Sample Data Sets

- Machine learning: compiled and hosted by the University of California at Irvine (UCI) http://archive.ics.uci.edu/ml/
- Data mining: compiled the University of Edinburgh (School of Informatics) http://www.inf.ed.ac.uk/teaching/courses/dme/html/datasets0405.html
- https://www.microsoft.com/en-us/research/project/urban-computing
- What dataset to use in homework #1?
  - If you had to ask, use the Iris data set from UCI
- What is "interpreting data"?
  - *Make some sense out of the data and/or results, bonus up to 20%*
- What to submit to Blackboard
  - Report: descriptions, figures, tables, examples (separate file)
  - Code
  - Data if applicable (link to a well-known public dataset is sufficient)

Code of Data Mining Algorithms

- Source codes for Frequent Pattern Mining, Clustering, *Time Series* and Web Mining allgorithms implemented by Chinese Univ. of Hong Kong: http://appsrv.cse.cuhk.edu.hk/~kdd/program.html
- FIMI workshops: Datasets and source codes for frequent itemset mining implementations: http://fimi.cs.helsinki.fi/
- Frequent itemset mining algorithm implementations by Bart Goethal: http://www.adrem.ua.ac.be/~goethals/software/
- Repository of implementations of UIUC data mining research package: IlliMine: http://illimine.cs.uiuc.edu/
- Weka: Weka 3 - Data Mining with Open Source Machine Learning Software in Java: http://www.cs.waikato.ac.nz/ml/weka/
- *Graph mining* algorithm implemtations: gSpan and CloseGraph java implementation

It's a Wild World Out There

- Known and Unknown

  "there are known knowns;
  there are things that we know that we know.
  We also know there are known unknowns; that is to say we know there are some things we do not know.
  But there are also unknown unknowns, the ones we don't know we don't know."

- Get Used to It

Data Mining:

Concepts and Techniques

— Chapter 2 —

Jiawei Han, Micheline Kamber, and Jian Pei

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	losses
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 (remember dots?)
- 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

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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*

example

example

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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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Chapter 2: Getting to Know Your Data

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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

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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: $\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$
  - *Trimmed* mean: chopping extreme values
- Median:
  - Middle value if odd number of values, or average of the middle two values otherwise
  - Estimated by interpolation (for *grouped data*): $median = L_1 + (\frac{n/2 - (\sum freq)l}{freq_{median}})width$

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

- Mode
  - Value that occurs most frequently in the data
  - Unimodal, bimodal, trimodal
  - Empirical formula (for unimodal data that is *moderately skewed*): $mean - mode = 3 \times (mean - median)$

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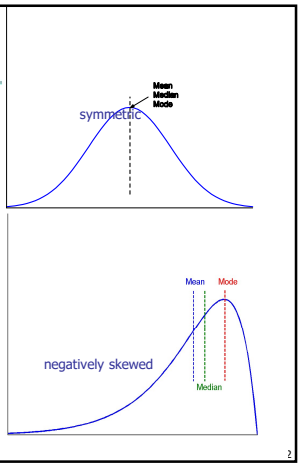
Symmetric vs. Skewed

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



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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 STD: s, population STD: 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*)*

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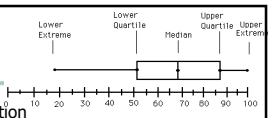
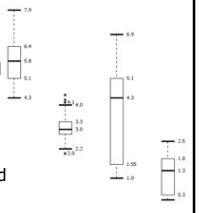
Boxplot Analysis



- **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 (e.g., 1.5 IQR, plotted individually



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Project Proposal

- **For CSC 440**
  - The 2-page proposal should summarize the papers and outline your project plan (e.g., problem statement, data acquisition, algorithm choices/ideas, experiment design, and performance evaluation). It would naturally be added to your final project report as the introduction after being expanded to include additional information if needed.
  - The proposal may contain a 1-2 figures.
- **For CSC 240**
  - Introduction: Background, problem statement, and problem importance
  - Methods: Major algorithms (hint: not 1, not 2, 5+) used to solve the problem
  - Results: Major results (from literature) and their implications
  - Critical Evaluation: Comments on the methods used and the major results. Advantages and disadvantages of the methods used. Discussion on alternative methods that may be considered for future work.

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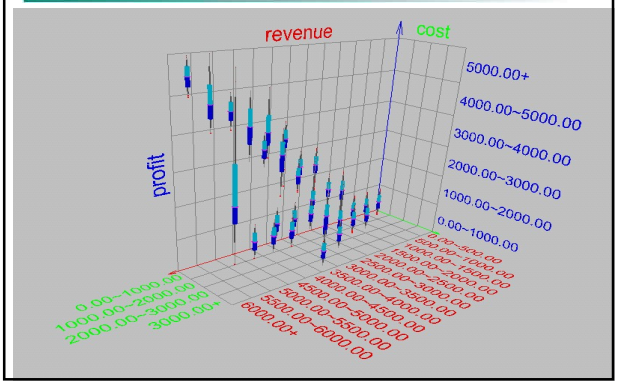
Visualization of Data Dispersion: 3-D Boxplots



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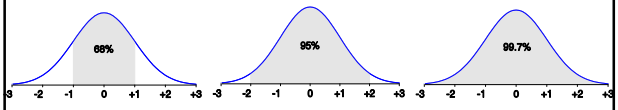
Properties of Normal Distribution Curve

- 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



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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 $\leq x_i$
- **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

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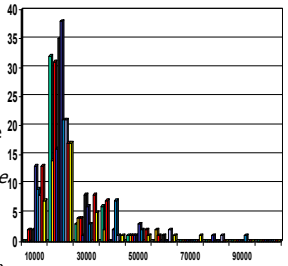
Histogram Analysis

- 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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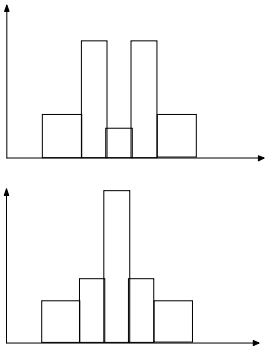
Histograms Often Tell More than Boxplots



- 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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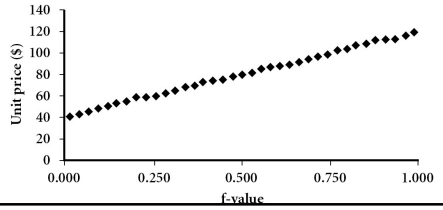
Quantile Plot

- 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



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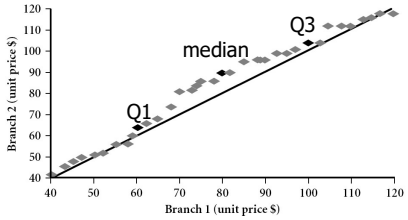
Quantile-Quantile (Q-Q) Plot

- 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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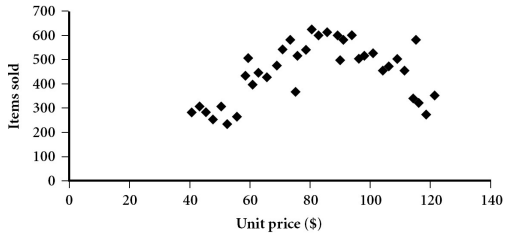
Scatter plot

- 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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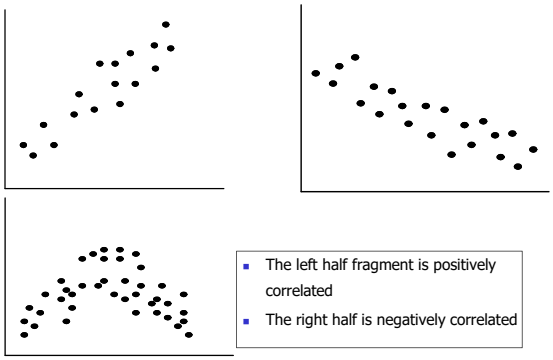
Positively and Negatively Correlated Data



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

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Uncorrelated Data

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Chapter 2: Getting to Know Your Data

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Data Visualization

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

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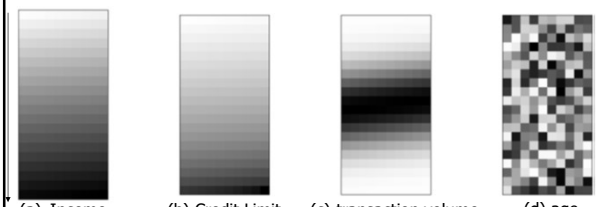
Pixel-Oriented Visualization Techniques

- 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 (raster scan order) to m pixels at the corresponding (2D) 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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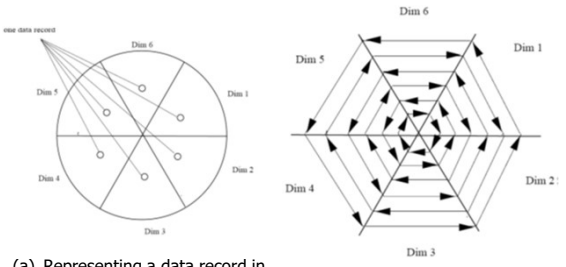
Laying Out Pixels in Circle Segments

- 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 (e.g. raster)

(b) Laying out pixels in circle segment ("raster" scan)

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Example

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Example

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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

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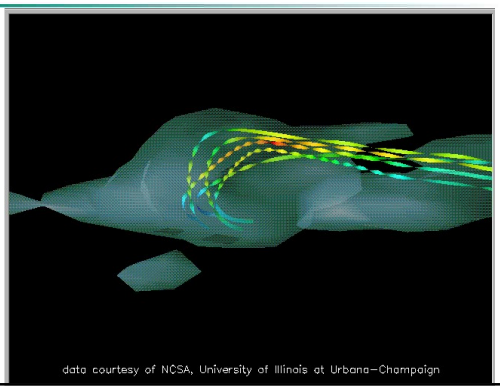
Direct Data Visualization

Ribbons with Twists Based on Vorticity



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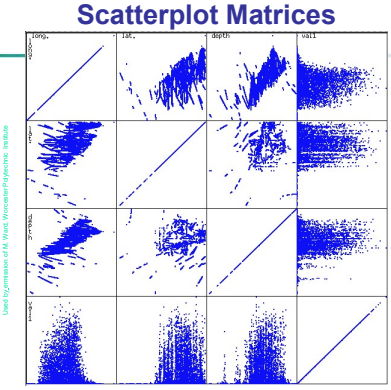
Scatterplot Matrices



Matrix of scatterplots (x-y-diagrams) of the k-dim. data [total of (k2/2-k) scatterplots]

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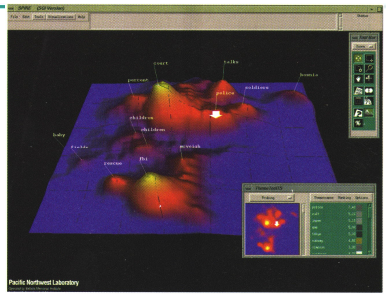
Landscapes



news articles visualized as a landscape

embedding

- 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

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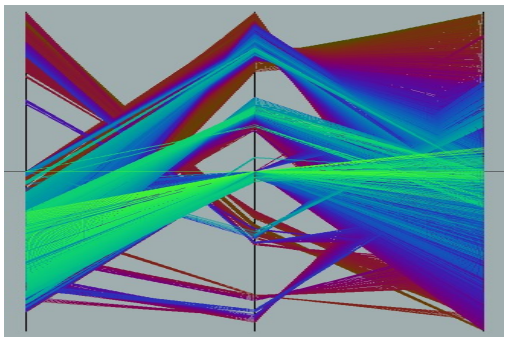
Parallel Coordinates of a Data Set



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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 2+ 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

Imagine a big crowd, visualize clusters as "tribes"

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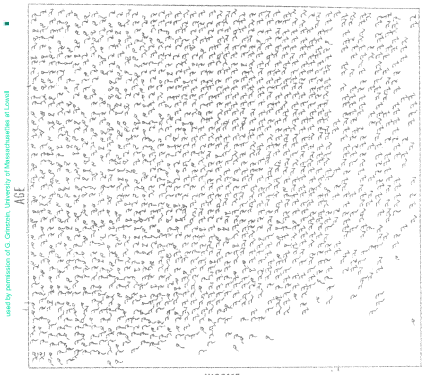
Stick Figure



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

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Hierarchical Visualization Techniques

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

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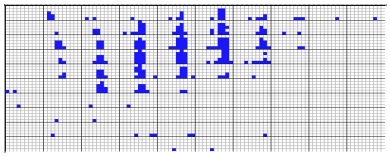
Dimensional Stacking



- 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 (3D)3^2
- Important to map dimensions appropriately

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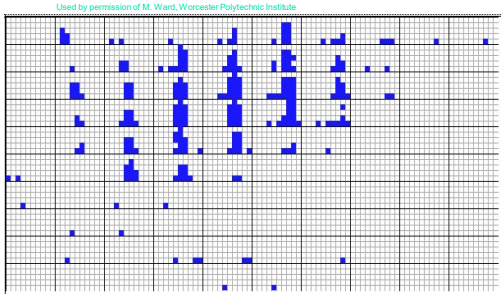
Dimensional Stacking

Used by permission of M. Ward, Worcester Polytechnic Institute



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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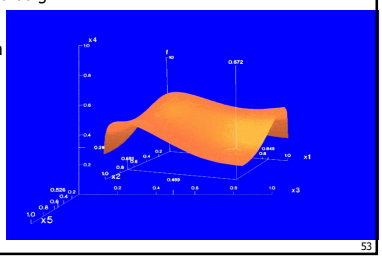
Worlds-within-Worlds

- 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



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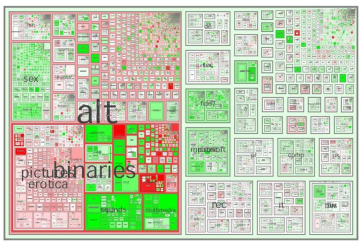
Tree-Map

- 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* (V-H-V-H...) according to the attribute values (classes)

MSR Netscan Image



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

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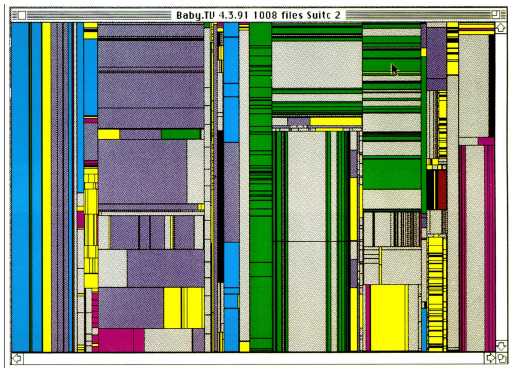
Tree-Map of a File System (Schneiderman)



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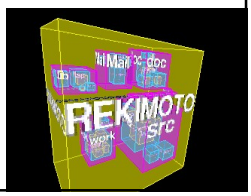
InfoCube

- 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



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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

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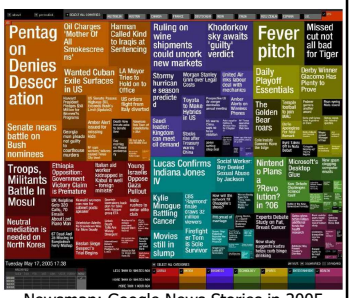
Visualizing Complex Data and Relations

- 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

Data Cloud vs Tag Cloud



Newsmap: Google News Stories in 2005

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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

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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
  - E.g., sim(i, j) = 1 – d(i, j) Sim = 1 – Diff? Not always!!!

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Data Matrix and Dissimilarity Matrix

- Data matrix
  - n data points with p dimensions (n x p)
  - Two modes (attributes)

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

- Dissimilarity matrix
  - n data points, but registers only the distance (n x n)
  - A triangular matrix (why?)
  - Single mode (attribute)

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

Confused? Wait until confusion matrix?

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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

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

- Method 2: Use a large number of binary attributes
  - creating a new binary attribute for each of the *M* nominal states

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Proximity Measure for Binary Attributes

- A *contingency table* for binary data

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

- Distance measure for symmetric binary variables:

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

- Distance measure for *asymmetric* binary variables:

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

- 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 (positive), and the value N 0 (negative)

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

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

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

Having similar disease?

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Standardizing Numeric Data

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

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

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

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

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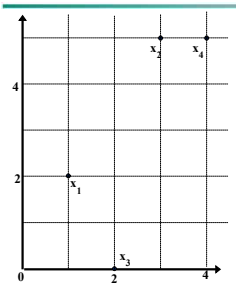
Example: Data Matrix and Dissimilarity Matrix



Data Matrix

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

Dissimilarity Matrix

(with Euclidean Distance)

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

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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

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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

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

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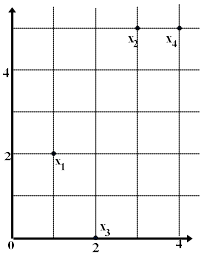
Example: Minkowski Distance

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 can be discrete or continuous
- Order is important, e.g., rank
- Can be treated like *interval-scaled*
  - replace x_{if} by their rank $r_{if} \in \{1, \ldots, M_f\}$
  - 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 (numeric) 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 into a single dissimilarity matrix

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

  - 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 $z_{if} = \frac{r_{if}-1}{M_f - 1}$
    - Treat z_{if} as interval-scaled

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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 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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Summary

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

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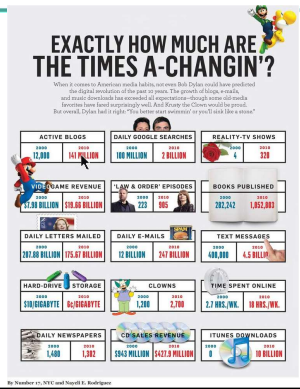
Data about Changing Times



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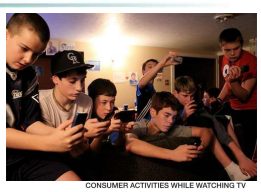
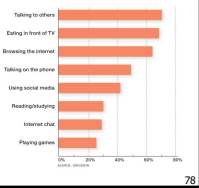
Pictures about Times



CONSUMER ACTIVITIES WHILE WATCHING TV



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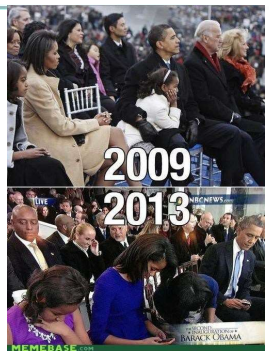
Pictures about Times

- Now and Then



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Big Data News

- "Dropbox Acquires KBVT's Computer Vision Geniuses To Mine Its Photos"
  - Dropbox or any other company could be sitting on a gold mine if they can figure out how to squeeze more strategic value out of photos or offer added benefits to users who store their treasured moments with them.

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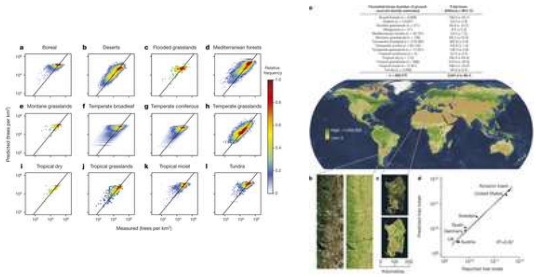
How many trees on earth?

Mapping tree density at a global scale

Nature **525**, 201–205, (10 September 2015)



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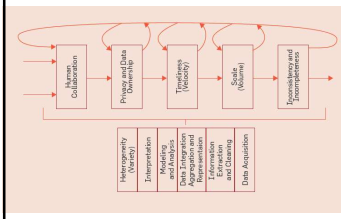
Position Paper

- Big Data and Its Technical Challenges
  - Communications of the ACM, Vol. 57 No. 7, Pages 86-94



- Big Data is revolutionizing all aspects of our lives ranging from enterprises to consumers, from science to government.
- Creating value from Big Data is a multi-step process: Acquisition, information extraction and cleaning, data integration, modeling and analysis, and interpretation and deployment. Many discussions of Big Data focus on only one or two steps, ignoring the rest.
- Research challenges abound, ranging from heterogeneity of data, inconsistency and incompleteness, timeliness, privacy, visualization, and collaboration, to the tools ecosystem around Big Data.
- Many case studies show there are huge rewards waiting for those who use Big Data correctly.

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