CS 412 Intro. to Data Mining

Chapter 8. Classification: Basic Concepts

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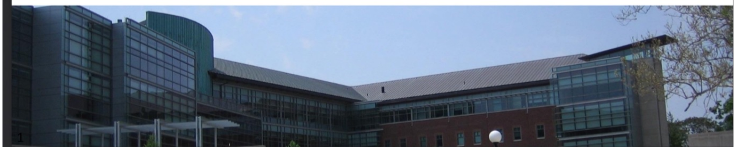

การสร้าง แบบมีผู้สอน (1) (2) แบ่งกลุ่มได้ 2 กลุ่มใหญ่ (1),(2)

Supervised vs. Unsupervised Learning (1)

สร้างโมเดลแบบไม่มีผู้สอน

- 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

Data แบ่งเป็น 2 ส่วน x, y

Training Data with class label:

ความน่าเชื่อถือ

การตัดสินใจ

age	income	student	credit_rating	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
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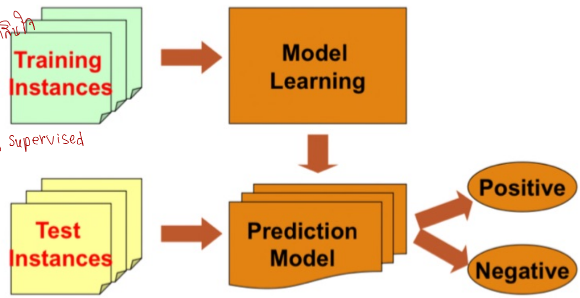
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

เป็นแบบ Supervised



Supervised vs. Unsupervised Learning (2)

- Unsupervised learning (clustering)

ไม่มีผู้สอน → ไม่มีจุดมุ่งหมายในการเรียน

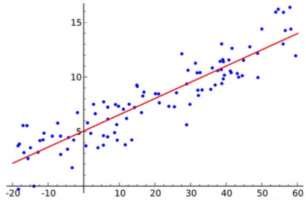
มีแค่ x ไม่มี y

  - 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
  - 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
  - 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

หากผลทำนายเป็นตัวเลข
จะเรียกว่า Regretion



Classification—Model Construction, Validation and Testing

- **Model construction** เอา Data ที่มีทั้ง ฟีเจอร์ และคำตอบมาเทรนโมเดล มาสร้างโมเดล โดย ออกลักษณะที่ต้องเฉพาะ
  - 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**: เอาโมเดลไปวัดผล ให้มันลองทำนายคำตอบดู แล้วดูว่ามันทำนายถูกหรือผิด มากน้อยแค่ไหน
  - **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 ต้นไม้ตัดสินใจ
- Bayes Classification Methods
- Linear Classifier
- Model Evaluation and Selection
- Techniques to Improve Classification Accuracy: Ensemble Methods
- Additional Concepts on Classification
- Summary

หลักการ คือ เลือกคำถามที่แบ่งข้อมูลได้ดี

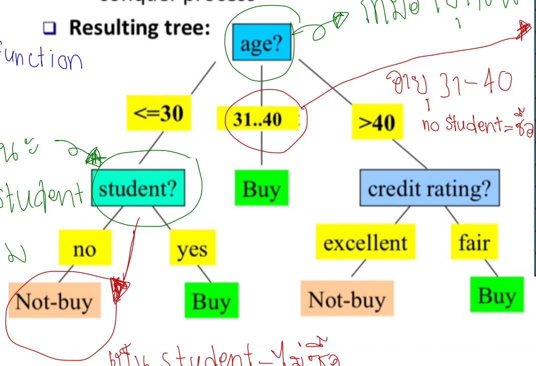
Decision Tree Induction: An Example

** จุดมุ่งหมาย

$y = f(x)$

สร้างให้เป็น function

- Decision tree construction:
  - A top-down, recursive, divide-and-conquer process
- Resulting tree:



x feature y (label)

Training data set: Who buys computer?

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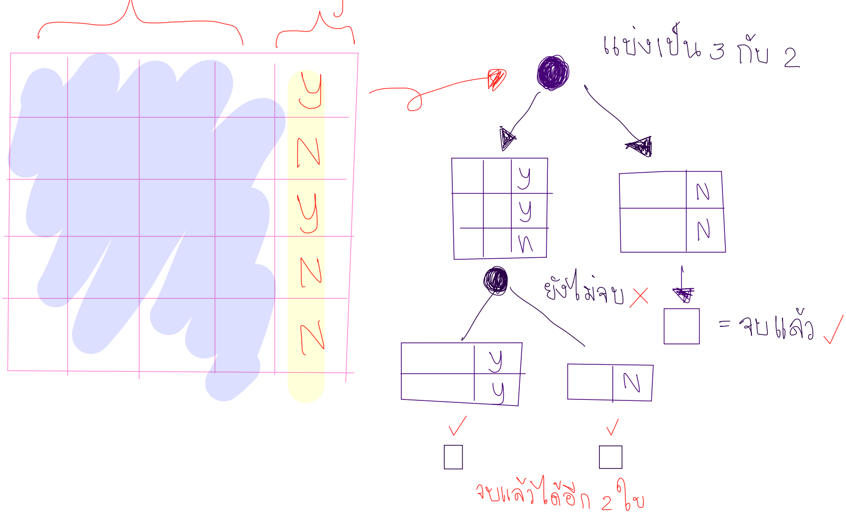
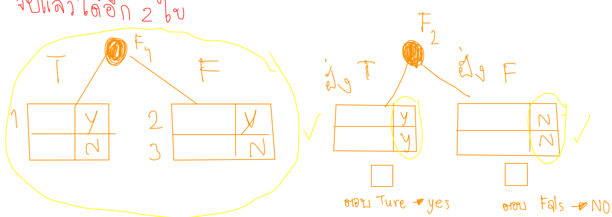
Note: The data set is adapted from "Playing Tennis" example of R. Quinlan



F1	F2	F3	F4
T	T	F	y
F	T	F	y
F	F	F	N
T	F	T	N



ไม่ใช้หลักการเดียวกันกับ และ หรือ ถ้าแล้ว ก็ต่อเมื่อ

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:

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

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

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

- 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"

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

<=30 = 5ตัว

age	p_i	n_i	$I(p_i, n_i)$
<=30	2	3	0.971
31…40	4	0	0
>40	3	2	0.971

$\frac{5}{14}$

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
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<=30　　31-40

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

$\frac{5}{14}I(2,3)$ 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

$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

$$Gain(credit\_rating) = 0.048$$

Bayes' Theorem: Basics

- Total probability Theorem:

$$p(B) = \sum_i p(B|A_i)p(A_i)$$

- Bayes' Theorem:

test data

A?　　B?　　　　traning data

$$\boxed{p(H|\mathbf{X})} = \frac{p(\mathbf{X}|H)P(H)}{p(\mathbf{X})} \propto \boxed{p(\mathbf{X}|H)}\,\boxed{P(H)}$$

มีx ลักษณะไหนบ้าง　　สิ่งที่เราทราบ

ฟีเจอร์เป็นข้อมูล ที่มีอยู่หลัง　posteriori probability　　likelihood　　prior probability

What we should choose　　What we just see　　What we knew previously

- **X:** a data sample ("*evidence*")
- H: X belongs to class C

Prediction can be done based on Bayes' Theorem:

Classification is to derive the maximum posteriori

Naïve Bayes Classifier: Training Dataset

Class:
C1:buys_computer = 'yes'
C2:buys_computer = 'no'

Data to be classified:
X = (age <=30, Income = medium,
Student = yes, Credit_rating = Fair)

age	income	student	credit_rating	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
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Training data

$P^y = P(b^{"y"}) P(a^{"y"} | b^{"y"}) P(i^{"y"} | b^{"y"}) P(s^{"y"} | b^{"y"}) P(c^{"y"} | b^{"y"})$

$P(H^{'y} | x') = ?$

$P(H^{'N} | x') = ?$

$= P(x | H'y) P(H'y)$ training data

Naïve Bayes Classifier: An Example

- $P(C_i)$: P(buys_computer = "yes") = 9/14 = 0.643
  P(buys_computer = "no") = 5/14= 0.357
- Compute $P(X|C_i)$ for each class
  P(age = "<=30"|buys_computer = "yes") = 2/9 = 0.222
  P(age = "<= 30"|buys_computer = "no") = 3/5 = 0.6
  P(income = "medium" | buys_computer = "yes") = 4/9 = 0.444
  P(income = "medium" | buys_computer = "no") = 2/5 = 0.4
  P(student = "yes" | buys_computer = "yes) = 6/9 = 0.667
  P(student = "yes" | buys_computer = "no") = 1/5 = 0.2
  P(credit_rating = "fair" | buys_computer = "yes") = 6/9 = 0.667
  P(credit_rating = "fair" | buys_computer = "no") = 2/5 = 0.4

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

- **X = (age <= 30 , income = medium, student = yes, credit_rating = fair)**

$P(X|C_i)$: P(X|buys_computer = "yes") = 0.222 x 0.444 x 0.667 x 0.667 = 0.044
P(X|buys_computer = "no") = 0.6 x 0.4 x 0.2 x 0.4 = 0.019

$P(X|C_i)*P(C_i)$: P(X|buys_computer = "yes") * P(buys_computer = "yes") = 0.028
P(X|buys_computer = "no") * P(buys_computer = "no") = 0.007

ความน่าจะเป็นที่จะซื้อ มากกว่าไม่ซื้อ

Therefore, X belongs to class ("buys_computer = yes")

$\frac{3}{9} \times \frac{6}{9} \times \frac{9}{14} = 0.33$

$\vec{x}$ = age = 42, student = yes ?

$P(H^{'y}_{'N} | \vec{x}) = ?$

การวัดผล

Model Evaluation and Selection

- Evaluation metrics
  - How can we measure accuracy?
  - Other metrics to consider?
- Use **validation test set** of class-labeled tuples instead of training set when assessing accuracy
- Methods for estimating a classifier's accuracy
  - Holdout method
  - Cross-validation
  - Bootstrap
- Comparing classifiers:
  - ROC Curves

Classifier Evaluation Metrics: Precision and Recall, and F-measures

- **Precision**: Exactness: what % of tuples that the classifier labeled as positive are actually positive?

$$P = \text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** Completeness: what % of positive tuples did the classifier label as positive?

$$R = \text{Recall} = \frac{TP}{TP + FN}$$

Model เราหาตัวที่เป็น pos จริง

  - Range: [0, 1]
- The "inverse" relationship between precision & recall
- ***F* measure** (or ***F*-score**)**:** harmonic mean of precision and recall
  - In general, it is the weighted measure of precision & recall

$$F_\beta = \frac{1}{\alpha \cdot \frac{1}{P} + (1-\alpha) \cdot \frac{1}{R}} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

Assigning β times as much weight to recall as to precision)

  - ***F1-measure* (balanced *F*-measure)**
    - That is, when β = 1, $F_1 = \frac{2PR}{P + R}$

Classifier Evaluation Metrics: Confusion Matrix

- **Confusion Matrix:** → ทำให้ทราบว่า Model Positives ถูกเท่าไหร่ และ Model Negra ถูกเท่าไหร่

Actual class\Predicted class	C_1	$\neg C_1$
C_1	**True Positives (TP)**	**False Negatives (FN)**
$\neg C_1$	**False Positives (FP)**	**True Negatives (TN)**

- In a confusion matrix w. *m* classes, $CM_{i,j}$ indicates # of tuples in class *i* that were labeled by the classifier as class *j*
  - May have extra rows/columns to provide totals
- **Example of Confusion Matrix:**

Positives Negatives

Actual class\Predicted class	buy_computer = yes	buy_computer = no	Total
buy_computer = yes	**6954**	**46**	7000
buy_computer = no	**412**	**2588**	3000
Total	7366	2634	10000

Classifier Evaluation Metrics: Accuracy, Error Rate, Sensitivity and Specificity

A\P	C	¬C	
C	**TP**	**FN**	**P**
¬C	**FP**	**TN**	**N**
	P'	**N'**	**All**

- **Classifier accuracy,** or recognition rate
  - Percentage of test set tuples that are correctly classified

    Accuracy = (TP + TN)/All
- **Error rate:** *1 – accuracy*, or

  Error rate = (FP + FN)/All

- **Class imbalance problem**
  - One class may be *rare*
    - E.g., fraud, or HIV-positive
  - Significant *majority of the negative class* and minority of the positive class
  - Measures handle the class imbalance problem
    - **Sensitivity** (recall): True positive recognition rate
      - **Sensitivity = TP/P**
    - **Specificity**: True negative recognition rate
      - **Specificity = TN/N**