

Data Mining: Concepts and Techniques

— Chapter 2 —

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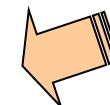
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Chapter 2: Getting to Know Your Data

- Data Objects and Attribute Types
- Basic Statistical Descriptions of Data
- Data Visualization
- Measuring Data Similarity and Dissimilarity
- Summary



Types of Data Sets

- Record
 - Relational records
 - Data matrix, e.g., numerical matrix, crosstabs
 - Document data: text documents: term-frequency vector
 - Transaction data
- Graph and network
 - World Wide Web
 - Social or information networks
 - Molecular Structures
- Ordered
 - Video data: sequence of images
 - Temporal data: time-series
 - Sequential Data: transaction sequences
 - Genetic sequence data
- Spatial, image and multimedia:
 - Spatial data: maps
 - Image data:
 - Video data:

	team	coach	play	ball	score	game	winn	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Important Characteristics of Structured Data

- Dimensionality
 - Curse of dimensionality
- Sparsity
 - Only presence counts
- Resolution
 - Patterns depend on the scale
- Distribution
 - Centrality and dispersion

Data Objects

- Data sets are made up of data objects.
- A **data object** represents an entity.
- Examples:
 - sales database: customers, store items, sales
 - medical database: patients, treatments
 - university database: students, professors, courses
- Also called *samples*, *examples*, *instances*, *data points*, *objects*, *tuples*.
- Data objects are described by **attributes**.
- Database rows -> data objects; columns -> attributes.

Attributes

- **Attribute** (or **dimensions, features, variables**):
a data field, representing a characteristic or feature
of a data object.
 - *E.g., customer_ID, name, address*
- Types:
 - Nominal
 - Binary
 - Numeric: quantitative
 - Interval-scaled
 - Ratio-scaled

Attribute Types

- **Nominal:** categories, states, or “names of things”
 - $Hair_color = \{auburn, black, blond, brown, grey, red, white\}$
 - marital status, occupation, ID numbers, zip codes
- **Binary**
 - Nominal attribute with only 2 states (0 and 1)
 - Symmetric binary: both outcomes equally important
 - e.g., gender
 - Asymmetric binary: outcomes not equally important.
 - e.g., medical test (positive vs. negative)
 - Convention: assign 1 to most important outcome (e.g., HIV positive)
- **Ordinal**
 - Values have a meaningful order (ranking) but magnitude between successive values is not known.
 - $Size = \{small, medium, large\}$, grades, army rankings

Numeric Attribute Types

- Quantity (integer or real-valued)
- **Interval**
 - Measured on a scale of **equal-sized units**
 - Values have order
 - E.g., *temperature in C° or F°, calendar dates*
 - No true zero-point
- **Ratio**
 - Inherent **zero-point**
 - We can speak of values as being an order of magnitude larger than the unit of measurement (10 K° is twice as high as 5 K°).
 - e.g., *temperature in Kelvin, length, counts, monetary quantities*

Discrete vs. Continuous Attributes

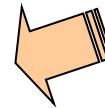
■ Discrete Attribute

- Has only a finite or countably infinite set of values
 - E.g., zip codes, profession, or the set of words in a collection of documents
- Sometimes, represented as integer variables
- Note: Binary attributes are a special case of discrete attributes

■ Continuous Attribute

- Has real numbers as attribute values
 - E.g., temperature, height, or weight
- Practically, real values can only be measured and represented using a finite number of digits
- Continuous attributes are typically represented as floating-point variables

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Basic Statistical Descriptions of Data

- 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 (algebraic measure) (sample vs. population):

Note: n is sample size and N is population size.

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad \mu = \frac{\sum x}{N}$$

- Weighted arithmetic mean:
- Trimmed mean: chopping extreme values

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

- Median:

- Middle value if odd number of values, or average of the middle two values otherwise

age	frequency
1–5	200
6–15	450
16–20	300
21–50	1500
51–80	700
81–110	44

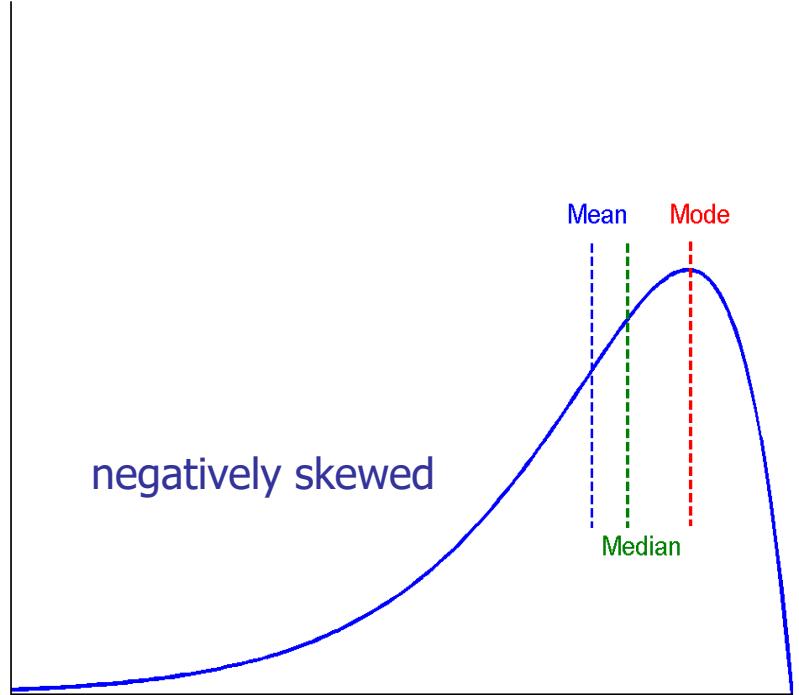
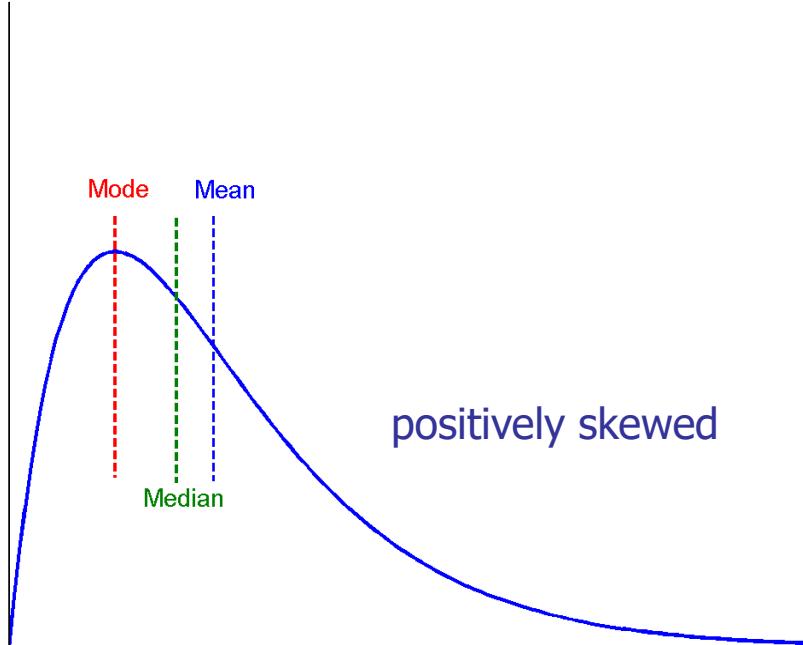
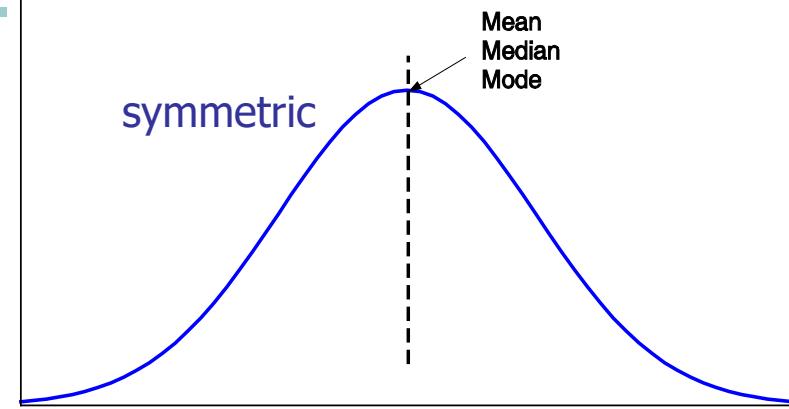
- Mode

$$median = L_1 + \left(\frac{n/2 - (\sum freq)l}{freq_{median}} \right) width$$

- Value that occurs most frequently in the data
- Unimodal, bimodal, trimodal
- Empirical formula: $mean - mode = 3 \times (mean - median)$

Symmetric vs. Skewed Data

- Median, mean and mode of symmetric, positively and negatively skewed data



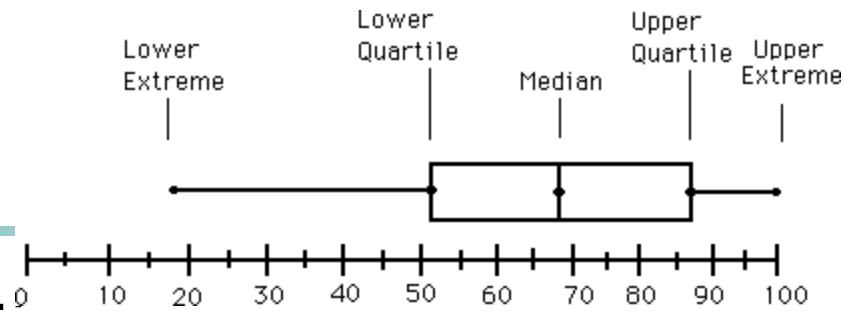
Measuring the Dispersion of Data

- Quartiles, outliers and boxplots
 - **Quartiles:** Q_1 (25^{th} percentile), Q_3 (75^{th} percentile)
 - **Inter-quartile range:** $\text{IQR} = Q_3 - Q_1$
 - **Five number summary:** min, Q_1 , median, Q_3 , max
 - **Boxplot:** ends of the box are the quartiles; median is marked; add whiskers, and plot outliers individually
 - **Outlier:** usually, a value higher/lower than $1.5 \times \text{IQR}$
- Variance and standard deviation (*sample: s, population: σ*)
 - **Variance:** (algebraic, scalable computation)

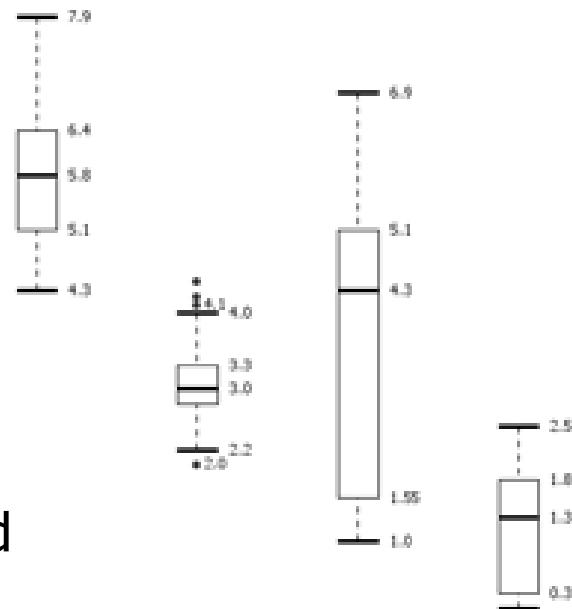
$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_i^2 - \frac{1}{n} (\sum_{i=1}^n x_i)^2 \right] \quad \sigma^2 = \frac{1}{N} \sum_{i=1}^n (x_i - \mu)^2 = \frac{1}{N} \sum_{i=1}^n x_i^2 - \mu^2$$

- **Standard deviation** s (or σ) is the square root of variance s^2 (or σ^2)

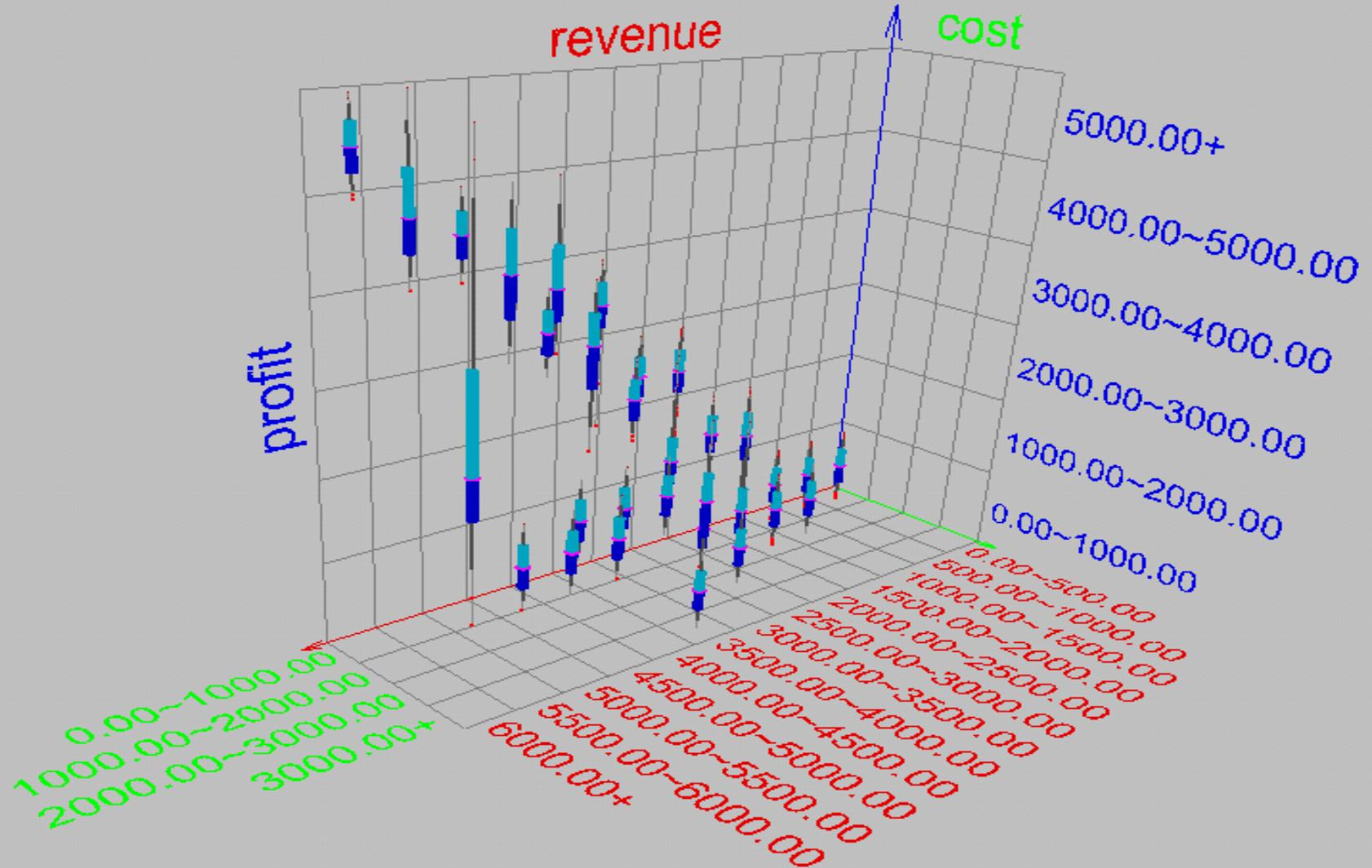
Boxplot Analysis



- **Five-number summary** of a distribution
 - Minimum, Q1, Median, 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
 - The median is marked by a line within the box
 - Whiskers: two lines outside the box extended to Minimum and Maximum
 - Outliers: points beyond a specified outlier threshold, plotted individually

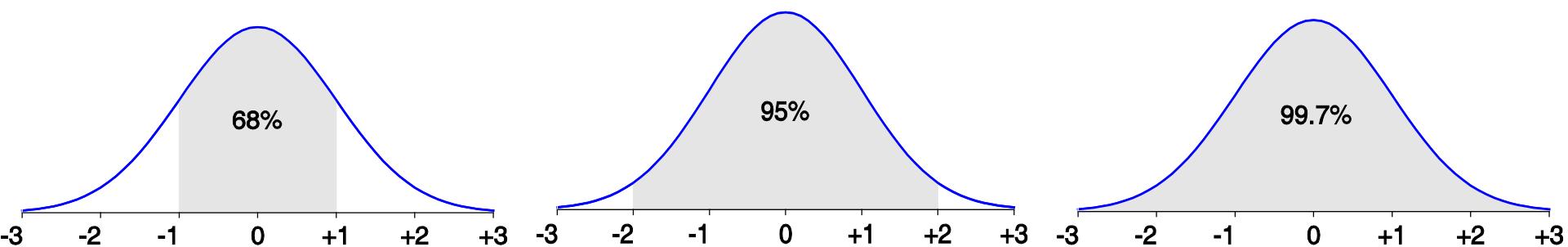


Visualization of Data Dispersion: 3-D Boxplots



Properties of Normal Distribution Curve

- The normal (distribution) curve
 - From $\mu-\sigma$ to $\mu+\sigma$: contains about 68% of the measurements (μ : mean, σ : standard deviation)
 - From $\mu-2\sigma$ to $\mu+2\sigma$: contains about 95% of it
 - From $\mu-3\sigma$ to $\mu+3\sigma$: contains about 99.7% of it

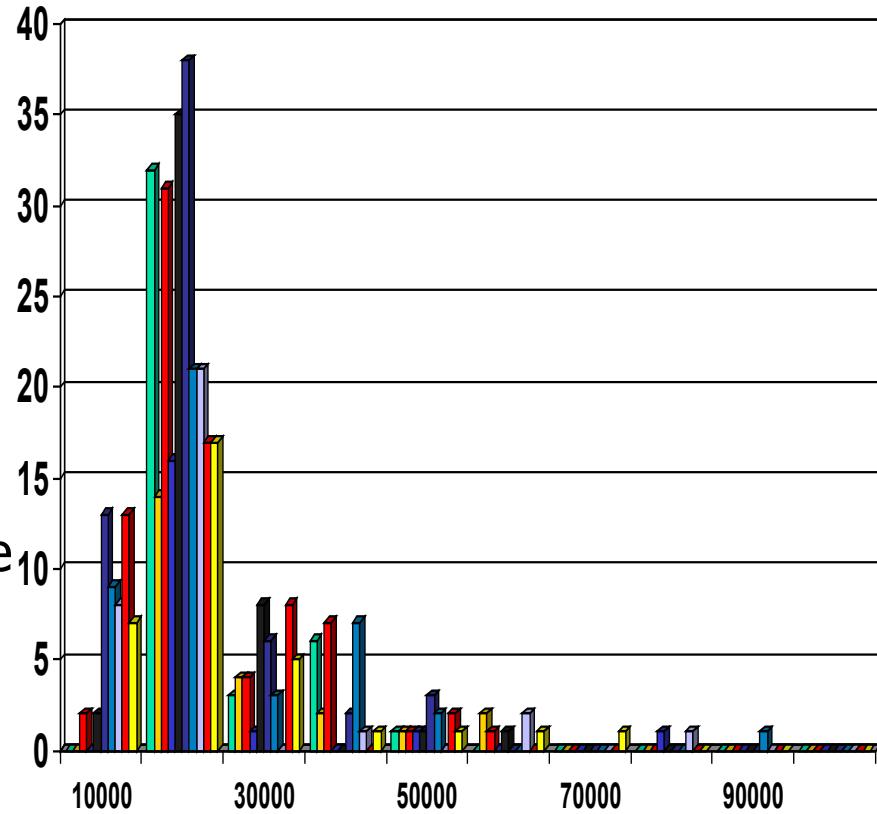


Graphic Displays of Basic Statistical Descriptions

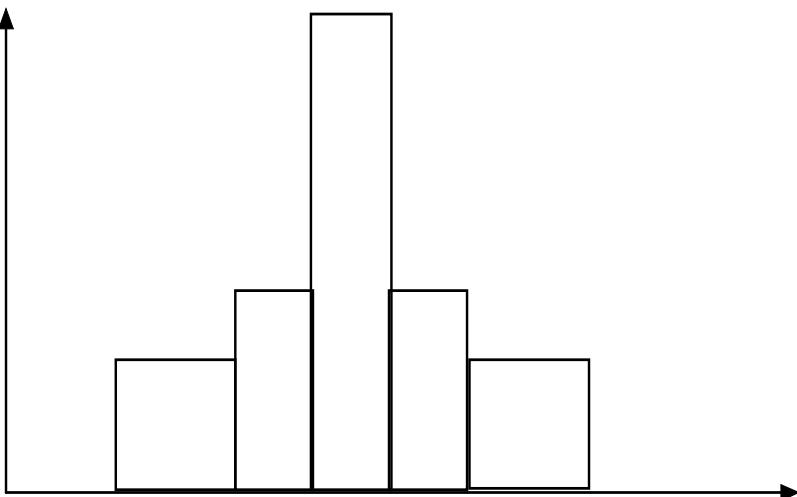
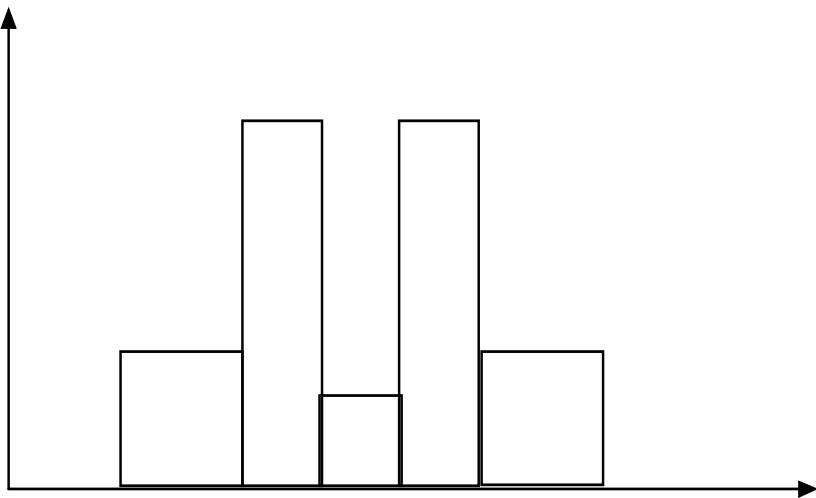
- **Boxplot:** graphic display of five-number summary
- **Histogram:** x-axis are values, y-axis repres. frequencies
- **Quantile plot:** each value x_i is paired with f_i indicating that approximately $100 f_i\%$ of data are $\leq x_i$
- **Quantile-quantile (q-q) plot:** graphs the quantiles of one 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

Histogram Analysis

- Histogram: Graph display of tabulated frequencies, shown as bars
- It shows what proportion of cases fall into each of several categories
- Differs from a bar chart in that it is the *area* of the bar that denotes the value, not the height as in bar charts, a crucial distinction when the categories are not of uniform width
- The categories are usually specified as non-overlapping intervals of some variable. The categories (bars) must be adjacent



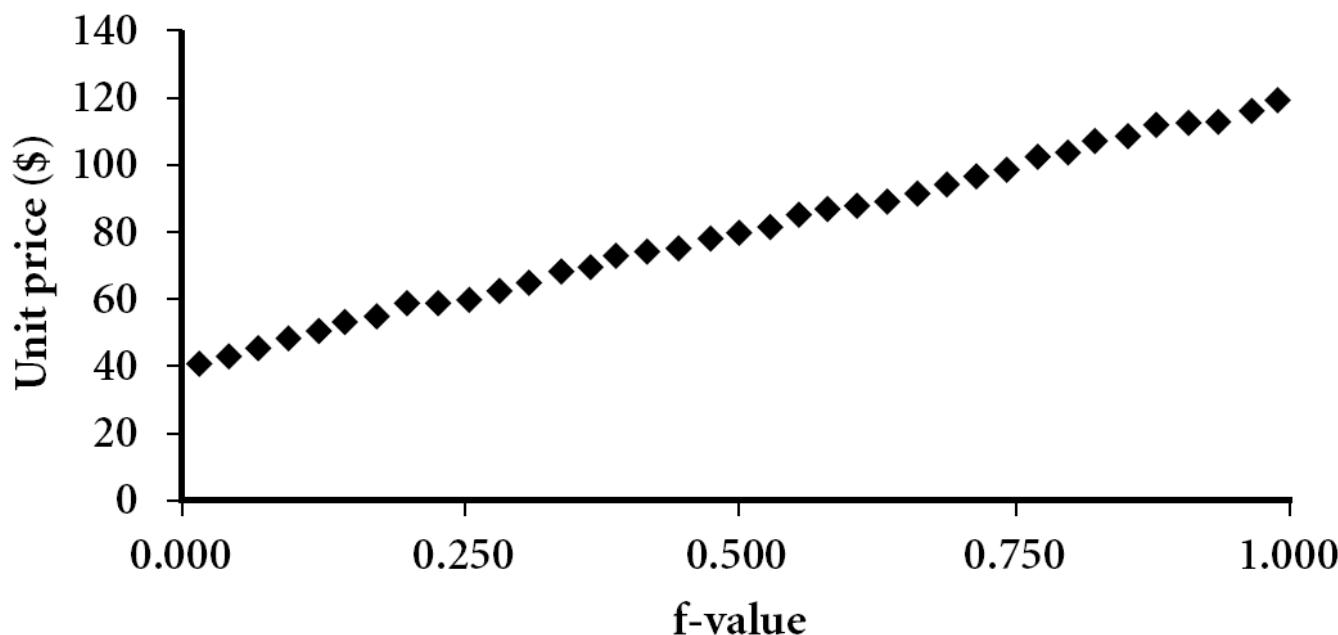
Histograms Often Tell More than Boxplots



- The two histograms shown in the left may have the same boxplot representation
 - The same values for: min, Q1, median, Q3, max
- But they have rather different data distributions

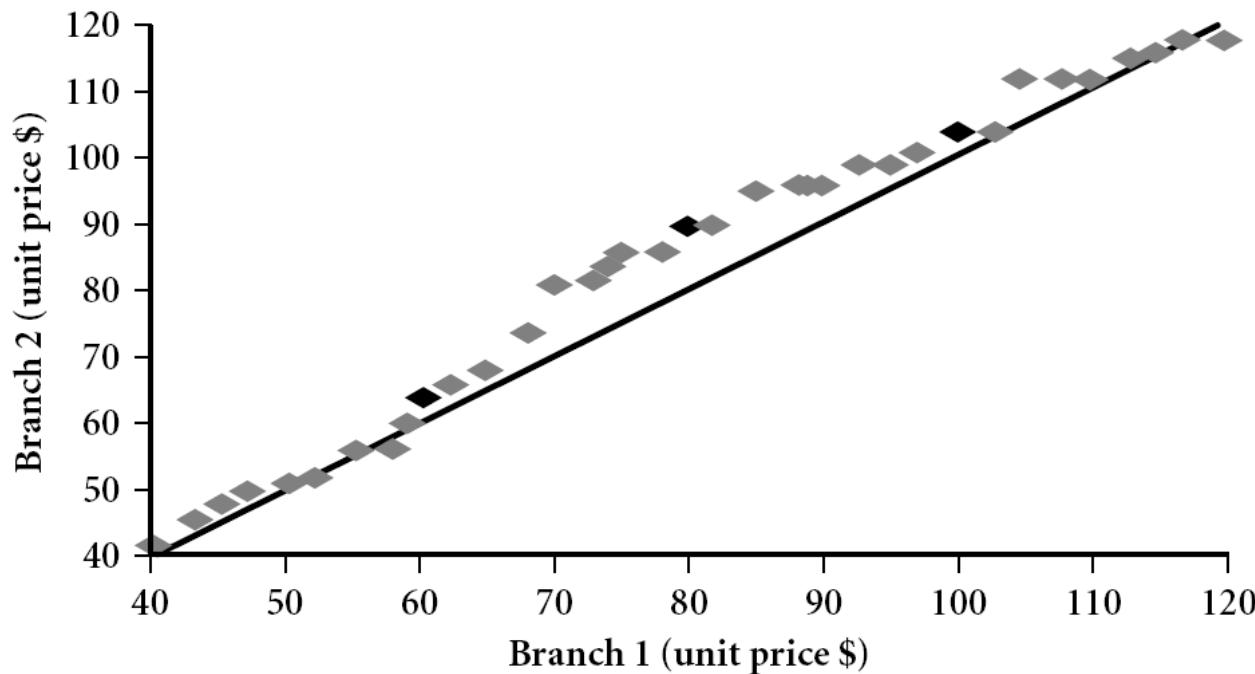
Quantile Plot

- 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



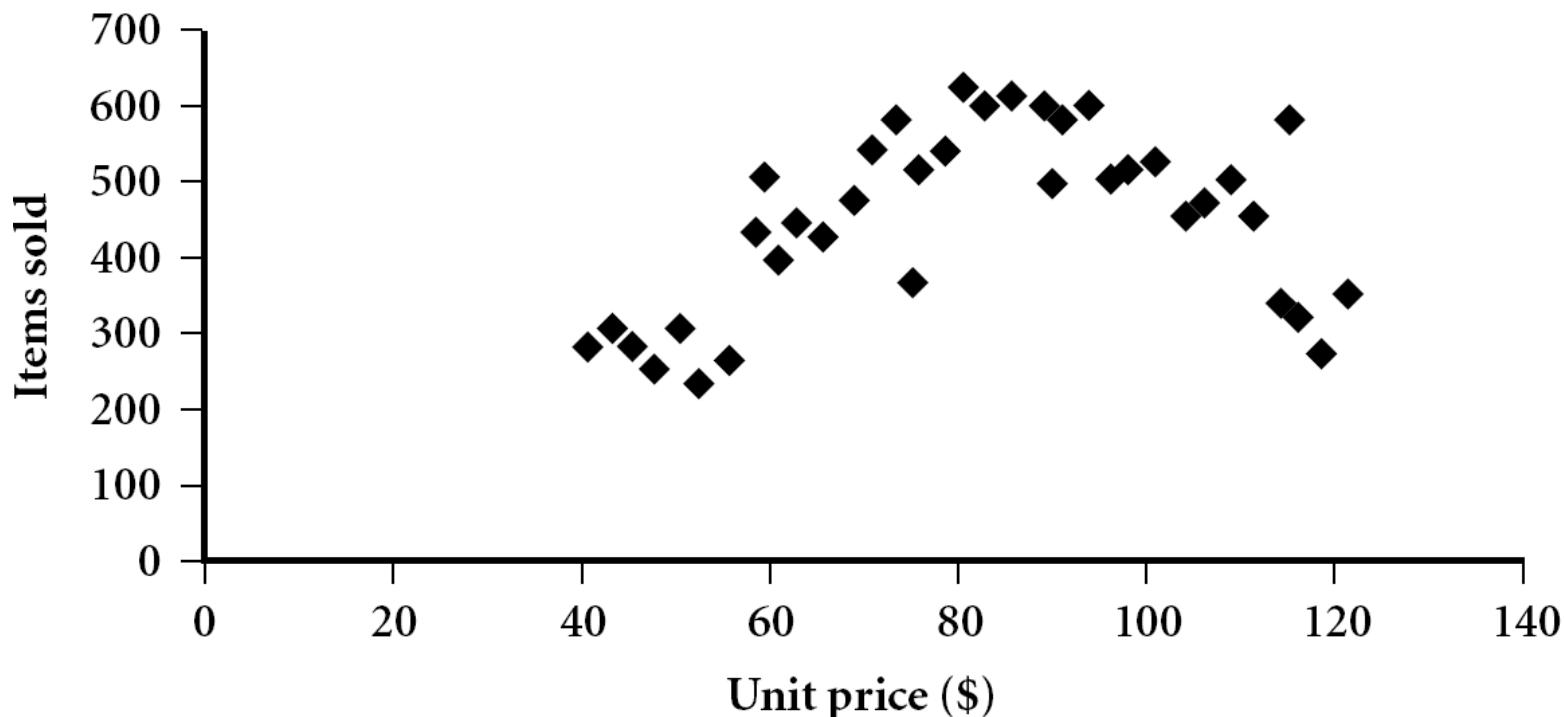
Quantile-Quantile (Q-Q) Plot

- Graphs the quantiles of one univariate distribution against the corresponding quantiles of another
- View: Is there is a shift in going from one distribution to another?
- Example shows unit price of items sold at Branch 1 vs. Branch 2 for each quantile. Unit prices of items sold at Branch 1 tend to be lower than those at Branch 2.

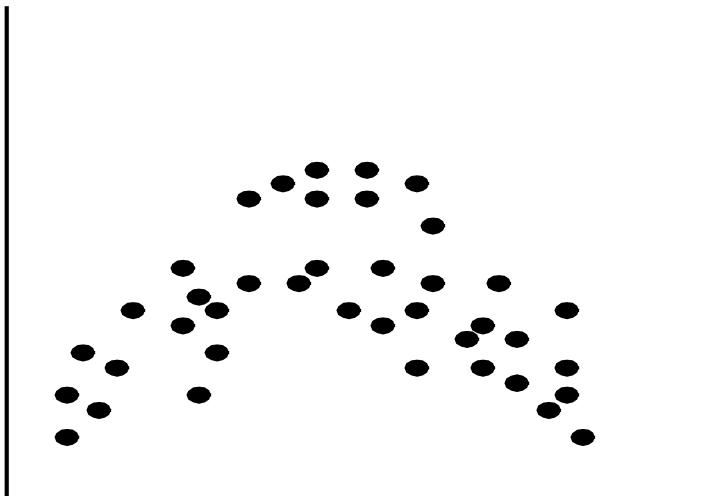
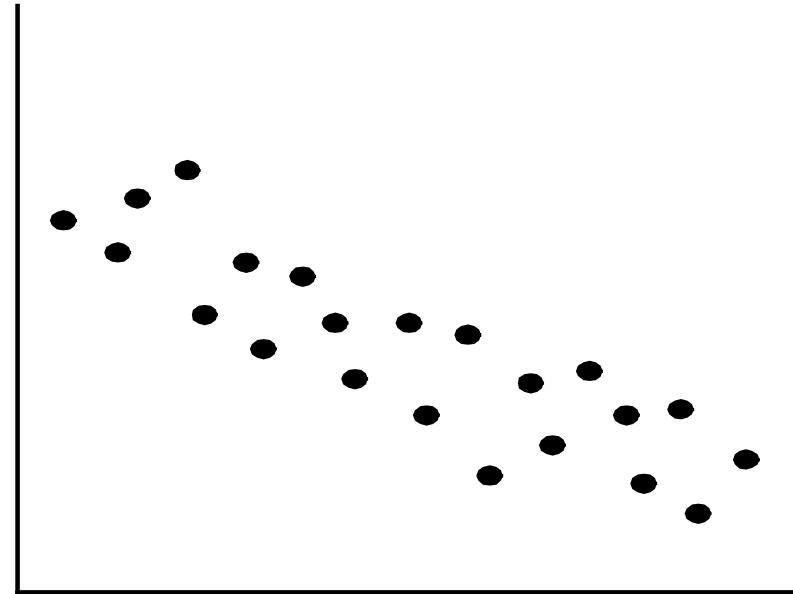
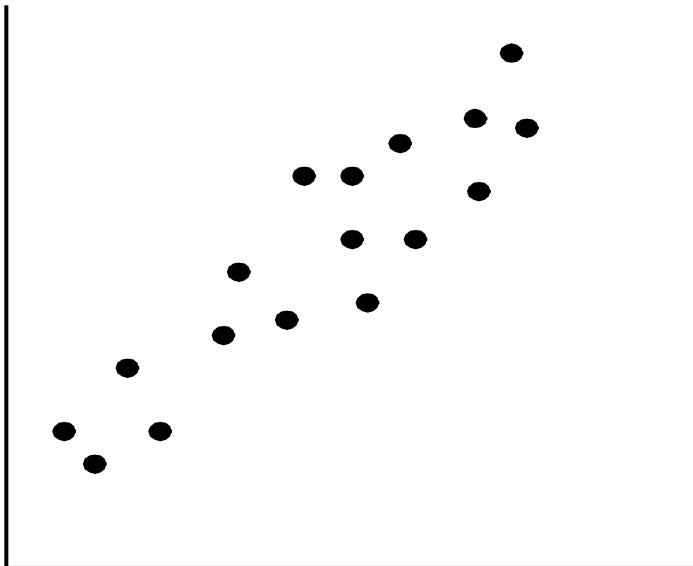


Scatter plot

- 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

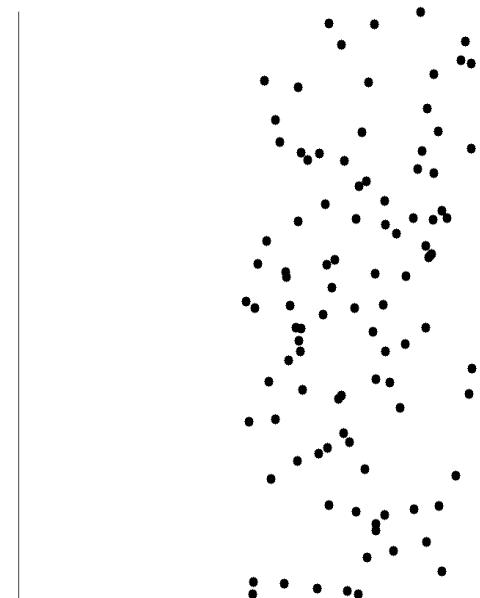
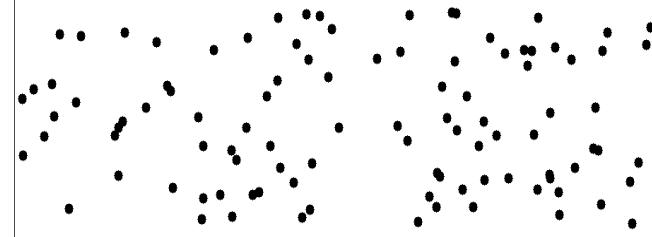
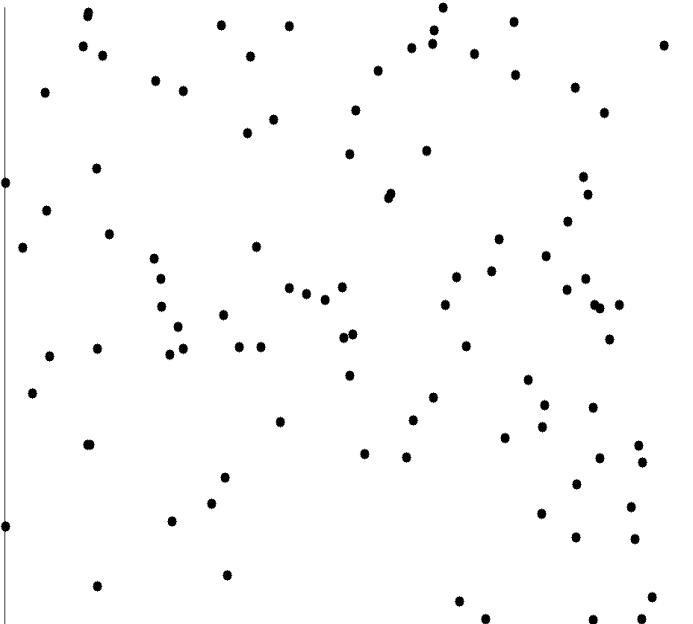


Positively and Negatively Correlated Data



- The left half fragment is positively correlated
- The right half is negative correlated

Uncorrelated Data



Chapter 2: Getting to Know Your Data

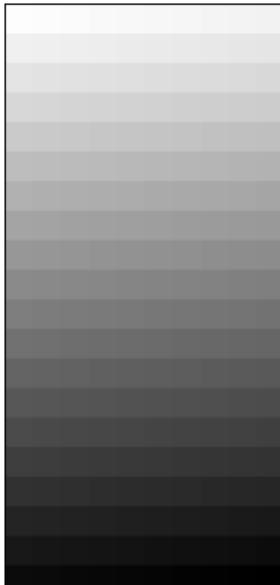
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Data Visualization

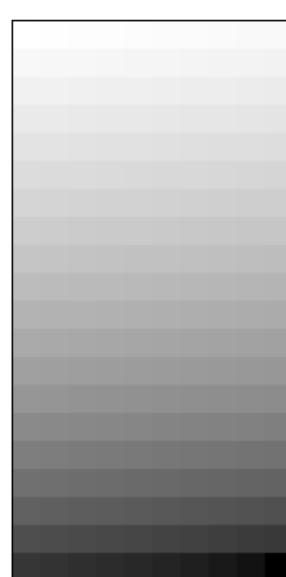
- Why data visualization?
 - Gain insight into an information space by mapping data onto graphical primitives
 - Provide qualitative overview of large data sets
 - Search for patterns, trends, structure, irregularities, relationships among data
 - Help find interesting regions and suitable parameters for further quantitative analysis
 - Provide a visual proof of computer representations derived
- Categorization of visualization methods:
 - Pixel-oriented visualization techniques
 - Geometric projection visualization techniques
 - Icon-based visualization techniques
 - Hierarchical visualization techniques
 - Visualizing complex data and relations

Pixel-Oriented Visualization Techniques

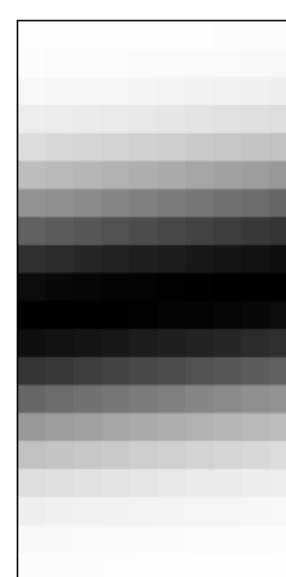
- For a data set of m dimensions, create m windows on the screen, one for each dimension
- The m dimension values of a record are mapped to m pixels at the corresponding positions in the windows
- The colors of the pixels reflect the corresponding values



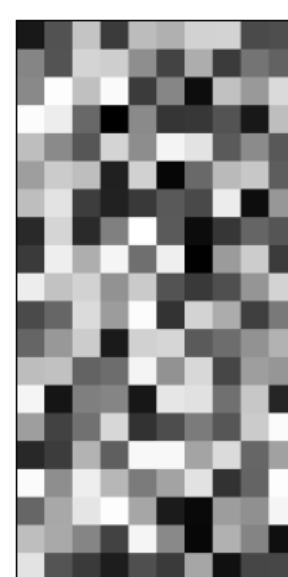
(a) Income



(b) Credit Limit



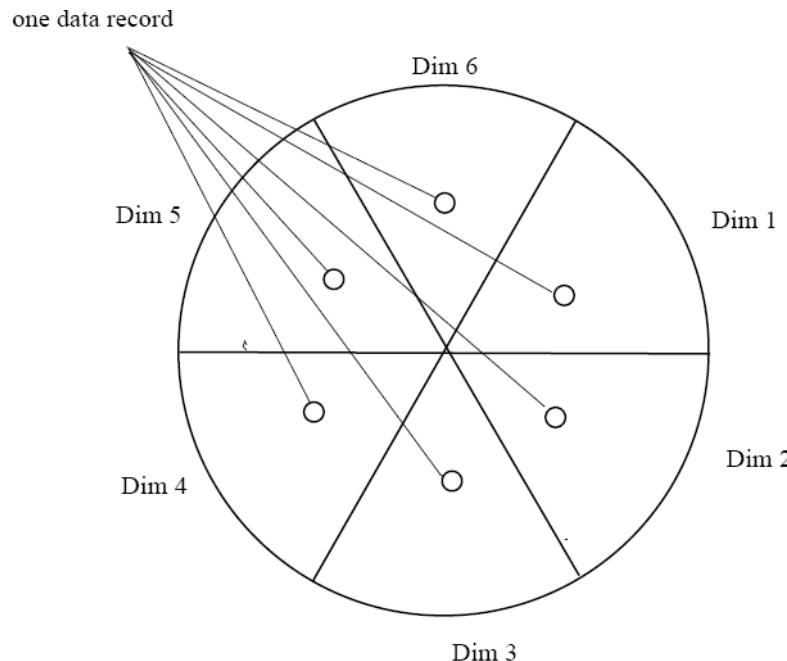
(c) transaction volume



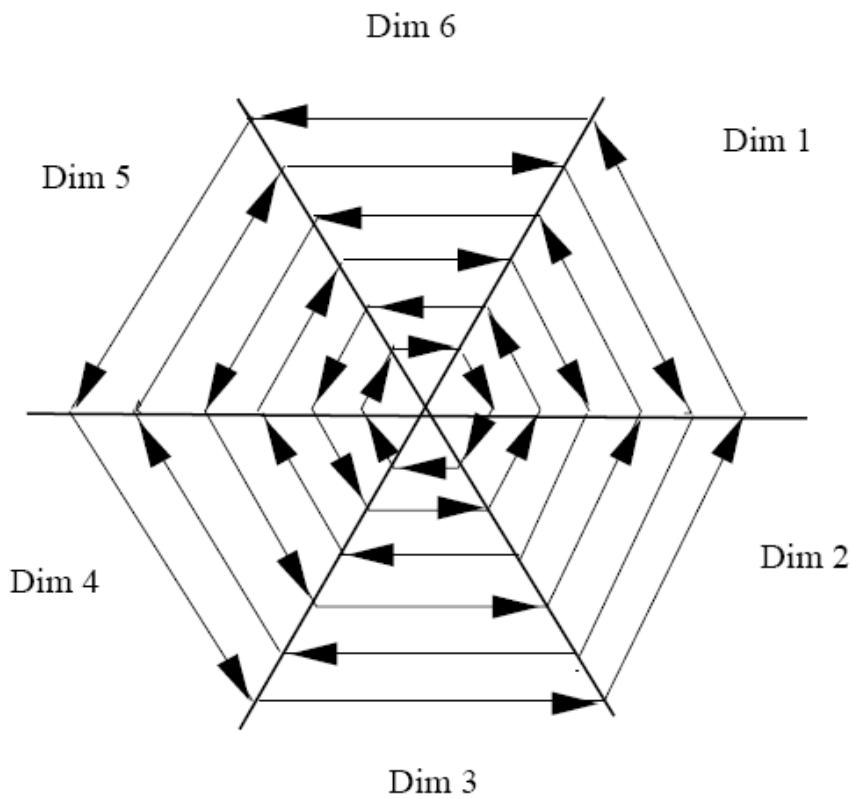
(d) age

Laying Out Pixels in Circle Segments

- To save space and show the connections among multiple dimensions, space filling is often done in a circle segment



(a) Representing a data record
in circle segment



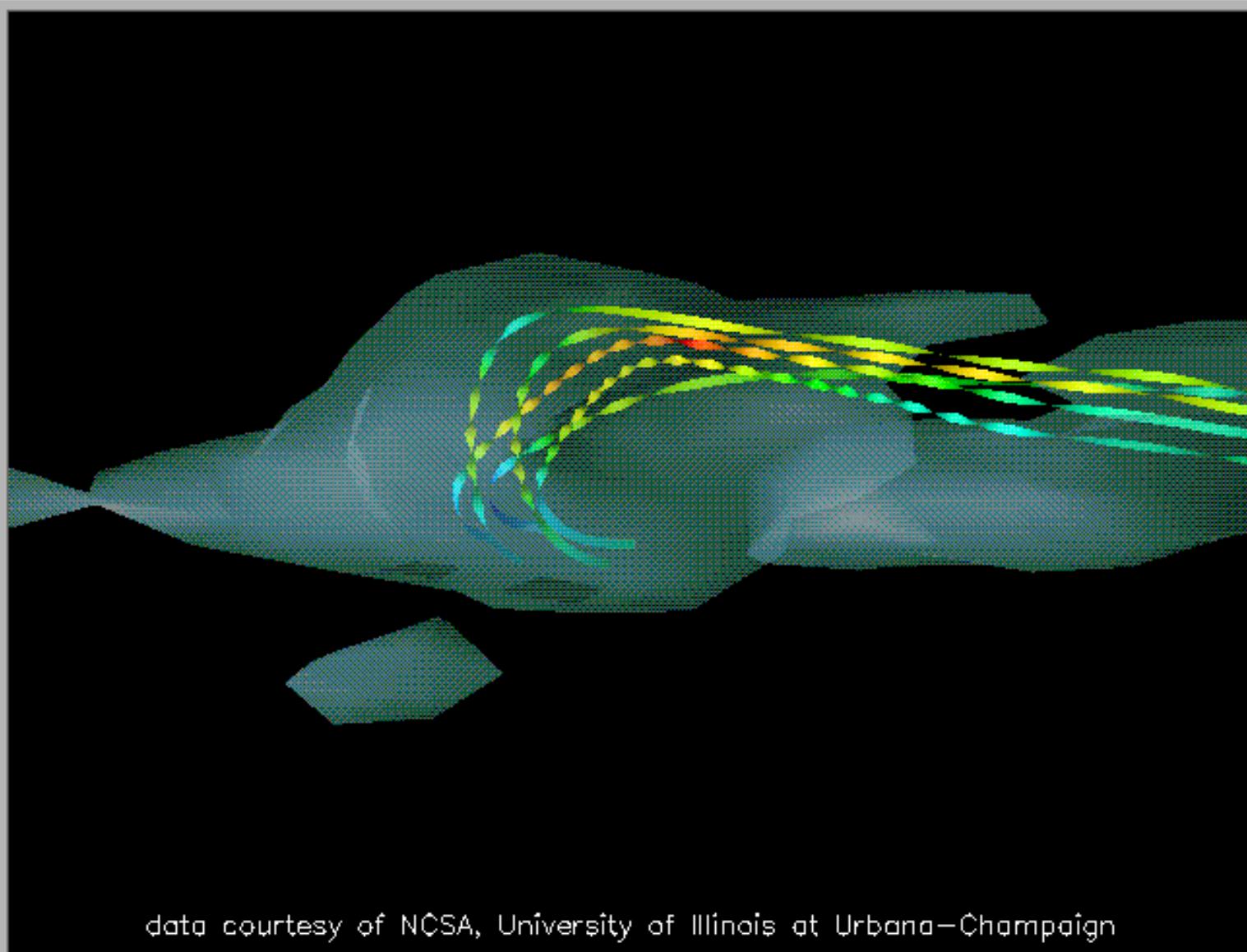
(b) Laying out pixels in circle segment

Geometric Projection Visualization Techniques

- Visualization of geometric transformations and projections of the data
- Methods
 - Direct visualization
 - Scatterplot and scatterplot matrices
 - Landscapes
 - Projection pursuit technique: Help users find meaningful projections of multidimensional data
 - Prosection views
 - Hyperslice
 - Parallel coordinates

Direct Data Visualization

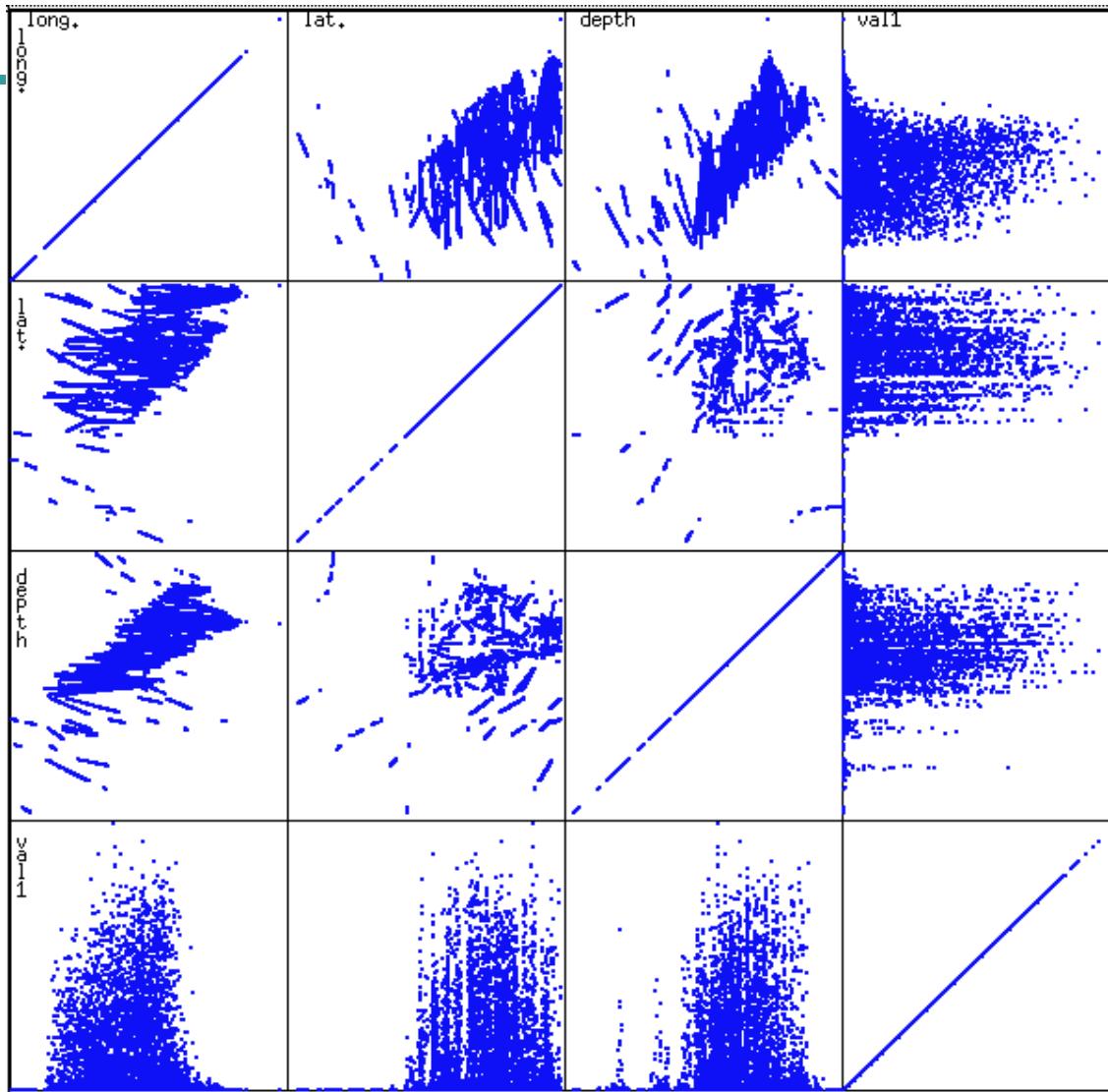
Ribbons with Twists Based on Vorticity



data courtesy of NCSA, University of Illinois at Urbana-Champaign

Scatterplot Matrices

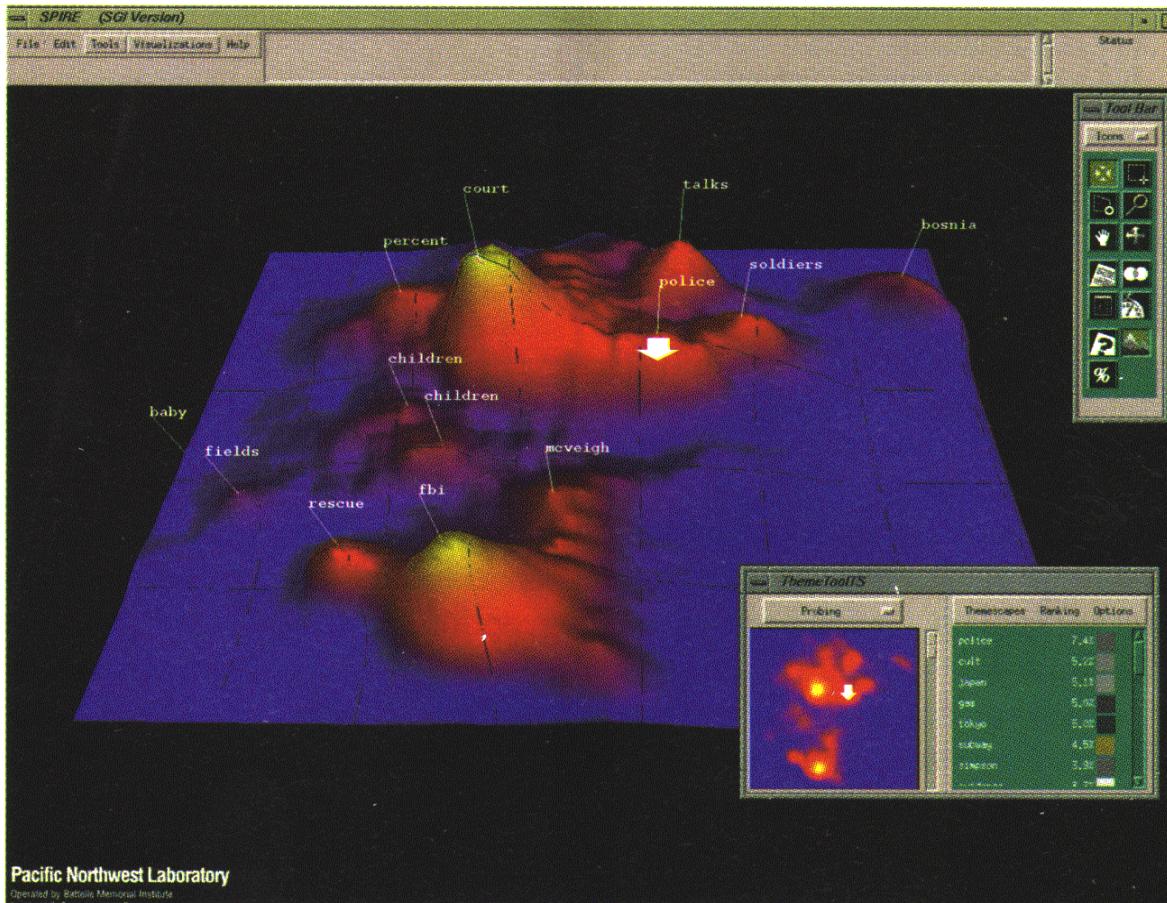
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Matrix of scatterplots (x-y-diagrams) of the k-dim. data [total of $(k^2/2-k)$ scatterplots]

Landscapes

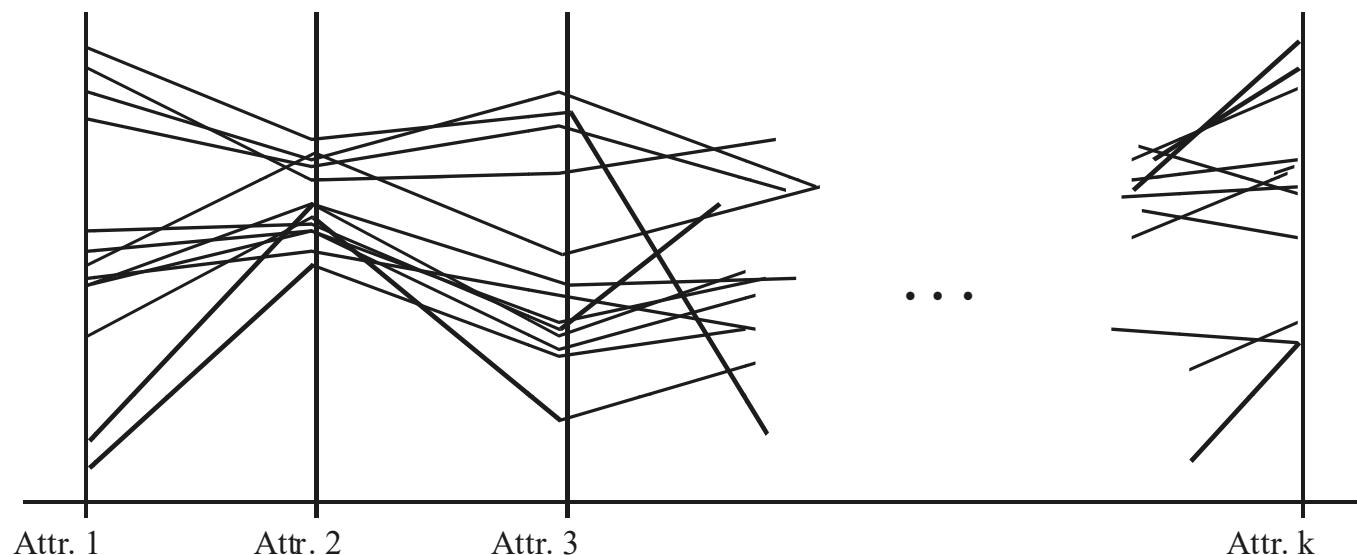
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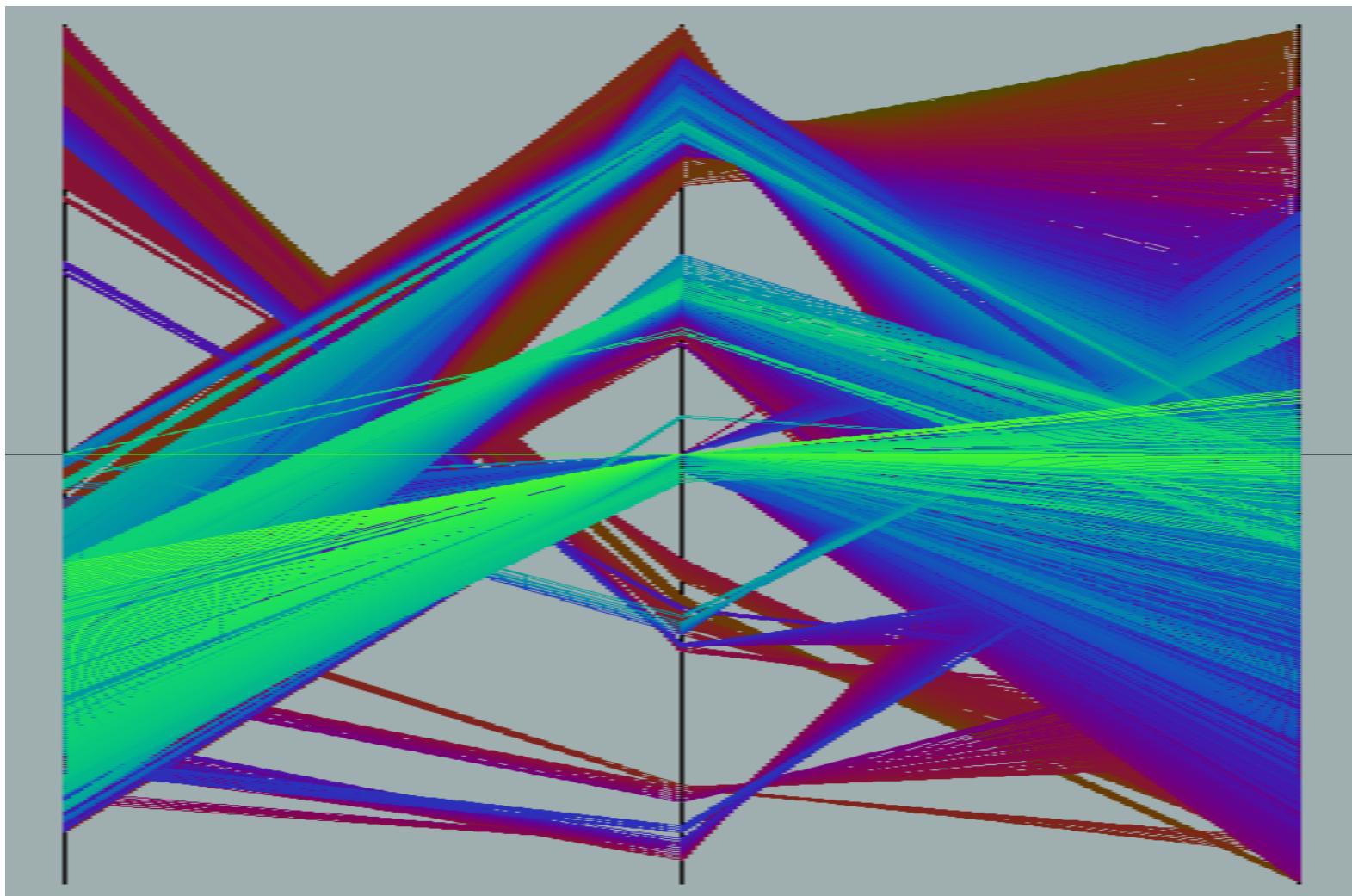
- Visualization of the data as perspective landscape
- The data needs to be transformed into a (possibly artificial) 2D spatial representation which preserves the characteristics of the data

Parallel Coordinates

- n equidistant axes which are parallel to one of the screen axes and correspond to the attributes
- The axes are scaled to the [minimum, maximum]: range of the corresponding attribute
- Every data item corresponds to a polygonal line which intersects each of the axes at the point which corresponds to the value for the attribute



Parallel Coordinates of a Data Set



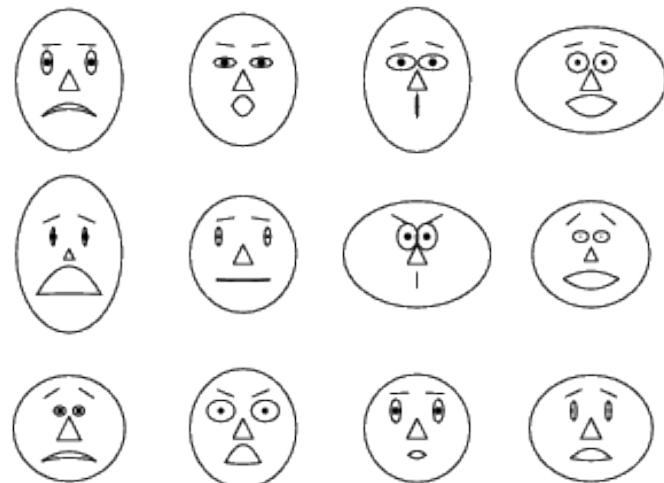
Icon-Based Visualization Techniques

- Visualization of the data values as features of icons
- Typical visualization methods
 - Chernoff Faces
 - Stick Figures
- General techniques
 - Shape coding: Use shape to represent certain information encoding
 - Color icons: Use color icons to encode more information
 - Tile bars: Use small icons to represent the relevant feature vectors in document retrieval

Chernoff Faces

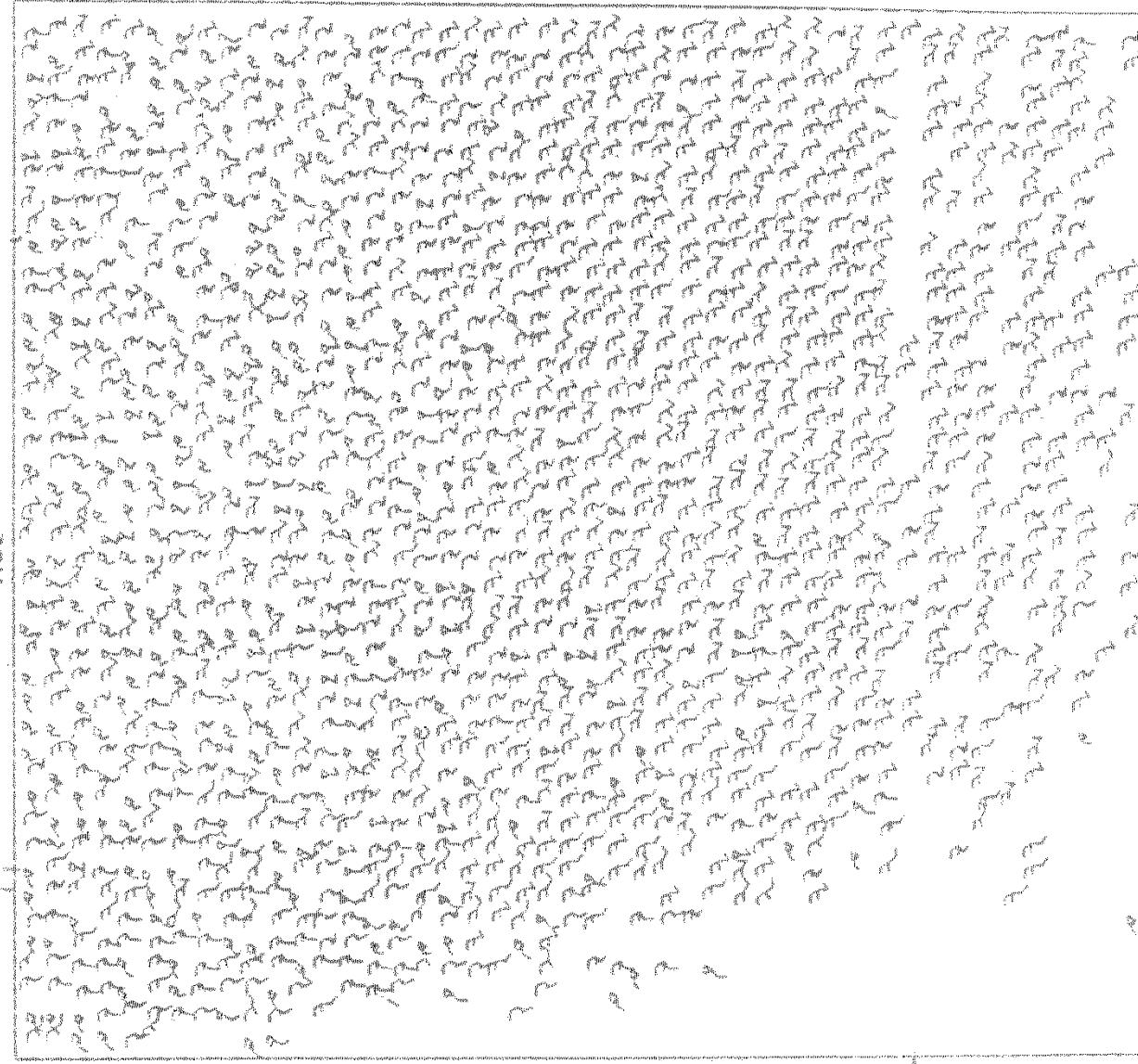
- A way to display variables on a two-dimensional surface, e.g., let x be eyebrow slant, y be eye size, z be nose length, etc.
- The figure shows faces produced using 10 characteristics--head eccentricity, eye size, eye spacing, eye eccentricity, pupil size, eyebrow slant, nose size, mouth shape, mouth size, and mouth opening): Each assigned one of 10 possible values, generated using *Mathematica* (S. Dickson)

- REFERENCE: Gonick, L. and Smith, W. *The Cartoon Guide to Statistics*, New York: Harper Perennial, p. 212, 1993
- Weisstein, Eric W. "Chernoff Face." From *MathWorld-A Wolfram Web Resource*.
mathworld.wolfram.com/ChernoffFace.html



Stick Figure

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Two attributes mapped to axes, remaining attributes mapped to angle or length of limbs". Look at texture pattern

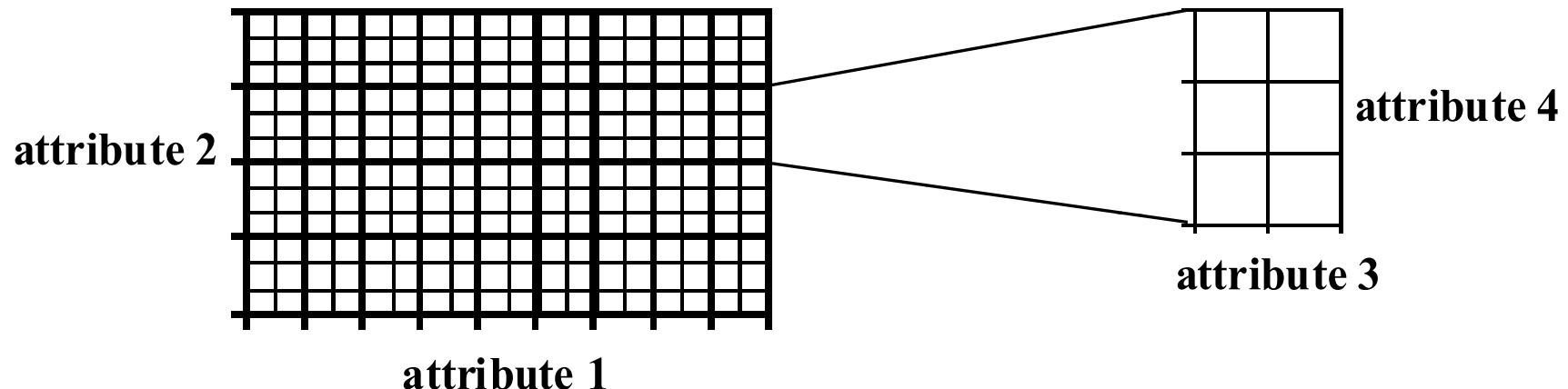
A census data figure showing age, income, gender, education, etc.

A 5-piece stick figure (1 body and 4 limbs w. different angle/length)

Hierarchical Visualization Techniques

- Visualization of the data using a hierarchical partitioning into subspaces
- Methods
 - Dimensional Stacking
 - Worlds-within-Worlds
 - Tree-Map
 - Cone Trees
 - InfoCube

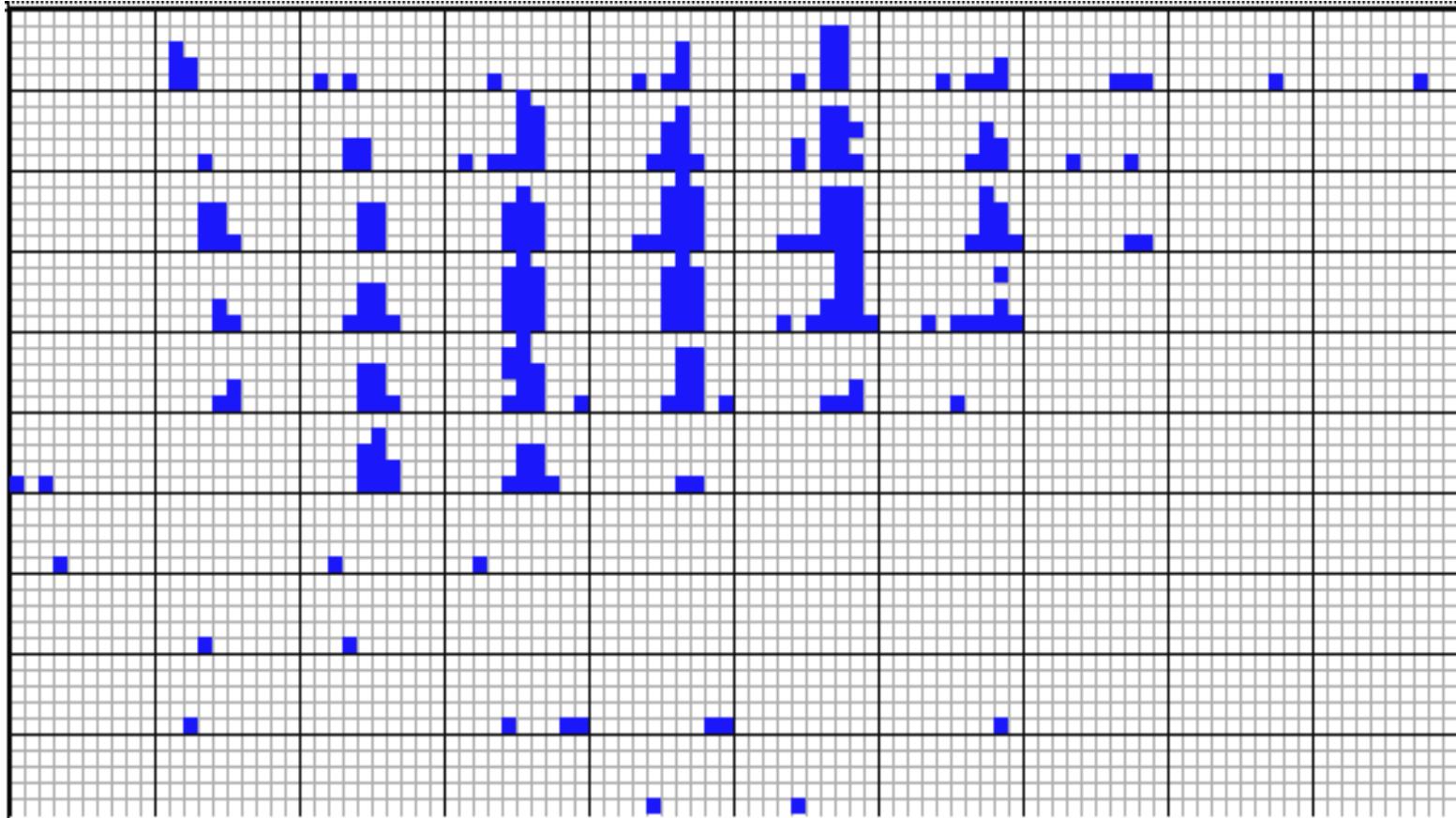
Dimensional Stacking



- Partitioning of the n-dimensional attribute space in 2-D subspaces, which are 'stacked' into each other
- Partitioning of the attribute value ranges into classes. The important attributes should be used on the outer levels.
- Adequate for data with ordinal attributes of low cardinality
- But, difficult to display more than nine dimensions
- Important to map dimensions appropriately

Dimensional Stacking

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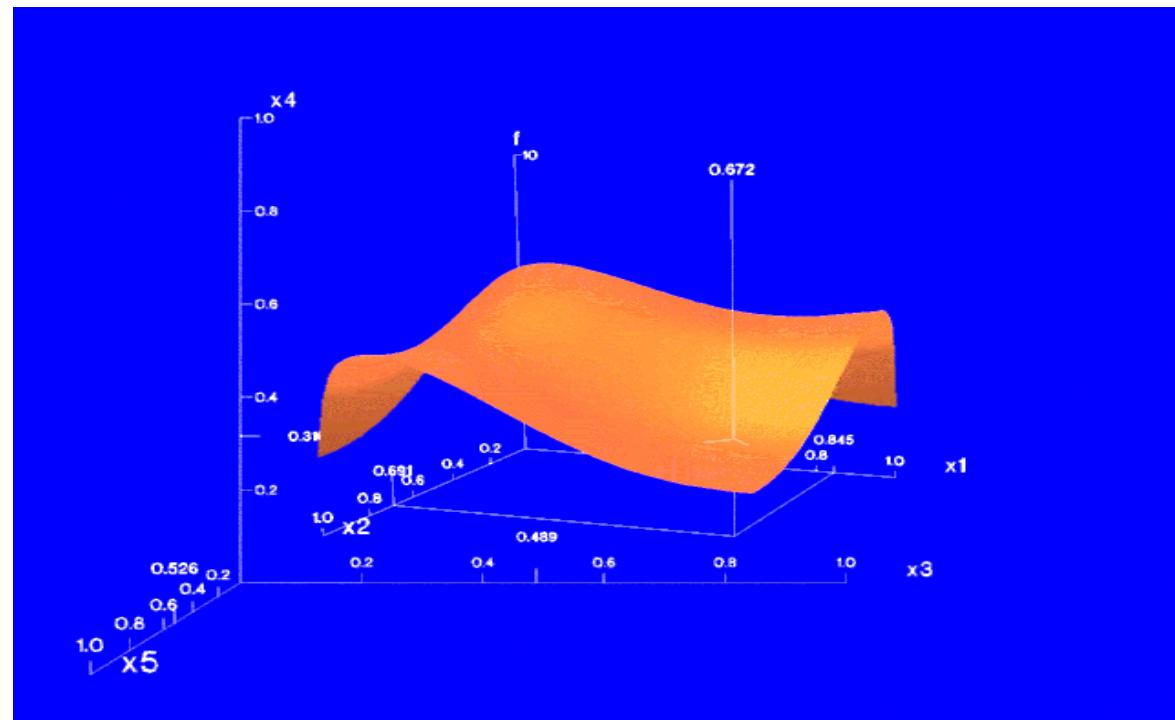


Visualization of oil mining data with longitude and latitude mapped to the outer x-, y-axes and ore grade and depth mapped to the inner x-, y-axes

Worlds-within-Worlds

- Assign the function and two most important parameters to innermost world
- Fix all other parameters at constant values - draw other (1 or 2 or 3 dimensional worlds choosing these as the axes)
- Software that uses this paradigm

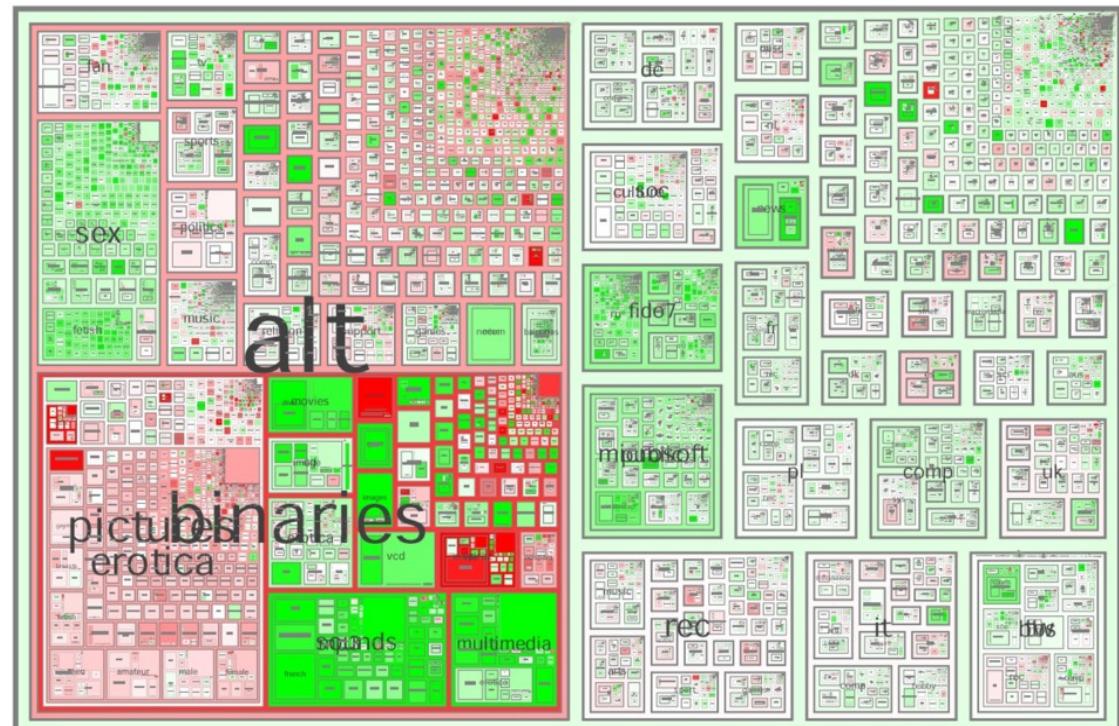
- N-vision: Dynamic interaction through data glove and stereo displays, including rotation, scaling (inner) and translation (inner/outer)
- Auto Visual: Static interaction by means of queries



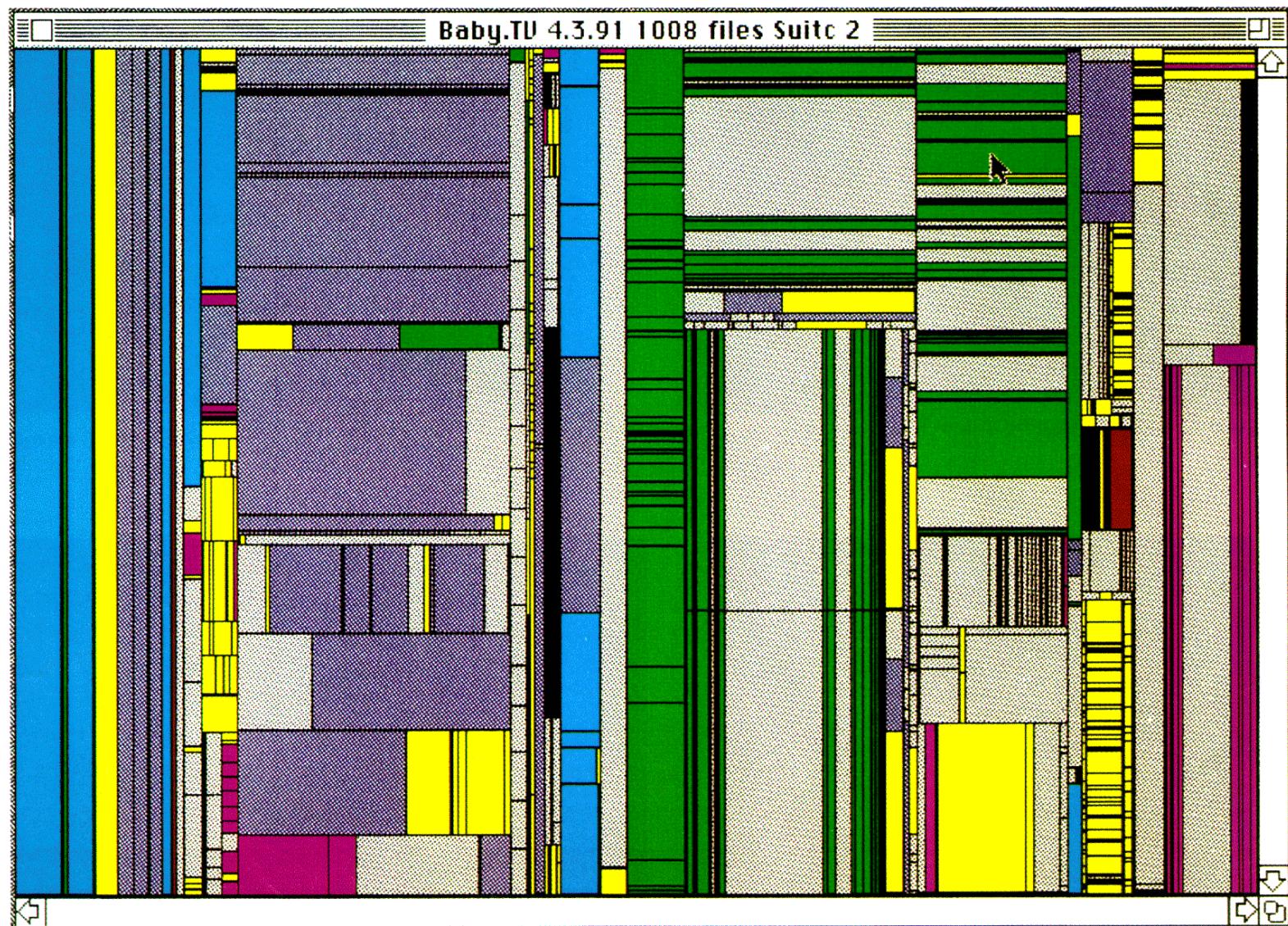
Tree-Map

- Screen-filling method which uses a hierarchical partitioning of the screen into regions depending on the attribute values
 - The x- and y-dimension of the screen are partitioned alternately according to the attribute values (classes)

MSR Netscan Image

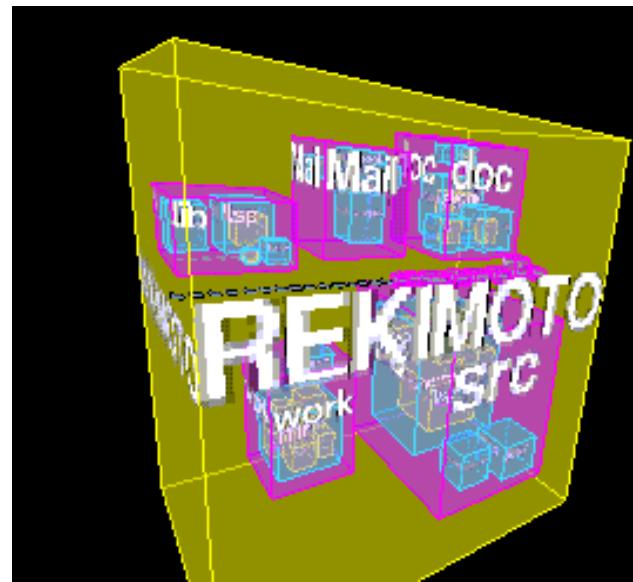


Tree-Map of a File System (Schneiderman)



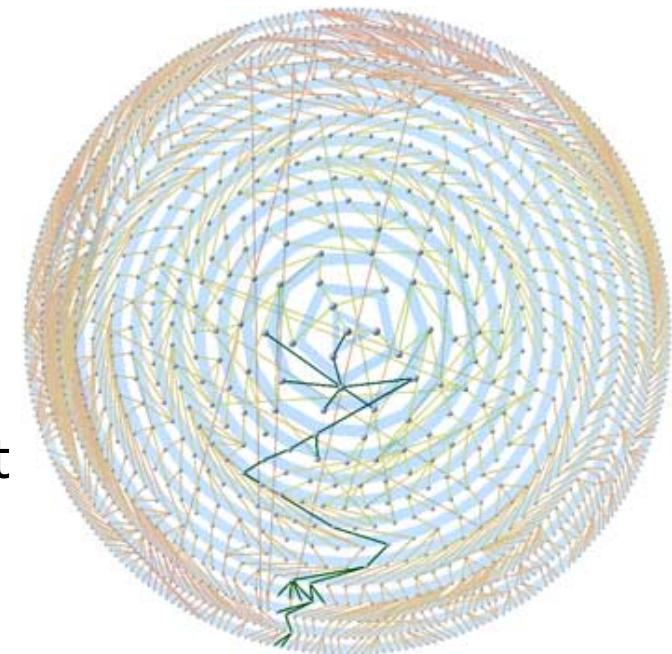
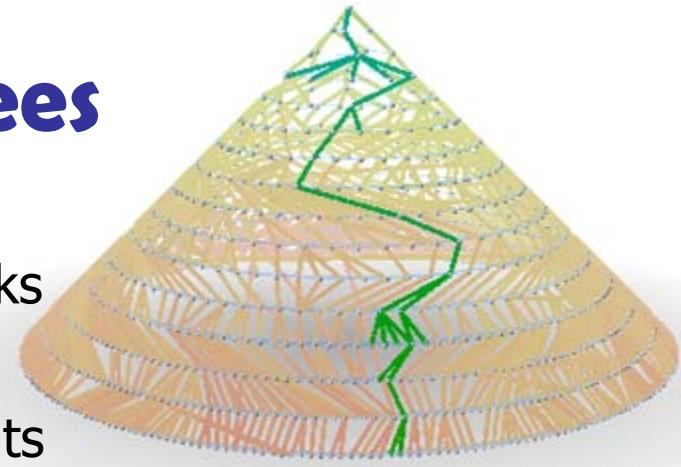
InfoCube

- A 3-D visualization technique where hierarchical information is displayed as nested semi-transparent cubes
- The outermost cubes correspond to the top level data, while the subnodes or the lower level data are represented as smaller cubes inside the outermost cubes, and so on



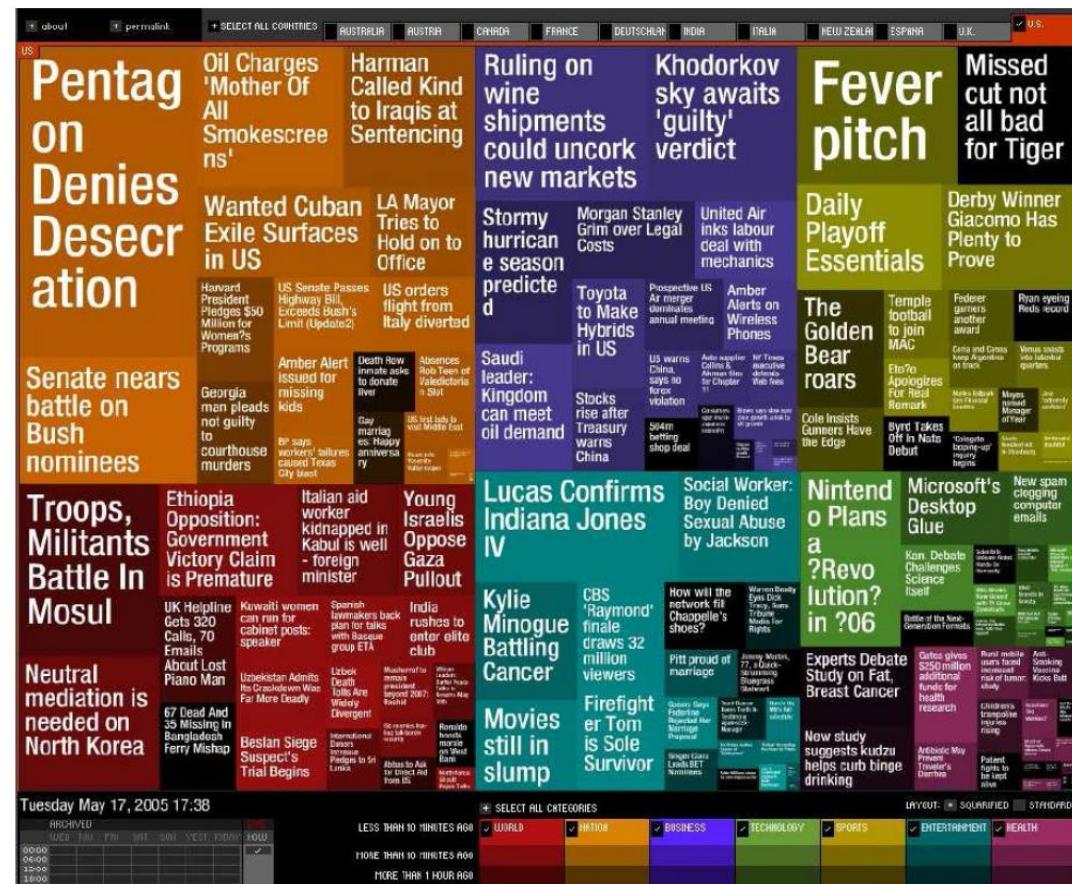
Three-D Cone Trees

- *3D cone tree* visualization technique works well for up to a thousand nodes or so
- First build a *2D circle tree* that arranges its nodes in concentric circles centered on the root node
- Cannot avoid overlaps when projected to 2D
- G. Robertson, J. Mackinlay, S. Card. "Cone Trees: Animated 3D Visualizations of Hierarchical Information", *ACM SIGCHI'91*
- Graph from Nadeau Software Consulting website: Visualize a social network data set that models the way an infection spreads from one person to the next



Visualizing Complex Data and Relations

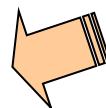
- Visualizing non-numerical data: text and social networks
- Tag cloud: visualizing user-generated tags
 - The importance of tag is represented by font size/color
- Besides text data, there are also methods to visualize relationships, such as visualizing social networks



Newsmap: Google News Stories in 2005

Chapter 2: Getting to Know Your Data

- Data Objects and Attribute Types
- Basic Statistical Descriptions of Data
- Data Visualization
- Measuring Data Similarity and Dissimilarity
- Summary



Similarity and Dissimilarity

- **Similarity**
 - Numerical measure of how alike two data objects are
 - Value is higher when objects are more alike
 - Often falls in the range [0,1]
- **Dissimilarity** (e.g., distance)
 - Numerical measure of how different two data objects are
 - Lower when objects are more alike
 - Minimum dissimilarity is often 0
 - Upper limit varies
- **Proximity** refers to a similarity or dissimilarity

Data Matrix and Dissimilarity Matrix

■ Data matrix

- n data points with p dimensions
- Two modes

$$\begin{bmatrix} x_{11} & \dots & x_{1f} & \dots & x_{1p} \\ \dots & \dots & \dots & \dots & \dots \\ x_{i1} & \dots & x_{if} & \dots & x_{ip} \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & \dots & x_{nf} & \dots & x_{np} \end{bmatrix}$$

■ Dissimilarity matrix

- n data points, but registers only the distance
- A triangular matrix
- Single mode

$$\begin{bmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ d(3,1) & d(3,2) & 0 & & \\ \vdots & \vdots & \vdots & \ddots & \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix}$$

Proximity Measure for Nominal Attributes

- Can take 2 or more states, e.g., red, yellow, blue, green (generalization of a binary attribute)
- Method 1: Simple matching
 - m : # of matches, p : total # of variables
- $$d(i, j) = \frac{p - m}{p}$$
- Method 2: Use a large number of binary attributes
 - creating a new binary attribute for each of the M nominal states

Proximity Measure for Binary Attributes

- A contingency table for binary data

		Object <i>j</i>		
		1	0	sum
Object <i>i</i>	1	q	r	$q + r$
	0	s	t	$s + t$
sum		$q + s$	$r + t$	p

- Distance measure for symmetric binary variables:

$$d(i, j) = \frac{r + s}{q + r + s + t}$$

- Distance measure for asymmetric binary variables:

$$d(i, j) = \frac{r + s}{q + r + s}$$

- Jaccard coefficient (*similarity* measure for *asymmetric* binary variables):

$$\text{sim}_{\text{Jaccard}}(i, j) = \frac{q}{q + r + s}$$

- Note: Jaccard coefficient is the same as “coherence”:

$$\text{coherence}(i, j) = \frac{\text{sup}(i, j)}{\text{sup}(i) + \text{sup}(j) - \text{sup}(i, j)} = \frac{q}{(q + r) + (q + s) - q}$$

Dissimilarity between Binary Variables

■ Example

Name	Gender	Fever	Cough	Test-1	Test-2	Test-3	Test-4
Jack	M	Y	N	P	N	N	N
Mary	F	Y	N	P	N	P	N
Jim	M	Y	P	N	N	N	N

- Gender is a symmetric attribute
- The remaining attributes are asymmetric binary
- Let the values Y and P be 1, and the value N 0

$$d(jack, mary) = \frac{0 + 1}{2 + 0 + 1} = 0.33$$

$$d(jack, jim) = \frac{1 + 1}{1 + 1 + 1} = 0.67$$

$$d(jim, mary) = \frac{1 + 2}{1 + 1 + 2} = 0.75$$

Standardizing Numeric Data

- Z-score:
$$z = \frac{x - \mu}{\sigma}$$
 - X: raw score to be standardized, μ : mean of the population, σ : standard deviation
 - the distance between the raw score and the population mean in units of the standard deviation
 - negative when the raw score is below the mean, "+" when above
- An alternative way: Calculate the mean absolute deviation

$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + \dots + |x_{nf} - m_f|)$$

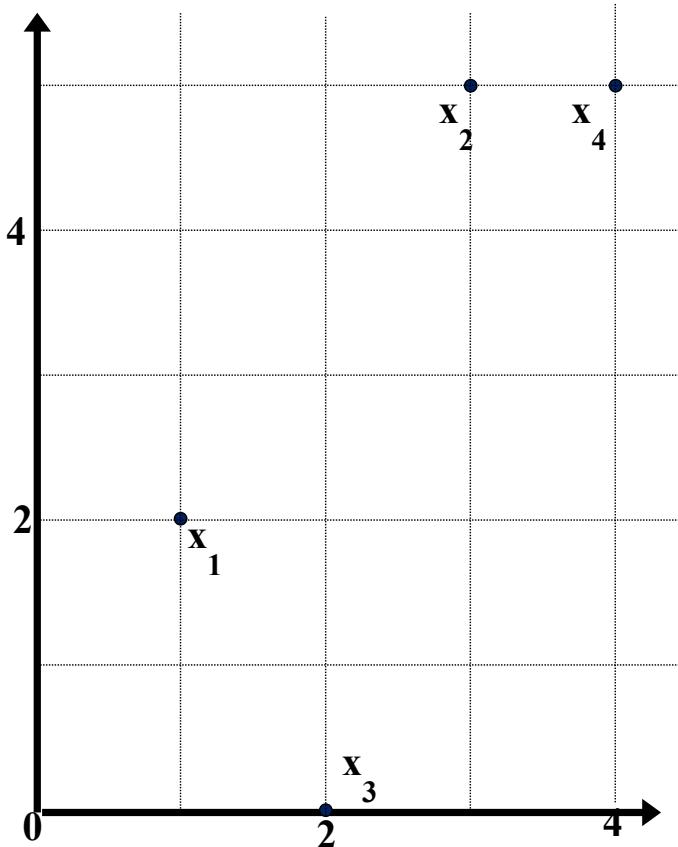
where $m_f = \frac{1}{n}(x_{1f} + x_{2f} + \dots + x_{nf})$.

$$z_{if} = \frac{x_{if} - m_f}{s_f}$$

- standardized measure (*z-score*):
- Using mean absolute deviation is more robust than using standard deviation

Example:

Data Matrix and Dissimilarity Matrix



Data Matrix

point	attribute1	attribute2
$x1$	1	2
$x2$	3	5
$x3$	2	0
$x4$	4	5

Dissimilarity Matrix

(with Euclidean Distance)

	$x1$	$x2$	$x3$	$x4$
$x1$	0			
$x2$	3.61	0		
$x3$	5.1	5.1	0	
$x4$	4.24	1	5.39	0

Distance on Numeric Data: Minkowski Distance

- *Minkowski distance*: A popular distance measure

$$d(i, j) = \sqrt[h]{|x_{i1} - x_{j1}|^h + |x_{i2} - x_{j2}|^h + \cdots + |x_{ip} - x_{jp}|^h}$$

where $i = (x_{i1}, x_{i2}, \dots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \dots, x_{jp})$ are two p -dimensional data objects, and h is the order (the distance so defined is also called L- h norm)

- Properties
 - $d(i, j) > 0$ if $i \neq j$, and $d(i, i) = 0$ (Positive definiteness)
 - $d(i, j) = d(j, i)$ (Symmetry)
 - $d(i, j) \leq d(i, k) + d(k, j)$ (Triangle Inequality)
- A distance that satisfies these properties is a **metric**

Special Cases of Minkowski Distance

- $h = 1$: Manhattan (city block, L_1 norm) distance
 - E.g., the Hamming distance: the number of bits that are different between two binary vectors

$$d(i, j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \dots + |x_{ip} - x_{jp}|$$

- $h = 2$: (L_2 norm) Euclidean distance

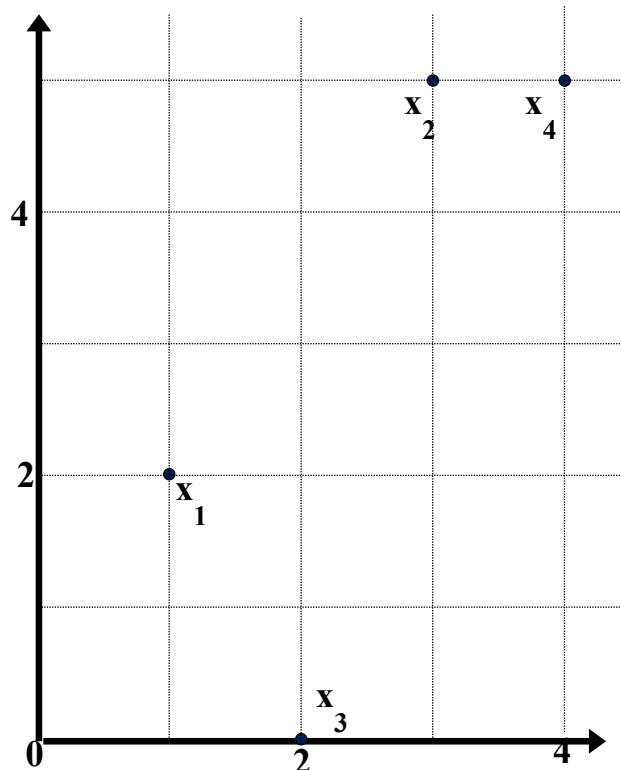
$$d(i, j) = \sqrt{(|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \dots + |x_{ip} - x_{jp}|^2)}$$

- $h \rightarrow \infty$. “supremum” (L_{\max} norm, L_∞ norm) distance.
 - This is the maximum difference between any component (attribute) of the vectors

$$d(i, j) = \lim_{h \rightarrow \infty} \left(\sum_{f=1}^p |x_{if} - x_{jf}|^h \right)^{\frac{1}{h}} = \max_f^p |x_{if} - x_{jf}|$$

Example: Minkowski Distance

point	attribute 1	attribute 2
x1	1	2
x2	3	5
x3	2	0
x4	4	5



Dissimilarity Matrices

Manhattan (L_1)

L	x1	x2	x3	x4
x1	0			
x2	5	0		
x3	3	6	0	
x4	6	1	7	0

Euclidean (L_2)

L2	x1	x2	x3	x4
x1	0			
x2	3.61	0		
x3	2.24	5.1	0	
x4	4.24	1	5.39	0

Supremum

L_∞	x1	x2	x3	x4
x1	0			
x2	3	0		
x3	2	5	0	
x4	3	1	5	0

Ordinal Variables

- An ordinal variable can be discrete or continuous
- Order is important, e.g., rank
- Can be treated like interval-scaled
 - replace x_{if} by their rank $r_{if} \in \{1, \dots, M_f\}$
 - map the range of each variable onto [0, 1] by replacing i -th object in the f -th variable by

$$z_{if} = \frac{r_{if} - 1}{M_f - 1}$$

- compute the dissimilarity using methods for interval-scaled variables

Attributes of Mixed Type

- A database may contain all attribute types
 - Nominal, symmetric binary, asymmetric binary, numeric, ordinal
- One may use a weighted formula to combine their effects

$$d(i, j) = \frac{\sum_{f=1}^p \delta_{ij}^{(f)} d_{ij}^{(f)}}{\sum_{f=1}^p \delta_{ij}^{(f)}}$$

- f is binary or nominal:
 $d_{ij}^{(f)} = 0$ if $x_{if} = x_{jf}$, or $d_{ij}^{(f)} = 1$ otherwise
- f is numeric: use the normalized distance
- f is ordinal
 - Compute ranks r_{if} and
 - Treat z_{if} as interval-scaled

$$z_{if} = \frac{r_{if} - 1}{M_f - 1}$$

Cosine Similarity

- A **document** can be represented by thousands of attributes, each recording the *frequency* of a particular word (such as keywords) or phrase in the document.

Document	team	coach	hockey	baseball	soccer	penalty	score	win	loss	season
Document1	5	0	3	0	2	0	0	2	0	0
Document2	3	0	2	0	1	1	0	1	0	1
Document3	0	7	0	2	1	0	0	3	0	0
Document4	0	1	0	0	1	2	2	0	3	0

- Other vector objects: gene features in micro-arrays, ...
- Applications: information retrieval, biologic taxonomy, gene feature mapping, ...
- Cosine measure: If d_1 and d_2 are two vectors (e.g., term-frequency vectors), then

$$\cos(d_1, d_2) = (d_1 \bullet d_2) / \|d_1\| \|d_2\|,$$

where \bullet indicates vector dot product, $\|d\|$: the length of vector d

Example: Cosine Similarity

- $\cos(d_1, d_2) = (d_1 \bullet d_2) / \|d_1\| \|d_2\|$,
where \bullet indicates vector dot product, $\|d\|$: the length of vector d
- Ex: Find the **similarity** between documents 1 and 2.

$$d_1 = (5, 0, 3, 0, 2, 0, 0, 2, 0, 0)$$

$$d_2 = (3, 0, 2, 0, 1, 1, 0, 1, 0, 1)$$

$$d_1 \bullet d_2 = 5*3 + 0*0 + 3*2 + 0*0 + 2*1 + 0*1 + 0*1 + 2*1 + 0*0 + 0*1 = 25$$

$$\|d_1\| = \sqrt{(5^2 + 0^2 + 3^2 + 0^2 + 2^2 + 0^2 + 0^2 + 2^2 + 0^2 + 0^2)} = \sqrt{42} \approx 6.481$$

$$\|d_2\| = \sqrt{(3^2 + 0^2 + 2^2 + 0^2 + 1^2 + 1^2 + 0^2 + 1^2 + 0^2 + 1^2)} = \sqrt{17} \approx 4.12$$

$$\cos(d_1, d_2) = 0.94$$

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Summary

- Data attribute types: nominal, binary, ordinal, interval-scaled, ratio-scaled
- Many types of data sets, e.g., numerical, text, graph, Web, image.
- Gain insight into the data by:
 - Basic statistical data description: central tendency, dispersion, graphical displays
 - Data visualization: map data onto graphical primitives
 - Measure data similarity
- Above steps are the beginning of data preprocessing.
- Many methods have been developed but still an active area of research.

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Data Mining:

Concepts and Techniques

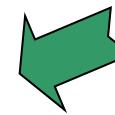
(3rd ed.)

— Chapter 3 —

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Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview 

 - Data Quality
 - Major Tasks in Data Preprocessing

- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary

Data Quality: Why Preprocess the Data?

- Measures for data quality: A multidimensional view
 - Accuracy: correct or wrong, accurate or not
 - Completeness: not recorded, unavailable, ...
 - Consistency: some modified but some not, dangling, ...
 - Timeliness: timely update?
 - Believability: how trustable the data are correct?
 - Interpretability: how easily the data can be understood?

Major Tasks in Data Preprocessing

- **Data cleaning**

- Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies

- **Data integration**

- Integration of multiple databases, data cubes, or files

- **Data reduction**

- Dimensionality reduction
 - Numerosity reduction
 - Data compression

- **Data transformation and data discretization**

- Normalization
 - Concept hierarchy generation

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Data Cleaning

- Data in the Real World Is Dirty: Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, transmission error
 - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
 - e.g., *Occupation*=“ ” (missing data)
 - noisy: containing noise, errors, or outliers
 - e.g., *Salary*=“–10” (an error)
 - inconsistent: containing discrepancies in codes or names, e.g.,
 - *Age*=“42”, *Birthday*=“03/07/2010”
 - Was rating “1, 2, 3”, now rating “A, B, C”
 - discrepancy between duplicate records
 - Intentional (e.g., *disguised missing* data)
 - Jan. 1 as everyone’s birthday?

Incomplete (Missing) Data

- Data is not always available
 - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
 - equipment malfunction
 - inconsistent with other recorded data and thus deleted
 - data not entered due to misunderstanding
 - certain data may not be considered important at the time of entry
 - not register history or changes of the data
- Missing data may need to be inferred

How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (when doing classification)—not effective when the % of missing values per attribute varies considerably
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
 - a global constant : e.g., “unknown”, a new class?!
 - the attribute mean
 - the attribute mean for all samples belonging to the same class: smarter
 - the most probable value: inference-based such as Bayesian formula or decision tree

Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may be due to
 - faulty data collection instruments
 - data entry problems
 - data transmission problems
 - technology limitation
 - inconsistency in naming convention
- Other data problems which require data cleaning
 - duplicate records
 - incomplete data
 - inconsistent data

How to Handle Noisy Data?

- Binning
 - first sort data and partition into (equal-frequency) bins
 - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
- Regression
 - smooth by fitting the data into regression functions
- Clustering
 - detect and remove outliers
- Combined computer and human inspection
 - detect suspicious values and check by human (e.g., deal with possible outliers)

Data Cleaning as a Process

- Data discrepancy detection
 - Use metadata (e.g., domain, range, dependency, distribution)
 - Check field overloading
 - Check uniqueness rule, consecutive rule and null rule
 - Use commercial tools
 - Data scrubbing: use simple domain knowledge (e.g., postal code, spell-check) to detect errors and make corrections
 - Data auditing: by analyzing data to discover rules and relationship to detect violators (e.g., correlation and clustering to find outliers)
- Data migration and integration
 - Data migration tools: allow transformations to be specified
 - ETL (Extraction/Transformation>Loading) tools: allow users to specify transformations through a graphical user interface
- Integration of the two processes
 - Iterative and interactive (e.g., Potter's Wheels)

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Data Integration

- **Data integration:**
 - Combines data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ B.cust-#
 - Integrate metadata from different sources
- **Entity identification problem:**
 - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
 - For the same real world entity, attribute values from different sources are different
 - Possible reasons: different representations, different scales, e.g., metric vs. British units

Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
 - *Object identification:* The same attribute or object may have different names in different databases
 - *Derivable data:* One attribute may be a “derived” attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by *correlation analysis* and *covariance analysis*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Correlation Analysis (Nominal Data)

■ **X² (chi-square) test**

$$\chi^2 = \sum \frac{(Observed - Expected)^2}{Expected}$$

- The larger the X² value, the more likely the variables are related
- The cells that contribute the most to the X² value are those whose actual count is very different from the expected count
- Correlation does not imply causality
 - # of hospitals and # of car-theft in a city are correlated
 - Both are causally linked to the third variable: population

Chi-Square Calculation: An Example

	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- χ^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250 - 90)^2}{90} + \frac{(50 - 210)^2}{210} + \frac{(200 - 360)^2}{360} + \frac{(1000 - 840)^2}{840} = 507.93$$

- It shows that like_science_fiction and play_chess are correlated in the group

Correlation Analysis (Numeric Data)

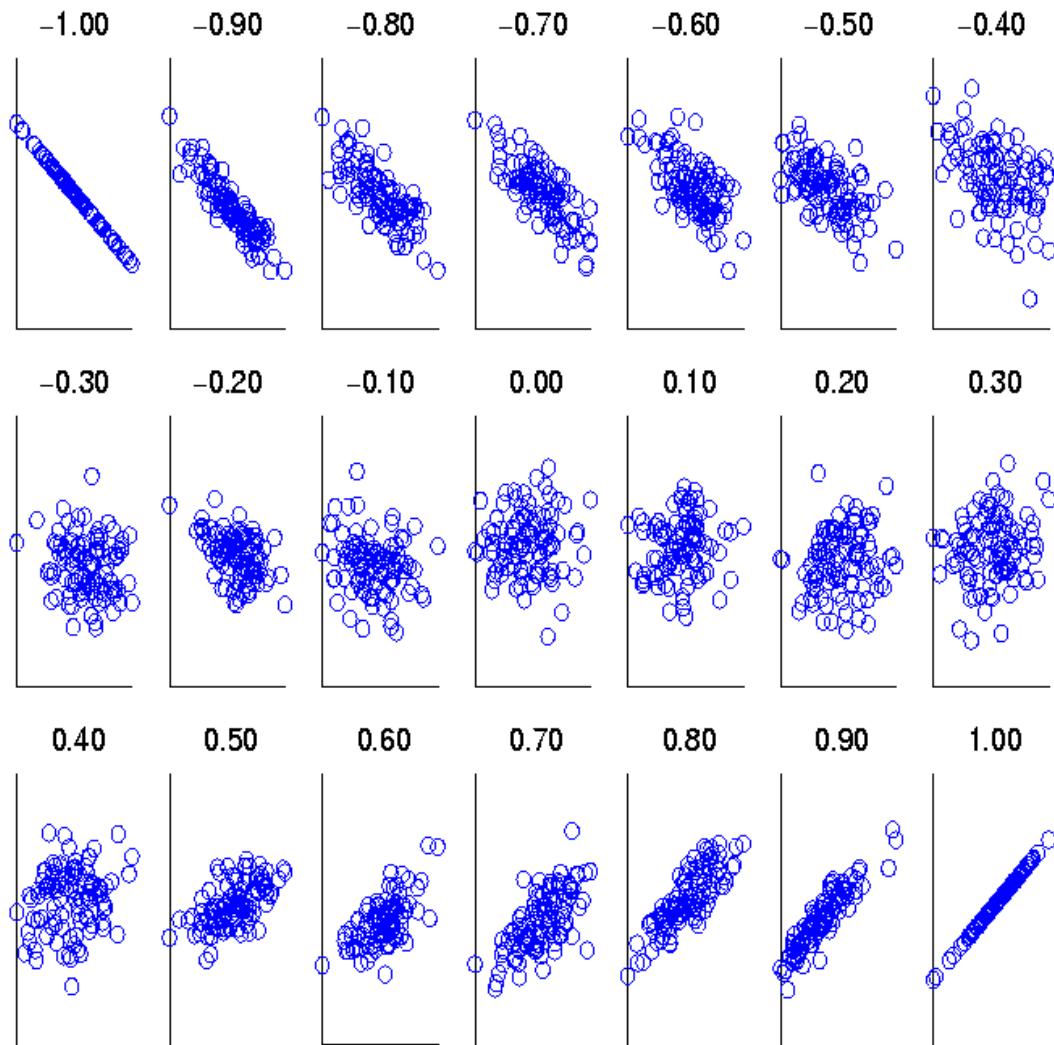
- Correlation coefficient (also called Pearson's product moment coefficient)

$$r_{A,B} = \frac{\sum_{i=1}^n (a_i - \bar{A})(b_i - \bar{B})}{(n-1)\sigma_A\sigma_B} = \frac{\sum_{i=1}^n (a_i b_i) - n\bar{A}\bar{B}}{(n-1)\sigma_A\sigma_B}$$

where n is the number of tuples, \bar{A} and \bar{B} are the respective means of A and B, σ_A and σ_B are the respective standard deviation of A and B, and $\Sigma(a_i b_i)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{AB} < 0$: negatively correlated

Visually Evaluating Correlation



**Scatter plots
showing the
similarity from
-1 to 1.**

Correlation (viewed as linear relationship)

- Correlation measures the linear relationship between objects
- To compute correlation, we standardize data objects, A and B, and then take their dot product

$$a'_k = (a_k - \text{mean}(A)) / \text{std}(A)$$

$$b'_k = (b_k - \text{mean}(B)) / \text{std}(B)$$

$$\text{correlation}(A, B) = A' \bullet B'$$

Covariance (Numeric Data)

- Covariance is similar to correlation

$$Cov(A, B) = E((A - \bar{A})(B - \bar{B})) = \frac{\sum_{i=1}^n (a_i - \bar{A})(b_i - \bar{B})}{n}$$

Correlation coefficient: $r_{A,B} = \frac{Cov(A, B)}{\sigma_A \sigma_B}$

where n is the number of tuples, \bar{A} and \bar{B} are the respective mean or **expected values** of A and B, σ_A and σ_B are the respective standard deviation of A and B.

- **Positive covariance:** If $Cov_{A,B} > 0$, then A and B both tend to be larger than their expected values.
- **Negative covariance:** If $Cov_{A,B} < 0$ then if A is larger than its expected value, B is likely to be smaller than its expected value.
- **Independence:** $Cov_{A,B} = 0$ but the converse is not true:
 - Some pairs of random variables may have a covariance of 0 but are not independent. Only under some additional assumptions (e.g., the data follow multivariate normal distributions) does a covariance of 0 imply independence

Co-Variance: An Example

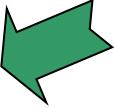
$$Cov(A, B) = E((A - \bar{A})(B - \bar{B})) = \frac{\sum_{i=1}^n (a_i - \bar{A})(b_i - \bar{B})}{n}$$

- It can be simplified in computation as

$$Cov(A, B) = E(A \cdot B) - \bar{A}\bar{B}$$

- Suppose two stocks A and B have the following values in one week:
(2, 5), (3, 8), (5, 10), (4, 11), (6, 14).
- Question: If the stocks are affected by the same industry trends, will their prices rise or fall together?
 - $E(A) = (2 + 3 + 5 + 4 + 6)/ 5 = 20/5 = 4$
 - $E(B) = (5 + 8 + 10 + 11 + 14) /5 = 48/5 = 9.6$
 - $Cov(A,B) = (2 \times 5 + 3 \times 8 + 5 \times 10 + 4 \times 11 + 6 \times 14) /5 - 4 \times 9.6 = 4$
- Thus, A and B rise together since $Cov(A, B) > 0$.

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Data Reduction Strategies

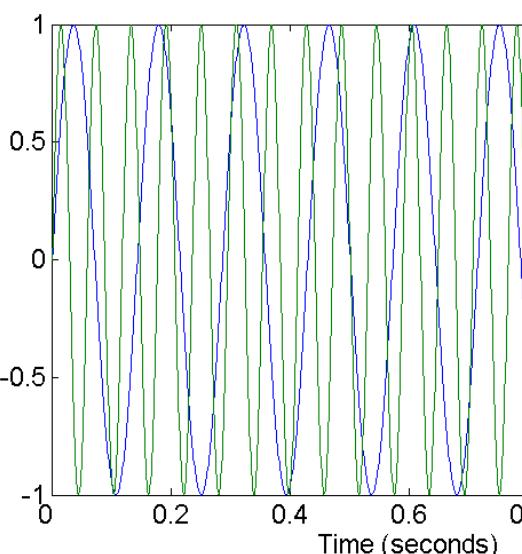
- **Data reduction:** Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.
- Data reduction strategies
 - Dimensionality reduction, e.g., remove unimportant attributes
 - Wavelet transforms
 - Principal Components Analysis (PCA)
 - Feature subset selection, feature creation
 - Numerosity reduction (some simply call it: Data Reduction)
 - Regression and Log-Linear Models
 - Histograms, clustering, sampling
 - Data cube aggregation
 - Data compression

Data Reduction 1: Dimensionality Reduction

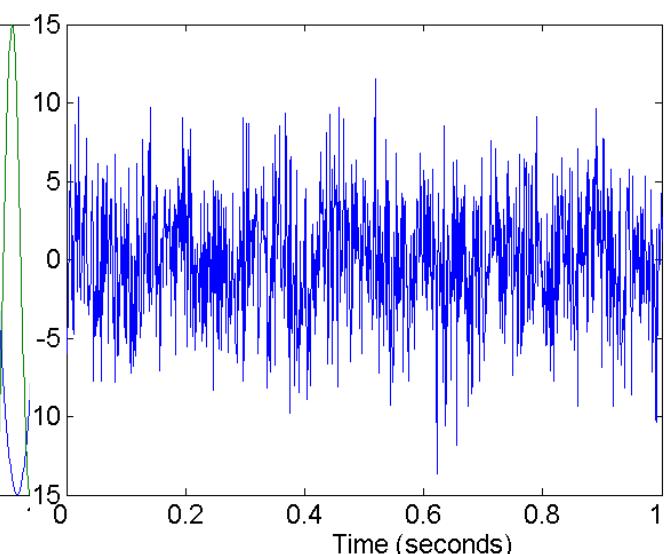
- **Curse of dimensionality**
 - When dimensionality increases, data becomes increasingly sparse
 - Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
 - The possible combinations of subspaces will grow exponentially
- **Dimensionality reduction**
 - Avoid the curse of dimensionality
 - Help eliminate irrelevant features and reduce noise
 - Reduce time and space required in data mining
 - Allow easier visualization
- **Dimensionality reduction techniques**
 - Wavelet transforms
 - Principal Component Analysis
 - Supervised and nonlinear techniques (e.g., feature selection)

Mapping Data to a New Space

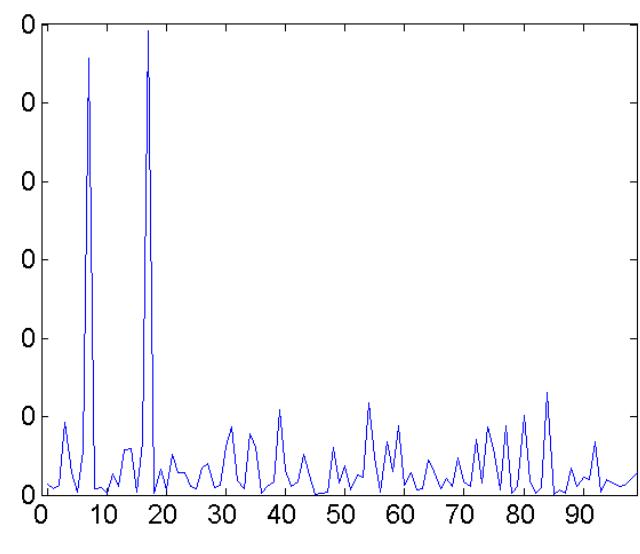
- Fourier transform
- Wavelet transform



Two Sine Waves



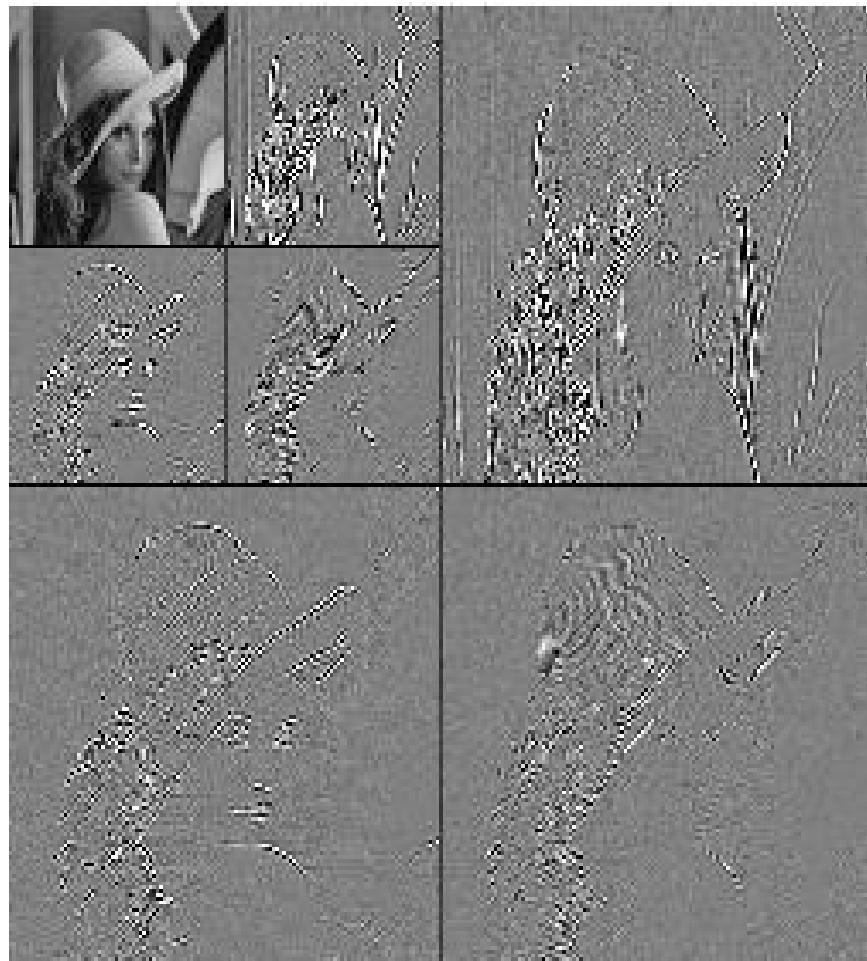
Two Sine Waves + Noise



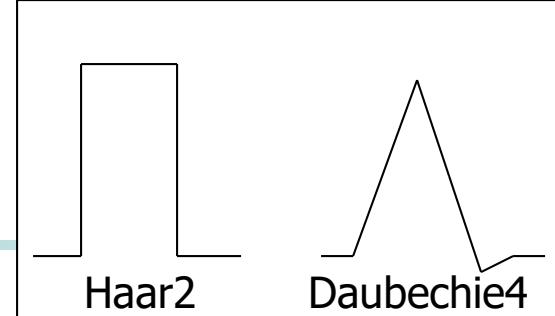
Frequency

What Is Wavelet Transform?

- Decomposes a signal into different frequency subbands
 - Applicable to n-dimensional signals
- Data are transformed to preserve relative distance between objects at different levels of resolution
- Allow natural clusters to become more distinguishable
- Used for image compression



Wavelet Transformation



- Discrete wavelet transform (DWT) for linear signal processing, multi-resolution analysis
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients
- Similar to discrete Fourier transform (DFT), but better lossy compression, localized in space
- Method:
 - Length, L , must be an integer power of 2 (padding with 0's, when necessary)
 - Each transform has 2 functions: smoothing, difference
 - Applies to pairs of data, resulting in two set of data of length $L/2$
 - Applies two functions recursively, until reaches the desired length

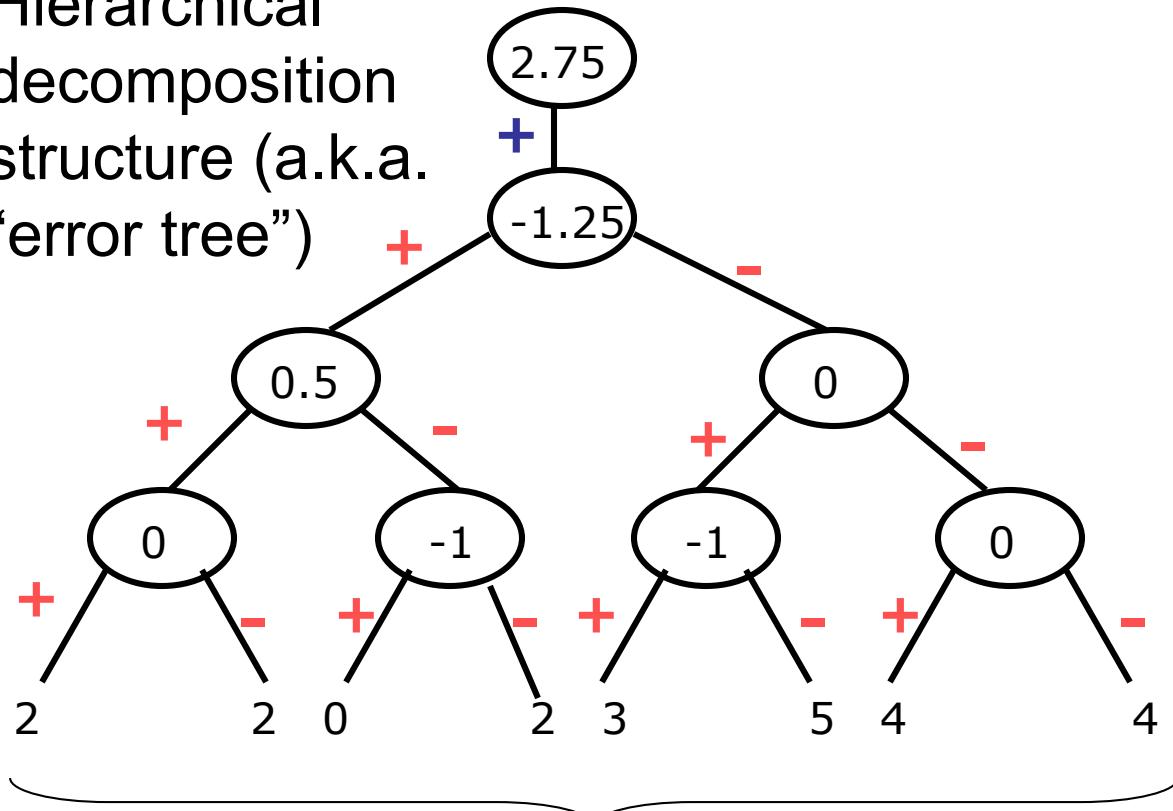
Wavelet Decomposition

- Wavelets: A math tool for space-efficient hierarchical decomposition of functions
- $S = [2, 2, 0, 2, 3, 5, 4, 4]$ can be transformed to $S_\wedge = [2^3/4, -1^1/4, 1/2, 0, 0, -1, -1, 0]$
- Compression: many small detail coefficients can be replaced by 0's, and only the significant coefficients are retained

Resolution	Averages	Detail Coefficients
8	$[2, 2, 0, 2, 3, 5, 4, 4]$	
4	$[2, 1, 4, 4]$	$[0, -1, -1, 0]$
2	$[1\frac{1}{2}, 4]$	$[\frac{1}{2}, 0]$
1	$[2\frac{3}{4}]$	$[-1\frac{1}{4}]$

Haar Wavelet Coefficients

Hierarchical decomposition structure (a.k.a.
“error tree”)



Original frequency distribution

Coefficient “Supports”

2.75

+

-1.25

+

-

0.5

+

-

0

+

-

0

+

-

-1

+

-

-1

+

-

0

+

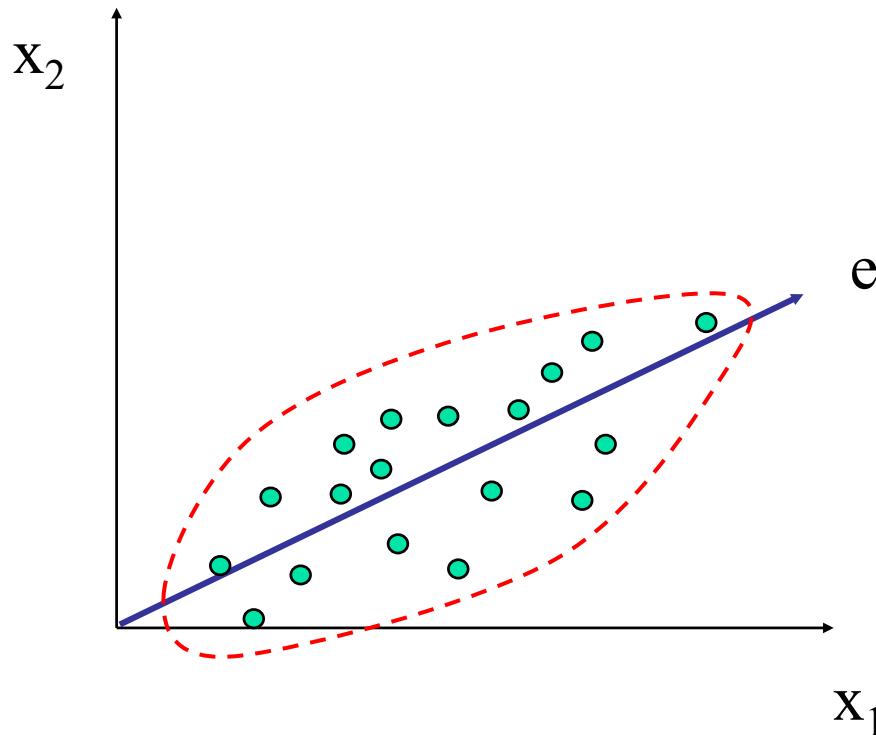
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Why Wavelet Transform?

- Use hat-shape filters
 - Emphasize region where points cluster
 - Suppress weaker information in their boundaries
- Effective removal of outliers
 - Insensitive to noise, insensitive to input order
- Multi-resolution
 - Detect arbitrary shaped clusters at different scales
- Efficient
 - Complexity $O(N)$
- Only applicable to low dimensional data

Principal Component Analysis (PCA)

- Find a projection that captures the largest amount of variation in data
- The original data are projected onto a much smaller space, resulting in dimensionality reduction. We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space



Principal Component Analysis (Steps)

- Given N data vectors from n -dimensions, find $k \leq n$ orthogonal vectors (*principal components*) that can be best used to represent data
 - Normalize input data: Each attribute falls within the same range
 - Compute k orthonormal (unit) vectors, i.e., *principal components*
 - Each input data (vector) is a linear combination of the k principal component vectors
 - The principal components are sorted in order of decreasing “significance” or strength
 - Since the components are sorted, the size of the data can be reduced by eliminating the *weak components*, i.e., those with low variance (i.e., using the strongest principal components, it is possible to reconstruct a good approximation of the original data)
- Works for numeric data only

Attribute Subset Selection

- Another way to reduce dimensionality of data
- Redundant attributes
 - Duplicate much or all of the information contained in one or more other attributes
 - E.g., purchase price of a product and the amount of sales tax paid
- Irrelevant attributes
 - Contain no information that is useful for the data mining task at hand
 - E.g., students' ID is often irrelevant to the task of predicting students' GPA

Heuristic Search in Attribute Selection

- There are 2^d possible attribute combinations of d attributes
- Typical heuristic attribute selection methods:
 - Best single attribute under the attribute independence assumption: choose by significance tests
 - Best step-wise feature selection:
 - The best single-attribute is picked first
 - Then next best attribute condition to the first, ...
 - Step-wise attribute elimination:
 - Repeatedly eliminate the worst attribute
 - Best combined attribute selection and elimination
 - Optimal branch and bound:
 - Use attribute elimination and backtracking

Attribute Creation (Feature Generation)

- Create new attributes (features) that can capture the important information in a data set more effectively than the original ones
- Three general methodologies
 - Attribute extraction
 - Domain-specific
 - Mapping data to new space (see: data reduction)
 - E.g., Fourier transformation, wavelet transformation, manifold approaches (not covered)
 - Attribute construction
 - Combining features (see: discriminative frequent patterns in Chapter 7)
 - Data discretization

Data Reduction 2: Numerosity Reduction

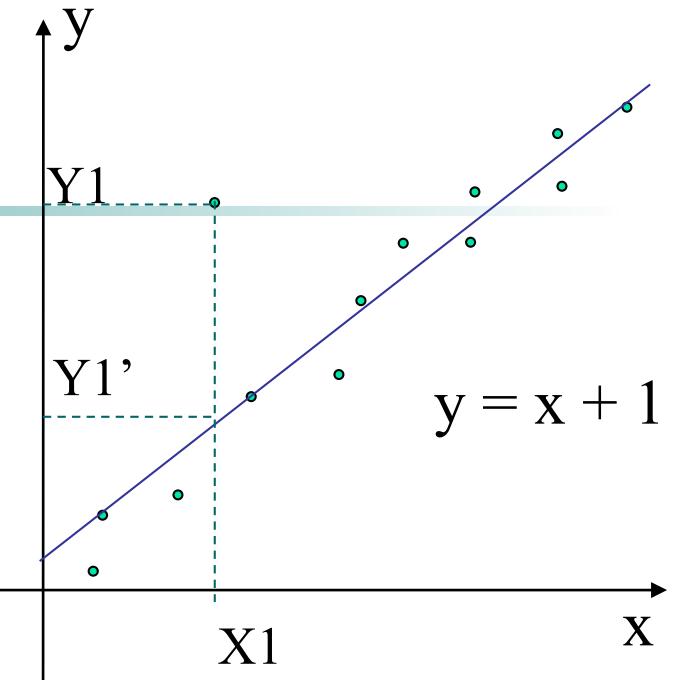
- Reduce data volume by choosing alternative, *smaller forms* of data representation
- **Parametric methods** (e.g., regression)
 - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
 - Ex.: Log-linear models—obtain value at a point in m -D space as the product on appropriate marginal subspaces
- **Non-parametric** methods
 - Do not assume models
 - Major families: histograms, clustering, sampling, ...

Parametric Data Reduction: Regression and Log-Linear Models

- **Linear regression**
 - Data modeled to fit a straight line
 - Often uses the least-square method to fit the line
- **Multiple regression**
 - Allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- **Log-linear model**
 - Approximates discrete multidimensional probability distributions

Regression Analysis

- Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a *dependent variable* (also called *response variable* or *measurement*) and of one or more *independent variables* (aka. *explanatory variables* or *predictors*)
- The parameters are estimated so as to give a "**best fit**" of the data
- Most commonly the best fit is evaluated by using the *least squares method*, but other criteria have also been used



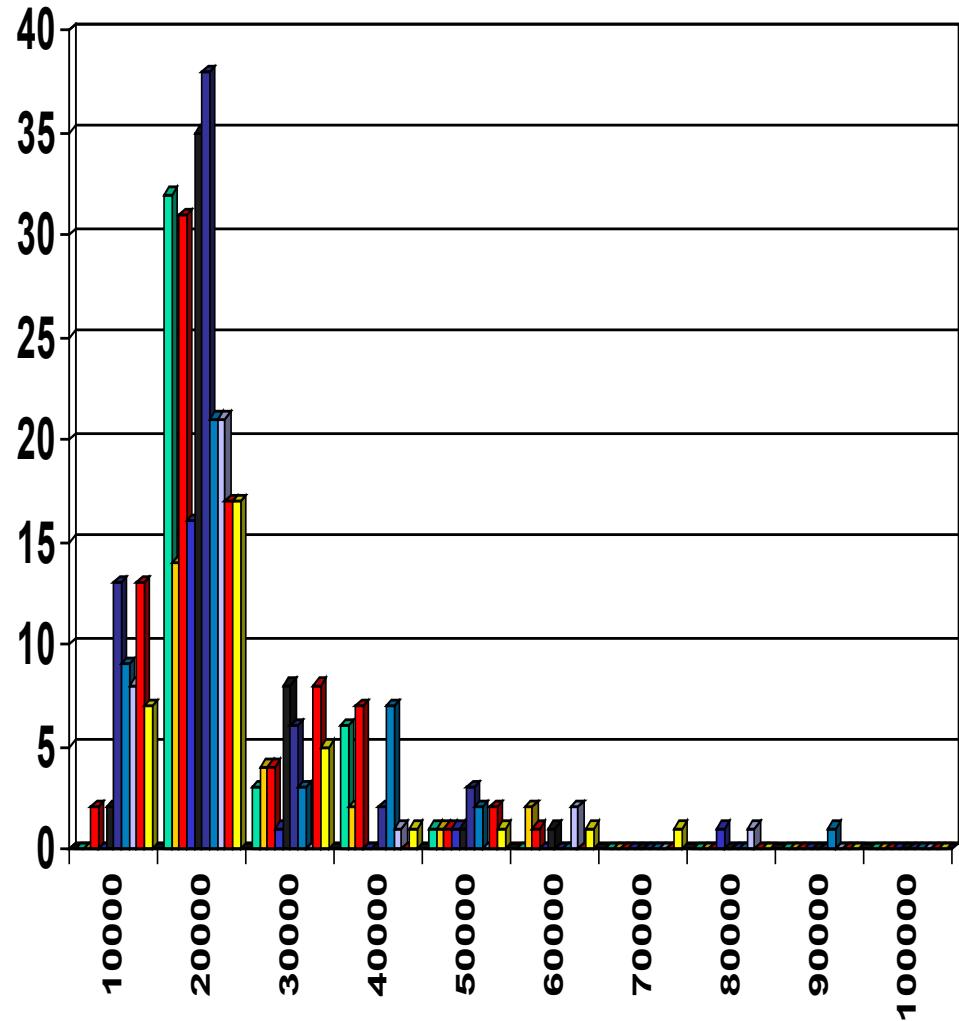
- Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships

Régress Analysis and Log-Linear Models

- Linear regression: $Y = wX + b$
 - Two regression coefficients, w and b , specify the line and are to be estimated by using the data at hand
 - Using the least squares criterion to the known values of $Y_1, Y_2, \dots, X_1, X_2, \dots$
- Multiple regression: $Y = b_0 + b_1 X_1 + b_2 X_2$
 - Many nonlinear functions can be transformed into the above
- Log-linear models:
 - Approximate discrete multidimensional probability distributions
 - Estimate the probability of each point (tuple) in a multi-dimensional space for a set of discretized attributes, based on a smaller subset of dimensional combinations
 - Useful for dimensionality reduction and data smoothing

Histogram Analysis

- Divide data into buckets and store average (sum) for each bucket
- Partitioning rules:
 - Equal-width: equal bucket range
 - Equal-frequency (or equal-depth)



Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is “smeared”
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth in Chapter 10

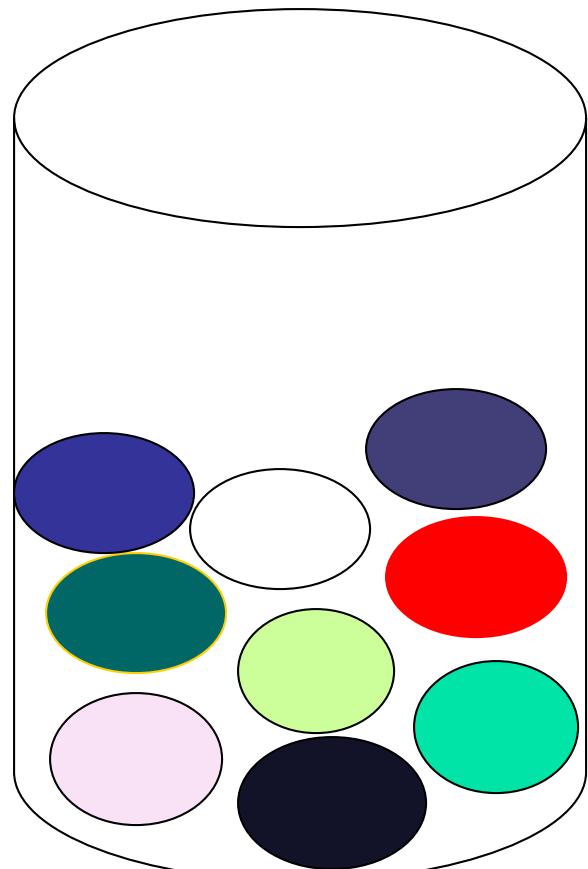
Sampling

- Sampling: obtaining a small sample s to represent the whole data set N
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Key principle: Choose a **representative** subset of the data
 - Simple random sampling may have very poor performance in the presence of skew
 - Develop adaptive sampling methods, e.g., stratified sampling:
- Note: Sampling may not reduce database I/Os (page at a time)

Types of Sampling

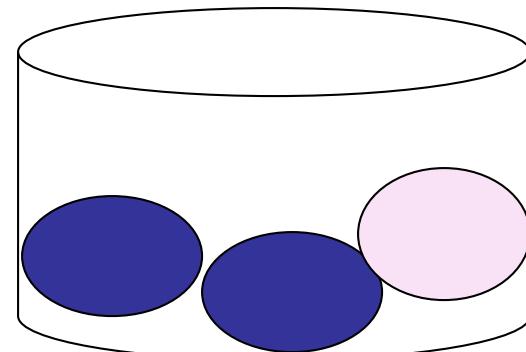
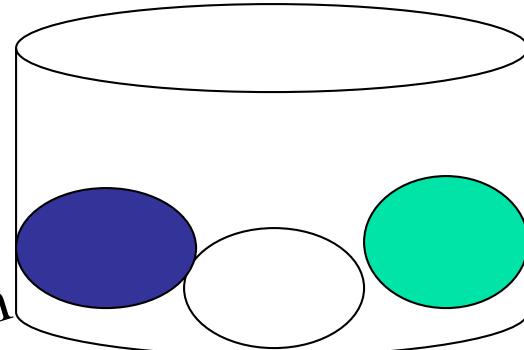
- **Simple random sampling**
 - There is an equal probability of selecting any particular item
- **Sampling without replacement**
 - Once an object is selected, it is removed from the population
- **Sampling with replacement**
 - A selected object is not removed from the population
- **Stratified sampling:**
 - Partition the data set, and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
 - Used in conjunction with skewed data

Sampling: With or without Replacement



SRSWOR
(simple random
sample without
replacement)

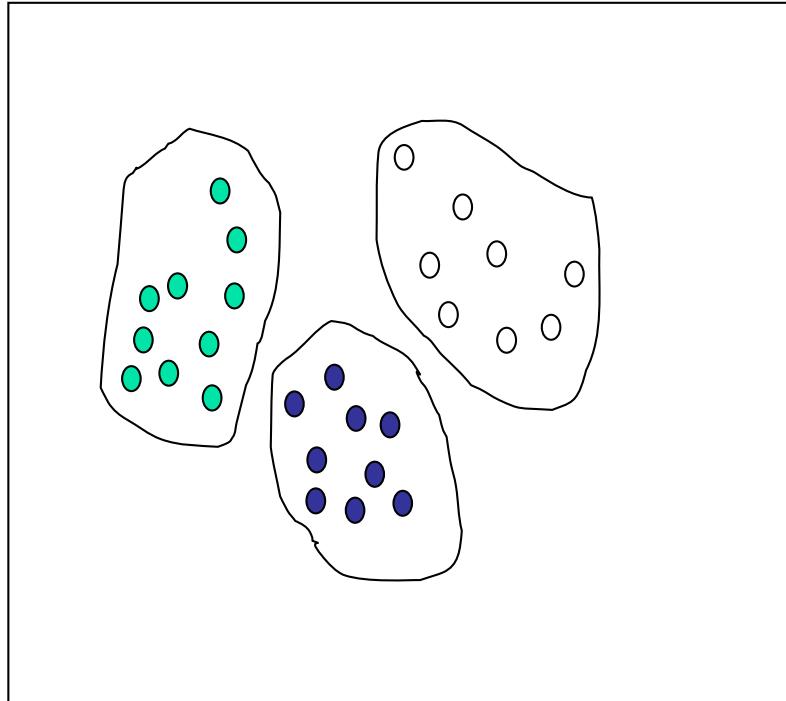
SRSWR



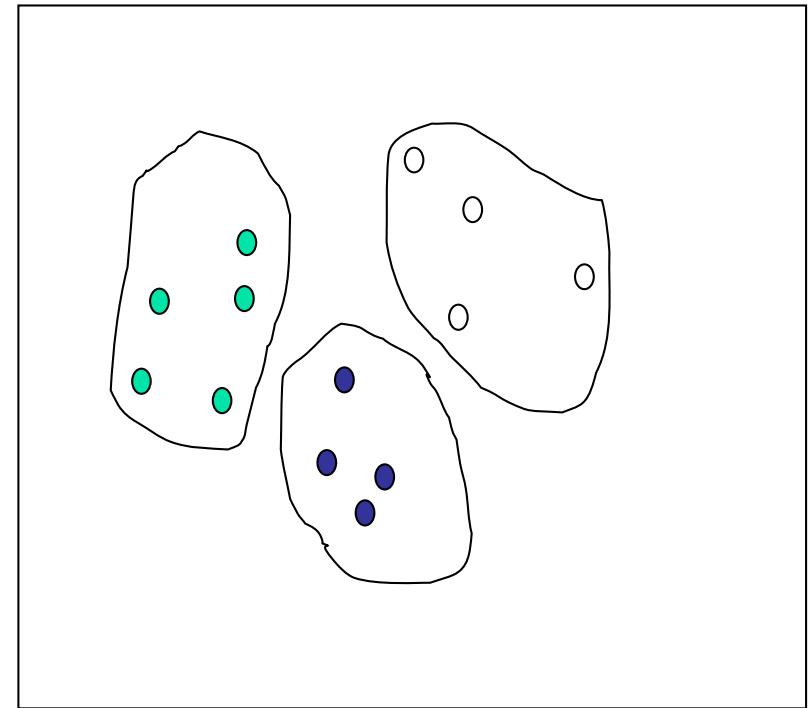
Raw Data

Sampling: Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample



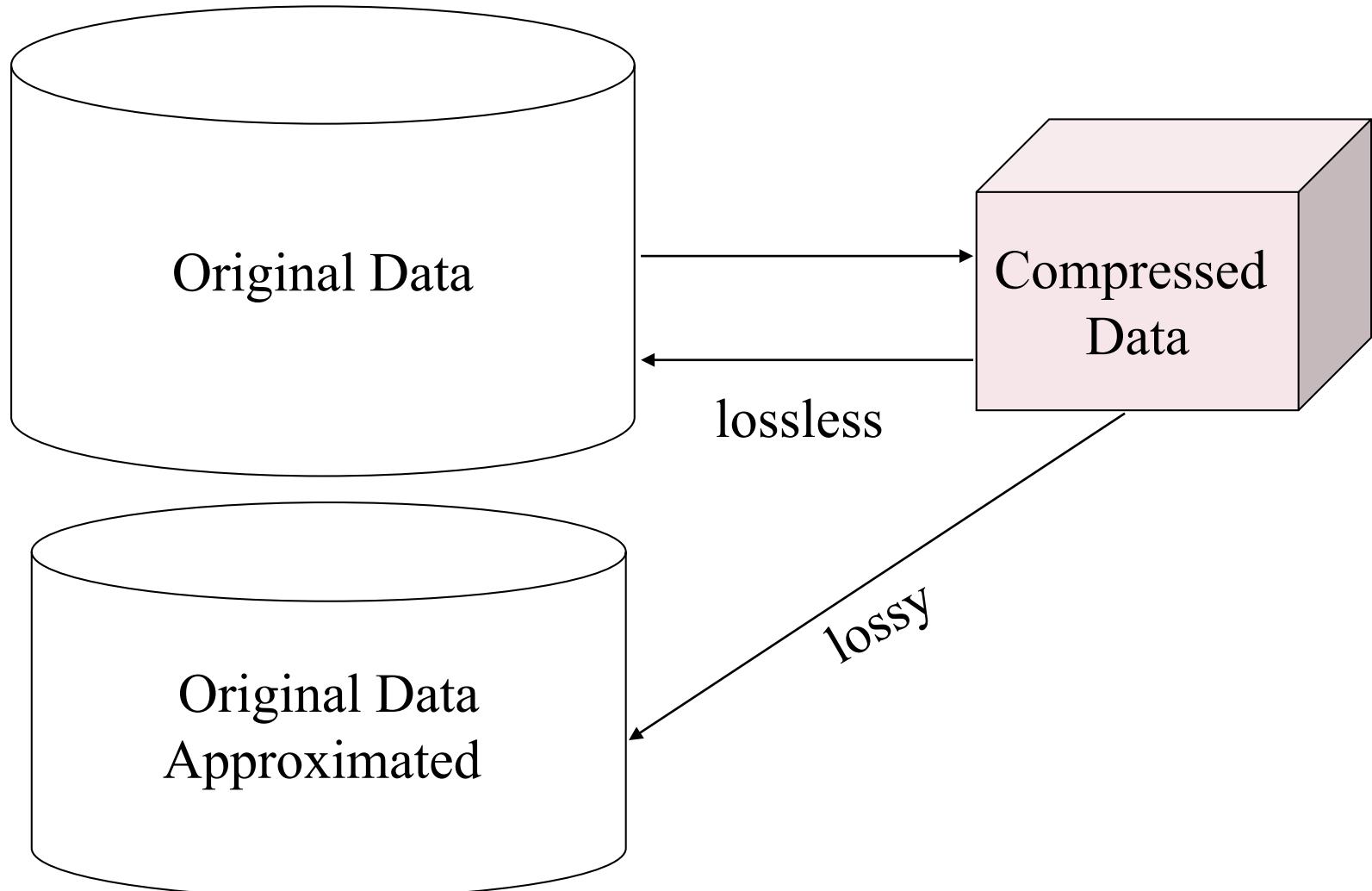
Data Cube Aggregation

- The lowest level of a data cube (base cuboid)
 - The aggregated data for an **individual entity of interest**
 - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
 - Further reduce the size of data to deal with
- Reference appropriate levels
 - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

Data Reduction 3: Data Compression

- String compression
 - There are extensive theories and well-tuned algorithms
 - Typically lossless, but only limited manipulation is possible without expansion
- Audio/video compression
 - Typically lossy compression, with progressive refinement
 - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
 - Typically short and vary slowly with time
- Dimensionality and numerosity reduction may also be considered as forms of data compression

Data Compression



Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
 - Data Quality
 - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary



Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods
 - Smoothing: Remove noise from data
 - Attribute/feature construction
 - New attributes constructed from the given ones
 - Aggregation: Summarization, data cube construction
 - Normalization: Scaled to fall within a smaller, specified range
 - min-max normalization
 - z-score normalization
 - normalization by decimal scaling
 - Discretization: Concept hierarchy climbing

Normalization

- **Min-max normalization:** to $[new_min_A, new_max_A]$

$$v' = \frac{v - min_A}{max_A - min_A} (new_max_A - new_min_A) + new_min_A$$

- Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to $\frac{73,600 - 12,000}{98,000 - 12,000} (1.0 - 0) + 0 = 0.716$
- **Z-score normalization** (μ : mean, σ : standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

- Ex. Let $\mu = 54,000$, $\sigma = 16,000$. Then $\frac{73,600 - 54,000}{16,000} = 1.225$
- **Normalization by decimal scaling**

$$v' = \frac{v}{10^j} \quad \text{Where } j \text{ is the smallest integer such that } \text{Max}(|v'|) < 1$$

Discretization

- Three types of attributes
 - Nominal—values from an unordered set, e.g., color, profession
 - Ordinal—values from an ordered set, e.g., military or academic rank
 - Numeric—real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
 - Interval labels can then be used to replace actual data values
 - Reduce data size by discretization
 - Supervised vs. unsupervised
 - Split (top-down) vs. merge (bottom-up)
 - Discretization can be performed recursively on an attribute
 - Prepare for further analysis, e.g., classification

Data Discretization Methods

- Typical methods: All the methods can be applied recursively
 - Binning
 - Top-down split, unsupervised
 - Histogram analysis
 - Top-down split, unsupervised
 - Clustering analysis (unsupervised, top-down split or bottom-up merge)
 - Decision-tree analysis (supervised, top-down split)
 - Correlation (e.g., χ^2) analysis (unsupervised, bottom-up merge)

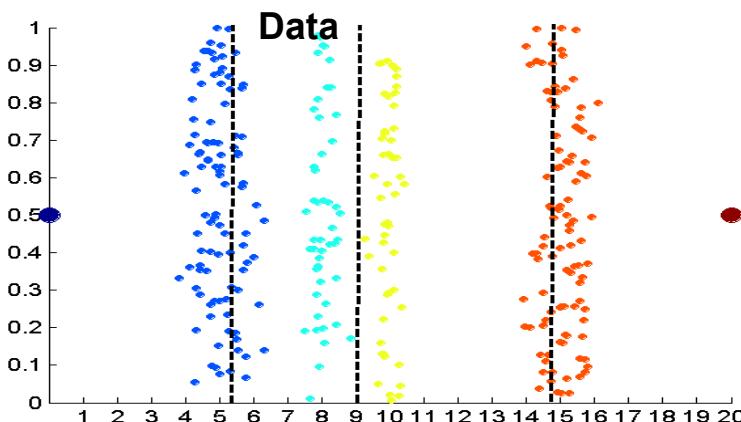
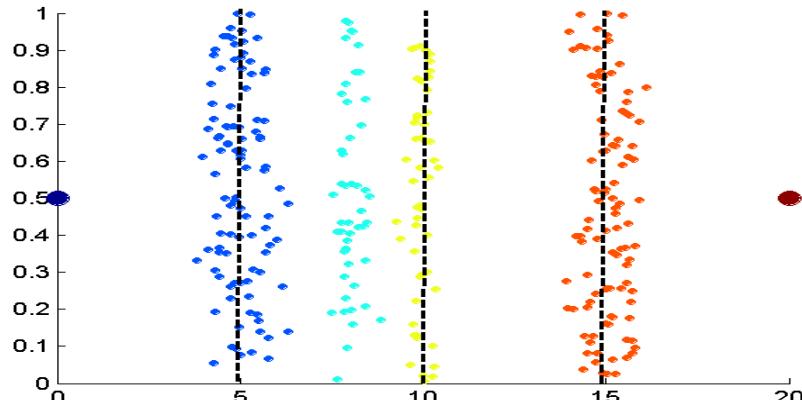
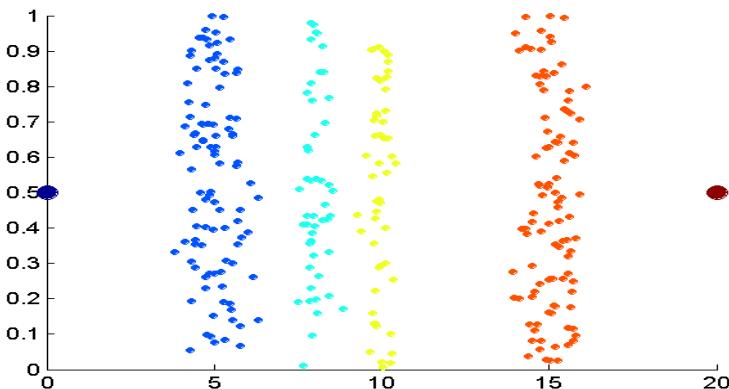
Simple Discretization: Binning

- Equal-width (distance) partitioning
 - Divides the range into N intervals of equal size: uniform grid
 - if A and B are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
 - The most straightforward, but outliers may dominate presentation
 - Skewed data is not handled well
- Equal-depth (frequency) partitioning
 - Divides the range into N intervals, each containing approximately same number of samples
 - Good data scaling
 - Managing categorical attributes can be tricky

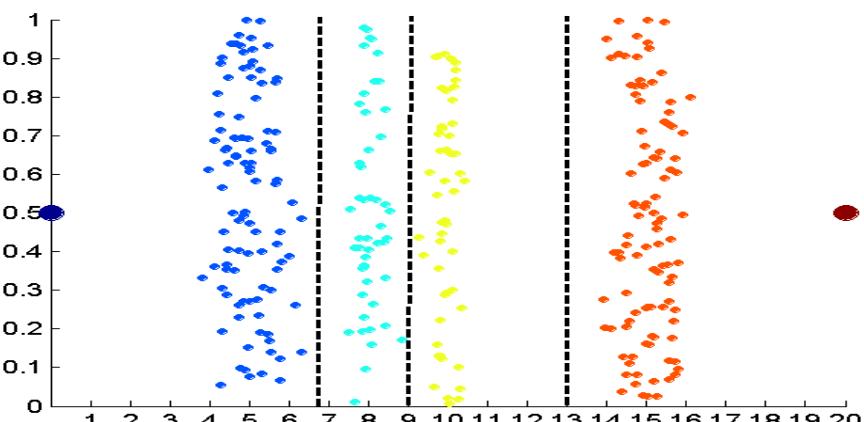
Binning Methods for Data Smoothing

- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34
- * Partition into equal-frequency (**equi-depth**) bins:
 - Bin 1: 4, 8, 9, 15
 - Bin 2: 21, 21, 24, 25
 - Bin 3: 26, 28, 29, 34
- * Smoothing by **bin means**:
 - Bin 1: 9, 9, 9, 9
 - Bin 2: 23, 23, 23, 23
 - Bin 3: 29, 29, 29, 29
- * Smoothing by **bin boundaries**:
 - Bin 1: 4, 4, 4, 15
 - Bin 2: 21, 21, 25, 25
 - Bin 3: 26, 26, 26, 34

Discretization Without Using Class Labels (Binning vs. Clustering)



Equal frequency (binning)



K-means clustering leads to better results

Discretization by Classification & Correlation Analysis

- Classification (e.g., decision tree analysis)
 - Supervised: Given class labels, e.g., cancerous vs. benign
 - Using *entropy* to determine split point (discretization point)
 - Top-down, recursive split
 - Details to be covered in Chapter 7
- Correlation analysis (e.g., Chi-merge: χ^2 -based discretization)
 - Supervised: use class information
 - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low χ^2 values) to merge
 - Merge performed recursively, until a predefined stopping condition

Concept Hierarchy Generation

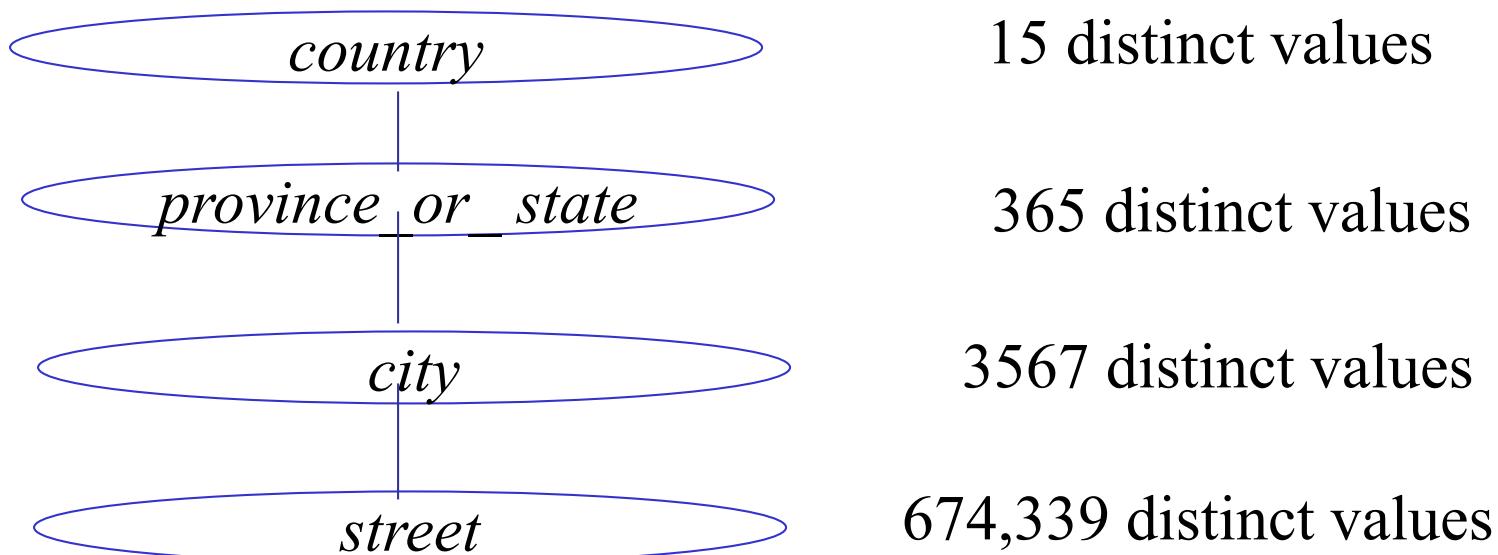
- **Concept hierarchy** organizes concepts (i.e., attribute values) hierarchically and is usually associated with each dimension in a data warehouse
- Concept hierarchies facilitate drilling and rolling in data warehouses to view data in multiple granularity
- Concept hierarchy formation: Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for *age*) by higher level concepts (such as *youth*, *adult*, or *senior*)
- Concept hierarchies can be explicitly specified by domain experts and/or data warehouse designers
- Concept hierarchy can be automatically formed for both numeric and nominal data. For numeric data, use discretization methods shown.

Concept Hierarchy Generation for Nominal Data

- Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts
 - $\textit{street} < \textit{city} < \textit{state} < \textit{country}$
- Specification of a hierarchy for a set of values by explicit data grouping
 - $\{\text{Urbana, Champaign, Chicago}\} < \text{Illinois}$
- Specification of only a partial set of attributes
 - E.g., only $\textit{street} < \textit{city}$, not others
- Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values
 - E.g., for a set of attributes: $\{\textit{street}, \textit{city}, \textit{state}, \textit{country}\}$

Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
 - The attribute with the most distinct values is placed at the lowest level of the hierarchy
 - Exceptions, e.g., weekday, month, quarter, year



Chapter 3: Data Preprocessing

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Summary

- **Data quality:** accuracy, completeness, consistency, timeliness, believability, interpretability
- **Data cleaning:** e.g. missing/noisy values, outliers
- **Data integration** from multiple sources:
 - Entity identification problem
 - Remove redundancies
 - Detect inconsistencies
- **Data reduction**
 - Dimensionality reduction
 - Numerosity reduction
 - Data compression
- **Data transformation and data discretization**
 - Normalization
 - Concept hierarchy generation

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Data Mining:

Concepts and Techniques

(3rd ed.)

— Chapter 4 —

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Chapter 4: Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts 
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Data Warehouse Implementation
- Data Generalization by Attribute-Oriented Induction
- Summary

What is a Data Warehouse?

- Defined in many different ways, but not rigorously.
 - A decision support database that is maintained **separately** from the organization's operational database
 - Support **information processing** by providing a solid platform of consolidated, historical data for analysis.
- "A data warehouse is a subject-oriented, integrated, time-variant, and nonvolatile collection of data in support of management's decision-making process."—W. H. Inmon
- Data warehousing:
 - The process of constructing and using data warehouses

Data Warehouse—Subject-Oriented

- Organized around major subjects, such as **customer, product, sales**
- Focusing on the modeling and analysis of data for decision makers, not on daily operations or transaction processing
- Provide **a simple and concise view around particular subject issues by excluding data that are not useful in the decision support process**

Data Warehouse—Integrated

- Constructed by integrating multiple, heterogeneous data sources
 - relational databases, flat files, on-line transaction records
- Data cleaning and data integration techniques are applied.
 - Ensure consistency in naming conventions, encoding structures, attribute measures, etc. among different data sources
 - E.g., Hotel price: currency, tax, breakfast covered, etc.
 - When data is moved to the warehouse, it is converted.

Data Warehouse—Time Variant

- The time horizon for the data warehouse is significantly longer than that of operational systems
 - Operational database: current value data
 - Data warehouse data: provide information from a historical perspective (e.g., past 5-10 years)
- Every key structure in the data warehouse
 - Contains an element of time, explicitly or implicitly
 - But the key of operational data may or may not contain “time element”

Data Warehouse—Nonvolatile

- A physically separate store of data transformed from the operational environment
- Operational update of data does not occur in the data warehouse environment
 - Does not require transaction processing, recovery, and concurrency control mechanisms
 - Requires only two operations in data accessing:
 - *initial loading of data* and *access of data*

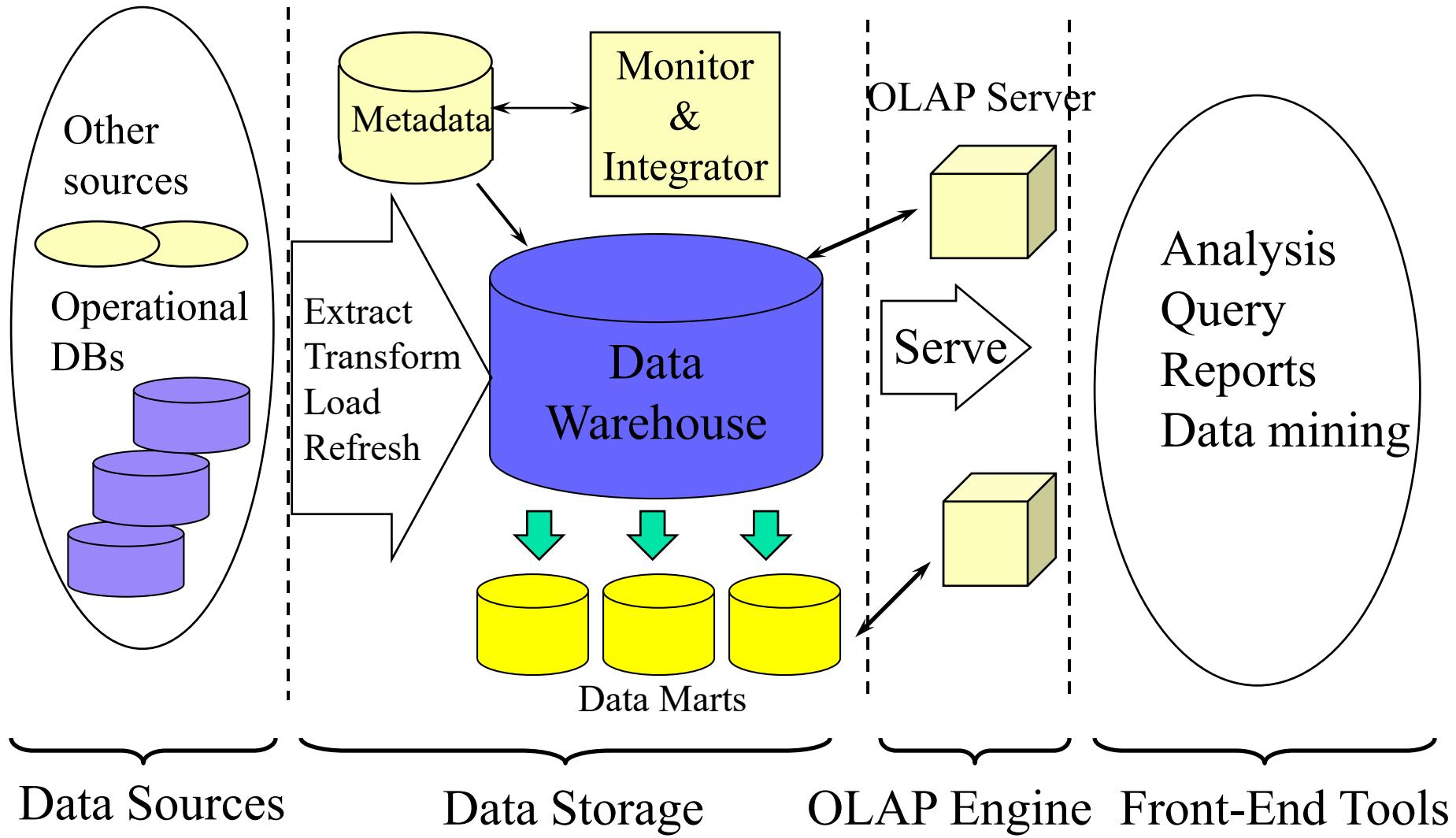
OLTP vs. OLAP

	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day to day operations	decision support
DB design	application-oriented	subject-oriented
data	current, up-to-date detailed, flat relational isolated	historical, summarized, multidimensional integrated, consolidated
usage	repetitive	ad-hoc
access	read/write index/hash on prim. key	lots of scans
unit of work	short, simple transaction	complex query
# records accessed	tens	millions
#users	thousands	hundreds
DB size	100MB-GB	100GB-TB
metric	transaction throughput	query throughput, response

Why a Separate Data Warehouse?

- High performance for both systems
 - DBMS— tuned for OLTP: access methods, indexing, concurrency control, recovery
 - Warehouse—tuned for OLAP: complex OLAP queries, multidimensional view, consolidation
- Different functions and different data:
 - missing data: Decision support requires historical data which operational DBs do not typically maintain
 - data consolidation: DS requires consolidation (aggregation, summarization) of data from heterogeneous sources
 - data quality: different sources typically use inconsistent data representations, codes and formats which have to be reconciled
- Note: There are more and more systems which perform OLAP analysis directly on relational databases

Data Warehouse: A Multi-Tiered Architecture



Three Data Warehouse Models

- Enterprise warehouse
 - collects all of the information about subjects spanning the entire organization
- Data Mart
 - a subset of corporate-wide data that is of value to a specific groups of users. Its scope is confined to specific, selected groups, such as marketing data mart
 - Independent vs. dependent (directly from warehouse) data mart
- Virtual warehouse
 - A set of views over operational databases
 - Only some of the possible summary views may be materialized

Extraction, Transformation, and Loading (ETL)

- **Data extraction**
 - get data from multiple, heterogeneous, and external sources
- **Data cleaning**
 - detect errors in the data and rectify them when possible
- **Data transformation**
 - convert data from legacy or host format to warehouse format
- **Load**
 - sort, summarize, consolidate, compute views, check integrity, and build indices and partitions
- **Refresh**
 - propagate the updates from the data sources to the warehouse

Metadata Repository

- **Meta data** is the data defining warehouse objects. It stores:
- Description of the **structure** of the data warehouse
 - schema, view, dimensions, hierarchies, derived data defn, data mart locations and contents
- **Operational** meta-data
 - data lineage (history of migrated data and transformation path), currency of data (active, archived, or purged), monitoring information (warehouse usage statistics, error reports, audit trails)
- The **algorithms** used for summarization
- The **mapping** from operational environment to the data warehouse
- Data related to **system performance**
 - warehouse schema, view and derived data definitions
- **Business data**
 - business terms and definitions, ownership of data, charging policies

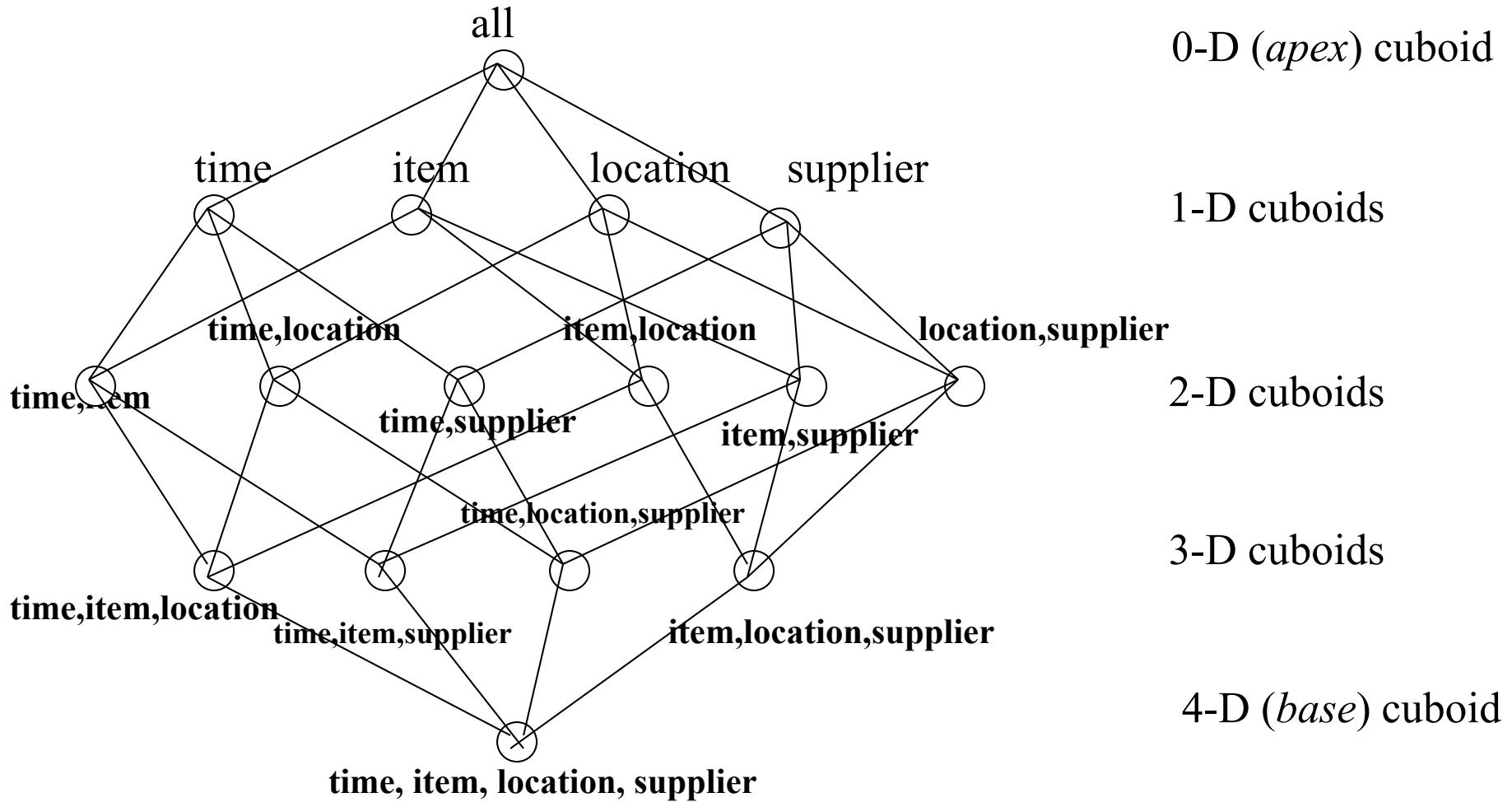
Chapter 4: Data Warehousing and On-line Analytical Processing

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From Tables and Spreadsheets to Data Cubes

- A **data warehouse** is based on a **multidimensional data model** which views data in the form of a data cube
- A data cube, such as **sales**, allows data to be modeled and viewed in multiple dimensions
 - **Dimension tables**, such as **item** (`item_name`, `brand`, `type`), or **time**(`day`, `week`, `month`, `quarter`, `year`)
 - **Fact table** contains **measures** (such as `dollars_sold`) and keys to each of the related dimension tables
- In data warehousing literature, an n-D base cube is called a **base cuboid**. The top most 0-D cuboid, which holds the highest-level of summarization, is called the **apex cuboid**. The lattice of cuboids forms a **data cube**.

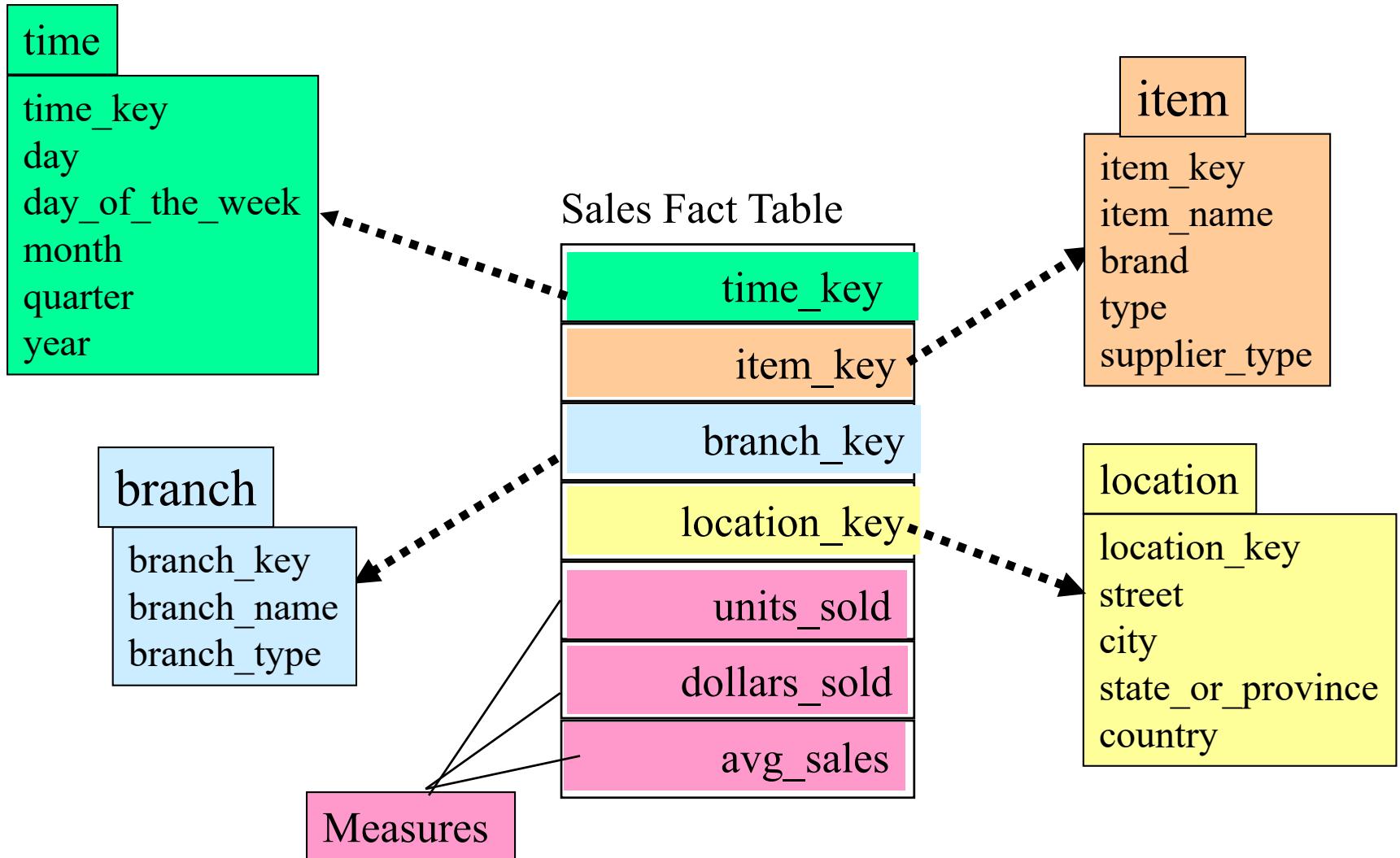
Cube: A Lattice of Cuboids



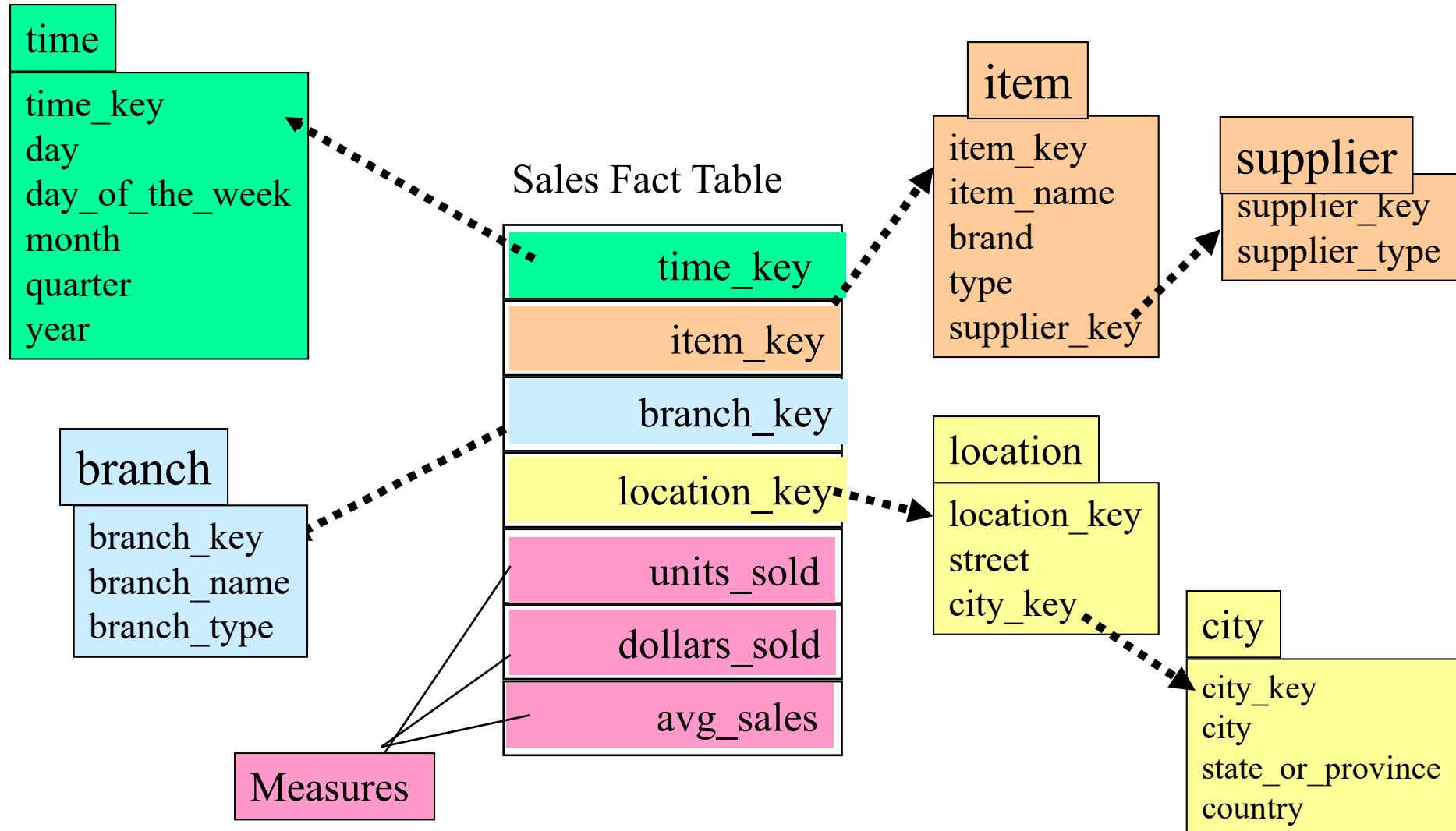
Conceptual Modeling of Data Warehouses

- Modeling data warehouses: dimensions & measures
 - Star schema: A fact table in the middle connected to a set of dimension tables
 - Snowflake schema: A refinement of star schema where some dimensional hierarchy is normalized into a set of smaller dimension tables, forming a shape similar to snowflake
 - Fact constellations: Multiple fact tables share dimension tables, viewed as a collection of stars, therefore called **galaxy schema** or fact constellation

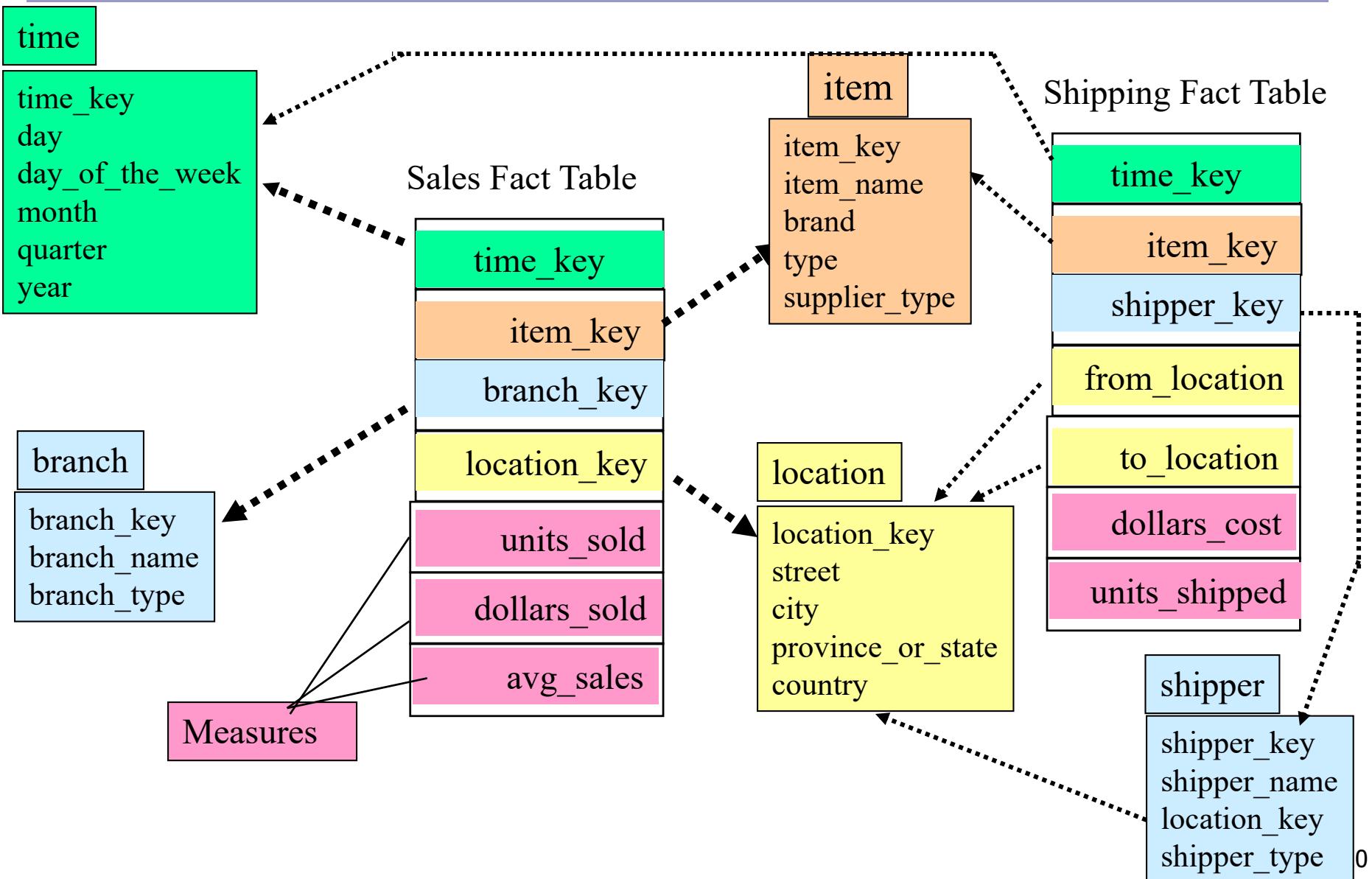
Example of Star Schema



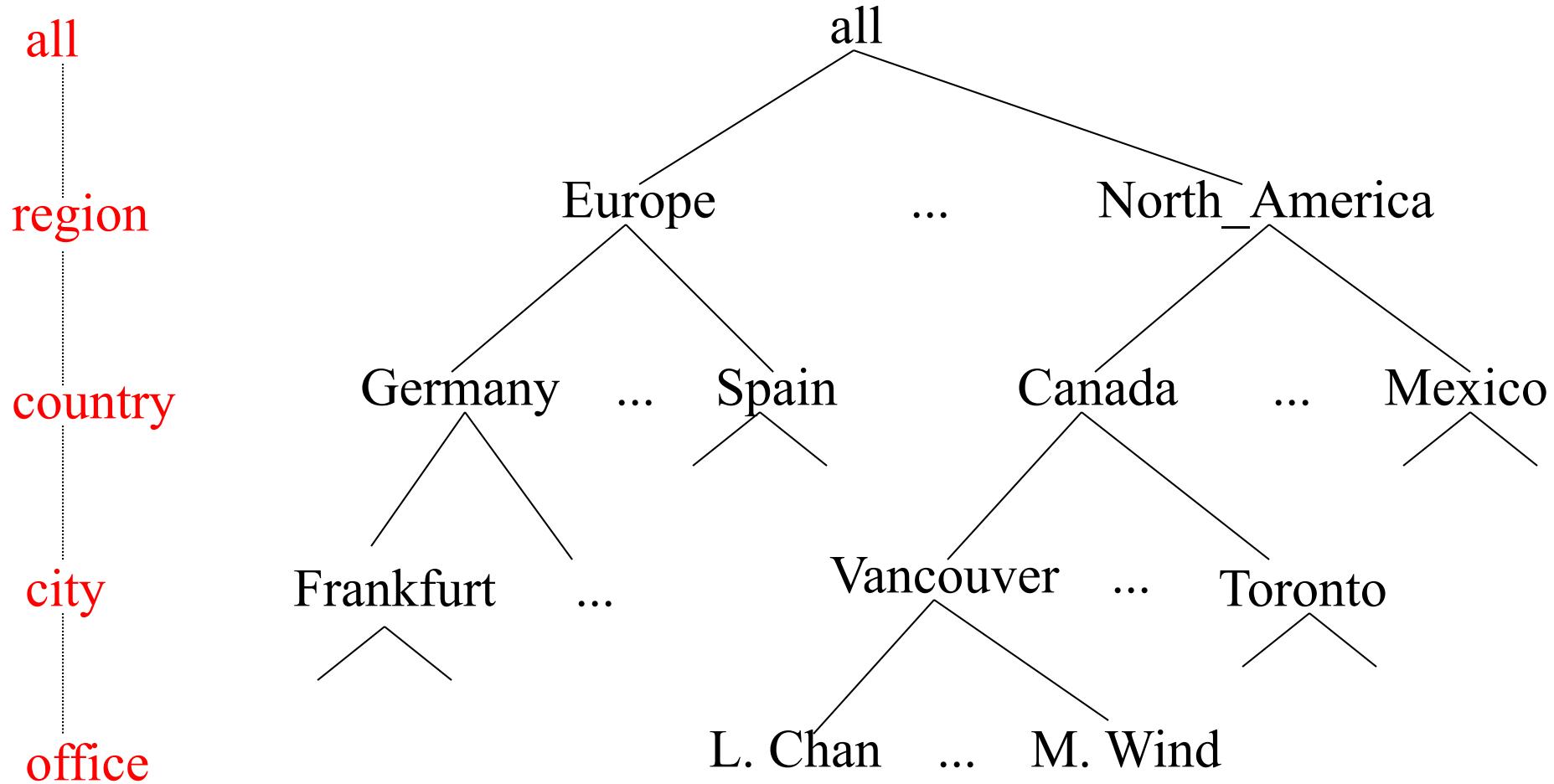
Example of Snowflake Schema



Example of Fact Constellation



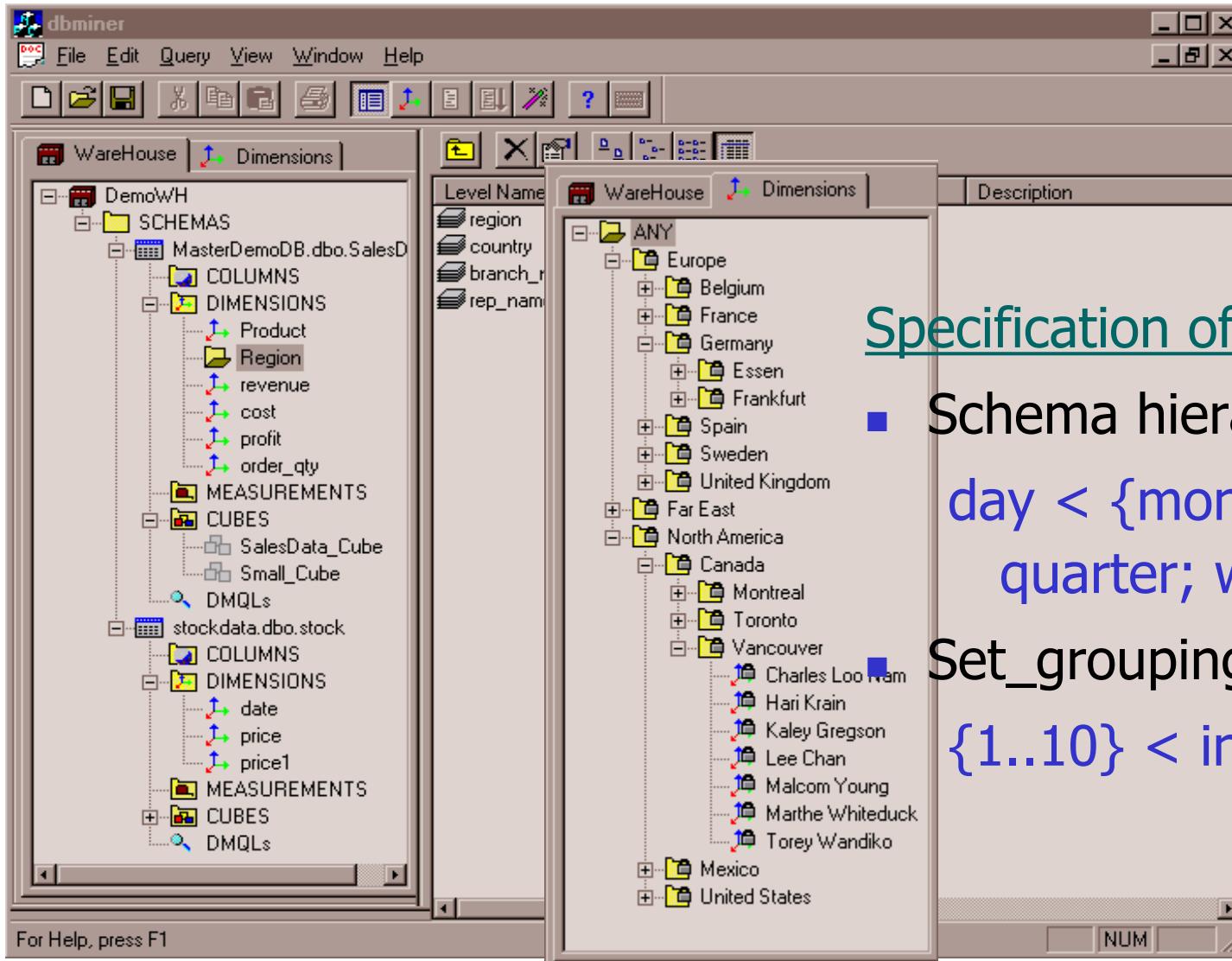
A Concept Hierarchy: Dimension (location)



Data Cube Measures: Three Categories

- **Distributive**: if the result derived by applying the function to n aggregate values is the same as that derived by applying the function on all the data without partitioning
 - E.g., count(), sum(), min(), max()
- **Algebraic**: if it can be computed by an algebraic function with M arguments (where M is a bounded integer), each of which is obtained by applying a distributive aggregate function
 - E.g., avg(), min_N(), standard_deviation()
- **Holistic**: if there is no constant bound on the storage size needed to describe a subaggregate.
 - E.g., median(), mode(), rank()

View of Warehouses and Hierarchies



Specification of hierarchies

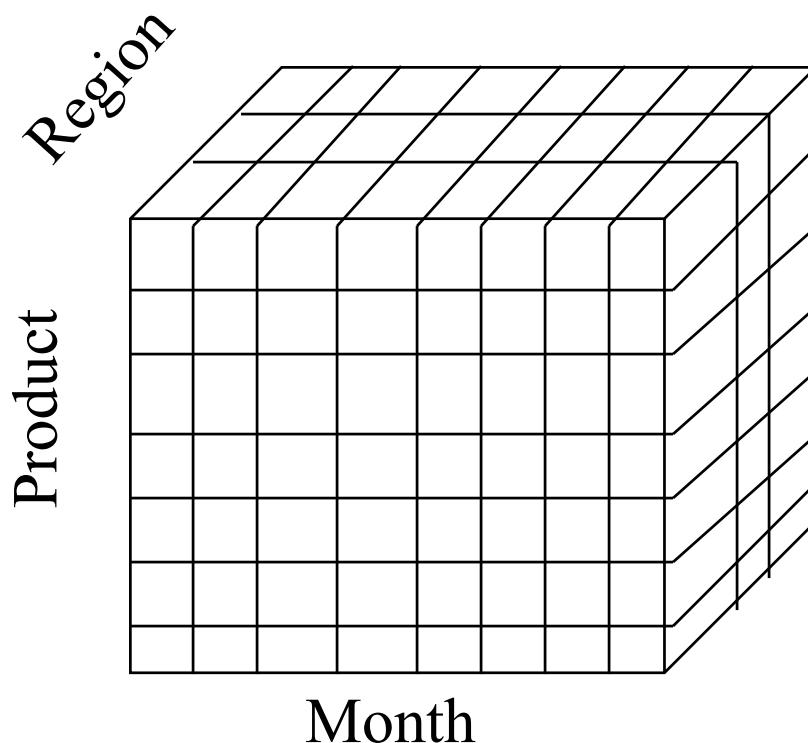
- Schema hierarchy
day < {month < quarter; week} < year

Set_grouping hierarchy

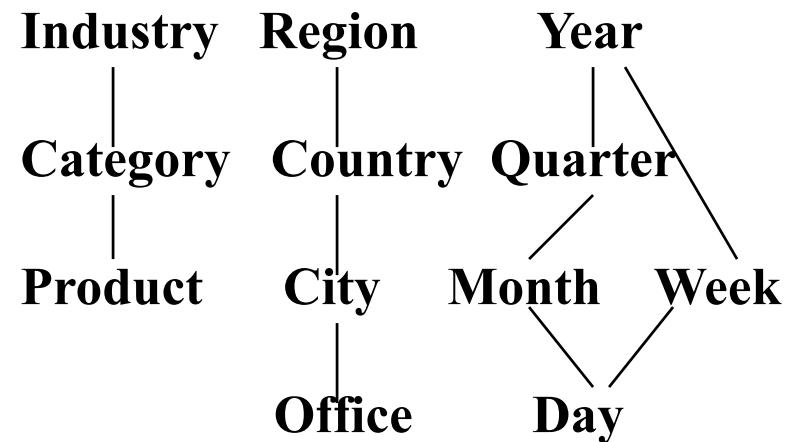
{1..10} < inexpensive

Multidimensional Data

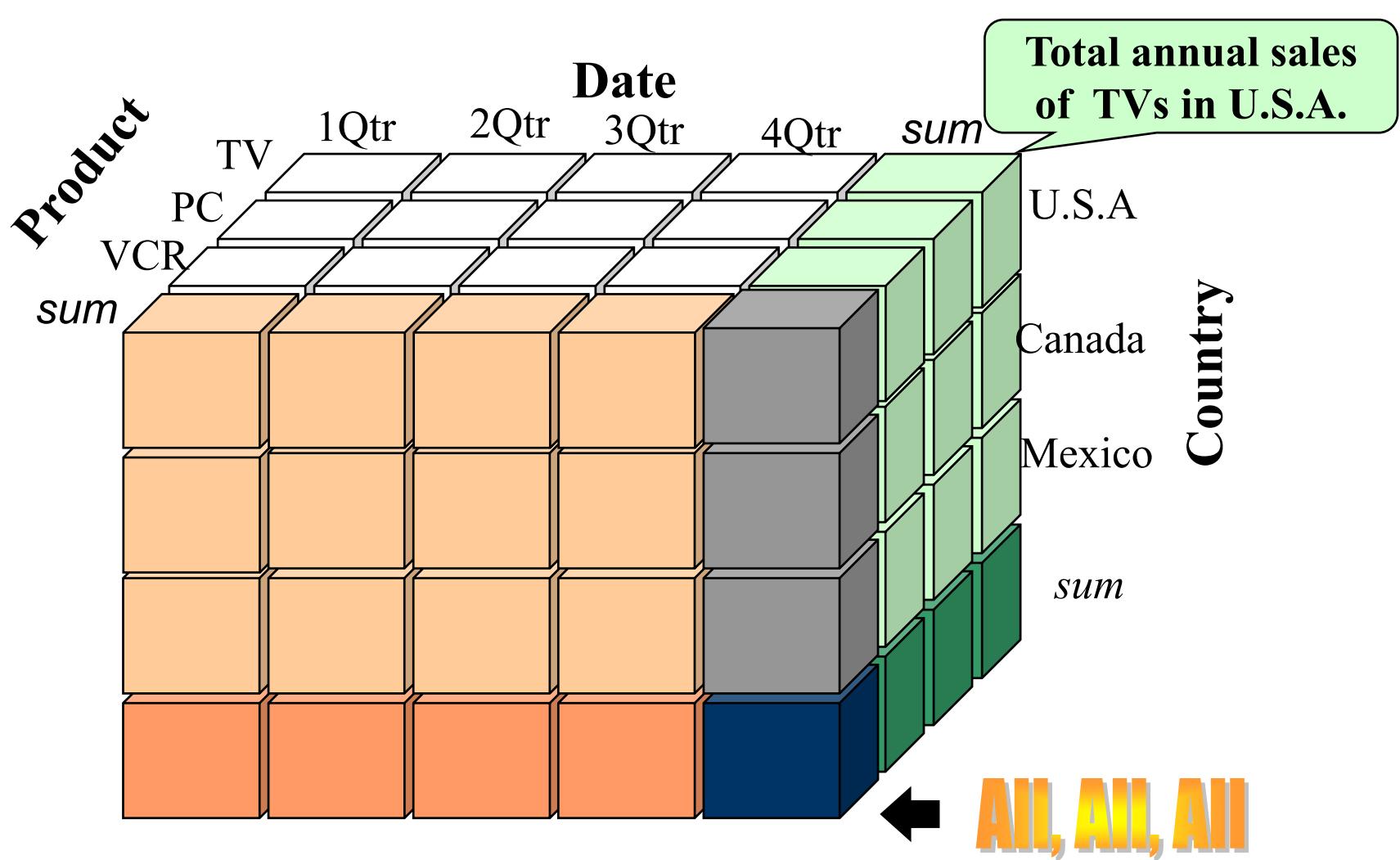
- Sales volume as a function of product, month, and region



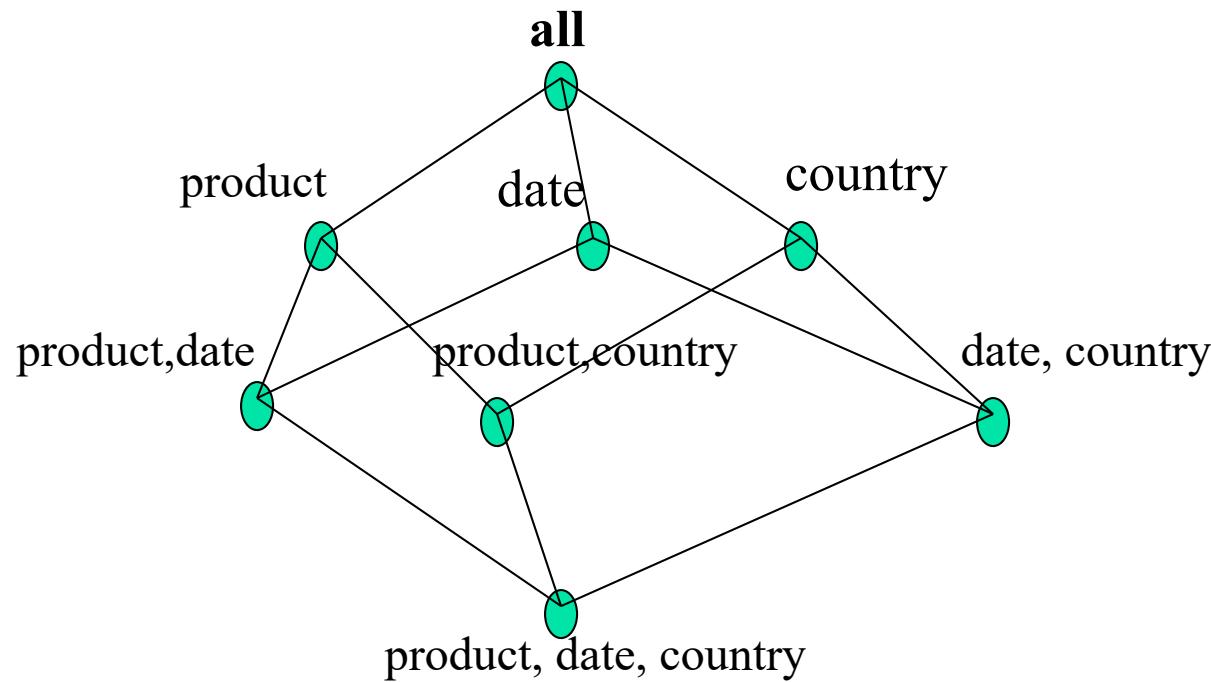
Dimensions: *Product, Location, Time*
Hierarchical summarization paths



A Sample Data Cube



Cuboids Corresponding to the Cube



0-D (*apex*) cuboid

1-D cuboids

2-D cuboids

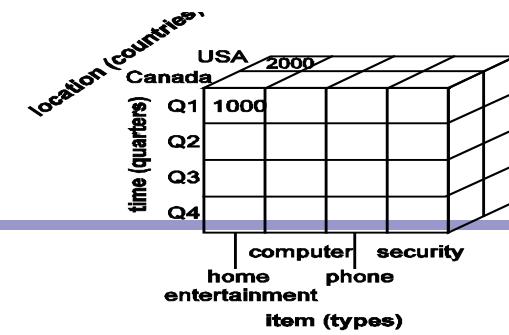
3-D (*base*) cuboid

Typical OLAP Operations

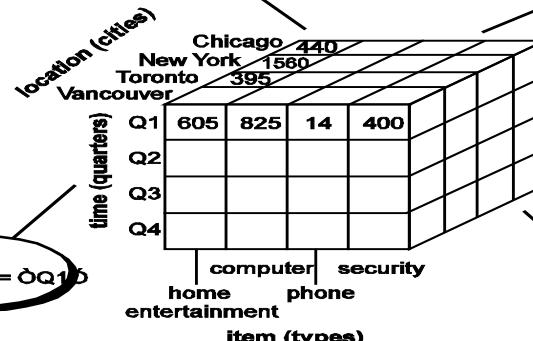
- Roll up (drill-up): summarize data
 - *by climbing up hierarchy or by dimension reduction*
- Drill down (roll down): reverse of roll-up
 - *from higher level summary to lower level summary or detailed data, or introducing new dimensions*
- Slice and dice: *project and select*
- Pivot (rotate):
 - *reorient the cube, visualization, 3D to series of 2D planes*
- Other operations
 - *drill across: involving (across) more than one fact table*
 - *drill through: through the bottom level of the cube to its back-end relational tables (using SQL)*



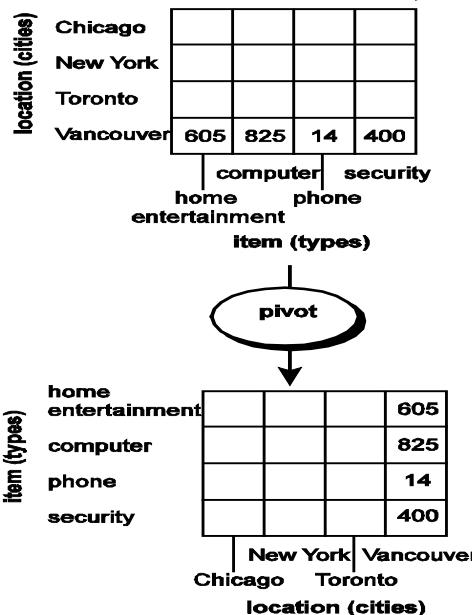
dice for
(location = "Toronto" or "Vancouver")
and (time = "Q1" or "Q2")
(item = "home entertainment" or "computer")



roll-up
on location
(from cities
to countries)



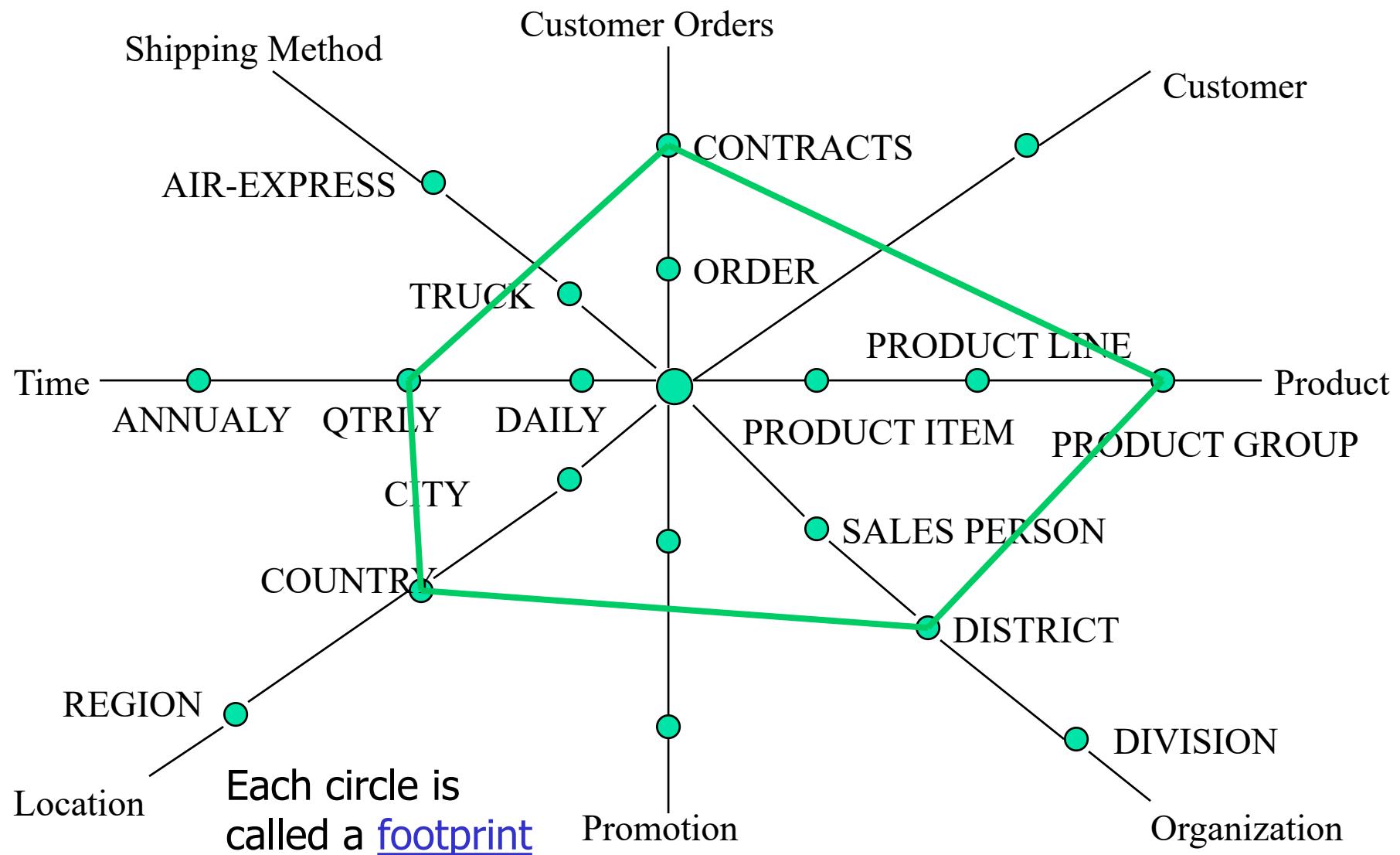
slice
for time = "Q1"



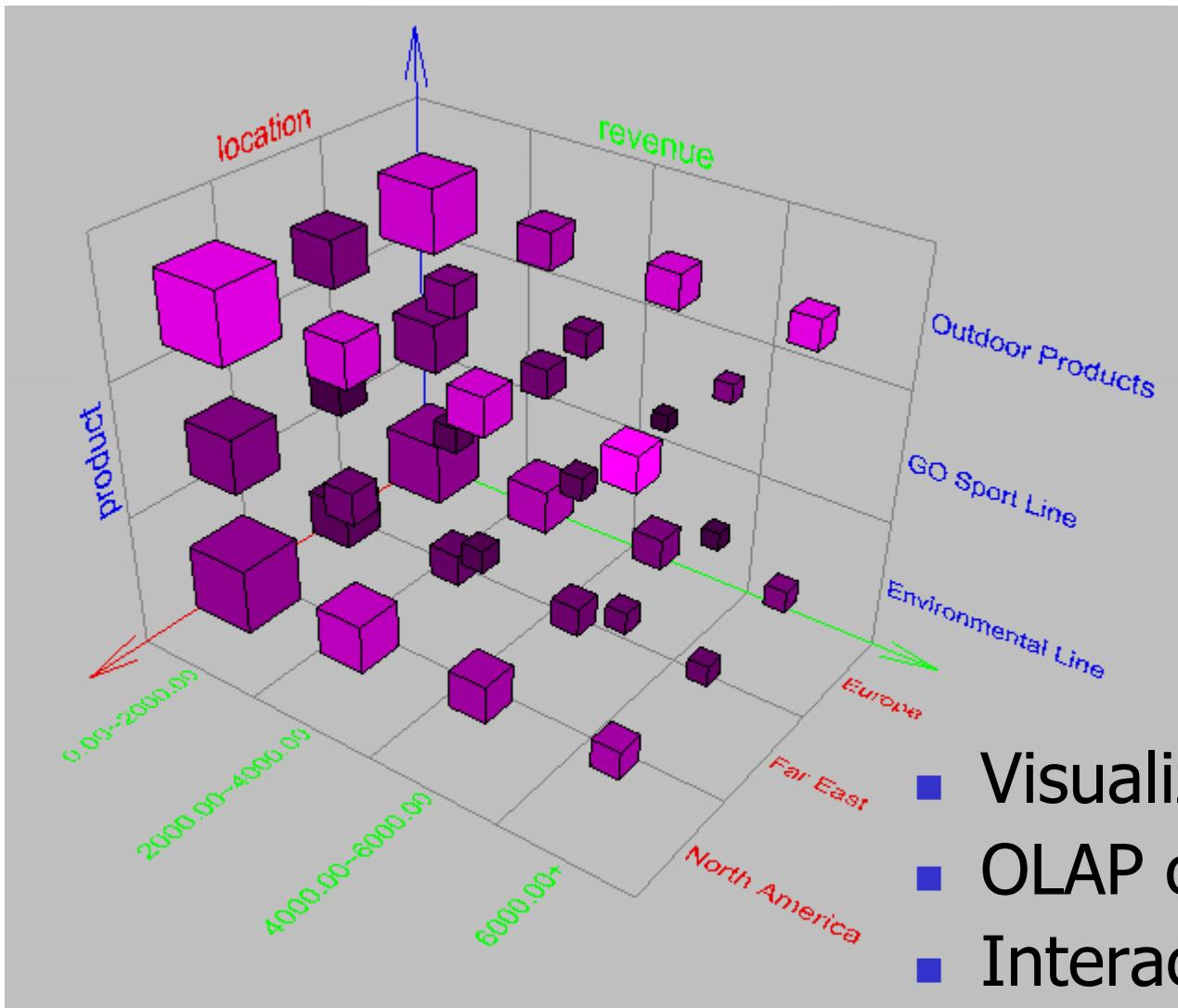
drill-down
on time
(from quarters
to months)

Fig. 3.10 Typical OLAP Operations

A Star-Net Query Model



Browsing a Data Cube



- Visualization
- OLAP capabilities
- Interactive manipulation

Chapter 4: Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts
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- Summary

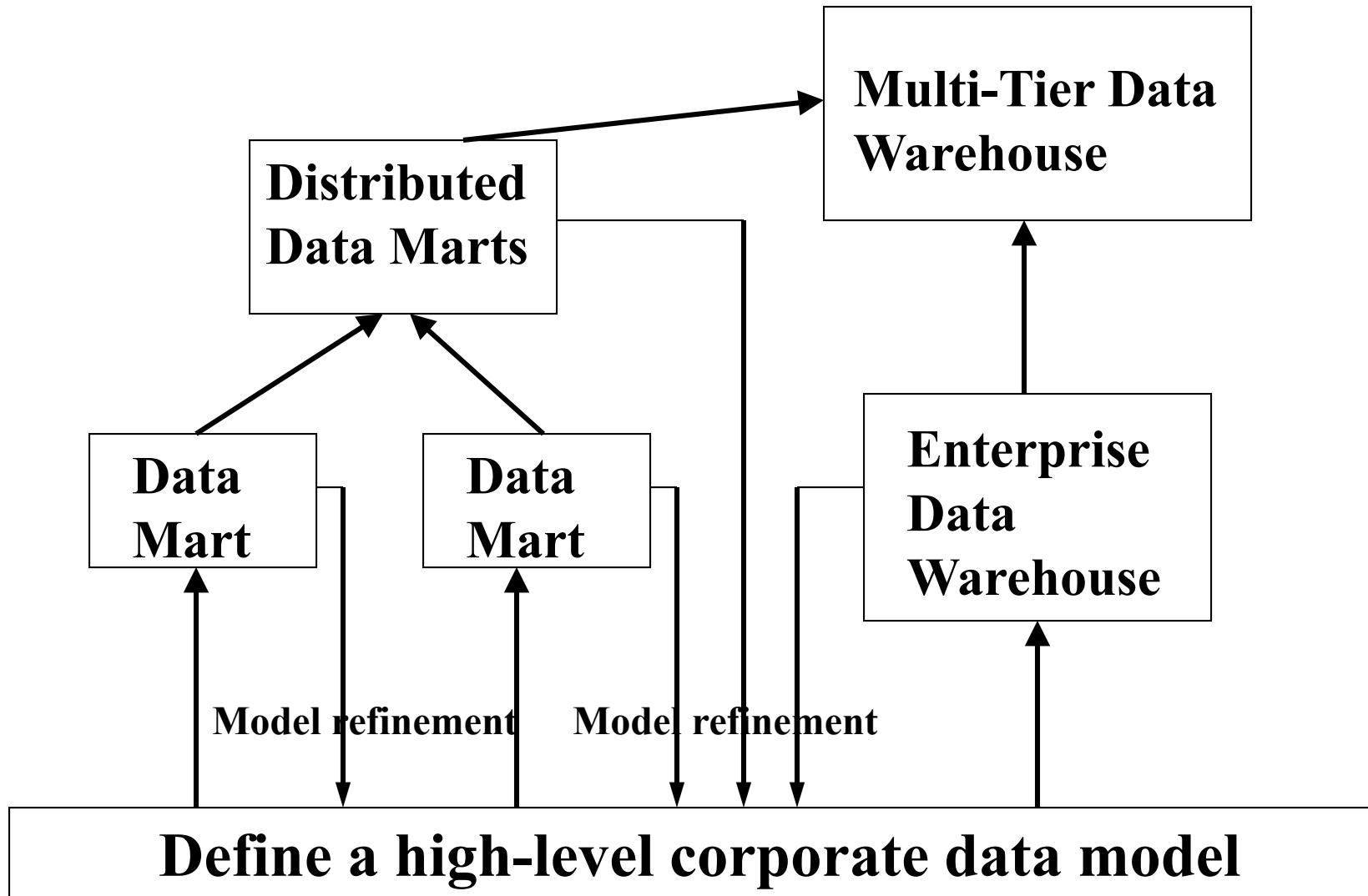
Design of Data Warehouse: A Business Analysis Framework

- Four views regarding the design of a data warehouse
 - **Top-down view**
 - allows selection of the relevant information necessary for the data warehouse
 - **Data source view**
 - exposes the information being captured, stored, and managed by operational systems
 - **Data warehouse view**
 - consists of fact tables and dimension tables
 - **Business query view**
 - sees the perspectives of data in the warehouse from the view of end-user

Data Warehouse Design Process

- **Top-down, bottom-up approaches or a combination** of both
 - Top-down: Starts with overall design and planning (mature)
 - Bottom-up: Starts with experiments and prototypes (rapid)
- **From software engineering point of view**
 - Waterfall: structured and systematic analysis at each step before proceeding to the next
 - Spiral: rapid generation of increasingly functional systems, short turn around time, quick turn around
- **Typical data warehouse design process**
 - Choose a **business process** to model, e.g., orders, invoices, etc.
 - Choose the ***grain (atomic level of data)*** of the business process
 - Choose the **dimensions** that will apply to each fact table record
 - Choose the **measure** that will populate each fact table record

Data Warehouse Development: A Recommended Approach



Data Warehouse Usage

- Three kinds of data warehouse applications
 - **Information processing**
 - supports querying, basic statistical analysis, and reporting using crosstabs, tables, charts and graphs
 - **Analytical processing**
 - multidimensional analysis of data warehouse data
 - supports basic OLAP operations, slice-dice, drilling, pivoting
 - **Data mining**
 - knowledge discovery from hidden patterns
 - supports associations, constructing analytical models, performing classification and prediction, and presenting the mining results using visualization tools

From On-Line Analytical Processing (OLAP) to On Line Analytical Mining (OLAM)

- Why online analytical mining?
 - High quality of data in data warehouses
 - DW contains integrated, consistent, cleaned data
 - Available information processing structure surrounding data warehouses
 - ODBC, OLEDB, Web accessing, service facilities, reporting and OLAP tools
 - OLAP-based exploratory data analysis
 - Mining with drilling, dicing, pivoting, etc.
 - On-line selection of data mining functions
 - Integration and swapping of multiple mining functions, algorithms, and tasks

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Efficient Data Cube Computation

- Data cube can be viewed as a lattice of cuboids
 - The bottom-most cuboid is the base cuboid
 - The top-most cuboid (apex) contains only one cell
 - How many cuboids in an n-dimensional cube with L levels?

$$T = \prod_{i=1}^n (L_i + 1)$$

- Materialization of data cube
 - Materialize every (cuboid) (**full materialization**), none (**no materialization**), or some (**partial materialization**)
 - Selection of which cuboids to materialize
 - Based on size, sharing, access frequency, etc.

The “Compute Cube” Operator

- Cube definition and computation in DMQL

define cube sales [item, city, year]: sum (sales_in_dollars)
compute cube sales

- Transform it into a SQL-like language (with a new operator **cube by**, introduced by Gray et al.'96)

SELECT item, city, year, SUM (amount)

FROM SALES

CUBE BY item, city, year

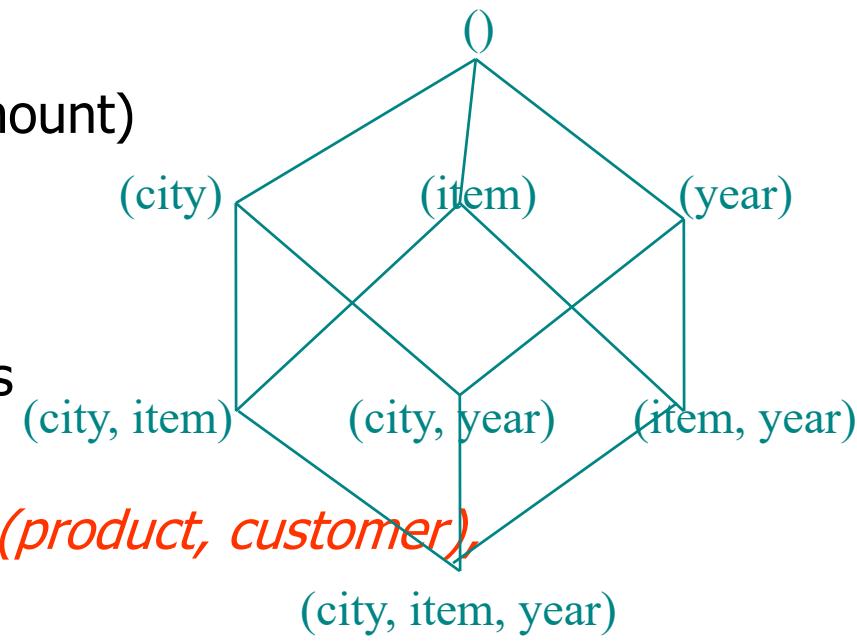
- Need compute the following Group-Bys

(date, product, customer),

(date,product),(date, customer), (product, customer),

(date), (product), (customer)

()



Indexing OLAP Data: Bitmap Index

- Index on a particular column
- Each value in the column has a bit vector: bit-op is fast
- The length of the bit vector: # of records in the base table
- The i -th bit is set if the i -th row of the base table has the value for the indexed column
- not suitable for high cardinality domains
- A recent bit compression technique, Word-Aligned Hybrid (WAH), makes it work for high cardinality domain as well [Wu, et al. TODS'06]

Base table

Cust	Region	Type
C1	Asia	Retail
C2	Europe	Dealer
C3	Asia	Dealer
C4	America	Retail
C5	Europe	Dealer

Index on Region

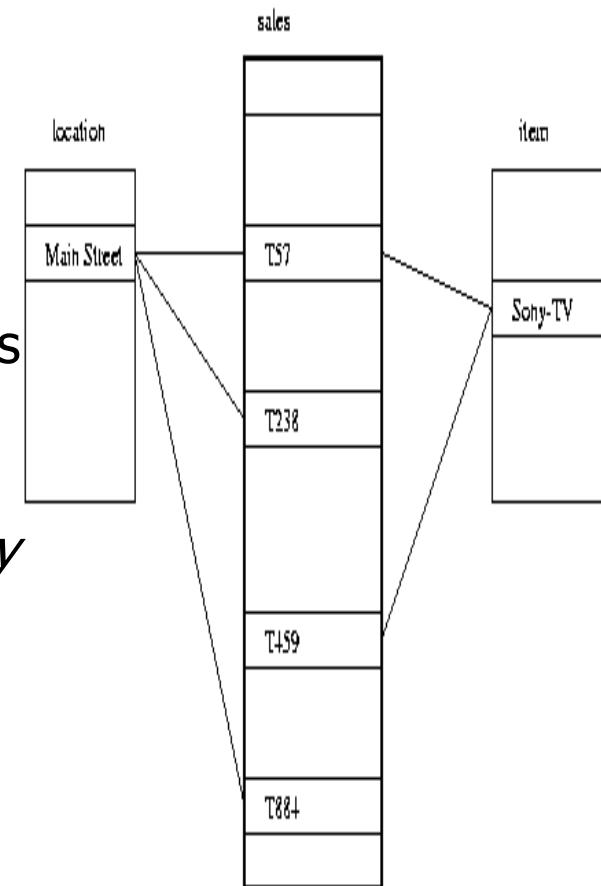
RecID	Asia	Europe	America
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	1
5	0	1	0

Index on Type

RecID	Retail	Dealer
1	1	0
2	0	1
3	0	1
4	1	0
5	0	1

Indexing OLAP Data: Join Indices

- Join index: $JI(R\text{-id}, S\text{-id})$ where $R (R\text{-id}, \dots) \bowtie S (S\text{-id}, \dots)$
- Traditional indices map the values to a list of record ids
 - It materializes relational join in JI file and speeds up relational join
- In data warehouses, join index relates the values of the dimensions of a start schema to rows in the fact table.
 - E.g. fact table: *Sales* and two dimensions *city* and *product*
 - A join index on *city* maintains for each distinct city a list of R-IDs of the tuples recording the Sales in the city
 - Join indices can span multiple dimensions



Efficient Processing OLAP Queries

- **Determine which operations** should be performed on the available cuboids
 - Transform **drill**, **roll**, etc. into corresponding SQL and/or OLAP operations, e.g., **dice** = selection + projection
- **Determine which materialized cuboid(s)** should be selected for OLAP op.
 - Let the query to be processed be on $\{brand, province_or_state\}$ with the condition " $year = 2004$ ", and there are 4 materialized cuboids available:
 - 1) $\{year, item_name, city\}$
 - 2) $\{year, brand, country\}$
 - 3) $\{year, brand, province_or_state\}$
 - 4) $\{item_name, province_or_state\}$ where $year = 2004$

Which should be selected to process the query?
- Explore indexing structures and compressed vs. dense array structs in MOLAP

OLAP Server Architectures

- Relational OLAP (ROLAP)
 - Use relational or extended-relational DBMS to store and manage warehouse data and OLAP middle ware
 - Include optimization of DBMS backend, implementation of aggregation navigation logic, and additional tools and services
 - Greater scalability
- Multidimensional OLAP (MOLAP)
 - Sparse array-based multidimensional storage engine
 - Fast indexing to pre-computed summarized data
- Hybrid OLAP (HOLAP) (e.g., Microsoft SQLServer)
 - Flexibility, e.g., low level: relational, high-level: array
- Specialized SQL servers (e.g., Redbricks)
 - Specialized support for SQL queries over star/snowflake schemas

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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 attribute removal or attribute generalization
 - Apply aggregation by merging identical, generalized tuples and accumulating their respective counts
 - Interaction with users for knowledge presentation

Attribute-Oriented Induction: An Example

Example: Describe general characteristics of graduate students in the University database

- Step 1. Fetch relevant set of data using an SQL statement, e.g.,
Select * (i.e., name, gender, major, birth_place,
birth_date, residence, phone#, gpa)
from student
where student_status in {"Msc", "MBA", "PhD"}
■ Step 2. Perform attribute-oriented induction
■ Step 3. Present results in generalized relation, cross-tab,
or rule forms

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
...

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

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

Attribute-Oriented Induction: Basic Algorithm

- 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.

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.,

$grad(x) \wedge male(x) \Rightarrow$

$birth_region(x) = "Canada"[t:53\%] \vee birth_region(x) = "foreign"[t:47\%]$.

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

Concept Description vs. Cube-Based OLAP

■ Similarity:

- Data generalization
- Presentation of data summarization at multiple levels of abstraction
- Interactive drilling, pivoting, slicing and dicing

■ Differences:

- OLAP has systematic preprocessing, query independent, and can drill down to rather low level
- AOI has automated desired level allocation, and may perform dimension relevance analysis/ranking when there are many relevant dimensions
- AOI works on the data which are not in relational forms

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Summary

- Data warehousing: A **multi-dimensional model** of a data warehouse
 - A data cube consists of *dimensions & measures*
 - Star schema, snowflake schema, fact constellations
 - **OLAP** operations: drilling, rolling, slicing, dicing and pivoting
- Data Warehouse Architecture, Design, and Usage
 - Multi-tiered architecture
 - Business analysis design framework
 - Information processing, analytical processing, data mining, **OLAM** (Online Analytical Mining)
- Implementation: Efficient computation of data cubes
 - Partial vs. full vs. no materialization
 - Indexing OALP data: Bitmap index and join index
 - OLAP query processing
 - OLAP servers: ROLAP, MOLAP, HOLAP
- Data generalization: Attribute-oriented induction

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Surplus Slides

Compression of Bitmap Indices

- Bitmap indexes must be compressed to reduce I/O costs and minimize CPU usage—majority of the bits are 0's
- Two compression schemes:
 - Byte-aligned Bitmap Code (BBC)
 - Word-Aligned Hybrid (WAH) code
- Time and space required to operate on compressed bitmap is proportional to the total size of the bitmap
- Optimal on attributes of low cardinality as well as those of high cardinality.
- WAH out performs BBC by about a factor of two