Agenda:

Key message – models can be complex, but the concepts, process and applications are not, and PSRWP digests the models for you

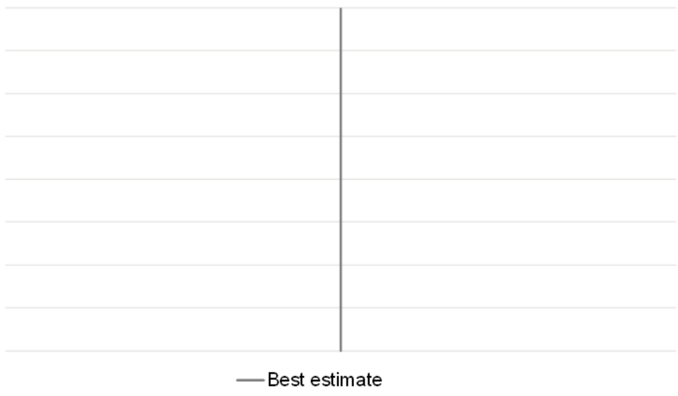
Background and concepts – background, risk modelling, PSRWP

Technical taster – models, bootstrapping, process and demo

Applications – some examples

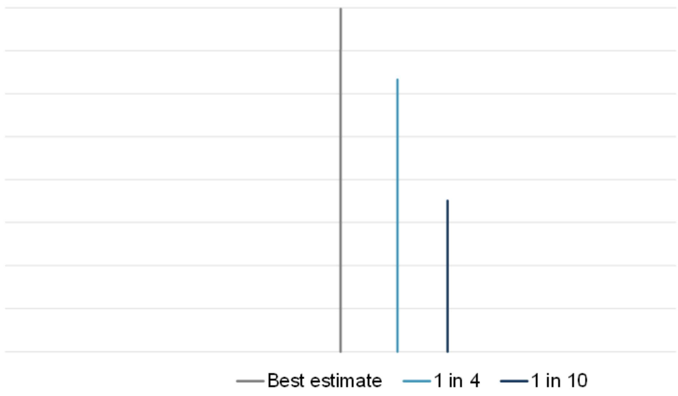
Possible future developments - Robert

Reserve best estimate



Deterministic reserving gives you a point (best) estimate to communicate to management

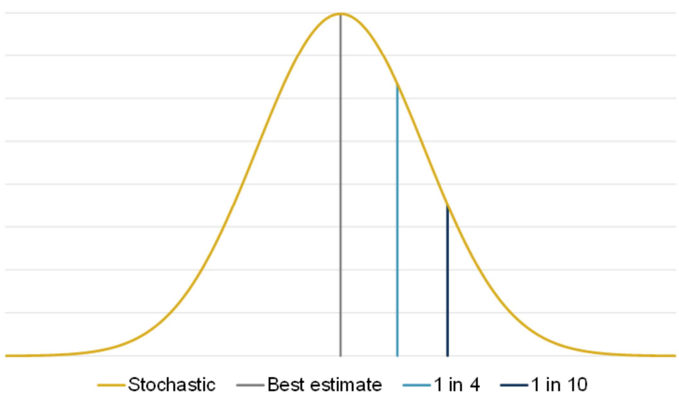
Reserve point estimates



Most common follow up question: what’s the chance of your best estimate being wrong?

Without stochastic reserving, other point estimates rely entirely on judgement/scenario testing

Reserve variability



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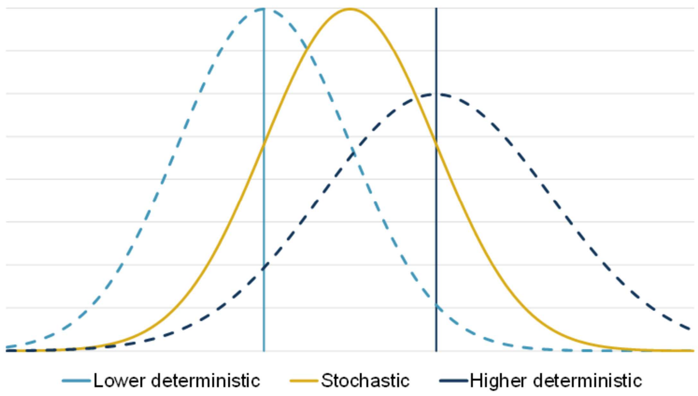
Stochastic reserving is all about how you estimate full reserve variability
Aiming for full distribution (mean -> CoV -> distribution -> return periods)
Scope is attritional claims – large claims modelled individually e.g. PPOs

Reserve variability



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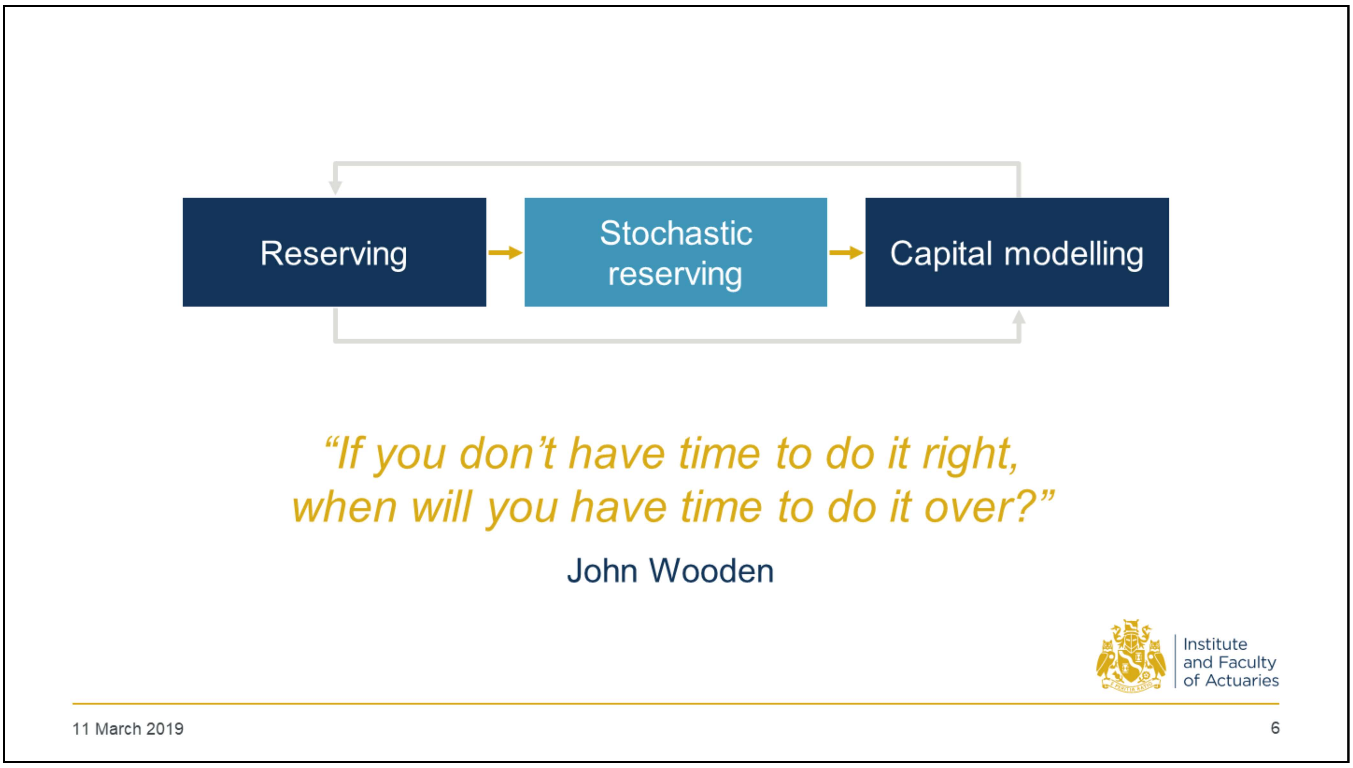
Stochastic model may have slightly lower or higher mean cf deterministic

Aim is to not decrease estimated CoV – scale (multiply) if deterministic is higher, shift (subtract) if deterministic is lower



Reserve risk is the risk that future claims exceed held reserves

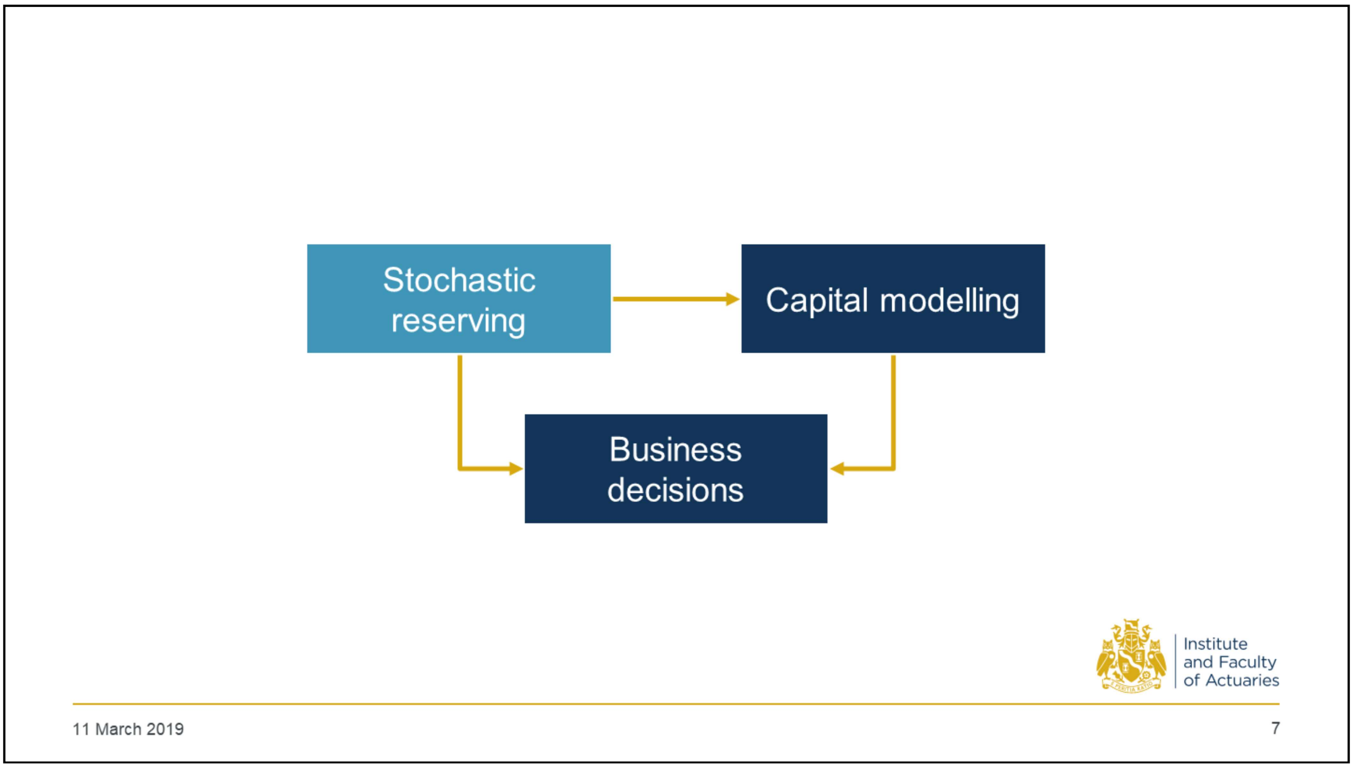
Capital modellers constantly having to go back to reserving actuaries when parameterising reserve risk, often relies on key reserve risk expert

Stochastic reserving fills the knowledge gap

Methods are seen as challenging, so sometimes ignored/left to last minute

Embedding into a regular process will help with negotiations and gives management a more accurate view of their business

Reserve risk must be parameterised anyway – doing this with stochastic reserving regularly allows actuaries to communicate more business knowledge



Stochastic reserving increases quality of business knowledge involved in making business decisions:

1. Regular quantification of risk improves communication of reserving results to management
2. Enhanced parameterisation of reserve risk in capital model, which in turn enhances capital model and its results

Industry moving towards this picture

Process error

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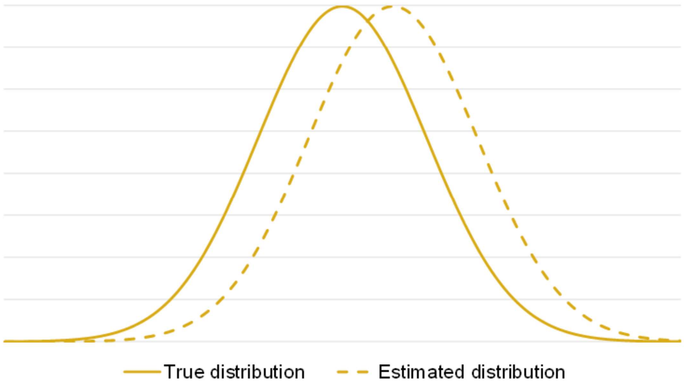
Process error (aka projection error) reflects natural randomness of claims

Parameter error



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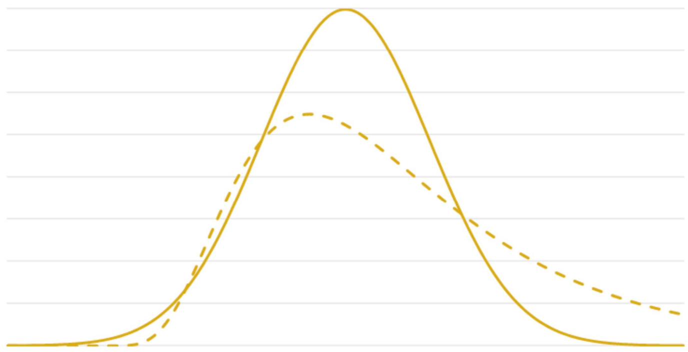
Parameter error (aka fitting error) reflects statistical randomness of sample estimation

Fermi ET example: http://www.jodrellbank.manchester.ac.uk/media/eps/jodrell-bank-centre-for-astrophysics/news-and-events/2017/uksrn-slides/Anders-Sandberg---Dissolving-Fermi-Paradox-UKSRN.pdf

Model error



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10

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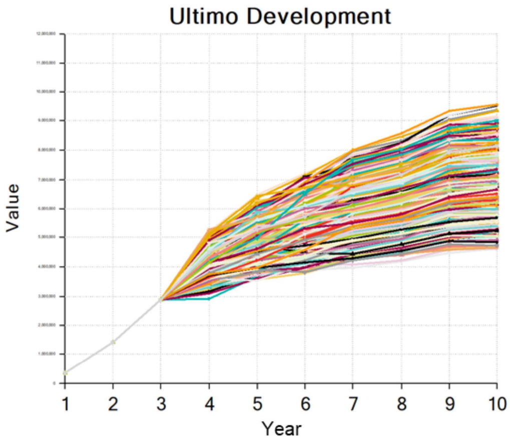
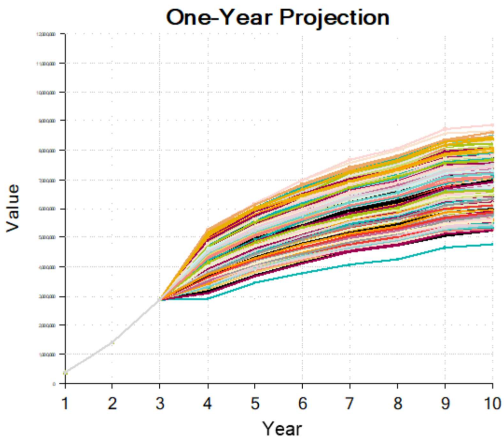
Model error is systemic risk of model selection – reflects natural randomness of model research and selection

Philosophical but can be significant

https://www.actuaries.org.uk/practice-areas/risk-management/disbanded-research-working-parties/model-risk

Time horizons





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Time horizon doesn’t affect mean (stationary assumption)

But time horizon will affect variability (unless assuming perfect foresight)

One-year movement in reserves affects profit

One-year time horizon needed for Solvency II

Taken from draft Paper 2 of the working party (see next slide)

Pragmatic Stochastic Reserving Working Party

Papers

- “A Practitioner’s Introduction to Stochastic Reserving” (2016)
- Sequel: “The One-Year View” (mid-2019)

Example models

- Ultimate and one-year
- Tyche
- Excel, R, Python

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PSRWP summarises research and practice as a guide to engaging with stochastic reserving

Papers are an excellent resource for engaging with stochastic reserving and exploring how it could help your business

“A Practitioner’s Introduction to Stochastic Reserving” published 2016

“A Practitioner’s Introduction to Stochastic Reserving: The One-Year View” due to be published 2019

https://www.actuaries.org.uk/practice-areas/general-insurance/research-working-parties/pragmatic-stochastic-reserving

The working party is making publicly available example models in Excel/VBA, R, Python and Tyche: https://github.com/robertmscarth/stochastic-reserving-wp

Current models

Model	Mean analogue	Analytic CoV?	Analytic distribution?
Mack	Incurred chain ladder	Yes	No
Over-dispersed Poisson	Paid chain ladder	Yes*	Yes*
Stochastic BF	Paid BF	No	No

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Most models have analytic means which are close to basic chain ladder / BF

Some models have analytic CoVs: Mack (ultimate and one-year), ODP (James Norman about to publish results, includes nice algorithm for simulating distribution directly)

Mack most widely used

ODP assumes positive increments

SBF is currently ODP with BF bolted on – additional source of parameter error in setting prior distributions

(Research into more generalised SBF is ongoing)

Bootstrapping triangles

Resample residuals

↓

Project from new triangle

↓

Simulate process error

… and repeat for every simulation

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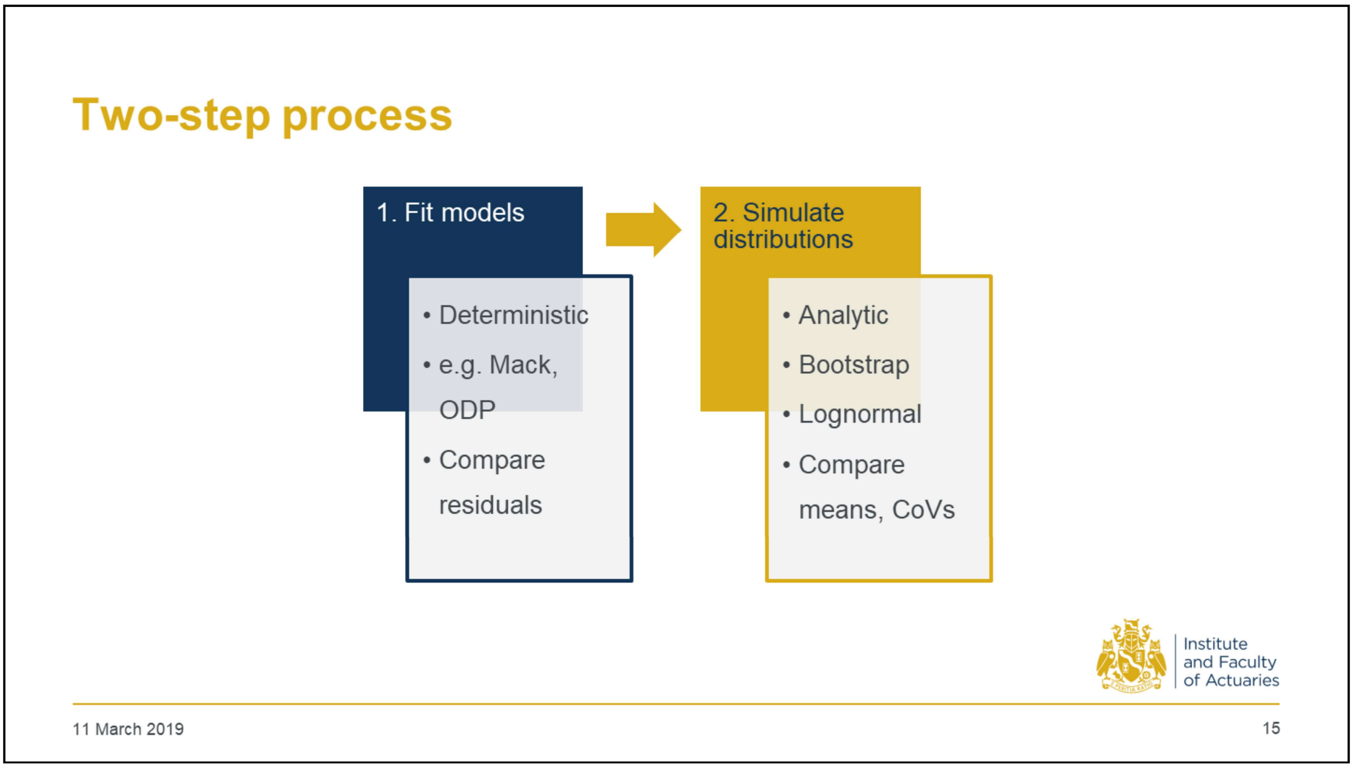
Bootstrapping refers to resampling residuals to generate new triangle (parameter error)
(Residuals are how far away each data point is from fitted triangle)
Projection uses parameters fitted to new triangle
Process error can be included by parametric distribution simulation or resampling residuals for future triangle
Computationally intensive, but recently technology has made it more practical



Select models to fit to data triangle, can adjust to bring more in line with best estimate – no simulations yet

Residuals are a standardised measure of departure of each triangle entry from the model – comparing helps select which models to take forward e.g. actual development factors cf average development factors

Then read off percentiles from simulated distribution

Analytic parametric distribution is ideal but may not exist

Bootstrapping good alternative but can be inefficient – often needs lots of sims and may then have to fit parametric distribution

Standard practice is often just to pick a CoV and assume lognormal distribution

Comparing means: may have slight shift to match stochastic result (additive down, multiplicative up)

Slight shift reflects the knowledge gap being filled

Then compare CoVs from different models/methods/selections

Key is to have evidence for final selection, can then read off percentiles

Additional tool for communication/negotiations with other stakeholders e.g. underwriters, management

Applications: examples

Capital model parameterisation

Actual versus expected

Risk premium estimation

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Reserving actuaries are better placed to parameterise reserve risk than capital modelling actuaries – can include more reserving business knowledge consistent with best estimate

Can be hard to tell whether movement in period is due to poor experience or poor reserving – comparing with return periods helps assess whether actual movements should be investigated further

Quantifying risk contributes to value of transaction – building this into regular reserving work can anticipate this and reduce amount of ad hoc analysis required

In summary: stochastic reserving great way for actuaries to add value to their business

Traditional models

Deterministic

- Chain Ladder – 1960s
- Bornhuetter-Ferguson - 1972

Stochastic

- Mack's model – 1993
- ODP - 1994

Challenges

- Stochastic models are stochastic versions of deterministic models
- Highly aggregated
- Ignore important real features e.g. calendar year effects
- Not clear how robust they are when data departs from model assumptions

How can we meet the challenges?

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The models mainly used by most actuaries are or are based on the chain ladder and the Bornhuetter-Ferguson.

These models are quite old now. Even in their stochastic form they are at least 25 years old.

There have been developments since then, but these developments either build on the older work, or have had next to no practical impact.

For example:

- Peter England showed us how to bootstrap the Mack and ODP
- The Merz-Wüthrich formula gives an analytic formula for the MSEP of the CDR within Mack's model
- The Actuary-in-the-box gives a method to get a distribution of the CDR from a bootstrap

There have been a great many papers published and other models proposed but the practical impact has been essentially zero.

There are a number of issues with these models:

- The stochastic models were developed to give the same mean as the deterministic methods. The stochastic methods therefore inherit issues from the deterministic methods
- They are highly aggregated
    - So basic model concepts like development factors do not map cleanly onto basic real-world concepts like reporting and settlement delays, and individual claims amounts
    - The models therefore do not provide a clear picture of what is driving claims behaviour. Different claims within a single class can behave very differently e.g. in Motor claims caused by rear-end car collisions are very different from those caused by head-on collisions. In Employer's Liability injuries like lower back strains develop differently from cuts and bruises.
    - There is always a trade-off between having enough data to get a good model fit, and fitting to a homogeneous set of claims data
    - As individual claims are aggregated it is difficult or impossible to model reinsurance adequately
- They ignore important real-world features e.g. calendar year effects

- Often used with a heavy dose of actuarial judgement
    - This makes it hard to correctly assess prediction error
    - It undermines one of the main assumptions of the actuary-in-the-box method
    - It also makes it harder to automate claims reserving processes and makes them slower and more expensive
- How the models behave when the data departs from the model assumptions is not very well studied or understood
- The traditional stochastic models inherit the above issues from the deterministic models. Can we develop stochastic models that avoid these issues?

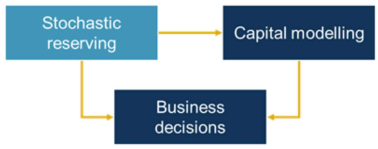
What is a model for?

Help managers understand the business and make decisions in a changing environment

- Interpretable and reflecting real-world features
- Models the key features of the business
- Copes robustly when reality departs from model assumptions or changes

Other important features

- More accurate predictions
- Automatable and runs quickly
- Can use the data that is available



Model choice is always a trade-off among the various advantages and disadvantages

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11 March 2019 18

The key thing for any business model is that it help the managers understand the business and make decisions in a changing environment.

The point of management making decisions is to change things.

By “interpretable” I mean that the model accurately reflects the features of the real-world that are key for how the business behaves, and so helps managers understand the business better, and how the business will behave if things change, and how it is likely to respond to management decisions. An interpretable model gives users more confidence in deciding when they can apply the model outwith the environment that it was originally fitted to.

The more interpretable a model is the easier it is to validate the model parameters and forecasts.

All models make simplifying assumptions. A model that is robust in the face of departures from those assumptions is better.

Stochastic chain ladder models are not very robust in the presence of calendar year effects. When there are calendar year effects in the data the model forecasts can sometimes be completely unreasonable.

Other important features include

- More accurate predictions
  This means that the prediction distributions are more tightly spread around the mean estimates
- Automatable and runs quickly
  This means that models can be run more frequently, or with different assumptions. It also means that the actuaries have more time to devote to developing a higher level understanding of the business and how it is developing.
- Can use the data that is available
  A model that needs more data than is available is not very useful no matter how good it is in other respects

Model selection is always a trade-off among the various advantages and disadvantages – there is no one-true-best-model

Possible future directions

Machine learning

- Broad topic, many different methods: Neural Nets, Gradient Boosting Machine, Random Forests, LASSO
- Could be used to identify important claims features
- Question about how interpretable these models are
- Gaussian processes
  - new but promising idea in claims reserving

Individual claims reserving

- Parodi 2012 – Triangle-free reserving

Better understanding of model limits

- How do models behave when the assumptions don't hold?

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More computing power makes the approaches below feasible. Features in the data can be investigated in much more detail.

Machine learning

- This is a vast subject, with many different methods
- There has been lots of interest in developing methods for use in claims reserving
- However practical methods are still lacking, and they are not well understood as a tool for claims reserving
- There is a lot of potential, ML methods can be highly automatable and flexible
- They could be used, for example, to automatically identify important claims features
- However some ML models are not very interpretable – many of them are just pattern matching to data. This raises questions about how confident users can be in applying the results of the models outwith the data and environment that they were originally fitted to. Our understanding of these models is not yet good enough to have much confidence when doing this.
- They also often need a lot of data
- Gaussian Processes
  - a very powerful machine learning technique which has been applied in image recognition, geostatistics, astrophysics and other fields. Essentially they provide a flexible way of learning a possibly highly non-linear functional form from data.
  - Only recently proposed to use these in claims reserving
  - One idea is to use them to estimate payment patterns. This would be an interesting incremental step from current models, and so might therefore be of some practical value
  - This is a promising new idea, that needs further development

Individual claims reserving

- Parodi (2012) roughly speaking used pricing techniques for claims reserving.
- Models reporting and settlement delays, and individual claims amounts. This gives a highly interpretable model

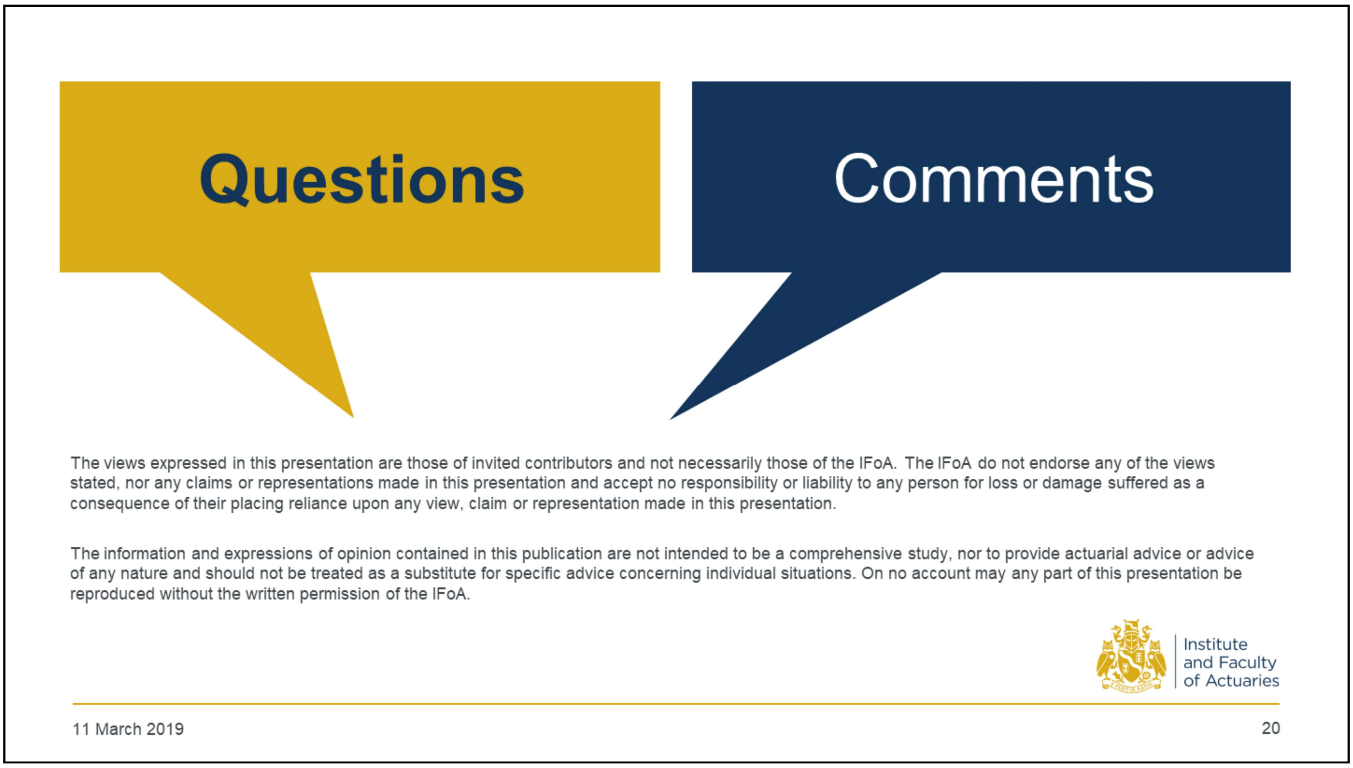
- However it needs a lot of granular data, consistent over a long period of time, that is often not available
- It has been little used in practice

Better understanding of limits

- This is not as glamorous a research topic as ML however I think it is worth consideration
- For traditional models
    - How do the models behave stochastically when model assumptions don't hold – this is not very well understood
- We also need to develop better understanding of new techniques (like ML), their limits, and how they behave in real-world situations so that they can be used with confidence

Final points to consider:

- Stochastic models should be integral to claims reserving
- The goal is to help managers understand the business and make decisions
- The next generation of models will leverage greater computing power and high performance platforms to do that much more effectively.



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