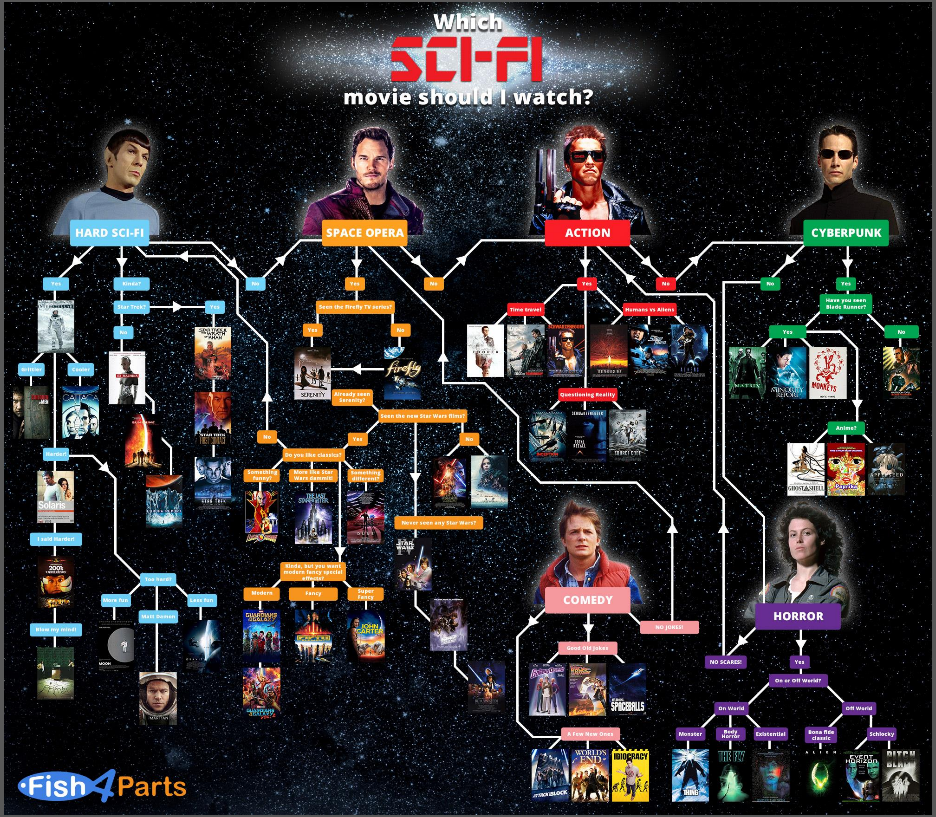
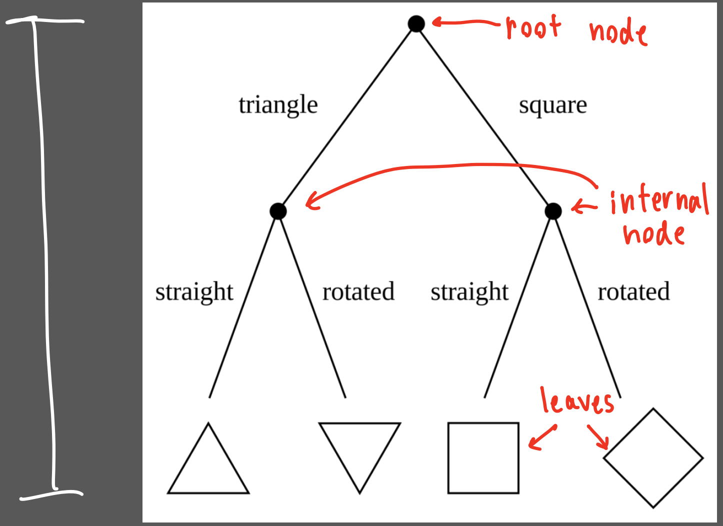


Discussion DeCsion Tree

Akinator


English
Play
Story of Akinator
Akinator on your smartphone
I think of
Edward Elric
Fullmetal Alchemist
© Copyright / IP Policy
Yes
No
their body
no no hi how how did he know that

Tree depth = 2


root node
triangle
square
internal node
straight
rotated
straight
rotated
leaves

Day	Outlook	Temperature	Humidity	Wind	Go outside
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

Example: Information Gain

// How to choose where to split //

Algorithm:
1. Calculate entropy of target class
2. Calculate entropy of each feature's values
3. Calculate information gain of each feature
4. Split at the maximum IG
5. Repeat #1 until no further class

// entropy = a measure of disorder or uncertainty, [0,1]

Example: Information Gain

Day	Outlook	Temperature	Humidity	Wind	Go outside
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

$$\text{Entropy}(S) = -P(Go = N)\log(P(Go=N)) - P(Go = Y)\log(P(Go=Y))$$

$$\Rightarrow P(Go = N) = \frac{5}{14}, \quad P(Go = Y) = \frac{9}{14}$$

$$\Rightarrow \text{Entropy}(S) = -\frac{5}{14}\log_2\left(\frac{5}{14}\right) - \frac{9}{14}\log_2\left(\frac{9}{14}\right)$$

$$= \underbrace{0.940}$$

Example: Information Gain

Day	Outlook	Temperature	Humidity	Wind	Go outside
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

$$IG(S, wind) = Ent(S) - P(w=weak)\,Ent(w=weak) - P(w=strong)\,Ent(w=strong)$$

// $P(w=weak) = \frac{8}{14}$, $P(w=strong) = \frac{6}{14}$ //

// $Ent(w=weak) =$ ← only count subset wind=weak

$$- P(Go=N)\log(P(Go=N)) - P(Go=Y)\log(P(Go=Y))$$

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

$$= 0.811$$ ←

Example: Information Gain

Day	Outlook	Temperature	Humidity	Wind	Go outside
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

// $Ent(w=strong) =$ ← only count subset wind = strong

$$-P(Go=N)\log(P(Go=N)) - P(Go=Y)\log(P(Go=Y))$$

$$= -\frac{3}{6}\log_2\left(\frac{3}{6}\right) - \frac{3}{6}\log_2\left(\frac{3}{6}\right)$$

$$= 1.0$$ //

max randomness, half yes half no

Example: Information Gain

Day	Outlook	Temperature	Humidity	Wind	Go outside
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

$$IG(S, wind) = 0.94 - \frac{8}{14}(0.811) - \frac{6}{14}(1)$$
$$= 0.048$$

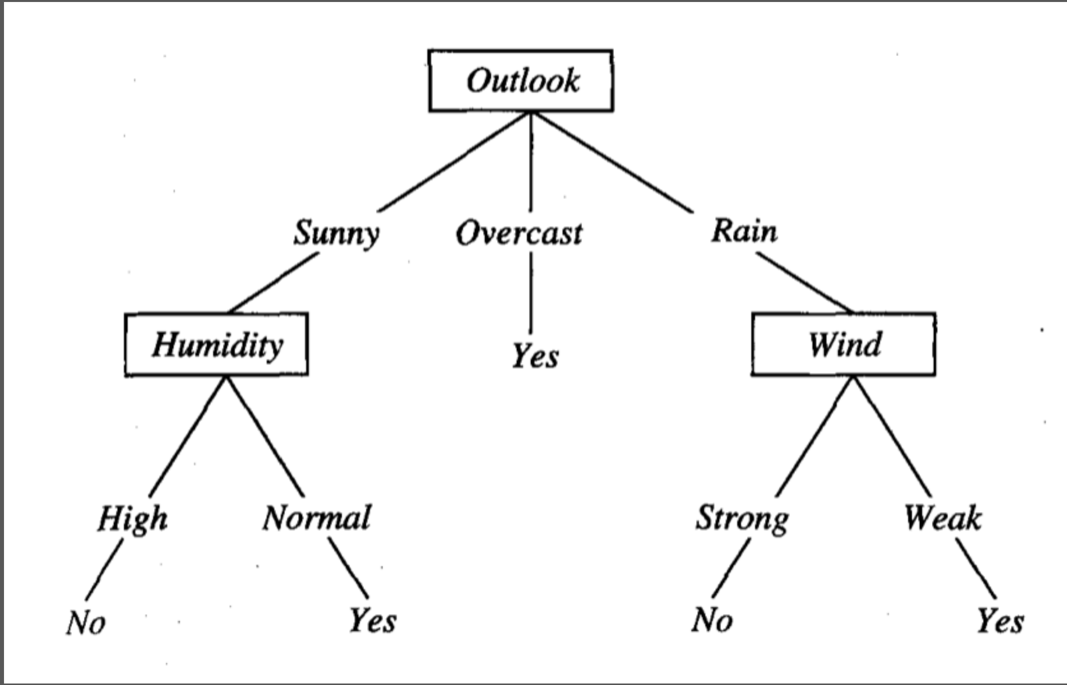
Example: Information Gain

Day	Outlook	Temperature	Humidity	Wind	Go outside
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

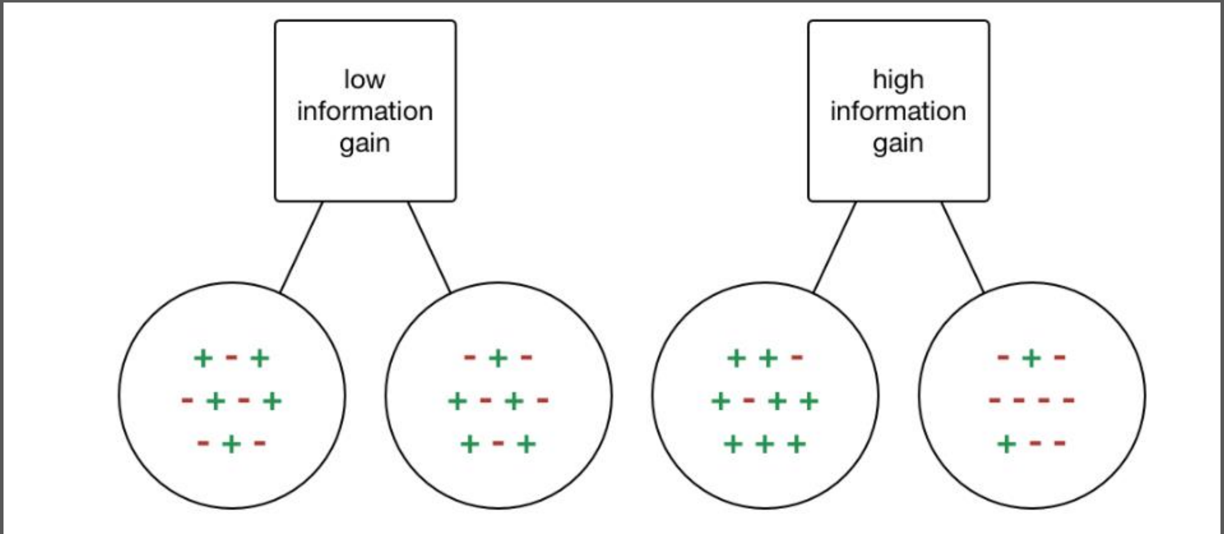
After computing information gain of every features, we have this:

$$IG(S, Wind) = 0.048$$
$$IG(S, Outlook) = 0.246$$
$$IG(S, Temperature) = 0.029$$
$$IG(S, Humidity\ ) = 0.151$$

Maximum information gain when splitting at Outlook, so we split at Outlook. Then keep repeating the process in each node after repeating a couple of time



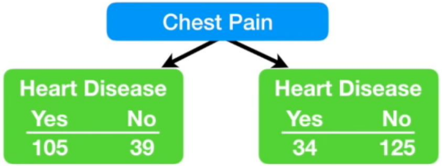
Visualize information gain



Another decision tree algorithm: Gini

Shrek Smith - the new genie

StatQuest: Decision Trees
(https://www.youtube.com/watch?v=7VeUPuFGJHk)



For this leaf, the Gini impurity $= 1 - (\text{the probability of "yes"})^2 - (\text{the probability of "no"})^2$

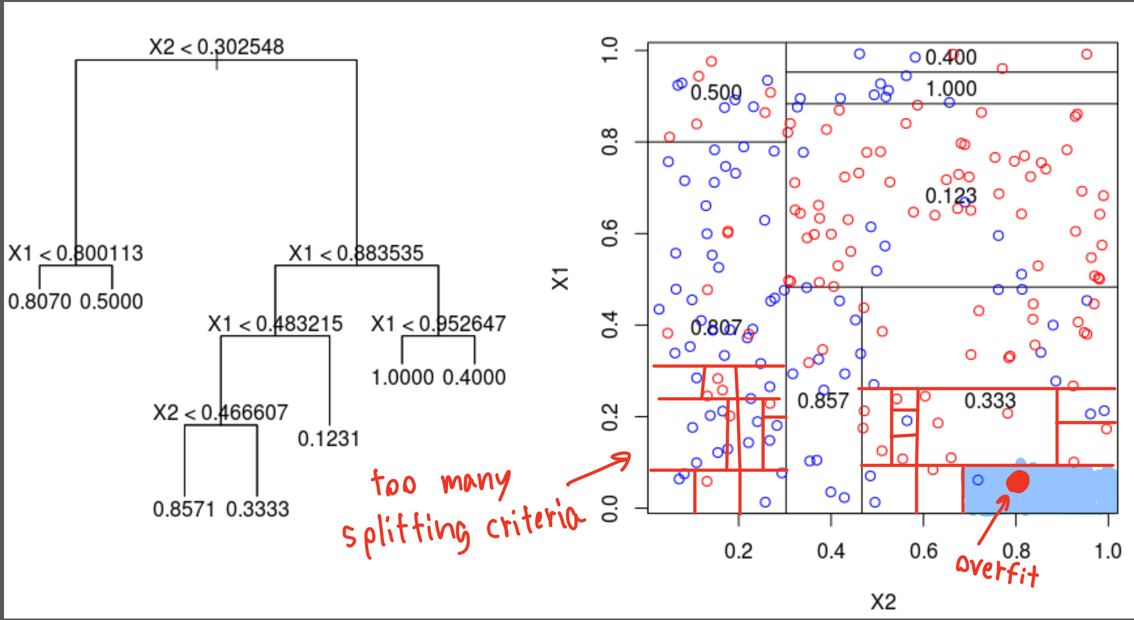
$$= 1 - \left(\frac{105}{105 + 39}\right)^2 - \left(\frac{39}{105 + 39}\right)^2$$

$$= 0.395$$

Continuous Data (number, and not categorical)

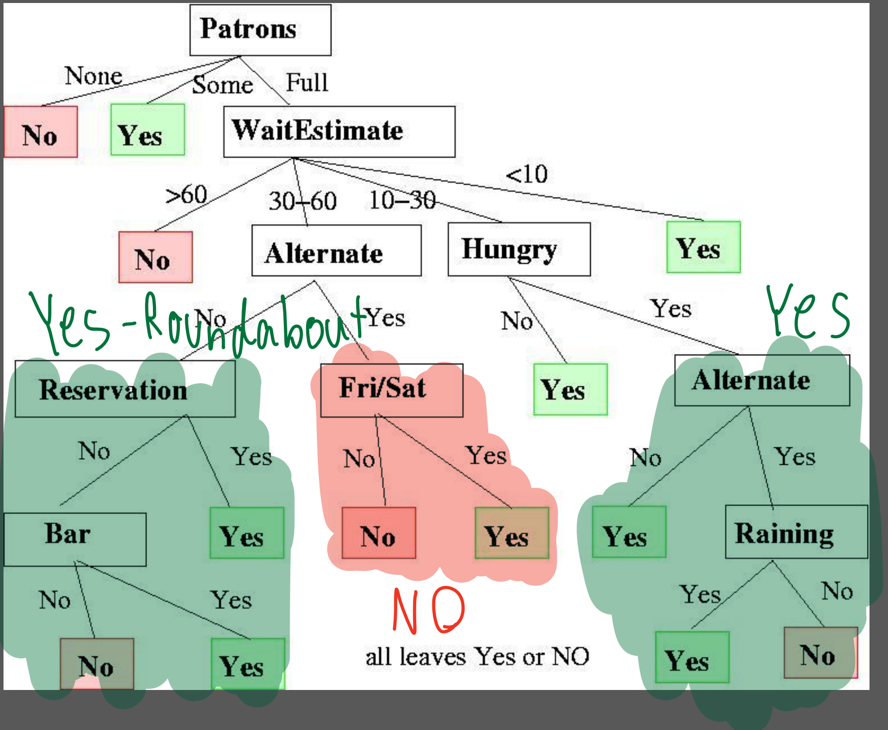
If the data is continuous data, you then sort, average for each adjacent row, and do the splitting algorithm at each average data

Overfit and Pruning



To fix overfitting problem, you can indicate what is the maximum tree's depth and stop there. (Pruning)

max_depth = 3



sklearn.tree.DecisionTreeClassifier

class sklearn.tree.**DecisionTreeClassifier**(**, criterion='gini', splitter='best', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features=None, random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, class_weight=None, ccp_alpha=0.0*) [source]

A decision tree classifier.

Read more in the User Guide.

Parameters:

criterion : *{"gini", "entropy"}, default="gini"*

The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain.

splitter : *{"best", "random"}, default="best"*

The strategy used to choose the split at each node. Supported strategies are "best" to choose the best split and "random" to choose the best random split.

max_depth : *int, default=None*

The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.

min_samples_split : *int or float, default=2*

The minimum number of samples required to split an internal node:

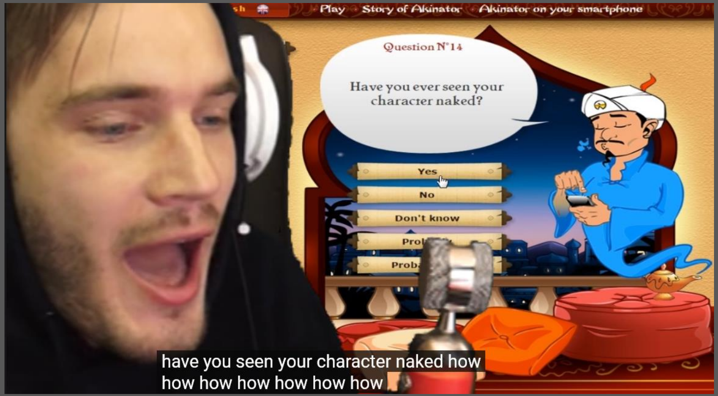
- If int, then consider `min_samples_split` as the minimum number.
- If float, then `min_samples_split` is a fraction and `ceil(min_samples_split * n_samples)` are the minimum number of samples for each split.

Gentle Introduction to Random Forest

https://youtu.be/J4Wdy0Wc_xQ

Might not do this

But you know, I learned something today



(internal)

- Decision Tree is used for classification by “step into” child nodes until reaching leaf node

- To prevent overfitting, pruning the tree