Machine Learning in GI Reserving
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Context from GI Pricing

Analytic Innovation: The imperative for accurate pricing drives the development and adoption of new analytic techniques.

- GLMs used for 20 years; now universal
- GBMs starting to be adopted
- Ensembles becoming possible
- Neural Networks some way off
Reserving as a GLM

• Plenty of actuarial reserving research to show that the Chain-ladder can be formulated as a GLM.

• From GI Pricing we know that Machine Learning (GBMs and Neural Networks) outperforms GLMs.

• So where are all the Machine Learning in reserving papers?
Reserving & Machine Learning

- 2017 to 2019 have been vintage years

DeepTriangle: A Deep Learning Approach to Loss Reserving

Kevin Kor

*Research, 500 Northern Ave, Boston, MA 02110, United States

Abstract

We propose a novel approach for loss reserving based on deep neural networks. The approach allows for jointly modeling of paid losses and claims outstanding, and incorporation of heterogeneous inputs. We validate the models on loss reserving data across lines of business, and show that they attain or exceed the predictive accuracy of existing stochastic methods. The models require minimal feature engineering and expert input, and can be automated to produce forecasts at a high frequency.

Keywords: loss reserving, machine learning, neural networks

JEL: G22
### Reserving & Machine Learning

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<tr>
<td>2016_09</td>
<td>Machine Learning Framework for Loss Reserving</td>
<td>KPMG</td>
<td>✔</td>
<td>GBMs with aggregated data old approach to tuning and validation</td>
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<td>2017_03</td>
<td>Machine Learning in Individual Claims Reserving</td>
<td>WUTHRIC</td>
<td>✔</td>
<td>Individual claim transactions with decision trees but no IBNR</td>
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<td>2017</td>
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<td>2017_12</td>
<td>Non parametric individual claim reserving in insurance</td>
<td>BAUDRY</td>
<td>✔ ✔</td>
<td>ML plus external data and IBNR, no code!</td>
</tr>
<tr>
<td>2018_05</td>
<td>Deep Triangle</td>
<td>KUO</td>
<td>✔ ✔</td>
<td>RNNs and code shared but complex!</td>
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Growing number of good papers available up to 2018

Even more during 2019

But awareness and accessibility can be difficult especially if you are new to Data Science.
BAUDRY: Non Parametric individual claim reserving

- Kaggle Master and PhD Student @ DAMI Paris.
- Expert knowledge in Machine Learning and Natural Language
- Supervisor Prof Christian Y Robert, provides Actuarial background.
BAUDRY: Non Parametric individual claim reserving

Baudry’s approach uses extra info beyond traditional “triangle” style claims data.

- Explicit use of this extra data, provides opportunities…
  - for the method to give improved results
  - to aid better understanding of influences on claim development

\[
\begin{align*}
T_{0,p} & \quad \text{Underwriting date} \\
t_i - T_{0,p} & \quad \text{Exposure to reserve date} \\
F_{t_i,p} & \quad \text{Policy Risk factors} \\
E_{T_{0,p}} & \quad \text{External info at UW date} \\
E_{T_{1,p}} & \quad \text{External info at Occurrence date} \\
E_{T_{2,p}} & \quad \text{External info at Report date} \\
I_{t_i,p} & \quad \text{Claim history up to valuation date}
\end{align*}
\]

RBNS uses \((T_{0,p}, t_i - T_{0,p}, F_{t_i,p}, E_{T_{0,p}}, E_{T_{1,p}}, E_{T_{2,p}}, I_{t_i,p})\)

IBNR uses \((T_{0,p}, t_i - T_{0,p}, F_{t_i,p}, E_{T_{0,p}})\)
Transactions and claims relating to individual policies are binned into discreet time periods, by UW time = rows and Calendar time = cols.

Presenting triangular data in a way machine learning can use is essential to success.

Format of data can be difficult to get used to if you come from a traditional triangle world.
KUO: Deep Triangle

- Software engineer at R Studio (references JJ Allaire and Francois Chollet).
- Associate of CAS, previous employment in Insurance with KPMG.

DeepTriangle: A Deep Learning Approach to Loss Reserving

Kevin Kuo

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Abstract

We propose a novel approach for loss reserving based on deep neural networks. The approach allows for jointly modeling of paid losses and claims outstanding, and incorporation of heterogeneous inputs. We validate the models on loss reserving data across lines of business, and show that they attain or exceed the predictive accuracy of existing stochastic methods. The models require minimal feature engineering and expert input, and can be automated to produce forecasts at a high frequency.

Keywords: loss reserving, machine learning, neural networks

JEL: G22
Kuo’s approach uses a special form of Neural Network which is ideally suited to sequential data.

- Applied to aggregated triangular industry data and code shared.
- Able to apply to own company data and replicate the results.
IFoA Machine Learning in Reserving WP

• Member interest in ML and AI continues to grow.
• Many more papers have been released since those highlighted here.

• Working party set up to:
  – Understand market position in ML adoption
  – Perform literature review
  – Undertake new areas of research
  – Answer common questions on ML techniques
  – Consider data requirements and source for ML
  – Consider Trust and Ethics implications
Closing remarks

- Exciting opportunities ahead with clear parallels to GI Pricing.
- GLM, GBM and Neural Network approaches to reserving all maturing rapidly.
- Path to adoption in Reserving could well be easier than Pricing.
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