

CS 412 Intro. to Data Mining

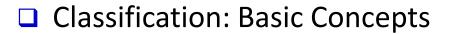
Chapter 8. Classification: Basic Concepts

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





Chapter 8. Classification: Basic Concepts





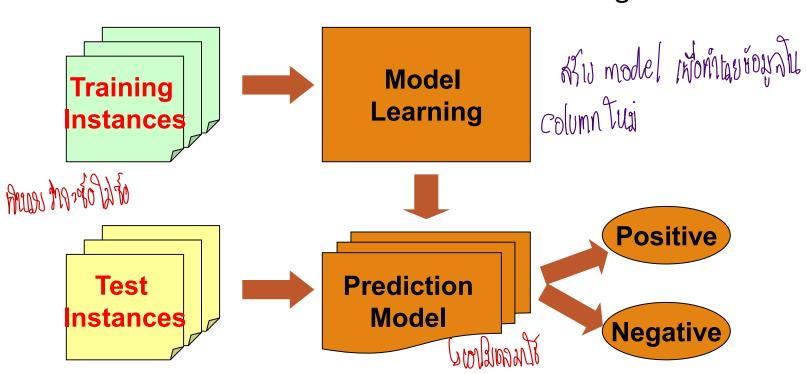
- Decision Tree Induction
- Bayes Classification Methods
- Linear Classifier
- Model Evaluation and Selection
- ☐ Techniques to Improve Classification Accuracy: Ensemble Methods
- Additional Concepts on Classification
- Summary

Supervised vs. Unsupervised Learning (1)

- Supervised learning (classification)
- Joain Louine Energe pendent run ciende
- 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

Training Data with class label:

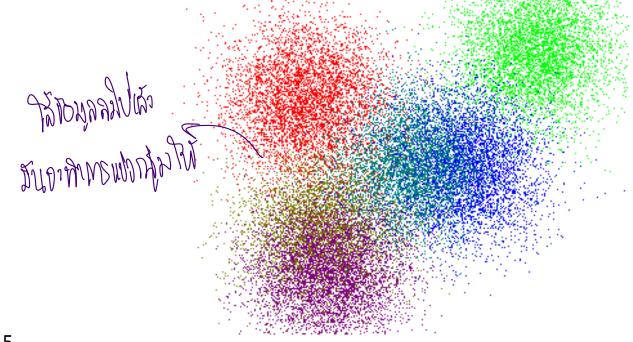
				. •
age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no 🥎
<=30	high	no	excellent	no
3140	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
3140	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
3140	medium	no	excellent	yes
3140	high	yes	fair	yes
>40	medium	no	excellent	no



Supervised vs. Unsupervised Learning (2)

- Unsupervised learning (clustering)
- Triparitumentumentumentum sunn custoring
- The class labels of training data are unknown
- Given a set of observations or measurements, establish the possible existence

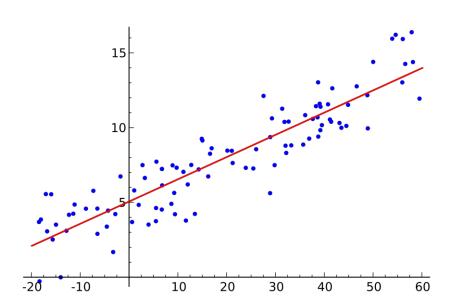
of classes or clusters in the data





Prediction Problems: Classification vs. Numeric Prediction

- Classification กรพันษาการเกราในน ให้กิจใช้
 - 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 พรท์บลุงเป็นที่เพื่อ
 - 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 (の) Data 所知のし、preder あるなり model
 - □ 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

Chapter 8. Classification: Basic Concepts

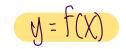
- Classification: Basic Concepts
- Decision Tree Induction



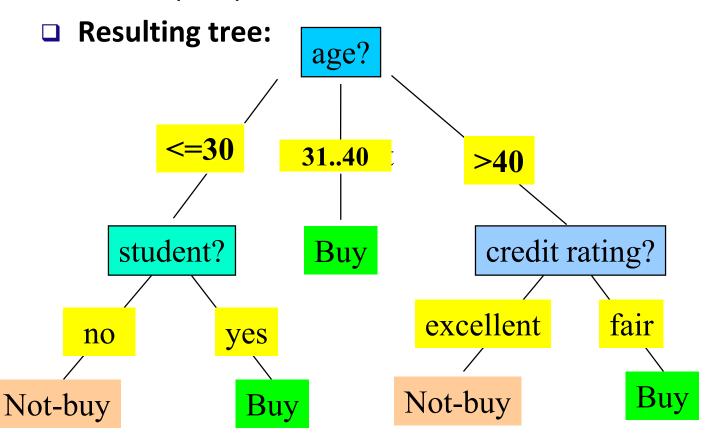
- Bayes Classification Methods
- Linear Classifier
- Model Evaluation and Selection
- Techniques to Improve Classification Accuracy: Ensemble Methods
- Additional Concepts on Classification
- Summary

Decision Tree Induction: An Example

□ Decision tree construction:



 A top-down, recursive, divide-andconquer process



Training data set: Who buys computer?

Y (label)

ageincomestudentcredit_ratingbuys_compute<=30highnofairno<=30highnoexcellentno3140highnofairyes>40mediumnofairyes>40lowyesfairyes>40lowyesexcellentno		<u> </u>			· /
<=30 high no excellent no 3140 high no fair yes >40 medium no fair yes >40 low yes fair yes	age	income	student	credit_rating	buys_computer
3140 high no fair yes >40 medium no fair yes >40 low yes fair yes	<=30	high	no	fair	no
>40 medium no fair yes >40 low yes fair yes	<=30	high	no	excellent	no
>40 low yes fair yes	3140	high	no	fair	yes
	>40	medium	no	fair	yes
>40 low yes excellent no	>40	low	yes	fair	yes
	>40	low	yes	excellent	no
3140 low yes excellent yes	3140	low	yes	excellent	yes
<=30 medium no fair no	<=30	medium	no	fair	no
<=30 low yes fair yes	<=30	low	yes	fair	yes
>40 medium yes fair yes	>40	medium	yes	fair	yes
<=30 medium yes excellent yes	<=30	medium	yes	excellent	yes
3140 medium no excellent yes	3140	medium	no	excellent	yes
3140 high yes fair yes	3140	high	yes	fair	yes
>40 medium no excellent no	>40	medium	no	excellent	no

Note: The data set is adapted from "Playing Tennis" example of R. Quinlan

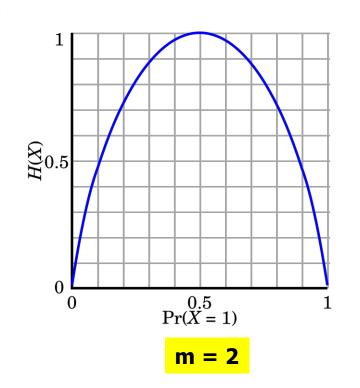
From Entropy to Info Gain: A Brief Review of Entropy

- Entropy (Information Theory)
 - A measure of uncertainty associated with a random number
 - \Box Calculation: For a discrete random variable Y taking m distinct values $\{y_1, y_2, ..., y_m\}$

$$H(Y) = -\sum_{i=1}^{m} p_i \log(p_i) \text{ where } p_i = P(Y = y_i)$$

- Interpretation
 - ☐ Higher entropy → higher uncertainty
 - Lower entropy → lower uncertainty
- Conditional entropy

$$H(Y|X) = \sum_{x} p(x)H(Y|X = x)$$



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 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:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i) \rightarrow 100$$

☐ Information needed (after using A to split D into v partitions) to classify D:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j) \xrightarrow{\gamma} \text{ minimum feative}$$

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"

$$Info(D) = I(9,5) = -\frac{9}{14}\log_2(\frac{9}{14}) - \frac{5}{14}\log_2(\frac{5}{14}) = 0.940$$

age	p _i	n _i	I(p _i , n _i)
<=30	2	3	0.971
3140	4	0	0
>40	3	2	0.971

ſ	age	income	student	credit_rating	buys_computer
	<=30 \	high	no	fair	no
	<=30 2	high	no	excellent	no
	31401	high	no	fair	yes
	>40	medium	no	fair	yes
	>40 2	low	yes	fair	yes
	>40 3	low	yes	excellent	no
	3140 ^૨	low	yes	excellent	yes
	<=30 }	medium	no	fair	no
	<=30 ¢	low	yes	fair	yes
	>40 4	medium	yes	fair	yes .
	<=30 5	medium	yes	excellent	yes
	31403	medium	no	excellent	yes
	31404	high	yes	fair	yes
	>40 5	medium	no	excellent	no

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

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

Hence

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

Similarly, we can get

$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

8=14

(row)