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Classification Lecture Notes

Classification
(Data Mining Book Chapters 5 and 7)

- **PART ONE:** Supervised learning and Classification
- Data format: training and test data
- Concept, or class definitions and description
- Rules learned: characteristic and discriminant
- Supervised learning = classification process = building a classifier.
- Classification algorithms
- Evaluating predictive accuracy of a classifier: the most common methods for testing
- Unsupervised learning= clustering
- Clustering methods

Part 2: Classification Algorithms (Models, Basic Classifiers)

- Decision Trees (ID3, C4.5)
- Neural Networks
- Genetic Algorithm
- Bayesian Classifiers (Networks)
- Rough Sets

Part 3: Other Classification Methods

- k-nearest neighbor classifier
- Case-based reasoning
- Fuzzy set approaches

PART 1: Learning Functionalities (1)
Classification Data

- **Data format:** a data table with key attribute removed. Special attribute- class attribute must be distinguished

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
30…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

Part 1: Learning Functionalities
Classification Training Data 2 (with objects)

rec	Age	Income	Student	Credit_rating	Buys_computer
r1	<=30	High	No	Fair	No
r2	<=30	High	No	Excellent	No
r3	31…40	High	No	Fair	Yes
r4	>40	Medium	No	Fair	Yes
r5	>40	Low	Yes	Fair	Yes
r6	>40	Low	Yes	Excellent	No
r7	31…40	Low	Yes	Excellent	Yes
r8	<=30	Medium	No	Fair	No
r9	<=30	Low	Yes	Fair	Yes
r10	>40	Medium	Yes	Fair	Yes
r11	<-=30	Medium	Yes	Excellent	Yes
r12	31…40	Medium	No	Excellent	Yes
r13	31…40	High	Yes	Fair	Yes
r14	>40	Medium	No	Excellent	No

Learning Functionalities (2)
Concept or Class definitions

- **Syntactically a Concept or a Class** is defined by the concept (class) attribute **c** and its value **v**
- **Semantically Concept or Class** – is any subset of records.
- **Concept or Class (syntactic) description** is written as : **c=v**
- **Semantically**, a concept, or a class defined by the attibute **c** is the set **C** of all records for which the attribute **c** has a value **v**.

Learning Functionalities (3)
Concept or Class definitions

- **Example:**

{ r1, r2, r6, r8, r14} of the Classification Training Data 2 on the previous slide

Syntactically it is defined by the concept attribute buys_computer and its value no

Concept (class) { r1, r2, r6, r8, r14} description is: buys_computer= no

Learning Functionalities (4)
Concept, Class characteristics

Characteristics of a class (concept) C

is a set of attributes a1, a2, … ak, and their respective values v1, v2, …. vk such that the intersection of set of all records for which a1=v1 & a2=v2&…..ak=vk with set ***C*** *is not empty*

Characteristics description *of* ***C*** *of is then syntactically written as a1=v1 & a2=v2&…..ak=vk*

REMARK: A concept ***C*** *can have many characteristic descriptions.*

Learning Functionalities (5)
Concept, Class characteristic formula

Definition:

A formula a1=v1 & a2=v2&…..ak=vk (of a proper language) is called ***a characteristic description*** *for* ***a class*** *(concept)* ***C***

If and only if

R1={r: *a1=v1 & a2=v2&…..ak=vk* ***} Λ C = not empty set***

Learning Functionalities (6)
Concept, Class characteristics

Example:

- *Some of the* ***characteristic descriptions***

of the concept ***C*** *with description****:*** **buys_computer= no**

are

- Age=<= 30 & income=high & student=no & credit_rating=fair
- Age=>40& income=medium & student=no & credit_rating=excellent
- Age=>40& income=medium
- Age=<= 30
- student=no & credit_rating=excellent

Learning Functionalities (7)
Concept, Class characteristics

- A formula
- Income=low is *a **characteristic description***

  *of the concept **C1** with description**:***

  buys_computer= yes

  and *of the concept **C2** with description**:***

  buys_computer= no
- A formula
- Age<=30 & Income=low is NOT *the **characteristic description***

  *of the concept **C1** with description**:*** **buys_computer= no**

because:

{ r: Age<=30 & Income=low } /\ {r: **buys_computer=no }= emptyset**

Characteristic Formula

Any formula (of a proper language) of a form

IF concept desciption THEN characteristics

is called a characteristic formula

Example:

- IF buys_computer= no **THEN** income = low & student=yes & credit=excellent
- IF buys_computer= no **THEN** income = low & credit=fair

Characteristic Rule (1)

- **A characteristic formula**

IF concept desciption THEN characteristics

is called **a characteristic rule** (for a given database)

if and only if it is **TRUE** in the given database, i.e.

{r: concept description} &{r: characteristics} = not empty set

Characteristic Rule (2)

EXAMPLE:

The formula

- IF buys_computer= no **THEN** income = low & student=yes & credit=excellent

Is a characteristic rule for our database because

{r: buys_computer= no **} = {**r1,r2, r6, r8, r16 **},**

{r: income = low & student=yes & credit=excellent **} =** **{**r6,r7**}**

and

{r1,r2, r6, r8, r16 **} /\ {**r6,r7**} =** not emptyset

Characteristic Rule (3)

EXAMPLE:

The formula

- IF buys_computer= no **THEN** income = low & credit=fair

Is NOT a characteristic rule for our database because

{r: buys_computer= no **} = {**r1,r2, r6, r8, r16 **},**

{r: income = low & credit=fair**} = {**r5, r9 **}**

and

{r1,r2, r6, r8, r16 **} /\ {**r5,r9**} =** emptyset

Discrimination

- *Discrimination is the process which aim is to find rules that allow us to* ***discriminate*** *the objects (records) belonging to a given concept (one class) from the rest of records (classes)*

If characteristics then concept

- *Example*
- ***If*** Age=<= 30 & income=high & student=no & credit_rating=fair

then buys_computer= no

Discriminant Formula

A discriminant formula is any formula

If characteristics then concept

- Example:
- IF Age=>40 & inc=low THEN buys_comp= no

Discriminant Rule

- A discriminant formula

  ***If* characteristics *then* concept**

  *is a **DISCRIMINANT RULE** (in a given database)*

iff

{r: Characteristic} $\subset$ ***{r: concept}***

Discriminant Rule

- ***Example:***

A discrimant formula

IF Age=>40 & inc=low THEN buys_comp= no

IS NOT a discriminant rule *in our data base because*

{r: Age=>40 & inc=low} = *{r5, r6}* *is not a subset of the set* *{r :*buys_comp= no}= {r1,r2,r6,r8,r14}

Characteristic and discriminant rules

- The inverse implication to the characteristic rule is usually NOT a discriminant rule
- Example : the inverse implication to our characteristic rule: ***If*** buys_computer= no **then** income = low & student=yes & credit=excellent is
- ***If*** income = low & student=yes & credit=excellent **then** buys_computer= no
- The above rule is NOT a discriminant rule as it can't discriminate between concept with description buys_computer= no and buys_computer= yes
- (see records r7 and r8 in our training dataset)

Supervised Learning Goal (1)

- Given a data set and a concept **c** defined in this dataset FIND a minimal set (or as small as possible set) characteristic, and/or discriminant rules, or other descriptions for the concept **c**, or class, or classes.

Supervised Learning Goal (2)

- We also want these rules to involve as few attributes as it is possible, i.e. we want the rules to have as short as possible length of descriptions.

Supervised Learning

- The process of creating discriminant and/or characteristic rules and TESTING them
- is called a learning process, and when it is finished we say that the concept has been learned (and tested) from examples (records in the dataset).

- It is called a supervised learning because we know the concept description and examples.

A small, full set DISCRIMINANT RULES for concepts: buys_comp=yes, buys_comp=no

- The rules are:

  IF *age* = "<=30" AND *student* = "*no*" THEN *buys_computer* = "*no*"

  IF *age* = "<=30" AND *student* = "*yes*" THEN *buys_computer* = "*yes*"

  IF *age* = "31…40" THEN *buys_computer* = "*yes*"

  IF *age* = ">40" AND *credit_rating* = "*excellent*" THEN *buys_computer* = "no"

  IF *age* = "<=30" AND *credit_rating* = "*fair*" THEN *buys_computer* = "yes"

Rules testing

- In order to use rules for testing, and later when testing is done and predictive accuracy is acceptable we write rules in a **predicate form**:

IF *age*(x, <=30) AND *student(x, no*) THEN

buys_computer (x, *no*)

IF *age(x*, <=30) AND *student* (x, *yes*) THEN

buys_computer (x, *yes)*

- Attributes and their values of the new record x are matched with the IF part of the rule and the record is is classified accordingly to the THEN part of the rule.

Test dataset

- The Test Dataset has the same format as the training dataset, i.e. the values of concept attribute are known
- We use it to evaluate the predictive accuracy of our rule
- PREDICTIVE ACCURACY of the set of rules, or any classification algorithm is a percentage of well classified data in the testing dataset.
- If the predictive accuracy is not high enough we chose a different learning and testing datasets and start process again
- There are many methods of testing the rules and they will be discussed later

Genaralization: Classification and Classifiers

- Given a data base table DB with a special atribute C, called a class attribute (or decision attribute). The values: C1, C2, ...Cn of the class atrribute are called class labels.
- Example:

a1	a2	a3	a4	C
1	1	m	g	c1
0	1	v	g	c2
1	0	m	b	c1

Classification and Classifiers

- The attribute C partitions records in the DB i.e. divides records into disjoint subsets defined by the attributes C values, called classes or shortly CLASSIFIES the records. It means we use the attribute C and its values to divide the set R of records od DB into n disjoint classes:

  $C1=\{ r \in DB: \ C=c1\}$ ...... $Cn=\{r \in BD: C=cn\}$

- Example (from our table)

  $C1 = \{ r: c=c1\} = \{r1,r3\}$

  $C2 = \{r: c=c2\}=\{r2\}$

Classification and Classifiers

- An algorithm (model, method) is called a classification algorithm if it uses the data and its classification to build a set of patterns: discriminant and /or characteristic rules or other pattern descriptions. Those patters are structured in such a way that we can use them to classify unknown sets of objects- unknown records.
- For that reason, and because of the goal a classification algorithm is often called shortly a classifier.
- The name classifier implies more then just classification algorithm.
- A classifier is a final product of the data set and a classification algorithm.

Building a Classifier

- Building a classifier consists of two phases:

  training and testing.

- In both phases we use data (training data set and disjoint with it test data set) for which the class labels are known for ALL of the records.
- We use the training data set to create patterns (rules, trees, or to train a Neural or Bayesian network).
- We evaluate created patterns with the use of of test data, which classification is known.
- The measure for a trained classifier accuracy is called predictive accuracy.
- **The classifier is build** i.e. we terminate the process if it has been trained and tested and predictive accuracy was on an acceptable level.

Classification = Supervised Learning (book slide)

- **Classification = Supervised learning goal:**

  Finding models (rules) that describe (characterize) or/ and distinguish (discriminate) classes or concepts for future prediction

  Example: classify countries based on climate, or classify cars based on gas mileage and use it to predict classification of a new car on a base of other attributes

  Presentation: decision-tree, classification rules, neural network

Classification vs. Prediction (book slide)

- Classification:

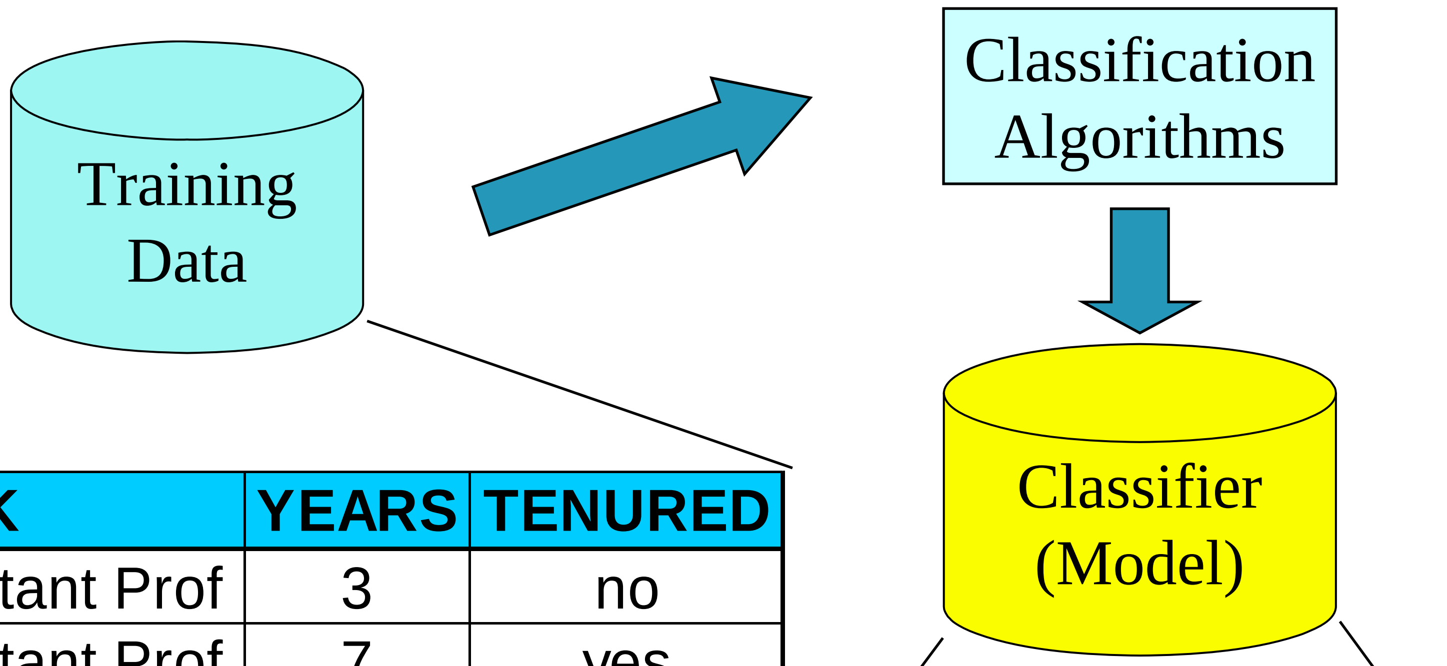
  When a classifier is build it predicts categorical class labels of new data – classifies unknown data. We also say that it predicts class labels of the new data

  Construction of the classifier (a model) is based on a training set in which the values of a decision attribute (class labels) are given and is tested on a test set

- Prediction

  Statistical method that models continuous-valued functions, i.e., predicts unknown or missing values

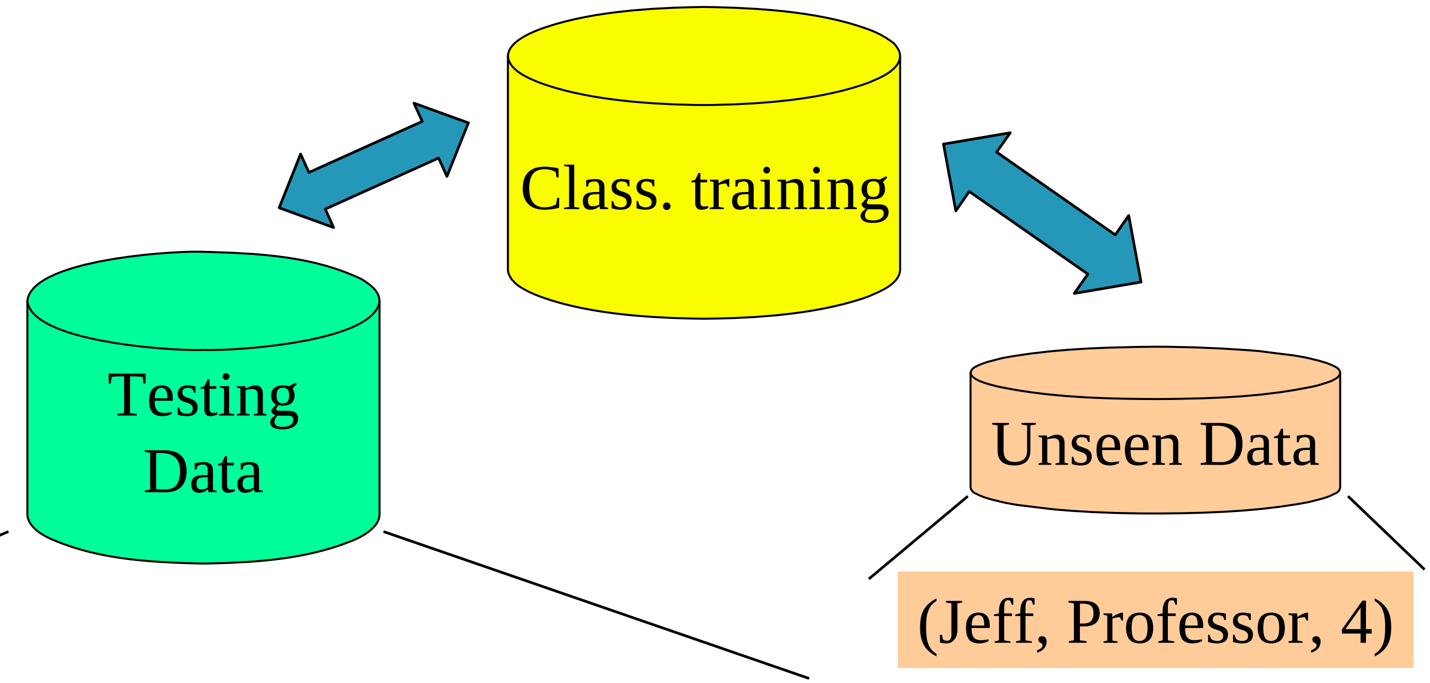
Classification Process : a Classifier (book slide)



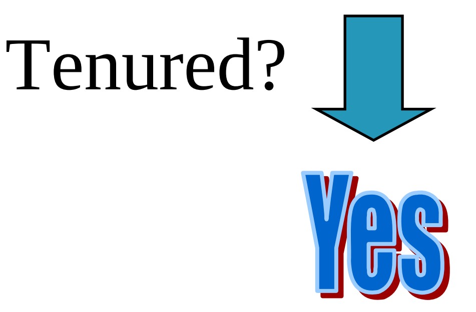
NAME	RANK	YEARS	TENURED
Mike	Assistant Prof	3	no
Mary	Assistant Prof	7	yes
Bill	Professor	2	yes
Jim	Associate Prof	7	yes
Dave	Assistant Prof	6	no
Anne	Associate Prof	3	no

IF rank = ‘professor’
OR years > 6
THEN tenured = ‘yes’

Testing and Prediction (book slide)



NAME	RANK	YEARS	TENURED
Tom	Assistant Prof	2	no
Merlisa	Associate Prof	7	no
George	Professor	5	yes
Joseph	Assistant Prof	7	yes



Classifiers Predictive Accuracy

- PREDICTIVE ACCURACY of a classifier is a percentage of well classified data in the testing data set.

- **Predictive accuracy depends heavily on a choice of the test and training data.**

- There are many methods of choosing test and and training sets and hence evaluating the predictive accuracy. This is a separate field of research.
- Basic methods are presented in TESTING CLASSIFICATION lecture Notes.

Predictive Accuracy Evaluation

The main methods of predictive accuracy evaluations are:

- Re-substitution (N ; N)
- Holdout (2N/3 ; N/3)
- x-fold cross-validation (N-N/x ; N/x)
- Leave-one-out (N-1 ; 1),

where N is the number of instances in the dataset (see separate presentaion)

- **The process of building and evaluating a classifier is also called a supervised learning, or lately when dealing with large data bases a classification method in Data Mining.**

Supervised vs. Unsupervised Learning (book slide)

- **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 a tested classifier

Supervised vs. Unsupervised Learning (book slide)

- **Unsupervised learning (clustering)**

The class labels of training data is unknown

We are given a set of records (measurements, observations, etc.)

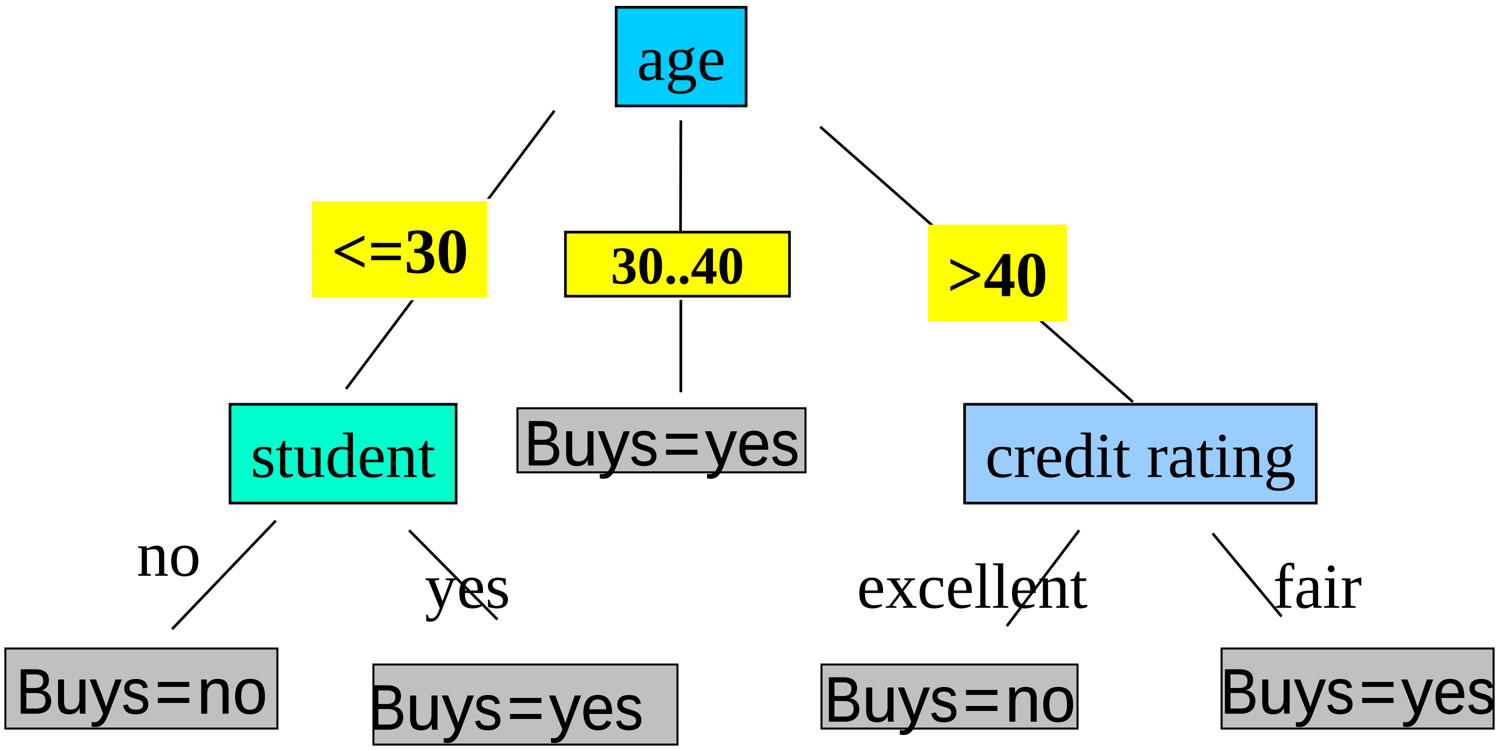
with the aim of establishing the existence of classes or clusters in the data

Part 2: Classification Algorithms (Models, Classifiers)

- Decision Trees (ID3, C4.5)
- Neural Networks
- Bayesian Networks
- Genetic Algorithms
- Rough Sets

PART 2: DECISION TREES:

An Example (book slide)



Classification by Decision Tree Induction

- Decision tree

  A flow-chart-like tree structure

  Internal node denotes an attribute

  Branch represents the values of the node attribute

  Leaf nodes represent class labels or class distribution

Classification by Decision Tree Induction (1)

- **Decision tree generation** consists of two phases

  Tree construction

  - **We choose recursively internal nodes (attributes) with their proper values as branches.**
  - **At start we choose one attribute as the root and put all its values as branches**
  - **We Stop when all the samples (records) are of the same class, then the node becomes the leaf labeled with that class**
  - **or there is no more samples (records) left or we apply MAJORITY VOTING to classify the node.**

  Tree pruning

  - **Identify and remove branches that reflect noise or outliers**

Classification by Decision Tree Induction (2)

Crucial point

Good choice of the root attribute and internal nodes attributes is a crucial point. Bad choice may result, in the worst case in a just another knowledge representation: relational table re-written as a tree with class attributes (decision attributes) as the leaves.

- **Decision Tree Induction Algorithms differ on methods of evaluating and choosing the root and internal nodes attributes.**

Basic Idea of ID3/C4.5 Algorithm (1)

- The basic algorithm for decision tree induction is a greedy algorithm that constructs decision trees in a top-down recursive divide-and – conquer manner.
- The basic strategy is as follows.
- Tree STARTS as a single node representing all training dataset (samples)
- IF the samples are ALL in the same class, THEN the node becomes a LEAF and is labeled with that class

  (or we may apply majority voting or other method to decide the class on the leaf)
- OTHERWISE, the algorithm uses an entropy-based measure known as *information gain* as a heuristic for selecting the ATTRIBUTE that will best separate the samples into individual classes. This attribute becomes the node-name (test, or tree split decision attribute)

Basic Idea of ID3/C4.5 Algorithm (2)

- A branch is created for each value of the node-attribute (and is labeled by this value - this is syntax) and the samples (it means the data table) are partitioned accordingly
- The algorithm uses the same process recursively to form a decision tree at each partition. Once an attribute has occurred at a node, it need not be considered in any other of the node's descendents
- The recursive partitioning **STOPS** only when any one of the following conditions is true.

Basic Idea of ID3/C4.5 Algorithm (3)

- All records (samples) for the given node belong to the same class or
- There are no remaining attributes on which the records (samples) may be further partitioning.
- In this case we convert the given node into a LEAF and label it with the class in majority among samples (*majority voting*)
- There is no records (samples) left – a leaf is created with majority vote for training sample

Training Dataset
(book slide)

This follows an example from Quinlan's ID3

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
30…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

Example: Building The Tree: class attribute “buys”

age

<=30

income	student	credit	class
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

>40

income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

31…40

income	student	credit	class
high	no	fair	yes
low	yes	excellent	yes
medium	no	excellent	yes
high	yes	fair	yes

Example: Building The Tree: we chose “age”

age

<=30

income	student	credit	class
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

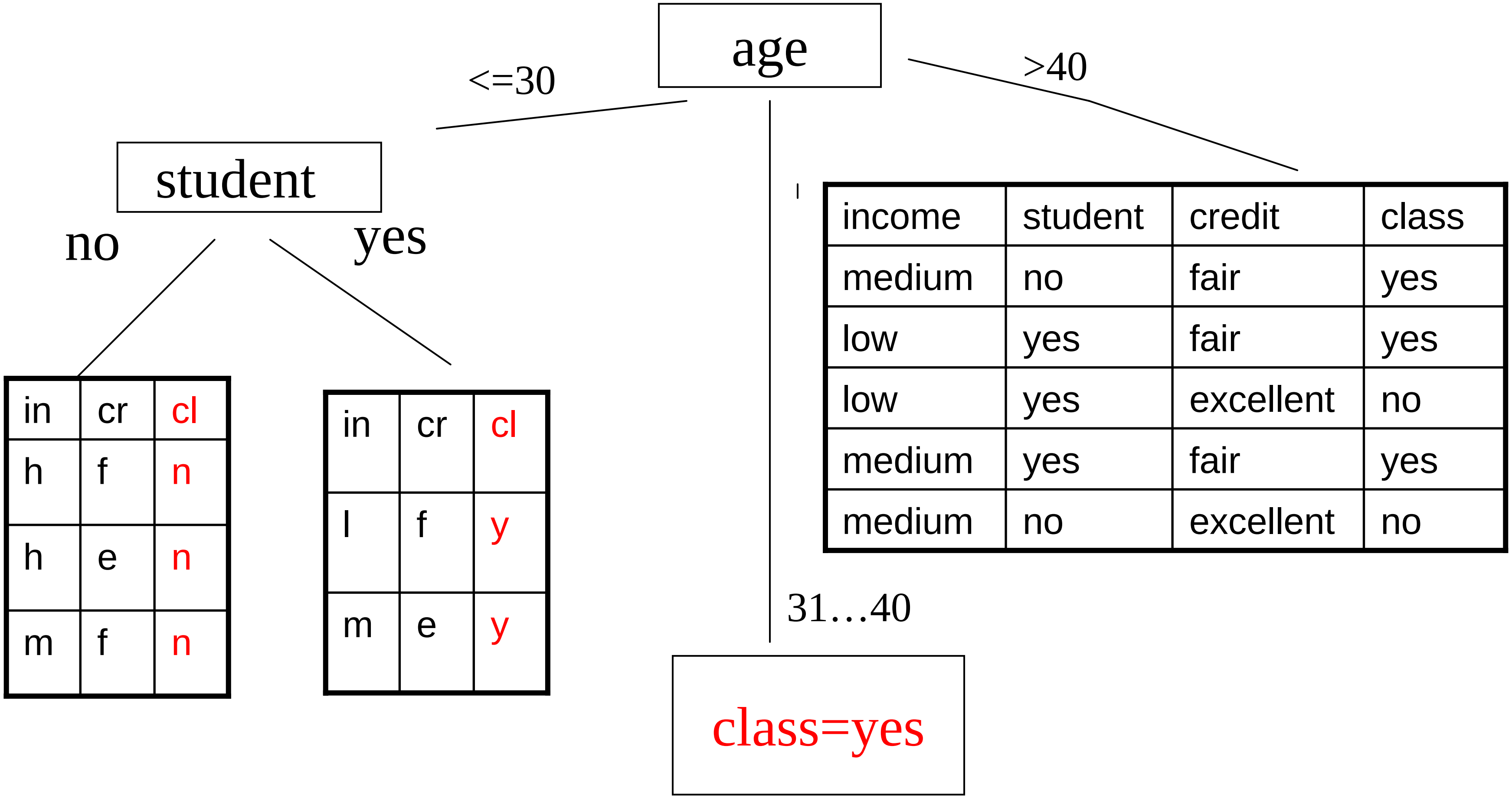
31…40

class=yes

>40

income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Example: Building The Tree: we chose “student” on <=30 branch

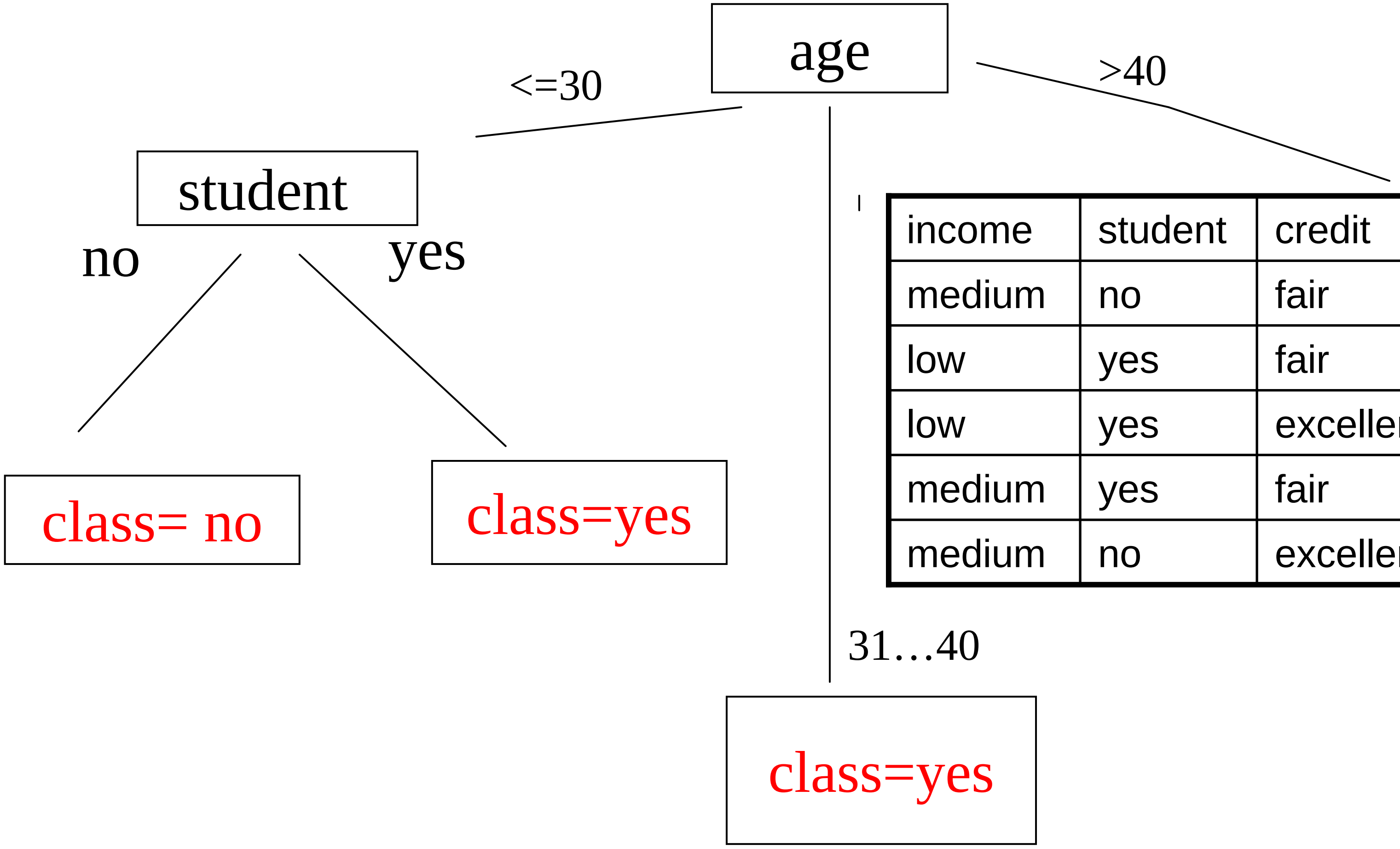


in	cr	cl
h	f	n
h	e	n
m	f	n

in	cr	cl
l	f	y
m	e	y

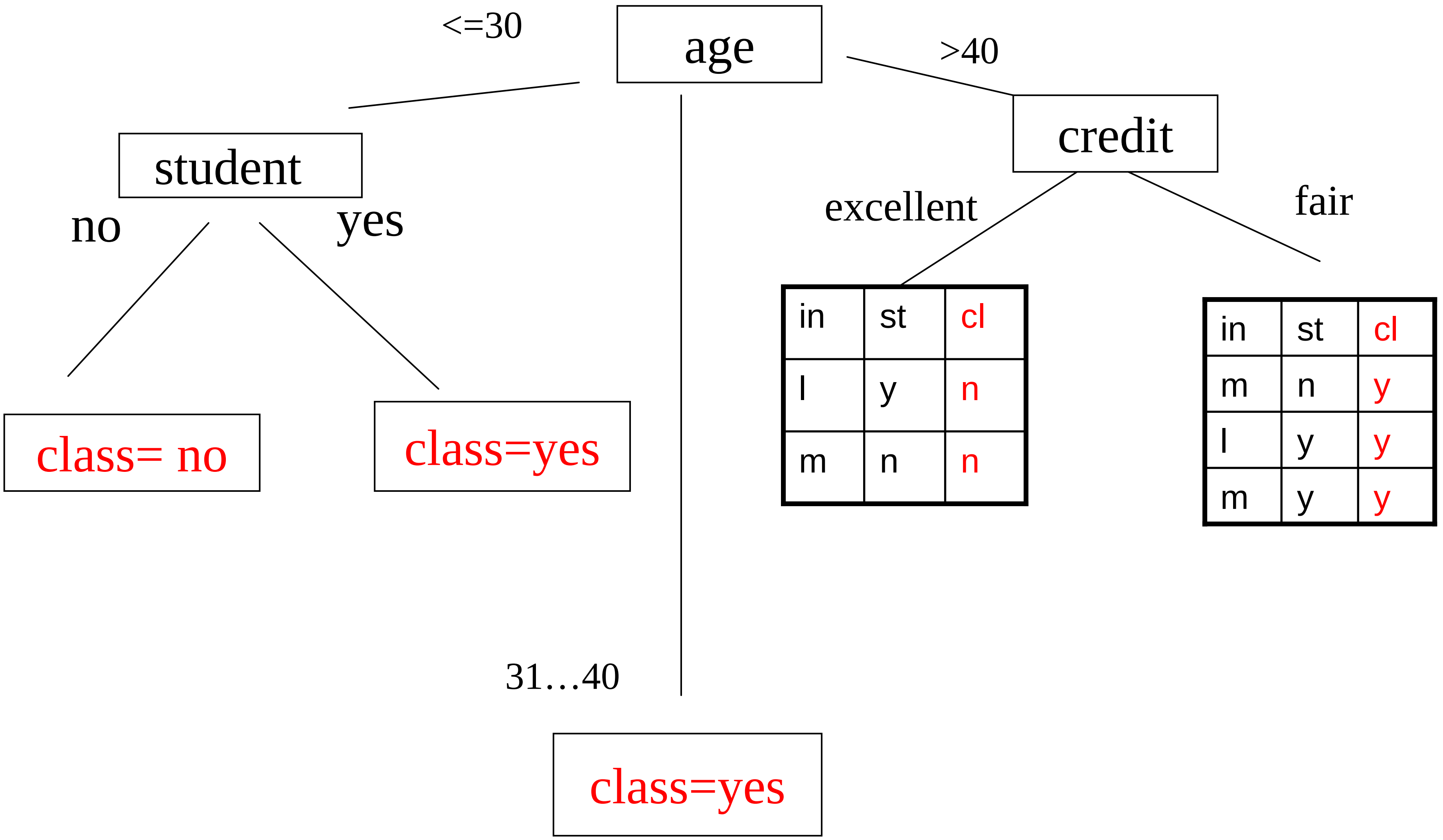
income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Example: Building The Tree: we chose “student” on <=30 branch



income	student	credit	class
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Example: Building The Tree: we chose “credit” on >40 branch



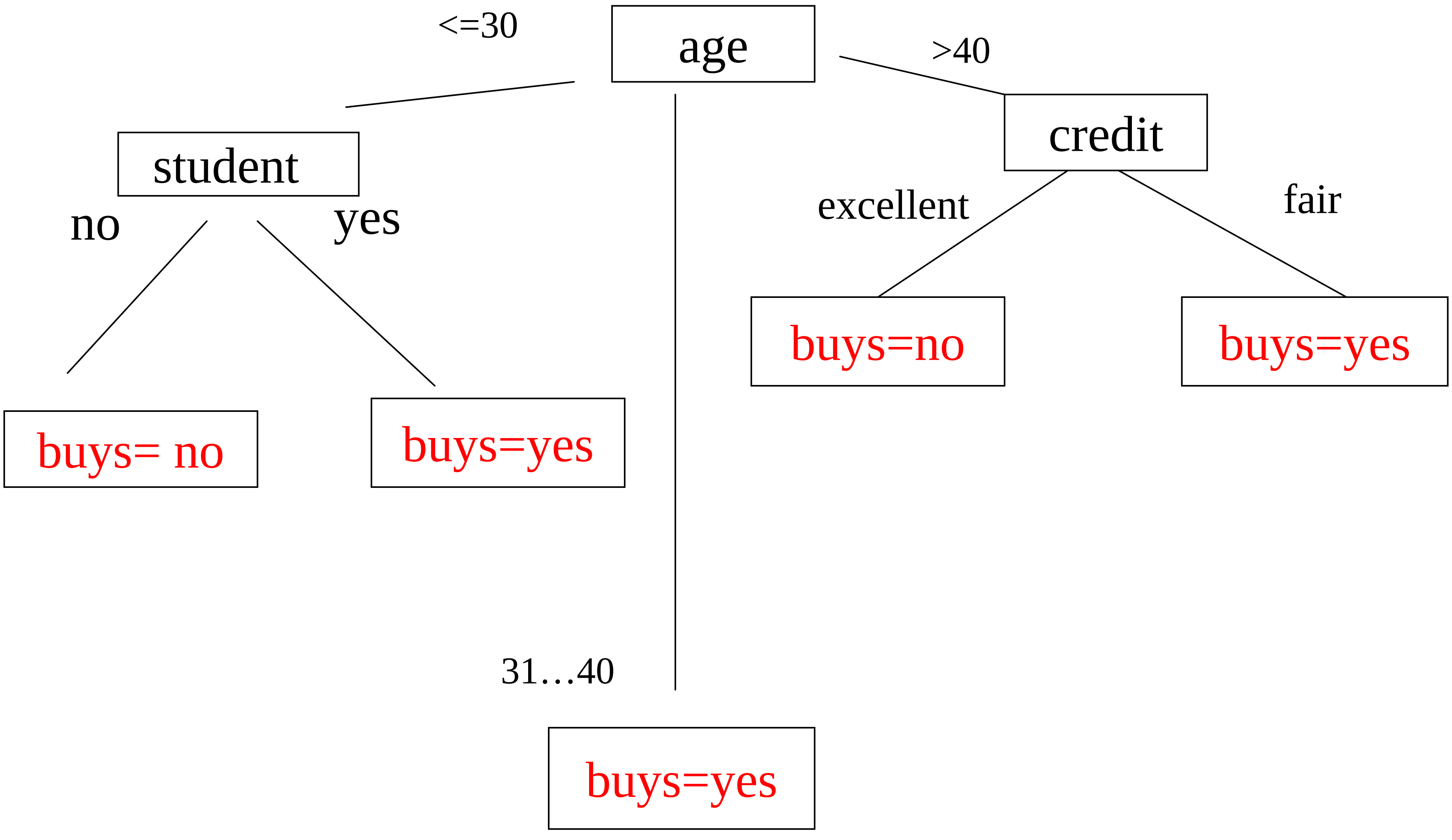
excellent

in	st	cl
l	y	n
m	n	n

fair

in	st	cl
m	n	y
l	y	y
m	y	y

Example: Finished Tree for **class="buys"**



Heuristics: Attribute Selection Measures

- Construction of the tree depends on the order in which root attributes are selected.
- Different choices produce different trees; some better, some worse
- Shallower trees are better; they are the ones in which classification is reached in fewer levels.
- These trees are said to be more efficient as the classification, and hence termination is reached quickly

Attribute Selection Measures

- Given a training data set (set of training samples) there are many ways to choose the root and nodes attributes while constructing the decision tree
- **Some possible choices:**
- Random
- Attribute with smallest/largest number of values
- Following certain order of attributes
- We present here a special order: information gain as a measure of the goodness of the split
- The attribute with the highest information gain is always chosen as the split decision attribute for the current node while building the tree.

Information Gain Computation (ID3/C4.5): Case of Two Classes

- **Assume there are two classes, *P* (positive) and *N* (negative)**

Let S be a training data set consisting of s examples (records): $|S|=s$

And S contains p elements of class P and n elements of class N

The amount of information, needed to decide if an arbitrary example (record) in S belongs to P or N is defined as

$$I(p,n) = -\frac{p}{p+n}\log_2\frac{p}{p+n} - \frac{n}{p+n}\log_2\frac{n}{p+n}$$

Information Gain Measure

- Assume that using attribute **A** a set S will be partitioned into sets $\{S_1, S_2, \ldots, S_v\}$ (v is number of values of the attribute A)

  If S_i contains p_i examples of P and n_i examples of N, the entropy E(**A**), or the expected information needed to classify objects in all sub-trees S_i is

$$E(A) = \sum_{i=1}^{v} \frac{p_i + n_i}{p + n} I(p_i, n_i)$$

- The encoding information that would be gained by branching on A

$$Gain(A) = I(p, n) - E(A)$$

Example: Attribute Selection by Information Gain Computation (book slide)

- **Class P: buys_computer = "yes"**
- **Class N: buys_computer = "no"**
- **I(p, n) = I(9, 5) =0.940**
- **Compute the entropy for**

age	p_i	n_i	$I(p_i, n_i)$
<=30	2	3	0.971
30…40	4	0	0
>40	3	2	0.971

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

Hence

$$Gain(age) = I(p, n) - E(age)$$

Gain(age)=0.246

Similarly

$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

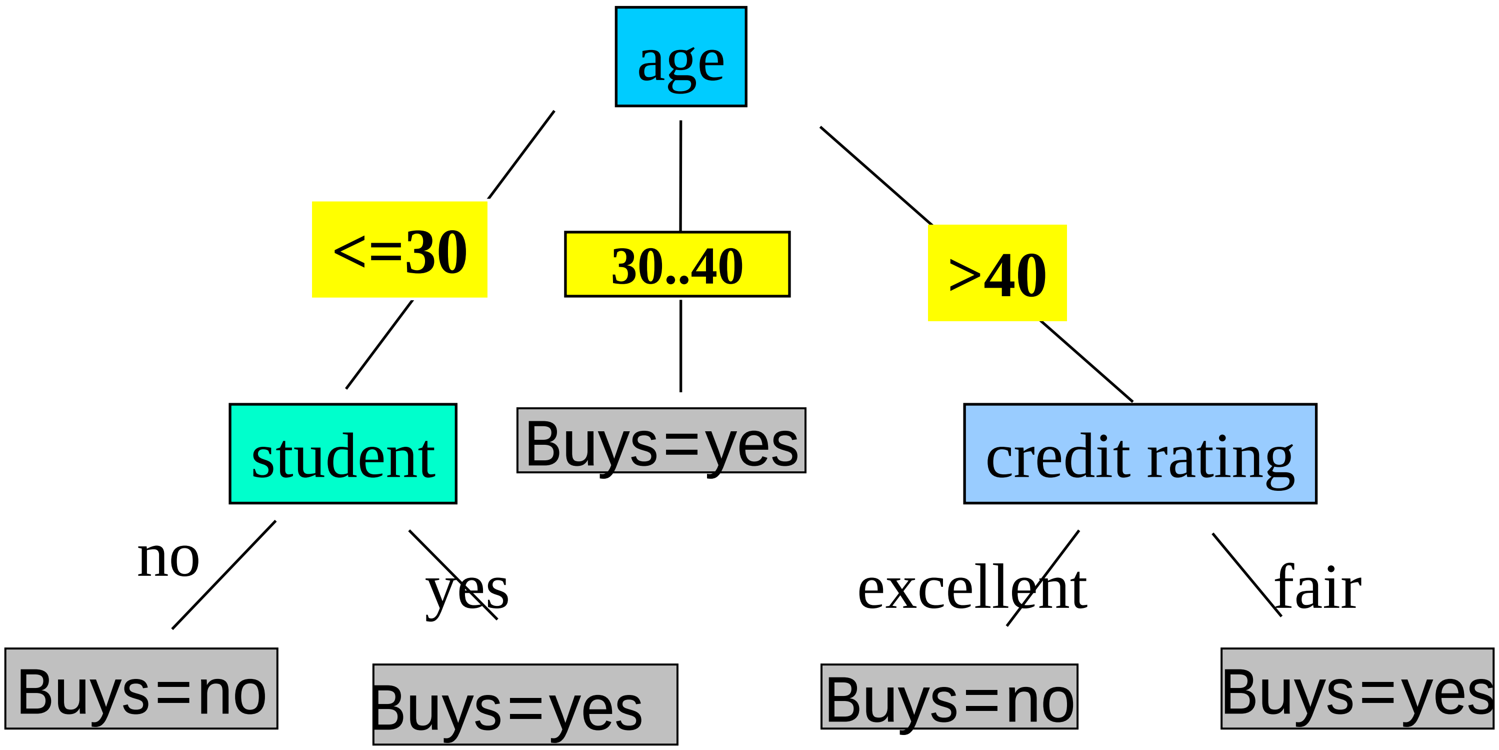
$$Gain(credit\_rating) = 0.048$$

The attribute "age" becomes the root.

Extracting Classification Rules from Trees

- Goal: Represent the knowledge in the form of IF-THEN rules
- One rule is created for each path from the root to a leaf
- Each attribute-value pair along a path forms a conjunction
- The leaf node holds the class prediction
- Rules are easier for humans to understand

The tree to extract rules from (book slide)



Extracting Classification Rules from Trees

- The rules are:

IF *age* = "<=30" AND *student* = "*no*" THEN *buys_computer* = "*no*"

IF *age* = "<=30" AND *student* = "*yes*" THEN *buys_computer* = "*yes*"

IF *age* = "31…40" THEN *buys_computer* = "*yes*"

IF *age* = ">40" AND *credit_rating* = "*excellent*" THEN *buys_computer* = "no"

IF *age* = "<=30" AND *credit_rating* = "*fair*" THEN *buys_computer* = "yes"

Rules format for testing and applications

- In order to use rules for testing, and later when testing is done and predictive accuracy is acceptable we write rules in a predicate form:

IF *age*(x, <=30) AND *student(x, no*) THEN

buys_computer (x, *no*)

IF *age(x*, <=30) AND *student* (x, *yes*) THEN

buys_computer (x, *yes)*

- Attributes and their values of the new record x are matched with the IF part of the rule and the record is is classified accordingly to the THEN part of the rule.