# INTRODUCTION TO DATA ANALYSIS_ UNDERSTANDING GROUPS

**$2^{nd}$ Sem, MCA**

# CONTENT

- Understanding Groups in Data Analysis
  - Clustering
  - Association rules
    - Market Basket Analysis
    - Recommendation system
    - Apriori algorithm
    - FP Growth Algorithm

# DATA ANALYSIS - GROUPING

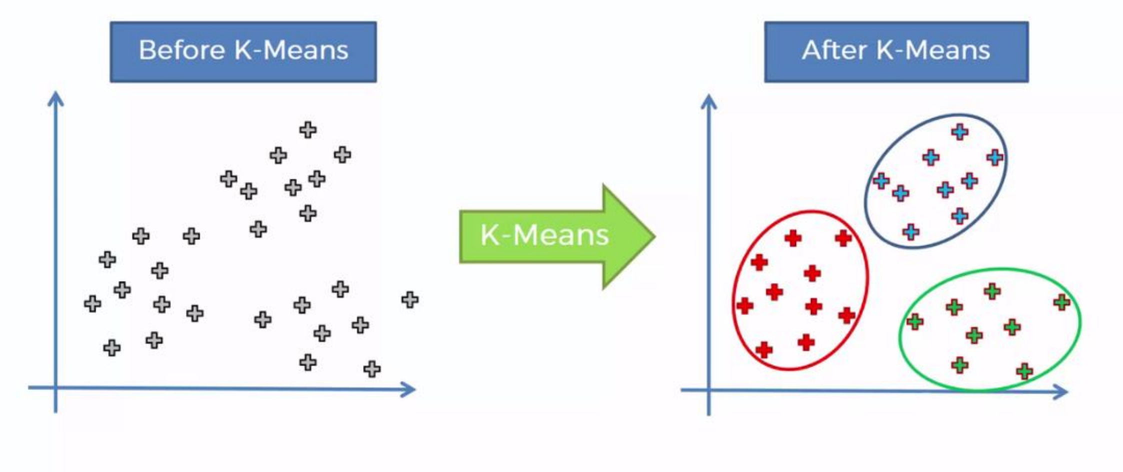
- Grouping and classification techniques are very important methods in data analysis.
- **Grouping Analysis** methods helps to determine natural groupings in data.
- Useful to decompose data set into simpler subsets → helps to make sense of entire collection of observations.
- For each group summary statistics, variety of graphs may help in better analysis
- Different ways to visualize and group observations,
  - *Clustering:* based on similarities of overall set of variables of interest.
  - *Association rule:* identify groups based on interesting combinations of predefined categories
  - *Decision tree:* groups observation based on combination of ranges of continuous variables or of specific categories.

# DATA ANALYSIS – CLUSTERING

- **Cluster**: group of (similar) objects that belongs to same class.
- **Clustering**: process of making a group of abstract objects into classes of similar objects.
- Given a data set of items, with certain features, and values for these features; the task is to categorize those items into groups.
  - Used to find similarity as well as relationship patterns among data samples and then cluster those samples into groups having similarity based on features.
  - Clustering is important because it determines the intrinsic grouping among the present unlabeled data.

Clustering methods –

- Partitioning Method
- Hierarchical Method; Agglomerative Approach, Divisive Approach
- Constraint-based Method
- Density-based Method
- Grid-Based Method
- Model-Based Method



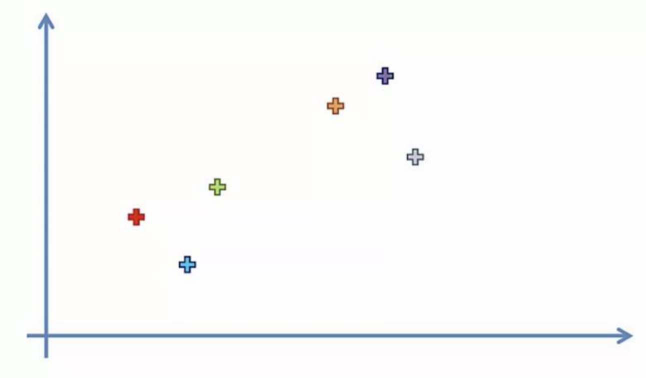
# Clustering

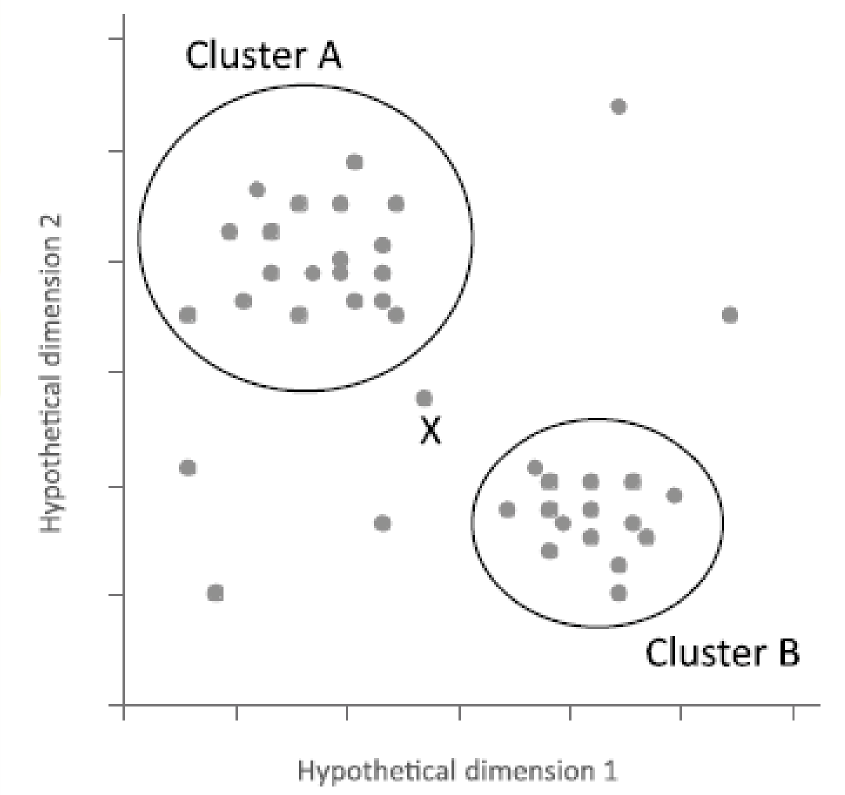
**Applications of Cluster Analysis**

- *Collaborative systems and customer segmentation:* help marketers discover distinct groups in their customer base → characterize customer groups based on purchasing patterns.
- helps in classifying documents on the web for information discovery.
- used in outlier detection applications; example detection of credit card fraud.
- *Biological data analysis:* used to derive plant and animal taxonomies, categorize genes with similar functionalities and gain insight into structures inherent to populations.
- Data summarization and compression
- Trend detection in dynamic data
- Social network analysis

# DATA ANALYSIS – CLUSTERING

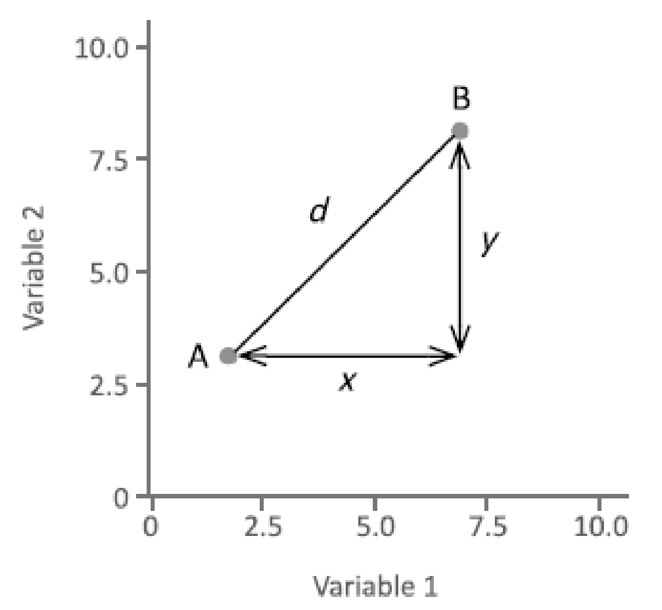
- Clustering is an *unsupervised* method for grouping.
- **Unsupervised**: groups are not known in advance.
- Clustering method chosen to subdivide data into groups applies automated procedure to discover groups based on some criteria.
- Many clustering methods.
- Each method will group data differently based on criteria it uses.
- For clustering, there is no way to measure accuracy (usefulness matters).
- **Distance** between two observations defines how similar they are to be in same cluster or not.





# DATA ANALYSIS – CLUSTERING

- Clustering needs a way to measure how similar the observations are to each other.
- To calculate similarity, distance between observations is computed.
- Simple distance between two observations can be calculated using simple trigonometry.




$$d = \sqrt{[(x_2 - x_1)^2 + (y_2 - y_1)^2]}$$

d: Euclidean distance
(x1, y1) → coordinate of first point
(x2, y2) → coordinate of second point.

$$x = 7 - 2 = 5$$
$$y = 8 - 3 = 5$$
$$d = \sqrt{x^2 + y^2} = \sqrt{25 + 25} = 7.07$$

- Distance metrics: **Euclidean, Jaccard**, City Block, Minkowski, Cosine, Spearman, Hamming, Mahalanobis etc.

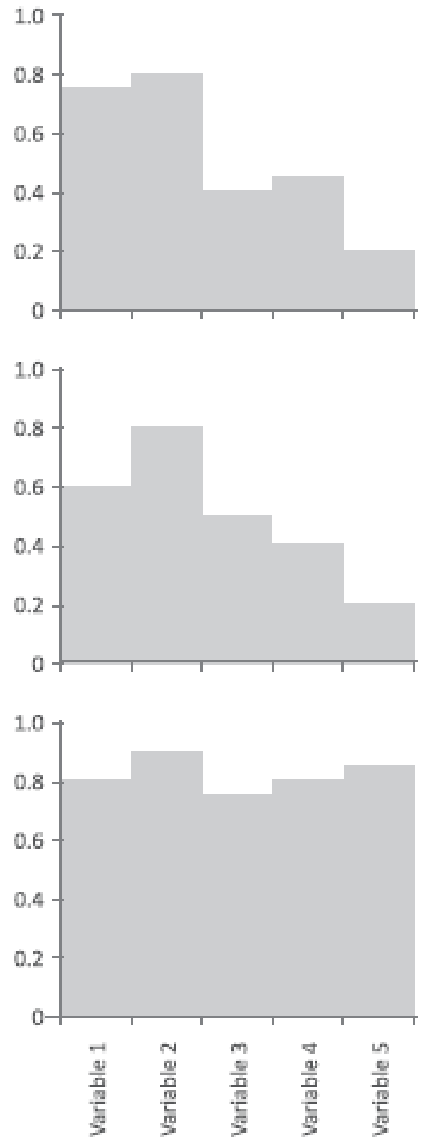
# DATA ANALYSIS – CLUSTERING

- **Euclidian Distance**: calculate distances between observations with more than two variables.

$$d = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$$

$$d = \sqrt{[(x_2 - x_1)^2 + (y_2 - y_1)^2]}$$

| ID | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 5 |
|---|---|---|---|---|---|
| A | 0.7 | 0.8 | 0.4 | 0.5 | 0.2 |
| B | 0.6 | 0.8 | 0.5 | 0.4 | 0.2 |
| C | 0.8 | 0.9 | 0.7 | 0.8 | 0.9 |



# DATA ANALYSIS – CLUSTERING

- **Euclidian Distance**: $d = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$

| ID | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 5 |
|---|---|---|---|---|---|
| A | 0.7 | 0.8 | 0.4 | 0.5 | 0.2 |
| B | 0.6 | 0.8 | 0.5 | 0.4 | 0.2 |
| C | 0.8 | 0.9 | 0.7 | 0.8 | 0.9 |

- Used to calculate distance between two observations p and q where each observation has n variables.
- Euclidean distance between A and B; A and C; B and C.

$$d_{A-B} = \sqrt{(0.7-0.6)^2 + (0.8-0.8)^2 + (0.4-0.5)^2 + (0.5-0.4)^2 + (0.2-0.2)^2}$$
$$d_{A-B} = 0.17$$

- More similarity between observations A-B than A-C.
- C is not closely related to either A or B.

The Euclidean distances between A and C is

$$d_{A-C} = \sqrt{(0.7-0.8)^2 + (0.8-0.9)^2 + (0.4-0.7)^2 + (0.5-0.8)^2 + (0.2-0.9)^2}$$
$$d_{A-C} = 0.83$$

The Euclidean distance between B and C is

$$d_{B-C} = \sqrt{(0.6-0.8)^2 + (0.8-0.9)^2 + (0.5-0.7)^2 + (0.4-0.8)^2 + (0.2-0.9)^2}$$
$$d_{B-C} = 0.86$$

# DATA ANALYSIS – CLUSTERING

- Euclidean distance metric can be used only for numerical variables.
- **Jaccard distance**: for binary variables.

| | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 5 |
|---|---|---|---|---|---|
| A | 1 | 1 | 0 | 0 | 1 |
| B | 1 | 1 | 0 | 0 | 0 |
| C | 0 | 0 | 1 | 1 | 1 |

- This approach is based on number of common or different (0/1) values between corresponding variables across each pair of observations.
  - *Count11: Count of all variables that are 1 in "Observation 1" and 1 in "Observation 2."*
  - *Count10: Count of all variables that are 1 in "Observation 1" and 0 in "Observation 2."*
  - *Count01: Count of all variables that are 0 in "Observation 1" and 1 in "Observation 2."*
  - ~~*Count00: Count of all variables that are 0 in "Observation 1" and 0 in "Observation 2."*~~
- **Jaccard distance (d):**

$$d = \frac{\text{Count}_{10} + \text{Count}_{01}}{\text{Count}_{11} + \text{Count}_{10} + \text{Count}_{01}}$$

# DATA ANALYSIS – CLUSTERING

- **Jaccard distance**: $$d = \frac{\text{Count}_{10} + \text{Count}_{01}}{\text{Count}_{11} + \text{Count}_{10} + \text{Count}_{01}}$$

| | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 5 |
|---|---|---|---|---|---|
| A | 1 | 1 | 0 | 0 | 1 |
| B | 1 | 1 | 0 | 0 | 0 |
| C | 0 | 0 | 1 | 1 | 1 |

  - *Count11: Count of all variables that are 1 in "Observation 1" and 1 in "Observation 2."*
  - *Count10: Count of all variables that are 1 in "Observation 1" and 0 in "Observation 2."*
  - *Count01: Count of all variables that are 0 in "Observation 1" and 1 in "Observation 2."*
  - ~~*Count00: Count of all variables that are 0 in "Observation 1" and 0 in "Observation 2."*~~

<u>Jaccard distance (d):</u>

- between A and B $d_{A-B} = (1 + 0)/(2 + 1 + 0) = 0.33$
- between A and C $d_{A-C} = (2 + 2)/(1 + 2 + 2) = 0.8$
- between B and C $d_{B-C} = (2 + 3)/(0 + 2 + 3) = 1.0$

# DATA ANALYSIS – CLUSTERING

**Example:** Calculate the Jaccard distance (replacing **None with 0, Mild with 1,** and **Severe with 2**) using the variables: Fever, Headaches, General aches, Weakness, Exhaustion, Stuffy nose, Sneezing, Sore throat, Chest discomfort, for the following pairs of patient observations:

(a) 1326 and 398

(b) 1326 and 1234

(c) 6377 and 2662

$$d = \frac{\text{Count}_{10} + \text{Count}_{01}}{\text{Count}_{11} + \text{Count}_{10} + \text{Count}_{01}}$$

| Patient ID | Fever | Headaches | General Aches | Weakness | Exhaustion | Stuffy Nose | Sneezing | Sore Throat | Chest Discomfor |
|---|---|---|---|---|---|---|---|---|---|
| 1326 | None | Mild | None | None | None | Mild | Severe | Severe | Mild |
| 398 | Severe | Severe | Severe | Severe | Severe | None | None | Severe | Severe |
| 6377 | Severe | Severe | Mild | Severe | Severe | Severe | None | Severe | Severe |
| 1234 | None | None | None | Mild | None | Severe | None | Mild | Mild |
| 2662 | Severe | Severe | Mild | Severe | Severe | Severe | None | Severe | Severe |
| 9477 | None | None | None | Mild | None | Severe | Severe | Severe | None |
| 7286 | Severe | Severe | Severe | Severe | Severe | None | None | None | Severe |
| 1732 | None | None | None | None | None | Severe | Severe | None | Mild |
| 1082 | None | Mild | Mild | None | None | Severe | Severe | Severe | Severe |
| 1429 | Severe | Severe | Severe | Mild | Mild | None | Severe | None | Severe |
| 14455 | None | None | None | Mild | None | Severe | Mild | Severe | None |
| 524 | Severe | Mild | Severe | Mild | Severe | None | Severe | None | Mild |
| 1542 | None | None | Mild | Mild | None | Severe | Severe | Severe | None |
| 8775 | Severe | Severe | Severe | Severe | Mild | None | Severe | Severe | Severe |
| 1615 | Mild | None | None | Mild | None | Severe | None | Severe | Mild |
| 1132 | None | None | None | None | None | Severe | Severe | Severe | Severe |
| 4522 | Severe | Mild | Severe | Mild | Mild | None | None | None | Severe |

# DATA ANALYSIS – CLUSTERING

**Euclidean distance** needs first the data to normalize before bring using. Also, as dimensionality increases, it becomes more complex and less useful.

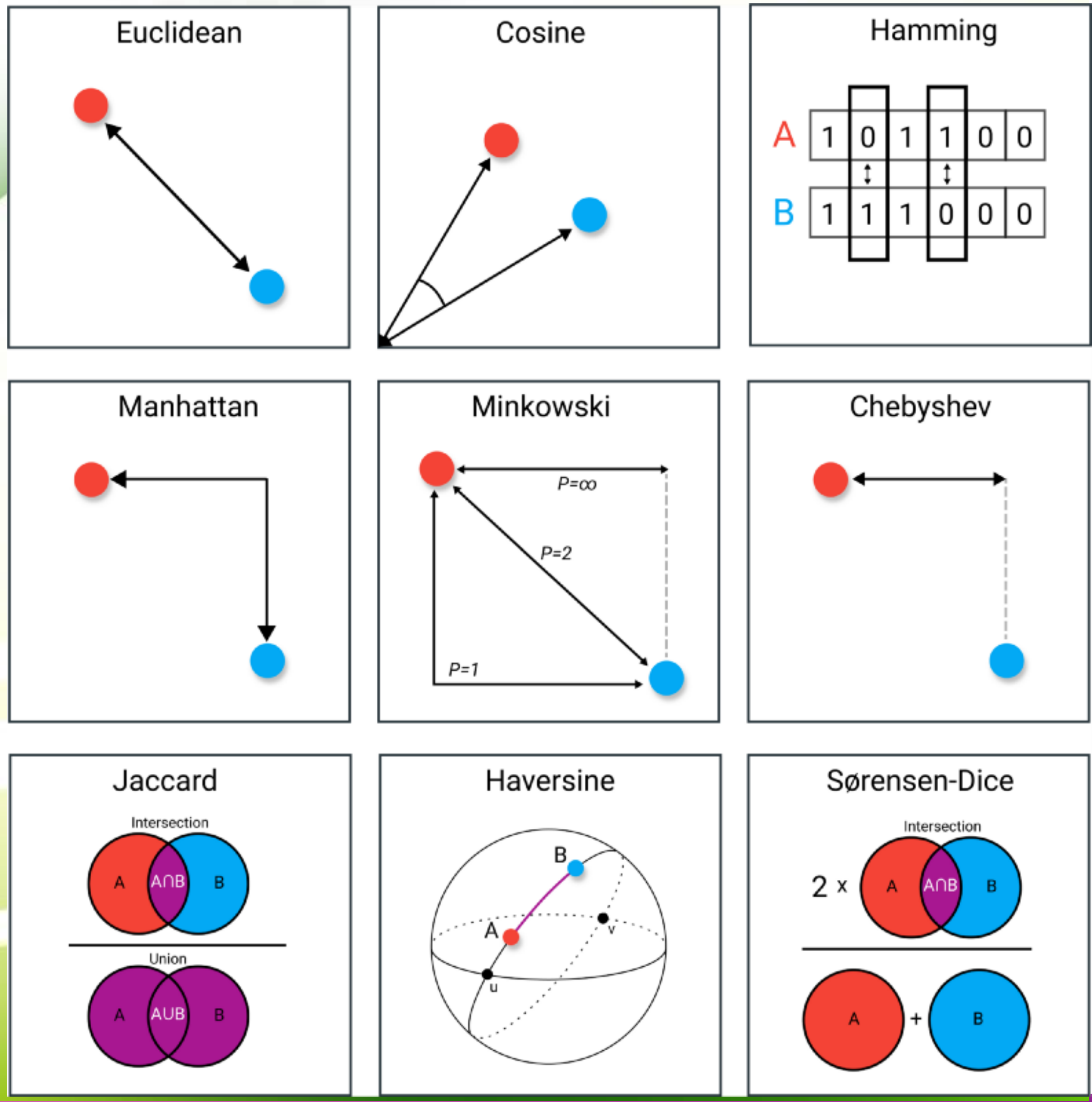
$$D(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2)}$$

**Manhattan distance**

- Taxicab distance or City Block distance

$$D(x,y)=\sum_{i=1}^{k}|x_i-y_i|$$

**Hamming distance** used to compare two binary strings of equal length (compares similarity by calculating number of characters that are different from each other).



# DATA ANALYSIS – CLUSTERING

**Chebyshev distance** (Chessboard distance)**:** maximum distance along one axis.

$$D(x,y) = \max_i \left( |x_i - y_i| \right)$$

**Minkowski distance**

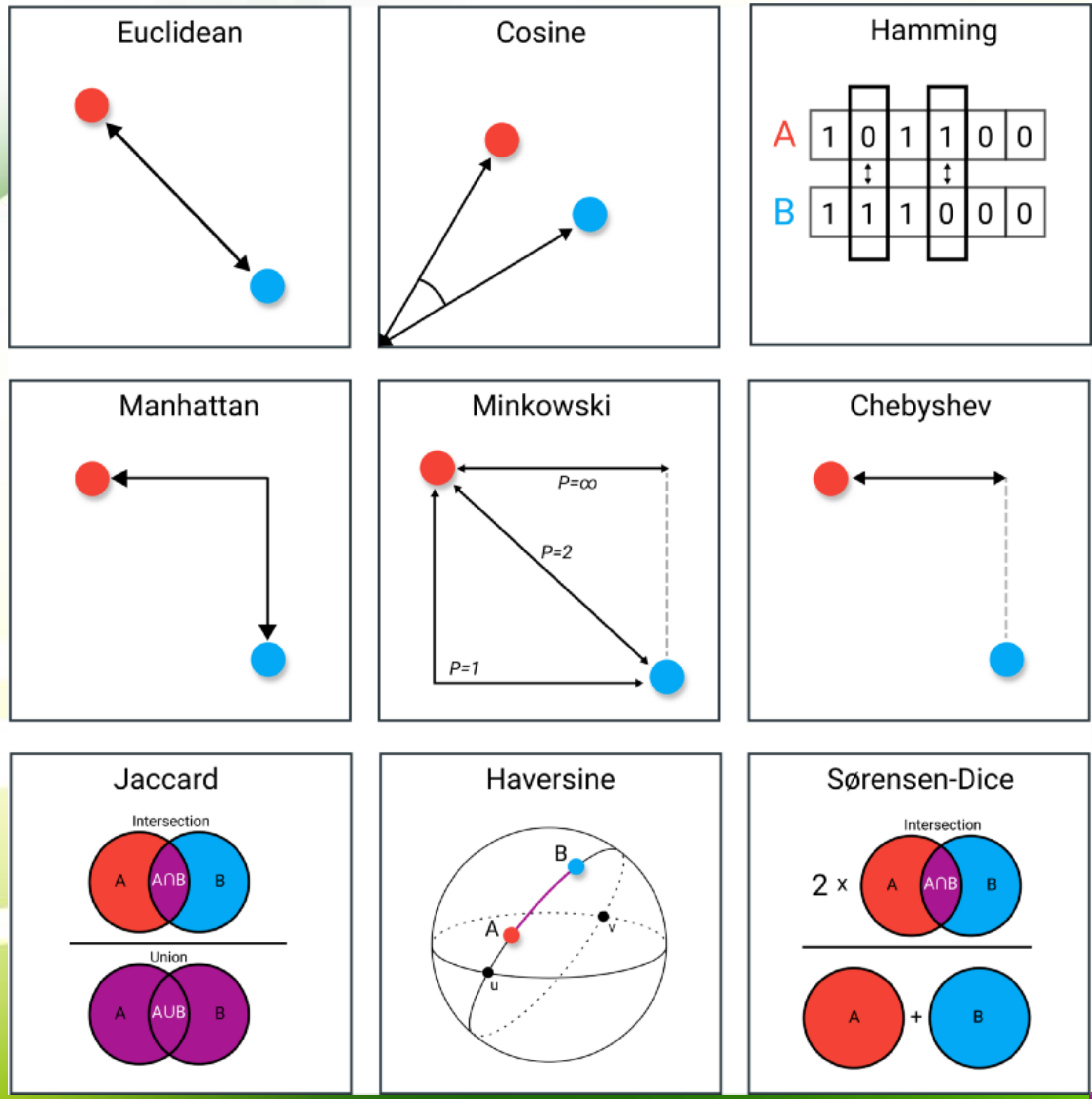
$$D(x,y) = \left( \sum_{i=1}^{n} |x_i - y_i|^p \right)^{\frac{1}{p}}$$

P = 1 → Manhattan distance
P = 2 → Euclidean distance
P = ∞ → Chebyshev distance

**Jaccard index** calculates similarity and diversity as size of intersection divided by size of union.

$$D(x,y) = 1 - \frac{|x \cap y|}{|y \cup x|}$$

$$d = \frac{\text{Count}_{10} + \text{Count}_{01}}{\text{Count}_{11} + \text{Count}_{10} + \text{Count}_{01}}$$



# DATA ANALYSIS - GROUPING

- Association rules method groups observations and attempts to discover links or associations between different attributes of the group.
- unsupervised grouping method
- **Association rule learning**: procedure to check for dependency of one data item on another data item and maps accordingly so that it can help in be more profitable analysis.
    - *If a customer buys bread, (s)he's 70% likely of buying milk.*
- **Association Rule:** simple If/Then statements that help discover relationships between seemingly independent relational databases or other data repositories.
    - Ways to find patterns in data; Helps in finding features (dimensions) which occur together (correlated).
    - Employed in *Market Basket analysis*, Web usage mining, Medical Diagnosis, etc.

*IF the customer is age 18 AND*
*the customer buys paper AND*
*the customer buys a hole punch*
*THEN the customer buys a binder*

*<<A package of products can be created for college students.>>*

# DATA ANALYSIS - GROUPING

**Advantages**

- rules are easy to understand

**Limitations**

- Generating rules can be computationally expensive (especially when dataset has many variables or many possible values per variable)
- can generate large numbers of rules that must be prioritized and interpreted.
- There are ways to make analysis run faster but they often compromise final results.
- forces to either restrict analysis to variables that are categorical or convert continuous variables to categorical variables.

# DATA ANALYSIS - GROUPING

**Grouping by Combinations of Values**

- Increasing number of variables or number of possible values for each variable or both → increases number of groups
- When number of groups becomes too large → impractical to generate all combinations

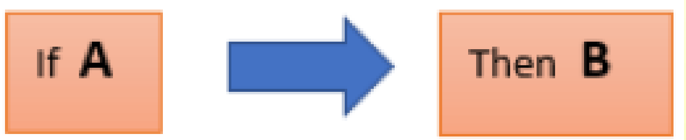
| Customer ID | Gender | Purchase |
|---|---|---|
| 932085 | Male | Television |
| 596720 | Female | Camera |
| 267375 | Female | Television |

| Group Number | Count | Gender | Purchase |
|---|---|---|---|
| Group 1 | 16,099 | Male | Camera or Television |
| Group 2 | 15,513 | Female | Camera or Television |
| Group 3 | 16,106 | Male or Female | Camera |
| Group 4 | 15,506 | Male or Female | Television |
| Group 5 | 7,889 | Male | Camera |
| Group 6 | 8,210 | Male | Television |
| Group 7 | 8,217 | Female | Camera |
| Group 8 | 7,296 | Female | Television |

| Group Number | Count | Gender | Purchase | Income |
|---|---|---|---|---|
| Group 1 | 16,099 | Male | Camera or Television | Below $50K or Above $50K |
| Group 2 | 15,513 | Female | Camera or Television | Below $50K or Above $50K |
| Group 3 | 16,106 | Male or Female | Camera | Below $50K or Above $50K |
| Group 4 | 15,506 | Male or Female | Television | Below $50K or Above $50K |
| Group 5 | 15,854 | Male or Female | Camera or Television | Below $50K |
| Group 6 | 15,758 | Male or Female | Camera or Television | Above $50K |
| Group 7 | 7,889 | Male | Camera | Below $50K or Above $50K |
| Group 8 | 8,210 | Male | Television | Below $50K or Above $50K |
| Group 9 | 8,549 | Male | Camera or Television | Below $50K |
| Group 10 | 7,550 | Male | Camera or Television | Above $50K |
| Group 11 | 8,217 | Female | Camera | Below $50K or Above $50K |
| Group 12 | 7,296 | Female | Television | Below $50K or Above $50K |
| Group 13 | 7,305 | Female | Camera or Television | Below $50K |
| Group 14 | 8,208 | Female | Camera or Television | Above $50K |
| Group 15 | 8,534 | Male or Female | Camera | Below $50K |
| Group 16 | 7,572 | Male or Female | Camera | Above $50K |
| Group 17 | 7,320 | Male or Female | Television | Below $50K |
| Group 18 | 8,186 | Male or Female | Television | Above $50K |
| Group 19 | 4,371 | Male | Camera | Below $50K |
| Group 20 | 3,518 | Male | Camera | Above $50K |
| Group 21 | 4,178 | Male | Television | Below $50K |
| Group 22 | 4,032 | Male | Television | Above $50K |
| Group 23 | 4,163 | Female | Camera | Below $50K |
| Group 24 | 4,054 | Female | Camera | Above $50K |
| Group 25 | 3,142 | Female | Television | Below $50K |
| Group 26 | 4,154 | Female | Television | Above $50K |

# DATA ANALYSIS – ASSOCIATION RULE

- Association rule learning works on the concept of If (**antecedent)** and Else Statement (**Consequent).**
  - *If a customer buys bread, (s)he's 70% likely of buying milk.*




- ***Single cardinality***: Association or relation between two items
  - If number of items increases, then cardinality also increases accordingly.

- **Important association metrics:**
  - **Support** (frequency)
  - **Confidence** (paired/conditional occurrence)
  - **Lift** (strength of rule)

# DATA ANALYSIS – ASSOCIATION RULE

If A → Then B

- **Support:** frequency of an event in dataset.
  - *Supp(e) = Freq(e) / Total transaction*
- **Confidence:** indicates how often the rule has been found to be true *(how often items X and Y occur together in dataset when occurrence of X is already given).*
  - *Confidence(X,Y) = Freq(X,Y) / Freq(X)* **Confidence = Group support / IF-part support**
- **Lift:** strength of any rule. *Ratio of observed support measure and expected support if X and Y are independent of each other.*
  - *Lift(R) = Supp(X,Y) / (Supp(X)*Supp(Y))* **Lift = Confidence / THEN-part support**

| Patient ID | Fever | Headaches |
|---|---|---|
| 1326 | None | Mild |
| 398 | Severe | Severe |
| 6377 | Severe | Severe |
| 1234 | None | None |
| 2662 | Severe | Severe |
| 9477 | None | None |
| 7286 | Severe | Severe |
| 1732 | None | None |

  - **Lift= 1**: probability of occurrence of antecedent and consequent is independent of each other.
  - **Lift>1**: determines the degree to which two itemsets are dependent to each other.
  - **Lift<1**: tells that rule body and rule head appear less often together than expected (negative effect on occurrence).

# DATA ANALYSIS – ASSOCIATION RULE

*Supp(e) = Freq(e) / Total transaction*

*Confidence(X,Y) = Freq(X,Y) / Freq(X)*

- **Confidence = Group support / IF-part support**

*Lift(R) = Supp(X,Y) / (Supp(X)*Supp(Y))*

- **Lift = Confidence / THEN-part support**

If **A** → Then **B**

$$Rule:\ X \Rightarrow Y$$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

**Rule 1**

IF Class of work is Private AND
Education is Doctorate
THEN Income is <=50K

**Rule 2**

IF Class of work is Private AND
Education is Doctorate
THEN Income is >50K

Total observations: 32,561
Class of work is Private: 22,696 observations
Education is Doctorate: 413 observations
Class of work is private and Education is Doctorate: 181 observations
Income is <=50K: 24,720 observations
Income is >50K: 7841 observations

**Association Rule Summary Table**

| | Rule 1 | Rule 2 |
|---|---|---|
| Count | 49 | 132 |
| Support | 0.0015 | 0.0041 |
| Confidence | 0.27 | 0.73 |
| Lift | 0.36 | 3.03 |

# DATA ANALYSIS - ASSOCIATION RULE

| Transaction ID | Items List |
|---|---|
| 1 | Cookies, Egg, Milk, Sandwich |
| 2 | Bottled Water, Burger, Chicken, Egg, Pizza, Salad |
| 3 | Beacon, Bottled Water, Egg, Sandwich, Yogurt |
| 4 | Burger, Pie, Pizza, Salad, Soda |
| 5 | Burger, Ice Cream, Pie, Pizza, Salad, Soda |
| 6 | Chocolate Shake, Cookies, Egg, Milk, Sandwich |
| 7 | Beacon, Chocolate Shake, Cookies, Milk, Yogurt |
| 8 | Bottled Water, Burger, Chicken, Chocolate Shake, Egg, Pie, Pizza, S |
| 9 | Beacon, Bottled Water, Egg, Milk, Pizza, Salad, Yogurt |
| 10 | Chocolate Shake, Cookies, Egg, Milk, Sandwich |
| 11 | Beacon, Burger, Salad |
| 12 | Cookies, Egg, Milk, Sandwich, Yogurt |
| 13 | Beacon, Bottled Water, Egg, Pie, Pizza, Sandwich |
| 14 | Cookies, Egg, Milk, Sandwich |
| 15 | Bottled Water, Burger, Chicken, Egg, Pie, Pizza, Salad |

| LHS | RHS | rules | support | confidence | lift |
|---|---|---|---|---|---|
| Ice Cream | Soda | {Ice Cream} => {Soda} | 0.07 | 1.00 | 5.00 |
| Soda | Ice Cream | {Soda} => {Ice Cream} | 0.07 | 0.33 | 5.00 |
| Ice Cream | Pie | {Ice Cream} => {Pie} | 0.07 | 1.00 | 3.00 |
| Pie | Ice Cream | {Pie} => {Ice Cream} | 0.07 | 0.20 | 3.00 |
| Ice Cream | Burger | {Ice Cream} => {Burger} | 0.07 | 1.00 | 2.50 |
| Burger | Ice Cream | {Burger} => {Ice Cream} | 0.07 | 0.17 | 2.50 |
| Ice Cream | Salad | {Ice Cream} => {Salad} | 0.07 | 1.00 | 2.14 |
| Salad | Ice Cream | {Salad} => {Ice Cream} | 0.07 | 0.14 | 2.14 |
| Ice Cream | Pizza | {Ice Cream} => {Pizza} | 0.07 | 1.00 | 2.14 |
| Pizza | Ice Cream | {Pizza} => {Ice Cream} | 0.07 | 0.14 | 2.14 |
| Soda | Chicken | {Soda} => {Chicken} | 0.07 | 0.33 | 1.67 |
| Chicken | Soda | {Chicken} => {Soda} | 0.07 | 0.33 | 1.67 |
| Soda | Chocolate Shake | {Soda} => {Chocolate Shake} | 0.07 | 0.33 | 1.25 |
| Chocolate Shake | Soda | {Chocolate Shake} => {Soda} | 0.07 | 0.25 | 1.25 |
| Soda | Pie | {Soda} => {Pie} | 0.20 | 1.00 | 3.00 |
| Pie | Soda | {Pie} => {Soda} | 0.20 | 0.60 | 3.00 |
| Soda | Burger | {Soda} => {Burger} | 0.20 | 1.00 | 2.50 |
| Burger | Soda | {Burger} => {Soda} | 0.20 | 0.50 | 2.50 |
| Soda | Bottled Water | {Soda} => {Bottled Water} | 0.07 | 0.33 | 0.83 |
| Bottled Water | Soda | {Bottled Water} => {Soda} | 0.07 | 0.17 | 0.83 |
| Soda | Salad | {Soda} => {Salad} | 0.20 | 1.00 | 2.14 |
| Salad | Soda | {Salad} => {Soda} | 0.20 | 0.43 | 2.14 |
| Soda | Pizza | {Soda} => {Pizza} | 0.20 | 1.00 | 2.14 |

# DATA ANALYSIS - ASSOCIATION RULE

| TID | Items |
|---|---|
| 1 | Bread, Milk |
| 2 | Bread, Diaper, Beer, Eggs |
| 3 | Milk, Diaper, Beer, Coke |
| 4 | Bread, Milk, Diaper, Beer |
| 5 | Bread, Milk, Diaper, Coke |

| | Beer | Bread | Milk | Diaper | Eggs | Coke |
|---|---|---|---|---|---|---|
| $T_1$ | 0 | 1 | 1 | 0 | 0 | 0 |
| $T_2$ | 1 | 1 | 0 | 1 | 1 | 0 |
| $T_3$ | 1 | 0 | 1 | 1 | 0 | 1 |
| $T_4$ | 1 | 1 | 1 | 1 | 0 | 0 |
| $T_5$ | 0 | 1 | 1 | 1 | 0 | 1 |

One-hot encoded Table

| | Rule 1 | Rule 2 |
|---|---|---|
| Count | 49 | 132 |
| Support | 0.0015 | 0.0041 |
| Confidence | 0.27 | 0.73 |
| Lift | 0.36 | 3.03 |

**Association Rule Summary Table**

$$Rule: \; X \Rightarrow Y$$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

{Diaper, Beer} ➔ Milk

- Support = 2/5, Confidence = 2/3

{Milk} ➔ {Diaper, Beer}

- Support = 2/5, Confidence = 2/4

{Milk, Diaper} ➔ Bread

- Support = 2/5, Confidence = 2/3

# DATA ANALYSIS - ASSOCIATION RULE

**Example: For the computer accessories purchase transaction, prepare the Association Rule Summary table by calculating the Support, Confidence & Life for the following Association rules.**

1. **If customer purchases Laptop, then (s)he also buys Monitor.**
2. **If customer purchases Monitor & Tablet, then (s)he also buys headset.**
3. **If customer purchases Laptop & Monitor, then (s)he also buys headset.**
4. **If customer purchases Laptop & Monitor, then (s)he also buys Printer.**

$$Rule: \; X \Rightarrow Y$$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

**Table 1.** Market basket transactions

| *Transaction ID* | *Items Bought* |
|---|---|
| 1 | {*Laptop, Printer, Tablet, Headset*} |
| 2 | {*Printer, Monitor, Tablet*} |
| 3 | {*Laptop, Printer, Tablet, Headset*} |
| 4 | {*Laptop, Monitor, Tablet, Headset*} |
| 5 | {*Printer, Monitor, Tablet, Headset*} |
| 6 | {*Printer, Tablet, Headset*} |
| 7 | {*Monitor, Tablet*} |
| 8 | {*Laptop, Printer, Monitor*} |
| 9 | {*Laptop, Tablet, Headset*} |
| 10 | {*Printer, Tablet*} |

# DATA ANALYSIS – ASSOCIATION RULE

- **Market Basket Analysis (MBA)**: popular examples and applications of association rule mining.
- Technique used by big retailers to determine association between items, as a marketing strategy.
    - *If a customer buys bread, (s)he most likely can also buy butter, eggs, or milk → these products are stored within a shelf or mostly nearby.*
- **Steps in MBA:**
    - *Establish possible Rules.*
    - *Calculate support, confidence, lift for each rule.*
    - *Validate the Rule(s).*

Rule: $X \Rightarrow Y$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

# DATA ANALYSIS – ASSOCIATION RULE

## BENEFITS OF MARKET BASKET ANALYSIS

- Customer Behavior analysis
- Optimization of in-store operations & stock management.
- Campaigns and promotions
- Item Recommendations
- Increasing market share

# DATA ANALYSIS – ASSOCIATION RULE

- **(Item) Recommendation system** makes prediction for user consumption.
- **Content-based** approach focused on information of items' own features, rather than using users' interactions and feedbacks.
    - *Example, movie attributes: genre, year, director, actor etc.*
- **Collaborative Filtering:** focused on users' historical preference.
    - Based on user's own past preference.
        - Basic assumption: *users who have agreed in past tend to also agree in future.*
        - *User regularly watches scientific videos → (s)he's recommended other such videos.*
    - Based on other users' (majority) past preference.
        - Collecting preferences or taste information from many users (collaborating).
        - Basic assumption: *if many have agreed in past, others will also agree in future.*
        - *Many users are watching budget analysis video → many other users also recommended same/such videos.*

# DATA ANALYSIS – ASSOCIATION RULE

- Collaborative Filtering focuses on users' historical preference, for Item Recommendation.
- User preference usually expressed by two categories.

- **Explicit Rating** given by user to an item on a sliding scale.
  - Example: 5 stars for a movie
  - Most direct feedback from users to show how much they like an item.

- **Implicit Rating** suggests users preference indirectly.
  - Example: page views, clicks, purchase records, whether or not listen to music track, etc.
  - Shows user's involvement/attention with the "content", time spent, etc. → value of the "content"

# DATA ANALYSIS – ASSOCIATION RULE

- **Steps in Grouping Analysis**:
  - Association rule learning → *Establish possible Rules.*
  - *Calculate support, confidence, lift for each rule.*
  - *Validate the Rule(s) with threshold/acceptance level.*

$$Rule:\ X \Rightarrow Y$$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

- **Types of Association rule learning**:
  - *Apriori Algorithm*
  - *F-P (Frequent Pattern) Growth Algorithm*
  - *Eclat (Equivalence Class Transformation) algorithm*

# DATA ANALYSIS - APRIORI

- **Apriori algorithm** uses frequently purchased item-sets to **generate association rules**.
  - Used in market basket analysis.
  - Helps to find frequent item-sets in transactions and identifies association rules between these items.
- Named Apriori because it uses prior knowledge of frequent itemset properties.
- Limitation is *frequent itemset generation* → needs to scan database many times leading to increased time and reduce performance (computationally costly step).
- Basic Assumption:
  - *All subsets of a frequent itemset must be frequent.*
  - *If an itemset is infrequent, all its supersets will be infrequent.*

| TID | ITEMSETS |
|---|---|
| T1 | A, B |
| T2 | B, D |
| T3 | B, C |
| T4 | A, B, D |
| T5 | A, C |
| T6 | B, C |
| T7 | A, C |
| T8 | A, B, C, E |
| T9 | A, B, C |

# Apriori Algorithm

| TID | ITEMSETS |
|---|---|
| T1 | A, B |
| T2 | B, D |
| T3 | B, C |
| T4 | A, B, D |
| T5 | A, C |
| T6 | B, C |
| T7 | A, C |
| T8 | A, B, C, E |
| T9 | A, B, C |

Given: Minimum Support= 2, Minimum Confidence= 50%

**Step-1: Calculating C1 and F1:**

- Create a table that contains each itemset's support count (frequency of each itemset individually in dataset). This table is called the **Candidate set or C1.**
- Take out all the itemsets that have the greater support count that the Minimum Support (2). It will give us the table for the **frequent itemset F1.**

| Itemset | Support_Count |
|---|---|
| A | 6 |
| B | 7 |
| C | 5 |
| D | 2 |
| ~~E~~ | ~~1~~ |

**Step-2: Candidate Generation C2, and F2:**

- Create the pair of the itemsets of F1 in the form of subsets.
- Again find support count for these pairs from the main transaction table of datasets **(C2).**
- Compare the C2 Support count with minimum support count, and eliminate the itemsets with less support count **(in F2).**

| Itemset | Support_Count |
|---|---|
| {A, B} | 4 |
| {A,C} | 4 |
| ~~{A, D}~~ | ~~1~~ |
| {B, C} | 4 |
| {B, D} | 2 |
| ~~{C, D}~~ | ~~0~~ |

# Apriori Algorithm

| TID | ITEMSETS |
|---|---|
| T1 | A, B |
| T2 | B, D |
| T3 | B, C |
| T4 | A, B, D |
| T5 | A, C |
| T6 | B, C |
| T7 | A, C |
| T8 | A, B, C, E |
| T9 | A, B, C |

**Step-3: Candidate generation C3, and F3:**

- Repeat the same two processes, but with subsets of three itemsets together.
- Create C3 and F3 accordingly.

Given: Minimum Support= 2, Minimum Confidence= 50%

**Step-4: Finding the association rules for the subsets:**

- To generate the association rules, first create a new table with all possible rules from the occurred combination {A, B.C}.
- For all the rules, calculate the Confidence using required formula.
- After calculating the confidence value for all rules, exclude the rules that have less confidence than the minimum threshold (50%).

| Itemset | Support_Count |
|---|---|
| {A, B, C} | 2 |
| ~~{B, C, D}~~ | ~~1~~ |
| ~~{A, C, D}~~ | ~~0~~ |
| ~~{A, B, D}~~ | ~~0~~ |

| Rules | Support | Confidence |
|---|---|---|
| A ^B → C | 2 | Sup{(A ^B) ^C}/sup(A ^B)= 2/4=0.5=50% |
| B^C → A | 2 | Sup{(B^C) ^A}/sup(B ^C)= 2/4=0.5=50% |
| A^C → B | 2 | Sup{(A ^C) ^B}/sup(A ^C)= 2/4=0.5=50% |
| C→ A ^B | 2 | Sup{(C^( A ^B)}/sup(C)= 2/5=0.4=40% |
| A→ B^C | 2 | Sup{(A^( B ^C)}/sup(A)= 2/6=0.33=33.33% |
| B→ B^C | 2 | Sup{(B^( B ^C)}/sup(B)= 2/7=0.28=28% |

- First three rules **A ^B → C, B^C → A, and A^C → B** can be considered as the strong association rules for the given problem.

# DATA ANALYSIS - APRIORI

| Transaction ID | Items bought |
|---|---|
| 1 | (Apple x 3), (Cabbage x 1), (Donut x 2) |
| 2 | (Bread x 2), (Cabbage x 3), (Egg x 1) |
| 3 | (Apple x 1), (Bread x 1), (Cabbage x 1), (Egg x 2) |
| 4 | (Bread x 3), (Egg x 4) |
| 5 | (Apple x 2), (Cabbage x 2), (Egg x 1) |

| Transaction ID | Items bought |
|---|---|
| 1 | A A A C D D |
| 2 | B B C C C E |
| 3 | A B C E E |
| 4 | B B B E E E E |
| 5 | A A C C E |

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

**Iteration-1**

| C1 | |
|---|---|
| Item-Set | Support |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {D} | 2 |
| {E} | 5 |

| F1 | |
|---|---|
| Item-Set | Support |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

- **Fix a threshold support level.**
- **Generally, 50% of total number of transaction = 2.5 (3)**
- **Discard item/itemset with frequency < threshold (3)**

# DATA ANALYSIS - APRIORI

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

| F1 | |
|---|---|
| Item-Set | Support |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

**Discard item/itemset with frequency < threshold (3)**

| C1 | |
|---|---|
| Item-Set | Support |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {D} | 2 |
| {E} | 5 |

Basic Assumption:

- *All subsets of a frequent itemset must be frequent.*
- ***If an itemset is infrequent, all its supersets will be infrequent.***

Iteration-2

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

→

| Only items in F1 | |
|---|---|
| C2 | |
| Item-Set | Support |
| {A,B} | 2 |
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

→

| F2 | |
|---|---|
| Item-Set | Support |
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

# DATA ANALYSIS - APRIORI

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

| F1 | |
|---|---|
| Item-Set | Support |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

| F2 | |
|---|---|
| Item-Set | Support |
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

**Discard item/itemset with frequency >= threshold (3)**

| F3 | |
|---|---|
| Item-Set | Support |
| {A,C,E} | 3 |
| {B,C,E} | 3 |

<u>Iteration-3</u>

- Grouping is done in a way that each item-set contains three items in them.
- Further, these will be divided into their **sub-sets.**
- Also, those with support value less than threshold (3), will be omitted → This process is known as **Pruning**.

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

→

| C3 | |
|---|---|
| Item-Set | In F2 ? |
| {A,B,C}, {A,B}, {A,C}, {B,C} | No |
| {A,B,E}, {A,B}, {A,E}, {B,E} | No |
| {A,C,E}, {A,E}, {A,C}, {C,E} | Yes |
| {B,C,E}, {B,C}, {B,E}, {C,E} | Yes |

# DATA ANALYSIS - APRIORI

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

| F1 | |
|---|---|
| Item-Set | Support |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

| F2 | |
|---|---|
| Item-Set | Support |
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

Discard item/itemset with frequency < threshold (3)

| F3 | |
|---|---|
| Item-Set | Support |
| {A,C,E} | 3 |
| {B,C,E} | 3 |

<u>Iteration-4</u>

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

→

| C4 | |
|---|---|
| Item-Set | Support |
| {A,B,C,E} | 2 |
| {A,B,C,D} | 1 |
| {B,C,D,E} | 1 |
| {A,C,D,E} | 1 |

→

Omitting items that are already omitted

| C4 | |
|---|---|
| Item-Set | Support |
| {A,B,C,E} | 2 |

In iteration-4, support of the only item-set having 4 items is less than threshold value (3) → Stop iterations → Take final item set to be F3.

# DATA ANALYSIS - APRIORI

**From F3,**

- If I = {A,C,E}, then subsets are {A,C}, {A,E}, {C,E}, {A}, {C} and {E}.
- If I = {B,C,E}, then subsets are {B,C}, {B,E}, {C,E}, {B}, {C} and {E}.

**Association Rules:** In order to filter out relevant item-sets, create association rules and apply them to subsets. (assume minimum confidence value = 60%)

- For every subset S of I, association rule is:

$$S \longrightarrow (I - S) \quad \text{if} \quad \frac{\text{Support (I)}}{\text{Support (S)}} \geq \text{Minimum confidence value i.e., 60\%}$$

'S' recommends 'I - S'

**Consider {A,C,E} from F3.**

**Rule 1:** {A,C} →({A,C,E} — {A,C}) which is **{A,C}** → **{E}**

| F3 | |
|---|---|
| **Item-Set** | **Support** |
| {A,C,E} | 3 |
| {B,C,E} | 3 |

| F2 | |
|---|---|
| **Item-Set** | **Support** |
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

| F1 | |
|---|---|
| **Item-Set** | **Support** |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

# DATA ANALYSIS - APRIORI

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

Rule: $X \Rightarrow Y$

$Support = \frac{frq(X,Y)}{N}$

$Confidence = \frac{frq(X,Y)}{frq(X)}$

$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$

**F1**

| Item-Set | Support |
|---|---|
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

**F2**

| Item-Set | Support |
|---|---|
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

**F3**

| Item-Set | Support |
|---|---|
| {A,C,E} | 3 |
| {B,C,E} | 3 |

$S \longrightarrow (I - S)$ if $\frac{\text{Support (I)}}{\text{Support (S)}} \geq$ Minimum confidence value i.e., 60%

'S' recommends 'I - S'

**Consider {A,C,E} from F3.**

**Rule 1:** {A,C} →({A,C,E} — {A,C}) which is **{A,C} → {E}**
Confidence = Support{A,C,E} / Support{A,C} = 3/4 = 75% > 60%
So rule 1 i.e., {A,C} →{E} is valid.

**Rule 2:** {A,E} →({A,C,E} — {A,E}) which is **{A,E} → {C}**
Confidence = Support{A,C,E} / Support{A,E} = 3/3 = 100% > 60%
So rule 2 i.e., {A,E} →{C} is valid.

**Rule 3:** {C,E} →({A,C,E} — {C,E}) which is **{C,E} → {A}**
Confidence = Support{A,C,E} / Support{C,E} = 3/4 = 75% > 60%
So rule 3 i.e., {C,E} →{A} is valid.

**Rule 4:** {A} →({A,C,E} — {A}) which is **{A} → {C,E}**
Confidence = Support{A,C,E} / Support{A} = 3/4 = 75% > 60%
So rule 4 i.e., {A} →{C,E} is valid.

**Rule 5:** {C} →({A,C,E} — {C}) which is **{C} → {A,E}**
Confidence = Support{A,C,E} / Support{C} = 3/5 = 60% !> 60% (not greater than 60%)
So rule 5 i.e., {C} →{A,E} is **rejected**.

**Rule 6:** {E} →({A,C,E} — {E}) which is **{E} → {A,C}**
Confidence = Support{A,C,E} / Support{E} = 3/5 = 60% !> 60% (not greater than 60%)
So rule 6 i.e., {E} →{A,C} is **rejected**.

# DATA ANALYSIS - APRIORI

**FOR {A,C,E} in F3, association rules generated earlier.**

**Calculate strength of each one.**

**Rule 1:** Lift = Support{A,C,E} / (Support{A,C} x Support{E}) = 3/(4x5) = 3/20 = **0.15**

**Rule 2:** Lift = Support{A,C,E} / (Support{A,E} x Support{C}) = 3/(3x5) = 3/15 = **0.20**

**Rule 3:** Lift = Support{A,C,E} / (Support{C,E} x Support{A}) = 3/(4x4) = 3/16 = **0.1875**

**Rule 4:** Lift = Support{A,C,E} / (Support{A} x Support{C,E}) = 3/(4x4) = 3/16 = **0.1875**

**Rule 5:** Lift = Support{A,C,E} / (Support{C} x Support{A,E}) = 3/(5x3) = 3/15 = **0.20**

**Rule 6:** Lift = Support{A,C,E} / (Support{E} x Support{A,C}) = 3/(5x4) = 3/20 = **0.15**

- Same steps can be applied to item-set {B,C,E}.
- Very small sample → Lift values do not vary much here .
- All Lift < 1 → None of association rule is strong to be accepted.
- For **larger data**; analysis is more evident.

| F1 | |
|---|---|
| **Item-Set** | **Support** |
| {A} | 4 |
| {B} | 4 |
| {C} | 5 |
| {E} | 5 |

| F2 | |
|---|---|
| **Item-Set** | **Support** |
| {A,C} | 4 |
| {A,E} | 3 |
| {B,C} | 3 |
| {B,E} | 4 |
| {C,E} | 4 |

| F3 | |
|---|---|
| **Item-Set** | **Support** |
| {A,C,E} | 3 |
| {B,C,E} | 3 |

Rule: $X \Rightarrow Y$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

| Transaction ID | Items bought |
|---|---|
| 1 | A C D |
| 2 | B C E |
| 3 | A B C E |
| 4 | B E |
| 5 | A C E |
| 6 | A B C D E |

# DATA ANALYSIS – APRIORI

**Example: For the purchase transaction given below, establish the association rules with Support threshold=50%, Confidence= 60%.**

| Transaction | List of items |
|---|---|
| T1 | I1,I2,I3 |
| T2 | I2,I3,I4 |
| T3 | I4,I5 |
| T4 | I1,I2 |
| T5 | I1,I2,I3,I5 |
| T6 | I1,I2,I3,I4 |

| | |
|---|---|
| 1-2 | 4 |
| 1-3 | 3 |
| 2-3 | 4 |
| 1-2-3 | 3 |

# DATA ANALYSIS – F-P GROWTH

**Shortcomings Of Apriori Algorithm**

- Needs generation of large number of candidate itemsets (for huge database).
- Needs multiple scans of database to check support of each itemset generated and this leads to high costs.

**Frequent Pattern (F-P) growth algorithm**

- Improved version of Apriori Algorithm (overcome these shortcomings)
- No need for candidate generation to generate frequent pattern.
- Represents database in form of tree structure (F-P tree) to extract most frequent patterns.
- F-P tree structure maintains the association (frequency patterns) between itemsets.
- Database is fragmented using one frequent item. This fragmented part is called "pattern fragment".
- Itemsets of these fragmented patterns are analyzed → Thus search for frequent itemsets is reduced comparatively.

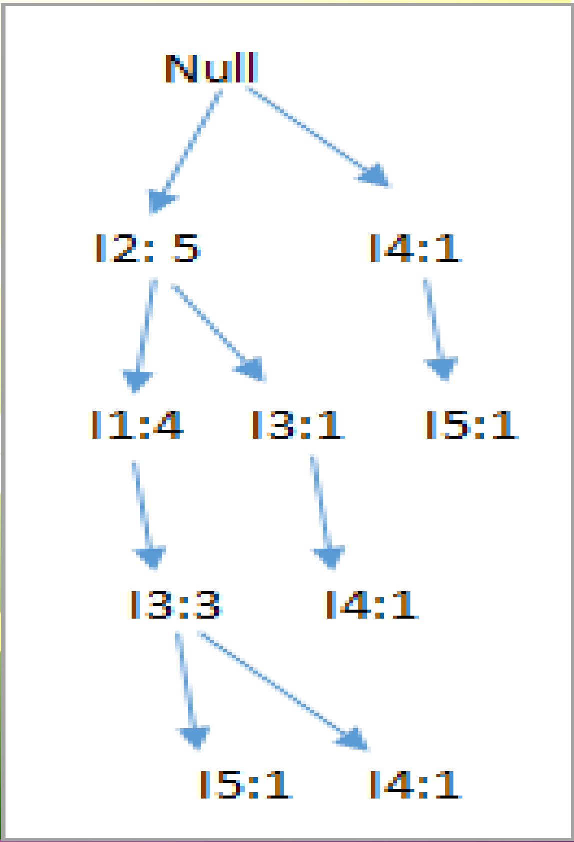
# DATA ANALYSIS – F-P GROWTH

**Frequent Pattern Tree**

- Tree-like structure that is made with initial itemsets of database.
- Every node of FP tree represents an item of that itemset.
- Root node represents null value whereas lower nodes represent itemsets of the data.
- Association of these nodes with lower nodes that is between itemsets is maintained while creating the tree.

| Transaction | List of items |
|---|---|
| T1 | I1,I2,I3 |
| T2 | I2,I3,I4 |
| T3 | I4,I5 |
| T4 | I1,I2 |
| T5 | I1,I2,I3,I5 |
| T6 | I1,I2,I3,I4 |

| Item | Count |
|---|---|
| I1 | 4 |
| I2 | 5 |
| I3 | 4 |
| I4 | 3 |
| I5 | 2 |



# DATA ANALYSIS – F-P GROWTH

**F-P Algorithm Steps**

1. Scan database to find occurrences of itemsets.
2. Construct FP tree by creating root (null) of the tree.
3. Scan database again. Tree Branch is constructed with transaction itemsets in descending order of count.
   - Examine first transaction and find out itemset in it. Itemset with max count is taken at top, the next itemset with lower count and so on.
4. Next transaction in database is examined. Itemsets are ordered in descending order of count.
   - If any itemset of this transaction is already present in another branch, then this transaction branch would share a common prefix to root.
   - i.e. common itemset is linked to new node of another itemset in this transaction.
5. Count of itemset is incremented as it occurs in transactions. Both common node and node count is increased by 1 as they are created and linked according to transactions.
6. Once all the transactions are scanned iteratively → **FP tree is created.**

7. **Mine the created FP Tree.** i.e. lowest node is examined first along with the links of lowest nodes.
   - Lowest node represents frequency pattern length 1. From this, traverse the path in FP Tree. This path(s) are called conditional pattern base (a sub-database consisting of prefix paths in FP tree occurring with lowest node/suffix).
8. Construct a Conditional FP Tree, which is formed by a count of itemsets in the path (itemsets meeting threshold support are considered in Conditional FP Tree).
9. Frequent Patterns are generated from the Conditional FP Tree.

# DATA ANALYSIS – F-P GROWTH

**Support threshold=50%** → min_sup=3, **Confidence= 60%**

| Transaction | List of items |
|---|---|
| T1 | I1,I2,I3 |
| T2 | I2,I3,I4 |
| T3 | I4,I5 |
| T4 | I1,I2 |
| T5 | I1,I2,I3,I5 |
| T6 | I1,I2,I3,I4 |

| Item | Count |
|---|---|
| I1 | 4 |
| I2 | 5 |
| I3 | 4 |
| I4 | 3 |
| **I5** | **2** |

**Freq count**

| Item | Count |
|---|---|
| I2 | 5 |
| I1 | 4 |
| I3 | 4 |
| I4 | 3 |

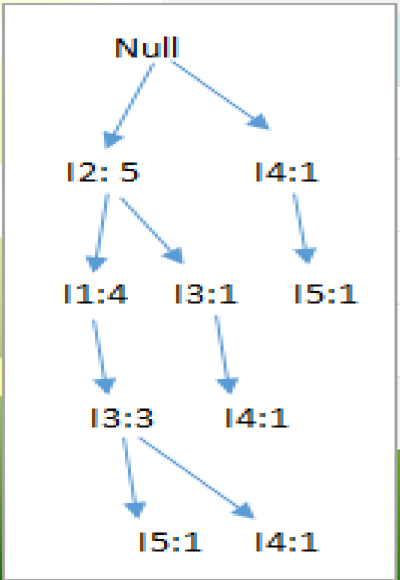
**Threshold filter & Sort**

# DATA ANALYSIS – F-P GROWTH

**Build FP Tree**

1. Considering the **root node** null.
2. First scan of Transaction **T1: I1, I2, I3** contains three items {I1:1}, {I2:1}, {I3:1}, where I2 is linked as a child to root, I1 is linked to I2 and I3 is linked to I1.
3. **T2: I2, I3, I4** contains I2, I3, and I4, where I2 is linked to root, I3 is linked to I2 and I4 is linked to I3. But this branch would share I2 node as common as it is already used in T1.
4. Increment the count of I2 by 1 and I3 is linked as a child to I2, I4 is linked as a child to I3. The count is {I2:2}, {I3:1}, {I4:1}.
5. **T3: I4, I5**. Similarly, a new branch with I5 is linked to I4 as a child is created.
6. **T4: I1, I2**. The sequence will be I2, and I1. I2 is already linked to the root node, hence it will be incremented by 1. Similarly I1 will be incremented by 1 as it is already linked with I2 in T1, thus {I2:3}, {I1:2}.
7. **T5:I1, I2, I3, I5**. The sequence will be I2, I1, I3, and I5. Thus {I2:4}, {I1:3}, {I3:2}, {I5:1}.
8. **T6: I1, I2, I3, I4**. The sequence will be I2, I1, I3, and I4. Thus {I2:5}, {I1:4}, {I3:3}, {I4 1}.

| Transaction | List of items |
|---|---|
| T1 | I1,I2,I3 |
| T2 | I2,I3,I4 |
| T3 | I4,I5 |
| T4 | I1,I2 |
| T5 | I1,I2,I3,I5 |
| T6 | I1,I2,I3,I4 |




| Item | Count |
|---|---|
| I2 | 5 |
| I1 | 4 |
| I3 | 4 |
| I4 | 3 |
| I5 | 2 |

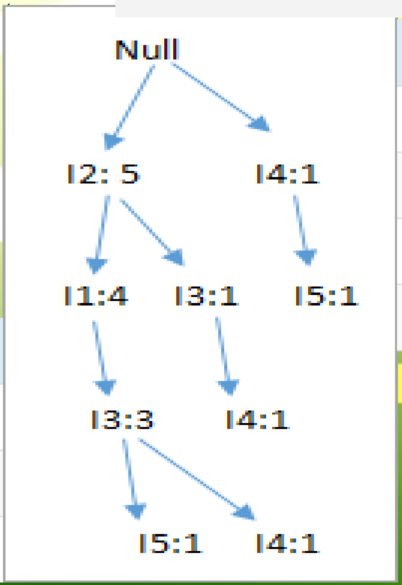
# DATA ANALYSIS – F-P GROWTH

**Mining of FP-tree:**

- Lowest node item I5 is deleted (threshold).
- Next lower node I4 occurs in 2 branches, {I2,I1,I3:1},{I2,I3:1}. This forms the conditional pattern base.
- Conditional pattern base is considered a transaction database & conditional FP-tree is constructed. This will contain {I2:2, I3:2, I1:1}. I1 is not considered as it does not meet the min support count.
- This path will generate all combinations of frequent patterns : {I2,I4:2},{I3,I4:2},{I2,I3,I4:2}
- For I3, prefix path is: {I2,I1:3},{I2:1}, this will generate a 2 node FP-tree : {I2:4, I1:3} and frequen patterns are generated: {I2,I3:4}, {I1:I3:3}, {I2,I1,I3:3}.
- For I1, prefix path is: {I2:4} this generates single node FP-tree: {I2:4} and frequent patterns are generated: {I2, I1:4}.

| Transaction | List of items |
|---|---|
| T1 | I1,I2,I3 |
| T2 | I2,I3,I4 |
| T3 | I4,I5 |
| T4 | I1,I2 |
| T5 | I1,I2,I3,I5 |
| T6 | I1,I2,I3,I4 |

| Item | Count |
|---|---|
| I2 | 5 |
| I1 | 4 |
| I3 | 4 |
| I4 | 4 |




| Item | Conditional Pattern Base | Conditional FP-tree | Frequent Patterns Generated |
|---|---|---|---|
| I4 | {I2,I1,I3:1},{I2,I3:1} | ~~{I2:2, I3:2}~~ | ~~{I2,I4:2},{I3,I4:2},{I2,I3,I4:2}~~ |
| I3 | {I2,I1:3},{I2:1} | {I2:4, I1:3} | {I2,I3:4}, {I1:I3:3}, {I2,I1,I3:3} |
| I1 | {I2:4} | {I2:4} | {I2,I1:4} |

# DATA ANALYSIS – F-P GROWTH

- Considering last column (frequent Pattern generation) & Support threshold=50% → min_sup=3
  - *3-item frequent set generated {I2,I1,I3:3}*
  - *2-Item frequent sets generated {I2,I3:4}, {I1,I3:3}, {I2,I1:4}.*
- All these set (association rules ) are distinct sets.
- Once association rules are generated; lift value can be calculated to further analysis *(same like apriori).*
- In comparison to Apriori Algorithm, only the frequent patterns are generated, NOT all combinations of different items & keep analyzing each (computationally costly).

| Transaction | List of items |
|---|---|
| T1 | I1,I2,I3 |
| T2 | I2,I3,I4 |
| T3 | I4,I5 |
| T4 | I1,I2 |
| T5 | I1,I2,I3,I5 |
| T6 | I1,I2,I3,I4 |

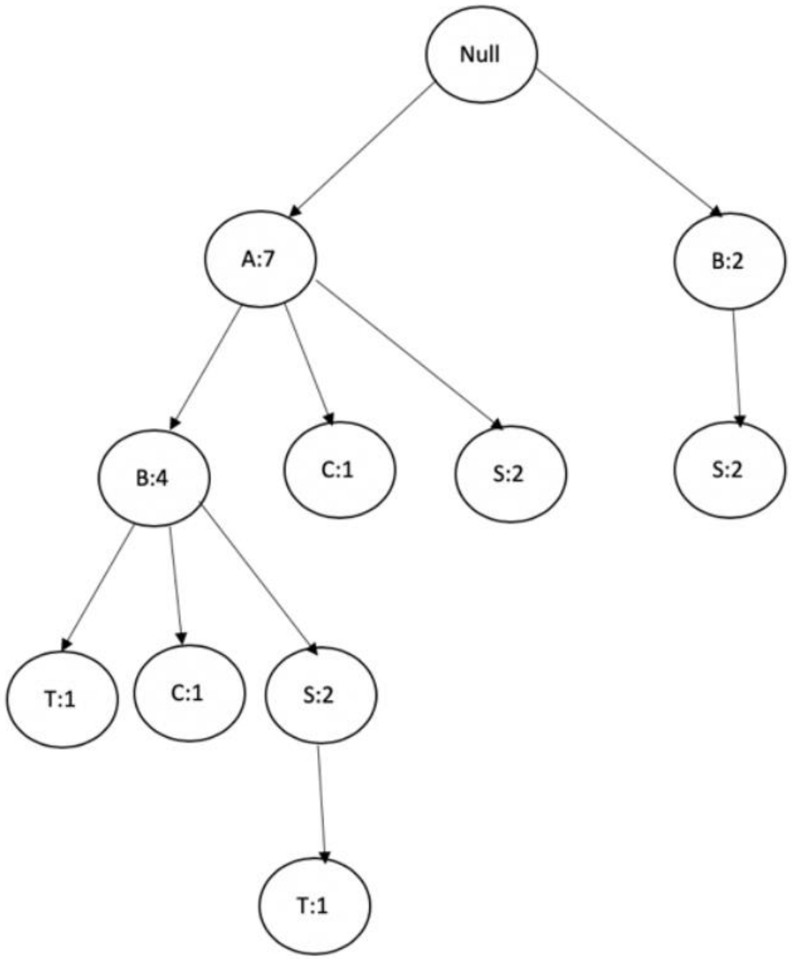
| Item | Conditional Pattern Base | Conditional FP-tree | Frequent Patterns Generated |
|---|---|---|---|
| I4 | {I2,I1,I3:1},{I2,I3:1} | {I2:2, I3:2} | {I2,I4:2},{I3,I4:2},{I2,I3,I4:2} |
| I3 | {I2,I1:3},{I2:1} | {I2:4, I1:3} | {I2,I3:4}, {I1:I3:3}, {I2,I1,I3:3} |
| I1 | {I2:4} | {I2:4} | {I2,I1:4} |

# DATA ANALYSIS – F-P GROWTH

- Asparagus (A), Corn (C), Beans (B), Tomatoes (T) & Squash (S)
- minimum count=2

| Transaction ID | List of items in transaction |
|---|---|
| T1 | B , A , T |
| T2 | A , C |
| T3 | A , S |
| T4 | B , A , C |
| T5 | B , S |
| T6 | A , S |
| T7 | B , S |
| T8 | B , A , S , T |
| T9 | B , A , S |

| Item | Support Count |
|---|---|
| Asparagus (A) | 7 |
| Beans (B) | 6 |
| Squash (S) | 6 |
| Corn (C) | 2 |
| Tomatoes (T) | 2 |




| Item | Conditional Pattern base | Conditional FP tree | Frequent Pattern Generation |
|---|---|---|---|
| Tomatoes (T) | {{A,B:1},{A,B,S:1}} | <A:2,B:2> | {A,T:2},{B,T:2},{A,B,T:2} |
| Corn (C) | {{A,B:1},{A:1}} | <A:2> | {A,C:2} |
| Squash (S) | {{A,B:2},{A:2},{B:2}} | <A:4,B:2>,<B:2> | {A,S:4},{B,S:4},{A,B,S:2} |
| Bean (B) | {{A:4}} | <A:4> | {A,B:4} |