Reserving with Machine Learning:
Innovations from Loyalty Programs to Insurance

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Agenda

Why loyalty programs?

Why individual claims?

Other examples of reserving with machine learning

Introduction to the snapshot date triangle

Modeling strategy

Analysis of simulated data

Most of you likely belong to at least one loyalty program

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

Relationship between loyalty programs and insurance

Loyalty Programs	Insurance
Everything we know about a member today	Everything we know about a claim today
↓	↓
Ultimate cost of that member to the loyalty program	Ultimate cost of that claim to the insurance company

What individual claims reserving (ICR) is

ICR is predicting the unpaid amount on an individual claim, based on everything we know about that claim today

What ICR isn’t

ICR is not the same as applying aggregate development factors to individual claims

- Instead, ICR is applying a unique development factor to each individual claim

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

Example #1

ASTIN (2017): Individual Claim Development with Machine Learning

Synopsis: Applied cascading artificial neural networks (ANNs) and a simple chain-ladder method to several datasets and compared the results on an aggregate basis and at the individual claim level

Conclusion:

Stable Development Patterns Across Accident Years	Claims Structure Changing Across Accident Years
Results in aggregate ◦ Chain-ladder ✓ ◦ ANNs ✓	Results in aggregate ◦ Chain-ladder ✗ ◦ ANNs ✓
Results for individual claims ◦ Chain-ladder ✗ ◦ ANNs ✓	Results for individual claims ◦ Chain-ladder ✗ ◦ ANNs ✓

Example #2

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

Synopsis:

- Compared traditional methods and machine learning methods on the same dataset

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**

Example #3

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

Synopsis

- Neural networks are used to model loss development factors at the individual claim level. Results are compared to aggregate development factors

Conclusion

- 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

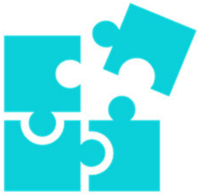
Summary

ICR with machine learning has benefits

Uses a lot of info simultaneously

Can help understand drivers of changes

Especially beneficial when underlying book of claims is changing



But there are some challenges

Difficult to incorporate dynamic predictors

Computationally intensive

A New Approach

Organizing claims into snapshot date triangles allows for use of dynamic features without the need to predict their future values

- Examples: Paid to date, time since last payment, legal involvement

Cloud computing services available today allow us to build models on billions of datapoints in a matter of hours

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

Example with two claims

Snapshot Date Triangle – Incremental Paid

Observation Age

Snapshot Date	1	2	3	4	5
12/31/2014					

Claim 1 - Accident Year 2015

Observation Year	Incremental Payments	Claim Status at Year-End
2015	0	Open
2016	8,063	Open
2017	6,503	Open
2018	3,225	Closed
2019	0	Closed

Claim 2 - Accident Year 2017

Observation Year	Incremental Payments	Claim Status at Year-End
2015		
2016		
2017	74	Open
2018	265	Open
2019	90	Open

Snapshot Date Triangle – Incremental Paid

Observation Age

Snapshot Date	1	2	3	4	5
12/31/2014	N/A	N/A	N/A	N/A	N/A

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Snapshot Date	1	2	3	4	5
12/31/2014	N/A	N/A	N/A	N/A	N/A
12/31/2015	8,063	6,503	3,225	0	
12/31/2016	6,503	3,225	0		
12/31/2017	3,225+265	0+90			

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Observation Year	Incremental Payments	Claim Status at Year-End
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Claim 2 - Accident Year 2017

Observation Year	Incremental Payments	Claim Status at Year-End
2015		
2016		
2017	74	Open
2018	265	Open
2019	90	Open

Accident Year vs. Snapshot Date Triangle – Difference #1

In an accident year triangle, each claim appears in only one row

Observation Age

Accident Year	1	2	3	4	5
2015	0	8,063	6,503	3,225	0
2016	0	0	0	0	
2017	74	265	90		
2018	0	0			
2019	0				

In a snapshot date triangle, rows are not mutually exclusive

- A claim can appear in more than one row

Observation Age

Snapshot Date	1	2	3	4	5
12/31/2014	N/A	N/A	N/A	N/A	N/A
12/31/2015	8,063	6,503	3,225	0	
12/31/2016	6,503	3,225	0		
12/31/2017	3,225 + 265	0 + 90			
12/31/2018	90				

Accident Year vs. Snapshot Date Triangle – Difference #2

In an accident year triangle, total unpaid losses are equal to the sum of the ultimate column in a "squared out" triangle minus paid to date

Observation Age

Accident Year	1	2	3	…	Ultimate
2015					
2016					
2017					
2018					
2019					

In a snapshot date triangle, total unpaid losses are equal to the sum of the last row (the row representing the relevant evaluation date)

Observation Age

Snapshot Date	1	2	3	…	Ultimate
12/31/2015					
12/31/2016					
12/31/2017					
12/31/2018					
12/31/2019					

Modeling Strategy with Snapshot Date Triangles

Modeling Steps

Select	Select a subset of Observation Ages for which we have data
Decision Trees	Build a decision tree for each selected observation age to predict [Cumulative Paid as of the Observation Date] using [Claim Characteristics] as predictors
Clustering	Cluster [Claims], [Snapshot Dates] into groups based on the predicted values from previous step
Square Triangles	Summarize results into Snapshot Date Triangles by cluster and apply triangular methods to square the triangle
Tail	Fit a tail factor if needed to account for development beyond the max observed Observation Age

Let’s do a simple example:

Step 1

Select a subset of Observation Ages for which we have data

- For simplicity, let’s select two Observation Ages. We select 6 and 12.

Step 2

Build a decision tree for each selected observation age to predict [Cumulative Paid as of the Observation Age] using [Claim Characteristics] as predictors

Returning to a snapshot date triangle:

Snapshot Date	1	2	3	4	5	6	7	8	9	10	11	12
Jan-19	2,500	4,900	6,900	8,500	9,900	11,200	11,200	11,200	11,200	11,200	12,300	19,800
Feb-19	2,400	4,400	6,000	7,400	8,700	8,700	8,700	8,700	8,700	9,800	17,300	
Mar-19	2,000	3,600	5,000	6,300	6,300	6,300	6,300	6,300	7,400	14,900		
Apr-19	1,600	3,000	4,300	4,300	4,300	4,300	4,300	5,400	12,900			
May-19	1,400	2,700	2,700	2,700	2,700	2,700	3,800	11,300				
Jun-19	1,300	1,300	1,300	1,300	1,300	2,400	9,900					
Jul-19	0	0	0	0	1,100	8,600						
Aug-19	0	0	0	1,100	8,600							
Sep-19	0	0	1,100	8,600								
Oct-19	0	1,100	8,600									
Nov-19	1,100	8,600										
Dec-19	7,500											

For the Observation Age 6 Decision Tree, use [Claim Characteristics] as of the Snapshot Date to predict cumulative paid at age 6

For the Observation Age 12 Decision Tree, use [Claim Characteristics] as of the Snapshot Date to predict cumulative paid at age 12

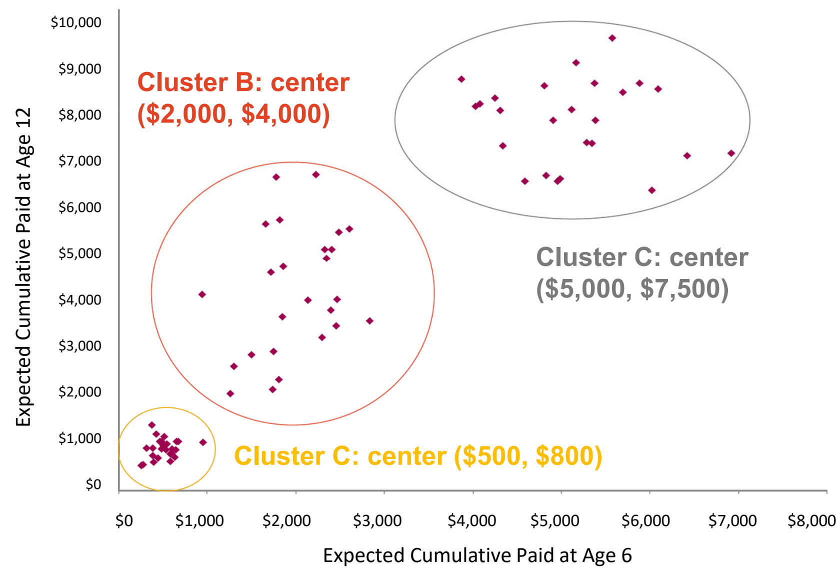
Step 3: Cluster [Claim], [Snapshot Dates] into groups based on the predicted values from step 2

For each observation with [Open Claim] > 0 as of the snapshot date, apply the two decision trees to produce a predicted cumulative paid at ages 6 and 12

Perform a clustering on the predicted cumulative paid at age 6 and 12

Step 3: Cluster [Claim], [Snapshot Dates] into groups based on the predicted values from step 2

Here is a simple graphical representation of the clustering. Each dot represents a [Claim], [Snapshot Date] combination.

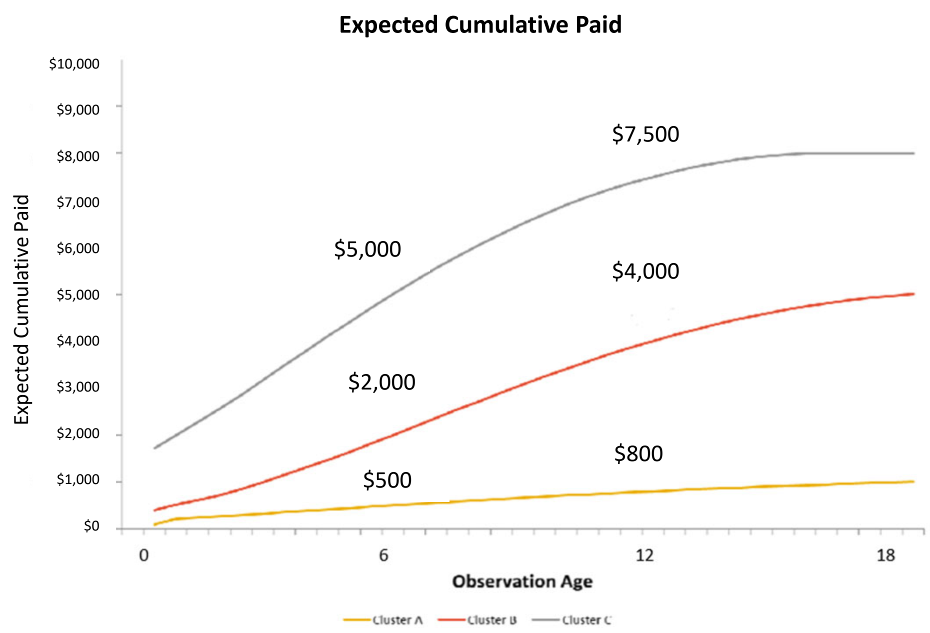


Each cluster has a different expected cumulative paid at age 6 and 12

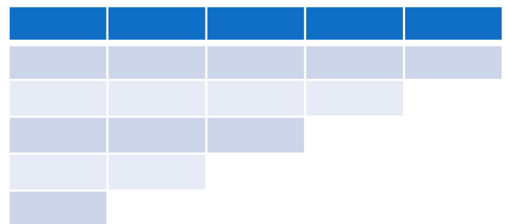
For example, the cumulative payment patterns for each cluster may look like this.

Note that we're using a simple interpolation/extrapolation for all observation ages other than 6 and 12 for illustration purposes.

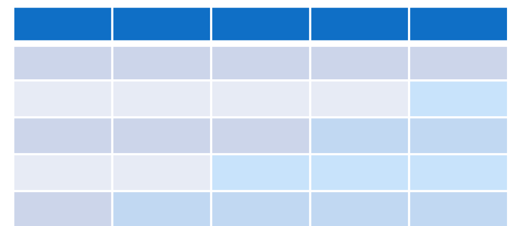
Modeling more ages would provide a more complete picture of the expected cumulative payment patterns.



Step 4: Summarize results into Snapshot Date Triangles by cluster and apply triangular methods to square the triangle

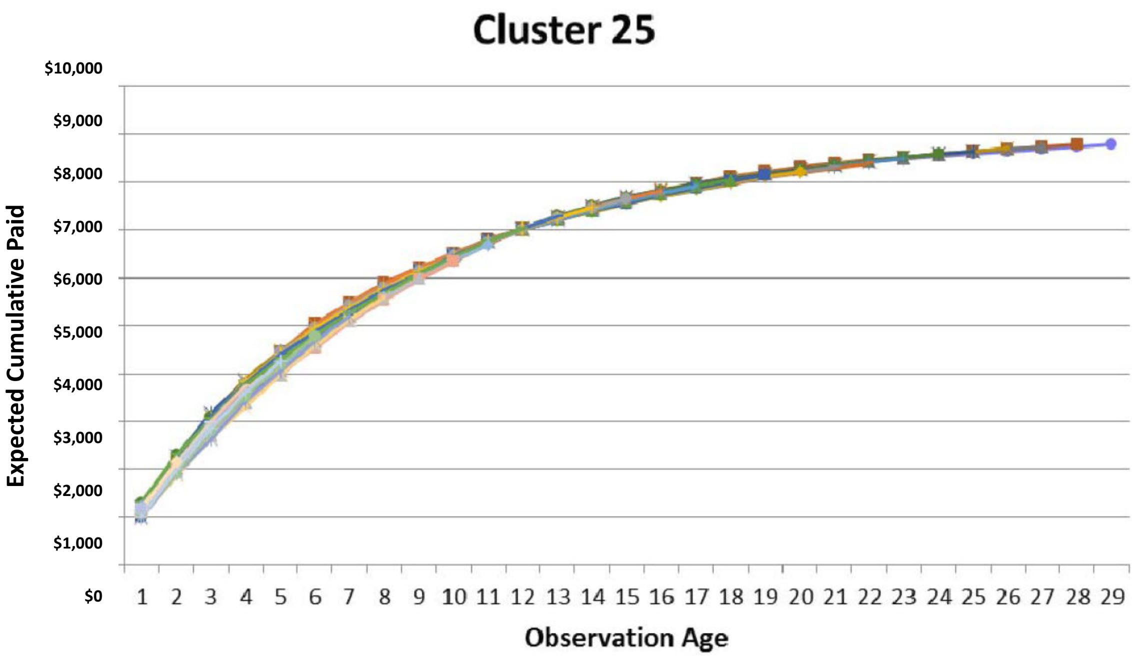


Summarize results by cluster to produce Snapshot Date Triangles for each cluster.



Apply triangular methods to square out the triangle

If the decision tree models perform well, we should see consistent patterns within each cluster



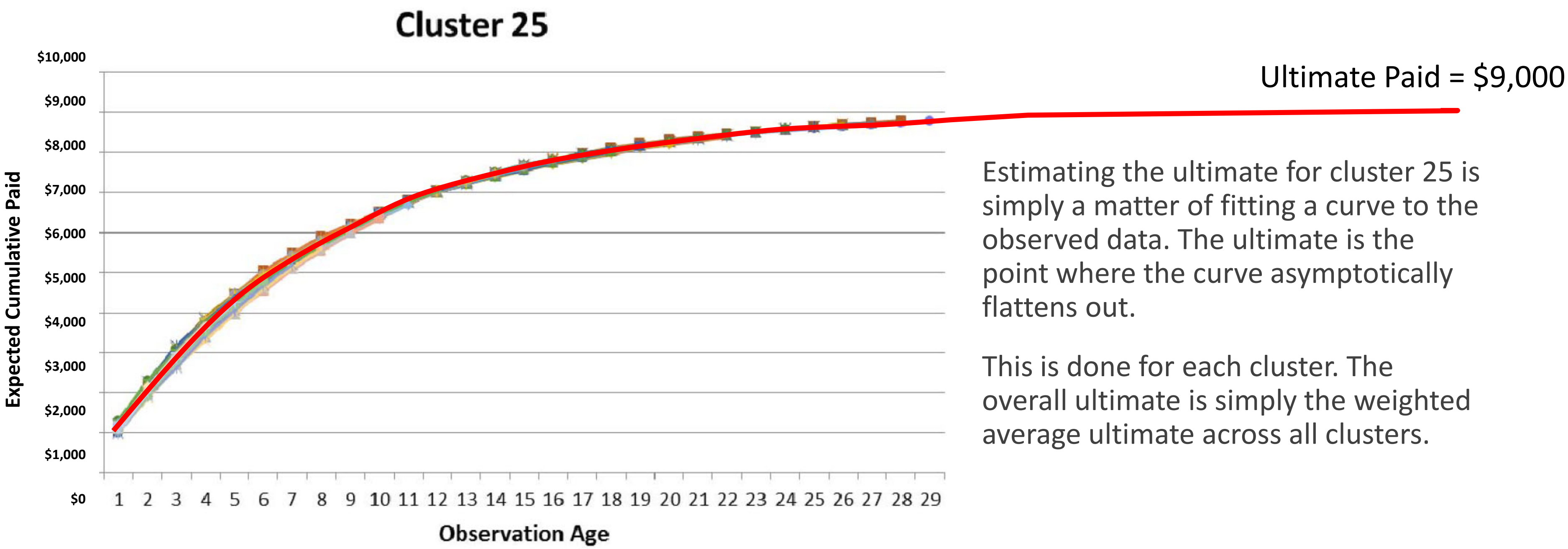
Here's an example of a typical output for one cluster.

Each line represents a Snapshot Date, and we're tracking actual cumulative paid as you move from left to right for claims that were in cluster 25 as of the Snapshot Date

The one thing that each line has in common is claims included in each line belong to cluster 25 as of the Snapshot Date (i.e., as of Observation Age 0)

The consistency of these patterns gives you a high degree of confidence of the average future payment pattern for a claim in cluster 25 today

Squaring out the triangle

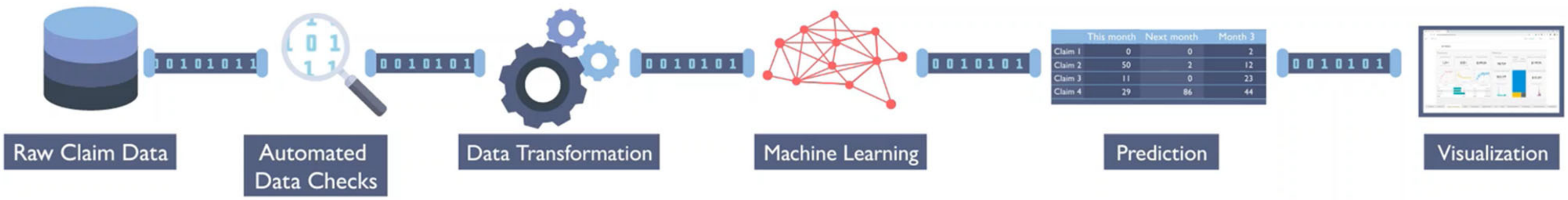


Estimating the ultimate for cluster 25 is simply a matter of fitting a curve to the observed data. The ultimate is the point where the curve asymptotically flattens out.

This is done for each cluster. The overall ultimate is simply the weighted average ultimate across all clusters.

Example Application on Simulated Insurance Data

KYROS



Complete Reserve Analysis in Hours!

Machine Learning Details

Static Predictors	Dynamic Predictors
Injury type	Paid to date
Claim code	Time since last payment
Line of business	Development age
Reporting delay	Insured age

Key differentiator: Dynamic predictors are easy to incorporate

KYROS

KYROS

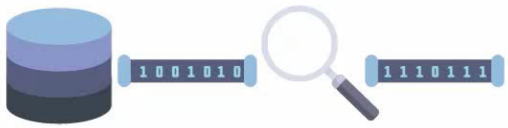
- Checking that data is in correct format
- Checking that there are no new levels for categorical variables
- Checking that the distribution of data looks correct

Automated Data Checks

KYROS

Stop pipeline, fix issues, rerun

KYROS



- Applying data cleaning steps
- Transforming data into the format needed for analysis

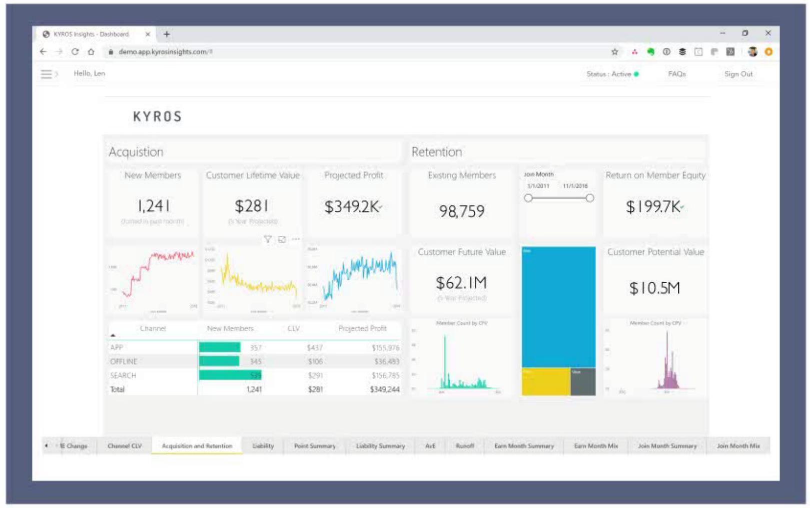
Data Transformation

KYROS

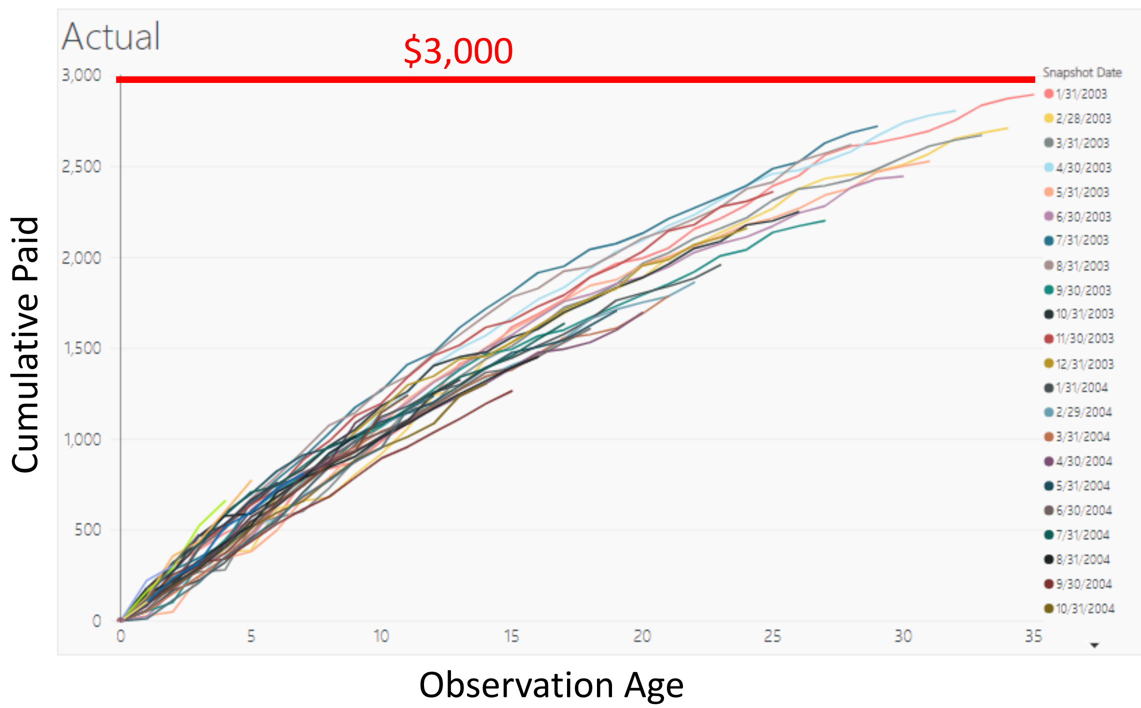
- Examining billions of data points
- Looking at everything we know about each individual claim
- Finding patterns impossible to detect with traditional methods

Machine Learning

KYROS

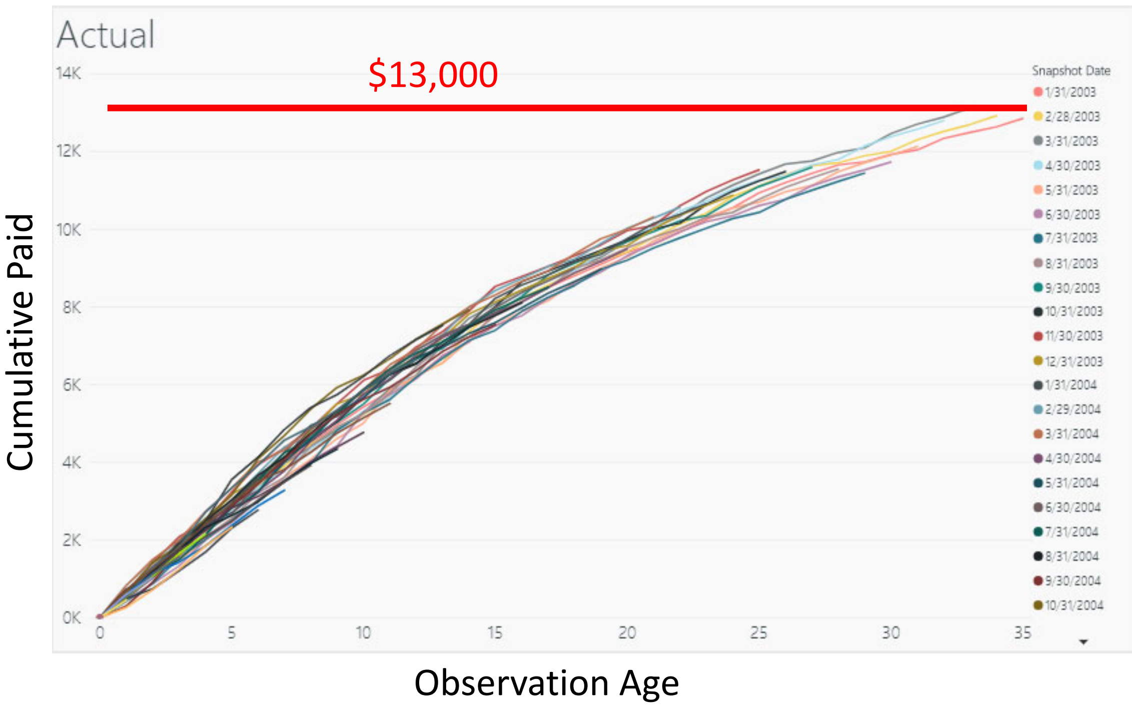


- Online dashboard summarizing predictions
- Self service dashboard allows "slicing and dicing" data
- Easily accessible and can be customized for each audience

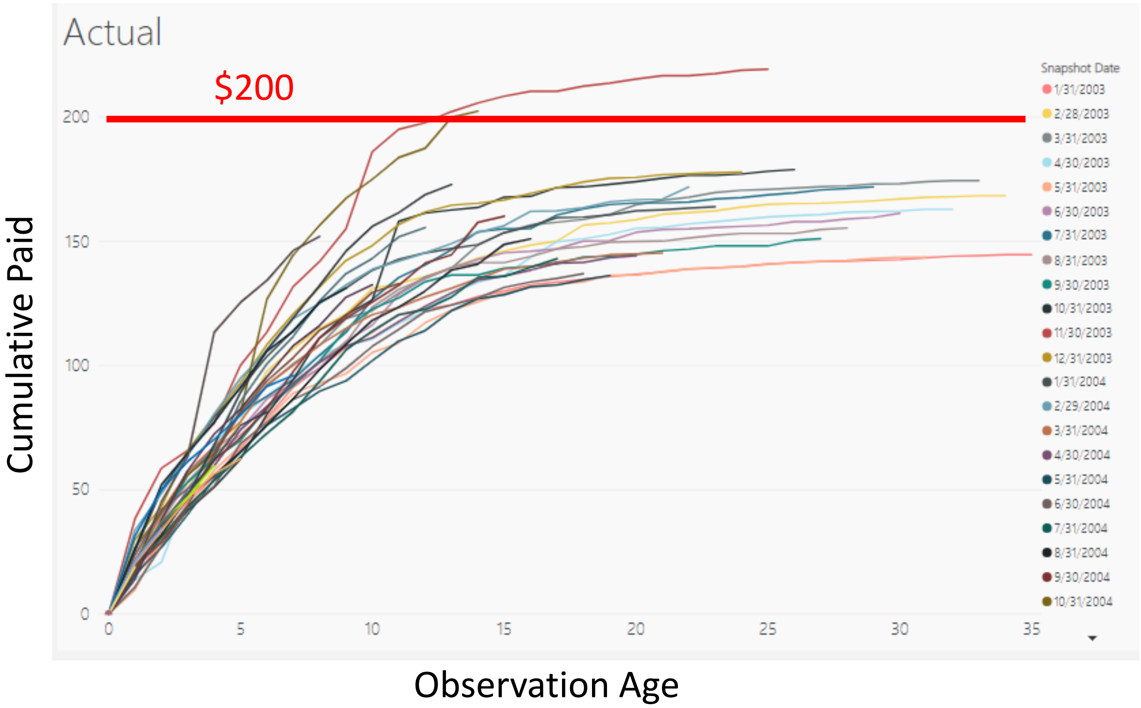


Machine learning can be used to find claim "types" with distinct development patterns

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



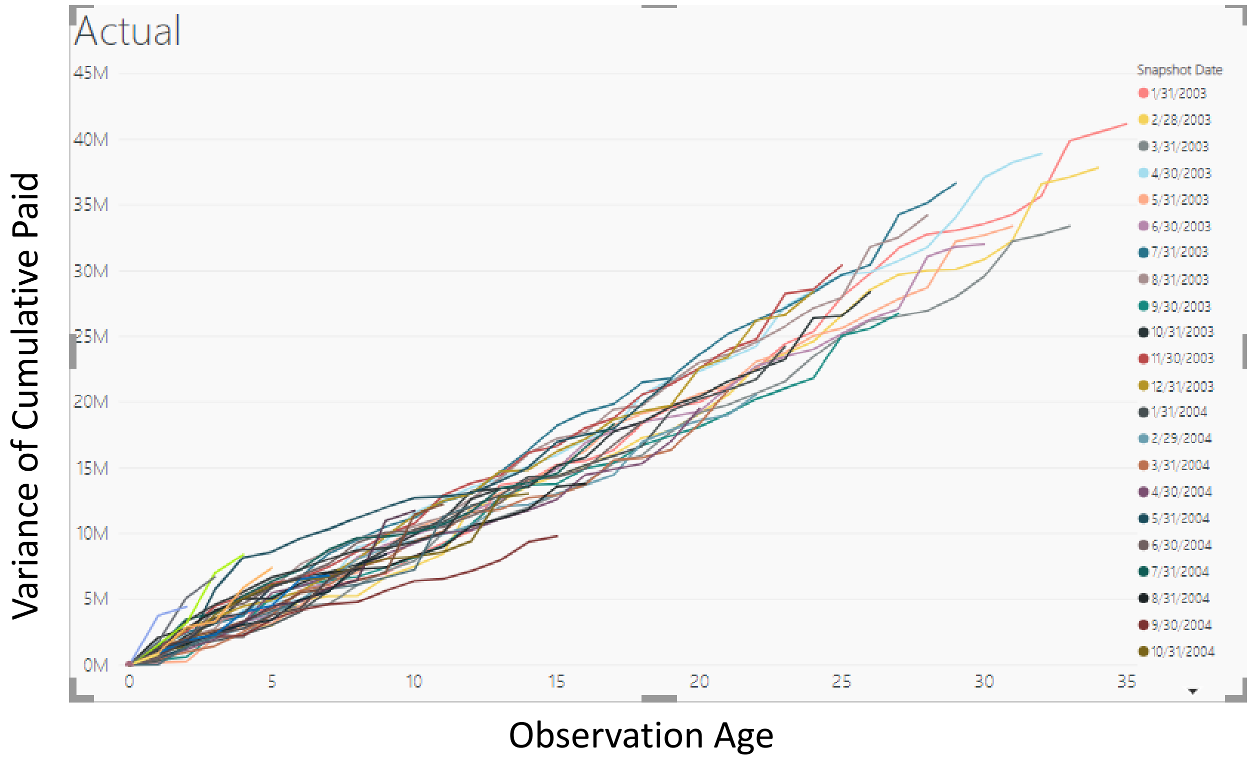
Claim Type 47: High future payments



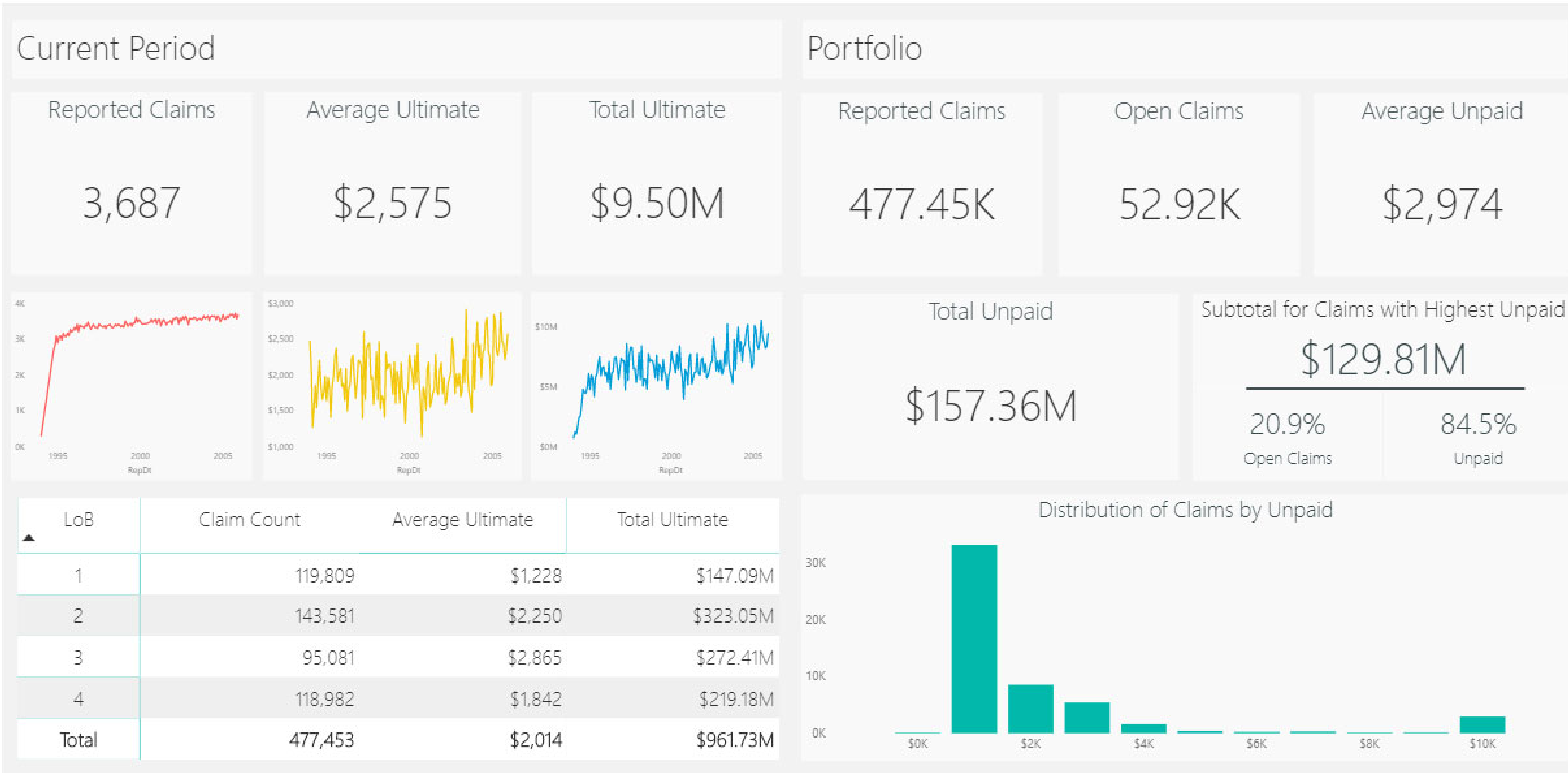
Claim Type 29: Low future payments

Studying Variance

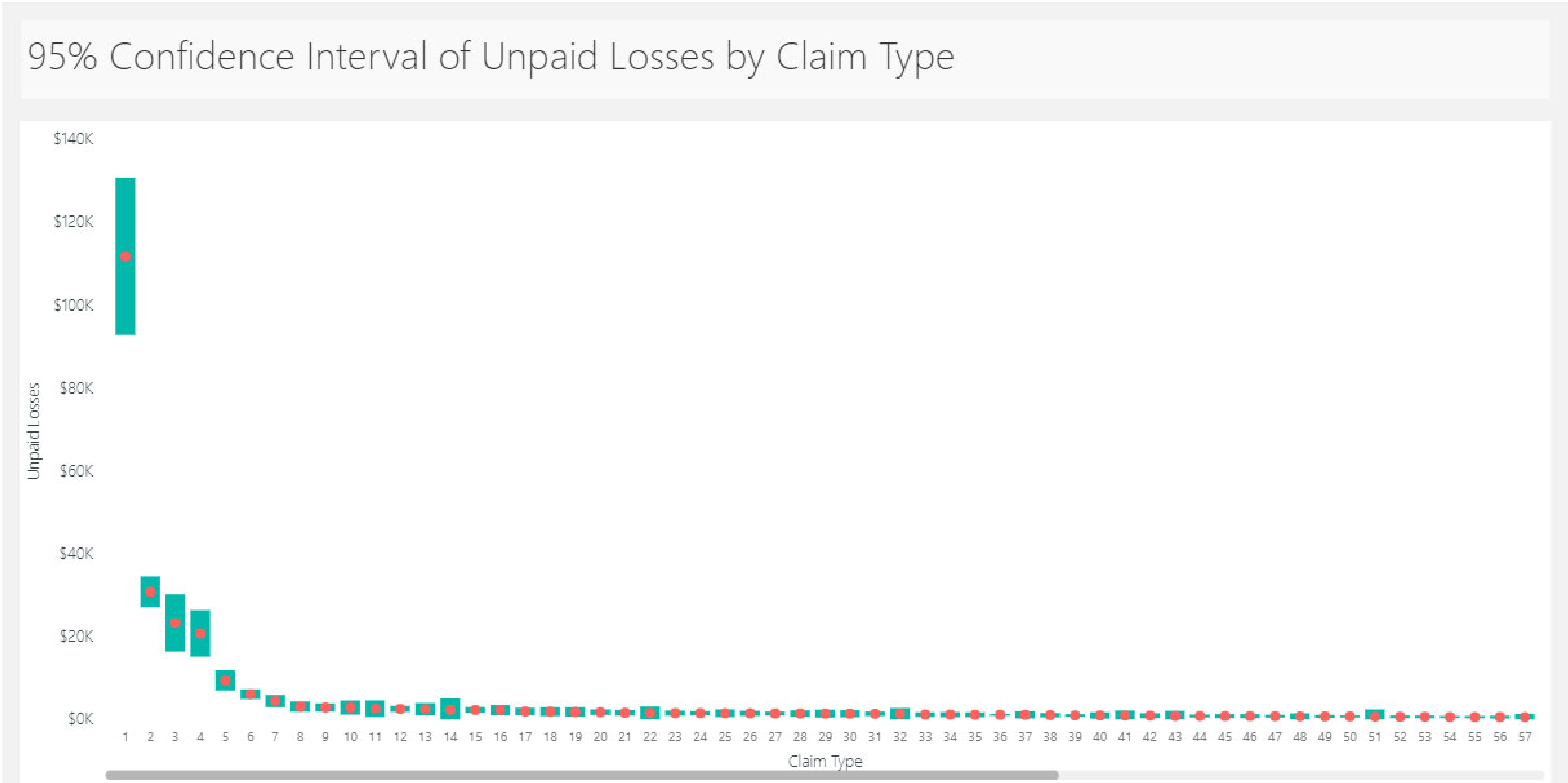
In addition to examining the average cumulative claim payments, we can examine the variance of the cumulative claim payments



Example Visualizations



LoB	Claim Count	Average Ultimate	Total Ultimate
1	119,809	$1,228	$147.09M
2	143,581	$2,250	$323.05M
3	95,081	$2,865	$272.41M
4	118,982	$1,842	$219.18M
Total	477,453	$2,014	$961.73M


95% Confidence Interval of Unpaid Losses by Claim Type
Unpaid Losses
$140K
$120K
$100K
$80K
$60K
$40K
$20K
$0K
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57
Claim Type

Claims with High Unpaid

Unpaid

$129.8M

For Claims with High Unpaid

Claims

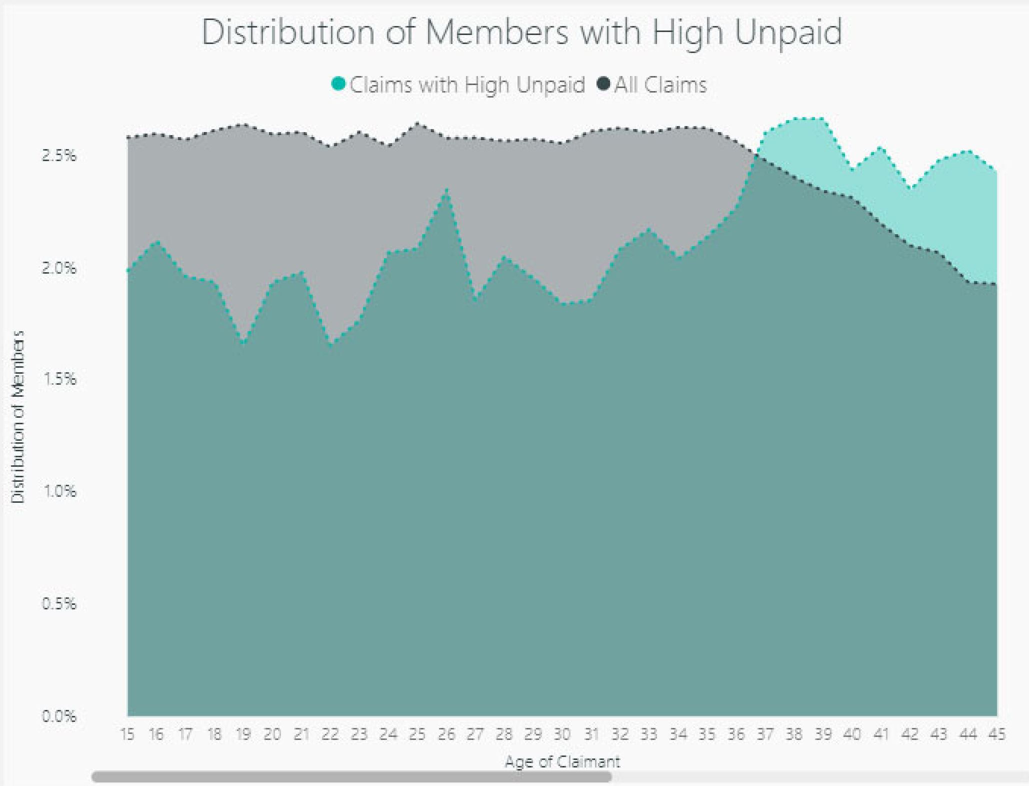
11K

20.9%
Claims

84.5%
Unpaid

Unpaid Threshold

$2,000



Claim ID	Unpaid
359	$2,817
413	$2,386
682	$2,817
770	$2,817
782	$2,221
926	$3,446
1100	$2,817
1593	$2,221
1661	$2,817
1734	$2,817
1827	$2,817
2026	$60,026
2547	$2,817
2774	$60,026
2951	$2,386
3015	$10,584
3563	$10,584
4039	$2,817
4118	$2,817
4468	$2,817
4636	$2,817

Benefits of Reserving with Machine Learning

Speed: automated analysis pipelines can run in hours

Deeper insights: leads to better understanding of changes in loss reserves, more accurate pricing, smarter loss prevention

Claims triage: uncovering new opportunities to proactively manage outcomes

Understanding variance: leads to more clearly articulated confidence intervals and risk levels

Three ways to learn more

1. Interested in helping with research?
   Visit us at **www.kyrosinsights.com/insurance**
2. Read our CAS E-Forum paper:
   Reserving with Machine Learning: Applications for Loyalty Programs and Individual Insurance Claims
3. Email us!
   len.llaguno@kyrosinsights.com
   julie.hagerstrand@kyrosinsights.com