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LASSO Regularised GLMs: Enhancements for Life Insurance Experience Analysis

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Contents

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Motivation

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Motivation

- Updated Education System
- Impact of Generative AI
- GLM Applications in Life Insurance Experience Analysis Increasingly Common
- Extension to More Modern GLM Approaches

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Relationship between Approaches

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Relationship between Approaches

Simplest Traditional Approach

$$\log(y_{\mathrm{i}}) = \beta_0 + \log(\mathrm{expected}_i)$$

or

$$\frac{y_{\mathrm{i}}}{\mathrm{expected}_i} = e^{\beta_0}$$

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Relationship between Approaches

Simplest Traditional Approach → GLM

$$\log(y_{\mathrm{i}}) = \beta_0 + \log(\mathrm{expected}_i)$$

or

$$\frac{y_{\mathrm{i}}}{\mathrm{expected}_i} = e^{\beta_0}$$

$$\log(y_{\mathrm{i}}) = \beta_0 + \beta_1 \mathrm{x}_1 + \beta_2 \mathrm{x}_2 + \ldots + \beta_n \mathrm{x}_n + \log(\mathrm{expected}_i)$$

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Relationship between Approaches

Simplest Traditional Approach → GLM → LASSO Regularised GLM

Simplest Traditional Approach

$$\log(y_{\mathrm{i}}) = \beta_0 + \log(\mathrm{expected}_i)$$

or

$$\frac{y_{\mathrm{i}}}{\mathrm{expected}_i} = e^{\beta_0}$$

GLM

$$\log(y_{\mathrm{i}}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \log(\mathrm{expected}_i)$$

LASSO Regularised GLM

GLM with enhancements 💖

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Relationship between Approaches

Traditional → GLM → **LASSO Regularised GLM**

$\log(y_i) = \beta_0 + \log(\text{expected}_i)$

$\log(y_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \log(\text{expected}_i)$

GLM with enhancements 💖

Standard GLM only has this

Regularisation = LASSO

$$Objective\ Function + \lambda \sum_j |\beta_j|$$

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Benefits of LASSO Regularised GLMs

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Interpretability

variable	relativity
(Intercept)	103%
genderM	80%
genderF	140%
occupation_White Collar	123%
occupation_Blue Collar	75%
genderM:occupation_Blue_Collar	130%

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Modelling Relative to a Target Table/ Assumptions

Modelling AvE Ratios

$$\log(\theta_x) = \beta_0 + \beta_{male}x_{male} + \beta_{smoker}x_{smoker} + \log(m_x^{Table} E_x)$$

$$\frac{\mu_x}{\mu_x^{Table}} = e^{\beta_0 + \beta_{male}x_{male} + \beta_{smoker}x_{smoker}} = e^{\beta_0} \cdot e^{\beta_{male}x_{male}} \cdot e^{\beta_{smoker}x_{smoker}}$$

$$\mu_x = \mu_x^{Table} \cdot e^{\beta_0} \cdot e^{\beta_{male}x_{male}} \cdot e^{\beta_{smoker}x_{smoker}}$$

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Good Results Comparable to Machine Learning Techniques

Using machine learning to model claims experience and reporting delays for pricing and reserving

By L Rossouw and R Richman

Presented at the Actuarial Society of South Africa's 2019 Convention
22–23 October 2019, Sandton Convention Centre

ABSTRACT
In this paper we review existing modelling approaches for analysing claims experience in the presence of reporting delays, reviewing the formulation of mortality incidence models such as GLMs. We then show how these approaches have traditionally been adjusted for late reporting of claims using either the IBNR approach or the more recent EBNER approach. We then go on to introduce a new model formulation that combines a model for late reported claims with a model for mortality incidence into a single model formulation. We then illustrate the use and performance of the traditional and the combined model formulations on data from a multinational reinsurer. We show how GLMs, lasso regression, gradient boosted trees and deep learning can be applied to the new formulation to produce results of superior accuracy compared to the traditional approaches.

KEYWORDS
Machine learning; IBNR; incurred but not reported; experience analysis; reinsurers; EBNER; analytics; gradient boosted trees; deep learning; mortality models; pricing and reserving

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Model	Poisson Deviance – Test Set
IBNR + GLM	22 944
EBNER + GLM	22 947
GLM	22 883
LASSO	22 826
Gradient Boosted Tree	22 822
Deep Learning	22 799

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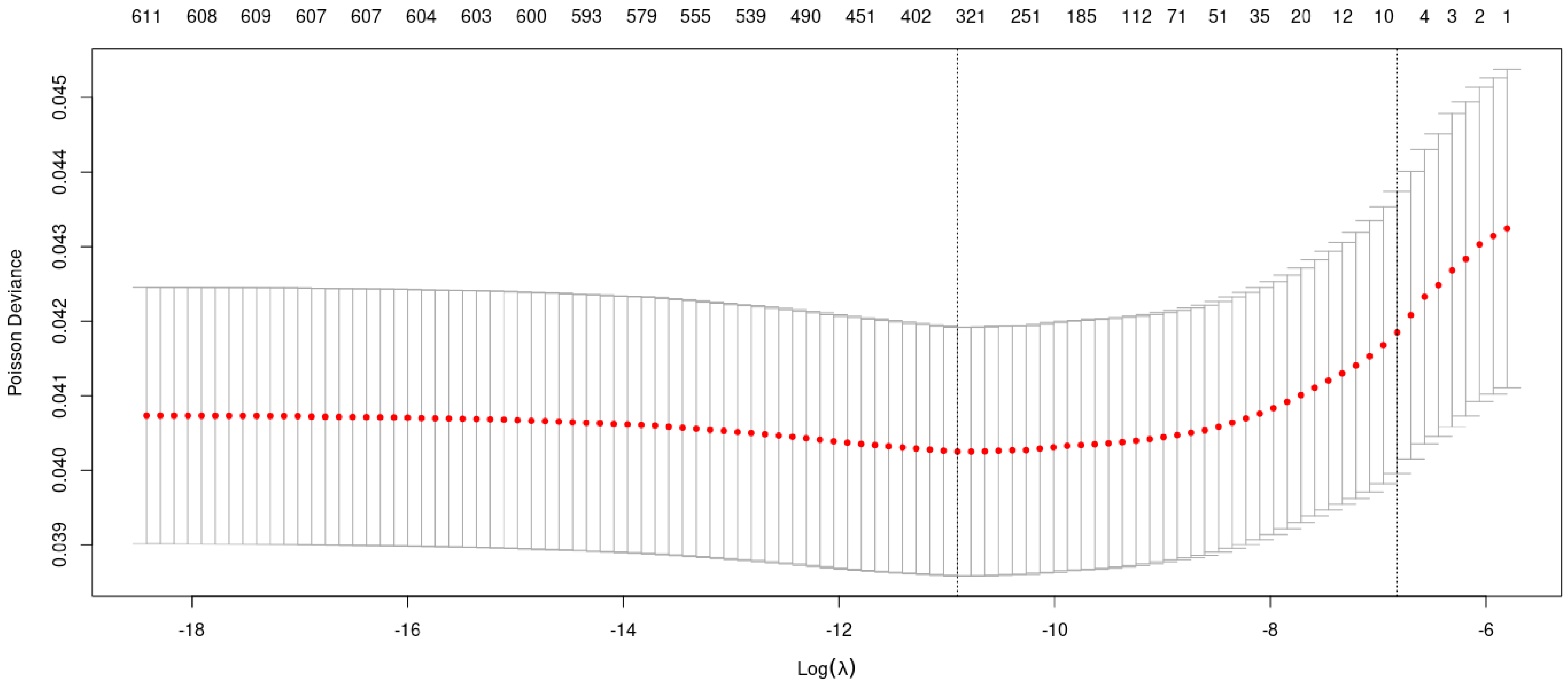
Variable Selection



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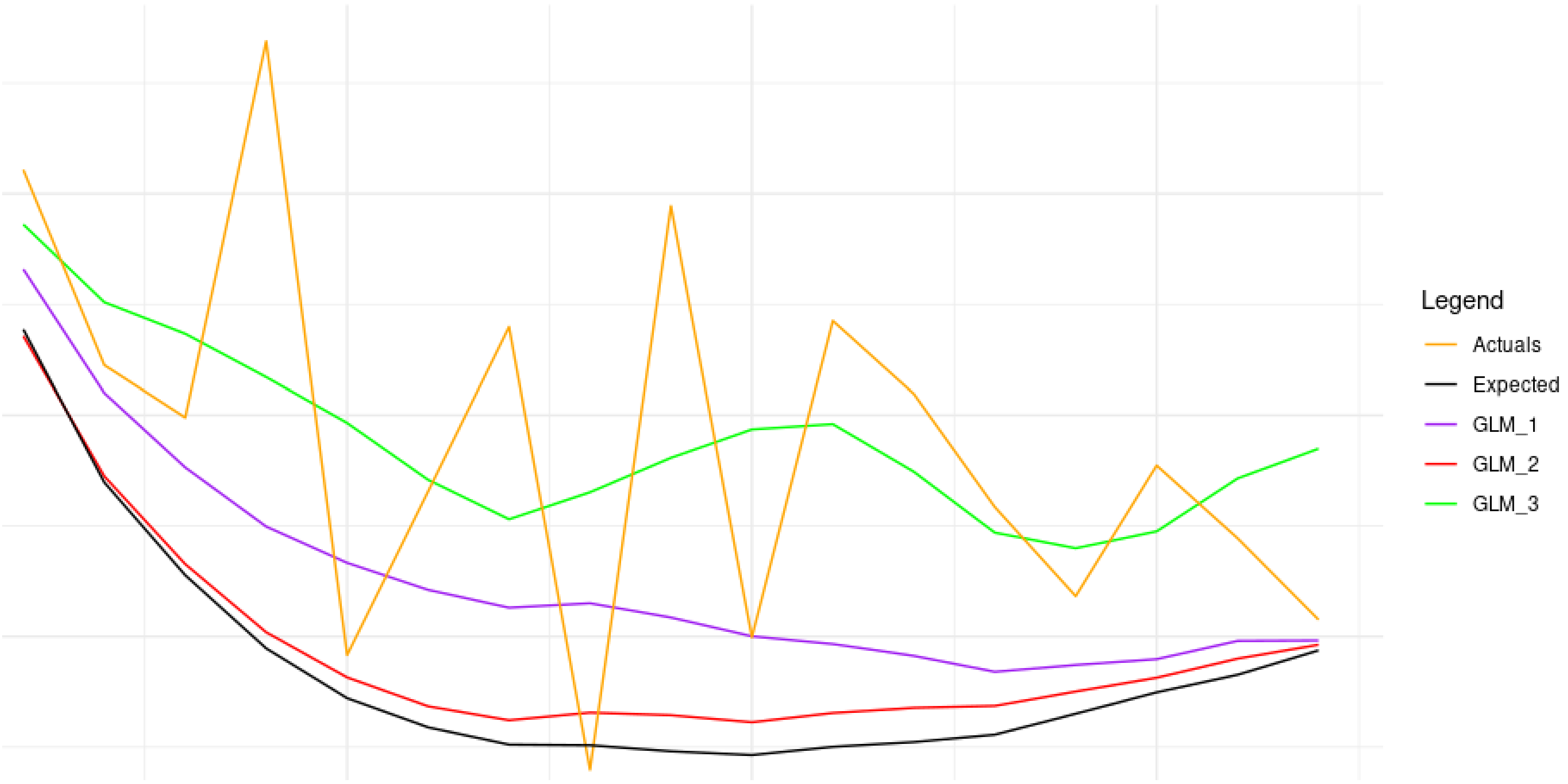
Similarity to Credibility Weighting



Case Study

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Context and Data

- New Zealand Disability Income Accident Incidence Data

Fit						Validate
2013	2014	2015	2016	2017	2018	2019

- Weight = Industry Table

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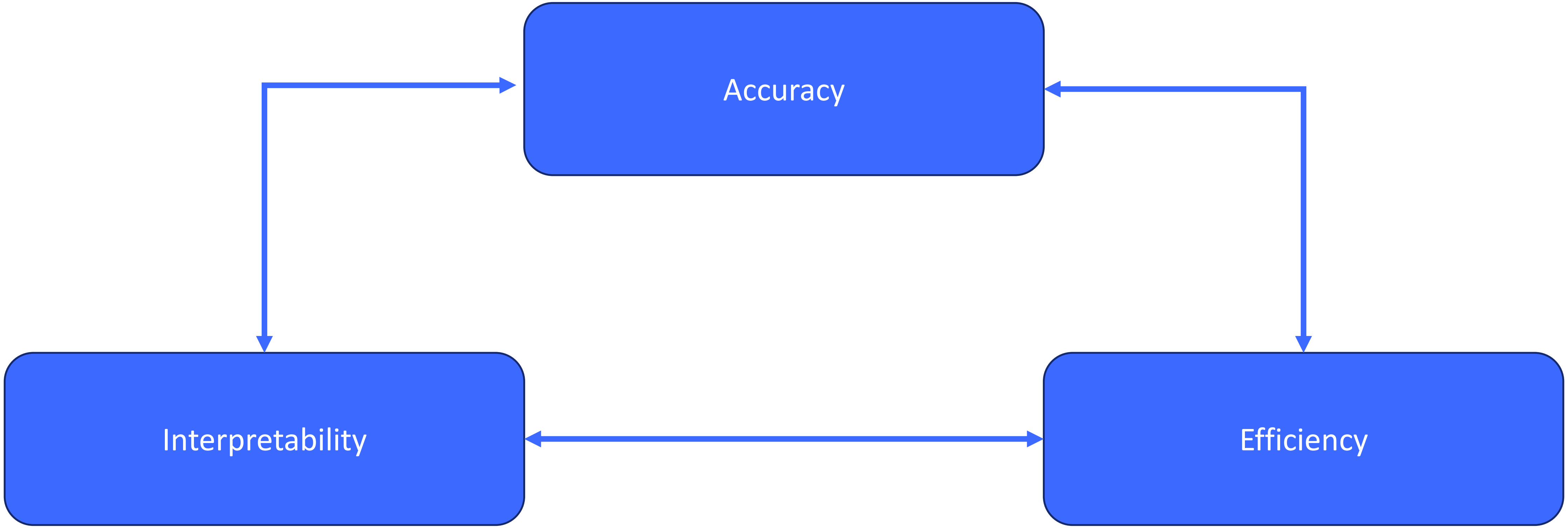
Considerations



Accuracy – Poisson Deviance

Poisson Deviance by Model

Traditional/GLM/GBM	Poisson Deviance Train	Poisson Deviance Validate
Traditional	0.0436657	0.0448884
LASSO Regularised GLM	0.0391431	0.0406055
GBM	0.0354692	0.0420414

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Accuracy – Pseudo R-Squared

$$R^2 = 1 - \frac{Sum\ of\ Squared\ of\ Residuals\ from\ Fitted\ Model}{Total\ Sum\ of\ Squares}$$

$$Pseudo\ R^2 = 1 - \frac{Poisson\ Deviance\ of\ Fitted\ Model}{Poisson\ Deviance\ of\ Null\ Model}$$

Accuracy – Pseudo R-Squared

Pseudo R Squared by Model

Traditional/GLM/GBM	Pseudo R-Squared Train	Pseudo R-Squared Validate
Traditional	0.0%	0.0%
LASSO Regularised GLM	10.4%	9.5%
GBM	18.8%	6.3%

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Interpretability

$\log(y_i) = \beta_0 + \log(\text{expected}_i)$

$\log(y_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \log(\text{expected}_i)$

GLM with enhancements

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Efficiency

Model	Model Run/Train Time	Explanation Time	Upstream Efficiency	Downstream Efficiency
Traditional Analysis	1 min	Less	Similar	• Assumption Structure for Projection Software • Business Understanding • Smoothness
LASSO RegularisedGLM	20 min	More		

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We pay our respect to the members of those communities, Elders past and present, and recognise and celebrate their continuing custodianship and culture.

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