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SOA Predictive Analytics Seminar – Malaysia

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Session 4

GLM and its application in life insurance

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GLM and Its Application in Life Insurance

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Agenda

- **Overview of Generalized Linear Model**
  - What is predictive modelling and its terminology
  - Components of Generalized Linear Model
  - Model building considerations
- **Sharing - Predictive Modelling Cases**
- **Introduction - RGA Data Science Team**

Overview of Generalized Linear Model

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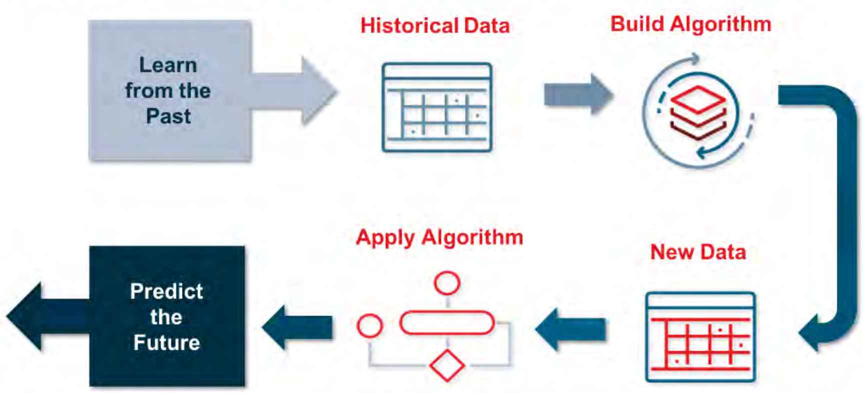
What Is Predictive Modeling?



- ✓ Predictive models use algorithms to discover complex patterns in historical datasets, and then apply those patterns to new data to make predictions about what will happen next.

Predictive Modeling Terminology

Supervised vs. Unsupervised Learning

- ***Supervised***: estimate expected value of *Y* given values of *X*.
  - **GLM**, Cox, CART, Random Forests, SVM, NN, etc.
- ***Unsupervised***: find interesting patterns amongst X; no target variable *Y*
  - Clustering, Correlation / Principal Components / Factor Analysis

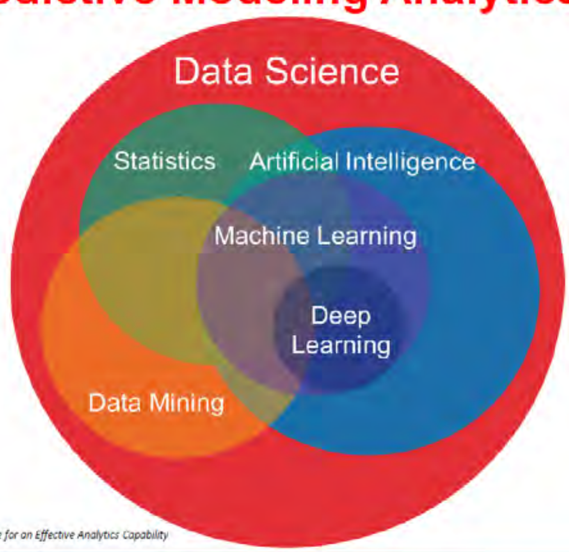
Classification vs. Regression

- ***Classification***: to segment observations into 2 or more categories
  - Fraud vs. Legitimate, Lapsed vs. Retained, UW class
- ***Regression***: to predict a continuous amount.
  - Dollars of loss for a policy, Ultimate size of claim

Parametric vs. Non-Parametric

- ***Parametric***: probabilistic model of data
  - Poisson Regression(claims count), Gamma (claim amount)
- ***Non-Parametric***: no probability model specified
  - Classification Trees, NN

Profile of Predictive Modeling Analytics Work



Graphic adapted from The Analytics Lifecycle Toolkit: A Practical Guide for an Effective Analytics Capability

Generalized Linear Model

- **Generalized Linear Model(GLM)**
  - Major focus of PM in insurance industry
  - Include most distributions related to insurance
  - Great flexibility in variance structure
  - (Relatively) Easy to understand and communicate
  - Multiplicative model intuitive & consistent with insurance practice
- **3 Components**
  - *Random component*
  - *Systematic component*
  - *Link function*

Generalized Linear Model

Random component

Observations $Y_1, \ldots, Y_n$ are independent w/ density from the exponential family

$$f_i(y_i;\theta_i,\phi) = exp\left\{\frac{y_i\theta_i - b(\theta_i)}{a_i(\phi)} + c(y_i,\phi)\right\}$$

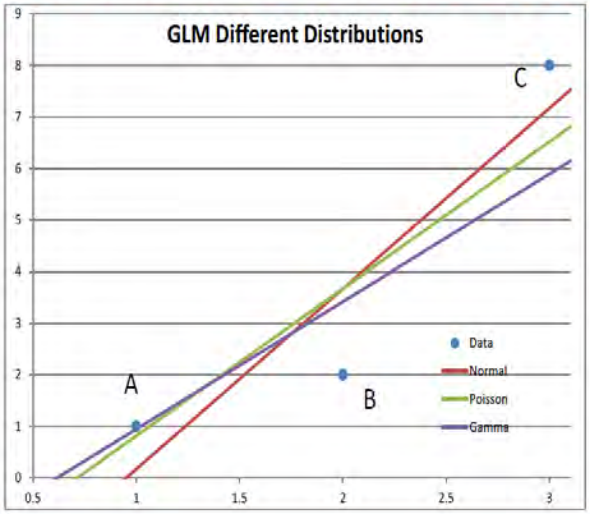
From maximum likelihood theory,

$$E(Y) = \mu = b'(\theta), \qquad var(Y) = b''(\theta)a(\phi) = a(\phi)V(\mu)$$

- Each distribution is specified in terms of mean & variance
- Variance is a function of mean

	Normal	Poisson	Binomial	Gamma
Name	$N(\mu,\sigma^2)$	$P(\mu)$	$B(m,\pi)/m$	$G(\mu,\nu)$
Range	$(-\infty,+\infty)$	$(0,+\infty)$	$(0,1)$	$(0,+\infty)$
$b(\theta)$	θ^2	e^θ	$\ln(1+e^\theta)$	$-\ln(-\theta)$
$\mu(\theta)$	θ	e^θ	$e^\theta/(1+e^\theta)$	$-1/\theta$
$V(\mu)$	1	μ	$\mu(1-\mu)$	μ^2

Why Distribution Will Affect Results



Variance of different distributions

- *Gaussian, constant*
- *Poisson, ~ mean*
- *Gamma, ~ mean^2*

Generalized Linear Model

Systematic component

A linear predictor $\eta_i = \sum_j x_{ij}\beta_j = X\beta$ for observation *i*

- Parameters (β) estimated by maximum likelihood

Link function

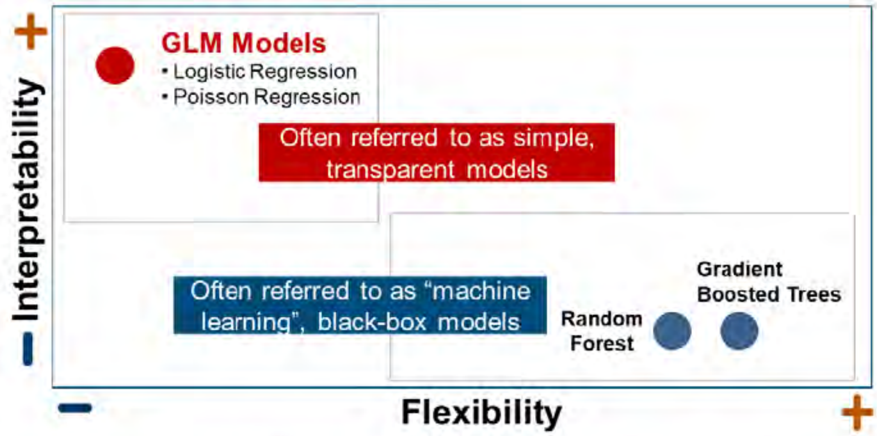
$\eta_i = g(\mu_i)$, random & systematic are connected by a smooth & invertible function

	Identity	Log	Logit	Reciprocal
$g(\mu_i)$	x	$\ln(x)$	$\ln(\frac{x}{1-x})$	$1/x$
$g^{-1}(\eta_i)$	x	e^x	$\frac{e^x}{1+e^x}$	$1/x$

Log is unique in insurance application - all parameters are multiplicative

- $y = \exp(\sum_j x_{ij}\beta_j) = \prod_j \exp(x_{ij}\beta_j) = \prod_j \exp(\beta_j)^{x_{ij}} = \prod_j f_j^{\,x_{ij}}$
- Consistent with most insurance practices
- Intuitively easy to understand and communicate

Algorithm Trade-Off



This is just a sample of **many** algorithms available

Algorithm Trade-Off

Interpretability "Transparent" Algorithms	**Flexibility** "Black-box" Algorithms
More human intervention	Less human intervention
More interpretable	Less interpretable
Require less data	Require more data
Faster to estimate a model	Slower to estimate a model
Good at handling smooth effects (e.g., age, income, etc.)	Not good at handling smooth effects (e.g., age, income, etc.)
The model we choose might not be a good match to reality, resulting in poor predictions.	Higher predictive accuracy because functional form is derived from the data, not assumed.
Less likely to over fit the data	More likely to over fit the data

Selecting an Algorithm

- **Business Considerations**
  - **Experience**
  - **Know Your Audience**
  - **Technical Implementation**
- **Statistical Considerations**
  - **Dependent Variable**
  - **Amount of Data**
  - **Model Validation**

Choosing the right algorithm is a combination of statistical and business considerations

Model Validation

Rather than build models on the entire dataset, we divide the data into two parts. The first set of data is used for training/building models, and the other set of data is **only** used to estimate model performance.

Procedure

1. Randomly select part (e.g., 30%, 40%) of your data to be your test set
2. Build models on **training data**
3. Estimate future performance by estimating models on **test data**

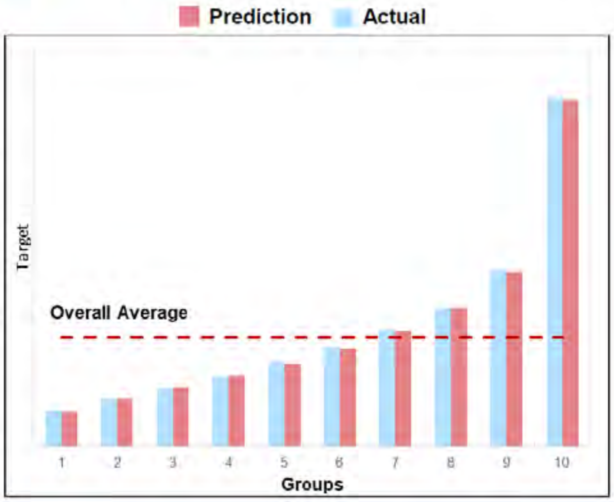
Interpreting Model Output – Lift Plot

What is it?

- Lift Plots capture how well the predictive model can discriminate low from high values.
- For example, if we are predicting "purchase propensity" we want to make sure our model can identify those that are the least likely to purchase from those that are the most likely to purchase.

Why show it?

- Clients like to see the additional value the model provides to their business. For example, our model shows that we can identify customers who are *M* times more likely to purchase than the average customer.
- Clients like to see how well our model predictions track actuality.



Sharing - Predictive Modelling Cases

Key Success Factors

Data Environment

- Quality and quantity of data
- Local regulations

Technology

- Statistical modelling expertise
- Computing/ programming expertise

People

- Business experience and insight
- Product and market expertise

Opportunities in Predictive Modelling

- Sales & Marketing
- In-Force Management
- Underwriting
- Pricing Analysis
- Experience Analysis
- Claims

✓ As long as there is data, there is potential to capitalize on it.

Claim Fraud Detection – SEA

To develop a fraud detection model which optimize the use of limited resources.

Objectives

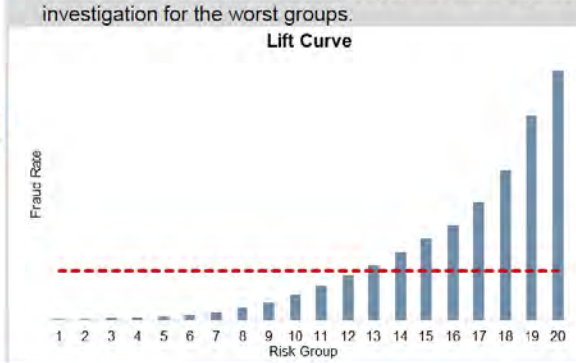
- Predict the likelihood of claim to be fraudulent at the stage of claim adjudication.
- Increase capability to detect fraudulent claim with greater certainty and allow appropriate action to be taken.

Data

- Claim data.
- Policy data.
- Customer data.
- Agent data.

Business Application

- Optimized deployment of claims investigation resources.
- No need to investigate the best groups, with more vigorous investigation for the worst groups.



Claim Cost Model – SEA

To develop a predictive model of claim/loss cost.

Objectives

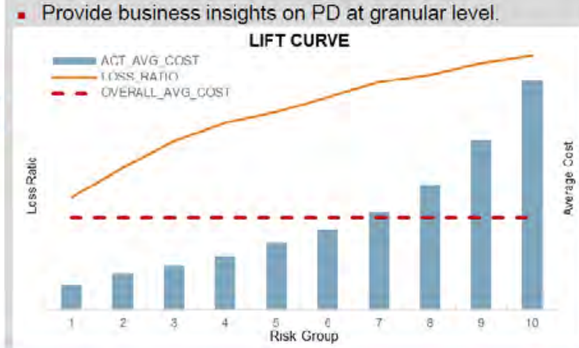
- Predict claim/loss cost.
- Systematically identify risk factors and quantify the effect of each, from internal and external data sources.
- Identify historical trend fast and effectively.

Data

- Policy data.
- Claim data.
- External weather data.

Business Application

- Warn future trend on loss cost/ratio quickly and accurately.
- Identify different combinations of risk factors to target certain customers of good risk for growth.
- Provide business insights on PD at granular level.



Introduction - RGA Data Science Team

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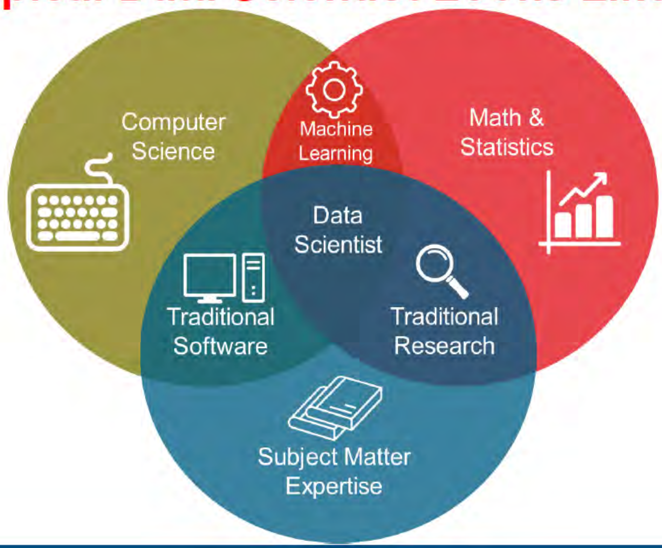
RGA Data Science Team – Global Presence, Local Focus

- The DS team collaborates with regional/local offices to focus on regional initiatives and local market projects
- We leverage local market knowledge to maximize data value & drive business outcomes

- Data Science team includes data scientists, actuaries and IT experts
- About 50% of the team have a Ph.D. and the rest have master's degrees
- Work closely with UW, actuarial, admin and IT

What A Typical Data Scientist Looks Like?



Thank You!

02/09/2019

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