A Paradigm Shift in Insurance Analytics

AI Modeling with Micro-Segmentation (AIMS)

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Introductions

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Disclaimer

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The case for change
Issue: A Paradigm shift in insurance analytics

**Insurers’ current state:**
- Rapidly changing insurance market with Insurtech and disruptive technology
- Need to reduce expenses and quote times, improve risk selection, increase speed to market, product flexibility
- Exploring artificial intelligence and machine learning to remain competitive and increase margins
- Siloed tools hinder cross-sharing of augmented intelligence across underwriting, claims, actuarial, and finance

**Insurance industry’s challenge for modernizing:**
- Lifting traditional analytical modeling to a more granular claim and exposure level approach through micro-segmentation requires resources and time to build. Implementing these new analytics is challenging due to competing priorities, manual processes, and older non-automated tools.
The winners are those that are continuously moving forward.

**Clear winners are those that**
- Best utilize data to drive insights for improved risk selection
- Execute efficiently to reduce wasted costs
- Move insight to action to bring the right product to the right customer
- Align across the organization for coordinated, responsive actions
- Optimize operations to increase speed to market

**If you don’t act now**
- How will you remain competitive against peers and those with scale?
- How will you explain to the board or the street actions being taken to advance the organization?
- How will you increase profitability – lower loss and/or expense ratio?
- How will you avoid being a victim of aggressive M&A activity?
- How will you remain flexible and best positioned to consistently adapt?
The changing analytics landscape

Level 1: Basic Insurance Analytics

- Traditional Actuarial Analysis
- ISO Ratemaking
- Basic Claims Metrics

Level 2: Enhanced Insurance Analytics

- GLMs in Pricing
- Preliminary Machine Learning Analytics in Claims
- Advanced Policy Admin Systems & Managing General Agent UW Portals

Level 3: Advanced Modernization AI Modeling with Micro-Segmentation

- AIMS Process
  - Current & historical claim & policy level data
  - Uncover hidden variables
  - Advanced analytical machine learning modeling

- Micro-segmentation
  - Best in class visualizations
  - Best in class visualizations
  - Natural language processing
  - Lasso models
  - Neural networks
  - Random forest
  - Gradient boosting

- Improve profitability
- Identify loss ratio deterioration sooner
- Efficiency gains

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Driving Value with Micro-Segmentation
What is Micro-Segmentation?

Granular modeling using advanced statistical models can help create a single view of profitability across Claims, Underwriting, Finance, and Actuarial

**Illustrative Inputs**
- Claims Data
- Policy Data
- Insurance Industry Data
- Claims Notes

**Policy Level Profitability**
- Illustrative Outputs
- Policy Level Profitability
- Claim Level Reserves
- Suit Specific Legal Expectation
- Claim Complexity Scoring

**Powered by ML models**

Detect information better
Case Study

When a major property and casualty insurance carrier experienced significant deterioration in one of its books of business, an investigation led to antiquated actuarial approaches that caused slow response times and ongoing performance issues. The Company was seeking to rectify the problem with advanced analytics and technologies.

Interviews were conducted with key underwriters, actuaries, product managers, claims handlers, litigation practitioners, and various executive stakeholders. Acting on this information, a machine learning model was built using claims and policy-level data to analyze the carrier’s loss of performance at a granular level. This enhanced view helped more accurately analyze its profitability by class, state, and other dimensions not previously available for study.

The increased transparency and enhanced output improved trust in the actuarial model and resulted in potential annual savings of tens of millions of dollars.
Case Study

Model overview

Generalized machine learning framework for Micro-segmentation

- Total IBNR Estimate
- Known Claims Models (IBNER)
  - Known Claims Models
  - Open Claim Propensity Models
- Pure IBNR Models
  - Future Reported Claim Models
  - Severity on Future Reported Claims Models
Case Study

Modeling Process

- Significant lift with readily available data
- Consider a variety of models
- Data structure is key to success
- Model validation
  - statistical measures
  - rigorous back-testing
### IBNER Approach

Calculation is performed at low level of granularity (e.g. Claim) – leveraging granular data assets

<table>
<thead>
<tr>
<th>IBNER</th>
<th>Actual Experience</th>
<th>Future Predicted Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Actual Incremental Paid Losses</td>
<td>2500</td>
<td>0</td>
</tr>
<tr>
<td>Known Claims Model Estimate</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Open Claim Propensity Estimate</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Conditional Probability of Open Estimate(^1)</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Estimated IBNER(^2)</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

---

**Example – not derived from any company sources**

1. Conditional probability of claim open at the beginning of each future period given that the claim is open at the beginning of period 4. (e.g. Conditional Probability of Open for Period 5 = 0.21/0.25 = 0.84)

2. Estimated IBNER = Known Claims Model Estimate \* Conditional Probability of Open
# Case Study

## Using Generalized Approach for Pure IBNR Estimation

### Calculation is performed at portfolio level (can be allocated to policy)

<table>
<thead>
<tr>
<th>Period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4(F)</th>
<th>5(F)</th>
<th>6(F)</th>
<th>7(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actual Newly Reported Claims</strong></td>
<td>1000</td>
<td>300</td>
<td>100</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><strong>Future Reported Claims Model Estimate</strong></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>30</td>
<td>20</td>
<td>12</td>
<td>5</td>
</tr>
<tr>
<td><strong>Severity on Future Reported Claims Model Estimate</strong></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>35,000</td>
<td>38,000</td>
<td>42,000</td>
<td>47,000</td>
</tr>
<tr>
<td><strong>Estimated Pure IBNR</strong></td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>1.05M</td>
<td>760k</td>
<td>504k</td>
<td>235k</td>
</tr>
</tbody>
</table>

### Example – not derived from any company sources

\[
\text{Total IBNR} = \text{IBNER} + \text{Pure IBNR}
\]
Sample Insights and Visuals

— Results provide insights in aggregate in recent years
— Key back-test is convergence in older years
— Significant detail under the surface
— Excel at identifying mix-shifts
Case Study

Tiering – Illustrative Analysis Results

<table>
<thead>
<tr>
<th>Profitable Classes</th>
<th>Unprofitable Classes</th>
<th>Remaining Classes</th>
<th>Total Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accident Year</strong></td>
<td><strong>&quot;A Classes&quot;</strong></td>
<td><strong>&quot;C Classes&quot;</strong></td>
<td><strong>Total All</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Earned Premium</strong></td>
<td><strong>Earned Premium</strong></td>
<td><strong>Total All</strong></td>
</tr>
<tr>
<td></td>
<td>(000s)</td>
<td>(000s)</td>
<td><strong>All Business</strong></td>
</tr>
<tr>
<td>2016</td>
<td>20,000</td>
<td>35,000</td>
<td>155,000</td>
</tr>
<tr>
<td>2017</td>
<td>21,000</td>
<td>42,000</td>
<td>165,000</td>
</tr>
<tr>
<td>2018</td>
<td>22,000</td>
<td>50,000</td>
<td>176,000</td>
</tr>
<tr>
<td>2019</td>
<td>23,000</td>
<td>60,000</td>
<td>189,121</td>
</tr>
<tr>
<td>2020</td>
<td>24,000</td>
<td>72,000</td>
<td>204,243</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>110,000</strong></td>
<td><strong>259,000</strong></td>
<td><strong>889,404</strong></td>
</tr>
<tr>
<td>2016-2018</td>
<td>63,000</td>
<td>127,000</td>
<td>496,040</td>
</tr>
<tr>
<td>2019-2020</td>
<td>47,000</td>
<td>132,000</td>
<td>393,364</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Ultimate Loss Ratio</strong></th>
<th><strong>Unprofitable Classes</strong></th>
<th><strong>Remaining Classes</strong></th>
<th><strong>Total Portfolio</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-2018</td>
<td>45.0%</td>
<td>115.0%</td>
<td>68.5%</td>
</tr>
<tr>
<td>2019-2020</td>
<td>43.7%</td>
<td>127.1%</td>
<td>80.9%</td>
</tr>
</tbody>
</table>

- Often decreasing as a portion of portfolio
- Traditional methods & allocations may show false adverse trends
- Often growing faster than other segments
- Traditional methods & allocations may show false favorable trends
- Often stagnant as a portion of the portfolio
- Traditional methods & allocations are often flat
- Loss experience has deteriorated
- Primarily driven by growth and deterioration of C Classes
- Failure to grow A Classes

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Lessons learned
Machine Learning is Not a Magic Bullet

Significant Levels of Actuarial Judgment & Expertise are Still Required

— Does the data need to be adjusted to consider the presence of distortions? Examples include:
  - Case Reserve Strengthening
  - Changes in Closure Rates
  - Portfolio Acquisitions
— How credible is the data?
  - Is the historical database sufficient for modeling?
  - Is the entire claim life cycle reflected in the data?
— How much historical data should we consider?
  - Trade off between focusing on recent trends and credibility
— Is the resulting model statistically valid?
Lessons learned

1. **Perfect data** and data system upgrades are **not needed** to achieve significant benefits.

2. Build models that are **accessible** and can be run by all frequently.

3. **Identify purpose** of model and output to explain findings and drive action.

4. **Leadership** buy-in is key to drive importance and communication around anticipated use of models.

5. In model design include personnel that understand both **AI/ML modeling** and **business needs**.

6. Deploy a solution that is **scalable** with multiple techniques.
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