2015 CAS Ratemaking and Product Management Seminar

Predicting the Unpredictable Commercial Line Business

Predictive Modeling Applications for Commercial Specialty Lines

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Dallas, TX

March 10th, 2015

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Agenda

1. Overview and challenges of modeling specialty lines

   Matt Carrier – Deloitte Consulting LLP

2. Modeling approach and considerations

   Denys Lebedev – Deloitte Consulting LLP

3. Effective implementation and change management for specialty lines

   Kim Holmes – XL Group

Overview and Challenges of Modeling Specialty Lines

Road to the “Insight Economy”

Trends: Internet Of Things | Big Data | Data Science / Machine Learning

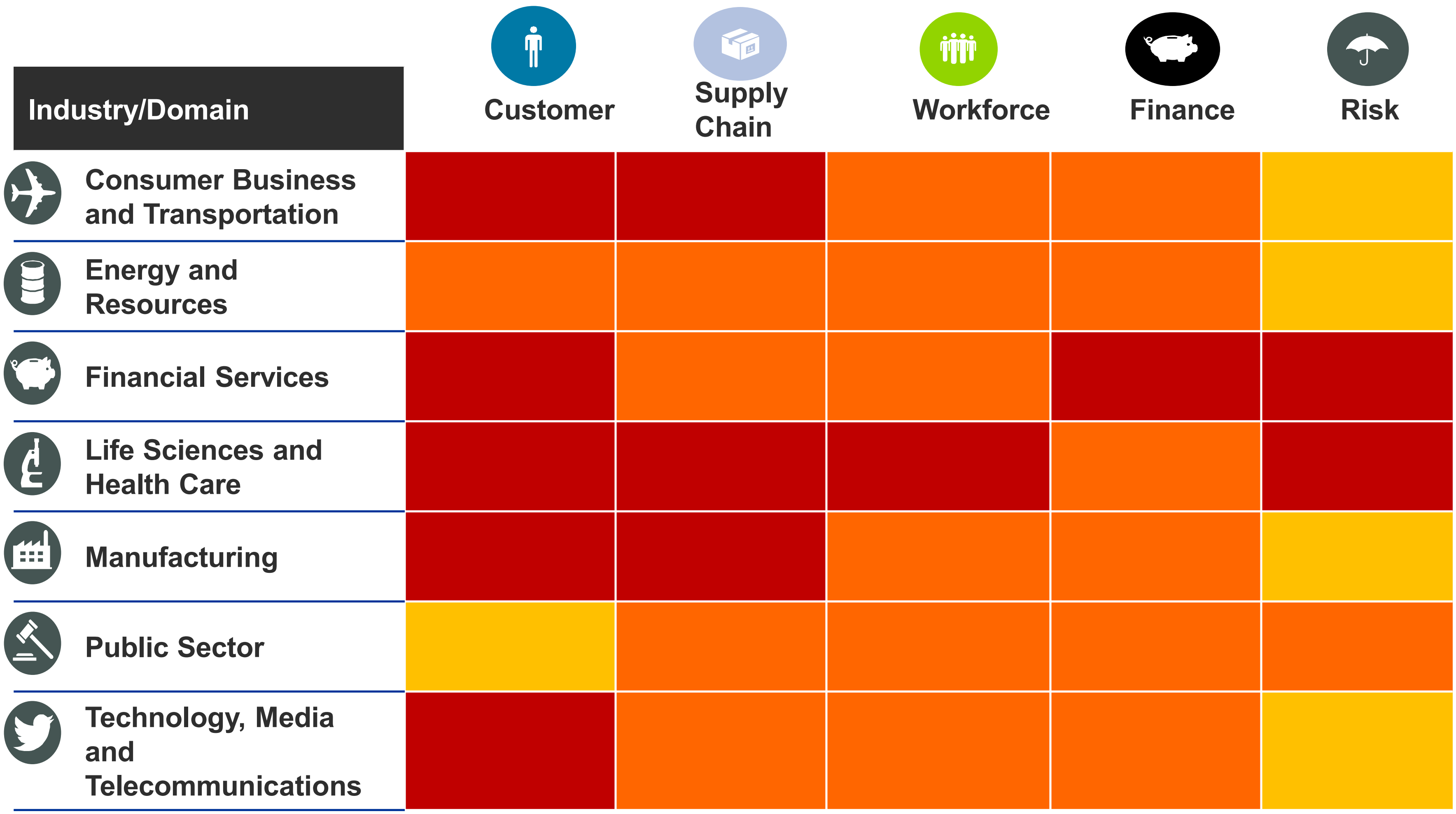
Innovation: New Data | New Processes | New Insights

Insight Economy

- **Zero Latency** information flow
- **Integrated ecosystem** – customers, employees, shareholders, suppliers
- **Secure data** exchange with opt-in permissions

- **Culture of data-driven decision making**
- **Integration of operational and behavioral data**
- **Machine-learning detection of patterns and trends for improved diagnostics**

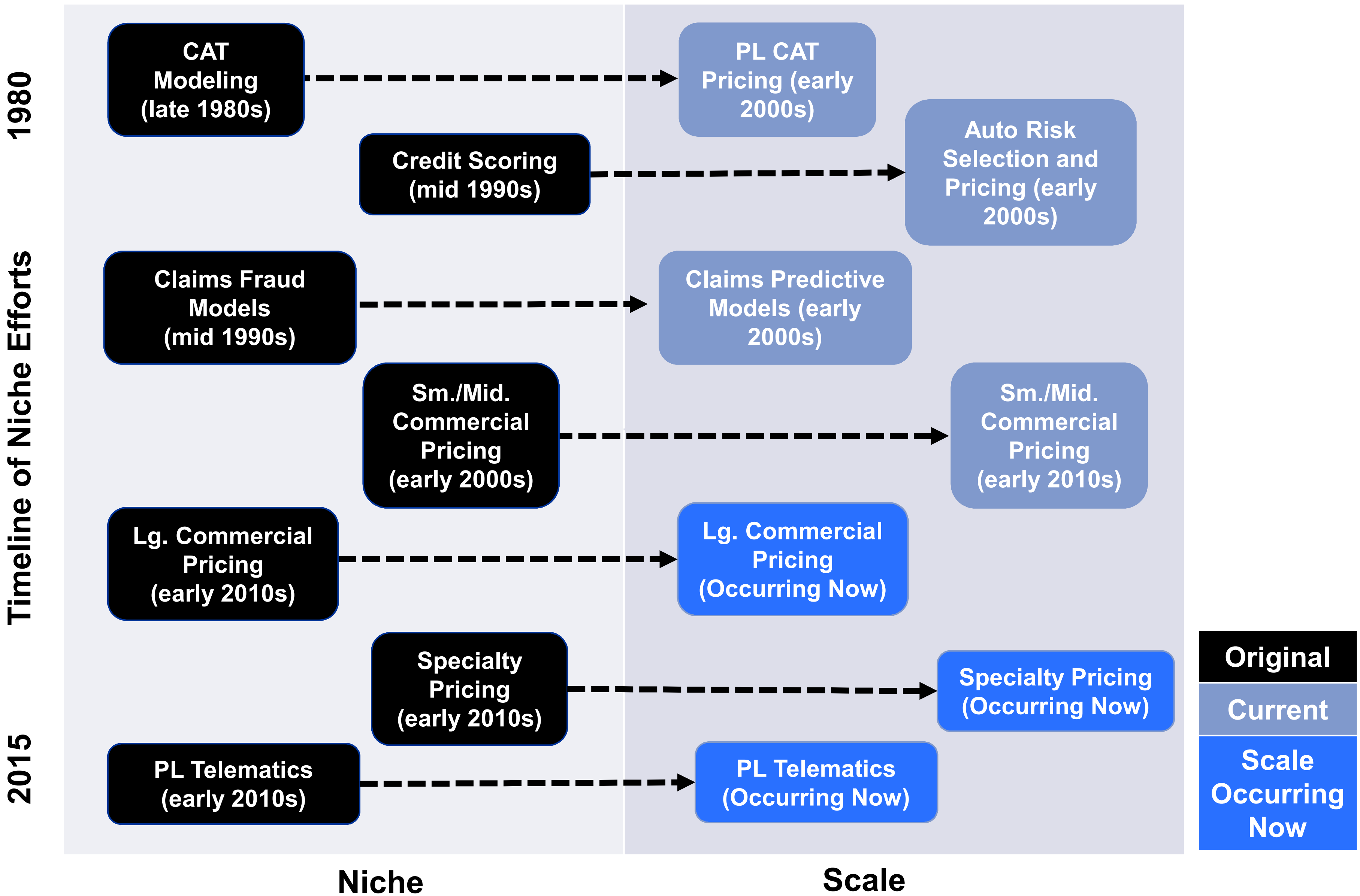
Where is analytics creating value?



Heat Map: Warm | Hot | Boiling

Source: Deloitte analysis, 2015

Analytics in P&C: "Table Stakes" Capabilities



Overview of Modeling Specialty Lines

- Liability driven business with a wide range of coverages: EPL, D&O, Crime, Fiduciary, E&O, etc.
- Products and coverage not uniform from one carrier to another
- Exposure vary greatly between Private vs. Public Companies
- "Account/multiple" products vs. "single" product
- Presence of multi-year policies
- Typically claims made policies, not occurrence
- Presence of complex reinsurance contracts

Challenges of Modeling Specialty Lines

- Very low frequency: on average, 1 claim per $100,000 premium compared to 5 claims per $100,000 for GL
- High severity: High claim values and policy limits can be as high as $10M+
- Long development patterns:
  - Strong upward case development
  - Late conversion of notice claims to real claims
- Data credibility: much less data points compared to personal or standard commercial line. Not uncommon to have only a few thousand data points for modeling
- Data quality issues:
  - Less standardization
  - More missing information
  - More subjective factors
- For different products, patterns and factors are different: calling for separate modeling by product

Modeling Approach and Considerations

High-Level Model Design

- Modeling by product / segment
- New vs. Renewal business

?

Do we have Combo policies?
What should we do with them?

D&O	EPL	E&O	Other Segments
New Business	**New Business**	**New Business**	**New Business**
Renewal Business	**Renewal Business**	**Renewal Business**	**Renewal Business**

?

Should we model New business
and Renewal business separately?

Modeling Approach

- Various modeling techniques can be used:
  - Regression
  - GLM
  - Neural Networks
  - Decision Trees
  - Etc.
- In Deloitte's experience, the better solution is to produce a linear scoring model
  - GLM technique with *link = log* and *distr = Tweedie*

$$LR = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_N X_N$$

  - Advantages:
    - Stability of model results
    - Easy to understand, not black box
    - Easy to explain
    - "Ranking" models are less sensitive to distribution assumptions or non-linear patterns than non-ranking models

Target File and Variable Creation

$$LR = \alpha + \underbrace{\beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_N X_N}_{\text{Predictive (independent) variables}}$$

Target (dependent) variable

Losses: use developed trended incurred loss and expense capped at policy limit

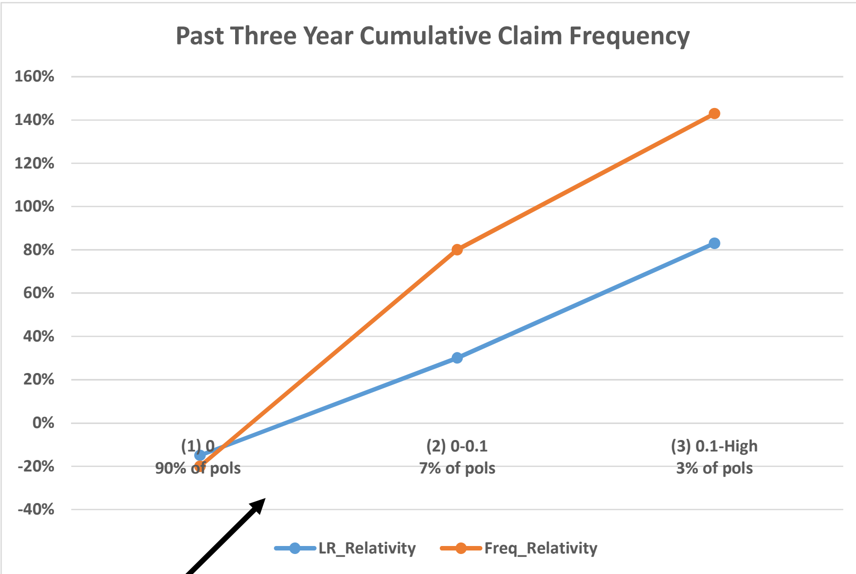
Premiums: use on-leveled “basic limit” manual premium

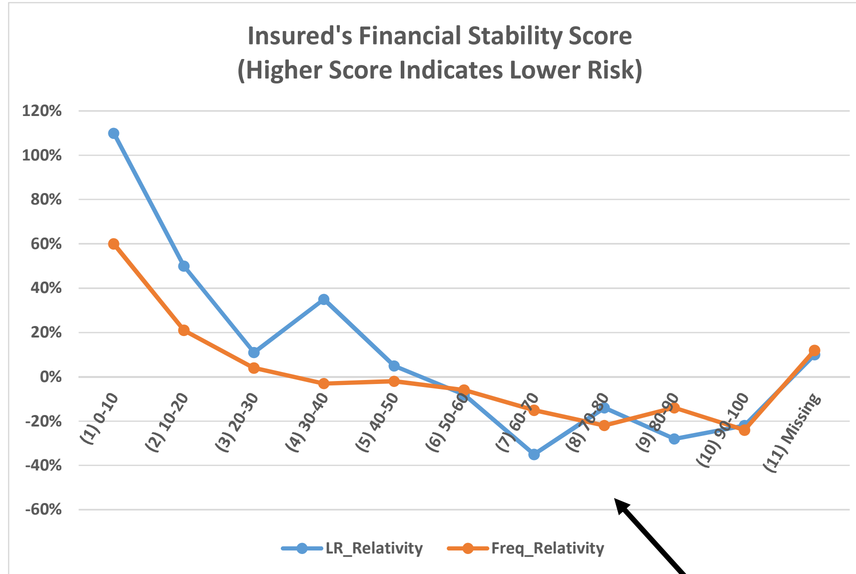
Predictive (independent) variables

Internal	**External**
Policy	Demographic Data
Agency	Insured’s Financial Stability Data
Billing	Litigation Data
Historical Loss	Other External Data

Industry/Segment Specific Vars

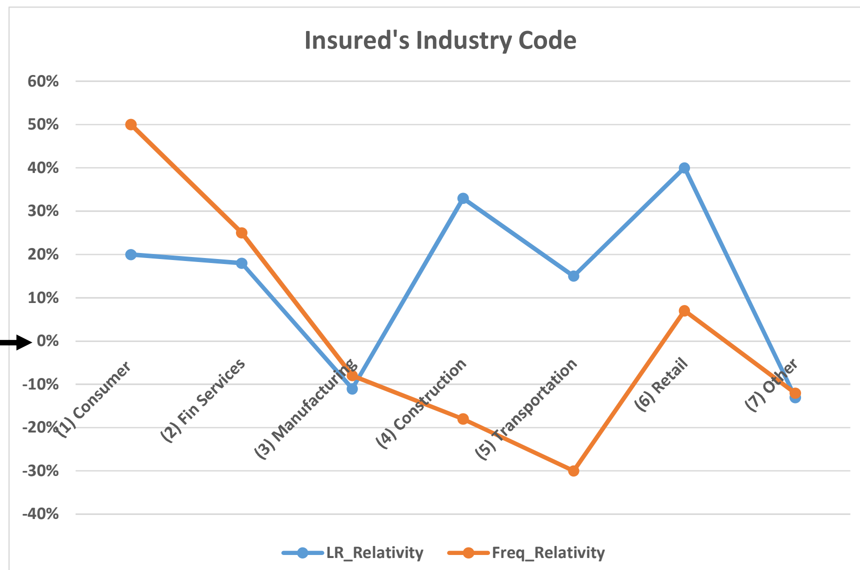
Univariate Analysis





Strong positive correlation between predictive and target variable

Strong negative correlation between predictive and target variable



Consider creating 0-1 indicators for some levels of categorical variable "Industry Code"

Model Build Process

Modeling Dataset

Correlation Analysis

Stepwise Regression & Principal Components

Modeling Iterations

Model Analytics

Modeling dataset production

- Review frequency distribution of predictive variables -> initial variable filtering criteria
- Review binning and create missing indicators

Correlation analysis

- Review all highly correlated pairs of variables
- 2nd variable filtering criteria

Stepwise & principal components analysis

- Run stepwise regression -> 3rd variable filtering criteria
- Assess correlated variables for statistical stability
- Reduce the number of model parameters

Modeling iterations

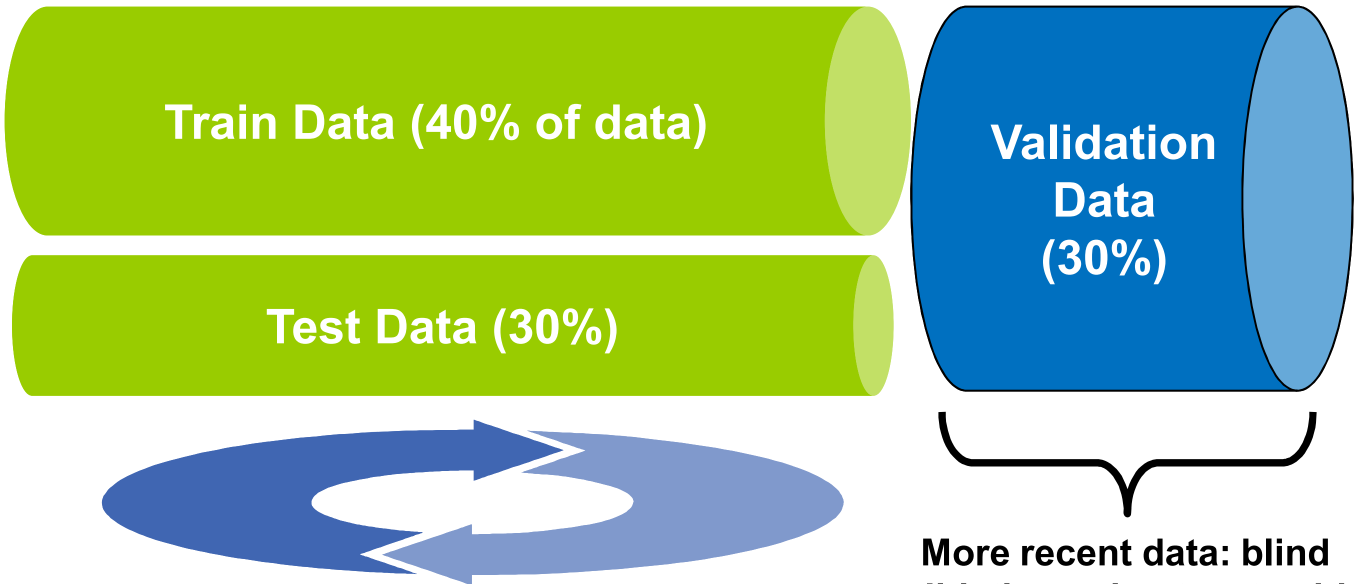
- Perform modeling iterations using various combinations of predictive and target variables
- Use multiple random splits to ensure the robustness of the model

Analytics to test model's reasonability

- Conduct blind validation to test the performance of the models
- Review results by different slices of data (industry, geography)

Train – Test – Validation Approach

The modeling dataset is split in 3 to help ensure the development of a robust model

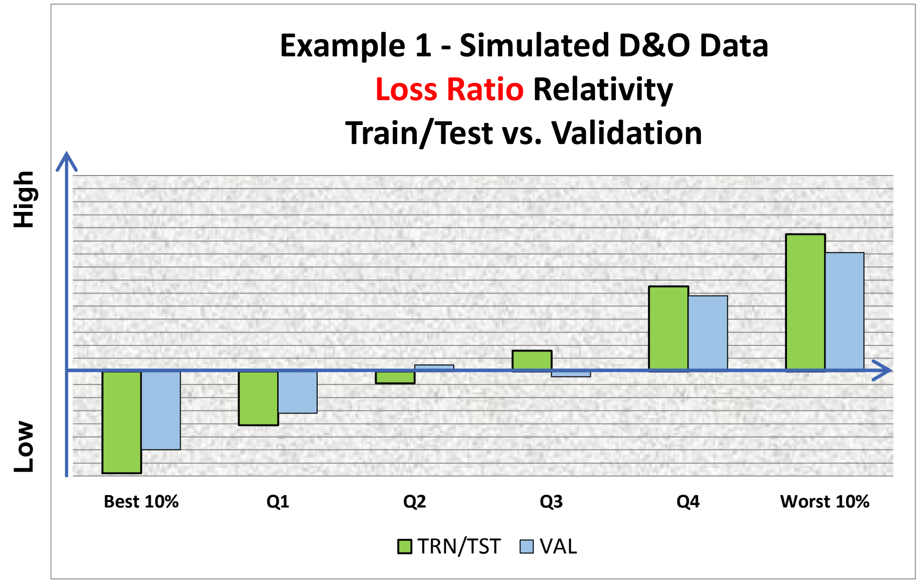


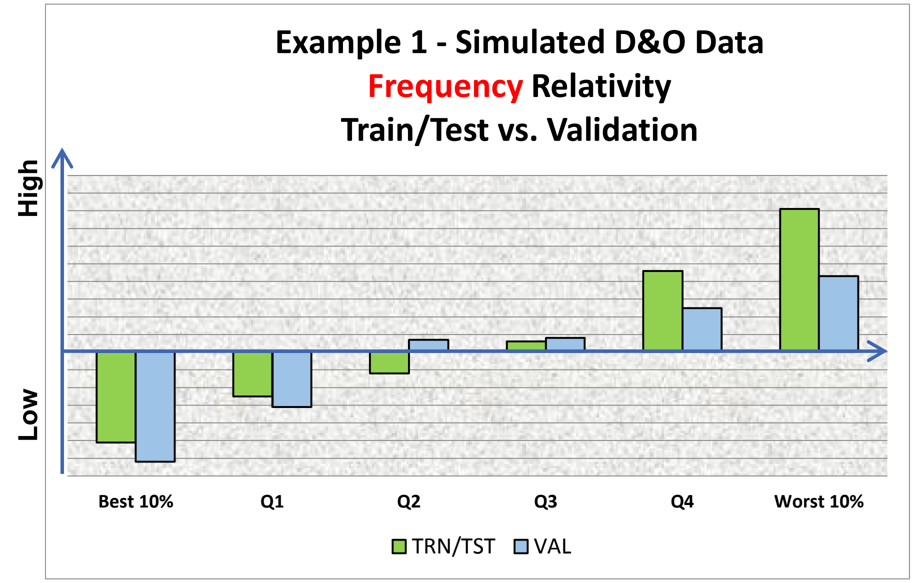
Iterative model building

More recent data: blind validation subset, set aside to evaluate model's performance

Model Performance Evaluation: Example #1

The example below illustrates successful application of the standard Train-Test-Validation approach to the simulated D&O dataset consisting of 10,000 policies

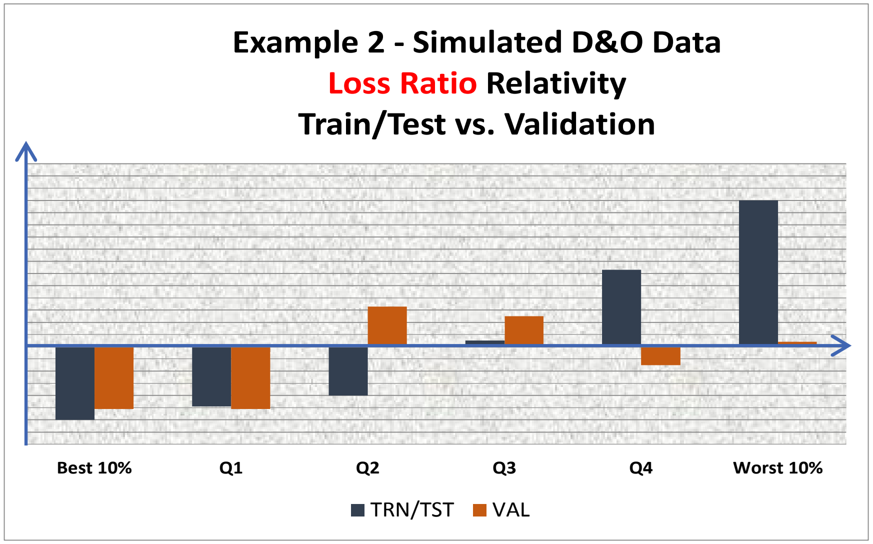


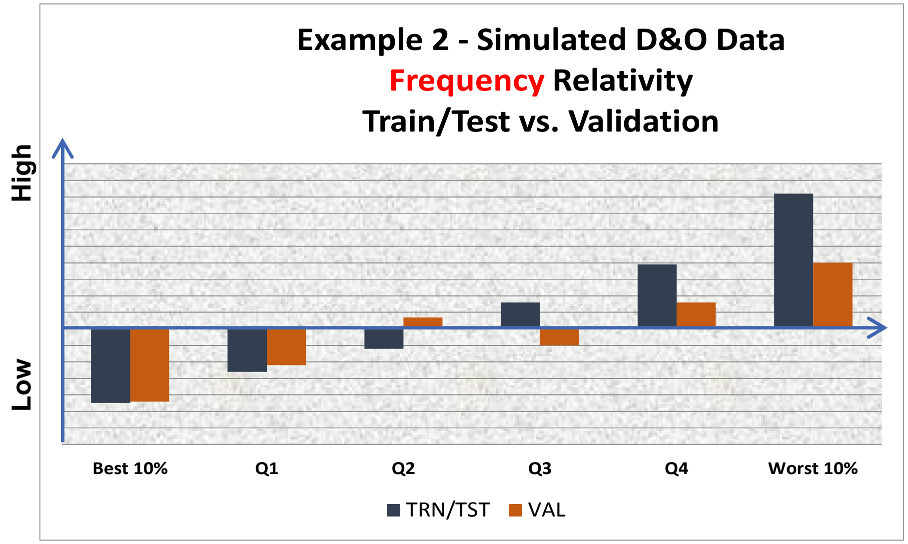


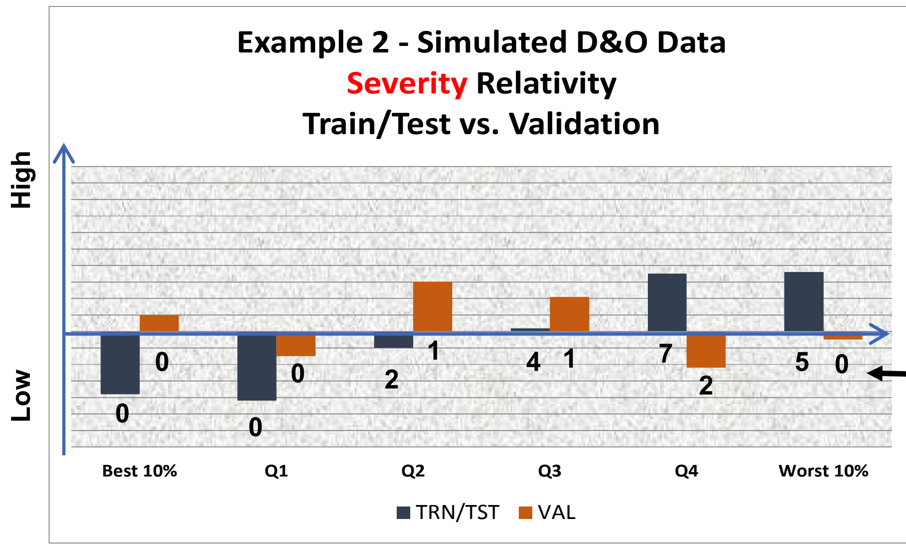
- Lift reversals may exist
- Focus on trend
- Review both loss ratio and frequency lift curves to ensure that the model is robust
- Look for consistency between loss ratio and frequency relativity patterns

Model Performance Evaluation: Example #2

What if the standard Train-Test-Validation approach yields less than optimal results? In the example below, frequency lift curve seems acceptable, while the loss ratio lift curve "crashes"







Claims greater than $200,000

Cross-Validation Approach

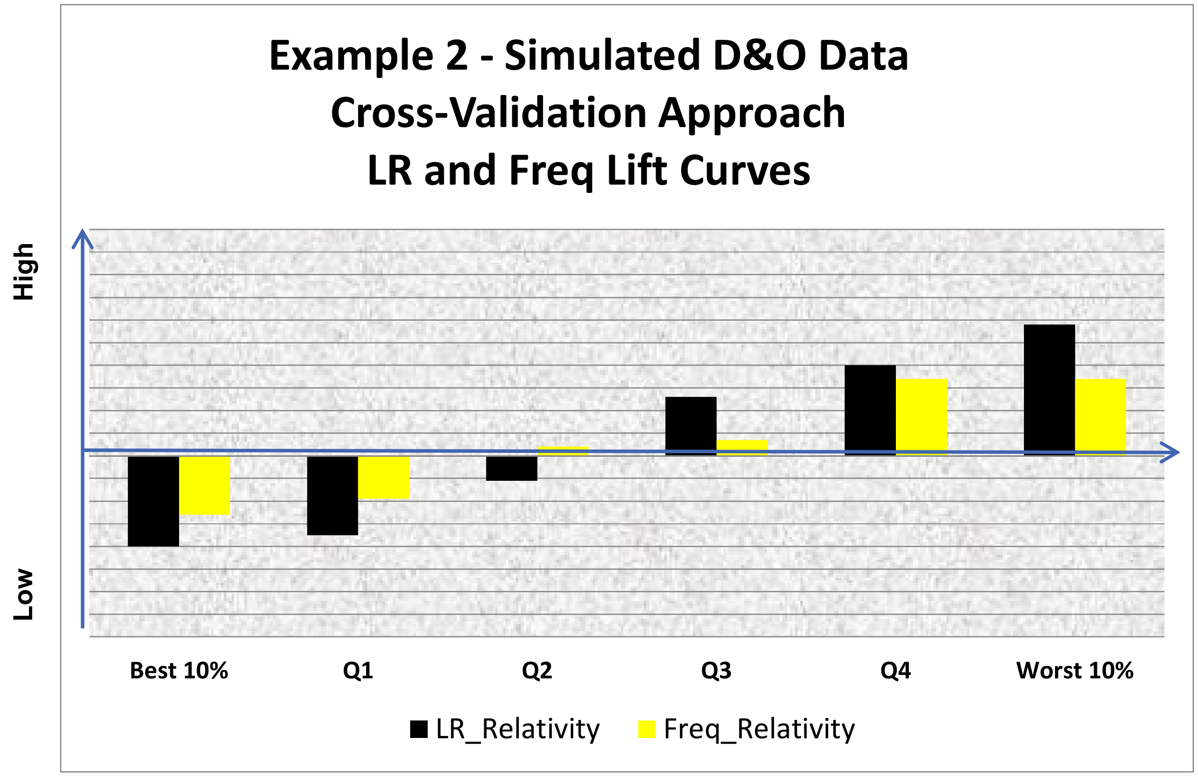
When modeling data is thin, standard Train-Test-Validation approach may not be feasible. Use of Cross-Validation will allow all data to be used to construct and test the model.

Cross Validation					
Model	Modeling Data				
	P1	P2	P3	P4	P5
M1	Test	Train	Train	Train	Train
M2	Train	Test	Train	Train	Train
M3	Train	Train	Test	Train	Train
M4	Train	Train	Train	Test	Train
M5	Train	Train	Train	Train	Test

- Data is randomly split into 5 bins (P1-P5)
- Model M1 is fitted P2-P5 and used to score P1, Model M2 is fitted on P1 and P3-P5 and used to score P2, etc.
- P1 to P5 test scores are put together to create a lift curve
- All data points were used to fit the model, and at the same time all data points were used to test the model**.**

Cross-Validation Approach in Action

The use of cross-validation approach solves the problem for Example #2 dataset. Now both loss ratio and frequency relativity lift curves display reasonable increasing pattern.



Other Measures of Model's Performance

- The signs of parameter estimates should be "intuitive" and easy to explain

$$LR = \alpha + \beta_1 X_1 - 0.123\ (3\ Year\ Claim\ Frequency) + \ldots + \beta_N X_N$$

?? ***Why is the sign negative? Will I be able to explain this to end-user?***

- The signs and magnitude of parameter estimates should also be stable across multiple random splits

	Split1	Split2	Split3	Split4	Split5
Variable X	0.204	0.197	0.231	0.228	0.184
…	…	…	…	…	…

The PEs show stable pattern. Good!

- The lift curves should exhibit stable patterns for various sub-groups of the dataset:
  - By year
  - By state/geography
  - By industry, etc.

Modeling Approach - Conclusions

- Given the many different modeling techniques, regression/GLM performs sufficiently
- A modeler should emphasize robustness of modeling results for specialty lines
- Lack of modeling data can be overcome with use of cross validation approach
- A modeler needs to objectively evaluate different aspects of model's performance
- With careful model design, segmentation can be achieved for specialty lines

Deloitte.

ADVANCED ANALYTICS FOR SPECIALTY LINES

Effective Implementation and Change Management

March 2015

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Agenda

- Implementation
- Change Management
- Benefits

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Implementation

Implementation – Business Rules

- How will decision makers will use the model?
  - How much flexibility to decision makers have to deviate from model recommendations
  - Will different types of business have separate rules – new v renewal, regions, etc.
- Best practices
  - The business decides the rules
  - Set a target improvement up front, before creating the rules
  - Establish rules that will deliver the target improvement
  - Adhere to all regulatory constraints
- Deliver to the business messaging that they can use when discussing submissions/quotes with agents

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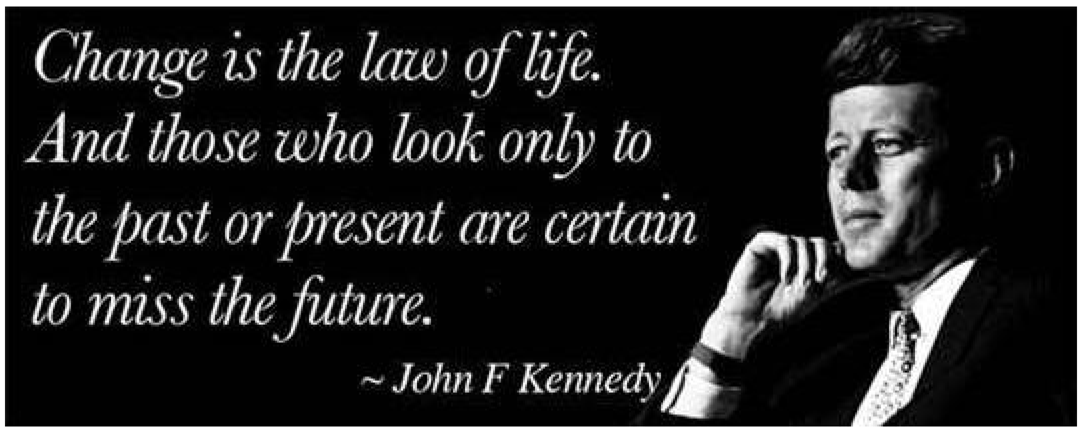
Implementation - Technology

Non-Negotiables	How to Make this Happen
• Users cannot opt out of using the model • Users cannot game the system • Model gets run at the beginning of the process • Save all data used and generated for future analysis	• Automate the triggering of the tool • Automate, to the extent possible, the capturing of data which feeds the tool • Monitor re-scoring • Ensure inputs are available at the time the tool will be run (do this at the beginning of model build!) • Embed tool into the beginning of process • Create appropriate data architecture to support data capture and reporting

Change Management



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Nothing improves without some change

Change management

- The most critical part. If you don't get adoption right, it doesn't matter how good your model is.
- The hardest part. Getting people to change behavior is much harder than the data and analytics are.
- Yet it is often the most overlooked part of the model development.

"I want you to find a bold and innovative way to do everything exactly the same way it's been done for 25 years."

Effective Change Management Starts at the Beginning

Focus on real business problems & businesses who want to work with you

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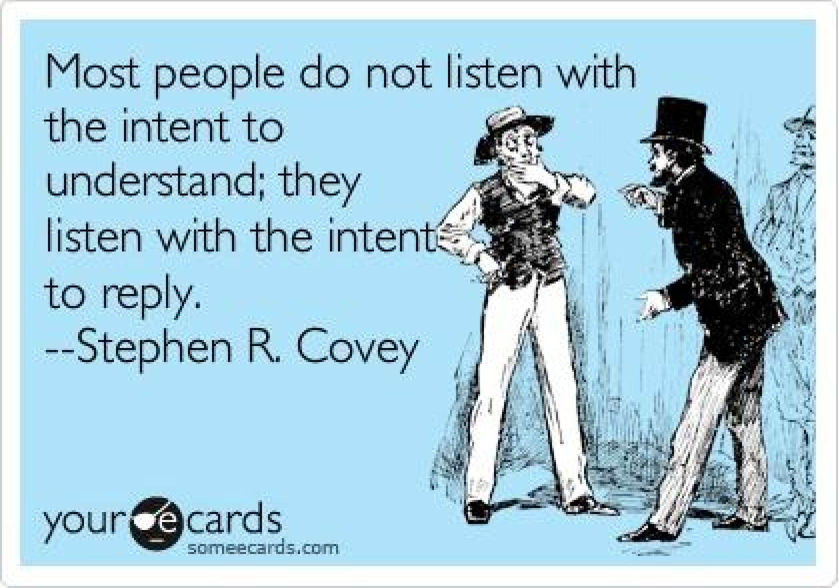
Focus on Change Management Throughout the Model Build

Partnership in Model Build

- It is the underwriters' model
  ... not the actuaries' model
  … not the modelers' model
- Business contributes to key decisions from design of experiment to final model
- Transparency is not enough. Involvement of the business is critical.

Change Management Advice

- Listen More.   Talk Less.
- You can't spend too much time on what's in it for them
- Get commitment up front about expected benefit
- Balance buy-in with model quality
- Never dismiss concerns
- Be positive and empathetic.   It is contagious.
- Address business adoption questions at early stages – ex: what do we say to agents?



Measuring Benefits

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Measuring the Benefit of a Segmentation Model

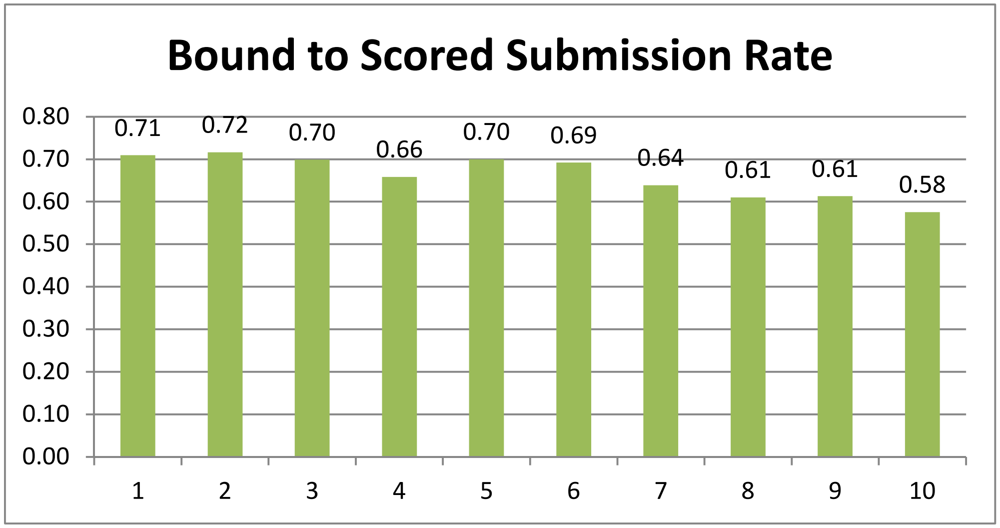
The business rules should reflect where the benefit comes from

- The worst risks are underpriced by the market
  - There is no achievable right price for a bad risk because a competitor will always charge less than your "right" price
  - Business should write fewer of the bad risks
- The best risks are overpriced by the market
  - Business should write more of the best risks
  - Best risks will be profitable, even with slightly reduced rates

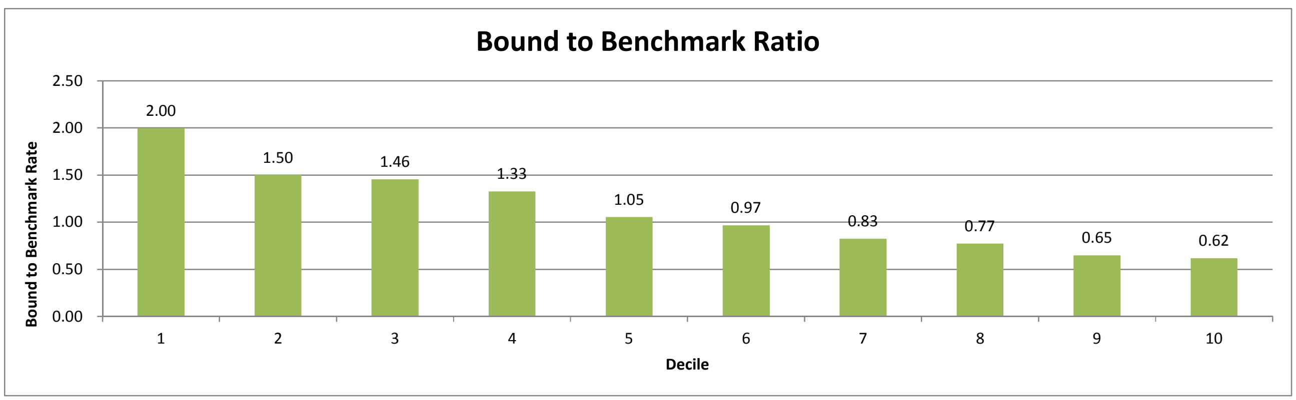
At a minimum we should measure

- The shift in mix of business – less of the bad, more of the good
- Rate change on renewals – how much decrease is necessary to grow the book of good risks?
- Rate adequacy of new business – how does market price compare to benchmark

Measure Results – If you measure it, behavior will follow



Is the business binding more of the lower deciles and fewer of the higher deciles?



What is happening to rate adequacy?

Questions?
Comments?

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