

## Society of Actuaries in Ireland

## **Life Reinsurance Forum 2019**

16<sup>th</sup> April 2019

### **Disclaimer**

The views expressed in this presentation are those of the presenter(s) and not necessarily those of the Society of Actuaries in Ireland or their employers.



## Society of Actuaries in Ireland

## Introduction

## Gavin Maguire



#### Life Reinsurance Committee

- Gavin Maguire (Chair)
- Sarah Lynch (Secretary)
- Aisling Bradfield
- Michael Culligan
- Ciara Fitzpatrick
- Thomas Moran
- Brian Morrissey
- Niall Mulvey
- Michelle Neary
- Viviana Pascoletti
- Cillian Ryan
- Philip Shier



## Life Re Committee

 Input into consultation responses issued to external parties (e.g. regulators, policymakers, Actuarial Association of Europe, AAE)

 Work with other committees of the Society so as to ensure consistency of views and a coherent approach

 To provide CPD and training opportunities for Members of the Society



## Life Re Committee

How do we better serve the wider membership?

 Particularly those in Non-Reserving or Non-HoAF roles?

 Working through a review of ToR and Modus Operandi

Call for membership

## Agenda

## The Theme for today is Data Analytics

#### Speaker(s)

Professor John Kelleher

**ADAPT Centre** 

Karl Murray & Eamon Comerford

Milliman

John Nolan Hannover Re

Aisling Bradfield SCOR



## Society of Actuaries in Ireland

## **Life Reinsurance Forum 2019**

Prof. John Kellegher



## Society of Actuaries in Ireland

# Data science usage and applications in life (re)insurance

Karl Murray & Eamon Comerford



# Data science usage and applications in life (re)insurance

Eamon Comerford Karl Murray



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#### Introduction

- Brief introduction to data science
- Results of recent <u>Milliman survey</u>
- Applications in life (re)insurance
- Other thoughts



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Milliman



#### What is Data Science?





#### **Data Science Methods**

Tools and Techniques used in the application of Data Science

D Α A Neural Linear Random ٧ **Network** Regressio **Forest** S U Α **Decision** Gradient **GLM** Tree **Boosting** S A 0 N Advanced Least Sophisticated Modelling

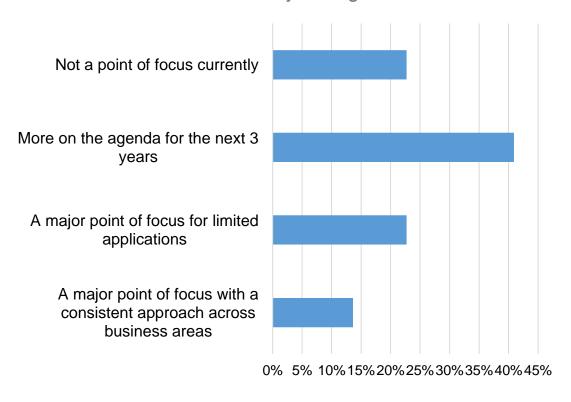


#### Milliman survey on the use of data science

- Scope & Strategy
- Data Usage
- Data Science Architecture and Tools
- Resourcing and Governance
- Benefits & Challenges



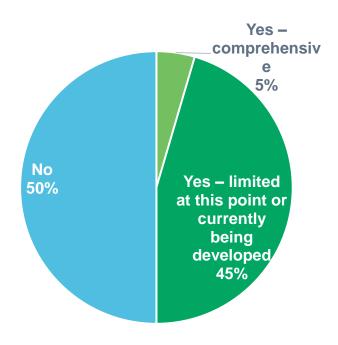
How does data science fit in to your organisation's overall strategy?



Over 75% expect to be using data science within the next 3 years, with over 35% already making it a point of focus.

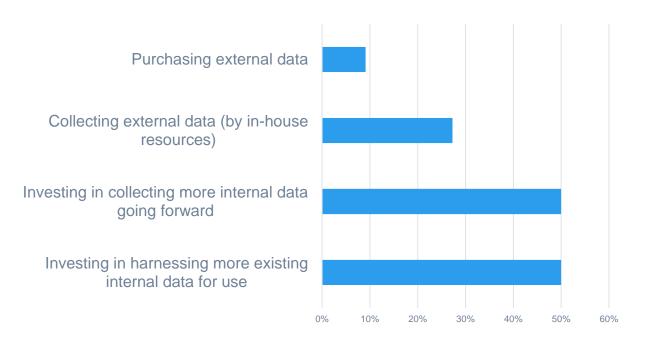


Does your organisation have a dedicated data architecture/infrastru



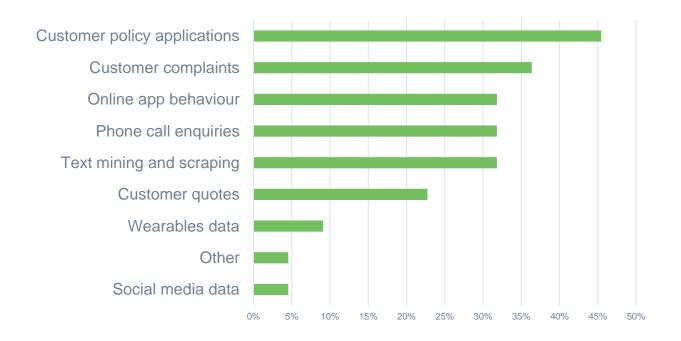


How would you describe your current activities relating to sourcing a Data Science applications?



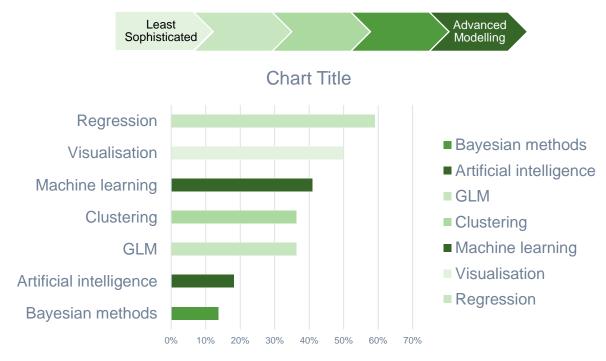


Which of the following sources or methods have you used to captur Science processing (or plan to use in the next 3 years)?





Which of the following types of tools or techniques have you used in Science (or plan to use in the next 3 years)?





#### **Common tools**

#### Programming language











#### **Visualisation**







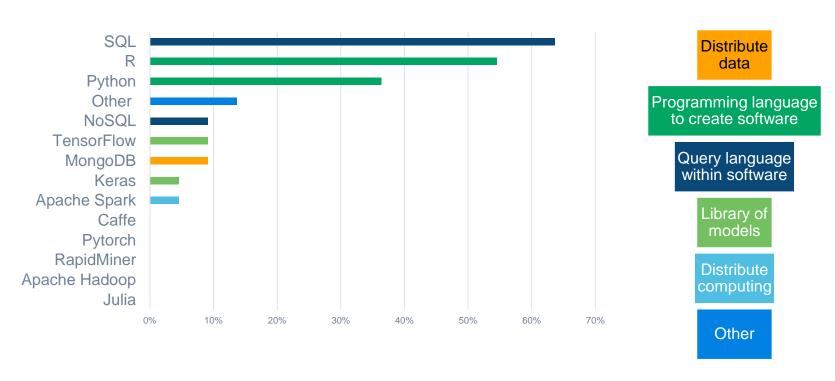
#### "Big data" sets





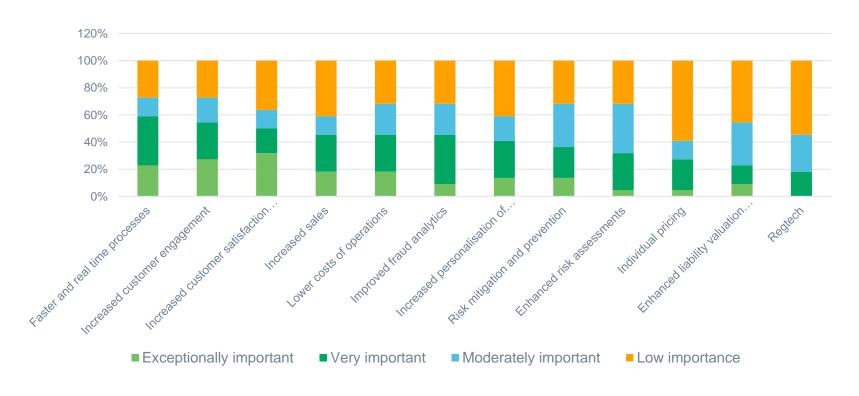


#### Software used



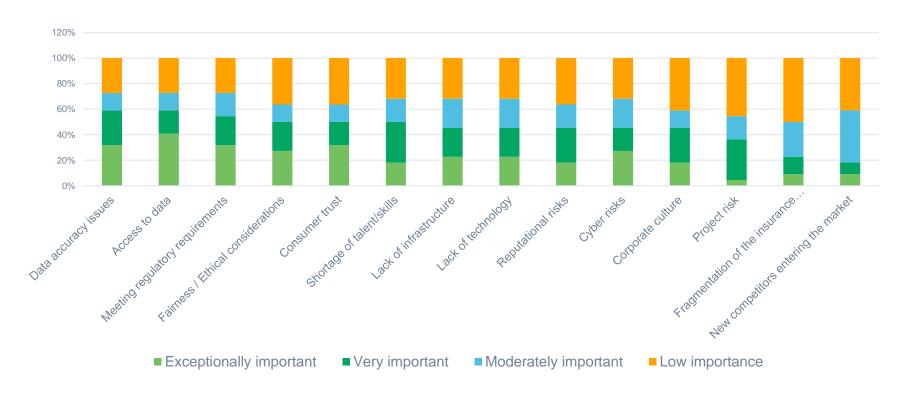


#### Main potential benefits?



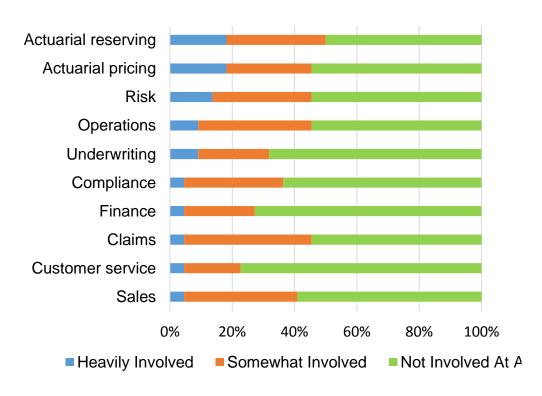


How relevant are the following challenges for your organisation?





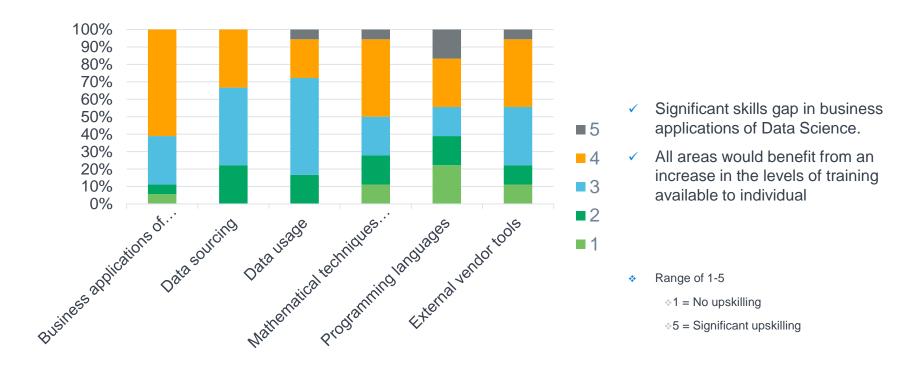
How involved are the business areas with data science applications?



- Actuarial and risk roles are the most heavily involved in data science applications.
- We would also expect an increased involvement over time from customer service, underwriting and sales functions.



What is the level of upskilling required by individuals in your organisation for the following areas?





#### **Data Science Applications for Life (Re)insurance**

Milliman Case Studies



#### Data validation and imputation

Dealing with incomplete and dirty data as well as a large number of diverse legacy portfolios

 Use of advanced techniques to identify missing data patterns to develop more credible experience analysis



#### **Model Validation**

Validating an internal model that forecasts future risk exposure

 Develop a transparent and robust validation process

#### **Distributor Oversight**

Improving distributor retention and performance



 Pinpoint underperforming distributors and improve allocation of company's resources

#### **Customer Behaviour**

Identifying the key drivers leading to transfers between unit-linked funds and guaranteed funds



 Understand policyholder behaviour and develop marketing actions to encourage/discourage the propensity to switch



#### **Data Science Applications for Life (Re)insurance**

Milliman Case Studies



#### **Cross selling and discounts**

Offering customers a discount for purchasing multiple product types

 Identify best targets, offers and delivery channels for different customer segments



#### **Quotations and pricing**

Asking fewer questions when offering an online quotation

 Improve customer experience and overall efficiency

#### **Customer Engagement**

Reducing high rates of policy lapsation



 Analytics on customer behaviour (e.g. premium payments, queries, complaints) to produce early warning indicators & trigger communications

#### **Targeted Products**

Understanding a complex target market with varied customer needs



 Improved product design and reduced conduct risk



#### **Data Science Applications for Life (Re)insurance**

Milliman Case Studies



 Development of a standardised data science framework across the organisation

#### **Inforce Management**

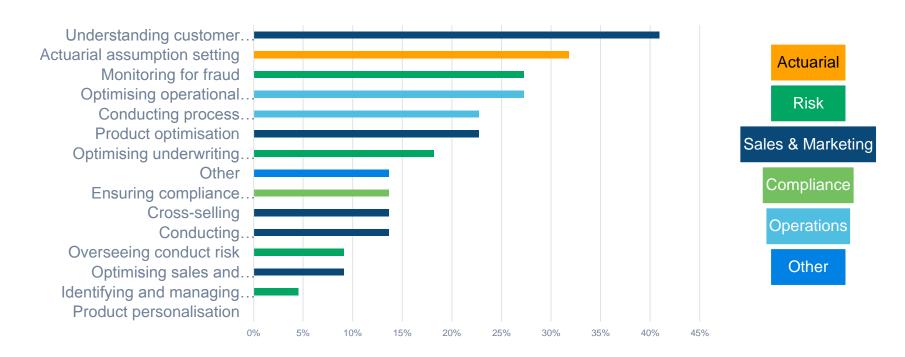
Understanding customers' use of policy options



- Identify distinct customer segments and apply predictive modelling to create behavioural profiles for each segment
- Use insights from behavioural finance, consumer behaviour, family, health, and other facets of the lives of customers



For what business decisions or applications is Data Science used at your company?





#### **Starting a Data Science Initiative**

#### **Choosing the right project**

Start with a narrowly scope and build on it

Align data science activities with the organisation's overall goals

Ensure adequate funding and access to data

#### Hiring the right people

Identify tradeoffs between budget and salaries, specialisation and generalisation etc.

**Domain knowledge** 

Start small and grow over time

#### **Creating the team**

**Encourage cross-functional knowledge sharing** 

Ensure that project managers have a strong technical understanding in order to have right expectations of their team



Key to Success

#### **Data Governance**

Develop an enterprise-wide set of principles around governance of data

Take advantage of emerging data sources such as sales and marketing data, lifestyle data captured by wearable devices, electronic medical records, etc.



#### **The Data Question**



- Data is everywhere
- First define the problem to be solved
- Importance of domain expertise
- Develop a framework for collecting data that is needed for this purpose
- Pay attention to GDPR and other legislative requirements
- Put a good data management structure in place



#### **Key takeaways from survey**

- Over 75% expect to be using data science within the next 3 years, with over 35% already making it a point of focus
- Most common uses of data science right now involve either assessment of customer behaviour or assumption setting
- Limited use of external datasets so far
- Actuaries and risk roles currently most heavily involved in applications
- Limited standardisation thus far around collection and use of data
- Data science is seen as a way to deliver major benefits in increasing customer engagement, increasing customer satisfaction and retention, increasing sales, improving fraud detection and achieving process efficiency
- Biggest challenges facing companies involve a lack of infrastructure and technology, cyber risks, regulatory expectations, a shortage of talent, data quality, and access to data





## Thank you



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## Society of Actuaries in Ireland

## Data Analytics: Views from a Lapse and Mortality Perspective

John Nolan & Aisling Bradfield



## Society of Actuaries in Ireland

## Linking Traditional Valuation Models to Analytics Platforms & Applications

John Nolan, FSAI

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# Agenda

- One Model Concept:
  - Valuation & Financial Reporting Model
  - Economic Capital Model
  - Experience Analysis
- Analytics ready
- Applications





#### One Model Concept - Overview

- Background: 3 separate models existed
  - Valuation & Financial Reporting
  - Economic Capital Model (ECM)
  - Experience Analysis (EA)

#### Rationalising Models:

- Removed redundant assumptions and tables.
- Removed over 50 tabs from our assumption file
- Coding changes
- One model: enhanced reporting model code for ECM and EA
- Improved model governance:
  - a) Model change policy
  - b) Model change log
  - c) Model run log

#### One Model Concept - Benefits

- One version of truth: Best Estimate
- No separate silos
- Efficiencies and Controls:
  - Efficiency of having a single set of controls applied to valuation and experience studies, rather than multiple independent controls
- A/E in same clean format
- Transparent





## **Analytics Ready**

#### Common Questions:

- What do we need and how can we get there?
- How can a Valuation Tool like Risk Agility give sufficiently granular detail?

#### Needs:

- Granular, segmented data
- Leverage the "group" field in RAFM

"Group" String Structure						
description	position	length	Example			
Treaty Code	1	2	TR			
Single or Joint	3	1	S			
Age Band 1	4	2	35			
Sex 1	6	1	M			
Smoker 1	7	1	S			
Age Band 2	8	2	45			
Sex 2	10	1	F			
Smoker 2	11	1	N			
Level / Decreasing	12	1	L			
Sales Channel	13	1	T.			
Benefit Term	14	3	120			

Final String: TRS35MS45FNLI120



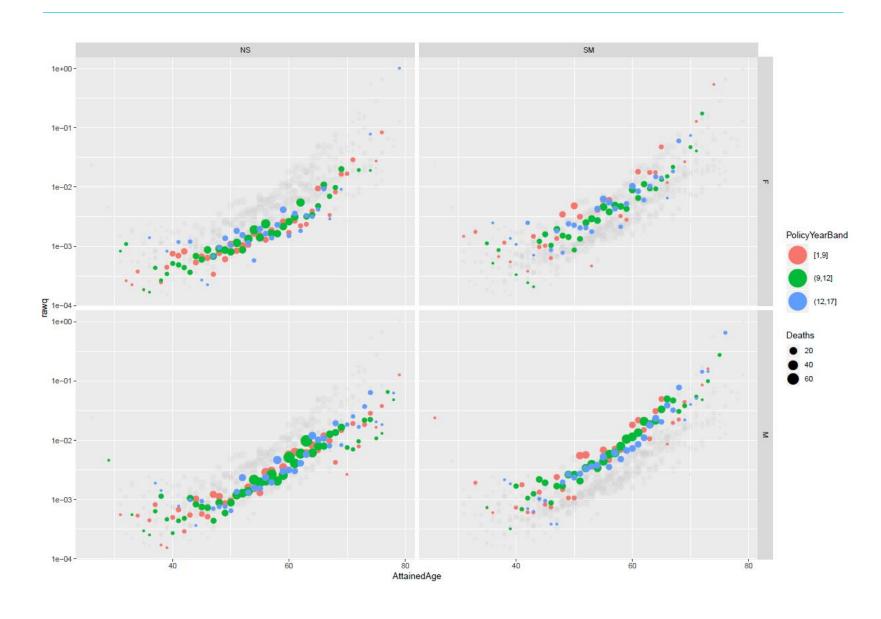
# **Analytics Ready**

#### • Model Output:

	g	roup		time	cal_y	year	pol	year	death_rate1_E	sum	_insured1	_E	
	TRS35M	IS45FNLI	120	-150	20	05		1	0.0010		1,000		
Treaty	PoTReap	SALA EPAIN	<b>13</b> 0)	(SI1410)	ke²%	<b>At</b> tai:	ned/	Age S	Sales Chánnel		Lîve9_E	An	nounts_E
TR		IS45FALI		1/1/58	20		25	1	0.φ012		<sup>1</sup> 0 <sup>2</sup> .005		12,000
TR		IS45FNLI		1/157	20		26	1	0.φ013		<sup>1</sup> 0 <sup>3</sup> 0 <sup>4</sup> 55		13,000
TR		1 <b>S45FNLI</b> 2006		1/1/56	200		27	1	0.0015		10464 10,105		14,000
TR	1 1	IS45FNLI 2007	_	15055 15055	200		28	1	0.0016		1,611 10,155		15,000
TR		IS45FNLI IS45FNLI		-144 MS <sub>3</sub>	200		29	1	0.0018		1,772 10,495		16,000
TR		1849FNL1 1849FNL1		-143 -MS <sub>2</sub>	200 200		30	1	0.0019 0.0021		201 <b>25</b> 5		17,000
TR		1549FWL1	_	-MS	200		31	1	0.0021		2038		18,000
TR		15461F1\\LI	_	-MB	20		32	1	0.0024		2 <b>9534</b> 5		19,000
	-	IS45FNLI		-139	20			1	0.0029		2,853		,
		IS45FNLI		-138	20			2	0.0031		3,138		

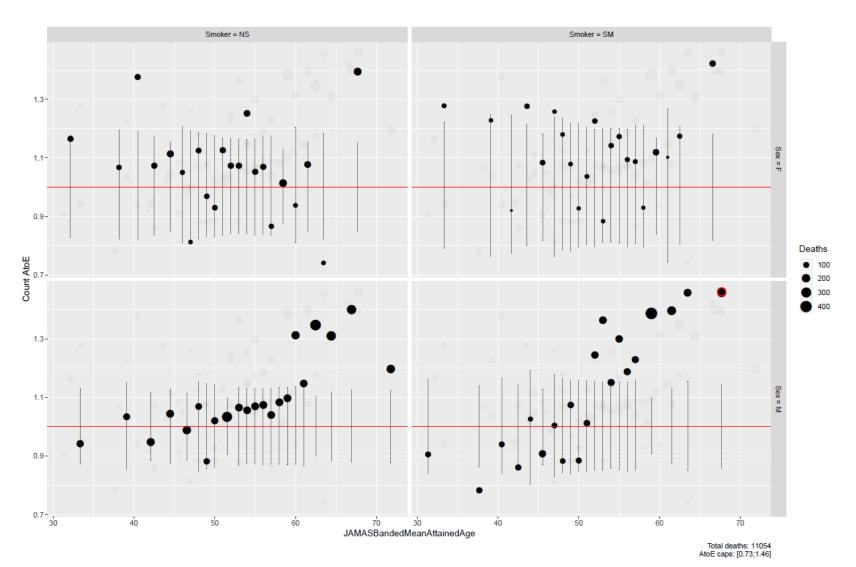


# Developing Applications – Raw Mortality Plot



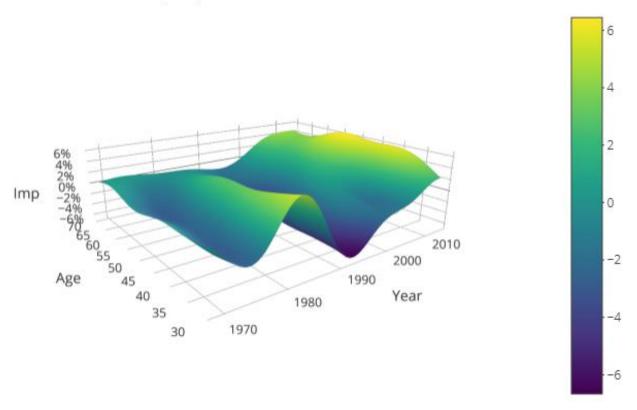


# Developing Applications – Confidence Intervals





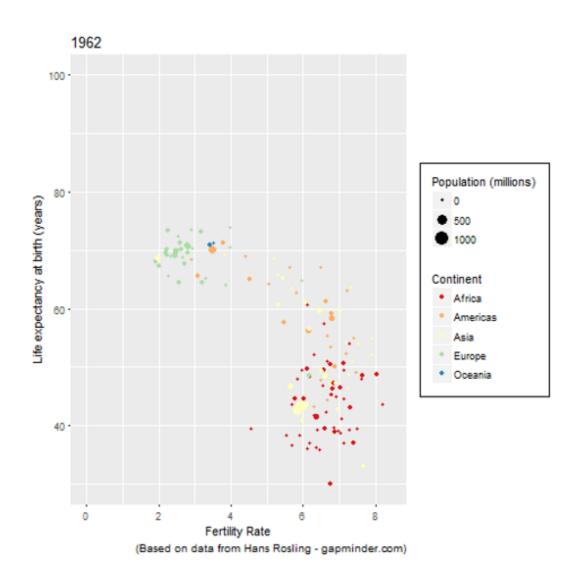
Mortality improvements for Russian Females



Source: <a href="IFOA's Data Visualisation Working Party">IFOA's Data Visualisation Working Party</a> (https://dataviz-wp.blogspot.com/)

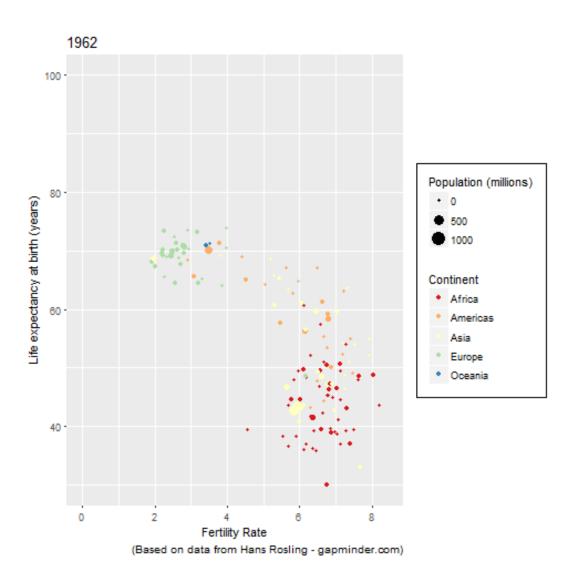


## Developing Applications – Animated Charts



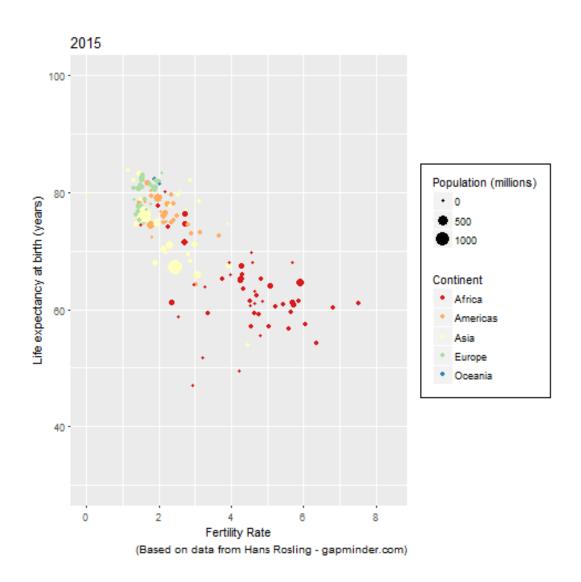


## Developing Applications – Animated Charts





## Developing Applications – Animated Charts

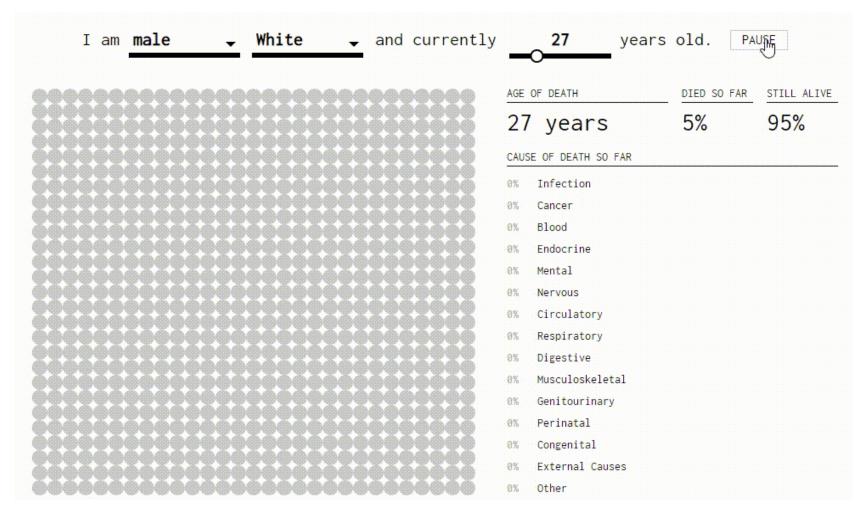






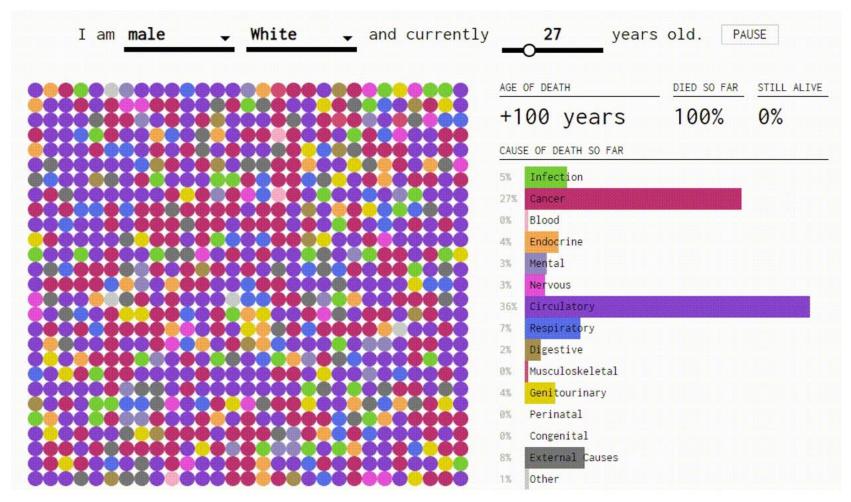
Source: <a href="https://flowingdata.com/2016/01/19/how-you-will-die/">https://flowingdata.com/2016/01/19/how-you-will-die/</a>





Source: <a href="https://flowingdata.com/2016/01/19/how-you-will-die/">https://flowingdata.com/2016/01/19/how-you-will-die/</a>





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## Society of Actuaries in Ireland

# Data Science Advantages in Lapse Analysis

Aisling Bradfield



### **GLM** for Lapse Analysis

- Generalised Linear Model Regression
  - Poisson distribution
  - Quasi-families
  - Negative Binomial
  - -Zero inflated models
  - -Tweedie
- Log link function
- Choose the factors explaining lapse variation (X)
- Calculate a co-efficient (b) for each possible option for each factor and an intercept (a)
- Test significance of various factors

```
Regression Analysis

Regression equation: linear, additive

eg: Y = a + b<sub>1</sub>X<sub>1</sub> + b<sub>2</sub>X<sub>1</sub> + b<sub>3</sub>X<sub>1</sub> + b<sub>4</sub>X<sub>4</sub>

Y: dependent variable
a: constant value, y-intercept
X<sub>2</sub>: independent variables, used to explain Y
b<sub>4</sub>: regression coefficients (measure impact of independent variables)
```



# Potential drivers of Lapse Behaviour

Issue Year

**Duration** 

Single V
Joint

Calendar Year **Product Type** 

Smoker status

Standard V Rated

Distribution Channel

Issue Age

Postcode

Sum Assured

Commission

Gender



#### **Interaction Terms**

- Model all possible variables
- Test variables for significance at a 99% confidence level
- Understand the relationship between variables

Variable	Estimate	Exp(Estimate)	P Value
Gender			
Male	0.007	1.01	0.0969
Female	0	1.00	
Issue Age			
18-29	0	1.00	
30-39	-0.4147	0.66	<.0001
40-49	-0.4305	0.65	0001
50-59	-0.3077	0.74	<.0001
60+	-0.2329	0.79	<.0001
Smoker			
Smoker	0.9548	2.60	<.0001
Non-smoker	0	1.00	
	_l	<u> </u>	<u> </u>

Lapse are higher at younger ages

Not significant at 99%

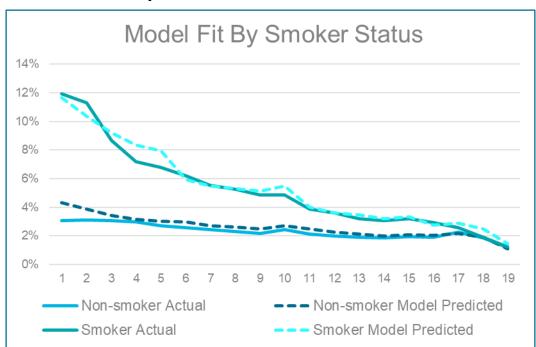
Interaction term captures smoker pattern

**Smoker & Duration Group** Estimate Exp() P Value Smoker dur01-05 1.00 0.76 < .0001Smoker dur06-10 -0.2785 Smoker dur11-15 -0.50090.61 < .0001-0.6659 Smoker dur16+ 0.51 < .0001



## Modelling interactions

- Hold-out data for cross-validation
- Review model results for the fit to actual experience by different splits.



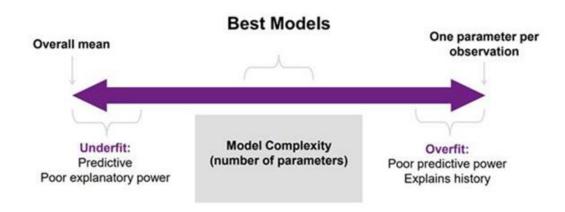
 See how the model captures the interaction between duration & smoker status



#### **Model Refinement**

#### Model considerations

Goal is to produce predictive model without overfitting

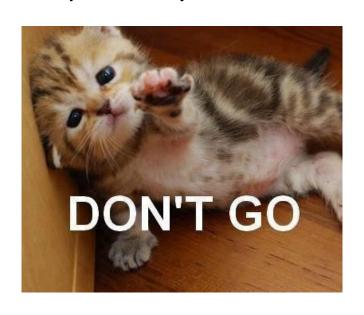


- Compare statistical model fit using Akaike information criterion (AIC) and Bayesian Information Criterion (BIC)
  - -the model with the lowest AIC/BIC is the best fit.
  - If adding an additional variable does not reduce AIC/BIC, the variable does not add further explanation of the lapse rates.



## Using the Lapse Model

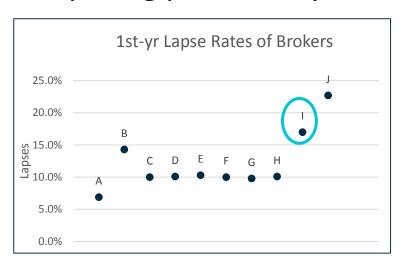
- Set assumptions
  - Predictive model provides a full set of lapse rates
- Build into model code
  - Regression equation instead large lapse rate tables
- Review lapse experience
  - Check actual to model predicted at each lapse study
  - Build Confidence Interval
- Manage persistency
  - Insights from modelling
  - Benchmark for comparison





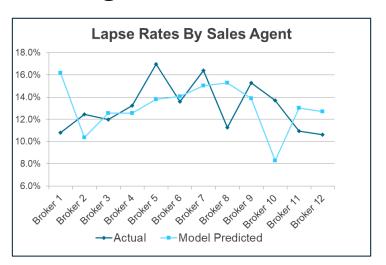
#### **Residual Variation**

Comparing persistency between sales agents



#### **Comparing lapse rates:**

- Differences in lapse experience may be attributed to business mix
- e.g. B & J write a lot of rated business, A only writes standard
- What can we say about Broker I?



#### **Compare lapse Vs model predicted:**

- Model accounts for other sources of difference
- Brokers 1 and 8 have better than expected persistency while 2 and 5 are showing higher actual lapse rates
- Benchmarking against predicted provides a clearer comparison



#### Conclusion

- One Model Concept
  - One version of best estimate, no silos
  - Integrated solution for traditional financial reporting and analytics platforms
  - Powerful visualisations to help assess your data



- Generalised Linear Modelling
  - Identifying key drivers for Lapses
  - Multivariate Analysis
  - Residual variation insights





# Society of Actuaries in Ireland

#### Questions

Life Re Forum, 16th April 2019

## Appendix: One Model Concept – Case Study

#### Dedicated Experience Study Team

"Improve the Experience Study delivery time, implement advanced analytics, reduce gaps to financial results and Model Study."

- Separate models for valuation (RAFM) and experience analysis (SQL)
- Large and complex models: E's are not completely consistent
- RAFM already has infrastructure to code q x exposure logic using values that are policy specific

#### Solution:

- Implement experience analysis logic into the valuation model
- See Appendix for Changes Required & Other Considerations
- Consistent best estimate
- One model run, several bases and output for policy and calendar year

Appendix: Case Study

#### Modest Changes Required:

- New input fields added:
  - Status (Live, Death, Lapse, etc.)
  - Exit Date
- Death rates and lapse rates updated for EA functionality:
  - Actual and Expected calculations
  - Daily exposure (if required)
  - Calendar year and policy year functionality
- New columns for:
  - Additional bases (rather than additional submodels)
  - Actual and expected amounts

Appendix: Case Study

#### Complications:

- Changing Net Amount at Risk (NAR) structure
- Changing policy details
- ...Overcome by having multiple policy records and start and end dates

#### Key Benefits:

- Consistent best estimate
- Input file in same format
- One model run, several bases and output for policy and calendar year