Towards machine pricing
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Agenda

Follow-up on “Computational intelligence techniques with applications to general insurance: a review. I – The role of statistical learning”… after big data, InsurTech, deep learning

Three main contentions:

A. Machine learning is not something to turbo-speed actuarial modelling – it is the right approach to modelling, big N and small N alike

B. Machine learning is the natural pathway to costing automation, including judgment

C. AI may also provide the tool (reinforcement learning) to address a more difficult problem, that of making strategic decisions such as pricing
A. Machine learning provides a sound theory of modelling

• *Experience rating* is an example of supervised learning, i.e. predictive models from data
• ML provides a clear framework for building models with the lowest prediction error (not only personal lines!)
B. What can be automated?

Big Data

Submission data

Methods
- MLE
- Monte Carlo
- EVT
- GLM
- Lasso regression
- ...

Data preparation and modelling

Expected cost of risk

Actuarial judgment

Knowledge base (theory and facts)

Past examples

Theory-building
B. What can be automated?

- Efficient automation of rating factors
- Sparse data - Smart combination of theory and data (e.g. EVT)
- Automation of data exploration and preparation (NLP, etc.)
- Smart use of portfolio data in F/S modelling
- Expected cost of risk
- Data preparation and modelling

Methods
- MLE
- Monte Carlo
- Extreme value theory
- GLM
- Lasso regression
- ...

Big Data

Submission data

Theory-building

Past examples
Knowledge base (theory and facts)

Actuarial judgment
B. What can be automated?

Data preparation and modelling

- MLE
- Monte Carlo
- EVT
- GLM
- Lasso regression
- ...

Expected cost of risk

Actuarial judgment

Knowledge base (theory and facts)

Past examples

How long does it take you to develop good judgment?

Submission data

Methods

Big Data

Theory-building

Big Data

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B. A pathway to machine costing – What it allows to do

- Increased number of actuarial investigations [relevant to our future!]
- Improved portfolio management through bots
- **Unbiased risk costing** and the clear-cut separation between pure cost and underwriting/actuarial adjustments
C. Towards machine *pricing*

- What supervised learning does for risk costing, reinforcement learning does for pricing and (in general) making decisions in a (partially unknown) environment

- Reinforcement learning is at the core of the science of making decisions
  - *Engineering*: optimal decisions; *neuroscience*: reward system; *psychology*: conditioning
  - Examples: fly stunt maneuvers in a helicopter, backgammon, controlling a power station, playing Atari games

- Main differences with supervised learning:
  - no supervision – only a reward signal
  - feedback is delayed
  - agent’s actions affect the subsequent data it receives
C. Towards machine *pricing* – Reinforcement learning

**Objectives**

*The agent*

- Observation ($O_t$: premiums in, claims out)
- Action ($A_t$: rate change)
- Estimated reward ($R_t$: profit)

**Environment**

- Very much like the dopamine-based reward system in the brain!

**Problems/limitations**

- Solutions can only be approximate, and the problem is NP-complete
- Large rare events make it difficult to calculate expectations
- In long-tail business, information about the environment may be collected too slowly...
- ... and may age too quickly
- The environment is not just a “blur” but is made of other agents
- Exploration vs exploitation – a delicate balance

These problems are not unique to machines!

*A separate issue*

You may get very different results if the agent is a single underwriter vs an insurance company!

**Objective**

Maximise cumulative rewards/utilities $U([t_0, t_1, ..., t_n, ...]) = \sum_{i=0}^{\infty} \gamma^i R_i$

**Mathematical framework**

- [partially observable] Markov decision processes

**Example of technique**

- Dynamic Bayesian networks

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Recapping… three main (proposed!) takeaways

A. Actuaries should learn machine learning not only to be à la page or to address Big Data but to be more rigorous in their modelling work

B. Machine learning’s biggest contribution will be as a help to automate the rating process, including much of actuarial judgment

C. Reinforcement learning is the right framework for looking at a more difficult problem, that of making a commercial pricing decision
GLOSSARY

AI-complete problem = a problem which is at least as difficult as that of producing an agent which exhibits general human intelligence
Bot = a piece of software that performs tasks on behalf of a user
Computational intelligence = a bashful term for artificial intelligence
Deep learning = a type of supervised/unsupervised learning based on many-layered artificial neural networks, allowing for a considerable abstraction in data representation
Dynamic Bayesian network = a methodology to find optimal solutions for POMDPs
Lasso regression = a regression method that can be used to select a model with the right rating factors automatically
Machine costing = the setting of the technical premium in an automated way
Machine pricing = the setting of the actual (commercial) premium in an automated way
Markov decision process (MDP) = a mathematical framework for decision making in a (fully known) stochastic environment
Natural language processing = a field of AI concerned with enabling machines to extract meaning from human language inputs
NP(non-deterministic polynomial)-complete = a problem for which no solution can (probably) be found in polynomial time – but which has a succinct certificate: i.e. the goodness of a proposed solution can be tested in polynomial time
Partially observable Markov decision process (POMDP) = a mathematical framework for decision making in a (partially known) stochastic environment
Reinforcement learning = making effective decisions by an appropriate reward system, e.g. dopamine-based system in the brain
Statistical learning = a bashful term for machine learning
Supervised learning = building predictive models by training algorithm with past examples/data
REFERENCES – 1 of 2

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• Parodi (2014), *Pricing in General Insurance*, CRC Press [Chapter 12 – What is this thing called modelling?]

On job automation:

• Frey and Osborne (2013), *The future of employment: how susceptible are jobs to computerization?*

• Amtz et al. (2016), *The risk of automation for jobs in OECD countries*

On reinforcement learning (and POMDPs) as the next step beyond machine learning as a framework for making decisions:

• Parodi (2012b), *Computational intelligence with applications to general insurance: A review. II – Dealing with uncertainty*, Annals of actuarial science

General references:


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- IA/BE (2015), Big data: an actuarial perspective, Institut des Actuaires en Belgique
- "I'm afraid I can't do that", The Economist, June 4th 2016
- Parodi (2010), From artificial fish to underwriters, The Actuary (March)
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Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged.

The views expressed in this presentation are those of the presenter.