



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

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

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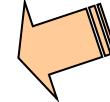




# Chapter 2. Getting to Know Your Data

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ជូនរាយព័ត៌មាន Data (រូបរាង)



- 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

ມີສົງ matrix

	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

\* ເນື້ອ Transaction  
ກ່ຽວຂ້ອງມາດຕະການ  
ໃຫ້ ອັນ ສອນໃຫຍ່  
ນຳນັ້ນ ສອນໃຫຍ່

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:

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

ນາຈາກ  
data beans

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

ແບບ relational  
+ ພາຍໃນຮູບ  
ເກີ່ມຂົນຂອງເງິນ  
ຕາມຕາມ

team	coach	y	pla	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	

ມີສົງ Document

\* ສ້າງ Document 1, 2, 3 / ບາຄາມ  
ເກີ່ມຂົນຂອງເງິນ: Document ມີໃນນັບຮູບ  
ໂລກໂງງວົງໂຈ່ງຈຳນານຫຼັດທີ່ວ່າ  
ກໍຄັງ ເນື້ອກົງເປັນທົກຄານ  
ເກີ່ມກົນ 0:1

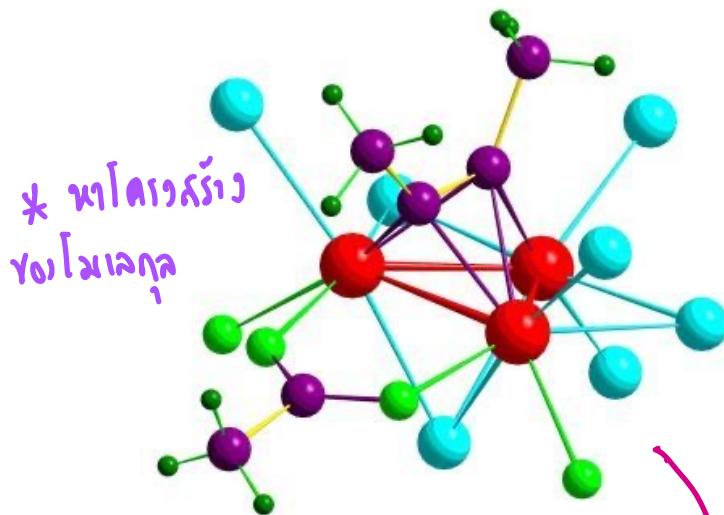
# Types of Data Sets: (2) Graphs and Networks

Transportation network

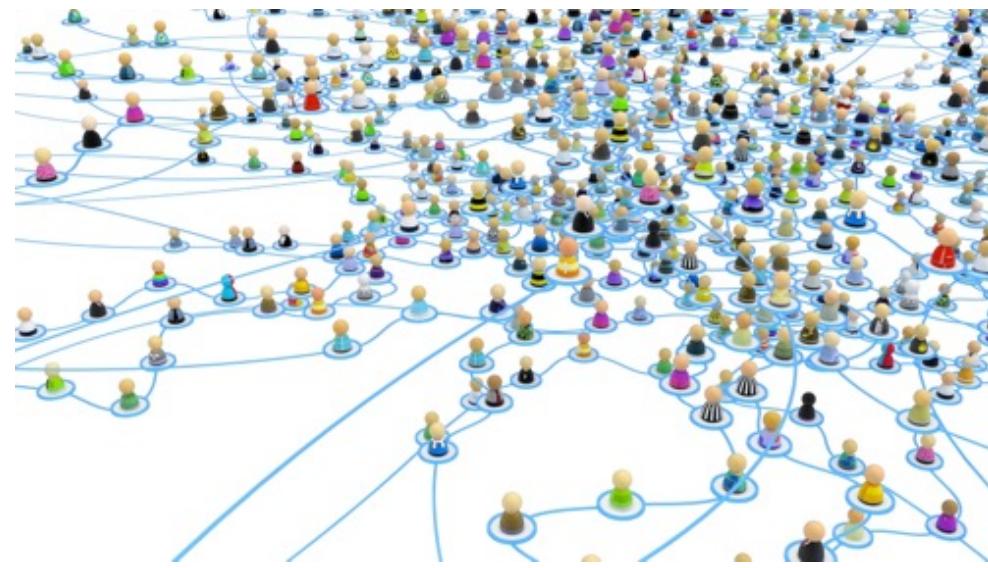


World Wide Web + ເຖິງກັນກາລິ້ງຈະວິນບ່ວນໂອນ

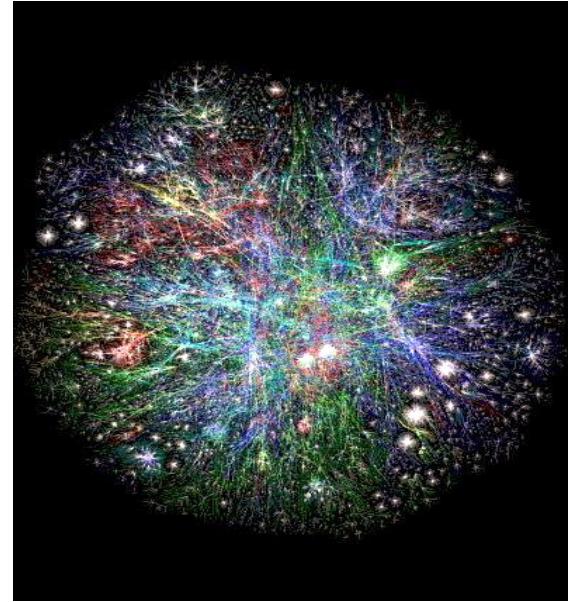
ຄູນເຕັກປັນ: 700 ວິນ  
ໄລຫີ່ຈຳຕົວເທົ່າ  
ໃຫຍ່ເຫຼື້ອນ



Molecular Structures



Social or information networks



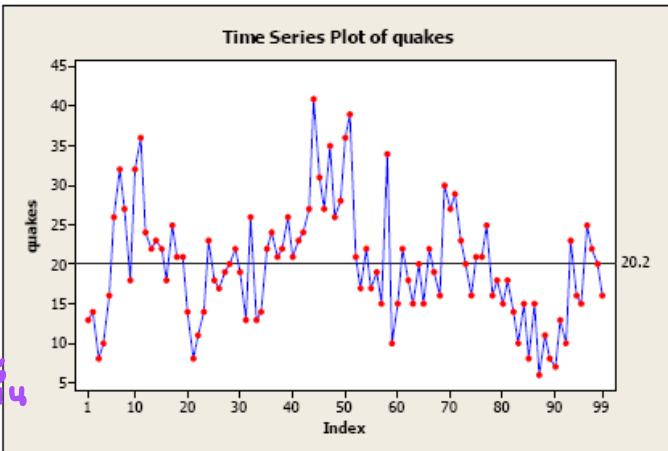
# Types of Data Sets: (3) Ordered Data

- Video data: sequence of images

\* ສະໃຈເລກໂຕວ່າໄລຍ່ມທົ່ວ່າ ທ່າງກັນ

\* ການຊັບນິກລັບ

- Temporal data: time-series



\* ອອກໄວ  
ໃຫ້ນັ້ນ  
\* ດີແລມເກີນ  
ວ່າງກາງຫຼາ ?  
ເພື່ອລົງຈະສັນະ ມີຫຼາ  
ນີ້?



\* ບອດລຳເລັ້ນເພື່ອງວ່າ  
ຄຸນກົງມາ:ໃນກໍ່ສັບຄົດ  
ໄດ້?

- Sequential Data: transaction sequences

Human	GTTTGAGG	-	ATGTTCAACAAATGCTCCTTCATTCCCTATTTACAGACCTGCCGCA
Chimpanzee	GTTTGAGG	-	ATGTTCAATAATGCTGCTTCACTCCCTATTTACAGACCTGCCGCA
Macaque	GTTTGAGG	-	ATGCTCAATAATGCTCCTTCATTCCCTACAAACTTGCGCA
Human	GACAATTCTGCTAGCAGCCTTGTGCTATTATCTGTTTCTAAACCTTAGTAATTGAGTGT	Start	
Chimpanzee	GACAATTCTGCTAGCAGCCTTGTGCTATTATCTGTTTCTAAACCTTAGTAATTGAGTGT		
Macaque	GACAATTCTGCTAGCAGCCTTGTGCTATTATCTGTTTCTAAACCTTAGTAATTGAGTGT		
Human	GATCTGGAGACTAA	-	CCTCTGAAATAAAAGCTGATTATTTATTTATTTCTCAAAACAA
Chimpanzee	GATCTGGAGACTAA	-	CCTCTGAAATAAAAGCTGATTATTTATTTATTTCTCAAAACAA
Macaque	TATCTGGAGACTAA	-	TCTGAAATAAAAGCTGATTATTTATTTATTTCTCAAAACAA
Human	CAGAACACGATTTAGCAAATTACTCTTAAGATATTATTTACATTTCTATATTCTCTA		
Chimpanzee	CAGAACACGATTTAGCAAATTACTCTTAAGATACTATTTACATTTCTATATTCTCTA		
Macaque	CAGAACATGATTTAGCAAATTACCTCTTAAGATATTATTTGCACCTTCTATATTCTCTA		
Human	CCCTGAGTTGATGTTGAGCAATATGTCACCTTCATAAAGCCAGGTATACAC	-	-TTATG
Chimpanzee	CCCTGAGTTGATGTTGAGCCGATATGTCACCTTCATAAAGCCAGGTATACAC	-	-TTATG
Macaque	CCCTGAGTTGATGTTGAGCAATATGTCACCTCCACAAAGCCAGGTATATACATTACG		
Human	GACAGGTAAGTAAAAACATATTATTTATCTACGTTTGTCCAAGAATTAAATTTC	H	I
Chimpanzee	GACAGGTAAGTAAAAACATATTATTTATCTACGTTTGTCCAAGAATTAAATTTC	I	Y
Macaque	GACAGGTAAGTAAAAACATATTATTTATCTACGTTTGTCCAAGAATTAAATTTC	S	F
Human	AACTGTTGCGCGTGTGGTAA	-	L
Chimpanzee	AACTGTTGCGCGTGTGGTAA	-	S
Macaque	AACTGTTGCGCGTGTGGTAA	-	K

- Genetic sequence data

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

ແມ່ນທີ່ 4

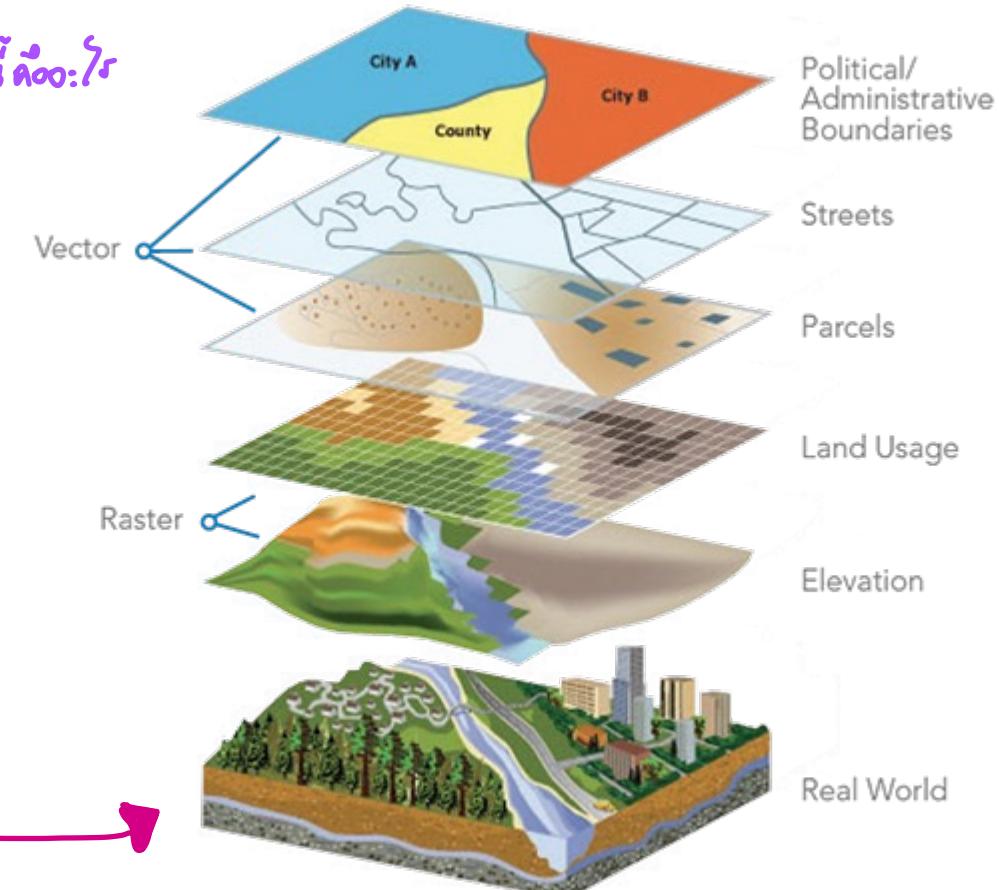
- Spatial data: maps ↗ \*



- Image data:

- Video data:

\* Spatio-temporal



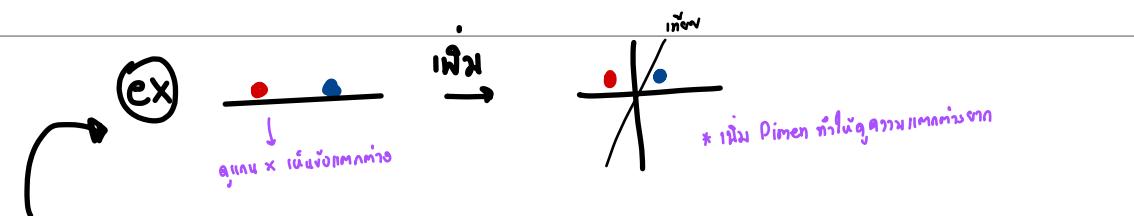
# Important Characteristics of Structured Data

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1

## □ Dimensionality ນິຕີ (ຈຳນານຄອລິນ)

□ Curse of dimensionality \* ດົງນິຕີນຳກຳ ຂັ້ນໄຟດ້າ



□ Sparsity ດາວກ່າວເປົ່ວ (ຄ່າ 0 / ດ້ວຍກ່າວ)

□ Only presence counts

□ Resolution ດາວລະເວັບຄະດູງຫັ້ນມູສ

□ Patterns depend on the scale

ໃຫ້ຫັ້ນມູສປະເທດ → ຈຳເປັດ → ອົບໄກໂອ

□ Distribution ດາວກະລາບຫັ້ນນີ້ ຢຸດ Dimen ທີ່ Distribution ເປັນເກົ່າໄຟໃຈໆ

□ Centrality and dispersion

# Data Objects

ຈົດໝາຍ Data ມີກົດ້າ

- Data sets are made up of data objects
- A **data object** represents an entity
- Examples:
  - sales database: customers, store items, sales
    - ↳ data ຂອງ / data point
    - ↳ relational
    - ↳ transaction
  - 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

## \* វិធានសង្គម Data point

## Ա. ԱՐԴԻ

↗ กมชช.เลิบบี

## □ Attribute (or dimensions, features, variables)

- ❑ A data field, representing a characteristic or feature of a data object.
  - ❑ *E.g., customer\_ID, name, address*

## □ Types:

# Attribute Types

- **Nominal:** categories, states, or “names of things” \* ไม่มีความสัมพันธ์ทางคณิตศาสตร์

- *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 \* ผลลัพธ์ที่ 1 / ผลลัพธ์ที่ 2 = ผลลัพธ์เดียวกัน
  - Asymmetric binary: outcomes not equally important. ex. ผลลัพธ์โรค
    - e.g., medical test (positive vs. negative) \* ผลลัพธ์ที่เป็นบวก มากกว่า -
    - Convention: assign 1 to most important outcome (e.g., HIV positive)

- **Ordinal** \* ผลลัพธ์ที่มีลำดับ

- Values have a meaningful order (ranking) but magnitude between successive values is not known
  - *Size* = {*small, medium, large*}, grades, army rankings

# Numeric Attribute Types

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- 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** ↗ 0 ↘
  - 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

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## 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**

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- 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:

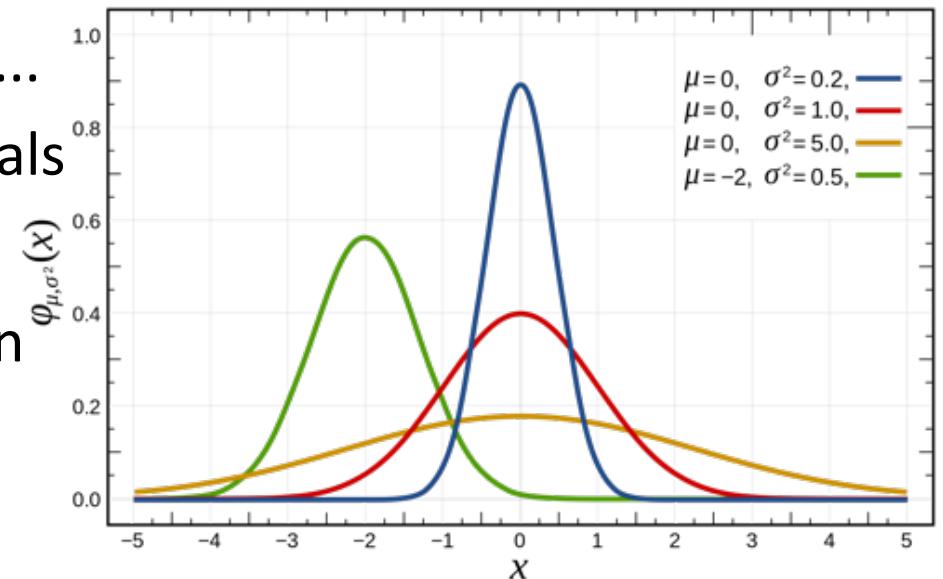
- Analyzed with multiple granularities of precision

- 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.

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad \text{Sample}$$
$$\mu = \frac{\sum x}{N} \quad \text{population}$$

- 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*):

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

Approximate  
median



Sum before the median interval

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

Low interval limit



Interval width ( $L_2 - L_1$ )



# Measuring the Central Tendency: (3) Mode

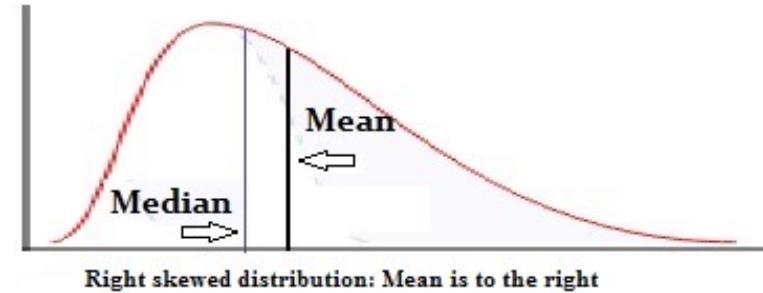
- Mode: Value that occurs most frequently in the data

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- Unimodal

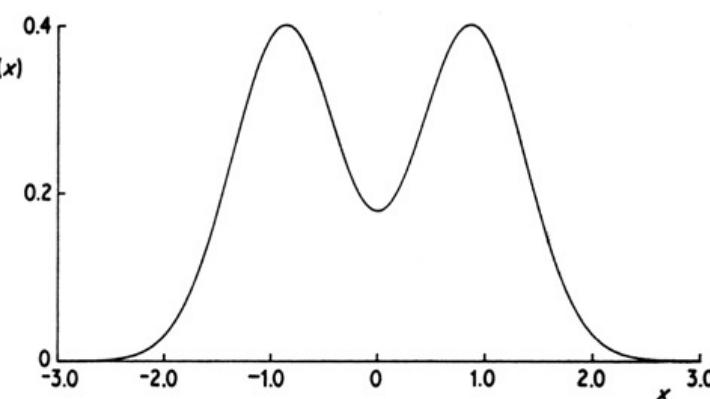
- Empirical formula:

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

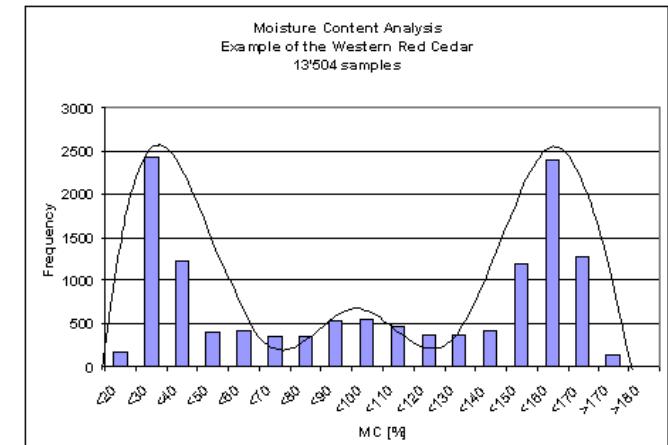
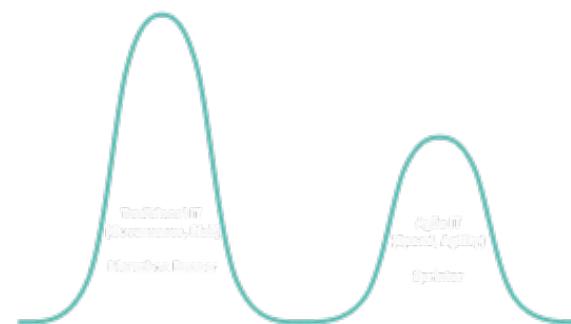


- Multi-modal

- Bimodal



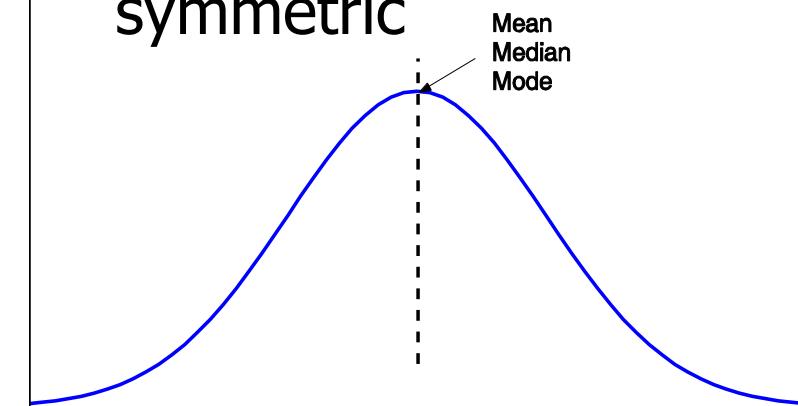
- Trimodal



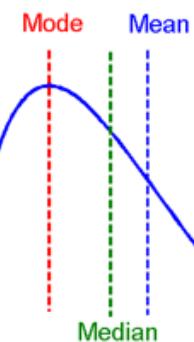
# Symmetric vs. Skewed Data

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

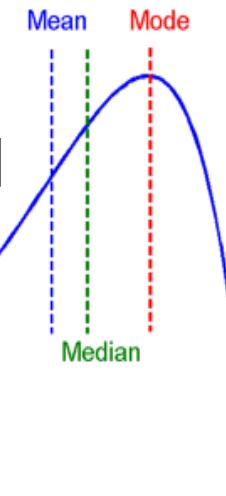
symmetric



positively skewed

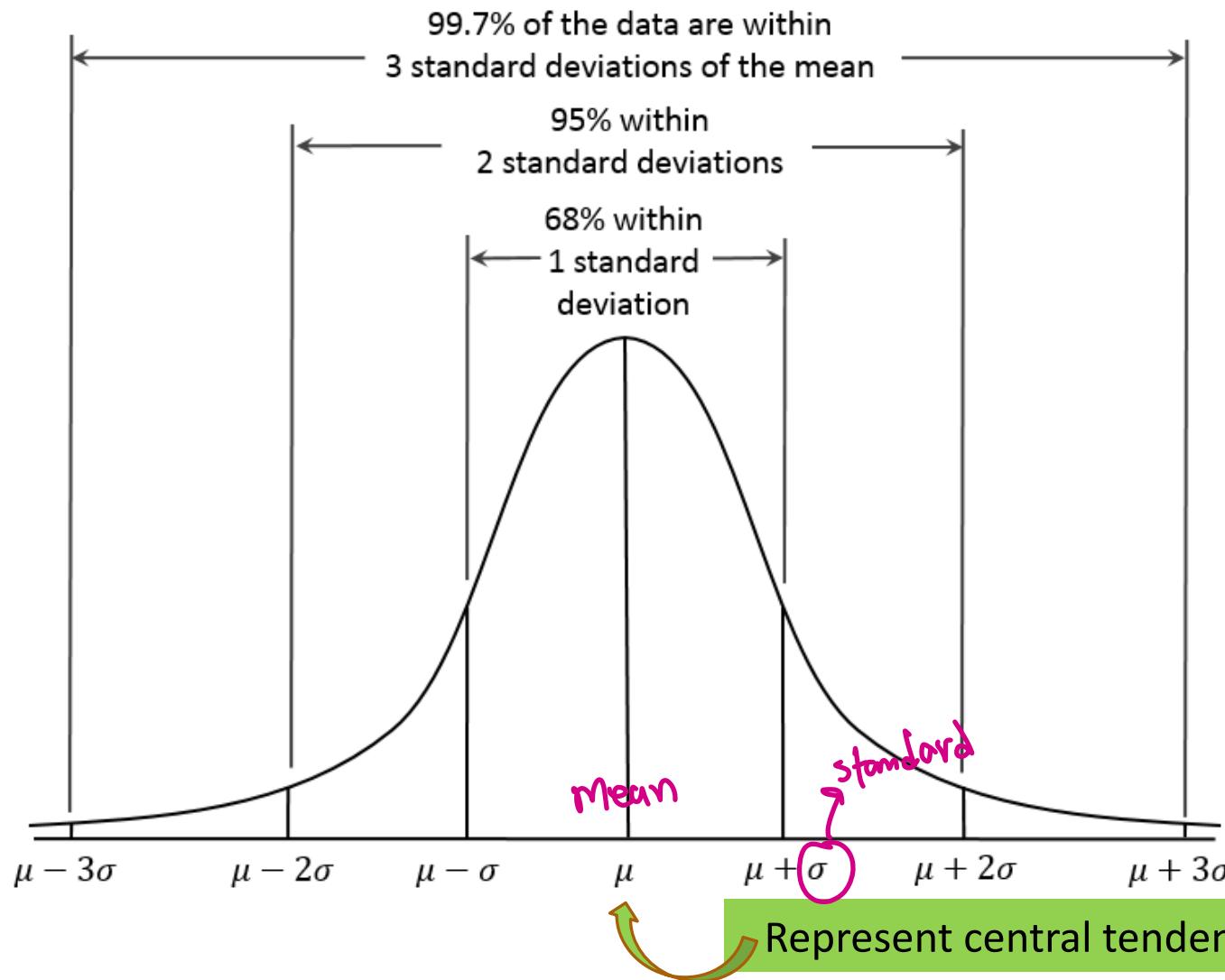


negatively skewed



# 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?

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

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

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

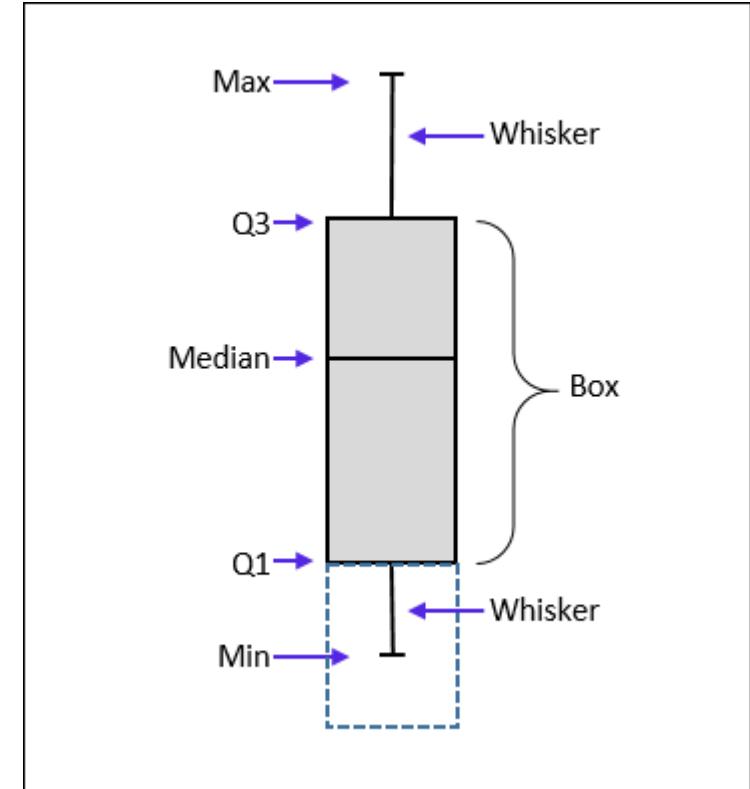
# Graphic Displays of Basic Statistical Descriptions

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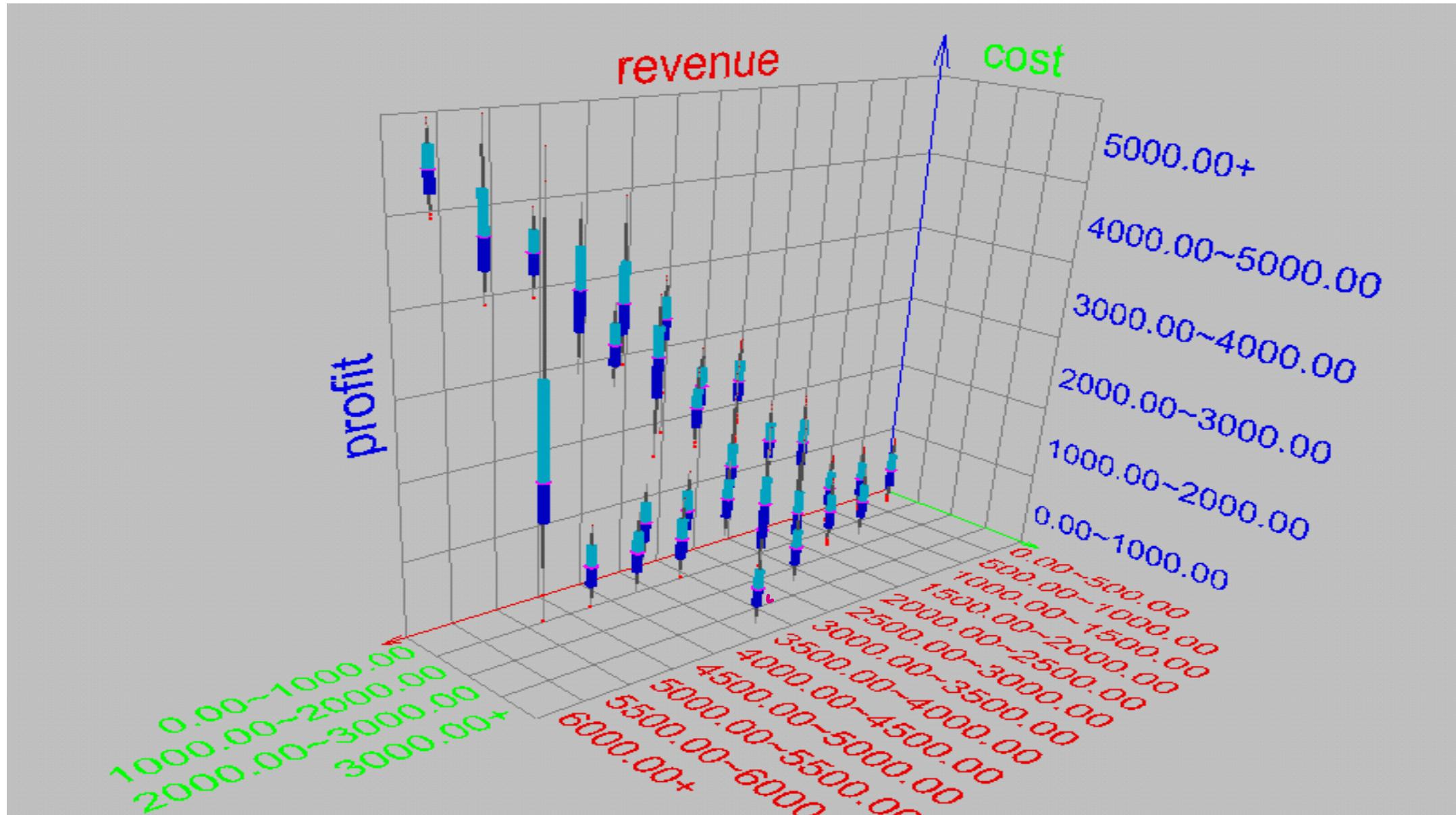
- Boxplot:** graphic display of five-number summary
- Histogram:** x-axis are values, y-axis repres. frequencies A. ၃
- Quantile plot:** each value  $x_i$  is paired with  $f_i$  indicating that approximately  $100 f_i \%$  of data are  $\leq x_i$
- Quantile-quantile (q-q) plot:** graphs the quantiles of one univariate 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:**  $Q_1$  ( $25^{\text{th}}$  percentile),  $Q_3$  ( $75^{\text{th}}$  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  $1.5 \times \text{IQR}$



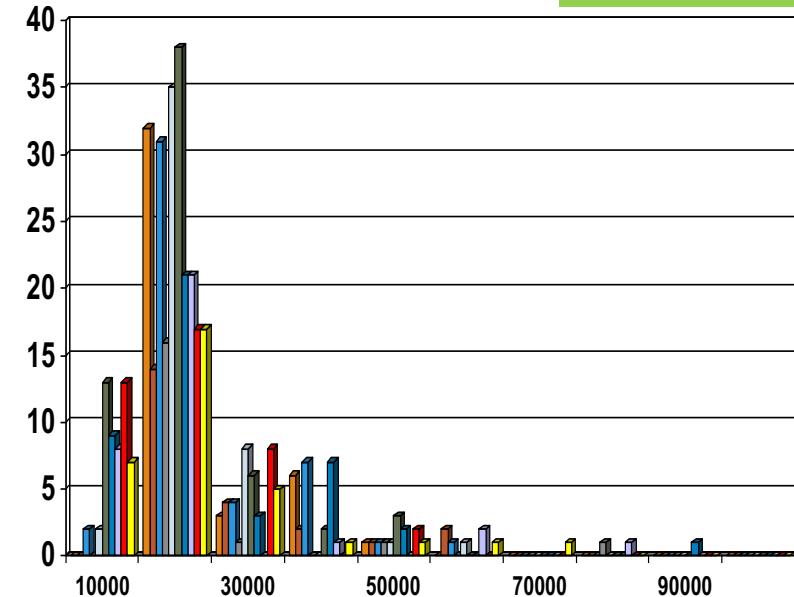
# Visualization of Data Dispersion: 3-D Boxplots



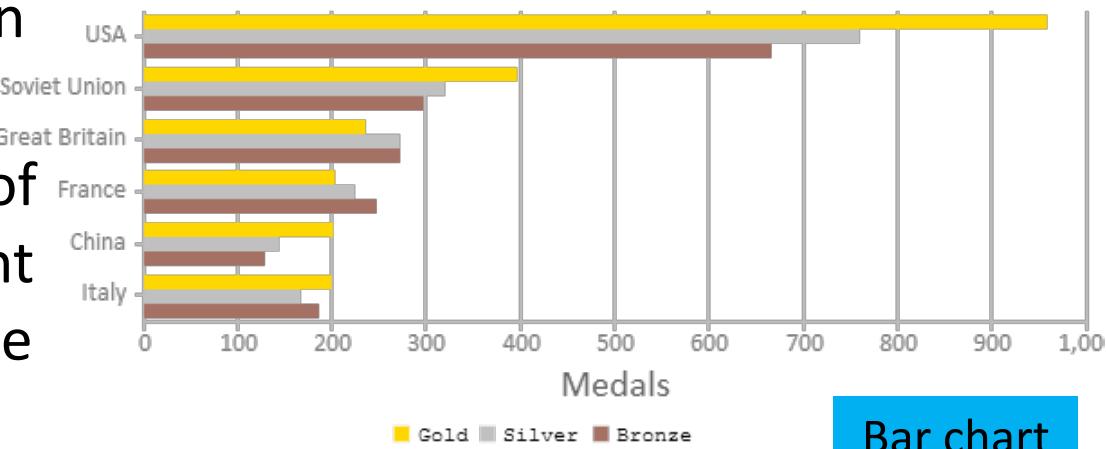
# Histogram Analysis

- ❑ 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



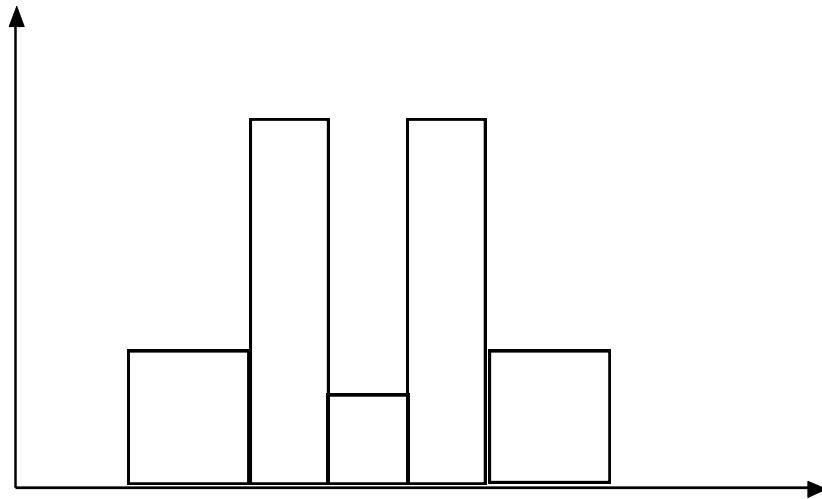
Olympic Medals of all Times (till 2012 Olympics)



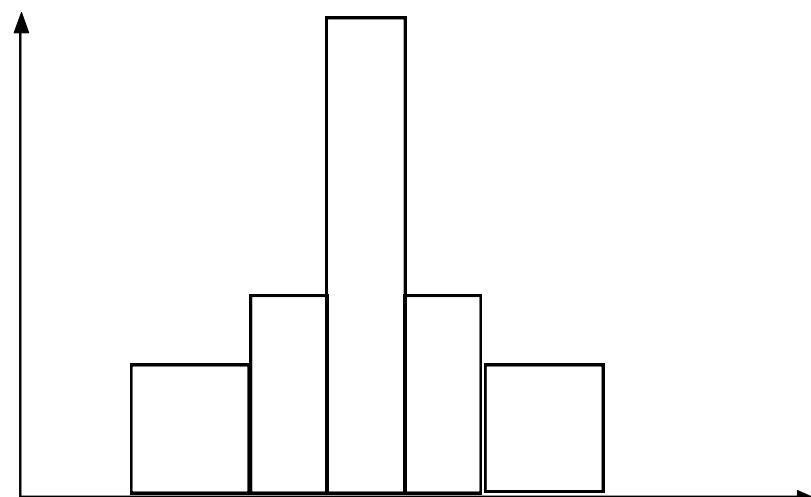
Bar chart

# Histograms Often Tell More than Boxplots

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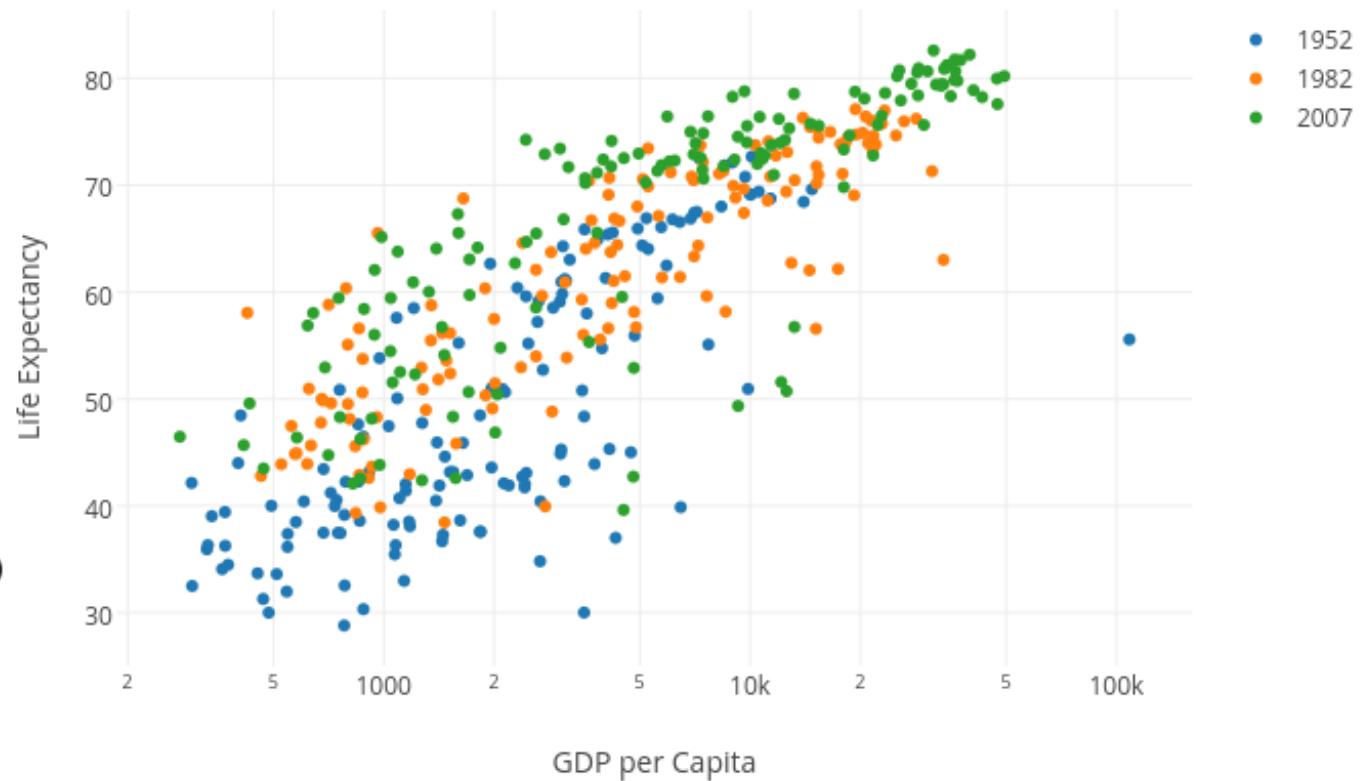
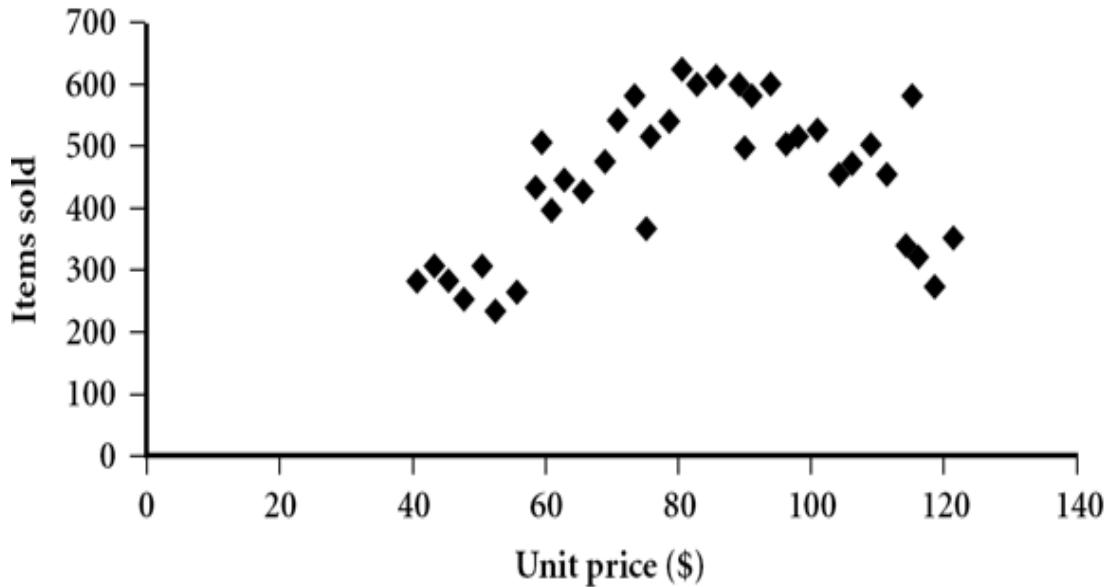


- ❑ The two histograms shown in the left may have the same boxplot representation
- ❑ The same values for: min, Q1, median, Q3, max
- ❑ But they have rather different data distributions

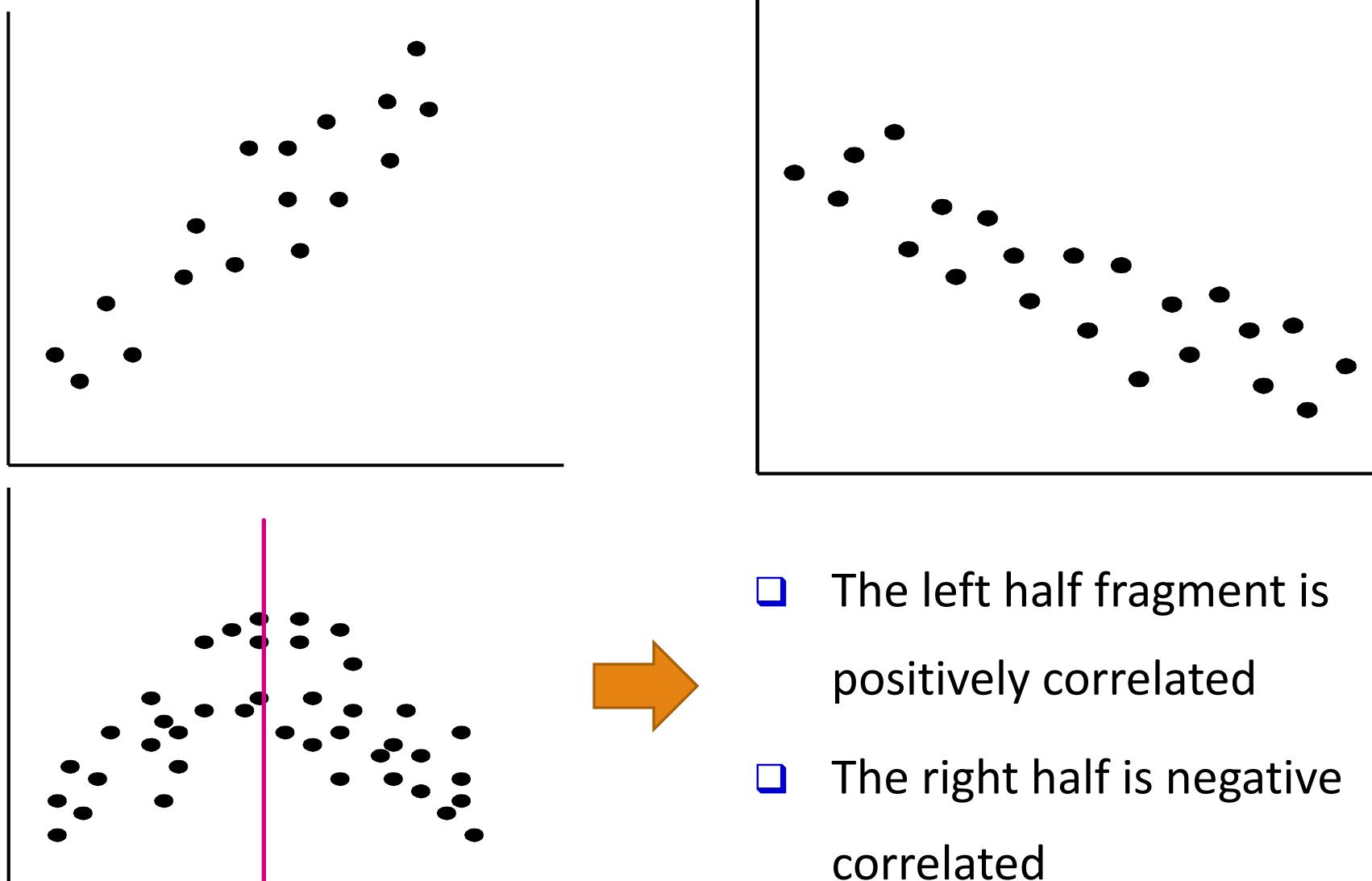


# Scatter plot

- 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

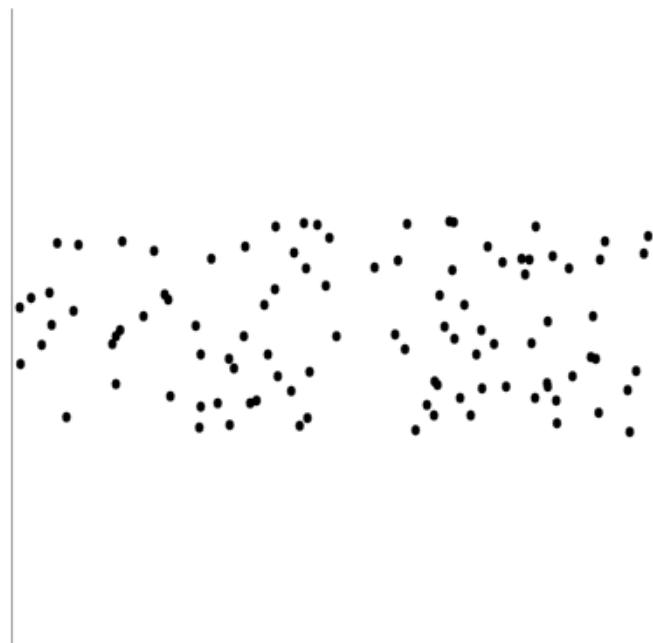


# Positively and Negatively Correlated Data



# Uncorrelated Data

ไม่ชัด. สงสัย



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

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# Data Visualization

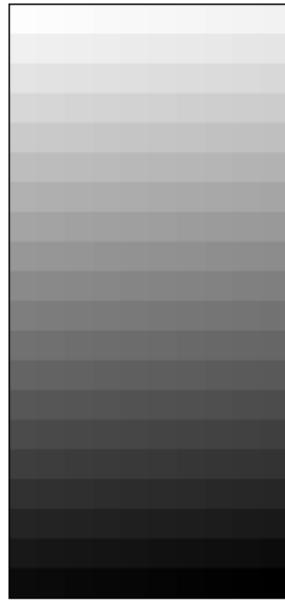
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- Why data visualization?
  - Gain insight into an information space by mapping data onto graphical primitives
  - Provide qualitative overview of large data sets
  - Search for patterns, trends, structure, irregularities, relationships among data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

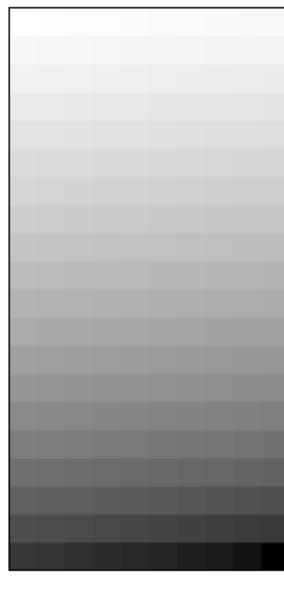
# Pixel-Oriented Visualization Techniques

- 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

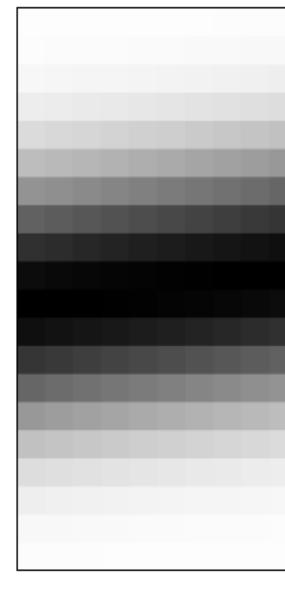
\* plot data តាមសំណង់



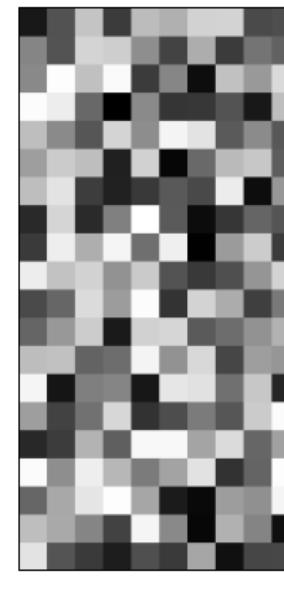
(a) Income



(b) Credit Limit



(c) transaction volume



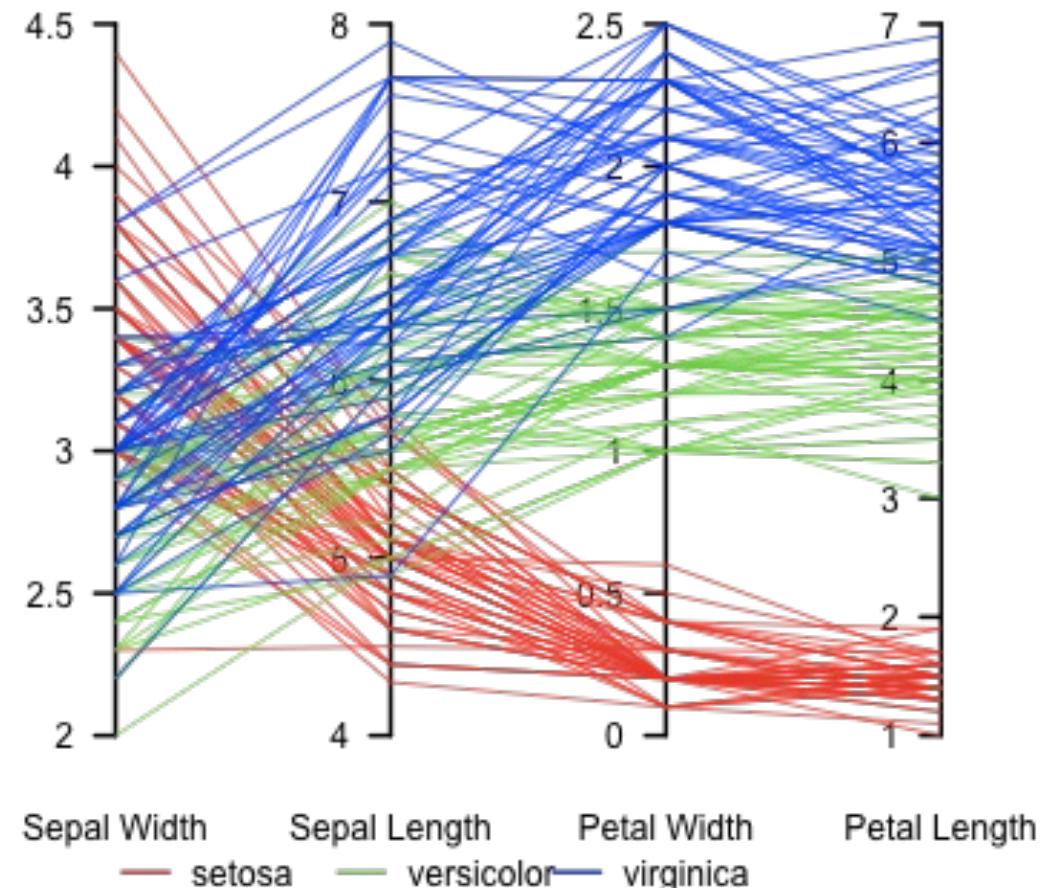
(d) age

# Parallel Coordinates

ອົດຕະການລົງຈະໂອກໃນ  
\* ໄມຕະເລຸກສອນໄວ

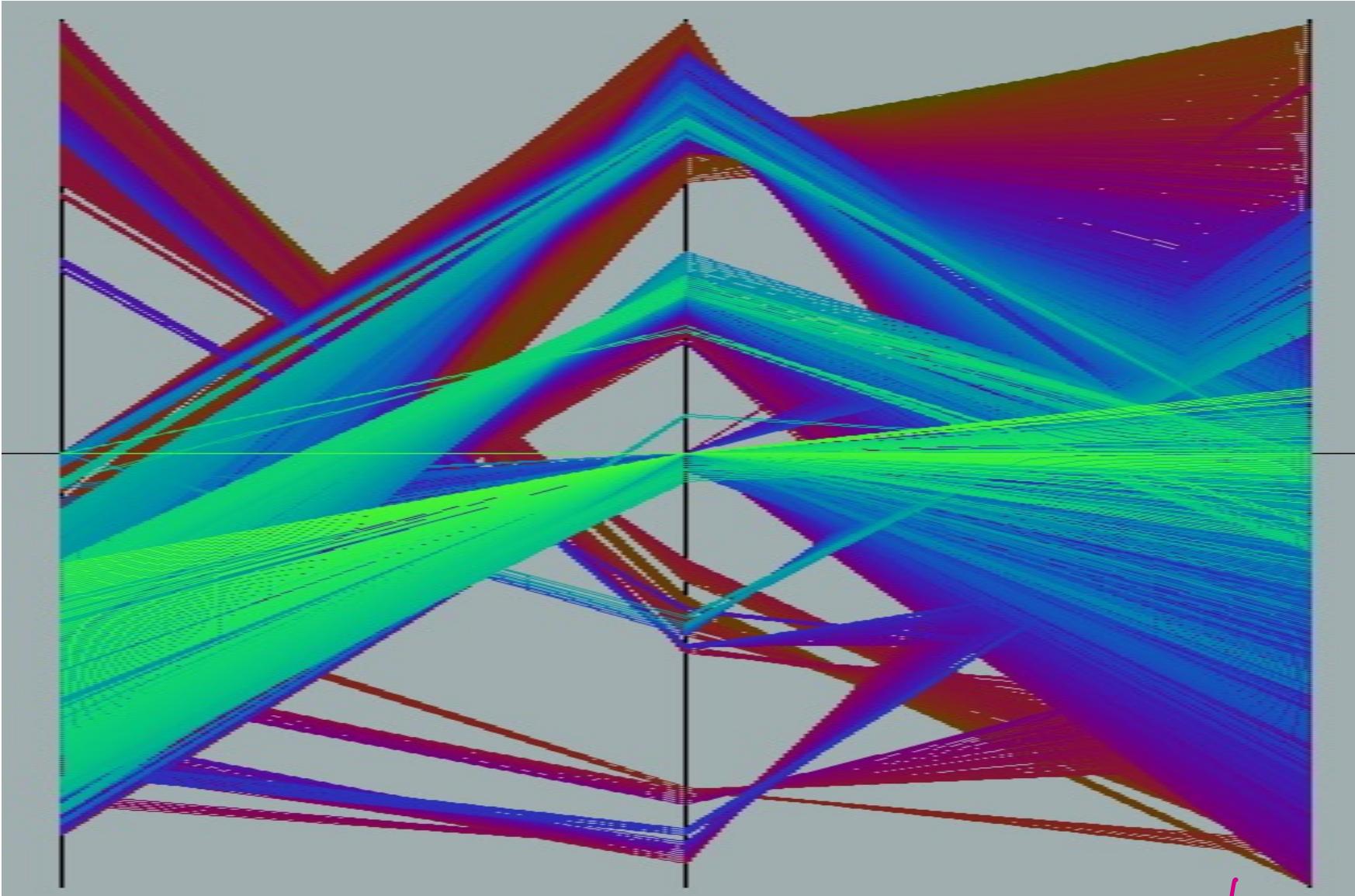
- n equidistant axes which are parallel to one of the screen axes and correspond to the attributes
- The axes are scaled to the [minimum, maximum]: range of the corresponding attribute
- Every data item corresponds to a polygonal line which intersects each of the axes at the point which corresponds to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

Parallel coordinate plot, Fisher's Iris data



# Parallel Coordinates of a Data Set

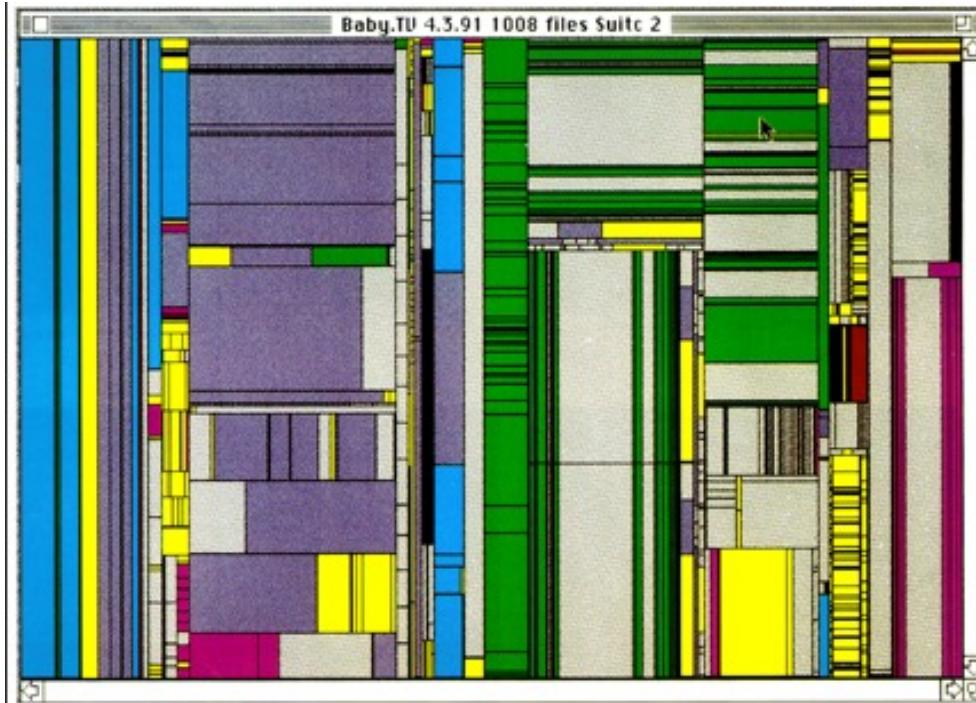
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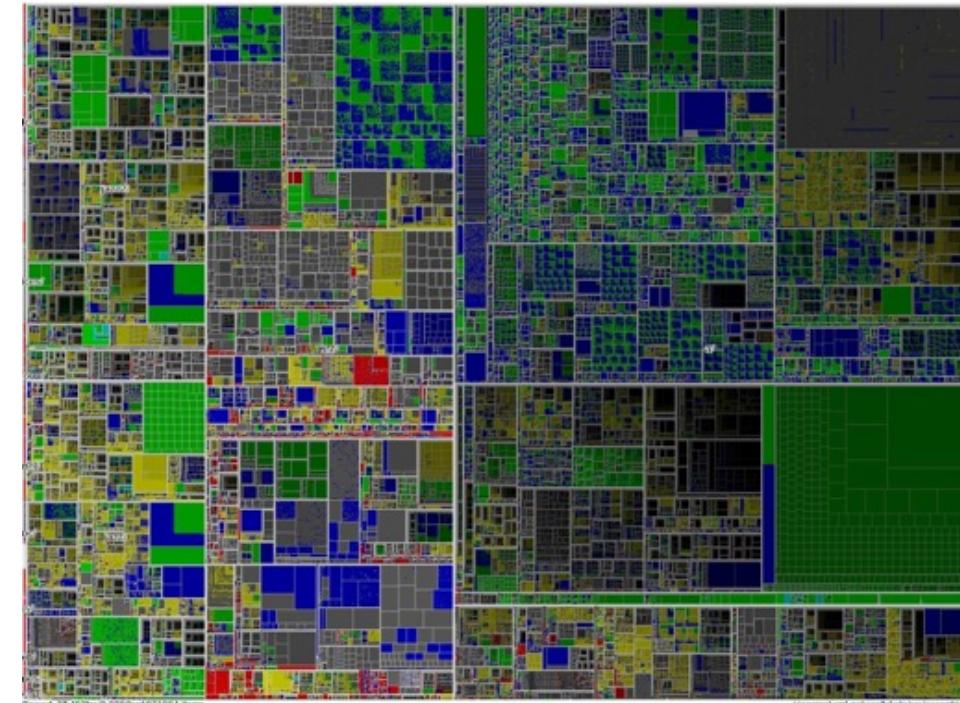
# Tree-Map

ໄປ່ນີ້ແກ່ໄຟ 100% ໂລັງໄປ່ ດາວໂຫຼດ  
ເຊັ່ນໃນຄລາສີ່ແລ້ວ ມາ ປິບພາດຕົ້ນ ພະຍາຕ່ງ  
ພື້ນຖານ

- 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)



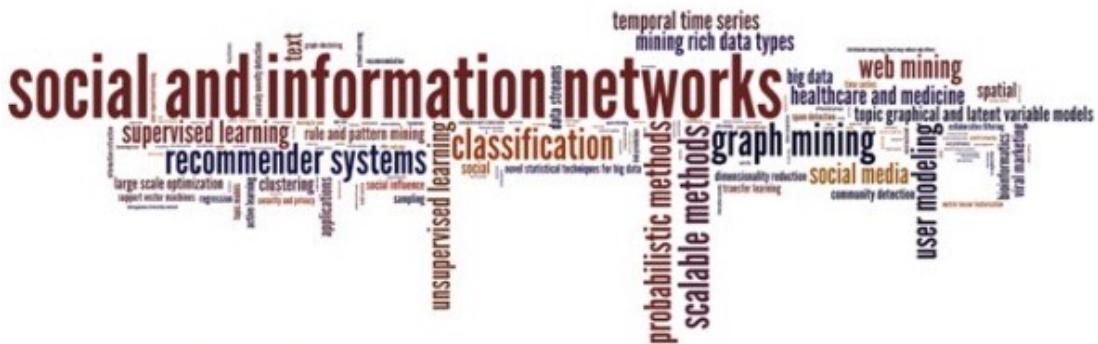
Schneiderman@UMD: Tree-Map of a File System



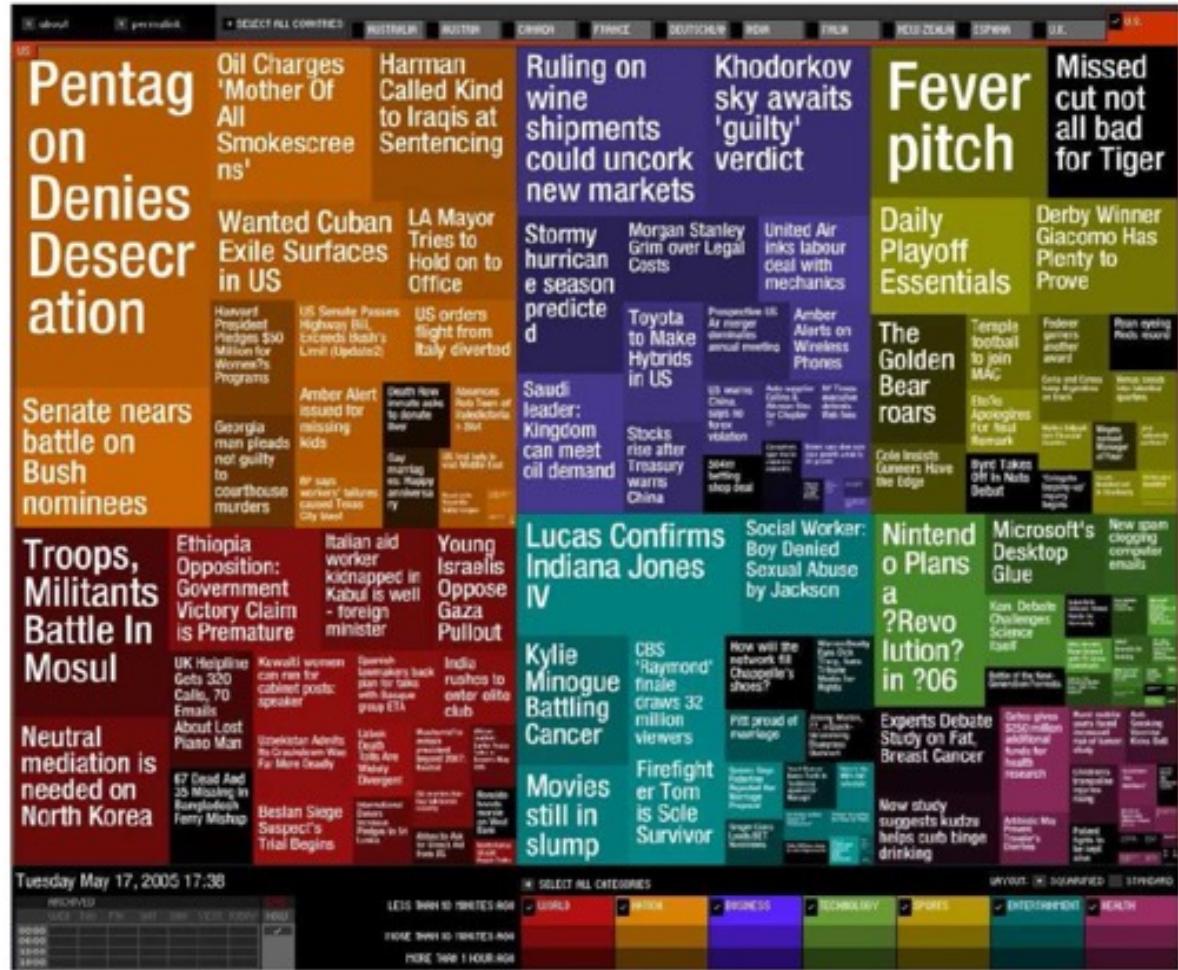
Schneiderman@UMD: Tree-Map to support large data sets of a million items

# 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



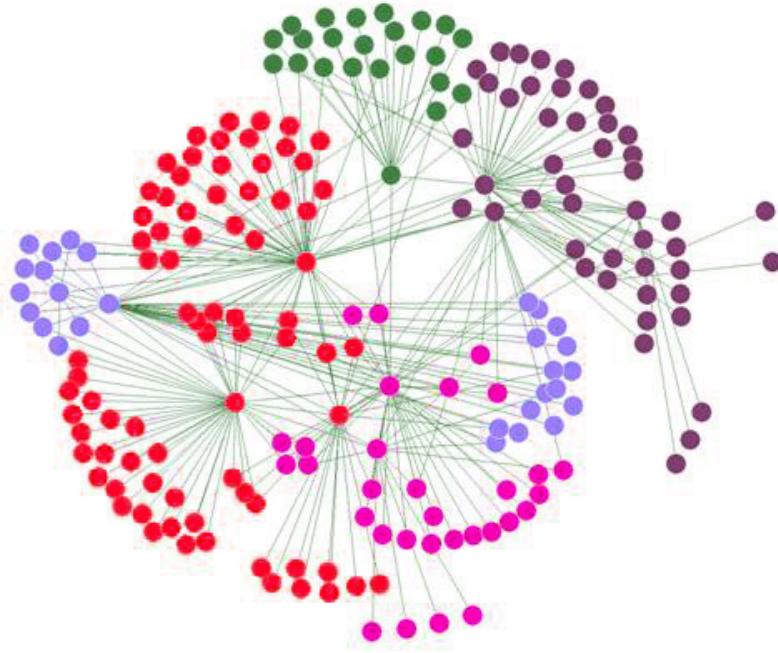
# KDD 2013 Research Paper Title Tag Cloud



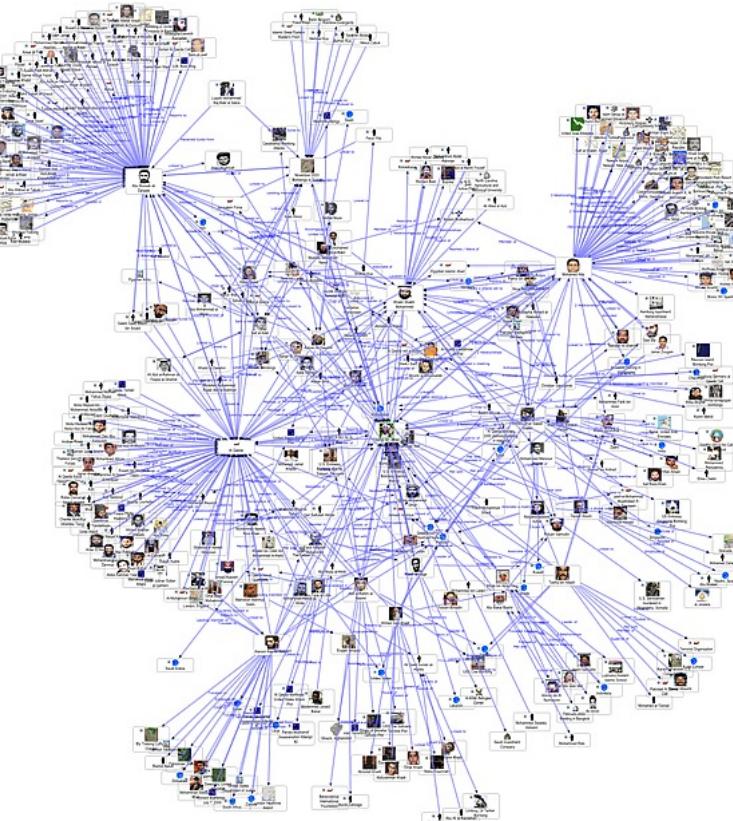
Newsmap: Google News Stories in 2005

# Visualizing Complex Data and Relations: Social Networks

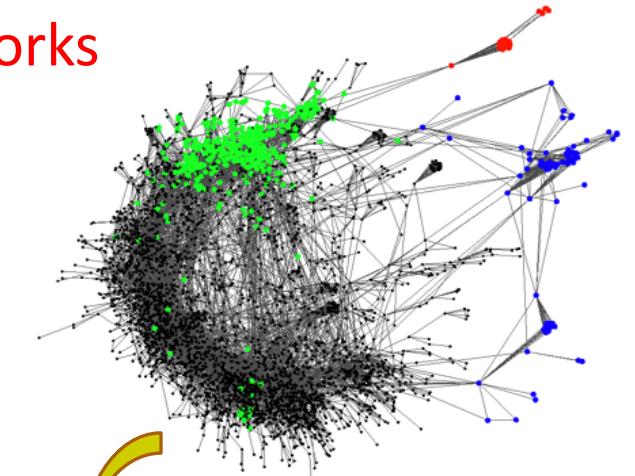
- Visualizing non-numerical data: social and information networks



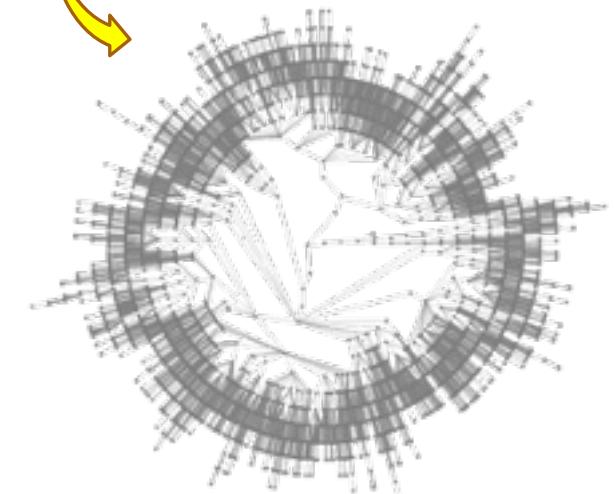
A typical network structure



A social network



organizing  
information networks



# Chapter 2. Getting to Know Your Data

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



# Similarity, Dissimilarity, and Proximity

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- **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 *ค่าความเห็นด้วย  
เชิงบวก มาก*
  - Often falls in the range [0,1]: 0: no similarity; 1: completely similar  
*สูง > Dissimilarity (คำ nghĩaค่า 0-1)*
- **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

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

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

# Standardizing Numeric Data

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- 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

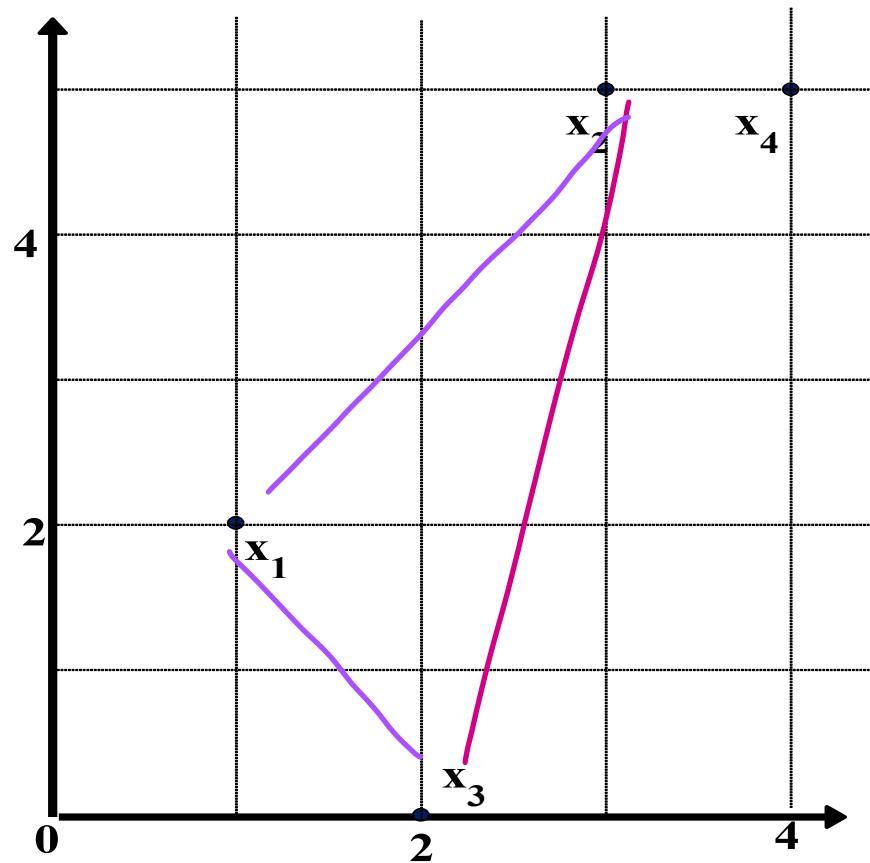
$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + \dots + |x_{nf} - m_f|)$$

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



$x_1 \rightarrow x_2, x_3 \text{ چونکه } x_1 \rightarrow x_3$

Data Matrix

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

$$z = \sqrt{x^2 + y^2} = \text{magnitude}$$

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

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- **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 ဘေးခန်း ?

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

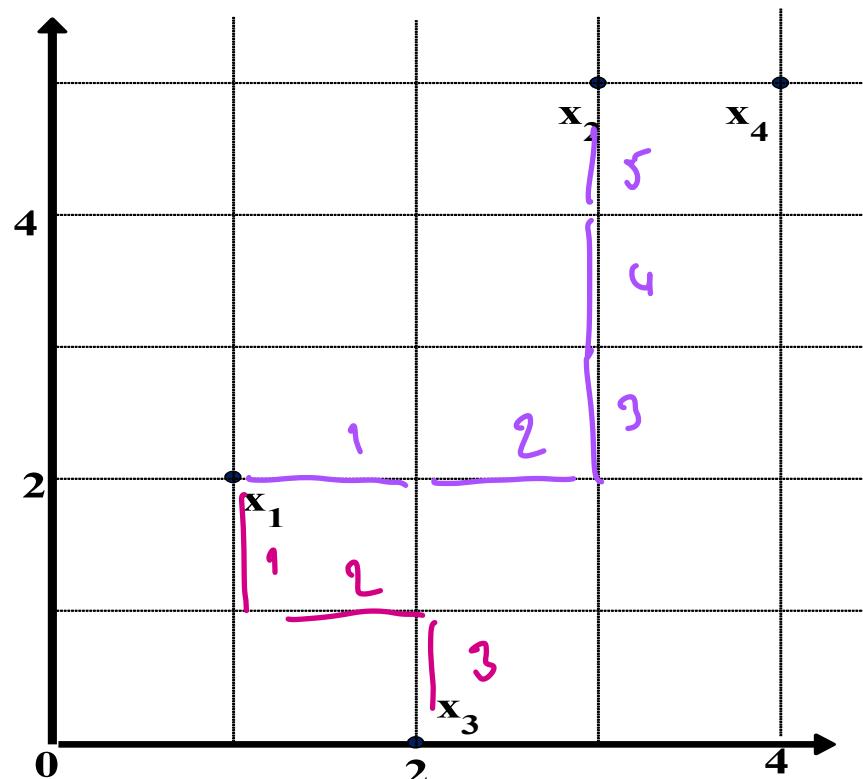
- $p \rightarrow \infty$ : ( $L_{\max}$  norm,  $L_\infty$  norm) “supremum” distance
  - The maximum difference between any component (attribute) of the vectors

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

# Example: Minkowski Distance at Special Cases

Data

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 <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	$\Sigma_{\text{row}}$
Jack		1	2	0
0		1	3	4
$\Sigma_{\text{col}}$		3	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:  $d(i, j) = \frac{r + s}{q + r + s}$

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

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

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

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

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

ex

	✓	✓	✓	✓
	C	N	R	B

black	Thai	✓	B	✓	O	✓
blue	Thai	✓	B	✓	A	✓

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

$m = 2$   
 $p = 4$

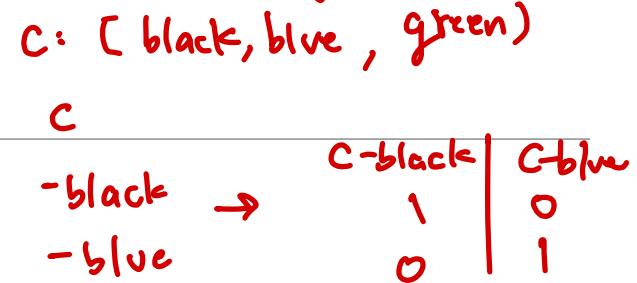
$$= \frac{4 - 2}{4}$$

$$= 0.5 *$$

Dummy Variable  
one-hot-Encode

# 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:  $d(\text{freshman}, \text{senior}) = \frac{2}{3}$ ,  $d(\text{junior}, \text{senior}) = 1/3$
- 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:

សរុបតម្លៃទាំងអស់

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

- 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

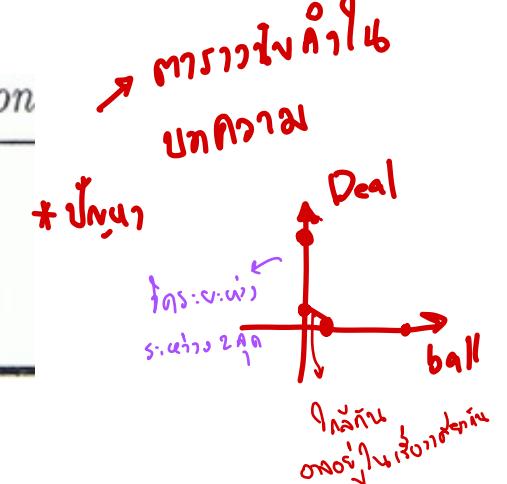
Document	team	coach	hockey	baseball	soccer	penalty	score	win	loss	season
Document1	5	0	3	0	2	0	0	2	0	0
Document2	3	0	2	0	1	1	0	1	0	1
Document3	0	7	0	2	1	0	0	3	0	0
Document4	0	1	0	0	1	2	2	0	3	0

- 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

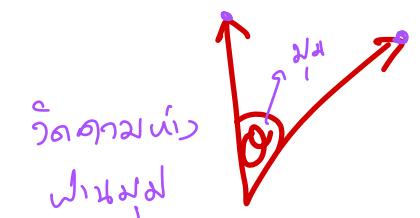
$$\cos(d_1, d_2) = \frac{d_1 \bullet d_2}{\|d_1\| \times \|d_2\|}$$

↑ ໄກສອນຝັດ  
↓ ພາຍໃຕ້ ໄກສອນຝັດ

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



\*Cosine Sim

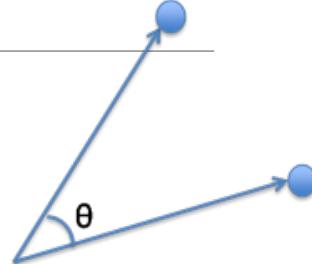


# Example: Calculating Cosine Similarity

- Calculating Cosine Similarity:

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

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



where • indicates vector dot product, ||d||: the length of vector d

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

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

- 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  $\|d_2\|$

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

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

*Այս անցույթը չի դիմում*

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

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

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



# Summary

សំគាល់ data  
ឬ ផ្តល់ព័ត៌មានទៅ

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

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