# The End of Triangles - Loss Reserves in The Digital Age

Casualty Loss Reserving Seminar & Workshops

September 12, 2017

# Motivation

- Stale reserving process, initially designed more than 50 years ago
- Technology innovation available today
  - Advanced Statistics
  - Data Lakes
  - Robotic Process Automation
  - Data Visualization
- Significant benefits from a modern reserve approach
  - Increased Insight
  - Faster Reaction
  - More frequent Valuation
  - Greater Efficiency
  - Seamless Communication

# Agenda

**Topic**

**Reserve modernization – a new vision to drive enterprise performance**

**Four core components – the interconnected building blocks of a renewed capability**

**Robotic process automation**

**Cognitive – reserving using machine learning**

**Data visualization**

**Enterprise response**

# Loss reserving - decades of the same approach

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

1850 1900 1950 2000 **2017**

## 1800's

- New York Insurance Law requires sufficient general reserves to pay all claims.

## 1934

- Tarbell paper in CAS Proceedings outlines a method of calculating one year runoff of pure IBNR, to add to case basis reserves.

## 1972

- Remarking how little has changed in reserving since 1934, Bornhuetter and Ferguson lay out methods of loss development, and the BF method that still underpins reserving techniques today.
- These are designed around batch computer printout reports, and green paper spreadsheets.

## 1980's

- Electronic spreadsheets like Visicalc, and later Excel, are adapted to calculate the 1972 methodologies, replacing the paper greensheets.

## 1990's

- Automated software tools are developed, such as ReservePro and ResQ that incorporate the 1972 methods.
- Advances like statistical ranges are introduced.

## 2000's

- Modern version of SAS, R introduced - computing power increases exponentially.
- Visualization tools such as Qlik and Tableau introduced.
- Later, tools such as Hive and Hadoop empower "big data" techniques, and RPA is introduced - these are little used in loss reserving.

## 2017

- Reserve modernization using detailed data, new tools, and computing power becomes practical.
- CAS introduced CSPA credential in 2016, showing the importance of Predictive Analytics in the profession
- While GLM and MCMC methods have been developed, they are not widely in use.

# Emerging technology - illustrative packages

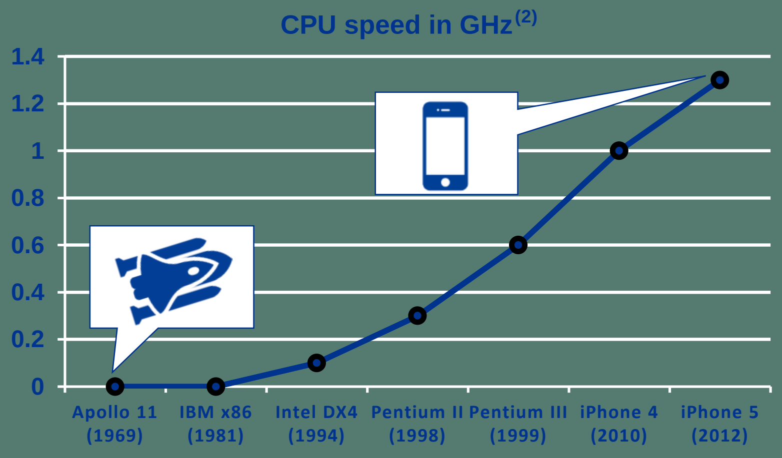
**The emergence of new technology, coupled with enhanced computing power, has the potential to radically disrupt this historic approach.**

| | |
|---|---|
| Data preparation | R, HIVE, python, hadoop |
| 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**




Source: [1]Experts Exchange, "Processing Power Compared"
Source: [2]Frost & Sullivan, "Addressing Mobile Cybersecurity"

# A new reserving vision – insight driven performance

**We envision a new way of doing reserving: broader more granular data feed sophisticated actuarial software that automatically determines correlations and predicts reserve levels. Accident-level detail enables flexible real-time analyses to identify trends faster and take coordinated actions sooner across all key departments to strengthen performance.**

| | Gather & Prepare Data | Develop Reserves | Review & Approve | Analyze & Communicate | Take Action |
|---|---|---|---|---|---|
| **Today** | – Structured files<br>– Manual cleansing<br>– Aggregate-level | – Speadsheet calculations<br>– Square the triangle<br>– Past experience<br>– Quarterly | – Judgment-based<br>– Large-change focus<br>– Summary-level | – Manual investigation into cause / effects<br>– Shadow department data and analyses<br>– Aggregate-level<br>– Std. Powerpoint reports | – Silo-ed departmental responses<br>– Delayed insight – delayed action |
| **Future** | – Structured files + unstructured data<br>– Granular accident / coverage-level information | – Statistical software<br>– Automated reserve selection<br>– Cognitive continual learning<br>– Any time update | – Initial test for fit, then increasing reliance<br>– Redirect effort on trend detection<br>– Focus on core causes / change drivers | – Fast trend identification, granular level insights<br>– Internal users enabled to conduct own research<br>– Visualization software: standard, tailored, ad hoc<br>– One common data source | – New operating model to quickly translate insight into action<br>– Coordination across all stakeholders<br>– Timely response / early corrective actions |

KPMG

# Potential benefits - 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 & quicker insight

- A more precise reserve setting processes
- Ability to identify trends and other business insight faster
- Sets reserves based on innate risk and claims characteristics
- Reserves are calculated ground up, and actually reflect the detailed risks

## 3 Faster reaction

- Realize changes in the environment more quickly, and react
- Reserving techniques that respond as claims are reported
- Reserve models re-parameterized regularly using machine learning techniques

## 4 Frequency of review

- Run reserve valuation with 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
- Reserve 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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**Reserve modernization – a new vision to drive enterprise performance**

**Four core components – the interconnected building blocks of a renewed capability**

**Robotic process automation**

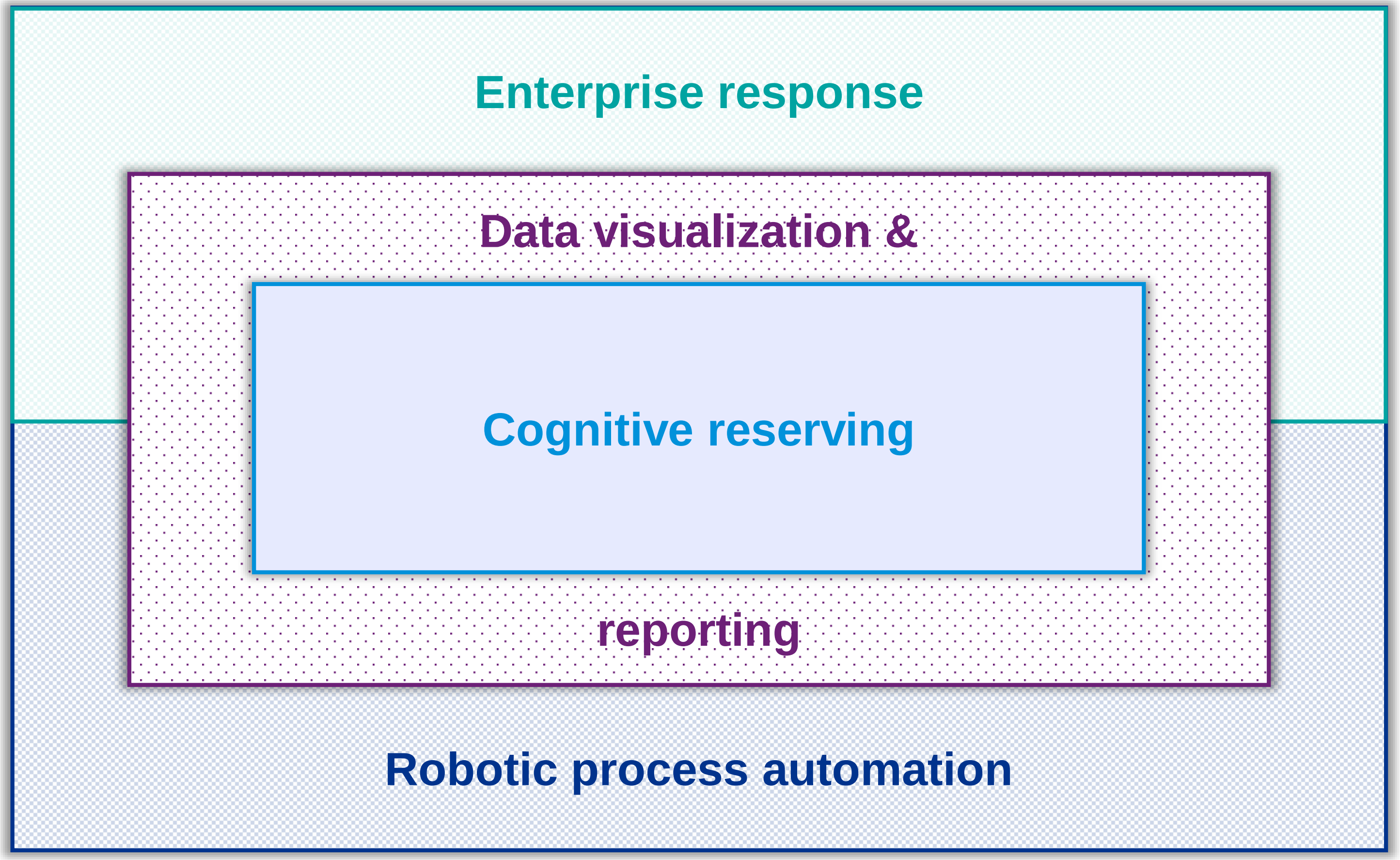
**Cognitive – reserving using machine learning**

**Data visualization**

**Enterprise response**

# Future reserving - four core components

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

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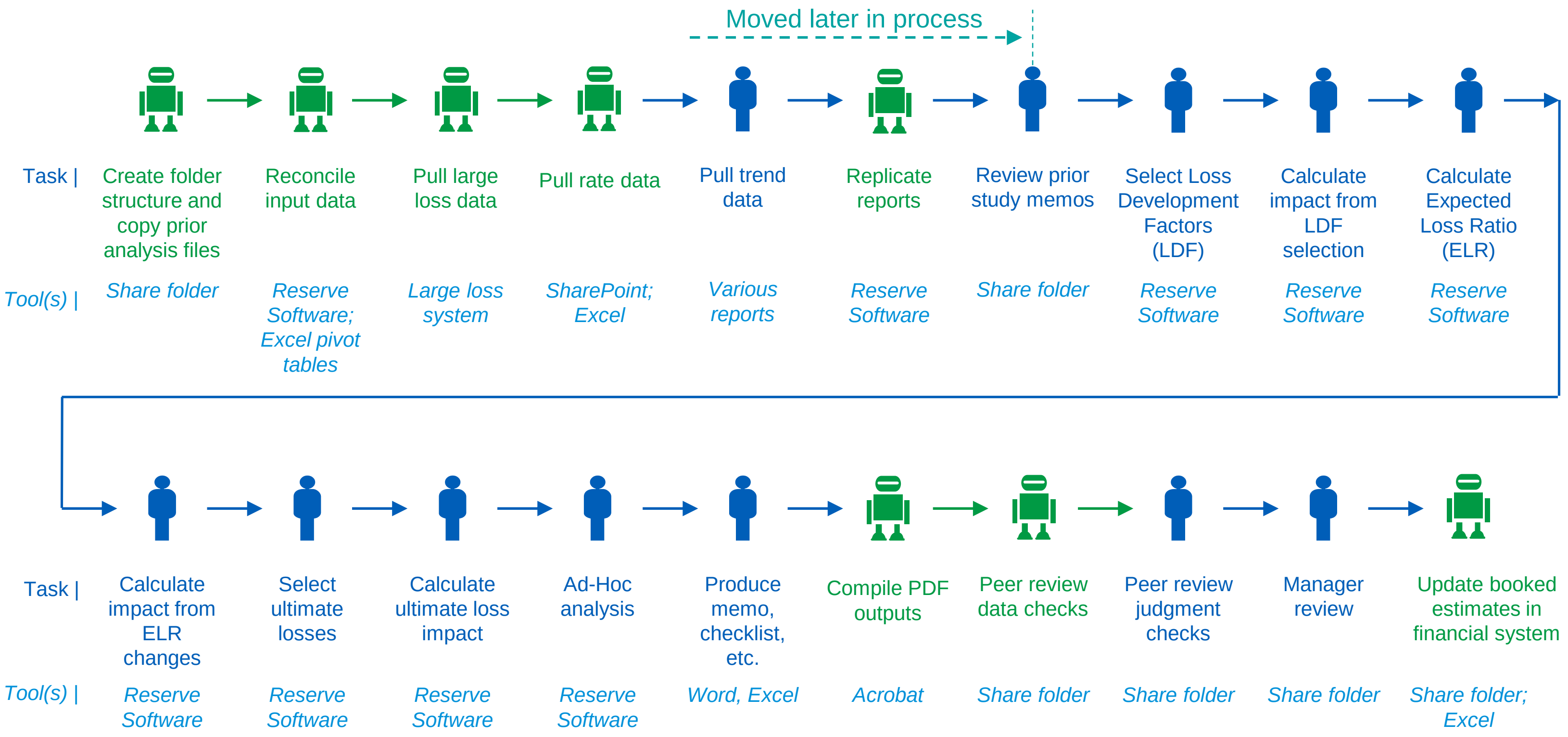
# Use case: RPA for commercial lines reserving

**Using RPA bot process automation, we have configured a bot to complete 8 of the 20 high-level manual tasks in the analyst's reserving process.**




- **In 10 weeks, we automated 18% of analyst effort in roll-forwards**
- **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 / reserving

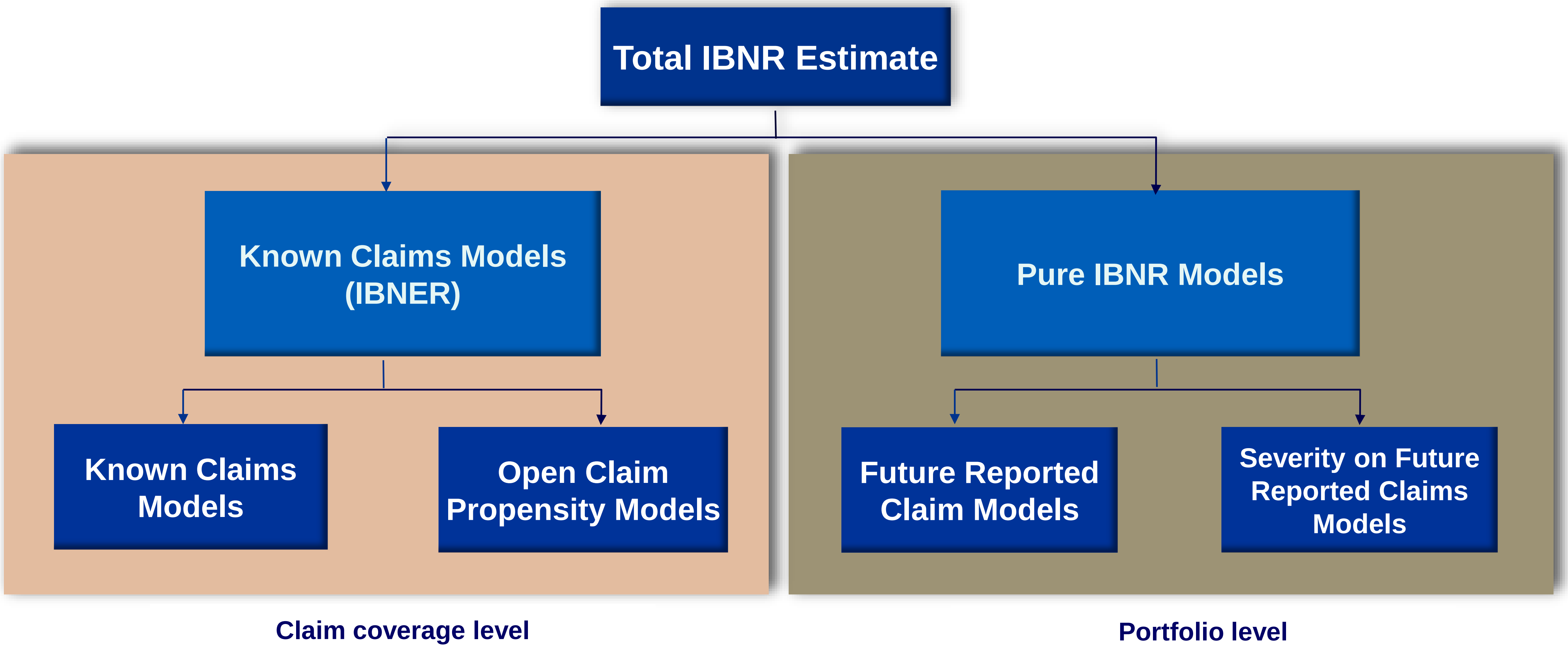
**<u>Cognitive Computing</u> –** Systems which mimic the functioning of the human brain such as the ability to learn, understand, reason, and interact.[1]

**<u>Cognitive Reserving</u>** refers to leveraging cognitive computing to make the actuarial reserving 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*

# Generalized machine learning framework for cognitive reserving



# Generalized machine learning framework for cognitive reserving

## Detailed description of models

| | | |
|---|---|---|
| IBNER | **Known Claims Models** | For open claim at evaluation time , estimates the future incremental paid/incurred losses conditional upon loss being “open” at the beginning of each period |
| | **Open Claim Propensity Models** | Estimates the probability of a claim being open at the beginning of a future period |
| Pure IBNR | **Future Reported Claim Models** | Estimates the expected number of newly reported claims in each future period |
| | **Severity on Future Reported Claims Models** | Estimates the ultimate severity associated with the future reported claims |

# Using Generalized Approach for IBNER Estimation

IBNER

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

| | 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)*

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

# Using Generalized Approach for Pure IBNR Estimation

Pure IBNR

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

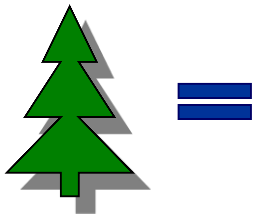
| | Actual Experience | | | Future Predicted Experience | | | |
|---|---|---|---|---|---|---|---|
| **Period** | **1** | **2** | **3** | **4(F)** | **5(F)** | **6(F)** | **7(F)** |
| Actual Newly Reported Claims | **1000** | **300** | **100** | NA | NA | NA | NA |
| Future Reported Claims Model Estimate | 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** |

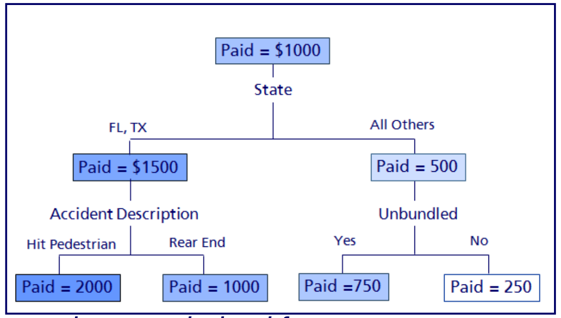
**Total IBNR = IBNER + Pure IBNR**

*Example – not derived from any company sources*

# Evaluating different modeling methods

## Many different model methods are available in modeling software

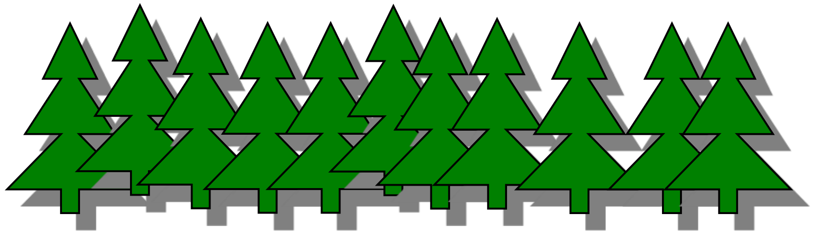





*Example – not derived from any company sources*

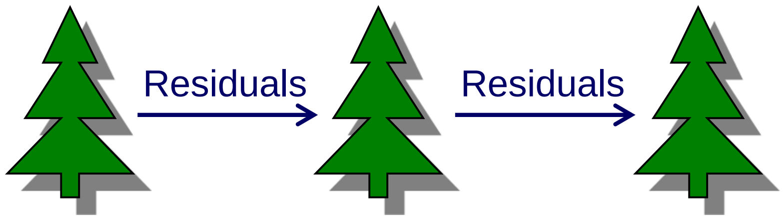
- A tree is a simple set of splitting rules on the data, what we call a "weak learner"
- A group of "weak learners" can come together to form a "strong learner"

**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**



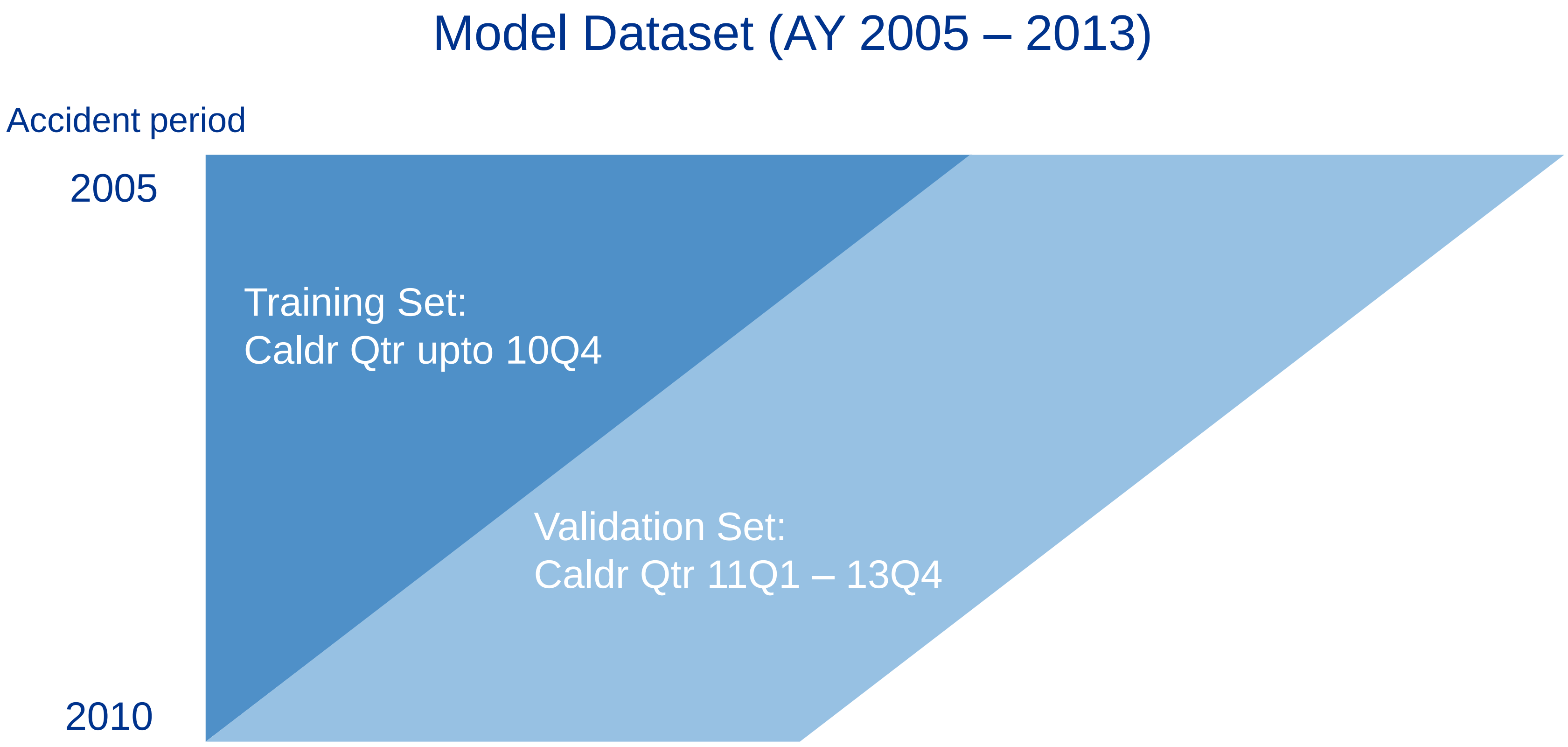

**Gradient Boosting** is a collection of "weak learners" (trees) used sequentially, with each tree focused on improving the prediction of the previous tree. In each step a bootstrap sample of data is taken. A tree is fit to the "current residuals" and the residuals are updated for the next step.

# Evaluating different model methods

## Pros and Cons exist for each modeling method

| | Pros | Cons |
|---|---|---|
| **Random Forest** | • Modeling non-linear and complex relationships<br>• Fast algorithms - can leverage parallel computing | • Can be difficult to explain<br>• Often “beat” by well-tuned GBMs |
| **Gradient Boosting Machine (GBM)** | • Modeling non-linear and complex relationships<br>• Algorithm has more “levers” in terms of hyperparameters | • Can be difficult to explain<br>• Can be difficult to tune due to large number of hyperparameters |
| **Generalized Linear Models (GLM)** | • Easy to explain<br>• Well established in Actuarial community | • Need to be more explicit about interactions and non-linear relationships |

# Model validation



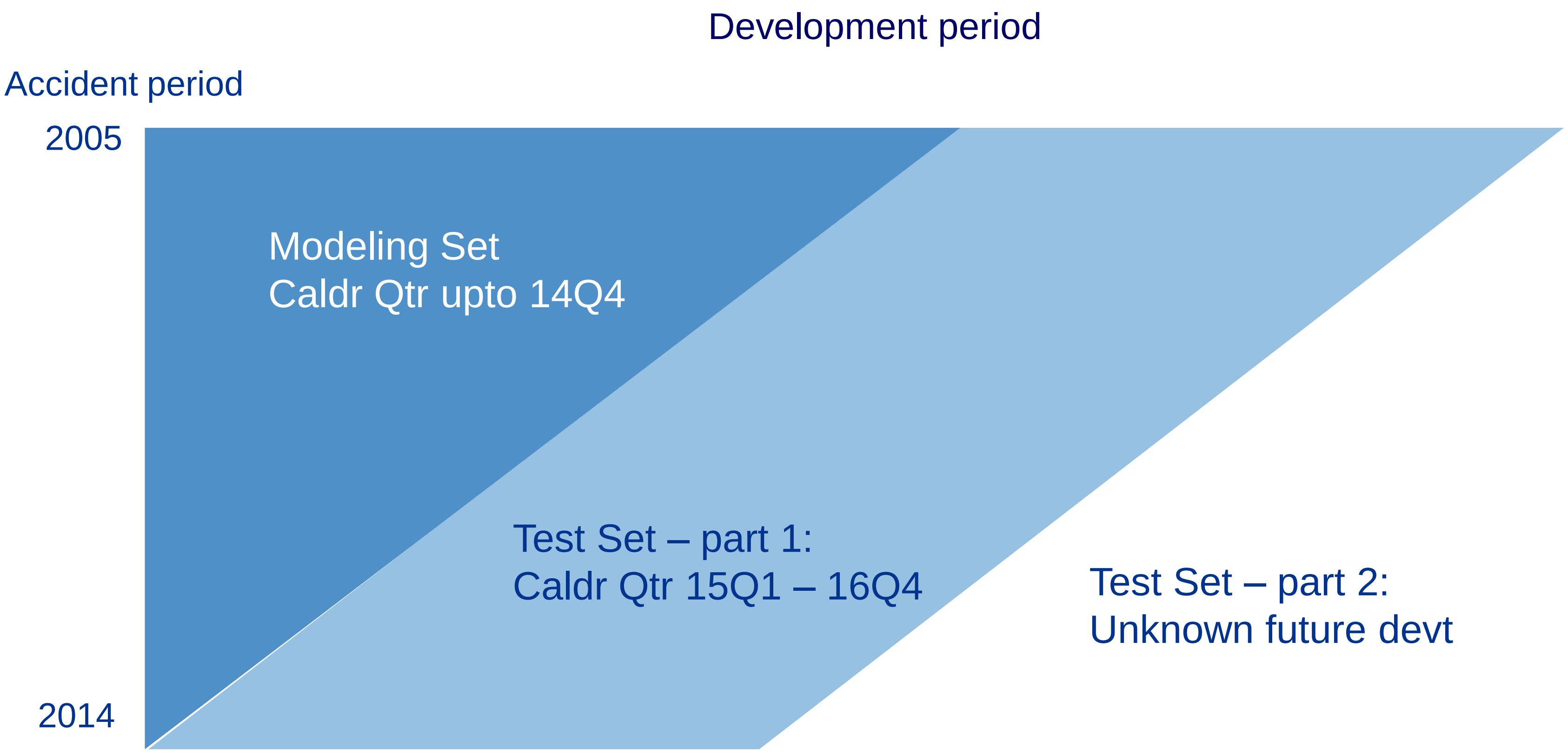

**Validation approach used for the selections of**

- **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**

# Test approach




## Test approach used to evaluate the model performance

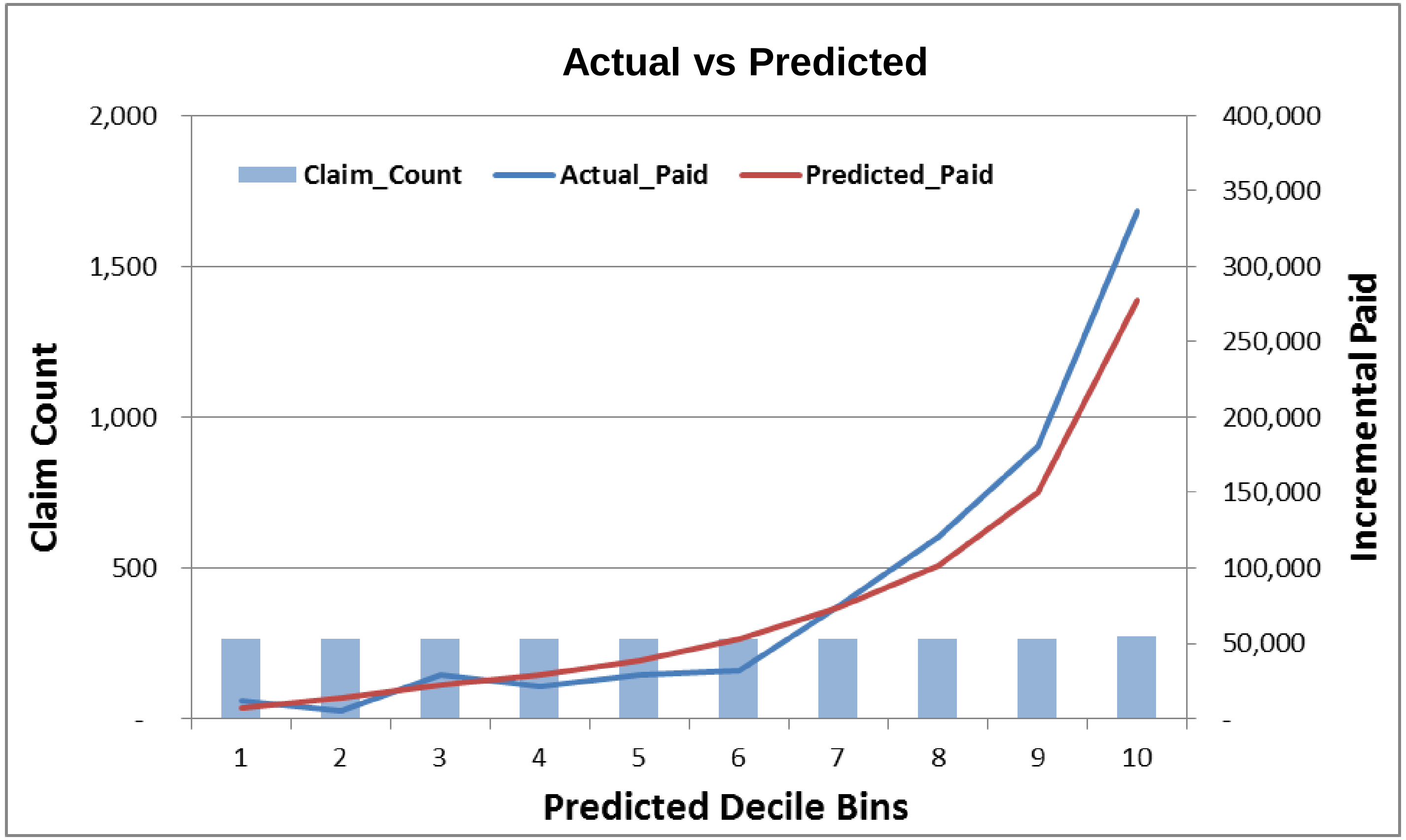
- **Do the selected methods with hyper parameters and variables generalize well in different time periods?**

## 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**

# Model lift

## Coverage 1 incremental paid loss model



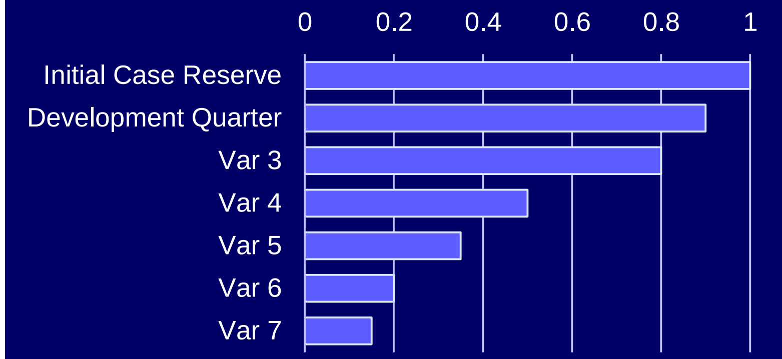

**Lift charts show the performance of the model on the test dataset (14Q1 – 16Q4).**

- **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.**

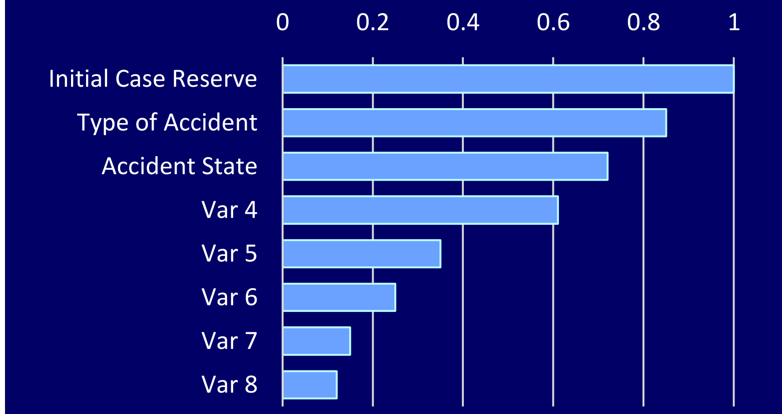
# Relative variable importance

- 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 1

Coverage 1 model – relative importance




Coverage 2 model – relative importance

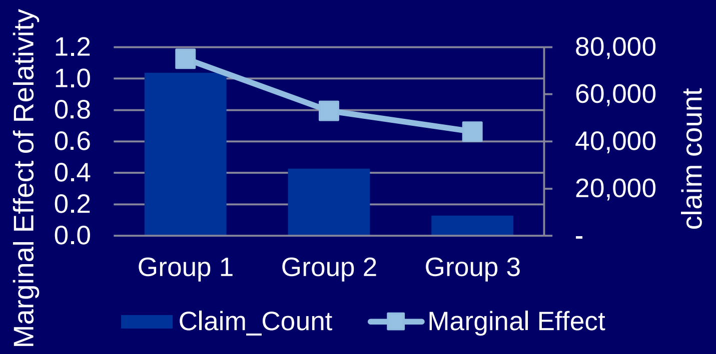



*Example – not derived from any company sources*

# Partial dependence 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*

# Legal disclaimer

The information in this presentation was compiled from sources believed to be reliable for informational purposes only. All sample policies and procedures herein should serve as a guideline, which you can use to create your own policies and procedures. We trust that you will customize these samples to reflect your own operations and believe that these samples may serve as a helpful platform for this endeavor. Any and all information contained herein is not intended to constitute advice (particularly not legal advice). Accordingly, persons requiring advice should consult independent advisors when developing programs and policies. We do not guarantee the accuracy of this information or any results and further assume no liability in connection with this presentation. We undertake no obligation to publicly update or revise any of this information, whether to reflect new information, future developments, events or circumstances or otherwise. The subject matter of this publication is not tied to any specific insurance product nor will adopting these policies and procedures ensure coverage under any insurance policy.

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**Robotic process automation**

**Cognitive – reserving using machine learning**

**Data visualization**

**Enterprise response**

# Why data visualization?

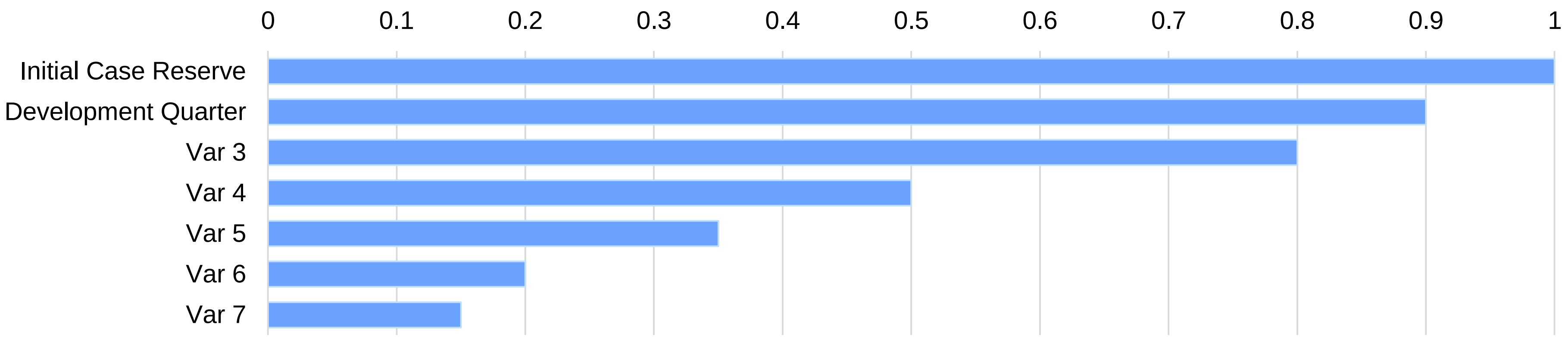
Incorporating Digital Visualization to the Reserve Analysis results enables **deep**, **timely**, and **widespread** understanding of **complex** actuarial reserving insights and the **interaction** of those insights.

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

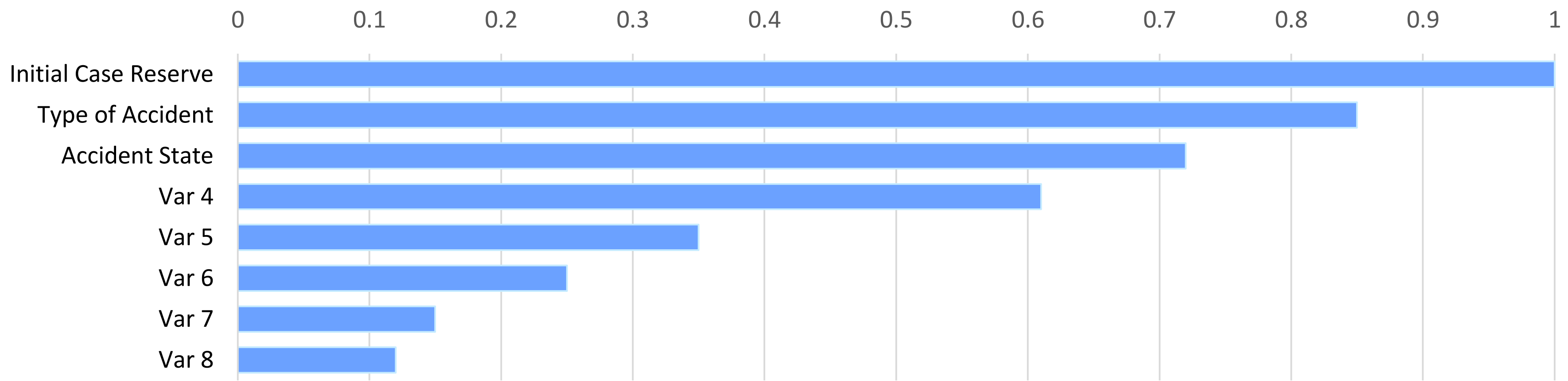
# Cognitive reserving - which variables are more predictive?

**These charts highlight potential analyses related to loss reserve movements by coverage**

**Coverage 1 model – relative importance**

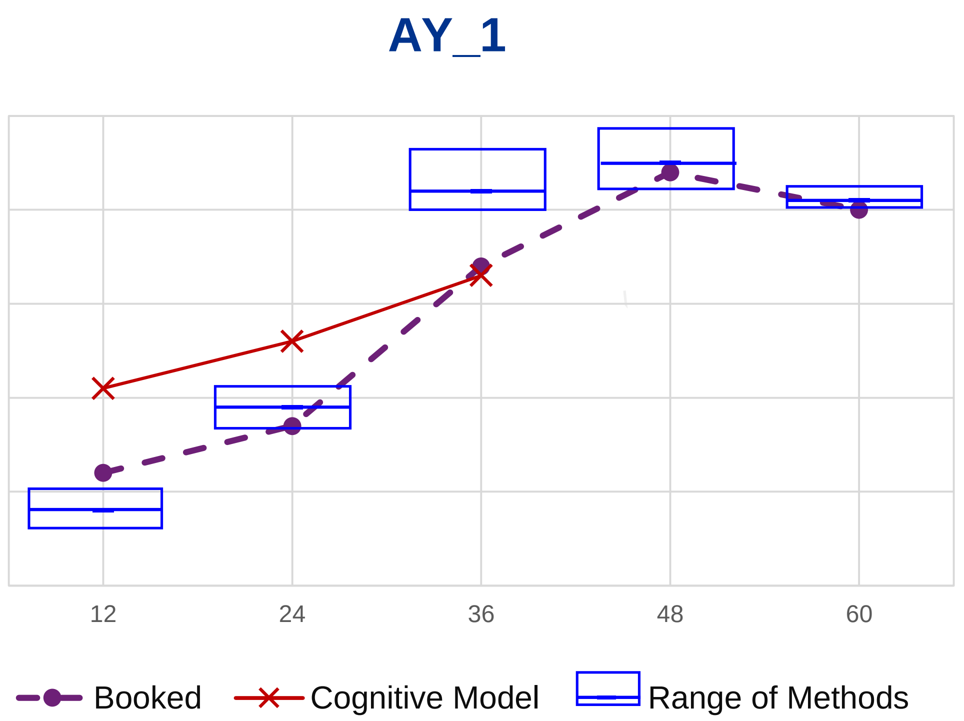


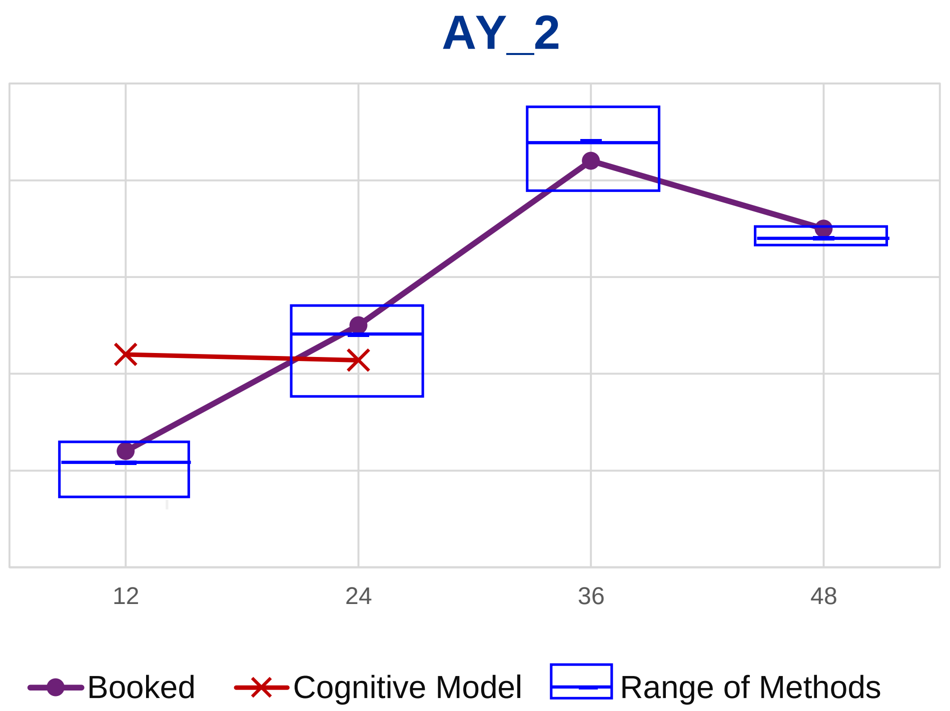

**Coverage 2 model – relative importance**



# Cognitive methods more responsive at early evaluations and stable

## Estimated Ultimate Development for the LOB




**More Accurate Early**

**More Accurate Early**

**Stable – No reversals**

**More Accurate Early**

# Cognitive reserving models provide fast insights

**Illustrative**

## ***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.

**Paid Link Ratios**

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 4.22 | 3.20 | 1.36 | 1.59 | 1.43 | 1.29 | 1.14 | 1.10 |
| 4.78 | 1.75 | 1.78 | 1.42 | 1.28 | 1.34 | 1.22 | |
| 6.46 | 2.00 | 1.41 | 1.39 | 1.24 | 1.23 | | |
| 4.75 | 1.72 | 1.82 | 2.50 | 1.28 | | | |
| 5.48 | 1.92 | 1.41 | 1.49 | | | | |
| 3.69 | 2.08 | 1.94 | | | | | |
| 3.59 | 3.54 | | | | | | |
| 3.88 | | | | | | | |

| | |
|---|---|
| Reported Claims | Normal |
| Closed Claims | VERY HIGH |
| Paid Severity | Normal |
| Paid Severity (ex. large) | Normal |

## *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) |
|---|---|---|---|---|---|
| EXTEMELY 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 |

# Cognitive actual vs. expected tool will provide insight at lower levels of granularity

**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 | Unbundled | - $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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# Enterprise response

1 Having the ability to deliver the insights broadly to management

2 Being positioned to make needed decisions/changes/reactions timely

3 Having the ability to put those into actions effectively

# Digital trust in automatic reserving

**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 loss reserve models may be held to higher standards of precision than models used for purposes where directional indications are sufficient.
- Increased frequency of reserve 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.

# A machine learning framework for loss reserving

**An aggregate triangular level approach**

## The link for the slides KPMG presented during 2016 CLRS meeting

**http://www.casact.org/education/clrs/2016/presentations/AR-1_1.pdf**

# Thank you!


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