A REVIEW ON ALGORITHM OF ASSOCIATION RULE MINING AND INDIRECT ASSOCIATION MINING

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Abstract: Data mining is a process to extort the knowledge and exciting patterns to expect useful information from massive databases for the user. Association Rule Mining is a vital research area and is helpful in marketing and other varied fields. It discovers the interesting associations among data items. Many techniques and measures are proposed to extract new rules. In this survey, the rules not brought together will call it as negative association rules, and it has received some notice and useful in the real world. But it is difficult to identify the negative association rules. To resolve this problem, Indirect Association Rule Mining has proposed. This paper is concerned with providing the concept of Association Rules, Negative Association Rules, Indirect Association Rules and an overview of existing algorithms.

Keywords: **Data mining, Association Rules, Positive and Negative Association Rules, Indirect Associations.**

I.INTRODUCTION

Data mining technique is the process of extracting implicit data, previously unknown, and potentially useful information from a massive volume of fact or data. Through the accretion of previous and current data with historical data, enterprises find themselves in possession of a more substantial amount of data sets in electronic form than at any time heretofore.

The research and application of data mining techniques are a hot spot in the database and artificial intelligence in recent years. Various methods have been employed to convert the data into information, including clustering, classification, regression, association rule induction, sequencing discovery, and these become the significant areas of interest in data mining. Among these Association Rule Mining mines useful information from a vast amount of data by generating rules.which has become an important research topic among the various data mining problems. Association rules have been an extensively comprehensive way of study in the literature for their usefulness in many application domains such as market basket analysis, recommender systems, diagnosis decisions support, telecommunication, intrusion detection, etc. Association Rules Mining first introduced by R. Agrawal. In association rule analysis is the task of discovering association rules that frequently occur in a given data set. A typical example of an association rule mining application is the technique of market basket analysis. In this process cycle, the behavior of the customers will observe, when buying different products in a shopping mall. The discovering knowledge of interesting patterns in the collection of data can lead to important marketing and strategic management.. For instance, if a customer purchases bread, what is the probability that he/she may buy milk as well? Depending on the likelihood of such an association, marketing stakeholders can develop better planning strategy to improve business. All the previous association algorithm, rule mining algorithms, were implemented to find the positive associations between product items. Based on positive associations, we refer to associations between objects existing in transactions (i.e., items bought). According to customer buying behavior, the negative association can provide valuable information, in devising marketing strategies.

II.BASIC CONCEPTS

Let I = $\{i_1, i_2,..., _n\}$ be a set of 'n' distinct constants called items. Let D be a collection of transactions, where each transaction T is a set of items and each transaction associated with a unique identifier called TID. Let A, called an itemset, be a set of items in I. The collection of items in the itemset is the length (or the size) of an itemset. Itemsets of length k will e referred to ask-itemsets. A transaction T is referred to contain A. if $A\subset T$, an association rule method is an implication of form A=>B, where $A\subset I$, $B \subset I$, and $A\cap B=\Phi$. We call A the antecedent of the rule, and B the consequent of the rule. The rule A=>B has support (denoted as support) **s** in DB if **s%** of the transactions in D contains A=>B. Besides, the support of the rule is the probability that A and B held together among all the possibilities presented cases. i.e. support(A=>B)=supp(AUB)=P(AUB). The rule A=>B has a measure of its strength called confidence (denoted as conf) c if c% of transactions in DB that contain A also contain B. Besides, the confidence of the rule is the conditional probability that consequent B is true under the condition of antecedent A, i.e. conf (A=>B)=P(B|A)=supp(AUB)/supp(A). The problem of discovering all the association rules from a set of transactions *D* consists of generating the rules, that have support and create confidence that greater than a given threshold. These rules referred to as strong rules, and the framework is known as the support-confidence framework for association rule mining.

A **contrary association rule** is an implication of form X =>┐Y (or ┐ X=>Yor ┐ X =>┐ Y), where the $X\subset I$, $Y \subset I$ and $X \cap Y = \Phi$, although the rule in the form of ┐ X =>┐ Y Contains harmful elements, it is equivalent to a definite association rule in the way of Y=>X. Therefore it is not considered as a contrary association rule. In contrast to real standards, a different control encapsulates the relationship between the frequent occurrences of one set of items with the not available of the other collection of objects. The rule X =>┐ Y has supports *% in* the data sets, ifs % of transactions in T contain article set *X* while do not contain itemsets. The support of a contrary association rule, support(X=>┐ Y), is the frequency of occurrence of transactions with item set Xin the absence of item set *Y*. Let*U* be the set of operations that contain all elements in *X*. The rule X=>┐ Y will hold in the given dataset (database) with confidence value c % if c% of transactions in *U* don't contain item set Y. The confidence of contrary association rule, conf (X=>┐ Y), can be calculated and formulated with P(X ┐ Y)/P(X), where P(.) is probability function. The most support and confidence of itemsets will derive during the following iterations. However, it is difficult to count the comfort and more assurance of non-existing items in transactions. To discard counting them directly, we can compute the measures through those of real rules.

A new class of patterns refers to **indirect associations**, and its utilities have examined in various application domains. The implied association is a new kind of infrequent pattern, which provides a new way of interpreting the value of unusual patterns and can effectively reduce the number of uninteresting uncommon models. The concept of indirect association technique is to "indirectly" connect two rarely co-occurred items via a frequent itemset called a mediator, and if appropriately utilized it can help to identify real interesting "infrequent item pairs" from databases. Consider a pair of items X and Y, that are the available group in the same layer transaction. If both the items are highly dependent on the presence of another itemset M, then the same pair (X, Y) is said to be indirectly associated through M. There are many advantages in long mining associations in the massive volume of datasets. For example, an indirect association between a collection of words in text files can be used to classify query results. For instance, the words *coal* mining and *data* mining can indirectly associates via mining. The word mining will use in a query, documents in both mining domains will return. It is discovering the indirect association between *coal* and *data*, which trigged us to classify the retrieved files into *coal* and *data mining*. Potential applications of indirect associations are real-world domains, such as competitive product analysis and stock market analysis. The indirect association is closely related to the negative association; both dealing with itemsets that do not have sufficiently high support. Indirect associations provide an effective way to detect interesting negative associations by discovering only "infrequent item pairs are highly expected to be frequent" without using negative items or domain knowledge.

Definition (Indirect Association).A pair of itemsets X and Y is indirectly associate through a mediator M if the following conditions hold:

1. Supp(X, Y)<t_s (Item pair Support Condition)
2. There exists a non-empty set of M, such that

(a) Supp(X∪M) ≥ t_f, it refers to sup(Y ∪ M) ≥ t_f ; (Mediator Support Condition)

(b) dep(X, M), ≥ t_d, dep(Y, M) ≥ t_d, where dep(P, Q) is a measure of the dependence between the itemsets P and Q. (Mediator Dependence Condition)

The thresholds above are called itemset pair support threshold (t_s), mediator support threshold (t_f), and mediator dependence threshold (t_d), respectively. In practice, it is reasonable to set $_f$≥ t_s.

Condition 1 is needed because an indirect relationship between two items is significant only if both pieces rarely occur together in the same transaction. Otherwise, it makes more sense to characterize the pair in terms of their direct association.

Condition 2(a) can be used to guarantee that the statistical significance of the mediator set. In particular, for market basket data, the support of an itemset affects the amount of revenue generated and justifies the feasibility of a marketing decision. Moreover, comfort has a gentle downward closure property which allows us to prune the combinatorial search space of the problem. Condition 2(b) ensures that only items that are highly dependent on the presence of x & y will occur and used, to develop the mediator set.

III.OVERVIEW ON ALGORITHMS OF ASSOCIATION RULE MINING

The following are the existing algorithms to generate association rules.

A. AIS

The algorithm [1] was the first algorithm to generate association rules. This algorithm discovers qualitative rules. The regulations found by this algorithm are in the form x=>I_j|α where x is a set of items and $I_j$is a single piece and α is the confidence of the rules. This algorithm makes too many scans over the database to generate too many large itemsets. That later turned to be small, and data structures are not specified to maintain large and candidate itemsets.

B. SETM

The SETM [2] algorithm was proposed to use SQL to compute large itemsets [3]. In this algorithm, each member of the fix a large itemset is in the form <TID, itemset> where TID is the transaction identifier and each member of the set of candidate itemsets is in the way <TID, itemset>. This algorithm makes multiple passes over the database. Due to the number of candidate sets, it requires more space to store a large amount of TIDs.

C. Apriori, AprioriTid, Apriori Hybrid

The exploitation of monotonicity property of the support of itemsets and confidence of association rules leads to develop the algorithm [4]. It uses the property that any subset of an itemset must also be frequent. This algorithm works will efficiently while generating the candidate itemsets than AIS and SETM for two issues, apriori generates candidate itemsets by joining the itemsets of the previous pass and performs pruning by deleting the itemsets which are not frequent based on apriori property. Apriori avoids the effort of wastage of counting the candidate itemsets that are not frequent. By this which reduces the computation, I/O cost, and memory requirement. But there is a disadvantage with this algorithm is that it scans the entire database many times. To this, the AprioriTid algorithm is a variation of apriori algorithm proposed by Agrawal, which uses the apriori-gen function to find the candidate itemsets before the beginning of the pass. The difference from apriori is that it does not use the database for counting support after the first pass. Instead of that it uses encoding the candidate's itemsets used in the previous pass. The advantage of the technique is that at each pass other than the first pass the scanning of the entire database is avoided. The AprioriTid also outperforms AIS and SETM and also apriori when candidate itemsets are relatively small. This algorithm performs well at a high level, whereas the conventional apriori performing better at lower levels. When they apply to significant problems, then the performance is degraded. To overcome, AprioriHybrid will propose which combines the advantageous features of Apriori and AprioriTid by Agrawal and Srikant. This algorithm depends on the idea that it is not necessary to use the same algorithm in all passes over data. Apriori has better performance in earlier passes, and AprioriTid outperforms Apriori in the first passes that the candidate itemset at the end of a pass.

D. Partitioning Method

The partitioning algorithm [6] divides the database D into n nonoverlapping partitions and scans the database two times to generate association rules. It consists of two phases. In phase1 the algorithm subdivides D into n partitions and finds the frequent itemsets local to each partition. Combine all frequent local itemsets to form candidate itemsets. In phase-II, a second scan of D will consider. The algorithm finds the frequent global itemsets among candidates, and the actual count of recurring item is gathered and at last find the frequent itemsets in D. In this algorithm, fragment size and the collection of partitions are set so that time is saved for doing I/O with this the performance of finding large itemsets increase in various ways.

E. Dynamic Itemset counting algorithm

In [7] proposed the DIC algorithm, divides the database into intervals of specific sizes and reduces the number of database scans to 1.5 as contrasting to 3 scans required by apriori method. The algorithm is based on the counting of itemsets, and it waits for completion of the previous pass.

F. CARMA

In [8] CARMA (Continuous Association Rule Mining Algorithm) algorithm was proposed, generates the itemsets, which is different from DIC. During the execution of the algorithm, the user can change the threshold values.

G. Sampling Method

Sampling is a data reduction technique applied to various data mining algorithms to reduce the number of database scans(computational overhead). Sampling helps the user to direct the data mining process by refining the criterion for interesting rules by which reduces the I/O costs and drastically shrinking the number of transactions will be considered. The validity of the sample can e determined by the size and quality of the example. The variety in the context of statistical sampling techniques refers to whether the sample captures the characters of the database [9]. Some researches considered the use of sampling techniques for reducing the processing overhead [13, 14, 15, 16]. Previous worth has concentrated on speeding up the phase by running a frequent itemset mining algorithm only on a small sample of database [12].

In [10] Toivonen proposed an algorithm which reduces the database activity. The algorithm uses a random sample and finds a superset of the collection of various sets and this superset is determined by applying the level-wise method on the sample and by using a lowered frequency threshold. All association rules are found by using this sample, and these re-verified against the entire database. This method is probabilistic. That is all the rules are not recognized and are missing are found in the second pass.

An efficient technique to progressively sample for association rule proposed by Parthasarathy [11]

The method relies on a novel measure of model accuracy (self-similarity of associations across successive samples), the identification process of a representative class of frequent itemsets that mimic (extremely accurately). The self-similarity values across the whole set of associations and that hide the overhead of attaining successive samples by overlapping it with expensive computation.

H. Hash-Based Itemset Counting

DHP (Direct Hashing & Pruning) as proposed by park [17]. It is a useful hash-based algorithm for candidate set generation for large two itemsets. This algorithm has three steps. First, it gets a set of large 1-itemsets and constructs a hash table for 2-itemsets. The second step generates a set of candidate itemsets, but it adds only the k-itemset into candidate set if that k-itemset is hash into a hash entry whose value greater than or equal to mins up. The third step is also the same as the second step, but it does not use the hash table in finding whether to include an itemset into candidate itemsets. This algorithm efficiently generates large itemsets and effectively reduces the size of the transaction database.

Later Soo [18] proposed a useful direct hashing and pruning algorithm for mining the association rules. It adopts pruning techniques and uses a hashing technique to screen the ineffective candidate frequent 2-items and avoids database scans in some passes to reduce the disk I/O cost involved.

A novel hash-based method is developed by [19] for mining frequent itemsets over data streams. This algorithm compresses the itemsets into a structure with a solid hash-based technique. This method expertly summarizes the information of full data stream by using a hash table to estimate the support counts of non-frequent itemsets and keeps only the frequent itemsets for speeding up the mining process.

John [20] proposed an Inverted Hashing and Pruning algorithm for mining association rule between words in text databases. The Apriori algorithm [I] & DHP are evaluated in the context of mining text databases and are compared with the THP algorithm and the results shown that the IHP algorithm has better performance for large text databases.

I. Parallelization

Association rule discovery techniques have been applied to parallel systems to take advantage of higher speed and greater storage capacity.FDM is an algorithm proposed by Cheung [20], is a parallelization of apriori to shared nothing machines, each with its partition of the database. At each level and on each computer the database scan is performed independently on the local partitions. Distributed pruning s done.

FPM (Fast Parallel Mining) proposed by Chaung [22]. It adopts the count distribution method and has incorporated two powerful candidate pruning technique. It has a simple communication scheme which performs only one round of message exchange in each iteration.

Parthasarathy[23] presented an excellent survey on parallel association rule mining with shared memory architecture covering most of the challenges, issues, and approaches adopted for parallel data mining.
Tang and Turkia[24] proposed a parallelization scheme which can be used to parallelize the efficient and fast frequent itemset mining algorithm based on FP trees.

J. FP Growth Method

FP growth algorithm has been developed by Han [26], which overcome the drawbacks of the apriori algorithm. This algorithm generates frequent itemsets with only two passes without candidate generation. It includes constructing FP-Tree and making recurring patterns from FP-Tree. But construction of FP-Tree is a time-consuming process. Later, Tree Projection [27] in 2001, H-mine [28] in 2001, Liu [29] in 2002, Grahne and Zhu [30] in 2003 algorithms is proposed.

IV.MULTIPLE MIN-SUPPORT ASSOCIATION RULES

Not only mine the association rules with single support but also undermine the association rules with various min-supports. If the threshold point is set too high, then most controls are missing and even rules involving rare items will not found. If the limit set too low, then there exist too many laws. Strategies used to overcome difficulties. [36, 37].

A) **NEGATIVE ASSOCIATION RULE MINING**

Negative association rules consider negated items (i.e., absent from transactions). Mining contrary association rule is a difficult task. The researches attack two critical problems in detrimental association rule mining. (1) How effectively search for interesting itemsets (2) how effectively identify contrary association rule of interest.
For the first time, negative relationships states by Brin[38]. A statistical test is used to verify the independence between two variables and correlation metric was used to check the positive or negative relationship. Their model is chi-squared based. This model rests on the normal approximation to the binomial distribution. This approximation breaks down when the expected point is small.
In [39], stated a new idea to my strong negative rules. It combines positive, frequent itemsets with domain knowledge in the form of taxonomy to mine negative association. However, their algorithm is hard to generalize. It's domain dependent and requires a predefined taxonomy.[7].
In [40], introduced the "interest" measure on the top of the support-confidence framework to generate both positive and negative association rule. The authors do not discover how to set it and what would be the impact on the results when changing this measure.
In [41], introduced an algorithm to generate positive and negative association rules. This method adds to the support-confidence framework the correlation coefficient to create strong positive and negative states. They combined the two phases and generated the relevant rules while analyzing the correlation within each candidate itemset. It avoids evaluating item combinations redundantly. In the end, they keep only those rules made from item combinations with strong associations. If the correlation is positive, then favorable rules are discovered; otherwise, negative controls will arise.
An innovative approach has proposed in [42]. In generating positive and negative association rules which consists of following four steps: (1) Generate all the positive frequent itemsets L (P1) (ii) for all itemsets I in L (P1), generate frequent negative itemsets of the form ┐ (I1I2) (iii) Generate all negative request itemsets ┐ I1 ┐ I2 (iv) Generate all frequent negative itemsets I1 ┐ I2 and (v) Generate all valid positive and negative association rules. Authors generated negative controls without adding additional interesting measure(s) to the support-confidence framework.
The proposed method came with a different approach with simple and effective [1]. It has not used any additional interesting measures and other database scans. They find negative itemsets by replacing a literal in a candidate itemset by its corresponding negated item. If a candidate itemset contains three elements, then it will produce corresponding three negative itemsets one for each literal.
In [43], the method that adds the conviction to the support-confidence framework to generate stronger positive and negative rules which do not require extra database scans. They proved that their algorithm could perform better than one in (MLA) on a real dataset.
In [44], an algorithm has proposed to generate both positive and negative association rules, which uses Yule's coefficient and works in the support-confidence framework. Its performance will e compared with MLA on a synthetic dataset. This algorithm performs better than MLA.

B) **INDIRECT ASSOCIATION RULE MINING**

The implied association is closely related to the negative association; they are both dealing with itemsets that do not have sufficiently high support. Indirect associations technique provide an effective way to detect interesting negative association by discovering only "infrequent data item pairs that are highly expected to be frequent" without using negative items or domain knowledge.
In [47], an internal measure of similarity between attributes X and Y are introduced and whose value depends on the benefits of X and Y columns and external means of similarity takes into account data from other columns (called prob attributes). Their idea of problem attributes is similar to mediators for indirect associations in [48]. The purpose of using problem attributes is to perform attribute clustering.
In [39] the intuition here is that items belonging to the same parent node in taxonomy are expected to have similar types of associations with other issues. If the observed support value is similar than its expected value, then there is a negative association exists between the objects. Again unlike long association, these types of regularities do not specifically look for mediating elements.

In relational databases, functional dependencies are the relationships that exist between attributes of a relation. In [48], they are used to find dependent and independent characteristics for application such as semantic query optimization and reverse engineering.

In [49], an efficient algorithm called HI-mine based on a new data structure called HI-struct has been proposed to mine the complete set of indirect associations between items. Their experimental results show that HI-mine's performance is significantly better than that of the previously developed algorithm for long mining association on both synthetic and real-world data sets over effective ranges of support specifications.

In [50], IAM algorithm proceeds in four phases: an initialization phase, a pruning phase, a bridge itemset calculation phase, and a ranking phase. The purpose of the initialization phases is to allocate the memory needed. The second phase is a process of pruning to minimize the search space of the problem. The threshold value of pruning is min-sup(s). The third phase, the Bridge Itemset Calculation Phase, is the most important for this algorithm. The last stage, a ranking phase, is mainly to finish the ranking operation according to' the closeness value in the linked vector Cfor the purpose of providing decision makers the most useful indirect association rules.

In [51], a new algorithm has been proposed to mine indirect associations between item pairs and itemsets by performing only one join operation and generating indirect associations for a couple of items and itemsets.

In [41], proposed an algorithm to discover all long negative association between itemsets in which mediator set is of form $\neg X^1 \neg Y^1$ and $\neg X^1 Y^1$. In incidental association mining for item pairs, an algorithm requires two join operations to overcome this disadvantage, a new algorithm to mine indirect associations between item pairs and itemsets by performing only one join operation and generating indirect positive and negative associations for a couple of items and itemsets.

In [52] proposed EMIA algorithm, improves the deficiency of the leading algorithm HI-mine*, alleviating unnecessary data transforming processes, thus can generate all indirect associations more efficiency using less memory storage. Experiments on both synthetic and real datasets are also made to show the effectiveness of proposed approaches.

V.CONCLUSION

In this article mainly discussed to develop a framework to generate valid positive and negative association rules, and to improve the efficiency for interesting rule generation. Number of interestingness measures have been proposed to identify the statistical significance of association rules. For our proposed method, we are trying to determine the correct estimation of these measures to be used for finding interesting negative indirect associations.

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