



Chapter 2. Getting to Know Your Data: Data Visualization

Meng Jiang
Data Science

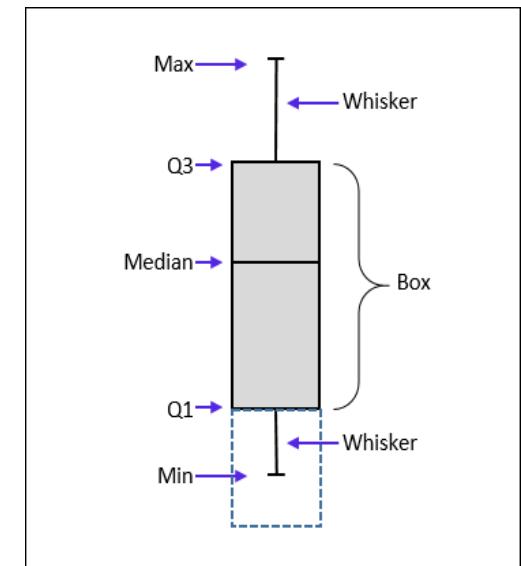
Chapter 2. Getting to Know Your Data

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

Measuring the Dispersion of Data:

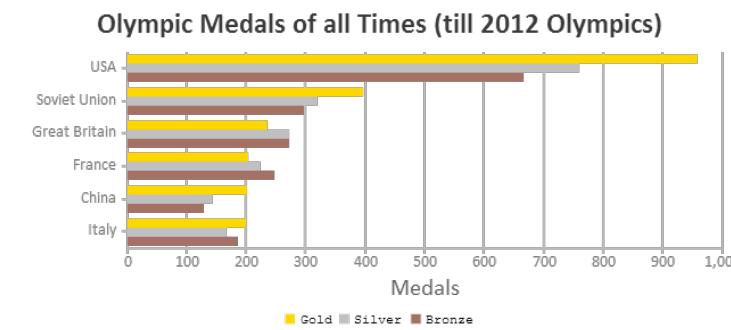
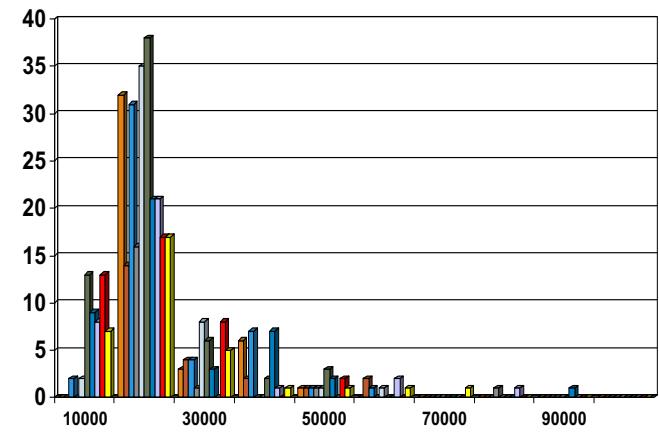
(1) Quartiles & Boxplots

- **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



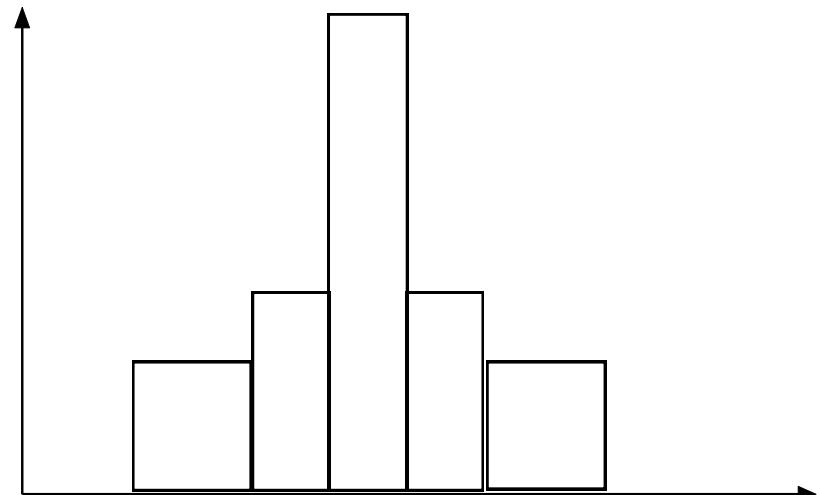
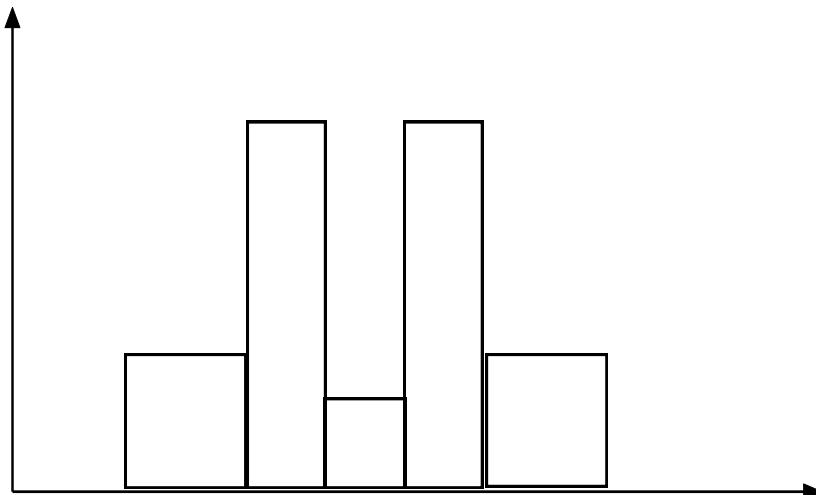
(2) Histogram Analysis

- **Histogram**: Graph display of **tabulated frequencies**, shown as bars
- 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**



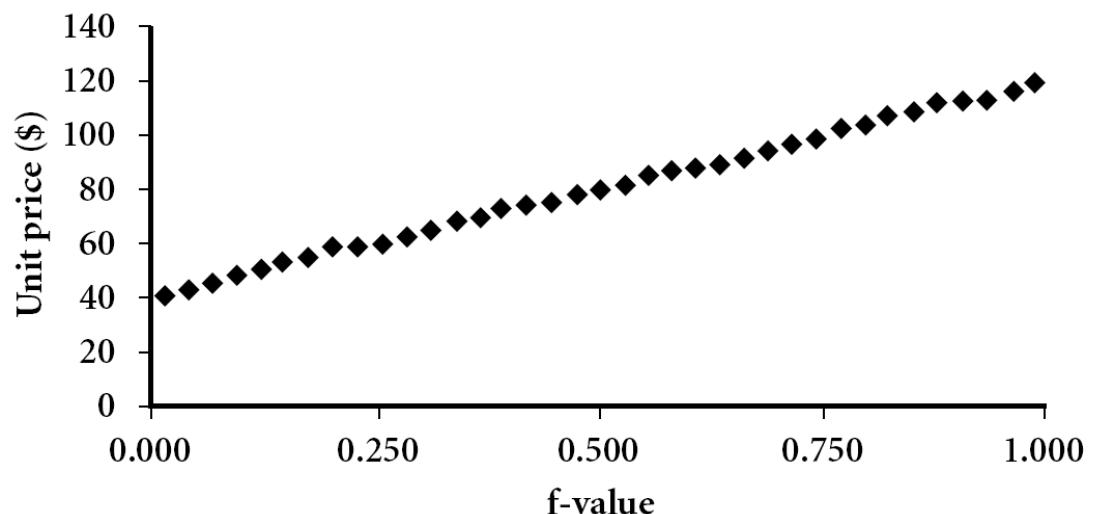
Histograms Often Tell More than Boxplots

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



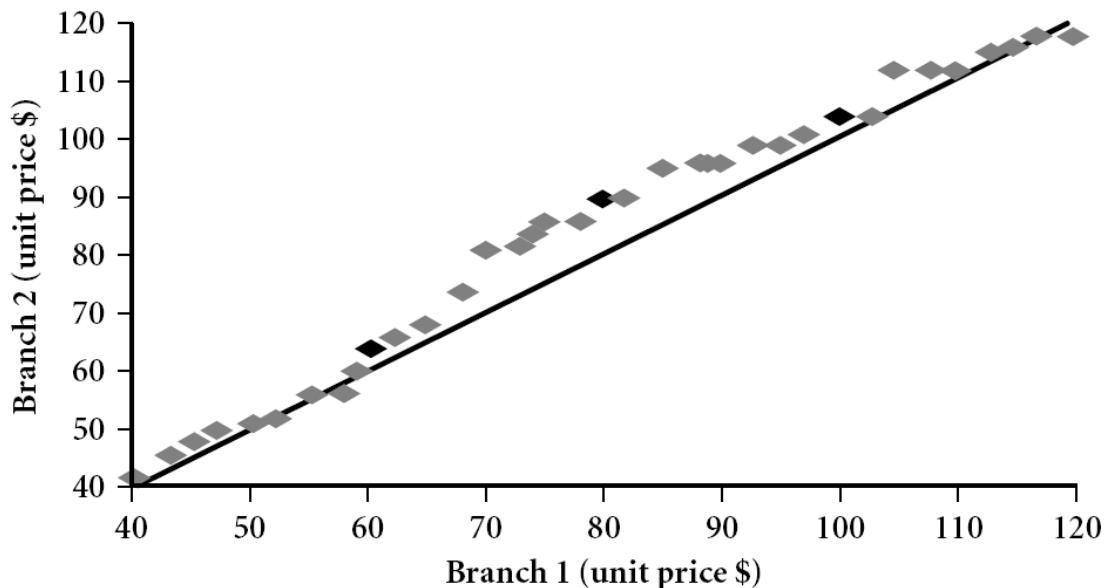
(3) Quantile Plot

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



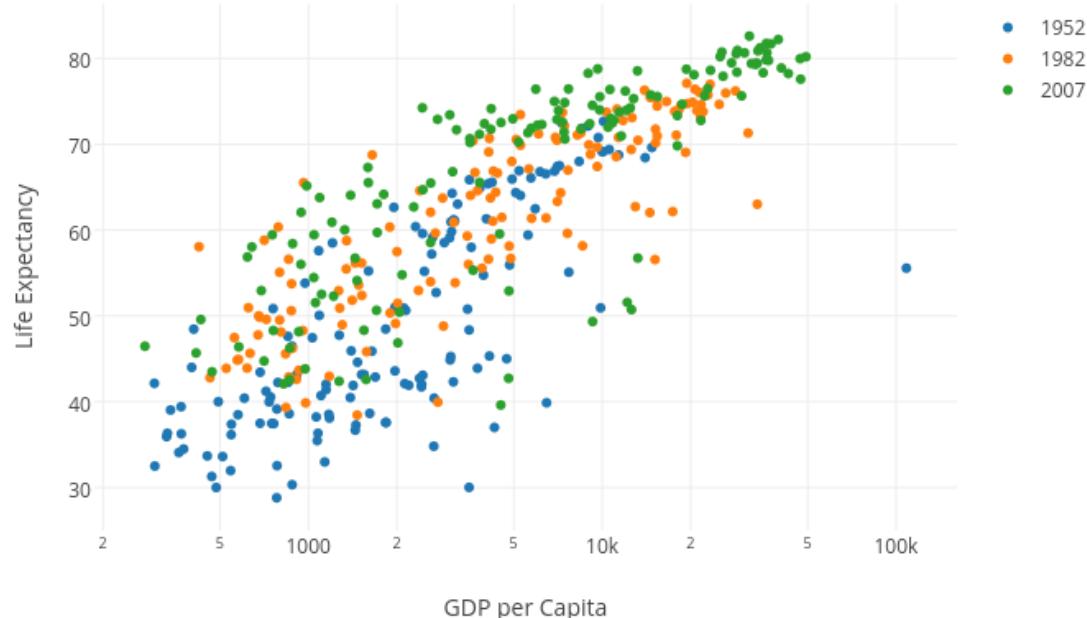
(4) Quantile-Quantile (Q-Q) Plot

- Graphs the quantiles of one univariate distribution against the corresponding quantiles of 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



(5) Scatter plot

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



Summary: Graphic Displays of Basic Statistical Descriptions

- **Boxplot:** graphic display of five-number summary
- **Histogram:** x-axis are values, y-axis representative frequencies
- **Quantile plot:** each value x_i is paired with f_i indicating that approximately $100f_i\%$ 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

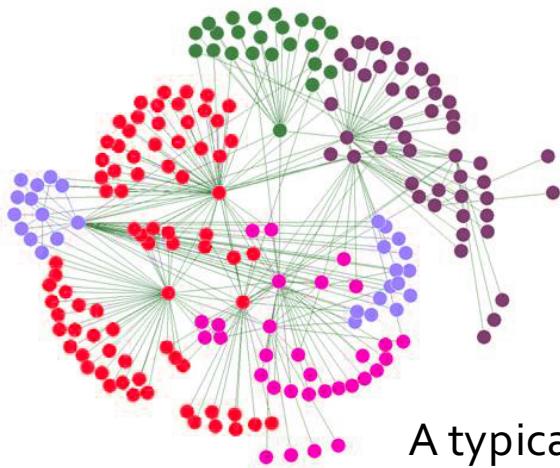
Other Visualization: Tag Cloud

KDD 2013 Research Paper Title

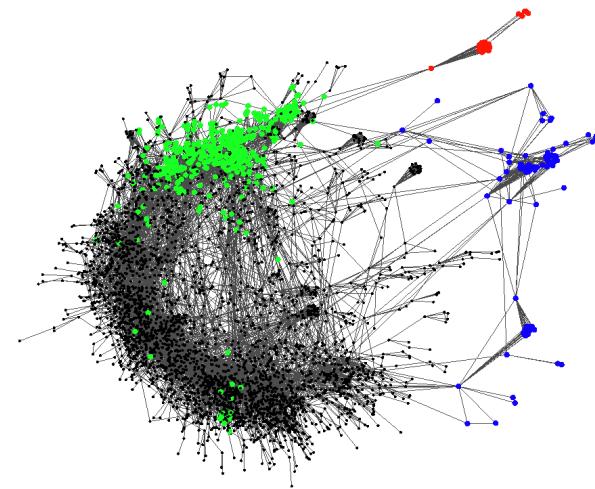


Newsmap: Google News Stories in 2005

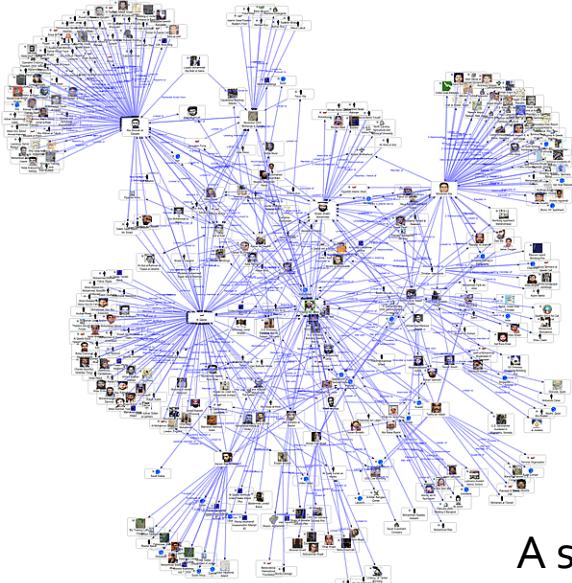
Other Visualization: Networks



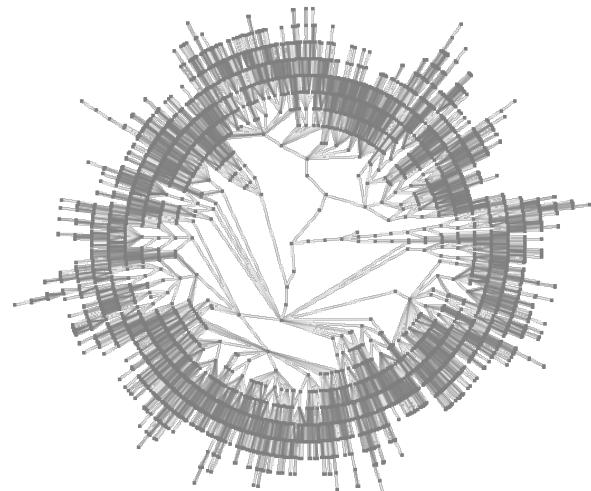
A typical network structure



organizing information networks



A social network



Chapter 2. Getting to Know Your Data

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

Similarity and Dissimilarity

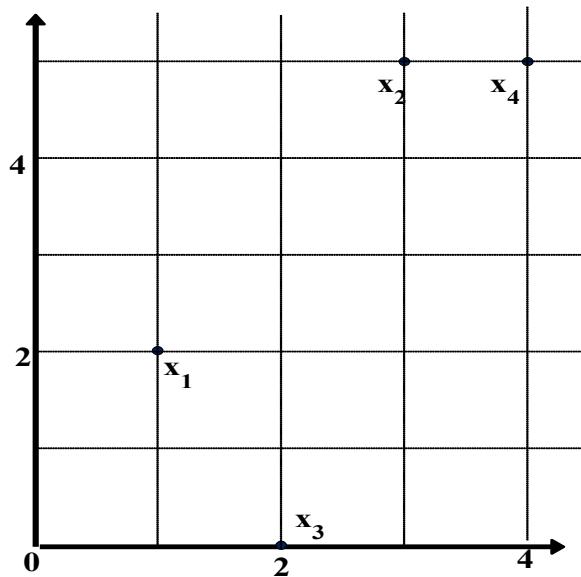
- **Similarity measure** or **similarity function**
 - A real-valued function that quantifies the similarity between two objects
 - Measure how two data objects are alike: The higher value, the more alike
 - Often falls in the range $[0,1]$: 0 : no similarity; 1 : completely similar
- **Dissimilarity**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

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 $d(i, j)$
 - Usually symmetric, thus a triangular matrix
 - Distance functions are usually different for real, boolean, categorical, ordinal variables
 - Weights can be associated with different variables based on applications and data semantics

$$D = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1l} \\ x_{21} & x_{22} & \dots & x_{2l} \\ & & \ddots & \\ x_{n1} & x_{n2} & \dots & x_{nl} \end{pmatrix}$$
$$\begin{pmatrix} 0 \\ d(2,1) & 0 \\ & \ddots \\ d(n,1) & d(n,2) & \dots & 0 \end{pmatrix}$$

Example: Euclidean Distance



Data Matrix

point	attribute	attribute
x_1	1	2
x_2	3	5
x_3	2	0
x_4	4	5

Dissimilarity Matrix (by Euclidean Distance)

	x_1	x_2	x_3	x_4
x_1	0			
x_2	3.61	0		
x_3	2.24	5.1	0	
x_4	4.24	1	5.39	0

Minkowski Distance

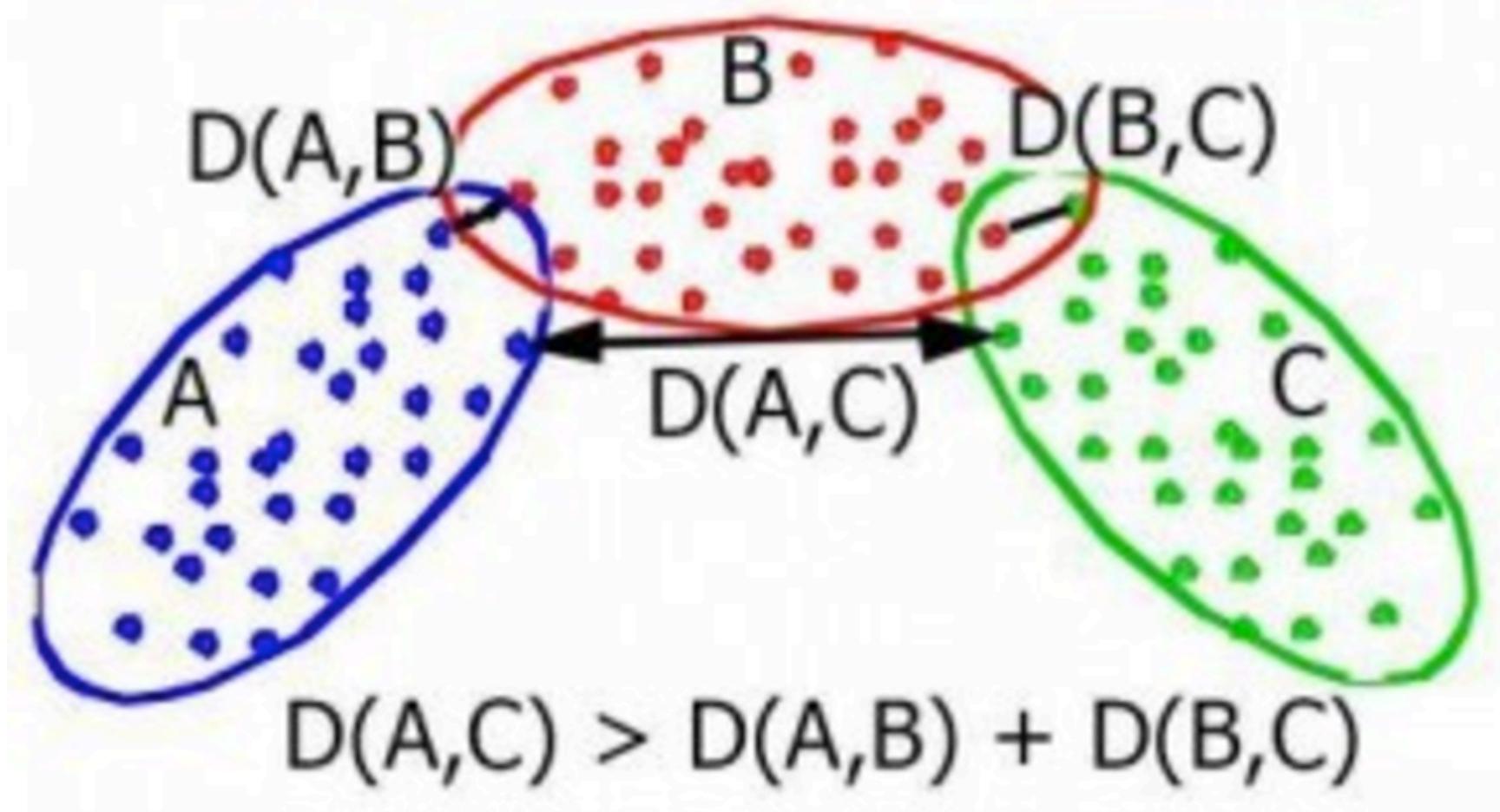
- Minkowski distance: A popular distance measure

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

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 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 difference*

Non Metric Dissimilarity: Triangle Inequality



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

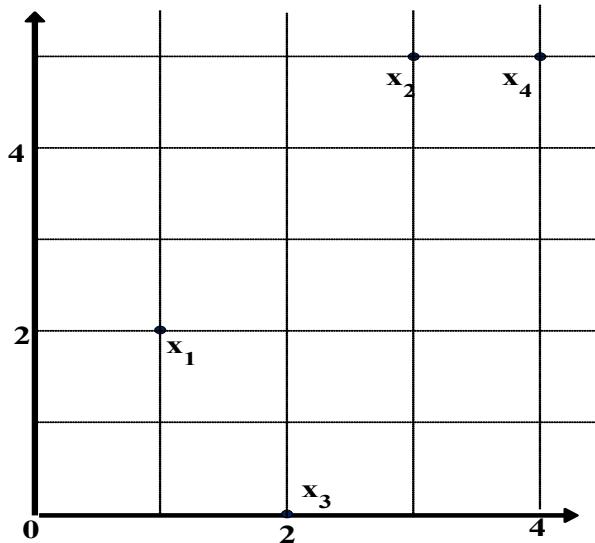
$$d(i, j) = \sqrt{|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \dots + |x_{il} - x_{jl}|^2}$$

- $p \rightarrow \infty$: (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	19	5

Proximity Measure for Binary Attributes

- A contingency table for binary data

		Object <i>j</i>		
		1	0	sum
Object <i>i</i>	1	<i>q</i>	<i>r</i>	<i>q + r</i>
	0	<i>s</i>	<i>t</i>	<i>s + t</i>
sum	<i>q + s</i>	<i>r + t</i>	<i>p</i>	

- 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):

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

- Note: Jaccard coefficient is the same as “coherence”:

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

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 and map the range of each variable onto $[0, 1]$:
 - 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

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

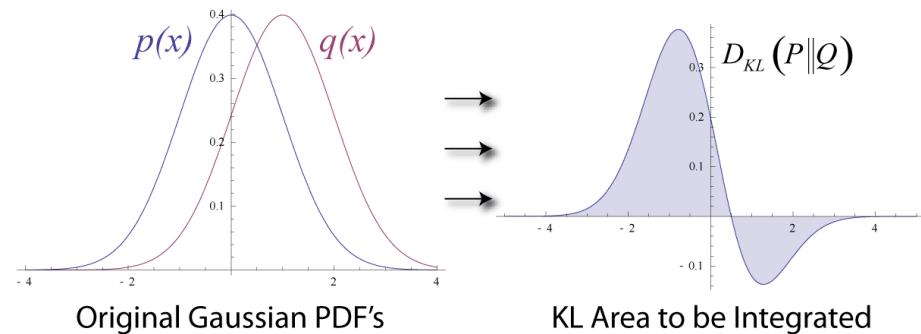
- Other vector objects: Gene features in micro-arrays
- Applications: Information retrieval, biological taxonomy, gene feature mapping, etc.
- Cosine measure:** If d_1 and d_2 are two vectors (e.g., term-frequency vectors), then

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

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

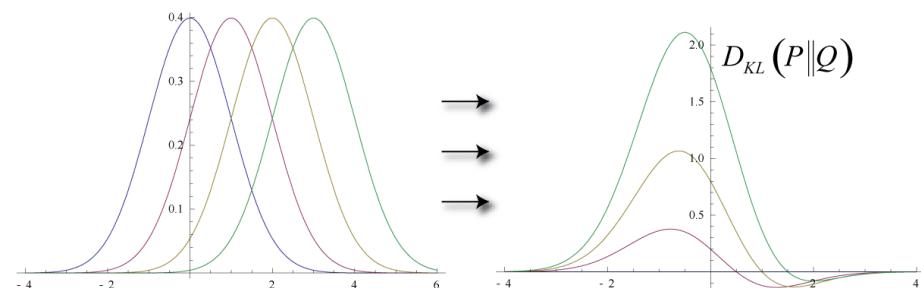
KL Divergence: Comparing Two Probability Distributions

- *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 $p(x)$**



Discrete form

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



Continuous form

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

Discussion

- Can you use Matrix Multiplication to compute Cosine Similarity between every pair of objects?
- Can you use KL divergence to find suspiciousness?
- Can you use KL divergence to find representative phrases for specific topics?

Summary

- Data attribute types: nominal, binary, ordinal ...
- Gain insight into the data by:
 - Basic data description: central tendency, outliersness
 - Data visualization
 - Measure data similarity and dissimilarity
- Above steps are the beginning of data preprocessing

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