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Commercial Lines Predictive Modeling - BOP

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Why Predictive Modeling?

Traditional pricing and underwriting models are built for:

- 1. Processing efficiency: expense saving
- 2. Operational efficiency: significant operational improvement
- 3. Pricing efficiency: lower pricing cost
- 4. Improved manual rating of risks through improvement in current rating factors and addition of new rating factors
- 5. Ability to use factors not included during rating
- 6. Improved prediction of book losses
- 7. Reduction of underwriting expense through automation
- 8. Consistent underwriting: flatten the underwriting cycle
- 9. Fast and cost-effective targeting of risks
- 10. Expansion into new markets
- 11. Reduction of market-share loss
- 12. Better / quantitative segmentation of risks
- 13. Reduction risk of adverse selection
- 14. First movers' advantage
- 15. Necessity!

Further Applications of Predictive Models

Credit models
Retention models
Agent/agency monitoring
Cross-sales models
Elasticity models
Target marketing
Lifetime Value models
Fraud detection
Customer segmentation/clustering

The various applications....should be integrated

BOP Is Different From Other Commercial Lines Products

BOP has:

- More uniformity by size
- Composite rating
- Lesser pricing flexibility
- Company (rather than bureau) driven pricing
- Simplified pricing / less information is captured
- Data quality is better

Some of these differences are being blurred by current developments (Split-rating, industry-specific products)

BOP Is Different From Personal Lines Products

BOP has:

- Heterogeneous classes/groups
- Less uniformity by size: a wider range of policy size
- Less standardization
- Heterogeneous exposures
- Less data available
- Less regulation

Some of these differences are being blurred by current developments (Split-rating, industry-specific products)

Predictive Modeling – Basic Requirements

Skills needed

- Statistical
- Actuarial
- Programming
- IT/Programming
- Project Management

Keys to Successful Predictive Models

- Strong project management skills
- Buy in from the company management and staff
- Careful model design
- A well conceived implementation plan for both business and IT implementation

BOP Models: An Evolution From Personal Lines Models

- Some of what we know from personal lines still works for BOP (credit scores, GLM, etc.)
- Similar actuarial design issues: premium on-leveling, loss development, large loss impact, etc.
- Move from pure premium (freq/severity) to loss ratio models
- Move from exposure level to policy level models

Predictive Modeling Pitfalls

First-time efforts often fail because one or more of the following is overlooked:

- Management buy-in
- Staff acceptance / internal politics
- IT challenges
- Modeling challenges (e.g., fit vs. memorization)
- Implementation challenges

Choices / Dichotomies

What kinds of model to build?

- Underwriting: New Business / Renewal Business
- Rating: Price / Coverage
- Coordinate Implementation
- Monitor Feedback/Adjust Implementation
- Multi-line Account / Line of Business

Factors to consider for BOP Models

- Size
- Exposure
- Geography
- Industry
- Class of risk
- Programs

The Modeling Process – Step By Step

1. Data Acquisition

- Research/Evaluate possible data sources
- Extract/purchase data
 - Company's internal data
 - Externally purchased data
- Check data for quality

2. Exploratory Data Analysis

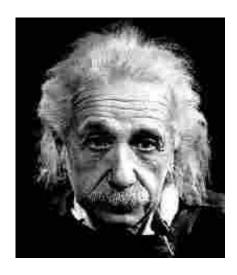
- Examine correlations among the variables
- Discuss specifics of variables with company experts (quantify tribal wisdom)
- Which data points to include/exclude?
- Eliminate redundant, weak, poorly distributed variables

The Modeling Process (continued)

- 3. Create Predictive And Target Variables
 - Which target variable to use?
 - Which predictive variables to consider?
- 4. Model Design
- 5. Build Candidate Models
 - How should model be evaluated?
 - Select final model
- 6. Implement
- 7. Recalibrate

Most Current Models Are Simplistic

Most models are still simple approximations of the reality they model, mainly due to the limitation of our tool and computational capacity



Everything should be made as simple as possible, but no simpler.

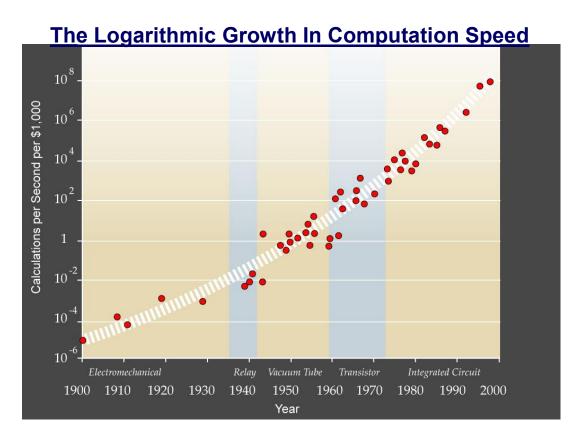
- Albert Einstein

Tools and Computational Capacity Is Improving

Statistical modeling tools are getting better

Availability of information is increasing

Computation and data processing capability is exploding



Trends in Modeling

Since antiquity, in our models of the world there is:

- A progression towards mathematical sophistication
- A progression towards non-linearity

And a consequent progression towards complexity:

- Rudimentary models with no common framework
- Simple Mathematics: a common framework that tries to quantify reality
- Development of more complex mathematics allows more robust models of real world phenomena
- Growing complexity, Cybernetics, Hierarchical Models, Neural Networks, Connection Machines, Cellular Automata, and Genetic Algorithms to Chaos Theory

Looking to the Future

Future is self organizing, goal seeking, and adaptive

- Solutions will be less linear
- Solution elements will be highly interdependent
- Solutions will use the shape of the problem
- Solutions will improve with each additional observation

Examples could include:

- Genetic algorithms: evolving and adaptive
- Expert systems + statistical models = a better brain-in-a-box
- The Hive Mind: a democracy of models
- Silicon + Carbon : you will be assimilated
- Human beings as parts of a communal mind (The Matrix)

Bibliography

Peter L. Bernstein - Against The Gods

W. Daniel Hillis - The Connection Machine, Massachusetts Institute of Technology, September, 1981

Nigel Snoad and Terry Bossomaier - MONSTER - the Ghost in the Connection Machine: Modularity Of Neural Systems in Theoretical Evolutionary Research

Anita M. Flynn and John G. Harris - Recognition Algorithms for the Connection Machine, MIT Artificial Intelligence Laboratory

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