2014 EAAC
TAIPEI TAIWAN

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BIG DATA and Opportunities in the Life Insurance Industry

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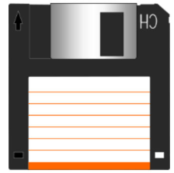
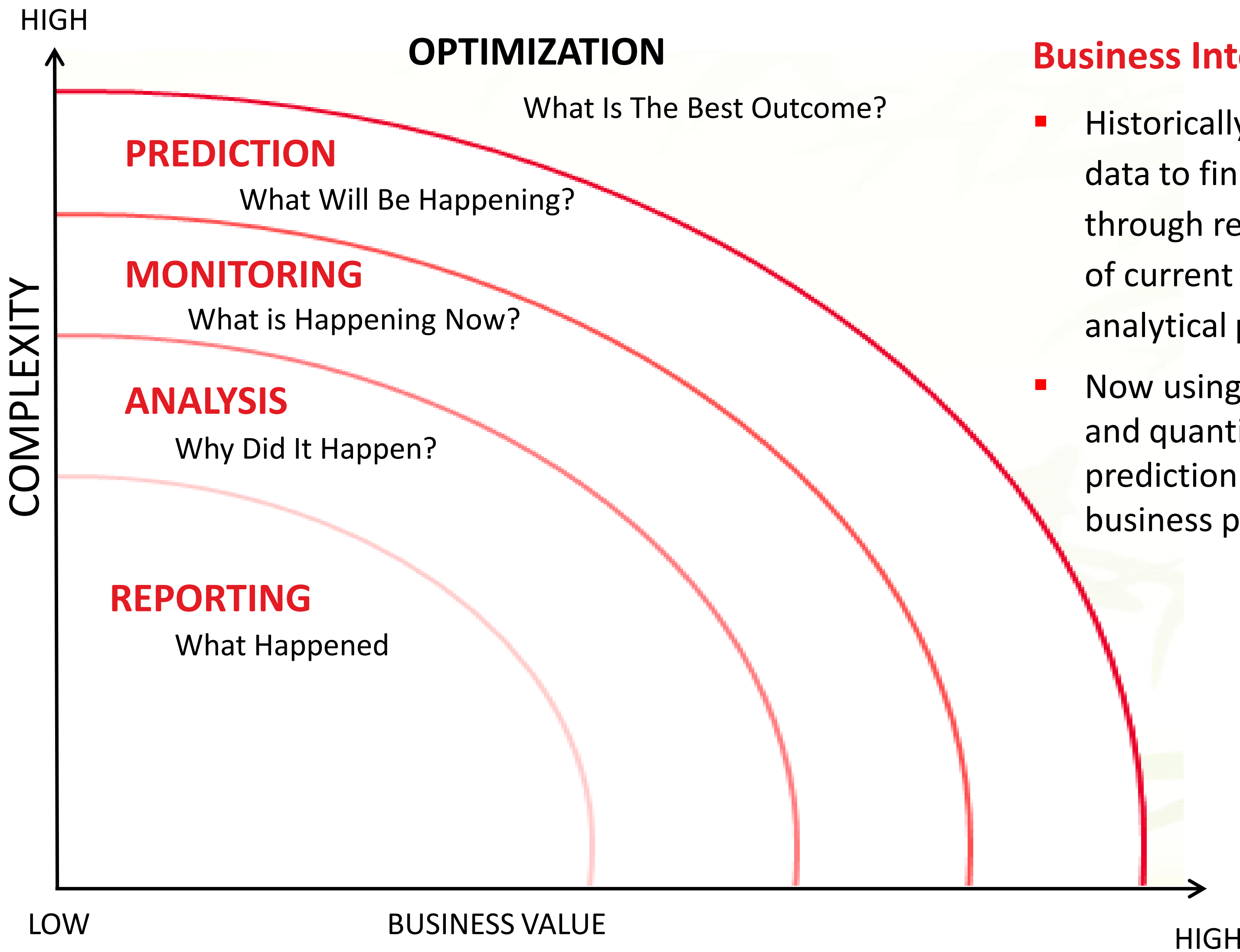
BIG DATA




*“ I keep saying the **sexy** job in the next ten years will be statisticians. People think I'm joking, but who would've guessed that computer engineers would've been the sexy job of the 1990s? “*

- Hal Varian, Chief Economist at Google

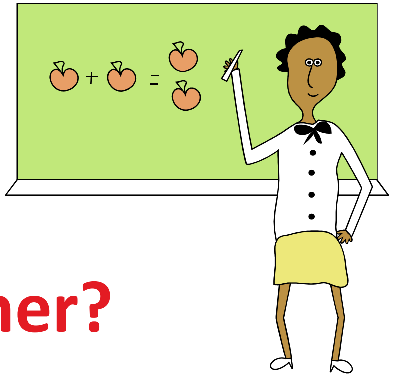
Evolution of Business Intelligence



Business Intelligence is Evolving

- Historically collected business data to find information primarily through reporting and monitoring of current activities using basic analytical processes.
- Now using advanced statistical and quantitative tools for prediction and optimization of business processes.

What is Predictive Modeling?



Put Simply…

Collect large **data** set(s)

↓

Analyze data, identify meaningful relationships

↓

Use these relationships to predict future defined outcomes to **drive decisions**

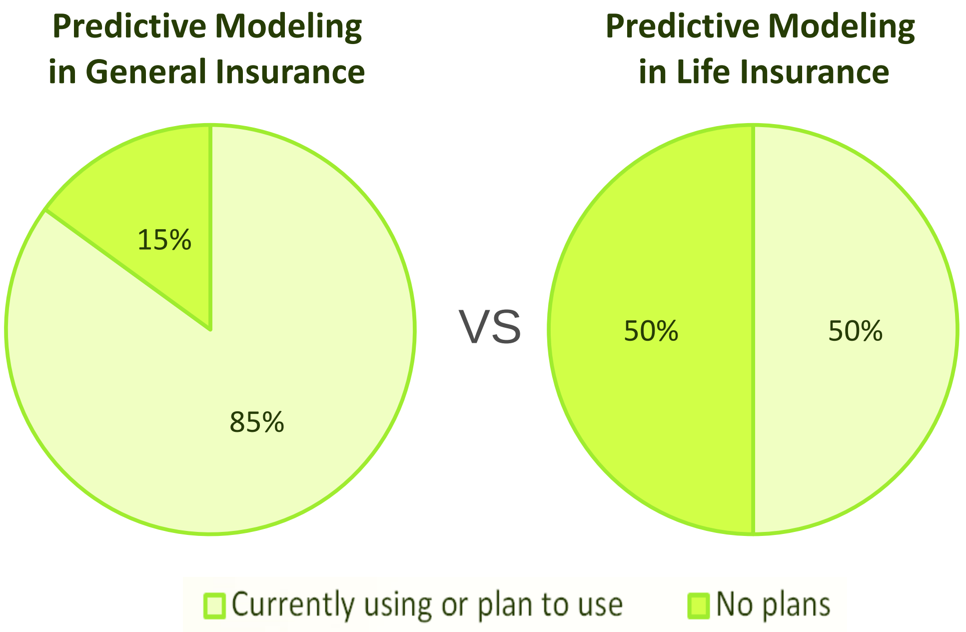
Why bother?

- Brings the rigor of advanced statistical algorithms to get the most benefit from proprietary data assets.
- Improve the efficiency of existing business processes:
  - Creates new opportunities to enhance the sales process for direct and intermediated distribution.
  - Claims management can be greatly improved.
  - More accurate and granular view of the factors that affect portfolio experience.
- The improvements allowed by predictive modeling can provide an advantage that competitors will find difficult to replicate.

Life Insurance is Lagging Behind

Key Inhibitors

- Lack of management familiarity.
- Product nature (long term & low frequency events).
- Ready access to required data.
- Implementation challenges:
  - Data preparation efforts
  - Lack of adequate data
  - Lack of skills and training
- Insufficient proof of accuracy and case studies.
- So many other priorities and opportunities!



Source:

Tower Watson: Predictive Modeling Providing Its Worth Among P&C Insurers (2012).
Society of Actuaries: *Report of the Society of Actuaries Predictive Modeling Survey Subcommittee (2012)*

Most Popular Uses of Predictive Modeling

- **Propensity to Buy Models** – use customer information to determine who is most likely to purchase a product and target them thereby reducing acquisition costs. RGA Project in Taiwan.
- **Predictive Underwriting models** – find the customers most likely to have a std. underwriting decision and offer them cover with reduced underwriting. RGA Projects in US, UK, Australia and South East Asia.
- **Experience Analysis Models** – understand the true drivers of experience using multivariate analysis. RGA Projects in US, UK, South Africa, Japan, China and Korea.
- **In Force Retention Models** – find out which policies are most likely to lapse and develop retention strategies for them. RGA Projects in the US and UK.
- **Fraud Detection Models** – use claims data to determine those claims that are most likely to be fraudulent and focus forensic efforts on them. RGA Project in India.
- **Agent Quality Assessment Models** – use policyholder and claims information to determine which agents add most value to the companies profitability.

Bancassurance Predictive Underwriting

Objectives

- Bancassurer wanting to achieve growth in sales via the bancassurance channel.
- Sell bank customers protection products on a guaranteed issue or simplified issue basis with minimal impact on product price.
- Improve the customer experience by:
    - Issue policies faster.
    - Reduce the UW process for customers most likely to be standard.
- Easy Identification and targeting of ‘good’ customers.
- Make the best use of internal data.

Bancassurance Predictive Underwriting

Used two different sets of data…

Predictors

- Demographic (Age, Gender, Location, Branch)
- Asset or Debt Related (Accounts, AUM, TRB)
- Transactional (Bank Account or Credit Purchases)

Response

The underwriting decision when normal underwriting applied:

- Standard risk
- Rated
- Declined

Linked to the same lives

Bancassurance Predictive Underwriting

The Model Building Process

Data	▪ De-personalized data provided to RGA. ▪ Limited number of cases: ○ A total of around 9,000 fully underwritten cases. ○ Target variable UW decision, with very low declined/rated cases < 5%. ▪ Each record had around 85 variables: ○ Many missing values especially for Sub-Standard lives. ○ Not all information collected at the time of underwriting.
Analytics	▪ Generalized Linear Model: easy to understand and gain acceptance in the business.
Outcome	▪ Model using 11 statistically significant variables. ▪ Good differentiation of risks: ○ For the best 20%, the average non-STD rate was 5x better than the overall average.

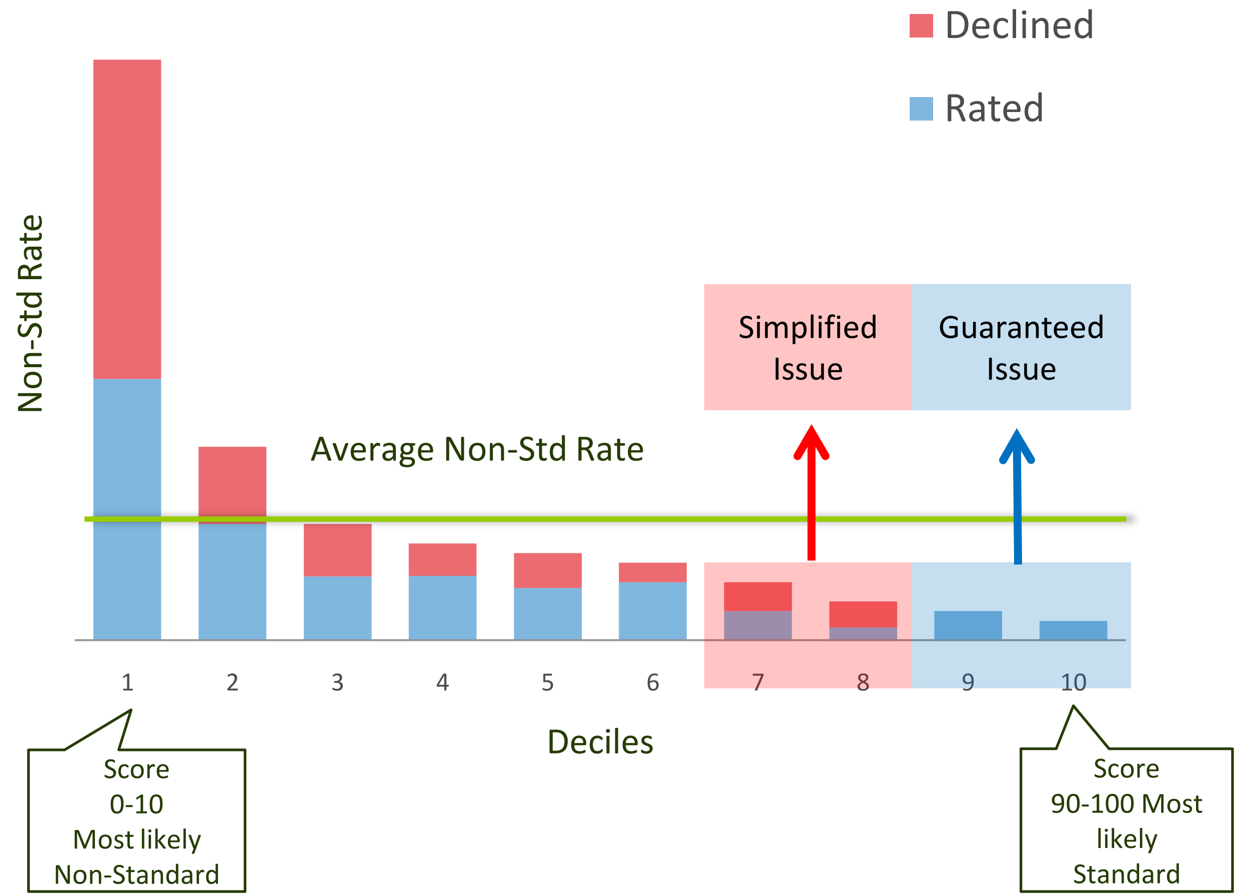
Bancassurance Predictive Underwriting

Model Results

Most Predictive Variables

- Age at entry
- Branch
- Assets Under Management
- Customer Segment
- Nationality

Lift Plot



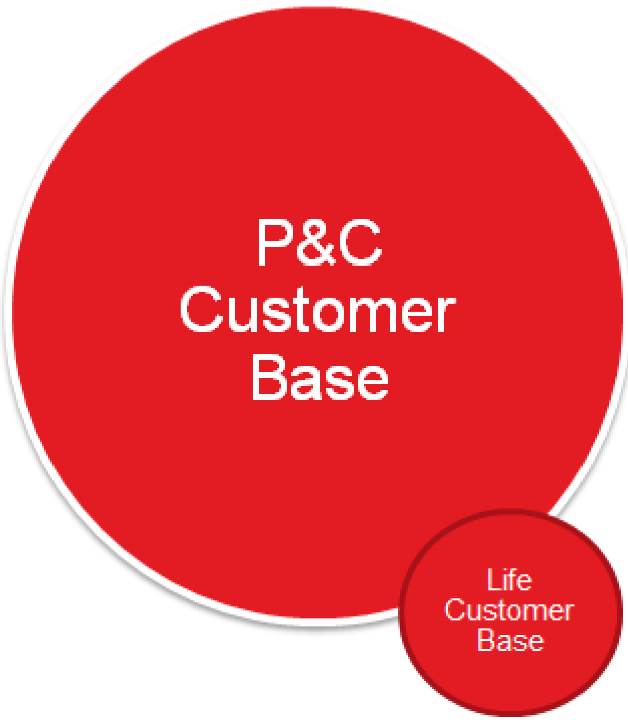
Multi-line Company Cross-sell Model

Background

- A large multi-line company with a very large P&C customer base.
- Low life product penetration.

Objectives

- Increase life insurance penetration and leverage data from their large in-force P&C customer base.
- Offer a simplified underwriting and sales process with a low decline rate to the best customers.
- Reduce acquisition costs, improve experience, shorten underwriting turn-around time.
- Improve persistency of P&C customers as a result of a deeper relationship with clients.



Multi-line Company Cross-sell Model

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Predictive Underwriting model built using two sets of data

Predictors

- P&C customer demographic, financial, underwriting, claims and admin data from both motor and home insurance.
- Other information normally collected at the life UW stage e.g. smoker status.
- Possible merger with 3rd party data sets.

P&C data greatly increases depth of data and risk differentiation

Response

The underwriting decision when normal underwriting applied:

- Standard risk
- Rated
- Declined

Linked to the same lives

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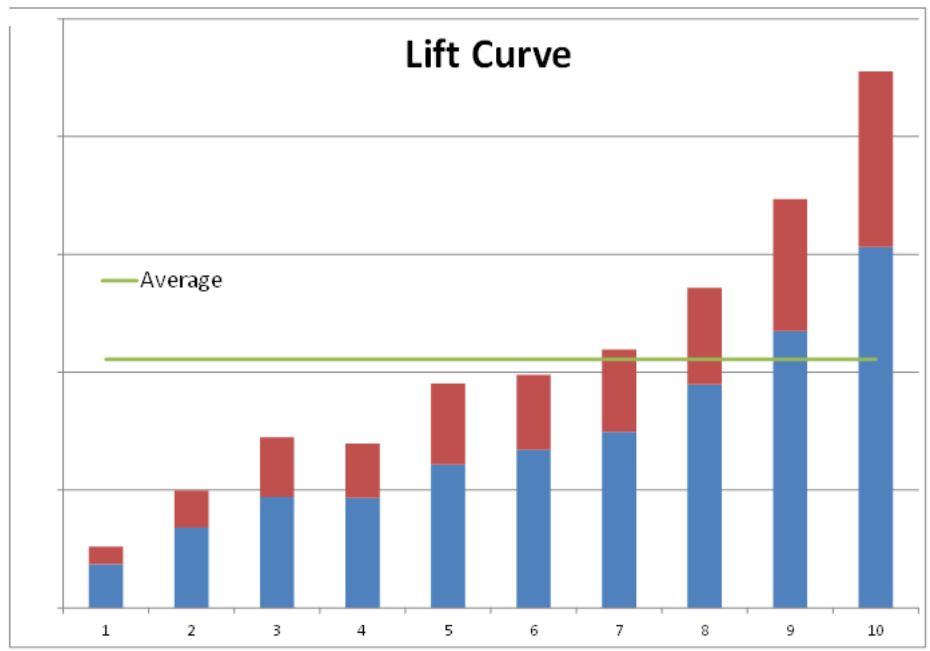
Multi-line Company Cross-sell Model

Model Results

- At least two dozen variables used for each model.
- Key variable examples: age, gender, auto violation points, liability limit, automobile type, no. of vehicles covered etc.
- Propensity to buy models were layered in on top of risk model to create a combined list of customers to target.

Source	variable	Type	Impact on being Tobacco
Group 1	Variable 1	Numerical	↓
	Variable 2	Numerical	↓
	Variable 3	Numerical	↓
	LIAB_LIMIT	Numerical	↓
	Variable 4	Numerical	↓
	Variable 5	Numerical	↓
	TOTAL_VIOLATION_POINTS	Numerical	↑
	Variable 6	Categorical	↓
	Variable 7	Categorical	↓
	Variable 8	Categorical	↓
	Variable 9	Categorical	↓
	Variable 10	Categorical	↓
	Variable 11	Categorical	↑
	Variable 12	Categorical	↑
	Variable 13	Categorical	M↑, F↓
	Auto_MAKE_NAME	Categorical	Economy↑;Luxury↓;Other ⇔
	Variable 14	Categorical	Auto↑ ; Allied Auto ↓



Fraudulent Claims Identification Model

CASE STUDY

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Objectives

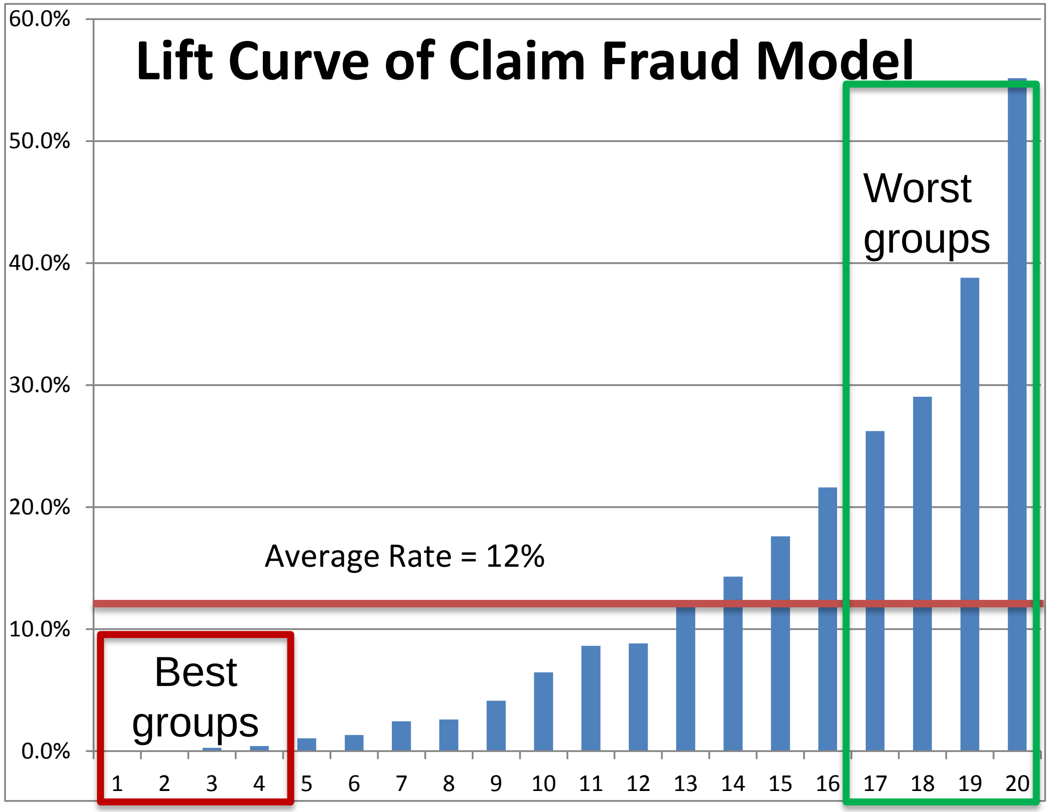
- Identify which medical claims to investigate for fraud so as to make the best use of limited claims resources.

Modeling Process

- Used a very comprehensive claims data set and built a GLM.
- Key Variable Examples: sum assured, duration, education, payment frequency, geography plus several interaction terms.

Results

- Good model: Worst 20% have a 37% fraudulent claims rate and best 20% has 0.2% fraudulent claims rate.



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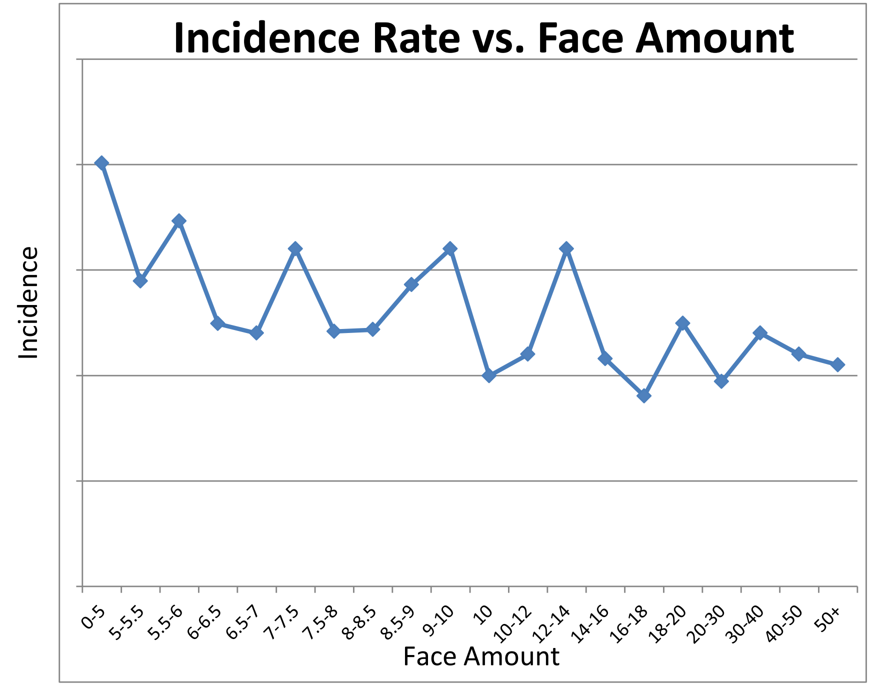
Non-Med Limit Risk Segmentation Model

Objectives

- Determine optimal non-medical limits that should be used for different customer segments.
- Streamline the underwriting process by enforcing more stringent measures for high risks & vice versa.
- Identify low risk policyholders for up-sell or cross-sell campaigns.
- Understand true drivers of experience to improve decision making.



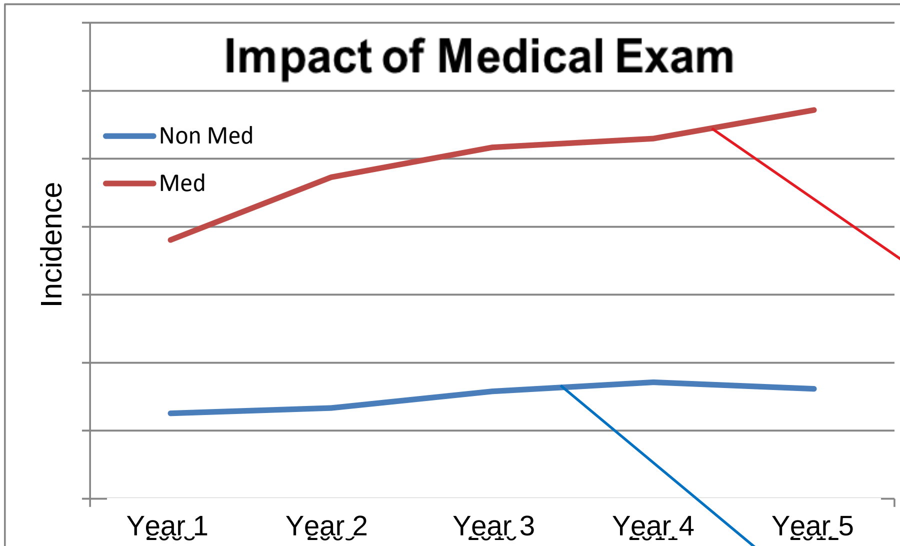
Data Source	In-force + claims
Study Period	5 years
Product	Critical Illness
Total Exposure	Around 7m life years
Total Claims	Around 10,000

Model Building Process

- GLM Model using only insurance company data e.g. age, gender, marital status, occupation, region, agent rating, claims and many other variables.

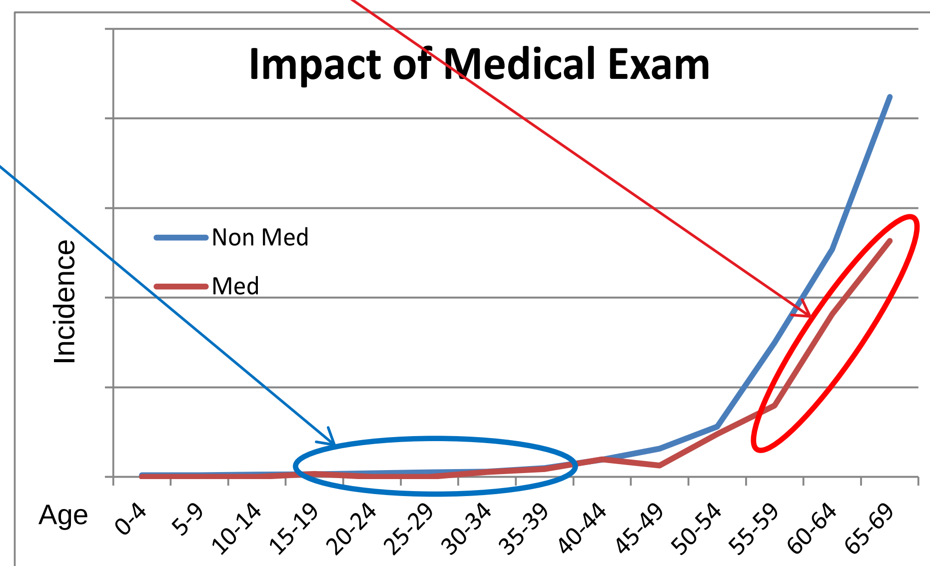
Non-Med Limit Risk Segmentation Model

Effectiveness of Medical Exams



Obvious example of how a univariate analysis doesn't allow us to understand the true drivers of experience.

Removing the impact of age helps us understand what is driving the differences in claims experience.



Non-Med Limit Risk Segmentation Model

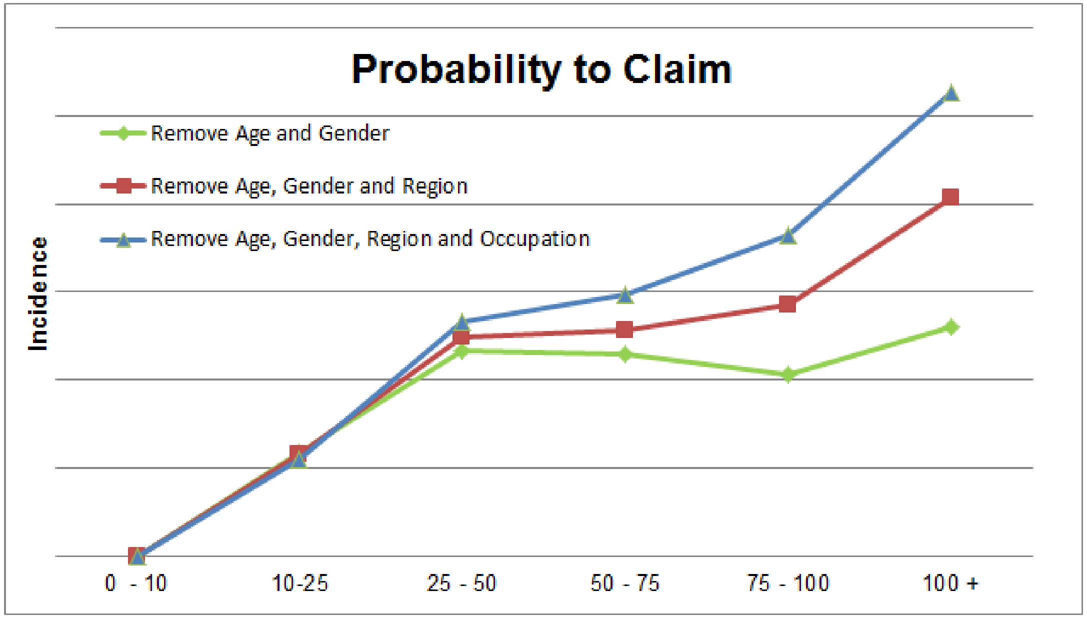
Most Predictive Variables

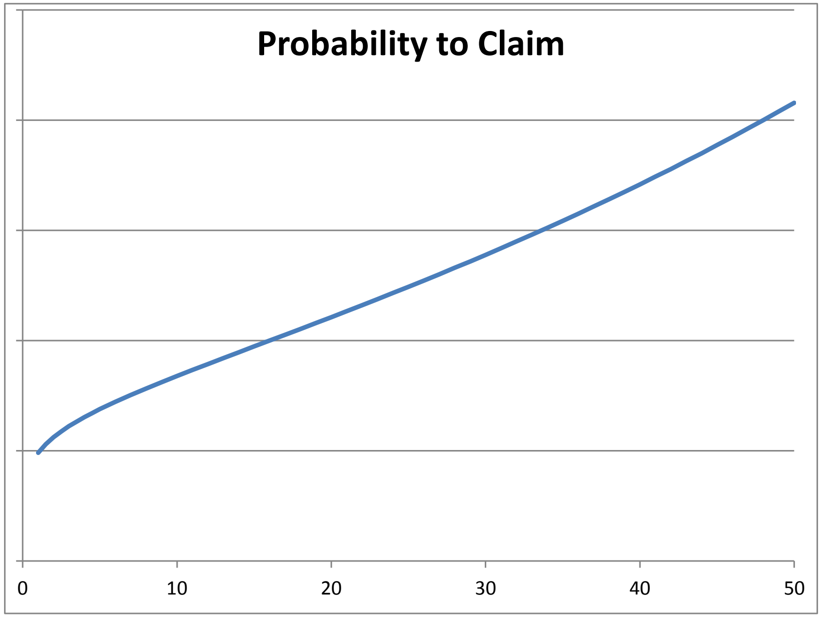
Variable	Type	Impact on claim
Age and Gender	Main/Interaction	age↑, M↑ F↓
Duration	Numeric	↓
Face Amount	Numeric	↑
Insured Smoking Indicator	Binary	Y↑
Region	Categorical	NE ↑ SW↓
Relationship to Policyholder	Categorical	Self↓
Agent Rating	Categorical	Tier X ↑ [illegible]
[illegible] GROUP	[illegible]	[illegible]

Non-Med Limit Risk Segmentation Model

Incidence vs. Face Amount

- Probability of claiming increases as face amount increases.
- Non-medical limit is necessary to help control risks.
- Anti-selection appears to be the dominating force up to the NML limit.

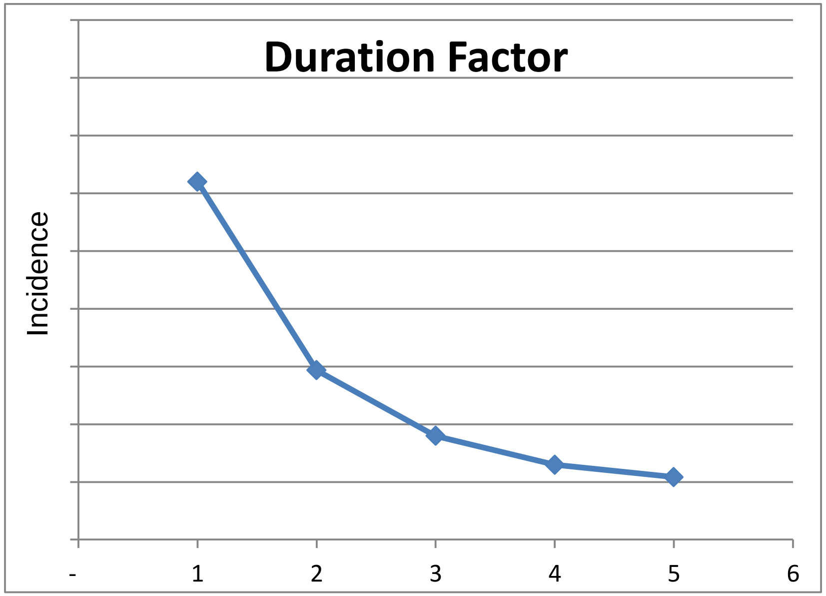


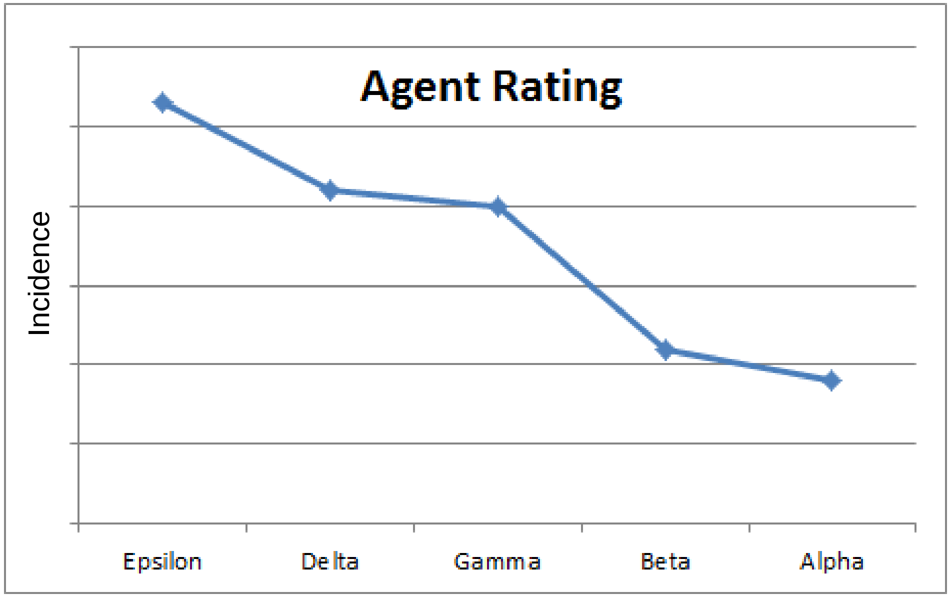


Non-Med Limit Risk Segmentation Model

Model Results

- By Duration: Incidence rates reduce as policy duration increases which indicates severe anti-selective behavior.
- Agency Rating: The insurers current rating system works well with better experience business coming from higher rated agents.

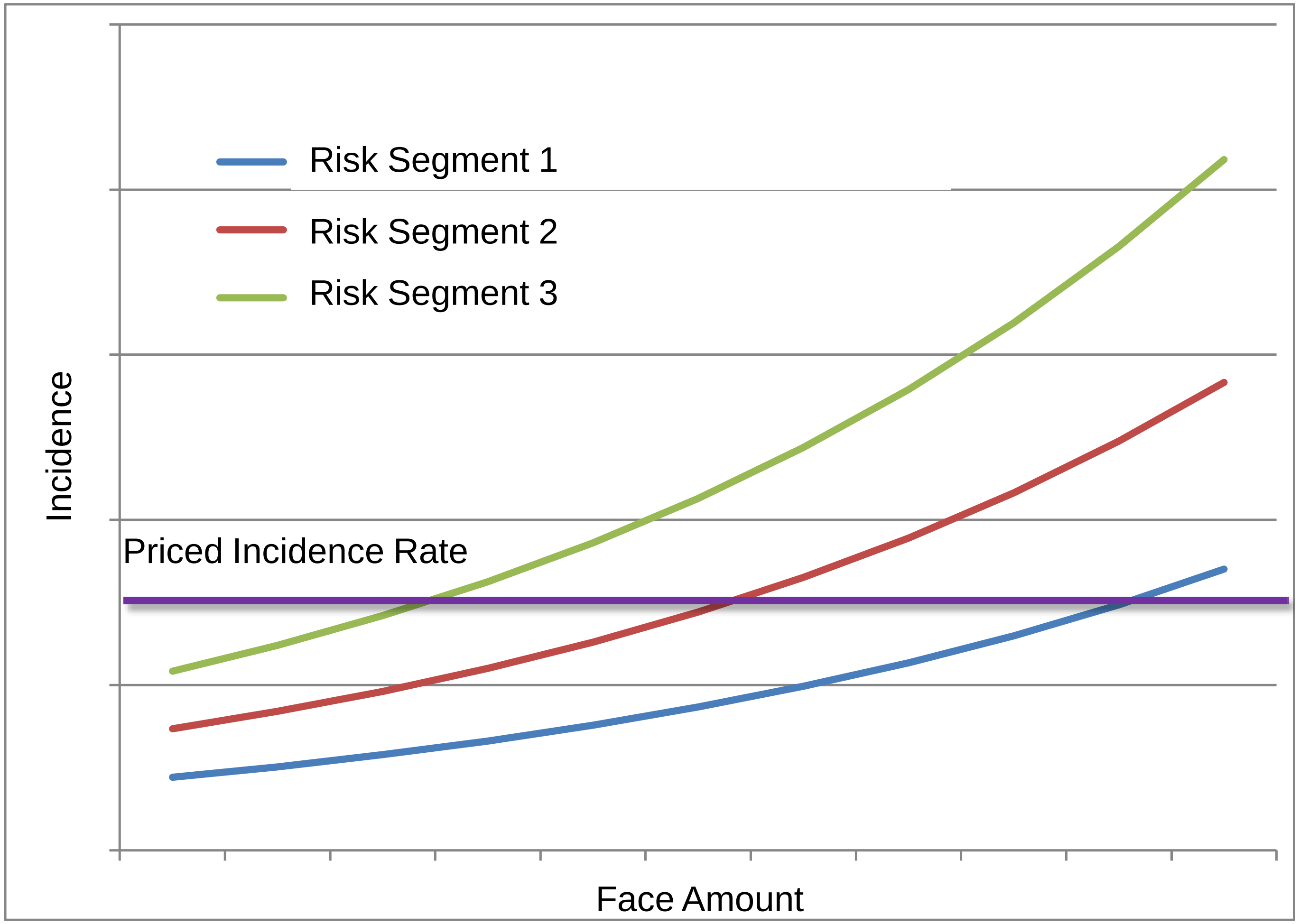




Non-Med Limit Risk Segmentation Model

Setting Non Medical Limits

- Segment customers and set the non medical limit at or below the pricing assumption.



TransUnion and RGA Mortality Study

Background

- Credit Bureaus in the US have enormous amounts of consumer credit data on nearly 200 million Americans. This data captures attributes of individuals related primarily to borrowing and repayment behaviors.
- Credit data captured by the credit bureaus results in nearly 1000 different variables that are used in many different credit scoring predictive models.
- RGA has been working closely with TransUnion (one of the 3 major credit bureaus in the United States), since April 2013 to better understand the predictive nature of credit data for life insurance.
- In early 2014, TransUnion completed work on the Credit Mortality Index (CMI) and shared the CMI values and 80 other credit variables on nearly 20 million individuals for RGA to complete an independent 12-year mortality study of the model.

TransUnion and RGA Mortality Study

Potential Applications

- Target Market:
  - Can be used to assist in the market segmentation process.
  - Focus on the best risks for new customers or upsell / cross-sell campaigns.
- Conversion near the end of the level-term period:
  - Assist in the selection of policies for conversion near end of term.
  - Offer favorable conversion terms to less risky policyholders.
- Simplified issue programs:
  - Used in conjunction with other real-time data (violations, Rx, MIB).
- Additional segmentation in full underwriting.
- Lapse prediction and related underwriting actions (premium, face, payment terms, etc.)

TransUnion and RGA Mortality Study

Credit Mortality Index (CMI) Modelling Process

① Started with total **credit-active population in 1998** – included 90% of adult population

↓

② 92m records gathered, results are **credible due to size of data:**

- 44m used to create CMI
- 30m used to test and validate CMI to avoid over-fitting the model
- 18m used for mortality study validation

↓

③ Deaths over 12 year observation period (1998-2010) were appended using the Social Security Master Death File, Oct 2011 version

↓

④ Started with 800 credit variables and the final model consists of 53 variables with the highest stability, highest predictive power and low correlation amongst variables.

Variable Examples:

- Months since oldest account opened
- Aggregate balance of all accounts, exc. Mortgage
- Payment pattern in last 18 months

↓

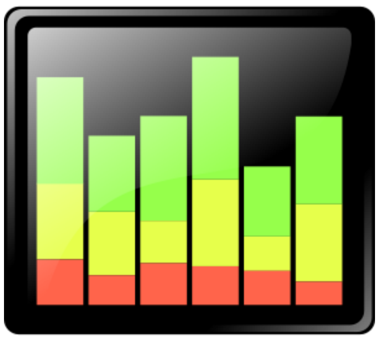
⑤ Final CMI score is a single number ranging from 0 – 100 (0 = lowest mortality risk)

TransUnion and RGA Mortality Study

Combining Mortality Study with CMI

① Created a **12-year** (1999-2010) traditional actuarial study on **18m lives**

② **CMI was appended** to the 18m records



③ Resulted in **194m exposure years**

④ mapped to **1.1m deaths** - Actual experience
(using the Social Security Master Death file, Oct 2011 Version)

⑤ Base mortality table – Expected experience:
1999 – 2010 historical US population mortality tables with adjustments:

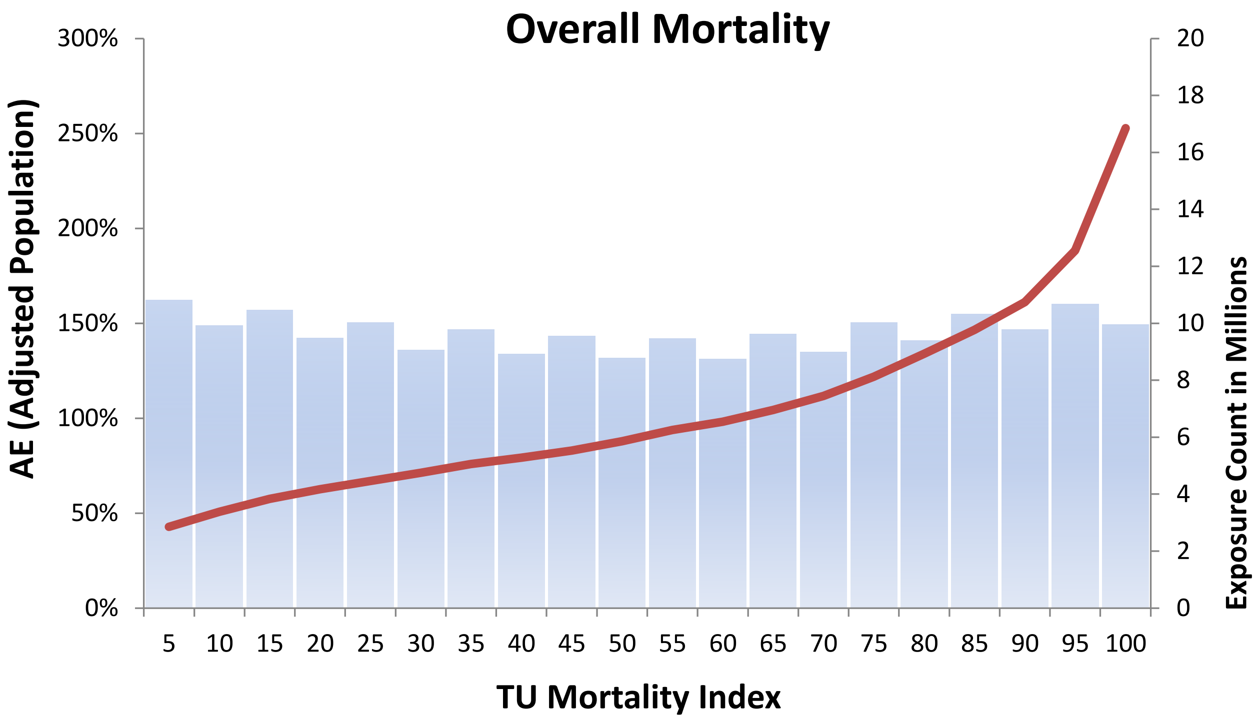
- Under-reported deaths in the Master Death file
- Gender mix in the data

⑥ **A/E = Actual Experience / Expected Experience**

TransUnion and RGA Mortality Study

Overall Results

- Blue bars represent exposure and we have a near uniform distribution of lives in the study.
- Each bar represents approximately 5% of the overall population.

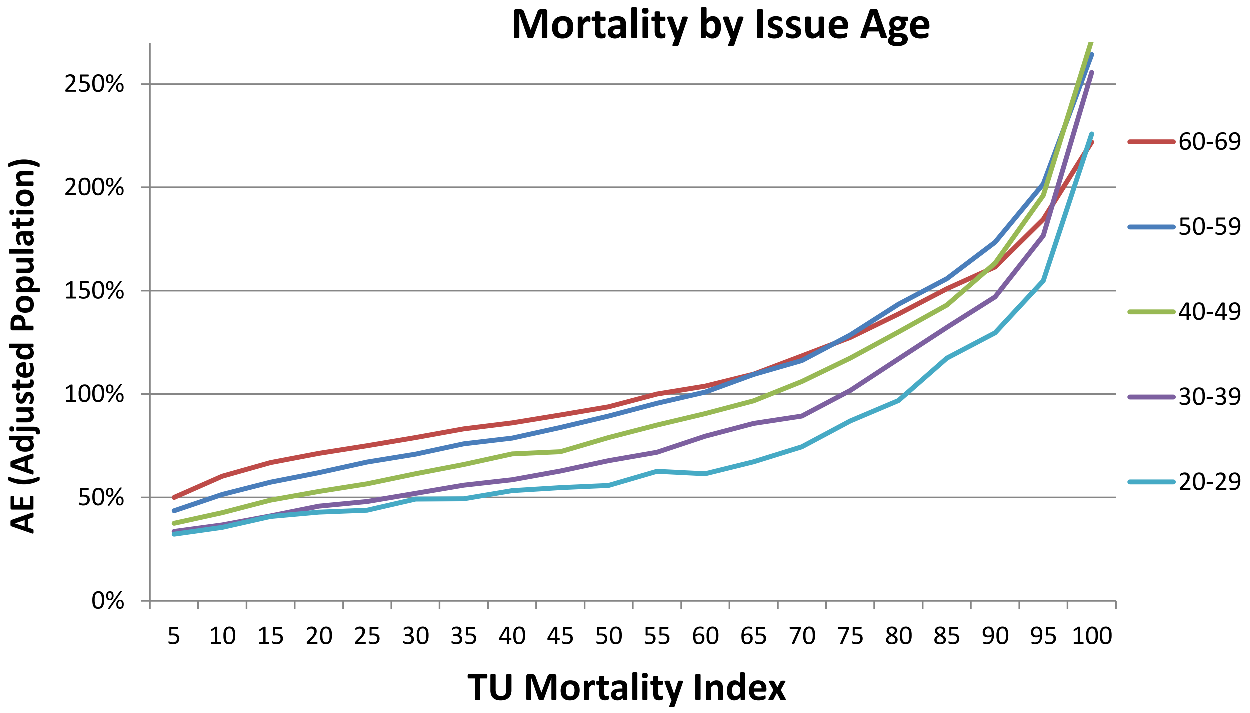


- Model produces an A/E curve that is smooth and monotonically increasing.
- Score appears to be very predictive of mortality.
- The worst 5% of risks has an A/E of more than 5 times that of best 5%.
- The worst 10% has A/E of about 4 times that of best 10%.

TransUnion and RGA Mortality Study

Results by Entry Age

- Similar but parallel upward shift as age increases.
- Younger individuals with established credit seem to have better mortality (relative to the general population) than older individuals.



- Study also splits results by gender, duration (since data archive date) and US state. There is no significant difference in results when splitting into these groups (although broader state groupings did yield differences).

Typical Predictive Modeling Process

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- **1. Define Purpose of the Model**
  - Identify Business Motivations
  - Identify Goals of the Model
- **2. Collect & Prepare the Data**
  - Gather Data
  - Understand Data
  - Clean Data
  - Transform Data?
  - Split Data into Training Data& Validation Data
- **3. Develop Models**
  - Model Type Selection
  - Identify Constraints
  - Train Model
  - Test Model
  - Validate Model
  - Meets Requirements?
- **4. Interpret & Apply Models**
  - Interpret Results
  - Communicate / Gain Acceptance
  - Create Rules
  - Train Staff
  - Deploy Model
- **5. Monitor Results & Update**
  - Monitor Output & Performance
  - Test Results Against Objectives
  - Refresh Data
  - Refine Model

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Closing Thoughts

Where do I begin…

- Figure out what current process needs to be optimized.
- Understand what your competitors are doing.

We don't have data…

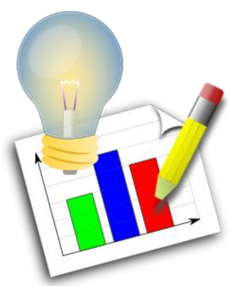
- Few companies do but you'll be amazed by how much can be predicted with the data you already have.
- Speak to your business partners about data sharing.
- Start capturing and digitizing data so you'll have something to work with in the future.

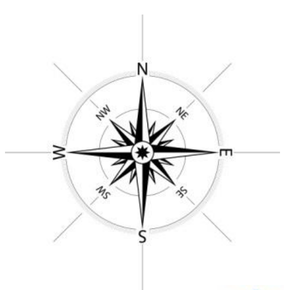
We don't have the expertize and risk appetite…

- Locate and leverage existing resources in your organizations data/analytics teams.
- Seek outside resources to help build models and share in potential risks.

Big projects are risky…

- Start with a pilot and proof of concept.
- Learn, expand and repeat.





I don't have the budget…

- Consider the costs, benefits and risks by building a business case.
- Probably not as difficult and as expensive as you think…