

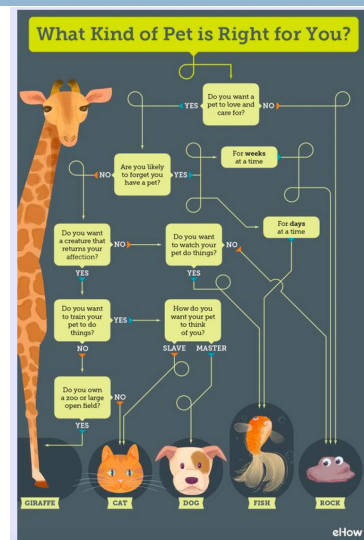
# DECISION TREE AND RANDOM FOREST

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# Decision Tree Algorithm

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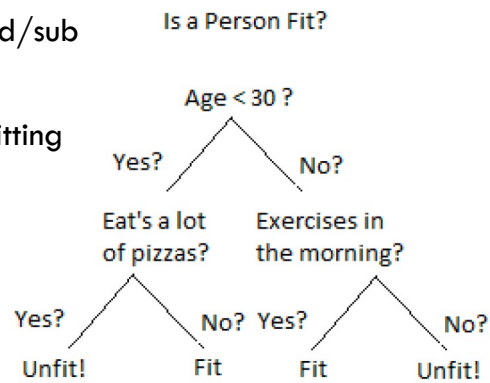
- Similar to how humans make many different decisions
- **Decision trees** look at one feature/variable at a time



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## Decision Tree Algorithm

- Root node
- Parent, child/sub nodes
- Branch, splitting
- Leaf nodes



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## Decision Tree Algorithm

- Training dataset



Day	Outlook	Temp	Humidity	Wind	Tennis?
1	Sunny	Hot	High	Weak	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Weak	Yes
4	Rain	Mild	High	Weak	Yes
5	Rain	Cool	Normal	Weak	Yes
6	Rain	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
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13	Overcast	Hot	Normal	Weak	Yes
14	Rain	Mild	High	Strong	No

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## Decision Tree Algorithm

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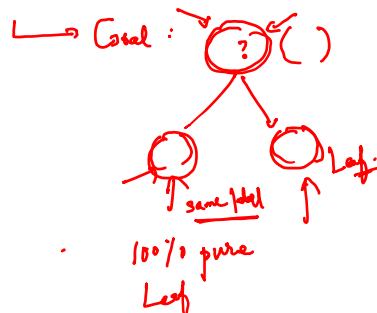
- How can we build a decision tree given a data set?

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## Decision Tree Algorithm

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- We will make the **best choice at each step**
- Identify the best feature/attribute for the **each node**



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## Decision Tree Algorithm

- Identify the best feature/attribute for **root node**
  - Best split: results of each branch should be as **homogeneous** (or **pure**) as possible
  - a feature that reduces **impurity** as much as possible
  - How do we **measure the impurity** in a set of examples
    - ✓ Entropy from information theory
    - Alternatively, use **Gini Index** →

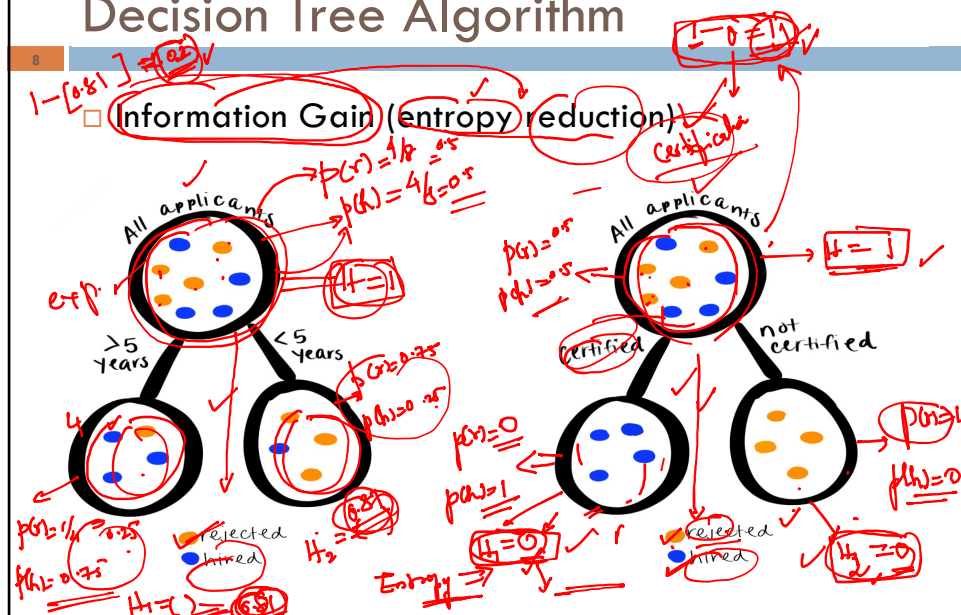
$$\text{InfoGain} = H_{\text{before}} - H_{\text{after}}$$

$$\text{InfoGain}(\text{feature}) = H - \sum (\text{weighted avg. of entropy of child nodes})$$

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## Decision Tree Algorithm

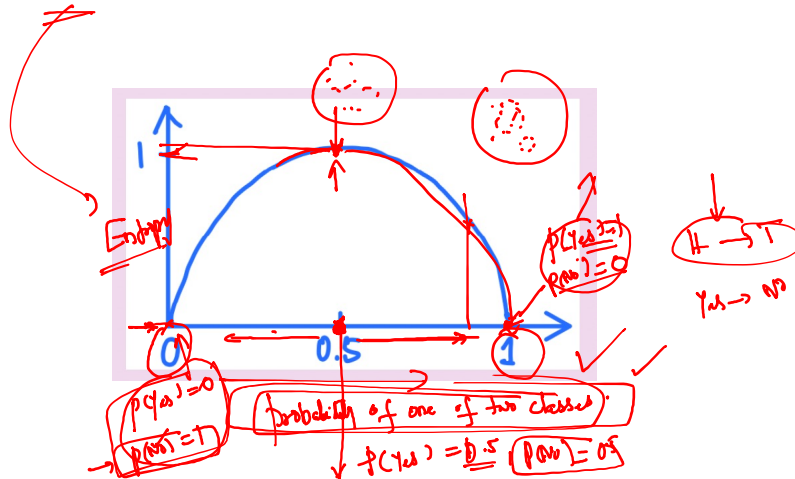
- **Information Gain** (entropy reduction)



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## Decision Tree Algorithm

- Entropy for a distribution over two outcomes



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## Decision Tree Algorithm

- Quantifying the information content of a feature

- entropy of the examples <sup>before split</sup> before testing the feature
  - minus the entropy of the examples after testing the feature

Information Gain

after the split  
 $H_{\text{before}} - H_{\text{after}}$

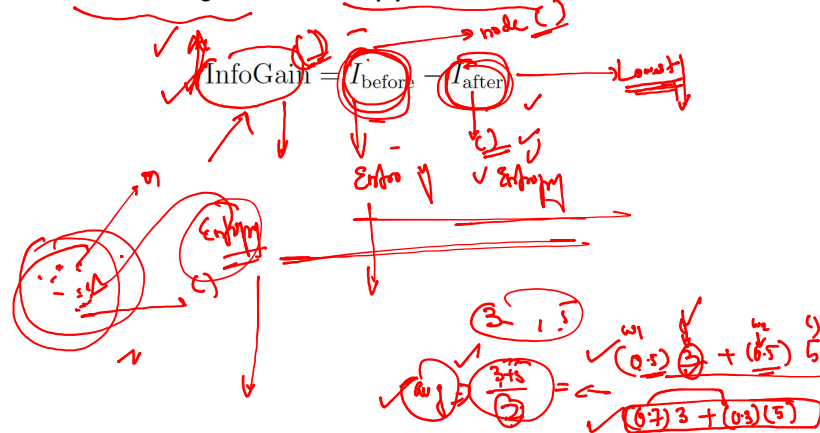
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## Decision Tree Algorithm

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### Quantifying the information content of a feature

#### Information gain or entropy reduction



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## Decision Tree Algorithm

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### Entropy of the examples before we select a feature for the root node

Entropy of the root node:  $H_{\text{before}} = -\left(\frac{9}{14} \log_2 \left(\frac{9}{14}\right) + \frac{5}{14} \log_2 \left(\frac{5}{14}\right)\right) \approx 0.94$

Handwritten notes:  $p(\text{Yes}) = \frac{9}{14}$ ,  $p(\text{No}) = \frac{5}{14}$

Day	Outlook	Temp	Humidity	Wind	Tennis?
1	Sunny	Hot	High	Weak	No
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Handwritten notes:  $p(\text{Yes}) = \frac{9}{14}$ ,  $p(\text{No}) = \frac{5}{14}$

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## Decision Tree Algorithm

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Information gain if we select **Outlook** for the root node

node

$w_1 H_1 + w_2 H_2 + w_3 H_3$   
 $w_1 = \frac{5}{14}, w_2 = \frac{4}{14}, w_3 = \frac{5}{14}$   
 $w_1 + w_2 + w_3 = \frac{14}{14} = 1$

Outlook = { Sunny 2+ 3- 5 total  
 Overcast 4+ 0- 4 total  
 Rain 3+ 2- 5 total }

$\text{Gain(Outlook)} = 0.94 - \left( \frac{5}{14} \cdot I\left(\frac{2}{5}, \frac{3}{5}\right) + \frac{4}{14} \cdot I\left(\frac{4}{4}, \frac{0}{4}\right) + \frac{5}{14} \cdot I\left(\frac{3}{5}, \frac{2}{5}\right) \right)$   
 $= 0.247$

$H(14) = 2.45$   
 $H(5) = 1.5$   
 $H(4) = 1$   
 $H(5) = 1.5$   
 $H(14) = 2.45$

$I(2/5, 3/5) = -[2/5 \log_2 2/5 + 3/5 \log_2 3/5]$   
 $I(4/4, 0/4) = 0$   
 $I(3/5, 2/5) = -[3/5 \log_2 3/5 + 2/5 \log_2 2/5]$

3-way split  $I(2/5, 3/5)$   
 $= -[2/5 \log_2 2/5 + 3/5 \log_2 3/5]$

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## Decision Tree Algorithm

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Information gain if we select **Humidity** for the root node

node

Humidity = { Normal 6+ 1- 7 total  
 High 3+ 4- 7 total }

$\text{Gain(Humidity)} = 0.94 - \left( \frac{7}{14} \cdot I\left(\frac{6}{7}, \frac{1}{7}\right) + \frac{7}{14} \cdot I\left(\frac{3}{7}, \frac{4}{7}\right) \right)$   
 $= 0.151$

$H(14) = 2.45$   
 $H(7) = 1.5$   
 $H(7) = 1.5$   
 $H(14) = 2.45$

$I(6/7, 1/7) = -[6/7 \log_2 6/7 + 1/7 \log_2 1/7]$   
 $I(3/7, 4/7) = -[3/7 \log_2 3/7 + 4/7 \log_2 4/7]$

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## Decision Tree Algorithm

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- Outlook has the greatest information gain

Gain(Outlook) = 0.247  
Gain(Temp) = 0.029  
Gain(Humidity) = 0.151  
Gain(Wind) = 0.048

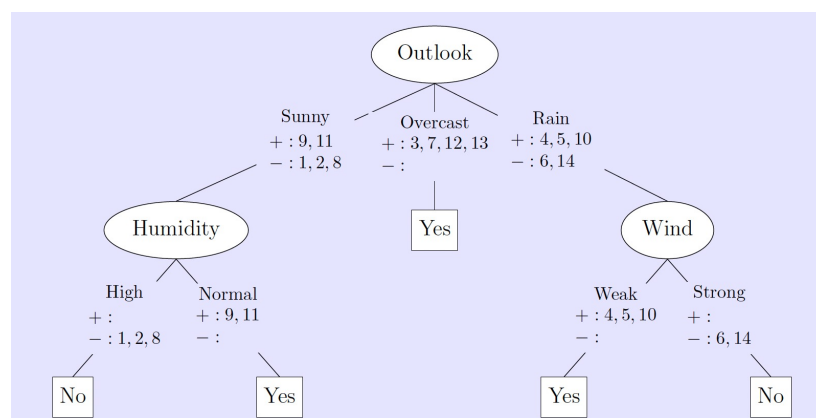
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## Decision Tree Algorithm

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- Outlook has the greatest information gain



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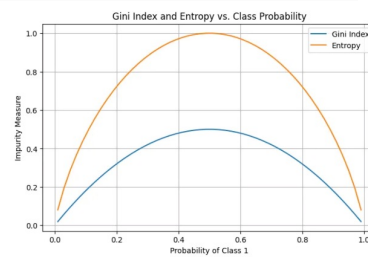


## Gini Impurity to Build Decision Trees

$$Gini(D) = 1 - \sum_{i=1}^k p_i^2$$

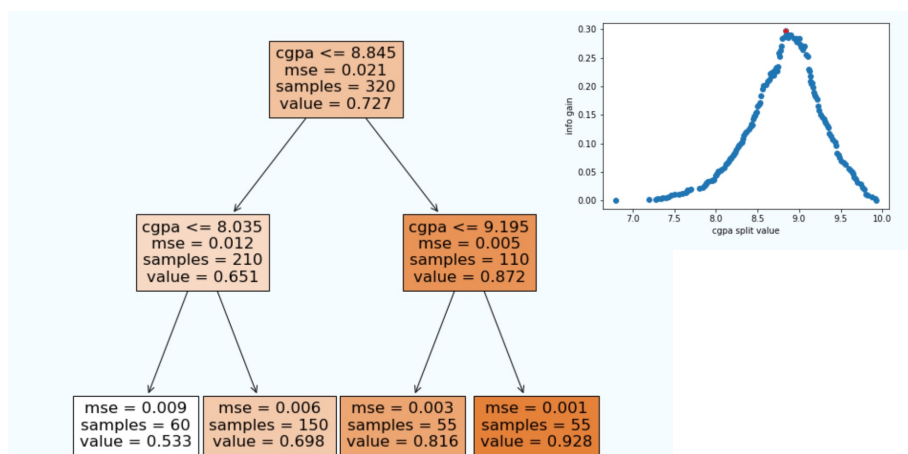
$$Gini_A(D) = \frac{n_1}{n} Gini(D_1) + \frac{n_2}{n} Gini(D_2)$$

$$\Delta Gini(A) = Gini(D) - Gini_A(D)$$



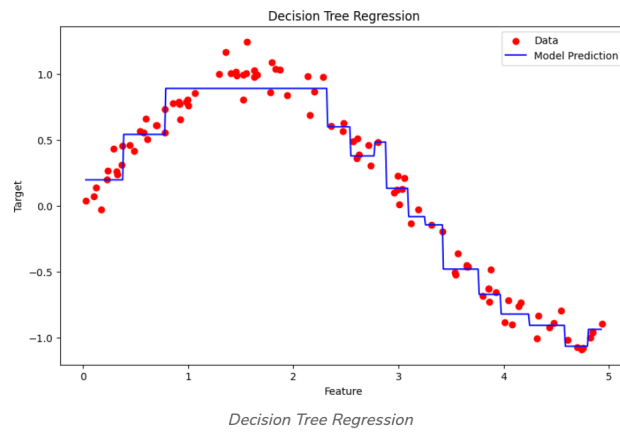
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## Decision Tree for Regression



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## Decision Tree for Regression



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Thank You!

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