Mining Frequent Colour Set Chosen by Customers Using Apriori

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ABSTRACT

Apriori is an algorithm for frequent item set mining and association rule learning over transactional database. It proceeds by identifying the frequent individual items in the database and extending them to larger and large item sets long as those item sets appear sufficiently often in the database. The frequent item sets determined by apriori can be used to determine association rules which highlight general trends in the database. This has applications in online shopping analysis the frequent color item sets using apriori algorithm.

1. INTRODUCTION

Apriori is an influential algorithm for mining frequent itemsets for Boolean association rules. The name of the algorithm based on the fact that the algorithm uses prior knowledge of frequent itemset properties.

2. APRIORI PROPERTIES

Apriori employs an iterative approach known as a level-wise search, where k-itemsets is are used to expore(k+1)-itemsets.

- The set of frequent 1-itemsets is found this denoted L1.
- L1 is used to find L2,the set of frequent 2-itemsets,which is used to find L3,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 presented below is used to reduce the search space.
- In order to use the apriori property, all nonempty subsets of a frequent itemset must also be frequent.
- The subset can be frequent the subnet can be removed is Anti-monotone.

3. TWO-STEP PROCESS

- The join step
- The prune step

3.1 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 l1 and l2 be itemsets in L_k-1.the L_k-1 L_k-1

3.2 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 include in C_k. A scan of the database to determine

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the count of each candidate in C_k would result in the determination of L_k.

All candidates having a count no less than the minimum support count are frequent by definition, and therefore belong to L_k.

Example

Online shopping company report on the frequent color itemsets

TID	List of colors_ID$_s$
T100	C1,C2,C5
T200	C2,C4
T300	C2,C3
T400	C1,C2,C4
T500	C1,C3
T600	C2,C3
T700	C1,C3,
T800	C1,C2,C3,C5
T900	C1',C2,C3

C1-Red, C2-Green, C3-pink, C4-blue, C5-yellow

C1

Item set	Sup.count
C1,C2	4
C1,C3	4
C1,C4	1
C1,C5	2
C2,C3	4
C2,C4	2
C2,C5	2
C3,C4	0
C3,C5	1
C4,C5	0

Find the min-support
Min-support=2
Sup.count<2

L2

Item Set	Sub.count
C1,C2	4
C1,C3	4
C1,C5	2
C2,C3	4
C2,C4	2
C2,C5	2

Min-support=2
Sub.count<2

C2

ItemSet	Sup.Count
C1,C2,C3	2
C1,C2,C5	2
C1,C3,C5	0
C1,C3,C4	0
C1,C5,C4	0

Min-support=2

Sub-Count<2

C3

ItemSet	Sub.Count
C1,C2,C3	2
C1,C2,C5	2

L3

ItemSet	Sub.Count
C1,C2,C3,C5	2

Steps:

1. In the first iteration of the algorithm of the algorithm,each item is a member of the set of candidate 1-itemsets,C1.
2. Suppose that the minimum transaction support count required is 2.the set of frequent 1-itemsets,L_1,can then be determined,it consists of the candidate 1-itemsets satisfying minimum support.
3. To discover the set of frequent 2-itemsets,L_2,the algorithm uses L_1 L_1
4. Next,the transaction check the minimum support count.
5. The set of frequent 2-itemsets,L_2 is then determined,consisting of those candidate 2-itemsets in C_2 having minimum support.
6. The generation of the set of candidate –itemset C_3.Let C_3= L_2 L based on the apriori property that all subsets of a frequent itemsetm must also be frequent,we can determine that the four latter candidates cannot possibly be frequent.we therefore remove them from C_3.
7. Candidate 3-itemsets in C_3 having minimum support
8. The algorithm uses L_3 L_3 to generate a candidate set of 4-itemsets of 4-itemsets,although the join in result [C1,C2,C3,C5]
9. This itemset is pruned since its subset [C1,C2,C3] is not frequent

Algorithm:

Input:

L_c-1 // Large colors items I – 1

Output:

C_c

Apriori-gen alogorithm:

C_c=Ø;

For each Iõ L_c-1 do

For each J'"IõL$_i$-1 do

If I – 2 of the elements in I and J are equal then

C_k=C U {I U J};

We use c_i to be the count for item I_i 1

Algorithm

Input

I //Itemsets

D // Database of transactions

S support

Output

L // Large Itemsets

Apriori algorithm

k=0; L=Ø;

C_1=I;

repeat

k=k+1;

L_k=Ø;

For each I_i õc_k do

C_i=0; // initial counts for each itemset are 0.

For each t_j õ D do

For each I_i õ c_k do

If I_i õ t_j then

$c_i = c_i + 1$;

For each I_i õ c_k do

If c e" (s×|D|) do

L_k=L_k U I_i;

L=LUL_k;

C_{k+1}=Apriori-gen(L_k)

Until $c_{k+1} = Ø$;

Conclusion

The company frequent color itemsets [C1,C2,C3,C5] so conclusion for the company can be report are red,green,pink and yellow colors on improve that the color itemsets.

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