Session 2

Leveraging Predictive Analytics for ERM

Janice Wang, ASA, CERA
David Wang, FSA, FIA, MAAA
Leveraging Predictive Analytics in ERM

JANICE WANG, ASA, CERA
Actuarial Associate
Milliman Inc.

DAVID WANG, FIA, FSA, MAAA
Principal & Consulting Actuary
Milliman Inc.

Agenda
- What is Predictive Analytics
- Application in ERM:
  - Economic capital calculation
  - Digital ERM dashboard
- Look into future

Janice Wang
Hong Kong
Janice.Wang@milliman.com

Education and Qualifications
The University of Hong Kong (2012-2016)
B.Sc. Actuarial Science

Current responsibilities
- Actuarial associate with Milliman life consulting practice in Hong Kong

David Wang
Seattle
David.Wang@milliman.com

Education and Qualifications
University of California at Berkeley, HAAS School of Business (2005 - 2006)
MFE, Financial Engineering
Nanyang Technological University (1994 - 1998)
B. Business

Current responsibilities
- Co-leads a Milliman team that specializes in applying data analytics to assist the life and annuity industry in the United States.
- Co-leads Milliman life consulting practice in Seattle
What is Predictive Analytics?
What is Predictive Analytics?

- **Business Intelligence** — a set of technologies and tools to understand and analyze business performance
- **Analytics** — the extensive use of data, statistical and quantitative analysis, explanatory and predictive models
- **Predictive Analytics** — predicting the value of an outcome, given a number of input measures

What is Predictive Analytics?

- A wide range of statistical methods and approaches e.g. machine learning, text mining, neural network
- Using large and granular data sets Various types and sources
- To predict future patterns Predictive vs. descriptive
- To obtain business insight and facilitate decision-making
Now comes its time…

Expanding Data

Management interest

Computational power

Predictive analytics Entering a new era

Competitive pressure

Wherever Decisions are made, there is Opportunity for Predictive Analytics

Marketing
- Brand management
- Target marketing
- Cross sell
- Product design

Underwriting
- Underwriting requirements
- Exposure audits

Pricing
- Rate relativities

Claims
- Fast track
- High risk case management
- Fraud detection

Distribution
- Agency selection
- Agency management
Application in ERM: Economic Capital Calculation

Economic Capital: Sufficient surplus to cover potential losses at a given risk tolerance level over a specified time horizon

Applications of Economic Capital:
- Product Pricing
- Capital Budgeting
- Determine Risk Profile
- Managing and Limiting Risk
- Applications of Economic Capital
- Long Term Value
- ALM
Typical Risks

Market Risk
- Equity & Interest rate: performance of underlying investments
- Volatility
- Misestimation

Policyholder Behavior Risk
- Persistency/Lapse: Early termination
- Catastrophe
- Volatility
- Misestimation

Insurance Risk
- Mortality/Longevity: Risk from misestimating mortality
- Catastrophe
- Volatility
- Misestimation
- Trend

Other Risks
- Counterparty: Risk of reinsurer failing to meet obligations
- Operational: Risk from inadequate or failed internal processes
- Expense: Risk of incurred expenses being higher than anticipated

Evaluation of Behavioral Tail Risk

Types of Lapse Tail Risk

Drift
- Risk that best estimate lapse rates vary under different market conditions
- Captured by a dynamic lapse component

Diffusion
- Risk that estimates of the entire lapse function are off
- Captured by simulation of lapse behaviour using predictive model

Extreme Event
- Risk that some unprecedented events may impact lapse in an extreme way
- Resort to some manner of judgement call
Lapse Behavior Simulation

\[ \text{logodds} \sim a + b_1 \cdot \text{Variable1} + b_2 \cdot \text{Variable2} + b_3 \cdot \text{Variable3} + \varepsilon \]

Model Assumptions:
- Each coefficient \( b_x \) is normally distributed
- The error term \( \varepsilon \) is normally distributed with a mean of 0
- Correlation between each predictive variable can be given by a correlation matrix
- The standard deviation of \( \varepsilon \) denoted by \( \Omega \) can be determined from the correlation matrix using numerical methods such as Cholesky decomposition

Lapse Behavior Simulation – Determine Best Estimate

- Consider the following model, where the only predictive variable considered is In-The-Moneyness

\[ \text{logodds} \sim a + b_1 \cdot \text{ITM} + \varepsilon \]

- After fitting your experience to the model, the following best estimate calibration is attained:

\[ \text{logodds} = 0.5 + (-2) \cdot \text{ITM} + 0 \]

Resulting best estimate lapse rate (\( \rho \)):

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Lapse Behavior Simulation – Simulating the Risk of Model Misestimation

- Alternatively, we can simulate lapse rates by allowing the coefficients to vary according to their standard deviation, assuming a multivariate normal distribution

\[ \log odds = 0.5 + N_1(0, \Omega) + (-2 + N_2(0, \Omega)) \times ITM \]

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Application in ERM: Digital ERM Dashboard
Why (digital) ERM Dashboards?

Digital ERM dashboards go beyond static dashboards by enabling quick access to the unbiased data needed to support decisions.

**Convenience**
- Imagine going to a board meeting with a printout of 1-2 pages from a dashboard you're logged into that allows complete drilldown ability on the fly.
- Drill in to answer questions and provide data to come to informed decisions.

**Timing issues**
- Hooking into source data eliminates issues of prioritizing time by the business units to acquire the needed data.
- Analysis can be updated in real time as experience emerges and market conditions evolve.

**Reporting bias**
- Taking business units out of the update process also reduces bias in reporting without reducing their opportunity to add commentary.

**Customized**
- Can be set up with a traffic light or heat map approach.
- Can grow as you identify important data points to monitor.
Empowering Digital ERM Dashboard

- Real-time data and refreshed models
- Continuous monitoring

Dashboard

- Identify areas for further investigation
- Generate ideas for why things may be unfolding as they are.
- But what is true, and what is errant data mining?

Predictive Modeling

- Test theories and create a desired level of confidence in the answer.
- Use machine learning to investigate what drives risk events

Market-Based Explanations

- A digital dashboard can connect straight to news feeds and to your admin system to put stats side by side
- Watch experience emerge next to changes in the economic environment, political environment, etc.
- Do spikes or drops in activity relate to the external world?

Hypothesis: lapse rates drop after a lag in response to a drop in the S&P, likely related to a rise in ITM
Actual vs Expected

- A dashboard can quickly and easily highlight which segments of business are performing as expected and which are diverging.
- This shows aggregate experience dipping into warning territory.

Note: Lapse rates have dropped recently relative to expectations.

Actual vs Expected

- Drilling deeper, you can identify segments of the block that are behaving closer to expectations, and some behaving even further from expected.

Note: Youngest ages are still lapsing as expected, older ages concentrate low lapses.
Economic Capital – Behavioral Sensitivities

- If we change our assumption, what’s the dollar impact?
- Adding a calculation possibly via Greeks, for the dollar impact of changes to policyholder behavior is a quick step to a traffic light indicator

Look into the (near) future
The use of Machine Learning and Artificial Intelligence (AI) adds value to every stage of ERM cycle

- Identify anomalies through structured and unstructured data
- Automate reports to deliver near real-time alerts and help generate business insights
- Predict exposure based on evolving business environment
- AI-based decision making in risk mitigation and control strategies

Illustration of Cyber Risk model

1. Risk Profiling
   - Identify and assess each risk
   - Cognitive mapping
   - Historical experience
   - Current indicators
   - Process, controls, and users

2. Model Construction
   - Establish causal chain between triggers and consequences
   - Performance of controls
   - Likelihood of cyber attacks after management actions
   - Potential outcomes (e.g., losses/reputation)

3. AI Integration
   - Model calibration with real-time data
   - Threat detection
   - Incorporation of unstructured data

4. Reporting & Ongoing Monitoring
   - Dynamic dashboard
   - Threat development
   - Establish learning process: predict, monitor, learn, predict again