

Data Mining:


Concepts and Techniques

(3rd ed.)

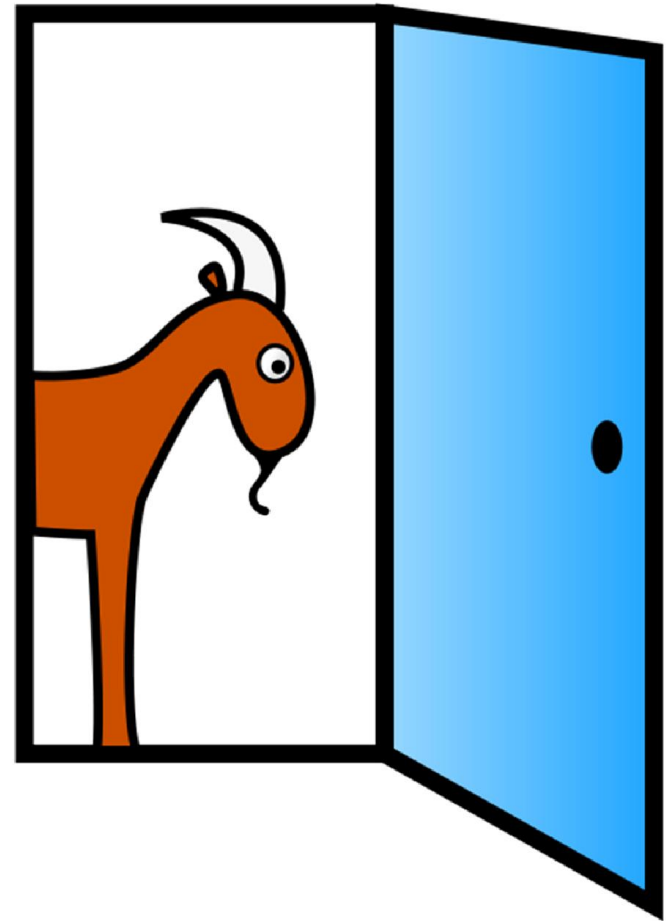
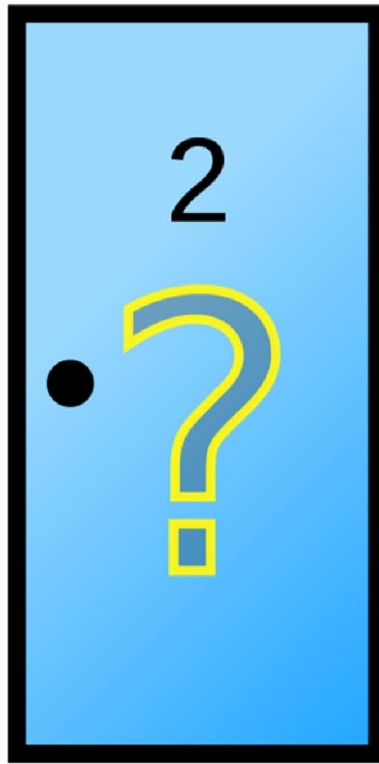
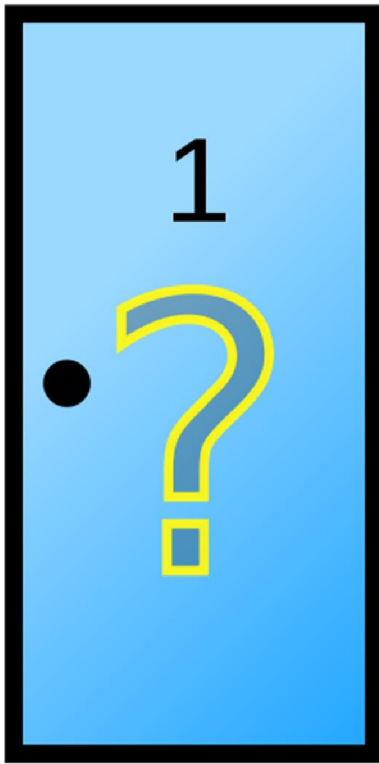
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Chapter 8. Classification – Cont.

- Bayes Classification Methods 
- Techniques to Improve Classification Accuracy:
Ensemble Methods
- Summary

Monty Hall



Bayesian Classification: Why?

- A statistical classifier: performs *probabilistic prediction*, i.e., predicts class membership probabilities
- Foundation: Based on Bayes' Theorem.
- Performance: A simple Bayesian classifier, *naïve Bayesian classifier*, has comparable performance with decision tree and selected neural network classifiers
- Incremental: Each training example can incrementally increase/decrease the probability that a hypothesis is correct — prior knowledge can be combined with observed data
- Standard: 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:
$$P(B) = \sum_{i=1}^M P(B|A_i)P(A_i)$$
- Bayes' Theorem:
$$P(H | \mathbf{X}) = \frac{P(\mathbf{X} | H)P(H)}{P(\mathbf{X})} = P(\mathbf{X} | H) \times P(H) / P(\mathbf{X})$$
 - Let \mathbf{X} be a data sample (“evidence”): class label is unknown
 - Let H be a *hypothesis* that X belongs to class C
 - Classification is to determine $P(H | \mathbf{X})$, (i.e., *posteriori probability*): the probability that the hypothesis holds given the observed data sample \mathbf{X}
 - $P(H)$ (*prior probability*): the initial probability
 - E.g., \mathbf{X} will buy computer, regardless of age, income, ...
 - $P(\mathbf{X})$: probability that sample data is observed
 - $P(\mathbf{X} | H)$ (likelihood): the probability of observing the sample \mathbf{X} , given that the hypothesis holds
 - E.g., Given that \mathbf{X} will buy computer, the prob. that X is 31..40, medium income

Prediction Based on Bayes' Theorem

- Given training data \mathbf{X} , *posteriori probability of a hypothesis* H , $P(H|\mathbf{X})$, follows the Bayes' theorem

$$P(H|\mathbf{X}) = \frac{P(\mathbf{X}|H)P(H)}{P(\mathbf{X})} = P(\mathbf{X}|H) \times P(H) / P(\mathbf{X})$$

- Informally, this can be viewed as
posteriori = likelihood x prior/evidence
- Predicts \mathbf{X} belongs to C_i iff the probability $P(C_i|\mathbf{X})$ is the highest among all the $P(C_k|\mathbf{X})$ for all the k classes
- Practical difficulty: It requires initial knowledge of many probabilities, involving significant computational cost

Classification Is to Derive the Maximum Posteriori

- Let D be a training set of tuples and their associated class labels, and each tuple is represented by an n -D attribute vector $\mathbf{X} = (x_1, x_2, \dots, x_n)$
- Suppose there are m classes C_1, C_2, \dots, C_m .
- Classification is to derive the maximum posteriori, i.e., the maximal $P(C_i | \mathbf{X})$
- This can be derived from Bayes' theorem

$$P(C_i | \mathbf{X}) = \frac{P(\mathbf{X} | C_i)P(C_i)}{P(\mathbf{X})}$$

- Since $P(\mathbf{X})$ is constant for all classes, only

$$P(C_i | \mathbf{X}) = P(\mathbf{X} | C_i)P(C_i)$$

needs to be maximized

Naïve Bayes Classifier

- A simplified assumption: attributes are conditionally independent (i.e., no dependence relation between attributes):
$$P(\mathbf{X} | C_i) = \prod_{k=1}^n P(x_k | C_i) = P(x_1 | C_i) \times P(x_2 | C_i) \times \dots \times P(x_n | C_i)$$
- This greatly reduces the computation cost: Only counts the class distribution
- If A_k is categorical, $P(x_k | C_i)$ is the # of tuples in C_i having value x_k for A_k divided by $|C_{i,D}|$ (# of tuples of C_i in D)
- If A_k is continuous-valued, $P(x_k | C_i)$ is usually computed based on Gaussian distribution with a mean μ and standard deviation σ

and $P(x_k | C_i)$ is

$$g(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$P(\mathbf{X} | C_i) = g(x_k, \mu_{C_i}, \sigma_{C_i})$$

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	com
<=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

Naïve Bayes Classifier: An Example

- $P(C_i)$: $P(\text{buys_computer} = \text{"yes"}) = 9/14 = 0.643$
 $P(\text{buys_computer} = \text{"no"}) = 5/14 = 0.357$
 - Compute $P(X|C_i)$ for each class
 - $P(\text{age} = \text{"<=30"} | \text{buys_computer} = \text{"yes"}) = 2/9 = 0.222$
 - $P(\text{age} = \text{"<= 30"} | \text{buys_computer} = \text{"no"}) = 3/5 = 0.6$
 - $P(\text{income} = \text{"medium"} | \text{buys_computer} = \text{"yes"}) = 4/9 = 0.444$
 - $P(\text{income} = \text{"medium"} | \text{buys_computer} = \text{"no"}) = 2/5 = 0.4$
 - $P(\text{student} = \text{"yes"} | \text{buys_computer} = \text{"yes"}) = 6/9 = 0.667$
 - $P(\text{student} = \text{"yes"} | \text{buys_computer} = \text{"no"}) = 1/5 = 0.2$
 - $P(\text{credit_rating} = \text{"fair"} | \text{buys_computer} = \text{"yes"}) = 6/9 = 0.667$
 - $P(\text{credit_rating} = \text{"fair"} | \text{buys_computer} = \text{"no"}) = 2/5 = 0.4$
 - **$X = (\text{age} \leq 30, \text{income} = \text{medium}, \text{student} = \text{yes}, \text{credit_rating} = \text{fair})$**
 - $P(X|C_i)$: $P(X|\text{buys_computer} = \text{"yes"}) = 0.222 \times 0.444 \times 0.667 \times 0.667 = 0.044$
 $P(X|\text{buys_computer} = \text{"no"}) = 0.6 \times 0.4 \times 0.2 \times 0.4 = 0.019$
 - $P(X|C_i) \cdot P(C_i)$: $P(X|\text{buys_computer} = \text{"yes"}) \cdot P(\text{buys_computer} = \text{"yes"}) = 0.028$
 $P(X|\text{buys_computer} = \text{"no"}) \cdot P(\text{buys_computer} = \text{"no"}) = 0.007$
- Therefore, X belongs to class ("buys_computer = yes")**

Avoiding the Zero-Probability Problem

- Naïve Bayesian prediction requires each conditional prob. be **non-zero**. Otherwise, the predicted prob. will be zero


$$P(X | C_i) = \prod_{k=1}^n P(x_k | C_i)$$

- Ex. Suppose a dataset with 1000 tuples, income=low (0), income= medium (990), and income = high (10)
- Use **Laplacian correction** (or Laplacian estimator)
 - *Adding 1 to each case*
Prob(income = low) = 1/1003
Prob(income = medium) = 991/1003
Prob(income = high) = 11/1003
 - The “corrected” prob. estimates are close to their “uncorrected” counterparts

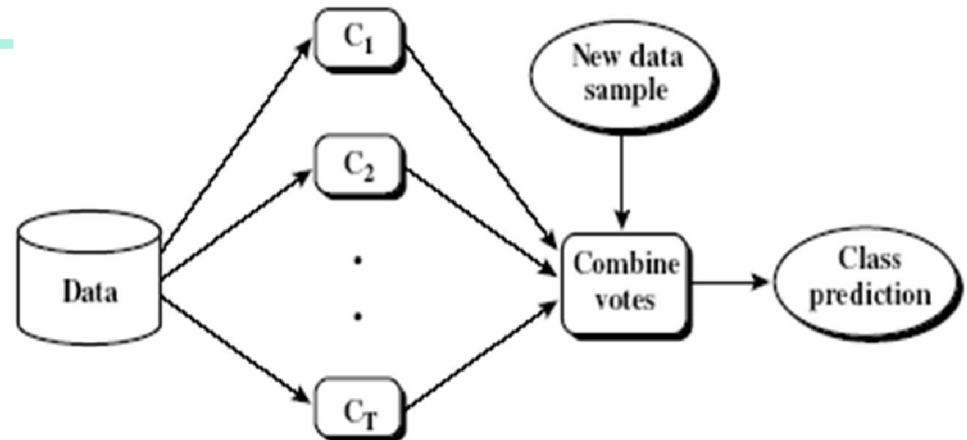
Naïve Bayes Classifier: Comments

- Advantages
 - Easy to implement
 - Good results obtained in most of the cases
- Disadvantages
 - Assumption: class conditional independence, therefore loss of accuracy
 - Practically, dependencies exist among variables
 - E.g., hospitals: patients: Profile: age, family history, etc.
Symptoms: fever, cough etc., Disease: lung cancer, diabetes, etc.
 - Dependencies among these cannot be modeled by Naïve Bayes Classifier
- How to deal with these dependencies? Bayesian Belief Networks (Chapter 9)

Chapter 8. Classification: Basic Concepts

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Ensemble Methods: Increasing the Accuracy



- Ensemble methods
 - Use a combination of models to increase accuracy
 - Combine a series of k learned models, M_1, M_2, \dots, M_k , with the aim of creating an improved model M^*
- Popular ensemble methods
 - Bagging: averaging the prediction over a collection of classifiers
 - Boosting: weighted vote with a collection of classifiers
 - Ensemble: combining a set of heterogeneous classifiers

Bagging: Bootstrap Aggregation

- Analogy: Diagnosis based on multiple doctors' majority vote
- Training
 - Given a set D of d tuples, at each iteration i , a training set D_i of d tuples is sampled with replacement from D (i.e., bootstrap)
 - A classifier model M_i is learned for each training set D_i
- Classification: classify an unknown sample X
 - Each classifier M_i returns its class prediction
 - The bagged classifier M^* counts the votes and assigns the class with the most votes to X
- Prediction: can be applied to the prediction of continuous values by taking the average value of each prediction for a given test tuple
- Accuracy
 - Often significantly better than a single classifier derived from D
 - For noise data: not considerably worse, more robust
 - Proved improved accuracy in prediction

Boosting

- Analogy: Consult several doctors, based on a combination of weighted diagnoses—weight assigned based on the previous diagnosis accuracy
- How boosting works?
 - **Weights** are assigned to each training tuple
 - A series of k classifiers is iteratively learned
 - After a classifier M_i is learned, the weights are updated to allow the subsequent classifier, M_{i+1} , to **pay more attention to the training tuples that were misclassified** by M_i
 - The final **M^* combines the votes** of each individual classifier, where the weight of each classifier's vote is a function of its accuracy
- Boosting algorithm can be extended for numeric prediction
- Comparing with bagging: Boosting tends to have greater accuracy, but it also risks overfitting the model to misclassified data

Adaboost (Freund and Schapire, 1997)

- Given a set of d class-labeled tuples, $(\mathbf{X}_1, y_1), \dots, (\mathbf{X}_d, y_d)$
- Initially, all the weights of tuples are set the same ($1/d$)
- Generate k classifiers in k rounds. At round i ,
 - Tuples from D are sampled (with replacement) to form a training set D_i of the same size
 - Each tuple's chance of being selected is based on its weight
 - A classification model M_i is derived from D_i
 - Its error rate is calculated using D_i as a test set
 - If a tuple is misclassified, its weight is increased, o.w. it is decreased
- Error rate: $\text{err}(\mathbf{X}_j)$ is the misclassification error of tuple \mathbf{X}_j . Classifier M_i error rate is the sum of the weights of the misclassified tuples:

$$\text{error}(M_i) = \sum_j^d w_j \times \text{err}(\mathbf{X}_j)$$

- The weight of classifier M_i 's vote is $\log \frac{1 - \text{error}(M_i)}{\text{error}(M_i)}$


Random Forest (Breiman 2001)

- Random Forest:
 - Each classifier in the ensemble is a *decision tree* classifier and is generated using a random selection of attributes at each node to determine the split
 - During classification, each tree votes and the most popular class is returned
- Two Methods to construct Random Forest:
 - Forest-RI (*random input selection*): Randomly select, at each node, F attributes as candidates for the split at the node. The CART methodology is used to grow the trees to maximum size
 - Forest-RC (*random linear combinations*): Creates new attributes (or features) that are a linear combination of the existing attributes (reduces the correlation between individual classifiers)
- Comparable in accuracy to Adaboost, but more robust to errors and outliers
- Insensitive to the number of attributes selected for consideration at each split, and faster than bagging or boosting

Classification of Class-Imbalanced Data Sets

- Class-imbalance problem: Rare positive example but numerous negative ones, e.g., medical diagnosis, fraud, oil-spill, fault, etc.
- Traditional methods assume a balanced distribution of classes and equal error costs: not suitable for class-imbalanced data
- Typical methods for imbalance data in 2-class classification:
 - **Oversampling**: re-sampling of data from positive class
 - **Under-sampling**: randomly eliminate tuples from negative class
 - **Threshold-moving**: moves the decision threshold, t , so that the rare class tuples are easier to classify, and hence, less chance of costly false negative errors
 - Ensemble techniques: Ensemble multiple classifiers introduced above
- Still difficult for class imbalance problem on multiclass tasks

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Summary (I)

- **Classification** is a form of data analysis that extracts **models** describing important data classes.
- Effective and scalable methods have been developed for **decision tree induction, Naive Bayesian classification**, and many other classification methods.