Performance Comparison of Classification Algorithms employed in Data Mining

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Abstract— Extracting information from past data and using it to predict future events by capturing relationships between explanatory and predicted variables is called Predictive Analytics. Various data mining techniques (like Classification, Association, Feature Extraction, Clustering, etc.) and related algorithms employed in predicting future events help us to solve various business and day-to-day problems. In this paper we shall focus on Predictive Analysis Operations and algorithms involved in the technique of Classification and evaluate the performance of each in solving the "Targeting the Right Customer" problem faced by Insurance industries, using a sample Insurance Customer database. We shall apply all the classification algorithms (Naïve Bayes, Decision Trees, Support Vector Machines, Generalized Linear Model) on this sample Insurance DB and compare the results obtained from each to finally determine the algorithm that best solves the problem of identification of right customer. The work would involve stages like exploring the customer database, performing Classification of existing customers into 2 groups – those who would buy the new insurance policy and those who would not buy, by applying different algorithms and then finally determining the best algorithm based on parameters like predictive confidence, average and overall accuracy ,etc.

Index Terms— Classification, Data Mining, Decision Trees, Generalized Linear Model, Insurance, Naïve Bayes, Predictive Analytics, Support Vector Machines, Targeting Right Customer

1 Introduction

Accurate forecasting of factors like budget, product inventory and demand, supplies, and operations play a vital role in determining any organization's success. All these in turn depend on the application of various predictive techniques and model that analysts in an organization deploy on the existing data to churn predictions of future events. The more accurate the applied tools and mechanisms are, the higher is the reliability of the results obtained.

Predictive Analytics is a branch of statistical analysis used for forecasting and modeling. It deals with extracting information from past data by capturing relationships between explanatory and predicted variables, and then using it to predict future behavioral patterns and trends [1]. We shall take a small overview of the use of Predictive Analysis in a variety of industries.

a. Marketing Industry: Proper data mining algorithms and predictive modeling not only narrow a users target audience but also allows users to tailor their ads with respect to each online customer as per the way the customer navigates their site [1]. The marketing team thus gets the opportunity to develop multiple advertisements based on the past clicks of their visitors. Predictive analytics can aid in choosing marketing methods, and marketing more efficiently [2].

b. Insurance Industry: Predictive operations gain much more importance especially when the industry is the one which deals with handling and movement of money at all points of time like an Insurance Industry. Insurance industry has always relied on forecasting [1]. Forecasting premiums and targeting best customer - what initially started as a simple guessing phenomenon with the advent of technology and in an extensive search for accurate results ultimately emerged as the best insurance industry practice of employing predictive analytics.

c. Data warehousing Industry: As per Hugh and Barbara [3] stated in their work, "Getting data in is the most challenging aspect of BI, requiring about 80 percent of the time and effort and generating more than 50 percent of the unexpected project costs." Oracle Data Mining also offers Data Cleansing functions which help remove redundant and erroneous data from the data sources before being used for any other purpose.

d. Population Analysis: Analysts keep studying the population and events in a given geographical area and the emerging trends and pattern of the population in the region. As per the statement by Ross, Ryan and Stephen [4] in their work "As event data are captured, algorithms and analysts search for unexpected events, and these unexpected events then trigger an alert. Application of predictive analytics to such data helps generate a kind of syndromic surveillance which tries to convert a reactive paradigm to a proactive paradigm [4].

e. Social Media Analytics: Roosevelt C. Mosley [5] in his paper on analyzing the Insurance Twitter posts has emphasized on the various concepts of data mining

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like data cleansing, clustering, and classification applied to Twitter posts. Data mining functionalities on social media can help related industries to proactively address potential market and customer issues more effectively [5].

f. Medical Industry: The type of data and the question raised may vary from one industry to other. Depending on the data and the problem statement to solve, the data analysis might include the application of statistical methods or other techniques [6]. Certain subsets of data may be selected or discarded depending on requirements. Cheu Eng Yeow [6] in his work has employed the Naïve Bayes Classifier to classify the Liver Disorders dataset and the importance of various attributes in alcohol induced liver disease. Similarly predictive analysis can be applied to Stock exchanges to predict better return yielding stocks for future.

All the present day industries have huge amount of historical data along with case studies which carry a lot of information. The general idea that "Data is critical and can be put to future use" is familiar with all the data divisions of these industries but how it can be achieved is still a big matter of concern. The problem is that not all of these industries are able to process and analyze this precious information from the past for predicting a better future. Some of them keep piling loads of data for long years until a time comes when they finally decide to discard this data by declaring it to be "of no-use".

Industries like insurance, medical and credit industries are the ones who suffer major losses because of lack of ways and instruments to analyze their past data. Manual analysis of data in databases or files on a large scale doesn't produce much fruitful results and is also a time consuming activity. This creates a need for data mining algorithms and some form of predictive modeling which could be applied to this historical data in databases for guiding future actions.

In the absence of proper data mining algorithms and predictive models following events occur very often:-

- Proper identification of a target audience/ customer for a product becomes difficult.
- The amount of money spent in closing a sale deal is high.
- Not much or little attention is being paid to customer demographics (i.e. customers for an organization are growing older or younger [4]).
- Marketing team is not able to narrow down what advertisement to be directed to which customer.

In Credit industries, the Credit rating of a loan seeking individual can be determined based on his past data records. In Insurance industries, proper data mining helps the Insurance agents to divert their energy and resources to those individuals who are more likely to buy insurance. In Medical industries, the effectiveness of a given medicine in curing a particular disease, the results of following a particular treatment order for curing a sickness and other such related data produce high quality measures which could be promoted and followed in future for effective treatments and results.

Classification is the most commonly used technique for predicting a specific outcome based on historical data. The various classifications for an Insurance industry customer, which can form different problem statements for an analyst, are of the form as listed underneath:

1. response / no-response
2. high / medium / low-value customer
3. likely to buy / not buy

As part of this dissertation work on 'Performance Comparison of Classification Algorithms employed in Oracle Data Mining', we will solve the **'Targeting the Right Customer'** problem faced by Insurance industries. For this work we shall take a sample 'Insurance Customer' database (DB) in Oracle, on which we would apply the Classification function from the class of available Oracle Data Mining functions in SQL Developer 3.0.

The Classification function in SQL Developer 3.0 can be implemented using any of the below listed 4 algorithms:

- Generalized Linear Model (Binary Logistic Regression)
- Naïve Bayes
- Support Vector Machine
- Decision Tree

We shall understand the theory for each of the four algorithms and their way of working. Next we shall explore the sample Insurance Customer DB to determine whether any useful interpretation can be made out of it using the SQL Developer's 'Explore Data' function. Later on we will apply all the classification algorithms on this sample Insurance DB and compare the results of each algorithm on the basis of the below listed parameters:

- Performance Measures
    - ➢ Predictive Confidence (%)
    - ➢ Average Accuracy (%)
    - ➢ Overall Accuracy (%)
- Performance Matrix (Confusion Matrix or Actual vs. Predicted Matrix)
- Receiver Operating Characteristics (ROC), a plot of False Positive Fraction vs. True Positive Fraction
- Lift (degree to which the predictions of a classification model are better than randomly-generated predictions)

2 Literature Review

Classification as the word suggests is the basic process of identifying and grouping objects with the same functionality and features into a single group called as a class. It can also be related to the concepts of Object Oriented Programming where objects of a class have similar attributes and functionalities with their individual data value being different. Taking a general example we can say that if we have a bundle of books belonging to different subjects say English, Hindi, Mathematics, and Science lying on a table, then if we are able to sort and create separate groups of books belonging to each subjects we have performed classification.

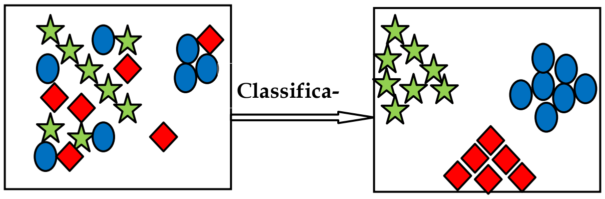


Fig.1. Classification

If we talk of the similar concept in terms of data in a database, we would describe Classification process as given below by Tan, Steinbach and Kumar [8]:

> Given a collection of records (training set)
> – Each record contains a set of attributes; one of the attributes is the class [8].

By the above statement we mean that for the given data set, the class assignments are available as one of the attribute. We need to find a model for this class attribute such that the class attribute can be expresses as a function of the values of other attributes [8]. The model so obtained should then be used to assign any new set of record to one of the identified set of classes with a high level of accuracy. The Accuracy of the model is determined by using a *Test Set*. In Oracle Data Mining, the data set under consideration is divided into two sets, namely *Training* and *Test*. The model is created using the training set and validated using the test set.

The attributes or features of a class can be divided into the following types:
(1) *Quantitative features* [12]:
(a) Continuous values (e.g., height, weight [12]);
(b) Discrete values (e.g., the number of computers, keyboards, mouse [12]);
(c) Interval values (e.g., the duration of an event).
(2) *Qualitative features* [12]:
(a) Nominal or unordered (e.g., color);
(b) Ordinal (e.g., military rank or qualitative evaluations of temperature (“cool” or “hot”) or sound intensity (“quiet” or “loud”)).

Classifications result in discrete values and it does not imply ordering of any sort. Depending on the kind of target attribute or problem the predictive model is chosen. Like for a numerical target the predictive model would uses a regression algorithm, instead of a classification algorithm. In general, there can be 2 types of classifications – *Binary classification* and *Multiclass classification*. Only two values are possible for the target attribute in case of binary classification: say, customer buys insurance or does not buy insurance. More than two target class values exist in case of multiclass classification: for example, customer may belong to any of the credit rating classes like low, medium, high, or unknown.

A classification algorithm detects the relationships that exist between the predictors and the target attributes during the model build (training) phase. The techniques for finding relationships differ for different classification algorithms. The relationships between attributes for a given class are summarized in a model, which are later applied to fresh or new data sets in which the class assignments are unknown to detect their classes.

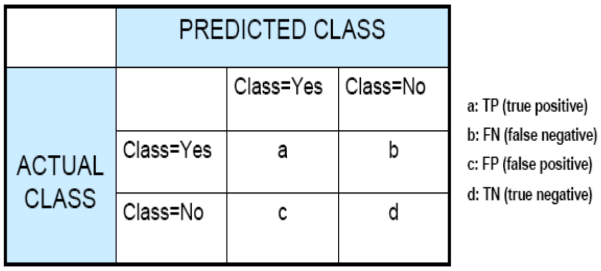
The models created during the training phase are tested by comparing the predicted values to known target values in a set of test data. In the Scoring process of a classification model, class assignments and probabilities for each record in the test data would also be determined. For example, an insurance classification model that would classify customers on credit rating parameter as low, medium, or high value would also predict the probability of each classification for each customer. The accuracy of a model in predicting the outcomes is measured based on certain values which are known as *Test metrics*.

Accuracy

Accuracy refers to the percentage of correct predictions made by the model when compared with the actual classifications in the test data [11].

Confusion Matrix

A confusion matrix displays the number of correct and incorrect predictions made by the model compared with the actual classifications in the test data [11]. For a binary classification model the confusion matrix is a 2-by-2 matrix. In case of classification resulting in multiple classes (say, n) the resultant matrix is a square matrix of size n-by-n. The rows of the matrix denote the count of actual classifications in the test data whereas the columns denote the count of predicted classifications which are made by the classification model under consideration. Fig. 2 below shows the Confusion Matrix for a binary classification model. The results ‘Yes’ can also be identified by number 1 and the results ‘No’ can be identified using number 0.



	PREDICTED CLASS		
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive)
b: FN (false negative)
c: FP (false positive)
d: TN (true negative)

Fig.2. Confusion Matrix for a Binary Classification Model

The following information can be derived from a confusion matrix:

- Correct predictions (a+d).

- Incorrect predictions (b+c).
- Total scored cases (a+b+c+d).
- Error rate (b+c)/(a+b+c+d)
- Overall accuracy rate (a+d)/(a+b+c+d)

Lift

This metric is a measure of winning edge that predictions from a classification model can provide over any randomly-generated predictions. Lift can only be calculated in case of binary classification. In case a model has multiple classes, then we can convert it to a binary model by identifying one of the available class as a positive class and the other classes as negative results from the model.

In mathematical terms, Lift can be defined as a ratio of two percentages: the percentage of correct positive classifications made by the model to the percentage of actual positive classifications in the test data [11].

Receiver Operating Characteristic (ROC)

All classification models use a decision point known as probability threshold for the purpose of making decisions, default value being 0.5 for binary classification. ROC measures the impact of changes in the probability threshold [11]. It is very similar to Lift and applies only to binary classification models. ROC provides the user with an insight about the chances with which the model would accurately predict the negative or the positive class for a given data or record.

The ROC Curve

ROC Curve is defined as the ratio of false positive rate (placed on X-axis) to the true positive rate (placed on the Y-axis) where true/false positive rate/fraction is described as below:

True positive fraction [11]: Hit rate. (True positives/ (true positives + false negatives))

False positive fraction [11]: False alarm rate. (False positives/ (false positives + true negatives))

Area under the Curve

It refers to the area under the ROC curve (AUC) which measures the likelihood of a binary classification model in identifying a given actual positive case of being positive, rather than an actual negative case, with higher probability. For data sets suffering from unbalanced target distribution this measure is highly useful.

ROC and Model Bias

The predictions made by a classification model change in inverse proportion to the changes in probability threshold. For example, if the threshold for predicting the positive class is raised from a value of 0.6 to 0.7 then it will result in fewer positive predictions. It will also affect the numbers of true/false positives and true/false negatives to change for the given model.

ROC can be used to find the probability thresholds that yield the highest overall accuracy or the highest per-class accuracy [11]. A Cost matrix is a convenient mechanism for changing the probability thresholds for model scoring.

3 Mathematical Model - Classification Algorithms

Following are the major Data Mining Classification algorithms under consideration for solving the “Targeting the Best Customer Problem” under consideration:

- *Decision Tree* - Decision trees automatically generate rules, which are conditional statements that reveal the logic used to build the tree [11].
- *Naive Bayes* **-** Naive Bayes uses Bayes' Theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data [11].
- *Generalized Linear Models (GLM)* - GLM is a popular statistical technique for linear modeling. Oracle Data Mining implements GLM for binary classification and for regression [11]. GLM provides extensive coefficient statistics and model statistics, as well as row diagnostics. GLM also supports confidence bounds [11].
- *Support Vector Machine* - Support Vector Machine (SVM) is a powerful, state-of-the-art algorithm based on linear and nonlinear regression. Oracle Data Mining implements SVM for binary and multiclass classification [11].

The nature of the data determines which classification algorithm will provide the best solution to a given problem. The algorithm can differ with respect to accuracy, time to completion, and transparency. Practically we can develop several models for each algorithm, select the best model for each algorithm, and then choose the best of those for deployment.

3.1 Decision Trees

A **decision tree** is a powerful and popular tool that uses a tree-like graph for decision making process. Decision trees are used to predict possible consequences of certain actions. It is most commonly utilized in the field of operations research to identify goal-oriented strategies, event outcomes, resource utility and costs. It is one way to display an algorithm which is based on conditional probabilities. Decision trees generate **rules** which are conditional statements in human readable and understandable form, which can be used to identify a set of records within a database. Rules not only provide an inside view of the working predictive model but also introduce transparency in the decision making process. In other words, they form the building blocks for the predictive model.

Target values in a decision tree are predicted through a series of questions which follow a particular sequence. The importance of sequence simply dictates that the questions asked at any given stage directly depend upon the answers to the questions asked in the previous stage. The main aim is to ask questions such that it leads to the identification of unique and specific target values, forming a graphical tree like structure. The fig. 3 displays a sample binary classification tree for solving the 'Targeting the Right Customer' problem for the insurance industry. Here we have 3 attributes under consideration – *Insured* {Yes, No}, *Married* {Yes, No}, *Has Children* {Yes, No} and we make predictions for the attribute *Buy Insurance {Yes, No}*. The text in red color in all the boxes denotes the answers to questions at the previous level. The text boxes in green color denote the final classification results reached. The set of decision rules that represent the decision tree in example are:

- IF (INSURED = "YES" AND MARRIED = "YES" AND HAS_CHILDREN = "YES") THEN BUY_INSURANCE = "YES"
- IF (INSURED = "YES" AND MARRIED = "YES" AND HAS_CHILDREN = "NO") THEN BUY_INSURANCE = "NO"
- IF (INSURED = "YES" AND MARRIED = "NO") THEN BUY_INSURANCE = "NO"
- IF (INSURED = "NO" AND MARRIED = "YES") THEN BUY_INSURANCE = "YES"
- IF (INSURED = "NO" AND MARRIED = "NO") THEN BUY_INSURANCE = "NO

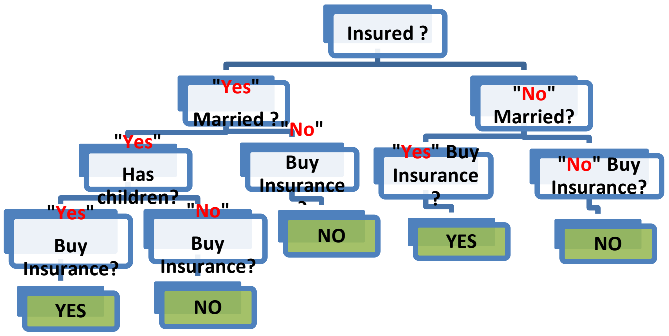


Fig.3. Sample Decision Tree (Binary classification) for 'Targeting the Right Customer'

The Decision Tree algorithm produces accurate and interpretable models with relatively little user intervention [11]. This algorithm can be used to split data into both binary and multiple classes i.e. it can be sued to solve both binary and multiclass classification problems. The test conditions (or Rules) can be specified based on the following two factors:

- Depending on the types of Attributes
- Depending on the type of Classification to be performed

3.1.1 *Attribute types*

The kinds of attributes that describe a given entity also play a key role in determining the classification results. We have the below types of attributes:
* ***Nominal*** (categorical attributes with no fixed order, Example: viral infections could be {cough, sore throat, cold} [13])

* ***Ordinal*** (categorical attributes with fixed order, Example: Temperature can be classified as {Extreme Cold, Cold, Moderate, Hot, Extremely Hot} with the rising order of temperature being Extreme Cold < Cold < Moderate < Hot < Extremely Hot)

* ***Continuous*** (numerical values like height, weight, salary etc form a part of these attributes)

3.1.2 *Classification types*

A decision tree can be used to perform the below two types of classifications:

* ***Binary Classification*** - It aims at performing a two-way split of the classification attribute under consideration. In case, the attribute has multiple classifications possible grouping of the attribute is done to form 2 classes as per the requirement. The figure shown above is an example of binary classification.

* ***Multiple Classifications*** - In this the attribute under consideration is split into multiple classes as shown in the fig. 4 below:

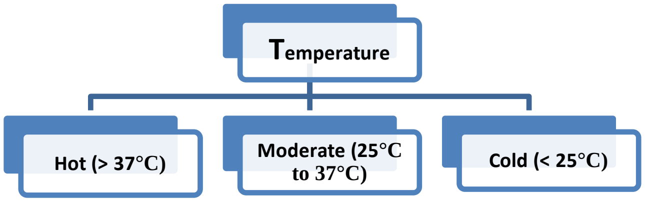


Fig.4. Multiple Classifications

One of the most important steps in the classification process using a decision tree is to perform the splitting of the records into two child nodes repeatedly in an efficient manner. For calculating the splits, Oracle Data Mining offers two homogeneity metrics - *gini* and *entropy,* [10] default being *gini.*

Homogeneity metrics, also referred to as *Purity,* perform the task of assessing the quality of alternative split conditions and promoting the selection of that split which would result in the formation of the most homogeneous child nodes. It is a measure of the degree to which records with same target value form a part of the resulting child nodes. It aims at maximizing the purity of the child nodes. For example, if the target classification result can be a binary value of the form yes or no, the objective of the gini would be to produce nodes where majority of the cases will be either Yes or No. The below formula is used for calculating Gini Index for a given node't' [8]

$$GINI(t) = 1 - \sum_j [p(j|t)]^2 \qquad (1)$$

Where, p (j | t) is the relative frequency of class j at node t [8].

Example, Consider the below binary classifications

C1	0
C2	7
GINI = **0.00**	

For Example 1a, GINI = 1 – [(0/7)^2 + (7/7)^2] = 0.00 (Information of High Interest)

C1	1
C2	6
GINI = 0.2449 (~**0.24**)	

For Example 1b, GINI = 1 – [(1/7)^2 + (6/7)^2] = 0.24

C1	3
C2	4
GINI = 0.4897 (~**0.5**)	

For Example 1c, GINI = 1 – [(3/7)^2 + (4/7)^2] = 0.5 (Information of Least Interest)

Higher the value of GINI, higher is the impurity of a node and less recommended is the split resulting in this value. A lower value of GINI indicates higher purity of the node and better split decision.

Entropy is a measure of the information content of the source and is also used for measuring the homogeneity of a node. As per Tan, Steinbach and Kumar, Entropy at a given node t is given by the below formula:

$$Entropy = -\sum_j \mathrm{p(j|t)} \log_2 \mathrm{p(j|t)} \qquad (2)$$

Where, p (j | t) is the relative frequency of class j at node t [8].

A given node contains least information if the records are equally distributed among all classes whereas if all records belong to one class then the node has the maximum information. In other words, both Entropy and GINI are very similar computations.

Different applications of data mining aim at providing different level of solutions. While some of the applications are *prediction-accuracy oriented* irrespective of the working model. Others, may be *decision-reason oriented* banking on the reasons based on which a decision was made and may require extensive explanation. For example, to ensure the complete success of a marketing campaign for a new insurance policy to be launched, the Marketing professional would not only be required to present his choice of customer segment for the new policy but would also need in-depth knowledge and descriptions of the available customer segments in the current database. For such a scenario, the Decision Tree algorithm for predictive analytics would be an ideal choice.

In a practical scenario, any Decision Tree algorithm grows each branch of the tree only till the extent that it is able to perfectly classify the training examples [11]. In some situations like noisy data or too small a training set, it may lead to an *Over-fitting* problem wherein the predictive classification model is able to predict accurately only the training data and any new data presented remains unclassified. Care should be taken to avoid such a situation.

3.2 Naïve Bayes Algorithm

The Naive Bayes algorithm has its roots deep inside the Bayes Theorem which states that given the probability of a prior event, the probability of occurrence of another event dependent on the prior event can be found. In other words we can say that Naïve Bayes algorithm is based on conditional probabilities [11]. As per Bayes' Theorem, probability is calculated by counting the frequency and combinations of values in the data set under consideration. In a statement form, if D represents a dependent event and P represents the prior event, then as per Bayes' theorem we have:

$$Prob(D\ given\ P) = Prob(P\ and\ D)/Prob(P) \qquad (3)$$

To find the probability of dependent event D occurring given prior event P has already occurred, we divide the count of the number of cases where P and D occur together by the number of cases where P occurs alone.

Suppose our task is to predict the chances that a customer under age of 21 will buy an insurance policy. For this scenario, '*under age of 21*' will form the prior condition (P) and '*buy insurance*' will be the dependent condition (D). We shall materialize this example by assuming a total of 500 customers in the training data set with 125 of them being less than 21years of age and 100 of them interested in buying an insurance policy. For this case, we have:

Prob (P and D) = 100/500 = 20%

Prob (P) = 125/500 = 25%

In this Bayes' Theorem would lead to the prediction that 80% of customers under the age of 21years are likely to buy an insurance policy (20/25). Certain special terminologies associated with the Bayes Theorem are:

- *Pairwise – Cases where both prior P and dependent D conditions occur together*
- *Singleton – Cases where only the prior condition P occurs*

With respect to the above terms, a Naive Bayes algorithm determines the probability as a result of the division of the % of *pairwise* occurrences by the % of *singleton* occurrences [11]. Very small values of predictor or prior percentages do not contribute to the model effectiveness. Usually a threshold value is set to ignore such very small values during the calculation process.

The above example is a very simple one which depicts a dependent event D based on a single independent event P. However, in case of Naïve Bayes algorithm the dependent event D is based on multiple independent events say {P$_1$,P$_2$, …,P$_n$} i.e. each predictor or prior event is conditionally independent of the other predictors [11]. The general statement for Naïve Bayes algorithm can be expressed as:

$$Prob(D|P1, P2, \ldots, Pn) = Prob(D)Prob(P1, P2, \ldots, Pn|D)/Prob(P1, P2, \ldots, Pn) \quad (4)$$

We derive the above equation from the below equation:

$$Prob\ (A|B) = Prob\ (A\ and\ B)/Prob\ (B) \quad (5)$$

$$Prob\ (B|A) = Prob\ (B\ and\ A)/Prob(A) \quad (6)$$

$$Prob\ (A\ and\ B) = Prob\ (B\ and\ A) \quad (7)$$

From Equations, (5), (6) and (7) we get Equation (8) as:

$$Prob(A|B) = Prob(A)Prob(B|A)/Prob(B) \quad (8)$$

Even if the independence assumption is violated in a practical scenario, the model's predictive accuracy isn't significantly degraded and makes Naïve Bayes a fast, computationally feasible algorithm [11].

Data input for a Naive Bayes classification algorithm usually requires binning which reduces the cardinality of various data columns to appropriate values. Say, for example continuous values like salary could be binned into ranges of the form – {high, medium and low} whereas categorical data could be binned into classes which are one level higher than current (for example, instead of cities regions like {North, South, East, West} could be used).

The Naive Bayes algorithm offers the following advantages:

1. Speed (It is fast.)
2. Highly scalable model building and scoring [11].
3. Linear scaling with the number of predictors and rows [11].
4. Parallelized build process
5. Useful for both binary and multiclass classification problems [11].

3.3 Generalized Linear Model

Generalized Linear Model (GLM) is a model which is used to express a dependent variable D as a linear combination of a given set of explanatory or predictor variables P {x$_1$, x$_2$, …,x$_n$} as per the below equation:

$$f(D) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad (9)$$

For some datasets, where the dependent variable (D) is continuous and can be assumed to be having a reasonably normal distribution, it isn't transformed at all and a multiple linear regression analysis can be performed. However, for datasets where the dependent variable D is binary (i.e. 0/1) like buys insurance – 1 and doesn't buy insurance – 0 logistic regression is performed, using the logit or logistic function. Oracle Data Mining Operations uses Binary Logistic Regression for performing classification operation.

When the response variable has several categories a model that allows for several categories in the response variable such as multinomial regression [14] can be used. Alternatively the response variable can be recoded to produce two categories and perform a binary logistic regression analysis. However, statistically it will not be as efficient as performing a true multinomial analysis.

Before getting into the details for Binary Logistic Regression algorithm we must understand the some basic concepts related to proportions, probabilities and binomial distribution. Proportions and probabilities differ from continuous variables [14] in a lot many ways. Both proportions and probabilities are bounded by 0 and 1in contrast to continuous variables whose values can be anything between plus or minus infinity. This simply emphasizes that proportions have no normality but a binomial distribution.

In cases of a normal distribution, the mean and variance are independent values. But in case of Binomial distribution the mean and variance are not independent of each other.

- For a Binomial Distribution, the mean is denoted by P and the variance by P*(1-P)/n, where n is the number of observations, and P denotes the probability of the event under consideration occurring [14] (e.g. the probability of buying an insurance policy) in any one 'trial' (for any one customer).

- For a Bernoulli distribution, the mean would be denoted by P and the variance by P*(1-P).

There are 2 sets of available transformations in Binary Logistic Regression:

- Logit (logistic transformation) is used when we have proportion as a response while defining the relationship between the dependent variable and the explanatory variables. It is of the form as shown below:

$$\mathrm{Logit(P)} = \log\left[\frac{\mathrm{P}}{(1-\mathrm{P})}\right] \qquad (10)$$

- Probit (probabilistic transformation) is used when we have probability as a response while defining the relationship between the dependent variable and the explanatory variables. It is of the form as shown below:

$$Probit(P) = \exp\left[\frac{P}{(1-P)}\right] \qquad (11)$$

The term within the square brackets defines the odds of an event occurring [14]. Using any of the available Logit or Probit transformations doesn't cause any change to the results because on transforming results from the logit scale to the probability scale, the predicted values will attain the values of at least 0 and at most 1.

3.3.1 Logistic Regression Theory

Let:
$P_i = \Pr(Y = 1 | X=x_i)$ [14]
Where, P_i – probability of a customer buying an insurance policy
x_i – customer being married
Then we can write the Binary Logistic equation for GLM as (Deriving Equation (4) from Equations (1) & (2)):

$$Logit(Pi) = \log[Pi/(1-Pi)] = \beta_0 + \beta_1 x_i \qquad (12)$$

Here,
β_0 Is the parameter that gives the log odds of a married customer being perceived to be buying an insurance policy (when x_i =0), and
β_1 Depicts how these odds differ for unmarried customer (when x_i =1).

Expressing the above GLM (Equation (4)) in terms of odds as:

$$[Pi/(1-Pi)] = \exp(\beta_0 + \beta_1 x_i) \qquad (13)$$

Or Equation (5) could be written in terms of Probability P_i as:

$$Pi = \exp(\beta_0 + \beta_1 x_i)/(1 + \exp(\beta_0 + \beta_1 x_i)) \qquad (14)$$

Conversely the probability of the expected event not occurring can be expressed as:

$$1 - Pi = 1/(1 + \exp(\beta_0 + \beta_1 x_i)) \qquad (15)$$

A residual term can also be included in the above classification model to account for a non-linear and not normal distribution as shown below:

$$Pi + fi = \exp(\beta_0 + \beta_1 x_i)/(1 + \exp(\beta_0 + \beta_1 x_i)) + fi$$
(16)

Class weights influence the weighting of target classes during the model build [11] and can be specified in the class weights table - CLAS_WEIGHTS_TABLE_NAME [11]. Similarly the build setting table - GLMS_REFERENCE_CLASS_NAME can be used to specify the target value to be used as a reference in a binary logistic regression model [14].

3.4 Support Vector Machines

Support Vector Machines (SVM), a kernel-based algorithm, is a very powerful, up-to-date algorithm that has its strong theoretical foundations rooted inside the Vapnik-Chervonenkis theory. SVM has its strength in its standardization (also known as r*egularization*) properties. *Regularization* is the process of generalization of a model to classify new data. SVMs are not only used for classification but also for regression purposes. They belong to the class of supervised learning models that can recognize patterns and also analyze data through the process of associated learning.

A support vector machine algorithm works by constructing either a single hyper-plane or a set of hyper-planes in a space of either high or infinite dimensionality, for the purpose of performing regression, classification, or other tasks. A good rule-of-thumb for a hyper-plane is to aim at achieving the largest separation distance with the nearest training data point belonging to any of the classes formed by the separating hyper-plane. This distance value is also known as the *Functional Margin*. With respect to a hyper-plane context the larger the value of the functional margin, the better is the generalization achieved resulting in a lower value of classifier generalization error. The function that performs the task of transforming the input data to a high-dimensional problem solving space is known as *Kernel*. Such functions can be of any form - linear or nonlinear.

Oracle Data Mining supports Linear and Gaussian (nonlinear) kernels [11]. Let us have a brief introduction of both these kernel functions.

- The linear kernel function creates a linear equation on the available attributes in the set of training data. A linear kernel function yields better results with high number of attributes in the training data set.

- The Gaussian kernel function performs the task of transforming each record in the available data set for training to a point in an n-dimensional space, where n is the number of records through the use of Radial Basis Functions (RBF networks). The RBF kernel function adds a bump around each data point to achieve state-of-the-art results and is one of the most popular functions. The SVM algorithm in this case attempts to place homogeneous target values into same subsets thereby separating the available points. The Gaussian kernel uses nonlinear separators, but within the kernel space it constructs a linear equation [11].

3.4.1 SVM Classification

In SVM classification, the hyper-planes defining the decision boundaries are known as *decision planes*. A decision plane segregates a given set of objects into different classes based on their class memberships. SVM finds the vectors ("support vectors") that define the separators giving the widest separation of classes [11]. With a high number of attributes (more than 100) in the available training data set, SVM uses the linear kernel function else it uses the Gaussian kernel function.

It can perform classification to produce both binary and multiclass results. If it is required to bias the classification results (i.e. differentiate between more and less important classes), then it can be done in SVM through assignment of class weights. By default SVM models achieve the best average prediction across all classes [11]. Biasing is required only in cases where the training data set doesn’t demonstrate a realistic distribution and classes may be under-represented. Increasing the weight for a class, should result in increase in the percent of correct predictions for that particular class. In ODM, SVM implements favorism for one class over another through the use of priors as a weight vector.

3.5 Design of the Proposed Solution

We will take a sample - Insurance Customer database with the past details and other attributes of a customer which would have influenced their past decisions for buying an insurance policy. We would explore the dataset initially using Oracle SQL Developer to determine its usefulness in making future predictions and then apply all the classification models to the same dataset. Since classification is a supervised learning process we shall use only 50% of the dataset for training and retain the rest 50% for testing the algorithm. Once all the models are applied to the same dataset we would obtain the stats for each and find out the best classification model that would earn us the highest cost savings calculated as per the below sample example.

3.5.1 Confusion Matrix

Let us assume a Confusion Matrix obtained from a Classification model ‘A’ as shown below:-

Table1. Confusion Matrix

		PREDICTED CLASS	
		Buy_Insurance = “YES”	**Buy_Insurance = “NO”**
ACTUAL CLASS	**Buy_Insurance = “YES”**	475 (True Positive)	25 (False Negative)
	Buy_Insurance = “NO”	10 (False Positive)	490 (True Negative)

Correct Predictions = 475+490 = 965
Incorrect Predictions = 25+10 = 35
Total Cases = 475+25+10+490 = 1000
Error Rate = 35/1000 = 0.035
Overall Accuracy Rate = 965/1000 = .965

$Lift =$
Percentage of Correct Positive Classifications made by Model/ /Percenta
$= (475/500) * 100/(500/1000) * 100$ = (95/50) = 1.9

True Positive Rate (Hit Rate) = 475/ (475+25) = 95
False Positive Rate (False Alarm Rate) = 10/ (10+490) = .02

3.5.2 Cost Matrix

Assuming the following costs are incurred to business,

* Cost for wrongly predicting a prospective customer as not interested in buying insurance by model (i.e. Cost for False Negative Prediction) = INR 1600

* Cost for wrongly classifying an un-interested (non-responding) customer as a prospective customer (i.e. Cost for False Positive Prediction) = INR 300

* Cost of including a customer in the Insurance promotion campaign = INR 100

Since all correctly classified un-interested candidates can be completely eliminated from the Insurance promotion campaign, the cost of correctly classifying an non-responding candidate would be a saving to the Insurance company and can be denoted as a negative cost to the company.

* Cost of True Negative Prediction = - INR 100 (benefit to the company)

For all True Positive Predictions, the Insurance Company will always gain benefit and we assume that the net cost for a true positive prediction is 0.

From all of these costs we can draw the Cost Matrix as shown below:-

Table2. Cost Matrix

PREDICTED CLASS

		Buy_Insurance = "YES"	**Buy_Insurance = "NO"**
ACTUAL CLASS	**Buy_Insurance = "YES"**	0 (True Positive)	1600 (False Negative)
	Buy_Insurance = "NO"	300 (False Positive)	-100 (True Negative)

Since negative costs in the cost matrix are interpreted as benefits to the Insurance Company, negative outcomes can be influenced using positive numbers in the cost matrix.

The Actual Cost born by the company using the Classification technique with confusion matrix as in Table1 and cost matrix as in Table2 is given by

Actual Cost = INR (0*475 + 1600*25 + 300*10 + (-100)*490)
= (40000 + 3000 – 49000)
= INR (- 6000)

The negative value here denotes the benefit that the Insurance Company will gain out of employing Classification technique of Predictive Analysis for Targeting the Best Customer. If there are multiple classification algorithms available, then a user can decide on which classification model to select by comparing the Overall Predictive Accuracy and Actual Cost obtained from different models.

4 IMPLEMENTATION

We shall use SQL Developer 3.0.0.4 to implement the solution to our problem.

4.1 About the sample DB

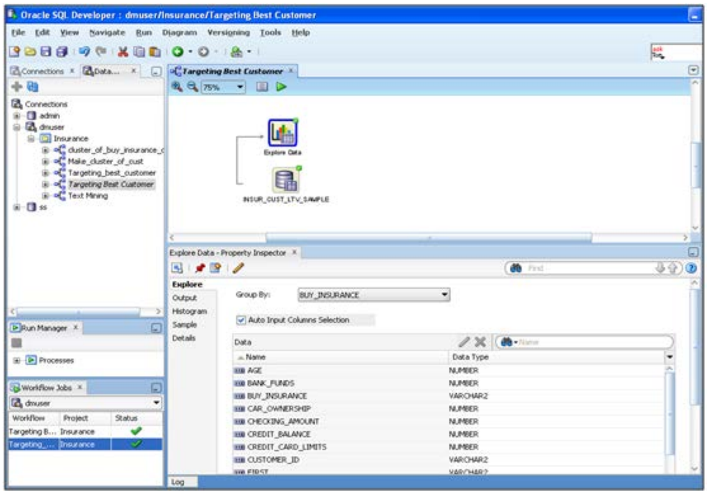
We take a sample - Insurance Customer database to find the best algorithm for solving our "targeting the best customer" problem in the Insurance industry for a newly launched Insurance policy. The sample Insurance database has the following columns as listed below:

Table3. INSUR_CUST_LTV_SAMPLE

Name	Data Type
AGE	NUMBER
BANK_FUNDS	NUMBER
BUY_INSURANCE	VARCHAR2
CAR_OWNERSHIP	NUMBER
CHECKING_AMOUNT	NUMBER
CREDIT_BALANCE	NUMBER
CREDIT_CARD_LIMITS	NUMBER
CUSTOMER_ID	VARCHAR2
FIRST	VARCHAR2
HAS_CHILDREN	NUMBER
HOUSE_OWNERSHIP	NUMBER
LAST	VARCHAR2
LTV	NUMBER
LTV_BIN	VARCHAR2
MARITAL_STATUS	VARCHAR2
MON-EY_MONTHLY_OVERDRAWN	NUMBER
MONTHLY_CHECKS_WRITTEN	NUMBER
MORTGAGE_AMOUNT	NUMBER
N_MORTGAGES	NUMBER
N_OF_DEPENDENTS	NUMBER
N_TRANS_ATM	NUMBER
N_TRANS_KIOSK	NUMBER
N_TRANS_TELLER	NUMBER
N_TRANS_WEB_BANK	NUMBER
PROFESSION	VARCHAR2
REGION	VARCHAR2
SALARY	NUMBER
SEX	VARCHAR2
STATE	VARCHAR2
T_AMOUNT_AUTOM_PAYMENTS	NUMBER
TIME_AS_CUSTOMER	NUMBER

4.2 Data Exploration

At any point of time in creation of a Prediction model, it is very important to be sure that the database under consideration is a valid one and has some predictable attribute. To check for this property in our sample DB we run an initial Explore Data function on this dataset as per the below figure to determine whether the data that we have has some useful attributes which can be used for making future predictions and analysis. Since we want to determine whether a given customer will be our target audience for new Insurance policy or not, we choose the 'BUY_INSURANCE' attribute under the group by choice for exploring the sample db.



Group By: BUY_INSURANCE

☑ Auto Input Columns Selection

Data

Name	Data Type
AGE	NUMBER
BANK_FUNDS	NUMBER
BUY_INSURANCE	VARCHAR2
CAR_OWNERSHIP	NUMBER
CHECKING_AMOUNT	NUMBER
CREDIT_BALANCE	NUMBER
CREDIT_CARD_LIMITS	NUMBER
CUSTOMER_ID	VARCHAR2
FIRST	VARCHAR2

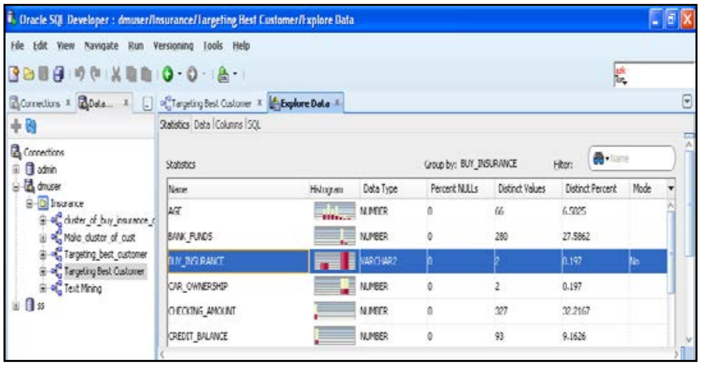
Workflow	Project	Status
Targeting B...	Insurance	✓
Targeting_...	Insurance	✓

Fig.5. Explore Data function run on sample Insurance table

The *Output* tab produces a list of all the columns (names and data type) in the data source. The *Histogram* tab lists the default maximum number (10) of bins (Categorical, Data and Numerical Bins) used for creating histograms. The *Sample* tab specifies whether all data should be selected for analysis or a percent of the original data should be sampled and used. By default a sampling size of 60% is used. The Statistics (Fig. 6) produced as a result of applying the explore data function are:

- Attribute name
- Data type
- Histogram
- No. of distinct values
- Mode (for character values)

Minimum, maximum, average, Standard Deviation, etc. (for Numeric Values)



Name	Histogram	Data Type	Percent NULLs	Distinct Values	Distinct Percent	Mode
AGE		NUMBER	0	66	6.5025	
BANK_FUNDS		NUMBER	0	280	27.5862	
BUY_INSURANCE		VARCHAR2	0	2	0.197	No
CAR_OWNERSHIP		NUMBER	0	2	0.197	
CHECKING_AMOUNT		NUMBER	0	327	32.2167	
CREDIT_BALANCE		NUMBER	0	93	9.1626	

Fig.6. Statistics of Explore Data function

4.3 Model Application

Once it has been ascertained that the data-set can be used to generate some kind of future predictions on the chosen 'group by' parameter, we apply the Classification model on the explored data as shown in below Fig. 7.

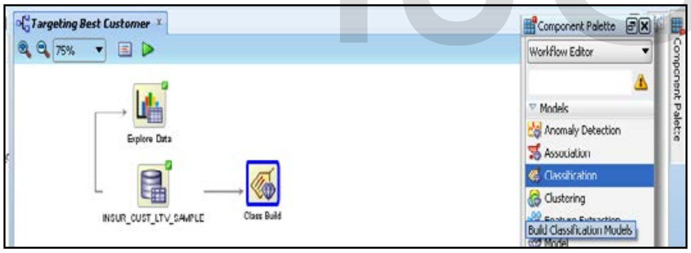


Fig.7. Applying Classification model to INSUR_CUST_LTV_SAMPLE

In our case the target field 'Buy Insurance' contains binary values (Yes/ No) so the Classification Node 'Class Build' builds models using the following four algorithms:

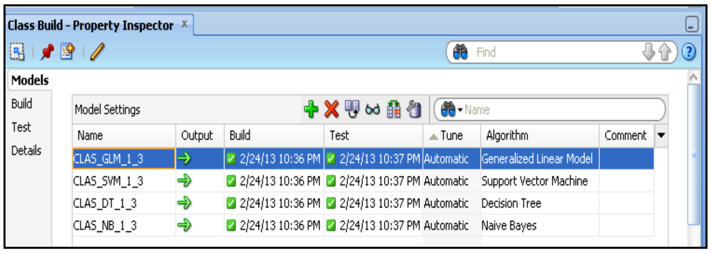
- GLM Classification Models
- SVM Classification Models
- Decision Tree Algorithm
- Naive Bayes

It is important to note that all 4 algorithms are used for a binary target whereas for non-binary targets, the GLM needs to be added explicitly and is not built by default.

Listed below are some important points to be kept in mind while comparing the classification models:

- The training and target data for all models is same.
- All models are tested by default.
- The available data set is randomly split into 2 parts - 50% training data set and 50% test data set which is also the default split ratio.
- Depending on the Kernel used for creating a model, the information is displayed in the model viewer. The Linear Kernel based model displays 3 tabs – Compare, Settings and Coefficients. The Gaussian kernel based model displays just 1 tab for Settings.

The results after all Classification algorithms are applied on the data set are as per the below Fig. 8.



Name	Output	Build	Test	Tune	Algorithm	Comment
CLAS_GLM_1_3	→	☑ 2/24/13 10:36 PM	☑ 2/24/13 10:37 PM	Automatic	Generalized Linear Model	
CLAS_SVM_1_3	→	☑ 2/24/13 10:36 PM	☑ 2/24/13 10:37 PM	Automatic	Support Vector Machine	
CLAS_DT_1_3	→	☑ 2/24/13 10:36 PM	☑ 2/24/13 10:37 PM	Automatic	Decision Tree	
CLAS_NB_1_3	→	☑ 2/24/13 10:36 PM	☑ 2/24/13 10:37 PM	Automatic	Naive Bayes	

Fig.8. Results of Classification Model applied to INSUR_CUST_LTV_SAMPLE

The details of each of the Classification algorithm listed in the above Fig. 8. can be viewed by right clicking on the Class Build model, selecting 'View Models' and then clicking the appropriate model name from the list. One important thing to note over here is that not all columns in a data source are used while building a model. This happens because some columns may not include any useful information. While in other cases it may happen that a column might contain values of a data type which a given algorithm may not support.

Let us have a look at the details of each of the model one by one:

4.3.1 Decision Tree Model

The classification model generated using the Decision tree algorithm lists the following details for all the nodes:

- Node number
- Prediction
- Support (number of records which satisfy the rule in a given training data set)
- Confidence (if a certain rule has been satisfied then Confidence denotes the likelihood or chances of the predicted outcome)
- No/ Yes Parameters (like, Count, Percentages, and Histogram)
- Split Condition for a node

The leaf nodes contain the final rules generated by the decision tree. The decision tree generated for solving the "Targeting the Best Customer" problem is as shown in the Fig. 9 below:

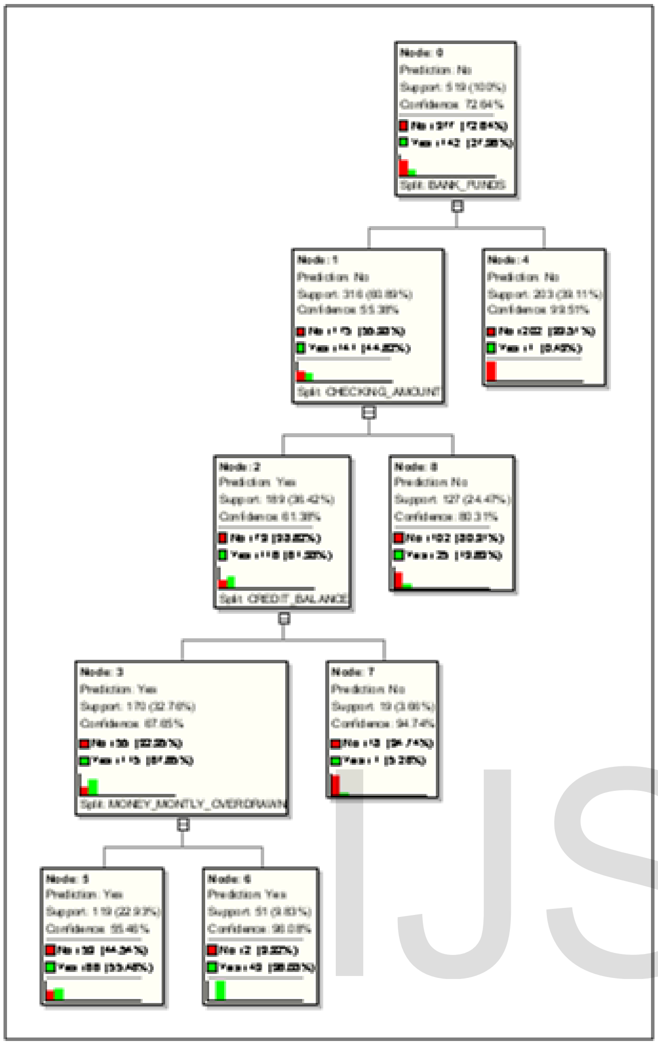
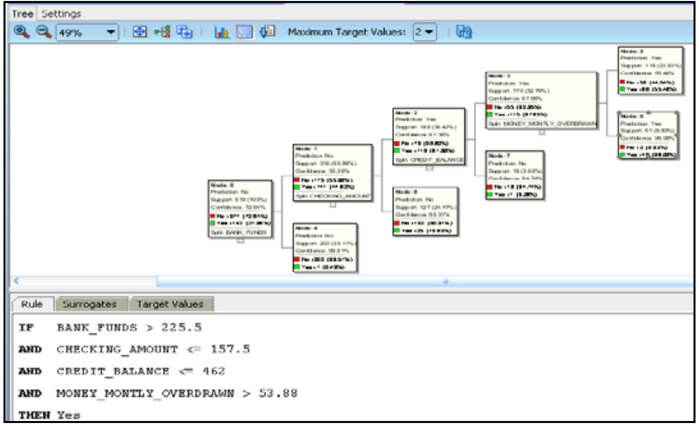


Fig.9. Decision Tree generated for "Targeting the Best Customer" problem

The 5 leaf nodes (Node 4, 5, 6, 7, 8) denote the five rules generated for solving our problem. The details of each of the rule can be obtained by clicking on each leaf node as shown in Fig. 10.



```
IF   BANK_FUNDS > 225.5
AND  CHECKING_AMOUNT <= 157.5
AND  CREDIT_BALANCE <= 462
AND  MONEY_MONTLY_OVERDRAWN > 53.88
THEN Yes
```

Fig.10. Rule generated for Node 6

All the generated rules are as listed below:

Rule for Node 4

IF BANK_FUNDS <= 225.5

THEN No

Rule for Node 8

IF BANK_FUNDS > 225.5

AND CHECKING_AMOUNT > 157.5

THEN No

Rule for Node 7

IF BANK_FUNDS > 225.5

AND CHECKING_AMOUNT <= 157.5

AND CREDIT_BALANCE > 462

THEN No

Rule for Node 6

IF BANK_FUNDS > 225.5

AND CHECKING_AMOUNT <= 157.5

AND CREDIT_BALANCE <= 462

AND MONEY_MONTLY_OVERDRAWN > 53.88

THEN Yes

Rule for Node 5

IF BANK_FUNDS > 225.5

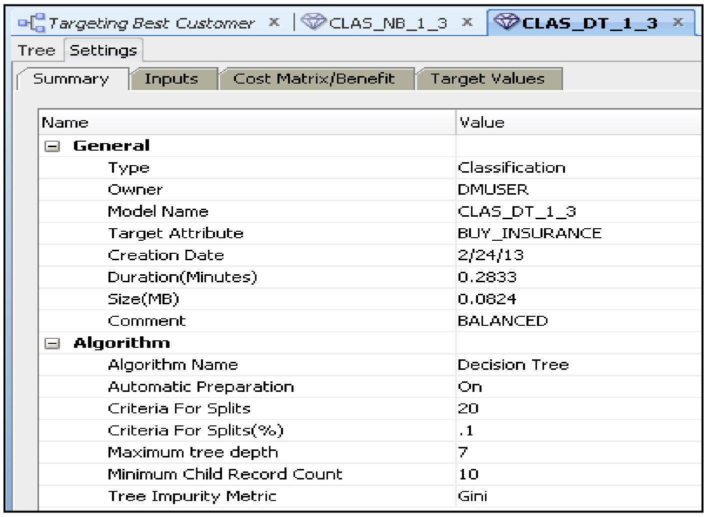
AND CHECKING_AMOUNT <= 157.5

AND CREDIT_BALANCE <= 462

AND MONEY_MONTLY_OVERDRAWN <= 53.88

THEN Yes

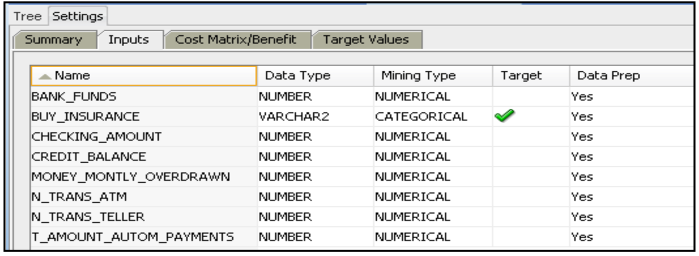
The summary of the Decision Tree generated is as per the below Fig. 11:



Name	Value
⊟ **General**	
Type	Classification
Owner	DMUSER
Model Name	CLAS_DT_1_3
Target Attribute	BUY_INSURANCE
Creation Date	2/24/13
Duration(Minutes)	0.2833
Size(MB)	0.0824
Comment	BALANCED
⊟ **Algorithm**	
Algorithm Name	Decision Tree
Automatic Preparation	On
Criteria For Splits	20
Criteria For Splits(%)	.1
Maximum tree depth	7
Minimum Child Record Count	10
Tree Impurity Metric	Gini

Fig.11. Summary of Decision Tree classification model

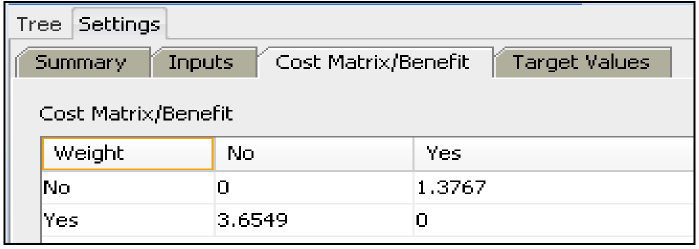
The various inputs considered while constructing the Decision tree are as shown in Fig. 12 below.



Name	Data Type	Mining Type	Target	Data Prep
BANK_FUNDS	NUMBER	NUMERICAL		Yes
BUY_INSURANCE	VARCHAR2	CATEGORICAL	✓	Yes
CHECKING_AMOUNT	NUMBER	NUMERICAL		Yes
CREDIT_BALANCE	NUMBER	NUMERICAL		Yes
MONEY_MONTLY_OVERDRAWN	NUMBER	NUMERICAL		Yes
N_TRANS_ATM	NUMBER	NUMERICAL		Yes
N_TRANS_TELLER	NUMBER	NUMERICAL		Yes
T_AMOUNT_AUTOM_PAYMENTS	NUMBER	NUMERICAL		Yes

Fig.12. Decision Tree Inputs

The Cost Matrix/ Benefit obtained for the decision tree is as shown belowin Fig. 13:



Cost Matrix/Benefit

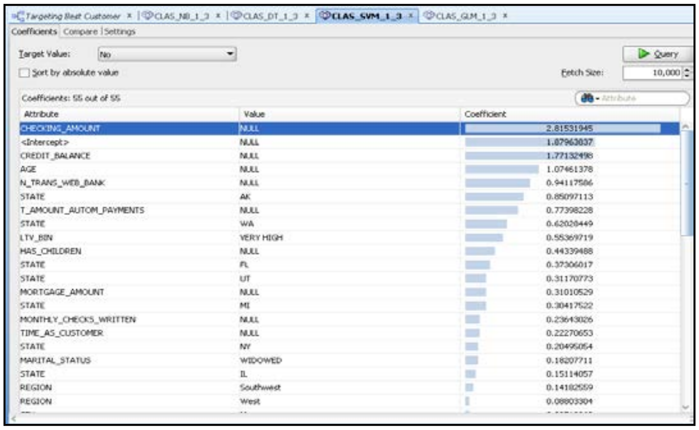
Weight	No	Yes
No	0	1.3767
Yes	3.6549	0

Fig.13. Cost Matrix/ Benefit for Decision Tree model

4.3.2 Support Vector Machine

The SVM model generated for solving the “Targeting the Best Customer” problem is generated using a Linear Kernel and contains the following tabs as shown in figure:

- *Coefficients*
- *Compare*
- *Settings*



Target Value: No

☐ Sort by absolute value

Fetch Size: 10,000

Coefficients: 55 out of 55

Attribute	Value	Coefficient
CHECKING_AMOUNT	NULL	2.81531945
<Intercept>	NULL	1.87963837
CREDIT_BALANCE	NULL	1.77132498
AGE	NULL	1.07461378
N_TRANS_WEB_BANK	NULL	0.94117586
STATE	AK	0.85097113
T_AMOUNT_AUTOM_PAYMENTS	NULL	0.77398228
STATE	WA	0.62028449
LTV_BIN	VERY HIGH	0.55369719
HAS_CHILDREN	NULL	0.44339488
STATE	FL	0.37306017
STATE	UT	0.31170773
MORTGAGE_AMOUNT	NULL	0.31010529
STATE	MI	0.30417522
MONTHLY_CHECKS_WRITTEN	NULL	0.23643026
TIME_AS_CUSTOMER	NULL	0.22270653
STATE	NY	0.20495054
MARITAL_STATUS	WIDOWED	0.18207711
STATE	IL	0.15114057
REGION	Southwest	0.14182559
REGION	West	0.08803304

Fig.14. SVM Classification Model for “Targeting the Best Customer” problem with Positive coefficients

Coefficients Grid (SVMC)

An empty grid indicates the absence of coefficients for target value under consideration. This grid has the below controls:

- *Target Value*
- *Sort By Absolute Value*
- *Fetch Size*

The coefficients grid contains the following columns:

Attribute: displays the name of the attribute

Value: contains the value of the attribute. It is a range in case the attribute is binned

Coefficient: is the probability for the value of the attribute. Light blue bars denote positive values and red bars denote negative values as shown in following figure.

Compare

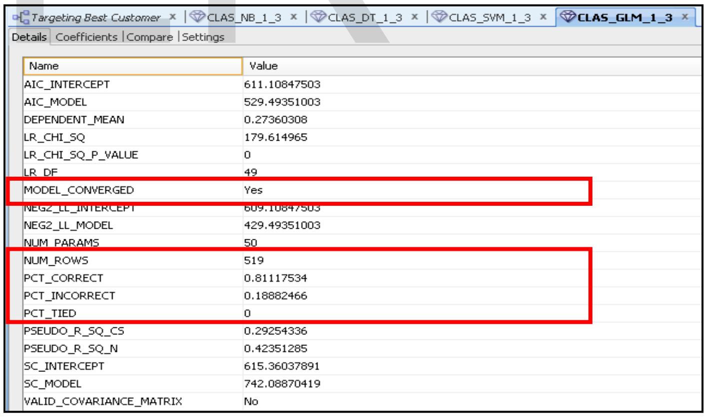
This tab allows for a comparison of results for two different target values.

Settings Tab (SVMC)

Information about how the model was built is displayed on the Settings tab. The Summary tab (SVMR) contains the algorithm and model settings. The Inputs tab (SVMC) holds all the attributes used to build the model and the targets can be found on the Target Values tab (SVMC). The cost matrix is displayed on the Cost Matrix/Benefit tab.

4.3.3 Generalized Linear Model

The Generalized Linear Model for solving the “Targeting the Best Customer” problem is as shown in figure below and contains 4 tabs – Details, Coefficients, Compare and Settings. The Model details tab lists global metrics (Name and Value of the metric) for the model as a whole. The following metrics (default) are displayed for any GLM. The metrics of high importance to us are highlighted in red in the figure. These contain:



Name	Value
AIC_INTERCEPT	611.10847503
AIC_MODEL	529.49351003
DEPENDENT_MEAN	0.27360308
LR_CHI_SQ	179.614965
LR_CHI_SQ_P_VALUE	0
LR_DF	49
MODEL_CONVERGED	Yes
NEG2_LL_INTERCEPT	609.10847503
NEG2_LL_MODEL	429.49351003
NUM_PARAMS	50
NUM_ROWS	519
PCT_CORRECT	0.81117534
PCT_INCORRECT	0.18882466
PCT_TIED	0
PSEUDO_R_SQ_CS	0.29254336
PSEUDO_R_SQ_N	0.42351285
SC_INTERCEPT	615.36037891
SC_MODEL	742.08870419
VALID_COVARIANCE_MATRIX	No

Fig.15. GLM metrics for “Targeting the Right Customer” problem

- MODEL_CONVERGED – indicates whether the model converged or not
- NUM_PARAMS – displays the number of parameters (coefficients, including the intercept)
- NUM_ROWS – displays the number of rows
- PCT_CORRCET – displays the percentage of true (correct) predictions made
- PCT_INCORRCET – displays the percentage of false (incorrect) predictions made
- PCT_TIED – displays percentage of those cases where probability of both cases is equal (tied)

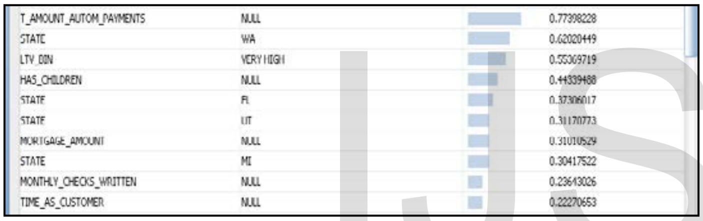
The other tabs for GLM Classification model viewer are similar to the SVM Classification model viewer except for the GLM Compare tab as GLM can only be built for binary classification models.

4.3.4 Naïve Bayes Model

The results generated for the Naïve Bayes model are visually similar to the results obtained for SVM model as blue and red bars with the only difference being in the generated tabs. The various tabs generated for Naïve Bayes model are explained below:

Probabilities (NB) Tab

The Probabilities calculated for each feature during the process of model build are listed under this tab. There is a selection box which allows the user to switch between the two target values – Yes and No. The blue bar in the grid as shown below in Fig. 16 represents positive values for probabilities whereas the red bar represents the negative values for probabilities. The tab also facilitates for sorting of displayed probabilities and also filtering of features whose probabilities are displayed. For features whose probability value gets close to zero, the bar may not be displayed at all.



T_AMOUNT_AUTOM_PAYMENTS	NULL	0.77398228
STATE	WA	0.62020449
LTV_BIN	VERY HIGH	0.55369719
HAS_CHILDREN	NULL	0.44339488
STATE	FL	0.37306017
STATE	UT	0.31170773
MORTGAGE_AMOUNT	NULL	0.31010529
STATE	MI	0.30417522
MONTHLY_CHECKS_WRITTEN	NULL	0.23643026
TIME_AS_CUSTOMER	NULL	0.22270653

Fig.16. Positive Probability values for features in Naïve Bayes model

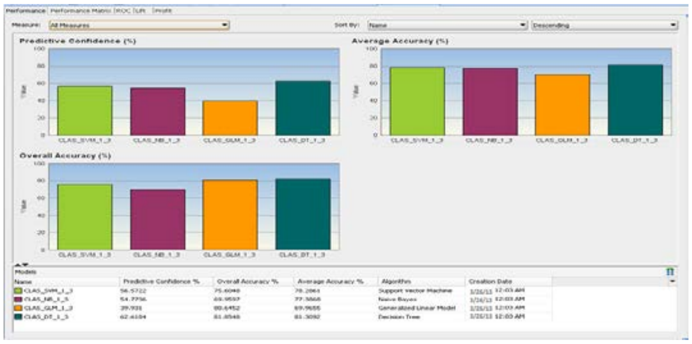
By default the probabilities for the value occurring least frequently are displayed.

Compare Tab

Using the compare tab results for two different target values can be compared. The selection boxes for Target Value1 and Target Value 2 used for selecting the target values to compare are shown populated with default values. The results of the comparison values selected for target value 1 and target value 2 are displayed in a grid which comprises of the following columns – Attribute (name of the attribute), Value, Propensity for target value, Propensity for target value 2 and histogram bar for both propensities (ranges between 1.0 and -1.0). Propensity is a measure of predictive relationship that a given target value has with a given attribute-value pair. It can be calculated in 2 ways – Propensity for a target value denoted by positive values and propensity against a target value denoted by negative values. The number of records fetched can be changed using the Fetch Sizre variable and the Grid Filter can be used to display specific values. Sort operation can also be performed by click on the grid column headings.

5 Results and Analysis

The performance of all the Classification models is compared against each other to determine the best classification model in solving the "Targeting the Right Customer" problem. The Fig. 17 below shows the comparative column chart for Predictive Confidence, Average Accuracy and Overall Accuracy measured in % obtained for each classification model.



Name	Predictive Confidence %	Overall Accuracy %	Average Accuracy %	Algorithm	Creation Date
🟩 CLAS_SVM_1_3	56.5722	75.6048	78.2861	Support Vector Machine	3/26/13 12:03 AM
🟪 CLAS_NB_1_3	54.7736	69.9597	77.3868	Naive Bayes	3/26/13 12:03 AM
🟧 CLAS_GLM_1_3	39.931	80.6452	69.9655	Generalized Linear Model	3/26/13 12:03 AM
🟩 CLAS_DT_1_3	62.6184	81.6548	81.3092	Decision Tree	3/26/13 12:03 AM

Fig.17. Comparative Performance Charts generated for classification models

The table below details the values obtained for each of the model. In all the categories the Decision Tree model generated fares much higher than any other generated model.

Table4. Performance values for generated classification models

Name	Predictive Confidence %	Overall Accuracy %	Average Accuracy %	Algorithm
CLAS_SVM_1_3	56.5722	75.6048	78.2861	Support Vector Machine
CLAS_NB_1_3	54.7736	69.9597	77.3868	Naïve Bayes
CLAS_GLM_1_3	39.931	80.6452	69.9655	Generalized Linear Model
CLAS_DT_1_3	62.6184	81.6548	81.3092	Decision Tree

We find that the decision tree model represented by CLAS_DT_1_3 provides the best performance amongst all the 4 algorithms in all the 3 performance categories. The formula for calculating the Predictive Confidence for a model is as shown below:

$$\text{Predictive Confidence} = 1 - (\text{Error of Predict})/(\text{Error of naive model}) \quad (17)$$

$$\text{Error of Predict} = 1 - (\text{A1} + \text{A2} + \text{A3})/\text{N} \quad (18)$$

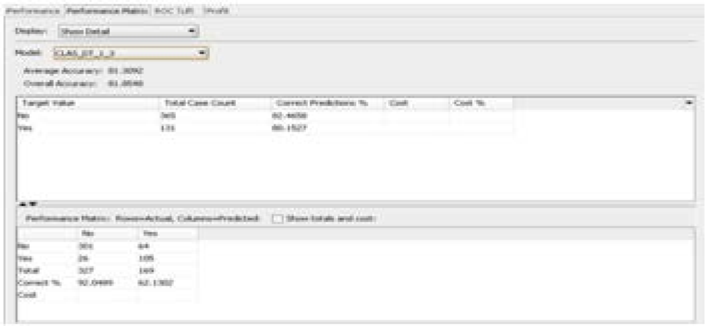
$$\text{Error of Naive Model} = (\text{N} - 1)/\text{N} \quad (19)$$

Where, A1 - accuracy for target class 1, A2 - accuracy for target class 2, etc, and N - number of target classes. The accuracy for each target class is obtained from the Performance matrix of each model.

For Example, we will calculate the Predictive Confidence of Decision tree model manually to understand the formula.

Error of predict = 1-(.824658+.801527)/2 = 1-(1.626185/2) = 1-.8130925 = 0.1869075
Error of naïve model = ((2-1)/2) = 0.50
Predictive confidence = 1-((0.1869075)/0.50) = 1-(.373815)
Predictive Confidence = 0.626185

Fig. 18 below displays the performance matrix for the Decision Tree model displaying the figures for overall and average accuracy. By selecting the appropriate model name from the model drop down box we can view the performance matrix for the other models in a similar fashion.



Display: Show Detail
Model: CLAS_DT_1_3
Average Accuracy: 81.3092
Overall Accuracy: 81.8548

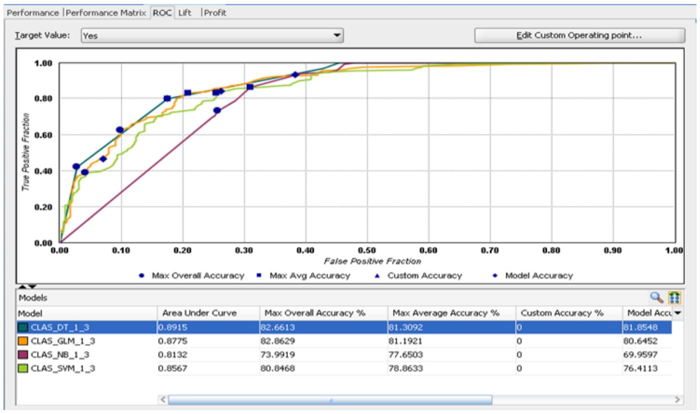
Target Value	Total Case Count	Correct Predictions %	Cost	Cost %
No	365	82.4658		
Yes	131	80.1527		

Performance Matrix: Rows=Actual, Columns=Predicted ☐ Show totals and cost

	No	Yes
No	301	64
Yes	26	105
Total	327	169
Correct %	92.0489	62.1302
Cost		

Fig.18. Performance Matrix for Decision Tree Model

The comparative ROC graph (Fig. 19) of the various Classification models compares the predicted and actual target values. It plots the figures – Max Overall Accuracy, Max Average Accuracy, Custom Accuracy and Model Accuracy, where the X-axis represents the False Positive Fraction and the Y-axis represents the True Positive Fraction.



Model	Area Under Curve	Max Overall Accuracy %	Max Average Accuracy %	Custom Accuracy %	Model Accu
CLAS_DT_1_3	0.8915	82.6613	81.3092	0	81.8548
CLAS_GLM_1_3	0.8775	82.8629	81.1921	0	80.6452
CLAS_NB_1_3	0.8132	73.9919	77.6503	0	69.9597
CLAS_SVM_1_3	0.8567	80.8468	78.8633	0	76.4113

Fig.19. Comparative ROC curve for all Classification Models

The ROC values generated for all the models are listed as per the below table. In this category too, the results obtained for generated Decision tree model are higher than any other model. However, the generated Generalized Linear Model has results that are in close competition with the obtained ROC values for the Decision tree model.

Table5. ROC Values for different Classification Models

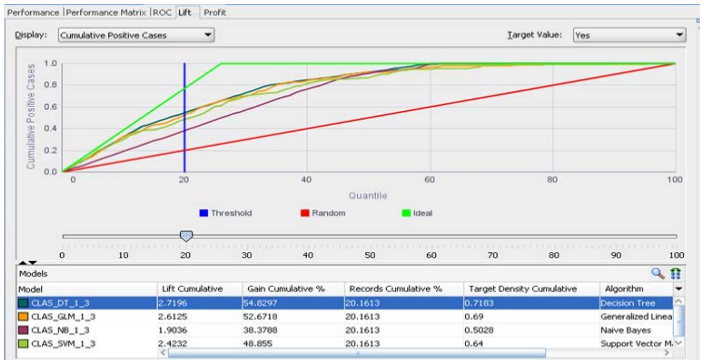
Name	Area Under Curve	Max Overall Accuracy %	Max Average Accuracy %	Custom Accuracy %	Model Accuracy
CLAS_DT_1_3	0.8915	82.6613	81.3092	0	81.8548
CLAS_GLM_1_3	0.8755	82.8629	81.1921	0	80.6452
CLAS_NB_1_3	0.8132	73.9919	77.6503	0	69.9597
CLAS_SVM_1_3	0.8567	80.8468	78.8633	0	76.4113

The Lift graph (Fig. 20) displays the trend for Cumulative Positive and Negative cases for the selected target Value (Yes/ No in our case) for all the models.

The red line in the figure below displays the random trend (for randomly generated predictions) and the green line displays the ideal trend values (for model generated predictions).

The blue line indicates the Threshold value. Each line in the graph representing a model displays the rate of convergence of model with the ideal values. The graph presents a comparative view of the degree to which the predictions obtained from one classification model are better than randomly-generated predictions. The table below the graph lists the other related Lift values for each model (Decision Tree/ Generalized Linear Model/ Naïve Bayes/ Support Vector Machine) like,

- Lift Cumulative
- Gain Cumulative %
- Records Cumulative %
- Target Density Cumulative


Performance | Performance Matrix | ROC | Lift | Profit
Display: Cumulative Positive Cases
Target Value: Yes
Cumulative Positive Cases
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100
Quantile
🟦 Threshold
🟥 Random
🟩 Ideal
0
10
20
30
40
50
60
70
80
90
100
Models

Model	Lift Cumulative	Gain Cumulative %	Records Cumulative %	Target Density Cumulative	Algorithm
CLAS_DT_1_3	2.7196	54.8297	20.1613	0.7183	Decision Tree
CLAS_GLM_1_3	2.6125	52.6718	20.1613	0.69	Generalized Linea
CLAS_NB_1_3	1.9036	38.3788	20.1613	0.5028	Naive Bayes
CLAS_SVM_1_3	2.4232	48.855	20.1613	0.64	Support Vector M.

Fig.20. Comparative Lift curve for Cumulative Positive Cases

The table below lists the different Lift values obtained for the various models. Since we had a uniform count of records being used for generating and evaluating each of the models, the values for Records Cumulative % remains same for all the models.

Table6. Lift Values for different Classification Models

Name	Lift Cumulative	Gain Cumulative %	Records Cumulative %	Target Density Cumulative	Algorithm
CLAS_DT_1_3	2.7196	54.0297	20.1613	0.7183	Decision Tree
CLAS_GLM_1_3	2.6125	52.6718	20.1613	0.69	Generalized Linear Model
CLAS_NB_1_3	1.9036	38.3788	20.1613	0.5028	Naïve Bayes
CLAS_SVM_1_3	2.4232	48.855	20.1613	0.64	Support Vector Machine

6 Conclusions and Future Scope

6.1 Conclusion

In this thesis, we have studied and applied various data mining Classification algorithms to solve the Insurance domain problem of “Targeting the Right Customer”, amongst a list of available customers in the Insurance database, for promoting a newly launched Insurance policy. We compared the results obtained from various algorithms on the basis of Performance Matrix, Receiver Operating Characteristics and Lift, and have reached at the following conclusions with respect to the initial defined problem:

- **Decision Tree algorithm based model** provides the best Average Accuracy (81.31%) , Overall Accuracy (81.65%) and Predictive Confidence (62.61%) to solve the “Targeting the Right Customer” problem at hand.

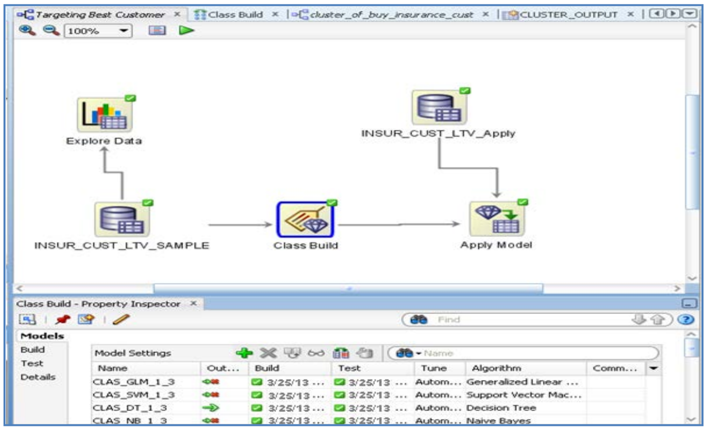
- The other algorithms follow the performance order - SVM (78.26%), Naïve Bayes (77.38%) and GLM (69.96%) for *Average Accuracy*; GLM (80.65%), SVM (75.60%) and Naïve Bayes (69.94%) for *Overall Accuracy*; and SVM (56.57%), Naïve Bayes (54.77%) and GLM (39.93%) for *Predictive Confidence*.

- The model based on **Decision Tree** algorithm also fares the best among the performance Matrix measure by scoring the highest correct predictions percentage of 82.47%.

- Under the ROC figure also, **Decision Tree algorithm** based model obtains the largest *Area under the Curve* and highest *Model Accuracy*, followed by GLM, Naïve Bayes and SVM for Area under the Curve and GLM, SVM and Naïve Bayes for Model Accuracy.

- The value for *Cumulative Lift* is also the highest for **Decision Tree based classification model**.

Taking into consideration all the above obtained conclusions with respect to the performance of a Classification model, we finally apply the Decision Tree Based model to solve our problem of Targeting the Right Customer for the promotion of the newly launched insurance policy (Fig. 21).



Name	Out...	Build	Test	Tune	Algorithm	Comm...
CLAS_GLM_1_3		3/25/13 ...	3/25/13 ...	Autom...	Generalized Linear ...	
CLAS_SVM_1_3		3/25/13 ...	3/25/13 ...	Autom...	Support Vector Mac...	
CLAS_DT_1_3		3/25/13 ...	3/25/13 ...	Autom...	Decision Tree	
CLAS_NB_1_3		3/25/13 ...	3/25/13 ...	Autom...	Naive Bayes	

Fig.21. Applying Decision Tree Model to the Insurance Customer Database

In our case, all the result for all performance factors went in favor of Decision Tree based Classification model. This may not be the case for all the other datasets. The performance measuring factors for a given company in the Insurance domain may differ. Some companies may pay higher weight-age to cost, others to ROC and some others to lift. In such a case, the classification model chosen for application may vary based on the assigned weights or prior conditions set for performance measures.

Also chances are there, that the chosen model may be a case of Over-fitting when all the data in the database is used only for creating the model. In such cases, the model would give accurate results for data it has already been trained on and not for new data sets.

In our case, we had taken 50% of data for model creation and 50% for testing so the Decision tree model by-passes the fear of being an Over-fitting model.

6.2 Future Scope

The classification problem for the Insurance domain has been solved using a Sample Insurance customer database and the performance of the classification algorithms is evaluated on the same data set. However, in a real life scenario, databases are of huge size and contain terabytes of data. Moreover the data sources that feed in data are not limited to hard copies of filled up forms or some system entry but come from a wide domain like the World Wide Web (which comprises of social groups, blogs, twitter posts, etc.). With data input from so many sources, data mining and classification becomes an essential part of business operations. It also becomes an important means of gaining competitive intelligence as it would handle huge volumes of data stored in data ware houses and marts and render it in a useful manner [18] by analyzing the same from different perspectives. The new classification systems would be smart enough to suggest hidden and unknown predictions which would ultimately enhance future decision making process.

In such scenarios, technologies like Big Data and Apache Hadoop step in. Almost all big industrial giants have started exploring and implementing the concepts of these new technologies and the ways in which they can utilize the clustering and classification algorithms provided so that new trends, relationships and correlations among the data could be generated (using multidimensional analysis) without incurring the cost of slow operational speeds.

Hadoop is a powerful new technology that is helping companies to focus on the most important information in the data collected so that evaluation and understanding of the behavior of potential customers becomes an easy task and this in turn results in capturing of the market. This confidence comes with the huge volumes of data that it can handle and also because of the feature that it can consume unstructured data that comes from sources like blogging sites, social networks and twitter posts.

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APPENDIX A

LIST OF FIGURES

APPENDIX B

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