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

What Is Bayesian Classification?

- <u>A statistical classifier</u>
  - Perform *probabilistic prediction* (*i.e.,* predict class membership probabilities)
- <u>Foundation</u>—Based on Bayes' Theorem
- <u>Performance</u>

  นาอีฟ, เอาทฤษฎีมาจัดกลุ่ม Classifier
  - A simple Bayesian classifier, *naïve Bayesian classifier*, has comparable performance with decision tree and selected neural network classifiers
- <u>Incremental</u>
  - Each training example can incrementally increase/decrease the probability that a hypothesis is correct—prior knowledge can be combined with observed data
- **<u>Theoretical Standard</u>**
  - Even when Bayesian methods are computationally intractable, they can provide a standard of optimal decision making against which other methods can be measured

Bayes' Theorem: Basics

- Total probability Theorem:

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

- Bayes' Theorem:

test data   trainning data

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

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: Making a Naïve Assumption

- Practical difficulty of Naïve Bayes inference: It requires initial knowledge of many probabilities, which may not be available or involving significant computational cost
- A Naïve Special Case
  - Make an additional $\boxed{\text{assumption}}$ to simplify the model, but achieve comparable performance.

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ถึงจะทำการคำนวณได้ง่าย attributes are conditionally independent (i.e., no dependence relation between attributes)

$$p(X|C_i) = \boxed{\prod_k p(x_k|C_i) = p(x_1|C_i) \cdot p(x_2|C_i) \cdots\cdots \boxed{p(x_n|C_i)}}$$

  - Only need to count the class distribution w.r.t. features

Naïve Bayes Classifier: Categorical vs. Continuous Valued Features

- If feature $\mathrm{x_k}$ is categorical, $\mathrm{p(x_k = v_k|C_i)}$ is the # of tuples in $\mathrm{C_i}$ with $\mathrm{x_k = v_k}$, divided by $|C_{i,D}|$ (# of tuples of C_i in D)

$$\mathrm{p}(\mathrm{X}|C_i) = \prod_{\mathrm{k}} \mathrm{p(x_k|C_i) = p(x_1|C_i) \cdot p(x_2|C_i) \cdots\cdots p(x_n|C_i)}$$

- If feature $\mathrm{x_k}$ is continuous-valued, $\mathrm{p(x_k = v_k|C_i)}$ is usually computed based on Gaussian distribution with a mean μ and standard deviation σ

$$\mathrm{p(x_k = v_k|C_i)} = N\left(\mathrm{x_k}\middle|\mathrm{\mu_{C_i}, \sigma_{C_i}}\right) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{C_i}}} e^{-\frac{\left(x-\mu_{C_i}\right)^2}{2\sigma^2}}$$

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
>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
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

training Data

$P(H^{-N} | X) = ?$

$P(H^{-Y} | X) = ?$

$= P(X | H^{-y}) P(H^{-Y})$ มีโอกาส Yes 9/14

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
<=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
31…40	medium	no	excellent	yes
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

0.044x 0.643

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

0.019x 0.357

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