Institute
and Faculty
of Actuaries

Interpretable Boosted GLM

łączenie mocy predykcyjnej ML z interpretowalnością GLM

Karol Gawlowski

20 March 2025

Predictive Power vs Explainability

		Interpretability	
		yes	no
Predictive Power	+		Machine Learning
	-	Statistical Modelling	

Institute and Faculty of Actuaries

Predictive Power vs Explainability

		Interpretability	
		yes	no
Predictive Power	+	XAI	Machine Learning
	-	Statistical Modelling	

SHAP, ICE, PDP, ALE...

Institute and Faculty of Actuaries

Predictive Power vs Explainability

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Interpretability</td></tr>
<tr><td>yes</td><td>no</td></tr>
<tr><td rowspan="2">Predictive Power</td><td>+</td><td>ML+XAI
EBM
Distill Trees
IBLM…</td><td>Machine Learning</td></tr>
<tr><td>-</td><td>Statistical Modelling</td><td></td></tr>
</table>

Institute and Faculty of Actuaries

Institute and Faculty of Actuaries

ML+XAI

17 April 2026

SHAP

Baseline Prediction

$$\hat{y} = \alpha_0 +$$

Model output

Institute and Faculty of Actuaries

SHAP

Baseline Prediction

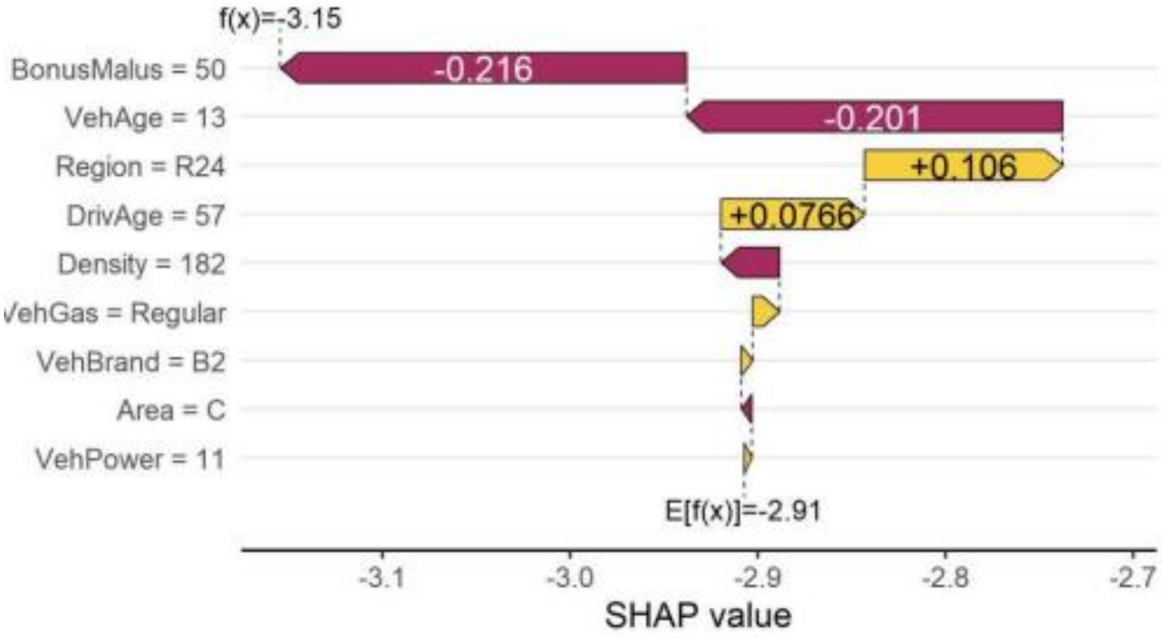
$$\hat{y} = \alpha_0 + \sum_{d} \alpha_i$$

Model output

Contribution of i-th predictor

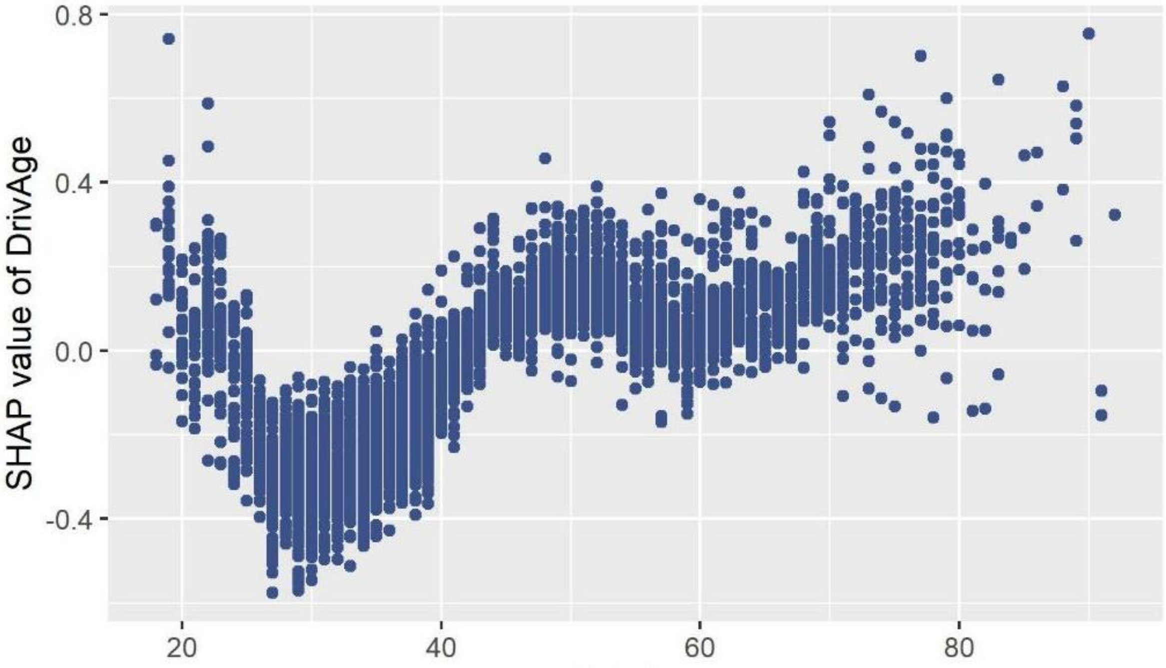
Institute and Faculty of Actuaries

SHAP



Institute and Faculty of Actuaries

SHAP



Institute and Faculty of Actuaries

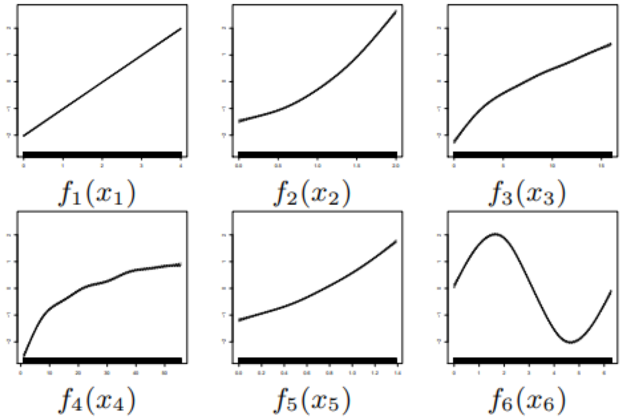
Institute and Faculty of Actuaries

Explainable Boosting Machine (EBM)

17 April 2026

Explainable Boosting Machine

GAMs: smooth shape functions



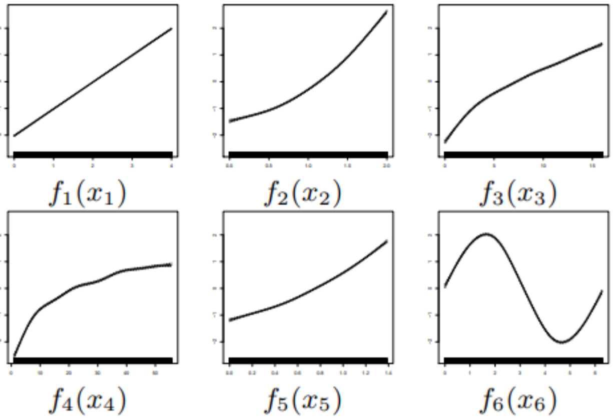
Sources: Lin Y. et al.: *Intelligible Models for Classification and Regression*

InterpretML: Another Way to Explain Your Model, Towards Data Science

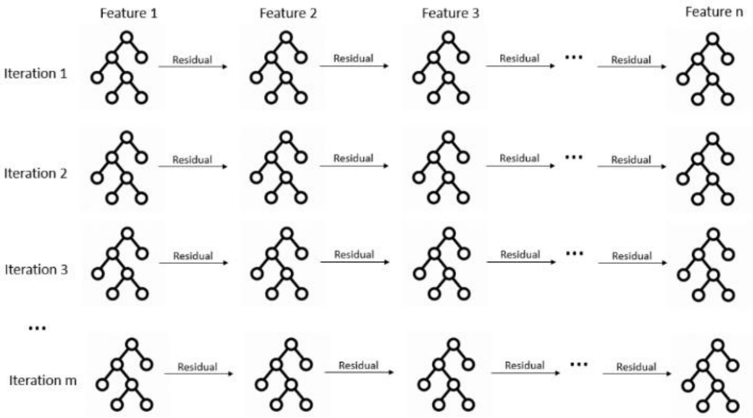
Institute and Faculty of Actuaries

Explainable Boosting Machine

GAMs: smooth shape functions



EBM: Tree-based shape functions



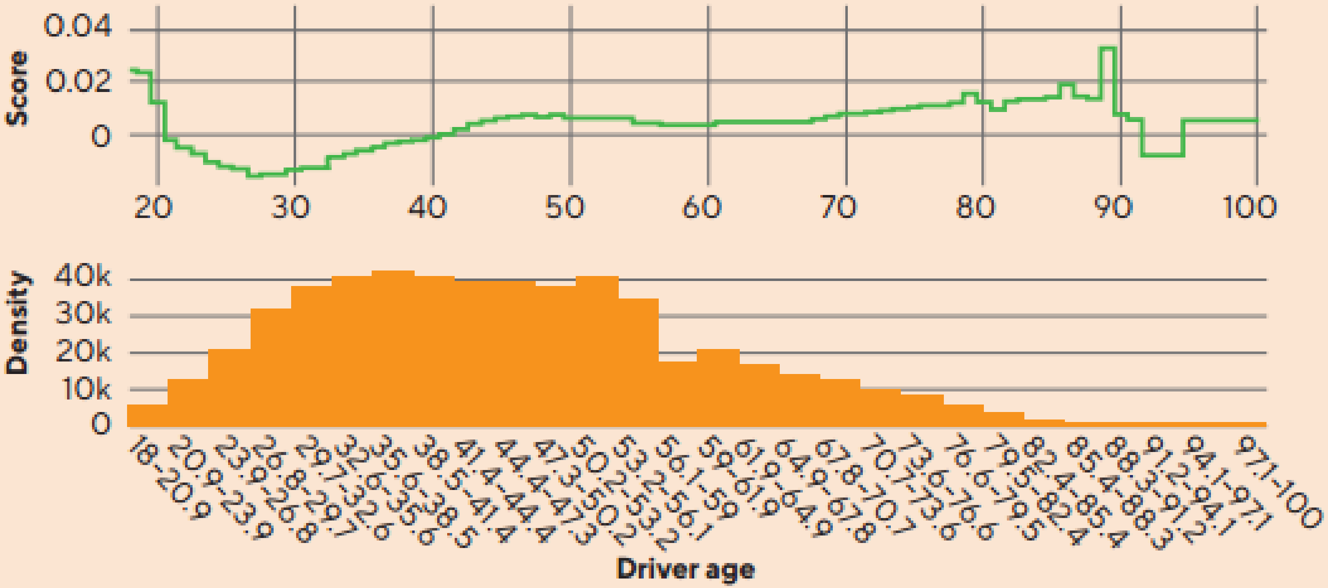
Sources: Lin Y. et al.: *Intelligible Models for Classification and Regression*

InterpretML: Another Way to Explain Your Model, Towards Data Science

Institute and Faculty of Actuaries

Explainable Boosting Machine

Figure 2: EBM score for driver age



Source: *Out with the opaque*, The Actuary

Institute
and Faculty
of Actuaries

Interpretable Boosted GLM (IBLM)

17 April 2026

Interpretable Boosted Linear Model

$$\widehat{y_{pred}} = y_{glm} + y_{xgb}$$

$$\widehat{y_{pred}} = y_{glm} \times y_{xgb}$$

Interpretable Boosted Linear Model

	Null	GLM	XGB	IBLM
Poisson Deviance	1.4195	1.3606	1.2386	1.2475
Pinball Score	0.00%	4.15%	12.74%	12.12%

Pinball score:

$$1 - \frac{D_m}{D_0}$$

- D_0 is the Poisson deviance of a null model
- D_m is the Poisson deviance of a predictive
- A higher pinball score means better performance

Key observations:

- Pure XGB is the best performer, but only marginally better than IBLM
- IBLM significantly better than GLM

Institute and Faculty of Actuaries

From GLM…

Intercept

$$\widehat{y_{pred}} = \exp\left(\lambda + \sum \beta_i \qquad x_i\right)$$

GLM β

Institute and Faculty of Actuaries

To SHAP – β corrections

Intercept

SHAP – β correction

$$y_{glm} \times y_{xgb} = \exp\left(\lambda + \sum(\beta_i + \boldsymbol{\alpha_i})x_i\right)$$

GLM β

Institute and Faculty of Actuaries

To SHAP – β corrections

Intercept

SHAP – β correction

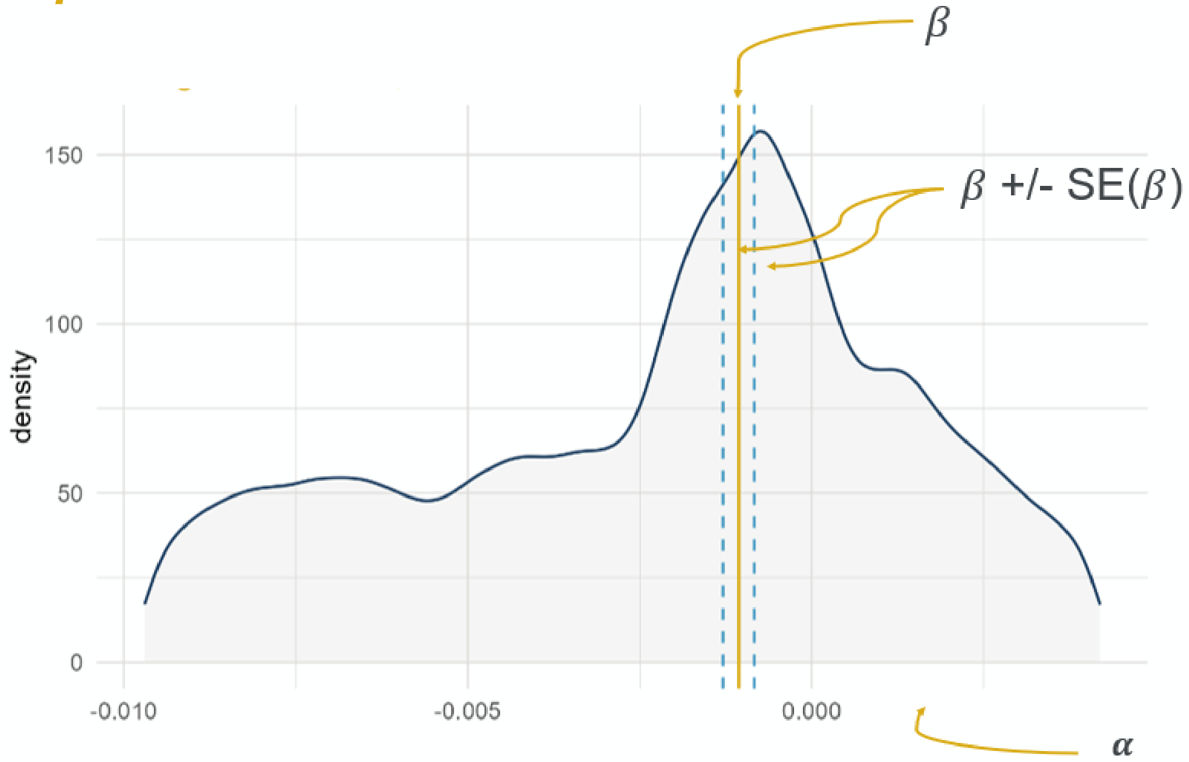
$$y_{glm} \times y_{xgb} = \exp\left(\lambda + \sum(\beta_i + \boxed{\alpha_i})x_i\right)$$

GLM β

	var1	var2	var3	lin pred	prediction
x_i	3	10	1		
β	0.4	-0.1	1.3	***1.5***	**4.48**
α	-0.07	0.02	0.09		
β'	0.33	-0.08	1.39	***1.58***	**4.85**

Institute and Faculty of Actuaries

SHAP – β corrections distribution

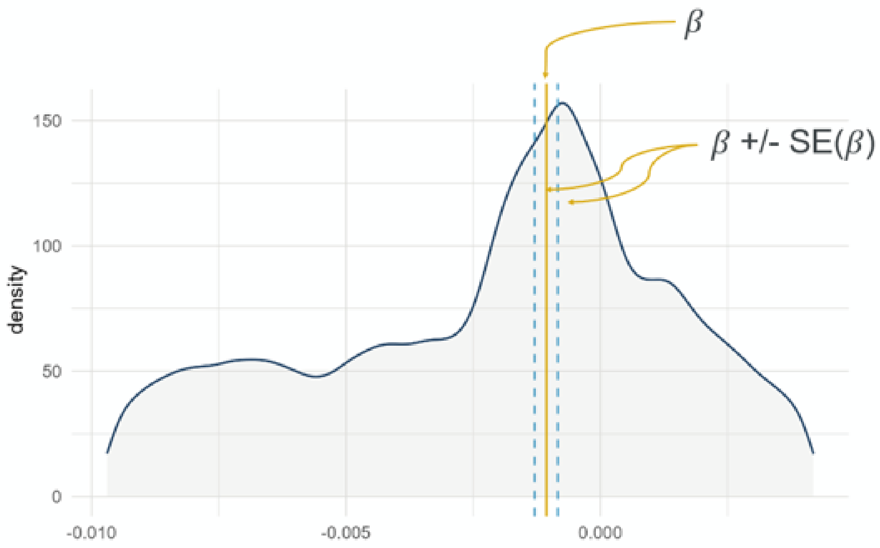


Institute and Faculty of Actuaries

Other SHAP Plots

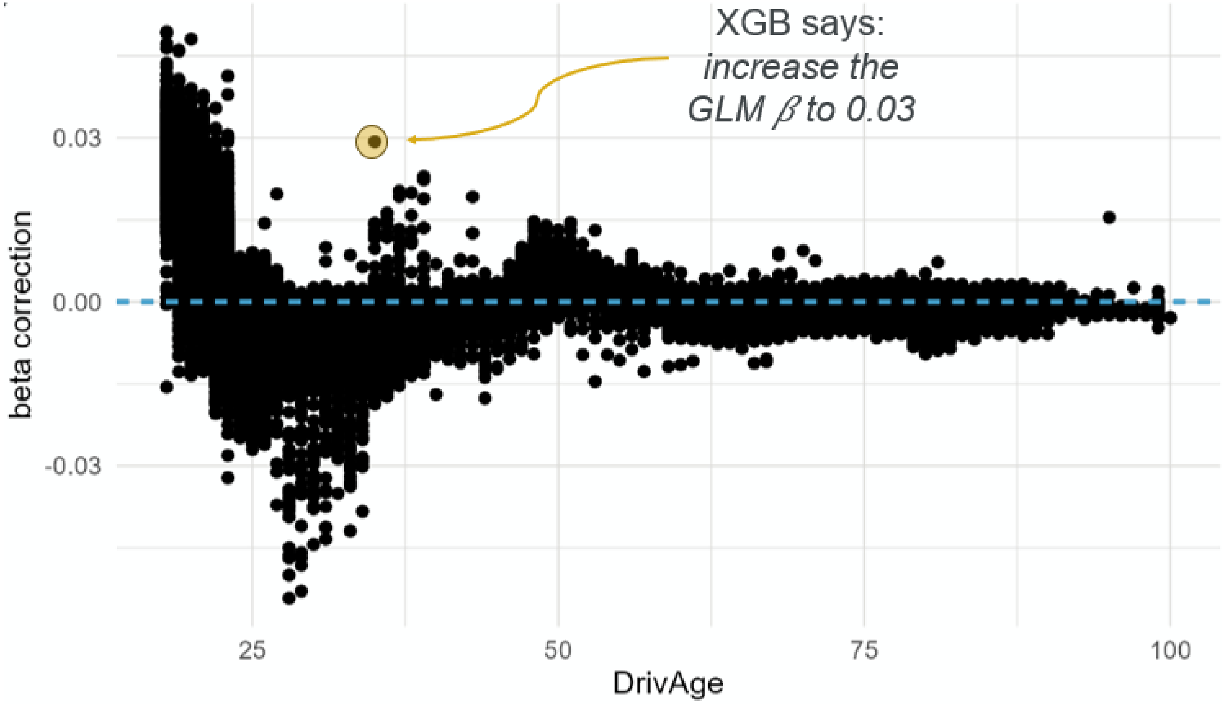
Observations:

- GLM is mostly correct: values centered around original model parameter
- Uncaught signal: Distribution spread outside the SE bands
- Interactions/non-linearity: Distribution asymmetry
- Non-linearity: range of distribution above and below 0 (β reversal)



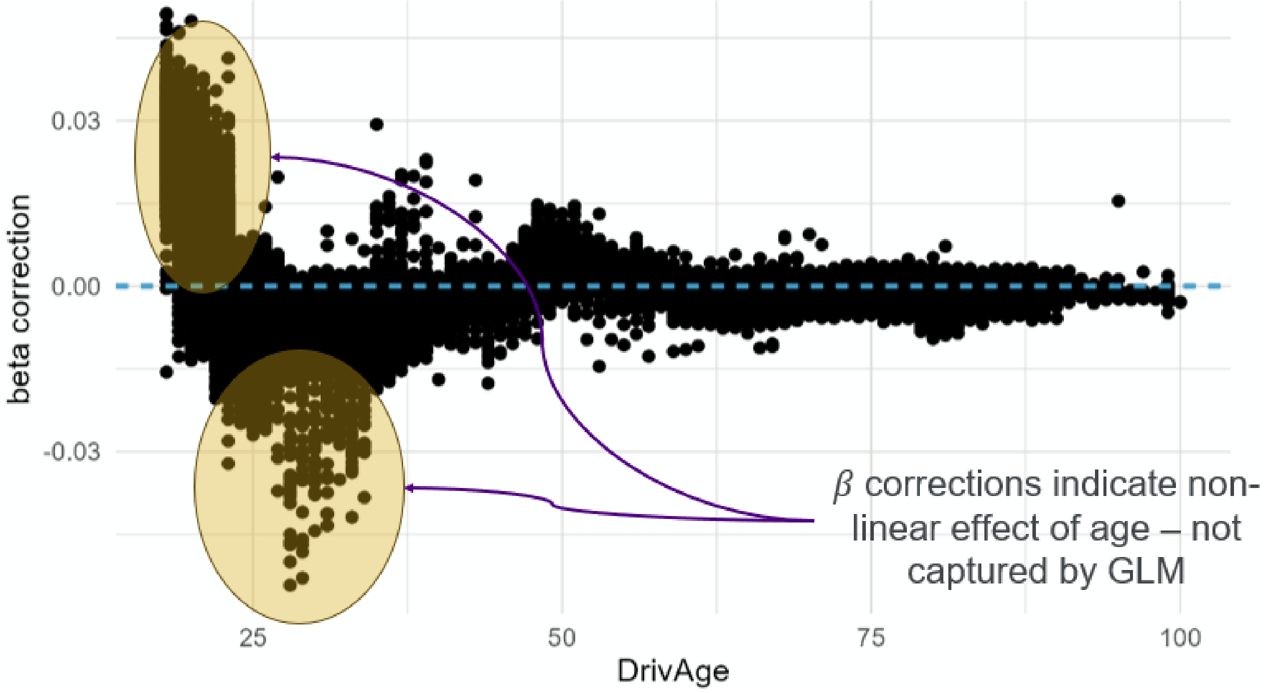
Institute and Faculty of Actuaries

Other SHAP Plots

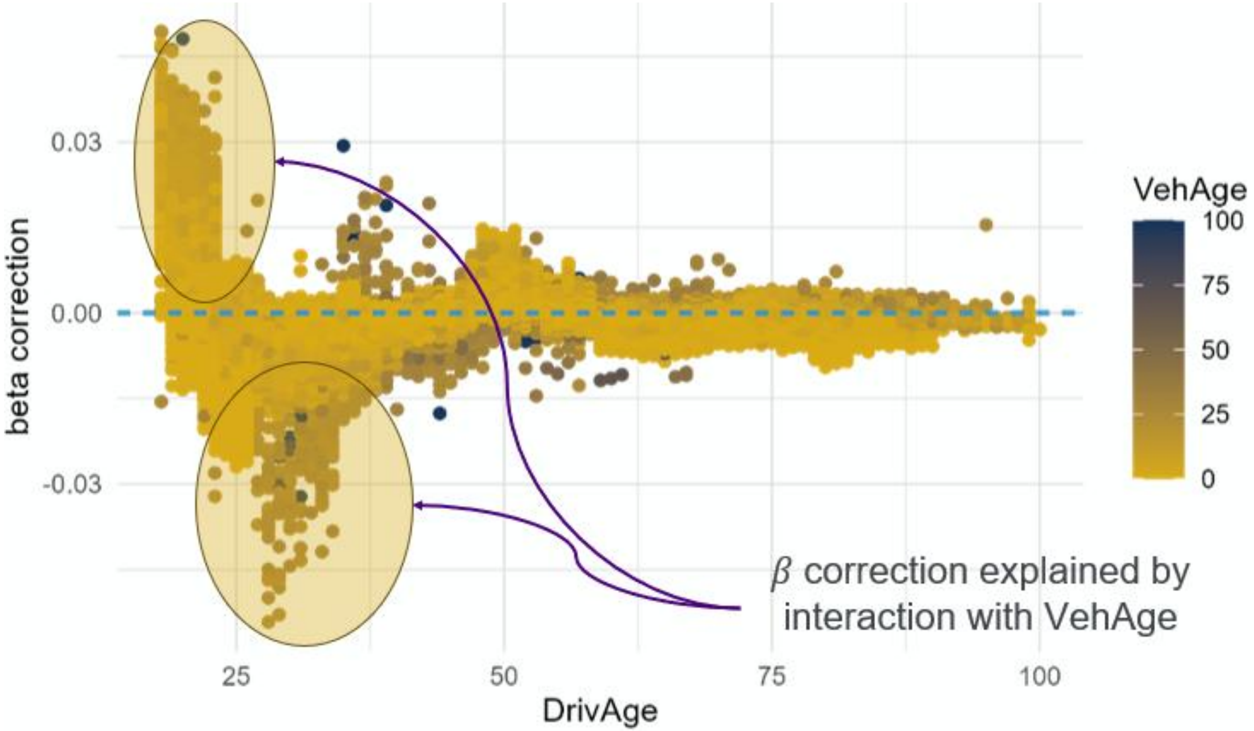


Institute and Faculty of Actuaries

Other SHAP Plots



Other SHAP Plots



Institute and Faculty of Actuaries

Institute
and Faculty
of Actuaries

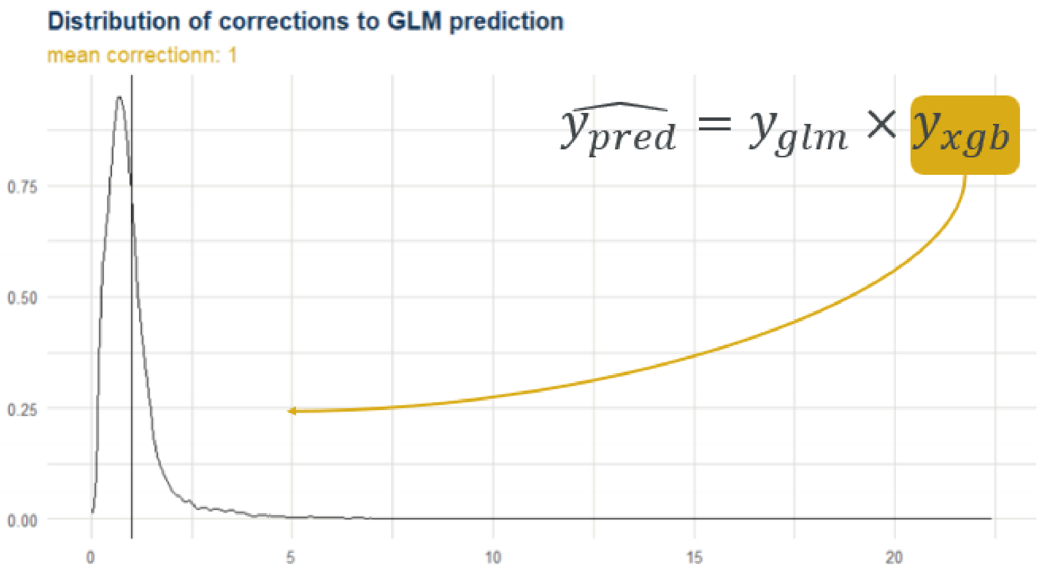
Customising the IBLM

17 April 2026

Distribution of corrections from the booster

Observations:

- GLM is correct on average => on average a correction of 1 (no correction) is applied
- XGB suggests extreme adjustments for some model points



Institute and Faculty of Actuaries

Distribution of corrections from the booster

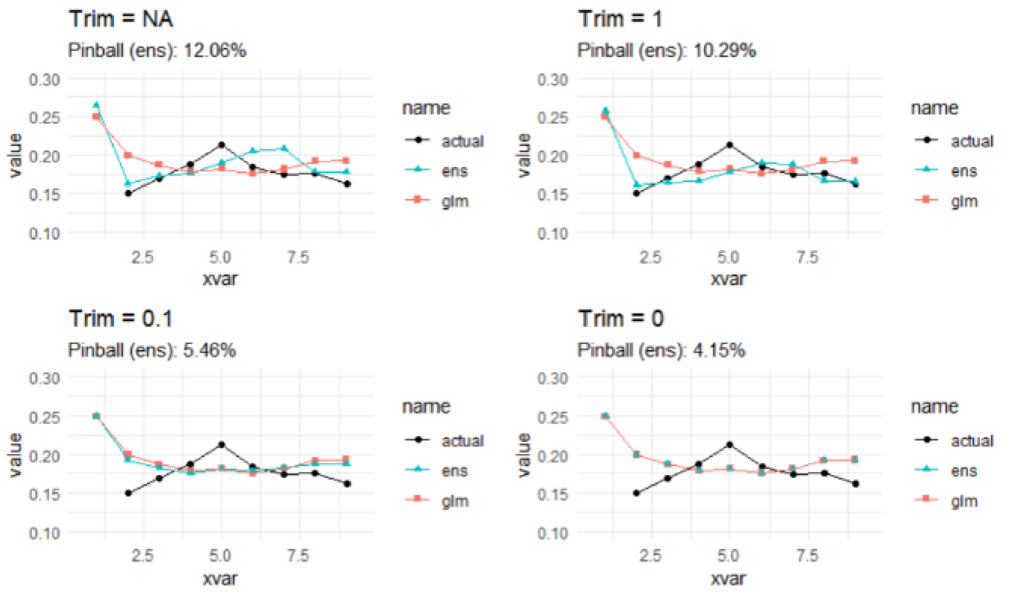
Observations:

- Booster corrections can be truncated to limit the impact of on the underlying model

Distribution of corrections from the booster

Observations:

- The more aggressive the truncation, the closer IBLM's performance is to the underlying GLM



Conclusions

IBLM

- Retains the formulaic expression of the GLM
- In our example achieves the performance matching XGB
- Allows for a smooth transition from a base model to ML-enhanced ensemble
- Inherent interpretability by design
- Easier implementation than Neural Networks

What’s next:

- v1.0.2 Package available on CRAN and Actuarial Data Science GitHub
- Package on the way – volunteers wanted!

Institute and Faculty of Actuaries

Questions

Comments

Institute and Faculty of Actuaries