

## \* Classification of Data

this chapter presents alternative techniques for building classification models from simple techniques such as rule based and nearest - neighbor classifier to more advanced techniques such as support vector machines and etc.

### A) Rule - Based Classifier

a rule based classifier is a technique for classifying records using a collection of "if---then---" rules. the rules for the model are represented in a disjunctive normal form,

$$R = (v_1 \vee v_2 \vee \dots \vee v_k)$$

where, 'R' is known as the rule set and  $v_i$ 's are the classification rules or disjuncts.

- $v_1$ : (Gives Birth = no)  $\wedge$  (Aerial creature = yes)  $\rightarrow$  Birds
- $v_2$ : (Gives Birth = no)  $\wedge$  (Aquatic creature = yes)  $\rightarrow$  Fishes
- $v_3$ : (Gives Birth = yes)  $\wedge$  (Body Temp. = warm blooded)  $\Rightarrow$  Mammals
- $v_4$ : (Gives Birth = no)  $\wedge$  (Aerial creature = no)  $\rightarrow$  Reptiles.
- $v_5$ : (Gives Birth = no)  $\wedge$  (Aquatic creature = semi )  $\rightarrow$  Amphibians

Each classification rule can be expressed in the following way.

$$v_i : (\text{Condition}) \rightarrow y_i$$

the left - hand side of the rule is called the rule antecedent it contains a conjunction of attribute tests.

Condition: =  $(A_1 \text{ op } V_1) \wedge (A_2 \text{ op } V_2) \wedge \dots \wedge (A_k \text{ op } V_k)$

where  $(A_j, V_j)$  is an attribute - value pair and op is a logical operator chosen from the set  $\{=, \neq, \leq, \geq\}$ . Each attribute test  $(A_j \text{ op } V_j)$  is known as a conjunct. The right-hand side of the rule is called the rule consequent, which contains the predicted classes  $y_i$ .

| Name         | Body Temperature | Skin Cover | Gives Birth | Aquatic Creature | Aerial Creature | Has legs | Hibernates |
|--------------|------------------|------------|-------------|------------------|-----------------|----------|------------|
| hawk         | warm blooded     | feather    | no          | no               | yes             | yes      | no         |
| grizzly bear | cocum blooded    | fur        | yes         | no               | no              | yes      | yes        |

$r_1$  covers the first vertebrate because its precondition is satisfied by the hawk's attributes. The rule does not cover the second vertebrate because grizzly bears give birth to their young and cannot fly, thus violating the precondition of  $r_1$ .

The quality of a classification rule can be evaluated using measures such as coverage and accuracy. Given a Data Set D and a classification rule  $r: A \rightarrow y$ , the coverage of the rule is defined as the fraction of records in D that trigger the rule r. On the other hand, its accuracy is defined as the fraction of records triggered by r.

$$\text{Coverage} (r) = \frac{|A|}{|D|}$$

$$\text{Accuracy} (r) = \frac{|A \cap Y|}{|A|}$$

where,  $|A|$  is the number of records that satisfy the rule antecedent,  $|A \cap Y|$  is the number of records that satisfy the both the antecedent and consequent, and  $|D|$  is the total number of records.

### A) How a Rule-Based Classifier Works.

A rule-based classifier classifies a test record based on the rule triggered by the record.

| Alame            | Body temperature | Skin Cover | Gives Birth | Aquatic Creature | Aerial Creature | Has legs | Hibernates |
|------------------|------------------|------------|-------------|------------------|-----------------|----------|------------|
| lemur            | warm blooded     | fur        | yes         | no               | no              | yes      | yes        |
| turtle           | cold blooded     | scales     | no          | semi             | no              | yes      | no         |
| dogfish<br>shark | cold blooded     | scales     | yes         | yes              | no              | no       | no         |

- The first vertebrate, which is a lemur, is warm blooded and gives birth to its young. It triggers the rule  $r_3$ , and thus, is classified as a mammal.
- The second vertebrate, which is a turtle, triggers the rules  $r_4$  and  $r_5$  since the classes predicted by the rules are contradictory (reptiles versus amphibians), their conflicting classes must be resolved.

- None of the rules are applicable to a dogfish shark. In this case, we need to ensure that the classifier can still make a reliable prediction even though a test record is not covered by any rule.

#### \* Mutually Exclusive Rules

The rules in a rule set  $R$  are mutually exclusive if no two rules in  $R$  are triggered by the same record.

This property ensures that every record is covered by at most one rule in  $R$ .

#### \* Exhaustive Rules

A rule set  $R$  has exhaustive coverage if there is a rule for each combination of attribute values. This property ensures that every record is covered by at least one rule in  $R$ .

$V_1$  : (Body temperature = cold blooded)  $\rightarrow$  non-mammals.

$V_2$  : (Body temperature = warm blooded)  $\wedge$   
(Gives Birth = yes)  $\rightarrow$  Mammals

$V_3$  : (Body temperature = warm blooded)  $\wedge$   
(Gives Birth = no)  $\rightarrow$  non-mammals.

If the rule set is not mutually exclusive then a record can be covered by several rules.

## \* Ordered Rules

the rules in which a rule set are ordered in decreasing order of their priority, ex (based on accuracy, coverage, total description length, or the order in which the rules are generated) An ordered rule set is also known as decision list

## \* Unordered Rules

this approach allocates a test record to trigger multiple classification rules and considers the consequent of each rule as a vote for a particular class.

Unordered rules are less susceptible to errors caused by the wrong rule being selected to classify a test record.

Model building is also less expensive because the rules do not have to be kept in sorted order. Nevertheless, classifying a test record can be quite an expensive task because the attributes of the test record must be compared against the precondition of every rule in the rule set.

Explain rule ordering scheme.

\* Comparison betn rule-based & class-based Ordering Schemes.

### Rule-Based Ordering

(Skin-cover = feathers,  
Aerial creature = yes)  $\Rightarrow$  Birds

(Body temperature = warm  
blooded, Gives Birth = yes)  
 $\Rightarrow$  Mammals

(Body temperature = warm  
blooded, Gives Birth = no)  
 $\Rightarrow$  Birds

(Aquatic Creature = semi)  
 $\Rightarrow$  Amphibians

(Skin Cover = scales,  
Aquatic Creature = no)  $\Rightarrow$  Reptiles

(Skin Cover = scales, Aquatic  
Creature = yes)  $\Rightarrow$  Fishes

(Skin Cover = none)  $\Rightarrow$  Amphibians

### Class-Based Ordering

(Skin cover = feathers, Aerial  
creature = yes)  $\Rightarrow$  Birds

(Body temperature = warm  
blooded, Gives Birth = no)  
 $\Rightarrow$  Birds

(Body temperature = warm  
blooded, Gives Birth = yes)  
 $\Rightarrow$  Mammals

(Aquatic Creature = semi)  
 $\Rightarrow$  Amphibians

(Skin Cover = none)  
 $\Rightarrow$  Amphibians

(Skin Cover = scales, Aquatic  
Creature = no)  $\Rightarrow$  Reptiles

(Skin cover = Scales, Aquatic  
Creature = yes)  $\Rightarrow$  Fishes

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## \* How to build a Rule based classifier

→ To build a rule based classifier we need to extract a set of rules that identifies a key relationship between the attributes of data and the class level. There are 2 broad classes of methods for extracting classification rules.

- 1) direct method :- which extract classification rules directly from the data.
- 2) indirect method :- which extract classification rules from other classification models such as decision trees and neural networks.

### 1) Direct Methods for Rule Extraction :-

#### \* Characteristics of rule Based classifier

- 1) The expressiveness of a rule set is almost equivalent to that of a decision tree because a decision tree can be represented by a set of mutually exclusive and exhaustive rules. Both rule-based and decision tree classifiers create rectilinear partitions of the attribute space & assign a class to each partition.
- 2) Rule Based classifier are generally used to produce descriptive models that are easier to interpret but gives comparable performance to the decision tree classifier.
- 3) ~~the~~ class If the rule based classifier allows multiple rules to be triggered for a given record then a more complex decision boundary can be constructed.
- 4) The class based ordering approach adopted by many rule-based classifiers is well suited for handling datasets with imbalanced class distributions.

How to build Rule base classifier DM

### (I) Direct Method

The sequential covering algorithm is often used to extract rule directly from data rules are grown in a greedy fashion based on a certain evaluation measure.

The algorithm extracts the rules of one class at a time for data sets that contain more than two classes.

For the vertebrates classification birds problem the sequential covering algorithm may generate rules for classifying birds first followed by the rules for classifying mammals, amphibians, reptiles and finally fishes.

|   |   |   |   |
|---|---|---|---|
| $\begin{bmatrix} + & + \\ - & + \\ - & + \end{bmatrix}$ | $\begin{bmatrix} - & - \\ - & R_1 \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ |
| $\begin{bmatrix} + & + \\ - & + \\ - & + \end{bmatrix}$ | $\begin{bmatrix} - & - \\ - & R_1 \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ |
| $\begin{bmatrix} + & + \\ - & + \\ - & + \end{bmatrix}$ | $\begin{bmatrix} - & - \\ - & R_1 \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ |
| $\begin{bmatrix} + & + \\ - & + \\ - & + \end{bmatrix}$ | $\begin{bmatrix} - & - \\ - & R_1 \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ | $\begin{bmatrix} - & - \\ R_1 & - \\ - & - \end{bmatrix}$ |

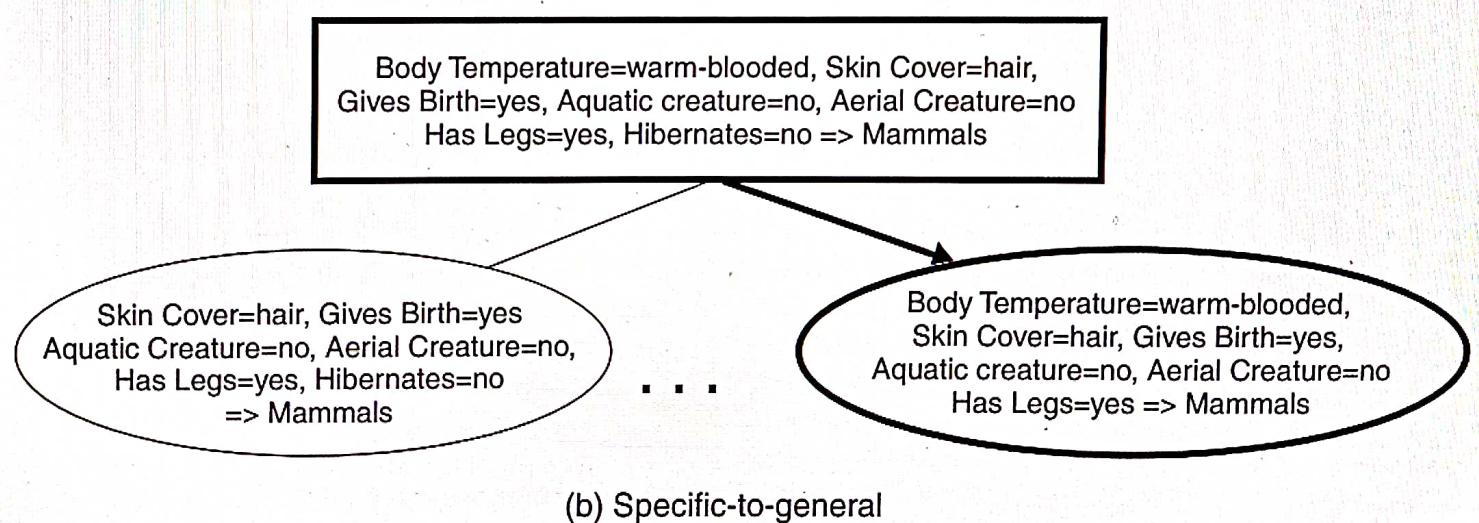
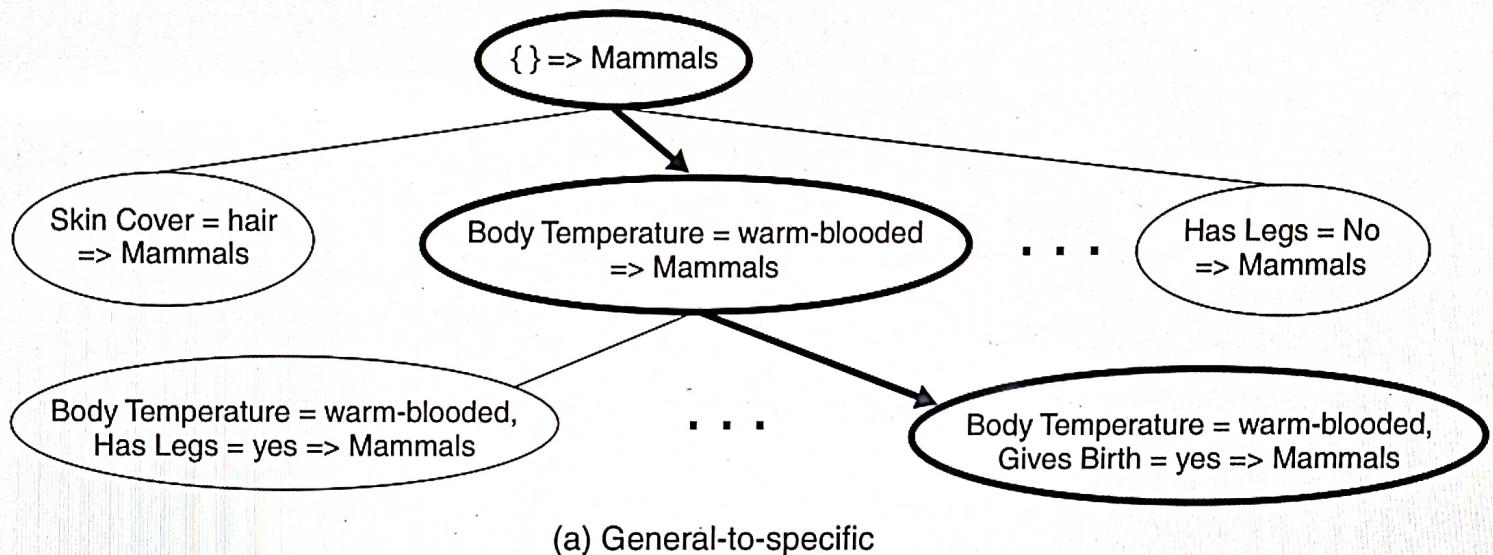
(a) original data

b) step 1      c) step 2      d) step 3

Fig:- An example of the sequential covering algorithm

- Learn -One - Rule Function :- The objective of the learn -One - Rule function is to extract the classification rules that covers many of the positive examples and none of the negative examples in the training set. The learn -One - Rule function addresses the exponential search problems by growing rules in the a greedy fashion.
- Rule Growing strategy : There are 2 common strategies for growing a classification rules
  - (1) General to specific
  - (2) Specific to general . Under the general -to -specific strategy , an initial rule  $\emptyset \rightarrow y$  is created , where the LHS is an empty set and RHS contains the target class. The rule has poor quality because it covers all the info example in the training sets .

Diagram on page (214) Fig 5.3



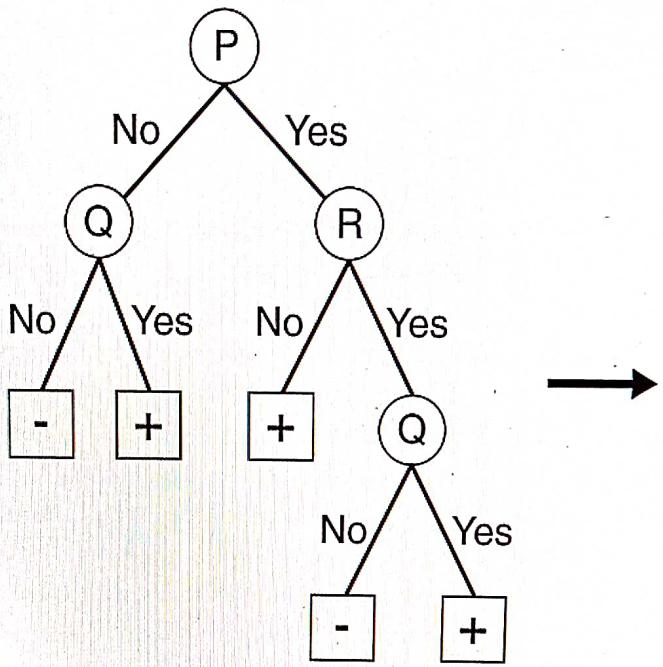
**Figure 5.3.** General-to-specific and specific-to-general rule-growing strategies.

\* Rule Evaluation: ~~Rule Evaluation~~

An evaluation matrix is needed to determine which concept should be added during the rule growing process having total classes and each node has a decision matrix for each rule.

\* Indirect method for rule extraction.

Every path from root node to the leaf node of a decision tree can be expressed as a classification rule if the rule set is exhaustive and contain mutually exclusive and exhaustive conditions.

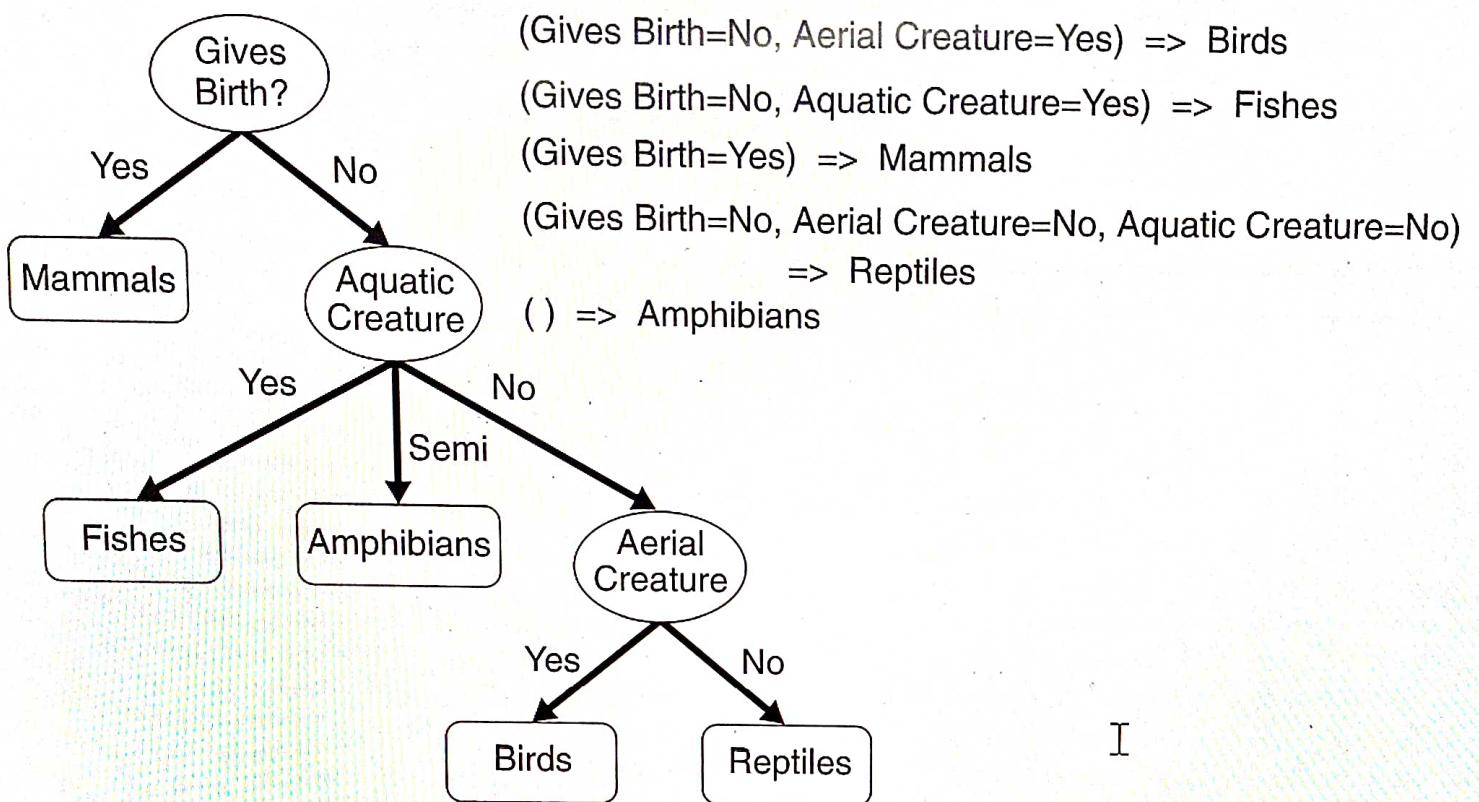


### Rule Set

- r1:  $(P=No, Q=No) \Rightarrow -$
- r2:  $(P=No, Q=Yes) \Rightarrow +$
- r3:  $(P=Yes, Q=No) \Rightarrow +$
- r4:  $(P=Yes, R=Yes, Q=No) \Rightarrow -$
- r5:  $(P=Yes, R=Yes, Q=Yes) \Rightarrow +$

**Figure 5.5.** Converting a decision tree into classification rules.

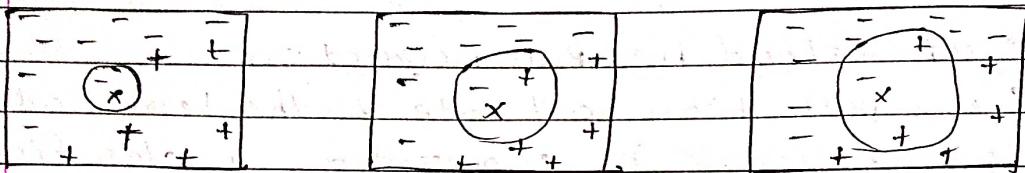
### Rule-Based Classifier:



**Figure 5.6.** Classification rules extracted from a decision tree for the vertebrate classification problem.

- ) Rule Generation:- classification rules are extracted for every path from the root to one of the leaf nodes in the decision tree. Given a classification rule  $\alpha : A \rightarrow y$ ,
  - ) Rule Ordering:- After generating the rule set, class-based ordering scheme to order the extracted rules. Rules that predict the same class are grouped together into the same subset.
- \* Nearest - Neighbors classifiers : The classification framework involves a 2 step process (1) An inductive step for constructing a classification model from data. (2) A deductive step for applying the model to test examples. Decision tree & rule-based classifiers are examples of eager learners.

because they are designed to learn a model that maps the input attributes to the class label as soon as the training data becomes available



- a) 1-nearest neighbor   b) 2-nearest neighbor   c) 3-nearest neighbor

Drawback of this approach is that some test record may not be classified because they do not match any of the training example. One way to make these approach more flexible is to find all the training examples that are relatively similar to the attributes of the test example, this examples which are known as nearest neighbors

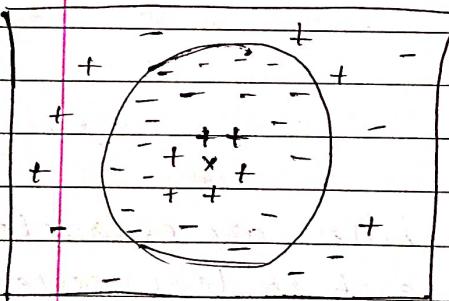


fig: K-nearest neighbor classification with large K.

If K is too small then the nearest neighbor classifier may be susceptible to overfitting because of noise in the training data. On the other hand if K is too large the nearest neighbor classifier may misclassify the test instance because the list of nearest neighbor may include data points that are located far away from its neighborhood.

## \* Characteristic of Nearest -Neighbour Classifiers

- 1) Nearest neighbor classification is a part of a more general technique known as instance based learning which uses specific training instance to make predictions without having to maintain an abstraction derive from data.
- 2) Lazy learner such as nearest neighbor classifier do not require model building
- 3) NNC make prediction based on the local information where as decision trees and rule base classifier attempts to find a global model.
- 4) The decision boundaries of the nearest neighbor classifier also have high variability because they depend on ~~decomposition~~<sup>depends on composition</sup> of training examples. Increasing the no. of nearest neighbor may reduce such variability.
- 5) NNC can produce wrong prediction unless the appropriate proximity measure and data processing steps are taken.

HQ. What is Bayesian classifier? Explain naive bayes classifier in detail.

Ans: Bayesian classifier is a probabilistic approach to learning and inference based on a different view of what it means to learn from data, in which probability is used to represent uncertainty about the relationship being learnt.

\* Bayes Theorem: Bayesian classifier uses Bayes theorem to predict the occurrence of any event. Bayesian classifier are the statistical classifier with the Bayesian probability understanding. The theory expresses how a belief expressed as a probability.

Bayes theorem comes into existence after Thomas Bayes, who first utilized conditions probability to provide an algorithm as evidence to calculate limits as an unknown parameter.

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Bayes theorem is expressed mathematically

$$P(x|y) = \frac{P(y|x) \cdot P(x)}{P(y)}$$

where  $x$  &  $y$  are events of  $P(y) \neq 0$   
 $P(x)$  and  $P(y)$  are the probabilities  
of occurring  $x$  and  $y$ .

eg: Consider a football game between  
two rival teams : Team 0 and Team 1.  
Suppose Team 0 wins 65% of the time  
and Team 1 wins the remaining  
matches. Among the games won by  
Team 0, only 30% of them came from  
Team playing on Team 1's football field.  
On the other hand, 75% of the  
victories for Team 1 are attained  
while playing at home. If Team 0 is to  
host the next match between the two  
teams, which team will most likely  
emerge as the winner.

- Let  $x$  be the random variable that represent team hosting the match
- Let  $y$  be random variable that represent winner at match

Ans: Probability Team 0 wins is  $P(y=0) = 0.65$   
 Probability Team 1 wins is  $P(y=1) = 1 - P(y=0)$   
 $= 0.35$

Probability Team 1 hosted the match it won is:  $P(x=1 | y=1) = 0.75$

Probability Team 1 hosted the match won by Team 0 is  $P(x=1 | y=0) = 0.3$

Our objective is to find  $P(y=1 | x=1)$ , which is conditional probability that Team 1 wins the next match if it will be hosting and compares it against  $P(y=0 | x=1)$ .

Using Bayes theorem, we obtain

$$P(y=1 | x=1) = \frac{P(x=1 | y=1) \times P(y=1)}{P(x=1)}$$

$$= \frac{P(x=1 | y=1) * P(y=1)}{P(x=1)}$$

No team will profit if  $P(y=1) < \frac{1}{2}$

$$= \frac{P(X=1|y=1) \times P(y=1)}{P(X=1, y=1) + P(X=1, y=0)}$$

$$= \frac{P(X=1|y=1) \times P(y=1)}{P(X=1|y=1)P(y=1) + P(X=1|y=0)P(y=0)}$$

$$= \frac{0.75 \times 0.35}{0.75 \times 0.35 + 0.3 \times 0.65}$$

$$= 0.5738$$

$$\text{Hence } P(y=0|X=1) = 1 - P(y=1|X=1)$$

$$= 1 - 0.5738$$

$$= 0.4262$$

Since  $P(y=1|X=1) > P(y=0|X=1)$

Team 1 has a better chance than Team 0 of winning the next match.

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### Naive Bayes classifier -

- > A naive Bayes classifier algorithm is a Supervise learning algorithm which is based on bayes theorem and use for solving classification prob.
- 2) It is mainly used in tex classification that includes the high dimensional training data set. naive bayes classifier is one of the simple and most important classifier. which helps in building the fast machine learning model that can make quick prediction. it is the probabilistic classifier which predicts on the basis of the probability of an object. some popular objects are shown by classifiers. and classifier two words -
- b) The Naive based classifier two words -  
Naive - It is called Naive because it assumes that because the accuracy of the certain feature is independent of the certain features. other feature.  
Such as a fruit is identified on the basis of colour, shape, and taste they spherical and sweet fruit is recognized as an

Hence, this feature individually attributes  
so each feature individually treat it  
is an apple without depend on each other,  
bay's it is called bayes theorem - because its  
depends on the principal of

$$p(x|y = 1) = \prod_{i=1}^d (p_{x_i|y=1})$$

where, each attributes set,

$x = \{x_1, x_2, \dots, x_d\}$  consist of  $d$  attributes.

Conditioned Independence - Let  $x, y, z$  denotes three  
sets of random variable.

The variables in  $x$  are said to be  
conditionally independent of  $y$  given  $z$ .

$$p(x|y, z) = p(x|z)$$

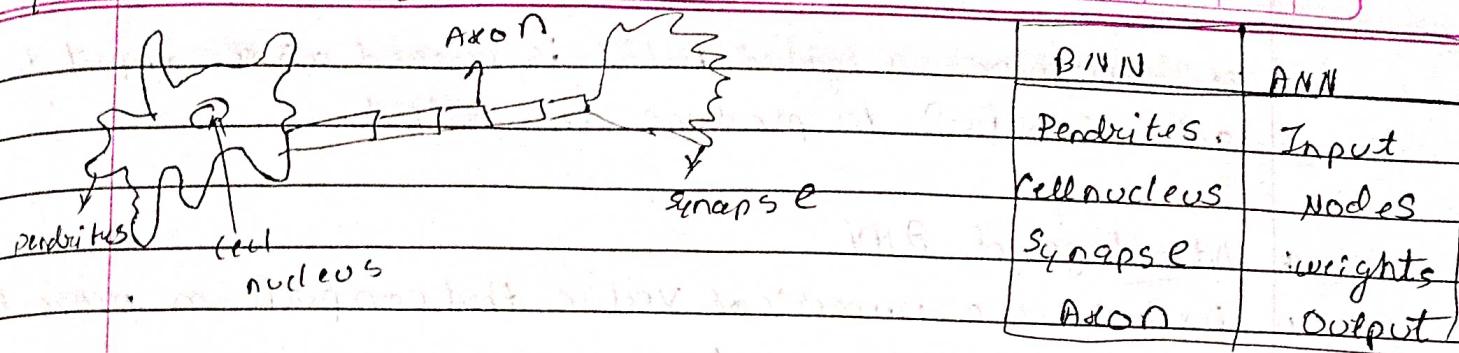
Conditional Independence between  
 $x$  and  $y$  are also said attributes,

$$p(x, y|z) = \frac{p(x, y, z)}{p(z)}$$

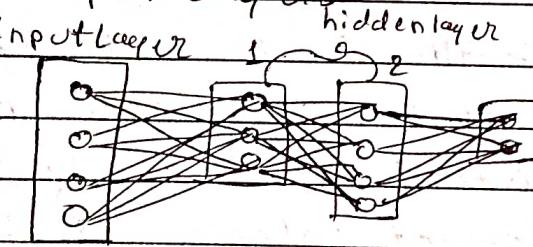
$$= \frac{p(x|y, z) \times p(y|z)}{p(z)}$$

$$= p(x|y, z) \times p(y|z)$$

$$= p(x|z) \times p(y|z)$$



\* ANN :- An ANN is the field of AI where it's attempts to mimic the network of neurons, makes up the human brain so that the computers will have an option to understand things and make decisions in a Human like manner. ANN is designed by programming computers to behave simply like interconnected brain cells. ANN primarily consists of 3 layers 1) Input layer 2) Hidden layer and 3) Output layers.



Architecture of ANN

- 1) Input layer :- It accepts input in several different formats provided by the programmer.
- 2) Hidden layer :- The hidden layer present between input & output layer it performs all the calculations to find hidden patterns and features
- 3) Output layer :- The input goes through a series of transformation using the hidden layer which finally results in output that is conveyed using this layer.

The ANN takes input and computes the weighted sum of inputs and includes a bias this computation is represented in the form of a transformation.  $\sum_{i=1}^n w_i * x_i + b$

$w_i$  :- Weighted function,  $b$  = bias  
 $x_i$  :- Input function

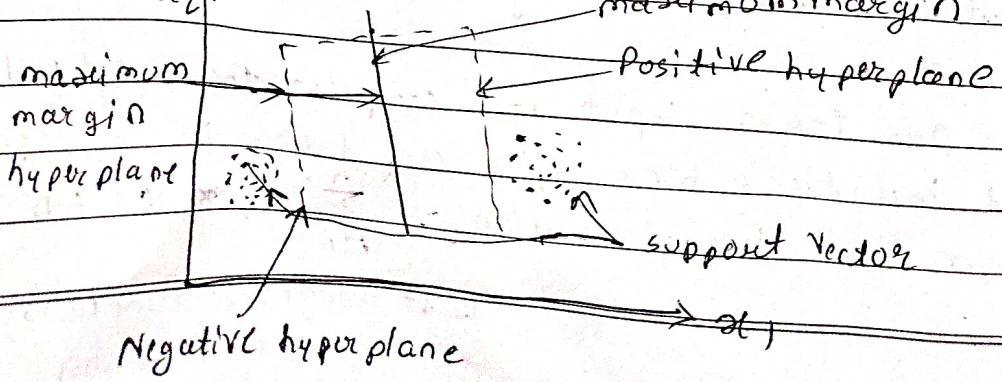
It determine weighted total is passed as an input to an activation fun to produce the output.

### \* Advantages of ANN

- 1) ANN have a numerical value that can perform more than 1 task simultaneously

### \* Support Vector Machine :-

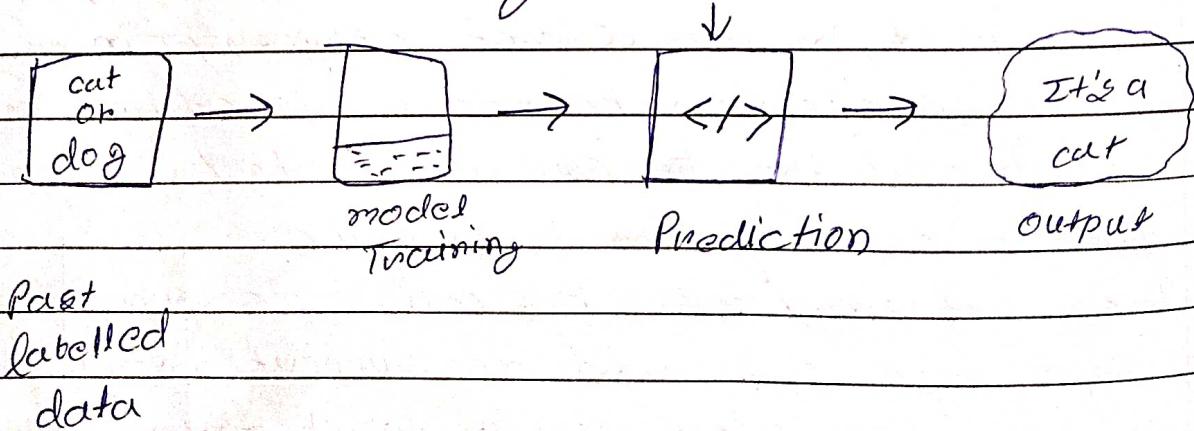
- 1) SVM is one of the most popular supervised learning algorithm which is used for classification as well as regression problems.
- 2) Primarily it is used for classification problems in ML
- 3) The goal of SVM algorithm is to create the best line or decision boundary, that can aggregate n dimensional space into classes so that we can easily put the new data point in the correct category in future.
- 4) This basted decision boundary is called a hyperplane
- 5) SVM chooses the extreme points / vector that helps in creating hyperplane.
- 6) These extrem cases are called as support vectors and hence algorithm is termed as SV Support Vector algorithm
- 7) Consider the below diagram in which there are 2 different categories that are classified using a decision boundary or hyperplane.



Ex

can be understood with the example that we have ~~using~~ used in KNN classifier. Suppose we see a strange cat that also have some features of dog so if we want a model that can actually identify whether it is a cat or dog so such a model can be created by using SVM algo. We were 1st train our model with lots of images of cats & dogs so that it can learn about the diff'rent features of cat & dogs then we test it with this strange creature so as support vector creates a decision boundary b/w this two data (cat & dog) & choose extreme cases. (Support vectors) if will see the extreme case of cat & dog on the basis of Support vectors it will classify it with a cat.

Consider the below fig. new data.



- SVM algo ~~is~~ can be used in face detection, image classification and text categorisation.

## Type of SVM.

SVM

linear SVM

Non linear SVM

### 1) linear SVM

linear SVM is used for linearly separable data which means a data set can be classified into two classes by using a single straight line. Then such data is formed as linearly separable data & classifier is used called as linear SVM classifier.

### 2) Non linear SVM

non linear SVM is used for non-linearly separable data which means if a data set can not be classified by using a straight line then such data is formed as non-linear data & classifier used is called as non-linear SVM classifier.

## Sub Algorithms

- 1) hyperplane.
- 2) Support Vectors

### 1) hyperplane

There can be multiple lines / decision boundaries to segregate the classes in  $N$ -dimensional space but we need to find out the best decision boundary that helps to classify the data points this best boundary is known as the hyperplane of SVM.

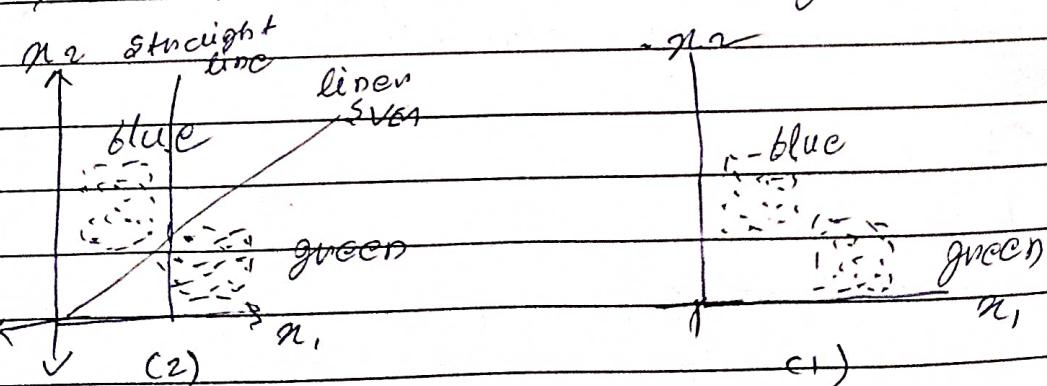
## 2) Support Vector.

the data point or vectors that are closest to the hyperplane which affects the position of hyperplane are termed as support vector. Since since this vectors support the hyperplane hence called support vector.

## Qn How does SVM works.

### (1) linear SVM

- the working of SVM algo can be understand by using an ex.
- suppose we have a data set that has two tags (green & blue) if the data set has two features  $n_1$  &  $n_2$
- we want a classifier that can classify a pair  $n_1, n_2$  of co-ordinates either green or blue



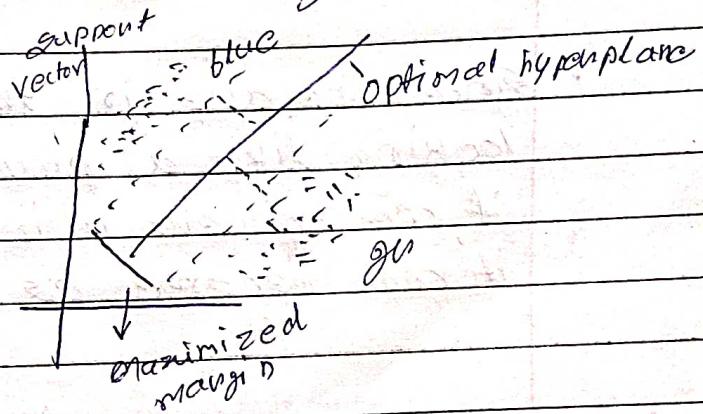
- so as it is 2D space so by just using a straight line we can easily separate these two classes but there can be multiple lines that can separate these classes.
- the SVM algo helps to find the best line or decision boundary these best boundary of region called as hyperplane.

Such algo finds a closer points of the lines from both the classes this points are called support vector.

The distance b/w the vectors of hyperplane is called as margin.

The goal of SVR is to minimize this margin.

The hyperplane with maximum margin is called the optimal hyperplane.

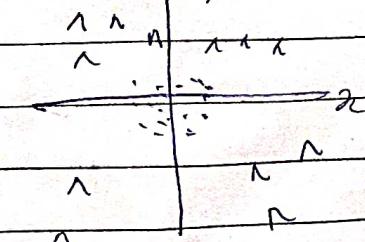


## (2) Non-linear SVM

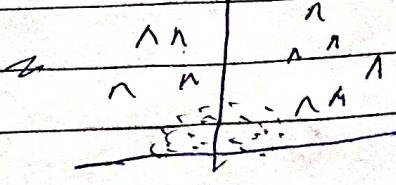
If data is linearly arranged then we can separate it by using a straight line but for non-linear data we can not draw single straight line.

Consider the below image.

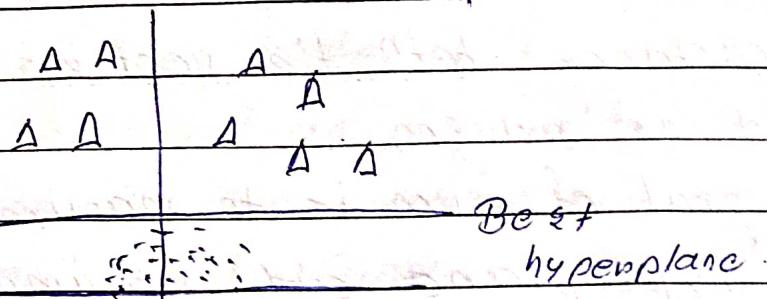
To separate this data points we need to add one more dimension. In linear data we have used two dimension  $x$  &  $y$  so for non linear data we will add third dimension  $z$  it can be calculated as  $z = x^2 + y^2$



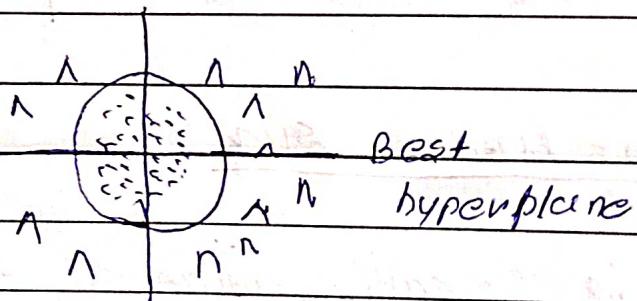
By adding the third dimension the sample space will become as shown.



- So now the SVD will divide the data set into classes in the following way. Consider below img.



- Since we are in third plane space hence it is looking like a plane parallel to the  $x$ -axis if we convert it in 2D Space with  $Z=1$  then it will become as



Hence we get a circumference of radius in case of non-linear data.

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## \* Association Analysis:-

Association analysis is the task of finding interesting relationships in large datasets. This interesting relationship can take two forms.

- 1) frequent Item sets.
- 2) Association Rules

- 1) Frequent item sets.  
→ Frequent item sets are a collection of items that frequently occur together.
- 2) Association Rules:-  
→ Association rule mining finds interesting associations and relationships among large set of data items. This rule shows how frequently a item set occurs in a transaction. The association rule is very useful in analysing data sets. The data is collected using bar code scanner in super market.

Such databases consists of a large no. of transaction records which list all items bought by a customer on a single purchase.

### \* Applications of association rule learning.

- 1) Market basket analysis
- 2) Bioinformatic
- 3) Medical diagnosis
- 4) Web mining
- 5) Scientific data analysis.
- 6) Protein Sequences

\* Terminology is related with association rule learning.

### 1) Item set:-

In association rule learning a collection of zero or more items is known as item sets. If an item set consists of  $k$ -items, then it is known as  $k$ -item set.

Ex:- {pizza, burger, sweet}.

{bread, milk}.

### 2) Support:-

Support is the measure that tells us how frequent an item set is in a given dataset. It is calculated by dividing the total no. of occurrences of an item set by the total no. of transactions.

formula:- Support =  $\frac{\text{no. of transaction containing item set}}{\text{total no. of transaction}}$ .

### 3) Confidence:-

For a rule  $x \rightarrow y$  confidence determines how frequently  $y$  has appeared in transaction that contain  $x$ .

$$\text{Confidence of } (x, y) = \frac{\text{support of } xy}{\text{support of } x}$$

### 4) Rule Generation:-

whose objective is to extract all the high confidence rule from the frequent item set

found in the previous state step. These rules are called strong rules.

\* Association rule learning works on the concept of if and else statement such as If A then B.

Here If element is called antecedent and then segment is called consequent.

Association rule learning can be divided into 3 algo

- ✓ 1) Apriori Algorithm.
- ✓ 2) FP algo - (Frequency pattern).
- ✗ 3) Eclat algo (Equivalence class Transformation)

### 1) Apriori algorithm.

Apriori algo refers to the algo which is used to calculate the association rules between objects. It means how 2 or more objects are related to one another. In other words we can say the apriori algo is an association rule learning that analyses that people who bought product A also bought product B.

Ex: You must have noticed that the pizza shop seller makes a pizza soft drink and bread stick combo together. He also offers a discount to their customer who buy these combos. Do you ever think

He thinks that customer who buy pizza also buy soft drinks and bread sticks however the

The apriori algorithm refers to an algorithm that used in mining frequent product sets and element association rules.

Generally, the apriori algo. operates on a database containing a huge no. of transaction for example the items customers at a big bazar.

#### \* Components of apriori algorithms.

1) Support

2) Confidence

3) Lift

1) Support:- Support refers to the default popularity of any product you find the support as a quotient of the division of the no. of transactions comprising that product by the total no. of transactions.

Out of 400 transactions

$$\text{Support}(\alpha) = \frac{\text{Freq}(\alpha)}{T}$$

## Frequent Pattern Growth

This algo is an improvement to the apriori method. A frequent pattern is generated without the need for candidate generation. (use a similarity between items to recommended item similar to what the user likes.)

FP growth algorithm represents the database in the form of a tree called a frequent pattern tree or FP tree. This tree structure will maintain the association between the item set. The database is fragmented using one frequent item. This fragmented part is called <sup>using</sup> Pattern fragment. The item set of this fragmented patterns are analysed with this method the search for frequent item set is reduced comparatively.

### \* FP Tree

Frequent pattern tree is a tree like structure that is made with the initial item set of the database. The purpose of the FP tree is to mine the most frequent pattern each node of the FP tree represents an item set. The root node represents null while the lowermost node represents the item sets. The association of the nodes with the lower nodes that is the item sets with the other item sets are maintained while forming the tree.

## → FP algorithm steps.

- Step 1) The first step is to scan the database and finds the occurrences of the item set in the database. This step is same as the first step of apriori. The count of one item set in the database is called support count.
- Step 2) The next step is to construct the FP tree. For this create a root of the tree. The root is represented by null.
- Step 3) The next step is to scan the database again and examine the transaction and find out the item set in it. Examine the first transaction and find out the item set in it. The item set with the max count is taken at the top. The next item set with lower count and so on. It means that the branch of the tree is constructed with transaction item set in descending order of count.
- Step 4) The next transaction in database is examined. The item sets are ordered in descending order of count. If any item set of this transaction is already present in another branch [for example in the first transaction then this transaction branch would share a common prefix to the rule].

This means that the common item set is link to the new node of another item set in the transaction.

Step 5) Also the count of the item set is incremented as it occur in the transaction. Both the common node and new node is increased by 1 as they are created and linked according to transactions.

Step 6) The next step is to mine the created FP tree for this lowest node. Examine first along with the links of the lowest node. The lowest node represents the frequency pattern length 1 from this traverse the path in the FP tree. This path is called conditional pattern base (conditional pattern base is sub database consisting of prefix path in the FP tree occurring with the lowest node. ~~not suffix~~)

Step 7) Construct a conditional FP tree which is formed by a count of item sets in the path. The item sets meeting with threshold support are considered in the FP tree.

Step 8) Frequent pattern are generated from the conditional FP tree.

DATE: / /

Support threshold 50%

Confidence 60%

Transaction list of items.

T<sub>1</sub> | I<sub>1</sub>, I<sub>2</sub>, I<sub>3</sub>T<sub>2</sub> | I<sub>2</sub>, I<sub>3</sub>, I<sub>4</sub>T<sub>3</sub> | I<sub>4</sub>, I<sub>5</sub>T<sub>4</sub> | I<sub>1</sub>, I<sub>2</sub>, I<sub>4</sub>T<sub>5</sub> | I<sub>1</sub>, I<sub>2</sub>, I<sub>3</sub>, I<sub>5</sub>T<sub>6</sub> | I<sub>1</sub>, I<sub>2</sub>, I<sub>3</sub>, I<sub>4</sub>

Support threshold = 50%

$$\text{Minimum support} = 0.5 \times 6 = 3$$

$$\text{Minimum support} = 3$$

Minimum support = 3

Item

Count

|                |   |
|----------------|---|
| I <sub>1</sub> | 4 |
| I <sub>2</sub> | 5 |
| I <sub>3</sub> | 4 |
| I <sub>4</sub> | 4 |
| I <sub>5</sub> | 2 |

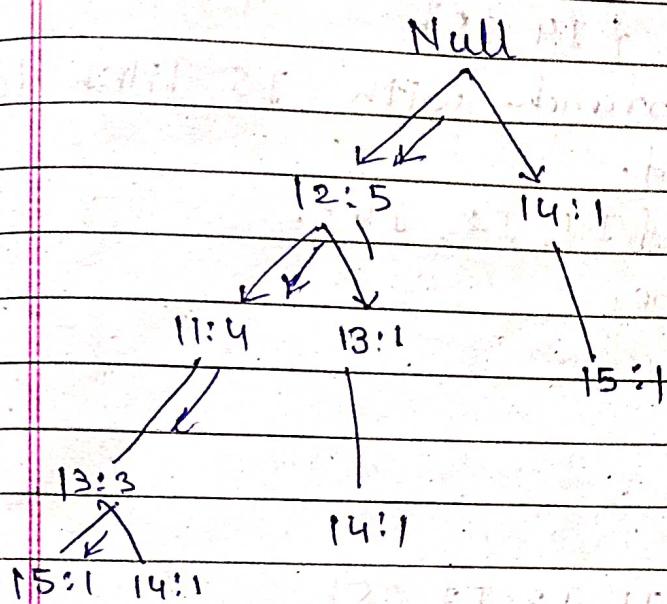
Arranging in descending order.

Item

Count

Order

|                |   |   |
|----------------|---|---|
| I <sub>2</sub> | 5 | 1 |
| I <sub>1</sub> | 4 | 2 |
| I <sub>3</sub> | 4 | 3 |
| I <sub>4</sub> | 4 | 4 |



### \* Built FP-tree :-

- 1) Considering the root node null
- 2) The first scan transaction  $T_1: \{I1, I2, I3\}$  contain 3 items  $\{I1:1\} \{I2:1\} \{I3:1\}$   
 $I2$  is linked with child to root.  
 $I1$  is linked to  $I2$  and  $I3$  is linked to  $I1$ .
- 3) Transaction  $T_2: \{I2, I3, I4\}$ .  
where  $I2$  is linked to root  
 $I3$  is linked to  $I2$ .  
and  $I4$  is linked to  $I3$ .  
but this branch would share the  $I2$  node  
as common as it is already used in  $T_1$
- 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  
 $\{I2:2\} \{I3:2\} \{I4:1\}$ .

5) Transaction 3<sup>rd</sup> {I4, I5}.

Similarly a new branch with I5 link to I4, as a child is created.

6) Transaction 4<sup>th</sup> {I1, I2, I4}.

The sequence will be {I2, I1, I4}. I2 is already linked to the root node hence it will be incremented by 1. As it is already linked with I2 in T1 {I2:3}, {T1:23} {I4:13}.

7) Transaction 5<sup>th</sup> {I1, I2, I3, I5}.

The sequence will be {I2, I1, I3, I5} thus {I2:4} {I1:3} {I3:2} {I5:1}.

8) Transaction 6<sup>th</sup> {I1, I2, I3, I4}.

The sequence will be {I2, I1, I3, I4} thus {I2:5} {I1:4} {I3:3} {I4:1}.



### Advantages:

- 1) This algorithm needs to scan the database once column compare to apriori which scans the transaction for each iteration.
- 2) The pairing of items is not done in the algorithm making it faster.
- 3) The database is stored in a compact version in memory.
- 4) It is efficient and scalable for mining both long and short frequent pattern.

## Disadvantages:

- 1) FP tree is more cumbersome and difficult to build than apriori.
- 2) It may be expensive.
- 3) The algorithm may not fit in the shared memory when the database is large.