Rough set Approach to Find the Cause of Decline of E – Business

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ABSTRACT
In this paper, I am finding the cause of decline of E-Business in our state by using Rough set theory.

General Terms
Your general terms must be any term which can be used for general classification of the submitted material such as Pattern Recognition, Security, Algorithms et. al.

Keywords
Set Theory, Data Analysis, Granular computing, Data mining

1. INTRODUCTION
The basic idea conceived looking at the present scenario of down fall of E-Business industries . Our intention is very clear the algorithm which we develop provide me the cause of down fall of E-Business . In this context I had taken statistics of several types of E-Business establishments. In the process we generate so much of data which production not only put us in dilemma but also it creates obstacle for us to derive the exact cause . which has created a challenge in the development of reduction of data set and to derive the exact data for a particular application. The application of rough set theory has a prime role to play for knowledge discovery in data base(s).The ever increasing field of knowledge discovery (KD) that helps in derivation of hidden information from large database[3]. Data mining is also considered as essential tool in this knowledge discovery process which uses techniques from different disciplines ranging from machine learning, statistics information sciences, database, visualization ([4]-[12]). Further, prediction of system failure needs a systematic and scientific study. The first approach to predict system failure (any establishment which fails due to lack of administration)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 to counter failure prediction problem. This approach gives rise the methods for general failure prediction based on multivariate statistical analysis (Altman ([13]-[15]), Beaver[17], Courtis[18]). Frydman*et al*[19] first employed recursive *et al*[16], multi-factor model by Vermeulen*et al*[23] are also other methods developed to counter failure prediction. This paper presents a methodology to generate certain basic attributes which actually responsible for this disparities ,reduction of attributes using rough set theory. Portioning, while Gupta *et a*l[20] use mathematical programming as an alternative to multivariate discriminate analysis for system failure prediction problem. Other methods used were survival analysis by Luoma, Laitinenl[21] which is a tool for company failure prediction, expert systems by Messier and Hansen[22] , neural network by Altman.

1.1 Rough set
Rough set theory as introduced by Z. Pawlak[2] is an extension of conventional set theory that support approximations in decision making.

1.1.1 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.

1.1.2 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.

1.1.3 Decision Table:
A decision table is a special case of information systems

S= (U , A= C U {d}), where d is not in C.

Attributes in C are called conditional attributes and d is a designated attribute called the decision attribute.

1.1.4 Approximation 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 εU | [e] ε X} and

The upper approximation of X by R in S is defined as

$$\overline{RX} = \{e \in U / [e] \cap X \neq \phi\}$$

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 Sif its boundary set is nonempty.

1.2 Dependency of Attributes
Let C and D be subsets of A. We say that D depends on C in a degree k (0 ≦ k ≦ 1) denoted by C →k D if

$$k = \gamma(C, D) = \frac{\mathrm{I}POS_C(D)\mathrm{I}}{\mathrm{I}U\mathrm{I}}$$

where $POS_C(D) = \underset{X \in U/D}{\cup} \underline{C}(X)$ *called a positive region of the partition* U / D *with respect to C, which is the set of all elements of* U *that can be uniquely classified to blocks of the 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

1.3 Dispensable and Indispensable Attributes

Let S = (U, A = C ∪ 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.

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.

1.4 Reduct and Core

Let S = (U, A=C U D) be a decision table.A subset R of C is a reduct of C, if POSR(D) = POSC(D) and S' = (U, RUD) is independent,ie., all attributes in R are indispensible in S'.Core of C is the set of attributes shared by all reducts of C. CORE(C) = ∩RED(C) where, RED(C) is the set of all reducts of C.Thereduct is often used in the attribute selection process to eliminate redundant attributes towards decision making.

1.5 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.

1.6 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 (I) 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.

1.7 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 hypothesis 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 pi is the probability of ith occurrence .Data selected at random there are two hypothesis null hypothesis and alternate hypothesis null denoted by H0 alternate hypothesis denoted by H1. H0 is the claim does follow the hypothesis and H1 is the claim does not follow the hypothesis here H1 is called the alternate hypothesis to H0.If the test value found out to be K then K can be calculated by the formula K=∑(OI-EI)2/ EI. Choice of significance level always satisfies type 1 error .

1.8 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

2. BASIC IDEA

The basic idea for the proposed work develop looking at the frequent down fall of E-Business industries. For this purpose we initially consider 1000 samples then by using correlation techniques , only 20 samples are selected which appears to be dissimilar then by applying rough set concept we reduced the number of attributes to develop the concept we consider .five conditional attributes such as 1.Globalisation of business 2.Lack of proper communication 3.Mis managements of software responsible for E-Business 4 Not providing correct information regarding the goods via website 5 No Proper Software available to verify the product code at initial stages and it's values are high, average and less and we have two decision attributes such as significant and insignificant.

2.1 Indiscernibility relation

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

2.2 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 RoughSetsTheory, being associated with the meaning of the approximations topological operations(Wuetal.,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.

a. Lower Approximation

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 R_L

b. 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 R_U.

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,iftheboundaryregionisaset$X\neq\phi$thesetX"Rough"isconsidered.In that the boundary region is BR =R_U-R_L.

The lower and the upper approximations of a set are.

3. DATA REDUCTION

As the volume of data is increasing every day , it is very difficult to find which type of data is important to decide which are actual responsible for decision making .The aim of data reduction is to find the relevant attributes(for decision making) that have all essential information of the data set. The process is illustrated through the following 20 samples by

using the rough set theory. For this paper we consider the conditional attributes that described in section 3 which can be applied to all types of data related to small scale industries which are collected from different sources To represent all these in the tabular form we rename the five the conditional attributes of small scale industries as 1.Globalization of business, as a_1 2 Lack of proper communication as a_2 3 Mismanagements of software responsible for E-Business as a_3 4. Not providing correct information regarding the goods via website as a_4 ,5. No Proper Software available to verify the product code at initial stages as a_5. Conditional attribute values are consider as, high ,average and less renamed as b_1, b_2 and b_3 respectively decision attribute d are considered as significant and insignificant renamed as c_1 and c_2 respectively. To start with we consider initial table which is generated from 20 samples which we get by the method of correlation techniques.

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_1
E_2	b_2	b_2	b_1	b_3	b_3	c_1
E_3	b_1	b_2	b_2	b_3	b_3	c_2
E_4	b_1	b_2	b_2	b_3	b_3	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_1
E_7	b_2	b_2	b_2	b_2	b_2	c_1
E_8	b_1	b_1	b_1	b_1	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_2
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	b_3	b_3	b_3	b_3	c_2
E_{15}	b_2	b_1	b_1	b_1	b_1	c_1
E_{16}	b_1	b_1	b_1	b_1	b_1	c_1
E_{17}	b_1	b_3	b_2	b_2	b_3	c_2
E_{18}	b_1	b_2	b_2	b_3	b_2	c_1
E_{19}	b_1	b_3	b_1	b_3	b_1	c_2
E_{20}	b_2	b_2	b_2	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 E_3,E_4, ambiguous in nature so both E_3,E_4 remove from the relational table -1 to produce the new table as our Table-2

Table -2

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_1
E_2	b_2	b_2	b_1	b_3	b_3	c_1
E_5	b_2	b_1	b_2	b_3	b_2	c_2
E_6	b_1	b_2	b_2	b_2	b_2	c_1
E_7	b_2	b_2	b_2	b_2	b_2	c_1
E_8	b_1	b_1	b_1	b_1	b_1	c_1
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_2	b_1	b_3	b_3	c_2
E_{12}	b_1	b_2	b_1	b_1	b_2	c_1
E_{13}	b_1	b_2	b_2	b_2	b_1	c_2
E_{14}	b_2	b_2	b_2	b_3	b_3	c_2
E_{15}	b_2	b_1	b_1	b_1	b_1	c_1
E_{16}	b_1	b_1	b_1	b_1	b_1	c_1
E_{17}	b_1	b_2	b_2	b_2	b_3	c_2
E_{18}	b_1	b_2	b_2	b_3	b_2	c_2
E_{19}	b_1	b_2	b_1	b_3	b_1	c_2
E_{20}	b_2	b_1	b_2	b_3	b_3	c_1

One groups consist of all positive case and other one all negative cases

$E_{(Significant)}$={ E_1, E_2, E_6, E_7, E_8, E_9 ,E_{12}, E_{15}, E_{16},E_{20}}…(1)

$E_{(insignificant)}$={ E_5, E_{10}, E_{11}, E_{13}, E_{14} ,E_{17}, E_{18}, }.....(2)

Here in this case lower approximation for Significance represented by the first equation and lower approximation for insignificant represented by the Second equation now we find the entities which are falls into different groups to generate different equivalence classes as follows . The equivalence class generated in this form given by

$E(a_1)_{b1}$ ={E_6, E_8, E_9, E_{10}, E_{12}, E_{16} ,E_{17}, E_{18}, E_{19}}

$E(a_1)_{b2}$ ={E_1, E_2, E_7, E_{11} ,E_{15}, E_{20}}

$E(a_1)_{b3}$ =={E_5, E_{13}, E_{14} },

Calculating the strength[11] of a_1 provide significant result considering high a_1 value will be about 40% similarly insignificant result in lowa_1 value is about 100% cent percent similarly for attribute a_2 with high significant is about 33% average significant a_2 will be about 45% and in significant result in low a_2 is nil . Similarly upon analyzing the attribute a_3 give rise the following result high a_3 provide about 75% significance result so we are not considering the average and low a_3 cases in the process. Now similarly analyzing a_4 high values of a_4 provide 100 percent significance and similarly upon analyzing low insignificance level for a_4 provide us about 14.2% , similarly upon analyzing a_5 we have the following high a_5 provide around 80% significant result similarly on the same basis low a_5 provide around 40% significant result where as low a_5 value also provide 60% significance it provide an ambiguous result . So in the subsequent section we drop a_1 ,a_5Next, we find the combination of two attributes each to generate the reduct such combinations are $E(a_1,a_2)$, $E(a_1,a_3)$, $E(a_1,a_4)$, $E(a_1,a_5)$ $E(a_1,a_2)_{b1}$={E_8,E_{16}}, $E(a_1,a_2)_{b2}$={E_1,E_2,E_7,E_{20}}

$E(a_1,a_2)_{b3}$={E_3,E_{14} } $E(a_1,a_3)_{b1}$={E_8,E_{16},E_{19}} $E(a_1,a_3)_{b2}$={E_7,E_{20}} similarly we combine the attributes (a_2,a_3)

(a_2,a_4) (a_2,a_5)

$E(a_1,a_2,a_3)_{b1}$ ={E_8,E_{16}} $E(a_1,a_2,a_3)_{b2}$ ={E_7,E_{20}} similarly for

(a_1,a_2,a_3,a_4), (a_1,a_2,a_3,a_4)

These equivalence classes are basically responsible for finding the dependencies with respect to the decision variable d in this paper besides all equivalence classes , I am trying to find out the degree of dependencies of different attributes of consideration with respect to decision attributes d considering that is $E(a_1)_{b1/b2}$ (significant) or(insignificant) cases can't classified as several ambiguity result found out that is {E_2,E_5} , {E_9,E_{10}}, {E_{12},E_3}, {E_{14},E_{15}},{E_{16},E_{17}} with respect to decision variable d a_1 gives insignificant result so this attribute has hardly any importance. similarly for a_2 we find the degree of dependency.($E(a_2)_{b1/b2}$(significance)= {E_1,E_2,E_6,E_7,E_9,E_{12}, E_8, E_{15},E_{16},E_{20}} so degree of dependency 10/20 for the significance cases with respect to decision variable d similarly the insignificance cases in a_2 cases are

= { E_1, E_2, E_6 E_7 ,E_8,E_9 E_{12},E_{15},E_{20}} E_{16},E_{19} Produces ambiguous result so here the degree dependency 9/20 on significant cases two ambiguous cases similarly the negative cases $E(a_3)$(insignificant)$_{b1/b2}$ ={E_{10},E_{11}, E_{13},E_{14},E_{17},E_{18},E_{19}} That is the degree of dependency will be 7/20 but upon analyzing the data which present in table-3 we have the following result like E_1, E_2, E_8,E_{12} produces the same result that is if in a_3 cases is high still we have insignificant result then we have significant cases similarly analyzing the insignificant cases we have similar result E_5,E_6 produces ambiguous result so we are consider these and for other cases E_{10}, E_{13},E_{14},E_{17},E_{18} produces the same result so upon analyzing the data a_3 produces insignificant result that is in some cases this attribute produce significance and in some cases it deliver insignificance result the number in both cases are nearly equal .So for that in case of the a_3 does not provide any information from which we can generate any definite rule dropping this attribute from the decision table may hamper the investigation process so we keep this attribute in the decision table for further investigation I have the following result .

$E(a_4)_{b2/b1}$(significance) ={ E_1,E_6, E_7,E_{12},E_{15},E_{16}} dependency factor in this cases will be 6/20

$E(a_4)_{b2/b1}$ (insignificance)={ E_5,E_{11}, E_{14},E_{18}} E_{19},E_{20} gives ambiguous result here dependency factor for negative cases will be 4/20 similarly upon analyzing we have $E(a_5)$b1/b2 (significance)={E_1,E_6, E_{15}} two ambiguity result E_8, E_{13} and E_{12} ,E_{18} in failure cases similarly in negative cases E_5, E_7 are ambiguous result so need not go for further investigation so we can drop two attributes from the tables that is a_1,a_5 from the table so we are having new table given below . We are considering the definite cases whether insignificance or significance the cases where we are not sure of the result we keep those attribute in the table for further investigation, the reduct table which we generate presented in Table 3.

Table-3

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_2	b_2	b_1	b_3	c_1
E_5	b_1	b_2	b_3	c_2
E_6	b_2	b_2	b_2	c_1
E_7	b_2	b_2	b_2	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{10}	b_2	b_2	b_2	c_2
E_{11}	b_2	b_1	b_3	c_2
E_{12}	b_2	b_1	b_1	c_1
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{15}	b_1	b_1	b_1	c_1

E_{16}	b_1	b_1	b_1	c_1
E_{17}	b_2	b_2	b_2	c_2
E_{18}	b_2	b_2	b_3	c_2
E_{19}	b_2	b_1	b_3	c_2
E_{20}	b_1	b_2	b_3	c_1

In table 3 we found E_1,E_{12} provides same values similarly E_6,E_7 also provide the same result and E_2,E_{11} ambiguous result so we keep one table E_1 for E_1,E_{12} and keep E_6 for E_6,E_7 and drop both E_2,E_{11} from the tables to leads to

(Reduct from table3)

Table 4

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_5	b_1	b_2	b_3	c_2
E_6	b_2	b_2	b_2	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{10}	b_2	b_2	b_2	c_2
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{15}	b_1	b_1	b_1	c_1
E_{16}	b_1	b_1	b_1	c_1
E_{17}	b_2	b_2	b_2	c_2
E_{18}	b_2	b_2	b_3	c_2
E_{19}	b_2	b_1	b_3	c_2
E_{20}	b_1	b_2	b_3	c_1

From the table-4 we get conclusion that E_5,E_{20} provides ambiguous result so we drop both E_5,E_{20} from the table leads to table table-5

Table-5

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_6	b_2	b_2	b_2	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{10}	b_2	b_2	b_2	c_2
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{15}	b_1	b_1	b_1	c_1
E_{16}	b_1	b_1	b_1	c_1
E_{17}	b_2	b_2	b_2	c_2
E_{18}	b_2	b_2	b_3	c_2
E_{19}	b_2	b_1	b_3	c_2

Again analyzing table -5 we have E_6,E_{10} produces ambiguous result and { E_{13},E_{17} }leads to single results that is E_{13} so table -5 further reduces to

table -6 by deleting the ambiguity and redundancy

Table-6

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{15}	b_1	b_1	b_1	c_1
E_{16}	b_1	b_1	b_1	c_1
E_{18}	b_2	b_2	b_3	c_2
E_{19}	b_2	b_1	b_3	c_2

Now further classification E_{15},E_{16} leads to same class that is{ E_{15},E_{16} }= E_{15} further reduction produces table-7 by deleting the redundant rows.

Table-7

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{15}	b_1	b_1	b_1	c_1
E_{18}	b_2	b_2	b_3	c_2
E_{19}	b_2	b_1	b_3	c_2

Continuing the reduction process we further reduces E_{14},E_{18} giving the same conclusion both leads to same result which generate the reduction table as table-8

Table-8

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{15}	b_1	b_1	b_1	c_1
E_{19}	b_2	b_1	b_3	c_2

The same procedure again gives us further reduction that is E_8, E_{15} also leads to same information sets so further reduction gives another tale named as table-9

Table-9

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{13}	b_2	b_2	b_2	c_2
E_{14}	b_2	b_2	b_3	c_2
E_{19}	b_2	b_1	b_3	c_2

Here in table -9 again we have E_9,E_{14} leads to ambiguous results so dropping both the table for further classification we have table-10

Table-10

E	a_2	a_3	a_4	d
E_1	b_2	b_1	b_1	c_1
E_8	b_1	b_1	b_1	c_1
E_9	b_2	b_2	b_3	c_1
E_{13}	b_2	b_2	b_2	c_2
E_{19}	b_2	b_1	b_3	c_2

Now next we find the the strength[27] of rules for attributes a_2, a_3, a_4 strength of rules for attributes define as strength for an association rule x→D define as is the the number of examples that contain xUD to the number examples that contains x

$(a_2=b_2)\rightarrow(d=c_1)=2/3=66\%$
,$(a_2=b_1)\rightarrow(d=c_1)=1=100\%$,,$(a_2=b_2)\rightarrow(d=c_2)=2/4=25\%$,
$(a_2=b_1)\rightarrow(d=c_2)$=nil now we calculate strength for a_3
$(a_3=b_1)\rightarrow(d=c_1)=2/3=66\%$,$(a_3=b_2)\rightarrow(d=c_1)=1/2=50\%$,$(a_3=b_1)$
$\rightarrow(d=c_2)=1/3=33\%$,

$(a_3=b_2)\rightarrow(d=c_2)=1/2=50$

Similarly strength for a_4 will be $(a_4=b_1)\rightarrow(d=c_1)=1=100\%$
$(a_4=b_2)\rightarrow(d=c_1)=1=100\%$,$(a_4=b_1)\rightarrow(d=c_2)$=nil
$(a_4=b_3)\rightarrow(d=c_2)=1/2=50\%$, $(a_4=b_2)\rightarrow(d=c_2)=100\%$

In this analysis we find a_2 and a_3 must important attributes in analyzing the data analysis as because we are having a result for a_4 that is available gives a failure result so the conditional attribute a_4 is not that important like a_2,a_3 from the above analysis we develop a rule that is

Rule

1. Average a2, high a3, high a4 implies significant result
2. High a2,a3,a4 provide significant result
3. Average a2,a3 and low a4 provide significant result
4. Average a2,a3,a4 provide insignificant result
5. Average a2,a3, low a4 provide insignificant result
6. Average a2 high a3 low a4 provide insignificant result

a1, a2, a3, a4, a5 , b1, b2, b3, c1, c2 has it's usual meaning

4. STATISTICAL VALIDATION

We basically focus on small scale industries of rural and semi urban areas that is why we found chi squared test to validate our claim.

4.1 Experimental section

I had taken a survey of those families depends on small scale industries survey of different areas and apply our statistical validation on those collected data

Expected15%,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 $\sum(Oi-Ei)2/ Ei$ where i=0,1,2,3,4,5 so the calculated as follows X2=(25-30)2/20+(14-20)2/20+(34-30)2/30+(45-40)2/40+(62-60)2/60+(20-30)2/30

X2=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

Our experiment result is lies quite below the tabular values ,so it lies in the acceptable region .So we accept the hypothesis H0 that of our experiment result is correct.

5. FUTURE WORK

Ourwork can be extended to different fields like student feedback system , Business data analysis, Medical data analysis.

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