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APPLICATIONS

OF

DATA MINING TECHNIQUES

IN

LIFE INSURANCE

*A research paper by*

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***ABSTRACT***

*Knowledge discovery in financial organization have been built and operated mainly to support decision making using knowledge as strategic factor. In this paper, we investigate the use of various data mining techniques for knowledge discovery in insurance business. Existing software are inefficient in showing such data characteristics. We introduce different exhibits for discovering knowledge in the form of association rules, clustering, classification and correlation suitable for data characteristics. Proposed data mining techniques, the decision- maker can define the expansion of insurance activities to empower the different forces in existing life insurance sector.*

***KEYWORDS***

*Insurance, Association rules, Clustering, Classification, Correlation, Data mining.*

## INTRODUCTION

Data mining is a powerful tool for extracting hidden patterns from large datasets, which can be particularly beneficial in the insurance sector. By leveraging data mining, insurance companies can enhance their understanding of customer behavior, improve underwriting, manage risks more effectively, and mitigate fraud. This paper explores how insurance firms can use advanced data mining techniques to reduce costs, increase profits, acquire and retain customers, and develop innovative products. Unlike traditional statistical methods that often rely on linear models for their interpretability required by regulators, data mining can augment these models by incorporating additional variables, interaction effects, and nonlinear relationships. More accurate models directly translate to higher profitability and cost efficiency. Specifically, data mining supports insurance companies in several key areas:

* Acquiring new customers.
* Retaining existing customers.
* Advanced classification methods.
* Analyzing the relationship between policy design and policy selection.

**1.1 Acquiring New Customers**

Acquiring new customers is a crucial challenge for insurance companies. Traditional strategies typically focus on broadening the sales team's efforts to expand the customer base, adhering to specific policy criteria. However, this approach often leads to diminishing returns as the marketing budget increases. A more effective strategy involves identifying specific segments within the existing customer base who represent uninsured prospects. Here, cluster analysis, a method widely used in various sectors for market segmentation, proves useful. This technique segments data into clusters based on similarities in predefined attributes, without predetermined group boundaries, requiring domain expertise for cluster interpretation.

**Example 1.1**

For instance, an insurance company might analyze existing data to segment potential customers based on demographics such as income, occupation, and age. Through clustering based on these attributes, the company can identify distinct groups for targeted marketing efforts. The insights gained from clustering help management develop specialized catalogs tailored to different demographic groups. These catalogs can then be used to target specific groups with customized policy offerings, enhancing the effectiveness of marketing campaigns and potentially increasing conversion rates.

In this way, the company can focus its marketing resources more efficiently, directing them towards groups identified as more likely to respond to specific types of policies. This targeted approach not only optimizes marketing spending but also enhances customer acquisition rates by appealing directly to the needs and characteristics of each cluster.

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Table 1.1 Sample data for example

|  |  |  |  |
| --- | --- | --- | --- |
| Age | Occupation | Income | Education |
| 35 | Employee | 15,000/- | Graduate |
| 25 | Employee | 10,000/- | Graduate |
| 55 | Employee | 65,000/- | Post-Graduate |
| 45 | Employee | 45,000// | Post-Graduate |
| 40 | Business | 70,000/- | Matriculate |
| 35 | Business | 90,000/- | Graduate |

The information they have about the customers include Age, Occupation, Income and education. Depending on the type of policy, not all attributes are important. For example, suppose advertising only for policy of Life security, we could target the customers having less income and occupation as employee. Hence the first group of people, is of younger employees having college degree, is suitable for Life security policies. The second group has higher qualification and also higher income is suitable for tax benefit policies, while last group has businessmen with higher income but low qualification and is suitable for investment policies.

DEFINITION 1.1. Given a database D = {t1,t2,…,tn } of tuples and an integer value k, the clustering problem is to define a mapping f : D → {1,…,k}where each ti is assigned to one cluster kj, 1≤ j ≤

k.A cluster kj, contains precisely those tuples mapped to it that is,kj

= { ti | f(ti) = kj, 1≤ i ≤ n, and ti Є D}

# Algorithm 1.1 k-means Clustering

K-means is an iterative clustering algorithm in which items are moved among sets of clusters until the desired set is reached

Input:

Output:

D= {t1, t2, t3,...,tn} //Set of elements k //Number of desired clusters

K //set of clusters

Algorithm:

assign initial values for means m1, m2, …, mk; repeat

assign each item ti to the cluster which has closest mean; calculate new mean for each cluster;

until convergence criteria is met.

Note that the initial values for means are arbitrarily assigned and the algorithm could stop when no or very small number of tuples are assigned to different clusters. As per the algorithm, first we have to find mean of each cluster. Hence accordingly mean for first cluster is 30, Employee, 13000, Graduate in terms of Age, Occupation, Income and Education. Similarly mean for second cluster is 50, Employee, 50000, Post-Graduate while the same for third cluster is 37, Business, 80000, Graduate. Suppose a customer with age 36, occupation Employee, Income 14000 and education Graduate will provide differences 6,0,1000,0 with average difference of 252 for first cluster. Similarly it provides average difference of 9003 and that of 16001 for third cluster. Hence observing the above means, it is clear that the closest cluster for this customer is the first cluster

i.e. of life security policy. Once the customer is added to one of the clusters its new mean will be automatically calculated.

## Retaining Existing Customers

As acquisition costs increase, insurance companies are beginning to place a greater emphasis on customer retention programs. Experience shows that a customer holding two policies with the same company is much more likely to renew than is a customer holding a single policy. Similarly, a customer holding three policies is less likely to switch than a customer holding less than three. By offering quantity discounts and selling bundled packages to customers, such as home and auto policies, a firm adds value and thereby increases customer loyalty, reducing the likelihood the customer will switch to a rival firm.

So we have determined the frequent item sets based on a predefined support. We have all the riders that are often sold together. We need to find all the associations where customers who bought a subset of a frequent item set, most of the time also bought the remaining items in the same frequent item set. Association refers to the data mining task of uncovering relationships among data. Data association can be identified through an association rule

# Example 1.2

Insurance companies can use association rules in market basket analysis. Here the data analyzed consist of information about what policies customer purchases. The insurance company can generate association rules that show what different policies are purchased with a specific policy. Based on these facts, company tries to capitalize on the association between different policies that are sold for different purposes. Experience shows that a customer holding two policies with the same company is much more likely to renew than is a customer holding a single policy. Similarly, a customer holding three policies is less likely to switch than a customer holding less than three. By offering quantity discounts and selling bundled packages to customers, such as life security and investment policies, a firm adds value and thereby increases customer loyalty, reducing the likelihood the customer will switch to a rival firm.

Table 1.2 Sample data for example

Transaction Items

T1 Life security, Market based

T2 Market based

T3 Investment

T4 Market based, Tax Benefit, Investment

T5 Market based, Tax Benefit

T6 Market based, Tax Benefit

T7 Life security, Market based, Tax Benefit, Investment

T8 Life security, Tax Benefit

T9 Life security, Market based, Tax Benefit

T10 Life security, Market based, Tax Benefit

A database in which an association rule is to be found is viewed as a set of tuples, where each tuple contains a set of items. Here there are ten transactions and four items: {Life security, Market based, Tax Benefit, Investment} which are to be considered as {S1,S2,S3,S4}.

Now we need to find all the situations where customers who bought a subset of a frequent itemset, most of the time also bought the remaining items in the same frequent itemset. Given a frequent itemset, say (S1, S2, S3), if a customer who buys a subsert formed by S1 and S2, also buys S3 80% of the times, then it is worth to consider the rule. This percentage is called the confidence of the rule and is defined as the ratio of the number of transactions that include all items in a particular frequent itemset to the number of transactions that include all items in the subset.

Let's consider the same insurance example below. We want to find the association rules that meet the following requirements:

Support - 30% - Only the riders that are bought together by at least 3 customers are considered. Confidence - 90% - The association rule has to be true in 90% of the transactions

Case1: (S1, S3) → (S2)(S1, S3) was bought by 5 customers but only 3 of them also bought S2. Confidence is 60%.

Case2: (S1, S2) → (S3)(S1, S2) was bought by 3 customers and all 3 of them bought S3 as well. Confidence is 100%. So this rule has a very strong confidence (above 90%) and has to be considered.

DEFINITION 1.2.1. Given a set of items I = {I1,I2,…,Im } and a database of transactions D = {t1,t2,…,tn } where ti = {Ii1,Ii2,…,Iik }

and Ijk Є I, an association rule is an implication of the form X ⇨ Y where X,Y ( I are sets of items called itemsets and X ∩ Y = ø

DEFINITION 1.2.2. The support (s) for an association rule X ⇨ Y is the percentage of transactions in the database that contain X U Y.

DEFINITION 1.2.3. The confidence or strength (α) for an association rule X ⇨ Y is the ratio of the number of transactions that contain X U Y to the number of transactions that contain X.

DEFINITION 1.2.4. Given a set of items I = {I1,I2,…,Im } and a database of transactions D = {t1,t2,…,tn } where ti = {Ii1,Ii2,…,Iik } and Ijk Є I, an association rule is to identify all association rules X ⇨ Y with a minimum support and confidence. These values (s, α) are given as input to the problem.

# Algorithm 1.2Apriori Algorithm

The Apriori algorithm is the most well known association rule algorithm and is used in most commercial products.

Input: Output:

Li-1 //Large itemsets of size i - 1 Ci //candidates of size i

Algorithm:

Ci = ø;

for each I Є Li-1 do

for each J ≠ Є Li-1 do

if i – 2 of the elements in I and J are equal then Ck = Ck U {I U J};

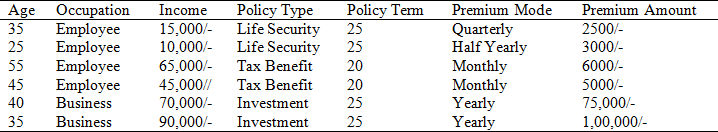
# Classification: Segment Databases

To improve predictive accuracy, databases can be segmented into more homogeneous groups. Then the data of each group can be explored, analyzed and modeled. Depending on the business question, segmentation can be done using variables associated with risk factors, profits or behaviors. Segments based on these types of variables often provide sharp contrasts, which can be interpreted more easily. Classification maps data into predefined groups or segments. Classification algorithms require that the classes be defined based on data attributes values. They often describe these classes by looking at the characteristics of data already known to belong to the classes. As a result, insurance companies can more accurately predict the likelihood of a policy based on the premium mode, premium amount, policy period depending upon age, income and occupation.

# Example 1.3

Insurance company can find a segment based on the income, preferred premium mode and premium amount. Such patterns can be stored in database. So while selling a specific policy to customer, agent can get the information of customer like income and age. This pattern can be compared to entries in a database and agent can suggest premium modes, premium amount and policy period to customer based on matched patterns.

Table 1.3 Sample data for example



This example assumes that the problem is to classify customers in terms of different policy attributes such as policy term, premium amount, premium mode and policy type. The policy type classification can simply be done using income as main criteria shown below

10,000 ≤ Income ≤ 40,000 Life Security

45,000 ≤ Income ≤ 70,000 Tax Benefit

Income ≥ 70,000 Investment

The policy term require complicated set of divisions using both Age and Occupation. Similarly premium mode require complicated set of divisions using both Income and Occupation while premium amount require much more complicated set of divisions using Age, Income and Occupation

DEFINITION 1.1. Given a database D = {t1,t2,…,tn } of tuples (items, records) and a set of classes C = {C1,…,Cm}, the classification problem is to define a mapping f : D → C where each ti is assigned to one class. A class Cj, contains precisely those tuples mapped to it that is, Cj = { ti | f(ti) = Cj, 1≤ i ≤ n, and ti Є D}

# Algorithm 1.3 K Nearest Neighbors

When classification is to be made for new item using K Nearest Neighbors algorithm, its distance to each item in the training set must be determined. The new item is then placed in the class that contains the most items from the (K) closest set.

Input:

Output:

T //Training data

K //Number of neighbors t //Input tuple to classify

c //class to which t is assigned

Algorithm:

N = ø

//Find the set of neighbors, N, for t For each d Є T do

If |N|≤ K, then N = N Ụ {d};

else

if u Є N such that sim(t,u) ≤ sim(t,d), then begin

N = N – {u};

N = N Ụ {d};

end

//Find class for classification C=class to which the most u Є N are classified;

For example, for life security policy there can be two groups as first is for customer with age 25 - 35, Income 10000/- to 15000/- and Occupation Employee with policy term of 20 years, premium mode quarterly and 16% premium amount of their income. Similarly second one is for customer with age 20 - 25, Income 5000/- to 10000/- and Occupation Employee with policy term of 25 years, premium mode half yearly and 30% premium amount. Suppose a customer with age 34, occupation Employee and Income 14000 purchasing Life security policy, will be suitable for first class i.e. customer with age 25 - 35, Income 10000/- to 15000/- and Occupation Employee can be suggested policy term of 25 years, premium mode quarterly and premium amount of 2200/-

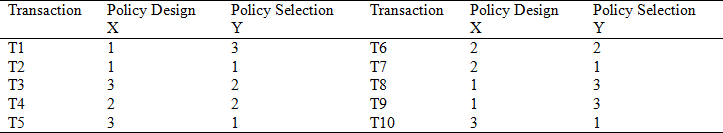
# Correlation between Policy designing and policy selection

While studying policy designing factor and policy selection factor as a two variables simultaneously for a fixed population, insurance company can learn much by displaying bivariate data in a graphical from that maintains the pairing. Such pair wise display of variables is called a scatter plot. When there is an increasing trend in the scatter plot, we say that the variables have a positive association. Conversely, when there is a decreasing trend in the scatter plot, we say that the variables have a negative association. If the trend takes shape along a straight line, then we say that there is a linear association between the two variables.

## Example 1.4

Insurance companies can consider the population consisting previous policy holders, and can investigate whether customers tend to purchase policy for the cause for which it is designed. To address this question, company needs to look at pairs of policy designing factor and policy selection factors.

Table 1.4 Sample data for example

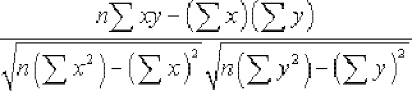


n=10

To do so we can assign numbers to different policy designing and selection factors such as 1 for life security, 2 for investment and 3 for tax benefit etc. Then while analyzing previous policies we can put a respective numbers both for policy designing and selection factors and from that bivariate data, we can find increasing or decreasing trends between two factors.

Consider the population consisting of purchasing transactions, and we want to investigate whether people tend to purchase policy for the reason for which it is designed. Going a sample size of n and bivariate data set on these individuals or objects, the strength and linear relationship between the two variables X and Y is measured by the sample correlation coefficient r, called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The linear correlation coefficient is sometimes referred to as the Pearson product moment correlation coefficient in honor of its developer Karl Pearson.

The mathematical formula for computing r is:



Where n is a sample size

The value of r is such that -1 < r < +1. The + and – signs are used for positive linear correlations and negative linear correlations, respectively.

Positive correlation: If x and y have a strong positive linear correlation, r is close to +1. An r value of exactly +1 indicates a perfect positive fit. Positive values indicate a relationship between x and y variables such that as values for x increases, values for y also increase.

Negative correlation: If x and y have a strong negative linear correlation, r is close to -1. An r value of exactly -1 indicates a perfect negative fit. Negative values indicate a relationship between x and y such that as values for x increase, values for y decrease.

No correlation: If there is no linear correlation or a weak linear correlation, r is close to 0. A value near zero means that there is a random, nonlinear relationship between the two variables

Note that r is a dimensionless quantity; that is, it does not depend on the units employed.

A perfect correlation of ± 1 occurs only when the data points all lie exactly on a straight line. If r

= +1, the slope of this line is positive. If r = -1, the slope of this line is negative. A correlation greater than 0.8 is generally described as strong, whereas a correlation less than 0.5 is generally described as weak.

## CONCLUSION

In the insurance industry, data mining can help firms gain business advantage mainly to support decision making. The insurance company needs to know the essentials of decision making and data mining techniques to compete in the market of life insurance. An understanding of probability and statistical distributions is necessary to absorb and evaluate acquiring new customers, retaining existing customers, performing sophisticated classification and correlation between policy designing and policy selection. Clustering technique can be used to acquire new customers in which first cluster specifies the group of customers holding life security policy while second group holds customer for Tax benefit policy and third group is for those customers holding policy for investment. When an agent approaches a particular customer, the agent will enter the demographic data of that customer in terms of age, occupation, income and education. Then each individual factor is compared with means of each cluster and the difference will be calculated. After comparing the each difference for each group, the closest cluster will be finalized which has the least difference. Association rule can be used to retain existing customers in which by reviewing previous data and by finding the required combinations according to confidence and support, agent can sell new policies to the existing customers to retain them. Similarly the company can also design such combo plans for their customer with additional benefits. Classification can be used to targeting customers or designing new products. Normally classes can be created according to policy term, premium mode and premium amount based on age, income and occupation. Policy term can be decided according to age and occupation while

premium mode and premium amount can be can be according to income and occupation. So particular class for particular customer can be created where policy term, premium mode and premium amount can be mentioned in it in terms of percentage. Same way correlation can be used to identify the relation between policy designing and selection factors. To do so we can assign numbers to different policy designing and selection factors such as 1 for life security, 2 for investment and 3 for tax benefit etc. Then while analyzing previous policies we can put a respective numbers both for policy designing and selection factors and from that bivariate data, we can find increasing or decreasing trends between two factors. It is no wonder that the general insurance actuary must be a practicing statistician to gain a greater understanding of their business to help reduce fraud, improve underwriting and enhance risk management.

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