CHAPTER-15

Mining Multilevel Association Rules from Transaction Databases

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15. Mining Multilevel Association Rules from Transaction Databases

In this section, you will learn methods for mining multilevel association rules, that is, rules involving items at different levels of abstraction. Methods for checking for redundant multilevel rules are also discussed.

15.1 Multilevel Association Rules

For many applications, it is difficult to find strong associations among data items at low or primitive levels of abstraction due to the sparsity of data in multidimensional space. Strong associations discovered at high concept levels that might represent common sense knowledge. However, what may represent common sense to one user may seem novel to another. Therefore, data mining systems should provide capabilities to mine association rules at multiple levels of abstraction and traverse easily among different abstraction spaces.

15.2 Approaches to mining multilevel Association Rules

"How can we mine multilevel association rules efficiently using concept hierarchies?" Let's look at some approaches based on a support-confidence framework. In general, a top-down strategy is employed, where counts are accumulated for the calculation of frequent itemsets at each concept level, starting at the concept level 1 and working towards the lower, more specific concept levels, until no more frequent itemsets can be found. That is, once all frequent itemsets at concept levels, until no more frequent itemsets can be found. That is, once all frequent itemsets at concept level 1 are found, then the frequent itemsets at level 2 are found, and so on. For each level, any algorithm for discovering frequent itemsets may be used, such as Apriori or its variations.

- Using uniform minimum support for all levels (referred to as uniform support) The same minimum support threshold is used when mining at each level of abstraction.

When a uniform minimum support threshold is used, the search procedure is simplified. The method is also simple in that users are required to specify only one minimum support threshold. An optimization technique can be adopted, based on the knowledge that an ancestor is a superset of its descendents; the search avoids examining itemsets containing any item whose ancestors do not have minimum support.
The uniform support approach, however, has some difficulties. It is unlikely that items at lower levels of abstraction will occur as frequently as those at higher levels of abstraction. If the minimum support threshold is set too high, it could miss several meaningful associations occurring at low abstraction levels. If the threshold is set too low, it may generate many uninteresting associations occurring at high abstraction levels. This provides the motivation for the following approach.

- Using reduced minimum support at lower levels (referred to as reduced support); Each level of abstraction has its own minimum support threshold. The lower the abstraction level, the smaller the corresponding threshold.

For mining multiple-level associations with reduced support, there are a number of alternative search strategies:

**Level-by-Level independent:** This is a full-breadth search, where no background knowledge of frequent itemsets is used for pruning. Each node is examined, regardless of whether or not its parent node is found to be frequent.

**Level-cross-filtering by single item:** An item at the ith level is examined if and only if its parent node at the (i-1)th level is frequent. In other words, we investigate a more specific association from a more general one. If a node is frequent, its children will be examined; otherwise, its descendents are pruned from the search.

**Level-cross filtering by -K-itemset:** A K-itemset at the ith level is examined if and only if its corresponding parent K-itemset at the (i-1)th level is frequent.

15.3 Checking for Redundant Multilevel Association Rules
Concept hierarchies are useful in data mining since they permit the discovery of knowledge at different levels of abstraction, such as multilevel association rules. However, when multilevel association rules are mined, some of the rules found will be redundant due to "ancestor of "IBM desktop computer" based on the concept hierarchy.

15.4 Mining Multidimensional Association Rules from Relational Databases and Data Warehouses

In this section, you will learn methods for mining multidimensional association rules, that is, rules involving more than one dimension or predicate (e.g., rules relating what a customer buys as well as the customer's age). These methods can be organized according to their treatment of quantitative attributes.

15.5 Multidimensional Association Rules

So far we have studied association rules that imply a single predicate, that is, the predicate buys. For instance, in mining our ABC company database, we may discover the Boolean association rule "IBM desktop computer" implies "Sony b/w printer". Which can also be written as

\[ \text{buys}(X, "IBM desktop computer") \implies \text{buys}(X, "sony b/w printer") \]

where \( X \) is a variable representing customers who purchased items in ABC company transactions. Following the terminology used in multidimensional database, we refer to each distinct predicate in a rule as a dimensional. Hence, we can refer to the above rule as a single-dimensional or intradimension association rule since it contains a single distinct predicate (e.g., buys) with multiple occurrences (i.e., predicate occurs more than once within the rule). Such rules are commonly mined from transactions data. Suppose, however, that rather than using a transactional database, sales and related information are stored in a relational database or data warehouse. Such data stores are multidimensional, by definition. For instance, in addition to keeping track of the items purchased in sales transactions, a relational database may record other attributes associated with the items, such as the quantity purchased or the price, or the branch location of the sale. Additional relational information regarding the customers who purchased the items, such as customer age, occupation, credit rating, income, and address, may also be stored. Considering each database attribute or warehouse dimension as a predicate, it can therefore be interesting to mine association rules containing multiple predicates, such as

\[ \text{age}(X, "20......29") \land \text{occupation}(X, "student") \implies \text{buys}(X, "laptop") \]
Association rules that involve two or more dimensions or predicates can be referred to as multidimensional association rules. The above rule contains three predicates (age, occupation, and buys), each of which occurs only once in the rule. Hence, we say that it has no repeated predicates. Multidimensional association rules with no repeated predicates are called inter-dimensional association rules. We may also be interested in mining multidimensional association rules with repeated predicates, which contain multiple occurrences of some predicates. These rules are called hybrid-dimensional association rules. An example of such a rule is the following, where the predicate buys is repeated:

\[ \text{Age}(X, "20..29") \land \text{buys}(X, \text{"laptop"}) \rightarrow \text{buys}(X, \text{"sony b/w printer"}) \]

Note that database attributes can be categorical or quantitative. Categorical attributes have a finite number of possible values, with no ordering among the values (e.g., occupation, brandy color). Categorical attributes are also called nominal attributes, since their values are "names of things." Quantitative attributes are numeric and have an implicit ordering among values (e.g., age, income, price). Techniques for mining multidimensional association rules can be categorized according to three basic approaches regarding the treatment of quantitative attributes.

In the first approach, quantitative attributes are discretized using predefined concept hierarchies. This discretization occurs prior to mining. For instance, a concept hierarchy for income may be used to replace the original numeric values of this attribute by ranges, such as "0...20k", "21k...30k", "31k...40k", and so on. Here, discretization is static and predetermined. The discretized numeric attributes, with their range values, can then be treated as categorical attributes (where each range is considered a category). We refer to this as mining multidimensional association rules using static discretization of quantitative attributes.

In the second approach, quantitative attributes are discretized into "bins" based on the distribution of the data. These bins may be further combined during the mining process. The discretization process is dynamic and established so as to satisfy some mining criteria, such as maximizing the confidence of the rules mined. Because this strategy treats the numeric attribute values as quantities rather than as predefined ranges or categories, association rules mined from this approach are also referred to as quantitative association rules.

In the third approach, quantitative attributes are discretized so as to capture the semantic meaning of such interval data. This dynamic discretization procedure considers the distance between data points. Hence, such quantitative association rules are also referred to as distance-based association rules.
Let's study each of these approaches for mining multidimensional association rules. For simplicity, we confine our discussion to interdimensional association rules. Note that rather than searching for frequent itemsets (as is done for single-dimensional association rule mining), in multidimensional association rule mining we search for frequent "predicate set of predicates (age, occupation, buys)" form the multidimensional rule is a 3-predicate set. Similar to the notation used for itemsets, we use the notation $L_k$ to refer to the set of frequent $k$-predicate sets

### 15.6 Mining Multidimensional Association Rules Using Static Discretization of Quantitative Attributes

Quantitative attributes, in this case, are discretized prior to mining using predefined concept hierarchies, where numeric values are replaced by ranges. Categorical attributes may also be generalized to higher conceptual levels if desired. If the resulting task-relevant data are stored in a relational table, then the a priori algorithm requires just a slight modification so as to find all frequent predicate sets rather than frequent itemsets (i.e., by searching through all of the relevant attributes, instead of searching only one attribute, like 'buys'). Finding all frequent $k$-predicate sets will require $k$ or $k+1$ scans of the table. Other strategies, such as hashing, partitioning, and sampling may be employed to improve the performance.

Alternatively, the transformed task-relevant data may be stored in a data cube. Data cubes are well suited for the mining for multidimensional association rules, since they are multidimensional by definition. Data cubes and their computation were discussed in detail in earlier. To review, a data cube consists of a lattice of cuboids that are multidimensional data structures. These structures can hold the given task-relevant data, as well as aggregate, group-by information.

Due to the ever-increasing use of data warehousing and OLAP technology, it is possible that a data cube containing the dimensions of interest to the user may already exist, fully materialized. "If this is the case, how can we go about finding the frequent predicate sets?" A strategy similar to that employed in a priori can be used, based on prior knowledge that every subset of a frequent predicate set must also be frequent. This property can be used to reduce the number of candidate predicate sets generated. In cases where no relevant data cube exists for the mining task, one must be created.

### 15.7 Mining quantitative Association Rules
quantitative association rules are multidimensional association rules in which the numeric attributes are
dynamically discretized during the mining process so as to satisfy some mining criteria, such as maximizing the
confidence or compactness of the rules mined. In this section, we will focus specifically on how to mine quantitative
association rules having two quantitative attributes on the left-hand side of the rule, and one categorical attribute
on the right-hand side of the rule, for example,

\[ \text{Aquan}^1 \land \text{Aquan}^2 \implies \text{Acat} \]

Where Aquan^1 and Aquan^2 are tests on quantitative attribute ranges (where the ranges are dynamically determined), and Acat tests a categorical attribute from the task-relevant data. Such rules have been referred to as
two-dimensional quantitative association rules, since they contain two quantitative dimensions. For
instance, suppose you are curious about the association relationship between pairs of quantitative attributes, like
customer age and income, and the type of television that customers like to buy.

"How can we find such rules"? Let's look at an approach used in a system called ARCS (Association Rule
Clustering System), which borrows ideas from image processing. Essentially, this approach maps pairs of quantitative
attributes onto a 2-D grid for tuples satisfying a given categorical attribute condition. The grid is then searched for
clusters of points, from which the association rules are generated. The following steps are involved in ARCS:

15.8 Binning:

Quantitative attributes can have a very wide range of values denning their domain. Just think about how big a 2-D
grid would be if we plotted age and income as axes, where each possible value of age was assigned a unique
position on one axis, and similarly, each possible value of income was assigned a unique position on the other axis!
To keep grids down to a manageable size, we instead partition the ranges of quantitative attributes into
intervals. These intervals are dynamic in that they may later be further combined during the mining process. The
partitioning process is referred to as binning, that is, where the intervals are considered "bins." Three common
binning strategies are

- **Equiwidth binning**, where the interval size of each bin is the same,
- **Equidepth binning**, where each bin has approximately the same number of tuples assigned to it, and
- **Homogeneity-based binning**, where bin size is determined so that the tuples in each bin are uniformly distributed.

ARCS uses equiwidth binning, where the user inputs the bin size for each quantitative attribute. A 2-D array each possible bin combination involving both quantitative attributes is created. Each array cell holds the corresponding count distribution for each possible class of the categorical attribute of the rule right-hand side. By creating this data structure, the task-relevant data need only be scanned once. The same 2-D array can be used to generate rules for any value of the categorical attribute, based on the same two quantitative attributes.

15.9 Finding frequent predicate sets:

Once the 2-D array containing the count distribution for each category is set up this can be scanned in order to find the frequent predicate sets (those satisfying minimum support) that also satisfy minimum confidence. Strong association rules can then be generated from these predicate sets, using a rule generation algorithm.

15.10 Mining Distance-Based Association Rules

The previous section described quantitative association rules where quantitative attributes are discretized initially by methods, and the resulting intervals are then combined. Such an approach, however, may not capture the semantics of intervals data—since they do not consider the relative distance between data points or between intervals.
Consider, for example, Table 3.1 which shows data for the attribute priori partitioned according to equiwidth and equidepth binning versus a distance-based partitioning. The distance-based partitioning seems the most intuitive, since it groups values that are close together within the same interval (e.g., [20, 22]). In contrast, equidepth partitioning groups distant values together (e.g., [22, 50]). Equiwidth must split values that are close together and create intervals for which there are no data clearly. A distance-based partitioning that considers the density or number of points an interval, as well as the "closeness" of points in an interval, helps produce a meaningful discretization. Intervals for each quantitative attribute can be established clustering the values for the attribute.

A disadvantage of association rules is that they do not allow for approximations of attribute values. Consider the following association rule:
Item_type(x,"electronic") ^ manufacturer(X,"foreign") implies price(X,200)

Where X is a variable describing items at ABCompany. In reality, it is more likely that the prices of foreign electronic items are close to or approximately $200, rather than exactly $20. It would be useful to have association rules that can express such a notion of closeness. Note that the support and confidence measures do not consider the closeness of values for a given attribute. This motivates the mining of distance-based association rules, which capture the semantics of interval data while allowing for approximation in data values. A two-phase algorithm can be used to mine distance-based association rules. The first phase employs clustering to find the intervals or clusters, adapting to the amount of available memory. The second phase obtains distance-based association rules by searching for groups of clusters that occur frequently together.

15.11 Review Questions

1. Explain about Multilevel Association Rules

2. Discuss the Approaches to mining multilevel Association Rules

3. Explain about Mining Multidimensional Association Rules from Relational Databases and Data Warehouses

4. Discuss multidimensional Association Rules

5. Explain Mining Multidimensional Association Rules Using Static Discretization of Quantitative Attributes
15.12 References

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