International Journal of Scientific Research in Computer Science, Engineering and Information Technology
 | Volume 3 | Issue 3 | ISSN : 2456-3307
DOI : https://doi.org/10.32628/CSEIT1833244

Analytical Study of Association Rule Mining Methods in Data Mining

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ABSTRACT

In data processing, the foremost common and effective technique is to spot frequent pattern victimization association rule mining. There are such a large amount of algorithms that provides simple and effective method of association rule mining, however still some analysis is required which might improve potency of association rule mining. As we have a tendency to operate with immense historical information (homogeneous or heterogeneous), it is important to spot frequent patterns quickly and accurately. Here during this analytical paper, we have been tried to incorporate survey of analysis systematically towards association rule mining from last many years to till date from totally different researchers. It's true that one paper isn't enough for complete analysis of all smart researches, however it'll facilitate in future to urge right direction towards association rule mining analysis for fascinating, effective and correct analysis.

Keywords: Itemset, Frequent Patterns, Algorithm, Minimum Support, Confidence, Association Rules

I. INTRODUCTION

In recent years, one of the attractive and important topic of research is data mining. There is a keen eye on research in this area from the experts of computer science, IT industry, scientific analysis, business application, medical, education and in our society because of large historical data. Data mining is usually known as knowledge discovery in database (KDD). KDD is one of the important process of extracting raw data to get fruitful knowledge which can be useful in DSS.

There are so many techniques in data mining, but one of the most interesting techniques is association rules mining.

Over the last seventeen years it has been developed at a very dynamic rate. Association Rule Mining is still in a stage of exploration and development.

II. LITERATURE SURVEY

Introduction of Association Rule Mining was done in [1]. As per researcher Agrawal, the formal statement is "Let itemset I = {I1,I2,…..In} can be a set of n binary attributes namely items. Let T = {T1,T2,…..Tn} can be a set of transactions which forms the database (D). Each transaction in 'T' has a unique transaction ID and contains a subset of the items in 'I'. One association rule is defined as an implication of the form $X \rightarrow Y$ where $X,Y \subseteq I$ and $X \cap Y=0$. The sets of items (for short itemsets) X and Y are called antecedent (LHS) and consequent (RHS) of the rule. ". The algorithm, described in [1], for searching association rules was referred the AIS Algorithm.

Research from Agrawal was the initiation of association rule mining algorithm and later on this topic became popular. Many researchers have undergone the research. From traditional association rule mining, markable research was made on mining in such areas as quantitative association rules, causal rules, exceptional rules, negative association rules, association rules in multi-databases, and association rules in small databases. And all these were continued to be the future topics of interest related to association rule mining.

III. RESEARCH STEP BY STEP FROM BEGINNING

Researchers have proposed some different methods in data mining like [76, 77, 79, 87, 92, 93, 94, 95], but association rule mining is one of the dominant techniques in exploring pattern of interest.

Earlier in 1993, the first algorithm “AIS algorithm” for association rule mining was shared by Imielinsky T., Agrawal R. and Swami A. This algorithm was very efficient at that time. In october 1993, STEM algorithm was presented by Houtsma M. and Swami A., which was far more effective than earlier.

Later in 1994, Agrawal R and Srikant R, derived two new popular algorithms, Apriori and AprioriTID [2]. These algorithms were truly differed from all previous algorithms. By experiments on both synthetic and real life data, the results of this new algorithm outperformed the previous algorithms. They also combined the best features of both these algorithms into a new algorithm, called AprioriHybrid. This algorithm had excellent scale-up properties. It also applies feasibility of mining association rules over very large historical database. These algorithms were developed in the context of Quest project at the IBM Almaden Research Center. Apriori is a classic algorithm for learning association rules. Apriori is designed to operate on databases containing transactions (for example, market basket analysis, or details of a website frequentation). During this year, Mannila H, Toivonen H and Verkamo A.I. presented one other algorithm [47] based on combinatorial analysis of the information obtained in the previous passes; which eliminate unnecessary candidate rules.

In 1995, Mueller A., [50] had presented algorithms related to sequential algorithms. This algorithm was an incremental partitioning which was slight improvement over the traditional partitioning technique. He presented performance analysis of the item-list based pass bundling and proved that it reduces both CPU and IO cost effectively without the cost caused by partitioning.

In 1996, Usama Fayyad et al. [20] presented a framework, which described links between data mining, KDD and other related fields. He also described relationship between KDD and data mining [17]. Park J.S. et al. [54] has described an algorithm for association rules with adjustable accuracy. He presented two methods with adjustable accuracy for mining association rules were developed. By conception of sampling, each strategy acquire some essential information from a sampled set first, and using that information perform efficient association rule mining on the whole database. Based on sampling size, method of relaxing the support factor was devised to achieve higher accuracy.

Meo R. et al. [49] presented a new SQL-like operator. This new operator, ‘MINE RULE’ was capable of expressing all the problems concerning mining of association rules. The use of the operator was demonstrated by means of several examples. It was a novel idea. It was an attempt to extend SQL language to satisfy problems of association rule mining.

In 1997, Thomas S. et al. [74] presented an incremental updating technique based on negative borders when new transaction data is deleted or added from a transaction database. The algorithm finds the new large itemsets with minimal re-computation. It also strives to reduce the I/O requirements for updating the set of large itemsets.

M.J.Zaki et al. [86] bestowed algorithm that utilizes the structural properties of frequent itemsets to make easy quick discovery. The group of related database items into clusters representing the potential peak frequent itemsets in the database. Every cluster induces sub lattice of the itemset lattice. Economical lattice traversal techniques were used to quickly and easily determine all the true peak frequent itemsets and all subsets. Brin S. et al. [11] presented an algorithm called correlation rules for generalization of association rules. Correlation rules are particularly useful in application going beyond standard market-basket setting. Chi-square analysis is used to analyze wide range of data.

In 1998, Bing Liu et al. [9] presented an algorithm to integrate two mining techniques, integration and classification. The integration was performed by focusing on a special subset of association rule mining, called 'class association rules' (CARs). To build a classifier based on the set of discovered CARs, an efficient algorithm was also given. Kai C.H. et al. [39] described a new thought of association rule mining with weighted items. According to research, items were given weights to reflect their importance to users. The weights may correspond to special promotions on some product, or profitability of different items. Weighted association rules were mined with weights. It was a new thought that opened a new direction of research.

Roberto J. Bayardo Jr. [65] discovered simple formula for mining long patterns from large database. No matter the length of the longest pattern, Main plan concerning this formula was to scale roughly linearly within the variety of largest patterns embedded in large database. The algorithm 'Max-Miner' has applied many new techniques for decreasing the space of itemsets considered through superset-frequency based pruning.

A bitmap based algorithm for association rule mining by Gardarin G. et al. [22] was presented. The basic thing used in this algorithm is that every couple of transaction and item (T, I) was represented by a bit in an index bitmap, and the logical operation AND can be used in place of the sort merge algorithm. The native bitmap algorithm (N-BM) and the hierarchical bitmap algorithm (H-BM) was proposed by him. An anti-skew algorithm by Jun Lin et al. [42] was presented to decrease no. of scans of database. To reduce the number of candidate itemsets and identify false candidate itemsets at an earlier stage, this algorithm uses advance knowledge during the mining. This technique decreases total number of scans less than 2. Hipp J. et al. [30] presented a new algorithm 'Prutax', to discover generalized frequent itemsets. Although it was a good new approach, butwas not better then former approaches.

In 1999, Roberto J. Bayardo Jr. and Rakesh Agrawal [7] presented a new optimized rule mining problem which allows a partial order in place of the typical total order on rules. The best rule must reside along a support/confidence border according to any metrics by their study. Bing Liu et al. [8] described an idea for Association Rule Mining with Multiple Minimum Supports. This technique allowed specifying multiple minimum supports to reflect the natures of the items and their varied frequencies in the database. Cohen E. et al. [15] presented an algorithm to find interesting associations without pruning the support. These algorithms were used with combination of sampling and hashing techniques.

Earlier in 2000, Webb G.I. [80] presented an algorithm to find association rules through direct searching instead of two stages in process of Apriori algorithm. He showed that when the database is large, Apriori algorithm imposes a large computational overhead. Zaki M.J. [87] presented algorithms to utilize the structural properties of the frequent itemsets to make fast discovery of association rules easy.

In 2001, Zaki M.J. [88] introduced another algorithm 'SPADE' for mining frequent sequences. It was an efficient and scalable algorithm for faster discovery of Sequential Patterns. Using economical lattice search techniques, it decomposes the initial drawback into smaller sub-problems that may be severally resolved in main-memory, and exploitation straightforward using join operations. Only 3 database scans are performed to discover all sequences.

Han J. et al. [26] showed the most effective idea to mine Frequent Patterns without Candidate Generation 'FP-Tree approach'. They described FP-tree structure. FP Tree is a prefix tree structure to store compressed and crucial information about frequent patterns, and also developed scalable and efficient FP-tree based association rule mining technique namely FP-growth to mine whole set of frequent patterns by growth of pattern fragment. Three techniques were used to judge efficiency of mining (1) A huge database is compressed into a condensed and smaller data structure namely FP-tree to avoid repetition of database scans to decrease the cost, (2) To avoid creation of a large no. of candidate sets, it uses a pattern-fragment growth method and (3) Divide-and-conquer which is a partitioning-based method was used to partition the data mining task into group of smaller tasks for mining confined patterns in conditional databases that dramatically reduces the search space.

An algorithm for association rule mining was presented by Jiangping Chen [36] based on spatial autocorrelation. It was absolutely a new technique to mine spatial association rules. It was based on taking account of the spatial autocorrelation with a theory of cell structure. It also describes spatial data with an algebra data structure and then the auto-correlation of the spatial data is calculated in algebra.

In 2002, Jian Pei [35] presented one research on "Pattern-Growth methods for frequent Pattern Mining". Efficient pattern-growth methods for mining various frequent patterns from large databases were presented. He also redesigned a pattern growth method 'FP-growth' for efficient mining of frequent patterns in large databases. This techniwue is very popular and still considered as one of the most efficient technique for mining association rules. Pudi V et al. [53, 54, 55] presented a survey of efficiency of existing algorithms using his own algorithm 'ARMOR'.

In 2003, Cheung W [12] presented a research on 'FREQUENT PATTERN MINING WITHOUT CANDIDATE GENERATION OR SUPPORT CONSTRAINT'. New data structure 'CATS Tree' was presented. CATS Tree was extension of the thought of FP-Tree to enhance storage compression and permit frequent pattern mining while not generation of candidate itemsets. It allows mining with a one pass over the database as well as addition or deletion of transactions in the finest granularity at any given time.

Tao F. et al. [73] described one issues to discover important binary relationships in transaction datasets in a weighted setting. They used traditional model of association rule mining to handle weighted association rule mining problems. Every items were allowed to have a weight. The goal was to focus on those significant relationships involving items with significant weights rather than insignificant relationships.

In 2004, a unique formula for mining complete frequent itemsets was bestowed by Song M. et al. [72]. It is referred to as the Transaction Mapping(TM) algorithm. In this algorithmic program, dealings ids[TIDs] of every itemset were mapped and compressed to continuous dealings intervals during a totally different area. After that, numeration of itemsets was performed by decussate these interval lists during a depth-first order on the authorship tree. This algorithmic program switches to dealings id intersection once the compression constant becomes smaller than the common range of comparisons for intervals intersection at an explicit level.

Palshikar G.K. et al. [53] presented an algorithm for association rule mining using the concept of heavy itemsets. Flank A. [21] developed the concept of multi-relational association rule mining in relational databases. He presented queries and rules in plain English.

Guil F. et al. [24] presented their work on temporal data mining. They given a replacement technique named TSET (as form of Temporal Set-Enumeration Tree) for frequent temporal pattern sequences) mining from datasets. This technique is based on the problem of inter transactional association mining. However it uses a unique tree based structure to store all the frequent patterns found in the mining process. Xia Y. et al. [83] generalized the privacy preserving association rule mining problem by permitting different attributes having different levels of privacy that is, using different randomization factors for values of different attributes in the randomization in process. They also proposed an efficient algorithm RE (Recursive Estimation) to estimate the support of itemsets under this framework.

For geographically distributed data sets, Ashrafi M.Z. et al. [4] presented a distributed algorithm, called Optimized Distributed Association Mining. ODAM creates support_count of candidate itemsets very faster than any other DARM algorithms and decreases the size of data sets, average transactions and message exchanges.

In 2005, Jotwani N. [38] proposed an efficient algorithm for online on hierarchical classification of items to be mined for association rules. The first section of formula carries out expeditiously in one pass, with tight bounds on the process effort needed, and modest memory necessities. The formula is therefore capable of on-line mining of associative rules from transaction streams.

Salleb-Aouissi A. et al. [66] developed a system `QuantMiner'. A Genetic formula for Mining Quantitative Association Rules. this technique is predicated on a genetic formula that dynamically discovers "good" intervals in association rules by optimizing each the support and therefore the confidence. Badawy o. et al. [6] redesigned with some improvements to QuantMiner

Liu P. et al. [44] presented a data mining system 'AR-Miner' based on their algorithm FAS. It is an efficient and scalable system with easily accessible and user-friendly interface for interactive mining that is based on frequent itemsets. To reduce the traversal of database, Margahny M.H. et al. [48] has presented an algorithm using ArrayList.

In 2006, Nan Jiang et al. [51] presented different research issues in data stream mining. These issues were related to different applications of data streams which require association rule mining, such as network traffic monitoring and web click streams analysis. Different from data in traditional static databases, data streams typically arrive continuously in high speed with huge amount and changing data distribution. Therefore it was needed to address these issues. These challenges have been thoroughly discussed by them.

Ishibuchi H. et al. [33] bestowed the applying of evolutionary multi-objective optimization (EMO) to association rule mining. They explained EMO rule selection as a post-In Processing In Procedure in classification rule mining. Pareto-optimal rule sets are, then, found from a large number of candidate classification rules, which are extracted from a database using an association rule mining technique.
Kumar K.B. et al. [41] planned algorithm for on-line In process of transactions. it had been single-pass algorithmic rule for mining association rules, given a hierarchical classification amongst things. In process

potency was achieved by utilizing 2 optimizations, hierarchy aware count and group action reduction, that become potential within the context of hierarchical classification. Dehuri S. et al. [16] bestowed a quick and climbable multi-objective association rule mining technique with the use of genetic algorithmic rule from massive database. The target functions like confidence factor; quality and powerfulness were thought of as totally different objectives of their association rule mining downside and were treated as the basic input to the genetic algorithmic rule. The outcomes of the algorithmic rule were the set of non-dominated solutions. However, because of massive historical database each in size and dimensions, the multi-objective genetic algorithm (MOGA) was little poor as compared to techniques used in most classical rule mining. So, to remove these problems, they described a quick and scalable technique using the inherent parallel In Processing nature of genetic algorithm and a homogeneous dedicated network of workstations (NOWs).

In 2007, Mangalampalli A. et al. [46] proposed methodology for Fuzzy Logic-based Pre-In Processing for Fuzzy Association Rule Mining. This pre-In Processing is essential to implement any fuzzy ARM algorithm.

Pasquier N. et al. [55] addressed the problem of finding frequent itemsets in database using closed itemset lattice framework. The search space was limited to the closed itemset lattice rather than the subset lattice. Their algorithm A-Close was intended to limit the no. of rules created, without any information loss.

Jianwei Li et al. [37] designed many algorithms for parallel association rule mining and clustering. These algorithms were based on identifying groups of items that most often occur together. They used parallel k-Means and parallel hierarchical algorithms to discover association rules from these groups.

In 2008, Sheibani R. et al. [69] presented an efficient algorithm named Fuzzy Cluster-Based Association.
Zaki M.J. [85] presented one algorithm 'CHARM' for closed association rule mining. He showed that it's not necessary to mine all frequent itemsets within the beginning; instead it's comfortable to mine the set of closed frequent itemsets, that is way smaller than the set of all frequent itemsets. He conjointly showed that it's conjointly not necessary to mine the set of all attainable rules. Any rule between itemsets is corresponding to some rule between closed itemsets. Therefore several redundant rules are often eliminated using these ules (FCBAR). The FCBAR technique is to create cluster tables by scanning the database once, and then clustering the transaction records to the k-th cluster table, where the length of a record is k. Moreover, the fuzzy large itemsets are generated by contrasts with the partial cluster tables. This prunes considerable amount of data, reduces the time needed to perform data scans and requires less contrast.

Ramraj E. et al. [61] developed some algorithms. The basic objective of these algorithms was to improve information quality through association rule mining.
Mangalampalli A. et al. [45] came up with a new fuzzy ARM algorithm meant for fast and efficient performance on very large datasets. The performance of this algorithm was far better than its previous counterparts.

Wu Jian et al. [82] developed an efficient algorithm to mining weighted association rules based on ISS (item sequence sets).
In 2009, Yang J. et al. [84] conducted a Study on the data mining algorithms, based on positive and negative association rules.

In 2010, Piao et al. [56] also conducted research on the same type of algorithm. Their research was based on mining negative and positive association rules, based on dual confidence. They defined a correlation measure and added it to mining algorithm for association rule. This algorithm reduce the scale of meaningless association rules, and mine a lot of interesting negative association rules.

Umaraani et al. [75] conducted a study on effective mining of association rules from huge databases. They proposed an implementable technique to prune datasets.

Veeramalai et al. proposed an intelligent association rule mining model for multidimensional data representation and modeling. They proposed an algorithm called Fuzzy-T ARM to classify the breast cancer dataset.

Wang P. conducted a survey on privacy preserving association rule mining research. He also suggested some useful future directions.

In 2011, Demitrijevic et al. [18] developed a web usage mining system. They implemented a system for the discovery of association rules in web log usage data as an object-oriented application and used it to experiment on a real life web usage log data set.
Sandhu et al. [67] proposed a new approach as multi utility association rules, based on profit and quantity. The result, presented by them, demonstrates effectiveness of the approach in generating high utility association rules.

Wang H. et al. proposed an algorithm to reduce bottlenecks of Apriori algorithm.

In 2012, Jadav et al. [34] presented some techniques to apply association rule mining on OLAP Cube to take advantage of both OLAP and data mining for more accurate results.

Radhika et al. [60] conducted a research based on association rule mining based on ontological relational weights. According to their approach they prune and filter discovered rules on the basis of ontological weights.

Raorane et al. [62] conducted a research to prove the effectiveness of association rule mining over conventional methods using market-basket analysis.

Raosulian et al. [63] conducted a research to explore the effect of data mining base on association rule mining in strategic management.

Shrivastava et al. [71] presented an overview of non-redundant association rule mining. They also proposed a non-redundant sequential association rule mining method.

In 2013, Zhi Liu,Tianhong Sunand Guoming Sang et al. [97] presented apriori based on sampling. through to the frequent itemsets generated process analysis of SamplingHT, Hash table technology can be effectively reduced frequent itemset's size especially the frequent 2-itemset's, and the algorithm’s running time is reduced. Although algorithms require additional space to store Hash table, the running time can be greatly reduced. With the continuous development of the hardware device, method what using space for time will be more and more widely. Finally, although SamplingHT algorithm is only suitable for dense database, through step by step method to reduce minimum support, it can save missing rate in sparse database.

In 2014, Muhammad Al-Maolegi, Bassam Arkok et al. [96] bestowed AN improved apriori. AN improved Apriori is planned through reducing the time consumed in transactions scanning candidate itemsets by reducing the amount of transactions to be scanned. Whenever the k of k-itemset will increase, the gap between improved Apriori and therefore the original Apriori will increase from read of your time consumed, and whenever the worth of minimum support will increase, the gap between improved Apriori and therefore the original Apriori decreases from read of your time consumed. The time consumed to come up with candidate support count in improved Apriori is a smaller amount than the time consumed within the original Apriori. An improved Apriori reduces the time consuming by 67.38%.

In 2016, Jiaoling Du, Xiangli Zhang, Hongmei Zhang and Lei Chen et al. [99] introduced an improved DC_Apriori algorithm to restructure database storage with improved connection of frequent item sets, only need to generate k-frequent item sets to join 1-frequent item sets with k-1-frequent item sets which reduced the number of connections and get frequent item sets by one prune operationby avoiding invalid candidate sets and decrease database scan. They have given example which will prove that DC_Apriori algorithm superiority based on the matrix. Less running time of DC_Apriori with same result is notably less than the Apriori algorithm.

IV. CONCLUSION AND FUTURE SCOPRE

In this paper, we have presented history of Association rule mining and step by step research progress towards association rule mining from 1993 to till date. Researchers have presented good and innovative ideas towards efficiency and accuracy of association rule mining. But some of the limitations describes as under requires serious consideration and improvement in recent algorithms.

Some limitations of association rule mining are listed as below:

1. Depth understanding and interpretation of good patterns, e.g., semantic annotation and contextual analysis of frequent patterns are required.
2. Assumptions in most of the cases should be avoided so that it can be used in practice. Also disclosure cost, communication and computation cost should be in priority.
3. Association rule algorithms should be developed using single scan of database in place of multiple scan.
4. Database-independent measurements should be established
5. For XML databases, accurate and efficient algorithm should be designed.
6. Social network should be analyzed for better usage of social community.
7. Software Error detection is now possible by association rule mining, but more scalable and effective algorithms are still required.
8. New applications should be explored.

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