Real World Uses of Big Data: Insurer Operational Applications

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Real World Uses of Big Data: Insurer Operational Applications

Insurers use predictive modeling to improve operations:

- Pricing
- Underwriting
- Marketing
- Claims
- Strategy
- Capital modeling
- Other

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Regulatory encounters with predictive modeling:

- Loss cost/rate filings
- Rule filings
- Financial exams
- ORSA filings
- “Hidden” encounters?

Real World Uses of Big Data: Insurer Operational Applications

Case Studies:

- #1: Strategy
- #2: Underwriting
- #3: Marketing
- #4: Claims

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Case Study #1:

Strategy

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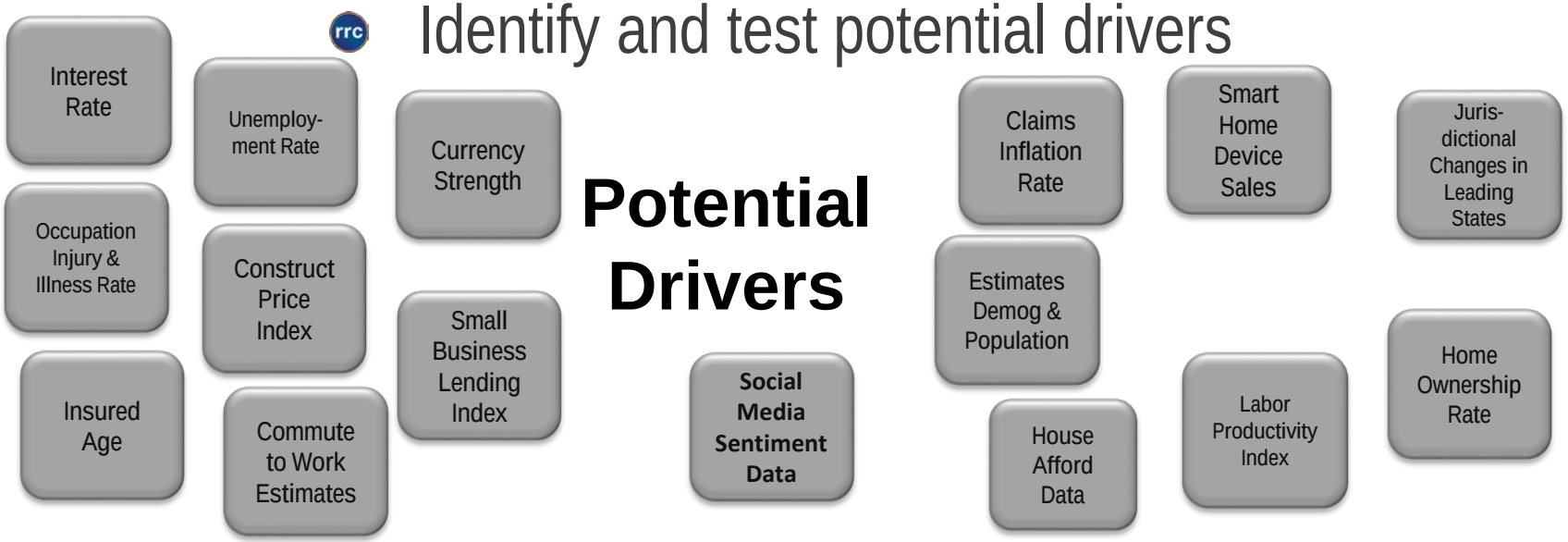
Strategic Questions

- What key variables are relatable to the performance and risk of a company?
- Are these variables economic, insurance, behavioral,…in nature?
- Are variables leading indicators, is there a causal relationship, do variables and performance outcomes have common drivers?

CASE STUDY #1: STRATEGY (CONTD.)

Strategic Example – Drivers of Performance

- Define a model that identifies leading indicators of company performance.
  - Identify and test potential drivers

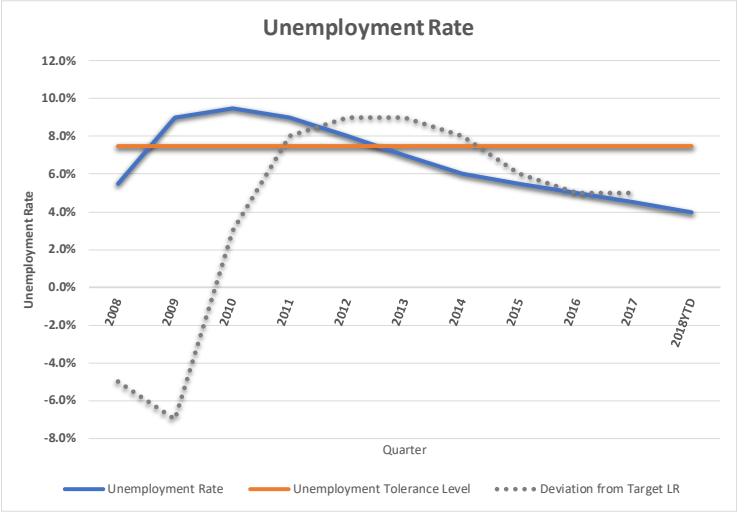


CASE STUDY #1: STRATEGY (CONTD.)

Strategic Example – Drivers of Performance

- Use of findings

Driver Monitoring



Business Plan Stress Testing

Unemployment Rate Scenarios				
Unemployment Rate	Business Plan Levels	0.5% Above BP	1.0% Above BP	1.5% Above BP
Premium	100	.	.	.
Total Reserves	135	.	.	.
Investible Assets	175	.	.	.
Net Income	45	.	.	.
Surplus	415	.	.	.
ROE	10.8%	.	.	.

Case Study #1: Strategy (contd.)

Strategic Example – Drivers of Performance Volatility

- Define a model that identifies key drivers of volatility and estimates volatility of account performance based on these drivers.
  - Volatility defined by standard deviation
  - Target metric is deviation from expected result

CASE STUDY #1: STRATEGY (CONTD.)

Strategic Example – Drivers of Performance Volatility

- Sample multiplicative algorithm based on base case volatility assumption adjusted for three key drivers:

Base Case Account Standard Deviation	**0.40**
Line of Business Relativity	
Commercial Auto	1.30
Property (Base)	1.00
Workers Compensation	1.10
Market Cycle Relativity	
Hard Market	0.75
Transitioning to Soft Market (Base)	1.00
Soft Market	1.30
Transitioning to Hard Market	0.90
Age of Insured Business Relativity	
New Business	1.50
One Year	1.40
Two Years	1.30
Three Years	1.10
Greater Than Three Years (Base)	1.00

CASE STUDY #1: STRATEGY (CONTD.)

Strategic Example – Drivers of Performance Volatility

Application of Algorithm to Sample Account:

Sample Account

New WC entrant as market appears to be hardening.

Calculation of Account Volatility Measure

Base Case Account Standard Deviation	**0.40**
Workers Compensation Relativity	**1.10**
Transitioning to Hard Market Relativity	**0.90**
New Business Relativity	**1.50**
Sample Account Standard Deviation	**0.59**

Translated into Required Capital for Account:

Required Capital: 0.31

Account requires 31 cents of capital per dollar of premium written.

CASE STUDY #1: STRATEGY (CONTD.)

Strategic Example – Drivers of Performance Volatility

Drivers of volatility can inform:

- Determination of required capital
- Allocation of capital to line or account
- Monitoring and optimization of portfolio mix
- Identification of common drivers of uncertainty across risks (pricing, reserving, investment,…)

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Case Study #2:

Underwriting

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Case Study #2: Small Commercial Lines Underwriting

BACKGROUND:

- Predictive underwriting model
- Developed several years ago
- Used for premium debit/credit
- Not used for underwriting decisions
- Scope: assess in light of current practices

Case Study #2: Underwriting (contd.)

Model Design:

- GLM: $Y = \beta_{\circ} + \Sigma\, \beta_i\, X_i$
- Y = predicted loss ratio
- X = independent variables
  - Internal
  - External
- Limited losses
- Grouping of variable values
- Calibration, Deciles

Case Study #2: Underwriting (contd.)

Information:

- Model documentation
  - Approach
  - Variables
  - Equations
  - Calibration
  - Results
- Additional implementation documentation
- Calculator for sensitivity testing
- Statistical analysis
- Model Lift

Case Study #2: Underwriting (contd.)

Conclusions

- Certain predictive variables missing/others redundant
  - External, e.g., economic
  - Internal, e.g., loss control
- Consider modelling loss cost/deviation from target
- Model needs re-calibration
  - External, e.g., industry trends
  - Internal, e.g., operational changes (explicitly include in model)
- Consider newer modeling methodologies/non-linear relationships/correlations
- Test impact of grouping, missing values, use of averages, limiting losses/premium
- Update model (not implement current)
- Involve underwriters in model development

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Case Study #3:

Marketing

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Renewal Retention Analysis

Case Study Introduction

- Improve customer retention by understanding:
  - Customer buying habits
  - Factors contributing to customer loyalty (long and short term)
  - Factors contributing to loss of customer
  - Linkage to customer loss experience

Case Study #3: Marketing (contd.)

Renewal Retention Analysis

Strategic Questions

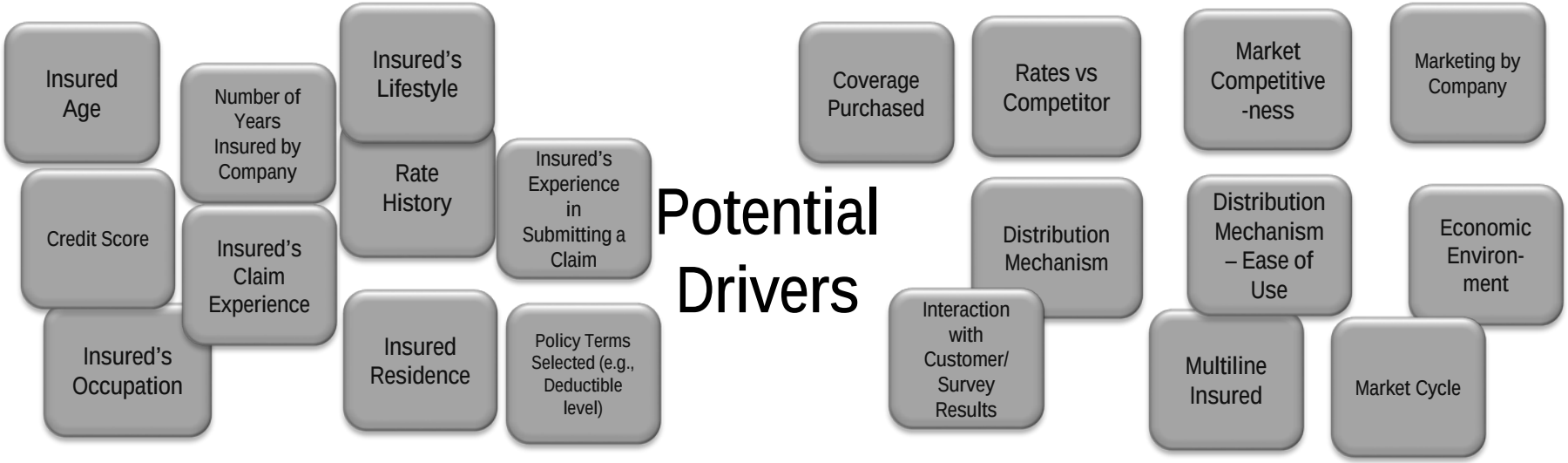
- What key variables are relatable to the success of binding a policy?
- How do variables differ in acquiring new business vs retaining renewal business?
- Are variables general in nature (i.e. younger insureds prefer to buy insurance online) or more specific to individual insured?

CASE STUDY #3: MARKETING (CONTD.)

Renewal Retention Analysis

Potential Drivers

- Define a model that provides insight into customers and customers' buying habits



CASE STUDY #3: MARKETING (CONTD.)

Renewal Retention Analysis

A Sample of Potential Sources of Information

- Insurer's Data (Individual and Aggregated)
- Competitive Rating Tools
- Insurance Industry Data
- Economic Indices
- Facebook, LinkedIn,…

Note: For analysis of new business hit ratios, sources and granularity may differ and rely more on external sources. Results of renewal retention analysis can be leveraged to identify target new customers.

CASE STUDY #3: MARKETING (CONTD.)

Renewal Retention Analysis
Wide Spectrum of Variable Representation

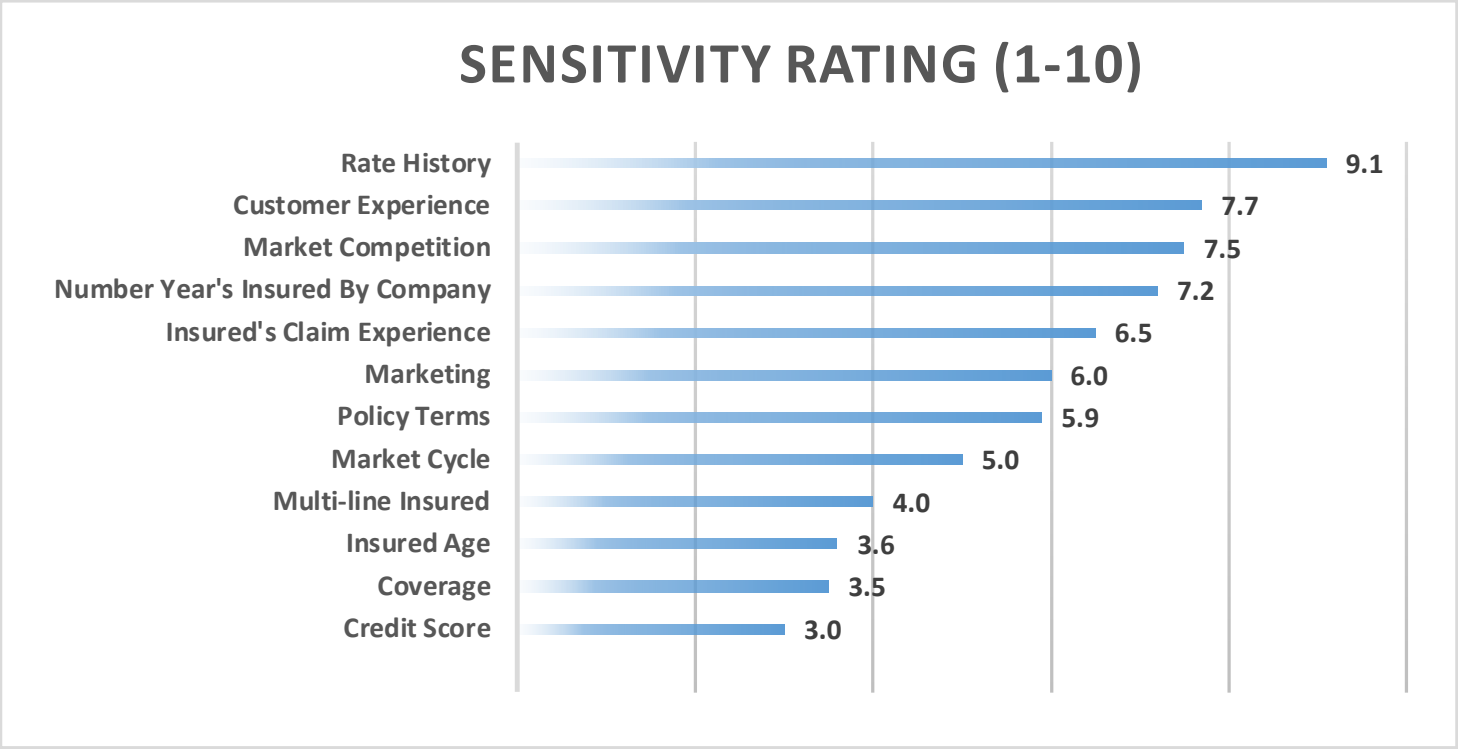
- The choice of variables and their representation have a significant effect on analysis results.

- Example: Rate history is selected as a variable, the data fields can take many forms:
  - Recent Year, 3 Year, 5 Year Rate Change
  - Number of Rate Changes Above 5%, 10%
  - Number of Rate Decreases, -5%, -10%
  - Frequency of Rate Changes
  - Policy Term Length
  - Reason for rate change (individual claim activity vs aggregate loss experience)
  - Raw rate change experience as-is

CASE STUDY #3: MARKETING (CONTD.)

Renewal Retention Analysis

Sample Findings



Case Study #3: Marketing (contd.)

Renewal Retention Analysis

Carryover of Findings to Target New Customer Profile

Target New Customer Profile (Based on Social Media Data)				
Sentiment	Positive	Neutral	Negative	
Location	Local	Intermediate	Broad	World
Frequency	Low	Med	High	Ultra
Time of Day	Business	Non-Business	Early/Late	All
Values Rating	Low	Med	High	
Hazard Rating	Low	Med	High	
Financial Rating	Poor	Med	High	
Profession Rating	Low	Med	High	

Target
Avoid

Case Study #3: Marketing (contd.)

Renewal Retention Analysis

Learnings

- What is important to customer and how customer makes coverage decision
- Why renewal retention results are what they are
- Where to place focus in directing the insurance portfolio profile towards company's target profile

Case Study #3: Marketing (contd.)

Renewal Retention Analysis

Integration of Findings

- Integration within marketing strategy and customer interaction platform
- Development loyalty rating methodology
- Guidance on implementation of rate changes
- Expansion of analysis to new business hit ratio
- Personalized marketing to target customer

Case Study #3: Marketing (contd.)

Renewal Retention Analysis

Potential Concerns

- Use of personal data to target particular profile
- Indirect incorporation of unfairly discriminatory variables into underwriting and ratemaking
- Others?

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Case Study #4:

Claims

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Case Study #4: Claims Predictive Modeling

Background:

- A commercial auto insurer implemented a claims predictive model for case reserving eighteen months ago.
- The model predicts ultimate settlement value for each claim based on information available 30 days after the report date.
- Management believes that the use of the model has resulted in higher case reserve adequacy in the aggregate.
- Management also believes that it is able to direct more experienced personnel to be assigned to claims with higher potential for adverse outcomes earlier in the life of the claim.

Case Study #4: Claims (contd.)

Questions (among others):

- Can traditional approaches such as Berquist-Sherman be used to estimate the potential change in case reserve adequacy?
  - If not, are alternative approaches viable?
- Can tests be devised to validate management's contention that potential high-value claims will be addressed with appropriate personnel faster?
  - If so, can those tests also quantify the potential impact on future development and ultimate cost?

Case Study #4: Claims (contd.)

Considerations:

- Case Reserve Adequacy
  - We do not know if settlement strategy has changed in tandem with the implementation of the model.
  - The assessment of case reserve adequacy should also consider changes in settlement patterns.

- Impact of Assigning Experienced Personnel to Potentially High-Value Claims Faster
  - The model has been in place for only two years.
  - Many claims reserved under the model in both year 1 and year 2 following implementation are yet to settle.
  - This complicates the assessment of the extent to which potential high-value claims are being settled earlier and for less than they otherwise would.

CASE STUDY #4: CLAIMS (CONTD.)

Supplementing Traditional Diagnostics: Claim Transition Matrix

- Bond default probabilities can be viewed through a transition matrix framework, e.g. the likelihood of a bond currently rated AA defaulting in the next year versus a bond currently rated A.
- Claims could be viewed in a similar manner, e.g. the probability of a claim reserved for $25,000 increasing to $250,000 or more in the next 12 months.
- Comparing this behavior for claims reported before and after model implementation may be useful in assessing the extent to which the model is having the desired effect.
  - For example, assume 5% of open claims reserved for $25,000 at 12 months increased to $250,000 or more in the next 12 months prior to the model implementation
  - If only 2% of open claims reserved for $25,000 at 12 months increase to $250,000 or more in the next 12 months, that could be viewed as support for management's contention that high potential claims are being addressed sooner.

Case Study #4: Claims (contd.)

Conclusions:

- Implementation of a claims predictive model for case reserving is likely to impact numerous behaviors in the claims management process.
- Quantifying the effects of these changes on ultimate costs is challenging, particularly when the model implementation is relatively recent.
- Consideration of traditional diagnostics (such as average case reserves) in combination with potentially non-traditional diagnostics (such as a claim transition matrix) may allow for improved judgment in the process of estimating these effects.

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