Agenda

• What are your objectives?
• Defining your analytics strategy
• Case study 1: Multi-factor reserving
• Case study 2: Diagnostics
• Building your business case
What are your objectives?

- Earlier identification of trends
- More robust results
- More time for value added analysis
- Quicker results
- Avoiding reserving surprises
- Saving time and money
- Reducing mundane work
- Improve management information
- Increased confidence in results

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## What are your objectives?

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Defining your analytics strategy

Focus for today, using techniques including:
- Clustering
- Hold-out sampling
- Feature engineering

Objectives

Enhancing traditional methods

Automation

Streamlining processes

AI
Case study 1: Multi-factor reserving

Traditional

• Reserving typically focused on one segmentation of the data
• Time consuming to consider alternative segmentations
• Challenging to give robust rationale for homogeneous risk groups

Enhanced

• A new automated reserving engine, prepares reserves in less than 5 minutes
• Multiple reserve estimates using alternative key risk factors / data segmentations
• Engine scores the quality of each reserve estimate
Automated reserving engine

A: Which segments should be grouped when calculating development patterns?

B: What averaging period should be used for each development pattern?

C: What averaging period should be used for initial expected loss ratio?

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A: Which segments should be grouped when calculating development patterns?
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- Which clustering method?
- Which linkage function?
- Should the variables be standardised?
- What is the optimal number of clusters?
- How to cluster segments with similar trending?
- How stable are the clusters?
A: Which segments should be grouped when calculating development patterns?
B: What averaging period should be used for each development pattern?

- Averaging period selected that best predicts emerging experience across 10 hold-out samples
- “Best” is defined as the smallest average difference between projected vs actual position

C: What averaging period should be used for initial expected loss ratio?

- Which cut-off point splits the ultimates into two groups that are most similar?
- Use measure of entropy, KL divergence, to compare different cut-off points. Choose cut-off point with smallest entropy.
Assessing the quality of each reserve estimate

Volatility

Options include:

• Stochastic Mack
• ODP bootstrap
• Rollforward volatility
  – Movement in reserve estimates between analyses
• Sub sample volatility
  – Repeat the reserving process on samples from the full set of individual claims data

Bias

Options include:

• ‘Recent experience will continue’
  – Emerging experience error
• ‘Nothing has changed’
  – Back-testing error
• ‘Wisdom of crowds’
  – Difference from other segmentations

The automated engine assesses a reserve estimate as “high quality” where it has low volatility and low bias – with options for how each is measured
Case study 1: Key outcomes

- Insights from investigating new key risk factors
- Easy to communicate final estimates, as based on well understood techniques
- Data driven rationale for selected segmentation
Case study 2: Diagnostics

Traditional
- Manual review of triangles
- Time consuming (ie, hours) to review all triangles, so typically consider a selected sample
- Potential to miss features

Enhanced
- Automated approach, which prioritizes top triangles to review
- Quick (ie, minutes) and scalable
- More time to understand the “why?”
What are we looking for?

“Sticking out”

“Fanning out”

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Feature engineering:

Using domain knowledge of the data to create features that make machine learning algorithms work

“Coming up with features is difficult, time-consuming, requires expert knowledge. Applied machine learning is basically feature engineering.”

Andrew Ng, Co-founder of Google Brain, Stanford Professor
Feature engineering

**Raw data**

- **Transactions:** Payment and reserve transactions by claim
- **Claim details:** (incident date, reporting date, head of damage etc)
- 10^6 rows, 10^2 columns

**Triangles**

- **Triangle:** total values by cohort and development (10 rows, 10^2 columns)
- **Value:** Paid, Incurred, claim count, average claim size (10)
- **Segmentation:** Line of business, head of damage, claim size (10^2)

**Features and metrics**

- **Features** (eg, 5 to 10)
- **Feature metrics** Anomaly/trend metrics for one anomaly/trend (eg, 5 to 10)
Feature engineering

**Fanning out**

- Drift ratio
- Number of cohorts in fan
- Fan direction
- Consistency

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Feature engineering

Sticking out

Earliest development period

Sticking out %

Minimum number of cohorts in a pack

Consistency

% of development periods cohort is in pack

Development

Value
Constructing feature metrics

Key steps

1. Brainstorm key metrics
2. Decide which feature metrics to create
3. Create the metrics
4. Check how well the metrics work
5. Improve metrics where needed
6. Go back to brainstorming and creating metrics if necessary

Helpful tips

Manually classify a large number yourself
Separate into distinct groups and choose best from each group
Work on code for one triangle with interim charts and checks. Then 'map' across all triangles
Order by one metric, chart a few examples from top, middle and bottom and see if you agree with ranking
Pick out examples that don’t work well and chart them. Are there common reasons for why the metric isn’t working?
Revisit the metrics discarded in step 2.

R notebooks are very useful!
Case study 2: Key outcomes

- Efficient identification of key features across multiple triangles
- Increased confidence that key trends and anomalies have been identified
- Structured approach to building knowledge of a book
Developing your business case

Virtuous engagement cycle

Your objectives

Business objectives

Return on investment

Cost calculations

Intermediate goals

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