

DECISION TREE

- **C**lassification and **R**egression **T**ree (**CART**)

Recommendation System - 1


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
- ☐ 

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: Man, works at a factory.
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: Man, works at a factory.
What app do we recommend?

- ☐  Pokémon Go
- ☐  WhatsApp
- ☒  Snapchat

Recommendation System - 3

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

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?

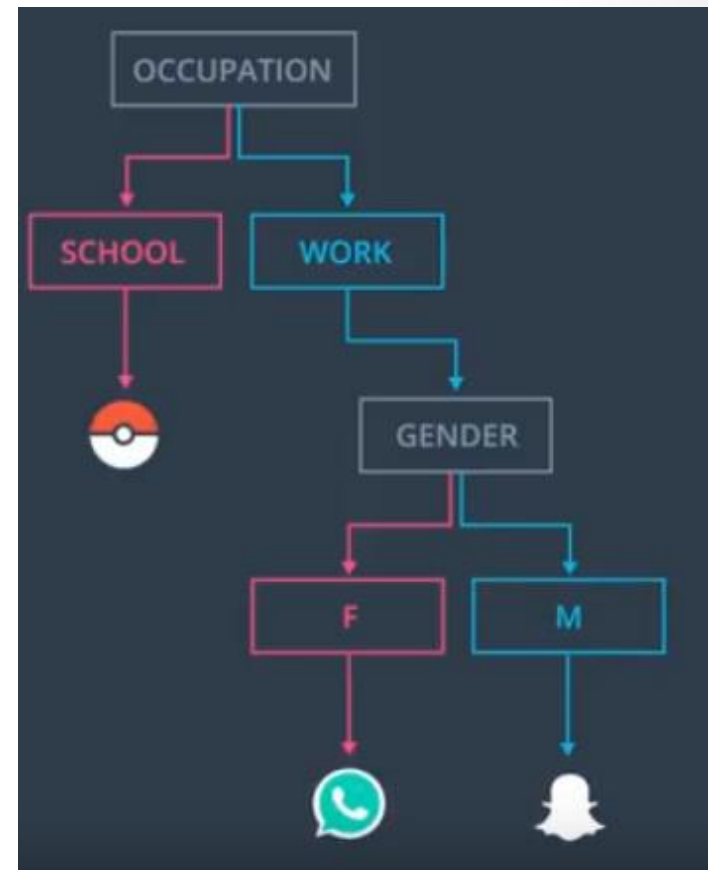
- ☐ Gender
- ☒ Occupation

Construction of a Tree

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	



Continuous Data

Student Admissions



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

Or

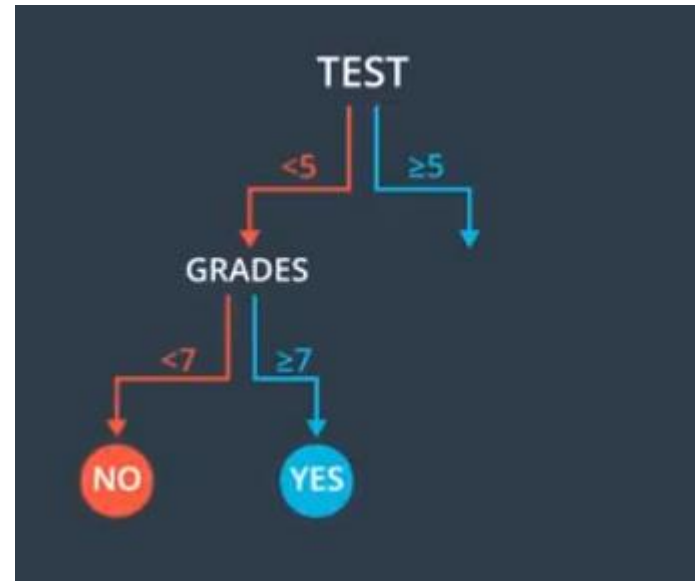
Quiz: Between a horizontal and a vertical line, which one would cut the data better?

- ☐ Horizontal
- ☐ Vertical

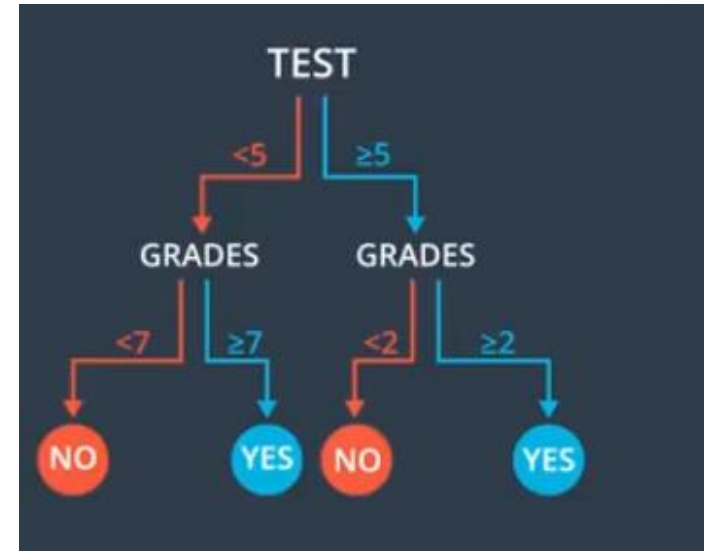
Horizontal vs Vertical



Construction of a Tree



Decision Tree – Manual Structure



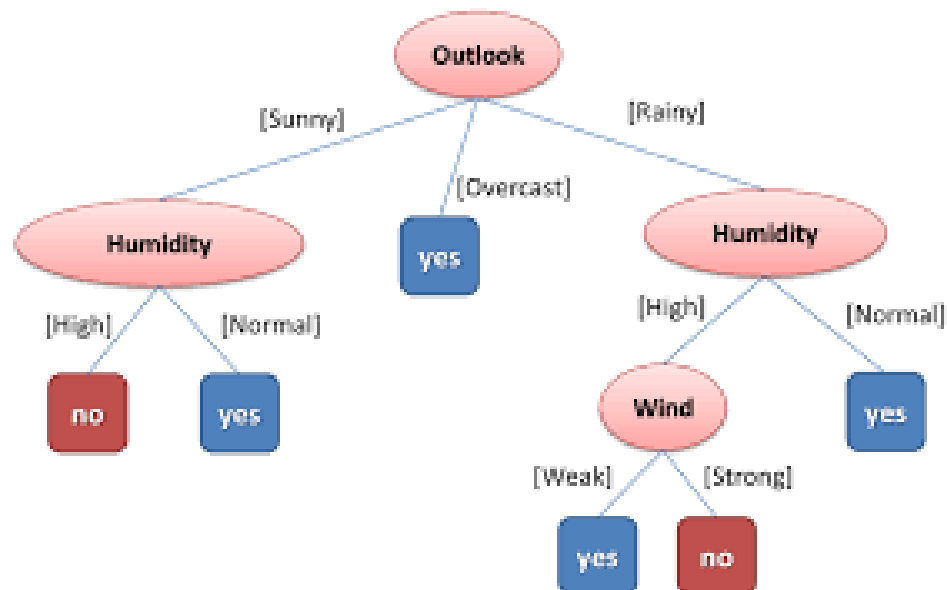
Supervised learning algorithm

Root Node

Decision node

Leaves

Structure of a Tree



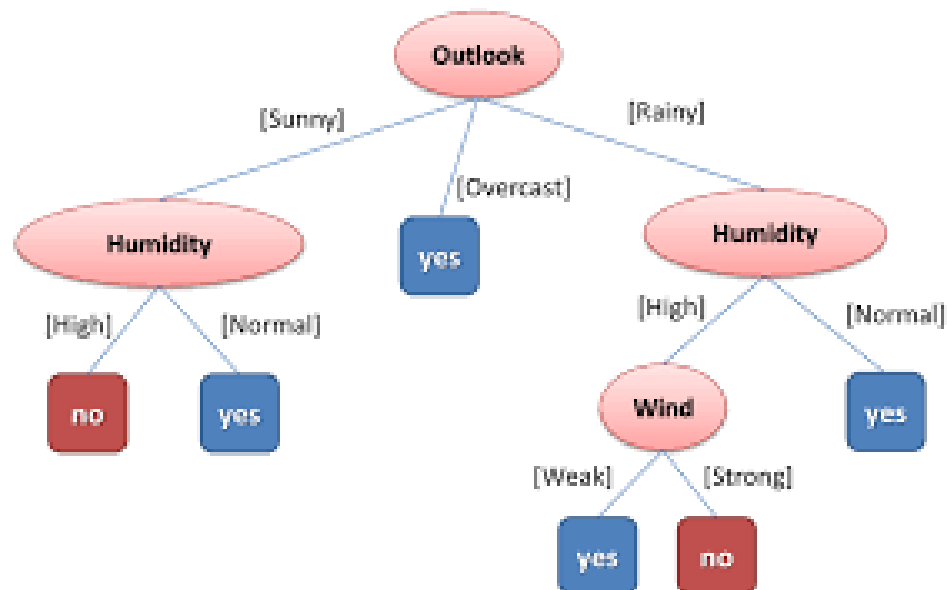
Supervised learning algorithm

Root Node - Outlook

Decision node - Humidity/Wind

Leaves - Yes/No

Structure of a Tree



HOW DECISION TREE ALGORITHM WORKS

HOW TO FIND ROOT (2 WAYS)

- Information gain
- Gini index

Information Gain & Entropy

Information Gain -> Information theory -> Entropy

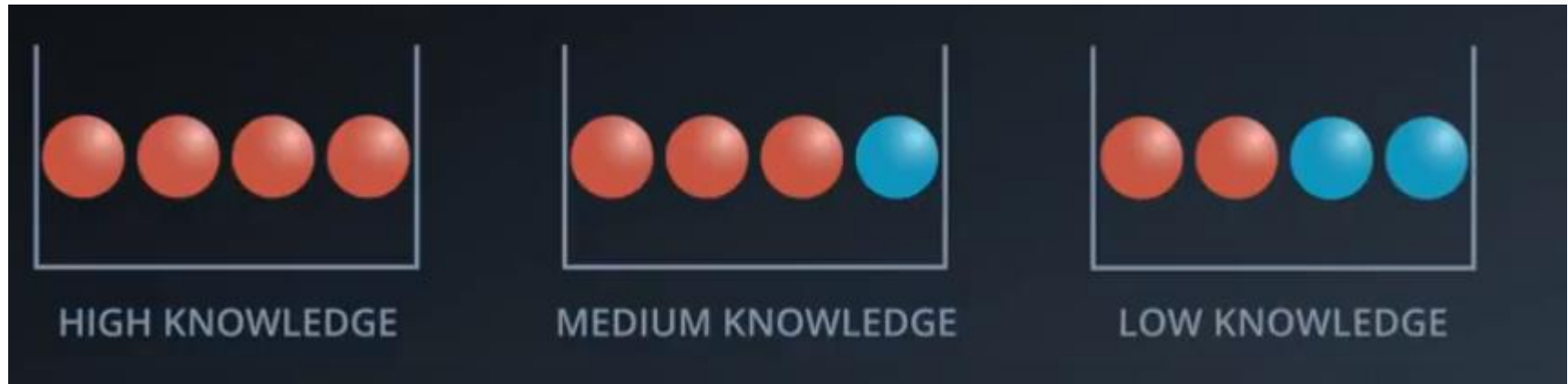
Entropy = **Randomness** or **Uncertainty** of a random variable.

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

Entropy - The measure of uncertainty




Entropy - The measure of uncertainty



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

Case Study – Golf Play Dataset



The diagram illustrates the structure of the dataset. A green bracket labeled "Predictors" spans the first four columns: Outlook, Temp., Humidity, and Windy. An orange bracket labeled "Target" spans the fifth column: Play Golf.

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
Yes
No



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



$$5 / 14 = 0.36$$



$$9 / 14 = 0.64$$

$$\begin{aligned}\text{Entropy}(\text{PlayGolf}) &= \text{Entropy}(5,9) \\ &= \text{Entropy}(0.36, 0.64) \\ &= -(0.36 \log_2 0.36) - (0.64 \log_2 0.64) \\ &= 0.94\end{aligned}$$

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


$$\begin{aligned} E(\text{PlayGolf}, \text{Outlook}) &= P(\text{Sunny}) * E(3,2) + P(\text{Overcast}) * E(4,0) + P(\text{Rainy}) * E(2,3) \\ &= (5/14) * 0.971 + (4/14) * 0.0 + (5/14) * 0.971 \\ &= 0.693 \end{aligned}$$

Activate
Go to PC

Information Gain - Outlook

$$\begin{aligned}\mathbf{G}(\text{PlayGolf}, \text{Outlook}) &= \mathbf{E}(\text{PlayGolf}) - \mathbf{E}(\text{PlayGolf}, \text{Outlook}) \\ &= 0.940 - 0.693 = 0.247\end{aligned}$$

Information Gain - All Attributes

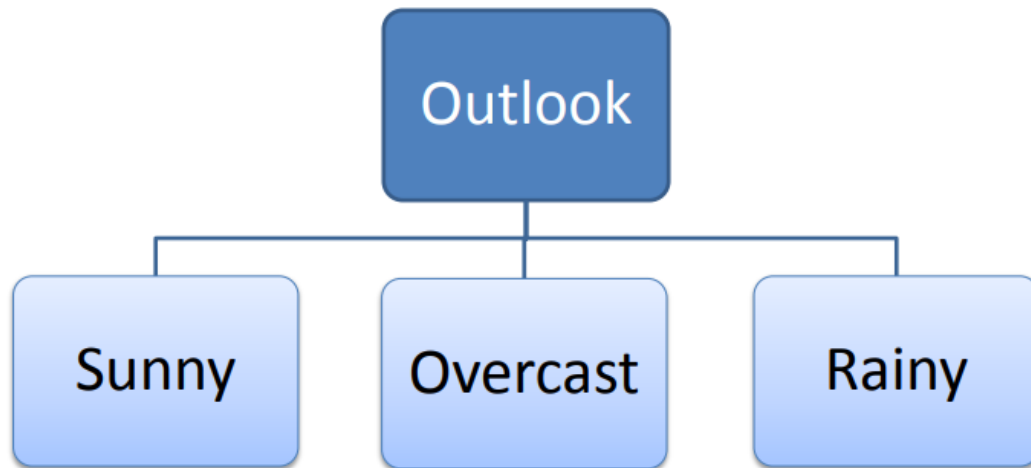
		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3
Gain = 0.247			

		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



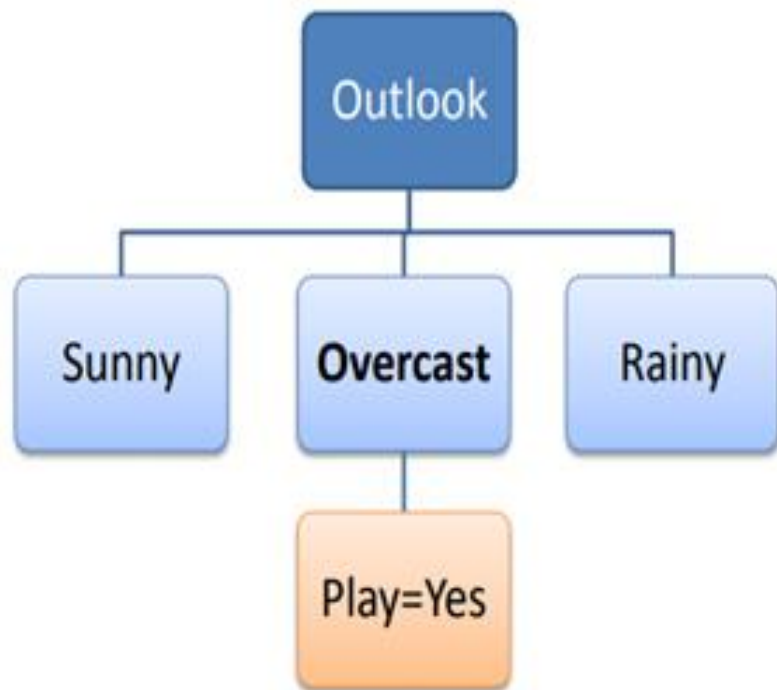
Outlook	Temp.	Humidity	Windy	Play Golf
Sunny	Mild	High	FALSE	Yes
Sunny	Cool	Normal	FALSE	Yes
Sunny	Cool	Normal	TRUE	No
Sunny	Mild	Normal	FALSE	Yes
Sunny	Mild	High	TRUE	No

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

Overcast

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

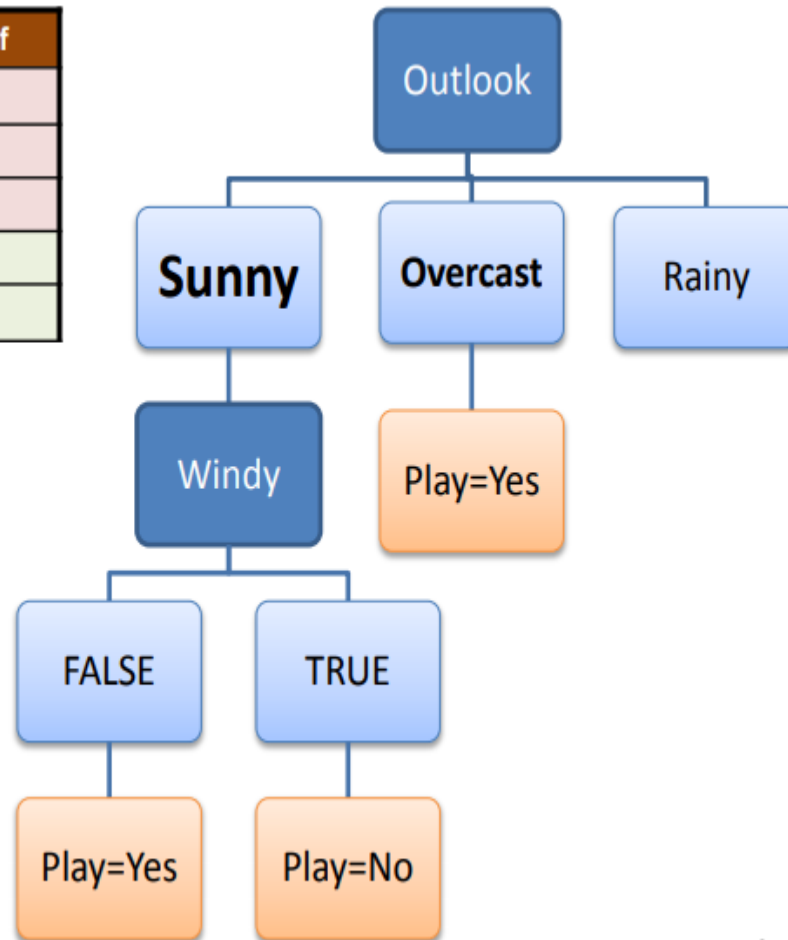
		Play Golf	
		Yes	No
Temp.	Mild	2	1
	Cool	1	1
Gain = 0.02			

		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



Rainy

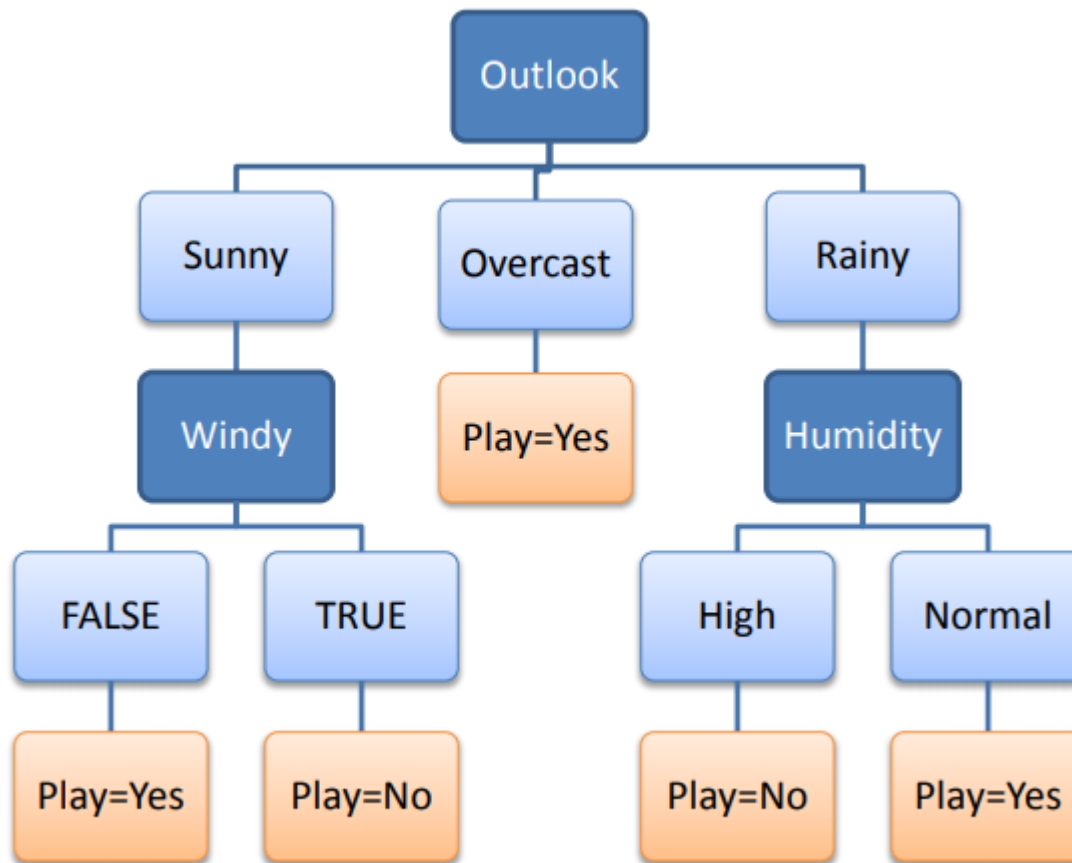
Temp.	Humidity	Windy	Play Golf
Hot	High	FALSE	No
Hot	High	TRUE	No
Mild	High	FALSE	No
Cool	Normal	FALSE	Yes
Mild	Normal	TRUE	Yes

		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			

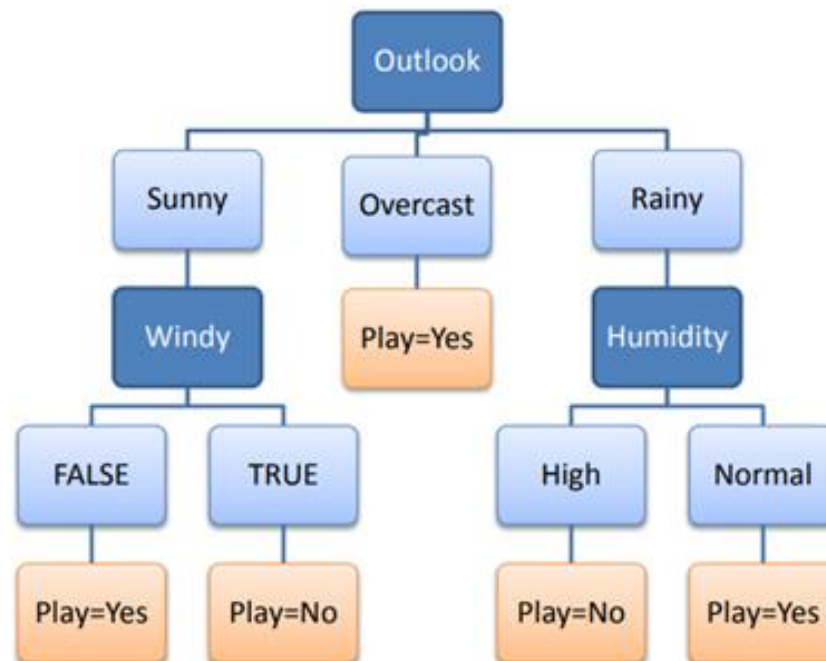
		Play Golf	
		Yes	No
Windy	False	1	2
	True	1	1
Gain = 0.02			

Final Tree Structure



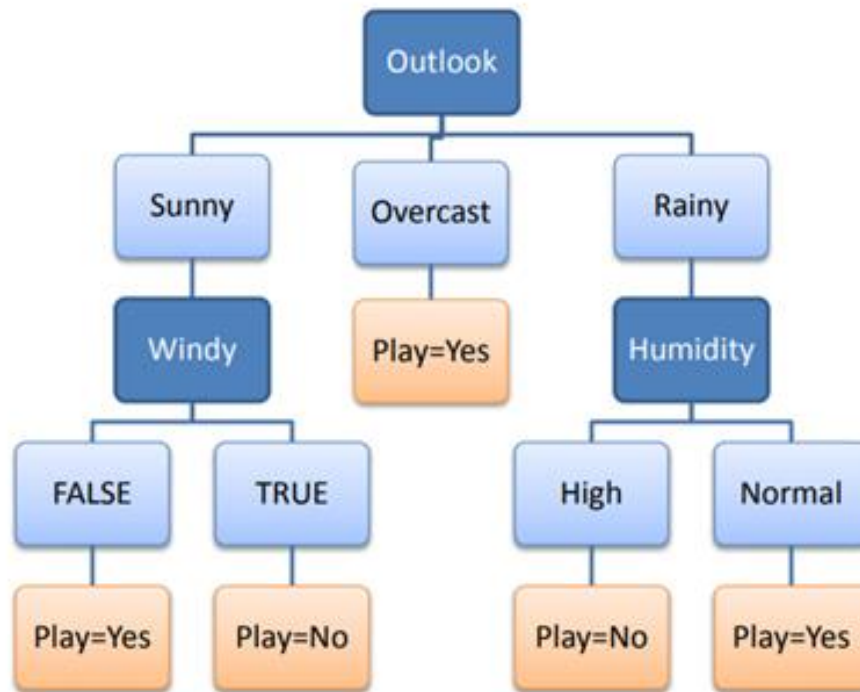
Predict the Play – D15 ?

Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Cool	Normal	FALSE	?



Predict the Play – D15 ?

Outlook	Temp	Humidity	Windy	Play Golf
Sunny	Cool	Normal	FALSE	Yes



Decision Rules – Traditional approach

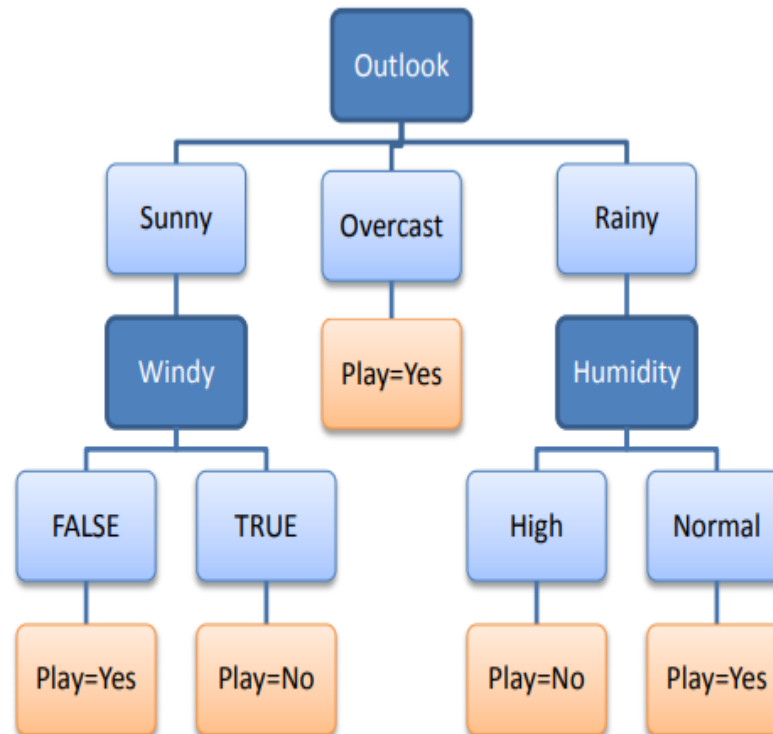
R₁: IF (Outlook=Sunny) AND (Windy=FALSE) THEN Play=Yes

R₂: IF (Outlook=Sunny) AND (Windy=TRUE) THEN Play=No

R₃: IF (Outlook=Overcast) THEN Play=Yes

R₄: IF (Outlook=Rainy) AND (Humidity=High) THEN Play=No

R₅: IF (Outlook=Rain) AND (Humidity=Normal) THEN Play=Yes

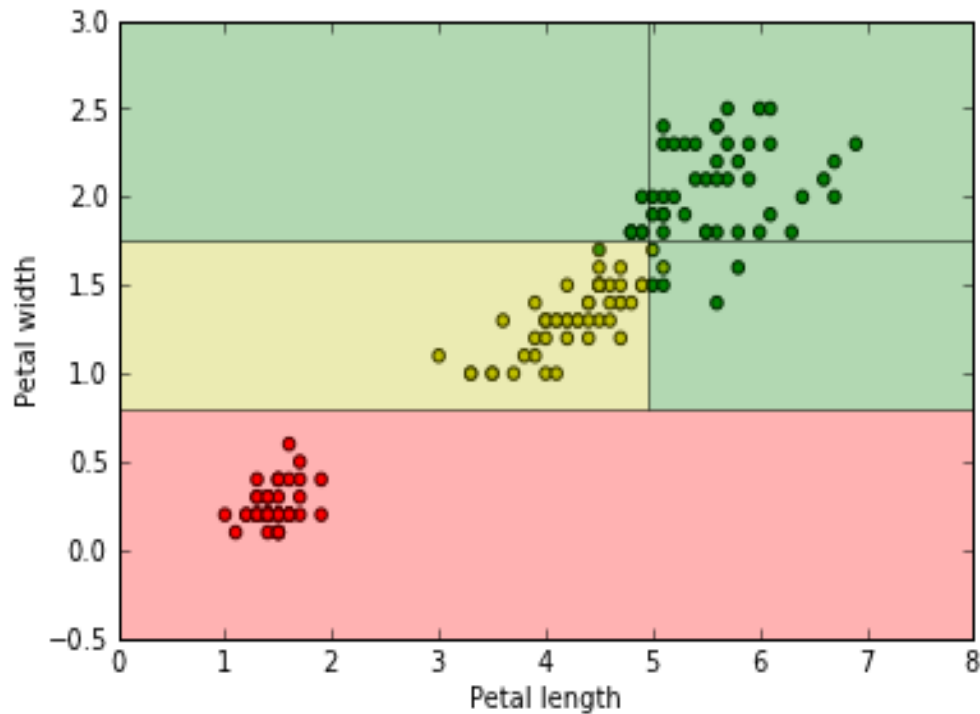


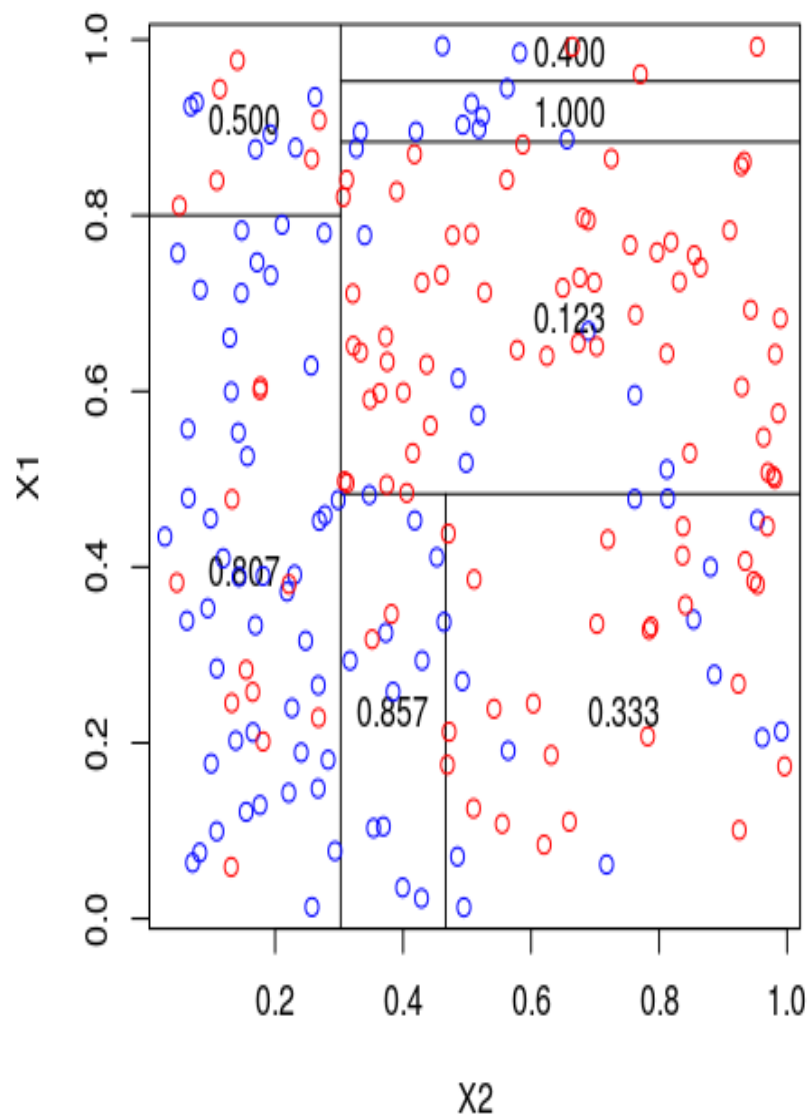
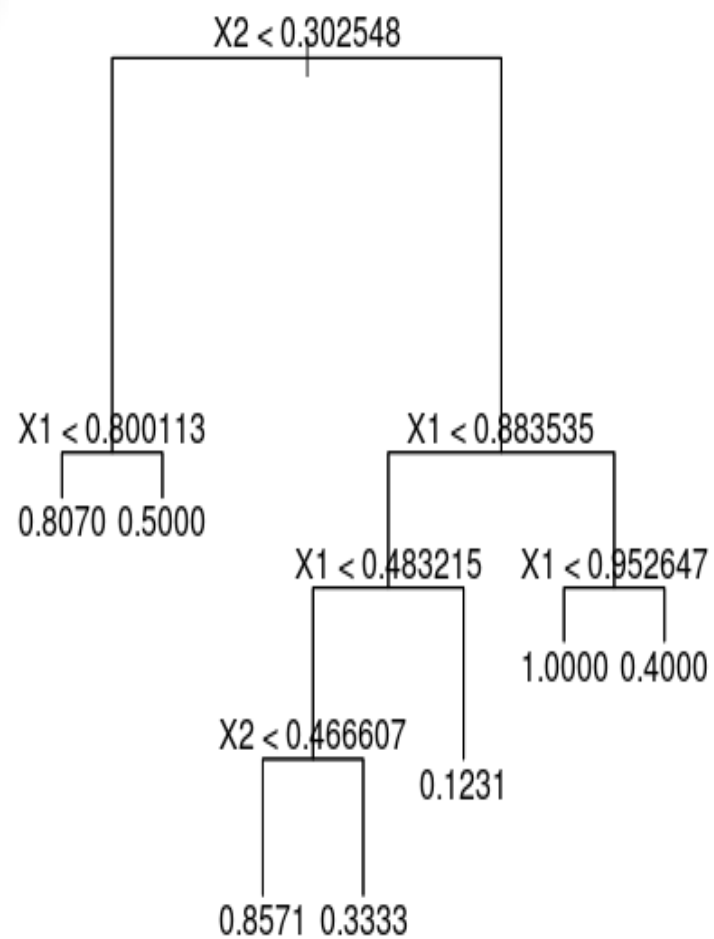
Finding Root using Gini Index

$$\text{Gini Index} = 1 - \sum_j p_j^2$$

1. The steps to build the tree using **Gini Index** approach is same as the Entropy with the only change in the Formula.
2. In Gini the attribute with the lowest Gini score is used as the ROOT
3. Gini Index is the default method of building the Decision Tree

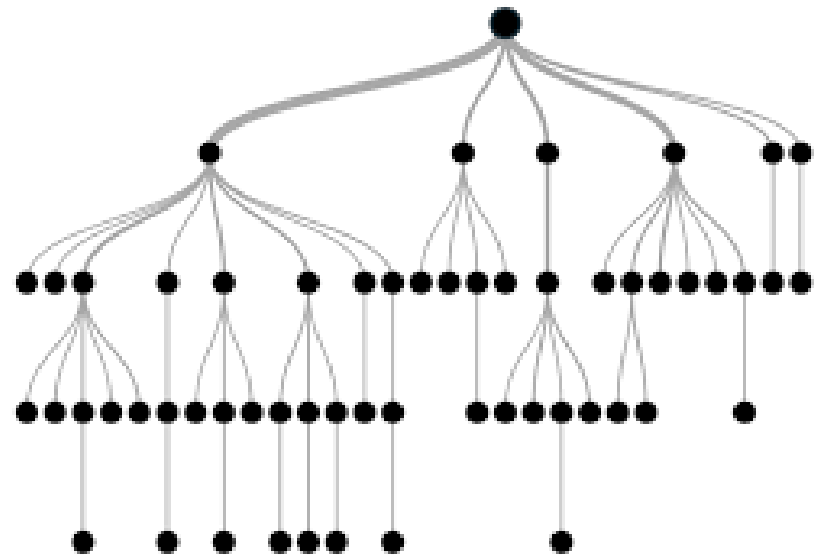
Disadvantage on using Continuous data





When to stop splitting ?

Overfitting



How to overcome Overfitting?

Pruning

- 1. Pre-pruning**
- 2. Post-pruning**

Classification vs Regression Tree

