Enhancing Claims Triage with Dynamic Data

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Introduction

What is claims triage?

- the practice of prioritizing and classifying claims by “urgency”
- Derived from the French word *trier*, which means “to sort”
- Emerged from the exigencies of war, and historically used in medical contexts

Claims triage is designed to enhance the decision-making process at FNOL

- exercise cost control
- flag suspicious and fraudulent claims
- prevent complaints and improve customer satisfaction
We focus on claims due to weather related perils, such as wind or hail. In 2020, over 6.2 million U.S. properties were affected by at least one damaging hail event, resulting in nearly $14.2 billion in hail property claims.

We explore the benefits of utilizing dynamic weather conditions in claims triage for property insurance

Two questions

- Does the pattern of weather conditions have an impact?
- How do we leverage weather dynamics to improve efficiency in claims management?
Let $Y$ be insured loss amount and $x$ (generic notation) summarize all triaging variables for the claim.

We consider a two-part framework as:

$$F(y|x) = \Pr(Y \leq y|x) = p(x) + (1 - p(x))G(y|x).$$

where $0 < p(x) < 1$ is the probability of zero payment and $G_i(\cdot|x)$ is a distribution function defined on $(0, +\infty)$ conditional on $x$. 
We consider a mixture model:

\[ G(y|x) = \sum_{k=1}^{K} \pi_k(x) G_k(y|x), \]

\[ \pi_k(x) \geq 0 \text{ for } k \in \{1, \ldots, K\}, \quad \sum_{k=1}^{K} \pi_k(x) = 1 \]

A generalized gamma model is used for \( G_k \)

\[ g_k(y|x) = \frac{\lambda_k^{\lambda_k}}{\sigma_k(x) \Gamma(\lambda_k) \sqrt{\lambda_k y}} \exp \left\{ \mathrm{sign}(q_k) \sqrt{\lambda_k u_k(x)} - \lambda \exp(q_k u_k(x)) \right\}, \]

\[ \lambda_k = |q_k|^{-2}, \quad u_k(x) = (\ln(y) - \eta_k(x))/\sigma_k(x) \]
Parameters are formulated via feedforward network. Define
\[ \pi(x) = (\pi_1(x), \ldots, \pi_K(x))', \eta(x) = (\eta_1(x), \ldots, \eta_K(x))', \text{ and} \]
\[ \sigma(x) = (\sigma_1(x), \ldots, \sigma_K(x))'. \]

\[
\begin{align*}
p(x) &= \text{sigmoid}\{\alpha_p + u'(x)w_p\} \\
\pi(x) &= \text{softmax}\{\alpha_\pi + W'_\pi u(x)\} \\
\eta(x) &= \alpha_\eta + W'_\eta u(x) \\
\sigma(x) &= \exp\{\alpha_\sigma + W'_\sigma u(x)\}
\end{align*}
\]

where

\[ u(x) = h_L(W_L, h_{L-1}(W_{L-1}, \ldots, h_1(W_1, x) \ldots)) \]
Dynamic Weather Measurements

Introduction

Method

Data

Analysis

Conclusion

Dynamic Weather Measurements

Wind Speed

Hour

Wind Direction

Hour

Wind Gust

Hour

Temperature

Hour

Components
- cosine
- sine
### Dynamic Weather Descriptors

<table>
<thead>
<tr>
<th>Hour</th>
<th>Precipitation Description</th>
<th>Hour</th>
<th>Precipitation Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>BR</td>
<td>13</td>
<td>VCTS, -RA, BR</td>
</tr>
<tr>
<td>2</td>
<td>BR</td>
<td>14</td>
<td>VCTS, -RA, TSRA, BR, +RA</td>
</tr>
<tr>
<td>3</td>
<td>BR</td>
<td>15</td>
<td>+GR, TSGR, +RA, TSRA, BR, VCTS, RA</td>
</tr>
<tr>
<td>4</td>
<td>VCTS, -RA, BR</td>
<td>16</td>
<td>TSRA, BR, -RA</td>
</tr>
<tr>
<td>5</td>
<td>VCTS</td>
<td>17</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>TSRA, BR, +RA, SQ, VCTS, -RA</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>-RA, VCTS, TSRA</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>-RA, TSRA</td>
<td>20</td>
<td>TS, +RA, TSRA, BR</td>
</tr>
<tr>
<td>9</td>
<td>TS</td>
<td>21</td>
<td>+RA, TSRA, BR, -RA</td>
</tr>
<tr>
<td>10</td>
<td>VCTS, -RA, BR</td>
<td>22</td>
<td>-RA, BR</td>
</tr>
<tr>
<td>11</td>
<td></td>
<td>23</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>TS, -RA, TSRA, BR, +RA, FG</td>
<td>24</td>
<td></td>
</tr>
</tbody>
</table>
Method

A high level summary of our approach:

- A LSTM network for dynamic weather measurements
- A self-attention for dynamic weather descriptors
- Categorical embedding for static triaging variables
Two data sources:

- A cross-sectional data set of insurance claims
  - Obtained a portfolio of hail damage property insurance claims
  - Personal homeowner insurance in the state of Missouri
  - Information on insured losses and triaging variables

- A longitudinal data set of weather dynamics
  - Obtained from Automated Surface Observing System (ASOS) and the Automated Weather Observing System (AWOS)
  - Supplemented by vendor data
Data

Empirical CDF vs. Amount of Insured Losses

Frequency vs. Insurer's Positive Payments
### Data

<table>
<thead>
<tr>
<th></th>
<th>Zero Losses Mean</th>
<th>SD</th>
<th>Positive Losses Mean</th>
<th>SD</th>
<th>Overall Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Building Age</strong></td>
<td>37.80</td>
<td>22.00</td>
<td>38.10</td>
<td>21.70</td>
<td>38.04</td>
<td>21.75</td>
</tr>
<tr>
<td><strong>Property Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outbuilding</td>
<td>0.45%</td>
<td></td>
<td>0.15%</td>
<td></td>
<td>0.20%</td>
<td></td>
</tr>
<tr>
<td>Single Family</td>
<td>98.90%</td>
<td></td>
<td>99.20%</td>
<td></td>
<td>99.11%</td>
<td></td>
</tr>
<tr>
<td>Others</td>
<td>0.68%</td>
<td></td>
<td>0.70%</td>
<td></td>
<td>0.69%</td>
<td></td>
</tr>
<tr>
<td><strong>Roof Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asphalt Shingle</td>
<td>96.70%</td>
<td></td>
<td>97.30%</td>
<td></td>
<td>97.21%</td>
<td></td>
</tr>
<tr>
<td>Others</td>
<td>3.33%</td>
<td></td>
<td>2.68%</td>
<td></td>
<td>2.79%</td>
<td></td>
</tr>
<tr>
<td><strong>Construction Type</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frame</td>
<td>73.10%</td>
<td></td>
<td>77.70%</td>
<td></td>
<td>76.86%</td>
<td></td>
</tr>
<tr>
<td>Masonry</td>
<td>26.50%</td>
<td></td>
<td>21.90%</td>
<td></td>
<td>22.68%</td>
<td></td>
</tr>
<tr>
<td>Others</td>
<td>0.43%</td>
<td></td>
<td>0.46%</td>
<td></td>
<td>0.45%</td>
<td></td>
</tr>
<tr>
<td><strong>Coverage Amount</strong></td>
<td>222.62</td>
<td>141.02</td>
<td>213.84</td>
<td>120.60</td>
<td>215.41</td>
<td>124.54</td>
</tr>
<tr>
<td><strong>Deductible</strong></td>
<td>643.00</td>
<td>615.00</td>
<td>574.00</td>
<td>475.00</td>
<td>586.49</td>
<td>503.74</td>
</tr>
<tr>
<td><strong>Reporting Delay</strong></td>
<td>51.40</td>
<td>82.90</td>
<td>40.80</td>
<td>72.60</td>
<td>42.66</td>
<td>74.66</td>
</tr>
<tr>
<td><strong>Hail Size</strong></td>
<td>1.60</td>
<td>0.84</td>
<td>1.94</td>
<td>1.00</td>
<td>1.88</td>
<td>0.98</td>
</tr>
<tr>
<td><strong>Number of Obs</strong></td>
<td>5,763</td>
<td></td>
<td>26,464</td>
<td></td>
<td>32,227</td>
<td></td>
</tr>
</tbody>
</table>
The predictive distribution is obtained by

\[ F_i(y|x_i; \hat{\theta}) = p(x_i; \hat{\theta}) + (1 - p(x_i; \hat{\theta}))G(y|x_i; \hat{\theta}), \]
Prediction

Mixture of Generalized Gamma Model

Gamma Generalized Linear Model
Model Comparison

- Model I (No Weather): This model only uses the traditional triaging variables for sorting claims. Standard feedforward networks are employed as building blocks in the two-part model.

- Model II (Static Weather): One constructs static weather summaries as inputs for the neural networks in the model.

- Model III (Dynamic Weather): We explicitly incorporate weather dynamics in the network structure.
## Model Comparison

<table>
<thead>
<tr>
<th></th>
<th>Point Forecast</th>
<th></th>
<th>Probabilistic Forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gini</td>
<td>S.E.</td>
<td>Diebold–Mariano</td>
</tr>
<tr>
<td>No Weather</td>
<td>11.925</td>
<td>0.524</td>
<td>-13.836</td>
</tr>
<tr>
<td>Static Weather</td>
<td>7.522</td>
<td>0.543</td>
<td>-7.472</td>
</tr>
</tbody>
</table>
Consider setting:

- Two types of claim adjusters: inexperienced and seasoned
- Define the sets of small and large claims as $C_s = \{y : y \in [0, c]\}$ and $C_l = \{y : y \in (c, +\infty)\}$
- Denote $\delta(x) = F(c|x, \hat{\theta})$, the probability that a claim belongs to classes $C_s$
- A claim is assigned to an inexperienced adjuster if $\delta(x) > \delta$
Denote by $d_s$ and $d_l$ the costs for a claim being missclassified into classes $C_s$ and $C_l$ respectively. The optimal $\delta^*$ by minimizing the average cost of the missclassification for the training data:

$$C(\delta) = \frac{1}{n} \sum_{i=1}^{n} \left\{ d_s \mathbf{1}_{A_s(\delta)}(i) + d_l \mathbf{1}_{A_l(\delta)}(i) \right\}$$

where $\mathbf{1}_A(\cdot)$ is the indicator function.
Hold-out sample comparison:

<table>
<thead>
<tr>
<th>Percentiles</th>
<th>Minimum</th>
<th>10th</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
<th>90th</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Weather</td>
<td>2.16%</td>
<td>3.58%</td>
<td>5.18%</td>
<td>6.39%</td>
<td>7.36%</td>
<td>7.94%</td>
<td>9.77%</td>
</tr>
<tr>
<td>Static Weather</td>
<td>2.01%</td>
<td>3.44%</td>
<td>4.24%</td>
<td>4.65%</td>
<td>5.52%</td>
<td>6.82%</td>
<td>8.19%</td>
</tr>
</tbody>
</table>
We investigated the effects of weather dynamics on the prediction of claim severity and its managerial implications for the claims management operation.

- We proposed a deep learning method to incorporate dynamic weather information in the predictive modeling of the insured losses for reported claims.
- Empirically we showed that leveraging weather dynamics in claims triage leads to a reduction of up to 8% - 10% in operational costs.
Thank you for your attention!