Decision Trees

- Decision trees are a simple hierarchically structured way to guide one's path to a decision.

- Decision tree learning is one of the most widely used techniques for classification.

    - Its classification accuracy is competitive with other methods, and
    - it is very efficient.

- The classification model is a tree, called decision tree.

Decision Trees Algorithm

- Employs the divide and conquer method
- Recursively divides a training set until each division consists of examples from one class

1. Create a root node and assign all of the training data to it
2. Select **the best splitting** attribute
3. Add a branch to the root node for each value of the split. **Split the data into mutually exclusive** subsets along the lines of the specific split
4. Repeat the steps 2 and 3 for each and every leaf node until the **stopping criteria** is reached

Decision Trees Algorithm

- Decision Tree algorithms mainly differ on
  - Splitting criteria
    - Which variable to split first? – Information Gain
    - What values to use to split?
    - How many splits to form for each node?
  - Stopping criteria
    - When to stop building the tree – Max tolerable error
  - Pruning (generalization method)
    - Pre-pruning versus post-pruning

Exercise: Decision tree to Predict ‘Play’

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

Question: How to Select the best splitting attribute

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	Normal	True	*??*

Evaluating the weather attributes

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

Attribute	Rules	Error	Total Error
Outlook	Sunny→No	2/5	

This represents previous outcomes (data) about
events that had occur and whether they resulted
in the game being played or not.

-Purpose: Predict the play decision given the atmospheric condition out there. The decision is to play or not to play.

Decision Trees are made to generate knowledge from test instances that can be used to a broad population and answer simple binary answers.

Evaluating the weather attributes

Outlook	**Temp**	**Humidity**	**Windy**	**Play**
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

Attribute	**Rules**	**Error**	**Total Error**
Outlook	Sunny→No	2/5	
	Overcast →yes	0/4	

Evaluating the weather attributes

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

Attribute	Rules	Error	Total Error
Outlook	Sunny→No	2/5	4/14
	Overcast →yes	0/4	
	Rainy →yes	2/5	

Decision Rule = Take the MAJORITY result for that attribute

EX: There is 5 outlooks for sunny —> 2/5 lead to "yes" play so since the MAJORITY of sunny is "no" we would say 2/5 of Sunny is an error (because those 2 rows are "yes" and are the minority results)

- Now we have the ROOT node —> now for the next nodes do this RECURSIVELY to find out what the decision should be

Evaluating the weather attributes

Outlook	Temp	Humidity	Windy	Play
Sunny	Hot	High	False	*No*
Sunny	Hot	High	True	*No*
Overcast	Hot	High	False	*Yes*
Rainy	Mild	High	False	*Yes*
Rainy	Cool	Normal	False	*Yes*
Rainy	Cool	Normal	True	*No*
Overcast	Cool	Normal	True	*Yes*
Sunny	Mild	High	False	*No*
Sunny	Cool	Normal	False	*Yes*
Rainy	Mild	Normal	False	*Yes*
Sunny	Mild	Normal	True	*Yes*
Overcast	Mild	High	True	*Yes*
Overcast	Hot	Normal	False	*Yes*
Rainy	Mild	High	True	*No*

Attribute	Rules	Error	Total Error
Outlook	Sunny→No	2/5	4/14
	Overcast →yes	0/4	
	Rainy →yes	2/5	
Temp	Hot →No	2/4	5/14
	Mild →Yes	2/6	
	Cool → Yes	1/4	
Humidity	High → No	3/7	4/14
	Normal →Yes	1/7	
Windy	False →Yes	2/8	5/14
	True →No	3/6	

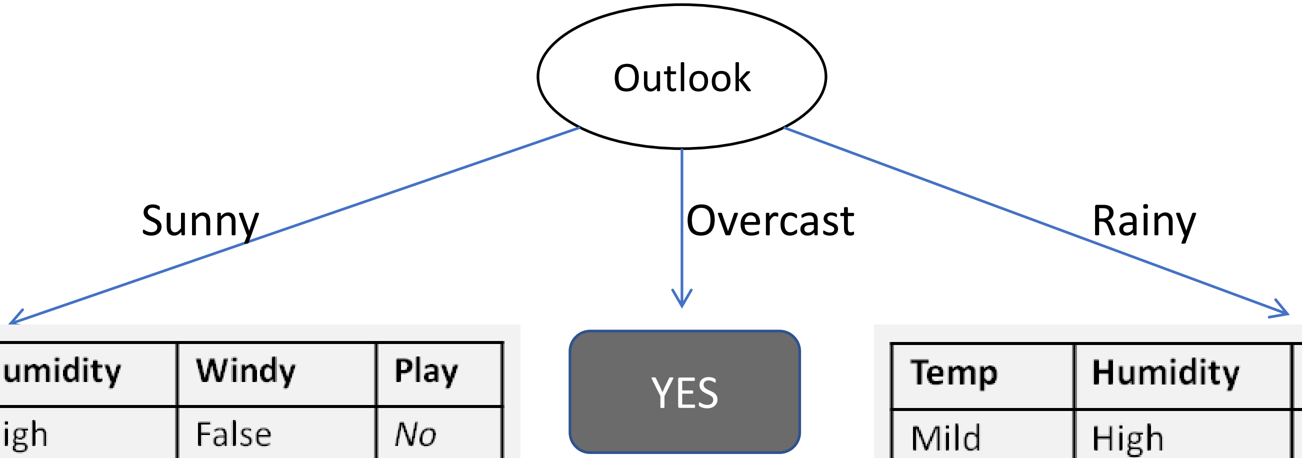
So outlook gives us 10 out of 14 correct decisions

Temp 9 out of 14 and so on

The value that has the LEAST error should be chosen as the first node

Decision tree after Iteration 1 (for weather/play problem)

Read Chapter 6 of Data Analytics



Temp	Humidity	Windy	Play
Hot	High	False	*No*
Hot	High	True	*No*
Mild	High	False	*No*
Cool	Normal	False	*Yes*
Mild	Normal	True	*Yes*

Temp	Humidity	Windy	Play
Mild	High	False	*Yes*
Cool	Normal	False	*Yes*
Cool	Normal	True	*No*
Mild	Normal	False	*Yes*
Mild	High	True	*No*

Decision tree after Iteration 1
(for weather/play problem)

Outlook

- Sunny
- Overcast → YES
- Rainy

Sunny

Temp	Humidity	Windy	Play
Hot	High	False	*No*
Hot	High	True	*No*
Mild	High	False	*No*
Cool	Normal	False	*Yes*
Mild	Normal	True	*Yes*

Attribute	Rules	Error	Total Error
Temp	Hot->No	0/2	1/5
	Mild ->No	1/2	
	Cool -> yes	0/1	
Humidity	High->No	0/3	0/5
	Normal->Yes	0/2	
Windy	False->No	1/3	2/5
	True->Yes	1/2	

Overcast

YES

Rainy

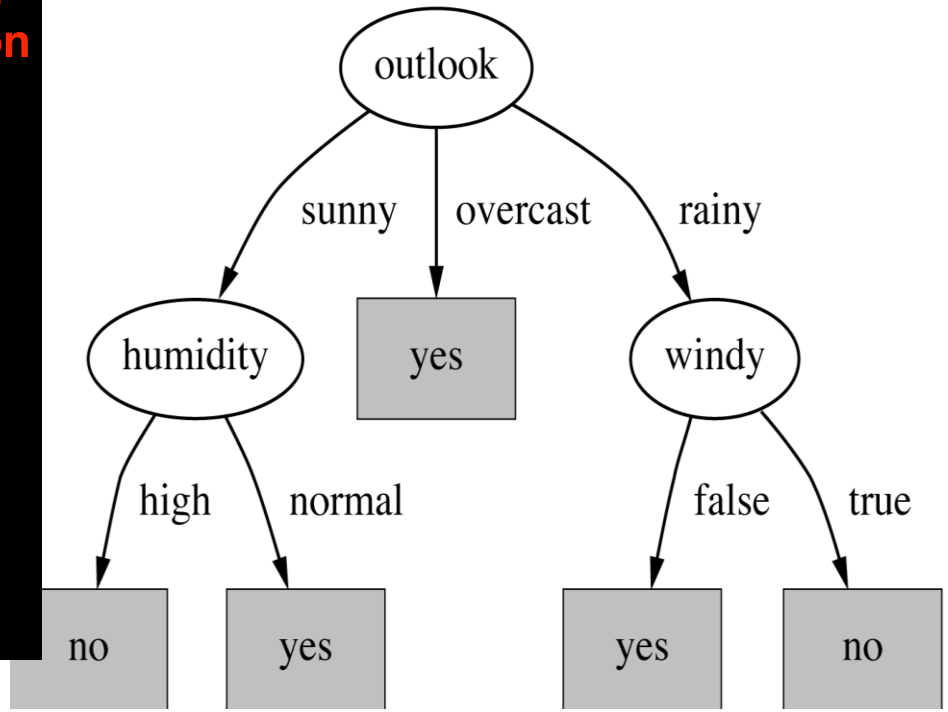
Temp	Humidity	Windy	Play
Mild	High	False	*Yes*
Cool	Normal	False	*Yes*
Cool	Normal	True	*No*
Mild	Normal	False	*Yes*
Mild	High	True	*No*

Attribute	Rules	Error	Total Error
Temp	Mild->Yes	1/3	2/5
	Cool->yes	1/2	
Humidity	High->No	1/2	1/5
	Normal->Yes	1/3	
Windy	False->Yes	0/3	0/5
	True-No	0/2	

NOTE:
-Purpose: Predict the play decision given the atmospheric condition out there. The decision is to play or not to play.
- To do this we should look at past experiences and see what decision was made in a similar instance if such instance exists.
- By having previous data of a situation within a database it is possible to match the current problem;
and the decision from that row to answer the current problem.
- However if there is no such past instance, then there is no guide to make a decision

Decision tree

(for weather/play problem)



Outloo k	Temp	Humidi ty	Wind y	Play
Sunny	Hot	Normal	True	*YES*

Predict using the mo

Decision Trees

1. Most import question should be first
aka the root node (one with the LEAST
errors) —> outlook in this case

2. Next determine the next DECISIONS
for each node and what they should be.
(This should be done to similar to the
previous slides where we find the MOST
popular decision and whichever attribute has the LEAST errors)

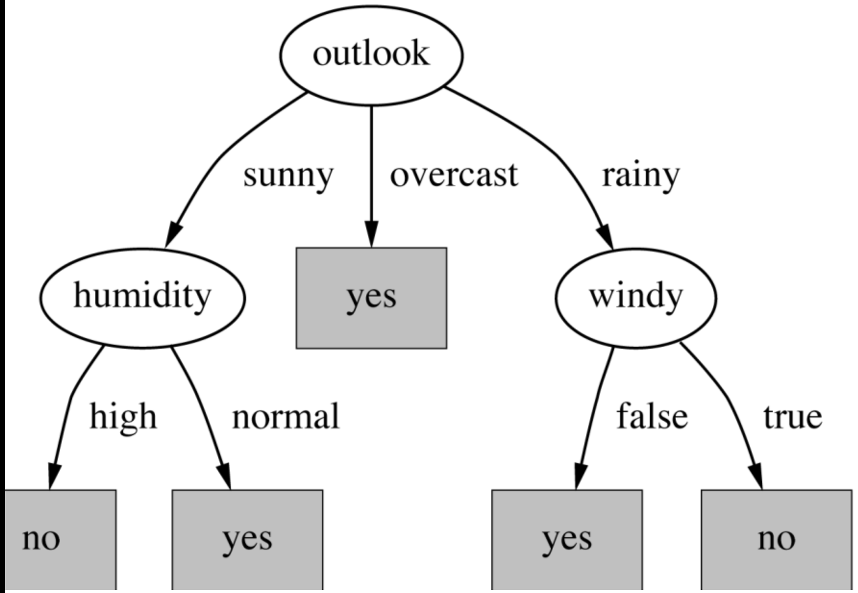
However, we separate the decisions based on the outlook no (sunny, rainy, overcast). And this idea is recursive as well

3. Then we have to find a point where the depth of the branch is too much

Decision tree (for weather/play problem)

Psuedo Code:

1. Create a root node and assign all of the training data to it
2. Select the best splitting attribute according to certain criteria
3. Add a branch to the root node for each value of the split
4. Split the data into mutually exclusive subsets along the lines of the specific split.
5. Repeat step 2 and 3 for each and every leaf node until a stopping criteria is reached



- Not all leaves need to be pure; sometimes identical instances have different class.
- Splitting stops when data can't be split any further

Decision Tree vs Table Lookup

	Decision Tree	**Table Lookup**
Accuracy	Varied level of accuracy	100% accurate
Generality	General. Applies to all situations	Applies only when a similar case occurred before
Frugality	Only three variables needed	All four variables are needed
Simple	Only one or two questions asked	All four variable values are needed
Easy	Logical, and easy to understand	Can be cumbersome to look up; no understanding of the logic behind the decision

Decision Trees (Part 2)

Now that we have an intuitive ideas how a decision tree is constructed. Let's focus on more precisely how to create a tree.

Remember the important question in tree construction is how to pick which attributes to split the tree on. This brings up the concept of information gain and entropy

Review links - explains more on Decision Tree

https://towardsdatascience.com/decision-tree-in-python-b433ae57fb93

https://towardsdatascience.com/enchanted-random-forest-b08d418cb411#.hh7n1co54

Decision Trees (Part 2)

Model Parameters:

- Max_depth : maximum depth of the trees
- Criterion: default is “gini”, other choice is “entropy”

```
model = DecisionTreeClassifier(max_depth=3, criterion='entropy’)
model = DecisionTreeClassifier(max_depth=3, criterion=‘gini')
```

Entropy and Information Gain

High Entropy

Messy = High Entropy

- Mixed cases = Heterogenous

  Example: 50% boy + 50% girls

If dataset is clean or "pure" = Low Entropy
- The goal is low entropy after we split the data

Low Entropy

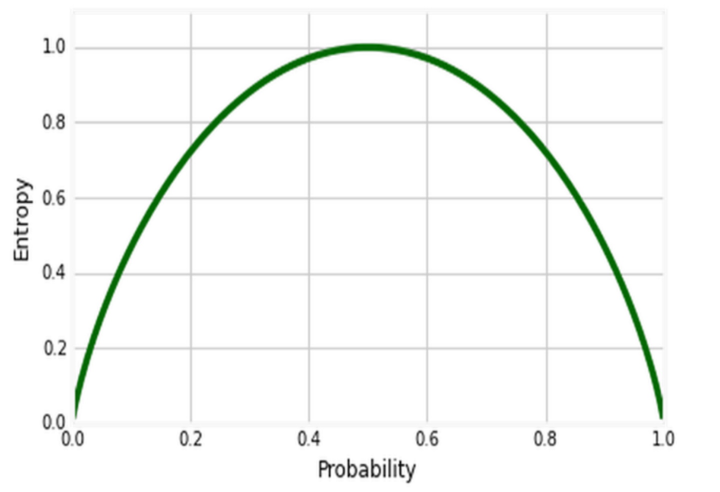
- Pure cases, homogenous
- Example: 90% boy + 10% girls
- or 10% boy + 90% girls

Information Gain from splitting a dataset S into different partition V

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

Entropy formula:

$$H = -\sum p(x) \log p(x)$$



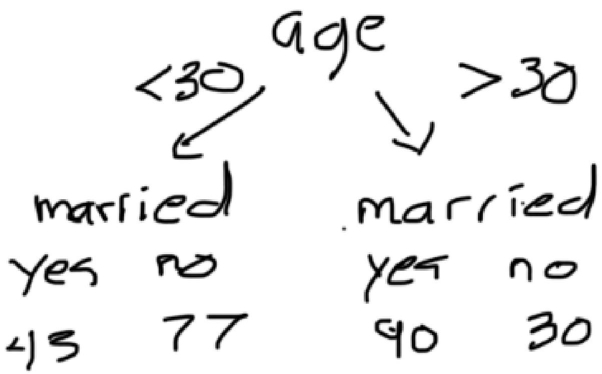
Entropy versus Probability of belonging to a class.

Gini Index: $G = \sum_{i=1}^{C} p(i) * (1 - p(i))$ **<— Gini Index**

$$G = \sum_{i=1}^{C} p(i) * (1 - p(i)) = \sum_{i=1}^{C} p(i) - p^2(i) = 1 - \sum_{i=1}^{C} p^2(i)$$

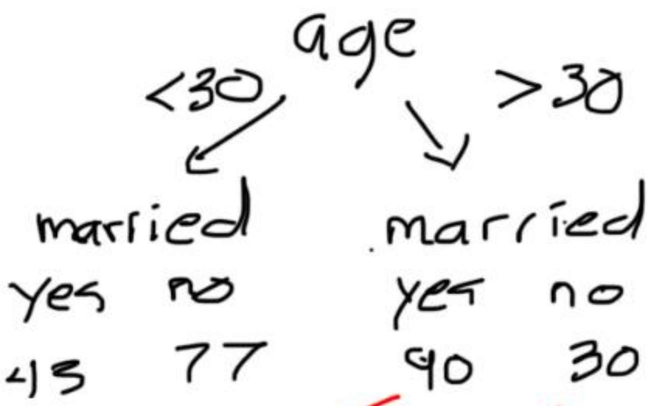
For pure class: When P(i) is 1 or 0, G = 0
For mix class: When P(i) = 0.5, G = 0.5

Left Impurity



$$\text{left Impurity} = 1 - \left(\frac{43}{43+77}\right)^2 - \left(\frac{77}{43+77}\right)^2 = 0.460$$

Right Impurity

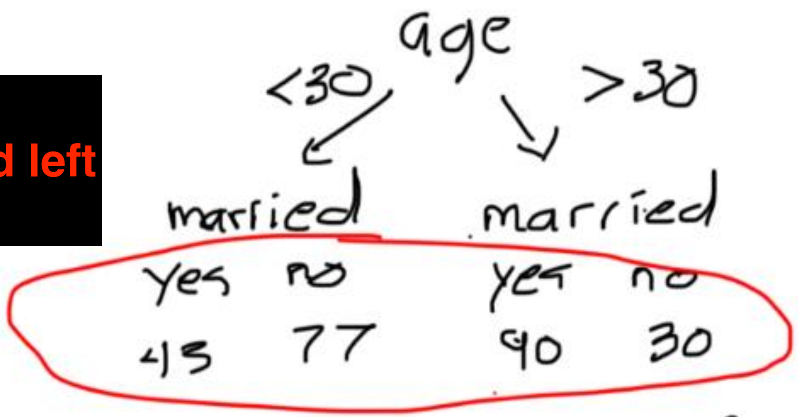


$$\text{right Impurity} = 1 - \left(\frac{90}{90+30}\right)^2 - \left(\frac{30}{90+30}\right)^2 = 0.375$$

Gini Index

Information gain is the difference in impurity before and after the split

Impurity combined left and right



$$Impurity = 1 - \left(\frac{120}{240}\right)^2 - \left(\frac{120}{240}\right)^2$$
$$= 0.5$$

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

$$\text{Information gain} = 0.5 - \left(\frac{120}{240}\right)(0.375) - \left(\frac{120}{240}\right)(0.460)$$
$$= 0.0825$$

Decision Tree Algorithms

Decision-Tree	C4.5	CART	CHAID
Full Name	Iterative Dichotomiser (ID3)	Classification and Regression Trees	Chi-square Automatic Interaction Detector
Basic algorithm	Hunt’s algorithm	Hunt’s algorithm	adjusted significance testing
Developer	Ross Quinlan	Bremman	Gordon Kass
When developed	1986	1984	1980
Types of trees	Classification	Classification & Regression trees	Classification & regression
Serial implementation	Tree-growth & Tree-pruning	Tree-growth & Tree-pruning	Tree-growth & Tree-pruning
Type of data	Discrete & Continuous; Incomplete data	Discrete and Continuous	Non-normal data also accepted
Types of splits	Multi-way splits	Binary splits only; Clever surrogate splits to reduce tree depth	Multi-way splits as default
Splitting criteria	Information gain	Gini’s coefficient, and others	*Chi*-square test
Pruning Criteria	Clever bottom-up technique avoids overfitting		Trees can become very large
Implementation	Publicly available	Publicly available in most packages	Popular in market research, for segmentation

10 models (trees) —> will repeatedly select the data w/ replacement and build a separate tree w/ each new training set. Each tree will be used to make a new forecast

Random Forests

- Repeatedly select data from the data set with replacement and build a separate tree with each new training set. Each of these trees built will be used to make new forecast. The class label that receive the most votes becomes the predicted class for that data point
- Each tree may be a "weak" classifier and is subject to overfitting from the specific training sample dataset. However, by building not just one tree, but multiple trees for different training samples, the hope is that the combined forecast from individual "weak" classifiers may become a "strong" classifier
- This is the basic idea behind the "Ensemble methods", in which we combine multiple machine learning algorithms to obtain better predictive performance. We'll run multiple models on the data and use the aggregate predictions, which will be better than a single model alone.

Decision Trees

Learning by doing