

Reserving in the Pressure Cooker

William Diffey, Apollos Dan, Laura Hobern



# Work undertaken by members of the Towards Optimal Reserving Process (TORP) working party

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William Diffey (Chair) Apollos Dan Fergal Dolan Laura Hobern

Asif John Alastair Lauder David Martin Cedric Morin Satraajeet Mukherjee Loan-Anh Nguyen Thomas Sithole Matthew Welsh

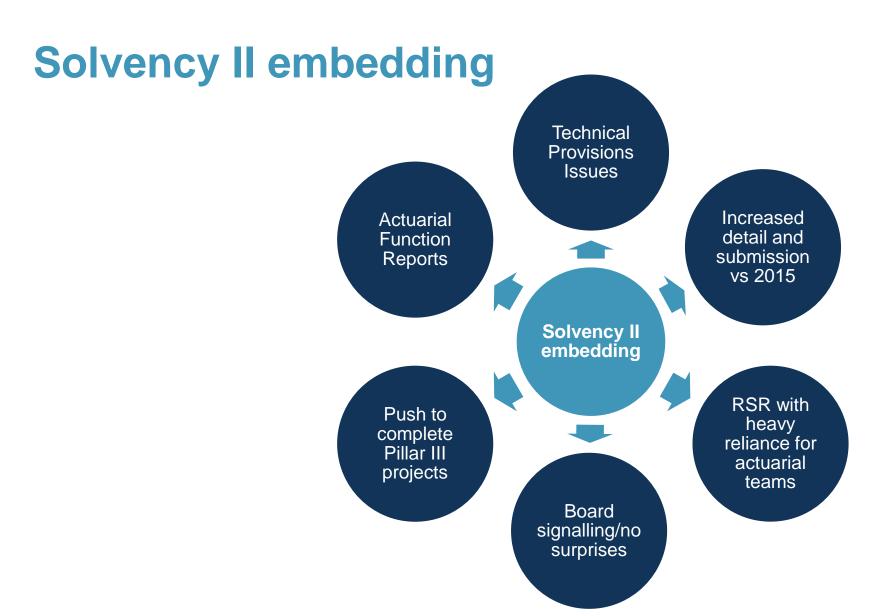
# Reserving in the Pressure Cooker

- Solvency II embedding
- Timescales and pressures on the Reserving Actuary
- No surprises reserving
- Deterministic vs stochastic methods
- Automation survey
- Machine Learning
- Questions

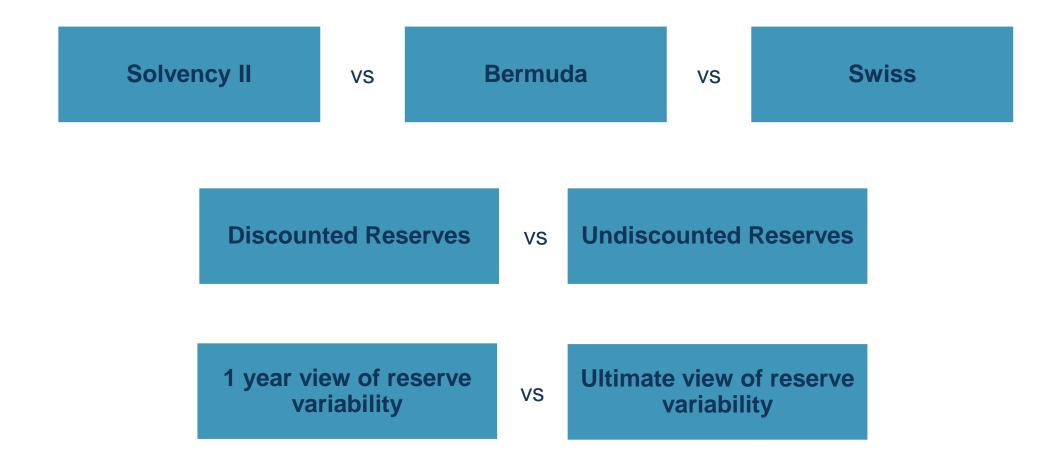




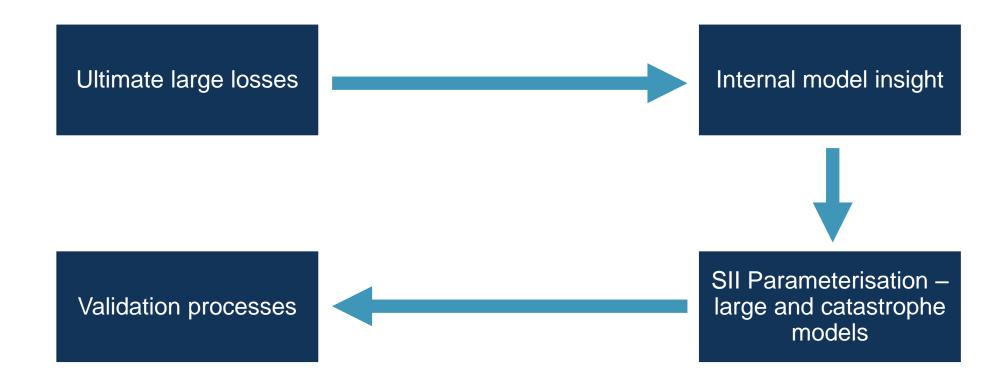




# Solvency II embedding (2)



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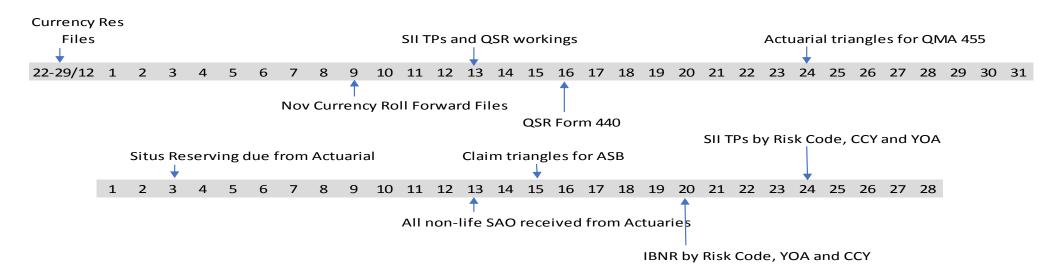


## **Timescales and pressures**

### Great pressure exists:

- On the reserving process caused by demand for faster and earlier close processes along with 'no surprises' for management
- For deep dives with relevant management information and controls information from the reserving processes to enhance operational controls over business
- Reduction in time available for actual insight into reserving position automation required to accelerate timings
- Soft market leads to added scrutiny by all (e.g. Management, underwriters and regulators)
- Optimal processes should be both efficient and add value.

### Sample timetable:



# Timescales and pressures

### **Timing**

- Early close with Roll forward
- 2018 Lloyd's reporting deadlines reduced by one week
- Process required to be moved earlier by one month - different dates? Benefits?
- SII ~ GAAP ~ Finance
- Time and iterations
- Increased familiarity and understanding of new requirements with time

### Quality

- Do tighter timescales lead to reduced quality?
- Capital models push more diversification;
   more classes needs more time for modelling
- Perfect storm tight deadlines and new / increased regulation
- Hopefully only temporary!
- Automation?
- Machine reserving?



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# No surprises reserving



# No surprises reserving

### No surprises for whom?

- Board or lower level committees (e.g. Reserving / UW committee)?
- What is the materiality level of a 'surprise'?
- Pre agreed actions?

# No surprises reserving

**Managing stakeholders** through the process No surprises for whom? When to cut data – balance date? Previous quarter? Early close and true up? • AvE - how often? When to flag to stakeholders? Discuss observed trends Highlight potential changes and impact (e.g. Ogden) Presentation to Reserve Committee in advance of booking numbers

# No surprises reserving

No surprises for whom? **Managing stakeholders** through the process

### **Closer Relationships**

- Closer to losses / included in discussions to minimise surprises
- Pricing / Reserving / Capital
   / Planning feedback loops
- Understand the business and how mix is changing
- Stress and scenario test potential events and impact
   / reaction if they occur
- Watchlists for potential claims (and probability)



# Deterministic vs stochastic reserving



# Deterministic BEL vs. Stochastic Reserving

### Deterministic Best Estimate Reserves

- GAAP Reserving
- Combination of projections and methods – average or single chain ladder scenario

### **Stochastic Mean Reserves**

- Internal model Reserve risk.
- Stochastic usually bootstrap.
   Many simulations; some not all together realistic

- Purpose (e.g. Point estimate, reserve ranges or full distribution)
- Segmentation and homogeneity of data
- Data volumes Reliability of stochastic projections
- User selection significant expert judgment, expertise of reserving Actuary

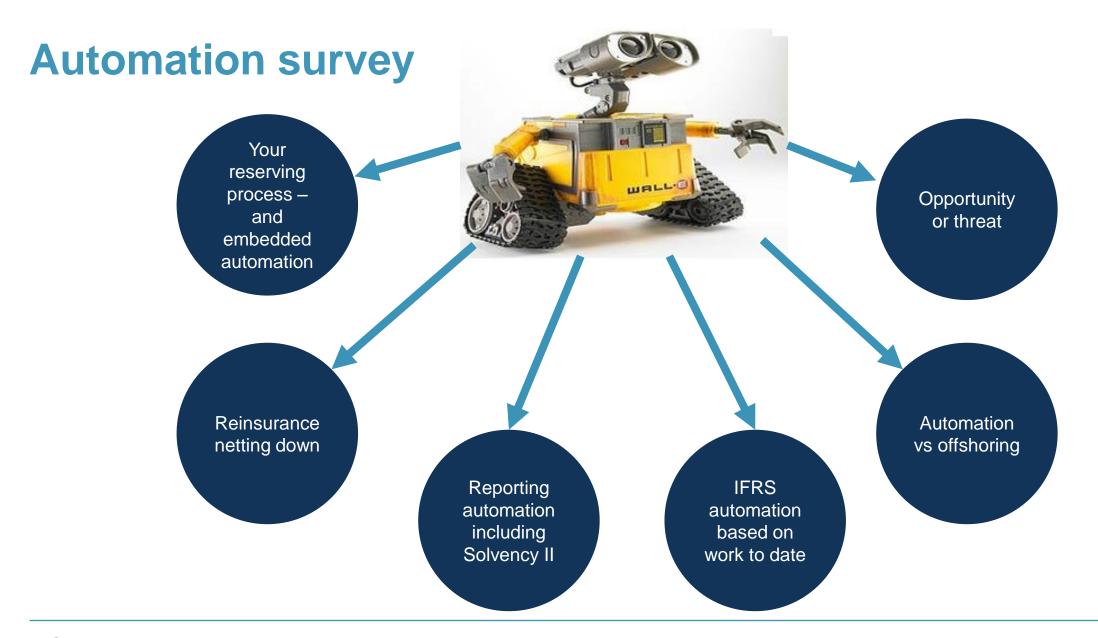
# Reserving Diagnostics, Reserve Risk Aspects

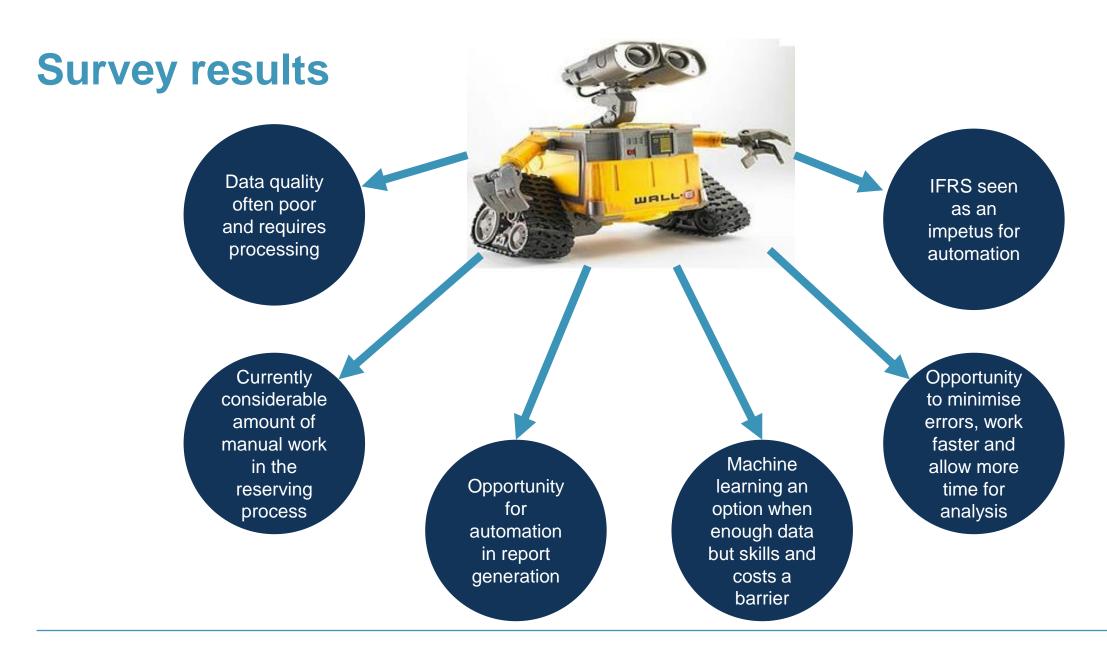
Reserving	Reserve risk	Link / Diagnostics tool
Best Estimate	Mean loss	<ul> <li>Understanding why the best estimate reserve and mean reserve are different will inform both Reserving and Reserve risk modelling. One is a benchmark to validate the other and vice versa.</li> <li>Overall reserving position, Methodologies, LoB Segmentation, Loss bucketing (e.g. Large loss threshold), Management margin, etc.</li> </ul>
Prior Year Development (Reserves release/increase)	Back-testing reserve risk distribution	The one-year reserve risk distribution can be back-tested by looking at past yearly movements in ultimates.  • Overall reserving position
Payment patterns	Inflation and discounting in the reserve risk model	The simulated reserve loss in the internal model is transformed into a cashflow by applying payment patterns from reserving. The future inflation and discounting are applied on the cashflow in the Internal model.  • ALM matching, Income recognition
Duration	Short tail versus long tail volatility reasonability testing	Long tails LoBs should exhibit higher volatilities per reserves, other things being equal. Otherwise, drill down for explanation, e.g. LoB impacted by Cat, high layer limits covers, etc.  • Methodology, Segmentation
Reserving timing and processes	Parameters update in the model	Align processes between reserve risk and reserving. Engage communication between the two in a timely manner, on time for internal model validation and submission to the regulator and on time for booking reserve best estimates.  • Model risk



# **Automation**





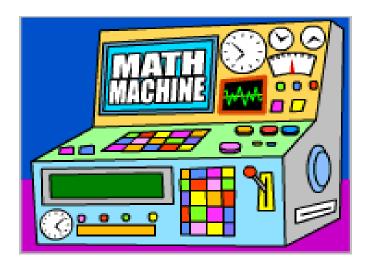


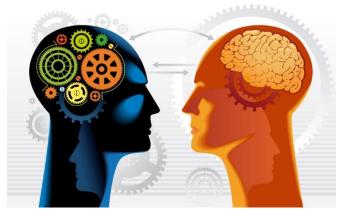


# **Machine Learning**



# **Machine Learning overview**





- Popularity of machine learning driving innovation
- Can Machine Learning be used for reserving?
- Reduce information loss and improve insight
- Uptake limited by trade off of simplicity vs accuracy
- Companies now investigating different predictive techniques to mitigate the Mean Absolute Error (MAE)
- Machine learning 'blackbox' like but different machine learning methods which we can use:
  - 1. GBM (Gradient Boosting Machine)
  - 2. Decision Tree (the random forest)
  - 3. LASSO (least absolute shrinkage and selection operator)

# A proposed METHOD

The errors in the reserving estimates (over or under reserving) can be reduced by using machine learning; but more importantly...

One emerging view is that the errors in the reserving estimates can be explained much better by using machine learning on granular claims data.

The classical reserving methods use a one-size-fits-all approach, so it is difficult to learn from the actual vs expected. Machine learning could give insight here

### **Example:**

If you use a single cumulative development factor for all bodily injury claims for the year 2016, the A vs E would not tell you which cohorts of injuries developed worse than expected.

Machine learning models use the claims and exposure features which affect the development, frequency and severity.

Simply put, machine learning would use algorithms to estimate a different development factor for brain injury vs muscle injury.

Parameter estimation involves learning from historical granular data, minimising the errors and back-testing the parameters.

It therefore allows for a more in-depth analysis of the actual vs expected, e.g. brain injuries may have deteriorated worse than expected

Although machine learning models are computationally intensive and complex, they can be implemented very easily once built.

Importantly, they can be rerun frequently within small intervals (say monthly) to monitor the actual vs expected.

One suggestion from the working party is not for machine learning to replace the traditional reserving techniques, but rather to **validate and enhance them.** 

**Importantly**, in this case machine learning models should be used to understand and explain the actual vs expected, and over time, help to develop more granular assumptions for traditional models such as loss ratios, development factors, frequency and severity.

# **Machine Learning illustrative results**

### **Summary Statistics**

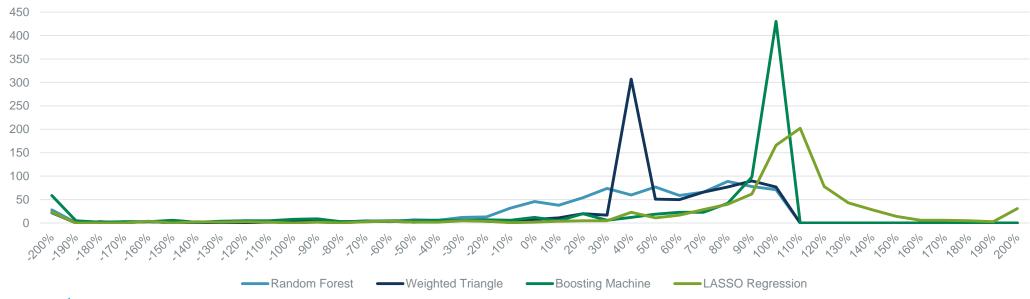
Method	Total Predicted	Actual	Actual vs Predicted	Mean Error %	Median Error %	Total Absolute Error	Absolute Error %
Triangle	16,764,770	15,685,367	1,079,403	7%	37%	12,474,066	80%
Forest	15,884,229	15,685,367	198,862	1%	43%	12,714,048	81%
GBM	15,639,526	15,685,367	(45,841)	0%	90%	20,462,309	130%
Lasso	25,064,981	15,685,367	9,379,614	60%	100%	32,916,272	210%

### **Comments**

- Triangle = has lowest Absolute error but suffers higher mean error
- Forest = has slightly higher absolute error but very low mean error
- GBM = has lowest mean error but very high absolute errors, see predictions which are very sticky around mean mark
- Lasso regression = performs worst due to linear effect of the model, cannot capture the non-linear trends in the data

# **Machine Learning overview**

### **Comparison of methods**



### **Commentary**

- Employer's Liability Bodily Injury
- Large losses are not capped, large loss is >100K
- Prediction Error is (Actual Expected)/Expected
- Total Claims 4815, split into 3972 Training 843 Tested (for prediction error check performance)
- Variables used Incurred, Paid, Case, Type of Injury, Part of Body, State

# Questions Comments

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