Comparative Study of Popular Data Mining Algorithms

T. Venkat Narayana Rao
Professor, Department of Computer Science and Eng.
Sreenidhi Institute of Science and Technology(SNIST)
Yamnampet, Hyderabad, TS, India.

Harsh Goel
Department of Computer Science and Engineering
Sreenidhi Institute of Science and Technology(SNIST)
Yamnampet, Hyderabad, TS, India.
Email:harshgoel1999@gmail.com

Abstract: Data Science is an appealing field , in the present world due to advancement of science as there is huge assortment of data which exist in numerous forms . Such data must be handled with care and store safely so that it can be retrieved as per needs. Some of the popular or commonly used algorithms are Apriori algorithm, K Means Clustering, Support Vector machines(SVM) and Association Rule Mining algorithms. This paper focus on the above mentioned algorithms and a comparison is made in terms of Technique, Time Utilization Software taking real time data examples.

Keywords*: Apriori, time, efficiency, Support Vector Machines(SVM),K Means clustering.*

*****

I. Introduction

Data science has been a term in the computing field since 1960. It is interdisciplinary, incorporating elements of statistics, data mining, and predictive analysis, and focusing on process and systems that extract knowledge from the data. Basically three methodologies are followed in data science namely classification, regression and similarity matching. A number of algorithms were built on statistical models that are available for data scientists and which algorithm is chosen is based on the goals that have been established prior to implementation. From the emergence of Big Data, data science began to be a fundamental requirement of any organization on working out how to analyze such massive amount of data. Comparative study tells us about various factors involved in algorithms such as system used, time utilization, memory usage , software needed etc[1][2].

II. Popular Data Mining Algorithms

A. Apriori algorithm:

Apriori is an algorithm for items which occur frequently over databases. It was proposed by Agrawal and Srikant in 1994. It starts by identifying ordinary things and extend them to bigger items as long they appear regularly. The common items set that are determined by Apriori can be used to find association rules which have application in domain such as market basket analysis and commercial transactions etc[10]. The Apriori algorithm functions on databases focusing on number of items that consumers buy. Apriori follows "bottom up" approach, where common subsets are extended one item at a time. The algorithm ends when no more successful extension is found. It uses breadth first search and a hash tree structure to calculate item sets efficiently[3][6].

Example of Apriori algorithm:

Suppose we want to find out what all items are commonly bought with other items from the given table. This can be found by following below steps with the aid of Table 1.

Table 1: Items bought

Transaction Id	Items bought in Quantity
T1	{QTY1,QTY2,QTY3,QTY4,QTY5, QTY6}
T2	{QTY7,QTY2,QTY3,QTY4,QTY5, QTY6}
T3	{QTY1,QTY8,QTY4,QTY5}
T4	{QTY1,QTY9,QTY10,QTY4,QTY6}
T5	{QTY10,QTY2,QTY2,QTY4,QTY11, QTY5}

Step 1: From the table 1, calculate number of occurrences of each item. QTY 2 occurs 4 times in total, but, it occurs in 3 transactions.

Table 2: Item Occurrences

Items	No of Occurrences
QTY 1	3
QTY 2	3
QTY 3	2
QTY 4	5

QTY 5	4
QTY 6	3
QTY 7	1
QTY 8	1
QTY 9	1
QTY 10	2
QTY 11	1

Step 2: The most frequently QTY is 3 times. From Table 2 remove all the items which occur less than 3 times and keep only items that are bought more than 3 times as shown in table 3.

Table 3: Item Occurrences which are more than 3

Items	**No of Occurrences**
QTY 1	3
QTY 2	3
QTY 4	5
QTY 5	4
QTY 6	3

Step3: Make pairs for items, like QTY1 QTY 3,QTY 1QTY 4,QTY 1QTY 5,QTY 1 QTY 6 and then we start with the second item like QTY 2 QTY 4,QTY 2 QTY 5,QTY 2 QTY 6 as shown in table 4.

Table 4 :Item Pairs

Item Pairs
QTY 1- QTY 2
QTY 1 -QTY 4
QTY 1- QTY 5
QTY 1- QTY 6
QTY 2- QTY4
QTY 2- QTY 5
QTY 2- QTY 6
QTY 4 -QTY 5
QTY 4 - QTY 6
QTY 5 -QTY 6

Step 4: From table 1,Calculate no of times each pair occurs. As shown in table 5 we get support of all the pairs.

Table 5 : Occurrences of item pairs

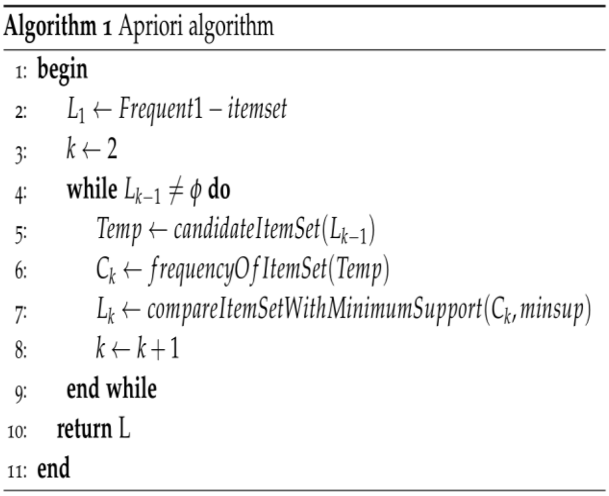
Item Pairs	**No of Occurrences**
QTY 1 QTY 2	1
QTY 1 QTY 4	3
QTY 1 QTY 5	2
QTY 1 QTY 6	2
QTY 2 QTY 4	3
QTY 2 QTY 5	3
QTY 2 QTY 6	2
QTY 4 QTY 5	4
QTY 4 QTY 6	3
QTY 5 QTY 6	2

Step 5: Remove all the item pairs with occurrences less than three and we are left with items whose occurrences is more than 3 as shown in table 6.

Table 6: Item pair occurrences which are more than 3

Item Pairs	**No of Occurrences**
QTY1 QTY4	3
QTY 2 QTY4	3
QTY 2 QTY 5	3
QTY 4 QTY 5	4
QTY 4 QTY 6	3

Pseudo code for Apriori algorithm:



Algorithm 1 Apriori algorithm

```
begin
  $L_1 \leftarrow Frequent1 - itemset$
  $k \leftarrow 2$
  while $L_{k-1} \neq \phi$ do
    $Temp \leftarrow candidateItemSet(L_{k-1})$
    $C_k \leftarrow frequencyOfItemSet(Temp)$
    $L_k \leftarrow compareItemSetWithMinimumSupport(C_k, minsup)$
    $k \leftarrow k+1$
  end while
  return L
end
```

Apriori algorithm advantages:

- Uses huge item set belongings.
- Easy to parallelize.
- Easy to apply

Disadvantages:

- Assume operation database is memory occupant.
- Requires a lot of database scan
- Final cluster pattern is dependent on initial.

B. K means clustering Algorithm

Clustering refers to minute group of objects which represents combinations into clusters. Clustering means separating data points into similar classes or clusters. When we have different objects, we put them into groups depending upon similarity.

Clustering Algorithms:

It analyzes data on the source of likeness. It identifies centroid of data points. For useful clustering it evaluates the distance amid each point from the centroid of cluster.

RAW DATA
CLUSTERING ALGORITHM
CLUSTERS OF DATA

Figure 1:Process of Clustering

K-means clustering is a vector quantization method that comes from signal processing. This algorithm partition *n* observations into *k* clusters wherein each observations belongs to the cluster with the closest mean(figure 1).

K-means is a simple unsupervised learning algorithms which follows easy way to sort a given data set through certain number of clusters (k clusters) . Primary purpose is to identify k centers, one of each cluster. The centers should be placed in right manner and some place them far from each other. Evaluate each point to a given data set and relate to the nearest center. If no point is left, then first step is completed and early group age is done. Then re-calculate k new centroids so that a fresh binding has to be completed between similar data set points and the adjacent new center so that loop gets formed. As a result of this loop it is noticed that k centers change their place step by step until no more changes exists. It also minimizes an objective function known as squared error function given by:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2$$

here,

'$||x_i - v_j||$' is the Euclidean distance between x_i and v_j, 'c_i' is number of data points in i^{th} cluster and 'c' is number of cluster centers.

Example of Kmeans clustering:

Suppose is a company desires to open petrol bunks in highways in a particular state. They want to open petrol outlets in such a way that it covers all highways. The test is to identify location of the petrol outlets so that the whole region is covered. To resolve this we can apply the concept of K means clustering.

K-means Clustering Procedure:

As shown in figure 2 we can tell if k is given, then K-means algorithm can be processed in following ways:

- Division of items into k non-empty items
- Resolve cluster centroids of the present partition.
- Transmission of every point to particular cluster
- Calculate distance from each point and allocate it where the distance from centroid is least.
- After re-allotting, identify the centroid of the new clusters generated.

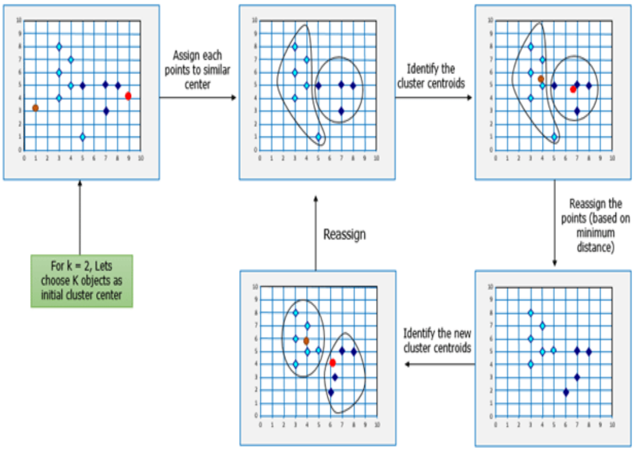
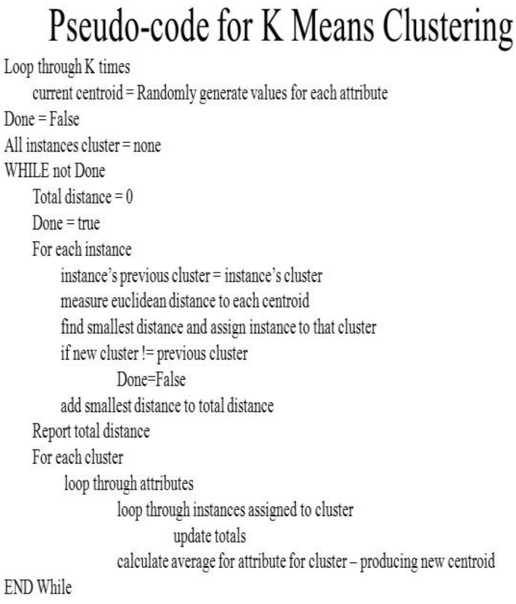

Assign each points to similar center
Identify the cluster centroids
Reassign the points (based on minimum distance)
Reassign
For k = 2, Lets choose K objects as initial cluster centre
Identify the new cluster centroids

Figure 2 : Step Wise Implementation of K means clustering algorithm

K-means will mix locations of maximum prone highways into clusters and tell cluster centroid for each and notify locations where to open petrol pumps. These Clusters centroids are at least distance from all points of a particular cluster so that the petrol pumps will be at minimum distance from all the highways within a cluster[5].



Pseudo-code for K Means Clustering

```
Loop through K times
    current centroid = Randomly generate values for each attribute
Done = False
All instances cluster = none
WHILE not Done
    Total distance = 0
    Done = true
    For each instance
        instance's previous cluster = instance's cluster
        measure euclidean distance to each centroid
        find smallest distance and assign instance to that cluster
        if new cluster != previous cluster
                Done=False
        add smallest distance to total distance
    Report total distance
    For each cluster
        loop through attributes
                loop through instances assigned to cluster
                        update totals
                calculate average for attribute for cluster – producing new centroid
END While
```

K-Means Advantages :

1) K-Means generates results faster than hierarchical clustering, if the k value is small.

2) It creates tighter clusters than hierarchical mainly if they are circular.

K-Means Demerits :

1) Difficult to foresee K-Value.

2) Diverse partitions initially can result in different clusters in final.

3) It do not work well with clusters of diverse dimension and diverse thickness.

C. Support vector machine (SVM):

The **support vector machines** clustering algorithm created by Hava Siegelmann and Vladimir Vapnik, which sorts unlabeled data and is one of the most extensively use clustering algorithms in industry applications.

This algorithm defines a hyperplane to separate data into two classes. A hyperplane is the line that divides a group but is based on a property or attribute rather than location. This algorithm can help to figure out an underlying separation mechanism between people who would buy a product and those who don't. In order to maintain the computational load sensible, techniques involve dot products of input data pairs which may compute effortlessly by declaring them with respect to kernel function. The hyperplanes are defined as set of points whose dot product in that space is steady[4][8].

Example:

Imagine there is a machine learning (ML) course is offered at a university. The course instructors have observed that students get the most out the curriculum if they are good at Mathematics or Statistics related courses. Over time, they have recorded the scores of the enrolled students in these subjects. For each student, they have a label depicting their performance "Good" or "Bad". Now the idea is to determine the relationship between Mathematics and Statistics scores and the performance in the ML course. We could draw a two-dimensional plot, where one axis represents scores in Mathematics, while the other represents scores in Statistics. A student with certain scores is shown as a point on the graph as shown in figure 3.

As shown in figure 3, the color of point green or red represents how he did on the ML course.

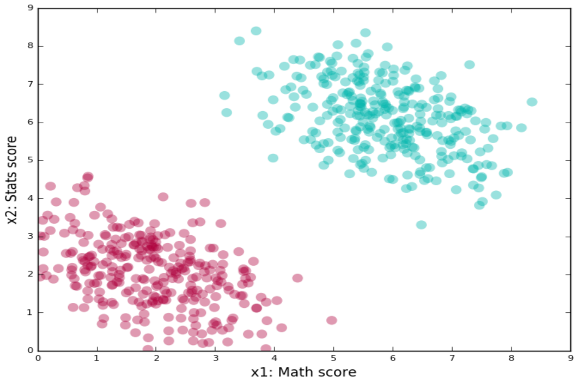


Figure 3: Relationship between Mathematics and Statistics scores and the performance in the ML course.

When a student requests for enrollment the instructors would ask her to supply Mathematics and Statistics scores. Based on the data they already have, they would make an informed guess about her performance in the ML course. In this case, finding a line that passes between the red and green clusters, and then determining which side of this line a score tuple lies on, is a good process to determine. For instance, based on the green side or the red side, a good indicator can be set for his/her to ascertain most likely chances to perform in the course.

As shown in figure 4 the line here is the separating boundary or classifier.

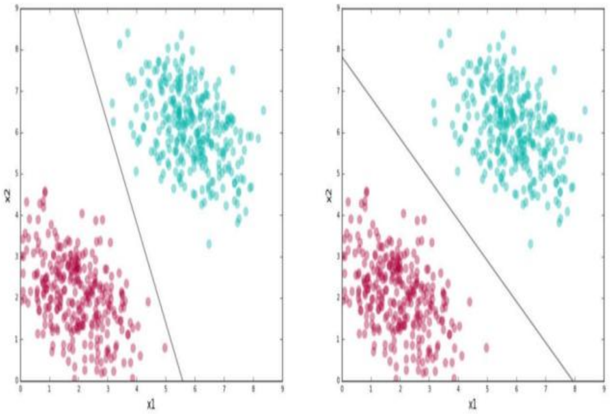


Figure 4: Finding of line that passes between the red and green clusters and to tell which side of this line a score tuple lies on.

Now how to identify good and bad classifiers. As shown in figure 5 the first line above seems a bit "skewed". Near its lower half it seems to run too close to the red cluster, and in its upper half it runs too close to the green cluster. This ensure that the line separates the training data perfectly, but if it sees a test point that is farther out from the clusters, there is a good chance it would get a label wrong. The second line doesn't have this issue. The second line stays as

ISSN: 2454-4248
129 – 135

far away as possible from both the clusters while getting the training data separation right. By being right in the middle of the two clusters, it is less "risky" and gives the data distributions for each class some wiggle room and thus generalizes well on test data[9].

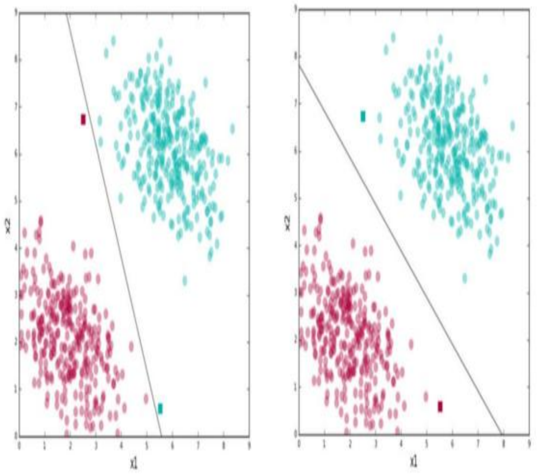


Figure 5: Identification of good and bad clusters

Non-linearly Separable Data

We have seen how Support Vector Machines systematically handle linearly separable data. How does it handle the cases where the data is absolutely not linearly separable? After all, plenty of real-world data falls in this category only. As shown in figure 6, we have only 75% accuracy on the training data the best possible with a line.

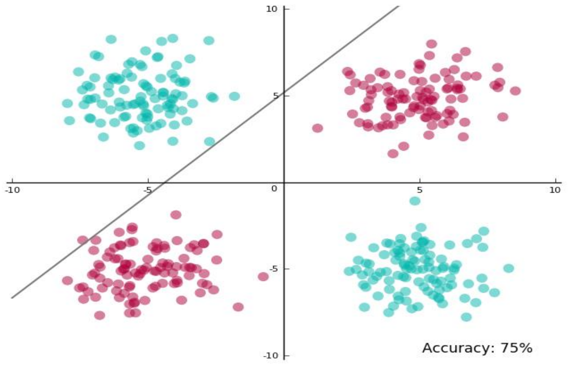


Figure 6- non-linearly separable data, shown with the linear classifier SVMs.

And this line passes very close to some of the data. The best accuracy is not appreciable, and to get even there, the line nearly straddles a few points. We start with the dataset in the above figure, and project it into a three-dimensional space where the new coordinates are :

$$X_1 = x_1^2$$
$$X_2 = x_2^2$$
$$X_3 = \sqrt{2}x_1x_2$$

Let the plane back be projected to the original two-dimensional space as shown in figure 7

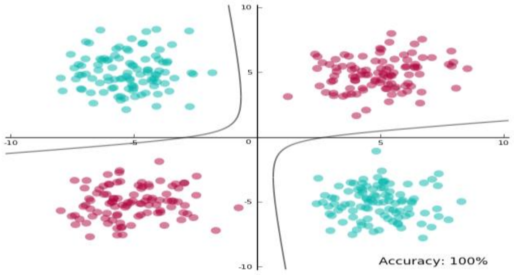
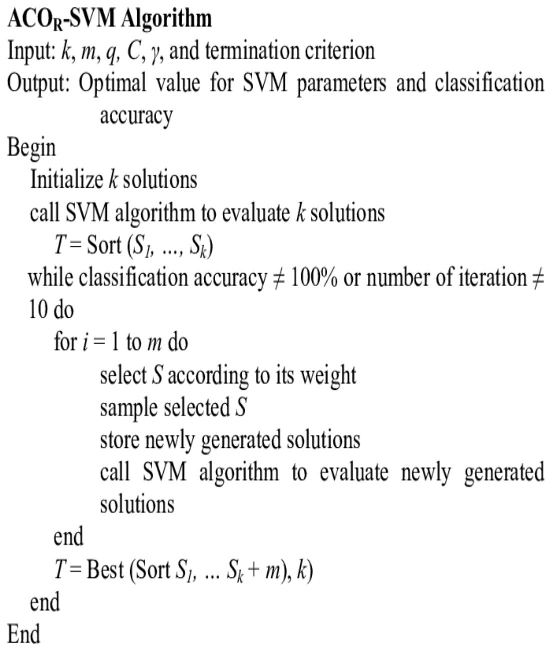


Figure 7- Separation of boundary in two dimension space

The figure 7 achieves an accuracy of 100%.

III. The SVM PSEUDOCODE



ACO$_R$-SVM Algorithm

```
Input: $k$, $m$, $q$, $C$, $\gamma$, and termination criterion
Output: Optimal value for SVM parameters and classification
        accuracy
Begin
  Initialize $k$ solutions
  call SVM algorithm to evaluate $k$ solutions
    $T$ = Sort ($S_1$, ..., $S_k$)
  while classification accuracy ≠ 100% or number of iteration ≠
  10 do
    for $i$ = 1 to $m$ do
        select $S$ according to its weight
        sample selected $S$
        store newly generated solutions
        call SVM algorithm to evaluate newly generated
        solutions
    end
    $T$ = Best (Sort $S_1$, ... $S_k$ + $m$), $k$)
  end
End
```

Advantages:

- SVM's are useful when we don't have that much knowledge on data.
- Works well with even unstructured and semi structured data like text, Images.
- The kernel trick is important part of SVM. With an appropriate kernel function, we can solve any complex problem.
- It scales relatively well with high dimensional data.
- SVM models have overview in practice, the risk of over fitting is less in SVM.

Disadvantages:

- Selecting a "good" kernel function is not easy.
- Much longer training time for large datasets.

Table 3: Comparison of 3 algorithms used

Parameters	Apriori	K means clustering	SVM
Technique	Use Apriori property and join and prune property	The k-means clustering algorithm divides a given unknown data set into fixed **clusters**(**k**) .The fixed number of k clusters are called centroids,	SVM is a **supervised** machine learning algorithm for classification or regression problems. A technique is used here called kernel trick to convert your data and finds out best boundary between possible outputs
Memory utilization	Since large number of candidates are registered so large memory space is needed	Memory use by k-means is essentially the output data size only	The **SVM** choice function is prolonged into a polynomial form and consolidate into classification function with significant lesser **memory footprint** and computational cost.
Time needed	Execution time is more	It has been Recently recognized as One of the best Algorithms for Clustering Unsupervised data	A fast and dependable classification algorithm that performs very well with a limited amount of data.
Time complexity	O(2^d)	O (m)	O(n3)
Space complexity	O(2^d)	O ((m+k)n)	O(n)
Data mining Software	Mahout machine learning library	Rapid Miner	LibSVM, WEKA

As shown in table 7 comparison between all 3 algorithms is drawn with various factors[3][4].

IV. Findings and observations

Apriori Algorithm:

Apriori algorithm assumes huge data set. for items which occur frequently over databases. It is used extensively in various online e –shopping platforms. It is useful in determining what all items are frequently bought together by customers with respective to an item and places that item accordingly. It is very useful and easy to implement[7].

K means clustering algorithm:

It is one among simple unsupervised learning algorithms that solves difficult clustering problems. It categorize given data set through number of clusters which refers to small group of objects. K means algorithm is widely used in order to determine various things like what all important areas are to be covered in order to construct or build any realistic entity[9].

Support Vector Machines algorithm:

It is supervised machine learning algorithm which helps to figure out an underlying separation mechanism between people/items who will buy/bought a product and those who won't. This algorithm defines hyperplane to separate data into two classes. A hyperplane is the line that divides a group but is based on a property or attribute rather than location. The kernel trick is important part of SVM. With an appropriate kernel function, we can solve any complex problem.

Conclusion

This paper exhibits the comparisons between Apriori ,K means clustering and Support vector machines algorithms. It has described the functioning of each algorithm and has shown some practical or real time examples for each algorithm. Each algorithm discussed in this paper has its own applications and merits. In today's world the growing size of data has huge impact on human in terms of taking day to day and business decisions. Thus, the study carried out has a good blend of comparison between three popular algorithms useful for real time implementations.

References

[1]. Agrawal, R., & Agrawal, J. (2017). Analysis of clustering algohm. *International Journal of Computer Applications*, *168*(13), 1–5. doi: 10.5120/ijca2017914522.

[2]. Amira, A., Vikas, P.,& Abdelaziz, A. (2015). Applying Association Rules Mining Algorithms *International Journal of Soft Computing and Engineering (IJSCE)*, *5*(4), 1–12.

[3]. Novitasari, W., Hermawan, A., Abdullah, Z., Sembiring, R. W., & Herawan, T. (2015). *International Journal of Software Engineering and Its Applications*, *9*(8), 51–66. doi: 10.14257/ijseia.2015.9.8.05.

[4]. Witten, I. H., Frank, E., Hall, M. A., & Pal, C. J. (2016). *Data mining: Practical machine learning tools and techniques*. Cambridge, MA: Morgan Kaufmann.

[5]. D.T. Pham, S.S. Dimov, and C.D. Nguyen, "Selection of K in K-means clustering", IMechE 2005, vol.219, pp.103-119, 2014.

[6]. Bhandari, Akshita, Ashutosh Gupta, Debasis Das, 2015. Improvised Apriori Algorithm Using Frequent Pattern Tree For Real Time Applications In Data Mining, in: Procedia Computer Science 46 (2015): 644-651.

[7]. Surbhi K. Solanki and Jalpa T. Patel, "A Survey on Association Rule Mining", Fifth International Conference on Advanced Computing & Communication Technologies, pp.212-216, 2015.

[8]. Zubair Khan, and Faisal Haseen, "Enhanced BitApriori Algorithm: An Intelligent Approach for Mining Frequent Itemset", Vol.1, pp.343-350, 2015.

[9]. Changxin "Research of Association Rule Algorithm Based On Data Mining," IEEE International Conference of Big Data Analytics (ICBDA), Pp.1- 4, 12-14 March 2016.

[10]. S. D. Patil and Dr R. R. Deshmukh, "Review and Analysis of Apriori Algorithm for Association Rule Mining," IEEE International Journal of Latest Trends in Engineering and Technologies (IJLTET), Volume 6, Issue 4, March 2016.