Improving Actuarial Reserve Analysis through Predictive Analytics

2017 CAS Spring Meeting

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Willis Towers Watson

Agenda

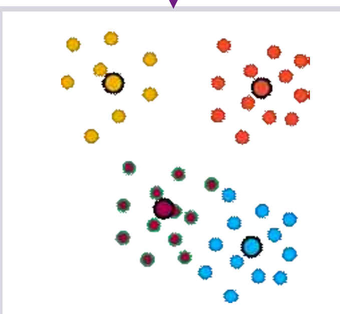
- Context of predictive models in reserving
- Structuring claims data for modeling
- Choosing model(s)
- Applications of model results in reserving
- Conclusions

Context

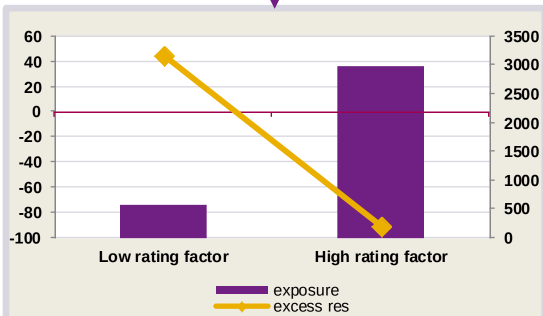
Applications of predictive models in the insurance sector

Marketing and Distribution → Customer Management → Underwriting and Risk Management → Pricing → Reserving and Claims Management → Asset Management

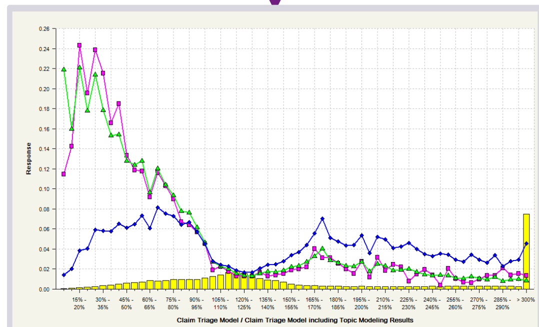
- Product development (UBI)
- Retention segmentation and program design
- Agent/Broker performance evaluation
- Fraud detection



P&C to Life cross-selling



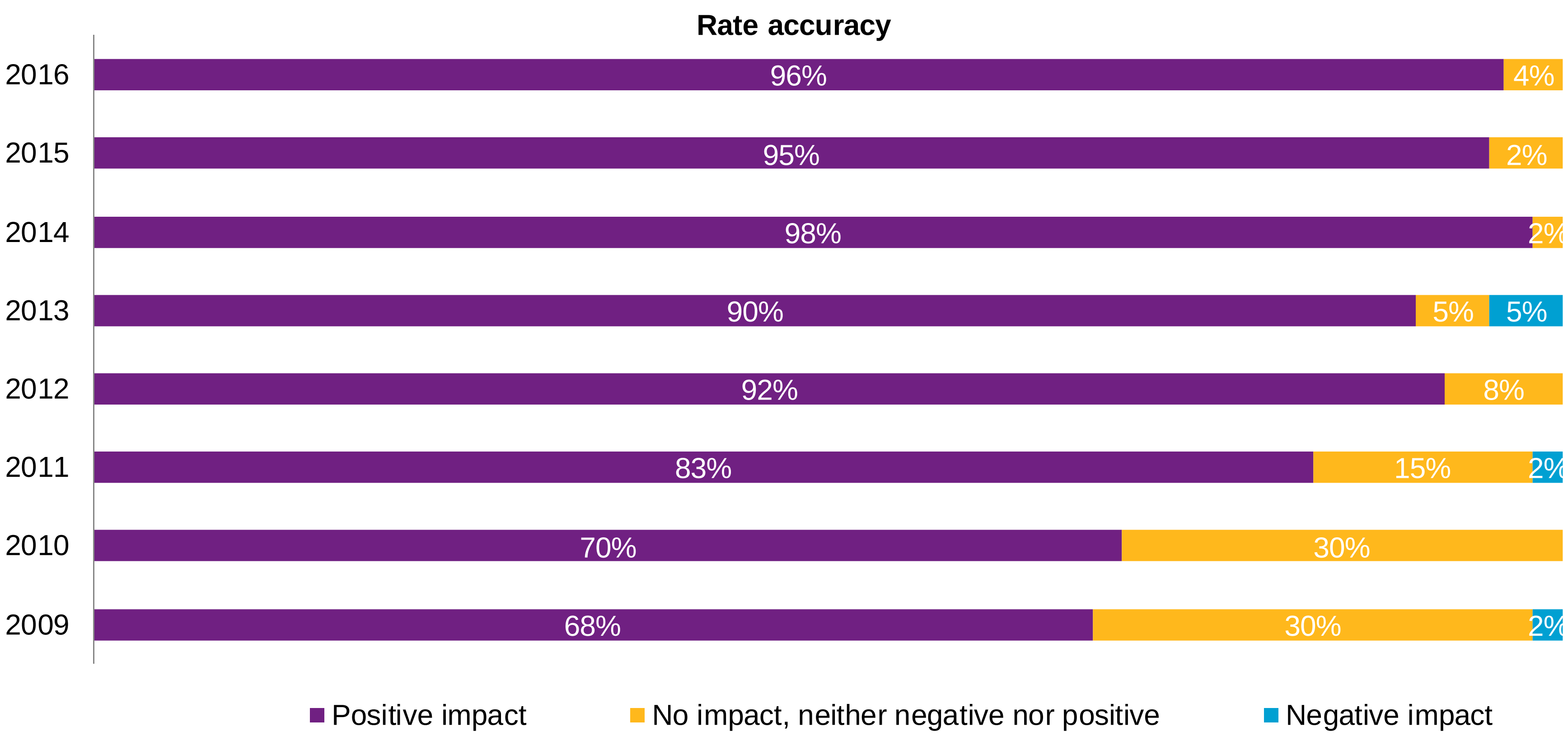
Web-scraping and feature design in commercial lines



Reserving and large loss modeling

Predictive models are a market standard in pricing

What impact has predictive modeling had in the following areas? (Q.7)

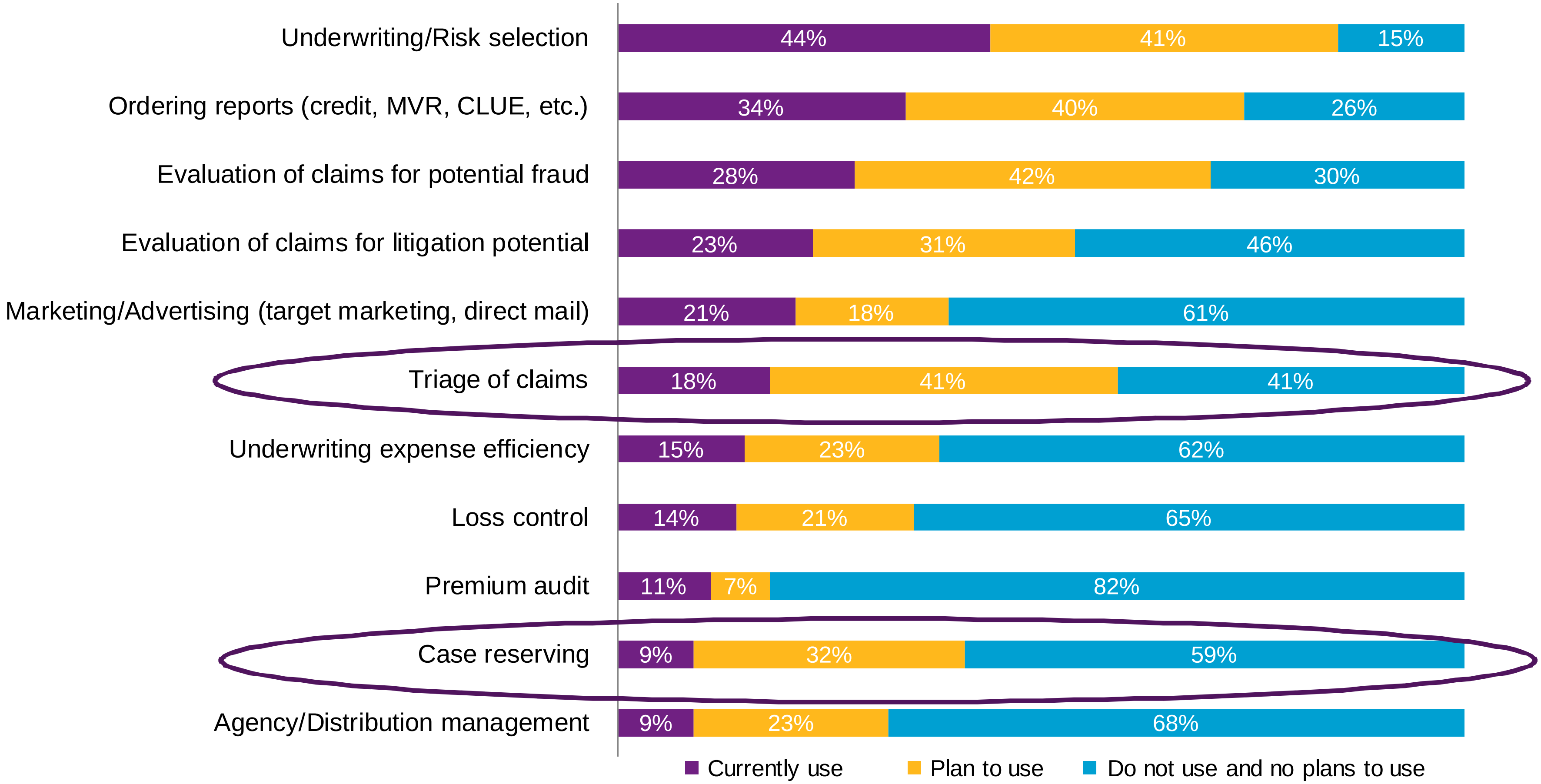


Base: U.S. respondents using predictive modeling for at least one line of business.

Plans to use predictive models elsewhere

Personal lines

Beyond rating/pricing, in which of the following areas in <u>personal lines</u> does your company group use, or plan to use, predictive modeling techniques in the next two years? (Q.5)

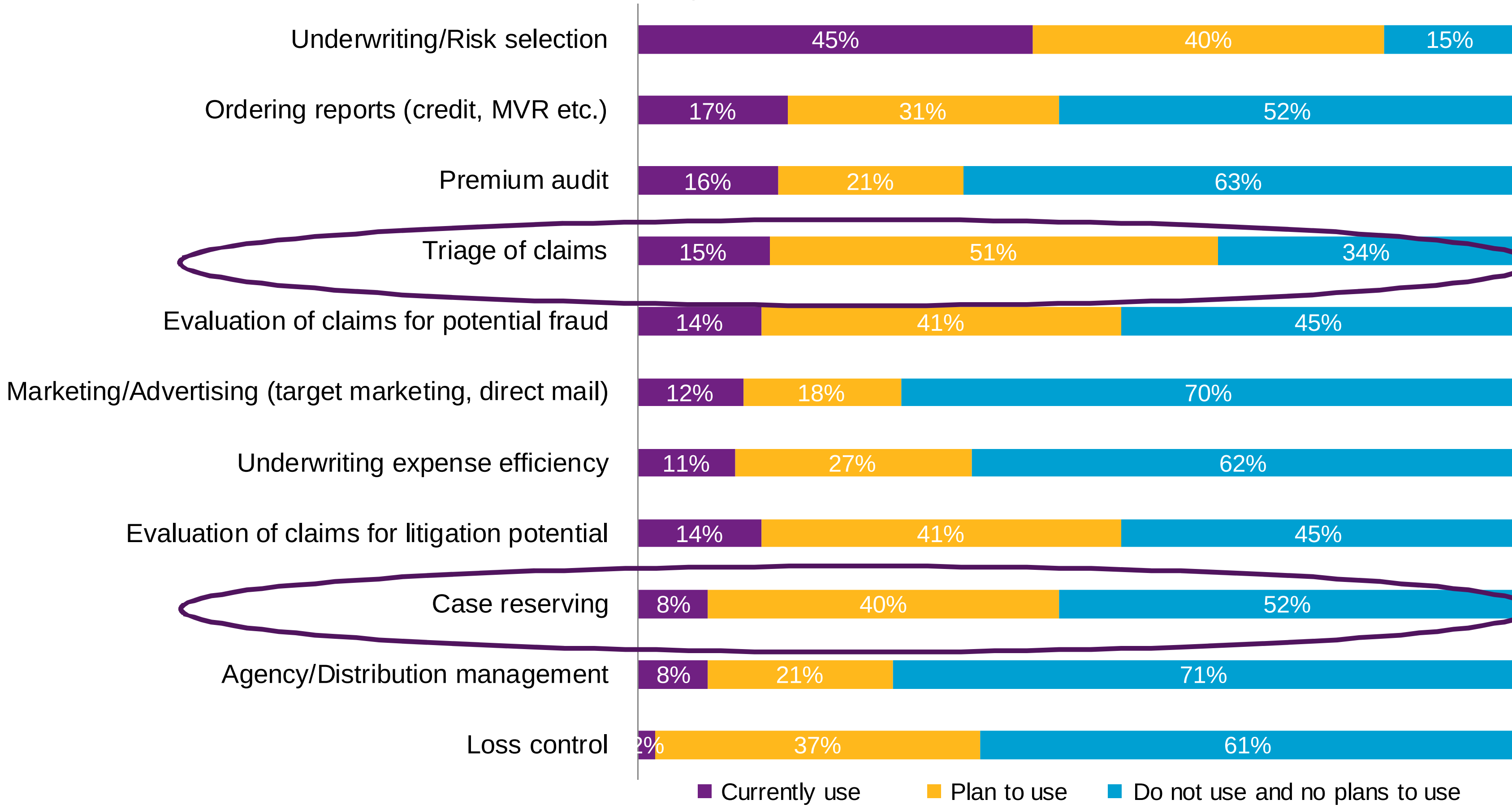


Base: U.S. respondents giving a valid answer (percentages exclude ‘Do not know/Not applicable’).

Plans to use predictive models elsewhere

Commercial lines

Beyond rating/pricing, in which of the following areas in commercial lines does your company group use, or plan to use, predictive modeling techniques in the next two years? (Q.6)



Base: U.S. respondents giving a valid answer (percentages exclude 'Do not know/Not applicable').

Why consider predictive models in reserving & claims management

Key points

- **Accuracy of traditional reserving methods hinges on consistency**
  - Claim closure rate
  - Case reserve adequacy
  - Inflation
  - Reinsurance

- **Traditional methods do not provide insights into the drivers of claim cost**
  - How much does age affect the cost of WC claims?
  - What is the impact of opioid usage on the cost of claims?
  - How much did reform measures impact claim costs?

Predictive models can address both of these challenges

An evolution of predictive models in reserving

Developing comfort, seeking greater insights

Predictive models were fit to the same data contained in a reserve triangle

- Using incremental losses instead of cumulative
- Only two predictors: Report year and lag
- Given appropriate statistical assumptions, the forecasts replicated chain ladder using volume-weighted average of the link ratios

→

Calendar Year was introduced as a predictor to enable calendar year changes in inflation to be reflected in the reserve estimation process

- Still need to extrapolate beyond the latest diagonal

—

Reserve accuracy of models fit to aggregated data still hinges on consistency in the data

→

Natural next steps

- Predictive modeling could be used to group claims with similar development behavior, such that separate triangles could be analyzed
- Predictive models could be fit to individual claims data

Structuring data

Traditional loss development methods

Traditional methods aggregate all claims in each cell within the historical triangle on a cumulative basis

Accident Year 2010 Cumulative Paid Losses

Claim	12	24	36	48
000001	0	1,000	1,000	5,000
000021	50	50	50	50
000060	0	0	0	250
000124	300	500	500	750
000328	125	400	400	400
000443	0	0	100	2,000
2010 Total	**475**	**1,950**	**2,050**	**8,450**

Traditional loss development methods

Repeat the process for each year until entire triangle is populated

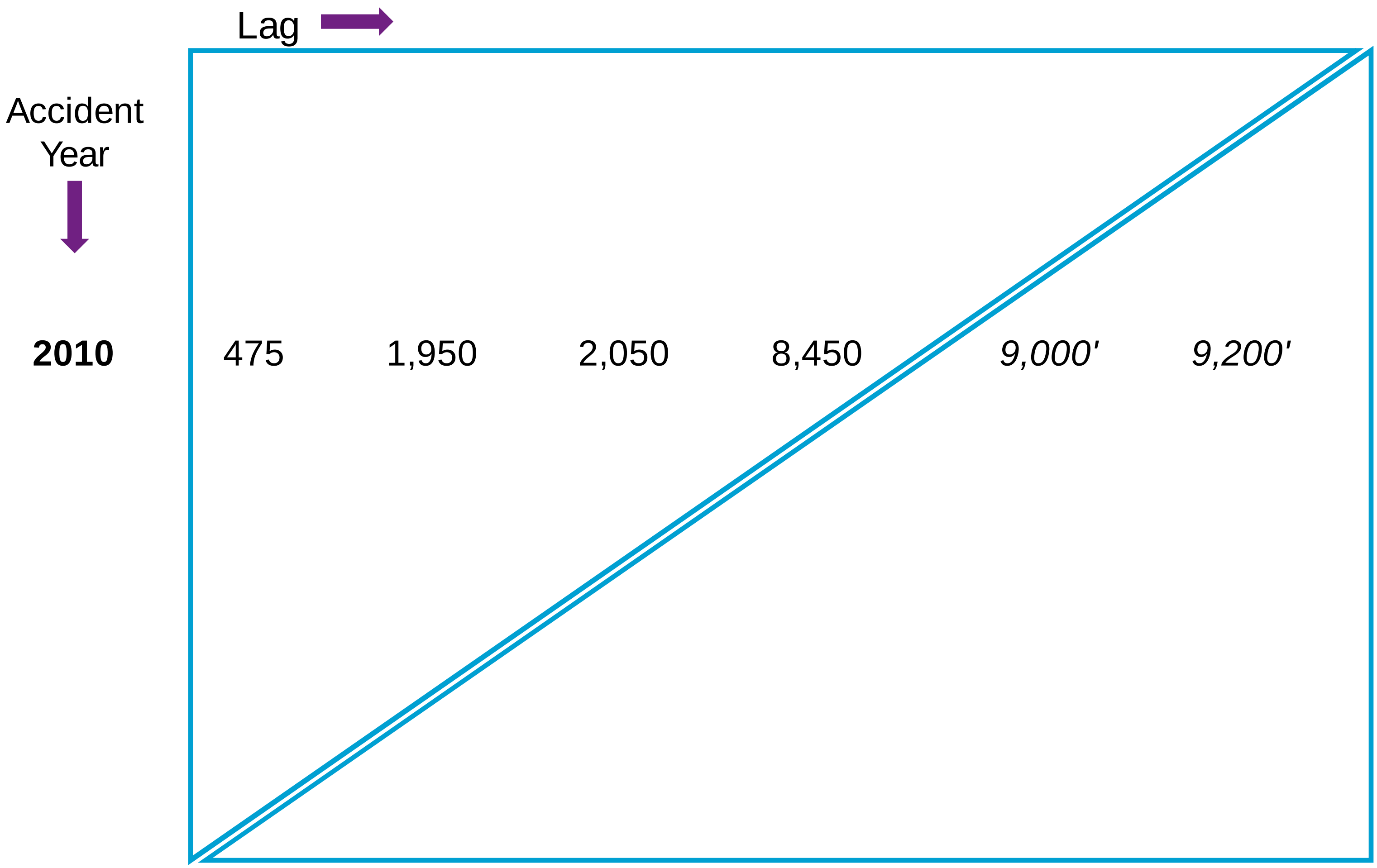
Lag

Accident Year

2010 475 1,950 2,050 8,450

Traditional loss development methods

Goal is to square up the triangle using link ratios



Predictive model

Aggregated data

A traditional aggregate loss development method can be replicated in a predictive modeling framework. Difference is that the data in the triangle is set to an incremental basis

Accident Year 2010 Incremental Paid Losses

Claim	12	24	36	48
000001	0	1,000	1,000	5,000
000021	50	50	50	50
000060	0	0	0	250
000124	300	500	500	750
000328	125	400	400	400
000443	0	0	100	2,000
2010 Total	475	1,950	2,050	8,450
2010 Incr	**475**	**1,475**	**100**	**6,400**

Predictive model

Individual claim data

When the data is organized at the individual claim level, the predictive model can be fit to the individual claim response

Lag

Year	Claim				
2010	000001	0	1,000	0	4,000
2010	000021	50	0	0	0
2010	000060	0	0	0	250
2010	000124	300	200	0	250
2010	000328	125	275	0	0
2010	000443	0	0	100	1,900

Predictive model

Individual claim predictors (Work comp example)

Insured Characteristics
- Policy start/ end date
- Months with company
- Number of employees
- Limits/ Deductible
- Class code
- Hazard group
- Prior Experience

Claimant Characteristics
- Age
- Number of dependents
- Previous disability
- Marital status
- Years employed
- Job level
- Performance evaluations
- Weekly Wage

Billing
- Payment history
- Payment plan
- Times delinquent

Loss Characteristics
- Cause of injury
- Body part injured
- Day of week
- Month
- State
- Report lag
- Loss date
- Type of loss

Service Providers
- Medical service provider
- Pharmaceuticals
- Attorney involvement

Geography
- Urban/Rural
- Distance to work

Predictive model

Individual claim data

Claim #	RY	Lag	Incr Paid	Lag12			Lag 36		
				Open	Age	Attorney	Open	Age	Attorney
30258B	2007	12	166	1	40	N	1	40	Y
30258B	2007	24	83	1	40	N	1	40	Y
30258B	2007	36	55	1	40	N	1	40	Y
30258B	2007	48	42	1	40	N	1	40	Y
30258B	2007	60	33	1	40	N	1	40	Y
30258B	2007	72	28	1	40	N	1	40	Y
30258B	2007	84	24	1	40	N	1	40	Y
30258B	2007	96	21	1	40	N	1	40	Y
48257K	2007	12	30	1	25	Y	0	25	Y
48257K	2007	24	249	1	25	Y	0	25	Y
48257K	2007	36	124	1	25	Y	0	25	Y
48257K	2007	48	—	1	25	Y	0	25	Y
48257K	2007	60	—	1	25	Y	0	25	Y
48257K	2007	72	—	1	25	Y	0	25	Y
48257K	2007	84	—	1	25	Y	0	25	Y
48257K	2007	96	—	1	25	Y	0	25	Y

Considerations

Individual claim data

- Claims should be coded to homogeneous claim types (basic Work Comp example)

Claim Type	**Payment Type**		
	Medical	Indemnity	Expenses
Medical Only	1	X	2
Lost Time	3	4	5

- Consider whether to use predictors that change over time
  - Depends on application
- New data trumps new methods
  - External sources: pharma, medical billing
  - Unstructured data (text)

Building models

Predictive models

- Models can be fit to a variety of responses and at different points in the claim lifecycle
- Different modeling approaches are suitable for different portfolios
  - Taylor & McGuire approach using Operational Time (claim closure rate) as a predictor to model severity is suited to lines where a single payment is made on the claim closure date
- For individual claim models, need to estimate pure IBNR (and potentially re-opens) separately

Types of predictive models

Statistical regression methods (e.g., GLM)

Response Variable **=** **Systematic Component** **+** **Random Component**

y = h (Linear Combination of Rating Factors) + Error

$g=h^{-1}$ is called the LINK function and is chosen to measure the signal most accurately

Combination of explanatory variables is the model structure

Error should reflect underlying process and comes from the exponential family

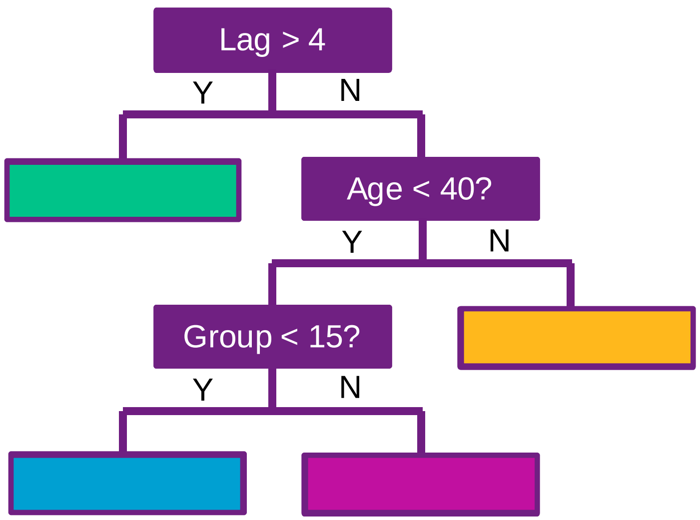
Output is set of parameters and a series of diagnostics

Types of predictive models

Machine learning approaches (e.g., random forest)

A tree

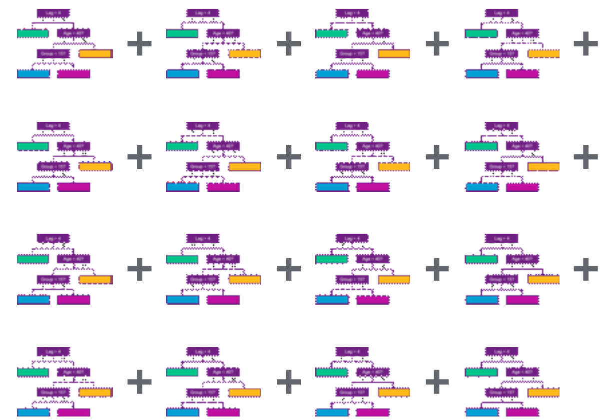
$$f_i(x)$$



A random forest

$$f(x) = \frac{1}{N}\sum_{n=1}^{N} f_n(x)$$

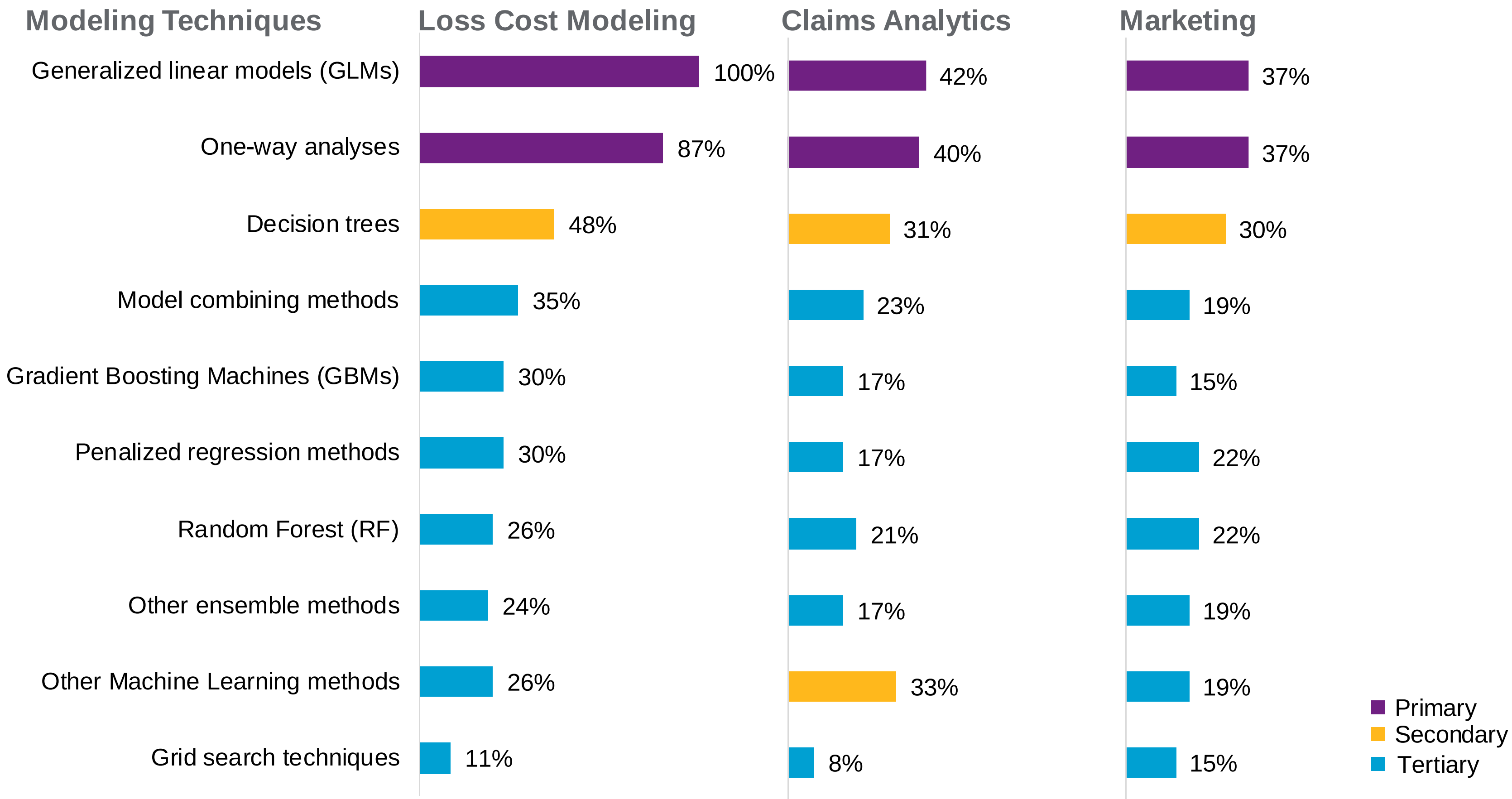
$$\frac{1}{N}$$



Output is the averaged result of a bunch of independent trees

What types of models are currently used?

For which business applications do you use or plan to use these methodologies? (Q.13)



Base: U.S. respondents who use or plan to use the methodology for the application specified (Loss Cost Modeling n = 46, Claims Analytics n = 48, Marketing n = 27).

One model may be most useful aiding another

Machine learning methods can be used in their own right (to forecast development) or can improve certain aspects of the analysis

- Topic modeling to create new structured data fields
- Penalized regression (e.g., elastic net) to select factors to include in analysis
- Multivariate adaptive regression splines to identify where separate models should be built (e.g., by lag or segment)
- GBMs or neural networks to validate regression results

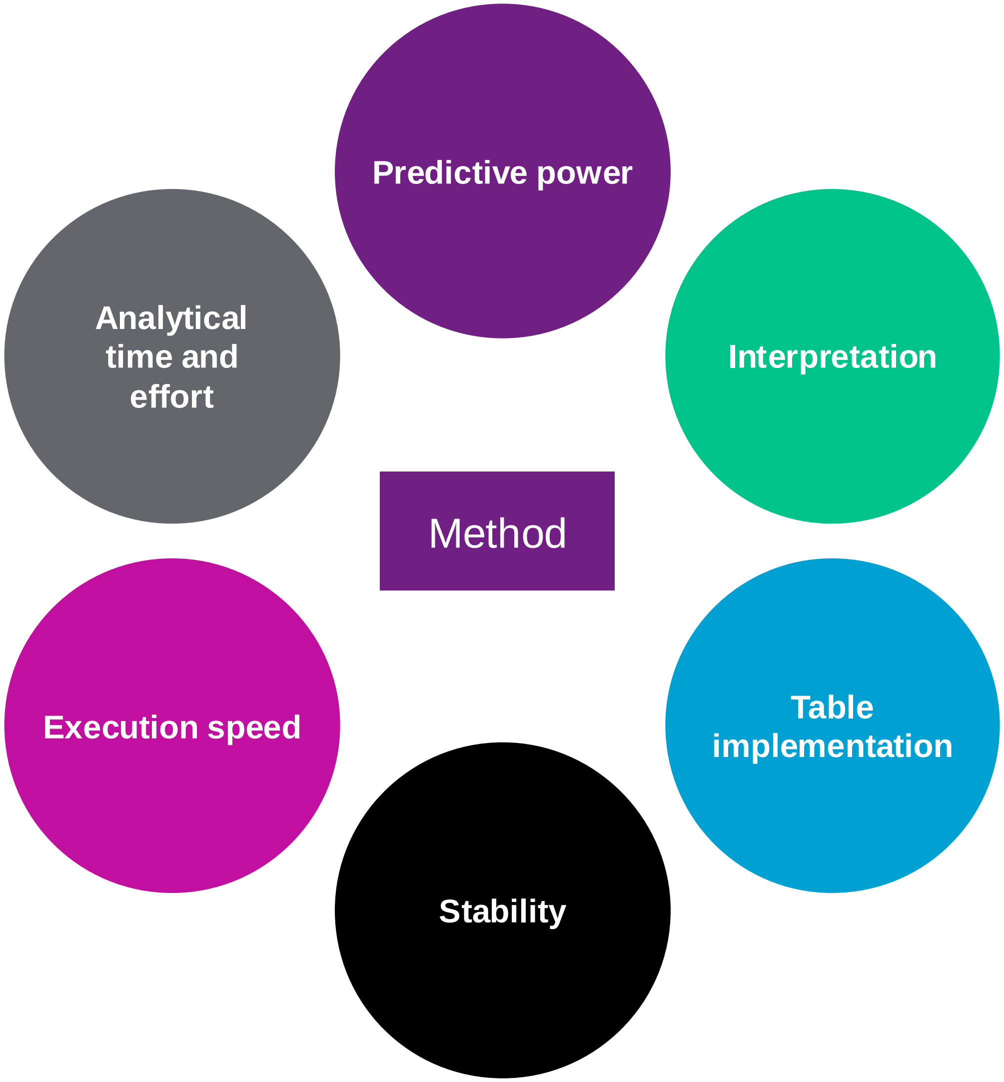
Applications

Applications of predictive models in reserving

- Validate traditional reserve estimates and assumptions
- Understand the influence of individual claims on reserves
- Assist adjusters to set individual case reserve estimates
- Micro-level stochastic loss reserving
- Predict large losses
  - Underwriting
  - Scenario test effect of different XOL reinsurance treaties
  - Economic capital models
- Input to claims triage exercise
  - Assigning adjusters and claims-handling protocols based on propensity of claim becoming complex
  - Complex can be defined as high probability to settle at large amount, high probability to escalate from early reserve, etc

Considerations

Evaluating predictive models for an application



Conclusions

- There is appetite to use predictive models in reserving to address inconsistencies in (aggregated) data and to provide additional insights into cost drivers
- Structuring data for modeling individual claims requires careful planning including – cause of loss coding, claim-level predictors at points in time and opportunities for additional data enrichment
- Model forms include statistical and machine learning, and often one model improves (rather than replaces) another
- Applications include reserving analyses validation, case reserve estimation, large loss prediction in UW, reinsurance, economic capital models and claims triage
- Domain experts must weigh predictive power with critical deployment considerations

Thank you

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