Unit III: Concept Description: Characterization and Comparison

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- DMDL Primitives and Queries
- Architectures of DM
- What is concept description?
- Data generalization and summarization-based characterization
- Analytical characterization: Analysis of attribute relevance
- Mining class comparisons: Discriminating between different classes
- Mining descriptive statistical measures in large databases
- Summary

What is Concept Description?

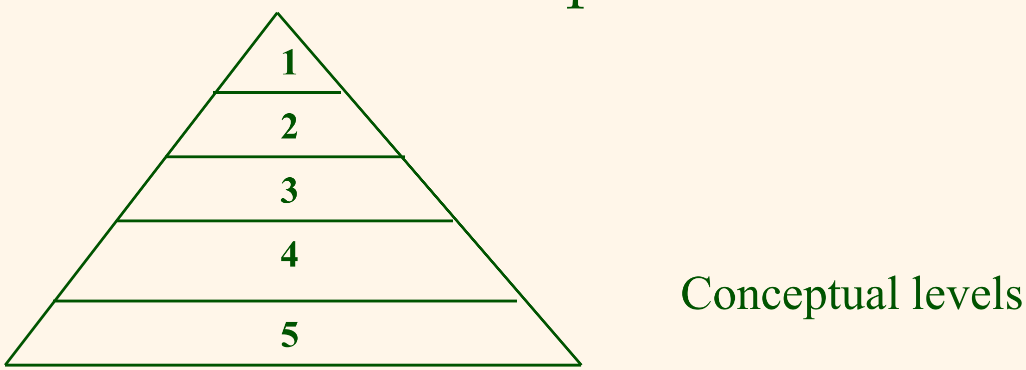
- Descriptive vs. predictive data mining
  - Descriptive mining: describes concepts or task-relevant data sets in concise, summative, informative, discriminative forms
  - Predictive mining: Based on data and analysis, constructs models for the database, and predicts the trend and properties of unknown data
- Concept description:
  - Characterization: provides a concise and succinct summarization of the given collection of data
  - Comparison: provides descriptions comparing two or more collections of data

Concept Description vs. OLAP

- Concept description:
  - can handle complex data types of the attributes and their aggregations
  - a more automated process
- OLAP:
  - restricted to a small number of dimension and measure types
  - user-controlled process

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.



  - **Approaches:**
    - **Data cube approach(OLAP approach)**
    - **Attribute-oriented induction (AOI) approach**

Implementation by Cube Technology

- Construct a data cube on-the-fly for the given data mining query
  - Facilitate efficient drill-down analysis
  - May increase the response time
  - A balanced solution: precomputation of "subprime" relation
- Use a predefined & precomputed data cube
  - Construct a data cube beforehand
  - **Facilitate not only the Attribute Oriented Induction(AOI), but also Attribute Relevance Analysis (ARA), dicing, slicing, roll-up and drill-down**
  - Cost of cube computation and the nontrivial storage overhead

Characterization vs. OLAP

- Similarity:
  - Presentation of data summarization at multiple levels of abstraction.
  - Interactive drilling, pivoting, slicing and dicing.
- Differences:
  - Automated desired level allocation.
  - Dimension relevance analysis and ranking when there are many relevant dimensions.
  - Sophisticated typing on dimensions and measures.
  - Analytical characterization: data dispersion analysis.

Characterization: Data Cube Approach (without using Attribute Oriented-Induction)

- Perform computations and store results in data cubes
- **Strength**
  - An efficient implementation of data generalization
  - Computation of various kinds of measures
    - e.g., count( ), sum( ), average( ), max( )
  - Generalization and specialization can be performed on a data cube by *roll-up* and *drill-down*
- **Limitations**
  - handle only dimensions of *simple nonnumeric data* and measures of *simple aggregated numeric values*.
  - Lack of intelligent analysis, can't tell which dimensions should be used and what levels should the generalization reach

Attribute-Oriented Induction

- Proposed in 1989 (KDD '89 workshop)
- **Not confined to categorical data nor particular measures**.
- **How it is done?**
  1. Collect the task-relevant data(*initial relation*) using a relational database query
  2. Perform generalization by attribute removal or attribute generalization.
  3. Apply aggregation by merging identical, generalized tuples and accumulating their respective counts.
  4. Interactive presentation with users.

Basic Principles of Attribute-Oriented Induction

- Data 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*.
- Attribute-threshold control: typical 2-8, specified/default.
- Generalized relation threshold control: control the final relation/rule size.

Basic Algorithm for Attribute-Oriented Induction

- InitialRel: Query processing of task-relevant data, deriving the *initial relation*.
- PreGen: Based on the analysis of the number of distinct values in each attribute, determine generalization plan for each attribute: removal? or how high to generalize?
- PrimeGen: Based on the PreGen plan, perform generalization to the right level to derive a "prime generalized relation", accumulating the counts.
- Presentation: User interaction: (1) adjust levels by drilling, (2) pivoting, (3) mapping into rules, cross tabs, visualization presentations.

Class Characterization: An Example

Initial Relation

Name	Gender	Major	Birth-Place	Birth_date	Residence	Phone #	GPA
Jim Woodman	M	CS	Vancouver,BC, Canada	8-12-76	3511 Main St., Richmond	687-4598	3.67
Scott Lachance	M	CS	Montreal, Que, Canada	28-7-75	345 1st Ave., Richmond	253-9106	3.70
Laura Lee	F	Physics	Seattle, WA, USA	25-8-70	125 Austin Ave., Burnaby	420-5232	3.83
…	…	…	…	…	…	…	…
Removed	Retained	Sci,Eng, Bus	Country	Age range	City	Removed	Excl, VG,..

Prime Generalized Relation

Gender	Major	Birth_region	Age_range	Residence	GPA	Count
M	Science	Canada	20-25	Richmond	Very-good	16
F	Science	Foreign	25-30	Burnaby	Excellent	22
…	…	…	…	…	…	…

Gender \ Birth_Region	Canada	Foreign	Total
M	16	14	30
F	10	22	32
Total	26	36	62

Example

- DMQL: 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" }
```

Presentation of Generalized Results

- Generalized relation:
  - Relations where some or all attributes are generalized, with counts or other aggregation values accumulated.
- Cross tabulation:
  - Mapping results into cross tabulation form (similar to contingency tables).
  - Visualization techniques:
  - Pie charts, bar charts, curves, cubes, and other visual forms.
- Quantitative characteristic rules:
  - Mapping generalized result into characteristic rules with quantitative information associated with it, e.g.,

$$grad(x) \wedge male(x) \Rightarrow$$
$$birth\_region(x) = "Canada"[t:53\%] \vee birth\_region(x) = "foreign"[t:47\%].$$

Presentation of Generalized Results (continued)

- t-weight:
  - Interesting measure that describes the **typicality** of
    - each disjunct in the rule
    - each tuple in the corresponding generalized relation

$$t\_weight = count(q_a) / \sum_{i=1}^{n} count(q_i)$$

- n – number of tuples for target class for generalized relation
- q_i … q_n – tuples for target class in generalized relation
- q_a is in q_i … q_n

Presentation – Generalized Relation

location	item	sales (in million dollars)	count (in thousands)
Asia	TV	15	300
Europe	TV	12	250
North_America	TV	28	450
Asia	computer	120	1000
Europe	computer	150	1200
North_America	computer	200	1800

Table 5.3: A generalized relation for the sales in 1997.

Presentation – Crosstab

location \ item	TV		computer		*both_items*	
	sales	count	sales	count	sales	count
Asia	15	300	120	1000	135	1300
Europe	12	250	150	1200	162	1450
North_America	28	450	200	1800	228	2250
all_regions	45	1000	470	4000	525	5000

Table 5.4: A crosstab for the sales in 1997.

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
    - filter out irrelevant or weakly relevant attributes
    - retain or rank the relevant attributes
  - relevance related to dimensions and levels
  - analytical characterization, analytical comparison

Attribute relevance analysis (cont'd)

- How?
  1. Data Collection
  2. Analytical Generalization
     - Use information gain analysis (e.g., entropy or other measures) to identify highly relevant dimensions and levels.
  3. Relevance Analysis
     - Sort and select the most relevant dimensions and levels.
  4. Attribute-oriented Induction for class description
     - On selected dimension/level
  5. 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)
  - gini index
  - (Chi-Square) χ^2 contingency table statistics
  - uncertainty coefficient

Information-Theoretic Approach

- Decision tree
  - each internal node tests an attribute
  - each branch corresponds to attribute value
  - each leaf node assigns a classification
- ID3 algorithm
  - 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

Training Examples

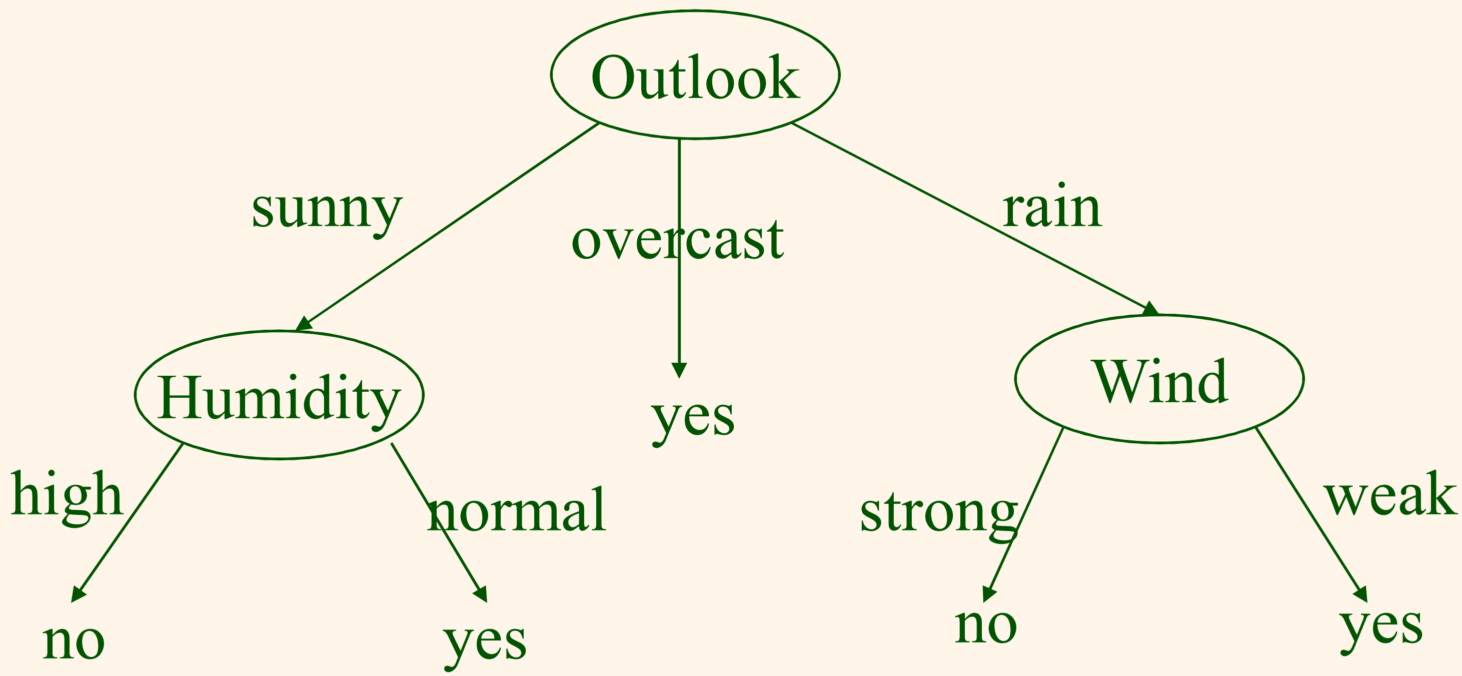
Training Examples

Day	Outlook	Temp.	Humidity
D1	Sunny	Hot	High
D2	Sunny	Hot	High
D3	Overcast	Hot	High
D4	Rain	Mild	High
D5	Rain	Cool	Normal
D6	Rain	Cool	Normal
D7	Overcast	Cool	Normal
D8	Sunny	Mild	High
D9	Sunny	Cool	Normal

Top-Down Induction of Decision Tree

Attributes = {Outlook, Temperature, Humidity, Wind}

PlayTennis = {yes, no}



Entropy and Information Gain

- S contains s_i tuples of class C_i for i = {1, …, m}
- Information measures info required to classify any arbitrary tuple

$$I(s_1, s_2, \ldots, s_m) = -\sum_{i=1}^{m} \frac{s_i}{s} \log_2 \frac{s_i}{s}$$

- **Entropy** (weighted average) of attribute A with values $\{a_1, a_2, \ldots, a_v\}$

$$E(A) = \sum_{j=1}^{v} \frac{s_{1j} + \ldots + s_{mj}}{s} I(s_{1j}, \ldots, s_{mj})$$

- **Information gained** by branching on attribute A

$$Gain(A) = I(s_1, s_2, \ldots, s_m) - E(A)$$

  – >info gained > discriminating attribute

Class Characterization: An Example

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…	…	…	…	…	…	…

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Example: Analytical Characterization

- Task
  - Mine general characteristics describing graduate students using analytical characterization
- Given
  - attributes *name, gender, major, birth_place, birth_date, phone#*, and *gpa*
  - $Gen(a_i)$ = concept hierarchies on a_i
  - U_i = attribute analytical thresholds for a_i
  - T_i = attribute generalization thresholds for a_i
  - 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_i
  - **attribute removal**
    - remove *name* and *phone#*
  - **attribute generalization**
    - generalize ***major, birth_place, birth_date*** **and** ***gpa***
    - accumulate counts
  - candidate relation: *gender, major, birth_country, age_range* and *gpa*

Example: Analytical characterization (2)

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

Candidate relation for Target class: Graduate students (Σ=120)

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

Candidate relation for Contrasting class: Undergraduate students (Σ=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"

$$I(s_{11}, s_{21}) = -\frac{84}{126}\log_2\left(\frac{84}{126}\right) - \frac{42}{126}\log_2\left(\frac{42}{126}\right) = 0.9183$$

Example: Analytical Characterization (4)

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

$$E(major) = \frac{126}{250} \overset{0.9183}{I(s_{11}, s_{21})} + \frac{82}{250} \overset{0.9892}{I(s_{12}, s_{22})} + \frac{42}{250} \overset{0}{I(s_{13}, s_{23})} = 0.7873$$

- Calculate information gain for each attribute

$$Gain(major) = \overset{0.9988}{I(s_1, s_2)} - \overset{0.7873}{E(major)} = 0.2115$$

  - 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_0) derivation
  - R (attribute relevance threshold) = 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_0: Graduate students

- 5. Perform attribute-oriented induction on W_0 using T_i

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:
    - 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

- 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)

- Given
  - attributes *name, gender, major, birth_place, birth_date, residence, phone*# and *gpa*
  - *Gen*(a_i) = concept hierarchies on attributes a_i
  - U_i = attribute analytical thresholds for attributes a_i
  - T_i = attribute generalization thresholds for attributes a_i
  - *R* = attribute relevance threshold

Example: Analytical comparison (3)

- 1. Data collection
  - target and contrasting classes
- 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)

Birth_country	**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

Birth_country	**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%

Quantitative Discriminant Rules

- Cj = target class
- q_a = a generalized tuple covers some tuples of class
  - but can also cover some tuples of contrasting class
- d-weight
  - range: [0.0, 1.0] or [0%, 100%]

$$d-weight = \frac{count(q_a \in C_j)}{\sum_{i=1}^{m} count(q_a \in C_i)}$$

Example: Quantitative Description Rule

Location/item		**TV**			**Computer**			**Both_items**	
	Count	***t-wt***	***d-wt***	***Count***	***t-wt***	***d-wt***	***Count***	***t-wt***	***d-wt***
Europe	80	25%	40%	240	75%	30%	320	100%	32%
N_Am	120	17.65%	60%	560	82.35%	70%	680	100%	68%
Both_ regions	200	20%	100%	800	80%	100%	1000	100%	100%

Crosstab showing associated t-weight, d-weight values and total number (in thousands) of TVs and computers sold at AllElectronics in 1998

- Quantitative description rule for target class *Europe*

$$\forall X, Europe(X) \Leftrightarrow$$

$$(item(X) = "TV")[\mathrm{t}:25\%, \mathrm{d}:40\%] \vee (item(X) = "computer")[\mathrm{t}:75\%, \mathrm{d}:30\%]$$

Quantitative Discriminant Rules

- High d-weight in target class indicates that concept represented by generalized tuple is primarily derived from target class
- Low d-weight implies concept is derived from contrasting class
- Threshold can be set to control the display of interesting tuples
- quantitative discriminant rule form

$$\forall X,\ target\_class(X) \Leftarrow condition(X) \quad [d : d\_weight]$$

Read: if X satisfies condition, there is a probability (d-weight) that x is in the target class

Mining Data Dispersion Characteristics

- Motivation
  - To better understand the data: central tendency, variation and spread
- Data dispersion characteristics
  - median, max, min, quantiles, outliers, variance, etc.
- Numerical dimensions correspond to sorted intervals
  - Data dispersion: analyzed with multiple granularities of precision
  - Boxplot or quantile analysis on sorted intervals
- Dispersion analysis on computed measures
  - Folding measures into numerical dimensions
  - Boxplot or quantile analysis on the transformed cube

Measuring the Central Tendency

- Mean $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$
  - Weighted arithmetic mean $\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$
- Median: A holistic measure
  - Middle value if odd number of values, or average of the middle two values otherwise
  - estimated by interpolation $median = L_1 + (\frac{n/2 - (\sum f)l}{f_{median}})c$
- Mode
  - Value that occurs most frequently in the data
  - Unimodal, bimodal, trimodal
  - Empirical formula: $mean - mode = 3 \times (mean - median)$

Measuring the Dispersion of Data

- Quartiles, outliers and boxplots
  - Quartiles: Q_1 (25th percentile), Q_3 (75th percentile)
  - Inter-quartile range: IQR = $Q_3 - Q_1$
  - Five number summary: min, Q_1, M, Q_3, 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
- Variance and standard deviation
  - **Variance s^2: (algebraic, scalable computation)**

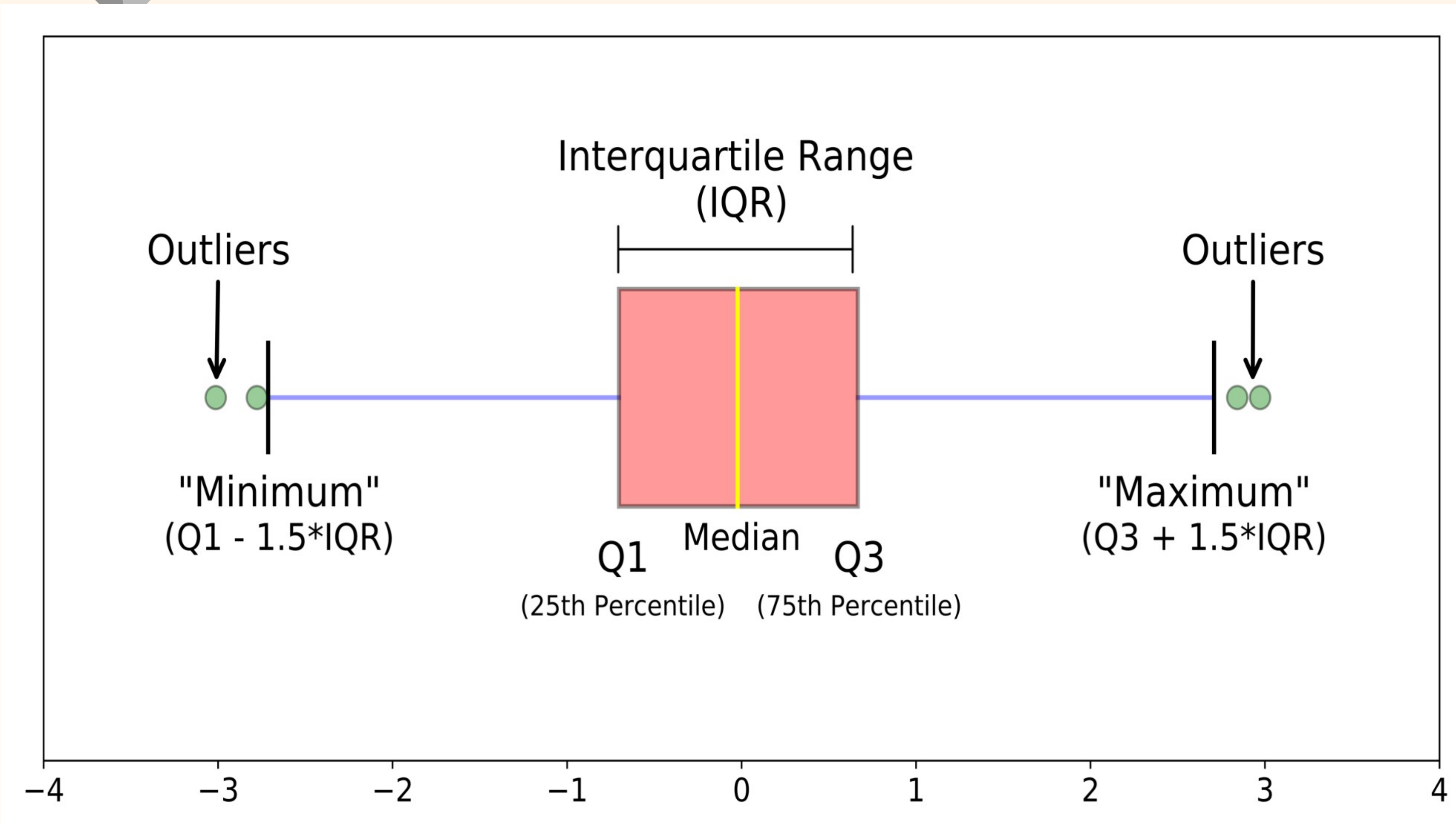
$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2 = \frac{1}{n-1}[\sum_{i=1}^{n} x_i^2 - \frac{1}{n}(\sum_{i=1}^{n} x_i)^2]$$

  - Standard deviation s is the square root of variance s^2

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 IQR (interquartile range)
  - The median is marked by a line within the box
  - Whiskers: two lines outside the box extend to Minimum and Maximum

A Boxplot



Interquartile Range
(IQR)
Outliers
Outliers
"Minimum"
(Q1 - 1.5*IQR)
Median
Q1
Q3
(25th Percentile)
(75th Percentile)
"Maximum"
(Q3 + 1.5*IQR)
−4
−3
−2
−1
0
1
2
3
4

Mining Descriptive Statistical Measures in Large Databases

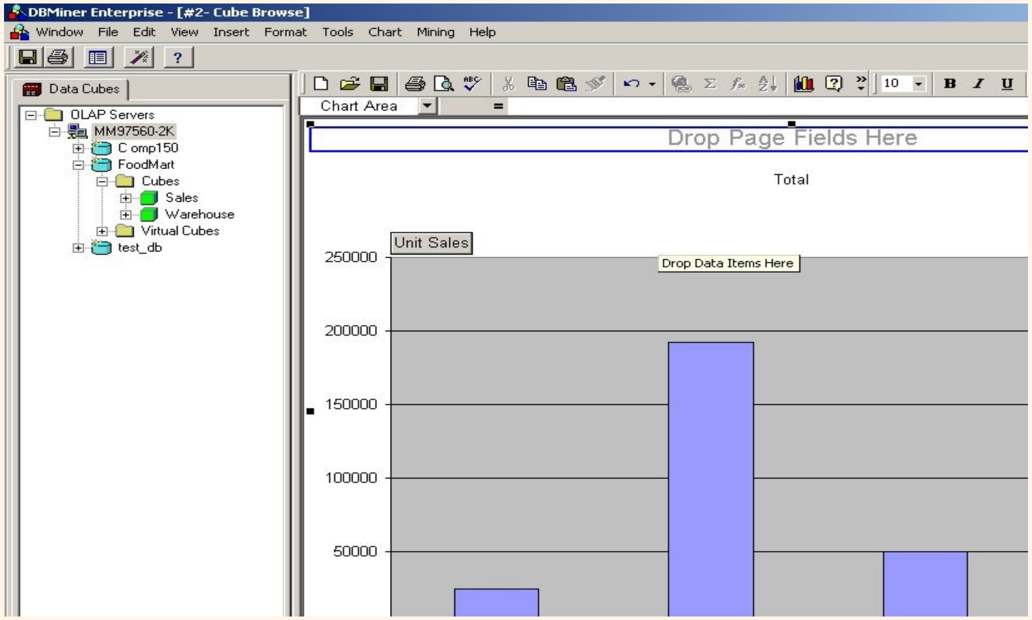
- Variance

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

- Standard deviation: the square root of the variance
  - Measures spread about the mean
  - It is zero if and only if all the values are equal
  - Both the deviation and the variance are algebraic

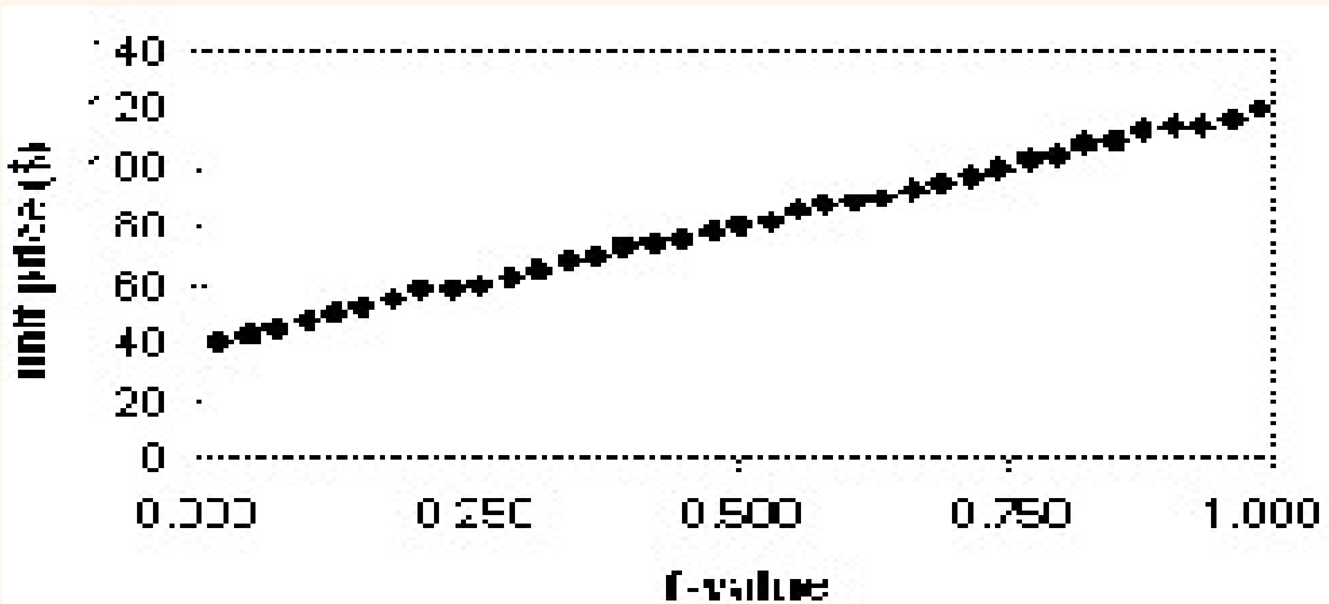
Histogram Analysis

- Graph displays of basic statistical class descriptions
  - Frequency histograms
    - A univariate graphical method
    - Consists of a set of rectangles that reflect the counts or frequencies of the classes present in the given data



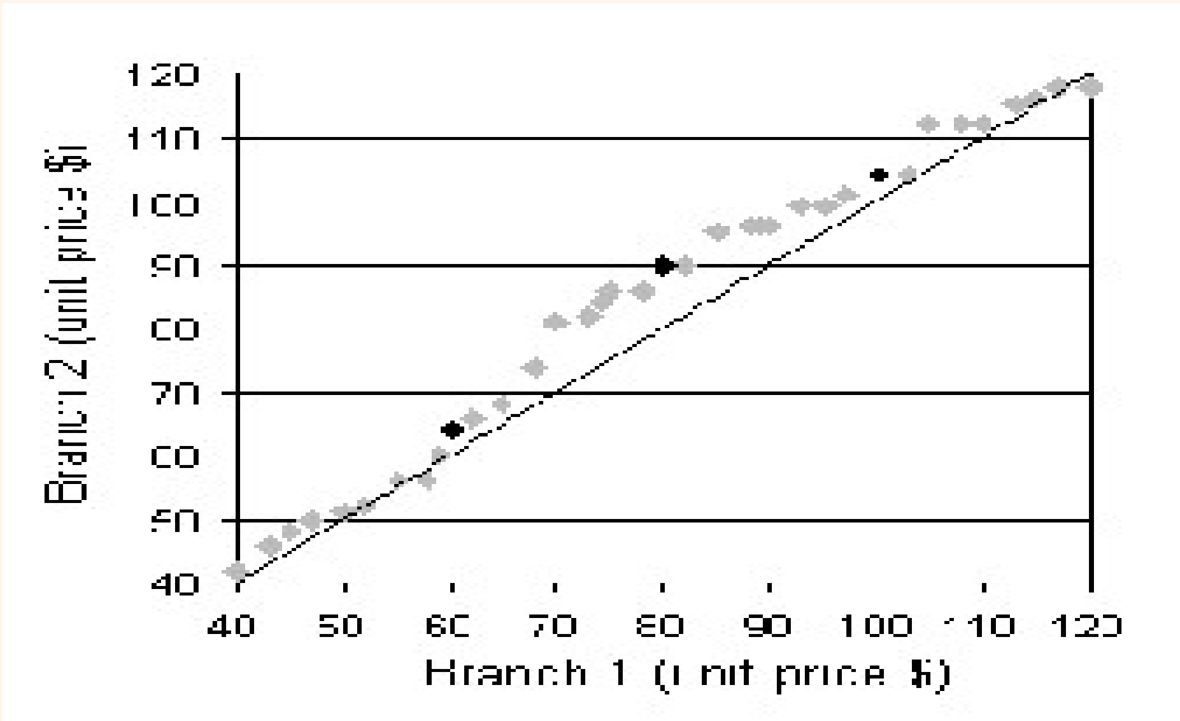
Quantile Plot

- Displays all of the data (allowing the user to assess both the overall behavior and unusual occurrences)
- Plots quantile information
  - For a data x_i data sorted in increasing order, f_i indicates that approximately 100 f_i% of the data are below or equal to the value x_i



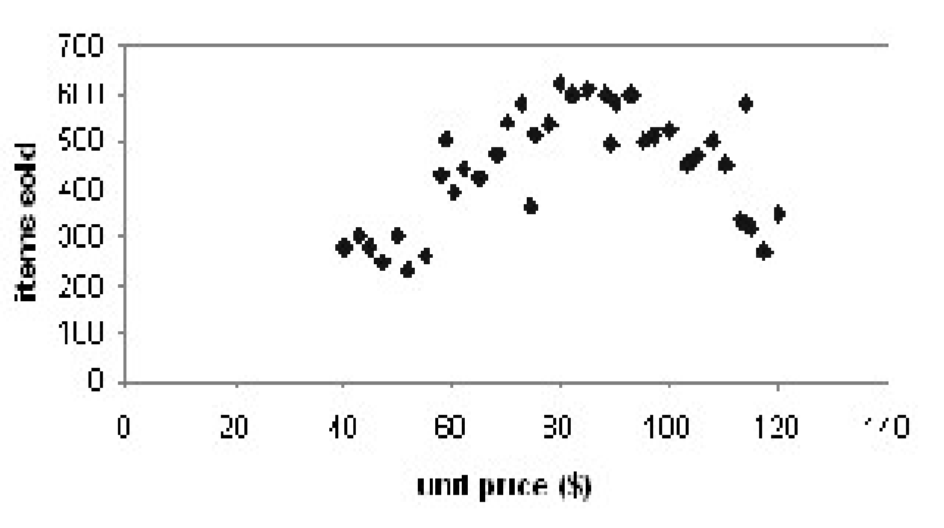
Quantile-Quantile (Q-Q) Plot

- Graphs the quantiles of one univariate distribution against the corresponding quantiles of another
- Allows the user to view whether there is a shift in going from one distribution to another



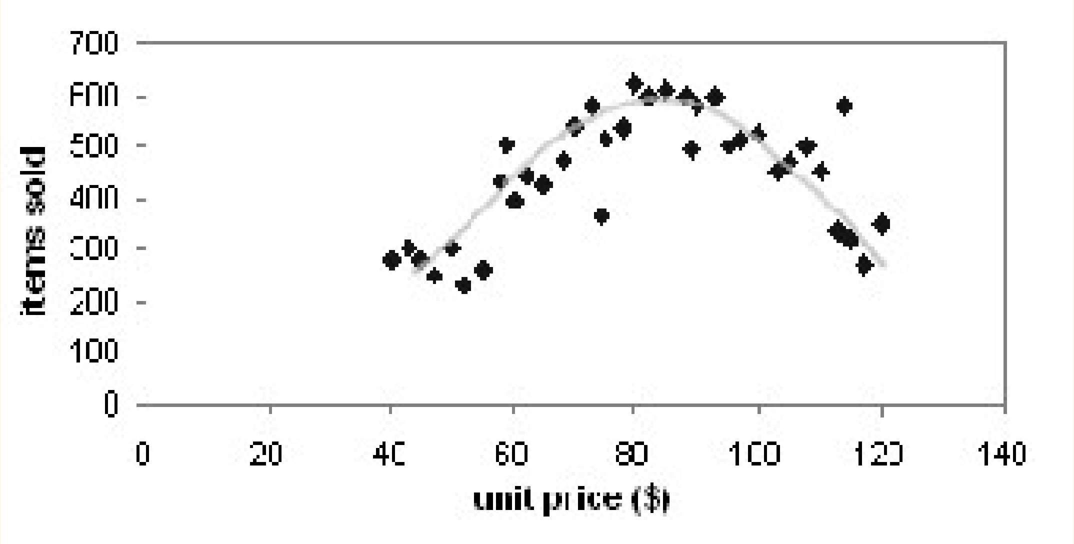
Scatter plot

- Provides a first look at bivariate data to see clusters of points, outliers, etc
- Each pair of values is treated as a pair of coordinates and plotted as points in the plane



Loess Curve

- Adds a smooth curve to a scatter plot in order to provide better perception of the pattern of dependence
- Loess curve is fitted by setting two parameters: a smoothing parameter, and the degree of the polynomials that are fitted by the regression



Graphic Displays of Basic Statistical Descriptions

- Histogram: (shown before)
- Boxplot: (covered before)
- Quantile plot: each value x_i is paired with f_i indicating that approximately 100 f_i % of data are $\leq x_i$
- Quantile-quantile (q-q) plot: graphs the quantiles of one univariant distribution against the corresponding quantiles of another
- Scatter plot: each pair of values is a pair of coordinates and plotted as points in the plane
- Loess (local regression) curve: add a smooth curve to a scatter plot to provide better perception of the pattern of dependence

Data Mining System Architectures

- Coupling data mining system with DB/DW system
  - **No coupling**—flat file processing, not recommended
  - **Loose coupling**
    - Fetching data from DB/DW
  - **Semi-tight coupling**—enhanced DM performance
    - Provide efficient implement a few data mining primitives in a DB/DW system, e.g., sorting, indexing, aggregation, histogram analysis, multiway join, precomputation of some stat functions
  - **Tight coupling**—A uniform information processing environment
    - DM is smoothly integrated into a DB/DW system, mining query is optimized based on mining query, indexing, query processing methods, etc.