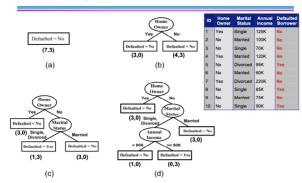
decision trees

Hunt's Algorithm



impurity measures = determining best split, with highest gain lowest impurity gain = P (impurity before split) - M (impurity after split)

 $\frac{gini \ index}{index} = \frac{c-1}{Gini \ Index} = 1 - \sum_{i=0}^{c-1} p_i(t)^2$ Where $p_i(t)$ is the frequency of class i at node t, and c is the total number of classes

• max = 1- = when all records are equally distrubuted among all classes (between)

min = ○ → when all records belong to one class

* gini index for a collection of nodes = $GINI_{split} = \sum_{i=1}^{n} \frac{n_i}{n} GINI(i)$

 n_i = number of records at child i,

* gini index for continuous attributes = 60,70,75,85,90,95 100,120,125,220

Sorted Values		Annual Income																					
		60 55		65		72		80		87		92		5 10 97		110		122		172		230	
		<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>	<=	>
	Yes	0	3	0	3	0	3	0	3	1	2	2	1	3	0	3	0	3	0	3	0	3	0
	No	0	7	1	6	2	5	3	4	3	4	3	4	3	4	4	3	5	2	6	1	7	0
	Gini 0.4		20	0.400		0.375		0.343		0.4	0.417		0.400		0(300		0.343		75	0.400		0.420	
Gini		0.420		0.400		0.375		0.343		0.417		0.400		0300		0/343		0.375		0.400		0.420	

$$\Rightarrow$$
 entropy measure = $Entropy = -\sum_{i=0}^{c-1} p_i(t)log_2p_i(t)$

• max = logo c, min = 0

*information gain: $Gain_{split} = Entropy(p) - \sum_{i=1}^{n} \frac{n_i}{n} Entropy(i)$

· impurity measures tend to prefer splits that result in large number of







partitions, each being small but pure

ves No. Family would contain the highest gain, all are pure Gainspille contains a contained to has the highest gain, all are pure

gain ratio = designed to overcome the disadvantage $\frac{Gain_{Split}}{Split Info}$ of information gain

Split Info = $-\sum_{i=1}^{n} \frac{n_i}{n} \log_2 \frac{n_i}{n}$

classification error= $Error(t) = 1 - \max_{i}[p_i(t)]$ max = 1-1/c, min=0

