Association of Governmental Risk Pools (AGRiP) – Fall Educational Forum

An Overview of Data, Predictive Modeling and Beyond with Underwriting Aspects

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Agenda

- Data Isn’t New – It’s How We Use It That Has Changed
- The Historic Approach in Insurance Pricing – Using Aggregate Data in the Actuarial Analysis
- Evolving Into Individual Data – Predictive Analytics Begins
- How These Techniques Are Used – Result of 2016 Predictive Modeling Survey
- Constructing a Predictive Model
- How Pools Can Use These Methods
- Technology Is Driving Change Too
- The Trend of Data Analytics Will Continue
Data Isn’t New

It’s How We Use It That Has Changed
Data “dates” back to the Mesolithic period
Data volume has grown exponentially in the last 15+ years

2010 - Google “the amount of data created in two days equals what was created from beginning of civilization to 2003”

2014 - Big Data is reported by 88% of business executives as a top priority

2017 – Ongoing challenges include privacy, security and intellectual property
The Historic Approach in Insurance Pricing

Using Aggregate Data in the Actuarial Analysis
Relevant aggregated data is a key analysis element

The purpose of actuarial analyses (for pooling and commercial insurance carriers) is to derive rates or liabilities to match the anticipated costs at the time coverage will be provided (rates) or for financial statement (liabilities)

- Insurance involves many time lags
  - Policy issuance
  - Accident or incident
  - Claim reporting
  - Claim investigation/settlement
These data types have advantages and disadvantages

<table>
<thead>
<tr>
<th></th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calendar-year</td>
<td>▶ Consistency with other non-insurance businesses</td>
<td></td>
</tr>
<tr>
<td></td>
<td>▶ Does not change over time</td>
<td>▶ Does not match exposure to loss</td>
</tr>
<tr>
<td>Policy-year</td>
<td>▶ Exact matching of exposure to loss</td>
<td>▶ Long development time</td>
</tr>
<tr>
<td></td>
<td>▶ Results change over time</td>
<td>▶ Results change over time</td>
</tr>
<tr>
<td>Calendar-accident (and calendar-report-year)</td>
<td>▶ Faster availability than policy-year</td>
<td>▶ Results change over time</td>
</tr>
</tbody>
</table>
For example, a triangle of data can be used to analyze past results

### History of Reported Losses ($ Millions)

<table>
<thead>
<tr>
<th>Accident Year</th>
<th>12 Months</th>
<th>24 Months</th>
<th>36 Months</th>
<th>48 Months</th>
<th>60 Months</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>$1.63</td>
<td>$5.04</td>
<td>$6.42</td>
<td>$7.15</td>
<td>$7.32</td>
</tr>
<tr>
<td>2013</td>
<td>1.90</td>
<td>5.72</td>
<td>7.61</td>
<td>8.23</td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>2.73</td>
<td>8.34</td>
<td>10.66</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>3.55</td>
<td>10.27</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2016</td>
<td>3.78</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The loss development method uses historical loss emergence to estimate ultimate losses

### Projected Ultimate Losses ($ Millions)

<table>
<thead>
<tr>
<th>Accident Year</th>
<th>Maturity at 12/31/16</th>
<th>Reported Losses at 12/16</th>
<th>Development Factor</th>
<th>Projected Ultimate Losses</th>
<th>Calendar Year Losses</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>60</td>
<td>$7.32</td>
<td>1.01</td>
<td>$7.38</td>
<td>$1.63</td>
</tr>
<tr>
<td>2013</td>
<td>48</td>
<td>8.23</td>
<td>1.05</td>
<td>8.62</td>
<td>5.31</td>
</tr>
<tr>
<td>2014</td>
<td>36</td>
<td>10.66</td>
<td>1.16</td>
<td>12.39</td>
<td>7.94</td>
</tr>
<tr>
<td>2015</td>
<td>24</td>
<td>10.27</td>
<td>1.49</td>
<td>15.32</td>
<td>11.77</td>
</tr>
<tr>
<td>2016</td>
<td>12</td>
<td>3.78</td>
<td>4.39</td>
<td>16.65</td>
<td>13.61</td>
</tr>
</tbody>
</table>
The ultimate losses are then used to develop a prospective pure premium (loss per exposure) in a ratemaking analysis.

Selecting the 2017 Pure Premium

<table>
<thead>
<tr>
<th>Accident Year</th>
<th>Projected Ultimate Losses</th>
<th>Earned Exposures</th>
<th>Pure Premium</th>
<th>Trend to 2017 (at 4%)</th>
<th>Pure Premium at 2017 Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>$7.38</td>
<td>15,375</td>
<td>$480</td>
<td>1.22</td>
<td>$586</td>
</tr>
<tr>
<td>2013</td>
<td>8.62</td>
<td>16,682</td>
<td>517</td>
<td>1.17</td>
<td>605</td>
</tr>
<tr>
<td>2014</td>
<td>12.39</td>
<td>22,287</td>
<td>556</td>
<td>1.12</td>
<td>623</td>
</tr>
<tr>
<td>2015</td>
<td>15.32</td>
<td>25,720</td>
<td>595</td>
<td>1.08</td>
<td>643</td>
</tr>
<tr>
<td>2016</td>
<td>8.33*</td>
<td>13,000</td>
<td>640</td>
<td>1.04</td>
<td>666</td>
</tr>
<tr>
<td>Avg.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>624</td>
</tr>
<tr>
<td>Selection</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>625</td>
</tr>
</tbody>
</table>

* Pro-rated for half an accident year
Evolving Into Individual Data

Predictive Analytics Begin
Predictive modeling uses individual data

A statistical process
- Estimates the impact that a given set of independent variables (predictors) have in determining a specified dependent variable (response or target)

Key Advantage: finds the true signal
- Allows looking at multiple variables simultaneously while taking into account their relationships (i.e., correlations)

Is advancing beyond GLM
- Personal lines - building proxies for human behavior beyond credit scoring
- Commercial lines – better evaluate risk exposures and focus on uses beyond pricing

Began as a generalized linear modeling (GLM) exercise

Predictive modeling is the predominant technique used in insurance product’s development
Here’s what predictive modeling looks like

Corrects methodological flaws: Signal vs. Noise

- Predictors – could be condition of premises, traffic density, age of claimant, day of week claim reported, new hire training and orientation, method of payment, etc.

- Response/Target – could be losses, claims, lapses, etc.
Why use it?

Data is available
- Finds information and relationships that are missed in simple trend analysis
- Computational power to crunch is cheap

Turns this information into decision rules aligned with the entity’s strategic direction – examples include:
- Underwriting guidelines
- Rating
- Loss control efforts
- Claim triaging
- Schedule rating
- Marketing targets
Predictive modeling assists in integrating all aspects of your operations and helps identify the value of all customers.

**Underwriting**
- Determine UW rules
- Perform credit analysis
- Evaluate agents/regions
- Target inspections

**Pricing**
- Set base rates
- Identify predictors
- Quantify relationships

**Marketing**
- Predict response rates
- Perform conversion analysis
- Determine retention

**Claims – handling and loss control**
- Set reserves
- Predict fraud
- Predict lawsuits

**Customer Value**
What’s different about this?

**Traditional Approach**
- One insured characteristic at a time
- Nearly all insurance related, e.g.:
  - Type of public entity
  - Location
  - Claims history

**Predictive Modeling**
- All characteristics in combination
- Supplement traditional insurance data with other information. For example,
  - Age of claimant
  - Day of week claim reported
  - New hire training/orientation

**The model can be updated based on its track record**
- Can even be designed to update itself (“learn”)
- Should be reviewed at least annually even if self-updates are more frequent
Why is predictive modeling powerful?

<table>
<thead>
<tr>
<th>Univariate analysis</th>
<th>Multivariate analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>▪ The traditional approach of examining the effect of a variable without consideration of any other factors</td>
<td>▪ Examining relationships across all factors simultaneously</td>
</tr>
</tbody>
</table>

Predictive modeling is a type of multivariate analysis

▪ Use of statistical and computational techniques to extract knowledge from large amounts of data
▪ Identify patterns, relationships and correlations across various data elements

Enable better business decisions
Predictive modeling is useful in underwriting

For a given rating plan, the model reveals economics within business segments
- Characteristics of members that “add value” versus “destroy value”

Target those you wish to write
- Based on “indicated” rate vs. “charged” rate

Align underwriting guidelines with targeted business

Evaluate claims experience to develop a “fair” rating plan for targeted segments
Predictive modeling is also helpful in pricing

- Increase the accuracy of rates
  - Adding or deleting factors from rating plan
  - Evaluating rating relativities
    - For both new and existing factors
    - Considering all factors in combination
  - Evaluating separately rated exposure definitions
- Evaluating rating “tiers”
  - Preferred, Standard, Sub-Standard
  - Define characteristics of members for each tier
- Reduce vulnerability to adverse selection
  - Versus competitors
  - Versus self-insurance
Let’s review what we have just discussed: Historical perspective – traditional approach

Historically, in underwriting and pricing, characteristics are evaluated separately

Univariate Analysis:
- Describes the traditional approach of estimating the impact of one factor
  - Without consideration of any other rating factors
- Also called a one-way analysis

Premium: $2M
Exposures: $2,000
Traditional (Univariate) analysis - estimates impact of one factor at a time

Class

<table>
<thead>
<tr>
<th>School More Dense</th>
<th>School Less Dense</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1,000 \times 1.1 \times 1.25$</td>
<td>$1,000 \times 1.1 \times 0.9$</td>
</tr>
<tr>
<td>$= 1,375$</td>
<td>$= 990$</td>
</tr>
</tbody>
</table>

Overall

$1,000 = (\$2M / 2,000)$

Population

<table>
<thead>
<tr>
<th>Town More Dense</th>
<th>Town Less Dense</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1,000 \times 0.85 \times 1.25$</td>
<td>$1,000 \times 0.85 \times 0.9$</td>
</tr>
<tr>
<td>$= 1,063$</td>
<td>$= 765$</td>
</tr>
</tbody>
</table>
Multivariate analysis - estimates the impact of all variables simultaneously

**Overall**

1,000

**Class and Population**

- School more dense: 1,200
- School less dense: 1,025
- Town more dense: 950
- Town less dense: 875

<table>
<thead>
<tr>
<th>School More Dense</th>
<th>School Less Dense</th>
<th>Town More Dense</th>
<th>Town Less Dense</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,375</td>
<td>990</td>
<td>1,063</td>
<td>765</td>
</tr>
</tbody>
</table>

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To summarize, the benefits of predictive modeling include:

- Explore impact of multiple variables simultaneously while taking into account their relationships (i.e., correlations),
  - We can evaluate many more variables than ever before, such as:
    - Location (more or less populated)
    - Credit worthiness
- In underwriting and pricing, it provides enhanced segmentation of risks
  - Avoids adverse selection, e.g., higher rated risks could be charged less
  - Increases the accuracy of rates (revised rating factors, evaluating separately rated exposures, evaluating rating tiers)
- Other uses
  - Does a better job of identifying claim drivers
  - Classifies claims more appropriately (i.e., settle vs. try)
  - Identify characteristics for loss control
How These Techniques Are Used

Results of 2016 Predictive Modeling Survey
Our Predictive Modeling Benchmark Survey shows that there is expanding use of predictive models in the U.S.

- The main use is in core risk selection and underwriting
- More commercial lines insurers indicate they are intent on building capabilities
  - Two thirds of carriers writing commercial liability are using, or plan to use, predictive models
    - A majority of carriers writing commercial auto as well as those that write commercial property currently use predictive modeling, or plan to within the next two years
    - Almost half of carriers writing workers compensation currently use predictive models, with another 25% planning to
    - The majority of carriers writing specialty lines use, or plan to use, predictive models
- As more carriers embrace predictive modeling
  - Variables and predictors used are expanding
  - Methods are evolving
- Expanding modeling applications bring new challenges
  - Many linked to accessing and unlocking the potential of data (from sources such as telematics and the Internet of Things (IoT))
Predictive modeling positively impacts a number of critical areas

- Carriers continue to report a favorable impact on rate accuracy, loss ratios and profitability
- Predictive modeling positively affects renewal retention, among other areas
  - Over half of carriers indicate predictive modeling has had a positive impact on renewal retention
  - 50% of respondents report that it has positively impacted expansion of underwriting appetite
  - 44% of respondents report that it has had a positive impact on market share
Commercial lines carriers consider predictive modeling essential to very important in rating/pricing

- More than two-thirds of small to mid and over half of large accounts/specialty lines carriers agree with this assessment (similar to recent surveys)

- How important do you consider sophisticated underwriting/risk selection, and/or rating/pricing, to be as a driver of performance or success in today’s market for the following lines? (Q.1)

<table>
<thead>
<tr>
<th></th>
<th>Small to mid</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essential</td>
<td>43%</td>
<td>25%</td>
</tr>
<tr>
<td>Very Important</td>
<td>43%</td>
<td>31%</td>
</tr>
<tr>
<td>Somewhat Important</td>
<td>14%</td>
<td>36%</td>
</tr>
<tr>
<td>Not at All Important</td>
<td>0%</td>
<td>8%</td>
</tr>
</tbody>
</table>
Two-thirds of insurers surveyed currently use predictive models for underwriting and risk selection (10% point increase since 2015)

- Insurers agree on the fundamental importance of using these techniques to drive success
- Equally, many carriers recognize there are ways to address the relative lack of homogenous risk data
- Carrier use of these models continues to expand:

<table>
<thead>
<tr>
<th></th>
<th>Now</th>
<th>In 2 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Claim triage</td>
<td>15%</td>
<td>66%</td>
</tr>
<tr>
<td>Fraud potential</td>
<td>14%</td>
<td>55%</td>
</tr>
<tr>
<td>Litigation potential</td>
<td>10%</td>
<td>50%</td>
</tr>
<tr>
<td>Report ordering</td>
<td>17%</td>
<td>48%</td>
</tr>
<tr>
<td>Case reserving</td>
<td>8%</td>
<td>48%</td>
</tr>
<tr>
<td>Loss control</td>
<td>2%</td>
<td>39%</td>
</tr>
</tbody>
</table>
Over half of carriers continue to indicate predictive modeling has had a positive impact on renewal retention

- 50% and 44% of respondents report that the use of predictive models has positively impacted expansion of underwriting appetites and market share, respectively.

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

<table>
<thead>
<tr>
<th></th>
<th>Renewal Retention</th>
<th>Expansion of Underwriting Appetite</th>
<th>Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essential</td>
<td>54%</td>
<td>50%</td>
<td>44%</td>
</tr>
<tr>
<td>Very Important</td>
<td>31%</td>
<td>13%</td>
<td>54%</td>
</tr>
<tr>
<td>Somewhat Important</td>
<td>15%</td>
<td>7%</td>
<td>2%</td>
</tr>
<tr>
<td>Not at All Important</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>
A company’s data driven characterization mirrors their depth of analytics

- The majority of midsize and large companies consider themselves data driven
- This characterization reflects data access, warehousing constraints and problems with IT bottlenecks and coordination
- The obstacles to progress in becoming data driven include
  - Availability of people with the right training and skills
  - Cost of accessing external data
  - Issues linked to identifying and accessing data of the right quality and reliability
- Getting beyond the obstacles and unlocking the value of data represents the most likely near-term opportunities of pricing accuracy, product differentiation and business outperformance
- Companies that want greater control over their destinies will invest in data capabilities
  - The key to success will be marrying the following
    - Flexibility in IT frameworks and analytical partners
    - The right analytic techniques and skills to effectively harvest the information
Constructing a Predictive Model
Stages of a Predictive Modeling Project

- Set project goals / review background
- Gather / prepare data
- Preliminary analysis
- Model build
- Validation of model
- Implementation
Data collection can be in a variety of ways

- Data collection considerations include
  - Who?
    - Internally handled claims
    - Third Party Administrators (TPAs)
  - What?
    - Specific to line of coverage
    - Extent of detail varies by entity
    - Completeness of all fields varies by entity
  - How?
    - Data warehouses
    - Data at the transactional level
There are a variety of data elements to consider

- Historical individual claims data
  - Traditional loss amount fields (case reserves, paid loss, paid allocated loss adjustment expenses, deductible amounts)
  - Accident date
  - Report date
  - Time of day of accident
  - Injury type
  - Adjuster notes on claims
  - Etc.

- Policy level data
  - Location of exposure
  - Gender of injured person
  - Date of birth of insureds
  - Etc.
The data collection process can be extensive

- Requires more granular data compared with classical approach
  - Extended dimensions fed through the model simultaneously
- Experience period captured depends upon nature of analysis - 5 years is not atypical
  - Data preparation is critical for the success of predictive modeling
  - Includes external data not captured by the pool
  - Data anomalies need to be cleaned before feeding a predictive model
  - Best performed with data warehouse where the experience data are already organized
- Examples of data fields to explore
  - Member characteristics
  - Credit
  - Workplace safety
  - Geo-demographic
The preliminary analysis results in a basic model

- Review the distribution of values and map them into levels or bands
  - To manage the level of detail within each field of data
- Perform univariate analysis to review the impact of each variable in isolation
- Perform multivariate analysis to review correlation and interaction of the key variables
- Build a basic model to test out the variables
A basic model is the basis of a model build

- Goal of predictive modeling is to produce a sensible model
  - Explains recent historical experience
  - Is likely to be predictive of future experience
- Good Practical Test:
  - Check for consistency of patterns over time or across random parts of a data set
- Select and test model form and evaluate appropriate variables
- Various metrics can be used to monitor model performance
- Iterative process
Validation of models is critical

Holdout samples are effective at validating models:

- Determine estimates based on part of data set
- Uses estimates to predict other part of data set

The model’s prediction of the unused claims compares well to the actual data.
How Pools Can Use These Methods
Traditional approaches are used in pooling ratemaking and underwriting

- **Examples include:**
  - rates that are different by entity type (school vs. municipality)
  - experience rating
  - schedule rating

- **Potential uses of predictive modeling today include**
  - Pricing – although less competition, depending on the state, more precise rating of sub-sections of risks (e.g., schools for municipalities)
  - Underwriting – A potential way to segment risks based on their characteristics (e.g., number of calls made to the pool, turnover rate of employees)
  - Loss control – identify high frequency or severity loss causes
  - Claim handling – potentially a way to effectively reduce costs, depending on the claim handling process (internal claim handling versus TPA)
Looking forward

What if?

- The commercial market becomes more active in the pooling space, and
- Have predictive models to better contain costs and result in more favorable loss costs?
- Both happen: the commercial market becomes more active in the pooling space, and has predictive model to:
  - Identify the risks they want to attract
  - The pooling membership becomes less loyal to pooling
  - Identify types of losses that are more frequent and/or high severity
    - Excludes them from coverage
    - Applies loss limit caps on the loss cause types
  - Offers specific/more effective loss mitigation
In a pooling case study example, the underwriting process includes a checklist of characteristics

- The following characteristics are currently reviewed to determine a premium/contribution

<table>
<thead>
<tr>
<th>Characteristics Considered</th>
<th>Type of public entity (municipality, town, school, county, special district) and the requirement of a natural extension of a municipality to insure statutory limits and protections in place</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The distribution of class codes (particularly for larger accounts)</td>
</tr>
<tr>
<td></td>
<td>Other characteristics, such as the levels of employee driving concentration and electrical exposure concentration</td>
</tr>
<tr>
<td>Other Survey-Related Information Considered</td>
<td>Loss control survey results are incorporated - larger accounts have an on-site evaluation (or multiple ones during the year). Smaller accounts use the remote results only</td>
</tr>
<tr>
<td></td>
<td>Reinsurer input, rating and approval is requested</td>
</tr>
<tr>
<td>Data Items Considered</td>
<td>A review of loss experience - the number of claims over $5,000, the level and extent of large open claims and repeat claimants</td>
</tr>
<tr>
<td></td>
<td>The modification factor is then factored into the evaluation</td>
</tr>
</tbody>
</table>

- Constructing a predictive model to use in the underwriting process would help validate the statistical relevance of these characteristics

  - Historical data and exposures would be mapped to the specific characteristics (known when an insured is initially underwritten)

  - See next slides for an illustration of possible individual variables reviewed to evaluate their respective correlations, and how they can collectively be used in an underwriting scoring algorithm
A predictive model might provide insights to statistically relevant underwriting criteria such as loss control survey results

- The following illustrates the potential output of correlating an example of a claimant characteristic (e.g., loss control survey results) with historical frequency

**Loss Control Survey Scores - assuming the higher the better**
Another potential example of the predictive modeling analysis might be a review of employee job requirements.
External data can bring valuable insights to underwriting

Credit-worthiness Evaluation

Claim Frequency Relativity

Credit-worthiness Score of Insured

ILLUSTRATIVE
After combining the predictive modeling results, a potential scoring metric in the underwriting review could be produced

<table>
<thead>
<tr>
<th></th>
<th>Insured 1</th>
<th>Insured 2</th>
<th>Insured 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type of Insured</strong></td>
<td>Municipality</td>
<td>Municipality</td>
<td>Municipality</td>
</tr>
<tr>
<td><strong>Manual Premium</strong></td>
<td>10,000</td>
<td>10,000</td>
<td>10,000</td>
</tr>
<tr>
<td><strong>Expected Loss Ratio</strong></td>
<td>70%</td>
<td>70%</td>
<td>70%</td>
</tr>
<tr>
<td><strong>Examples of Underwriting Characteristics</strong></td>
<td><strong>SCORE</strong></td>
<td><strong>SCORE</strong></td>
<td><strong>SCORE</strong></td>
</tr>
<tr>
<td>▪ Claims in Prior 5 Years</td>
<td>15</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>▪ Renewal Years</td>
<td>2</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>▪ Credit-worthiness score (1-5)</td>
<td>2</td>
<td>3</td>
<td>108</td>
</tr>
<tr>
<td>▪ Reinsurer Feedback (High/Low)</td>
<td>H</td>
<td>L</td>
<td>0</td>
</tr>
<tr>
<td>▪ Loss Control Survey Score Tier</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>▪ Class Code Distribution Tier</td>
<td>3</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>▪ Driving Concentration &gt;25%</td>
<td>18</td>
<td>0-25%</td>
<td>0</td>
</tr>
<tr>
<td>▪ All Other Variables</td>
<td>46</td>
<td>38</td>
<td>147</td>
</tr>
<tr>
<td><strong>Total Underwriting Score</strong></td>
<td>369</td>
<td>151</td>
<td>570</td>
</tr>
<tr>
<td><strong>Predicted Loss Ratio</strong></td>
<td>70%</td>
<td>42%</td>
<td>122%</td>
</tr>
</tbody>
</table>
Although the example is hypothetical, it illustrates the output and potential underwriting uses of predictive modeling

- Historical pool data is used to build a model supplemented with external data, if available
  - Beyond loss and exposure history, characteristics of insureds are mapped to the history
- The output of the model can provide useful insights to what characteristics are statistically predictive
- The scoring approach can produce another objective guideline for underwriting and can be used in conjunction with other rating criteria and judgment
Technology is Driving Change Also
Like data, predictive analytics techniques continue to evolve

General linear models (GLMs) have long been the industry standard for predictive modeling

- Robust statistical framework
- High level of transparency and algorithmic form aligns well with insurance rating engines

Difficult to imagine machine learning will completely replace GLMs

- Machine learning is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed

Machine learning is augmenting GLMs

- Creates new variables
- More efficiently whittles down a list of hundreds or thousands of predictor variables
- Identifies model shortcomings
- Identifies opportunities to build hierarchies of models (a large number of well-defined, simple models rather than a small number of more complex models)
Commercial lines data use considerations are different than personal lines

Availability of more data for commercial carriers requires careful examination
- Many vendors do not have useful data

Information from cameras and sensors on commercial properties would be helpful
- Example - SmartPatch promises "effective structural health monitoring" of buildings, towers, bridges, and tunnels (http://smart-patch.com/)

Commercial carriers struggle with telematics
- Fleet managers have data but nobody wants insurers to have it
- Another difficulty - limitations on using personal information

Converting text to data may also unearth more predictive power
- Availability of data in some areas but scarcity of data in others leaves unanswered questions about risk
Technology advancements are impacting insurance operations

<table>
<thead>
<tr>
<th>Use of barometers in smartphones and watches</th>
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<tbody>
<tr>
<td>▪ “Crowd sourcing” weather—allow individuals to share barometer information on their phones for weather forecasting</td>
</tr>
<tr>
<td>▪ Potential for localized weather tracking—“see” claims volume before the storm even hits and understand claims trends in finer detail</td>
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<tr>
<th>Real-time monitoring and catastrophe management</th>
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<tbody>
<tr>
<td>▪ SpatialKey—Capabilities for underwriting, real-time monitoring of catastrophe events, portfolio optimization and profitability analysis</td>
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<tr>
<th>The rise of the mobile app</th>
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<tr>
<td>▪ Forces insurers to rethink marketing and allows disrupters such as Lemonade to take advantage</td>
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<tr>
<th>New tools from Symbility and Encircle</th>
</tr>
</thead>
<tbody>
<tr>
<td>▪ Engage customers in claims by allowing them to share photos and/or videos from their smartphones to expedite settlement</td>
</tr>
</tbody>
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<tr>
<th>Drones can potentially change underwriting and claims processes</th>
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<tbody>
<tr>
<td>▪ Provide an efficient safe way to assess property. State Farm, AIG and USAA already have FAA approval to operate drones commercially</td>
</tr>
<tr>
<td>▪ Images from drones underlie 3-D computer models of structures, making it easier to look at the property—not just data</td>
</tr>
</tbody>
</table>
Technology, like smart homes, is expected to impact future costs of risks

- IOT provides new ways to avoid preventable loss - shift to low-frequency / high severity
- AIG launched Smart Build in 2015 to provide consultation on latest technologies and best building practices for residential construction projects with budgets of $5+ million
The largest insurance segment – personal auto will be the most vulnerable

“We are investigating telematics and broadening the value proposition for the connected customer. If we are not effective in anticipating the impact of changing technology, including automotive technology, our ability to successfully operate may be impaired.”

- Allstate (currently $18bn of auto DPW, 66% of total premium)

<table>
<thead>
<tr>
<th>Now</th>
<th>2020</th>
<th>2030</th>
<th>2040</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safety</td>
<td>Ride Sharing</td>
<td>Telematics</td>
<td>Demographic Shifts</td>
</tr>
</tbody>
</table>

U.S. market shrinks from $180bn to $120bn

$80bn of premium from car manufacturers and infrastructure providers

Exposure reduction, premium falls

Premium moves to commercial writers

Will personal auto insurance premium eventually disappear?
The Trend of Data Analytics Will Continue
Expanding data impacts will change the industry landscape

The nature of risk may change

- IoT, autonomous mobility and 3D printing will create fundamentally new liability scenarios for companies in almost every sector
- Technology may be a major driver of liability claims, with increasing new threats
- Workplace accidents (and workers compensation claims) will likely decline
- Driverless cars are expected to reduce accident rates (currently 90% of auto accidents are caused by human error)
  - Autonomation is likely to lead to increased product liability
- Business models in the digital economy will become more complex

Pools need to understand these implications

- Similar impacts on public entity coverages
- Mobile devices provide more evidence for liability exposures

Pools also can benefit from data and analytics

- Understand current data assets and begin collecting more
- Use external data to supplement pool’s specific data
Thank You
<table>
<thead>
<tr>
<th>Name</th>
<th>Title</th>
<th>Contact Information</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>T +1 617 638 3774</td>
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<td>E <a href="mailto:ann.conway@willistowerswatson.com">ann.conway@willistowerswatson.com</a></td>
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<td></td>
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<td>E <a href="mailto:maureen.stazinski@willistowerswatson.com">maureen.stazinski@willistowerswatson.com</a></td>
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Willis Towers Watson