Decision Tree and Concept Learning

CS3025, Knowledge-Based Systems
Lecture 18

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Outline

- Types of learning
  - Supervised learning
  - Unsupervised learning
- Decision trees

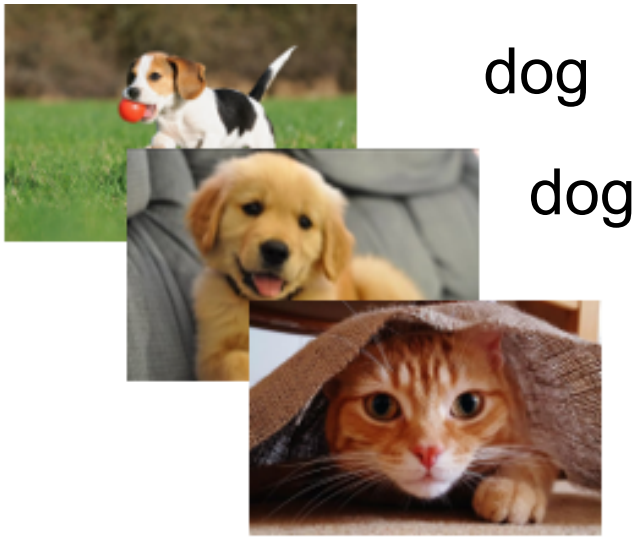
Why should programs learn?

- All the programs seen up to now have been **static**:
  - if we run the programs again on the same data, they will do exactly the same as before
- We would like programs to learn from their experience.
- We would like the possibility of learning being continuous.

How do you learn?

- By being told – relies on:
  - someone to do the telling
  - something to tell!
- By finding a teacher, who provides a set of pre-classified examples (i.e. I/O pairs), or taking action and obtaining correct answer from observations: **Supervised learning**
- By searching for regularities in unclassified data (e.g. clusters): **Unsupervised learning**

Supervised learning



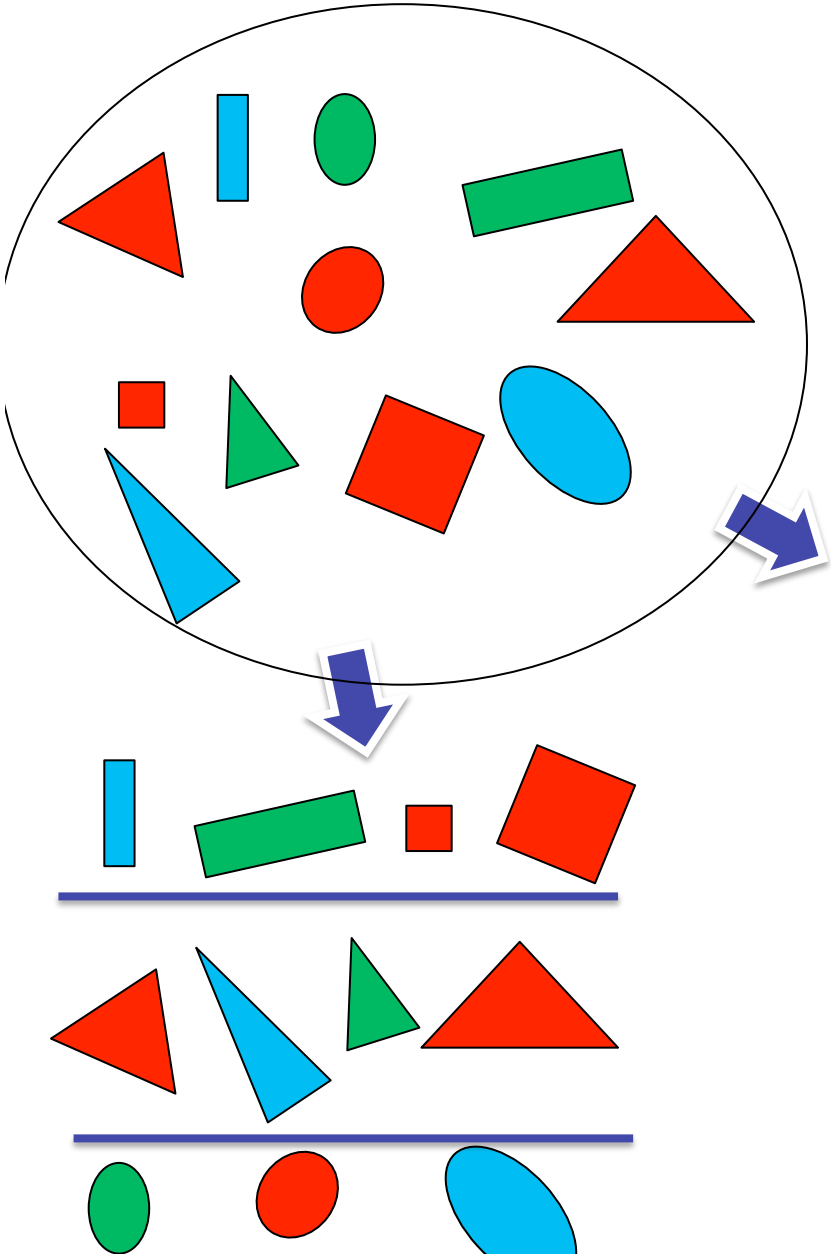
dog

dog

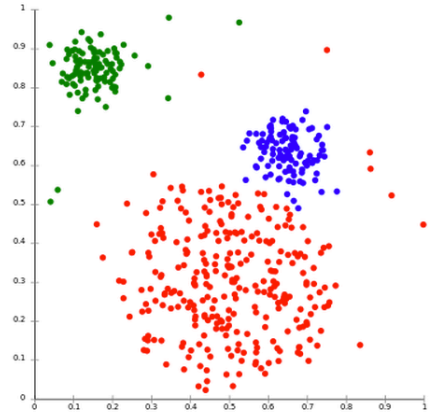
cat

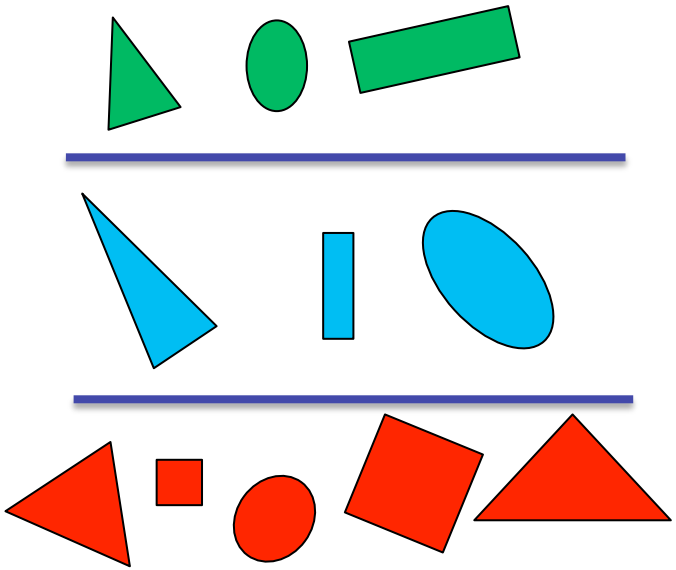
unsupervised learning

Unsupervised Learning



- Cluster analysis or clustering: putting “similar” together.
- How to define similarity





Supervised Learning

- ‘Learning by example’ (inductive learning)
  - teacher provides good training instances and the learner is expected to generalise
  - in knowledge acquisition it is often easier to get an expert to give examples than to give rules
  - this is how experimental science works
    (the 'teacher' is the natural world)

Supervised Classification

- **Supervised learning**:
  - the machine learning task of inferring a function from **labeled training data**
  - Knowledge is represented as **function** (input – output)

- Given:
  - **Target**: a fixed set of **classes**: Y = {y_1, y_2,…, y_n}, e.g. {sports, politics, …, music}
  - **Training data**: a collection of data objects *X with known classes Y, i.e.* (X, Y) = {(x_1,y_1), (x_2, y_2)… (x_n, ,y_n)}. E.g {(doc1, sports), (doc2, sports), (doc3, music) …}.
  - **Testing data**: a description of an unseen instance, D_{new} *e.g. a new document* ***without*** *class label information*
- Goal:
  - Predict the category/class of D_{new}: $y(x) \in Y$, where $y(x)$ is a *classification function*, *aka trained model*, whose domain is X and whose range is Y.

What can you do with classification?

Applications:

- Topic classification
  - Given a news article, predict the topic of the article, e.g., *finance* vs. *sports*
- Spam Classification
  - Given an email, predict whether it is a spam or not
- Medical Diagnosis
  - Given a list of symptoms, predict whether a patient has cancer or not
- Weather
  - Based on temperature, humidity, etc… predict if it will rain tomorrow

Knowledge as a function

- Knowledge (performance element) can be described as a function:
  - given a description, *x*, for a given object or situation, the output is given by *f(x)* where *f* embodies the knowledge contained in the performance element.
  - could be:
    - analytical mathematical function
    - lookup table
    - rule set (including STRIPS rules)
    - neural network
    - decision tree
    - etc.

Application of knowledge (**deduction**)

Knowledge → Output 1

Knowledge → Output 2

Chimpanzee

Panda

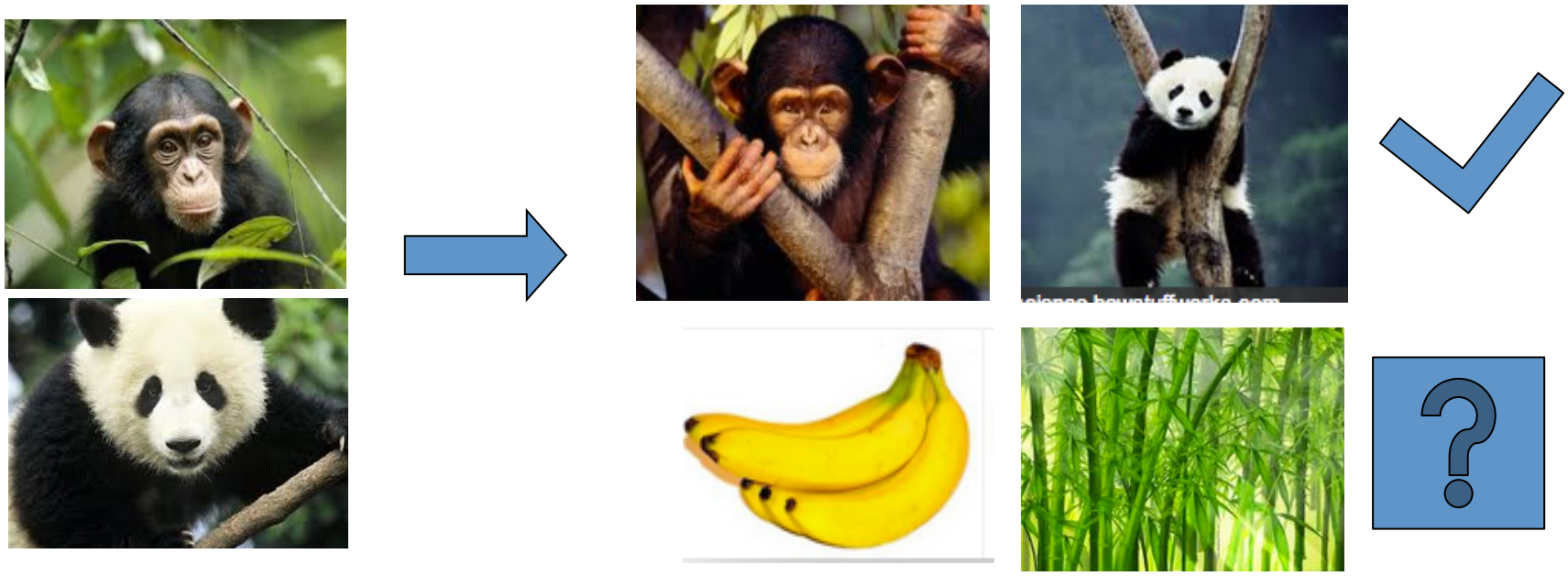
...

We have
- inputs
- knowledge

We get
- outputs

An Important Assumption

- Training and unseen (test) data
  - in the **same feature space**
  - follow the **same distribution**



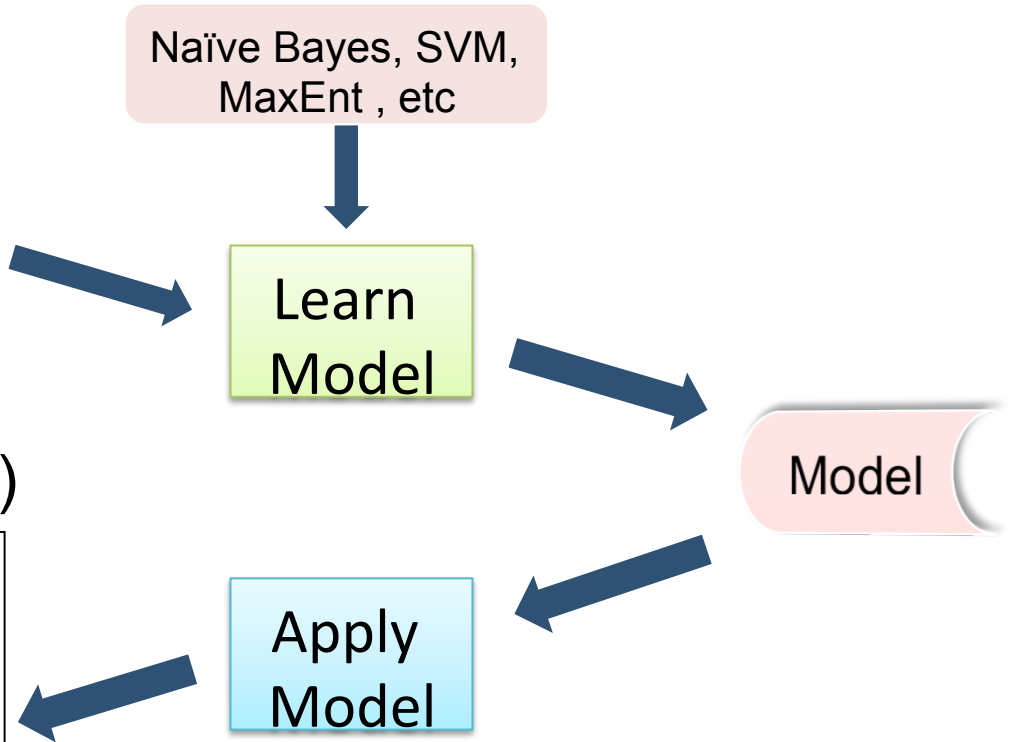
Training data

Unseen data

Supervised Classifier

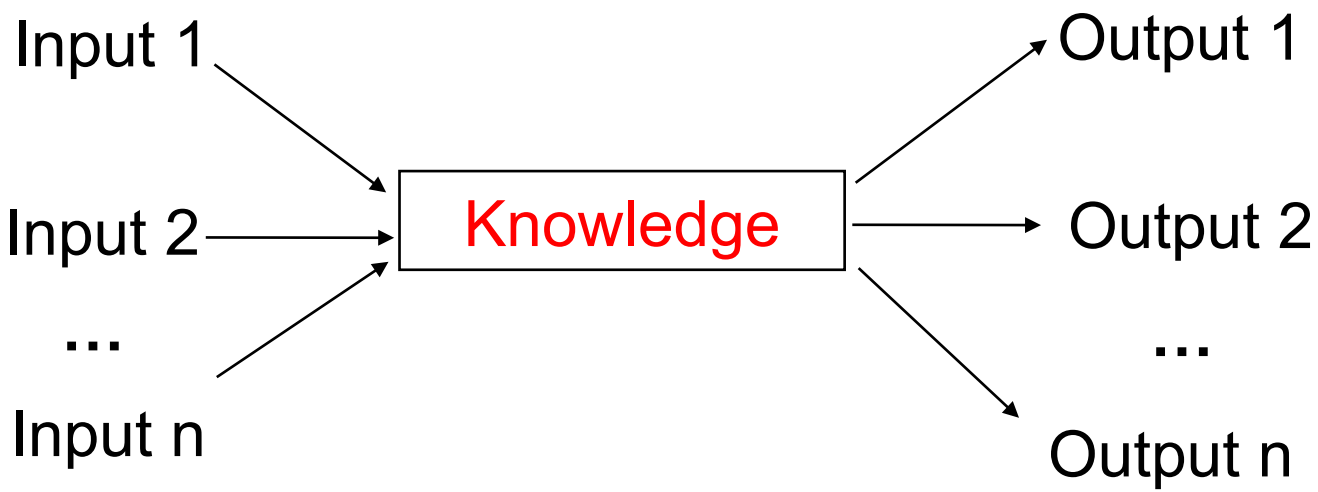
Training set (corpus)

Test set



- Rely on syntactic or co-occurrence patterns in large text corpora

Inductive learning (**induction**)



We have
- inputs
- outputs

We get
- knowledge

Definition of inductive learning

- Given a set of input/output pairs (examples):

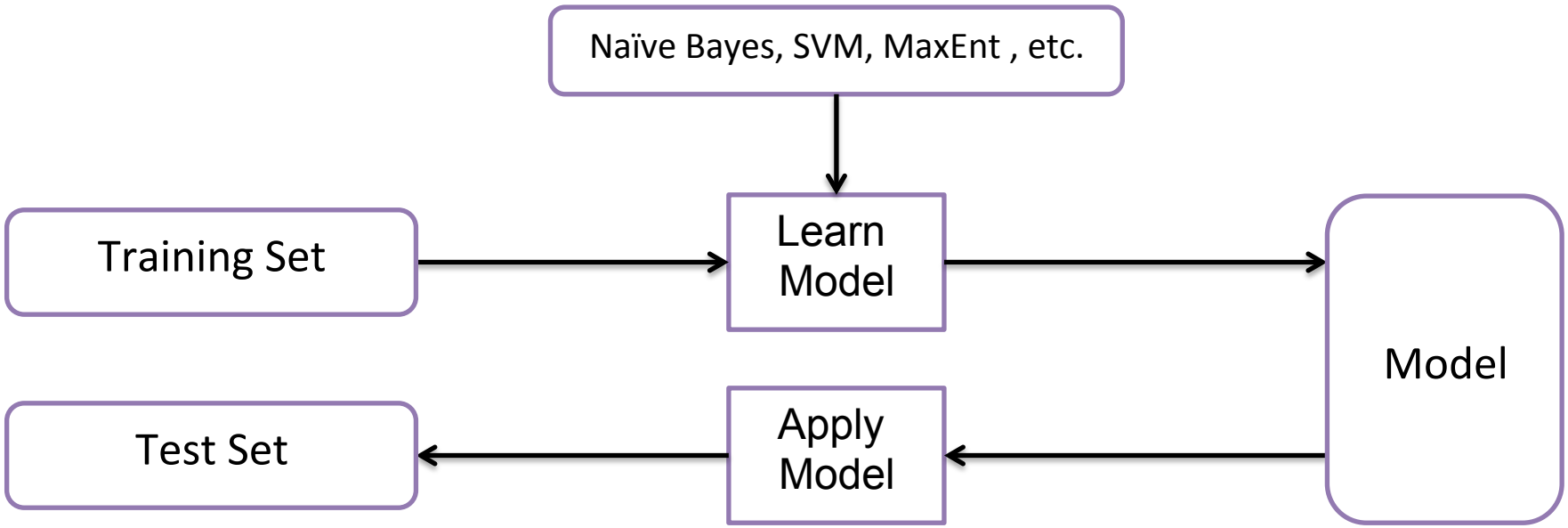
  (x, f(x))

  – where *f* is unknown, but the output *f(x)* is provided with its corresponding input, *x.*

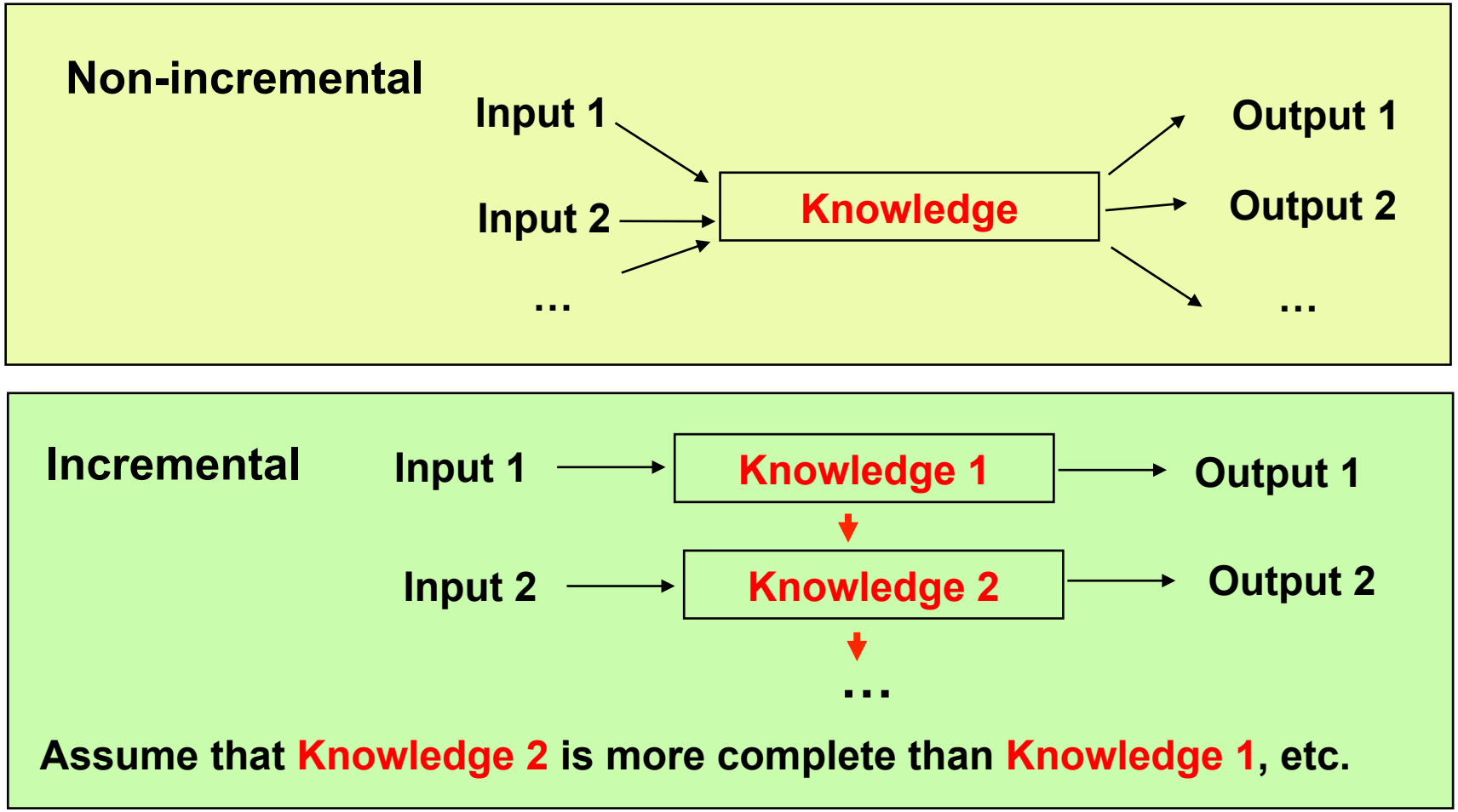
  – ***find* a function**, *h(x)* (hypothesis) which best approximates *f(x)*.

  – 'finding' implies *searching* in a space of different possible hypotheses.

Supervised Classification



Inductive learning



Non-incremental vs. Incremental

- Non-incremental
  - learning from all examples at once
- Incremental
  - learning by **refining** from successive examples
- If you haven't seen all possible examples, you can never *know* that the system is going to give the correct answer for a previously unknown example.
- You may never see all possible examples.





Outline

- Types of learning
  - Supervised learning
  - Unsupervised learning
- **Decision trees**

The Supervised Classification Task

- **Input**: Collection of instances with a set of **pairs** (attributes x and a special nominal attribute Y called class attribute)
- **Output**: A model that accurately predicts y from x on previously unseen instances
  - Previously unseen instances are called test set
- Usually input collection is divided into
  - Training set for building the required model
  - Test set for evaluating the model built

Supervised Learning for Classification

- Many commercial systems (partly) rely on classification techniques (MSN, Verity, Enkata, Yahoo!, …)
  - Naive Bayes (simple, common method)
  - Decision trees (intuitive, powerful)
  - Support-vector machines (new, more powerful)
  - plus many other methods …
- No free lunch: requires hand-classified training data
- But data can be built up (and refined) by amateurs, e.g., Amazon Mechanical Turk
- Note that many commercial systems use a mixture of methods

Example Data

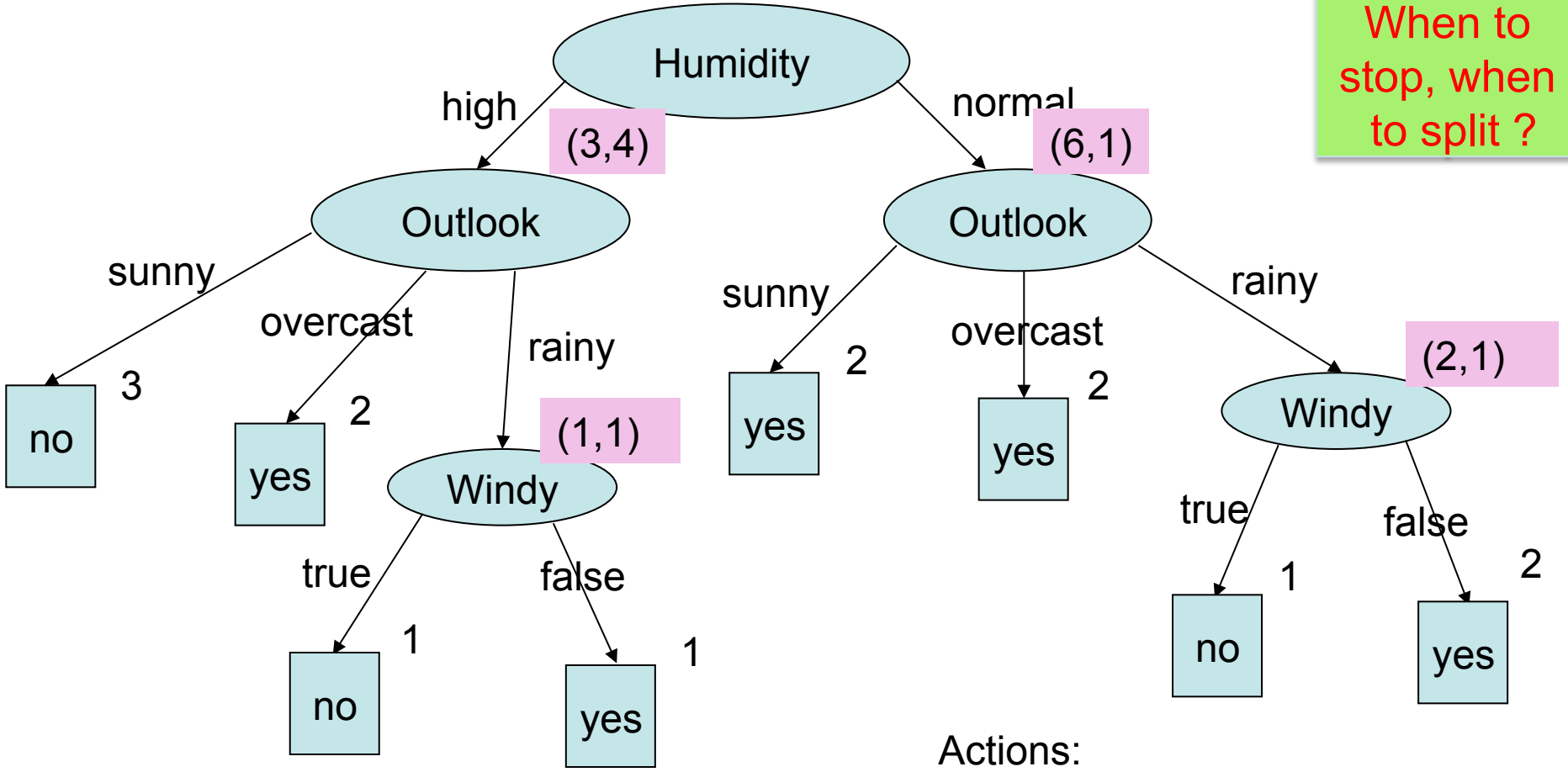
Class Attribute

Outlook	Temperature	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**

Decision Tree Construction

- Recursive procedure
  - Select an attribute to place at the **root** node
  - Make one **branch** for each possible value of the selected attribute
  - For each branch repeat the above two steps recursively
    - Using only those instances that actually reach the branch
  - **Stop** developing a branch if it has instances belonging to the same class, otherwise split the branch
- Several decision trees are possible
  - Based on the order of the selection of the attributes

Example Decision Tree 1



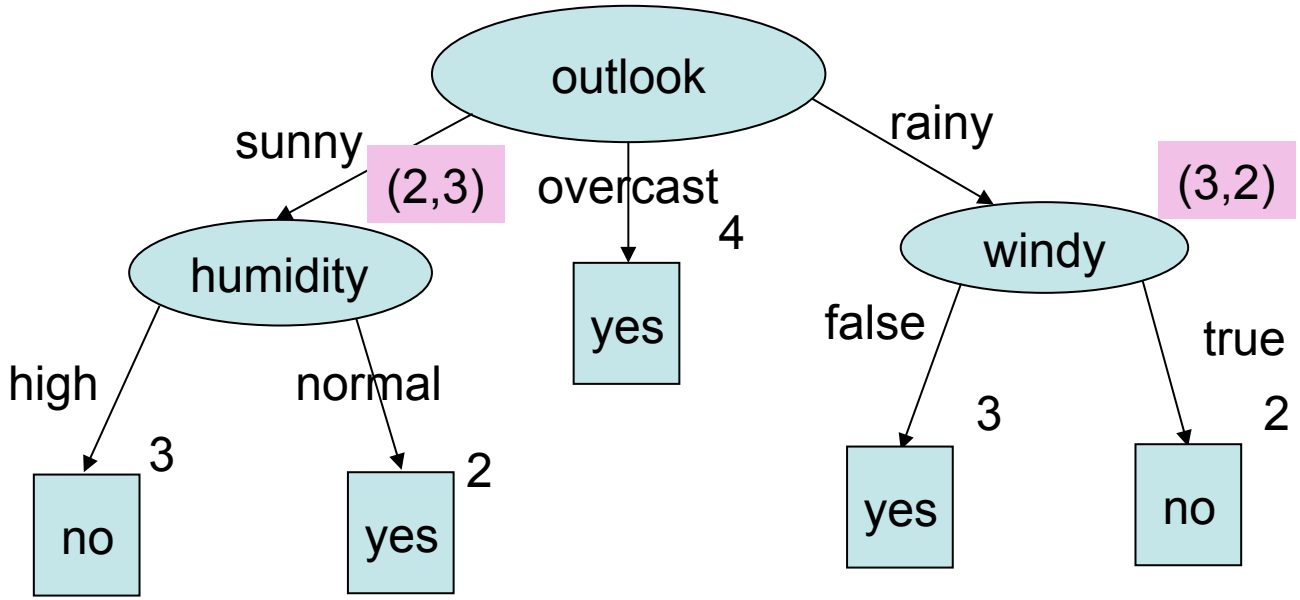
Observations:
Outlook and windy repeated in this tree
Windy tested only when outlook is rainy

Actions:

Start the tree with Outlook

Test windy when outlook is rainy

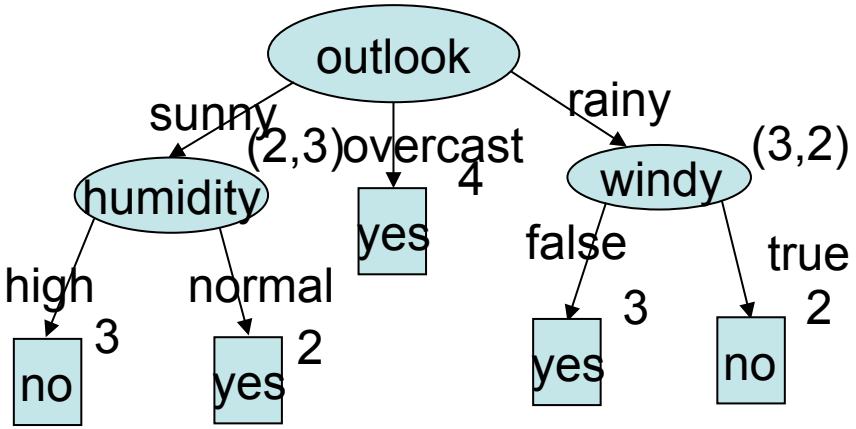
Example Decision Tree 2



When to stop, when to split ?

```
(defrule decision-tree
     (weather (outlook ?o)(humiidty ?h)(windy ?w))
     =>
     (if ( or (and (= sunny ?o) (= high ?h) )
              (and (= rainy ?o) (= true ?w) )
         )
     then ((printout t "decision: NO" crlf))
     else ((printout t "decision: YES" crlf))
     }
)
```

Jess code (1)




```
(defrule decision-tree-1
    (weather (outlook sunny)(humiidty high))
    =>
   (printout t "decision: NO" crlf)) )
```

```
(defrule decision-tree-2
    (weather (outlook sunny)(humiidty normal))
    =>
   (printout t "decision: YES" crlf)) )
```

```
(defrule decision-tree-3
    (weather (outlook overcast) )
    =>
   (printout t "decision: YES" crlf)) )
```

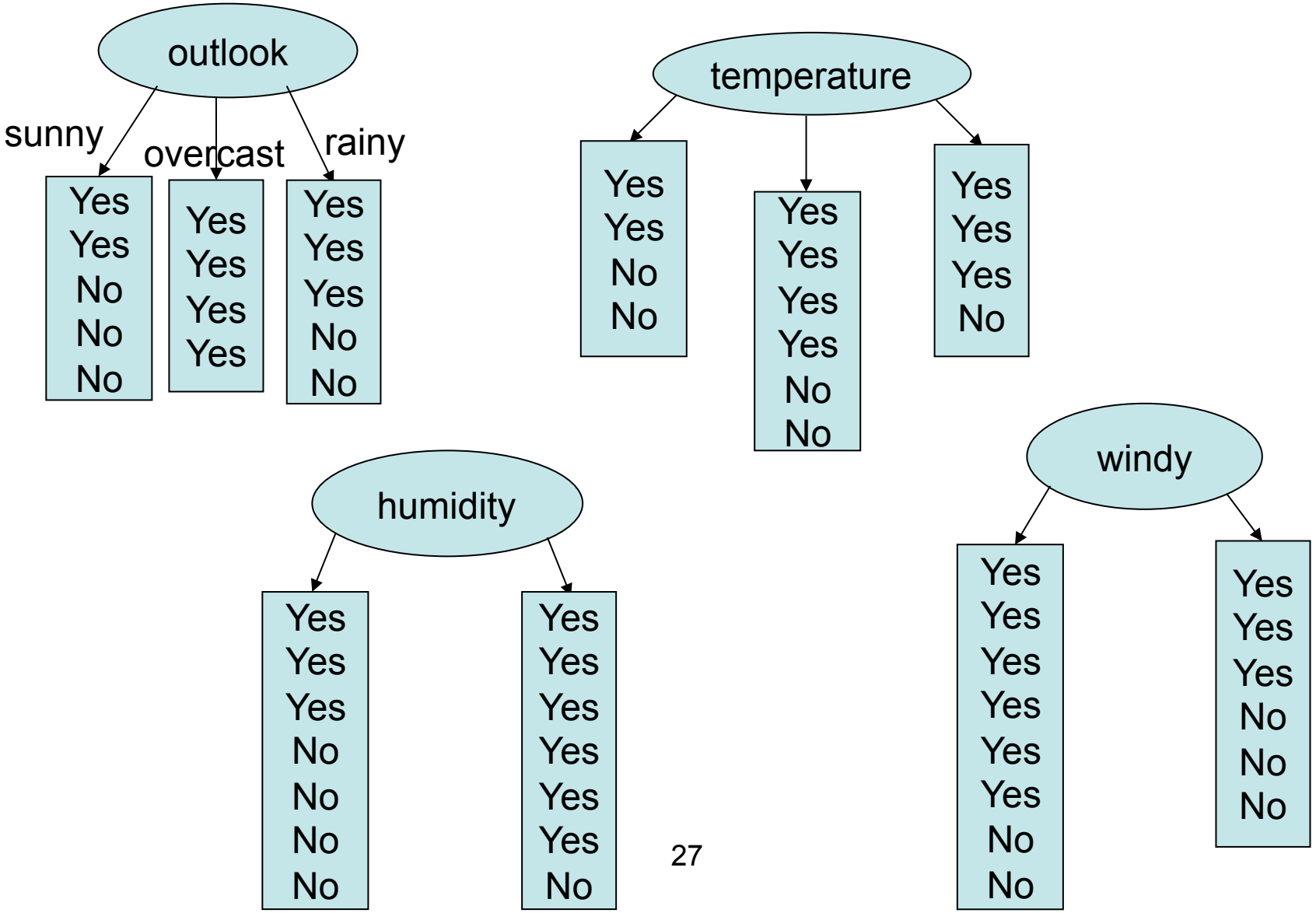
```
(defrule decision-tree-4
    (weather (outlook rainy)(windy false))
    =>
   (printout t "decision: YES" crlf)) )
```

```
(defrule decision-tree-5
    (weather (outlook rainy)(windy true))
    =>
   (printout t "decision: NO" crlf)) )
```

Jess code (2)

Which code is more efficient?

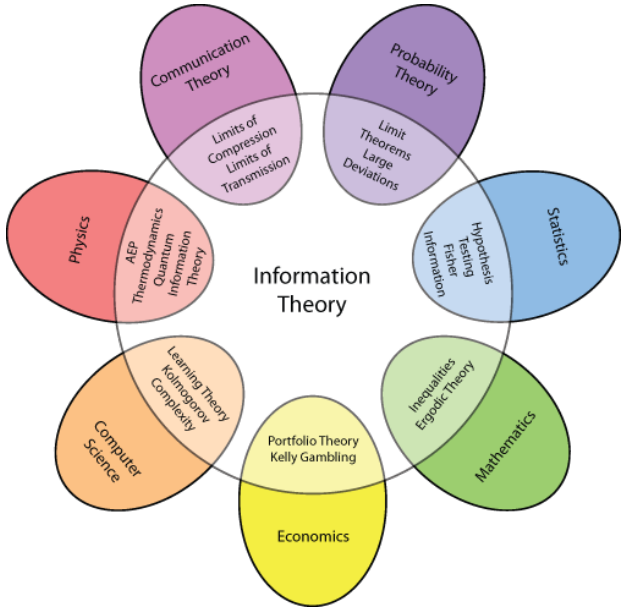
Tree stumps for the weather data



Splitting heuristic

- Select the node which '**provides the most information**' first
- Based on information theoretic measure (Shannon)
- Aims to **minimise** the number of tests needed to provide a classification
- Applied to our two decision trees describing the weather data
  - Decision tree 2 is preferable to decision tree 1
- Small decision trees are better
  - **Attribute ordering** makes the difference

Information Theory (Shannon)



- Want a numerical measure for each attribute
  - Maximum when attribute is perfect (provides perfect separation)
  - Minimum when attribute is useless (no separation)
- Suppose attribute has *n* possible values; the i^{th} value has prior probability P_i
- Information content of the attribute is:

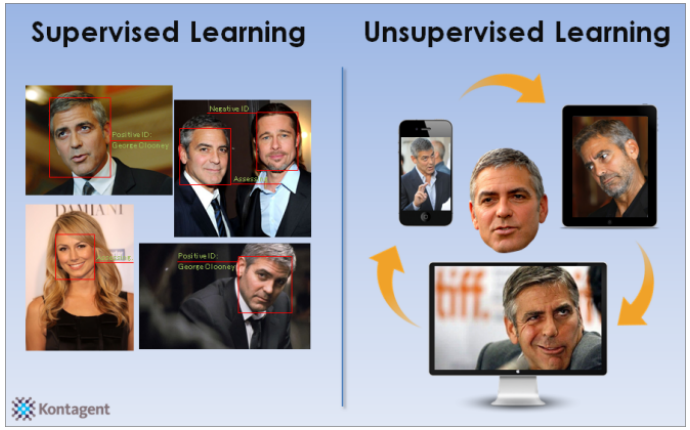
$$I(P_1, P_2, \ldots P_n) = \sum -P_i \log_2 P_i$$

- Chose attribute with **highest information content**.
- [Bit more complex – see R&N]

Attribute Selection for Splitting

- In our case, outlook is a better attribute at the root than others
  - Because when outlook is at the root, one of its branches (overcast) immediately leads to a ‘pure’ daughter node which terminates further tree growth
  - **Pure nodes** have the same class label for all the instances reaching that node
- We need a generic function that helps to rank order attributes
  - The function should reward attributes that produce ‘pure’ daughter nodes

What you should know



- Two different types of learning
  - Supervised learning (inductive learning)
  - Unsupervised learning

- Decision Tree
  - supervised learning algorithm
  - Attribute selection for splitting