Gradient Boosting Machines in Claim Reserve Prediction

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Based on joint research with Mathias Lindholm, Richard Verrall and Felix Wahl

Outline

- The Collective Reserving Model
- Model fitting
- Numerical illustration

Number of claims

$$N_{ij} \sim \text{ODP}(\nu_{ij}, \phi)$$

for accident year i = 1, ..., I and reporting delay j = 0, ..., I - 1

Number of payments

$$N_{ijk}^{\mathrm{paid}} \mid N_{ij} \sim Po\left(N_{ij}\lambda_{ijk}\right)$$

for payment delay k = 0, ..., I - 1

Aggregated payments

$$X_{ijk} = \sum_{l=1}^{N_{ijk}} Y_{ijkl}$$

Individual payments i.i.d.

$$\mathbb{E}\left[Y_{ijkl}\right] = \mu_{ijk}$$

$$\operatorname{Var}\left(Y_{ijkl}\right) = \sigma_{ijk}^{2}$$

Conditional moments of RBNS payments, uncorrelated by construction

$$\mathbb{E}\left[X_{ijk} \mid N_{ij}\right] = \mu_{ijk}\lambda_{ijk}N_{ij}$$

$$\operatorname{Var}(X_{ijk} \mid N_{ij}) = \frac{\mu_{ijk}^2 + \sigma_{ijk}^2}{\mu_{ijk}} \mathbb{E}[X_{ijk} \mid N_{ij}]$$

Assumptions for parameter fitting

$$\frac{\mu_{ijk}\lambda_{ijk} = \psi_{ijk}}{\mu_{ijk}^2 + \sigma_{ijk}^2} = \varphi$$

...meaning we can use quasi-Poisson log-likelihood!

(Quasi-)Poisson log-likelihood

$$l\left(\nu_{ij} \mid \mathcal{F}_0\right) = \sum_{i,j:i+j \le I} \left(N_{ij} \log \nu_{ij} - \nu_{ij}\right)$$

$$l\left(\psi_{ijk} \mid \mathcal{F}_{0}\right) = \sum_{i,j,k:i+j+k \leq I} \left(X_{ijk} \log\left(N_{ij}\psi_{ijk}\right) - N_{ij}\psi_{ijk}\right)$$

GLM formulation

$$\nu_{ij} = e^{a_i + b_j}$$

$$=e^{\alpha_i+\beta_j+\gamma_k}$$

$$\psi_{ijk} = e^{\alpha_i + \beta_j + \gamma_k}$$

GBM formulation

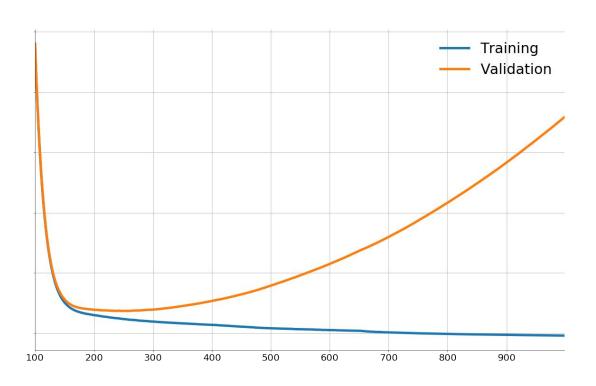
$$\nu_{ij} = e^{g(i,j)}$$

$$\psi_{ijk} = e^{h(i,j,k)}$$

GBM functions

$$g(i,j) = G_0 + \epsilon \sum_{b=1}^{B} r(i,j;\gamma_b)$$
$$h(i,j,k) = H_0 + \epsilon \sum_{b=1}^{B} r(i,j,k;\theta_b)$$

Early stopping



- Data from Gabrielli, Andrea, and Mario V Wüthrich. "An individual claims history simulation machine." Risks 6.2 (2018): 29.
- 6 different LoBs
- I = 12
- Aggregate data to get N_{ij} and X_{ijk}

Aggregate the data into two portfolios of equal size

$$\mathcal{N}_{0}^{t} = \{ N_{ij}^{t} : i + j \leq I \}$$

$$\mathcal{N}_{0}^{v} = \{ N_{ij}^{v} : i + j \leq I \}$$

Such that

$$N_{ij}^v + N_{ij}^t = N_{ij}$$

Split the data into two portfolios of equal size

$$\mathcal{X}_{0}^{t} = \left\{ X_{ijk}^{t} : i + j + k \le I \right\}$$

$$\mathcal{X}_{0}^{v} = \left\{ X_{ijk}^{v} : i + j + k \le I \right\}$$

Such that

$$X_{ijk}^t + X_{ijk}^v = X_{ijk}$$

Predict reserves

$$\hat{R} = \sum_{i,j,k:i+j+k>I} \mathbb{E}_{\hat{\psi},\hat{\nu}} \left[X_{ijk} \mid \mathcal{N}_0 \right]$$

$$\mathbb{E}_{\hat{\psi},\hat{\nu}} \left[X_{ijk} \mid \mathcal{N}_0 \right] = \mathbb{E}_{\hat{\nu}} \left[N_{ij} \mid \mathcal{N}_0 \right] \hat{\psi}_{ijk}$$

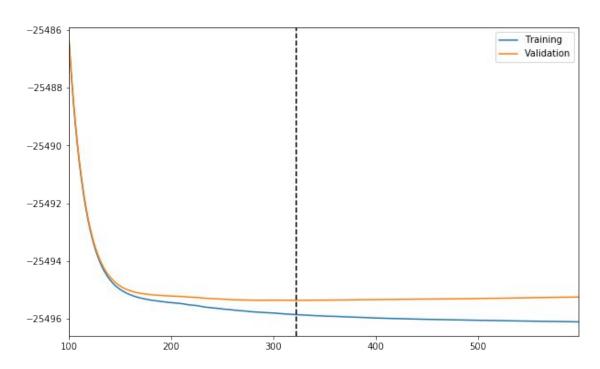
$$\mathbb{E}_{\hat{\nu}} \left[N_{ij} \mid \mathcal{N}_0 \right] = \begin{cases} N_{ij}, & i+j \leq I \\ \nu_{ij}, & i+j > I \end{cases}$$

Number of claims training, LoB 1

Max depth: 2

Step size: 0.1

Number of trees: 322

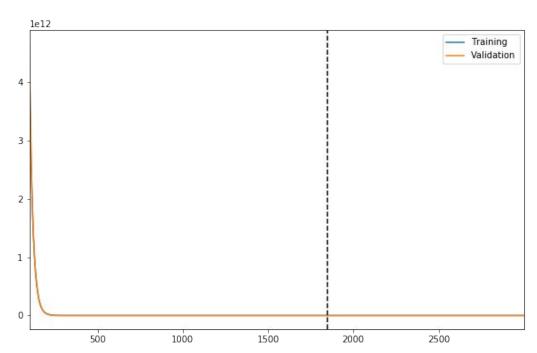


Aggregated payment training, LoB 1

Max depth: 1

Step size: 0.1

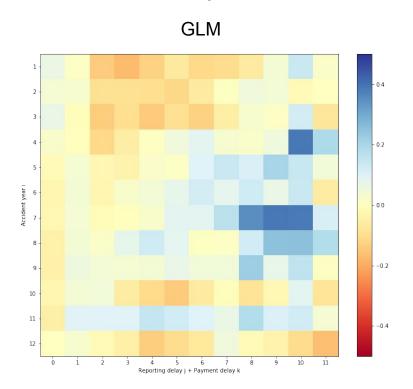
Number of trees: 1847

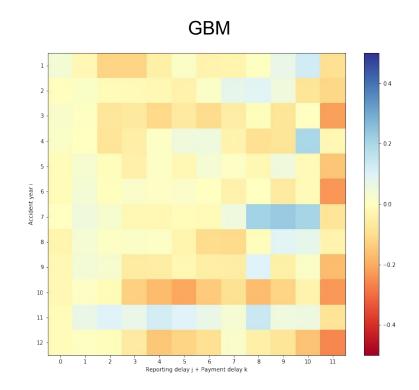


Reserve residuals

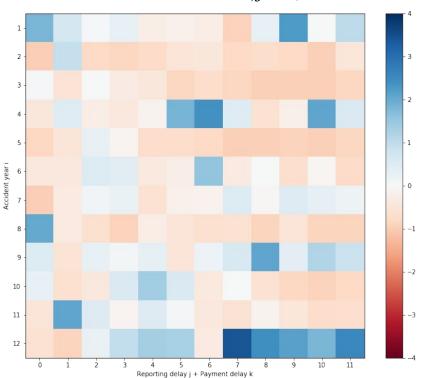
	LoB 1	LoB 2	LoB 3	LoB 4	LoB 5	LoB 6
CL	-2.82%	-4.26%	-7.02%	-5.66%	-3.28%	-5.49%
GLM	-3.45%	-5.12%	-8.42%	-6.40%	-4.23%	-6.25%
GBM	+2.17%	+0.03%	-5.17%	-1.75%	-0.76%	-1.29%

Residual heatmaps, LoB 1





Aggregated payment (over)overdispersion $\, arphi_{i,j+k}/arphi - 1 \,$, LoB 1



Thank you for listening

References

Lindholm, Mathias, et al. "Machine Learning, Regression Models, and Prediction of Claims Reserves." *Casualty Actuarial Society E-Forum Summer 2020*.

Friedman, Jerome H. "Greedy function approximation: a gradient boosting machine." *Annals of statistics* (2001): 1189-1232.

Wahl, Felix, Mathias Lindholm, and Richard Verrall. "The collective reserving model." *Insurance: Mathematics and Economics 87 (2019)*: 34-50.

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