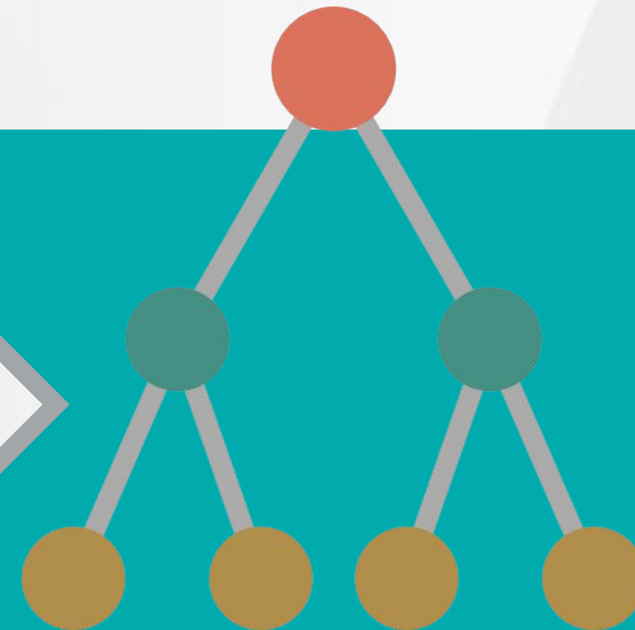
203105453 – Data Mining & Business Intelligence

Unit-6
Classification and Prediction



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Outline

- Introduction to classification
- Classification & prediction issues
- Classification methods
- Prediction methods

Introduction to classification

- Classification is a **supervised learning method.**
- It is a data mining function that **assigns items in a collection to target categories or classes**.
- The **goal of classification** is to **accurately predict the target class** for each case in the data.
- **For example**, a classification model could be used to identify loan applicants as low, medium, or high credit risks.
- In supervised learning, the learner(computer program) is provided with two sets of data, **training data set** and **test data set**.
- The idea is for the learner to “learn” from a set of labeled examples in the training set so that it can identify **unlabeled examples** in the **test set with the highest possible accuracy**.

Introduction to classification (Cont..)

- Suppose a Database D is given as **D = {t1,t2,..tn}** and a set of desired classes are **C={C1,…,Cm}.**

- The **classification problem** is to define the mapping m in such a way that which tuple of database **D belongs to which class of C**.

- Actually we divides D into **equivalence classes.**

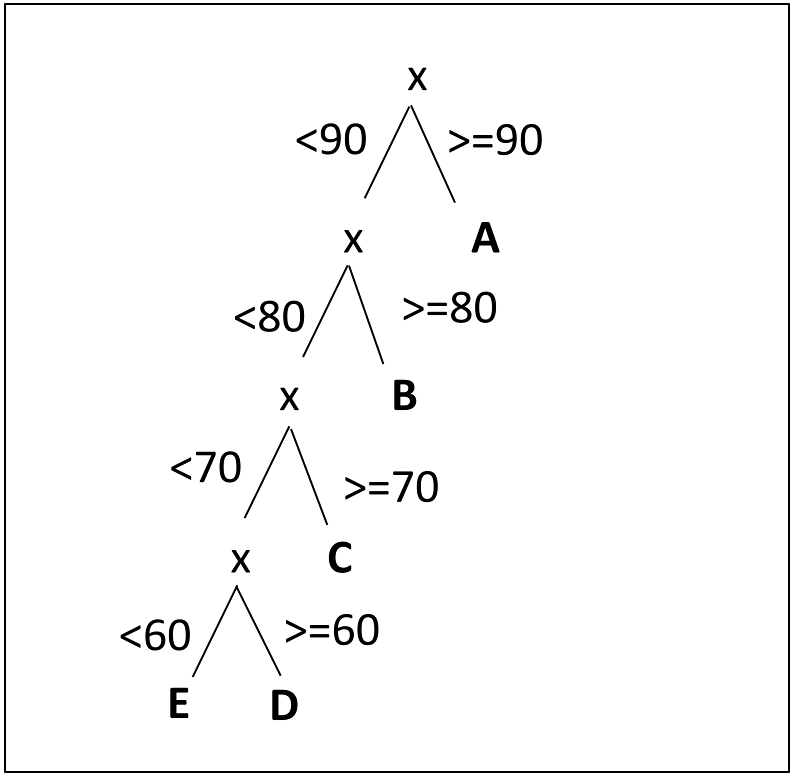
- **Prediction** is similar, but it viewed as **having infinite number of classes**.

Classification Example

- Teachers **classify** students grades as **A,B,C,D or E**.
- Identify individuals with **credit risks** (high, low, medium or unknown).
- In **cricket** (batsman, bowler, all-rounder)
- **Websites** (educational, sports, music)

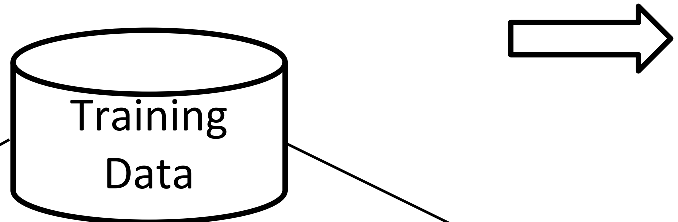
Classification Example (Cont..)

- How teachers give grades to students based on their obtained marks?
  - If x >= 90 then **A** grade.
  - If 80 <= x < 90 then **B** grade.
  - If 70 <= x < 80 then **C** grade.
  - If 60 <= x < 70 then **D** grade.
  - If x < 60 then **E** grade.

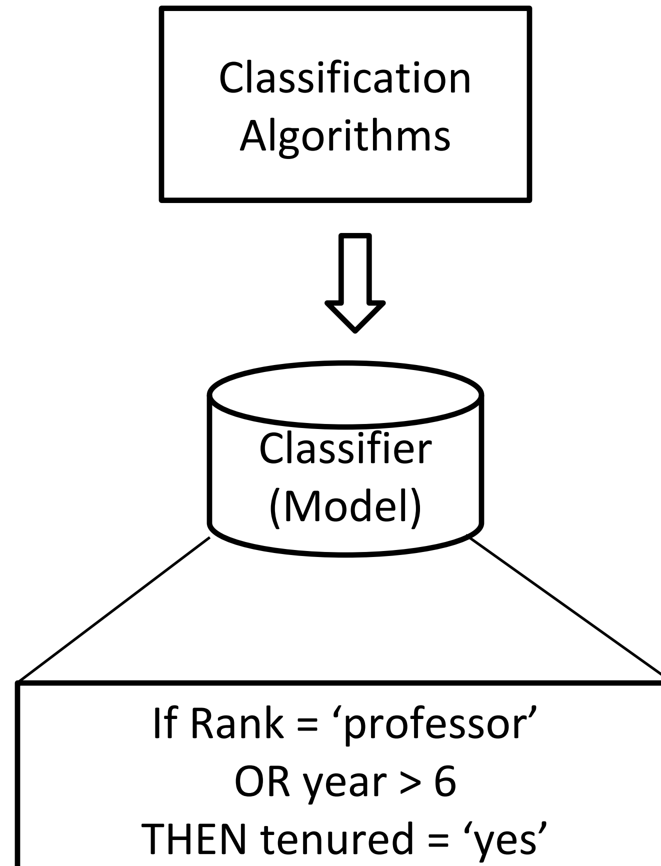


Classification : a two step process

1) Model Construction

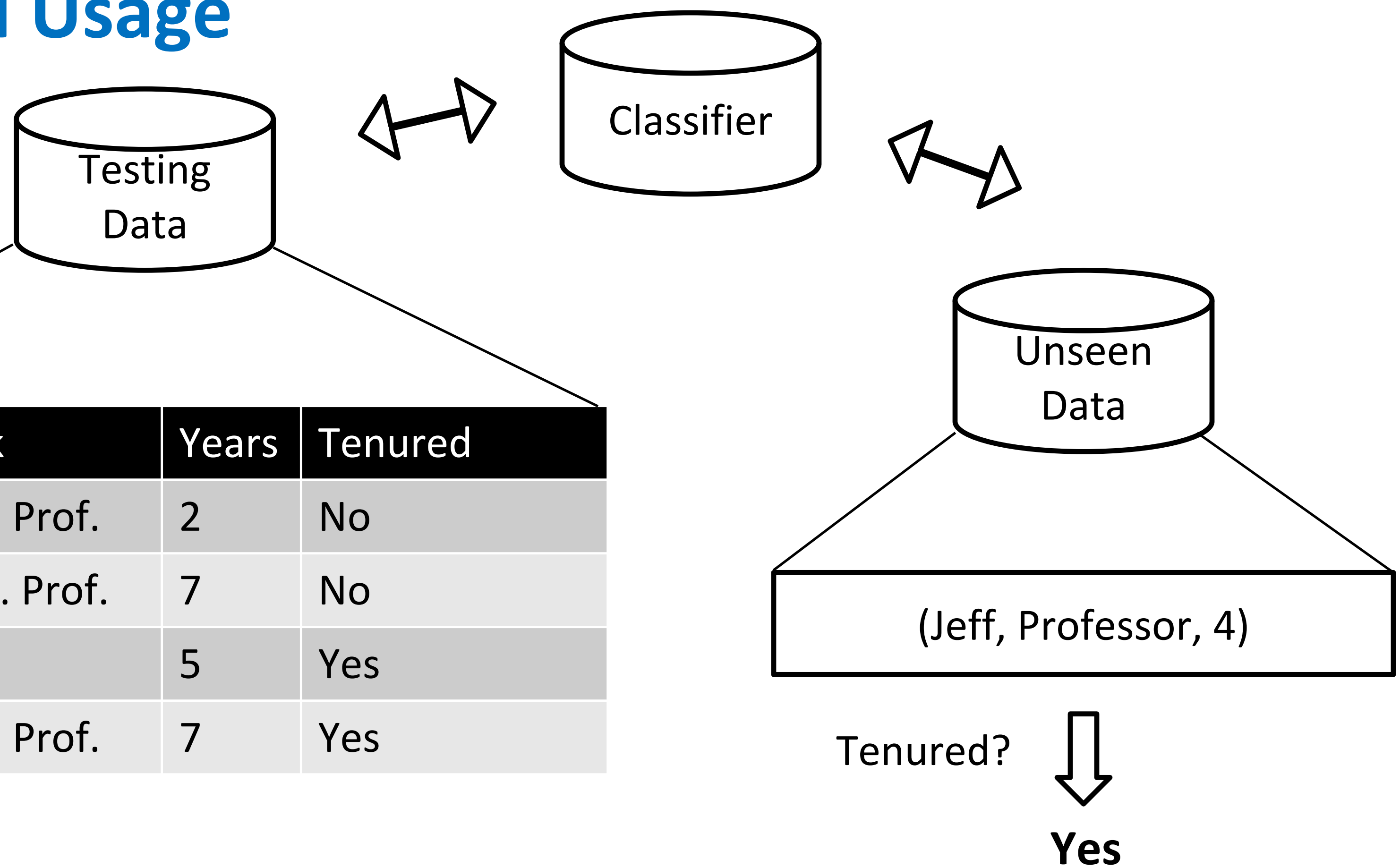


Name	Rank	Years	Tenured
Mike	Asst. Prof.	3	No
Mary	Asst. Prof.	7	Yes
Bill	Prof.	2	Yes
Jim	Asso. Prof.	7	Yes
Dave	Asst. Prof.	6	No
Anne	Asso. Prof.	3	No



Classification : a two step process (Cont..)

2) Model Usage



Name	Rank	Years	Tenured
Tom	Asst. Prof.	2	No
Merlisa	Asso. Prof.	7	No
George	Prof.	5	Yes
Joseph	Asst. Prof.	7	Yes

Classification : a two step process (Cont..)

1) **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 called as **training set**.
  - The model is represented as **classification rules**, **decision trees**, **or mathematical formulae**.

2) **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.

Classification & prediction issues

<u>Data Preparation</u>

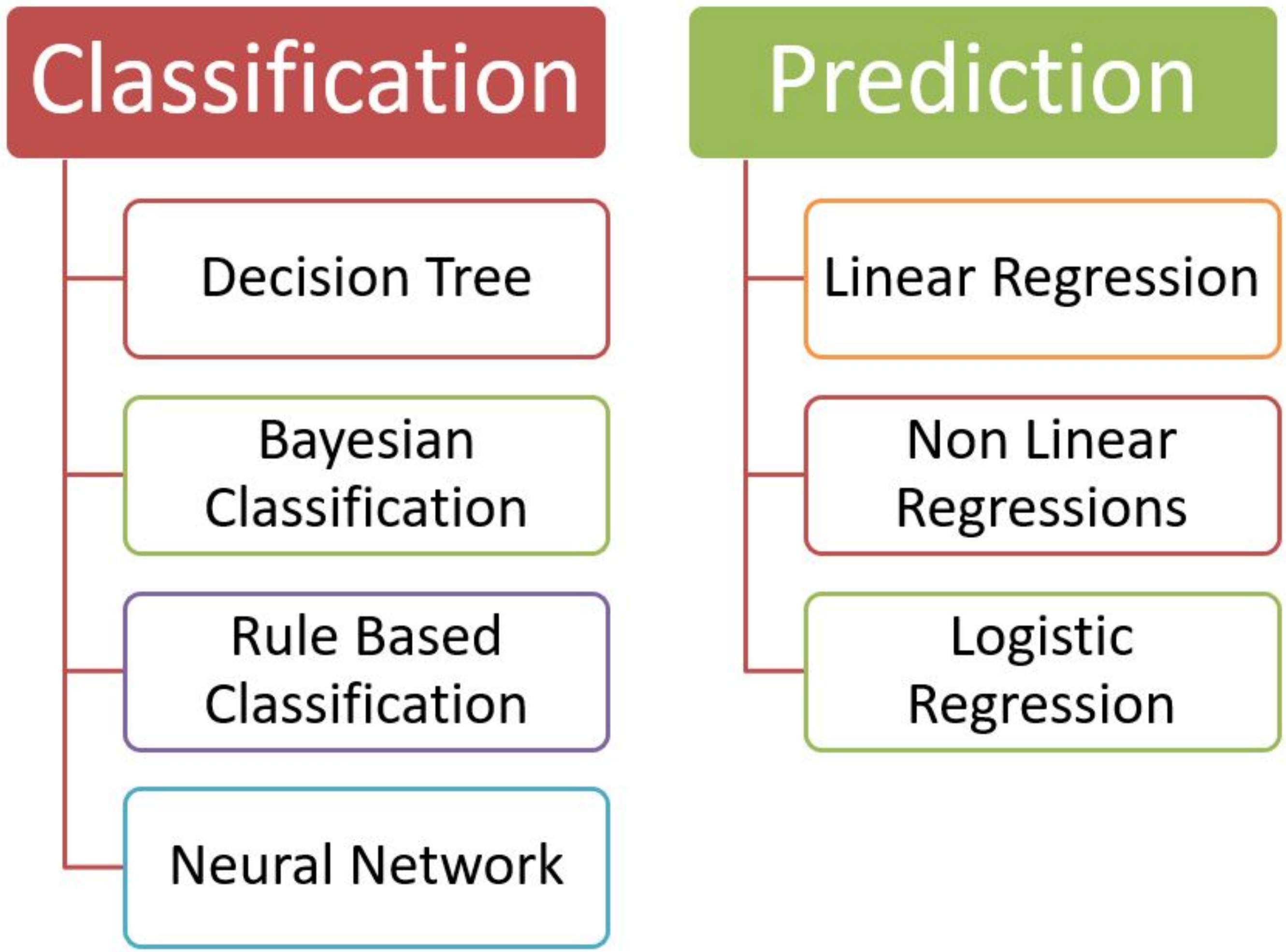
- **Data cleaning**
  - **Pre-process data** in order to **reduce noise and handle missing values**.
- **Relevance analysis** (Feature selection)
  - **Remove** the irrelevant or **redundant attributes**.
- **Data transformation**
  - Generalize the data to higher level concepts using **concept hierarchies** and/or normalize data which involves scaling the values.

Classification & prediction issues (Cont..)

Evaluating Classification Methods

- **Predict accuracy**
  - This refers the ability of the model **to correctly predict the class** label of new or previously unseen data.
- **Speed and scalability**
  - Time to **construct** model
  - Time to **use** the model
- **Robustness**
  - Handling noise and missing values
- **Interpretability**
  - Understanding and insight provided by model
- **Goodness of rules**
  - Decision **tree size**
  - Strongest rule or not

Classification & prediction methods



Decision tree

- One of the most **common tasks is to build models** for the prediction of the class of an object on the basis of its attributes.

- The objects can be seen as a customer, patient, transaction, e-mail message or even a single character.

- **Attributes of patient object** can be heart rate, blood pressure, weight and gender etc.

- The class of the patient object would most commonly be **positive/negative** for a certain **disease**.

Decision tree (Cont..)

- In decision tree are represented by a **fixed set of attributes** (e.g. gender) and their values (e.g. male, female) described as **attribute-value pairs**.

- If the attribute has **small** number of **disjoint possible values** (e.g. high, medium, low) or there are only two possible classes (e.g. true, false) then decision tree learning is easy.

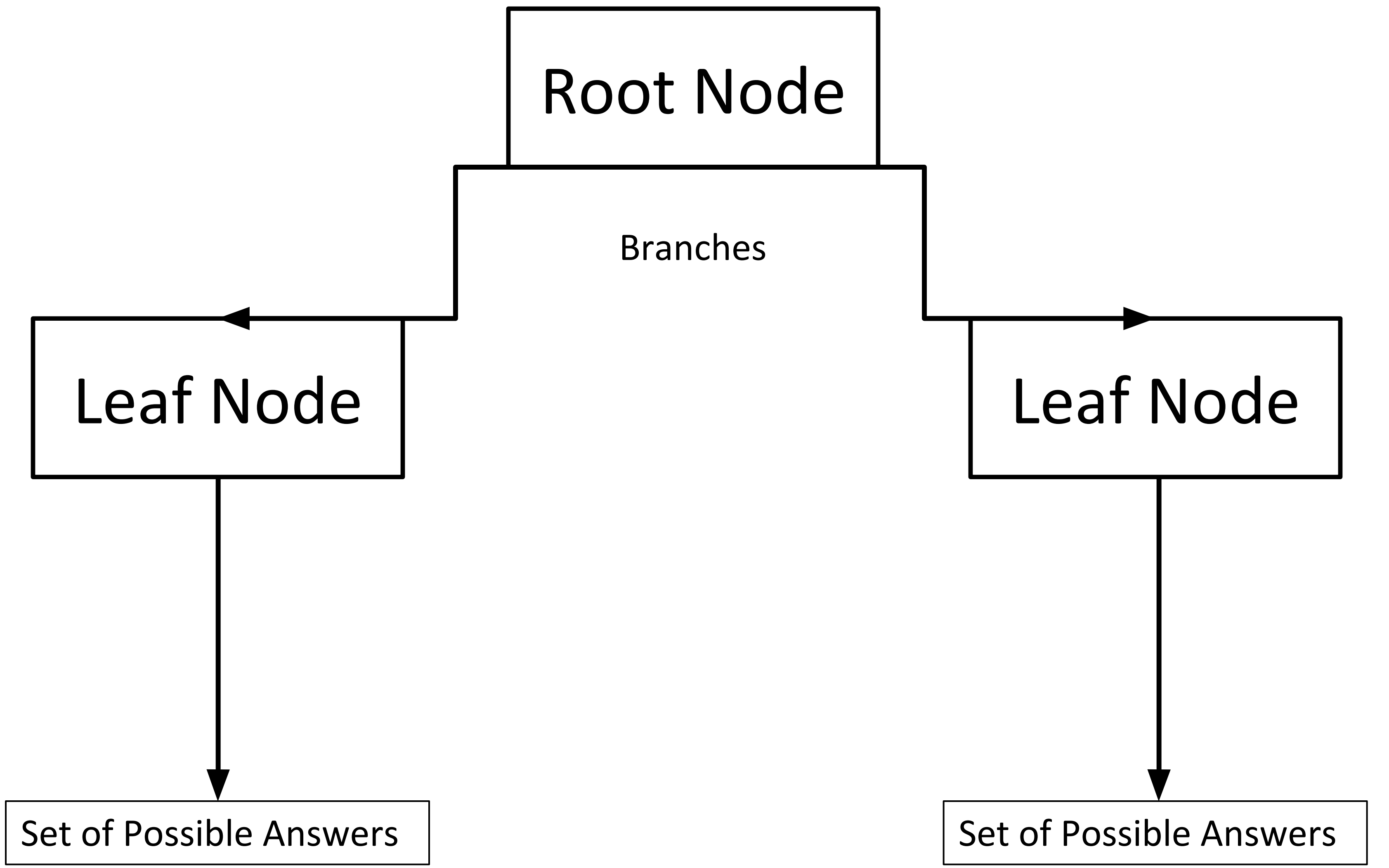
- Extension to decision tree algorithm also handles real value attributes (e.g. salary).

- It gives a class label to each instance of dataset.

Decision tree (Cont..)

- Decision tree is a classifier in the form of a tree structure
  - **Decision node**: Specifies a test on a single attribute
  - **Leaf node**: Indicates the value of the target attribute
  - **Arc/edge**: Split of one attribute
  - **Path**: A disjunction of test to make the final decision

Decision tree representation- example



Key requirements for classification

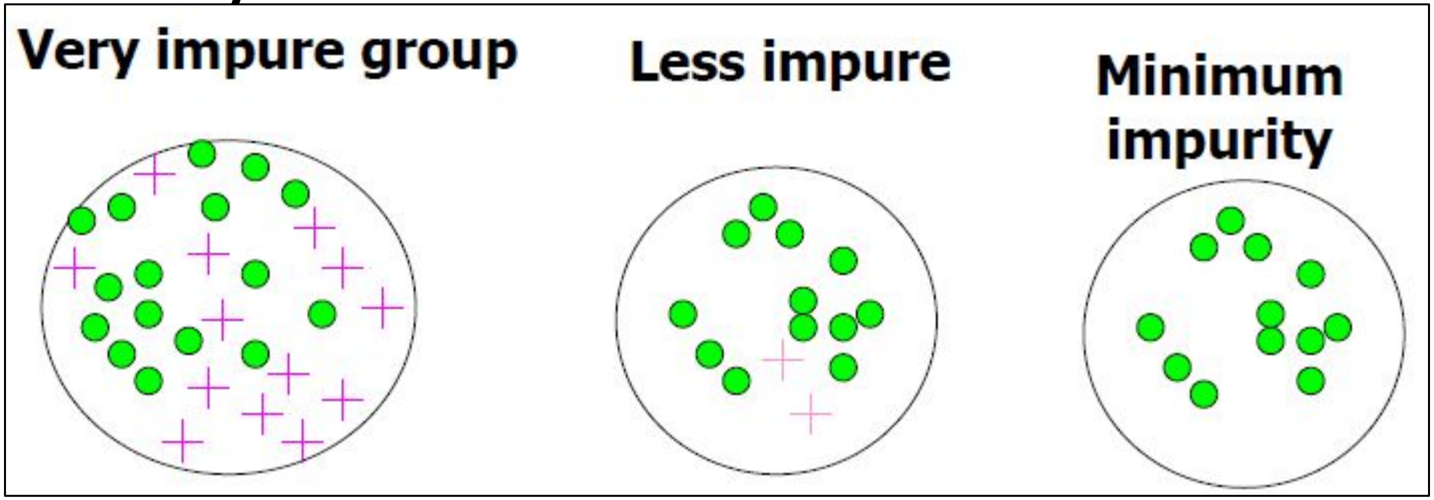
- **Sufficient data:**
  - **Enough training cases** should be provided to learn the model.
- **Attribute-value description:**
  - **Object** or case must be expressible in terms of a **fixed collection of properties or attributes** (e.g., hot, mild, cold).
- **Predefined classes (target values):**
  - The target function has **discrete output values** (boolean or multiclass)

Important terms for decision tree

- **Entropy**
- **Information Gain**
- **Gini Index**

Entropy (E)

- It defines the **certainty of a decision**
  - **1** if **completely certain**,
  - **0** if **completely uncertain**,
  - Normally data remains between 0 to 1 as entropy, a probability-based measure used to **calculate the amount of uncertainty**.



Entropy (E) (Cont..)

- It measures that of **how much information we don't know** (how uncertain we are about the data).

- It can be also **used to measure how much information** we gain from an attribute when the target attribute is revealed to us.

- **Which attribute is best?**

  - The attribute with the **largest expected reduction in entropy** is the 'best' attribute to use next.

  - Because if we have a large expected reduction it means taking away that attribute has a big effect, meaning it must be very certain.

Entropy (E) (Cont..)

- A decision tree is built **top-down** from a root node and involves partitioning the data into subsets that contain instances with similar values (homogenous).
- ID3 algorithm uses entropy to calculate the homogeneity of a sample.
- If the sample is completely homogeneous the entropy is zero and if the sample is an equally divided it has entropy of one.

Information Gain

- Information gain can be used for **continues-valued** (numeric) **attributes**.
- The attribute which has the **highest information gain** is selected **for split**.
- Assume, that there are two classes P(positive) & N(negative).
- Suppose we have **S** samples, out of these **p** samples belongs to **class P** and **n** samples belongs to **class N**.
- The amount of information, needed to decide split in S belongs to P or N & that is defined as

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

Gini Index

- Assume there exist several possible split values for each attribute.
- We may need other tools, such as clustering, to get the possible split values.
- It can be modified for categorical attributes.
- An alternative method to information gain is called the **Gini Index.**
- Gini is used in CART (Classification and Regression Trees).
- If a dataset T Contains examples from n classes, gini index, gini(T) is defined as

$$\text{Gini (T)} = 1 - \sum_{j=1}^{n} {p_j}^2$$

  - **n**: the number of classes
  - **pj**: the probability that a tuple in D belongs to class Ci

Gini Index (Cont..)

- After splitting T into two subsets T1 and T2 with sizes N1 and N2, the gini index of the split data is defined as

$$\mathbf{Gini_{split}\ (T)} = \frac{N_1}{N}\ \mathrm{gini}\ (T_1) + \frac{N_2}{N}\ \mathrm{gini}\ (T_2)$$

Example – ID3

Age	Income	Student	Credit_Rating	Class : 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

Solution – ID3

- **Class P** : buys_computer = “Yes” (9 records)
- **Class N** : buys_computer = “No” (5 records)
- Total number of Records **14**.
- Now, Information Gain = I (p,n)

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

$$I(9,5) = -\frac{9}{14}\log_2\frac{9}{14} - \frac{5}{14}\log_2\frac{5}{14}$$

$$\boxed{I(9,5) = 0.940}$$

Solution – ID3 (Age <=30,31..40,>40)

Age	Income	Student	Credit_Rating	Buys_Computer
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
<=30	Medium	No	Fair	No
<=30	Low	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes

Age	Income	Stu.	Cr_Rating	Buys
31..40	High	No	Fair	Yes
31..40	Low	Yes	Excellent	Yes
31..40	Medium	No	Excellent	Yes
31..40	High	Yes	Fair	Yes

Age	Income	Stu.	Cr_Rating	Buys
>40	Medium	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	No	Excellent	No
>40	Medium	Yes	Fair	Yes
>40	Medium	No	Excellent	No

Solution – ID3 (Age <=30)

- Compute the information gain & Entropy For Age **<=30**,
  - Pi = Yes class = 2
  - Ni = No class = 3

So, Information Gain = I (p,n)

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

$$\mathrm{I}(2,3) = -\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}$$

$$\boxed{\mathrm{I}(2,3) = 0.971}$$

Solution – ID3

Age	Pi	Ni	I (Pi , Ni)
<=30	2	3	0.971
31..40	4	0	0
>40	3	2	0.971

- So the expected information needed to classify a given sample if the samples are partitioned according to age is,
- Calculate entropy using the values from the Table and the formula given below:

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

$$\boxed{E(\text{Age}) = \frac{5}{14} I\ (2,3)\ + \frac{4}{14} I\ (4,0) + \frac{5}{14} I\ (3,2)}$$

$$\boxed{E(\text{Age}) = 0.694}$$

Solution – ID3

Gain (Age) = I (p, n) – E (Age)

= 0.940 – 0.694

= 0.246

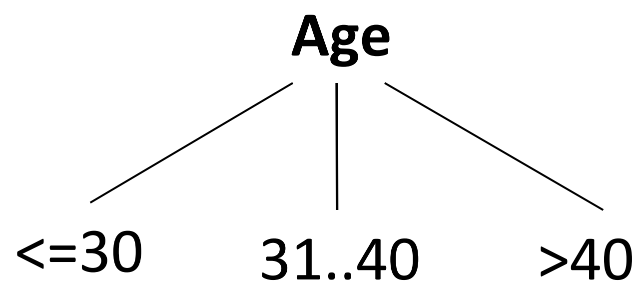
Similarly,

Gain	value
Gain (age)	0.246
Gain (income)	0.029
Gain (student)	0.151
Gain (credit_rating)	0.048

So, here we start decision tree with root node **Age**.

Solution – ID3

- Now the age has highest information gain among all the attributes, so select age as test attribute and create the node as age and show all possible values of age for further splitting.



Solution – ID3 (Age <= 30)

Age	Income	Student	Credit_Rating	Buys_Computer
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
<=30	Medium	No	Fair	No
<=30	Low	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes

Solution – ID3 (Age <=30)

- Compute Information gain & Entropy for Age with sample S<=30.
- For age <=30,
  - Pi = Yes = 2
  - Ni = No = 3

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

$$I(2,3) = -\frac{2}{5} log_2 \frac{2}{5} - \frac{3}{5} log_2 \frac{3}{5}$$

$$\boxed{I(3,2) = 0.971}$$

Solution – ID3 (Age <= 30, Income)

Income	Pi	Ni	I (Pi , Ni)
High	0	2	0
Medium	1	1	1
Low	1	0	0

In above table high (0,2) homogeneous so I(0,2) = 0, Medium equal portion so I(1,1) = 1 & Low I(1,0) = 0.

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

$$E(\text{Income}) = \frac{2}{5} I\ (0,2) + \frac{2}{5} I\ (1,1) + \frac{1}{5} I\ (1,0)$$

$$\boxed{E(\text{Income}) = 0.4}$$

Gain ($S_{<=30}$,Income)

= I (p, n) – E (Income)

= 0.971 – 0.4

= 0.571

Solution – ID3 (Age <= 30, Student)

student	Pi	Ni	I (Pi , Ni)
No	0	3	0
Yes	2	0	0

In above table I (0,3) = 0 & I (2,0) = 0 So E(Student) is 0.

$$\boxed{E(\text{Student}) = 0}$$

Gain (S<=30,Student) = I (p,n) – E(Student)

= 0.971 – 0

= 0.971

Solution – ID3 (Age <= 30,

credit_rating	Pi	Ni	I (Pi , Ni)
Fair	1	2	0.918
Excellent	1	1	1

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

$$\mathrm{E(credit\_rating)} = \frac{3}{5}\,\mathrm{I}\ (1,2) + \frac{2}{5}\,\mathrm{I}\ (1,1)$$

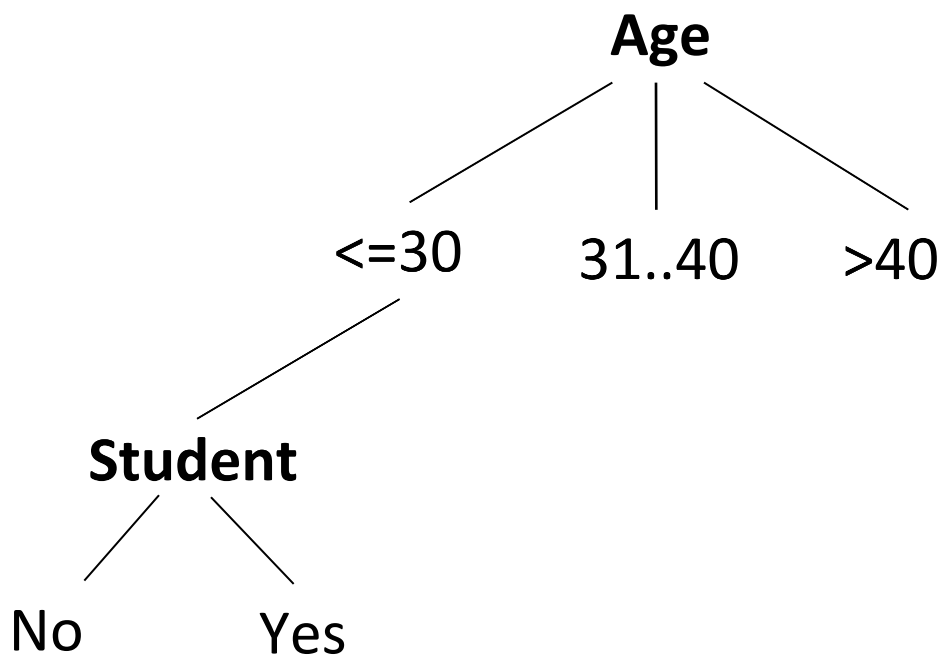
$$\boxed{\mathrm{E(credit\_rating)} = 0.951}$$

Gain ($S_{<=30}$,credit_rating) = I (p, n) – E (credit_rating)
= 0.971 – 0.951
= 0.020

Solution – ID3 (Age <=30)

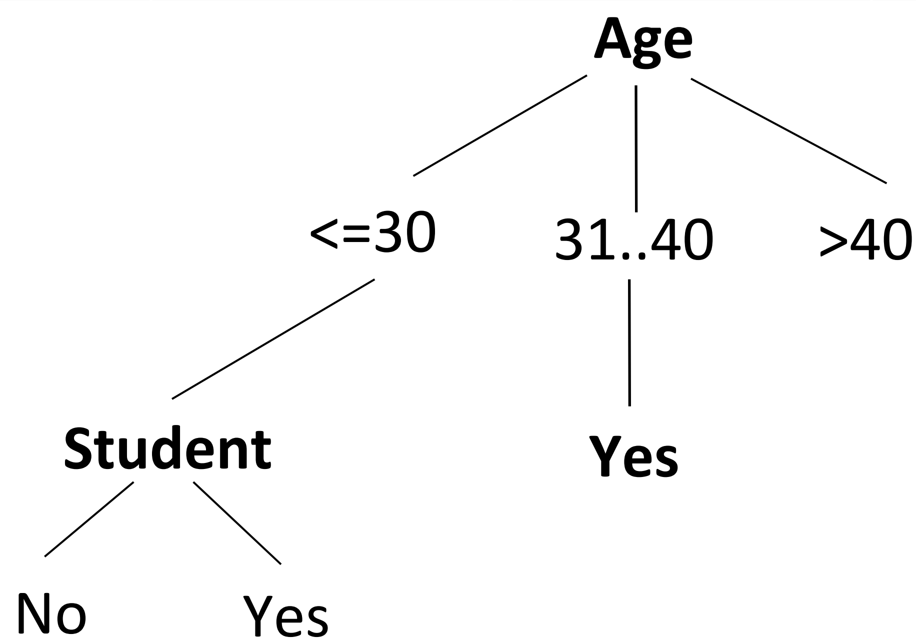
Gain (Age <= 30)	value
Income	0.571
Student	0.971
Credit_rating	0.020

As shown in table we get maximum gain for student so, select **student** as leaf node for age <=30



Solution – ID3 (Age 31..40)

Age	Income	Student	Credit_Rating	Buys_Computer
31..40	High	No	Fair	**Yes**
31..40	Low	Yes	Excellent	**Yes**
31..40	Medium	No	Excellent	**Yes**
31..40	High	Yes	Fair	**Yes**



Solution – ID3 (Age > 40)

Age	Income	Student	Credit_Rating	Buys_Computer
>40	Medium	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	No	Excellent	No
>40	Medium	Yes	Fair	Yes
>40	Medium	No	Excellent	No

Solution – ID3 (Age > 40)

- Compute Information gain for Age with sample S>40.
- For age > 40,
  - Pi = Yes = 3
  - Ni = No = 2

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

$$I(3,2) = -\frac{3}{5} log_2 \frac{3}{5} - \frac{2}{5} log_2 \frac{2}{5}$$

$$\boxed{I(3,2) = 0.971}$$

Solution – ID3 (Age > 40, Income)

Income	Pi	Ni	I (Pi , Ni)
High	0	0	0
Medium	2	1	0.918
Low	1	1	1

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

$$E(\text{Income}) = \frac{0}{5} I(0,0) + \frac{3}{5} I(2,1) + \frac{2}{5} I(1,1)$$

$$\boxed{E(\text{Income}) = 0.951}$$

Gain (S>40,Income)

= I (p, n) – E (Income)

= 0.971 – 0.951

= 0.020

Solution – ID3 (Age > 40, credit_rating)

Credit_rating	Pi	Ni	I (Pi , Ni)
Fair	3	0	0
Excellent	0	2	0

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

$$E(\text{credit\_rating}) = \frac{3}{5} I\ (3{,}0) + \frac{2}{5} I\ (0{,}2)$$

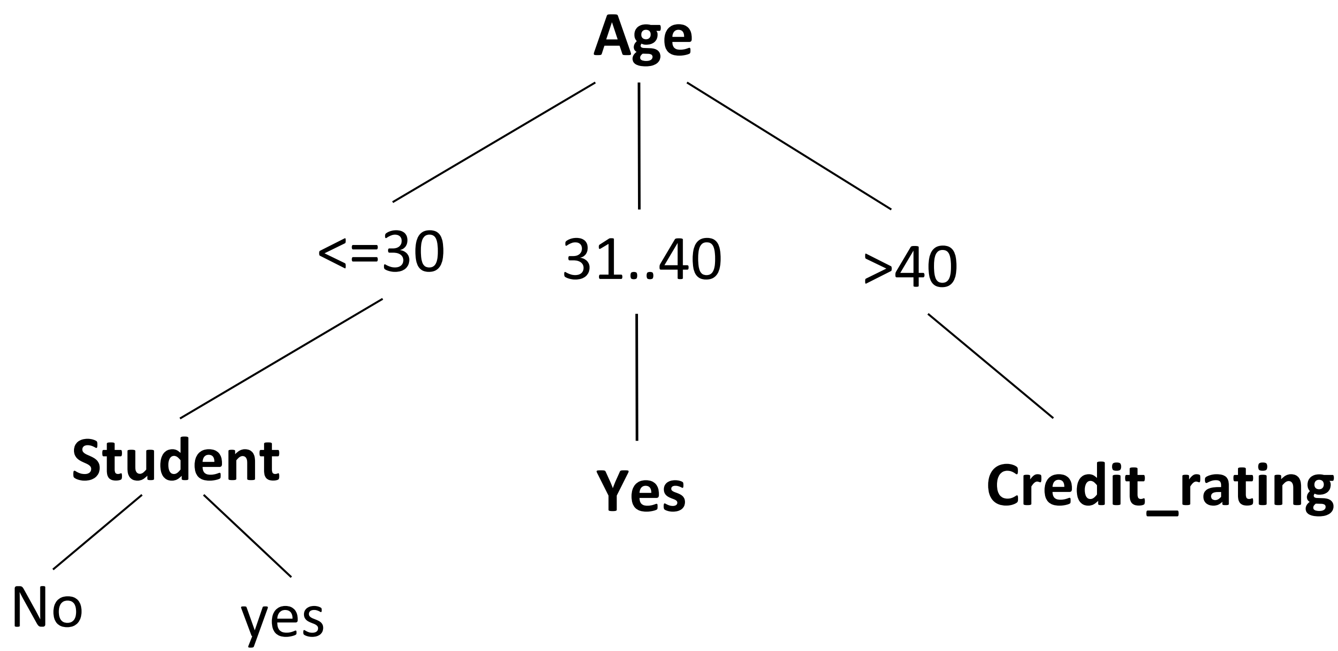
$$\boxed{E(\text{credit\_rating}) = 0}$$

Gain (S>40,credit_rating) = I (p, n) – E(credit_rating)
= 0.971 – 0
= 0.971

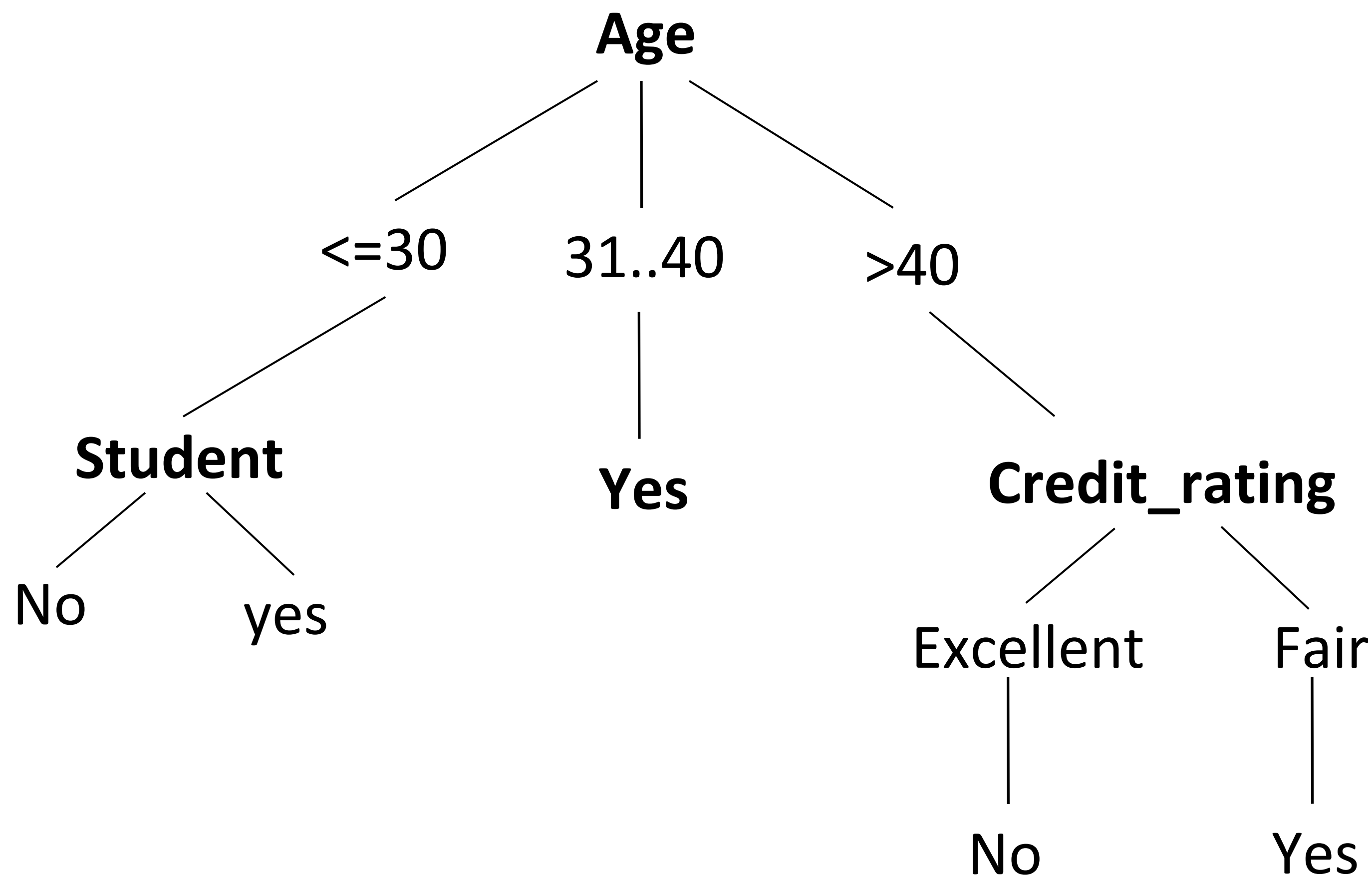
Solution – ID3 (Age > 40)

Gain (Age > 40)	value
Income	0.020
Credit_rating	0.971

As shown in table we get maximum gain for credit_rating so, select credit_rating as leaf node for age > 40



Decision Tree – ID3



Classification rules from decision tree

- 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 = “>40” AND credit_rating = “fair” THEN buys_computer = “yes”

Bayesian Classification

- Thomas Bayes, who proposed the Bayes Theorem so, it named Bayesian theorem.
- It is statistical method & supervised learning method for classification.
- **It can solve problems involving both categorical and continuous valued attributes**.
- Bayesian classification is used to find conditional probabilities.

The Bayes Theorem

- The Bayes Theorem:
  - $P(H|X) = \dfrac{\mathbf{P(X|H)\ P(H)}}{\mathbf{P(X)}}$
- **P(H|X)** : Probability that the customer will buy a computer given that we know his age, credit rating and income. (Posterior Probability of H)
- **P(H)** : Probability that the customer will buy a computer regardless of age, credit rating, income (Prior Probability of H)
- **P(X|H)** : Probability that the customer is 35 years old, have fair credit rating and earns $40,000, given that he has bought computer (Posterior Probability of X)
- **P(X)** : Probability that a person from our set of customers is 35 years old, have fair credit rating and earns $40,000. (Prior Probability of X)

Naïve Bayes classifier - Example

Age	Income	Student	Credit_Rating	Class : 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

Naïve Bayes classifier - Solution

Age		
P (<=30 | **Yes**) = 2/9	P (<=30 | **No**) = 3/5	P (**Yes**) = 9/14 P (**No**) = 5/14
P (31..40 | **Yes**) = 4/9	P (31..40 | **No**) = 0/5	
P (> 40 | **Yes**) = 3/9	P (> 40 | **No**) = 2/5	
P (High | **Yes**) = 2/9	P (High | **No**) = 2/5	
P (Medium | **Yes**) = 4/9	P (Medium | **No**) = 2/5	
P (Low | **Yes**) = 3/9	P (Low | **No**) = 1/5	
P (No | **Yes**) = 3/9	P (No | **No**) = 4/5	
P (Yes | **Yes**) = 6/9	P (Yes | **No**) = 1/5	
P (Fair | **Yes**) = 6/9	P (Fair | **No**) = 2/5	
P (Excellent | **Yes**) = 3/9	P (Excellent | **No**) = 3/5	

Naïve Bayes classifier - Solution

- **An unseen sample Y** = **(<=30**, **Low, Yes, Excellent)**
- P(Y|Yes).P(Yes) = P(<=30|Yes). P(Low|Yes). P(Yes|Yes). P(Excellent|Yes) . P(Yes)

= 2/9 * 3/9 * 6/9 * 3/9 * 9/14

= 0.010582

- P(Y|No).P(No) = P(<=30|No). P(Low|No). P(Yes|No). P(Excellent|No) . P(No)

= 3/5 * 1/5 * 1/5 * 3/5 * 5/14

= 0.005142

Choose the class so that it maximizes this probability, this means that new instance will be classified as **Yes** (Buys_computer)

Try yourself (Bayesian Classification)

Car No	Color	Type	Origin	Stolen?
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Yellow	Sports	Domestic	No
5	Yellow	Sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes

<u>Unseen Data</u>

Y = <Red, Domestic, SUV>

<u>Actual Data</u>

Y = <Red, Sports, Domestic>

0.024,0.072 (Unseen)

0.192, 0.096 (Actual)

Rule Based Classification

- It is featured by building rules based on an object attributes.
- Rule-based classifier makes use of a set of **IF-THEN rules** for classification.
- We can express a rule in the following from
  - IF condition THEN conclusion
- Let us consider a rule R1,

R1: **IF age=youth AND student=yes THEN buy_computer=yes**

- The IF part of the rule is called rule antecedent or precondition.
- The THEN part of the rule is called rule consequent (conclusion).
- The antecedent (IF) part the condition consist of one or more attribute tests and these tests are logically ANDed.
- The consequent (THEN) part consists of class prediction.

Rule Based Classification (Cont..)

- We can also write rule R1 as follows:

  R1: ((age = youth) ^ (student = yes)) => (buys_computer = yes)

  - If the condition (that is, all of the attribute tests) in a rule antecedent holds true for a given tuple, we say that the rule antecedent is satisfied and that the rule covers the tuple.

- A rule **R can be assessed by its coverage and accuracy**.
- Given a tuple X, from a class labeled data set D, let it covers the number of tuples by R; the number of tuples correctly classified by R; and |D| be the number of tuples in D.
- We can define the coverage and accuracy of R as

Coverage (R) = $\frac{n_{covers}}{|D|}$ Accuracy (R) = $\frac{n_{correct}}{n_{covers}}$

Neural Network

- Neural Network is a set of connected **INPUT/OUTPUT UNITS**, where each connection has a **WEIGHT** associated with it.
- Neural Network learning is also called CONNECTIONIST learning due to the connections between units.
- Neural Network learns by adjusting the weights so It is able to correctly classify the training data and after testing phase, to classify unknown data.
- **Strengths of Neural Network:**
  - It can handle against complex data. (i.e., problems with many parameters)
  - It can handle noise in the training data.
  - The Prediction accuracy is generally high.
  - Neural Networks are robust, work well even when training examples contain errors.
  - Neural Networks can handle missing data well.

Regression

- Regression is a **data mining function that predicts a number or value**.
- Age, weight, distance, temperature, income, or sales attributes can be predicted using regression techniques.
- For example, a regression model could be used to predict children's height, given their age, weight and other factors.
- A regression task begins with a data set in which the **target values are known**.
- For example, a regression model that predicts children's height could be developed based on observed data for many children over a period of time.
- The data might track age, height, weight, developmental milestones, family history etc.

Regression (Cont..)

- Height would be the target, the other attributes would be the predictors, and the data for each child would constitute a case.

- **Regression models are tested by computing various statistics that measure the difference between the predicted values and the expected values**.

- It is required to understand the mathematics used in regression analysis to develop quality regression models for data mining.

- The goal of regression analysis is to determine the values of parameters for a function that cause the function to fit best in a set of data observations that we provide.

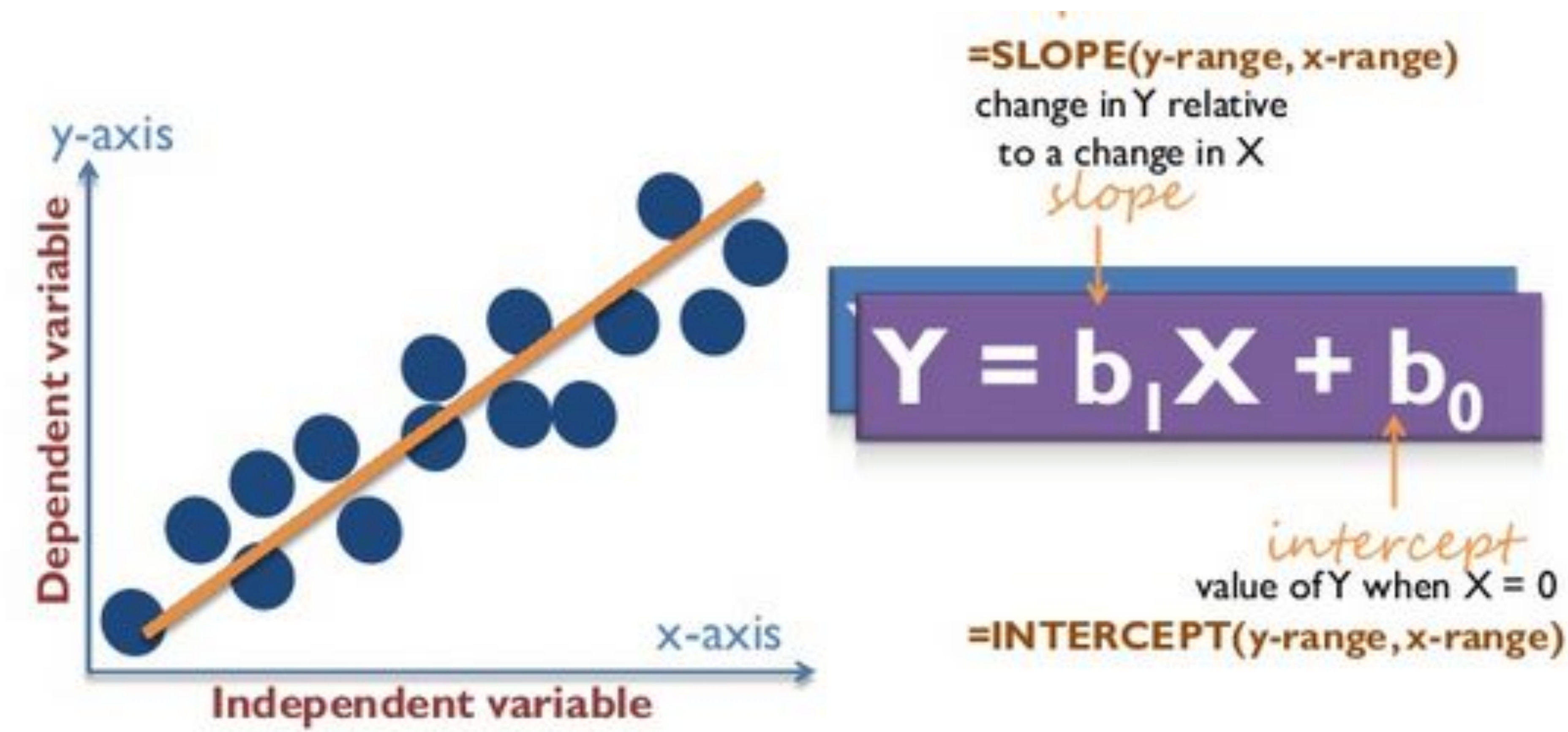
Linear Regression

- The simplest form of regression to visualize is linear regression with a **single predictor**.
- A linear regression technique can be used **if the relationship between x and y can be approximated with a straight line**.
- Linear regression with a single predictor can be expressed with the following equation with one dependent and one independent variable is defined by the given formula

$$\boxed{\mathbf{Y = b1X + b0 + u}}$$

  - Where y = Dependent variable which we are trying to predict, b1 = The Slope, and X = independent variable, b0 = The Intercept, u = Random Error/Residual

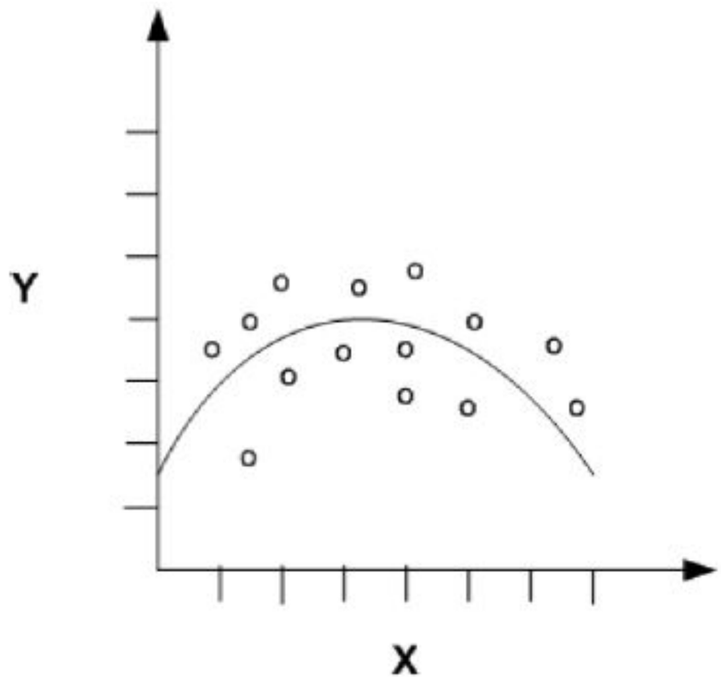
Linear Regression (Cont..)



Nonlinear Regression

- Often the relationship between x and y cannot be approximated with a straight line or curve for that nonlinear regression technique may be used.

- Alternatively, the data could be preprocessed to make the relationship linear.



Multiple Linear Regression

- Multiple Linear regression is an **extension of simple linear regression analysis**.

- It uses two or more independent variables to predict the outcome and a single continuous dependent variable, Like..

$$\boxed{\mathbf{Y = b0 + b1X1 + b2X2 + b3X3 + \ldots + bnXn + u}}$$

- Where Y = dependent variable or response variable

  X1,X2,….Xn are the independent variables or predictors

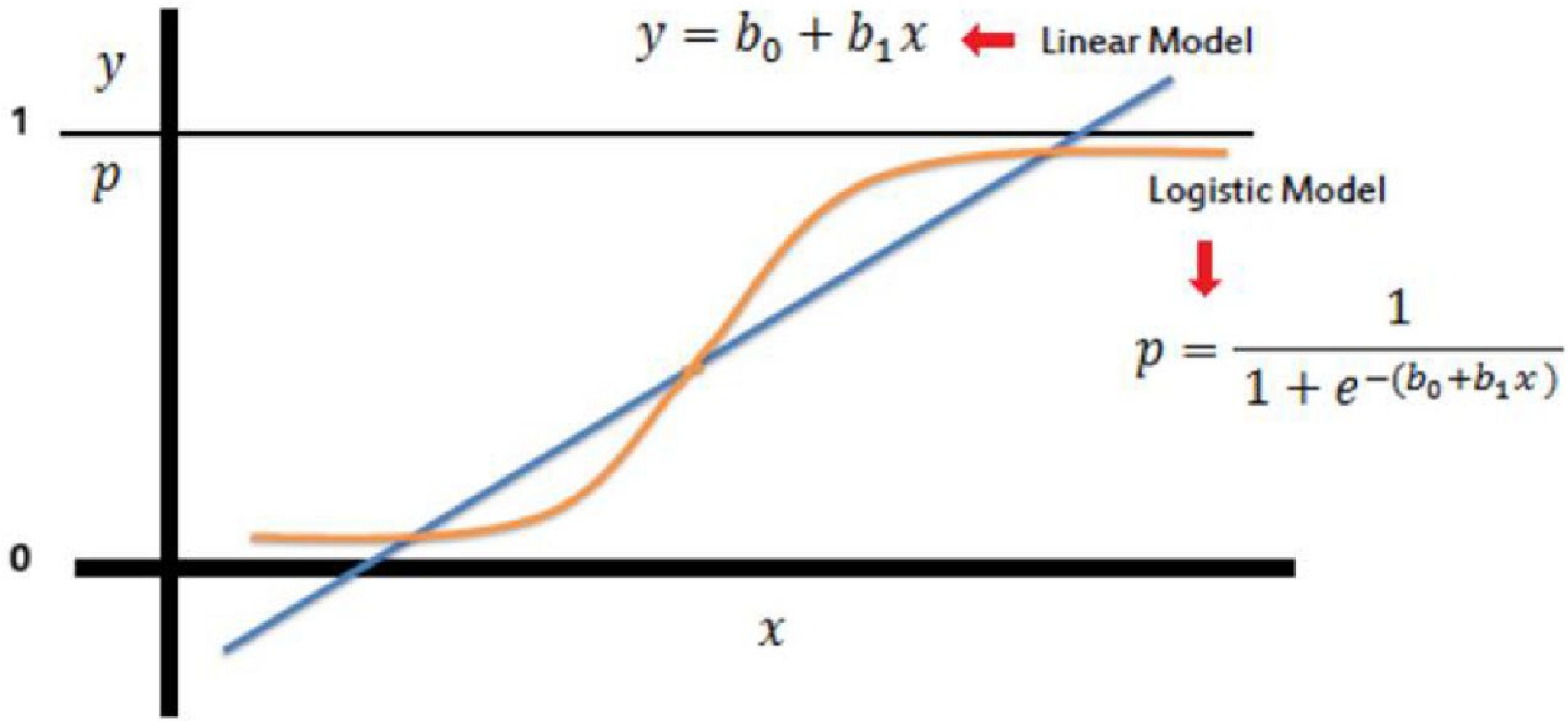
  u = Random Error

  b0,b1,b2,….bn are the regression coefficients

Logistic Regression

- A linear regression is not appropriate for predicting the value of a binary variable for two reasons:
  - A linear regression will predict values outside the acceptable range (e.g. predicting probabilities outside the range 0 to 1).
  - Since the experiments can only have one of two possible values for each experiment, the residuals(random errors) will not be normally distributed about the predicted line.
- **A logistic regression produces a logistic curve, which is limited to values between 0 and 1**.
- Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm “odds” of the target variable, rather than the probability.

Logistic Regression (Cont..)



Thank you!