Algorithms for Predictive Classification in Data Mining: A Comparison of Evaluation Methodologies

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Abstract*—Empirical studies which has used data mining (DM) techniques has tried to assess the importance of one model over the other based on confusion-matrix-derived parameters of prediction accuracy, lift charts or receiver operating characteristic curve (ROC). A different approach of comparison based on evaluation composite indicators (ECI) has been adopted by references [2] and [3]. Study [3] has used four different input variable selection alternatives (IVSA) (original, aggregated, principal components, and stacking based variables) for a customer churn problem and has used comparison criteria (parameters) like accuracy, interpretability, robustness, and speed. Study [2] has used the same results for these four criteria along-with a newly defined fifth criteria which has been named as residual efficiency (RE) and is based on the idea of characteristics of interest (COI) of for classifiers [19]. Both studies [3] and [2] have compared five predictive classifiers but using different weighting methods and normalization techniques. Study [3] has used three weighting criteria (equal weights and two randomly assigned unequal weights) along with two normalization methods (z-score and min-max) and study [2] has used analytical hierarchy process (AHP) as weighting criteria along with a step wise utility functions (SWUF) of [18] as normalization technique. This article has used AHP weights which are normalized with a new continuous-band utility function (CBUF) used by [5] and min-max (for comparison). Finally, comparison of the results from all these studies has been presented.[*]

***Index Terms*—Knowledge Discovery and Data Mining (KDDM), Multi-criteria Decision Making (MCDM), Customer Churn Problem, Prediction Classifiers**

I. Introduction

Knowledge discovery in databases and data mining (DM) techniques has been applied to a variety of application domains. Data mining taxonomy includes predictive models and descriptive models. Predictive models can be regressor or classifiers [1]. Empirical studies regarding importance of various predictive classifiers reveal that there is no objective conclusion about superiority of one classifier over the other, rather performance of any classifier depends on the nature of problem, type of dataset to be used and behavior of variables [2]. Classification methods of data mining has been applied for customer churn prediction problem as in [3], for early warning system to predict Asian financial crisis (twin banking and currency crisis of 1998) in a pioneer study on the topic [4], for comparison of social objectives for decision-making in housing corporations [5], and [6] for list of references).

II. Review of Literature

Comparison of various DM methods has been provided in various studies [7]-[9]. In DM literature, application of certain DM method is also being backed by other multi-criteria decision making (MCDM) techniques like Analytical Hierarchy Process (AHP) whose use in multiplicity of environments is well documented [10]. AHP has been also used in the context of DM in studies like [6], [11]-[15], and [16]. However, all these studies have used AHP for input variable selection to be used in DM. By unearthing the patterns or knowledge from the data itself, data mining methods obviate the need for eliciting knowledge from a human expert [6]. Reference [12] calls it extra-database information. Study [17] has also used the knowledge derived from the expertise, experience, and judgment of the decision makers that uses additional decision rules to conceptualize and structure the domain in DM problems.

The study [11] has used AHP to prioritize alternatives like keyboard size, monitor size, low-pitch sound, fan design, and battery charging efficiency based on preferences of each cluster of customers which were used as criteria factors. The study [13] describes that monitoring of organizational systems (OS) (such as primary health care network) requires continuously measurement of performances and events by various indicators. AHP has improved the monitoring of OS based on hierarchical assessments. Reference [12] has used extra-database knowledge approach where AHP has been used to conceptualize and structure the domain before applying data mining techniques in case study of brain trauma intensive care unit. The study [14] has used AHP for determining the weighting of the importance of individual data elements toward the calculation of risk in aerospace performance factor within operational risk management assessment system concept and found that AHP lags behind as are traditional incident investigation

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and reporting process and is to be replaced with data driven, rule driven and physics driven modeling and simulations that incorporate time and dynamics to significantly improve risk forecasting and substantially enhance decision making processes for any aviation organization. A paper [18] proposed an integrated AHP–DEA methodology to evaluate bridge risks of hundreds or thousands of bridge structures. The study [6] has applied human expertise through AHP to allocate the 'labels of credit customers' and then applied the DM algorithms to improve the acquired results of data mining algorithms.

Then there is altogether a different breed of studies ([3] and [2]) which have used AHP as weighting criteria to directly assess the rank of the five prediction classifiers named logistic regression (LR), classification tree (CT), neural network (NN), random forest (RF) and AdaBoost (AB). Both studies used the results derived based on four different input alternatives (original (OV), aggregated (AV), principal component analysis (PV) and stacking based variables (SV)) in customer churn prediction problem which was originally conducted by [3]. However, differences in both come from the number of AC used, methods used for weighting of AC and normalization methods (NM). The study [3] has used four AC i.e. accuracy (A), interpretability (I), robustness (R) and speed (S). It has used three weighting criteria (WC), one gives equal weights to all AC, and other two give random weights and thus punish some AC and reward certain others) for the calculation of ECIs. It uses two NM which are z-score (z) and min-max (mm). Second study [2] has used five AC out of which four are same as of study [3] (i.e. A, I, R and S) and fifth one is new calculated by study [2]. The name of this new AC is Residual Efficiency (RE). RE was based on characteristics of interest (COI) as has been described by [19] and see reference [2] for details of its calculation. Another different aspect of study [2] is that it has used analytical hierarchy process (AHP) for assigning weights to AC and a step wise utility functions (SWUF) of [18] as normalization technique. In this article, same AHP weighting technique has been used for weighing in combination with a continuous band utility function (CBUF) used by [5] for normalization. Besides, this study has compared the results for all these normalization techniques (i.e. z-score and min-max used by [3], SWUF of [18] and (CBUF) used by [5] with all the four types of weighting criteria (i.e. an equal weight, two randomly punishing and rewarding ones and AHP).

III. Data Description

In order to rank the DM techniques for classification, various authors have considered different ACs. Three ACs used by study [1] are A, I and S, four in study [12] adding R and lift to A and I, five in study [3] which included 'ease of use' (EOU) instead of lift but left EOU out from calculation of ECIs. In general the area under the ROC curve (AUC) is a commonly used for accuracy. R is equal to (AUCtest - AUCtrain)) and can be measured as an interval number from 0 to 1, where 0 means completely stable and 1 means completely unstable. Interpretability of individual classifiers has been defined in study [3] on a four point scale based on four categories for null, poor, medium, and high interpretability with respective scores of 1, 2, 3 and 4. Execution time (speed) is time it takes to train a model and make predictions about new cases (see [3] for details about this AC). Keep in mind that ACs are different from measures of interestingness (MOI). Taxonomy of MOI as stated in study [20] has two categories: objective MOI (coverage, support, accuracy) and subjective MOI (unexpected, actionable, novel) and [21] has added semantics-based as well.

In this article, results (without normalization) of various Assessment Criteria (AC) for Classifier-IVSA pairs from ref. [3] for A, I, R and S and scores for RE from ref. [2] as shown in table 1 below. RE was based on characteristics of interest (COI) as has been described by [19]. We have used ten COI (labeled as COI-1 to COI-10) in order to arrive at RE. The details of these ten COIs have been provided in study [2]. The information on these COIs have been gathered from various sources like [3], [20], [16], [17], [22], [23], and [24]. Information gathered about ten COIs which has been used to arrive at results (without normalization) for "RF-AV pair" for Residual Efficiency (RE) in table 1 (bold) can be described as: COI-1 (5), COI-2 (6), COI-3 (5), COI-4 (6), COI-5 (5), COI-6 (6), COI-7 (6), COI-8 (6), COI-9 (5), COI-10 (5) which totaled 55. Explanation for values in brackets for ten COIs for this RF/AV pair means that because RF is an ensemble method (i.e. present) so it got a score of 3 and IVSA is AV here which is not an ensemble method (i.e. absent) so it got a score of 2. Thus the value in respective bracket for C-10 is 5 (see the full table for RE for RF-IVSA combinations in [2]).

TABLE I: Results (Without Normalization) of Various Assessment Criteria (AC) for Classifier-IVSA Pairs

	A	I	R	S	RE
LR-OV	0.80	3	0.04	15	52
CT-OV	0.77	4	0.04	05	54
NN-OV	0.80	2	0.03	05	50
AB-OV	0.73	2	0.16	13	55
RF-OV	0.79	2	0.01	06	56
LR-AV	0.80	3	0.05	21	51
CT-AV	0.78	4	0.03	05	53
NN-AV	0.77	2	0.03	05	49
AB-AV	0.77	2	0.16	20	54
RF-AV	0.81	2	0.00	70	55
LR-PV	0.80	1	0.04	04	52
CT-PV	0.66	1	0.06	02	54
NN-PV	0.56	1	0.03	02	50
AB-PV	0.65	1	0.15	06	55
RF-PV	0.68	1	0.00	16	56
LR-SV	0.79	1	0.08	215+1	54
CT-SV	0.79	1	0.07	215+1	56
NN-SV	0.82	1	0.04	215+1	52
AB-SV	-	-	-	-	57
RF-SV	-	-	-	-	58

Calculated values for RE from the information provided by ten COIs, form only one entry in Table I (bolded). Data about all five ACs used for calculation of ECIs have been given in Table I.

IV. Methodology

Five DM classifiers (named LR, T, NN, AB and RF) has been combined with four IVSA to rank different "DM classifiers - IVSA pairs" based on five AC, using various WC and NM. Weighting Criteria can be either of equal weights, weights based on statistical models (like Principal components analysis, Data envelopment analysis, regression analysis, and un-observed components models) or based on expert opinion (i.e. Budget allocation, AHP, and Conjoint analysis). But as different ACs have different dimensions or units of measurement (UOM), there is a problem of incommensurability and different NMs can be used to handle this issue. The study [3] has used two NM, z-score (z) and min-max (mm), to make difference in UOM to disappear. Study [2] has used SWUF of [18] and current study has used CBUF of [5]. WCs used by [3] are equal weights to all four AC, giving 34% weight to A and 22% to rest of three ACs (I, R & S) or a criteria assigns 30% weights to A & I and 20% to S & R and used in [2] and WC in this article is based on AHP. To assess the normalized relative importance weights of different ACs, we have used pair wise comparisons (PWC) by using Saaty's scale interval of [9, 1/9]. Based on PWC [9-1] scale in conventional AHP, our value judgment for AC_i can be that it has absolutely more importance, much more importance, more importance, little bit more importance and same importance as compared to AC_j and thus values assigned are 9, 7, 5, 3 and 1 respectively [25]. PWC technique takes advantage of human psychology based on Weber's law (of 1846) regarding a stimulus of measurable magnitude which states that people are unable to make choices from an infinite set implying that people cannot distinguish between two very close values of importance, say 3.00 and 3.02. Psychological experiments have also shown that individuals cannot simultaneously compare more than seven objects (plus or minus two) [26]. Also Blumenthal's [27] cognitive psychology's experiments tell us that people are born with an ability to make comparisons between two alternatives and to rate alternatives one at a time against an ideal in memory. This is the main reasoning used by Saaty to establish 9 as the upper limit of his scale, 1 as the lower limit and a unit difference between successive scale values [28]. Information regarding guidelines for

TABLE II: AHP BASED PWC MATRIX OF AC

	A	I	R	S	RE
A	1	3	5	7	9
I	1/3	1	3	5	7
R	1/5	1/3	1	5	5
S	1/7	1/5	1/5	1	5
RE	1/9	1/7	1/5	1/5	1

PWCs can come from literature [2]. Using Matlab or even Excel, PWC matrix (Table 2) can be solved by using principal right eigenvector method (EM) [28]. The objective of AHP is to compare decision alternatives (i.e. 20 Classifier-IVSA pairs) with respect to each ACs and to determine the relative composite priorities for the total weights of Classifier-IVSA pairs after aggregating ACs. Solution to our pair wise matrix has given following weights for A, I, R, S and RE respectively as 0.498531, 0.256196, 0.148403, 0.066924 and 0.029945.

TABLE III: RULES FOR AC SCORES TO BE USED IN CBUF OF [5]

Score	A	I	R	S	RE
0	If < 0.65	If < 2	If > 0.19	If >100	If < 50
(Rlzed-Min) / (Max-Min)	b/w 0.66 - 0. 79	b/w 2 - 8	b/w 0.04 - 0.19	b/w 6 - 100	b/w 50 - 57
1	If > 0.80	If > 8	If < 0.04	If < 6	If > 57

Notes: (1) Formula (Rlzed-Min) / (Max-Min) means (Realized Value minus Minimum Value of AC) divided by (Maximum Value minus Minimum Value AC) and it gives the CBUF of [5]

TABLE IV: FINAL ECI VALUES FOR AHP WEIGHTING AND NORMALIZATIONS WITH CBUF

	A	I	R	S	RE
LR-OV	0.499	0.0427	0.1484	0.061	0.009
CT-OV	0.399	0.0854	0.1484	0.067	0.017
NN-OV	0.499	0	0.1484	0.067	0
AB-OV	0.266	0	0.0297	0.062	0.0214
RF-OV	0.465	0	0.1484	0.067	0.0257
LR-AV	0.499	0.0427	0.1385	0.056	0.0043
CT-AV	0.432	0.0854	0.1484	0.067	0.0128
NN-AV	0.399	0	0.1484	0.067	0
AB-AV	0.399	0	0.0296	0.057	0.017
RF-AV	0.499	0	0.1484	0.0214	0.0214
LR-PV	0.499	0	0.1484	0.067	0.0086
CT-PV	0.033	0	0.1286	0.067	0.017
NN-PV	0	0	0.1484	0.067	0
AB-PV	0	0	0.0396	0.067	0.0214
RF-PV	0.1	0	0.1484	0.06	0.0257
LR-SV	0.465	0	0.1088	0	0.017
CT-SV	0.465	0	0.1187	0	0.0257
NN-SV	0.499	0	0.1484	0	0.0086
AB-SV	0	0	0	0	0.0299
RF-SV	0	0	0	0	0.0299

The comparison results without normalization, for Classifier - IVSA pairs based on empirical results from churn prediction problem for four ACs (A, I, S and R) as has been calculated by [3] and for fifth AC (i.e. RE) as has been calculated from COIs for various Classifier-IVSA pairs by [2] has been used. All these have been shown in Table I. As various ACs have various UOM, we can normalize these results by using a utility function which was used by [5]. This CBUF, as is called in this study, is a simple utility function which define a unit per AC that sets a desired level (or upper boundary) and a minimum level (or lower boundary). A minimum score indicates that the objective of the criteria has overall not been achieved (i.e. score = 0). A higher score indicates that the objective of the criteria has been reached completely (i.e. score = 1). Scores between minimum and desired level are increasing from 0 to 1 (i.e. function is continuous within a band of values between lower and upper boundaries). This means that everything achieved above the upper boundary for a criteria does not count and there is no penalization if a criteria perform far under the lower boundary for that criteria. Although within the continuous band, CBUF is essentially like Min-max as scale is 0 to 1 but conceptually these methods are significantly different because of wide range of results of various weights (before normalization) for different classifiers from churn problem [3]. Table III below describes the rules for AC Scores to be used in CBUF of [5]. For A, I and RE, greater value is better while for R and S, lower values are worthy ones. General considerations for our ACs can be described as follow.

TABLE V: ECI VALUES FOR THE DIFFERENT NM AND WC FOR VARIOUS CLASSIFIERS AND IVSA

NM – WC combos below	LR	CT	NN	AB	RF
	Original Variables (OV)				
mm&1	2nd	1st	3rd	4th	5th
4CBUF&1	2nd	1st	3rd	5th	4th
CBUF&1	3rd	2nd	4th	5th	1st
mm&2	2nd	1st	3rd	5th	4th
mm&3	2nd	1st	3rd	5th	4th
z&1	2nd	1st	3rd	5th	4th
z&2	2nd	1st	3rd	5th	4th
z&3	2nd	1st	3rd	5th	4th
SWUF&AHP	2nd	1st	3rd	5th	4th
CBUF&AHP	1st	2nd	3rd	4th	3rd
mm&AHP	2nd	1st	3rd	5th	4th
Aggregate Variables (AV)					
mm&1	2nd	1st	3rd	5th	4th
4CBUF&1	2nd	1st	3rd	5th	4th
CBUF&1	2nd	1st	4th	5th	3rd
mm&2	2nd	1st	4th	5th	3rd
mm&3	2nd	1st	4th	5th	3rd
z&1	2nd	1st	4th	5th	3rd
z&2	2nd	1st	4th	5th	3rd
z&3	2nd	1st	4th	5th	3rd
SWUF&AHP	2nd	1st	3rd	4th	5th
CBUF&AHP	2nd	1st	4th	5th	3rd
mm&AHP	2nd	1st	5th	4th	3rd
Principal Component Analysis based Variables (PV)					
mm&1	1st	3rd	4th	5th	2nd
4CBUF&1	1st	4th	3rd	5th	2nd
CBUF&1	1st	3rd	4th	5th	2nd
mm&2	1st	3rd	4th	5th	2nd
mm&3	1st	3rd	4th	5th	2nd
z&1	1st	3rd	5th	4th	2nd
z&2	1st	3rd	5th	4th	2nd
z&3	1st	3rd	5th	4th	2nd
SWUF&AHP	1st	2nd	5th	4th	3rd
CBUF&AHP	1st	3rd	4th	5th	2nd
mm&AHP	1st	3rd	5th	4th	2nd
Stacking based Variables (SV)					
mm&1	1st	2nd	3rd	-	-
4CBUF&1	3rd	2nd	1st	-	-
CBUF&1	3rd	1st	2nd	4th	4th
mm&2	3rd	2nd	1st	-	-
mm&3	3rd	2nd	1st	-	-
z&1	3rd	2nd	1st	-	-
z&2	3rd	2nd	1st	-	-
z&3	3rd	2nd	1st	-	-
SWUF&AHP	3rd	1st	2nd	5th	4th
CBUF&AHP	3rd	2nd	1st	4th	4th
mm&AHP	3rd	2nd	1st	5th	4th

For accuracy (AUC test), larger value is considered better than smaller value. Similar is the case for two other ACs: interpretability, and residual efficiency. On the other hand, for robustness and speed, lower value is better than higher one. Individual parameters results of Table I has been normalized with CBUF of ref. [5] for various pairs of Classifiers-IVSA for all five AC (A, I, R, S and RE) and presented in Table IV. ECI values calculated for this paper using various combinations i.e. using AHP weighting with CBUF as NM (in %), using equal weighting with 4CBUF (here 4 meaning four ACs has been used) as NM and equal weighting with CBUF (used five ACs) as NM, have been given in Table V. Results from study [3] using for four ACs with min-max and z-score NMs and three WCs, from study [2] using five ACs with SWUF as NM and AHP as WC and from current study (as given in Table V) have been provided in Table V.

V. RESULTS

Results in Table V are self explanatory. However, few points are important to mention here. First of all no classifier has gained absolute superiority on the other regarding usage of different variables in the customer churn problem in these classifiers. Thus thinking of applying any particular classifier in all the situations of same type of variables because of some organization and technology specific situations should be off the table. Secondly classification tree has performed best in either original variable or aggregate variables case over even logistic regression classifier consistently. However, logistic regression has surpassed tree in case of PV based selection of variables. May be small no. of sorted variables makes it easy for logistic regression to predict classes and so seems the case for random forest that was consistently second in case of PV. When dataset becomes non linear because of use of SV, neural network has performed in the top rank. Surprisingly classification tree which is generally considered good only for linear datasets have performed second in non linear dataset case of SV. These results are in conformity with some empirical studies which have shown that effectiveness of different DM models or algorithms depends on problem in hand, type of dataset, depth of database, types, and nature of relationships among input variables and/or target variables. Thus depending on these factors, ranking of classifiers should change. This is the case with our results which has provided a different ranking of DM classifiers for all four different types of input variables. On the other hand, the results from study [3] have kept almost the same hierarchy only with few minor exceptions. We has also tested whether there was any difference between CBUF and Min-max WCs in ranking different predictive classifiers because of their seemingly similarity as mentioned in methodology section. Results (in Table V) for rows of "mm&1," "4CBUF&1," "CBUF&1," "CBUF&AHP" and "mm&AHP" for various variables are of interest in this regards, especially of the first two ones. Looking at rows for "mm&1" and "4CBUF&1" shows that rankings have been changed between AB-OV and RF-OV, CT-PV and NN-PV as well as LR-SV and NN-SV. Last but not least, CBUF&AHP was able to rank all the classifiers for all variable types as opposed to study [3] which was not able to rank AB and RF for SV. In short, the new methodology using CBUF as NM to tackle the issue of incommensurability because of difference in UOM for ACs (or criteria) is significantly different than Min-max as NM and that AHP as WC has worked well than other weighting methods in ranking data mining algorithms.

VI. Conclusion

There are three valuable value additions of this study. First that this study has used a new normalization method (i.e. CBUF) for ranking predictive classifier in data mining, which seems to have mathematical similarities, but is significantly different from min-max as NM conceptually as well as with regards to empirical results. Secondly, for comparison purposes, various combinations of WC and NM was used on data from study [3] and calculations thereof in studies [2] and [3] as shown in Table I. These are calculations of ECIs from NM&WC combinations like "4CBUF&1," "CBUF&1," "CBUF&AHP" and "mm&AHP." Thirdly, this article has compared the ECIs for all NM&WC combinations from this study with those of [2] and [3] as presented in Table V.

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