



## II-4 GETTING STARTED WITH PRICE OPTIMIZATION

– Concepts, Models, and Hurdles

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### Agenda

- Defining Price Optimization
- Simple Scenarios
- The Flip Side: Opportunity to Profitability
- The Flop Side: Hurdle and Concern
- The Benefit: Simulation Exercise

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### Price Optimization – A Key Battle Field

- A pricing scheme that optimizes business measure of success in a specific investment horizon
  - Business measure includes, but not limited to, growth, profitability, customer satisfaction, cross-sell
  - Business goals can be achieved via also underwriting, marketing, claims handling strategies
  - Investment horizon is key as price optimization is usually served as Profit and Expense deferral mechanism
  - Price Optimization in very short: Cost + Demand

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## Loss Cost Modeling

- Widely studied by industrial players and academia
- GLM: A convergence of industrial practice
  - Standard text for CAS Exam 8
  - Effective publicity of CAS and vendors
  - Acceptance by regulators
  - Cost of exploring/implementing GLM can be very low

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## Demand Modeling

- Relatively less studied
- Difficulty in collecting good quality quote information
- Not as many well-established literature available
- Many choose to use GLM to model instead

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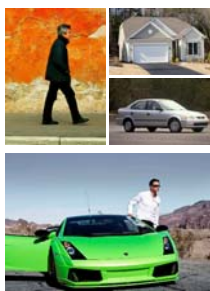
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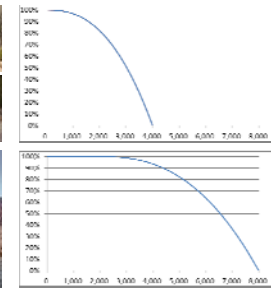
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## Demand Modeling: Strong Premium interaction



Conversion Likelihood against Premium



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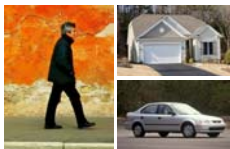
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## Price Optimization – Scenario I



Break Even Premium = \$ 1,200

Company A: \$ 2,000  
 Company B: \$ 2,500  
 Company C: \$ 2,200

**Optimal Price = \$ 1,900**

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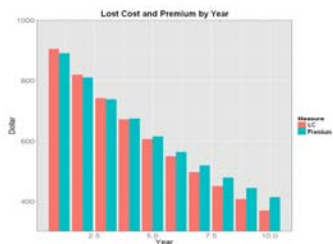
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## Price Optimization – Scenario II

- Loss cost usually decreases as policyholder ages (reversal may happen at the tail)




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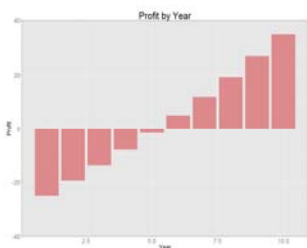
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## Price Optimization – Scenario II

- The initial loss that secures the conversion of customer can be beneficial




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## Price Optimization – The opportunity

- Since the battle field is relatively new, a simplified price optimization can serve as a good start.
  - e.g. Deriving a pricing algorithm by tempering 1 variable

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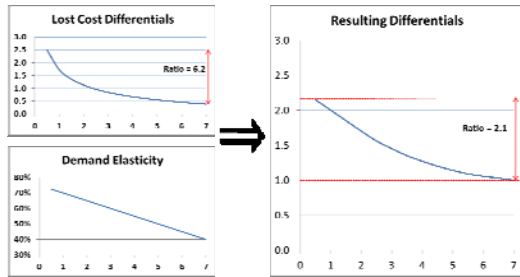
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## Resulting Differentials

### Rating Variable X



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## Price Optimization – The opportunity

- Since the battle field is relatively new, a simplified price optimization can serve as a good start.
  - e.g. Deriving a pricing algorithm by tempering 1 variable
- As understanding of the mechanism increases, so the complexity of the price optimization
- Thus, the start-up cost of price optimization can be affordable

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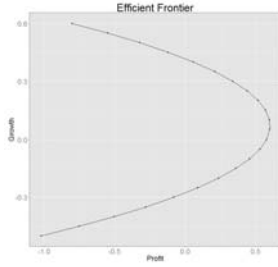
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## Evaluating a Pricing Strategy



### • Efficient Frontier

- Create a view of growth vs. profitability (or any business measures)
- Decision makers can pick any feasible members according to business appetite

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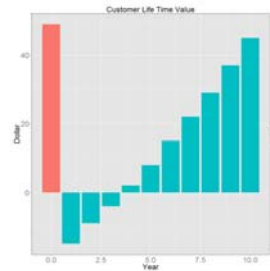
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## Evaluating a Pricing Strategy



### • Customer Lifetime Value

- Present values of profitability
- Easy to explain to the audience with only 1 measure
- Scenarios are comparable
- Simplified modeling
- Could result in outrageous premium increase to loyal policyholders

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## Scope can vary a lot

- By number of components: Claim Frequency, Severity, Conversion, Retention, Expense, Convictions, Mid-term cancellation etc...

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## Model Components to be considered

- **Expense Modeling**
  - Fixed vs. Variable
- **Mid-term cancellation and Penalty**
- **Interest Rates**
- **Conviction and Claims Rates**
  - Leads to claims/conviction free reward
  - Feedback to the rating algorithm

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## Scope can vary a lot

- **By number of components:** Claim Frequency, Severity, Conversion, Retention, Expense, Convictions, Mid-term cancellation etc...
- **By the modeling techniques for the component:** GLM, GAM, Neural Network, Boosting etc...

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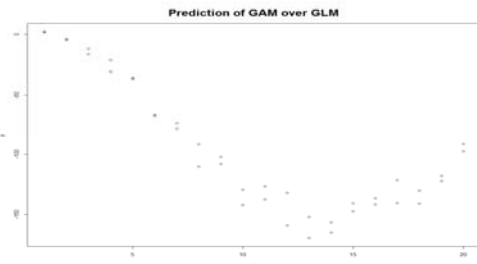
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## GLM vs. GAM vs. Data Mining

- **GLM is intuitive**



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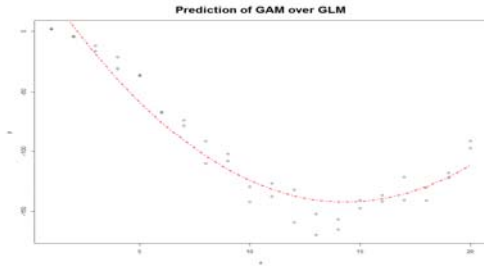
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## GLM vs. GAM vs. Data Mining

- GLM is intuitive



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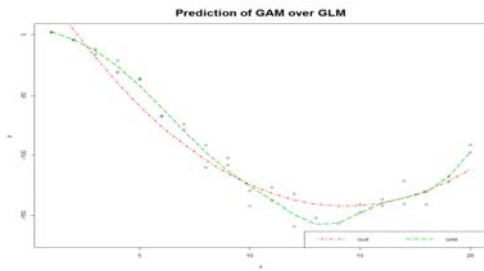
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## GLM vs. GAM vs. Data Mining

- GAM helps temper the extrapolation concern



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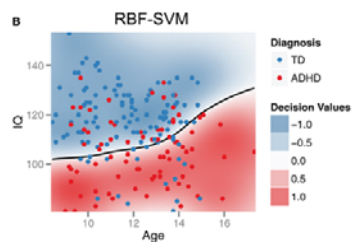
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## GLM vs. GAM vs. Data Mining

- Explanatory variables has interaction usually



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## Scope can vary a lot

- By number of components: Claim Frequency, Severity, Conversion, Retention, Expense, Convictions, etc...
- By the modeling techniques for the component: GLM, GAM, Neural Network, Boosting etc...
- **By number of products: Auto + Property + Life**

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## Scope can vary a lot

- By number of components: Claim Frequency, Severity, Conversion, Retention, Expense, Convictions, etc...
- By the modeling techniques for the component: GLM, GAM, Neural Network, Boosting etc...
- By number of products: Auto + Property + Life
- **By the constraints: dislocation limit, minimum growth, etc...**
- **By the projection periods**

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## Results are highly sensitive to error

- **Reliance on highly accurate underlying models**
  - Combining models
  - Robustness of Assumptions
- **A deviation can be magnified under long projection horizon.**
- **An Alternative is to specify a short to medium**

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## Simulation – Goal

- Goal: Derive a price optimization algorithm to maximize net present value of the personal auto business
- The algorithm is in the form of multiplicative differentials
- Compare the results of various modeling techniques (GLM vs. GAM vs. data mining vs. actual)
- Attempt to quantify the modeling risk for various predictive models

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## Simulation – Underlying Assumption

- Variables:
  - Multi-line (Y/N)
  - Years Claims Free (0-5 Years)
  - Loyalty(0 to 10 Years)
  - Age (25-50)
  - Premium
- 4 models:
  - Claims Frequency – Poisson
  - Conversion – Bernoulli
  - Retention – Bernoulli
  - Severity – Assumed to be constant at 10,000 for simplicity

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## Simulation – Assumptions (Cont'd)

- Interactions and non-linearity exist in all models
- Measure to optimized: Net Present Value of the portfolio
- We also assume all customers' lifespan is 50 years.
- Interest rate/ ROE/ yield = 10%

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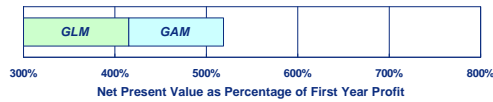
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## Base Case Scenario

- We use GLM/GAM to model the loss cost without considering demand models.
- GLM NPV as year 1 profitability = 415 %
- GAM NPV as year 1 profitability = 519%



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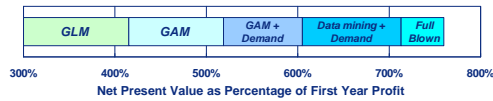
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## Pricing with Demand Consideration

- Considering also the demand models, NPV will significantly increased.
- GLM LC + Demand NPV = 554%
- GAM LC + Demand NPV = 605%
- Data mining LC + Demand NPV = 713%
- Actual optimal NPV = 760%



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## Other Issues

- Consistency of implementation
  - Prospective vs. Retrospective
- Legal environment
- Competition

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