Statistical Learning and Data Mining

Lecture: Classification

Prof. Pradeep Ravikumar
pradeepr@cs.utexas.edu

Adapted From: Pang-Ning Tan, Steinbach, Kumar

Classification: Definition

- Given a collection of records (*training set*)
  - Each record contains a set of *attributes*, one of the attributes is the *class*.
- Find a *model* for class attribute as a function of the values of other attributes.

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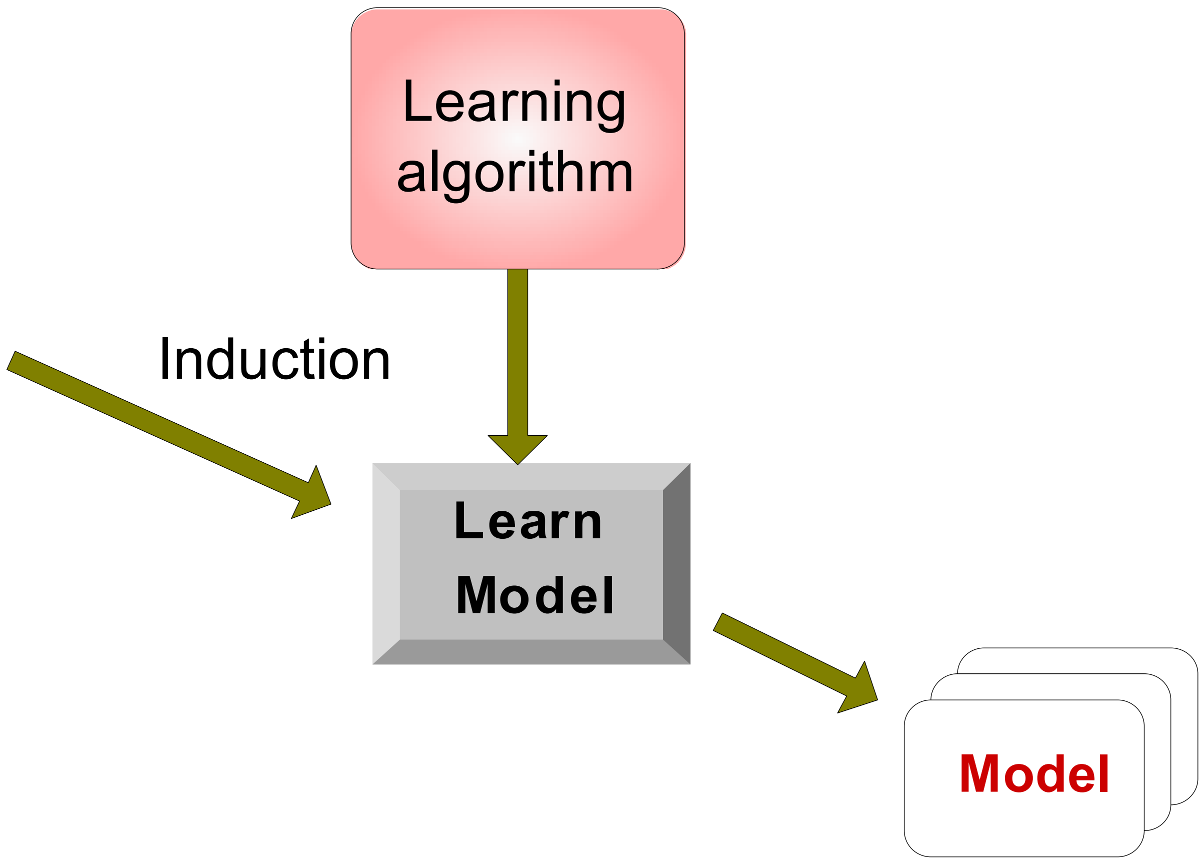
- Find a *model* for class attribute as a function of the values of other attributes.
- Goal: previously unseen records should be assigned a class as accurately as possible.
  - A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.

Classification: Illustration

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



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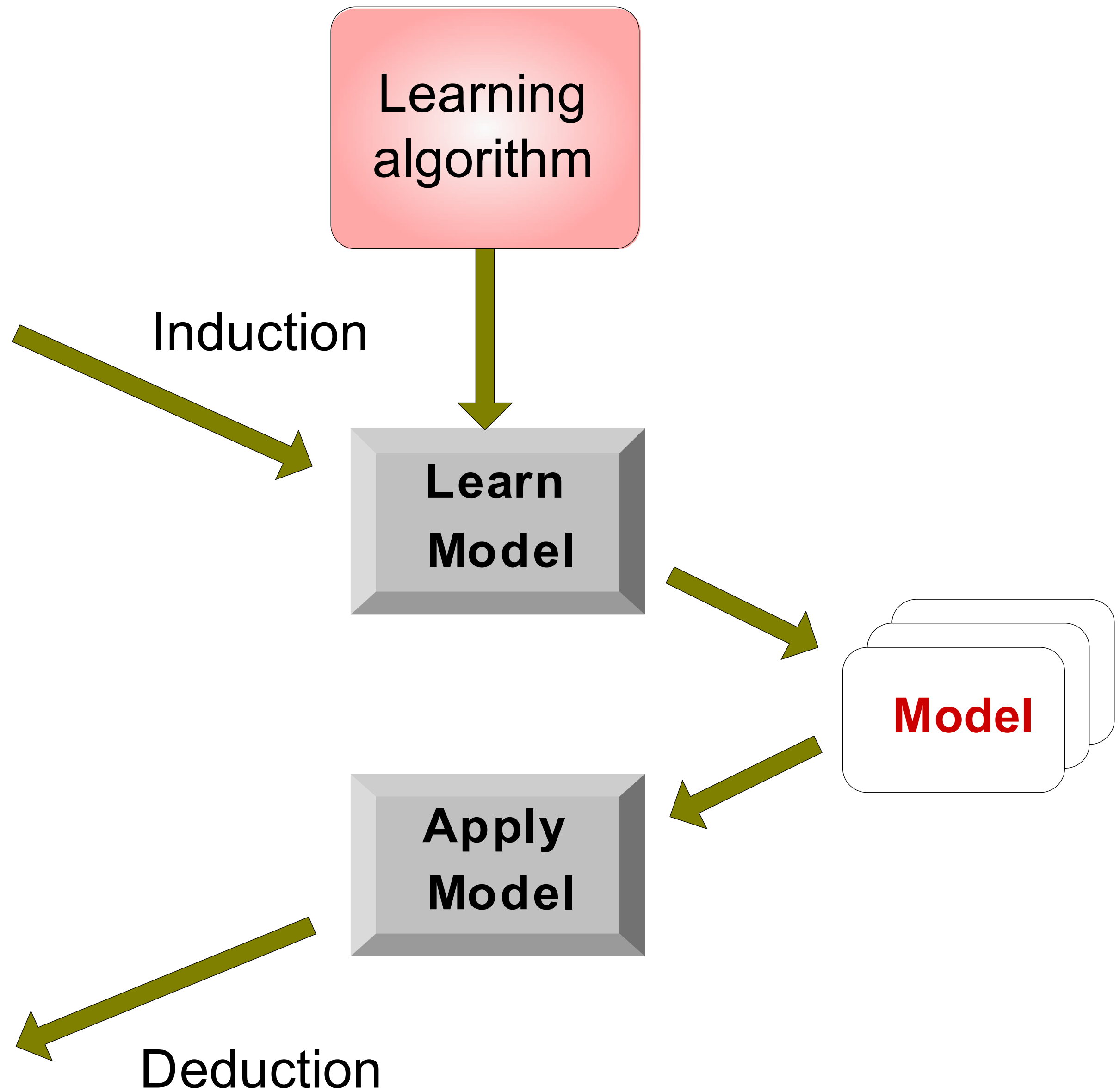

Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

Test Set

Classification: Examples

- Predicting tumor cells as benign or malignant

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- Classifying credit card transactions as legitimate or fraudulent

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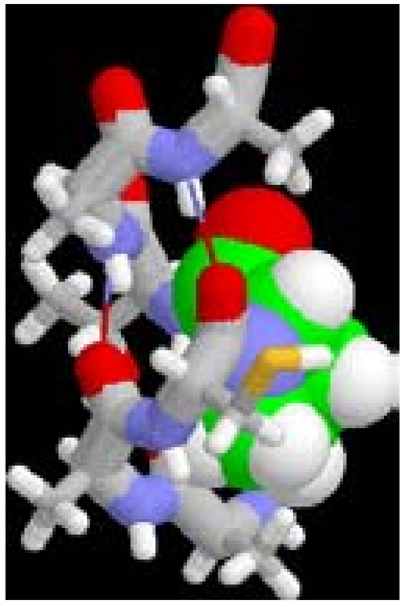
- Classifying secondary structures of protein as alpha-helix, beta-sheet, or random coil



Classification: Examples

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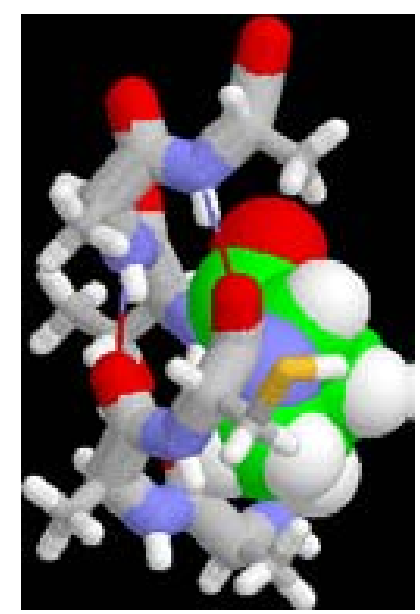

- Categorizing news stories as finance, weather, entertainment, sports, etc

Classification: Techniques

- Decision Tree based Methods
- Rule-based Methods
- Memory based reasoning
- Neural Networks
- Naïve Bayes and Bayesian Belief Networks
- Support Vector Machines

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Example I: Decision Tree

categorical categorical continuous class

Tid	Refund	Marital Status	Taxable Income	Cheat
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
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Training Data

Your “model” or “system”

Example I: Decision Tree

	categorical	categorical	continuous	class
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1	Yes	Single	125K	**No**
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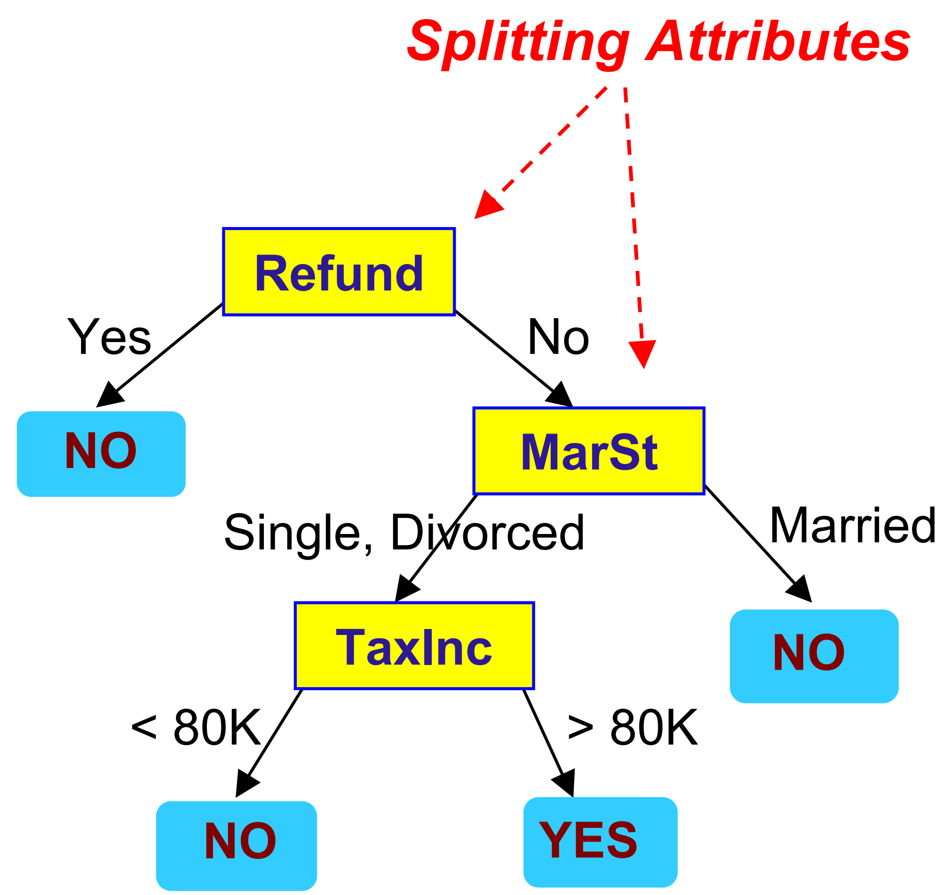
Training Data



Model: Decision Tree

Example II: Decision Tree

categorical categorical continuous class

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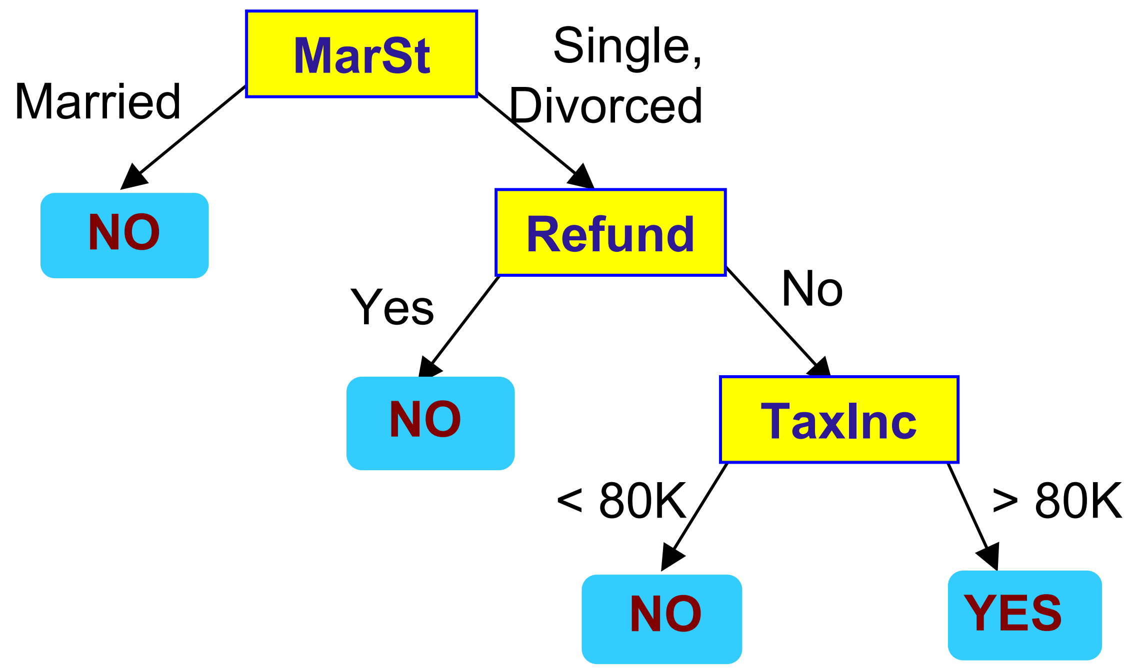

There could be more than one tree that fits the same data!

Decision Tree Classification

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
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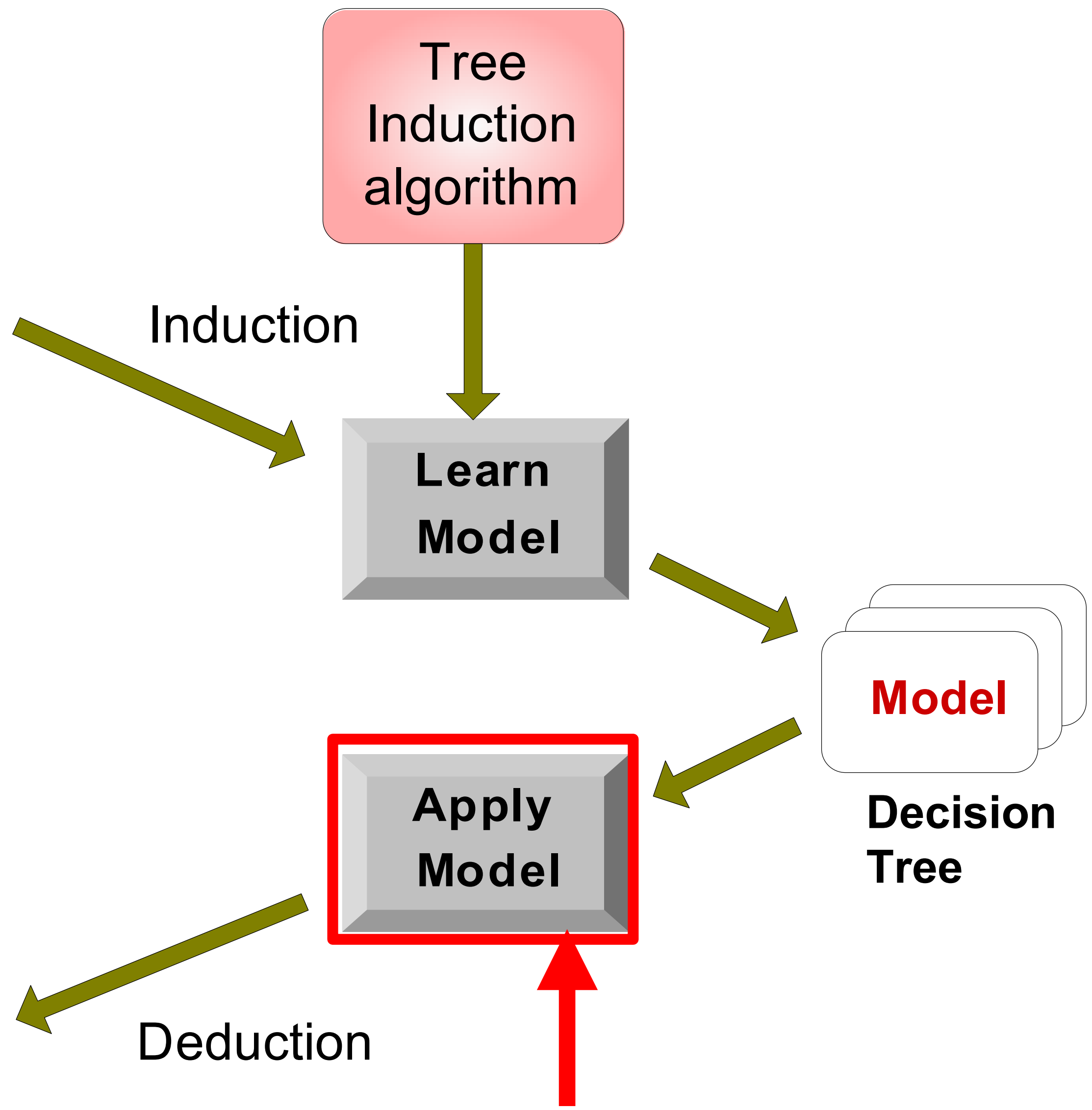
Training Set



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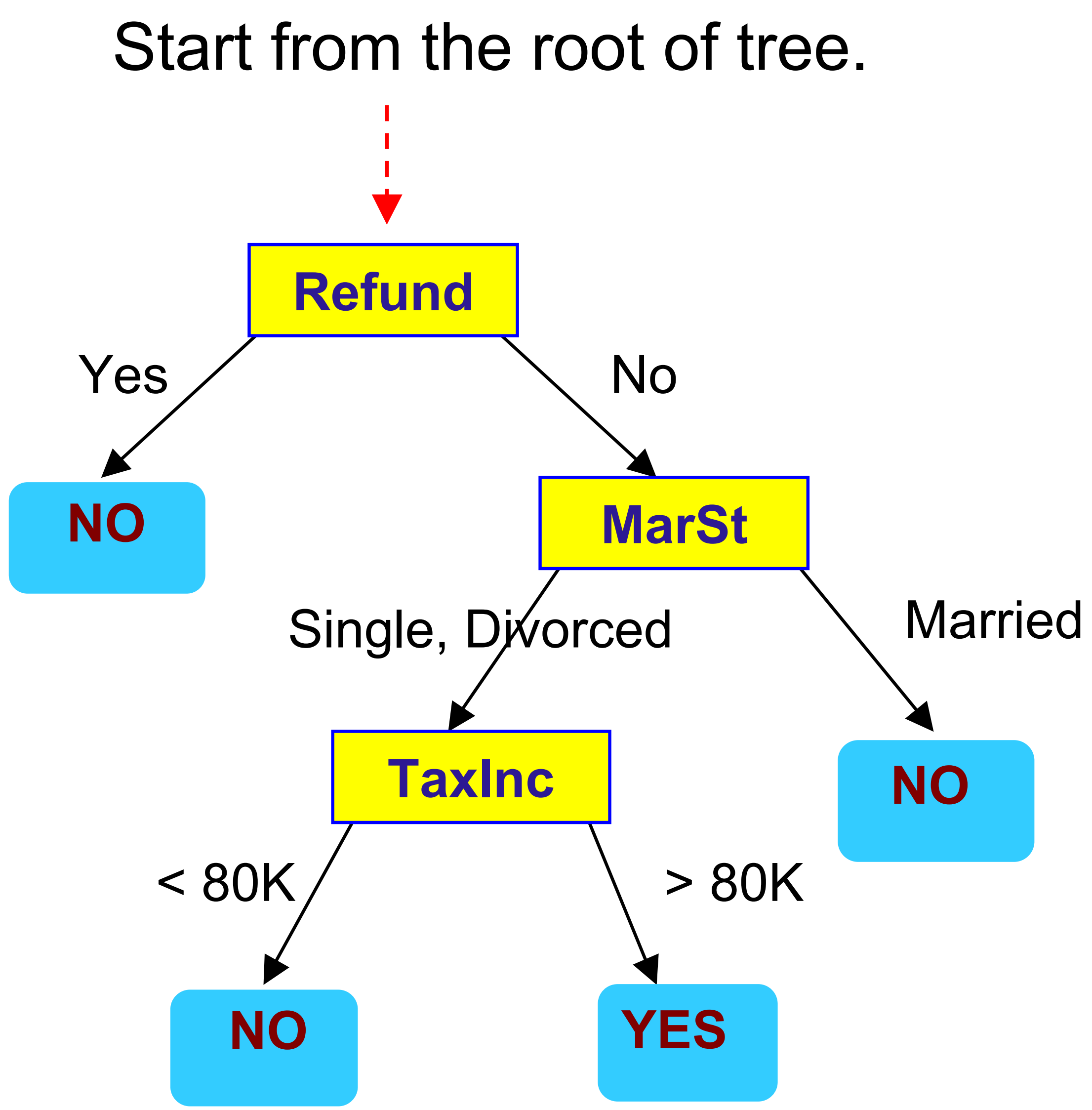
Test Set

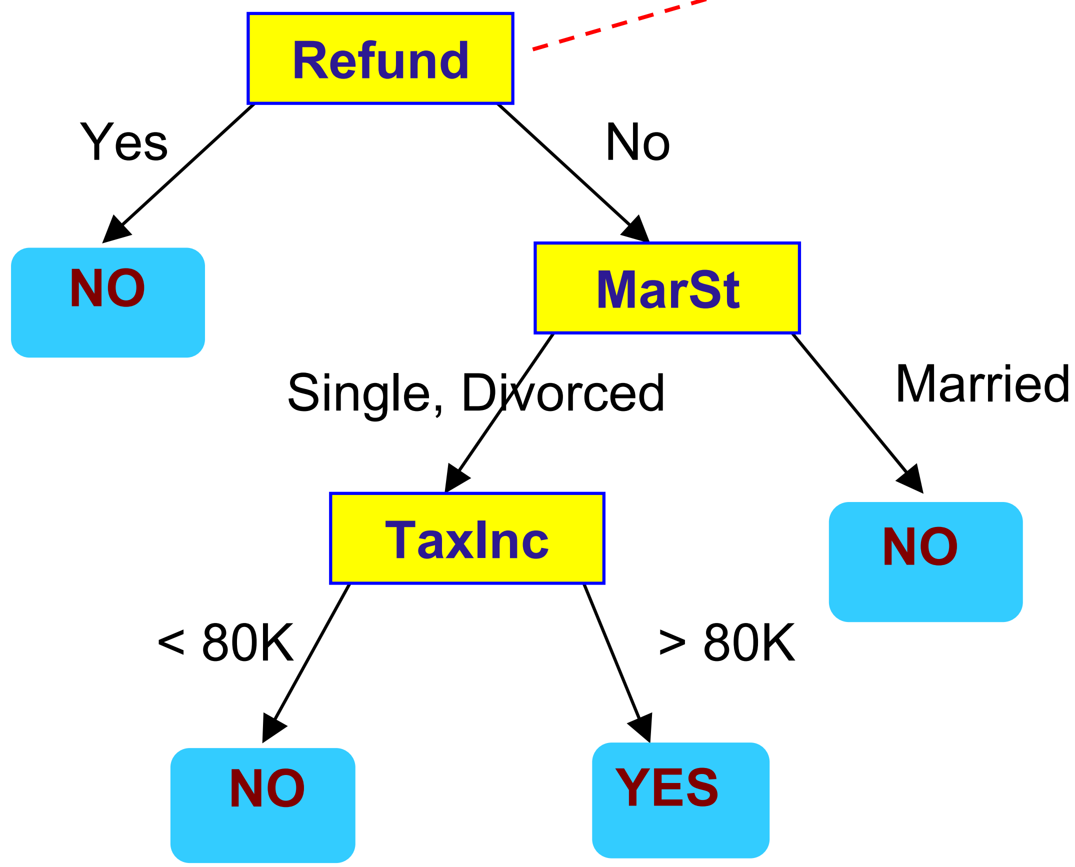
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
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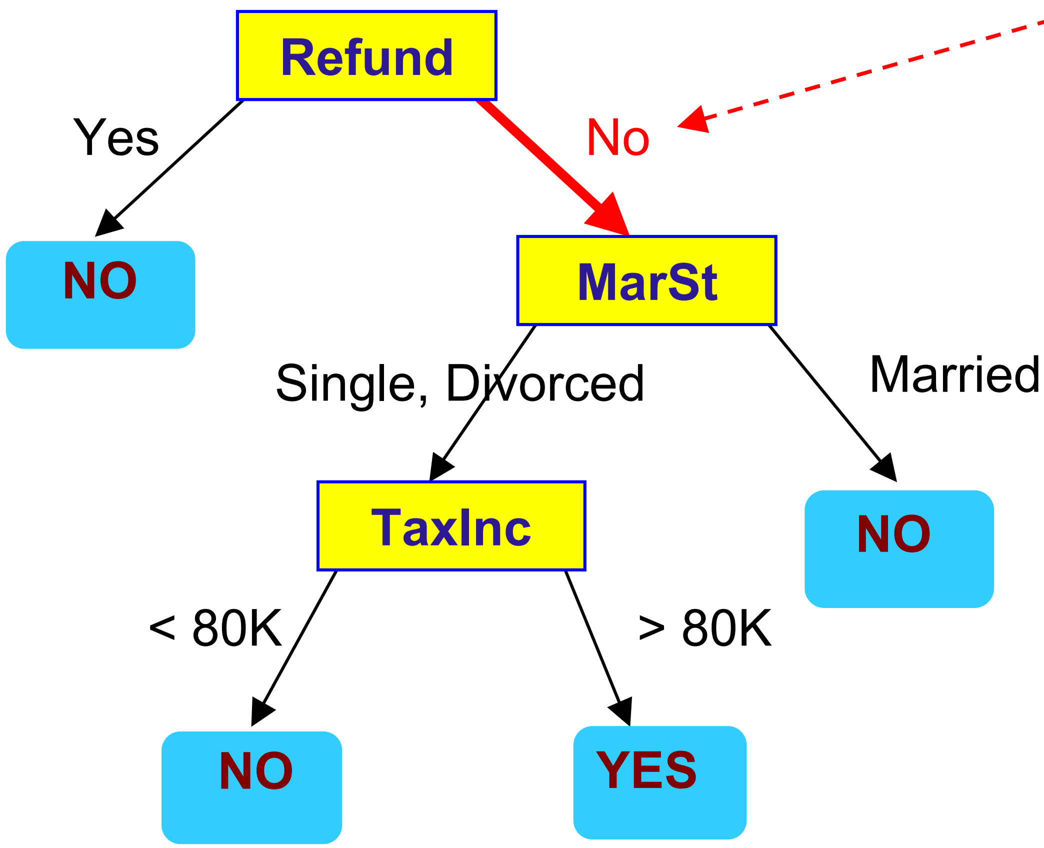

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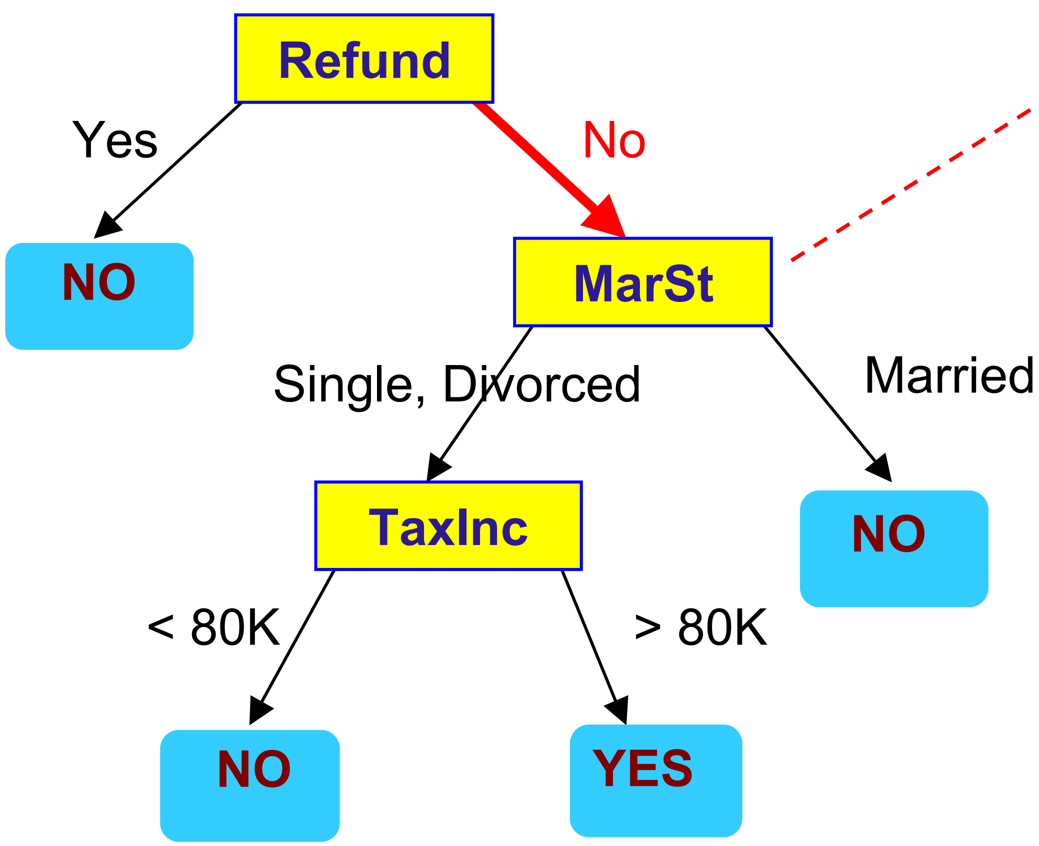

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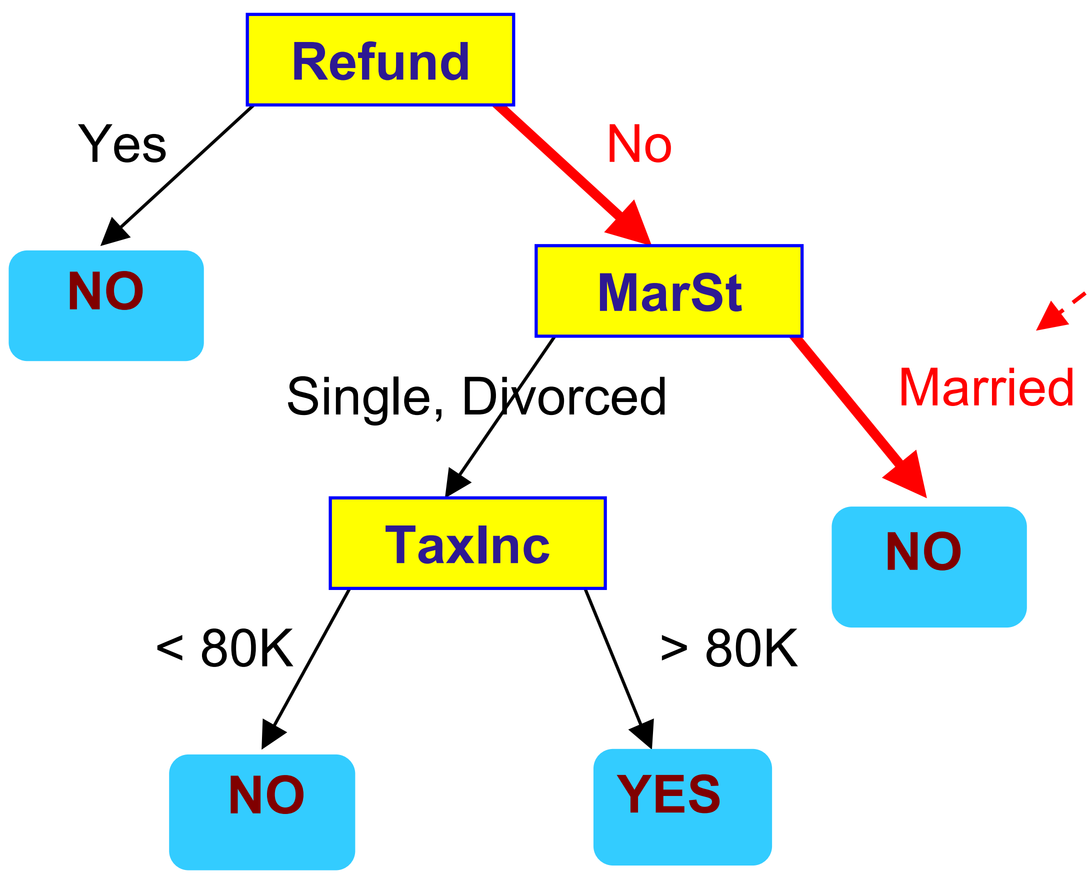

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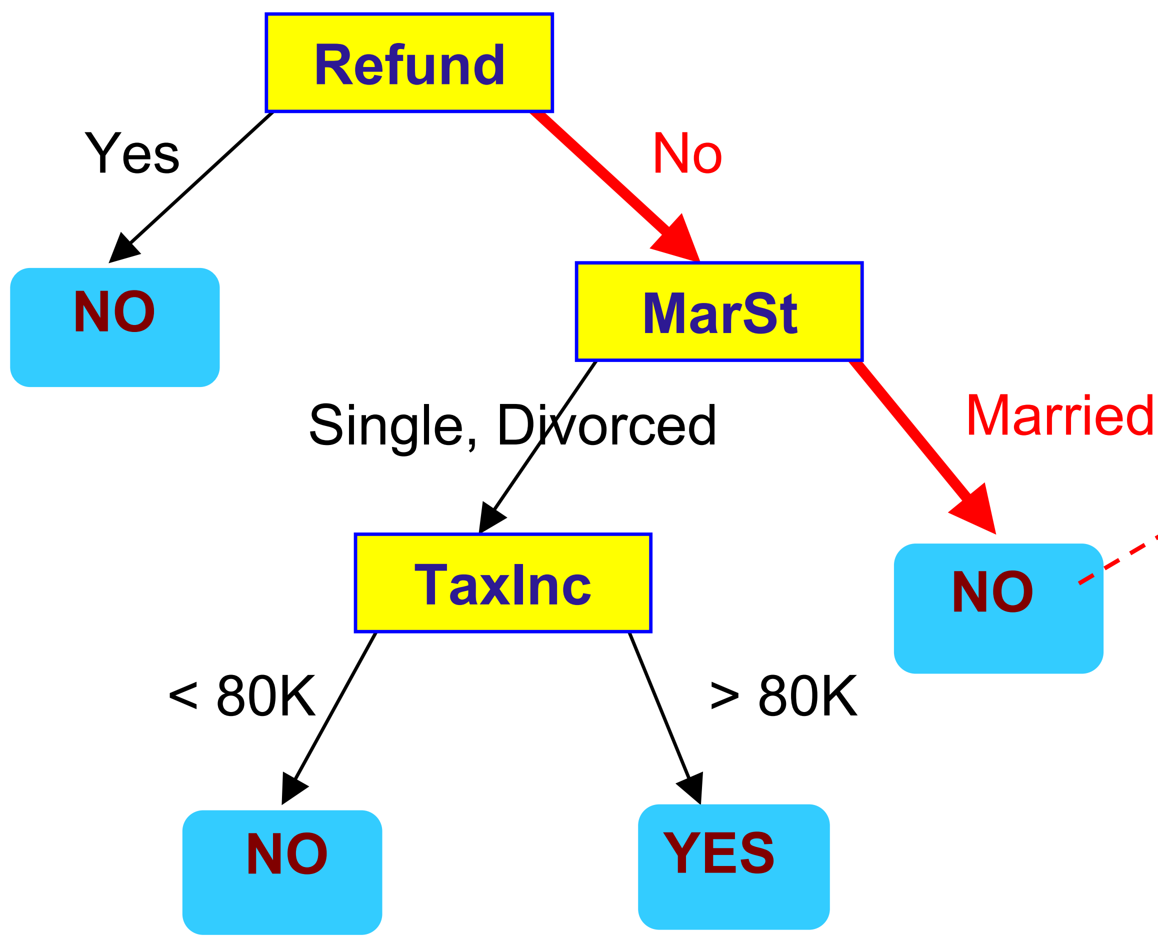

Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Assign Cheat to “No”

Decision Tree Classification

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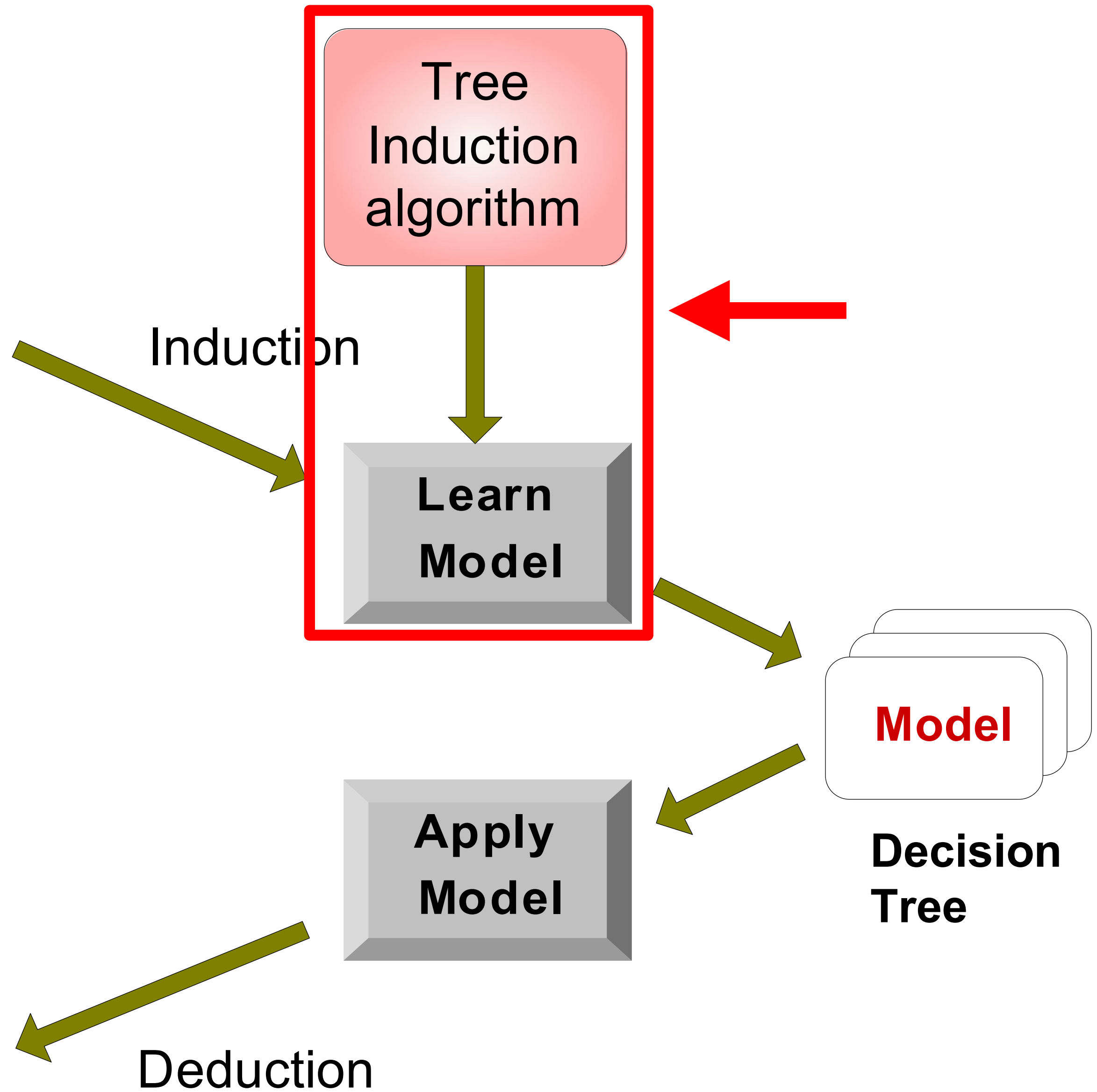

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Decision Tree Induction

- Many Algorithms:
  - Hunt's Algorithm (one of the earliest)
  - CART
  - ID3, C4.5
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- Let D_t be the set of training records that reach a node t

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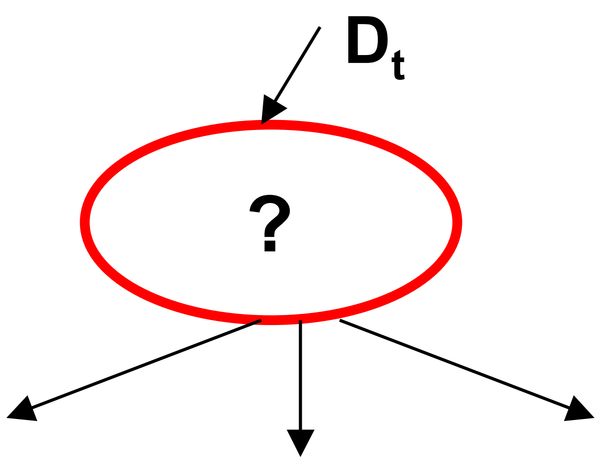

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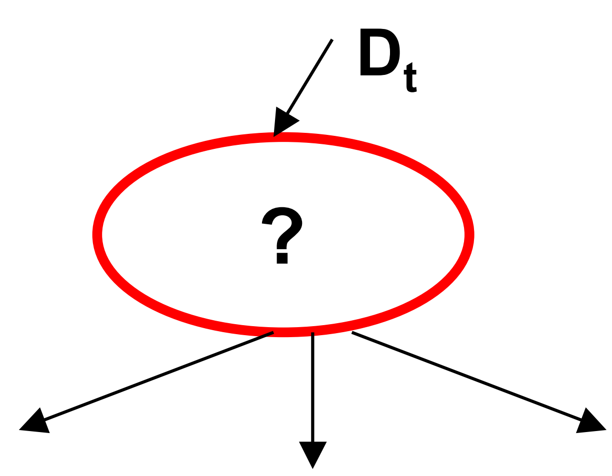

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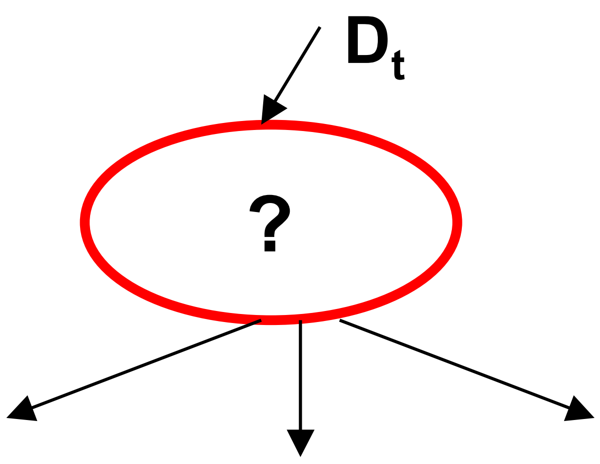

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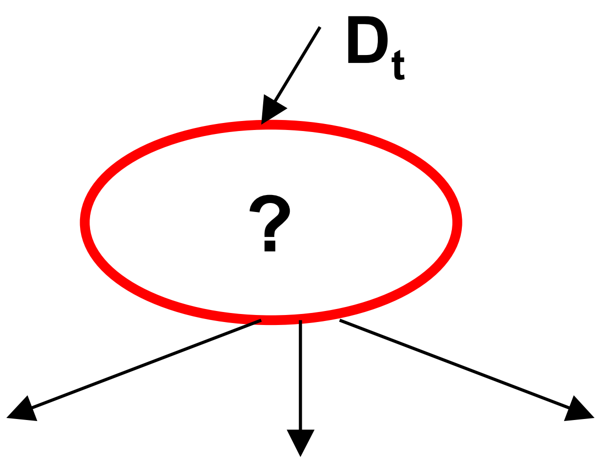

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  - If D_t contains records that belong to more than one class, use an attribute test to split the data into smaller subsets. Recursively apply the procedure to each subset.

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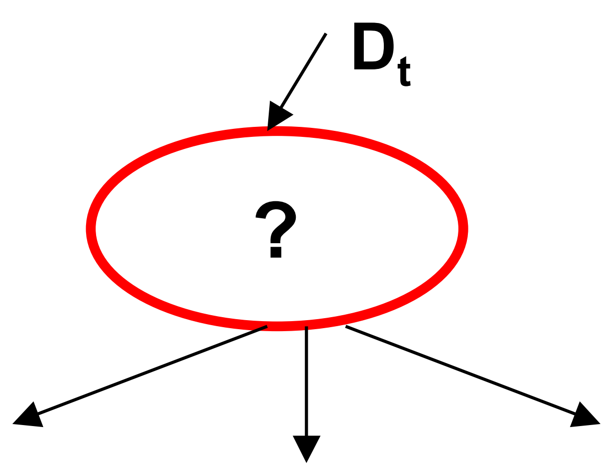

Hunt's Algorithm: Example

Don't Cheat

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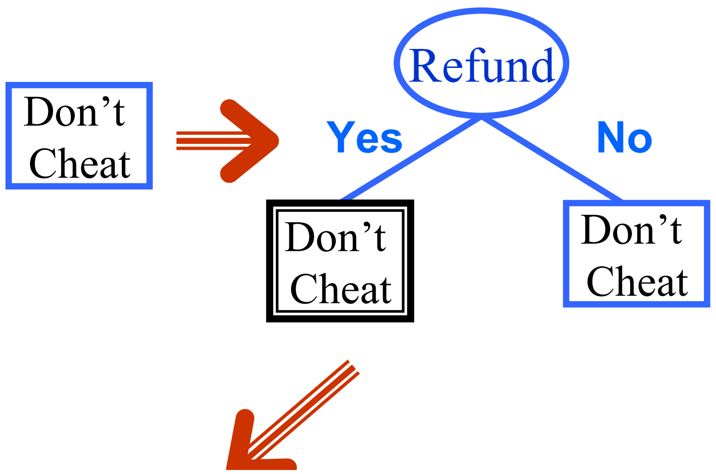

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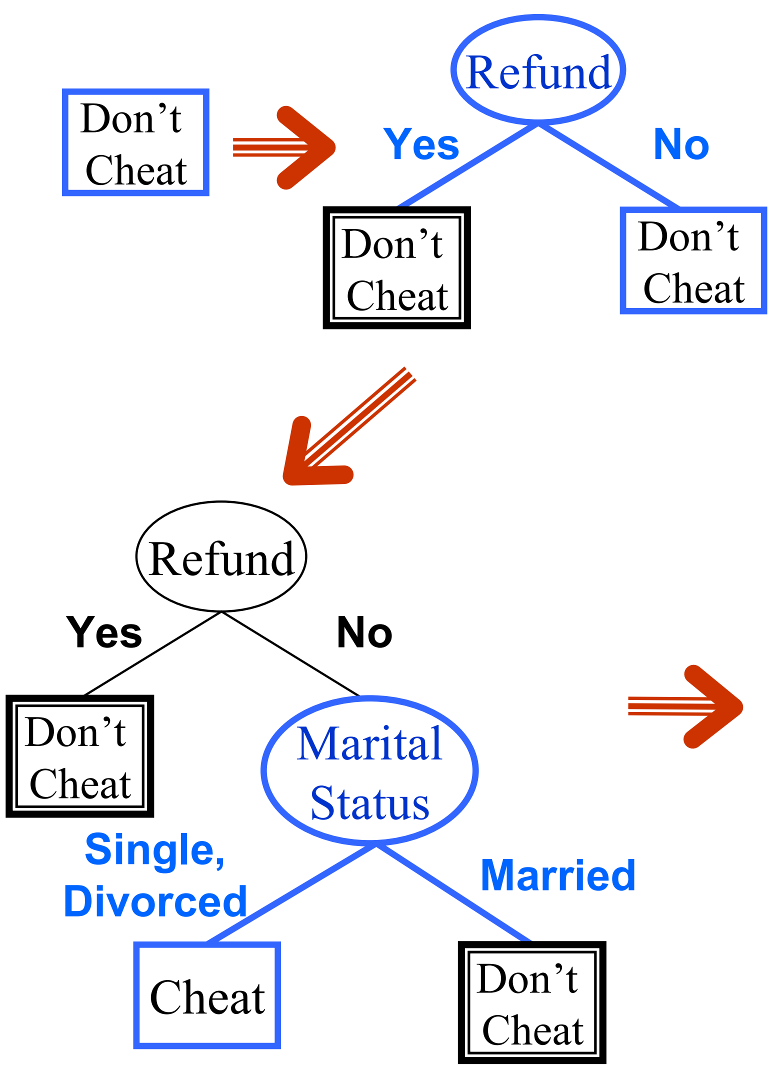

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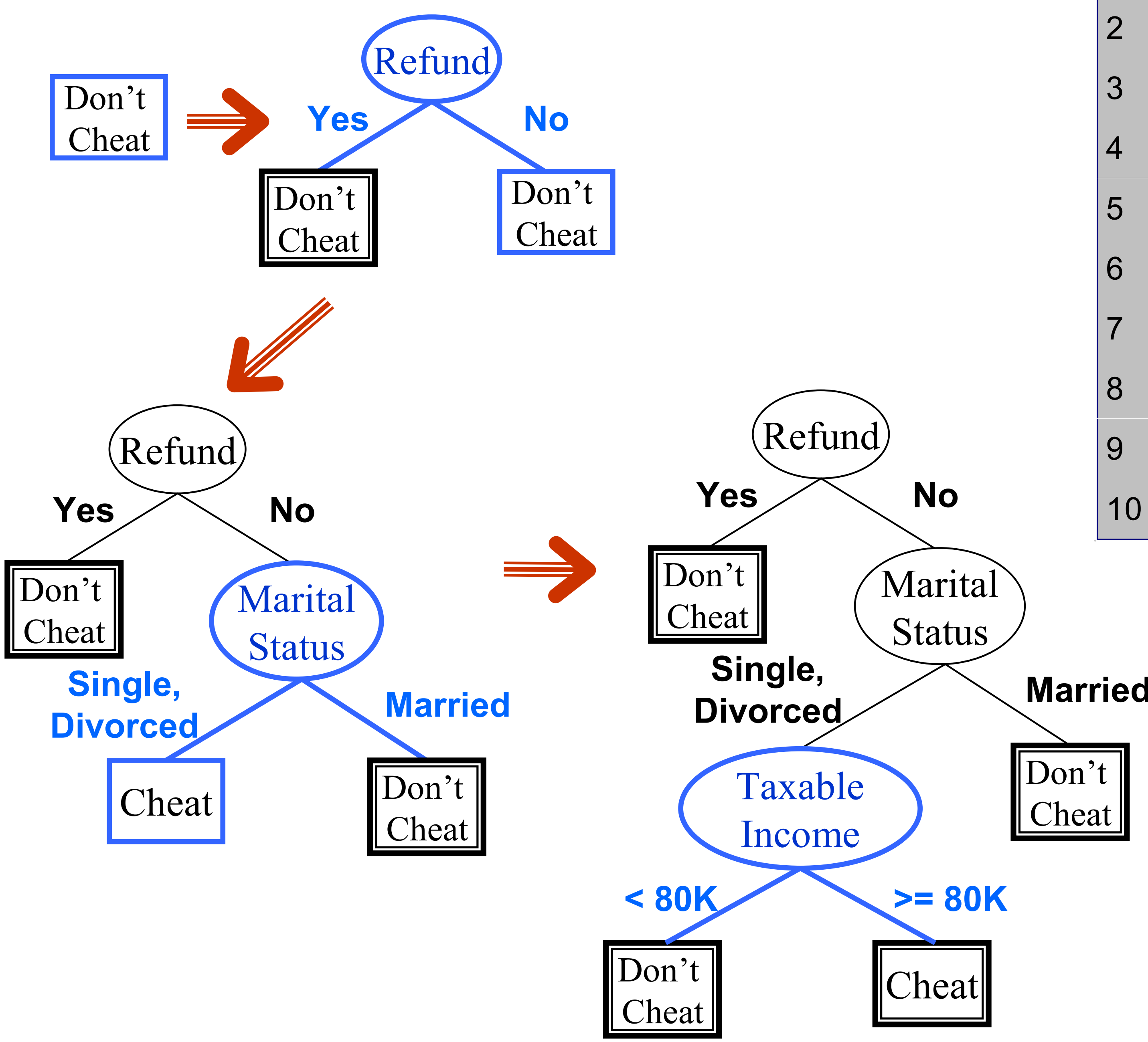

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Tree Induction

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

- 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

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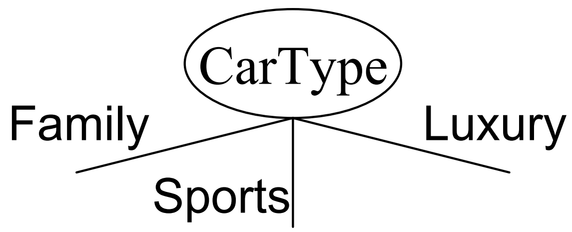
How to Specify Test Condition

- Depends on attribute types
  - Nominal
  - Ordinal
  - Continuous

- Depends on number of ways to split
  - 2-way split
  - Multi-way split

Splitting based on **Nominal** Attributes

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



Splitting based on **Nominal** Attributes

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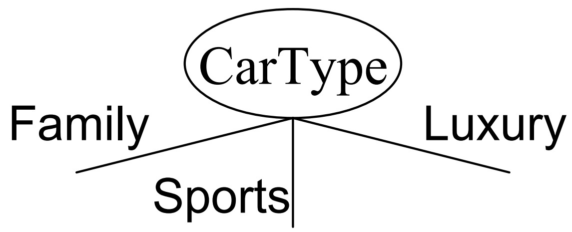
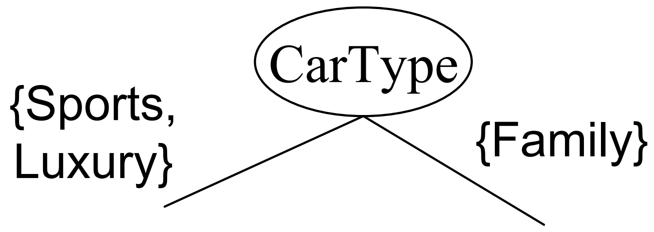
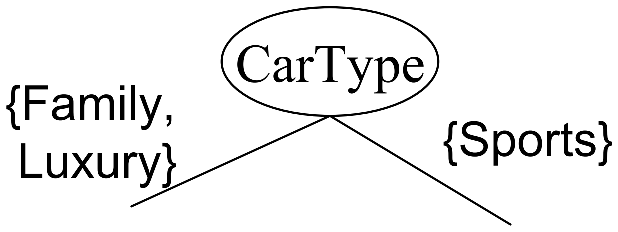


- Binary split: Divides values into two subsets. Need to find optimal partitioning.

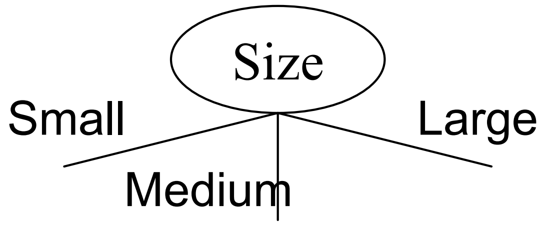


OR



Splitting based on **Ordinal** Attributes

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



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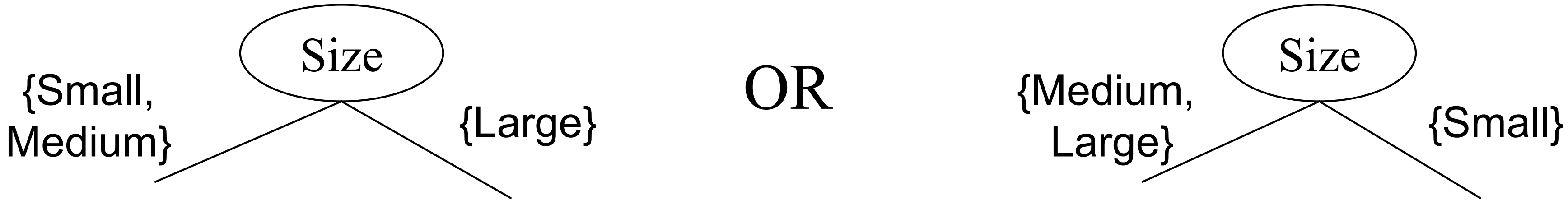
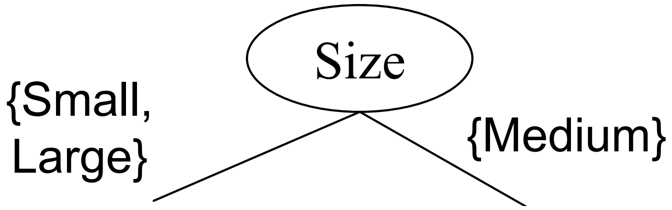


- What about this split?



Splitting based on Continuous Attributes

- Different ways of handling
  - Discretization to form an ordinal categorical attribute

Splitting based on Continuous Attributes

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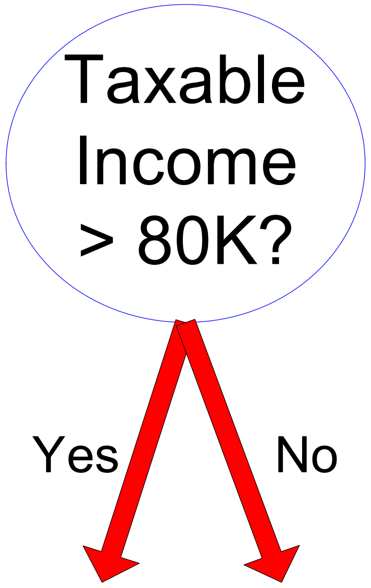
  - Discretization to form an ordinal categorical attribute
    - Static – discretize once at the beginning
    - Dynamic

Splitting based on Continuous Attributes

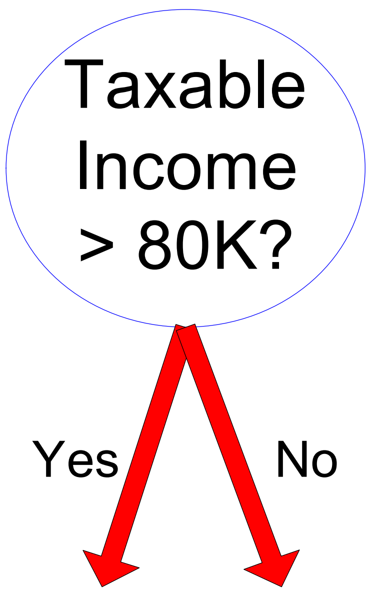
- Different ways of handling
  - Discretization to form an ordinal categorical attribute
    - Static – discretize once at the beginning
    - Dynamic
  - Binary Decision: $(A < v)$ or $(A \geq v)$
    - consider all possible splits and finds the best cut
    - can be more compute intensive

Splitting based on Continuous Attributes



(i) Binary split

Splitting based on Continuous Attributes



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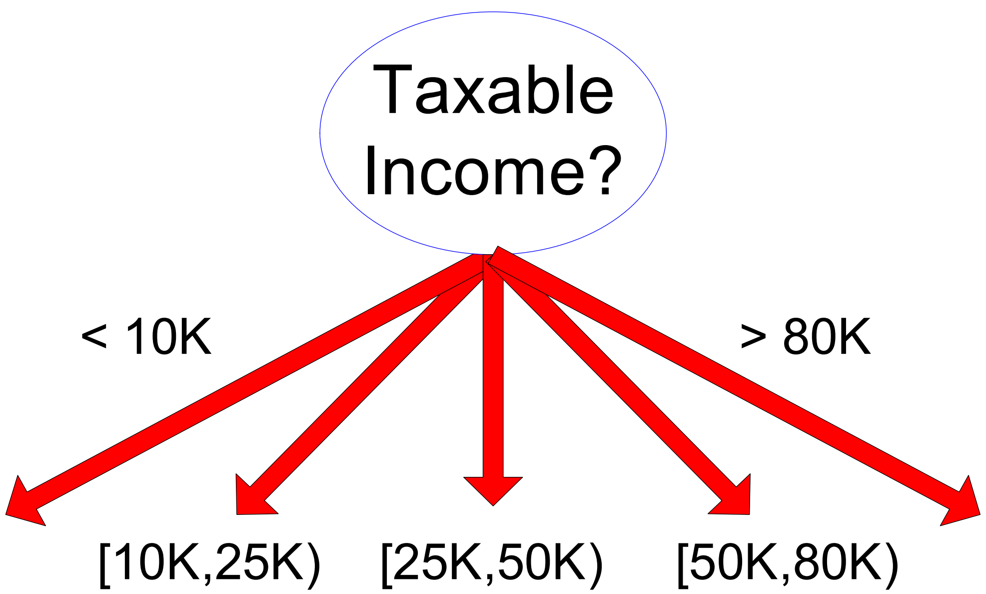

(ii) Multi-way split

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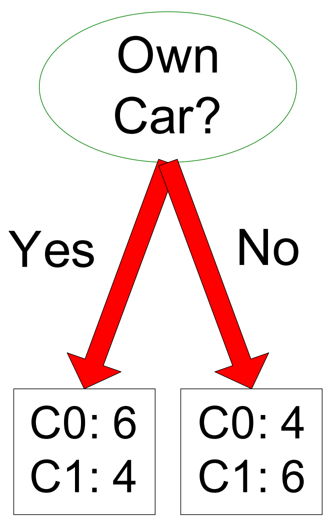
Tree Induction

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



Tree Induction

Before Splitting: 10 records of class 0,
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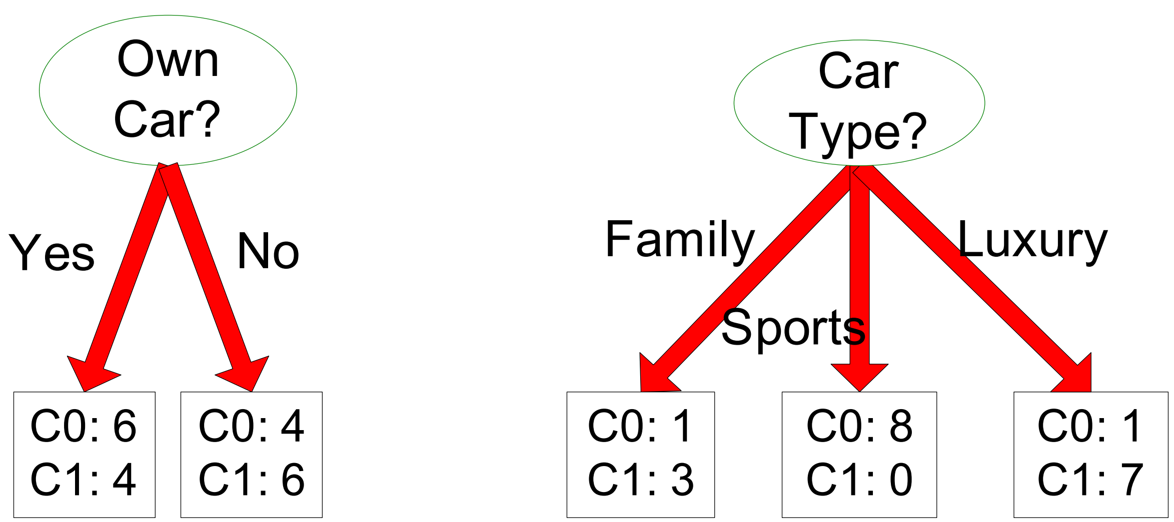

Which test condition is the best?

Tree Induction

Before Splitting: 10 records of class 0,
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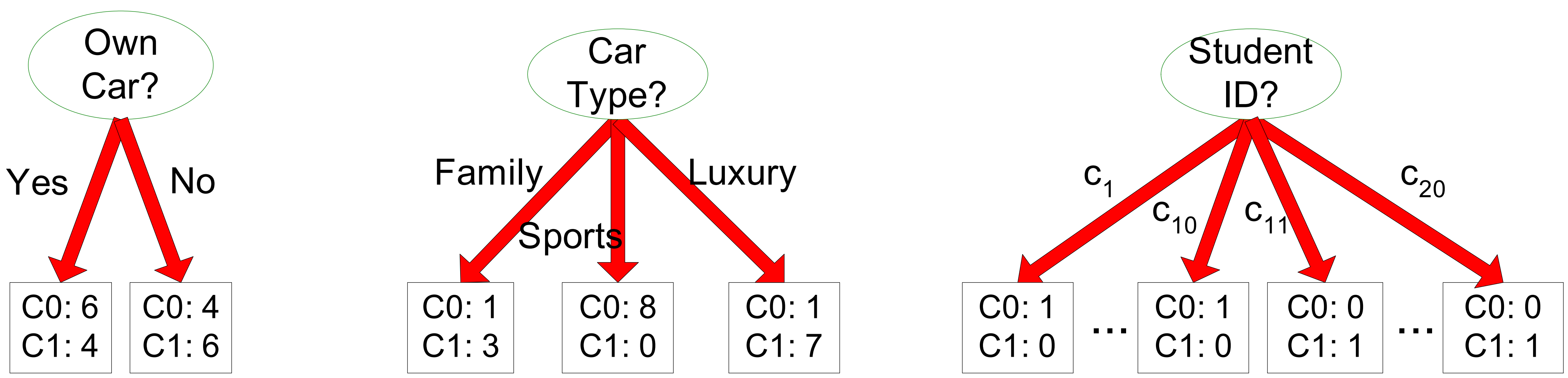


Which test condition is the best?

How to determine best split

- Greedy approach:
  - Nodes with homogeneous class distribution are preferred
- Need a measure of node impurity:

C0: 5 C1: 5	C0: 9 C1: 1
Non-homogeneous, **High degree of impurity**	**Homogeneous,** **Low degree of impurity**

Measures of Node Impurity

- Gini Index
- Entropy
- Misclassification error

How to find Best Split

No. of records with class C0

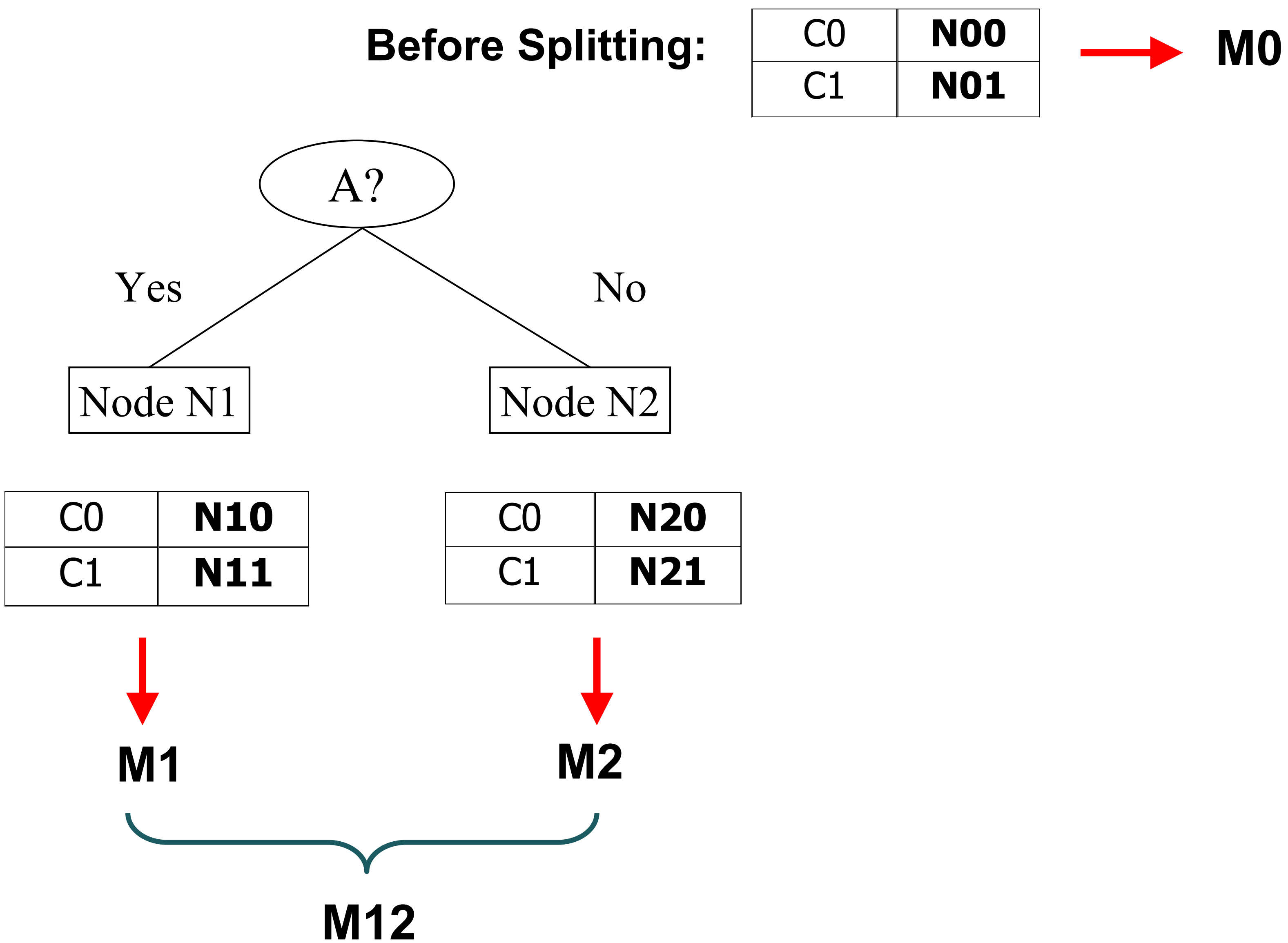
Before Splitting:

C0	**N00**
C1	**N01**

M0 Class Homogeneity Measure

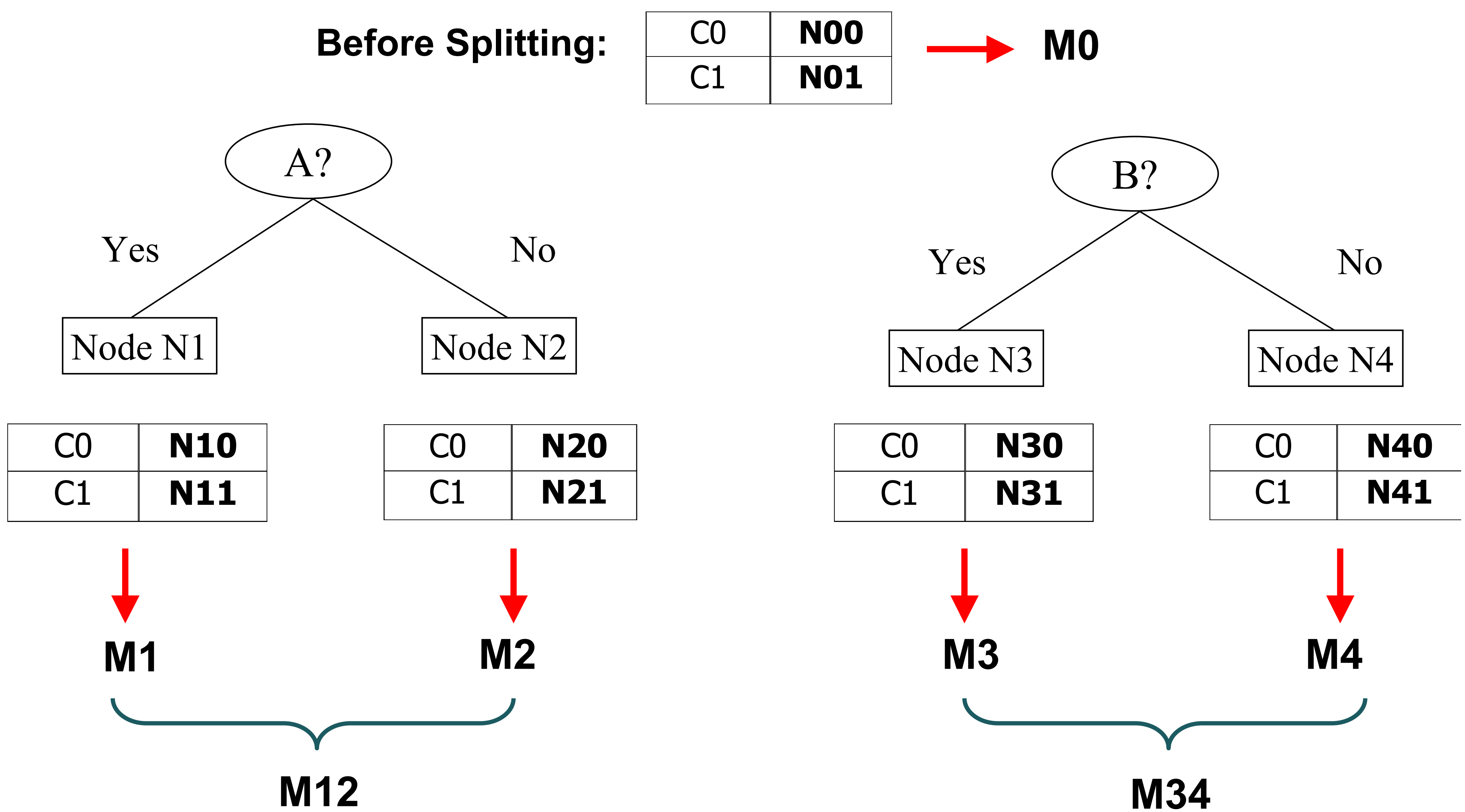
No. of records with class C1

How to find Best Split

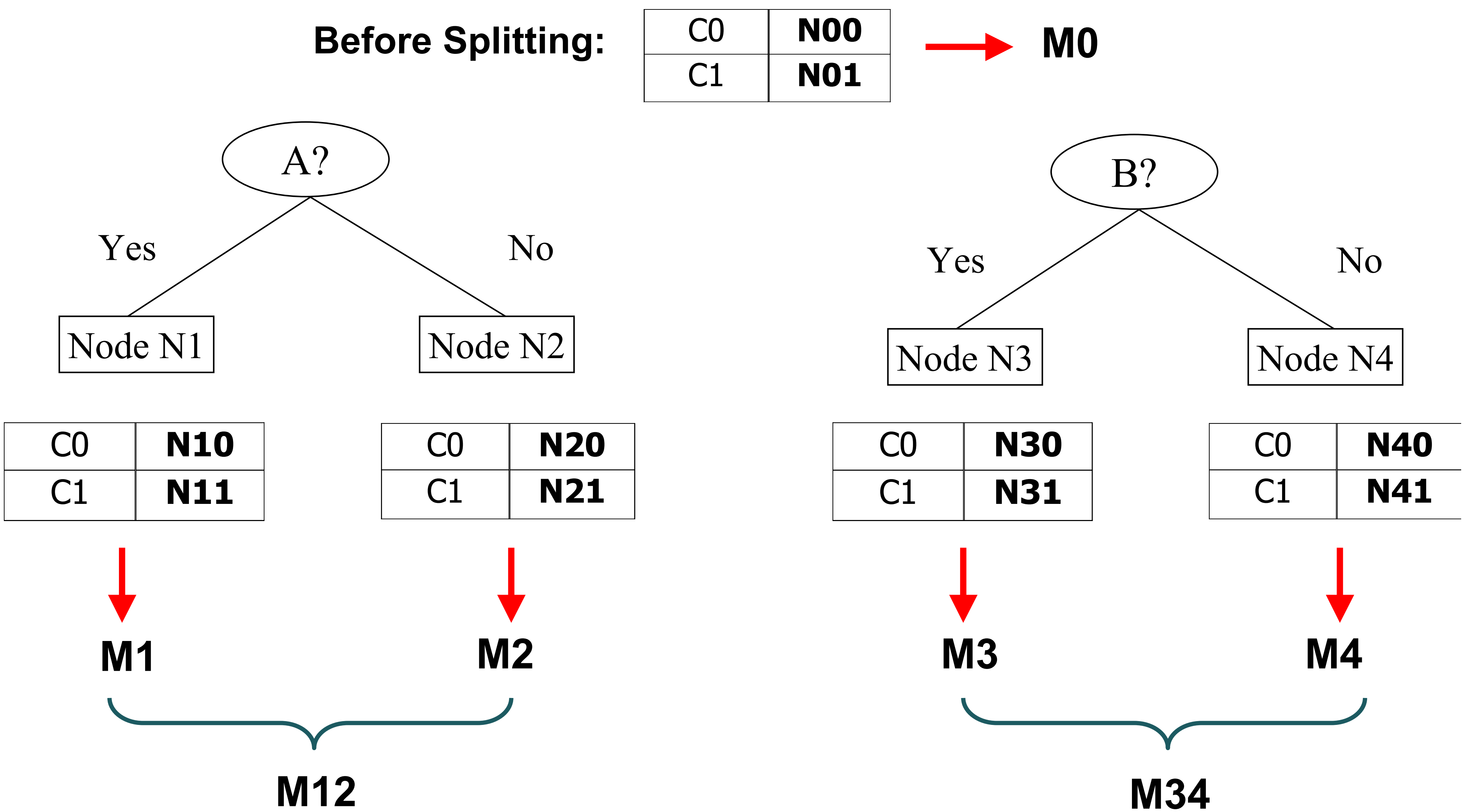


M12 combines the homogeneity measures M1 and M2: a joint measure of the split

How to find Best Split



How to find Best Split



Gain = M0 – M12 vs M0 – M34

Measure of Impurity

- Gini Index for a given node t :

$$\boxed{GINI(t) = 1 - \sum_{j} [p(j \mid t)]^2}$$

(NOTE: $p(j \mid t)$ is the relative frequency of class j at node t).

Measure of Impurity

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Measure of Impurity

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  - Minimum (0.0) when all records belong to one class, implying most interesting information

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	

GINI: Examples

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

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 – $(2/6)^2$ – $(4/6)^2$ = 0.444

Splitting based on GINI

- Used in CART, SLIQ, SPRINT.
- When a node p is split into k partitions (children), the quality of split is computed as,

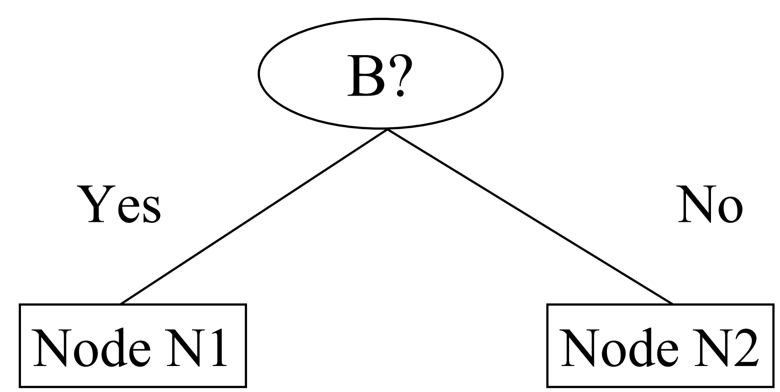
$$\boxed{GINI_{split} = \sum_{i=1}^{k} \frac{n_i}{n} GINI(i)}$$

where, n_i = number of records at child i,

n = number of records at node p.

Computing GINI: Binary Attributes

- Splits into two partitions
- Effect of Weighing partitions:
  - Larger and Purer Partitions are sought for.



	Parent
C1	**6**
C2	**6**
GINI = 0.50	

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**
GINI = 0.371		

Gini(Children)

= (7/12) * 0.408 + (5/12) * 0.32
= 0.371

Computing GINI: Categorical Attributes

- For each distinct value, gather counts for each class in the dataset
- Use the count matrix to make decisions

Multi-way split

	CarType		
	Family	**Sports**	**Luxury**
C1	1	2	1
C2	4	1	1
Gini	**0.393**		

Two-way split
(find best partition of values)

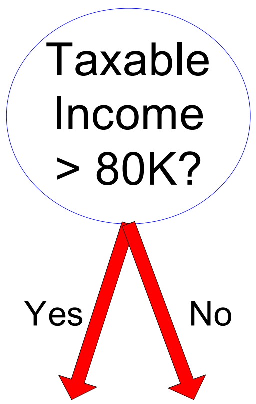
	CarType	
	{Sports, Luxury}	**{Family}**
C1	3	1
C2	2	4
Gini	**0.400**	

	CarType	
	{Sports}	**{Family, Luxury}**
C1	2	2
C2	1	5
Gini	**0.419**	

Computing GINI: Continuous Attributes

- Use Binary Decisions based on one value
- Several Choices for the splitting value
  - Number of possible splitting values = Number of distinct values
- Each splitting value 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! Repetition of work.

Tid	Refund	Marital Status	Taxable Income	Cheat
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



Computing GINI: Continuous Attributes

- For efficient computation: for each attribute,
  - Sort the attribute on values
  - Linearly scan these values, each time updating the count matrix and computing gini index
  - Choose the split position that has the least gini index

Cheat		No		No		No		Yes		Yes		Yes		No		No		No		No		
	Taxable 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	0.420		0.400		0.375		0.343		0.417		0.400		*0.300*		0.343		0.375		0.400		0.420	

Alternative Splitting Criteria: Entropy

- Entropy at a given node t:

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

(NOTE: $p(j \mid t)$ is the relative frequency of class j at node t).

  – Measures homogeneity of a node.
    - Maximum ($\log n_c$) when records are equally distributed among all classes implying least information
    - Minimum (0.0) when all records belong to one class, implying most information
  – Entropy based computations are similar to the GINI index computations

Computing Entropy: Examples

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

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) $\log_2$ (1/6) = 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

Other “Information-theoretic” Criteria

- Information Gain:

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

Parent Node, p is split into k partitions;

n_i is number of records in partition i

  – Measures Reduction in Entropy achieved because of the split. Choose the split that achieves most reduction (maximizes GAIN)
  – Used in ID3 and C4.5
  – Disadvantage: Tends to prefer splits that result in large number of partitions, each being small but pure.

Other “Information-theoretic” Criteria

- Gain Ratio:

$$GainRATIO_{split} = \frac{GAIN_{Split}}{SplitINFO} \qquad SplitINFO = -\sum_{i=1}^{k} \frac{n_i}{n} \log \frac{n_i}{n}$$

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!
  – Used in C4.5
  – Designed to overcome the disadvantage of Information Gain

Splitting Criteria: Classification Error

- Classification error at a node t :

$$\boxed{Error(t) = 1 - \max_{i} P(i \mid t)}$$

- Measures misclassification error made by a node.
  - Maximum $(1 - 1/n_c)$ when records are equally distributed among all classes, implying least interesting information
  - Minimum (0.0) when all records belong to one class, implying most interesting information

Computing Classification Error: Examples

$$Error(t) = 1 - \max_i P(i \mid t)$$

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

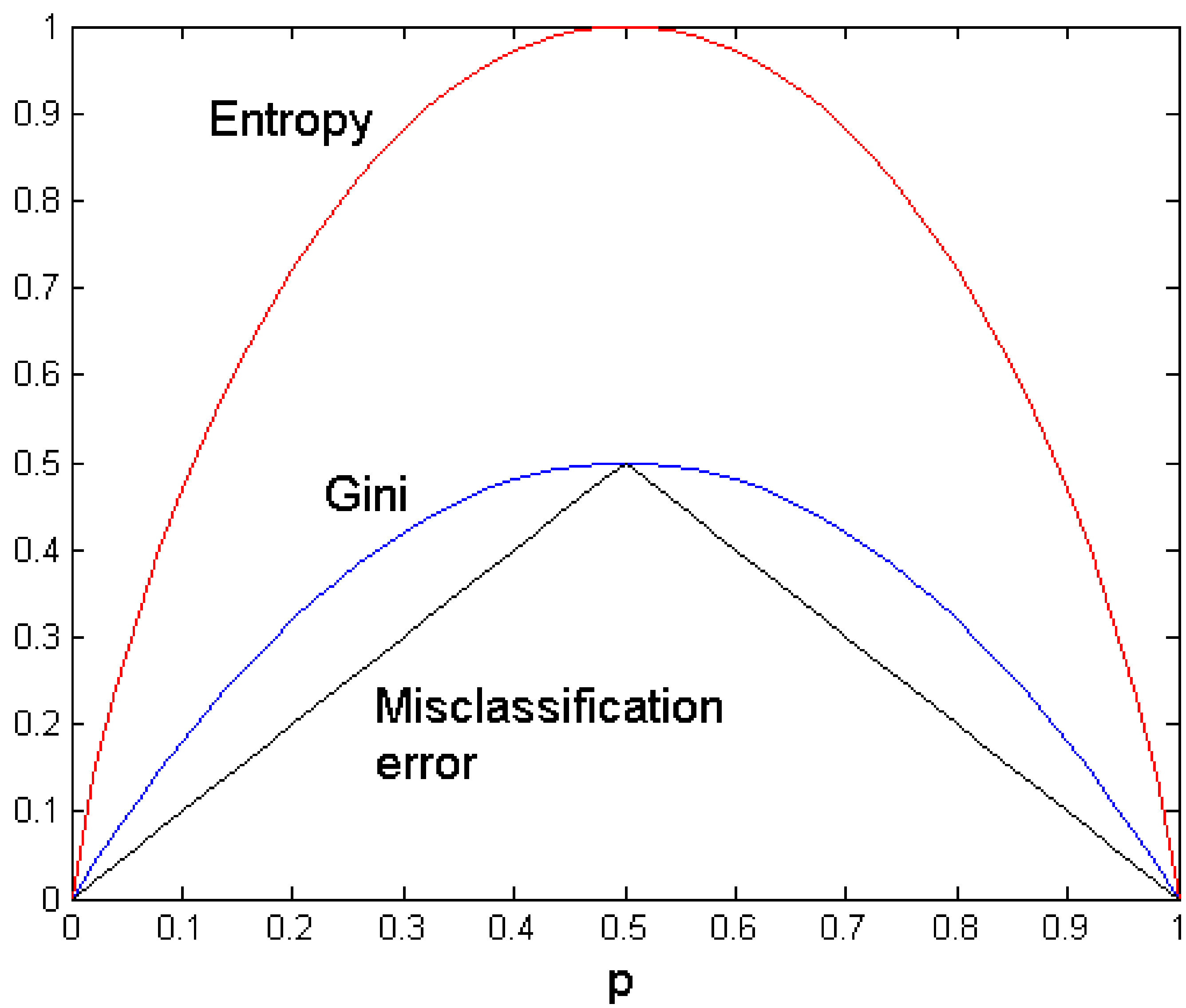
C1	**2**
C2	**4**

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

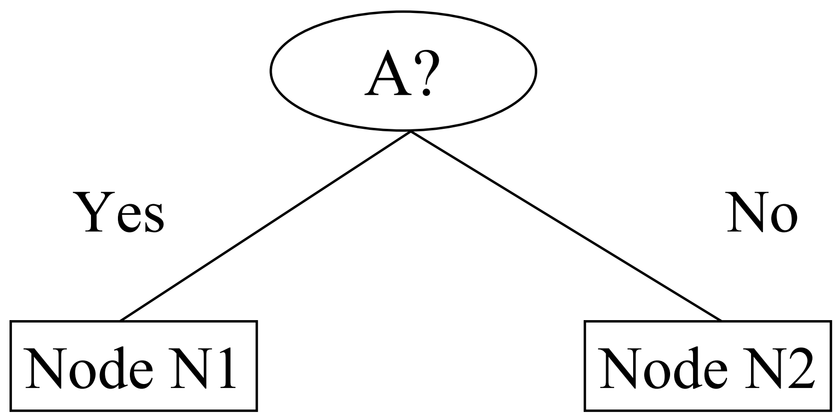
Error = 1 – max (2/6, 4/6) = 1 – 4/6 = 1/3

Comparison among Splitting Criteria

For a 2-class problem:



Misclassification Error Vs GINI



	Parent
C1	**7**
C2	**3**
GINI = 0.420	

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

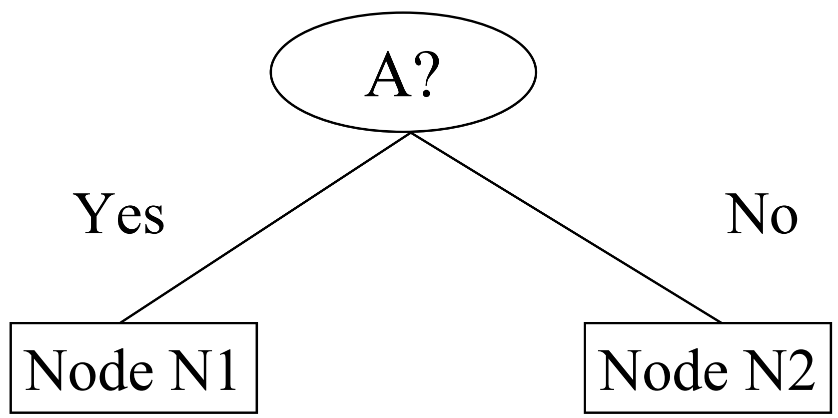
Gini(N2)
$= 1 – (4/7)^2 – (3/7)^2$
$= 0.489$

	N1	**N2**
C1	**3**	**4**
C2	**0**	**3**
GINI = 0.342		

Gini(Children)
= 3/10 * 0
+ 7/10 * 0.489
= 0.342

Gini improves !!

Misclassification Error Vs GINI



	Parent
C1	**7**
C2	**3**

ERR = 3/10

Err(N1)
= 1 - max(0/3 , 3/3)
= 0

Err(N2)
= 1 - max(4/7 , 3/7)
= 3/7

	N1	N2
C1	**3**	**4**
C2	**0**	**3**

ERR = 3/10

Err(Children)
= 3/10 x 0 + 7/10 x 3/7
= 3/10

ERR remains the same!

Tree Induction

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

- 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

Stopping Criteria for Tree Induction

- Stop expanding a node when all the records belong to the same class

- Stop expanding a node when all the records have similar attribute values

Stopping Criteria for Tree Induction

- Stop expanding a node when all the records belong to the same class
- Stop expanding a node when all the records have similar attribute values
- Early termination (to be discussed later)

Decision Tree Based Classification

- Advantages:
  - Inexpensive to construct
  - Extremely fast at classifying unknown records
  - Easy to interpret for small-sized trees
  - Accuracy is comparable to other classification techniques for many simple data sets

Example: C4.5

- **Simple Recursive Construction.**
- Uses Information Gain
- Sorts Continuous Attributes at each node.
- Needs entire data to fit in memory.
- Unsuitable for Large Datasets.
  - Needs out-of-core sorting.

- You can download the software from:
  http://www.cse.unsw.edu.au/~quinlan/c4.5r8.tar.gz