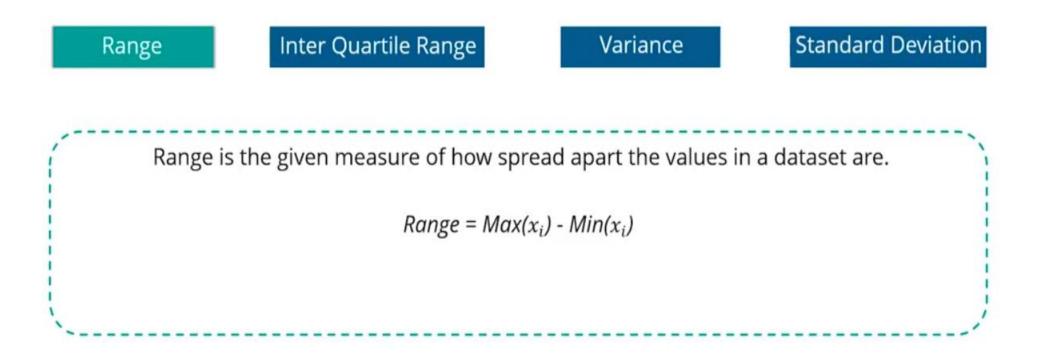
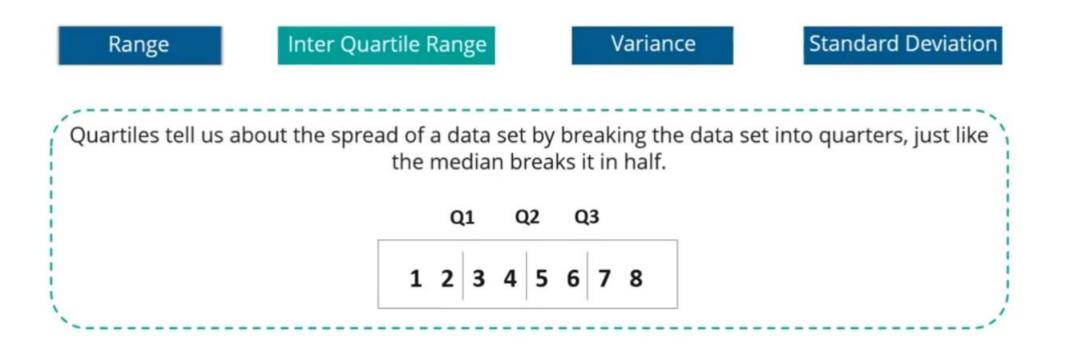
# **TYPES OF STATISTICS-2**

#### Measures of Spread



#### Inter quartile Range



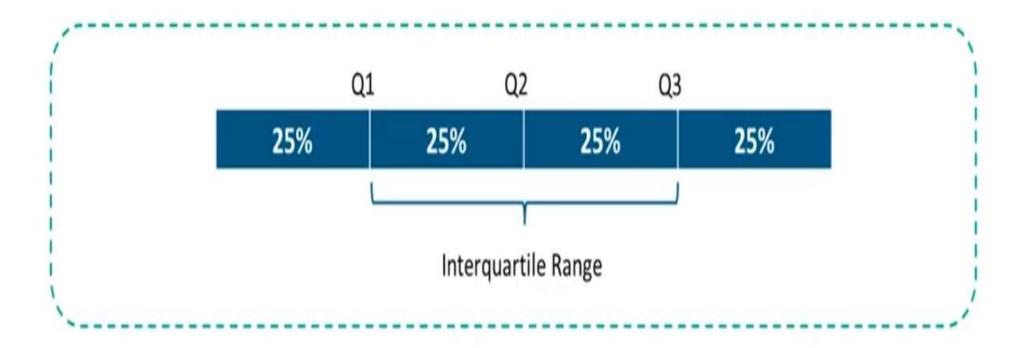
## Example

Consider the marks of the 100 students below, ordered from the lowest to the highest scores

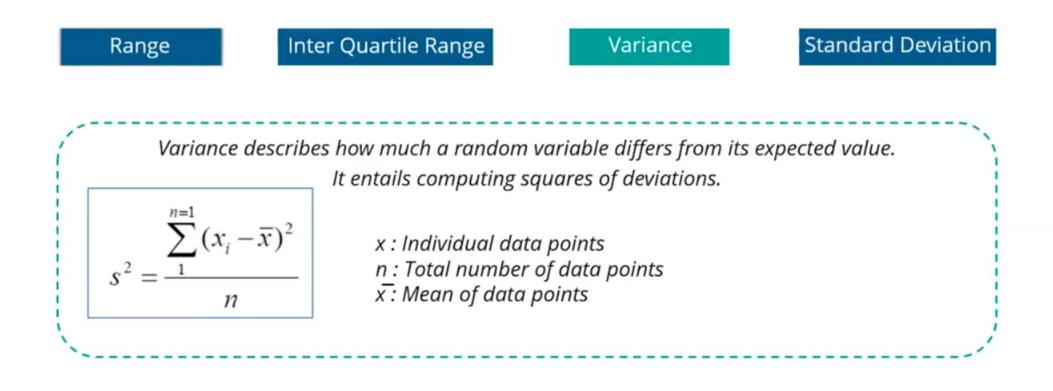
	Order	Score	Order	Score	Order	Score	Order	Score	Order	Score	
	1st	35	21st	42	41st	53	61st	64	81st	74	
	2nd	37	22nd	42	42nd	53	62nd	64	82nd		
The first quartile (Q1) lies	3rd	37	23rd		43rd	54	63rd	65	83rd		
	4th	38	24th		44th	55	64th	66	84th	75	
petween the 25th and 26th.	5th	or other Designation of the local division o	25th		45th			67	85th		
$Q1 = (45 + 45) \div 2 = 45$	6th	-	26th		46th	56	_	67	86th	76	
	7th	39	27th	45	47th	57	67th	67	87th	77	
	8th	39	28th	45	48th	57	68th	67	88th	77	The second supertile (02)
	9th	39	29th	47	49th	58	69th	68	89th	79	The second quartile (Q2)
	10th	40	30th		50th	58	70th	69	90th	80	<ul> <li>between the 50th and 51st.</li> </ul>
	11th	40	31st	-	51st	59	71st	69	91st		
	12th	40	32nd	49	52nd	60	72nd		92nd		$Q2 = (58 + 59) \div 2 = 58.5$
	13th	40	33rd	49	53rd	61	73rd	70	93rd		
	14th	40	34th	49	54th	62	74th	70	94th	81	
	15th	40	35th	51	55th	62	75th	71	95th	81	
	16th	41	36th	51	56th	62	76th	71	96th	81	The third exectile (02)
	17th	41	37th	51	57th	63	77th		97th	83	The third quartile (Q3)
	18th	42	38th	51	58th	63	78th	72	98th	84	<ul> <li>between the 75th and 76th.</li> </ul>
	19th	42	39th	52	59th	64	79th	74	99th	84	
	20th	42	40th	52	60th	64	80th	74	100th	85	$Q3 = (71 + 71) \div 2 = 71$

Inter Quartile Range(IQR) is the measure of variability, based on dividing a dataset into quartiles.

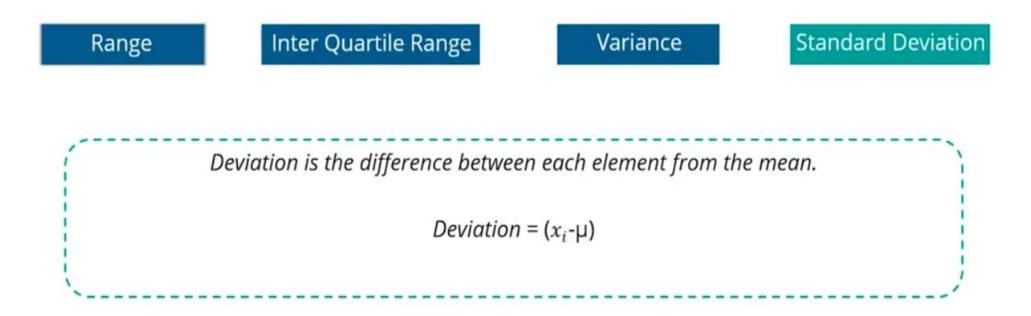
- Quartiles divide a rank-ordered data set into four equal parts, denoted by Q1, Q2, and Q3, respectively
- The interquartile range is equal to Q3 minus Q1, i.e., IQR = Q3 Q1

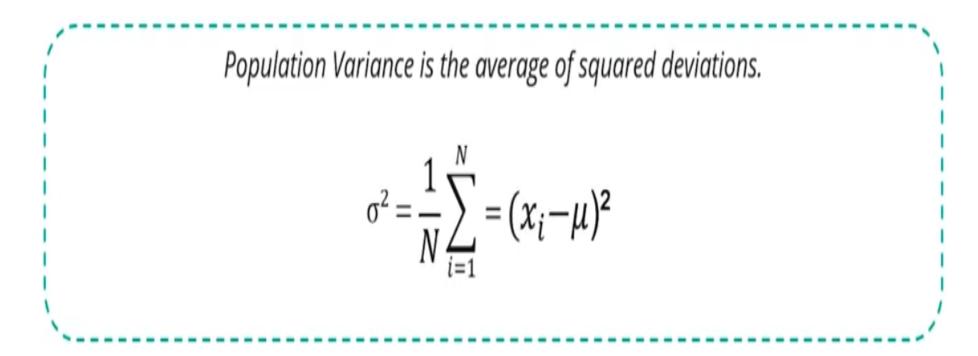


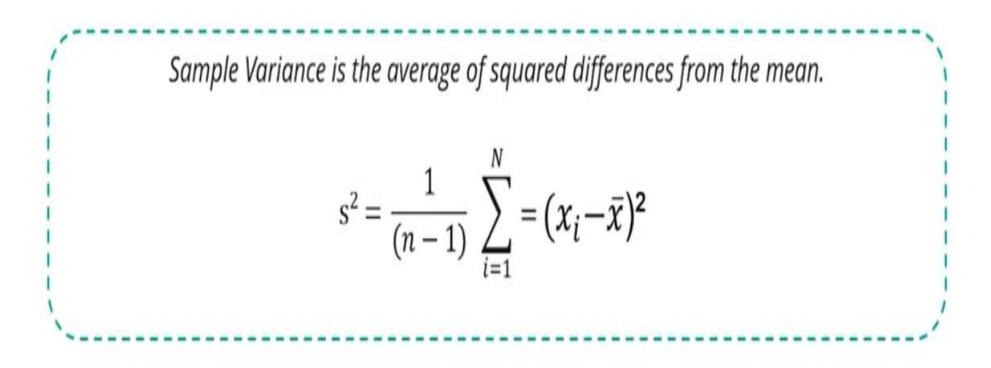
#### Variance

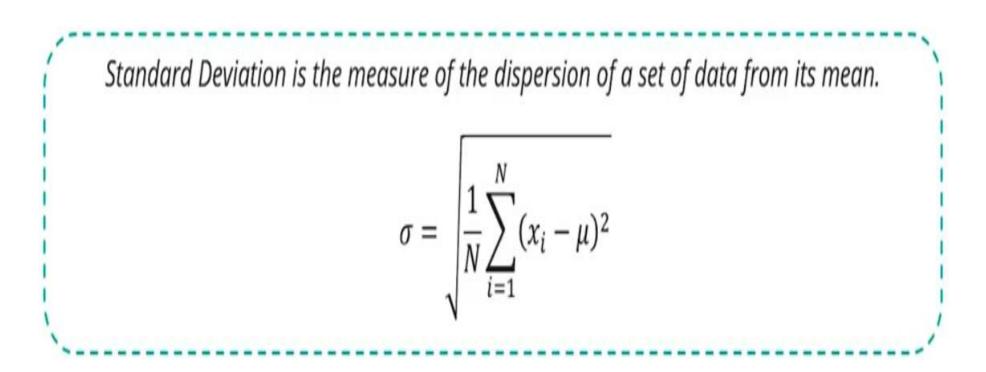


#### Standard Deviation

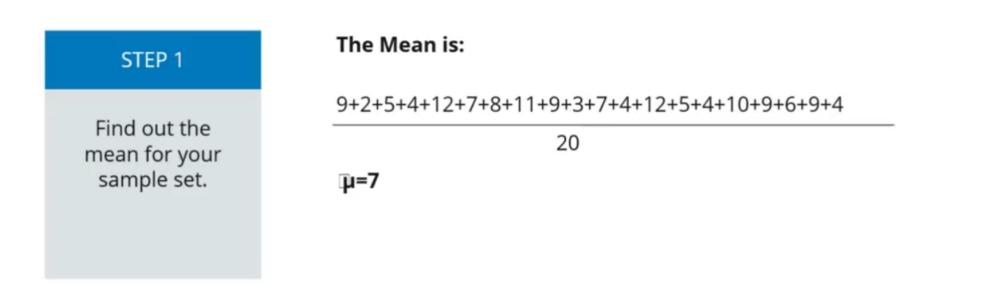






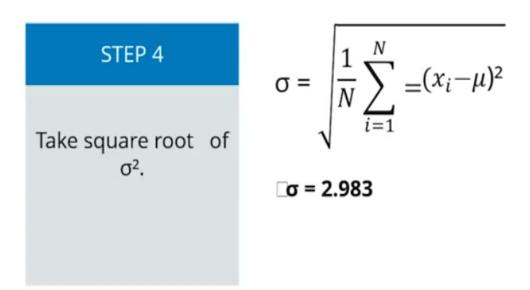


#### Example



	$(x_i - \mu)^2$
STEP 2	<b>(9-7)²</b> = 2²=4
Then for each number, subtract the Mean and square the	(2-7) <sup>2</sup> = (-5) <sup>2</sup> =25 (5-7) <sup>2</sup> = (-2) <sup>2</sup> =4 And so on
result.	□We get the following results: 4, 25, 4, 9, 25, 0, 1, 16, 4, 16, 0, 9, 25, 4, 9, 9, 4, 1, 4, 9

STEP 3	$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2}$
Then work out the mean of those	$\sqrt{\frac{i=1}{4+25+4+9+25+0+1+16+4+16+0+9+25+4+9+9+4+1+4+9}}$
squared differences.	20
	_σ² = 8.9



## Information Gain and Entropy

Entropy

*Entropy measures the impurity or uncertainty present in the data.* 

$$H(S) = -\sum_{i=1}^{N} p_i \log_2 p_i$$

where:

- S set of all instances in the dataset
- N number of distinct class values
- pi event probability

Information Gain (IG)

IG indicates how much "information" a particular feature/ variable gives us about the final outcome.

$$Gain(A,S) = H(S) - \sum_{j=1}^{v} \frac{|S_j|}{|S|} \cdot H(S_j) = H(S) - H(A,S)$$

where:

*H*(*S*) – entropy of the whole dataset *S* 

|Sj| – number of instance with j value of an attribute A

|S| – total number of instances in dataset S

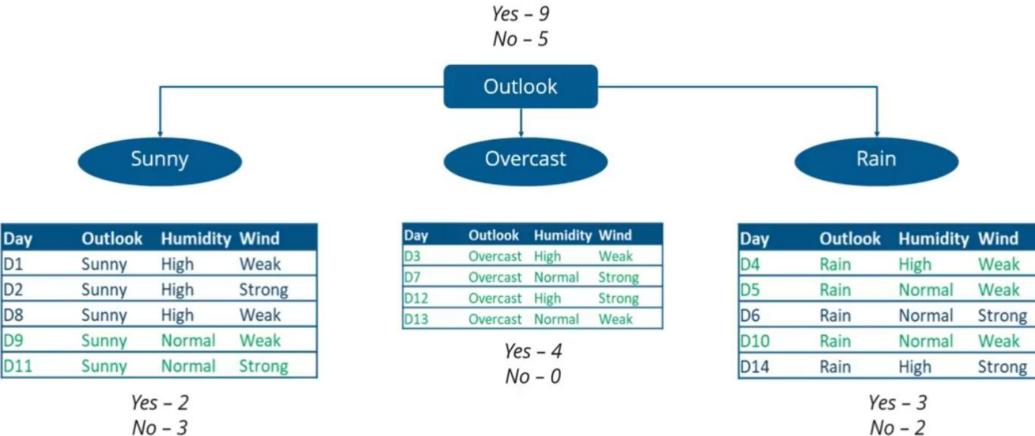
- v set of distinct values of an attribute A
- H(Sj) entropy of subset of instances for attribute A

• H(A, S) – entropy of an attribute A

#### Use Case



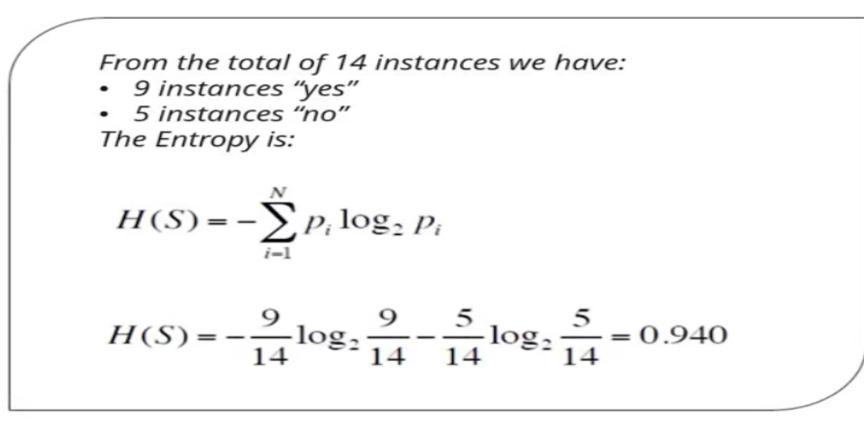
Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes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



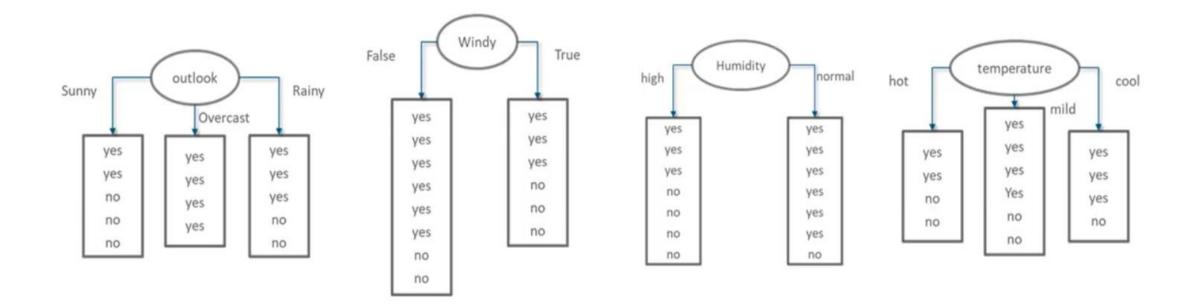
No - 3

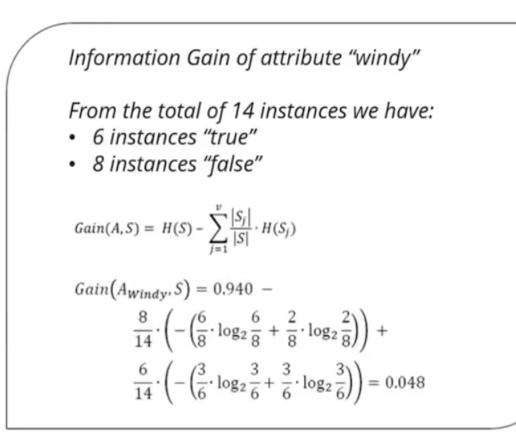
D1

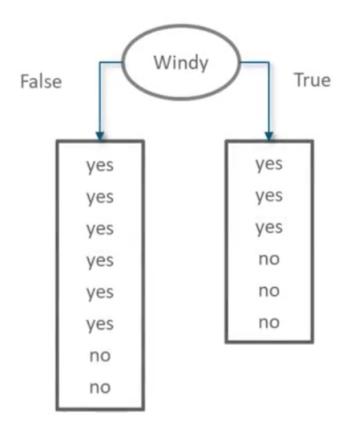
D2

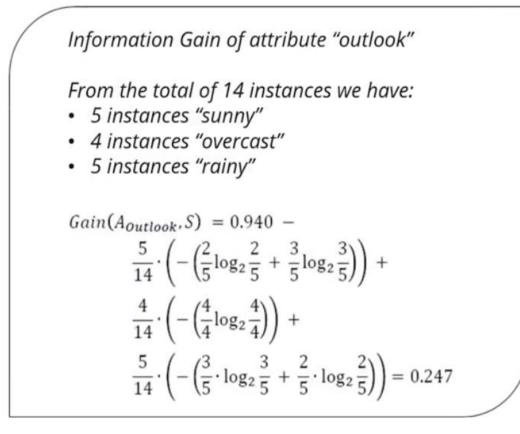


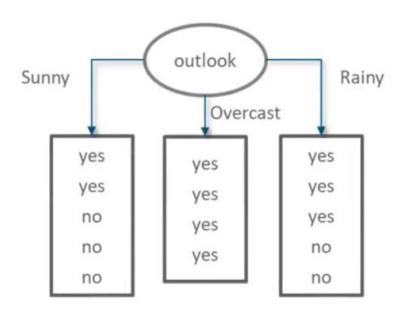
#### Selecting the root variable

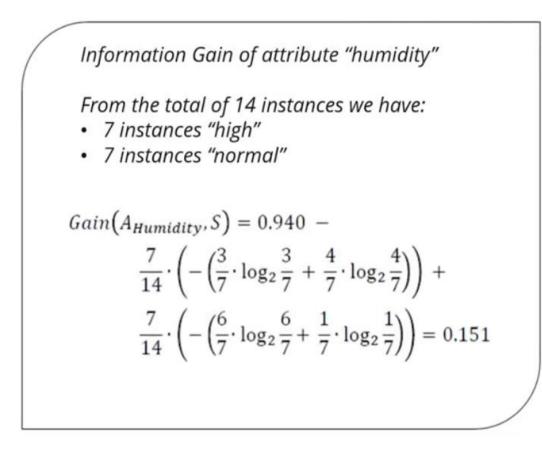


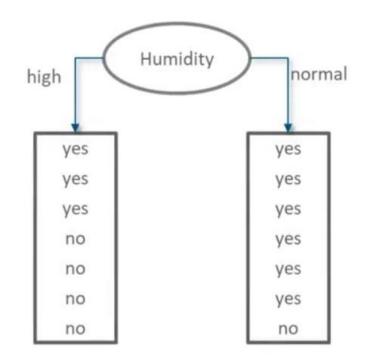




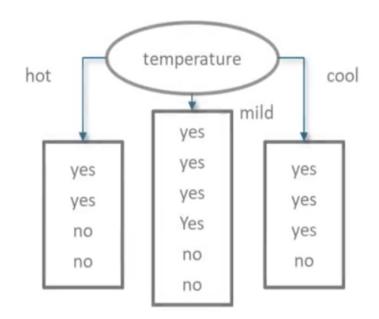


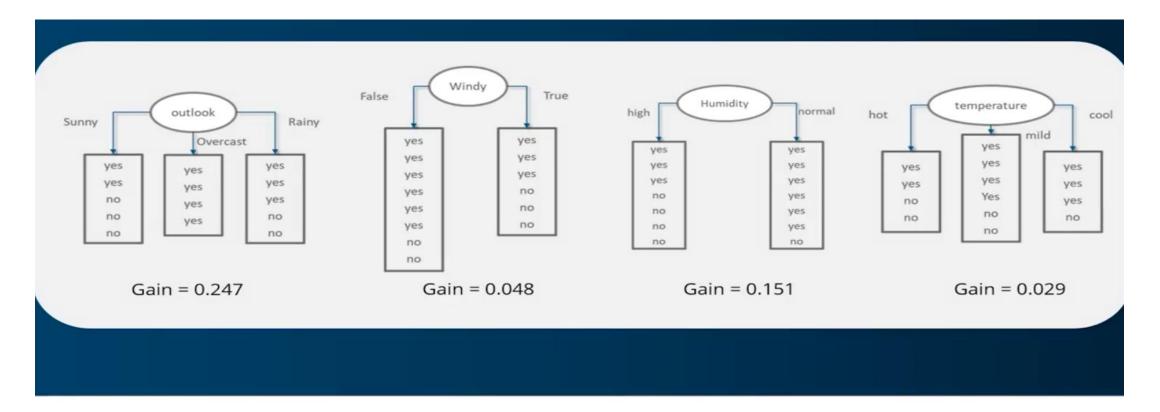




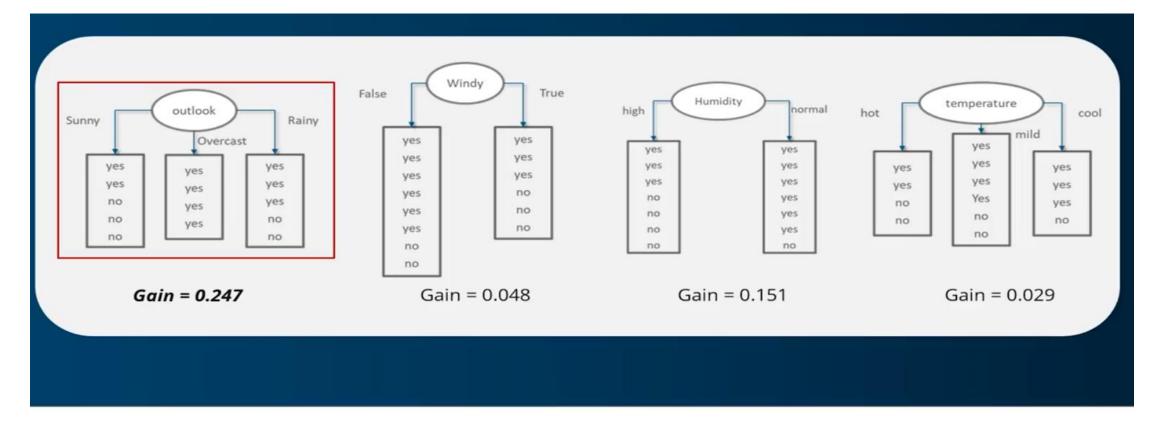


#### Information Gain of attribute "temperature" From the total of 14 instances we have: 4 instances "hot" 6 instances "mild" 4 instances "cool" $Gain(A_{Temperature}, S) = 0.940 \frac{4}{14} \cdot \left( -\left(\frac{2}{4} \cdot \log_2 \frac{2}{4} + \frac{2}{4} \cdot \log_2 \frac{2}{4}\right) \right) +$ $\frac{6}{14} \cdot \left( -\left(\frac{4}{6} \cdot \log_2 \frac{4}{6} + \frac{2}{6} \cdot \log_2 \frac{2}{6}\right) \right) +$ $\frac{4}{14} \cdot \left( -\left(\frac{3}{4} \cdot \log_2 \frac{3}{4} + \frac{1}{4} \cdot \log_2 \frac{1}{4}\right) \right) = 0.029$





The variable with the highest IG is used to split the data at the root node.



The variable with the highest IG is used to split the data at the root node. The 'Outlook' variable has the highest IG, therefore it can be assigned to the root node.

#### Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.

Confusion Matrix represents a tabular representation of Actual vs Predicted values You can calculate the accuracy of your model with:

True Positives + True Negatives

True Positives + True Negatives + False Positives + False Negatives

- There are two possible predicted classes: "yes" and "no"
- The classifier made a total of 165 predictions
- Out of those 165 cases, the classifier predicted "yes" 110 times, and "no" 55 times
- In reality, 105 patients in the sample have the disease, and 60 patients do not



n=165	Predicted: NO	Predicted: YES
Actual:		
NO	50	10
Actual:		
YES	5	100

