

## CS 412 Intro. to Data Mining

Chapter 8. Classification: Basic Concepts

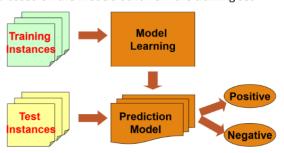
Jiawei Han, Computer Science, Univ. Illinois at Urbana-Champaign, 2017



#### Supervised vs. Unsupervised Learning (1)

- Supervised learning (classification)
- Supervision: The training data such as observations or measurements are accompanied by labels indicating the classes which they belong to
- New data is classified based on the models built from the training set



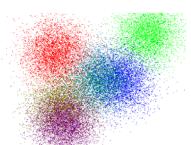


### Supervised vs. Unsupervised Learning (2)

- Unsupervised learning (clustering)
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- The class labels of training data are unknown

Given a set of observations or measurements, establish the possible existence

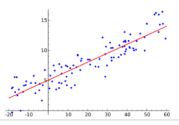
of classes or clusters in the data





#### **Prediction Problems: Classification vs. Numeric Prediction**

- Classification
- THILLY PORT PURMY President
- Predict categorical class labels (discrete or nominal)
- Construct a model based on the training set and the class labels (the values in a classifying attribute) and use it in classifying new data
- Numeric prediction
- Regression
- Model continuous-valued functions (i.e., predict unknown or missing values)
- Typical applications of classification
- Credit/loan approval
- Medical diagnosis: if a tumor is cancerous or benign
- Fraud detection: if a transaction is fraudulent
- Web page categorization: which category it is



### Classification—Model Construction, Validation and Testing

- Model construction
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- Each sample is assumed to belong to a predefined class (shown by the class label)
- The set of samples used for model construction is training set
- Model: Represented as decision trees, rules, mathematical formulas, or other forms
- Model Validation and Testing:
  - Test: Estimate accuracy of the model
  - ☐ The known label of test sample is compared with the classified result from the model
  - □ Accuracy: % of test set samples that are correctly classified by the model
  - Test set is independent of training set
- Validation: If the test set is used to select or refine models, it is called validation (or development) (test) set
- □ Model Deployment: If the accuracy is acceptable, use the model to classify new data

#### **Decision Tree Induction: An Example** Training data set: Who buys computer? Decision tree construction:

A top-down, recursive, divide-andconquer process



<=30 31..40 credit rating? student's

excellent

Not-buy

	age	income	student	credit_rating	buys_computer
_	<=30	high	no	fair	no
	<=30	high	no	excellent	no
	3140	high	no	fair	yes
	>40	medium	no	fair	yes
	>40	low	yes	fair	yes
	>40	low	yes	excellent	no
	3140	low	yes	excellent	yes
	<=30	medium	no	fair	no
	<=30	low	yes	fair	yes
	>40	medium	yes	fair	yes
	<=30	medium	yes	excellent	yes
	3140	medium	no	excellent	yes
	3140	high	yes	fair	yes
	>40	medium	no	excellent	no
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Note: The data set is adapted from "Playing Tennis" example of R. Quinlan

#### Information Gain: An Attribute Selection Measure

- □ Select the attribute with the highest information gain (used in typical decision tree induction algorithm: ID3/C4.5)
- $\Box$  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:

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

☐ Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_{A}(D)$$

#### **Example: Attribute Selection with Information Gain**

☐ Class P: buys\_computer = "yes"

Not-buy

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☐ Class N: buys\_computer = "no" N  $Info(D) = I(9.5) = -\frac{9}{-9} \log_{10}(\frac{9}{2})$   $\frac{5}{100} \log_{10}(\frac{5}{2})$ 

11g0(2) - 1	14	1 1052	14	$14^{1052}(14$
	age	pi	n <sub>i</sub>	l(p <sub>i</sub> , n <sub>i</sub> )
	<=30	2	3	0.971
	3140	4	0	0
	- 40	2	2	0.071

	>40	3	2 0.97	1
age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	/ no
3140	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
3140	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
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<=30	medium	yes	excellent	yes
3140	medium	no	excellent	yes
3140	high	yes	fair	yes /
>40	medium	no	evcellent	no

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ta 2240 14 Ma (-10)
$Info_{age}(D) = \frac{5}{14}I(2,3) + \frac{4}{14}I(4,0)$
$+\frac{5}{14}I(3,2) = 0.694$
7(2,3) means "age <=30" has 5 out of 14

samples, with 2 yes'es and 3 no's. C แผลง คำภาพ Hence

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

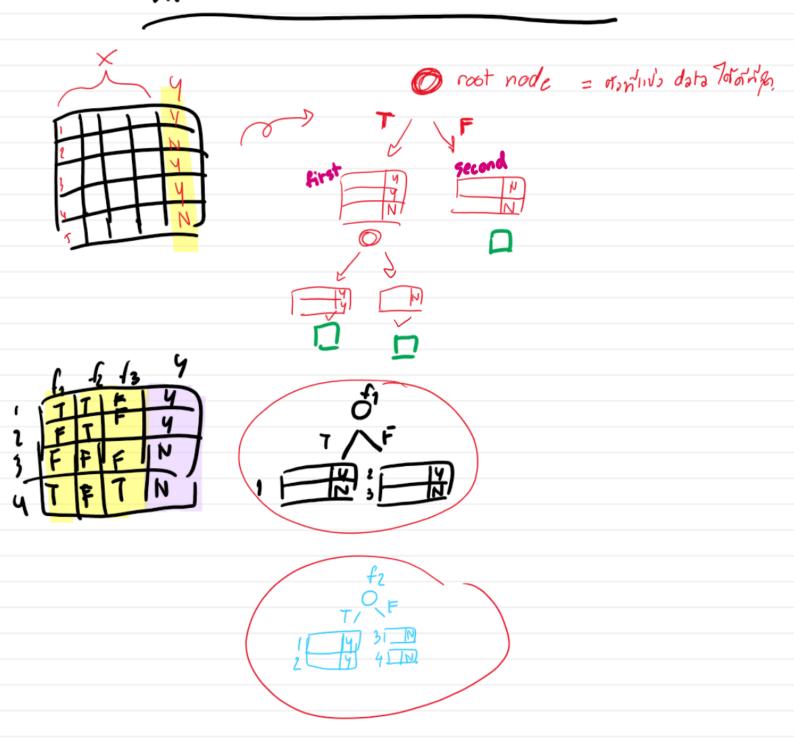
Similarly, we can get

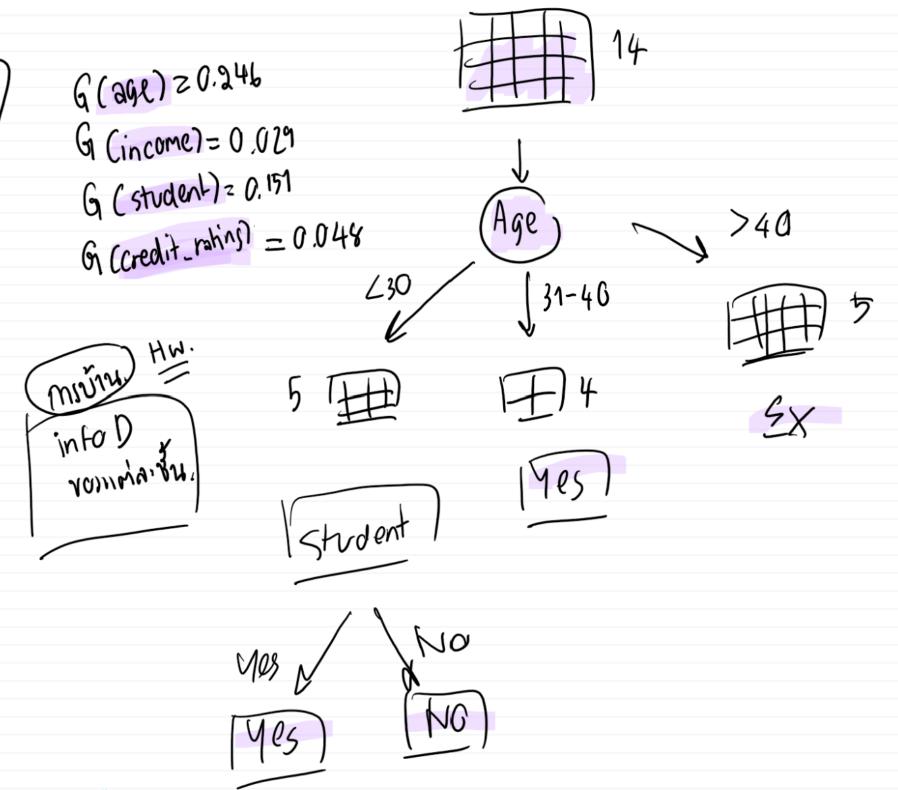
Gain(income) = 0.029

Gain(student) = 0.151

 $Gain(credit\ rating) = 0.048$ 

# narmialis decision tree





Info (D) =  $I(2,3) = -2 \log_2 2 - 3 \log_2 3$ Info income (D) = 2 I(0,2) + 2 I(1,1) + 1 I(1,0)Into student (D) = 2 I(2,0) + 3I(0,3)Fair

z 3 I (1,2,

$$Info(0) = I(4,0) = -\frac{4}{4} | 092 \frac{4}{4} - \frac{0}{4} | 092 \frac{0}{4}$$

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$$Info(0) = I(4,0) + \frac{1}{4}I(0,1) + \frac{1}{4}I(1,0)$$

$$Info(0) = \frac{2}{4}I(1,1) + \frac{1}{4}I(0,1) + \frac{1}{4}I(1,0)$$

$$Info(0) = \frac{2}{4}I(2,0) + \frac{2}{4}I(2,0)$$

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