A Novel Prescriptive Approach for Health Care Management Using Predictive and Descriptive Analysis of Data Mining

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Abstract: Hiking in price of healthcare leads to the ways of optimizing the care efficiency. In this paper, we present a new methodological called prescriptive analysis that makes use of predictive and modelling approaches to figure out theanalytical significance of the data mining approaches in health care management. Supervised model is the process of building a confined model that emerges in prediction on target variable and unsupervised model is the process of forming sub-units of data points with similar values of all variables not only the target variable. In this paper we propose a novel fusion of supervised and un- supervised model called prescriptive approach to analyze their effectiveness when being applied to health care management. Our experimental results proves to be vital that aids in selecting the appropriateclustering method that excels in prescriptive approach for healthcare resource management according to circumstances. The experimentation were done on five bench marked data sets and these methods are found to be justified and efficaciously applied to health care resource management department.

Keywords:Clustering, Classification,Prescriptive Analysisand Healthcare modeling.

I INTRODUCTION

With immense increase of exigency for medical care, health care resource management require an efficient system for managing the entries of patient and derive approximate decisions accordingly. Thus, a Decision Support System (DSS) is set forth based on data mining approaches that helps to mount the operational and tactical decisions. For planning and logistic purposes, prediction estimates are used that foresees the class of new clients, to have time based projections and to identify the variables that explain the intense of a disease with respect to patient’s behavior. The patterns found among care consumption must be track down from care services, for management purposes. Organizations secure all the relevant information that lift the decision making and analyze it to find the effects and follow through of these decisions. Thus, we propose a modelling environment based on data warehousing and data mining approaches that supports in exploring the privileges of our approach fully.

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This allows one to analyze the criticality of a disease, to go in detail on medico-social resource planning and simulate them to evaluate their performances at the end. The main aim of the proposed prescriptive analysis is to uplift the decisional performances by recognizing some links between data and check hypotheses (observations). The objective is to establish the contribution of data mining approach for health care management. The application concerns in predicting the intensely affected patients admitted to hospital management department. As of past few decades, a lot of applications for Machine Learning (ML) are used and the most significant of which is predictive data mining which is concerned with classification problems. Classification, being one of the most used learning models, helps to recognize the model that forecasts morrow behaviors of database records based on certain criteria.The classifier thus obtained marks the class labels to the testing instances. It is done as the value of class label is unknown whereas the values of predictor features are known.There are few familiar tools that is used for classification are: Linear Regression, Neural Networks decision trees, if-then -else rules, Bayesian networks, Naive Bayes classifiers, neural networks, Super vector machines and Regression (tree regression, logistic regression, support vector regression).Clustering [1], however, is an unsupervised learning approach. It attempts to discover subgroups of examples or clusters with homogenous values of all variables, not simply the target variable. In reality, the target variable is typically not even defined in clustering process. The end result is a collection of clusters and no longer always their descriptions or representations, however usually we can hyperlink new examples to the built clusters based totally on examples, vicinity in the variable space. Predictive modeling and clustering are consequently regarded as quite different strategies. Yet, varying viewpoints also be present [2] which pressure numerous likenesses that a few predictive modeling methods (strategies which divides the space of examples consisting of tree and rule induction) and clustering segment. Predictive modelling approaches (trees and rules) divides the space of examples into subspaces with similar values of the target variable, whilst (distance-based) clustering strategies seek subspaces with similar values of all the attributes. In this work, we bear in mind the challenge of prescriptive approach, which includes elements of each predictive modelling and clustering and generalizes them to a degree. In prescriptive modelling, you could simultaneously take into account homogeneity along the goal variables and the attributes involved in the process.

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Correspondingly, symbolic explanations of the discovered clusters can be produced in the sorts of trees and rules (which may associate intently to the predictive modelling versions). We suggest a novel method to prescriptive modelling, namely, four clustering approaches along with learning method on them. The scheme of gaining knowledge of PCRs (Prescriptive Clustering Rules) simplifies the undertaking of rule induction, on one hand, and clustering, and especially itemset confined clustering, on the opposite. It is as a result essential for constraint-based data mining and inductive databases (IDB). By way of IDBs are the utmost likely method to locating a standard framework for data mining, conveying the two widely used data mining process a stage nearby is a stage on this progression. Also, constraint-primarily based clustering is clearly an advisable researched topic in constraint-based data mining. In the following section, we discuss in more detail aboutprediction and clustering, then define the task of prescriptive modelling and in particular the task of learning PCRs, followed by a prescriptive modeling algorithm and discussion of related work. Before concluding and outlining directions for further work, we present a preliminary experimental evaluation.

II OUR APPROACH: PREDICTION, CLUSTERING AND PRESCRIPTIVE MODELLING

The two primeval and classically addressed tasks for data mining (analysis of data) are: Predictive modelling and Clustering. To make the best out of it, we combine both these and present a futuristic novel approach called Prescriptive Modelling.

Predictive Modeling:

Predictive modeling focusses on constituting models that can visualize a target property of an object delivered with narrative of the same. The procedure of learning includesobtaininginformation from set of examples. Every example consumes a value pair (A, T) where A delivers the object description with T as its target property value. A broad range of languagescomprisingpropositional, first order logic, etc., have been used for A, whereas T has a solereliant variable called ‘class’. The nature of the variable ‘class’ can signify the kind of problem such as,

(i) Discrete nature says, that the problem dealt is a classification problem(ii) Continuous nature stands for regression problems. In run-through, A is made up of a vector of independent variables called attributes (attribute-value illustration). In the remainder of the paper, both A and V are considered to be vector of attributes which might be either discrete or real-valued. Provided with T, a vector with several target variables then the task of predictive modelling is entitled as multi-objective projection. Based on its content, (i) constituting only the discrete variables refers to as multi-objective classification. (ii) Found to be only with continuous variables, it is labelled as multi-objective regression. A multitude of ways are available using which predictive models can be represented ranging from linear equations to logic programs. Two familiar types of models are decision trees and rules. The eminence of trees and rules lies in the fact that they frame the space of examples into sub spaces unlike regression equations that provide a single predictive model for the entire space. In addition, they also come up with a simple prediction or predictive model for each one of them. The subspaces defined by trees (i.e. leafs) do not overlap whereas they do overlap when rules come into play for defining.

Significant Elements: Clustering, Clustering Trees and Clustering Rules

Clustering in general deals with categorizing objects into classes of similar objects. Provided with a set of examples (object descriptions), the task of clustering involves segregating these examples into subsets, called clusters. An important point to be marked here is that only an object depiction (which is usually a vector of attributes A) can be found but not the target property to be predicted. The ultimate aim of clustering is to fulfill the requirement of high similarity between objects of same individual clusters and lower to that of different clusters. The former method of conventional clustering is totally on the based on distance analysis. The concept of a distance is key here: examples are measured to be themes in a metric space (a space with a distance measure). For instance, a sample model can also be used as arepresentation for a cluster. E.g., the mean or mediods is used generate the other records of the clusters that possess minimum distance present in the cluster with minimum .A metaphorical representation of the cluster divisions are framed in conceptual clustering. Therefore, every cluster can be deliberated as a perception as like a class in classification.

In this scenario a decision tree is employed to characterize a hierarchicalclustering, which often referred as clustering tree. Its components i.e. nodes, stand for an individual cluster. As a vital requirement, each cluster has the symbolic explanation in the form of a rule (IF conjunction of conditions, THEN cluster). It is clearly visible that clusters on different branches of tree do not overlap. For creating a cluster with no hierarchy, i.e., a flat set of clusters, a set of clustering rules are provided. Each cluster would be represented by a rule (IF conjunction of conditions THEN cluster). But, there rises no necessity for being disjunctmandatorily and the clusters mayoverlay each other. Based on various references, it can be observed that the predictive modeling approaches including decision tree and rule induction go along with the concept of clustering. Both seek for partitioning the space of examples into subspaces but the former goes with homogeneous values of the target variable whereas the latter with attributes respectively.

On the other hand, predictive modelling differs from distance based approach by opting the conceptual clustering.

Prescriptive Modelling:

This technique includes the elements of both prediction as well as clustering. As a common procedure, clustering is done by gathering of similar clusters together. Also, predictive models for individual clusters are sought so as to associate with them. Thus, the models provide a prediction of the target variables T with respect to the attributes A.

Usually, prescriptive model application to a cluster would be the prospects of T of the patterns of the respective cluster. In case of continuous single variable, a simple average of T would be utilized whereas for discrete variable a probability distribute may be used. Let,T is assumed to be the vector, then prototype will be a vector of averages and probability distributions. This is a new kind of exceptional case, where every cluster is subjected to both a symbolic description (in terms of a language bias over A) and a predictive model (a prototype in T) related to it. The consequential tree-based and rule-based representations are called predictive clustering trees and predictive clustering rules respectively. Prescriptive models stands amidst covering the features of both.i.e.Predictive modelling and clustering. That is, it considers homogeneity for both A and T.

Prescriptive modelling- An Algorithmic View

Step 1 Generate a set of examples E, where every example takes the form O = (A, T)

Step 2 Analyze a declarative bias(B)over the language for giving explanation on examples

Step 3 Compute a distance measured by calculating the distance between two examples

Step 4 Apply a prototype function p that computes the prototype of a set of examples

Formulate a collection of clusters, where,

Every cluster is associated with a description expressed in B

Every cluster has an associated prediction expressed as a prototype

And have the within-cluster distance asminimum (highly cohesive) and

Between-cluster distance is Maximum (low coupling)

Learning Prescriptive Approach Rules (PAR) For Multi-Objective Classification (MOC):

Prescriptive Modelling and focus on learning rules for multi-objective classification are the two crucial things to be addressed here. Immediate further works to follow up include the extension of the proposed approach to multi-objective regression and multi-objective prediction. Vectors being divided into attributes and target variables become our examples where attributes can be either discrete or continuous. The declarative bias will inhibit our hypothesis language to rules which are conjunctions of attribute-value conditions over the attributes A. Only T is assumed by distance measure d as it is correlated with prediction. But, it is found that distance has two constituents, one over the attributes and the other over the targets:

$$d = (1 - \tau)dA + \tau\ dT \quad (1)$$

This measure is made use of as a heuristic for the purpose of searching of rules. The distance d (including dA and dT) is computed as a weighted sum of distances along each (normalized) dimension. For continuous variables, the absolute difference is taken. In case of discrete variables, the distances between probability distributions being the sum of absolute differences over the probabilities are taken as they are presumed to be probability distributions.

A (partial) rule that encases a set of examples S is given. Its quality is projected as the average distance of an example in S to the prototype of. This is referred to as the “compactness” of the rule. Only the dT part is required for the evaluation of the predictive performance (accuracy). The dA part also allows the compactness of (average distance between) the examples wrapped by the rules, in the attribute space. A set of examples is given as input to the prototype function which in turn returns a prototype that is computed per dimension. This depends on nature of variable as, average for continuousvariables and the probability distribution across possible values for discrete variables.

III RELATED WORKS

Data mining allows to locate the models and patterns from the data acquirable. Data Mining is a field of study at the interface of statistics and information technologies: databases, artificial intelligence and machine learning.Data Mining is inclusive of descriptive data mining algorithms that helps to expose the interesting patterns in the data, like associations, clusters and subgroups. It also comprises predictive data mining algorithm that produces models capable of prediction and classification.The ultimate aim of data mining is to extract useful information from large quantities of data spontaneously. Data Mining can be presented in two ways as: predictive and descriptive. The objectives are found to be to predict the value of a particular attribute from given existing data in the former whereas to derive patterns to outline the underlying relationships in the data in the latter.

Data Mining is hence a vital part of knowledge discovery, which is the overall process of tracking down the useful information from the data by conversion of raw data into knowledge.

In [3], four core data mining tasks are identified and are:

1. Predictive Modelling:
   On the basis of explanatory variables, a predictive model for a target variable is built. There are two methods to predict a discrete outcome namely Classification and Regression (E.g., whether or not somebody will do something) and an extrapolation of continuous output (E.g., what the future value of a measurement will be).
2. Attribute Selection:
   Attribute Selection is an important aspect that involve space of attributes for the subset that is most likely to predict the class. This selection is supported by Machine Learning algorithms that marks the appropriate attributes (predictor variables) to use for making decisions.
3. Association Analysis:
   The goal of this analysis is to find the implication rules. That is, it discovers the patterns that describe the strongly associated features in the data. E.g., it can be observed in supermarket that people who buy milk will also buy bread and similarly people who buy beer will also buy snacks.

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4. Cluster Analysis:
   Cluster Formation includes grouping of similar observations together such that they have more related behavior than with observations in other group. For e.g., it is possible to find the group of customers with related behavior.
5. Anomaly Detection:
   The term 'anomaly' indicates the different characteristic that helps it to stay unique from other data. Thus, the task is to detect outliers. The features of a good anomaly detector are: low error rate whereas high detection rate. E.g., detection of spam mail.
   Since last decade, many works cover on the contribution of implementing information systems in health care organizations in order to examine the health care quality indicator.

Provocation of reviews of classification methods and combining techniques are presented by theoretical models that are found to be on this basis of statistical pattern recognition. This is well described in [4,5, and 6]. [7]Acquainted with a start of art concerning 291 papers published between 1999 and 2013. This covers on various journals like data mining and medicine. As a result, the authors put forth five approaches for data mining which are: Classification, Regression, Clustering, Association and Hybrid. Though the above article can cover a wide area of medicine, the authors focus on only structural data.

Both regression tree and classification tree work in a similar fashion but the former is capable of producing the numeric as well as continuous response variable (case of surgery duration or LOS in the health care department). Thus, regression tree is most suitable for predictive type of problems.Various methods and approaches like Regression trees, SVM, Decision Tree, Multi-layer Perceptron, Bayesian networks, etc., can be studied and the end limits of those can be found.In case of global acceptance of models, it requires a single predictive formula to hold over the entire data space. Linear regression and polynomial regression falls under this category. When it involves more features that are interactive and complex, then a single global model making is tedious.

The results declared by [8], show that the prediction of presence of coronary artery disease (CAD) goes on well with top 5 approaches as follows (best to worst):

1. MLP- Multi-Layer Perceptron
2. LR- Logistic Regression
3. CART- Classification And Regression Tree
4. RBF- Radial Basis Function
5. SOFM- Self Organizing Feature Maps.

The performances of various approaches are compared with Hierarchical Cluster Analysis (HCA), ROC Curve and Multi-Dimensional Scaling (MDS). Many applications show that logistic regression gives excellent results.To predict the examination of Dementia with the help of variables, which are selected either by domain experts or by a statistical driven procedure. [9]put forward the prediction models which rely on Logistic Regression algorithm [10]. The aim of this study is to enhance the performance of a recent application of Bayesian belief networks using a surrogate approach based on Logistic Regression.

In correlating the predictive accuracy of regression trees with that of Logistic Regression models for predicting in-hospital mortality in heart failure patients. [11]derived a conclusion that logistic regression stands ahead than Regression Tress. It is also noted that the Regression trees produce different sets that are grown in random samples. The authors mark that logistic regression can consider the underlying linear relationships between key continuous covariates and the log-odds of in-hospital mortality.The main advantage of Logistic Regression lies in the fact that it produces probabilities rather than predictions. For each class value, it is capable of evaluating the probability of a particular instance upon the condition the target variable should be discrete.In our case, the target variable is continuous in nature which should be discretized in order to make use of Logistic Regression. But, our objective is to foresee the LOS in ED and not an interval of LOS. Regression analysis inquires functional relationships among variables that is formulated as an equation or a model connecting response or dependent variable and the explanatory variables. But the difficulties caused by noisy data or outliers have been known in Linear regression earlier like it can be identified visually but it is unclear whether it is an error or a correct value. (For e.g., in our study, the patient absconded of the ED, and we do not have this information in our data).Despite the fact that outliers affect the usual least squares regression because the squared distance measure accentuates the influence of points far away the regression line, we opt to have a look at ordinary least squares (OLS) regression to derive a simple model. It can be enhanced by using an absolute-value measure instead of usual squared one. However, we will explore all the classification/prediction techniques in order to recognize the “best” one.In this context predictive modelling and clustering will have different perception.Various approaches were proposed in the literature for addressing different aspects of predictive modelling and clustering, but there exists only limitedmethodsthat consider the both or attempt to relate them. An odd kind of perspective is employed by Langley [12] that predictive modelling and clustering consumenumerousresemblances, which has inspiredcertain recent research on combining prediction and clustering.

The approach presented in this paper is closely related to clustering trees [12], which also address the task of prescriptivemodelling. The systems TILDE [12] and CLUS [13] use a modified top-down induction of decision trees algorithm to construct clustering trees (which can predict values of more than one target variables simultaneously). So far, however, distances used in TILDE and CLUS systems have considered attributes or classes separately, but not both together, even though the idea was presented in [14].Our approach uses a rule-based representation for prescriptive modelling. As such, it is closely related to approaches for rule induction, and among these in particular CN2 [15]. However, it extends rule induction to the more general task of multi-objective prediction.

While some work exists on multi-objective classification with decision trees (e.g., [16]), the authors are not aware of any work on rule-induction for multi-objective classification. Also, little work exists on rule-based regression (some recent examples come from the area of ILP, e.g., FORS [17), let alone rule-based multi-objective regression (or multi-objective prediction in general, with mixed continuous and discrete targets). Related to rule induction is subgroup discovery [18], which tries to find and describe interesting groups of examples. While subgroup discovery algorithms are similar to rule induction ones, they have introduced interesting innovations, including the weighted covering approach used in our system. Another related approach to combining clustering and classification is item set constrained clustering [19, 20]. Here the attributes describing each example are separated in two groups, called feature items and objective attributes. Clustering is done on the objective attributes, but only clusters which can be described in terms of frequent item sets (using the feature items attributes) are constructed. As a result each cluster can be classified by a corresponding frequent item set.

As in our approach, itemset classified clustering tries to find groups of examples with small variance of the objective attributes. As compared to item set classified clustering, our approach allows both discrete (and not only binary attributes / items) and continuous variables on the feature/attribute side, as well as the objective/target side. Item set constrained clustering is also related to sub-group discovery, as it tries to find interesting groups of examples, rather than a set of (overlapping) clusters that cover all examples.

IV IMPLEMENTATION AND RESULTS:

The current implementation of four approaches of predictiveclustering has been tested on the five different bench marked data sets with different target attributes. Two sets of experiments have been performed. First, we tried to test the performance of our method when predicting target attributes with respect to accuracy and run time complexity. In the second set of experiments we investigated the influence of the target attribute (AT) on the precision, recall and f-measure compactness of induced rules.

In our experimentation, as we mentioned earlier prescriptive modelling is the novel fusion of prediction and clustering. Thus in this experimentation, we carried out the experimental execution in two aspects. i.e. After performing the data pre-processing(removal of outliers) we clustered the five different bench marked data set as mentioned in the table 1 using four well know clustering methods called i) Expectation Maximization (EM) ii) Farthest First (FF) iii) K-Means and iii) Learning Vector Quantization (LVQ). We clustered the data set with the above mentioned clustering approaches with number of clusters as 2 for all the data sets and calculated the run time of each execution, then generated clusters are gathered separately for further processing. As second stage of our experimentation we applied classifier individually on every clusters of each clustering approach and calculated the classification accuracy with respect to target variable for each of the generated clusters. As we are handling health care data set, it is a significant factor that our prescriptive approach should have keen concentration on the parameters like true positives, true negatives, false positives and false negatives, Thus to enrich this aspect our experimentation continues in evaluating each of the approaches with respect to measures like Precision, Recall and F- Measure etc.

Data Set:

We employed five types of bench marked health care data sets that are available in UCI machine repository[21] and small description about them are given in below mentioned table 1. Since these data sets have the values that indicates the significant impact of a particular disease. Hence there is requirement to have proper predictive clustering that help the health care resource managers, experts and doctors planning the resource and the treatment accordingly. In this work the accuracy of the approach alone cannot be taken as measure to analyse the effectiveness of the approach, because they are life threat issues other kind of factors like False positive and False negatives are to be considered based on the analytical process and the data set that were employed.

Table 1 Data set Description

S.No	Data Set	Total No of Instances	No of Attributes	Class Attributes
1.	Indian Live Patient Data Set(ILPD)	583	11	11^{th} Attribute
2.	Lung Cancer Data Set	32	57	1^{st} Attribute
3.	Echocardiogram Data Set	132	13	13^{th} Attribute
4.	Chronic Kidney Disorder	400	25	class

1.2 Analysis of Prescriptive Modelling Approaches using Accuracy and Run time Complexity:

Figure 1 depicts the classification accuracy that are obtained by running the classifier on clustered data set. We infer, out of these well-known prescriptive approaches Expectation Maximization (EM), Farthest First (FF), K – Means and Linear Vector Quantization (LVQ). Expectation Maximization seems to gain better accuracy that is approximately 80% and above fairly for all kinds of data set utilized in this experimentation. Whereas K-means seems to be the second optimum prescriptive approach. In every clustering approaches Length of Stay data set is seems to having accuracy nearly 60%, which is considered to be lowest factor, but this have raised due to the presence of the trivial correlation that may exist between the attributes of the data set.

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K-means approach is the well-defined mechanisms that works better if the number of clusters to be generated are suitably chosen. In order to predict the appropriate number of clusters we need to perform more number of experiments with different seed values and variable number of clusters, once we attained the clusters with optimal distance that number of clusters can be chosen for further analysis. Since Expectation Maximization is the extended version of K-means approach which appears to be the optimum than K-Means. And moreover K-means approach is sensitive to outliers, this may be the kind of reason to drag down the classification accuracy when compared to Expectation Maximization.

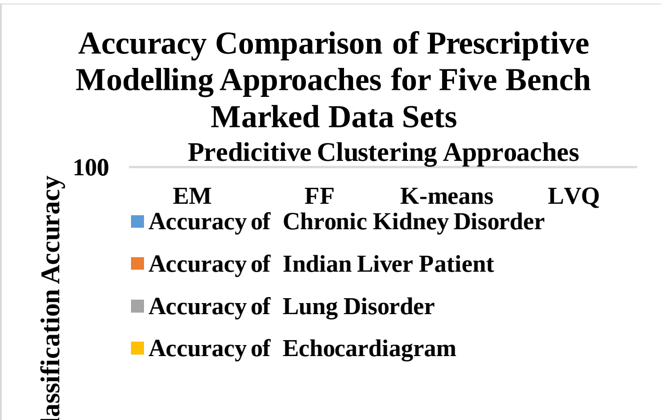

Figure 1 Accuracy Comparison of Prescriptive Modelling Approaches

Figure 2 representscomparison of runtime of the above mentioned prescriptive approaches for these five different data sets. Practically it is not fare enough to compare the performance of each of the approaches across the data sets, since different data set possess varying amount of records, attributes and different level of correlation. However from this figure we restrict our analysis in comparing the run time of various prescriptive approaches within each data set. While doing so, it clearly stat able that Farthest First approach is capable of generating clusters with minimum run time and K-Means approach seems to be the second optimum with respect to rum time.

Analysis of Predictive Clustering Approaches in terms of Precision, Recall and F-Measure:

Figure 3 represents the comparative analysis of the four prescriptive approaches on five bench marked data sets with respect to other significant measures called Precision, Recall and F-Measure. Since this experimentation deals with health care data sets analysing the prescriptive approaches with respect to classification accuracy and run time is not feasible and reliable. These data set analysis are very much sensitive to true positives, true negatives, false positives and false negatives measures, it is important to include Precision, Recall and F-measure into analysis to justify the optimum prescriptive approach according to the nature of the data set. From this experimentation in term of precision, recall and F-Measure Expectation Maximization proves to be the optimum one for all kinds of data set and as usual with other approaches K-Means takes the second minimum.

From the experimental analysis with respect to accuracy, run time, precision, recall and F-Measure we state the best prescriptive analysis approach for health care data set is the Expectation Maximization Approach. Though Expected maximization fails to prove its effectiveness in run time, because it purely relays on the probability correlation computation between the attributes. By having it to be the recommendation of prescriptive analytical model for health care systems, we suggest EM to be the optimum one in all scenarios.

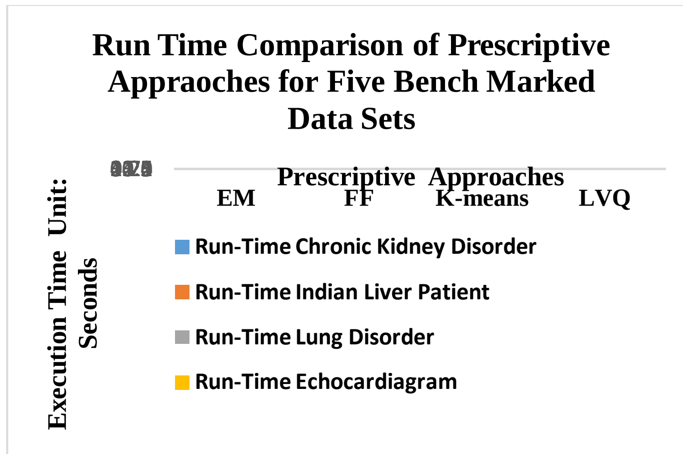

Figure 2 Run- Time Comparison of Prescriptive Modelling Approaches

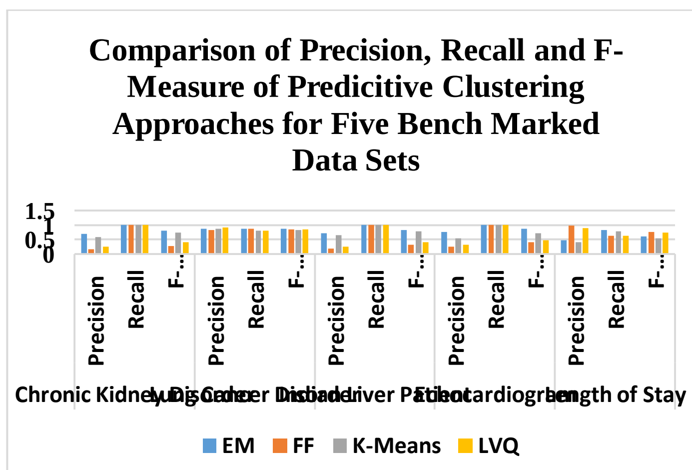

Figure 3 Comparison of other measures

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V CONCLUSION:

We proposed a novel fusion of predictive modelling and descriptive modelling often referred as prescriptive analysis for health care system. Our approach can be effectively utilized by the health care managers, doctors, researches and medical workers to have optimum insight in delivering the care to the patients involved in the process. We explicitly proved the efficiency of this approach through intense experimentation over the five kinds of bench marked data sets. Through this prescriptive analysis we state and declare that Expectation Maximization would be the optimized prescriptive approach to deal with versatile health care data set with utmost accuracy and reliability. In future we would like to extend this approach for multi objective problem of data mining in health care systems.

REFERENCE:

1. Kaufman, L. and Rousseeuw, P. J. (1990): Finding groups in data: An introduction to cluster analysis, John Wiley & Sons.
2. Langley, P. (1996): Elements of Machine Learning. Morgan Kaufman.
3. Tan, P.., 2007. Introduction to Data Mining. Pearson Education.
4. Jain, A.K., Duin, R.P.W., Mao, J., 2000. Statistical pat-tern recognition: a review. IEEE Trans. Pattern Anal. Mach. Intell. 22, 4–37.
5. Kotsiantis, S.B., 2007. Supervised Machine Learning: A Review of Classification Techniques, in: Pro-ceedings of the 2007 Conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI Systems with Ap-plications in eHealth, HCI, Information Retrie-val and Pervasive Technologies. IOS Press, Amsterdam, the Netherlands, the Netherlands, pp. 3–24.
6. Kotsiantis, S.B., Zaharakis, I.D., Pintelas, P.E., 2006. Machine learning: a review of classification and combining techniques. Artif. Intell. Rev. 26, 159–190.
7. Esfandiari, N., Babavalian, M.R., Moghadam, A.-M.E., Tabar, V.K., 2014. Knowledge discovery in medicine: Current issue and future trend. Expert Syst. Appl. 41, 4434–4463.
8. Austin, P.C., Tu, J.V., Lee, D.S., 2010. Logistic regres-sion had superior performance compared with regression trees for predicting in-hospital mor-tality in patients hospitalized with heart failure. J. Clin. Epidemiol. 63, 1145–1155.
9. Mazzocco, T., Hussain, A., 2012. Novel logistic regression models to aid the diagnosis of dementia. Expert Syst. Appl. 39, 3356–3361.
10. Landwehr, N., Hall, M., Frank, E., 2003. Logistic Model Trees, in: Lavrač, N., Gamberger, D., Blockeel, H., Todorovski, L. (Eds.), Machine Learning: ECML 2003, Lecture Notes in Computer Science. Springer Berlin Heidelberg, pp. 241–252.
11. Kurt, I., Ture, M., Kurum, A.T., 2008. Comparing performances of logistic regression, classification and regression tree, and neural networks for predicting coronary artery disease. Expert Syst. Appl. 34, 366–374.
12. Blockeel, H., De Raedt, L., and Ramon, J. (1998): Top-down induction of clustering trees. Proceedings of the 15th International Conference on Machine Learning, pages 55–63, Morgan Kaufmann.
13. Blockeel, H. and Struyf, J. (2002): Efficient algorithms for decision tree cross-validation, Journal of Machine Learning Research, 3(Dec):621–650, Microtome Pub-lishing.
14. Blockeel, H. (1998): Top-down induction of first order logical decision trees. PhD thesis, Department of Computer Science, KatholiekeUniversiteit, Leuven.
15. Clark, P. and Niblett, T. (1989): The CN2 Induction Algorithm, Machine Learning, 3:261–283, Kluwer.
16. [Sese, J. and Morishita, S. (2004): Itemset Classified Clustering. Proceedings of the Eighth European Conference on Principles and Practice of Knowledge Discovery in Databases (PKDD'04), pages 398–409, Springer.
17. Karaliˇc, A. and Bratko, I. (1997): First Order Regression. Machine Learning, 26:147– 176, Kluwer.
18. Lavraˇc, N., Kavˇsek, B., Flach, P., and Todorovski, L. (2004): Subgroup discovery with CN2-SD, Journal of Machine Learning Research, 5(Feb):153–188, Microtome Publishing.
19. Sese, J., Kurokawa, Y., Kato, K., Monden, M., and Morishita, S. (2004) Con-strained clusters of gene expression profiles with pathological features. Bioinfor-matics.
20. Suzuki, E., Gotoh,M., and Choki, Y. (2001): Bloomy Decision Tree for Multi-objective Classification. Proceedings of the Fifth European Conference on Princi-ples and Practice of Knowledge Discovery in Databases (PKDD'01), pages 436-447, Springer.
21. Rajesh, M., and J. M. Gnanasekar. "Path Observation Based Physical Routing Protocol for Wireless Ad Hoc Networks." Wireless Personal Communications 97.1 (2017): 1267-1289.
22. Rajesh, M., and J. M. Gnanasekar. "Sector Routing Protocol (SRP) in Ad-hoc Networks." Control Network and Complex Systems 5.7 (2015): 1-4.
23. Rajesh, M. "A Review on Excellence Analysis of Relationship Spur Advance in Wireless Ad Hoc Networks." International Journal of Pure and Applied Mathematics 118.9 (2018): 407-412.
24. Rajesh, M., et al. "SENSITIVE DATA SECURITY IN CLOUD COMPUTING AID OF DIFFERENT ENCRYPTION TECHNIQUES." Journal of Advanced Research in Dynamical and Control Systems 18.
25. Rajesh, M. "A signature based information security system for vitality proficient information accumulation in wireless sensor systems." International Journal of Pure and Applied Mathematics 118.9 (2018): 367-387.
26. Rajesh, M., K. Balasubramaniaswamy, and S. Aravindh. "MEBCK from Web using NLP Techniques." Computer Engineering and Intelligent Systems 6.8: 24-26.