Classification

Logistic Regression

Logistic Regression

- Logistic regression is kind of like linear regression but is used when the dependent variable is not a number, but something else (like a Yes/No response)
- Its called Regression but performs classification as based on the regression it classifies the dependent variable into either of the classes

Logistic Regression

- Logistic regression is used for prediction of output which is binary
- For example, if a credit card company is going to build a model to decide whether to issue a credit card to a customer or not, it will model for whether the customer is going to “Default” or “Not Default” on this credit card.

Logistic Regression

K-Nearest Neighbors (K-NN)

K-Nearest Neighbors (K-NN)

- it is used to identify the data points that are separated into several classes to predict the classification of a new sample point
- K-NN is a **non-parametric,** lazy learning algorithm
- It classifies new cases based on a similarity measure (e.g. distance functions)

K-Nearest Neighbors (K-NN)

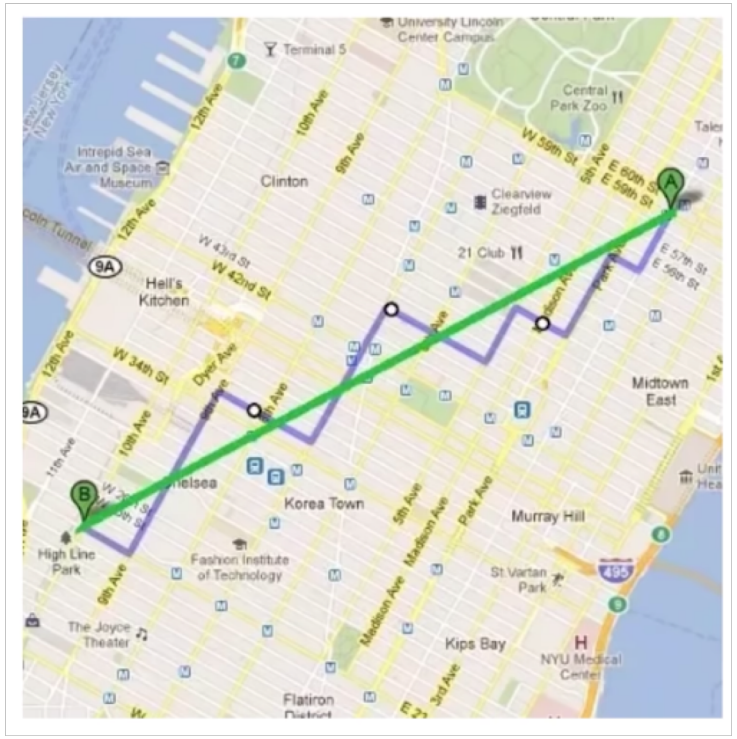
- K is the number of neightbors to the consider
- Scaling is important
- K should be odd in order to avoid the ties
- Voting can be weighted by the distance to each neighbor
- Does not scale to large data well

K-Nearest Neighbors (K-NN)

- K-Nearest Neighbor does not learn
- It is lazy and just memorizes the data
- Works well with a small number of input variables but struggles when the number of inputs is very large

K-Nearest Neighbors (K-NN)

- Distance Algorithms
  - Euclidean distance
  - Manhattan distance



Support Vector Machine

Support Vector Machine

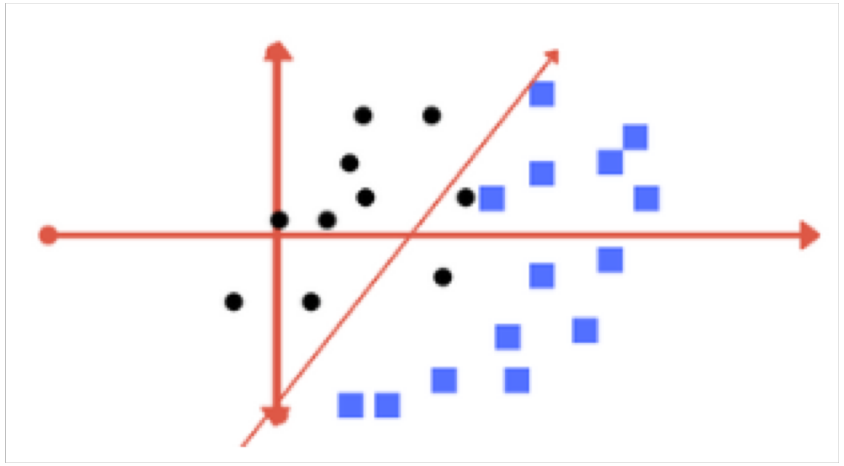
- used for both regression and Classification
- It is based on the concept of decision planes that define decision boundaries
- A decision plane(hyperplane) is one that separates between a set of objects having different class memberships
- It performs classification by finding the hyperplane that maximizes the margin between the two classes with the help of support vectors.

Support Vector Machine - Terminologies

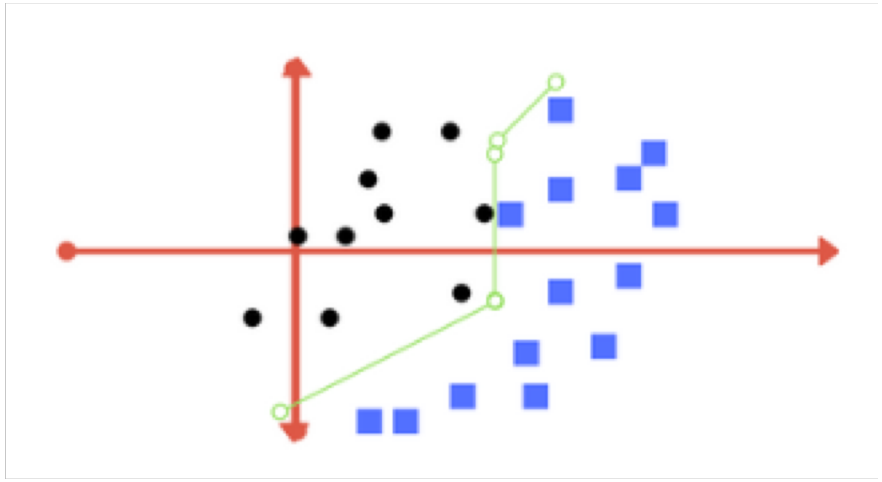
- **Regularization**
  - The Regularization parameter tells the SVM optimization how much you want to avoid misclassifying each training example
  - For large values of C, the optimization will choose a smaller-margin hyperplane if that hyperplane does a better job of getting all the training points classified correctly
  - Conversely, a very small value of C will cause the optimizer to look for a larger-margin separating hyperplane, even if that hyperplane misclassifies more points

Support Vector Machine - Terminologies

- **Regularization**



Low Regularization value



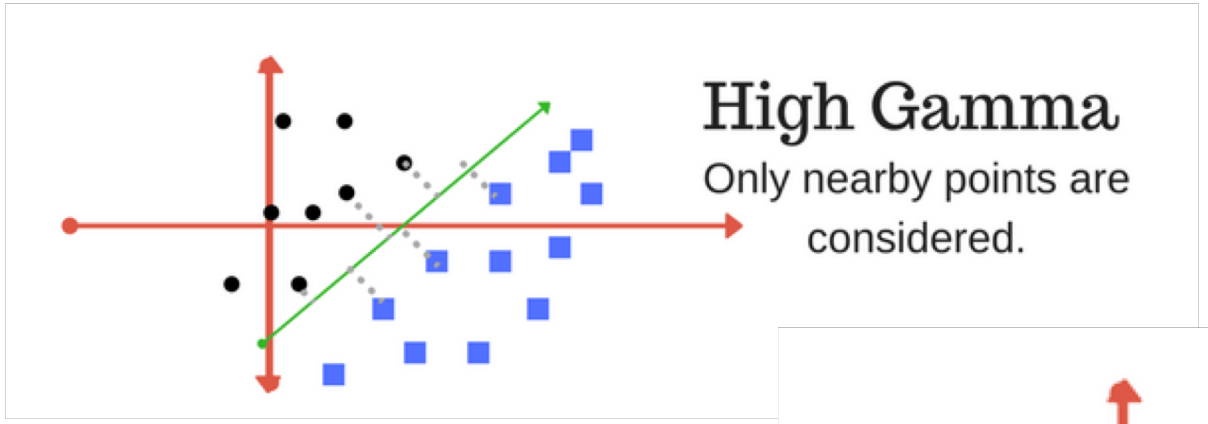
High Regularization value

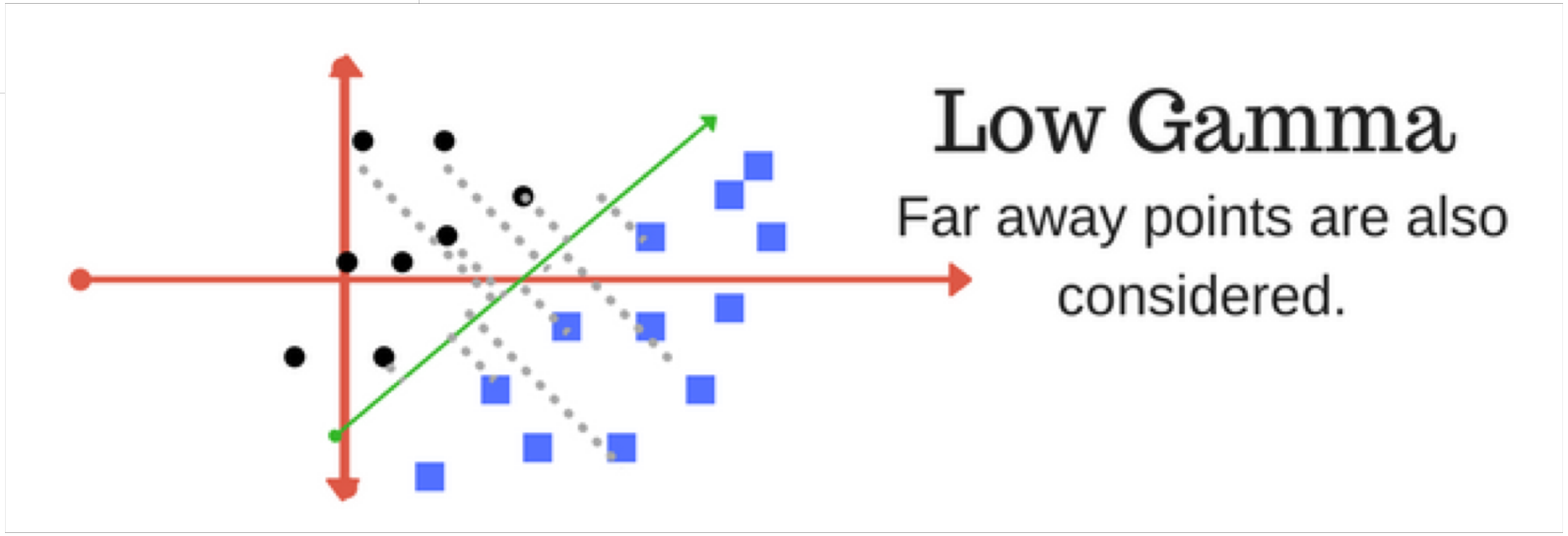
Support Vector Machine - Terminologies

- Gamma
  - The gamma parameter defines how far the influence of a single training example reaches
  - low values meaning ‘far’
    - points far away from plausible separation line are considered in calculation for the separation line
  - high values meaning ‘close’
    - the points close to plausible line are considered in calculation

Support Vector Machine - Terminologies

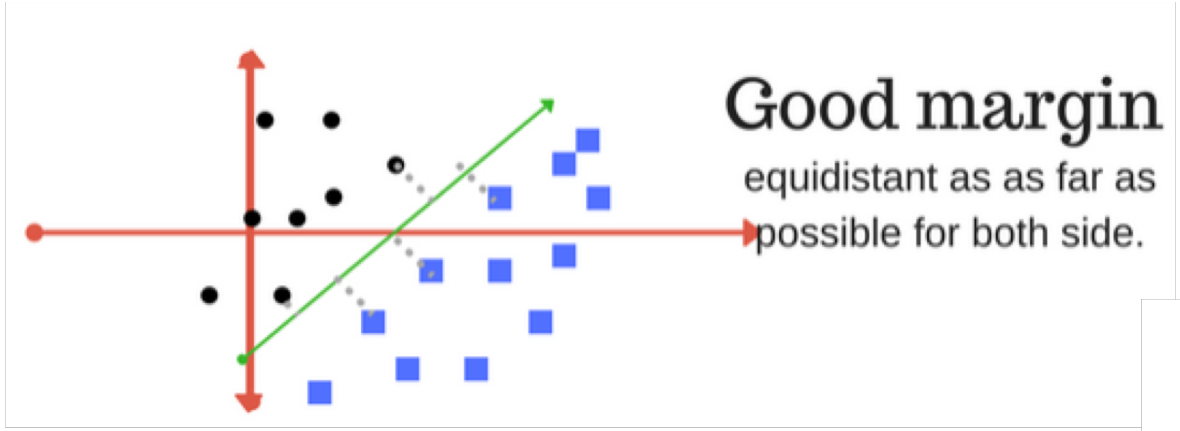
- Gamma

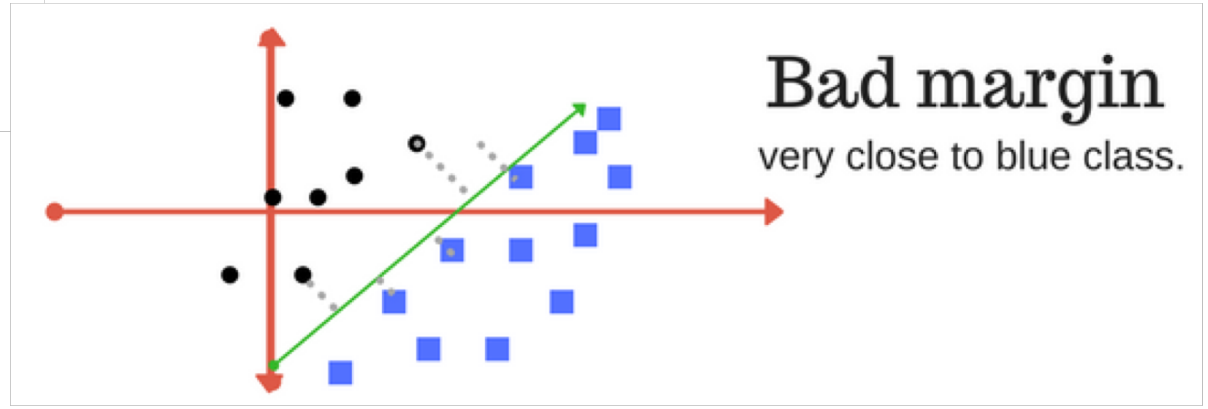




Support Vector Machine - Terminologies

- Margin
  - A margin is a separation of line to the closest class points
  - A ***good margin*** is one where this separation is larger for both the classes





Support Vector Machine - Terminologies

- Kernel
  - The learning of the hyperplane in linear SVM is done by transforming the problem using some linear algebra
  - The function which does the transformation is called as kernel
  - For **linear kernel**
    - f(x) = B(0) + sum(ai * (x,xi))
  - For **polynomial kernel**
    - *K(x,xi) = 1 + sum(x * xi)^d*
  - *For* **exponential kernel**
    - *K(x,xi) = exp(-gamma * sum((x — xi²))*

SVM - Advantages

- **High Dimensionality**
  - SVM is an effective tool in high-dimensional spaces, which is particularly applicable to document classification and sentiment analysis where the dimensionality can be extremely large.

SVM - Advantages

- **Memory Efficiency**
  - Since only a subset of the training points are used in the actual decision process of assigning new members, just these points need to be stored in memory (and calculated upon) when making decisions.

SVM - Advantages

- **Versatility**
  - Class separation is often highly non-linear. The ability to apply new kernels allows substantial flexibility for the decision boundaries, leading to greater classification performance.

SVM - Disadvantages

- **Kernel Parameters Selection**
  - SVMs are very sensitive to the choice of the kernel parameters
  - In situations where the number of features for each object exceeds the number of training data samples, SVMs can perform poorly

Decision Tree

Decision Tree

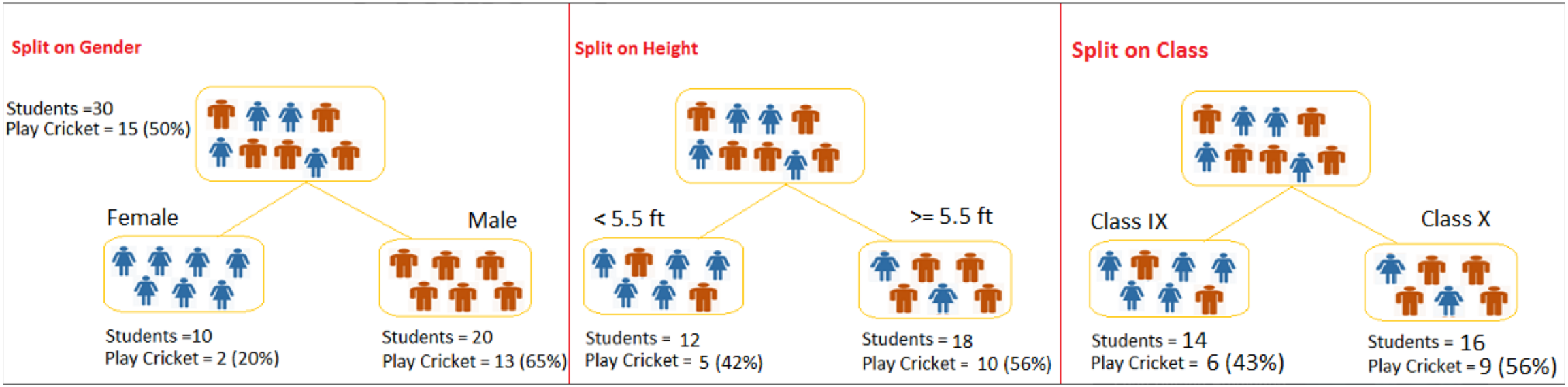
- used mostly in classification
- we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter / differentiator in input variables

Decision Tree

- Let’s say we have a sample of 30 students with three variables Gender (male/female), Class(IX/X) and Height (5 to 6 ft). 15 out of these 30 play cricket in leisure time.
- Consider following data
  - Male players: 10 and female players: 20
    - 20% of female students and 65% of male students play cricket
  - Students < 5.5ft: 12 and >= 5.5ft: 18
    - 42% of cricket players are below 5.5ft and 56% are above or equal 5.5ft
  - Class IX: 14, X: 16
    - 43% of class IX and 56% of class X play cricket

Decision Tree

- variable Gender is able to identify best homogeneous sets compared to the other two variables



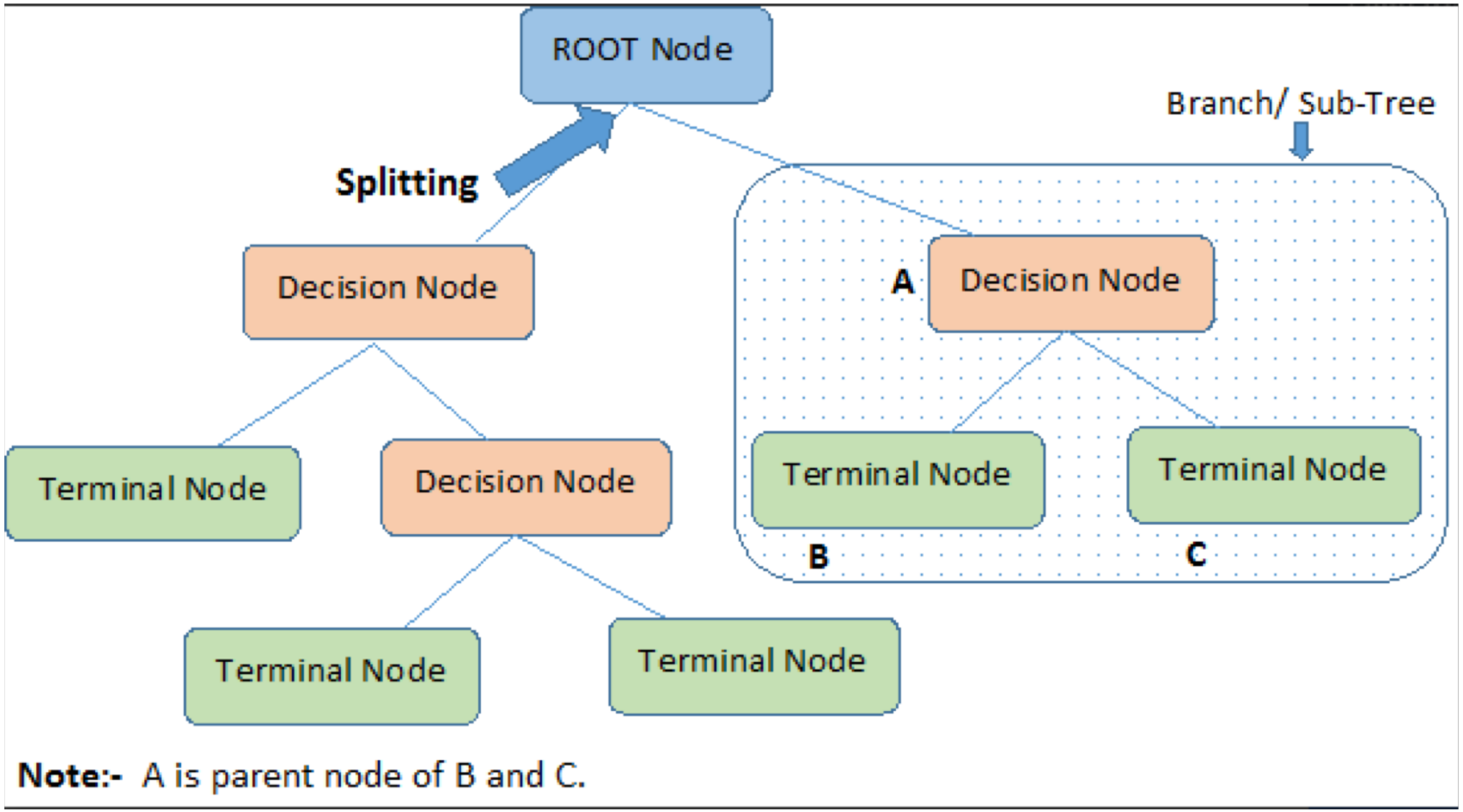
Decision Tree - Types

- **Categorical Variable Decision Tree**
  - Decision Tree which has categorical target variable then it called as categorical variable decision tree
  - E.g. Student will play cricket or not: “Yes” or “NO”
- **Continuous Variable Decision Tree**
  - Decision Tree has continuous target variable then it is called as Continuous Variable Decision Tree
  - E.g. Age

Decision Tree - Algorithms

- CART
  - Classification and Regression Trees
- ID3
  - Iterative Dichotomiser 3
- CHAID
  - Chi-square Automatic Interaction Detector

Decision Tree - Terminologies



Decision Tree - Terminologies

- **Root Node**
  - It represents entire population or sample and this further gets divided into two or more homogeneous sets
- **Splitting**
  - It is a process of dividing a node into two or more sub-nodes
- **Decision Node**
  - When a sub-node splits into further sub-nodes, then it is called decision node
- **Leaf/ Terminal Node**
  - Nodes do not split is called Leaf or Terminal node

Decision Tree - Terminologies

- **Pruning**
  - When we remove sub-nodes of a decision node, this process is called pruning
  - It is opposite process of splitting
- **Branch / Sub-Tree**
  - A sub section of entire tree is called branch or sub-tree
- **Parent and Child Node**
  - A node, which is divided into sub-nodes is called parent node of sub-nodes where as sub-nodes are the child of parent node

Decision Tree - Terminologies

- Gini Index
  - if we select two items from a population at random then they must be of same class and probability for this is 1 if population is pure
  - It works with categorical target variable “Success” or “Failure”
  - It performs only Binary splits
  - Higher the value of Gini higher the homogeneity
  - CART (Classification and Regression Tree) uses Gini method to create binary splits

Decision Tree - Terminologies

- **Chi-Square**
  - It is an algorithm to find out the statistical significance between the differences between sub-nodes and parent node
  - It works with categorical target variable “Success” or “Failure”
  - Higher the value of Chi-Square higher the statistical significance of differences between sub-node and Parent node
  - Chi-square = $\sqrt{\frac{(actual - expected)^2}{Expected}}$
  - It generates tree called CHAID (Chi-square Automatic Interaction Detector)

Decision Tree - Terminologies

- **Entropy**
  - Metric to measure the impurity of the data

$$entropy(s) = -P(yes) * \log_2 P(yes) \ - P(no) * \log_2 P(no)$$

Where

s is total sample space

Decision Tree - Terminologies

- **Information Gain**
  - Measure of the reduction in entropy
  - Decides which attribute should be selected as decision node

- Information Gain = Entropy(S) – [(Weighted Avg) * Entropy(feature)]

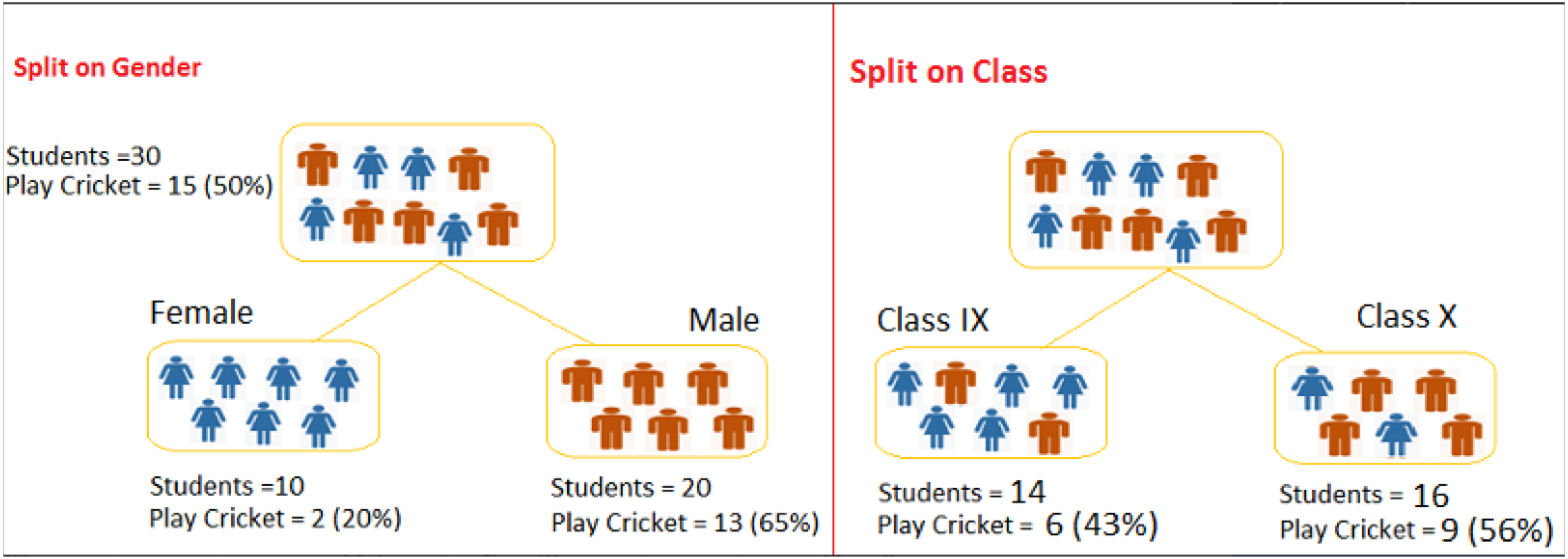
Gini Index

Decision Tree – Gini Index

- (use the previous example ☺) we want to segregate the students based on target variable (playing cricket or not)
- we can split the population using two input variables Gender and Class
- we want to identify which split is producing more homogeneous sub-nodes using Gini index

- Calculate Gini for sub-nodes, using formula
  - sum of square of probability for success and failure (p^2+q^2)
  - Calculate Gini for split using weighted Gini score of each node of that split

Decision Tree – Gini Index



Decision Tree – Gini Index

- **Split on Gender**
  - Calculate, Gini for sub-node Female = (0.2)*(0.2)+(0.8)*(0.8)=0.68
  - Gini for sub-node Male = (0.65)*(0.65)+(0.35)*(0.35)=0.55
  - Calculate weighted Gini for Split Gender = (10/30)*0.68+(20/30)*0.55 = **0.59**

- **Split on Class**
  - Gini for sub-node Class IX = (0.43)*(0.43)+(0.57)*(0.57)=0.51
  - Gini for sub-node Class X = (0.56)*(0.56)+(0.44)*(0.44)=0.51
  - Calculate weighted Gini for Split Class = (14/30)*0.51+(16/30)*0.51 = **0.51**

Chi-Square

Chi-Square

- Split of Gender

Node	Play Cricket	Not Play Cricket	Total	Expected Play Cricket	Expected Not Play Cricket	Deviation Play Cricket	Deviation Not Play Cricket	Chi-Square	
								Play Cricket	Not Play Cricket
Female	2	8	10	5	5	-3	3	1.34	1.34
Male	13	7	20	10	10	3	-3	0.95	0.95
							Total Chi-Square	4.58	

Chi-Square

- Split of Class

Node	Play Cricket	Not Play Cricket	Total	Expected Play Cricket	Expected Not Play Cricket	Deviation Play Cricket	Deviation Not Play Cricket	Chi-Square	
								Play Cricket	Not Play Cricket
IX	6	8	14	7	7	-1	1	0.38	0.38
X	9	7	16	8	8	1	-1	0.35	0.35
							Total Chi-Square	1.46	

Information Gain

Information Gain

- We have four X values (outlook, temp, humidity and windy)
- use the attribute with the highest ***information gain*** *to build the tree*

outlook	temp.	humidity	windy	play
sunny	hot	high	false	no
sunny	hot	high	true	no
overcast	hot	high	false	yes
rainy	mild	high	false	yes
rainy	cool	normal	false	yes
rainy	cool	normal	true	no
overcast	cool	normal	true	yes
sunny	mild	high	false	no
sunny	cool	normal	false	yes
rainy	mild	normal	false	yes
sunny	mild	normal	true	yes
overcast	mild	high	true	yes
overcast	hot	normal	false	yes
rainy	mild	high	true	no

Information Gain

- Out of 14 instances we have 9 yes and 5 no
- Calculate Entropy of sample [E(S)]

$$E(S) = - P(yes) \log P(yes) – P(no) \log P(no)$$
$$= - (9/14) * \log (9/14) – (5/14) * \log(5/14)$$
$$= 0.41 + 0.53$$
$$= 0.94$$

Information Gain

E(outlook = Sunny)

= -2/5 log (2/5) – 3/5 log (3/5) = 0.971

E(outlook = Overcast)

= -1 log (1) – 0 log (0) = 0

E(outlook = Rainy)

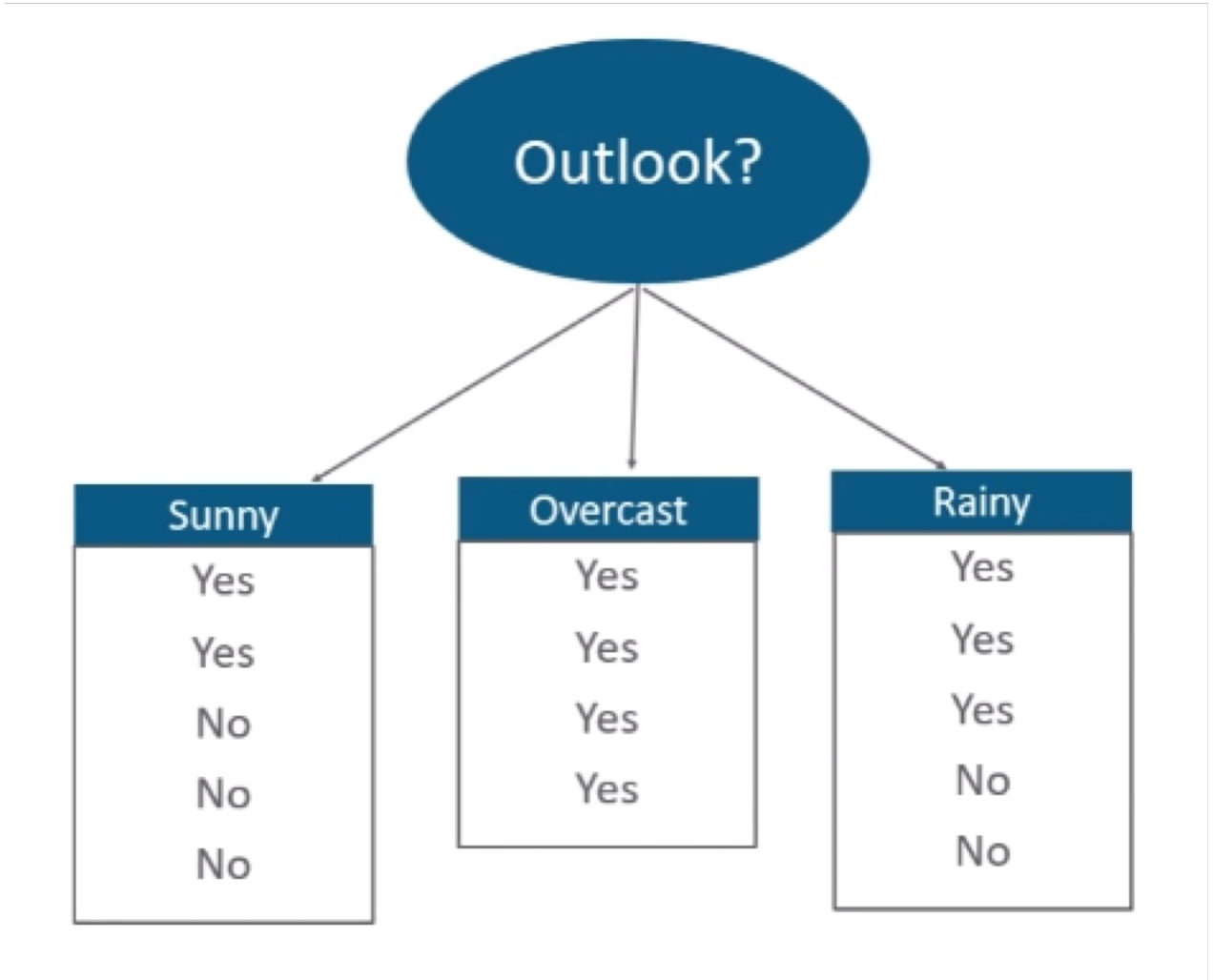
= – 3/5 log (3/5) -2/5 log (2/5) = 0.971

Information from Outlook [I(O)]

= 5/14 * 0.971 + 4/14 * 0 + 5/14 * 0.971 = 0.693

Information Gain from Outlook

= E(S) – I(0utlook) = 0.94 – 0.693 = 0.247



Information Gain

E(windy = True)

= -1/2 log (1/2) – 1/2 log (1/2) = 1

E(windy = False)

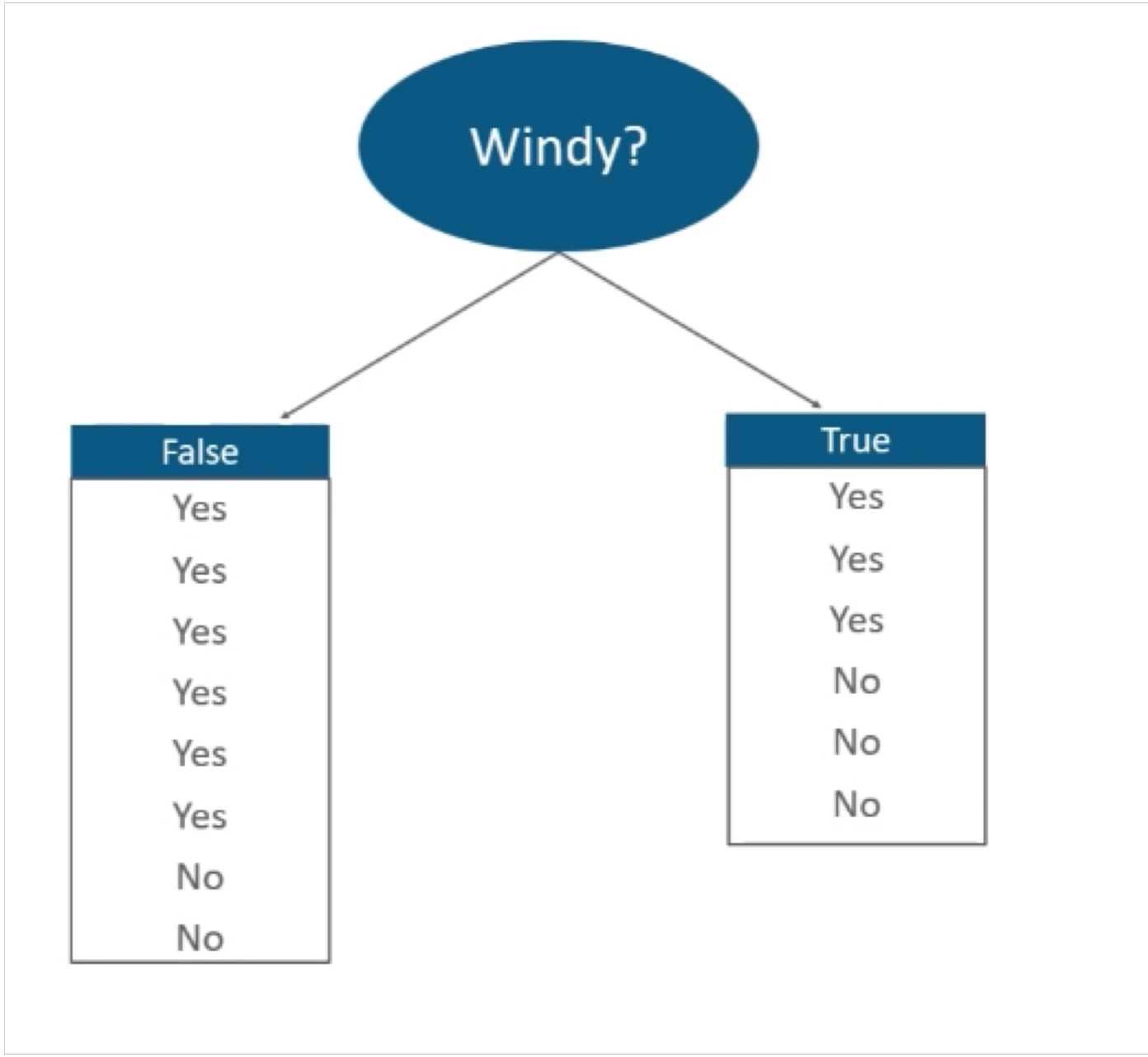
= – 6/8 log (6/8) -2/8 log (2/8) = 0.811

Information from Windy [I(Windy)]

= 8/14. * 0.811 + 6/14 * 1 = 0.892

Information Gain from Windy

= E(S) – I(0utlook) = 0.94 – 0.892 = 0.048



Information Gain

Outlook:

Info	0.693
Gain: 0.940-0.693	0.247

Temperature:

Info	0.911
Gain: 0.940-0.911	0.029

Humidity:

Info	0.788
Gain: 0.940-0.788	0.152

Windy:

Info	0.892
Gain: 0.940-0.982	0.048

Decision Tree - Advantages

- **Easy to Understand**
  - Decision tree output is very easy to understand even for people from non-analytical background
  - It does not require any statistical knowledge to read and interpret them
  - Its graphical representation is very intuitive and users can easily relate their hypothesis
- **Less data cleaning required**
  - It requires less data cleaning compared to some other modelling techniques
  - It is not influenced by outliers and missing values to a fair degree

Decision Tree - Advantages

- **Useful in Data exploration**
  - Decision tree is one of the fastest way to identify most significant variables and relation between two or more variables
- **Data type is not a constraint**
  - It can handle both numerical and categorical variables

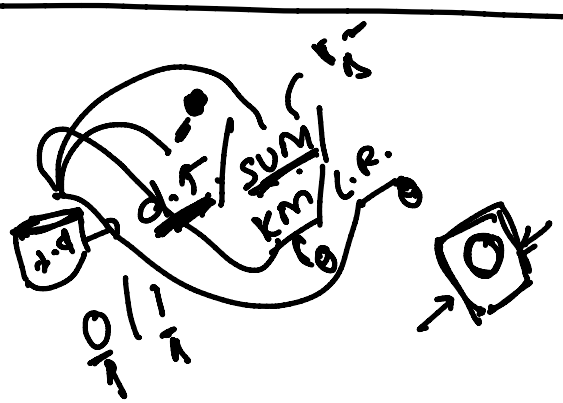
Decision Tree - Disadvantages

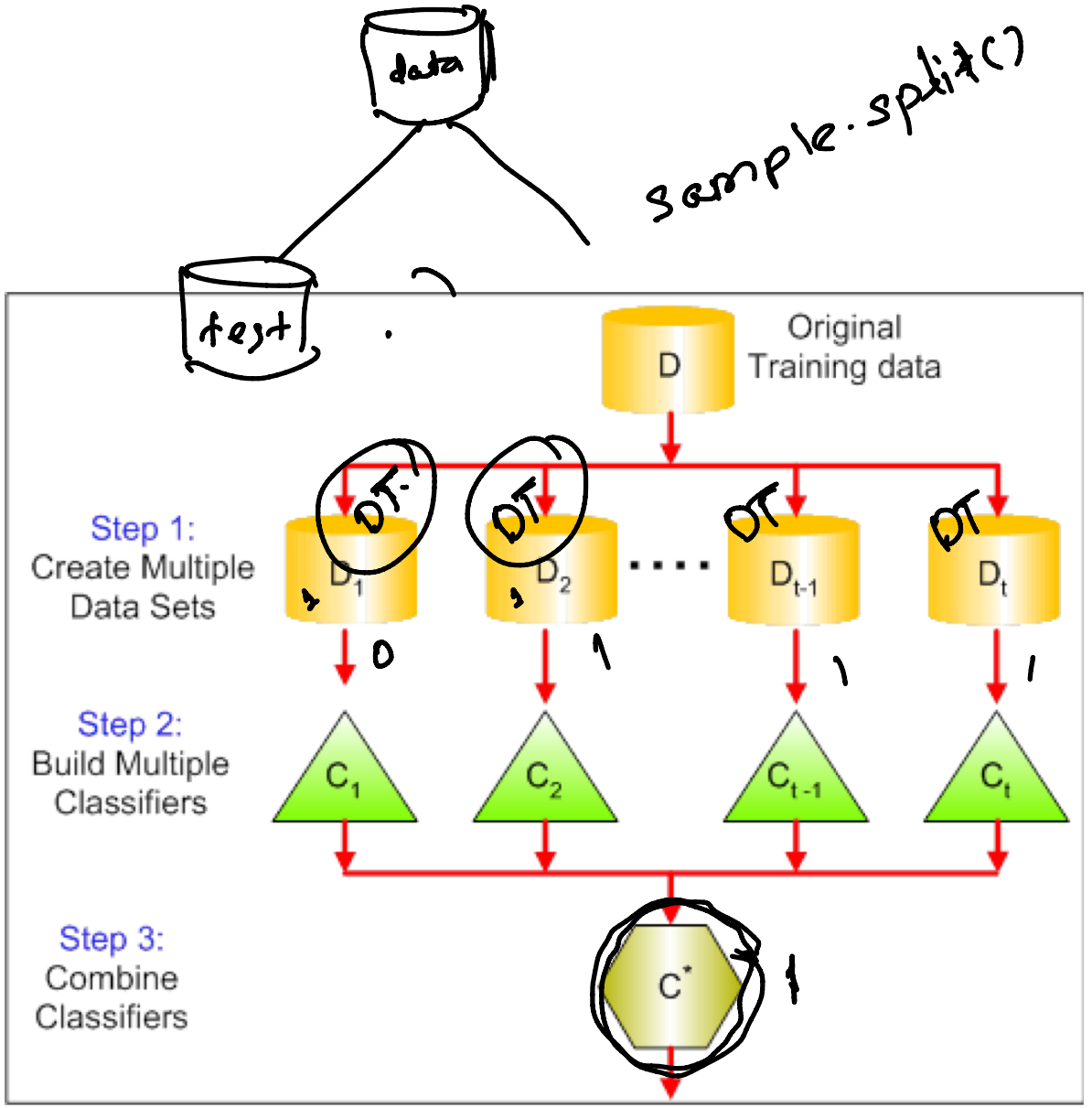
- **Over fitting**
  - This problem gets solved by setting constraints on model parameters and pruning
- **Not fit for continuous variables**
  - While working with continuous numerical variables, decision tree looses information when it categorizes variables in different categories

Random Forest

Bagging

- Is a technique used to reduce the variance of predictions by combining the result of multiple classifiers modeled on different sub-samples of the same data set





Bagging - Steps

- Create multiple data sets
  - Sampling is done *with replacement* on the original data and new datasets are formed
  - The new data sets can have a fraction of the columns as well as rows, which are generally hyper-parameters in a bagging model
- Build multiple classifiers
  - Classifiers are built on each data set
  - Generally the same classifier is modeled on each data set and predictions are made

Bagging - Steps

- Combine Classifiers
  - The predictions of all the classifiers are combined using a mean, median or mode value depending on the problem at hand
  - The combined values are generally more robust than a single model

accuracy of bagging technique $\geq$ accuracy of a single model

Random Forest

- versatile machine learning method capable of performing both regression and classification
- we grow multiple trees as opposed to a single tree in CART model
- To classify a new object based on attributes, each tree gives a classification (voting)
- The forest chooses the classification having the most votes

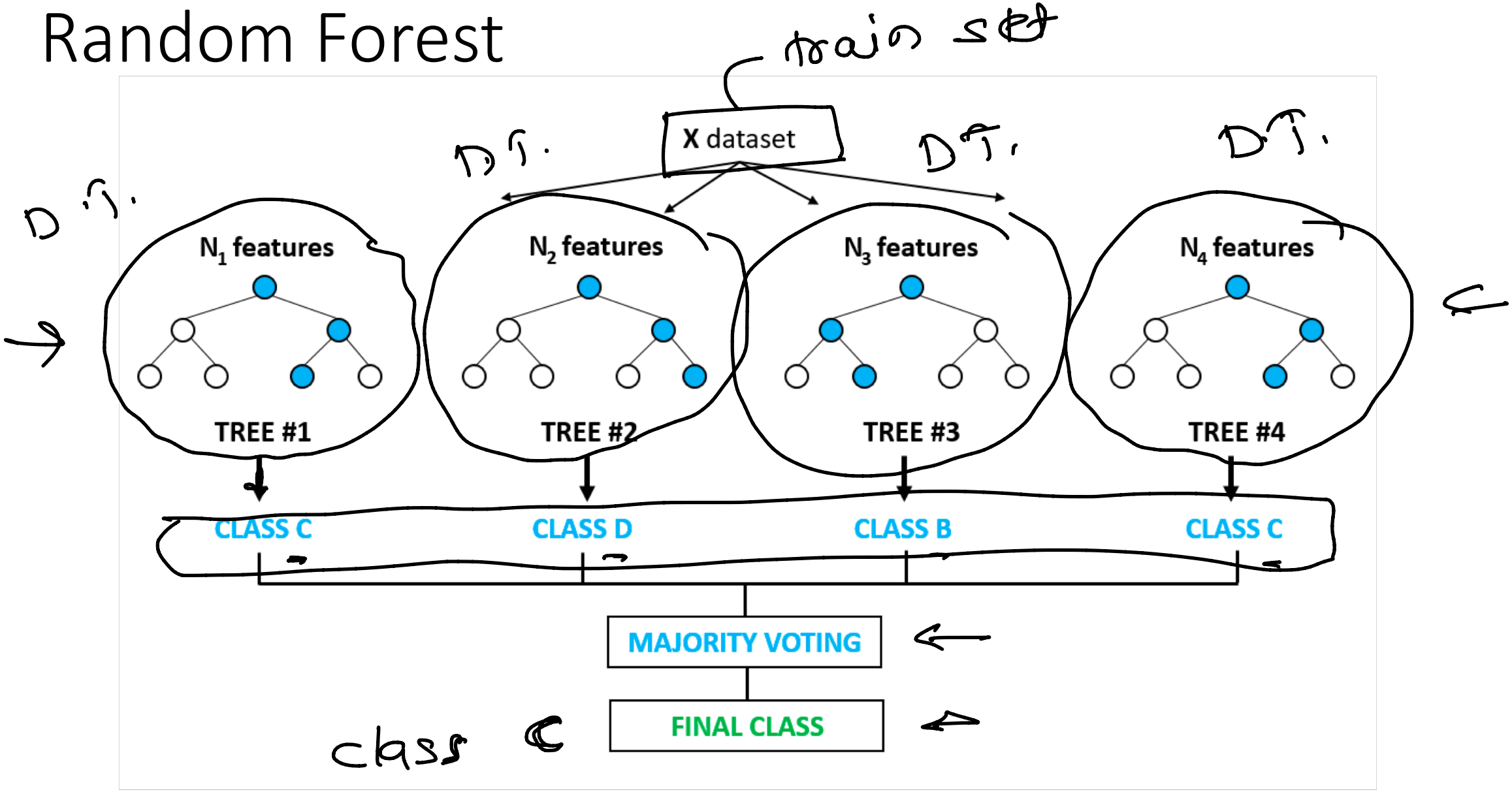
↓

mean / mode / median

Random Forest - Steps

- Assume number of cases in the training set is N. Then, sample of these N cases is taken at random but *with replacement*. (This sample will be the training set for growing the tree)
- If there are M input variables, a number m<M is specified such that at each node, m variables are selected at random out of the M
- Each tree is grown to the largest extent possible and there is no pruning
- Predict new data by aggregating the predictions of the ntree trees

Random Forest



Random Forest

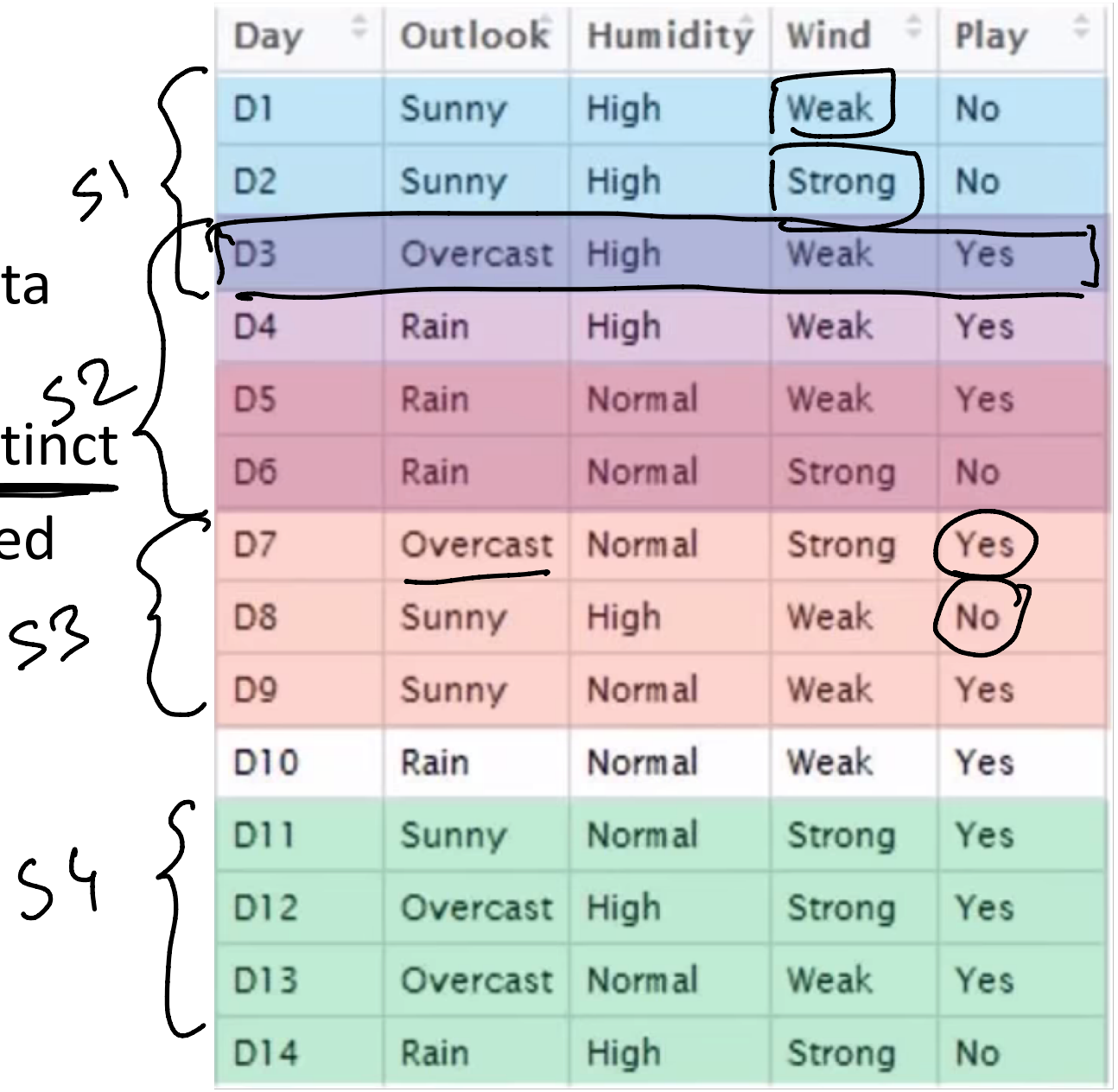
- We have taken dataset consisting of
  - Weather information of last 14 days
  - Whether match was played or not

- Using random forest we need to predict whether the game will happen if the weather condition is
  - Outlook = Overcast
  - Humidity = High
  - Wind = Weak
  - Play = ?

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

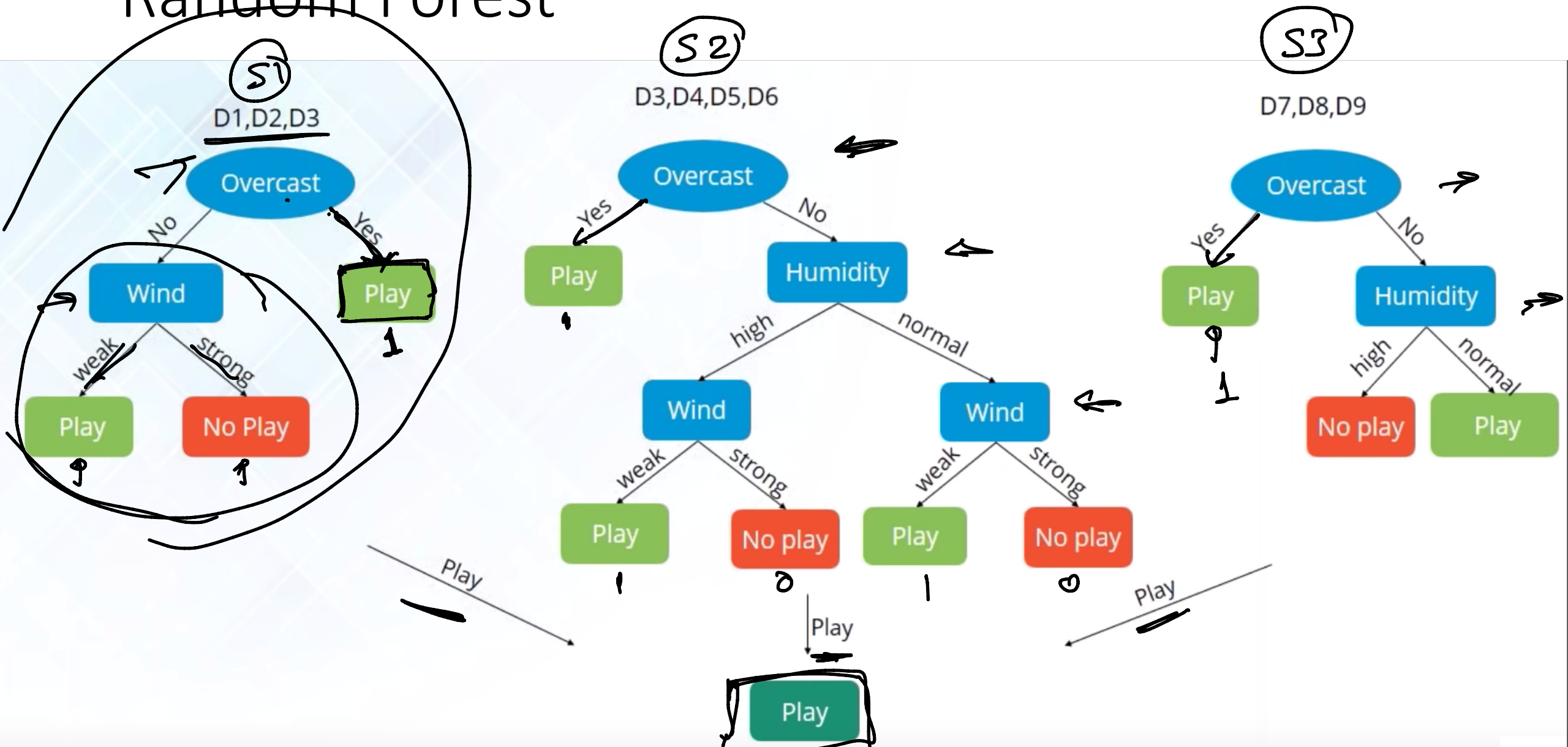
Random Forest

- The first step is to divide the data into smaller subsets
- Every subset need not to be distinct
- Some subsets may be overlapped



Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Random Forest



Random Forest - Advantages

- One of the most accurate learning algorithms
- Works well for both classification and regression
- Runs efficiently on large datasets
- Requires almost no input preparation
- Performs implicit feature selection
- Can be easily grown in parallel

Naïve Bayes Classifier

Naïve Bayes

- Is a simple algorithm based on Bays theorem
- Given a hypothesis H and evidence E, Bayes theorem states that the relationship between the probability of the hypothesis before getting the evidence P(H) and the probability of the hypothesis after getting the evidence P(H|E) is

$$\mathrm{P(H|E)} = \frac{P(E|H)}{P(E)} . P(H)$$

Naïve Bayes

- Revision ☺

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(B|A) = \frac{P(B \cap A)}{P(A)}$$

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

Naïve Bayes - examples

- NEWS Categorization
- SPAM Filtering
- Medical Diagnosis
- Weather Predictions

Naïve Bayes - Types

- Gaussian
- Multinomial
- Bernoulli

Naïve Bayes

- Consider the dataset and predict whether the game will happen if the weather condition is
  - Outlook = Rainy
  - Humidity = High
  - Wind = Weak
  - Play = ?

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Naïve Bayes

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
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D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Frequency Table		Play		
		Yes	No	
Outlook	Sunny	3	2	5
	Overcast	4	0	4
	Rainy	3	2	5

Frequency Table		Play		
		Yes	No	
Humidity	High	3	4	7
	Normal	6	1	7

Frequency Table		Play		
		Yes	No	
Wind	Strong	6	2	8
	Weak	3	3	6

Naïve Bayes

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} = \frac{P(\text{sunny}|\text{yes}) \cdot P(\text{yes})}{P(\text{sunny})}$$

$$P(\text{yes}|\text{sunny}) =$$

Likelihood Table		Play		
		Yes	No	
Outlook	Sunny	3/10	2/4	5/14
	Overcast	4/10	0/4	4/14
	Rainy	3/10	2/4	5/14
		10/14	4/14	

$P(x|c) = P(\text{Sunny}|\text{Yes}) = 3/10 = 0.3$

$P(x) = P(\text{Sunny}) = 5/14 = 0.36$

$P(c) = P(\text{Yes}) = 10/14 = 0.71$

Likelihood of 'Yes' given Sunny is

$P(c|x) = P(\text{Yes}|\text{Sunny}) = P(\text{Sunny}|\text{Yes}) * P(\text{Yes}) / P(\text{Sunny})$ = (0.3 x 0.71) /0.36 = 0.591

Similarly Likelihood of 'No' given Sunny is

$P(c|x) = P(\text{No}|\text{Sunny}) = P(\text{Sunny}|\text{No}) * P(\text{No}) / P(\text{Sunny})$ = (0.4 x 0.36) /0.36 = 0.40

Naïve Bayes

Likelihood table for Humidity

Likelihood Table		Play		
		Yes	No	
Humidity	High	3/9	4/5	7/14
	Normal	6/9	1/5	7/14
		9/14	5/14	

$P(Yes|High) = 0.33 \times 0.6 / 0.5 = 0.42$

$P(No|High) = 0.8 \times 0.36 / 0.5 = 0.58$

Likelihood table for Wind

Likelihood Table		Play		
		Yes	No	
Wind	Weak	6/9	2/5	8/14
	Strong	3/9	3/5	6/14
		9/14	5/14	

$P(Yes|Weak) = 0.67 \times 0.64 / 0.57 = 0.75$

$P(No|Weak) = 0.4 \times 0.36 / 0.57 = 0.25$

Naïve Bayes

Suppose we have a day with the following values

Outlook	=	Rain
Humidity	=	High
Wind	=	Weak
Play	=	?

Likelihood of 'Yes' on that Day = P(Outlook = Rain|Yes)*P(Humidity= High|Yes)* P(Wind= Weak|Yes)*P(Yes)

= 2/9 * 3/9 * 6/9 * 9/14 = 0.0199

Likelihood of 'No' on that Day = P(Outlook = Rain|No)*P(Humidity= High|No)* P(Wind= Weak|No)*P(No)

= 2/5 * 4/5 * 2/5 * 5/14 = 0.0166

Naïve Bayes

$$P(\text{Yes}) = 0.0199 / (0.0199 + 0.0166) = 0.55$$

$$P(\text{No}) = 0.0166 / (0.0199 + 0.0166) = 0.45$$