Plenary 1: InsurTech / Future of Pricing

Speakers: Mohammad Khan and Harry Haggith, PwC

Executive Summary
What we want to share with you today

The future of pricing and the future of insurance
Executive Summary
This is an exciting time to be in insurance (and pricing)

- New data
- More processing power
- New software
- Reduced hardware costs
- New use cases
- A period of experimentation
- A time of rapid change

But it is also a time of risk and uncertainty

Customer/Insurer interactions today
Executive Summary

Digital platforms are taking an increasing share of our everyday interactions

Facebook
Google
Twitter
Amazon

Executive Summary

Customer/Insurer interactions tomorrow?

Amazon Alexa
Nest Learning Thermostat
Hive
Google Home
Survey

Do you know what supervised machine learning is?

Survey

Do you understand how unsupervised machine learning could be used to improve pricing?
Survey

Do you know how the Blockchain works?

Survey

Have you talked with an InsurTech firm?
Survey

Do you have a plan to take advantage of new data or new techniques?

Executive Summary

We are at an inflection point

Changes to pricing

- New data sources
- Supervised machine learning
- Unsupervised machine learning

Powerful individually
Revolutionary together
Executive Summary

Is now the time to change?

Mounting external pressure to change

Broader changes

Blockchain

InsurTech

Changes to Pricing
New data sources

https://www.youtube.com/watch?v=5ROVWsnGBmM

Video on data created by drones
New data sources

Marine telematics

- Data acquisition
- Data transformation
- Feature engineering
- Analysis
- Visualisation/Output

New data sources

Relevance and use

Relevance

- IoT brings connectivity into the ‘real world’
- Unsupervised learning converts that granular data into meaning
- Supervised learning converts meaning into prices

Use new data sources in combination with the right tools
Supervised / Unsupervised Machine Learning

Supervised

Predictors ➔ Response

Unsupervised

Variables ➔ Labels

Supervised machine learning

Replaces existing GLMs

From our testing

Accuracy

Speed

Flexibility

Not a miracle technology
  • Initial fit
  • Expert intervention required
  • Data manipulation, refinement, challenging assumptions
  • Senior analyst review
Supervised machine learning

Motor pricing hypothetical example

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<th>Model Name</th>
<th>Model Code</th>
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<th>Cross Validation (Gini Norm)</th>
<th>Cross Validation (RMSLE)</th>
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Supervised machine learning

Motor pricing hypothetical example

Nystroem Kernel SVM Regressor (M50)
Supervised machine learning
Motor pricing hypothetical example

ENET Blender (M83)

Supervised machine learning
Motor pricing hypothetical example

Elastic-Net Regressor (M52)
Supervised machine learning
Motor pricing hypothetical example

Advanced AVG Blender (M82)

Total Claims (£)

Bin
Actual  Predicted

Supervised machine learning
Motor pricing hypothetical example

ENET Blender X-Ray (Age)

Age (Years)

Partial Dependence  Prediction Mean  Actual Mean
Supervised machine learning

Motor pricing hypothetical example

Supervised machine learning

Motor pricing hypothetical example
Supervised machine learning
Motor pricing hypothetical example

Supervised machine learning
Motor pricing hypothetical example
Supervised machine learning

Make the most of supervised learning

- Take advantage of the increased flexibility and reduced cost of experimentation
- Test new data sources (quickly and cheaply)
  - reduce time on data manipulation
- Test new product structures
  - reduce time assessing product structures
- Test suggestions from management
  - reduce time managing stakeholders

Unsupervised machine learning

- Take granular data and convert into meaning
- For example, geocoding (postcode grouping) or telematics

What is unsupervised learning

- Find the 'labels' that describe the data
- There are many different approaches for setting these labels
- We often attempt to characterize collections of observations for which the observed frequency is unusually high
  - Think of grouping together peaks in a probability density function (the traditional normal distribution having only one peak)
Unsupervised machine learning
Cluster analysis

Types of clustering:
• Clustering for understanding
  – Biology
  – Information retrieval.
• Clustering to simplify
  – Dimension reduction.
  – Data compression.

K means clustering example

K means algorithm
• $k$ is number of clusters (set initially)
• Place $k$ points called ‘centroids’ in random locations
  – Assign each observation to its nearest centroid (i.e. create a ‘cluster’)
  – Reposition each centroid to be located at the mean position of all the observations in the corresponding cluster.
• Repeat until centroids remain unchanged
Unsupervised machine learning

**Association rules**

**Examples**
- Market basket analysis
- Cross marketing
- Catalogue design

**Supermarket shopping**

Finding patterns from sets that frequently occur together

- Diapers ⇒ Beer

**Unsupervised machine learning**

**Apriori algorithm**

- Combinations of factors
- One factor added at a time
- Prunes infrequent combinations
- Output
  - A set of frequently occurring factors
  - Probabilistic rules
- Telematics
- Geocoding

**Rule Generation for Apriori Algorithm**

Lattice of rules
Unsupervised machine learning

Make the most of unsupervised learning

- Large datasets
- Low frequency events
- Iterate
- Link with supervised learning

A period of rapid transformation in insurance pricing

- Improved prices
- Risk prevention
- Customer interaction optimisation
Broader Changes

Blockchain

- Back-end technology
- Data exchange
- Smart contracts
- Permanent
- Immutable
- Decentralised (public/private)
Blockchain

How it works

Hashing
• ‘One-way function’
• Fixed output length

Each block contains
• New transactions (unhashed)
• Hash of new transactions (the Merkle Root)
• Hash of previous block
• Timestamp

Blockchain in insurance

Reducing fraud

The shared data can be used to combat insurance fraud – multiple claims on the same policy can be flagged by a regulator.

Permissions could be set to enable only specific data to be viewed.

The data cannot be altered – if data changes, a new block has to be created.

The shared data is visible to all connected parties.

Every connected ‘node’ anonymously submits data.
Blockchain in insurance

Wholesale proof of concept

https://www.youtube.com/watch?v=OlOA4tnDq-g

1:39 – 2:51

Scenario: A Broker has a risk to insure on behalf of their client

• Step 1: The broker inputs details of the risk
• Step 2: The insurer submits an offer
• Step 3: The broker accepts the offer

Historical offers and transactions are visible to the regulator and all connected parties

Blockchain

Success

Complex technology
Many use cases
Bridging the understanding gap
Take time to test the use case

Start-ups: Blockverify, Everledger, Etherisc
InsurTech

Brolly  “We’re fixing insurance”

Lemonade  “Make insurance delightful”

Etherisc  “A decentralised insurance and reinsurance marketplace”

“Regulatory and capital barriers to enter the insurance industry limit the impact of ‘standalone’ FinTechs. However, the marriage of FinTech capabilities with a backer who brings in capital, regulatory fit and a recognised brand would be transformational for the sector.”

Relationship Management Director/SVP at a large insurer from the UK.

Sourced from: “Opportunities await: How InsurTech is reshaping insurance, Global FinTech Survey” June 2016

InsurTech

Lemonade

https://www.youtube.com/watch?v=6U08uhV8c6Y

1:40 – 2:21

A change in how insurance works?
InsurTech

Etherisc

https://www.youtube.com/watch?v=ED1-HaWEnRs

Testing smart contracts

• Flight delays (digitally verifiable)
• Social insurance (spokesperson verification)

Digital verification in the Internet of Things?
**InsurTech**

**Longer term challenges**

How do insurers demonstrate their value to customers over peer to peer risk sharing?

Who is best placed to lead an insurance company that uses artificial intelligence and big data to prevent risks before they happen?

__________________________ An insurer or a tech giant?

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**InsurTech**

**Two new emerging business models?**

Value-added risk prevention

- De-coupling of return from risk
- IP driven businesses

Peer to peer

- Low cost
- Ethical insurance
- Social businesses

Amongst many other possibilities
InsurTech

Implications for us (pricing actuaries)

Value-added risk prevention

- Risk prevention algorithms
- Data skills
- Risk skills
- Predictive modelling
- Insurance experience

Peer to peer

- Business as usual
- New back-end
- Reduced execution costs
- Agility
- Still need a

Can’t insurers do this?

So are we all now redundant?
Summary of changes

New data → Supervised learning → Unsupervised learning

Blockchain → InsurTech → What should we do now?

Actions you could consider taking
Actions you could consider taking

Test supervised learning
Develop an innovation strategy (VC unicorns?)
Data teams
Data capture
Access to resource and capability
Contributors and thanks

Mohammad Khan (insurance lead)
Harry Haggith (impact of technology on pricing)
Jamie Kirk (supervised machine learning)
Sam Hastings (unsupervised machine learning)
Andrew Daniels (Blockchain implementation)