Casualty Actuarial Society Annual Meeting

Using Predictive Analytics for Claim Modeling

Todd Lehmann, FCAS, MAAA, CPCU - Quincy Mutual Fire Insurance
Stan Smith - Milliman, Inc.
Brian Z. Brown, FCAS, MAAA – Milliman, Inc., CAS President-Elect

November 13-16, 2016

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Image Analytics In Claims

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Topics

- Intro
- Google Earth, Drones and Satellites
- Case Study
- Smart Phone Apps

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- Today's overhead images
  - High resolution
  - Captured by drones and satellites
  - Archived
- Insurance applications
  - Underwriting
  - Developing Pricing models
  - Claims

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Property

- You look up any property and get 3-8 images taken over the past 2 years at any given time
  - Overhead pictures
  - Street-view pictures

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Auto

- You look up any auto and get multiple images taken over a selected timeframe
  - Categorized by License plate
  - Taken by roving vehicles at any given time

- What are the possibilities of this level of imagery data in Insurance?
  - Risk assessment at Point of Sale
  - Underwriting the in-force book
  - Pricing
  - Claims

Property Claims

- Claims adjusters can see the roof condition prior to the accident
  - Was it in good condition?
    - Any pre-existing obvious damage?
  - Consistent with normal wear or has there been faster deterioration than what roof age would suggest?

Survey of Claims Adjusters

- Would you want to know...
  - What is the condition prior to loss?
  - Was the property remediated as expected?
  - What does the repaired property look like?
  - Comments and concerns

Property and Auto

- Claims implications are possibly more powerful for Property than Auto because
  - We have multiple angle images before the loss
  - We have a better way of knowing the condition before the loss
- Depending on the frequency or speed of image capture (drones on demand), we can see the damage real time

Property Claims

- For every land parcel in the US, we have images to view property condition
  - Before loss
  - After loss event
  - After remediation is completed/Claim is paid
- These images can be part of the Claims file for FNOL and Case Adjuster review
  - Are significant features or trees missing in this sequence?
  - Are the images consistent with the Claims file notes?

Property Claims

- Claims adjusters can see what work has been done once the repairs have been completed
  - What material chosen?
  - Has there been any expansion or new features added?
  - Approximately when the work was completed?

Winter Storm Event – 2015

Shingles seen shifting and lifting from the roof after the Winter Storm Event

Roof replaced

Operationalizing Image Technology

- Potential Barriers
  - Cost
  - IT
    - The need for an integrated Claims and Underwriting platform sharing data seamlessly is critical
  - Where to store and how long to keep
- Security concerns

Integrating Claims Data and Images

- Winter storm severity modeling post event
- Understanding ice dam factors and causes
- Assisting in reserve setting

Weather-Related Claims

- Detailed maps and images of weather data aggregated to show event impacts by peril
  - Hail size and intensity
  - Rain fall
  - Wind speed (gust intensity)
  - Collected by US Climate Reference Network and other sources

Weather-Related Claims

- Overlay these maps with insured locations
  - Regularly done for Fire storms occurring in the Western US
  - Now we can do this analysis with any weather/natural peril related event
  - Variety of mapping options
    - Google Earth with KMZ files
    - Commercial software

Weather-Related Claims

- What can you do with this?
  - Triage adjusters
    - Obvious damage
    - Severe damage needing expert
    - Area with little or no damage
  - Identify Potential Claims

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Weather-Related Claims

- Example: August 4, 2015 Hail Storm in Metrowest Boston

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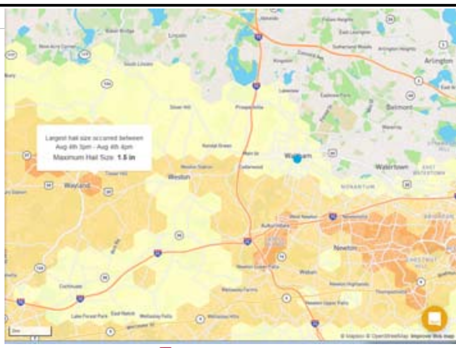

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Smart Phones

- Claims Apps utilizing smart phone technology
  - Customers taken their own photos of losses
    - Time-stamped
    - Geo-stamped
  - Submitted to insurers immediately
- For Property claims, the adjuster sees
  - Whether this is a covered location
  - Whether damage is consistent with a covered cause

- Then
  - A picture is worth a thousand words
- Now
  - A picture is worth a lot more than words

Predictive Models for Case Reserves

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Insurers cannot rest

- "Companies that have not actively invested in improving their pricing sophistication, efficiency and risk management are at a competitive disadvantage and will not be relevant in the long term".
- Source: A.M. Best

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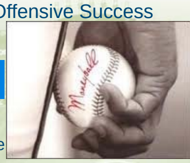
MONEYBALL AND SABERMETRICS

Indicators of Offensive Success

TRADITIONAL MEASURE

- Home Runs
- Batting Average
- Stolen Bases
- RBI's



Runner on...	0 out	1 out	2 out
Empty Bases	0.454	0.249	0.095
1st Base	0.783	0.478	0.209
2nd Base	1.068	0.699	0.348
3rd Base	1.277	0.897	0.382
1st and 2nd	1.380	0.888	0.457
1st and 3rd	1.639	1.088	0.494
2nd and 3rd	1.946	1.371	0.661
Bases Loaded	2.254	1.546	0.798

Expected Future Runs Scored in an inning given certain conditions. (1961-77 data set)

MONEYBALL MEASURES

- On-Base %-age
- Slugging %-age
- Pitch Data

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Winning an unfair game

"People operate with beliefs and biases.

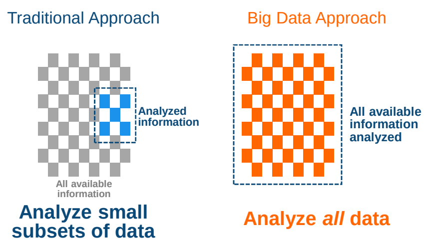
To the extent you can eliminate both and replace them with data, you gain a clear advantage."

Michael Lewis,

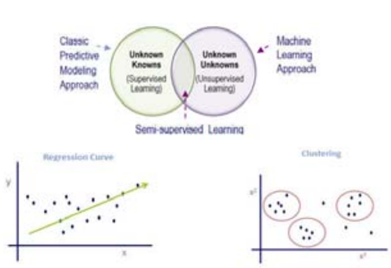
Moneyball: The Art of Winning an Unfair Game

Analytics can help identify "Useful" data

- Leverage more of the data being captured



Supervised versus Unsupervised approaches



Text mining variables

- Text mining refers to the process of deriving relevant and usable text that can be parsed and codified into a word or numerical value.
- Text mining can identify co-morbid conditions and/or situations that will have profound impact on the outcome of a claim.

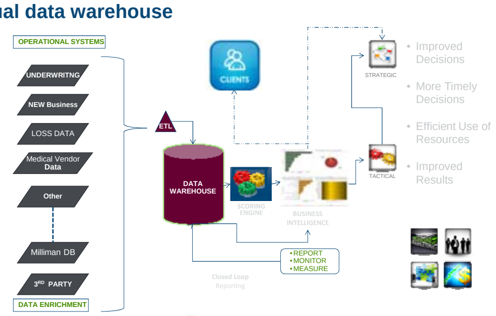
SAMPLE KEY WORDS/PHRASES
▪ Diabetes/insulin/injections
▪ Packs day/coughing
▪ Pain killers/anti-depression
▪ Children/school
▪ Pain unchanged
▪ Height/Weight
▪ Homemaker wife went to work
▪ c/o, CXR, FB, FX
▪ CBT – Cognitive Behavior Therapy

Text sources: Adjuster notes, medical reports, independent medical exams, etc.

Modeling architecture

- **Data Store.** All historical data collected and organized.
- **Training.** Identifying company/internal/external data specific patterns.
- **Testing.** Using "hold out" sets to measure the accuracy of predictions.

Virtual data warehouse



Complementary Analytics Solutions

Underwriting
Better Decisions

- Leveraging data and analytics
- Improved pricing and segmentation
- Improved client targeting

WC Claim
Better Outcomes

- Predictive Modeling - pro-active claim management
- Data Warehouse - comprehensive view of internal data

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Decision support example - claims

Quickly identify "creeping catastrophic" claims.
- Less than 20% of claims cause 80% of losses

Create better claims outcomes with more timely and more detailed information.
- Loss cost reductions that generally range from 3-6% per year

"Operationalize" into claims/medical protocols/rules.

Integrate management of all available sources of data/information.

"Second pair of eyes" on existing claim/medical vendors.

Ancillary benefits.
- Data driven culture

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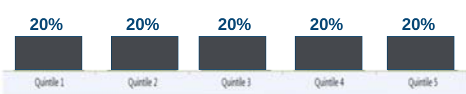
Segmentation analysis

Divide All Claims into 5 buckets of 20% each.
- After Scoring distribute by Risk Score
- Highest Risk to the Right
- Lowest Risk to the Left
- Each Claim has an individual score
- Worst Claim far right vs. Best Claim far left
- Then add actual losses to test model accuracy



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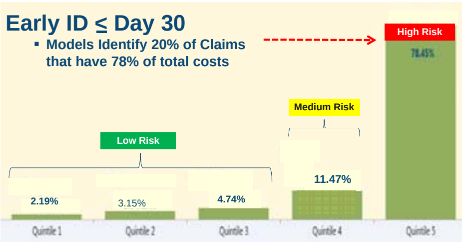
Predictive modeling in action



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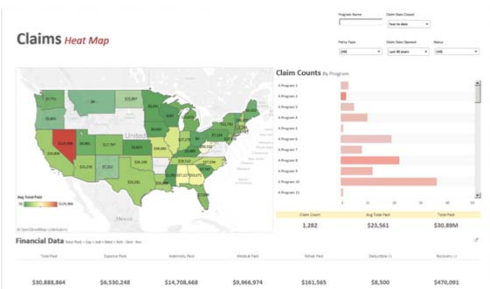

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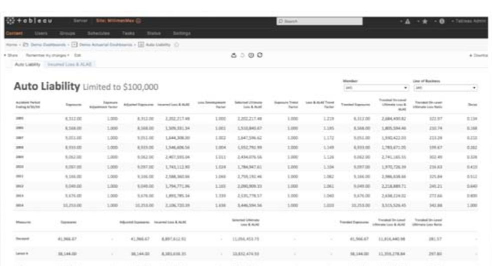
Actuarial Dashboard – Auto Liability



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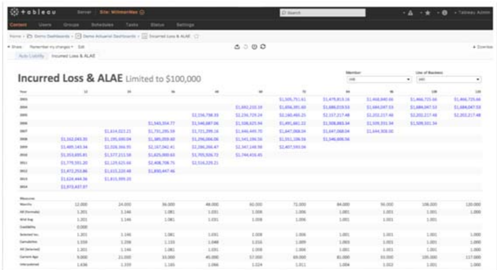
Actuarial Dashboard – Incurred Loss & ALAE



Predictive model case studies

Closed Claim Impact

Client Case Study #1

Payment Trends – Totals over 10 Year Period

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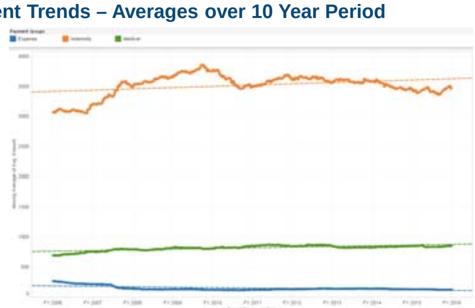
Payment Trends – Averages over 10 Year Period



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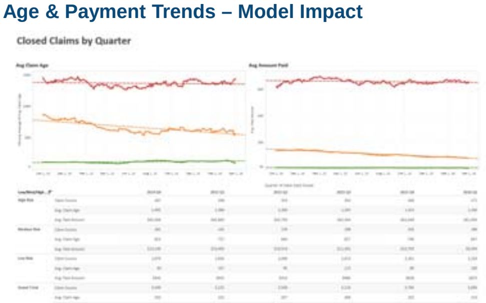
Claim Age & Payment Trends – Model Impact



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Reserving Impact
Client Case Study #2

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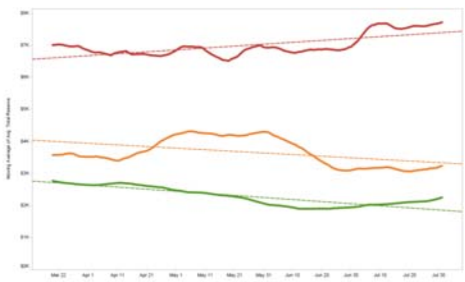
Reserving Trends – Model impact first 30 days



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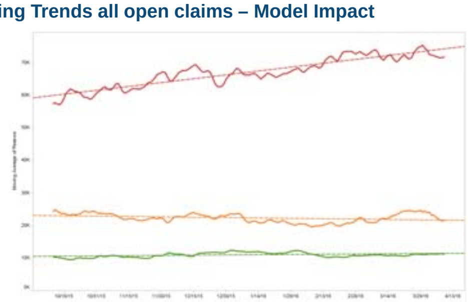
Reserving Trends all open claims – Model Impact



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Implementation considerations

Implementation planning is critical

Who has access to the model and its results? Access to the model and its output could potentially influence behavior

- **Could impact how case reserves are set in the future if claims adjusters have access to the model output**
  - **Impacts development patterns used for traditional actuarial reserving and ratemaking techniques**
  - **Would model still be relevant or applicable if underlying inputs are being changed?**

Staff morale. Be cognoscente of how various business units might react to the implementation of the model

- **Intentions of model should be communicated to those who might be affected by the model**
  - **Fear of job elimination (claims adjusters, traditional reserving actuaries)**

How to measure return on investment? Predictive modeling can be costly; make sure you're getting the most out of your investment

- **Designate benchmarks before modeling**

Regulation. Will regulators at some point need to review model?

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Evaluating Model Accuracy

Introduction

"It's hard to make predictions, especially when they are about the future."

-Baseball legend Yogi Berra

Predictive Model

- Now that we have a model, what are the most important questions
  - Does it work
  - How well does it work
  - Would a different model work better

Evaluating Model Accuracy

- Check on unseen data
  - Randomly selected hold out data
  - Compare model prediction to actual answer

Overfitting and Underfitting

- Typical diagnostic measures like R^2 are not as useful for machine learning
- Overfitting: model captures both data and noise in the training set
- Underfitting: model does not predict well with training data or hold out data
- Cross validation
  - Training data – used to build model
  - Validation data (subset of training data) – used to modify model
  - Hold out data – test performance of modified model

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Binary Classification

- Output includes a score (e.g., 0 to 100)
  - 1 indicates claim is unlikely to develop adversely and 99 indicates it is likely to develop adversely
- Need to select a threshold point and compare scores of individual claims against it
- Score higher than threshold positive result (e.g., jumper claim)

Actual Result	Jumper Claim	Missed Jumper Claim	Correct
	Stationary Claim	Correct	False Positive
		Stationary Claim	Jumper Claim
		Predicted Result	

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Binary Classification (cont'd)

- By moving the line to the right (higher score), will have fewer false positives but more missed jumper claims
- Part of implementing the model depends on your goals
- If jumper claims require significant time and effort by claim staff, you may want few false positives
  - Able to start slow to show benefit
- Alternatively, if you can manage the overall outcome of jumper claims better when they are identified, it may be OK to have more false positives
  - Will still need to manage missed claims

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Model Accuracy Criterion

- Accuracy
  - Percentage of total predictions (i.e., positive & negative) that are correct
- Precision
  - Percentage of predicted positives that are actual positives (= correct predicted positives / total predicted positives)
  - Base is predicted positive
- Recall
  - Percentage of actual positives that are predicted positive
  - Base is actual positive
- Other
  - Ability of model to predict a higher score for positive events

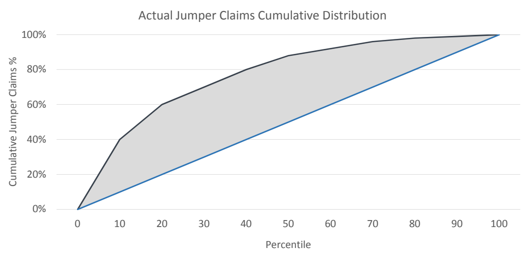
Lift Charts

- Measure performance of model against random guessing
  - Useful to compare accuracy of different models
  - Helpful in selecting cut-off points

Lift Curve

Percentile	Number of Claims	Actual Jumper Claims	Relative Lift
0 - 10	10,000	2,000	4.0
11 - 20	10,000	1,000	2.0
21 - 30	10,000	500	1.0
31 - 40	10,000	500	1.0
41 - 50	10,000	400	0.8
51 - 60	10,000	200	0.4
61 - 70	10,000	200	0.4
71 - 80	10,000	100	0.2
81 - 90	10,000	50	0.1
91 - 100	10,000	50	0.1
Total	100,000	5,000	1.0

Lift Curve (cont'd)



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Reserve Adjustments

- Early intervention may reduce development in later years and improve results (e.g., improved medical care early on)
- Monitor claim reserves before and after initiative (helpful if base is range of claim outcomes)
- Reserve analysis requires additional work and is company / situation specific
  - Berquist-Sherman Methods
  - Adjust patterns
    - Reports
    - Payout
  - Adjust Loss Ratios

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Thank you

tlehmann@quincymutual.com
stan.smith@milliman.com
brian.brown@milliman.com