

# 2014 Centennial Celebration and Annual Meeting

New York Hilton Midtown  
New York City, NY, USA  
November 9–12, 2014



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A black silhouette of a city skyline, including various skyscrapers and buildings, is positioned horizontally across the middle of the image.

**CELEBRATING  
OUR PAST,**

**FOCUSED ON  
THE FUTURE**

# Session C-31: Predictive Analytics in P&C Insurance

- **Tuesday, November 11, 2014: 01:00 p.m. - 02:30 p.m.**, New York Hilton Midtown, Sutton North
- **Wednesday, November 12, 2014: 08:00 a.m. - 09:30 a.m.**, New York Hilton Midtown, Beekman
- **Tim Fleming:** FCAS, Commercial Lines Actuarial, CNA Insurance
- **Brian M. Stoll:** FCAS, MAAA, Director, Towers Watson
- **JF. Breton:** BSc. Maths, MBA, Senior Application Engineer, MathWorks



# Introduction

- **Who we are:**
  - **Tim Fleming:** FCAS, AVP & Actuary - Pricing, CNA Insurance
  - **Brian M. Stoll:** FCAS, MAAA, Director, Towers Watson
  - **JF. Breton:** BSc. Maths, MBA, Senior Financial Engineer now at MathWorks
- **In this session:**
  - We will cover different best-practice predictive modeling techniques in property and casualty insurance from a practical point of view (no theory today)
  - How can predictive models complement P&C actuarial work?
- **At the conclusion of the session you will be able to:**
  - understand the role of predictive modeling in actuarial work and also understand some specific predictive models and how these models can be used in P&C insurance.



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# Agenda

- Intro
- Predictive modeling background
- P&C Insurance Applications Part 1
- P&C Insurance Applications Part 2
- Q&A



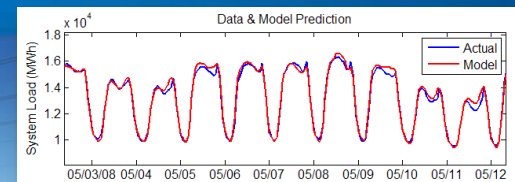
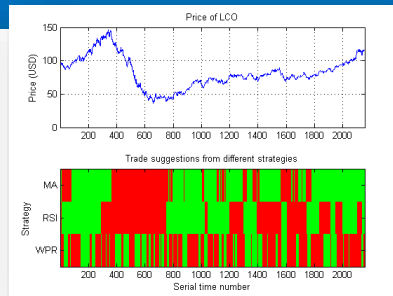
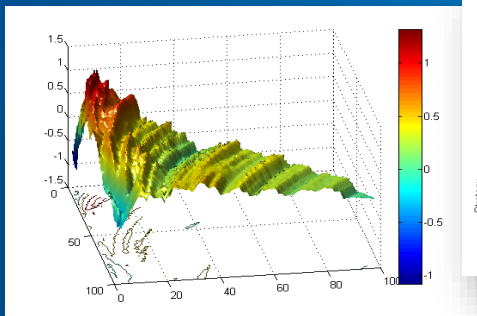
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# What is predictive modeling?

- Use of mathematical language to make predictions about the future
- More of an art than a science



## Generic examples:



Trading strategies

Electricity Demand

# Macro trends that drive the use of these models

- Available technology and large amount of data
- Increased need for customized products/services
- Pressure on top/bottom line of income statement

(ref: 2013 SOA Annual Conference Session 180: Looking Toward the Future)



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# State of the art: 2013 P&C Insurance predictive modeling survey

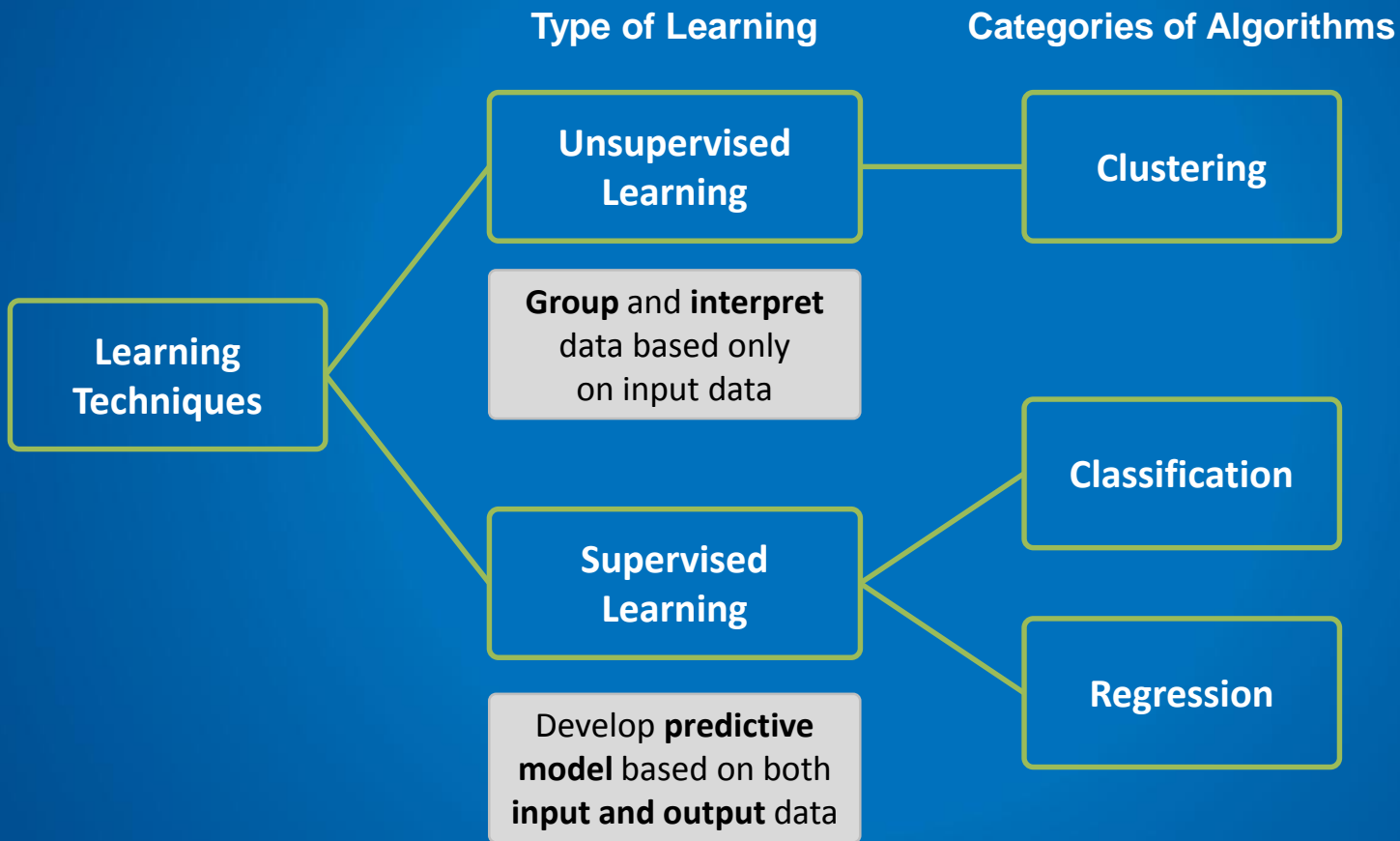
- **Impacts**
  - Predictive models now widely used
  - Pricing and underwriting are main applications
  - Benefits seen on profitability, risk reduction and operational efficiency
- **Challenges**
  - Lack of sufficient data attributes and skilled modelers
  - Data prep and model deployment can often take +3 months each
  - Big Data is currently mainly leveraged by large insurers

(Source: Earnix)



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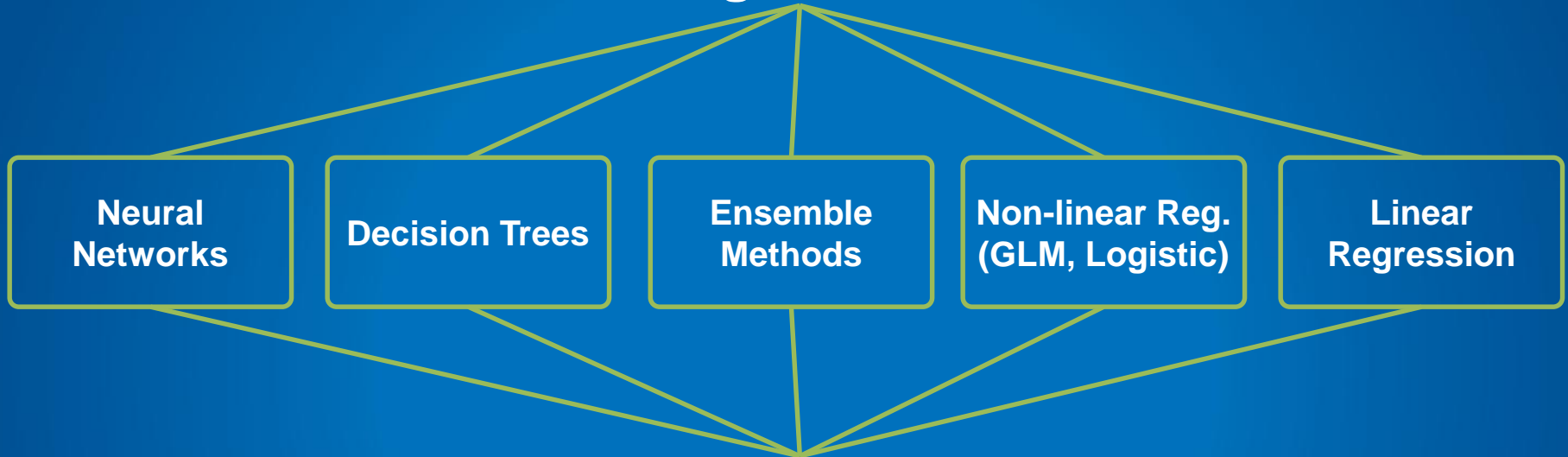
# Overview – Learning Techniques



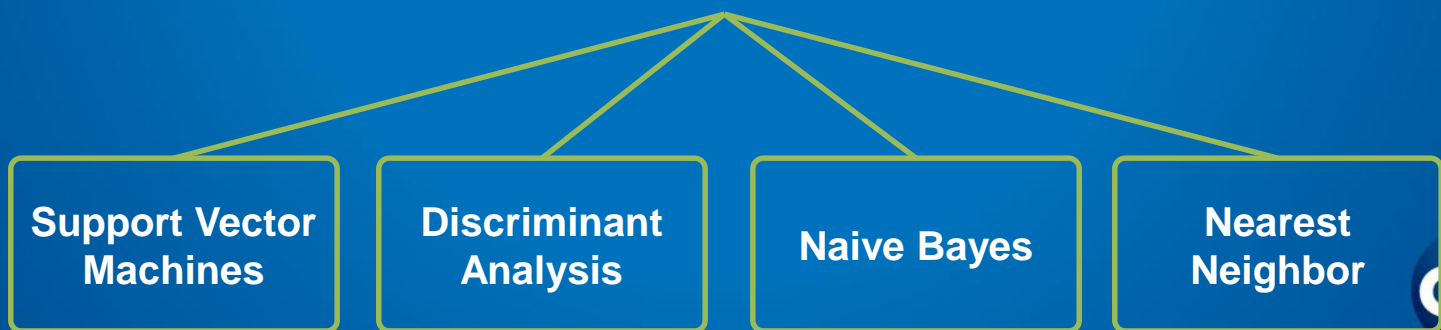


# Regression vs Classification techniques

## Regression



## Classification



# Entry point: Generalized Linear Models

GLMs have become the most common tool for model development in life insurance as a result of their ability to accommodate forms other than normal, and for being relatively easy to explain

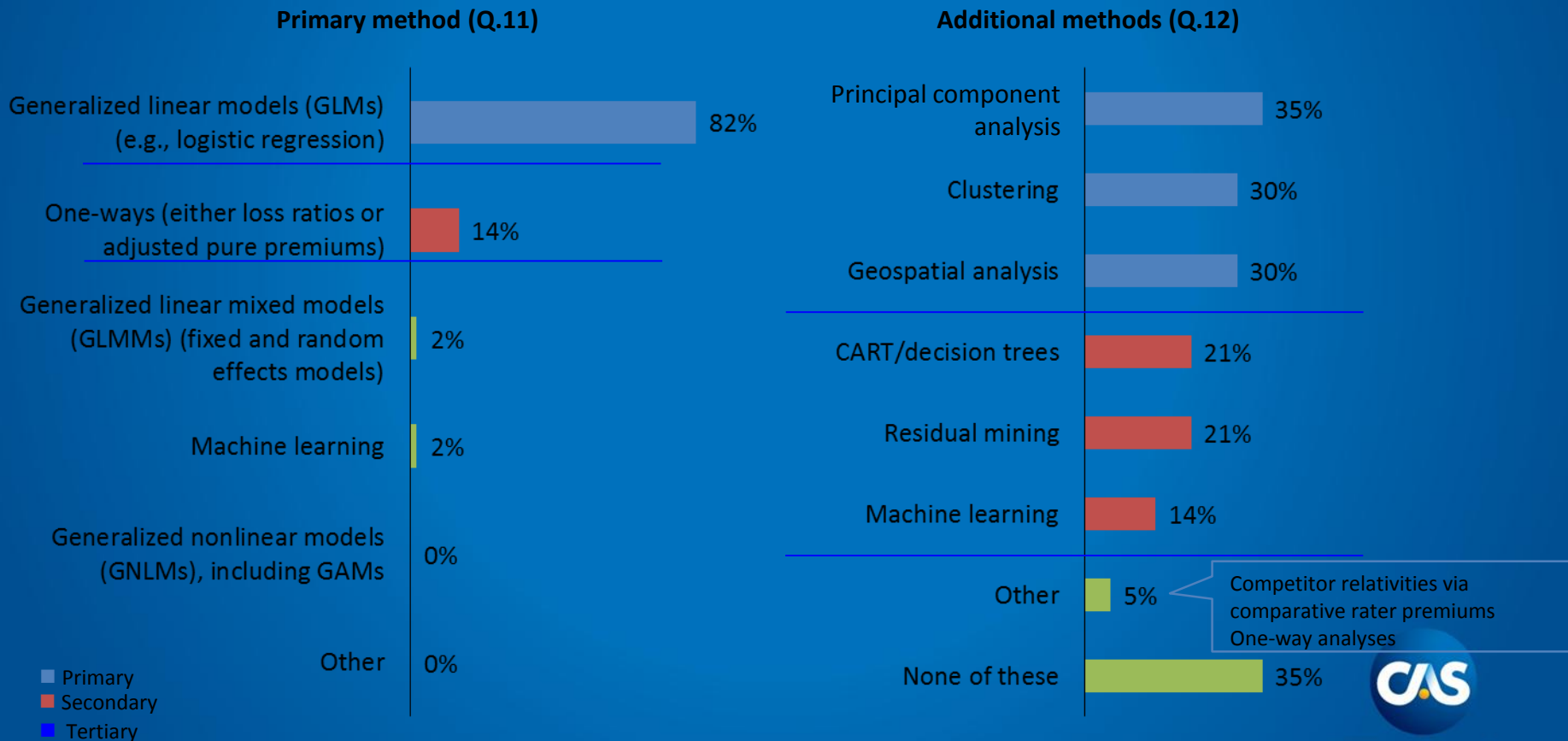
## Common GLM Applications:

Technique	Link Function	Distribution	Application
Classical Regression (Ordinary Least Squares)	Identity: $g(\mu)=\mu$	Normal	<b>General Scoring Models</b>
Logistical Regression	Logit: $g(\mu)=\log[\mu/(1-\mu)]$	Binomial	<b>Binary Target Applications (i.e. Retention)</b>
Frequency Modeling	Log: $g(\mu)=\log(\mu)$	Poisson Negative Binomial	<b>Count Target Variable Frequency Modeling</b>
Severity Modeling	Inverse: $g(\mu)=(-1/\mu)$	Gamma	<b>Size of claim modeling</b>
Severity Modeling	Inverse Squared: $g(\mu)=(-1/\mu^2)$	Inverse Gaussian	<b>Size of claim modeling</b>

# Most carriers rely on GLMs as their primary method of loss cost analysis; principal components analysis, clustering and geospatial analysis are common secondary approaches

What is your primary method for analyzing loss cost differentials for pricing/underwriting? (Q.11)

What additional methods, if any, do you use to augment (or validate) your analysis for loss cost differentials? (Q.12)



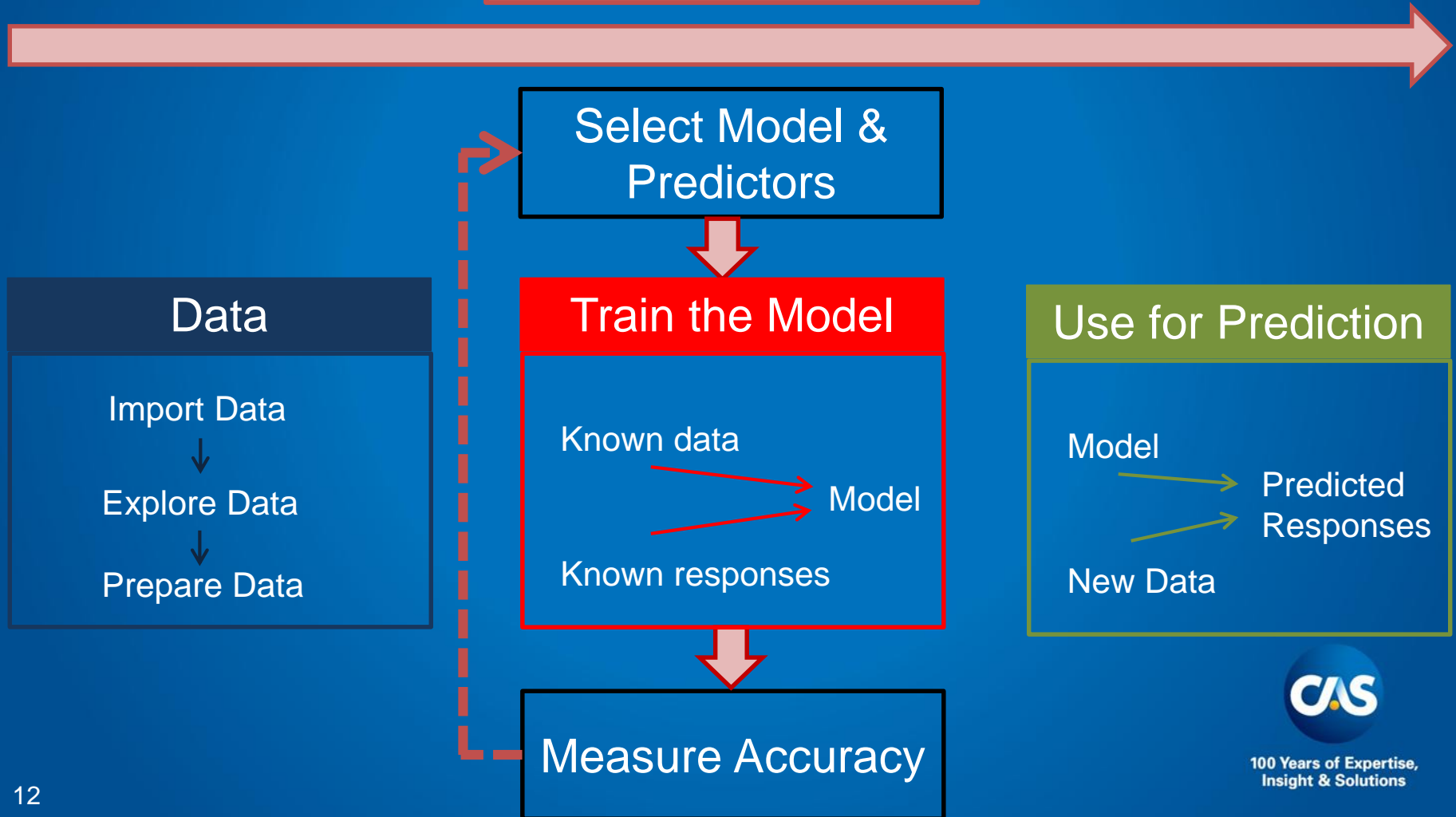
Base: U.S. respondents currently using predictive modeling for at least one line of business (n = 43).



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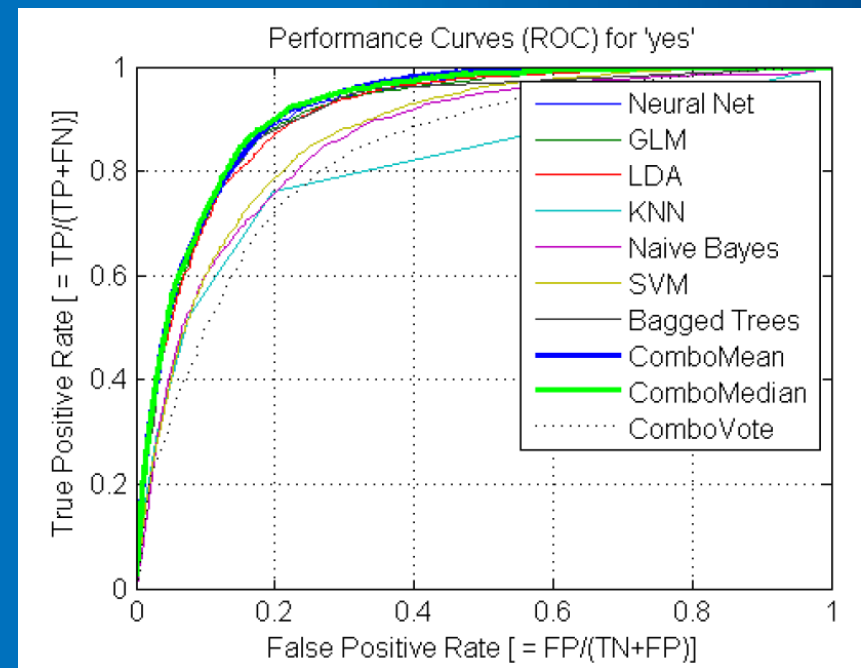
# Predictive modeling workflow

Speed up Computations



# Best practices and measures of quality

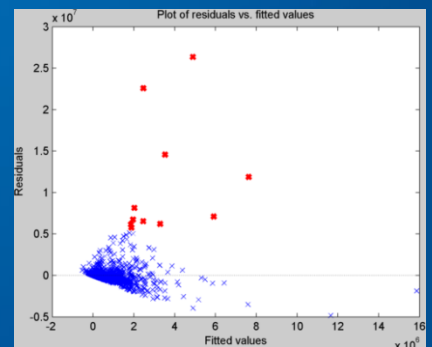
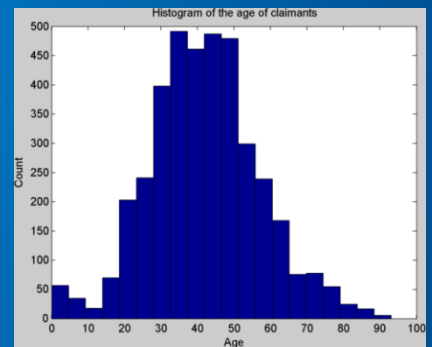
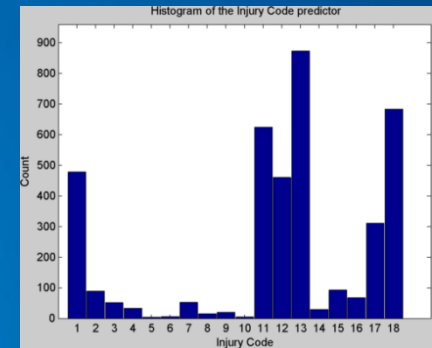
- **Best-practices**
  - Split the available data between a training set and a testing set
  - Try out and compare different models
  - Measure the accuracy of the models
  - Simplify your model when possible
- **Some measures of accuracy**
  - **Regression**
    - $R^2$
    - Standard deviation / variance
    - Mean Absolute Percentage Error
  - **Classification**
    - Area under the Receiver Operating Characteristic (ROC) curve
    - Cross-entropy
    - Confusion matrix



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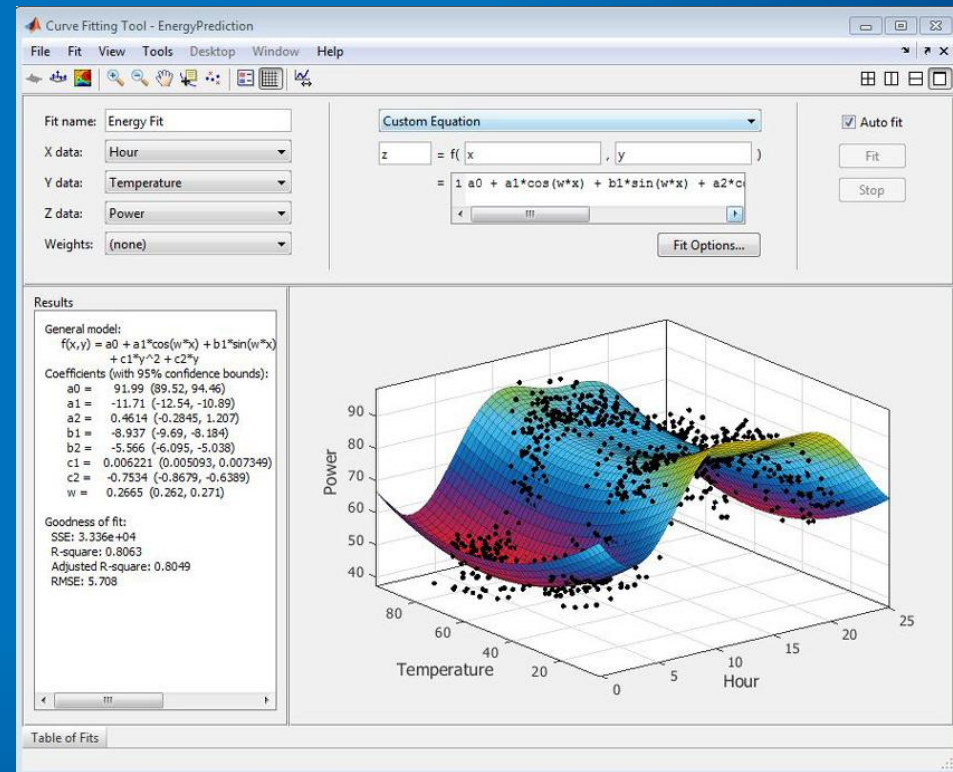
# Short Example – Claim Settlements Forecasting

- Goal:
  - Produce accurate model to predict insurance claim settlement amount
- Approach:
  - Train a regression model using different techniques
  - Measure accuracy and compare approaches
  - Use model for prediction



# Predictive analytics software

- Many packages for different applications, platform and modeling skills
- **Some packages used in P&C insurance:**
  - Angoss KnowledgeStudio
  - Excel
  - IBM SPSS Modeler
  - MATLAB
  - Oracle Data Mining
  - R
  - SAS Predictive Analytics
  - Towers Watson Emblem



# Agenda

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- Predictive Modeling Background
- P&C Insurance Applications Part 1
- P&C Insurance Applications Part 2
- Q&A

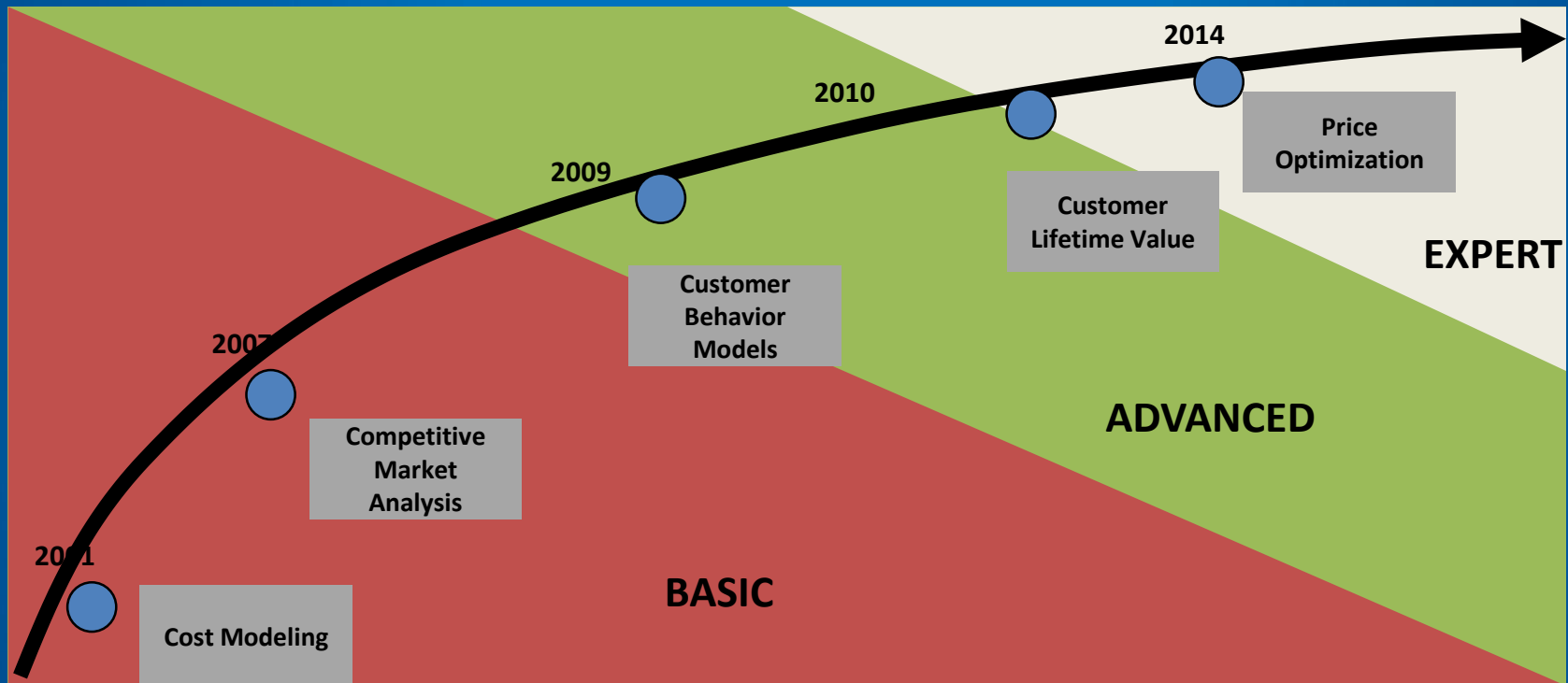


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# The industry has continued to move towards more sophisticated analyses, such as customer lifetime value assessment and optimization

- The timeline required to develop an integrated solution can be lengthy



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# Predictive modeling applications have become increasingly diverse in recent years

- Predictive modeling is being used to help integrate all aspects of companies' operations and identify the true customer value

## Technical Pricing

Pricing factors  
Company assignment  
Credits/debits

## Claims

Adjuster assignment  
Fraud identification  
Chronic opioid use  
PBM effectiveness  
Provider bill review  
Efficacy of treatment alternatives

## Risk Appetite

Risk selection  
Evaluate producers/regions  
Premium audit/inspections  
Credit analysis

## Marketing

Elasticity  
New Business Conversion  
Retention Impact and Renewal Strategies  
Campaign response rates

# P/C Applications of Predictive Modeling – Part 1

- 1) Competitive Market Analysis**
- 2) Claim Triage Modeling
- 3) Public D&O Modeling



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# All forms of competitive analysis resonate for personal lines carriers, but product market analysis appears most important for commercial lines, followed by qualitative competitive market analysis

What type of competitive information do you incorporate into your rate-setting process? (Q.20)

	Personal Lines		Standard Commercial		
	Personal auto (n = 40)	Home-owners (n = 37)	CMP/BOP (n = 42)	Comm. auto (n = 47)	WC (n = 34)
We obtain information from a qualitative review of competitor rate manuals, including a review of variables used, degree of segmentation, interaction between variables, etc. ( <b>qualitative competitive market analysis</b> )	70%	70%	43%	47%	35%
We obtain competitor premiums from agents, a comparative rating engine or hand-rating to gauge our competitive position ( <b>quantitative competitive market analysis</b> )	73%	70%	31%	34%	29%
We compare our product to products offered by competitors to understand differences in coverage options, terms and conditions ( <b>product competitive market analysis</b> )	65%	70%	57%	66%	32%
Not applicable — we do not gather competitive information for this line of business	10%	14%	24%	19%	35%

Base: U.S. respondents gathering competitive information for at least one line of business (percentages exclude 'Not applicable — we do not gather competitive information for this line of business' and 'Not applicable — we do not write this line of business').



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# Qualitative CMA focuses on a qualitative assessment of variables used, as well as the degree of segmentation and interaction between them.....

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## Summary Comparison of Rating Sophistication

Variable Type/Category	Factor Range	Combined Degree of Segmentation/Interaction						
		Company A	Company B	Company C	Company D	Company E	Company F	Company G
Coverage	N/A	Medium	Very high	Medium	High	High	Medium	Very high
Insurance score/tier	.4/1.8	High	High	High	High	High	Very high	Medium
Territory	.5/2.5	Very high	High	Medium	Very high	Medium	Very high	Medium
Driver-related	.6/1.5	Medium	Medium	High	High	High	Very high	Medium
Vehicle-related	.5/2.0	High	Medium	Medium	High	Medium	Medium	Medium
Household-related	.7/1.3	Medium	Medium	Medium	High	Medium	High	High
Miscellaneous	.8/1.2	High	High	N/A	Medium	N/A	Medium	Very high
<b>Overall</b>	<b>100%</b>	High	Medium	Medium	High	Medium	High	Medium

N/A    
 Low    
 Medium    
 High    
 Very high

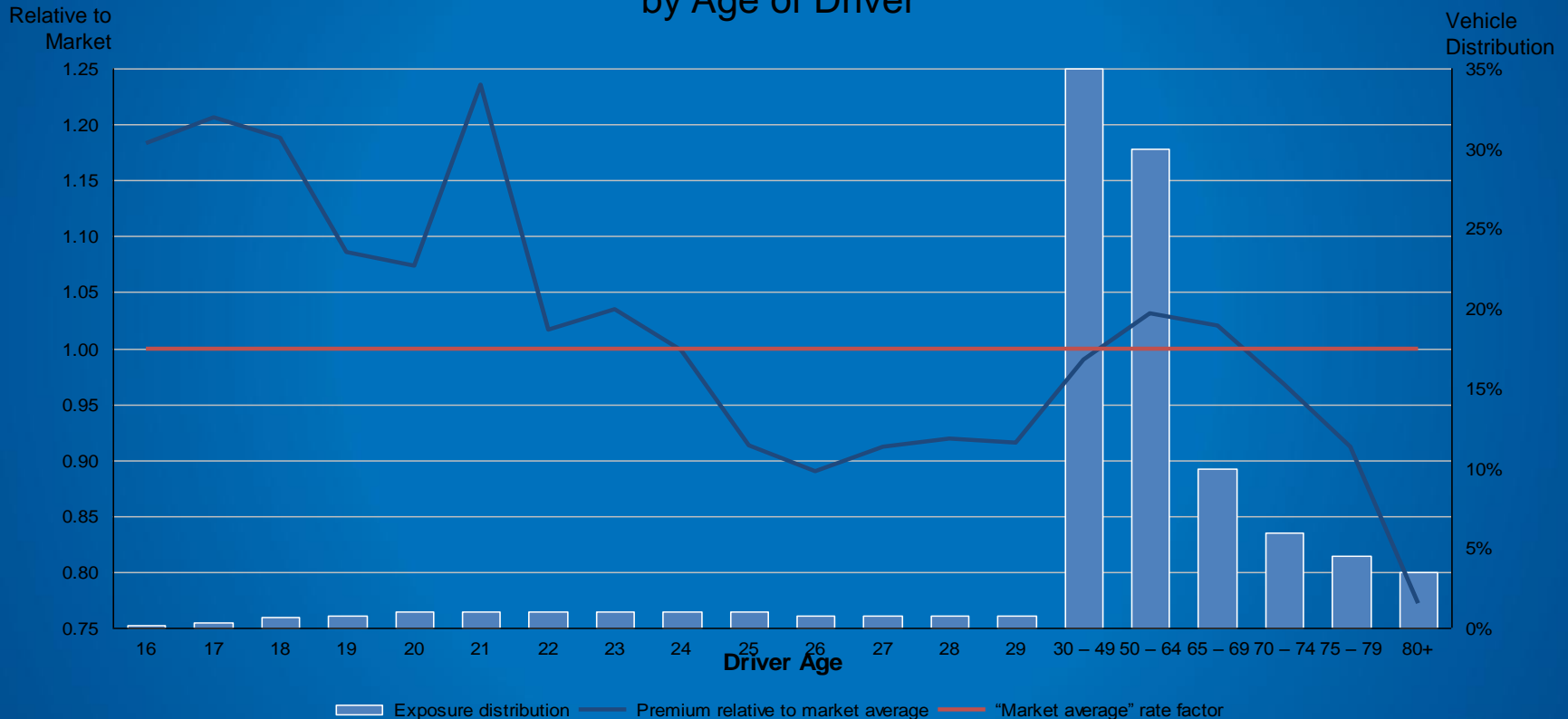


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# Quantitative CMA focuses on the competitiveness of the rating plan at an aggregate level and by and by rating factor/segment

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## Rate Competitiveness by Age of Driver



Use of a market average premium requires a distribution to be selected across competitors — simple average or weighted average



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# Small personal lines carriers place a greater emphasis on qualitative and quantitative CMA, while large carriers focus equally on product CMA

What type of competitive information do you incorporate into your rate-setting process? (Q.20)

	Personal Automobile			Homeowners		
	Small (n = 8)	Medium (n = 13)	Large (n = 19)	Small (n = 8)	Medium (n = 10)	Large (n = 19)
We obtain information from a qualitative review of competitor rate manuals, including a review of variables used, degree of segmentation, interaction between variables, etc. ( <b>qualitative competitive market analysis</b> )	88%	62%	68%	88%	50%	74%
We obtain competitor premiums from agents, a comparative rating engine or hand-rating to gauge our competitive position ( <b>quantitative competitive market analysis</b> )	100%	69%	63%	100%	70%	58%
We compare our product to products offered by competitors to understand differences in coverage options, terms and conditions ( <b>product competitive market analysis</b> )	63%	85%	53%	63%	80%	68%
Not applicable — we do not gather competitive information for this line of business	0%	0%	21%	0%	10%	21%

Base: U.S. respondents gathering competitive information for at least one line of business (percentages exclude 'Not applicable — we do not gather competitive information for this line of business' and 'Not applicable — we do not write this line of business').



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# Commercial lines carriers of all sizes focus more on product CMA and qualitative CMA relative to quantitative CMA

What type of competitive information do you incorporate into your rate-setting process? (Q.20)

	CMP/BOP			Commercial Automobile			Workers Compensation	
	Small (n = 9)	Medium (n = 18)	Large (n = 20)	Small (n = 8)	Medium (n = 15)	Large (n = 19)	Small and Medium (n = 18)	Large (n = 16)
We obtain information from a qualitative review of competitor rate manuals, including a review of variables used, degree of segmentation, interaction between variables, etc. ( <b>qualitative competitive market analysis</b> )	56%	44%	45%	63%	27%	47%	28%	44%
We obtain competitor premiums from agents, a comparative rating engine or hand-rating to gauge our competitive position ( <b>quantitative competitive market analysis</b> )	22%	50%	25%	25%	47%	21%	39%	19%
We compare our product to products offered by competitors to understand differences in coverage options, terms and conditions ( <b>product competitive market analysis</b> )	56%	78%	60%	50%	60%	58%	17%	50%
Not applicable — we do not gather competitive information for this line of business	22%	11%	25%	13%	20%	32%	33%	38%

Base: U.S. respondents gathering competitive information for at least one line of business (percentages exclude 'Not applicable — we do not gather competitive information for this line of business' and 'Not applicable — we do not write this line of business').



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# Carriers face common challenges across all lines — identifying the specific competitor company, obtaining manuals and testing proposed rating plan changes

What challenges do you face in preparing *competitive market analysis*? (Q.21)

	Personal Lines		Standard Commercial		
	Personal auto (n = 35)	Home-owners (n = 31)	CMP/BOP (n = 30)	Comm. auto (n = 25)	WC (n = 18)
Determining in which specific company or companies a competitor is writing new business	54%	55%	50%	40%	50%
Obtaining complete rate/rule manuals for competitors	51%	55%	67%	60%	56%
Knowing whether proposed rating plan changes will improve our competitive position	51%	51%	57%	56%	39%
Using the results to establish and execute on an action plan	23%	19%	37%	32%	22%
Gaining internal consensus as to who our competitors are	11%	0%	13%	8%	6%
None of these — we do not have any challenges preparing competitive market analysis for this line of business	17%	16%	10%	16%	22%

Base: U.S. respondents conducting competitive market analysis for at least one line of business.



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## Personal lines carriers see more challenges to preparing accurate qualitative CMA, but commercial lines carriers need to account for schedule and experience rating plans

What challenges do you face in preparing *qualitative competitive market analysis*? (Q.22)

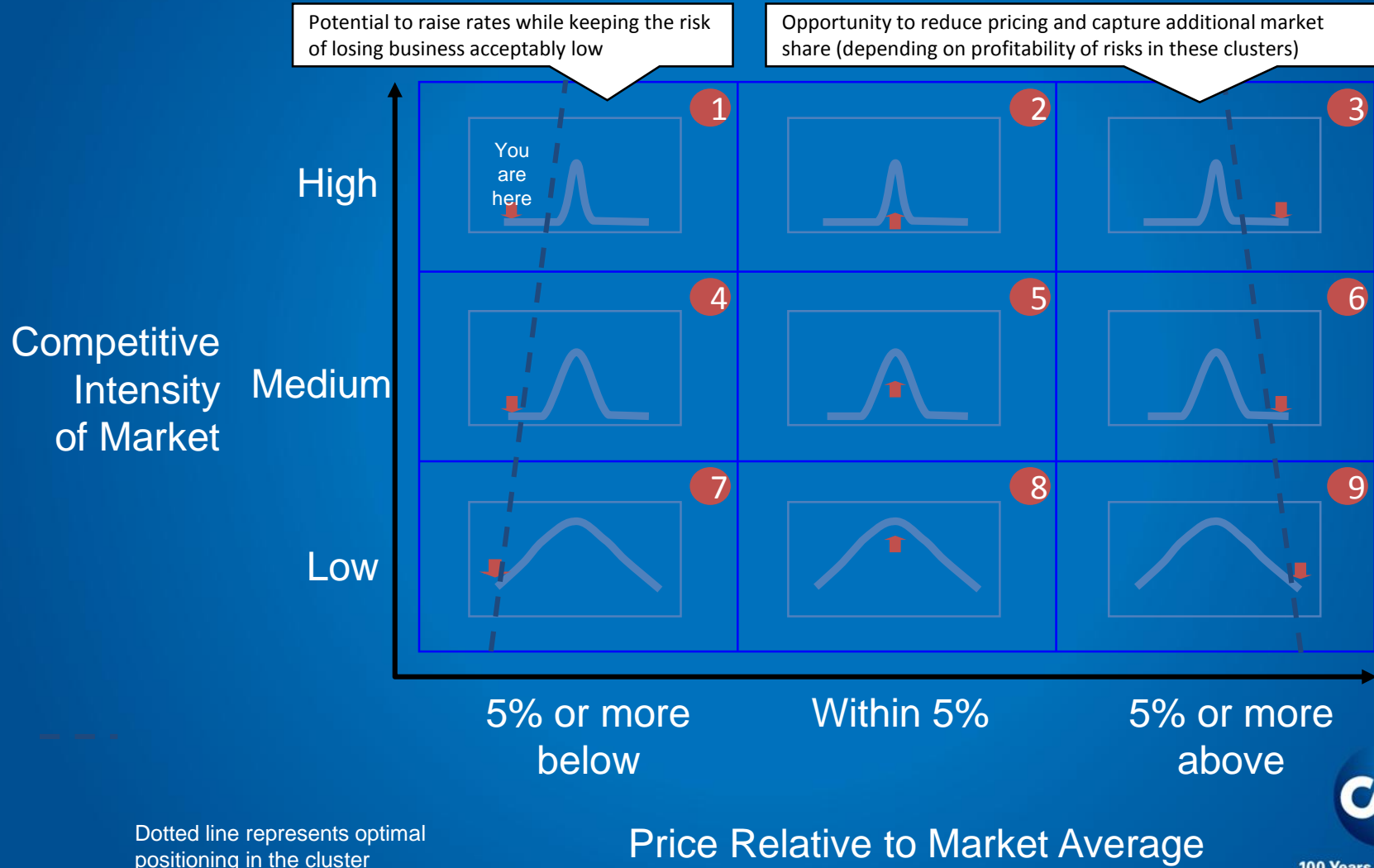
	Personal Lines		Standard Commercial		
	Personal auto (n = 28)	Home-owners (n = 26)	CMP/BOP (n = 22)	Comm. auto (n = 18)	WC (n = 12)
Identifying variables or attributes that determine competitors' tier assignment	75%	81%	59%	39%	58%
Identifying the credit-based insurance score used by competitors	71%	65%	46%	39%	42%
Comparing use of additional individual risk details (i.e., information about an insured other than credit attributes, such as education level, occupation, employment status, SIC codes)	64%	54%	46%	44%	50%
Comparing competitors' usage-based insurance programs	57%	12%	18%	28%	17%
Keeping abreast of competitor changes	36%	42%	50%	28%	33%
Comparing geodemographic information used by competitors (i.e., information about the area in which the risk is based)	32%	31%	23%	17%	17%
Identifying components of competitor schedule rating plans	11%	12%	41%	39%	50%
Identifying components of competitor experience rating plans	11%	12%	27%	22%	17%
None of these — we do not have any challenges preparing qualitative competitive market analysis for this line of business	4%	4%	23%	28%	25%

Base: U.S. respondents conducting qualitative competitive market analysis for at least one line of business.



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# Additionally, competitive position can be segmented in a cluster analysis; the clusters suggest potential pricing strategies



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# Three Quick Applications of Predictive Modeling

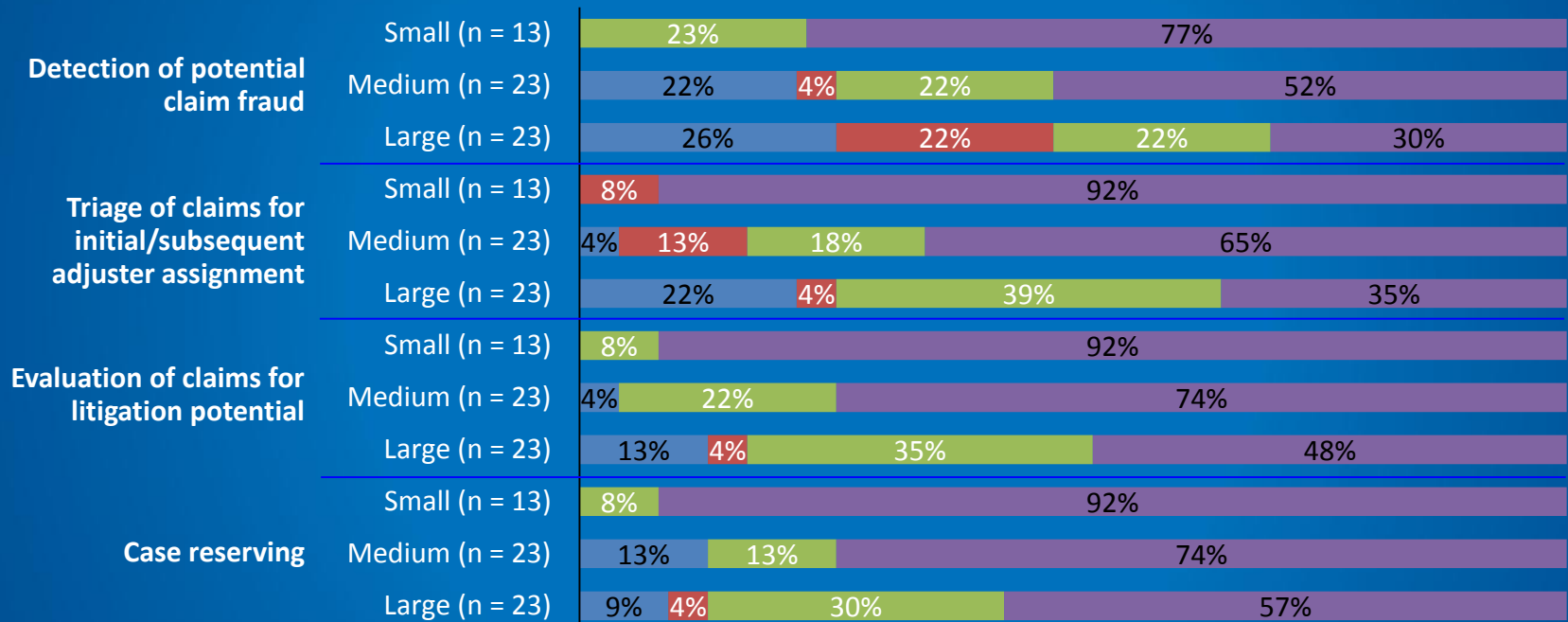
- 1) Competitive Market Analysis
- 2) Claim Triage Modeling**
- 3) Public D&O Modeling



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# Large carriers have been more active in applying predictive analytics in claims applications; few small carriers have plans for claims-related applications

Have you applied predictive analytics in your claim operations for the following purposes? (Q.8)



- Already using claim-related predictive analytics
- In process or nearly ready to roll out claim-related predictive analytics
- Initiating exploration of claim-related predictive analytics
- Not applying/exploring claim-related predictive analytics

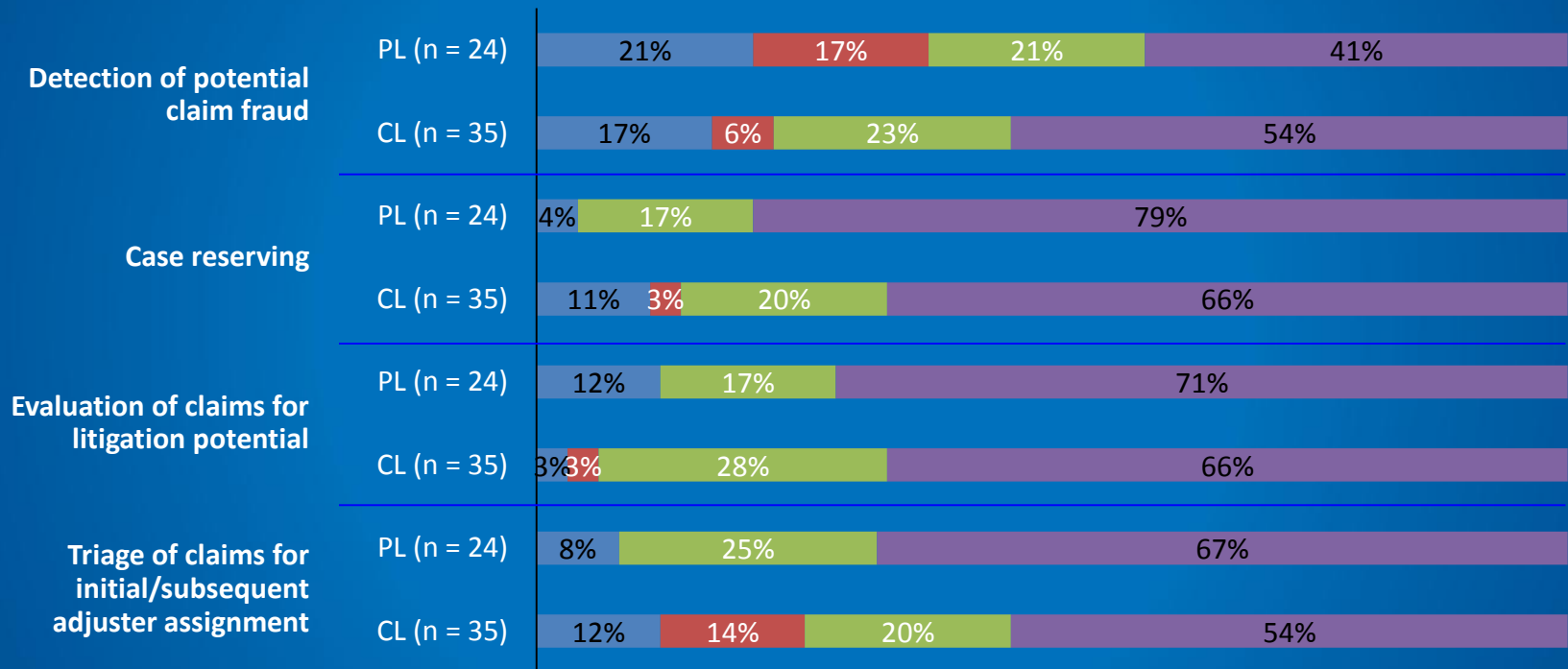


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Base: U.S. respondents (n = 59).

# Personal lines carriers have been (and will continue to be) more active in fraud applications; commercial lines carriers have been more active in all other applications

Have you applied predictive analytics in your claim operations for the following purposes? (Q.8)



- Already using claim-related predictive analytics
- In process or nearly ready to roll out claim-related predictive analytics
- Initiating exploration of claim-related predictive analytics
- Not applying/exploring claim-related predictive analytics



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Base: U.S. respondents (n = 59).

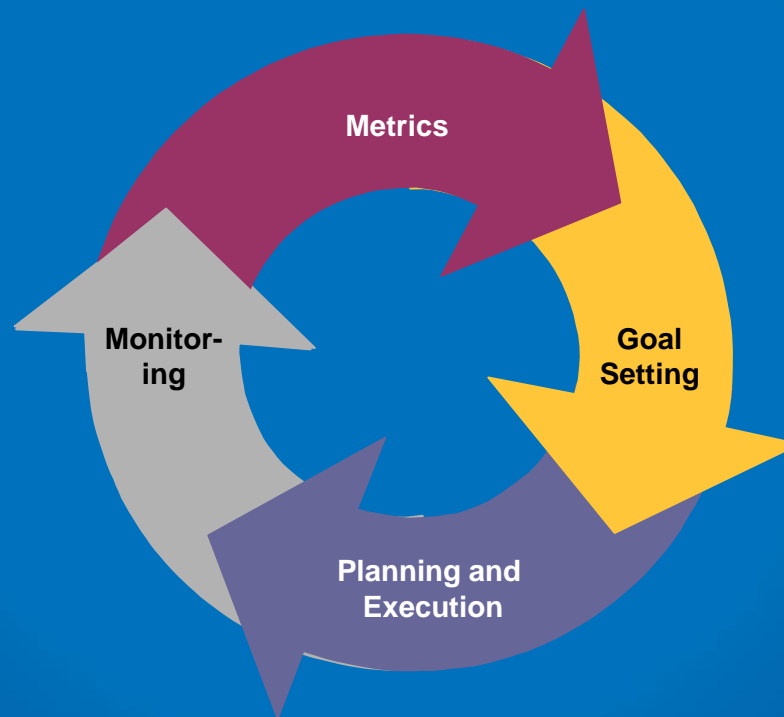
# Claim Officers have a Renewed Focus on Effectively Measuring and Improving Claim Performance

## DEVELOP VIEW OF THE FUTURE

- Define primary measure of success
- Identify key factors that will drive improved performance
- Identify metrics, or key performance indicators, that best capture performance in these areas

## MONITOR PERFORMANCE

- Performance against primary measure
- Detailed diagnosis
- Identify internal/external performance gaps
- Refine and adjust



## SET TARGETS FOR PERFORMANCE

- Set target for primary measure
- Translate goals into operational performance levels

## DEVELOP PLANS AND TAKE ACTION

- Identify key areas where new capabilities need to be developed
- Identify key areas where underperforming
- Apply claim analytics as appropriate



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# The adept use of technology improvements creates the next-generation claim performance scorecard

The New Claim Scorecard – Illustrative Examples				
Claim Performance Indicator	Traditional Measure	Issues and Limitations	Enhanced/Detailed Operational Metrics	Benefits of Enhanced Metrics
Outcomes	Calendar year severity change	<ul style="list-style-type: none"> <li><input type="checkbox"/> Subject to extraneous distortions</li> <li><input type="checkbox"/> Cannot isolate internal vs. external drivers</li> <li><input type="checkbox"/> Difficult to translate into action</li> <li><input type="checkbox"/> Hindsight review</li> </ul>	Accident year severity change by size of loss	<ul style="list-style-type: none"> <li><input type="checkbox"/> Allows isolation of areas of underperformance or excellence</li> <li><input type="checkbox"/> Eliminates extraneous influence</li> <li><input type="checkbox"/> Broader scope – big picture</li> <li><input type="checkbox"/> Clearer focus facilitates action</li> </ul>
Outcomes	QA Reviews	<ul style="list-style-type: none"> <li><input type="checkbox"/> Normally broad but not deep</li> <li><input type="checkbox"/> Draw on small fraction of files</li> <li><input type="checkbox"/> Expensive</li> </ul>	Aggregate comparative negligence performance	<ul style="list-style-type: none"> <li><input type="checkbox"/> Enables aggregate analysis</li> <li><input type="checkbox"/> Based upon known cost drivers</li> <li><input type="checkbox"/> Splits CN frequency/severity</li> </ul>
Speed	Claim Closure Ratio	<ul style="list-style-type: none"> <li><input type="checkbox"/> Impacted by variable intake</li> <li><input type="checkbox"/> Measure counts vs. results</li> <li><input type="checkbox"/> Difficult to translate into action</li> <li><input type="checkbox"/> Root causes unidentified</li> </ul>	Accident year disposal ratios by size of loss	<ul style="list-style-type: none"> <li><input type="checkbox"/> Actionable information</li> <li><input type="checkbox"/> Pinpoints drivers of overall results</li> <li><input type="checkbox"/> Accident year allows adjustments for timing and mix by age</li> </ul>
Speed	Average Cycle Time	<ul style="list-style-type: none"> <li><input type="checkbox"/> Outliers distort averages</li> <li><input type="checkbox"/> Assumes uniform closure practices</li> </ul>	Cycle time distributions with key milestone detail available	<ul style="list-style-type: none"> <li><input type="checkbox"/> Ability to size opportunities and evaluate initiatives</li> <li><input type="checkbox"/> Can sterilize for practice changes</li> </ul>
Efficiency	Calendar Year ALAE vs. Budget or Losses	<ul style="list-style-type: none"> <li><input type="checkbox"/> Subject to budget anomalies</li> <li><input type="checkbox"/> Mix of heterogeneous costs (independent adjuster, legal, other)</li> <li><input type="checkbox"/> Provides little insight</li> <li><input type="checkbox"/> Internally focused</li> </ul>	Detailed ALAE by number of units purchased and cost per unit	<ul style="list-style-type: none"> <li><input type="checkbox"/> Highlights cost drivers and areas of over-utilization</li> <li><input type="checkbox"/> Can isolate heterogeneous costs</li> <li><input type="checkbox"/> Facilitates actionable analyses</li> </ul>
Financial Outcomes	Number of fraud or subrogation referrals	<ul style="list-style-type: none"> <li><input type="checkbox"/> Subject to quality anomalies</li> <li><input type="checkbox"/> Unrelated to results</li> <li><input type="checkbox"/> Provides little insight</li> </ul>	Fraud or subrogation predictive models	<ul style="list-style-type: none"> <li><input type="checkbox"/> Uniform application of available information maximizes returns</li> <li><input type="checkbox"/> Models highlight opportunities</li> </ul>



# Exploring the next frontier – predictive modeling applications for claim

## Initial Claim Handling Triage/ Litigation Potential

- Categorize claims based upon modeled severity and/or complexity
- Combine claim, claimant, and policyholder characteristics
- Practical applications – liability, workers compensation, total loss
- Assign handler and unit based upon claim characteristics

## Claim Valuation Model

- Based upon claim and claimant characteristics later in claim life cycle
- Existing vendor applications for liability and workers compensation
- Provides value for case reserving and actuarial reserving
- Can facilitate benchmarking of handler and office performance
- Can be tailored for total loss salvage, subrogation, litigation decision support

## Fraud Detection and Response Models

- Based upon claim and claimant characteristics
- Flag claims for referral to SIU
- Data mining for organized (attorney and/or provider) fraud
- Models can link disparate characteristics into predictive patterns



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# Claim Triage Modeling

Auto liability – purpose to assign skilled handlers to complex/high value claims

- Initial FNOL and thirty day triage points
- Call center data capture – codifying the policyholder’s story
- What information in adjuster notes needs to be captured electronically?
- Flag claims for severity and litigation potential – consider loss and ALAE
- Quantifying lift/evaluating model performance – how is triage done today?
  - Type 1 error – Classify claim as complex/severe when it is standard/lower cost: result is overqualified handler adjusting the claim – minimal financial impact
  - Type 2 error – Classify claim as standard/lower cost when it is complex/severe: result is an underqualified handler adjusting the claim – significant potential financial impact



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# Potential Predictive Variables

Data Element Category	Sample Data Elements
Injury	Type/Nature/Body Part/Preexisting Condition
Claimant	Age/Sex/Marital Status/Weight/Employment
Litigation	Attorney rep/Suit/Demand/Offer
Accident	Speed of Vehicles/Police/Comparative Negligence
Damages	Medical Incurred/Out of Work Days/Colossus Valuation



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# Three Quick Applications of Predictive Modeling

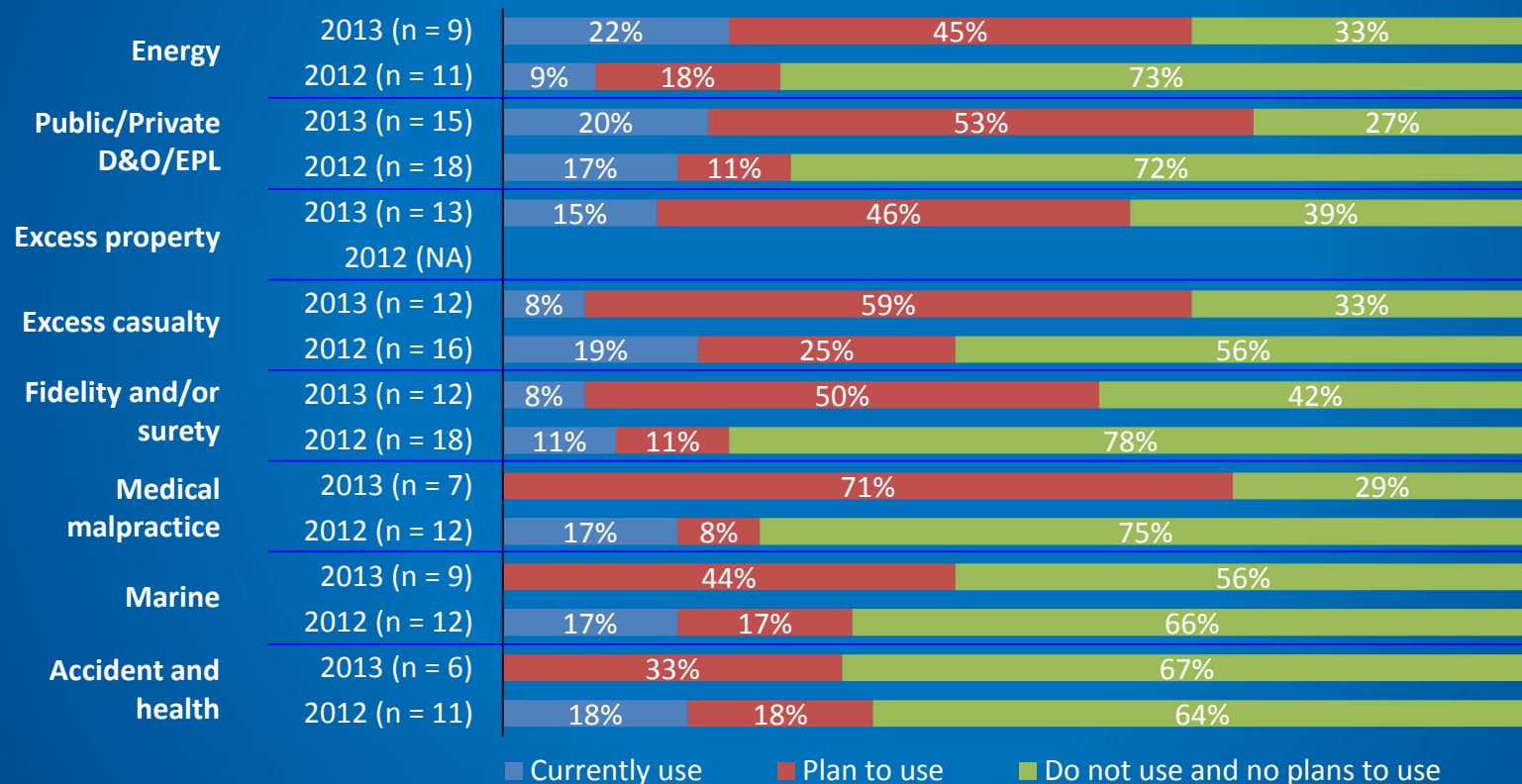
- 1) Competitive Market Analysis
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# While carriers in some specialty lines have aggressive plans to model, there continue to be some specialty lines where more than half of carriers have no plans to model

Does your company group currently use, or plan to use, predictive modeling in underwriting/risk selection and/or rating/pricing for the following *specialty lines of business*? (Q.3)



■ Currently use ■ Plan to use ■ Do not use and no plans to use



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Base: U.S. respondents giving a valid answer (percentages exclude 'Do not write this line of business').

# Public D&O Modeling

Public D&O – Purpose to assess ground up and excess settlement likelihood

- Utilize industry experience as available
- Consider carrier appetite primary/excess
- Tailor data to carrier firmographics
- Consider internal and external sources

Modeling goal – allow ‘new’ underwriter to objectively review risk like a veteran; and support better and more objective underwriting decisions



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# Compiling a Modeling Dataset

Data Element Category	Sample Data Sources
Historical SCAs	Advisen/Cornerstone/NERA
Financial Performance	S&P/Moody's/Bloomberg
Financial Ratings	S&P/Moody's
Management Acumen	Center for Financial Risk Analysis/Corporate Library
Internal Data	Historical Policyholder Experience/Submission Data



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# Potential Predictive Variables

Data Element Category	Sample Data Sources
Historical SCAs	Filing Date/Settlement Date/Settlement Amount
Financial Performance	Absolute/Change in Market Cap/Assets/Revenues
Financial Ratings	S&P/Moody's
Management Acumen	Management Stability/Management Strength
Internal Data	Historical Loss/ALAE/Exposure/UW Data/Claim Data



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# GLM Modeling Results - The Public D&O models we build significantly outperform “conventional wisdom”

### Filing Frequency by S&P Rating and Filing Year

FilingYr	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	D	Tot Rtd
1994	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	N/A	0.0%	2.8%
1995	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	1.9%
1996	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.6%
1997	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.3%
1998	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	3.1%
1999	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.8%
2000	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.8%
2001	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	6.0%
2002	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.8%
2003	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.5%
2004	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.6%
2005	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.2%
2006	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	1.4%
2007	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	2.0%
2008	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	N/A	0.0%	1.5%
Grand Total	5.6%	1.7%	3.5%	3.9%	3.2%	3.5%	3.0%	3.2%	2.5%	3.4%	3.9%	5.2%	4.3%	4.1%	3.4%	8.9%	6.6%	6.5%	7.8%	5.4%	0.0%	6.1%	3.8%

■ Low      ■ Average      ■ High

Relative Frequency Measures Tolerances of +/- .005 to Overall Frequency by Filing Year

### Filing Frequency by MVA Score Decile and Filing Year

Filing Year	1	2	3	4	5	6	7	8	9	10	Total
1994											2.8%
1995											1.9%
1996											1.6%
1997											2.3%
1998											3.1%
1999											2.8%
2000											2.8%
2001											6.0%
2002											2.8%
2003											2.5%
2004											2.6%
2005											2.2%
2006											1.4%
2007											2.0%
2008											1.5%
Total	0.6%	0.7%	0.8%	1.2%	1.3%	1.8%	2.5%	3.0%	4.1%	7.6%	2.6%

■ Low      ■ Average      ■ High

Relative Frequency Measures Tolerances of +/- .005 to Overall Frequency by Filing Year

# Agenda

- Intro
- Predictive Modeling Background
- P&C Insurance Applications Part 1
- P&C Insurance Applications Part 2
- Q&A

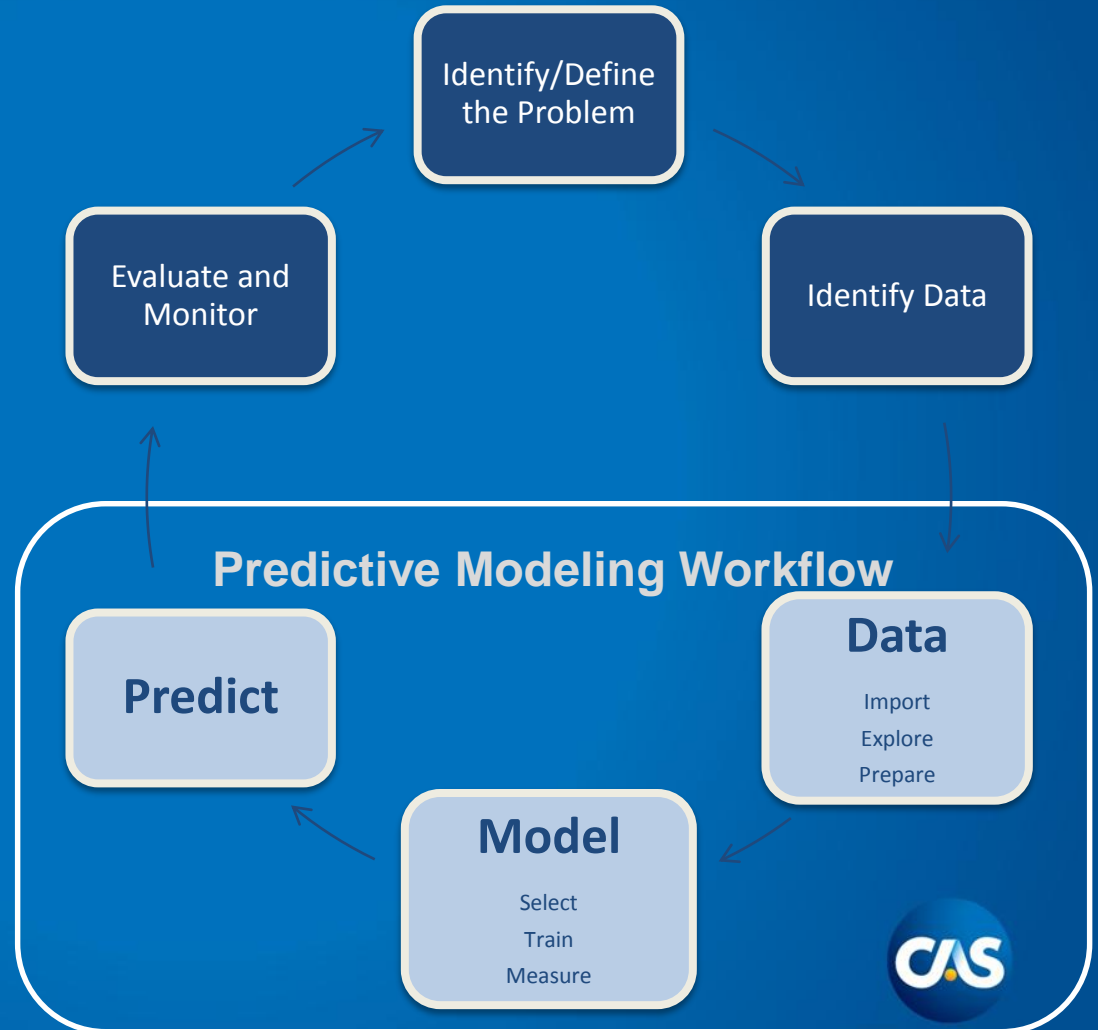


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# P&C Application Part 2: Client scoring model in Commercial Insurance

Predictive models are a powerful tool to help solve problems.....

This section is about a real life challenge we were facing and how CNA used predictive models as part of our approach.



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# Identify/Define the Problem: Start with Why!

**Why:** Establish a consistent, repeatable prospect development process that will enhance current sales efforts, leverage marketing spend and provide the necessary insights to sell to more people and sell more to the people we know.

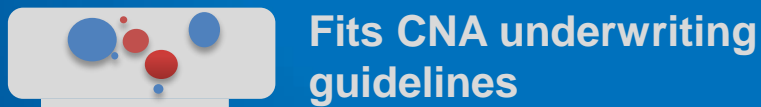
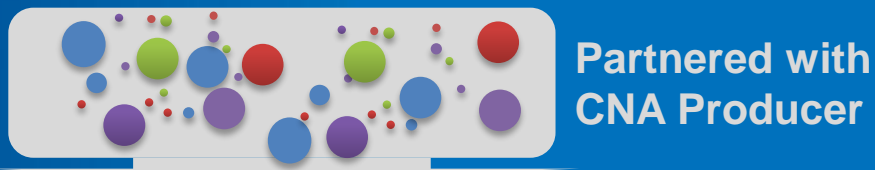
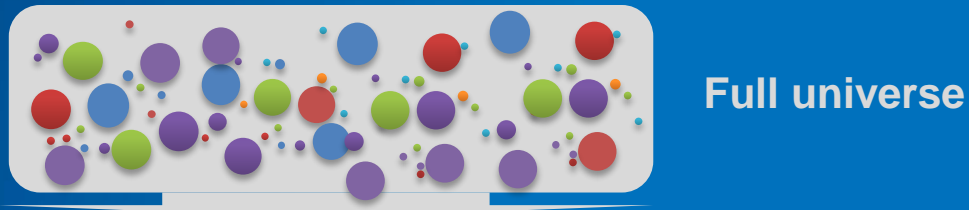
**How:** Among other things....Prioritize prospects and provide insight into desirability with a scoring model.

**What:** Build a predictive scoring model.  
.....Yes, this is what we are here to talk about....



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# Identify/Define the Problem: Frame the questions to answer



## 3 Questions:

1. Will they fit our Appetite?
2. Will they meet our UW criteria?
3. Will they accept our quote?

Basic Underwriting  
and Pricing Flow



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# Identify/Define the Problem: Approach

Model each question/decision individually:

1. Will they fit our Appetite?
2. Will they meet our UW criteria?
3. Will they accept our quote?

Model each Line of Business separately:

- WC
- Auto
- GL
- Property
- Etc...

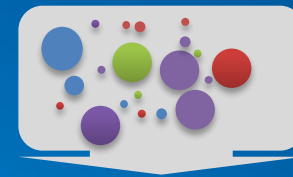
Combine each question score for each LOB to create an aggregate score.



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# Identify the Data: Question 1 – Appetite Fit

Identify Target Variable  
submission declined = N  
(not the yellow ones)



Submitted to  
CNA



Fits CNA  
appetite

## Identify Predictors

How is the Decision Made?

Ask the people who make the decision.

- Geography
- Industry
- Line of business
- Prior history
- Producer relationship
- Revenue

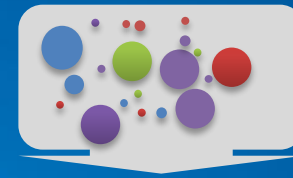


Decision Key	Potential Variable
Geography	State group State Demographic group
Industry	SIC group
Prior History	Prior policyholder
Producer	Producer Segment
Size	Revenue

# Prepare the Data: Question 1 – Appetite Fit

## Data Set:

2 years of submission data



Submitted to  
CNA



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appetite

## Identify Data Sources

	Potential Variable	Pre-Submission Source	Available in Data
Geography	State group	Map Address	Y
	State	Address	Y
	Demographic group	EASI	N
Industry	SIC group	DnB	Y
Prior History	Prior policyholder	Fuzzy match	Y
Producer	Producer Segment	Not available	N
Size	Revenue	DnB	N

## Prepare Data

Import

Enrich

Create Variables

Organize



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# Build the Model: Question 1 – Appetite Fit

## Select the Model

Target Variable: *Submission Declined = N*

- Known => GLM
- Binary => **Logistical Regression**



Submitted to  
CNA



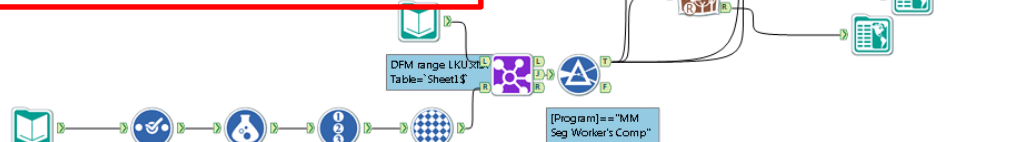
Fits CNA  
appetite

## Measure the Model

## Train the Model

Known data  
Known responses

Model



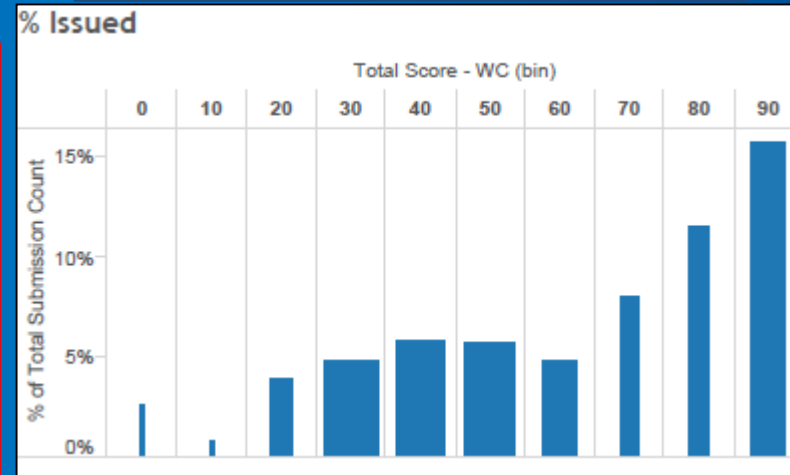
Copy of Submission  
data output with  
appetite v2>:Isr:  
Table= data1\$

```

Issued Indicator=IF
[Issued Count]=1
THEN "Y" ELSE "N"
ENDIF
Declined Indicator=IF
[Submission Declined
Count]=1 OR
[Quo...
Year=Left
([Agreement Effective
Date {YYYYMMDD}),
4)
    
```

## Select Parameters:

- Statistical fit
- Practicality
- Clarity



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# Use for Prediction: Opportunity Score – bring it all together

$$\text{Opportunity Score} = \sum_{lob,quest} \text{Score}_{lob,quest} \times \text{Weight}_{lob,quest}$$

## LOB Example: Work Comp

### **Appetite:**

Target Variable  
Not Declined

#### Predictors

- Geography
- Industry
- History
- Producer
- Size

### **Underwriting:**

Target Variable  
Quoted | Not Declined

#### Predictors

- Loss experience
- Return to work
- Risk Control

### **Pricing:**

Target Variable  
Margin  
Hit Ratio

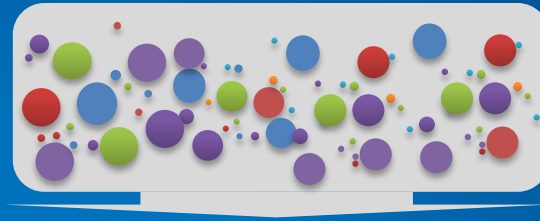
#### Predictors

- Geography
- Industry

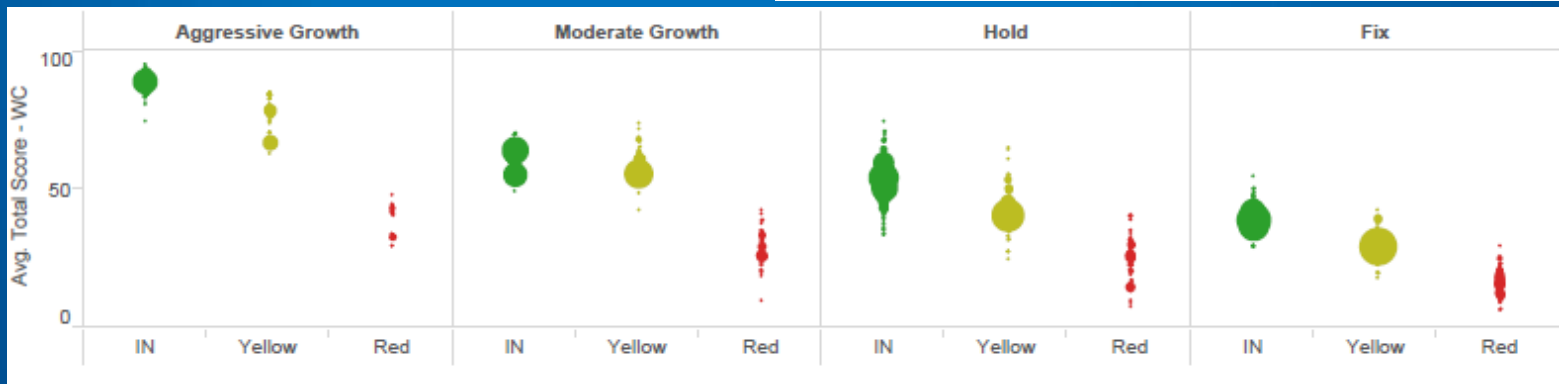
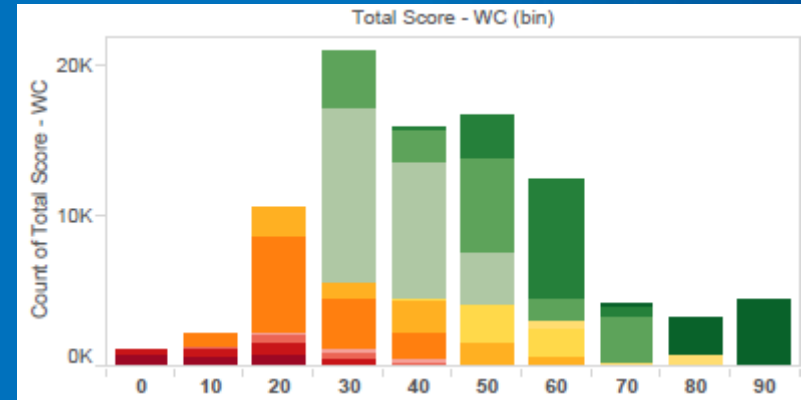
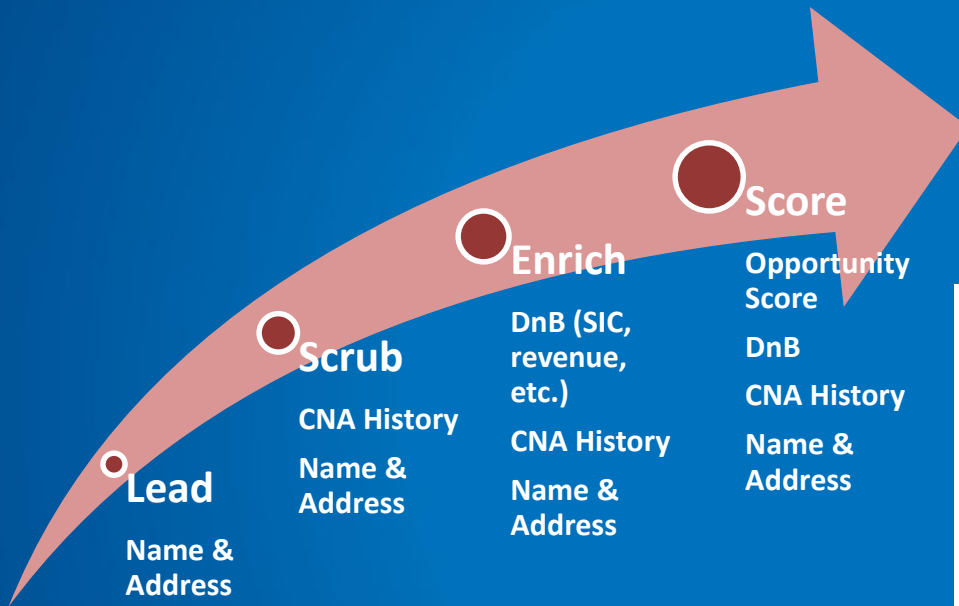


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# Use for Prediction: Bringing it all together



Full  
universe



# Use for Prediction: Opportunity Score – Sample Cases



ACME Oil and Chemical  
Score: 31

Operations: Petroleum Lubricating Oil and Grease Manufacturing

Location: Rockford, IL

GL Score: 35  
Auto Score: 40  
Property Score: 28  
WC Score: 27

Driver of score: Out of appetite SIC

*Low score implies high likelihood of decline.*



Metals Incorporated  
Score: 58

Operations: Sheet Metal Work Manufacturing

Location: Utica, NY

GL Score: 73  
Auto Score: 65  
Property Score: 77  
WC Score: 30

Driver of score: Low WC pricing scores. High scores for GL and Prop margin.

*Average score implies lower likelihood of decline but average chance of success on quote*



Best Ever Metals Corporation  
Score: 80

Operations: Sheet Metal Work Manufacturing

Location: Rankin, PA

GL Score: 85  
Auto Score: 78  
Property Score: 84  
WC Score: 75

Driver of score: Low score for WC state. High scores for everything else.

*High score implies lower likelihood of decline and above average chance of success on quote*

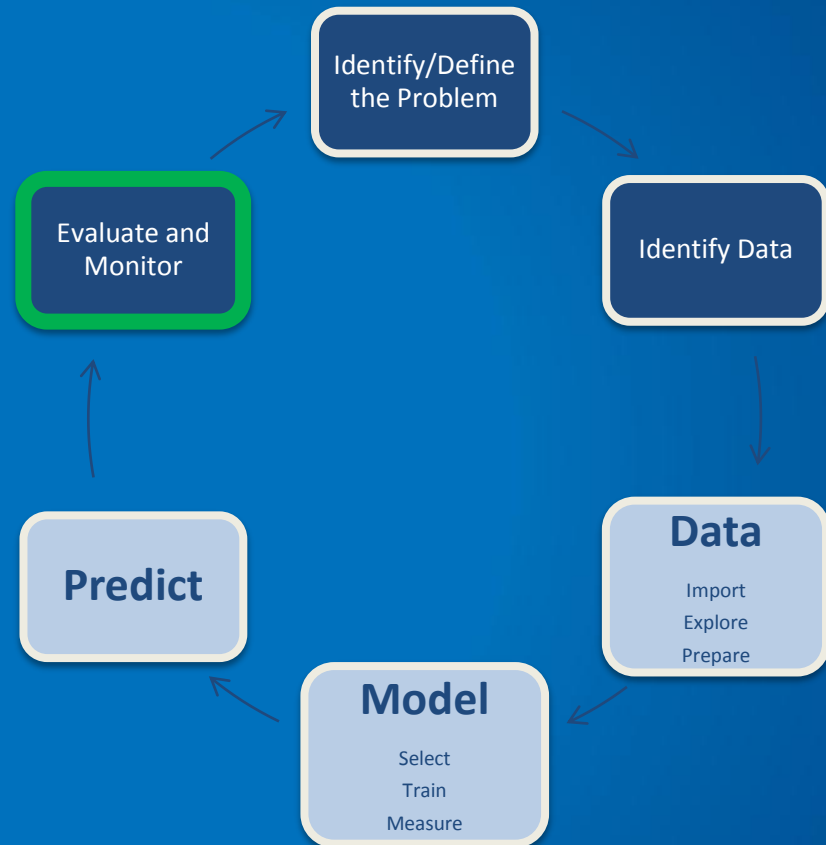
# Evaluate and Monitor: Where we are at

## Pilot program

- Limited scale rollout
- Test scoring
- Build business process

## Plan for enhancements

- Broader application
- Deeper models
- More information (big data)



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# Closing points

## This presentation:

We saw an overview of different predictive modeling techniques and how they could be applied in specific P&C applications and how they could complement actuarial work.

## Main Takeaway:

With the right support and a good thought process, actuaries of any background can use predictive analytics to help solve key business problems in powerful ways



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# Q&A

- Questions?
  - To break the ice: What should be the role of actuaries in predictive analytics?
  - ...

