



CLASSIFICATION

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OUTLINE

- Introduction
- Applications
- Decision tree induction
- Algorithm
- Rule based classification



Introduction

2-Steps:

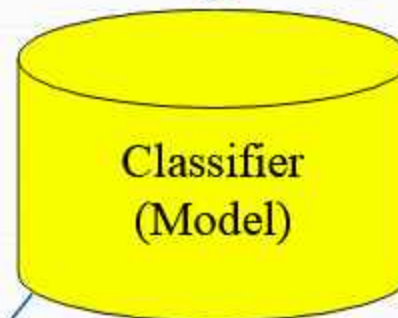
- Learning
- Classification



Step-1 : Learning



Classification
Algorithms

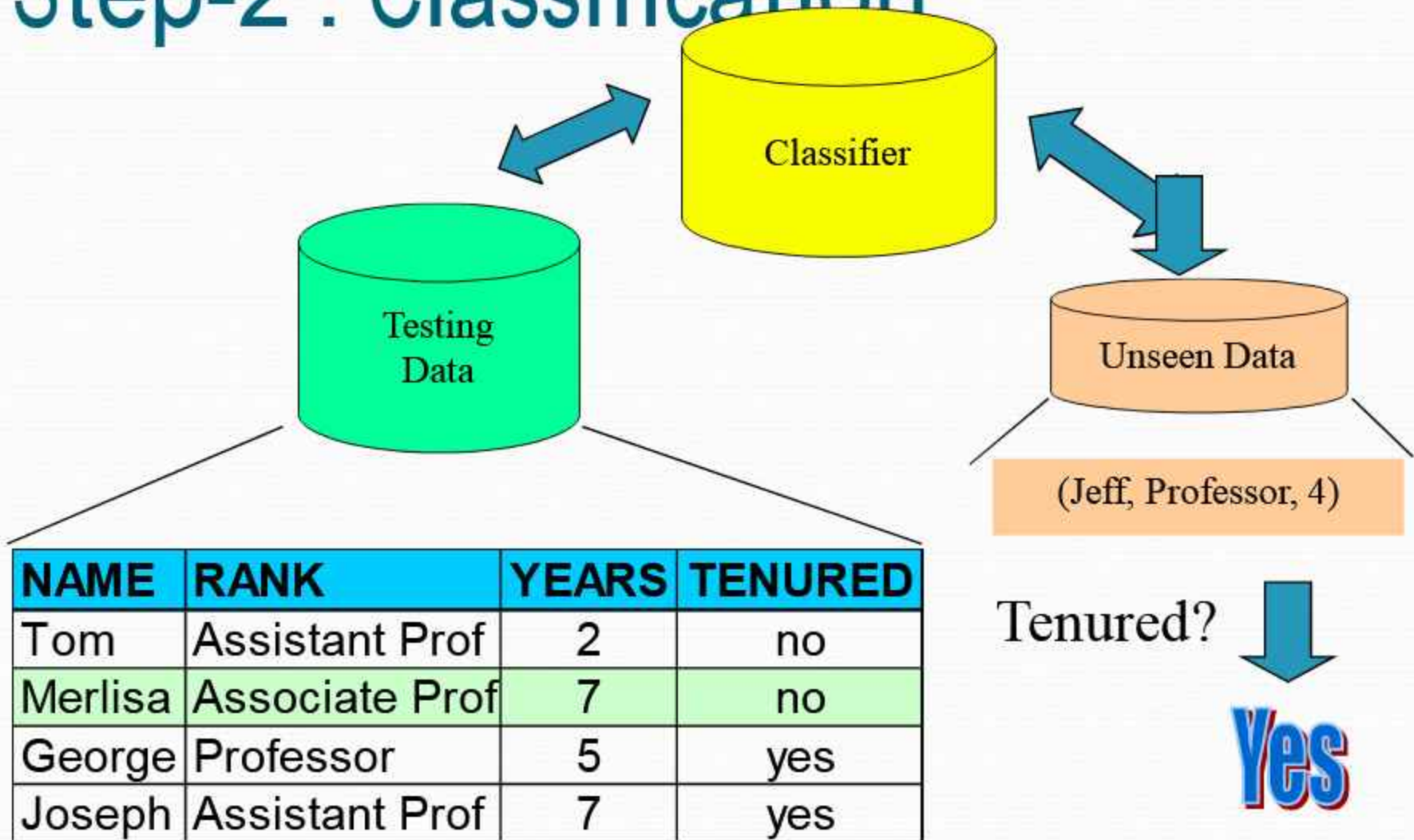


NAME	RANK	YEARS	TENURED
Mike	Assistant Prof	3	no
Mary	Assistant Prof	7	yes
Bill	Professor	2	yes
Jim	Associate Prof	7	yes
Dave	Assistant Prof	6	no
Anne	Associate Prof	3	no

IF rank = 'professor'
OR years > 6
THEN tenured = 'yes'



Step-2 : Classification





Applications

- Credit card approval
- Target marketing
- Medical diagnosis



Classification by decision tree

Induction

Decision tree:

- Flowchart
- Internal node
- Branch
- Leaf node

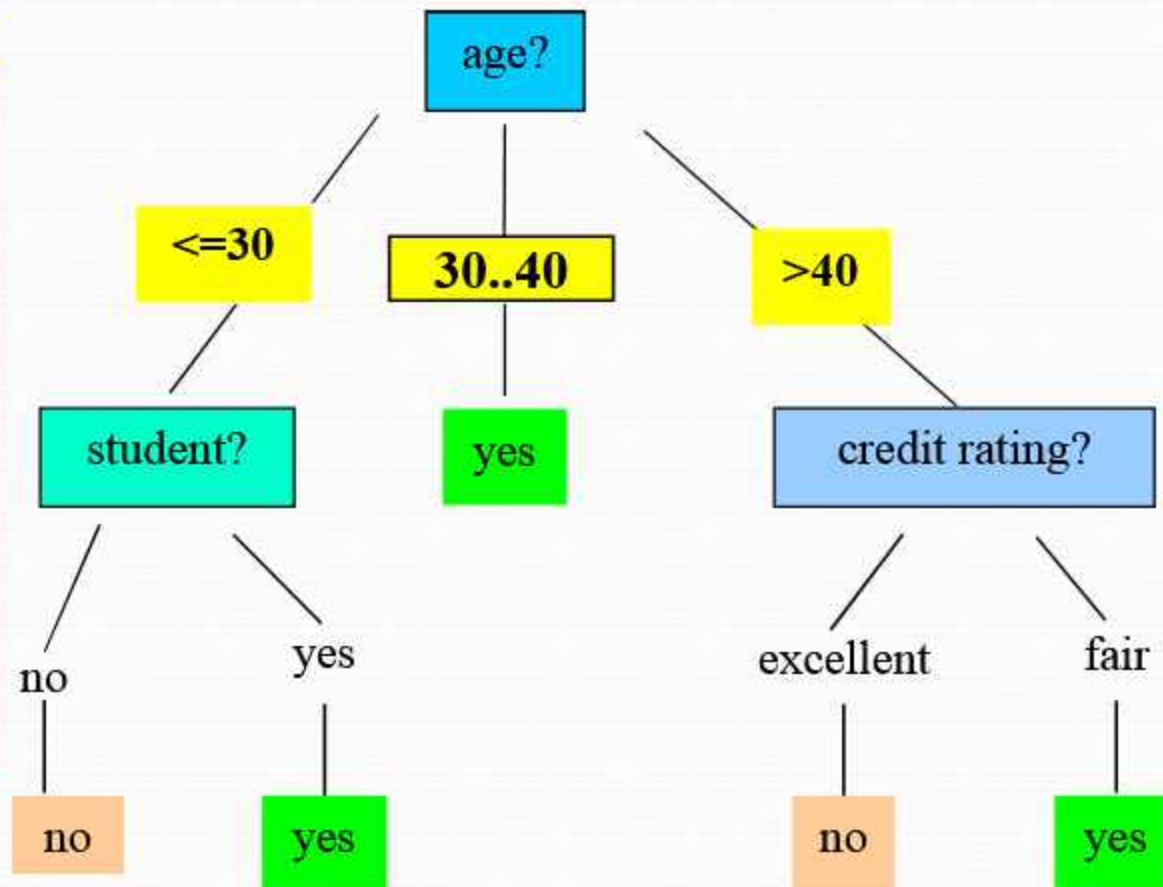
2-Phases:

- Tree construction
- Tree pruning



Example

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





Algorithm

Greedy algorithm:

- Top-Down approach
- Training data at root
- Attribute for measurement
 1. Information gain(ID3/C4.5)
 2. Gini index (IBM intelligent miner)



Information gain(ID3/C4.5)

- All attributes are categorical
- Modified for continuous value attribute
- Select the attribute for high information gain
- 2 classes, P&N

Samples sc P element of P class & n element of N class

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



Cont..

- Information gain measure used to select S, samples

- $I(s_1, s_2, \dots, s_m) = - \sum_{i=1}^m p_i \log_2 p_i$

Where p_i , probability & m , distinct value

Information encoded in bits $p_i = \frac{s_i}{s}$

$$\text{Entropy, } E(A) = \sum_{i=1}^v I(s_{1j}, s_{2j}, \dots, s_{mj}) \frac{s_{1j}, s_{2j}, \dots, s_{mj}}{s}$$

$$\text{Subset, } I(s_{1j}, s_{2j}, \dots, s_{mj}) = - \sum_{i=1}^m p_{ij} \log_2 p_{ij}$$

$$P_{ij} = \frac{s_{ij}}{|s_{ij}|}$$



Cont..

- $\text{Gain}(A) = I(s1, s2, sm) - E(A)$
- $I(s1, s2) = -9/14 \log_2 (9/14) - 5/14 \log_2 (5/14)$
 $= 0.940$

Age ≤ 30

Age 31...40

Age > 40



Gini index(IBM intelligent miner)

- Attribute having continuous value
- Possible split values for each attribute
- Modified for categorical attributes
- Data set T contains n classes,

$$\text{Gini}(t) = 1 - \sum_{j=1}^n p_j^2 \quad \text{Where } p_j, \text{ relative frequency } j \text{ in } T$$

Dataset splits into 2 subset T1 & T2 with N1 & N2

$$\text{Gini}_{\text{split}}(T) = \frac{N_1}{N} \text{gini}(T_1) + \frac{N_2}{N} \text{gini}(T_2)$$

$$\begin{aligned} \text{Gini}(d) &= 1 - (9/14)^2 - (5/14)^2 \\ &= 0.459 \end{aligned}$$

$$\begin{aligned} \text{gini}_{\text{income}}(\text{low,medium})(D) &= 10/14 \text{gini}(D_1) + 4/14 \text{gini}(D_2) \\ &= 10/14 (1 - (7/10)^2 - (3/10)^2) + 4/14 (1 - (2/4)^2 - (2/4)^2) \\ &= 0.443 = \text{gini}_{\text{income}(\text{high})}(D) \end{aligned}$$



Tree Pruning

- Reflected noise branches are removed
- 2 types
 1. Post pruning
 2. Pre pruning



Rule based classification

- IF THEN rules are used
- Each attribute- conjunction
- Example:

IF age $\leq$ 30 & student=no THEN buys-computer=no

IF age $\leq$ 30 & student=Yes THEN buys-computer=Yes