Association Rule Mining

finding association Rules

What are association rules?

basket = transaction = # items present in a basket

- Association Rules is one of the very important concepts of machine learning being used in market basket analysis
- In a store, all vegetables are placed in the same aisle, all dairy items are placed together and cosmetics form another set of such groups
- Investing time and resources on deliberate product placements like this not only reduces a customer's shopping time, but also reminds the customer of what relevant items (s)he might be interested in buying, thus helping stores cross-sell in the process
- Association rules help uncover all such relationships between items from huge databases → # transactions

Applications

- Finding the set of items that has significant impact on business
- Collection information from numerous transactions
- Generating rules from count in transactions

Apriori

Overview

itemset = set of items in a transaction

- **Apriori algorithm** is given by R. Agrawal and R. Srikant in 1994 for finding frequent itemsets in a dataset for boolean association rule
- Name of the algorithm is Apriori because it uses prior knowledge of frequent itemset properties
- We apply an iterative approach or level-wise search where k-frequent itemsets are used to find k+1 itemsets
- To improve the efficiency of level-wise generation of frequent itemsets, an important property is used called *Apriori property* which helps by reducing the search space
- **Apriori Property:** All non-empty subset of frequent itemset must be frequent
- The key concept of Apriori algorithm is its anti-monotonicity of support measure

Terminology - Itemset

- It is a representation of the list of all items which form the association rule
- E.g.
  - Itemset = {Bread, Egg, Milk}

Terminology - Support

- This measure gives an idea of how frequent an *itemset* is in all the transactions
- E.g.
  - *itemset1* = {bread} and *itemset2* = {shampoo}
  - There will be far more transactions containing bread than those containing shampoo
  - So *itemset1* will generally have a higher support than *itemset2*
- *E.g.*
  - *itemset1* = {bread, butter} and *itemset2* = {bread, shampoo}
  - Many transactions will have both bread and butter on the cart but bread and shampoo are not so much
  - So in this case, *itemset1* will generally have a higher support than *itemset2*
- Mathematically support is the fraction of the total number of transactions in which the itemset occurs

$$Support(\{X\} \rightarrow \{Y\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Total\ number\ of\ transactions}$$

Terminology - Confidence

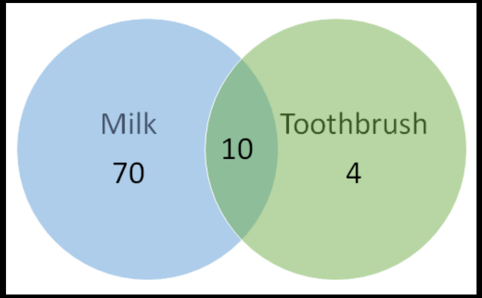
- This measure defines the likeliness of occurrence of consequent on the cart given that the cart already has the antecedents
- Technically, confidence is the conditional probability of occurrence of consequent given the antecedent

$$Confidence(\{X\} \rightarrow \{Y\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Transactions\ containing\ X}$$

will purchase
consequent

already purchased
antecedent

- E.g.
  - Confidence for {Toothbrush} ⟶ {Milk} will be 10/(10+4) = 0.7



Summary

- **Association Rule**: Ex. $\{X \longrightarrow Y\}$ is a representation of finding Y on the basket which has X on it
- **Itemset:** Ex. {X,Y} is a representation of the list of all items which form the association rule
- **Support:** Fraction of transactions containing the itemset
- **Confidence**: Probability of occurrence of {Y} given {X} is present
- **Lift**: Ratio of *confidence* to baseline probability of occurrence of {Y}

Example

- Given the transactions generate rules using Apriori algorithm.
- Consider support = 50% and confidence = 75%

Transaction Id	Items Purchased
1	Bread, Cheese, Egg, Juice
2	Bread, Cheese, Juice
3	Bread, Milk, Yogurt
4	Bread, Juice, Milk
5	Cheese, Juice, Milk

item	# transactions	support
Bread	4	4/5 = 0.8
Cheese	3	3/5 = 0.6
Egg	1	1/5 = 0.20 ✗
Juice	4	4/5 = 0.80
Yogurt	1	1/5 = 0.20 ✗
Milk	3	3/5 = 0.60

itemset	# transactions	Confidence	
{ Bread, cheese }	2	2/3 = 0.66	
{ Bread, Juice }	3	3/4 = 0.75	✓
{ Bread, milk }	2	2/3 = 0.66	
{ cheese, Bread }	2	2/4 = 0.50	
{ cheese, Juice }	3	3/4 = 0.75	✓
{ cheese, milk }	1	1/3 = 0.33	
{ juice, bread }	3	3/4 = 0.75	✓
{ juice, cheese }	3	3/3 = 1	✓
{ juice, milk }	2	2/3 = 0.66	

Disadvantages

- It may need to generate a huge number of candidate sets
- It may need to repeatedly scan the database and check a large setoff candidates

FP-Growth

Overview

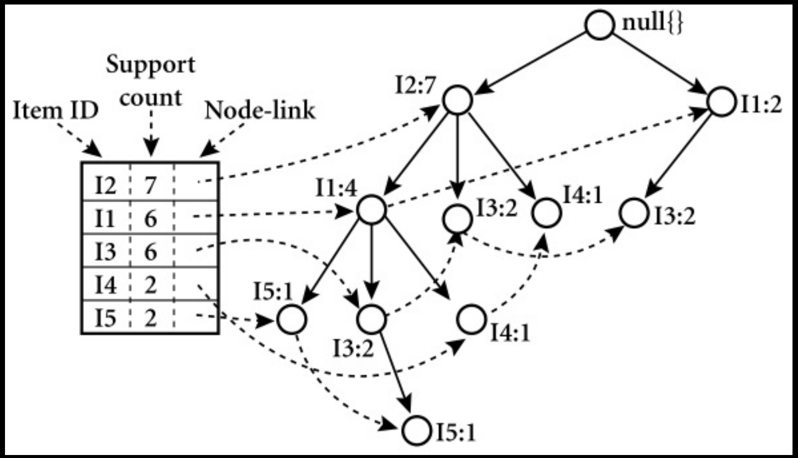
- Mining frequent itemsets without candidate generation
- The FP-Growth Algorithm, proposed by Han
- It is an efficient and scalable method for mining the complete set of frequent patterns by pattern fragment growth, using an extended prefix-tree structure for storing compressed and crucial information about frequent patterns named frequent-pattern tree (FP-tree)
- In his study, Han proved that his method outperforms other popular methods for mining frequent patterns, e.g. the Apriori Algorithm
- It has better performance than other methods

Steps

- Find frequent item sets without candidate generation
- Compress the database representing items into a frequent-pattern tree or FP-tree which retains the itemset association information
- Divide the compressed database into a set of conditional database, each associated with one frequent item or pattern fragment
- Mine each database separately

FP-Tree

- The frequent-pattern tree (FP-tree) is a compact structure that stores quantitative information about frequent patterns in a database
- It contains
  - One root labelled as null with a set of item-prefix subtrees as children and frequent-item-header table
  - Each node in the item-prefix subtree consists of three fields
  - Item-name: registers which item is represented by the node
  - Count: the number of transactions represented by the portion of the path reaching the node;
  - Node-link: links to the next node in the FP-tree carrying the same item-name, or null if there is none.
  - Each entry in the frequent-item-header table consists of two fields:
  - Item-name: as the same to the node;
  - Head of node-link: a pointer to the first node in the FP-tree carrying the item-name.



Example

- Generate FP tree for following data set

Id	Items
1	E, A, D, B
2	D, A, C, E, B
3	C, A, B, E
4	B, A, D
5	D
6	D, B
7	A, D, E
8	B, C