COMP30120

Decision Trees

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Overview

- What is a Decision Tree?
- Feature Selection
  - Good v Bad features
  - Information Theory - Entropy
- How to build a Decision Tree?
  - ID3 top-down algorithm
  - Information Gain
- Decision Trees in Weka

Decision Tree Learning

- Goal: Build a tree model that splits the training set into subsets in which all examples have the same class.
- A feature can be used to split the training set, one for each value or range of the feature…
  - e.g. insured = {true, false}
  - e.g. income = {low, average, high}
  - e.g. height < 6ft, height ≥ 6ft
- If necessary, each subset can be split again using another feature, and so on until all examples have the same class.
- Selecting a feature on which to split can be done using a measure based on uncertainty.
- Once the tree is built, we can use it to quickly classify new input examples (i.e. eager learning).

Example: Apples v Pears

- 10 training examples such that: each has a class label ("apple" or "pear"), and each is described with 6 features.

Example	***Colour***	***Height***	***Width***	***Taste***	***Weight***	***H/W***	***Class***
1	210	60	62	Sweet	186	0.97	Apple
2	220	70	53	Sweet	180	1.32	Pear
3	215	55	50	Tart	152	1.10	Apple
4	180	76	40	Sweet	152	1.90	Pear
5	220	68	45	Sweet	153	1.51	Pear
6	160	65	68	Sour	221	0.96	Apple
7	215	63	45	Sweet	140	1.40	Pear
8	180	55	56	Sweet	154	0.98	Apple
9	220	68	65	Tart	221	1.05	Apple
10	190	60	58	Sour	175	1.03	Apple

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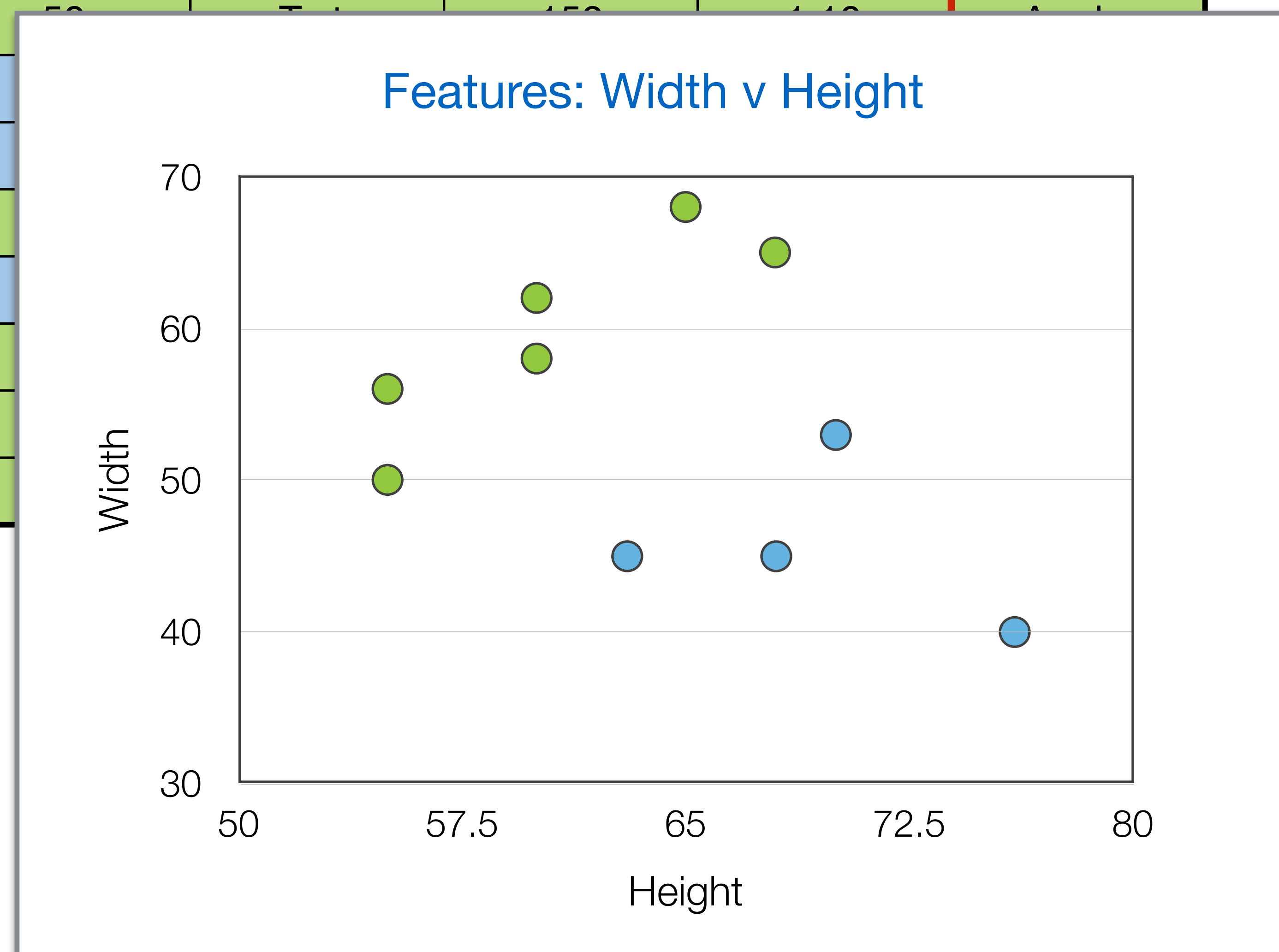
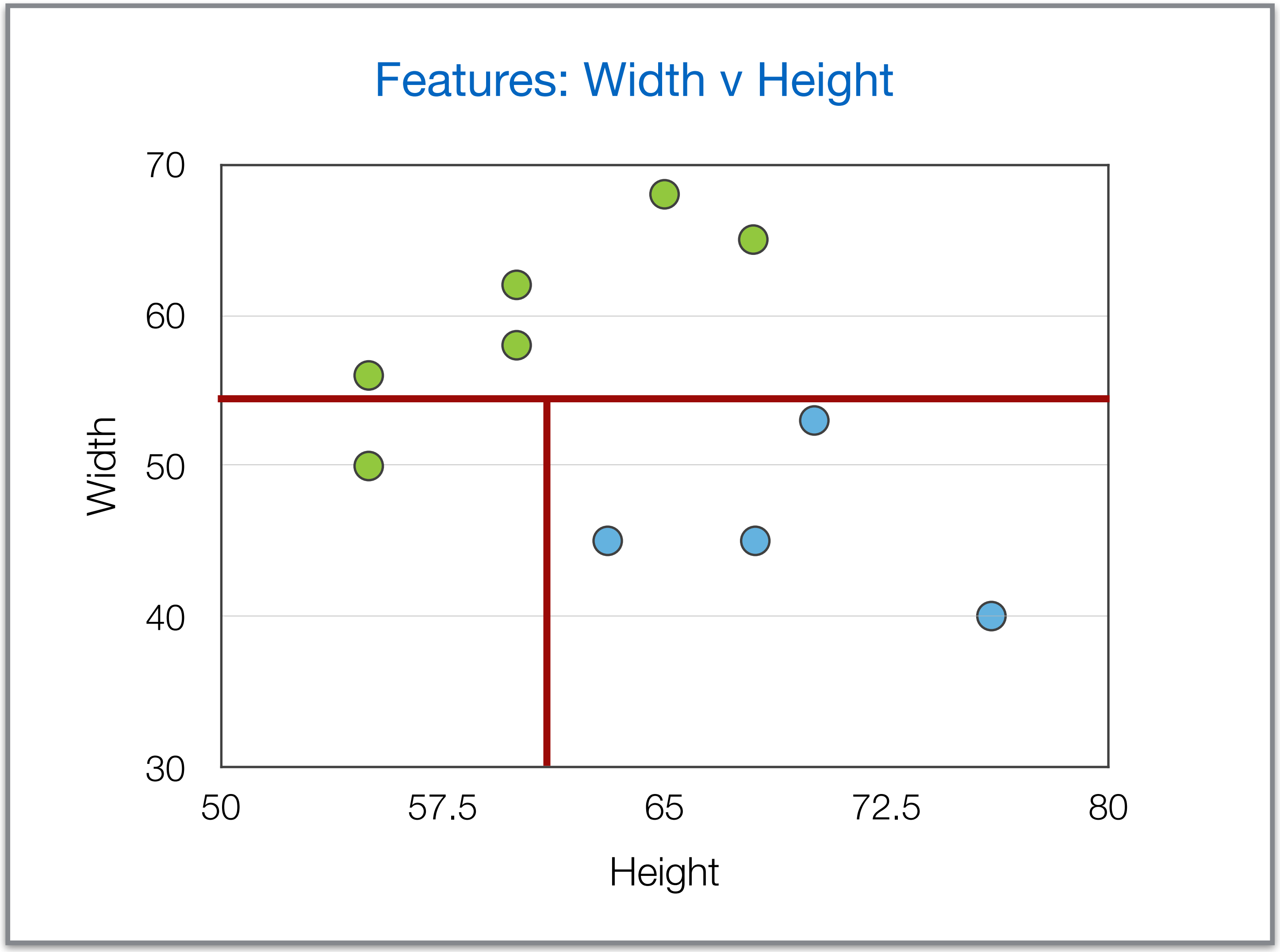
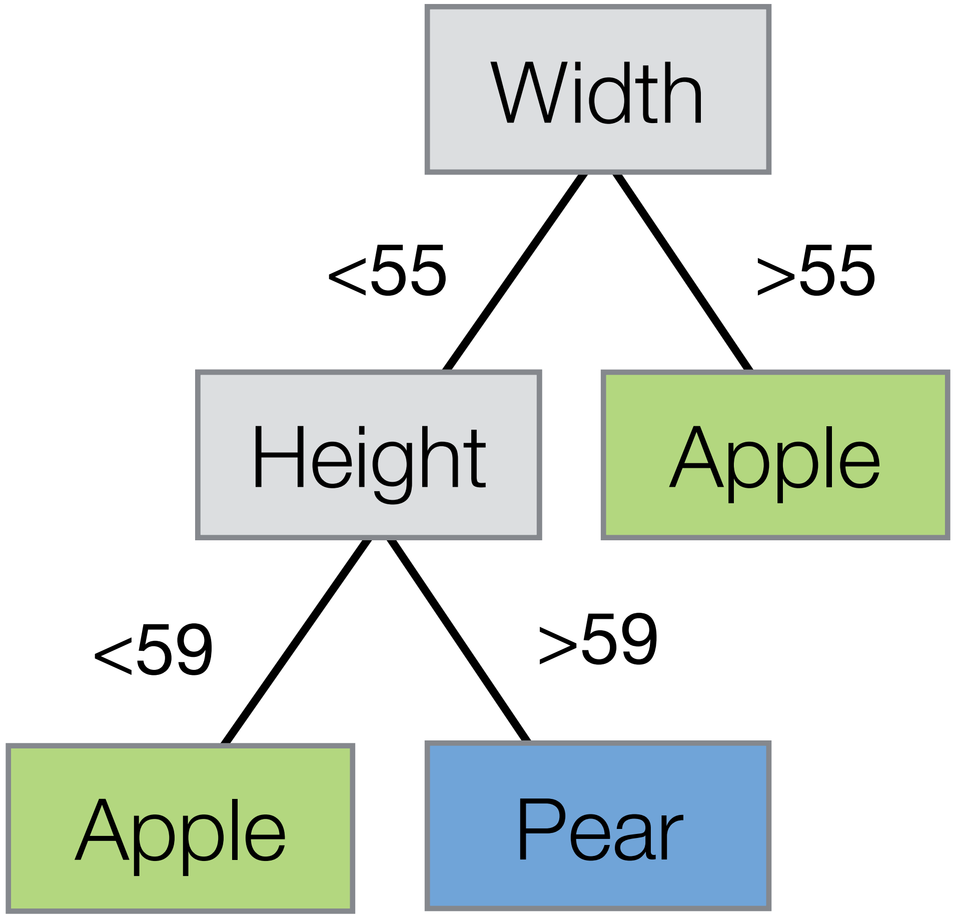
Example	*Colour*	*Height*	*Width*	*Taste*	*Weight*	*H/W*	*Class*
1	210	60	62	Sweet	186	0.97	Apple
2	220	70	53	Sweet	180	1.32	Pear
3	215	55	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	180	76					
5	220	68					
6	160	65					
7	215	63					
8	180	55					
9	220	68					
10	190	60					



Example: Apples v Pears

- Simple decision tree for classifying Apples v Pears using only 2 features: {Height, Weight}





Just 2 features can split the data based on these decision rules.

Example: Apples v Pears

- 10 training examples such that: each has a class label (“apple” or “pear”), and each is described with 6 features.

Example	Colour	Height	Width	Taste	Weight	H/W	Class
1	210	60	62	Sweet	186	0.97	Apple
			53	Sweet	180	1.32	Pear
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			68	Sour	221	0.96	Apple
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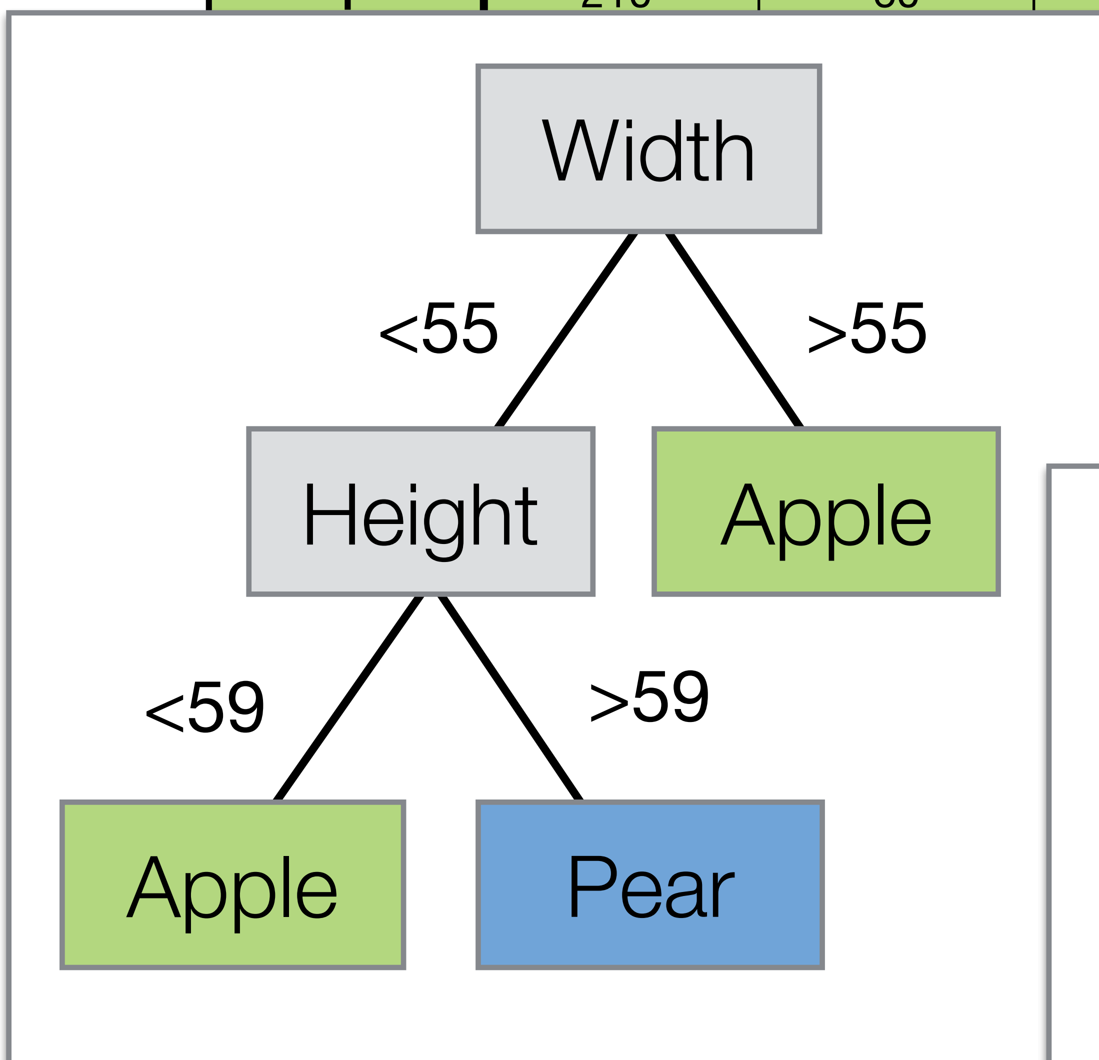
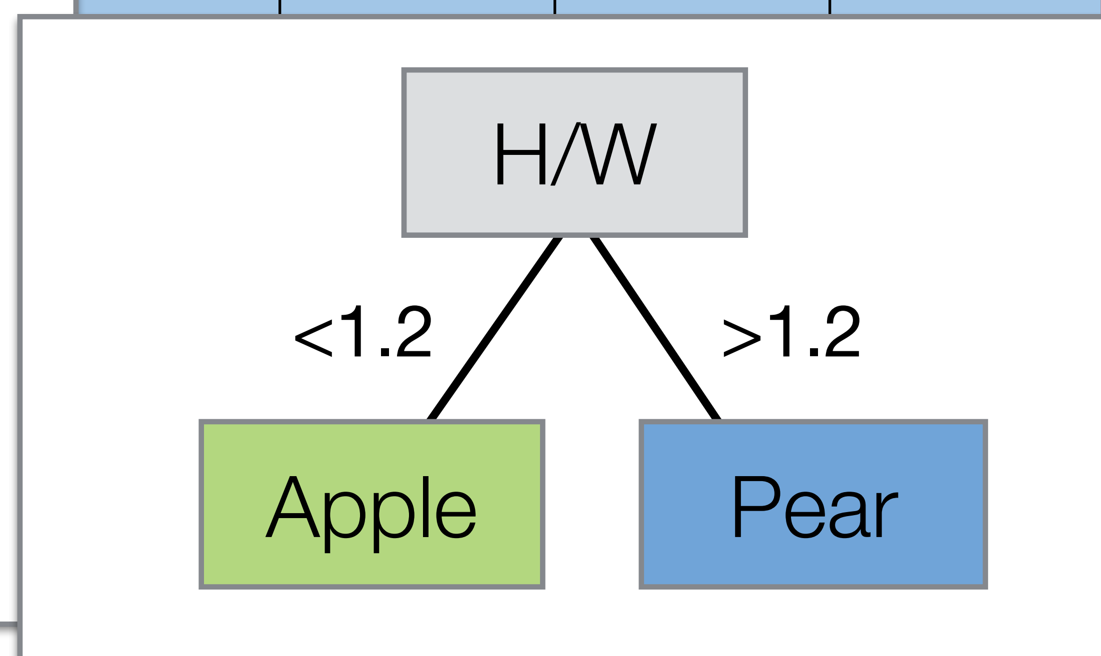
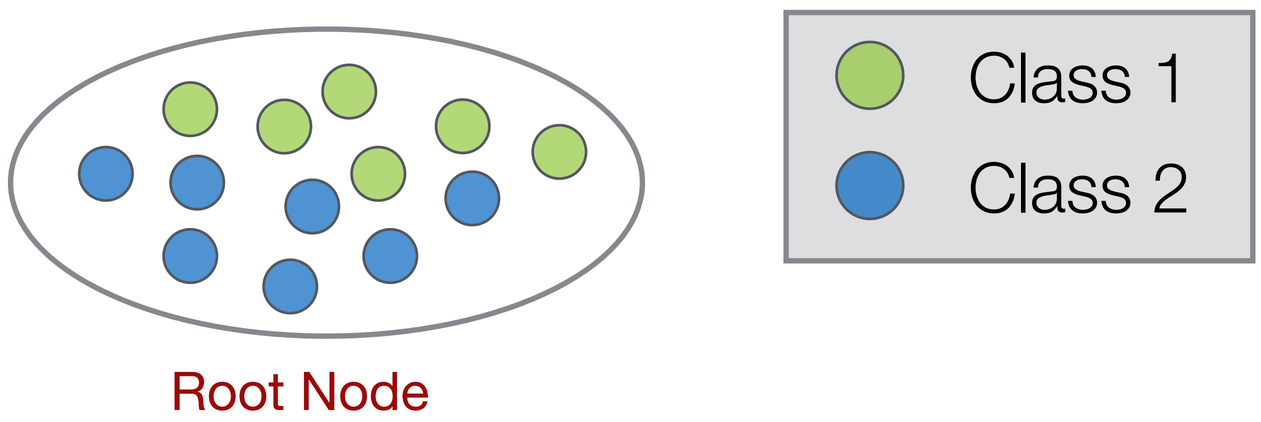


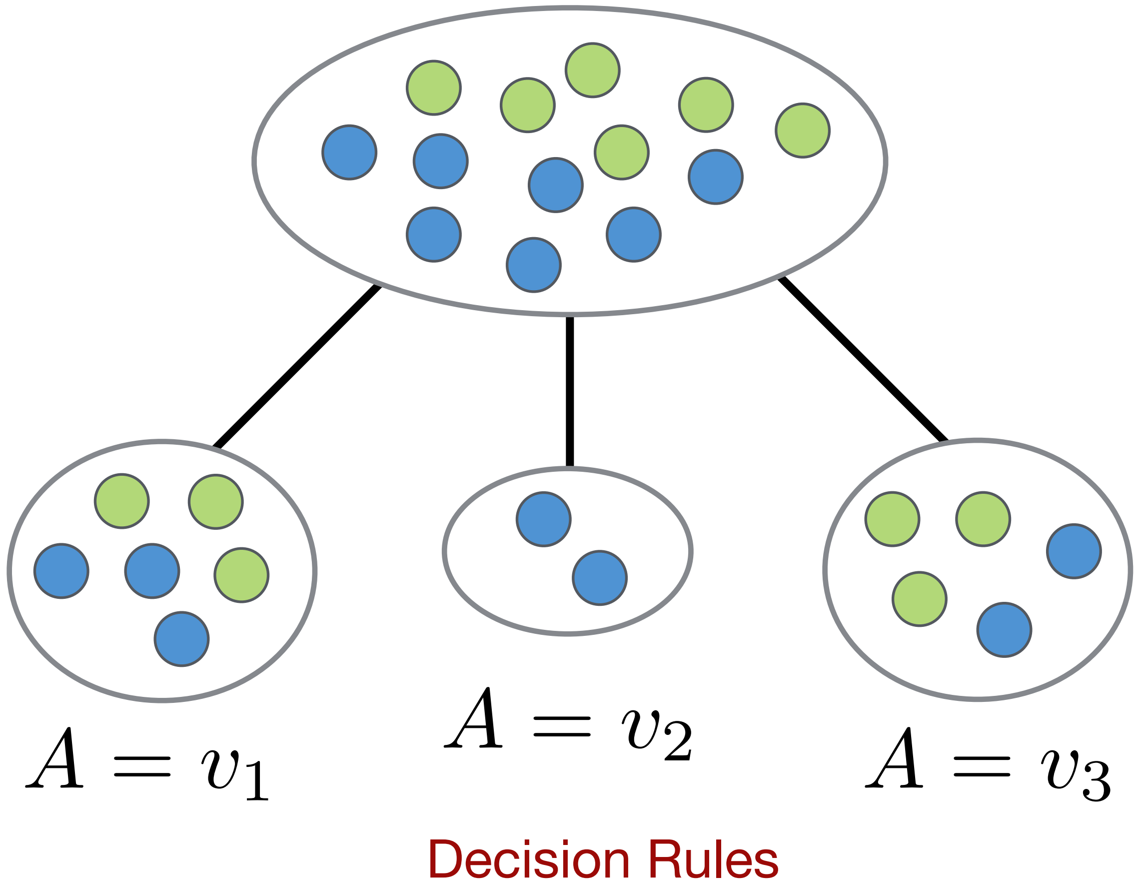


Decision Tree Learning

1. Initially all examples in the training set are placed at the root node of the tree.

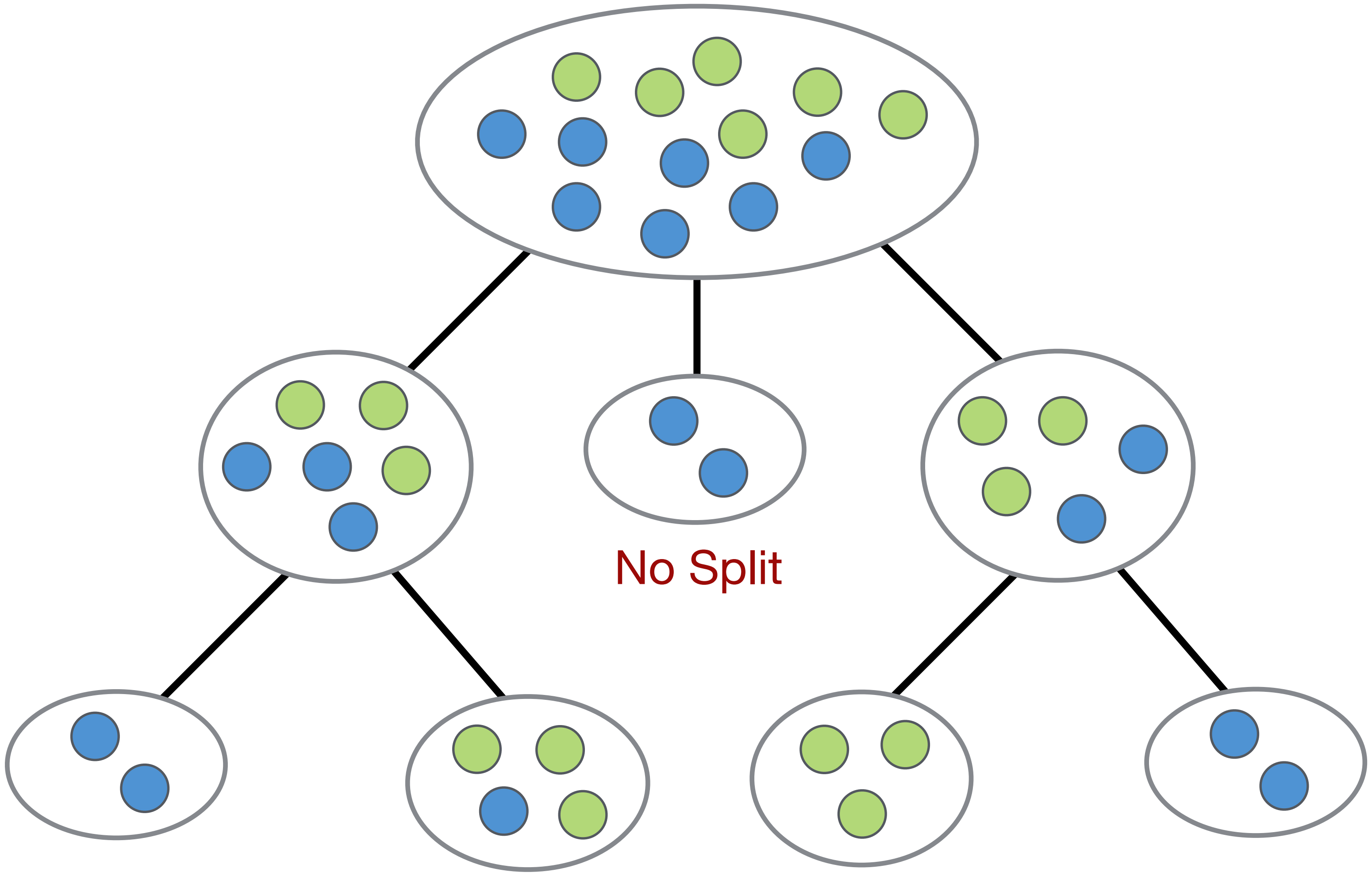


2. One of the available features (*A*) is now used to split the examples at the root node into two or more child nodes containing subsets of examples.



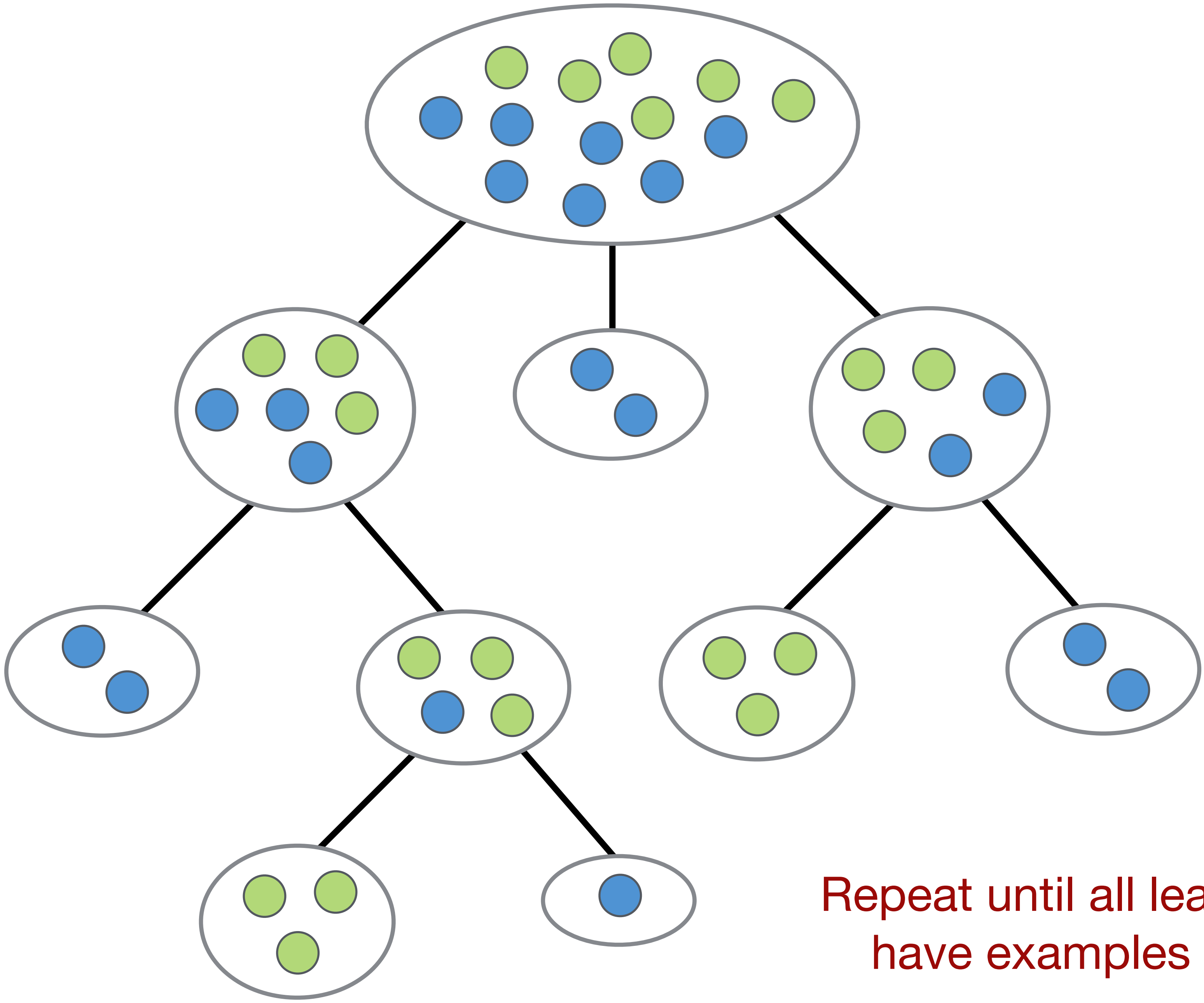
Decision Tree Learning

3. The same process is now applied to each child node, except for any child node at which all examples have the same class.



Decision Tree Learning

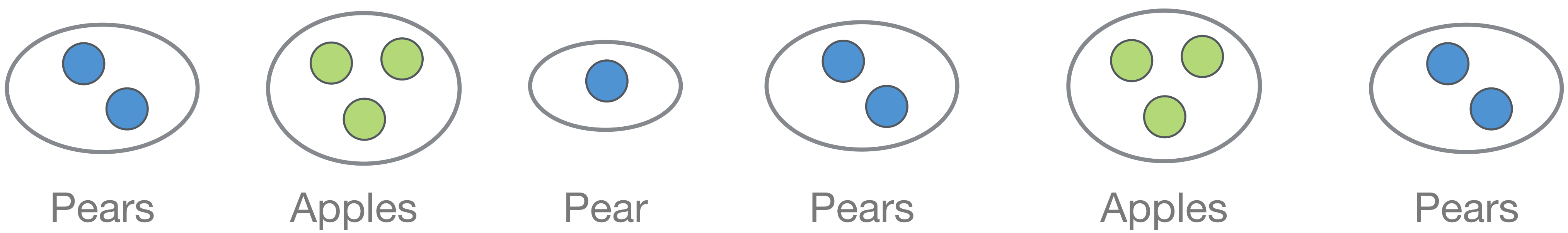
4. This continues until the training set has been divided into subsets in which all the examples have the same class.



Repeat until all leaf nodes in the tree have examples with same class

Node Purity

- A tree node is pure if all examples at that node have the same class label.



- A decision tree in which all the leaf nodes are pure can always be constructed provided there are no clashes in the data.
  - i.e. examples having the same "description" in terms of features, but with different class labels.
- Most decision tree algorithms use some measure of node (im)purity to choose features to split when building the tree. This measure guides the learning process.

Decision Trees Example

Q. "Will a customer wait for a restaurant table?"
Russell & Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall, 2009.

Binary classification task (WillWait = {Yes,No}), with examples described by 10 different features:

Feature	Description
Alternate	Is a suitable alternative restaurant nearby? (Yes/No)
Bar	Does the restaurant have a comfortable bar area to wait in? (Yes/No)
Fri/Sat	True on Fridays and Saturdays, False otherwise.
Hungry	Is the customer hungry? (Yes/No)
Patrons	How many people are in the restaurant: {None, Some, Full}?
Price	Restaurant's price range: {€, €€, €€€}
Raining	Is it raining outside? (Yes/No)
Reservation	Has the customer made a reservation? (Yes/No)
Type	Type of restaurant: {French, Italian, Thai, Burger}
WaitEstimate	Length of wait estimated by the host: {0-10, 10-30, 30-60, > 60 minutes}

Decision Trees Example

Q. "Will a customer wait for a restaurant table?"
Russell & Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall, 2009.

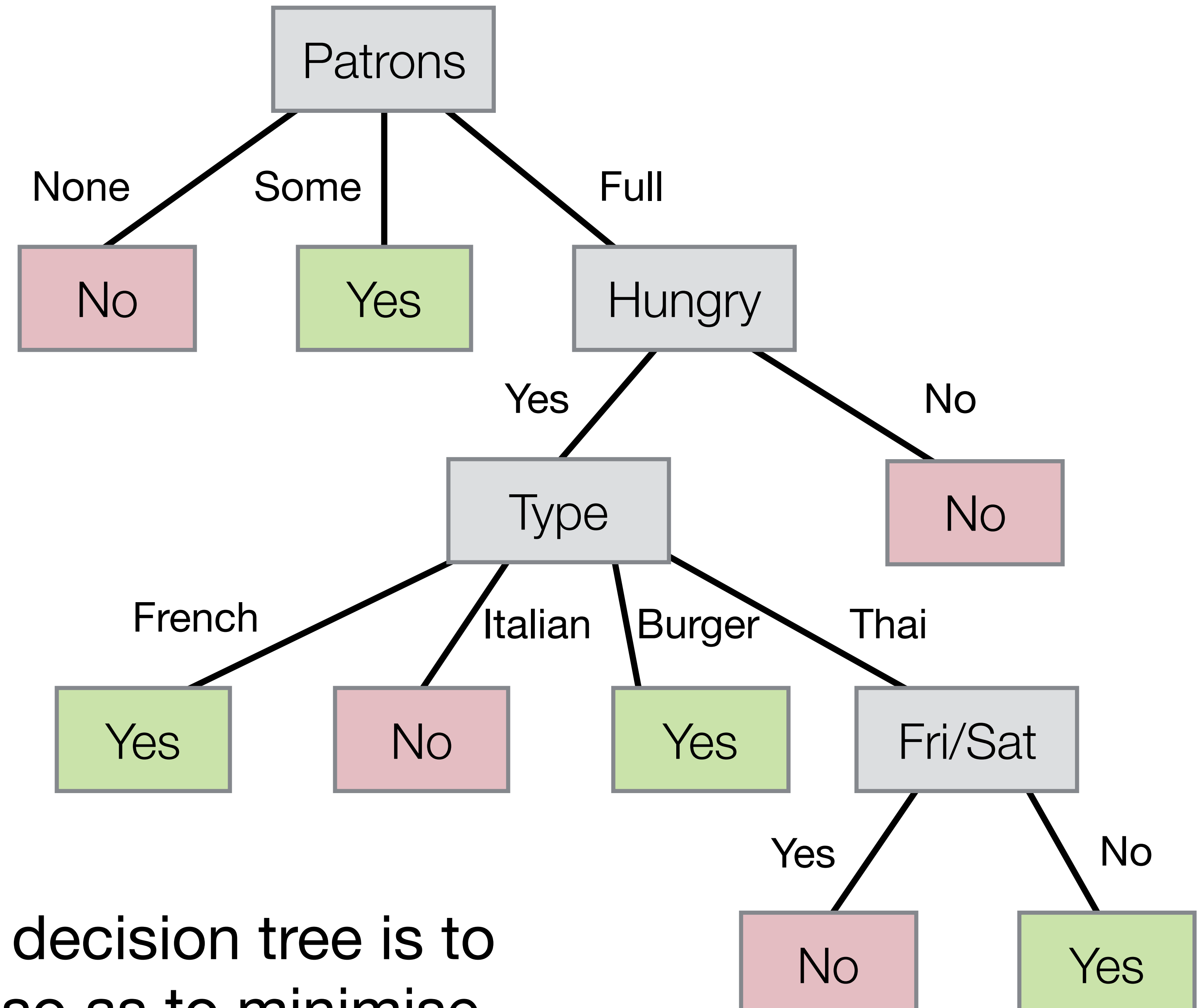
Binary classification task (WillWait = {Yes,No}), with examples described by 10 different features:

Example	Alternate	Bar	Fri/Sat	Hungry	Patrons	Price	Raining	Reservation	Type	WaitEst	WillWait?
1	Yes	No	No	Yes	Some	€€€	No	Yes	French	0-10	Yes
2	Yes	No	No	Yes	Full	€	No	No	Thai	30-60	No
3	No	Yes	No	No	Some	€	No	No	Burger	0-10	Yes
4	Yes	No	Yes	Yes	Full	€	No	No	Thai	10-30	Yes
5	Yes	No	Yes	No	Full	€€€	No	Yes	French	>60	No
6	No	Yes	No	Yes	Some	€€	Yes	Yes	Italian	0-10	Yes
7	No	Yes	No	No	None	€	Yes	No	Burger	0-10	No
8	No	No	No	Yes	Some	€€	Yes	Yes	Thai	0-10	Yes
9	No	Yes	Yes	No	Full	€	Yes	No	Burger	>60	No
10	Yes	Yes	Yes	Yes	Full	€€€	No	Yes	Italian	10-30	No
11	No	No	No	No	None	€	No	No	Thai	0-10	No
12	Yes	Yes	Yes	Yes	Full	€	No	No	Burger	30-60	Yes

➡ How do we build a "good" decision tree for this data set?

Decision Trees - Objective

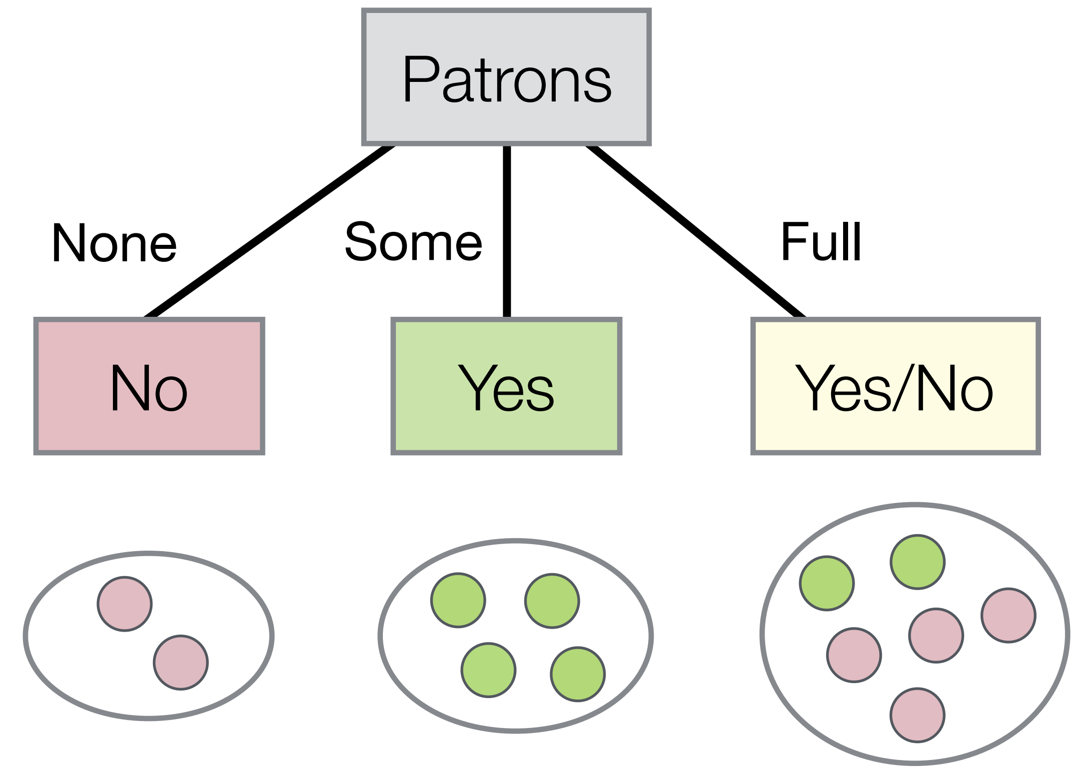
A "good" decision tree will classify all examples correctly using as few tree nodes as possible.



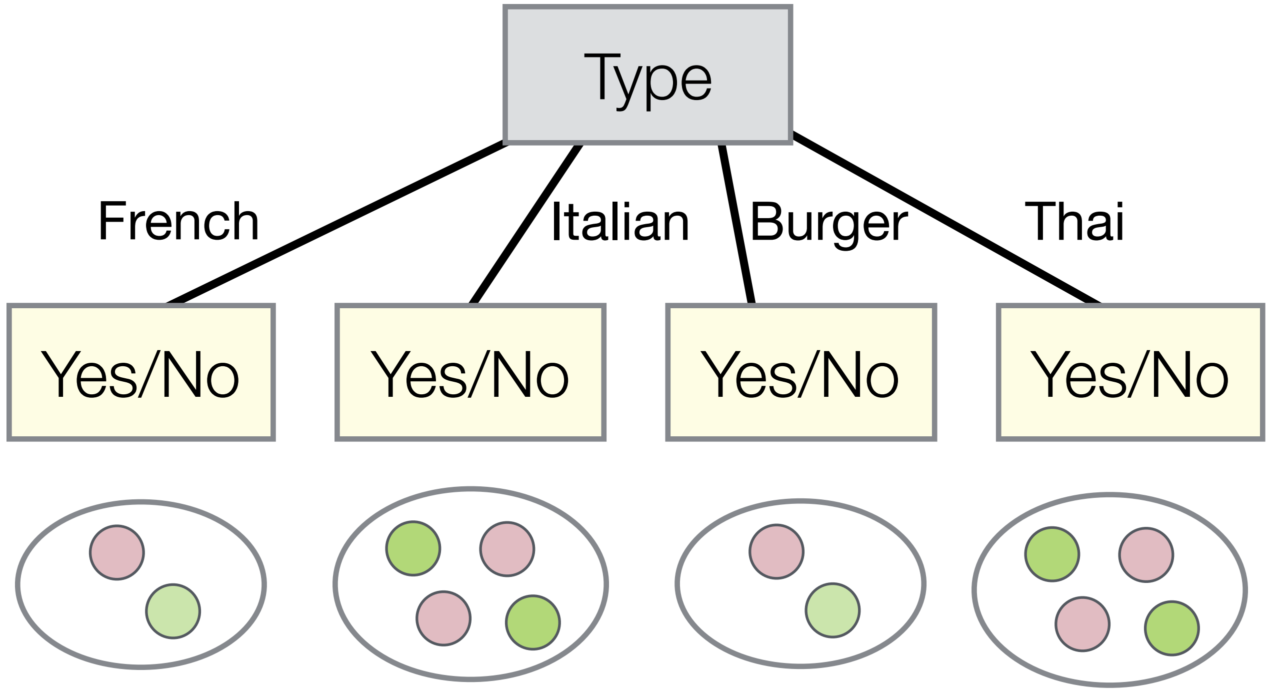
Objective in building a decision tree is to choose good features so as to minimise the depth of the tree.

Good v Bad Features

- Good Features:
  A perfect feature divides examples into categories of one class
  ⇒ high purity



- Bad Features:
  A poor choice of feature produces categories of mixed classes
  ⇒ high impurity



Feature Selection

- Goal: Find good features which divide examples into categories of a single class.
- Feature selection algorithms have been developed which use impurity as an objective to guide feature selection (e.g. Entropy, Gini impurity).

- **Common selection strategy in decision trees:**
  - For each feature, some measure of impurity is applied to the current set of tree nodes.
  - The feature that maximises the reduction in impurity is selected as the next most useful feature.

Entropy

- Entropy: In information theory, a measure of uncertainty around a source of information. Low for predictable sources, higher for more random sources.

- In the context of decision trees, entropy provides a measure of impurity - how uncertain we are about the decision for a given set of examples.

High uncertainty
→ High entropy

Low uncertainty
→ Low entropy

- **Definition:**

Entropy of a set of examples S with class labels $\{C_1, \ldots, C_n\}$:

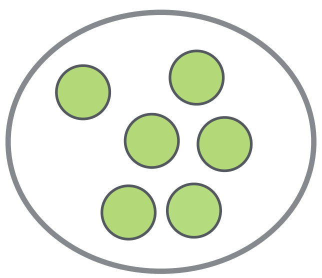
$$H(S) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

where p_i is the relative frequency (probability) of class C_i.

Entropy Examples

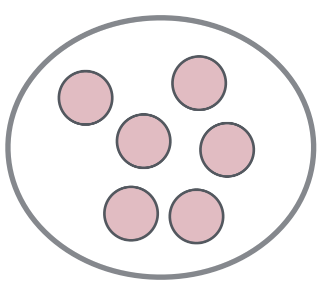
- The lowest possible entropy (i.e. zero) occurs when all examples have the same class label.
- The highest entropy occurs when we are most uncertain.

NB: Define $\log_2(0)=0$



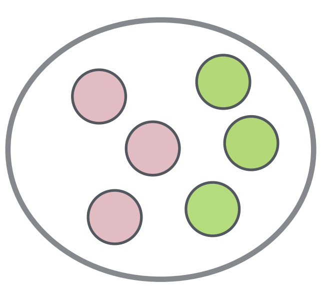
$$p_1 = 6/6 = 1.0 \qquad p_2 = 0/6 = 0.0$$

$$H(S) = -((1 \times \log_2(1)) + (0 \times \log_2(0))) = -(0+0) = 0$$



$$p_1 = 0/6 = 0.0 \qquad p_2 = 6/6 = 1.0$$

$$H(S) = -((0 \times \log_2(0)) + (1 \times \log_2(1))) = -(0+0) = 0$$



$$p_1 = 3/6 = 0.5 \qquad p_2 = 3/6 = 0.5$$

$$H(S) = -((0.5 \times \log_2(0.5)) + (0.5 \times \log_2(0.5))) = -(-0.5-0.5) = 1$$

Top-Down Induction of Decision Trees

- ID3 Algorithm: Popular algorithm which repeatedly builds a decision tree from the top down (Quinlan, 1986).
- Start with an empty tree and set of all training examples *S*.

ID3(S):

- IF all examples in S belong to the same class C THEN
  - Return new leaf node and label it with class C.
- ELSE
  - Select a feature A based on some feature selection criterion.
  - Generate a new tree node with A as the test feature.
  - FOR EACH value v_i of A:
    - Let $S_i \subset S$ contain all examples with $A = v_i$.
    - Build subtree by applying ID3(S_i)

Criterion: Information Gain

- Information Gain (IG): Popular information theoretic approach for selecting features in decision trees, based on entropy.
- Measures a feature's overall impact on entropy when used to split a set of training examples into two or more subsets.
  - How much information do we learn by splitting on the feature?
  - How much is the reduction in entropy?

- **Definition:**

IG for feature A that splits a set of examples S into $\{S_1, \ldots, S_m\}$:

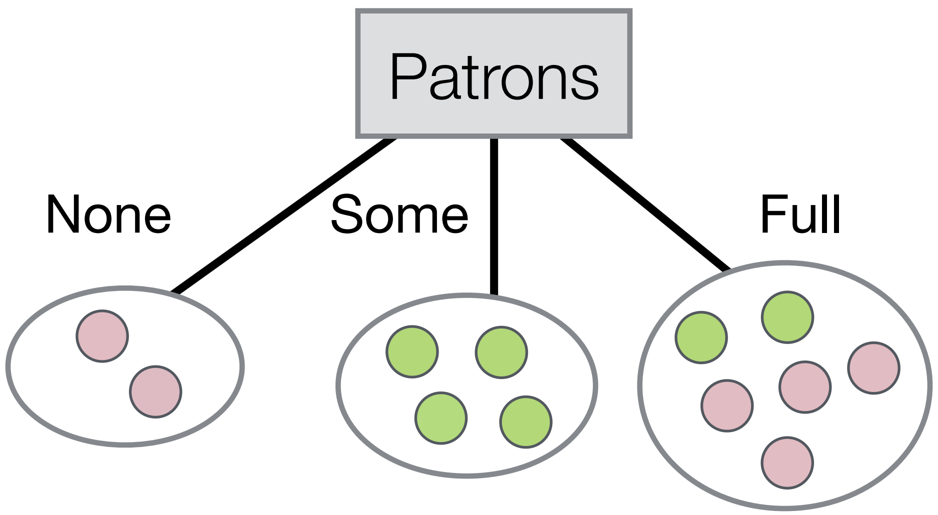
$$IG(S, A) = \text{(original entropy) - (entropy after split)}$$

$$IG(S, A) = H(S) - \sum_{i=1}^{m} \frac{|S_i|}{|S|} H(S_i)$$

Each subset is weighted in proportion to its size

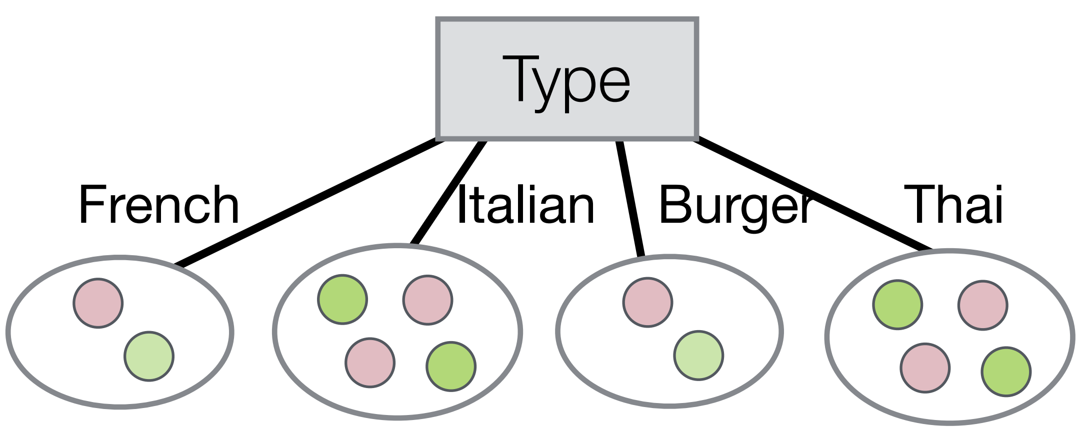
Information Gain Example

- Previous example: Initial training set has 6 Yes, 6 No examples.
- Which feature should we select to split at the root node?



$$IG = H([\frac{6}{12}, \frac{6}{12}]) - \left(\frac{2}{12}H([0,1]) + \frac{4}{12}H([1,0]) + \frac{6}{12}H([\frac{2}{6}, \frac{4}{6}])\right)$$

$$IG(\text{Patrons}) = 1 - 0.459 = 0.541$$



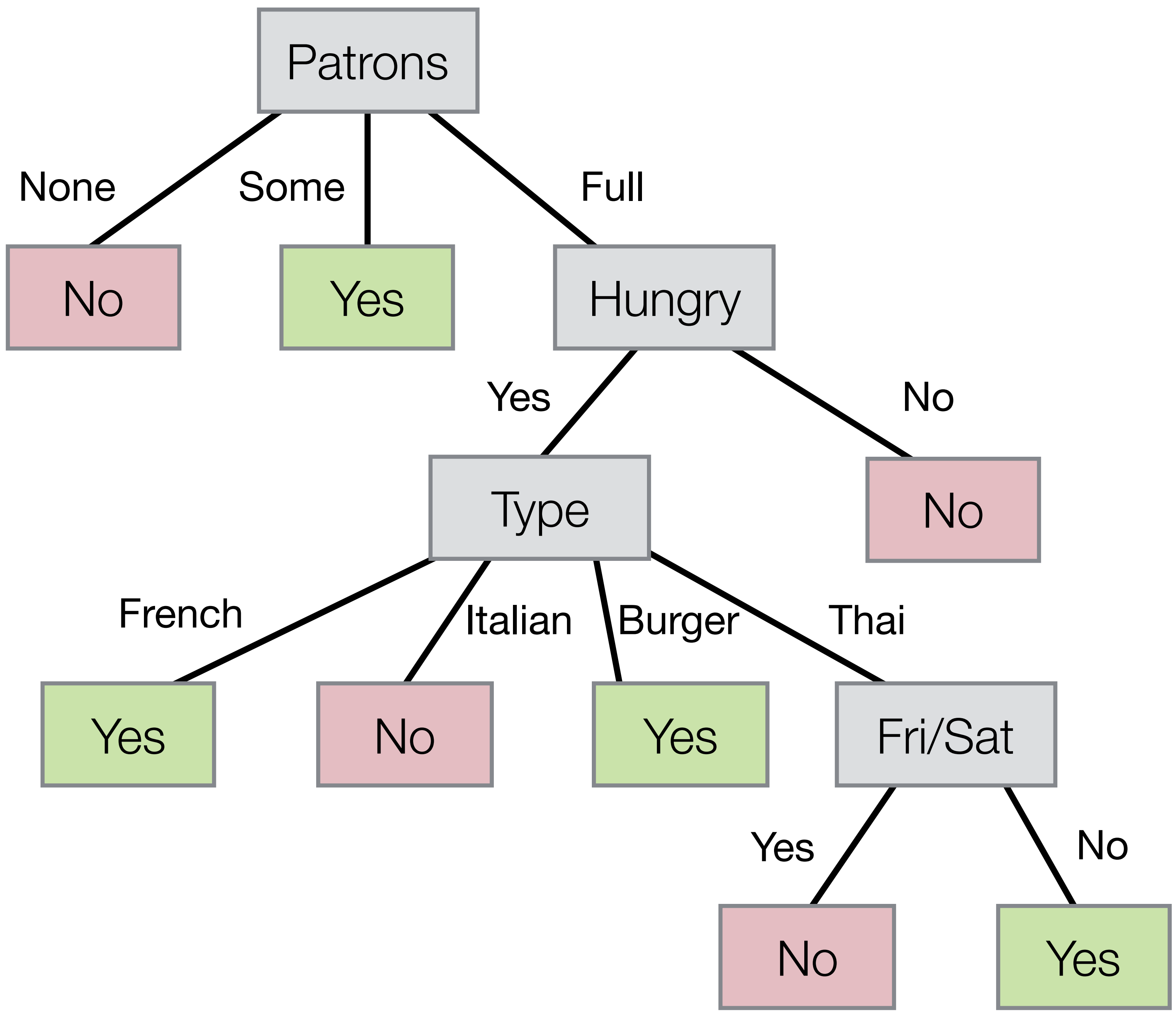
$$IG = H([\frac{6}{12}, \frac{6}{12}]) - \left(\frac{2}{12}H([\frac{1}{2}, \frac{1}{2}]) + \frac{4}{12}H([\frac{2}{4}, \frac{2}{4}]) + \frac{2}{12}H([\frac{1}{2}, \frac{1}{2}]) + \frac{4}{12}H([\frac{2}{4}, \frac{2}{4}])\right)$$

$$IG(\text{Type}) = 1 - 1 = 0$$

➡ Feature "Patrons" has higher IG, so a better choice for splitting.

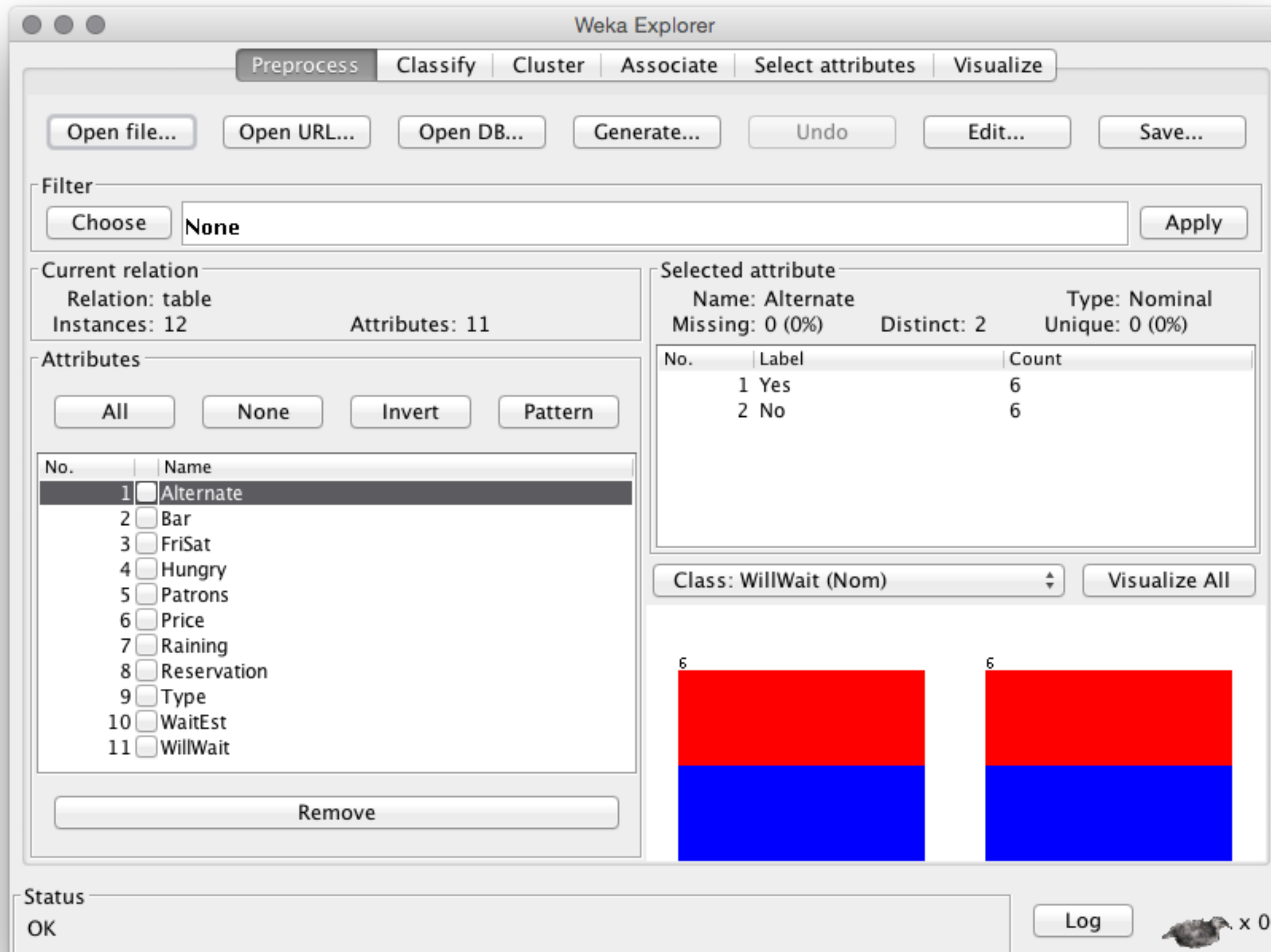
Information Gain Example

- ID3 repeats the feature selection + splitting process until all examples have the same class, or no features are left to split.



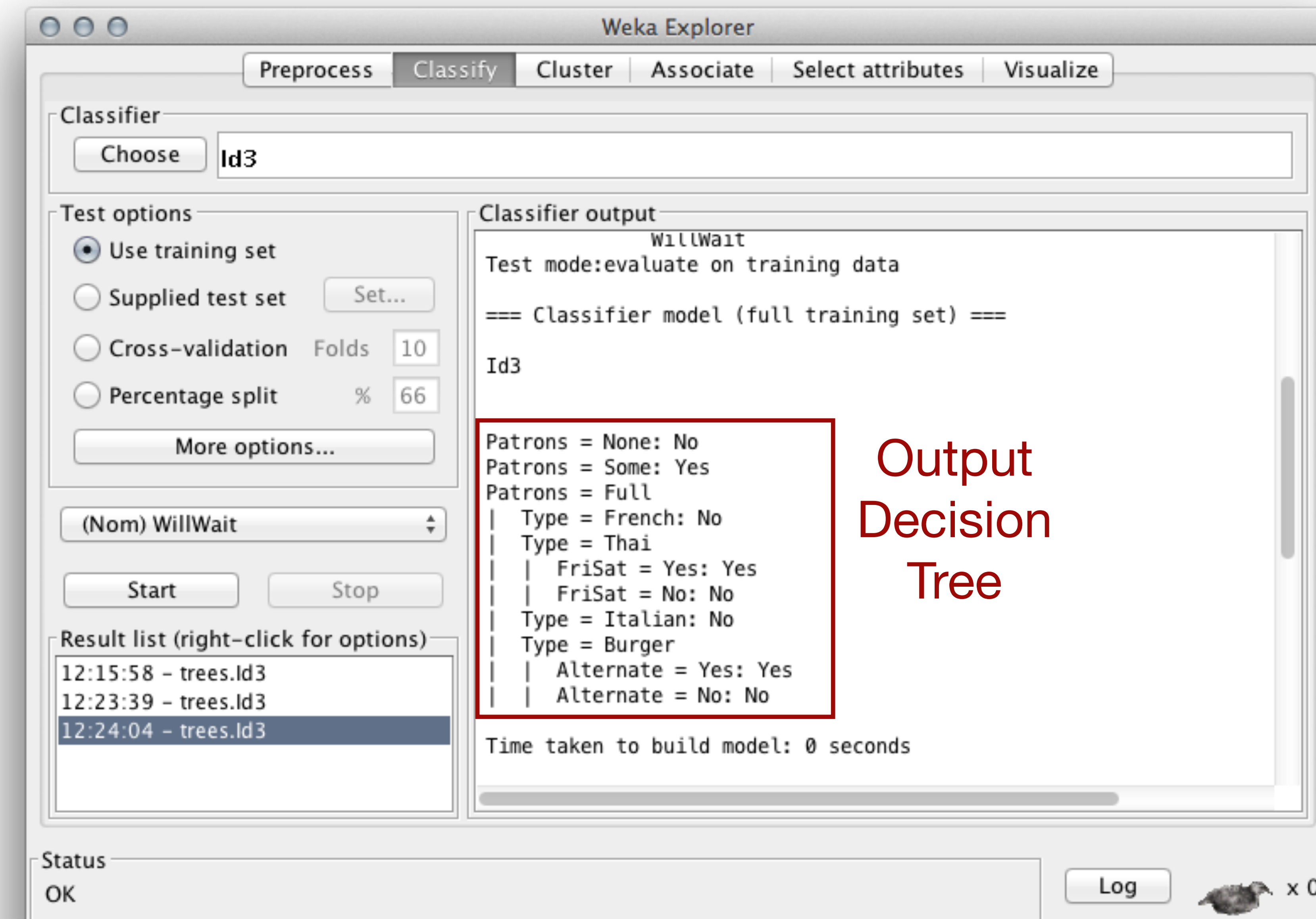
Decision Trees in Weka

1. Launch the WEKA application and click on the *Explorer* button.
2. *Open File* - table.arff



Decision Trees in Weka

3. In *Classify* tab, click *Choose* and find *Trees→ID3* on the list.
4. Select *Test options: Use Training Set* (for this example).
5. Choose *(Nom) WillWait* as class label from drop-down list.
6. Click *Start*.



Summary

- A decision tree is an eager learning algorithm where the model is induced from the data in the form of decision rules.
- Many different trees can correctly model same training data.
- We want the simplest tree possible that can generalise to new unseen examples.
- Information Gain helps us select features to use when building simple decision trees.
- Note: ID3 algorithm for decision trees does not handle numeric data. The extended C4.5 algorithm can handle this type of feature (Quinlan, 1993).
- Both ID3 and C4.5 are available in the Weka Explorer.

Assignment 1 - Introduction to Weka

Objectives:

The objectives of this assignment are to get started using the WEKA Machine Learning environment and to perform a comparative evaluation of the performance of a range of classifiers on a supplied dataset.

Data:

The data source relates to restaurant reviews, each represented by 24 summary features. Each review also has a binary class label, indicating that it is either deemed "helpful" or "unhelpful" for other users.

You should download your personal dataset for the assignment from the URL:

http://mlg.ucd.ie/datasets/comp30120/restaurant/<STUDENT_NUMBER>.arff

For example, if your student number is 126023491, your dataset is at the URL:

http://mlg.ucd.ie/datasets/comp30120/restaurant/126023491.arff

Tasks:

Complete all tasks on your dataset, discuss the results in your report.
See full assignment PDF on Moodle for task details.

Assignment 1 - Introduction to Weka

Guidelines:

1. When downloading the dataset, please ensure your student number is correct. Only use your assigned dataset. Submissions using an incorrect dataset will receive a 0 grade.
2. This is an individual assignment. Plagiarism will be treated seriously. Evidence of plagiarism in the assignment will result in a 0 mark.
3. Recommended page length for the report is 2-3 pages, although there is no penalty for exceeding this length.
4. Submit your report as **a single PDF** via the COMP30120 CS Moodle page. Include your full name and student ID number in the report.
5. Assignment should be submitted on or before **Monday September 28th**. Note this is a **hard deadline**.

See full assignment PDF on Moodle

15% of overall grade

References

- Russell & Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall, 2009.
- Quinlan, J. R. 1986. “Induction of Decision Trees”. Machine Learning 1, 1 (Mar. 1986), 81-106.
- Mitchell, Tom M. Machine Learning. McGraw-Hill, 1997. pp. 55–58.
- Quinlan, J. R. C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers, 1993.