1 Module 14: Decision Trees

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	• being very interpretable	
	• require much less training data	
	• capable of intaking categorical data	
	• handle collinearity well	

Composition

Root node: beginning of tree

Internal nodes: can be split further (2 or more branches)

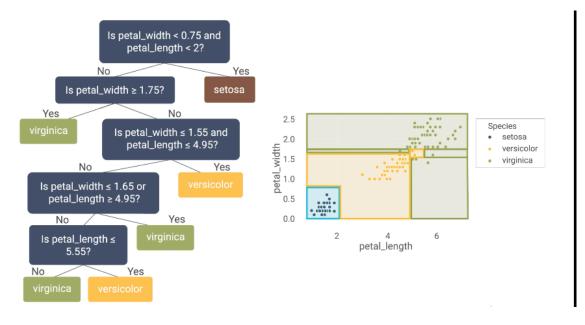
Leaf nodes: can no longer be split

Impure nodes: leaf nodes which do not encapsulate a single class (have multiple

classes w/i)

Algorithm

- Determine root node
- Calculate class entropy
- Calculate entropy for each attribute after split
- Calculate information gain from each split
- Perform splits until decision tree is complete
- Assess accuracy of decision tree



from sklearn import tree

```
model = tree.DecisionTreeClassifier(criterion = 'entropy')
model.fit(X, y)
```

Visualize tree thru sklearn

Viz thru Graphviz

import graphviz

Entropy

$$S = -\sum_{c} p_c \log_2 p_c$$

for proportion of each class c: p_c

Entropy cases:

- $-1\log_2 1 = 0$: All data in node is part of same class
- $-0.5\log_2 0.5 0.5\log_2 0.5 = 1$: Data is evenly split between two classes
- $3 \times -0.33\log_2 0.33 = 1.58$: Evenly split between three classes
- ... $C \times -\frac{1}{C} \log_2 \frac{1}{C} = \log_2 C$: Evenly split between C classes

Weighted Entropy: entropy \times fraction of samples in that node, s.t. weighted entropy decreases at each level

We use weighted entropy to decide which split to use – we want the highest change in weighted entropy.

1.1 Overfitting

For decision trees, more features \neq overfitting

To avoid overfitting, restrict decision tree complexity.

Prevent (unnecessary) growth

- Disallow splitting after a sample threshold i.e. 11% using min_sample_split
- Cap node depth using max_depth
- Do not create splits where weighted entropy is too small i.e. $\delta WS < 0.01$

Pruning: Allow tree to grow & cut branches afterward

• Use validation set to prune – run model with & without branch