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Machine Learning Modelling on Triangles

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Agenda

This presentation builds on previous work presented at the 2021 IFoA Spring Conference* and is aimed at those relatively new to machine learning

- Reminder of machine learning framework for modelling triangle data
- Data
- Results
- Diagnostic charts
- Next steps
- Q&A

*https://institute-and-faculty-of-actuaries.github.io/mlr-blog/post/f-mlr3example/

Machine Learning in Reserving Working Party

- Who are we?
  - International group of actuaries, data scientists and academics from diverse backgrounds, chaired by Sarah MacDonnell

- What are our aims?
  - Learn how machine learning (ML) can be used in non-life reserving
  - Carry out research on the use of ML in reserving

- Our workstreams
  - Foundations
  - Literature Review
  - Survey
  - Data
  - Research

Find us at https://institute-and-faculty-of-actuaries.github.io/mlr-blog/

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Framework

Incremental loss triangle

Available data

To be predicted

Development period

Accident period	1	2	3	4	5
1	47,401	554,104	741,907	908,901	915,388
2	111,019	364,224	715,306	958,406	
3	48,953	357,500	794,413		
4	57,679	418,971			
5	68,434				

Incremental loss data table

Training data

Test data

Accident period	Development period	Incremental loss
1	1	47,401
1	2	554,104
1	3	741,907
1	4	908,901
1	5	915,388
2	1	111,019
2	2	364,224
2	3	715,306
2	4	958,406
2	5	
3	1	48,953
3	2	357,500
3	3	794,413
3	4	
3	5	
4	1	57,679
4	2	418,971
4	3	
4	4	
4	5	
5	1	68,434
5	2	
5	3	
5	4	
5	5	

Framework

X = “Features” or “Predictors” or “Inputs” or “Independent variables”

$$Y \approx f(X)$$

Accident period	Development period	Incremental loss
1	1	47,401
1	2	554,104
1	3	741,907
1	4	908,901
1	5	915,388
2	1	111,019
2	2	364,224
2	3	715,306
2	4	958,406
2	5	
3	1	48,953

$$\left(Y - f(X)\right)^2$$

Y = “Target” or “Output” or “Response” or “Dependent variable”

Features

X

Y	1.30	3.00	8.30	6.30	11.00
Angle_h	45	90	255	195	330
Angle_m	180	0	180	180	0

E.g. calendar period

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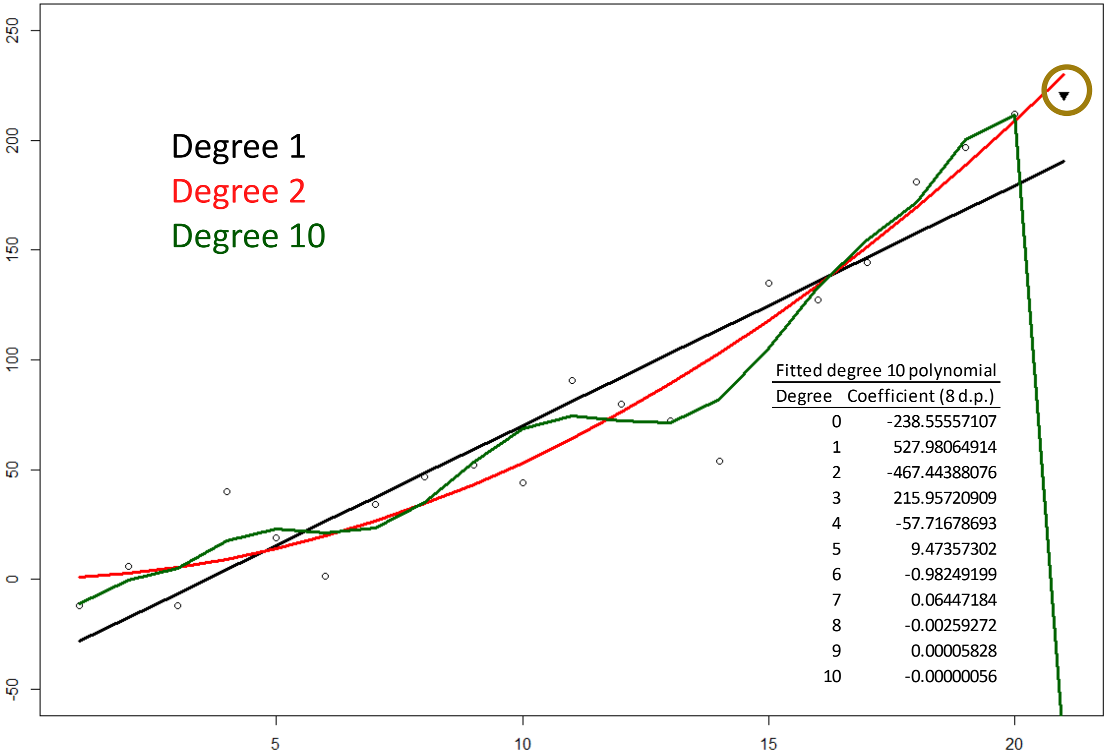
*Based on an example from the book “Deep Learning with R” by Francois Chollet with J.J. Allaire

Hyperparameters and tuning

Polynomials of degree 1, 2 and 10 fitted to 20 x-y pairs of a quadratic (plus noise) and used to predict value at x = 21



Fitted degree 10 polynomial

Degree	Coefficient (8 d.p.)
0	-238.55557107
1	527.98064914
2	-467.44388076
3	215.95720909
4	-57.71678693
5	9.47357302
6	-0.98249199
7	0.06447184
8	-0.00259272
9	0.00005828
10	-0.00000056

- Example – quadratic plus random noise
- Fit a polynomial using first 20 points (training data)
- Predict the value at x = 21 (test data)
- Degree of polynomial is a hyperparameter

Cross validation

Acc	Dev	Incremental loss	**Cross validation fold**
1	1	47,401	**2**
1	2	554,104	**2**
1	3	741,907	**1**
1	4	908,901	**3**
1	5	915,388	**2**
2	1	111,019	**1**
2	2	364,224	**1**
2	3	715,306	**3**
2	4	958,406	**3**
2	5		**N/A**
3	1	48,953	**3**
3	2	357,500	**3**
3	3	794,413	**2**
3	4		**N/A**
3	5		**N/A**
4	1	57,679	**1**
4	2	418,971	**2**
4	3		**N/A**
4	4		**N/A**
4	5		**N/A**
5	1	68,434	**1**
5	2		**N/A**
5	3		**N/A**
5	4		**N/A**
5	5		**N/A**

- Withhold some training data from fitting process
- Use this data to estimate performance out-of-sample for candidate hyperparameter
- Random 3-fold cross validation: fit model to data using folds 1 and 2 and predict target in fold 3. Compare prediction to (known) actual in fold 3 to estimate out-of-sample performance.

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LASSO

Select λ → Fit model (fits a β_i for each feature x_i)

$$e^{\beta_0+\beta_1 x_1+\cdots\beta_p x_p}$$

Minimise the expression below:

$$-\sum_{m=1}^{n} l(y_m;\hat{\beta}) + \lambda \sum_{r=1}^{p} |\hat{\beta}_r|$$

Hyperparameter

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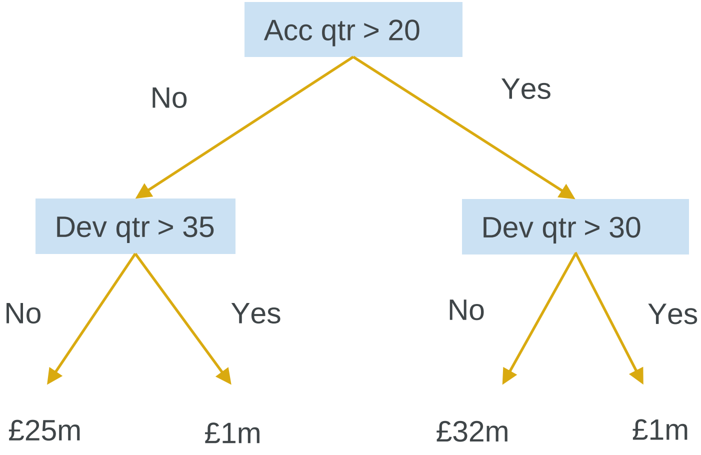
XGBoost



- Individual decision tree model typically performs poorly
- XGBoost outputs a collection of decision trees – combined prediction much better
- Several hyperparameters control how the collection of decision trees is constructed – number of trees to use, rate of adjustment from one tree to the next, tree depth and many more
- Outstanding track record in data science prediction competitions
- Not easy to grasp the details behind fitting procedure

Data

The SynthETIC R package* implements a simulation machine for claims data using the methodology described by Avanzi et al, 2020.

Four interesting environments are already in the public domain**

We simulated twenty triangles for each environment

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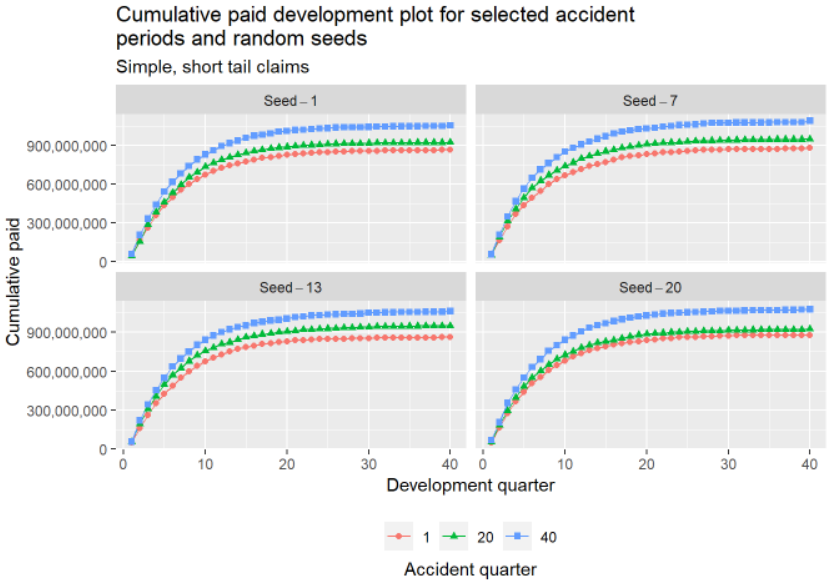
*https://institute-and-faculty-of-actuaries.github.io/mlr-blog/post/synthetic/ for background

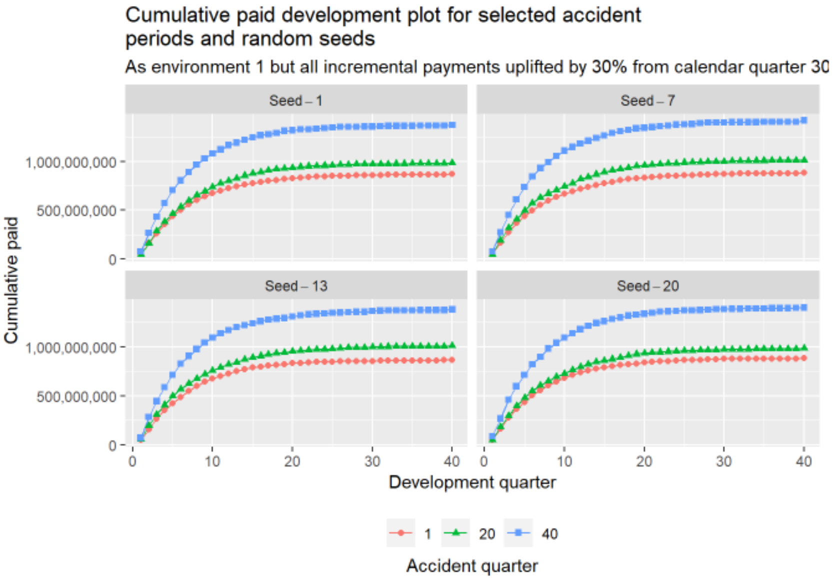
**https://github.com/agi-lab/reserving-MDN-ResMDN

Data

Environment 1



Environment 2



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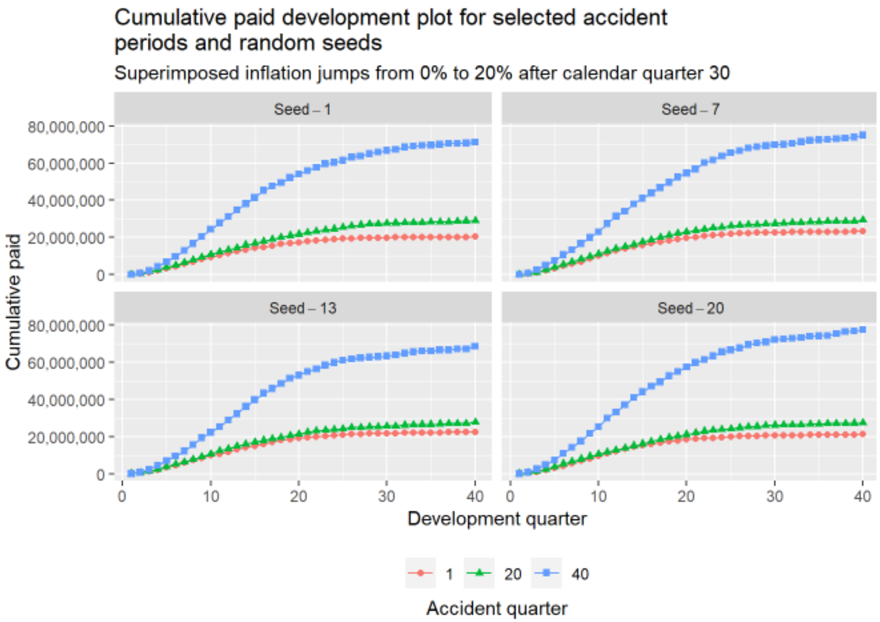
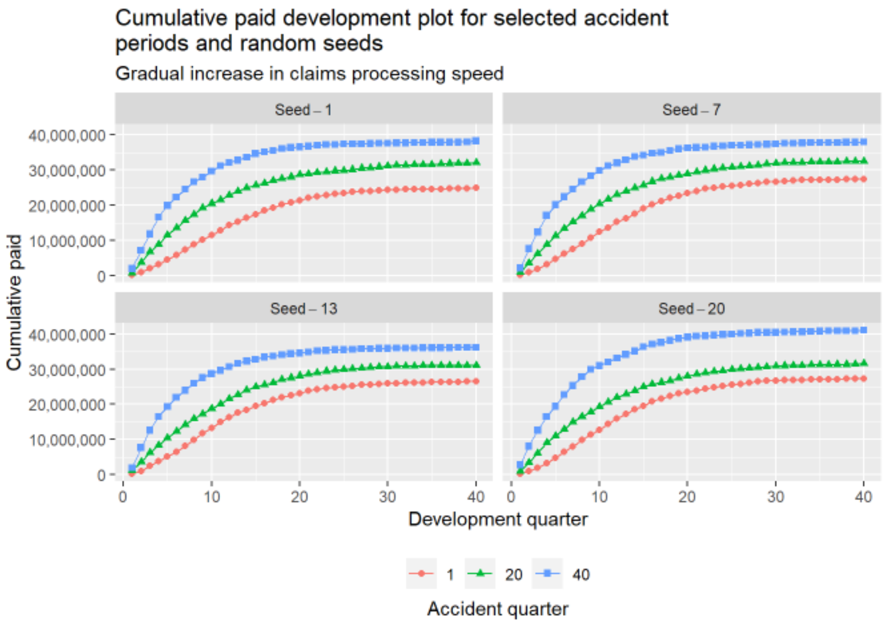
Data

Environment 3



Environment 4



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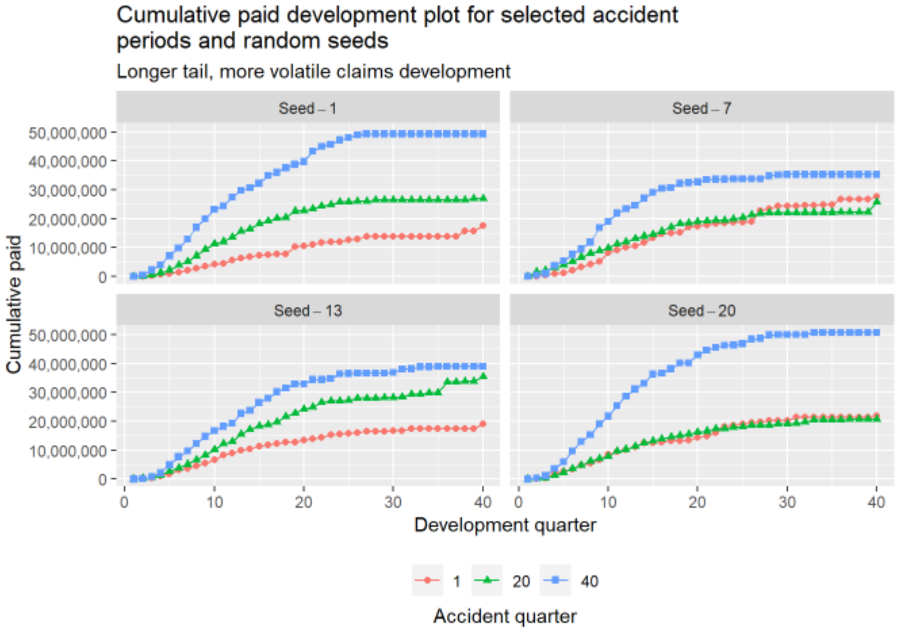
Data

Environment 5



Summary of modelling approach

- 20 simulations of 40 x 40 triangle of accident x development quarter.
- Training data is calendar quarter <= 40, test data is calendar quarter>40
- Chain ladder (volume all), LASSO and XGBoost fit using accident and development quarter factors as features ("_Basic" models)
- 5-fold random cross validation
- LASSO lambda tuned per blog post* and XGBoost n_rounds tuned
- Additional features engineered based on LASSO blog post* to capture interactions and calendar/accident/development period trends. LASSO and XGBoost fitted to this data ("_Extra" models)

*https://institute-and-faculty-of-actuaries.github.io/mlr-blog/post/f-lasso/

Caveat

- The examples here are intended to be instructional rather than conclusive
- We make no claims about the superiority/inferiority of any individual machine learning method for reserving in general.
- Real world data will introduce more problems
- Better performance in our examples may be possible with more time to tune the hyperparameters/different cross validation approach/different loss function
- Full code will be released on the blog site (soon)

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Results

Average reserve error [(predicted future paid / actual future paid) – 1] across all 20 random seeds

Environment	Description	Chain ladder	LASSO_Basic	LASSO_Extra	XGBoost_Basic	XGBoost_Extra
1	Simple, short tail	1%	13%	0%	2%	-3%
2	30% uplift to incremental paid from cal qtr 30 onwards	9%	21%	1%	6%	0%
3	Superimposed inflation jumps to 20% after cal qtr 30	-33%	-39%	-3%	-54%	-25%
4	Gradual increase in claims processing speed	95%	111%	2%	65%	9%
5	Longer tail, more volatile claims development	53%	3%	23%	-21%	-25%

Results

- Shiny app walkthrough

Conclusion

- In simulated data, ML methods were able to reproduce CL results on simple development data and pick up on calendar / accident period trends that cause CL problems
- R Shiny is a useful environment for analysing diagnostic plots that support results interpretation
- Lots more work to do!

Further work on triangles

- Rolling origin cross validation
- Loss function – claims development result
- Real-world data
- Further model interpretation and diagnostics

Questions

Comments

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