Concepts and Techniques

— Chapter 2 —
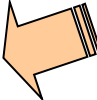
Jiawei Han, Micheline Kamber, and Jian Pei

University of Illinois at Urbana-Champaign

Simon Fraser University

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	win	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: "red", "black", "blue", …
  - Binary: 1/0, TRUE/FALSE
  - 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
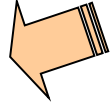
- **Discrete Attribute**
  - Has only a **finite or countably infinite** set of values
    - E.g., zip codes, profession, or the set of words in a collection of documents
  - Sometimes, represented as integer variables
  - Note: Binary attributes are a special case of discrete attributes
- **Continuous 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):

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

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

  - 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*):

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

- Mode

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

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

Symmetric vs. Skewed Data

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

symmetric

Mean
Median
Mode

positively skewed

Mode
Mean
Median

negatively skewed

Mean
Mode
Median
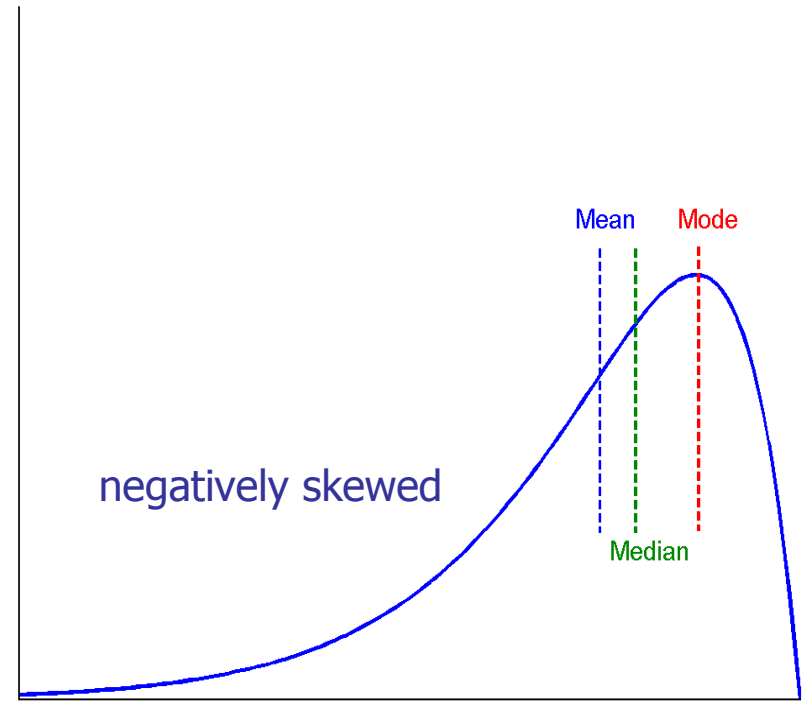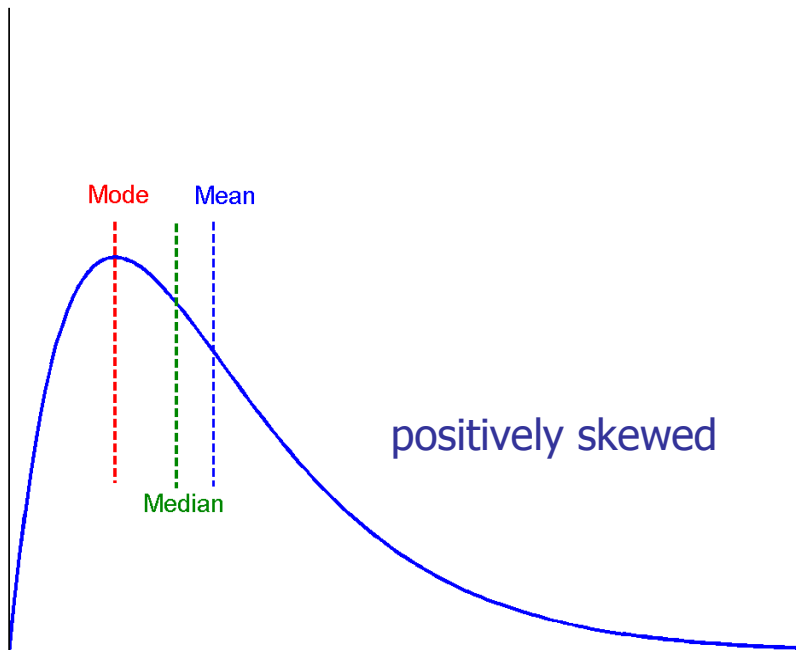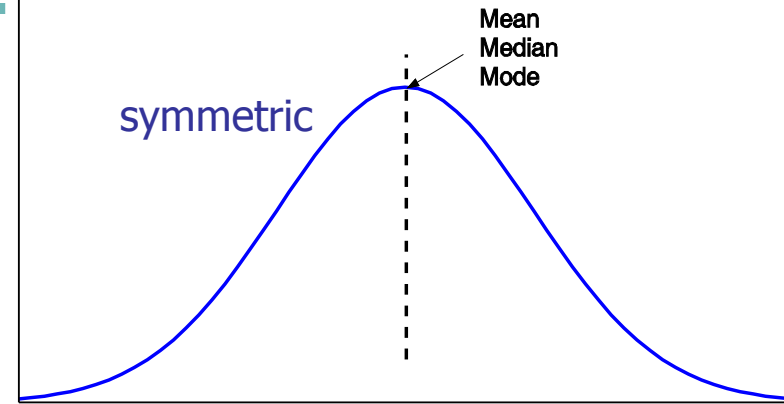
Measuring the Dispersion of Data

- Quartiles, outliers and boxplots

  - **Quartiles**: Q_1 (25th percentile), Q_3 (75th percentile)

  - **Inter-quartile range**: IQR = $Q_3 - Q_1$

  - **Five number summary**: min, Q_1, 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 x IQR

- Variance and standard deviation (*sample: s, population: σ*)

  - **Variance**: (algebraic, scalable computation)

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

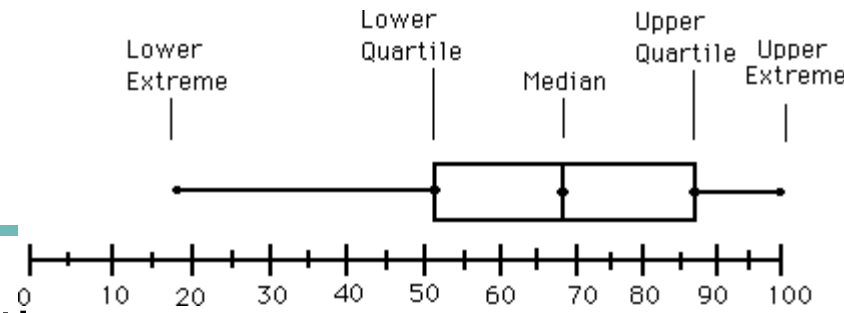 - **Standard deviation** *s (or σ)* is the square root of variance s^2 *(or σ^2)*

Properties of Normal Distribution Curve

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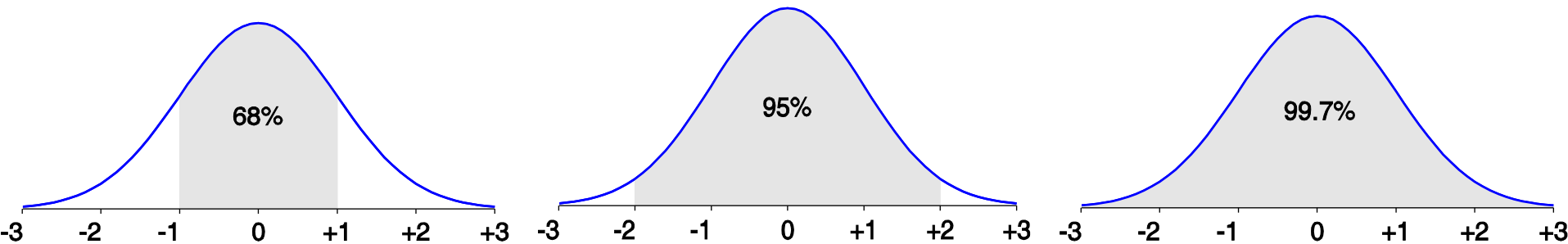
Boxplot Analysis

- **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
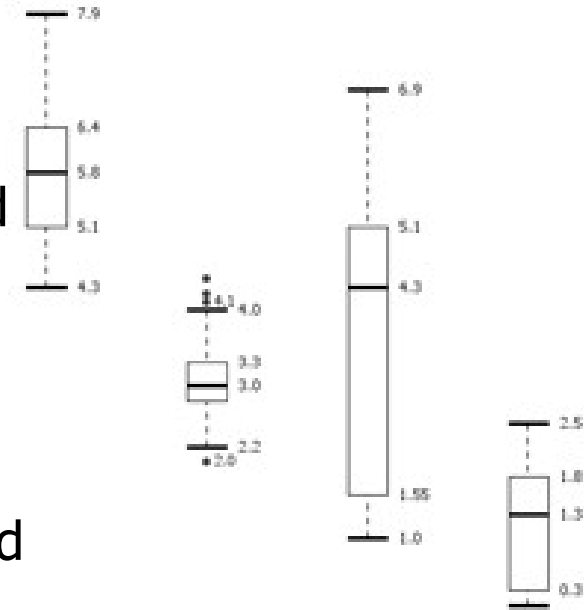
Visualization of Data Dispersion: 3-D Boxplots
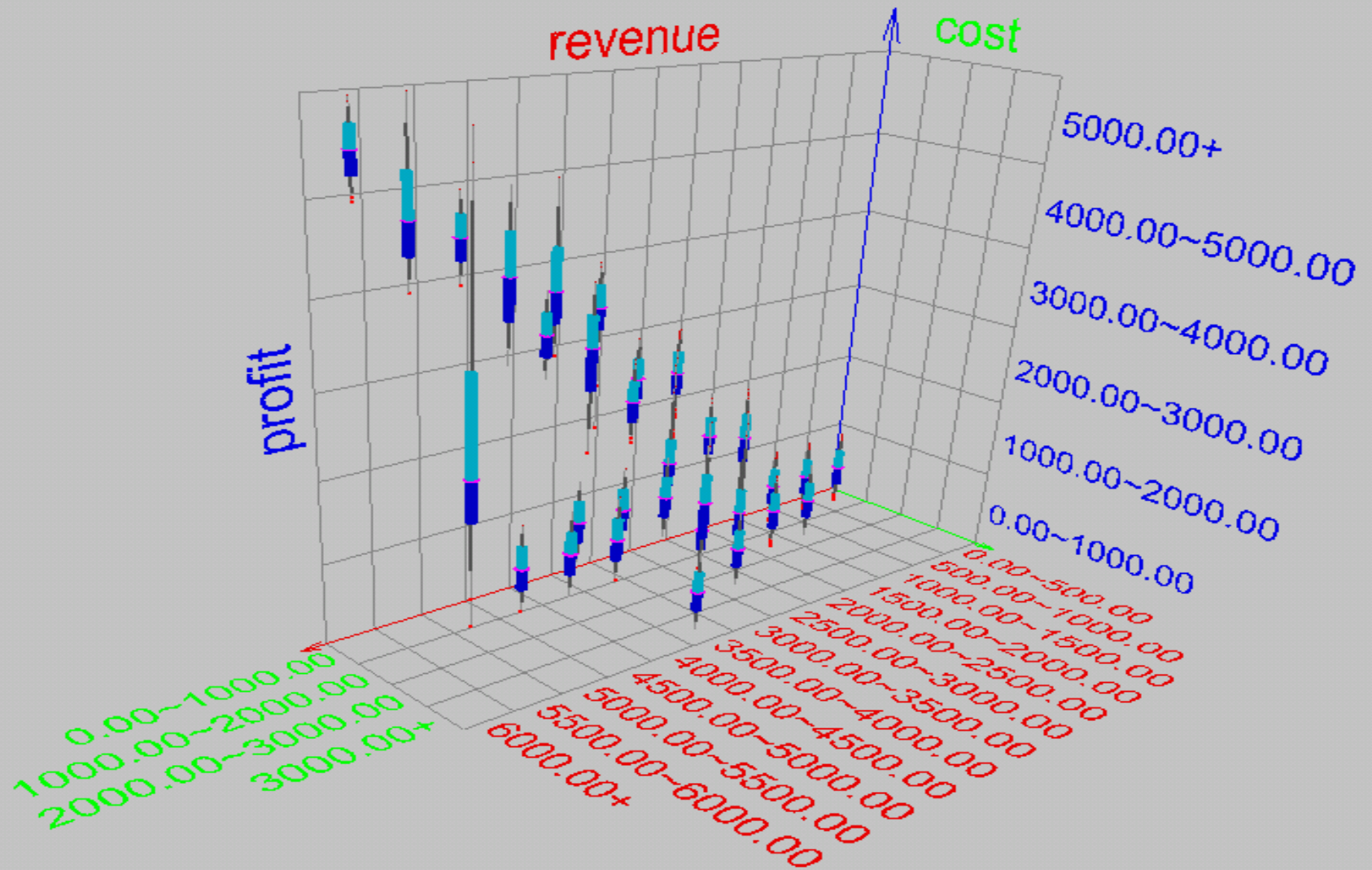
Graphic Displays of Basic Statistical Descriptions

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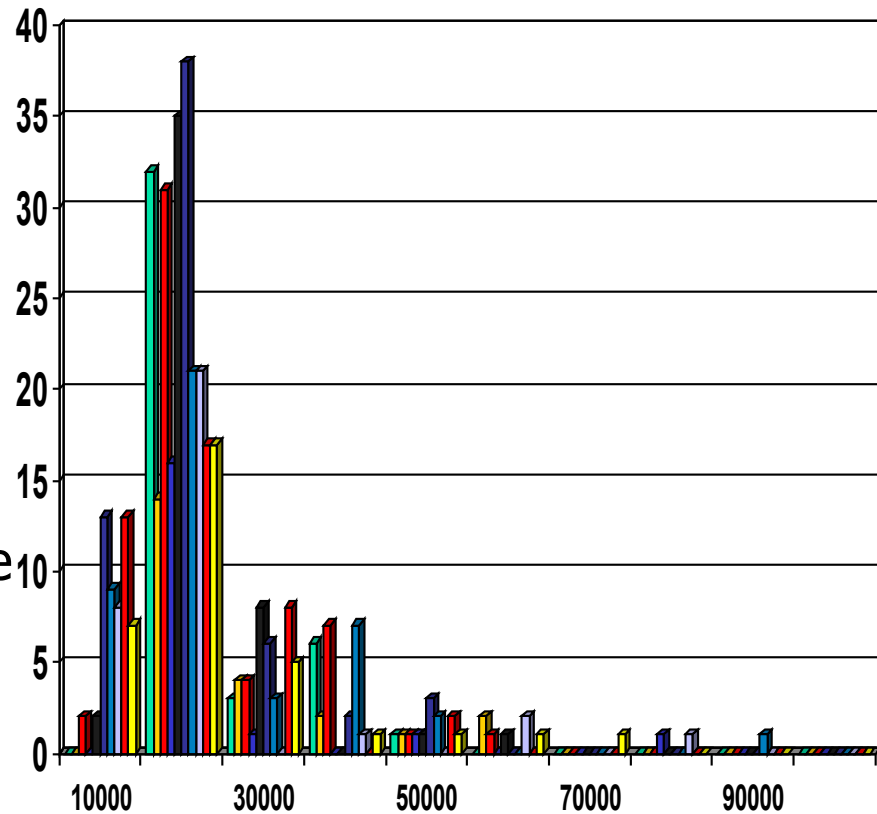
Histograms Often Tell More than Boxplots
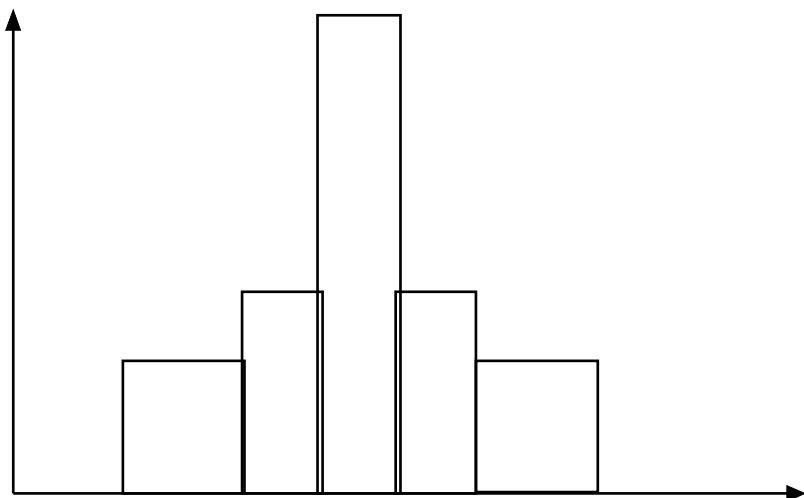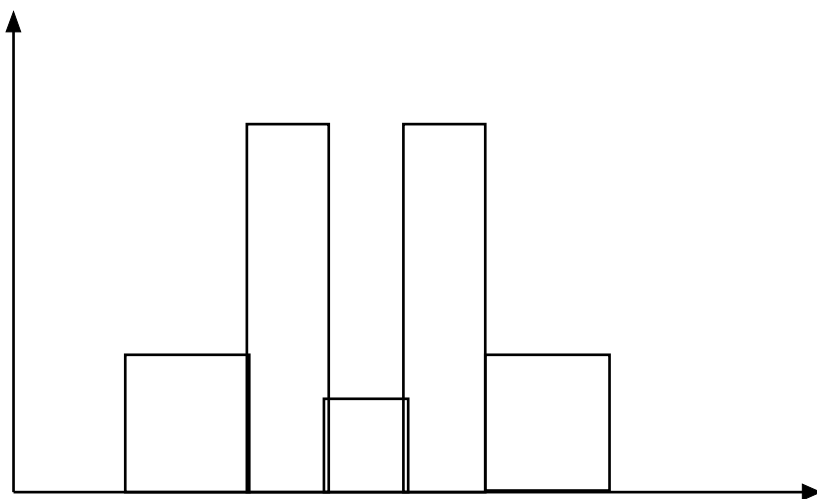
- The two histograms shown in the left may have the same boxplot representation
  - The same values for: min, Q1, median, Q3, max
- But they have rather different data distributions

Quantile Plot

- Displays all of the data (allowing the user to assess both the overall behavior and unusual occurrences)
- Plots **quantile** information
    - Let data x_i data sorted in increasing order
    - f_i indicates that approximately $100\ f_i\%$ of the data $\leq$ to the value x_i
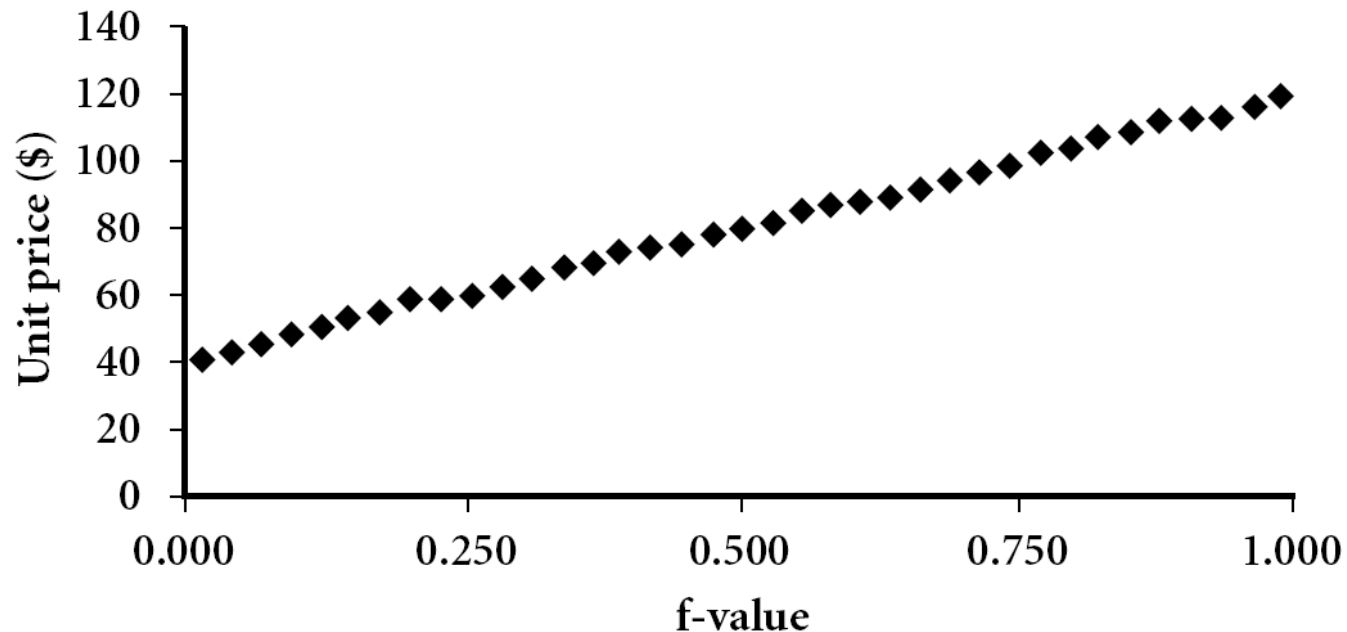
Quantile-Quantile (Q-Q) Plot

- 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.
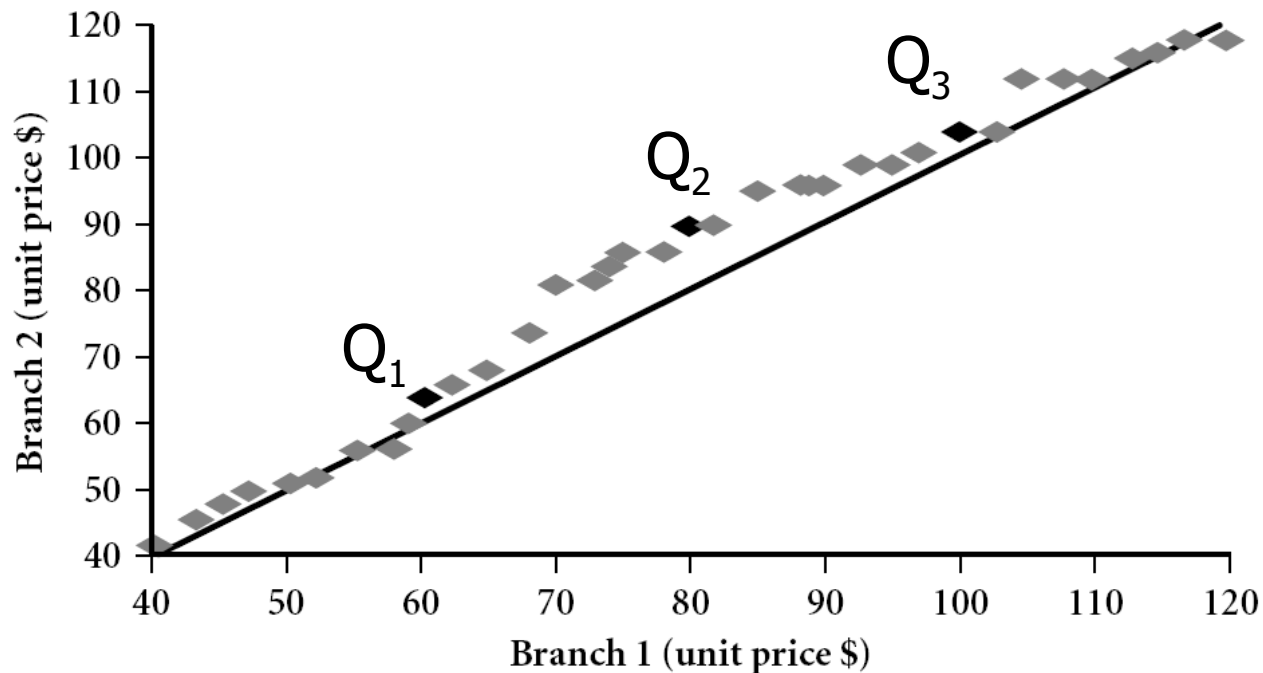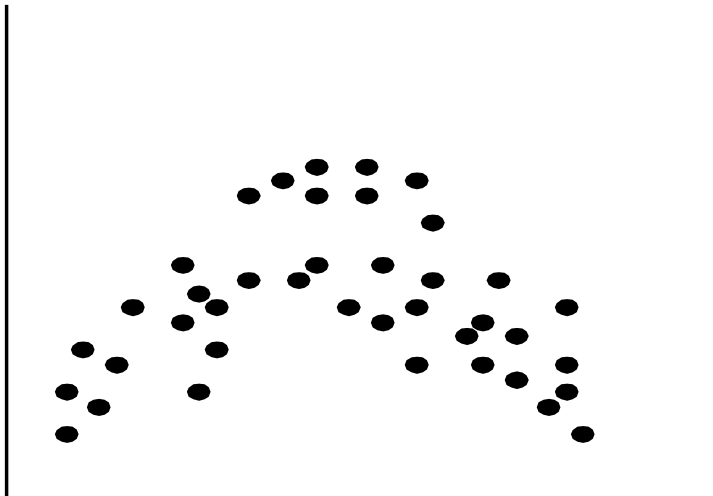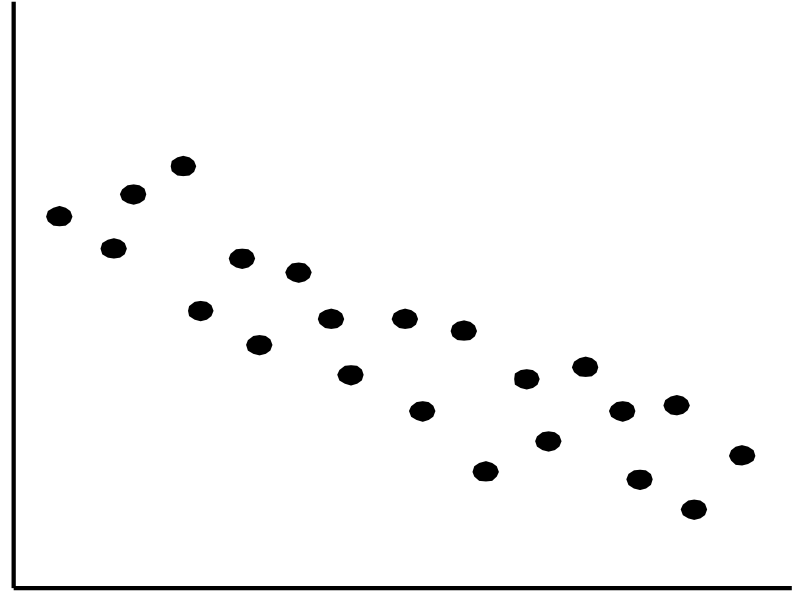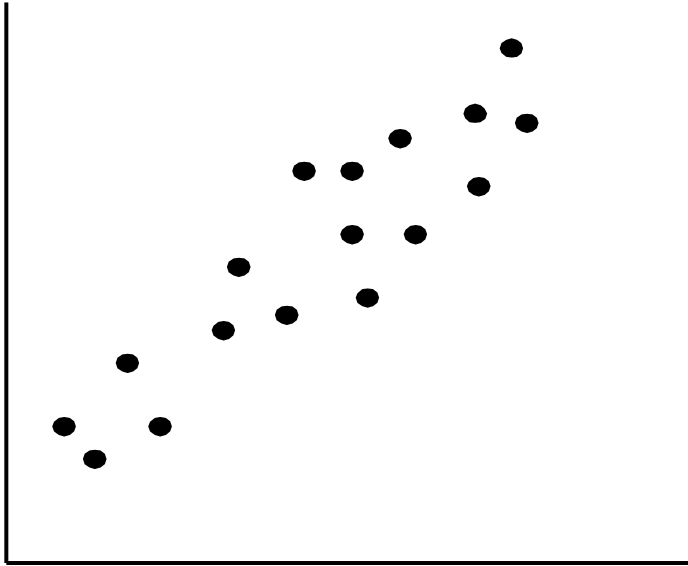
Scatter plot

- 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
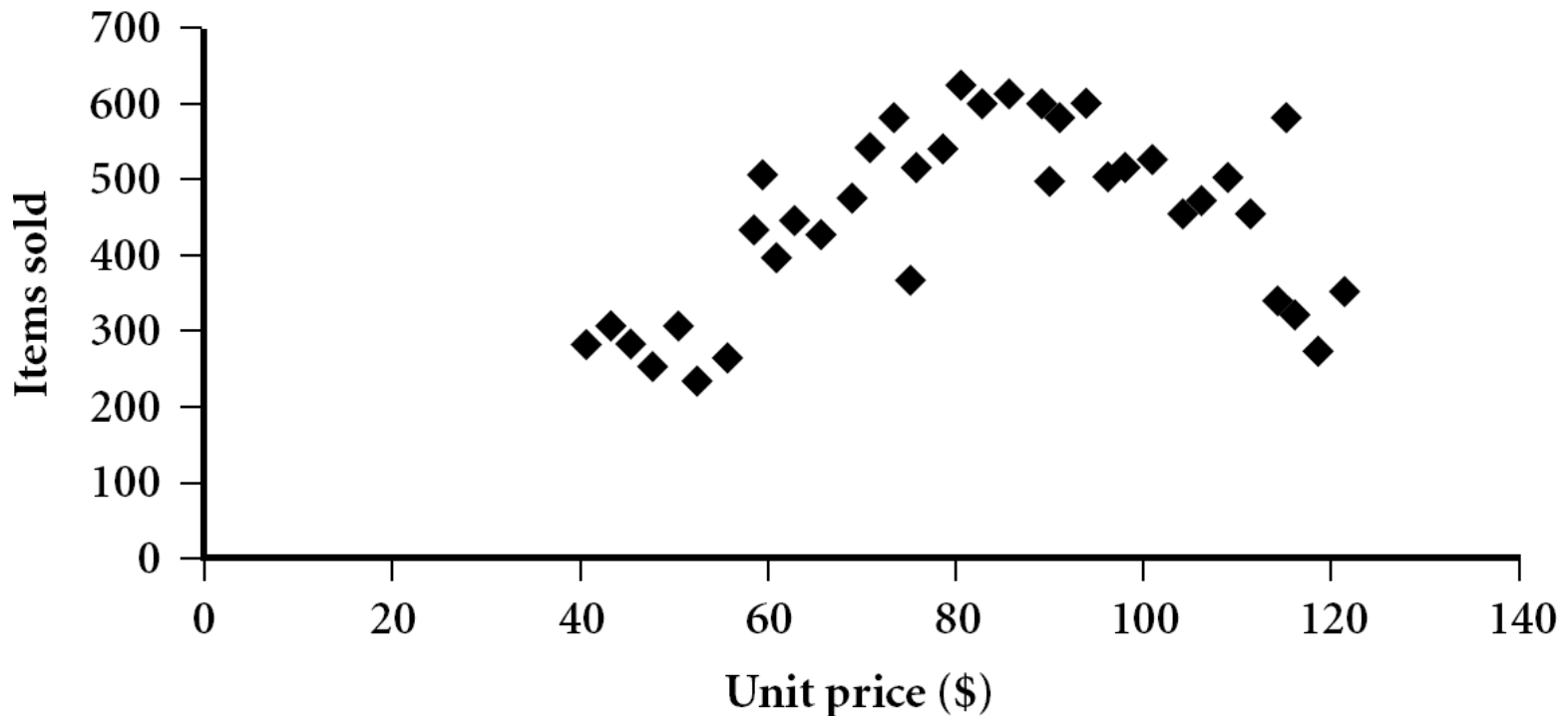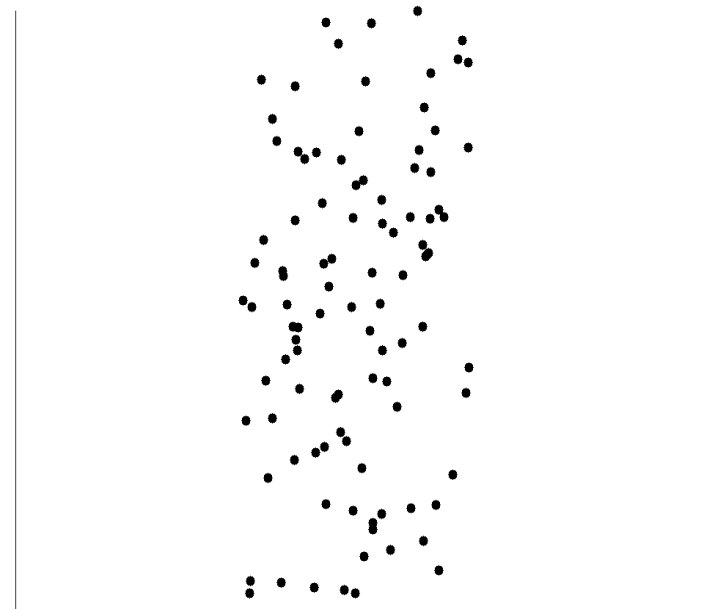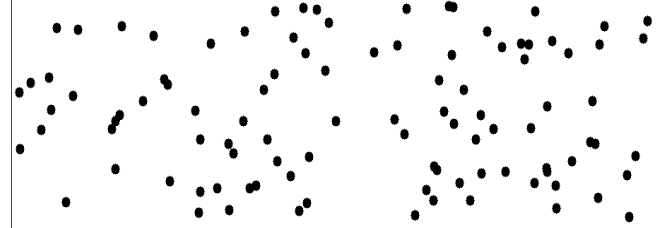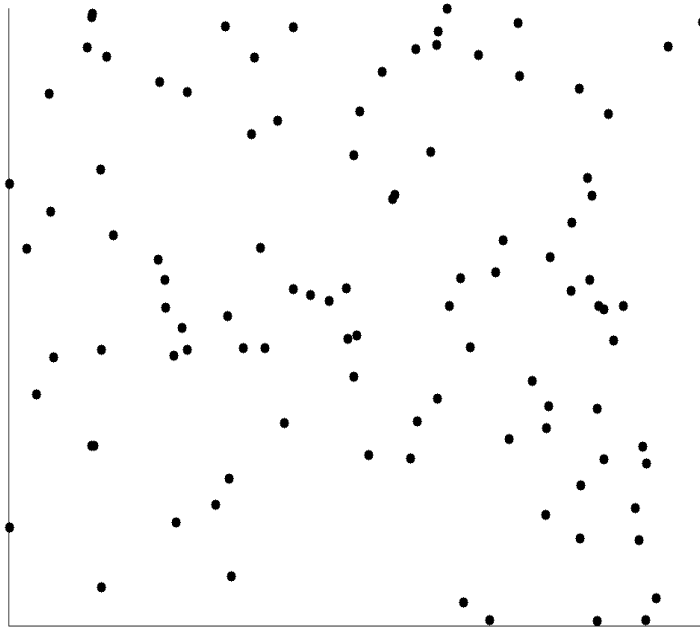
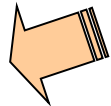# Positively and Negatively Correlated Data

- 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
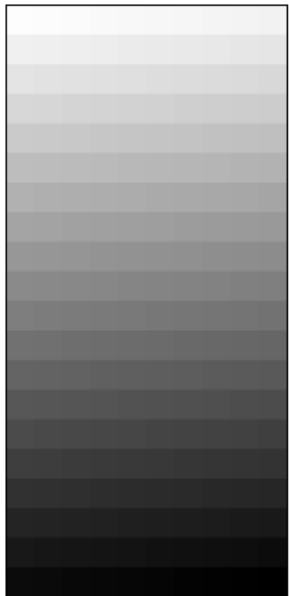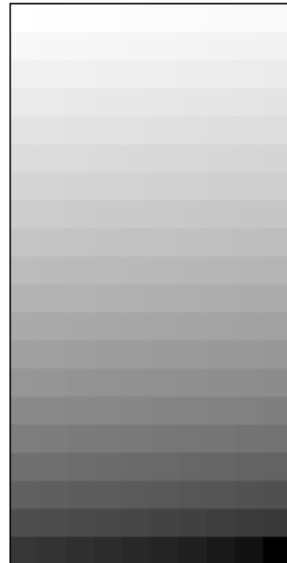
(a) Income   (b) Credit Limit   (c) transaction volume   (d) age
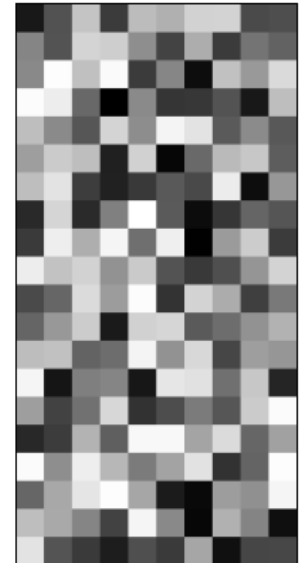
Laying Out Pixels in Circle Segments

- To save space and show the connections among multiple dimensions, space filling is often done in a circle segment
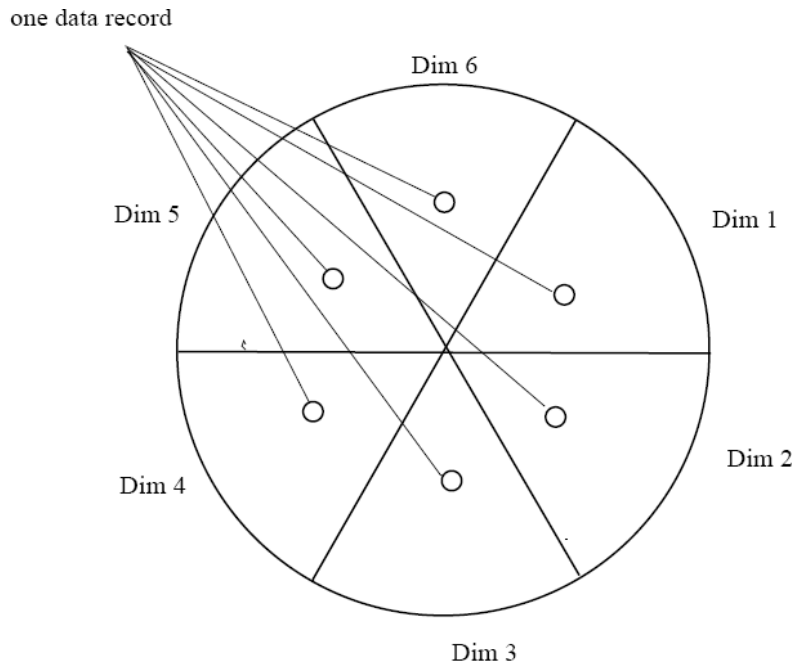
(a) Representing a data record in circle segment
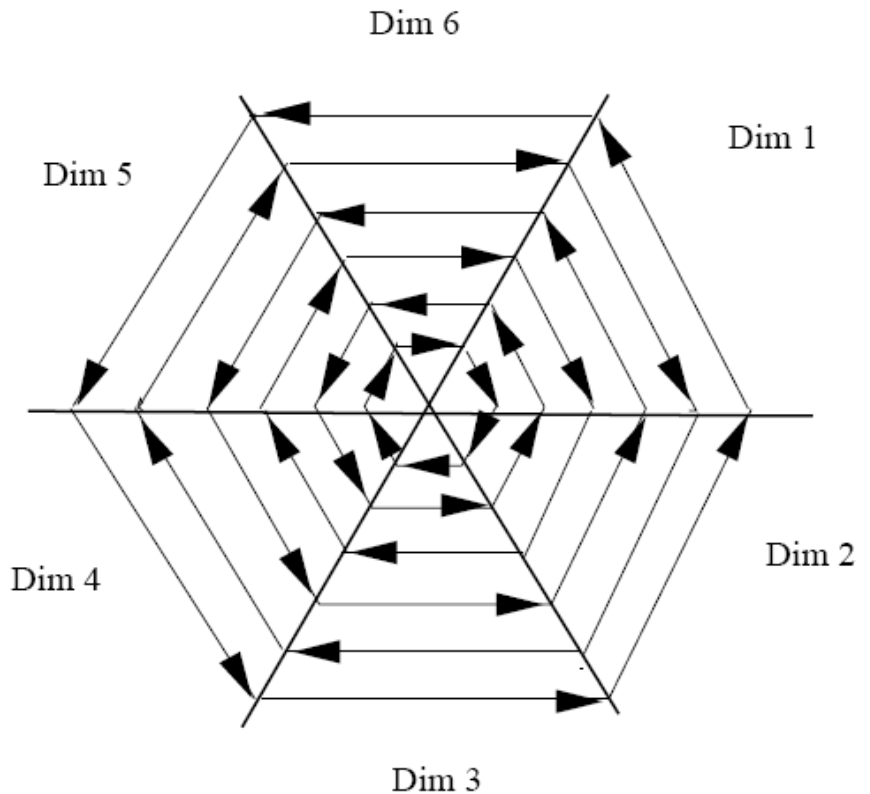
(b) Laying out pixels in circle segment

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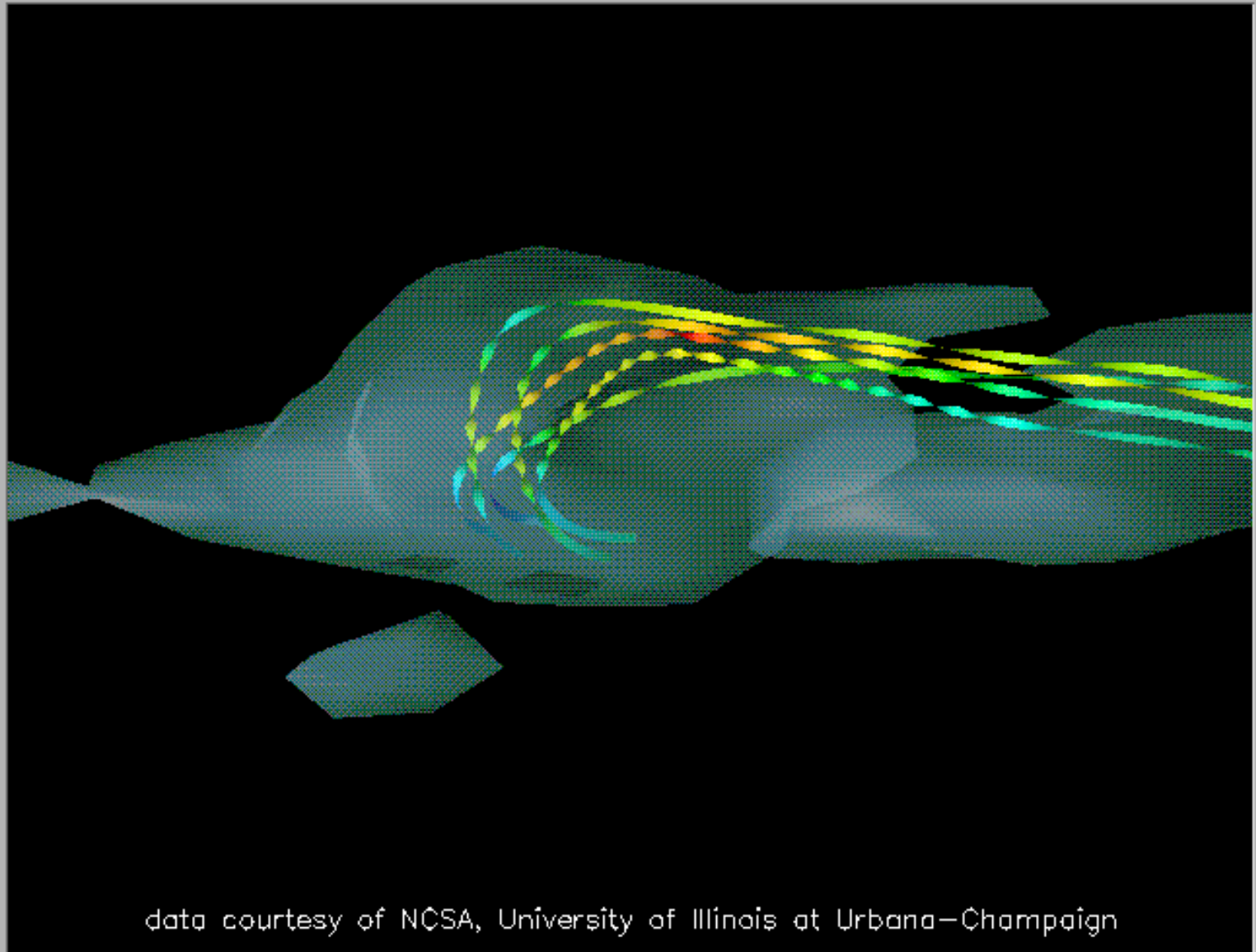
data courtesy of NCSA, University of Illinois at Urbana-Champaign

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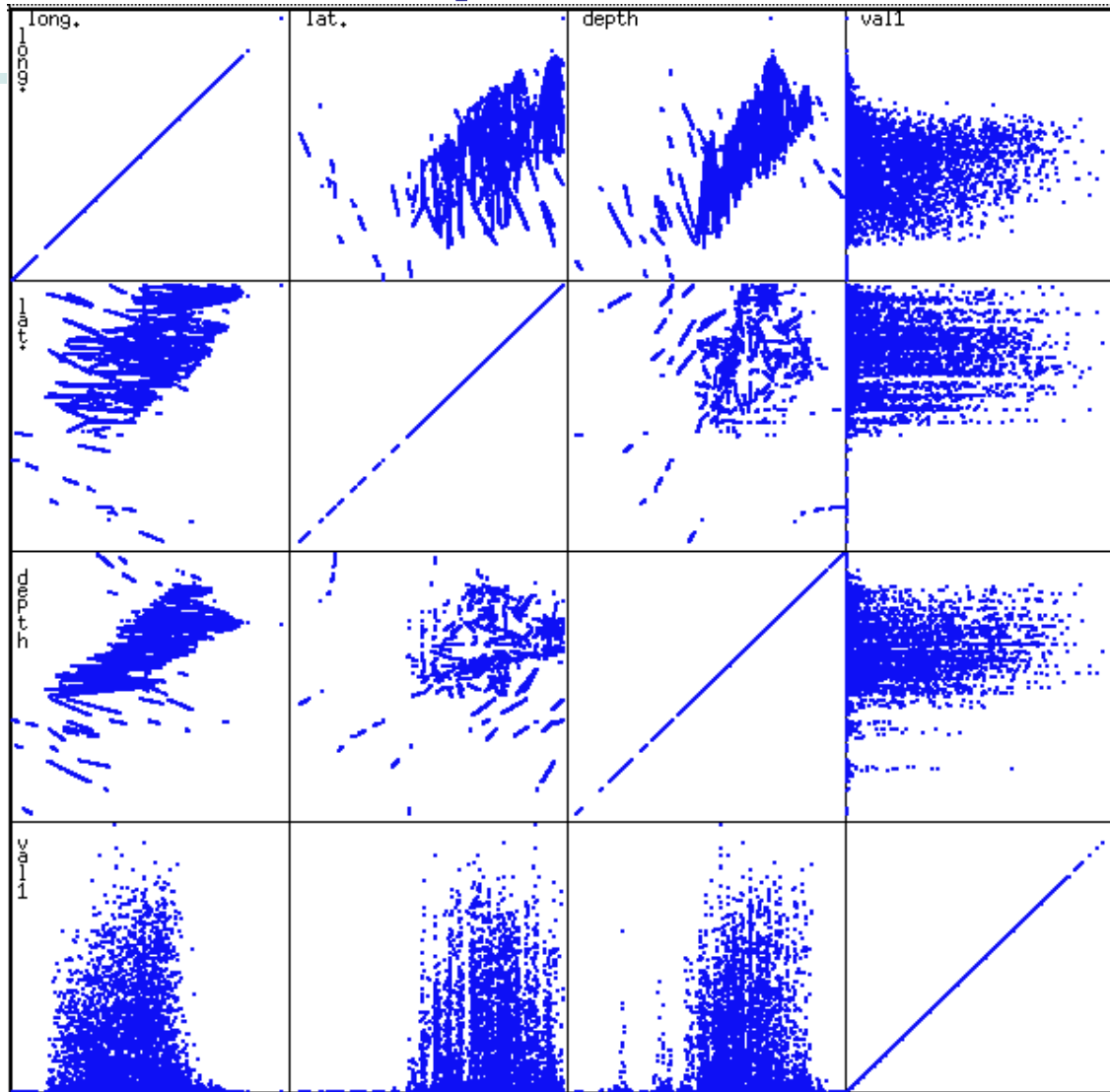
Matrix of scatterplots (x-y-diagrams) of the k-dim. data [total of $(k^2/2 - k)$ scatterplots]

Landscapes
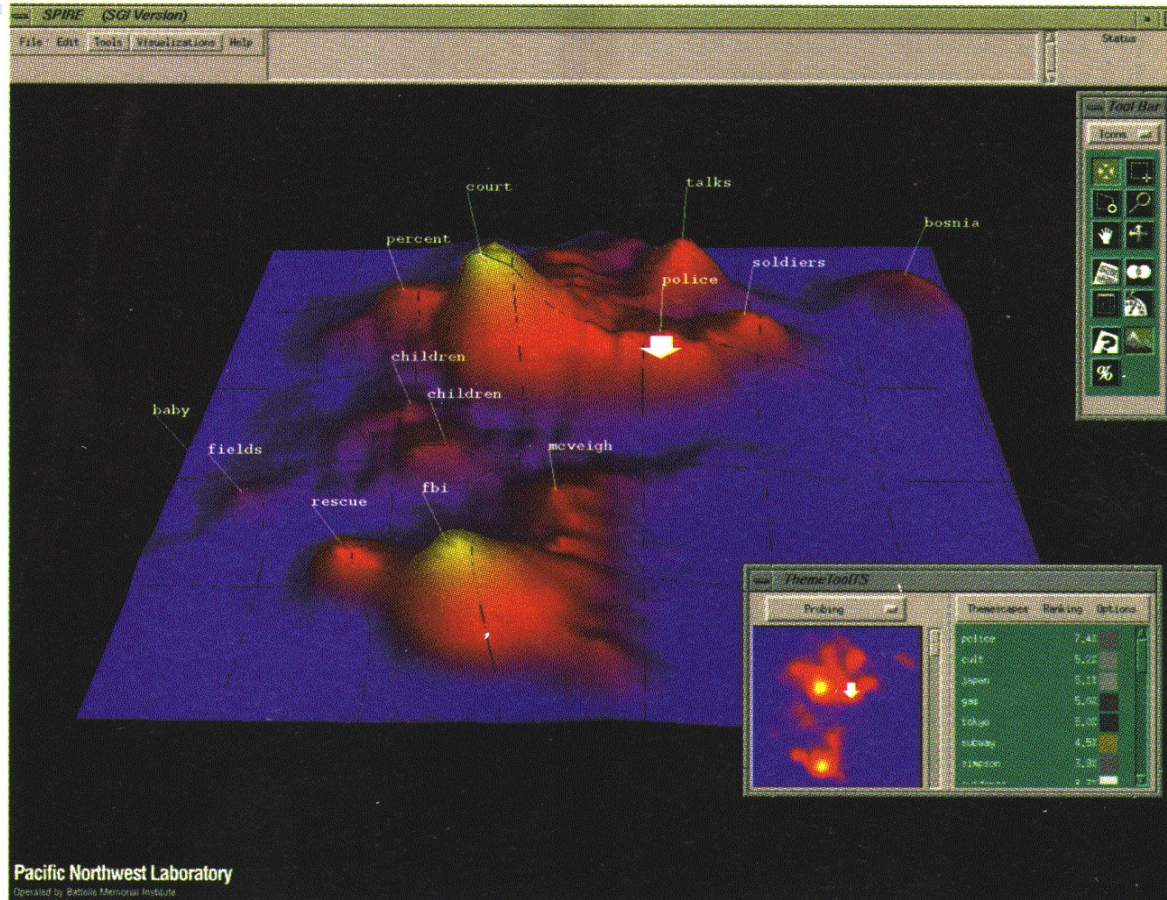
news articles visualized as a landscape

- 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

. . .

A t tr. 1   A t tr. 2   A t tr. 3   A t tr. k

Parallel Coordinates of a Data Set
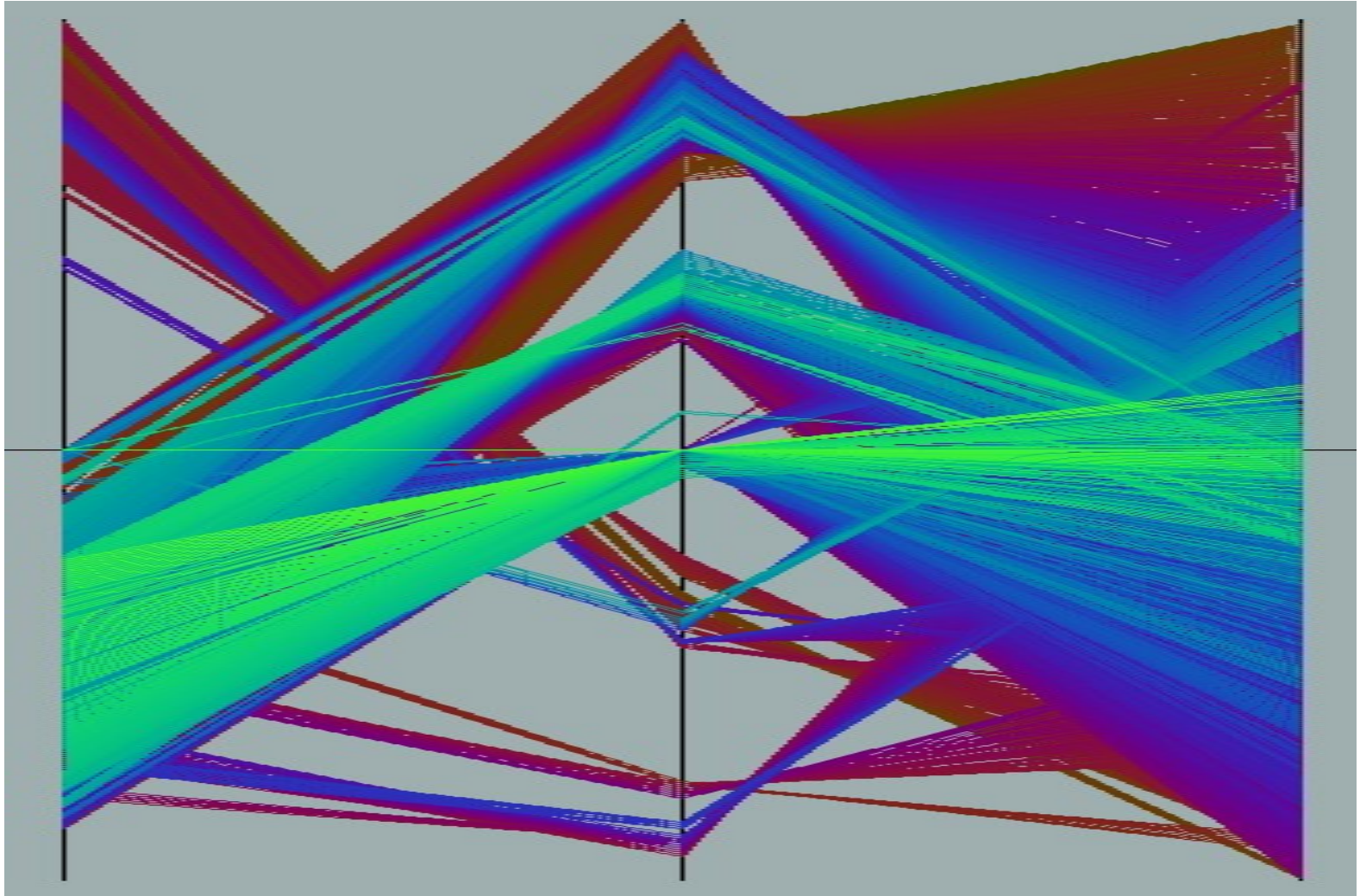
Icon-Based Visualization Techniques

- 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
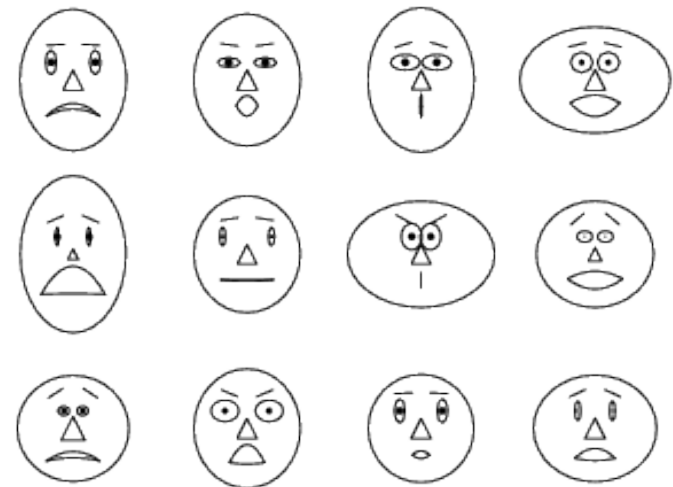
Stick Figure

used by permission of G. Grinstein, University of Massachusettes at Lowell
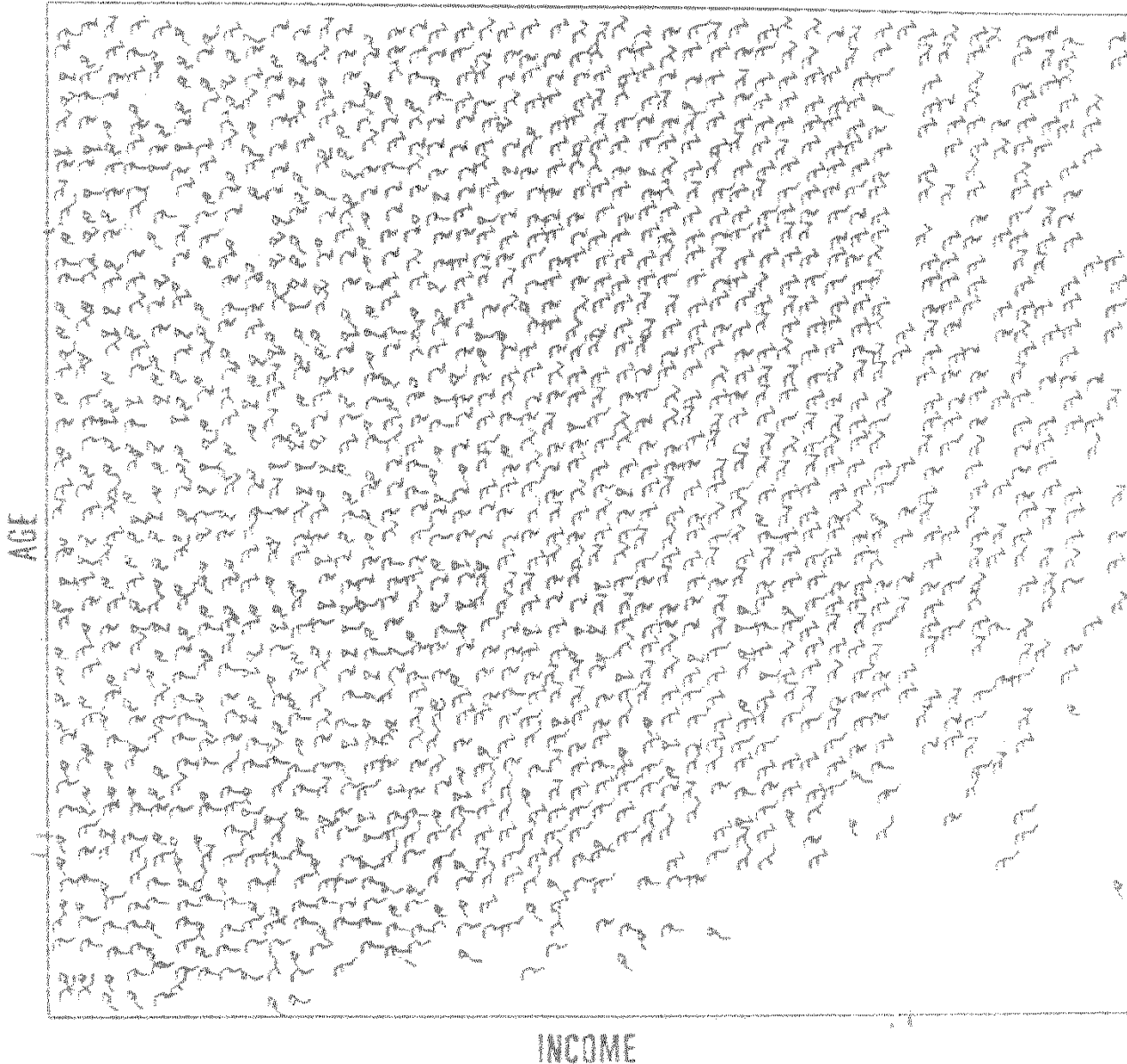
INCOME

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

a t t r i b u te 4

a t t r i b u te 2

a t t r i b u te 3

a t t r i b u te 1

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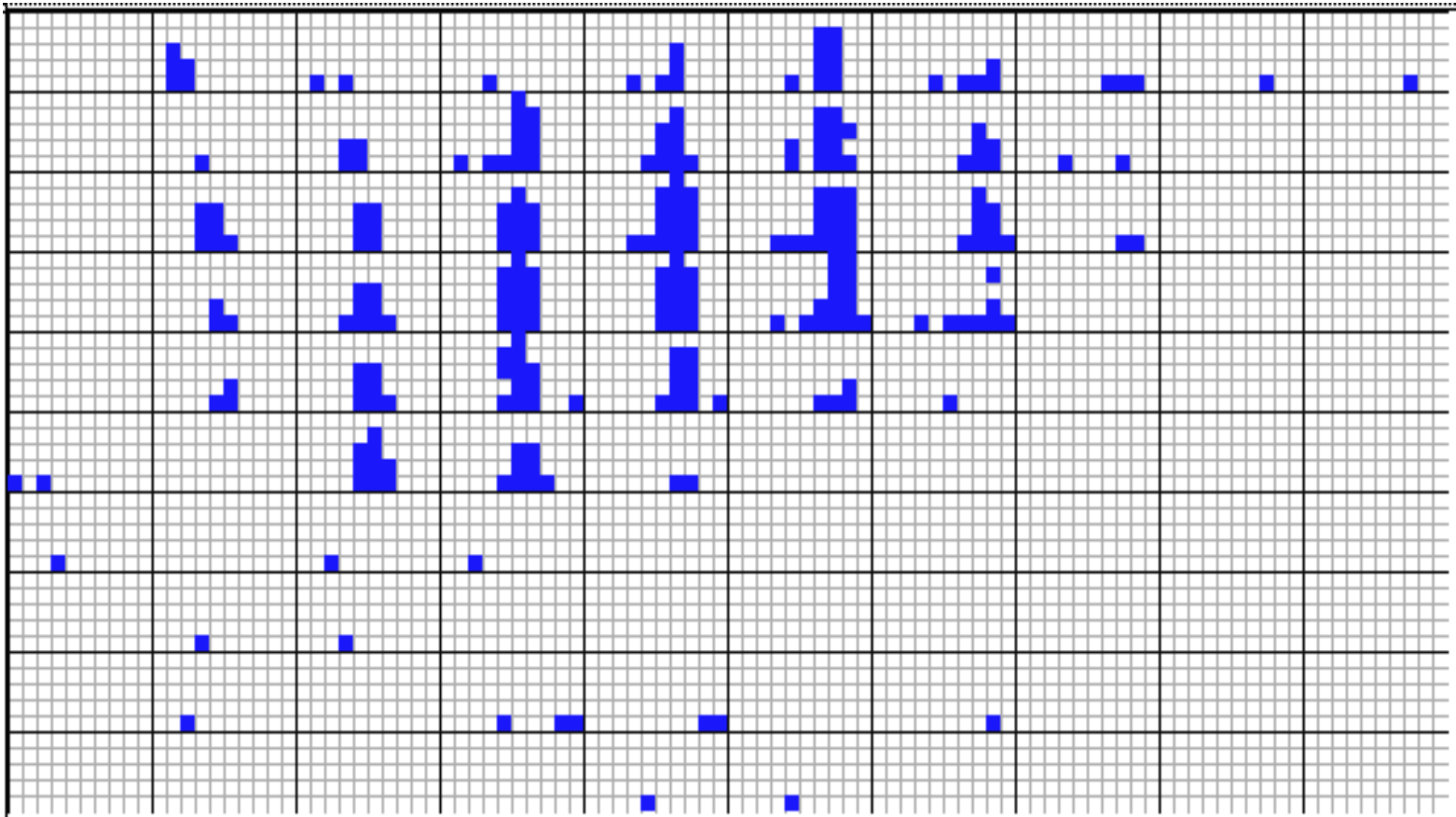
Visualization of oil mining data with longitude and latitude mapped to the outer x-, y-axes and ore grade and depth mapped to the inner x-, y-axes

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
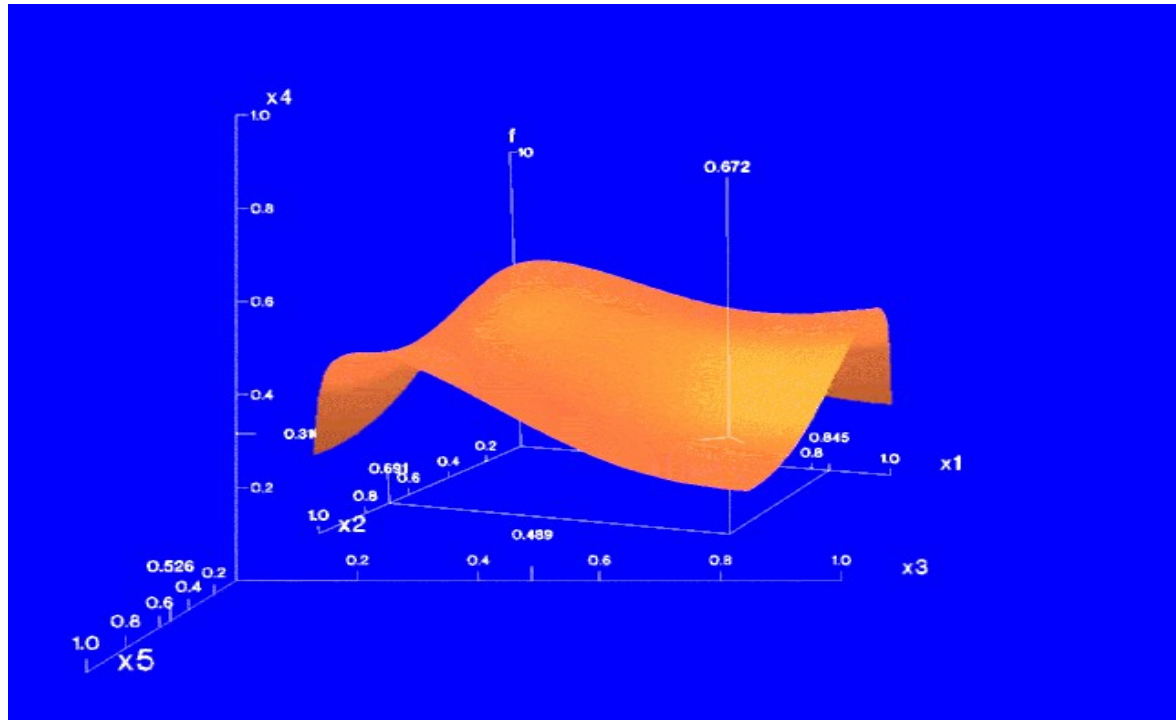
Tree-Map

- 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

Ack.: http://www.cs.umd.edu/hcil/treemap-history/all102001.jpg

43
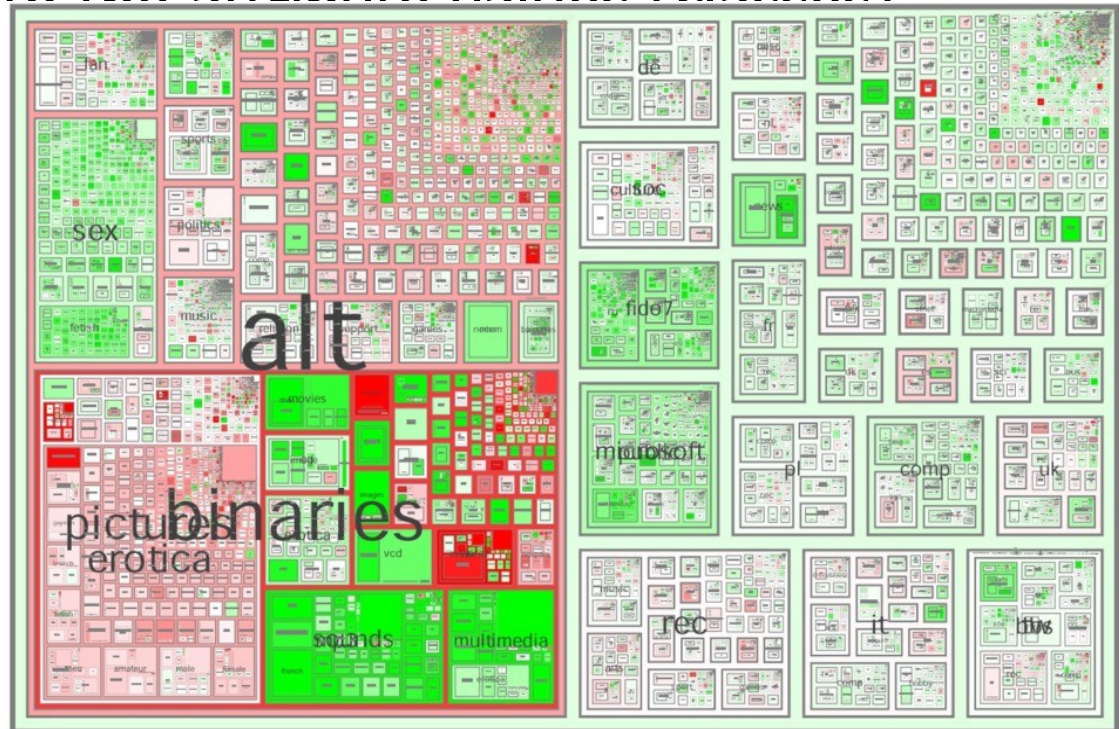
Tree-Map of a File System (Schneiderman)

Baby.TV 4.3.91 1008 files Suite 2
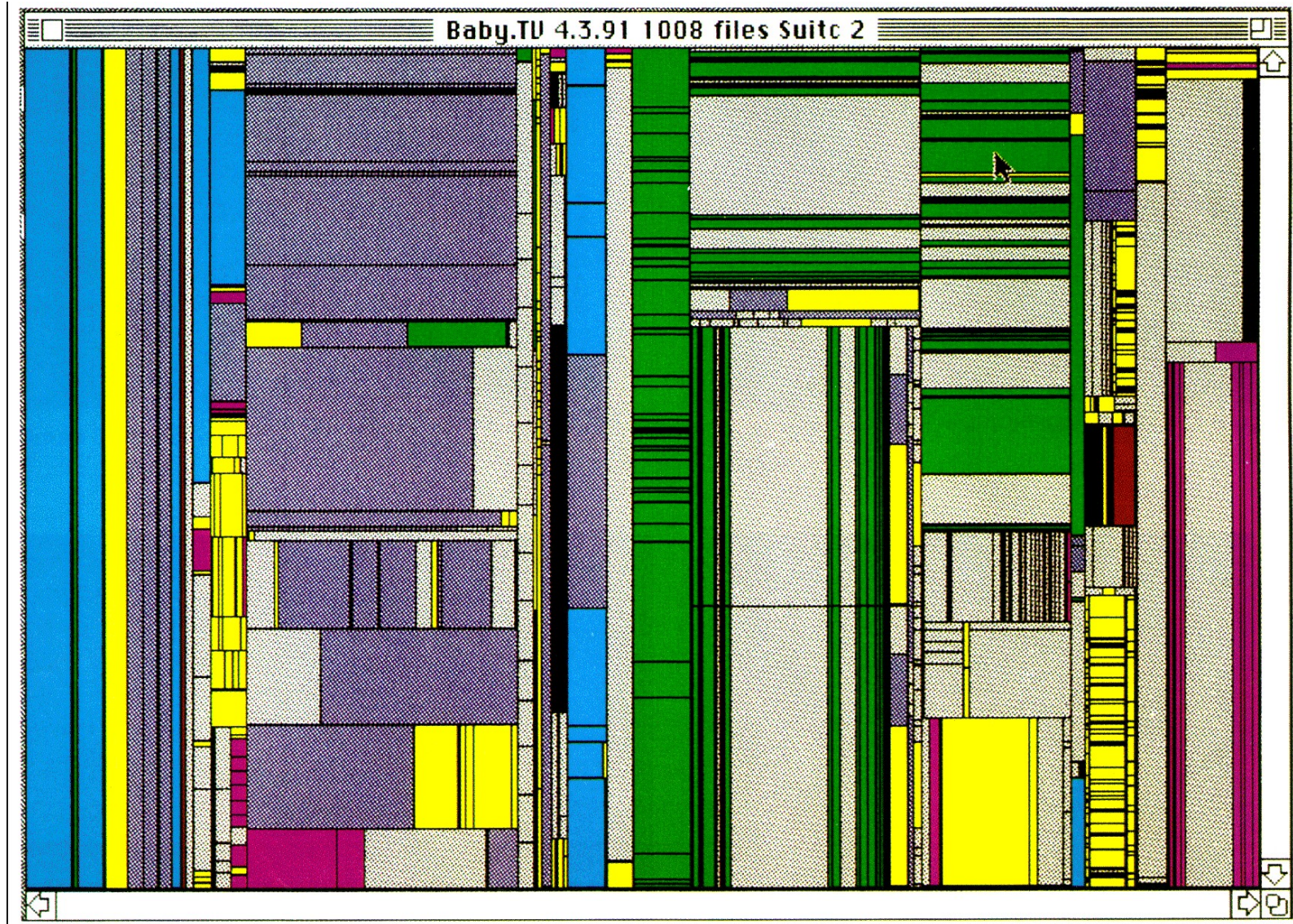
InfoCube

- 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
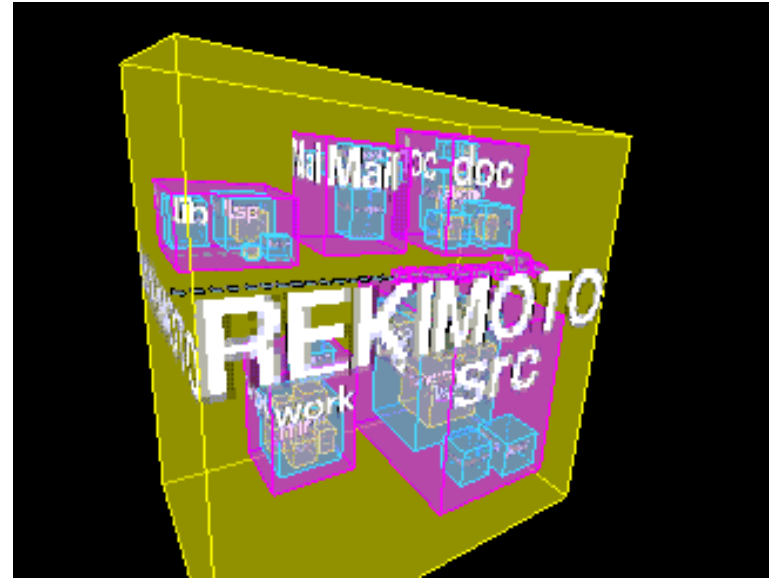
Three-D Cone Trees

- *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
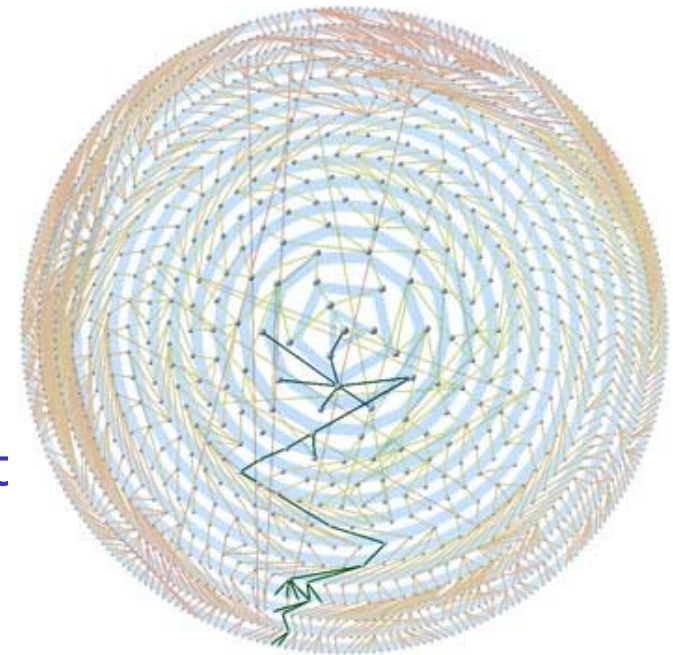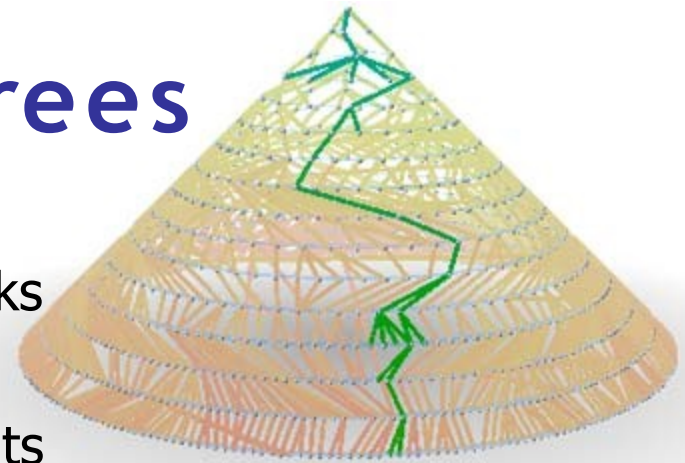
Ack.: http://nadeausoftware.com/articles/visualization

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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- Data Visualization

- Measuring Data Similarity and Dissimilarity

- Summary
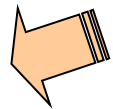
Similarity and Dissimilarity

- **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

p dimensions

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

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

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

Proximity Measure for Nominal Attributes

- Attribute an 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 $\qquad$ (see next slide)

Proximity Measure for Binary Attributes

A contingency table for binary data

Object j

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

- A contingency table for binary data

- Distance measure for symmetric binary variables:

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

- Distance measure for asymmetric binary variables (q = both 1's):

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

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

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

- 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

- ## Example

Name	Gender	Fever		Cough		Test-1		Test-2		Test-3		Test-4	
Jack	M	Y	1	N	0	P	1	N	0	N	0	N	0
Mary	F	Y	1	N	0	P	1	N	0	P	1	N	0
Jim	M	Y	0	P	0	N	0	N	0	N	0	N	0

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

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

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

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

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

	1 mary	0
jack 1	q: 2	r: 0
0	s: 1	t: 3

Standardizing Numeric Data

- Z-score: $z = \dfrac{x - \mu}{\sigma}$
  - 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

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

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

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

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

Example:
Data Matrix and Dissimilarity Matrix
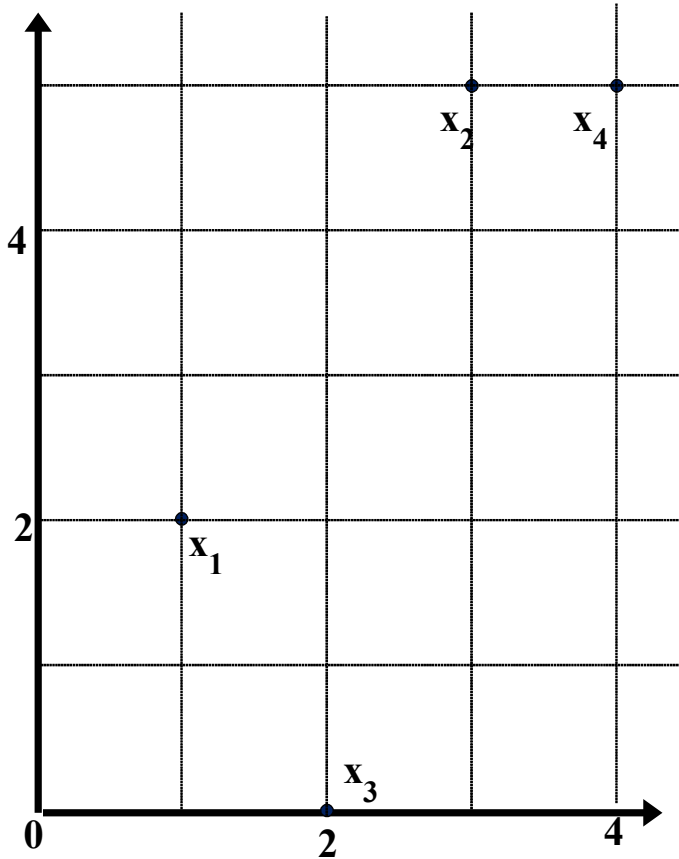
Data Matrix

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 $i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \ldots, x_{jp})$ 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 ≠ j, and d(i, i) = 0 (Positive definiteness)
  - d(i, j) = d(j, i)   (Symmetry)
  - d(i, j) ≤ 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

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

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

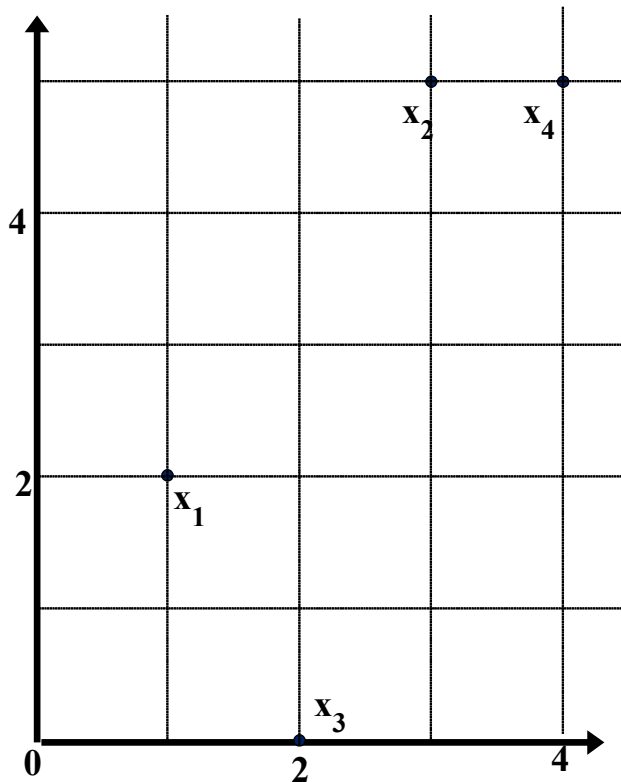$$d(i,j) = \sqrt{(|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \ldots + |x_{ip} - x_{jp}|^2)}$$

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

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

Example: Minkowski Distance

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

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$_\infty$	x1	x2	x3	x4
x1	0			
x2	3	0		
x3	2	5	0	
x4	3	1	5	0

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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 $\qquad r_{if} \in \{1,\ldots,M_f\}$

  - 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.

  $d_1 = (5, 0, 3, 0, 2, 0, 0, 2, 0, 0)$
  $d_2 = (3, 0, 2, 0, 1, 1, 0, 1, 0, 1)$

  $d_1 \bullet d_2 = 5*3+0*0+3*2+0*0+2*1+0*1+0*1+2*1+0*0+0*1 = 25$
  $||d_1|| = (5*5+0*0+3*3+0*0+2*2+0*0+0*0+2*2+0*0+0*0)^{0.5} = (42)^{0.5}$
  $\quad = 6.481$
  $||d_2|| = (3*3+0*0+2*2+0*0+1*1+1*1+0*0+1*1+0*0+1*1)^{0.5} = (17)^{0.5}$
  $\quad\quad = 4.12$
  $\cos(d_1, d_2) = 0.94$

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

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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