



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 7, July 2014

Best Project Selection of Student's through Rough Set, Bayes' Theorem Approach and Conflict Analysis

Sonu Rana¹, Dr. Abhoy Chand Mondal²

Assistant Professor of Aryabhata Institute of Engineering & Management, Department of CSE, Panagarh, Dist
Burdwan, Pin-713148, West Bengal, India

Associate Professor, The University Of Burdwan, Department of CSE, Dist-Burdwan, West Bengal, India

ABSTRACT: This article based on project selection procedure of student with help of rough set approach insight into Bayes' theorem which help to compute to prior or posterior probabilities structure of the data being analyzed through which can draw conclusion of data and also compute the relationship in between Bayes' theorem and flow graph [11] and the granularity or conflict analysis of data can be represented in a form of a flow graph, and the relation between granules obeys Bayes' theorem that leads a new relation of data of decision table [12,13,16].

KEYWORDS: Rough Set, Bayes' Theorem, Flow Graph, Conflict Analysis.

I. INTRODUCTION OF ROUGH SET

Rough set theory is a new mathematical approach to imperfect knowledge. The problem of imperfect knowledge has been tackled for a long time by philosophers, logicians and mathematicians. Recently it became also a crucial issue for computer scientists, particularly in the area of artificial intelligence. There are many approaches to the problem of how to understand and manipulate imperfect knowledge. The most successful one is, no doubt, the fuzzy set theory proposed by Zadeh [2]. Rough set theory proposed by the author in [1] presents still another attempt to this problem. The theory has attracted attention of many researchers and practitioners all over the world, who contributed essentially to its development and applications

II. INDISCRENIBILITY MATRIX

Let $I=(U, A)$ be an information system (attribute-value system), where 'U' is a non-empty set of finite objects (the universe) and 'A' is a non-empty, finite set of attributes such that $a:U \rightarrow V_a$ for every $a \in A$. 'V_a' is the set of values that attribute 'a' may take. The information table assigns a value $a(x)$ from 'V_a' to each attribute 'a' and object 'x' in the universe 'U' with any $B \subseteq A$ there is an associated equivalence relation $IND(B)$ [3,4,5,6].

Indiscrenibility-matrix is, $IND(B)=\{(x,y) \in U^2 \mid \forall a \in B, a(x) = a(y)\}$,

III. UPPER APPROXIMATION, LOWER APPROXIMATION & BOUNDARY REGION

The indiscrenibility relation will be used next to define approximations, basic concepts of rough set theory. Now approximations can be defined as follows: $B_*(X) = \{x \in U : B(x) \subseteq X\}$, $B^*(X) = \{x \in U : B(x) \cap X \neq \emptyset\}$, assigning to every subset X of the universe U two sets $B_*(X)$ and $B^*(X)$ called the B-lower and the B-upper



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 7, July 2014

approximation of X , respectively. The set $BN_B(X) = B^*(X) - B_*(X)$ will be referred to as the B -boundary region of X .

IV . INTRODUCTION OF BAYES' THEOREM

The Bayes' theorem is the essence of statistical inference. The result of the Bayesian data analysis process is the posterior distribution that represents a revision of the prior distribution on the light of the evidence provided by the data" [7]. "Opinion as to the values of Bayes' theorem as a basic for statistical inference has swung between acceptance and rejection since its publication on 1763" [8]. Rough set theory offers new insight into Bayes' theorem [9]. The look on Bayes' theorem offered by rough set theory is completely different to that used in the Bayesian data analysis philosophy. It does not refer either to prior or posterior probabilities, inherently associated with Bayesian reasoning, but it reveals some probabilistic structure of the data being analyzed. It states that any data set (decision table) satisfies total probability theorem and Bayes' theorem. The Bayes' theorem is the essence of statistical inference.

V . INFORMATION SYSTEMS AND DECISION RULES

Every decision table describes decisions (actions, results etc.) determined, when some conditions are satisfied. In other words each row of the decision table specifies a decision rule which determines decisions in terms of conditions. In what follows we will describe decision rules more exactly. Let $S = (U, C, D)$ be a decision table. Every $x \in U$ determines a sequence $c_1(x), \dots, c_n(x), d_1(x), \dots, d_m(x)$ where $\{c_1, \dots, c_n\} = C$ and $\{d_1, \dots, d_m\} = D$. The sequence will be called a *decision rule induced by x* (in S) and denoted by $c_1(x), \dots, c_n(x) \rightarrow d_1(x), \dots, d_m(x)$ or in short $C \rightarrow_x D$. The number $supp_x(C, D) = |C(x) \cap D(x)|$ will be called a *support* of the decision rule $C \rightarrow_x D$ and the number $\sigma_x(C, D) = \frac{supp_x(C, D)}{|U|}$

, will be referred to as the *strength* of the decision rule $C \rightarrow_x D$, where $|X|$ denotes the cardinality of X .

With every decision rule $C \rightarrow_x D$ we associate the *certainty factor* of the decision rule, denoted $cer_x(C, D)$

and defined as follows: $cer_x(C, D) = \frac{|C(x) \cap D(x)|}{|C(x)|} = \frac{supp_x(C, D)}{|C(x)|} = \frac{\sigma_x(C, D)}{\pi(C(x))}$, where

$\pi(C(x)) = \frac{|C(x)|}{|U|}$. The certainty factor may be interpreted as a conditional probability that y belongs to

$D(x)$ given y belongs to $C(x)$, symbolically $\pi_x(D | C)$. If $cer_x(C, D) = 1$, then $C \rightarrow_x D$ will be called a *certain decision rule* in S ; if $0 < cer_x(C, D) < 1$ the decision rule will be referred to as an *uncertain decision rule* in S . Besides, we will also use a *coverage factor* of the decision rule, denoted $cov_x(C, D)$ defined as

$cov_x(C, D) = \frac{|C(x) \cap D(x)|}{|D(x)|} = \frac{supp_x(C, D)}{|D(x)|} = \frac{\sigma_x(C, D)}{\pi(D(x))}$ where $\pi(D(x)) = \frac{|D(x)|}{|U|}$. Similarly

$cov_x(C, D) = \pi_x(C | D)$. We need also *approximate equivalence* of formulas which is defined as follows: $\Phi \equiv_k \Psi$ if and only if $cer(\Phi, \Psi) = cov(\Phi, \Psi) = k$. Besides, we define also *approximate equivalence* of formulas with the *accuracy* ε ($0 \leq \varepsilon \leq 1$), which is defined as follows: $\Phi \equiv_{k, \varepsilon} \Psi$ if and only if $k = \min\{cer(\Phi, \Psi), cov(\Phi, \Psi)\}$ and $|cer(\Phi, \Psi) - cov(\Phi, \Psi)| \leq \varepsilon$.

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 7, July 2014

VI. PROPOSED WORK

An example of decision table shown in below Table1. In this table S1,S2,S3,S4,S5,S6 are students who are submitting their project and waiting for their selection, so, the selection procedure totally depended some conditions or criteria i.e. $C1=Project\ field, C2=Project\ topic, C3=Project\ design, C4=Project\ implement, C5=Project\ performance$. Table 1 illustrates the problem of finding the relationship between project selection conditions and decision conditions.

Student	C1	C2	C3	C4	C5	Decisions	Supports
S1	Vgd	Gd	Gd	Gd	Gd	Select	440
S2	Gd	Gd	Md	Gd	Gd	Select	100
S3	Gd	Bad	Md	Md	Md	Reject	90
S4	Vgd	Gd	Md	Bad	Md	Reject	40
S5	Vgd	Vgd	Gd	Vgd	Gd	Select	210
S6	Gd	Gd	Md	Bad	Md	Reject	50

Table 1: Decision Table

The example provided above that some decisions cannot be described by means of conditions. However, they can be described with some approximations. So, the approximation of above table 1 are [10]-

- The set {5} is lower approximation of the set {1,2,5} in which *maximal* set of facts that can be *certainty* classified as selection in term of conditions.
- The set {1,2,3,4,5} is upper approximation of the set {1,2,3,4,5,6} in which the set of facts that *possibly* can be classified as selection in term of conditions.
- The set {1,2,3,4} is boundary region of the set {1,2,3,4,5} in which the set of facts can be classified neither select nor reject of project in term of conditions.
-

VII. COMPUTING STRENGTH, CERTAINTY COVERAGE FACTOR

for decision table are shown in Table 2.

Student	Strength	Certainty	Coverage
S1	0.47	0.94	0.10
S2	0.10	0.08	0.89
S3	0.09	0.92	0.99
S4	0.04	0.06	0.0006
S5	0.22	1.00	0.11
S6	0.05	1.00	0.99

Table 2: Strength, Certainty, Coverage factor of decision table

Bellow a decision algorithm associated with Table 1 is presented.

- 1) If criteria $C1\ vgd \ \& \ C4\ gd$ then $Decision \rightarrow Select$
- 2) If criteria $C1\ gd \ \& \ C4\ gd$ then $Decision \rightarrow Select$
- 3) If criteria $C1\ gd \ \& \ C4\ md$ then $Decision \rightarrow Reject$
- 4) If criteria $C1\ vgd \ \& \ C4\ bad$ then $Decision \rightarrow Reject$
- 5) If criteria $C4\ vgd$ then $Decision \rightarrow Select$
- 6) If criteria $C4\ bad$ then $Decision \rightarrow Reject$

The certainty factor of the decision rules lead the following conclusion:

-94% student project have been selected .

-8% student project have been selected

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 7, July 2014

- 92% student project have been rejected.
- 6% student project have been rejected.
- All student project have been selected.
- All student project have been rejected.

In other words :

-the most probability of select project 0.94 and 0.08 and all rejection probability 1.00 or selection probability 1.00.

Now let compute the inverse decision algorithm, which is given bellow :

- 1) If *Decision*→*Select* then criteria *C1* vgd & *C4* gd.
- 2) If *Decision*→*Select* then criteria *C1* gd & *C4* gd.
- 3) If *Decision*→*Reject* then criteria *C1* gd & *C4* md.
- 4) If *Decision*→*Reject* then criteria *C1* vgd & *C4* bad.
- 5) If *Decision* →*Select* then criteria *C4* vgd.
- 6) If *Decision*→*Reject* then criteria *C4* bad.

Now computing the inverse decision algorithm and the coverage factor we get the following explanation of decisions:

-decision for select projects are most probability 0.10 if *C1* vgd and *C4* gd and decision for all select project probability is 0.11 if *C4* is vgd.or probability for all reject project is 0.99.

VIII . FLOW GRAPH

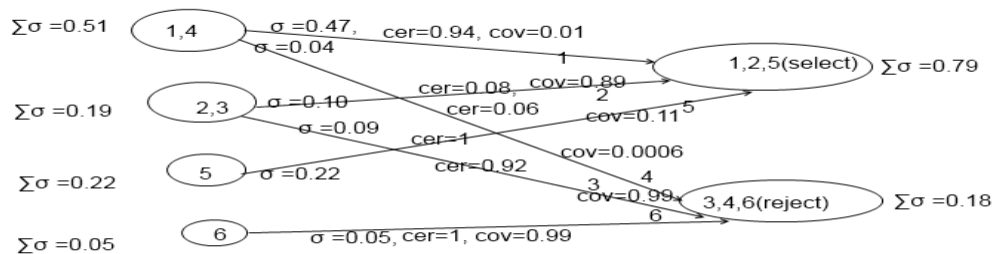


Fig 1:Flow graph of decision Table 2

So, with respect of rule 1 the condition *C1* and *C4* are approximately equivalent for selection project result where, $k=0.89$ and $\epsilon=0.81$, and the *C4* of project according to rule 3 is approximate equivalent to rejection result where, $k=0.99$, and $\epsilon=0.01$ or selection result where, $k=0.11$, and $\epsilon=0.89$.

IX . CONFLICT SPACE and CONFLICT GRAPH

With every decision table having one n-valued decision attribute we can associated n-dimensional Euclidean space where values of the decision attribute determine n axis of the space and condition attribute values (equivalence classes) determine point of the space. Strengths of decision rules are to be understood as coordinates of corresponding points[14,15].Distance $\delta(x, y)$ between granules x and y in an n-dimensional decision space is defined as

$$\delta(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

where $x=(x_1, \dots, x_n)$ and $y=(y_1, \dots, y_n)$ are vectors of strength of corresponding decision rules[16].Conflict Space for Table 1 is shown in Fig 2:

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 7, July 2014

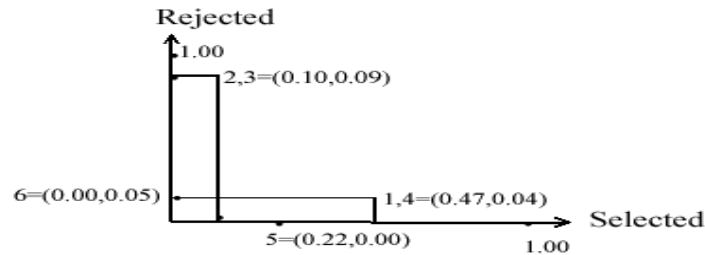


Fig 2: Conflict Space of Decision Table 1

So, the conflict graph or distances between granules (1,4),(2,3),(5),(6) are shown in bellow.

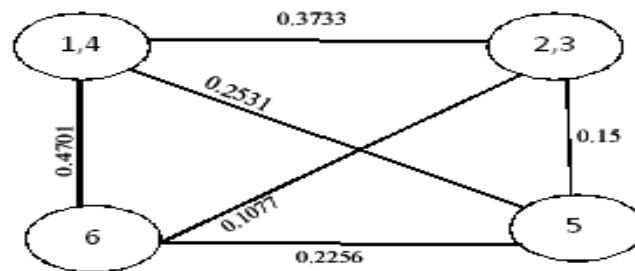


Fig 3: Conflict Graph

X . CONCLUSION

In this article, Bayes' theorem consists of prior or posterior probabilities and rough set approach to Bayes' theorem reveals data pattern, which normally used to draw conclusions from data in the form of decision rules[11]. Besides the rough set rules Bayes' approach invert rules for getting actual decision which shown in example in this article as well as it also help to associated to draw flow graph which gives a new tool to decision analysis. Besides, the relation between condition and decision granules are represented as flow graph and a conflict space is defined to analyze similarity of data granules[16].

REFERENCES

- [1] Z. Pawlak: Rough sets, International Journal of Computer and Information Sciences, 11, 341-356, 1982
- [2] L. Zadeh: Fuzzy sets, Information and Control, 8, 338-353, 1965
- [3] Z. Pawlak (1991), Rough Sets "Theoretical Aspects of Reasoning about Data".Kluwer Academic Publishers, Dordrecht.
- [4] Z. Pawlak: Rough sets, Int. J. of Information and Computer Sciences, 11, 5, 341-356, 1982
- [5] Z. Pawlak, A. Skowron: Rough membership function, in: R. E Yeager, M. Fedrizzi and J. Kacprzyk (eds.), Advances in the Dempster-Schafer of Evidence, Wiley, New York, 1994, 251-271
- [6] L. Polkowski, A. Skowron: Rough mereological calculi granules: a rough set approach to computation, computational intelligence: An International Journal 17, 2001, 472-479
- [7] G. E. P. Box, G. C. Tiao: Bayesian Inference in: Statistical Analysis, John Wiley and Sons, Inc., New York, Chichester, Brisbane, Toronto, Singapore, 1992



International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 7, July 2014

- [8] M. Berthold, D. J. Hand: Intelligent Data Analysis, an Introduction, Springer-Verlag, Berlin, Heidelberg, New York, 1999
- [9] Z. Pawlak: Rough Sets and Decision Algorithms, in: W. Ziarko, Y. Y. Yao (eds.), Second International Conference, Rough Sets and Current Trends in Computing, RSCTC 2000, Banff, Canada, October 2000, LNAI 2000, 30-45
- [10] Z. Pawlak: A Primer on Rough Set: A New Approach to Drawing Conclusions from Data.
- [11] Z. Pawlak: Bayes' Theorem – The Rough Set Perspective. Institute of Theoretical and Applied Informatics, Polish Academy of Sciences, ul. Bałtycka 5, 44 100 Gliwice, Poland.
- [12] Pawlak, Z. (1998). An Inquiry into Anatomy of Conflicts, Journal of Information Sciences, 109, 65-68.
- [13] Pawlak, Z. (2002). Rough Sets, Bayes' Theorem and Flow Graphs, IMPU 2002, To appear.
- [14] Slowinski, R. (1995). Rough Set Approach to Decision Analysis, AI Expert 10, 18-25.
- [15] "CONFLICTS AND DECISIONS", Zdzisław Pawlak, University of Information Technology and Management ul. Nowelska 6, 01 447 Warsaw, Poland.
- [16] Z. Pawlak, "Theorize with Data using Rough Sets", University of Information Technology and Management, Nowelska 6, 01 447 Warsaw, Poland

BIOGRAPHY



Ms. Sonu Rana, Assistant Professor of Aryabhata Institute Of Engineering & Management, Durgapur in Computer science and Engineering department. Received P.G degree from Dr.B.C.Roy Engineering college, Durgapur. Now pursuing Phd from Burdwan university under Dr. Abhoy Chand Mondal, Associate Professor of Burdwan University in CSE department. Interested research areas are Fuzzy, Ahp, Rough Set and Genetic Algorithm.



Dr. Abhoy Chand Mondal, He is an Associate Professor of Dept. of Computer Science, The University of Burdwan. He was born in 27/02/1964. He received his B.Sc.(Math-Hons.) degree from The University of Burdwan in 1987, M.Sc.(Math) and MCA from Jadavpur University in 1989 and 1992 respectively. He received his Ph.D. degree from Burdwan University in 2004. His research interest is in Soft Computing, Document Processing, Web Mining etc. He has 1 year industry experience and 168 years of teaching and research experience. No. of papers published is 50 (No. of Journal papers 20). So far two students awarded Ph.D. degree under his guidance. Currently 8 students are undergoing their Ph.D. work under his supervision.