

CS 412 Intro. to Data Mining

Chapter 8. Classification: Basic Concepts

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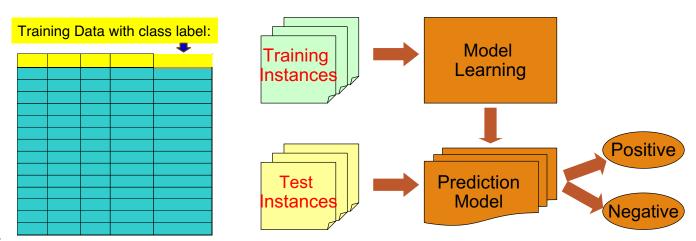
Classification: Basic Concepts



- Decision Tree Induction
- Bayes Classification Methods
- Linear Classifier
- Model Evaluation and Selection
- Techniques to Improve Classification Accuracy: Ensemble Methods
- Additional Concepts on Classification
- Summary

Supervised vs. Unsupervised Learning (1)

- Supervised learning (classification) → ร้องริงนิ เป็นจุดหุ่งแมาง (รู่ ผู้รงน)
 - 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



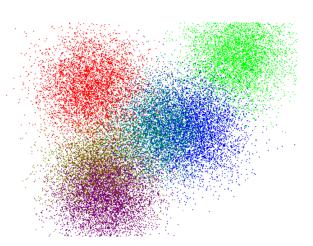
Supervised vs. Unsupervised Learning (2)

□ Unsupervised learning (clustering) → ไม่นี้ ผู้ ผู้น

🗅 The class labels of training data are unknown 🛮 เม่ว 0 ลุ่ม เฉ น ๆ

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

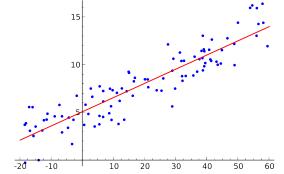
of classes or clusters in the data





Prediction Problems: Classification vs. Numeric Prediction

- 🗆 Classification -> เป็น binary ท้านาจว่าอยู่กล่รไทน
 - 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 → เป็นตาเลข "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

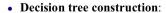


Classification—Model Construction, Validation and Testing

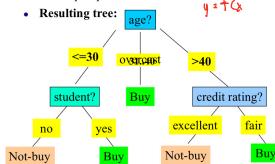
- Model construction 101 Data \$ featured + mason to
 - Each sample is assumed to belong to a predefined class (shown by the class label)
- The set of samples used for model construction is training set
- Model: Represented as decision trees, rules, mathematical formulas, or other forms
- Model Validation and Testing:
 - Test: Estimate accuracy of the model เด้า ชี ทั้งผางปลา
 - 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





· A top-down, recursive, divide-andconquer process



Training data set: Who buys computer?							
age	income	student	credit_rating	t	uys_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		

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)
- Let pi be the probability that an arbitrary tuple in D belongs to class Ci, estimated by |Ci, D|/|D|
- Expected information (entropy) needed to classify a tuple in D: $Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$

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

Information needed (after using A to split D into v partitions) to classify D: $Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$

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

• 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"
- Class N: buys_computer = "no"

• Class N. ouys $\frac{1}{2}$ $\log_2(\frac{9}{14}) = \frac{5}{14} \log_2(\frac{5}{14}) = \frac{9}{14} \log_2(\frac{5}{14}) = \frac{$

	2230 3111 40
	$Info_{age}(D) = \frac{5}{14}I(2,3) + \frac{4}{14}I(4,0)$
=0.940	$+\frac{5}{14}I(3,2) = 0.694$
	$\frac{5}{14}I(2,3)$ means "age <=30" has 5 out of 14

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

	>40	3	3	2	0.97	1		
ge	income	stude	nt	credit	rating	buys	computer	
30	high	no	f	air			no	
30	high	no	е	exceller	nt		no	
40	high	no	f	air			yes	
)	medium	no	f	air			yes	Si
)	low	yes	fa	air			yes	
	Louis	1100		wallas				

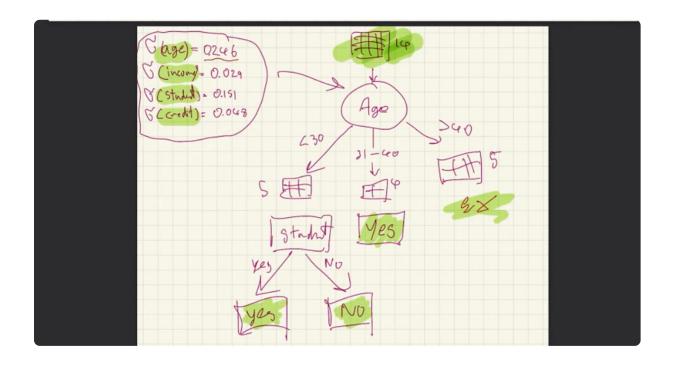
 $Gain(age) = Info(D) - Info_{age}(D) = 0.246$ Similarly, we can get

Gain(income) = 0.029Gain(student) = 0.151

 $Gain(credit_rating) = 0.048$ (0) m 21 a 2/0

	>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

vannisin Decision tree



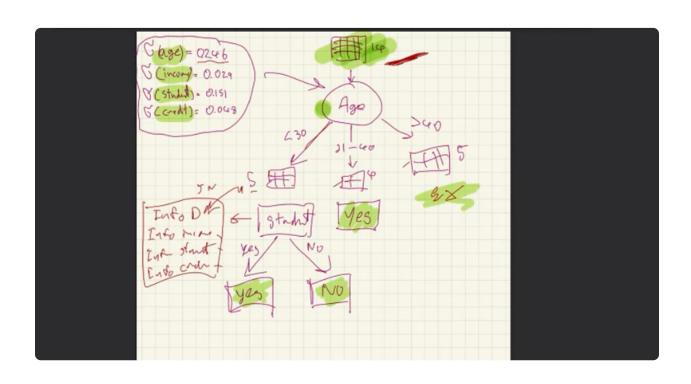
$$Info(D) = I(2,3) = -\frac{2}{5}log_{25} - \frac{3}{5}log_{25}$$
high we kimm low

$$Info_{income}(D) = \frac{2}{5}I(0,2) + \frac{2}{5}I(1,1) + \frac{1}{5}I(1,0)$$

$$Info_{stadut}(D) = \frac{2}{5}I(2,0) + \frac{3}{5}I(0,0)$$

$$Info_{stadut}(D) = \frac{2}{5}I(2,0) + \frac{3}{5}I(0,0)$$

$$Info_{cridit}(D) = \frac{3}{5}I(1,2) + \frac{2}{5}(1,1)$$



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