Data Mining and Machine Learning
Bioinspired computational methods
Biological data mining

Getting to Know your Data

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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

A **cross tab** is a type of table in a matrix format that displays the (multivariate) frequency distribution of the variables.
Example:

	Right-handed	Left-handed	Totals
Males	43	9	52
Females	44	4	48
Totals	87	13	100

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

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Important Characteristics of Structured Data

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

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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.

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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

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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 (division makes no sense)
- **Ratio**
  - Inherent **zero-point (natural zero-point such as temperature in Kelvin)**
  - 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

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Measuring the Central Tendency

- **Mean (algebraic measure):**

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

where N is sample size.

- **Weighted arithmetic mean:** $$\bar{x} = \frac{\sum_{i=1}^{N} w_i x_i}{\sum_{i=1}^{N} w_i}$$

- **Trimmed mean:** mean obtained by chopping out extreme values (for instance the top and bottom 2% before computing the mean)

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Measuring the Central Tendency

- Median:
  - Middle value if odd number of values, or average of the middle two values otherwise
  - Holistic measure: must be computed on the entire dataset as a whole
  - Estimated by interpolation (for *grouped data*):

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

Lower boundary of the median interval

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

Sum of the frequencies of all the intervals that are lower than the median interval

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Measuring the Central Tendency

- Mode
  - Value that occurs most frequently in the data
  - Unimodal, bimodal, trimodal
  - Empirical formula:

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

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Symmetric vs. Skewed Da

Positively skewed, where the mode occurs at a value that is smaller than the median or **negatively skewed, where the mode occurs at a value greater than the** median

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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 $\le x_i$
- **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

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Measuring the Dispersion of Data

- *k*th percentile of a set of data in numerical order: value x_i having the property that *k* percent of the data entries lie at or below x_i.

- The median is the 50th percentile.
  - **Quartiles**: Q_1 (25th percentile), Q_3 (75th percentile)
  - **Inter-quartile range**: $IQR = Q_3 - Q_1$

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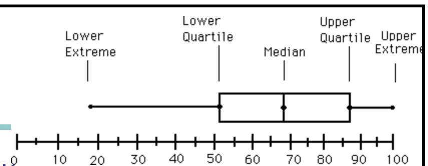
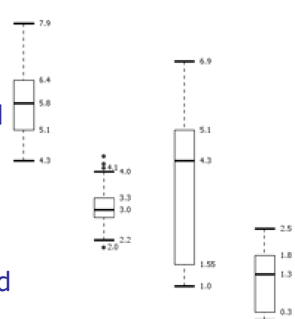
Boxplot Analysis



- **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 (usually, a value higher/lower than 1.5 x IQR)



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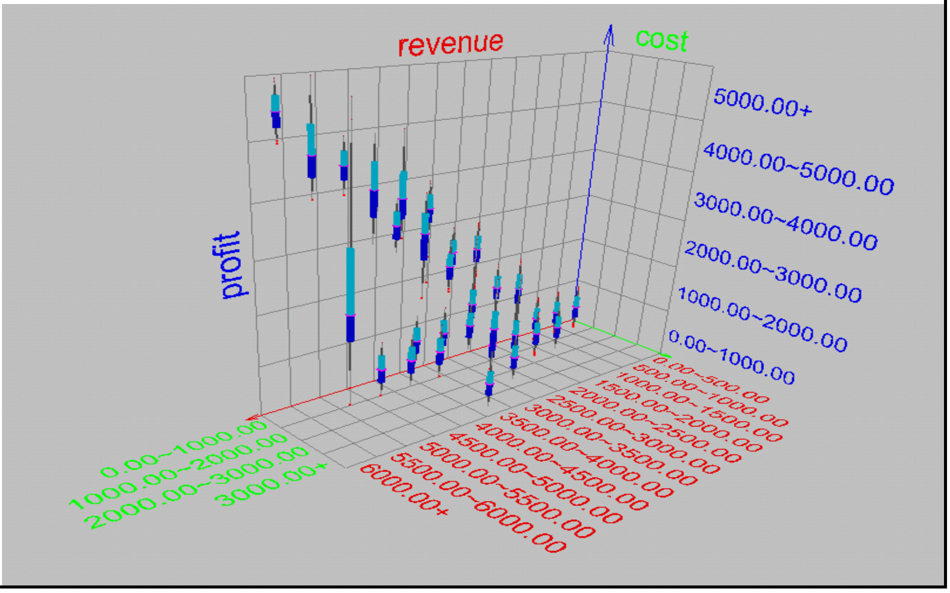
Visualization of Data Dispersion: 3-D Boxplots



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Measuring the Dispersion of Data

- Variance and standard deviation σ
  - **Variance**: (algebraic, scalable computation)

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 = \frac{1}{N}\sum_{i=1}^{N}x_i^{\,2} - \bar{x}^2$$

  - **Standard deviation** σ is the square root of variance σ^2
    - Measures the spread about the mean
- The variance and the standard deviation are algebraic measures because they can be computed from distributive measures.

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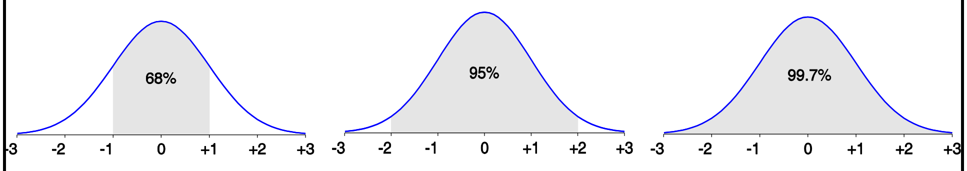
Properties of Normal Distribution Curve

- The normal (distribution) curve
  - From $\bar{x} - \sigma$ to $\bar{x} + \sigma$: contains about 68% of the measurements
  - From $\bar{x} - 2\sigma$ to $\bar{x} + 2\sigma$: contains about 95% of it
  - From $\bar{x} - 3\sigma$ to $\bar{x} + 3\sigma$: contains about 99.7% of it



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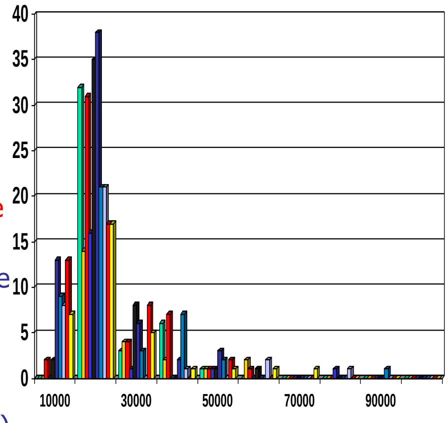
Histogram Analysis

- 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



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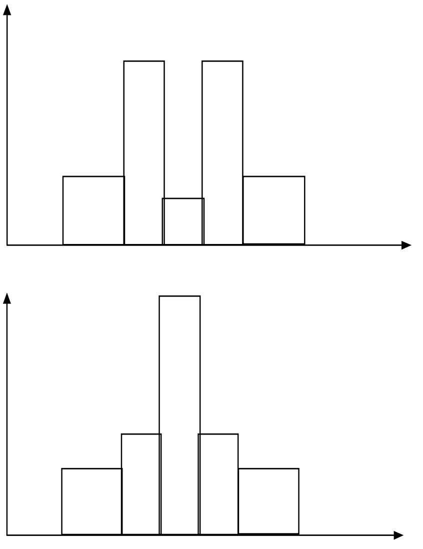
Histograms Often Tell More than Boxplots



- 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

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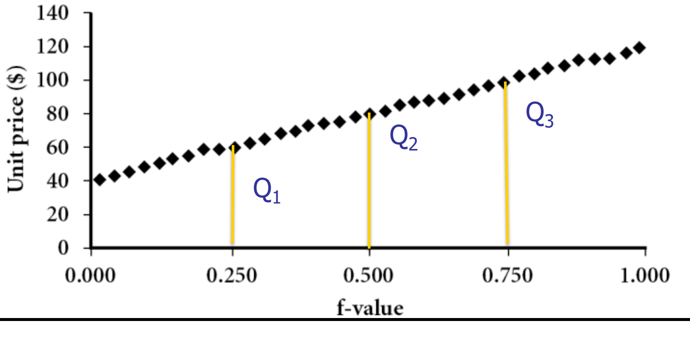
Quantile Plot

- 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. Note that 0.25, 0.5 and 0.75 quantiles correspond to the quartile Q_1, the median and the quartile Q_3, respectively.



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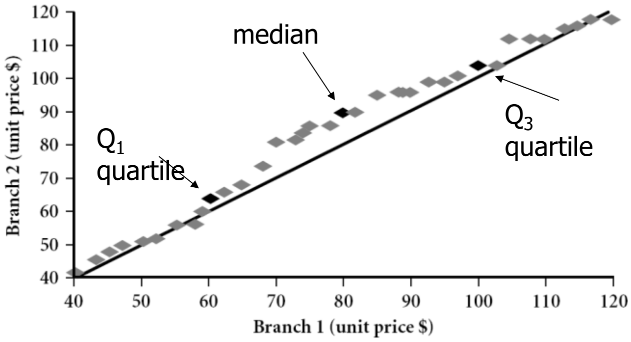
Quantile-Quantile (Q-Q) Plot

- 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.



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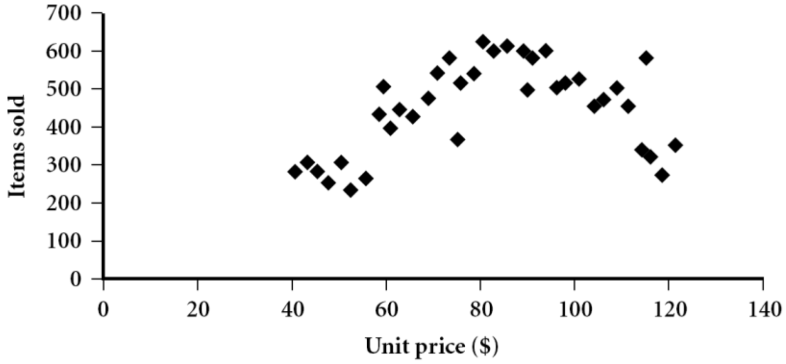
Scatter plot

- 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



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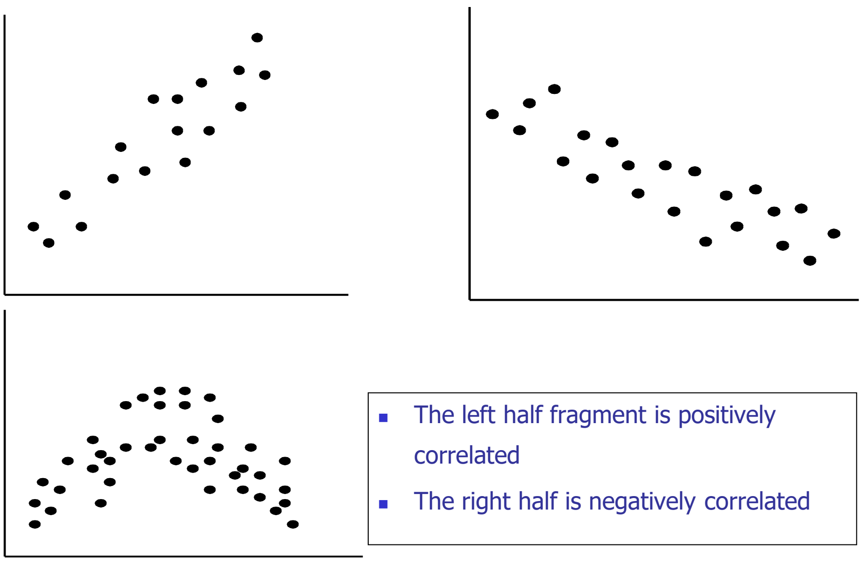
Positively and Negatively Correlated Data



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

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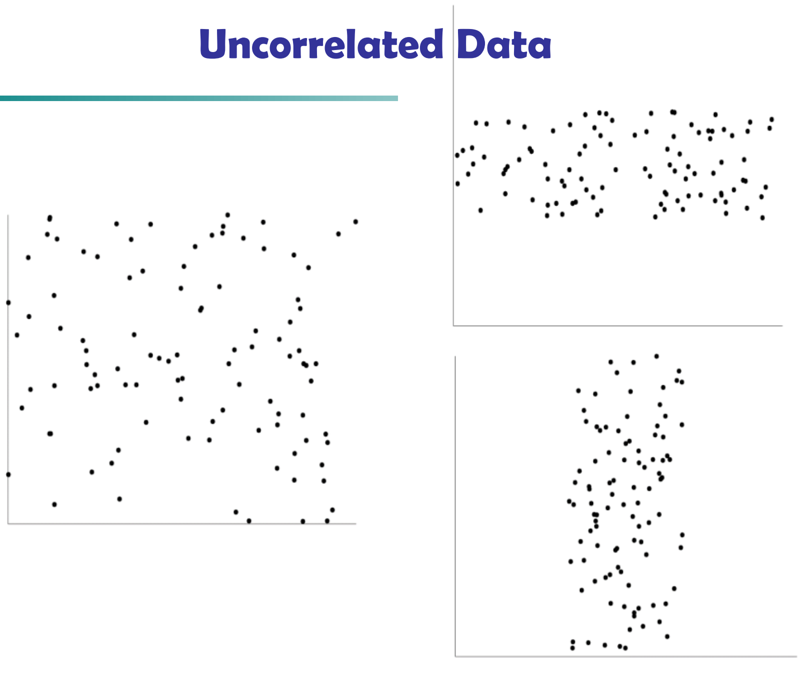
Uncorrelated Data



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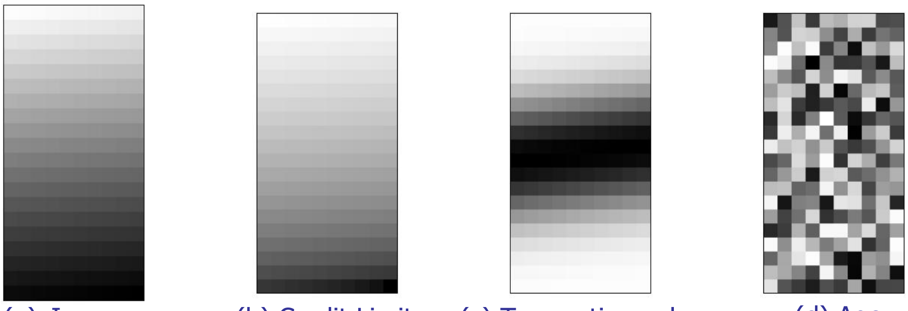
Data Visualization

- 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 from data
- 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

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Geometric Projection Visualization Techniques

- Visualization of geometric transformations and projections of the data
- Methods
  - **Scatterplot and scatterplot matrices**
  - **Parallel coordinates**
  - **Icon-based**
  - **Projection pursuit technique: Help users find meaningful projections of multidimensional data**

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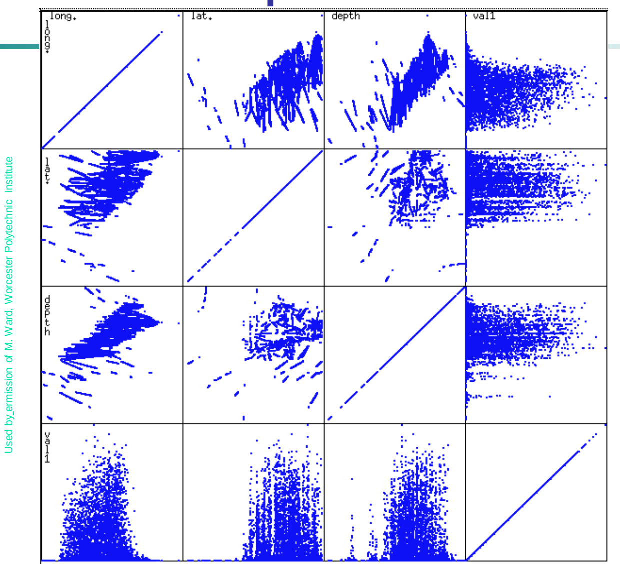
Scatterplot Matrices



Matrix of scatterplots (x-y-diagrams) of the k-dim. data

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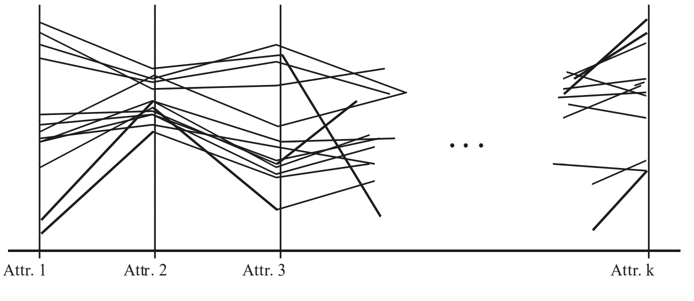
Parallel Coordinates

- 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



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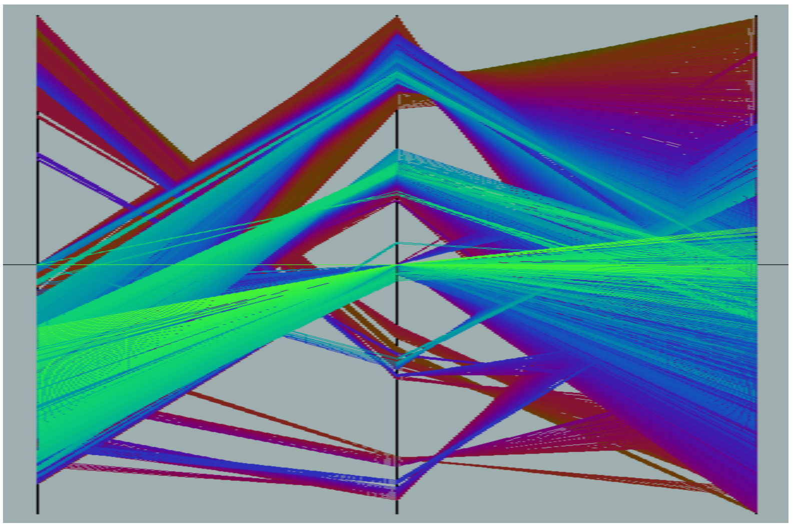
Parallel Coordinates of a Data Set



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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

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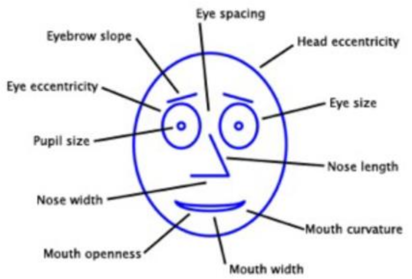
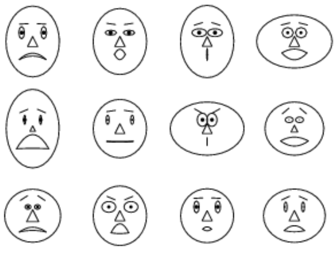
Chernoff Faces

- 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)





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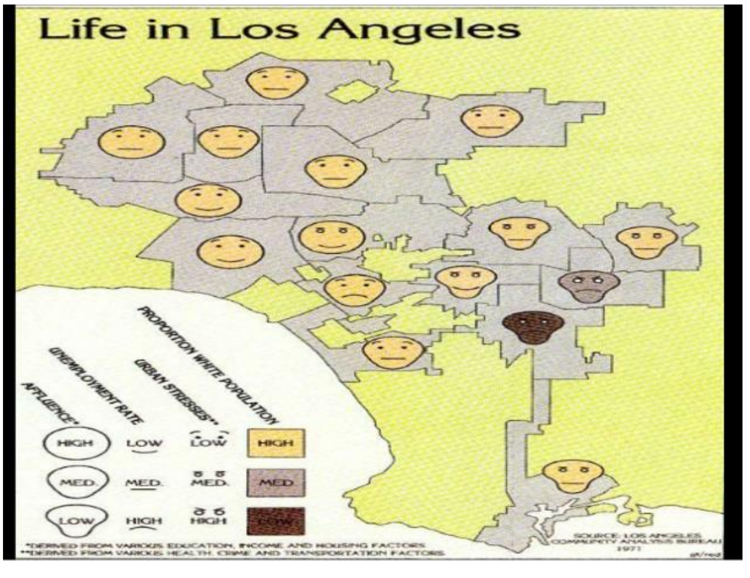
Chernoff Faces



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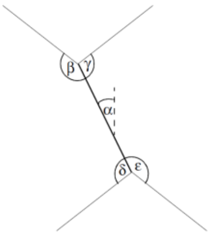
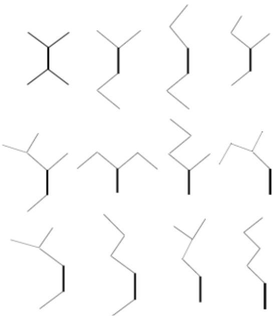
Stick Figure

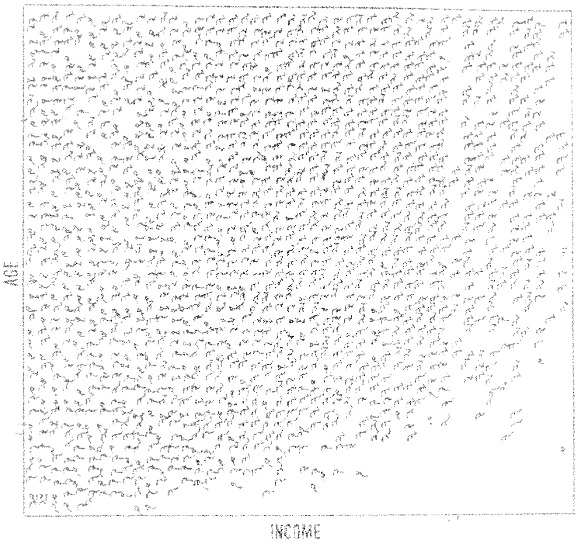
- A very simple type of drawing made of lines and dots, often of the human form or other animals
  - two attributes of the data are mapped to the display axes and the remaining attributes are mapped to the angle and/or length of the limbs
  - texture patterns in the visualization how certain data characteristics





Stick Figure

A very simple type of drawing made of lines and dots, often of the human form or other animals.



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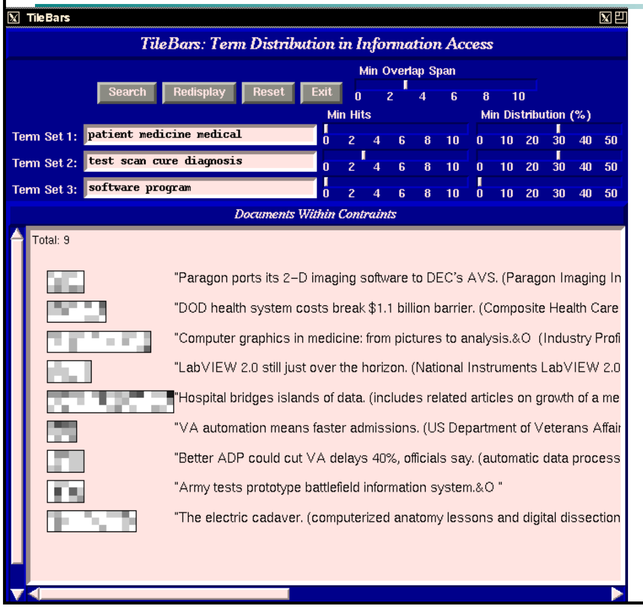
A census data figure showing age, income, gender, education, etc.

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

Tile bar



Rectangles correspond to documents.

The query is specified in terms of k topics, one topic per line, called term sets.

Columns in rectangles correspond to document segments.

A square corresponds to a specific term set in a specific text segment.

The darkness of a square indicates the frequency of terms in the segment from the corresponding TermSet. 41

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Hierarchical Visualization Techniques

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

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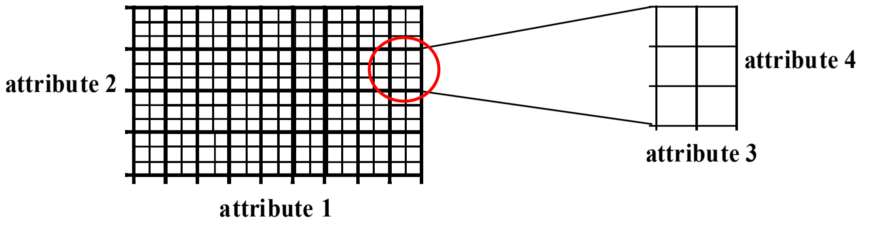
Dimensional Stacking



- 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

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Dimensional Stacking

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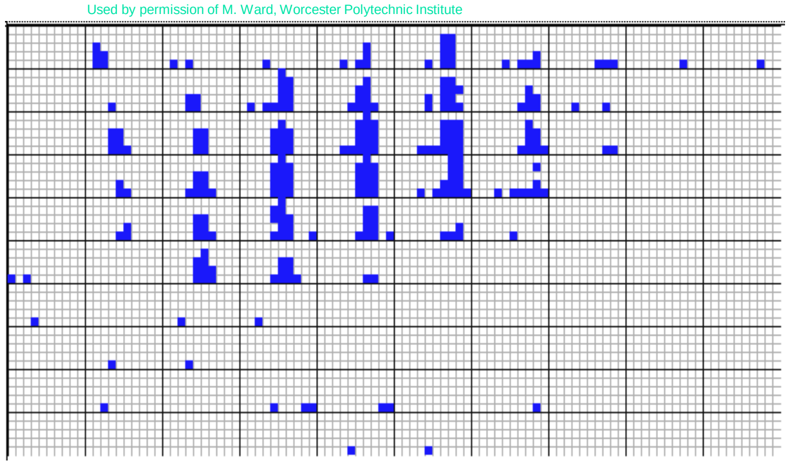

Visualization of oil mining data with longitude and latitude mapped to the outer x-, y-axes and ore grade and depth mapped to the inner x-, y-axes

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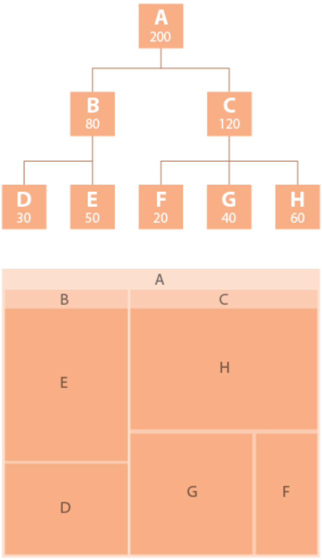
Tree-Map

- 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)



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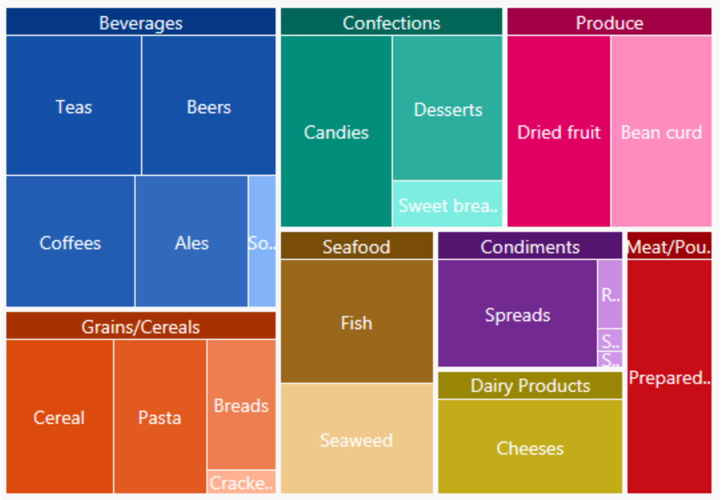
Tree-Map

- Examples



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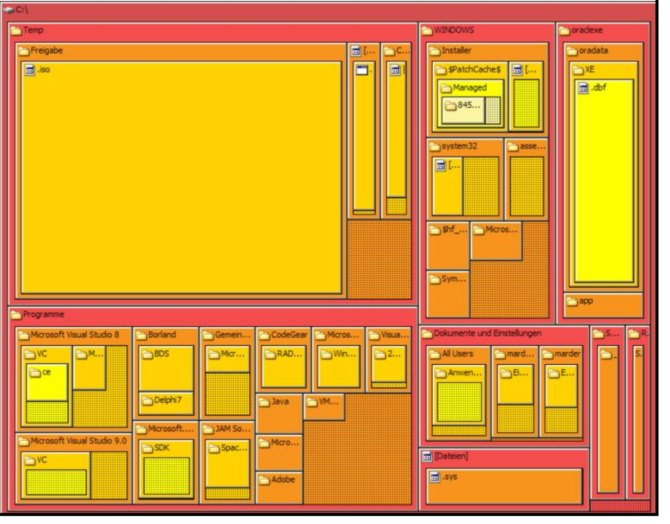
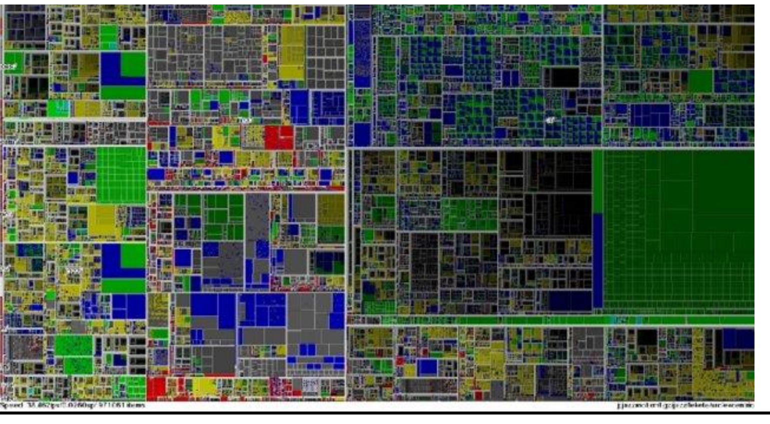
Tree-Map

Example: an overview of the organization of file and directory



Tree-Map of a File System

The treemap represents each file as a colored rectangle, the area of which is proportional to the file's size. The rectangles are arranged in such a way, that directories again make up rectangles, which contain all their files and subdirectories. So their area is proportional to the size of the subtrees. The color of a rectangle indicates the type of the file.



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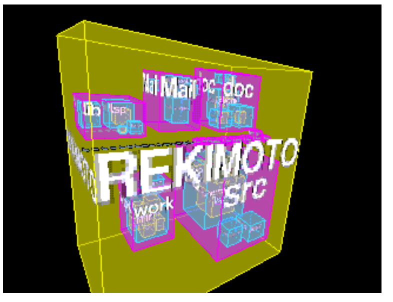
InfoCube

- 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



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

Tag Cloud: Example

- Example of Tag Cloud

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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

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Data Matrix and Dissimilarity Matrix

- Data matrix
  - n data points with p dimensions
  - Two modes (rows and columns represent different entities)

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

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

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

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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

$$d(i, j) = \frac{p - m}{p}$$

Example: Variables: eye color and hair color

i = (green, blond)

j = (green, black)

$$d(i, j) = \frac{2 - 1}{2} = 0.5$$

Proximity Measure for Nominal Attributes

- Method 2: Use a large number of binary attributes
  - creating a new binary attribute for each of the *M* nominal states (for instance, for color, create binary attributes red, yellow, blue, green, and so on)

Objects described by eye color ad hair color

Eye color = {black, green, blue}

Hair_color = {auburn, black, blond, brown, grey, red, white}

i = {*black, green, blue, auburn, black, blond, brown, grey, red, white*}

Boolean (true or false)

Proximity Measure for Binary Attributes

- A contingency table for binary data

Number of variables

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

- Distance measure for symmetric binary variables (a binary variable is symmetric if both of its states are equally valuable and carry the same weight):

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

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Proximity Measure for Binary Attributes

- Distance measure for asymmetric binary variables:

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

- 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":

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

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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 be 0 (use only asymmetric values)

    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) $=\frac{1+2}{1+1+2} = 0.75$

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Standardizing Numeric Data

- Z-score (conversion to unitless variables): $z = \frac{x-\mu}{\sigma}$
  - 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

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

where $m_f = \frac{1}{N}(x_{1f} + x_{2f} + ... + x_{Nf})$.

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

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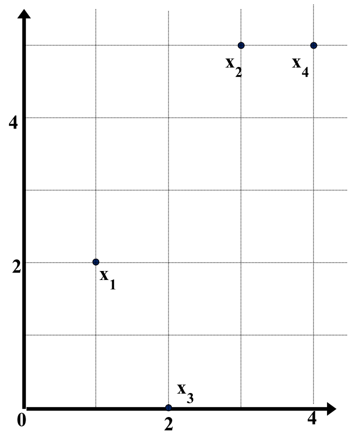
Example: Data Matrix and Dissimilarity Matrix



Data Matrix

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

Dissimilarity Matrix

(with Euclidean Distance)

L2	x1	x2	x3	x4
x1	0			
x2	3.61	0		
x3	2.24	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

$$d(i,j) = |x_{i_1} - x_{j_1}| + |x_{i_2} - x_{j_2}| + ... + |x_{i_p} - x_{j_p}|$$

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

$$d(i,j) = \sqrt{(|x_{i_1} - x_{j_1}|^2 + |x_{i_2} - x_{j_2}|^2 + ... + |x_{i_p} - x_{j_p}|^2)}$$

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

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

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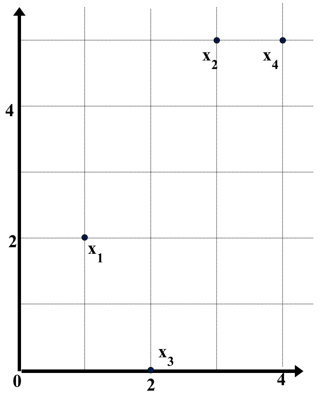
Example: Minkowski Distance

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

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Ordinal Variables

- An ordinal variable is similar to a categorical variable. The difference between the two is that there is a clear ordering of the variables. For example, suppose you have a variable, economic status, with three categories (low, medium and high).
- An ordinal variable can be discrete or continuous
- Order is important, e.g., rank $r_{if} \in \{1, \ldots, M_f\}$
- Can be treated like interval-scaled
  - replace x_{if} by their rank
  - map the range of each variable onto [0, 1] by replacing *i*-th object in the *f*-th variable by

{*small, medium, large*}
{ *1* , *2* , *3* }

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

{*small, medium, large*}
{ *0* , *0.5* , *1* }

  - compute the dissimilarity using methods for interval-scaled variables

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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

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

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

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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

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

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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

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.