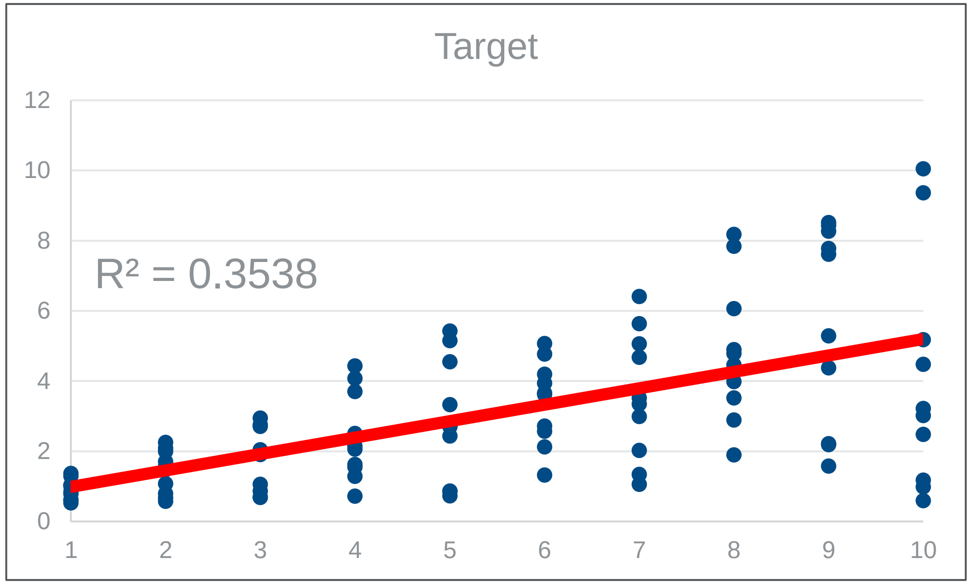
ISO

An Application of Machine Learning in Ratemaking

Caolan Kovach-Orr, Ph.D., CSPA (Verisk)
Lijuan Zhang, FCAS (AIG)

SERVE | ADD VALUE | INNOVATE

GLMs



Generalized Linear Models

- Relate Multiple Predictors to Frequency, Severity, or Pure Premium

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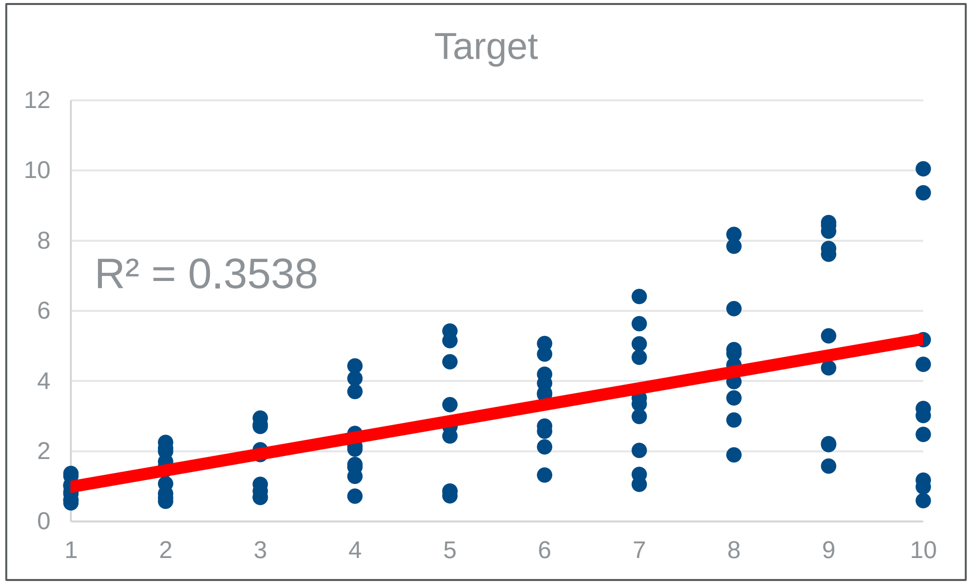

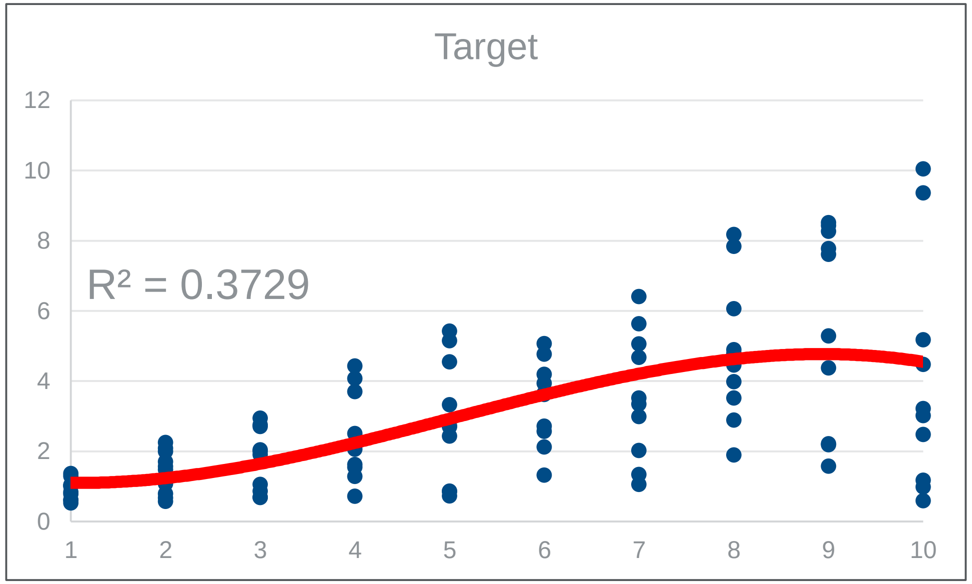

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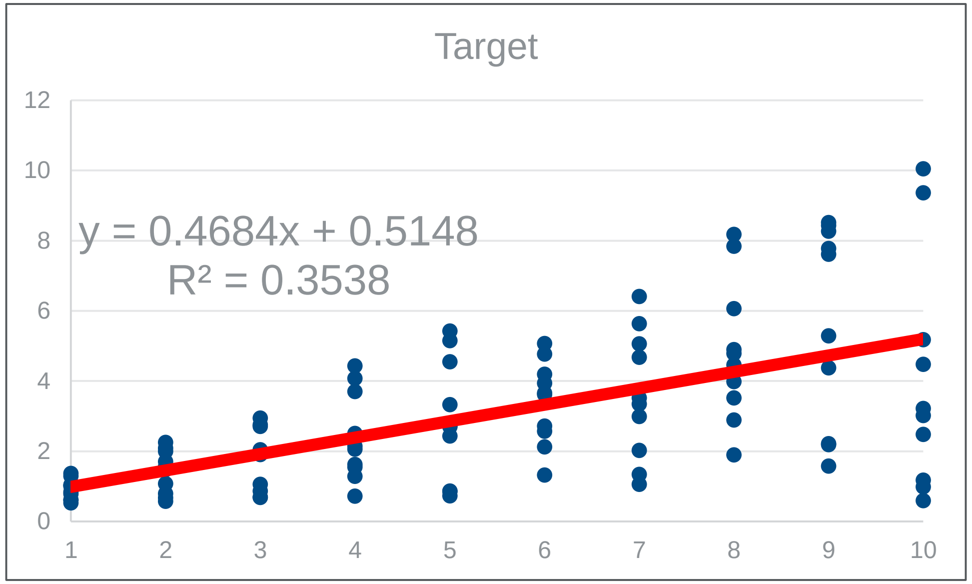
- Interpretable
- Well established for Ratemaking & Underwriting
- Proven Track Record with Regulators



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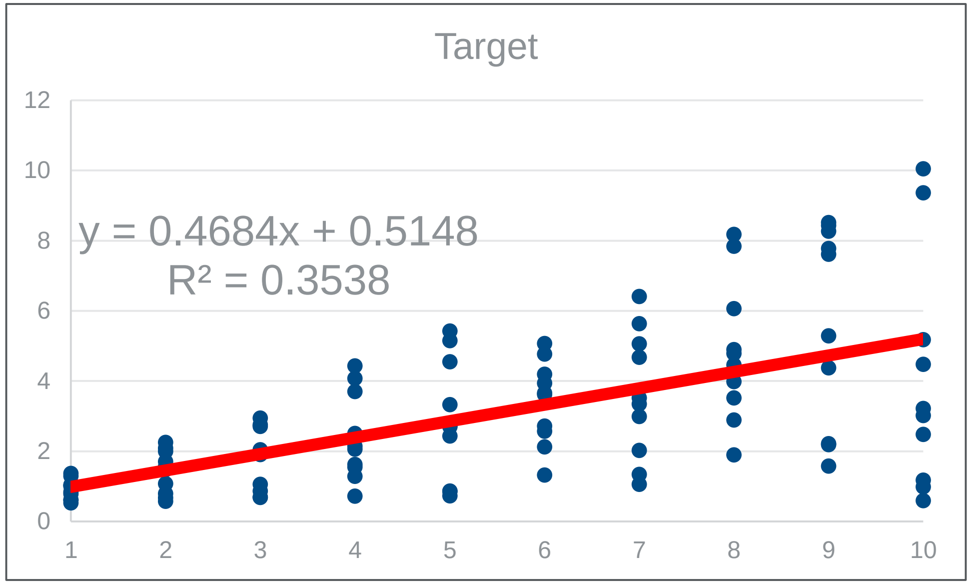

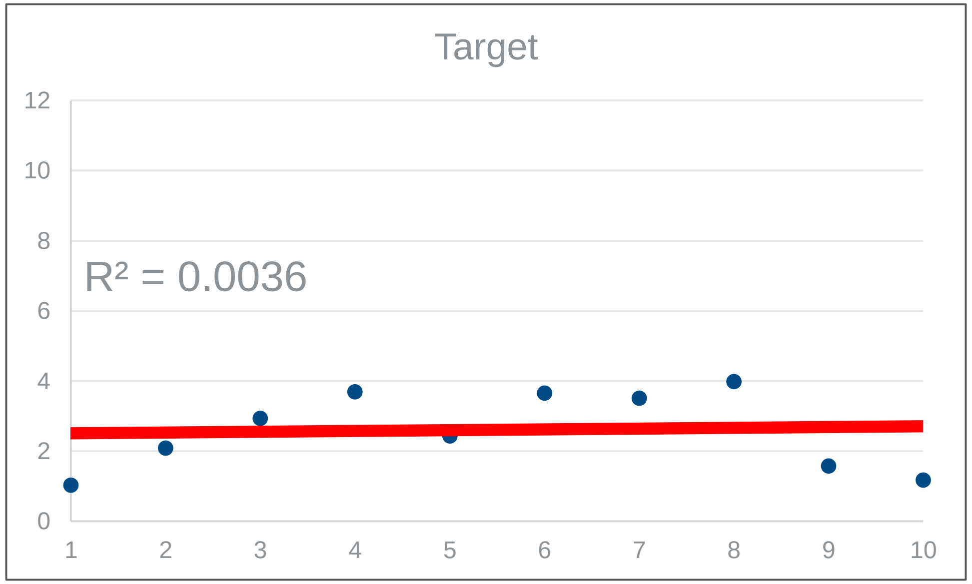

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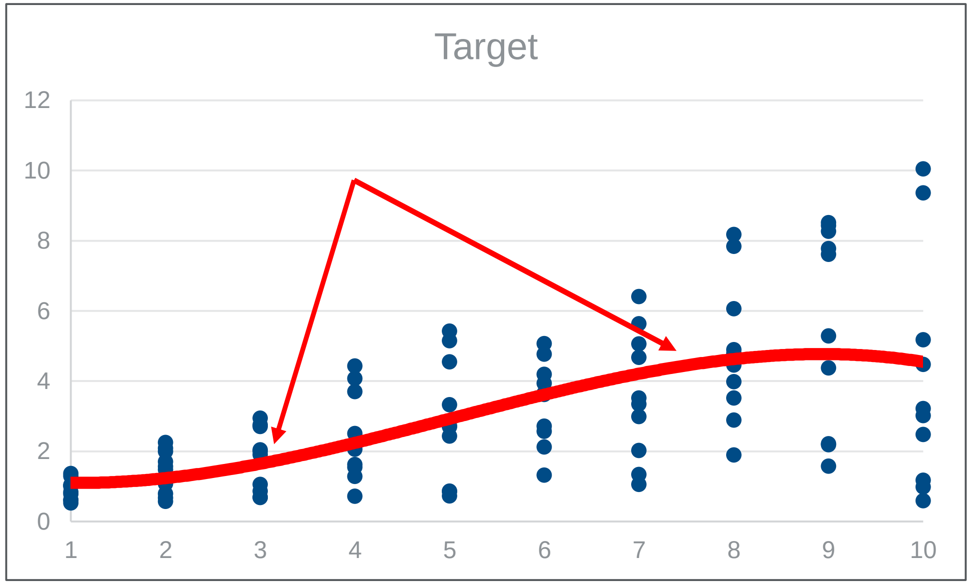
  - ++ Manual Effort (expensive & slow)



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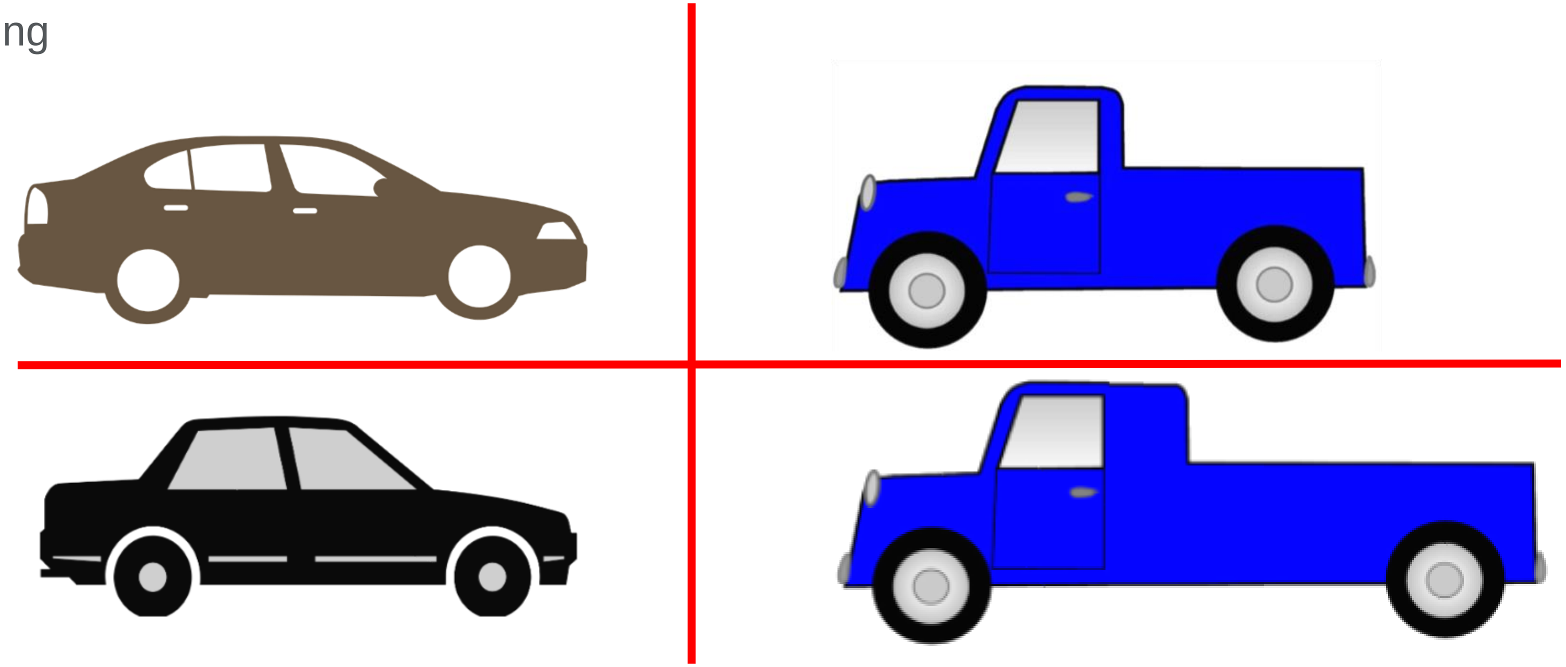

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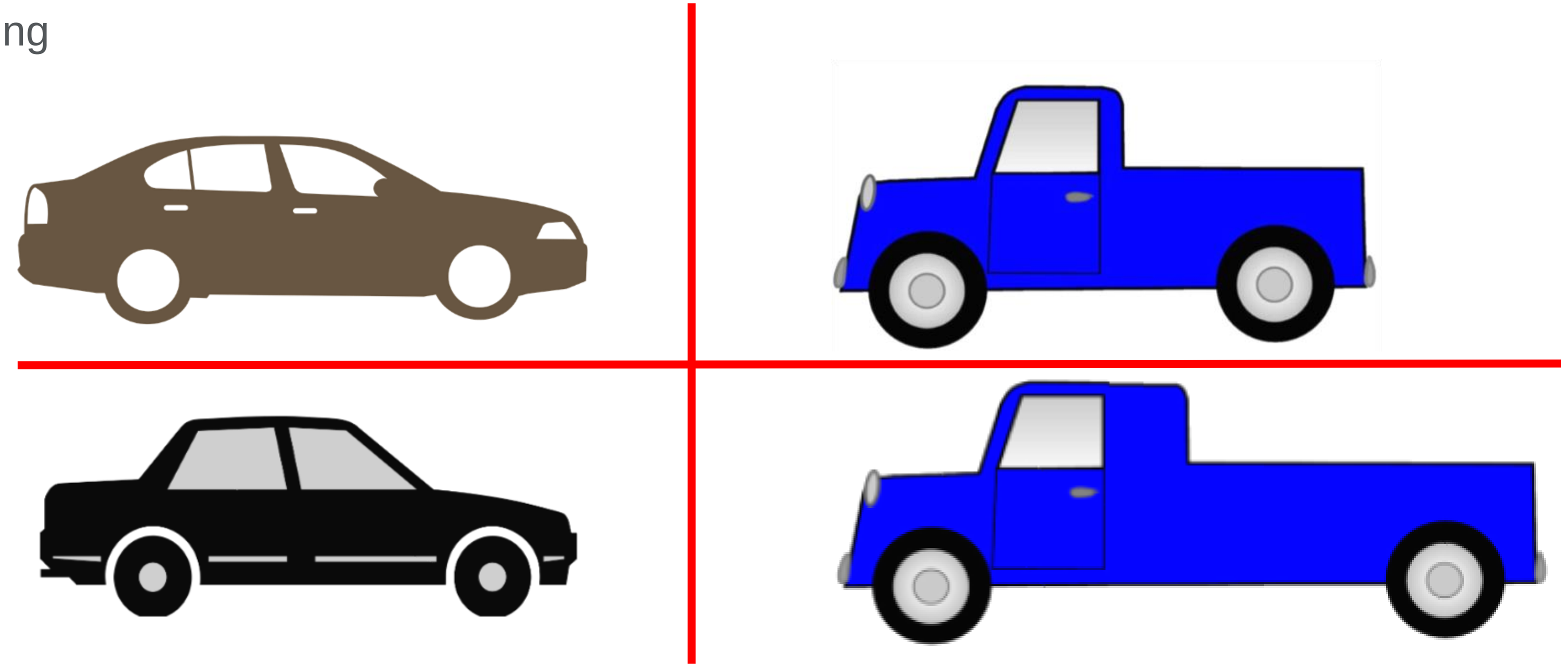

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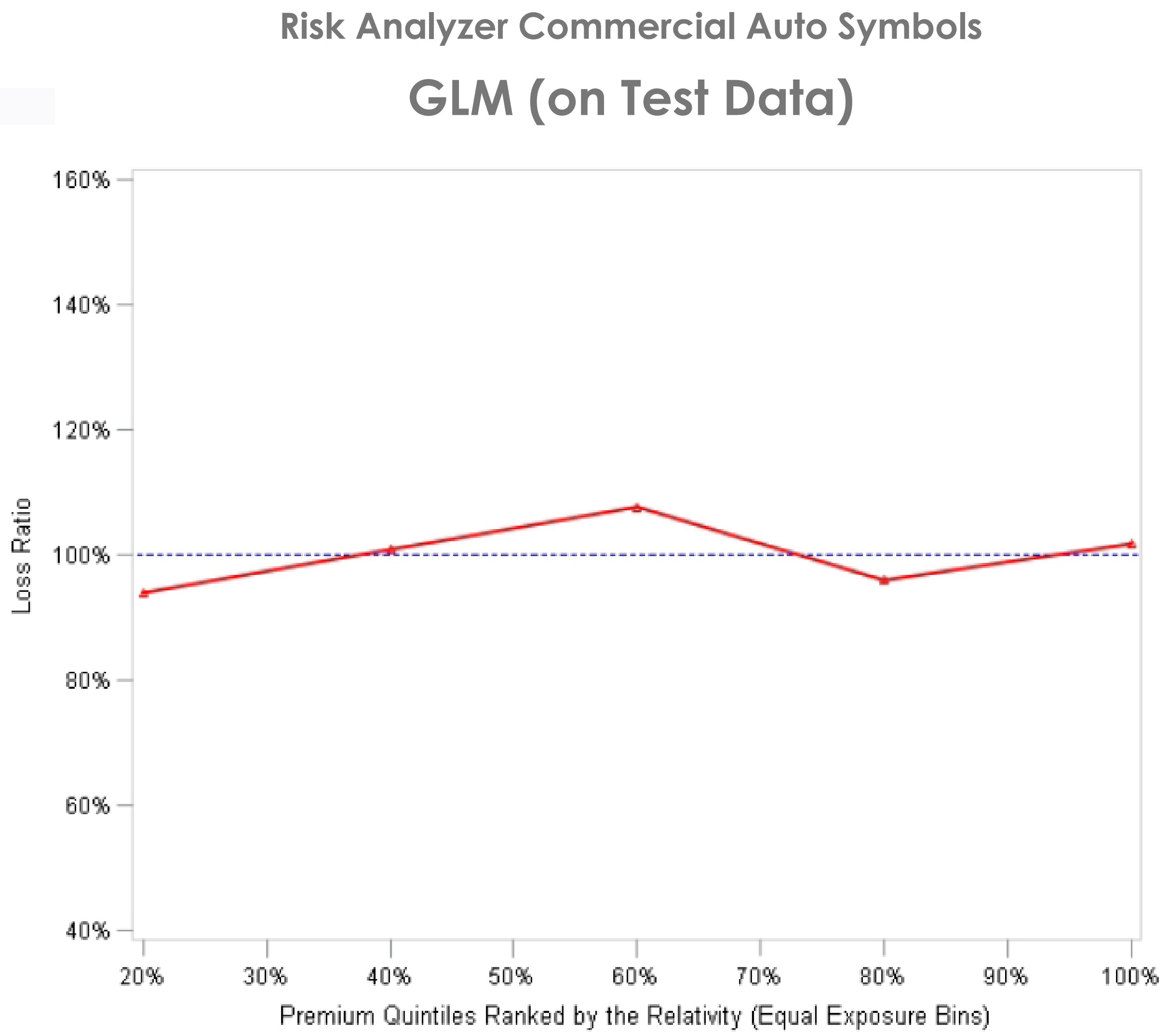

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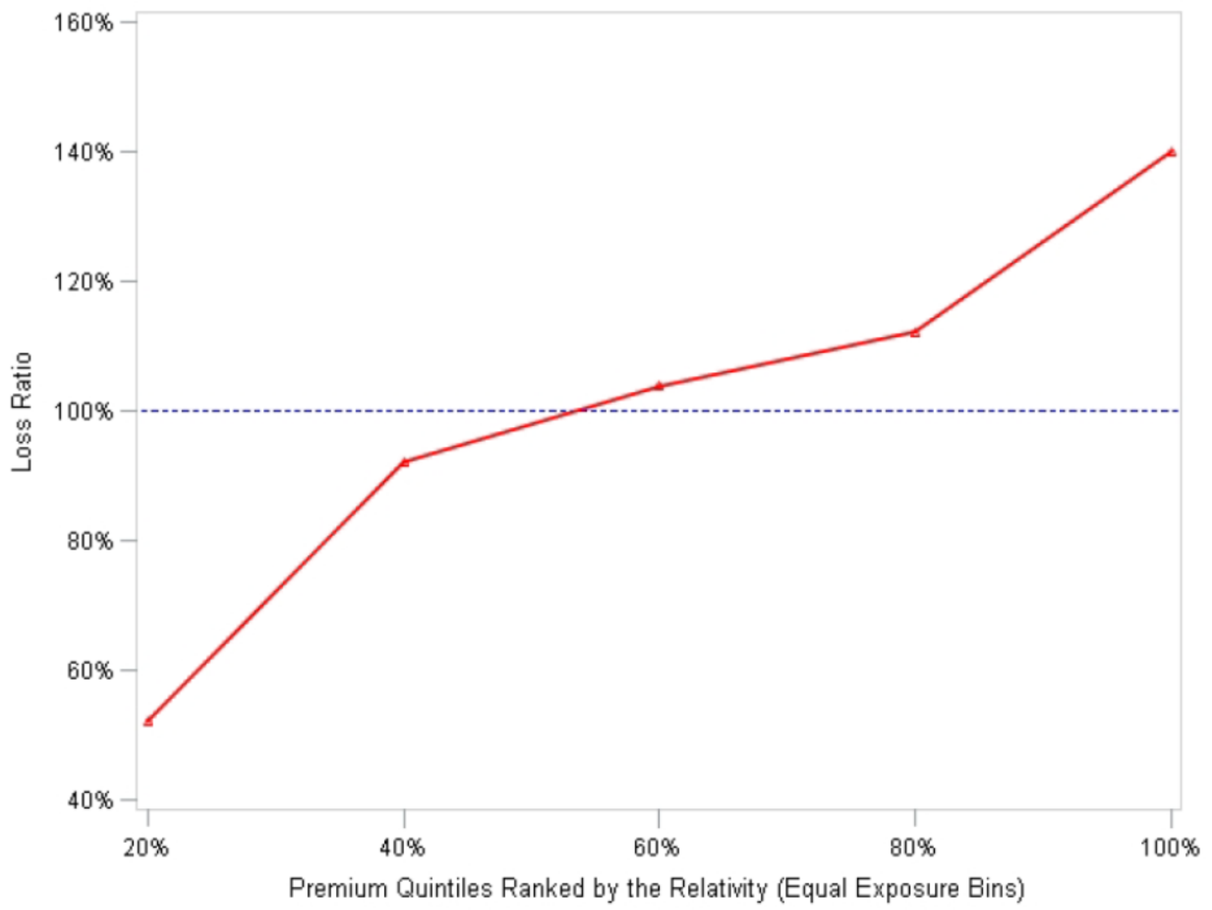
Risk Analyzer Commercial Auto Symbols

ML (on Test Data)



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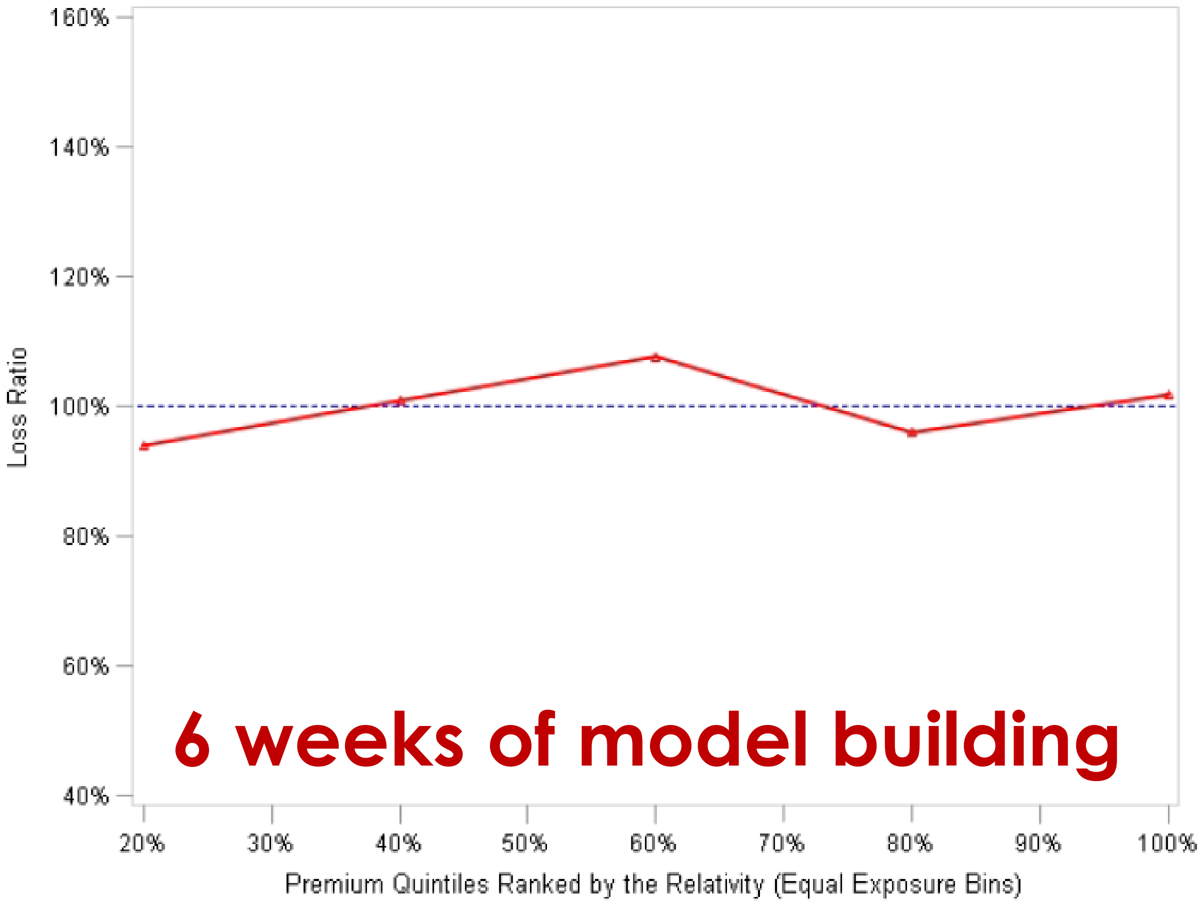

GLMs

Gradient Boosted Trees (GBT)

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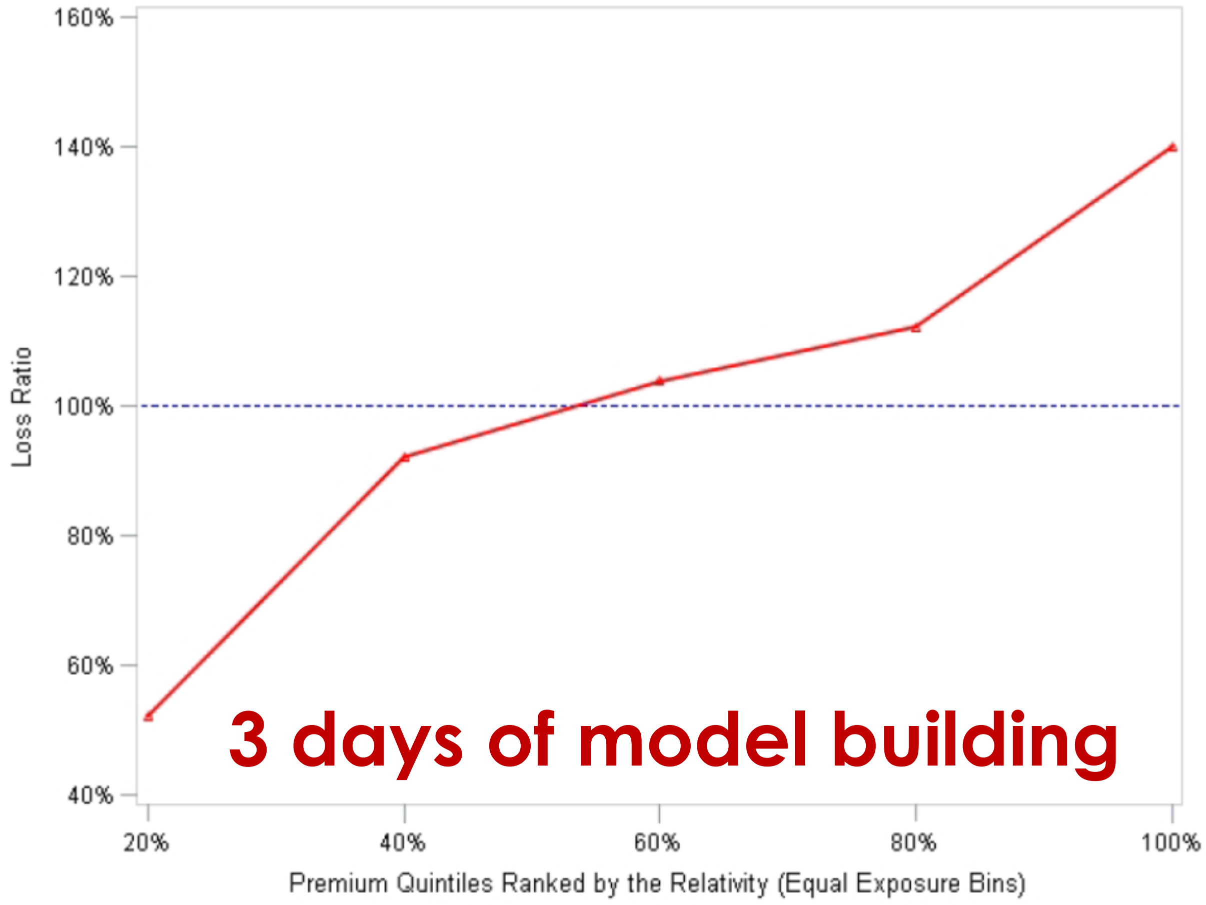

Clarifications

- NOT Artificial Intelligence
  - We build a model and that’s the final product, it doesn’t adapt, change, evolve, etc. over time.
    - Machine Learning = we let the machine build the best model
- Exactly the same data for GBTs and GLMs
- We can output every decision and look at them (although, there are thousands)

- This isn’t cutting edge technology
  - The first GBTs were built in 1997

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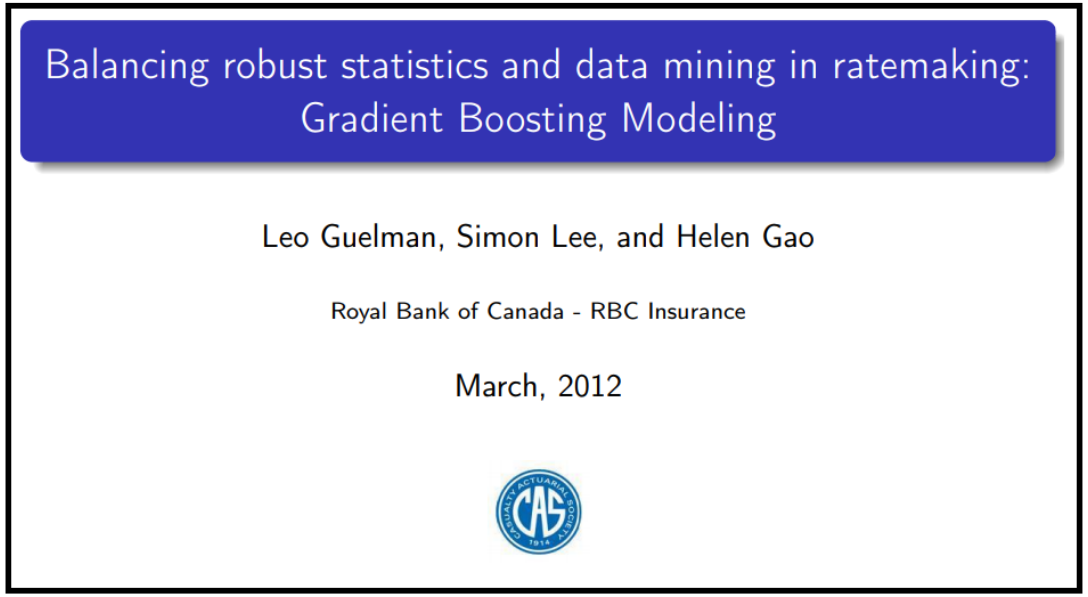

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Leo Guelman, Simon Lee, and Helen Gao

Royal Bank of Canada - RBC Insurance

March, 2012

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Yi Yang[*], Wei Qian[†] and Hui Zou[‡]

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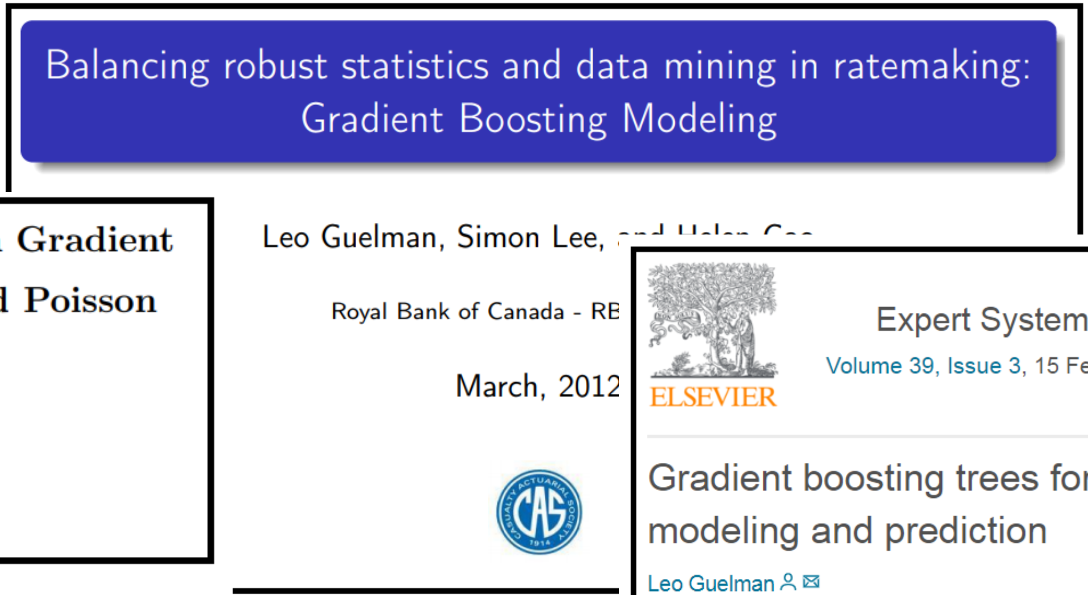
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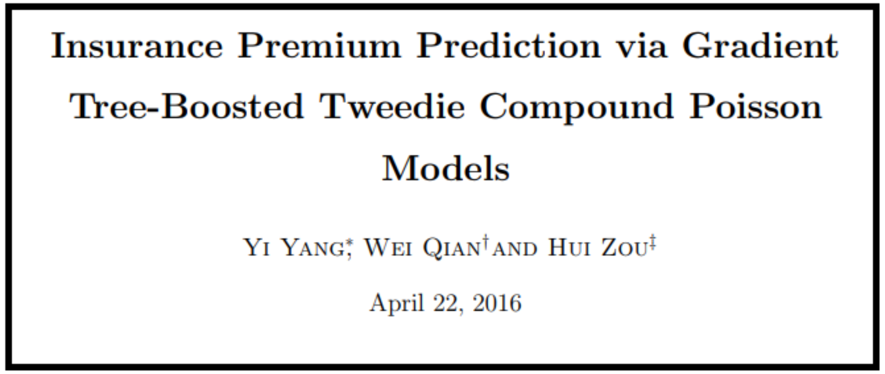
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Expert Systems with Applications

Volume 39, Issue 3, 15 February 2012, Pages 3659-3667

Gradient boosting trees for auto insurance loss cost modeling and prediction

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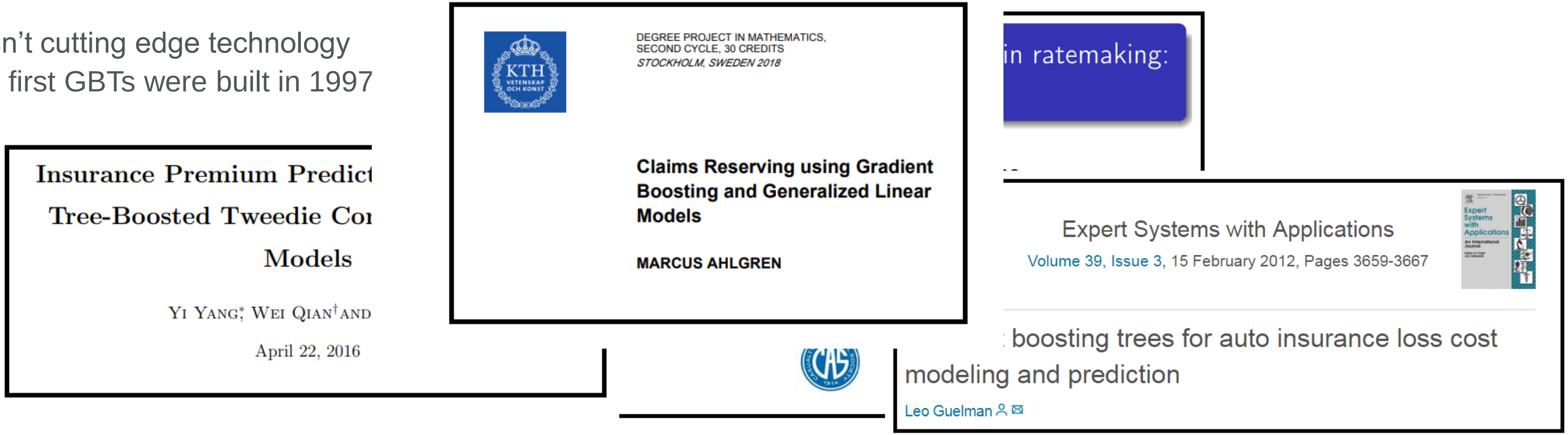

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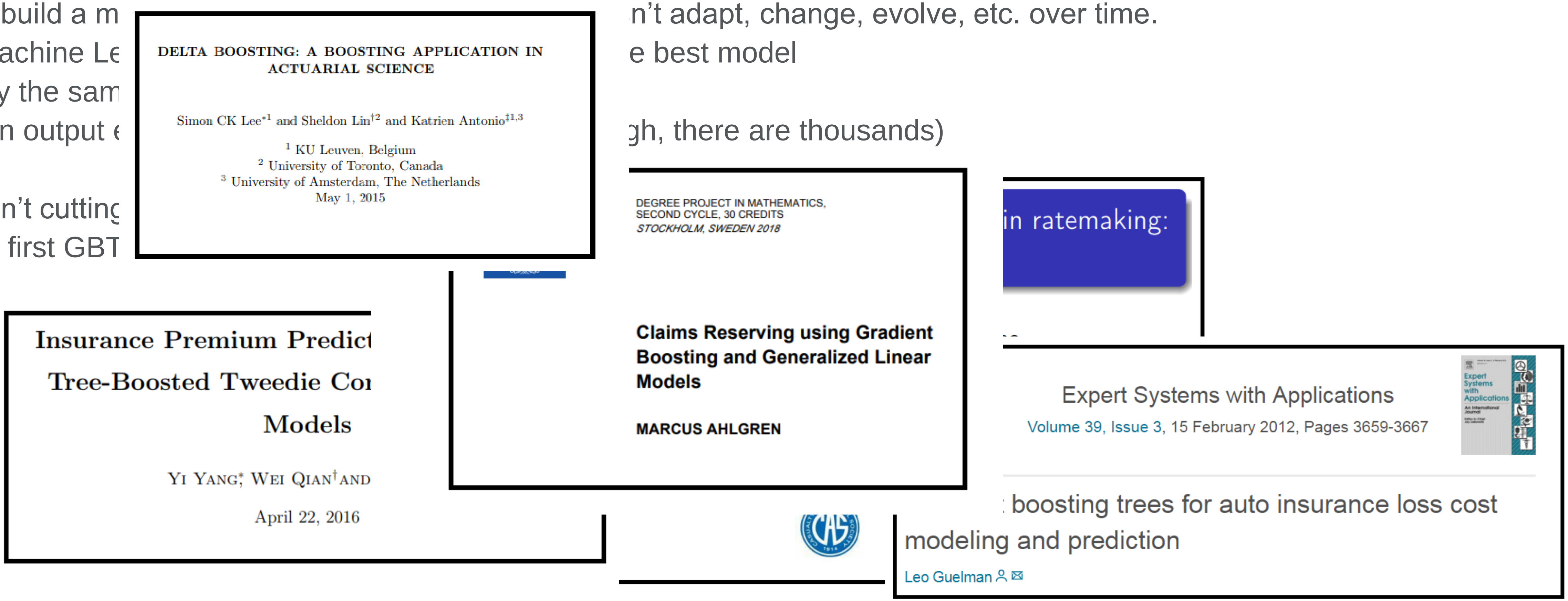

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  - Random Forests have already been filed for Verisk Personal Auto Telematics Model

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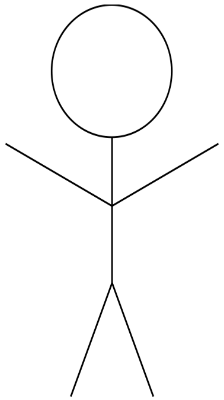
GBT = Gradient Boosted Trees

Analogy

John is OK at guessing weights



John: 182

Act: 180

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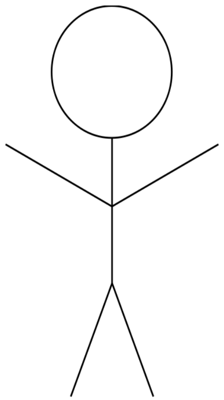

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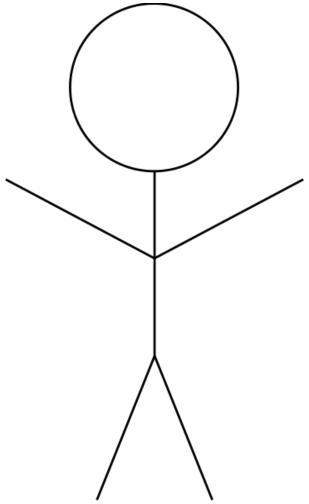
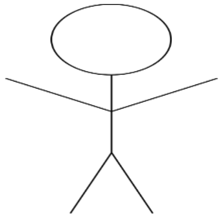
I notice John has a bias



John: 215

Act: 200



John: 130

Act: 145

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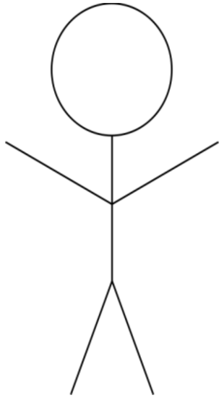

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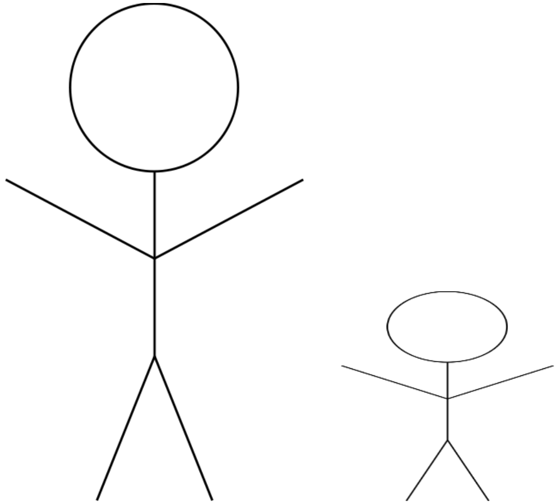

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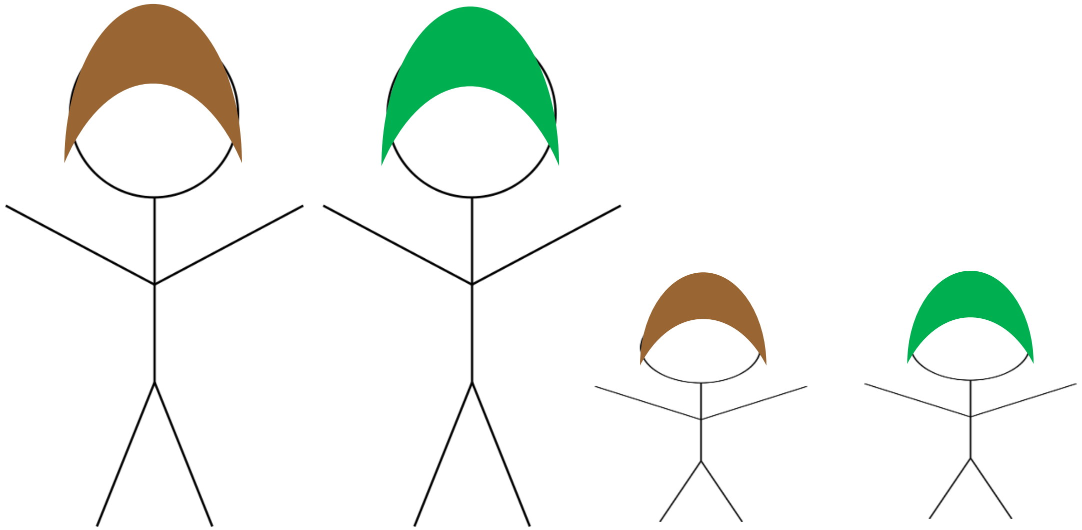
Jane notices I have a partial bias



CKO: 195

Act: 200

CKO: 205

Act: 200

CKO: 145

Act: 145

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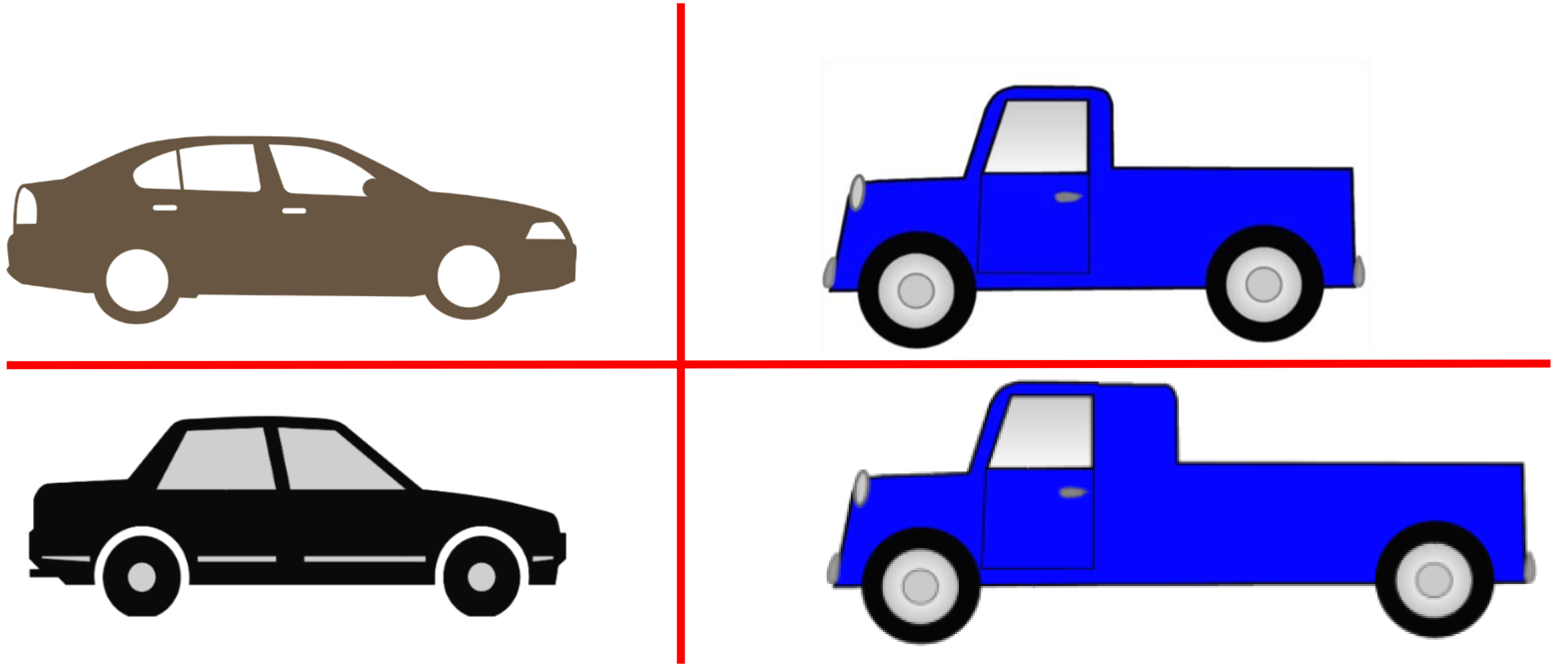

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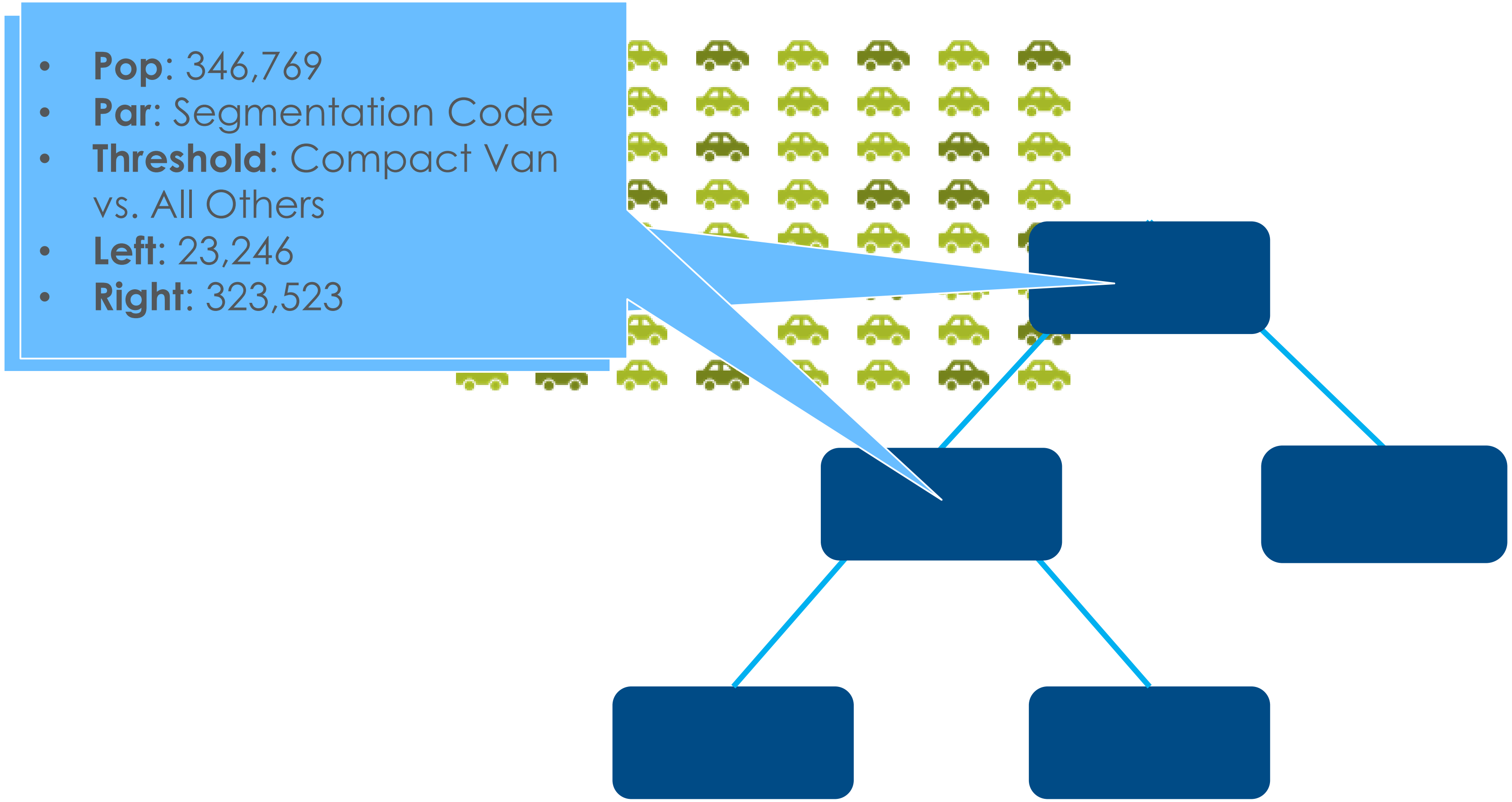

GBT = Gradient ***Boosted*** Trees

- Decision Trees provide instructions for scoring a risk based on its characteristics
- But decision trees can over-fit the training data
- The solution is to use the residuals of the first tree to reweight the data (greater weight given to higher residuals), this ‘reweighted’ data is used to create the next tree

GBT = ***Gradient*** Boosted Trees

- A function that controls ‘reweighting’ based on residuals
- Prevents ‘overcompensation’

GBT Quality

Predictive Accuracy

- Same metrics for GLM and GBT (Lift Charts, Gini, Deviance)

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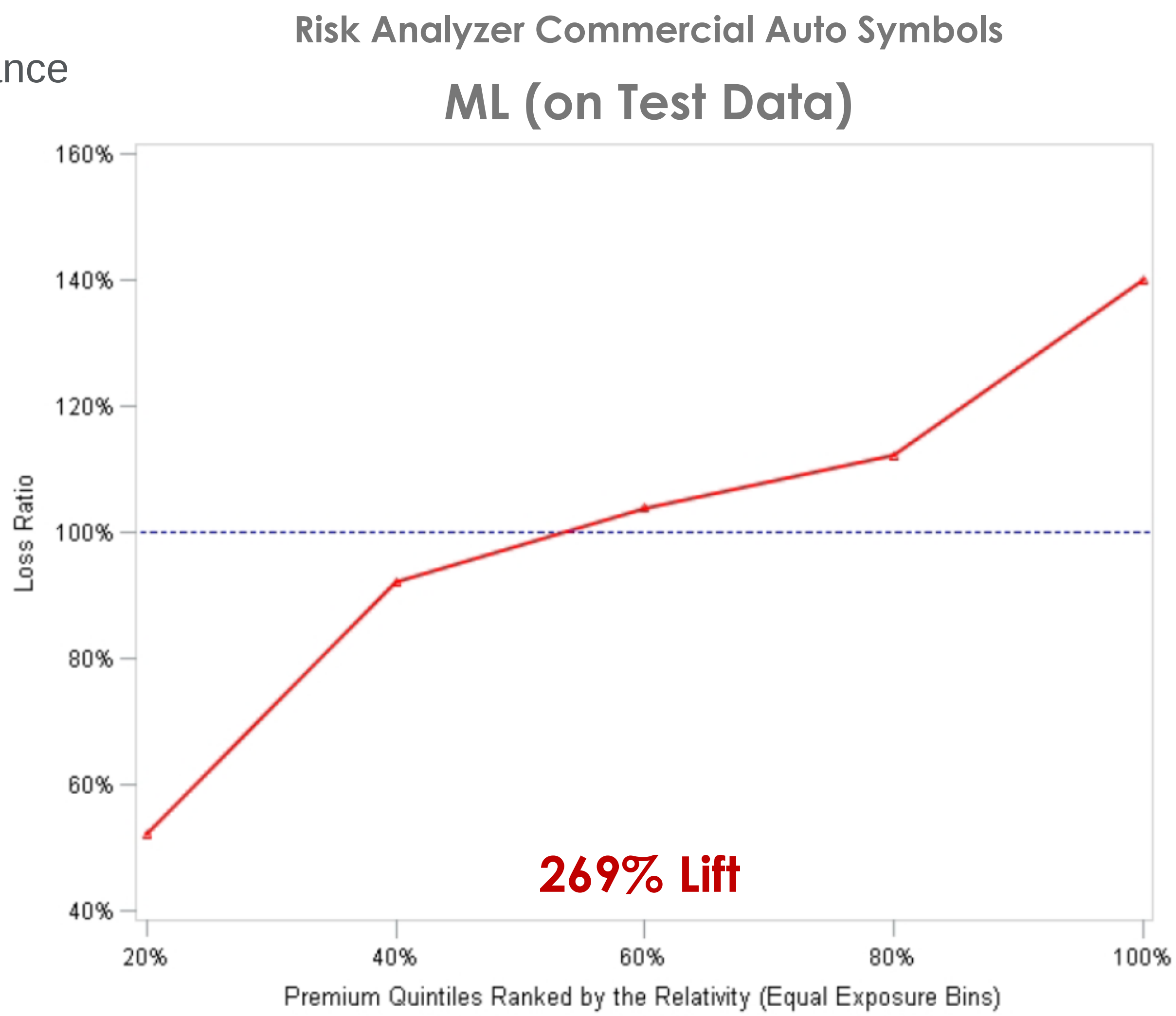

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Predictive Accuracy

Ethical & Salable

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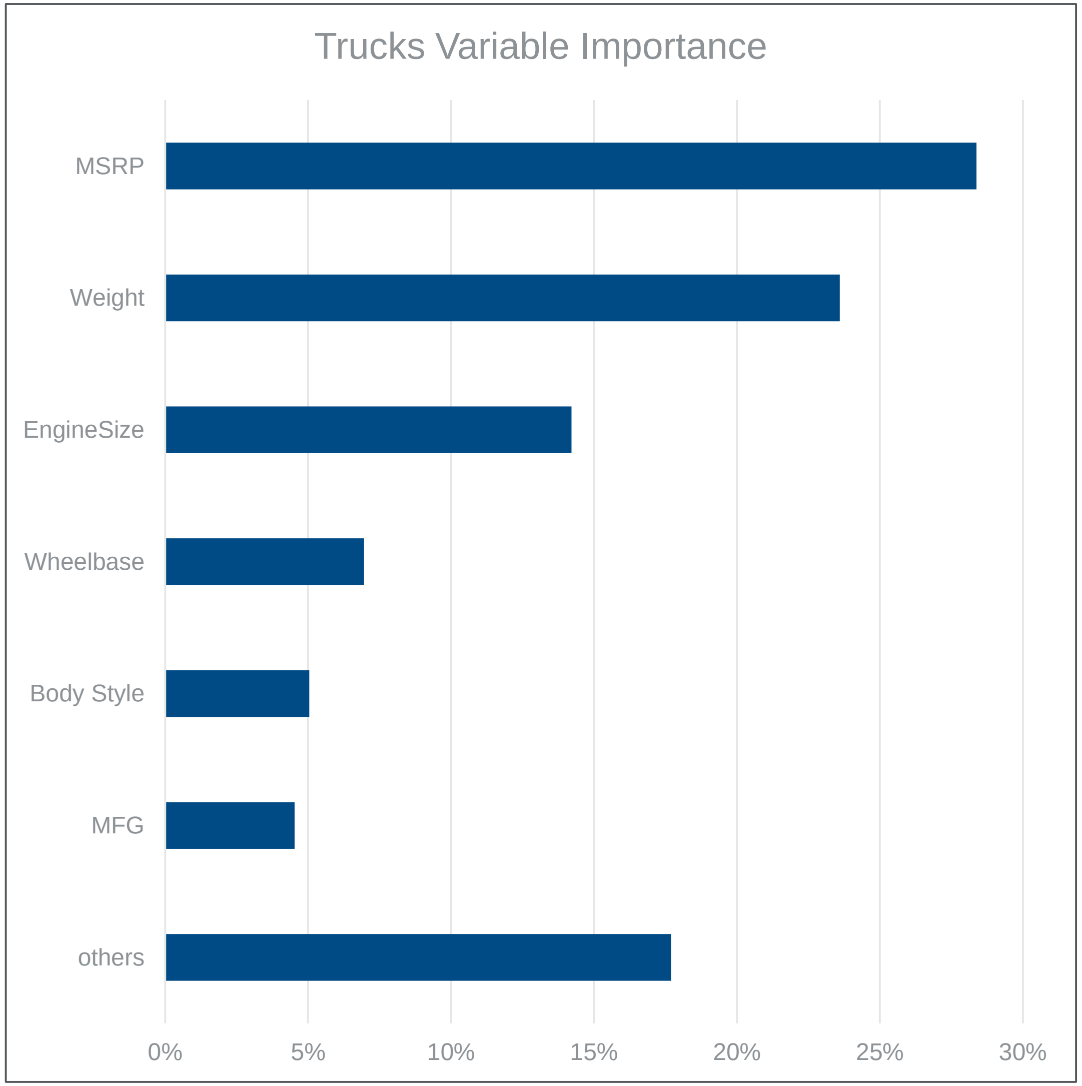
- Interpretability
  - Variable Importance
    - Weighted measure of how many records are affected by each Variable throughout entire GBT

Variable Importance



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  - Individual Conditional Expectation (ICE)
    - Show Correlation between Variable's Value and GBT Prediction
    - Hard to interpret
  - Partial Dependence Plots
    - Requires rerunning of the model while iteratively setting each variable to a constant level
      - Long process, only takes a ~'univariate' approach and leaves out 2+ way interactions
    - Hard to interpret

Summary

GBTs are

- Not AI
- Well Established
- Faster & easier than GLMs
- Very Accurate
- More interpretable than people realize

Model Implementation

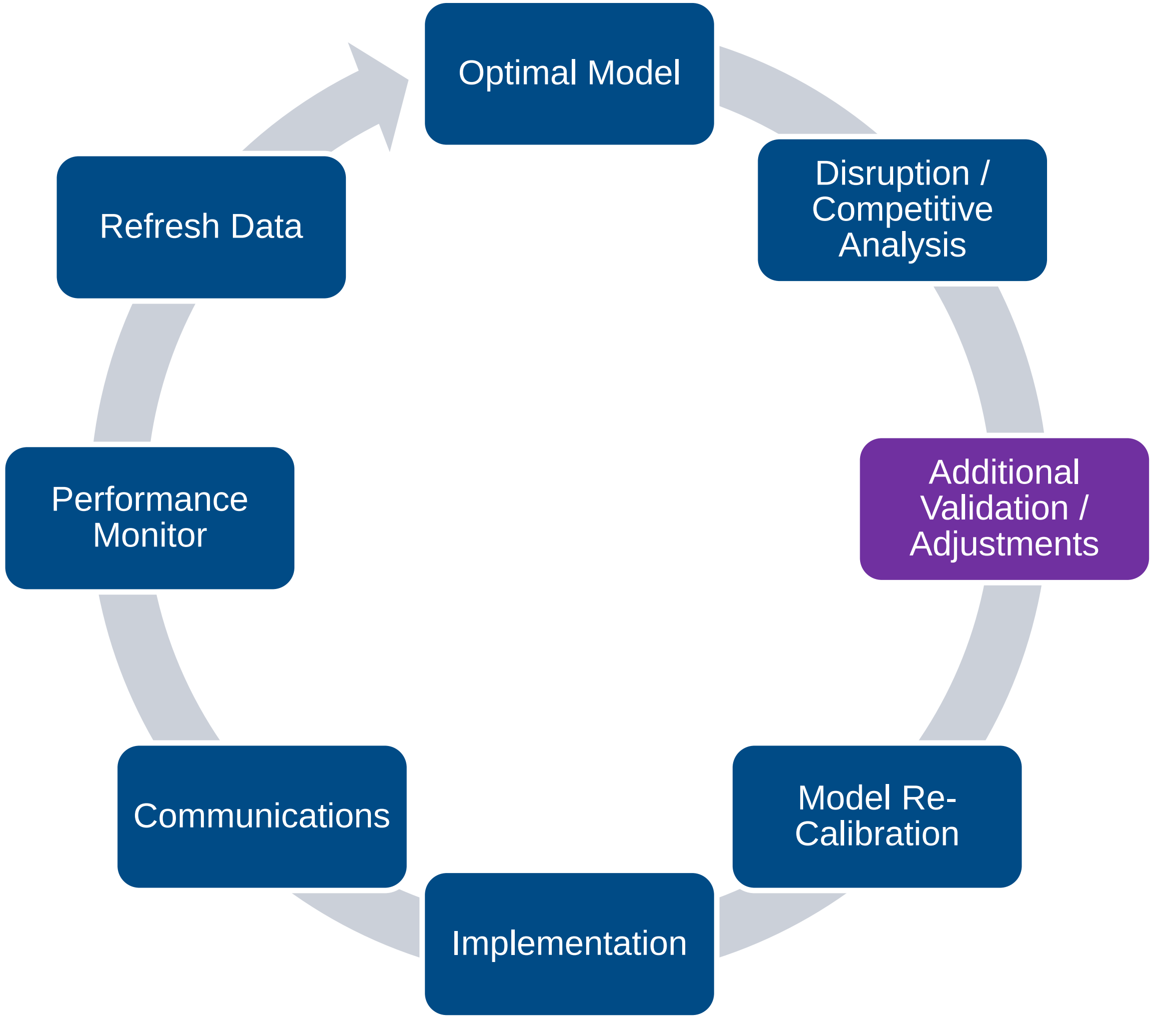
- A Diamond Cutting And Polishing Process
- Lijuan Zhang
- AIG

Building a Good Rating Plan

- Ensure rate adequacy by segments
- Ensure rate adequacy by overall
- Base on an “optimum” model that
  - has ability to separate risk
  - Accurately and precisely predict losses.
  - has Interpretable outputs

- From model outputs :
  - Simplified “optimum” model with additional validations and adjustments
  - Other considerations such as business strategy and competitor rates

Model Implementation Process Flow Chart



Reasons for Additional Validations

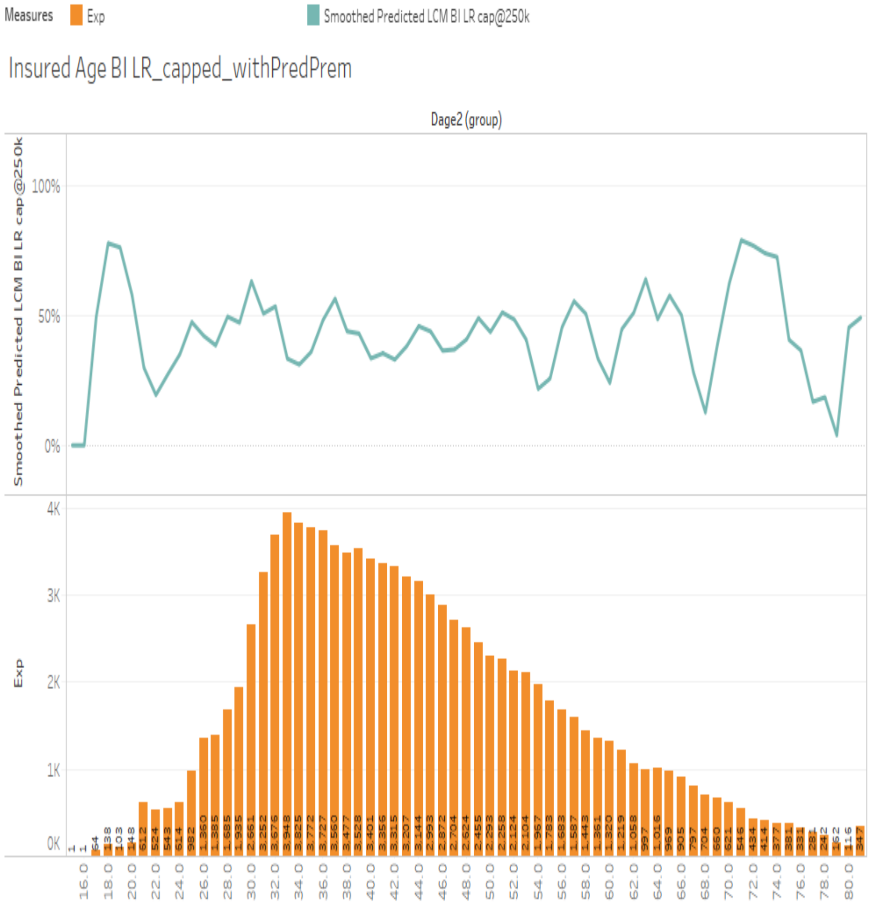
- Model was developed and validated on the historical model dataset with good predictive accuracy. Are results still valid since we are building a rating plan to be used tomorrow?
  - *Validation on an out of time data*

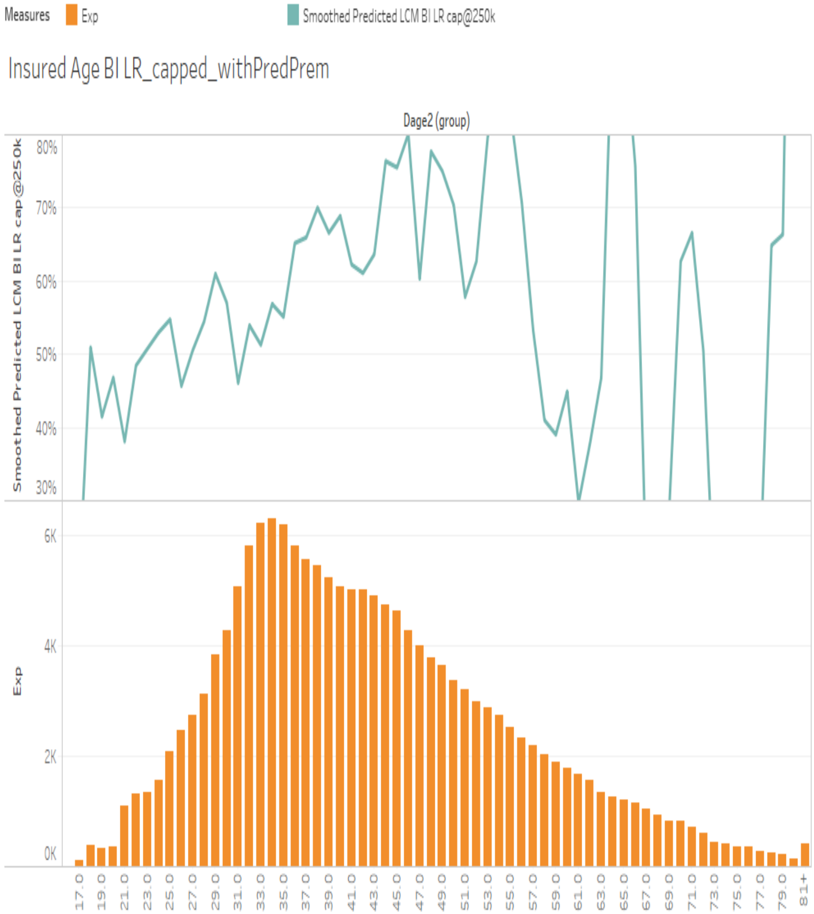
- Model was developed and validated on the full model dataset with good predictive accuracy. Are results still valid when we are building a rating plan to be used in some segments?
  - *Validation on segments*

- Example: 2010 -2014 data was used to build an auto Loss Cost model

Bodily Injury Residuals: 2014 Accident Year vs. 2015 Accident Year

i.e. Bodily Injury Incurred / Bodily Injury Predicted Premium





Bodily Injury Residuals (Older Drivers vs. Younger Drivers)

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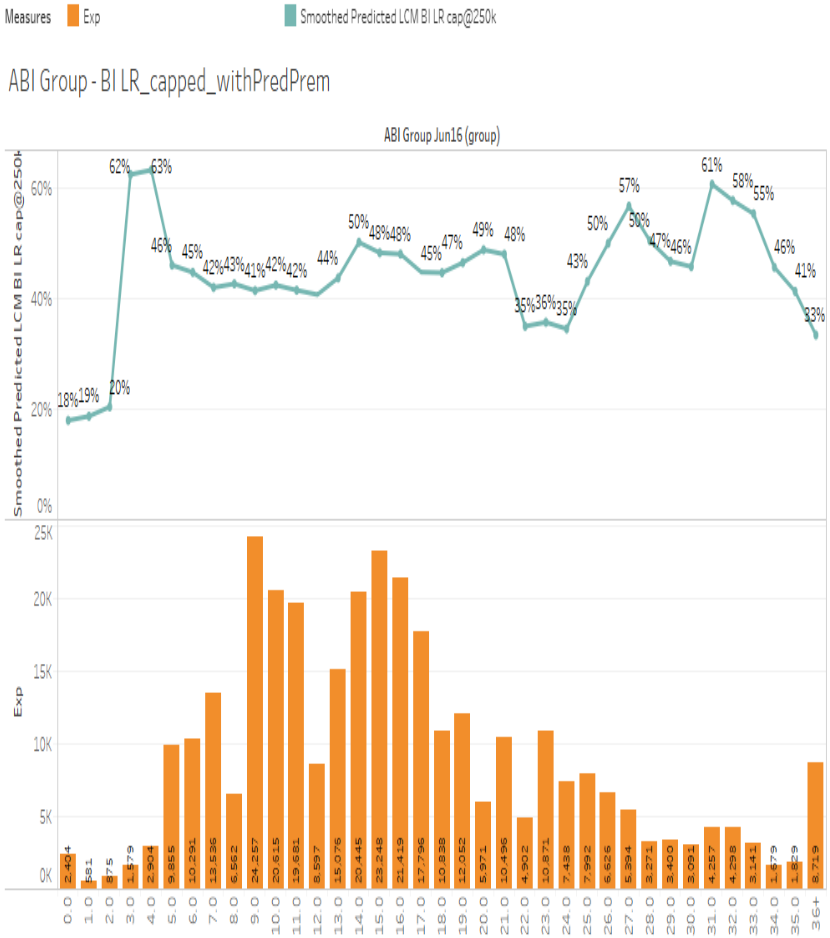

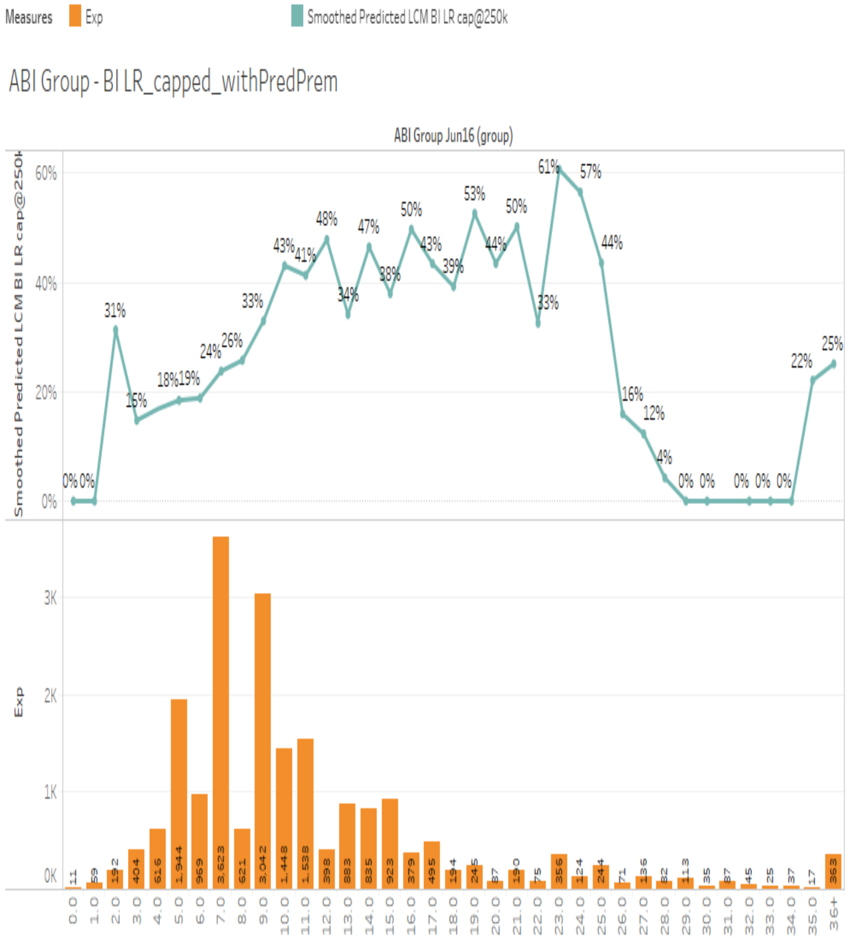

Reasons for Adjusting Model Results

- Competitor Analysis/Market Constrains
- IT System Limitations
- Regulatory/Legal Requirements
- Moral Hazards/Adverse Selection

Adjustments To Model Results

- Competitive Analysis:
  - Vehicle age curve from Country A Auto model look too flat compared to the current structure as well as that of our competitors.
    - Factors are modified up a bit and model is re-fitted
  - Adjust the factors for target segments due to “Brand Awareness”
    - Charge a bit cheaper than a ‘recognizable’ company to win the segments
- Market Constrains:
  - In Mexico, some agents, especially independent agents like to have a quotation quickly with a few questions answered by customers. Same dose sales person in a new car dealers : use another variable from same dataset to derive an approximate variable to be used to refit model.
    - Exmaple: vehicle_kept_overnight vs ZIP codes

Adjustments To Model Results

- IT System Limitations:
  - 3-ways interaction variable can not be implemented in the old IT system in Country B.
    - Create a new variable
  - If “payment plan’ is a variable to be used in the proposed rating structure, can IT system handle the additional charge due to the monthly payment?
    - Using existing field that accepted the size of this variable
  - Determined fields by length and size in the IT system: Territory code to ZIP code

Adjustments To Model Results

- Regulatory/Legal Requirements :
  - In US, regulations are always changing and they are different by states
  - In Japan, only certain group of variables can be used for personal line product pricing
  - In Ireland, there are gender discrimination rules which means females/males cannot be rated separately. *Attributes which are highly correlated with the variables banned by regulations need special considerations in the pricing structure:*
    - Occupation
      - ✓ Rating fireman/firewoman, rabbi/ priest differently could be religious discrimination.
      - ✓ It could be illegal to give discounts to nurses since 80% of nurses are female
    - Marital Status
      - ✓ If civil partnership is significant in the model, it would be illegal to distinguish between civil partnership and married

Adjustments To Model Results

- Moral Hazard or adverse selection: Variables may change existing customer behavior rather tan targeting different group of customers if they are used in the rating structure:
  - **Use of Vehicle-** leisure use and travel to work
  - **Occupations**-courier driver and delivery driver
  - **Gender of Rated Driver** - Male and Female
  - **No Claim Discount (NCD) Protection** – model suggests that customers who pay for NCD protection are less likely to have a claim. However, if we encourage NCD Protection by offer a very low premium , every customer would end up taking NCD Protection
  - **Voluntary Excess / Deductible** – Care needs to be taken that the reduction in premium by increasing a deductible is not greater than the deductible itself.
    - For example, If relativities for deductible of $0 are 1 and for $100 are 0.9. If the customer annual premium is $500, these relativities can make sense. At annual premium is $2,000, most customers will chose the higher deductible because the reduction in premium of $200 is more than the $100 reduction in claim pay-out in the event of a claim

Building the New Rating Structure

-When model does not say anything

- Pricing elements usually are not included in the modeling work but have to be taken care when we're ready to build the pricing structure
  - Minimum Premium
  - Add on coverages/perils (windscreen cover, identity theft, classical art…)
  - CAT
- Small segments that we do not have a model
  - UM (Uninsured Motorists) or UIM (Underinsured Motorist) , Collection cars, Electronic cars
  - Commercial use vehicle included in personal auto polices
  - Homeowners policy under bank mortgage account

Questions?