



# **CS 412 Intro. to Data Mining**

## **Chapter 2. Getting to Know Your Data**

**Jiawei Han, Computer Science, Univ. Illinois at Urbana-Champaign, 2017**





# 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: (1) Record Data

- Relational records
  - Relational tables, highly structured
- Data matrix, e.g., numerical matrix, crosstabs

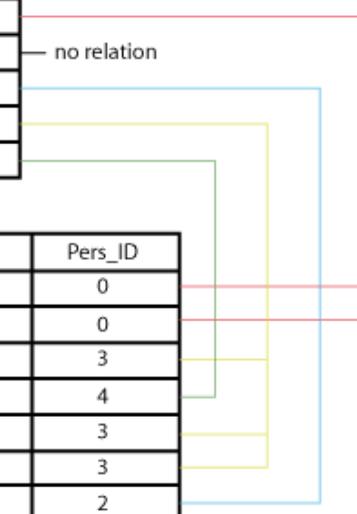
	China	England	France	Japan	USA	Total
Active Outdoors Crochet Glove		12.00	4.00	1.00	240.00	257.00
Active Outdoors Lycra Glove		10.00	6.00		323.00	339.00
InFlux Crochet Glove	3.00	6.00	8.00		132.00	149.00
InFlux Lycra Glove		2.00			143.00	145.00
Triumph Pro Helmet	3.00	1.00	7.00		333.00	344.00
Triumph Vertigo Helmet		3.00	22.00		474.00	499.00
Xtreme Adult Helmet	8.00	8.00	7.00	2.00	251.00	276.00
Xtreme Youth Helmet		1.00			76.00	77.00
<b>Total</b>	14.00	43.00	54.00	3.00	1,972.00	2,086.00

Person:

Pers_ID	Surname	First_Name	City
0	Miller	Paul	London
1	Ortega	Alvaro	Valencia
2	Huber	Urs	Zurich
3	Blanc	Gaston	Paris
4	Bertolini	Fabrizio	Rom

Car:

Car_ID	Model	Year	Value	Pers_ID
101	Bentley	1973	100000	0
102	Rolls Royce	1965	330000	0
103	Peugeot	1993	500	3
104	Ferrari	2005	150000	4
105	Renault	1998	2000	3
106	Renault	2001	7000	3
107	Smart	1999	2000	2



- Transaction data

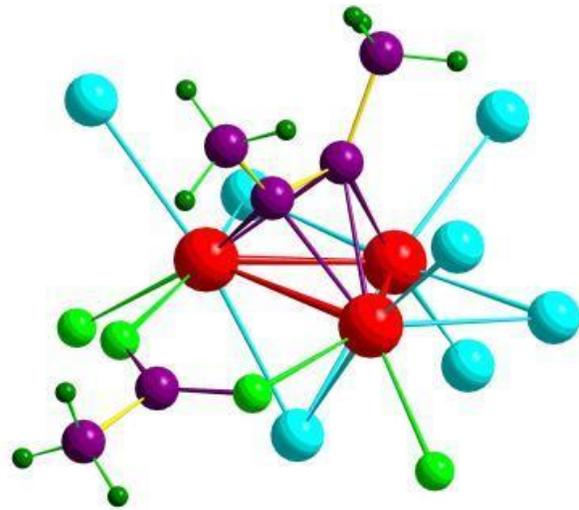
TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

	team	coach	pla y	ball	score	game	wi n	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

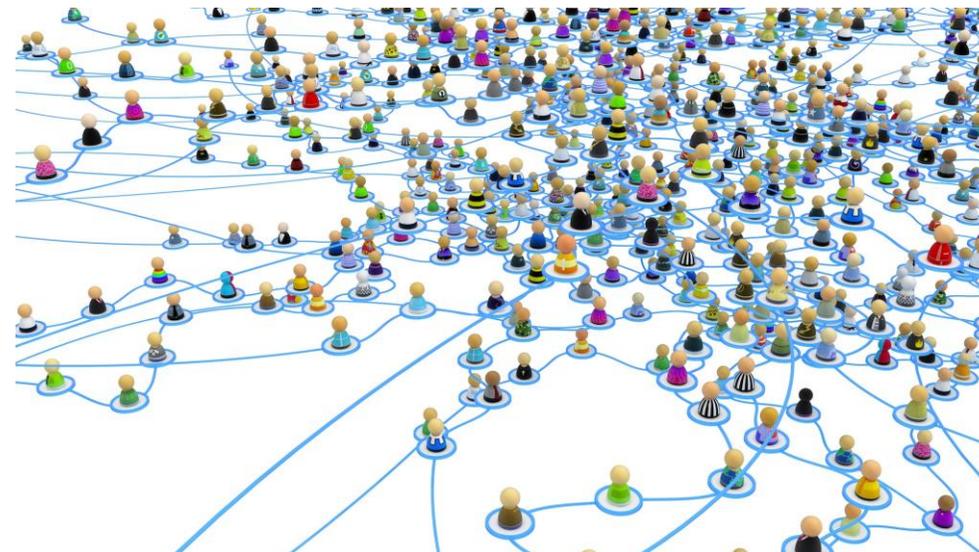
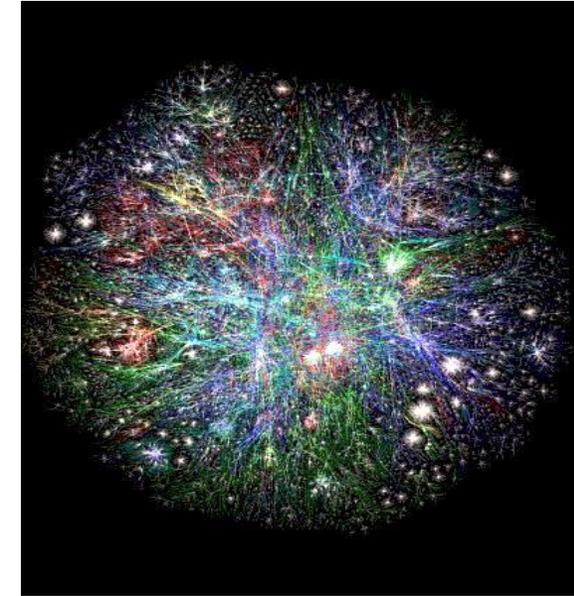
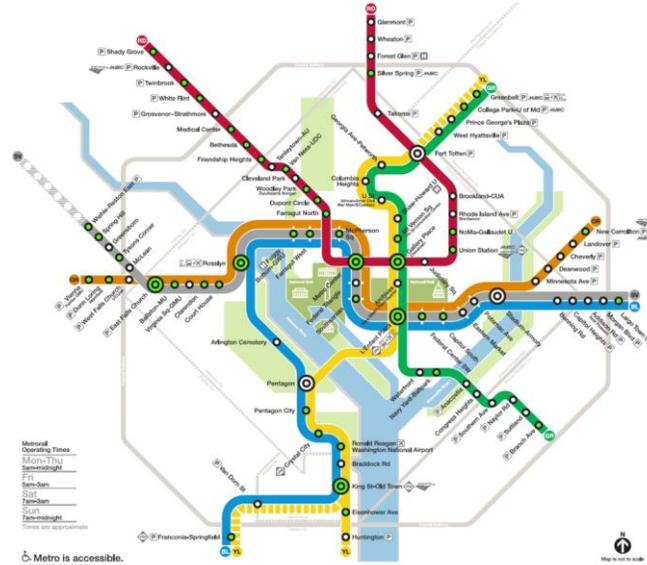
- Document data: Term-frequency vector (matrix) of text documents

# Types of Data Sets: (2) Graphs and Networks

- ❑ Transportation network
- ❑ World Wide Web



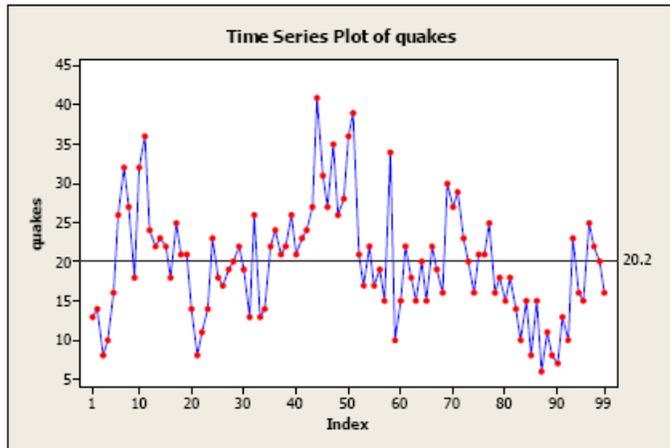
- ❑ Molecular Structures
- ❑ Social or information networks



# Types of Data Sets: (3) Ordered Data

□ Video data: sequence of images

□ Temporal data: time-series



□ Sequential Data: transaction sequences

□ Genetic sequence data

	Start
Human	GTTTGGAGG --- ATGTTCAACAAATGCTCCTTTCATTCCCTATTTACAGACCTGCCGCA
Chimpanzee	GTTTGGAGG --- ATGTTCAATAAATGCTGCTTTCACCTCCCTATTTACAGACCTGCCGCA
Macaque	GTTTGGAGG --- ATGTCACAATAAATGCTCCTTTCATTCCCTATTTACAAACTTGCCGCA
Human	GACAATTCGCTAGCAGCCTTTGTGCTATTATCTGTTTTCTAAACTTAGTAATTGAGTGT
Chimpanzee	GACAATTCGCTAGCAGCCTTTGTGCTATTATCTGTTTTCTAAACTTAGTAATTGAGTGT
Macaque	GACAATTCGCTAGCAGCCTTTGTGCTATTATCTGTTTTCTAAACTTAGTAATTGAGTGT
Human	GATCTGGAGACTAA - CTC TGAATAAATAAGCTGATTATTTATTTATTTCTCAAAAACAA
Chimpanzee	GATCTGGAGACTAAACCTGTAATAAATAAGCTGATTATTTATTTATTTCTCAAAAACAA
Macaque	TATCTGGAGACTAAACCTGTAATAAATAAGCTGATTATTTATTTATTTCTCAAAAACAA
Human	CAGAATACGATTTAGCAAATTAATCTCTTAAGATATATTTTACATTTCTATATTTCTCCTA
Chimpanzee	CAGAATACGATTTAGCAAATTAATCTCTTAAGATATATTTTACATTTCTATATTTCTCCTA
Macaque	CAGAATATGATTTAGCAAATTAATCTCTTAAGATATATTTTGCACTTCTATATTTCTCCTA
Human	CCCTGAGTTGATGTGTGAGCAATATGTCACCTTTCATAAAGCCAGGTATACA --- TTATG
Chimpanzee	CCCTGAGTTGATGTGTGAGCCGATATGTCACCTTTCATAAAGCCAGGTATACA --- TTATG
Macaque	CCCTGAGTTGATGTGTGAGCAATATGTCACCTTTCACAAAGCCAGGTATATATACATTACG
Human	GACAGGTAAGTAAAAAACATATTATTTATTCTACGTTTTGTCCAAAATTTTAAATTTCT
Chimpanzee	GACAGGTAAGTAAAAAACATATTATTTATTCTACGTTTTGTCCAAAATTTTAAATTTCT
Macaque	GACAGGTAAGTAAAAA - CATATTATTTATTCTAGBTTTTGTCCAAAAGATTTTAAATTTCT
Human	AAC TGT TGC CGT GTG T TGG TAA --- TGT AAAAC AAAC TCAGTACA
Chimpanzee	AAC TGT TGC CGT GTG T TGG TAA --- TGT AAAAC AAAC TCAGTACA
Macaque	AAC TGT TGTGCATGTGTTGGTAA --- CBT AAAAC AAAATTCAGTACG

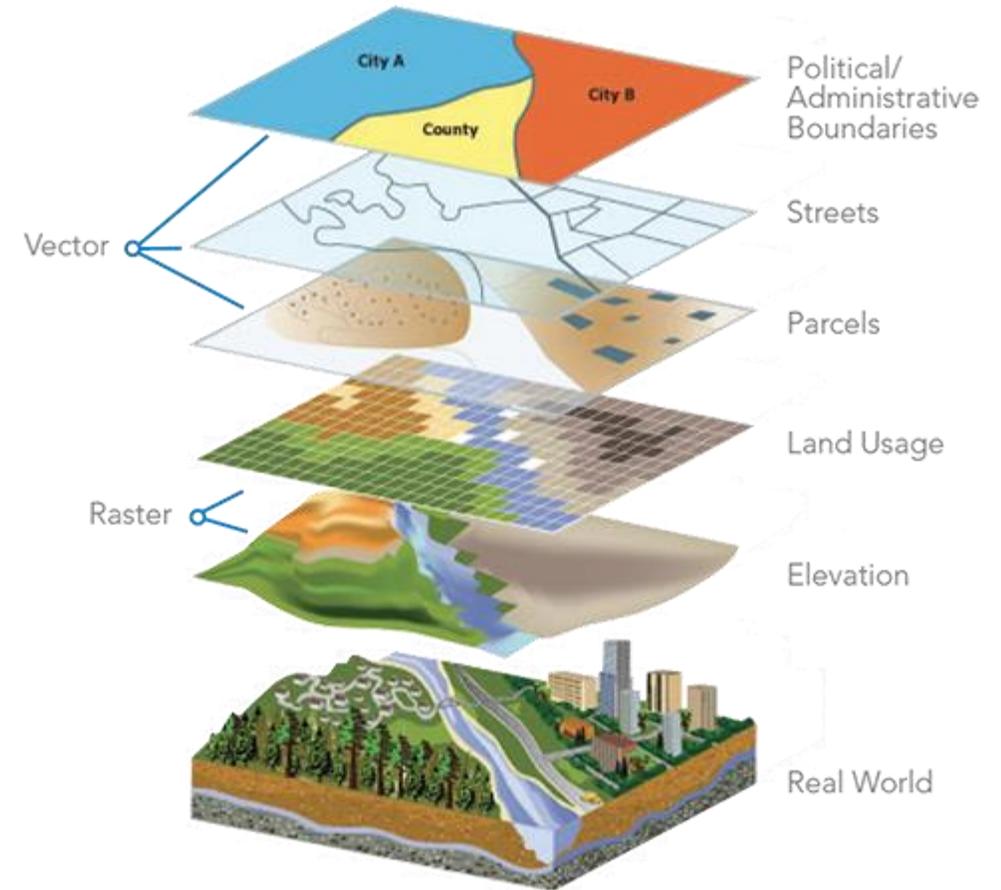
# Types of Data Sets: (4) Spatial, image and multimedia Data

- Spatial data: maps



- Image data:

- Video data:



# 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 (e.g., red, blue)
  - ❑ Binary (e.g., {true, false})
  - ❑ Ordinal (e.g., {freshman, sophomore, junior, senior})
  - ❑ Numeric: quantitative
    - ❑ Interval-scaled: 100°C is interval scales
    - ❑ Ratio-scaled: 100°K is ratio scaled since it is twice as high as 50 °K
- ❑ Q1: Is student ID a nominal, ordinal, or interval-scaled data?
- ❑ Q2: What about eye color? Or color in the color spectrum of physics?

# 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

# 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

# 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, ...

## □ Numerical dimensions correspond to sorted intervals

- Data dispersion:

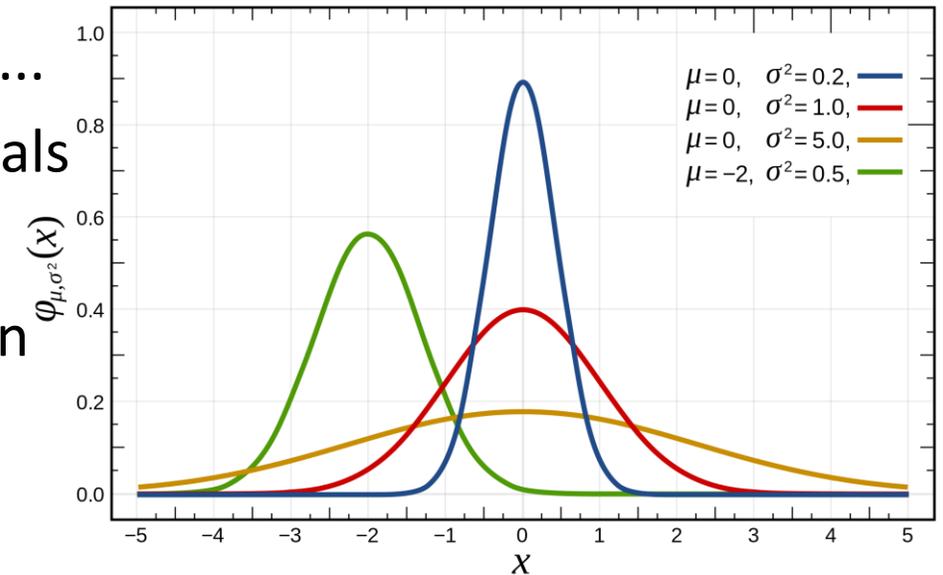
- Analyzed with multiple granularities of precision

- 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: (1) Mean

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

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


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


$$\mu = \frac{\sum x}{N}$$

- 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 (e.g., Olympics gymnastics score computation)

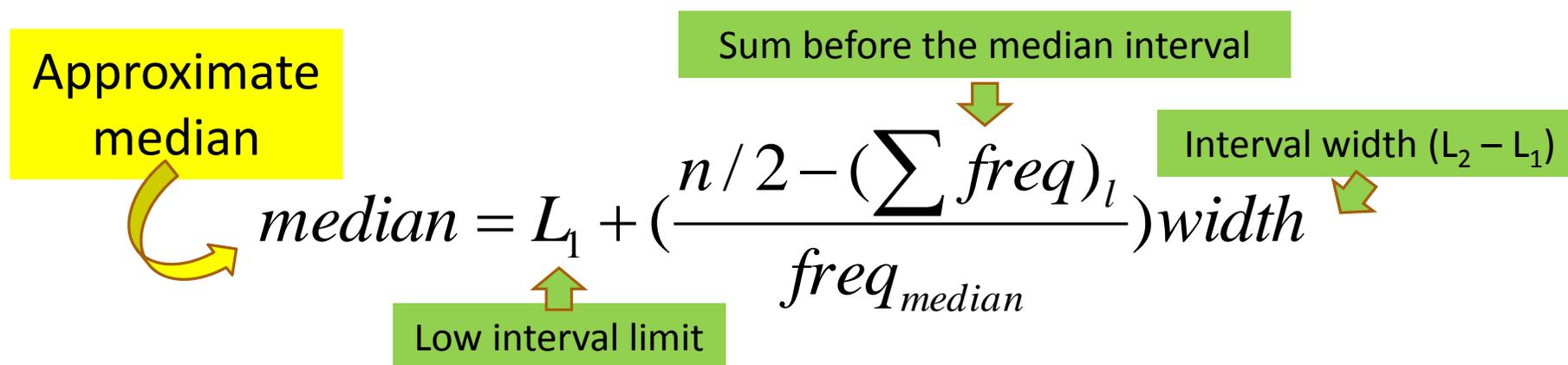
# Measuring the Central Tendency: (2) Median

## □ Median:

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

□ Estimated by interpolation (for *grouped data*):

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



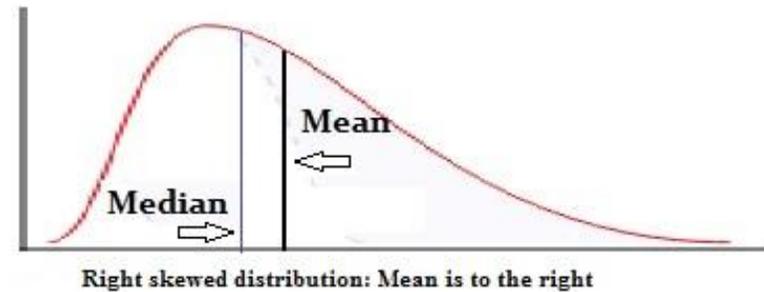
# Measuring the Central Tendency: (3) Mode

□ Mode: Value that occurs most frequently in the data

□ Unimodal

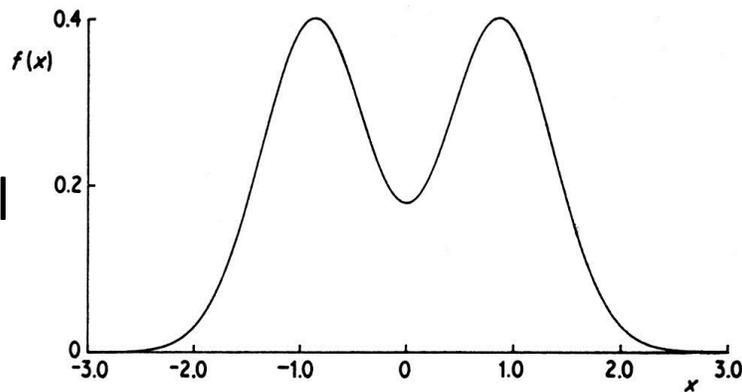
□ Empirical formula:

$$\text{mean} - \text{mode} = 3 \times (\text{mean} - \text{median})$$

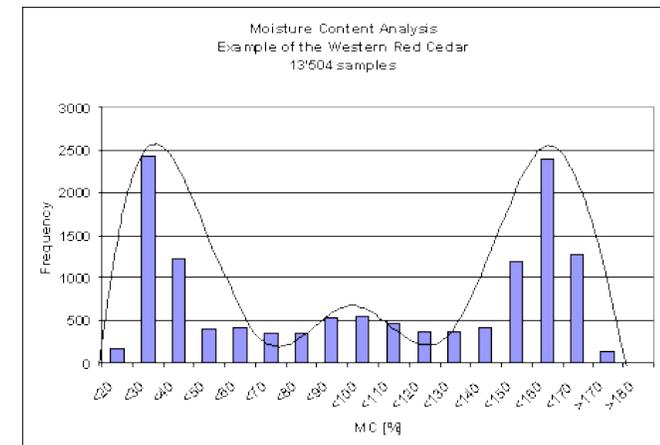
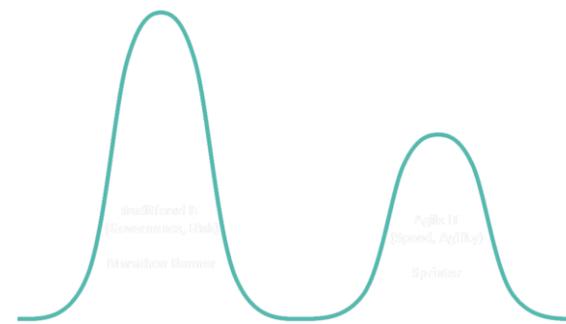


□ Multi-modal

□ Bimodal

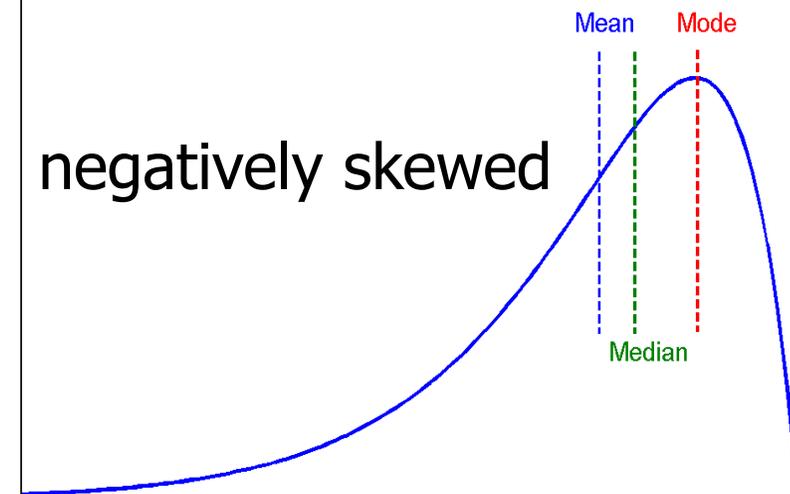
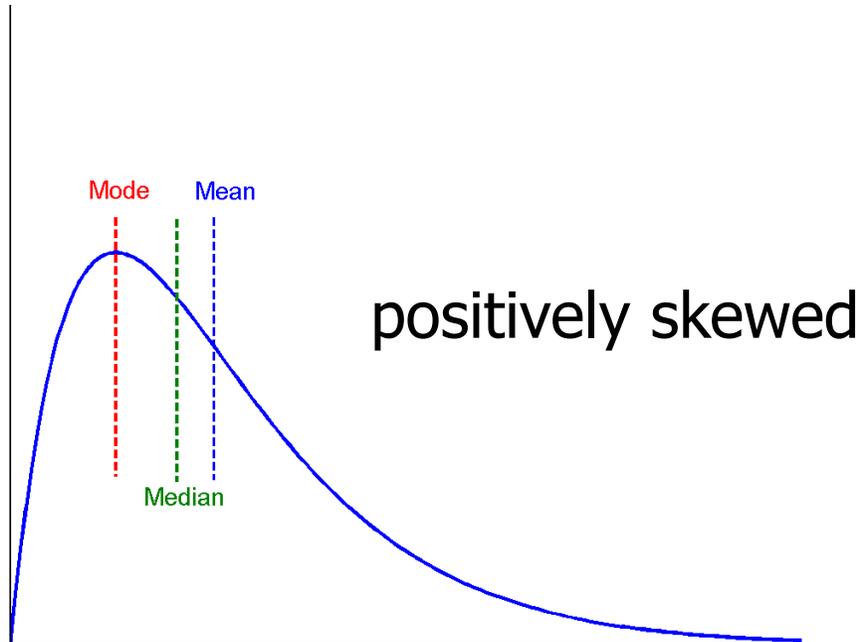
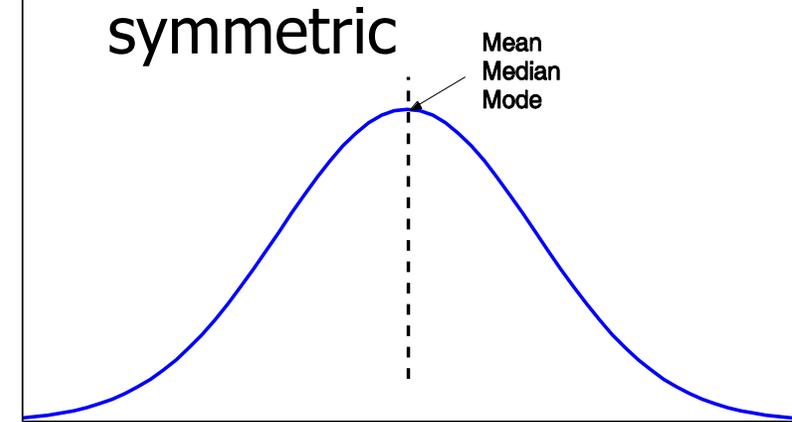


□ Trimodal



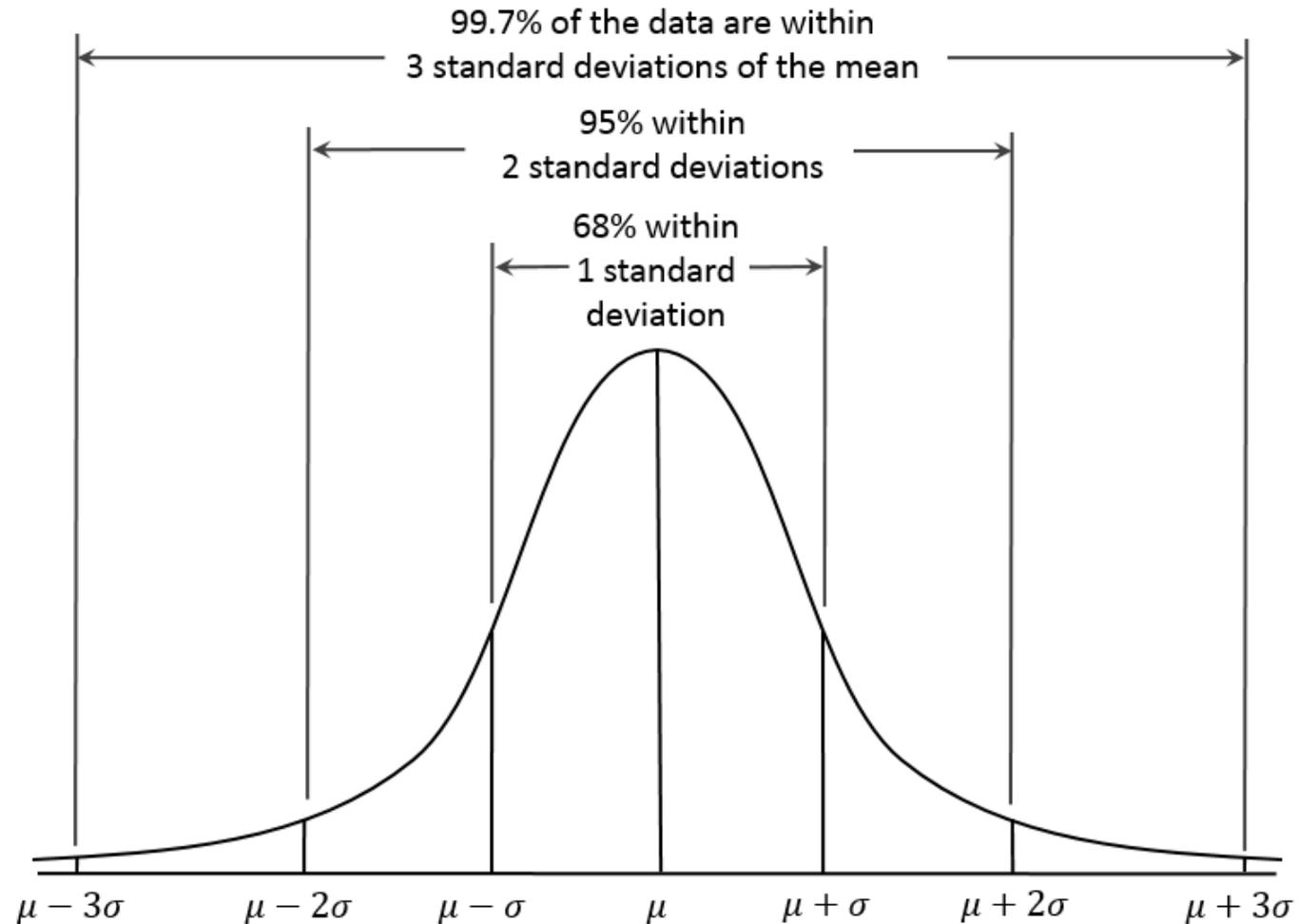
# Symmetric vs. Skewed Data

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



# Properties of Normal Distribution Curve

← — — — — Represent data dispersion, spread — — — — →



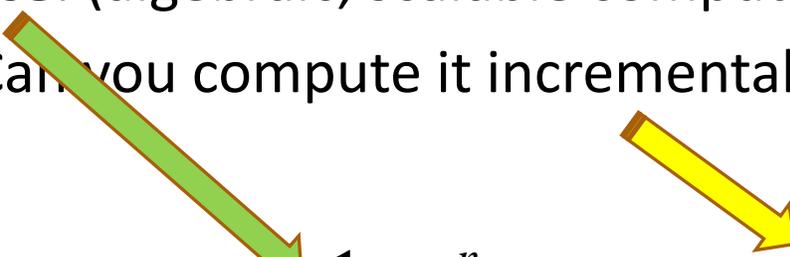
↪ Represent central tendency

# Measures Data Distribution: Variance and Standard Deviation

□ Variance and standard deviation (*sample:  $s$ , population:  $\sigma$* )

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

□ Q: Can you compute it incrementally and efficiently?


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

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^n (x_i - \mu)^2 = \frac{1}{N} \sum_{i=1}^n x_i^2 - \mu^2$$

□ **Standard deviation  $s$  (or  $\sigma$ )** is the square root of variance  $s^2$  (or  $\sigma^2$ )

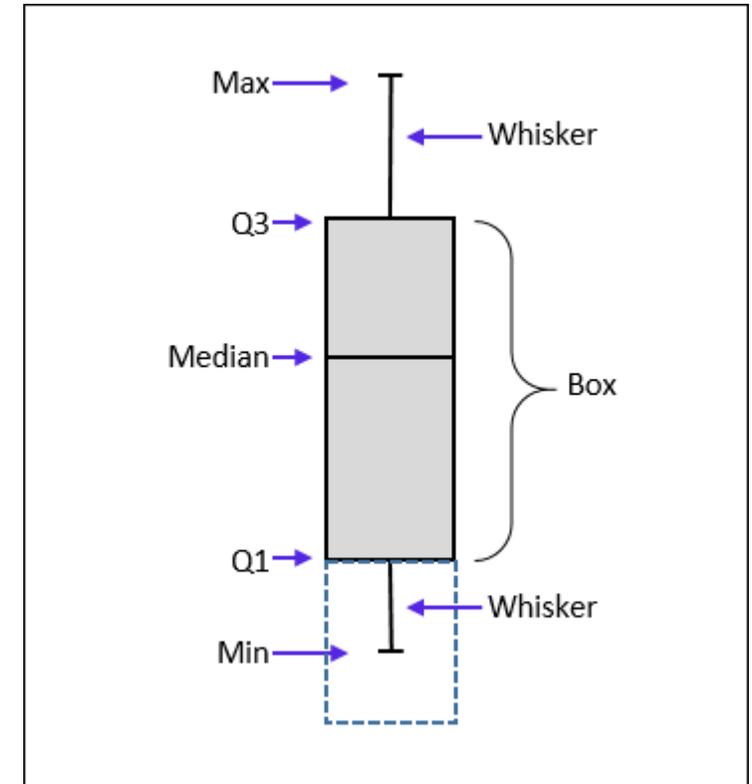
# Graphic Displays of Basic Statistical Descriptions

---

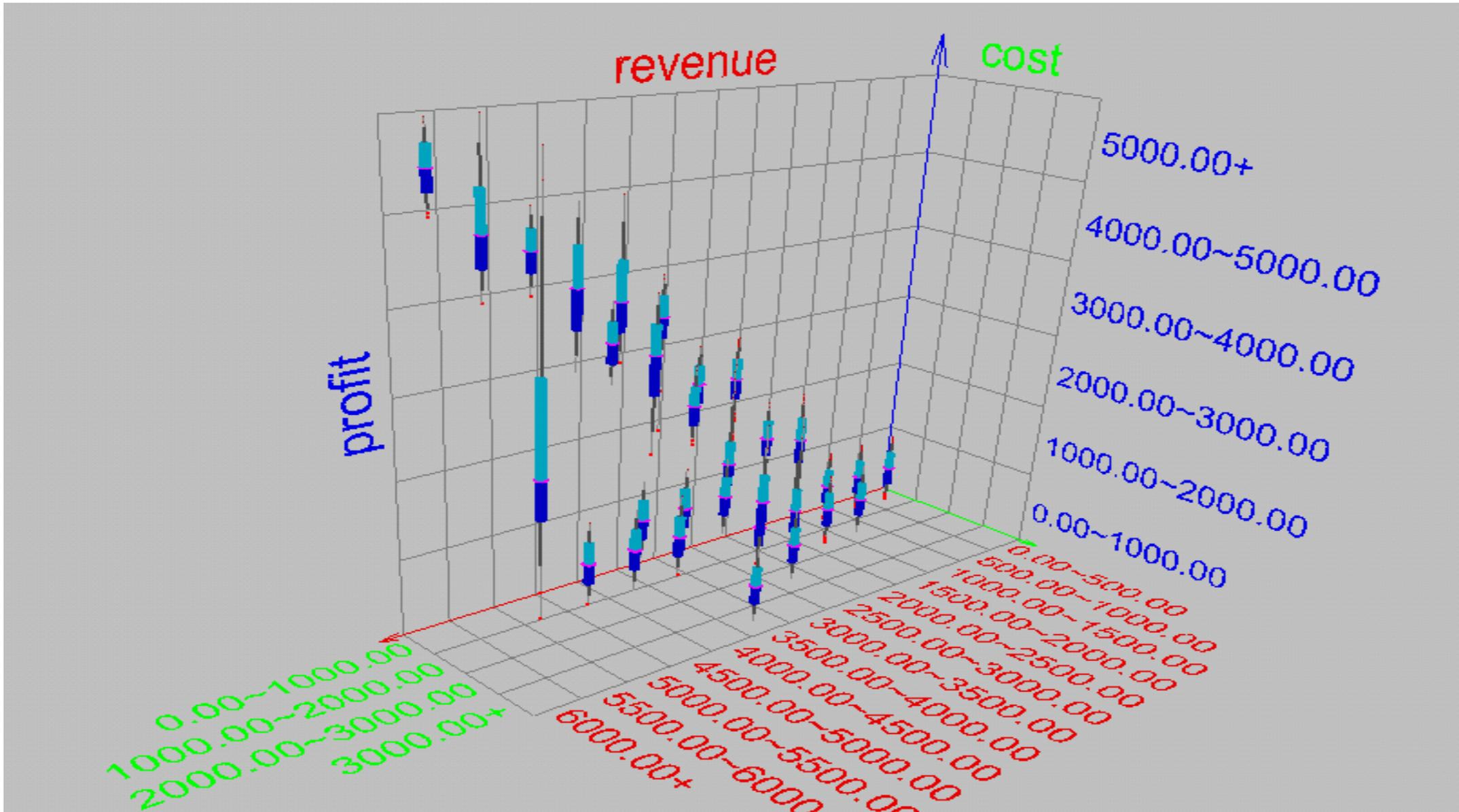
- ❑ **Boxplot:** graphic display of five-number summary
- ❑ **Histogram:** x-axis are values, y-axis repres. frequencies
- ❑ **Quantile plot:** each value  $x_i$  is paired with  $f_i$  indicating that approximately  $100 f_i \%$  of data are  $\leq x_i$
- ❑ **Quantile-quantile (q-q) plot:** graphs the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

# Measuring the Dispersion of Data: Quartiles & Boxplots

- ❑ **Quartiles:**  $Q_1$  (25<sup>th</sup> percentile),  $Q_3$  (75<sup>th</sup> percentile)
- ❑ **Inter-quartile range:**  $IQR = Q_3 - Q_1$
- ❑ **Five number summary:** min,  $Q_1$ , median,  $Q_3$ , max
- ❑ **Boxplot:** Data is represented with a box
  - ❑  $Q_1$ ,  $Q_3$ , IQR: The ends of the box are at the first and third quartiles, i.e., the height of the box is IQR
  - ❑ Median ( $Q_2$ ) 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
    - ❑ **Outlier:** usually, a value higher/lower than  $1.5 \times IQR$



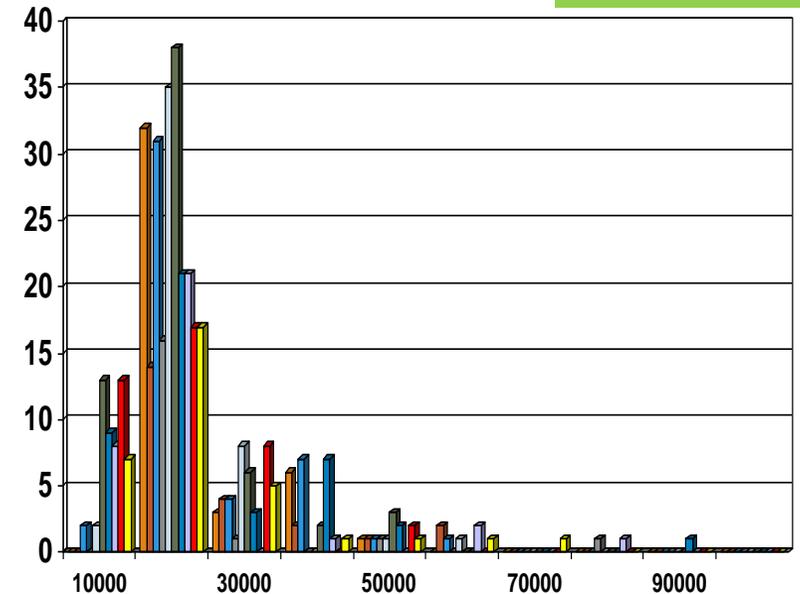
# Visualization of Data Dispersion: 3-D Boxplots



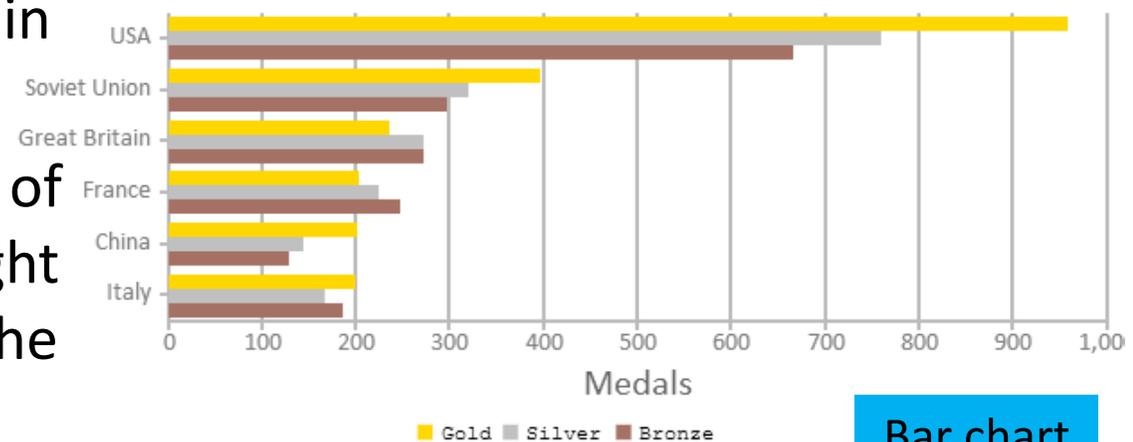
# Histogram Analysis

Histogram

- ❑ Histogram: Graph display of tabulated frequencies, shown as bars
- ❑ Differences between histograms and bar charts
  - ❑ Histograms are used to show distributions of variables while bar charts are used to compare variables
  - ❑ Histograms plot binned quantitative data while bar charts plot categorical data
  - ❑ Bars can be reordered in bar charts but not in histograms
  - ❑ 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

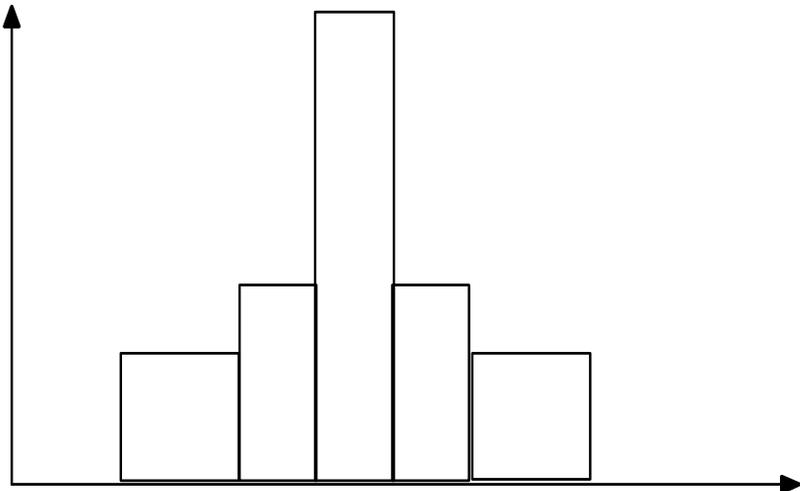
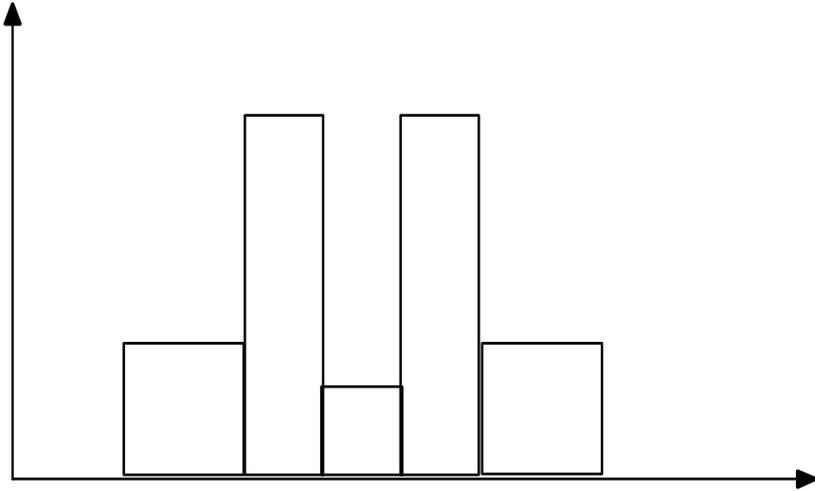


Olympic Medals of all Times (till 2012 Olympics)



Bar chart

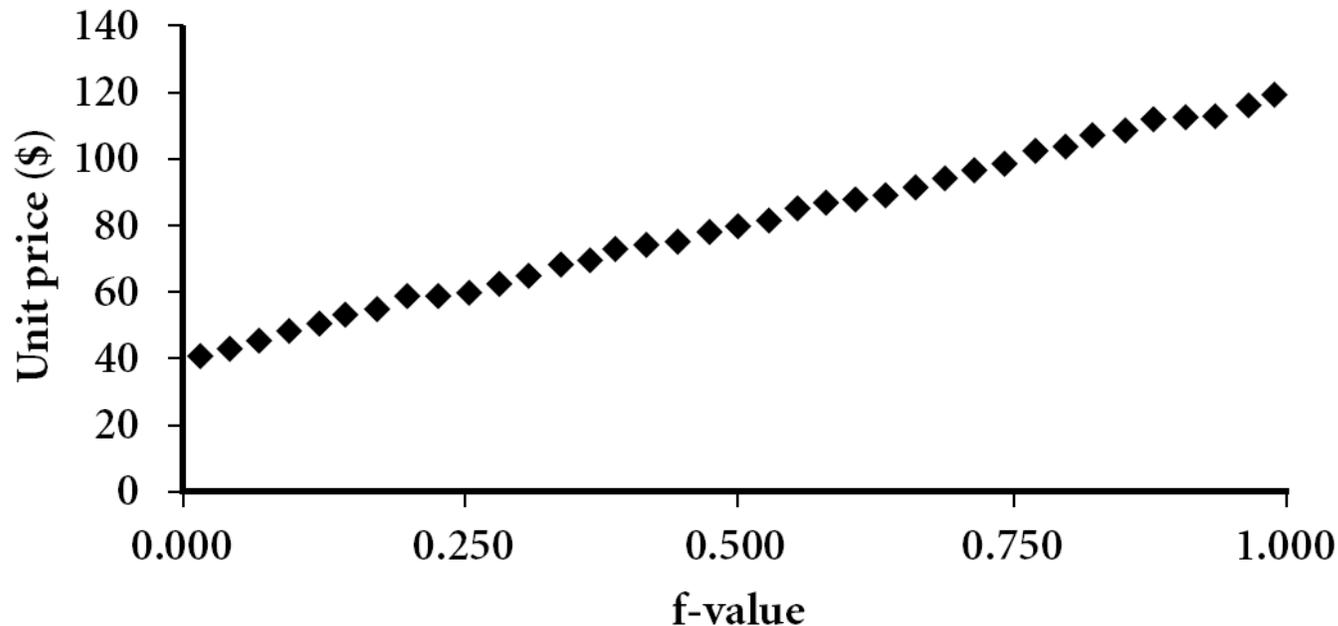
# Histograms Often Tell More than Boxplots



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

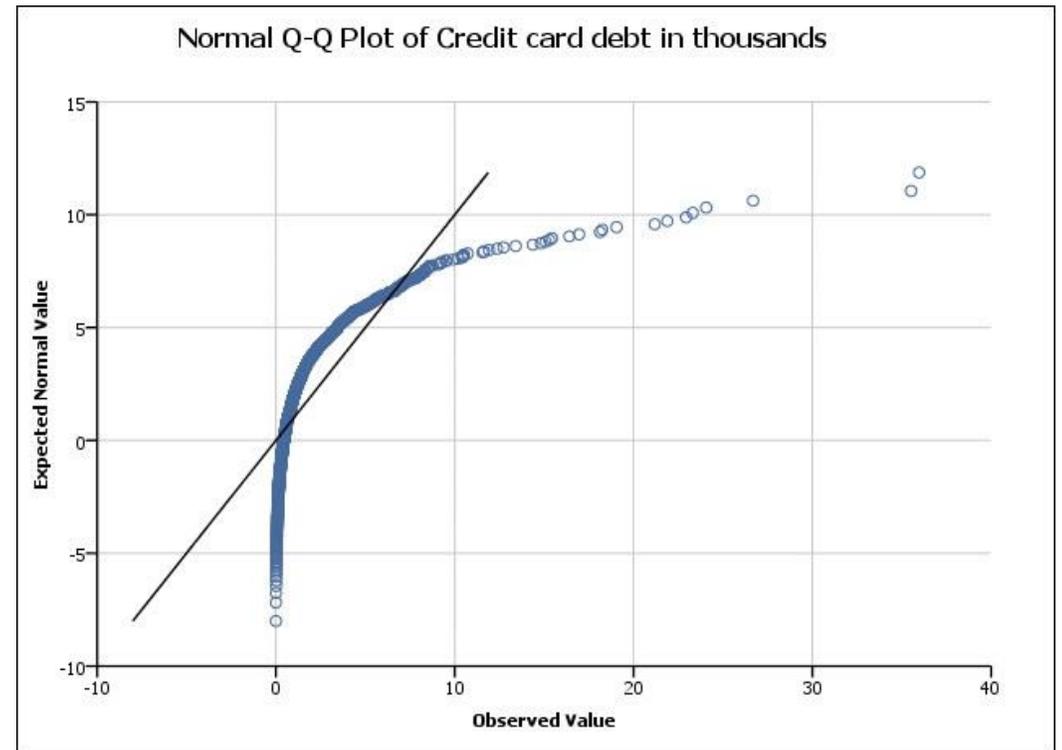
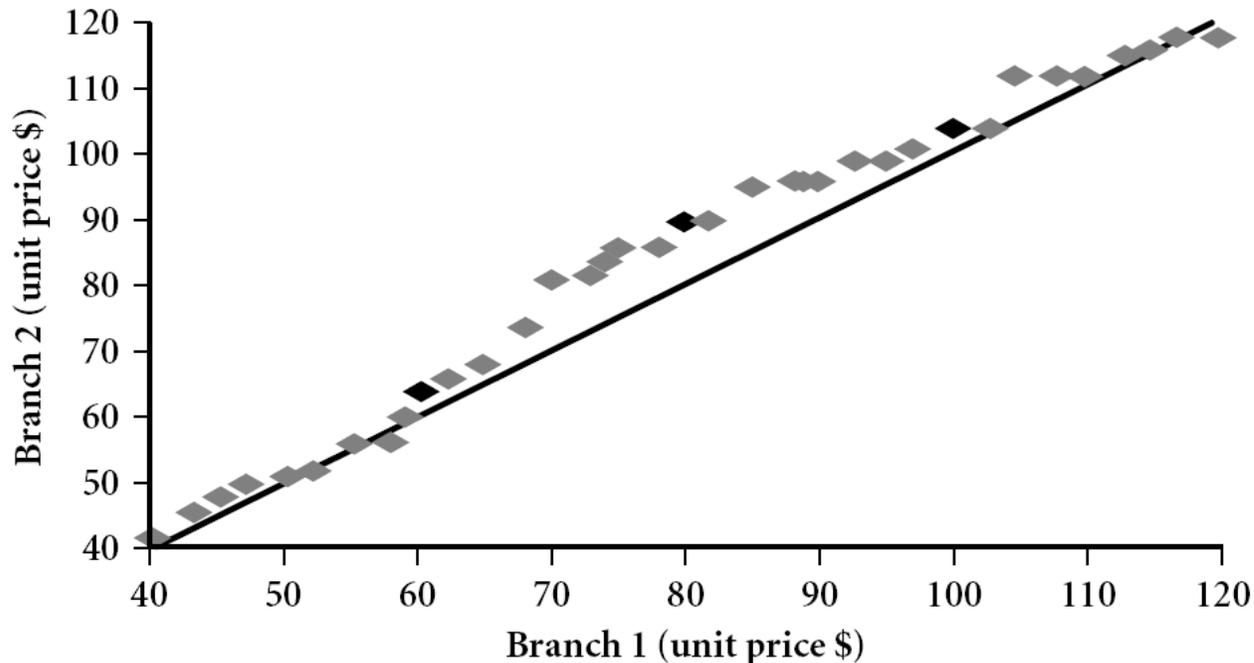
# Quantile Plot

- Displays all of the data (allowing the user to assess both the overall behavior and unusual occurrences)
- Plots **quantile** information
  - For a data  $x_i$  data sorted in increasing order,  $f_i$  indicates that approximately 100  $f_i$ % of the data are below or equal to the value  $x_i$



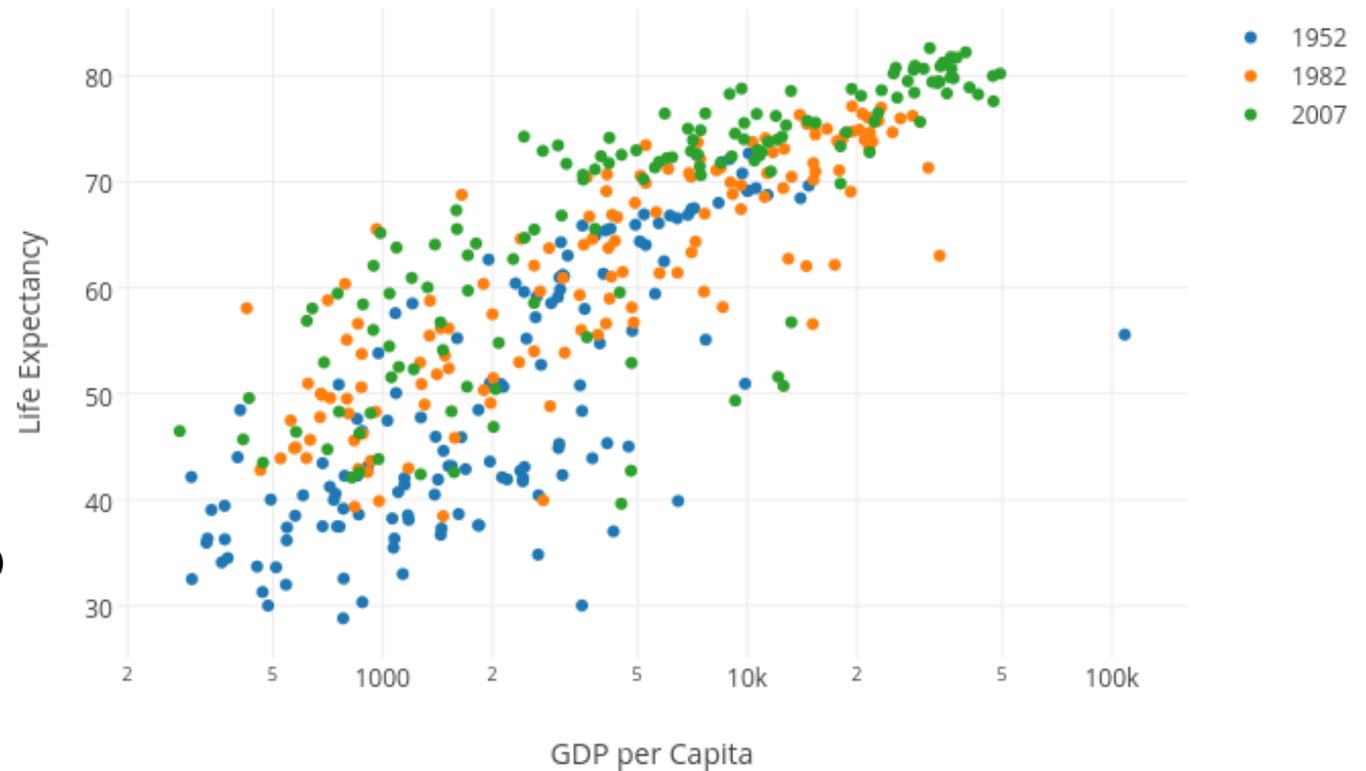
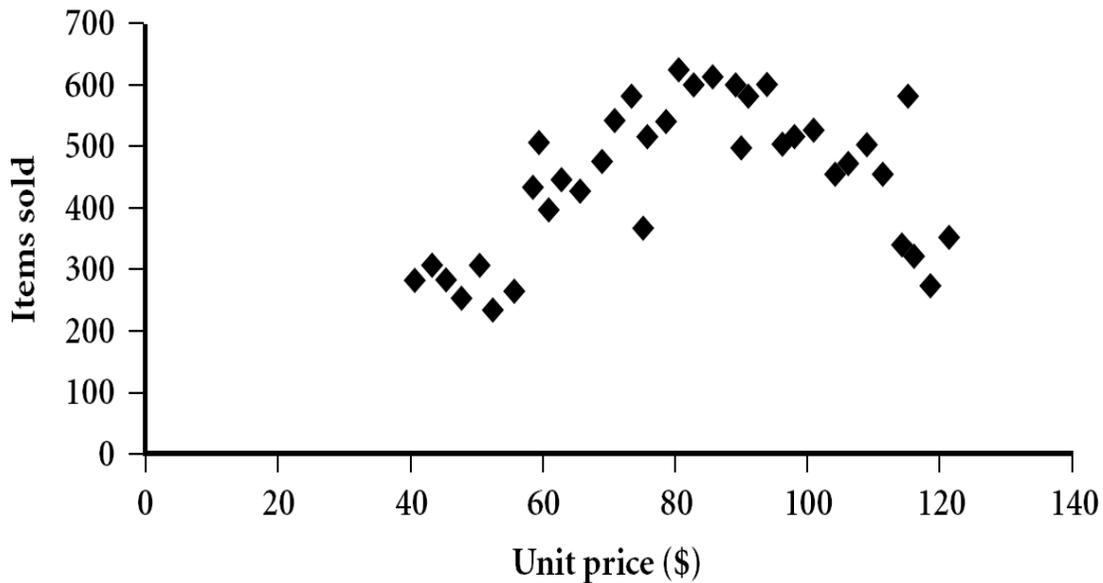
# Quantile-Quantile (Q-Q) Plot

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

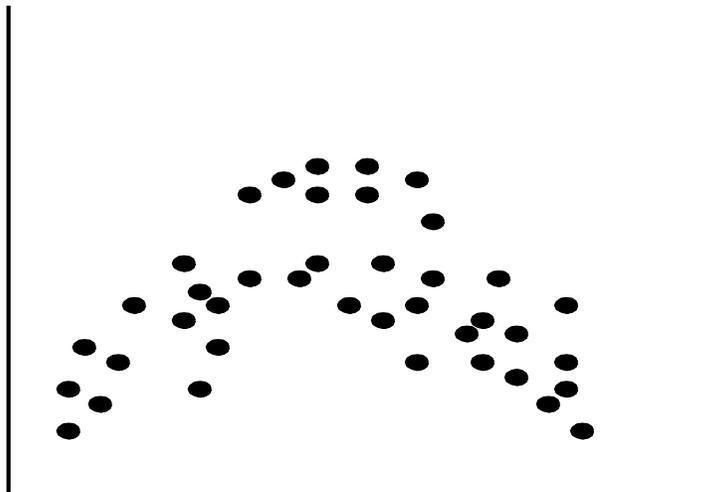
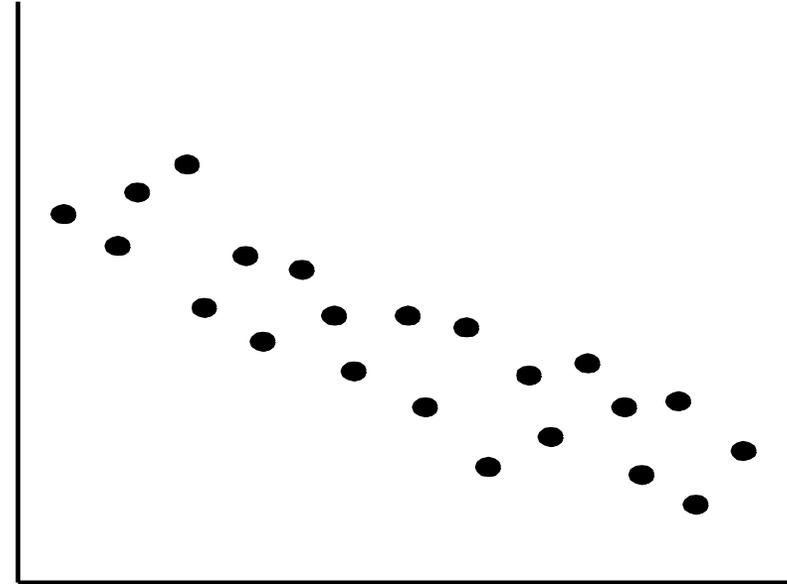
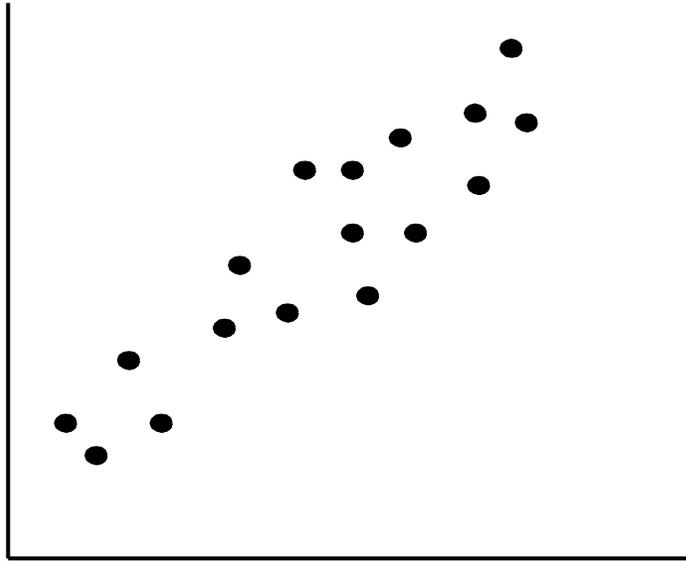


# Scatter plot

- ❑ Provides a first look at bivariate data to see clusters of points, outliers, etc.
- ❑ Each pair of values is treated as a pair of coordinates and plotted as points in the plane



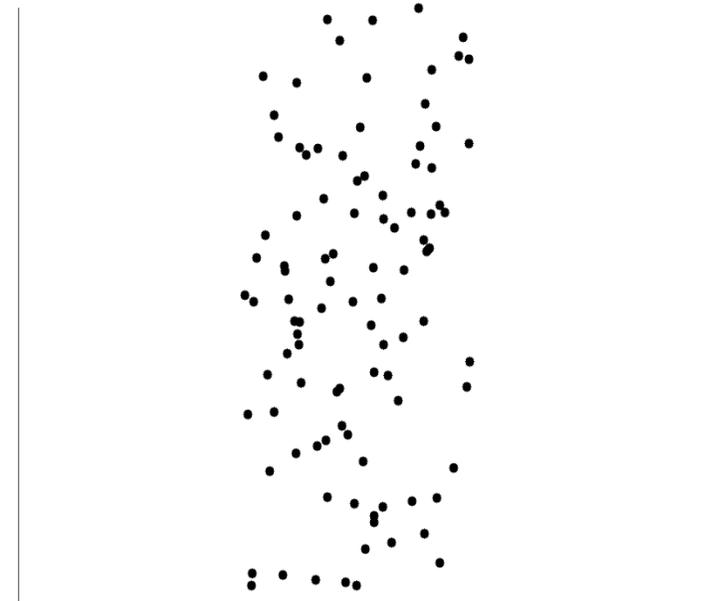
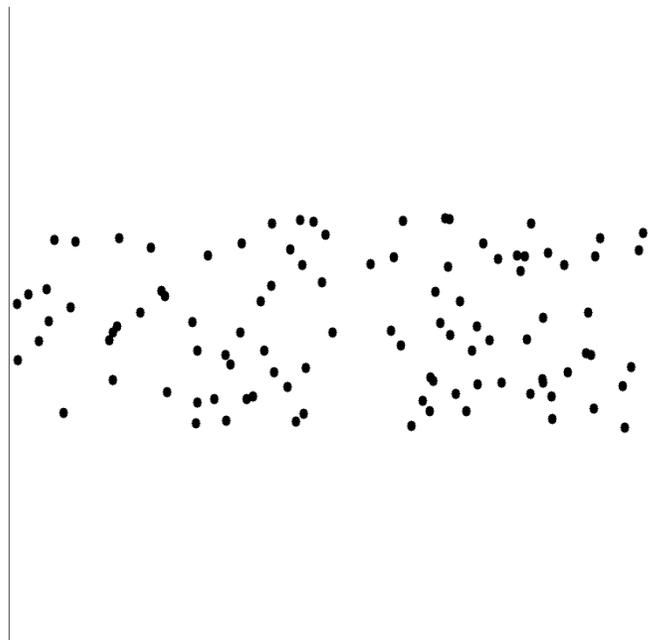
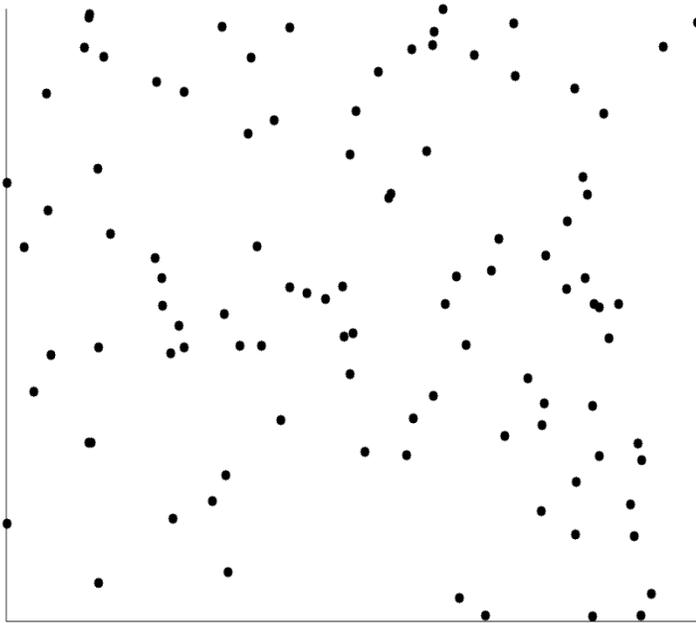
# Positively and Negatively Correlated Data



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

# Uncorrelated Data

---



# Chapter 2. Getting to Know Your Data

---

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

# Data Visualization

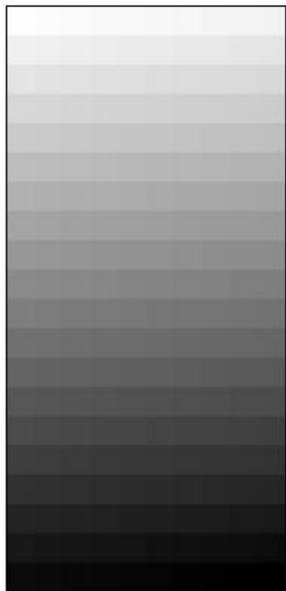
---

- 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**

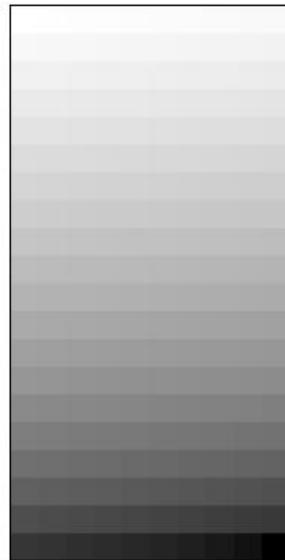
# Pixel-Oriented Visualization Techniques

---

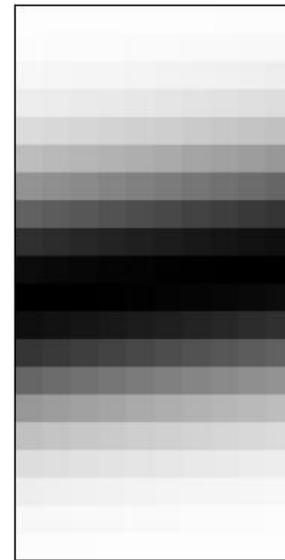
- ❑ For a data set of  $m$  dimensions, create  $m$  windows on the screen, one for each dimension
- ❑ The  $m$  dimension values of a record are mapped to  $m$  pixels at the corresponding positions in the windows
- ❑ The colors of the pixels reflect the corresponding values



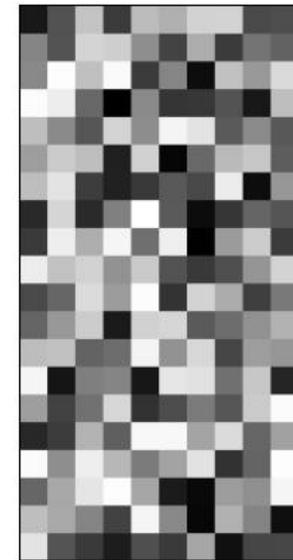
(a) Income



(b) Credit Limit



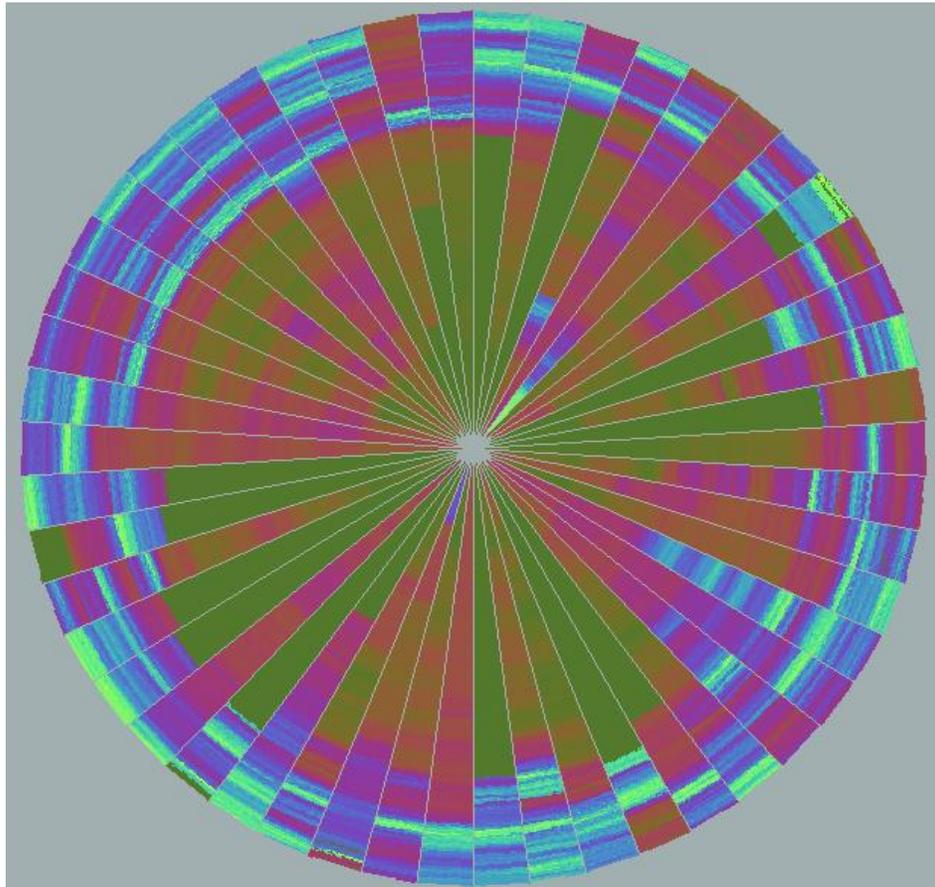
(c) transaction volume



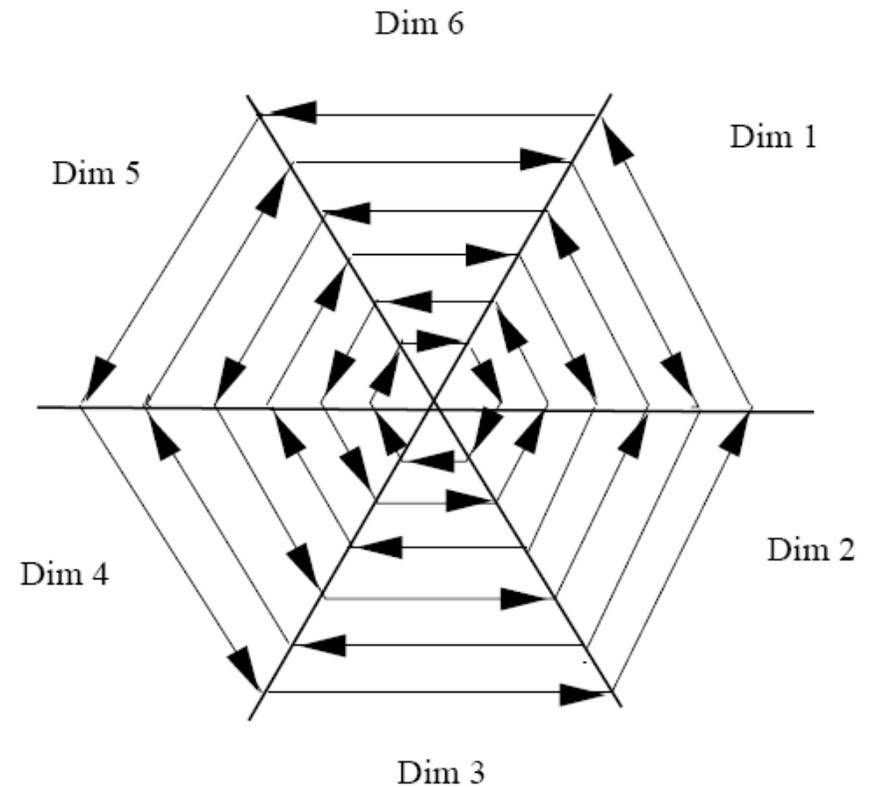
(d) age

# 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



Representing about 265,000 50-dimensional Data Items with the 'Circle Segments' Technique



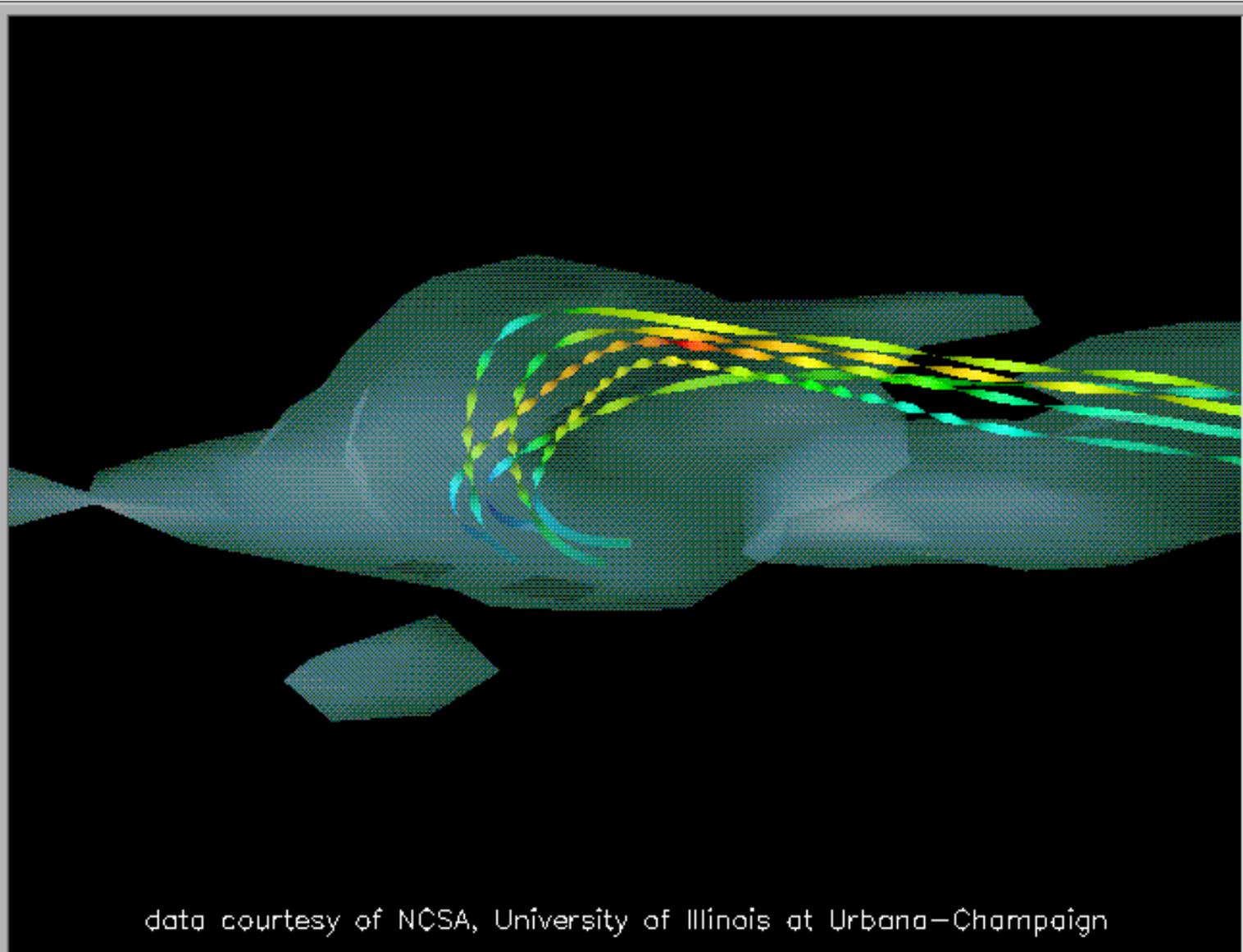
(b) Laying out pixels in circle segment

# 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

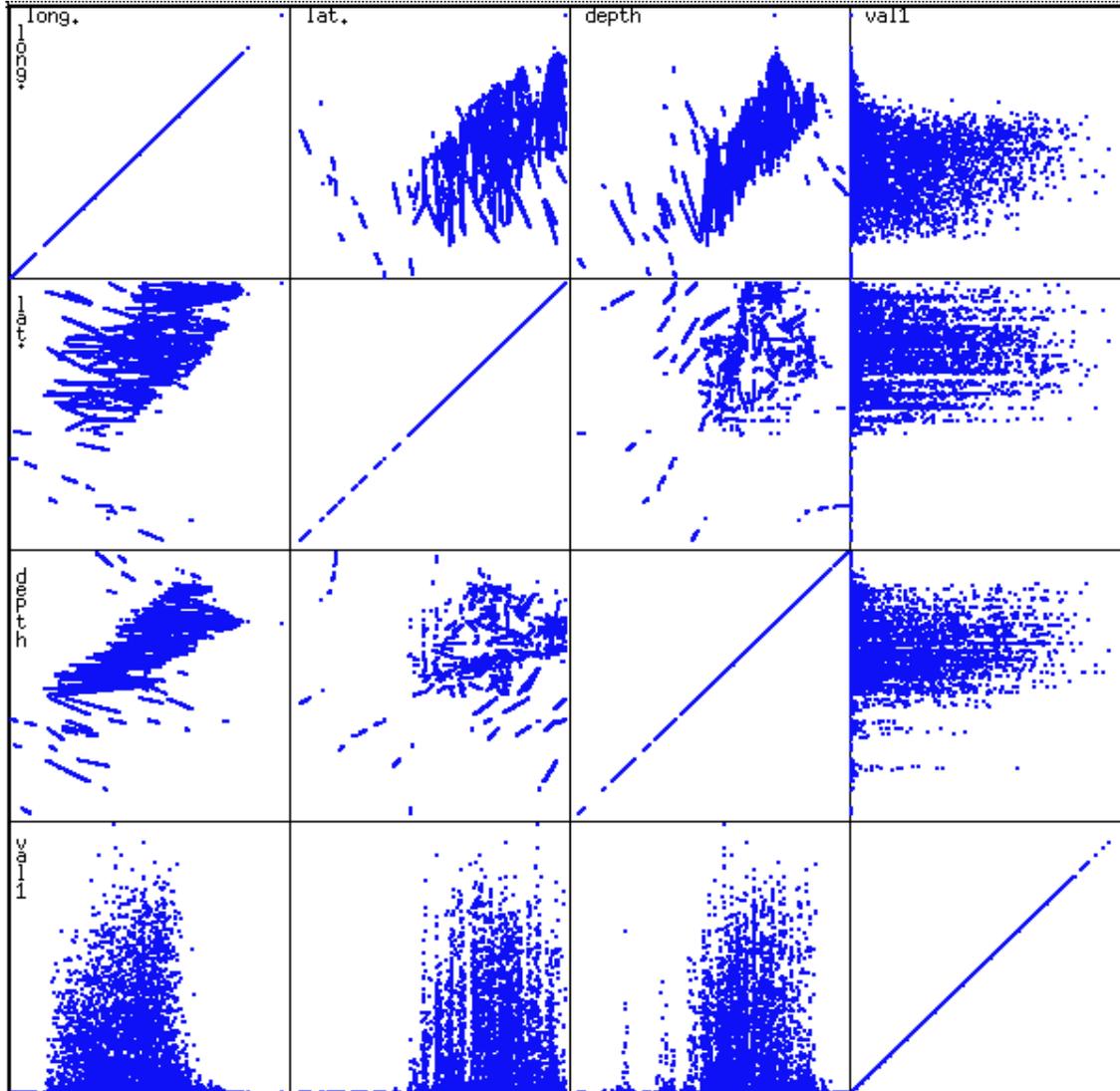
# Direct Data Visualization



Ribbons with Twists Based on Vorticity

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

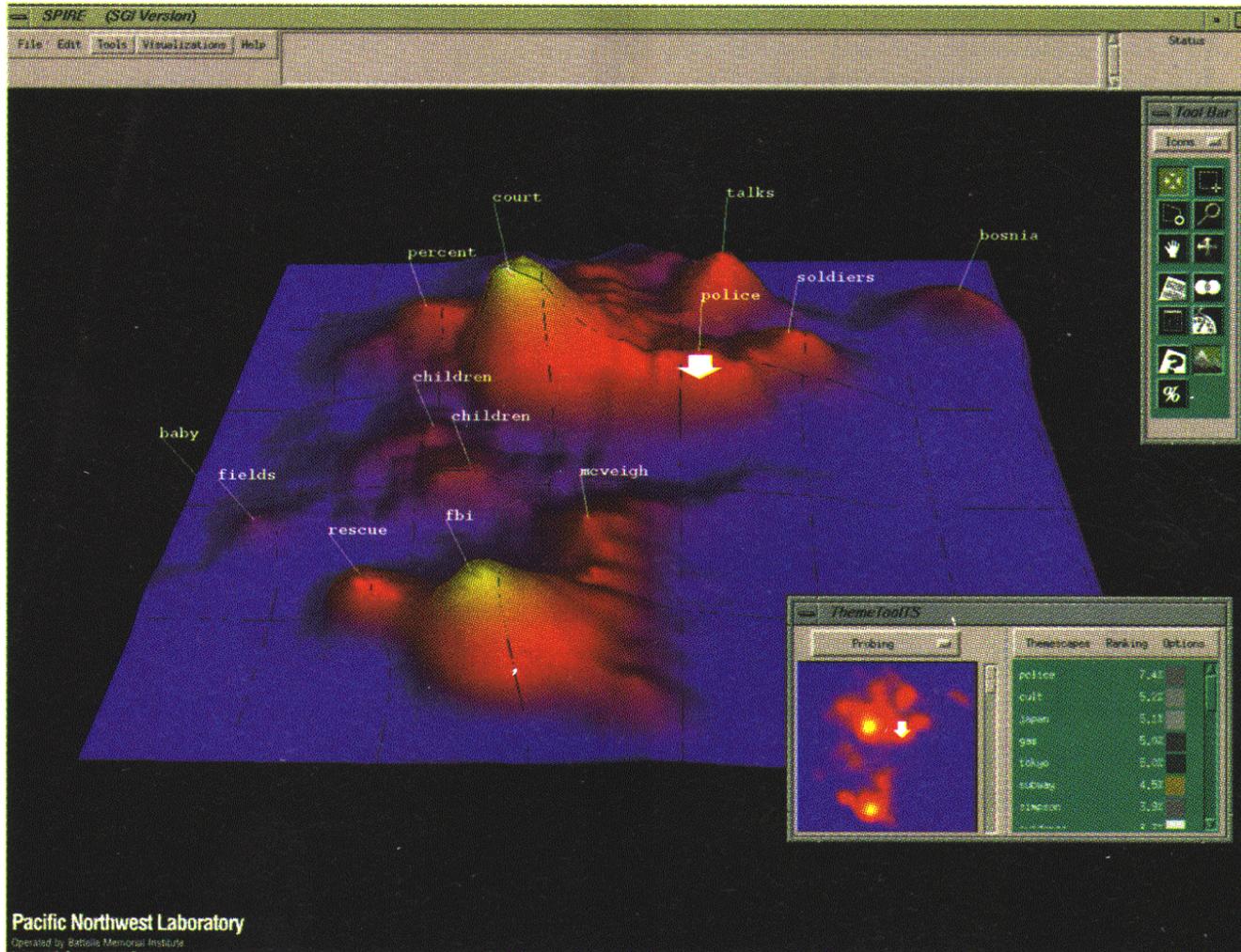
# Scatterplot Matrices



- Matrix of scatterplots (x-y-diagrams) of the k-dim. data
- A total of  $k(k-1)/2$  distinct scatterplots

# Landscapes

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

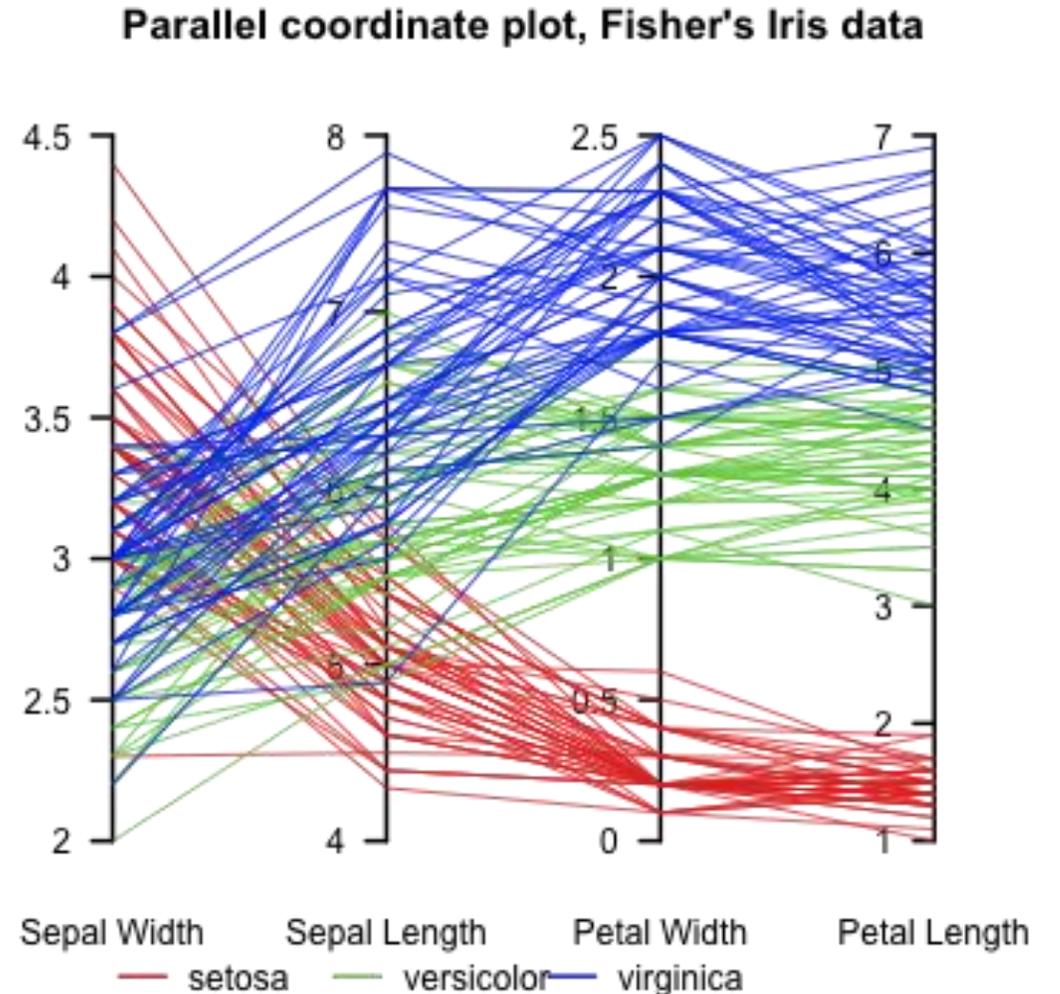


- ❑ Visualization of the data as perspective landscape
- ❑ The data needs to be transformed into a (possibly artificial) 2D spatial representation which preserves the characteristics of the data

news articles visualized as a landscape

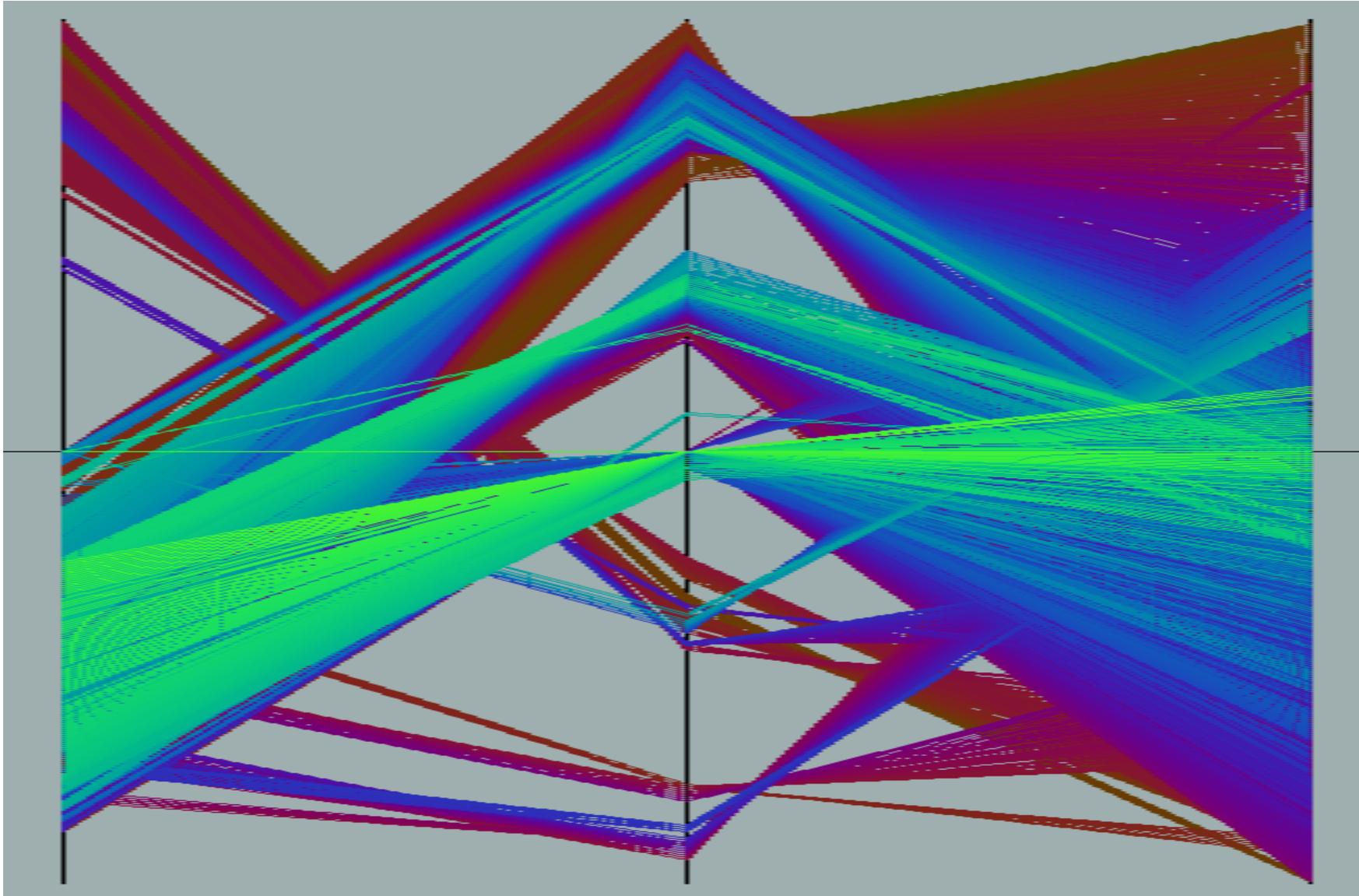
# Parallel Coordinates

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



# Parallel Coordinates of a Data Set

---



# Icon-Based Visualization Techniques

---

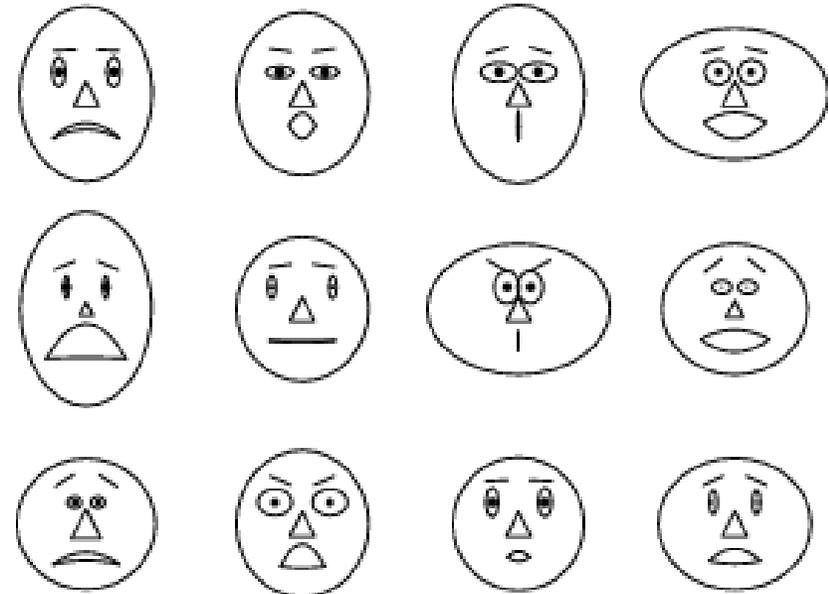
- ❑ Visualization of the data values as features of icons
- ❑ Typical visualization methods
  - ❑ Chernoff Faces
  - ❑ Stick Figures
- ❑ General techniques
  - ❑ Shape coding: Use shape to represent certain information encoding
  - ❑ Color icons: Use color icons to encode more information
  - ❑ Tile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

# Chernoff Faces

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

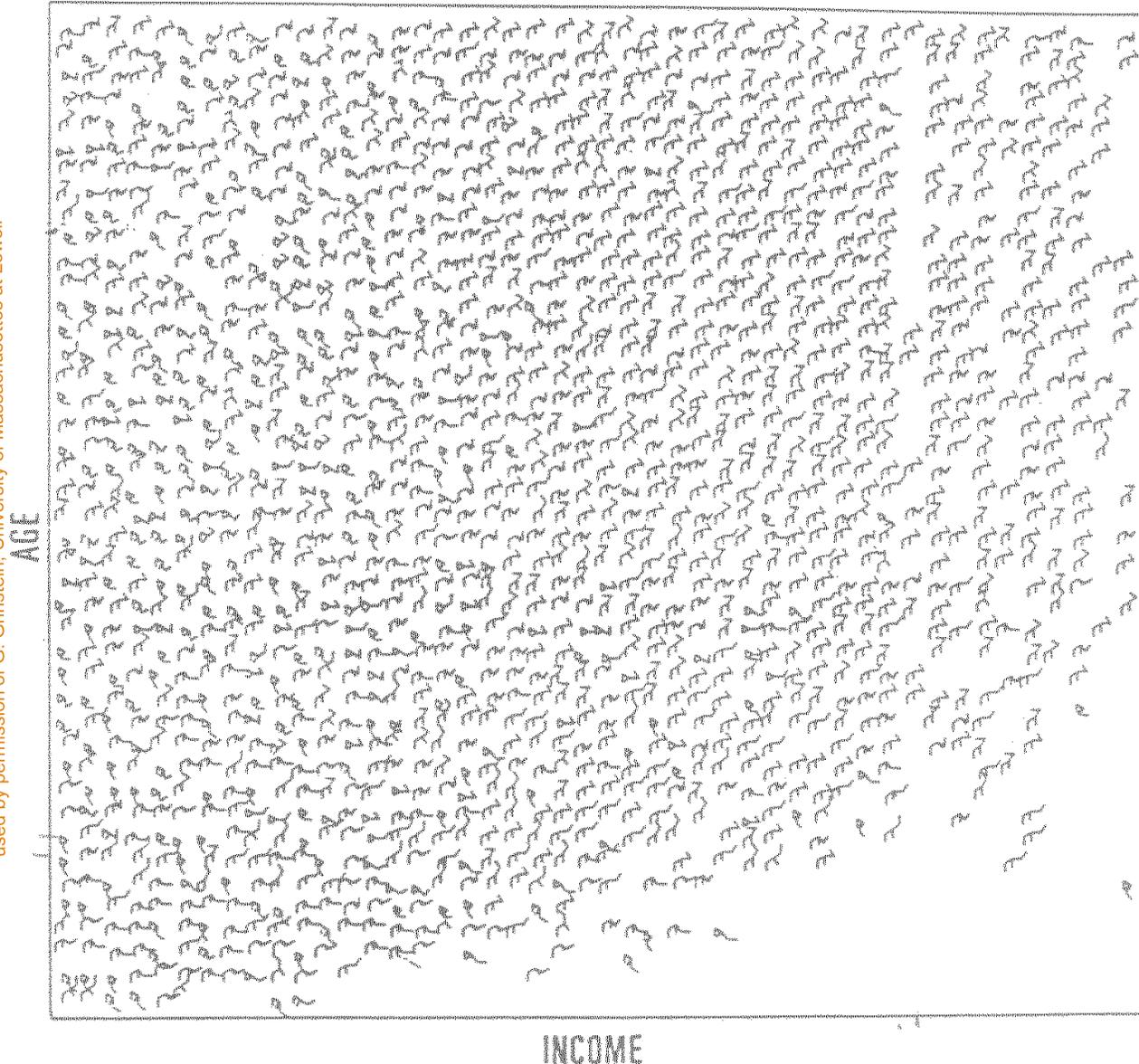
- ❑ REFERENCE: Gonick, L. and Smith, W. [The Cartoon Guide to Statistics](#). New York: Harper Perennial, p. 212, 1993

- ❑ Weisstein, Eric W. "Chernoff Face." From *MathWorld*--A Wolfram Web Resource. [mathworld.wolfram.com/ChernoffFace.html](http://mathworld.wolfram.com/ChernoffFace.html)



# Stick Figure

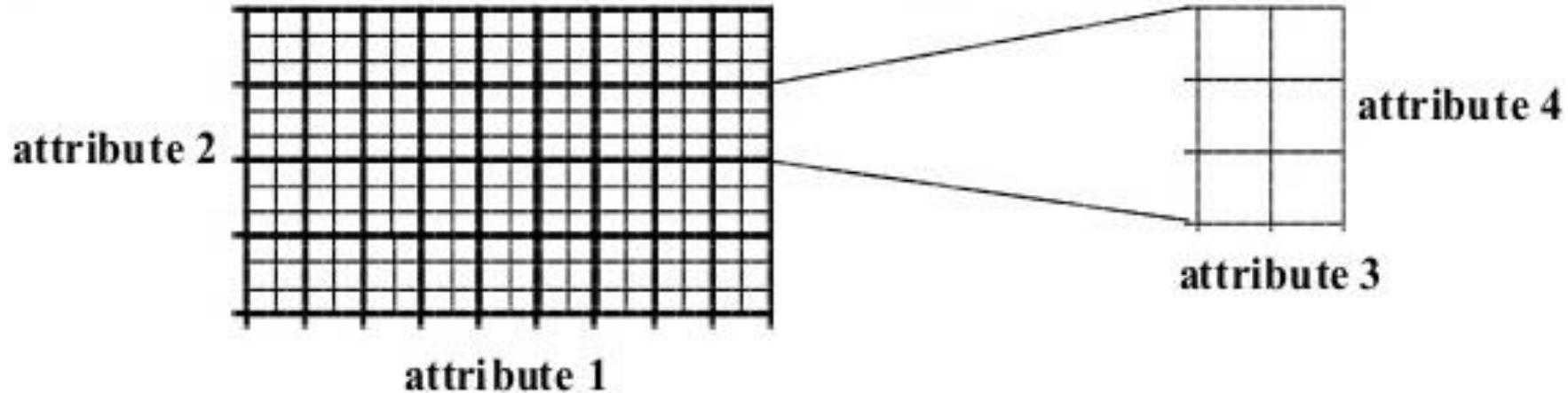
used by permission of G. Grimstein, University of Massachusetts at Lowell



- ❑ A census data figure showing age, income, gender, education, etc.
- ❑ A 5-piece stick figure (1 body and 4 limbs w. different angle/length)



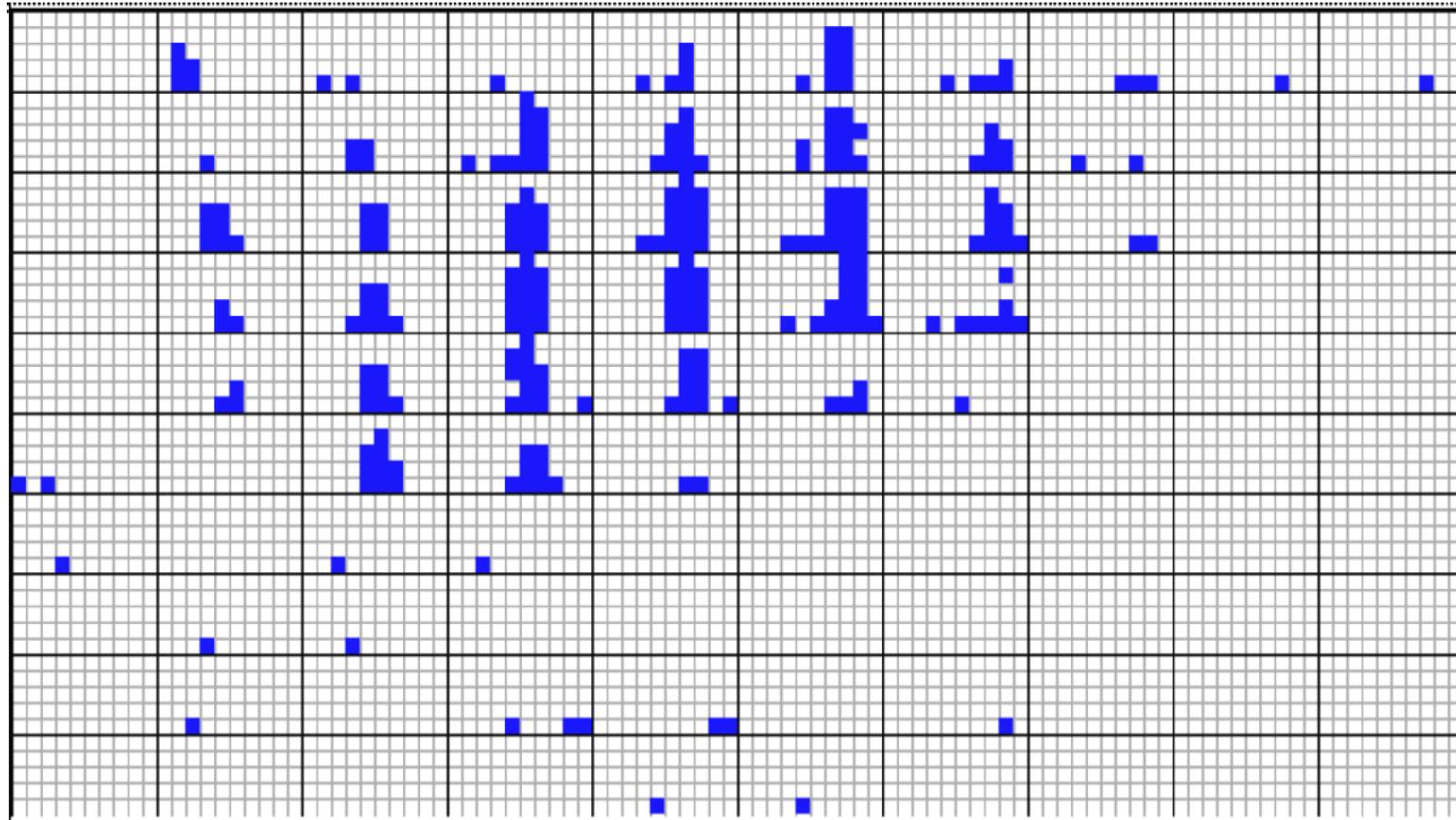
# Dimensional Stacking



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

# Dimensional Stacking

Used by permission of M. Ward, Worcester Polytechnic Institute

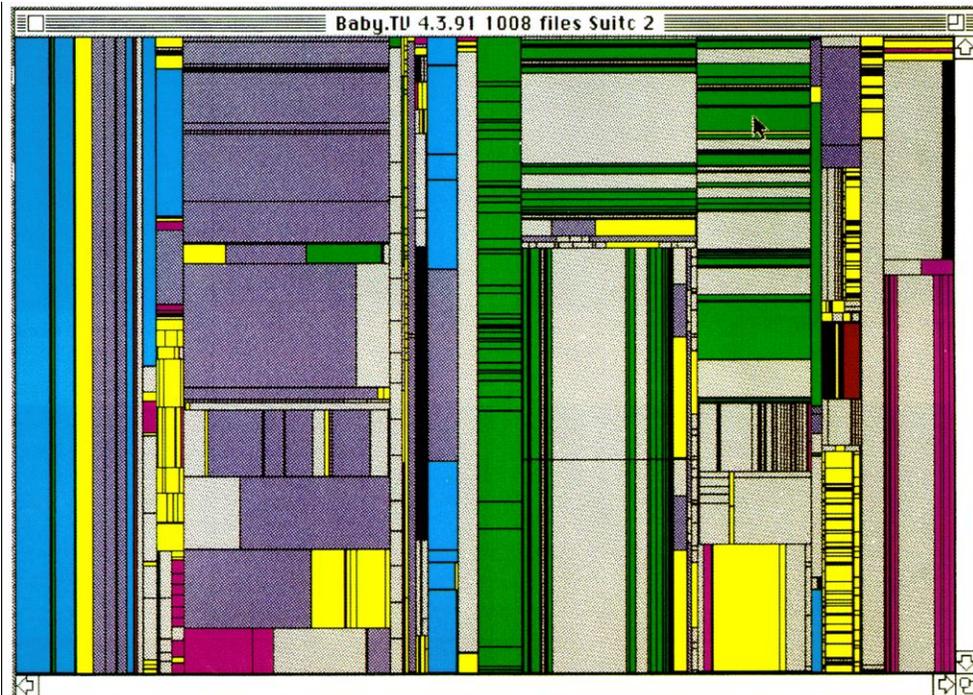


Visualization of oil mining data with longitude and latitude mapped to the outer x-, y-axes and ore grade and depth mapped to the inner x-, y-axes

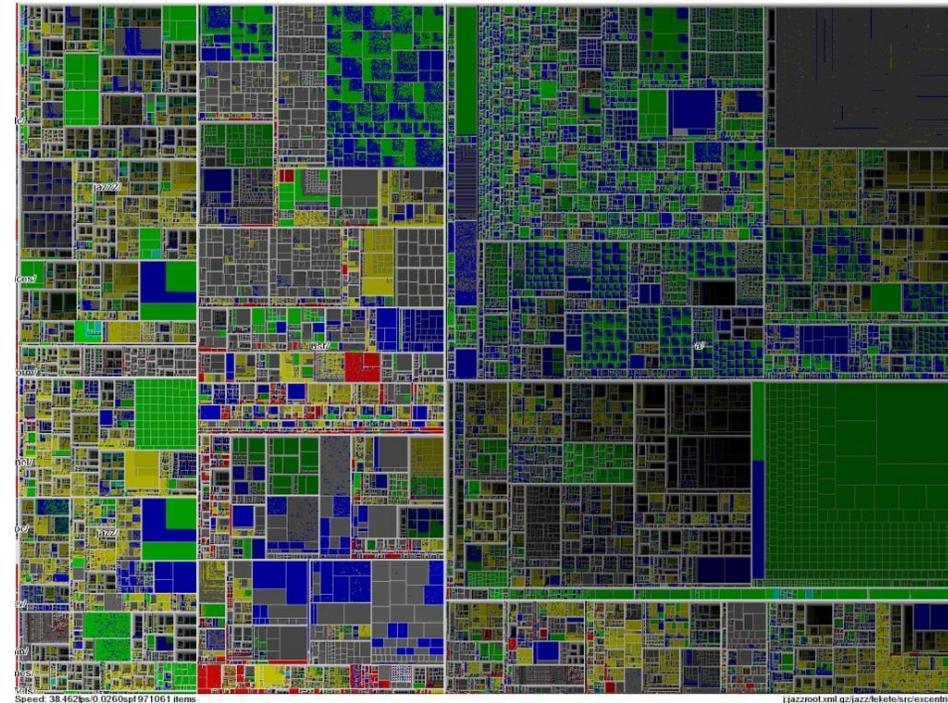


# Tree-Map

- ❑ 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)



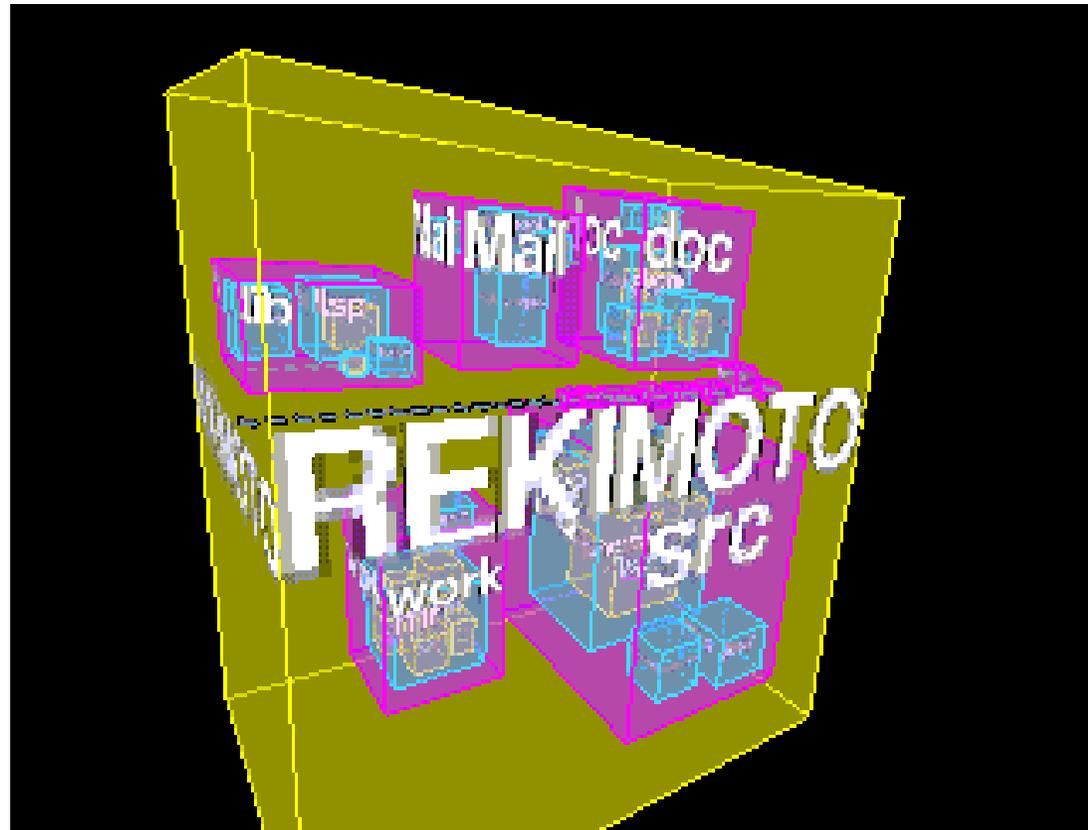
Schneiderman@UMD: Tree-Map of a File System



Schneiderman@UMD: Tree-Map to support large data sets of a million items

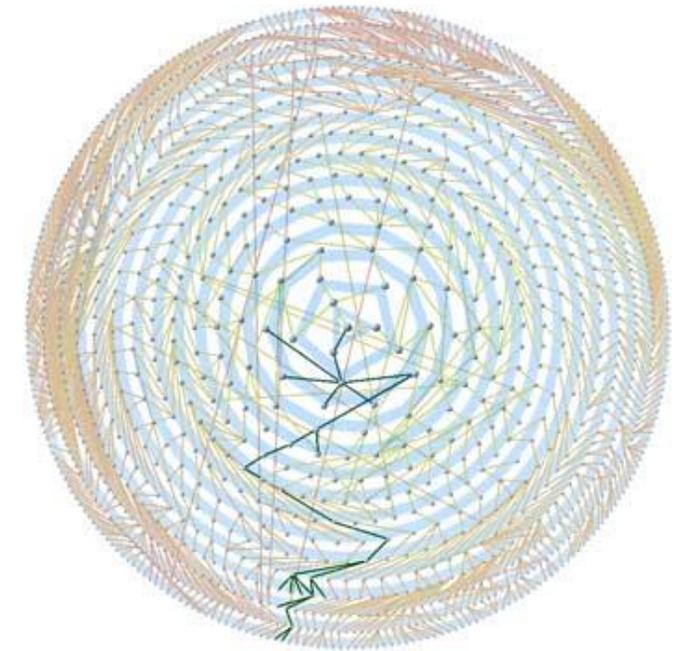
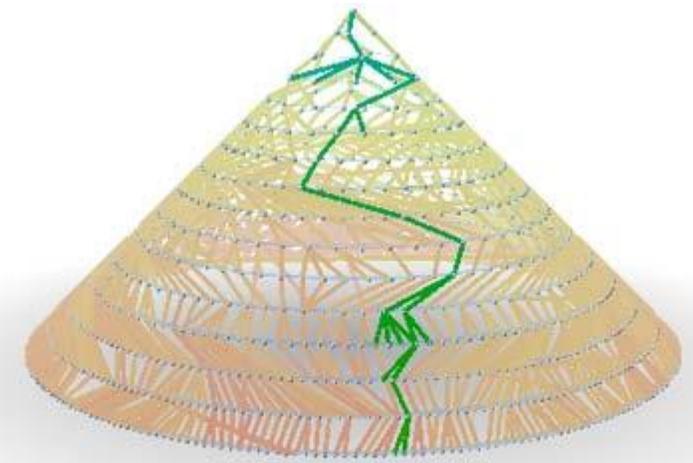
# InfoCube

- ❑ 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, etc.



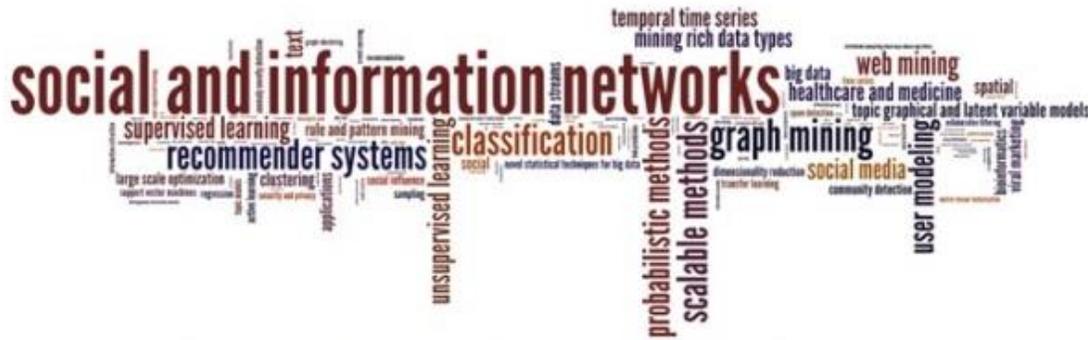
# Three-D Cone Trees

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

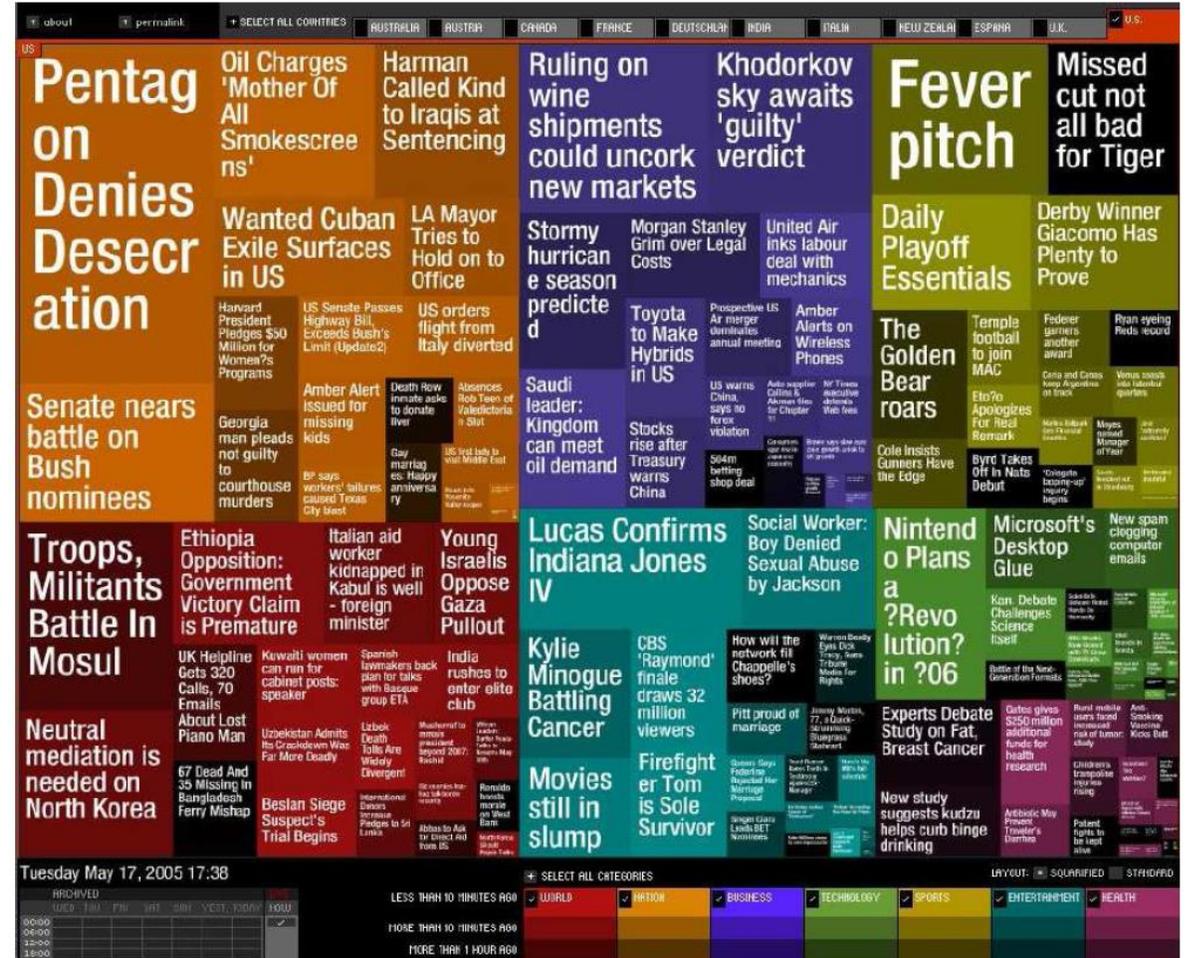


# Visualizing Complex Data and Relations: Tag Cloud

- Tag cloud: Visualizing user-generated tags
  - The importance of tag is represented by font size/color
  - Popularly used to visualize word/phrase distributions



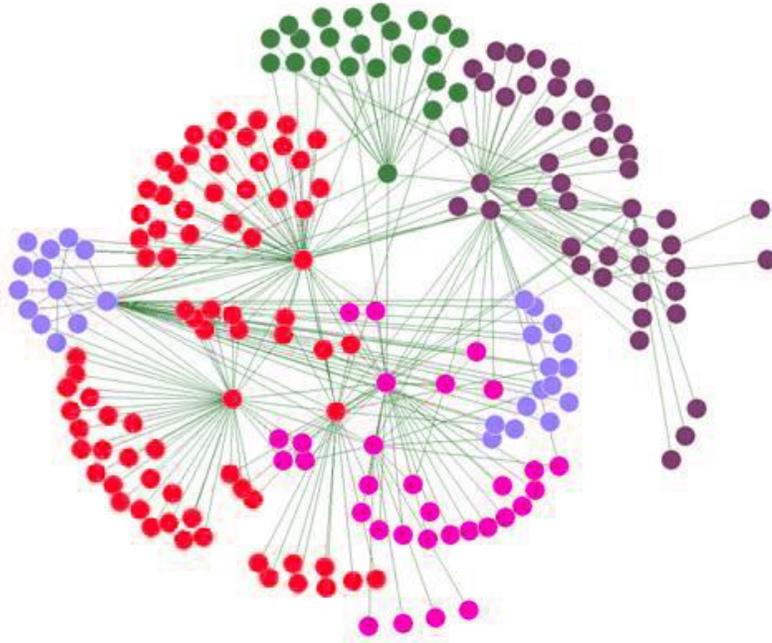
KDD 2013 Research Paper Title Tag Cloud



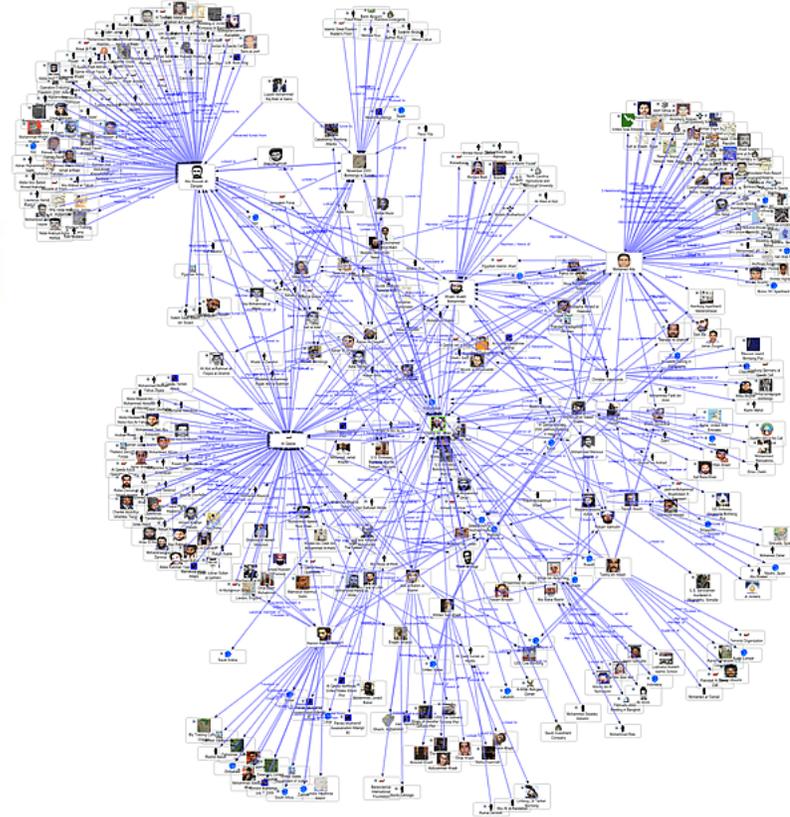
Newsmap: Google News Stories in 2005

# Visualizing Complex Data and Relations: Social Networks

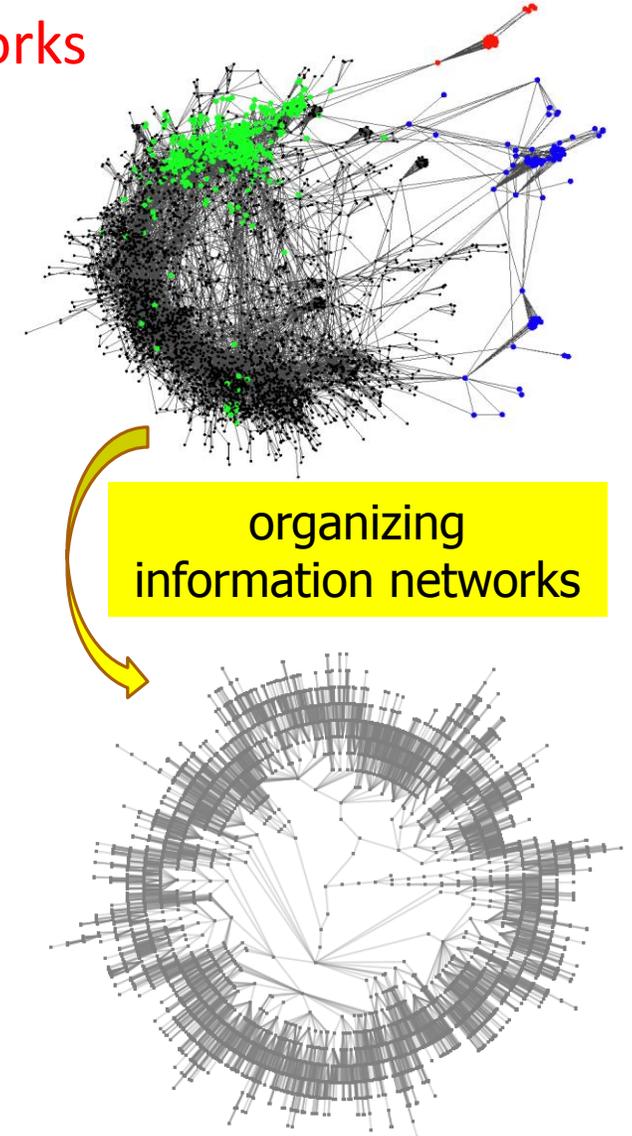
- Visualizing non-numerical data: **social and information networks**



A typical network structure



A social network



organizing  
information networks

# Chapter 2. Getting to Know Your Data

---

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

# Similarity, Dissimilarity, and Proximity

---

- **Similarity measure or similarity function**

- A real-valued function that quantifies the similarity between two objects
- Measure how two data objects are alike: The higher value, the more alike
- Often falls in the range  $[0,1]$ : 0: no similarity; 1: completely similar

- **Dissimilarity (or distance) measure**

- Numerical measure of how different two data objects are
- In some sense, the inverse of similarity: The lower, the more alike
- Minimum dissimilarity is often 0 (i.e., completely similar)
- Range  $[0, 1]$  or  $[0, \infty)$ , depending on the definition

- **Proximity** usually refers to either similarity or dissimilarity

# Data Matrix and Dissimilarity Matrix

- Data matrix

- A data matrix of  $n$  data points with  $l$  dimensions



$$D = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1l} \\ x_{21} & x_{22} & \dots & x_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nl} \end{pmatrix}$$

- Dissimilarity (distance) matrix

- $n$  data points, but registers only the distance  $d(i, j)$  (typically metric)



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

- Usually symmetric, thus a triangular matrix

- **Distance functions** are usually different for real, boolean, categorical, ordinal, ratio, and vector variables

- Weights can be associated with different variables based on applications and data semantics

# Standardizing Numeric Data

---

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

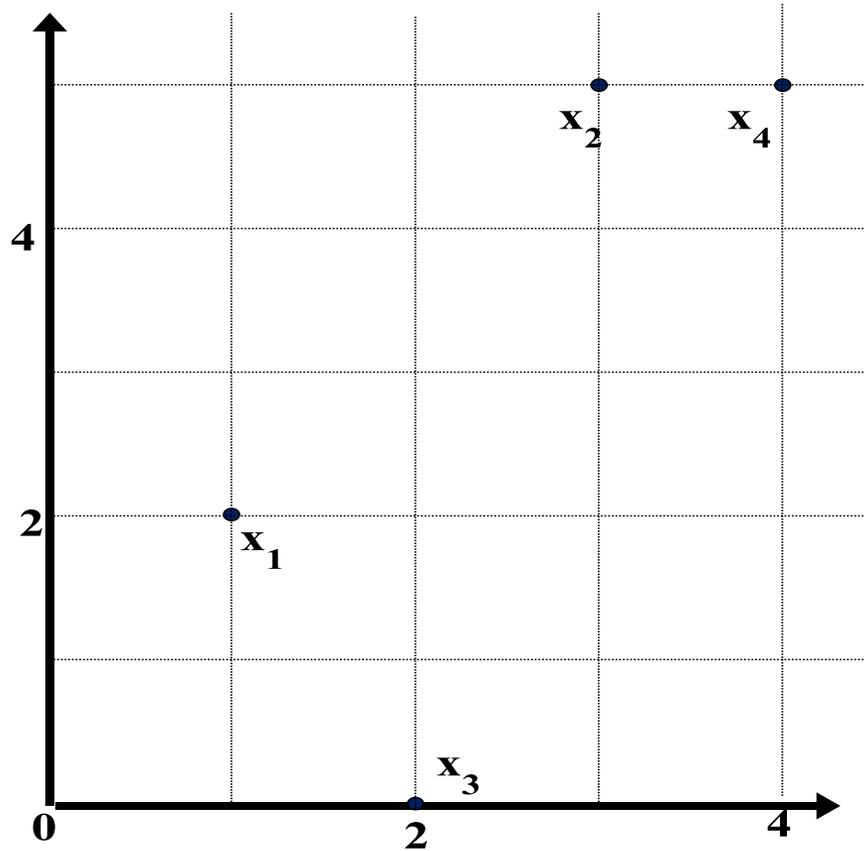
$$s_f = \frac{1}{n} (|x_{1f} - m_f| + |x_{2f} - m_f| + \dots + |x_{nf} - m_f|)$$

where

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

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

# Example: Data Matrix and Dissimilarity Matrix



Data Matrix

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

Dissimilarity Matrix (by **Euclidean Distance**)

	$x1$	$x2$	$x3$	$x4$
$x1$	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

$$d(i, j) = \sqrt[p]{|x_{i1} - x_{j1}|^p + |x_{i2} - x_{j2}|^p + \dots + |x_{il} - x_{jl}|^p}$$

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

- Properties
  - $d(i, j) > 0$  if  $i \neq j$ , and  $d(i, i) = 0$  (Positivity)
  - $d(i, j) = d(j, i)$  (Symmetry)
  - $d(i, j) \leq d(i, k) + d(k, j)$  (Triangle Inequality)
- A distance that satisfies these properties is a **metric**
- Note: There are nonmetric dissimilarities, e.g., set differences

# Special Cases of Minkowski Distance

---

- $p = 1$ : ( $L_1$  norm) **Manhattan (or city block) distance**

- E.g., the Hamming distance: the number of bits that are different between two binary vectors

$$d(i, j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \cdots + |x_{il} - x_{jl}|$$

- $p = 2$ : ( $L_2$  norm) **Euclidean distance**

$$d(i, j) = \sqrt{|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \cdots + |x_{il} - x_{jl}|^2}$$

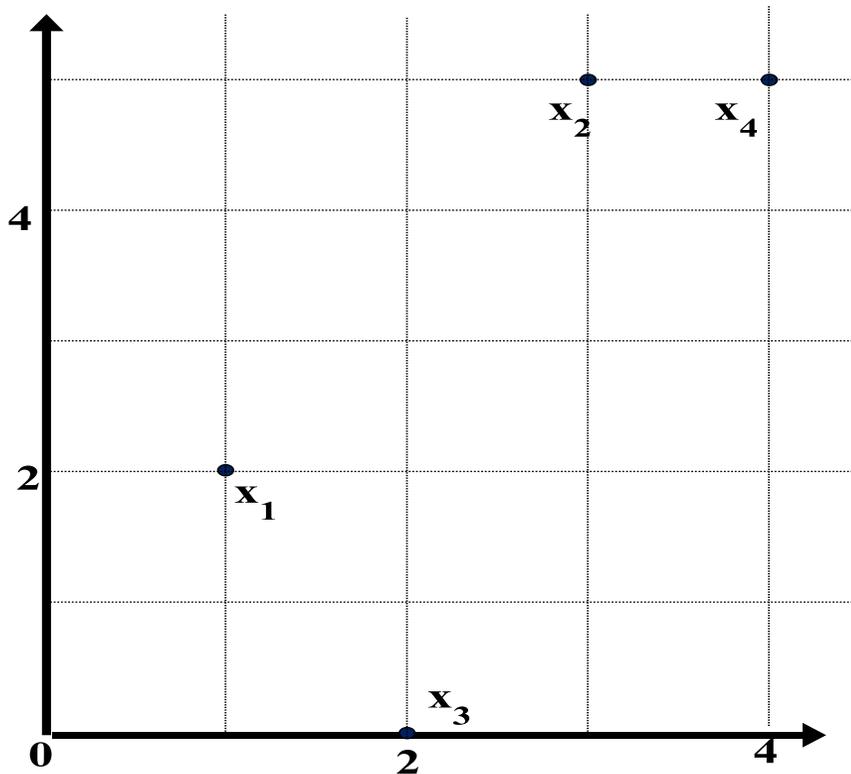
- $p \rightarrow \infty$ : ( $L_{\max}$  norm,  $L_{\infty}$  norm) **“supremum” distance**

- The maximum difference between any component (attribute) of the vectors

$$d(i, j) = \lim_{p \rightarrow \infty} \sqrt[p]{|x_{i1} - x_{j1}|^p + |x_{i2} - x_{j2}|^p + \cdots + |x_{il} - x_{jl}|^p} = \max_{f=1}^l |x_{if} - x_{jf}|$$

# Example: Minkowski Distance at Special Cases

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 ( $L_\infty$ )

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

# Proximity Measure for Binary Attributes

- A contingency table for binary data

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

- Distance measure for symmetric binary variables

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

- Distance measure for asymmetric binary variables:

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

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

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

- Note: Jaccard coefficient is the same as

(a concept discussed in Pattern Discovery)

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

# Example: Dissimilarity between Asymmetric Binary Variables

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

- Gender is a symmetric attribute (not counted in)
- The remaining attributes are asymmetric binary
- Let the values Y and P be 1, and the value N be 0
- Distance:  $d(i, j) = \frac{r + s}{q + r + s}$

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

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

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

		Mary		
		1	0	$\Sigma_{row}$
Jack	1	2	0	2
	0	1	3	4
$\Sigma_{col}$		3	3	6

		Jim		
		1	0	$\Sigma_{row}$
Jack	1	1	1	2
	0	1	3	4
$\Sigma_{col}$		2	4	6

		Mary		
		1	0	$\Sigma_{row}$
Jim	1	1	1	2
	0	2	2	4
$\Sigma_{col}$		3	3	6

# Proximity Measure for Categorical Attributes

---

- Categorical data, also called nominal attributes
  - Example: Color (red, yellow, blue, green), profession, etc.
- 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

# Ordinal Variables

---

- ❑ An ordinal variable can be discrete or continuous
- ❑ Order is important, e.g., rank (e.g., freshman, sophomore, junior, senior)
- ❑ Can be treated like interval-scaled
  - ❑ Replace *an ordinal variable value* by its rank:  $r_{if} \in \{1, \dots, M_f\}$
  - ❑ Map the range of each variable onto  $[0, 1]$  by replacing  $i$ -th object in the  $f$ -th variable by
$$z_{if} = \frac{r_{if} - 1}{M_f - 1}$$
  - ❑ Example: freshman: 0; sophomore: 1/3; junior: 2/3; senior 1
    - ❑ Then distance:  $d(\text{freshman}, \text{senior}) = 1$ ,  $d(\text{junior}, \text{senior}) = 1/3$
  - ❑ Compute the dissimilarity using methods for interval-scaled variables

# Attributes of Mixed Type

---

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

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

- If  $f$  is numeric: Use the normalized distance
- If  $f$  is binary or nominal:  $d_{ij}^{(f)} = 0$  if  $x_{if} = x_{jf}$ ; or  $d_{ij}^{(f)} = 1$  otherwise
- If  $f$  is ordinal
  - Compute ranks  $z_{if}$  (where  $z_{if} = \frac{r_{if} - 1}{M_f - 1}$ )
  - Treat  $z_{if}$  as interval-scaled

# Cosine Similarity of Two Vectors

- A **document** can be represented by a bag of terms or a long vector, with each attribute recording the *frequency* of a particular term (such as word, keyword, or phrase) in the document

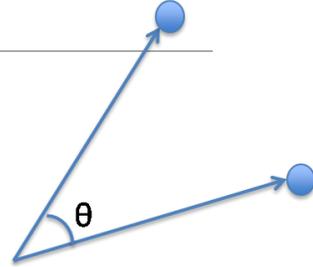
<i>Document</i>	<i>teamcoach</i>	<i>hockey</i>	<i>baseball</i>	<i>soccer</i>	<i>penalty</i>	<i>score</i>	<i>win</i>	<i>loss</i>	<i>season</i>
Document1	5	0	3	0	2	0	2	0	0
Document2	3	0	2	0	1	1	0	1	1
Document3	0	7	0	2	1	0	3	0	0
Document4	0	1	0	0	1	2	2	3	0

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

$$\cos(d_1, d_2) = \frac{d_1 \bullet d_2}{\|d_1\| \times \|d_2\|}$$

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

# Example: Calculating Cosine Similarity



□ Calculating Cosine Similarity: 
$$\cos(d_1, d_2) = \frac{d_1 \bullet d_2}{\|d_1\| \times \|d_2\|} \quad \text{sim}(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

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

- Ex: Find the **similarity** between documents 1 and 2.

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

- First, calculate vector dot product

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

- Then, calculate  $\|d_1\|$  and  $\|d_2\|$

$$\|d_1\| = \sqrt{5 \times 5 + 0 \times 0 + 3 \times 3 + 0 \times 0 + 2 \times 2 + 0 \times 0 + 0 \times 0 + 2 \times 2 + 0 \times 0 + 0 \times 0} = 6.481$$

$$\|d_2\| = \sqrt{3 \times 3 + 0 \times 0 + 2 \times 2 + 0 \times 0 + 1 \times 1 + 1 \times 1 + 0 \times 0 + 1 \times 1 + 0 \times 0 + 1 \times 1} = 4.12$$

- Calculate cosine similarity:  $\cos(d_1, d_2) = 25 / (6.481 \times 4.12) = 0.94$

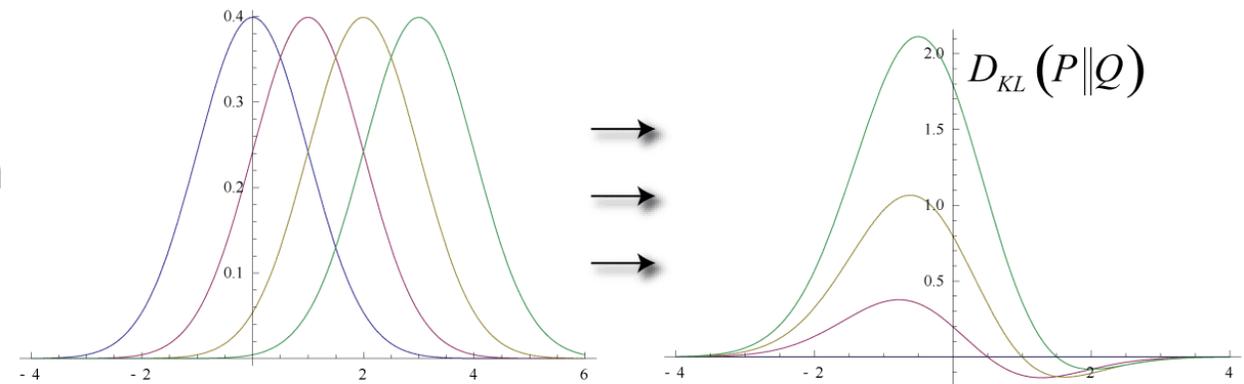
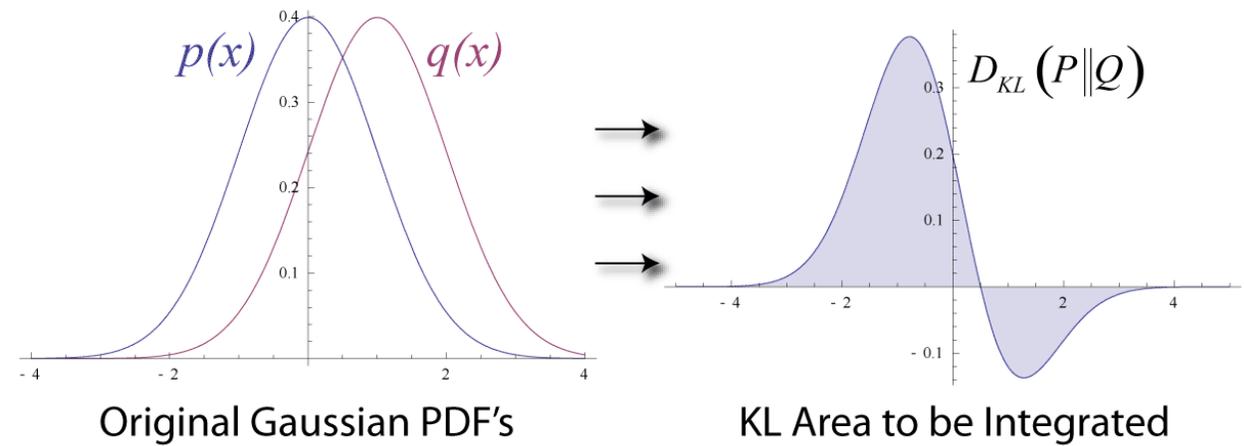
# Announcements: Meetine of the 4th Credit Project

---

- ❑ CS412: **Assignment #1** was distributed last Tuesday!
  - ❑ The due date is Sept. 15. No late homework will be accepted!!
- ❑ **Waitlist is cleared:** We took 50 additional students into the video only session
  - ❑ Please find your status with Holly. You are either in or out (wait for Spring 2017)
- ❑ Meeting for **Project for the 4th Credit**
  - ❑ You can change from 4 to 3 credit or from 3 to 4 credits by sending me e-mails
  - ❑ **Meeting time and location: 10-11am Friday (tomorrow!) at 0216 SC**
  - ❑ This project is part of WSDM 2017 Cup
  - ❑ Choice #1: **Triple Scoring:** Computing relevance scores for triples from type-like relations
  - ❑ Choice #2: **Vandalism Detection** for Wikipages
  - ❑ Tas/PhD student/postdoc will give you the details in the Friday meeting! **Must attend if you want to do the 4<sup>th</sup> credit project!!!**

# KL Divergence: Comparing Two Probability Distributions

- *The Kullback-Leibler (KL) divergence:* Measure the difference between two probability distributions over the same variable  $x$
- From information theory, closely related to *relative entropy*, *information divergence*, and *information for discrimination*
- $D_{KL}(p(x) || q(x))$ : divergence of  $q(x)$  from  $p(x)$ , measuring the information lost when  $q(x)$  is used to approximate  $p(x)$



Ack.: Wikipedia entry: *The Kullback-Leibler (KL) divergence*

Discrete form →

$$D_{KL}(p(x)||q(x)) = \sum_{x \in X} p(x) \ln \frac{p(x)}{q(x)}$$

$$D_{KL}(p(x)||q(x)) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)} dx \quad \leftarrow \text{Continuous form}$$

# More on KL Divergence

$$D_{KL}(p(x)||q(x)) = \sum_{x \in X} p(x) \ln \frac{p(x)}{q(x)}$$

- ❑ The KL divergence measures the expected number of extra bits required to code samples from  $p(x)$  ("true" distribution) when using a code based on  $q(x)$ , which represents a theory, model, description, or approximation of  $p(x)$
- ❑ The KL divergence is not a distance measure, not a metric: asymmetric, not satisfy triangular inequality ( $D_{KL}(P \ Q)$  does not equal  $D_{KL}(Q \ P)$ )
- ❑ In applications,  $P$  typically represents the "true" distribution of data, observations, or a precisely calculated theoretical distribution, while  $Q$  typically represents a theory, model, description, or approximation of  $P$ .
- ❑ The Kullback–Leibler divergence from  $Q$  to  $P$ , denoted  $D_{KL}(P \ Q)$ , is a measure of the information gained when one revises one's beliefs from the prior probability distribution  $Q$  to the posterior probability distribution  $P$ . In other words, it is the amount of information lost when  $Q$  is used to approximate  $P$ .
- ❑ The KL divergence is sometimes also called the information gain achieved if  $P$  is used instead of  $Q$ . It is also called the relative entropy of  $P$  with respect to  $Q$ .

# Subtlety at Computing the KL Divergence

- Base on the formula,  $D_{KL}(P, Q) \geq 0$  and  $D_{KL}(P || Q) = 0$  if and only if  $P = Q$
- How about when  $p = 0$  or  $q = 0$ ?
  - $\lim_{p \rightarrow 0} p \log p = 0$
  - when  $p \neq 0$  but  $q = 0$ ,  $D_{KL}(p || q)$  is defined as  $\infty$ , i.e., if one event  $e$  is possible (i.e.,  $p(e) > 0$ ), and the other predicts it is absolutely impossible (i.e.,  $q(e) = 0$ ), then the two distributions are absolutely different
- However, in practice,  $P$  and  $Q$  are derived from frequency distributions, not counting the possibility of unseen events. Thus *smoothing* is needed
- Example:  $P : (a : 3/5, b : 1/5, c : 1/5)$ .  $Q : (a : 5/9, b : 3/9, d : 1/9)$ 
  - need to introduce a small constant  $\epsilon$ , e.g.,  $\epsilon = 10^{-3}$
  - The sample set observed in  $P$ ,  $SP = \{a, b, c\}$ ,  $SQ = \{a, b, d\}$ ,  $SU = \{a, b, c, d\}$
  - Smoothing, add missing symbols to each distribution, with probability  $\epsilon$
  - $P' : (a : 3/5 - \epsilon/3, b : 1/5 - \epsilon/3, c : 1/5 - \epsilon/3, d : \epsilon)$
  - $Q' : (a : 5/9 - \epsilon/3, b : 3/9 - \epsilon/3, c : \epsilon, d : 1/9 - \epsilon/3)$
  - $D_{KL}(P' || Q')$  can then be computed easily

$$D_{KL}(p(x)||q(x)) = \sum_{x \in X} p(x) \ln \frac{p(x)}{q(x)}$$

# 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

# References

---

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

