



CS 412 Intro. to Data Mining

Chapter 2. Getting to Know Your Data

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





Data

Data

1	12	2	5
2	11	7	2
1	15	9	3
0	10	1	-3
-1	20	12	-2
1	19	6	-5

Data

1	12	2	5
2	11	7	2
1	15	9	3
0	10	1	-3
-1	20	12	-2
1	19	6	-5

2D

1	12	2	5
2	11	7	2
1	15	9	3
0	10	1	-3
-1	20	12	-2
1	19	6	-5

3D

1	12	2	5
2	11	7	2
1	15	9	3
0	10	1	-3
-1	20	12	-2
1	19	6	-5

1	12	2	5
2	11	7	2
1	15	9	3
0	10	1	-3
-1	20	12	-2
1	19	6	-5

1	12	2	5
2	11	7	2
1	15	9	3
0	10	1	-3
-1	20	12	-2
1	19	6	-5

4D

Data

1 มิติ = กว้าง / ยาว

2 มิติ = กว้าง & ยาว

3 มิติ = 2 มิติซ้อนกัน

4 มิติ = 3 มิติมาเรียงต่อกัน

ตัว Data มี Attribute ซ้ำกัน ข้อมูลจะเป็นชุดเดียวกัน

	Attribute 1	Attribute 2	Attribute 3	Attribute 4
Record 1	1	12	2	5
Record 2	2	11	7	2
Record 3	1	15	9	3
Record 4	0	10	1	-3
Record 5	-1	20	12	-2
Record 6	1	19	6	-5

Chapter 2. Getting to Know Your Data

- Data Objects and Attribute Types



ວອບເຈົກຕີ້ນ້ອມຸດແລະປະເປດແອທກຮົບາຕີ

- 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
Total	14.00	43.00	54.00	3.00	1,972.00	2,086.00

- Transaction data ចំណាំទូទាត់ក្រុម

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

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

Person: ពារាងខ្សែតាម

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

no relation

Car: ពារាងខ្សែរថយន្ត

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

ចារាងដែលមេងកំណែ

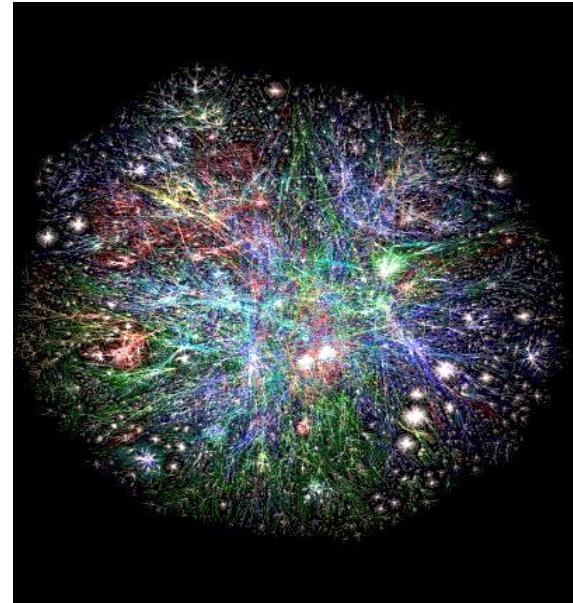
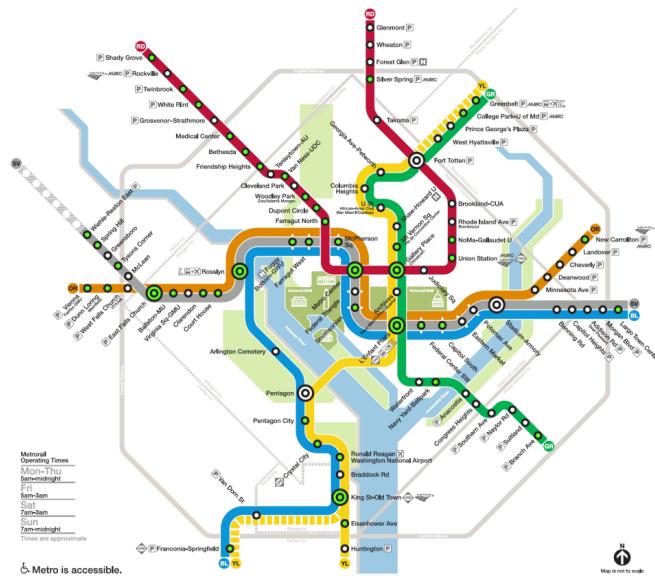
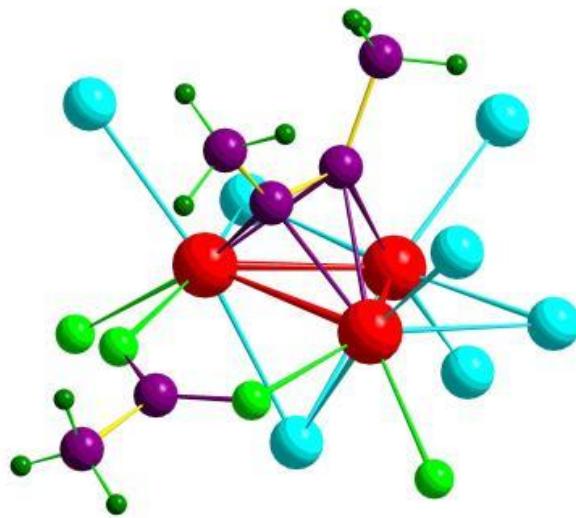
team	coach	pla y	ball	score	game	n	wi	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

||| បញ្ជាក់ថា គម្រោងមិនមេងកំណែ

Types of Data Sets: (2) Graphs and Networks

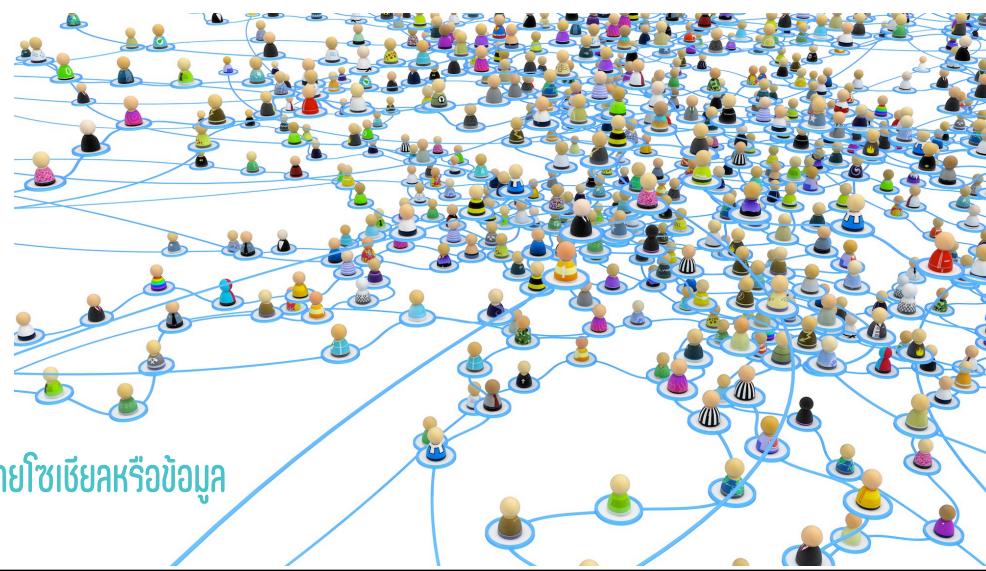
เครือข่ายการขนส่ง

- ❑ Transportation network
 - ❑ World Wide Web



□ Molecular Structures โครงสร้างโมเลกุล

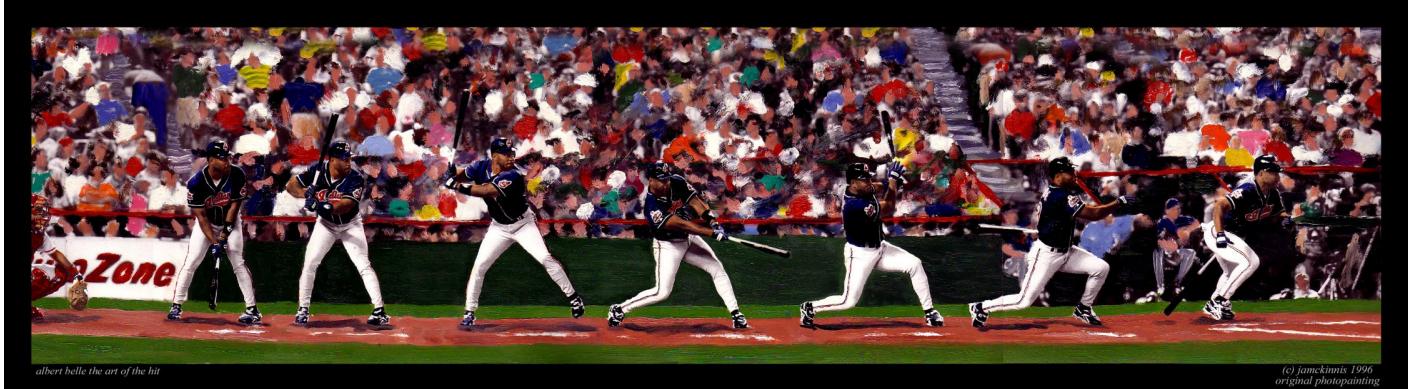
- Social or information networks เครือข่ายโซเชียลหรือข้อมูล



Types of Data Sets: (3) Ordered Data

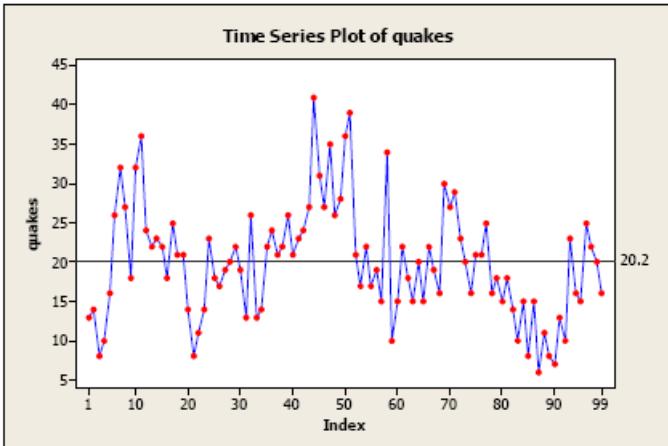
ข้อมูลที่มีความเกี่ยวข้อง

- Video data: sequence of images



- Temporal data: time-series

Ex. ราคาหุ้น



- Sequential Data: transaction sequences

- Genetic sequence data

Human	GTTTGAGG	-	ATGTTCAAC	AAATGCTC	TTTCATTCCCT	CATTTCATTTACAGAC	CTGCCGCA
Chimpanzee	GTTTGAGG	-	ATGTTCAATAAATGCTG	CTTTCACTCC	CTATTACAGAC	CTGCCGCA	
Macaque	GTTTGAGG	-	ATGCTCAATAAATGCTC	TTTCATTCCCT	CCATTACAAACTTGCGCA		
Human	GACAATTCTGCTAGC	AGCCTTGTGCTATTATCTG	TTTCTAAAC	TTAGTAATTGAGTGT			
Chimpanzee	GACAATTCTGCTAGC	AGCCTTGTGCTATTATCTG	TTTCTAAAC	TTAGTAATTGAGTGT			
Macaque	GACAATTCTGCTAGC	AGCCTTGTGCTATTATCTG	TTTCTAAAC	TTAGTAATTGAGTGT			
Human	GATCTGGAGACTAA	-	CTCTGAAATAAA	AAAGCTGATTATTTAT	TTTCTCAAAACAA		
Chimpanzee	GATCTGGAGACTAA	-	CTCTGAAATAAA	AAAGCTGATTATTTAT	TTTCTCAAAACAA		
Macaque	TATCTGGAGACTAA	-	CTCTGAAATAAA	AAAGCTGATTATTTAT	TTTCTCAAAACAA		
Human	CAGAACATCGATTAG	CAAATTACTCTTAAGA	ATATTAC	TTTACATTTC	CTATATTCTCTA		
Chimpanzee	CAGAACATCGATTAG	CAAATTACTCTTAAGA	ATATTAC	TTTACATTTC	CTATATTCTCTA		
Macaque	CAGAACATCGATTAG	CAAATTACCTCTTAAGA	ATATTTC	GCAC	TTCTATATTCTCTA		
Human	CCCTGAGTTGATG	TGTGAGCAATATGTC	ACTTTCAT	AAAGCCAGGTATAC	A---TTATG		
Chimpanzee	CCCTGAGTTGATG	TGTGAGCAATATGTC	ACTTTCAT	AAAGCCAGGTATAC	A---TTATG		
Macaque	CCCTGAGTTGATG	TGTGAGCAATATGTC	ACTTCC	ACAAAGCCAGGTATATAC	ATTACATTACG		
Human	GACAGGTAAGTAAA	ACATATTATTTAT	TATTCACG	TTTGTCTCAAGA	ATTTAAATTTC		
Chimpanzee	GACAGGTAAGTAAA	ACATATTATTTAT	TATTCACG	TTTGTCTCAAGA	ATTTAAATTTC		
Macaque	GACAGGTAAGTAAA	-CATATTATTTAT	TCTAGG	TTTGTCTCAAGA	GTTTAAATTTC		
Human	AACTGTTGCGCGTGT	GGTAA	-	TGTAAAAACAAACT	TCAGTACA		
Chimpanzee	AACTGTTGCGCGTGT	GGTAA	-	TGTAAAAACAAACT	TCAGTACA		
Macaque	AACTGTTGCGCGTGT	GGTAA	-	CBTAAAAACAAAT	TCAGTACA		

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

ເຮັດວຽກ

ຂ້ອງມູນຄະເລີງເຮັດວຽກ

- Spatial data: maps

ກວາງ
(X)

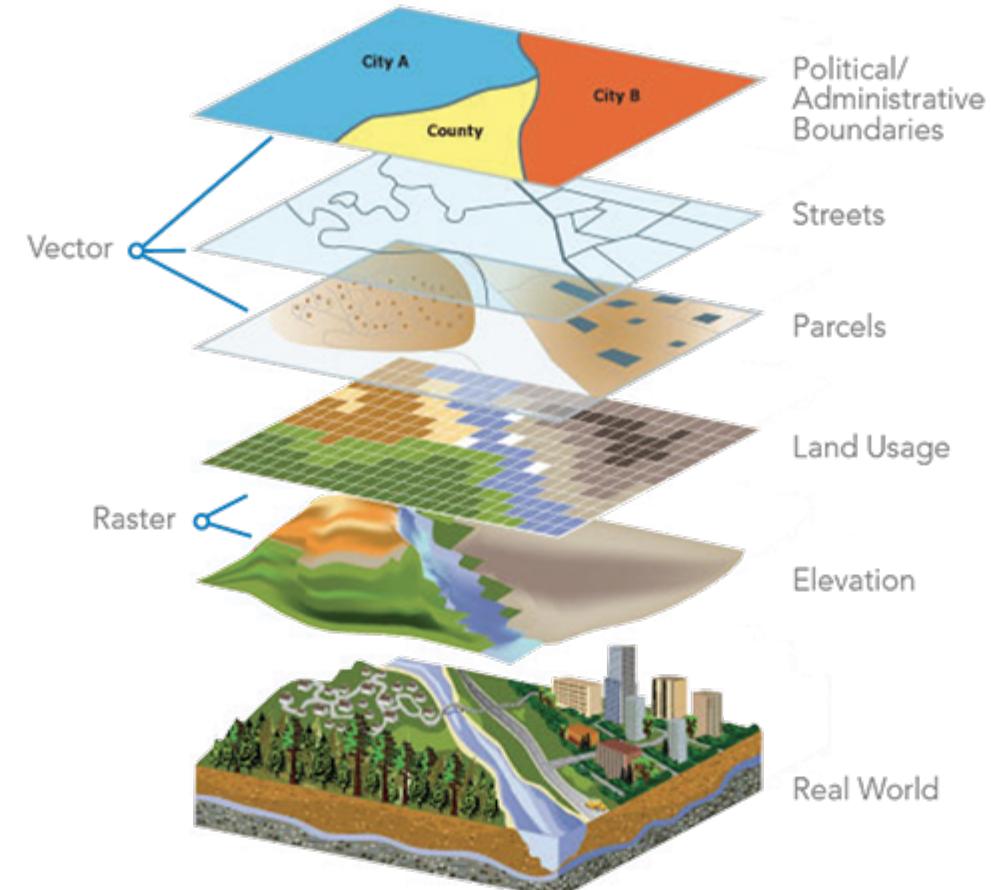


ຢາງ
(Y)

- Image data:  ການມາຊ່ວນກັນຫຍາຍ໌ຮູບ

ເຮັດວຽກ

- Video data: Spacious-temporal ກາພ / VDO ມາຊ່ວນກັນ



Important Characteristics of Structured Data

คุณลักษณะสำคัญของข้อมูล

- Dimensionality ข้อมูลมีมิติยังไง?
 - Curse of dimensionality
- Sparsity สนใจแต่ตัวที่มีข้อมูล ถ้าไม่มีข้อมูลไม่เอา
 - Only presence counts
- Resolution ความละเอียดในการเก็บ
 - Patterns depend on the scale รูปแบบขึ้นอยู่กับขนาด
- Distribution การกระจายตัวของข้อมูล
 - Centrality and dispersion จุดค่ากลางข้อมูล

Data Objects

ข้อมูลตามแนวนอน

- ❑ Data sets are made up of data objects ข้อมูลที่ได้มาประกอบไปด้วยหลายๆ ข้อมูลมาร่วมกัน
- ❑ A **data object** represents an entity ข้อมูลแต่ละตัวจะประกอบไปด้วย 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** ข้อมูลจะถูก描述โดย attributes
- ❑ Database rows → data objects; columns → attributes

Attributes

ข้อมูลตามแนวตั้ง

- Attribute (or dimensions, features, variables)
 - A data field, representing a characteristic or feature of a data object.
 - E.g., *customer_ID, name, address*
- Types: ชนิดของข้อมูล
 - Nominal (e.g., red, blue) ข้อมูลที่เป็นชื่อของกลุ่ม/ชนิด
 - Binary (e.g., {true, false}) ข้อมูลที่มี 2 ค่า
 - Ordinal (e.g., {freshman, sophomore, junior, senior}) ข้อมูลเรียงลำดับ
 - Numeric: quantitative ข้อมูลที่เป็นตัวเลข
 - Interval-scaled: 100°C is interval scales การที่นำ balk ลบ คูณ หาร และมีความหมาย
 - 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? Numeric

Attribute Types

ชนิดของ Attribute

- **Nominal:** categories, states, or “names of things” บวกซึ่งกันและกัน
 - *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 ความสัมพันธ์เท่ากัน
 - e.g., gender Ex. ณัดมือซ้ายหรือมือขวา , ชอบคิกหรือเป๊ปซี่
 - Asymmetric binary: outcomes not equally important. ความสัมพันธ์ไม่เท่ากัน
 - e.g., medical test (positive vs. negative) Ex. คนเดินเข้ามอ แล้วนำไปตรวจว่าคนนี้มีตั้งครรภ์เป็นและไม่เป็น
 - 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 Ex. ขนาดที่ต่างกัน , เกรด , ตำแหน่ง
 - *Size* = {*small, medium, large*} , grades, army rankings

Numeric Attribute Types

ข้อมูลที่เป็นตัวเลข

- Quantity (integer or real-valued)

คุณิตแท้ = คุณิตไม่มี เช่น มีเงิน 0 บาท / มีปากกา 0 แท่ง
คุณิตไม่แท้ = เช่น อุณหภูมิ

- Interval ไม่มีคุณิตแท้

- 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 มีคุณิตแท้

- 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*

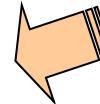
Discrete vs. Continuous Attributes

-
- Discrete Attribute** ไม่มีค่าอะไรมากกว่าตัวนั้น
 - 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** มีค่าอยู่ต่ำสูงตามที่ต้องการ
 - Has real numbers as attribute values จำนวนจริง
 - 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

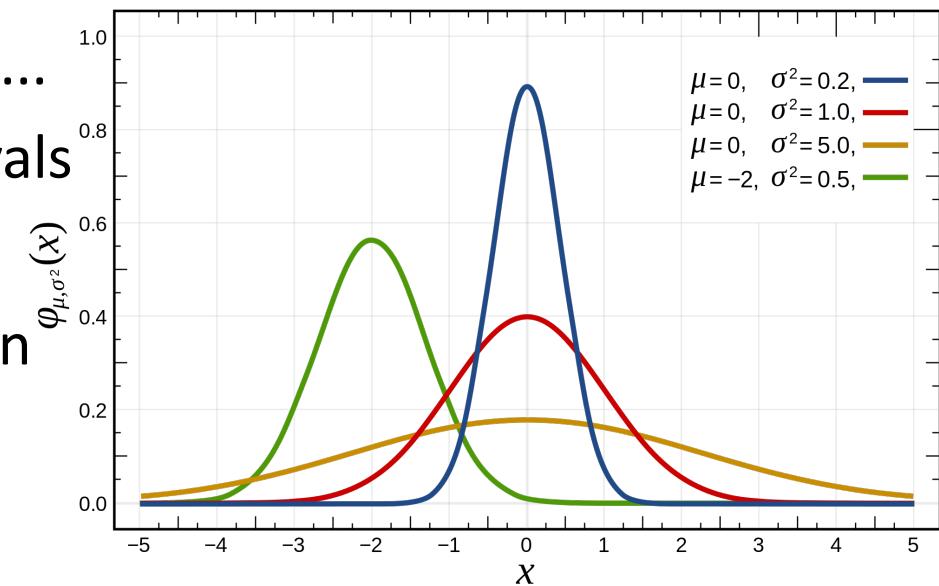
- Data Objects and Attribute Types
- Basic Statistical Descriptions of Data
- Data Visualization
- Measuring Data Similarity and Dissimilarity
- Summary

คำอธิบายทางสถิติพื้นฐานของข้อมูล



Basic Statistical Descriptions of Data

- Motivation แรงบันดาลใจ
 - To better understand the data: central tendency, variation and spread
- Data dispersion characteristics
 - Median, max, min, quantiles, outliers, variance, ...
ค่ามัธยฐาน ปริมาณ ค่าผิดปกติ ค่าเบี่ยงเบน
- 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): សំណគោ Mean

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

$$\bar{x} \quad \frac{1}{n} \sum_{i=1}^n x_i \quad \xrightarrow{\hspace{1cm}} \quad \frac{x}{N}$$

- Weighted arithmetic mean:

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

- 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*):

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

Approximate median

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

Low interval limit

Sum before the median interval

Interval width ($L_2 - L_1$)

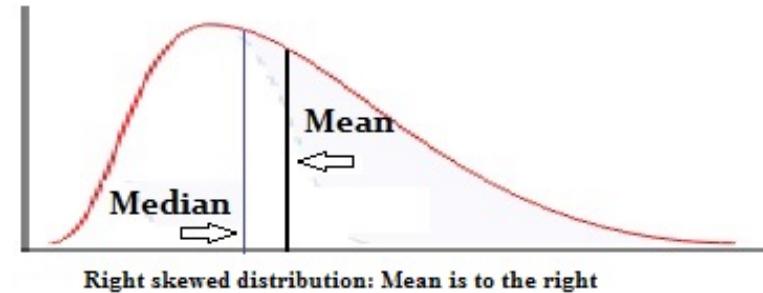
Measuring the Central Tendency: (3) Mode

- Mode: Value that occurs most frequently in the data

- Unimodal

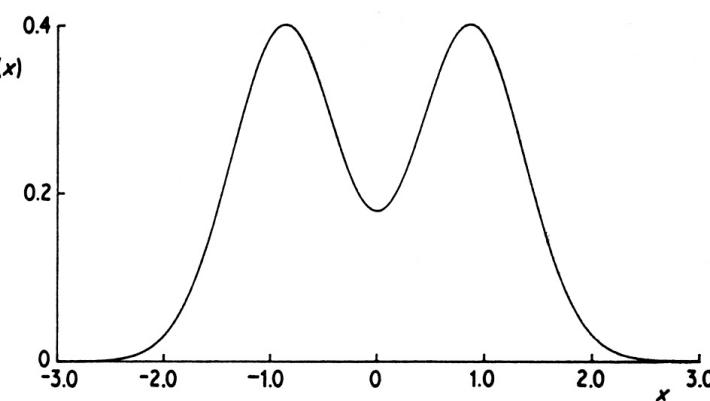
- Empirical formula:

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

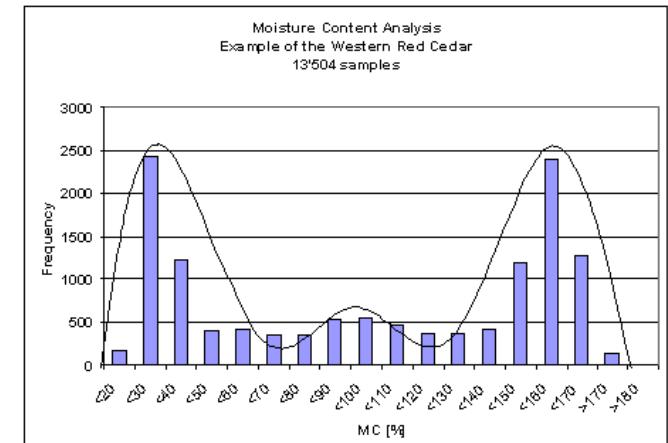
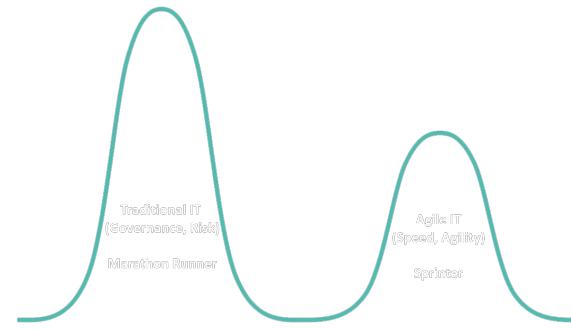


- Multi-modal

- Bimodal



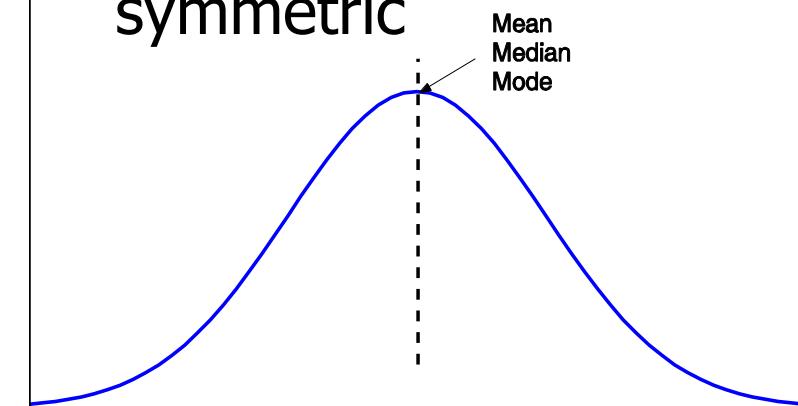
- Trimodal



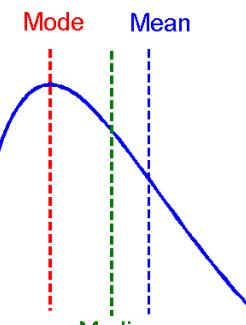
Symmetric vs. Skewed Data

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

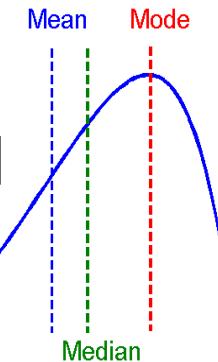
symmetric



positively skewed

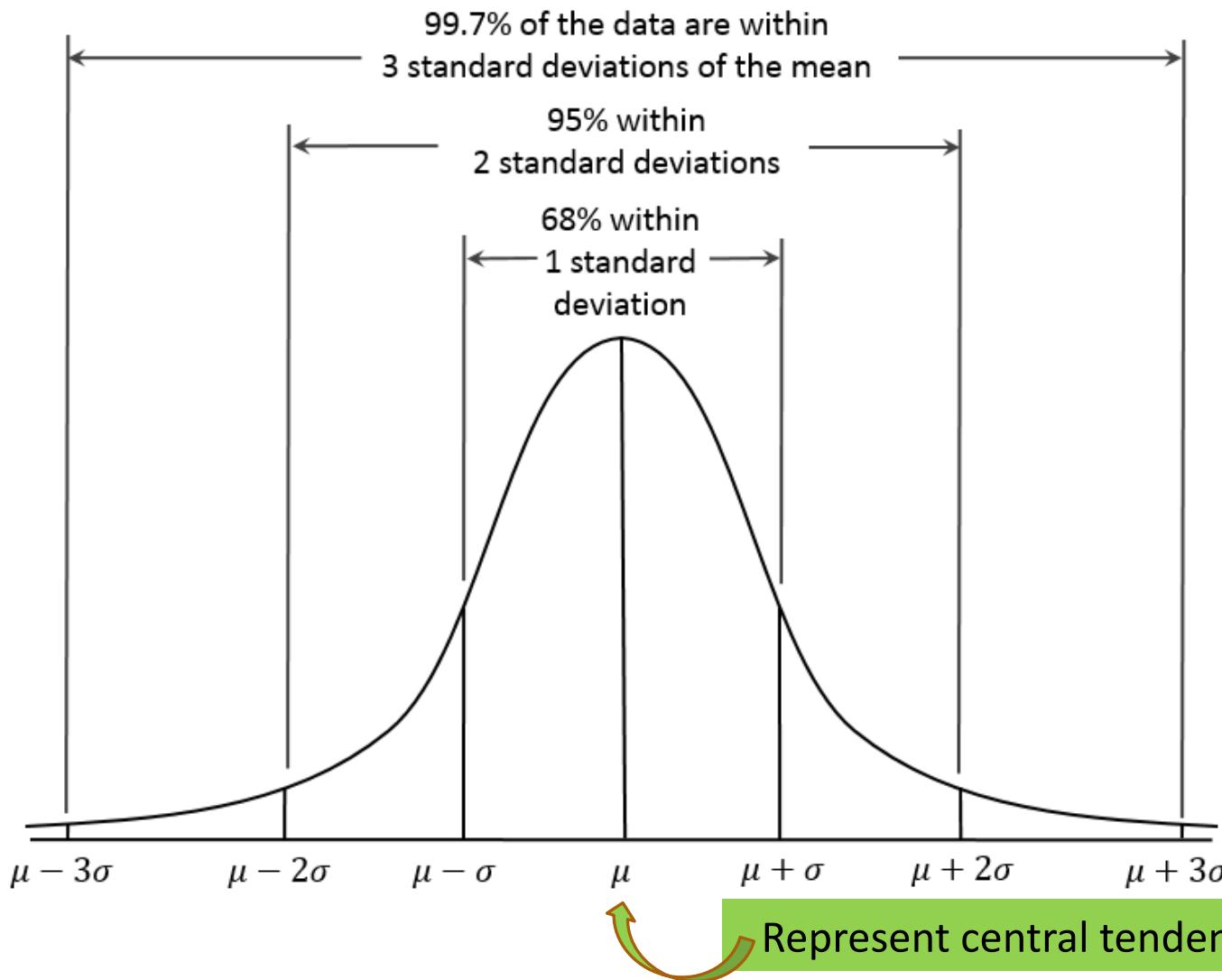


negatively skewed



Properties of Normal Distribution Curve

← ----- Represent data dispersion, spread ----- →



Measures Data Distribution: Variance and Standard Deviation

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

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

- ❑ Q: Can you compute it incrementally and efficiently?

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

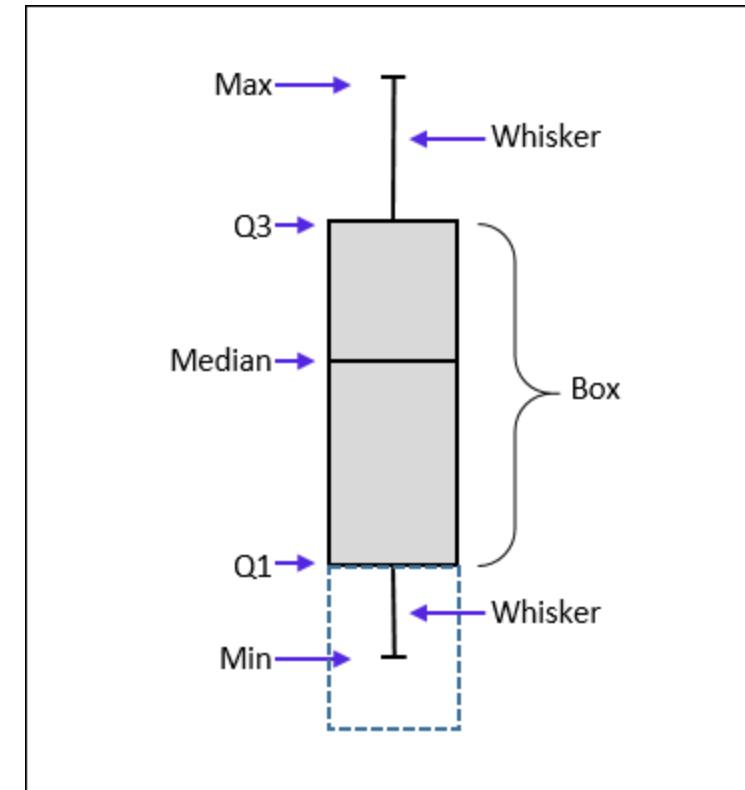
- ❑ **Standard deviation s (or σ)** is the square root of variance s^2 (*or σ^2*)

Graphic Displays of Basic Statistical Descriptions

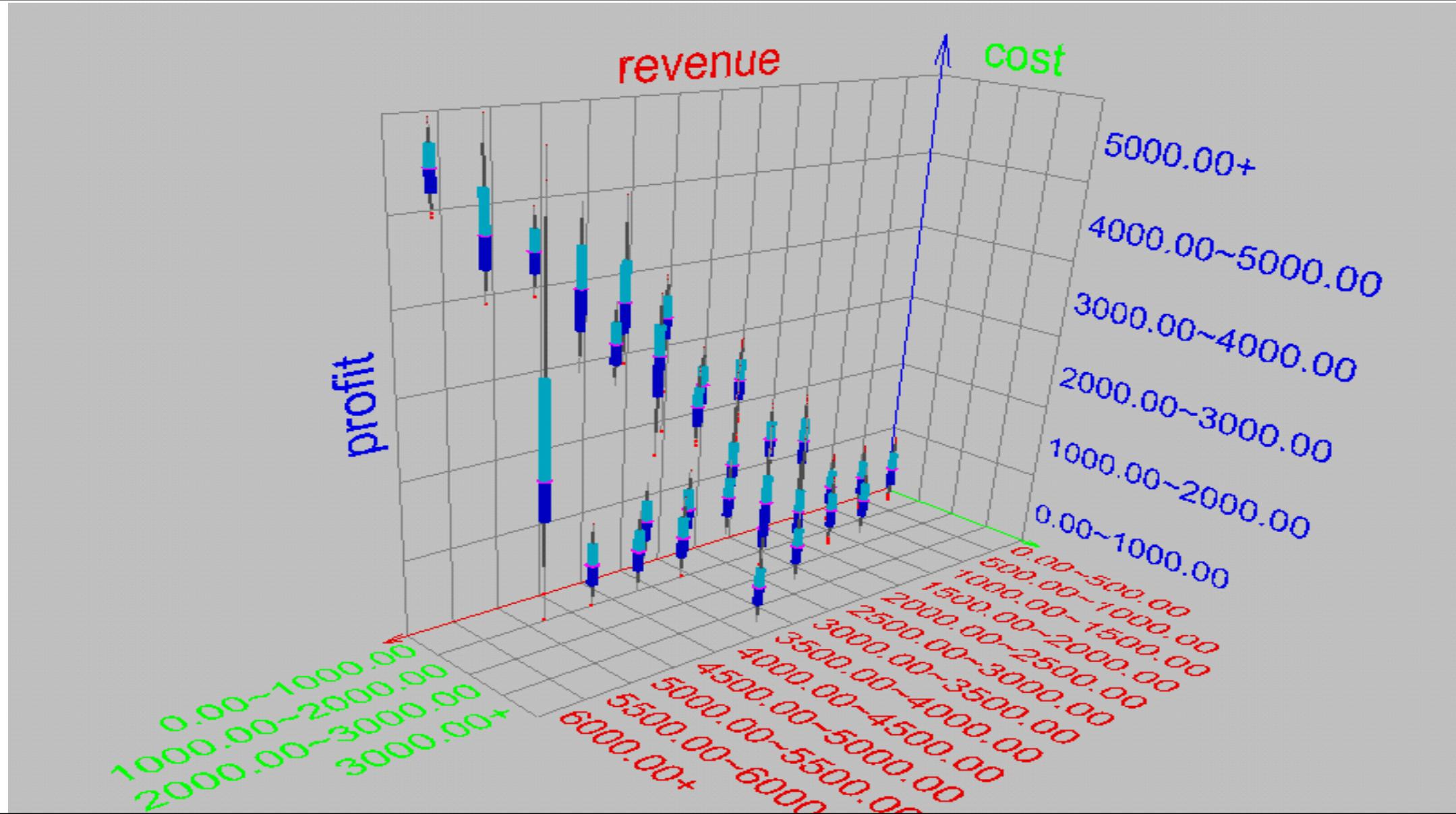
- **Boxplot:** graphic display of five-number summary
- **Histogram:** x-axis are values, y-axis repres. frequencies
- **Quantile plot:** each value x_i is paired with f_i indicating that approximately $100 f_i \%$ of data are $\leq x_i$
- **Quantile-quantile (q-q) plot:** graphs the quantiles of one 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^{th} percentile), Q_3 (75^{th} percentile)
- **Inter-quartile range:** $\text{IQR} = Q_3 - Q_1$
- **Five number summary:** min, Q_1 , median, Q_3 , max
- **Boxplot:** 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 $1.5 \times \text{IQR}$



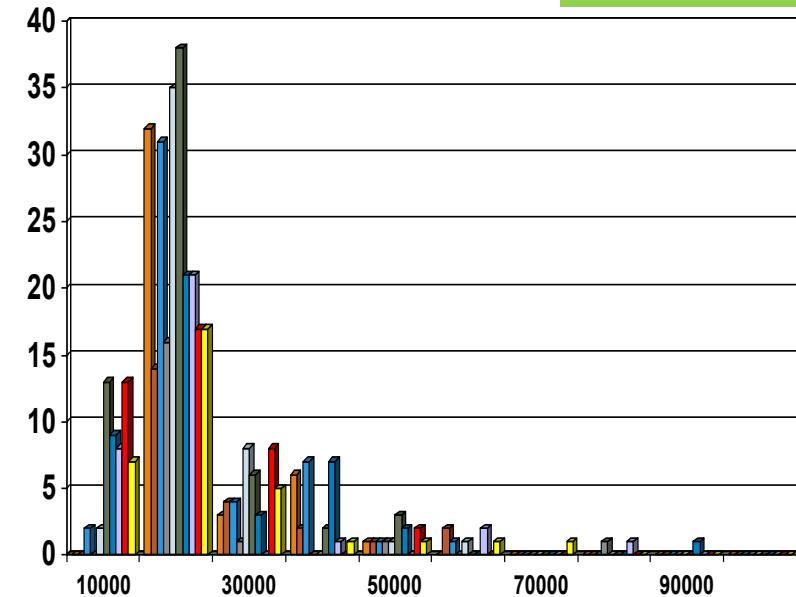
Visualization of Data Dispersion: 3-D Boxplots



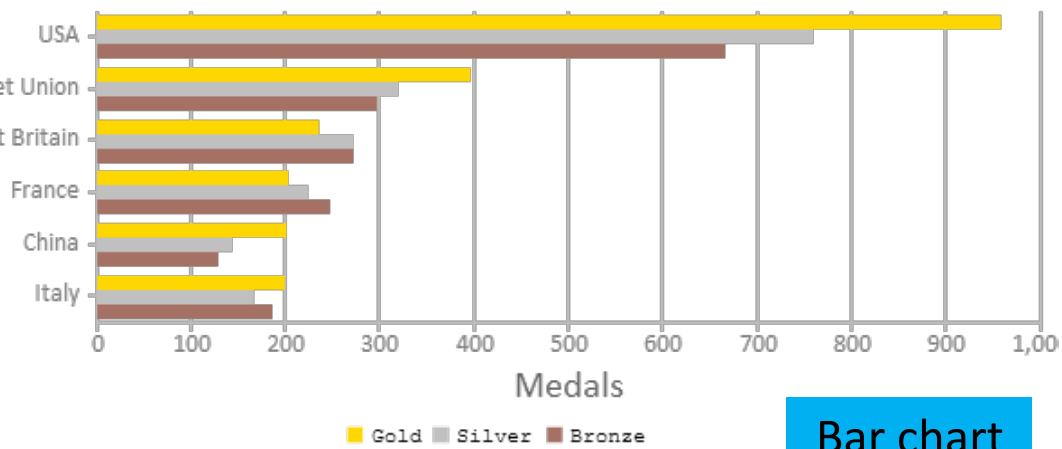
Histogram Analysis

- ❑ 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

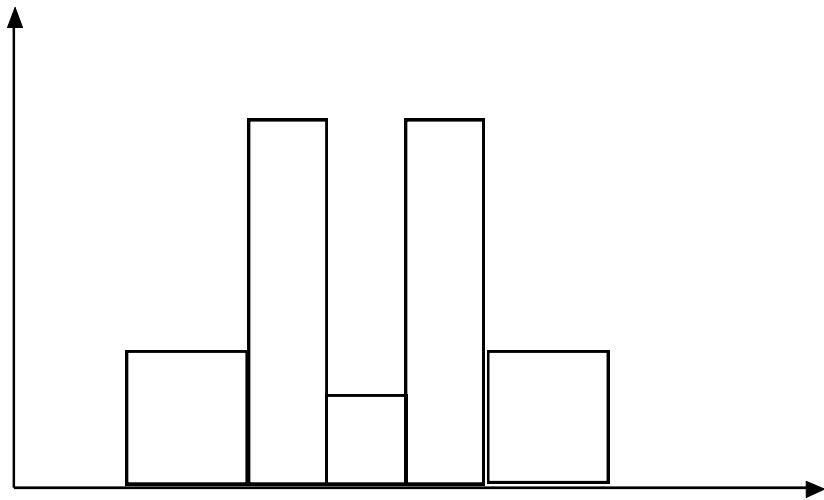
Histogram



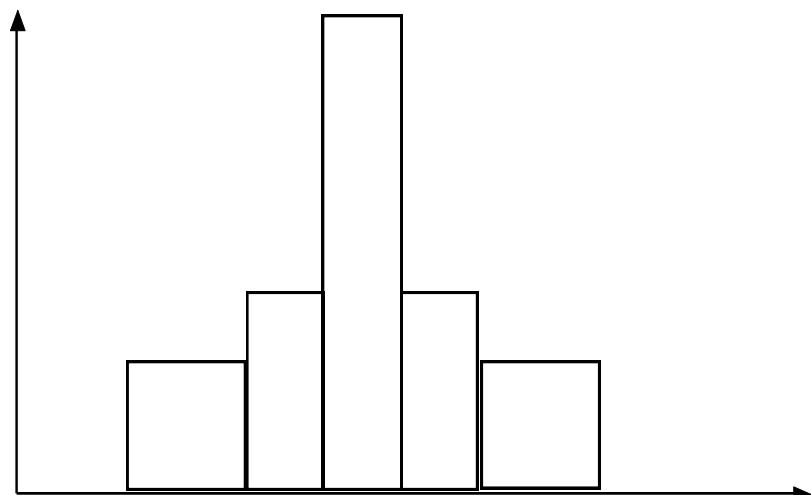
Olympic Medals of all Times (till 2012 Olympics)



Histograms Often Tell More than Boxplots

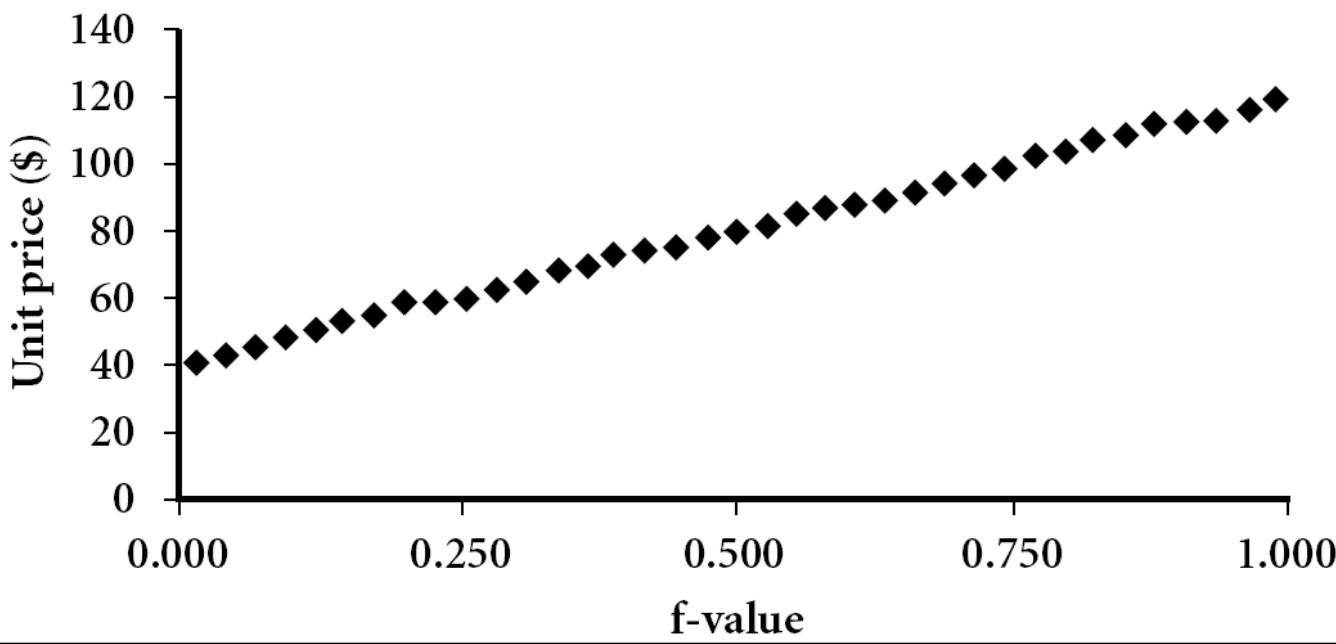


- ❑ The two histograms shown in the left may have the same boxplot representation
- ❑ The same values for: min, Q1, median, Q3, max
- ❑ But they have rather different data distributions



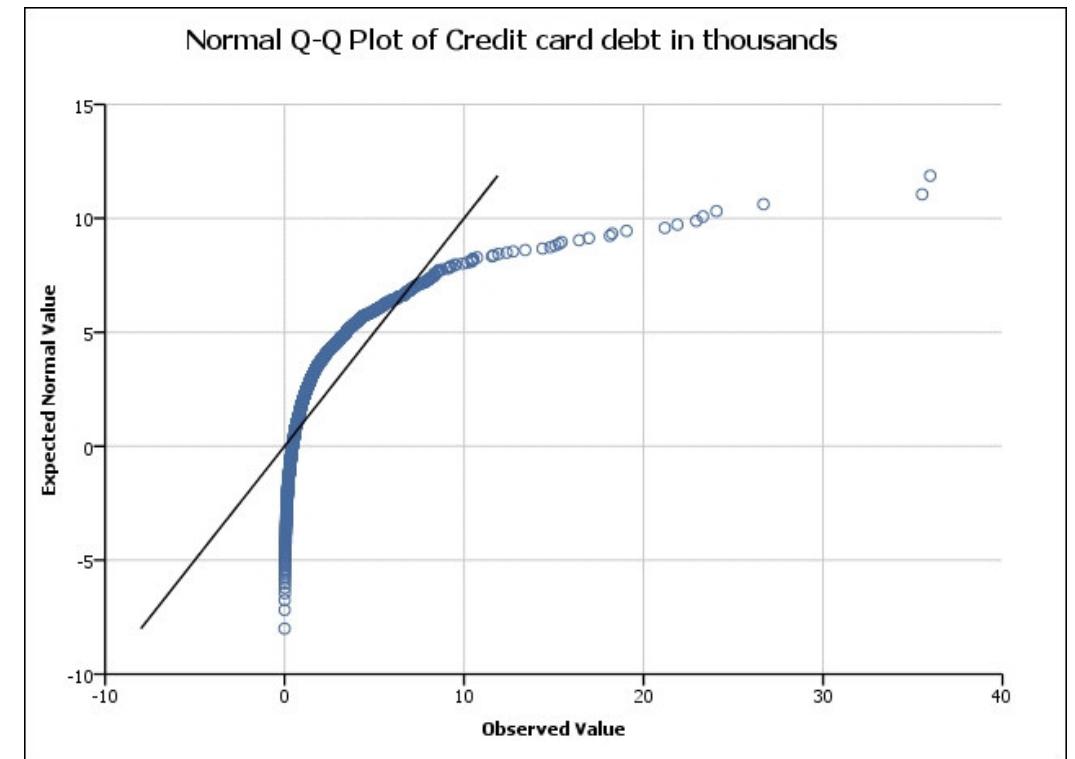
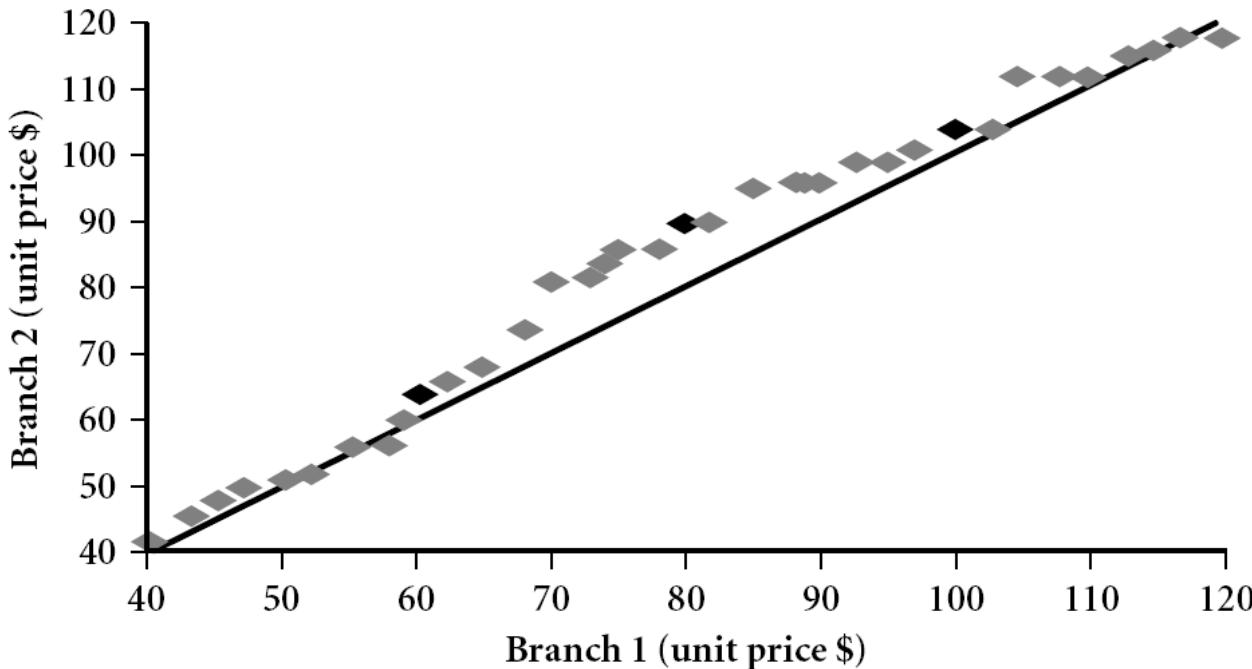
Quantile Plot

- 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 $100f_i\%$ of the data are below or equal to the value x_i



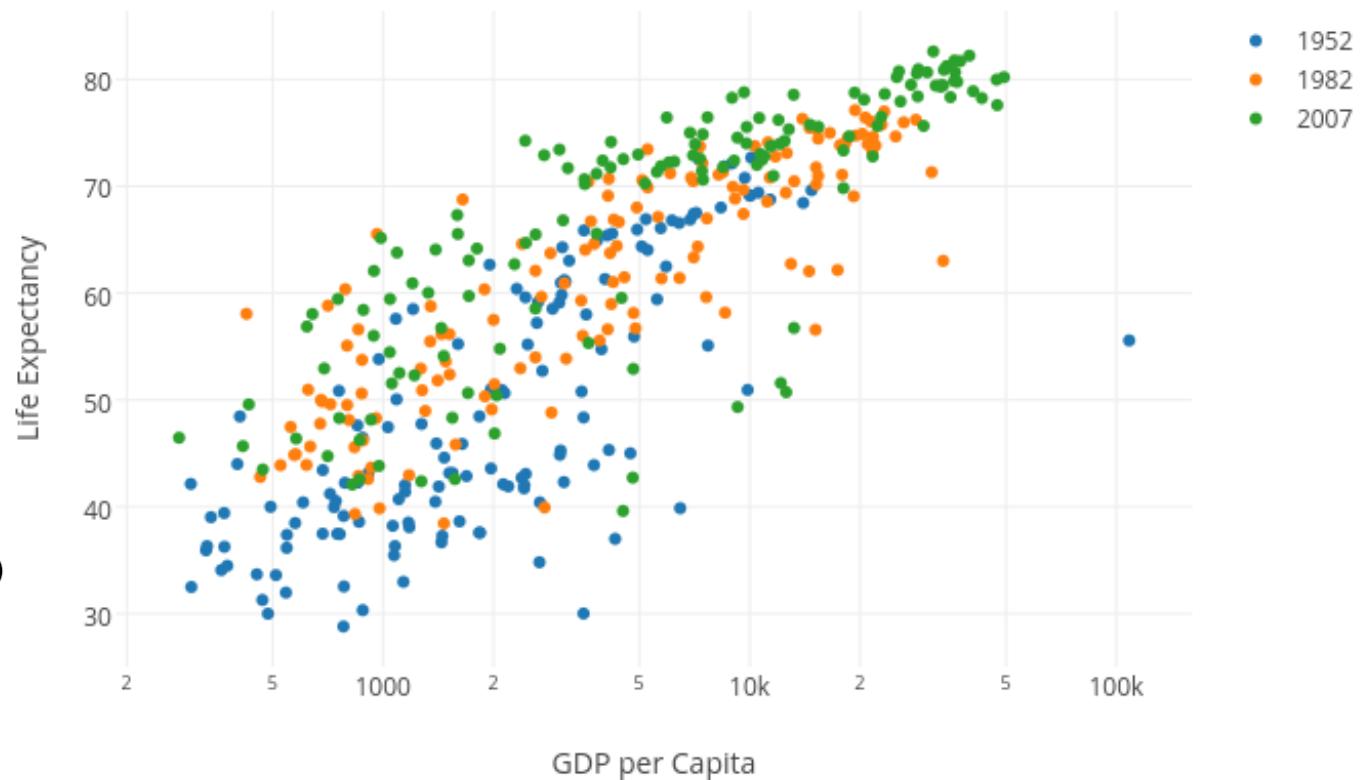
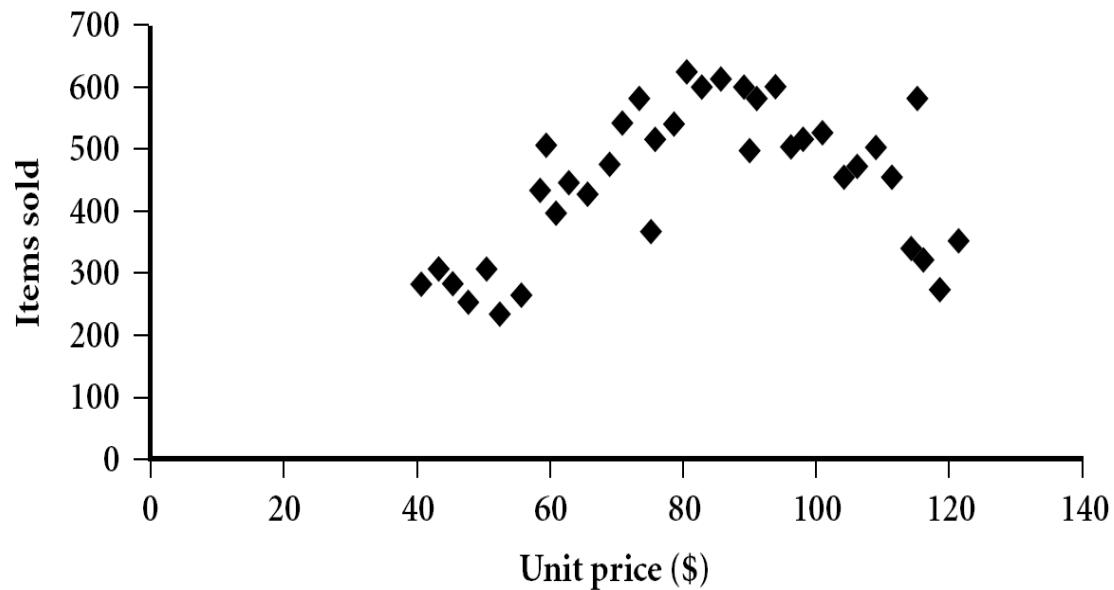
Quantile-Quantile (Q-Q) Plot

- 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

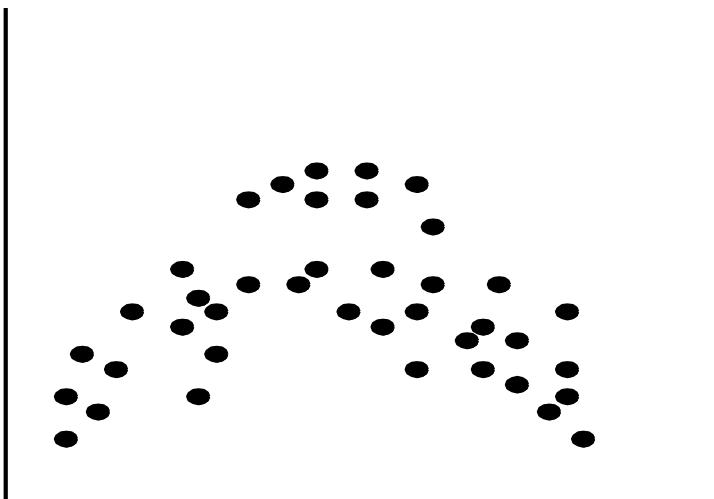
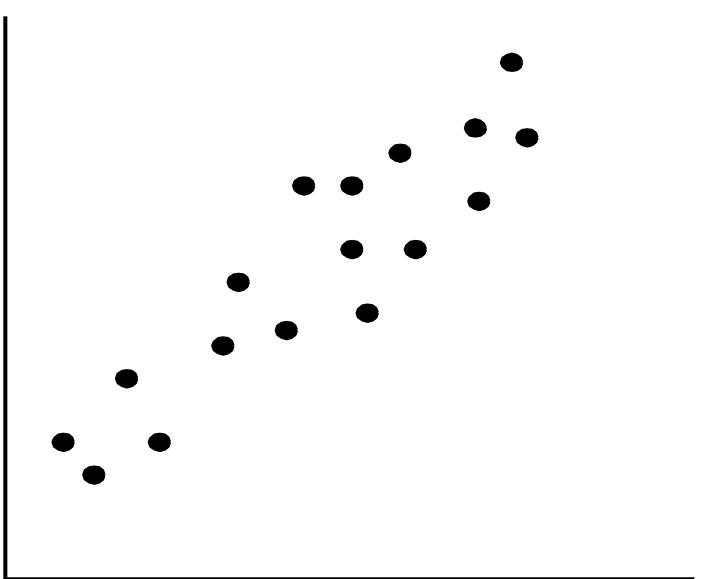


Scatter plot

- ❑ 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

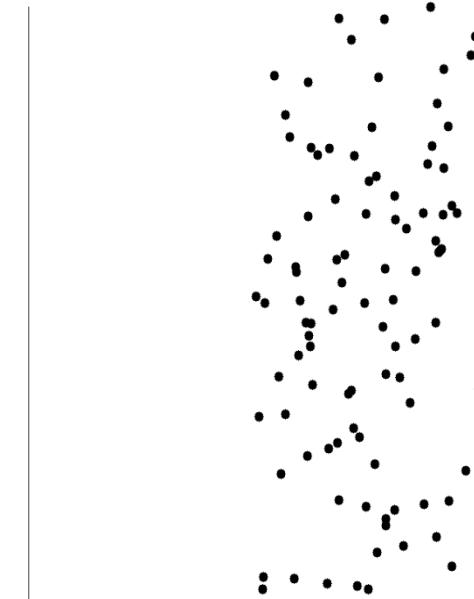
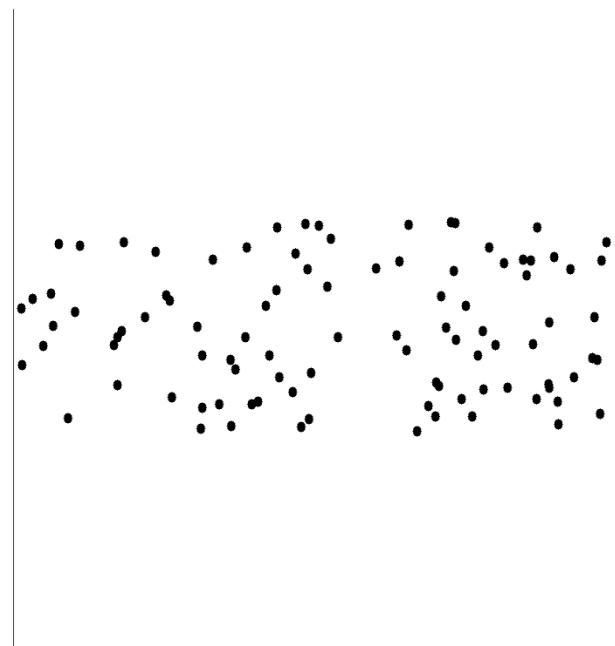
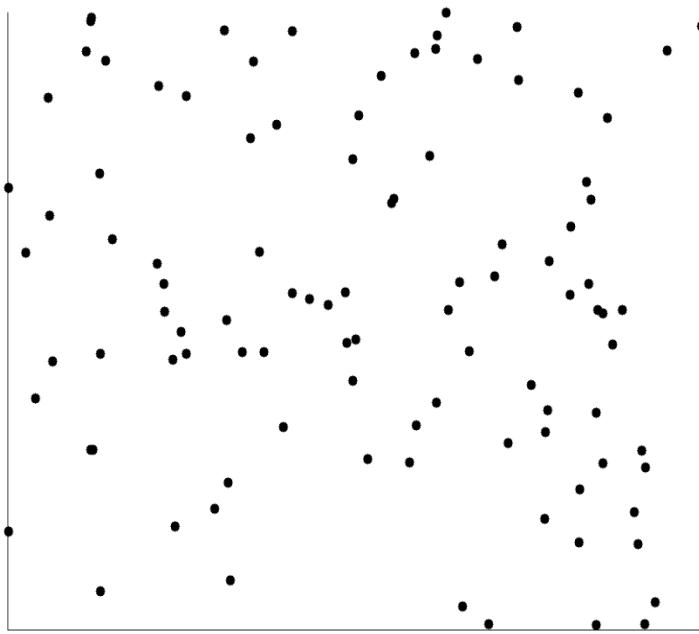


Positively and Negatively Correlated Data



- 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

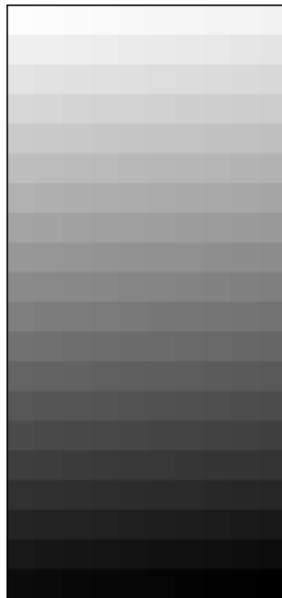


Data Visualization

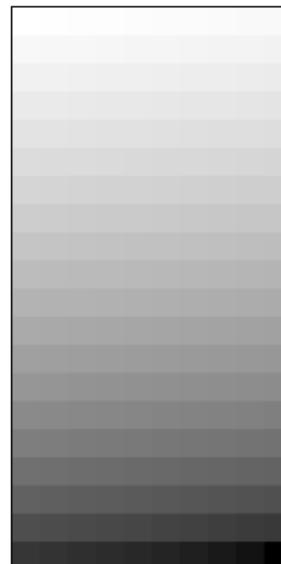
- Why data visualization?
 - Gain insight into an information space by mapping data onto graphical primitives
 - Provide qualitative overview of large data sets
 - Search for patterns, trends, structure, irregularities, relationships among data
 - Help find interesting regions and suitable parameters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

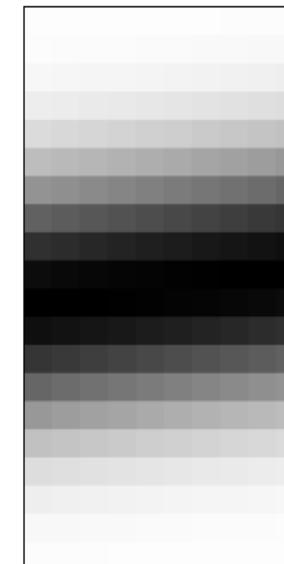
- ❑ For a data set of m dimensions, create m windows on the screen, one for each dimension
- ❑ The m dimension values of a record are mapped to m pixels at the corresponding positions in the windows
- ❑ The colors of the pixels reflect the corresponding values



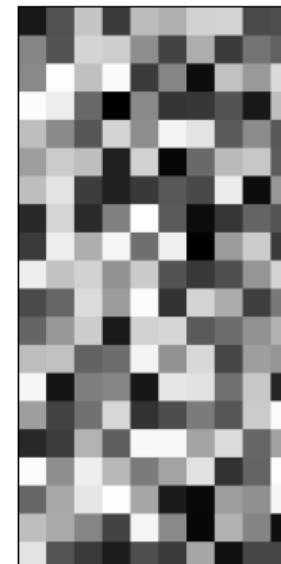
(a) Income



(b) Credit Limit



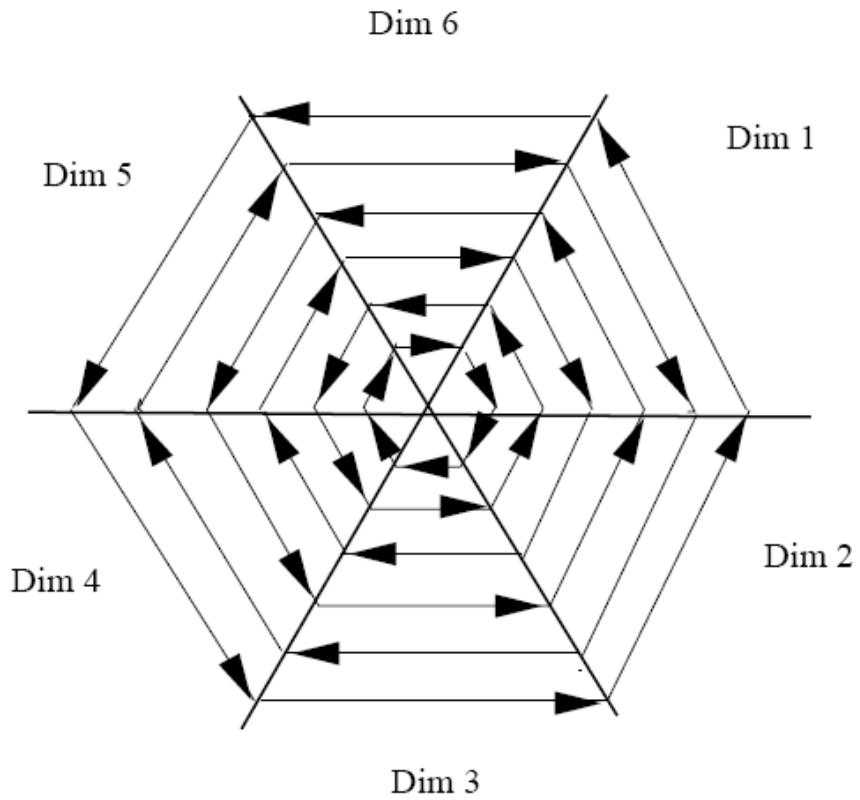
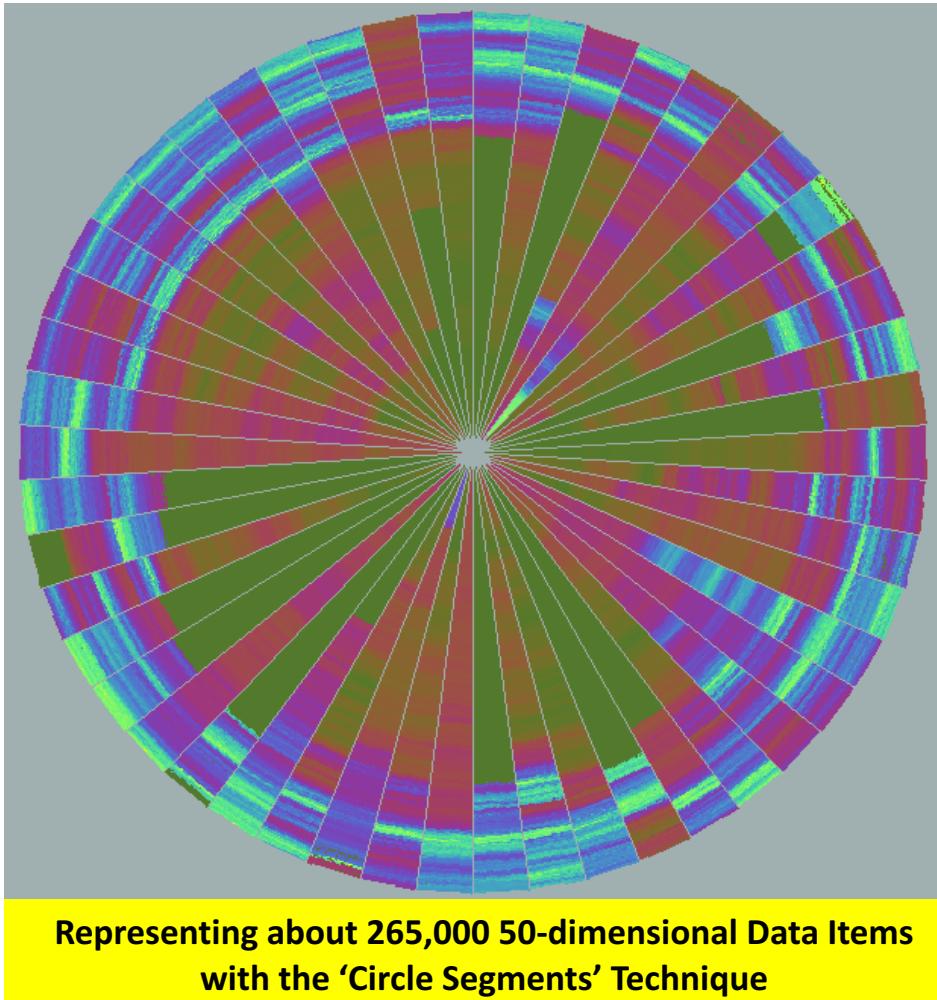
(c) transaction volume



(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



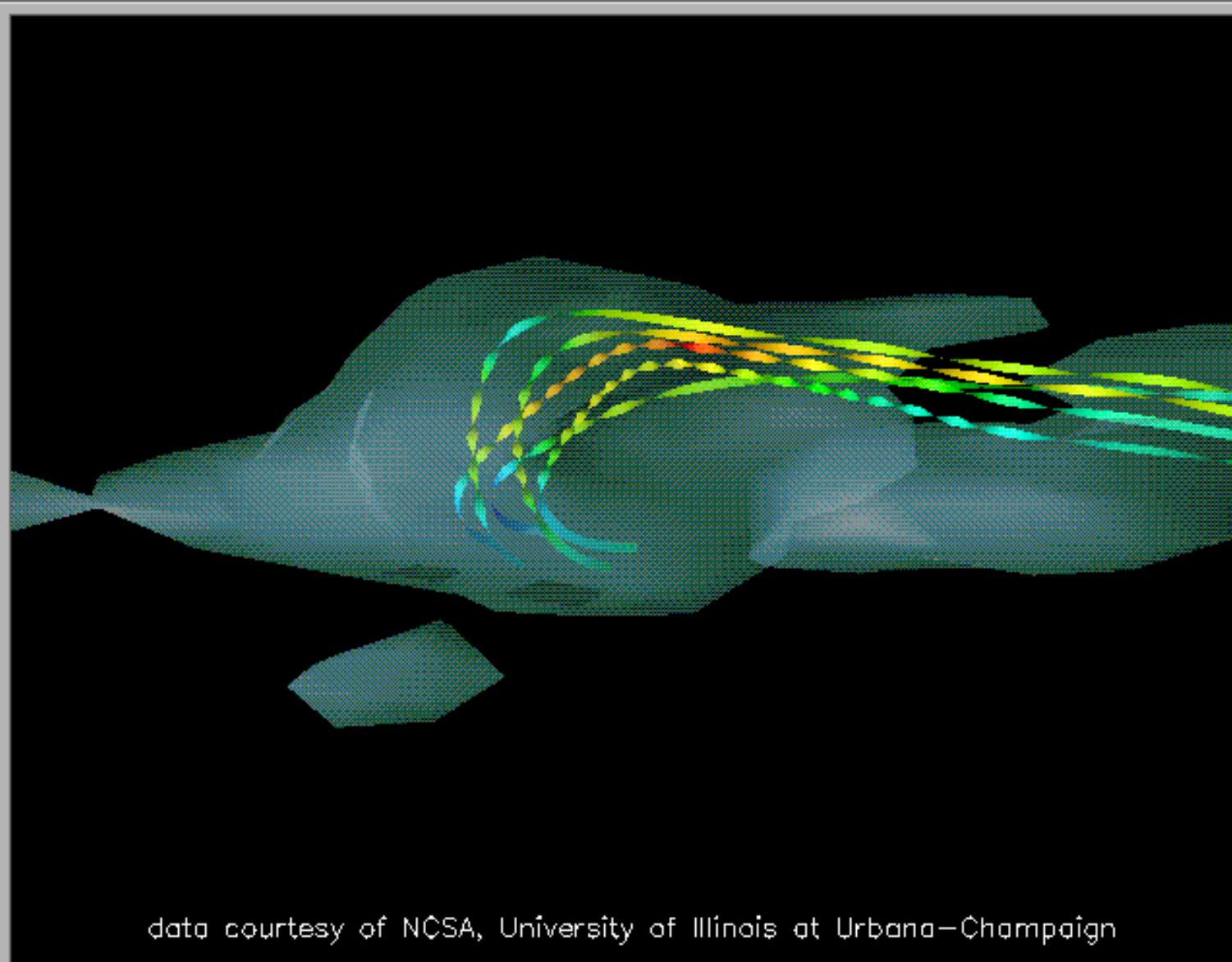
(b) Laying out pixels in circle segment

Geometric Projection Visualization Techniques

- Visualization of geometric transformations and projections of the data
- Methods
 - Direct visualization
 - Scatterplot and scatterplot matrices
 - Landscapes
 - Projection pursuit technique: Help users find meaningful projections of multidimensional data
 - Prosection views
 - Hyperslice
 - Parallel coordinates

Direct Data Visualization

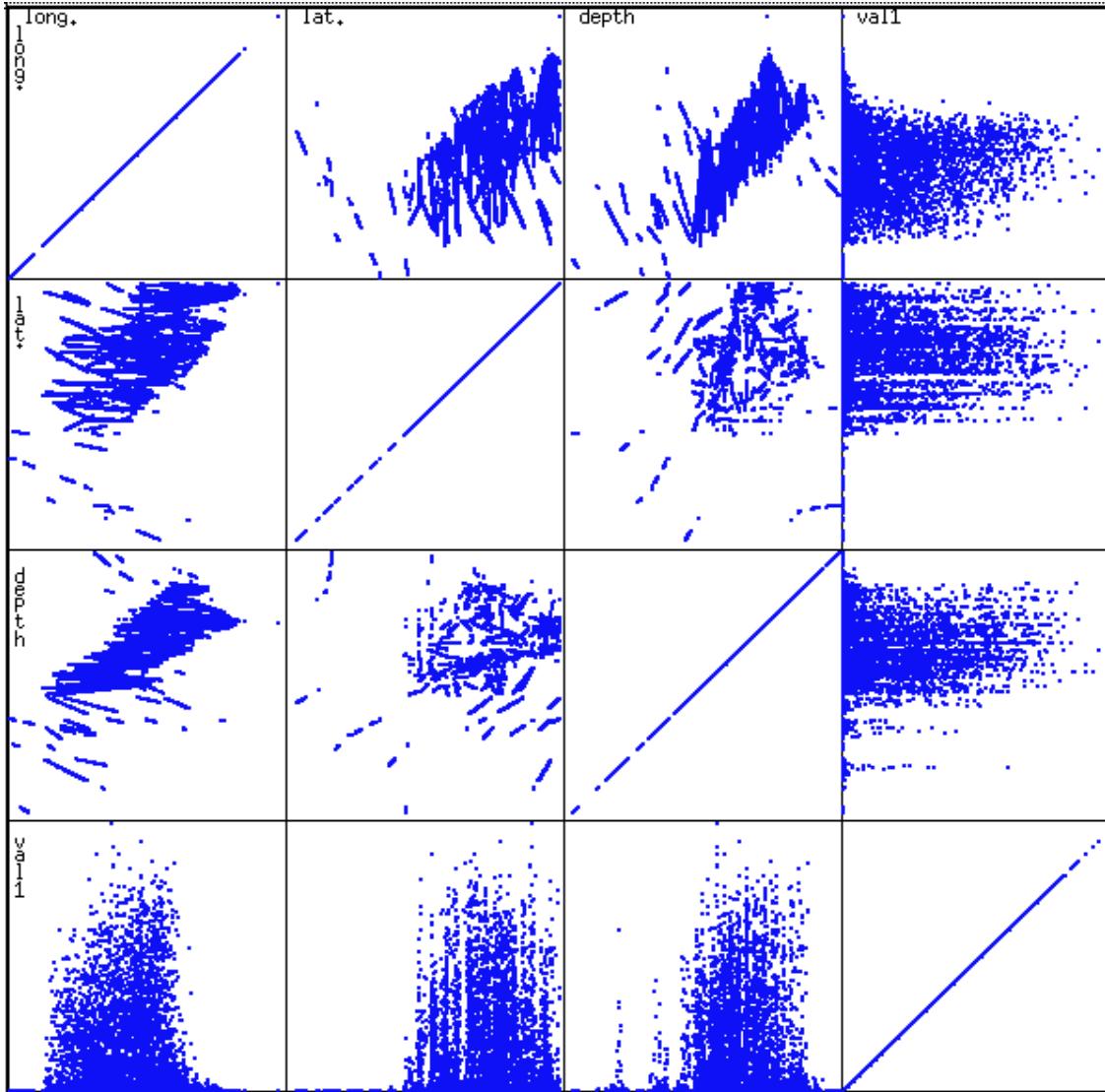
Ribbons with Twists Based on Vorticity



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

Scatterplot Matrices

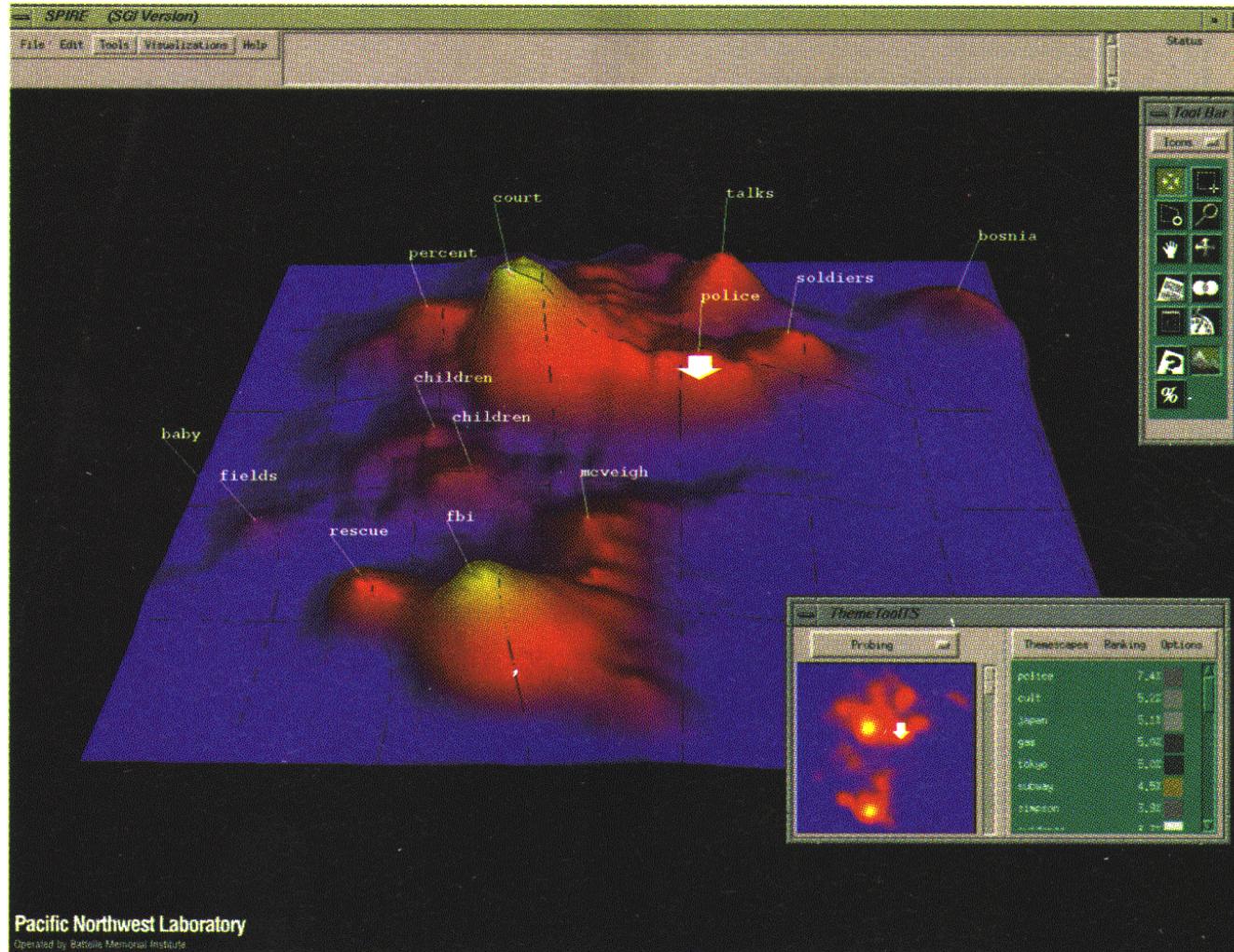
Used by permission of M. Ward, Worcester Polytechnic Institute



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

Landscapes

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

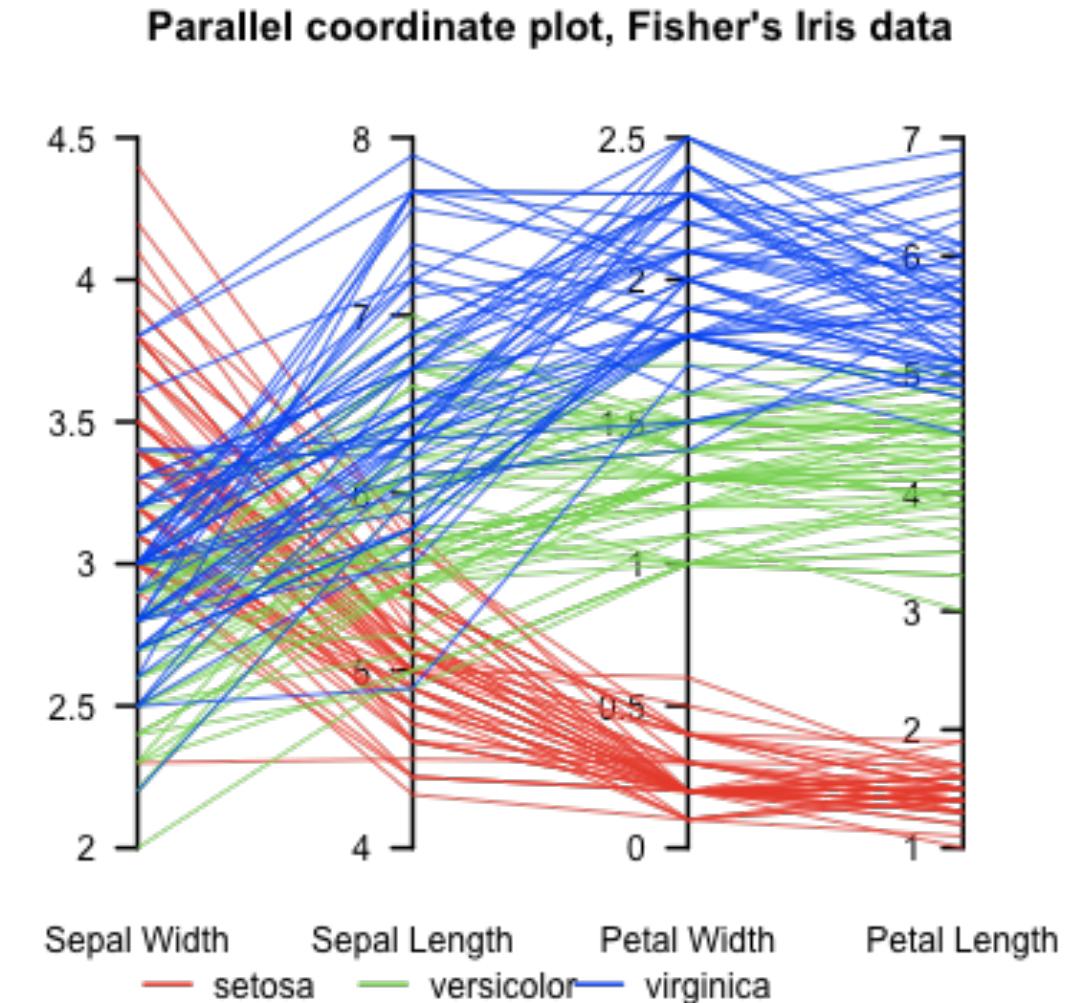


news articles visualized as a landscape

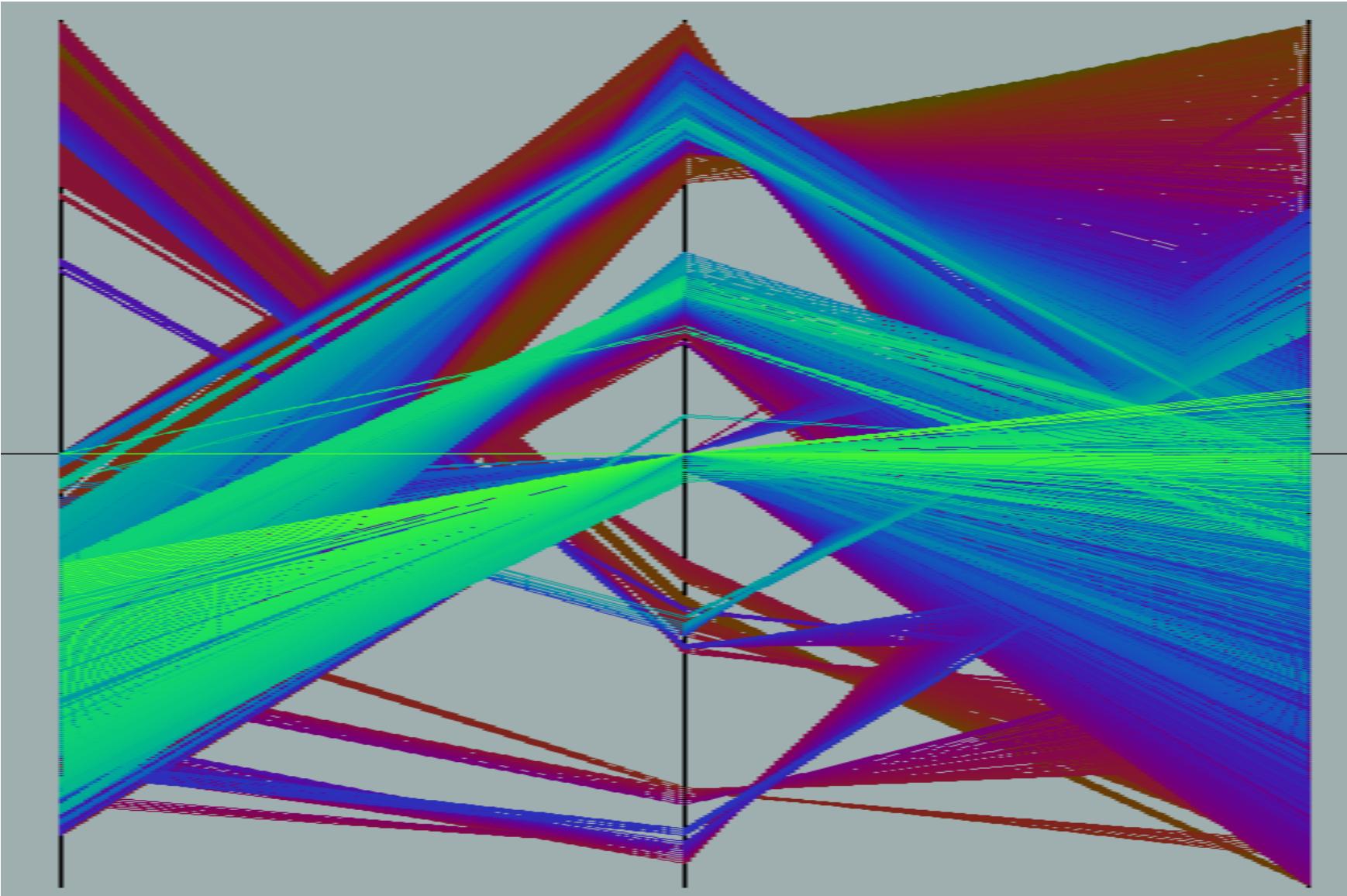
- Visualization of the data as perspective landscape
- The data needs to be transformed into a (possibly artificial) 2D spatial representation which preserves the characteristics of the data

Parallel Coordinates

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



Parallel Coordinates of a Data Set

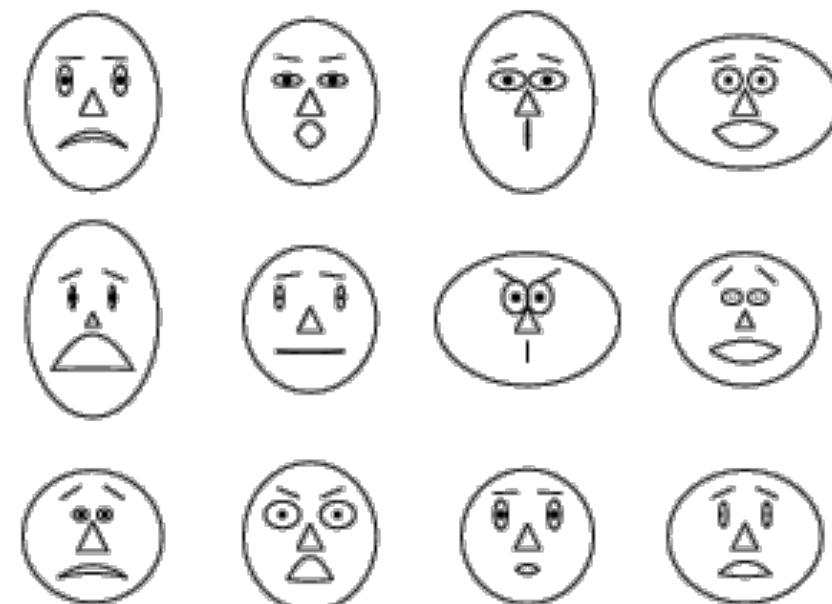


Icon-Based Visualization Techniques

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

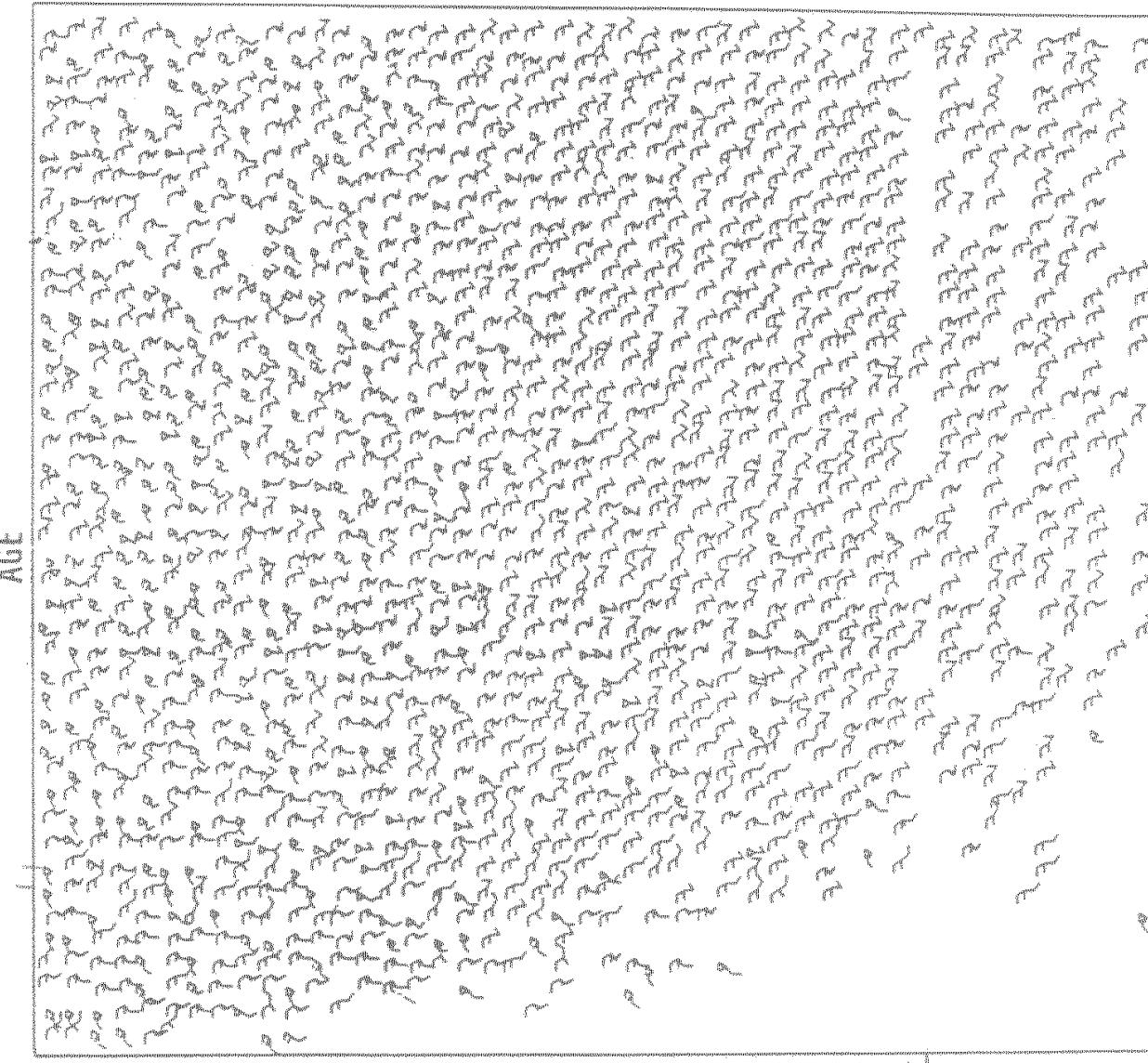
Chernoff Faces

- A way to display variables on a two-dimensional surface, e.g., let x be eyebrow slant, y be eye size, z be nose length, etc.
- The figure shows faces produced using 10 characteristics--head eccentricity, eye size, eye spacing, eye eccentricity, pupil size, eyebrow slant, nose size, mouth shape, mouth size, and mouth opening): Each assigned one of 10 possible values, generated using [*Mathematica*](#) (S. Dickson)
- REFERENCE: Gonick, L. and Smith, W. [*The Cartoon Guide to Statistics*](#). New York: Harper Perennial, p. 212, 1993
- Weisstein, Eric W. "Chernoff Face." From *MathWorld--A Wolfram Web Resource*.
mathworld.wolfram.com/ChernoffFace.html



Stick Figure

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

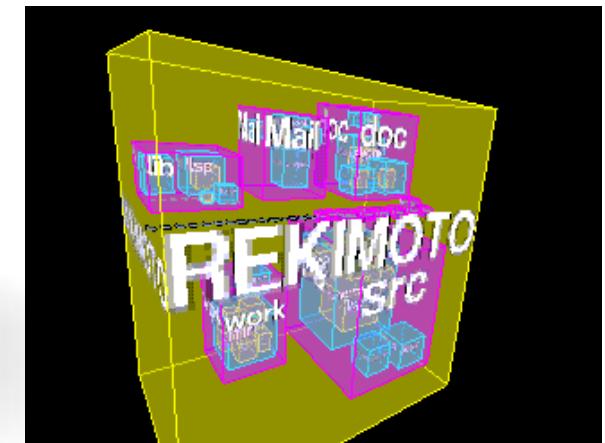
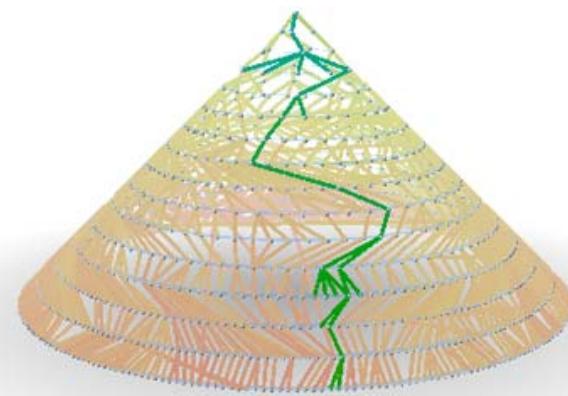
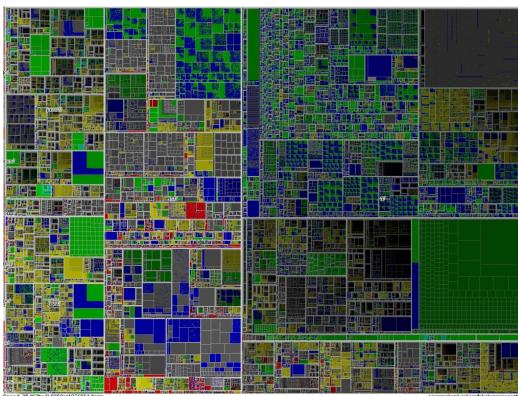
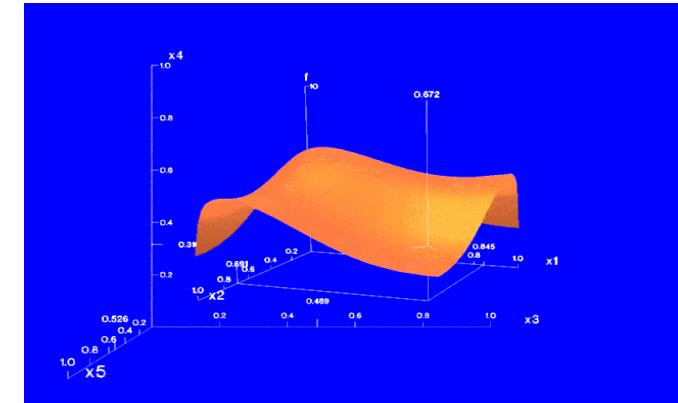
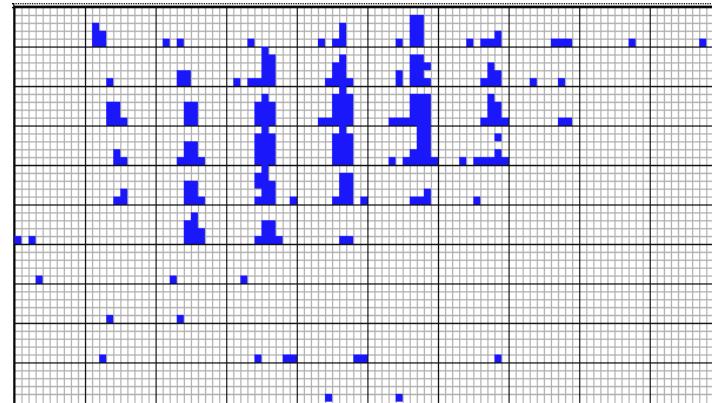


- A census data figure showing age, income, gender, education, etc.

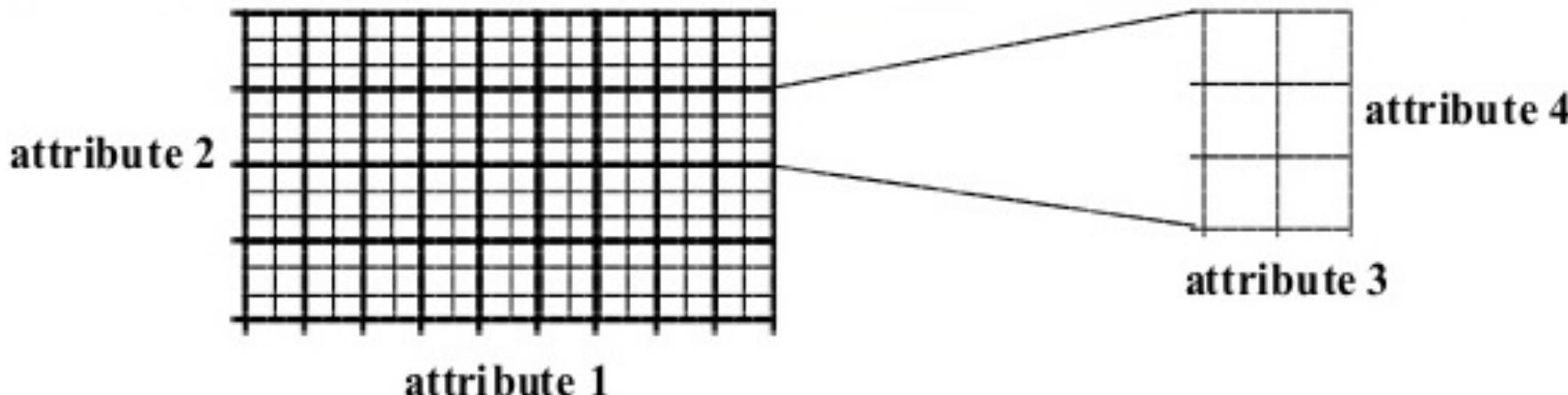
- A 5-piece stick figure (1 body and 4 limbs w. different angle/length)

Hierarchical Visualization Techniques

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



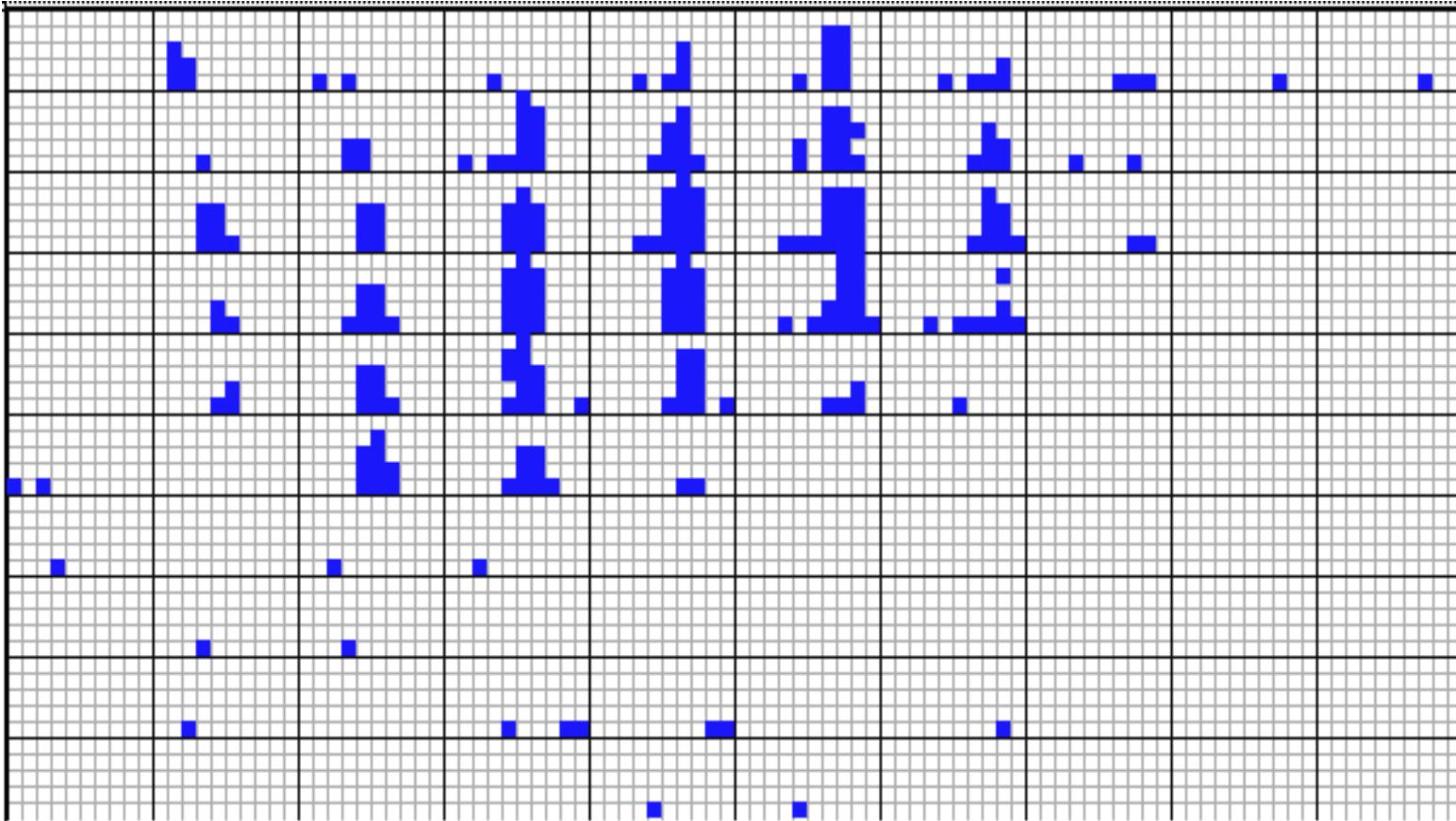
Dimensional Stacking



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

Dimensional Stacking

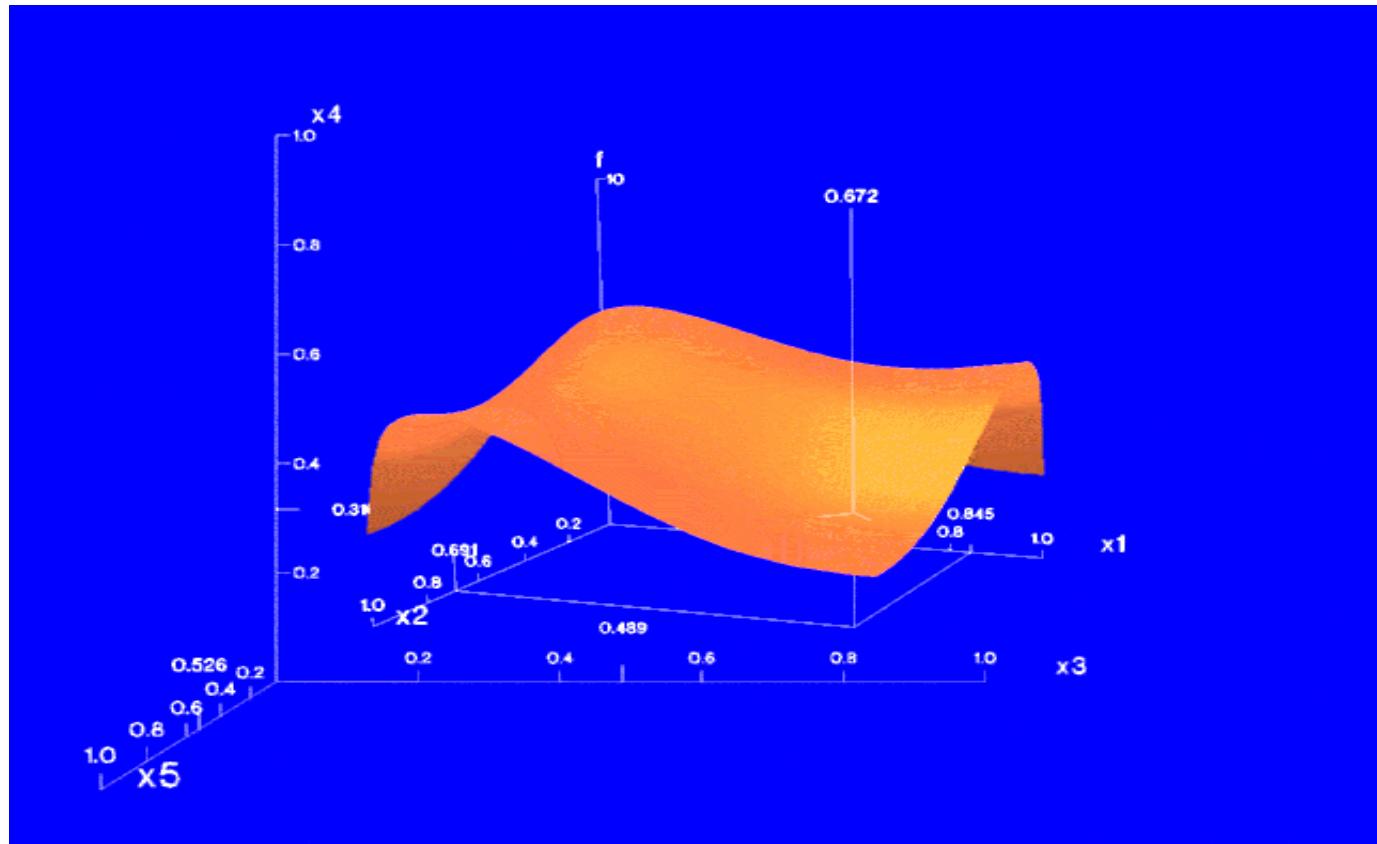
Used by permission of M. Ward, Worcester Polytechnic Institute



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

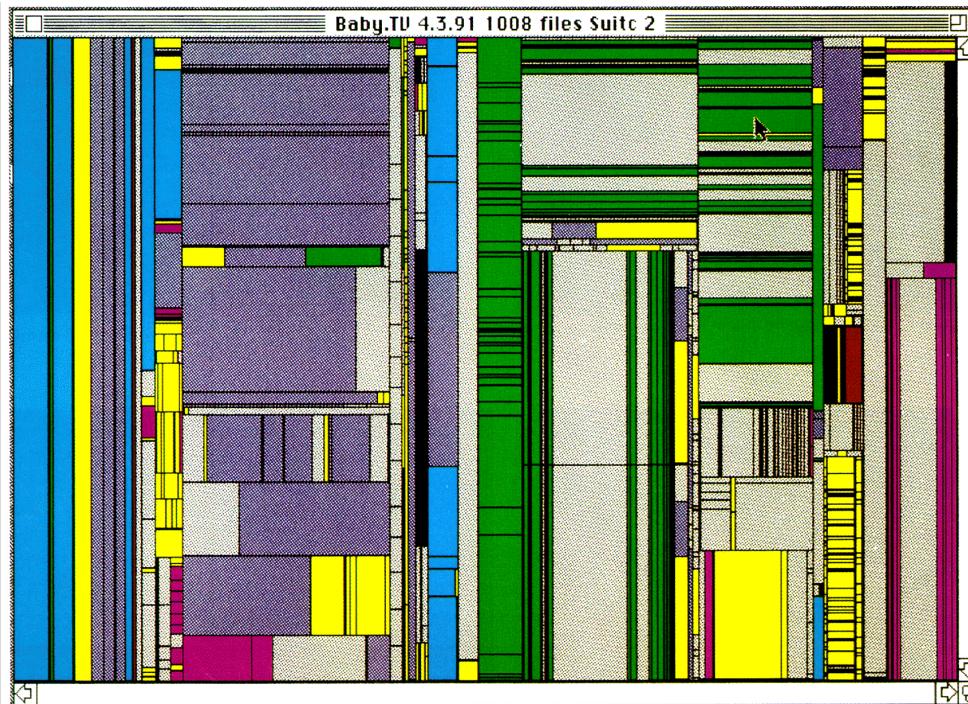
Worlds-within-Worlds

- Assign the function and two most important parameters to innermost world
- Fix all other parameters at constant values - draw other (1 or 2 or 3 dimensional worlds choosing these as the axes)
- Software that uses this paradigm
 - N-vision: Dynamic interaction through data glove and stereo displays, including rotation, scaling (inner) and translation (inner/outer)
 - Auto Visual: Static interaction by means of queries

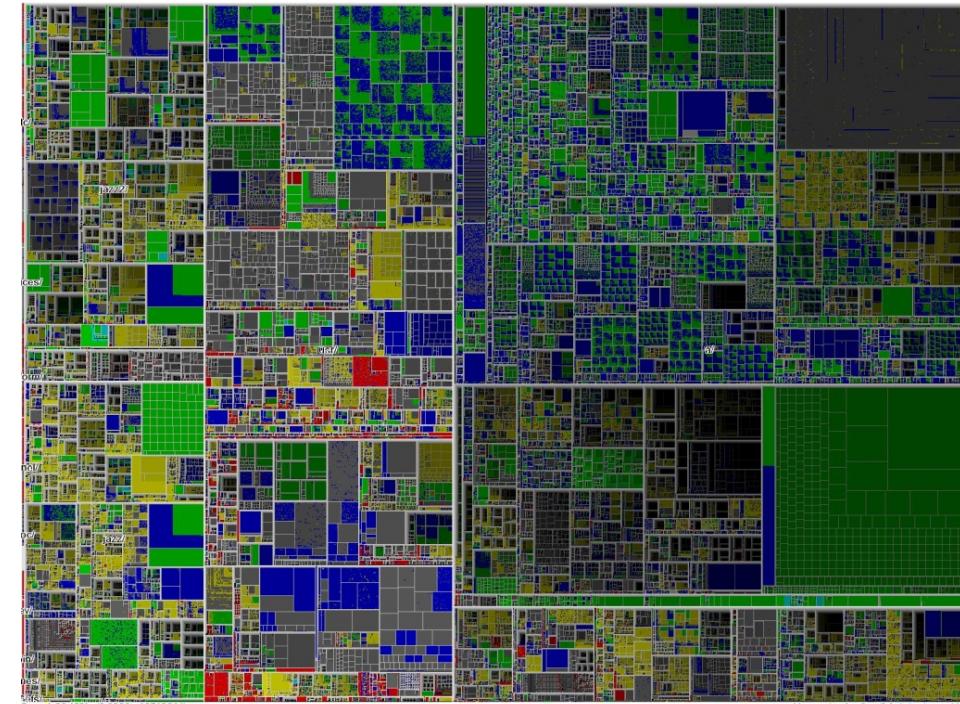


Tree-Map

- Screen-filling method which uses a hierarchical partitioning of the screen into regions depending on the attribute values
- The x- and y-dimension of the screen are partitioned alternately according to the attribute values (classes)



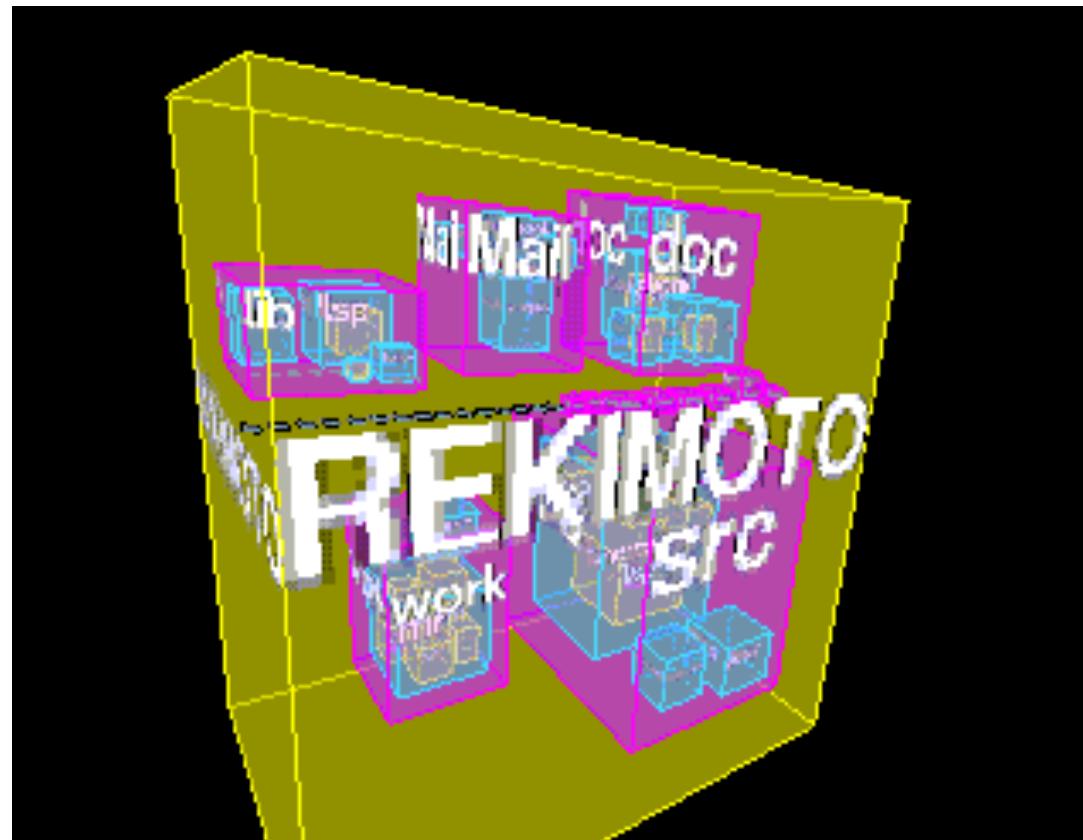
Schneiderman@UMD: Tree-Map of a File System



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

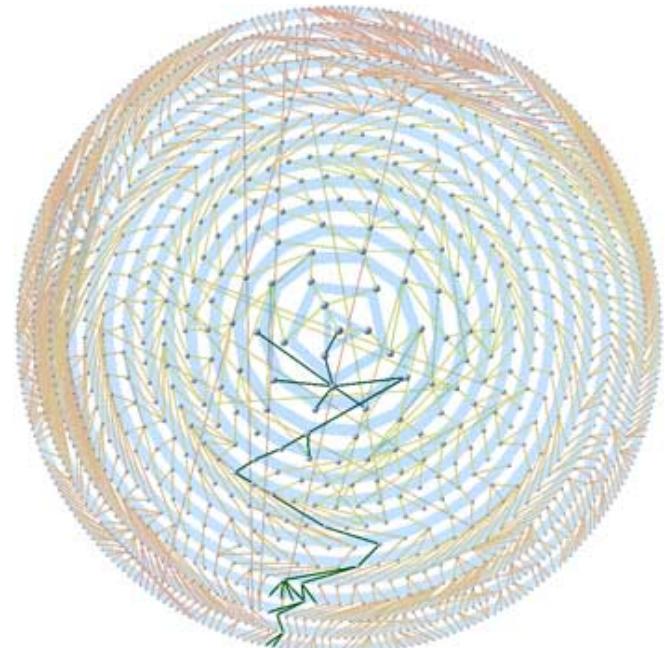
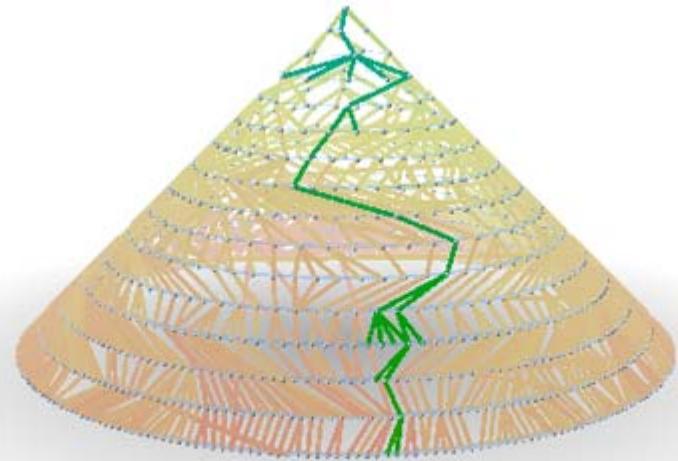
InfoCube

- 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.



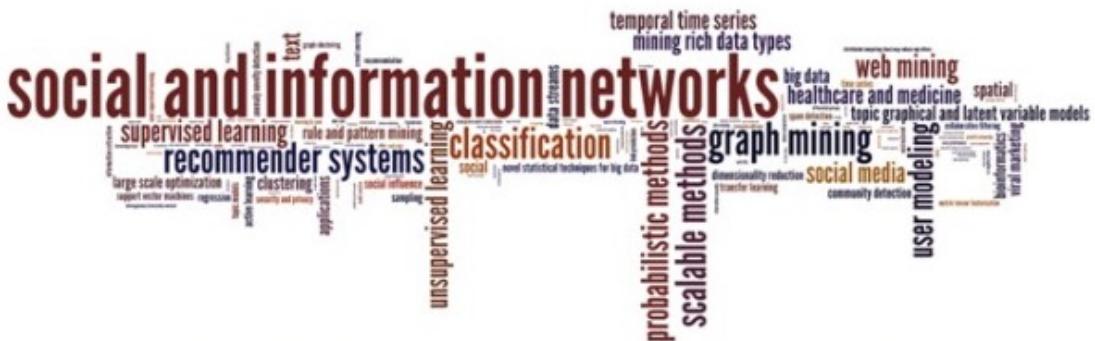
Three-D Cone Trees

- *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

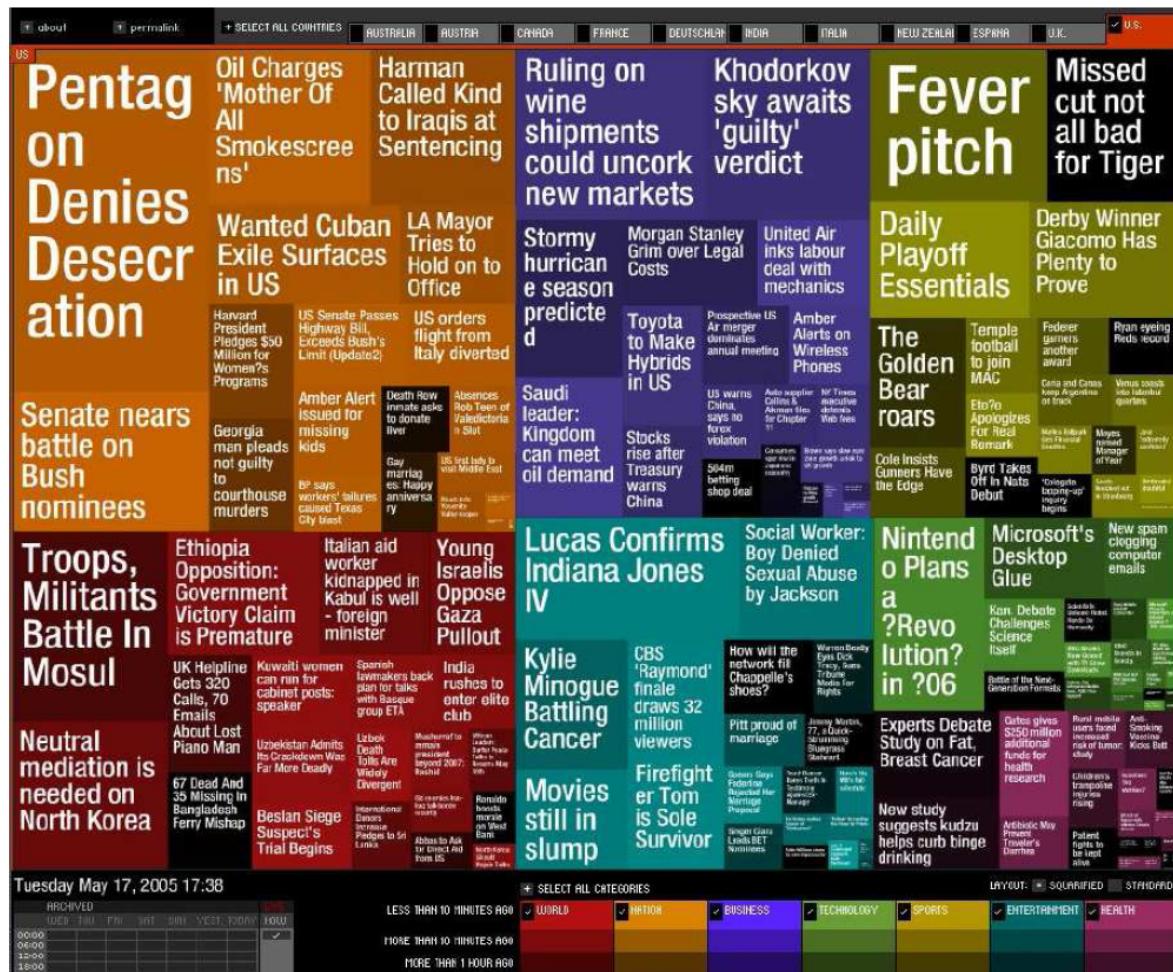


Visualizing Complex Data and Relations: Tag Cloud

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



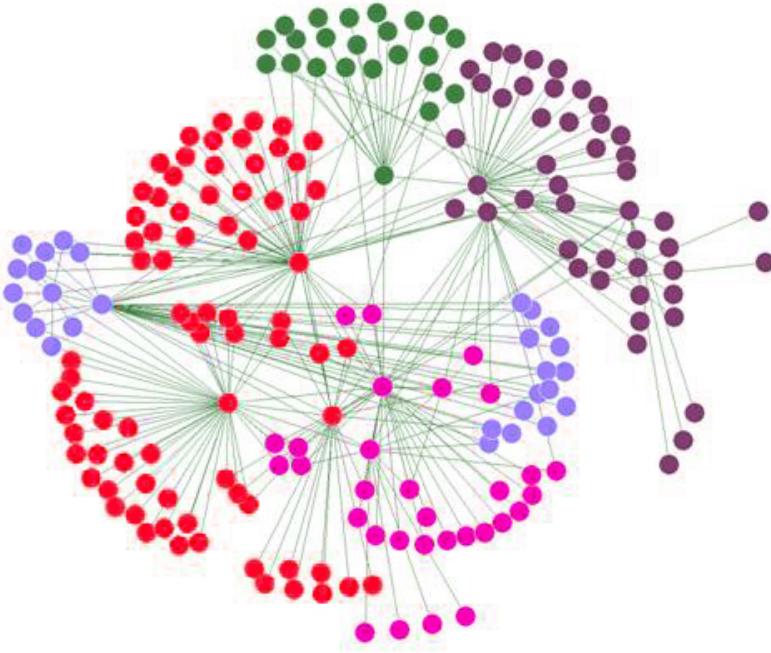
KDD 2013 Research Paper Title Tag Cloud



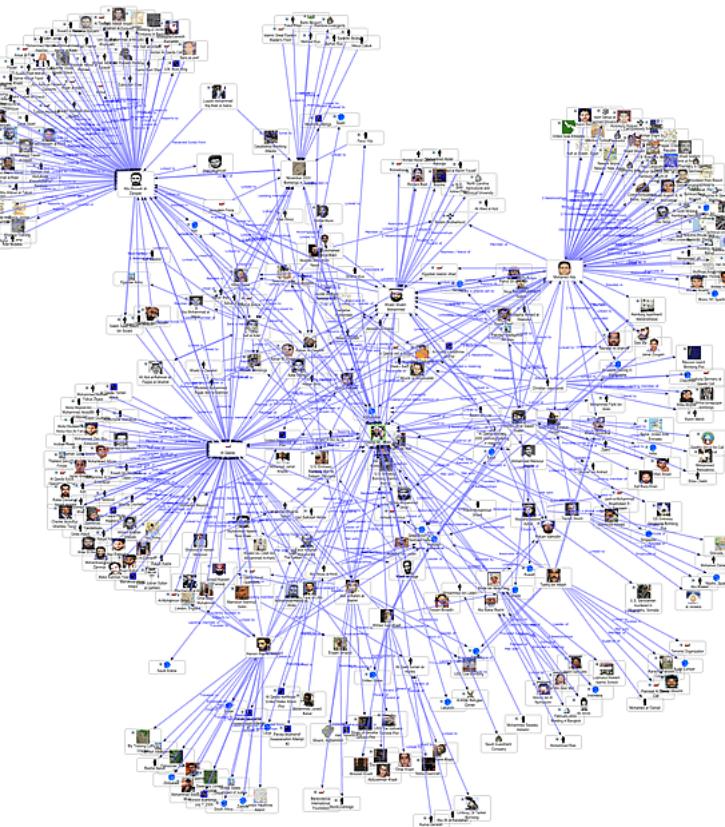
Newsmap: Google News Stories in 2005

Visualizing Complex Data and Relations: Social Networks

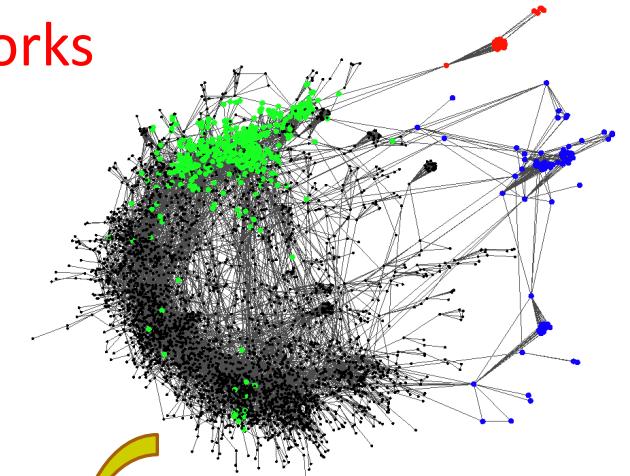
- Visualizing non-numerical data: social and information networks



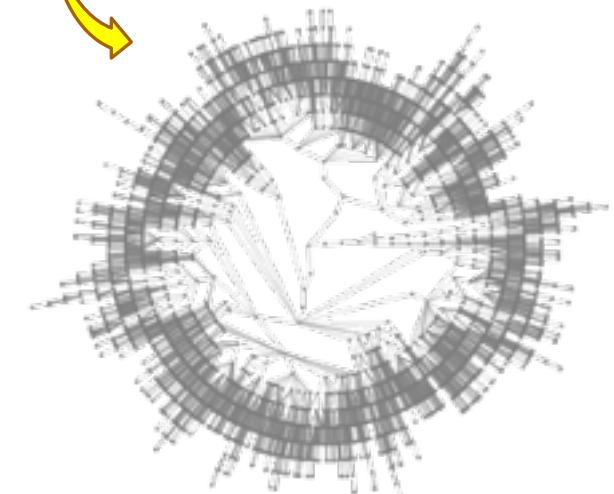
A typical network structure



A social network



organizing
information networks



Chapter 2. Getting to Know Your Data

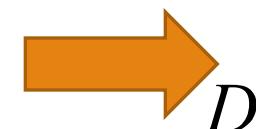
- Data Objects and Attribute Types
- Basic Statistical Descriptions of Data
- Data Visualization
- Measuring Data Similarity and Dissimilarity
- Summary



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 
 - Dissimilarity (distance) matrix
 - n data points, but registers only the distance $d(i, j)$ (typically metric)
 - 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
- | | | | |
|----------|----------|-----|----------|
| x_{11} | x_{12} | ... | x_{1l} |
| x_{21} | x_{22} | ... | x_{2l} |
| M | M | O | M |
| x_{n1} | x_{n2} | ... | x_{nl} |
| 0 | | | |
| $d(2,1)$ | 0 | | |
| M | M | O | |
| $d(n,1)$ | $d(n,2)$ | ... | 0 |

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

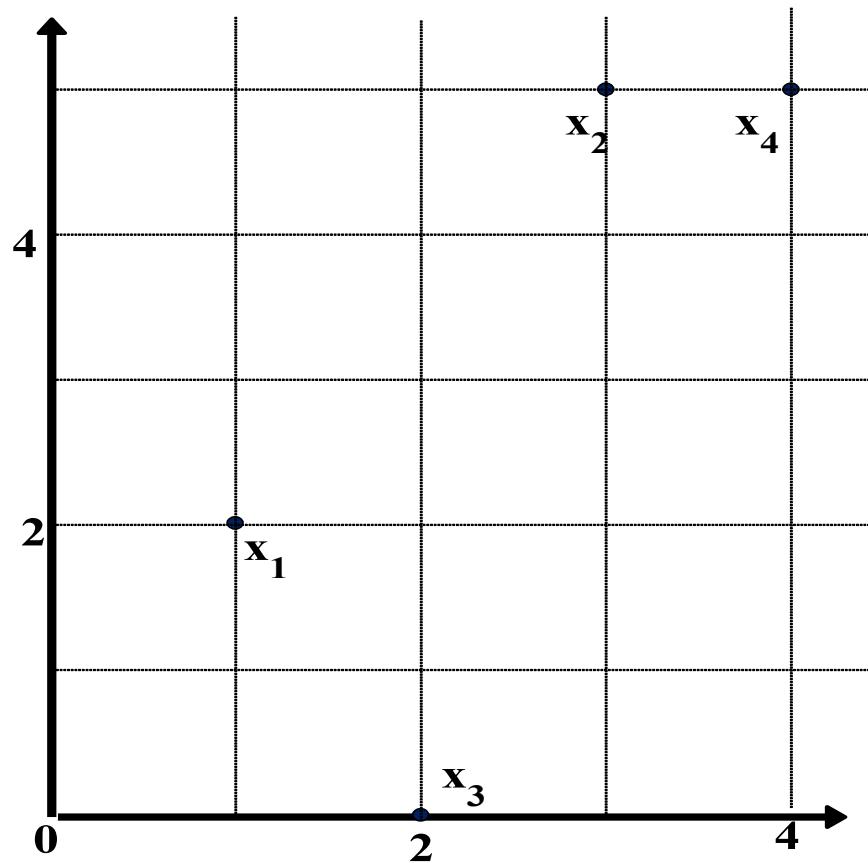
$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + \dots + |x_{nf} - m_f|)$$

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

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

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

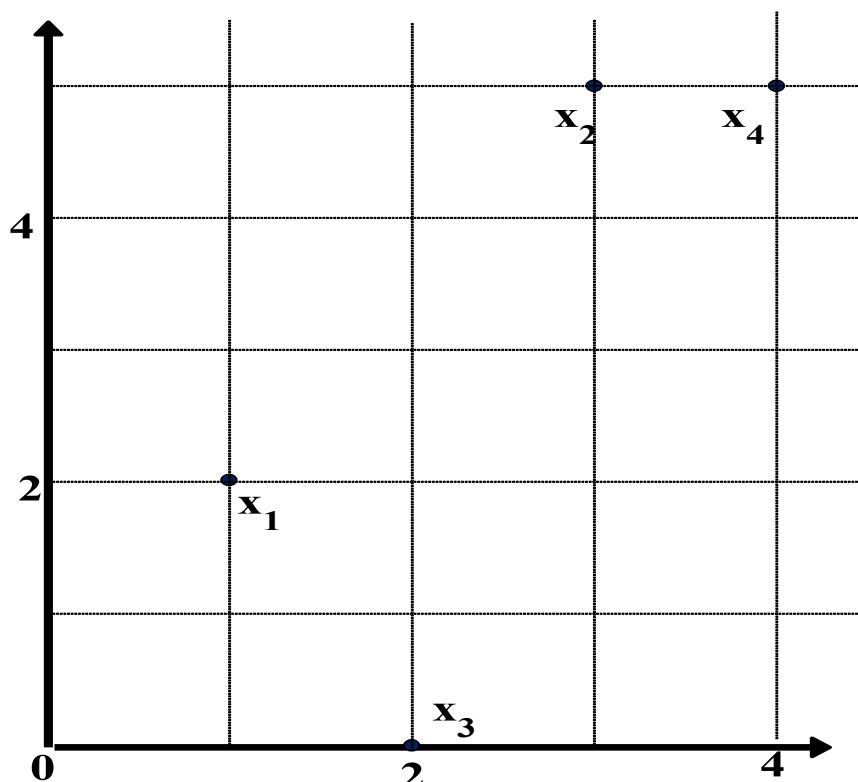
$$d(i, j) = \sqrt{|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \dots + |x_{il} - x_{jl}|^2}$$

- $p \rightarrow \infty$: (L_{\max} norm, L_{∞} norm) **“supremum” distance**
 - The maximum difference between any component (attribute) of the vectors

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

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_∞)

L	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 <i>j</i>		
		1	0	sum
Object <i>i</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

		Mary		
		1	0	Σ_{row}
Jack		1	2	0
		0	1	3
		Σ_{col}	3	6

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

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

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

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

		Jim		
		1	0	Σ_{row}
Jack		1	1	2
		0	1	3
		Σ_{col}	2	6

		Mary		
		1	0	Σ_{row}
Jim		1	1	2
		0	2	4
		Σ_{col}	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: $r_{if} \quad \{1, \dots, M_f\}$
 - 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 $z_{if} = \frac{r_{if}}{M_f - 1}$)
 - 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

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, etc.
- Cosine measure: If d_1 and d_2 are two vectors (e.g., term-frequency vectors), then

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

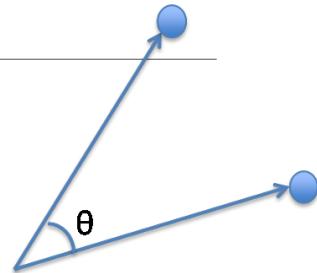
where \bullet indicates vector dot product, $\|d\|$: the length of vector d

Example: Calculating Cosine Similarity

- Calculating Cosine Similarity:

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

$$sim(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$



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

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

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

- 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 $\|d_2\|$

$$\begin{array}{r} \|d_1\| \quad \sqrt{5^2 + 3^2 + 2^2 + 1^2 + 0^2 + 1^2 + 0^2 + 2^2 + 0^2 + 0^2} = \sqrt{25} = 5 \\ \|d_2\| \quad \sqrt{3^2 + 2^2 + 1^2 + 1^2 + 0^2 + 1^2 + 1^2 + 0^2 + 0^2 + 1^2} = \sqrt{13} \end{array}$$

- Calculate cosine similarity: $\cos(d_1, d_2) = 25 / (5 \times \sqrt{13}) = 0.94$

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 4th credit project!!!**

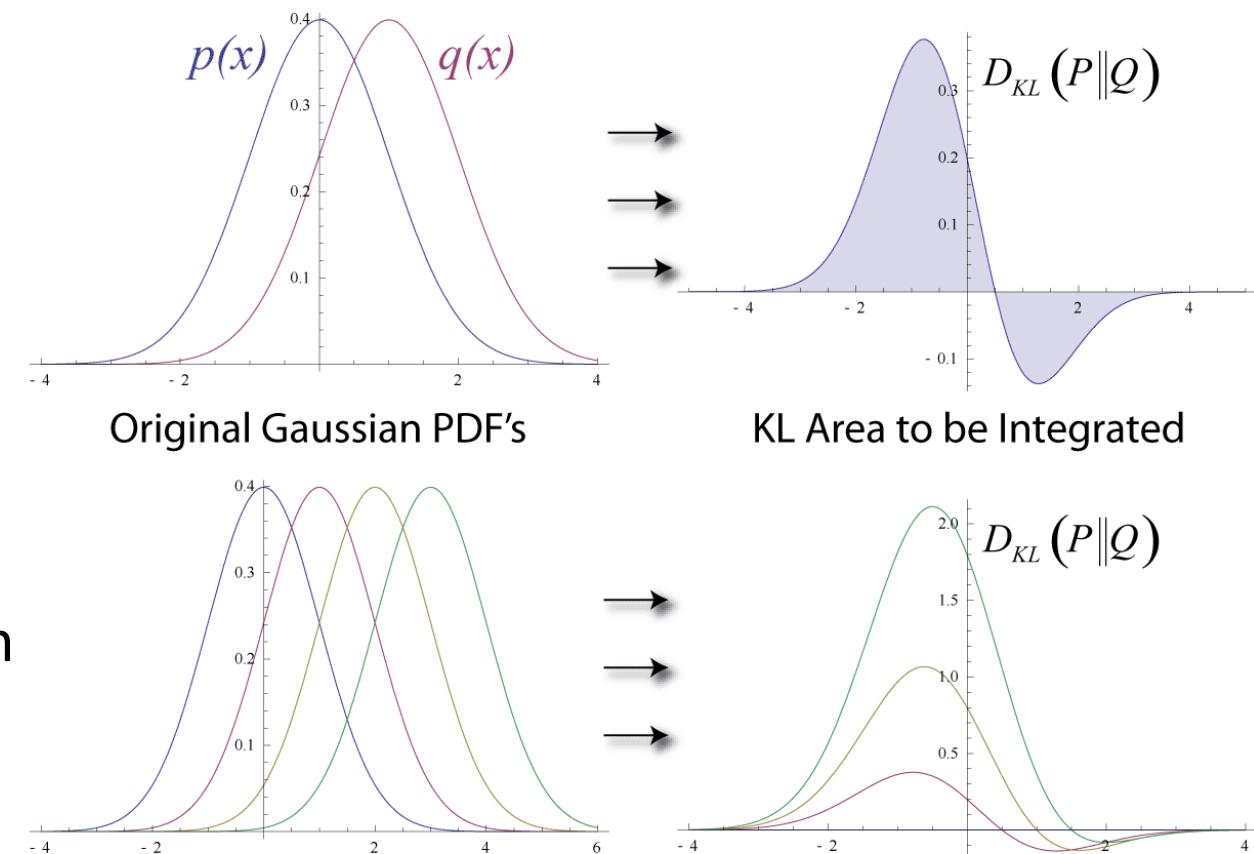
KL Divergence: Comparing Two Probability Distributions

- *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*
- $D_{KL}(p(x) \parallel q(x))$: divergence of $q(x)$ from $p(x)$, measuring the information lost when $q(x)$ is used to approximate $p(x)$

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

Discrete form ↗

$$D_{KL}(p(x) \parallel q(x)) = \int_{-\infty}^{\infty} p(x) \ln \frac{p(x)}{q(x)} dx$$



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

← 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 ∞ , 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 ϵ , 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 ϵ
 - $P' : (a : 3/5 - \epsilon/3, b : 1/5 - \epsilon/3, c : 1/5 - \epsilon/3, d : \epsilon)$
 - $Q' : (a : 5/9 - \epsilon/3, b : 3/9 - \epsilon/3, c : \epsilon, d : 1/9 - \epsilon/3)$
 - $D_{KL}(P' || Q')$ 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, 2nd ed., Graphics Press, 2001
- C. Yu, et al., Visual data mining of multimedia data for social and behavioral studies, Information Visualization, 8(1), 2009

