#### VICTORIA UNIVERSITY OF WELLINGTON Te Whare Wananga o te Upoko o te Ika a Maui



School of Engineering and Computer Science

COMP 307 — Lecture 06

## Machine Learning 3

## **Decision Tree Learning Method**

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# **Decision Trees vs Decision Tree Learning**

- Representation of the classifier: decision trees
  - An alternative representation for classifiers
  - Symbolic, not probabilistic
  - "Easier" to interpret
- Learning process: decision tree learning (method)
  - Specify a procedure for deciding on a class
  - One of the oldest classification learning methods in AI
  - Also developed independently in Statistics/Operations Research
- Decision tree = decision tree learning?

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### **Outline**

- Decision tree learning vs learned decision trees
- How to build a decision tree using set of instances
- How to measure a DT node: (im)purity measures
- Numeric attributes: splitting points

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# **Example (Training) Data Set**

	Job	Deposit	Family	Class
A	true	low	single	Approve
В	true	low	couple	Approve
C	true	low	single	Approve
D	true	high	single	Approve
Е	false	high	couple	Approve
1	true	low	couple	Reject
2	false	low	couple	Reject
3	true	low	children	Reject
4	false	low	single	Reject
5	false	high	children	Reject

Decision Trees

Family children

Couple

Job

Deposit

Reject

high

Approve

Approve

Job

false

Reject

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# **Building A Good Decision Tree**

- Input: Instances described by attribute-value pairs
- Output: a "good" decision tree classifier

false

Reject

true

Approve

- Critical issue: choosing which attribute to use next
- DT algorithm:

Examine set of instances in the root node
If set is "pure" enough, or no more attributes
 then stop
Else

Construct subsets of instances in the subnodes Compute average "purity" of subnodes Choose the best attribute

Recurse on each subnode

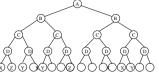
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## **Building Decision Trees**

• You can always build a decision tree trivially

- Choose some order on the attributes

- Build tree with one attribute for each level
- Label each leaf with appropriate class



#### • Problems

- Each leaf represents a possible instance
- All we are doing is remembering every instance no generalisation, no prediction, no learning

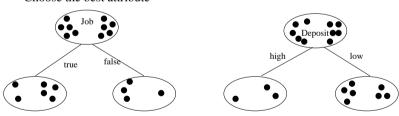
#### Solution

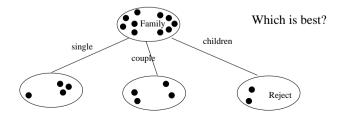
- Find a small decision tree
- capture the common features of instances
- probably generalise to predict classes for unseen instances

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### **Decision Tree Building**

Choose the best attribute





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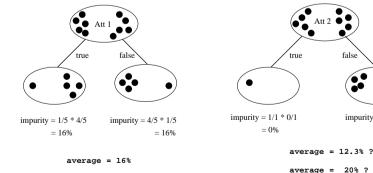
## **Measuring Purity**

- Need a measure of how "pure" a node is
  - all one class  $\longrightarrow$  pure  $\longrightarrow$  can predict the class
  - mixture of classes  $\longrightarrow$  impure  $\longrightarrow$  have to ask more questions
- Several functions
  - probability based
  - information theory based
  - **–** ... ...
- Choose the attribute whose children have the best purity

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### Weighting the Impurities

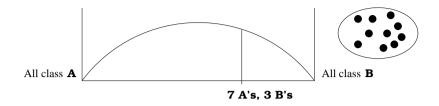
• How do we take the average?



• Need to weight the nodes by probability of going to node:

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### (Im)Purity Measure: P(A)P(B)



• Impurity:

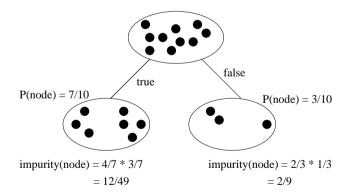
$$P(A)P(B) = \frac{m}{m+n} \times \frac{n}{m+n} = \frac{mn}{(m+n)^2}$$

m: number of A's, n: number of B's

- Goodness of attribute:
  - average impurity of subnodes

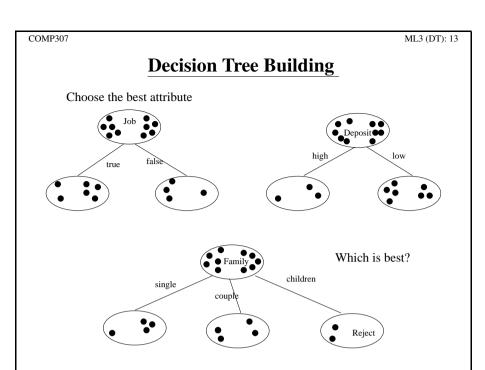
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### **Weighting the Impurities (Continued)**



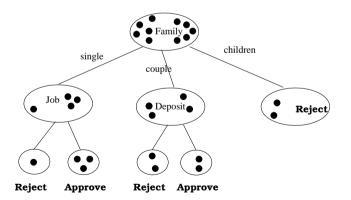
• Goodness of attribute = weighted average impurity of subnodes =  $\sum_{i} [P(node_i) \times impurity(node_i)]$ 

$$= (7/10 \times 12/49) + 3/10 \times 2/9 + = 84/490 + 6/90 = 0.238$$



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### **Decision Tree Building**



- Identify and label pure nodes
- Recurse on impure nodes
  - $-\longrightarrow$  Consider attributes "Job" and "Deposit"

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## **Learning Decision Trees**

• Job:

- true: 6/10 instances (4 approved, 2 rejected)

- false: 4/10 instances (1 approved, 3 rejected)

- impurity of node 1:  $2/6 \times 4/6$ - impurity of node 2:  $3/4 \times 1/4$ 

- weighted impurity:  $6/10 \times (2/6 \times 4/6) + 4/10 \times (3/4 \times 1/4) = 21\%$ 

• Deposit:

- weighted impurity:  $3/10 \times (1/3 \times 2/3) + 7/10 \times (4/7 \times 3/7) = 24\%$ 

• Family:

– weighted impurity:  $4/10 \times (1/4 \times 3/4) + 4/10 \times (2/4 \times 2/4) + 2/10 \times (0/2 \times 2/2) = 18\%$ 

• Which one should we choose?

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## **Summary**

- Decision tree learning vs learned decision trees
- Method of building a decision tree: DT learning algorithm
- Purity measures: weighted average impurities
- Next lecture:
  - numeric attributes: splitting points
  - Perceptron learning
- Suggested reading: section 20.5 (2nd edition) or section 18.7 (3rd edition) and web