# Trees based methods

## Decision Trees, Random Forests and Gradient Boosting

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- It works for both categorical and continuous input and output variables.
- In this technique, we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter/differentiator in input variables.

# Decision trees

# A decision tree example

Training examples: **9 yes / 5 no**

| 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 |

New data:

| Day | Outlook | Humidity | Wind | Play |
|---|---|---|---|---|
| D15 | Rain | High | Weak | ? |

Figure 1: Playing tennis?

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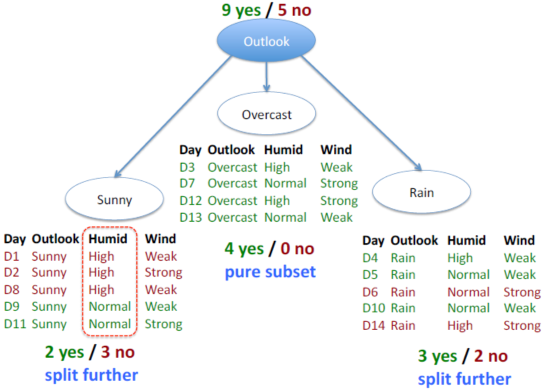
Figure 2: Playing tennis?

# A decision tree example

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# A decision tree example

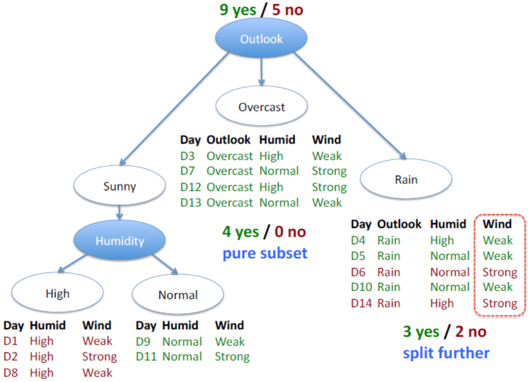


Figure 4: Playing tennis?

# A decision tree example

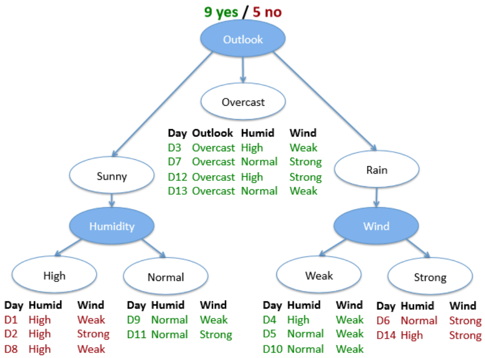


Figure 5: Playing tennis?

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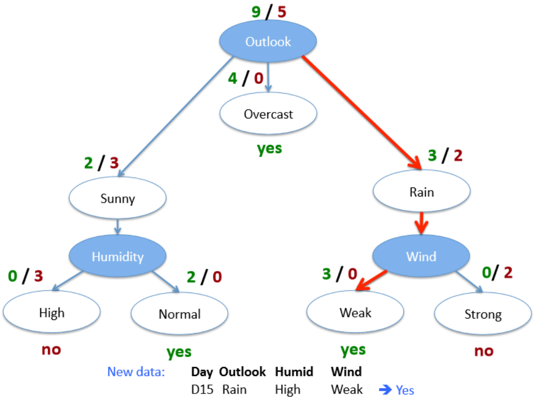


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6. **Branch / Sub-Tree:** A sub section of entire tree is called branch or sub-tree.
7. **Parent and Child Node:** A node, which is divided into sub-nodes is called parent node of sub-nodes where as sub-nodes are the child of parent node.

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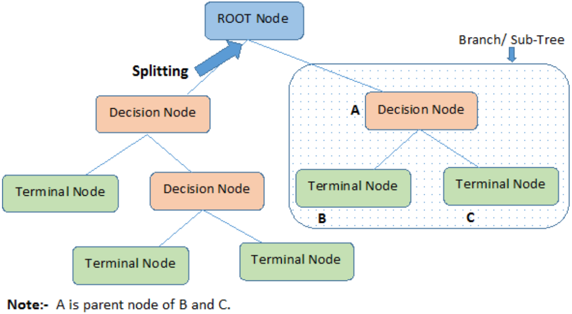


Figure 7: Trees Terminology

# Advantages & disadvantages

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- Easy to Understand:

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- Data type is not a constraint.
- Non parametric method.

## Disadvantages

- Over fitting
- Not fit for continuous variables

# How does a tree decide where to split?

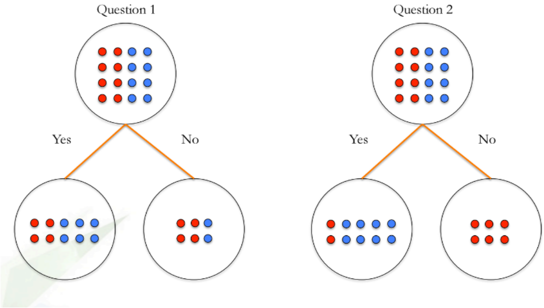


Figure 8: Tree spliting

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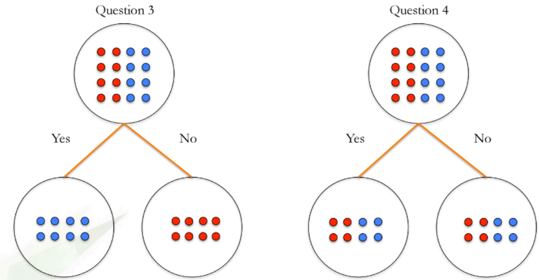


$$E(S) = -p_+ log(p_+) - p_- log(p_-)$$

Figure 9: Compute the entropy

# How does a tree decide where to split?

$$-\left(\frac{8}{8}\right) log_2 \left(\frac{8}{8}\right) - \left(\frac{0}{8}\right) log_2 \left(\frac{0}{8}\right) = 0$$

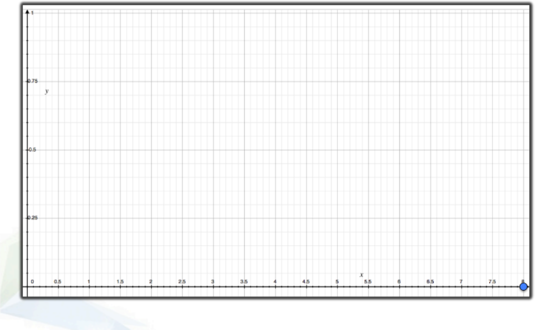


Figure 10: Compute the entropy

# How does a tree decide where to split?

$$-\left(\frac{7}{8}\right) log_2 \left(\frac{7}{8}\right) - \left(\frac{1}{8}\right) log_2 \left(\frac{1}{8}\right) = 0.54$$

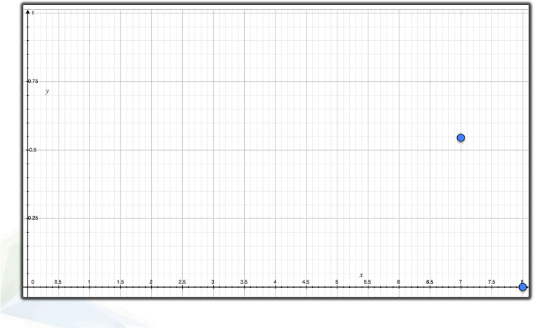

Figure 11: Compute the entropy

# How does a tree decide where to split?

$$-\left(\frac{6}{8}\right) log_2 \left(\frac{6}{8}\right) - \left(\frac{2}{8}\right) log_2 \left(\frac{2}{8}\right) = 0.81$$

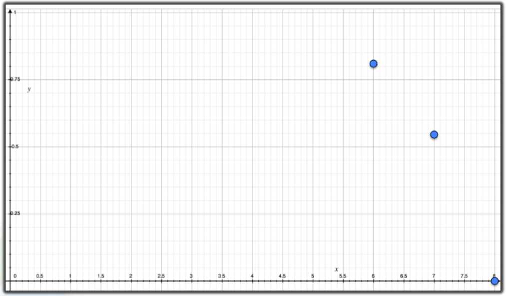


Figure 12: Compute the entropy

# How does a tree decide where to split?

$$-\left(\frac{5}{8}\right) log_2 \left(\frac{5}{8}\right) - \left(\frac{3}{8}\right) log_2 \left(\frac{3}{8}\right) = 0.95$$

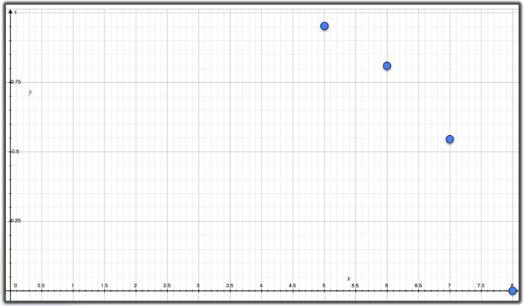


Figure 13: Compute the entropy

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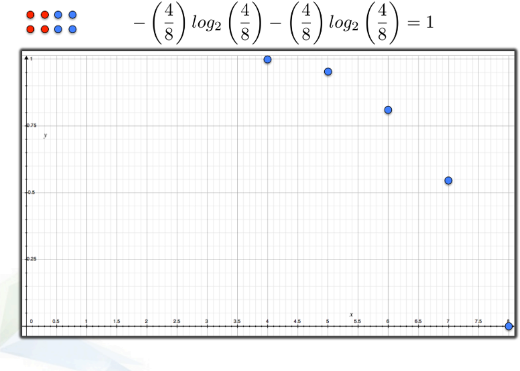


Figure 14: Compute the entropy

# How does a tree decide where to split?

$$-\left(\frac{3}{8}\right) log_2 \left(\frac{3}{8}\right) - \left(\frac{5}{8}\right) log_2 \left(\frac{5}{8}\right) = 0.95$$

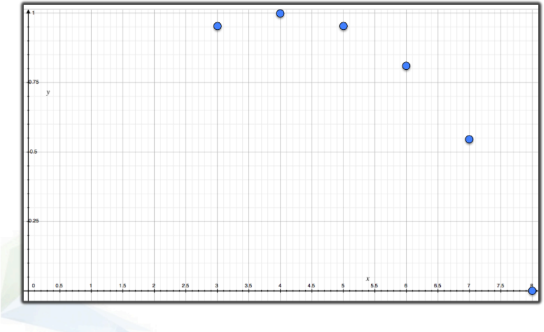


Figure 15: Compute the entropy

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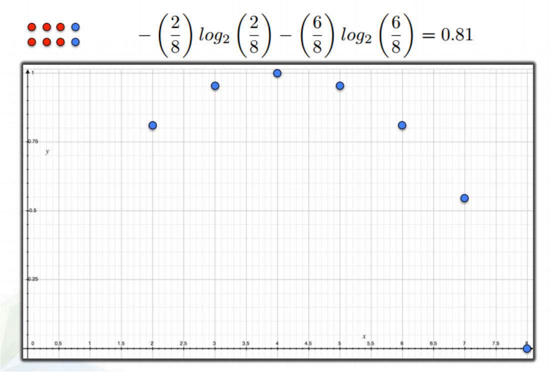


Figure 16: Compute the entropy

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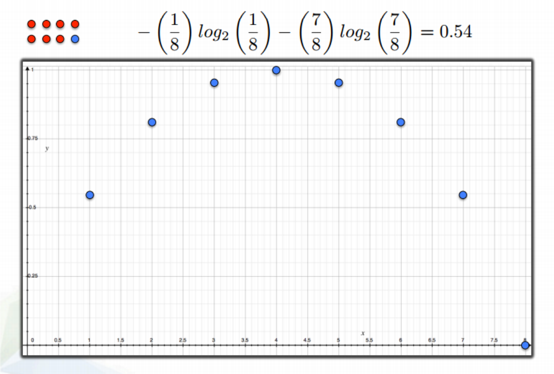


Figure 17: Compute the entropy

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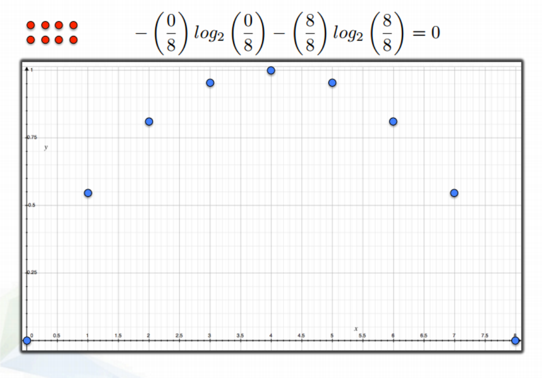


Figure 18: Compute the entropy

# How does a tree decide where to split?

$$y = -\sum_{i=1}^{k} p_i log_k(p_i)$$

$$y = -\underbrace{\left[\left(\frac{1}{10}\right) log_4 \left(\frac{1}{10}\right)\right]}_{\text{Red}} - \underbrace{\left[\left(\frac{3}{10}\right) log_4 \left(\frac{3}{10}\right)\right]}_{\text{Green}} - \underbrace{\left[\left(\frac{2}{10}\right) log_4 \left(\frac{2}{10}\right)\right]}_{\text{Blue}} - \underbrace{\left[\left(\frac{4}{10}\right) log_4 \left(\frac{4}{10}\right)\right]}_{\text{Yellow}}$$

Figure 19: Compute the entropy

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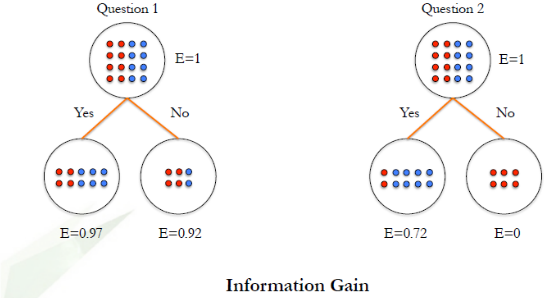


$$G(S,Q) = E(S) - \sum_{i=1}^{k} p_i E(S,Q_i)$$

Figure 20: Compute information gain

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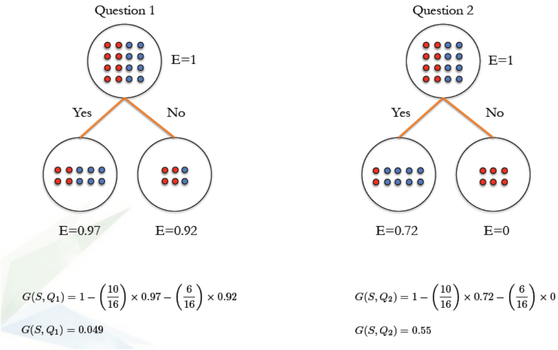


Figure 21: Compute information gain

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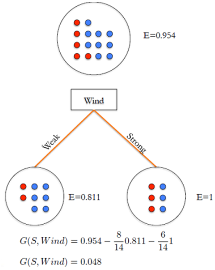


Figure 22: Compute information gain

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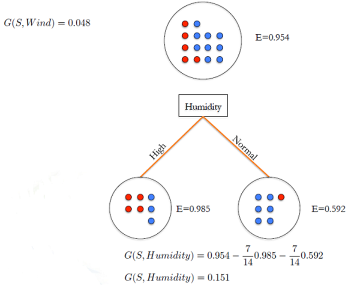


Figure 23: Compute information gain

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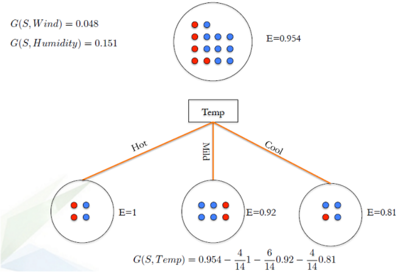


Figure 24: Compute information gain

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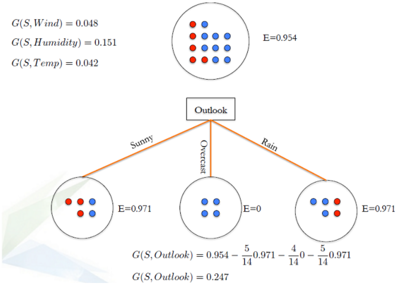


Figure 25: Compute information gain

## key parameters of tree modeling

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  - Tree pruning

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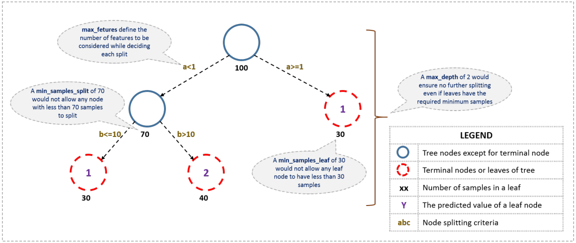


Figure 26: constraints on tree size

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5. Maximum features to consider for split

# Tree pruning

1. Make the decision tree to a large depth.

Suppose a split is giving us a gain of say -10 (loss of 10) and then the next split on that gives us a gain of 20. A simple decision tree will stop at step 1 but in pruning, we will see that the overall gain is $+10$ and keep both leaves.

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- If there is a high non-linearity andcomplex relationship between feature and label tree model will outperform a classical regression method.
- If you need to build a model which is easy to explain to people, a decision tree model will always do better than a linear model. Decision tree models are even simpler to interpret than linear regression!

# Working with decision trees in R

**Go to the notebook**