KPMG

Artificial Intelligence in Insurance

Actuarial analysis in the digital age

Actuarial Society of Greater New York – 2017 Annual Meeting

November 13, 2017

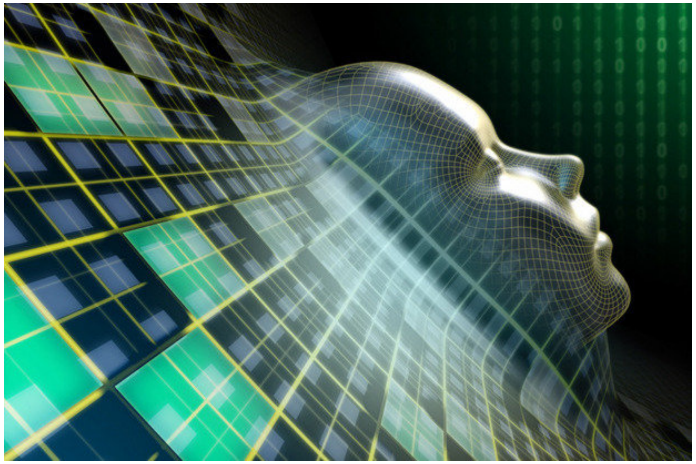
Motivation

— Many new technological innovations are available today

— A wide berth of industries will be affected by artificial intelligence

— Question:

  - How about Insurance industry?



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

Insurance modernization

— Recent changes
  - Underwriting
  - Claim handling

— How actuarial analysis is performed 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.

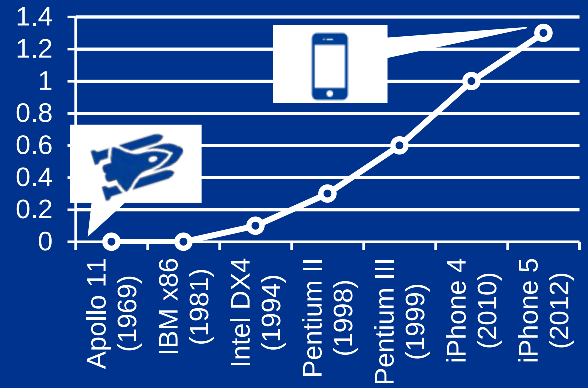
Data preparation	**R, HIVE, python, hadoop**
Cognitive – machine learning	sas, R, python
Visualization	tableau, Qlik
Robotic process automation	AUTOMATION ANYWHERE, blueprism

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.

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

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 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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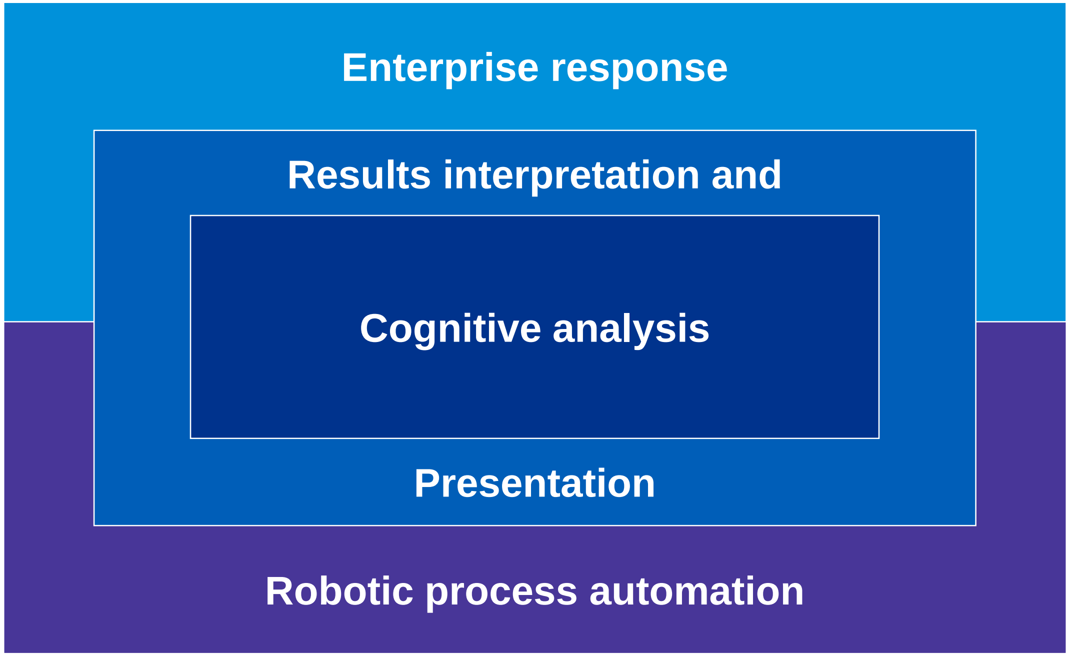
Four core components

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	— 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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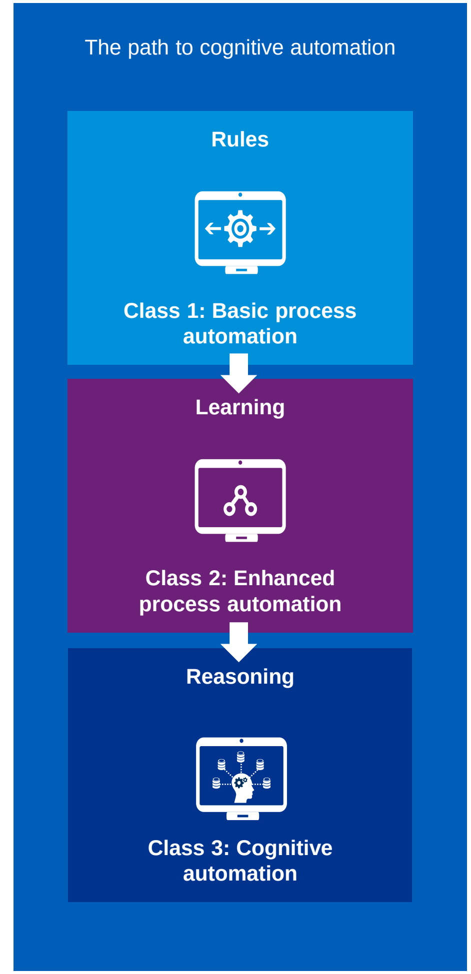
RPA – Reserving as part of broader claim play

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

First Notice of Loss	Case Creation	Segmentation	Assignment	Investigation	Evaluation	Reserving	Litigation Management	Payment	Recovery
FNOL	Collect Information	Collect Additional Information	Assign Handling Office	Verify Policy Details	Analyze Information	Prepare Data	Notification of Legal Matter	Cross Verification	Reinsurance Recovery
Duplicate FNOL Identification	Identify Policy	Score and Segment	Assign Supervisor	Verify Coverage	Complete Claim Evaluation Report	Aggregate Data	Creation of Legal Matter	Verify Claim Details	Subrogation
Reference Number Generation	Verify Basic Policy Information		Assign Claim Adjuster	Perform Appraisals	Review Claims	Square Triangle	Assignment of Legal Matter	Verify Reserves	Salvage
	Validate and Register Claim		Send Notification to Adjuster	Verify Statements & Documents	BI/Medical Audit	Set/Allocate Reserves	Creation of Budget	Verify Policy Limits	Claim Closure
	Generate Claim Number			Bureau Scene Investigation	Determine Liability	Update Reserves	Review of Invoice	Duplicate Payment Check	Updating Policy Records w/Claim History
				Review Claim History	Assess Recovery	Analysis/ Trends	Payment of Invoice	Approvals	Closing the Claim
				Refer to Litigation	Litigation	Document Insights	Closing of Legal Matter	Finance to Process and Issue Payment	
				Refer to Investigator	Calculate Claim Value	Corrective Action	Fraud Management	Adjust for Recovery	
				Detect/Manage Fraud	Validate Recipients		Secondary Fraud Investigation Research	Issue Check	
					Negotiation		Scene Investigation	Inform Customer	
					Liability Decision		Approval/Rejection of Claim		

Legend:

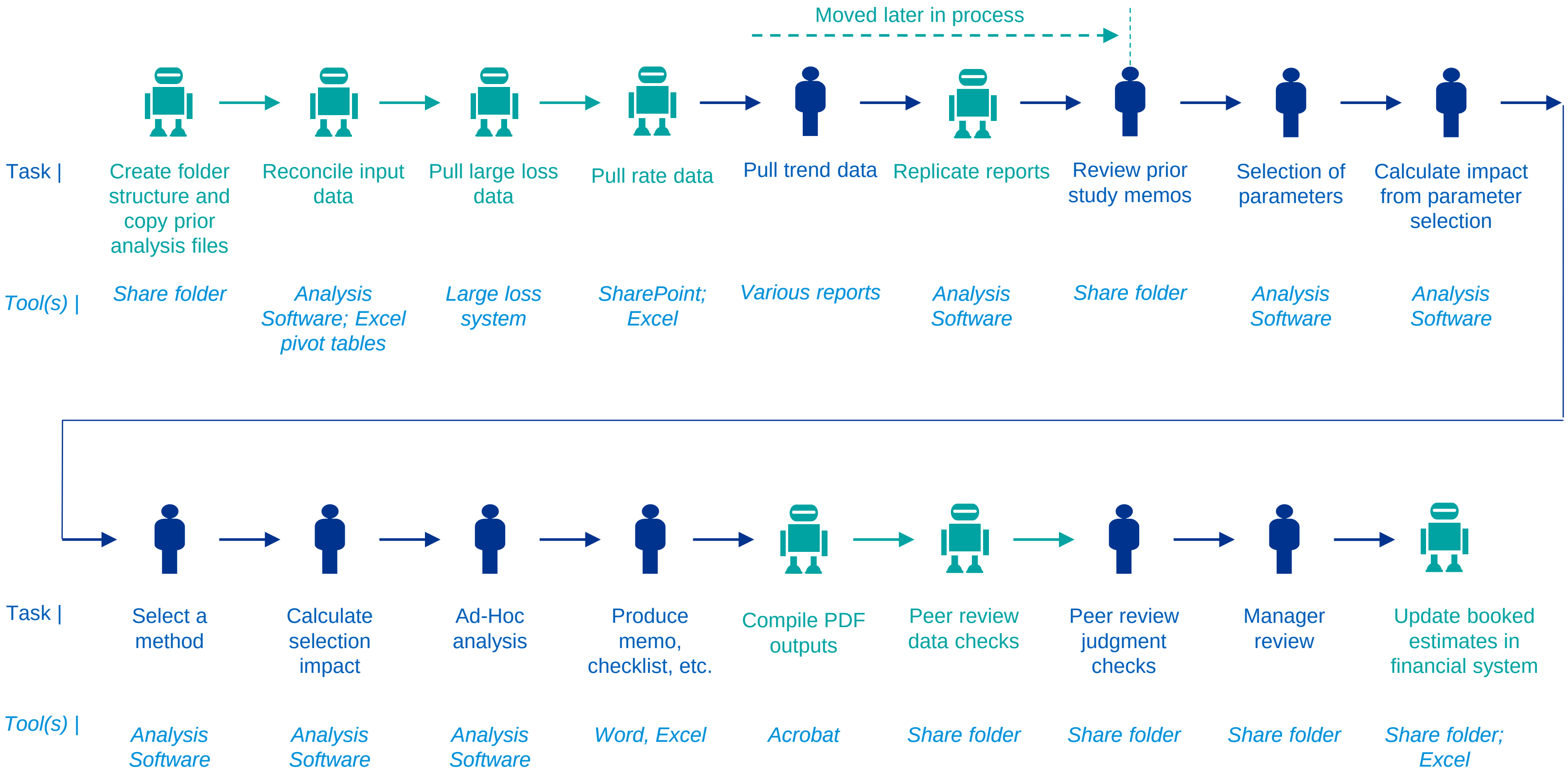
- CLASS 1: Basic Process Automation
- CLASS 2: Enhanced Process Automation
- CLASS 3: Autonomic/Cognitive
- Limited RPA opportunities or not enough information



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

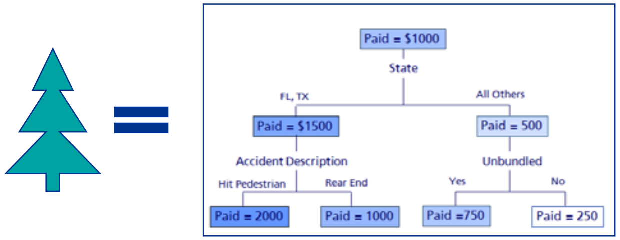
Cognitive computing – Systems which mimic the functioning of the human brain such as the ability to learn, understand, reason, and interact.[1]

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

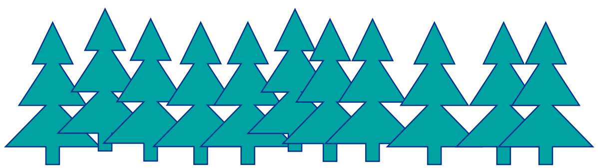
Model types



Example – not derived from any company sources

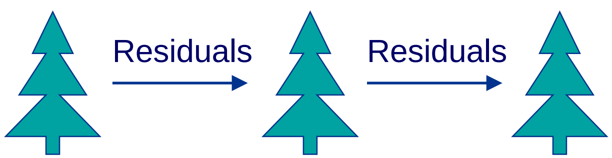
- A tree is a simple set of splitting rules on the data, what we call a "weak learner"
- A group of "weak learners" can come together to form a "strong learner"

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.

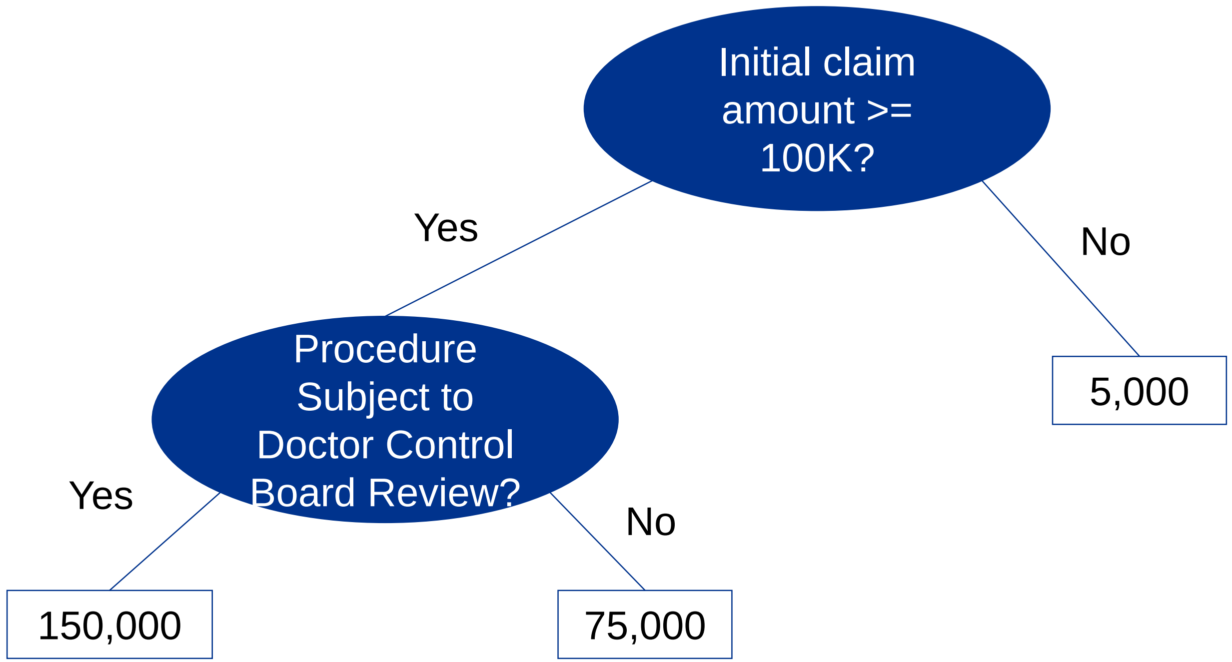
Gradient Boosting



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

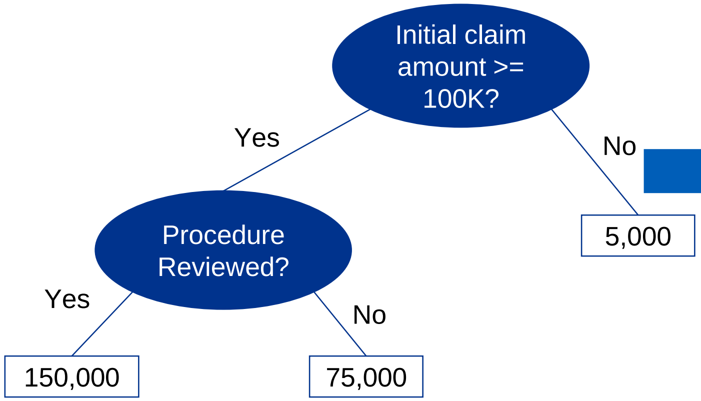


**via a very simplified illustrative example*

Decision tree heuristics (continued)

One decision tree

Not so great performance

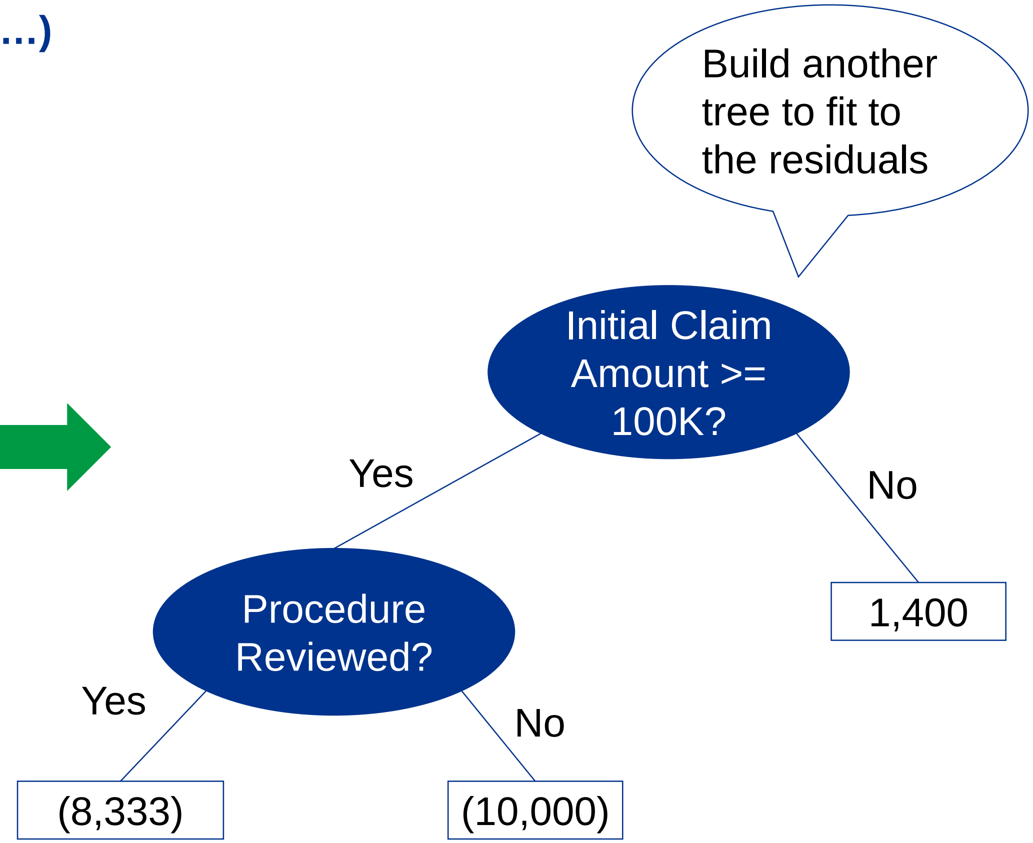


Initial Claim Amount	Procedure Reviewed?	Incremental Loss	Predicted	Residual
150,000	Yes	100,000	150,000	(50,000)
10,000	No	15,000	5,000	10,000
5,000	Yes	3,000	5,000	(2,000)
200,000	Yes	200,000	150,000	50,000
100,000	No	10,000	5,000	5,000
125,000	No	50,000	75,000	(25,000)
50,000	No	8,000	5,000	3,000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

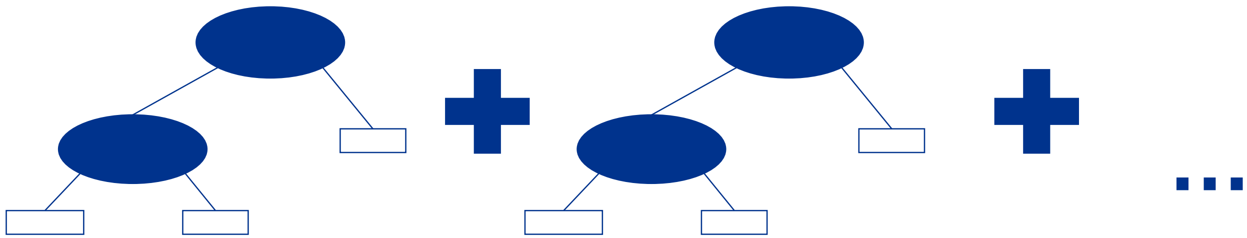
Boosting (more decision trees…)

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 (1st tree)	Prediction (2nd tree)	Residual (2nd 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)

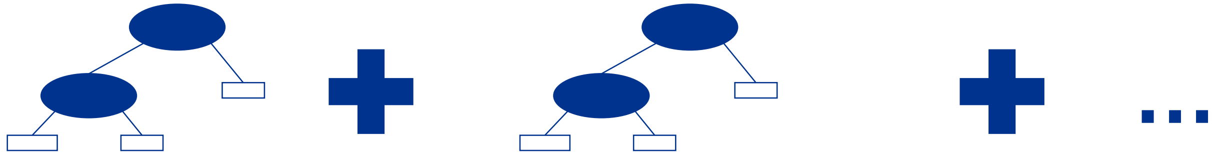
10,000 – 1,400 = 8,600

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

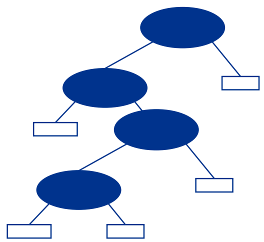
Decision tree hyperparameters

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

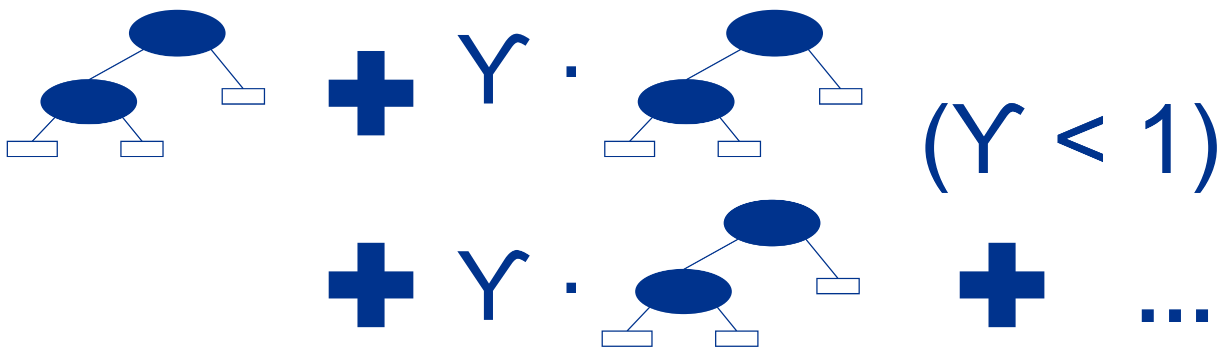
- Number of trees



- Depth of trees



- Learning rate



Pros and cons

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

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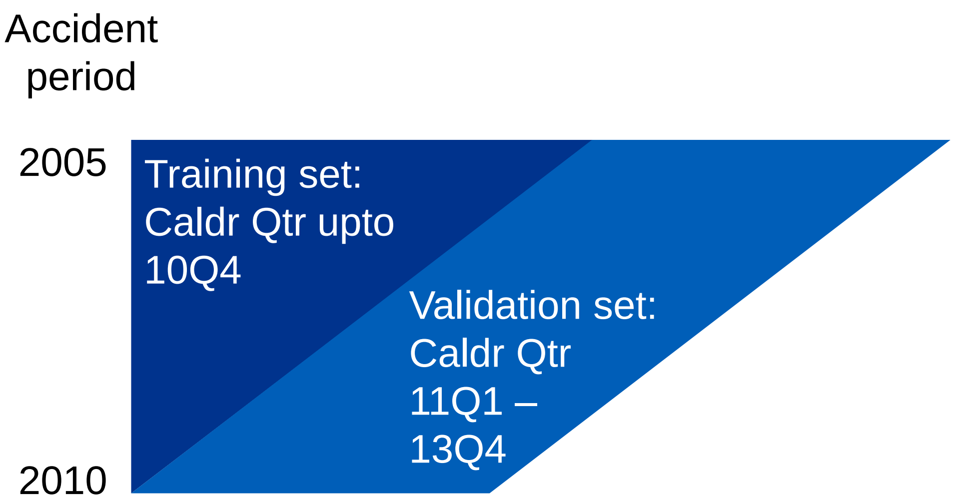
Model validation

Model dataset (AY 2005 – 2013)



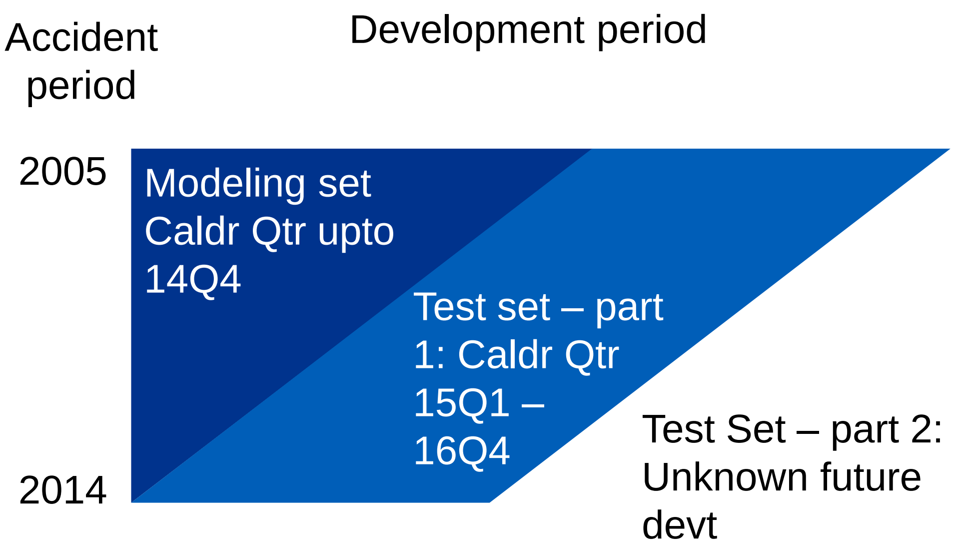
Validation approach used for the selections of

- 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?

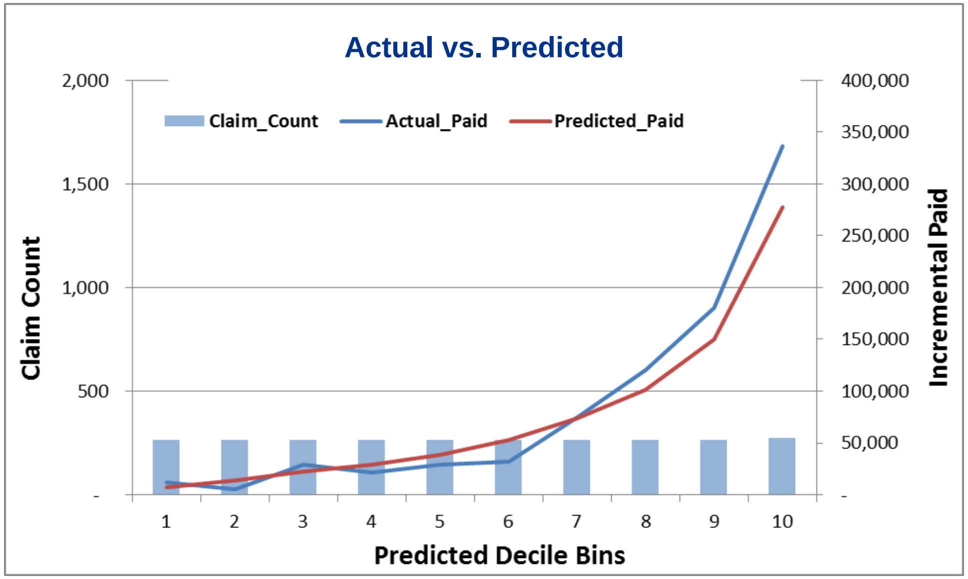
Two approaches test

— 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

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.

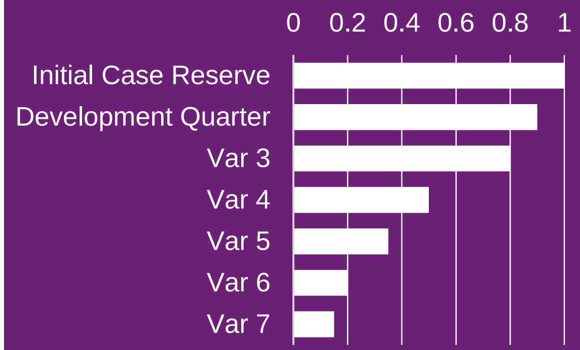
Relative variable importance

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

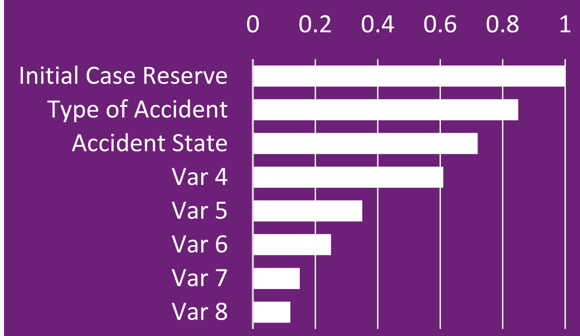
— Importance of a variable calculated by crediting it with the reduction in the sum of squares

— 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

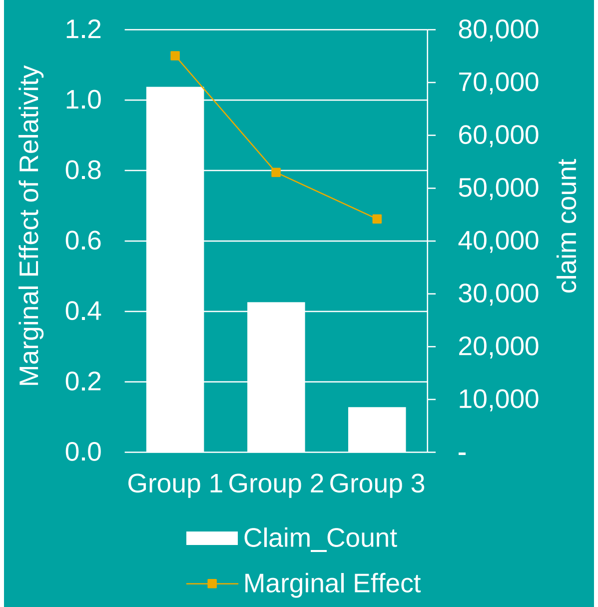


Example – not derived from any company sources

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};
}
```

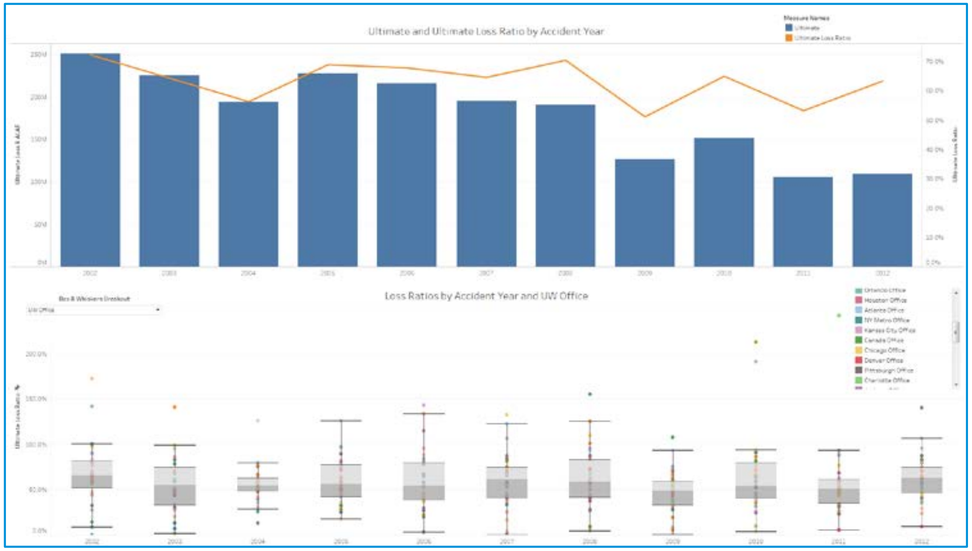
Data visualization

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

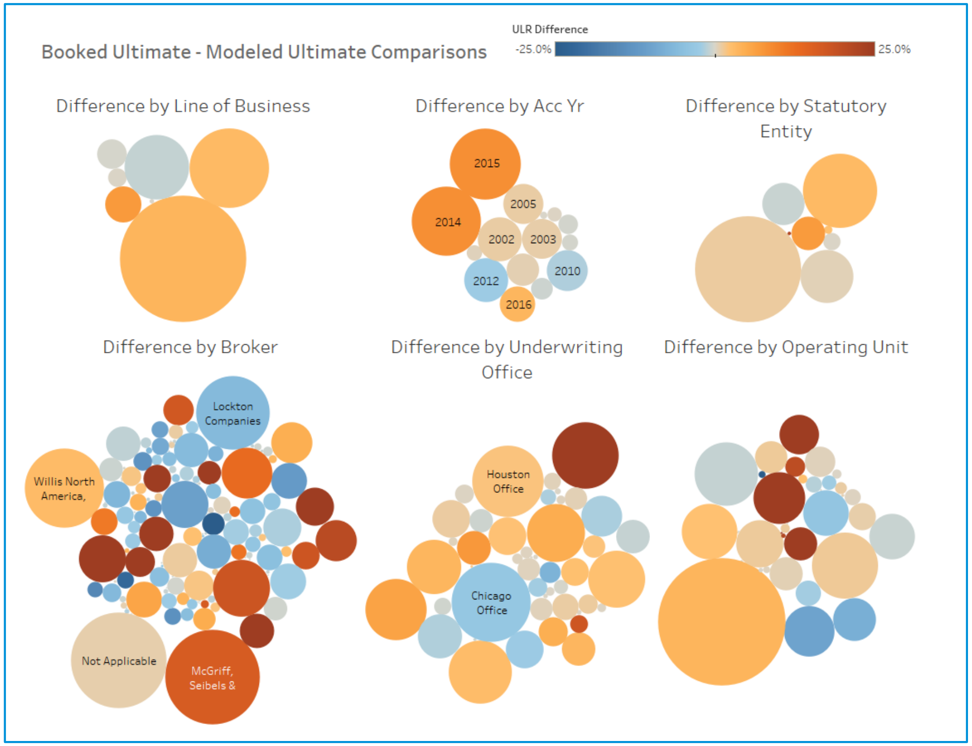


Dynamic charts enable detailed understanding of results

- 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

Case studies

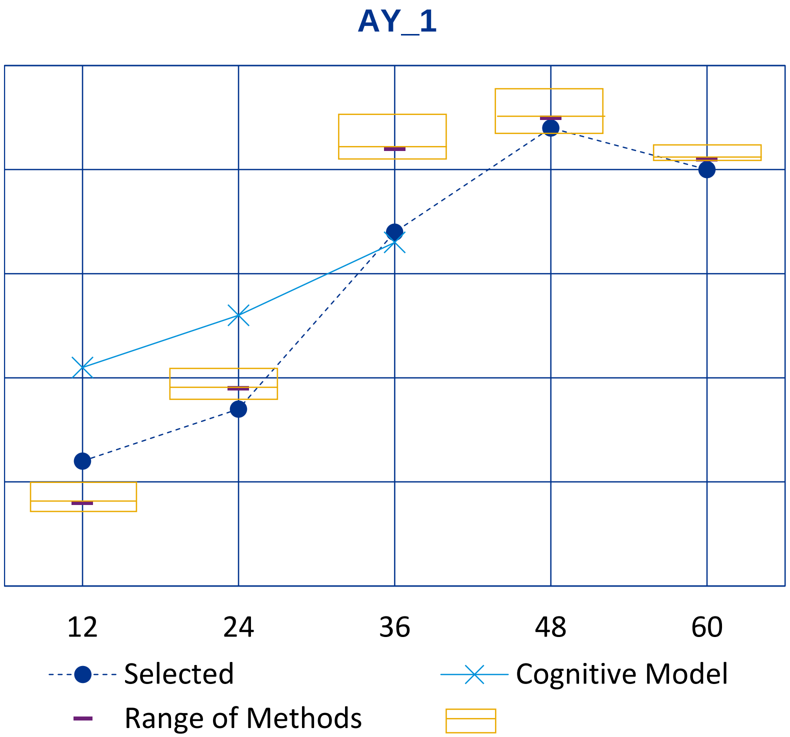
Case 1 – U.S. Operation of Global P&C Insurer – Cognitive Reserving Solution leveraging a Gradient Boosting Model to proactively identify deterioration of a problematic business segment

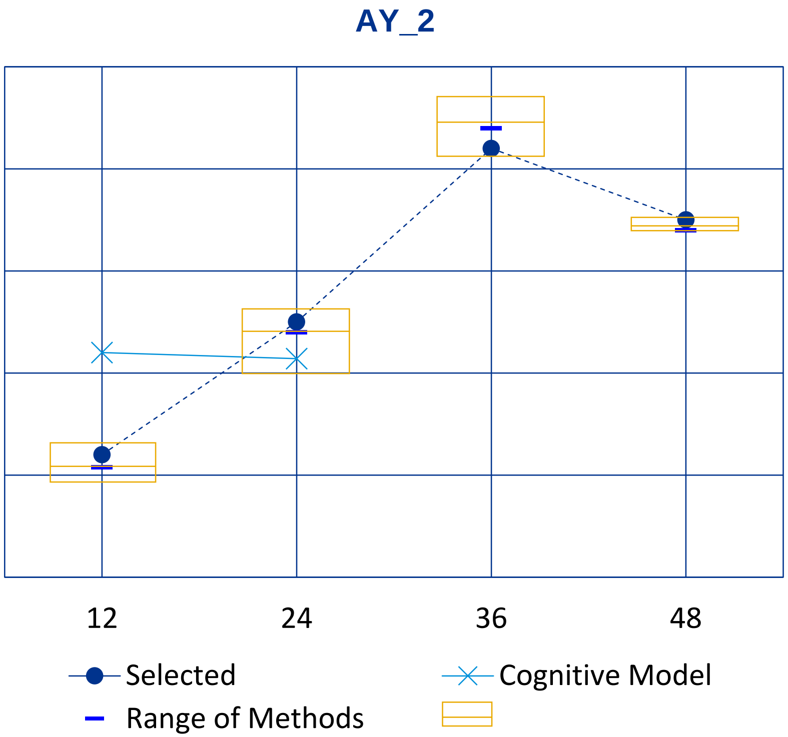
Case 2 – U.S. Life Operation of Global Multi-Line Insurer – Cognitive Reserving Solution using a Random Forest Model to predict state changes impacting universal life cash flows

Case 1

Responsiveness of cognitive methods

Estimated ultimate development for the LOB





More accurate early

More accurate early

Stable – No reversals

More accurate early

Case 1

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.

Paid link ratios ***Illustrative***

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

Case 1

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.

Case 2

Prediction of state change

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

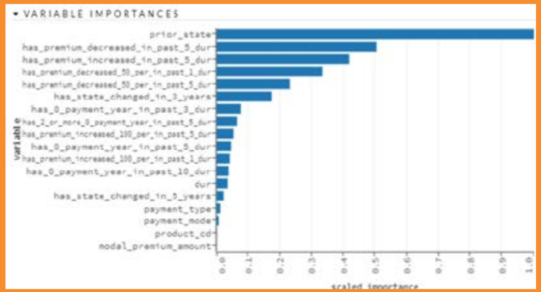
Case 2

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



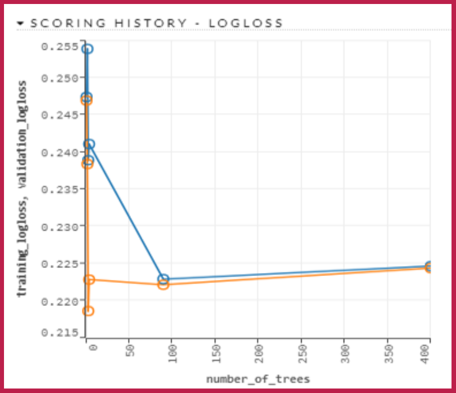
Case 2

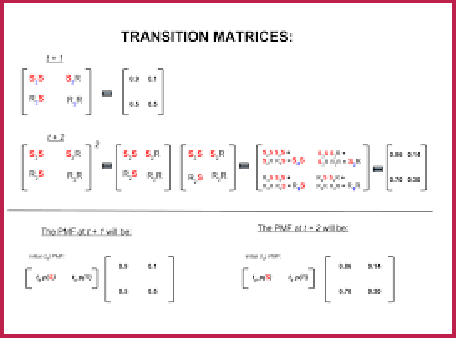
Model implementation

— 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





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

Enterprise response

1 Having the ability to deliver the insights broadly to management

2 Being positioned to make timely decisions/changes/reactions

3 Having the ability to put those into actions effectively

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.

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

Life

- Cash Flow Projection
- Mortality Table Modeling
- Lapse and Surrender Analysis

Health

- Health Plan Enrollment Reconciliation
- Medical Cost Forecasting
- Automation of Clinical Quality Reporting

- 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 consumer behavior to optimize health care 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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