Ratemaking, Product and Modeling Seminar and Workshops

March 15–17, 2021
Virtual Conference
CAS Machine Learning
Working Party

Context and Key Issues in Ratemaking
Presenters

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Introduction
What is Machine Learning?

- Catch-all term for a lot of concepts
- *Usually* involves a flexible algorithm that is *iteratively* adjusted based on optimizing some function of the data
  - E.g., take all the data, apply some transformations, and calculate how far you are from the answer you wanted, make adjustments, repeat
- Usually no closed-form solution to optimization problem, which necessitates iterative solutions
  - Computer vision
  - E-mail spam filtering
  - Netflix recommendations
What is Machine Learning?
Machine Learning Pros

- Good for open-ended problems (like computer vision) where it would be hard to manually engineer a model
- Good for finding “hidden” relationships in data or selecting optimal subsets of predictors
- “On-line” learning and predicting possible
- Can fit highly non-linear functions that may be challenging for traditional approaches like GLMs
- Open-source software makes it easy!
Machine Learning Cons

- Not as transparent as statistical methods
- Not all statistical tools are available for evaluating model performance
- Can over-fit to data and create highly non-linear functions where you don’t expect
- Computational cost - many of these models take a long time and a lot of computing power!
Why Should We Care About Machine Learning?

- It can get much better results than more traditional models
- It can help explain results and identify patterns you might otherwise miss
- It’s going to be everywhere
- It’s cool, and it will make you cool!
Potential Applications to Ratemaking

- ML algorithms can enhance conventional models
- ML can enhance other insurance company functions
- ML can provide additional monitoring tools
- ML can enhance customer segmentation
- ML can expand profitability
- ...

[Image: CAS logo]
Practical Applications
ML in action
The data contains motor third-party liability policies from a French Insurer. Claim numbers and claim amounts, alongside a selection of risk features are available for analysis.
Variables

**DRIVER**
- Age
- Region
- Density

**VEHICLE**
- Age
- Brand
- Power
- Fuel Type

**POLICY**
- Exposure
- Bonus/Malus
- Claim Count
- Claim Amount
The Models
Models Considered

- GLMs - The Classic Generalized Linear Model
- GBM - An approach that uses many weak predictors to generate robust estimates
- NN - Layers of “neurons” that “learn” to reproduce desired output based on input
- MARS - An automatic GLM that only uses linear splines
- RF - A large number of big trees (vs GBMs which use small trees)
Models Considered

- **GBM**
  - RMSE: 1,994.93
  - Gini Index: 0.1077

- **RF**
  - RMSE: 2,007.76
  - Gini Index: 0.3800

- **NN**
  - RMSE: 1,995.17
  - Gini Index: 0.1686

- **MARS**
  - RMSE: 1,995.39
  - Gini Index: 0.0000

- **GLM**
  - RMSE: 1,995.22
  - Gini Index: 0.1646

- **MARS**
  - RMSE: 1,995.27
  - Gini Index: 0.0814

- **NN**
  - RMSE: 1,994.57
  - Gini Index: 0.1115

- **GBM**
  - RMSE: 1,995.63
  - Gini Index: 0.3133

- **RF**
  - RMSE: 2,007.76
  - Gini Index: 0.3800

Approach:
- Frequency/Severity
- Loss Cost
Comparison of Approaches across Models

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<tr>
<th>Approach / Model</th>
<th>Frequency/Severity</th>
<th>Loss Cost</th>
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<td>GBM</td>
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Communications Issues in ML
Towards Explainable AI (XAI)
Occam’s Razor

The simplest explanation is usually the best

“...accuracy and simplicity (interpretability) are in conflict. For instance, linear regression gives a fairly interpretable picture of the $x, y$ relation. But its accuracy is usually less than that of the less interpretable neural nets.”

L. Breiman
Start by Considering the Audience

- **Technical Stakeholders**
  - Other Actuaries

- **Non-Technical Stakeholders**
  - **External**
    - Regulators
    - Auditors
  - **Internal**
    - Profit Center Executives
    - Sales & Marketing
    - Agents & Insureds
“...another actuary qualified in the same practice area could make an objective appraisal of the reasonableness...”
ASOP 41 - ML Issues

- The model includes the algorithm, data, hyperparameters, fitting methods
- ML is often “ad hoc” - many models are unique for their application
- ML algorithms and their underlying data are often proprietary
Regulators May Lack ML Capabilities

NAIC survey from 2017 indicates that:

- Not all states have personnel qualified to review GLMs
- Plurality of respondents note that filing complexity and/or lack of resources or expertise impeded their department’s ability to review GLMs
- Not all states have an effective mechanism to protect confidentiality of models or other information submitted with a rate filing
Regulatory Issues

- Need to demonstrate that rates are not inadequate, excessive, or unfairly discriminatory
  - “Unfairly discriminatory” may be a challenge unless we can explain why a model produces a particular outcome.
- Need to file a rating plan
  - Does a black box meet the legal definition of a “filed rate”?
  - Is it necessary to convert the ML model to relativities for implementation?
Internal Communications

- Is the price change consistent with the corporate strategy and messaging?
- How do we explain the change to our management?
- Will our agents be able explain the change to their insureds?
- What do you say to insured whose premium changes because the model changed?
- Who will be impacted the most?
Bridging the Communication Gap
Basic Idea

ML can be a black box - let there be light!
MODEL INTERPRETATION

GLOBAL

Trying to understand the predictions on an overall level – *In general, why does a model behave the way it does?*

LOCAL

Trying to understand predictions for specific records – *For a given record, what led the model to predict what it did?*
Global Interpretation Strategies

**TECHNICAL**
- Variable Importance
- Interaction Effect Analysis
- Feature Effect Analysis
- Model Lift
- Gini Index/Gini Plot

**NON-TECHNICAL**
- Partial Dependence Plots
Partial Dependence Plots
Partial Dependence - DensityBand

- Level
- Value

Data points:
- (0,50): 102.01
- (1e+03, 2e+03]: 136.82
- (2e+03, 3e+03]: 131.68
- (3e+03, Inf]: 126.37
- (50, 100]: 103.74
- (100, 200]: 124.27
- (200, 400]: 123.02
- (400, 1e+03]: 134.89
Variable Importance

- Based on Permutation-based Loss Dropout
- Each rating variable is shuffled and model recomputed
- Degree of difference in RMSE w.r.t. original model indicates variable importance
Interaction Effects

- Based on Partial Dependence (PD) - studies how model predictions depend on individual predictors
- Uses the Friedman H-Statistic
- Measures the degree of impact the joint PD of 2 variables has on the overall PD of the combination, intuitively,

\[ PD(X, Y) = PD(X) + PD(Y) + PD(X \& Y) \]
Non-Technical Communication Strategies

- For the rating plan, the model must be converted to relativities.
  - Tools such as Lime may be needed to generate the relativities.

- ML can replace “judgement” in some rating plan components. For example:
  - Clustering used in a classification analysis
  - AI used to generate a brush-fire hazard map

- Rating examples help stakeholders can get a “feel” for what the model does.
References


References, Continued


Wuthrich, Mario V., Neural Networks Applied to Chain-Ladder Reserving (July 6, 2018). Available at SSRN: https://ssrn.com/abstract=2966126 or http://dx.doi.org/10.2139/ssrn.2966126


References, Continued


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