Ratemaking, Product and Modeling

Seminar and Workshops

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Virtual Conference

CAS Machine Learning Working Party

Context and Key Issues in Ratemaking

Presenters

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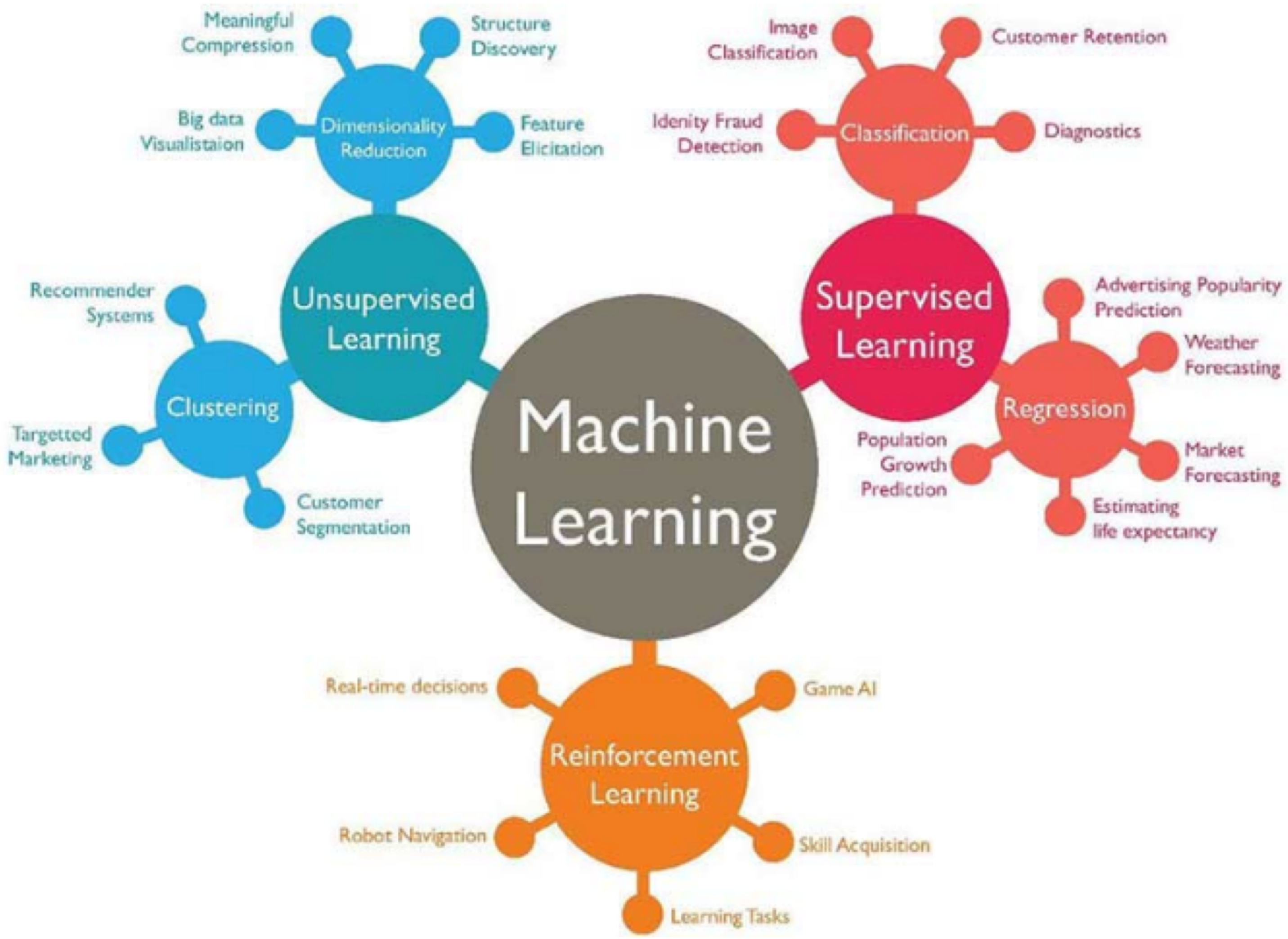
Introduction

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
- ...

Practical Applications

ML in action

The Data

freMPTL2 from R’s *CASdatasets* package.

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

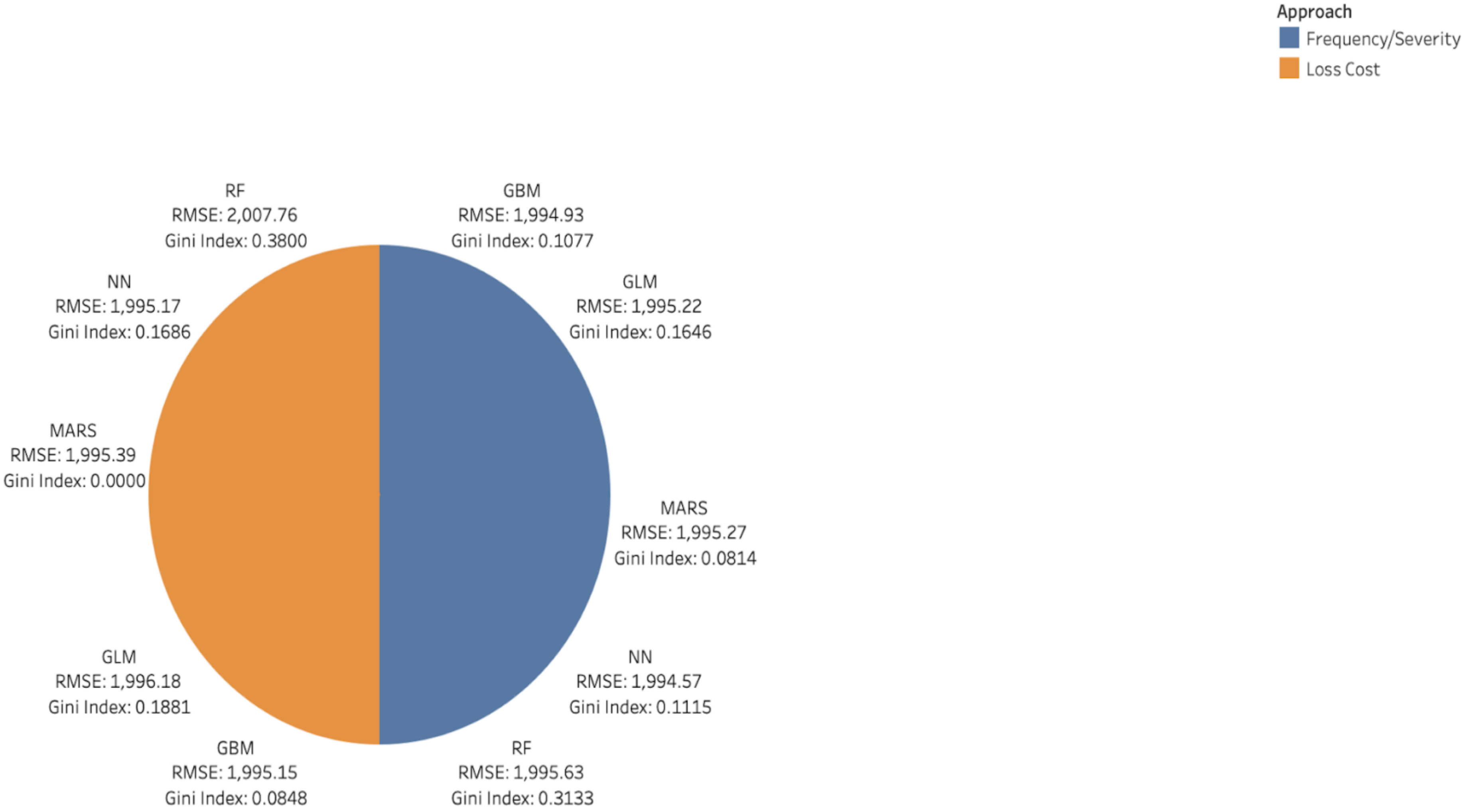
- Exposure
- Bonus/Malus
- Claim Count
- Claim Amount

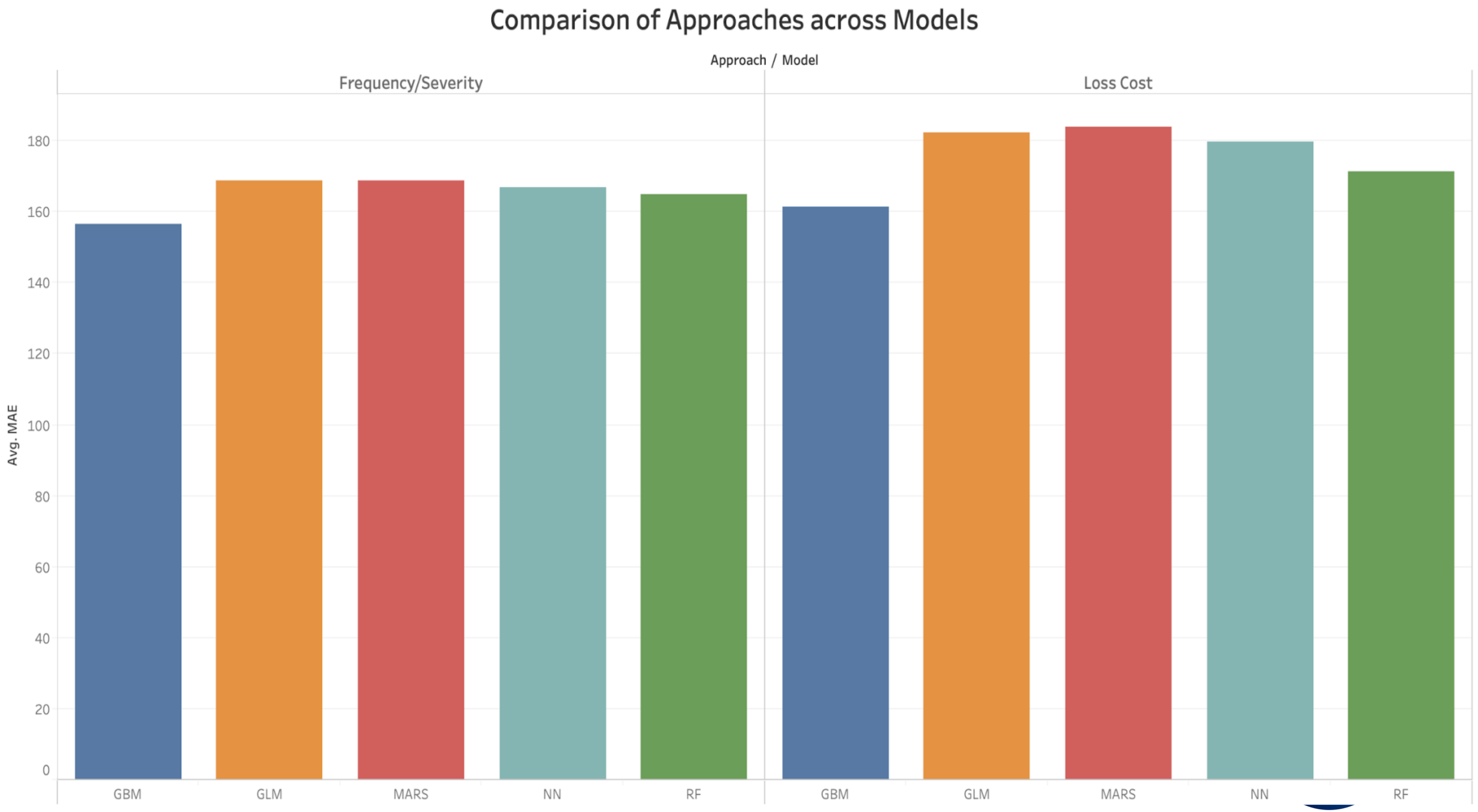
The Models

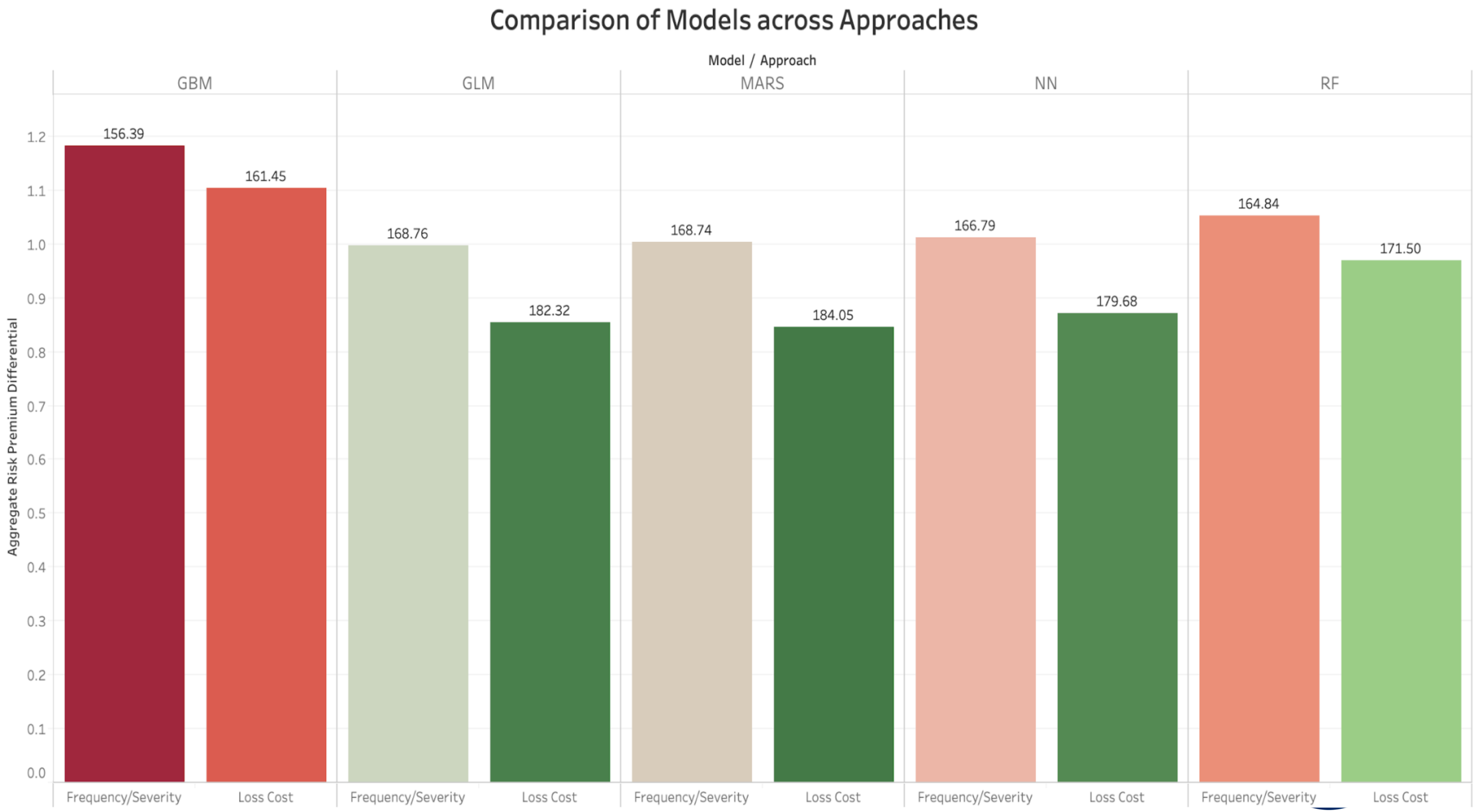
Models Considered

- 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




Comparison of Approaches across Models
Approach / Model
Frequency/Severity
Loss Cost
Avg. MAE
0
20
40
60
80
100
120
140
160
180
GBM
GLM
MARS
NN
RF
GBM
GLM
MARS
NN
RF


Comparison of Models across Approaches
Model / Approach
GBM
GLM
MARS
NN
RF
Aggregate Risk Premium Differential
1.2
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
156.39
161.45
168.76
182.32
168.74
184.05
166.79
179.68
164.84
171.50
Frequency/Severity
Loss Cost
Frequency/Severity
Loss Cost
Frequency/Severity
Loss Cost
Frequency/Severity
Loss Cost
Frequency/Severity
Loss Cost

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

ASOP 41 - Actuarial Communications

"...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

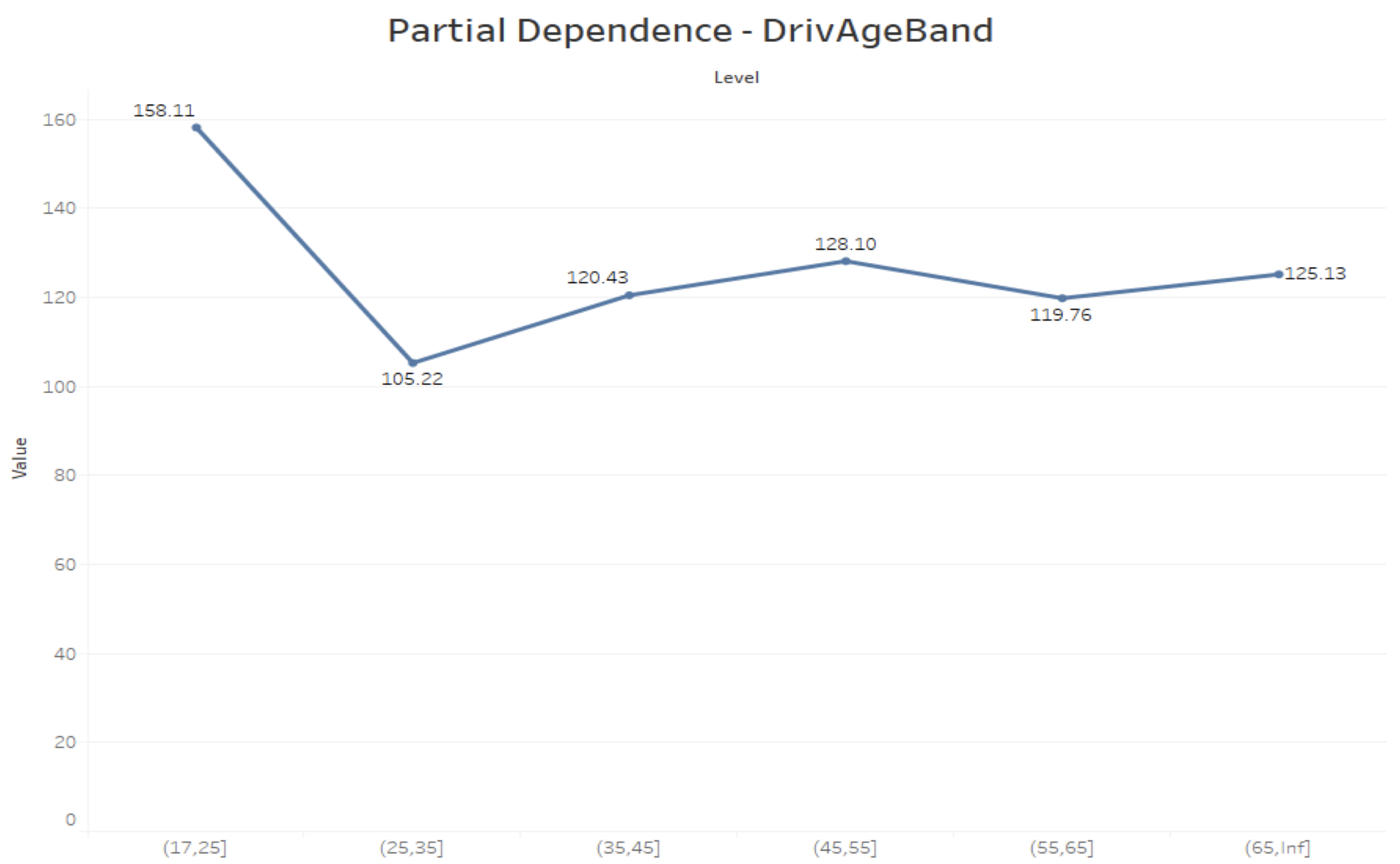
TECHNICAL

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

NON-TECHNICAL

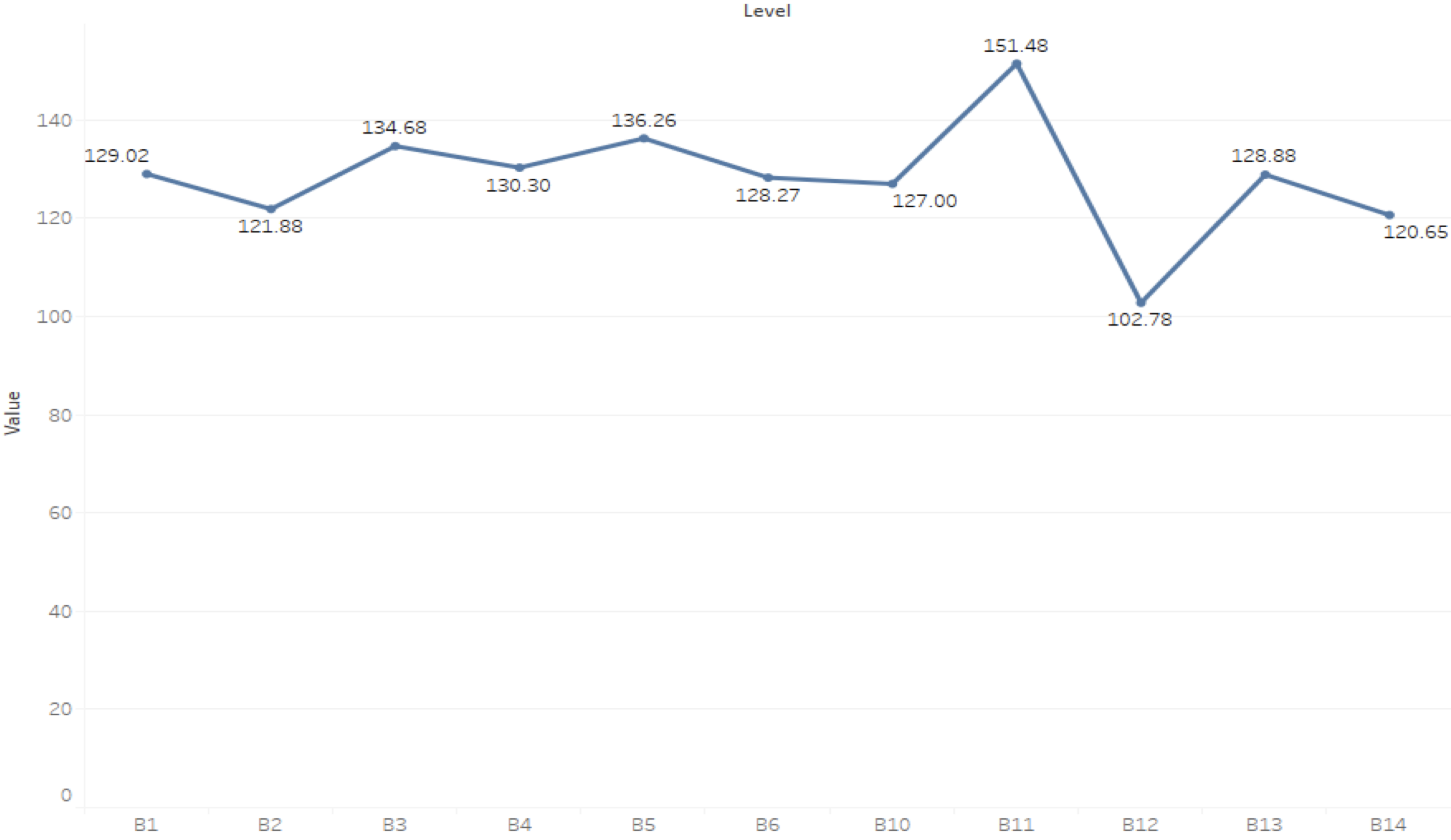
- Partial Dependence Plots

Partial Dependence Plots

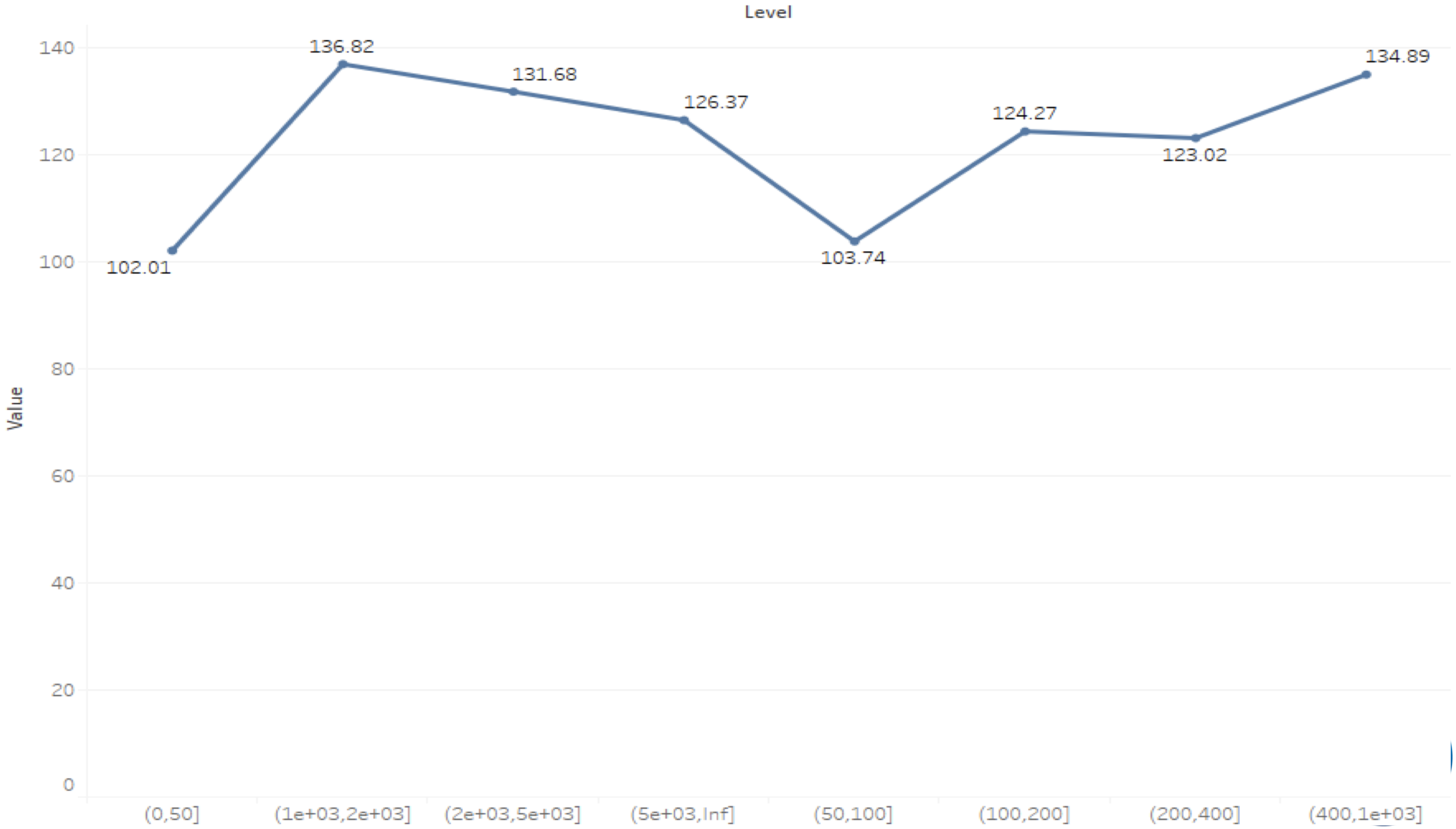


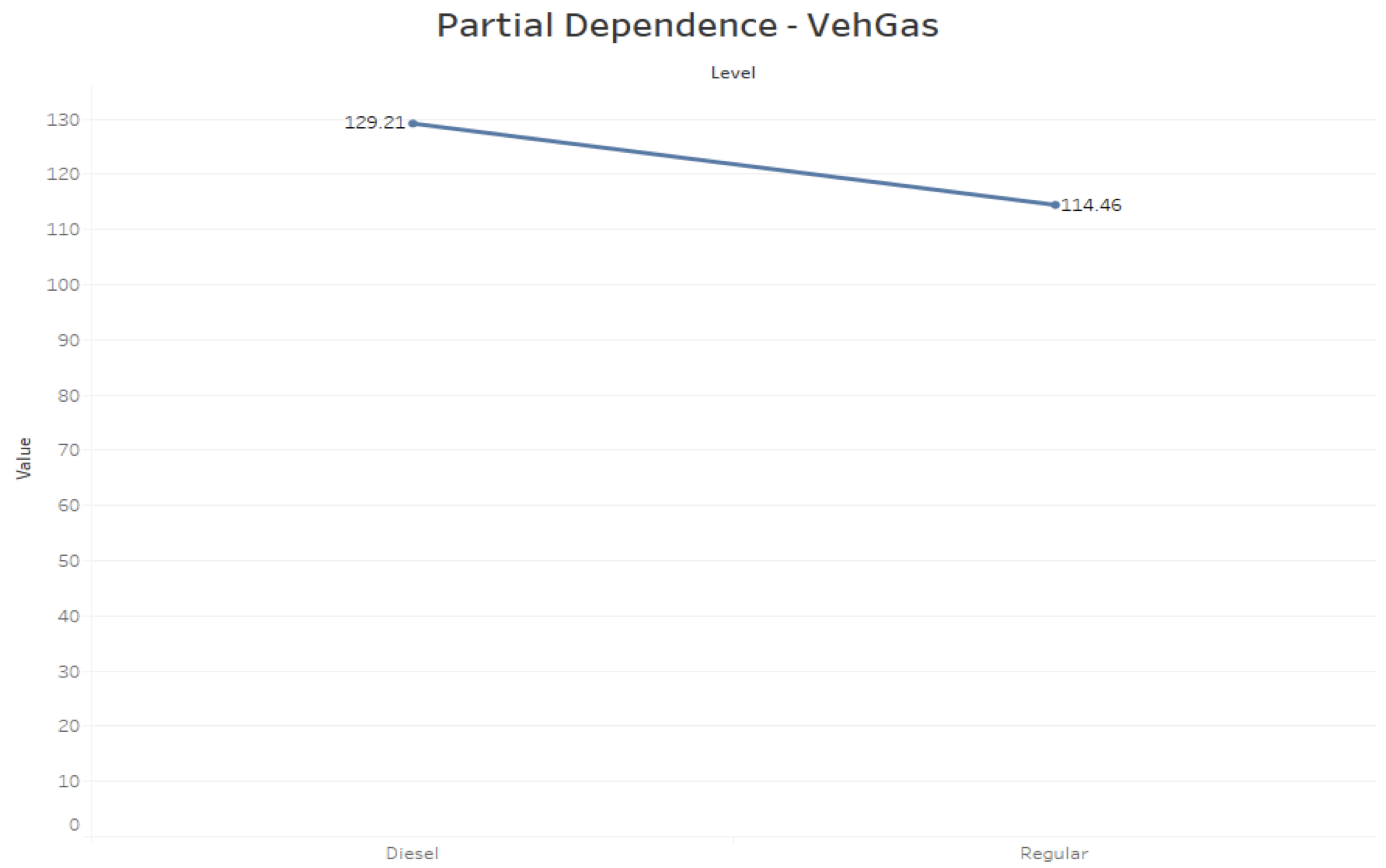
Partial Dependence - DrivAgeBand
Level
Value
160
140
120
100
80
60
40
20
0
158.11
105.22
120.43
128.10
119.76
125.13
(17,25]
(25,35]
(35,45]
(45,55]
(55,65]
(65,Inf]

Partial Dependence - VehBrand



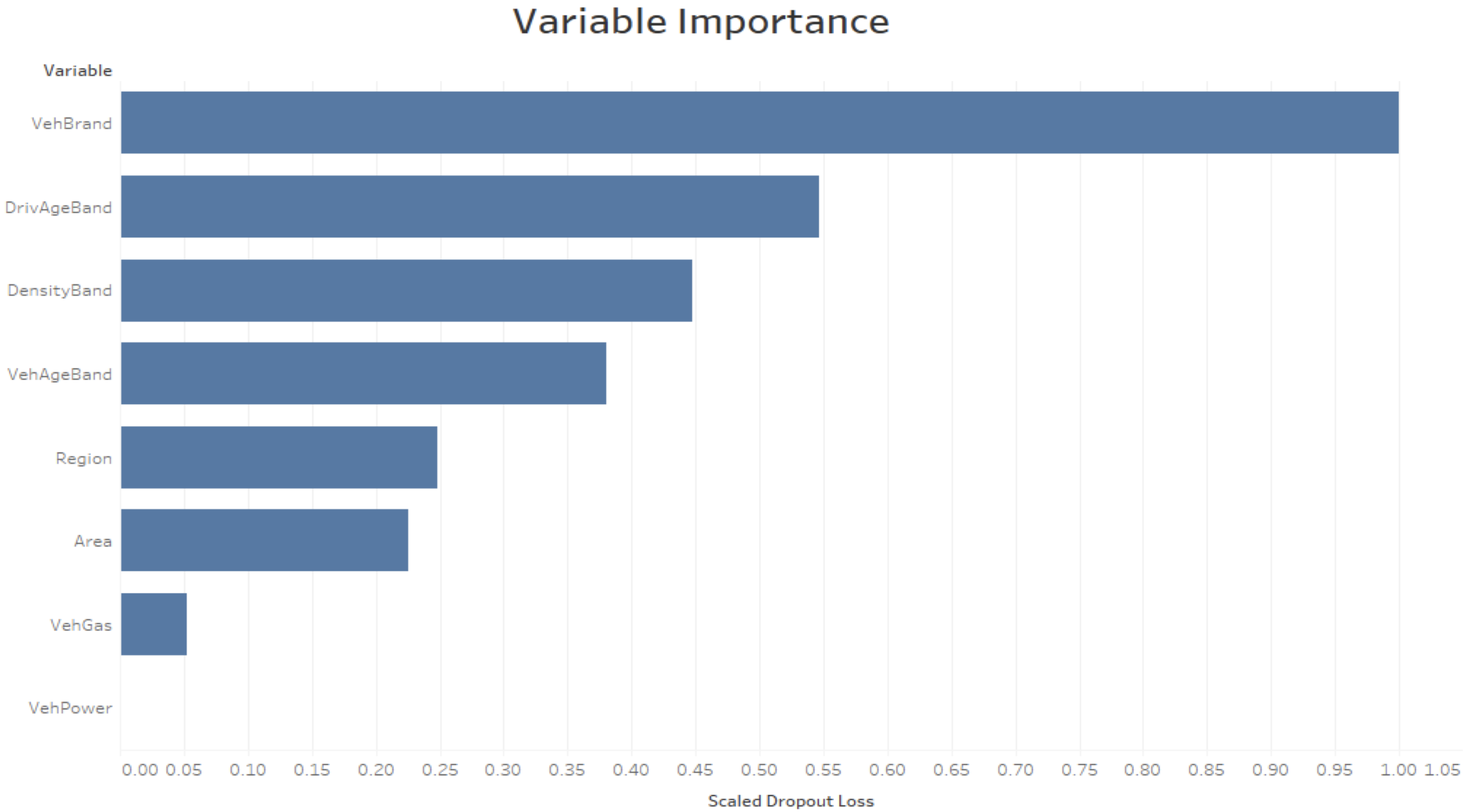
Partial Dependence - DensityBand




Partial Dependence - VehGas
Level
Value
130
120
110
100
90
80
70
60
50
40
30
20
10
0
129.21
114.46
Diesel
Regular

Variable Importance

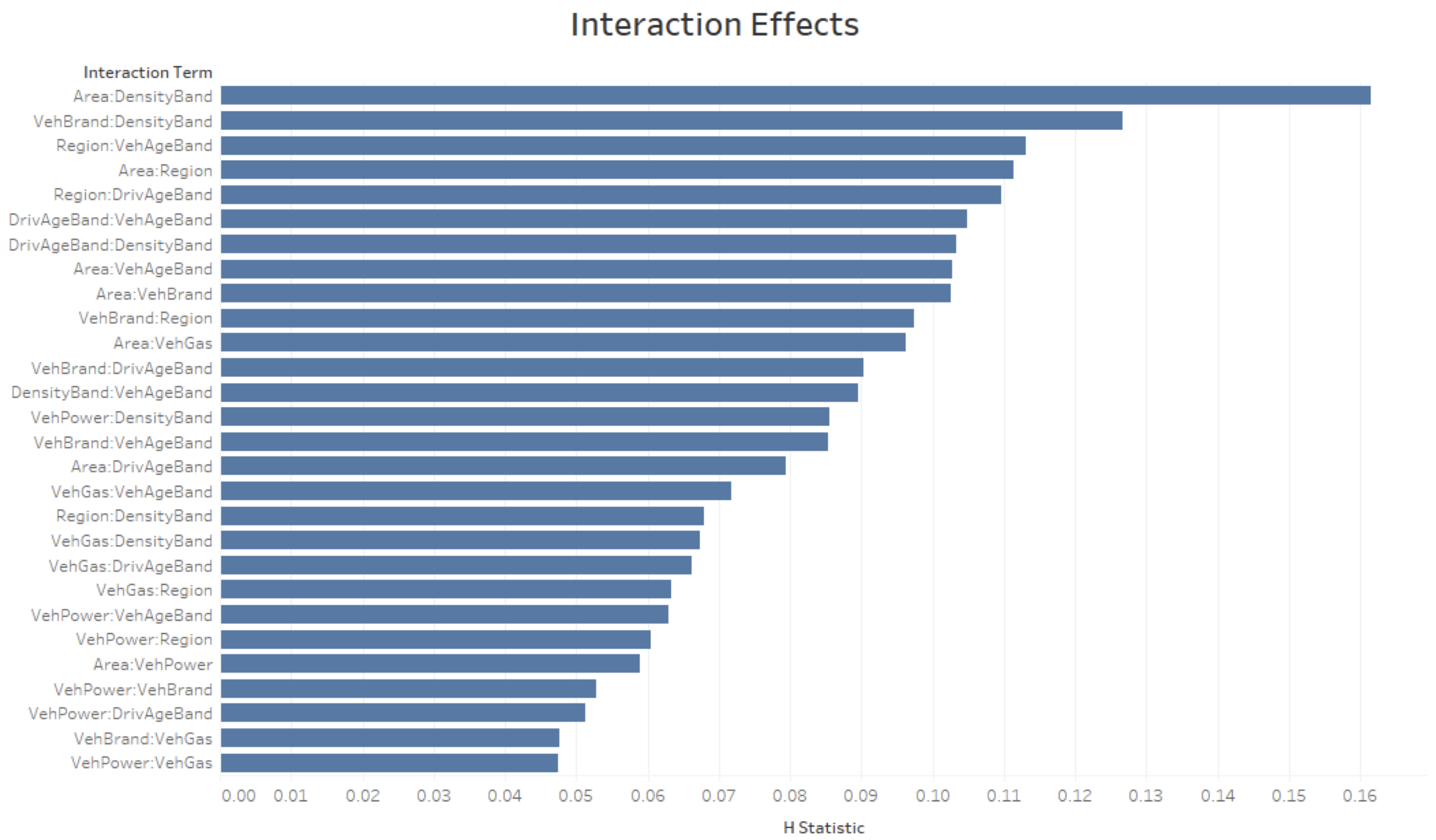
- Based on Permutation-based Loss Dropout
- Each rating variable is shuffled and model recomputed
- Degree of difference in RMSE w.r.t. original model indicates variable importance


Variable Importance
Variable
VehBrand
DrivAgeBand
DensityBand
VehAgeBand
Region
Area
VehGas
VehPower
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 0.55 0.60 0.65 0.70 0.75 0.80 0.85 0.90 0.95 1.00 1.05
Scaled Dropout Loss

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,

$$PD(X, Y) = PD(X) + PD(Y) + PD(X \,\&\, Y)$$


Interaction Effects
Interaction Term
Area:DensityBand
VehBrand:DensityBand
Region:VehAgeBand
Area:Region
Region:DrivAgeBand
DrivAgeBand:VehAgeBand
DrivAgeBand:DensityBand
Area:VehAgeBand
Area:VehBrand
VehBrand:Region
Area:VehGas
VehBrand:DrivAgeBand
DensityBand:VehAgeBand
VehPower:DensityBand
VehBrand:VehAgeBand
Area:DrivAgeBand
VehGas:VehAgeBand
Region:DensityBand
VehGas:DensityBand
VehGas:DrivAgeBand
VehGas:Region
VehPower:VehAgeBand
VehPower:Region
Area:VehPower
VehPower:VehBrand
VehPower:DrivAgeBand
VehBrand:VehGas
VehPower:VehGas
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07 0.08 0.09 0.10 0.11 0.12 0.13 0.14 0.15 0.16
H Statistic

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.

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