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The Effect of Attribute Weighting on Prediction Accuracy of Subscription of Term Deposits

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***Abstract* - There are several marketing strategies that are prevailing in the universe of business community. Internet, globalization, and hyper-competition have redefined the manner in which companies and marketers interact with consumers. The bankers adopting several measures and luring the customers to subscribe to their deposits and other schemes. With the advent of the technology, finding the potential customers who are central cohesive source of support and stability became placid. Most of the companies adopting manual measures and finding the potential customers by allocating special wings with respective field experts. But in these recent days, the new trend in technology changing the lineament of marketing strategies. A well advanced technology which most of the companies espousing is data mining. This paper proposes a model which improves the prediction accuracy by considering the weighting of the attributes. The model carries in two phases, first phase carries the preprocessing of the data missing value treatment, attribute subset selection and second phase carries development of model to predict the unknown class label i.e subscription of term deposit. The model is built by Naïve Bayesian classification with best number of relevant attributes that influence the class label. The accuracy of the prediction is good.**

***Keywords* –attribute weighting ,classifier, preprocessing, subscription**

I INTRODUCTION: Almost everything the people do, short of taking a long, lonely walk in the woods or something, leaves little bits of electronic data behind. Every time while search in the Internet, punch something into mobile phone or write on someone's Facebook wall, Toothpaste to life insurance, the data mining business, as it's known, is growing 10 percent a year, and to the astonishment of the market the amount of data produced is booming [1].

Marketing which means a transaction between buyers and sellers about a product or service. In these innovative days marketing is one of the target components for entrepreneurship. Integration of wants, needs, demand product, price, promotion, place ruling the present marketing strategies. Modern marketing strategies like teli marketing, SMS, e mails dominating the olden strategies like print media, electronic media, advertisements, business magazines, pamphlets. Banks must pay attention to the fact that customers are getting more educated and have better tools, such as the Internet, at their disposal to entertain the policies with more discrimination. The customer is king, Kotler asserts[2]. Thus, now more than ever before, it is vital that marketers continually strive to meet customers' needs; because that is the only way they will succeed in this increasingly competitive marketplace. The necessity of meeting the customer to achieve their targets the banks are implementing several strategies, one among those is subdue the constraints in the field of research and development(R&D) wing. The R&D department substituting several various manual methodologies with the new trend technologies. So this wing grabbing the roots emanating from the fast growing software technology. With the invention of new technologies the information hide in the raw data is processed and discovering the hidden knowledge from the raw data. For this reason data mining has high importance in present time of research [3-6]. The extraction of knowledge in data analysis is becoming very essential in various fields like manufacturing and production [7][8],telecommunication [9], medical field [10],internet based global information system(www) [11], Science and technology [12], financial and business management [13-17]. In this scenario many companies, organizations and scientific communities

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focusing on discovering the new patterns of knowledge.

This paper proposes such one kind of data mining technique which reduces the cumbersome efforts of the marketing manager(MR) to find the potential customers. The companies/banks trying attract the customers to indulge them in their schemes by luring them that they would get high benefits for small investments in minimum duration. The newly appointed MRs are well trained from their wings and scattering to catch the customers to reach their targets. They are following the traditional and most important methods i.e meeting the customer. Most of the times, they couldn't gauge the customers who positively accepts their advice/request. The paper proposes the important factors on which marketing person should mostly concentrate and not to concentrate which in turn waste their time and energy which they can put for other issues.

II DATA SET: The data set [18] is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be (or not) subscribed. One data set is chosen from the available two data sets from UCI machine repository [19]. The elected data set contains 10% of the un chosen data set (45211 instances) as the later consumes more time for the same prediction that would attain with former data set. The data set contains 4521 examples with 17 attributes including the result/class attribute. The first 16 attributes are considered as input variables and the 17th attribute is output variable which contains subscription of term deposit. The 17 attributes and their short forms and data types are elaborated in Table 1. The input variables are bank client data and output variable is whether the client subscribed or not.

III DATA PREPROCESSING: There is a possibility of non existing, in consistent and noise data that is extracted from data base, data warehouse, World Wide Web and other repositories which are multiple and heterogeneous data. This raw data should be preprocessed to get the accurate and consistent data and to eliminate accumulation of mistakes and increase the efficiency of the further processing. There are several phases in the pre processing and they are well known with data cleaning, data integration and transformation, and data reduction.

Most of the raw data is noisy and discrepant or in complete. This should be preprocessed before further analyzing and extracting the information. If there is no proper pre processing that leads to production of inaccurate and vague results. The preprocessing step includes managing the basic difficulties carried by raw data. The bank deposit data which is used here are preprocessed for finding missing values and inconsistency of data. Some of the algorithms can manage the missing values by incorporating some methodologies like ignoring the tuple or replace the missing value with respective attribute mean

TABLE 1
SUBSCRIPTION OF TERM DEPOSIT – META DATA

S.No	Attribute	Attribute description	Data type
1	age	Age	numeric
2	job	type of job	categorical
3	marital	marital status	categorical
4	education	education qualification	categorical
5	default	has credit in default	binary
6	balance	average yearly balance(euros)	numeric
7	housing	has housing loan?	binary
8	loan	has personal loan?	binary
9	contact	contact communication type	categorical
10	day	last contact day of the month	numeric
11	month	last contact month of year	categorical
12	duration	last contact duration(in seconds)	numeric
13	campaign	number of contacts performed during this campaign and for this client	numeric
14	pdays	number of days that passed by after the client was last contacted from a previous campaign	numeric
15	previous	number of contacts performed before this campaign and for this client	numeric
16	poutcome	outcome of the previous marketing campaign	categorical
17	Y	has the client subscribed a term deposit?	binary

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S.No	Attribute	Data type	Value – types
1	age	Num	real number
2	job	Cat	admin, unknown, unemployed, management, housemaid, entrepreneur, student, blue-collar, self-employed, retired, technician, services
3	marital	Cat	married, divorced, single
4	education	Cat	unknown, secondary, primary, tertiary
5	default	Binary	yes, no
6	balance	Num	Real number
7	housing	Binary	yes, no
8	loan	Binary	yes, no
9	contact	Cat	unknown, telephone, cellular
10	day	Num	real number
11	month,	Cat	jan, feb, mar, ..., nov, dec
12	duration	num,	real number
13	campaign	Num	real number
14	pdays	Num	-1 means client was not previously contacted)
15	previous	num	real number
16	poutcome	catz	unknown, other, failure, success
17	Y	binary	yes, no

TABLE 2

ATTRIBUTES - VALUES

. Data normalization and attribute selection also performed in the preprocessing step. In data normalization, the attribute data are scaled so that they fall within the specified small range say 0 to 1. Some of the algorithms carry this normalization internally before analyzing the data with the respective algorithm. Further the outlier (the data that is not comply with the existing data) data to be identified and removed and the noise data (confusing data) to be polished. In data reduction process, the huge data is reduced to a limited data that facilitates the mining without deviating from integrity. A reduced set of data is obtained that is smaller in volume but produces same analysis results what would get with the full unreduced data. Data can be reduced in various steps such as data aggregation while construction of data cube [20], detection and removal of weakly relevant or redundant attributes, reduction of dimensionality using wavelet transforms which uses linear signal processing technique [21] and discretization technique which reduces the continues attribute value in to intervals (numerous continues values are replaced by small number of interval labels). The attributes in the data base are allocated weights depending up on their contribution to deciding the class label. The approach used for it gradient descent technique [22] and other classification techniques [23-26].

IV RELATED WORK: Balint CSATARI, Zoltan proposed a method [25] of class based attribute weighting for time series classification. The model proposed two weighting methods for Euclidean nearest neighbor algorithm and compare them with global weighting methods. The model introduced global internal and global external average distances. The concept behind weight calculations are internal and external average distances. The high value of the attributes during classification corresponds to minimum interval distance that is the attribute has similar value compared with other sequences from the same class. The low value of the attribute during classification means external distance for the attribute is high that is the attribute showing huge deviation from other classes, and the attribute have a role in differentiating the given class from others. The results of this model using different weighting operators compared with other models on widely accepted time series data and produced good results.

Manan Gupta [23][23] proposed a dynamic k-nearest neighbor (k-NN) with attribute weighting for automatic web page classification. This modified attribute weighted dynamic k-Nearest Neighbor classification algorithm, using k-means clustering used for web page classification in WWW. The process regulated in three steps, clustering through three different methods –number of classes, rule of thumb and Elbow method, neighborhood size selection; attribute weighting and simple majority voting. The algorithm evaluated for webKB data sets and obtained valuable results when compared with traditional k-NN algorithm.

V BAYESIAN CLASSIFICATION**:** Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given tuple belongs to a particular class. Bayesian classification is based on Bayes' theorem. The simple Bayesian classifier is also known as naive Bayesian classifier, this assume that

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the effect of an attribute value on a given class is independent of the values of the other attributes, this assumption also called as class conditional independence. It is made to simplicity the computations involved and, in this sense, is considered “naïve”, where as Bayesian belief networks are graphical models which includes representation of dependencies among subsets of attributes. This Bayesian belief networks are also used for classification. Thomas Bayes a non conformist English clergyman who did early work in probability and decision theory had formulated this network, this classification is named after him as Bayesian classification. In this **X** be a data tuple, in Bayesian term, **X** is considered as evidence. The Bayesians classifiers are the statistical classifiers that can predict the probabilities of class membership.

Let H be some hypothesis that the data tuple **X** belongs to a specified class C. In classifications problems, P(H/**X**) is used which indicates the probability that the hypothesis H holds given the “evidence” or observed data tuple **X** or the probability that tuple X belongs to class C, given the attribute description of **X**. This P(H/**X**) is the posterior probability. The other probability used in Bayesian theorem is P(H) (a priori probability, that the given tuple is belongs to class C, without any other tuple information), P(**X**/H) (the posterior probability of **X** conditioned on H) and P(X) prior probability of **X**). Bayes theorem is P(H/**X**) = [P(**X**/H)P(H)]/ P(**X**), Various empirical studies of this classifier in comparison to decision tree and neural network classifiers have found it to be comparable in some domains. In theory, Bayesian classifiers have the minimum-error rate in comparison to all other classifier. However, in practice this is not valid due to assumptions that are inaccurate such as class conditional independence, and the lack of available probability data[27]. Bayesian belief networks allow class conditional independence to be defined between subsets of variables. This specify joint conditional probability distributions. Bayesian belief networks are also known as belief networks, Bayesian networks and probability networks. They allow class conditional independencies to be defined between subsets of variables. They provide a graphical model of causal relationships, on which learning can be performed. It consists of two components one is Directed acyclic graph, second one is conditional probability tables. Solutions for learning the belief network structure from training data given observable variables are proposed in Cooper and Herskovits[28], Butine[29], and Heckerman, Geiger, and Chickering[30]. Algorithms for inference on belief networks can be found in Rusell and Norvig[31] and Jensen[32].

VI METHODOLOGY: The proposed model improves the performance of prediction of classifier by finding the reasonable set of attributes which are sufficient to classify the future unlabeled data. This model proceeds in 2 phases as shown in Fig. 1, architecture of the model.

In the first phase the raw data is preprocessed by two of the data cleaning methodologies that is missing value treatment and normalization. The missing values are replaced by the attribute mean method, after this treatment data is normalized as the distance based mining algorithms such as neural networks and nearest- neighbor algorithms would yield good result while analyzing the data set. The cleaned data is further reduced to get meaningful reduced set of data. The attribute weighting is classified by using the Naïve bayes classifier. The accuracy of the classifier is measured by Receiver Operating Characteristic (ROC) area. ROC is basically a visual tool for comparing classification models. ROC curve shows the trade-off between sensitivity or true positive rate (proportion of positive tuples that are correctly classified) and the false positive rate (proportion of negative tuples that are incorrectly classified as positive) for a specific model. The detailed process of this method is explained below in the sequence of steps.

1. All the attributes from age to poutcome (excluding class attribute) are evaluated for weighting by different methods. The methods used for weighting are information gain (IG),information gain ratio (IGR),gini index (GI), chi-square (CS), and weights by correlation (CR).
2. The ranking with respect to weights for all the 16 attributes with all the methods are collected. The average of the weights is calculated for individual attributes which obtained in different methods.

Weight of the attribute=average(weight of the attribute by the method IG, IGR, GI, CS and CR)

3 Arrange the attributes in ascending order from lowest weight to highest weight

4 Find the reduced set of attributes by following sequence of steps

4.1 Construct classification tree for all n attributes

4.2 Find the ROC area- classification accuracy

4.3 Reduce one attribute whose weight(rank) is lowest and assign n for number of attributes

4.4 If n= 1 stop, move to step 5 else move to step 4.1.

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5 Draw a graph between 'number of attributes' and corresponding ROC area. (Fig. 1.1)

6 Pick the 'number of attributes' value x whose accuracy value is high among all other attribute sets,16 to 1.

7 Consider the classification model with high accuracy and corresponding x.

In second phase as shown in Fig. 1.2, the decision tree produced from the reduced set of attributes is taken as model to find the unknown class label of the future tuple (score set) whose class label is not known. The classifier built using training set (70% of total data set) and classifier refined by test set (20% of total data), evaluation set (10% of total data set) asses the expected accuracy of the model. Reduced set of attributes are considered from the score set to find the class label, thus minimizing the cumbersome traverse in the heavy classification tree with all the unreduced data set.

VII RESULTS AND ANALYSIS: Weighting of the attributes are evaluated from 5 possible methods. The ranking of the attributes with all the five methods is normalized and given in Table 3. The average of the attribute weighting for individual attributes is calculated by considering the weighting for respective individual attributes. The average attribute weighting in ascending order is given in Table 4.The results are evaluated with Waikato Environment for knowledge Analysis 3.6.6 and RapidMiner 5.2.008. The classification is proceeded by using Naïve Bayes classifier for all the attributes first, calculated classification accuracy by ROC area, then by eliminating one lowest weighting attribute and find ROC and continue as explained in step .4. The results obtained for all set of attributes is given Table 5.

The observed ROC area increases slowly and reaches a certain saturation point for one particular set of attributes, .then decreases. The set of attributes where the accuracy (ROC) reaches the saturation is considered as ideal set of attributes for further classification of test tuples. From the graph in Fig. 2, the highest accuracy obtained for 10 attributes (x), 'duration' to 'loan' from Table 3 whose ranking is highest for 10 attributes is considered as ideal set.

The model obtained with this ideal set of attributes is considered to predict the new unknown class label of test tuple. The example test tuple with obtained class value is given in Table 5 for 2 tuples.

TABLE 4

AVERAGE ATTRIBUTE WEIGHTING

Attribute	Average weighting
DEFAULT	0
EDUCATION	0.048
DAY	0.0508
BALANCE	0.0516
MARITAL	0.052
CAMPAIN	0.0636
LOAN	0.066
JOB	0.0901
HOUSING	0.1118
CONTACT	0.1534
PREVIOUS	0.1876
PDAYS	0.2536
MONTH	0.2718
AGE	0.3074
POUTCOME	0.5082
DURATION	1

TABLE 5

VARIATION OF CLASSIFIER ACCURACY WITH NUMBER OF ATTRIBUTES

Number of attributes	ROC Area
16	0.845
15	0.845
14	0.844
13	0.845
12	0.858
11	0.857
10	0.872
9	0.864
8	0.859
7	0.859
6	0.84
5	0.838
4	0.836
3	0.843
2	0.837
1	0.803

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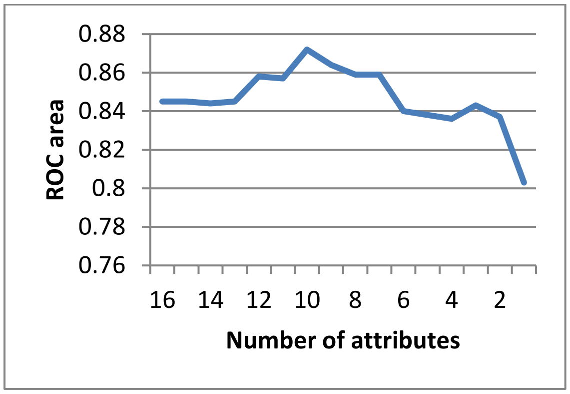

Fig. 2. Selection of set of attributes

From these observations, the MR who joins newly in the banking organization need not concentrate more on the attributes which are not available in ideal set of attributes, thus saving the energy and time and can put more effort to get the details of the attributes which comes under these ideal set of attributes.

VIII CONCLUTIONS: The model developed here gave commercial aspects to the R& D wing of the company to adopt new marketing strategies and better training to the MRs to get the details of the ideal set of attributes. Further it is easy for the company to forecast whether the customer subscribes for deposited or not and treat the customer accordingly. The same scenario can be applied in disease diagnosis system, stock market data, business forecasting and various fields of interest where there is need of minimizing complicated methods of prediction and manual power in data collection. Further the model can be enhanced by considering various accuracy measures like kappa statistics , FP rate, root mean square error, F-measure and proceed as ROC (in this model) could lead to better result. And also the output is further narrowed by using the concept of fuzzy set theory instead of classifying yes or no, in the class label, the probabilistic occurrence of the event is fuzzified by allocating membership function to the class label and dividing individual class label in to 3 or 5 categories depending up on the fuzzy nature of the input characteristics.

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Annexure

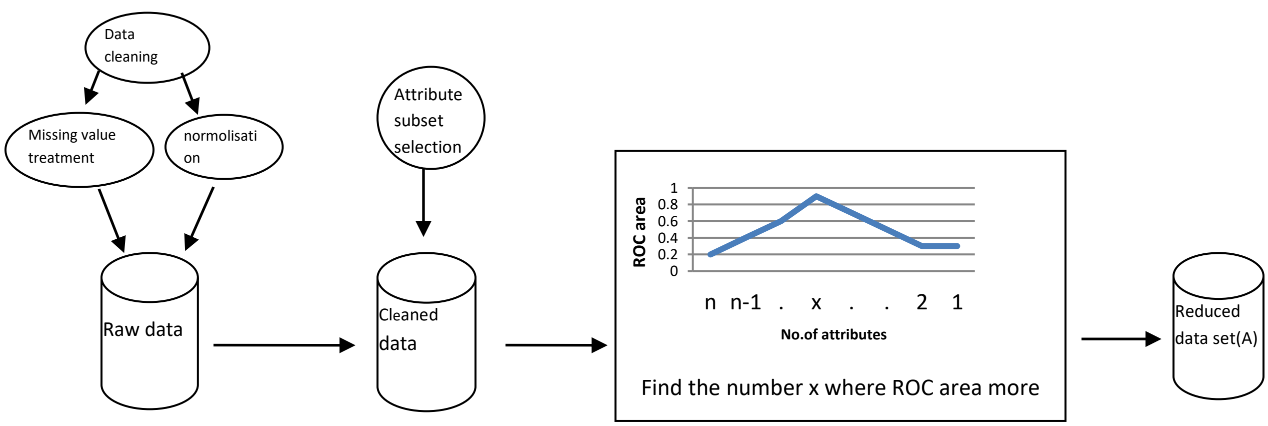

Fig. 1.1.Archetecture of the model - Data preprocessing and reduced data set from saturated ROC area.

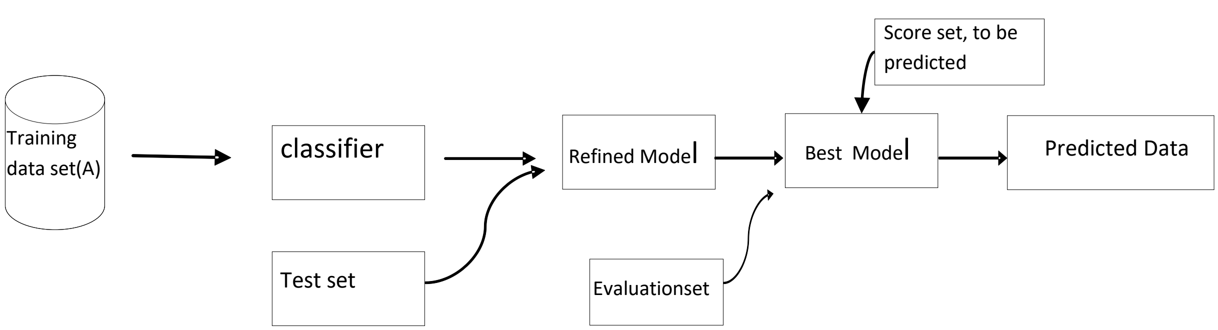

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Fig. 1.2.Archetecture of the model - Model for prediction

TABLE 3

ATTRIBUTE WEIGHTING BY 5 METHODS

Attribute	IG	Attribute	IGR	Attribute	GI	Attribute	CS	Attribute	CR
DEFAULT	0	DEFAULT	0	DEFAULT	0	DEFAULT	0	DEFAULT	0
DAY	0.026	EDUCATION	0.006	AGE	0.155	BALANCE	0.01	DAY	0.025
EDUCATION	0.033	MARITAL	0.01	EDUCATION	0.027	DAY	0.016	BALANCE	0.042
MARITAL	0.041	JOB	0.014	DAY	0.03	CAMPAIN	0.017	EDUCATION	0.104
CAMPAIN	0.042	LOAN	0.029	CAMPAIN	0.03	EDUCATION	0.022	MONTH	0.104
LOAN	0.057	HOUSING	0.034	MARITAL	0.033	MARITAL	0.027	AGE	0.11
BALANCE	0.074	MONTH	0.045	LOAN	0.039	LOAN	0.032	MARITAL	0.15
HOUSING	0.108	CONTACT	0.06	BALANCE	0.058	HOUSING	0.071	CAMPAIN	0.15
AGE	0.134	BALANCE	0.074	HOUSING	0.087	JOB	0.099	JOB	0.169
JOB	0.138	CAMPAIN	0.079	JOB	0.121	PREVIOUS	0.1	LOAN	0.173
PREVIOUS	0.224	PREVIOUS	0.117	CONTACT	0.154	CONTACT	0.126	CONTACT	0.202
CONTACT	0.225	DAY	0.157	PREVIOUS	0.208	AGE	0.138	PDAYS	0.257
PDAYS	0.225	POUTCOME	0.177	PDAYS	0.21	PDAYS	0.218	HOUSING	0.259
MONTH	0.412	PDAYS	0.358	MONTH	0.439	MONTH	0.359	PREVIOUS	0.289
POUTCOME	0.518	DURATION	0.711	POUTCOME	0.678	POUTCOME	0.555	POUTCOME	0.613
DURATION	1	AGE	1	DURATION	1	DURATION	1	DURATION	1

TABLE 5.1

DATA SET BEFORE CLASSIFICATION

SNo	Age	Job	Marital	Education	Default	Balance	Housing	Loan
1	28	management	Single	tertiary	no	80	no	No
2	40	admin.	Single	secondary	no	462	yes	Yes

SNo	Contact	Day	Month	Duration	Campaign	Pdays	Previous	poutcome	Y(class label)
1	cellular	20	oct	676	2	146	2	failure	?
2	cellular	6	apr	272	1	335	4	other	?

TABLE 5.2

DATA SET BEFORE CLASSIFICATION

SNo	Age	Job	Marital	Education	Default	Balance	Housing	Loan
1	28	management	Single	tertiary	no	80	no	No
2	40	admin.	Single	secondary	no	462	yes	Yes

SNo	Contact	Day	Month	Duration	Campaign	Pdays	Previous	poutcome	Y(class label)

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1	cellular	20	oct	676	2	146	2	failure	**Yes**
2	cellular	6	apr	272	1	335	4	other	**No**

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