Classification

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Classification and Prediction

- What is classification? What is prediction?
- Issues regarding classification and prediction
- Classification by decision tree induction
- Bayesian Classification
- Classification by backpropagation
- Classification based on concepts from association rule mining
- Other Classification Methods
- Prediction
- Classification accuracy
- Summary

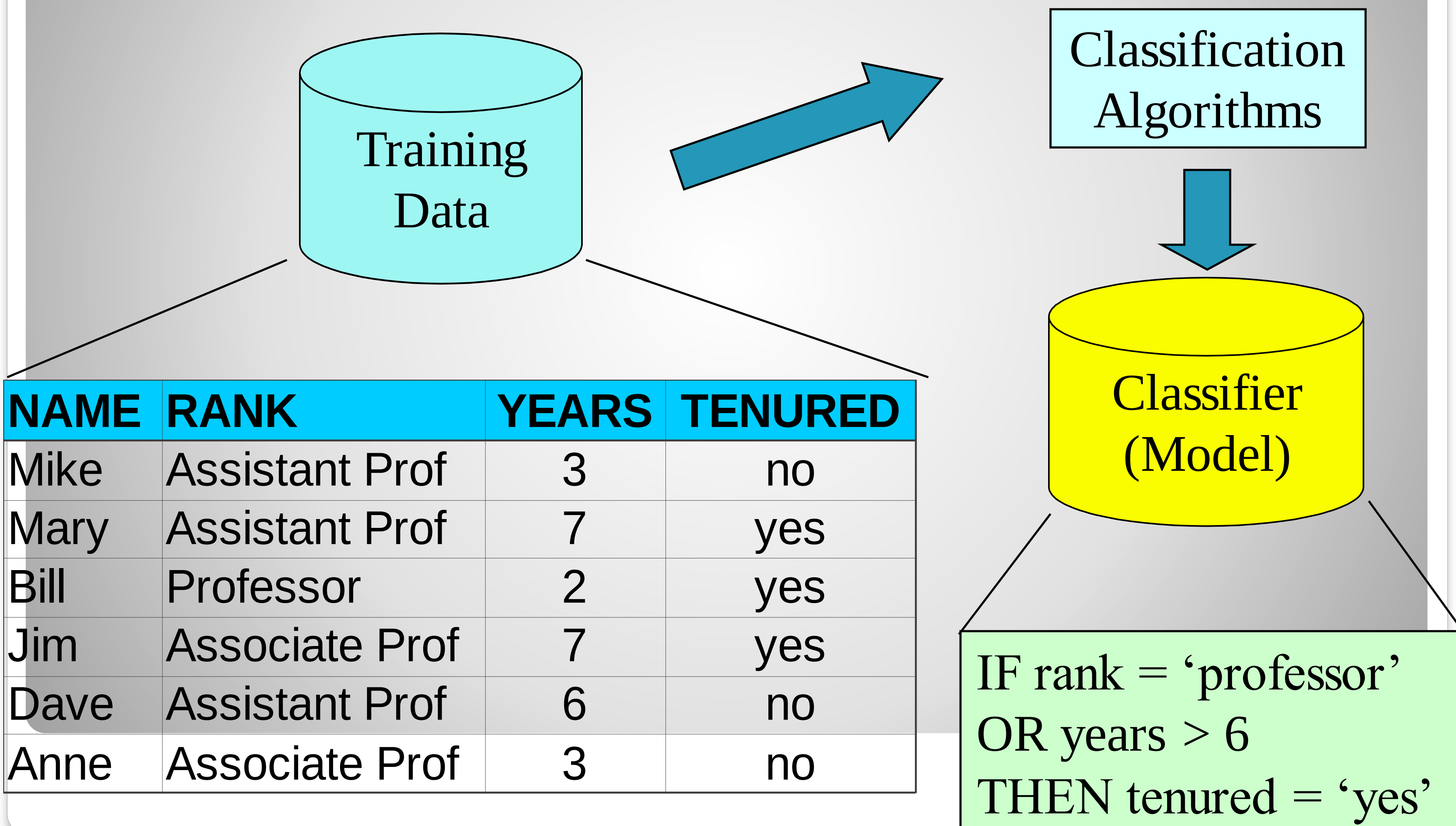
Classification vs. Prediction

- Classification:
  - predicts categorical class labels
  - classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data
- Prediction:
  - models continuous-valued functions, i.e., predicts unknown or missing values
- Typical Applications
  - credit approval
  - target marketing
  - medical diagnosis
  - treatment effectiveness analysis

Classification—A Two-Step Process

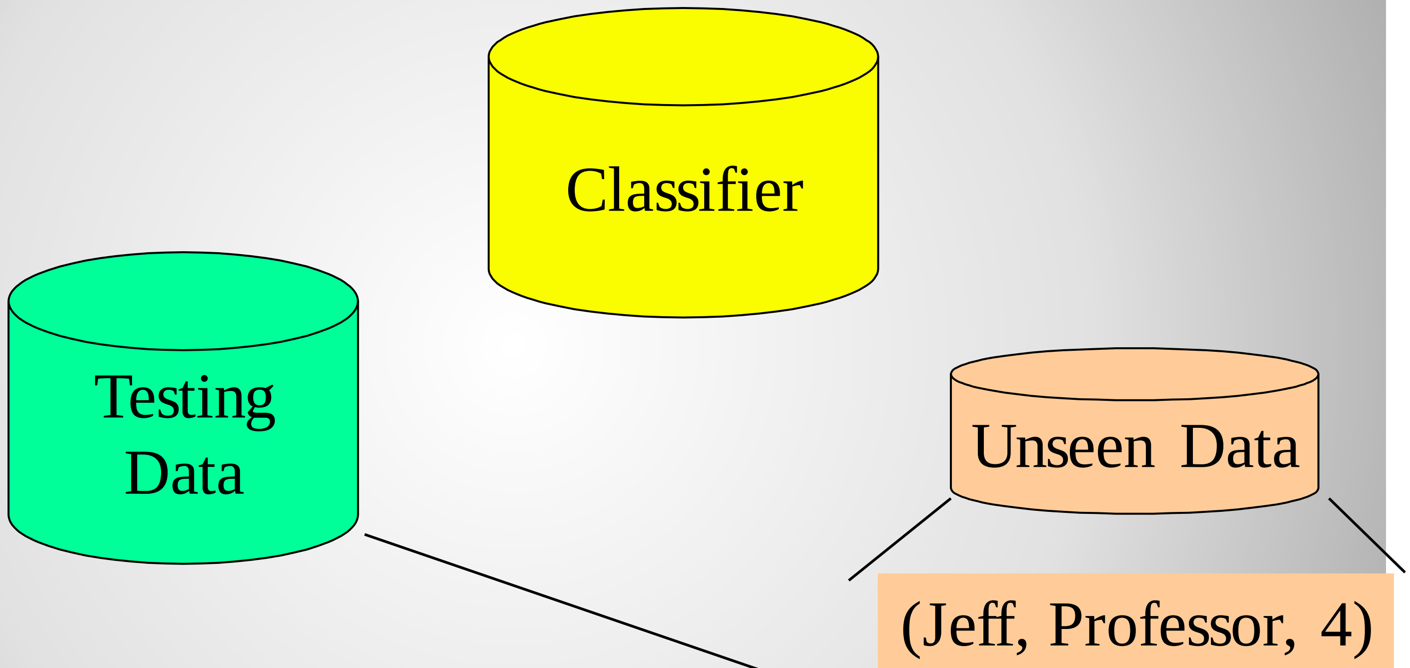
- Model construction: describing a set of predetermined classes
  - Each tuple/sample is assumed to belong to a predefined class, as determined by the class label attribute
  - The set of tuples used for model construction: training set
  - The model is represented as classification rules, decision trees, or mathematical formulae
- Model usage: for classifying future or unknown objects
  - Estimate accuracy of the model
    - The known label of test sample is compared with the classified result from the model
    - Accuracy rate is the percentage of test set samples that are correctly classified by the model
    - Test set is independent of training set, otherwise

Classification Process (1): Model Construction



NAME	RANK	YEARS	TENURED
Mike	Assistant Prof	3	no
Mary	Assistant Prof	7	yes
Bill	Professor	2	yes
Jim	Associate Prof	7	yes
Dave	Assistant Prof	6	no
Anne	Associate Prof	3	no

Classification Process (2): Use the Model in Prediction



NAME	RANK	YEARS	TENURED
Tom	Assistant Prof	2	no
Merlisa	Associate Prof	7	no
George	Professor	5	yes
Joseph	Assistant Prof	7	yes

Tenured?

Yes

Supervised vs. Unsupervised Learning

- Supervised learning (classification)
  - Supervision: The training data (observations, measurements, etc.) are accompanied by labels indicating the class of the observations
  - New data is classified based on the training set
- Unsupervised learning (clustering)
  - The class labels of training data is unknown
  - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data.

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Issues (1): Data Preparation

- Data cleaning
  - Preprocess data in order to reduce noise and handle missing values
- Relevance analysis (feature selection)
  - Remove the irrelevant or redundant attributes
- Data transformation
  - Generalize and/or normalize data

Issues (2): Evaluating Classification Methods

- Predictive accuracy
- Speed and scalability
  - time to construct the model
  - time to use the model
- Robustness
  - handling noise and missing values
- Scalability
  - efficiency in disk-resident databases
- Interpretability:
  - understanding and insight provded by the model
- Goodness of rules
  - decision tree size
  - compactness of classification rules

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Training Dataset

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

Bayesian Classification: Why?

- Probabilistic learning: Calculate explicit probabilities for hypothesis, among the most practical approaches to certain types of learning problems
- Incremental: Each training example can incrementally increase/decrease the probability that a hypothesis is correct. Prior knowledge can be combined with observed data.
- Probabilistic prediction: Predict multiple hypotheses, weighted by their probabilities
- Standard: Even when Bayesian methods are computationally intractable, they can provide a standard of optimal decision making against which other methods can be measured

Bayesian Theorem

- Given training data *D, posteriori probability of a hypothesis h, P(h|D)* follows the Bayes theorem

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)}$$

- MAP (maximum posteriori) hypothesis

$$P(D|h)P(h).$$

- Practical difficulty: require initial knowledge of many probabilities, significant computational cost

Bayesian classification

- The classification problem may be formalized using a-posteriori probabilities:
- $P(C|X)$ = prob. that the sample tuple $X=<x_1,\ldots,x_k>$ is of class C.
- E.g. P(class=N | outlook=sunny,windy=true,…)
- Idea: assign to sample X the class label C such that $P(C|X)$ is maximal

Estimating a-posteriori probabilities

- Bayes theorem:

$$P(C|X) = P(X|C)\cdot P(C) \,/\, P(X)$$

- $P(X)$ is constant for all classes
- $P(C)$ = relative freq of class C samples
- C such that $P(C|X)$ is maximum =
  C such that $P(X|C)\cdot P(C)$ is maximum
- Problem: computing $P(X|C)$ is unfeasible!

Naïve Bayesian Classification

- Naïve assumption: attribute independence

  $$P(x_1,\ldots,x_k|C) = P(x_1|C)\cdot\ldots\cdot P(x_k|C)$$

- If i-th attribute is categorical: $P(x_i|C)$ is estimated as the relative freq of samples having value x_i as i-th attribute in class C
- If i-th attribute is continuous: $P(x_i|C)$ is estimated thru a Gaussian density function
- Computationally easy in both cases

Outlook	Temperature	Humidity	Windy	Class
sunny	hot	high	false	N
sunny	hot	high	true	N
overcast	hot	high	false	P
rain	mild	high	false	P
rain	cool	normal	false	P
rain	cool	normal	true	N
overcast	cool	normal	true	P
sunny	mild	high	false	N
sunny	cool	normal	false	P
rain	mild	normal	false	P
sunny	mild	normal	true	P
overcast	mild	high	true	P
overcast	hot	normal	false	P
rain	mild	high	true	N

P(p) = 9/14

P(n) = 5/14

outlook

P(sunny|p) = 2/9 **P(sunny|n) = 3/5**

P(overcast|p) = 4/9 **P(overcast|n) = 0**

P(rain|p) = 3/9 **P(rain|n) = 2/5**

temperature

P(hot|p) = 2/9 **P(hot|n) = 2/5**

P(mild|p) = 4/9 **P(mild|n) = 2/5**

P(cool|p) = 3/9 **P(cool|n) = 1/5**

humidity

P(high|p) = 3/9 **P(high|n) = 4/5**

P(normal|p) = 6/9 **P(normal|n) = 2/5**

windy

P(true|p) = 3/9 **P(true|n) = 3/5**

P(false|p) = 6/9 **P(false|n) = 2/5**

Play-tennis example: classifying X

- An unseen sample X = <rain, hot, high, false>

- $P(X|p) \cdot P(p) = P(rain|p) \cdot P(hot|p) \cdot P(high|p) \cdot P(false|p) \cdot P(p) = 3/9 \cdot 2/9 \cdot 3/9 \cdot 6/9 \cdot 9/14 = 0.010582$
- $P(X|n) \cdot P(n) = P(rain|n) \cdot P(hot|n) \cdot P(high|n) \cdot P(false|n) \cdot P(n) = 2/5 \cdot 2/5 \cdot 4/5 \cdot 2/5 \cdot 5/14 = 0.018286$
- Sample X is classified in class n (don't play)

The independence hypothesis…

- … makes computation possible
- … yields optimal classifiers when satisfied
- … but is seldom satisfied in practice, as attributes (variables) are often correlated.
- Attempts to overcome this limitation:
  - Bayesian networks, that combine Bayesian reasoning with causal relationships between attributes
  - Decision trees, that reason on one attribute at the time, considering most important attributes first

Example of Naïve Bayesian:

Unknown sample---- { Red, SUV, Domestic,**?**}

Example No.	Color	Type	Origin	Stolen?
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Yellow	Sports	Domestic	No
5	Yellow	Sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes

Color	
P(Red|Yes)=3/5	P(Red|No)=2/5
P(Yellow|Yes)=2/5	P(Yellow|No)=3/5
Type	
P(SUV|Yes)=1/5	P(SUV|No)=3/5
P(Sports|Yes)=4/5	P(Sports|No)=2/5
Origin	
P(Domestic|Yes)=2/5	P(Domestic|No)=3/5
P(Imported|Yes)=3/5	P(Imported|No)=2/5

P(Yes) * P(Red | Yes) * P(SUV | Yes) * P(Domestic|Yes)
= 5/10 * 3/5 * 2/5 * 1/5 = 0.024
and for
v = No,
P(No) * P(Red | No) * P(SUV | No) * P (Domestic | No)
= 5/10 * 2/5 * 3/5 * 3/5 = 0.072

Since 0.072 > 0.024, our example gets classified as ’NO’