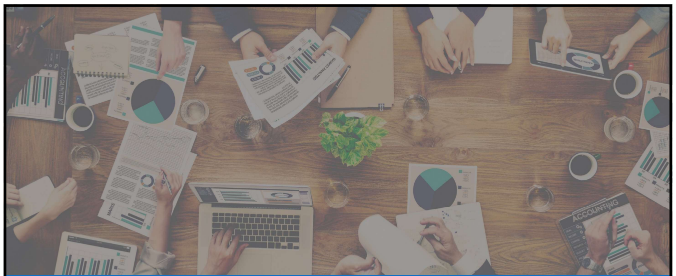

Reserving with Machine Learning:
Innovations from Loyalty Programs to Insurance

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1

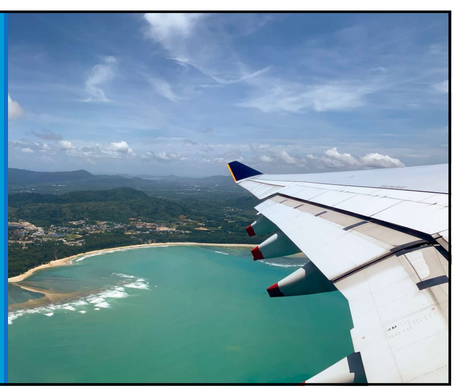
Agenda

- Why loyalty programs?
- Why individual claims?
- Other examples of reserving with machine learning
- Introduction to the snapshot date triangle
- Analysis of simulated data

2

Who here earned miles from a frequent flyer program on your flight to Hawaii?

Those miles represent a **liability** to the airline



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Loyalty programs are constantly trying to change member behavior

Trends in the data mean standard actuarial methods based on aggregate triangles don't work well

The solution is member-level modeling with machine learning

The actuarial toolbox built for loyalty programs can also be used for individual claims reserving for insurance companies

4

Benefits of Individual Claims Reserving (ICR) with Machine Learning

- MORE ACCURATE PRICING
- CLAIMS TRIAGE
- LOSS PREVENTION
- DEEP DIVE IN CHANGES IN LOSS RESERVES
- FREQUENT MONITORING POSSIBLE

5

What ICR isn't

Claim 1 LDF = 1,000 / 500 = 2

Claim 2 LDF = 2,100 / 300 = 7

Aggregate LDF = 3,100 / 800 = 3.875

Applying aggregate development factors to individual claims produces the correct ultimate in aggregate, but can lead to suboptimal decisions at the individual claim level

6

Examples of ICR with Machine Learning

ASTIN (2017): Individual Claim Development with Machine Learning

Cascading Artificial Neural Networks (ANNs) vs. Simple Chain-ladder

Stable Development Patterns Across Accident Years

Results in aggregate
- Chain-ladder ✓
- ANNs ✓

Results for individual claims
- Chain-ladder ✗
- ANNs ✓

Claims Structure Changing Across Accident Years

Results in aggregate
- Chain-ladder ✗
- ANNs ✓

Results for individual claims
- Chain-ladder ✗
- ANNs ✓

7

Examples of ICR with Machine Learning

ASTIN (2018): Machine Learning & Traditional Methods Synergy in Non-Life reserving

Chain ladder and GLMs vs. various machine learning methods
- For claims reported but not settled:
  - Known Claims Model – Future incremental paid losses conditional on claim being open
  - Open Propensity Model – Probability of claim being open

Conclusion:
- Machine learning not necessarily superior to traditional reserving methods, but can **help explain drivers of changes in losses and provide additional information around individual claims**

8

Examples of ICR with Machine Learning

Wüthrich (2018) : Neural Networks Applied to Chain-Ladder Reserving

- Benefits:
  - Considers all data simultaneously; there may be useful information across multiple lines of business that get lost in traditional chain ladder method
  - Can set up claim reserves for different types of claims
- Limitations:
  - Only considers static feature information; dynamic features add complexity as their future values must be predicted
  - Computational time is too large to analyze prediction uncertainty

9

A New Approach

Organizing claims into snapshot date triangles allows for:
- Use of dynamic features without the need to predict their future values
- Use of all available information as of a given date to make predictions about future behavior

10

Snapshot date terminology

Snapshot Date:
The date at which we define and begin tracking a given cohort

In our case, we define the cohort to be open claims as of each snapshot date

Observation Date:
A date subsequent to the Snapshot Date at which we observe some characteristic of the cohort being tracked

In our case, we will be tracking incremental paid losses

Observation Age:
Observation Date - Snapshot Date

Often in months, but we'll show in years here

11

Example with two claims

(Video)

12

Model Details

After we organize each claim into a snapshot date triangle, we have a large and powerful dataset to consider everything we know about each claim to produce the reserve estimate:

Dynamic Characteristics (change over time)
- Paid to date
- Time since last payment
- Development age
- Insured age

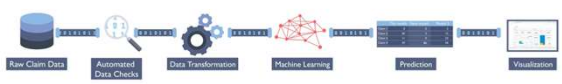
Static Predictors (do not change over time)
- Injury type
- Claims code
- Line of business
- Reporting delay

Target: Pattern of incremental payments after the snapshot date

If we know what a claim looks like at a certain point in time, we can predict what it will look like in the future

13

KYROS

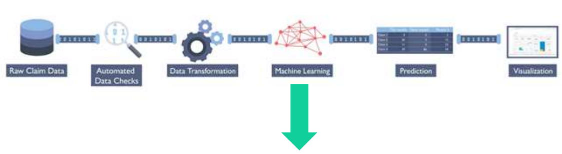


An Automated Analysis Pipeline

14

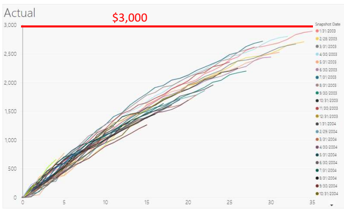
KYROS

Demo video



Complete Actuarial Analysis in Hours

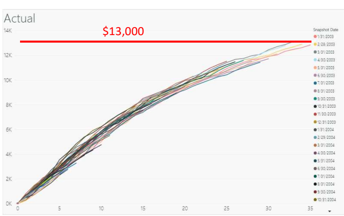
15



Machine learning can be used to find claim "types" with distinct development patterns

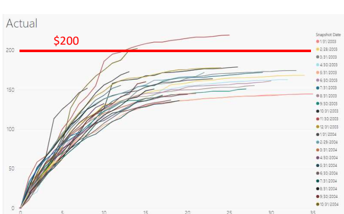
Claim Type 41: Expected payments of ~$3,000 over next 35 months

16



Claim Type 47: High future payments

17

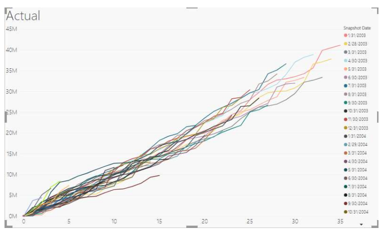


Claim Type 29: Low future payments

18

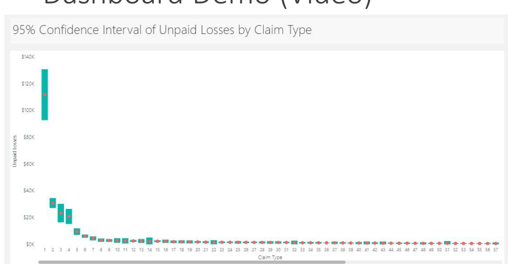
Studying Variance

In addition to examining the average cumulative claim payments, we can examine the variance of the cumulative claim payments



19

Dashboard Demo (Video)



20