

Data Mining: Concepts and Techniques

— Chapter 6 —

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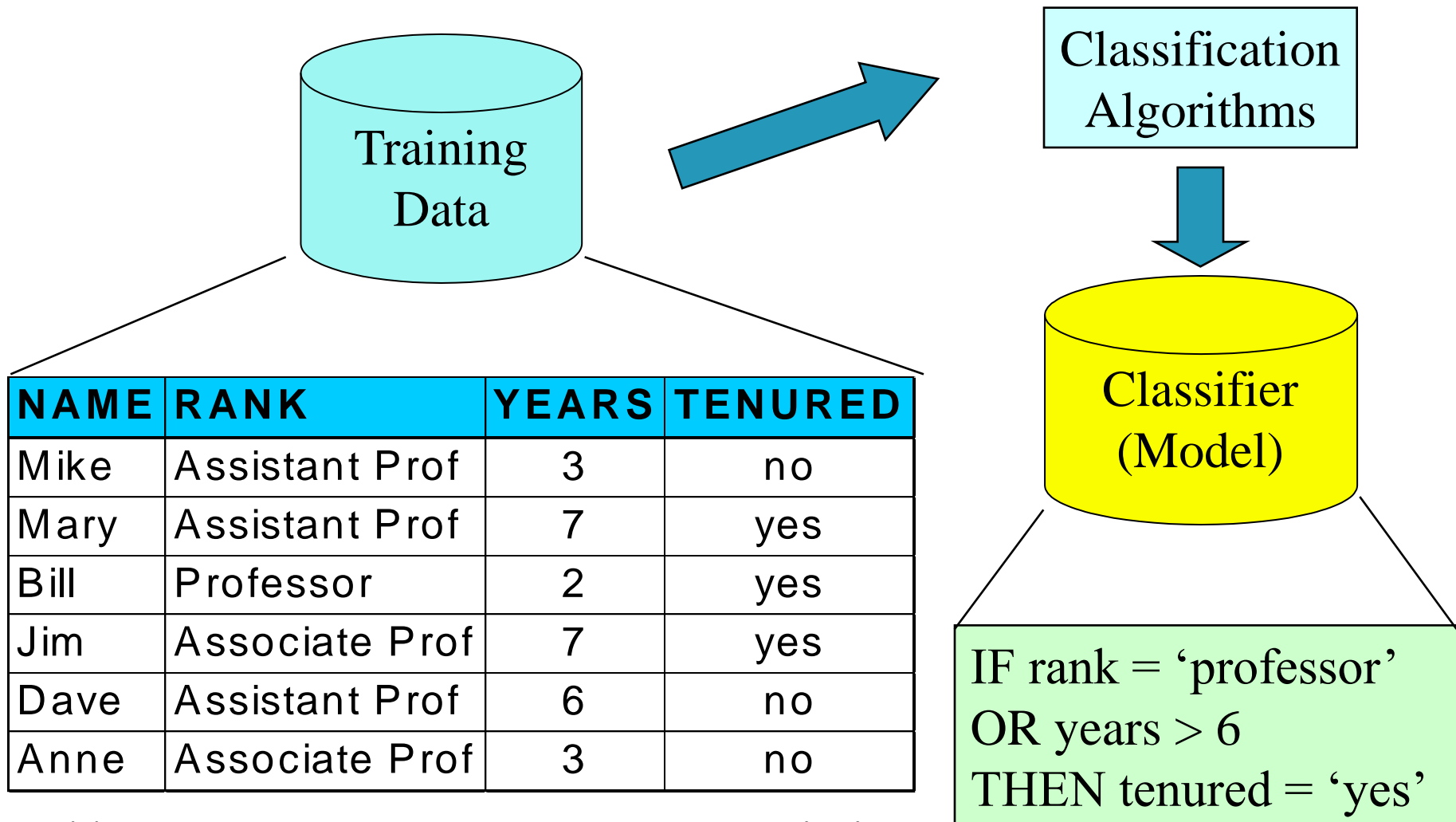
Classification vs. Prediction

- Classification
 - predicts categorical class labels (discrete or nominal)
 - classifies data (constructs a model) based on the training set and the values (**class labels**) in a classifying attribute and uses it in classifying new data
- Prediction
 - models continuous-valued functions, i.e., predicts unknown or missing values
- Typical applications
 - Credit approval
 - Target marketing
 - Medical diagnosis
 - Fraud detection

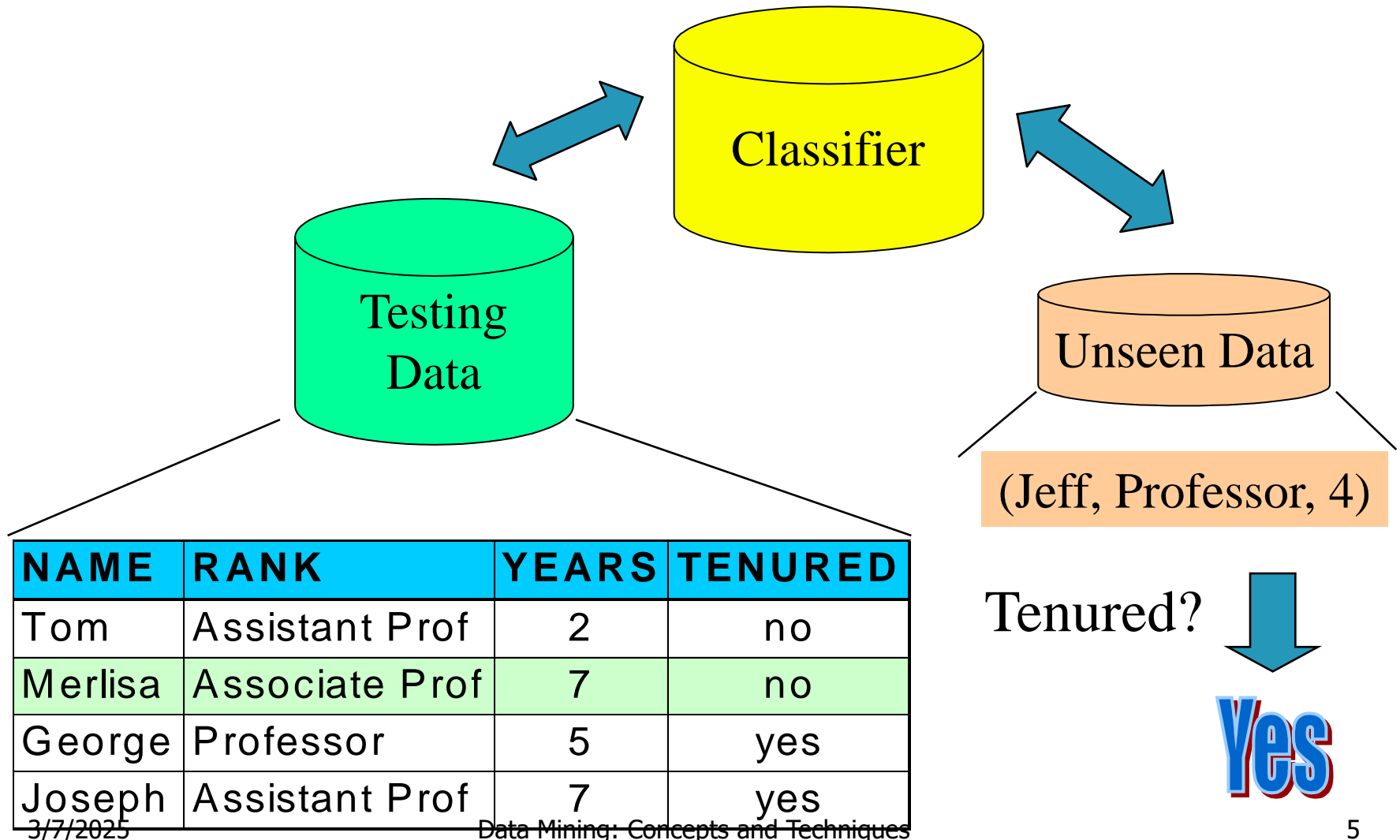
Classification—A Two-Step Process

- **Model construction**: describing a set of predetermined classes
 - Each tuple/sample is assumed to belong to a predefined class, as determined by the **class label attribute**
 - The set of tuples used for model construction is **training set**
 - The model is represented as classification rules, decision trees, or mathematical formulae
- **Model usage**: for classifying future or unknown objects
 - **Estimate accuracy** of the model
 - The known label of test sample is compared with the classified result from the model
 - Accuracy rate is the percentage of test set samples that are correctly classified by the model
 - Test set is independent of training set, otherwise over-fitting will occur
 - If the accuracy is acceptable, use the model to **classify data** tuples whose class labels are not known

Process (1): Model Construction



Process (2): Using the Model in Prediction



Supervised vs. Unsupervised Learning

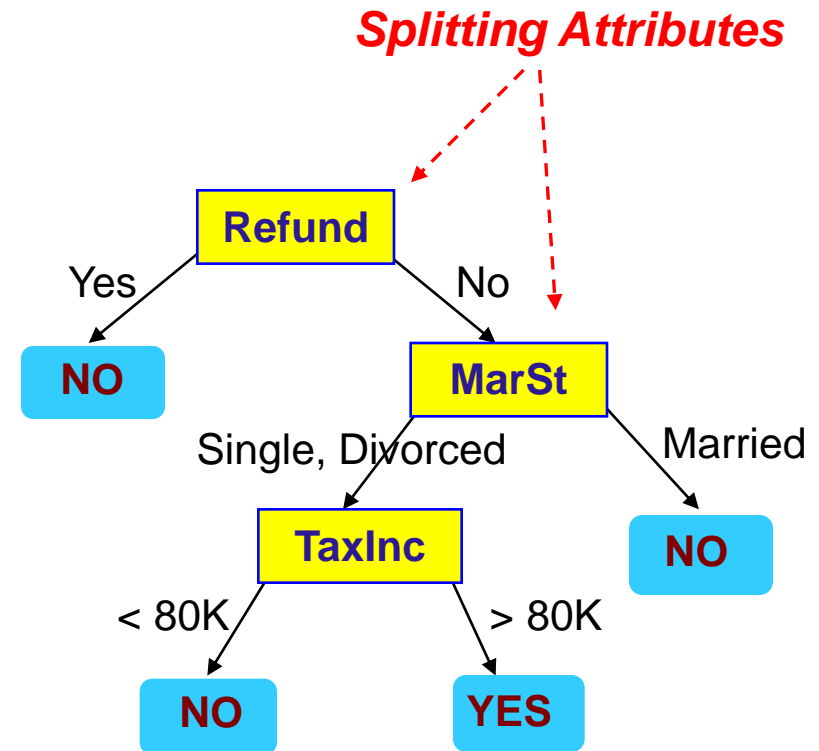
- Supervised learning (classification)
 - Supervision: The training data (observations, measurements, etc.) are accompanied by labels indicating the class of the observations
 - New data is classified based on the training set
- Unsupervised learning (clustering)
 - The class labels of training data is unknown
 - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

Example of a Decision Tree

categorical
categorical
continuous
class

<i>Tid</i>	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

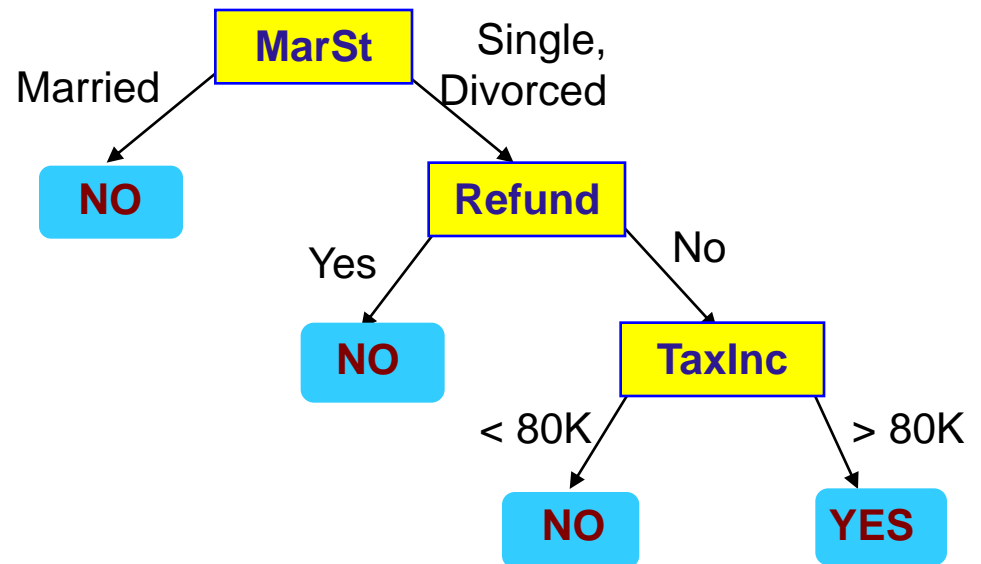
Training Data



Model: Decision Tree

Another Example of Decision Tree

<i>Tid</i>	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



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

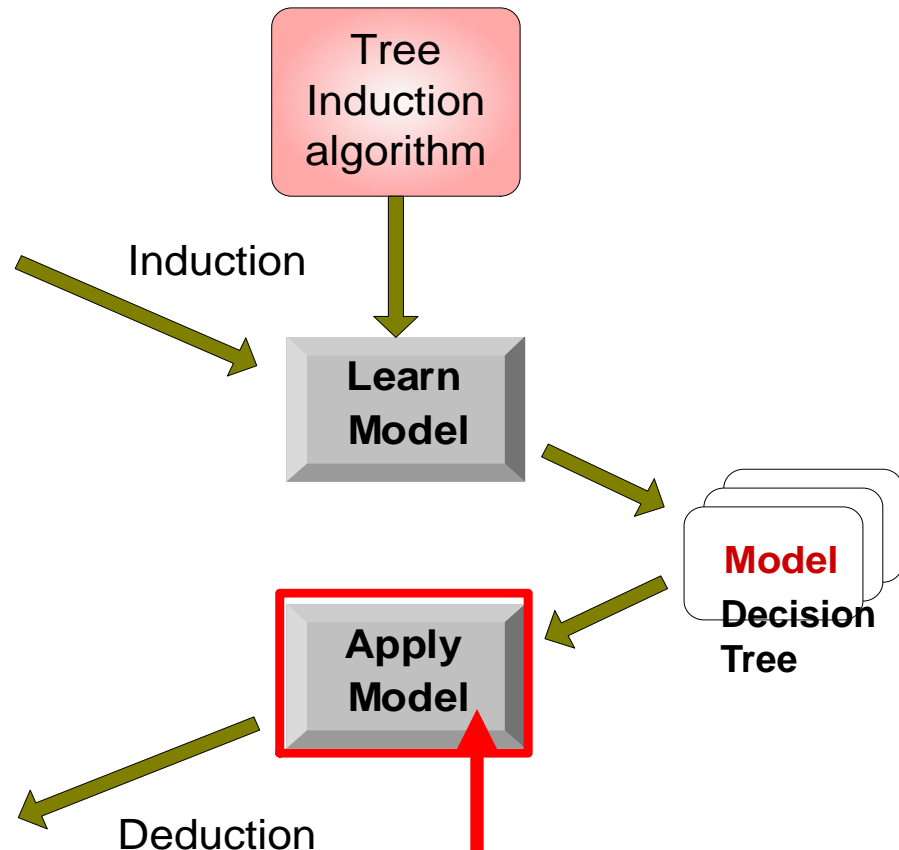
Decision Tree Classification Task

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

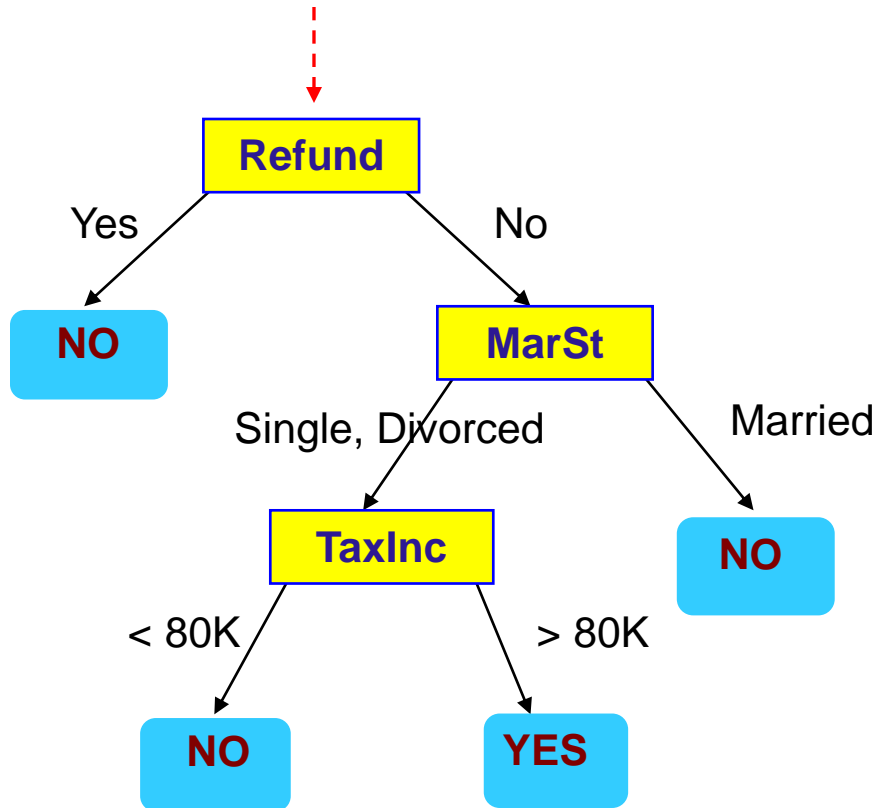


Apply Model to Test Data

Test Data

Start from the root of tree.

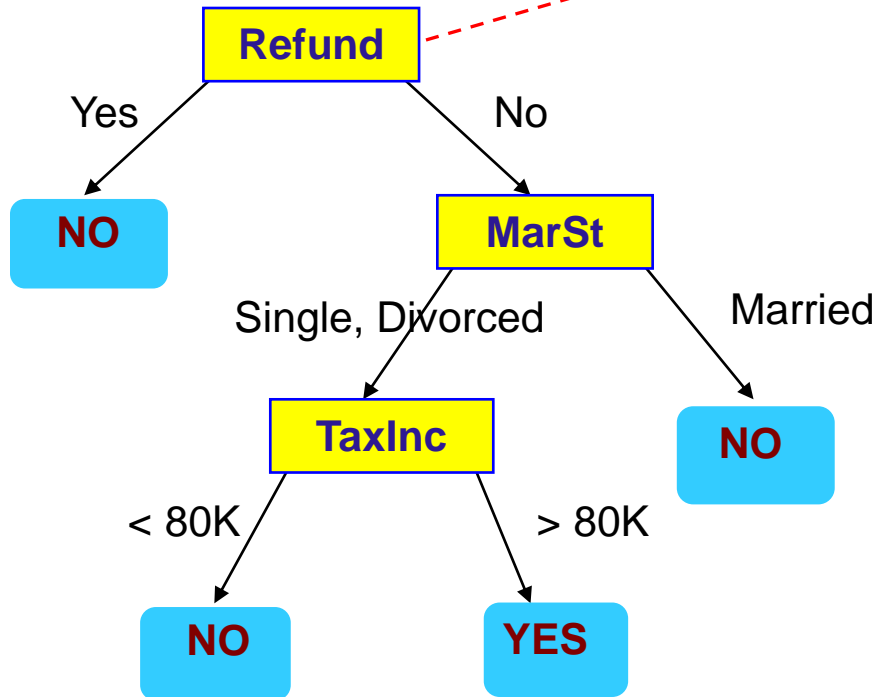
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

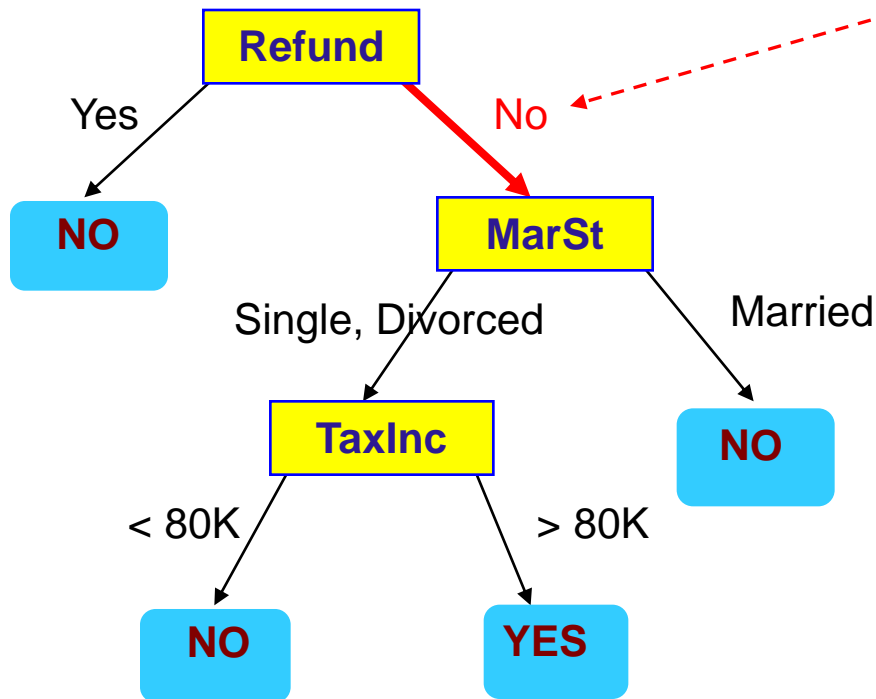
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

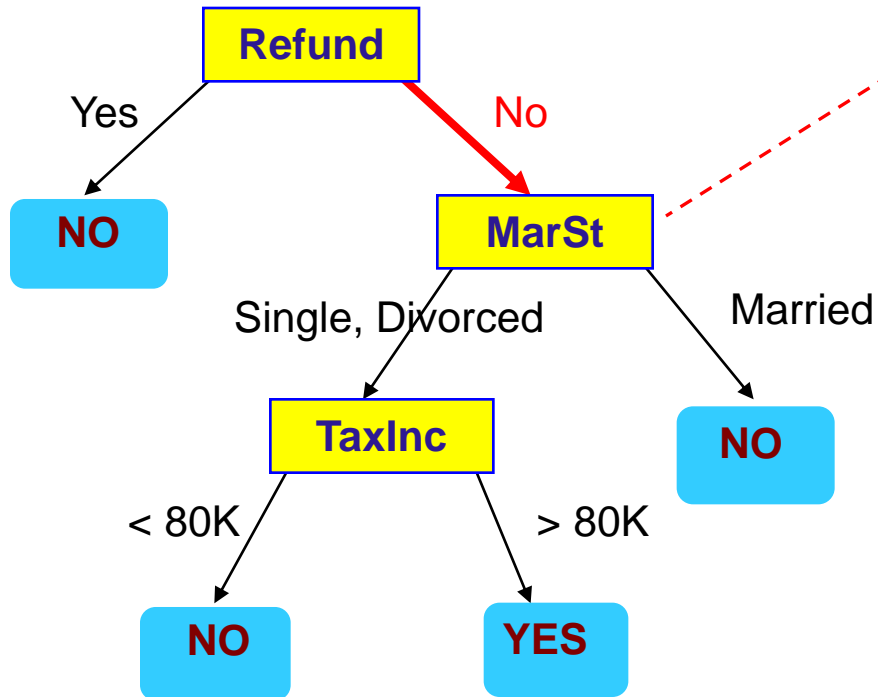
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

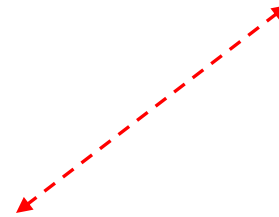
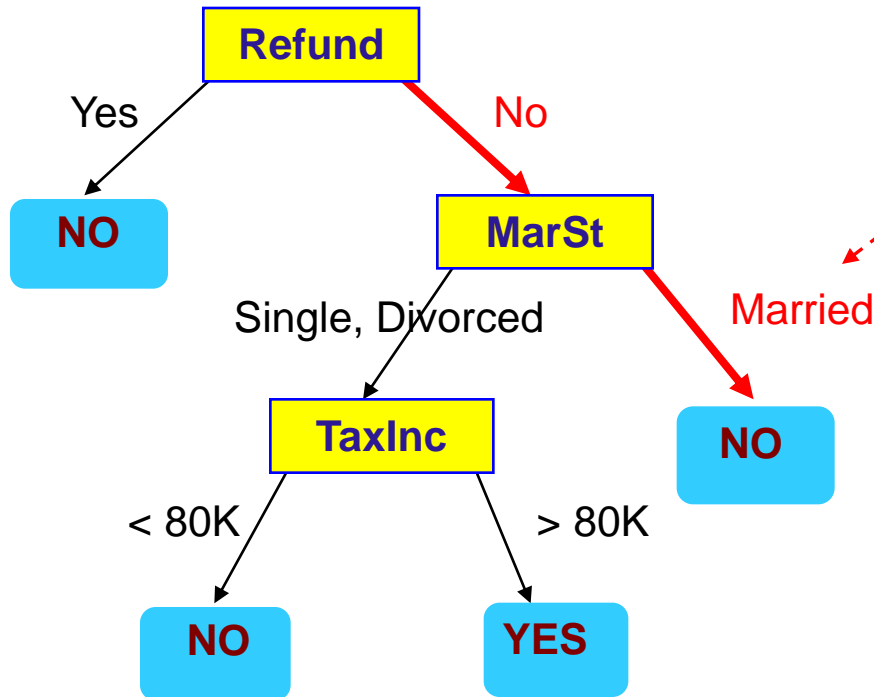
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

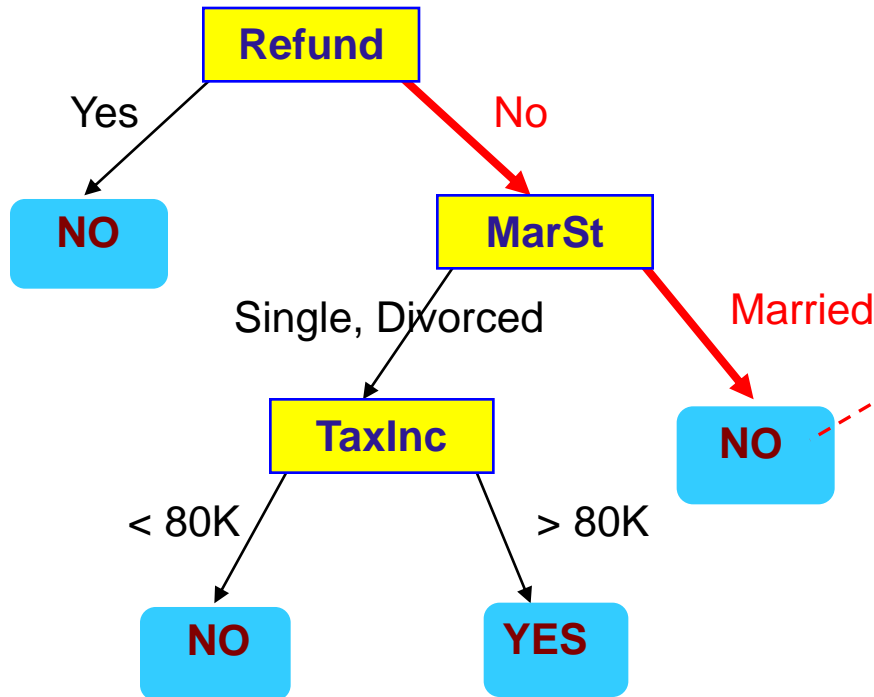
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data

Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Assign Cheat to "No"

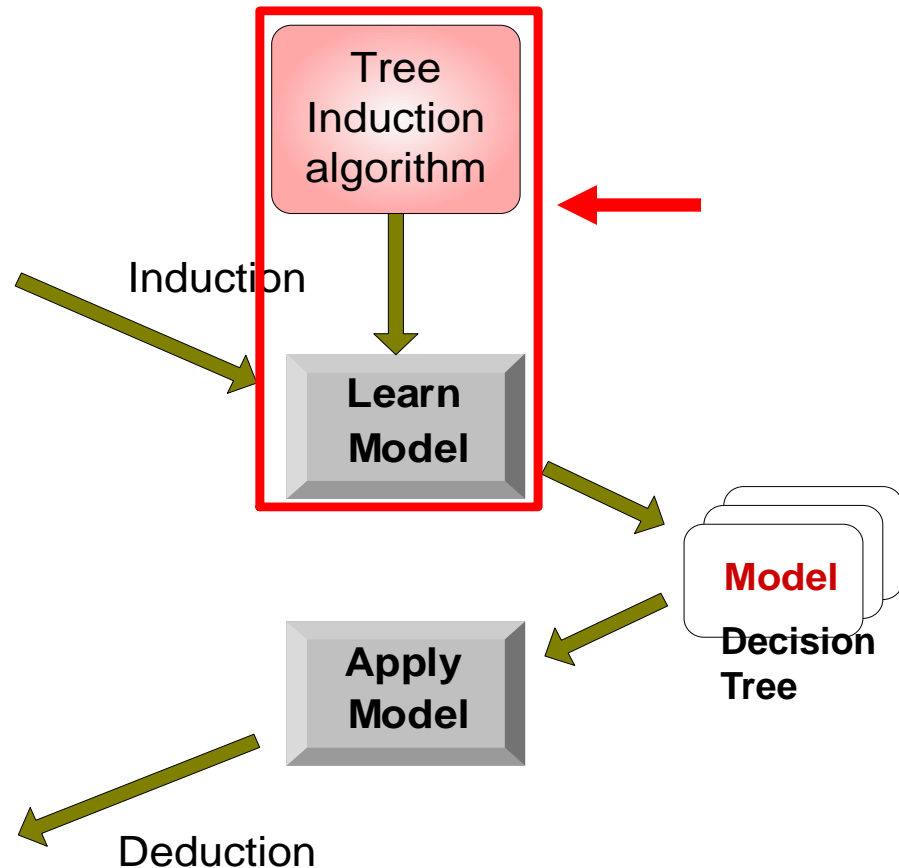
Decision Tree Classification Task

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Training Set

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15	No	Large	67K	?

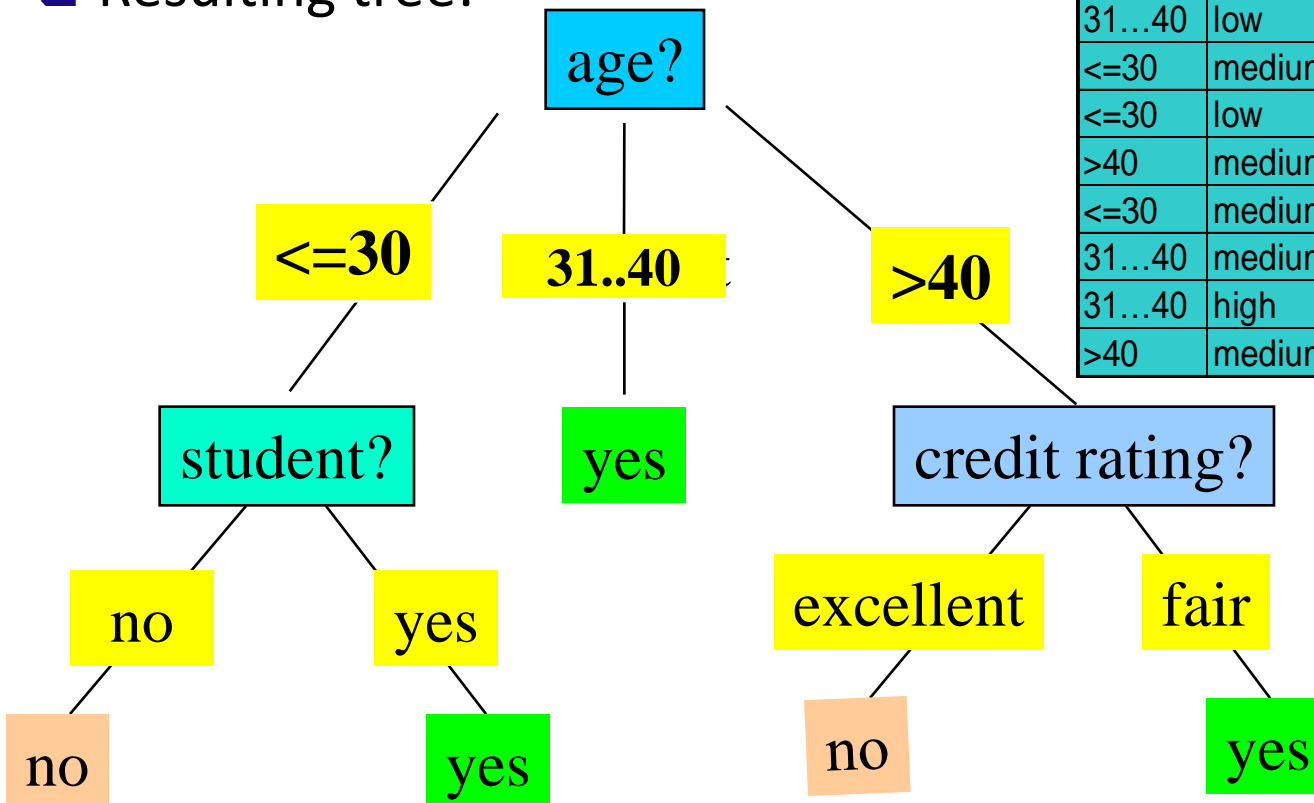
Test Set



Decision Tree Induction: An Example

- ❑ Training data set: Buys_computer
- ❑ The data set follows an example of Quinlan's ID3 (Playing Tennis)
- ❑ Resulting tree:

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no



Algorithm for Decision Tree Induction

- Basic algorithm (a greedy algorithm)
 - Tree is constructed in a **top-down recursive divide-and-conquer manner**
 - At start, all the training examples are at the root
 - Attributes are categorical (if continuous-valued, they are discretized in advance)
 - Examples are partitioned recursively based on selected attributes
 - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., **information gain**)
- Conditions for stopping partitioning
 - All samples for a given node belong to the same class
 - There are no remaining attributes for further partitioning – **majority voting** is employed for classifying the leaf
 - There are no samples left

Attribute Selection Measure: Information Gain (ID3/C4.5)

- Select the attribute with the highest information gain
- Let p_i be the probability that an arbitrary tuple in D belongs to class C_i , estimated by $|C_{i,D}|/|D|$
- Expected information (entropy) needed to classify a tuple in D :

$$Info(D) = -\sum_{i=1}^m p_i \log_2(p_i)$$

- Information needed (after using A to split D into v partitions) to classify D :

$$Info_A(D) = \sum_{j=1}^v \frac{|D_j|}{|D|} \times Info(D_j)$$

- Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_A(D)$$

Attribute Selection: Information Gain

■ Class P: buys_computer = “yes”

■ Class N: buys_computer = “no”

$$Info_{age}(D) = \frac{5}{14} I(2,3) + \frac{4}{14} I(4,0) + \frac{5}{14} I(3,2) = 0.694$$

$$Info(D) = I(9,5) = -\frac{9}{14} \log_2\left(\frac{9}{14}\right) - \frac{5}{14} \log_2\left(\frac{5}{14}\right) = 0.940$$

age	p _i	n _i	I(p _i , n _i)
<=30	2	3	0.971
31...40	4	0	0
>40	3	2	0.971

$\frac{5}{14} I(2,3)$ means “age <=30” has 5 out of 14 samples, with 2 yes’es and 3 no’s. Hence

$$Gain(age) = Info(D) - Info_{age}(D) = 0.246$$

Similarly,

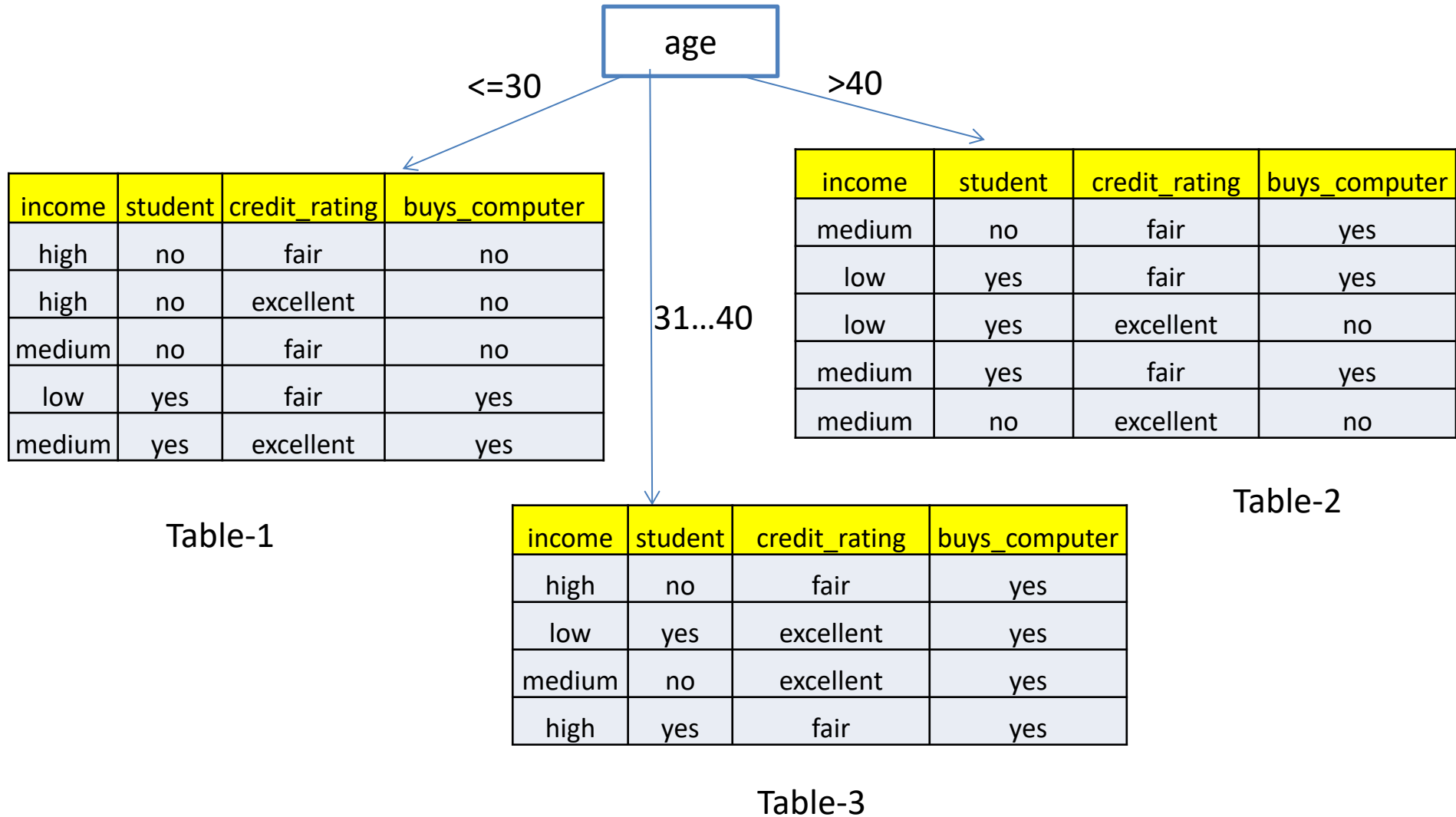
$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

$$Gain(credit_rating) = 0.048$$

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no

DT after Iteration-1



Iteration-2

- Consider Table-1

income	student	credit_rating	buys_computer
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

$$\text{Info}(D)=I(2,3)= 0.9704$$

$$\begin{aligned}\text{Info}_{\text{income}}(D) &= 2/5 * I(0,2) + 2/5 * I(1,1) + 1/5 * I(1,0) \\ &= 2/5 * 0 + 2/5 * 0.999 + 1/5 * 0 \\ &= 0.3996\end{aligned}$$

$$\text{Gain}(\text{income}) = 0.9704 - 0.3996 = 0.5708$$

Student has maximum gain and we consider student as next node

$$\begin{aligned}\text{Info}_{\text{student}}(D) &= 2/5 * I(2,0) + 3/5 * I(0,3) \\ &= 0\end{aligned}$$

$$\text{Gain}(\text{student}) = 0.9704 - 0 = 0.9704$$

$$\begin{aligned}\text{Info}_{\text{credit_rating}}(D) &= 3/5 * I(1,2) + 2/5 * I(1,1) \\ &= 3/5 * 0.9178 + 2/5 * 0.999 \\ &= 0.9503\end{aligned}$$

$$\text{Gain}(\text{credit_rating}) = 0.9704 - 0.9503 = 0.0201$$

- Calculate for Table-2

income	student	credit_rating	buys_computer
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Final tree

