Bayes' Theorem: Basics

Total probability Theorem:

 $p(B) = \sum_{i} p(B|A_i)p(A_i)$

Bayes' Theorem:

orem:
$$p(H|\mathbf{X}) = \frac{p(\mathbf{X}|H)P(H)}{p(\mathbf{X})} \propto p(\mathbf{X}|H)P(H)$$
 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 <u>assumption</u> to simplify the model, but achieve comparable performance.

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

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

Naïve Bayes Classifier: Categorical vs. Continuous Valued Features

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

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

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

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

Naïve Bayes Classifier: Training Dataset

Class:

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

Data to be classified:

| 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 . |

Naïve Bayes Classifier: An Example

- $P(C_i)$: P(buys computer = "yes") = 9/14 = 0.643P(buys computer = "no") = 5/14 = 0.357
- Compute P(X | C_i) for each class

```
P(age = "<=30" | buys computer = "ves") = 2/9 = 0.222
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P(age = "<= 30" | buvs computer = "no") = 3/5 = 0.6

P(income = "medium" | buys computer = "yes") = 4/9 = 0.444

P(income = "medium" | buys computer = "no") = 2/5 = 0.4P(student = "yes" | buys computer = "yes) = 6/9 = 0.667

P(student = "ves" | buys computer = "no") = 1/5 = 0.2

P(credit rating = "fair" | buys computer = "ves") = 6/9 = 0.667

| P(credit_rating = "fair" buys_computer = "no") = 2/5 = 0 | , = - | • | | _ | • | | • | | |
|--|--------------------------|----|-----|------|----------|------|-------|-------|----|
| | P(credit_rating = "fair" | bı | uys | _con | nputer = | "no" |) = 2 | ./5 = | 0. |

| 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 |

- 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

 $P(X|buys computer = "no") = 0.6 \times 0.4 \times 0.2 \times 0.4 = 0.019$

 $P(X|C_i)*P(C_i): P(X|buys computer = "yes") * P(buys computer = "yes") = 0.028$

P(X|buys computer = "no") * P(buys computer = "no") = 0.007

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

$$\hat{x} = age = 42, student = yes$$

$$P(x^{1}|\hat{x}) = 9.$$

$$P(H = y|coge = 42, student = yes) = P(age = 42|y) P(stu = yes|y) P(y)$$

$$= \frac{2}{4} \times \frac{1}{4} \times \frac{1}{14}$$

$$P(H_{boy} = N|coge = 42, stv = yes) = Roge = 42|v) P(stv = yes|y) P(v)$$

