The Power of Data: Using AI to Bring Real Value
(Create Real impact and Retain Members)

Presented by:
Aaron Shapiro & Chase Pettus
Prediction
McKinsey

• In 2030, manual underwriting ceases to exist for most personal and small-business products across property and casualty insurance.

• Underwriting is reduced to a few seconds as the majority of underwriting is automated and supported by [AI models] machine and deep learning models built within the technology stack.
Prediction
Accenture’s Tech Vision for Insurance Study

• Competition is fierce.
• More than half of Fortune 500 companies have gone out of business since 2000.

• *AI is set to take this disruption to a new level* in the insurance industry.

• Insurers expect *AI to completely transform* the way they run their businesses *in the next three years*
CONCLUSION
• **AI** will transform the way insurers of tomorrow organize, manage, and grow their programs

• Central to this is increased efficiencies, speed, and precision in **underwriting** and **claims handling**

• This technology is already here.
The Real Question Is...

Where will your Pool be in 2030?
Carriers, TPAs, **Pools** that adopt a mind-set focused on creating opportunities from these disruptive technologies...

...instead of viewing them as a threat to their current business...

...will thrive in the insurance industry in 2030.
What is Big Data (BD) (from Michael Stonebraker @ MIT)

**Big Volume**
(Simple SQL analytics, Complex non-SQL)

**Big Velocity**
(Drink from a fire hose)

**Big Variety**
(Large # of diverse data sources for integration)
**What is Business Intelligence (BI)**

*BI is the practice of understanding what truly happened in the past to enable data driven informed decision-making.*
What is Predictive Analytics (PA)

**Predictive analytics** is the practice of extracting information from existing data sets in order to determine patterns and predict future outcomes and trends. **Predictive analytics** does not tell you what will happen in the future.

- Webopedia
What is Machine Learning (ML)

A type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed.

Arthur Lee Samuel
How AI / ML & Big Data are transforming Insurance

• Traditionally, insurance has had a reputation for being traditional, risk-averse and slower than other sectors to react to and adopt technical innovation and change.

• AI and machine learning will revolutionize all aspects of insurance from underwriting to claims management.
What to look for in a Partner

• Insurance industry specific AI and Machine Learning Predictive Analytics Expertise
• Experience with Risk Pools
• Deep expertise in both Insurance Technology and Data Science
• Track Record
What AI / ML Predictive Analytics Solutions Are Out There?

**Claims Management Products**
- Risk Ranking (most expensive claims)
- Case-level Reserving
- Large Loss (Excess) Predictions
- Subrogation
- Claim Settlement
- Litigation & Representation Risk
- Automation Support for Straight-through Processing

**Underwriting Product**
- Risk Ranking (best and worst risks)
- Premium Targeting
- Severity and Frequency
- Automation Support for Straight-through Processing
Partner’s Data Assets

+ Your Data

+ Supplemental 3rd Party Data

= Powerful Data Landscape for Predictive Analytics Solutions
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.

SAMPLE KEY WORDS/PHRASES

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

Text sources: Adjuster notes, medical reports, independent medical exams, etc.
Leveraging the Power of Data

Gradient's Data

Client's Structured Data

Client's Unstructured Data

Other 3rd Party Data

Preprocessing

NLP, Neural Nets

Preprocessing

NLP, Neural Nets

Feature Extraction

Machine Learning Algos

APIs, Dashboards

Predictions
Fitting Data with a *Linear* Model

**Loss Ratio Segmentation (Base + Health + IRS + Claim)**

![Bar chart showing loss ratio segmentation.](chart.png)
Fitting Data with a Non-Linear Model

Loss Ratio Segmentation (Final Model)
What are some of the solutions being adopted by Pools today?
## Daily Claim Alerts

### Alert Information

<table>
<thead>
<tr>
<th>Adjuster</th>
<th>Claim Number</th>
<th>Member</th>
<th>Department Group</th>
<th>Department</th>
<th>Incident Location Desc</th>
<th>Injury Date</th>
<th>Lag</th>
<th>Claim</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>0123348</td>
<td>Town of Coventry</td>
<td>Police Department</td>
<td>PD POLICE DEPT.</td>
<td>MANCHESTER COON AND FOX CLUB</td>
<td>9/23/2015</td>
<td>2</td>
<td>25</td>
<td>Low to Medium</td>
<td></td>
</tr>
<tr>
<td>0123620</td>
<td>Tolland Board of Education</td>
<td>Education</td>
<td>Birch Grove Primary School</td>
<td>TOLLAND BOARD OF EDUCATION</td>
<td>9/28/2015</td>
<td>4</td>
<td>18</td>
<td>Medium to Low</td>
<td></td>
</tr>
<tr>
<td>0119605</td>
<td>New Haven BOE</td>
<td>Education</td>
<td>Hooker School</td>
<td>WORTHINGTON HOOKER SCHOOL</td>
<td>5/11/2015</td>
<td>1</td>
<td>161</td>
<td>Medium to High</td>
<td></td>
</tr>
<tr>
<td>0121548</td>
<td>Plainfield Bd. OF Ed.</td>
<td>Education</td>
<td>BD SCHOOL DEPT.</td>
<td>EARLY CHILDHOOD CENTER</td>
<td>7/22/2015</td>
<td>1</td>
<td>89</td>
<td>Low to Medium</td>
<td></td>
</tr>
<tr>
<td>0092302</td>
<td>Town of Rocky Hill</td>
<td>General Government</td>
<td>GG MISC NOC DEPT.</td>
<td>TOWN OF ROCKY HILL</td>
<td>1/29/2013</td>
<td>1</td>
<td>993</td>
<td>High</td>
<td></td>
</tr>
<tr>
<td>0114587</td>
<td>Town of Waterford</td>
<td>Public Works</td>
<td>PW HIGHWAY DEPT.</td>
<td>TOWN OF WATERFORD-TRANSFER STATION</td>
<td>12/22/2014</td>
<td>1</td>
<td>301</td>
<td>Medium to Low</td>
<td></td>
</tr>
<tr>
<td>0123468</td>
<td>Cooperative Educational S.</td>
<td>Education</td>
<td>BD SCHOOL DEPT.</td>
<td>SPECIAL EDUCATION</td>
<td>9/29/2015</td>
<td>0</td>
<td>21</td>
<td>Medium to High</td>
<td></td>
</tr>
<tr>
<td>0123683</td>
<td>Norwalk Board of Education</td>
<td>Education</td>
<td>BD JEFFERSON ELEM</td>
<td>JEFFERSON ELEMENTARY</td>
<td>9/30/2015</td>
<td>5</td>
<td>15</td>
<td>Medium to Low</td>
<td></td>
</tr>
<tr>
<td>0118341</td>
<td>Town of Middlebury</td>
<td>Public Works</td>
<td>PW PUBLIC WORK NOC</td>
<td>PUBLIC WORKS</td>
<td>3/31/2015</td>
<td>1</td>
<td>202</td>
<td>Low to Medium</td>
<td></td>
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<tr>
<td>0121396</td>
<td>Winchester BOE</td>
<td>Education</td>
<td>PW SCHOOL DEPT.</td>
<td>BATCHELER ELEMENTARY SCHOOL</td>
<td>7/13/2015</td>
<td>2</td>
<td>97</td>
<td>Medium to High</td>
<td></td>
</tr>
<tr>
<td>0123209</td>
<td>Town of Cromwell</td>
<td>Public Works</td>
<td>PW HIGHWAY DEPT.</td>
<td>TOWN OF CROMWELL</td>
<td>9/21/2015</td>
<td>1</td>
<td>28</td>
<td>Low to Medium</td>
<td></td>
</tr>
</tbody>
</table>

### Claimant Detail

<table>
<thead>
<tr>
<th>Claim Nu.</th>
<th>Claimant Name</th>
<th>Claimant Type</th>
<th>Injury Cause</th>
<th>Loss Description Narrative</th>
<th>Paid Amount</th>
<th>Reserve Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>0119605</td>
<td>MORRISON, MARY</td>
<td>Lost Time</td>
<td>Slip/fall</td>
<td>WHILE SITTING DOWN IN THE CHAIR THE LEG ON THE CHAIR BROKE. SHE FELL STRAIGHT DOWN TO THE FLOOR ONTO HER HIP (CENTER)</td>
<td>$8,297.49</td>
<td>$13,250.00</td>
</tr>
</tbody>
</table>

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**Risk Drivers**

- Notes discuss authorization
- Notes discuss therapy
- Notes discuss One Call Medical
- Notes discuss physical
- Notes discuss communication
- Notes discuss MRI
- Notes discuss ortho
- Notes discuss continuing developments
- Notes exhibit uncertainty

**Treatment Category**

- Surgery: Low to High
- Imaging: MRI/CT Scan/Other
- Electrodiagnostic Studies
- Pain Management Procedures
- Opioid Prescriptions
- PT & Chiropractic Treatment

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**Gradient**

Leveraging the Power of Data
Detailed Claim Analysis

Score Chart
Claim risk scores displayed over time

Claim Number
Type in a claim number

0119119

Treatment Category
- Surgery: Low
- Imaging: MRI, CT, Scans/Other: Low
- Electrodagnostic Studies: Low
- Pain Management Procedures: Low
- Opioid Prescriptions: Low
- PT & Chiropractic Treatment: Low

Likelihood
- High

Risk Drivers
Shown for points selected on the Score Chart

1. Notes discuss recommendations
2. Notes discuss repair
3. Notes discuss surgery
4. Notes discuss a tear
5. Notes discuss therapy
6. Notes discuss communication
7. Notes indicate future development

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

Claim Number (ClaimScore): 0119119
Score Ref Date: 9/30/2015
Model Score: 72.61
Low Risk Threshold: 0
Medium Risk Threshold: 39.9812
High Risk Threshold: 73.65522
Paid Amount: 7,249
Reserve Amount: 27,470
Case-level Reserving

Case-Level Reserving Open Claims

Summary

<table>
<thead>
<tr>
<th>Category</th>
<th>Payments</th>
<th>Predicted Future Reserves</th>
<th>Predicted Incurred Net</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indemnity</td>
<td>$5,051,239</td>
<td>$16,754,800</td>
<td>$21,642,786</td>
</tr>
<tr>
<td>Medical</td>
<td>$12,999,281</td>
<td>$11,121,179</td>
<td>$23,762,650</td>
</tr>
<tr>
<td>Expense</td>
<td>$3,890,785</td>
<td>$3,680,922</td>
<td>$7,481,352</td>
</tr>
<tr>
<td>Grand Total</td>
<td>$21,941,306</td>
<td>$31,556,901</td>
<td>$52,886,787</td>
</tr>
</tbody>
</table>

Claim Detail

<table>
<thead>
<tr>
<th>Claim Number</th>
<th>State</th>
<th>Payments</th>
<th>Adjuster Future Reserves</th>
<th>Predicted Future Reserves</th>
<th>Adjuster Incurred Net</th>
<th>Predicted Incurred Net</th>
<th>Incurred Difference</th>
<th>% Incurred Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1001100001643</td>
<td>NC</td>
<td>$158,930</td>
<td>$61,663</td>
<td>$72,240</td>
<td>$220,433</td>
<td>$231,010</td>
<td>($10,578)</td>
<td>-5%</td>
</tr>
<tr>
<td>1001100003054</td>
<td>NC</td>
<td>$20,267</td>
<td>$15,091</td>
<td>$11,167</td>
<td>$35,278</td>
<td>$31,354</td>
<td>$3,924</td>
<td>12%</td>
</tr>
<tr>
<td>1001110003047</td>
<td>NC</td>
<td>$20,142</td>
<td>$23,059</td>
<td>$28,832</td>
<td>$43,158</td>
<td>$48,931</td>
<td>($5,772)</td>
<td>-12%</td>
</tr>
<tr>
<td>1001110031130</td>
<td>NC</td>
<td>$114,615</td>
<td>$12,162</td>
<td>$68,489</td>
<td>$126,762</td>
<td>$183,090</td>
<td>($56,328)</td>
<td>-21%</td>
</tr>
<tr>
<td>1001120030993</td>
<td>SC</td>
<td>$550,931</td>
<td>$524,608</td>
<td>$573,661</td>
<td>$1,075,031</td>
<td>$1,124,084</td>
<td>($49,053)</td>
<td>-4%</td>
</tr>
<tr>
<td>1001120031638</td>
<td>NC</td>
<td>$1,145</td>
<td>$1,172</td>
<td>$295</td>
<td>$2,313</td>
<td>$1,436</td>
<td>$877</td>
<td>61%</td>
</tr>
</tbody>
</table>
How are these solutions benefiting Pools today?
Model is accurate segmenting policies by profitability

- **Lowest Risk Business**: policies with a predicted loss ratio of less than 30%
- **Average Risk Business**: policies with a predicted loss ratio between 30% and 75%
- **Highest Risk Business**: policies with a predicted loss ratio of greater than 75%
## Selections

**Prediction Categories**
- (All)
- Average Risk Business
- Highest Risk Business
- Lowest Risk Business

**Size of Business**
- (All)
- $0-$5,000
- $5,000-$25,000
- $25,000+

## Model Segmentation

<table>
<thead>
<tr>
<th></th>
<th>Lowest Risk Business</th>
<th>Average Risk Business</th>
<th>Highest Risk Business</th>
<th>Loss Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Loss Ratio</td>
<td>0.27</td>
<td>0.45</td>
<td>0.81</td>
<td>0.48</td>
</tr>
</tbody>
</table>

## Financial Summary

<table>
<thead>
<tr>
<th></th>
<th>Lowest Risk Business</th>
<th>Average Risk Business</th>
<th>Highest Risk Business</th>
<th>Grand Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Application Count</td>
<td>523</td>
<td>2,677</td>
<td>192</td>
<td>3,392</td>
</tr>
<tr>
<td>Underwriter Quoted Premium</td>
<td>$6,267,662</td>
<td>$53,376,810</td>
<td>$7,952,562</td>
<td>$67,597,034</td>
</tr>
<tr>
<td>Actual Loss</td>
<td>$1,682,053</td>
<td>$24,157,913</td>
<td>$6,438,104</td>
<td>$32,278,070</td>
</tr>
<tr>
<td>Proxy for Underwriter Forecasted Loss</td>
<td>$4,011,304</td>
<td>$34,161,158</td>
<td>$5,089,640</td>
<td>$43,262,102</td>
</tr>
<tr>
<td>Underwriter % Difference from Actual</td>
<td>138.48%</td>
<td>41.41%</td>
<td>20.95%</td>
<td>34.03%</td>
</tr>
<tr>
<td>Model Predicted Loss</td>
<td>$1,298,116</td>
<td>$24,826,196</td>
<td>$7,374,525</td>
<td>$33,498,837</td>
</tr>
<tr>
<td>Model % Difference from Actual</td>
<td>29.58%</td>
<td>2.69%</td>
<td>12.70%</td>
<td>3.64%</td>
</tr>
</tbody>
</table>
Pricing flexibility exists within Organization’s best rated policies

Financial Summary

<table>
<thead>
<tr>
<th>Metric</th>
<th>Lowest Risk Business</th>
</tr>
</thead>
<tbody>
<tr>
<td>Application Count</td>
<td>523</td>
</tr>
<tr>
<td>Underwriter Quoted Premium</td>
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<td>29.58%</td>
</tr>
</tbody>
</table>
Identifying complex claims earlier & eliminating wasted efforts

<table>
<thead>
<tr>
<th>Organization vs Model: Claim Misclassification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Claims Tested</td>
</tr>
<tr>
<td>192,771</td>
</tr>
<tr>
<td>Catch %</td>
</tr>
<tr>
<td>20%</td>
</tr>
<tr>
<td>40%</td>
</tr>
<tr>
<td>60%</td>
</tr>
<tr>
<td>65%</td>
</tr>
<tr>
<td>80%</td>
</tr>
</tbody>
</table>

Find your most expensive claims early, reducing severity while there’s still time

Same catch count as adjuster

Our models reduce wasted efforts from misidentification
Improving the **Organization’s** operational efficiency: organizations are catching more high cost claims over time

<table>
<thead>
<tr>
<th>Claim Age</th>
<th>Baseline catch rate</th>
<th>Production catch rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before June 2017</td>
<td>June 2017 - Today</td>
</tr>
<tr>
<td>Day 30</td>
<td>35%</td>
<td>50%</td>
</tr>
<tr>
<td>Day 90</td>
<td>45%</td>
<td>70%</td>
</tr>
<tr>
<td>Day 180</td>
<td>45%</td>
<td>75%</td>
</tr>
<tr>
<td>Day 365</td>
<td>75%</td>
<td>85%</td>
</tr>
</tbody>
</table>
Implementing Strategic Reserving Procedures for Improved Capitol Allocation

Reserve accuracy at day 30 on 249,518 claims in the last three years

Model delivers value across all ultimate cost groups at 30 days.
Organization Implements Strategic Reserving Procedures

Consider the math:

6,356 claims  
× 38% (improvement in % accurately reserved)  
× $75,000 (average claim cost)  
× 45% (average reserving improvement)

$81,515,700 in now correctly allocated capital
Strategically reallocate med-only resources

**Adjuster vs Model | Claim Classification**

<table>
<thead>
<tr>
<th>Total Claims Tested</th>
<th>High Cost Claims</th>
</tr>
</thead>
<tbody>
<tr>
<td>3,444</td>
<td>319</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Catch Perc</th>
<th>Adj Catch Ct</th>
<th>Adj False Pos Ct</th>
<th>Adj False Pos Perc</th>
<th>Model Catch Ct</th>
<th>Model False Pos Ct</th>
<th>Model False Pos Perc</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td></td>
<td></td>
<td></td>
<td>64</td>
<td>6</td>
<td>9%</td>
</tr>
<tr>
<td>25%</td>
<td>72</td>
<td>68</td>
<td>49%</td>
<td>80</td>
<td>8</td>
<td>9%</td>
</tr>
<tr>
<td>40%</td>
<td></td>
<td></td>
<td></td>
<td>128</td>
<td>21</td>
<td>14%</td>
</tr>
<tr>
<td>60%</td>
<td></td>
<td></td>
<td></td>
<td>191</td>
<td>57</td>
<td>23%</td>
</tr>
<tr>
<td>80%</td>
<td></td>
<td></td>
<td></td>
<td>252</td>
<td>223</td>
<td>47%</td>
</tr>
</tbody>
</table>

**Improve your catch rate from 25% to 60% and maintain the same false-positive count using the model.**

Our models identify med-only claims accurately while sustaining precision.
Lowering Claims Costs

- Total Paid → While client maintained steady contribution volume
  - $35,074,200 Baseline Year
  - $32,408,600 Year One
  - $28,816,900 Year Two

Year 1: $2,665,600 (8% savings)
Year 2: $3,591,700 (11% savings)

→ Customer averaged 10-15x payback per year
QUESTIONS