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# A Way to Generate Frequent Pattern Mining using Vertical Partitioning of Data with Parallel Computing

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***Abstract:*** ***The performance of association rule algorithms is also evaluated based on time-complexity and accuracy of frequent item set Also, Frequent item set is highly dependent on the user input status such as minimum support. It is difficult to know the meticulous minimum support because these it generate logically incorrect or irrelevant FIS and sometime loose of worthy FIS. These issues can be resolved with the help of Proposed Vertical Approach In this paper, a detailed comparison has been made for the frequent pattern mining with normal approach and vertical approach with proper example. It shows that how can we achieve logically relevant FIS as well as Produces FIS for few categories that are lesser in demand but have higher worth using vertical approach. The Proposed vertical Approach provides a multi-level view of the dataset by clustering w.r.t. to category of the product.***

***Keywords: Frequent item set, Association rule Mining, Apriori, Large database , Vertical approach***

## I. INTRODUCTION

Association rule mining attempt to determine relations among transactions in a transactional database. Ascertaining valuable frequent pattern unknown in database play vital role to increase the business profit in the applications like retail stores, online shopping database etc. ARM can be used to advance decision making in a wide variety of applications. Data mining can abstract important facts such as frequent item set from large data set – nevertheless sometimes it is challenging to achieve all frequent item set if these datasets are fragmented into many clusters when there is a large dataset.

Fast development in technology has resulted increase of great amount of data for any e-commerce organization and therefore now a days fetching needed information from huge dataset has been a big challenge. The discovered interesting patterns from transactional records can help many organizations for decision-making processes like catalog preparations, cross-marketing and to analyze the customer shopping behavior. The basic concept of frequent pattern mining is to find out the patterns of frequent item sets presence in the database is more than a specified minimum support or threshold.

$$\text{Min. Support } (A \Rightarrow B) = P\,(A \cup B)$$

Where A and B is items of transactions. & Min. Support is the % of transactions in which contain both items A and B.

$$\text{Confidence } (A \Rightarrow B) = P\,(B|A)$$

Confidence is ratio of transactions in datasets which containing number of times item A with respect to item B.

Association rule mining is a method for discovered the set of frequent items or interesting pattern based on minimum support and rules based on confidence.

In the method of computing the speed of the occurrences of a remarkable frequent items within the large transactional database and its computational time always could be a big factor of attention for researchers. to get rid of the exponentially more number of candidates, many algorithms, which are most often employed by researchers, try to get less Candidate with user defined min support. while with pruning, finding all frequent item sets from large datasets requires high computation power of CPU and required plenty of memory.

This research paper evaluates the performance of proposed algorithm with Apriori, FP-Growth, ECLAT frequent itemset mining algorithms. This research is limited to frequent itemset mining. By limiting the experimentation to a single implementation of frequent itemset mining this research is able to evaluate the characteristics of the dataset such as number of FIS, transaction, Minimum support affect the performance of all algorithms. So the concept of association rule mining is to discover the sets of items nurture to associate with the others in the database.

The remaining of this paper is organized as: section 3 discuss the literature review in the related field, section 4 emphasize the proposed vertical approach and concern existing normal approach, section 5 gives the experimentation results of the implemented system with example, finally, section 6 will be concluded along with future work.

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## II. LITERATURE REVIEW

The foremost famous is that the Apriori algorithm which has been brought in 1993 by Agrawal et al. [1] which uses association rule mining[2][3][4] [5][6] Association rules are usually required to satisfy a user-specified minimum support and a user-specified minimum confidence at the identical time. Association rule generation is usually get a divorce into two separate steps: 1. Minimum support (threshold) is applied to go looking out all frequent item-sets during a very database. 2. These frequent item-sets and also the minimum confidence constraints are accustomed form rules. In order to spice up the performance of association rule mining, many researchers tried to distribute dataset into the mining computation over quite one processor or a standard computer have multicore for executing a task[7][8][9]. A method of accelerating the computational speed is by using all core within one computer.

Jun Yang, Haoxiang Huang et al. [10] in their paper, used the Apriori algorithm to mine the frequent access pattern in the web access paths. Aiming at the shortcomings of Apriori algorithm, an improved algorithm named AC-Apriori based on traditional Apriori algorithm is proposed and implemented. The AC-Apriori algorithm combines the Apriori algorithm with the AC automation. Compared with the traditional Apriori algorithm, AC-Apriori algorithm reduces the time scanning database, reduces the runtime and improves the efficiency

Li Zhan, Fusheng Yu et al. [11] proposed a quick algorithm for temporary organization rules. In this paper, the tests in the synthetic dataset and the original data show the best performance of the proposed new algorithm and the efficiency test shows that the proposed new algorithm can obtain the rules of transient integration successfully. The proposed new algorithm can only be acquired temporarily for organization rules on purchase data, but not throughout the time series.

Xiaorong Cheng et al. [12] aimed at the problem of updating the association rules when extending data sets while keeping minimal support unchanged, on the basis of the FUP algorithm, this paper proposes a matrix-based integration of the mining rules algorithm, namely the MBFUP algorithm. The algorithm only scans the data scanner once, which greatly reduces the complexity of the space and the complexity of the algorithm.

LIU Jian-ping et al. [13] has proposed a new type of Pre-FP algorithm based on the concept of large-scale objects. The main idea is that by predicting a "top" and "bottom" support framework, it sets up large-scale forecasts other than the usual and impossible things. This method has reduced the time to delete real transaction data.

Siqing Shan et al.[14] have discovered the problem of continuous updating of large data in their paper. They have proposed a method to reduce data size during the reconstruction process. They have given a description and algorithm for T-tree marketing. The order of things in every T-Tree is different from that in FP-Tree. They have proposed a general continuous algorithm or CIU algorithm in brief. Use of the CIU algorithm, and studied its performance compared to the FP-growth algorithm in big data is seen in this paper.

Anjana Gosain [15] et al. presented an analysis of different association rules proposed by different authors to deal with quantitative data. In this paper, they have examined the rules of the association for various parameters and provided a comparative study of the tabular method. The direct application of organization management to the data may produce a large number of very important rules, so domain knowledge, data features, and application intent to be developed should be considered during the mining process. For future work, they have proposed a framework that involves association rules for data warehouses that exceed the above problems observed by various authors in current findings and implementation.

Jun Tan, Yingyong Bu et al. [16] have proposed Fd-Tree method that does not require scanning of the entire data stream and only scans the revised transactions simultaneously without involving the election generation. Test results in synthetic and real-time data show that the new algorithm surpasses other algorithms not only in terms of speed of algorithms, but also in their memory usage and robustness. They propose, a new approach to the expanding organization that governs mines over data sources. This method is based on the structure of the Fd tree that requires the scanning of the original data and only scans the updated ones simultaneously without involving the candidate generation.

Guoling Liu et al. [17] designed a new and efficient algorithm and proposed parameter C as a stamp. Using the lift, the noise rules are removed from the local branch mines. It avoids I/O transmission and network connectivity. It focuses on the number of resources and the level of support, thereby greatly increasing the accuracy of the global association rule mining. It only looks at all the details of a single database and avoids re-scanning of old data to retrieve new information from incremental addition to dataset. This paper discusses only the positive association rule mining over multiple databases. Future work will consist of negative cases of association mining over multiple databases.

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Wenjuan Dong et al. [18] have proposed a new MIIWIU algorithm, the algorithm uses an improved Apriori algorithm and a set of common input elements. The traditional Algorithm Apriori treats each item as identical, ignoring the differences of all objects. The concept of weight is added to the algorithm. Negative association rules exist not only in frequent itemset, bur more exist in infrequent item set. Incremental updating algorithm is important for mining infrequent itemset in dynamic databases.

V.S Tseng et al. [19] propose two algorithms, namely utility pattern growth (UP-Growth) and UP-Growth+, for mining high utility item sets with a set of effective strategies for pruning candidate item sets. Mining high utility item sets from a transactional database refers to the discovery of item sets with high utility like profits. Although a number of relevant algorithms have been proposed, they incur the problem of producing a large number of candidate item sets for high utility item sets. Such a large number of candidate item sets degrades the mining performance in terms of execution time and space requirement.

S. Barua et al. [20] proposed a method for finding patterns based on a statistical test. The proposed model for the null distribution of features, spatial auto-correlation is taken into account and design an algorithm for finding both co-location and segregation patterns. Also it develops two strategies to reduce the computational cost compared to a naïve approach based on simulations of the data distribution, and proposed an approach to reduce the runtime of our algorithm even further by using an approximation of the neighbourhood of features.

## III. PROPOSED VERTICAL APPROACH

In proposed vertical approach, category-wise layout is considered. The dataset is split into 21 unique category cluster. For each category, clusters are generated. Each of the Local FIS result is combined to get the Global FIS result.

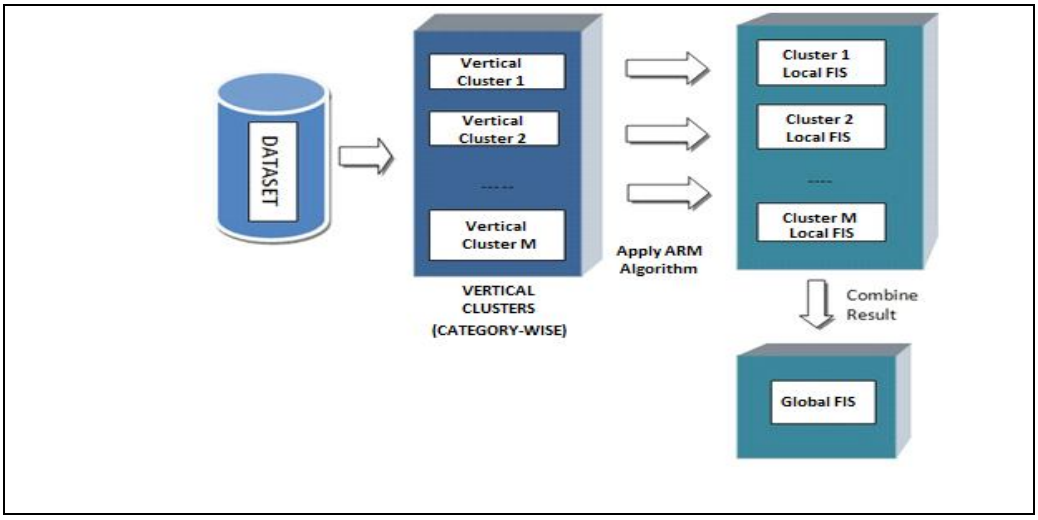



Fig. 4.3: Proposed Vertical Approach

Fig 4.3 shows the visualization of how Proposed Vertical approach works. It shows that how dataset is divided into 'M' clusters and each cluster generates their Local FIS. For FIS generation, the ARM algorithm is applied on each cluster. All Local FISs are combined and the Global FISs are stored in the Database.

### *A. General Concerns of Existing Normal Approach*

In Normal and Horizontal approach, it was observed that due to constant Minimum support across all categories and clusters, it creates two specific issues:

1) *Loss of worthy FIS:* For categories that have lesser number of buyers but have more worth are discarded from Final FIS. Since the number of transactions are comparatively lesser in few categories, the minimum support threshold for that category must be lower.
2) *Inter-Category Issue:* For cases, where minimum support is lower, FIS generated contains irrelevant patterns of items that are practically possible but logically does not have any association. These issues can be resolved with the help of Proposed Vertical Approach. As each level of abstraction must have their own Minimum support threshold, the Proposed vertical Approach provides a multi-level view of the dataset by clustering w.r.t. to category of the product.

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## IV. EXPERIMENTATION RESULTS

Let us consider a dataset consisting of 50 Transactions (T1-T50) and 24 items (I1-I24).

Table 1: Transactional Dataset to demonstrate Proposed Vertical Approach

| Transaction | Item1 | Item2 | Item3 | Item4 | Item5 | Item6 | Item7 | Item8 | Item9 |
|---|---|---|---|---|---|---|---|---|---|
| T1 | Charger | Handset | Bread | Oil | Milk | Oven | Mixer | | |
| T2 | Handset | Bread | Rice | Tea | Oven | | | | |
| T3 | Battery | Handset | Cover | Bread | Sauce | Tea | Fridge | Mixer | Stove |
| T4 | Handset | Bread | Oil | Sauce | Milk | TV | Oven | Stove | |
| T5 | Battery | Cover | Selfistick | Rice | Tea | Milk | Dal | Fridge | Mixer |
| T6 | Battery | Handset | Selfistick | Oil | Tea | TV | Iron | Oven | |
| T7 | Powerbank | Oil | Tea | TV | Oven | | | | |
| T8 | Rice | Milk | Dal | Oven | | | | | |
| T9 | Handset | Oven | | | | | | | |
| T10 | Battery | Cover | Selfistick | Rice | Tea | Dal | | | |
| T11 | Charger | Handset | Cover | Rice | Sauce | Tea | | | |
| T12 | Battery | Powerbank | Selfistick | Oil | Sauce | Milk | | | |
| T13 | Cover | Selfistick | Rice | | | | | | |
| T14 | Cover | Powerbank | Bread | Tea | Dal | | | | |
| T15 | Powerbank | Selfistick | Sauce | Milk | | | | | |
| T16 | Charger | Battery | Cover | Bread | Oil | Tea | | | |
| T17 | Handset | Cover | Selfistick | Oil | Sauce | Milk | | | |
| T18 | Charger | Handset | Selfistick | Oil | Tea | Milk | | | |
| T19 | Battery | Handset | Cover | Rice | Oil | Sauce | | | |
| T20 | Handset | Cover | Selfistick | Bread | Dal | | | | |
| T21 | Charger | Powerbank | Bread | Sauce | Milk | | | | |
| T22 | Cover | Selfistick | Bread | Sauce | Tea | | | | |
| T23 | Battery | Cover | Selfistick | Rice | Oil | Sauce | Milk | | |
| T24 | Handset | Selfistick | Rice | Oil | Tea | | | | |
| T25 | Charger | Cover | Selfistick | Oil | Tea | | | | |
| T26 | Handset | Powerbank | Bread | Sauce | Dal | | | | |
| T27 | Battery | Cover | Selfistick | Oil | Sauce | Tea | Dal | | |
| T28 | Battery | Selfistick | Rice | Oil | Tea | | | | |
| T29 | Cover | Bread | Oil | Tea | | | | | |
| T30 | Charger | Battery | Selfistick | Sauce | | | | | |
| T31 | Charger | Bread | Oil | Dal | | | | | |
| T32 | Handset | Cover | Oil | Sauce | | | | | |
| T33 | Battery | Selfistick | Bread | Sauce | | | | | |
| T34 | Powerbank | Selfistick | Rice | Milk | Dal | | | | |
| T35 | Handset | Selfistick | Bread | Tea | | | | | |
| T36 | Charger | Cover | Tea | TV | Mixer | Stove | | | |
| T37 | Battery | Powerbank | Oil | Sauce | Iron | Oven | | | |
| T38 | Cover | Selfistick | Milk | Fridge | Oven | | | | |
| T39 | Powerbank | Battery | Bread | Tea | Dal | Fridge | Oven | Stove | |
| T40 | Charger | Cover | Rice | TV | Oven | | | | |
| T41 | Battery | Selfistick | Oil | Sauce | Jeans | T-shirt | Fridge | Iron | |
| T42 | Handset | Cover | Rice | Dal | T-shirt | TV | Iron | Stove | |
| T43 | Cover | Bread | Oil | Tea | Jeans | Shirt | Oven | | |
| T44 | Battery | Powerbank | Selfistick | Bread | Oil | Fridge | TV | Oven | |
| T45 | Charger | Battery | Selfistick | Oil | T-shirt | Shirt | Iron | Stove | |
| T46 | Handset | Powerbank | Bread | Milk | Jeans | Fridge | Oven | | |
| T47 | Cover | Selfistick | Bread | Sauce | Dress | TV | Stove | | |
| T48 | Battery | Cover | Selfistick | Oil | Jeans | Fridge | TV | Oven | |
| T49 | Charger | Cover | Oil | Tea | Dal | TV | Iron | Mixer | Stove |
| T50 | Handset | Selfistick | Bread | Milk | Jeans | Dress | TV | | |

Solving above dataset using Apriori algorithm for Min. support = 0.2 with Normal approach,

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Following were the Global FIS obtained using both the approach,

Table 2: FIS generated in Normal Approach

| Normal Approach (FIS) | | |
|---|---|---|
| S. No | Item1 | Item2 |
| 1 | Charger | |
| 2 | Sauce | |
| 3 | Tea | |
| 4 | Milk | |
| 5 | Dal | |
| 6 | Battery | |
| 7 | TV | |
| 8 | Oven | |
| 9 | Handset | |
| 10 | Cover | |
| 11 | Powerbank | |
| 12 | Selfistick | |
| 13 | Bread | |
| 14 | Rice | |
| 15 | Oil | |
| 16 | Battery | Selfistick |
| 17 | Battery | Oil |
| 18 | Cover | Tea |
| 19 | Cover | Selfistick |
| 20 | Cover | Oil |
| 21 | Selfistick | Sauce |
| 22 | Selfistick | Tea |
| 23 | Selfistick | Oil |
| 24 | Oil | Tea |

As shown in Table 2, As shown in the Table 4.11, number of FIS generated using Normal Approach = 24 and particular frequent item sets such as {Fridge, Oven}, {TV, Oven}, {TV, Stove} are electronics product which are costlier than groceries/accessories but at the same time, they are less purchased by the buyers. In Normal Approach, such FIS are directly discarded due to a uniform Minimum support threshold for all categories

Now, Solving Table 1 dataset using Apriori algorithm for Min. support = 0.2 with Vertical approach,

*1)* For Proposed Vertical Approach No. of Clusters = No. of Categories,
*2)* For current dataset No. of Categories = 4 (Accessories, Grocery, Electronics, Clothing)

| Category No. | Category Name | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 | Item 6 | Item 7 |
|---|---|---|---|---|---|---|---|---|
| Category-1 | MOBILE | Charger | Battery | Handset | Cover | Powerbank | Selfistick | |
| Category-2 | GROCERIES | Bread | Rice | Oil | Sauce | Tea | Milk | Dal |
| Category-3 | CLOTH | Jeans | T-Shirt | Dress | Kurtis | Shirt | | |
| Category-4 | APPLIANCES | Fridge | Tv | Iron | Oven | Mixer | Stove | |

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Now, Table 3 shows the Global FIS obtained using Vertical the approach,

Table 3: FIS generated in Proposed Vertical Approach

| Vertical Approach (FIS) | | |
|---|---|---|
| S. No | Item1 | Item2 |
| 1 | Charger | |
| 2 | Sauce | |
| 3 | Tea | |
| 4 | Milk | |
| 5 | Dal | |
| 6 | Jeans | |
| 7 | T-shirt | |
| 8 | Dress | |
| 9 | Shirt | |
| 10 | Fridge | |
| 11 | Battery | |
| 12 | TV | |
| 13 | Iron | |
| 14 | Oven | |
| 15 | Mixer | |
| 16 | Stove | |
| 17 | Handset | |
| 18 | Cover | |
| 19 | Powerbank | |
| 20 | Selfistick | |
| 21 | Bread | |
| 22 | Rice | |
| 23 | Oil | |
| 24 | Fridge | Oven |
| 25 | Battery | Selfistick |
| 26 | TV | Oven |
| 27 | TV | Stove |
| 28 | Cover | Selfistick |
| 29 | Oil | Tea |

As shown in the Table 2, number of FIS generated using Normal Approach = 24 whereas in Table 3, number of FIS generated using Proposed Vertical Approach = 29. With vertical approach, we observed that both issues that arise in Normal approach were handled in Vertical approach.

In the Vertical Approach, a reasonable Minimum support threshold is used based on number of transactions within that category, this results in the generation of FIS even from those categories.

Frequent item sets such as {Battery, Oil}, {Cover, Tea}, {Selfistick, Sauce}, etc these item sets, even though, they surpass the Minimum support threshold and does have a logical association.

In Normal Approach, such FIS are considered but in the Vertical approach, the inter-category issue is resolved as clusters are formed of similar category items only.

## V. CONCLUSION AND FUTURE WORK

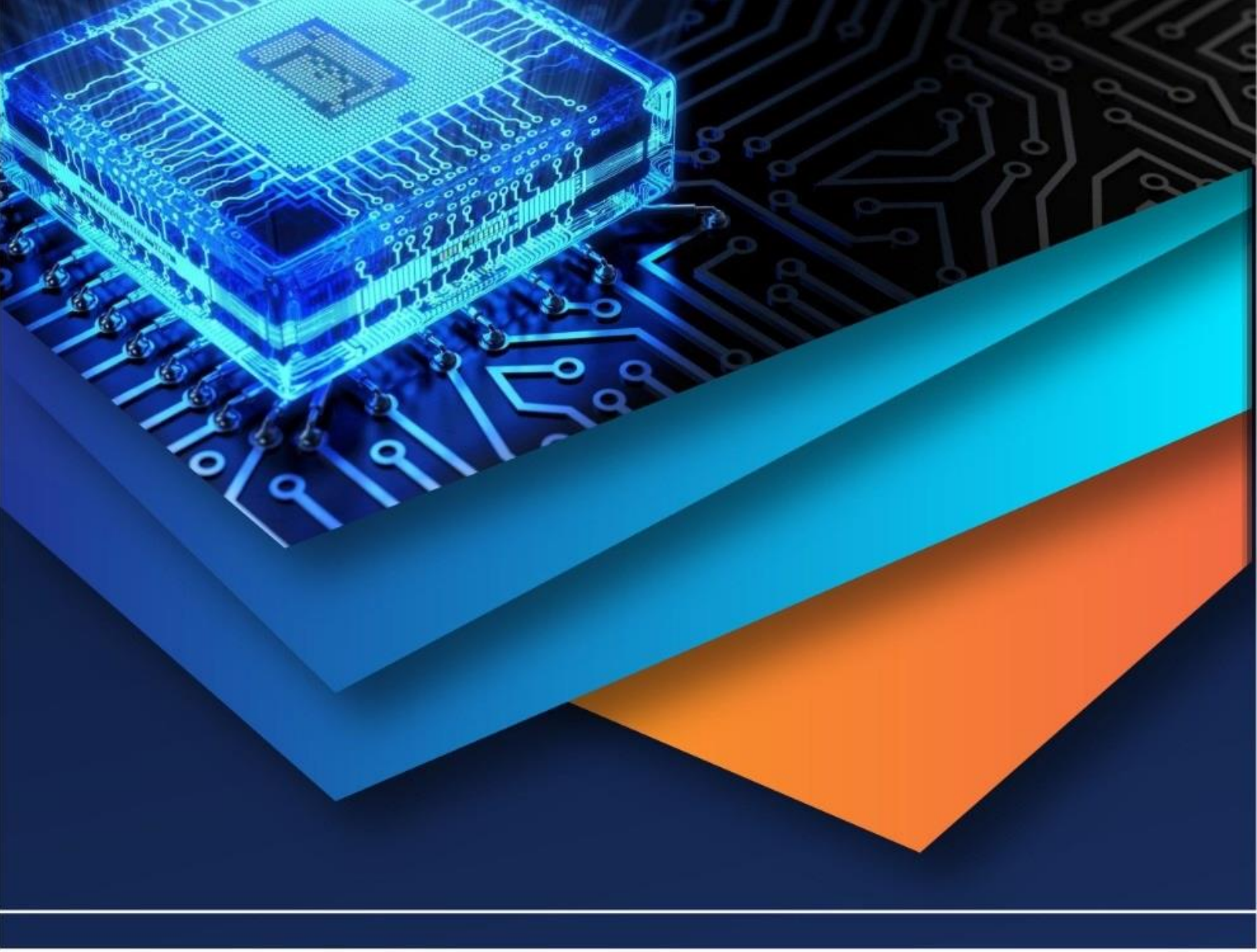
It conclude that vertical approach, (A) Resolves Inter-Category issue of irrelevant FIS generation. (B) Generates FIS based on proportionate Minimum support values for clusters. (C)Produces FIS for few categories that are lesser in demand but have higher worth. In future, This paper can be extend to hybrid approach to generate association rule from the generated frequent itemsets in an efficient manner.

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