

Data Mining: Concepts and Techniques

— Chapter 2 —

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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	pla y	ball	score	game	n	vi	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
- Estimated by interpolation (for *grouped data*):

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

■ Mode

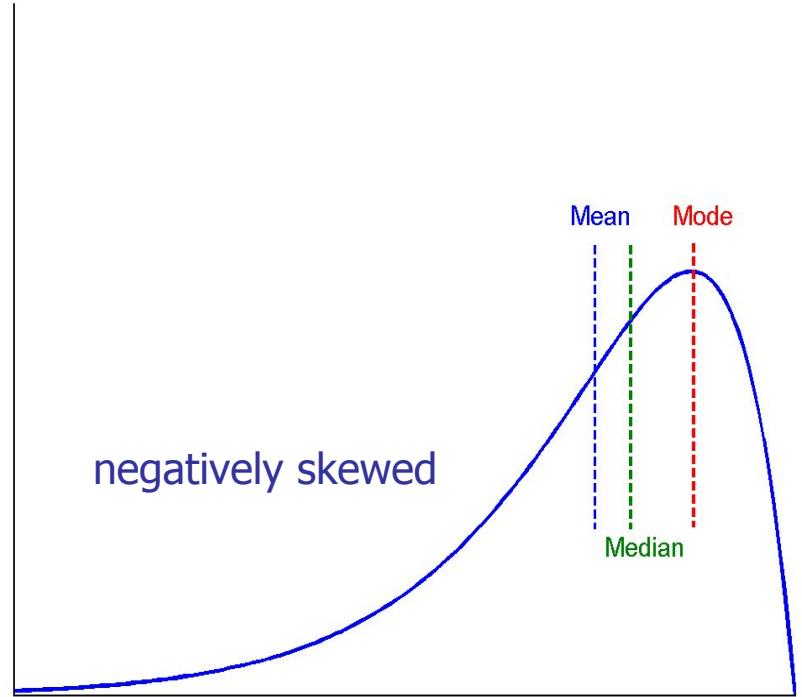
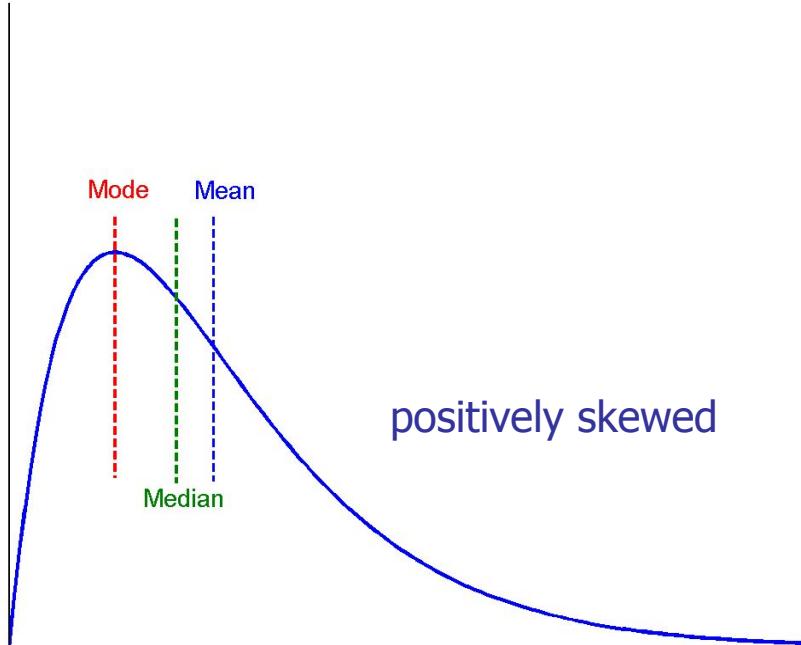
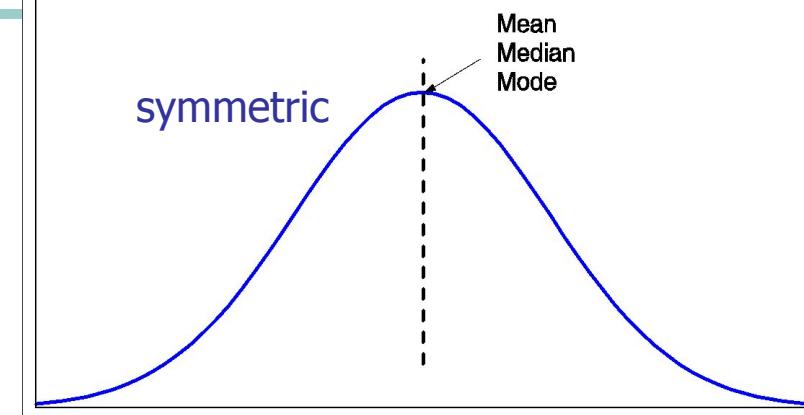
$$median = L_1 + \left(\frac{n/2 - (\sum freq)l}{freq_{median}} \right) width$$

- 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



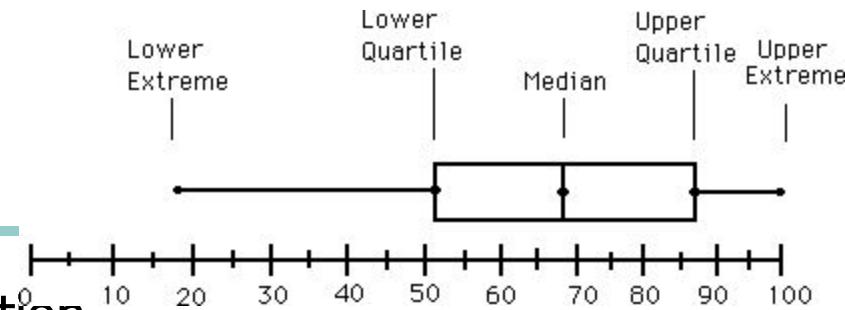
Measuring the Dispersion of Data

- 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)

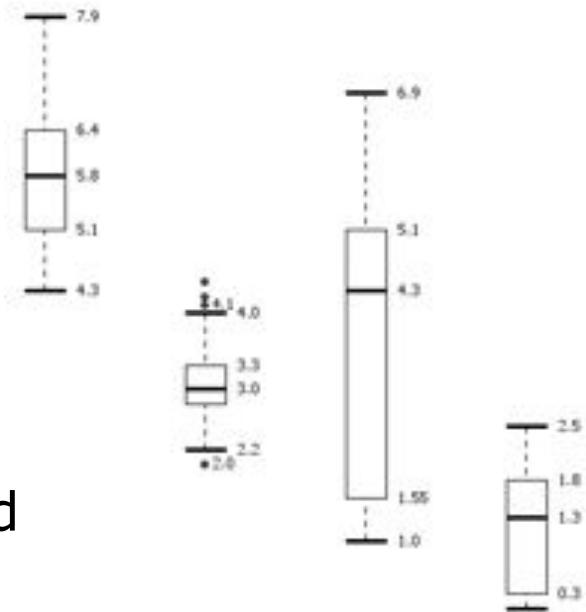
$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{1}{n-1} \left[\sum_{i=1}^n x_i^2 - \frac{1}{n} (\sum_{i=1}^n x_i)^2 \right] \quad \sigma^2 = \frac{1}{N} \sum_{i=1}^n (x_i - \mu)^2 = \frac{1}{N} \sum_{i=1}^n x_i^2 - \mu^2$$

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

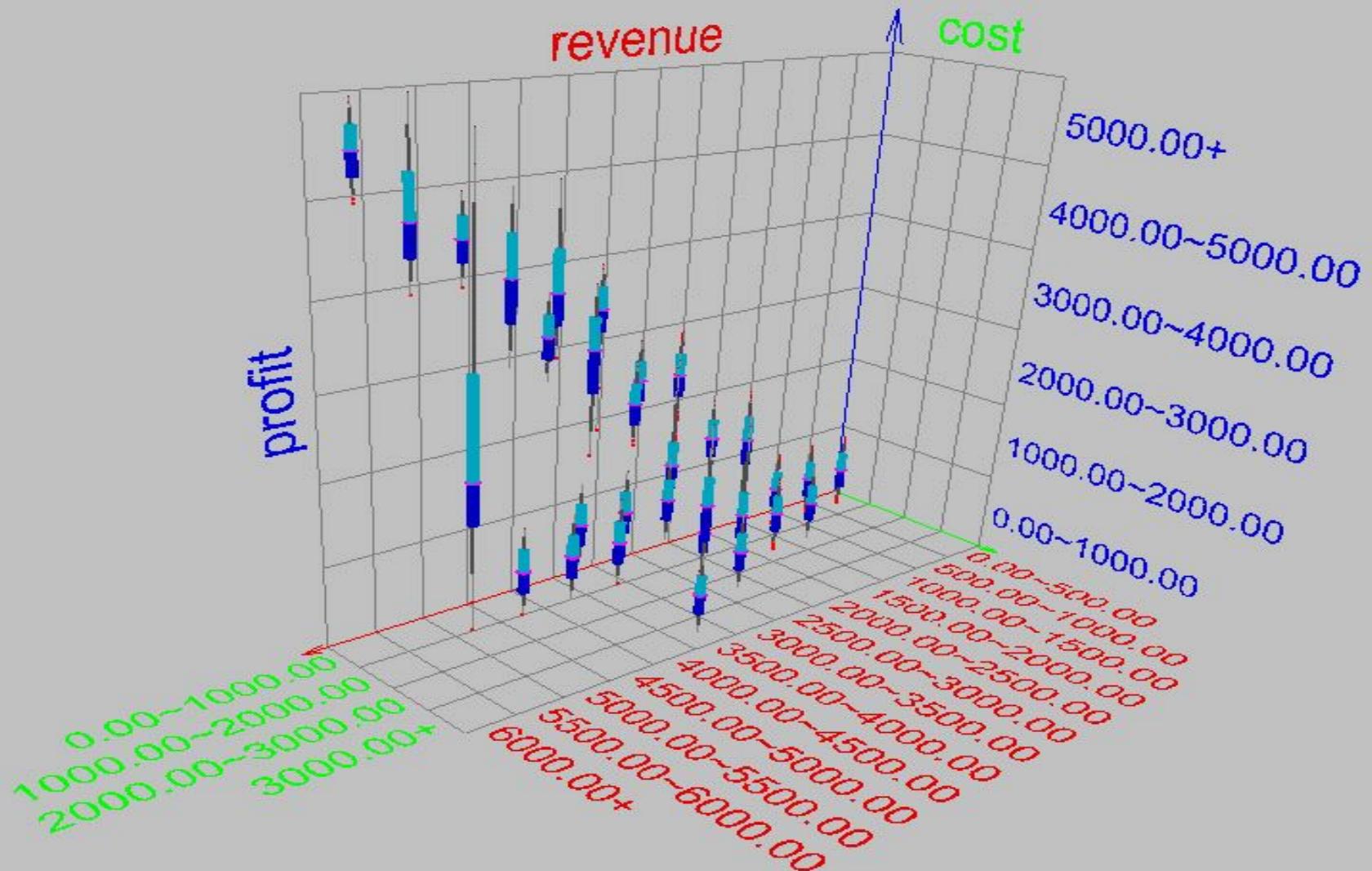
Boxplot Analysis



- **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

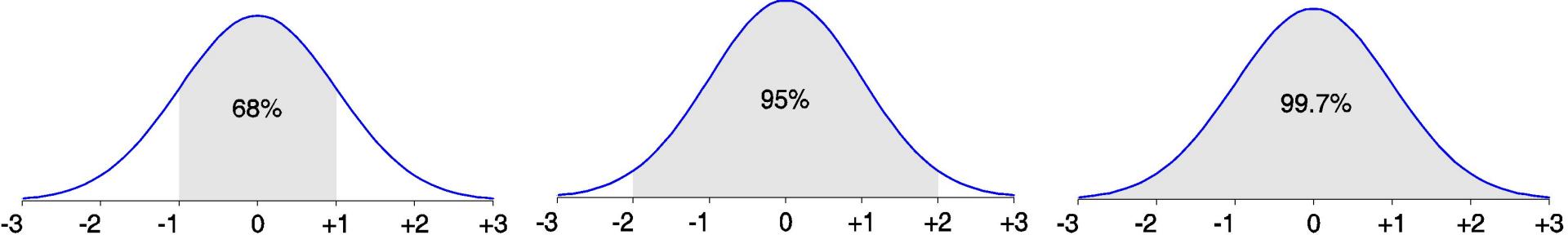


Visualization of Data Dispersion: 3-D Boxplots



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

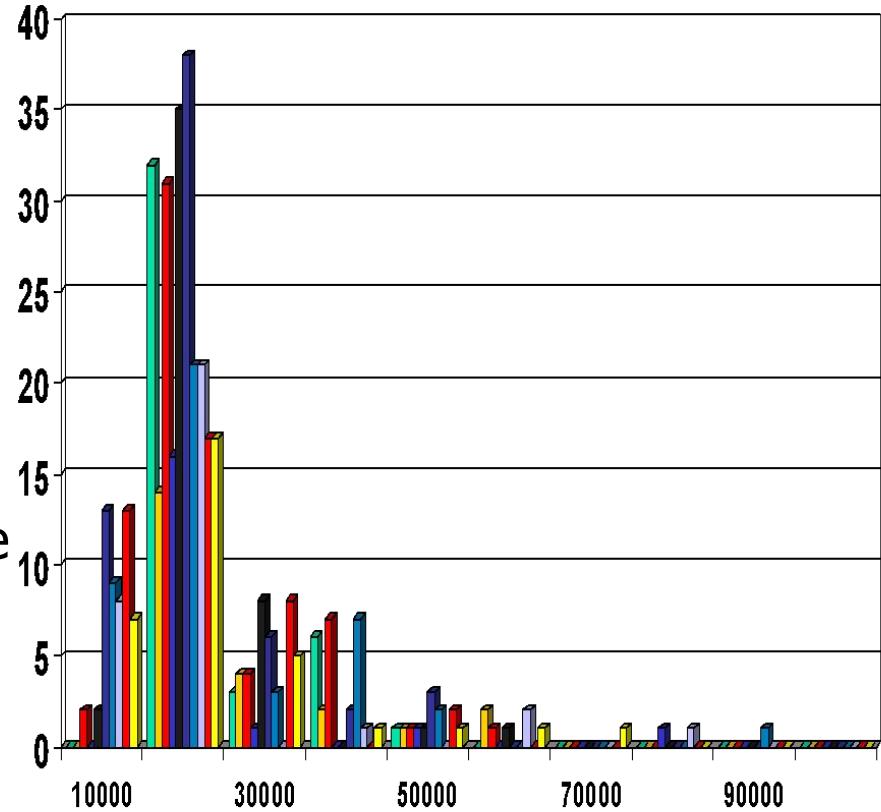


Graphic Displays of Basic Statistical Descriptions

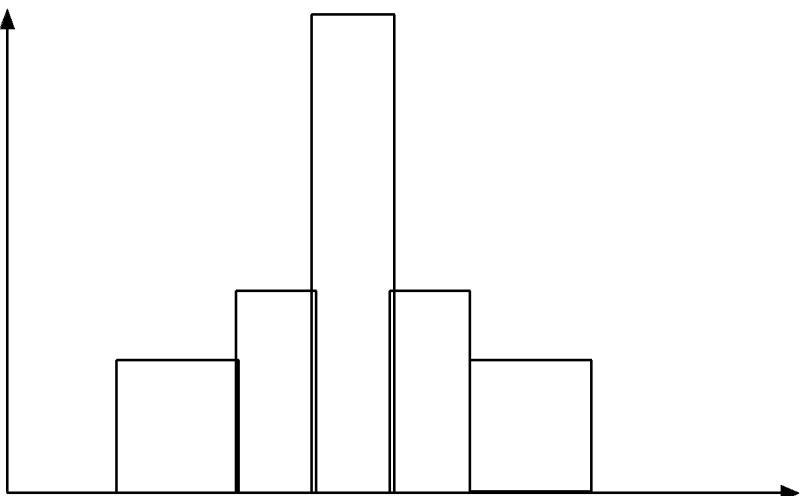
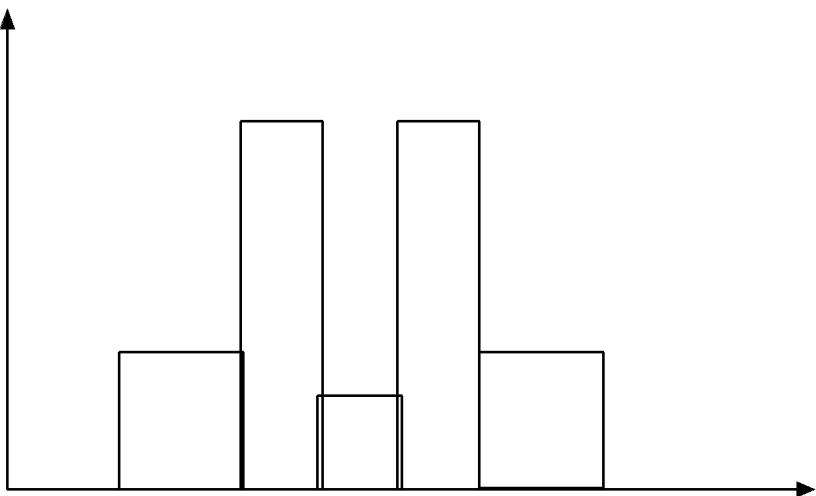
- **Boxplot:** graphic display of five-number summary
- **Histogram:** x-axis are values, y-axis repres. frequencies
- **Quantile plot:** each value x_i is paired with f_i , indicating that approximately $100 f_i \%$ of data are $\leq x_i$
- **Quantile-quantile (q-q) plot:** graphs the quantiles of one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



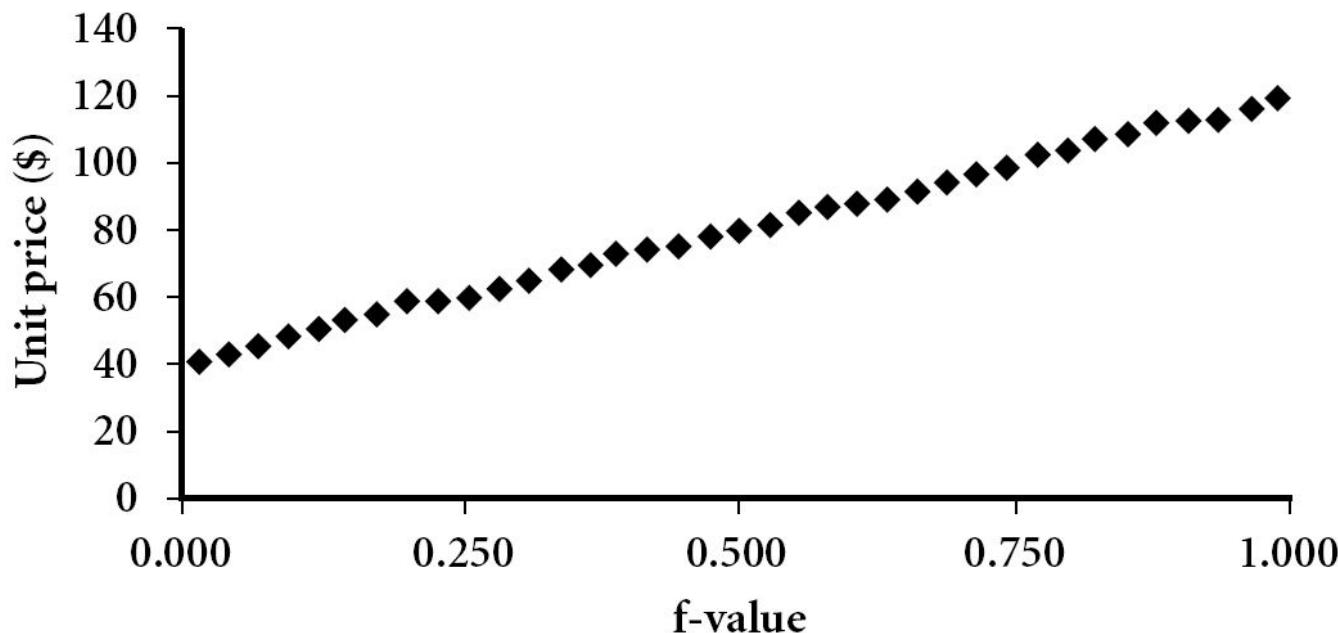
Histograms Often Tell More than Boxplots



- 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

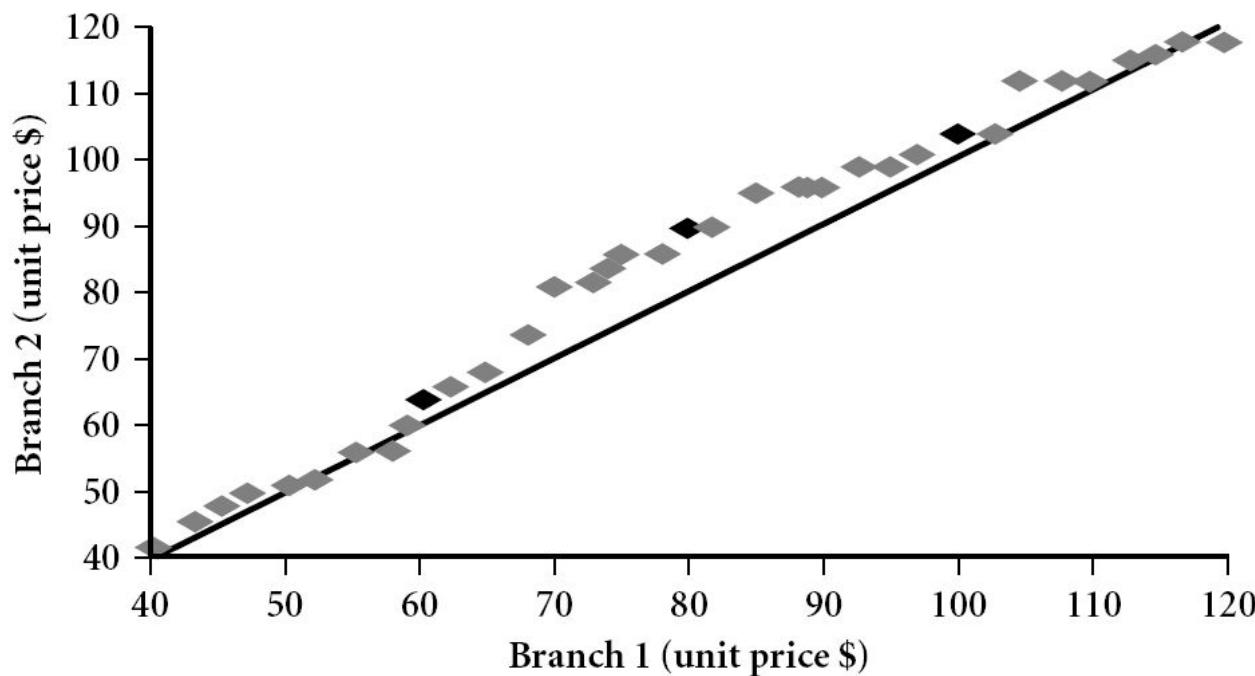
Quantile Plot

- 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



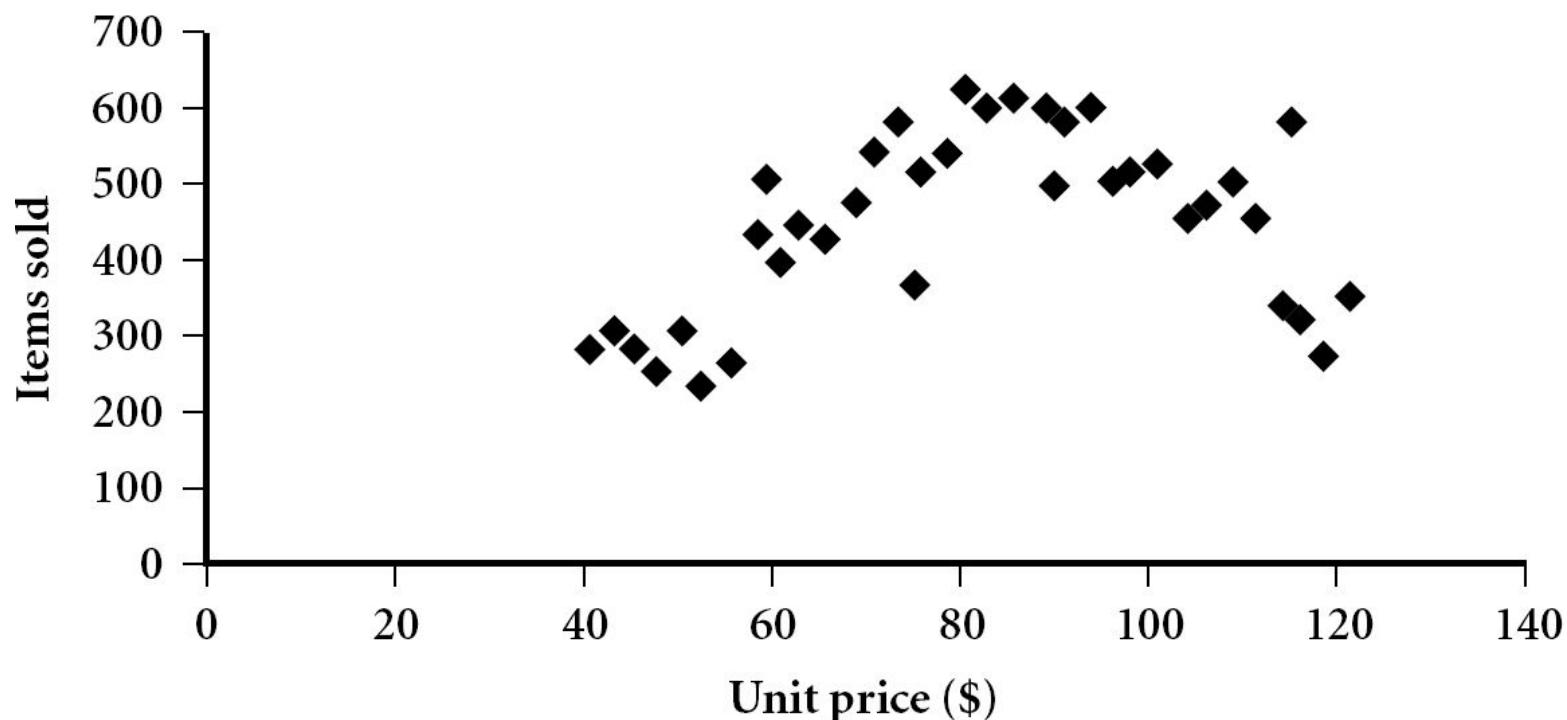
Quantile-Quantile (Q-Q) Plot

- 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.

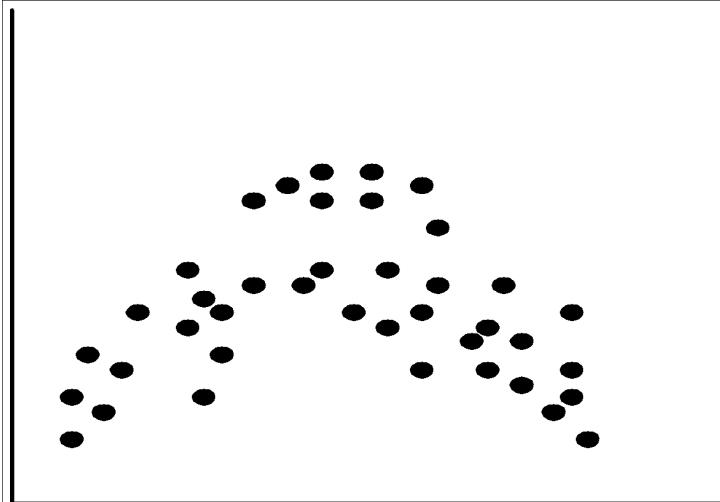
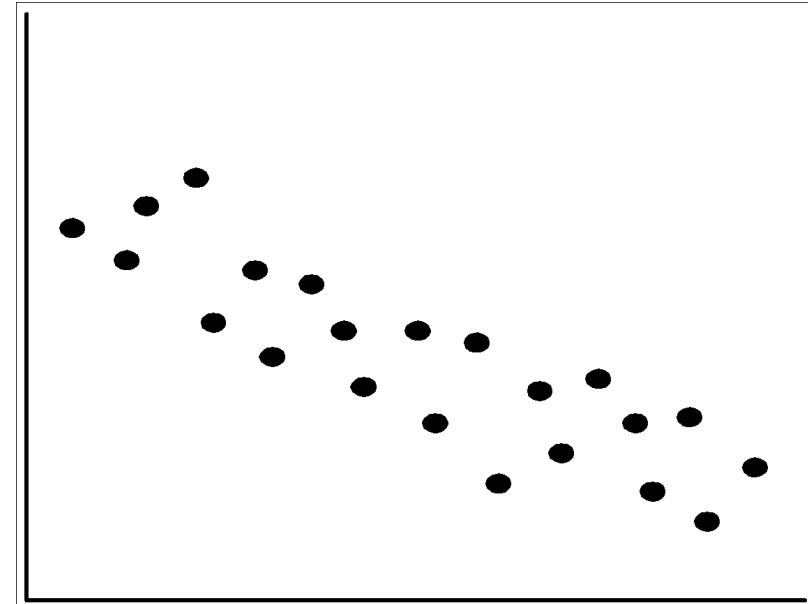
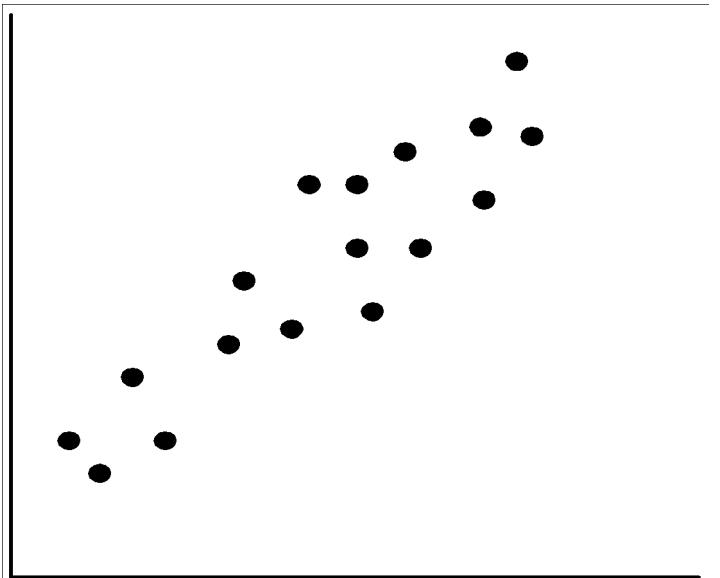


Scatter plot

- 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

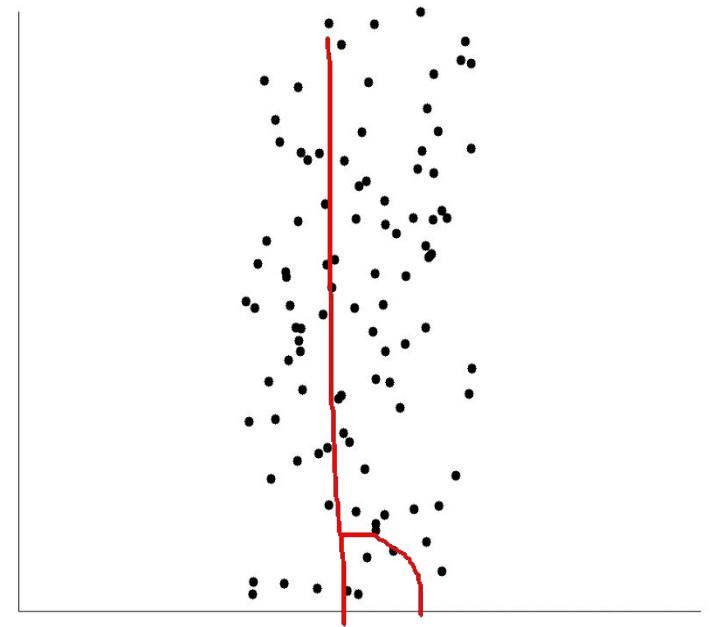
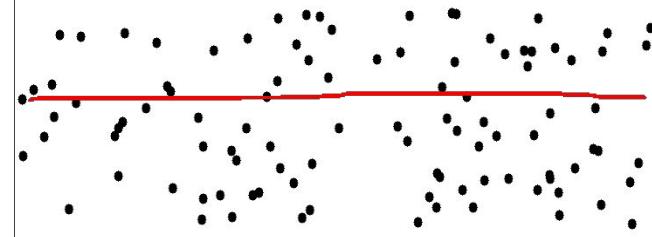
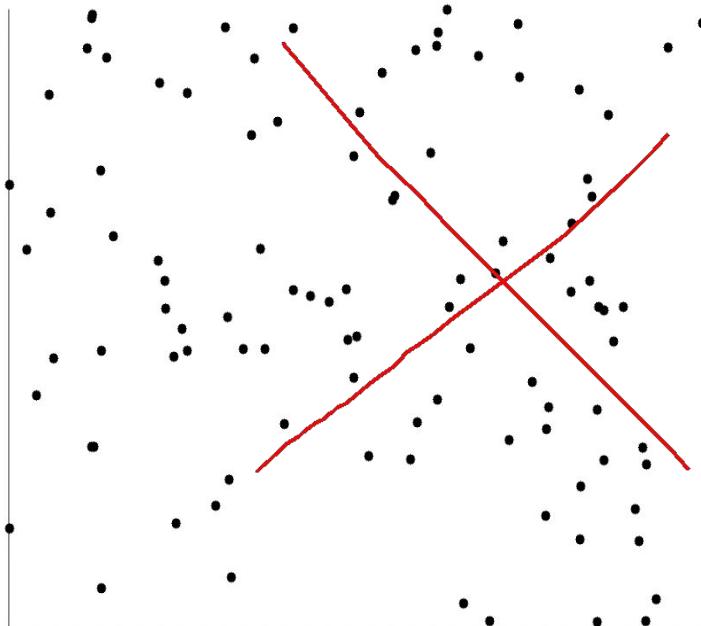


Positively and Negatively Correlated Data



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

Uncorrelated Data



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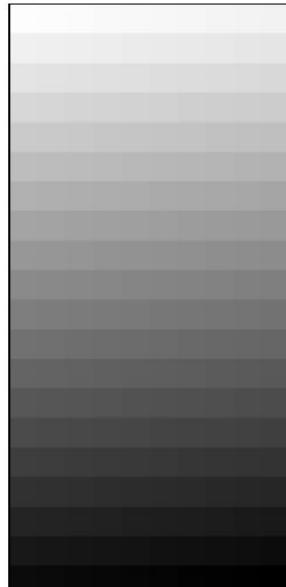


Data Visualization

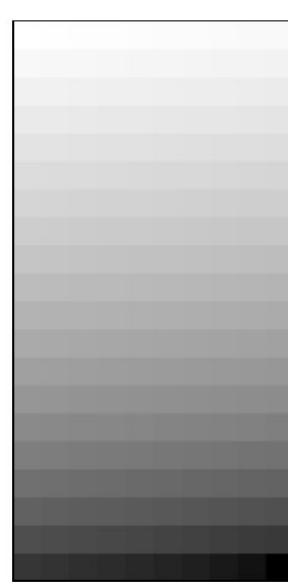
- Why data visualization?
 - Gain insight into an information space by mapping data onto graphical primitives
 - Provide qualitative overview of large data sets
 - Search for patterns, trends, structure, irregularities, relationships among data
 - Help find interesting regions and suitable parameters 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

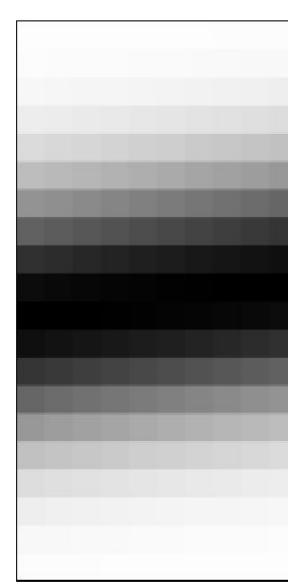
- For a data set of m dimensions, create m windows on the screen, one for each dimension
- The m dimension values of a record are mapped to m pixels at the corresponding positions in the windows
- The colors of the pixels reflect the corresponding values



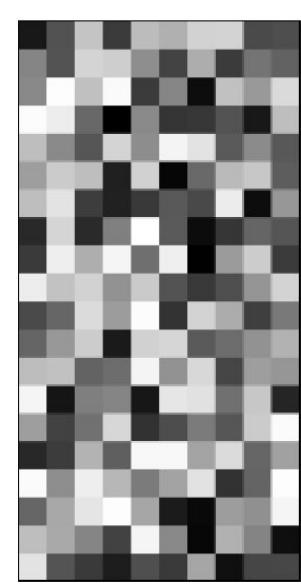
(a) Income



(b) Credit Limit



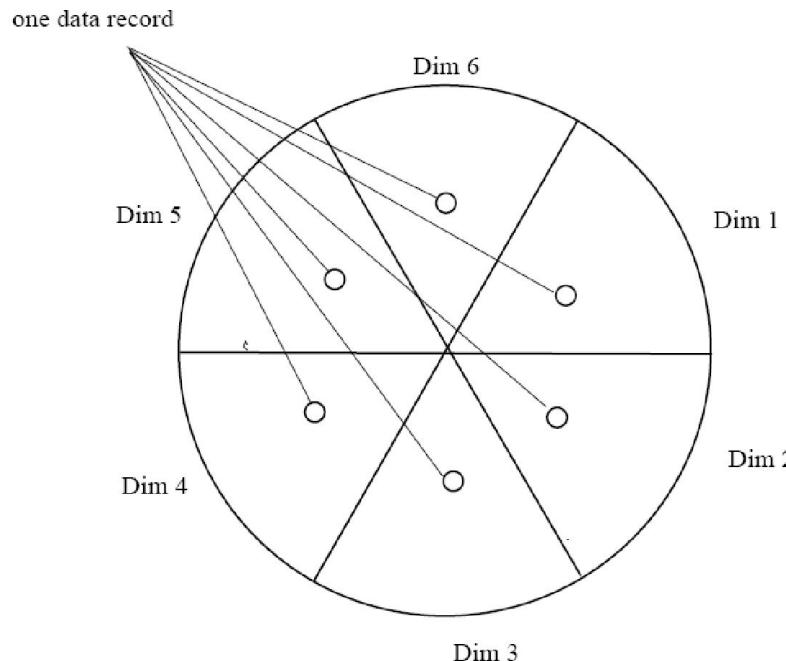
(c) transaction volume



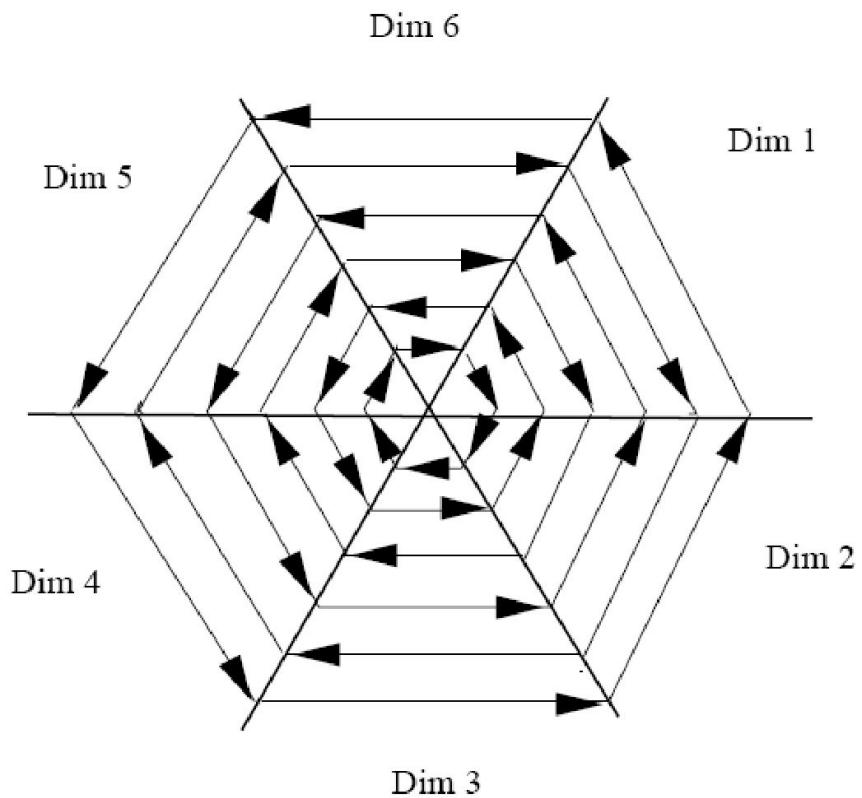
(d) age

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



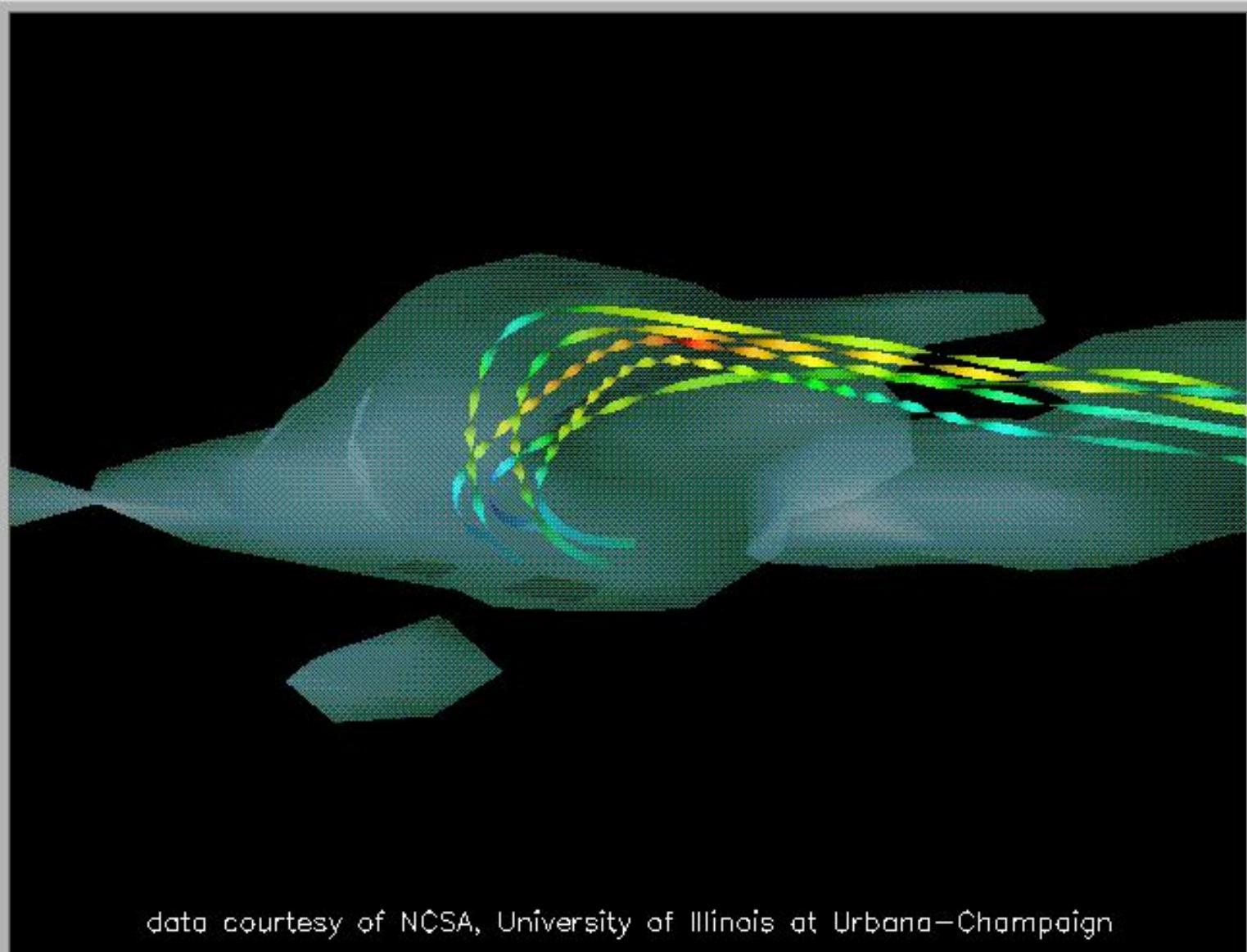
(b) Laying out pixels in circle segment

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

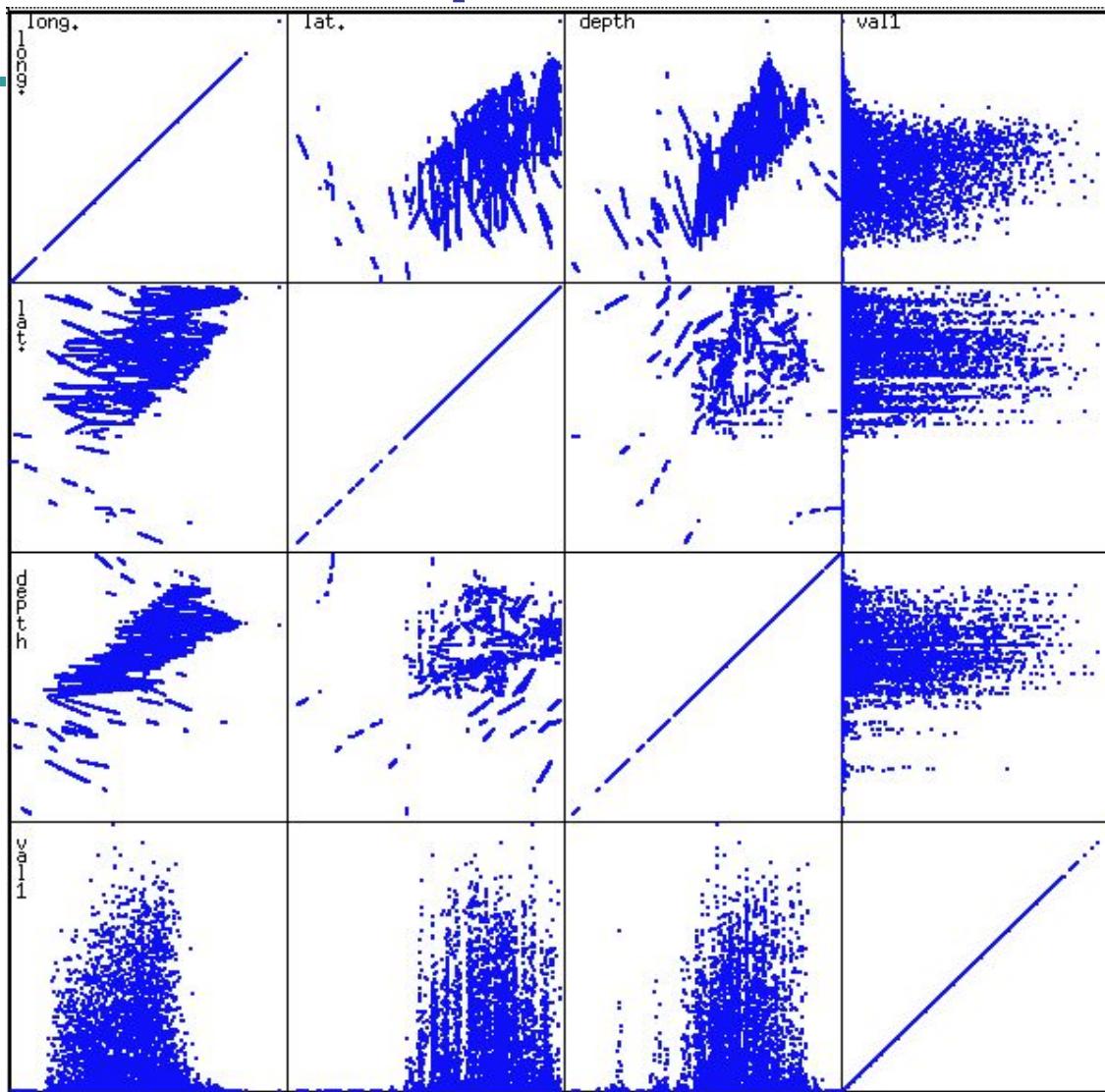
Ribbons with Twists Based on Vorticity



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

Scatterplot Matrices

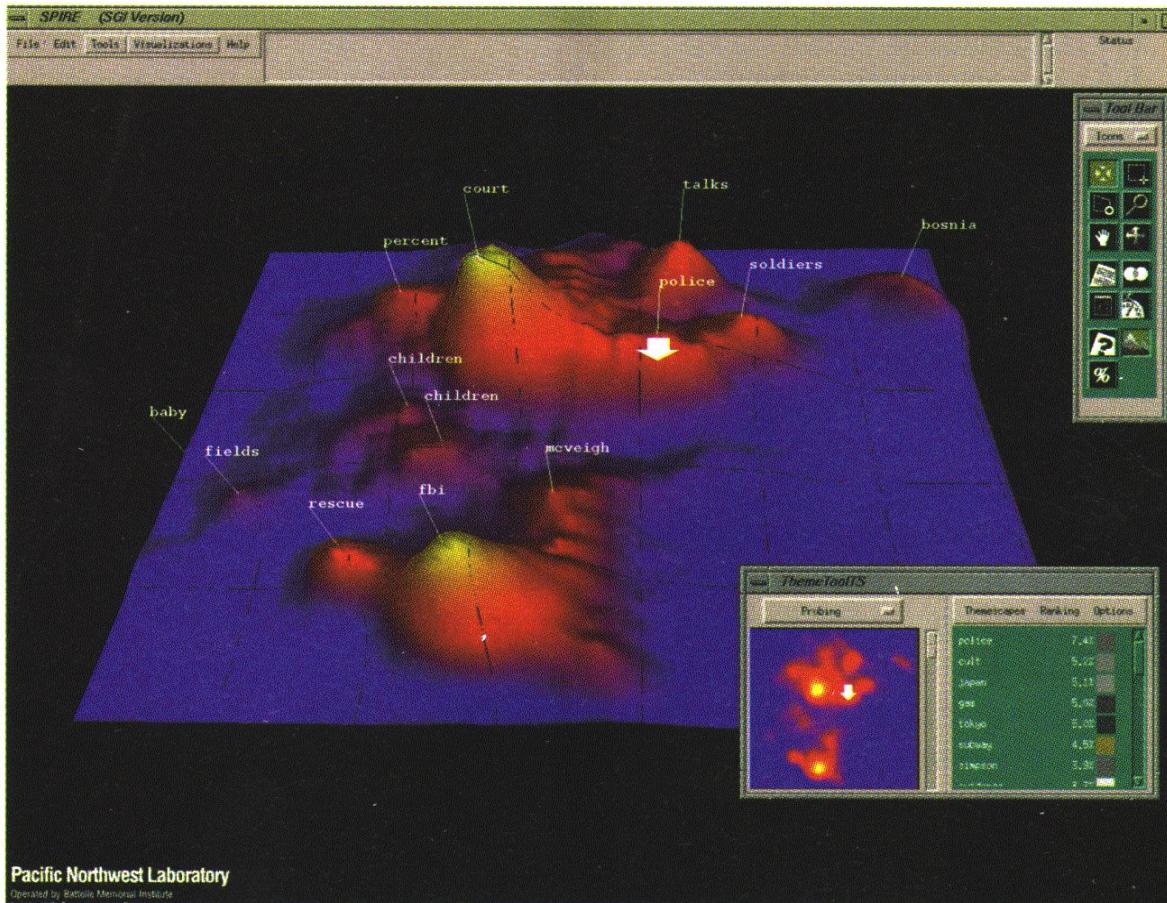
Used by permission of M. Ward, Worcester Polytechnic Institute



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

Landscapes

Used by permission of B. Wright, Visible Decisions Inc.

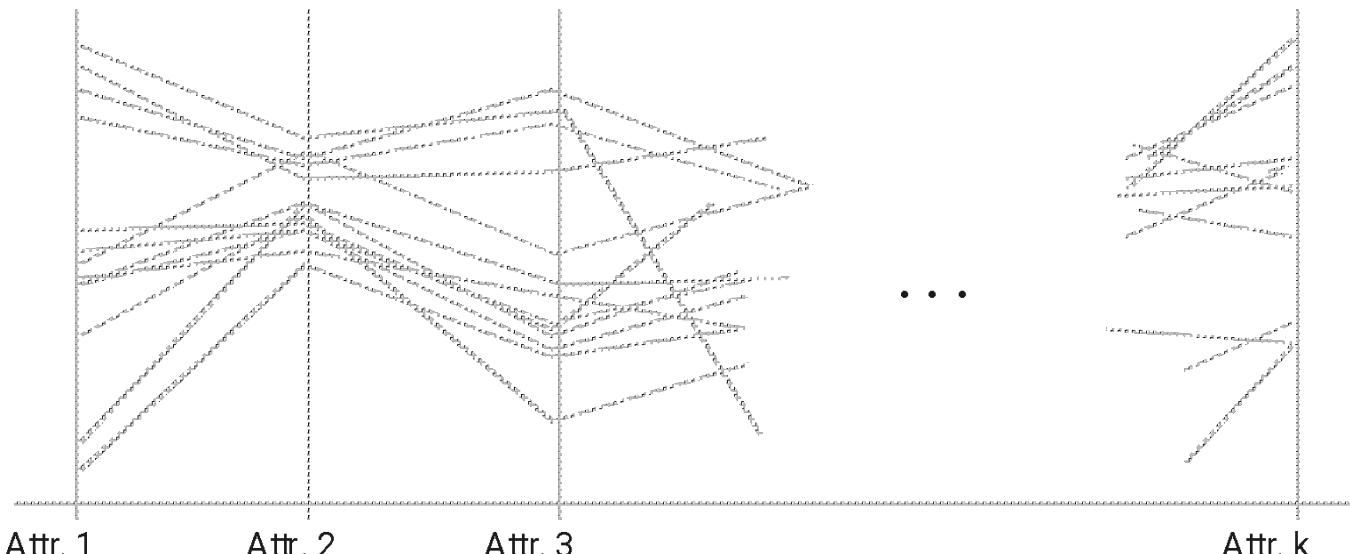


news articles
visualized as
a landscape

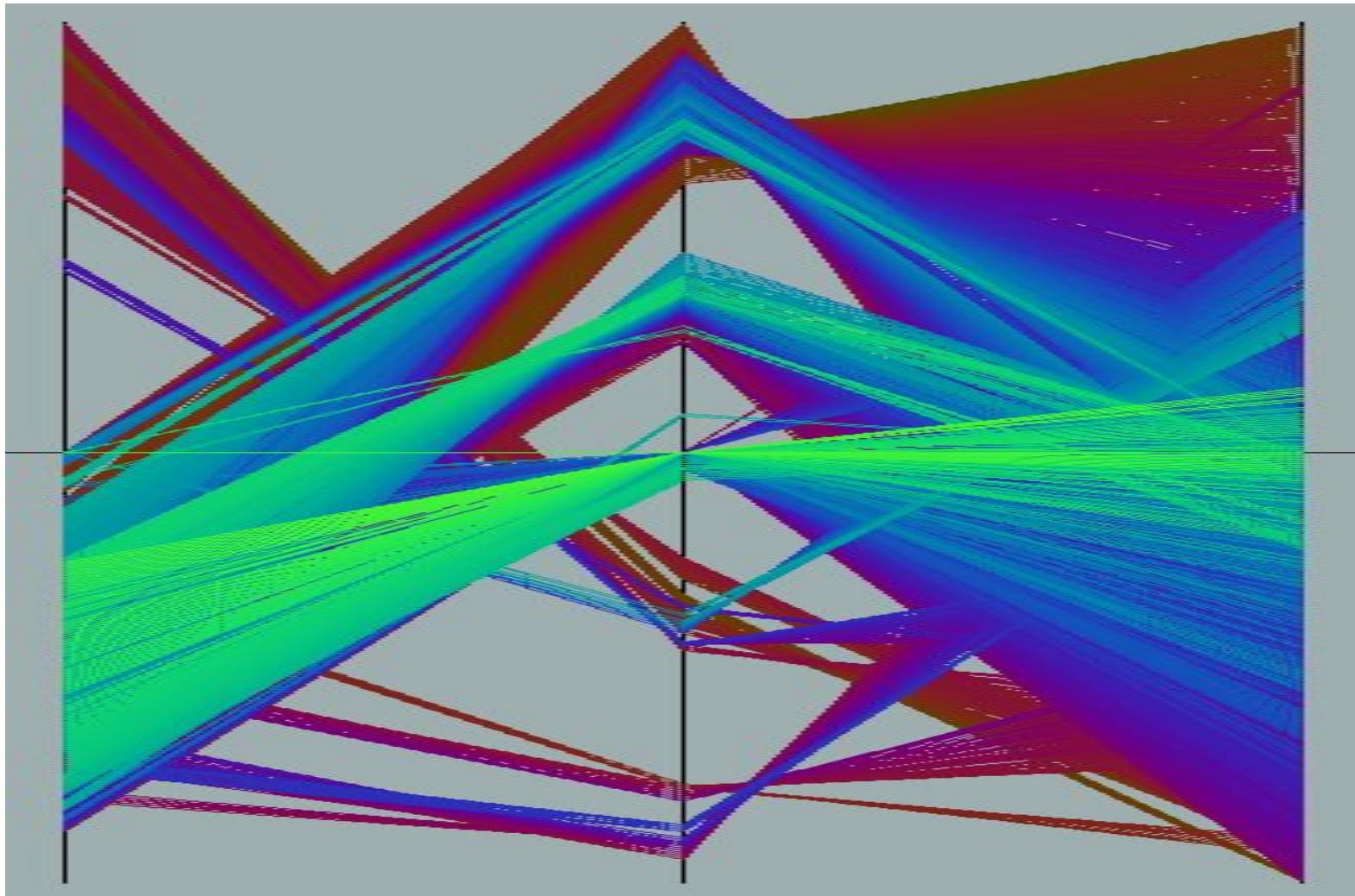
- Visualization of the data as perspective landscape
- The data needs to be transformed into a (possibly artificial) 2D spatial representation which preserves the characteristics of the data

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



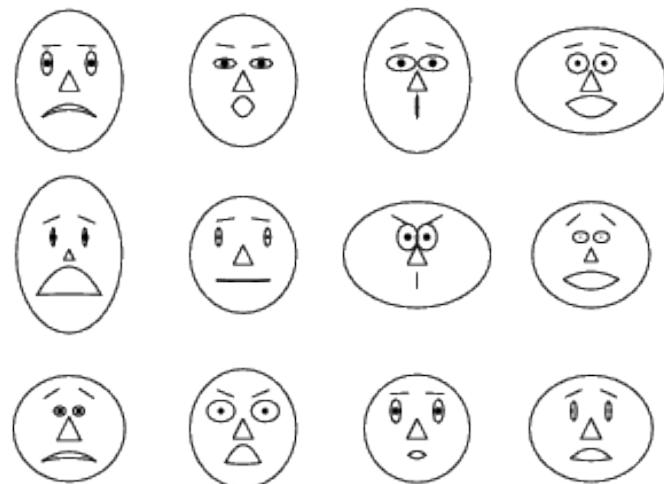
Icon-Based Visualization Techniques

- 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

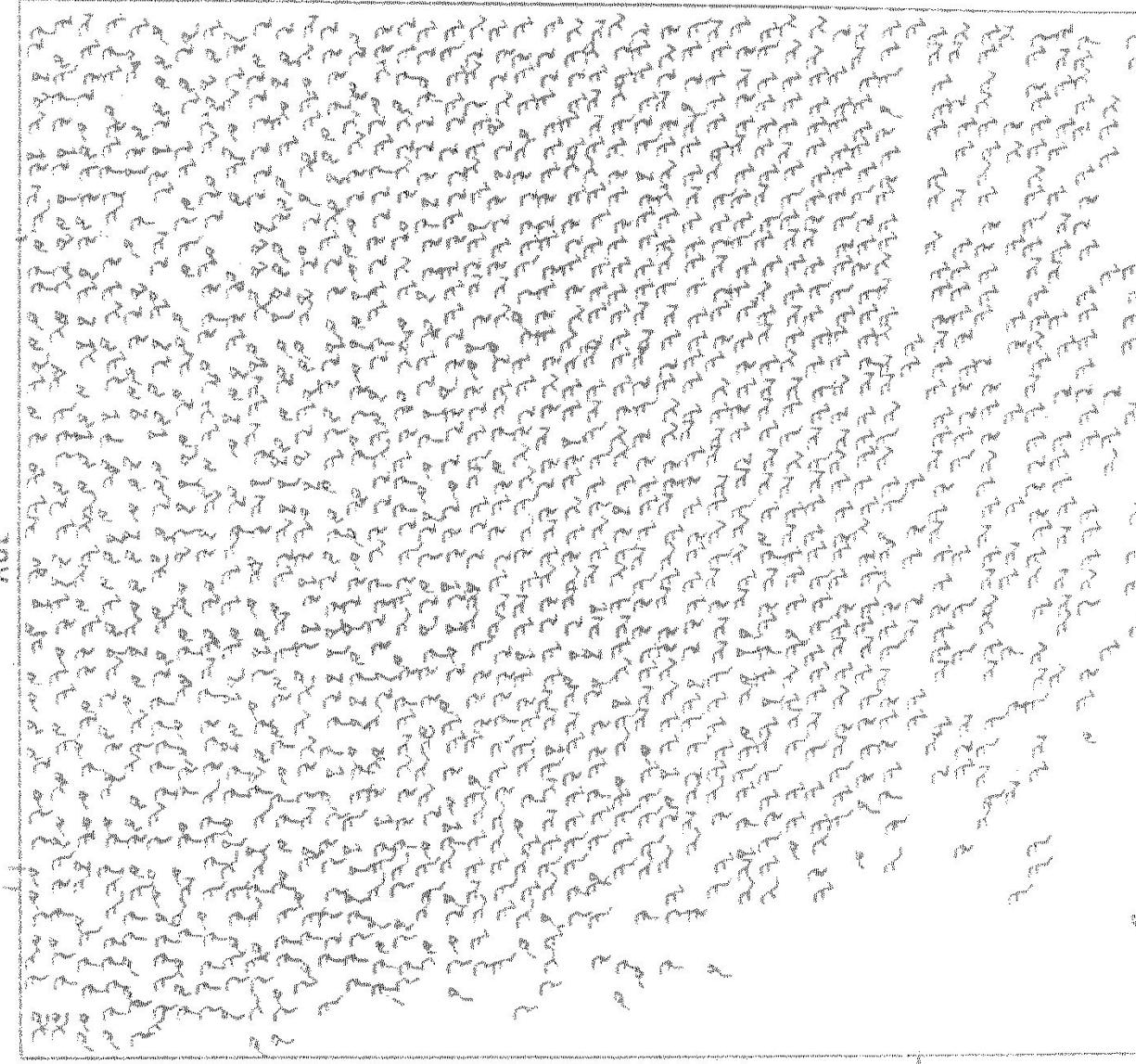
Chernoff Faces

- 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



used by permission of G. Grinstein, University of Massachusetts at Lowell

CC

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

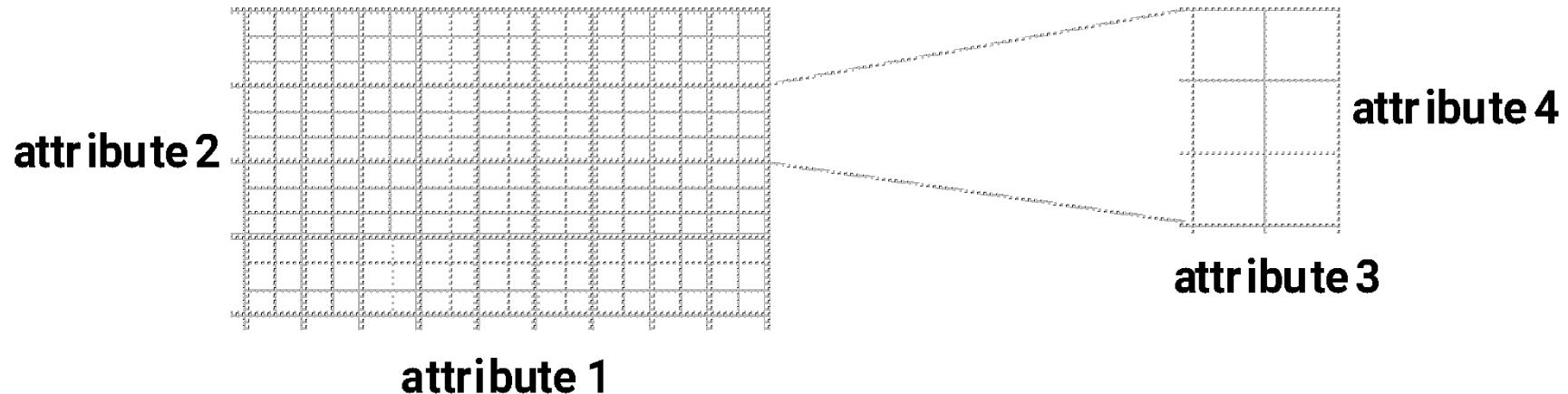
A 5-piece stick figure (1 body and 4 limbs w. different angle/length)

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

Hierarchical Visualization Techniques

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

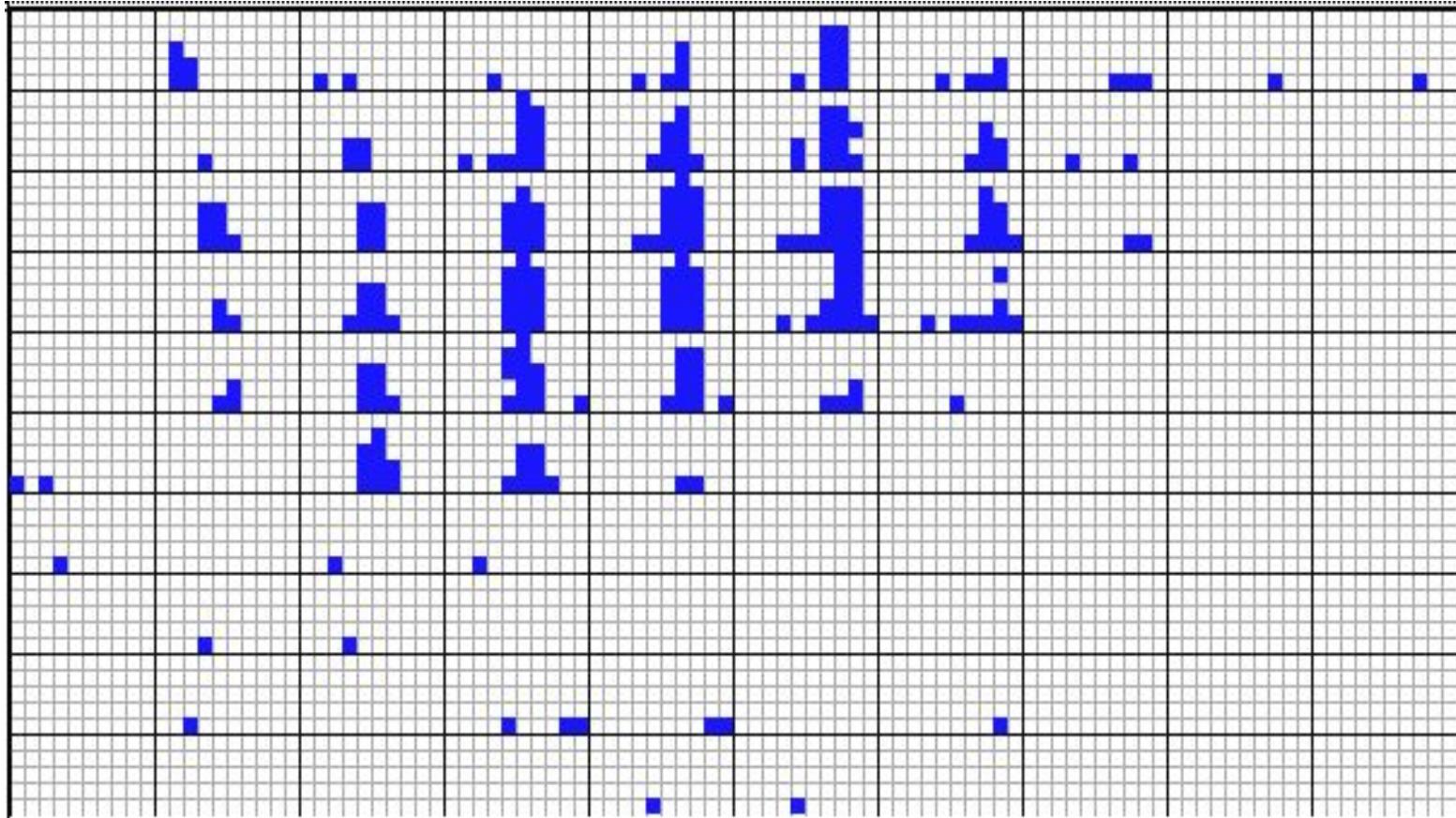
Dimensional Stacking



- 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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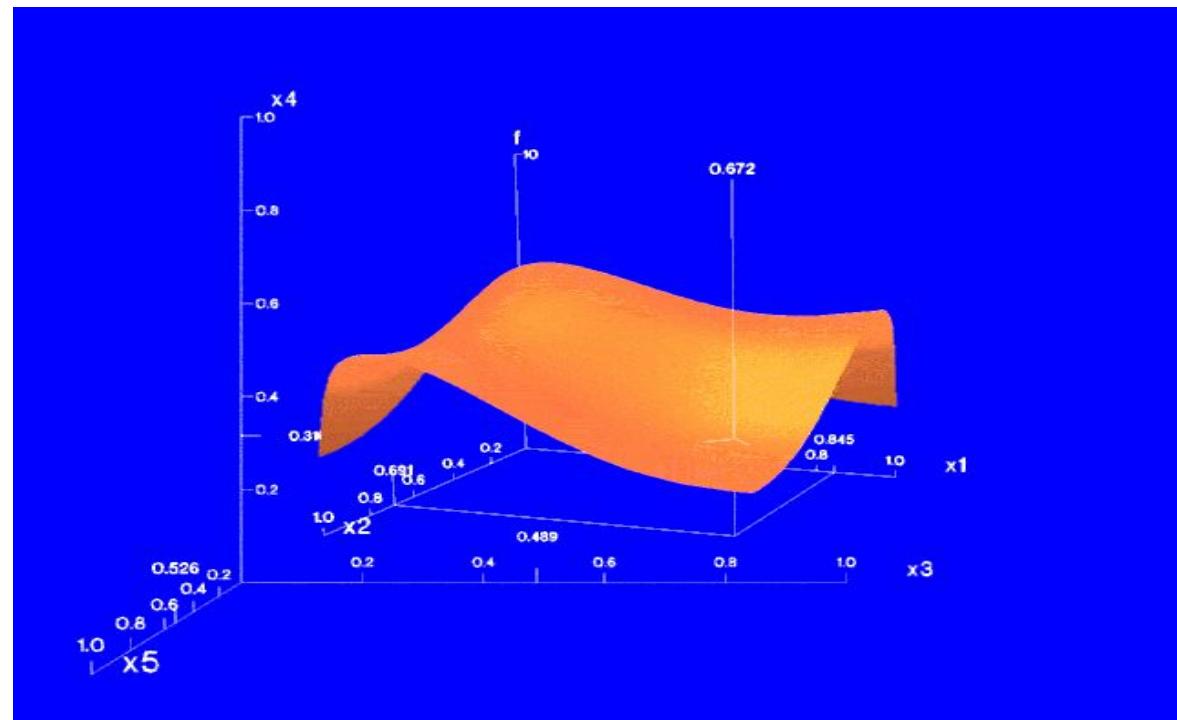


Visualization of oil mining data with longitude and latitude mapped to the outer x-, y-axes and ore grade and depth mapped to the inner x-, y-axes

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

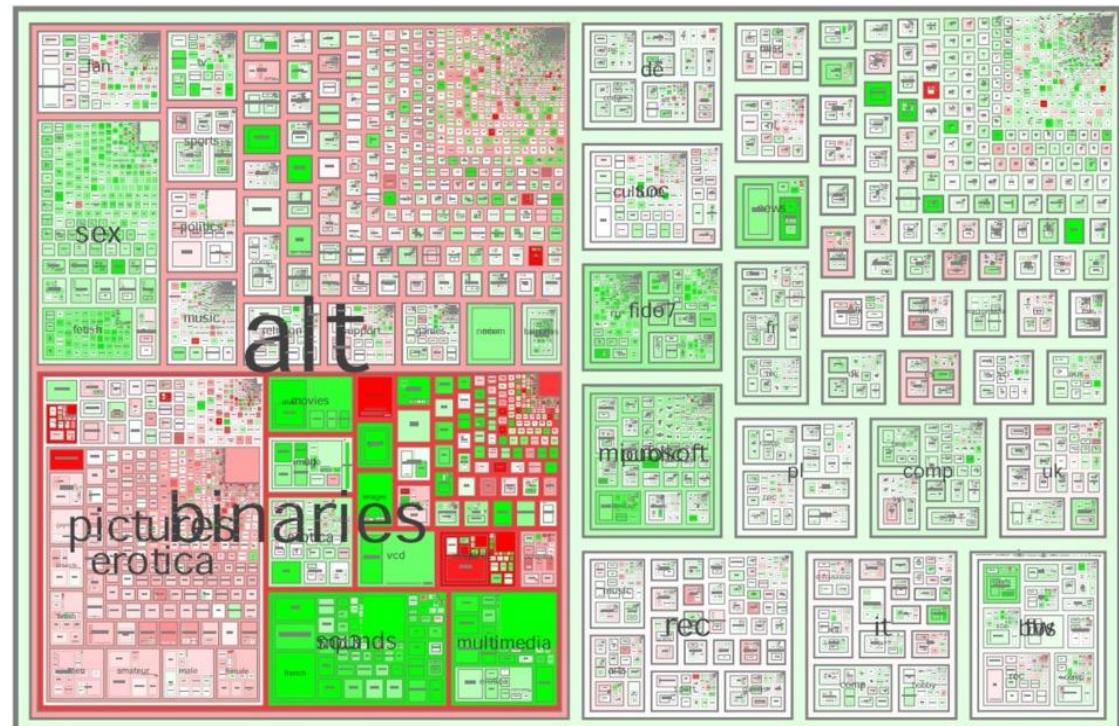
- N-vision: Dynamic interaction through data glove and stereo displays, including rotation, scaling (inner) and translation (inner/outer)
- Auto Visual: Static interaction by means of queries



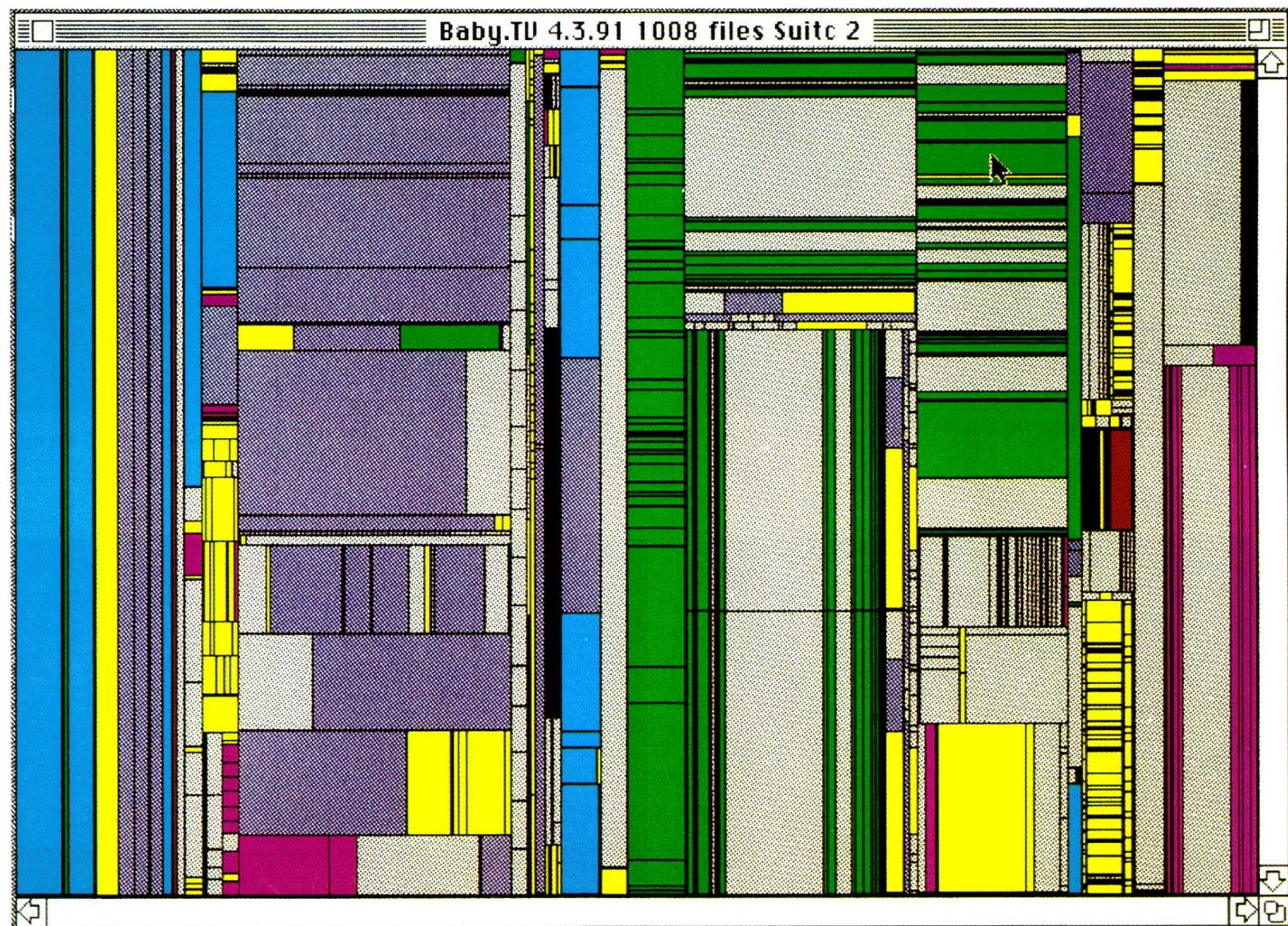
Tree-Map

- 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)



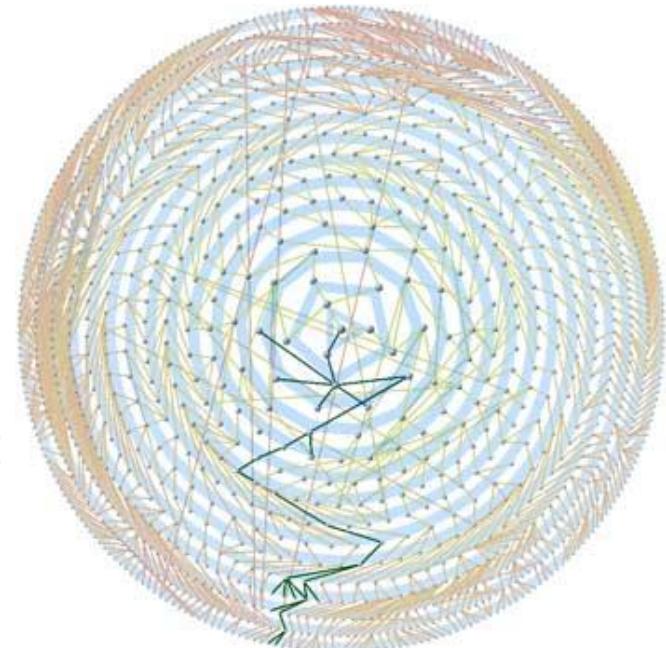
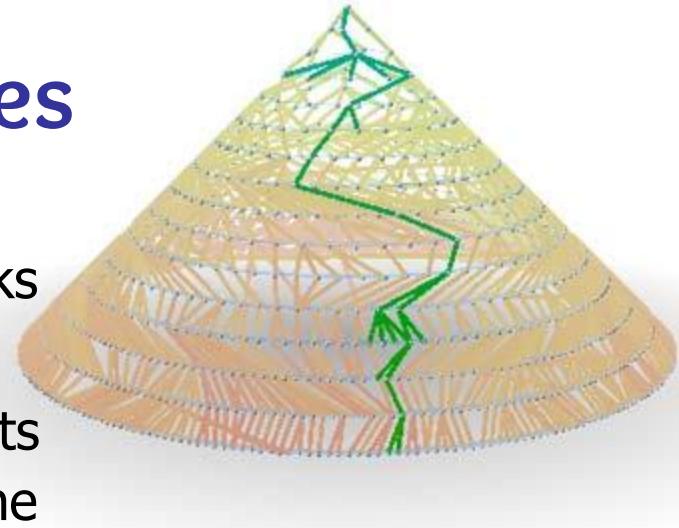
InfoCube

- 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

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

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

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

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

- Note: Jaccard coefficient is the same as "coherence":

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

Dissimilarity between Binary Variables

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

		Object j	
		1	0
1	1	q	r
	0	s	t
sum		$q + s$	$r + t$
			p

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

$$r = 0, \\ s = 1, \\ q = 2, \\ t = 3$$

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

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

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

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

		Object j			
		Object i	1	0	sum
Obj i	Obj j	1	q	r	q+r
		0	s	t	s+t
		sum	q+s	r+t	p

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

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

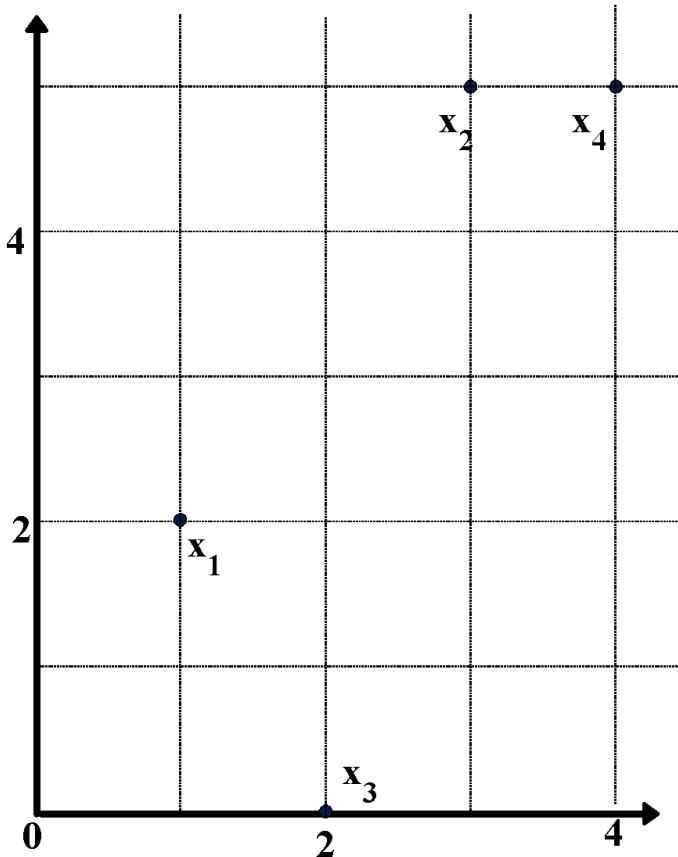
where
$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + \dots + |x_{nf} - m_f|)$$

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

- standardized measure (z-score):
$$z_{if} = \frac{x_{if} - m_f}{s_f}$$
- Using mean absolute deviation is more robust than using standard deviation

Example:

Data Matrix and Dissimilarity Matrix



Data Matrix

point	attribute1	attribute2
x_1	1	2
x_2	3	5
x_3	2	0
x_4	4	5

Dissimilarity Matrix

(with Euclidean Distance)

	x_1	x_2	x_3	x_4
x_1	0			
x_2	3.61	0		
x_3	5.1	5.1	0	
x_4	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

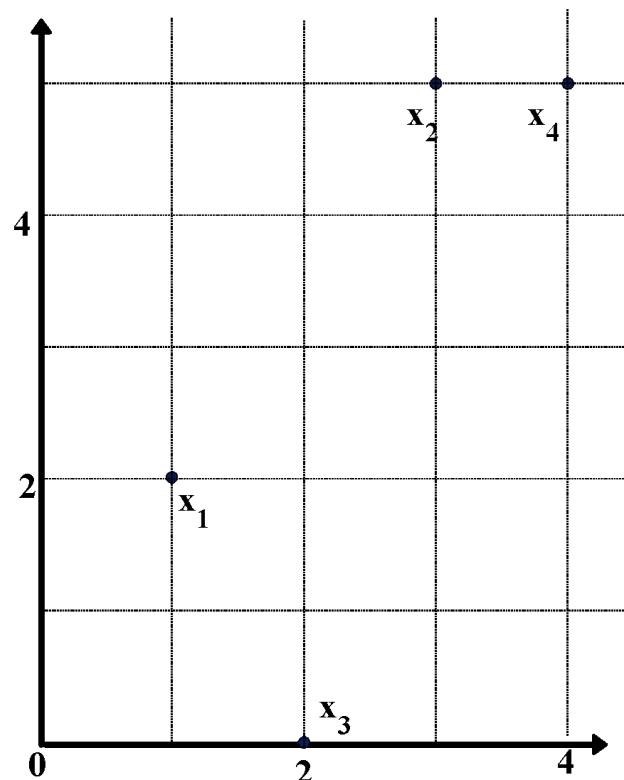
$$d(i, j) = \sqrt{(|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \dots + |x_{ip} - x_{jp}|^2)}$$

- $h \rightarrow \infty$. “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
 - map the range of each variable i onto $[0; 1]^M$ 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

Army_rank = Soldier, L10, Cap, Maj, Col, G
1, 2, 3, 4, 5, 6

J = M, Ma = Col, J = General

J = (4-1)/(6-1) = 3/5, Ma = (5-1)/(6-1) = 4/5, J = (6-1)/(6-1) = 1

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

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

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

Example: Cosine Similarity

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

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

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

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

$$\|d_1\| = \sqrt{(5*5 + 0*0 + 3*3 + 0*0 + 2*2 + 0*0 + 0*0 + 2*2 + 0*0 + 0*0)}^{0.5} = (42)^{0.5} \\ = 6.481$$

$$\|d_2\| = \sqrt{(3*3 + 0*0 + 2*2 + 0*0 + 1*1 + 1*1 + 0*0 + 1*1 + 0*0 + 1*1)}^{0.5} = (17)^{0.5} \\ = 4.12$$

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

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



Assignment

- A CSV will be shared having some data that is divided into some columns/attributes
- Say, there are 4 attributes, X, Y, Z, W
- W is the target attr.
- Your task is to analyze the data and visualize it if needed to figure out the relation/correlation with /impacts of X, Y, Z, (X, Y), (Y, Z), (X, Z) or (X, Y, Z) on W
- 14 days after the assignment is announced
- Work in a group of 2
- JT's complexity and construction time may be affected by the following attributes:

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.

References

- W. Cleveland, Visualizing Data, Hobart Press, 1993
- T. Dasu and T. Johnson. Exploratory Data Mining and Data Cleaning. John Wiley, 2003
- U. Fayyad, G. Grinstein, and A. Wierse. Information Visualization in Data Mining and Knowledge Discovery, Morgan Kaufmann, 2001
- L. Kaufman and P. J. Rousseeuw. Finding Groups in Data: an Introduction to Cluster Analysis. John Wiley & Sons, 1990.
- H. V. Jagadish, et al., Special Issue on Data Reduction Techniques. Bulletin of the Tech. Committee on Data Eng., 20(4), Dec. 1997
- D. A. Keim. Information visualization and visual data mining, IEEE trans. on Visualization and Computer Graphics, 8(1), 2002
- D. Pyle. Data Preparation for Data Mining. Morgan Kaufmann, 1999
- S. Santini and R. Jain," Similarity measures", IEEE Trans. on Pattern Analysis and Machine Intelligence, 21(9), 1999
- E. R. Tufte. The Visual Display of Quantitative Information, 2nd ed., Graphics Press, 2001
- C. Yu , et al., Visual data mining of multimedia data for social and behavioral studies, Information Visualization, 8(1), 2009