Data Mining:

3. Klassifikation

A) Basic Concepts, Decision Trees

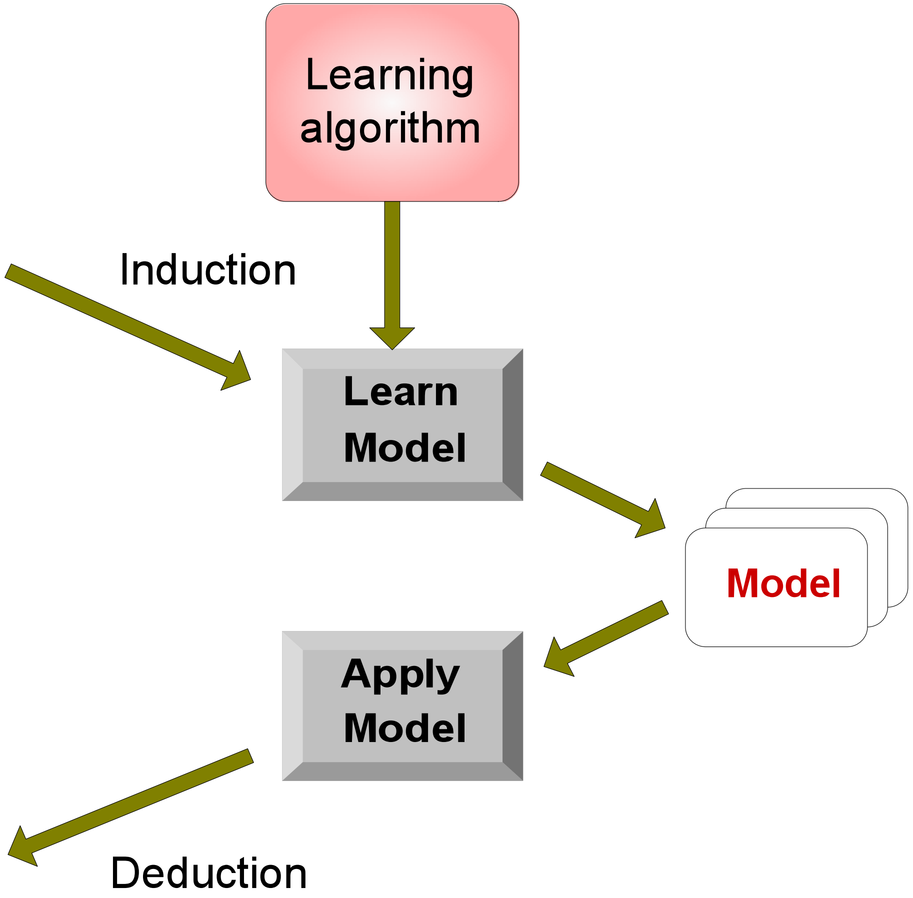
Classification: Definition

- Given a collection of records (*training set*)
  - Each record is a tuple of *attributes*, one of the attributes is the *class*.
- Goal 1: “Learn” a *model* for the class attribute as a function of the values of other attributes.
- Goal 2: Previously unseen records should be assigned a class as accurately as possible by “apply”ing the model (*prediction*).
- Validation: A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model, and with test set used to validate it.

Illustrating Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

Training Set



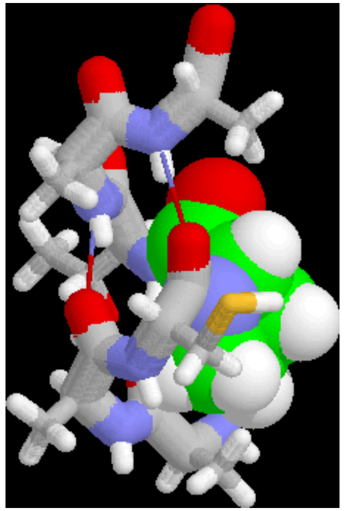
Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

Test Set

Examples of Classification Task

- Classifying credit card transactions as legitimate or fraudulent

- Classifying secondary structures of protein as alpha-helix, beta-sheet, or random coil



- Categorizing news stories as finance, weather, entertainment, sports, etc

More Examples of Classification Task

Task	Set of Input Attributes	Class label
Categorizing email messages	Features extracted from email message header and content	spam or non-spam
Identifying tumor cells	Features extracted from MRI scans	malignant or benign cells
Cataloging galaxies	Features extracted from telescope images	Elliptical, spiral, or irregular-shaped galaxies

Classification Techniques

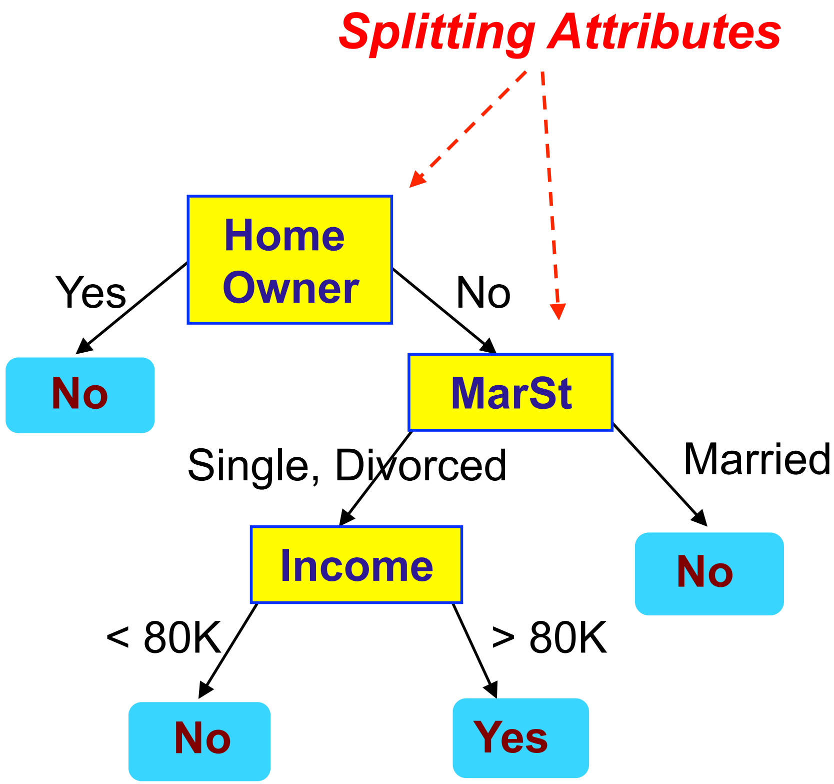
- Base Classifiers
  - Decision Tree based Methods
  - Rule-based Methods
  - Nearest Neighbours
  - Naïve Bayes and Bayesian Belief Networks
  - Support Vector Machines
  - Neural Networks

- Ensemble Classifiers
  - Boosting, Bagging, etc.

Example of a Decision Tree

categorial categorial continuous class

ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

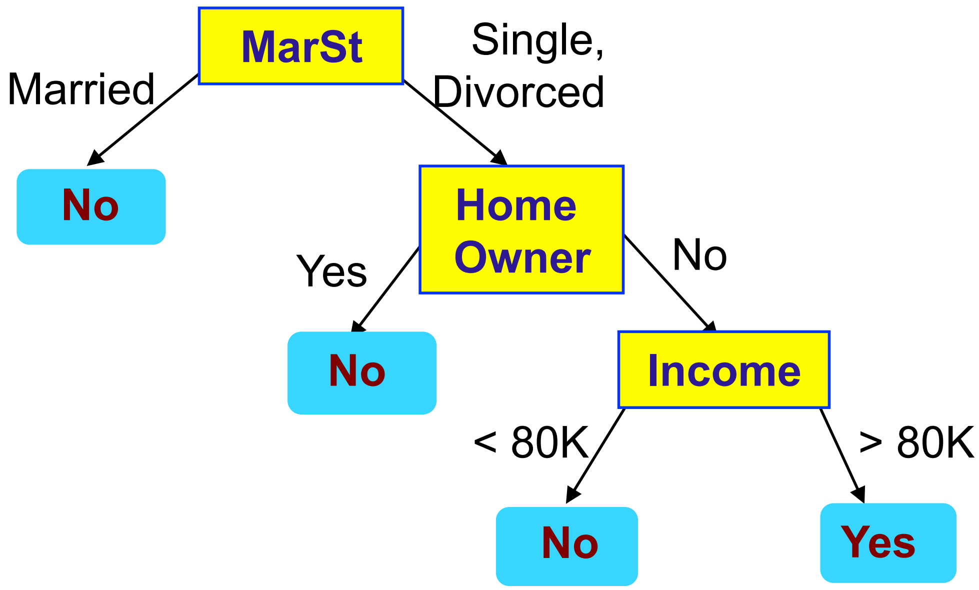


Training Data

Model: Decision Tree

Another Example of Decision Tree

ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
	categorial	categorial	continuous	class
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

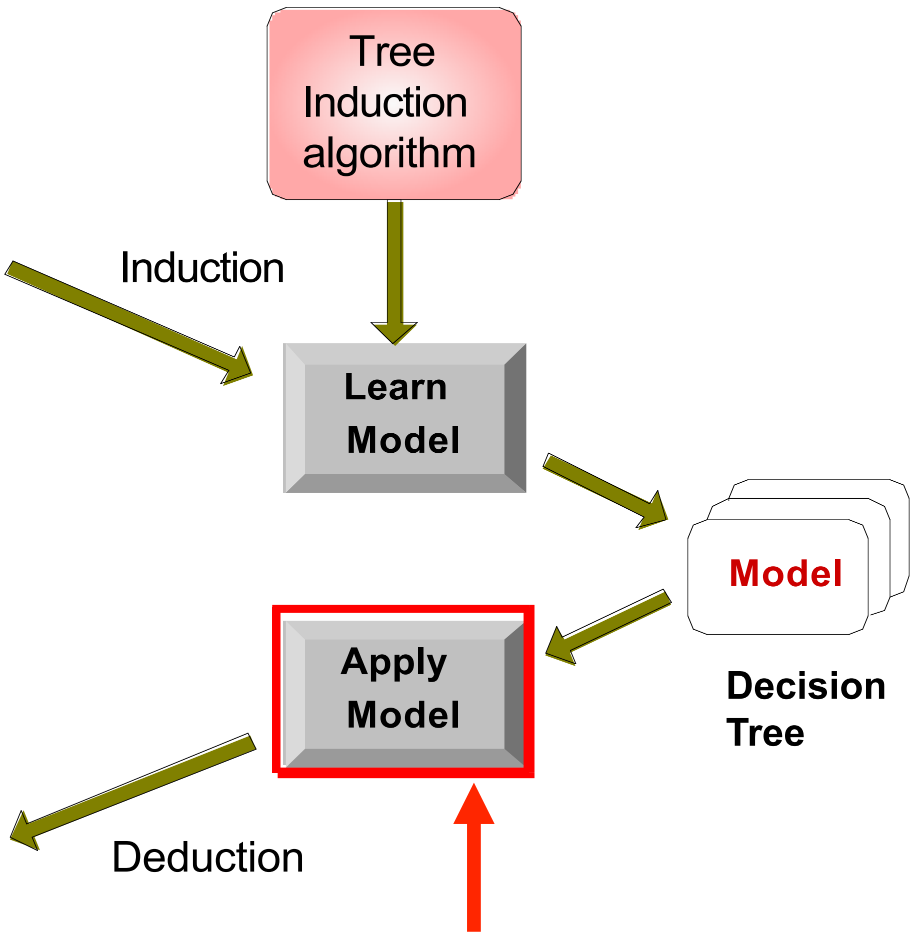


There could be more than one tree that fits the same data.

Decision Tree Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

Training Set

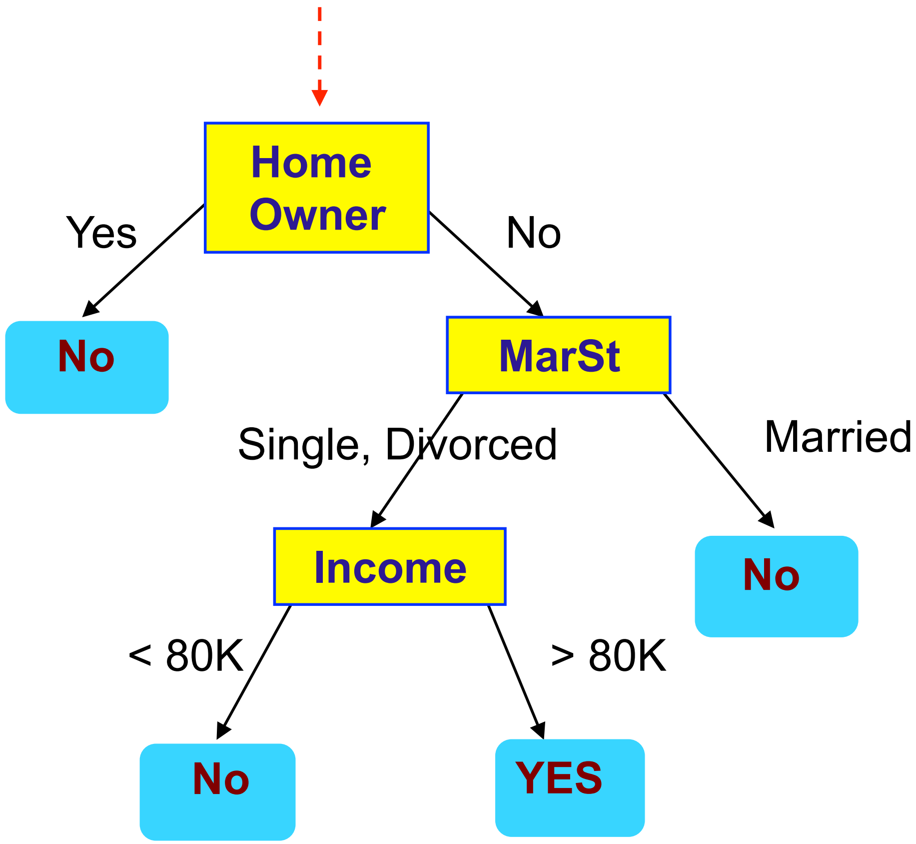


Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

Test Set

Apply Model to Test Data

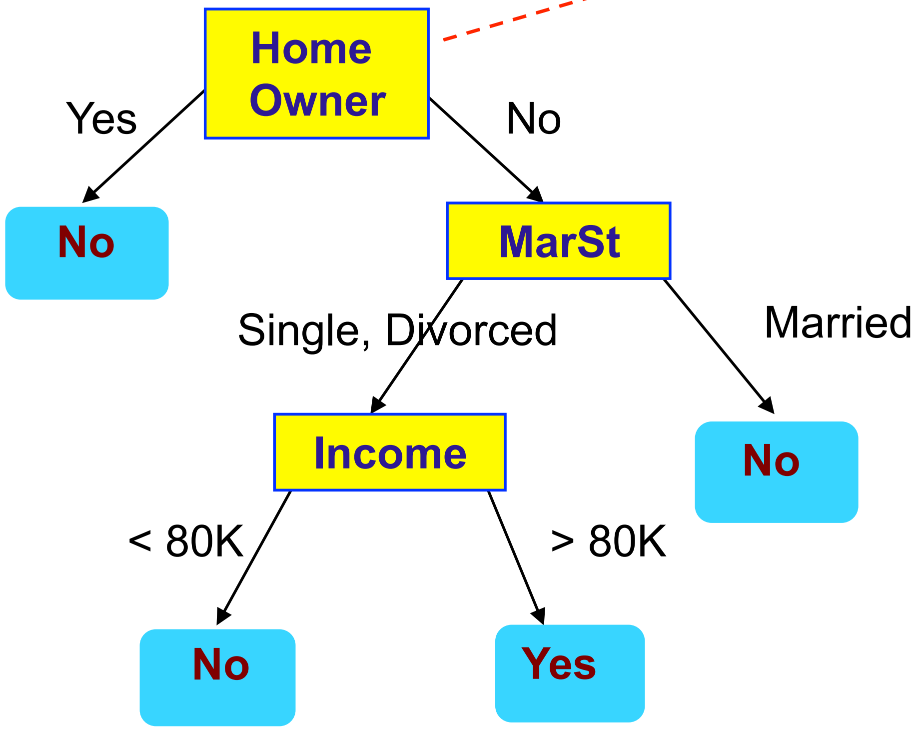
Start from the root of tree.



Test Data

Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?

Apply Model to Test Data



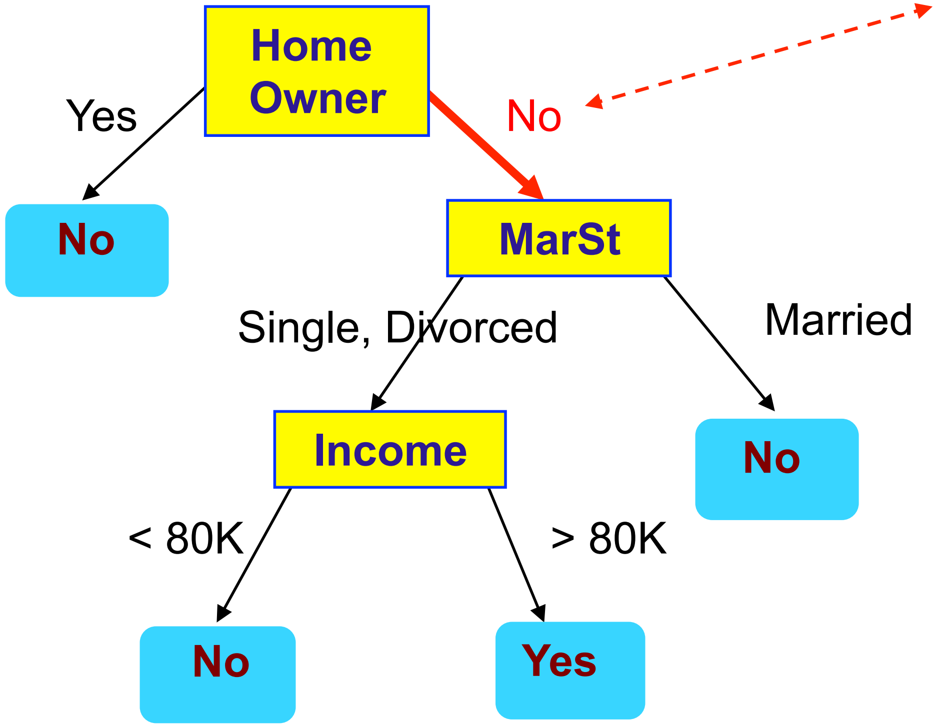
Test Data

Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?

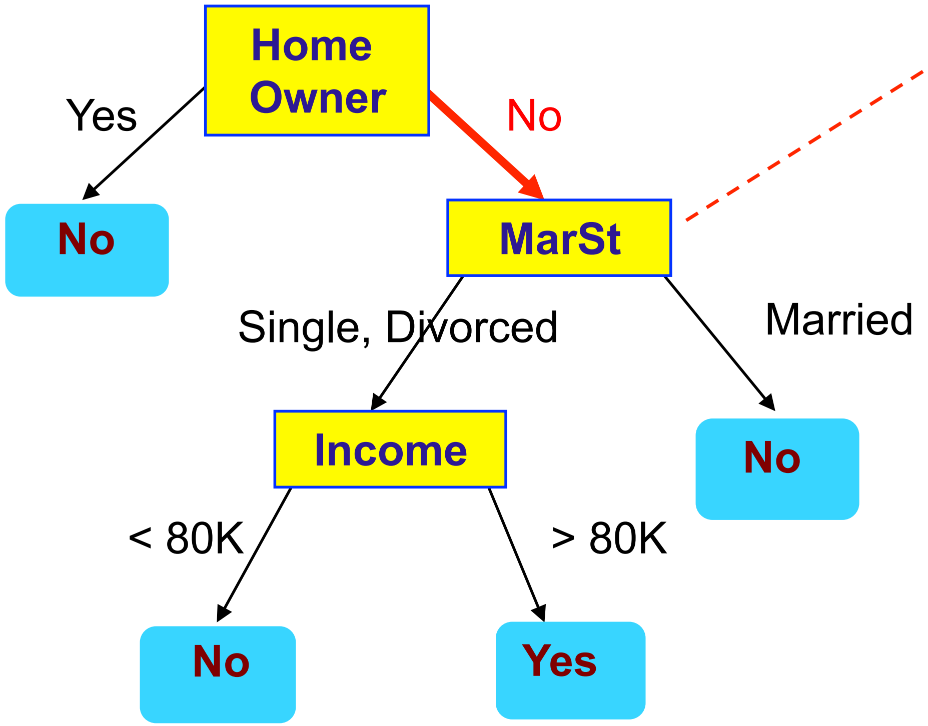
Apply Model to Test Data

Test Data

Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?



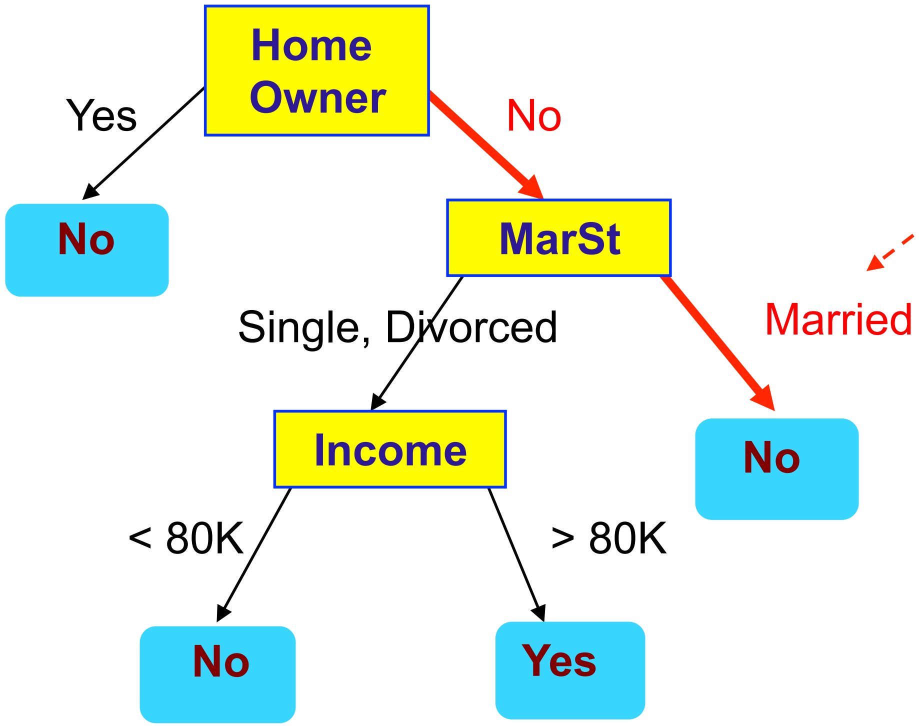
Apply Model to Test Data



Test Data

Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?

Apply Model to Test Data



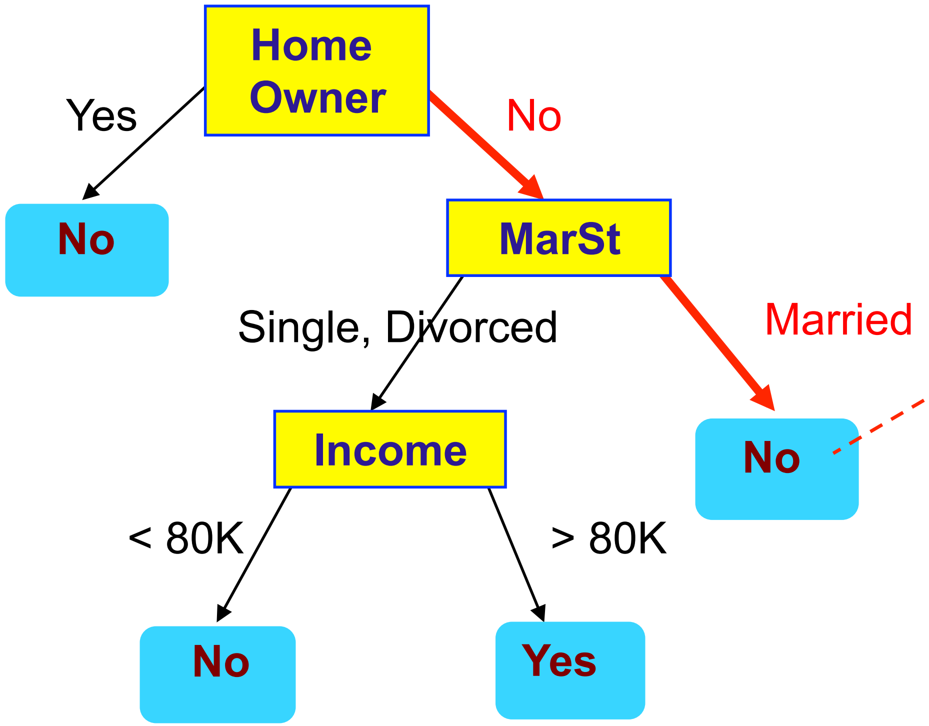
Test Data

Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?

Apply Model to Test Data

Test Data

Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?



Assign Defaulted to "**No**"

Decision Tree Classification Task

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
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4	Yes	Medium	120K	No
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8	No	Small	85K	Yes
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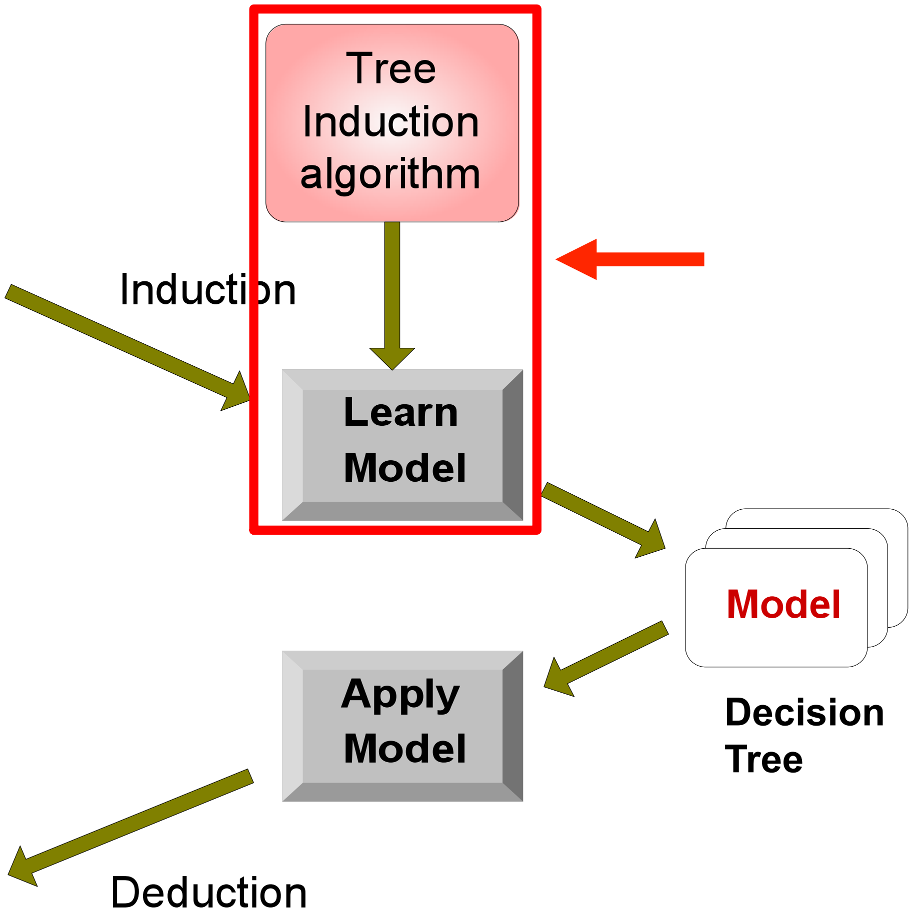
Training Set



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Test Set

Decision Tree Induction

- Many Algorithms:
  - Hunt's Algorithm (one of the earliest: 1986)
  - CART
  - ID3, C4.5
  - SLIQ,SPRINT

General Structure of Hunt's Algorithm

- Generate a new node t; return pointer.
- Let D_t be the set of training records that reach this node t (implicit parameter)
- Start at root with all training records.
- General Procedure:
  - If D_t contains records that all belong to the same class y_t, then t is a leaf node labeled as y_t
  - If D_t is an empty set, then t is a leaf node labeled by the default class, y_d
  - If D_t contains records that belong to more than one class, *find an attribute test to split* the data into smaller subsets.

    Recursively apply the procedure to each subset to construct subtrees.

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2	No	Married	100K	No
3	No	Single	70K	No
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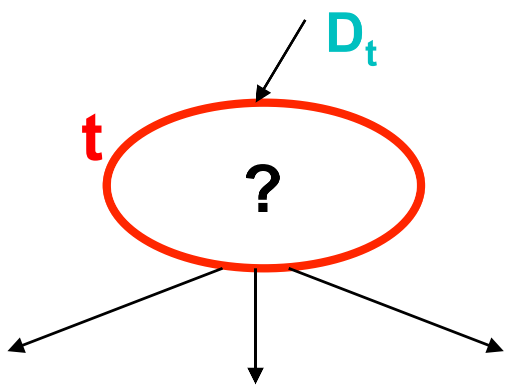
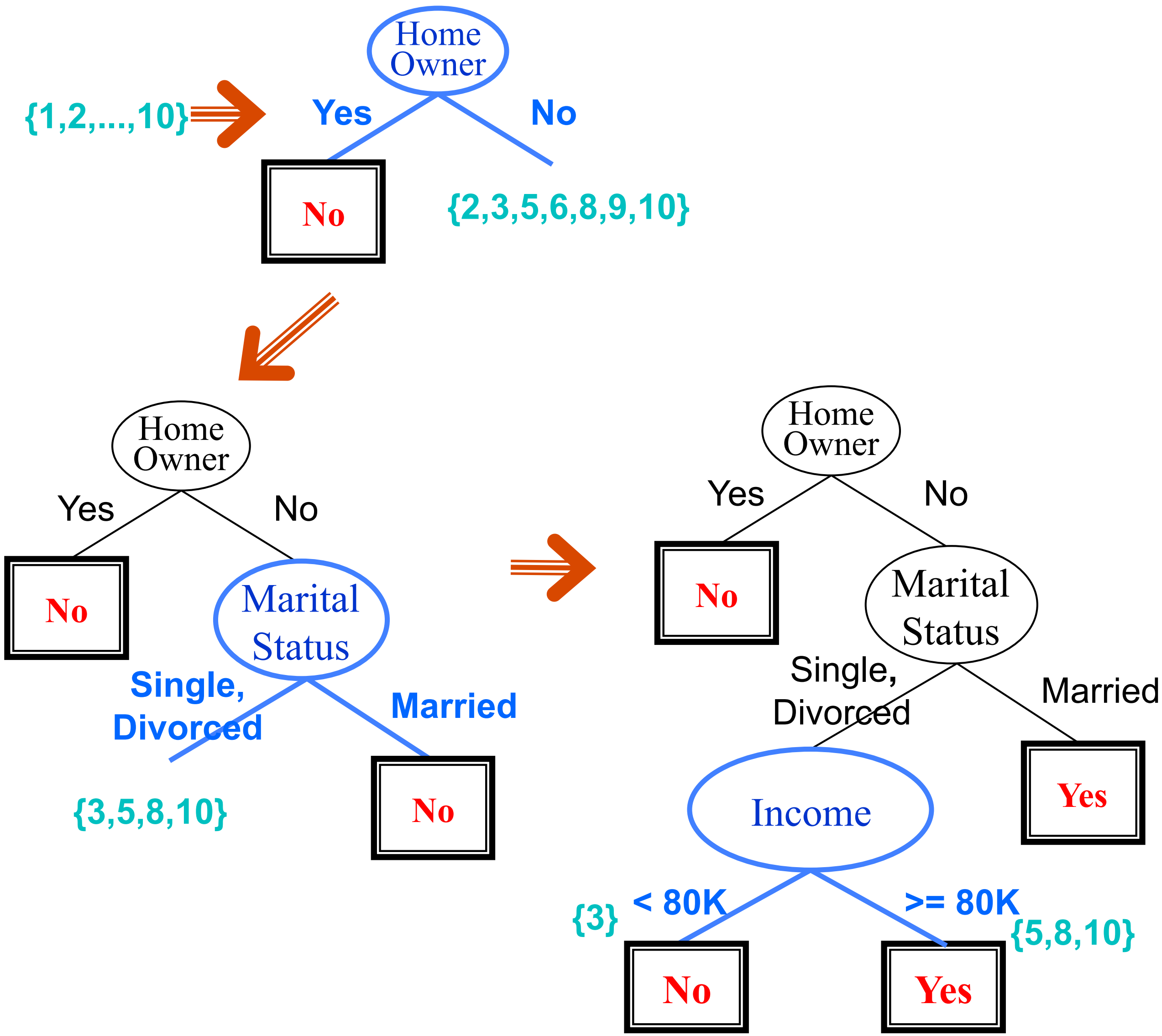
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes



Hunt's Algorithm: Following the record sets



ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
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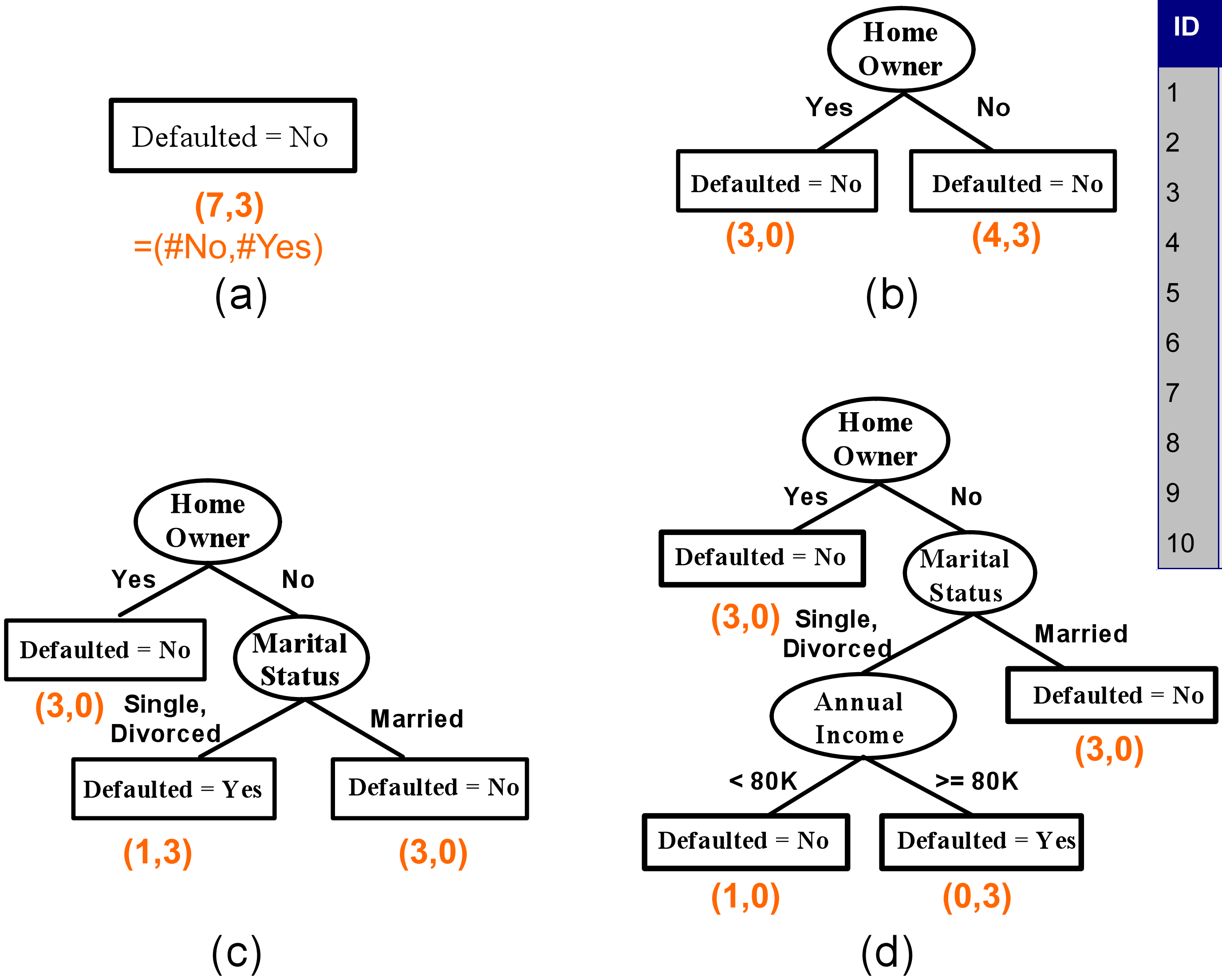
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Hunt's Algorithm: Or checking purity of decisions



ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
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6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

This will be checked by the Gini criterion below.

Tree Induction

- Greedy strategy
  – Split the records based on an attribute test that optimizes certain criteria.

- Design issues
  – Determine how to split the records
    - How to specify the attribute test condition?
    - How to determine the best split?
  – Determine when to stop splitting

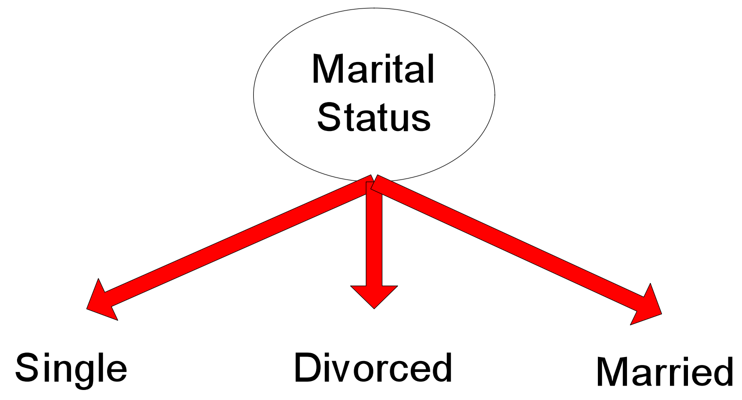
How to Specify the Test Condition?

- Depends on attribute types
  - Categorial (“nominal”)
  - Categorial and ordered (“ordinal”)
  - Continuous

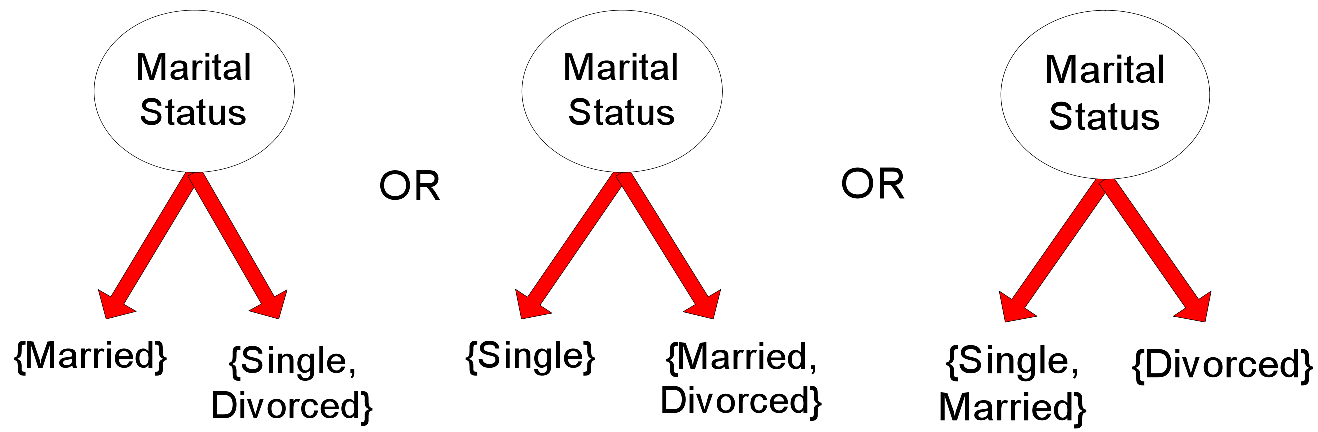
- Depends on number of ways to split
  - Binary (2-way) split
  - Multi-way split

Test Condition for Nominal Attributes

- Multi-way split:
  - Use as many partitions as distinct values.

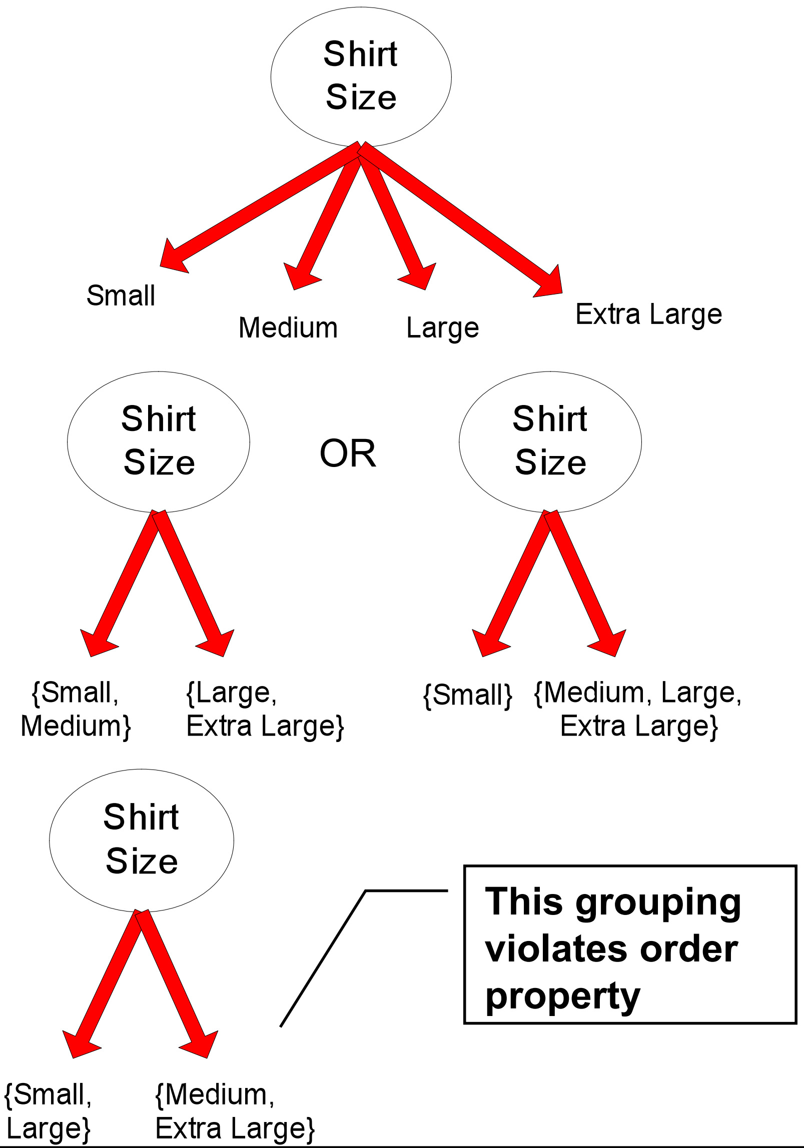


- Binary split:
  - Divide values into two subsets.
    - Need to find optimal partitioning

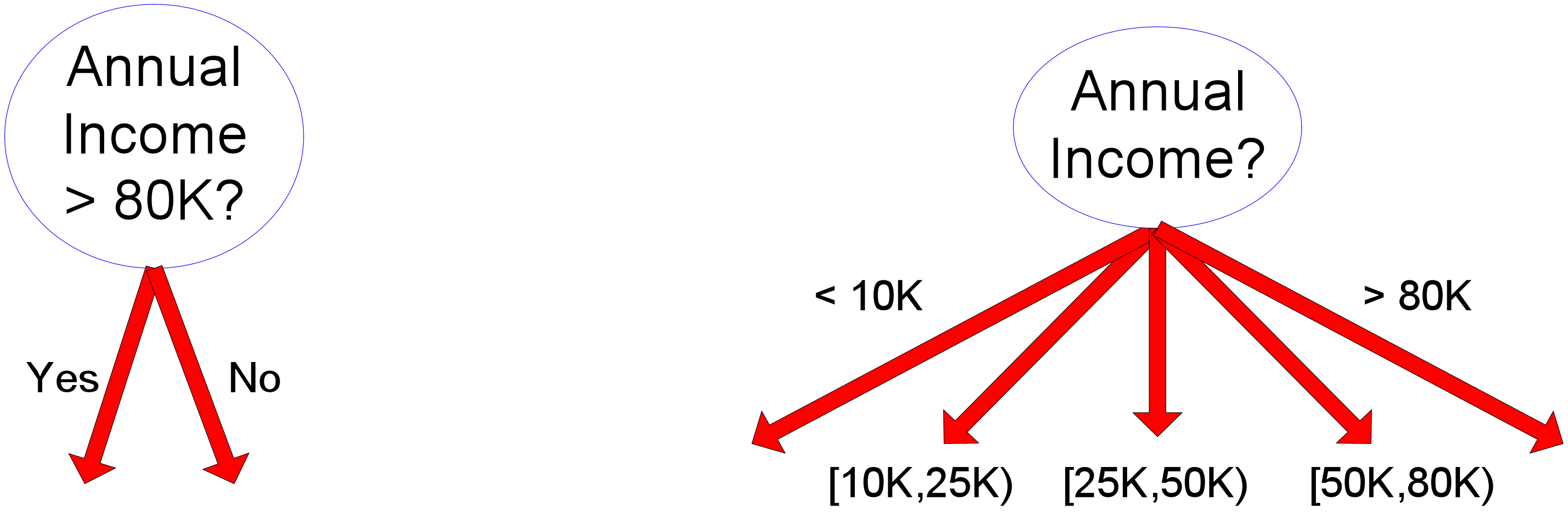


Test Condition for Ordinal Attributes

- Multi-way split:
  - Use as many partitions as distinct values
- Binary split:
  - Divide values into two subsets
  - Preserve order property among attribute values



Test Condition for Continuous Attributes



(i) Binary split

(ii) Multi-way split

Splitting Based on Continuous Attributes

- Different ways of handling
  - Binary Decision: $(A < v)$ or $(A \geq v)$
    - consider all possible splits and find the best cut
    - can be more computing intensive
  - Discretization to form an ordinal attribute
    - Static – discretize once at the beginning
    - Dynamic – ranges can be found
      by equal interval / frequency bucketing
      or clustering of the remaining test records.

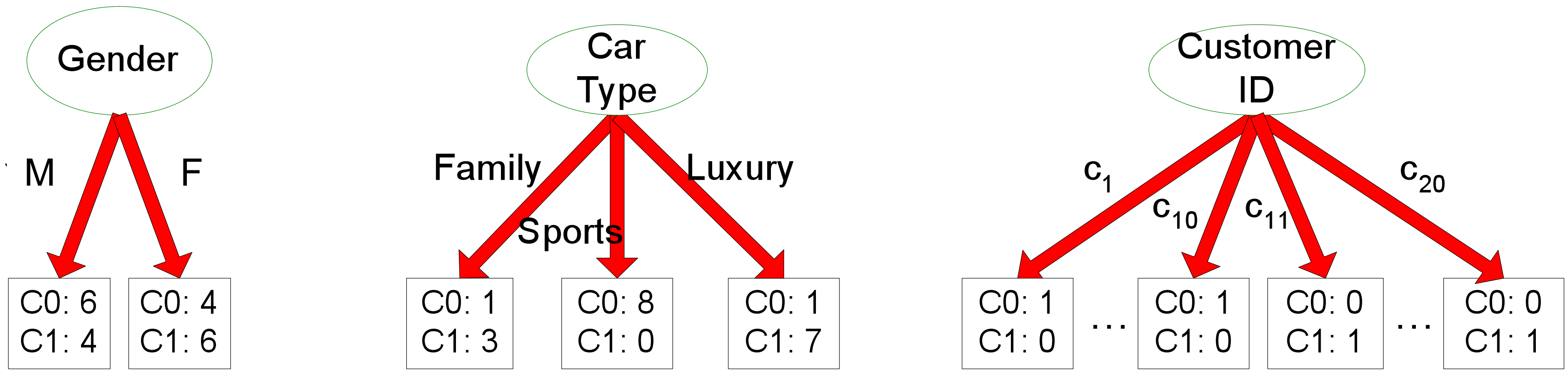
How to Determine the Best Split

Example:

Before Splitting: 10 records of class 0,
10 records of class 1

After Splitting:

Customer Id	Gender	Car Type	Shirt Size	Class
1	M	Family	Small	C0
2	M	Sports	Medium	C0
3	M	Sports	Medium	C0
4	M	Sports	Large	C0
5	M	Sports	Extra Large	C0
6	M	Sports	Extra Large	C0
7	F	Sports	Small	C0
8	F	Sports	Small	C0
9	F	Sports	Medium	C0
10	F	Luxury	Large	C0
11	M	Family	Large	C1
12	M	Family	Extra Large	C1
13	M	Family	Medium	C1
14	M	Luxury	Extra Large	C1
15	F	Luxury	Small	C1
16	F	Luxury	Small	C1
17	F	Luxury	Medium	C1
18	F	Luxury	Medium	C1
19	F	Luxury	Medium	C1
20	F	Luxury	Large	C1



Which split (choice of attribute and choice of test condition) is the best ?

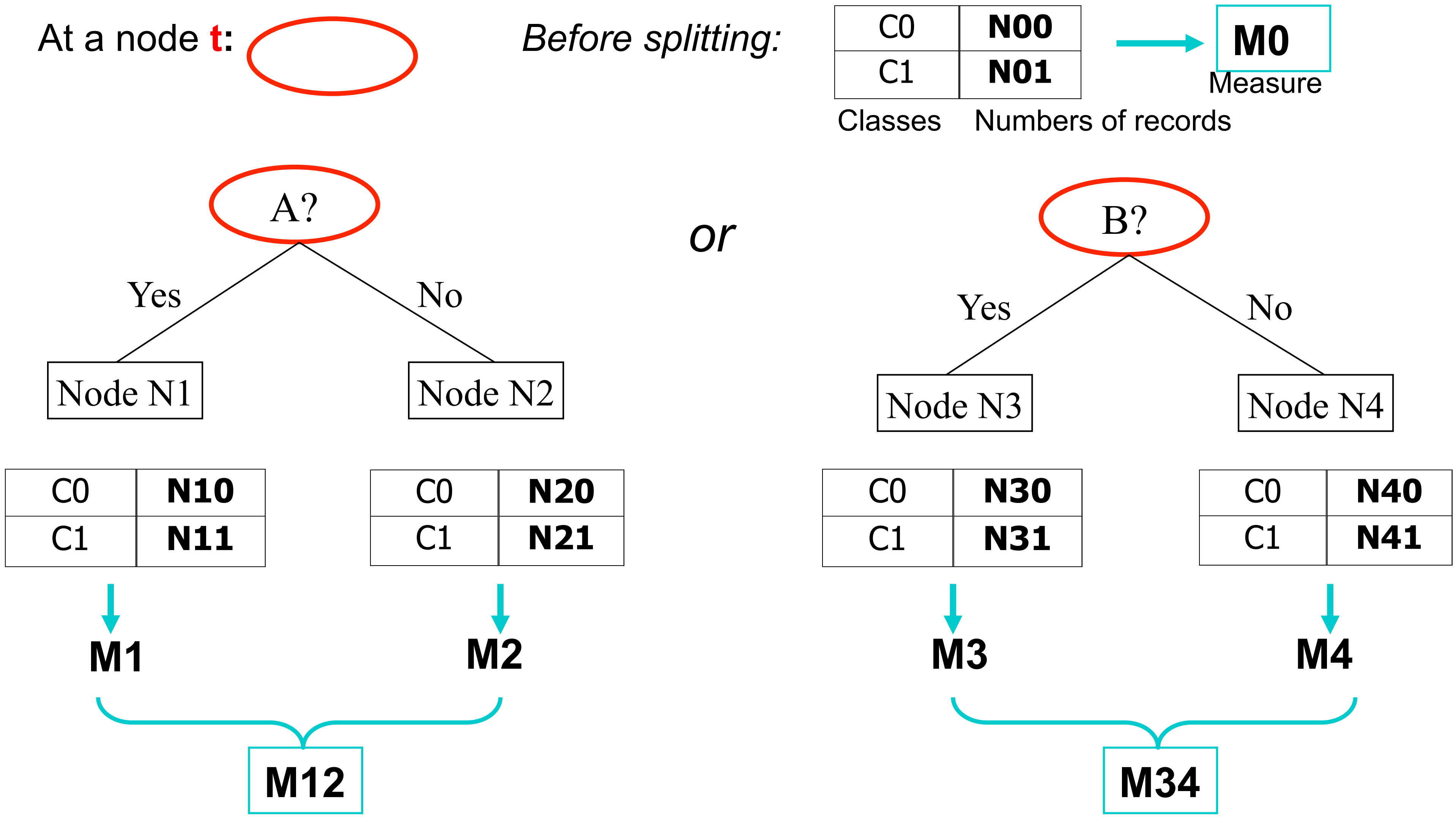
How to Determine the Best Split

- Idea (for greedy approach):
  - Nodes with purer class distribution are preferred !

- Needs a measure of node impurity:

C0: 5	C0: 9
C1: 5	C1: 1
non-homogeneous	**more homogeneous**
high degree of impurity	**low degree of impurity**
	preferred

How to Determine the Best Split



By splitting, maximize **Gain** = **M0 – M12** vs **M0 – M34**! I.e. minimize child measures **M12** vs **M34**.

How to Determine the Best Split

1. Compute impurity measure (M0) before splitting
2. Compute impurity measure (M) after splitting
   - Compute impurity measure of each child node
   - M is the weighted impurity of children
3. Choose the attribute test condition that produces the highest gain

   Gain = M0 – M

   or equivalently, that produces the lowest impurity measure after splitting (M)

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification Error

Measure of Impurity: GINI

[Corrado Gini: ital. Statistiker]

- Gini Index for a given node t :

$$GINI(t) = 1 - \sum_j [p(j \mid t)]^2$$

(Note: $p(j|t)$ is the relative frequency of class j at node t, j=1…n_c)

  – Maximum (1 - 1/n_c) when records are equally distributed among all classes, implying impurest information ($p(j|t)$=1/n_c) (n_c=number of classes)

  – Minimum (0.0) when all records belong to one class, implying purest information

- Example:

C1	**0**
C2	**6**
GINI=0.000	

C1	**1**
C2	**5**
GINI=0.278	

C1	**2**
C2	**4**
GINI=0.444	

C1	**3**
C2	**3**
GINI=0.500	

Examples for Computing GINI

$$GINI(t) = 1 - \sum_j [p(j \mid t)]^2$$

C1	**0**
C2	**6**

p(C1) = 0/6 = 0 p(C2) = 6/6 = 1

GINI = 1 – p(C1)^2 – p(C2)^2 = 1 – 0 – 1 = 0

C1	**1**
C2	**5**

p(C1) = 1/6 p(C2) = 5/6

GINI = 1 – (1/6)^2 – (5/6)^2 = 0.278

C1	**2**
C2	**4**

p(C1) = 2/6 p(C2) = 4/6

GINI = 1 – (2/6)^2 – (4/6)^2
= 4/9 = 0.444

For 2-class problem:
GINI = $1 - p^2 - (1-p)^2$
= 2p (1-p)

Note: Without squaring, GINI would always be 0.

Splitting Based on GINI

- Used in algorithms CART, SLIQ, SPRINT.
- When a parent node is split into k partitions (children), the measure of this split is computed as the weighted average

$$GINI_{split} = \sum_{i=1}^{k} \frac{n_i}{n} GINI(i)$$

where, n_i = number of records at child i,
n = number of records at parent node.

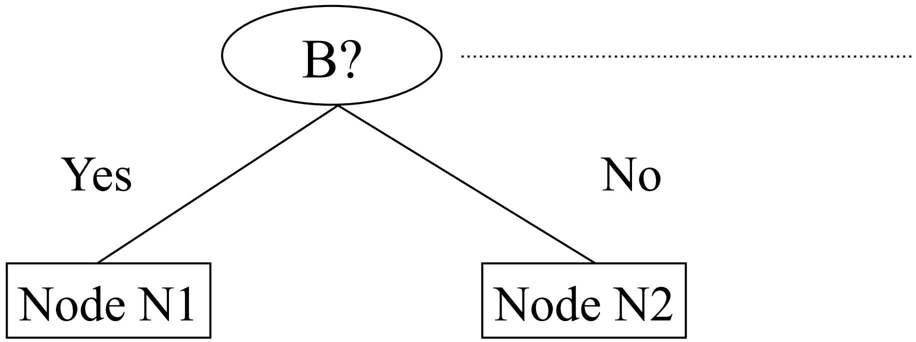
- Since we want to maximize the difference

$GINI$(parent node) - $GINI_{split}$,

we have to find a split with minimal $GINI_{split}$ value.

Binary Attributes: Computing GINI Index

- Splits into two partitions
- Effect of weighing partitions:
  – Larger and purer partitions are sought for.



	Parent
C1	**6**
C2	**6**
GINI = 0.500	

GINI(N1)
$= 1 - (5/7)^2 - (2/7)^2$
$= 0.408$

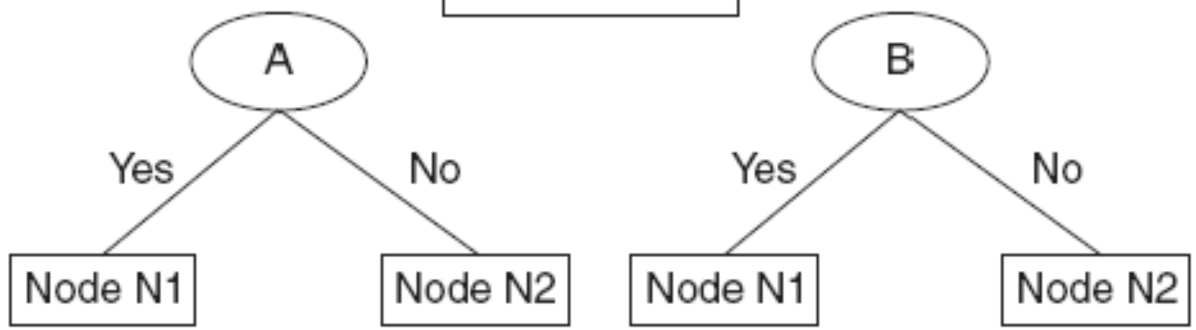
GINI(N2)
$= 1 - (1/5)^2 - (4/5)^2$
$= 0.32$

	N1	N2
C1	**5**	**1**
C2	**2**	**4**
$\textbf{GINI}_{split}$**=0.371**		

$\textbf{GINI}_{split}$**(Children)**
$= 7/12 * 0.408 +$
$5/12 * 0.32$
$= 0.371$

Binary Attributes: Computing GINI Index

	Parent
C0	6
C1	6
Gini = 0.500	



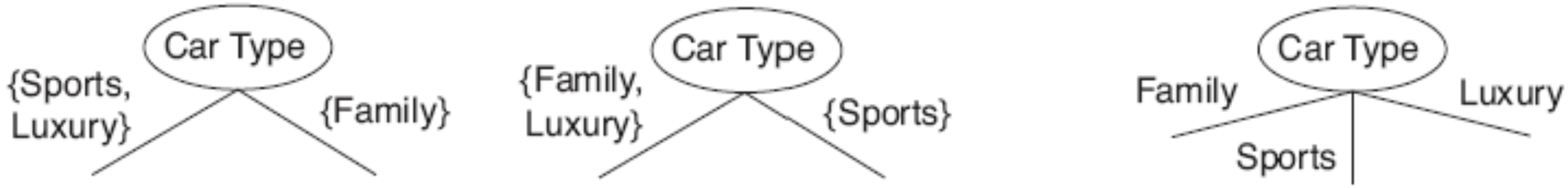
	N1	N2
C0	4	2
C1	3	3
$Gini_{split} = 0.486$		

	N1	N2
C0	1	5
C1	4	2
$Gini_{split} = 0.371$		

← Prefer this split

Figure 4.14. Splitting binary attributes.

Nominal Attributes: Computing GINI Index



	Car Type	
	{Sports, Luxury}	{Family}
C0	9	1
C1	7	3
$Gini_{split}$	0.468	

	Car Type	
	{Sports}	{Family, Luxury}
C0	8	2
C1	0	10
$Gini_{split}$	0.167	

(a) Binary split

	Car Type		
	Family	Sports	Luxury
C0	1	8	1
C1	3	0	7
$Gini_{split}$	0.163		

(b) Multiway split

Figure 4.15. Splitting nominal attributes.

Continuous Attributes: Computing GINI Index

- Use Binary Decisions based on one value
- Several choices for the splitting value
  - Number of possible splitting values = Number of distinct values(N)+1
- Each splitting value v has a count matrix associated with it
  - Class counts in each of the partitions, A < v and A ≥ v
- Simple method to choose best v
  - For each v, scan the database to gather count matrix and compute its GINI index
  - Computationally inefficient! $O(N^2)$. Repetition of work.

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1	Yes	Single	125K	No
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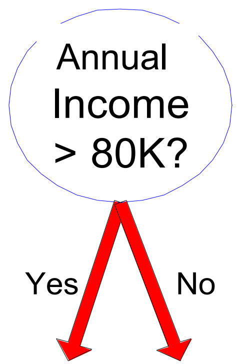
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes



	≤ 80	> 80
Yes	0	3
No	3	4

Continuous Attributes: Computing GINI Index

- For efficient computation: for each attribute,
  - Sort the attribute on values: O(N log N)
  - Linearly scan these values, each time updating the count matrix and computing GINI index: O(N)
  - Choose the split position that has the least GINI index: within latter step

Class	No	No	No	Yes	Yes	Yes	No	No	No	No
	Annual Income									
Sorted Values →	60	70	75	85	90	95	100	120	125	220

Split Positions →	55		65		72		80		87		92		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
$Gini_{split}$	0.420		0.400		0.375		0.343		0.417		0.400		*0.300*		0.343		0.375		0.400		0.420	

Figure 4.16. Splitting continuous attributes.

Alternative Measure

- Entropy at a given node t:

$$Entropy(t) = -\sum_{j} p(j\,|\,t)\log_2 p(j\,|\,t)$$

(Note: $p(j\,|\,t)$ is the relative frequency of class j at node t; 0log0:=0)

  – Measures "information content" of a node
    (optimal coding of class memberships, exploiting probabilities)
    - Maximum (log n_c) when records are equally distributed among all classes implying least information / longest coding
    - Minimum (0.0) when all records belong to one class, implying most information / shortest coding

  – Entropy computations are similar to Gini-index computations

Examples for Computing Entropy

$$Entropy(t) = -\sum_{j} p(j \mid t) \log_2 p(j \mid t)$$

C1	**0**
C2	**6**

p(C1) = 0/6 = 0   p(C2) = 6/6 = 1

Entropy = – 0 log 0 – 1 log 1 = – 0 – 0 = 0

C1	**1**
C2	**5**

p(C1) = 1/6   p(C2) = 5/6

Entropy = – (1/6) $\log_2$ (1/6) – (5/6) $\log_2$ (5/6) = 0.65

C1	**2**
C2	**4**

p(C1) = 2/6   p(C2) = 4/6

Entropy = – (2/6) $\log_2$ (2/6) – (4/6) $\log_2$ (4/6) = 0.92

Splitting Based on Entropy

- Again, the gain (measure at parent - avg measure of children) of a split has to be maximized (here called Information Gain):

$$GAIN_{split} = Entropy(p) - \left(\sum_{i=1}^{k} \frac{n_i}{n} Entropy(i) \right)$$

$(...) = Entropy_{split}$

- Used in algorithms ID3 and C4.5
- Disadvantage: Tends to prefer splits that result in large number of partitions, each being small but pure (Entropy=0).
- Avoiding this disadvantage: Use binary splits only
  or use Gain Ratio instead of Gain …

Splitting, Adjusted

- Gain Ratio:

$$GainRATIO_{split} = \frac{GAIN_{split}}{SplitINFO}$$

$$SplitINFO = -\sum_{i=1}^{k} \frac{n_i}{n} \log \frac{n_i}{n}$$

(parent node p is split into *k* partitions; n_i is the number of records in partition *i*)

  - Adjusts Information Gain by the entropy of the partitioning (SplitINFO). Higher entropy partitioning (large number of small partitions) is penalized!
  - E.g. *k* partitions of same size 1/*k*: SplitINFO = $\log_2 k$
  - Used in C4.5
  - Designed to overcome the disadvantage of Inf.Gain

Yet another measure

- Misclassification error at a node *t* (with classes *j*):

$$Error(t) = 1 - \max_{j} p(j \mid t)$$

  - Measures misclassification error made by a node.
    - Maximum $(1 - 1/n_c)$ when records are equally distributed among all classes, implying maximally unclear classification
    - Minimum (0.0) when all records belong to one class, implying no misclassification
  - Simplest measure, but least differentiating.

Examples for Computing Error

$$Error(t) = 1 - \max_{j} p(j \mid t)$$

C1	**0**
C2	**6**

p(C1) = 0/6 = 0 p(C2) = 6/6 = 1

Error = 1 – max (0, 1) = 1 – 1 = 0

C1	**1**
C2	**5**

p(C1) = 1/6 p(C2) = 5/6

Error = 1 – max (1/6, 5/6) = 1 – 5/6 = 1/6

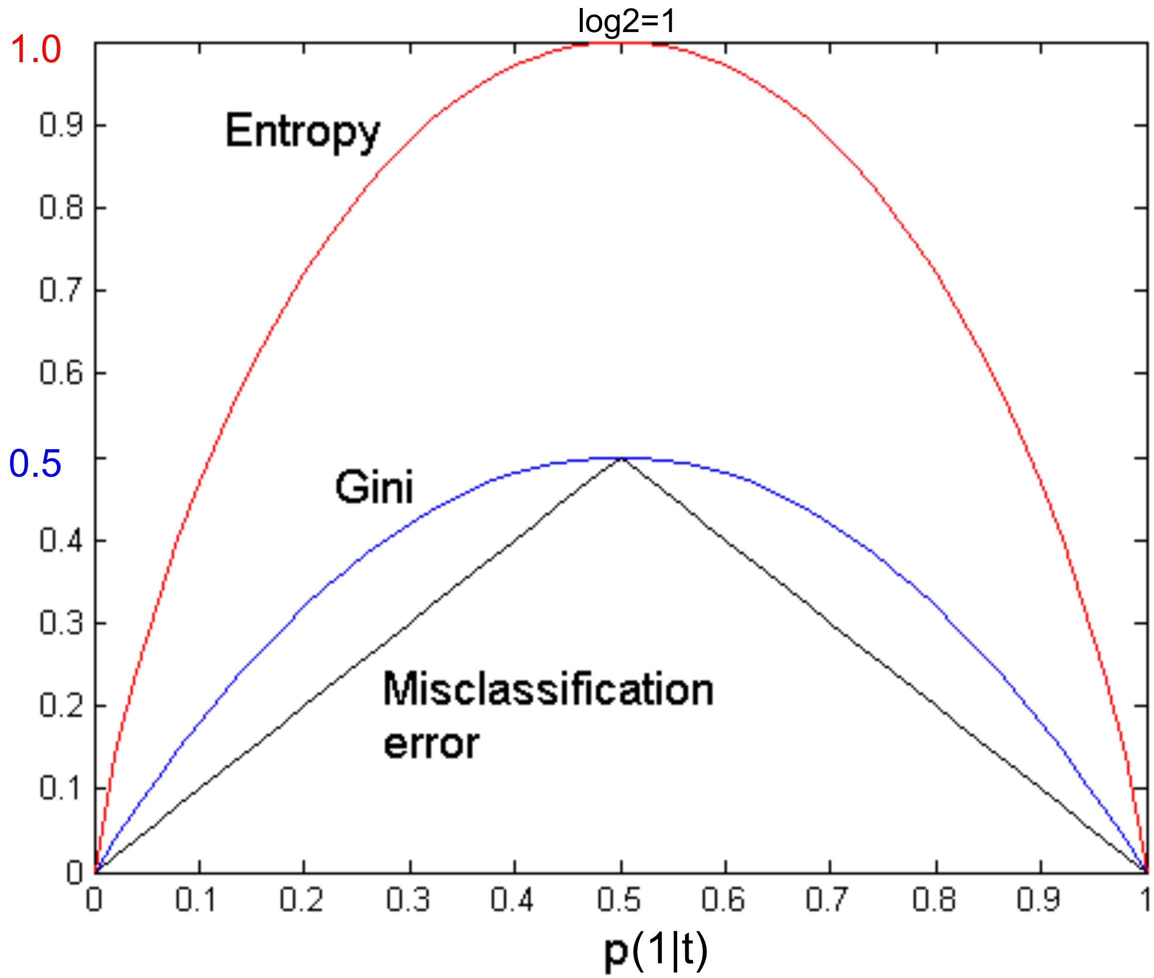
C1	**2**
C2	**4**

p(C1) = 2/6 p(C2) = 4/6

Error = 1 – max (2/6, 4/6) = 1 – 4/6 = 1/3

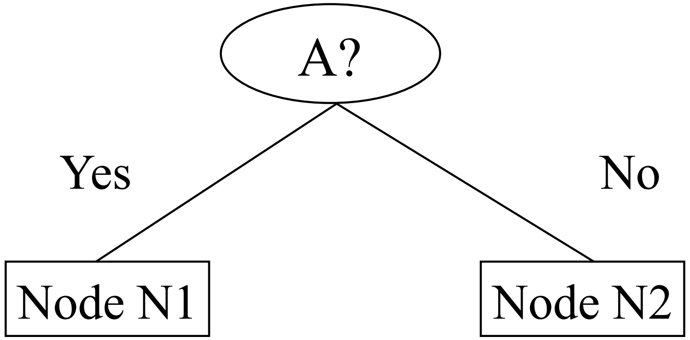
Comparison among Impurity Measures

For a binary classification problem:



(values of one node, not of a split)

Misclassification Error vs Gini – Example



	Parent
C1	**7**
C2	**3**
GINI = 0.42, Error = 0.3	

GINI(N1)
$= 1 – (3/3)^2 – (0/3)^2$
$= 0$

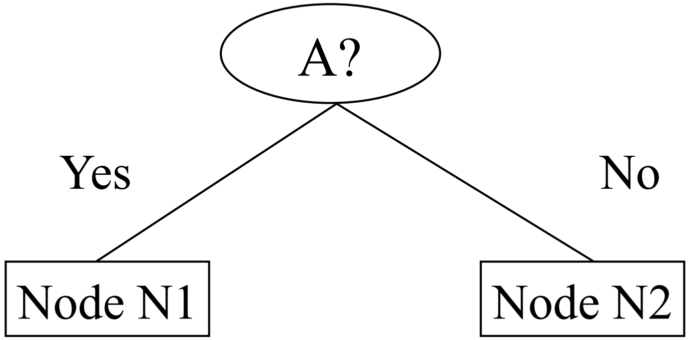
GINI(N2)
$= 1 – (4/7)^2 – (3/7)^2$
$= 0.489$

	N1	N2
C1	**3**	**4**
C2	**0**	**3**
$GINI_{split}$=0.342		

$GINI_{split}$(Children)
$= 3/10 * 0$
$+ 7/10 * 0.489$
$= 0.342$

GINI improves !!

Misclassification Error vs Gini – Example



	Parent
C1	**7**
C2	**3**
GINI = 0.42, Error = 0.3	

Error(N1)
= 1 – max(3/3,0/3)
= 0

Error(N2)
= 1 – max(4/7,3/7)
= 3/7

	N1	N2
C1	**3**	**4**
C2	**0**	**3**
$GINI_{split}$=0.342, $Error_{split}$=0.3		

$Error_{split}$(Children)
= 3/10 * 0
+ 7/10 * 3/7
= 0.3

GINI improves,
Error does not !!

Tree Induction

- Greedy strategy
  - Split the records based on an attribute test that optimizes certain criteria.

- Design issues
  - Determine how to split the records
    - How to specify the attribute test condition?
    - How to determine the best split?
  - **Determine when to stop splitting**

Stopping Criteria for Tree Induction

- Stop expanding a node when all the records belong to the same class
- Stop expanding a node when all represented records have similar attribute values
- Early termination (using default or majority class) to avoid overfitting the model [to be discussed later]

Tree Induction Algorithm

Algorithm A skeleton decision tree induction algorithm.

```
TreeGrowth (E, F)
if stopping_cond(E,F) = true then
    leaf = createNode().
    leaf.label = Classify(E).
    return leaf.
else
    root = createNode().
    root.test_cond = find_best_split(E, F).
    let V = {v|v is a possible outcome of root.test_cond }.
    for each v ∈ V do
        E_v = {e | root.test_cond(e) = v and e ∈ E}.
        child = TreeGrowth(E_v, F).
        add child as descendent of root and label the edge (root → child) as v.
    end for
end if
return root.
```

E training records, F attribute set, *label* assigned class (usually, the class *j* with maximal *p(j|t)*)

Example Algorithm: C4.5

- Simple depth-first tree construction.
- Uses Information Gain
- Sorts Continuous Attributes at each node.
- Needs entire data to fit in memory.
- Unsuitable for Large Datasets.
  - would need out-of-core sorting
- You can download the software or use it in Weka.

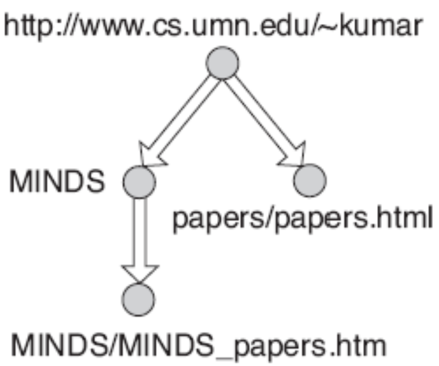
Decision Tree Based Classification

- Advantages:
  - Inexpensive to construct
    (but many splitting options may have to be calculated
  - Extremely fast at classifying unknown records
  - Easy to interpret for small-sized trees
  - Robust to noise
    (especially when methods to avoid overfitting are employed)
  - Can easily handle redundant or irrelevant attributes
    (unless the attributes are interacting)
- Disadvantages:
  - Space of possible decision trees is exponentially large. Greedy approaches are often unable to find the best tree.
  - Does not take into account interactions between attributes
  - Each decision boundary involves only a single attribute

An Application: Web Robot Detection

Session	IP Address	Timestamp	Request Method	Requested Web Page	Protocol	Status	Number of Bytes	Referrer	User Agent
1	160.11.11.11	08/Aug/2004 10:15:21	GET	http://www.cs.umn.edu/~kumar	HTTP/1.1	200	6424		Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.0)
1	160.11.11.11	08/Aug/2004 10:15:34	GET	http://www.cs.umn.edu/~kumar/MINDS	HTTP/1.1	200	41378	http://www.cs.umn.edu/~kumar	Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.0)
1	160.11.11.11	08/Aug/2004 10:15:41	GET	http://www.cs.umn.edu/~kumar/MINDS/MINDS_papers.htm	HTTP/1.1	200	1018516	http://www.cs.umn.edu/~kumar/MINDS	Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.0)
1	160.11.11.11	08/Aug/2004 10:16:11	GET	http://www.cs.umn.edu/~kumar/papers/papers.html	HTTP/1.1	200	7463	http://www.cs.umn.edu/~kumar	Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.0)
2	35.9.2.2	08/Aug/2004 10:16:15	GET	http://www.cs.umn.edu/~steinbac	HTTP/1.0	200	3149		Mozilla/5.0 (Windows; U; Windows NT 5.1; en-US; rv:1.7) Gecko/20040616

(a) Example of a Web server log.



(b) Graph of a Web session.

Attribute Name	Description
totalPages	Total number of pages retrieved in a Web session
ImagePages	Total number of image pages retrieved in a Web session
TotalTime	Total amount of time spent by Web site visitor
RepeatedAccess	The same page requested more than once in a Web session
ErrorRequest	Errors in requesting for Web pages
GET	Percentage of requests made using GET method
POST	Percentage of requests made using POST method
HEAD	Percentage of requests made using HEAD method
Breadth	Breadth of Web traversal
Depth	Depth of Web traversal
MultiIP	Session with multiple IP addresses
MultiAgent	Session with multiple user agents

(c) Derived attributes for Web robot detection.

Figure 4.17. Input data for Web robot detection.

An Application: Web Robot Detection

Decision Tree:

```
depth = 1:
| breadth> 7 :   class 1
| breadth<= 7:
| | breadth <= 3:
| | | ImagePages> 0.375:   class 0
| | | ImagePages<= 0.375:
| | | | totalPages<= 6:   class 1
| | | | totalPages> 6:
| | | | | breadth <= 1:   class 1
| | | | | breadth > 1:   class 0
| | breadth > 3:
| | | MultiIP = 0:
| | | | ImagePages<= 0.1333:   class 1
| | | | ImagePages> 0.1333:
| | | | breadth <= 6:   class 0
| | | | breadth > 6:   class 1
| | | MultiIP = 1:
| | | | TotalTime <= 361:   class 0
| | | | TotalTime > 361:   class 1
depth> 1:
| MultiAgent = 0:
| | depth > 2:   class 0
| | depth < 2:
| | | MultiIP = 1:   class 0
| | | MultiIP = 0:
| | | | breadth <= 6:   class 0
| | | | breadth > 6:
| | | | | RepeatedAccess <= 0.322:   class 0
| | | | | RepeatedAccess > 0.322:   class 1
| MultiAgent = 1:
| | totalPages <= 81:   class 0
| | totalPages > 81:   class 1
```

Figure 4.18. Decision tree model for Web robot detection.

class 1: web robots
class 0: human users

An Application: Web Robot Detection

The data set for classification contains 2916 records, with equal numbers of sessions due to Web robots (class 1) and human users (class 0). 10% of the data were reserved for training while the remaining 90% were used for testing. The induced decision tree model is shown in Figure 4.18. The tree has an error rate equal to 3.8% on the training set and 5.3% on the test set.

The model suggests that Web robots can be distinguished from human users in the following way:

1. Accesses by Web robots tend to be broad but shallow, whereas accesses by human users tend to be more focused (narrow but deep).

2. Unlike human users, Web robots seldom retrieve the image pages associated with a Web document.

3. Sessions due to Web robots tend to be long and contain a large number of requested pages.

4. Web robots are more likely to make repeated requests for the same document since the Web pages retrieved by human users are often cached by the browser.