Enhancing Claims Triage with Dynamic Data

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Outline

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.

Method

- We consider a mixture model:

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

$$\pi_k(x) \geq 0 \text{ for } k \in \{1, \dots, K\}, \sum_{k=1}^{K} \pi_k(x) = 1$$

- A generalized gamma model is used for G_k

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

$$\lambda_k = |q_k|^{-2},\ u_k(x) = (\ln(y) - \eta_k(x))/\sigma_k(x)$$

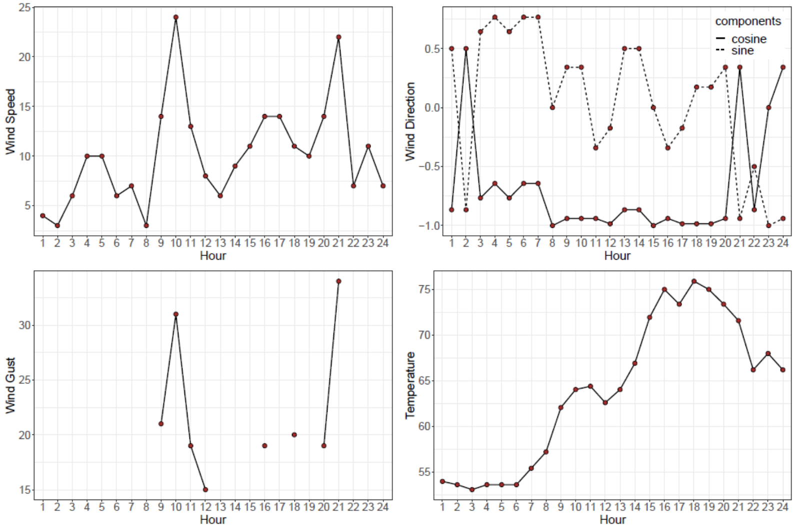
Parameters are formulated via feedforward network. Define $\boldsymbol{\pi}(x) = (\pi_1(x), \ldots, \pi_K(x))'$, $\boldsymbol{\eta}(x) = (\eta_1(x), \ldots, \eta_K(x))'$, and $\boldsymbol{\sigma}(x) = (\sigma_1(x), \ldots, \sigma_K(x))'$.

$$\begin{cases} p(x) = \text{sigmoid}\{\alpha_p + u'(x) w_p\} \\ \boldsymbol{\pi}(x) = \text{softmax}\{\boldsymbol{\alpha}_\pi + W'_\pi u(x)\} \\ \boldsymbol{\eta}(x) = \boldsymbol{\alpha}_\eta + W'_\eta u(x) \\ \boldsymbol{\sigma}(x) = \exp\{\boldsymbol{\alpha}_\sigma + W'_\sigma u(x)\} \end{cases}$$

where

$$u(x) = h_L(W_L, h_{L-1}(W_{L-1}, \cdots, h_1(W_1, x) \cdots))$$

Dynamic Weather Measurements



Dynamic Weather Descriptors

Hour	Precipitation Description	Hour	Precipitation Description
1	BR	13	VCTS, -RA, BR
2	BR	14	VCTS, -RA, TSRA, BR, +RA
3	BR	15	+GR, TSGR, +RA, TSRA, BR, VCTS, RA
4	VCTS, -RA, BR	16	TSRA, BR, -RA
5	VCTS	17	
6	TSRA, BR, +RA, SQ, VCTS, -RA	18	
7	-RA, VCTS, TSRA	19	
8	-RA, TSRA	20	TS, +RA, TSRA, BR
9	TS	21	+RA, TSRA, BR, -RA
10	VCTS, -RA, BR	22	-RA, BR
11		23	
12	TS, -RA, TSRA, BR, +RA, FG	24	

A high level summary of our approach:

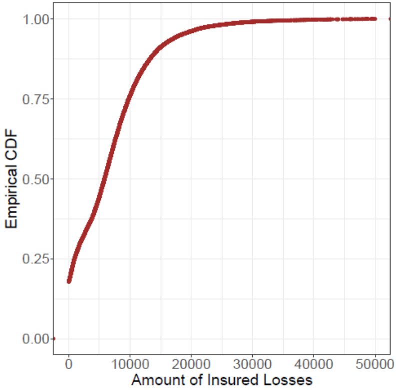
- A LSTM network for dynamic weather measurements
- A self-attention for dynamic weather descriptors
- Categorical embedding for static triaging variables

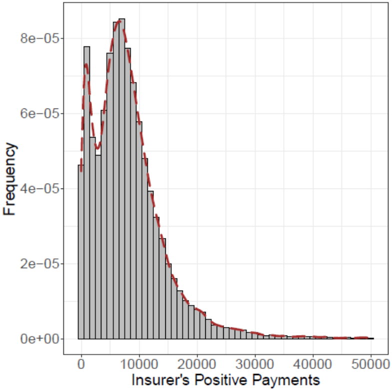
Data

Two data sources:

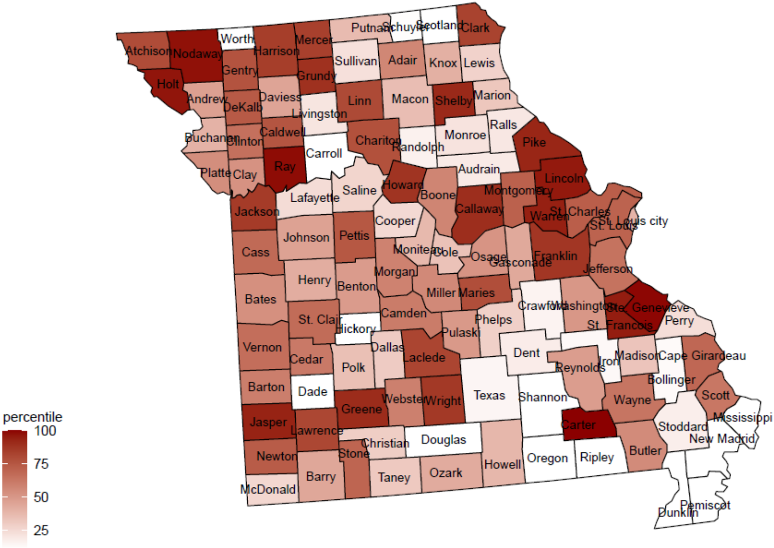
- A cross-sectional data set of insurance claims
  - Obtained a portfolio of hail damage property insurance claims
  - Personal homeowner insurance in the state of Missouri
  - Information on insured losses and triaging variables
- A longitudinal data set of weather dynamics
  - Obtained from Automated Surface Observing System (ASOS) and the Automated Weather Observing System (AWOS)
  - Supplemented by vendor data

Data


1.00
0.75
0.50
0.25
0.00
Empirical CDF
0
10000
20000
30000
40000
50000
Amount of Insured Losses


8e−05
6e−05
4e−05
2e−05
0e+00
Frequency
0
10000
20000
30000
40000
50000
Insurer's Positive Payments

Data

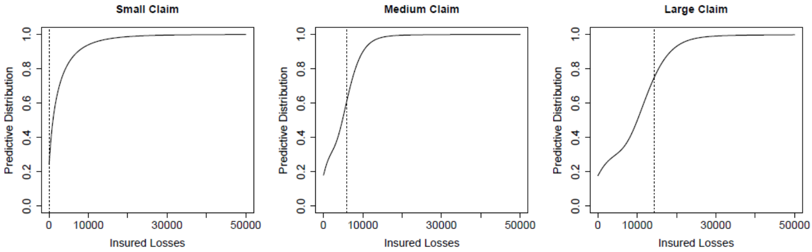

percentile
100
75
50
25
Atchison
Nodaway
Worth
Harrison
Mercer
Putnam
Schuyler
Scotland
Clark
Holt
Gentry
Grundy
Sullivan
Adair
Knox
Lewis
Andrew
DeKalb
Daviess
Livingston
Linn
Macon
Shelby
Marion
Buchanan
Clinton
Caldwell
Carroll
Chariton
Randolph
Monroe
Ralls
Pike
Platte
Clay
Ray
Audrain
Lincoln
Jackson
Lafayette
Saline
Howard
Boone
Montgomery
Callaway
Warren
St. Charles
St. Louis
St. Louis city
Cass
Johnson
Pettis
Cooper
Moniteau
Cole
Osage
Gasconade
Franklin
Jefferson
Bates
Henry
Benton
Morgan
Miller
Maries
Crawford
Washington
Ste. Genevieve
St. Francois
Perry
Vernon
St. Clair
Hickory
Camden
Pulaski
Phelps
Dent
Iron
Madison
Cape Girardeau
Cedar
Polk
Dallas
Laclede
Reynolds
Bollinger
Barton
Dade
Texas
Shannon
Wayne
Scott
Jasper
Greene
Webster
Wright
Carter
Stoddard
Mississippi
New Madrid
Lawrence
Christian
Douglas
Newton
Stone
Howell
Oregon
Ripley
Butler
Barry
Taney
Ozark
McDonald
Dunklin
Pemiscot

Data

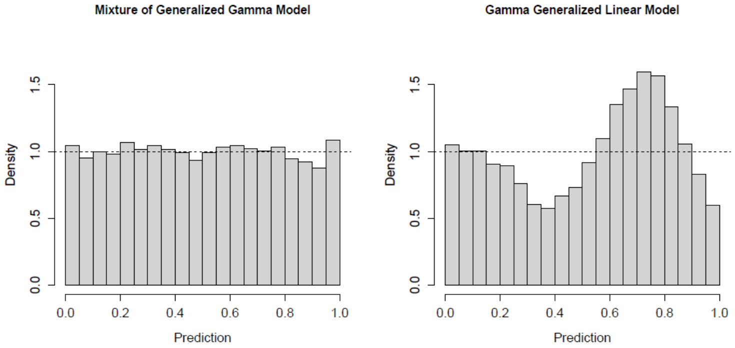
	Zero Losses		Positive Losses		Overall	
	Mean	SD	Mean	SD	Mean	SD
Building Age	37.80	22.00	38.10	21.70	38.04	21.75
Property Type						
Outbuilding	0.45%		0.15%		0.20%	
Single Family	98.90%		99.20%		99.11%	
Others	0.68%		0.70%		0.69%	
Roof Type						
Asphalt Shingle	96.70%		97.30%		97.21%	
Others	3.33%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

The predictive distribution is obtained by

$$F_i(y|x_i;\hat{\boldsymbol{\theta}}) = p(x_i;\hat{\boldsymbol{\theta}}) + (1 - p(x_i;\hat{\boldsymbol{\theta}}))G(y|x_i;\hat{\boldsymbol{\theta}}),$$



Prediction


Mixture of Generalized Gamma Model
Density
0.0
0.5
1.0
1.5
0.0
0.2
0.4
0.6
0.8
1.0
Prediction
Gamma Generalized Linear Model
Density
0.0
0.5
1.0
1.5
0.0
0.2
0.4
0.6
0.8
1.0
Prediction

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.

	Point Forecast		Probabilistic Forecast	
	Gini	S.E.	Diebold–Mariano	p-value
No Weather	11.925	0.524	-13.836	< 0.001
Static Weather	7.522	0.543	-7.472	< 0.001

Operation Cost

Consider setting:

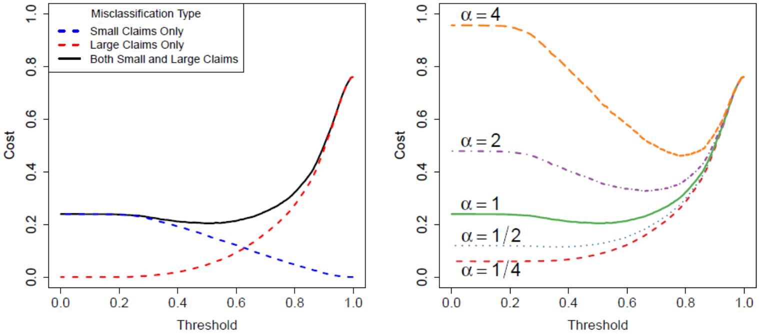
- Two types of claim adjusters: inexperienced and seasoned
- Define the sets of small and large claims as $C_s = \{y : y \in [0, c])\}$ and $C_l = \{y : y \in (c, +\infty)\}$
- Denote $\delta(x) = F(c|x, \hat{\boldsymbol{\theta}})$, the probability that a claim belongs to classes C_s
- A claim is assigned 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 δ^* by minimizing the average cost of the missclassification for the training data:

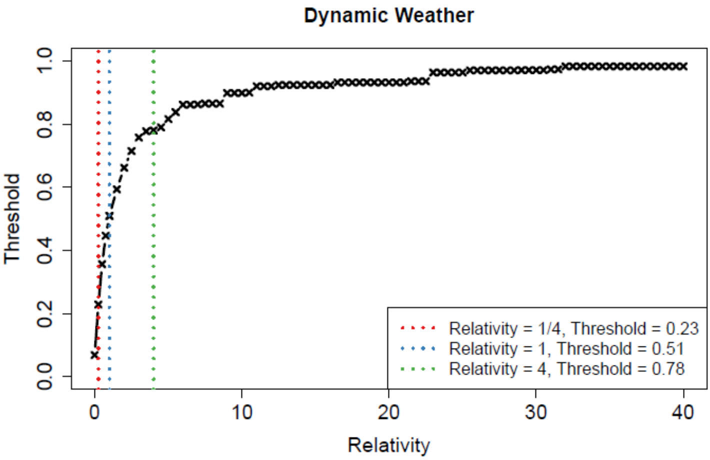
$$C(\delta) = \frac{1}{n}\sum_{i=1}^{n}\left\{d_s \mathbf{1}_{A_s(\delta)}(i) + d_l \mathbf{1}_{A_l(\delta)}(i)\right\}$$

where $\mathbf{1}_A(\cdot)$ is the indicator function.

Operation Cost



Operation Cost



Hold-out sample comparison:

	Percentiles						
	Minimum	10th	25th	50th	75th	90th	Maximum
No Weather	2.16%	3.58%	5.18%	6.39%	7.36%	7.94%	9.77%
Static Weather	2.01%	3.44%	4.24%	4.65%	5.52%	6.82%	8.19%

Conclusion

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.

Hail Risk
Peng Shi
Introduction
Method
Data Analysis
Conclusion

Thank you for your attention!