dm24s1

Topic 10 : Classification2

Part 01 : Classification2-Overview

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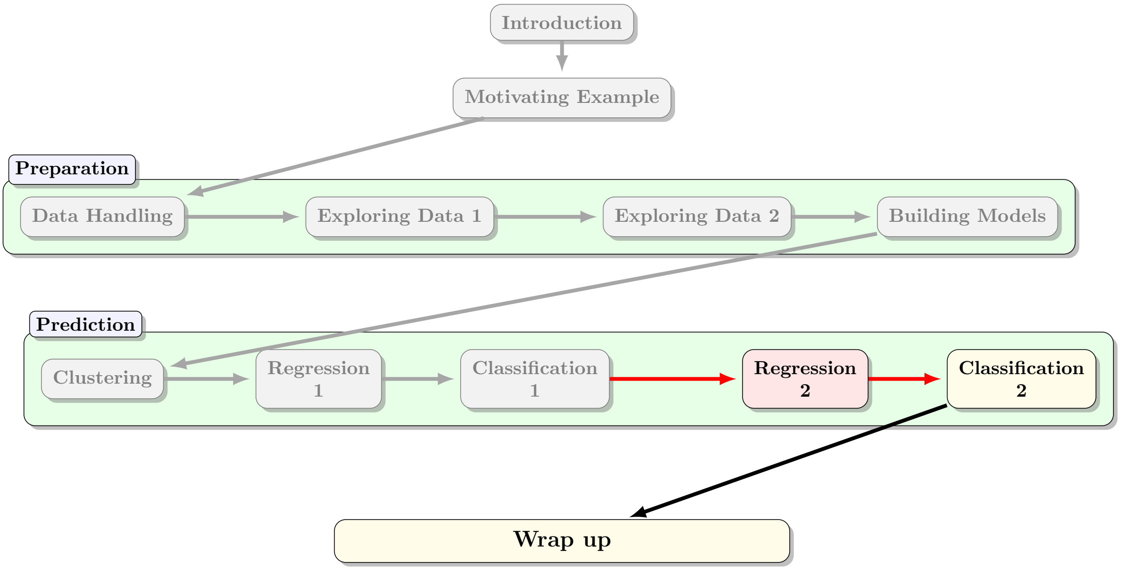
Autumn Semester, 2024

Outline

- Decision Trees
- Naive Bayes

Data Mining (Week 10)



Classification2-Overview — Summary

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These are two of the Top 10 algorithms in data mining (**WuKumarRossQuinlanEtAl2008**), each with its own strengths and weaknesses.

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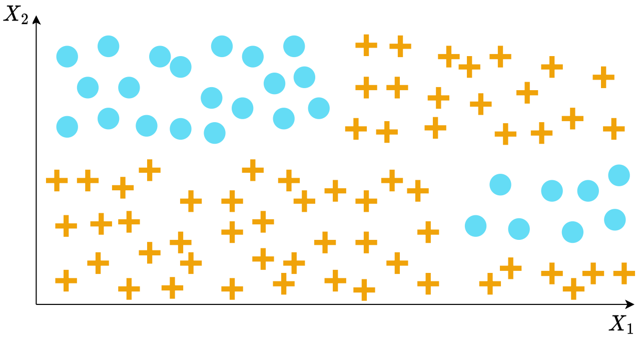
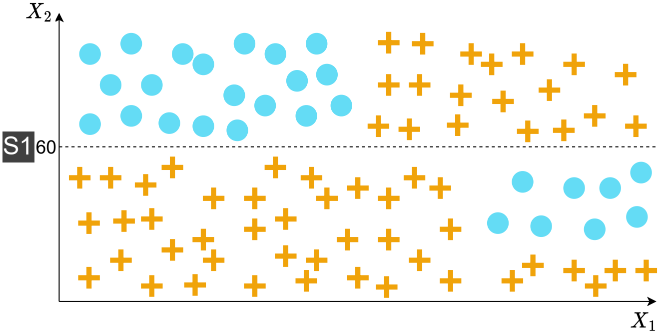
- The rules which generate the binary splits are applied in a greedy fashion and are intended to reduce the *impurity* in each nodes' children as quickly as possible
- the algorithm proceeds top-down from the root (all data), recursively generating rules as it goes
- Prediction is simple: the rules are applied along the path from root to leaf. The predicted class value is either the most frequent value at the leaf, or the leaf's probability vector.

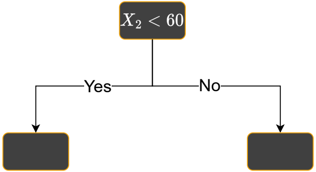
Classification tree: Example Data



Task: learn from this training data, to classify new data as either orange cross or blue disk

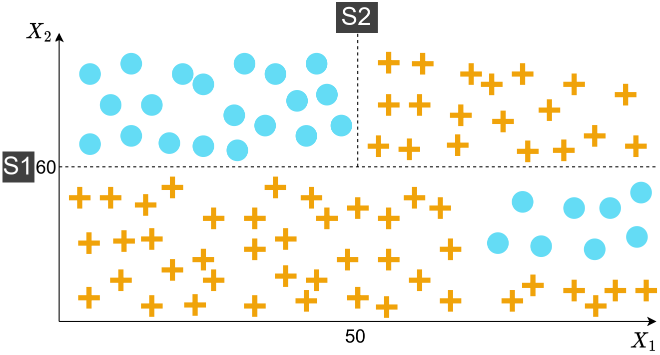
Classification tree: Example Data - First Split

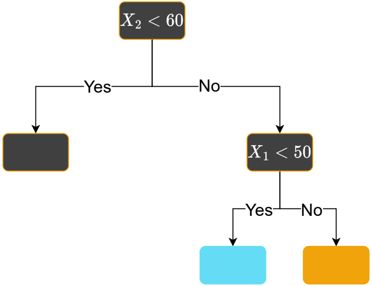




First split is on X_2; purity is improved (less mixing in each subset)

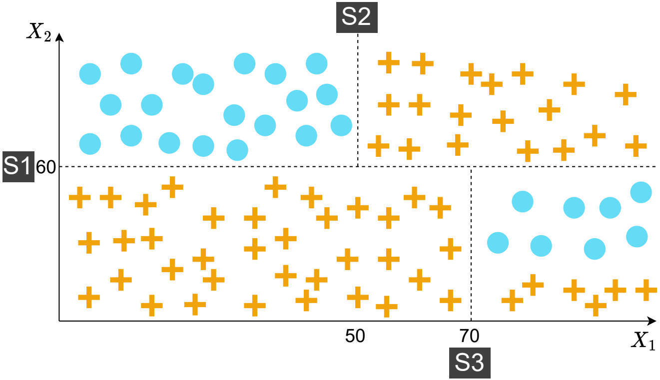
Classification tree: Example Data - Second Split

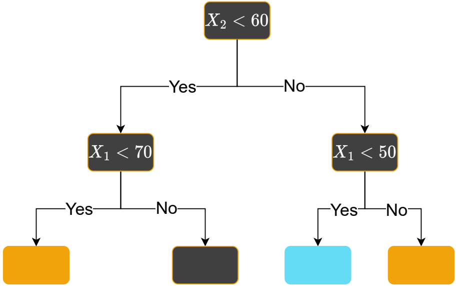




Second split is on X_1 so one region is pure (all blue disks) - can continue.

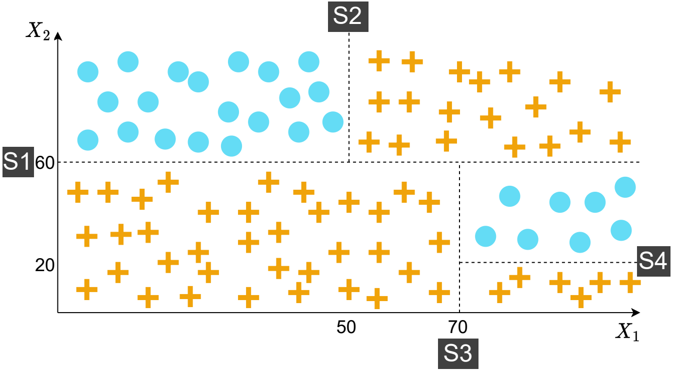
Classification tree: Example Data - Third Split

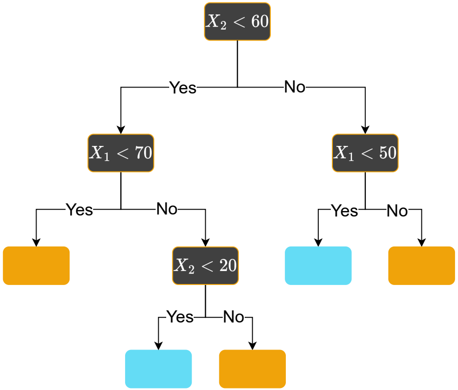




Third split on X_1 adds two extra pure regions.

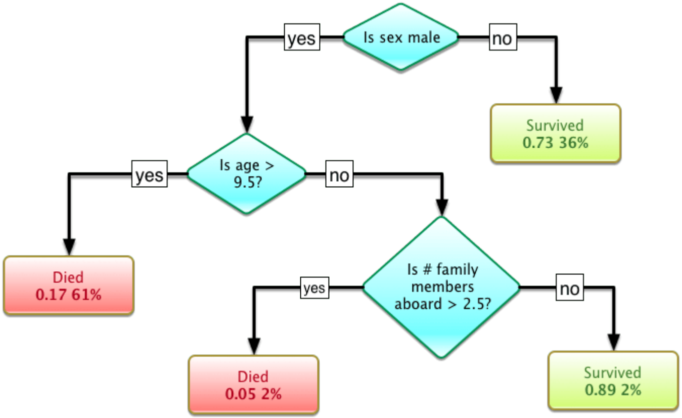
Classification tree: Example Data - Fourth Split





After fourth split on X_2, all regions are pure, so we stop.

Classification tree example: Titanic survival



- First split is on Sex, as that attribute was the most important predictor of survival.

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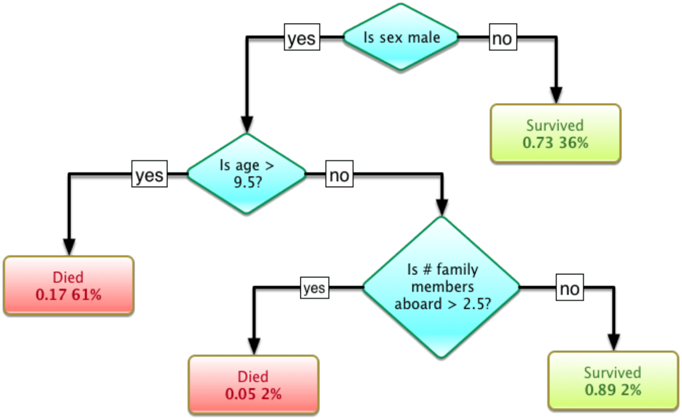

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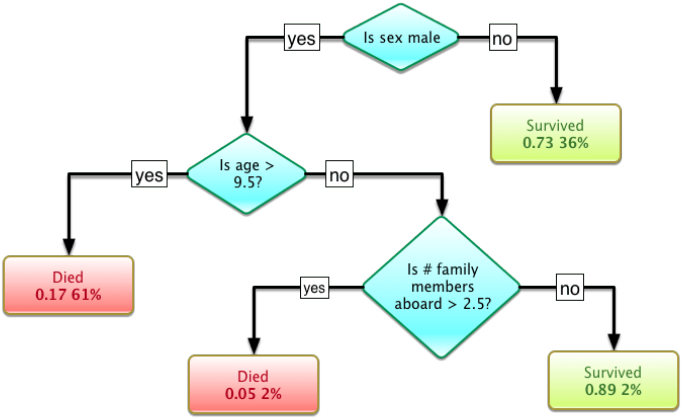

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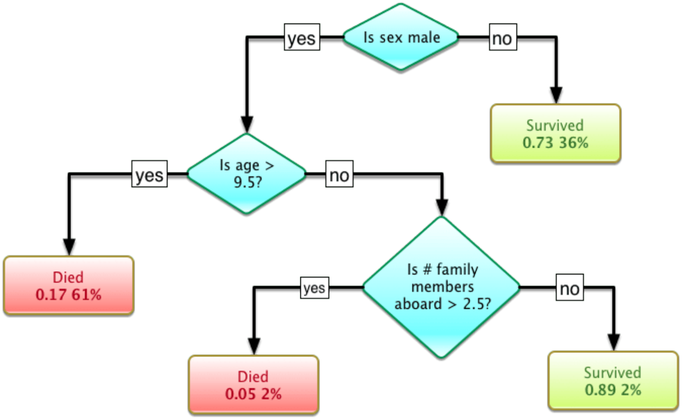

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- Leaf colour indicates p(survival) $\approx$ 1 (green) or p(survival) $\approx$ 0 (red)

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How information is measured

Information is measured in bits, and is computed from the probability $P(x)$ using $h(x) = -\log_2(P(x))$.

Information Entropy: Applied to classification

Classification and entropy

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$$H(X) = -\sum_{i=1}^{n} P(x_i)\log_2(P(x_i))$$

where $X = \{x_i\}$. If all probabilities are equal (X is uniformly distributed), $H(X) = 1$. If they differ, $H(X) < 1$. Remember the weather forecasting example!

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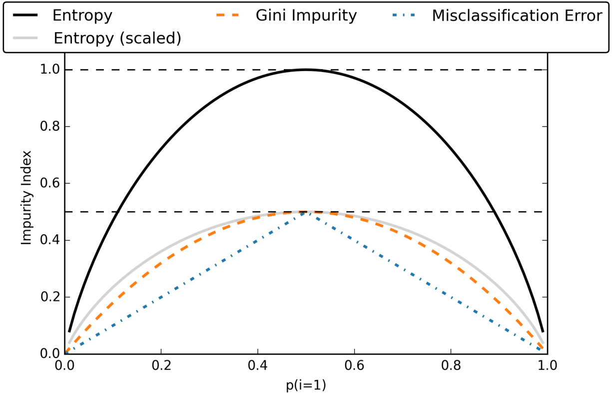
A decision tree recursively partitions a set so as to increase the purity (equivalently: reduce the mixing) of the set of observations X at each node as we move from the root to the leaves.

Classification tree metrics for rule building



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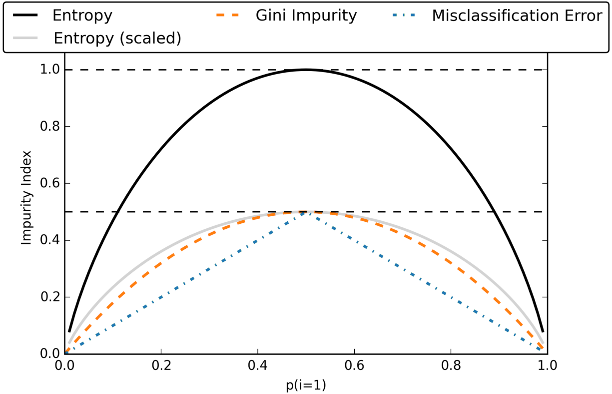

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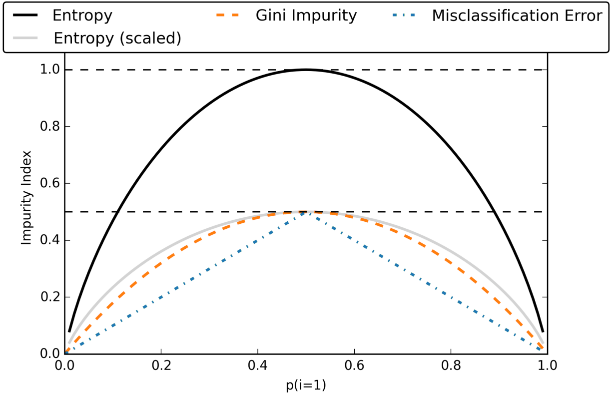

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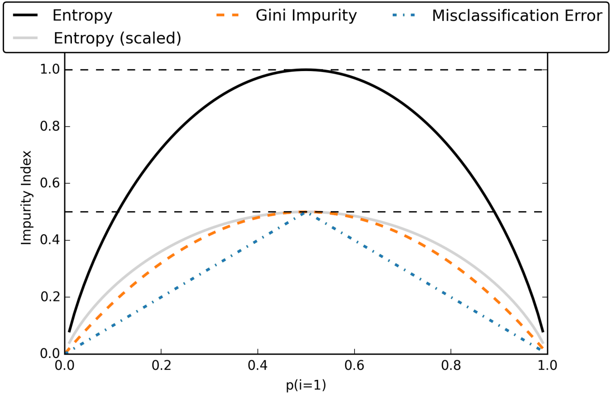

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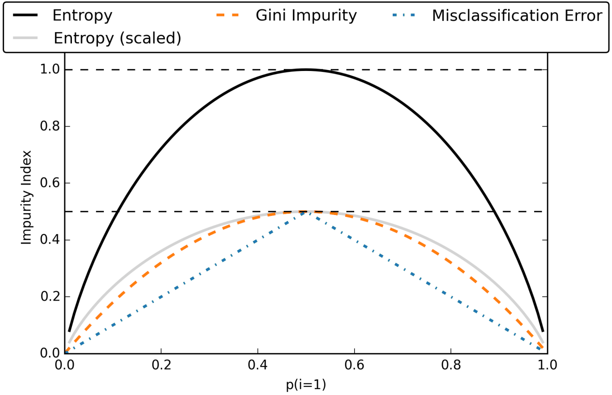

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- Mathematically, it is defined for *one attribute* T as $H(T) = -\sum_{j=1}^{J} p_j \log_2 p_j$, in a collection of size N where there are J unique elements of T, hence $p_j = \frac{n_j}{N}$ where there are n_j elements of type j.

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- For *two attributes* T and X, $H(T,X) = \sum_{c \in X} P(c)E(c)$ where each c represents a level of the X attribute.

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Example: PlayTennis example data

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
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sunny	mild	normal	true	yes
overcast	mild	high	true	yes
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rainy	mild	high	true	no

Source: Mitchell, *Machine Learning*, 1997.

PlayTennis example calculations

Example 4 (H(play))

$$\begin{aligned} H(\text{play}) &= -\left(p(\text{play}=\text{yes})\log_2 p(\text{play}=\text{yes}) + p(\text{play}=\text{no})\log_2 p(\text{play}=\text{no})\right) \\ &= H_{9,5} \\ &= -\left(\frac{9}{14}\log_2\left(\frac{9}{14}\right) + \frac{5}{14}\log_2\left(\frac{5}{14}\right)\right) \approx 0.94 \end{aligned}$$

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$$\begin{aligned} H(\text{play}, \text{outlook}) &= p(\text{outlook} = \text{sunny}) H(\text{play}\&(\text{outlook} = \text{sunny})) + \ldots \\ &= p(\text{outlook} = \text{sunny}) H_{3,2} + p(\text{outlook} = \text{overcast}) H_{4,0} + \ldots \\ &\approx \frac{5}{14} 0.97 + \frac{4}{14} 0 + \frac{5}{14} 0.97 \\ &\approx 0.69 \end{aligned}$$

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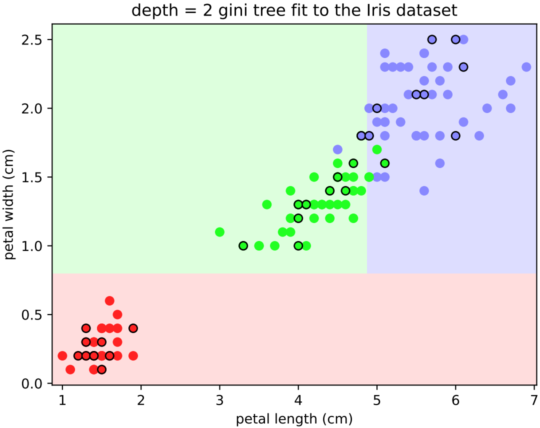
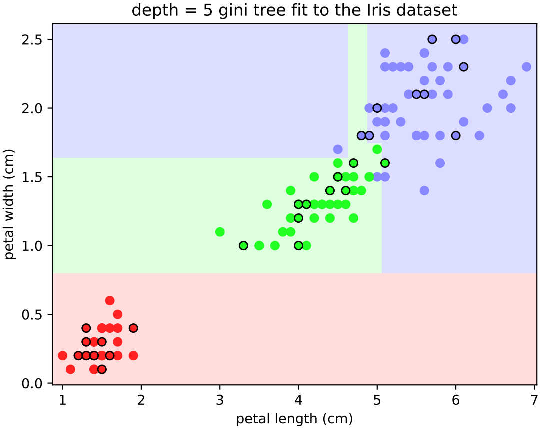
When growing decision trees, at a given node we search over the attributes for splitting, and choose the one that gives the maximum information gain, until we reach a leaf, which has an entropy of zero.

Classification tree examples: Iris Data





Note the rectangular regions (because each split is over one variable) and the greater complexity when the maximum depth of the tree increases.

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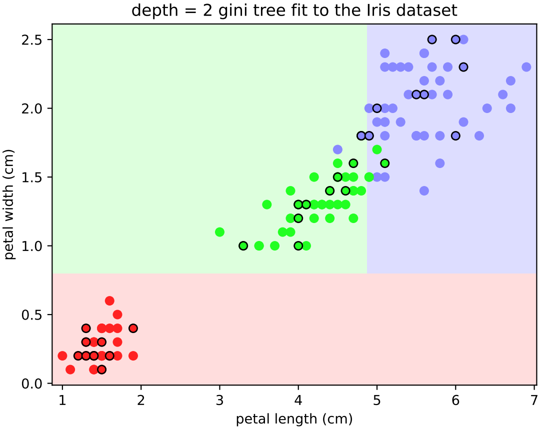

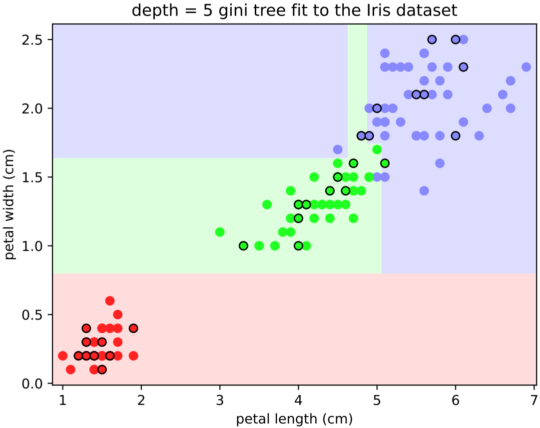

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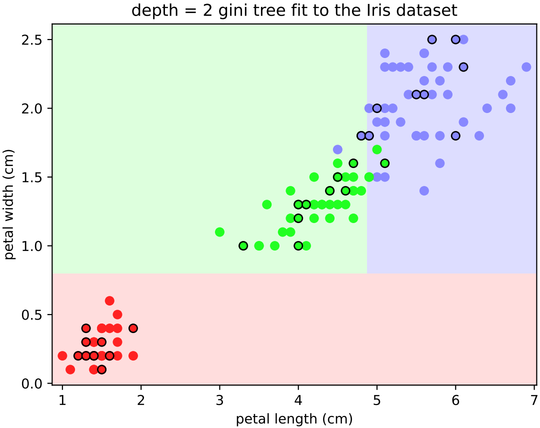

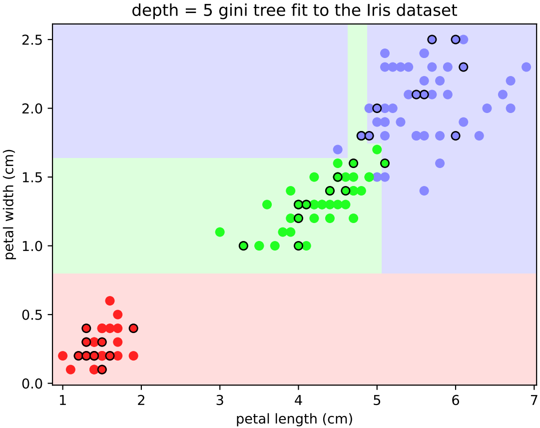

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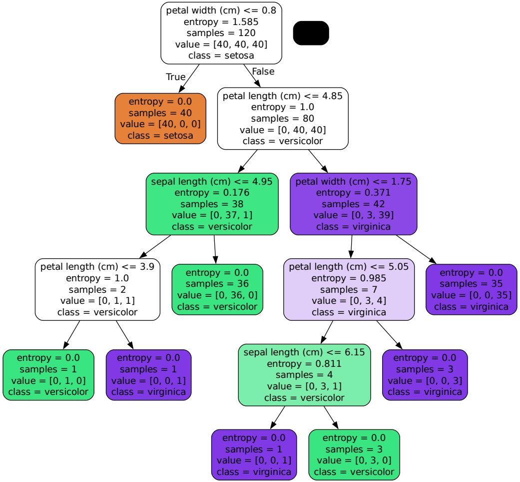
The choice of metric (Gini impurity or Information Gain) makes only slight changes to fit.

Classification tree view: Iris Data

- Note that the leaf nodes are pure (entropy=0) and are coloured according to predicted value (species label): brown for *I. setosa*, green for *I. versicolor* and purple for *I. virginica*.
- Also, the maximum entropy occurs at the root, where there are 40 of each of the 3 species, resulting in entropy = $\log_2(3)$.



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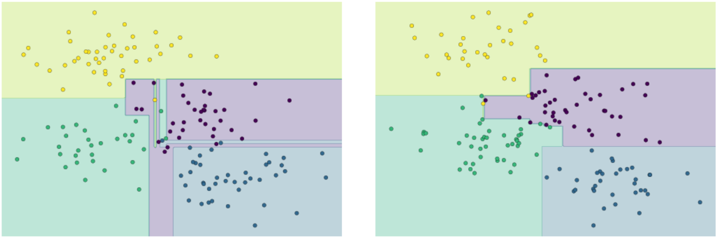
Python can extract paths from the root to each leaf as a set of if-then-else rules, to explain decisions.

Be careful of overfitting. . .



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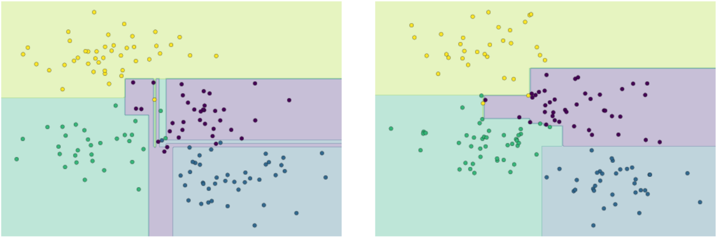

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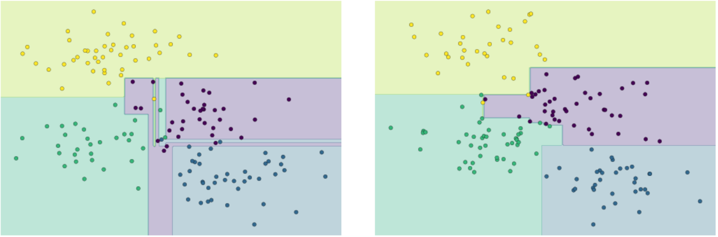

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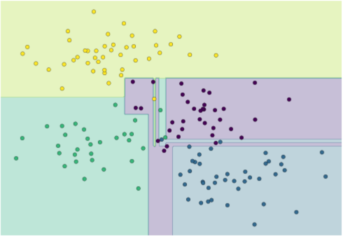

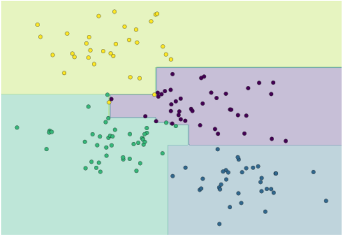

- Given two very similar (generated) data sets, all leaves in each fitted decision tree are *pure*.
- The resulting trees look very different.
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- Control by a) limiting depth or b) limiting number of leaves.

Classification trees in python

```
tree = DecisionTreeClassifier(criterion=criterion, max_depth=treeDepth, random_state=0)
tree.fit(Xtrain, ytrain)
y_treeTest = tree.predict(Xtest)
print(accuracy_score(ytest, y_treeTest))
print(confusion_matrix(ytest, y_treeTest))
print(classification_report(ytest, y_treeTest, digits=3))
```

After creating the classifier object, fit the training data and then use the fit to predict yTest from xTest. I have also shown how to get some diagnostic output. Similar diagnostics can be obtained for other classifiers.

Outline

Rev. Bayes and his theorem

Rev. Thomas Bayes, 1702–1761

Usage

Given $P(E|H)$ (Probability of Evidence (attributes) given the Hypothesis (the known classes) in the *training* set), Bayes theorem shows how to invert this relationship to get $P(H|E)$ (Probability of the Hypothesis (class) given the evidence (attributes) with an (unseen) *test case*).

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$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

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where $P(X|Y)$ is the conditional probability of X given that we know Y is true.

Application to classification

By convention, $A = H$ and $B = E$, where H is the hypothesis and E is the evidence in support of that hypothesis.

With this interpretation, the Bayes identity can be used to predict class probabilities (hypothesis) from features (evidence).

Conditional probabilities and Bayes terminology

Definition 6 (Conditional Probability)

If A and B are events, the Probability of A, given that B is true (has happened), written $P(A|B)$ is defined as follows:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{2}$$

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Given Bayes Theorem 1, we have

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$P(A)$	Class prior; Prior probability
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- In data mining, B might represent the features (derived from the Data) for a given instance and A might represent the *predicted label* for these features.
- If A and B are independent events, $P(A \cap B) \equiv P(A)P(B)$, so $P(A|B) = P(A)$ and $P(B|A) = P(B)$.

Extended and Bayes

In practice, there would be multiple features/evidence so $B = \{B_1, B_2, \ldots, B_n\}$

.

Definition 7 (Extended Bayes Theorem)

The extended form, when $\{B_j\}$ partition B, so $B = \cup_j B_j$ and $B_p \cap B_q \equiv \emptyset$ unless $p = q$, is

$$P(A|\{B_i\}) = \frac{P(\{B_i\}|A)P(A)}{P(\{B_i\})} \tag{3}$$

which is the component-wise version of the standard Bayes Theorem.

Side note: Prosecutor's Fallacy

Note that $P(A|B) \neq P(B|A)$ in general. If the ratio $\frac{P(A)}{P(B)}$ is not close to 1, lawyers can mislead jurors regarding guilt or innocence. *Probability of Guilt given the evidence is not the same as the probability of the evidence assuming the defendant is guilty.*

Naive Extended Bayes

Definition 8 (Naive Bayes)

If the features B are assumed to be independent of each other, it can be shown that

$$P(B) = P(B_1 \cap B_2 \cap \ldots B_n) = \prod_i P(B_i) \tag{4}$$

$$P(B|A_j) = \prod_k P(B_i|A_j) \tag{5}$$

The naïve form of Bayes theorem becomes

$$P(A_j|B) = \frac{\prod_i P(B_i|A_j)P(A_j)}{\prod_i P(B_i)} \tag{6}$$

Naive Bayes classifier

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- It is then assigned to the class for which its conditional probability is greatest.

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  - $P(B_i|A_j)$ (the evidence that the feature valued B_i predicts the class label A_j).
- From this, we can use the naive version of the extended Bayes Theorem 6 to predict $P(A_j|B)$, the posterior probability of class label A_j given all the evidence from the features B.

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- One of the features of Naïve Bayes (with $P(A|B)$), like decision trees (with $P(A \cap B)$), is the direct role played by probability
- When training Naïve Bayes, it is convenient to compute a table of *marginal counts*, as seen in the next slide, and to use these for prediction.

Fruit classification example

Example: Fruit classification

Type	Long	¬Long	Sweet	¬Sweet	Yellow	¬Yellow	*Total*
Banana	400	100	350	150	450	50	*500*
Orange	0	300	150	150	300	0	*300*
Other	100	100	150	50	50	150	*200*
Total	*500*	*500*	*650*	*350*	*800*	*200*	*1000*

Source: stackoverflow

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Fruit classification : Precalculations

P(<Fruit>) = Total_<Fruit> / Total_*
P(<Feature>) = Total_<Feature> / Total_*
P(<Feature> | <Fruit>) = <Fruit,Feature> / Total_<Fruit>

$\rightarrow$ P(Other) = 200/1000 = 0.2
$\rightarrow$ P(Sweet) = 650/1000 = 0.65
$\rightarrow$ P(Sweet | Other) = 150/200 = 0.75

Fruit classification example: prediction

Given observation: Long=L, Sweet=S, Yellow=Y fruit, which is it?

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Banana - B

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$$\frac{P(\mathrm{L}|\mathrm{B})P(\mathrm{S}|\mathrm{B})P(\mathrm{Y}|\mathrm{B})P(\mathrm{B})}{P(\mathrm{L})P(\mathrm{S})P(\mathrm{Y})}$$

$$= \frac{0.8 \times 0.7 \times 0.9 \times 0.5}{0.5 \times 0.65 \times 0.8}$$

$= 0.97$

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Orange - O

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$$= \frac{0.5 \times 0.75 \times 0.25 \times 0.2}{0.5 \times 0.65 \times 0.8}$$

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$= 0.07$

According to the MAP criterion, the observation (mystery fruit) is a banana!

Fruit classification example: prediction

Given observation: Long=L, Sweet=S, Yellow=Y fruit, which is it?

Banana - B

$P(\mathrm{B}|L,S,Y) =$

$$\frac{P(\mathrm{L}|\mathrm{B})P(\mathrm{S}|\mathrm{B})P(\mathrm{Y}|\mathrm{B})P(\mathrm{B})}{P(\mathrm{L})P(\mathrm{S})P(\mathrm{Y})}$$

$$= \frac{0.8 \times 0.7 \times 0.9 \times 0.5}{0.5 \times 0.65 \times 0.8}$$

$= 0.97$

Orange - O

$P(\mathrm{O}|L,S,Y) =$

$$\frac{P(\mathrm{L}|\mathrm{O})P(\mathrm{S}|\mathrm{O})P(\mathrm{Y}|\mathrm{O})P(\mathrm{O})}{P(\mathrm{L})P(\mathrm{S})P(\mathrm{Y})}$$

$$= \frac{0.0 \times 0.5 \times 1.0 \times 0.3}{0.5 \times 0.65 \times 0.8}$$

$= 0$

Other = R

$P(\mathrm{R}|L,S,Y) =$

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Given the 3 binary-valued attributes, there are $2^3 = 8$ possible combinations - Naïve Bayes will classify each of these 8 combinations as one of the 3 fruit classes.

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- Implementations exist in `sklearn`: `from sklearn.naive_bayes import GaussianNB`, etc.

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In the meantime, either Regression or Classification is used, with caveats...

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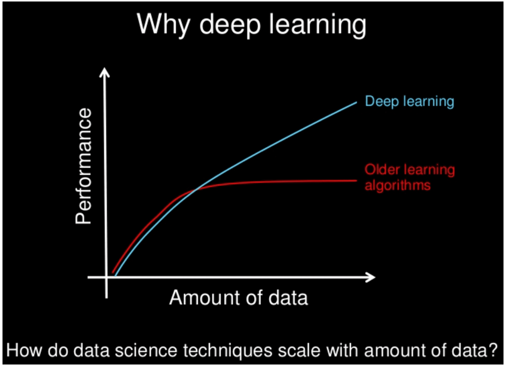
Classification is sometimes confused with clustering - will cover this clustering next lecture.

But is that the last word on Classification?



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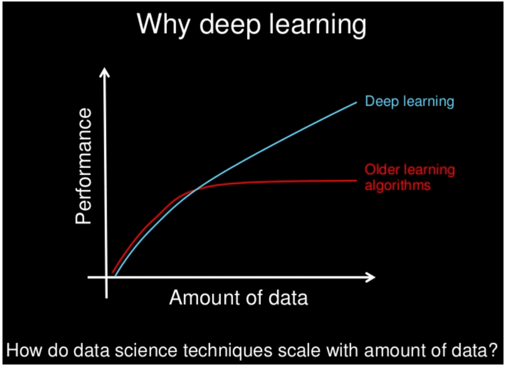

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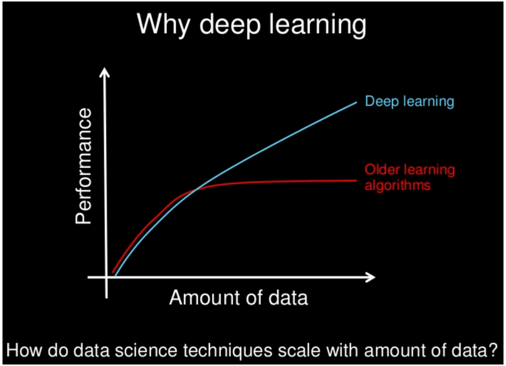

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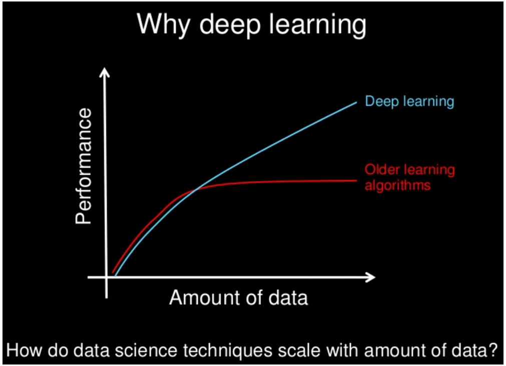

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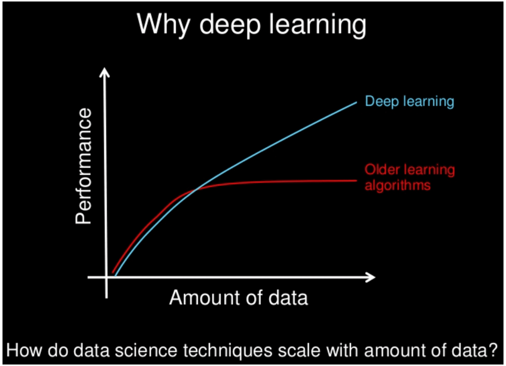

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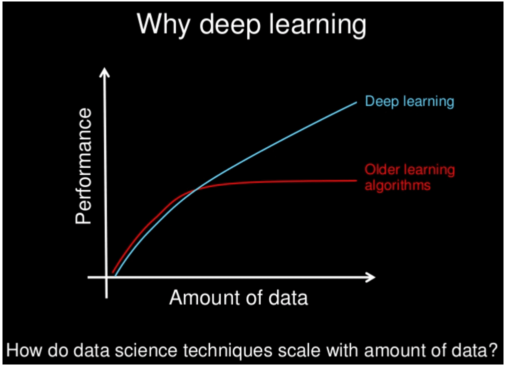

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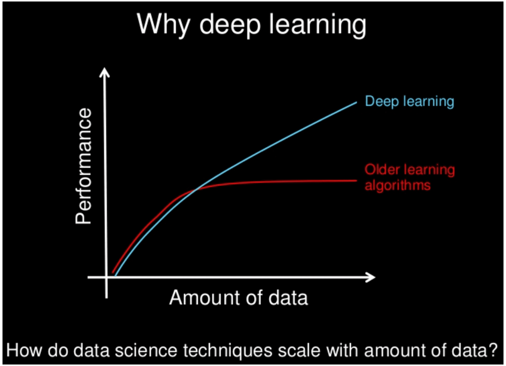

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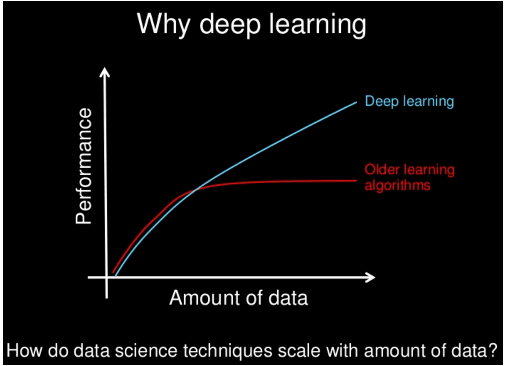

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Deep Learning will probably be covered in semester 2…

General References