Implementing a Data Mining Solution for an Automobile Insurance Company: Reconciling Theoretical Benefits with Practical Considerations

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EXECUTIVE SUMMARY

The insurance company in this case study operates in a highly competitive environment. In recent years it has explored data mining as a means of extracting valuable information from its huge databases in order to improve decision making and capitalise on the investment in business data. This case study describes an investigation into the benefits of data mining for an anonymous Australian automobile insurance company.[1] Although the investigation was able to demonstrate quantitative benefits of adopting a data mining approach, there are many practical issues that need to be resolved before the data mining approach can be implemented.

BACKGROUND

Melbourne Automobile Insurers (MAI) is a leading car insurer in Australia. It was established in the early 1970s. Today it has more than 40 branches and has nearly two million policy holders with an underwriting profit of over $50 million.

MAI, like all insurance companies, operates in a highly competitive environment. In recent years, there has been a proliferation of non-traditional retailers of car insurance that has caused great concern for MAI. Banks and finance companies are now joined by manufacturers and distributors of cars in the marketing of car insurance. Many of MAI's competitors have been intent on maintaining their market share and have kept premium rises to a minimum, thereby discouraging their policy holders from shopping around for a better price. The competitive environment extends beyond premium pricing issues to include a range of value-added products and incentives such as "liftetime rating 1" and discounts on multiple policies.

The Australian general insurance market went through a turbulent year in 2000. General business issues such as Y2K, the implementation of a new tax system, including the introduction of a goods and services tax, and corporate law reform program (CLERP) consumed a great deal of non-productive time and resources.

SETTING THE STAGE

In 1999, MAI established a SAS data warehouse. Periodically, data was extracted from their operational system and deposited into the data warehouse. The variables extracted included:

- Policy holders' characteristics such as age, gender
- Vehicle characteristics such as age, category, area in which vehicle was garaged
- Policy details such as sum insured, premium, rating, number of years policy held, excess

The Information System Department is responsible for maintaining the data warehouse. The Business Analysis Department extract data from the data warehouse for periodic reporting and as well as statistical analysis. The statistical analysis is done using Excel spreadsheets and on-line analytical processing (OLAP).

MAI realised that their current method of premium pricing has its limitations. With increased competition, MAI knew that they needed better tools to analyse data in their data warehouse to gain competitive advantage. They hoped to obtain a greater leverage on their investment in the data warehouse.

In the meantime, Jack Pragg, the account manager of SAS, had been trying to convince MAI that the next logical step to take is to embark on data mining and that the SAS data mining suite Enterprise Miner was the most appropriate tool for them. According to SAS "the Enterprise Miner is the first and only data mining solution that addresses the entire data mining process—all through an intuitive point-and-click graphical user interface (GUI). Combined with SAS data warehousing and OLAP technologies, it creates a synergistic, end-to-end solution that addresses the full spectrum of knowledge discovery."

MAI did not have data mining expertise and wanted an independent opinion before they invested in the SAS Enterprise Miner. The CEO of MAI, Ron Taylor, approached his former university lecturer, Professor Rob Willis, for help. Rob was at the time the Head of School of Business Systems at Monash University. Monash University has a Data Mining Group Research Group headed by Dr. Kate Smith. The aims of the group are to provide advanced research and training in data mining for business, government and industry.

Rob together with Kate conducted a proof-of-concept study to determine whether there was scope for data mining. In determining the optimal pricing of policies there was a need to find a balance between profitability and growth and retention. The study looked at the sub-problems of customer retention classification and claim cost modelling. A neural network

Table 1. Main Players and Their Roles in the Case

Organization	Players	Role
Monash University	Dr. Kate Smith Angie Young	Supervior of PhD Student PhD Student
Melbourne Automobile Insurers	Mark Brown Sophie Green Andrew Boyd Charles Long Ryan Lee	Business Analyst Manager Business Analyst Business Analyst System Analyst Pricing Manager

was developed to predict the likelihood of a policy being renewed or terminated and clustering was able to identify groups with high cost ratios. The initial study demonstrated the potential of data mining.

The case that follows describes the subsequent three-year project: its aims, outcomes, and the implementation issues currently facing the organization. The main players in the case, and their respective roles, are summarised in Table 1.

CASE DESCRIPTION

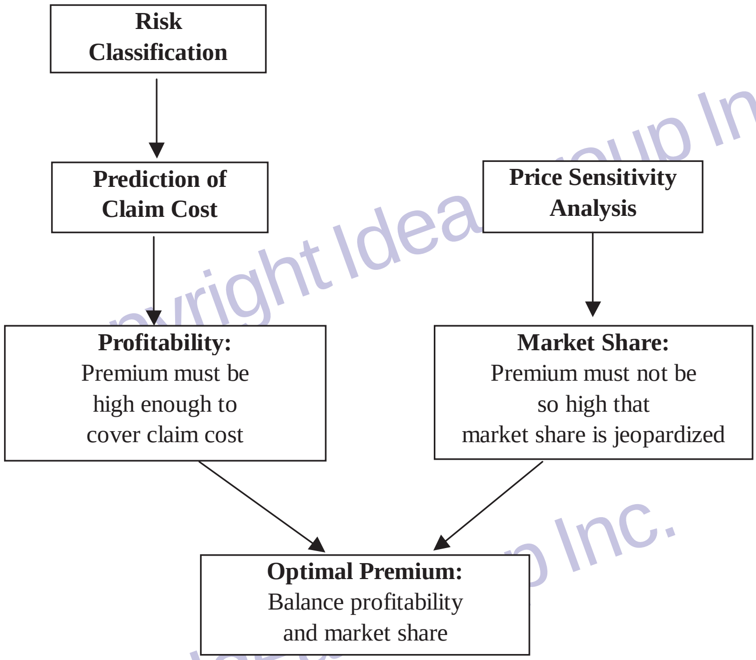
MAI decided to engage Monash University in a three-year extended study which aimed to produce quantitative evidence of the benefits of data mining. Kate had a prospective PhD student, Angie Young, who was interested in data mining and was looking for sponsorship. MAI agreed to provide a scholarship for Angie to carry out the data mining research at MAI under the supervision of Kate.

Mark Brown, the Business Analysis manager, was in charge of co-ordinating the data mining project. He had worked in the company for more than twenty years and he knew the business very well. He was also familiar with the data and had knowledge of the processes behind the data collection. He was able to determine useful questions for analysis and select potentially relevant data to answer these questions.

MAI is driven by two main concerns: the need to return a profit to their shareholders and investors, and the need to achieve market growth and retain a certain level of market share. These two goals are seen as imperatives to success, but are often conflicting. Premiums play a critical role in enabling MAI to find a balance between these two goals. The challenge is to set premiums so that expected claims are covered and a certain profitability is achieved, yet not to set premiums so high that market share is jeopardised as consumers exercise their right to choose their insurer. In other words, MAI has to balance profitability and market share when setting premiums. This involves combining the results of three main tasks: risk classification, prediction of claim cost and price sensitivity analysis (see Figure 1). The initial study showed that data mining could be of benefit to premium setting, but the three-year extended study needed to show the quantitative benefits of the approach.

In the automobile insurance industry, companies adopt "class ratings" to determine premiums. Policy holders are assigned to various risk groups based on factors which are considered predictors of claim cost and premiums are charged based on the risk group to which they belong. An insurance company has to discriminate between good and bad risks so that they can engage in selective marketing, otherwise they may end up losing good customers due to uncompetitive premiums that are inadequate to compensate for the risks of customers of dubious quality. "Bad risks drive out good risks," when the same premium

Figure 1. Balancing Profitability and Market Share



is charged (van Gelder, 1982). Another reason for discriminating between good and bad risks is so that premiums can be set equitably. The premium should be fair in the sense that each policy holder, or group of policy holders, should be charged a rate which reflects the policy holder's expectation of loss (Athearn, 1969; Denenberg, 1974).

Having classified policy holders into various risk groups, an insurance company has to decide on an appropriate method for predicting claim costs within each group. Currently MAI uses a point system. Each rating factor is scaled such that the higher the risk, the higher the points. For each risk factor, the policy holder will be assigned points. These points are aggregated for all factors and premium is charged accordingly. The higher the aggregated points, the higher the premium. The points system has some limitations however, and these will be illustrated with an example. For simplicity, we assume that points are assigned to policy holders based on only two factors: the policy holder's age and vehicle age (see Table 2). The aggregated points for the various risk groups are shown in Table 3. Continuing the illustrative example, Table 4 shows an example of what the cost ratio (claim cost/premium) matrix may look like for the various risk groups (claim cost and premium information have been intentionally omitted for brevity).

Suppose the company is not happy with the cost ratio of 94% (policy holder age group D and vehicle age group E) and would like to increase the premium to cover the high claim cost of the risk group. Since the premium is calculated based on points, the company would have to either increase the points of policy holder age group D or vehicle age group E. However, this would this would increase the points for other cells in the row or column even though the company may be satisfied with their cost ratio. Ideally, premium should be charged

Table 2. Points for Risk Factors

Policy Holder Age Group	Points	Vehicle Age Group	Points
A	50	A	0
B	40	B	1
C	35	C	2
D	30	D	3
E	25	E	4

Table 3. Aggregated Points of Risk Groups

Vehicle Age Group	Policy Holder Age Group A	B	C	D	E
A	50	40	35	30	25
B	51	41	36	31	26
C	52	42	37	32	27
D	53	43	38	33	28
E	54	44	39	34	29

Table 4. Cost Ratio of Risk Groups

Vehicle Age Group	Policy Holder Age Group A	B	C	D	E
A	57%	65%	74%	75%	72%
B	54%	57%	70%	78%	71%
C	58%	48%	71%	75%	76%
D	66%	62%	72%	83%	79%
E	72%	72%	83%	94%	70%

based on a reflection of actual risk. We could change the points for that particular cell in isolation, but if many variables are considered this point system becomes very large and complicated

In determining optimal premiums, MAI has to be mindful of the effect of changes in premiums on retention rates. In a competitive environment, setting the premium at too high a level can lead to a loss in market share. The broad framework shown in Figure 1 was used in the initial study to guide the data mining tasks, and now became the basis of the three-year investigation.

A business analyst, Sophie Green, was recruited to carry out data mining. Sophie's background was in statistics and she was not familiar with data mining tools. Although she attended an introductory course in data mining run by Monash University shortly after she joined MAI, she found it difficult to use the Enterprise Miner. She did not know which tools were appropriate for analysis. She found herself going back to statistical analysis she was familiar with using an Excel spreadsheet.

Angie was not familiar with many of the terms of the insurance industry. She had to learn about the business before she could begin any data mining. She spent a substantial amount of time understanding the business. Mark was a great help in this respect. She also required the help of Mark to interpret intermediate results of the analysis. At times they found that the results indicated that there were problems with the data used for analysis and it was back to the drawing board.

Charles Long, a system analyst, was asked to extract data sets from the data warehouse. He knew what data was available, exactly where the data could be found and how different sources could be combined. Charles extracted two data sets (training and test sets) consisting of 29 variables and 12 months of comprehensive motor insurance policies of one of the Australian states, New South Wales. The training set consisted of 146,326 policies with due dates from 1 January to 31 December 1998 while the test set consisted of 186,658 policies with due dates from 1 July 1998 to 30 June 1999. Restricted by the availability of data at the time of collection, the period of overlap was to enable comparison of exposure and retention rates over a one-year period and to ensure that sample sizes are sufficiently large. Forty percent of the policies in the test set were new policies. The training set was used to train the models while the test set was used to evaluate the results.

Charles had to convert some of the variables into a format required for data mining. For example, age of policy holders and vehicles were computed based on date of birth and year of manufacture respectively. While Angie was obtaining some descriptive statistics of the data sets to familiarise herself with the data, she discovered some errors. For example, a few of the policy holders had an age of 999. She removed records with errors from the data sets. She also noticed that there were several types of excess and she aggregated the various amounts.

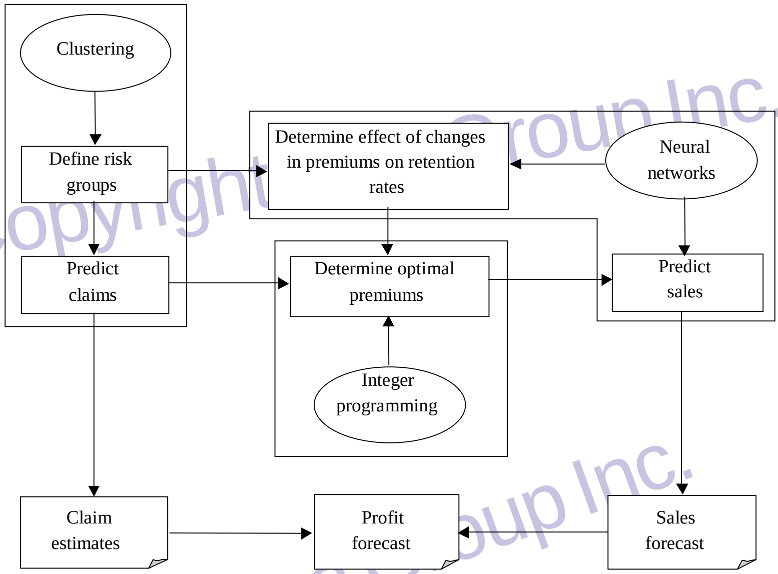
Nine months after the project began, Sophie resigned. Andrew Boyd was recruited to take her place but also resigned after a month. Angie found herself carrying out the project on her own. Although it was agreed that Angie was to make monthly presentations to the management of MAI on the progress of her research, it turned out that during her three years she only managed four presentations. It was difficult for the MAI management team (some based in Melbourne and others in Sydney) to find a common time slot for the presentations.

Angie met with Kate weekly to report on the progress of her research. With the help of Kate she was able to decide which data mining algorithm or tool was most suited to address the various research questions and interpret the results. At the end of her three-year research at MAI, Angie proposed a detailed data mining framework (see Figure 2) to determine the premiums to charge automobile insurance policy holders in order to arrive at an optimal portfolio.

The framework, which is a holistic approach, consists of three main components:

- The first component involves identifying risk classifications and predicting claim costs using clustering. The total premiums charged must be sufficient to cover all claims made against the policies and return a desired level of profit.
- The second component involves price sensitivity analysis using neural networks. Premiums cannot be set at too high a level as customers may terminate their policies thus affecting market share.
- The third component combines the results of the first two components to provide information on the impact of premiums on profitability and market share. The optimal mix of premiums to achieve a pre-specified termination rate while maximising profit is determined by integer programming.

Figure 2. Data Mining Framework for Determining Optimal Premiums



The first component of the data mining framework involves identifying risk classifications and predicting claim costs. In designing a risk classification structure, insurance companies attempt to maximise homogeneity within each risk group and heterogeneity between the risk groups. This can be achieved through clustering. The k-means clustering model was used to classify polices. The k-means clustering model performs disjoint cluster analysis on the basis of Euclidean distances computed from variables and seeds that are generated and updated by k-means algorithm (Anderberg, 1973; MacQueen, 1967). Least squares is the clustering criterion used to measure the distance between data observations and seeds. Using the least squares clustering criterion, the sum of the squared distances of observations to the cluster means is minimised. Thirteen variables were used for clustering. They were:

- Policy holder's age
- Policy holder's gender
- Area in which the vehicle was garaged
- Rating of policy holder
- Years on current rating
- Years on rating one
- Number of years policy held
- Category of vehicle
- Sum insured
- Total excess
- Vehicle use

- Vehicle age
- Whether or not the vehicle is under finance

Having classified the policy holders into risk groups, the price sensitivity within each cluster was examined; the second component of the data mining framework. Neural networks were trained to classify policy holders into those who are likely to terminate their policies and those who are likely to renew. Neural networks are ideal tools for solving this problem due to their proven ability to learn to distinguish between classes, and to generalise their learning to unseen data (Bigus, 1996; Han & Kamber, 2001; Smith, 1999). A multilayered feedforward neural network was constructed for each of the clusters with 25 inputs, 20 hidden neurons and one output neuron (whether the policy holder renews or terminates to contract). The inputs consist of the thirteen variables used for risk classification plus the following premium and sum insured variables:

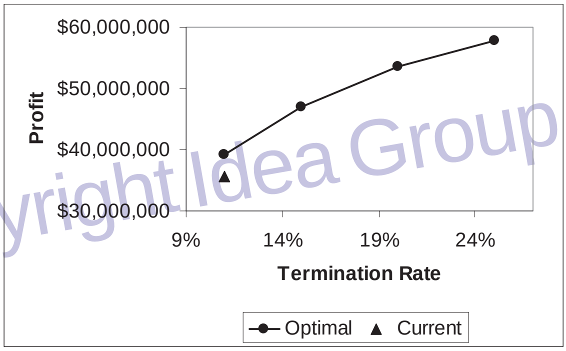
- "old" premium (premium paid in the previous period)
- "new" premium (premium indicated in renewal notice)
- "old" sum insured (sum insured in the previous period) which was also included as input in the clustering model
- "new" sum insured (sum insured indicated in renewal notice)
- change in premium ("new" premium–"old" premium)
- change in sum insured ("new" sum insured–"old" sum insured)
- percentage change in premium
- percentage change in sum insured
- ratio of "old" premium to "old" sum insured
- ratio of "new" premium to "new" sum insured
- whether there is a change in rating
- whether there is a change in postcode
- whether there is a change in vehicle

Sensitivity analysis was then performed on the neural networks to determine the effect of premium changes on termination rate of each cluster. Separate data sets were created from each cluster with all variables remaining unchanged except for new premium and related variables. These data sets were scored against the trained neural networks to determine the predicted termination rates under variations of premium.

The third component of the data mining framework combines the results of the first two components to provide information on the impact of premiums on profitability and market share. The problem of determining optimal premium is akin to portfolio optimisation where an investor strives to find a balance between risk and return across their portfolio of investments (Markowitz, 1952). In portfolio theory, an asset has a given rate of return and risk. In the insurance optimisation problem, the termination rate and the profit earned from each cluster depend on the premium that is charged. Integer programming was proposed to determine the premium to charge for each cluster to maximise total profit for a given overall termination rate. The termination rates of individual clusters may vary to maximise the profit but the overall termination rate for the portfolio will be constrained by a user-defined parameter (Yeo et al., 2002)

The optimisation problem was solved for varying termination rates. The results are shown in Figure 3. The curve is similar to the efficient frontier of portfolio optimisation. It

Figure 3. Optimal Profit for Varying Termination Rates



is a smooth non-decreasing curve that gives the best possible trade-off between profit and termination rate. If MAI selects an acceptable termination rate, the model will then determine a portfolio (mix of premiums to charge various risk groups) that maximizes profit. If MAI were to maintain its current termination rate of 11%, profits could be increased by changing the mix of premiums.

Thus Angie was able to provide MAI with clear evidence of the quantitative benefits of adopting a data mining approach to premium pricing.

CURRENT CHALLENGES/PROBLEMS FACING THE ORGANISATION

MAI were quite excited about the outcome of Angie's research. The MAI management was in the process of reviewing their current point system of premium pricing and they agreed that it needed to be revamped. Angie's results had shown that strong quantitative benefits were theoretically possible if the proposed data mining solution was adopted.

However there were several issues that needed to be resolved before MAI could begin to implement the data mining approach. Firstly the approach needs to be validated; for the various Australian states. The research was based on only one of the Australian states and there were differences in the premium pricing for the various states. Should the approach be validated using real cases or historical data? Also, the data mining framework does not model the effect of competition. Can the approach be implemented if it has only considered the dynamics of MAI in isolation from their competitors? How can competition be factored into the framework? If it is mathematically too difficult to consider the effect of competition, how should MAI proceed?

MAI do not have any data mining expertise and none of the MAI staff were very involved in the Angie's research project. It is therefore difficult to transfer the skills and knowledge acquired during the project to MAI staff to carry out the validation and implementation. MAI realise that data mining is more than just acquiring the software. Data mining expertise is required to decide which algorithm is most suited for a problem and to interpret the results. Should they recruit people with the data mining skills or should they train the current business analysts to do future data mining work?

Implementing the proposed data mining framework will also require significant business process re-engineering. How will staff react to the changes? How can resistance to change be managed? How are they going to integrate data mining into the existing information system infrastructures?

Since the data mining approach is "modular", the pricing manager, Ryan Lee, suggested implementing the data mining approach in phases. They could use the MAI's existing risk groups to replace the clustering stage of component one, and use neural networks to model the price sensitivity of these risk groups. If the neural networks proved to be successful, they could then look at implementing the integer programming for determining the optimal premium to charge for each risk group. The final phase would be to look at implementing the clustering method of risk classification.

Clearly there are many practical considerations that MAI need to resolve before the proposed data mining approach can be adopted. Some of these are related to personnel and change management, while others are more technological considerations. Until these issues have been resolved, the project has only shown the theoretical benefits that could be obtained.

ENDNOTE

[1] The name of the company and the names of its employees have been changed to protect their anonymity.

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BIOGRAPHICAL SKETCHES

Ai Cheo Yeo *became a Fellow Member of The Association of Chartered Certified Accountants in 1990. She obtained her Master of Business Systems in 1998. She has worked* *as an auditor in the Singapore Auditor-General's Office, a bank and an oil company. She was also a lecturer with the Business Administration Department of the Singapore Polytechnic. Ai Cheo is currently a lecturer with the School of Business Systems, Monash University, Australia. She has recently completed her PhD focusing on Data Mining in the Automobile Insurance Industry. She has published several refereed journal papers and book chapters on this topic.*

***Kate A. Smith** is an associate professor in the School of Business Systems, Monash University, Australia, where she also fulfills the roles of deputy head, director of research, and director of the Data Mining Research Group. She holds a BSc(Hons) in Mathematics and a PhD in Electrical Engineering, both from the University of Melbourne, Australia. Kate has published two books on neural networks in business, and more than 100 journal and international conference papers in the areas of neural networks, combinatorial optimization, and data mining. She is a member of the organizing committee for several international data mining and neural network conferences, and regularly acts as a consultant to industry in these areas.*