# Decision Tree
# Random Forest

# Decision Tree Example

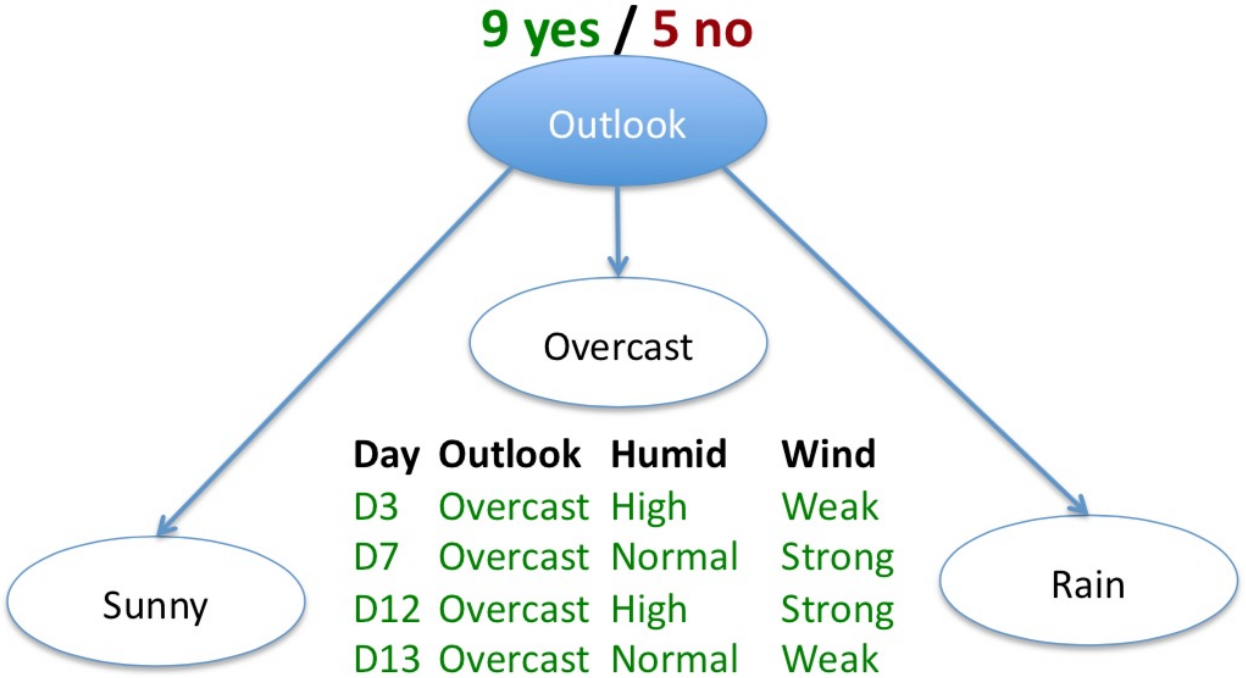
Training examples: **9 yes / 5 no**

| 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:

| | | | | |
|---|---|---|---|---|
| D15 | Rain | High | Weak | ? |

# Decision Tree Example




| Day | Outlook | Humid | Wind |
|---|---|---|---|
| D3 | Overcast | High | Weak |
| D7 | Overcast | Normal | Strong |
| D12 | Overcast | High | Strong |
| D13 | Overcast | Normal | Weak |

**4 yes / 0 no**
**pure subset**

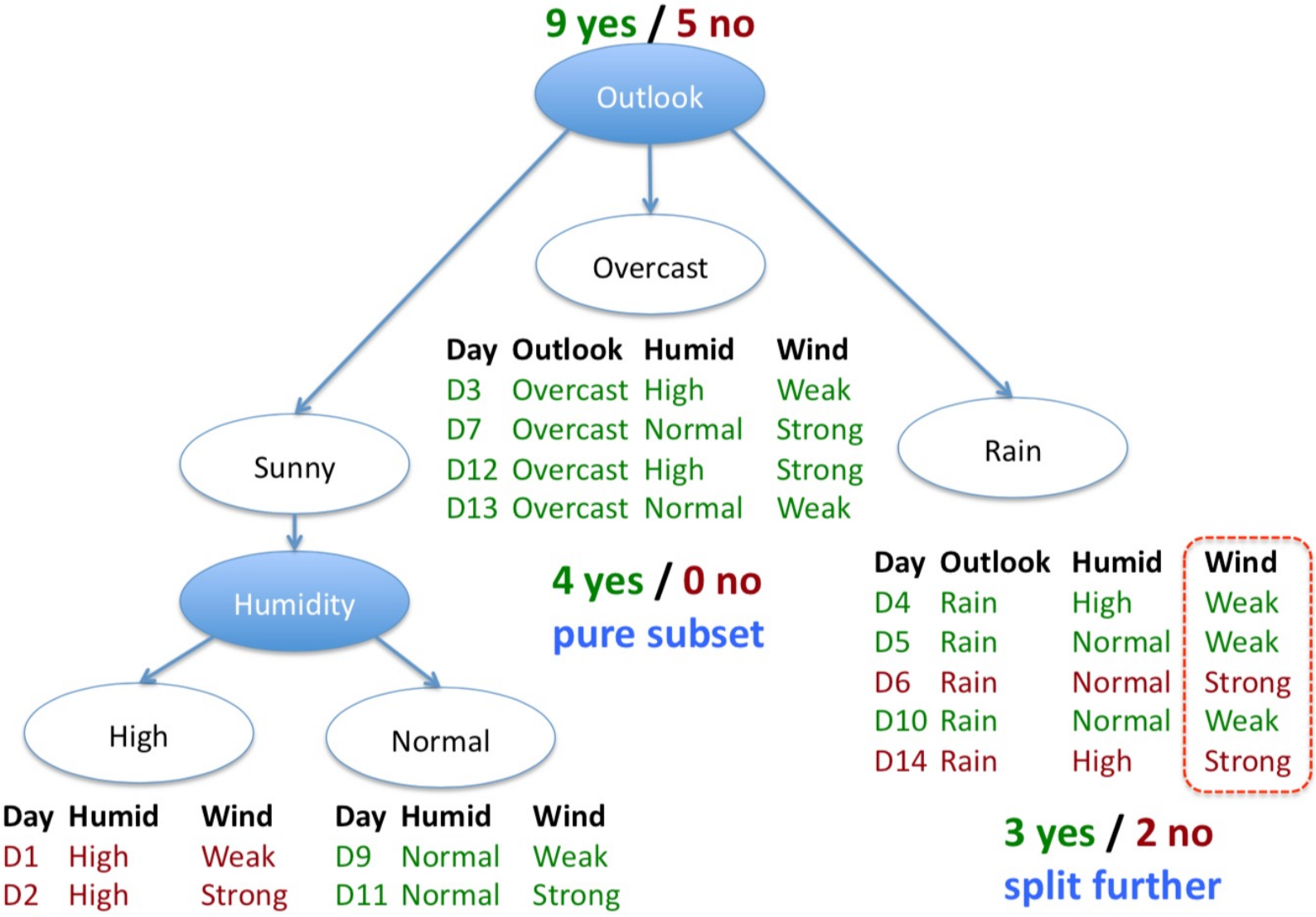
| Day | Outlook | Humid | Wind |
|---|---|---|---|
| D1 | Sunny | High | Weak |
| D2 | Sunny | High | Strong |
| D8 | Sunny | High | Weak |
| D9 | Sunny | Normal | Weak |
| D11 | Sunny | Normal | Strong |

**2 yes / 3 no**
**split further**

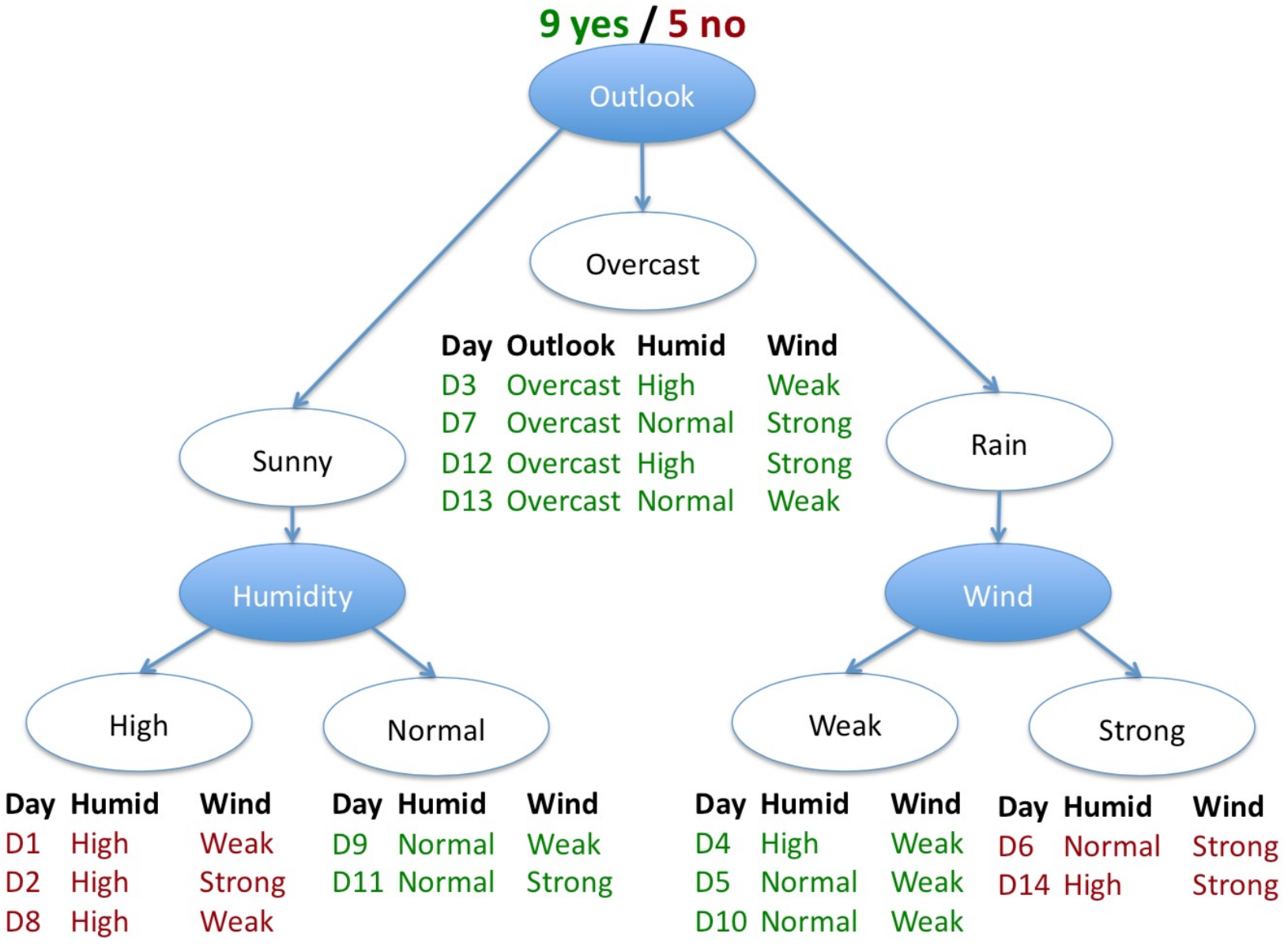
| Day | Outlook | Humid | Wind |
|---|---|---|---|
| D4 | Rain | High | Weak |
| D5 | Rain | Normal | Weak |
| D6 | Rain | Normal | Strong |
| D10 | Rain | Normal | Weak |
| D14 | Rain | High | Strong |

**3 yes / 2 no**
**split further**

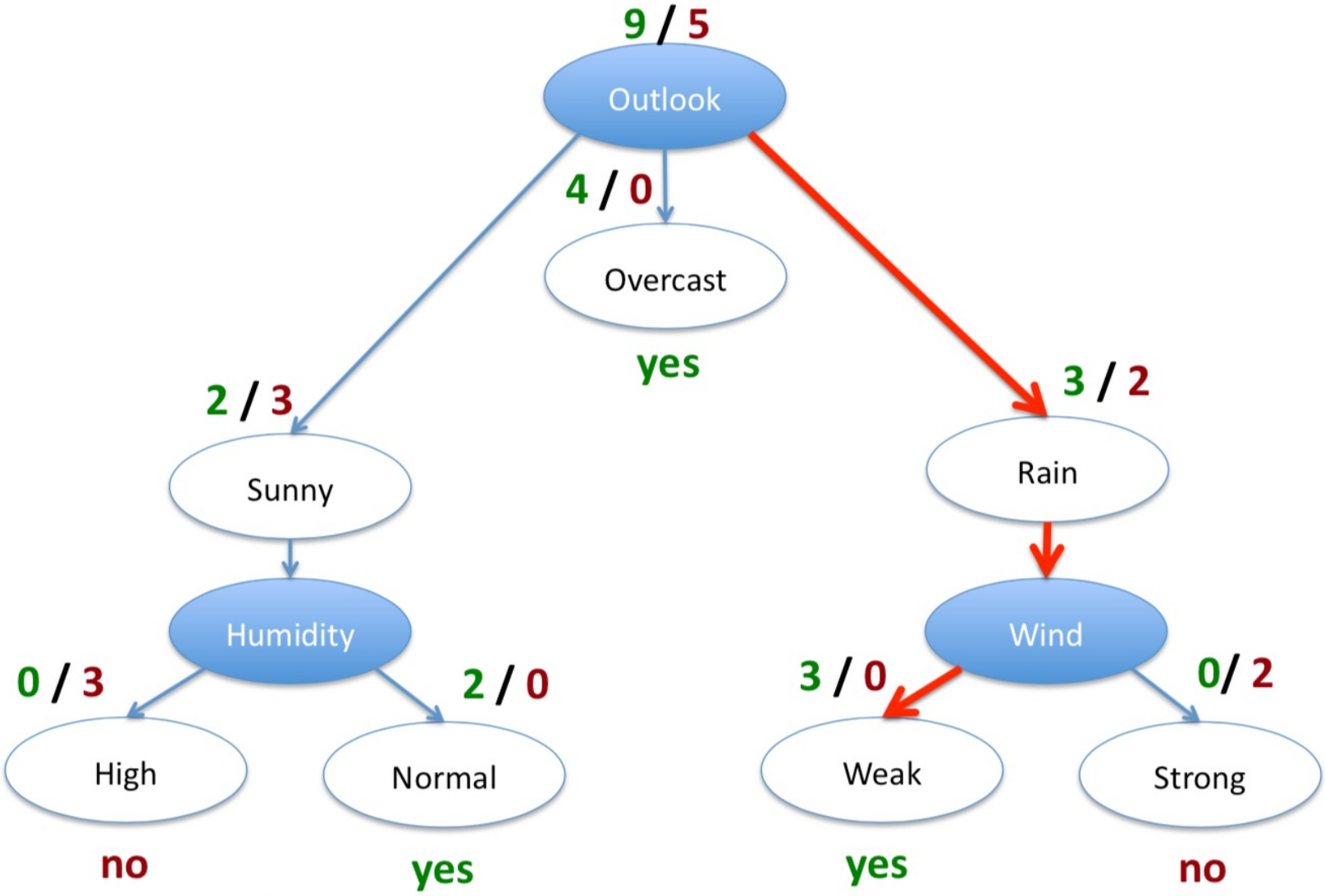
# Decision Tree Example



# Decision Tree Example



# Decision Tree Example




New data:

| Day | Outlook | Humid | Wind | |
|---|---|---|---|---|
| D15 | Rain | High | Weak | → Yes |

# ID3 Algorithm

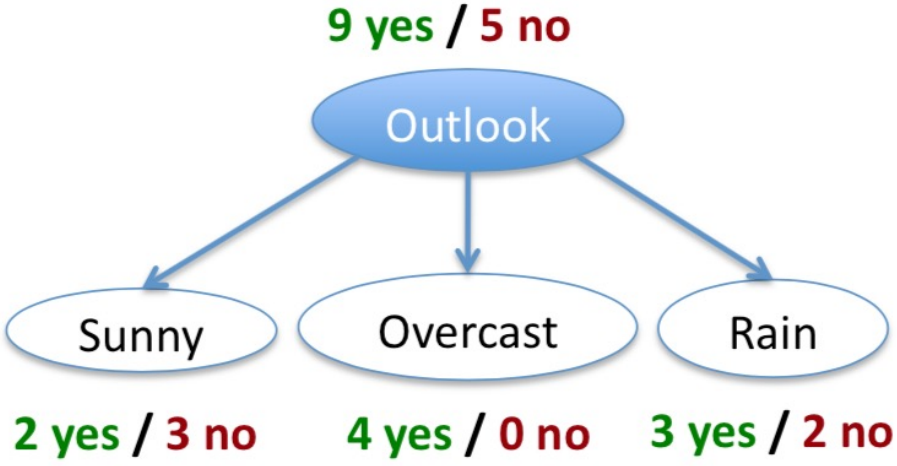
**node** = Root

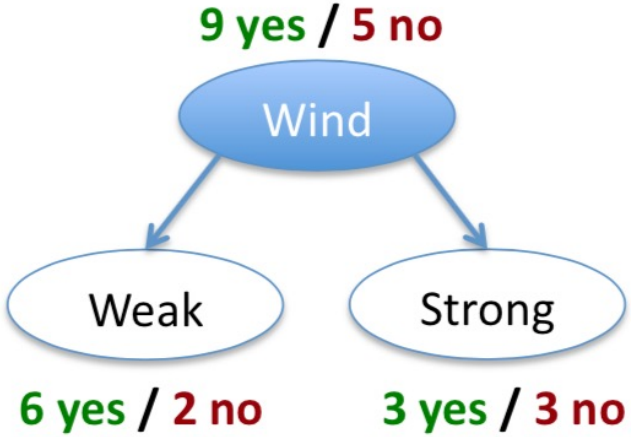
examples = Training Set

Split (**node**, {**examples**} ):

1. Find A, the ***best attribute*** for splitting the {**examples**}
2. Create decision nodes for attribute A (i.e., **child nodes** of **node**)
3. Split training {**examples**} to **child nodes**
4. If examples perfectly classified (subset is pure): STOP
   else: iterate over new child nodes
   Split (**child_node**, {**subset of examples**} )

# Find The Best Attribute




- Want to measure "purity" of the split
  - more certain about Yes/No after the split
    - pure set (4 yes / 0 no) => completely certain (100%)
    - impure (3 yes / 3 no) => completely uncertain (50%)
  - can't use P("yes" | set):
    - must be symmetric: 4 yes / 0 no as pure as 0 yes / 4 no

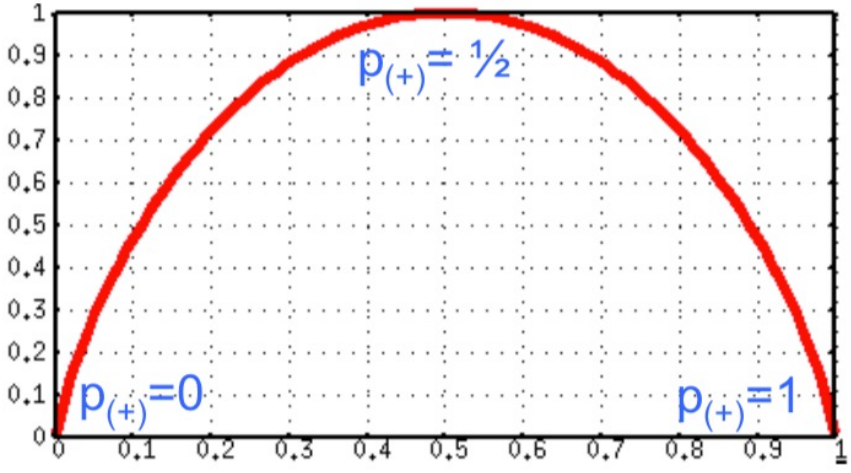
# Entropy

- Entropy: $H(S) = - p_{(+)} \log_2 p_{(+)} - p_{(-)} \log_2 p_{(-)}$ bits
  - S … subset of training examples
  - $p_{(+)}$ / $p_{(-)}$ … % of positive / negative examples in S
- Interpretation: assume item X belongs to S
  - how many bits need to tell if X positive or negative
- impure (3 yes / 3 no):

$$H(S) = -\frac{3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6} = 1 \text{ bits}$$

- pure set (4 yes / 0 no):

$$H(S) = -\frac{4}{4}\log_2\frac{4}{4} - \frac{0}{4}\log_2\frac{0}{4} = 0 \text{ bits}$$



# Information Gain

- Want many items in pure sets
- Expected drop in entropy after split:

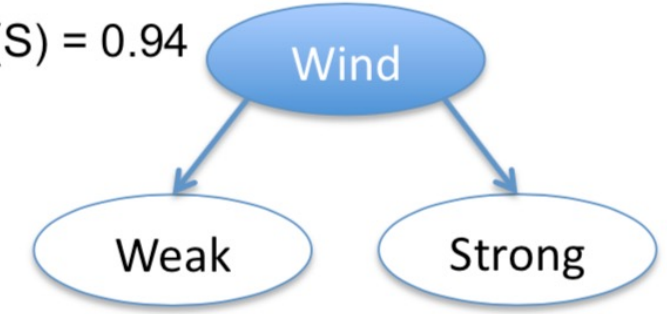
$$Gain(S,A) = H(S) - \sum_{V \in Values(A)} \frac{|S_V|}{|S|} H(S_V)$$

V … possible values of A
S … set of examples {X}
$S_v$ … subset where $X_A = V$

- Mutual Information
  - between attribute A and class labels of S

$-\frac{9}{14}\log_2\frac{9}{14} - \frac{5}{14}\log_2\frac{5}{14}$ **9 yes / 5 no**

H(S) = 0.94




**6 yes / 2 no**

$-\frac{6}{8}\log_2\frac{6}{8} - \frac{2}{8}\log_2\frac{2}{8}$

$H(S_{weak}) = 0.81$

**3 yes / 3 no**

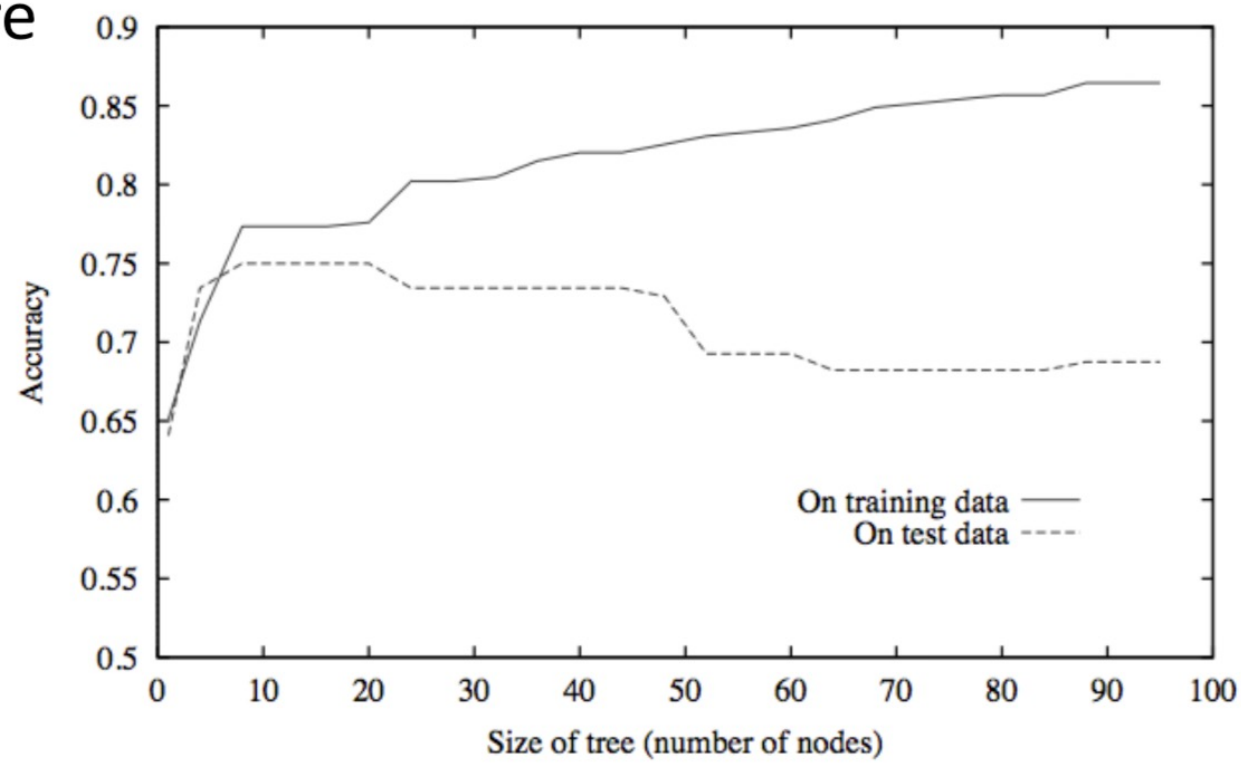
$-\frac{3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6}$

$H(S_{strong}) = 1.0$

Gain (S, Wind)
$= H(S) - {}^{8}/_{14}\, H(S_{weak}) - {}^{6}/_{14}\, H(S_{Strong})$
$= 0.94 - {}^{8}/_{14} * 0.81 - {}^{6}/_{14} * 1.0$
$= 0.049$

# Overfitting in Decision Tree

- Can always classify training examples perfectly
  - keep splitting until each node contains 1 example
  - singleton = pure
- Doesn't work on new data



# Avoid Overfitting

**How can we avoid overfitting?**

- Stop growing when data split is not statistically significant.
- Acquire more training data.
- Remove irrelevant attributes (manual process – not always possible)
- Grow full tree, then post-prune.

**How to select "best" tree**:

- Measure performance over training data
- Measure performance over separate validation data set
- Add complexity penalty to performance measure

**Pre-pruning** that stop growing the tree earlier, before it perfectly classifies the training set.
**Post-pruning** that allows the tree to perfectly classify the training set, and then post prune the tree.

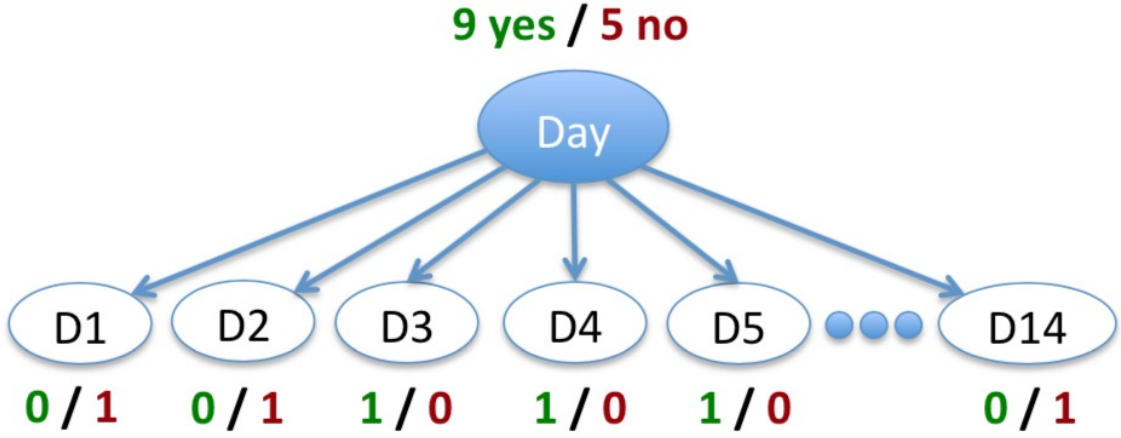
# General Structure

**Task**: classification, discriminative

- Model structure: decision tree
- Score function
  - Information gain at each node
  - Preference for short trees
  - Preference for high-gain attributes near the root
- Optimization / search method
  - Greedy search from simple to complex
  - Guided by information gain

# Problem With Information Gain

- Biased towards attributes with many values
- Won't work for new data: D15 Rain High Weak
- Use GainRatio:




all subsets perfectly pure => optimal split

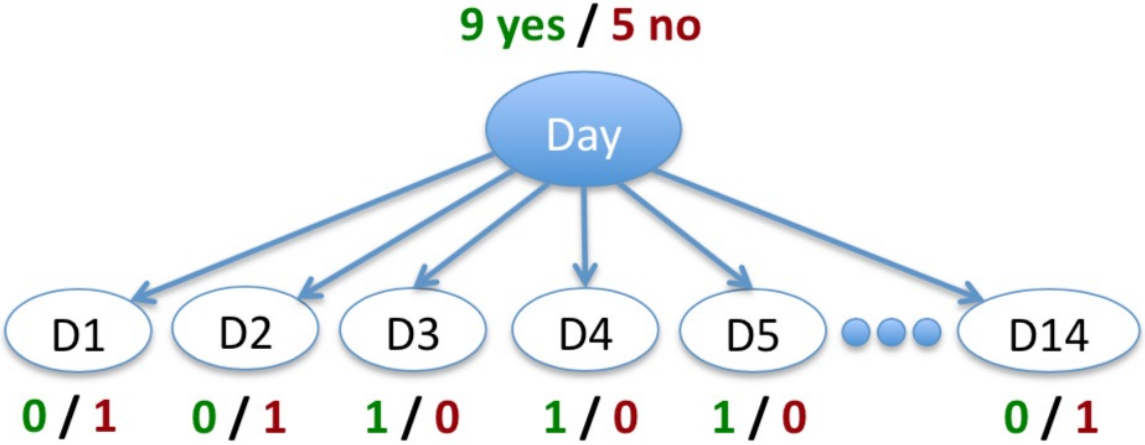
$$SplitEntropy(S,A) = -\sum_{V \in Values(A)} \frac{|S_V|}{|S|} \log \frac{|S_V|}{|S|}$$

A … candidate attribute
V … possible values of A
S … set of examples {X}
$S_v$ … subset where $X_A = V$

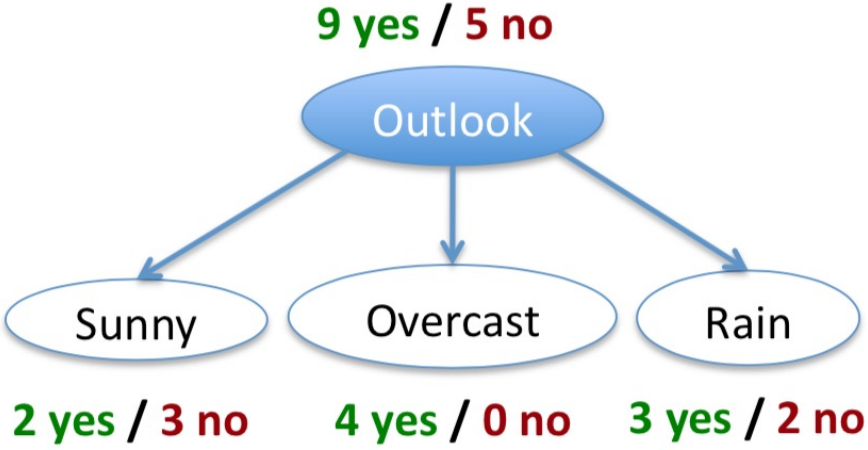
$$GainRatio(S,A) = \frac{Gain(S,A)}{SplitEntropy(S,A)}$$

penalizes attributes with many values

# Problem With Information Gain



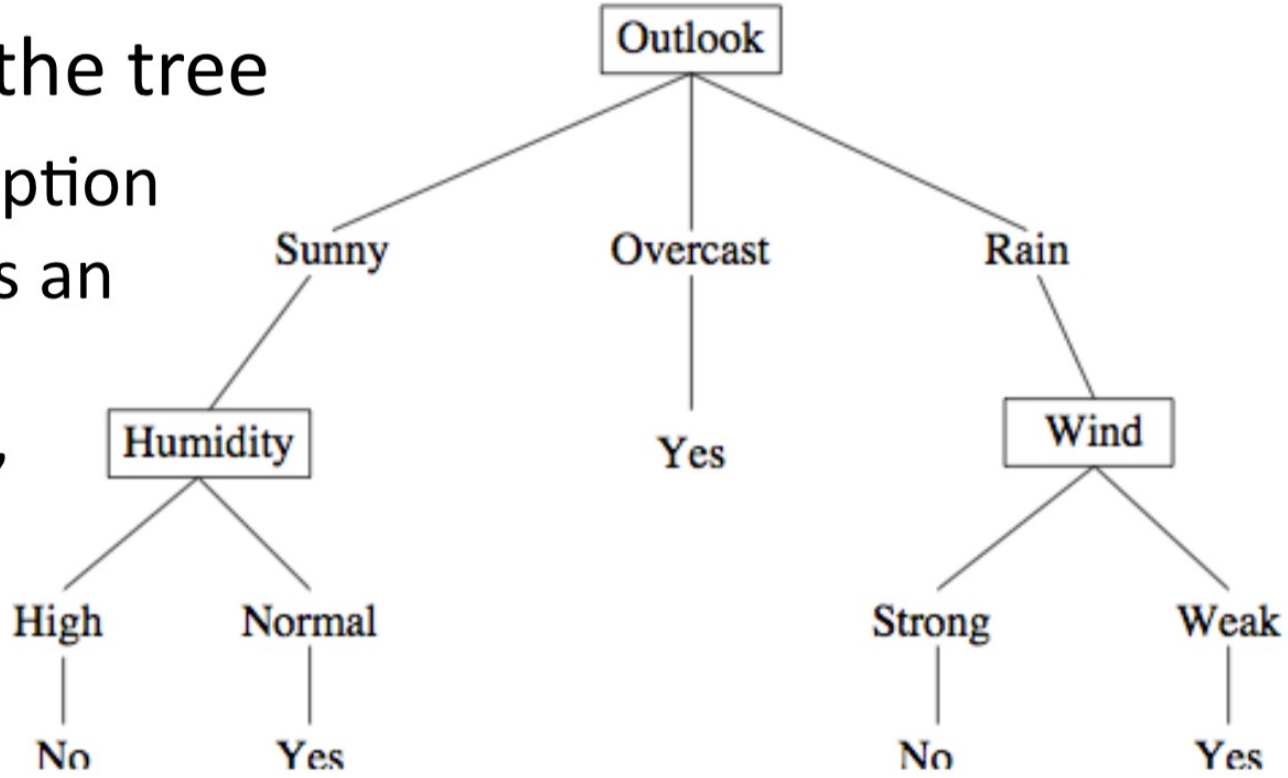

$$SplitEntropy(S, Day)$$
$$= -14\left(\frac{1}{14} log \frac{1}{14}\right) = 3.80$$




$$SplitEntropy(S, Outlook)$$
$$= -\frac{5}{14} log \frac{5}{14} - \frac{4}{14} log \frac{4}{14} - \frac{5}{14} log \frac{5}{14} = 1.57$$

# Interpretation of Trees

- Read rules off the tree
  - concise description of what makes an item positive
- No "black box"
  - important for users



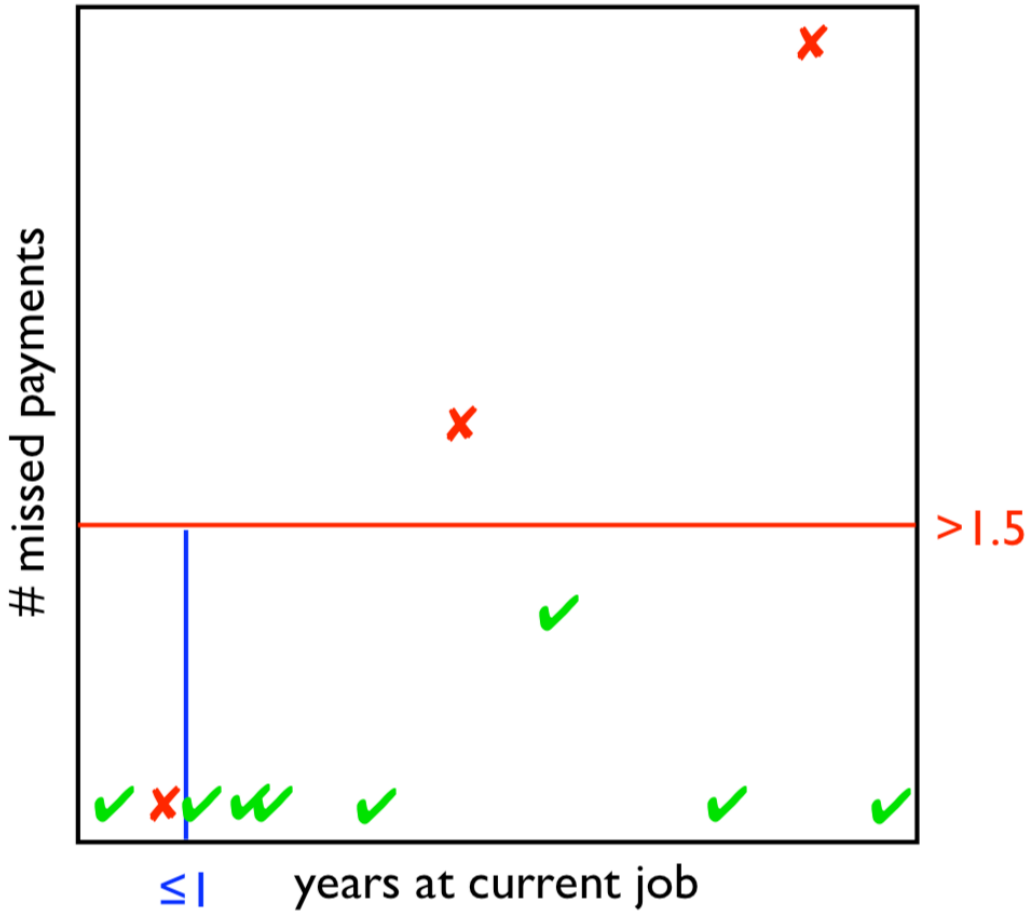

Rule:

(Outlook = Overcast) ∨
(Outlook = Rain ∧ Wind = Weak) ∨
(Outlook = Sunny ∧ Humidity = Normal)

# Continuous Variables

Predicting credit risk

| years at current job | # missed payments | defaulted? |
|---|---|---|
| 7 | 0 | N |
| 0.75 | 0 | Y |
| 3 | 0 | N |
| 9 | 0 | N |
| 4 | 2 | Y |
| 0.25 | 0 | N |
| 5 | 1 | N |
| 8 | 4 | Y |
| 1.0 | 0 | N |
| 1.75 | 0 | N |



# Continuous Variables

| Outlook | Temp | Humidity | Windy | Play |
|---|---|---|---|---|
| Sunny | 85 | 85 | False | No |
| Sunny | 80 | 90 | True | No |
| Overcast | 83 | 78 | False | Yes |
| Rainy | 70 | 96 | False | Yes |
| Rainy | 68 | 80 | False | Yes |
| Rainy | 65 | 70 | True | No |
| Overcast | 64 | 65 | True | Yes |
| Sunny | 72 | 95 | False | No |
| Sunny | 69 | 70 | False | Yes |
| Rainy | 75 | 80 | False | Yes |
| Sunny | 75 | 70 | True | Yes |
| Overcast | 72 | 90 | True | Yes |
| Overcast | 81 | 75 | False | Yes |
| Rainy | 71 | 80 | True | No |

# Continuous Temperature Attribute

- First, sort the temperature values, including the class labels
- Then, check all the cut points and choose the one with the best information gain.

| 64 | 65 | 68 | 69 | 70 | 71 | 72 | 72 | 75 | 75 | 80 | 81 | 83 | 85 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yes | No | Yes | Yes | Yes | No | No | Yes | Yes | Yes | No | Yes | Yes | No |

- Temp < 71.5: yes = 4, no = 2
- Temp ≥ 71.5: yes = 5, no = 3

How to compute:

- $H(Temp < 71.5) = ?$
- $H(Temp \geq 71.5) = ?$
- $H(S) = ?$
- $Gain(S, Temp) = ?$

# Continuous Temperature Attribute

| 64 | 65 | 68 | 69 | 70 | 71 | 72 | 72 | 75 | 75 | 80 | 81 | 83 | 85 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yes | No | Yes | Yes | Yes | No | No | Yes | Yes | Yes | No | Yes | Yes | No |

Temp < 71.5: yes = 4, no = 2

Temp ≥ 71.5: yes = 5, no = 3

$$H(Temp < 71.5) = -\frac{4}{6}\log\frac{4}{6} - \frac{2}{6}\log\frac{2}{6} = 0.918$$

$$H(Temp \geq 71.5) = -\frac{5}{8}\log\frac{5}{8} - \frac{3}{8}\log\frac{3}{8} = 0.954$$

$$H(S) = -\frac{9}{14}\log\frac{9}{14} - \frac{5}{14}\log\frac{5}{14} = 0.940$$

$$Gain(S, Temp) = H(S) - \frac{6}{14}H(Temp < 71.5) - \frac{8}{14}H(Temp \geq 71.5)$$

$$= 0.940 - \frac{6}{14} * 0.918 - \frac{8}{14} * 0.954 = 0.001$$

# Continuous Temperature Attribute

- First, sort the temperature values, including the class labels
- Then, check all the cut points and choose the one with the best information gain.

| 64 | 65 | 68 | 69 | 70 | 71 | 72 | 72 | 75 | 75 | 80 | 81 | 83 | 85 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Yes | No | Yes | Yes | Yes | No | No | Yes | Yes | Yes | No | Yes | Yes | No |

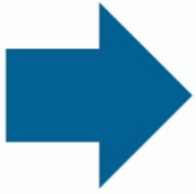
- Temp < 71.5: yes = 4, no = 2
- Temp ≥ 71.5: yes = 5, no = 3

- Place split points **halfway** between values.
- Able to evaluate all split points in **one pass.**

# Information Gain for Humidity

| Humidity | Play |
|---|---|
| 65 | Yes |
| 70 | No |
| 70 | Yes |
| 70 | Yes |
| 75 | Yes |
| 78 | Yes |
| 80 | Yes |
| 80 | Yes |
| 80 | No |
| 85 | No |
| 90 | No |
| 90 | Yes |
| 95 | No |
| 96 | Yes |

sort the attribute values



| Humidity | Play |
|---|---|
| 65 | Yes |
| 70 | No |
| 70 | Yes |
| 70 | Yes |
| 75 | Yes |
| 78 | Yes |
| 80 | Yes |
| 80 | Yes |
| 80 | No |
| 85 | No |
| 90 | No |
| 90 | Yes |
| 95 | No |
| 96 | Yes |

compute the gain for every possible split

what is the information gain if we split here?

# Information Gain for Humidity

| Humidity | Play | # of Yes | % of Yes | # of No | % of No | Weight | Entropy Left | # of Yes | % of Yes | # of No | % of No | Weight | Entropy Right | Information Gain |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 65 | Yes | 1 | 100.00% | 0 | 0.00% | 7.14% | 0.00 | 8.00 | 0.62 | 5.00 | 0.38 | 92.86% | 0.96 | 0.0477 |
| 70 | No | 1 | 50.00% | 1 | 50.00% | 14.29% | 1.00 | 8.00 | 0.67 | 4.00 | 0.33 | 85.71% | 0.92 | 0.0103 |
| 70 | Yes | 2 | 66.67% | 1 | 33.33% | 21.43% | 0.92 | 7.00 | 0.64 | 4.00 | 0.36 | 78.57% | 0.95 | 0.0005 |
| 70 | Yes | 3 | 75.00% | 1 | 25.00% | 28.57% | 0.81 | 6.00 | 0.60 | 4.00 | 0.40 | 71.43% | 0.97 | 0.0150 |
| 75 | Yes | 4 | 80.00% | 1 | 20.00% | 35.71% | 0.72 | 5.00 | 0.56 | 4.00 | 0.44 | 64.29% | 0.99 | 0.0453 |
| 78 | Yes | 5 | 83.33% | 1 | 16.67% | 42.86% | 0.65 | 4.00 | 0.50 | 4.00 | 0.50 | 57.14% | 1.00 | 0.0903 |
| 80 | Yes | 6 | 85.71% | 1 | 14.29% | 50.00% | 0.59 | 3.00 | 0.43 | 4.00 | 0.57 | 50.00% | 0.99 | 0.1518 |
| 80 | Yes | 7 | 87.50% | 1 | 12.50% | 57.14% | 0.54 | 2.00 | 0.33 | 4.00 | 0.67 | 42.86% | 0.92 | 0.2361 |
| 80 | No | 7 | 77.78% | 2 | 22.22% | 64.29% | 0.76 | 2.00 | 0.40 | 3.00 | 0.60 | 35.71% | 0.97 | 0.1022 |
| 85 | No | 7 | 70.00% | 3 | 30.00% | 71.43% | 0.88 | 2.00 | 0.50 | 2.00 | 0.50 | 28.57% | 1.00 | 0.0251 |
| 90 | No | 7 | 63.64% | 4 | 36.36% | 78.57% | 0.95 | 2.00 | 0.67 | 1.00 | 0.33 | 21.43% | 0.92 | 0.0005 |
| 90 | Yes | 8 | 66.67% | 4 | 33.33% | 85.71% | 0.92 | 1.00 | 0.50 | 1.00 | 0.50 | 14.29% | 1.00 | 0.0103 |
| 95 | No | 8 | 61.54% | 5 | 38.46% | 92.86% | 0.96 | 1.00 | 1.00 | 0.00 | 0.00 | 7.14% | 0.00 | 0.0477 |
| 96 | Yes | 9 | 64.29% | 5 | 35.71% | 100.00% | 0.94 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00% | 0.00 | 0.0000 |

Left branch, e.g., < 67.5

Right branch, e.g., ≥ 67.5

# Multi-class Classification

Multiclass classification:

- Predict the **best attribute** to split on.
- Entropy:

$$\boldsymbol{H(S) = -\sum_c p_c \, log_2(p_c).}$$

- $p_c$: % of examples of class **c** in S.

# Random (Decision) Forest

**Training**: grow **K** different decision trees:

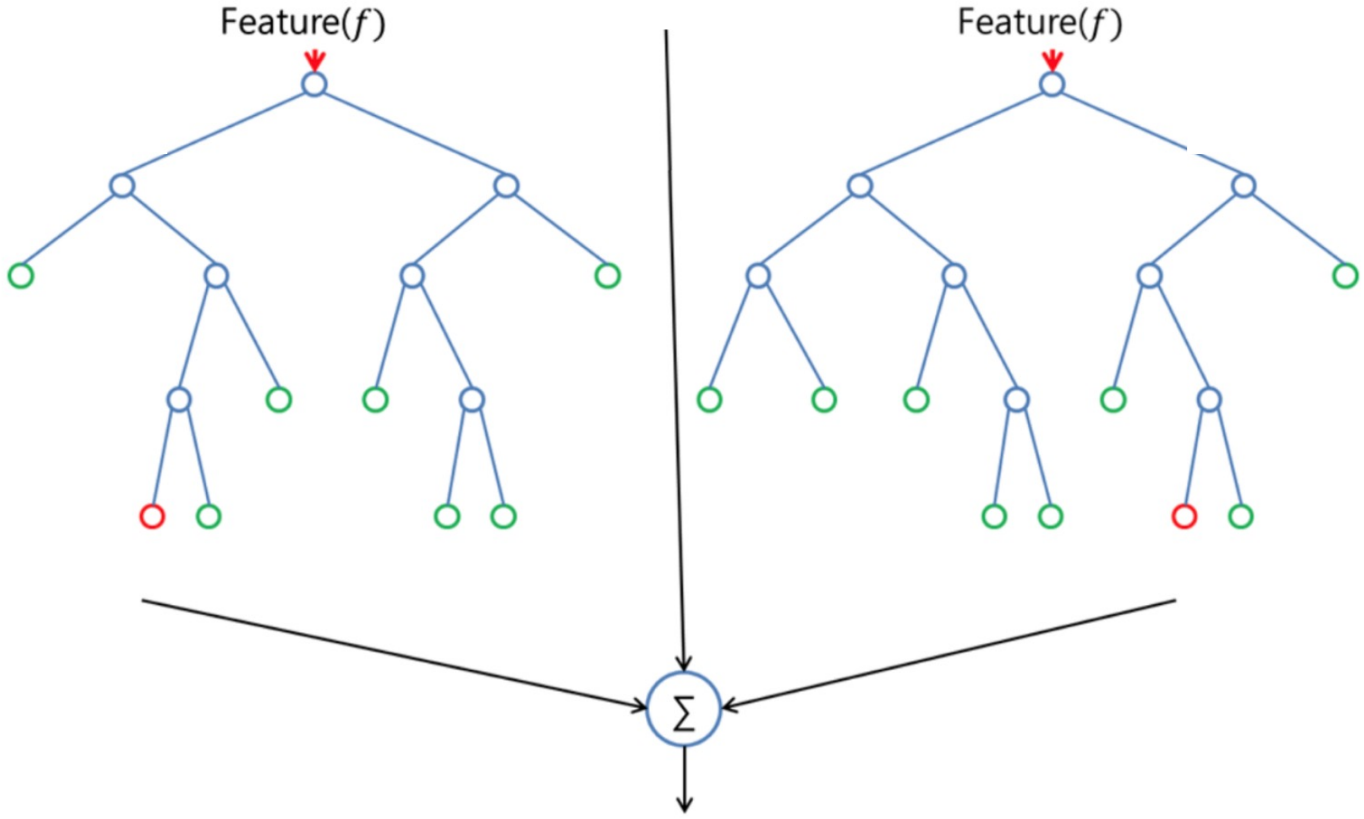
- Pick a **random subset $S_{random}$** of training examples.
- Grow a full decision tree (no pruning), compute information gain based on **$S_{random}$** instead of full set.
- Repeat for **K decision trees.**

**Inference**: given a new data point X:

- Classify X using each of the K trees.
- Use majority vote: class predicted most often.

Fast, scalable, state-of-the-art performance.

# Random (Decision) Forest




Random forest with majority voting

# Gini impurity – An alternative of Entropy

**Gini impurity** (or **Gini index**) of a dataset D indicates the likelihood of new, random data sample being misclassified if the sample is given a random class label according to the class distribution in the dataset.

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

Probability of the sample belonging to class *i*

Probability of the sample **not** being classified to class *i* (i.e., misclassified).

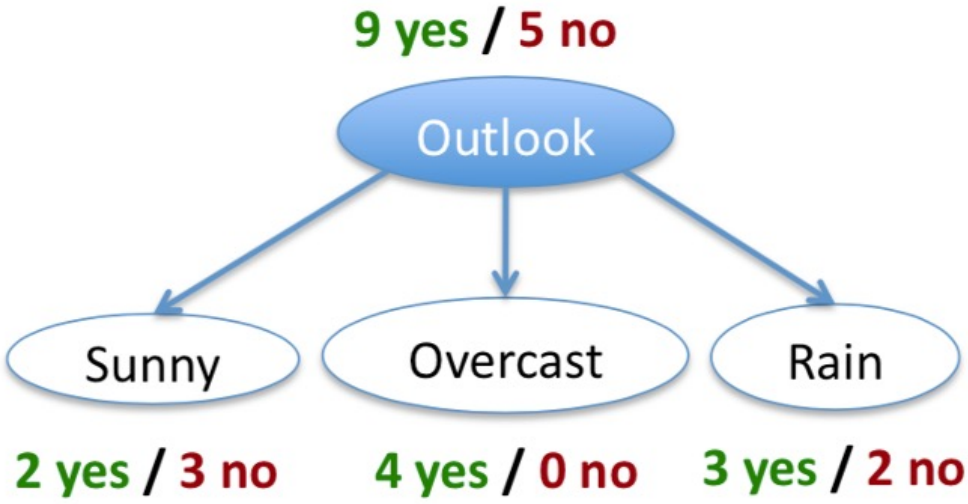
# Gini impurity of a dataset

**Gini impurity** (or **Gini index**) of a dataset D indicates the likelihood of new, random data sample being misclassified if the sample is given a random class label according to the class distribution in the dataset.

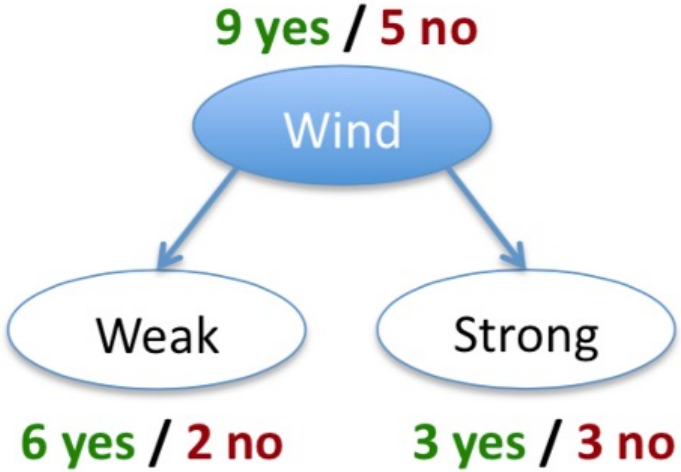
$$Gini(D) = \sum_{i=1}^{k} p_i(1 - p_i) = 1 - \sum_{i=1}^{k} p_i^2$$

Probability of the sample belonging to any class is given by $\sum_{i=1}^{k} p_i = 1$

# Gini impurity of a dataset




$Gini(Sunny) = 0.48$ $Gini(Overcast) = 0$ $Gini(Rain) = 0.48$

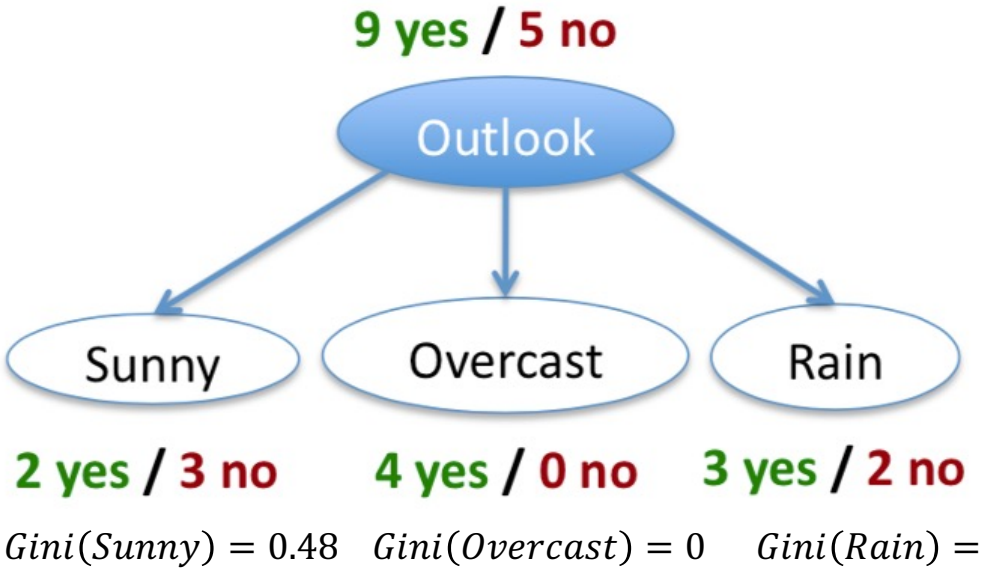


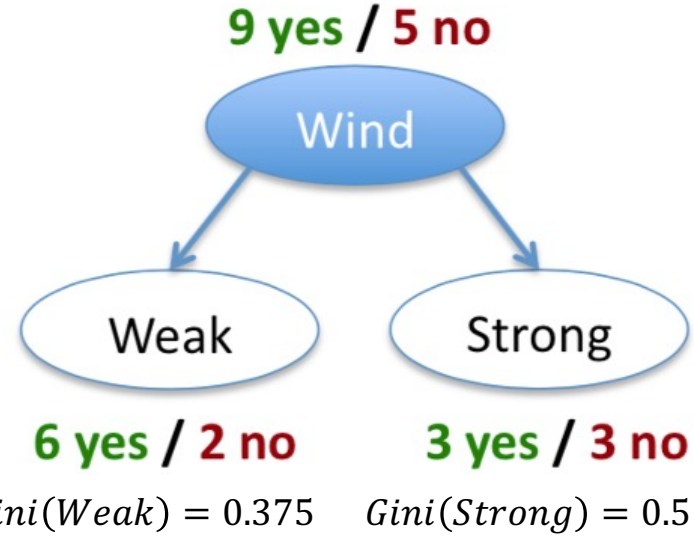

$Gini(Weak) = 0.375$ $Gini(Strong) = 0.5$

$$Gini(Sunny) = \frac{2}{5}\left(1 - \frac{2}{5}\right) + \frac{3}{5}\left(1 - \frac{3}{5}\right) = 1 - \left(\frac{2}{5}\right)^2 - \left(\frac{3}{5}\right)^2 = 0.48$$

$$Gini(Weak) = \frac{6}{8}\left(1 - \frac{6}{8}\right) + \frac{2}{8}\left(1 - \frac{2}{8}\right) = 1 - \left(\frac{6}{8}\right)^2 - \left(\frac{2}{8}\right)^2 = 0.375$$

# Gini impurity of a dataset

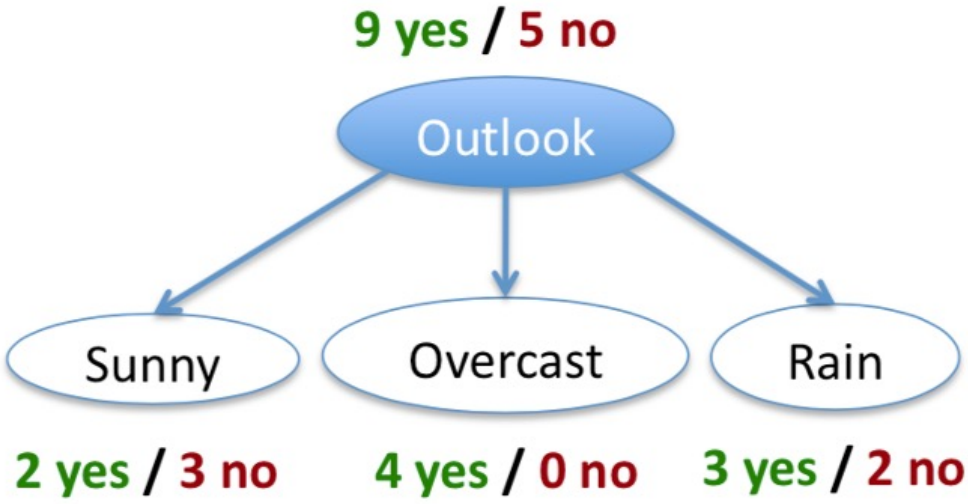


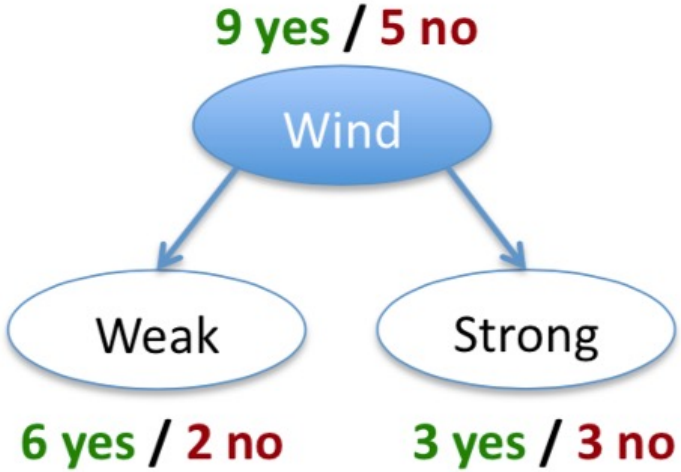




In multi-class classification problem, Gini impurity varies between values 0 and 1 (take an example of 10 data samples and 5 classes):

- Gini = 0: **pure** dataset (e.g., 0/10/0/0/0).
- Gini = 0.5: **equal** distribution over *some* classes (e.g., 5/0/5/0/0).
- Gini = 1: **random** distribution across *all* classes (e.g., 1/2/3/2/2).

# Gini impurity of an attribute



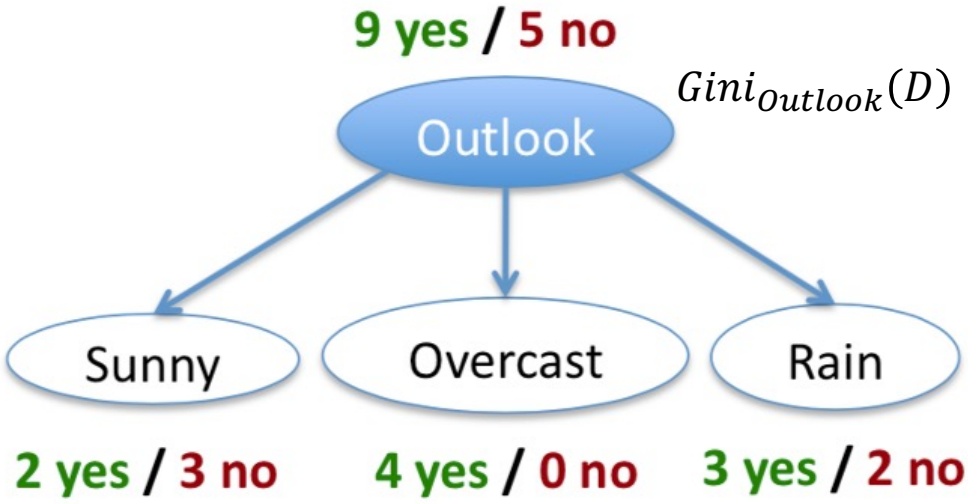




If a dataset D is split on an attribute A into m subsets $\{D_1, \ldots, D_m\}$, the Gini impurity can be defined as:

$$Gini_A(D) = \sum_{s=1}^{m} \frac{|D_s|}{|D|} Gini(D_s)$$

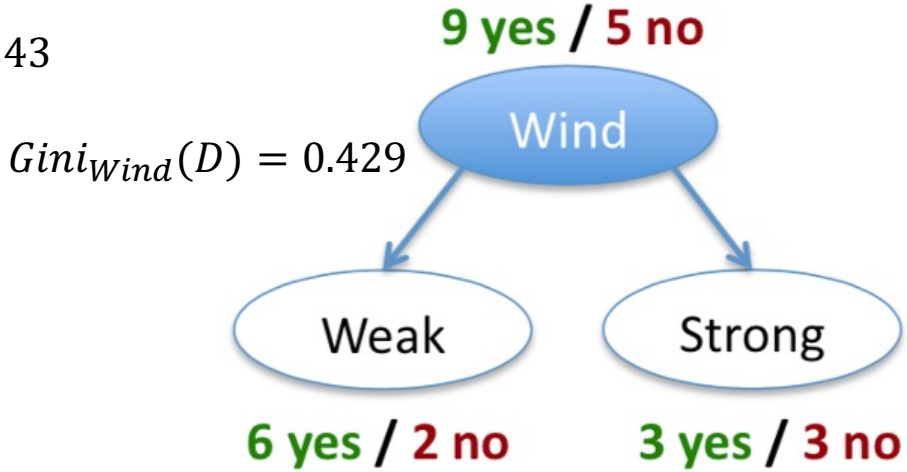
Attribute **minimizing the Gini impurity** is chosen to split the node.

# Gini impurity of an attribute




$Gini_{Outlook}(D) = 0.343$

$Gini(Sunny) = 0.48$ $Gini(Overcast) = 0$ $Gini(Rain) = 0.48$




$Gini_{Wind}(D) = 0.429$

$Gini(Weak) = 0.375$ $Gini(Strong) = 0.5$

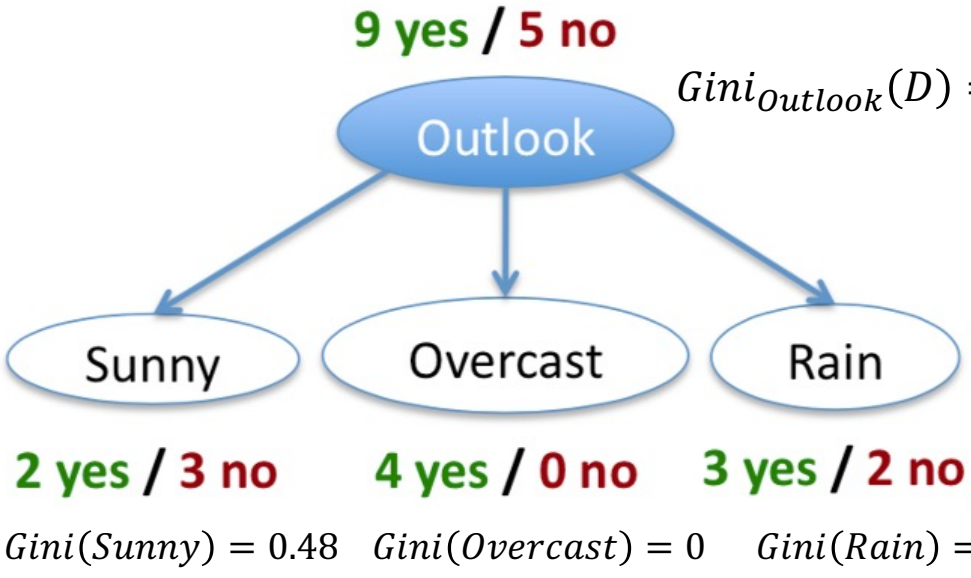
$$Gini_{Outlook}(D) = \frac{5}{14}0.48 + \frac{4}{14}0 + \frac{5}{14}0.48 = 0.343$$

$$Gini_{Wind}(D) = \frac{8}{14}0.375 + \frac{6}{14}0.5 = 0.429$$

**Outlook is chosen!**

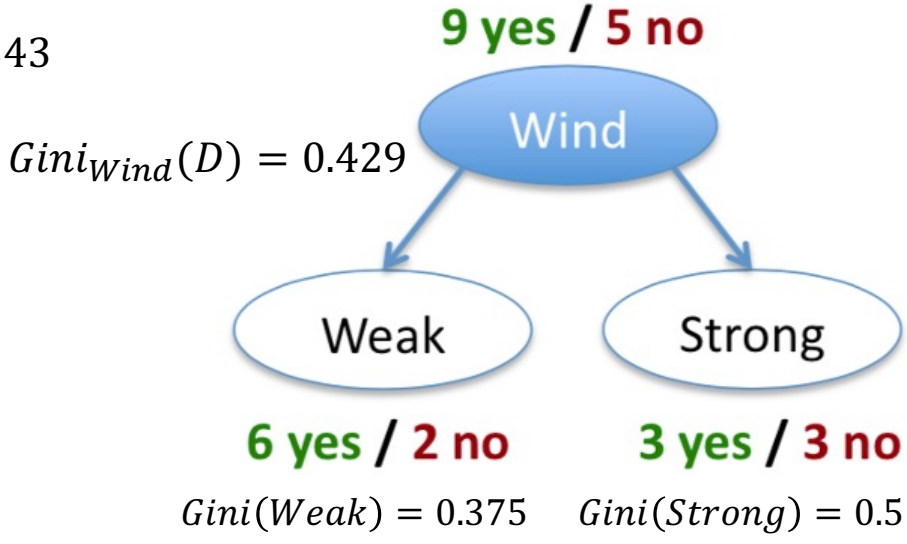
# Gini information gain

$$Gini(D) = \frac{9}{14}\left(1 - \frac{9}{14}\right) + \frac{5}{14}\left(1 - \frac{5}{14}\right) = 0.459$$




$Gini_{Outlook}(D) = 0.343$

$Gini(Sunny) = 0.48$ $Gini(Overcast) = 0$ $Gini(Rain) = 0.48$




$Gini_{Wind}(D) = 0.429$

$Gini(Weak) = 0.375$ $Gini(Strong) = 0.5$

Gini information gain for an attribute (A) is the weighted impurities of the branches is subtracted from the original impurity.

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

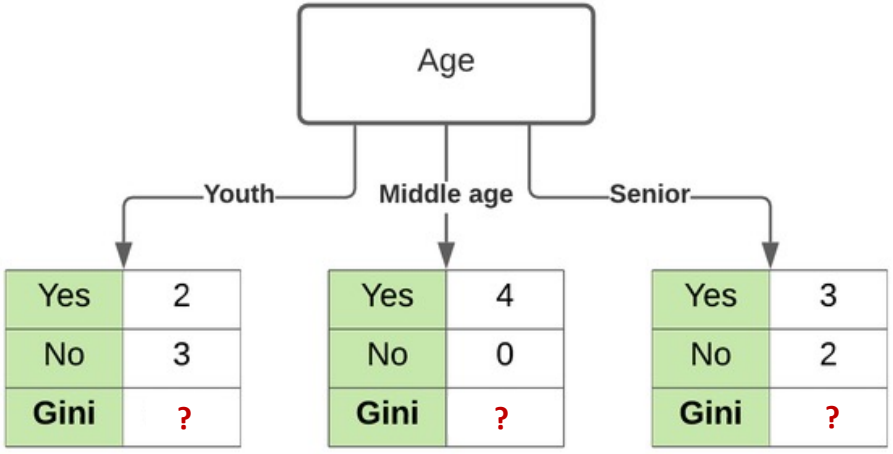
Attribute **maximizing the Gini information gain** is chosen to split.

$\Delta Gini(Outlook) = 0.459 - 0.343 = 0.116$

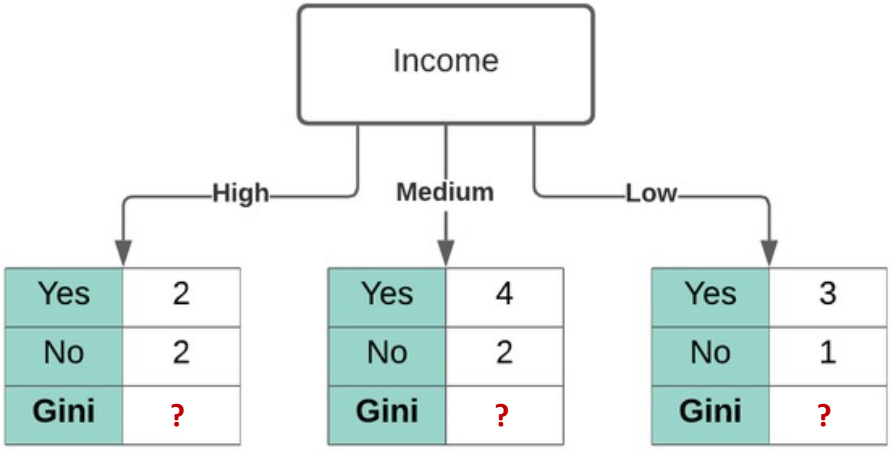
$\Delta Gini(\text{Wind}) = 0.459 - 0.429 = 0.03$

**Outlook is chosen!**

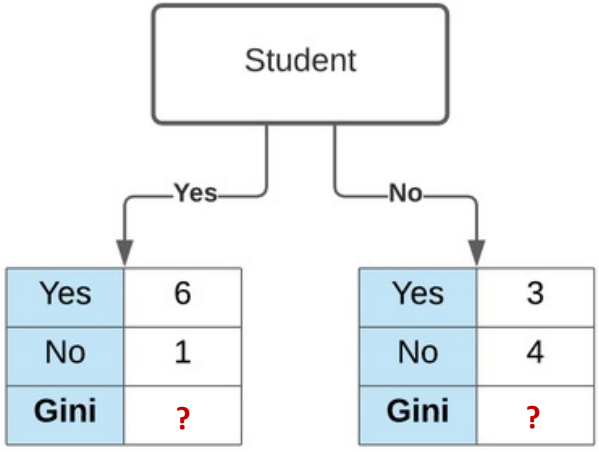
# Gini impurity exercise



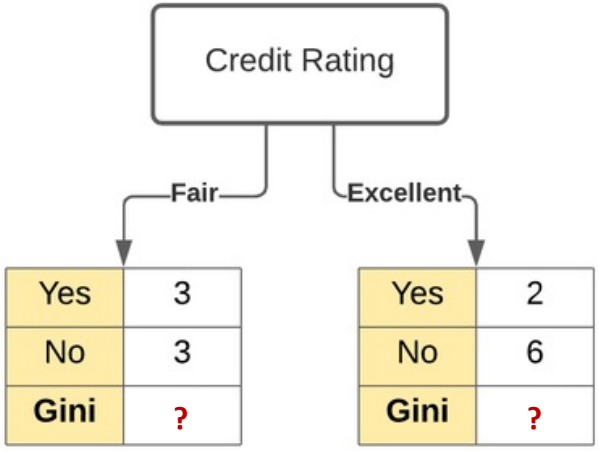

Gini Impurity for Age is ?




Gini Impurity for Income is ?



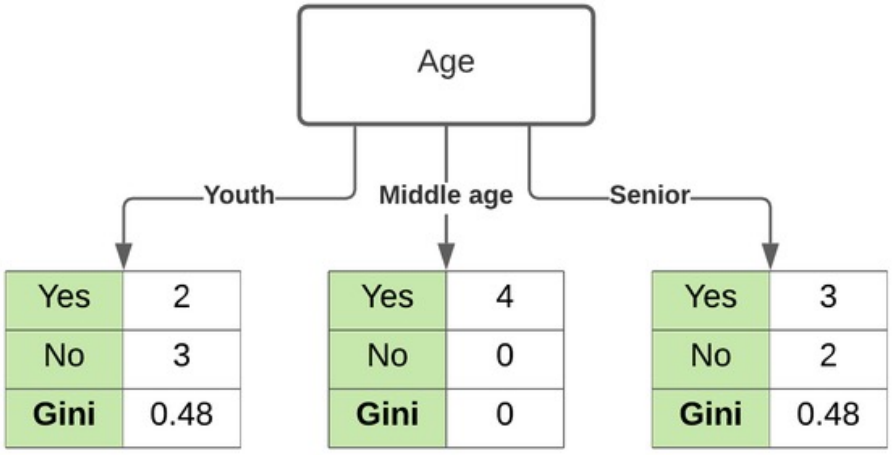

Gini Impurity for Student is ?




Gini Impurity for Credit Rating is ?

What is the best attribute to split?

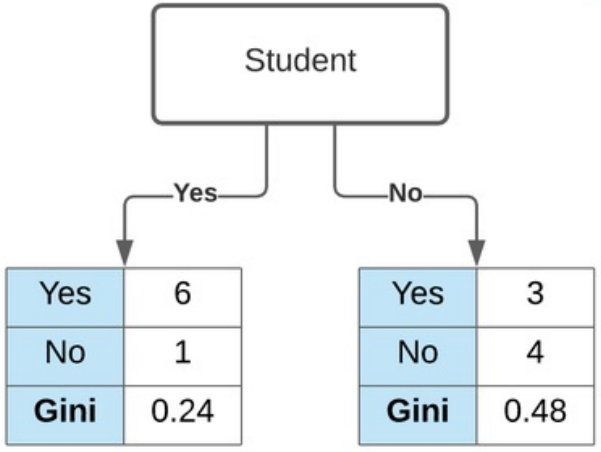
# Gini impurity exercise



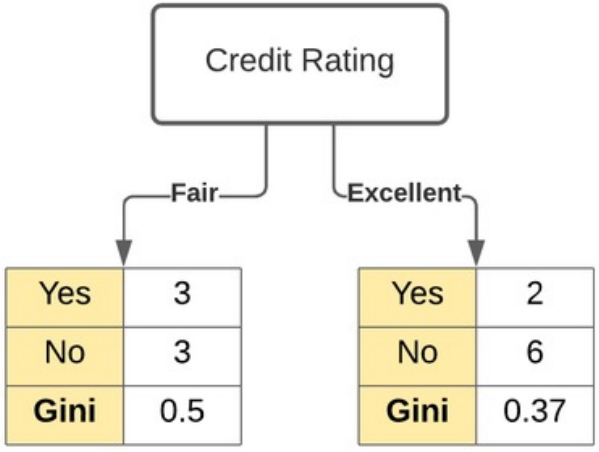

Gini Impurity for Age is 0.343


Gini Impurity for Income is 0.440

Best




Gini Impurity for Student is 0.367




Gini Impurity for Credit Rating is 0.429

# Regression tree

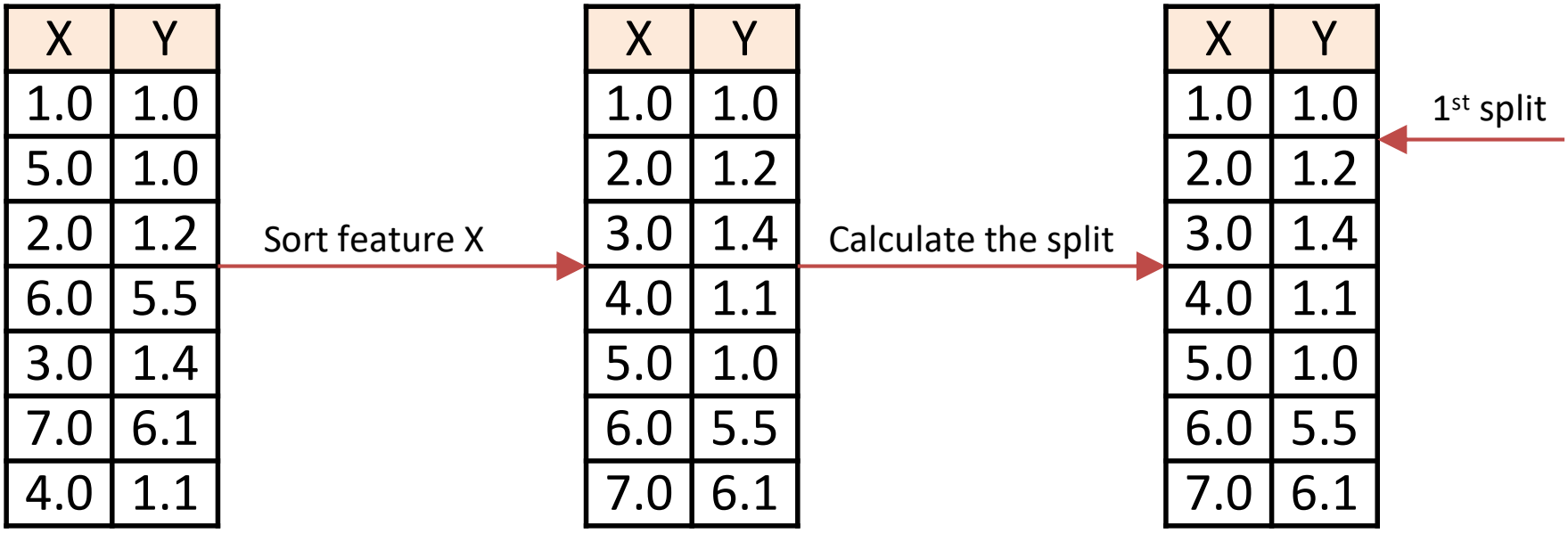
**What if the label is not categorial but numeric?**

There are two types of decision tree:

- Classification tree: is used when the label is categorical (discrete values).
- Regression tree: is used when the label is numeric (continuous values)

| X | Y |
|---|---|
| 1.0 | 1.0 |
| 5.0 | 1.0 |
| 2.0 | 1.2 |
| 6.0 | 5.5 |
| 3.0 | 1.4 |
| 7.0 | 6.1 |
| 4.0 | 1.1 |

# Regression tree




Idea: find the best point to split the dataset into 2 parts so that the Mean Squared Error (MSE) is minimized at that point.

Steps:

- **Sort** the data according to its features (n data samples in total).
- **Brute-force** all possible split points, calculate corresponding MSE values.
- After have n-1 MSE calculated, **choose** the split/threshold of minimum MSE.

# Regression tree

| X | Y |
|---|---|
| 1.0 | 1.0 |
| 5.0 | 1.0 |
| 2.0 | 1.2 |
| 6.0 | 5.5 |
| 3.0 | 1.4 |
| 7.0 | 6.1 |
| 4.0 | 1.1 |

Sort feature X →

| X | Y |
|---|---|
| 1.0 | 1.0 |
| 2.0 | 1.2 |
| 3.0 | 1.4 |
| 4.0 | 1.1 |
| 5.0 | 1.0 |
| 6.0 | 5.5 |
| 7.0 | 6.1 |

Calculate the split →

| X | Y |
|---|---|
| 1.0 | 1.0 |
| 2.0 | 1.2 |
| 3.0 | 1.4 |
| 4.0 | 1.1 |
| 5.0 | 1.0 |
| 6.0 | 5.5 |
| 7.0 | 6.1 |

← 1st split

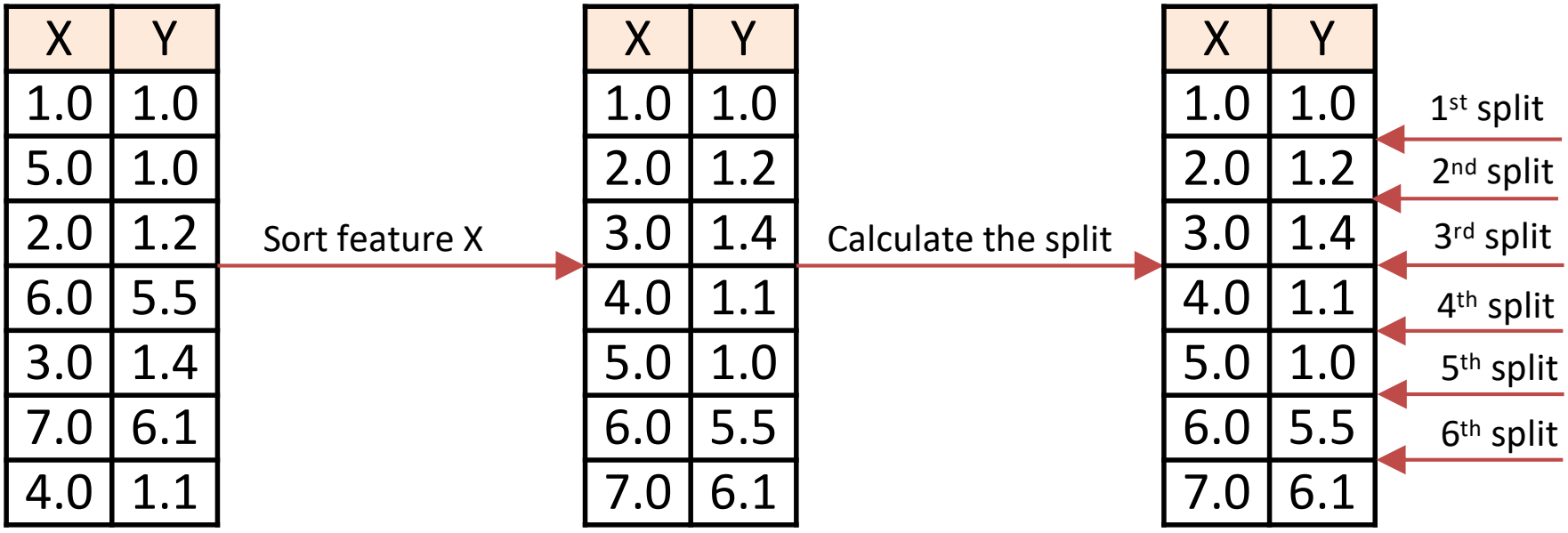
1st split at value (1+2)/2 = 1.5. There are two groups:

- Group 1 (X < 1.5): {(1.0,1.0)}. Average Y value is 1.0 ($\hat{y}_{left}$).
- Group 2 (X ≥ 1.5): all other points. Average Y value is 2.72 ($\hat{y}_{right}$).

Calculate the MSE of the 1st split by (given $n=n_{left}+n_{right}$):

$$\mathrm{MSE}(1^{\mathrm{st}}\,\mathrm{split}) = \mathrm{MSE}(1^{\mathrm{st}}\,\mathrm{left}) + \mathrm{MSE}(1^{\mathrm{st}}\,\mathrm{right}) = \frac{1}{n}\left(\sum_{i=1}^{n_{left}} (y_i - \hat{y}_{left})^2 + \sum_{j=1}^{n_{right}} (y_j - \hat{y}_{right})^2\right)$$

# Regression tree




Similarly calculate MSE of all other possible splits. The chosen split/threshold is the one **having minimum MSE**.

# Feature importance - A single decision tree

Idea: calculate a score representing the "importance" of each data feature. The **higher the score**, the **larger the effect** of that feature on the model prediction.

$$I_i = \sum_{i_n = i} \left( p(n) purity(n) - \sum_{n_{child}} p(n_{child}) purity(n_{child}) \right)$$

Importance of feature i.

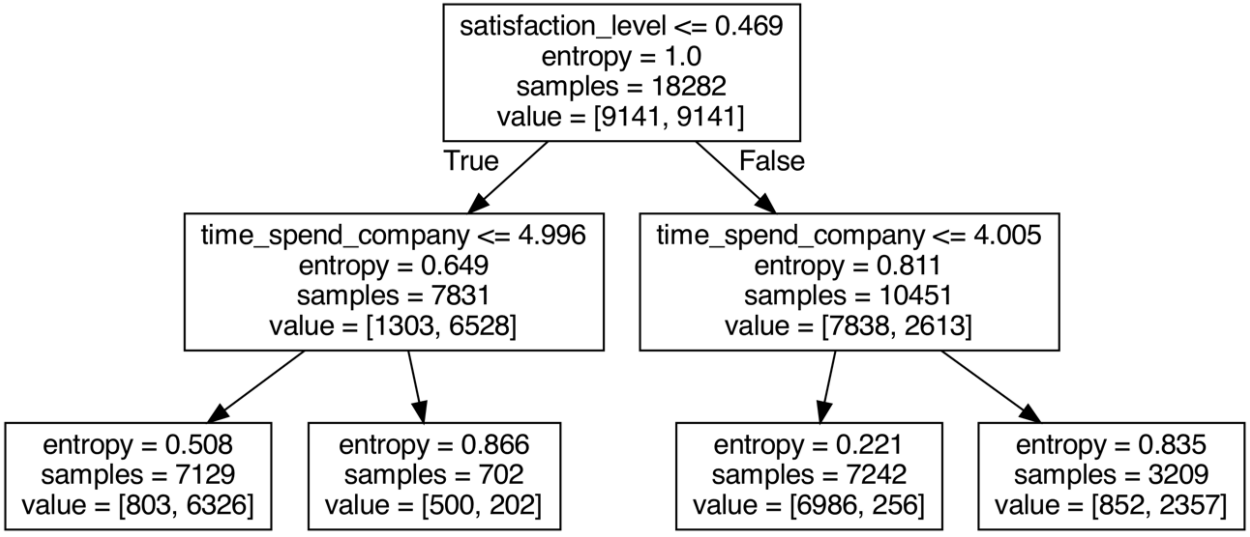
Sum over all nodes of the tree that use feature i.

Probability of using of a node for a sample data point.

Purity of a node, such as Entropy, Gini, Squared Error.

# Feature importance – Example with Entropy

Assume that this is the tree after training

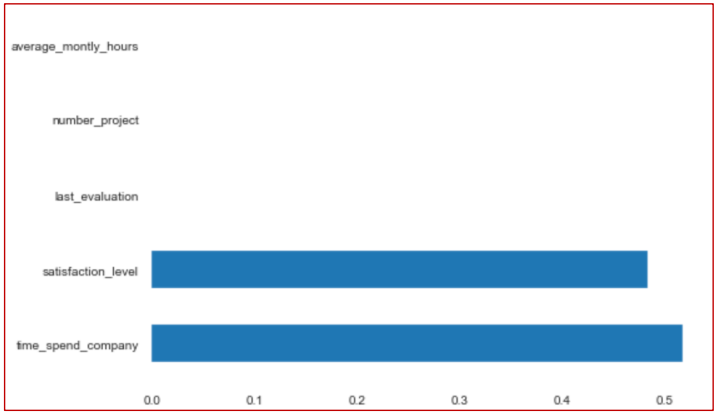



| | |
|---|---|
| satisfaction_level | 0.482504 |
| last_evaluation | 0.000000 |
| number_project | 0.000000 |
| average_montly_hours | 0.000000 |
| time_spend_company | 0.517496 |
| Work_accident | 0.000000 |
| promotion_last_5years | 0.000000 |
| Department_IT | 0.000000 |
| Department_RandD | 0.000000 |
| Department_accounting | 0.000000 |
| Department_hr | 0.000000 |
| Department_management | 0.000000 |
| Department_marketing | 0.000000 |
| Department_product_mng | 0.000000 |
| Department_sales | 0.000000 |
| Department_support | 0.000000 |
| Department_technical | 0.000000 |
| salary_high | 0.000000 |
| salary_low | 0.000000 |
| salary_medium | 0.000000 |

satisfaction_level = 18282/18282*1.0-7831/18282*0.649-10451/18282*0.811 = 0.2584

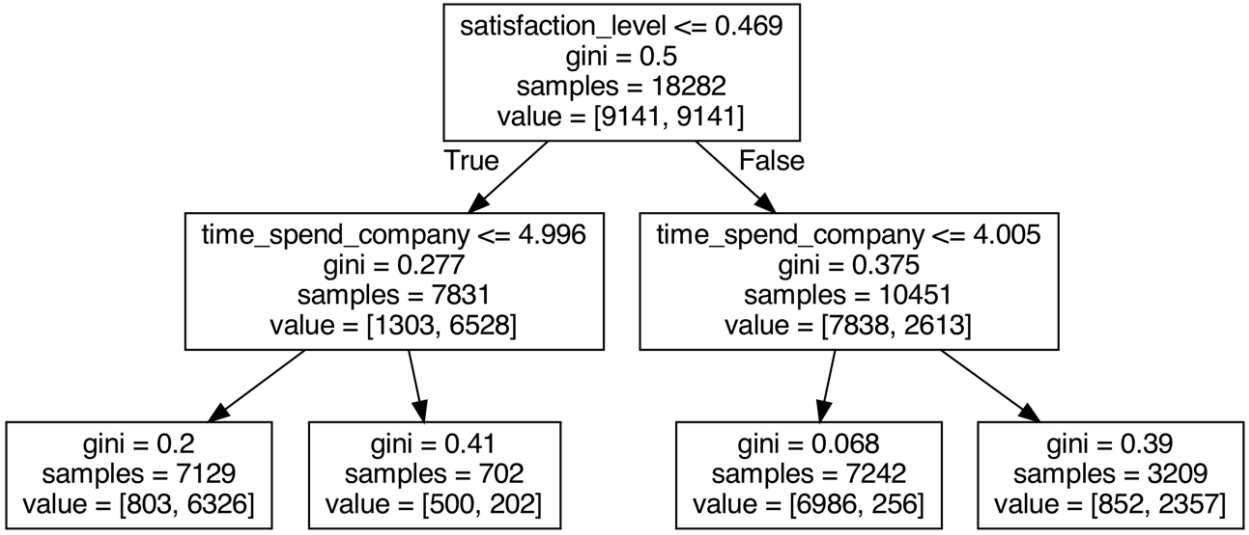
time_spend_company
= (7831/18282*0.649-7129/18282*0.508-702/18282*0.866)
+ (10451/18282*0.811-7242/18282*0.221-3209/18282*0.835)
= 0.0466 + 0.2295 = 0.2761

Then normalize the sum value to 1, we have:
**satisfaction_level** = 0.2584/(0.2584+0.2761) = **0.4834**
**time_spend_company** = 0.2761/(0.2584+0.2761) = **0.5166**



# Feature importance – Example with Gini

Assume that this is the tree after training

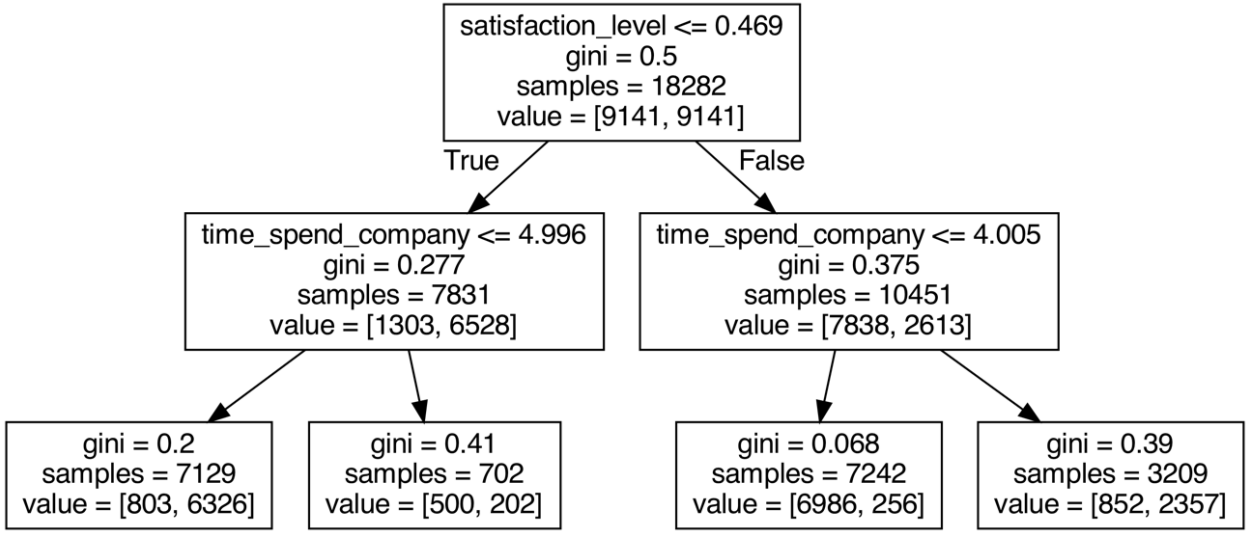



What is the feature importance score of

- satisfaction_level = ?
- time_spend_company = ?

# Feature importance – Example with Gini

Assume that this is the tree after training

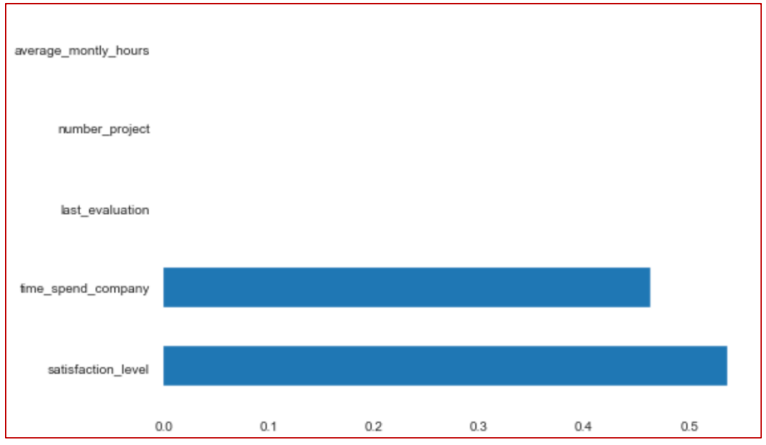



satisfaction_level = 18282/18282*0.5-7831/18282*0.277-10451/18282*0.375 = 0.1670

time_spend_company
= (7831/18282*0.277-7129/18282*0.2-702/18282*0.41)
+ (10451/18282*0.375-7242/18282*0.068-3209/18282*0.39)
= 0.0250 + 0.1190 = 0.1440

Then normalize the sum value to 1, we have:
**satisfaction_level** = 0.1670/(0.1670+0.1440) = **0.5369**
**time_spend_company** = 0.1440/(0.1670+0.1440) = **0.4631**

| | |
|---|---|
| satisfaction_level | 0.536586 |
| last_evaluation | 0.000000 |
| number_project | 0.000000 |
| average_montly_hours | 0.000000 |
| time_spend_company | 0.463414 |
| Work_accident | 0.000000 |
| promotion_last_5years | 0.000000 |
| Department_IT | 0.000000 |
| Department_RandD | 0.000000 |
| Department_accounting | 0.000000 |
| Department_hr | 0.000000 |
| Department_management | 0.000000 |
| Department_marketing | 0.000000 |
| Department_product_mng | 0.000000 |
| Department_sales | 0.000000 |
| Department_support | 0.000000 |
| Department_technical | 0.000000 |
| salary_high | 0.000000 |
| salary_low | 0.000000 |
| salary_medium | 0.000000 |



# Feature importance – Random forest

Idea: importance of a feature in a random forest is the sum of importance scores of that feature in all trees in the random forest.

$$I_i = \frac{1}{|B|} \sum_{T \in B} I_i(T)$$

Importance of feature i.

Total number of trees in random the forest.

Importance of feature i for a single tree T

# Summary

- Decision tree.
- Entropy, information gain, gain ratio.
- Continuous variable in decision tree.
- Random forest.
- Gini impurity of a dataset/attribute, Gini information gain.
- Regression tree.
- Feature importance.

# Q&A

Thank you