# DECISION TREE AND RANDOM FOREST

1

## Decision Tree Algorithm

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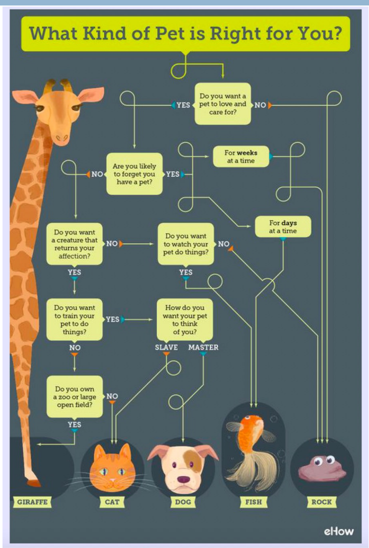
- Similar to how humans make many different decisions
- Decision trees look at one feature/variable at a time

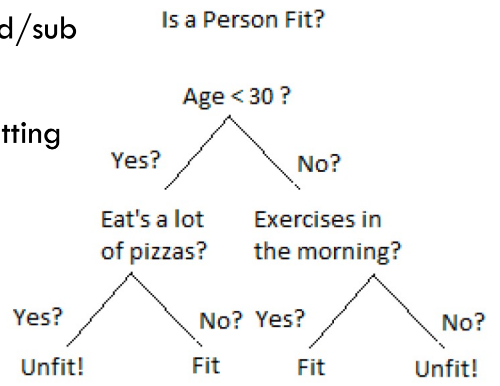



2

# Decision Tree Algorithm

3

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




3

# Decision Tree Algorithm

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- 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 |
| 8 | Sunny | Mild | High | Weak | No |
| 9 | Sunny | Cool | Normal | Weak | Yes |
| 10 | Rain | Mild | Normal | Weak | Yes |
| 11 | Sunny | Mild | Normal | Strong | Yes |
| 12 | Overcast | Mild | High | Strong | Yes |
| 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

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- 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

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## Decision Tree Algorithm

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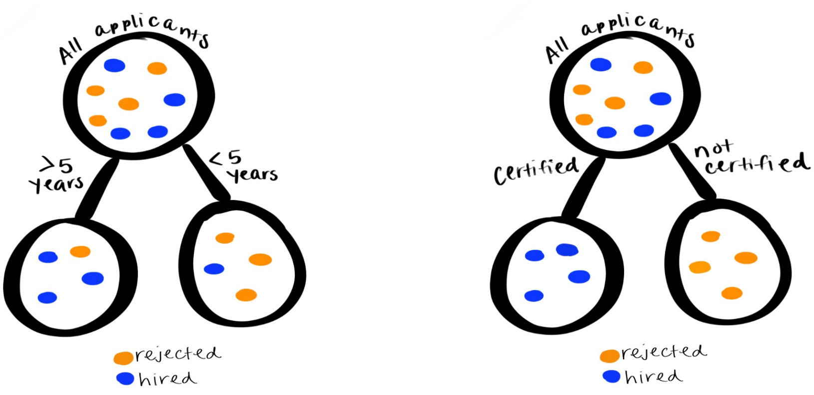
- Information Gain (entropy reduction)

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## Decision Tree Algorithm

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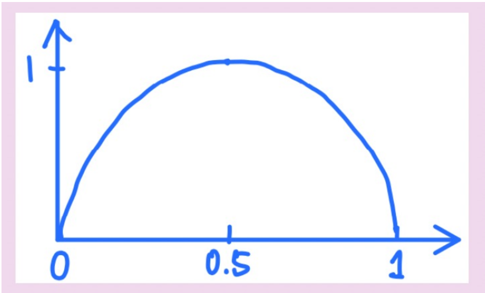
- Entropy for a distribution over two outcomes

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## Decision Tree Algorithm

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- Quantifying the information content of a feature
  - entropy of the examples before testing the feature minus the entropy of the examples after testing the feature – Information Gain

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## Decision Tree Algorithm

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- Quantifying the information content of a feature
  - Information gain or entropy reduction

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

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## Decision Tree Algorithm

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

$$H_{\text{before}} = -\left(\frac{9}{14}\log_2\left(\frac{9}{14}\right) + \frac{5}{14}\log_2\left(\frac{5}{14}\right)\right)$$
$$\approx 0.94$$

| 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 |
| 8 | Sunny | Mild | High | Weak | No |
| 9 | Sunny | Cool | Normal | Weak | Yes |
| 10 | Rain | Mild | Normal | Weak | Yes |
| 11 | Sunny | Mild | Normal | Strong | Yes |
| 12 | Overcast | Mild | High | Strong | Yes |
| 13 | Overcast | Hot | Normal | Weak | Yes |
| 14 | Rain | Mild | High | Strong | No |

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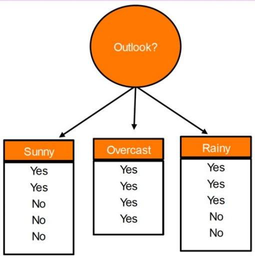
# Decision Tree Algorithm

13

- Information gain if we select Outlook for the root node

$$\text{Outlook} = \begin{cases} \text{Sunny} & 2+ \quad 3- \quad 5 \text{ total} \\ \text{Overcast} & 4+ \quad 0- \quad 4 \text{ total} \\ \text{Rain} & 3+ \quad 2- \quad 5 \text{ total} \end{cases}$$

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




| 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 |
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| 12 | Overcast | Mild | High | Strong | Yes |
| 13 | Overcast | Hot | Normal | Weak | Yes |
| 14 | Rain | Mild | High | Strong | No |

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# Decision Tree Algorithm

14

- Information gain if we select Humidity for the root node

$$\text{Humidity} = \begin{cases} \text{Normal} & 6+ \quad 1- \quad 7 \text{ total} \\ \text{High} & 3+ \quad 4- \quad 7 \text{ total} \end{cases}$$

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

| 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 |
| 8 | Sunny | Mild | High | Weak | No |
| 9 | Sunny | Cool | Normal | Weak | Yes |
| 10 | Rain | Mild | Normal | Weak | Yes |
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| 12 | Overcast | Mild | High | Strong | Yes |
| 13 | Overcast | Hot | Normal | Weak | Yes |
| 14 | Rain | Mild | High | Strong | No |

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# Decision Tree Algorithm

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- Outlook has the greatest information gain

Gain(**Outlook**) = **0.247**   Gain(Humidity) = 0.151

Gain(Temp) = 0.029   Gain(Wind) = 0.048

| 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 |
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# Decision Tree Algorithm

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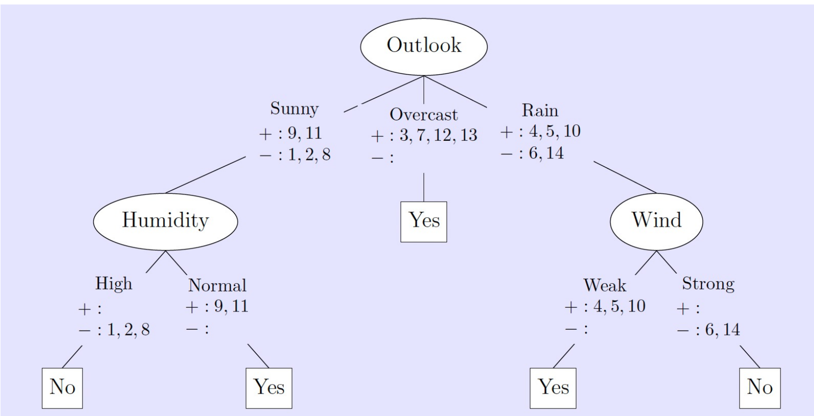
- Outlook has the greatest information gain

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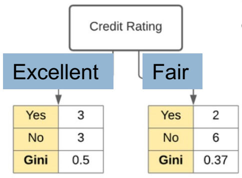
# Gini Impurity to Build Decision Trees

```
age  income student credit_rate default
0        youth    high      no        fair      no
1        youth    high      no   excellent      no
2   middle_age    high      no        fair     yes
3       senior  medium      no        fair     yes
4       senior     low     yes        fair     yes
5       senior     low     yes   excellent      no
6   middle_age     low     yes   excellent     yes
7        youth  medium      no        fair      no
8        youth     low     yes        fair     yes
9       senior  medium     yes        fair     yes
10       youth  medium     yes   excellent     yes
11  middle_age  medium      no   excellent     yes
12  middle_age    high     yes        fair     yes
13      senior  medium      no   excellent      no
```

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

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

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


Gini Impurity for Credit Rating is 0.429

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# Thank You!

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