

Apriori Algorithm

- Invented by Rakesh Agrawal and Ramakant Srikant (1994)
- Can we speed up than pure brute force?
- Apriori: acknowledges the prior knowledge
 - If any itemset is not frequent, its superset cannot be frequent
 - An itemset can be frequent only if all its subsets are frequent

How does it work?

- Step 0: create 1-size frequent *itemsets* list that meet threshold support, $k=1$
- Step 1: Expand the *itemsets* list
 - From the k sized *itemsets* list combine overlapping sets to $k+1$ size *itemsets* list
- Step 2: Prune the expanded *itemsets* list using apriori property,
 - $k=k+1$
- Step 3: remove infrequent *itemsets* from the list
- Repeat Step 1,2,3 till no more further expansion possible

1
2
3
4
5
6

Step 1

1
2
3
4
5
6

Step 2

1
2
3
4
5

Step 3

1,2
1,3
1,4
1,5
2,3
2,4
2,5
3,4
3,5
4,5

Step 1

1,2
1,3
1,4
1,5
2,3
2,4
2,5
3,4
3,5
4,5

Step 2

1,2
1,3
2,4
3,4
3,5
4,5

Step 3

1,2,3
1,2,4
1,3,4
1,3,5
2,3,4
2,4,5
3,4,5

Step 1

3,4,5

Step 2,3

L_1 {1}, {2}, {3}, {4}, {5}, L_2 {1,2}, {1,3}, {2,4}, {3,4}, {3,5}, {4,5}, L_3 {3,4,5}

Apriori(T, ϵ)

$L_1 \leftarrow \{\text{large singleton itemsets}\}$

$k \leftarrow 2$

while L_{k-1} is not empty

$C_k \leftarrow \text{Generate_candidates}(L_{k-1}, k)$

for transactions t in T

$D_t \leftarrow \{c \text{ in } C_k : c \subseteq t\}$

for candidates c in D_t

$\text{count}[c] \leftarrow \text{count}[c] + 1$

$L_k \leftarrow \{c \text{ in } C_k : \text{count}[c] \geq \epsilon\}$

$k \leftarrow k + 1$

return Union(L_k) over all k

Generate_candidates(L, k)

result \leftarrow empty_set()

for all $p \in L, q \in L$ where p and q differ in exactly one element

$c \leftarrow p \cup q$

if $u \in L$ for all $u \subseteq c$ where $|u| = k-1$

result.add(c)

return result

- Different types of association rules (Categorical, hierarchical, cyclic)
- Eclat Algorithm
 - Equivalence Class Transformation: a depth-first search strategy
- FP-Growth
 - Frequent Pattern Growth: a compact data structure called the FP-tree (Frequent Pattern tree) to compress the dataset

Applications

- Text classification
 - Classify emails into spam / non-spam
 - NLP Problems
 - Tagging: Classify words into verbs, nouns, etc.
- Risk management, Fraud detection, Computer intrusion detection
 - Given the properties of a transaction (items purchased, amount, location, customer profile, etc.)
 - Determine if it is a fraud
- Machine learning / pattern recognition applications
 - Vision
 - Speech recognition etc.
- All of science & knowledge is about predicting future in terms of past
 - So classification is a very fundamental problem with ultra-wide scope of applications

- We collect different measurements/facts/about certain features
- $x = (x_1, x_2, \dots, x_d)$
 - In the above example, x_1, x_2 are diameter and weight
- $y \in \{1, 2, \dots, K\} = [K]$
- If $K = 2$ binary classification, else, multi-class classification

- What is classifier?
- How to measure 'goodness' of a classifier?
- If only 1% population has cancer, then a test for cancer that classifies all people as non-cancer will predict 99% of the trials correctly

	y_i	0	1
0		TN	FP
1		FN	TP

$$P = FN + TP$$

$$N = TN + FP$$

$$\text{Accuracy} = \frac{TP + TN}{P + N}$$

$$\text{Recall / sensitivity} = \frac{TP}{P} = \frac{TP}{TP + FN} \quad (\text{TPR})$$

$$\text{Precision} = \frac{TP}{FP + TP} \quad (\text{Positive predictive value, PPV})$$

$$FNR = \frac{FN}{P} \quad TPR + FNR = 1$$

$$TNR = \frac{TN}{N} \quad TNR + FPR = 1$$

$$FPR = \frac{FP}{N}$$

\hat{y}_i	0	1
0	TN	FP
1	FN	TP

$$P = FN + TP$$

$$N = TN + FP$$