

# **2019 Predictive Analytics Symposium**

## **Session 18: AP - Using Predictive Models for Life Insurance Assumptions**

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# Using Predictive Models for Life Insurance Assumptions

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# Overview

- Assumptions of life insurance
- Modeling structure: A/E model v.s. incident rate model
- Case study: B.E. model
- Case study: principle based reserve model
- Case study: pricing assumption settings

# Assumptions of Life Insurance

- Pricing
- Statutory reserve
- Best estimate (B.E.)
- Lapse

# A/E Model v.s. Incident Rate Model

## ■ A/E model:

- Use this type of models to understand the deviation of actual experience from the current assumption settings.
- Example model structure:
  - $\bar{A} = \bar{E} * e^{X\beta}$
  - $e^{X\beta}$  is interpreted as the overall model suggested adjustment (msadj)
  - $msadj = \exp(X_{age}\beta_{age}) \exp(X_{gender}\beta_{gender}) \dots \exp(X_{cmpygrp}\beta_{cmpygrp})$

## ■ Incident rate model

- Use this type of models to understand mortality when no prior knowledges of assumption exist.
- Example model structure
  - $\bar{A} = \overline{EXPOSURE} * e^{X\beta}$
  - $e^{X\beta}$  is interpreted as the adjustment needed for each factor that is included in the model

# Basic Modeling Techniques

- Regression model v.s. advanced machine learning algorithms
  - Generalized linear model
  - Random forest; neural network (are they really needed?)
- Variable selection criterion: AIC; p-value
  - Use AIC to balance the measure between model complexities and goodness-of-fit.
  - Use p-value to assess the statistical significance of each individual variable.
  - Business implication, ease of implementation and compliance (e.g. degree of freedom of modeling v.s. implementation).
- Feature engineering
  - Spline; polynomial transformation;
  - Piecewise;
  - Regrouping

# Case Study: B.E. Mortality Study

- Background

- The actuarial team has an existing B.E. mortality assumption setting and would like to verify it using predictive modeling.

- Challenges

- The current assumption setting is table-based and each table may contain adjustments on multiple variables. How can we design a modeling ‘process’ to assess the current adjustments?
- Interpretability is critical.
- Large data set that cannot be efficiently handled with open source R packages.

- Solution

- A multi-stage model process to evaluate the existing adjustment tables one-by-one.
- Hadoop based parallel computing.

# Multi-Stage Model (Simplified)

Variables	Base-model	Stage-1 Model	Stage-2 Model	...
<b>Reference Assumption</b>	Assumption-Base	Base*Table1	Base*Table1*Table2	B.E.
<b>Age</b>	✓	-	-	-
<b>Gender</b>	-	-	-	-
<b>Var1</b>	✓	✓	-	-
<b>Var2</b>	✓	✓	✓	-
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
<b>VarN</b>	✓	-	-	-



# Handling Big Data Using Parallel Computing

- Modeling process requires hundreds of iteration or even more.
- The capability of building models quickly is practically very important
- Allows real-time communication and getting feedbacks from audience.
- Speed comparison on a data of size ~ 40 GB; ~ 57 millions records

System	SQL Query	GLM Model
Terminal Server (Windows Server)	90 seconds	350 seconds
Distributed Cluster System (Hadoop Based)	5+ seconds	12 seconds

# Learnings/Conclusions

- Designed a diagnostic modeling 'process' to assess current B.E. assumption settings.
- Discuss and accommodate changes when appropriate.
- Only a fraction of variables show statistic significance, implying the current assumption is mostly efficient.
- Certain underwriting class shows experience deviating from current assumption and the model suggests for adjustments.
- Downward trends against a few time variables, including calendar year and issue year. Does this imply mortality improvement or is it due to newer policies?
- Be patient and collect more data.

# Case Study: Principle Base Reserve

## Background

- Generates PBR mortality assumption for valuation team, using predictive model.
- Would like to use existing industry table as the reference line.

## Challenges

- No prior works.
- A purely model-based solution may overlook the business implications and could lead to overfitting.

## Solution

- An A/E model that can generate adjustment table.
- Work with the actuarial team to incorporate their insights to avoid ‘overfitting’.

# Learnings/Conclusions

- Standard A/E model provides a good starting point

But ...

- Considering model structure beyond statistics
  - Linear trend v.s. step-wise adjustment.
  - Handling data with thin exposure: theory v.s. practice.
- Seeming noise v.s. actual noise e.g. impact of anti-selection; contestable period.
- Combine modeling technique with actuarial judgement: e.g. grouping of categorical variables.

# Case Study: Use Predictive Model for Pricing Assumption

- Background
  - An actuarial group would like to use predictive model to create a new price assumption for their products.
- Challenges
  - Need to make sure the model is not crazily different from the existing assumptions.
  - Data is not clean and shows puzzling patterns that could lead to biases.
- Solution
  - Build an incident model.
  - Use statistics to smooth out small scale issues and avoid potential biases caused by data.
  - Extensive validation process to address actuarial concerns over multiple items.

# Puzzling Mortality Decreasing over Age

Mortality Data

The mortality data shows some decreasing trend against age. Without controlling variable age, the downward trend will be modeled.

— Actual Rate — Model Rate

The model is formulated to force a monotonic mortality increase against age

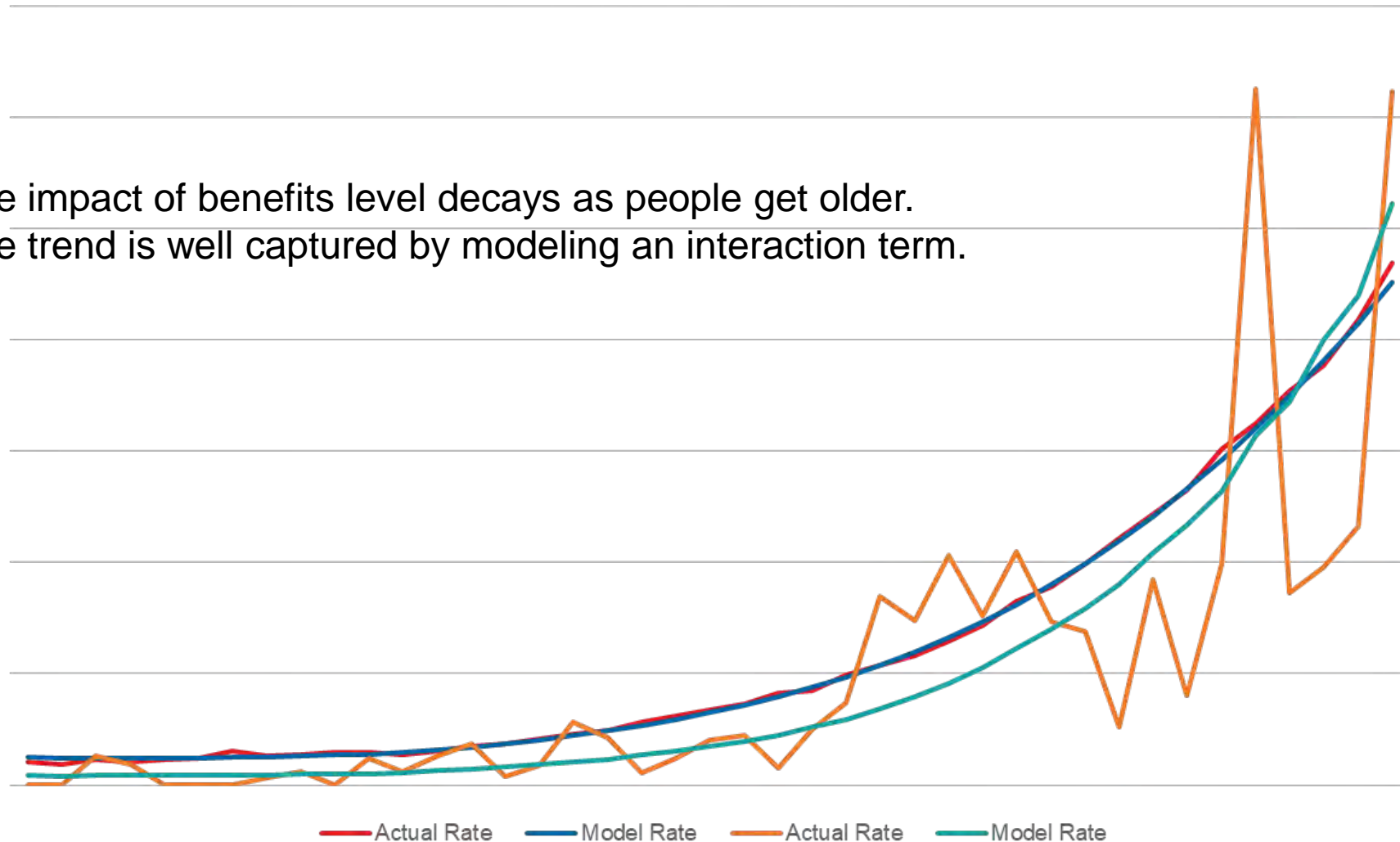
Mortality

Age

# The Power of Modeling Interaction Terms

Mortality v.s. Age-Benefit

The impact of benefits level decays as people get older.  
The trend is well captured by modeling an interaction term.



# Leanings/Conclusions

- Build two incident models.
- The mortality experience for certain age-bands shows a downward trend. The model needs to be structured to correct this absurd trend.
- There is a data cohort that contains a few thousands of valid claims but its “product” cannot be figured out. Can we simply drop the claims?
- The power of interaction terms: benefit amount : age.
- Compare existing assumption settings and be comfortable with the model: validate beyond statistic metrics.
- Assess the implication on premium/profits.



# Summary

- Setting assumption is not a button-click modeling practice.
- Multiple iterations are generally needed.
- Convert ideas into mathematical language: formulate your model properly to assess the questions.
- It is critical to communicate with actuaries to build a model that can be implemented.
- Statistical significance v.s. actuarial significance.
- Make changes as needed. Be open-minded.