Association Rule Mining

rules ⇒ assication of items

{ bread } → { butter }

milk → toast


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What are association rules?

- 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

→ two parts

basket = transaction

→ set of purchased products

Applications

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

market basket analysis

Apriori

a prior knowledge of
data (products)

Overview

- **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

itemset = set of items

{ milk, bread, butter }

Terminology - Itemset

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

{ bread } → { butter }

antescendent → consequent

already present → recommend

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

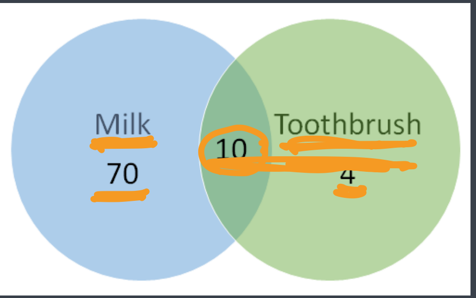
$$Support(\{X\} \rightarrow \{Y\}) = \frac{Transactions\ containing\ both\ X\ and\ Y}{Total\ number\ of\ transactions}$$

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

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

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



Terminology - Lift

- Lift controls for the *support* (frequency) of consequent while calculating the conditional probability of occurrence of {Y} given {X}
- Think of it as the *lift* that {X} provides to our confidence for having {Y} on the cart
- To rephrase, *lift* is the rise in probability of having {Y} on the cart with the knowledge of {X} being present over the probability of having {Y} on the cart without any knowledge about presence of {X}
- Mathematically

$$Lift(\{X\} \rightarrow \{Y\}) = \frac{(Transactions\ containing\ both\ X\ and\ Y)/(Transactions\ containing\ X)}{Fraction\ of\ transactions\ containing\ Y}$$

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

	items	count	support	
1	Bread	4	4/5 = 0.8	✓
2	cheese	3	3/5 = 0.6	✓
	~~Egg~~	~~1~~	~~1/5 = 0.2~~	✗
3	Juice	4	4/5 = 0.8	✓
4	milk	3	3/5 = 0.6	✓
	~~Yogurt~~	~~1~~	~~1/5 = 0.2~~	✗

itemset	count	support	confidence
bread → cheese	2	2/5 = 0.4	
bread → Juice	3	3/5 = 0.6 ✓ →	3/4 = 0.75 ✓
bread → milk	2	2/5 = 0.4	
cheese → bread	2	2/5 = 0.4	
cheese → Juice	3	3/5 = 0.6 ✓ →	3/3 = 1.0 ✓
cheese → milk	1	1/5 = 0.2	
Juice → bread	3	3/5 = 0.6 ✓ →	3/4 = 0.75 ✓
Juice → cheese	3	3/5 = 0.6 ✓ →	3/4 = 0.75 ✓
Juice → milk	2	2/5 = 0.4	
milk → bread	2	2/5 = 0.4	
milk → cheese	1	1/5 = 0.2	
milk → Juice	2	2/5 = 0.4	

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

Perform Apriori in R

```
library(arules)

transactions = read.transactions('Market_Basket_Optimisation.csv', rm.duplicates = TRUE, sep = ',')
itemFrequencyPlot(transactions, topN=10)
rules = apriori(transactions, parameter = list(confidence = 0.4, support = 0.04))
summary(rules)
inspect(rules)
```

FP-Growth

frequent Patterns

↳ frequent itemsets

Overview

No need to generate permutations & combination

- 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

role

FP-Tree

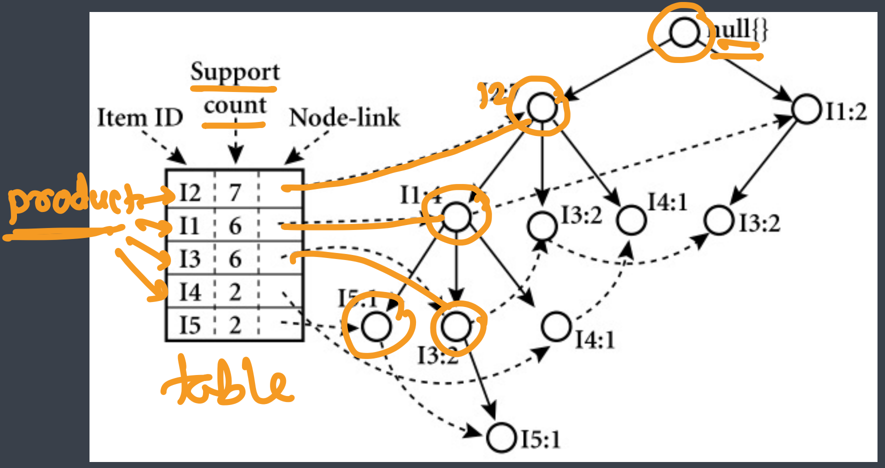
- The frequent-pattern tree (FP-tree) is a compact structure that stores quantitative information about frequent patterns in a database

  ↳ Frequent Pattern → [count]

- 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.

tree

root



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

unique item	count
A	5
B	6
C	3
D	6
E	4

descending order of items based on the count = B, D, A, E, C

No	original	reordered
1	E A D B	B D A E ✓
2	D A C E B	B D A E C ✓
3	C A B E	B A E C ✓
4	B A D	B D A ✓
5	D	D ✓
6	D B	B D ✓
7	A D E	D A E ✓
8	B C	B C

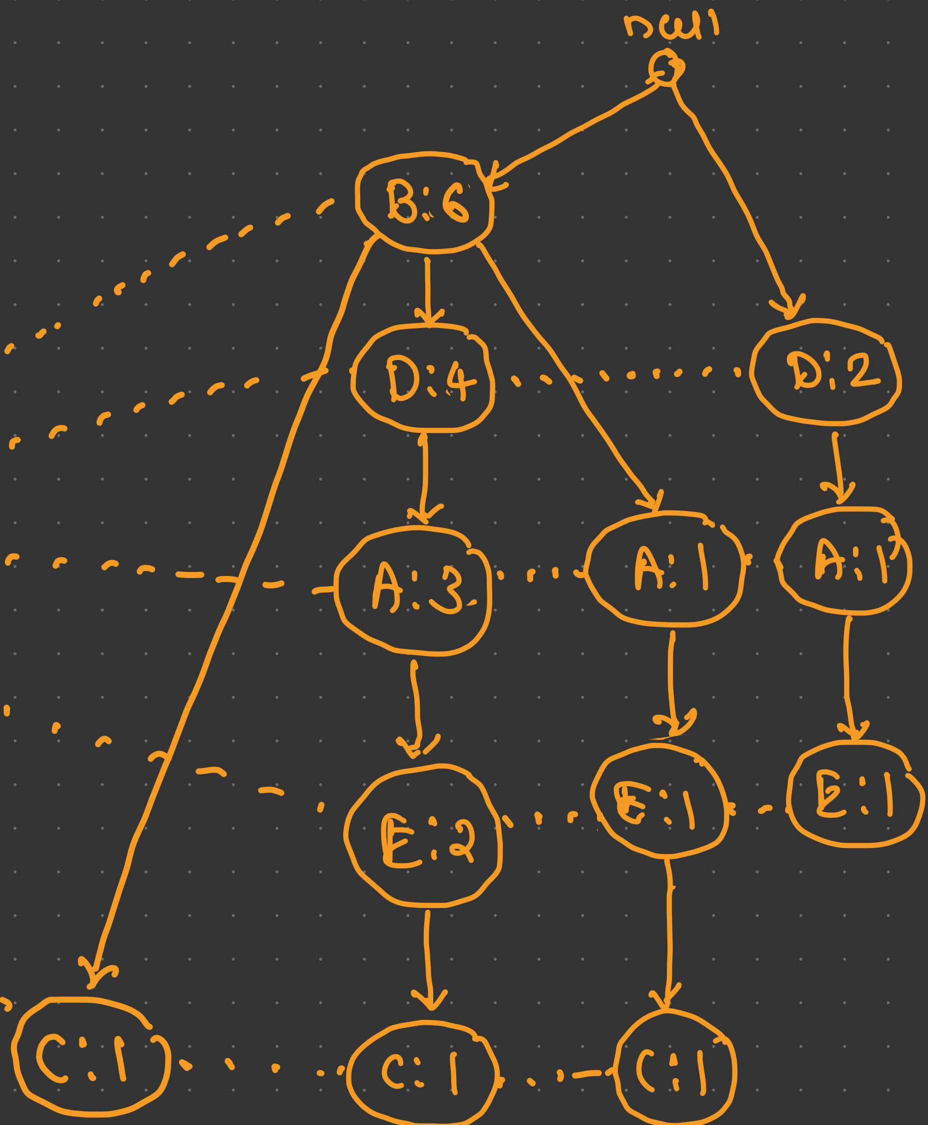
B, D, A, E, C

order

item name	count	Ptr
B	6	
D	6	
A	5	
E	4	
C	3	

FP-table

FP-Tree



AR = { B, DD }

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