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Predictive Modelling
Not just an underwriting tool

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Predictive Modelling - Agenda

- Predictive Modelling
  - High level overview
- Some uses:
  - Lapse propensity
  - Geodemographics
  - Business mixes

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Predictive Modelling – How does it work?

Take data where you know results

Build a model to fit

Use model to predict unknown results

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Predictive Modelling in General Insurance

Personal

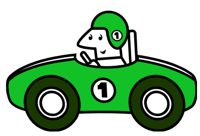
- Driving history
- Type of car
- Age
- Gender
- Marital status
- Address
- etc

Internal data

Credit score

- Length credit history
- Payment history
- Debts
- etc

External data



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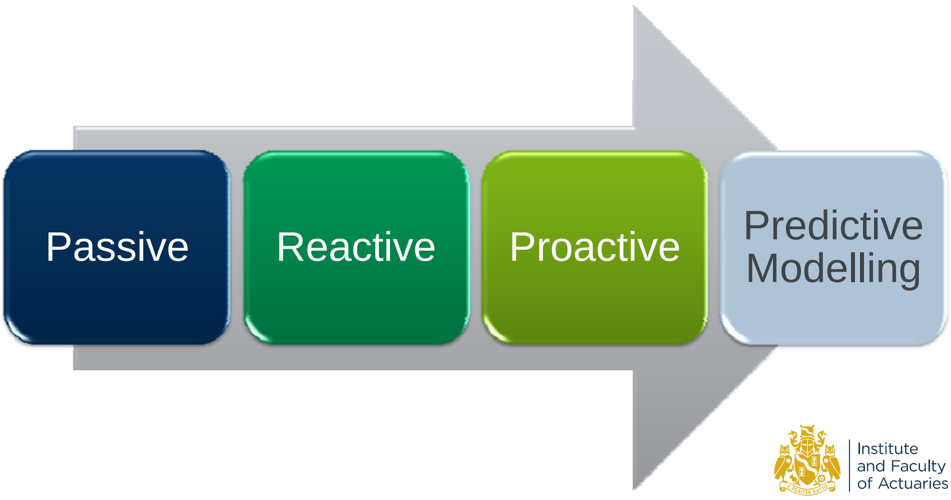
Retention Modelling

Retention Strategies



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Retention – Case Study

- UK bancassurer
- Large block of life and CI business
- Lapses modelled
  - Understand drivers
  - Target likely lapsers
- Lots of lapses
  - Good for predictive modelling
- Approx 200,000 policies
- 244 different fields of data
  - Policy + Banking

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Some General Principles

Try and identify main variables & eliminate what you don't need

Produce model using single variables, eliminate non-significant

Produce model with interactions

Check fit and refine variables if necessary

Produce model, refine etc

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Step 1

- Try and identify main variables & eliminate what you don't need
- Produce model using single variables, eliminate non-significant
- Produce model with interactions
- Check fit and refine variables if necessary
- Produce model, refine etc

First name

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Step 2

- Try and identify main variables & eliminate what you don't need
- Produce model using single variables, eliminate non-significant
- Produce model with interactions
- Check fit and refine variables if necessary
- Produce model, refine etc

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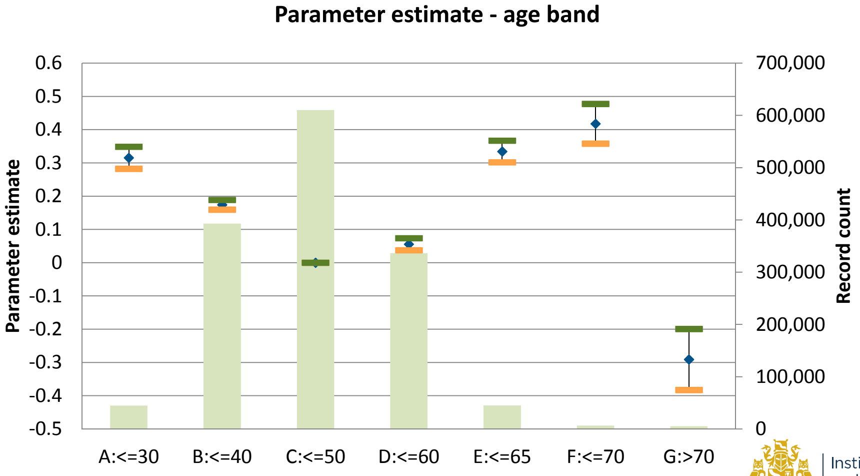
Example - Age band (Significant)



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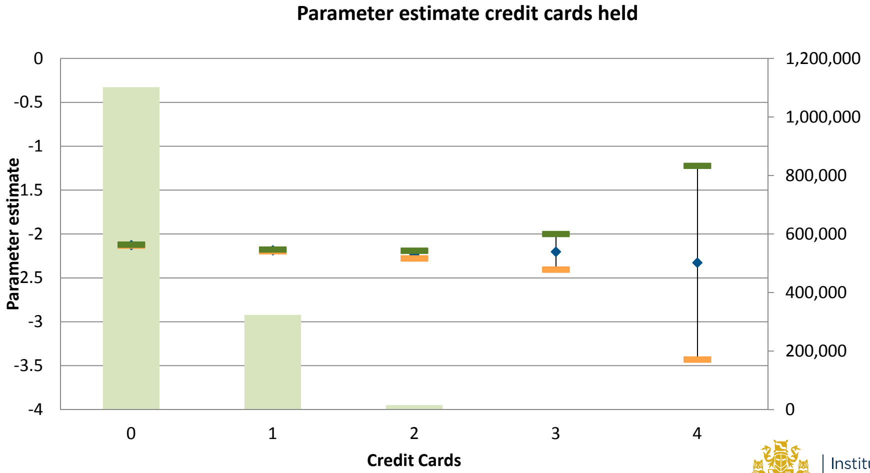
Example – Credit Card Holdings (not significant)



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Step 3

- Try and identify main variables & eliminate what you don't need
- Produce model using single variables, eliminate non-significant
- Produce model with interactions
- Check fit and refine variables if necessary
- Produce model, refine etc

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Interactions – Lapse Example

	Lapse Rate
Males	13%
Females	12%

	Lapse Rate
Non-Smokers	12.5%
Smokers	12.5%

	Lapse Rate
Male non-smokers	15%
Male smokers	5%
Female non-smokers	10%
Female smokers	20%

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Step 4

- Try and identify main variables & eliminate what you don’t need
- Produce model using single variables, eliminate non-significant
- Produce model with interactions (NB need example)
- Check fit and refine variables if necessary
- Produce model, refine etc

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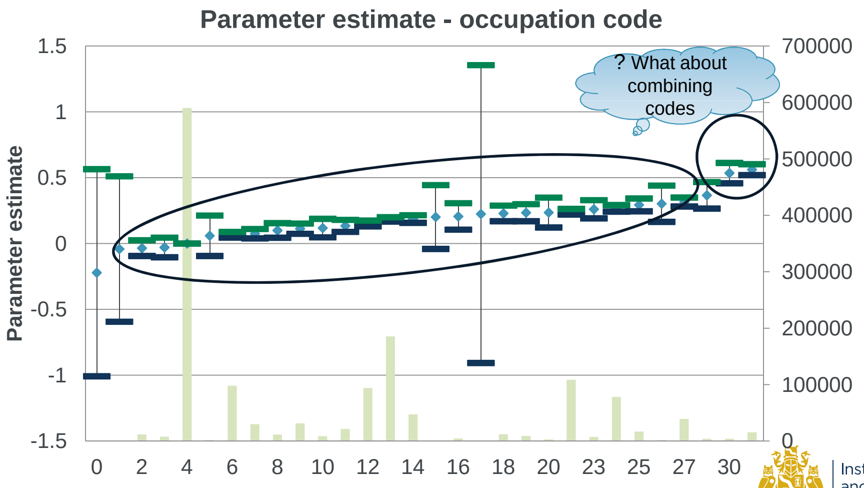
Example - Occupation code



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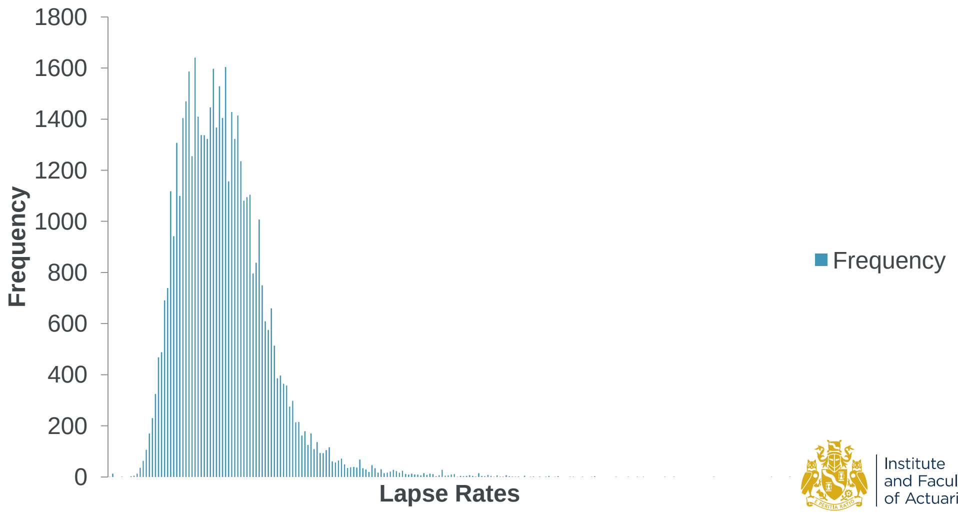
Step 5

- Try and identify main variables & eliminate what you don't need
- Produce model using single variables, eliminate non-significant
- Produce model with interactions (NB need example)
- Check fit and refine variables if necessary
- Produce model, refine, produce model, refine …………………………

Annual Predicted Lapse Rates (sample)



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South African Case Study

- Large SA protection writer
- Whole of Life Mortality business
- 800,000 policies
- Modelling similar to UK example but
  - Split data up into monthly chunks
  - Added external economic data

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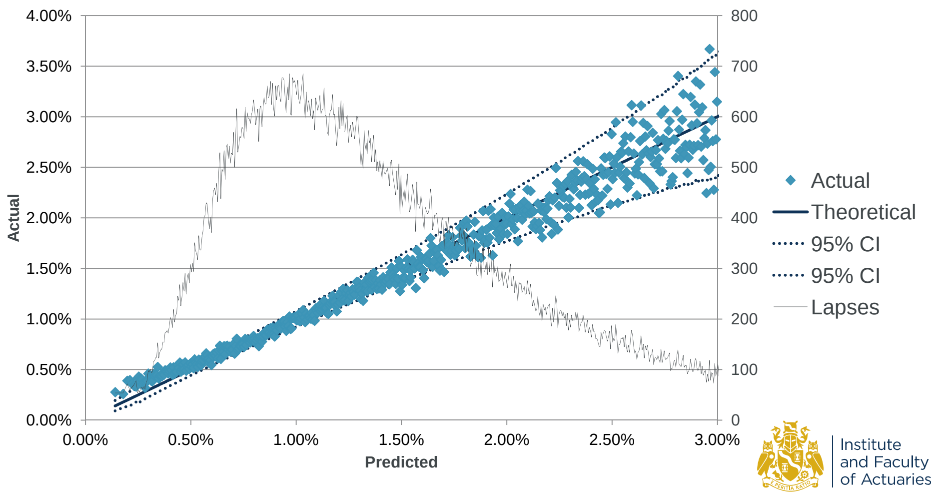
Predicted vs. Actual



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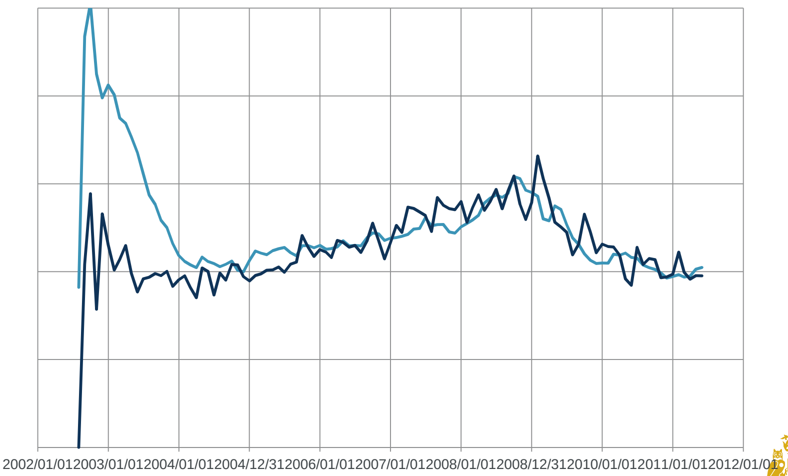
Predicted vs. Actual Lapses



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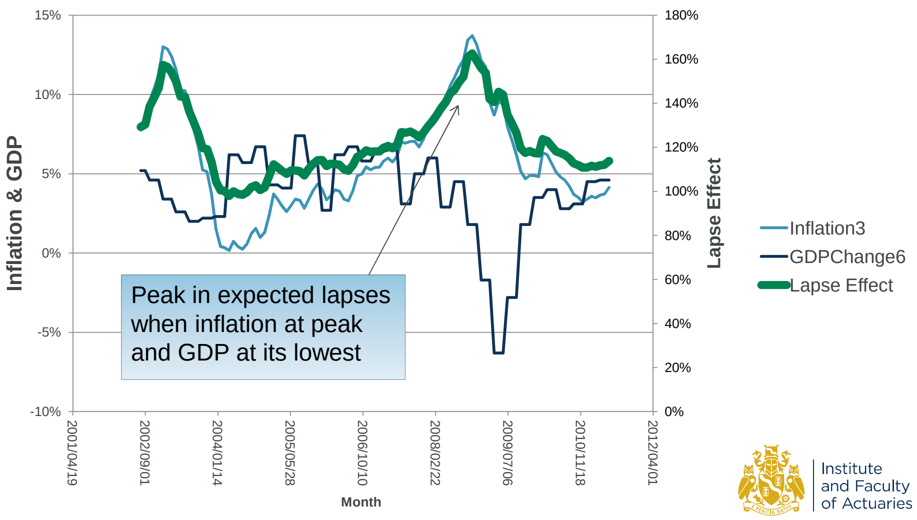
Inflation & GDP



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Retention Modelling

Other information about the life assured
- Income
- Household status
- Credit scores
- Health ...

Traditional factors
- Term
- Duration
- Smoking
- Distribution ...

External information
- Economic indices
- Stock market indices

Predictive Model

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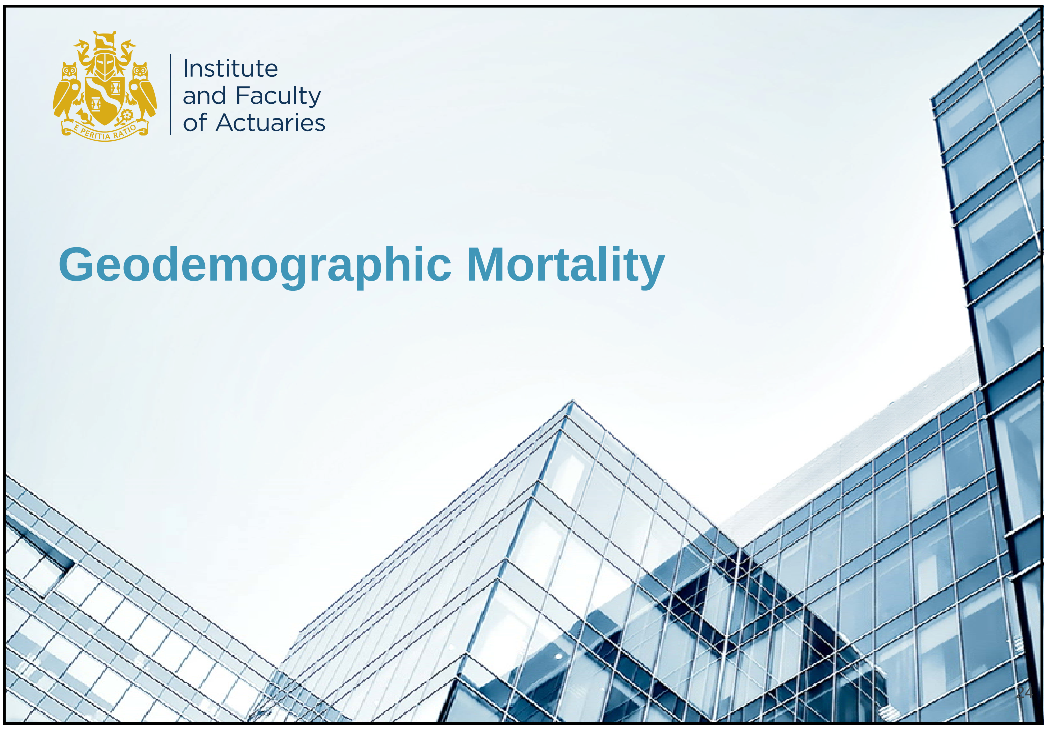

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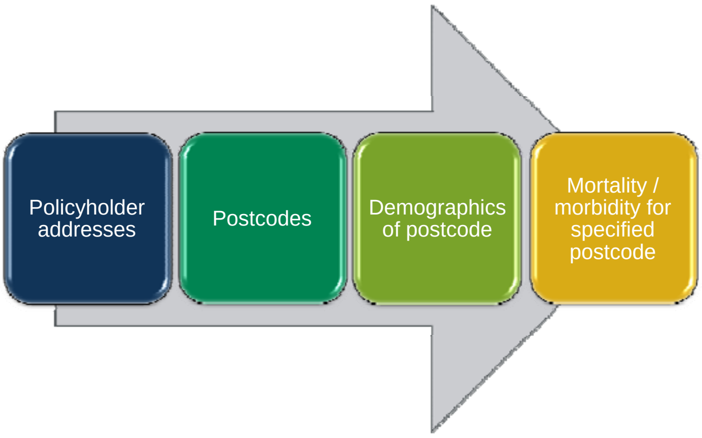
Geodemographic Mortality

Predictive Model



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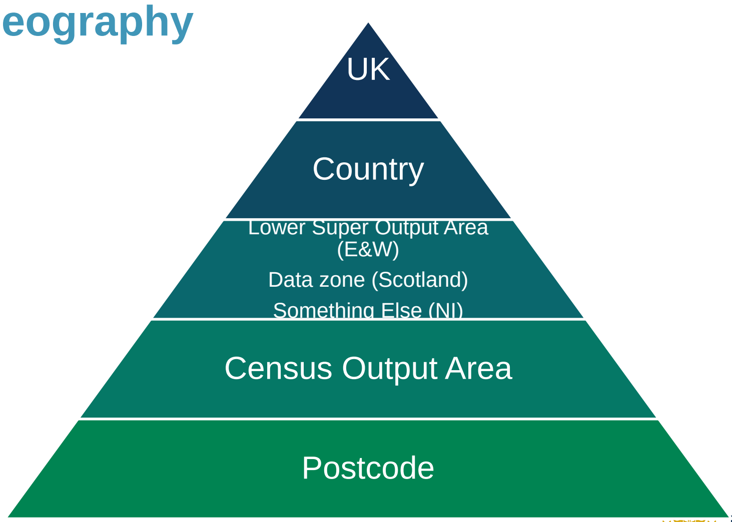
UK Geography



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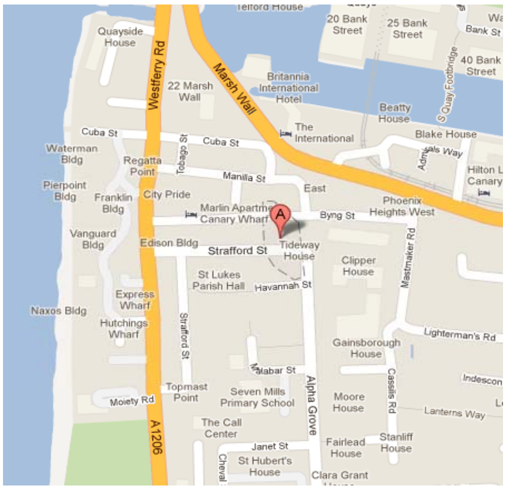
Postcodes

- 2.5m+
- Approx 15 addresses
- Links to
  - Mosaic (Experian)
  - Acorn (CACI)



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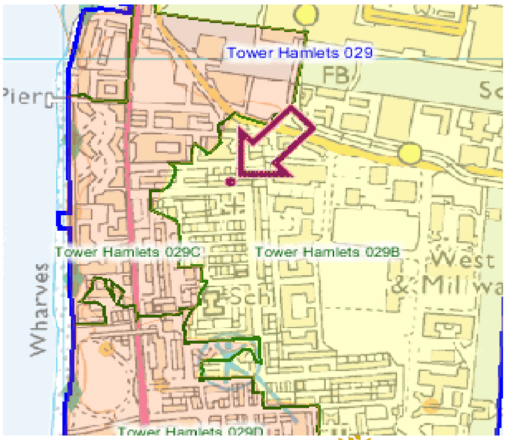
Census Output Areas

- On average 11 postcodes
- England
  - 214 adults (20 - 4000)
- Scotland
  - 88 adults (5 - 2350)
- Census Data
  - Education
  - Socio Economic Class
  - Home type
  - Etc.



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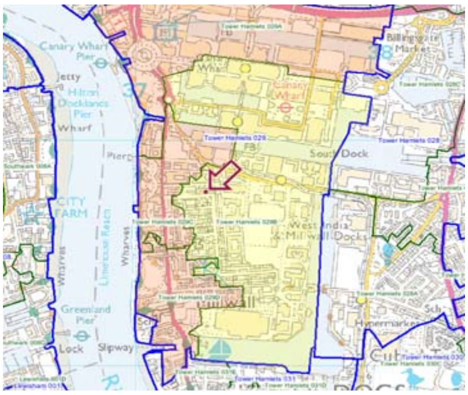
Lower Super Output Areas

- OA Grouped Together
  - Automated
  - Set minimum size = 1000
  - Average 1500
  - Data Zone 500 -1000
- Key small area units
- Links to
  - Index for Multiple Deprivation
- http://neighbourhood.statistics.gov.uk



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Index of Multiple Deprivation

- 4 Available: England, Wales, Scotland & NI
- Lower Super Output Area (England)
- Measures “deprivation”
- Domains
  - Income
  - Employment
  - Health
  - Education, Skills & Training
  - Access to Services
  - Housing
  - Crime
- Different weights and actual measures in each country

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Census

- Uses output areas (lower level)
- Map postcodes to output areas
- Multiple variables
- Predictive model
  - Identifies significant and non-significant variables
  - Models mortality outcomes (or underwriting assessments)
  - Needs lots of data!

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Results – Mortality Example

- Level of highest education proved an important variable
- 50% variation after allowing for expected differences by SA
- Comparable to gender variation
- Greater than SA variation

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Applications of Postcode Modelling

- Pricing
- Reporting
- Marketing
  - Target areas for marketing
  - Special offers
- Distribution
  - Understand characteristics of business by distributor

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Predictive Modelling – Gender Mixes

- Initial model produced pre 21/12/2012
- One way splits only provide limited information
- Predictive model considers multiple interactions e.g.
  - Sum assured and age
  - Age and term
- Output = % males for combination of multiple variables

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Significant and Non-significant variables

Significant variables	Insignificant variables
Occupation class	Policy year
Age	Policy month
Cease age	
Policy term	
Family status	
Sum assured	
Product type (e.g. LTA, DTA)	
Smoker status	

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Final Variables and Combinations Used

Variables in Final Model	
1) Cease age + age at entry	11) Product type + term
2) Cease age + term	12) Product type + sum assured
3) Family status + age at entry	13) Term
4) Family status + term	14) Term + age at entry
5) Family status + sum assured	15) Sum assured
6) Age at entry	16) Sum assured + term
7) Product type	17) Smoker status + cease age
8) Product type + cease age	18) Smoker status + family status
9) Product type + family status	19) Smoker status + product type
10) Product type + age at entry	

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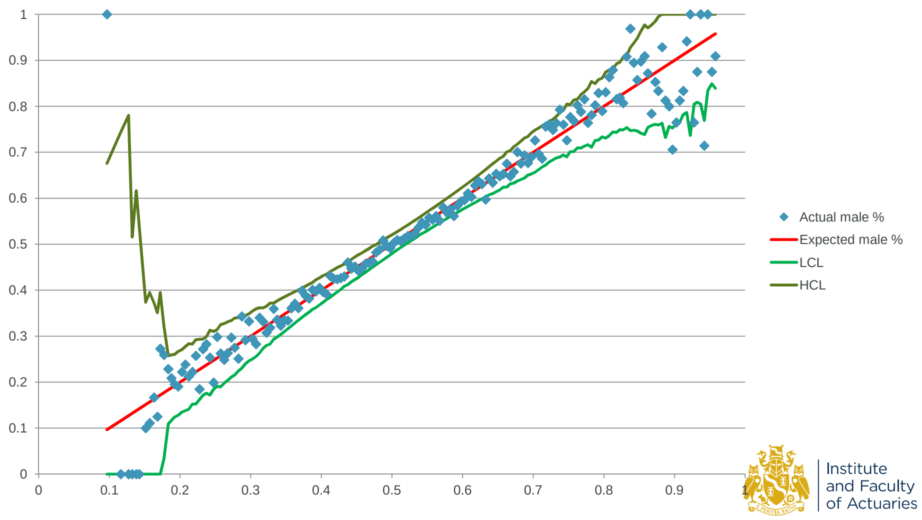
Model Fit



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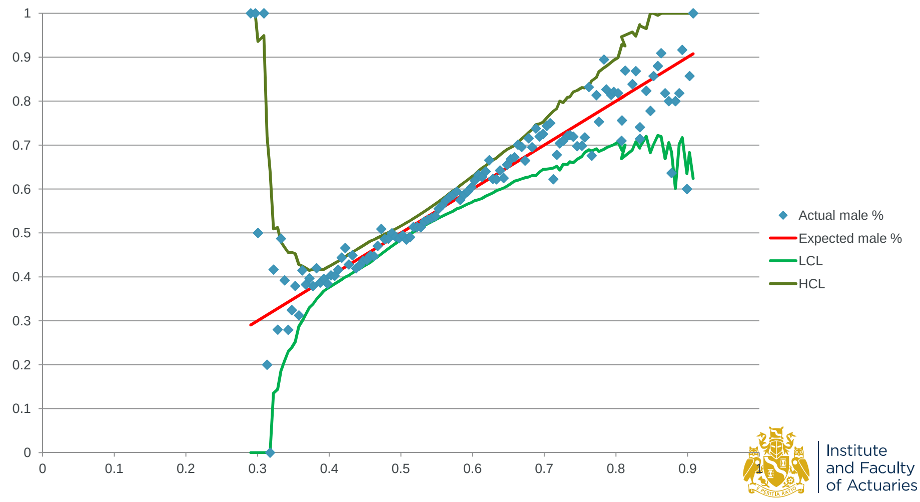
Model Fit excl Family Status



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Sample Output

Rating factor	Value
Age Next Birthday at entry (whole years)	45
Policy Term (whole years)	20
Smoker status	Y
Sum assured	£150,000
Cover type	Level Term Assurance

% Male

56%

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Variations

Rating factor	Value
Age Next Birthday at entry (whole years)	45
Policy Term (whole years)	20
Smoker status	Y
Sum assured	£500,000
Cover type	Level Term Assurance

% Male
71%

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Uses for Business Mix Model

- Pre G-day
  - Predicting mix for pricing
- Now
  - Monitoring mixes
  - Targeting specific segments
- Predictive modelling can be used to predict any type of mix (not just gender)

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Conclusions

- Predictive Modelling enables you to get more out of your data
- You can use it for almost anything!
- All you need are a few clever actuaries!

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