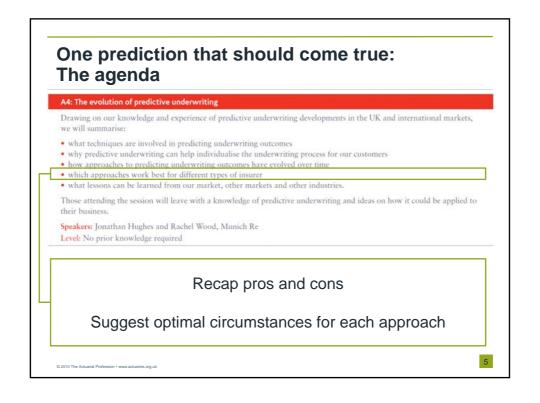
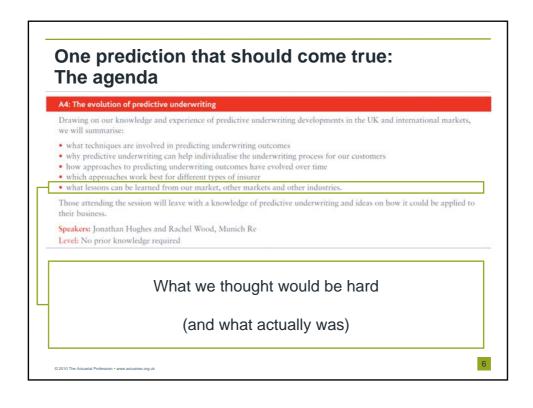
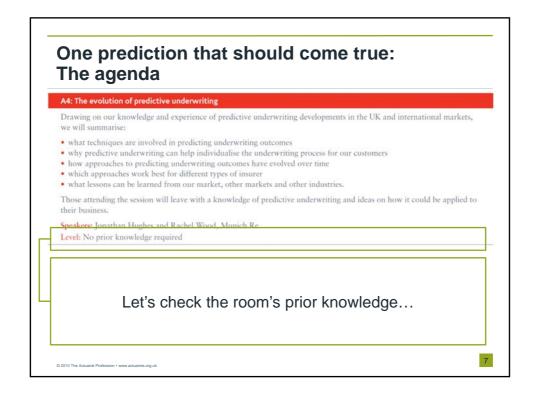


# One prediction that should come true: The agenda A4: The evolution of predictive underwriting Drawing on our knowledge and experience of predictive underwriting developments in the UK and international markets, we will summarise: • what techniques are involved in predicting underwriting outcomes • why predictive underwriting can help individualise the underwriting process for our customers • how approaches to predicting underwriting outcomes have evolved over time • which approaches work best for different types of insurer • what lessons can be learned from our market, other markets and other industries. Those attending the session will leave with a knowledge of predictive underwriting and ideas on how it could be applied to their business. Speakers: Jonathan Hughes and Rachel Wood, Munich Re Level: No prior knowledge required A simple approach from 10 years ago A more recent example The next stage of evolution





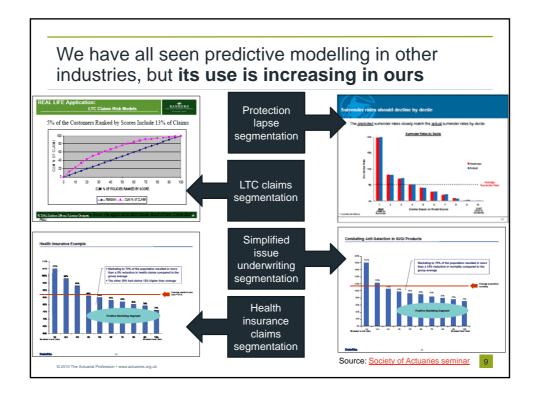


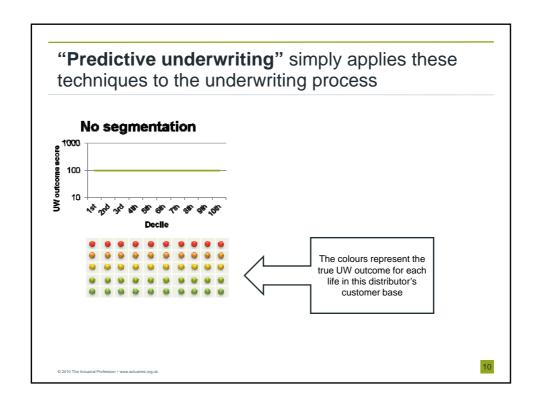
The Actuarial Profession making financial sense of the future

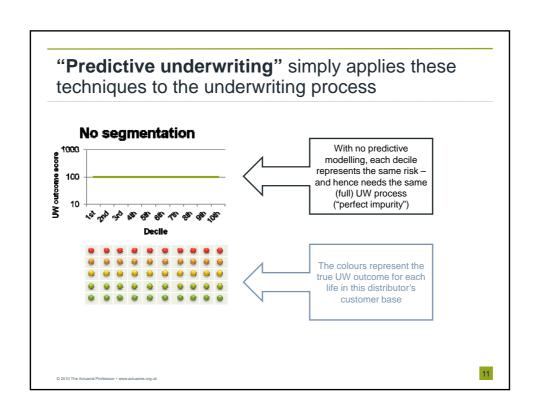
What techniques are involved in predicting underwriting outcomes

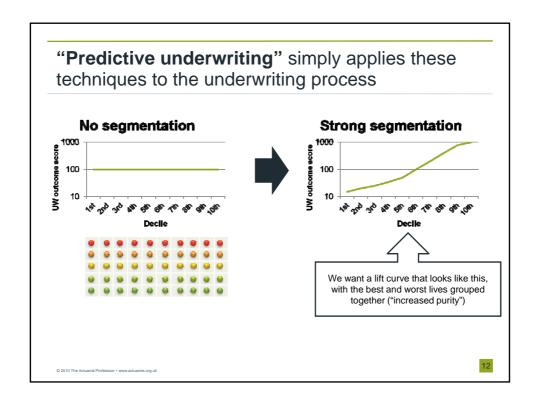
Fundamental result of a predictive underwriting exercise

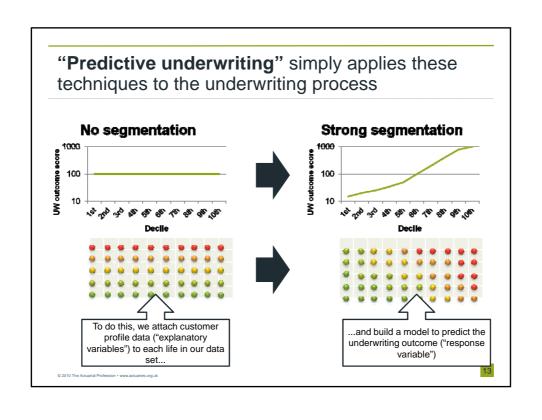
A non-technical summary of modelling approaches

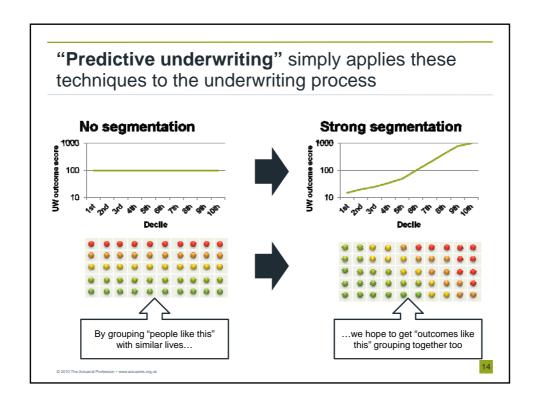


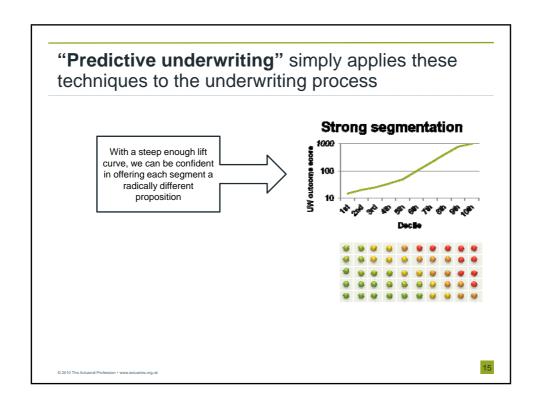


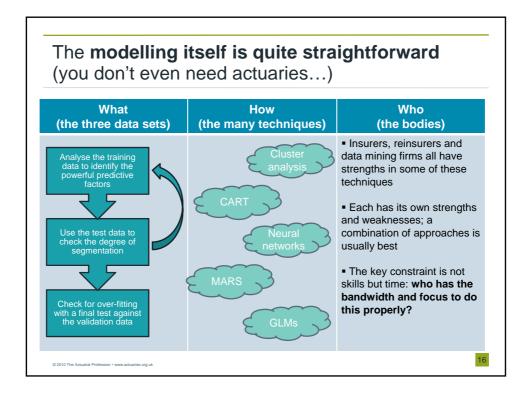


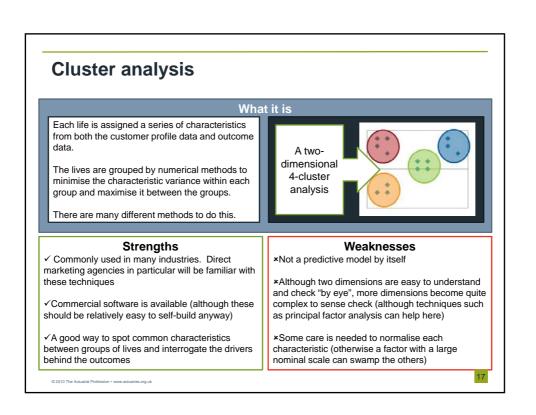












### **CART**

(Classification and regression trees)

What it i

The aim is to maximise the "purity" of each segment.

Start by finding the one "cut" you can make to the data that yields the most increase in purity (e.g. split by gender).

Then look at each segment in turn and keep cutting (e.g. split into under and over 40s).

### Weaknesses

- Strengths
  ✓ Simpler than MARS (equivalent to using a step function instead of "hockey sticks")
- ✓Like MARS, cross-validation is part of the process, ensuring you don't "over cut"
- ✓ Easy to understand (although the maths determining when to stop cutting is a bit trickier)
- √Gives clear decision rules for segmentation

Gives cicai accision raics i

- Does not always yield the optimal split (although adjustments to the approach can be made to improve this)
- \*Less flexible than MARS
- \*Although good for data exploration, it does not yield by itself a predictive model

1

### MARS

(Multivariate adaptive regression splines)

What it is

MARS is a linear collection of "hockey stick" functions plus their interactions.

In essence, you start by drawing a straight line. Where it diverges from the data, you add a new line

Overfit the data, then prune it back until you have the best fit.

## TICIS

### Strengths

- ✓ Like CART, cross-validation is a part of the modelling process, ensuring you don't add too many "knots"
- $\checkmark \text{Provides a finer segmentation than, say, decision tree approaches}$
- ✓ Generally faster to build and implement than, say, neural nets

### Weaknesses

- $\ensuremath{\mathbf{x}}$  Simple MARS models can actually be equivalent to GLMs
- \*Actuaries are generally less familiar with these techniques => harder to build and maintain an analytical capability

D 2010 The Actuarial Profession • www.actuaries.org.u

19

### **Neural networks**

### What it is

A neural network models Y as a non-line; function of X.

The "input layer" represents X<sub>1</sub>, X<sub>2</sub>, etc.

The "output layer" represents Y.

The connections between each node transform the incoming signal.

### In essence, the model is specified by the layer architecture and associated weights: Input layer Hidden layer Output layer

### Strengths

- ✓ Very flexible: can be designed to mimic pretty much any non-linear function
- ✓ Better than decision trees for continuous
- √ No need to assume linearity on the link function scale (unlike GLMs)

© 2010 The Actuarial Profession • www.actuaries.org.u

### Weaknesses

- Often considered a black box (although this need not actually be the case)
- \* Although there is some decent software out there, it less commonly used by actuaries, who are more familiar with GLMs
- ★ Since a logit GLM actually closely resembles a neural net in some instances, we tend to prefer GLMs

2

GLMs

(Generalised linear models)

### What it is

Choose a response variable and look at your data to quantify the impact of each potential explanatory variable on the response.

You specify a model and then solve for the coefficients to minimise the error.

The model outputs the impact each explanatory variable has on the response.

## it is

### Strengths

- √ Relaxes many of the linearity assumptions of classic regression – can use any member of the exponential family of distributions
- ✓ Excels at stripping out mix of business effects to quantify the true underlying variable
- √Commonly used among actuaries, with good commercial software available => generally the technique with the lowest overhead

### Weaknesses

- **×** Becomes unwieldy with large numbers of interactions between variables
- \*The user specifies in advance the model structure (although there are ways to test appropriateness)
- \*Still requires linearity in the link function, so not as flexible / universal as, say, neural nets (although GLMs can be extended with techniques such as GAMs etc)

© 2010 The Actuarial Profession • www.actuaries.org.u

21

