

Data Mining Classification: Basic Concepts and Techniques

Lecture Notes for Chapter 3

Introduction to Data Mining, 2nd Edition
by
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Classification: Definition

- | Given a collection of records (training set)
 - Each record is by characterized by a tuple (x,y) , where x is the attribute set and y is the class label
 - ◆ x : attribute, predictor, independent variable, input
 - ◆ y : class, response, dependent variable, output
- | Task:
 - Learn a model that maps each attribute set x into one of the predefined class labels y

Examples of Classification Task

Task	Attribute set, x	Class label, y
Categorizing email messages	Features extracted from email message header and content	spam or non-spam
Identifying tumor cells	Features extracted from x-rays or MRI scans	malignant or benign cells
Cataloging galaxies	Features extracted from telescope images	Elliptical, spiral, or irregular-shaped galaxies

General Approach for Building Classification Model

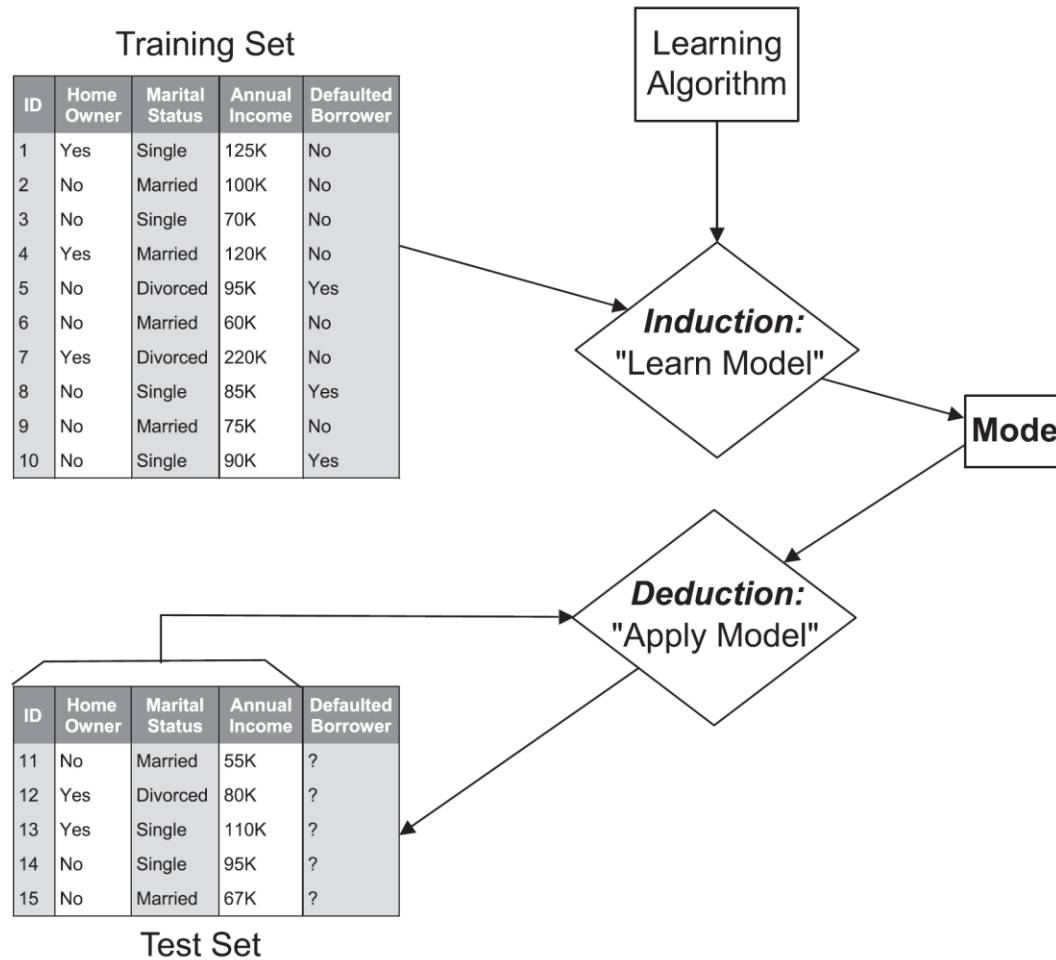


Figure 3.3. General framework for building a classification model.

Classification Techniques

□ Base Classifiers

- Decision Tree based Methods
- Rule-based Methods
- Nearest-neighbor
- Naïve Bayes and Bayesian Belief Networks
- Support Vector Machines
- Neural Networks, Deep Neural Nets

□ Ensemble Classifiers

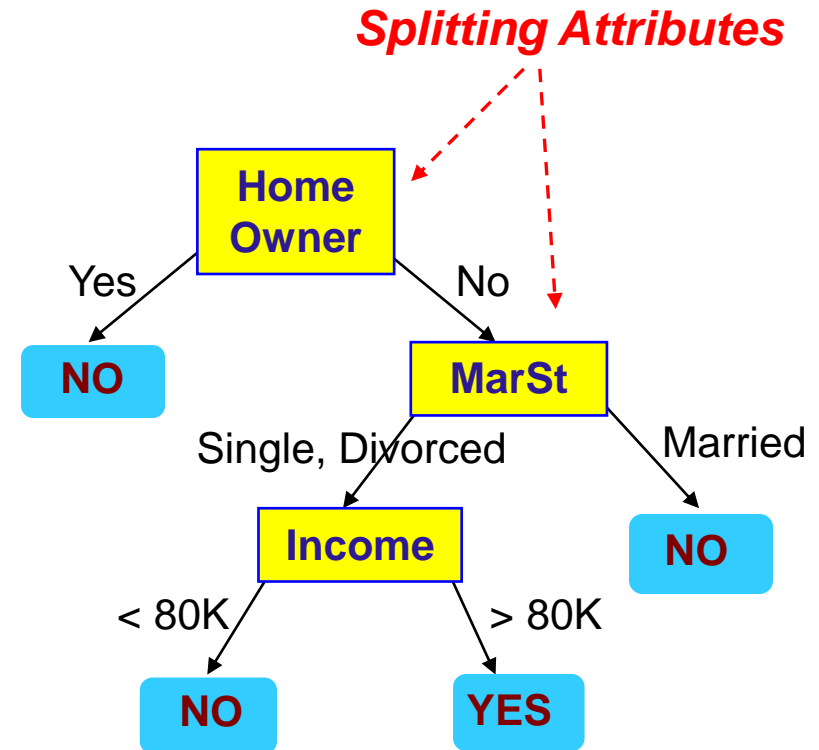
- Boosting, Bagging, Random Forests

Example of a Decision Tree

categorical
categorical
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

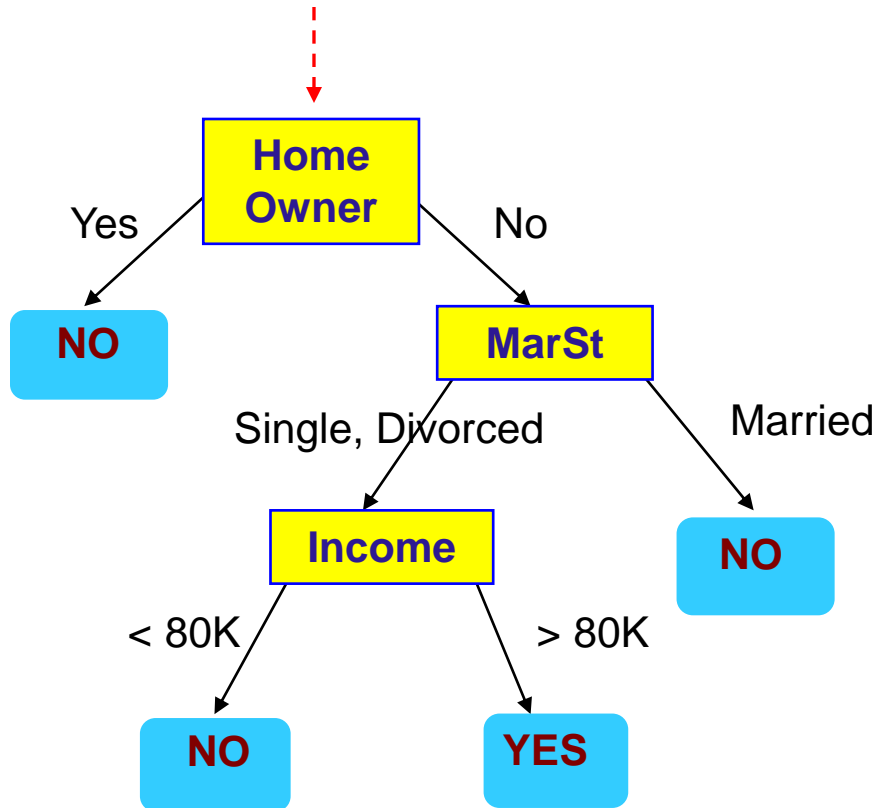
Training Data



Model: Decision Tree

Apply Model to Test Data

Start from the root of tree.



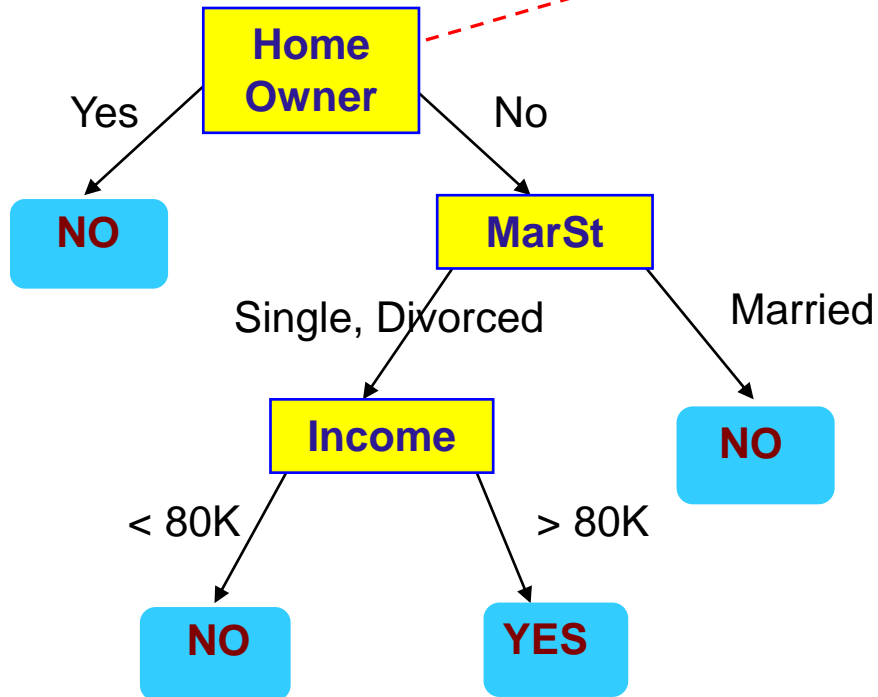
Test Data

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

Apply Model to Test Data

Test Data

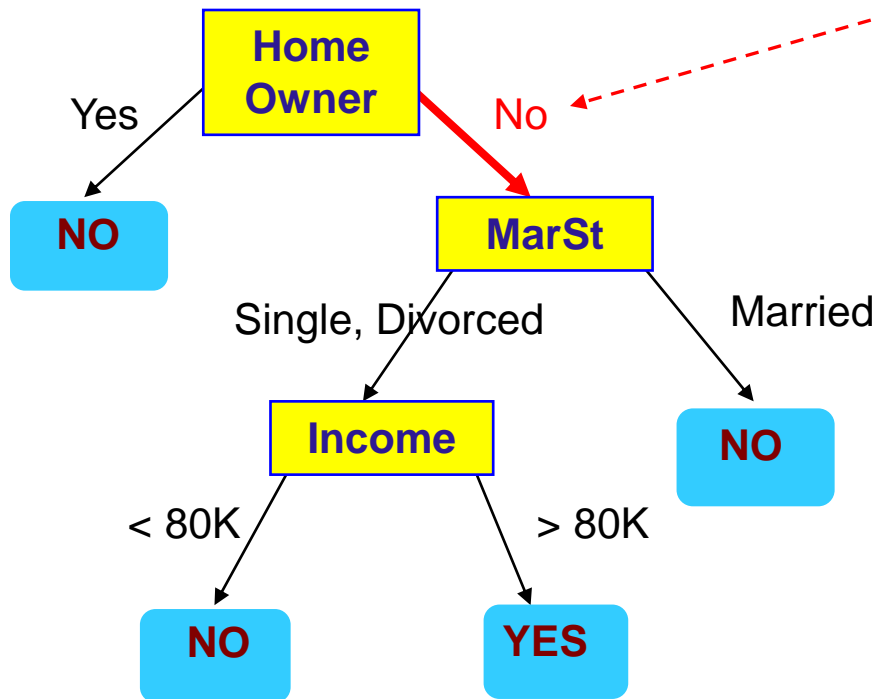
Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?



Apply Model to Test Data

Test Data

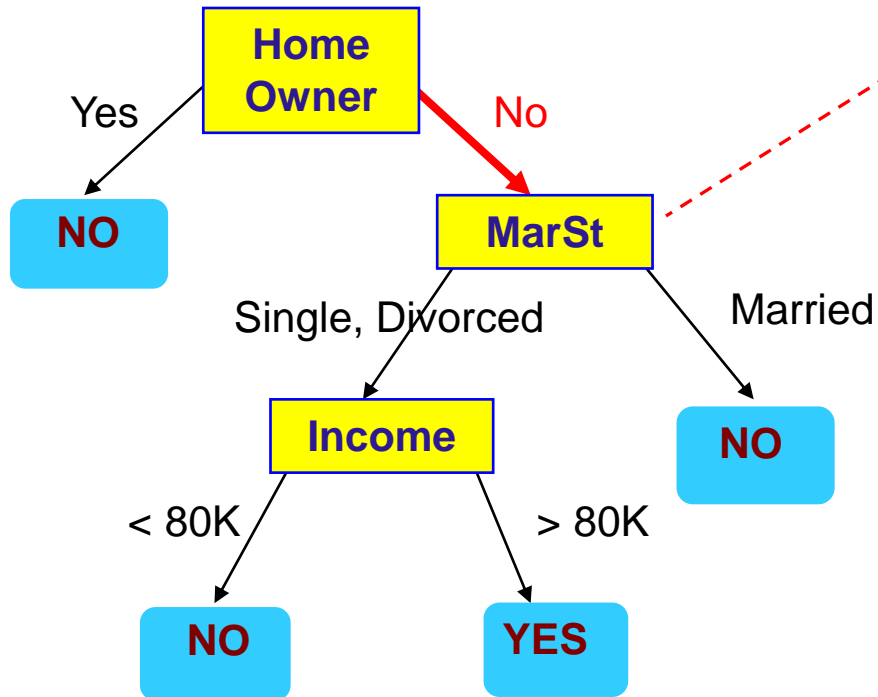
Home Owner	Marital Status	Annual Income	Defaulted Borrower
No	Married	80K	?



Apply Model to Test Data

Test Data

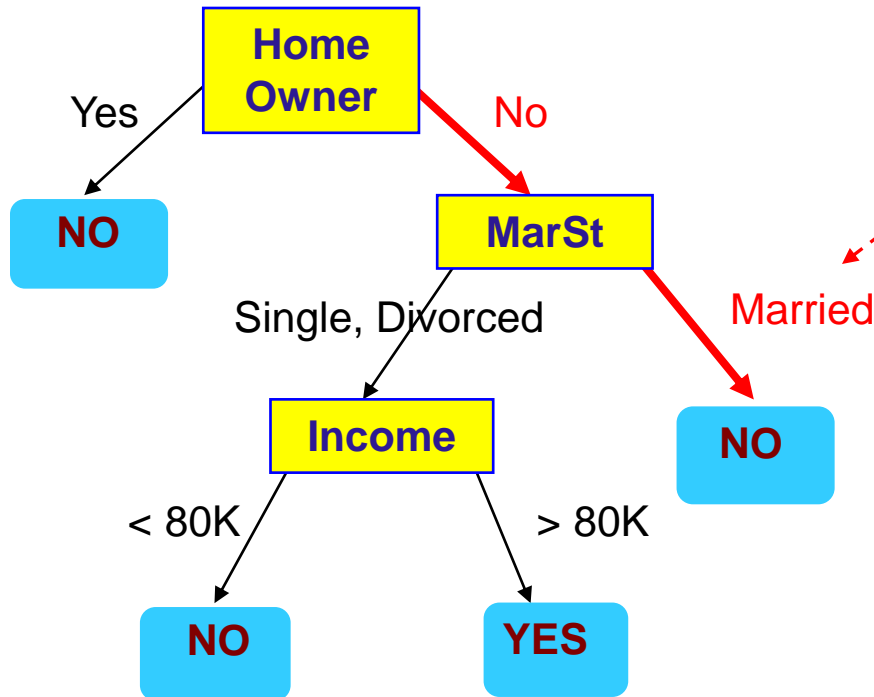
Home Owner	Marital Status	Annual Income	Defaulted Borrower
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Apply Model to Test Data

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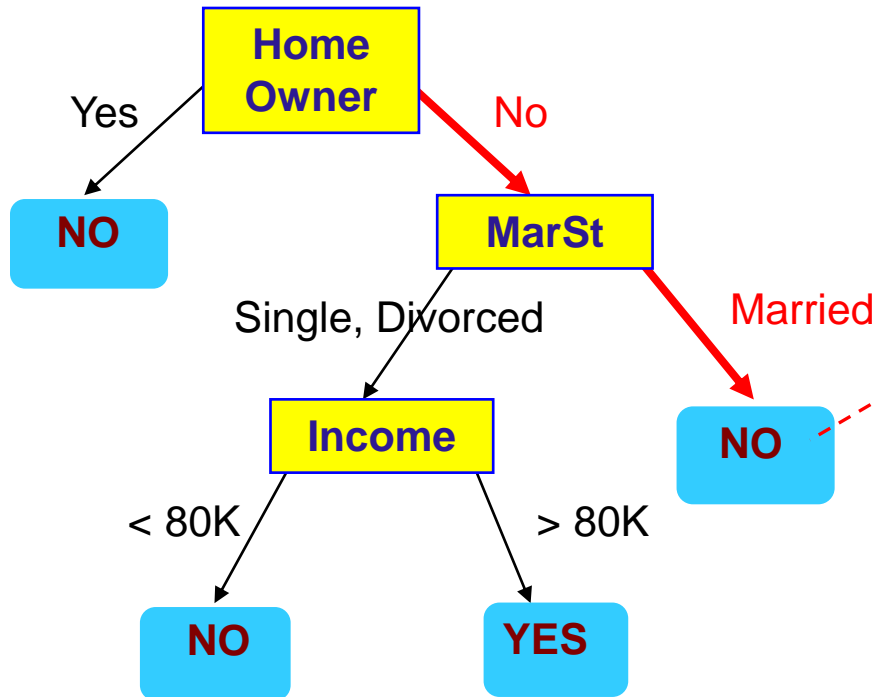
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Apply Model to Test Data

Test Data

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

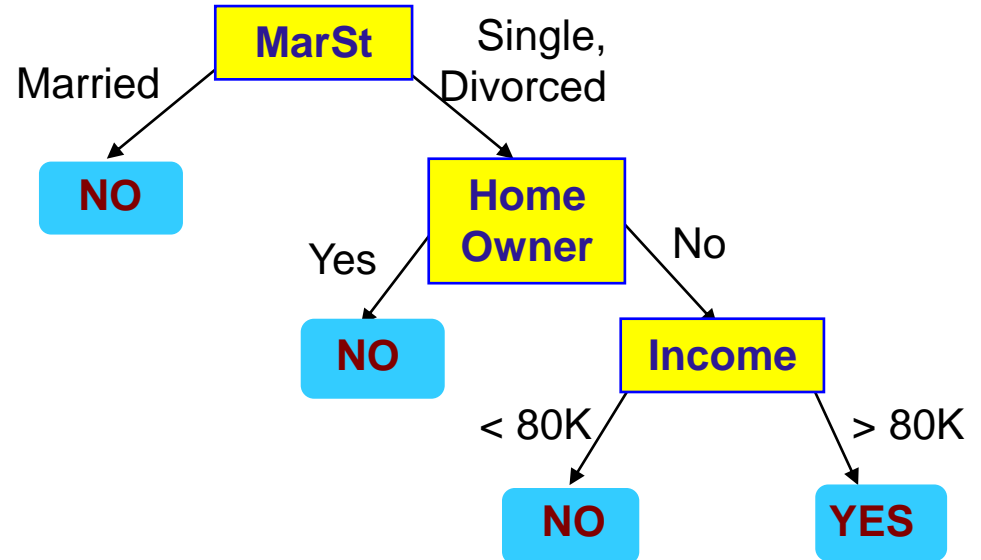


Assign Defaulted to
"No"

Another Example of Decision Tree

categorical
categorical
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



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

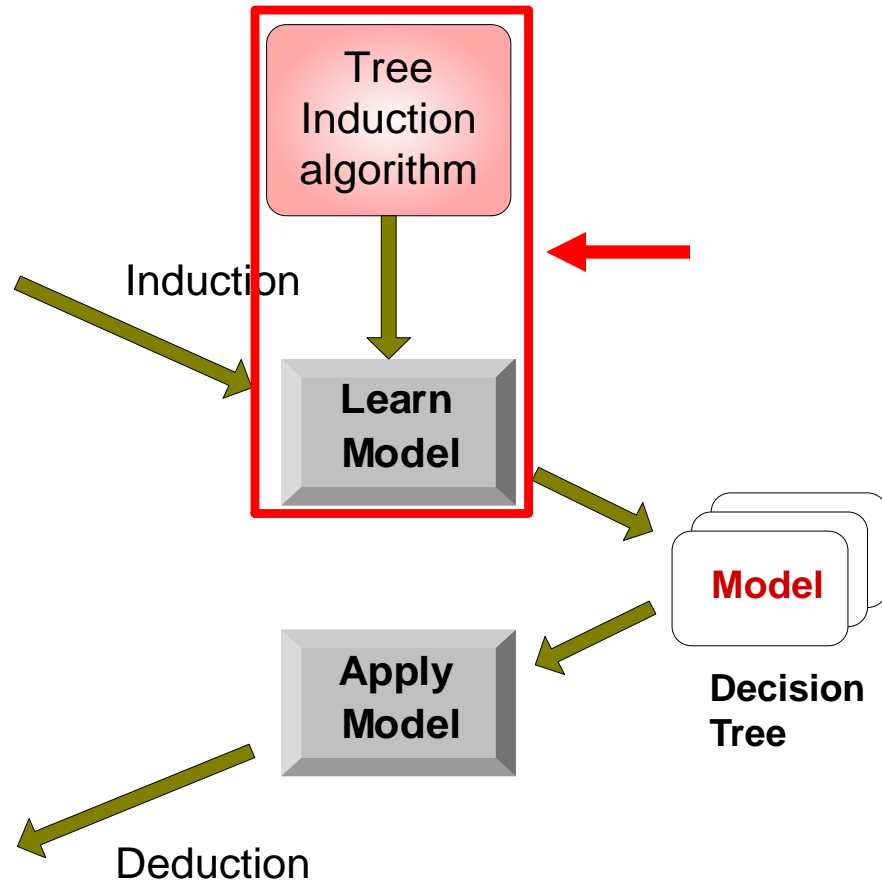
Decision Tree Classification Task

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



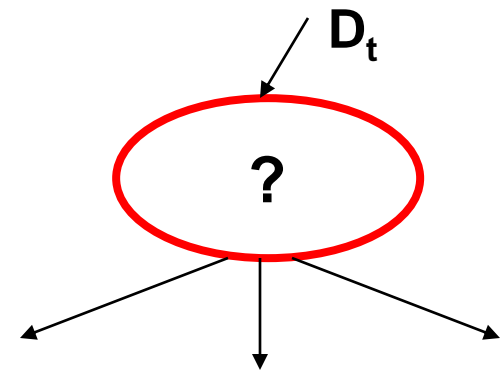
Decision Tree Induction

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

General Structure of Hunt's Algorithm

- | Let D_t be the set of training records that reach a node t
- | General Procedure:
 - If D_t contains records that belong the same class y_t , then t is a leaf node labeled as y_t
 - 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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3	No	Single	70K	No
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7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes



Hunt's Algorithm

Defaulted = No

(7,3)

(a)

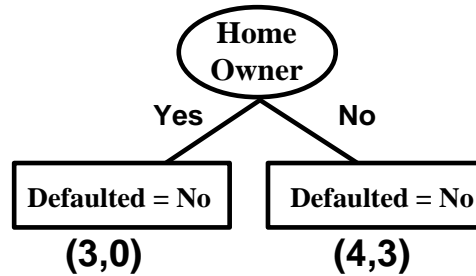
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7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Hunt's Algorithm

Defaulted = No

(7,3)

(a)



(b)

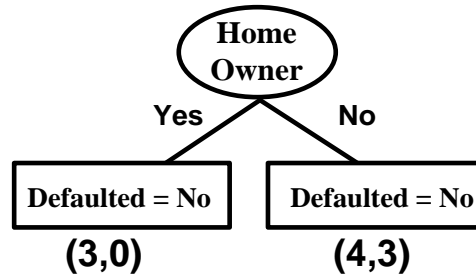
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Hunt's Algorithm

Defaulted = No

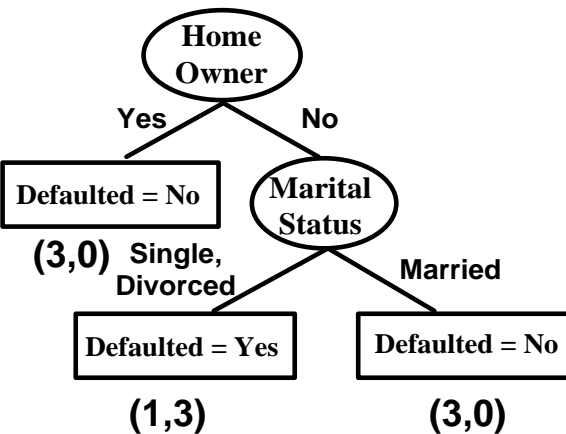
(7,3)

(a)



(b)

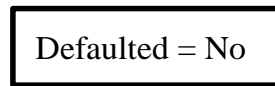
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9	No	Married	75K	No
10	No	Single	90K	Yes



(c)

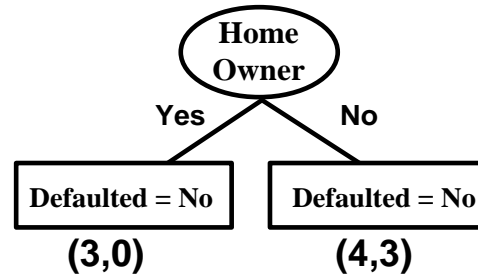
Hunt's Algorithm

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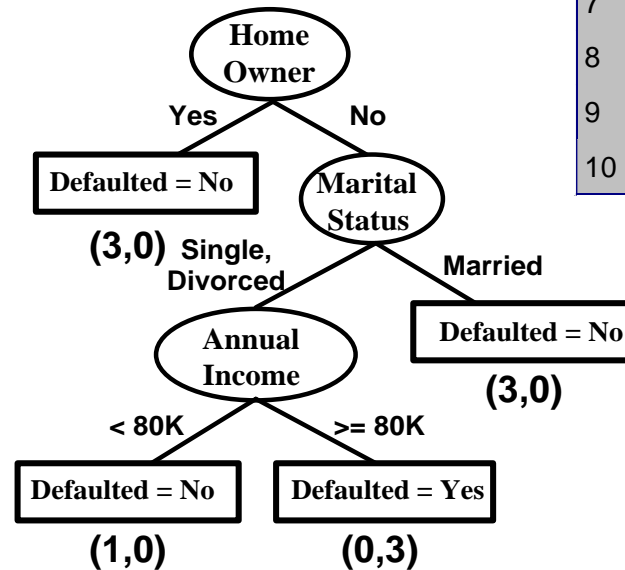


(7,3)

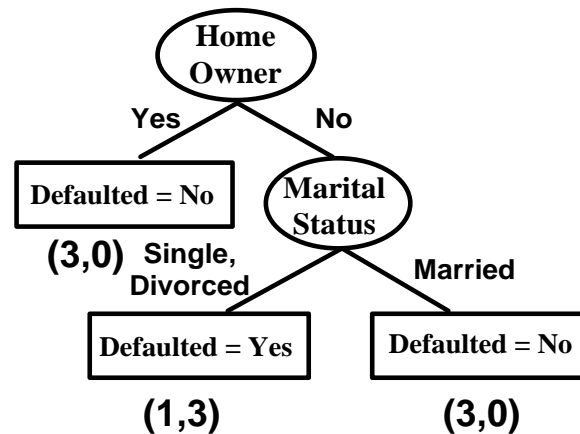
(a)



(b)



(d)



(c)

Design Issues of Decision Tree Induction

- | How should training records be split?
 - Method for expressing test condition
 - ◆ depending on attribute types
 - Measure for evaluating the goodness of a test condition
- | How should the splitting procedure stop?
 - Stop splitting if all the records belong to the same class or have identical attribute values
 - Early termination

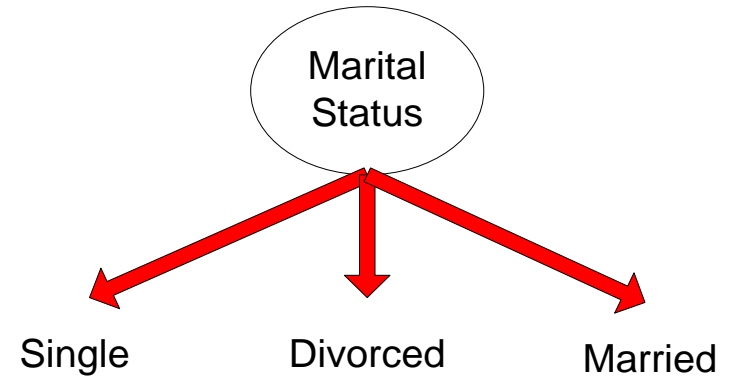
Methods for Expressing Test Conditions

- | Depends on attribute types
 - Binary
 - Nominal
 - Ordinal
 - Continuous

Test Condition for Nominal Attributes

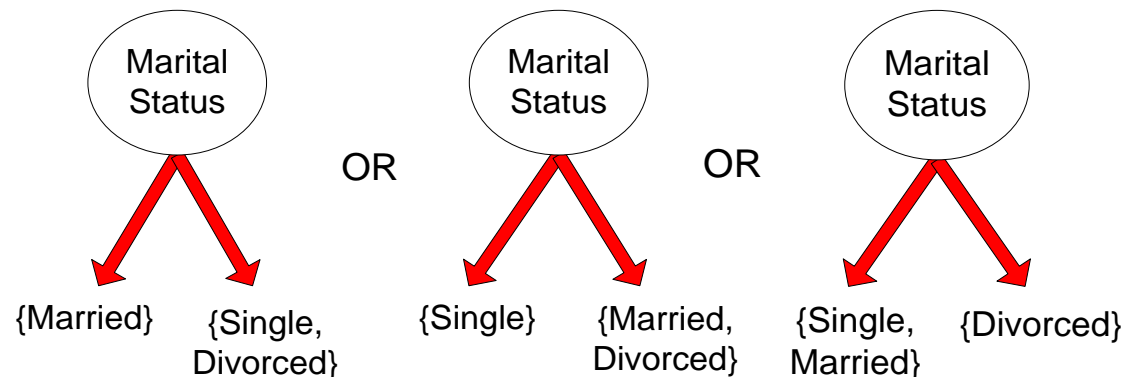
□ Multi-way split:

- Use as many partitions as distinct values.



□ Binary split:

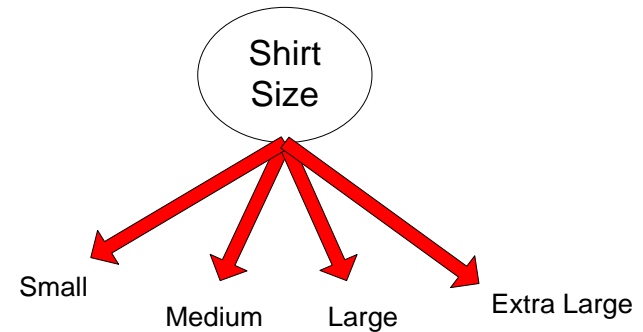
- Divides values into two subsets



Test Condition for Ordinal Attributes

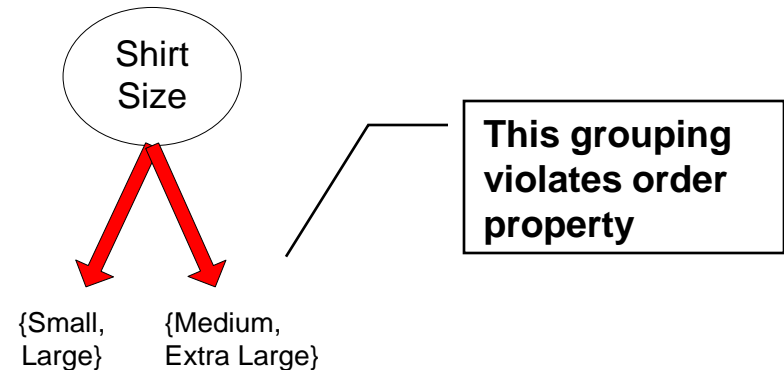
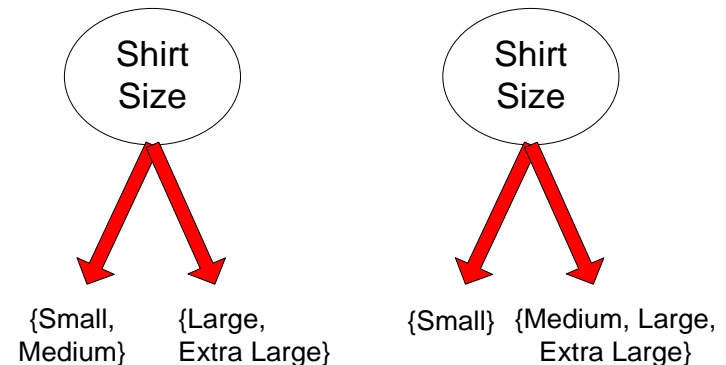
| Multi-way split:

- Use as many partitions as distinct values

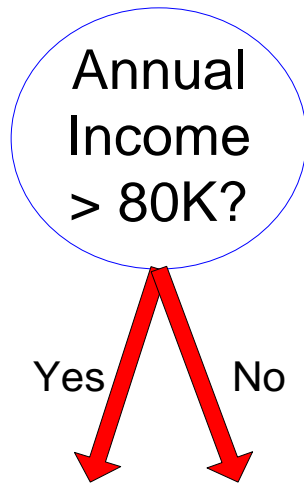


| Binary split:

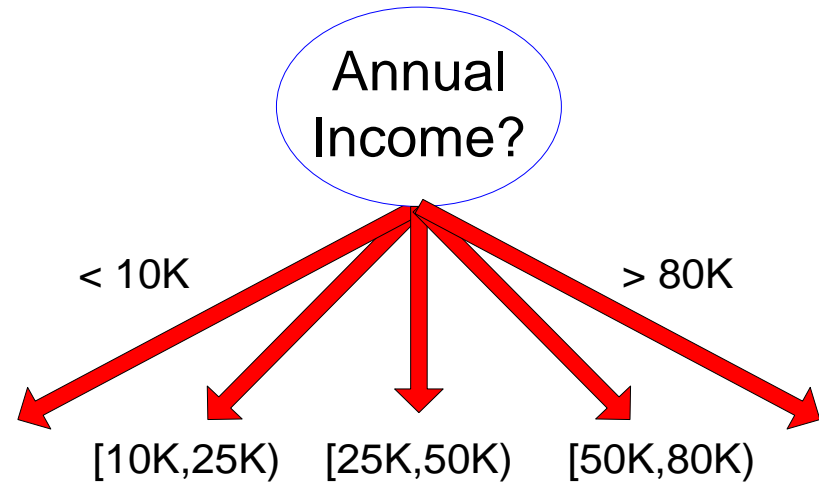
- Divides values into two subsets
- Preserve order property among attribute values



Test Condition for Continuous Attributes



(i) Binary split



(ii) Multi-way split

Splitting Based on Continuous Attributes

- Different ways of handling

- **Discretization** to form an ordinal categorical attribute

Ranges can be found by equal interval bucketing, equal frequency bucketing (percentiles), or clustering.

- ◆ Static – discretize once at the beginning
 - ◆ Dynamic – repeat at each node

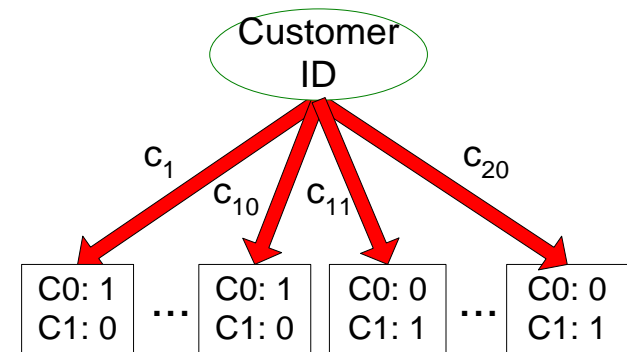
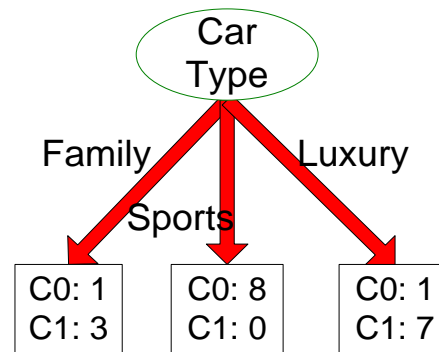
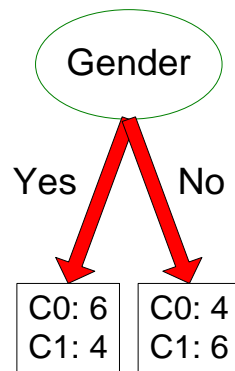
- **Binary Decision**: $(A < v)$ or $(A \geq v)$

- ◆ consider all possible splits and finds the best cut
 - ◆ can be more compute intensive

How to determine the Best Split

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

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 test condition is the best?

How to determine the Best Split

- | Greedy approach:
 - Nodes with **pur**er class distribution are preferred
- | Need a measure of node impurity:

C0: 5
C1: 5

High degree of impurity

C0: 9
C1: 1

Low degree of impurity

Measures of Node Impurity

| Gini Index

$$Gini\ Index = 1 - \sum_{i=0}^{c-1} p_i(t)^2$$

Where $p_i(t)$ is the frequency of class i at node t , and c is the total number of classes

| Entropy

$$Entropy = - \sum_{i=0}^{c-1} p_i(t) \log_2 p_i(t)$$

| Misclassification error

$$Classification\ error = 1 - \max[p_i(t)]$$