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The European knowledge centre for actuaries

Making machine learning techniques interpretable in the context of non-life pricing

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Agenda

1. Challenges of pricing in non-life insurance
2. Current market standards: Generalized Linear Models
3. A non-exhaustive reminder to some useful ML techniques for non-life pricing
4. Adding complexity means increasing need for interpretability
5. An introduction to ML interpretation tools
6. Conclusions: how to make the most of ML techniques in the context of pricing

Non-life insurers are facing many challenges putting pressure on their business model and profitability

Main challenges faced by insurance companies

Increasing competition

- Commoditisation of insurance products
- Sophistication in pricing
- Pricing comparison systems

Availability of new data sources

- External data (IoT, open data,…)
- Use of unstructured data

New customers behavior

- Digitalisation of underwriting process
- Direct vs Brokers
- Focus on price (made possible thanks to pricing comparison systems)

To adress these challenges, Insurers have to

- Innovate in product development and surrounding services
- Capture and identify relevant features for pricing models
- Adapt faster to market changes (identification, building of new models, faster deployement)
- Optimise retention and renewal pricing

Focus on technical pricing models in this presentation

Methods used in non-life pricing are evolving at a fast pace

Technical vs commercial pricing

- The **pure premium** is the amount the insurance company should charge in order to be able to indemnify all the claims, without loss nor profit (in a sufficiently large portfolio).
  - The **technical tariff** aims to evaluate as accurately as possible the pure premium for each policyholder
  - Statistically speaking, the goal is to **explain the total annual claims amount** (y) in function of all the available **relevant information about the risk** ($x_1, x_2, \ldots, x_n$): $y \sim f(x_1, x_2, \ldots, x_n)$
- Market premiums often differ from those computed by actuaries and listed in the technical tariff due to positioning, commercial, IT or legal **constraints**

Methods used for technical pricing

- The technical pricing of non-life insurance products is performed for nearly two decades with the help of **Generalized Linear Models** (GLM).
  - The advantage of GLM is that the final result is usually **easily interpretable** (multiplicative tariff)
- **Machine learning techniques** are now more and more popular in the insurance industry and can also be used in the context of non-life pricing.
  - Machine Learning is the continuation of the evolution of tools and technologies used by actuaries and statisticians to **analyze historical claims data**: trying to improve the predictive power of models, solving the same problems with new methods, data and computer power available

Goals of this presentation

The problem

- Whereas advanced Machine learning techniques (e.g. random forest or neural networks) usually have a better predictive power than GLM, their main drawback is that they are black-box and **their results are difficult to understand/interpret**.

Two different strategies to use ML in non-life pricing

- There are basically 2 strategies to use ML techniques in non-life pricing
  1. **Replacing** traditional pricing models (e.g. GLM) by ML models
  2. **Combining** the pros of traditional and ML models to improve pricing

- The goals of this presentation are therefore to
  - Briefly **remind some useful machine learning techniques** and explain why it is difficult to interpret their results
  - Present several techniques that have been developed in order to **better understand the results** of machine learning techniques
  - Explain how these **interpretation techniques** can be used to implement the 2 strategies presented above and improve technical pricing

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Generalized Linear Models are still widely used by insurance companies for non-life pricing and other applications

Generalized Linear Model ("GLM")

- $Y = g^{-1}(\beta 0 + \beta_1 . X_1 + \cdots + \beta_n . X_n) + \varepsilon$
- Y is now a **function (g^{-1}) of a linear combination** of the explanatory variables
- The distribution of the response variable **does not need to be Gaussian anymore.** It can Poisson, Gamma, Binomial,…

Distributions
$Bin(1, \mu)$
$Poi(\mu)$
$Nor(\mu, \sigma^2)$
$Gam(\mu, \alpha)$
$IGau(\mu, \sigma^2)$

Main advantage: the final tariff is usually multiplicative and therefore easily interpretable

- Let's take a dummy example: starting from the results of the fit, we can easily build a tariff where the basis premium is modulated by multiplicative factors function of the values of the explanatory variables

Variable	Modality	β	$exp(\beta)$
Base		5.02	151.41
Fuel	Gasoil	0.21	123%
	Petrol	0	100%
Split	Monthly	0.52	168%
	Twice	0.22	125%
	Once	0	100%

→

Basis premium

Variable	$exp(\beta)$
Base	151.41

×

Fuel Factor

Variable	Modality	$exp(\beta)$
Fuel	Gasoil	123%
	Petrol	100%

×

Split Factor

Variable	Modality	$exp(\beta)$
Split	Monthly	168%
	Twice	125%
	Once	100%

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What is machine learning?

Objectives of Machine Learning ("ML")

ML algorithms aim at <u>finding</u> <u>by themselves</u> the method that best <u>predicts</u> the outcome of the studied phenomenon.

Supervised vs. Unsupervised learning

- **Supervised learning:**
  - Inputs and examples of their desired outputs are provided
  - The goal is to learn a **general rule that maps inputs to outputs**.

➔ *Given a set of training examples ($x_1, x_2, \dots, x_n, y$), where y is the variable to be predicted , what is the most efficient algorithm to best approximate the realizations of y*

  - 2 main techniques
    - ✓ **Classification** : inputs are divided into two or more classes, and the learner must produce a model that assigns unseen inputs to one (or multi-label classification) or more of these classes.
    - ✓ **Regression**: the outputs are continuous rather than discrete.

- **Unsupervised learning:**
  - No labels are given to the learning algorithm
  - The goal is to **find structure in its input** (discovering hidden patterns in data).
  - Main technique
    - ✓ **Clustering**: a set of inputs is to be divided into groups. Unlike in classification, the groups may not be known beforehand.

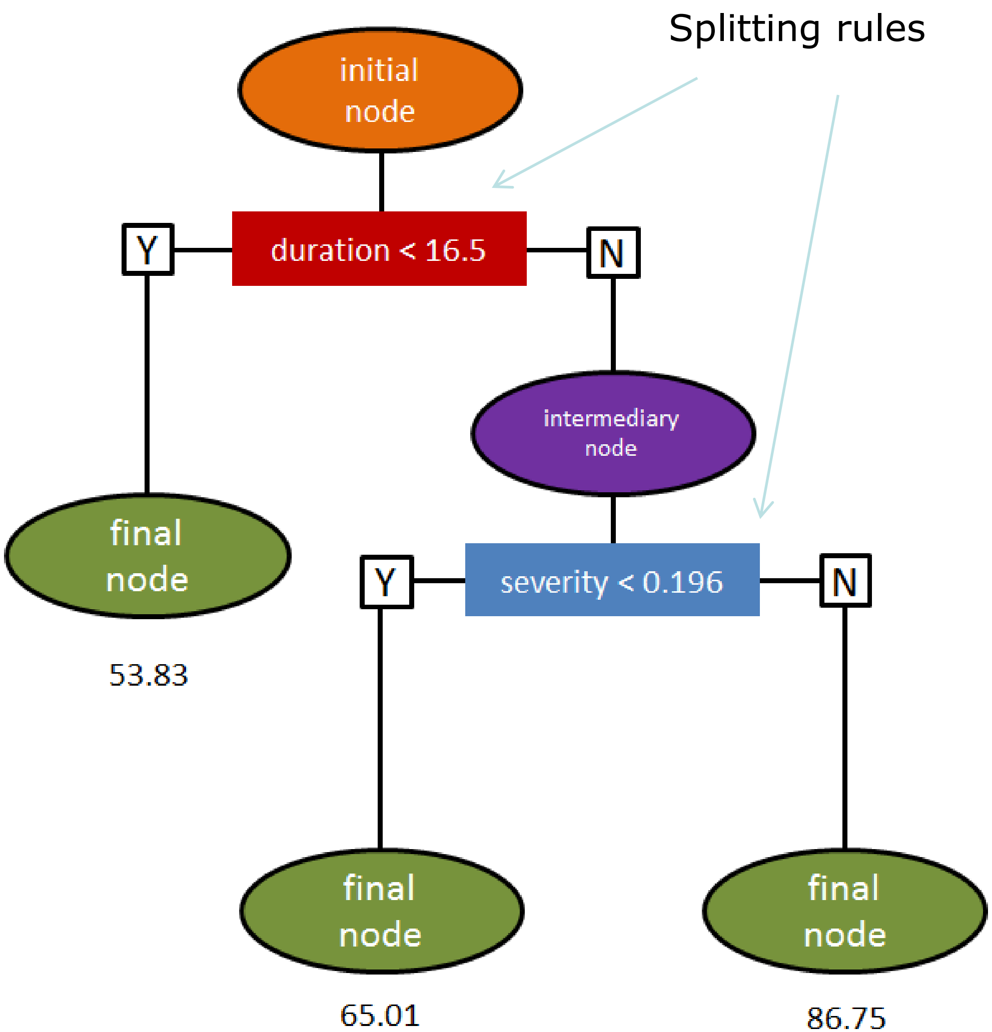
Main use in non-life pricing

- Typically used to model **pricing or underwriting related variables**
  - Regression: frequency (#claims) or severity (claims cost)
  - Classification: lapse rates, conversion rates

- Typically used for **features engineering** (i.e. creating new variables)
  - E.g. vehicle classification, zoning,…

Focus on supervised models

A first simple ML model: Classification and regression trees (CART)



Purpose

- Tree enables to **segment the predictor space** into a number of simple homogenous regions defined according to the covariates
- **Splitting rules** can be summarized in a tree view
- For each region the prediction is set as the **region average**

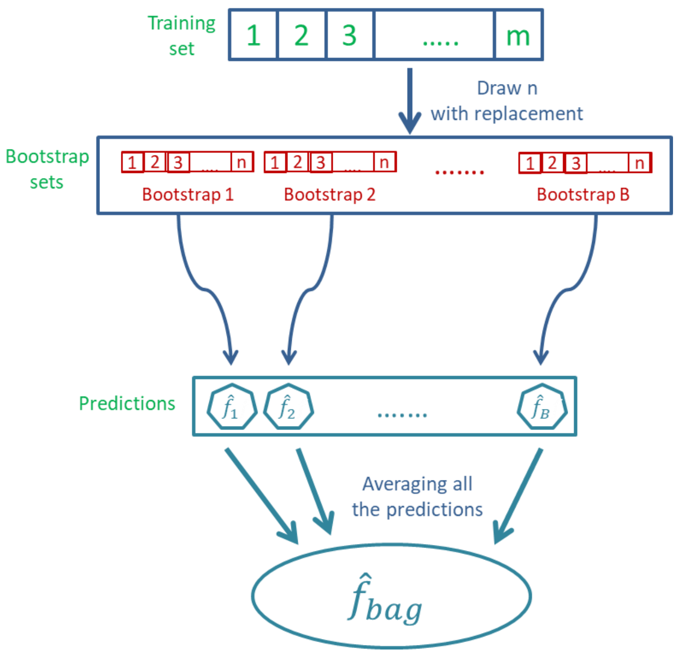
Definitions

- The *root node* in orange:
  - at the top of the tree
  - contains the whole population
- The splitting rules set aim at segmenting the predictor space into a number of **simple regions** that are as **homogeneous** as possible with respect to the response variable
- The *leaves nodes* in green at the bottom of the tree: that is a node that is not further split.

An example of a more complex ML model: Bootstrap aggregation (Bagging)

Main idea

- **B**ootstrap **agg**regation, or **Bagg**ing, is a general-purpose procedure for reducing the variance of a statistical learning method
- Recall that given a set of n independent observations $Z_1, Z_2, \dots, Z_n$ each with variance σ^2, the variance of the mean $\bar{Z}$ of the observations is given by $\frac{\sigma^2}{n}$.
- **Averaging a set of observations reduces variance**.



Algorithm

1. Bootstrap, by taking **repeated samples** from the training data set.
2. Generate B different training data sets.
3. **Train our method** (e.g. regression tree) on the bth bootstrapped training set in order to get $\hat{f}_b(x)$ the prediction at point x.
4. We then **average all the predictions** to obtain:

$$\hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B}\hat{f}_b(x)$$

➡ The final prediction is **difficult to understand** as it is an **average** of a large number of intermediate predictions

➡ Similar difficulty in interpreting results is also an issue for other widely used ML models (**Random Forests, Gradient Boosting Models, Artificial Neural Networks**,….)

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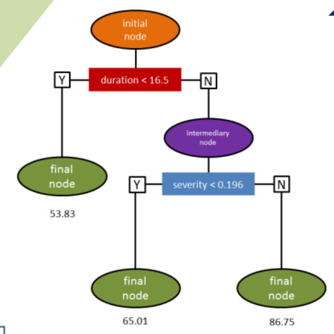
Some machine learning techniques are black boxes and interpretation of the results can be quite difficult

Increasing complexity to boost predictive power often means decreasing the interpretability of the results

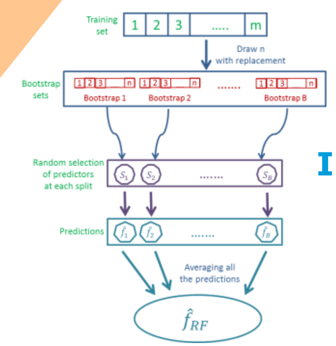
Complexity

Interpretability

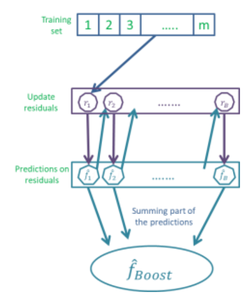
In the case of regression trees, understanding how the model predicts claims' cost or frequency values for new data points is not a problem, as it is very intuitive.

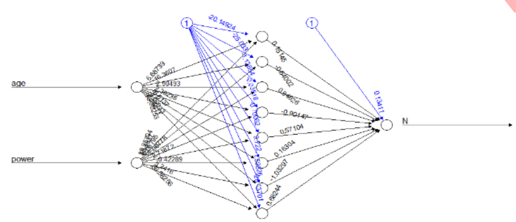


In the case of more complex methods such as Bagging and Random forests, even understanding how the model predicts values for new data points is rather difficult.



Things may be even worse for GBM and NN.





Understanding the results of ML models is nevertheless key for sound business decision-making as many stakeholders use the results of the models

Quant (Actuaries, data scientist,…)

- Are able to understand the technical details
- Trust its outputs based on cross-validation, error measures and assesment plots

Other stakeholders

- Not necessarily « quantitative people »
- Should nevertheless understand and trust results to take decisions

Machine learning techniques usually improve predictive power but at the expense of a certain loss of interpretability ➔ Find trade-off between

- Predictive power
- Capacity to understand the results
- Ability to take sound decisions based on the results

High-end questions

Who will use the results? For what purpose? With which impact?

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Global vs local Interpretability of ML techniques

- **Global Model Interpretability**
  - How does the trained model make predictions?
    - ✓ Which features are **important** and what kind of **interactions** between them take place?
    - ✓ Global model interpretability helps to understand the **distribution of the target outcome based on the features**.
    - ✓ Global model interpretability is very difficult to achieve in practice → Any model that exceeds a handful of parameters or weights is difficult to understand
    - ✓ Some models are interpretable at a parameter level :
      - For linear models, the interpretable parts are the weights,
      - For trees interpretable parts are the splits (selected features plus cut-off points) and leaf node predictions.
  - Global Interpretation tools
    - ✓ Interpretable Models by nature (eg. Linear models, Regression Tree)
    - ✓ Feature Importance
    - ✓ Partial Dependant Plot (PDP) and Individual Conditional Expectation (ICE)
    - ✓ Interaction Measures (H-statistic)

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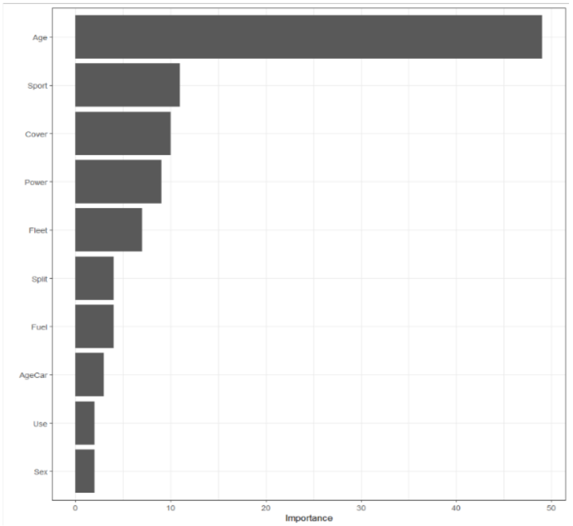
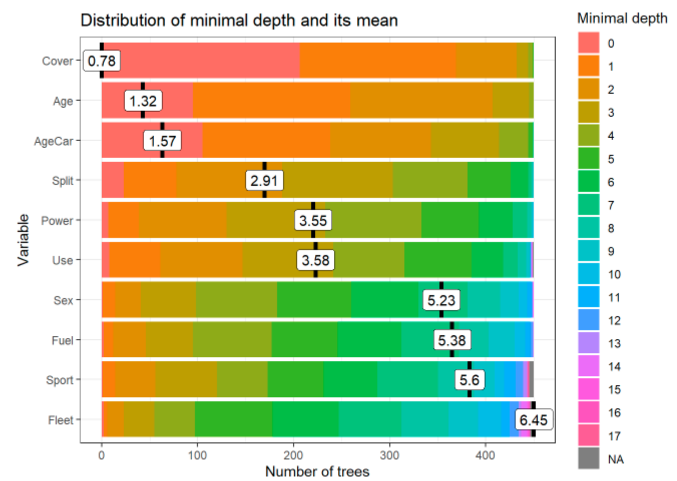
Global Model Interpretation
Features Importance

- **Features Importance**
  - In a tree-based method : Go through all the splits for which the feature was used and measure how much it has reduced the Loss Function (eg. Gini, MSE, Poisson Deviance,…) compared to the parent node.
  - The sum of all importance measures is scaled to 100.
  - This means that each variable importance can be interpreted as share of the overall model importance

- One can get additional measures such as:
  - Minimal depth and its mean :
    - Which variables were the most often on the top of the tree
    - Mean depth of first split

- Features Importance can be used as a **features' selection tool**
  - Goal: Identify the **most relevant variables**
  - Pay attention: when some variables are correlated, their **global impact can be spread** between them, therefore reducing individual importance of each variable





Partial Dependence Function/Plot

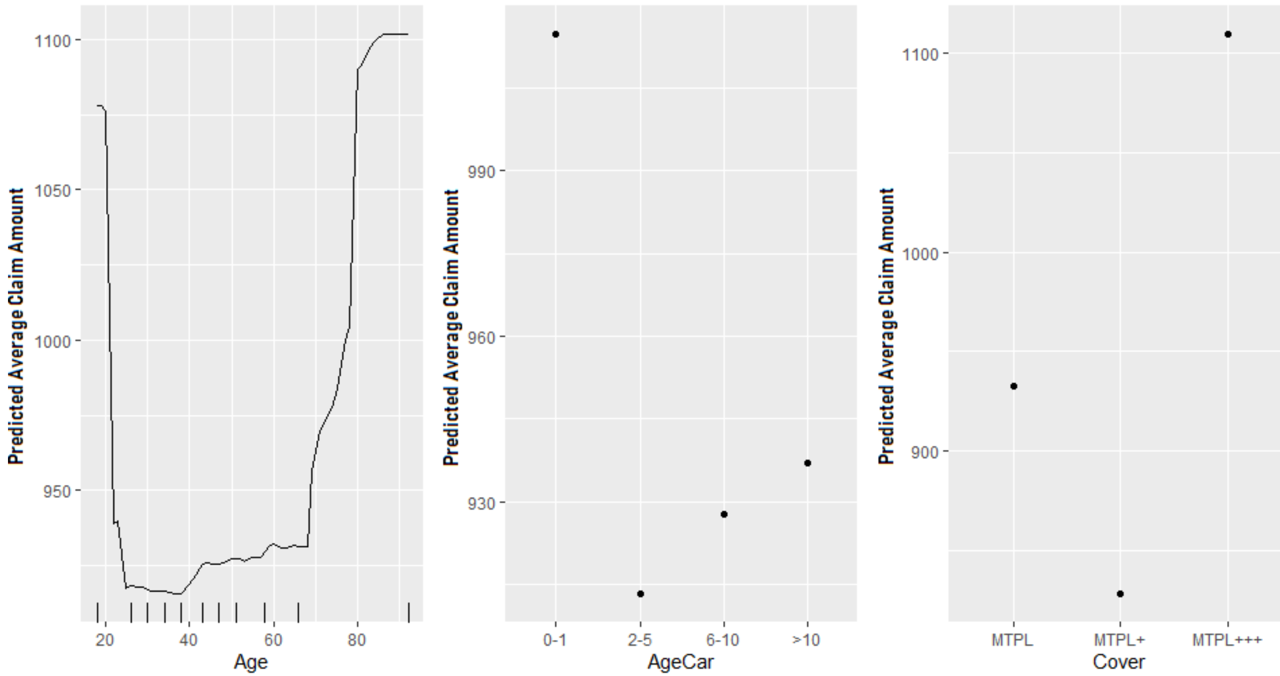
- Partial dependence plot (short PDP or PD plot) shows the **marginal effect one or two features** have on the predicted outcome of a machine learning model
- Partial dependence plot can show whether the **relationship between the target and a feature** is linear, monotonic or more complex. It can be computed as

$$PD_{age}(age) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}\left(age, agecar^{i}, cover^{i}, \ldots\right)$$

- In this formula, $agecar^{i}$,… are actual features' values from the dataset for the features in which we are not interested, $\hat{f}$ is the trained model and n is the number of instances in the dataset.
- So we marginalize model outputs over the distribution of the features we are not interested in (e.g. agecar, cover, …)
  - → the function shows the relationship between the feature age we are interested in and the predicted outcome.
  - → By marginalizing over the other features, we get a function that depends only on features age, interactions with other features included.

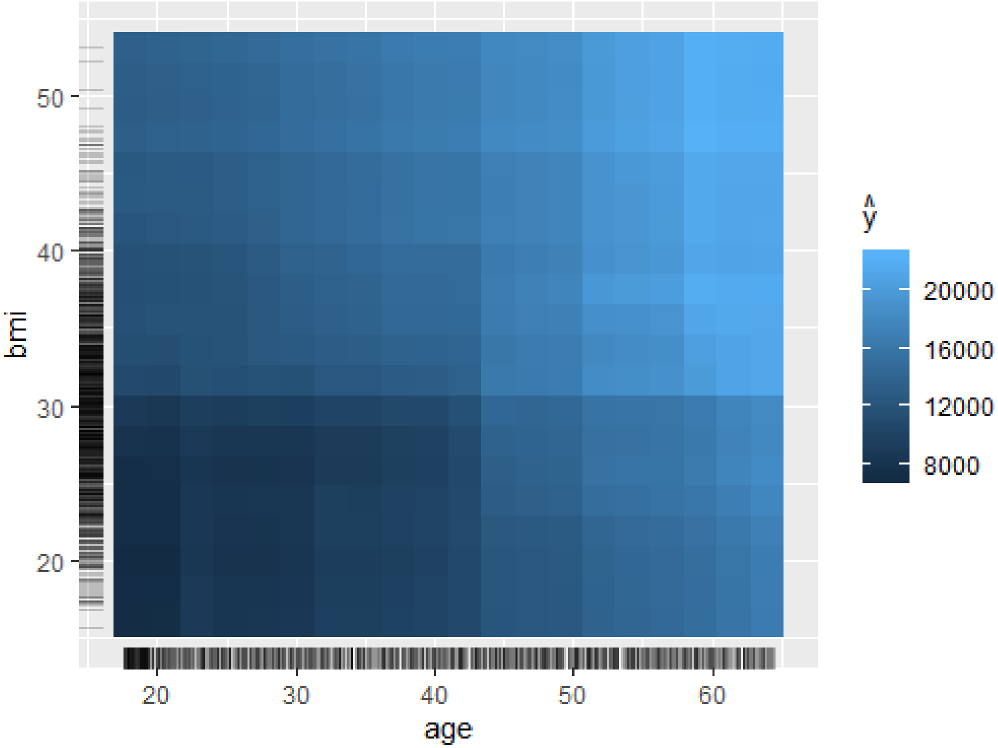
Global Model Interpretation
Partial dependence plot

- Example of Partial Dependence Plot (1D) on Average Claim Amount :



- Partial dependence plot can be used as **a features' impact explanation tool**
  - It allows to better understand the marginal impact of a variable on the prediction
  - It is very similar to the interpretation of the multiplicative factors we obtain in a GLM or GAM model

- Example of Partial Dependence Plot (2D) :
  - PD can be generalized to more than one feature
  - PDP -2D can be very useful to highlight interactions



Interaction Measures (H-Statistics)

- In case of interaction, prediction cannot be expressed as the sum of the feature effects, because the effect of one feature depends on the value of the other feature

- **How to measure the level of interaction between two features?**

→ Have a look at H-Statistic. The main idea is:

✓ If two features do not interact, we can decompose the partial dependence function

$$PD_{age,power}(age,power) = PD_{age}(age) + PD_{power}(power)$$

✓ Measure the difference between the observed partial dependence function and the decomposed one without interactions.

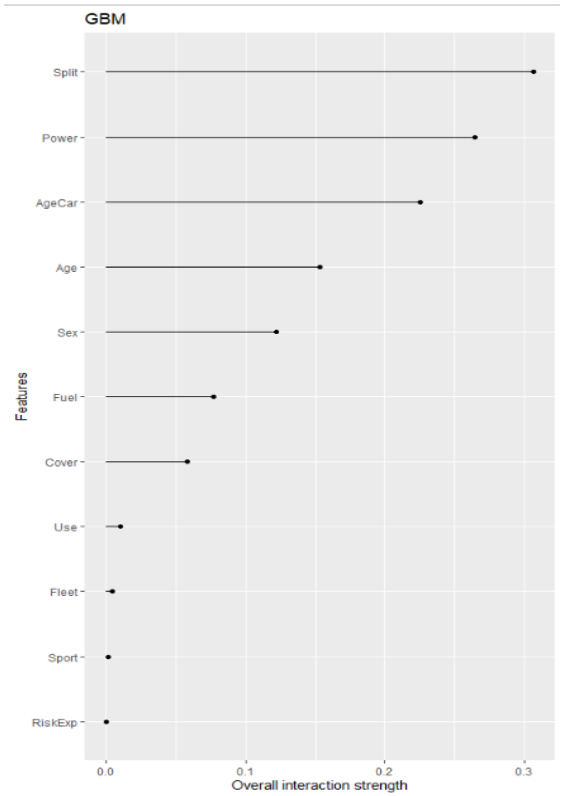
$$H^2 = \sum_{i=1}^{n}\left[PD_{age,power}\left(age^i,power^i\right) - PD_{age}\left(age^i\right) - PD_{power}\left(power^i\right)\right]^2 \Big/ \sum_{i=1}^{n} PD_{age,power}{}^2\left(age^i,power^i\right)$$

✓ *H is 0 if there is no interaction at all*

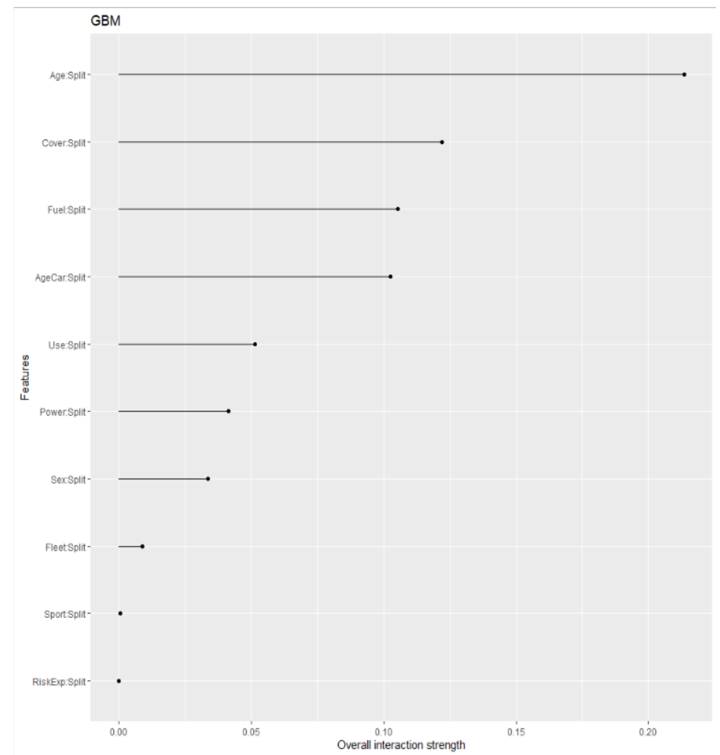
✓ *A value H of 1 between two features means that each single PD function is constant and the effect on the prediction only comes through the interaction.*

- It is also possible to measure the **total interaction** of a feature which tells us **whether and to what extent a feature interacts** in the model **with all other features**

Total interaction for each feature with all other features



2-way interactions between the split feature and the other features



- H-Statistics can be used as a **features' interaction identification tool**
  - It allows to identify features strongly interacting with other features
  - It can then be used for **features enginering** (e.g. creating a new feature as an interaction between 2 features)

Global vs local Interpretability of ML techniques

- **Local Interpretability for a Single Prediction**
  - Why did the model make a certain prediction for an instance?
    - ✓ If you look at an individual prediction, the behavior of the otherwise complex model might behave more pleasantly.
    - ✓ You can zoom in on a single instance and examine what the model predicts for this input, and explain why.
      - Shapley Value
      - Breakdown

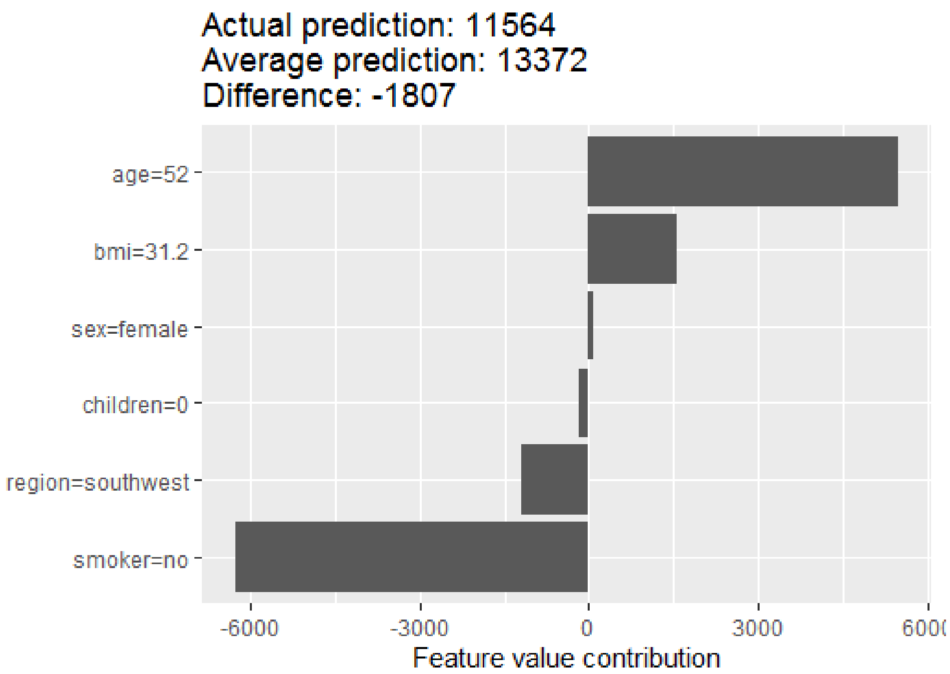
- **Local Interpretability for a Group of Predictions**
  - Why did the model make specific predictions for a group of instances?
    - ✓ Model predictions for multiple instances can be explained either with global model interpretation methods or with explanations of individual instances.
    - ✓ The global methods can be applied by taking the group of instances, treating them as if the group were the complete dataset, and using the global methods with this subset.
      - LIME (Local Interpretable Model-agnostic explanations)
      - LIVE
    - ✓ The individual explanation methods can be used on each instance and then listed or aggregated for the entire group.

Local Interpretability for a Single Prediction

- **Shapley Value :**
  - The shapley value measures for a single prediction how much each specific feature value will contribute to make the instance prediction different from the overall prediction
  - The computation time increases exponentially with the number of features.

From Game Theory

- *The Shapley value is the average marginal contribution of a feature value across all possible coalitions (= sets composed of different number of features).*
- *For each of these coalitions we compute the prediction with and without the feature value of interest and take the difference to get the marginal contribution.*
- *The Shapley value is the (weighted) average of marginal contributions across all the coalitions.*



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Two different strategies

1. Replacing traditional pricing models (e.g. GLM) by ML models
2. Combining the pros of traditional and ML models to improve pricing

Replacing traditional pricing models by ML models

- The main drawback of this approach is the **black-box effect of the ML results**

- There is therefore a strong need in **using interpretations tools**
  - **Feature importance** to select the most relevant variable (e.g. if we have too many variables available and/or we want to limit the number of pricing variables)
  - **PDP and/or H-Statistics** to understand the impact of the selected variables on the prediction and identify the potential interactions
  - **Shapley value** to better understand the prediction of specific profiles

Combining traditional and ML models

- ML methods would then be used to perform **features extraction, features selection and/or features engineering**
  - **Feature extraction** = reducing the dimensionality of too voluminous datasets (in terms of # features)
  - **Feature selection** = selecting the most relevant variables to our problem
  - **Feature engineering** = identifying the best representation of the sample data to learn a solution to your problem (e.g. interactions)

- The selected/engineered variables could then be **introduced in a GLM in order to obtain easily interpretable results**