LEVERAGING DATA FOR STRATEGIC ADVANTAGE

MAY 19, 2017

RYAN DRAUGHN, DIRECTOR OF INFORMATION TECHNOLOGY, NLC MUTUAL
MARK SNODGRASS, CHIEF INFORMATION OFFICER, CIS
STAN SMITH, PRACTICE LEADER, GRADIENT AI, A MILLIMAN COMPANY
<table>
<thead>
<tr>
<th>Loss Date</th>
<th>Reported Date</th>
<th>Status</th>
<th>Department</th>
<th>TOTAL PAID</th>
<th>TOTAL RESERVES</th>
<th>TOTAL RECOVERIES</th>
<th>TOTAL RECOVERIES</th>
<th>TOTAL INCURRED</th>
</tr>
</thead>
<tbody>
<tr>
<td>06/06/2006</td>
<td>06/12/2006</td>
<td>Open</td>
<td>DPW</td>
<td>$599,712</td>
<td>$282,786</td>
<td>$0</td>
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<td>06/14/2006</td>
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<td>$0</td>
<td>$407,009</td>
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<td>07/05/2006</td>
<td>Open</td>
<td>Fire</td>
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<td>$494,936</td>
<td>$92,250</td>
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<td>07/28/2006</td>
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<td>$414,811</td>
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<td>07/21/2006</td>
<td>07/25/2006</td>
<td>Open</td>
<td>Social Services</td>
<td>$369,246</td>
<td>$444,521</td>
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<td>09/15/2006</td>
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<td>$869,136</td>
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<td>10/10/2006</td>
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<td>Water</td>
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<td>$648,924</td>
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<td>11/22/2006</td>
<td>11/27/2006</td>
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<td>Maintenance</td>
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<td>$217,973</td>
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<td>$0</td>
<td>$0</td>
<td>$409,672</td>
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<td>01/30/2007</td>
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<td>$0</td>
<td>$0</td>
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<td>DPW</td>
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<td>$418,097</td>
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<td>$0</td>
<td>$0</td>
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<tr>
<td>02/23/2007</td>
<td>02/26/2007</td>
<td>Open</td>
<td>Transportation</td>
<td>$423,321</td>
<td>$18,755</td>
<td>$0</td>
<td>$0</td>
<td>$442,076</td>
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<tr>
<td>03/02/2007</td>
<td>03/08/2007</td>
<td>Closed</td>
<td>Highway</td>
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<td>$0</td>
<td>$0</td>
<td>$459,769</td>
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<tr>
<td>03/17/2007</td>
<td>03/20/2007</td>
<td>Closed</td>
<td>Police</td>
<td>$417,741</td>
<td>$0</td>
<td>$0</td>
<td>$0</td>
<td>$417,741</td>
</tr>
<tr>
<td>04/03/2007</td>
<td>04/05/2007</td>
<td>Open</td>
<td>Fire</td>
<td>$598,613</td>
<td>$207,254</td>
<td>$166,553</td>
<td>$31,444</td>
<td>$607,870</td>
</tr>
</tbody>
</table>
Global Safety Dashboard - YTD

29 SERIOUS INCIDENTS
47 LOST TIME INCIDENTS
29 REPORTED INJURIES
2089 TOTAL INCIDENTS

Last 18 Months Frequency Rates

Lost Time Incidents by Gender
38 % Male
62 % Female

Incident Details by Body Location

Lost Time Incidents

- April 2016: 1
- July 2016: 2
- October 2016: 1

Serious Lost Time Incidents

- April 2016: 2
- July 2016: 2
- October 2016: 1

Total Recorded Injuries

- April 2016: 1
- July 2016: 2
- October 2016: 2

Incident Count by Body Location

- Back: Avg 39
- Hands/Fingers: 10
- Trunk: 2
- Ankle: 2
- Arms: 5
- Eyes: 2
- Buttocks: 1
- Face: 2
- Wrist: 1
- Shoulder: 1
- Head: 1
- Feet/Tiess: 1
- Knee: 1


NLC Mutual Insurance Company
660 Capitol Street NW Suite 450 Washington, DC 20001
Tracking Driver Movements via GPS/Blackbox

- Your location
- How long you have been driving for
- How fast you accelerate
- How harsh or smooth your braking is
- Your cornering

1. They fit a clever little device into your car
2. The device measures how well you drive
3. View feedback on how you’re driving
4. Good drivers could save money on their car insurance

https://www.confused.com/car-insurance/black-box/telematics-explained
Changing how decisions are made

“Carriers may no longer need to compete on price; they instead may be able to assess the risk of individual customers based on their actual behaviors”

“Additionally, commercial insurance increasingly will be able to focus on providing customized, flexible products and value-added services that involve working with the clients to proactively avoid or reduce losses and manage risks.”

– PriceWaterhouseCoopers
Overview

THE IMPORTANCE OF LEVERAGING INFORMATION
## Potential Benefits & Uses of Data

<table>
<thead>
<tr>
<th>Benefit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pools need it to be successful and relevant to their members</td>
<td>NLC needs it to continue to be successful and relevant to you, our members</td>
</tr>
<tr>
<td>The industry is moving (or has moved) in this direction – we need to keep up!</td>
<td>Allows for ability to make better decisions – Trustees and Staff</td>
</tr>
<tr>
<td>Technology is evolving (constantly and quickly)</td>
<td>New and Innovative way to spot trends and apply strategic measures</td>
</tr>
<tr>
<td>• We can’t even begin to imagine the possibilities of what might be available to us in even 3-5 years.</td>
<td></td>
</tr>
</tbody>
</table>
Leveraging Pool Data: 

A GAME CHANGER
Evolution of Data Analytics

Credit: Cray, Inc.
Data Analytics & Reporting Spectrum

**Basic**
- Standard or traditional reporting
- Manual process for data gathering
- Excel spreadsheets and charting

**Intermediate**
- Utilizing business intelligence and visualization tools for better decision-making
- Automated data gathering from disparate systems

**Advanced**
- Building a culture of data
- Beginning to utilize Predictive Analytics

**Future**
- Basing business decisions on results of predictive analytics
- Capturing data in real-time
- Leveraging machine learning and artificial intelligence
Why it Matters

Drive EFFICIENCIES to better serve your members

- Claims Management
- Pricing
- New Products/Coverages
- Marketing to Members

Database

Geographical Analysis
- Machine Learning
- Internet of Things
- Social Media
- Interactions
- Claim Notes
Intersection of Big Data and “Cloud”

As datasets grow, they need to be managed and stored somewhere. Your data should be:

- Economical
- Meet Compliancy Regulations
- Prevent Unauthorized Access
- Accessible for Fast Retrieval/Backup
- Optimized for Analytics

The evolution of cloud data storage and online big data tools now provide a mechanism to capitalize on our valued data.
Leveraging Data

Mark Snodgrass
CIS, Chief Information Officer
Leveraging Data

Strategic Plan Scorecard

Strategic Plan Objectives

# of strategies meeting or exceeding goals

#1: "Think digital, act analog" to develop and maintain relationships across a broad spectrum of CIS.

#2: Introduce programs/services that respond to member needs, reduce costs, and create long-term value.

#3: Better integrate systems, products, and information.

#4: Determine "optimal" levels for rates and reserves, and develop a five-year plan for achieving those levels.

#5: Introduce programs/services that respond to member needs, reduce costs, and create long-term value.

#6: Communicate with members and others so as to understand their needs, and to continually demonstrate the value of CIS in meeting them.
Leveraging Data

Strategic Plan Scorecard

Strengthen our use of technology and data and to better understand the nature of risk, reduce claims and costs, and connect members with CIS.

4 of 6 strategies meeting or exceeding goal

- **Continue to develop tools for staff to produce ad hoc reports and analysis.**
  - **Goal:** 500
  - **Actual:** 400

- **Define key metrics in all trusts and develop monitoring dashboards around them.**
  - **Goal:** 100%
  - **Actual:** 0%

- **Develop key metrics in each line of coverage for members of different sizes and produce monitoring tools for members and their assigned CIS staff.**
  - **Goal:** 80%
  - **Actual:** 90%

- **Continue to use benefits data to drive underwriting decisions and health risk management initiatives.**
  - **Goal:** 100
  - **Actual:** 150

- **Expand existing member databases to include comprehensive data on all Oregon counties, cities and CIS-eligible organizations, including key officials, budgets (particularly for insurance/employee benefits), number of employees, and coverage outside of CIS.**
  - **Goal:** 10,000
  - **Actual:** 11,000

- **Provide user-friendly access to CIS electronic services across multiple platforms.**
  - **Goal:** 1,000
  - **Actual:** 1,100
## Leveraging Data

### CIS Activity Scorecard

<table>
<thead>
<tr>
<th>Category</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-Loss Events</td>
<td>17</td>
</tr>
<tr>
<td>WC Claims</td>
<td>17</td>
</tr>
<tr>
<td>PL Claims</td>
<td>36</td>
</tr>
<tr>
<td>Member Contacts</td>
<td>4</td>
</tr>
<tr>
<td>Contact Changes</td>
<td>35</td>
</tr>
<tr>
<td>Interim Changes</td>
<td>701</td>
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</table>
### Benefits Analyzer

#### Medical

<table>
<thead>
<tr>
<th>EBS</th>
<th>AOCIT</th>
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<tbody>
<tr>
<td><strong>Loss Ratio</strong></td>
<td><strong>Loss Ratio</strong></td>
</tr>
<tr>
<td>↑ 98.74%</td>
<td>↑ 111.44%</td>
</tr>
<tr>
<td><strong>Gain/Loss</strong></td>
<td><strong>Gain/Loss</strong></td>
</tr>
<tr>
<td>↓ $166,723</td>
<td>↑ -$792,108</td>
</tr>
<tr>
<td><strong>Employees</strong></td>
<td><strong>Employees</strong></td>
</tr>
<tr>
<td>↑ 5,289</td>
<td>↑ 2,915</td>
</tr>
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</table>
# Leveraging Data

## Predictive Algorithms

<table>
<thead>
<tr>
<th>Data</th>
<th>Input</th>
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</thead>
<tbody>
<tr>
<td>Date Reported</td>
<td>11/9/2011</td>
</tr>
<tr>
<td>Date of Injury</td>
<td>11/2/2011</td>
</tr>
<tr>
<td>Dept</td>
<td>Juvenile</td>
</tr>
<tr>
<td>Hire Date</td>
<td>5/1/2011</td>
</tr>
<tr>
<td>Birthdate</td>
<td>2/6/1954</td>
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<tr>
<td>Cause Code</td>
<td>Caught in, under, or between, UNS</td>
</tr>
<tr>
<td>MO/Indemnity</td>
<td>Indemnity</td>
</tr>
<tr>
<td>Injury Type</td>
<td>Strain</td>
</tr>
<tr>
<td>Body Part</td>
<td>Shoulder</td>
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</table>
## Leveraging Data

### Predictive Algorithms

<table>
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<tr>
<th>Projection</th>
<th>OUTPUT</th>
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</thead>
<tbody>
<tr>
<td>Risk Score</td>
<td>44</td>
</tr>
<tr>
<td>MO Projection</td>
<td>$2,033</td>
</tr>
<tr>
<td>Expected (Mean)</td>
<td>$16,943</td>
</tr>
<tr>
<td>Indemnity Projection</td>
<td>$29,819</td>
</tr>
<tr>
<td>Time Loss</td>
<td>46</td>
</tr>
<tr>
<td>Claim Close Days</td>
<td>156</td>
</tr>
</tbody>
</table>

**Actual Cost**

-imator Projected Cost: $2,033

- Expected (Mean) Projected Cost: $16,943

- Indemnity Projected Cost: $29,819

**Time Loss**

- Claim Close Days: 156
## Leveraging Data

### Return to Work Cost Savings

<table>
<thead>
<tr>
<th>Claim Number</th>
<th>Claimant</th>
<th>Event Date</th>
<th>Referral Date</th>
<th>MDA Cost Savings</th>
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<tbody>
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<td>2012-2013</td>
<td></td>
<td></td>
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<td>$1,005.42</td>
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<tr>
<td>WCALB2013060836</td>
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<td>5/11/2013</td>
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<td>2014-2015</td>
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<tr>
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<td>6/8/2016</td>
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<td>2/23/2015</td>
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<td>2015-2016</td>
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<td>WCALB2016069503</td>
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<td>1/22/2016</td>
<td>$5,144.69</td>
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<td>$295.49</td>
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<td>2016-2017</td>
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<td></td>
<td></td>
<td>$4,117.47</td>
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<td>7/2/2016</td>
<td>7/12/2016</td>
<td>$4,117.47</td>
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<tr>
<td><strong>Total:</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>$29,463.74</strong></td>
</tr>
</tbody>
</table>
Member Comparison

GL Avg. Cost/Claim Comparison

-$0$

-$5,000$

-$10,000$

-$15,000$

Lincoln City: $2,970

Cities w/ Pop. 5K to 10K

Pool: $10,116

Pool: $9,315
Leveraging Data

Member Comparison

GL Loss Ratio Comparison

- Lincoln City: 24%
- Pool: 54%
- Cities w/ Pop. 5K to 10K: 54%
Artificial Intelligence and Advanced Decision Support

Stan Smith
May 19, 2017
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 Dec. 2015
Advanced Math - for non-mathematicians!
Moving Away from Linear (Traditional) Models

Predict health given height and weight

- Healthy Individual
- Unhealthy Individual
Moving Away from Linear (Traditional) Models

Predict health given height and weight

- Healthy Individual
- Unhealthy Individual

Logistic Regression
Moving Away from Linear (Traditional) Models

Predict health given height and weight

Logistic Regression

Healthy Individual
Unhealthy Individual
Moving Away from Linear (Traditional) Models

Predict health given height and weight

- Healthy Individual
- Unhealthy Individual

Decision Trees
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
What is Different about Artificial Intelligence?

- Technology platform provides rapid and continuous assessment of new data sources
  - Is new data useful or useless?
  - Measure impact across multiple applications – Underwriting, Claims and Loss Control
    - Can be assessed at any level – by individual client, by client group (similar risks – different geographies)
    - Identifies “hard to identify” relationships that drive significant “predictability”
  - Professional Liability example:
    - Staffing level – little direct correlation to losses
    - Procedure complexity/severity level – surprisingly little direct correlation to losses
    - Combined into one or more “Synthetic” variable(s) - very strong correlation to future losses
A.I. is only part of the solution

The amount of data matters

- Internal data – from ALL your systems
- External data
  - 3rd Party – census, socio-economic, housing, etc.
  - Accessing aggregated Data
- In our work we have the ability to leverage:
  - Millions of work comp claims
  - Health data – millions of lives per year How similar are your results
- Health data – 70+ million lives per year of individual data collected, de-identified and aggregated
Virtual Data Warehouse

- Improved Decisions
- More Timely Decisions
- Efficient Use of Resources
- Improved Results

DATA ENRICHMENT

1. Milliman DB
2. 3rd PARTY
3. Medical Vendor Data
4. LOSS DATA
5. Associated Exposure DATA
6. EXPOSURE

OPERATIONAL SYSTEMS

ETL

DATA WAREHOUSE

SCORING ENGINE

BUSINESS INTELLIGENCE

CLIENTS

• REPORT
• MONITOR
• MEASURE

Closed Loop Reporting

STRATEGIC

TACTICAL

May 10, 2017
Analytics can help identify “Useful” data

- Leverage more of the data being captured

Traditional Approach

All available information

Analyzed information

Analyze small subsets of data

Big Data Approach

All available information analyzed

Analyze all data
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/situations that will have profound impact on the outcome of a claim.

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

Text sources: Adjuster notes, medical reports, independent medical exams, etc.
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
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
Leveraging all Client data – Claim Example

§ All claim system data – notes and details

▪ All clinical data
  § Transactional medical billing data
  § Pharmacy data – prescription, pill count, dispensing location, etc.
  § Field Nurse Case Management, notes and recommendations

§ All other vendor data

▪ Third party data
  § Claimant background
  § Social Media

§ Milliman aggregated DB
  § Aggregated and anonymized to enrich and improve model results
External Data Sources

*Below is a description of data sources that have been experimented with in addition to the data provided directly by the client*

Geographic Data
Where an insured is based geographically contains valuable information, however typically this is codified in a database with a zip code. Since the zip code is *just* a number, it is hard for the model to interpret what it means and how different zip codes compare to each other. In order to help the model understand trends between different types of regions, we try adding additional features (e.g., comorbidities, socioeconomic) to the model that describe the area an insured is located.

Class Code Data
Understanding what someone’s occupation is can be very important for modeling, however this is usually codified in a database by a “class code”. Similar to zip codes, class codes are just numbers and are difficult for the model to interpret and compare on their own. To help the model, we experiment with using our own database of more than 1 million Worker’s Compensation claims to calculate some class-code-level statistics. This can help the model understand which class codes are similar and the risks involved in each.

Hospital Data
CMS collects data on more than 3000 hospitals in the US and the statistics of 100 different types of procedures performed at those hospitals, including the average cost, the number per year, the average contribution from Medicare. For claims where have have the hospital “provider ID”, we can look up these statistics for that hospital and incorporate that into the model.
Claims Management Models

- **Early Intervention (EI)** models identify complex claims early – within first 30 days:
  - Identify majority of “Creeping Cat” claims
  - Maximize resource utilization on claims that offer highest return
  - Allow optimum Adjuster workload by claim complexity
  - Reduce inefficient and ineffective resource utilization on low risk low cost claims

- **Claim Glidepath™ (GP)** models track claims - day 30 through closure:
  - Monitor all open claims and alerts on changes to expected outcomes
  - Also monitor all closed claims to identify any claims that could re-open
  - Serves as a foundation for additional complementary models
Decision Support - 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 (e.g., TPA transformation, data driven culture)
**Segmentation Analysis** - Tests Model Accuracy

Divide *all scored claims* into segments

**Lowest Risk**
*Best Claims*

- Quintile 1: 20% of scored claims
- Quintile 2: 20% of scored claims
- Quintile 3: 20% of scored claims

**Highest Risk**
*Worst Claims*

- Quintile 4: 20% of scored claims
- Quintile 5: 20% of scored claims
Testing Model Performance
Model Segmentation *Example*  
Early Intervention

MO Model Output Segmentation for Scores from Week 4 to Week 6

- **Avg Ultimate Claim Cost:** $2,000
- **Avg Ultimate Claim Cost:** $30,000
Model Segmentation Example

Early Intervention

MO Model Output Segmentation for Scores from Week 4 to Week 6

Avg Ultimate Claim Cost: $2,000
(Least Risky Segment)

Least Risky

Most Risky

Avg Ultimate Claim Cost: $30,000
(Most Risky Segment)
Model Segmentation *Example*
GlidePath (3 months)

**MO Model Output Segmentation for Scores from Week 11 to Week 14**
- Least Risky
- Most Risky

$4,000

**LT Model Output Segmentation for Scores from Week 11 to Week 14**
- Least Risky
- Most Risky

$95,000
Model Segmentation *Example*
GlidePath (6 months to 9 months)

MO Model Output Segmentation for Scores from Month 6 to Month 9

- Least Risky
- Most Risky

LT Model Output Segmentation for Scores from Month 6 to Month 9

- Least Risky
- Most Risky

$8,000

$150,000
Case-Level Reserving

Dashboards
# Case-Level Reserving Dashboard

## Aggregate Claim Summary

<table>
<thead>
<tr>
<th>Breakdown</th>
<th>Manual Incurred (scored)</th>
<th>Incurred</th>
<th>Difference</th>
<th>Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indemnity</td>
<td>6,932,729,974</td>
<td>6,541,214,730</td>
<td>391,515,244</td>
<td>5.99%</td>
</tr>
<tr>
<td>Medical</td>
<td>6,712,130,731</td>
<td>6,045,570,737</td>
<td>2,066,559,994</td>
<td>31.10%</td>
</tr>
<tr>
<td>Expense</td>
<td>1,897,893,162</td>
<td>1,729,836,064</td>
<td>168,057,098</td>
<td>9.27%</td>
</tr>
<tr>
<td>Rehab</td>
<td>77,936,586</td>
<td>57,837,305</td>
<td>20,099,281</td>
<td>34.75%</td>
</tr>
<tr>
<td>Grand Total</td>
<td>17,620,690,453</td>
<td>14,974,456,836</td>
<td>2,646,231,617</td>
<td>17.67%</td>
</tr>
</tbody>
</table>

## Claim Totals

<table>
<thead>
<tr>
<th>Breakdown</th>
<th>Claim Count</th>
<th>Reserve</th>
<th>Recovered</th>
<th>Manual Incurred</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indemnity</td>
<td>4,227,200,048</td>
<td>2,959,922,945</td>
<td>-220,462,919</td>
<td>6,932,729,974</td>
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<tr>
<td>Medical</td>
<td>5,362,986,877</td>
<td>3,512,042,195</td>
<td>-162,903,341</td>
<td>8,712,130,731</td>
</tr>
<tr>
<td>Expense</td>
<td>1,284,502,790</td>
<td>646,383,040</td>
<td>-32,952,668</td>
<td>1,897,893,162</td>
</tr>
<tr>
<td>Rehab</td>
<td>39,819,876</td>
<td>38,376,942</td>
<td>-260,232</td>
<td>77,936,586</td>
</tr>
<tr>
<td>Grand Total</td>
<td>10,914,511,592</td>
<td>7,122,795,022</td>
<td>-416,816,161</td>
<td>17,620,690,453</td>
</tr>
</tbody>
</table>

## Claim Loss St., NCCI Injury Type, Body Part, Nature Code, Injury Source, Injury Type, Paid, Recovered, Manual Incurred, Incurred

<table>
<thead>
<tr>
<th>Claim Loss St.</th>
<th>NCCI Injury Type</th>
<th>Body Part</th>
<th>Nature Code</th>
<th>Injury Source</th>
<th>Injury Type</th>
<th>Paid</th>
<th>Recovered</th>
<th>Manual Incurred</th>
<th>Incurred</th>
<th>Difference</th>
<th>Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IL</td>
<td>0008</td>
<td>9070</td>
<td>6056</td>
<td>1508</td>
<td>302,665</td>
<td>-694</td>
<td>444,270</td>
<td>231,605</td>
<td>341,444</td>
<td>102,626</td>
<td>30.12%</td>
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<tr>
<td>IL</td>
<td>0135</td>
<td>9034</td>
<td>6340</td>
<td>1404</td>
<td>301,992</td>
<td>-99</td>
<td>445,335</td>
<td>143,343</td>
<td>12,131</td>
<td>32,131</td>
<td>7.75%</td>
</tr>
<tr>
<td>IL</td>
<td>0131</td>
<td>9004</td>
<td>6904</td>
<td>1420</td>
<td>75,415</td>
<td></td>
<td>229,242</td>
<td>155,827</td>
<td>33,038</td>
<td>23,29%</td>
<td>23.29%</td>
</tr>
<tr>
<td>IL</td>
<td>0227</td>
<td>9034</td>
<td>6844</td>
<td>1102</td>
<td>74,693</td>
<td></td>
<td>78,697</td>
<td>4,004</td>
<td>7,306</td>
<td>3,391</td>
<td>45.05%</td>
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<tr>
<td>IL</td>
<td>0200</td>
<td>9003</td>
<td>6314</td>
<td>1012</td>
<td>449</td>
<td></td>
<td>4,875</td>
<td>796</td>
<td>4,077</td>
<td>510.90%</td>
<td>510.90%</td>
</tr>
<tr>
<td>IL</td>
<td>0293</td>
<td>9004</td>
<td>6004</td>
<td>1002</td>
<td>12,254</td>
<td></td>
<td>34,164</td>
<td>19,919</td>
<td>14,245</td>
<td>76.58%</td>
<td>76.58%</td>
</tr>
<tr>
<td>IL</td>
<td>0209</td>
<td>9035</td>
<td>6382</td>
<td>1302</td>
<td>138,009</td>
<td>-2,354</td>
<td>208,837</td>
<td>72,776</td>
<td>135,061</td>
<td>33,561</td>
<td>19.15%</td>
</tr>
<tr>
<td>IL</td>
<td>0090</td>
<td>9009</td>
<td>6360</td>
<td>1102</td>
<td>107,260</td>
<td>-8</td>
<td>168,472</td>
<td>60,212</td>
<td>9,956</td>
<td>8.56%</td>
<td>8.56%</td>
</tr>
<tr>
<td>IL</td>
<td>0039</td>
<td>9008</td>
<td>6326</td>
<td>1202</td>
<td>64,509</td>
<td>-36</td>
<td>64,705</td>
<td>266</td>
<td>-266</td>
<td>-0.19%</td>
<td>-0.19%</td>
</tr>
<tr>
<td>IL</td>
<td>0230</td>
<td>9007</td>
<td>6772</td>
<td>1514</td>
<td>121,760</td>
<td></td>
<td>588</td>
<td>151,344</td>
<td>785</td>
<td>1.28%</td>
<td>1.28%</td>
</tr>
<tr>
<td>IL</td>
<td>0232</td>
<td>9005</td>
<td>6514</td>
<td>1514</td>
<td>122,676</td>
<td></td>
<td>292,191</td>
<td>169,515</td>
<td>37,324</td>
<td>22.10%</td>
<td>22.10%</td>
</tr>
<tr>
<td>IL</td>
<td>0107</td>
<td>9008</td>
<td>6502</td>
<td>1508</td>
<td>57,515</td>
<td></td>
<td>113,791</td>
<td>56,276</td>
<td>9,056</td>
<td>8.56%</td>
<td>8.56%</td>
</tr>
</tbody>
</table>
Decision Support – Adjusters use A.I. Estimates to make more accurate Claim Level Reserves

Median Segmentation Plot for Pre-Model versus Post-Model Adjuster Behavior

- Pre-Model Adjuster Behavior
- Post-Model Adjuster Behavior

Increasing Total Incurred
Example EI & GP Dashboards
Daily Claim Alert Email – Example #2

noreply@millimanmax.com
To: Danny Wendt, Stan Smith
Notification for Claim Number 15-032339: 2015-05-07:

Claimant Name: HEIMAN, BROCK, W
Employer Name: Sunram Construction, Inc.
Incident Date: 2015-04-27
Claim Number: 15-032339
Claim Age: 9 Days
Claimant Type: Lost Time
Model Type: Early Intervention
Risk Change: Medium to High
Profile Claim Data – Sample Dataset

At 5 years the 95th percentile of claims will have 150k paid to date

Total Paid

Claim Duration

1 Year
5 Years
12 Years
Daily Claim Alert Dashboard

Daily Claim Alerts

Alert Information

Alert Counts

Risk Drivers

Claimant Detail

Daily Claim Alert Dashboard

Alert Information

Alert Counts

Risk Drivers

Claimant Detail
Claim Analysis Dashboard

Claim Analysis

Score Chart
Claim risk scores displayed over time

Risk Drivers
Shown for point selected on the Score Chart

- Notes discuss recommendations
- Notes discuss repair
- Notes discuss surgery
- Notes discuss therapy
- Notes discuss communication
- Notes indicate future development

Model Score: 72.61
Claim Age: 155
Paid Amount: $7,248.52
Reserve Amount: $27,469.80

Claim Number (ClaimScore): 01191119
Score Ref Date: 9/30/2015
Claim Age: 155
Model Score: 72.61
Low Risk Threshold: 39.9812
Medium Risk Threshold: 73.65522
High Risk Threshold: 77.249
Reserve Amount: 27,469.80
Case-Level Reserving Dashboard
Beyond Risk Scores
A.I. Helps with the Opioid Crisis
CDC Guidelines (subset)

- **USE IMMEDIATE-RELEASE OPIOIDS WHEN STARTING**
  - When starting opioid therapy for chronic pain, clinicians should prescribe immediate-release opioids instead of extended-release/long-acting (ER/LA) opioids.

- **USE THE LOWEST EFFECTIVE DOSE**
  - When opioids are started, clinicians should prescribe the lowest effective dosage. Clinicians should use caution when prescribing opioids at any dosage, should carefully reassess evidence of individual benefits and risks when considering increasing dosage to ≥50 morphine milligram equivalents (MME)/day, and should avoid increasing dosage to ≥90 MME/day or carefully justify a decision to titrate dosage to ≥90 MME/day.

- **PRESCRIBE SHORT DURATIONS FOR ACUTE PAIN**
  - Long-term opioid use often begins with treatment of acute pain. When opioids are used for acute pain, clinicians should prescribe the lowest effective dose of immediate-release opioids and should prescribe no greater quantity than needed for the expected duration of pain severe enough to require opioids. Three days or less will often be sufficient; more than seven days will rarely be needed.
Identifying Claims that have **NOT** had > 50 MED Opioid Dosage but **WILL**
Identifying Claims that have **NOT** had > 90 MED Opioid Dosage but **WILL**
A.I. Helps define the financial impact of Opioids
Pharma Spend Driven by Opioids

Segmentation Plot for Predicting Additional Medical Spend

- Average Additional Med Spend ($)
- Percentile Score

Legend:
- Day 90
- Day 180
- Day 365
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
- The Clearinghouse – national WC claim transaction database
A.I. in Underwriting - Impacting Profits

- Greater risk pricing and selection capabilities
- Individual policies are priced to reflect the specific risk
- Experience ratings
  - Experience – over weighted
  - Lack of experience – over valued
Following Examples

- “Segmentation”
  - Objective way to measure Model Accuracy
  - Objective way to determine if “External Data” adds value
  - Measures each additional type of external elements used
- Can be a few or many segments
- Lift Ratio is the difference between best and worst segments
- Can be the start of a new rate plan
Segmentation Analysis - Underwriting

Divide All Policies into segments

• After Scoring distribute by Risk Score
  ▪ Highest Risk to the Right
  ▪ Lowest Risk to the Left
  ▪ Each Policy has a individual score
  ▪ Worst Policy far right vs. Best Policy far left
  ▪ Then add actual losses to test model accuracy
Lift Ratio: 5.2
Analysis on Internal vs. Internal and External data

"Lift" with and without Milliman DB

Lift with Milliman Data 59.5
Lift without Milliman Data 22.1
Making Data Actionable

- Ease of Access
- Visualization
- Following example of a single state “SIG”
  - Work Comp book
Minnesota
Map of All (1-5) Scored Policies
Minnesota
Map of Best (1-4) Scored Policies
Minnesota
Map of Worst (5) Scored Policies
North of Minneapolis
Map of Premium by Zip Code - 55449
Click on any pie chart, and see a detailed snapshot that describes the policy.
Summary

THE IMPORTANCE OF LEVERAGING INFORMATION
Loss Cause Word Cloud – Prioritized by Claim Count

- GL - Pot Hole/Uneven Pavement
- Strain/Sprain
- Collision
- Auto - Damaged Vehicle/Equipment
- Fall/Slip
- GL - Sewer
- GL - Vehicle Damage - Including Tires
- Lifting Injury
- GL - Property Damage
- Cut/Puncture/Scrape
- Struck Or Injured
- Exertion
- GL - Municipal Practices/Procedures
- Police - Chasing Subject
- Police - Combative Subject
- Prop - Building Loss/Damage
- GL - Water
- Police - EPL Non-Monetary Defense
- Prop - Signs/Guardr/Hyd/Lights Loss/Damg
- Prop - Building Loss/Damage
- Foreign Body - Ear
- Prop - Building Loss/Damage - Fire

Count:
- 669
- 23

NLC Mutual Insurance Company
660 Capitol Street NW Suite 450 Washington, DC 20001
Loss Cause Word Cloud – Prioritized by Loss Amount

59m Sum of Amount

$4,451,102

$8,334,885

Prop - Building Loss/Damage - Fire
GL - Employment Practice
Strain/Sprain

GL - Municipal Practices/Procedures
Prop - Building Loss/Damage
GL - Property Damage

Auto - Pedestrian Accident
GL - Building Damage
GL - Hit While Driving
GL - Operations

Foreign Body - Eye
Prop - Signs/Guards/Hyd/Lights Loss/Damag

Foreign Body - Splinter
GL - Pollutants

Prop - Equipment Loss/Damage - Lightning
Auto - Medical Payments Driver
GL - Property Damage

Exposure - Disease/Parasite

Jan 6, 2012 - Dec 30, 2016

NLC Mutual Insurance Company
660 Capitol Street NW Suite 450 Washington, DC 20001

81
Leveraging Pool Data: *A Game Changer*

Imagine If Pools Could Do Collectively

- Most meaningful collection of public entity risk data
- Evolution of data analytics technology and tools
- Analytics and benchmarking with peers at national level
- Leverage data to maximize advantage in a competitive insurance market
- Continuously evolving world with Deep Learning Systems
- Cost savings of managing and storing data (trending to “zero”)

We Believe We Can!
Calendar Year Total Claim Count – Three State Pools

Main Claim Data - Claim Count in 2015

Jan 1, 2015 - Dec 31, 2015, by Month
Claim Count over Last 5 Years

Jan 1, 2012 - Dec 31, 2016, by Month

Count of Date Closed Text

Max 186
Avg 110.2
Min 65
## Development Triangle Example

### Payments over Time

<table>
<thead>
<tr>
<th>TRANSACTION_YEAR</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>RUNNING TOTAL TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>REPORTED_YEAR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>2,719,032.33</td>
<td>4,927,429.54</td>
<td>4,156,378.78</td>
<td>4,389,137.43</td>
<td>2,357,934.40</td>
<td>18,549,912.48</td>
</tr>
<tr>
<td>2013</td>
<td>3,547,063.56</td>
<td>4,805,824.63</td>
<td>6,228,519.87</td>
<td>5,707,613.93</td>
<td>20,289,021.99</td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>4,086,712.47</td>
<td>5,097,714.52</td>
<td>4,192,486.54</td>
<td>13,376,913.53</td>
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<td></td>
</tr>
<tr>
<td>2015</td>
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<td>4,659,019.70</td>
<td>7,507,553.61</td>
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<tr>
<td>2016</td>
<td>3,104,960.20</td>
<td>3,104,960.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GRAND TOTAL</td>
<td>2,719,032.33</td>
<td>8,474,493.10</td>
<td>13,048,915.88</td>
<td>18,563,905.73</td>
<td>20,022,014.77</td>
<td>62,828,361.81</td>
</tr>
</tbody>
</table>
THANK YOU!