DECISION TREE

DECISION TREE

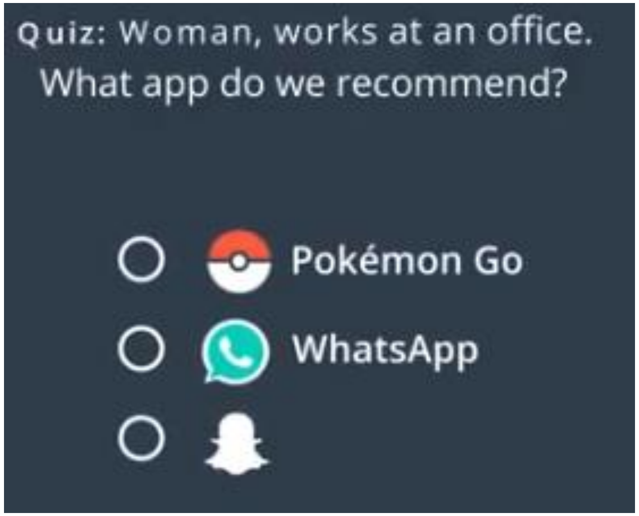
- **C**l**A**ssification and **R**egression **T**ree (CART)

You are building a recommendation system and you are suppose to provide recommendations of suggesting App based on Gender and occupation

Which one you would suggest for the following people ?

Recommendation System - 1

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	



Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Quiz: Woman, works at an office.
What app do we recommend?

- ○ Pokémon Go
- ● WhatsApp
- ○ Snapchat

Recommendation System - 2

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Quiz: Girl, goes to high school. What app do we recommend?

- Pokémon Go
- WhatsApp
- Snapchat

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Quiz: Girl, goes to high school. What app do we recommend?

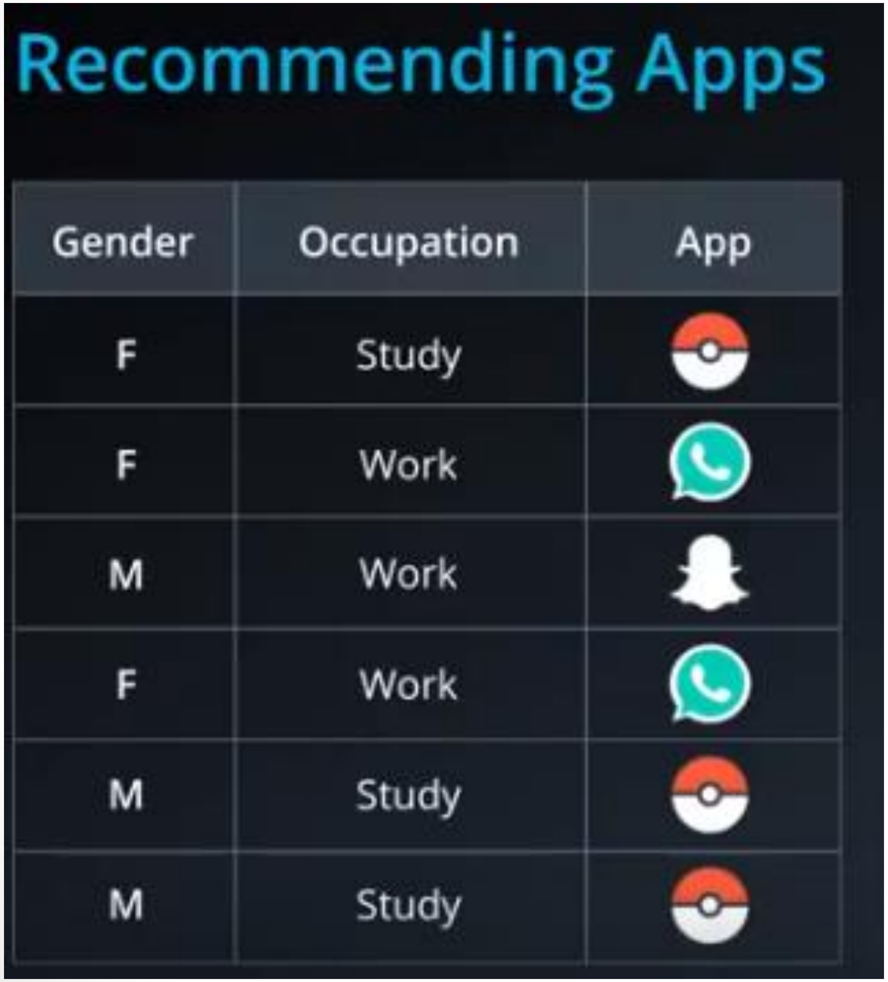
- Pokémon Go
- WhatsApp
- Snapchat

That was pretty Easy right …

That was pretty Easy right …

But what if we had to choose between Gender and Occupation to suggest an App

Way Machine approaches



Recommending Apps

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Quiz: Between **Gender** and **Occupation**, which one seems more decisive for predicting what app will the users download?

- ○ **Gender**
- ○ **Occupation**

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

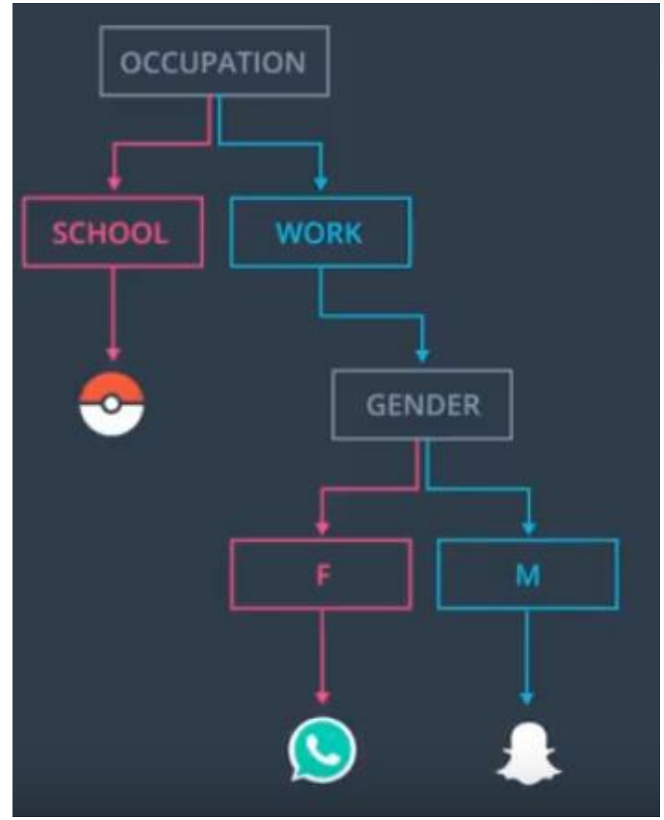
Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	

Quiz: Between **Gender** and **Occupation**, which one seems more decisive for predicting what app will the users download?

- ○ **Gender**
- ● **Occupation**

Gender	Occupation	App
F	Study	
F	Work	
M	Work	
F	Work	
M	Study	
M	Study	



Decision Tree Algorithm also works in the same way as we think …

Terminologies

Terminologies

Root Node

Decision node

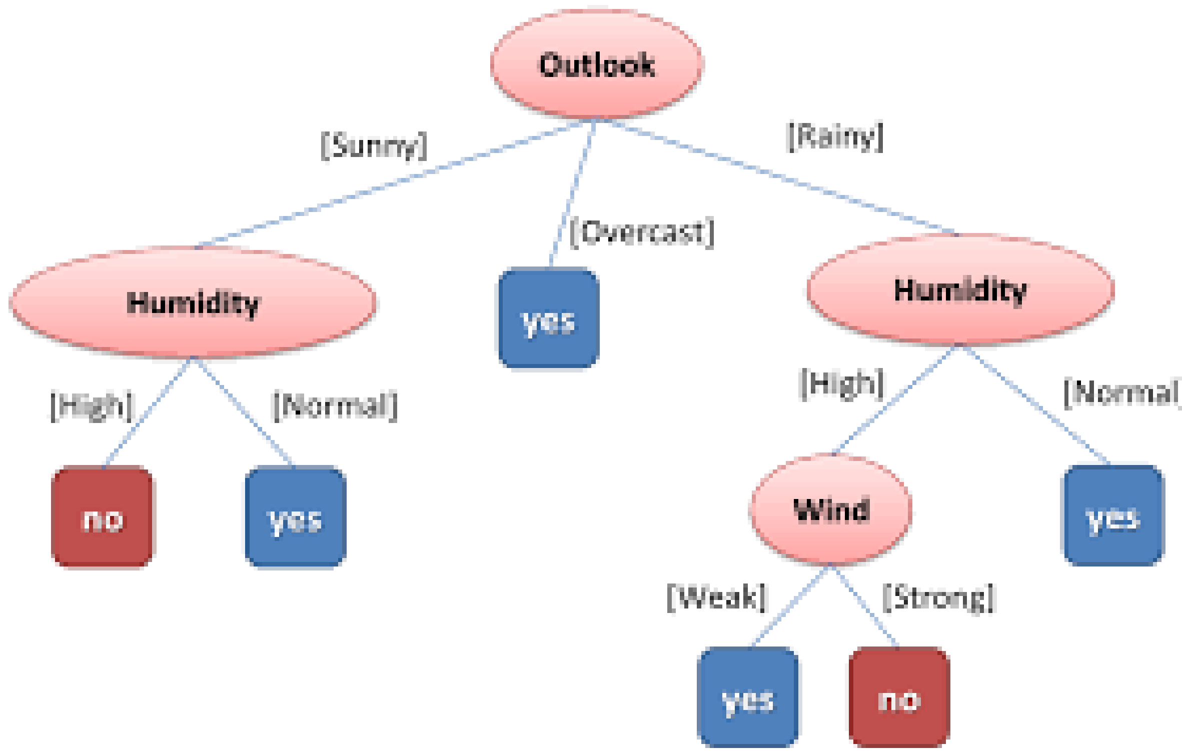
Leaves

Supervised learning algorithm

Root Node -

Decision node -

Leaves -



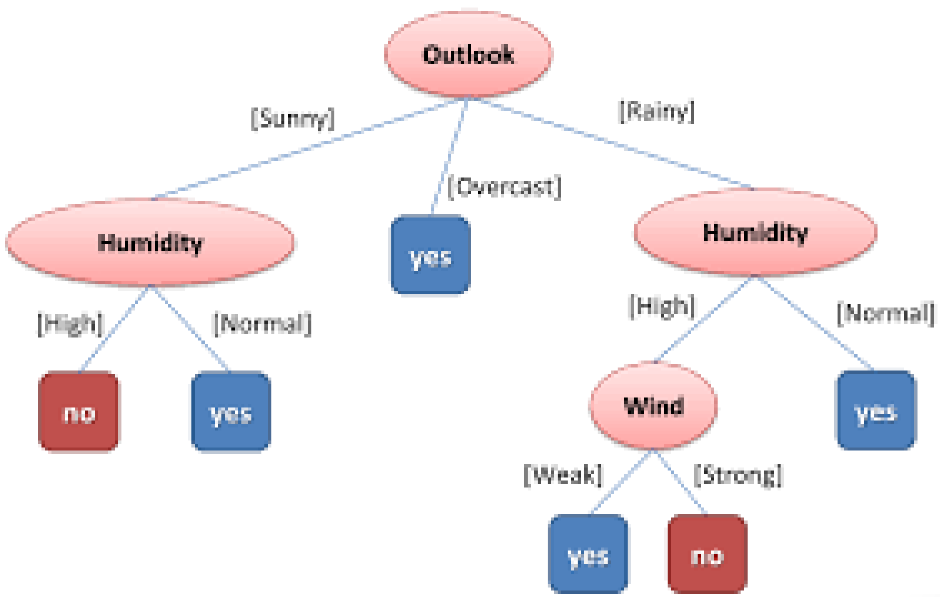
Supervised learning algorithm

Root Node - Outlook

Decision node - Humidity/Wind

Leaves - Yes/No

Structure of a Tree



How do we find the Root node ?

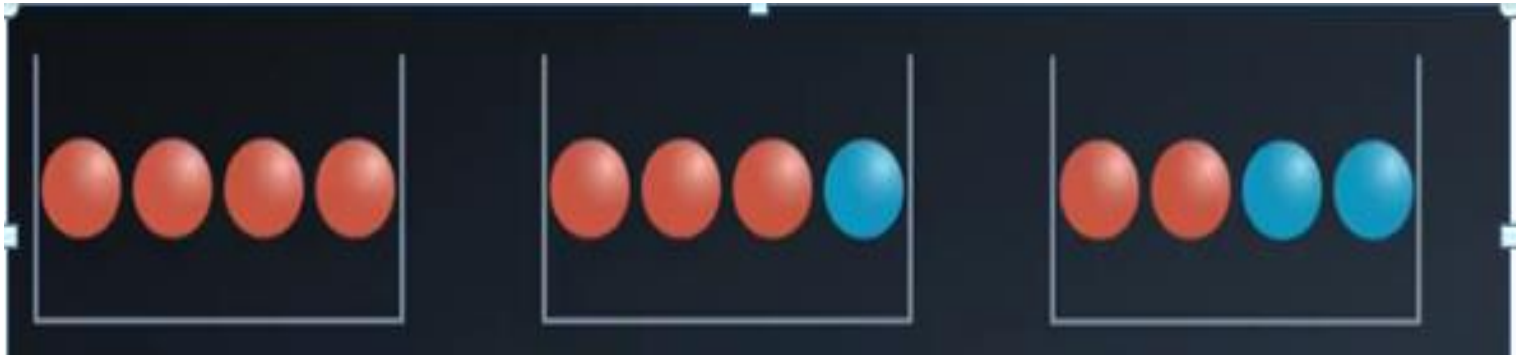
HOW TO FIND ROOT (2 WAYS)

- **Information gain(Entropy)**
- **Gini index**

Understand Entropy you will get to understand Information Gain

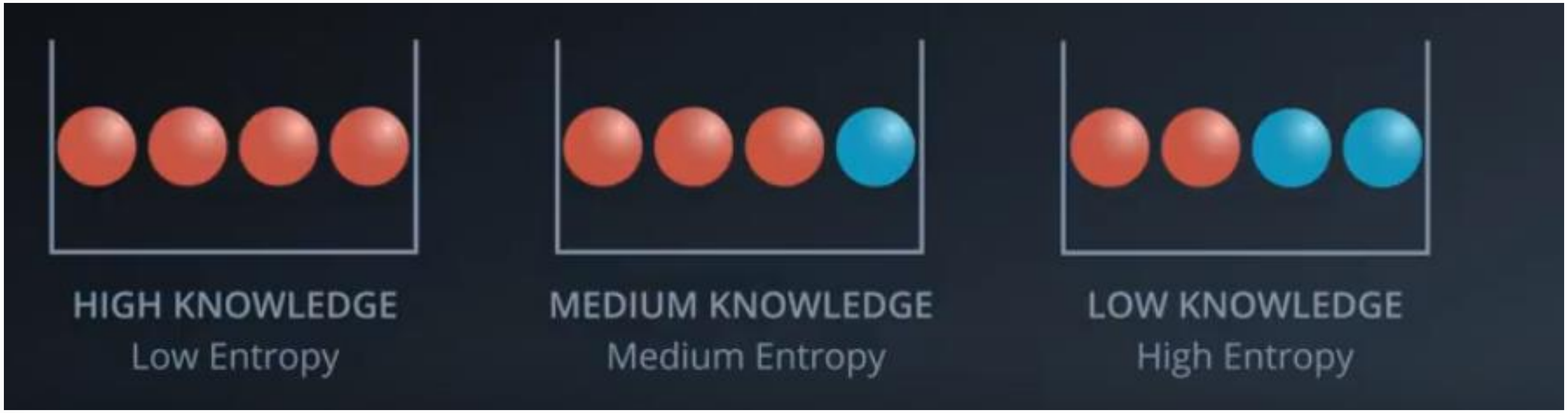
Entropy or Randomness

- The measure of uncertainty



Entropy - The measure of uncertainty

Entropy - The measure of uncertainty



$$H(X) = \mathbb{E}_X[I(x)] = -\sum_{x \in \mathbb{X}} p(x) \log p(x).$$

Information Gain | Entropy

Information Gain & Entropy

Information Gain -> Information theory -> Entropy

Entropy = **Randomness** or **Uncertainty** of a random variable.

Information Gain & Entropy

Information Gain -> Information theory -> Entropy

Entropy = **Randomness** or **Uncertainty** of a random variable.

There are **2 steps for calculating information gain** for each attribute:

- Calculate entropy of Target.
- Calculate the Entropy for every attribute.

Information gain = Entropy of target - Entropy of attribute

Case Study

Case Study – Golf Play Dataset

Predictors | Target

Outlook	Temp.	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Entropy of Target

Play Golf
No
No
Yes
Yes
Yes
No
Yes
No
Yes
Yes
Yes
Yes
Yes
No

Sort

Play Golf
No
No
No
No
No
Yes
Yes
Yes
Yes
Yes
Yes
Yes
Yes
Yes

5 / 14 = 0.36

9 / 14 = 0.64

Entropy(PlayGolf) = Entropy (5,9)

= Entropy (0.36, 0.64)

$= -(0.36 \log_2 0.36) - (0.64 \log_2 0.64)$

= 0.94

Frequency Table

Frequency Table – 4 Attributes

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3

		Play Golf	
		Yes	No
Temp.	Hot	2	2
	Mild	4	2
	Cool	3	1

		Play Golf	
		Yes	No
Humidity	High	3	4
	Normal	6	1

		Play Golf	
		Yes	No
Windy	False	6	2
	True	3	3

Entropy - Outlook

		Play Golf		
		Yes	No	
Outlook	Sunny	**3**	**2**	**5**
	Overcast	**4**	**0**	**4**
	Rainy	**2**	**3**	**5**
				14

Entropy - Outlook

		Play Golf		
		Yes	No	
Outlook	Sunny	**3**	**2**	**5**
	Overcast	**4**	**0**	**4**
	Rainy	**2**	**3**	**5**
				14

E(PlayGolf, Outlook) = **P**(Sunny)***E**(3,2) + **P**(Overcast)***E**(4,0) + **P**(Rainy)***E**(2,3)

$$= (5/14)*0.971 + (4/14)*0.0 + (5/14)*0.971$$

$$= 0.693$$

Information Gain - Outlook

$$\mathbf{G}(\text{PlayGolf, Outlook}) = \mathbf{E}(\text{PlayGolf}) - \mathbf{E}(\text{PlayGolf, Outlook})$$

$$= 0.940 - 0.693 = 0.247$$

Information Gain - All Attributes

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

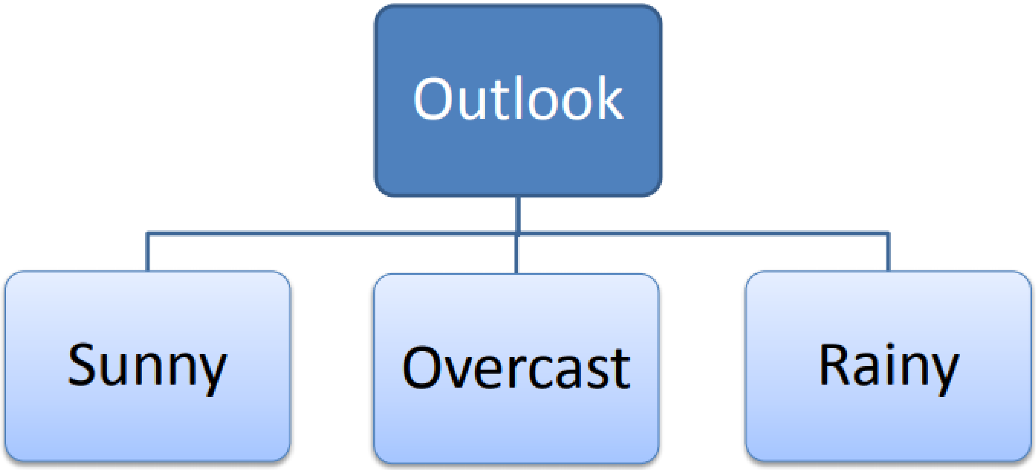
		Play Golf	
		Yes	No
Temp.	Hot	2	2
	Mild	4	2
	Cool	3	1
Gain = 0.029			

		Play Golf	
		Yes	No
Humidity	High	3	4
	Normal	6	1
Gain = 0.152			

		Play Golf	
		Yes	No
Windy	False	6	2
	True	3	3
Gain = 0.048			

Construction of Tree

Construction of Tree



Golf Play Dataset

Outlook	Temp.	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

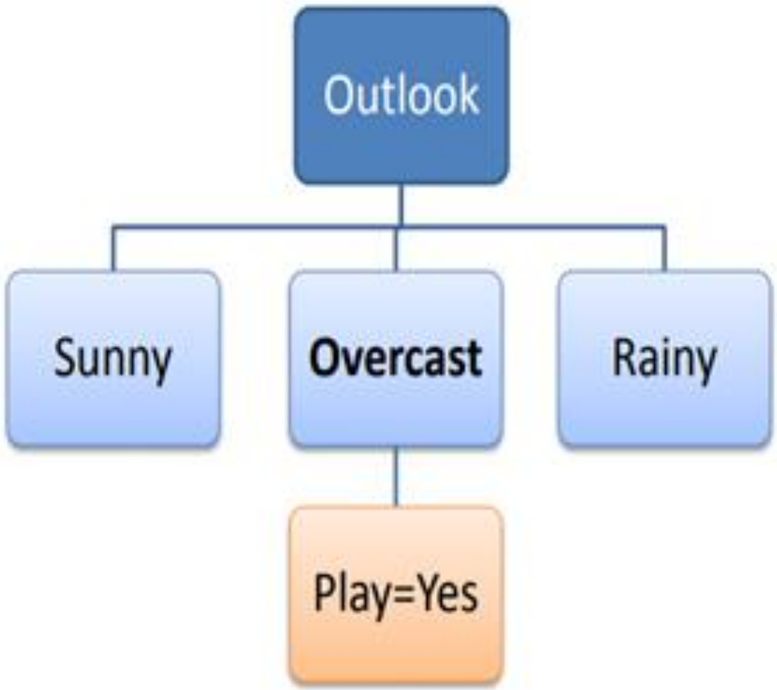
Let's iterate the process (excluding **Outlook**)

Outlook	Temp.	Humidity	Windy	Play Golf
Sunny	Mild	High	FALSE	Yes
Sunny	Cool	Normal	FALSE	Yes
Sunny	Cool	Normal	TRUE	No
Sunny	Mild	Normal	FALSE	Yes
Sunny	Mild	High	TRUE	No
Rainy	Hot	High	FALSE	No
Rainy	Hot	High	TRUE	No
Rainy	Mild	High	FALSE	No
Rainy	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	TRUE	Yes
Overcast	Hot	High	FALSE	Yes
Overcast	Cool	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes

Next **Overcast**

Overcast

Temp.	Humidity	Windy	Play Golf
Hot	High	FALSE	Yes
Cool	Normal	TRUE	Yes
Mild	High	TRUE	Yes
Hot	Normal	FALSE	Yes



Next **Sunny**

Sunny

Temp.	Humidity	Windy	Play Golf
Mild	High	FALSE	Yes
Cool	Normal	FALSE	Yes
Cool	Normal	TRUE	No
Mild	Normal	FALSE	Yes
Mild	High	TRUE	No

Outlook	Temp.	Humidity	Windy	Play Golf
Sunny	Mild	High	FALSE	Yes
Sunny	Cool	Normal	FALSE	Yes
Sunny	Cool	Normal	TRUE	No
Sunny	Mild	Normal	FALSE	Yes
Sunny	Mild	High	TRUE	No
Rainy	Hot	High	FALSE	No
Rainy	Hot	High	TRUE	No
Rainy	Mild	High	FALSE	No
Rainy	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	TRUE	Yes
Overcast	Hot	High	FALSE	Yes
Overcast	Cool	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes

Sunny

Temp.	Humidity	Windy	Play Golf
Mild	High	FALSE	Yes
Cool	Normal	FALSE	Yes
Cool	Normal	TRUE	No
Mild	Normal	FALSE	Yes
Mild	High	TRUE	No

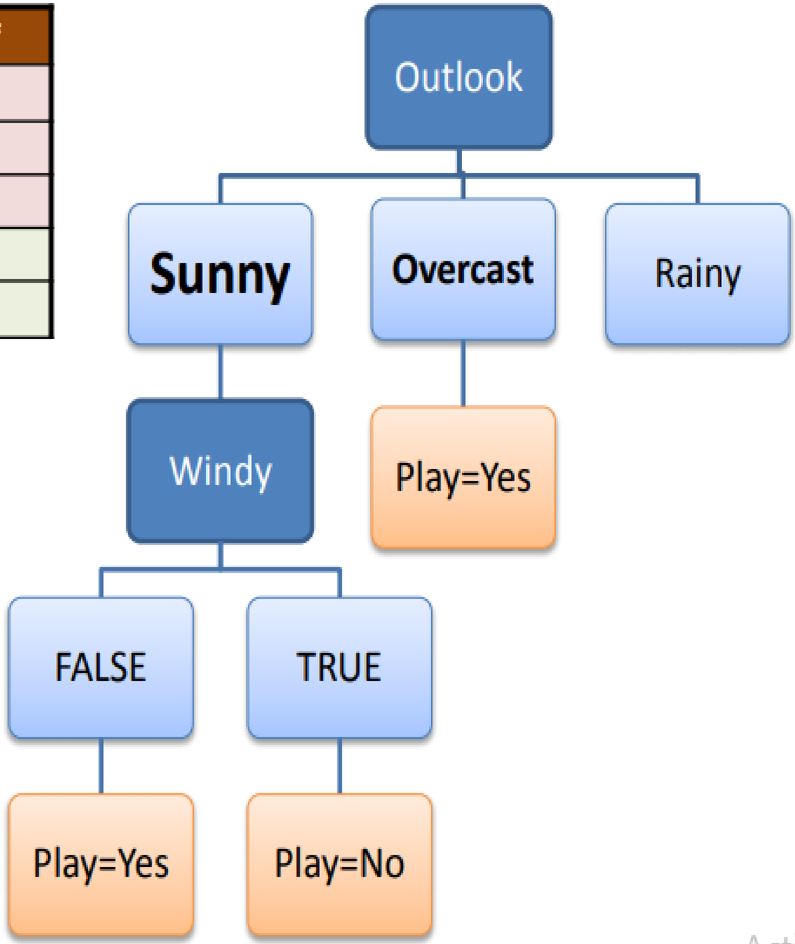
		Play Golf	
		Yes	No
Temp.	Mild	2	1
	Cool	1	1
Gain = 0.02			

		Play Golf	
		Yes	No
Humidity	High	1	1
	Normal	2	1
Gain = 0.02			

		Play Golf	
		Yes	No
Windy	False	3	0
	True	0	2
Gain = 0.97			

Construction of Tree

Temp.	Humidity	Windy	Play Golf
Mild	High	FALSE	Yes
Cool	Normal	FALSE	Yes
Mild	Normal	FALSE	Yes
Cool	Normal	TRUE	No
Mild	High	TRUE	No



Next **Rainy**

Rainy

Temp.	Humidity	Windy	Play Golf
Hot	High	FALSE	No
Hot	High	TRUE	No
Mild	High	FALSE	No
Cool	Normal	FALSE	Yes
Mild	Normal	TRUE	Yes

Rainy

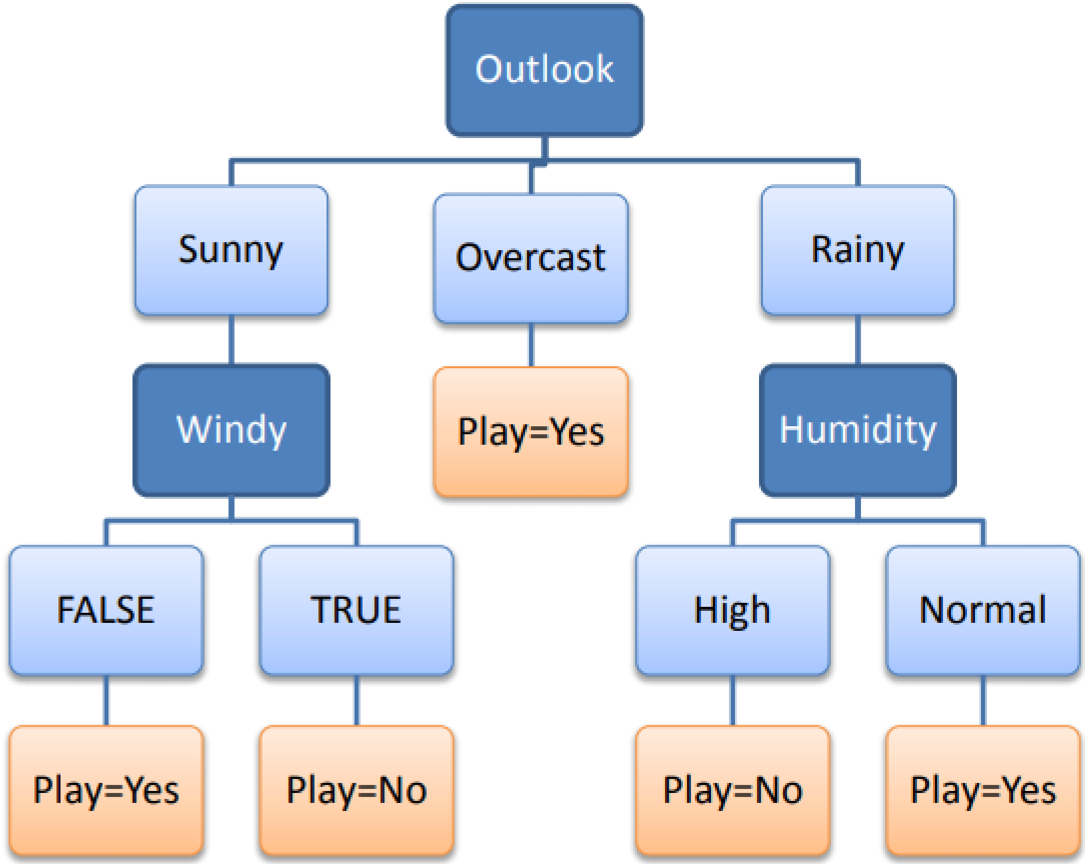
Temp.	Humidity	Windy	Play Golf
Hot	High	FALSE	No
Hot	High	TRUE	No
Mild	High	FALSE	No
Cool	Normal	FALSE	Yes
Mild	Normal	TRUE	Yes

		Play Golf	
		Yes	No
Temp.	Hot	0	2
	Mild	1	1
	Cool	1	0
Gain = 0.57			

		Play Golf	
		Yes	No
Humidity	High	0	3
	Normal	2	0
Gain = 0.97			

		Play Golf	
		Yes	No
Windy	False	1	2
	True	1	1
Gain = 0.02			

Final Tree Structure

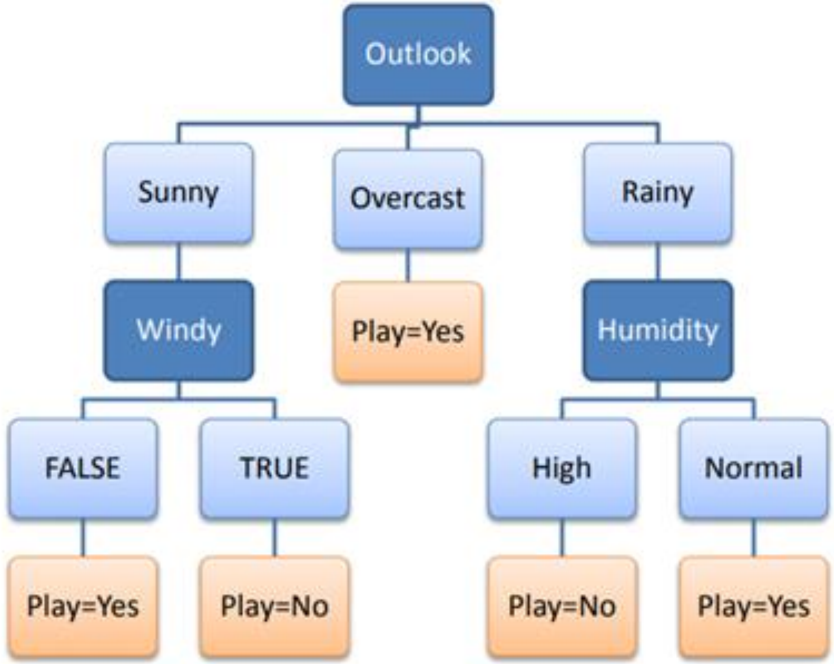


Predict the Play – D15 ?

Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Cool	Normal	FALSE	?

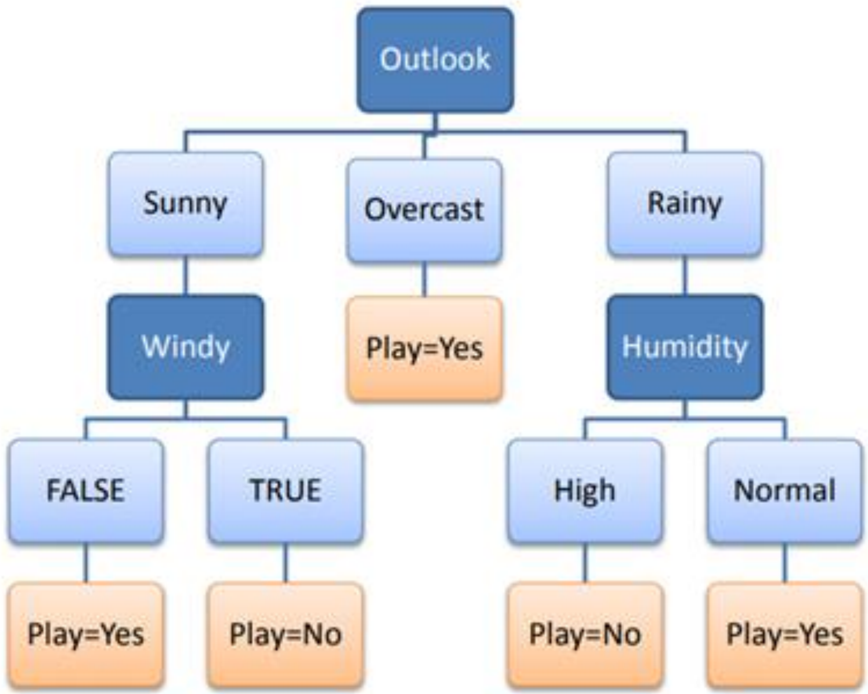
Predict the Play – D15 ?

Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Cool	Normal	FALSE	?



Predict the Play – D15 ?

Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Cool	Normal	FALSE	Yes



Decision Rules – Traditional approach

Decision Rules – Traditional approach

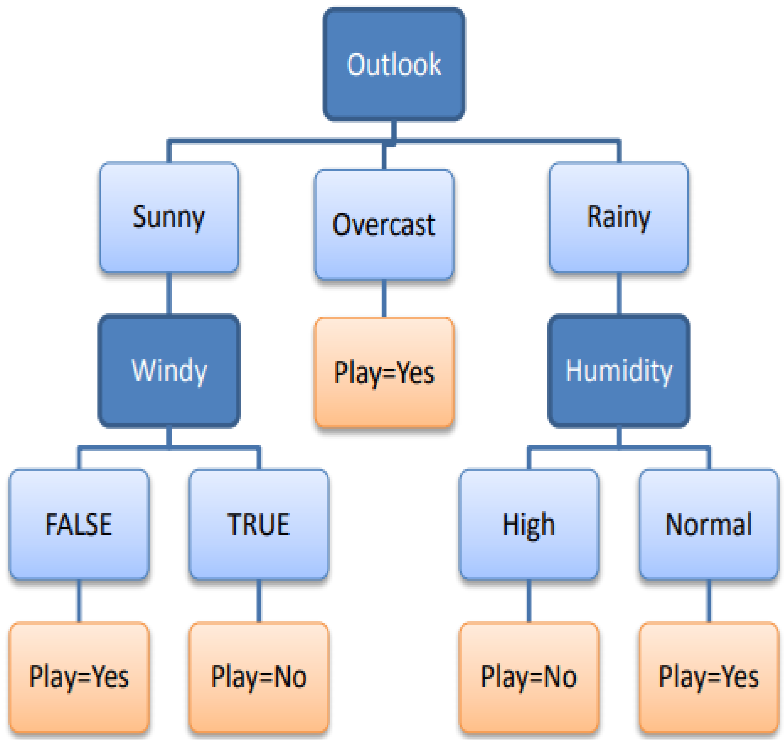
R_1: IF (Outlook=Sunny) AND (Windy=FALSE) THEN Play=Yes

R_2: IF (Outlook=Sunny) AND (Windy=TRUE) THEN Play=No

R_3: IF (Outlook=Overcast) THEN Play=Yes

R_4: IF (Outlook=Rainy) AND (Humidity=High) THEN Play=No

R_5: IF (Outlook=Rain) AND (Humidity=Normal) THEN Play=Yes



Gini Index

Finding Root using Gini Index

$$Gini\ Index = 1 - \sum_j p_j^2$$

1. The steps to build the tree using **Gini Index** approach is same as the Entropy.
2. Gini Index is the default method of building the Decision Tree

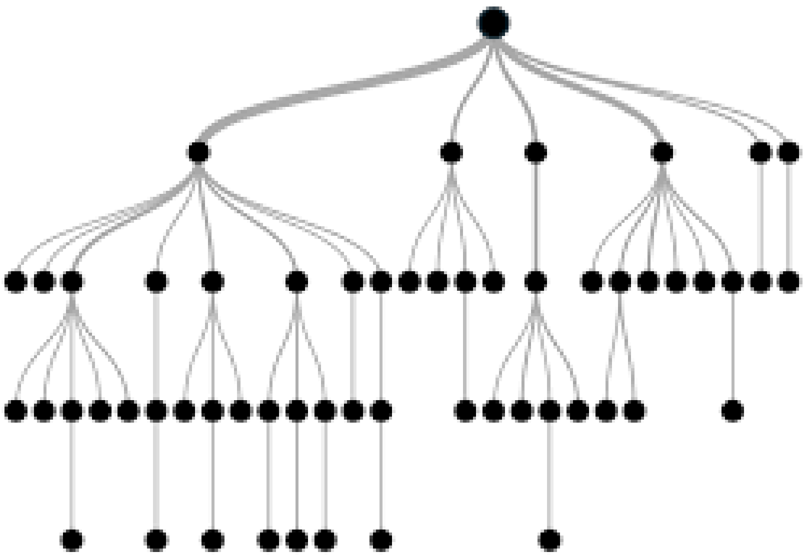
Problem with Trees

Problem with Trees

How will a tree structure look if there are N columns

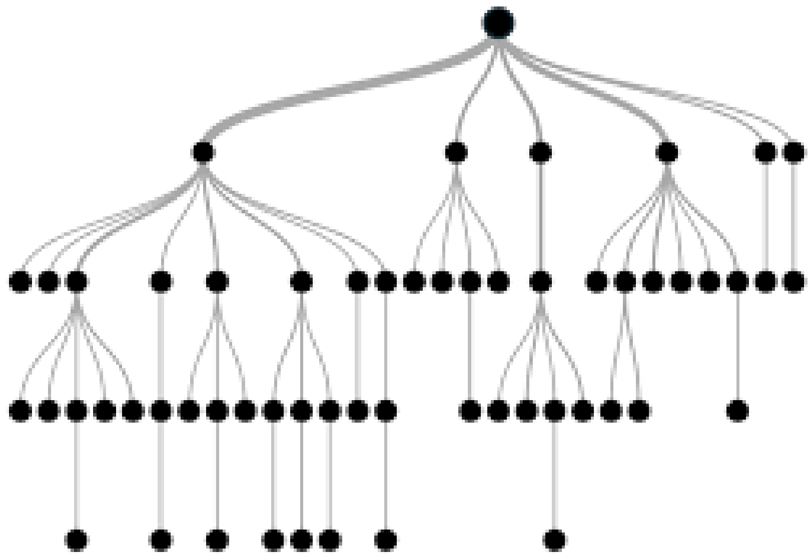
Problem with Trees

How will a tree structure look if there are N columns

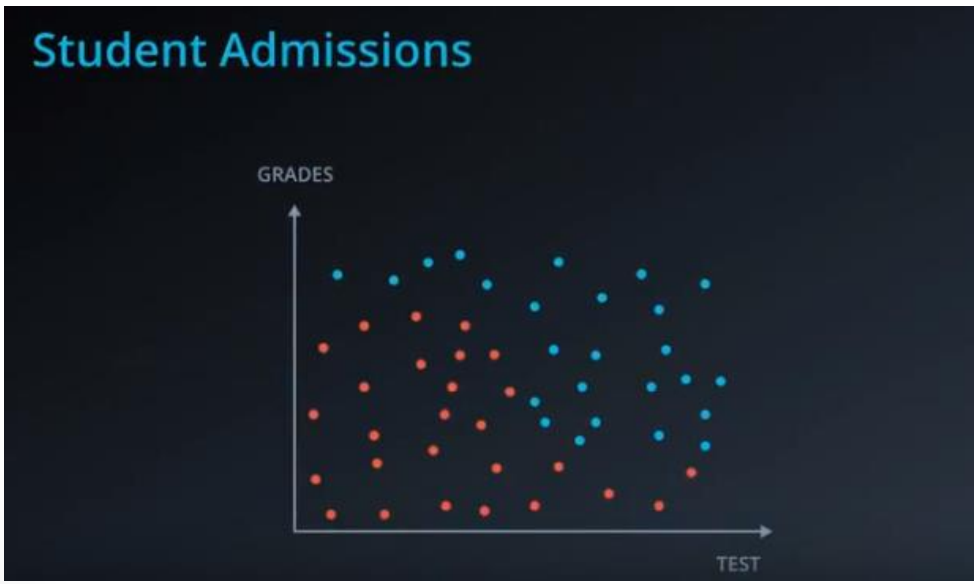


Overfitting

How will a tree structure look if there are 30 columns



Continuous Data



Quiz: Between grades and test, which one determines student acceptance better?

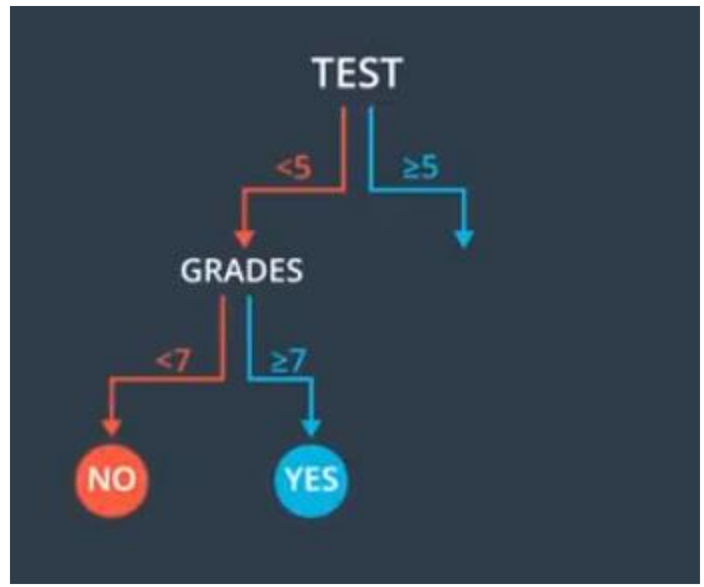
Or

Quiz: Between a horizontal and a vertical line, which one would cut the data better?

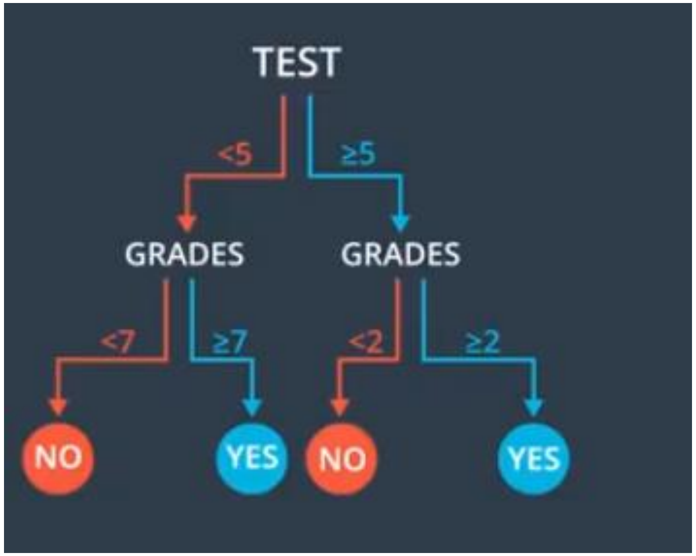
- ○ **Horizontal**
- ○ **Vertical**

Horizontal vs Vertical

Construction of a Tree



Decision Tree – Manual Structure



Ensemble

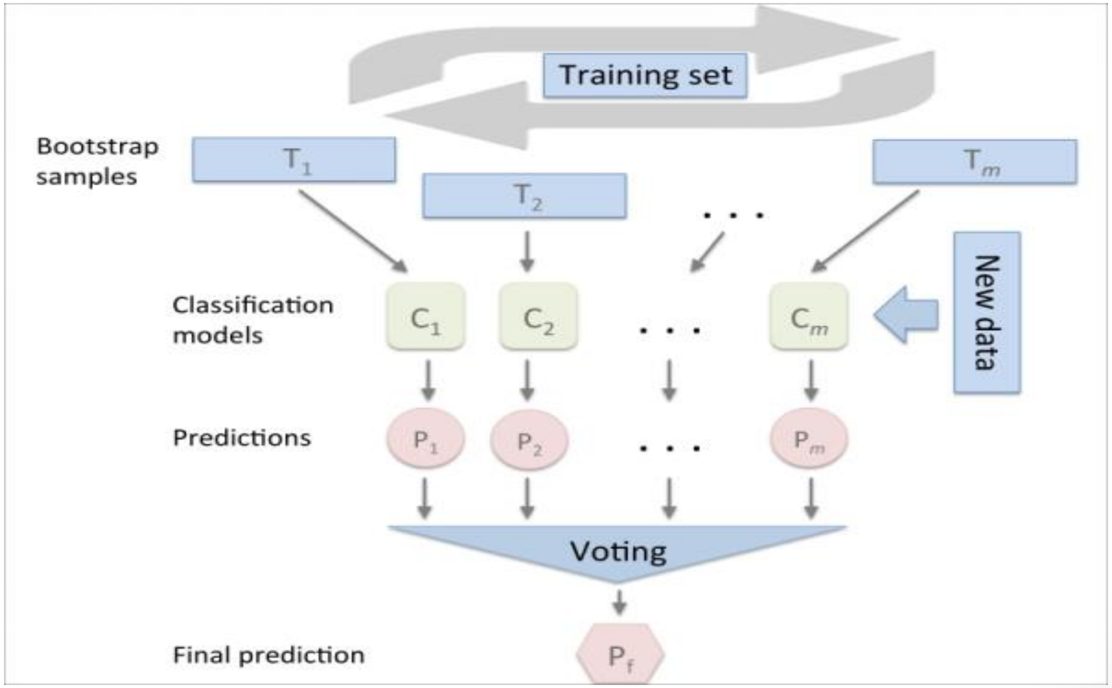
Ensemble

1. Bagging
2. Boosting

Ensemble

Machine learning paradigm which combine weak learners to become a strong learner

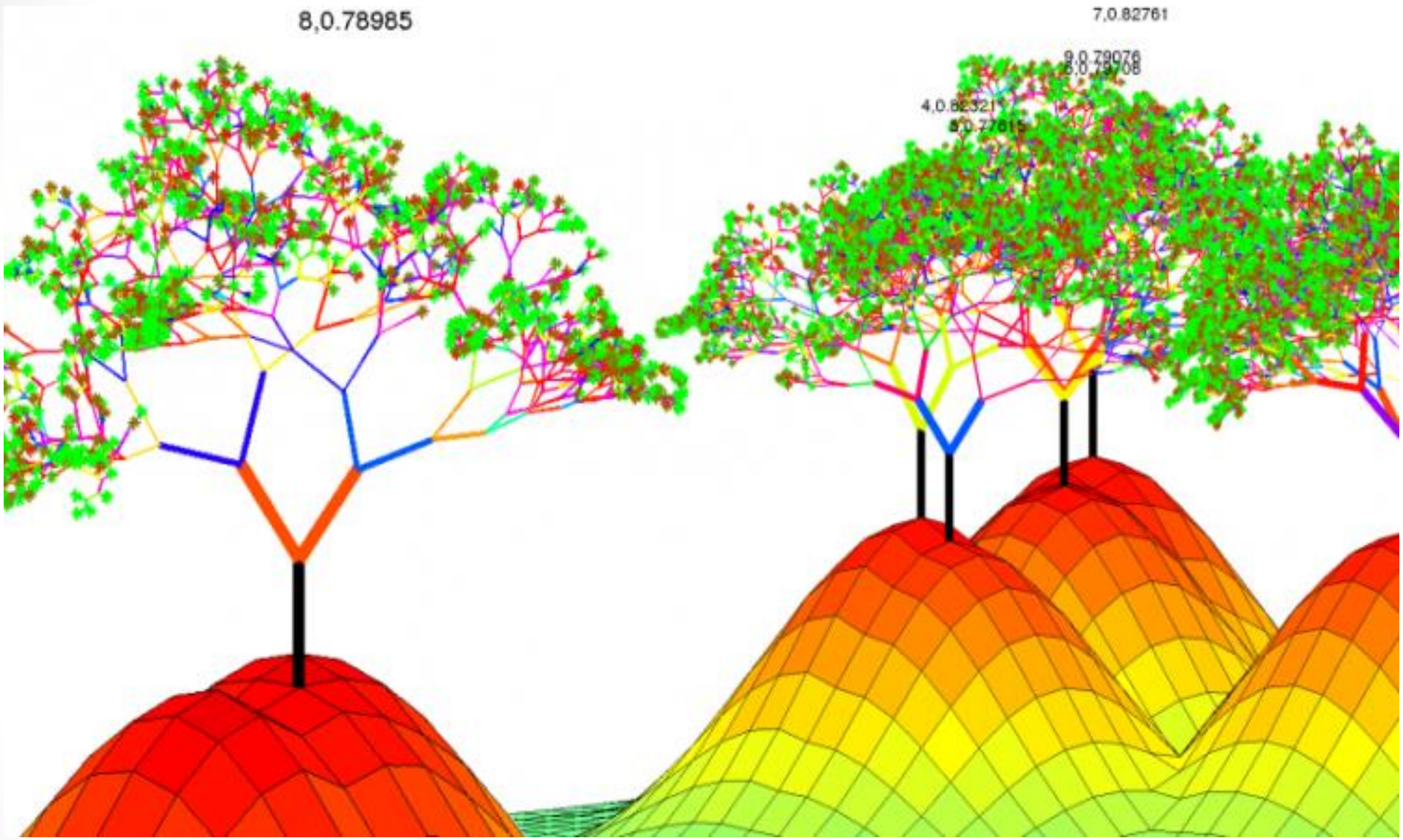
Model1	Model2	Model3	VotingPrediction
1	0	1	1



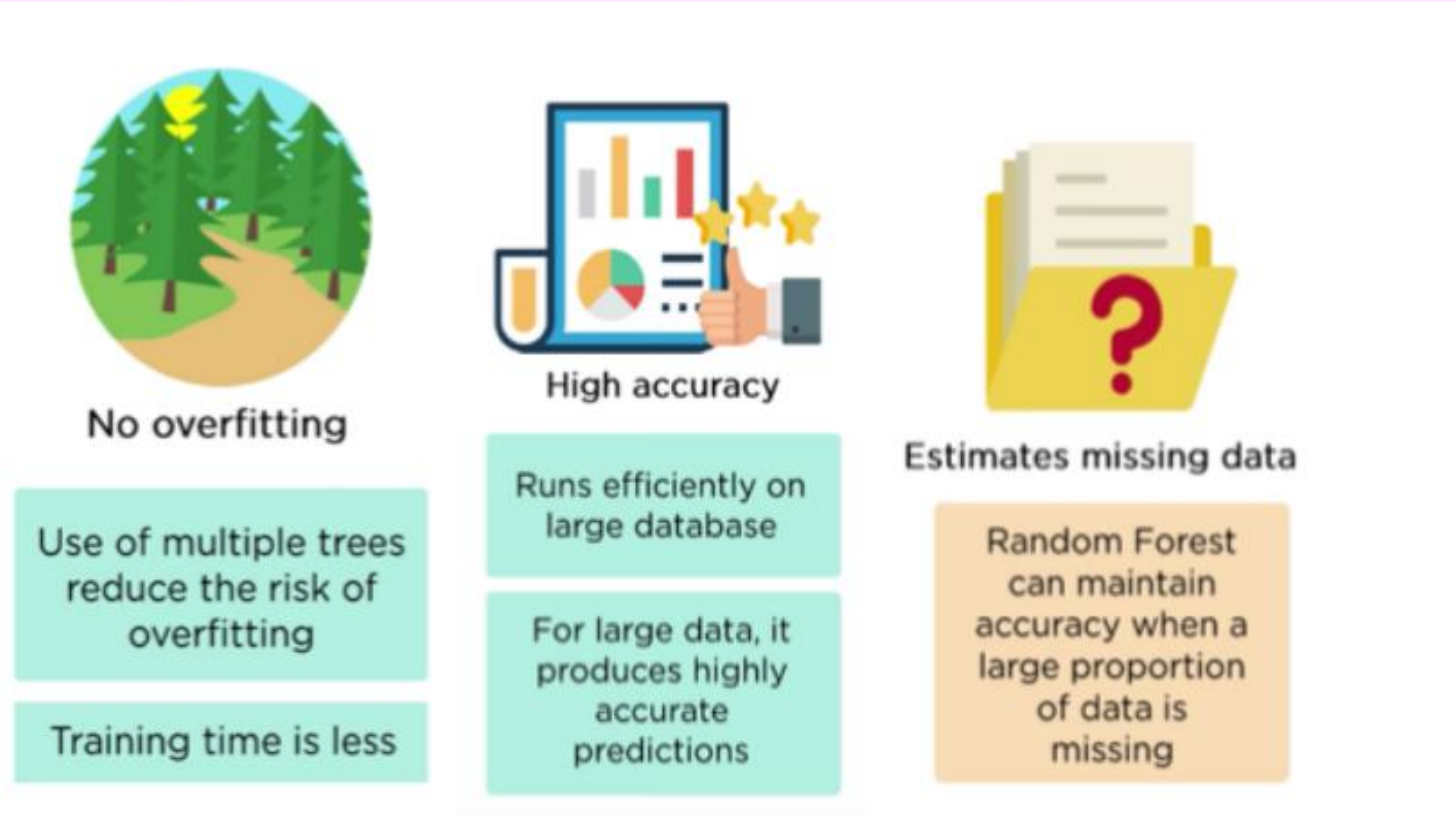
Random Forest (*Most used algorithm*)

Random Forest *(Most used algorithm)*

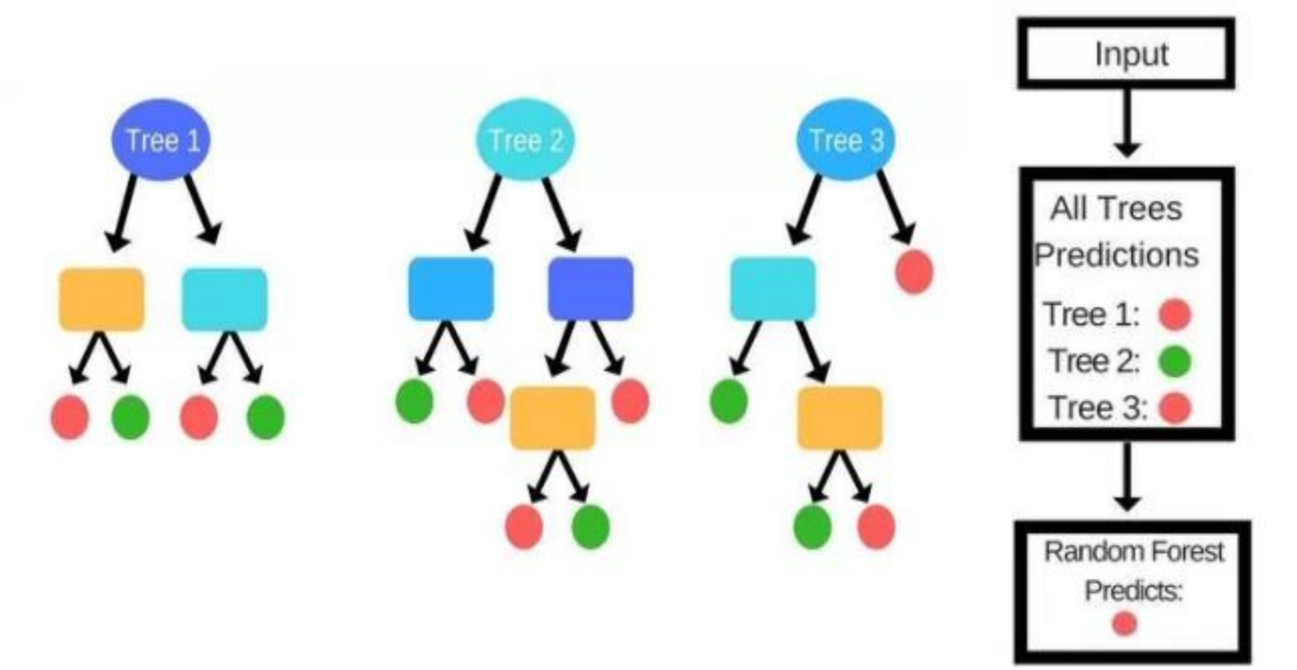
- Bagging Technique (**B**ootstrap **agg**regat**ing** - **Bagging**)


8,0.78985
7,0.82761
9,0.79076
4,0.82321

Why Random Forest?



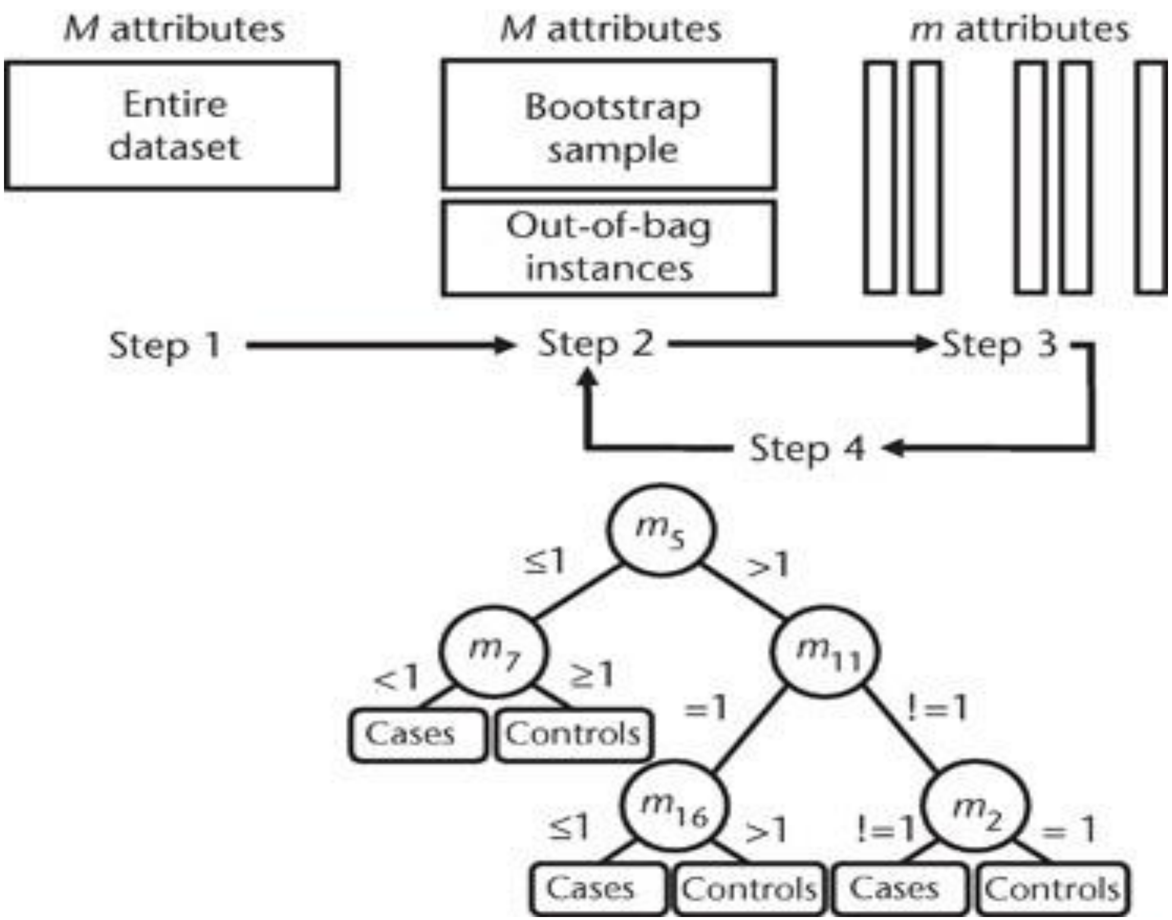
HOW THE RANDOM FOREST ALGORITHM WORKS IN MACHINE LEARNING



- Supervised learning algorithm

- Regression and classification problems

Bagging



M attributes
Entire dataset
M attributes
Bootstrap sample
Out-of-bag instances
m attributes
Step 1
Step 2
Step 3
Step 4
m_5
≤1
>1
m_7
m_{11}
<1
≥1
Cases
Controls
=1
!=1
m_{16}
m_2
≤1
>1
!=1
= 1
Cases
Controls
Cases
Controls

Random Forest pseudocode

- Randomly select **“k”** features from total **“m”** features.

  Where **k << m**

  For classification a good default is: k = sqrt(m)
  For regression a good default is: k = m/3

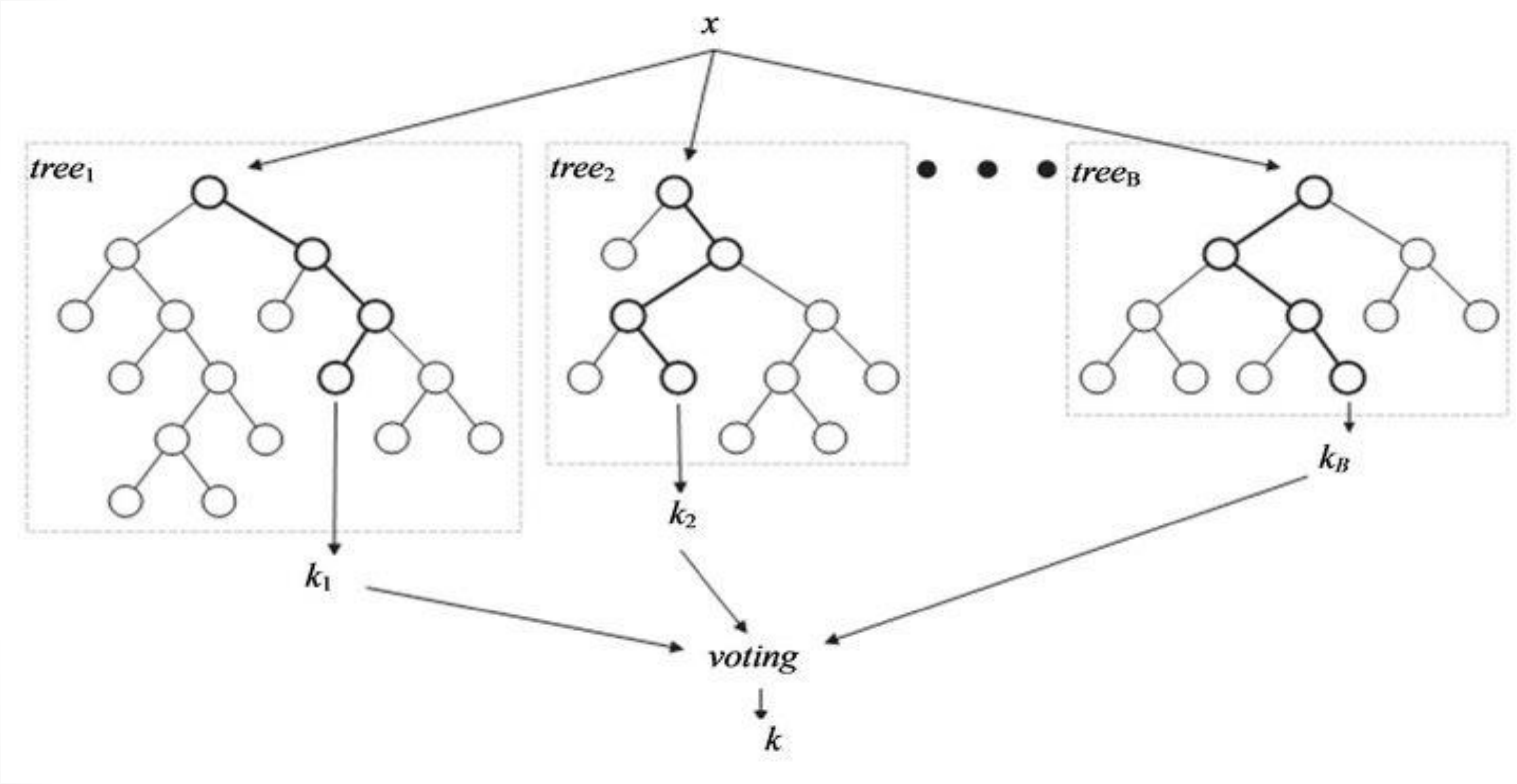
- Among the **“k”** features, calculate the node **“d”**.
- Split the node into **daughter nodes**.
- Repeat **1 to 3** steps
- Build forest by repeating steps **1 to 4** for “n” number times to create **“n” number of trees**.

Key Points

- **Majority voting**.
- **Higher the number** of trees in the forest = **High accuracy**.

- When we have more trees in the forest, random forest classifier won't **overfit** the model.
- For each bootstrap sample taken from the training data, there will be samples left behind that were not included. These samples are called **Out-Of-Bag samples** or OOB.
- The performance of each model on its left out samples when averaged can provide an estimated accuracy of the bagged models. This estimated performance is often called the **OOB estimate of performance**.

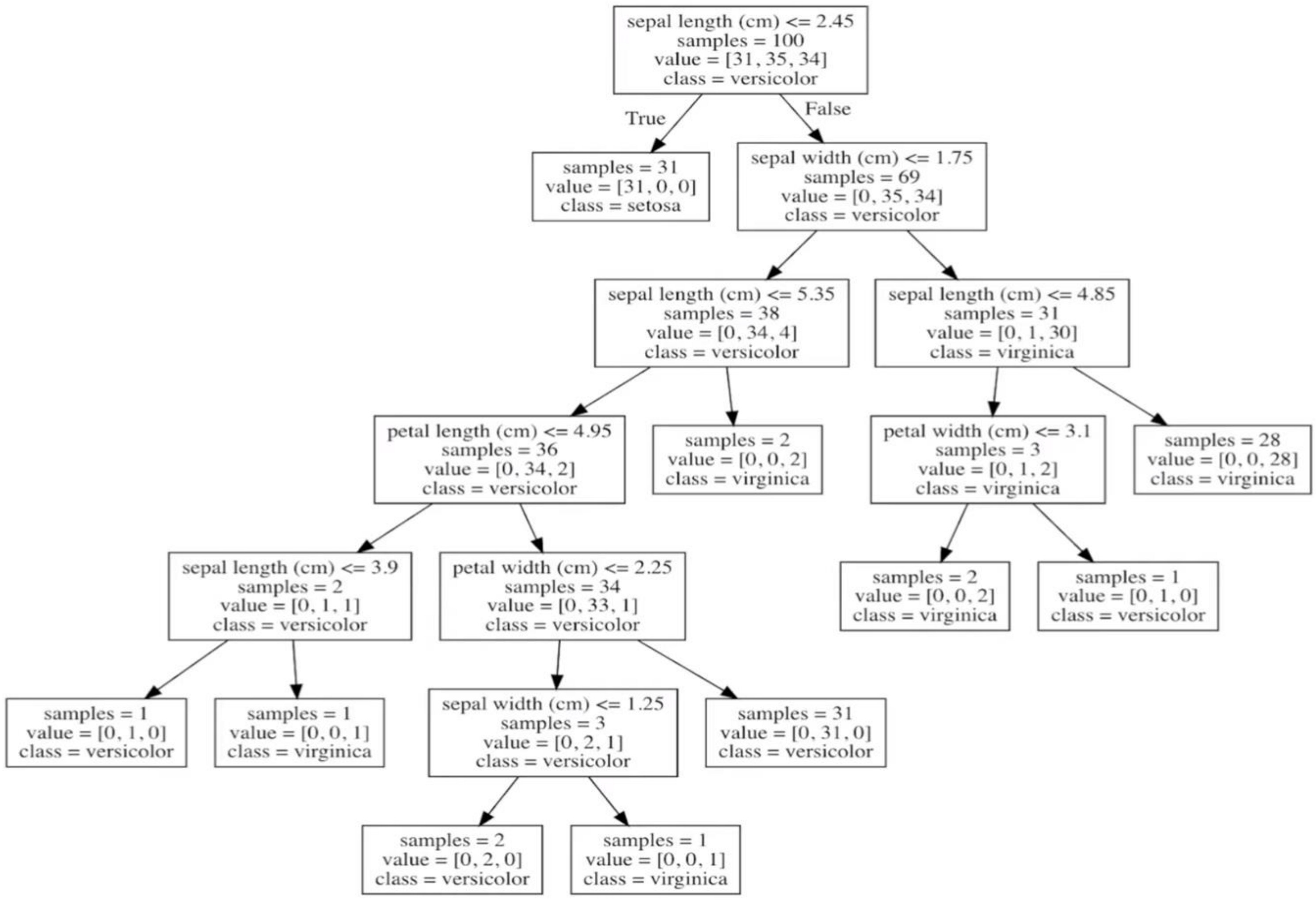
Random Forest - Skeleton



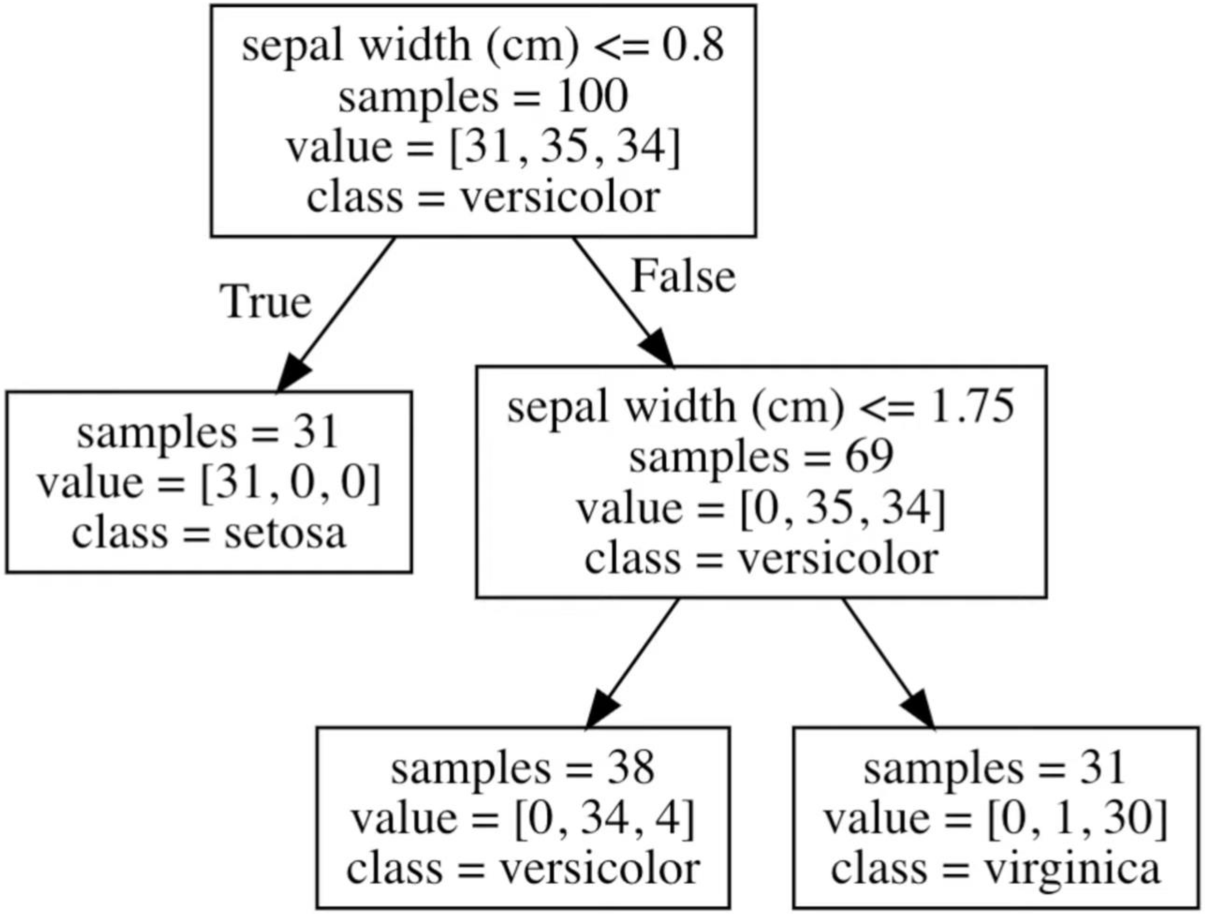
Important hyper-parameters for RF tuning:

- n_estimators
- max_features
- max_depth
- min_sample_split
- min_sample_leaf
- n_jobs
- oob_score
- random_state

Before max_depth tuning:

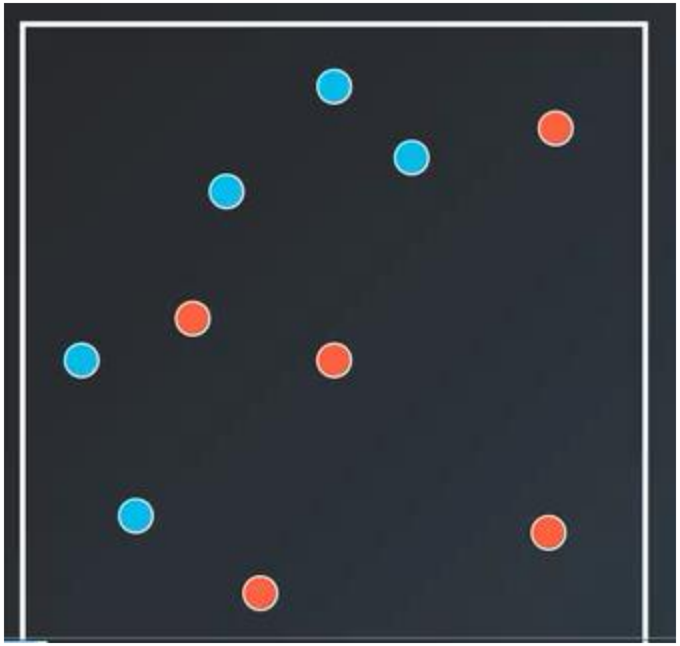


After max_depth tuning:

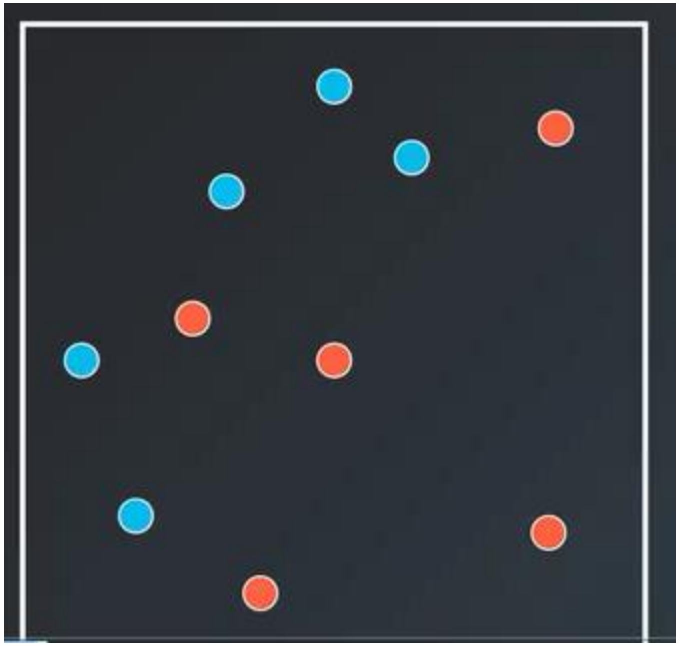


Boosting

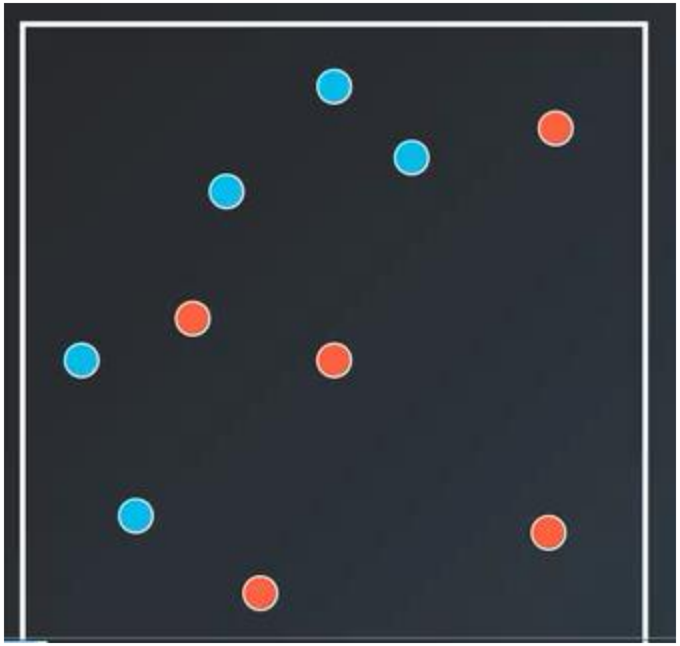
AdaBoost (**Ada**ptive **Boost**ing)

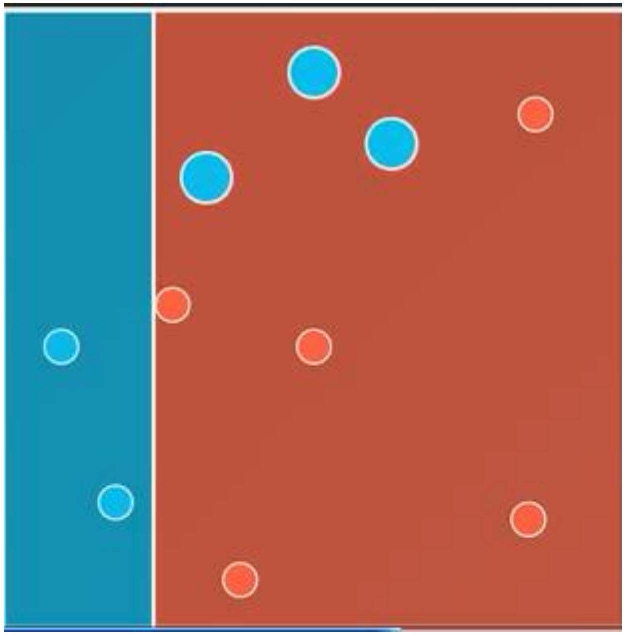


AdaBoost – Pattern 1

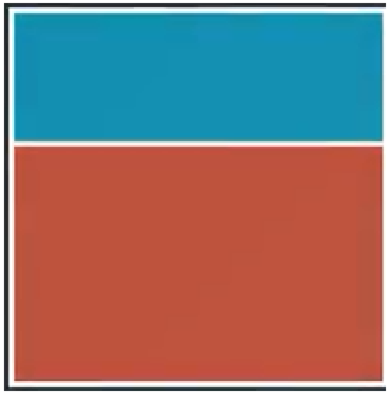


AdaBoost – Pattern 1





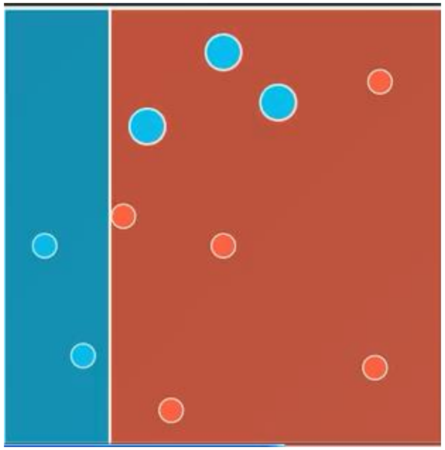
AdaBoost – Pattern 2

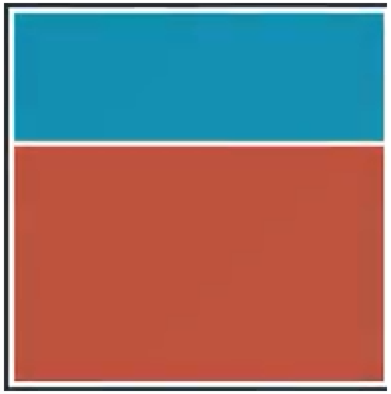


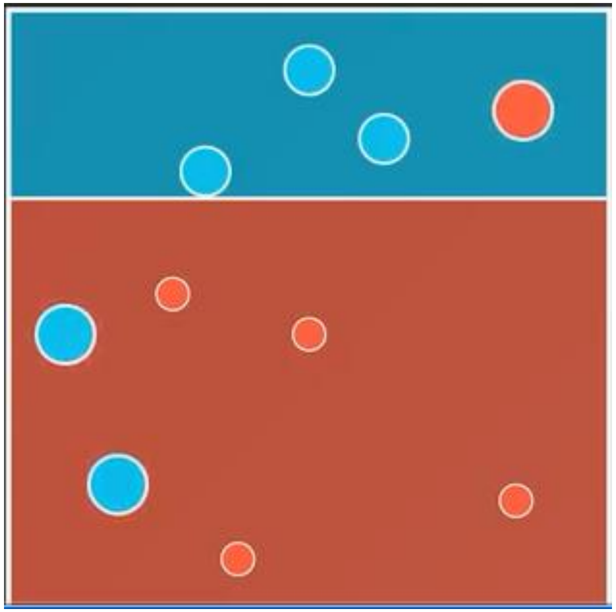
Apply pattern 2 on the Input Data from pattern 1

AdaBoost – Pattern 2

Input Data





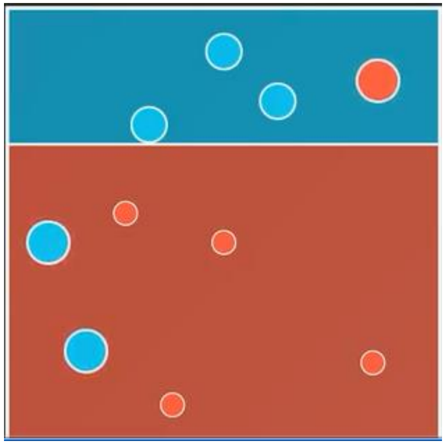


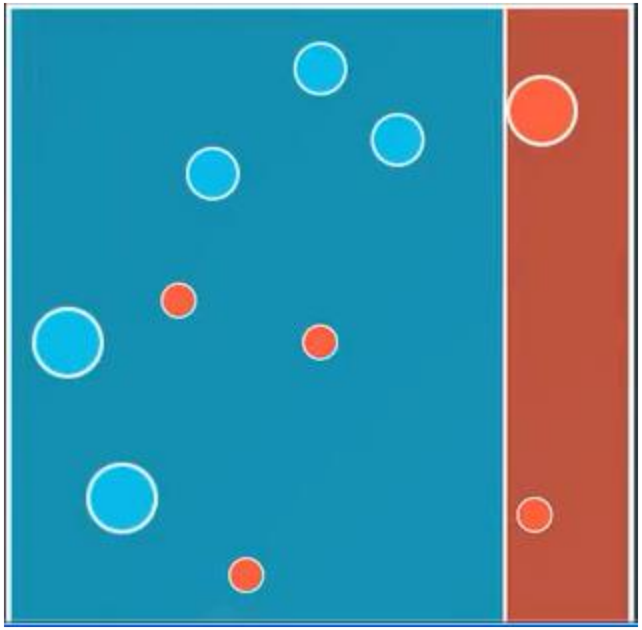
AdaBoost – Pattern 3

Apply pattern 3 on the Input Data from pattern 2

AdaBoost – Pattern 3

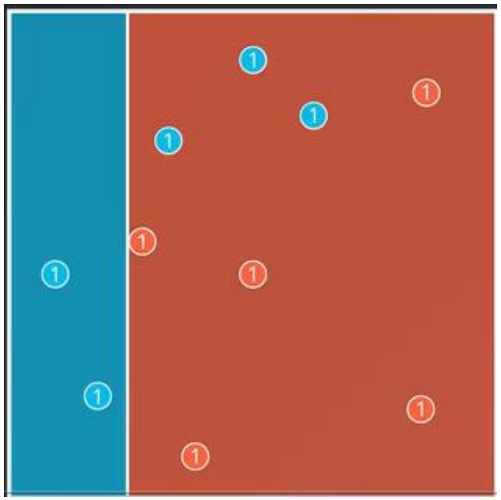
Input Data



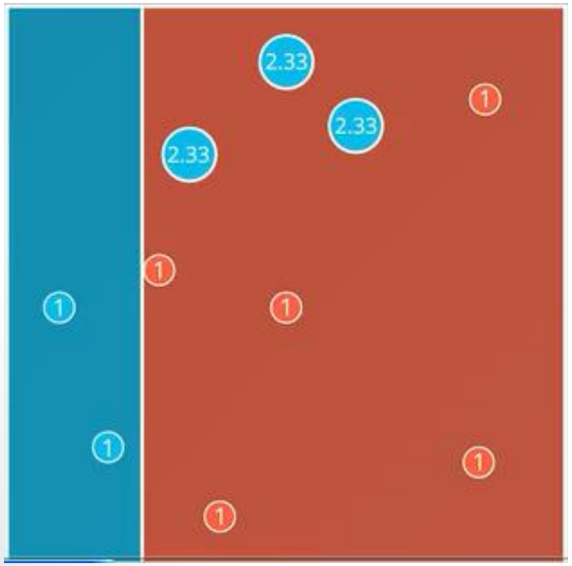


AdaBoost – Pattern 1

Weights after applying pattern 1



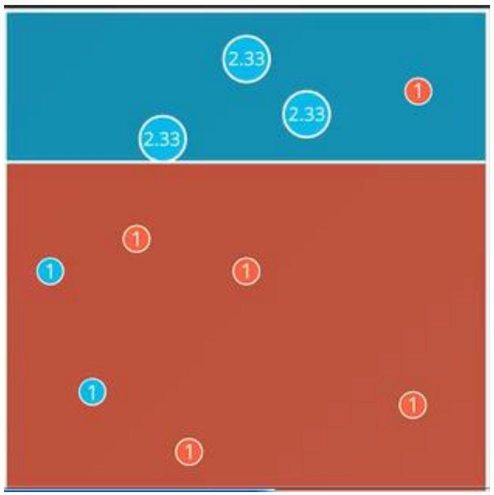
Correct: 7
Incorrect: 3



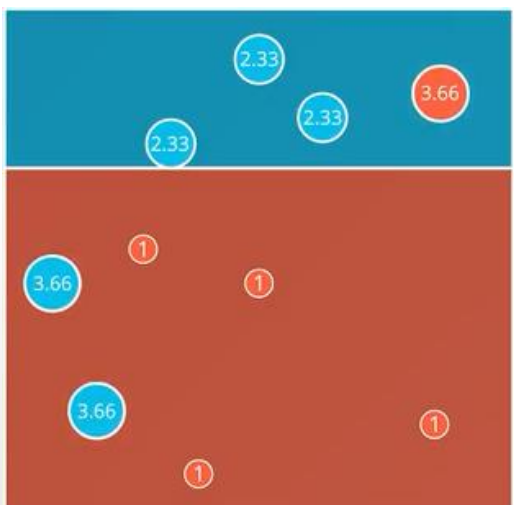
Correct: 7
Incorrect: 7

AdaBoost – Pattern 2

Weights after applying pattern 2



Correct: 11
Incorrect: 3



Correct: 11
Incorrect: 11

AdaBoost – Pattern 3

Weights after applying pattern 3

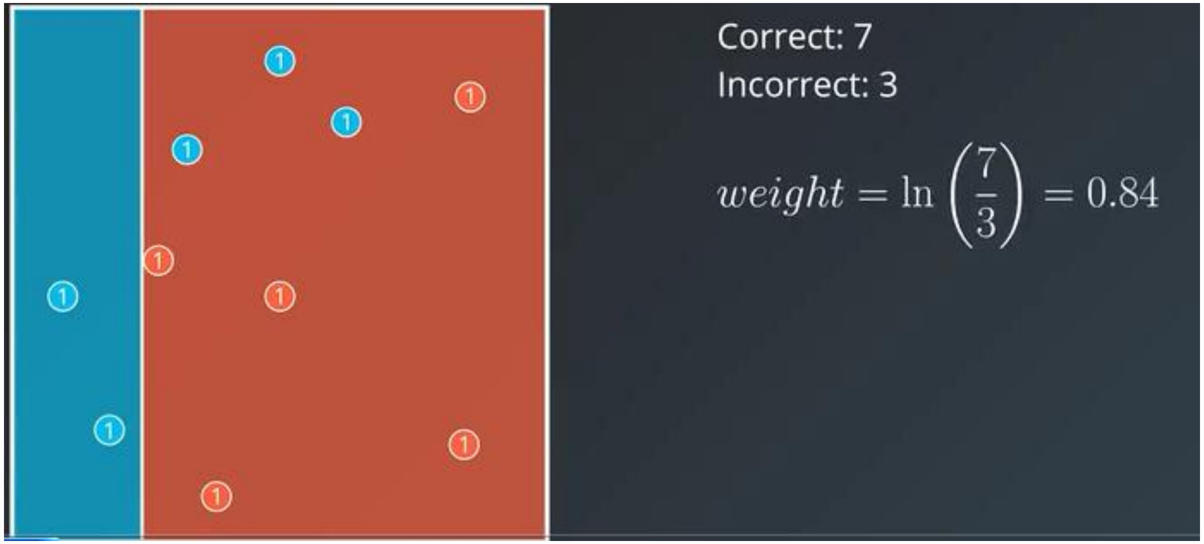
Correct: 19
Incorrect: 3

AdaBoost – 3 Models

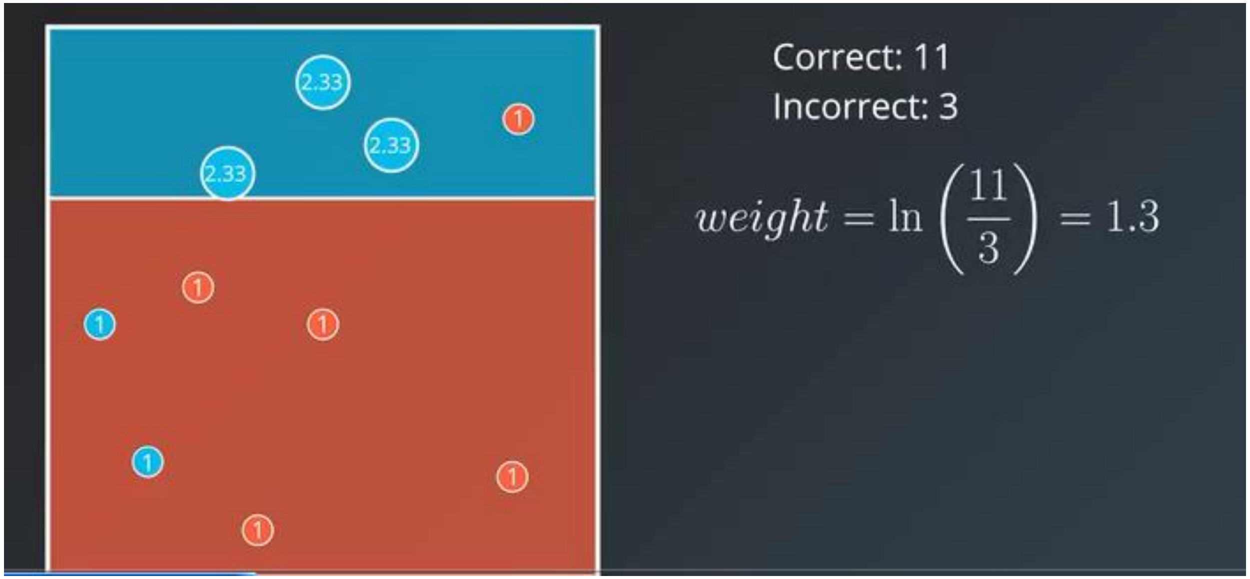
Weightage of a Model

$$weight = \ln\left(\frac{\#correct}{\#incorrect}\right)$$

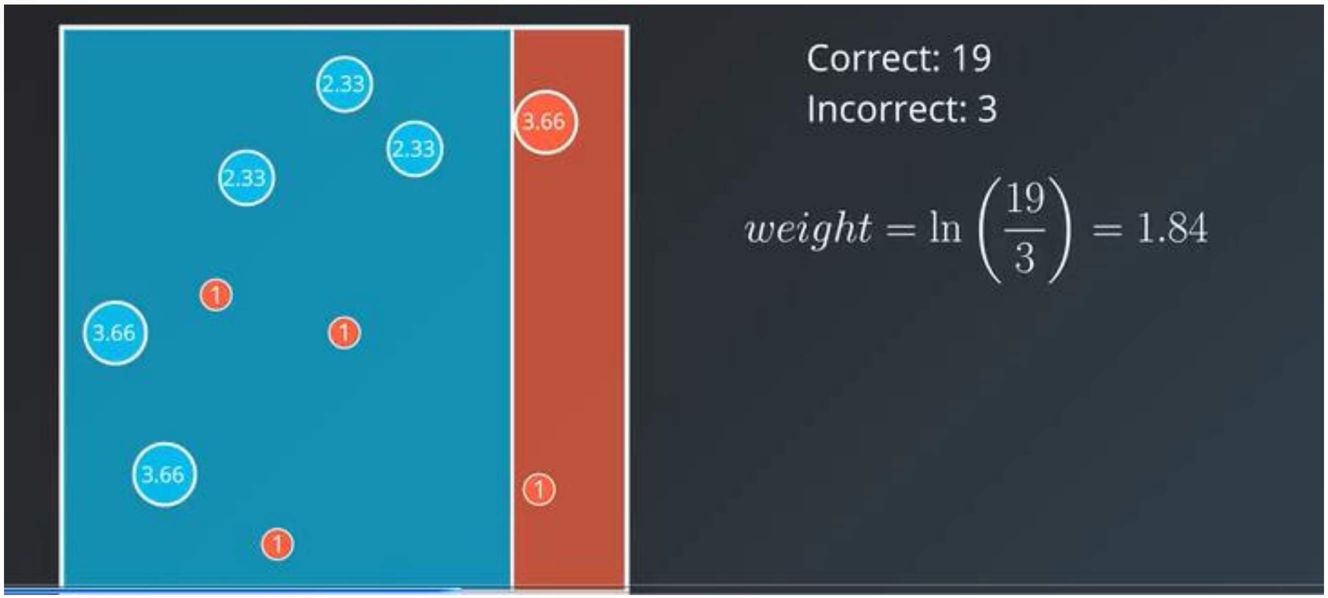
Weight of Model 1



Weight of Model 2



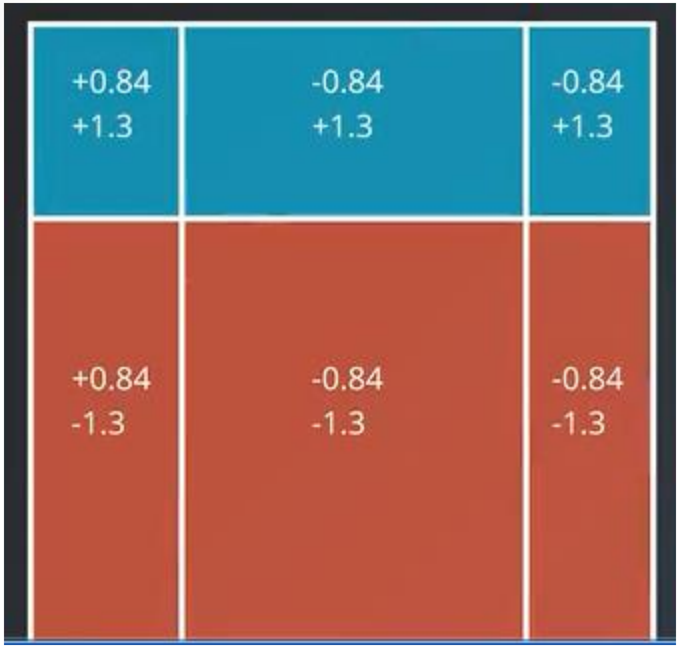
Weight of Model 3

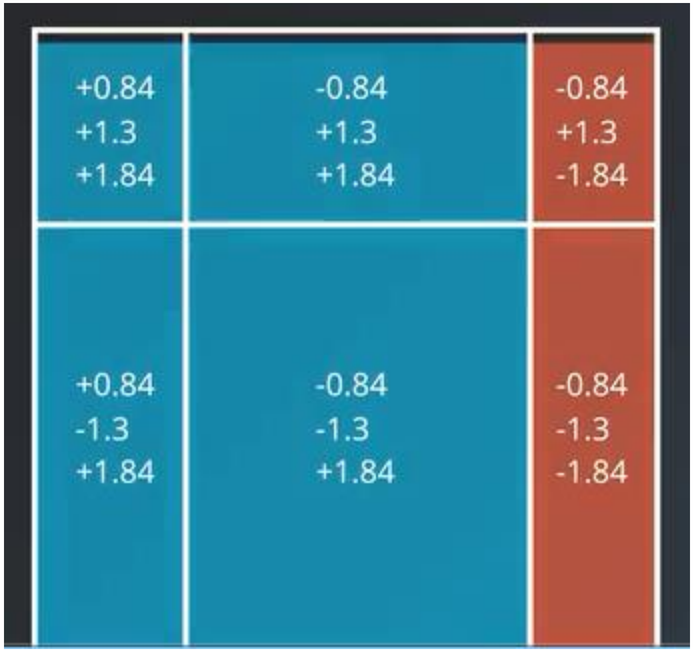


Weight of 3 Models

Assinging weights to 2 categories


+0.84
-0.84
-0.84
+0.84
-0.84
-0.84

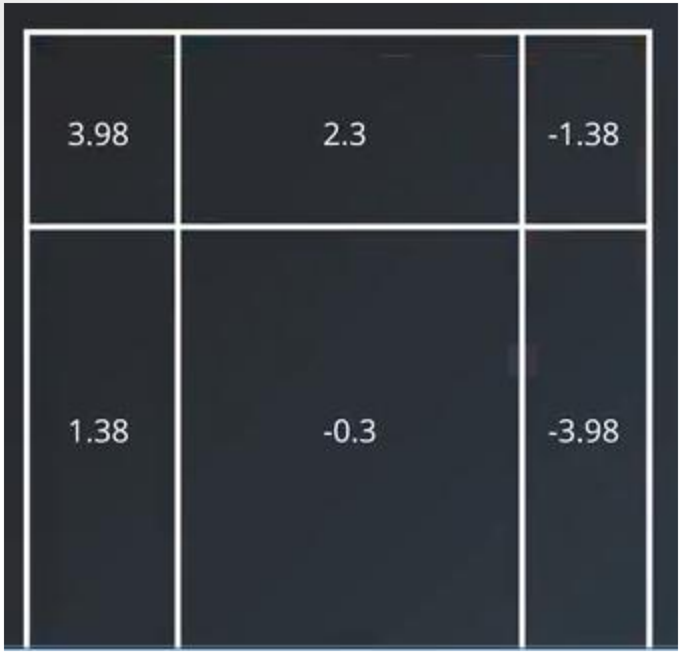
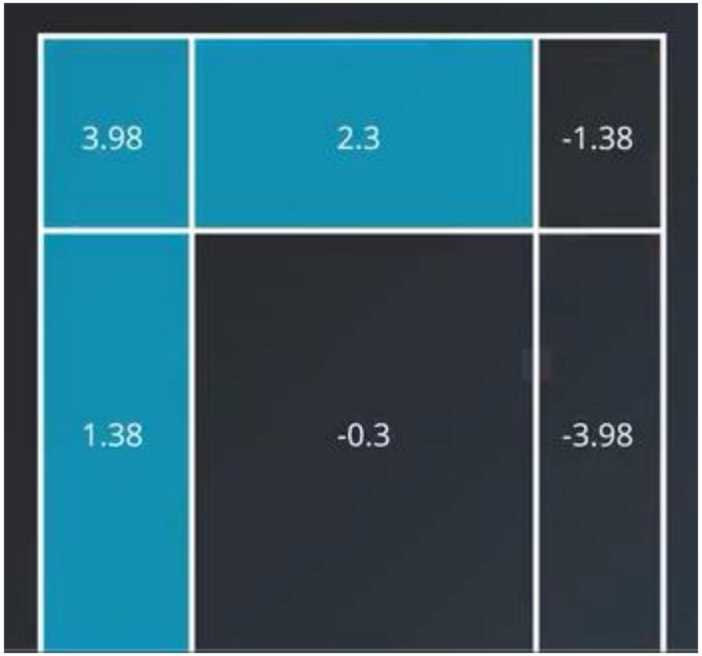

+0.84
+1.3
-0.84
+1.3
-0.84
+1.3
+0.84
-1.3
-0.84
-1.3
-0.84
-1.3


+0.84
+1.3
+1.84
-0.84
+1.3
+1.84
-0.84
+1.3
-1.84
+0.84
-1.3
+1.84
-0.84
-1.3
+1.84
-0.84
-1.3
-1.84

3.98	2.3	-1.38
1.38	-0.3	-3.98

3.98	2.3	-1.38
1.38	-0.3	-3.98

3.98	2.3	-1.38
1.38	-0.3	-3.98


3.98
2.3
-1.38
1.38
-0.3
-3.98

3.98
2.3
-1.38
1.38
-0.3
-3.98

3.98
2.3
-1.38
1.38
-0.3
-3.98

Final Model