

# Society of Actuaries in Ireland

# **Machine Learning**

### **Duncan Anderson**

**Managing Director, Willis Towers Watson** 

21 March 2018

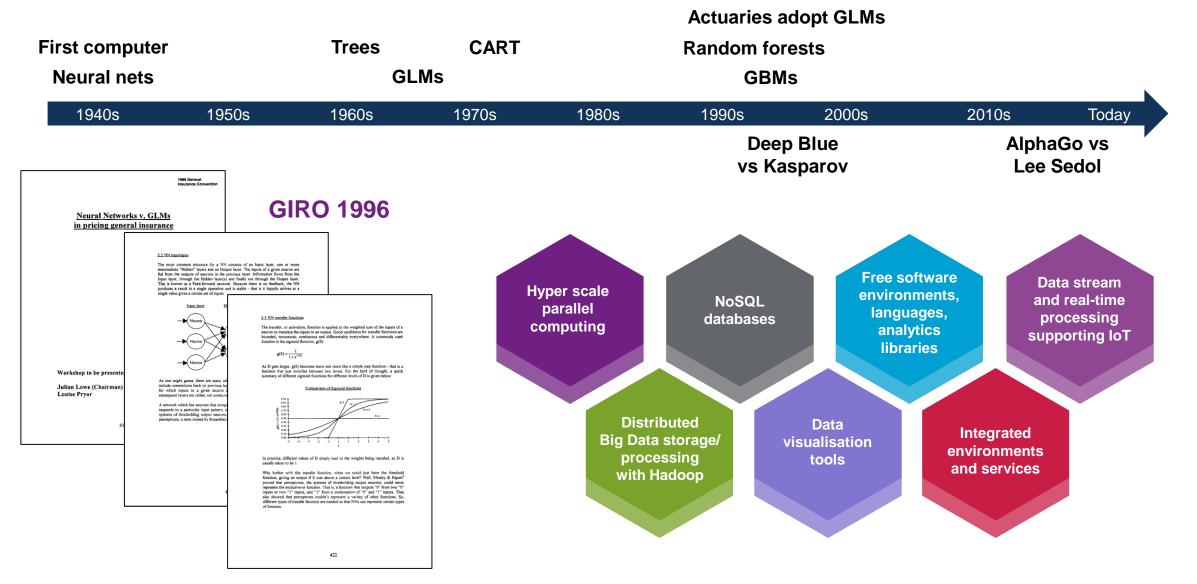
# GIRO 2016, Dublin - Response to machine learning

# Don't panic!

# We're doomed!



### This is not all new



### There is a spectrum of complexity

"Vastly more risky than North Korea"

GLM stepwise macro

Al comprehension Bespoke image recognition Speech analytics Machine learning predive modelling Full autonomous driving Object recognition Topic modelling Automated GLMs



Hard
Evolving
Requires significant expertise



Not at all hard
Already in use
Existing teams can normally do this stuff

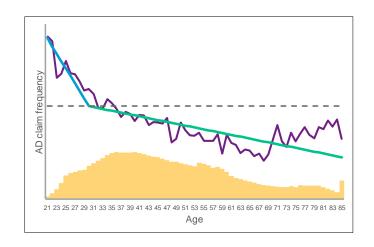
# **Example machine learning methods**

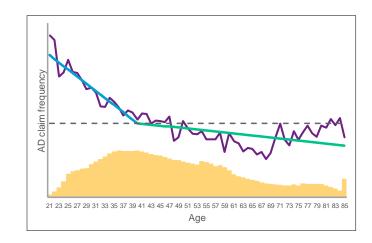
Gradient Ensemble Classifications K-Means "Earth" Boosting Methods Clustering Trees **Machines** Support Vector Naïve Bayes **Neural Networks Elastic Net** Random Forests Machines Principal K-nearest Regression Ridge Components Lasso Neighbours Regression Trees Analysis

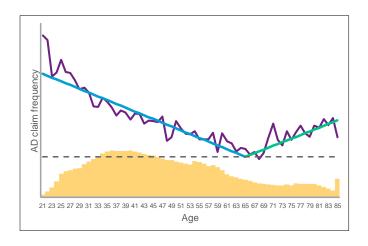
## **Example machine learning methods**

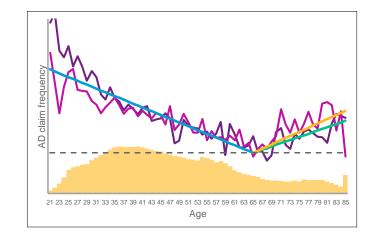
"Earth" **Elastic Net** Ridge Lasso Regression

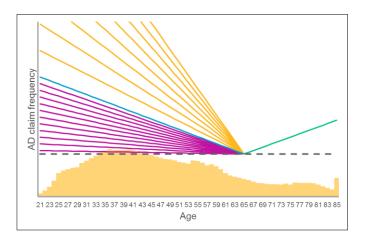
# Multivariate adaptive regression splines ("Earth")





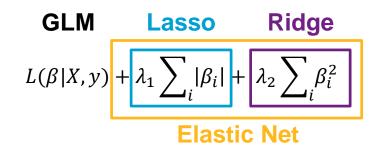


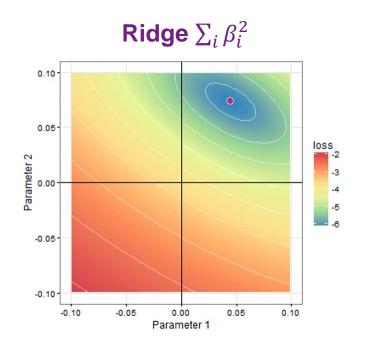




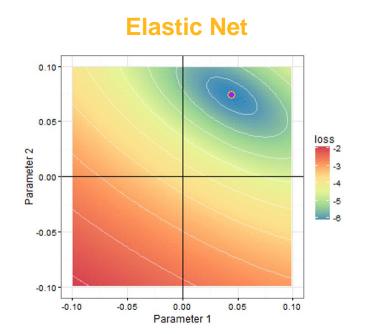
### **Penalised Regression**

 $f(\underline{x}) = g^{-1}(\mathbf{X}.\underline{\beta})$  where  $\underline{\beta}$  estimated by minimising

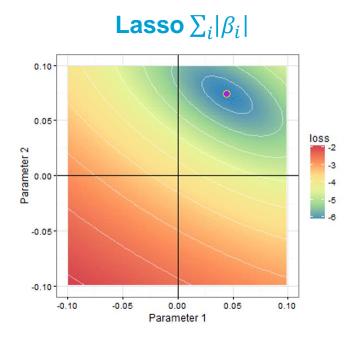




Heavily penalises large parameters, but does not reduce parameters to zero



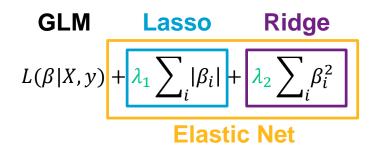
Mix of the two



Penalty reduces insignificant parameter values to zero - useful for variable selection

# **Penalised Regression**

 $f(\underline{x}) = g^{-1}(\mathbf{X}.\underline{\beta})$  where  $\underline{\beta}$  estimated by minimising



1	2	3	4	5
Fit	Fit	Fit	Fit	Test
Fit	Fit	Fit	Test	Fit
Fit	Fit	Test	Fit	Fit
Fit	Test	Fit	Fit	Fit
Test	Fit	Fit	Fit	Fit
Holdout	Holdout	Holdout	Holdout	Holdout

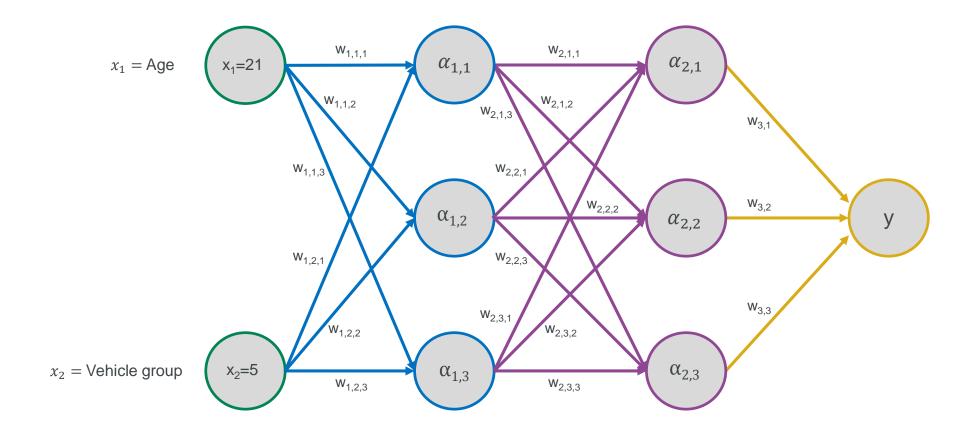
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# **Example machine learning methods**

**Neural Networks** 

### **Neural networks**



# Neural networks - some assumptions required!

# Input layer

913 nodes; one-hot encoding;  $"\le x"$  indicators

### Dropout

No dropout applied

# Hidden layers

1 hidden layer; 50 nodes; fully connected

# Output layer

1 node; output log(premium); minimise RMSE

# Optimisation algorithm

Adam

## **Epochs**

Trained 1,000 epochs with cross validation and early stopping

# Learning rate

Start at 0.001; decay to 0 over model training

# Batch size

1% of training data

# Regularisation

L1 penalty with  $\alpha$  = 1E-6

# Initial weights

Randomly distributed – Glorot Uniform

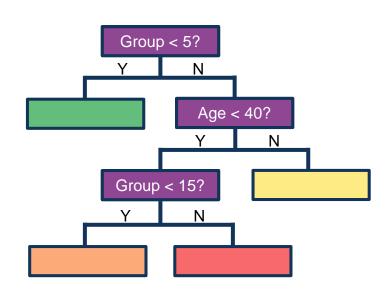
# Activation functions

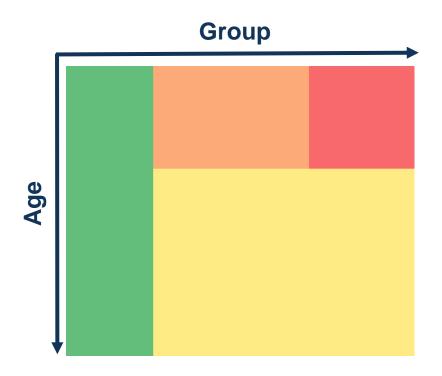
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# **Example machine learning methods**

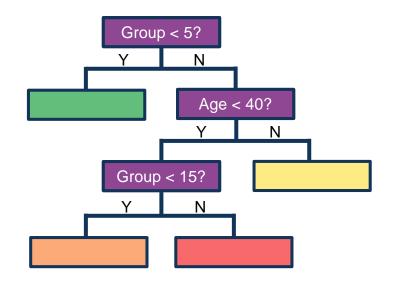
Gradient Classifications Boosting Trees Machines Random Forests Regression Trees

### **Decision trees**





### **Random Forests**

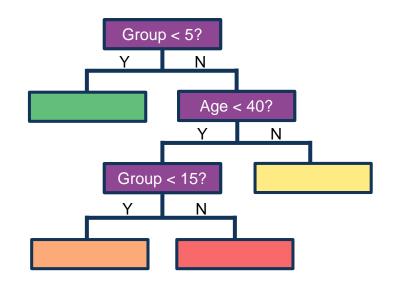


### A random forest

$$f(x) = \frac{1}{N} \sum_{n=1}^{N} f_n(x)$$

$$\frac{1}{N}$$

### **Gradient Boosted Machine or "GBM"**



### **A GBM**

$$f(x) = \lambda \sum_{n=1}^{N} f_n(x)$$

$$\lambda + \lambda + \lambda + \lambda + \lambda + \lambda + \lambda + \lambda$$

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### **Gradient Boosted Machine or "GBM"**

λ

(learning rate or "shrinkage")

N

(number of trees)

Bag fraction

(proportion of data used at each iteration)

Interaction depth (number of splits on each tree)

### **A GBM**

$$f(x) = \lambda \sum_{n=1}^{N} f_n(x)$$

$$\lambda + \lambda + \lambda + \lambda + \lambda + \lambda + \lambda$$

$$\lambda + \lambda + \lambda + \lambda + \lambda$$

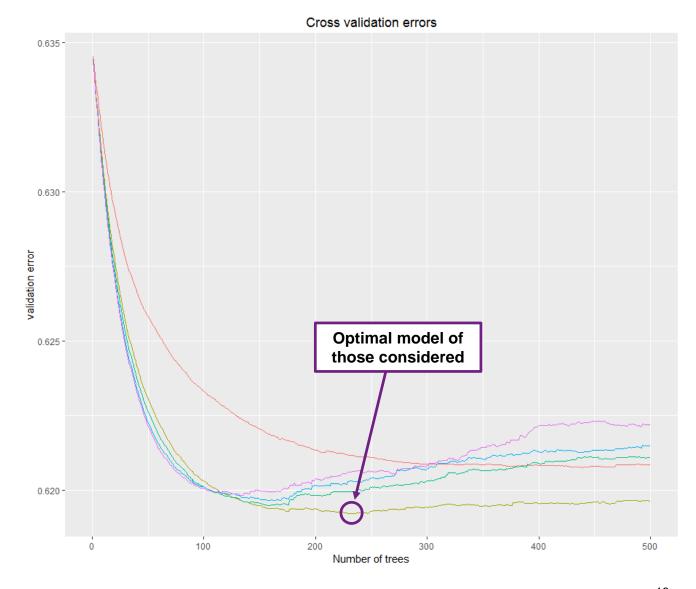
### **Gradient Boosted Machine or "GBM"**

λ (learning rate or "shrinkage")

N (number of trees)

Bag fraction (proportion of data used at each iteration)

Interaction depth (number of splits on each tree)



# **Example machine learning methods**

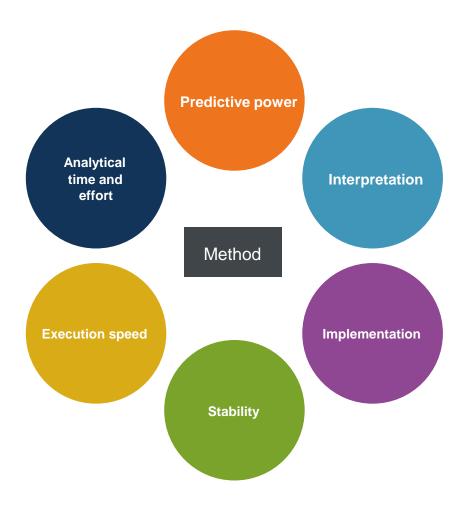
Ensemble Methods

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# Do they add value?

Gradient Ensemble Classifications K-Means "Earth" Boosting Methods Clustering Trees Machines Support Vector Naïve Bayes **Elastic Net Neural Networks** Random Forests Machines Principal K-nearest Regression Ridge Components Lasso Neighbours Trees Regression Analysis





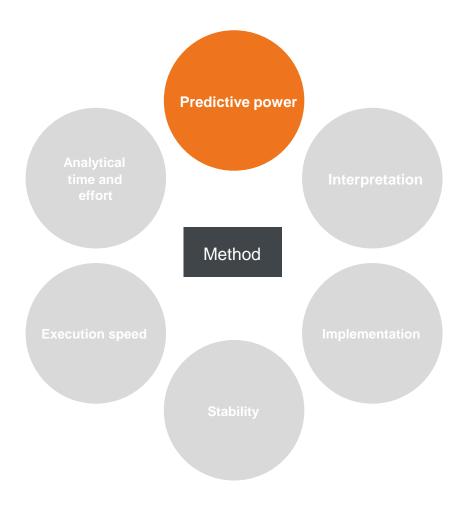
- Data Gain Curve

  100

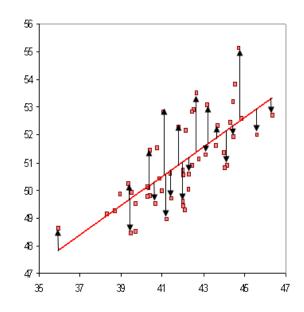
  Ginl

  0.7215
  - Think of a model...
  - Multiply it by 123
  - Square it
  - Add 74½ billion

...and you get the same Gini coefficient!

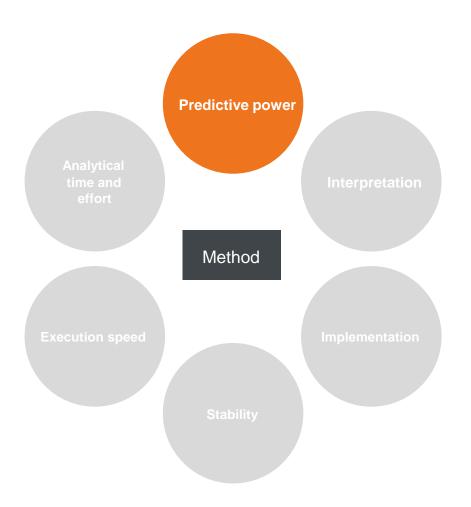


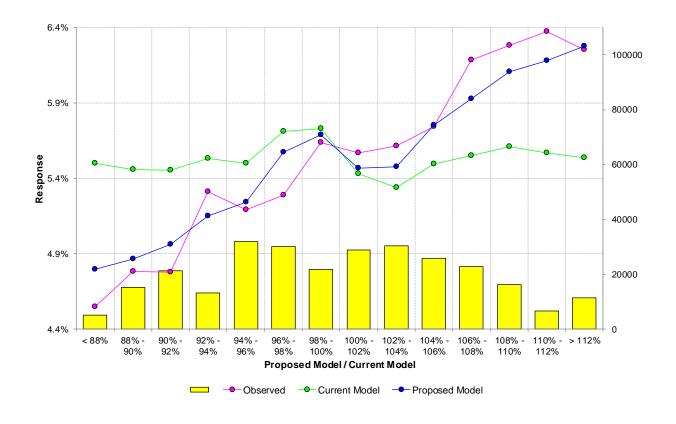


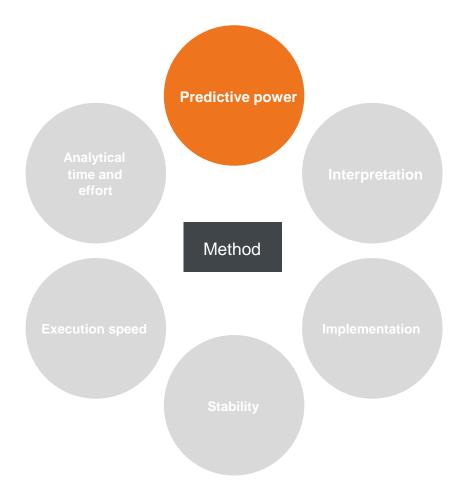


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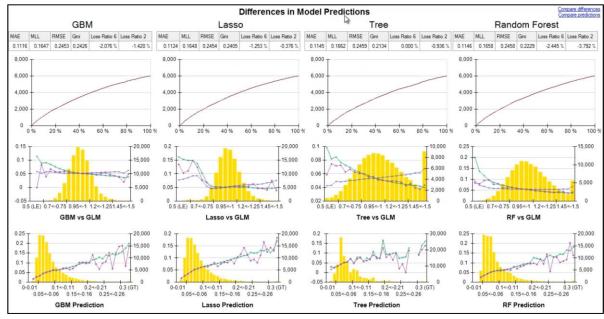
Model	RMS Error
GLM	34.7%
Neural Net	33.1%
GBM	31.0%



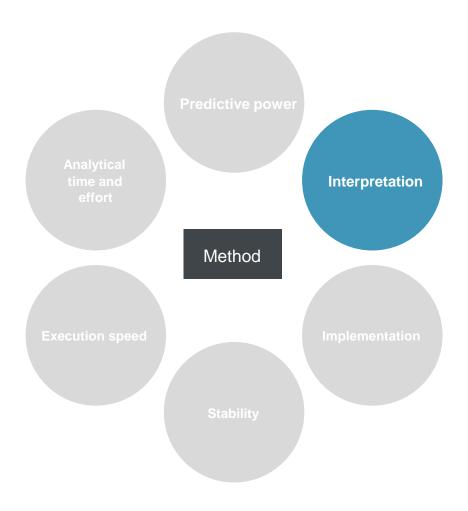


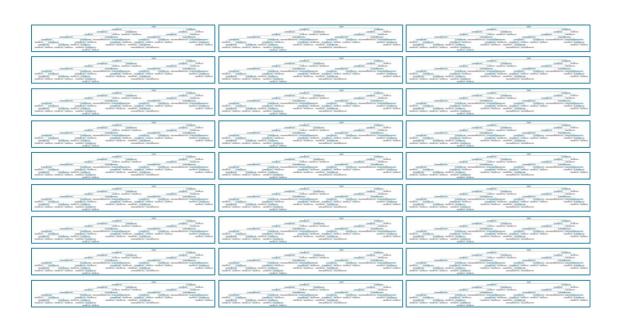




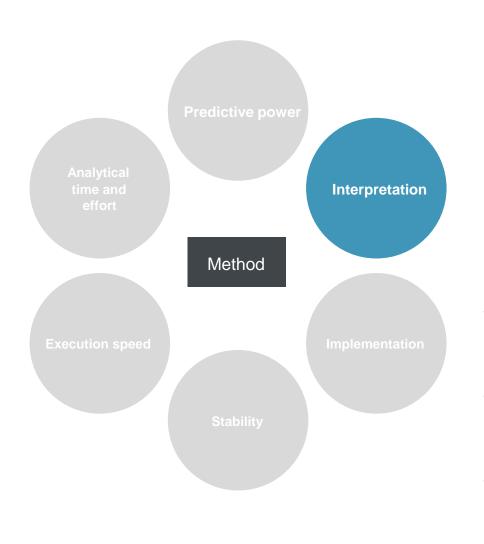


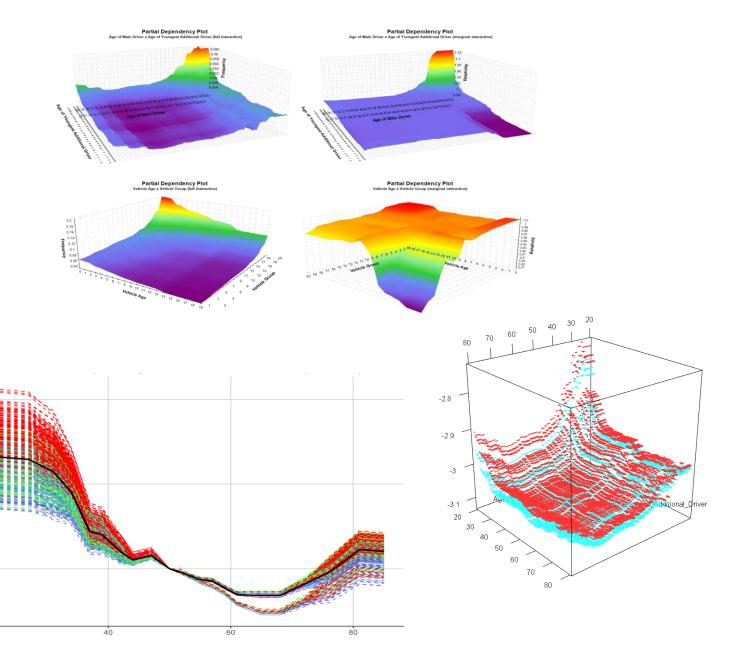
Loss ratio improvement 3.1%!

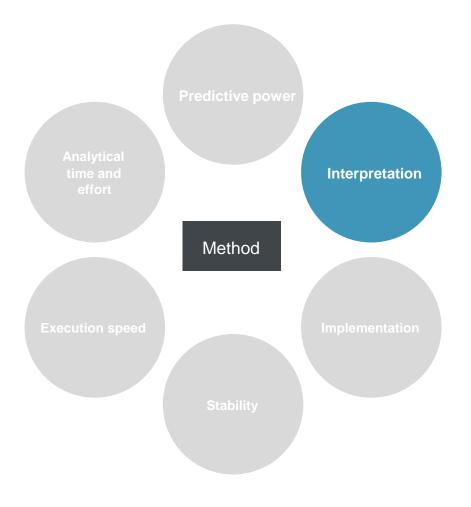




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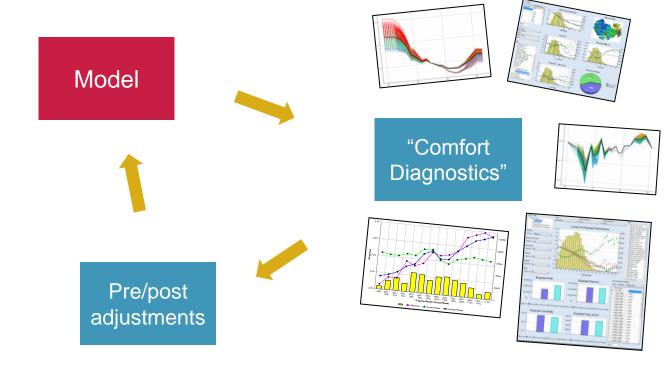


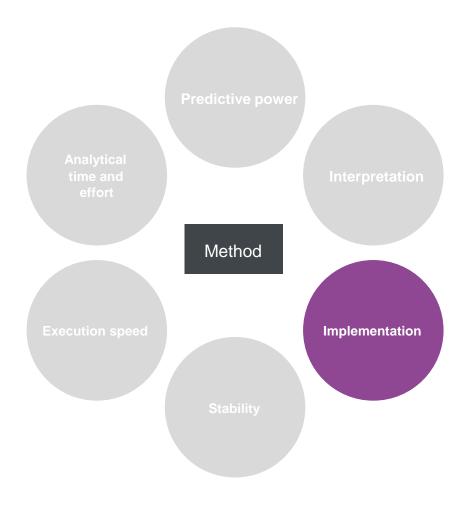




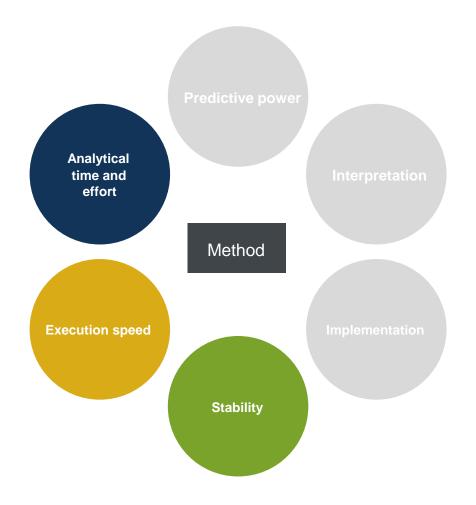
- How much do you need to understand?
  - How much would you normally understand? (eg vehicle classification)
  - Cost of error? (eg marketing)
  - Regulatory requirements
  - Professional standards

### "Comfort diagnostics"

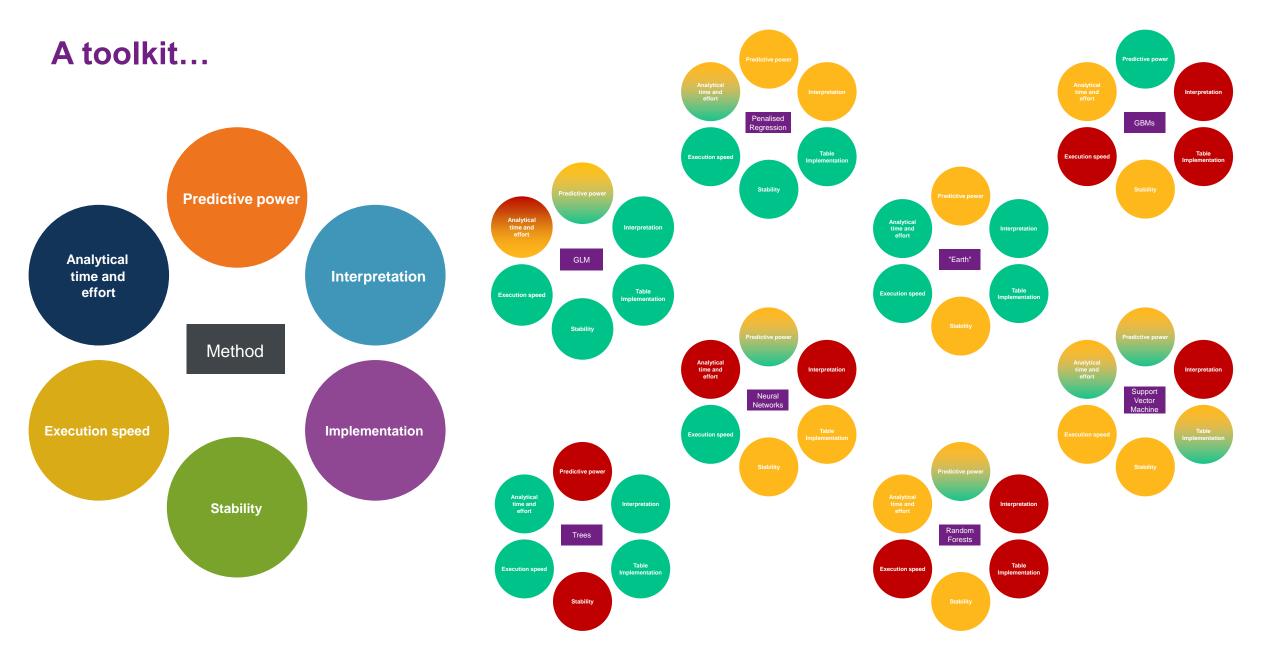




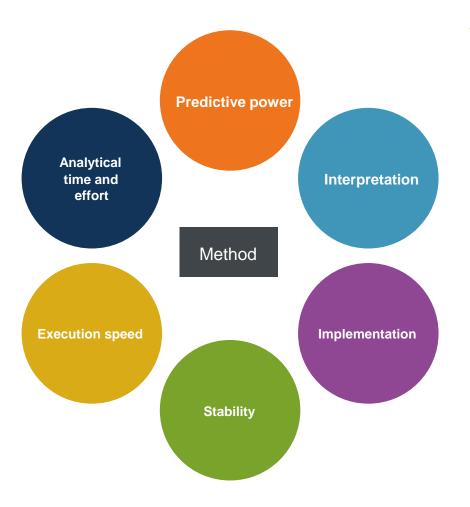








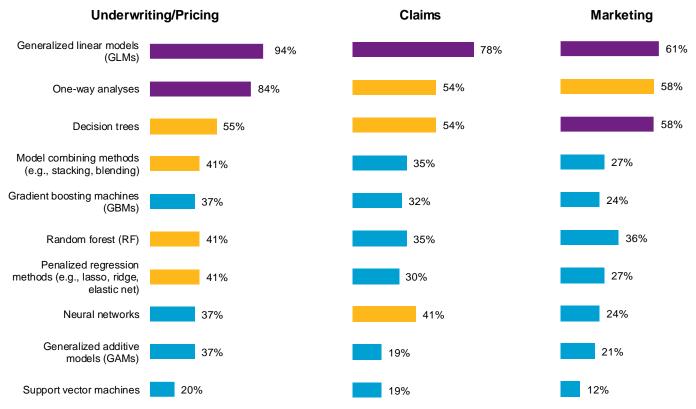
### That is already in use...





### 2017 US market survey

For which business applications do you use or plan to use these methods?



Willis Towers Watson Predictive Modeling Survey 2017

### That spectrum of complexity

# Happening now



Al comprehension Bespoke image recognition Speech analytics Machine learning predive modelling Full autonomous driving Object recognition Topic modelling Automated GLMs



This end could be interesting...



#### 1\_Ferrari.jpg

#### ferrari 24.15 %

nissan 13.55 % jaguar 10.12 % mclaren 7.32 %

ford 6.14 % Elapsed: 2968





#### 2\_Ford.jpg

#### ford 79.46 %

dodge 6.30 %

chevrolet 5.08 %

am 2.15 % gmc 1.81 %

Elapsed: 1422



### 3\_LandRover.jpg

#### land 64.69 %

jeep 21.45 %

mazda 4.73 %

am 1.89 %

toyota 0.84 %

Elapsed: 1391



#### 4\_Mini.jpg

#### mini 68.86 %

chrysler 7.02 %

spyker 5.95 %

bmw 5.16 %

aston 3.39 %

Elapsed: 1390



#### 09\_Volkswagen.jpg

#### volkswagen 21.89 %

suzuki 12.35 %

acura 9.27 %

gmc 7.50 %

cadillac 7.09 %

Elapsed: 1406



#### 5 Tesla.jpg

#### tesla 20.04 %

porsche 18.24 % jaguar 8.88 %

lamborghini 6.47 %

honda 5.27 %

Elapsed: 1359



#### 6\_Ford.jpg

#### ford 22.99 %

honda 21.39 %

suzuki 10.98 %

hyundai 9.37 %

cadillac 8.37 %

Elapsed: 1390



#### 7 Mini.jpg

#### mini 64.58 %

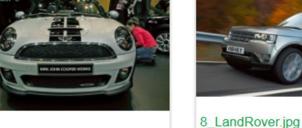
**chrysler** 15.28 %

buick 2.64 %

infiniti 2.01 %

ford 1.94 %

Elapsed: 1500



#### land 63.36 %

audi 6.88 %

volvo 6.02 %

bmw 6.01 %

bentley 4.64 %

Elapsed: 1375



#### 10 Mitsubishi.jpg

#### mitsubishi 33.07 %

chrysler 13.51 %

toyota 12.34 %

acura 7.06 %

buick 5.92 %

Elapsed: 1406





So...

Machine learning is already in use

**Actuaries are already involved** 

It's not just about methods

**Data beats models** 

It's not just about methods

Working out what to model matters - Data beats factor engineering beats models

It's not just about predictiveness

A broader set of problems can be analysed - rapid basic insight adds value

**Evolution not revolution** 

Models are complementary to existing methods

## Issues for the Profession(s)

### Role of the actuary

- Domain expertise matters (at least currently)
- Easier for an actuary to pick up machine learning than for a data scientist to understand insurance?
- Siloed teams don't work
- Familiarity and the right vernacular can help
- Scope of involvement?
   Pricing ✓ Reserving ✓ Claims analytics ✓
   Customer management? Marketing???

### **Training**

- A generation less familiar with stats?
- CAS, SOA ahead? (eg CSPA)
- GIRO too big now to help?
- IFoA on the case, but fast enough?

### Regulatory issues

- TAS: Judgement what judgement?
- GDPR
- Government Select Committee (Science and Technology)



# Society of Actuaries in Ireland

# **Machine Learning**

### **Duncan Anderson**

**Managing Director, Willis Towers Watson** 

21 March 2018