Elevating Trust in High-Stakes Decisions Using Glass-Box Models and Robust Feature Selection

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Motivation

The Need for Explainable and Robust AI in High-Stakes Decision-Making

High Predictive Power vs. High Risk

- Modern machine learning methods are extremely powerful for modeling complex, high-dimensional data at scale (Jordan & Mitchell, 2015; LeCun et al., 2015).
- However, in high-stakes applications (e.g. insurance), model performance alone is insufficient. Decisions must be interpretable, transparent, and robust to maintain trust and meet ethical, regulatory, and societal requirements (Doshi-Velez & Kim, 2017; Karimian et al., 2022; Svetlova, 2022).

Limitations of Post-Hoc Explainability

- Popular methods like SHAP and LIME offer approximations, but are often unstable and unfaithful to the model's true decision logic (Lundberg & Lee, 2017; Ribeiro et al., 2016; Rudin, 2019).
- Regulatory frameworks such as the EU AI Act and GDPR demand explanations that are consistent, understandable, and reproducible (EU AI Act, 2024; GDPR, 2016).

Challenges Beyond Explainability: Robustness

Need for Intrinsic Transparency and Robustness

- Even inherently interpretable models (e.g., GAMs, rule-based methods) lose credibility if the chosen features or relationships shift drastically due to minor data perturbations (Hamer & Dupont, 2021; Kalousis et al., 2007).
- In high-stakes applications, domain experts often prioritize a more stable feature selection process over one that yields slightly higher accuracy but exhibits greater variability (Hamer & Dupont, 2021).

Research Contribution: Interpretable Modeling + Robust Feature Selection

Neural Additive Models (NAMs)

- We employ NAMs, which leverage deep learning to learn feature-wise relationships while maintaining an interpretable additive structure (Agarwal et al., 2021).
- Unlike black-box models, NAMs allow for direct visualization and an **exact** explanation of how each feature influences predictions, ensuring faithful and reliable explanations.

Robust Feature Selection

- We extend the Single Feature Introduction Test (SFIT) (Horel & Giesecke, 2022) by integrating a mean-based selection criterion into a forward-selection scheme.
- Using bootstrap aggregation, we identify features that are consistently important across resampled datasets—boosting robustness to data perturbations.

Modeling Framework

Transparent Models + Robust Feature Selection

Model Comparison

- **GLM:** Industry baseline
- **GAM:** Classical transparent model
- **Feed-Forward Neural Net:** Black-box benchmark
- **Gradient Boosting Machine:** Black-box benchmark
- **Neural Additive Model (NAM):** Deep Learning Glassbox Model

Unified Pipeline

- **Step 1:** Apply forward feature selection using modified SFIT across bootstraps
- **Step 2:** Select features that are consistently useful
- **Step 3:** Fit final models on selected features

Robust Feature Selection

Efficient, Stable, and Model-Agnostic

Key Idea:

- Test each feature's value by asking:
  "Does this feature consistently reduce prediction error?"

Our Approach:

- Build on the SFIT framework (Horel & Giesecke, 2022)
- Use a mean-based test (Diebold-Mariano) to assess importance
- Add features forward if they significantly improve model performance
- Repeat on many bootstrap samples to ensure stability

Why It Matters:

- **No need to retrain:** Efficient & scalable
- **Handles interactions** without exhaustive search
- **Robust to data noise:** Final feature set is stable and credible

Experimental Workflow

Datasets

1. Public MTPL Dataset

- 163k policyholders; standard benchmark in actuarial research (Denuit & Lang, 2004; Henckaerts et al., 2021).
- Policy periods range from 1 day to 1 year; static risk factors.

2. Proprietary Motor Dataset

- Real-world dataset from German insurer.
- 10M records with detailed policy & claims data.

Modeling Pipeline Overview

Unified Pipeline for Frequency and Severity Modeling:

1. Train/test split (80/20, stratified)
2. Generate $B = 25$ bootstrap samples
3. Robust feature selection:
   - Select main & interaction effects (keep if selected in $\geq 60\%$ of runs)
4. Tune model hyperparameters via random search
5. Refit final model on selected features (100 bootstraps)

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Predictive Performance - Poisson Deviance

Table 1: Poisson Deviance Loss by Dataset

Dataset	Model	Mean Loss	Lower 95% CI	Upper 95% CI
Public MTPL Test Set	GLM-Frequency	0.5320	0.5318	0.5323
	GAM-Frequency	0.5319	0.5317	0.5322
	FFNN-Frequency	0.5334	0.5322	0.5344
	NAM-Frequency	0.5316	0.5310	0.5322
	GBM-Frequency	**0.5292**	0.5284	0.5300
Proprietary Test Set	GLM-Frequency	0.2193	0.2193	0.2193
	GAM-Frequency	0.2192	0.2192	0.2193
	FFNN-Frequency	0.2192	0.2190	0.2196
	NAM-Frequency	**0.2192**	0.2191	0.2194
	GBM-Frequency	0.2194	0.2190	0.2209

Results

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Predictive Performance - Gamma Deviance

Table 2: Gamma Deviance Loss by Dataset

Dataset	Model	Mean Loss	Lower 95% CI	Upper 95% CI
Public MTPL Test Set	GLM-Severity	2.2667	2.2618	2.2733
	GAM-Severity	2.2667	2.2618	2.2733
	FFNN-Severity	2.3742	2.2720	2.4124
	NAM-Severity	2.2605	2.2584	2.2633
	GBM-Severity	**2.2598**	2.2444	2.2774
Proprietary Test Set	GLM-Severity	0.9928	0.9917	0.9938
	GAM-Severity	0.9925	0.9912	0.9936
	FFNN-Severity	0.9966	0.9852	1.0138
	NAM-Severity	**0.9923**	0.9856	1.0010
	GBM-Severity	0.9931	0.9922	0.9948

Results

Interpretability - Feature Selection

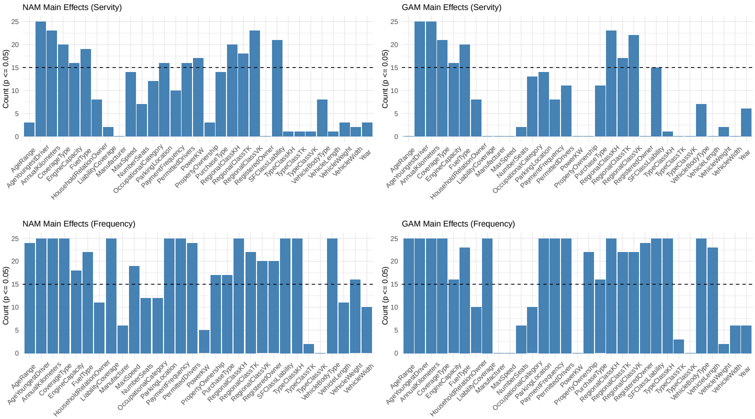
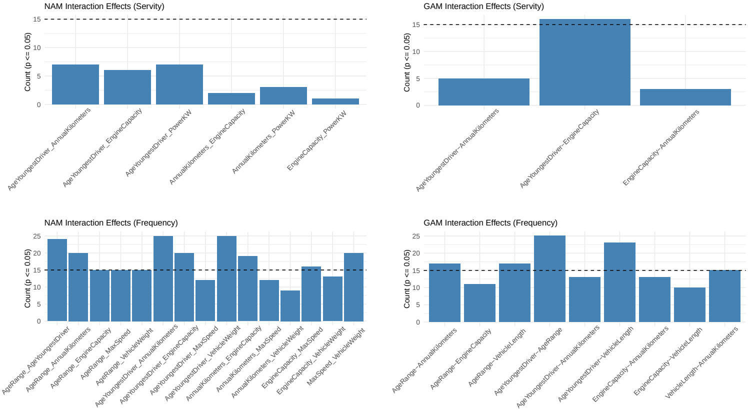


Figure 1: Robust Feature Selection for Main Effects in GAM and NAM.

Results

Interpretability - Feature Selection



Interpretability - Feature Effects

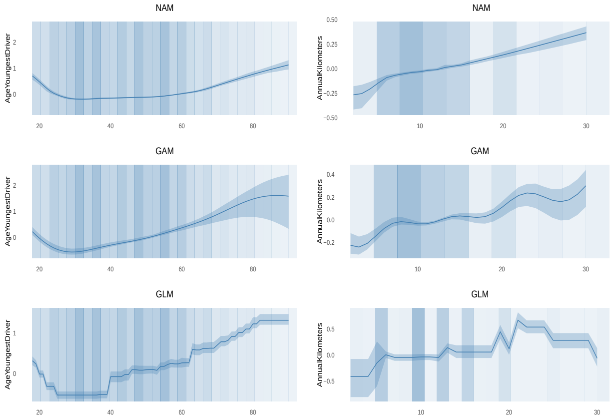


Figure 3: Partial Effect Plots fo the Age of the Youngest Driver and the Annual Kilometers the Frequency Models.

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