

## Frequent Itemset Mining Methods

### Apriori Algorithm: Finding Frequent Itemsets by Confined Candidate generation

The name of the algorithm is based on the fact that the algorithm uses *prior knowledge* of frequent itemset properties. Apriori employs an iterative approach known as a *level-wise* search, where  $k$ -itemsets are used to explore  $(k+1)$ -itemsets. First, the set of frequent 1-itemsets is found by scanning the database to accumulate the count for each item, and collecting those items that satisfy minimum support. The resulting set is denoted by  $L_1$ . Next,  $L_1$  is used to find  $L_2$ , the set of frequent 2-itemsets, which is used to find  $L_3$ , and so on, until no more frequent  $k$ -itemsets can be found. The finding of each  $L_k$  requires one full scan of the database.

To improve the efficiency of the level-wise generation of frequent itemsets, an important property called the **Apriori property** is used to reduce the search space.

**Apriori property:** *All nonempty subsets of a frequent itemset must also be frequent.*

The Apriori property is based on the following observation. By definition, if an itemset  $I$  does not satisfy the minimum support threshold, *min sup*, then  $I$  is not frequent, that is,  $P(I) < \text{min sup}$ . If an item  $A$  is added to the itemset  $I$ , then the resulting itemset (i.e.,  $I \cup A$ ) cannot occur more frequently than  $I$ . Therefore,  $I \cup A$  is not frequent either, that is,  $P(I \cup A) < \text{min sup}$ .

This property belongs to a special category of properties called **antimonotonicity** in the sense that *if a set cannot pass a test, all of its supersets will fail the same test as well*. It is called *antimonotonicity* because the property is monotonic in the context of failing a test.

A two-step process is followed, consisting of **join** and **prune** actions.

- 1. The join step:** To find  $L_k$ , a set of **candidate**  $k$ -itemsets is generated by joining  $L_{k-1}$  with itself. This set of candidates is denoted  $C_k$ . Let  $l_1$  and  $l_2$  be itemsets in  $L_{k-1}$ . The notation  $li[j]$  refers to the  $j$ th item in  $li$ . For efficient implementation, Apriori assumes that items within a transaction or itemset are sorted in lexicographic order. For the  $(k-1)$ -itemset, this means that the items are sorted such that  $li[1] < li[2] < \dots < li[k-1]$ . The join,  $L_{k-1} \times L_{k-1}$ , is performed, where members of  $L_{k-1}$  are joinable if their first  $(k-2)$  items are in common. That is, members  $l_1$  and  $l_2$  of  $L_{k-1}$  are joined if  $(l_1[1] = l_2[1]) \wedge (l_1[2] = l_2[2]) \wedge \dots \wedge (l_1[k-2] = l_2[k-2]) \wedge (l_1[k-1] < l_2[k-1])$ . The condition  $l_1[k-1] < l_2[k-1]$  simply ensures that no duplicates are generated. The resulting itemset formed by joining  $l_1$  and  $l_2$  is  $\{l_1[1], l_1[2], \dots, l_1[k-2], l_1[k-1], l_2[k-1]\}$ .
- 2. The prune step:**  $C_k$  is a superset of  $L_k$ , that is, its members may or may not be frequent, but all of the frequent  $k$ -itemsets are included in  $C_k$ . A database scan to determine the count of each candidate in  $C_k$  would result in the determination of  $L_k$  (i.e., all candidates having a count no less than the minimum support count are frequent by definition, and therefore belong to  $L_k$ ).  $C_k$ , however, can be huge, and so this could involve heavy computation. To reduce the size of  $C_k$ , the Apriori property is used as follows. Any  $(k-1)$ -itemset that is not frequent cannot be a subset of a frequent  $k$ -itemset. Hence, if any  $(k-1)$ -subset of a candidate  $k$ -itemset is not in  $L_{k-1}$ , then the candidate cannot be frequent either and so can be removed from  $C_k$ .