# Data Mining: Characterization

## **Concept Description: Characterization and Comparison**

- **%** What is concept description?
- Bata generalization and summarization-based characterization
- **#** Analytical characterization: Analysis of attribute relevance
- Hining class comparisons: Discriminating between different classes
- Hining descriptive statistical measures in large databases
- Summary

# What is Concept Description?

Bescriptive vs. predictive data mining

- Descriptive mining: describes concepts or task-relevant data sets in concise, summarative, informative, discriminative forms
- Predictive mining: Based on data and analysis, constructs models for the database, and predicts the trend and properties of unknown data

**Concept description:** 

- ○<u>Characterization</u>: provides a concise and succinct summarization of the given collection of data
- Comparison: provides descriptions comparing two or more collections of data

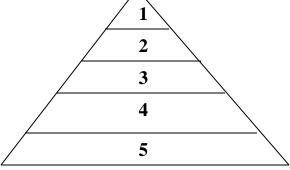
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Data Generalization and Summarization-based Characterization

#### ∺ Data generalization

A process which abstracts a large set of task-relevant data in a database from a low conceptual levels to higher ones.



Conceptual levels

### Attribute-Oriented Induction

% Proposed in 1989 (KDD `89 workshop)

Not confined to categorical data nor particular measures.

#### How it is done?

Collect the task-relevant data( *initial relation*) using a relational database query

Perform generalization by <u>attribute removal</u> or <u>attribute generalization</u>.

Apply aggregation by merging identical, generalized tuples and accumulating their respective counts.

 $\square$ Interactive presentation with users.

### Basic Principles of Attribute-Oriented Induction

- Bata focusing: task-relevant data, including dimensions, and the result is the *initial relation*.
- Attribute-removal: remove attribute A if there is a large set of distinct values for A but (1) there is no generalization operator on A, or (2) A's higher level concepts are expressed in terms of other attributes.
- Attribute-generalization: If there is a large set of distinct values for A, and there exists a set of generalization operators on A, then select an operator and generalize A.
- <u>Attribute-threshold control</u>: typical 2-8, specified/default.
- Size.
  Size.

# Example

**#** Describe general characteristics of graduate students in the Big-University database **use** Big\_University\_DB mine characteristics as "Science Students" in relevance to name, gender, major, birth\_place, birth date, residence, phone#, gpa **from** student where status in "graduate" **#** Corresponding SQL statement: **Select** name, gender, major, birth\_place, birth\_date, residence, phone#, gpa from student where status in {"Msc", "MBA", "PhD" }

### **Class Characterization: An Example**

Initial Relation	Name Jim Woodma Scott Lachance Laura Lo	e M	]	Major CS CS Physics	Birth-Pla Vancouv Canada Montrea Canada Seattle, W 	er,BC, l, Que,	8-1 28-7		351 Rick 345 Rick 125	idence 1 Main St., hmond 1st Ave., hmond Austin Ave., naby	Phone #           687-4598           253-9106           420-5232	GPA 3.67 3.70 3.83 	
	Removed	Retai		Sci,Eng, Bus	Country		Age	range	City	7	Removed	Excl, VG,	
		Gender	Major	r Bir	th_region	Age_1	range	Resid	ence	GPA	Count		
Prime		М	Scien	ce C	lanada	20-	-25	Richn	nond	Very-good	16		
Genera		F	Scien	ce F	oreign	25-	-30	Burna	ıby	Excellent	22		
Relatio	n					•							
				Bir Gender	th_Region	Canac	la	Foreig	1	Total			
					М	16		14		30			
					F	10		22		32			

26

36

62

Total

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# Attribute Relevance Analysis

#### ₩Why?

○ Which dimensions should be included?

△How high level of generalization?

Automatic vs. interactive

Reduce # attributes; easy to understand patterns

₩What?

statistical method for preprocessing data
 in filter out irrelevant or weakly relevant attributes
 in relevant or rank the relevant attributes
 in relevance related to dimensions and levels
 in analytical characterization, analytical comparison

# Attribute relevance analysis (cont'd)

#### <mark>∺How?</mark>

Data Collection

Analytical Generalization

☑Use information gain analysis (e.g., entropy or other measures) to identify highly relevant dimensions and levels.

Relevance Analysis

⊠Sort and select the most relevant dimensions and levels.

Attribute-oriented Induction for class description

⊠On selected dimension/level

OLAP operations (e.g. drilling, slicing) on relevance rules

# **Relevance Measures**

₩Quantitative relevance measure determines the classifying power of an attribute within a set of data.

% Methods

- △information gain (ID3)
- Gain ratio (C4.5)
- $\Delta \chi^2$  contingency table statistics

Ouncertainty coefficient

# Information-Theoretic Approach

#### ∺ Decision tree

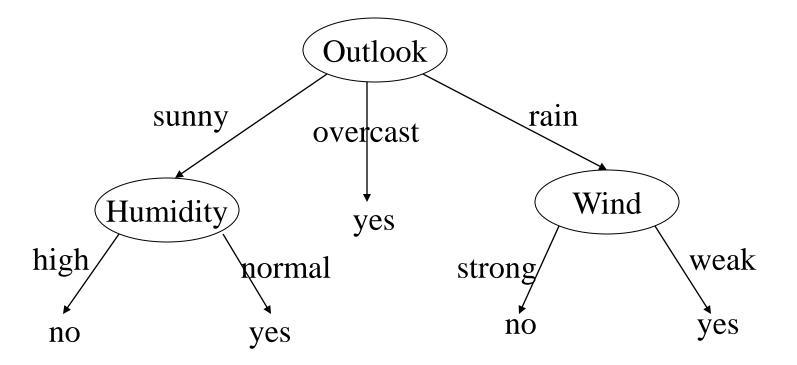
- each internal node tests an attribute
- each branch corresponds to attribute value
- each leaf node assigns a classification

#### 

- build decision tree based on training objects with known class labels to classify testing objects
- rank attributes with information gain measure
- ☐minimal height
  - ⊠the least number of tests to classify an object

#### Top-Down Induction of Decision Tree

Attributes = {Outlook, Temperature, Humidity, Wind} PlayTennis = {yes, no}



# **Example: Analytical Characterization**

#### <mark>೫</mark> Task

Mine general characteristics describing graduate students using analytical characterization

**#**Given

Attributes name, gender, major, birth\_place, birth\_date, phone#, and gpa

 $\bigtriangleup Gen(a_i) = \text{concept hierarchies on } a_i$ 

 $\square U_i$  = attribute analytical thresholds for  $a_i$ 

 $rac{T_i}$  = attribute generalization thresholds for  $a_i$ 

 $\triangle R$  = attribute relevance threshold

# Example: Analytical Characterization (cont'd)

#### ∺1. Data collection

△target class: graduate student

Contrasting class: undergraduate student

#### **2.** Analytical generalization using U<sub>i</sub>

Attribute removal

⊠remove *name* and *phone#* 

△attribute generalization

Seneralize *major*, *birth\_place*, *birth\_date* and *gpa* 

⊠accumulate counts

Candidate relation: gender, major, birth\_country, age\_range and gpa

# **Example: Analytical characterization (2)**

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gender	major	birth_country	age_range	gpa	count
М	Science	Canada	20-25	Very_good	16
F	Science	Foreign	25-30	Excellent	22
М	Engineering	Foreign	25-30	Excellent	18
F	Science	Foreign	25-30	Excellent	25
М	Science	Canada	20-25	Excellent	21
F	Engineering	Canada	20-25	Excellent	18

Candidate relation for Target class: Graduate students ( $\Sigma$ =120)

gender	major	birth_country	age_range	gpa	count
Μ	Science	Foreign	<20	Very_good	18
F	Business	Canada	<20	Fair	20
Μ	Business	Canada	<20	Fair	22
F	Science	Canada	20-25	Fair	24
Μ	Engineering	Foreign	20-25	Very_good	22
F	Engineering	Canada	<20	Excellent	24

Candidate relation for Contrasting class: Undergraduate students ( $\Sigma$ =130)

## **Example: Analytical characterization (3)**

**3**. Relevance analysis

Calculate expected info required to classify an arbitrary tuple

$$I(s_1, s_2) = I(120, 130) = -\frac{120}{250} \log 2\frac{120}{250} - \frac{130}{250} \log 2\frac{130}{250} = 0.9988$$

#### Calculate entropy of each attribute: e.g. major

For major= "Science":  $s_{11}=84$   $s_{21}=42$   $I(s_{11},s_{21})=0.9183$ For major= "Engineering":  $s_{12}=36$   $s_{22}=46$   $I(s_{12},s_{22})=0.9892$ For major= "Business":  $s_{13}=0$   $s_{23}=42$   $I(s_{13},s_{23})=0$ Number of grad students in "Science" Number of undergrad students in "Science"

# **Example: Analytical Characterization (4)**

Calculate expected info required to classify a given sample if S is partitioned according to the attribute

$$E(major) = \frac{126}{250}I(s_{11}, s_{21}) + \frac{82}{250}I(s_{12}, s_{22}) + \frac{42}{250}I(s_{13}, s_{23}) = 0.7873$$

**#** Calculate information gain for each attribute

 $Gain(major) = I(s_1, s_2) - E(major) = 0.2115$ 

#### ☐ Information gain for all attributes

Gain(gender)	= 0.0003
Gain(birth_country)	= 0.0407
Gain(major)	= 0.2115
Gain(gpa)	= 0.4490
Gain(age_range)	= 0.5971

# **Example: Analytical characterization (5)**

**#4.** Initial working relation (W<sub>0</sub>) derivation

- $\triangle R = 0.1$
- remove irrelevant/weakly relevant attributes from candidate relation => drop gender, birth\_country
- remove contrasting class candidate relation

major	age_range	gpa	count
Science	20-25	Very_good	16
Science	25-30	Excellent	47
Science	20-25	Excellent	21
Engineering	20-25	Excellent	18
Engineering	25-30	Excellent	18

**Initial target class working relation W**<sub>0</sub>**: Graduate students** 

**5.** Perform attribute-oriented induction on W<sub>0</sub> using T<sub>i</sub>

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# **Mining Class Comparisons**

% Comparison: Comparing two or more classes.
% Method:

- Partition the set of relevant data into the target class and the contrasting class(es)
- Generalize both classes to the same high level concepts
- Compare tuples with the same high level descriptions
- Present for every tuple its description and two measures:

 $\boxtimes$  support - distribution within single class

⊠comparison - distribution between classes

☐ Highlight the tuples with strong discriminant features

₭ Relevance Analysis:

Find attributes (features) which best distinguish different classes.

# **Example: Analytical comparison**

#### <mark>∺</mark>Task

Compare graduate and undergraduate students using discriminant rule.

DMQL query

use Big\_University\_DB
mine comparison as "grad\_vs\_undergrad\_students"
in relevance to name, gender, major, birth\_place, birth\_date, residence, phone#, gpa
for "graduate\_students"
where status in "graduate"
versus "undergraduate\_students"
where status in "undergraduate"
analyze count%
from student

# **Example: Analytical comparison (2)**

#### <mark>∺</mark>Given

- Attributes name, gender, major, birth\_place, birth\_date, residence, phone# and gpa
- $\bigcirc$  Gen(a<sub>i</sub>) = concept hierarchies on attributes a<sub>i</sub>
- $\square U_i$  = attribute analytical thresholds for attributes  $a_i$
- $rac{1}{\sim} T_i$  = attribute generalization thresholds for attributes  $a_i$
- $\triangle R$  = attribute relevance threshold

# **Example: Analytical comparison (3)**

#### 

# **≈ 2.** Attribute relevance analysis remove attributes *name, gender, major, phone#*

#### ₩3. Synchronous generalization

Controlled by user-specified dimension thresholds
prime target and contrasting class(es)
relations/cuboids

# **Example: Analytical comparison (4)**

<b>Birth_country</b>	Age_range	Gpa	Count%
Canada	20-25	Good	5.53%
Canada	25-30	Good	2.32%
Canada	Over_30	Very_good	5.86%
	•••	•••	•••
Other	Over_30	Excellent	4.68%

Prime generalized relation for the target class: Graduate students

<b>Birth_country</b>	Age_range	Gpa	Count%
Canada	15-20	Fair	5.53%
Canada	15-20	Good	4.53%
	•••	•••	•••
Canada	25-30	Good	5.02%
Other	Over_30	Excellent	0.68%

Prime generalized relation for the contrasting class: Undergraduate students

# **Example: Analytical comparison (5)**

# 4. Drill down, roll up and other OLAP operations on target and contrasting classes to adjust levels of abstractions of resulting description

**∺** 5. Presentation

As generalized relations, crosstabs, bar charts, pie charts, or rules

Contrasting measures to reflect comparison between target and contrasting classes

⊠e.g. count%

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### Mining Data Dispersion Characteristics

#### **#** Motivation

To better understand the data: central tendency, variation and spread

#### Bata dispersion characteristics

△ median, max, min, quantiles, outliers, variance, etc.

#### **K** <u>Numerical dimensions</u> correspond to sorted intervals

Data dispersion: analyzed with multiple granularities of precision

○ Boxplot or quantile analysis on sorted intervals

#### **Bispersion analysis on computed measures**

○ Folding measures into numerical dimensions

Boxplot or quantile analysis on the transformed cube

### **Measuring the Central** Tendency

**#** Mean 
$$\overline{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$$
  
Weighted arithmetic mean

**Hedian:** A holistic measure

 $\overline{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$ 

Middle value if odd number of values, or average of the middle two values otherwise estimated by interpolation

#### **∺** <u>Mode</u>

Value that occurs most frequently in the data

🗠 Unimodal, bimodal, trimodal

Empirical formula:

median = 
$$L_1 + (\frac{n/2 - (\sum f)l}{f_{median}})c$$

$$nean - mode = 3 \times (mean - median)$$

# Measuring the Dispersion of Data

- - $\square$  Quartiles: Q<sub>1</sub> (25<sup>th</sup> percentile), Q<sub>3</sub> (75<sup>th</sup> percentile)
  - $\square$  Inter-quartile range: IQR =  $Q_3 Q_1$
  - $\square$  Five number summary: min, Q<sub>1</sub>, M, Q<sub>3</sub>, max
  - Boxplot: ends of the box are the quartiles, median is marked, whiskers, and plot outlier individually
  - Outlier: usually, a value higher/lower than 1.5 x IQR
- Kariance and standard deviation
  - $\square$  Variance  $s^2$ : (algebraic, scalable computation)
  - $\bigtriangleup$  Standard deviation *s* is the square root of variance  $s^2$

$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{i} - \overline{x})^{2} = \frac{1}{n-1} \left[ \sum_{i=1}^{n} x_{i}^{2} - \frac{1}{n} (\sum_{i=1}^{n} x_{i})^{2} \right]$$

### **Boxplot Analysis**

₭ Five-number summary of a distribution: Minimum, Q1, M, Q3, Maximum

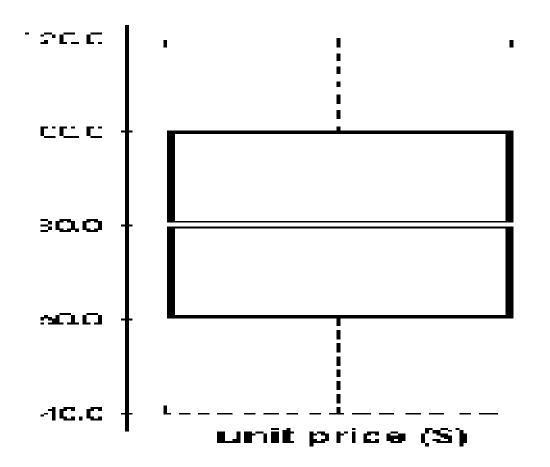
🔀 Boxplot

△ Data is represented with a box

- △The ends of the box are at the first and third quartiles, i.e., the height of the box is IRQ
- The median is marked by a line within the box
- Whiskers: two lines outside the box extend to Minimum and Maximum

### **A Boxplot**

A boxplot



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# Summary

- **#** Concept description: characterization and discrimination
- **#** OLAP-based vs. attribute-oriented induction
- **#** Efficient implementation of AOI
- Analytical characterization and comparison
- Hining descriptive statistical measures in large databases
- Discussion
  - Incremental and parallel mining of description
     Descriptive mining of complex types of data

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