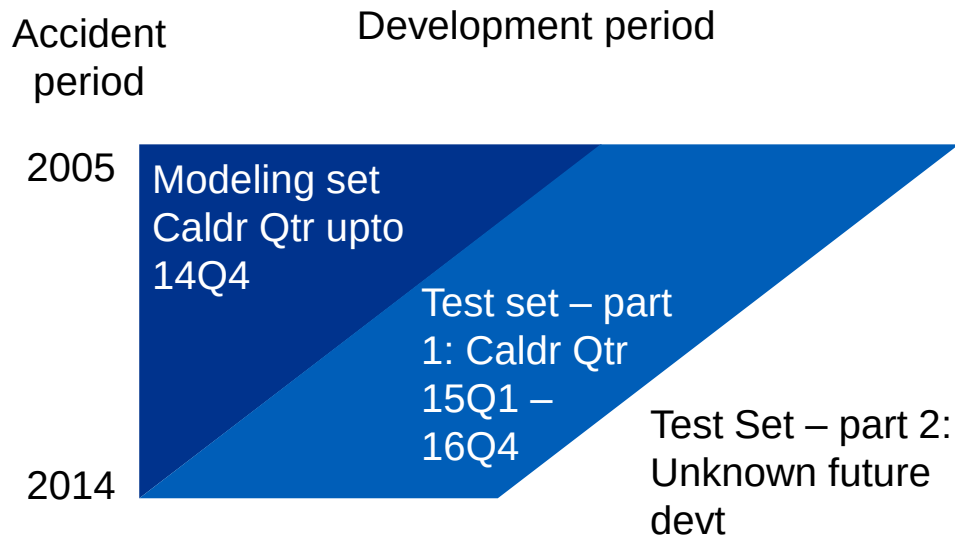
- Model methods
- Hyper parameters
- Predictive variables

To ensure the models working properly

- Model Dataset could be split into training and validation by three calendar quarter cuts by:
 - 10Q4
 - 11Q2
 - 11Q4



Model testing



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 emergence
 - Using data test set – part 1
- Model predicted ultimates vs. traditional methods predicted ultimates
 - Using data test set – part 1 + part 2



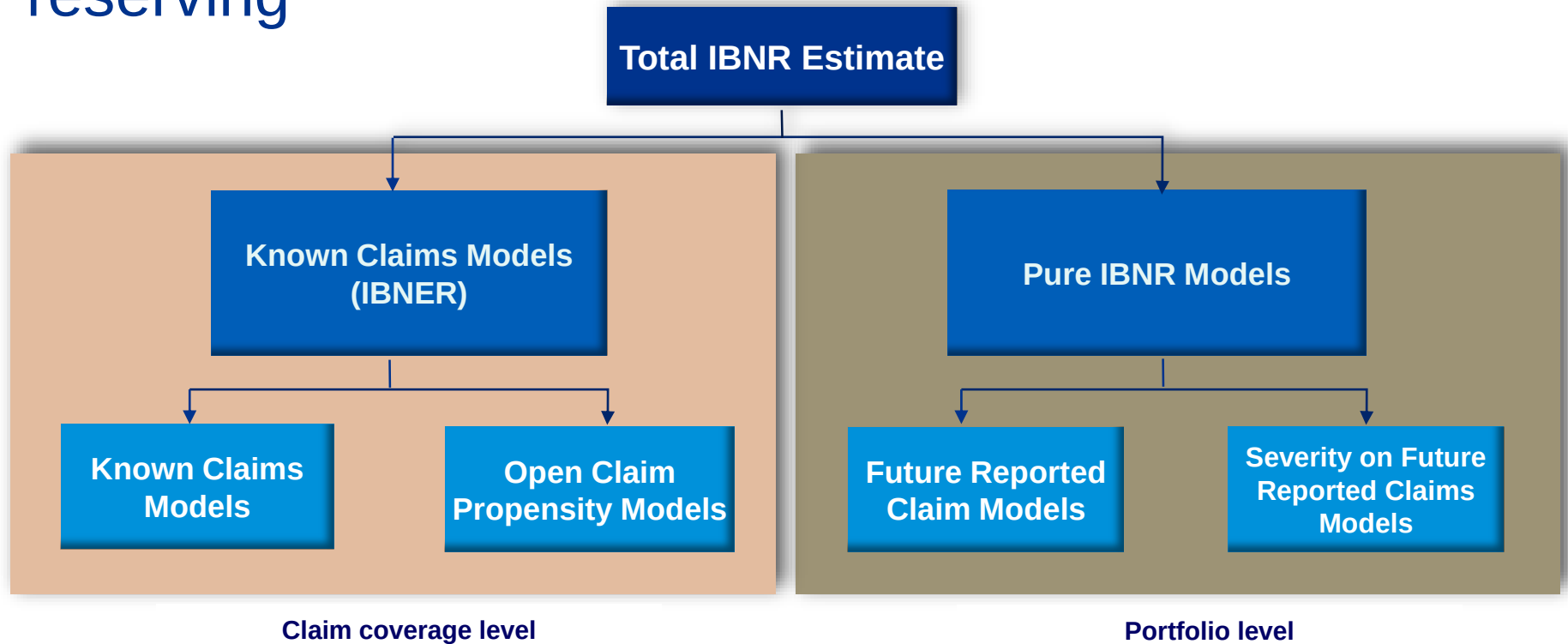
Case study

U.S. Operation of Global P&C Insurer – Cognitive Reserving Solution leveraging a Gradient Boosting Model to proactively identify deterioration of a problematic business segment



Model Overview

Generalized machine learning framework for cognitive reserving



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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

¹Conditional 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 = $0.21 / 0.25 = 0.84$)

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



Pure IBNR Approach

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

Pure IBNR

Period	Actual Experience			Future Predicted Experience			
	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

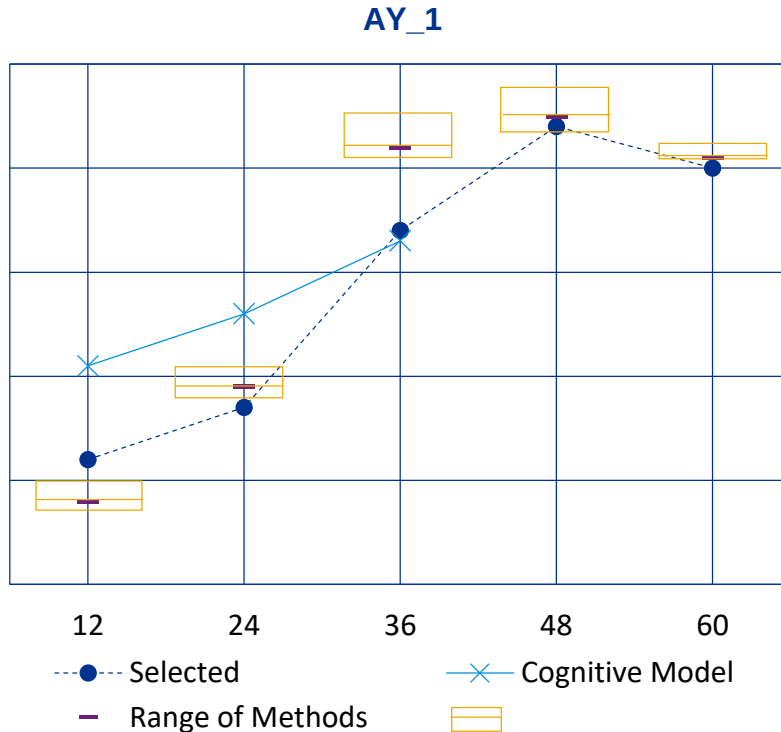
Example – not derived from any company sources

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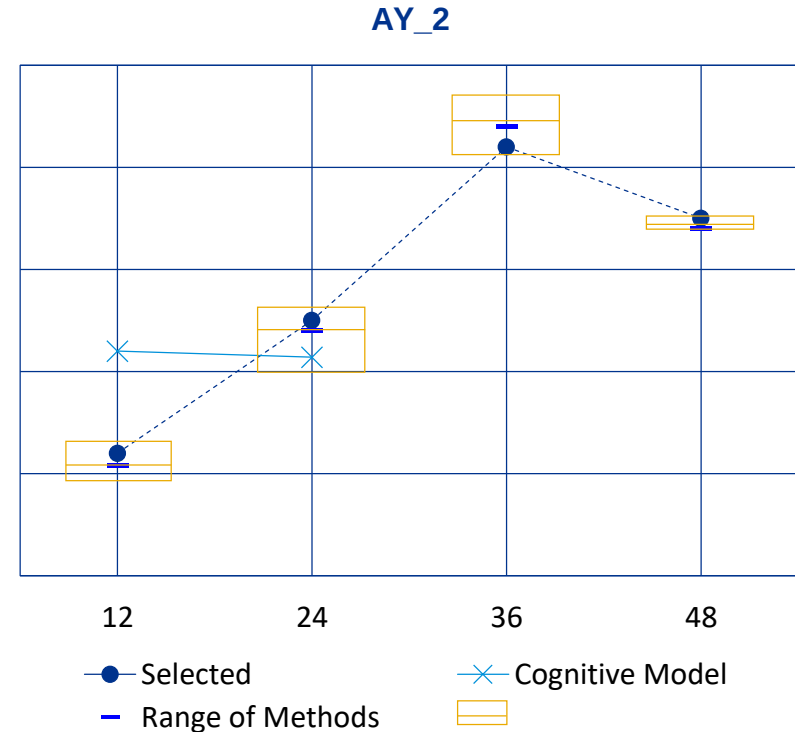


Responsiveness of cognitive methods

Estimated ultimate development for the LOB



More accurate early **More accurate early** **Stable – No reversals**



More accurate early

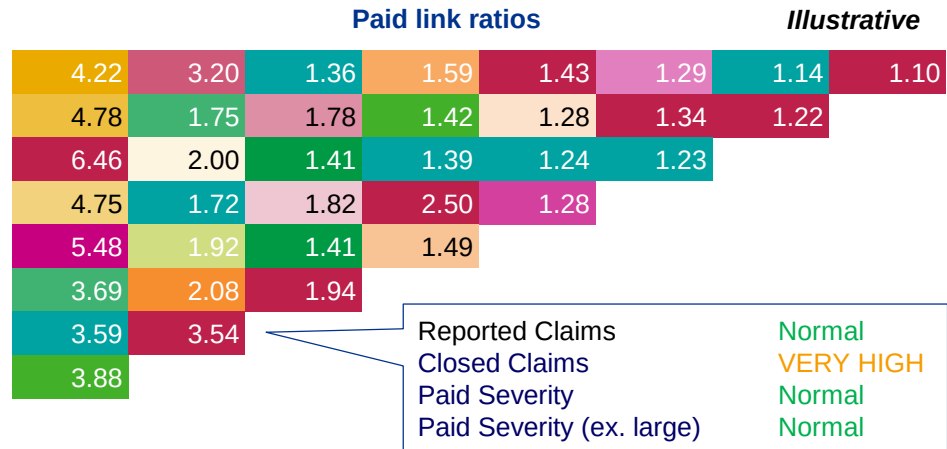


Additional insights

What is causing this anomaly?

- Severity and claim reporting patterns are normal
- High Closed Claim Counts are causing the anomaly**
 - New claims are being closed faster

Cognitive insights quickly rule out some hypotheses and confirm others.



How do Cognitive Methods know what is normal?

Machine Learning methods provide prediction *ranges* and *percentiles*, not just expected values. These ranges tell us which results are normal and which are unusually low or high.

	Percentiles	Reported claim counts	Closed claim counts	Paid severity (\$000s)	Paid severity (Ex. Large) (\$000s)
EXTREMELY LOW	(Lowest 1%) 0	< 13	< 4	< 2	< 2
VERY LOW	1 – 9	13 – 30	4 – 15	2 – 4	2 – 4
Low	10 – 19	30 – 36	15 – 21	4 – 6	4 – 6
Normal	20 – 79	36 – 56	21 – 36	6 – 22	6 – 21
High	80 – 89	56 – 63	36 – 43	22 – 38	21 – 35
VERY HIGH	90 – 98	63 – 87	43 – 61	38 – 91	35 – 50
EXTREMELY HIGH	(Highest 1%) 99	> 87	> 61	> 91	> 50



Granularity of results

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.



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Digital trust in AI analysis

In its common and broadest form, digital trust involves customers, data and errors, and misuse or unintended consequences of related analytics. The pillars of digital trust are equally applicable in the context of loss reserve analysis and provide a framework for management and regulators to assess the actuary's analysis.

Quality

- Are the data management practices appropriate?
- Is the data timely, internally consistent, and complete?
- Data quality assurance for first-generation machine learning approaches that build on existing actuarial data should not be significantly different from current quality requirements for actuarial data formats and segmentations.

Accepted use

- Confirmation that the estimation methods being developed are fit for their intended purpose will take on heightened importance.
- The use, segmentation, and manipulation of data will have to be appropriate, documented, suitable for its intended purpose, and defensible.

Accuracy

- Predictions and insights must provide timely actionable information that reflects reality.
- We must also consider that models may be held to higher standards of precision than models used for purposes where directional indications are sufficient.
- Increased frequency of analysis (e.g., from quarterly to weekly) is likely to be one factor in monitoring accuracy.

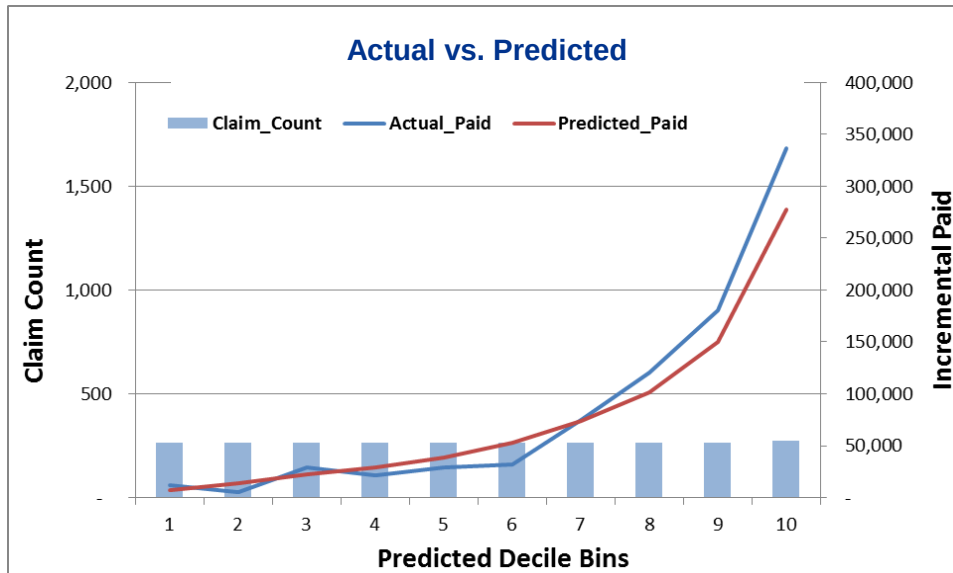
Integrity

- Data, models, and resulting predictions must be managed ethically and with the utmost attention to the veracity of the estimates.
- Methods that rely upon actuarial judgment or are prone to manipulation could be compromised by perception of bias.



Model lift

Coverage one incremental paid loss model



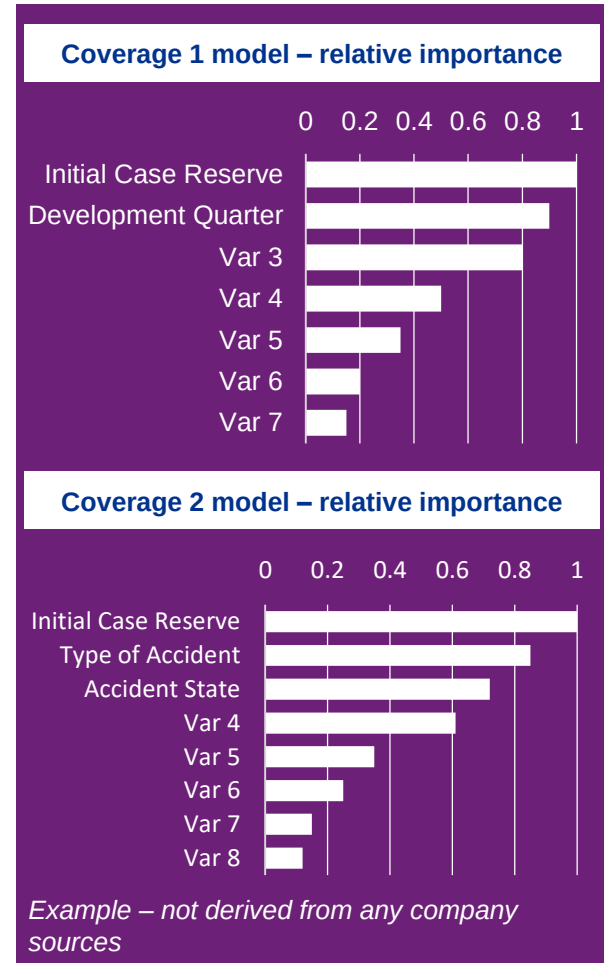
Lift charts show the performance of the model on the test dataset (14Q1 – 16Q4).

- 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.



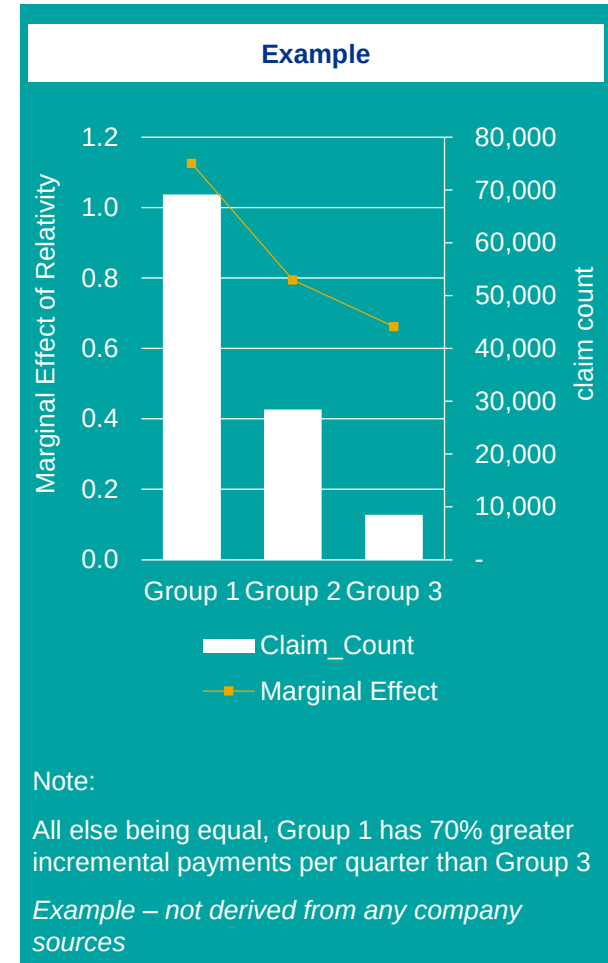
Relative variable importance

- 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



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



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 = 318, number of visited nodes = 6, static init size = 308
    // {01000100 00101010 10000000 00011100}
    public static final byte[] GRPSPLIT0 = new byte[] {34, 84, 1, 56};
}
```



Data visualization

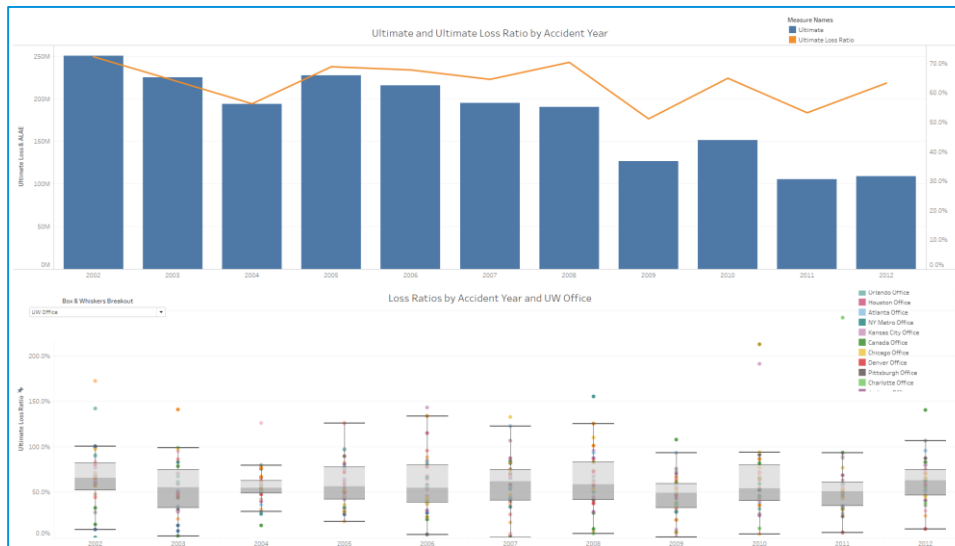
Incorporating Digital Visualization to the Analysis results enables **deep, timely, and widespread** understanding of **complex** actuarial insights and the **interaction** of those insights.

The solution drives a **faster recognition** of claim developments and **root cause analysis**, with an **intuitive interface** for actuaries and executives alike.



Data visualization

Granularity of insights



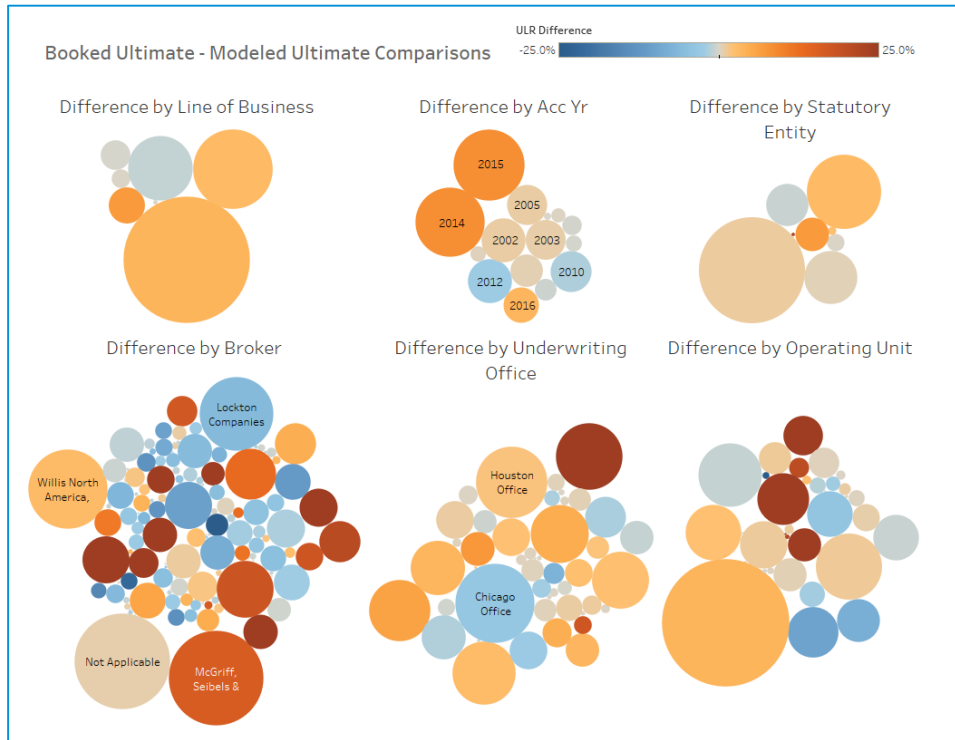
Dynamic charts enable detailed understanding of results

- Granularity of visuals matches granularity of analysis
- Supports quick investigation of outliers



Data visualization

Insights into existing methods



Comparisons of traditional and cognitive results can assist with validation of:

- Traditional procedures (e.g., reserve allocations)
- Model performance

Similar dash-boarding concepts can help evaluate performance by business segment



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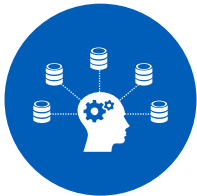
Actuarial response

1



Have the ability to deliver the insights broadly to management

2



Be positioned to make timely decisions/changes/reactions

3



Have the ability to put those into actions effectively



Preparing for evolving actuarial roles

- Learn R, Python, Blue Prism, etc.
- Study Machine Learning Methods and Output
- Creatively Assess Potential Benefits



Potential benefits of AI in actuarial analysis

General

- Reserve Analysis Transformation
- Actuarial Pricing Transformation
- Underwriting Analysis Transformation

Property/Casualty

- Case Reserve Estimation
- Claims Triage Analysis
- Property Damage Assessment

Life/Health

- Cash Flow Projection
- Mortality Table Modeling
- Medical Cost Forecasting
- Lapse and Surrender Analysis

- These tools can be used to simplify and streamline most data processing and reconciliation
- New tools present opportunities for actuaries to expand our role as business experts with advanced analytical and statistical capabilities
- No reason that we cannot apply these techniques throughout the insurance space to:
 - Model claimant behavior to optimize outcomes and provide superior quality of service to policy holders
 - Apply modeling and automation to improve the sales, underwriting, and claims handling processes





Thank you

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