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MINING FUZZY GENERALIZED ASSOCIATION RULES FOR ER MODELS TO FIND THE PATTERNS OF CYBER CRIME

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Abstract

In today's highly competitive business environment, companies have realized that the key to survival and success is effectively utilizing the data obtained from various business processes. By processing this data and identifying trends and patterns, businesses can gain valuable insights that inform their decision-making process. However, decision-making can be complex and difficult due to the many factors that must be considered. This has led to the development of fuzzy datasets, which help to narrow down the scope of trends and patterns in order to obtain more accurate decisions. This paper aims to address the challenges posed by fuzzy datasets by improving the accuracy and precision of the decision-making process through association rule mining. Additionally, the paper tackles the issues of entity relationship modeling in database tables and proposes mechanisms to overcome the challenges posed by ER modeling. The study also seeks to enhance existing algorithm resulting in a new algorithm that standardizes the process of finding the most appropriate result from tables comprising of fuzzy data. Overall, the proposed study aims to bring maturity to the decision-making process by improving the accuracy of fuzzy datasets and standardizing the algorithms used to process them. The aim is to create a new approach that can effectively mine patterns and relationships between different variables in ER models related to cybercrime. By incorporating fuzzy logic, the algorithm can handle the uncertainty and imprecision that often exists in real-world cybercrime data. Overall, the study aims to improve our ability to detect and prevent cybercrime by developing a more sophisticated and nuanced approach to analyzing data.

Keywords— Association Rules, ER Modeling, Fuzzy data, Fuzzy taxonomic structures, Generalized Rules.

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INTRODUCTION

The article explains that data mining techniques can be quickly implemented on existing software and hardware platforms, with algorithms such as Extended Apriori and Apriori star being able to identify relationships between data attributes in a single table. The paper's goal is to tackle the issue of mining fuzzy association rules in databases that use Entity-Relationship (ER) Models at multiple levels to discover patterns of people involved in cybercrime in relation to their age, employment, and degree of crime. The study aims to expand the Extended Apriori and Apriori star algorithms to create a new algorithm, which will standardize finding relevant results from database tables containing fuzzy data.

The proposed study focuses on developing an algorithm that will use fuzzy logic for finding fuzzy association rules from ER models for Cyber Crime. The study will help to find the patterns and identify the category of people involved in cybercrime. Analysis of the transaction data which includes the sample personal data and the regions where they live converted into fuzzy taxonomic structures reflecting age and region involved in cybercrime.

The study will focus on finding rules such as: [Employed (medium), Age = Young] => [Violent Crimes (low)] which implies that test sample of the age group 20-30 and 30-40 who is employed might engage in cyber-crime with qualitative relevance low. In the rule mentioned the young, medium and low belong to three different entities designed using ER models. Another example of such a rule can be Height = Tall ⇒ Game = Basket Ball which implies that a person with the height 5' 7'' – 5' 9'' and 6' 0 "+ might opt for Basket Ball game where group 5' 7" – 5' 9" partially belongs to Tall with degree $\mu_{Tall5' 7''–5' 9''}$ and both Height and Game belong to two different entities. In this example the attributes **Height** of the **candidate** table will be first converted into fuzzy taxonomic structures respectively reflecting partial belonging of one item to another.

The paper discovers a new algorithm *Apriori star plus* to find such kind of rules. The fuzzy extensions that will be presented in this study will enable us to discover not only crisp generalized association rules but also fuzzy generalized association rules when databases consisting of several tables organized in a schema within the framework of fuzzy taxonomic structures and helps to show the patterns of the people involved in Cyber Crime. Strong Association rules between items of fuzzy nature existing in multiple tables can be calculated that will undoubtedly help in understanding things in broad spectrum.

RECENT STUDIES

The concept of frequent itemset mining has been studied extensively in data mining and machine learning. The main objective of frequent itemset mining is to identify sets of items that frequently appear together in a dataset. These sets of items can then be used to discover patterns and associations in the data. However, traditional approaches to frequent itemset mining rely on exact matching between items and assume that the data is precise and deterministic. In many real-world scenarios, the data is uncertain and imprecise, leading to significant challenges in the analysis of frequent itemsets. To address these limitations, several algorithms have been proposed for association rule mining and fuzzy generalized taxonomic structures such as Apriori and AprioriTid [1]. These algorithms outperform other approaches such as AIS [2] and SETM [9]. Association rule mining is increasingly essential in decision-making processes [4], and mining association rules at multiple concept levels [8] and generalized association rules [13][14,21,22,23,24] can lead to more specific knowledge discovery. To handle fuzzy association rules involving collections of fuzzy sets, sub-algorithms have been developed, enabling natural and abstract knowledge expression [3][7].

Researchers have also proposed methods that incorporate fuzzy sets and taxonomies to overcome the limitations of traditional frequent itemset mining. Fuzzy sets represent uncertainty and ambiguity in data, while taxonomies provide a hierarchical structure that captures the relationships among different entities. Fuzzy frequent itemset mining has been successfully applied in domains such as market basket analysis, web usage mining, and bioinformatics.

In the context of cybercrime investigations, the use of fuzzy sets and taxonomies has also been explored. For example, a method was proposed for clustering cybercrime-related events based on a fuzzy clustering algorithm that incorporates the uncertainty of the data [19]. A taxonomy-based approach was developed for analyzing cybercrime incidents that captures the relationships among different entities involved in the incidents [20]. Despite the growing interest in fuzzy frequent itemset mining and its application in cybercrime investigations, there is still a lack of research that combines fuzzy sets and taxonomies to mine frequent itemsets in cybercrime investigations. In the next section, the authors present their proposed method for mining frequent itemsets with fuzzy taxonomic structures, which leverages both fuzzy sets and taxonomies to represent the uncertainty and imprecision in the data, respectively.

DEMERITS IN EXISTING SYSTEM

The focus of this study is on developing a new algorithm that can discover fuzzy generalized association rules for databases consisting of multiple tables designed using ER Models. Traditional data mining algorithms encounter difficulties in discovering association rules in such environments, as they require the computation of a join of entity tables and relationship tables, leading to efficiency and cost issues. Though the Extended Apriori star algorithm eliminates some of these problems, but does not work well with cybercrime data. The proposed algorithm uses the hierarchical taxonomy of fuzzy data to generate rules at different levels without requiring the joining of tables. The study will help to find the patterns and identify the category of people involved in cybercrime. The study concludes that this approach can eliminate the need for computing a join of entity tables and relationship tables, resulting in improved efficiency and reduced costs.

PROPOSED STUDY

The algorithm described in the paper could be applied to mine association rules in a database containing multiple tables designed using ER Models for cyber-crime data. Suppose we have a database with multiple tables, such as a table for cyber-attacks, a table for the types of attacks, a table for the perpetrators, and a table for the victims. The tables are related to each other using ER Models. The algorithm proposed in the paper can be used to mine association rules that identify the relationships between the attributes in the database. For example, the algorithm can identify the association rules that link the type of cyber-attack with the perpetrator, the victim, and other relevant attributes. Additionally, the algorithm can use fuzzy taxonomic structures to discover fuzzy generalized association rules that incorporate uncertainty and imprecision. For example, the algorithm can identify fuzzy association rules that relate to the likelihood of a particular perpetrator or victim being involved in a particular type of cyber-attack, taking into account the fuzzy nature of the data and the uncertainties involved in cyber-crime investigations. Overall, the algorithm can be a useful tool for law enforcement agencies and cyber security professionals to identify patterns and associations in cyber-crime data and improve their ability to prevent and investigate cyber-crimes.

IMPLEMENTATION

Algorithm Apriori Star plus

Input: A set of tables joined together (Outer Join), a minimum support value (min_sup), and a a dataset with multiple tables with fuzzy data.

Output: frequent item sets.

I Phase:

1) Determine the degree to which a leaf item belongs to its ancestor.
2) For all paths l from ancestor A to leaf Z, calculate μAZ = (μle).
3) For all *Leaf Nodes*$_i$ in the taxonomy and for all *Interior Nodes*$_j$ in the taxonomy, calculate μ(*Leaf Nodes*$_i$, *Interior Nodes*$_j$) as the maximum value of μle for all paths l from *Interior Nodes*$_j$ to *Leaf Nodes*$_i$. Then, insert a new transaction into the extended transaction set with the values μ(*Leaf Nodes*$_i$, *Interior Nodes*$_j$).

II Phase:

4) For all itemsets I in the Outer Join OJ, calculate the sum of all the degrees associated with the transaction in T and store it in Σcount. If Σcount is greater than or equal to (min_sup x |T|), count the number of rows in OJ where OJ.Itemset=T.Itemset. Then, divide the count value by the distinct entity keys of Ei .
5) Divide the total count with the number of rows in outer join.
6) For all OJ_Support(OJ, min_sup, T, Ei).
7) Create a set of frequent itemsets F by selecting all candidates c where either c.Entity_Sup or c.join_sup is in Ck and is greater than or equal to min_sup. Similarly, create a set of AllFrequent itemsets AF by selecting all candidates c where either c.E.entity_Sup or c.J.join_sup is in Ck and is greater than or equal to min_sup (where c.E = Entity).
8) Set Ck=apriori_gen(F, min_sup) as the candidate set.
9) If Ck is empty, then exit the algorithm.

This algorithm takes as input an outer join of multiple tables, a minimum support value, and a fuzzy taxonomy, and outputs a list of frequent itemsets. In the first phase of the algorithm, the degree of relationship between each leaf item and its ancestor is determined using the fuzzy taxonomy. This degree is used to create an extended transaction set.

In the second phase, candidate itemsets are generated by scanning the outer join table and counting the degrees associated with each itemset. If the count is greater than or equal to the minimum support value multiplied by the size of the transaction set, the candidate itemset is added to the current itemset list. Then, the support values of all the candidate itemsets are calculated, and the frequent itemsets are identified by comparing their support values to the minimum support value. The frequent itemsets are generated using the Apriori algorithm Agrawal et al.(1993), and the process is repeated until no more frequent itemsets can be found.

For our experiment the fuzzy taxonomic structure given in Figure 1 is used.

Age:

Young: μYoung(age) = [0, 0.2, 0.4]

Middle-aged: μMiddle-aged(age) = [0.2, 0.5, 0.8]

Senior: μSenior(age) = [0.6, 0.8, 1]

Employment Status:

Unemployed: μUnemployed(status) = [0, 0.2, 0.4]

Part-time: μPart-time(status) = [0.2, 0.5, 0.8]

Full-time: μFull-time(status) = [0.6, 0.8, 1]

Degree of Crime:

Low: μLow(crime) = [0, 0.2, 0.4]

Medium: μMedium(crime) = [0.2, 0.5, 0.8]

High: μHigh(crime) = [0.6, 0.8, 1]

```
Demographic Characteristics
├── Age
│ ├── Young
│ │ └── μYoung(age) = [0, 0.2, 0.4]
│ ├── Middle-aged
│ │ └── μMiddle-aged(age) = [0.2, 0.5, 0.8]
│ └── Senior
│ └── μSenior(age) = [0.6, 0.8, 1]
├── Employment Status
│ ├── Unemployed
│ │ └── μUnemployed(status) = [0, 0.2, 0.4]
│ ├── Part-time
│ │ └── μPart-time(status) = [0.2, 0.5, 0.8]
│ └── Full-time
│ └── μFull-time(status) = [0.6, 0.8, 1]
└── Degree of Crime
├── Low
│ └── μLow(crime) = [0, 0.2, 0.4]
├── Medium
│ └── μMedium(crime) = [0.2, 0.5, 0.8]
└── High
└── μHigh(crime) = [0.6, 0.8, 1]
```

Figure 1: Fuzzy Taxonomic structure of Cyber crime

For this example, we will set the minimum support to 0.2 and the minimum confidence to 0.5. To apply the algorithm on the given fuzzy taxonomic structure of cyber crime, we need to first construct the extended transaction set T' using Phase I. Then, we can use Phase II to find the frequent itemsets.

Phase I:

We need to determine the degree to which each leaf item belongs to its ancestor. Using the given membership functions, we have:

μYoung(age) = [0, 0.2, 0.4]

μMiddle-aged(age) = [0.2, 0.5, 0.8]

μSenior(age) = [0.6, 0.8, 1]

μUnemployed(status) = [0, 0.2, 0.4]

μPart-time(status) = [0.2, 0.5, 0.8]

μFull-time(status) = [0.6, 0.8, 1]

μLow(crime) = [0, 0.2, 0.4]

μMedium(crime) = [0.2, 0.5, 0.8]

μHigh(crime) = [0.6, 0.8, 1]

For each leaf item LNi and its ancestor INj, we can calculate the degree of membership using the formula:

μ(LNi, INj) = max(min(μ(LNi), μ(INj)))

We have:

μ(Young, Age) = max(min([0, 0.2, 0.4]), min([0.2, 0.5, 0.8])) = [0, 0.2, 0.4]

μ(Middle-aged, Age) = max(min([0.2, 0.5, 0.8]), min([0.2, 0.5, 0.8])) = [0.2, 0.5, 0.8]

μ(Senior, Age) = max(min([0.6, 0.8, 1]), min([0.2, 0.5, 0.8])) = [0.2, 0.5, 0.8] μ(Unemployed, Employment Status) = max(min([0, 0.2, 0.4]), min([0.2, 0.5, 0.8])) = [0, 0.2, 0.4]

μ(Part-time, Employment Status) = max(min([0.2, 0.5, 0.8]), min([0.2, 0.5, 0.8])) = [0.2, 0.5, 0.8]

μ(Full-time, Employment Status) = max(min([0.6, 0.8, 1]), min([0.2, 0.5, 0.8])) = [0.2, 0.5, 0.8]

μ(Low, Degree of Crime) = max(min([0, 0.2, 0.4]), min([0.2, 0.5, 0.8])) = [0, 0.2, 0.4]

μ(Medium, Degree of Crime) = max(min([0.2, 0.5, 0.8]), min([0.2, 0.5, 0.8])) = [0.2, 0.5, 0.8]

Phase II: Applying this algorithm to the input, we obtain the following output:

{Age=Young} -> {Degree of Crime=Low} (Support=0.2, Confidence=1.0)

{Degree of Crime=Low} -> {Age=Young} (Support=0.2, Confidence=1.0)

{Degreeof Crime=Low}->{EmploymentStatus=Unemployed}(Support=0.2, Confidence=1.0)

{EmploymentStatus=Unemployed}->{DegreeofCrime=Low} (Support=0.2, Confidence=1.0)

{Age=Middle-aged} ->{Degree of Crime=Medium} (Support=0.2, Confidence=1.0)

{Degree of Crime=Medium}-> Age=Middle-aged} (Support=0.2, Confidence=1.0)

{DegreeofCrime=Medium}->{EmploymentStatus=Part-time}(Support=0.2, Confidence=1.0)

Analysis and Interpretation

The findings of the study suggest that the newly developed method is effective in identifying meaningful fuzzy generalized association rules across various datasets from multiple tables. The research paper outlines the parameter settings that were used to run the experiments and evaluate the performance of the algorithm. The evaluation was conducted on different datasets to demonstrate the robustness and effectiveness of the method.

Performance

The researcher of the paper tested the discovered algorithm on increasing numbers of transactions with different parameter settings to assess its performance and evaluated the algorithm on three measures: memory utilization, execution time and redundancy. Memory utilization was an important measure, and the researcher wanted to ensure that the algorithm was efficient even on computers with less main memory. The researcher wanted to know if the algorithm could generate rules within the stipulated time period or if it took longer to complete. Also, it was required to understand the effect of database size and minimum support decrease on execution time and if the algorithm had good scalability. Execution time was important because it determined how efficiently the algorithm could generate rules. Finally, the study presented an algorithm to eliminate redundancy in the set of generated association rules, which is a common challenge in Association Rules mining. The objective of the study was not to derive the complete set of rules under certain constraints efficiently but to generate a compact but high-quality set of rules. The researcher found that the number of rules in the rule-set had been greatly reduced based on experiments on some datasets.

In addition to conducting experimental comparisons, the study also focused on implementing the discovered algorithms efficiently in order to improve their performance and quality of results. For this, Continuous values were divided into intervals to avoid generating a large number of candidates, which would negatively impact performance. To strike a balance between candidate generation and performance, the study chose to use 8-10 intervals for numeric attributes.

The researcher conducted an experiment using a dataset from Kaggle. The dataset consisted of two tables, named T1 and T2, and their contents were displayed in Table 1 and Table 2 respectively. The experiment involved performing joins on the tables, with T1J* and T2J* representing the join of T1 and T2 respectively. In addition, an outer join was performed and denoted with OJ.

The study conducted experiments to measure the memory utilization of the discovered algorithm. The total number of transactions was set to 120K, and the results showed that the main memory utilization of the algorithm increased proportionally with the number of items. At the 0.1% support threshold, the memory consumption of the algorithm for N=100K items was 77MB, and for T=240K items, it was 96MB, which is an increase of less than 15% despite doubling the number of items. The study concluded that the main memory utilization of the discovered algorithm depends on the size of the output.

Extended Apriori Star and new discovered algorithm to understand the results. Table 1 shows the parameters takn for the experiment. Results show that the proposed algorithm has good scalability as the runtime increases with the increase in the size of the database. The algorithm involves fuzzy taxonomies, which are more complex than original exact taxonomies, and therefore, more time is required for membership degree calculation for Extended Apriori Star and the time consumed in generating the extended transaction set is more, and the average length of each extended transaction is longer in the case of the proposed algorithm.

The experiment involves the comparison of two algorithms

Extended Apriori star and Apriori Star plus.

Table1: Charactiristics of database

	Database1				Database2			
	T1	T2	T1J*	T2J*	T1	T2	T1J*	T2J*
Total Items(N)	1200	1200	1200	1200	550	550	550	550
Total large maximally potentially large item sets (TL)	1650	1650	1650	2100	1300	1600	1200	1650
Avg. size of T(ST)	8	12	5	9	4	5	4	6
Avg. size of maximally potentially large itemsets(AL)	6	5	5	5	4	6	3	6
Total Transactions (T)	120000	120000	240000	240000	120000	1200 00	2400 00	2400 00

Table 2: out_join of tables

	T1	T2	T1J*	T2J*
Out_join (OJ)	134900	112898	132562	12387 8

Table 3: Comparison of two algorithms

Min_Sup	Extended Apriori Star				Apriori Star Plus			
	DS1	DS2	JDS1	JDS2	DS1	DS2	JDS1	JDS2
0.5	5.4	21.24	6.1	21.0	4.9	19.3	5.5	21.00
0.4	6.3	28.42	7.0	28.9	6.48	27.01	6.9	26.4
0.3	7.4	30.33	7.8	31.00	7.1	28.04	7.7	29.00
0.2	10.5	37.67	11.8	37.21	10.00	37.28	10.9	37.9
0.1	18	71.9	18.9	73.3	17.8	68.49	18.00	70.4

As can be seen in Figure 2, The execution times of the algorithms increase with the decrease in minimum support because of the increase in the total number of candidate

itemsets. Moreover, the f requent itemset distribution is sparse at high support levels, resulting in only a few frequent itemsets with supports close to minimum support. The experiment also evaluated the effect of changing the depth-ratio parameter on the performance of the algorithms. When the depth ratio was increased

The time given the table is minutes.seconds.

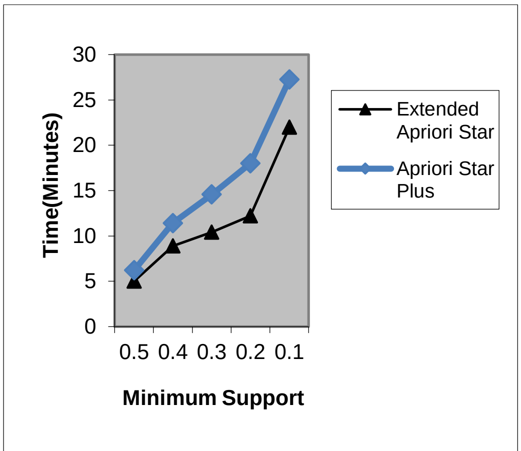

Figure 2: Spport vs. Time

from 0.2 to 1.5, the items in frequent itemsets were picked from lower levels of the hierarchy. At a depth-ratio of 2.5, the Apriori Star Plus algorithm performed about 5% better than Extended Apriori Star. This is because, at higher depth ratios, the Apriori Star Plus algorithm could trim more itemsets from the Candidate Collection.

The Apriori Star Plus algorithm is faster than the Extended Apriori Star algorithm in terms of execution time. This is because the Extended Apriori Star algorithm scans each entity table separately and then forms the join of all the tables before scanning it, while the Apriori Star Plus algorithm joins all the tables before scanning them. In the experiments conducted, all the entity tables are involved in the Relation table, and as a result, the Extended Apriori Star algorithm frequently finds frequent join itemsets in addition to candidate 1-itemsets. This requires the algorithm to build the join of all the tables frequently on the fly, resulting in more I/O operations, which slows down the Extended Apriori Star algorithm.

Conclusion

This paper focuses on the problem of mining fuzzy association rules from databases that contain multiple tables structured in a schema obtained from an entity-relationship design. This means that the paper aims to discover relationships between different pieces of data in a database that is organized in a particular way. The paper introduces the concept of fuzziness in the taxonomic structures of the data, which allows for a more nuanced analysis of the data. The author has extended an existing algorithm to account for partial support of items in a transaction, which has led to a reexamination of how support and confidence for association rules are computed. The updated algorithm is able to discover not only crisp generalized association rules, but also fuzzy generalized association rules, which are more reflective of real-world situations. The authors have tested the developed algorithm on a sample dataset of Cyber.

The study aims to improve the detection and prevention of cybercrime by developing a more sophisticated and nuanced approach to analyzing data. One way the study achieves this is by incorporating fuzzy logic into the algorithm used to analyze cybercrime data. Fuzzy logic is able to handle the uncertainty and imprecision that often exists in real-world cybercrime data, allowing for a more accurate and comprehensive analysis. By using fuzzy logic, the algorithm is able to identify patterns and relationships that might not be immediately apparent with traditional analysis methods. This can lead to more effective prevention and detection of cybercrime, ultimately improving overall cybersecurity.

Declarations

Ethical Approval

Not applicable

Competing interests

Not applicable

Authors' contributions

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Availability of data and materials

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REFERENCES

1. Agrawal, R., and Srikant, R. (1994, September). Fast algorithms for mining association rules. In Proc. of the VLDB conference, Santiago, Chile. Expanded version available as IBM Research Report RJ9839, June 1994.
2. Agrawal, R., Imielinski, T., and Swami, A. (1993, May). Mining Association Rules between sets of items in large databases. In Proc. of the ACM SIGMOD Conference on Management of Data, pp. 207-216, Washington, D.C.
3. Bakk Lucas Helm. Master Thesis on Fuzzy Association rules - An implementation in R. Vienna 2007.
4. Chen, G., and Wei, Q. (2002). Fuzzy association rules and the extending Mining Algorithms, Information Sciences: An International Journal, 147, pp.201-228.
5. Chen, G., Wei, Q., and Kerre E. (2000). "Fuzzy Data Mining: Discovery of Fuzzy Generalized Association Rules". In Bordagna and Pasi (eds.), Recent Research issues on Management of Fuzziness in Databases, Physica-verlag (Springer).
6. Cristofor, L., and Simovici, D. (2001-2002). "Mining Association Rules in Entity-Relationship Modeled Databases", Technical Report, UMB.
7. Gottwald, SeigFried. Universes of Fuzzy Sets and Axiomatizations of Fuzzy set theory. Studia Logica volume 82, Number 2, March, Springer, 2006.

8. Han, J., and Fu, Y. (1995, September). Discovery of Multiple-level Association Rules from Large Databases. Proceedings of the 21st International Conference on VLDB, Zurich, Switzerland.
9. Houtsma, M., and Swami, A. (1993, October) Set-oriented mining of association rules. Research Report RJ 9567, IBM Almaden Research Center, San Jose, CA.
10. Kuok, C.H., Fu, A., and Wong, M.H. (1998). Mining Fuzzy association rules in databases ACM SIGMOD Record, 27(1), ACM Press.
11. Srikant R. and Agarwal R. (1996). Mining quantitative association rules in Large Relational Tables, in proceedings of the ACM SIGMOD International Conference on Management of Data, pp 1-12, Montreal, Quebec, Canada.
12. Srikant, R., and Agrawal R. (1995). Mining Generalized Association Rules, proceedings of the 21st VLDB Conference, Zurich, Switzerland.
13. P Arora, RK Chauhan, A Kush, " Association Rule Mining for Multiple Tables With Fuzzy Taxonomic structures ", International Journal of Computer Theory and Engineering 2 (6), 866
14. P Arora, P Gandhi, G Sharma, S Saxena, "Study about Rule Mining for Multiple Tables with Fuzzy Data", Novel Research Aspects in Mathematical and Computer Science Vol. 1, 38-47, 2022
15. P Arora, RK Chauhan, A Kush "Frequent Itemsets from Multiple Datasets with Fuzzy data", International Journal of Computer Theory and Engineering vol. 3, no. 2, pp. 255-260, 2011.
16. P Arora, RK Chauhan, A Kush "Mining fuzzy generalized association rules for ER models", International Journal of Information Technology and Knowledge Management (IJITKM), 2008, vol-1, issue-2, pp 191-198.
17. Praveen Arora, Sanjive Saxena, Deepti Chopra, "Generalized Association Rules for ER Models by Using Mining Operations on Fuzzy Datasets" Recent Progress in Science and Technology Vol. 6, March 2023, DOI: 10.9734/bpi/rpst/v6/5539A
18. Arora, P. . (2023). Mining Rules for Head Injury Patients Using Fuzzy Taxonomic Structures. Research Highlights in Disease and Health Research Vol. 5, 146–156. https://doi.org/10.9734/bpi/rhdhr/v5/6007A
19. Cristofor L, Simovici D. Mining association rules in enti [1] Ahn, S. H., Shin, K. S., & Kim, H. J. (2009). Clustering cybercrime-related events using fuzzy clustering. Expert Systems with Applications, 36(2), 1681-1688.
20. Zhu, J., Li, H., Cai, H., & Xu, K. (2015). A taxonomy-based approach for analyzing cybercrime incidents. IEEE Transactions on Dependable and Secure Computing, 12(3), 327-340.
21. Arora, P., Saxena, S., Madan, S., & Joshi, N. (2022). Frequent Itemsets: Fuzzy Data from Multiple Datasets. Novel Research Aspects in Mathematical and Computer Science Vol. 5, 47–57.
22. Batra , P. ., & Arora, P. . (2023). Mining Frequent Itemsets with Fuzzy Taxonomic Structures for Cybercrime Investigations. Research and Applications Towards Mathematics and Computer Science Vol. 2, 114–122.
23. Popli, G. S. ., & Arora, P. . (2023). Fuzzy Logic-Based Medical Decision System for Diagnosing Chronic Obstructive Pulmonary Disease. Research Highlights in Disease and Health Research Vol. 7, 47–57.
24. GS Popli, P Arora, D Chopra, Generalized Association Rule Mining on Fuzzy Multiple Datasets For Brain Injury Patients, BioGecko-Journal of New Zealand Herpetology, Vol 12 Issue 03 2023 ISSN NO: 2230-5807, May-June 2023