Institute and Faculty of Actuaries

Plenary 1: InsurTech / Future of Pricing

Speakers: Mohammad Khan and Harry Haggith, PwC

07 June 2017

Executive Summary

What we want to share with you today

The future of pricing and the future of insurance

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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

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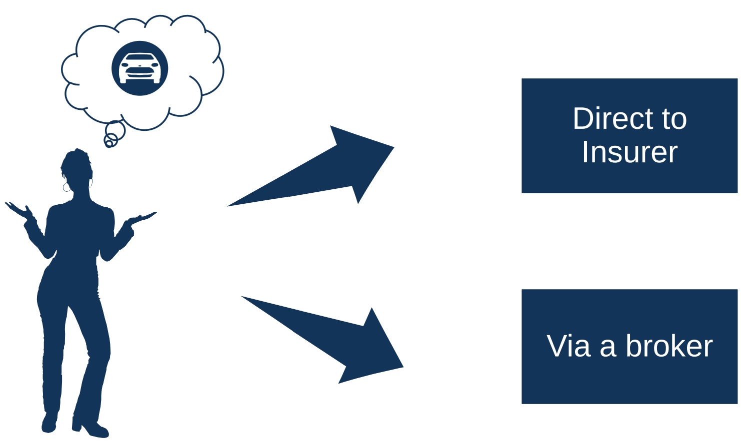
Customer/Insurer interactions today



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Executive Summary

Digital platforms are taking an increasing share of our everyday interactions

Facebook

Google

Twitter

Amazon

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Executive Summary

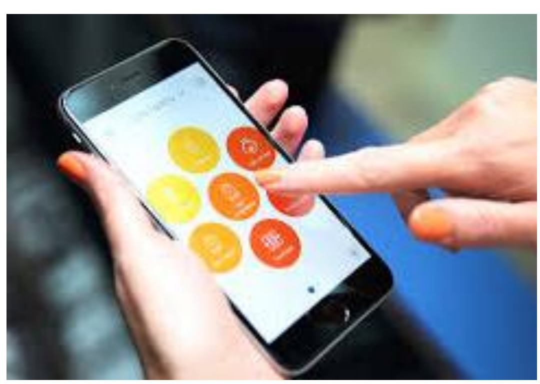
Customer/Insurer interactions tomorrow?

Amazon Alexa

Nest Learning Thermostat

Hive

Google Home



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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?

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Survey

Have you talked with an InsurTech firm?

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Survey

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

Executive Summary

We are at an inflection point

New data sources

Changes to pricing

Supervised machine learning

Unsupervised machine learning

Powerful individually

Revolutionary together

Executive Summary
Is now the time to change?

Broader changes

Blockchain

InsurTech

Mounting external pressure to change

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New data sources

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

Video on data created by drones

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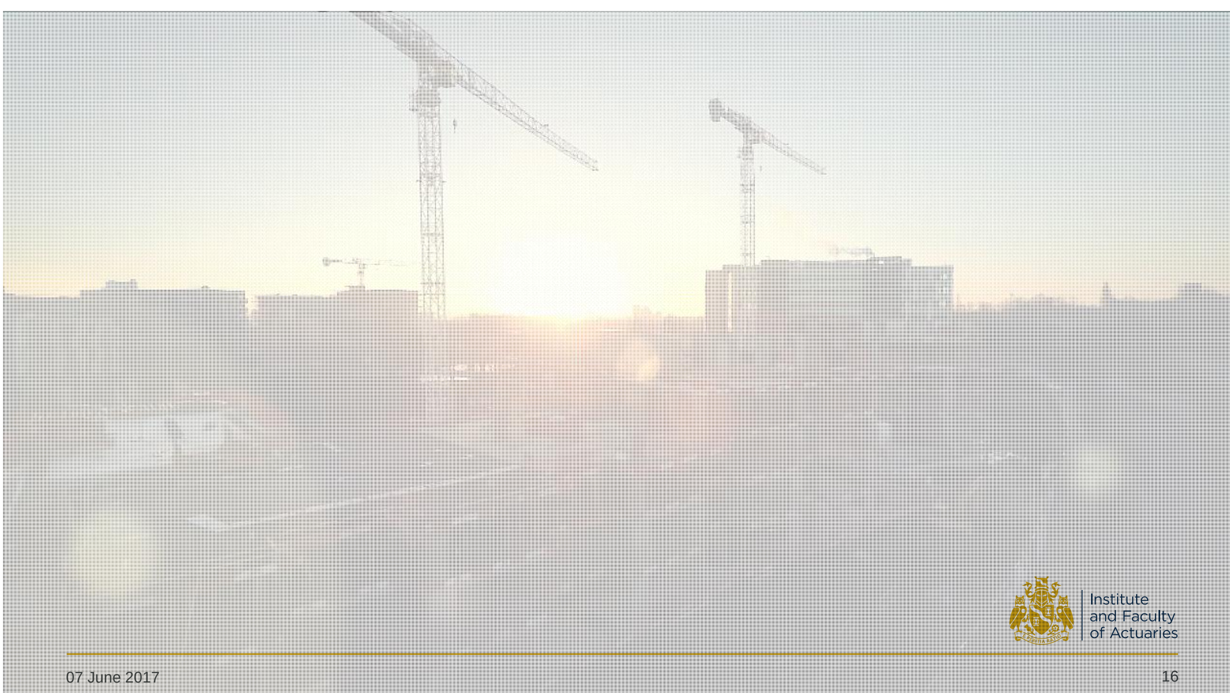


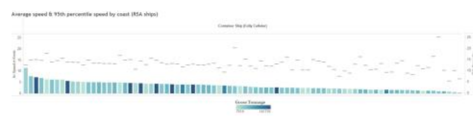
New data sources

Marine telematics

Data acquisition → Data transformation

Feature engineering ⇄ Analysis

Visualisation/ Output



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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

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Supervised / Unsupervised Machine Learning

Supervised

Predictors → Response

Unsupervised

Variables → Labels

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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

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Supervised machine learning

Motor pricing hypothetical example

Model Name	Model Code	Cross Validation (Tweedie Variance)	Cross Validation (Gini Norm)	Cross Validation (RMSLE)
Nystroem Kernel SCM Regressor	M50	75.3457	0.3429	4.5063
ENET Blender	M83	75.3556	0.3425	4.5165
Elastic-Net Regressor	M52	75.5097	0.3383	4.5087
Advanced AVG Blender	M82	75.3858	0.3445	4.5080

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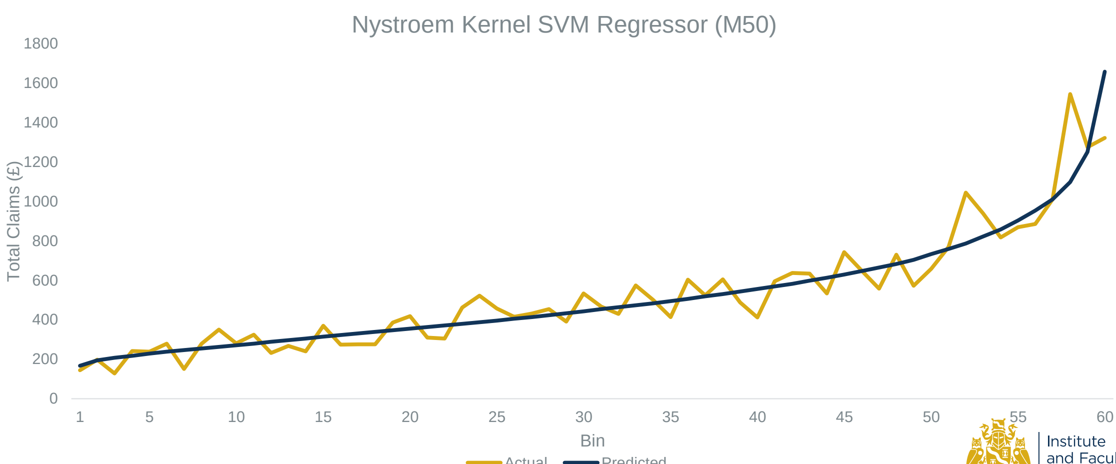
Supervised machine learning

Motor pricing hypothetical example



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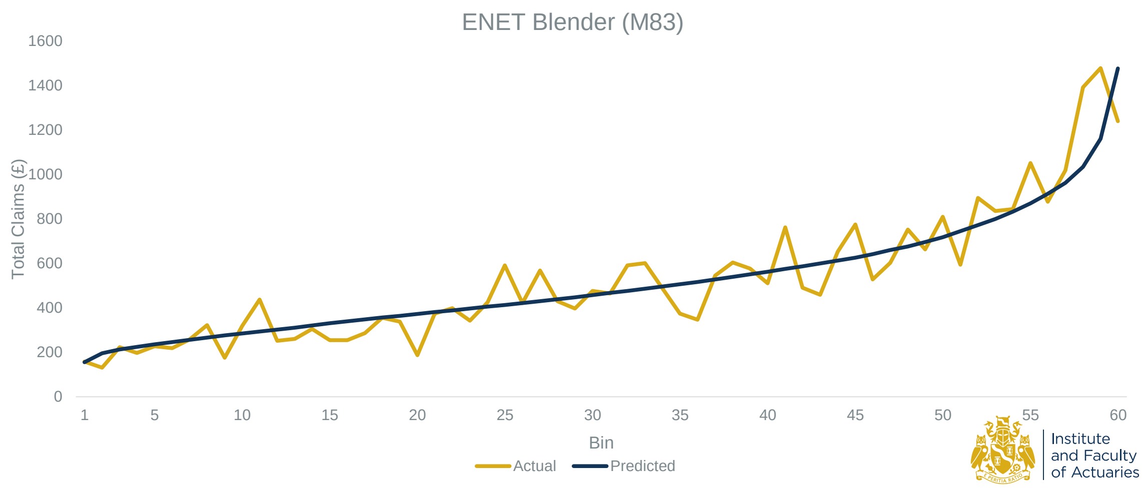
Supervised machine learning

Motor pricing hypothetical example



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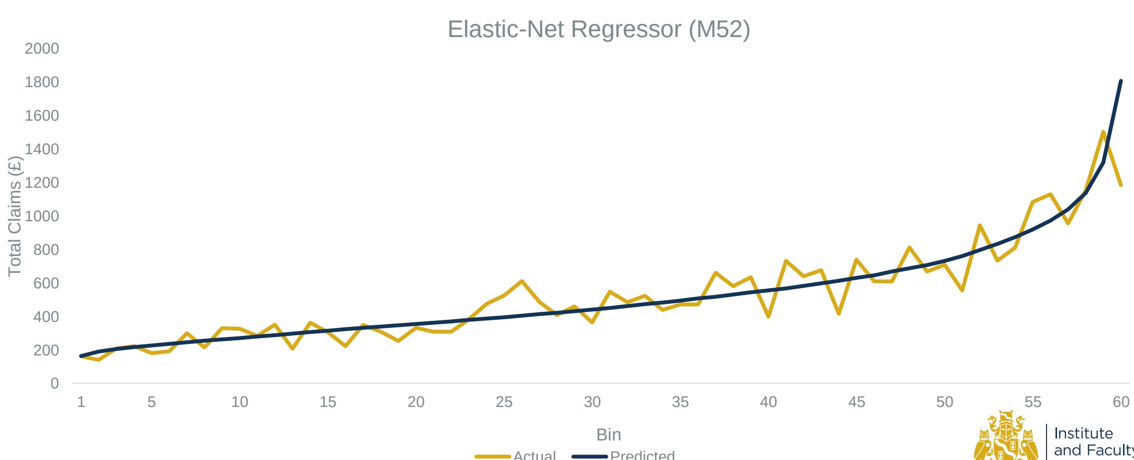
Supervised machine learning

Motor pricing hypothetical example



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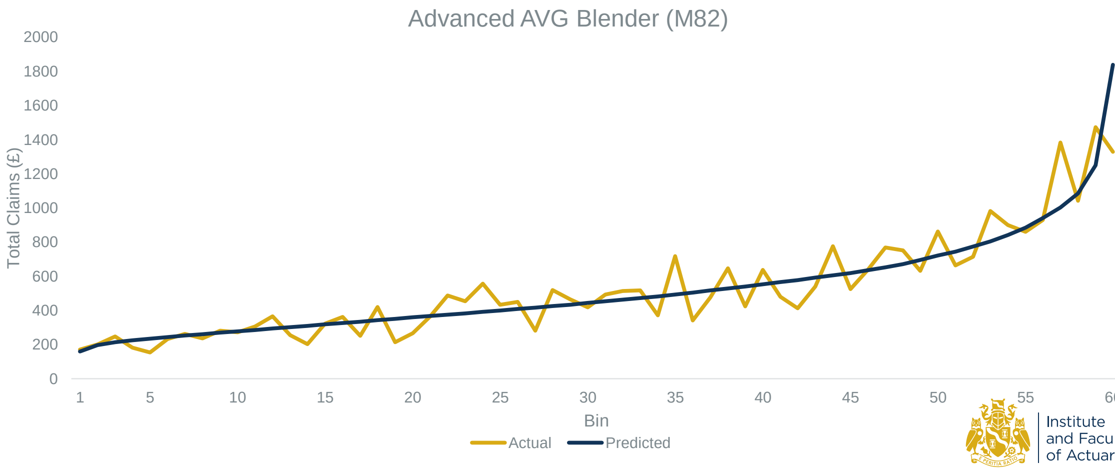
Supervised machine learning

Motor pricing hypothetical example



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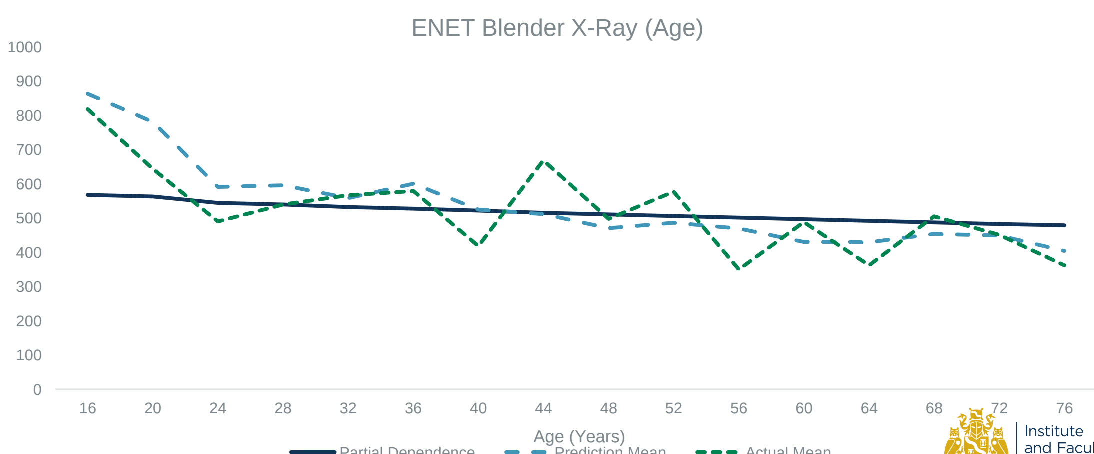
Supervised machine learning

Motor pricing hypothetical example



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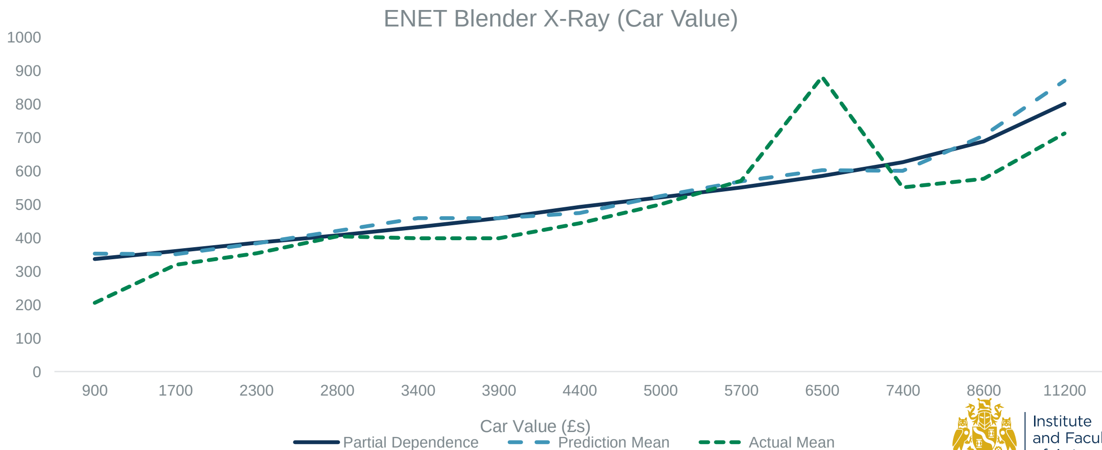
Supervised machine learning

Motor pricing hypothetical example



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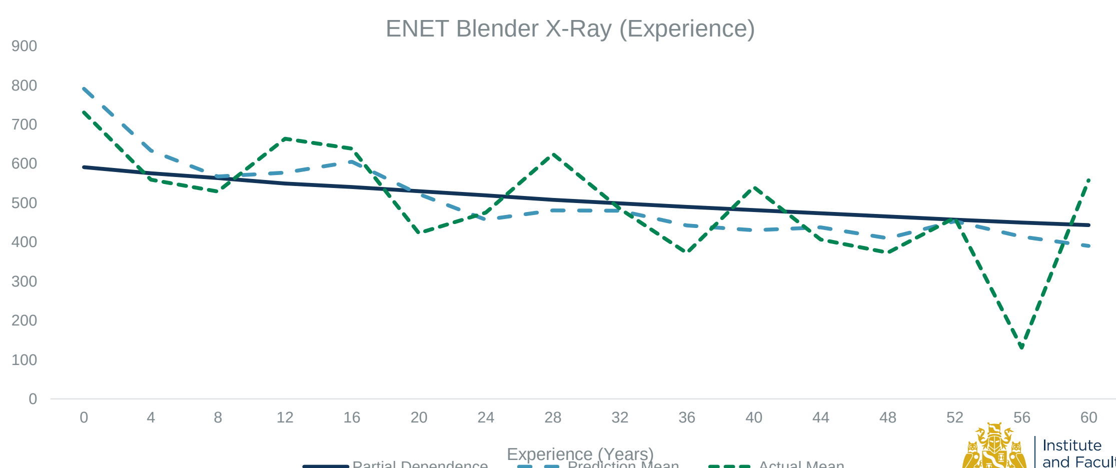
Supervised machine learning

Motor pricing hypothetical example



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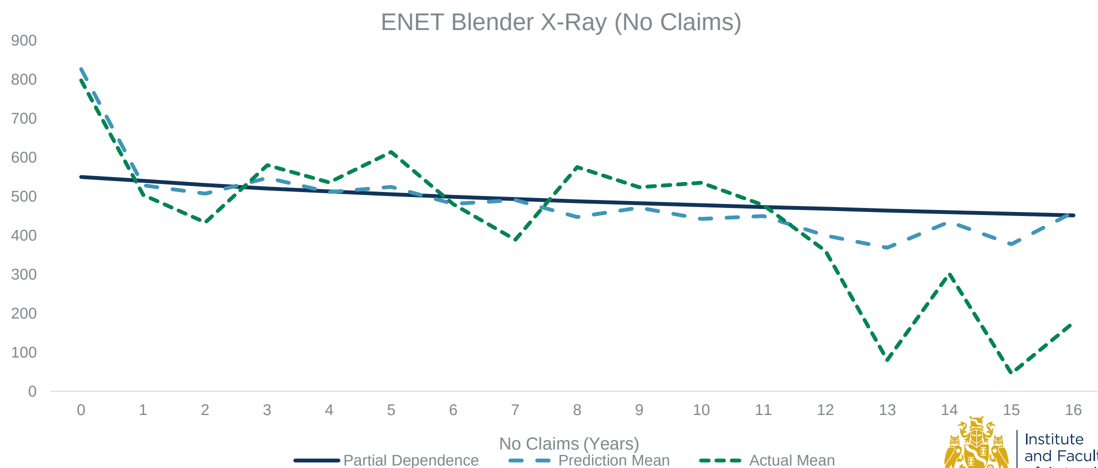
Supervised machine learning
Motor pricing hypothetical example



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Supervised machine learning
Motor pricing hypothetical example

Prediction	Reason 1 Strength	Reason 1 Feature	Reason 1 Value	Reason 2 Strength	Reason 2 Feature	Reason 2 Value	Reason 3 Strength	Reason 3 Feature	Reason 3 Value
£2964.47	+++	Car Value	£23850.67	++	Car Use	Work	+	Peak Use	True
£2592.16	+++	Car Value	£18274.63	++	Profession	Student	++	Car Use	Commute
£2452.96	+++	Car Value	£18798.30	++	Profession	Student	++	Car Use	Commute
£2343.19	+++	Car Value	£17883.02	++	Profession	Student	++	Car Use	Commute
£2197.45	+++	Car Value	£12426.50	+++	Car Use	Work	++	Profession	Student
£119.22	---	Car Value	£616.75	--	Car Use	Social	--	No Claims	13
£119.15	+++	Profession	Retired	---	Car Value	£614.23	--	No Claims	20
£106.70	---	Car Value	£733.74	--	Car Use	Social	--	No Claims	12
£71.49	---	Car Value	£654.97	++	Profession	Retired	--	No Claims	13
£64.37	---	Car Value	£316.95	--	No Claims	18	++	Profession	Retired

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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

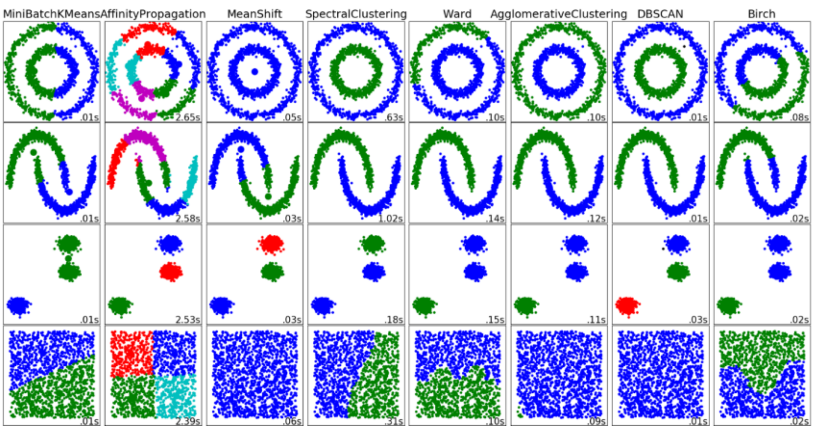
- Take granular data and convert into meaning
- For example, geocoding (postcode grouping) or telematics

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.

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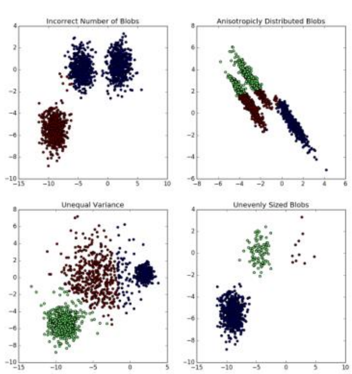
Unsupervised machine learning

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

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Unsupervised machine learning
Association rules

Examples

Market basket analysis

Cross marketing

Catalogue design

Customer analysis

Supermarket shopping

Diapers ⇒ Beer

Finding patterns from sets that frequently occur together

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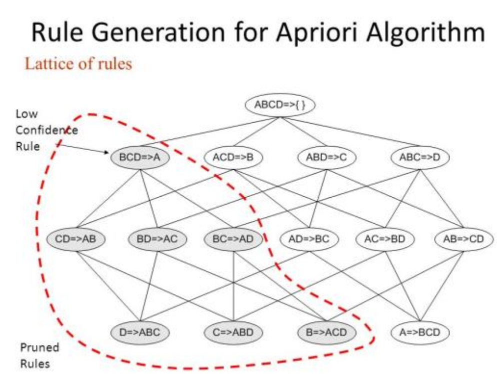
Unsupervised machine learning
Apriori algorithm

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



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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

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Broader Changes

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Blockchain

Back-end technology

Data exchange

Smart contracts

Permanent

Immutable

Decentralised (public/private)

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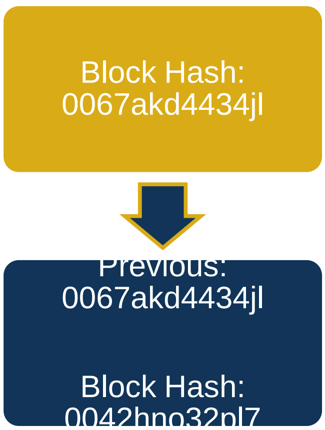
Blockchain
How it works



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

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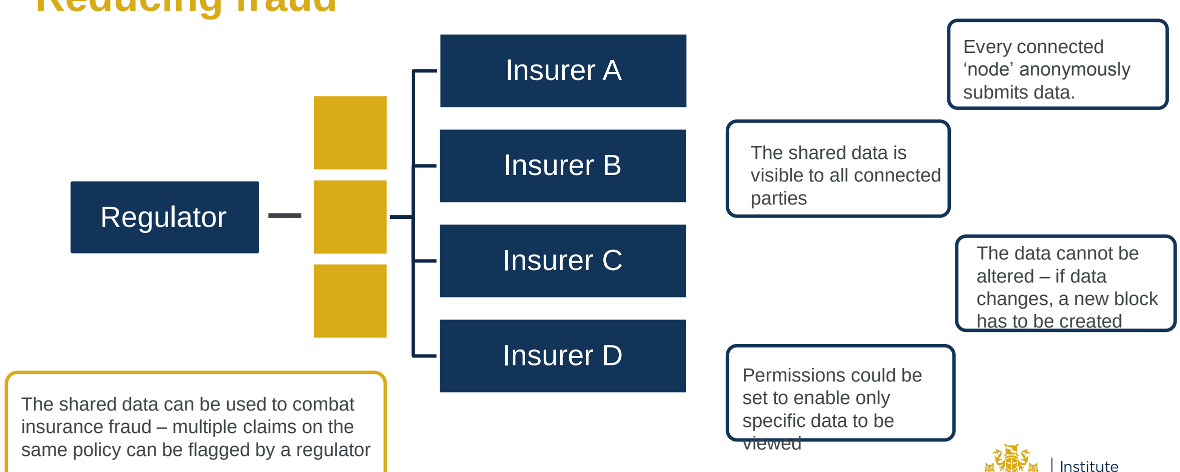
Blockchain in insurance
Reducing fraud



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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

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Blockchain

Success

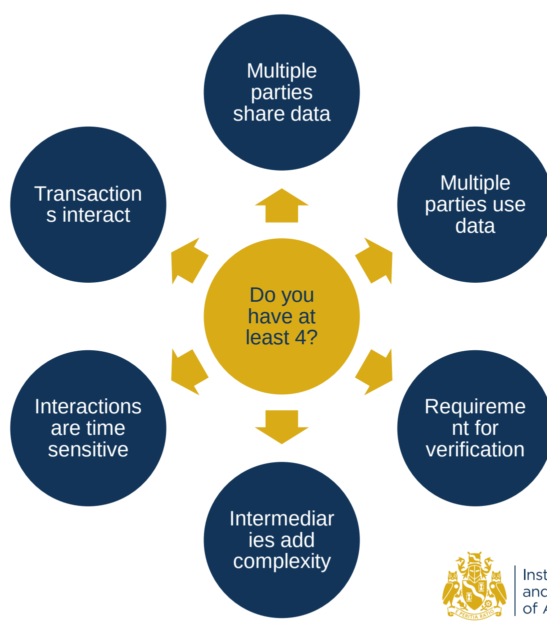
Complex technology

Many use cases

Bridging the understanding gap

Take time to test the use case

Start-ups: Blockverify, Everledger, Etherisc



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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?

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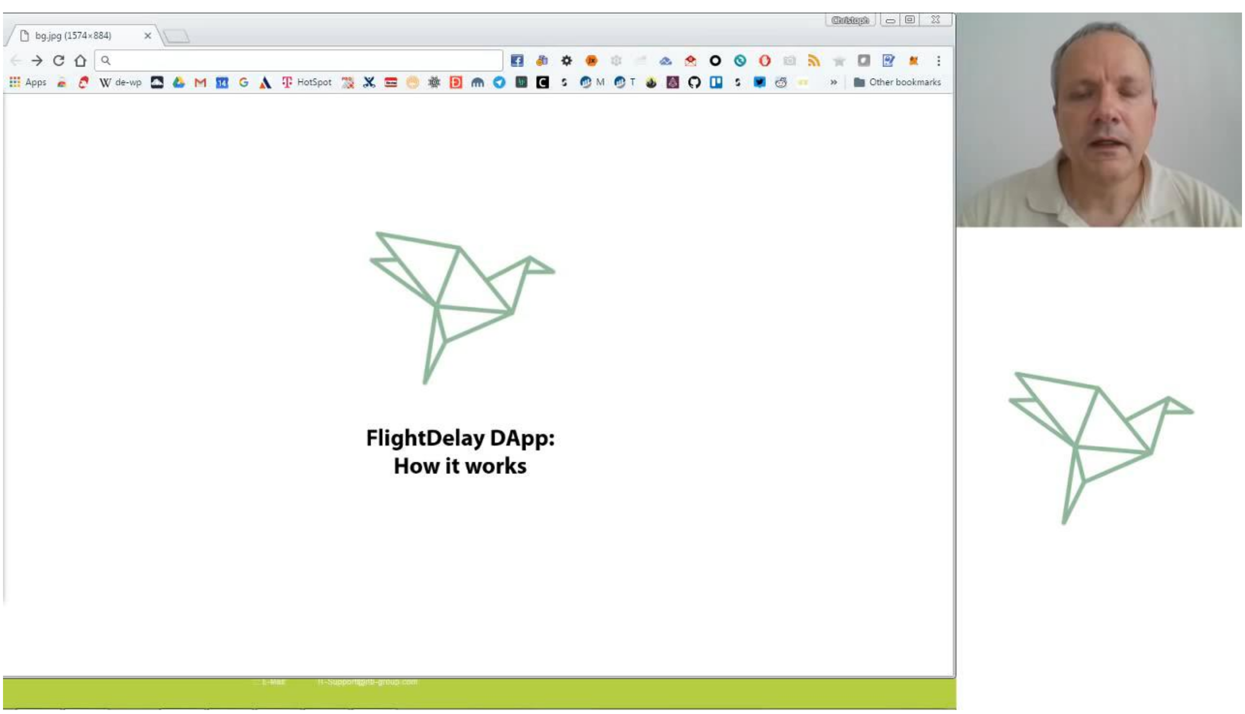

InsurTech

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
- Driven by artificial

Peer to peer

- Low cost
- Ethical insurance
- Social businesses

Amongst many other possibilities

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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?

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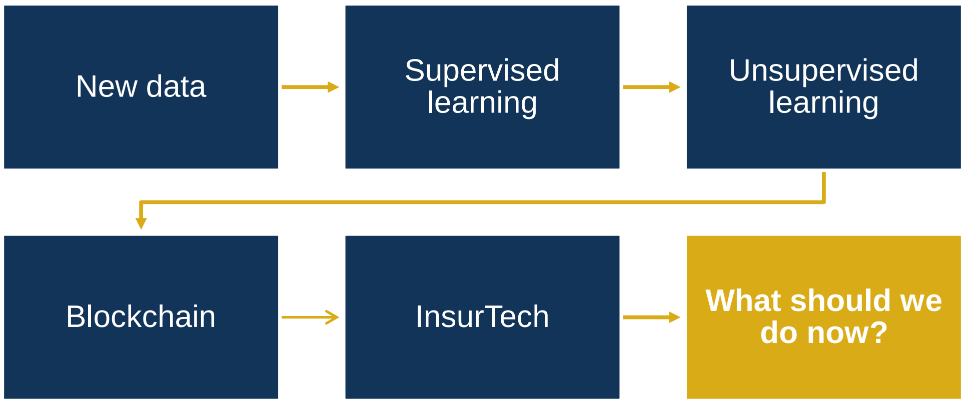
So are we all now redundant?

Summary of changes



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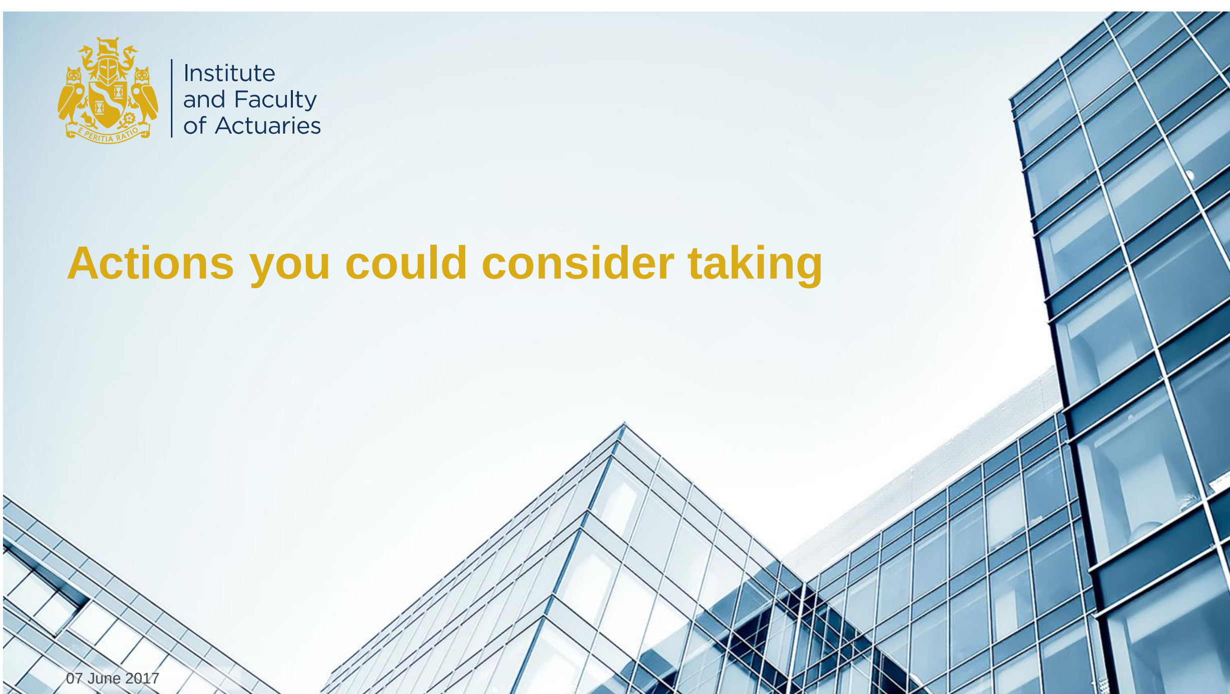

Actions you could consider taking

Test supervised learning

Develop an innovation strategy (VC unicorns?)

Data teams

Data capture

Access to resource and capability

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Contributors

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)

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Questions

Comments

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