

Rough Set Approach for Development of College Industry a New Theory

Sujogya Mishra
Research Scholar, Utkal
University
Bhubaneswar-751004,
India

Shakti Prasad Mohanty
Department of Mathematics,
College of Engineering and
Technology
Bhubaneswar-751003,
India

Radhanath Hota
Department of Computer
Science,
College of Basic Science and
Hum. OUAT
Bhubaneswar-751003, India

ABSTRACT

The college industry in particular private engineering college fail to survive because of proper planning. Once the student strength decreases, the proprietor of the college usually face huge financial loss. To avoid such loss and to sustain in the market we proposed an algorithm which is simple and it is based on rough set theory and then validate this concept by using statistical validation method. Initially we start with 100 samples then by using correlation technique we find 20 dissimilar samples, we then apply rough set theory on those data to develop an algorithm. The entire paper sub divided in to three sections. Section 1 deal with literature review and last two section deals with the experimental result and validation of our proposed algorithm.

Keywords

Rough Set Theory, college related data, Granular computing, Data mining.

1. INTRODUCTION

The increasing business demand and use of internet for the growth of business resulted huge data generation. The large amount of data that generated not only confuses the mind of the user but also it creates problem to extract the meaningful data for the application. This is a challenge for the researchers to find a precised data set and derive the relevant data for their application. The application of rough set theory is very good in knowledge discovery findings from the data base. The ever growing field of knowledge discovery (KD) helps in extraction of hidden information from large database [3]. Data mining is also considered as an essential tool in this knowledge discovery process which uses techniques from different disciplines ranging from machine learning, statistical information, database, visualization ([4]-[12]). Further, prediction of business failure needs a systematic and scientific study. The first approach to predict business failure started in 1995 by Zopounidis ([24]-[26]). The methods proposed are the "five C" methods, the "LAPP" method, and the "credit-men" method. Then, financial ratios methodology was developed for business failure prediction problem. This approach gives rise the methods for business failure prediction based on multivariate statistical analysis (Altman ([13]-[15]), Beaver[17], Curtis[18]). Frydman et al[19] first employed recursive partitioning, while Gupta et al[20] use mathematical programming as an alternative to multivariate discriminant analysis for business failure prediction problem. Other methods used were survival analysis by Luoma, Laitinen[21] which is a tool for company failure prediction, expert systems by Messier and Hansen[22], neural network by Altman et al[16], multi-factor model by

Vermeulen et al[23] are also other methods developed for business failure prediction. This paper presents a methodology for business success by reduction of attributes using rough set theory.

2. PRILIMINARIES

2.1 Rough set

Rough set theory as introduced by Z. Pawlak [8] is an extension of conventional set theory that support approximations in decision making.

2.1.1 Approximation Space:

An Approximation space is a pair (U, R) where U is a non empty finite set called the universe R is an equivalence relation defined on U .

2.1.2 Information System:

An information system is a pair $S = (U, A)$, where U is the non-empty finite set called the universe, A is the non-empty finite set of attributes

2.1.3 Decision Table:

A decision table is a special case of information systems $S = (U, A = C \cup \{d\})$, where d is not in C . Attributes in C are called conditional attributes and d is a designated attribute called the decision attribute

2.1.4 Approximations of Sets:

Let $S = (U, R)$ be an approximation space and X be a subset of U . The lower approximation of X by R in S is defined as $RX = \{e \in U \mid [e] \subseteq X\}$ and the upper approximation of X by R in S is defined as $\overline{RX} = \{e \in U \mid [e] \cap X \neq \emptyset\}$ where $[e]$ denotes the equivalence class containing e . A subset X of U is said to be R -definable in S if and only if $\overline{RX} = RX$. A set X is rough in S if its boundary set is nonempty.

2.2 Dependency of Attributes

Let C and D be subsets of A . We say that D depends on C in a degree k ($0 \leq k \leq 1$) denoted by

$$C \rightarrow_k D \text{ if } K = y(C, D) = \frac{|POS_C(D)|}{|U|}$$

where $POS_C(D) = \cup C(x)$, is called positive region of the partition U/D with respect to C where $x \in u/d$, which is all elements of U that can be uniquely classified to the block of partition U/D . If $k = 1$ we say that D depends totally on C . If $k < 1$ we say that D depends partially (in a degree k) on C .

2.3 Dispensable and Indispensable

Attributes

Let $S = (U, A = C \cup D)$ be a decision table. Let c be an attribute in C . Attribute c is dispensable in S if $POSC(D) = POS(C - \{c\})(D)$ otherwise, c is indispensable. A decision table S is independent if all attributes in C are indispensable. Let $S = (U, A = C \cup D)$ be a decision table.

Rough Set Attribute Reduction (RSAR) provides a filter based tool by which knowledge may be extracted from a domain in a concise way; retaining the information content whilst reducing the amount of knowledge involved.

2.4 Reduct and Core

Let $S = (U, A = C \cup D)$ be a decision table. A subset R of C is a reduct of C , if $POSR(D) = POSC(D)$ and $S' = (U, R \cup D)$ is independent, i.e., all attributes in R are indispensable in S' . Core of C is the set of attributes shared by all reducts of C . $CORE(C) = \cap RED(C)$ where, $RED(C)$ is the set of all reducts of C . The reduct is often used in the attribute selection process to eliminate redundant attributes towards decision making.

2.5 Correlation

Correlation define as a mutual relationship or connection between two or more things .The quantity r , called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The linear correlation coefficient is sometimes referred to as the Pearson product moment correlation coefficient in honor of its developer Karl Pearson. The mathematical formula for its coefficient given by the formula

$$r = \frac{n \sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \sqrt{n(\sum y^2) - (\sum y)^2}}$$

2.6 Goodness of fit

The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question.

2.7 Chi squared distribution

A chi-squared test, also referred to as χ^2 test, is any statistical hypothesis test in which the sampling distribution of the test statistic is a chi squared distribution when the null hypothesis is true. Also considered a chi-squared test is a test in which this is asymptotically true, meaning that the sampling distribution (if the null hypothesis is true) can be made to approximate a chi-squared distribution as closely as desired by making the sample size large enough. The chi-square (χ^2) test is used to determine whether there is a significant difference between the expected frequencies and the observed frequencies in one or more categories. Do the number of individuals or objects that fall in each category differ significantly from the number you would expect? Is this difference between the expected and observed due to sampling variation, or is it a real difference

2.8 Further analysis of chi square test

Basic properties of chi squared goodness fit is that it is non symmetric in nature .How ever if the degrees of freedom increased it appears to be to be more symmetrical .It is right tailed one sided test. All expectation in chi squared test is greater than 1. $EI = npi$ where n is the number samples

considered p_i is the probability of i th occurrence .Data selected at random there are two hypothesis null hypothesis and alternate hypothesis null hypothesis denoted by H_0 alternate hypothesis denoted by H_1 . H_0 is the claim does follow the hypothesis and H_1 is the claim does not follow the hypothesis here H_1 is called the alternate hypothesis to H_0 . If the test value found out to be K then K can be calculated by the formula $K = \sum(OI - EI) / EI$. Choice of significance level always satisfies type 1 error.

2.9 Different types of error

1. Type 1 error-Rejecting a hypothesis even though it is true
2. Type 2 error-Accepting the hypothesis when it is false
3. Type 3 error-Rejecting a hypothesis correctly for wrong reason

3. BASIC IDEA

The basic idea being conceived by looking at the present scenario of college industries . Once student strength decreases , the college management take whimsical decision by randomly disengaged the employees to counter the financial crisis by doing this they make the situation more complex , to counter this problem if they adopt a proper plan then the financial loss can be checked for this paper we consider five alter natives then by the use of rough set we develop an algorithm after developing the algorithm we also statistically validate it . The alter native we consider are as follows 1st alternative is to terminate all employees above 50,000 thousand salary 2nd alternative is to terminate all women employees 3rd alternative is to terminate all non teaching employees 4th alternative to terminate all employees between the range 21-26 years of age 5th alternative is to reduce the salary of the employees up to 40% For this paper we rename alternative 1, alternative 2, alternative 3, alternative 4, alternative 5 as a1, a2, a3, a4, a5 respectively And the values of the alter native as b1, , b2, b3 as adopt, partially adopt and ignore and two conditional attributes as c1,c2 for success and failure as respectively . We collected the data by appointing a regulating authority who in charge of collecting the data about the college management's attitude towards these alternative to counter the financial crisis .The five alternatives we mentioned is a part of research analysis . Our intention not to humiliate or hurt any body's sentiment.

4. DATA REDUCTION

As the volume of data is increasing day by day, it is very difficult to find which attributes which are actually important and which are not for a particular application. The aim of data reduction is to find the relevant attributes that have all essential information of the data set. The process is illustrated through tables for rough classification. In this particular problem we consider the conditional attributes as alternative 1, alternative 2, alternative 3, alternative 4, alternative 5 and their values as adopt partially adopt, ignore and decision attributes as success and failure which are analyze from table one to table 8 .For better clarity we substitute the original conditional and decision attributes as (a1, a2, a3, a4, a5) and d it's values re name by (b1, , b2, b3) and (c1,c2) respectively presented in in the table -1

Table-1:

E	a ₁	a ₂	a ₃	a ₄	a ₅	d
E ₁	b ₂	b ₂	b ₁	b ₁	b ₁	c ₂
E ₂	b ₂	b ₂	b ₁	b ₁	b ₁	c ₁
E ₃	b ₁	b ₂	b ₂	b ₃	b ₃	c ₁
E ₄	b ₁	b ₂	b ₂	b ₃	b ₁	c ₁
E ₅	b ₃	b ₃	b ₃	b ₃	b ₂	c ₂
E ₆	b ₁	b ₂	b ₂	b ₂	b ₂	c ₂
E ₇	b ₂	c ₁				
E ₈	b ₁	c ₂				
E ₉	b ₁	b ₂	b ₂	b ₃	b ₃	c ₁
E ₁₀	b ₁	b ₂	b ₂	b ₂	b ₂	c ₂
E ₁₁	b ₂	b ₃	b ₃	b ₃	b ₃	c ₁
E ₁₂	b ₁	b ₂	b ₃	b ₁	b ₂	c ₁
E ₁₃	b ₃	b ₂	b ₂	b ₂	b ₁	c ₂
E ₁₄	b ₃	c ₁				
E ₁₅	b ₂	b ₁	b ₁	b ₁	b ₁	c ₂
E ₁₆	b ₁	c ₂				
E ₁₇	b ₁	c ₂				
E ₁₈	b ₁	b ₂	b ₂	b ₃	b ₂	c ₂
E ₁₉	b ₁	b ₃	b ₁	b ₃	b ₃	c ₂
E ₂₀	b ₁	b ₂	b ₁	b ₃	b ₃	c ₁

The decision table -1 , takes the initial values before finding the reduct looking at the data table it is found that entities E1,E2, ambiguous in nature and E16, E17 gives same result so both E1,E2 drop from the table and from the records E16,E17 we keep one record that is either E16 or E17 for our purpose so the new table appears as table -2 is called reduce table now we apply the rough set concept on table -2 to find the strength[27]

Table-2

E	a ₁	a ₂	a ₃	a ₄	a ₅	d
E ₃	b ₁	b ₂	b ₂	b ₃	b ₃	c ₁
E ₄	b ₁	b ₂	b ₂	b ₃	b ₁	c ₁

E ₅	b ₃	b ₃	b ₃	b ₃	b ₂	c ₂
E ₆	b ₁	b ₂	b ₂	b ₂	b ₂	c ₂
E ₇	b ₂	c ₁				
E ₈	b ₁	c ₂				
E ₉	b ₁	b ₂	b ₂	b ₃	b ₃	c ₂
E ₁₀	b ₁	b ₂	b ₂	b ₂	b ₂	c ₂
E ₁₁	b ₂	b ₃	b ₃	b ₃	b ₃	c ₁
E ₁₂	b ₁	b ₂	b ₃	b ₁	b ₂	c ₁
E ₁₃	b ₃	b ₂	b ₂	b ₂	b ₁	c ₁
E ₁₄	b ₃	c ₁				
E ₁₅	b ₂	b ₁	b ₁	b ₁	b ₁	c ₂
E ₁₆	b ₁	c ₂				
E ₁₈	b ₁	b ₂	b ₂	b ₃	b ₂	c ₂
E ₁₉	b ₁	b ₃	b ₁	b ₃	b ₃	c ₂
E ₂₀	b ₁	b ₂	b ₁	b ₃	b ₃	c ₁

4.1 Indiscernibility Relation

Indiscernibility Relation is the relation between two or more objects where all the values are identical in relation to a subset of considered attributes.

4.2 Approximation

The starting point of rough set theory is the indiscernibility relation, generated by information concerning objects of interest. The indiscernibility relation is intended to express the fact that due to the lack of knowledge it is unable to discern some objects employing the available information Approximations is also other an important concept in Rough Sets Theory, being associated with the meaning of the approximations topological operations (Wu et al., 2004). The lower and the upper approximations of a set are interior and closure operations in a topology generated by the indiscernibility relation. Below is presented and described the types of approximations that are used in Rough Sets Theory.

4.2.1 Lower approximations

Lower Approximation is a description of the domain objects that are known with certainty to belong to the subset of interest. The Lower Approximation Set of a set X, with regard to R is the set of all objects, which can be classified with X regarding R, that is denoted as RL.

4.2.2 Upper Approximation :

Upper Approximation is a description of the objects that possibly belong to the subset of interest. The Upper Approximation Set of a set X regarding R is the set of all of objects which can be possibly classified with X regarding R . Denoted as RU

4.2.3 Boundary Region (BR) :

Boundary Region is description of the objects that of a set X regarding R is the set of all the objects, which cannot be classified neither as X nor -X regarding R. If the boundary region $X = \phi$ then the set is considered "Crisp", that is, exact in relation to R; otherwise, if the boundary region is a set $X \neq \phi$ the set X "Rough" is considered. In that the boundary region is $BR = RU - RL$.

The lower and the upper approximations of a set are interior and closure operations in a topology generated by a indiscernibility relation. In discernibility according to decision attributes in this case has divided in to two groups one group consist of positive case and another group consists of negative cases

$E_{success} = \{E3, E4, E7, E11, E12, E13, E14, E20\} \dots (1)$

$E_{failure} = \{E5, E6, E8, E9, E10, E15, E16, E18, E19\} \dots (2)$

$E(a1)_{adopt} = \{E3, E4, E6, E8, E9, E10, E12, E16, E18, E19, E20\} \dots (3)$

$E(a1)_{partialadopt} = \{E7, E11, E15\} \dots (4)$

$E(a1)_{ignore} = \{E5, E13, E14\} \dots (5)$

The above result when compared with the success cases $E(a1)_{adopt}$ strength[27]

Found to be 4/11 about 36% where as for failure cases of adopt $E(a1)$ strength[27] is 7/11 about 63% similarly for partially adopt failure case $E(a1)$ strength[27] gives rise to be 1/3 about 33% , so we see that adopting case a1 we have success is 36% and failure is about 63% and partially adopting a1 we have a success about 33% from this analysis we find strength[27] of failure in case adopting alternative 1 is higher than the success so alter native 1 does not give any significant result so we drop the attribute in the subsequent table now analyzing alternative 2 we have the following

$E(a2)_{adopt} = \{E8, E15, E16\} \dots (6)$

$E(a2)_{partialadopt} = \{E3, E4, E6, E7, E9, E10, E13, E18, E20\} \dots (7)$

$E(a2)_{ignore} = \{E5, E11, E14, E19\} \dots (8)$

Strength[27] for adopting alternative 2 is found to be nil and strength[27] of success by ignoring alternative 2 is 2/4 about 50% similarly partially adopting alternative 2 strength[27] will be 2/3 about 66% partially adopting means women employee whose husband's are in white collar job similarly failure strength[27] in partially adopting will be about 1/3 about 33% so this somehow justify for success similarly analyzing a3 we have the following result

$E(a3)_{adopt} = \{E8, E12, E15, E16\} \dots (9)$

$E(a3)_{partialadopt} = \{E3, E4, E6, E7, E9, E10, E13\} \dots (10)$

$E(a3)_{ignore} = \{E5, E11, E12, E14\} \dots (11)$

Now the strength[27] of success adopting a3 ¼ about 25% where as failure is about ¾ about 75% So now up to this stage adopting attribute a1 and a3 no longer helpful in the business for further analysis now in the analysis of attribute a4 we have the following result that is

$E(a4)_{adopt} = \{E8, E12, E15, E16\} \dots (12)$

$E(a4)_{partialadopt} = \{E6, E7, E10, E13\} \dots (13)$

$E(a4)_{ignore} = \{E3, E4, E5, E9, E11, E14, E20\} \dots (14)$

Adopting a4 strength[27] for success case is ¼ about 25% ignoring a4 the strength[27] of success case is 5/8 is about 62.5% so ignoring a4 gives a significant result so we keep a4 for further analysis now analyzing a5 finding $E(a5)_{adopt} = \{E4, E8, E9, E13, E15, E16\} \dots (15)$

$E(a5)_{partialadopt} = \{E5, E6, E10, E12\} \dots (16)$

$E(a5)_{ignore} = \{E5, E6, E10, E12\} \dots (17)$

$E(a5)_{ignore} = \{E3, E9, E11, E14, E19, E20\} \dots (18)$

Strength[27] adopting a5 success is 2/6 about 33% and partially adopting Strength[27] 1/5 is about 20% so a5 does not provide any significant result in the college business success now we can get one conclusion that partially ignoring attribute a2 has some amount of significance so we can drop the attribute a2 from the table to get some significant result which is presented in table-3 now in the table -3 we have a set of values

Table-3

E	a ₁	a ₃	a ₄	a ₅	d
E ₃	b ₁	b ₂	b ₃	b ₃	c ₁
E ₄	b ₁	b ₂	b ₃	b ₁	c ₁
E ₅	b ₃	b ₃	b ₃	b ₂	c ₂
E ₆	b ₁	b ₂	b ₂	b ₂	c ₂
E ₇	b ₂	b ₂	b ₂	b ₂	c ₁
E ₈	b ₁	b ₁	b ₁	b ₁	c ₂
E ₉	b ₁	b ₂	b ₃	b ₃	c ₂
E ₁₀	b ₁	b ₂	b ₂	b ₂	c ₂
E ₁₁	b ₂	b ₃	b ₃	b ₃	c ₁
E ₁₂	b ₁	b ₃	b ₁	b ₂	c ₁
E ₁₃	b ₃	b ₂	b ₂	b ₁	c ₁
E ₁₄	b ₃	b ₃	b ₃	b ₃	c ₁
E ₁₅	b ₂	b ₁	b ₁	b ₁	c ₂
E ₁₆	b ₁	b ₁	b ₁	b ₁	c ₂
E ₁₈	b ₁	b ₂	b ₃	b ₂	c ₂
E ₁₉	b ₁	b ₁	b ₃	b ₃	c ₂
E ₂₀	b ₁	b ₁	b ₃	b ₃	c ₁

As analyzing table -3 we find E6, E10 and E8, E16 forms a group so we keep one record from E6, E10 and E8, E11 respectively now the reduced table is represented

Reduced table -4 that is as follows from Table-3

E	a ₁	a ₃	a ₄	a ₅	d
E ₃	b ₁	b ₂	b ₃	b ₃	c ₁
E ₄	b ₁	b ₂	b ₃	b ₁	c ₁
E ₅	b ₃	b ₃	b ₃	b ₂	c ₂
E ₆	b ₁	b ₂	b ₂	b ₂	c ₂
E ₇	b ₂	b ₂	b ₂	b ₂	c ₁
E ₈	b ₁	b ₁	b ₁	b ₁	c ₂
E ₉	b ₁	b ₂	b ₃	b ₃	c ₂
E ₁₁	b ₂	b ₃	b ₃	b ₃	c ₁
E ₁₂	b ₁	b ₃	b ₁	b ₂	c ₁
E ₁₃	b ₃	b ₂	b ₂	b ₁	c ₁
E ₁₄	b ₃	b ₃	b ₃	b ₃	c ₁
E ₁₅	b ₂	b ₁	b ₁	b ₁	c ₂
E ₁₈	b ₁	b ₂	b ₃	b ₂	c ₂
E ₁₉	b ₁	b ₁	b ₃	b ₃	c ₂
E ₂₀	b ₁	b ₁	b ₃	b ₃	c ₁

Upon analyzing table-4 we have a very peculiar result that is attribute a₁ we find a lot of ambiguity result for example with respect to attribute a₁ value b₁ is ambiguous for the group (E₃,E₄,E₁₂,E₂₀) ambiguous with the group (E₆,E₈,E₉,E₁₈,E₁₉) similarly with respect to value b₂ of attribute a₁ (E₇,E₁₁) group ambiguous with E₁₅ similarly if we consider the value b₃ for attribute a₁ is also giving ambiguous result that is E₅ ambiguous with the group (E₁₃,E₁₄) so we find this not important from the point of adopting it so we remove this attribute from the table as we are having lots of ambiguous result in this attribute so adopting the attribute is not in the success result now table reduced table -4 it provide the following result

Reduced table -5 that is as follows from Table-4

E	a ₃	a ₄	a ₅	d
E ₃	b ₂	b ₃	b ₃	c ₁
E ₄	b ₂	b ₃	b ₁	c ₁
E ₅	b ₃	b ₃	b ₂	c ₂
E ₆	b ₂	b ₂	b ₂	c ₂

E ₇	b ₂	b ₂	b ₂	c ₁
E ₈	b ₁	b ₁	b ₁	c ₂
E ₉	b ₂	b ₃	b ₃	c ₂
E ₁₁	b ₃	b ₃	b ₃	c ₁
E ₁₂	b ₃	b ₁	b ₂	c ₁
E ₁₃	b ₂	b ₂	b ₁	c ₁
E ₁₄	b ₃	b ₃	b ₃	c ₁
E ₁₅	b ₁	b ₁	b ₁	c ₂
E ₁₈	b ₂	b ₃	b ₂	c ₂
E ₁₉	b ₁	b ₃	b ₃	c ₂
E ₂₀	b ₁	b ₃	b ₃	c ₁

Now analyzing the table -5 we have (E₃,E₉) and (E₆,E₇) are ambiguous in nature and (E₈,E₁₅) and (E₁₁,E₁₅) forms a group so we eliminate all records that is present in E₃ in E₉ and E₆ in E₇ respectively and keep single record from (E₈,E₁₅) and (E₁₁,E₁₅) so now the new table -6 we get from table-5 so we have the following result that is

Reduced table -6 that is as follows from Table-5

E	a ₃	a ₄	a ₅	d
E ₄	b ₂	b ₃	b ₁	c ₁
E ₅	b ₃	b ₃	b ₂	c ₂
E ₈	b ₁	b ₁	b ₁	c ₂
E ₁₁	b ₃	b ₃	b ₃	c ₁
E ₁₂	b ₃	b ₁	b ₂	c ₁
E ₁₃	b ₂	b ₂	b ₁	c ₁
E ₁₈	b ₂	b ₃	b ₂	c ₂
E ₁₉	b ₁	b ₃	b ₃	c ₂
E ₂₀	b ₁	b ₃	b ₃	c ₁

After analyzing the table -6 in particular attribute a₃ for value b₁ shows E₈ and E₂₀ ambiguous in nature similarly upon analyzing the the value b₂ for the attribute a₃ provide ambiguous result E₁₃ and E₁₈ similarly analyzing the attribute a₃ for the value b₃ also has an ambiguous result as we are getting lots of ambiguity in a₃ so we drop a₃ attribute from the table -6 to get new table-7

Reduced Table -7 that is as follows from Table-6

E	a ₄	a ₅	d
E ₄	b ₃	b ₁	c ₁
E ₅	b ₃	b ₂	c ₂
E ₈	b ₁	b ₁	c ₂
E ₁₁	b ₃	b ₃	c ₁
E ₁₂	b ₁	b ₂	c ₁
E ₁₃	b ₂	b ₁	c ₁
E ₁₈	b ₃	b ₂	c ₂
E ₁₉	b ₃	b ₃	c ₂
E ₂₀	b ₃	b ₃	c ₁

Now upon analyzing the table-7 we have (E5,E18) forms a group and (E19,E20) ambiguous result so we drop E19,E20 from the table and keep one record from E5,E18 now we have the reduced table-7 from table - 6 gives the following result that is new table given below

Reduced table -8 that is as follows from Table-7

E	a ₄	a ₅	d
E ₄	b ₃	b ₁	c ₁
E ₅	b ₃	b ₂	c ₂
E ₈	b ₁	b ₁	c ₂
E ₁₁	b ₃	b ₃	c ₁
E ₁₂	b ₁	b ₂	c ₁
E ₁₃	b ₂	b ₁	c ₁

From table -8 we have the following decision present as an algorithm

State as follows that is

Step-1 Ignoring alternative -4 and adopting alternative -5 leads to success

Step-2 Ignoring alternative -4 and partially adopting alternative -5 leads to failure

Step-3 Adopting alternative -4 and alternative -5 leads to failure

Step-4 Ignoring alternative -4 and alternative -5 leads to success

Step-5 Adopting alternative -4 and partially adopting alternative -5 leads to success

Step-6 Partially adopting alternative -4 and adopting alternative -5 leads to success

Running time of this comparison will take $O(n^2)$ as every time we compare to find the reduct every record compare with rest n records then $n-1$ records till we reach 1 record so total running time will be $n+(n-1)+ (n-2) + \dots + 1 = n(n+1)/2$

Of order n^2 . And further breaking the table will take $O(n \lg n)$ so total time complexity will take $O(n \lg n + n^2)$

5. STATISTICAL VALIDATION

For validate our findings we basically depends upon chi-square test for this purpose we consider we take a survey by taking data regarding the positive case and we are not focused on one medical centre to collect data we approached several hospital and the apply chi square test to validate our claim. Chi square test- Expected 15%, 10%, 15%, 20%, 30%, 15% and the Observed samples are 25, 14, 34, 45, 62, 20 so totaling these we have total of 200 samples so expected numbers of samples per each day as follows 30, 20, 30, 40, 60, 30. We then apply chi square distribution to verify our result assuming that H_0 is our hypothesis that is correct H_1 as alternate hypothesis that is not correct, Then we expect sample in six cases as chi squared estimation formula is $\sum (O_i - E_i)^2 / E_i$ where $i=0,1,2,3,4,5$ so the calculated as follows $X^2 = (25-30)^2/20 + (14-20)^2/20 + (34-30)^2/30 + (45-40)^2/40 + (62-60)^2/60 + (20-30)^2/30$

$$X^2 = 25/20 + 36/20 + 16/30 + 25/40 + 4/60 + 100/30$$

$= 7.60$ the tabular values we have with degree of freedom 5 we get result 11.04

As we find our result lies much below the critical values so this result is statistically validate

Future work- this work can be extended and applicable to different business house like film industry, software industries small and large scale industries.

6. REFERENCES

- [1] S.K. Pal, A. Skowron, Rough Fuzzy Hybridization: A new trend in decision making, Berlin, Springer-Verlag, 1999
- [2] Z. Pawlak, "Rough sets", International Journal of Computer and Computer and Information Sciences, Vol. 11, 1982, pp.341–356
- [3] Z. Pawlak, Rough Sets: Theoretical Aspects of Reasoning about Data, System Theory, Knowledge Engineering and Problem Solving, Vol. 9, The Netherlands, Kluwer Academic Publishers, Dordrecht, 1991
- [4] Han, Jiawei, Kamber, Micheline, Data Mining: Concepts and Techniques. San Francisco CA, USA, Morgan Kaufmann Publishers, 2001
- [5] Ramakrishnan, Naren and Grama, Y. Ananth, "Data Mining: From Serendipity to Science", IEEE Computer, 1999, pp. 34-37.
- [6] Williams, J. Graham, Simoff, J. Simeon, Data Mining Theory, Methodology, Techniques, and Applications (Lecture Notes in Computer Science/ Lecture Notes in Artificial Intelligence), Springer, 2006.
- [7] D.J. Hand, H. Mannila, P. Smyth, Principles of Data Mining. Cambridge, MA: MIT Press, 2001

- [8] D.J. Hand, G.Blunt, M.G. Kelly, N.M.Adams, “Data mining for fun and profit”, *Statistical Science*, Vol.15, 2000, pp.111-131.
- [9] C. Glymour, D. Madigan, D. Pregibon, P.Smyth, “Statistical inference and data mining”, *Communications of the ACM*, Vol. 39, No.11,1996,pp.35-41.
- [10] T.Hastie, R.Tibshirani, J.H. Friedman, *Elements of statistical learning: data mining, inference and prediction*, New York: Springer Verlag, 2001
- [11] H.Lee, H. Ong, “Visualization support for data Mining”, *IEEE Expert*, Vol. 11, No. 5, 1996, pp. 69-75.
- [12] H. Lu, R. Setiono, H. Liu, “Effective data Mining using neural networks”, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 8, No. 6, 1996, pp. 957-961.
- [13] E.I Altman, “Financial ratios, discriminants analysis and prediction of corporate bankruptcy”, *The journal of finance*, Vol. 23 , 1968, pp.589-609
- [14] E.I.Altman, R.Avery, R.Eisenbeis, J. Stnkey, “Application of classification techniques in business, banking and finance. *Contemporary studies in Economic and Financial Analysis*”, vol.3, Greenwich, JAI Press,1981.
- [15] E.I Altman, “The success of business failure prediction models: An international surveys”, *Journal of Banking and Finance* Vol. 8, no.2, 1984, pp.171-198
- [16] E.I Altman, G. Marco, F. Varetto, “Corporate distress diagnosis: Comparison using discriminant analysis and neural networks”, *Journal of Banking and Finance*, Vol.18, 1994, pp. 505-529
- [17] W.H Beaver, “Financial ratios as predictors of failure *Empirical Research in accounting : Selected studies*”, *Journal of Accounting Research Supplement to Vol-4*, 1966, pp.71-111
- [18] J.K Courtis, “Modelling a financial ratios categoric frame Work”, *Journal of Business Finance and Accounting*, Vol. 5, No.4, 1978, pp71-111
- [19] H.Frydman, E.I Altman ,D-IKao, “Introducing recursive partitioning for financial classification: the case of financial distress”, *The Journal of Finance*, Vol.40, No. 1 1985, pp. 269-291.
- [20] Y.P.Gupta, R.P.Rao, P.K. , “Linear Goal programming as an alternative to multivariate discriminant analysis a note *journal of business fiancé and accounting* Vol.17, No.4, 1990, pp. 593-598
- [21] M. Louma, E, K. Laitinen, “Survival analysis as a tool for company failure prediction”. *Omega*, Vol.19, No.6, 1991, pp. 673-678
- [22] W.F. Messier, J.V. Hanseen, “Including rules for expert system development: an example using default and bankruptcy data”, *Management Science*, Vol. 34, No.12, 1988, pp.1403-1415
- [23] E.M. Vermeulen, J. Spronk, N. Van der Wijst., *The application of Multifactor Model in the analysis of corporate failure*. In: Zopounidis,C.(Ed), *Operational corporate Tools in the Management of financial Risks*, Kluwer Academic Publishers, Dordrecht, 1998, pp. 59-73
- [24] C. Zopounidis, A.I. Dimitras, L. Le Rudulier, *A multicriteria approach for the analysis and prediction of business failure in Greece*. *Cahier du LAMSADE*, No.132, Universite de Paris Dauphine, 1995.
- [25] C. Zopounidis, N.F. Matsatsinis, M. Doumpos, “Developing a multicriteria knowledge-based decision support system for the assessment of corporate performance and viability: The FINEVA system”, *Fuzzy Economic Review*, Vol. 1, No. 2, 1996, pp. 35-53.
- [26] C. Zopounidis, M. Doumpos, N.F. Matsatsinis, “Application of the FINEVA multicriteria knowledge decision support systems to the assessment of corporate failure risk”, *Foundations of Computing and Decision Sciences*, Vol. 21, No. 4, 1996, pp. 233-251
- [27] 11 Renu Vashist Prof M.L Garg *Rule Generation based on Reduct and Core :A rough set approach International Journal of Computer Application(0975-887) Vol 29 September -2011*