
# Chapter 2. Getting to Know Your Data

Meng Jiang

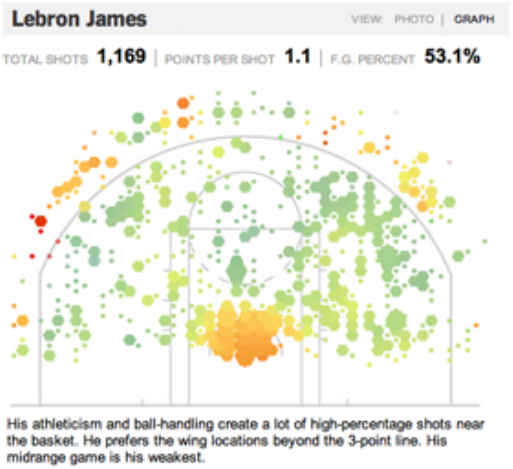
CS412 Summer 2017:

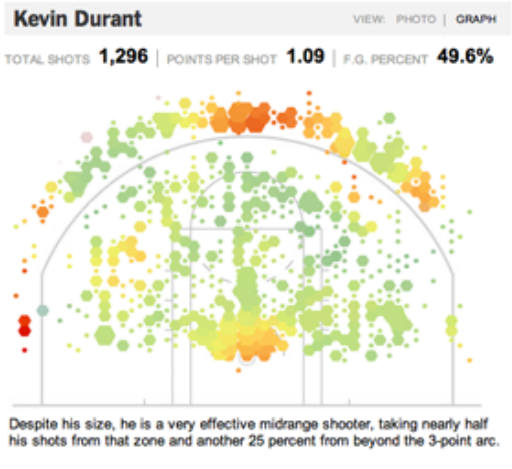
Introduction to Data Mining

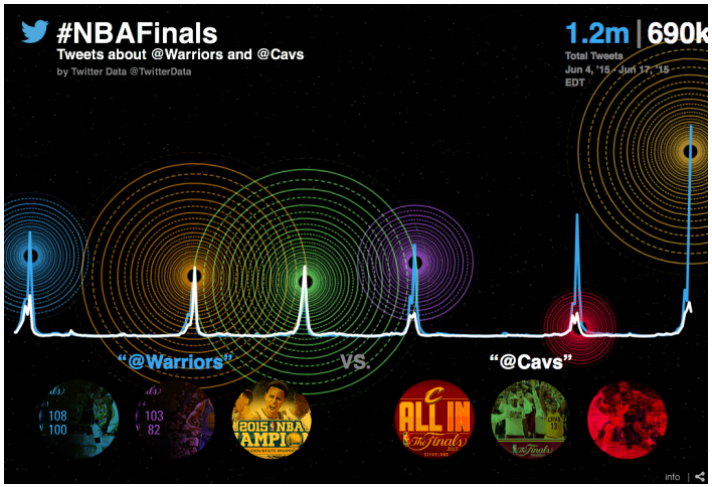
# From Data to Knowledge

| PLAYER | P | MIN | PTS | FGM | FGA | FG% | 3PM | 3PA | 3P% | FTM | FTA | FT% | OREB | DREB | REB | AST |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LeBron James | F | 38 | 34 | 15 | 27 | 55.6 | 1 | 6 | 16.7 | 3 | 4 | 75.0 | 0 | 5 | 5 | 6 |
| Kevin Love | F | 41 | 17 | 6 | 13 | 46.2 | 3 | 5 | 60.0 | 2 | 2 | 100 | 2 | 15 | 17 | 5 |
| Tristan Thompson | C | 37 | 7 | 3 | 4 | 75.0 | 0 | 0 | 0.0 | 1 | 2 | 50.0 | 1 | 6 | 7 | 0 |
| JR Smith | G | 26 | 5 | 2 | 4 | 50.0 | 1 | 2 | 50.0 | 0 | 0 | 0.0 | 1 | 0 | 1 | 3 |
| Kyrie Irving | G | 41 | 42 | 15 | 22 | 68.2 | 4 | 7 | 57.1 | 8 | 9 | 88.9 | 0 | 3 | 3 | 4 |
| Richard Jefferson | | 6 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 |
| Deron Williams | | 18 | 2 | 1 | 2 | 50.0 | 0 | 1 | 0.0 | 0 | 0 | 0.0 | 0 | 1 | 1 | 1 |
| Kyle Korver | | 20 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 3 | 3 | 4 |
| Iman Shumpert | | 10 | 5 | 2 | 2 | 100 | 1 | 1 | 100 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 |

| Eastern Conference | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| TEAM | W | L | WIN% | GB | CONF | DIV | HOME | ROAD |
| 1 e - Boston | 53 | 29 | .646 | - | 36 - 16 | 11 - 5 | 30 - 11 | 23 - 18 |
| 2 c - Cleveland | 51 | 31 | .622 | 2 | 35 - 17 | 8 - 8 | 31 - 10 | 20 - 21 |
| 3 * - Toronto | 51 | 31 | .622 | 2 | 34 - 18 | 14 - 2 | 28 - 13 | 23 - 18 |
| 4 se - Washington | 49 | 33 | .598 | 4 | 32 - 20 | 8 - 8 | 30 - 11 | 19 - 22 |
| 5 * - Atlanta | 43 | 39 | .524 | 10 | 30 - 22 | 6 - 10 | 23 - 18 | 20 - 21 |
| 6 * - Milwaukee | 42 | 40 | .512 | 11 | 27 - 25 | 10 - 6 | 23 - 18 | 19 - 22 |
| 7 * - Indiana | 42 | 40 | .512 | 11 | 26 - 26 | 8 - 8 | 29 - 12 | 13 - 28 |



# Your Data

| | Number |
|---|---|
| Students who provide us data | ? |
| Count of words in total | ? |
| Average count of words per student | ? |
| Count of non-stop-words in total | ? |
| Average count of non-stop-words per student | ? |
| Number of words (size of vocabulary) | ? |
| Number of non-stop-words | ? |

# Your Data

| | Number |
|---|---|
| Students who provide us data | ? |
| Count of words in total | 1,175 |
| Average count of words per student | ? |
| Count of non-stop-words in total | ? |
| Average count of non-stop-words per student | ? |
| Number of words (size of vocabulary) | ? |
| Number of non-stop-words | ? |

# Your Data

| | Number |
|---|---|
| Students who provide us data | 29 |
| Count of words in total | 1,175 |
| Average count of words per student | 40.5 |
| Count of non-stop-words in total | 494 |
| Average count of non-stop-words per student | 17.0 |
| Number of words (size of vocabulary) | 426 |
| Number of non-stop-words | 298 |

# Your Data

| Word | Count |
|---|---|
| i | 74 |
| to | 45 |
| a | 43 |
| in | 39 |
| and | 38 |
| am | 32 |
| the | 29 |
| of | 26 |
| data | 23 |
| my | 15 |
| this | 14 |

| Word | #Students |
|---|---|
| i | 27 |
| a | 25 |
| to | 22 |
| am | 22 |
| in | 20 |
| and | 19 |
| the | 18 |
| data | 15 |
| of | 13 |
| this | 11 |
| my | 11 |

# Your Data

| Word | Count |
|---|---|
| data | 23 |
| student | 10 |
| major | 9 |
| engineering | 9 |
| class | 8 |
| mining | 7 |
| students | 7 |
| science | 6 |
| grad | 6 |
| learning | 6 |
| interested | 6 |

| Word | #Students |
|---|---|
| data | 15 |
| student | 9 |
| major | 8 |
| engineering | 8 |
| class | 7 |
| mining | 6 |
| science | 5 |
| learning | 5 |
| graduate | 5 |
| interested | 5 |
| students | 5 |

# Knowledge (Patterns) You Want

- Students' personal interests (activities) and connect them with like-minded individuals * 2
- Correlation between classes students have taken and their grades
- Correlation between nationalities and interests in data mining
- Correlation between handwriting patterns and academic performance
- Classify students by their background knowledge of data mining
- Clustering students by their interests or backgrounds
- …

# Knowledge (Patterns) You Want

- Students' personal interests (activities) and connect them with like-minded individuals * 2
- Correlation between classes students have taken and their grades
- Correlation between nationalities and interests in data mining
- Correlati…ademic performa…
- Classify s…of data mining
- Clusterin…nds
- …

During the 5-minute break (11:40-11:45),
if you'd like to contribute,
please grab a paper and
write down your self-introduction and
give it to me at the end of class.
Pay attention to privacy issue!

# Knowledge/Patterns We Can Have: Phrase Structures

| Phrase | Score |
|---|---|
| civil engineering | 0.94 |
| machine learning | 0.93 |
| big data | 0.93 |
| classify group | 0.84 |
| master student | 0.82 |
| cs knowledge | 0.81 |
| students' academic performance matches | 0.81 |
| human body | 0.81 |
| favoriate colors | 0.80 |
| skill levels | 0.80 |
| algorithm design | 0.80 |

| Phrase | Score |
|---|---|
| masters in computer science | 0.70 |
| academic history and transcripts | 0.70 |
| sophomore majored in statistics | 0.70 |
| professor of music history | 0.70 |
| addition to computer science | 0.70 |
| control modeling and management | 0.69 |

| Phrase | Score |
|---|---|
| $4^{th}$ year phd candidate | 0.68 |
| soccer and practice guitar | 0.67 |

| Phrase | Score |
|---|---|
| a computer | 0.08 |
| the data | 0.08 |
| and major | 0.08 |

# Knowledge/Patterns We Can Have: Phrase Structures

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| Phrase | Score |
|---|---|
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| sophomore majored in statistics | 0.70 |
| professor of music history | 0.70 |
| addition to computer science | 0.70 |
| control modeling and management | 0.69 |
| | Score |
| | 0.68 |
| | 0.67 |
| | Score |
| | 0.08 |
| | 0.08 |
| and major | 0.08 |

Jingbo Shang, Jialu Liu, Meng Jiang, Xiang Ren, and Jiawei Han, "Automated Phrase Mining from Massive Text Corpora". arXiv: 1702:04457

# Chapter 2. Getting to Know Your Data

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

# Types of Data Sets: (1) Record Data

- Relational records in relational tables: highly structured
- Data matrix: numerical matrix
- Transaction data
- Document data: Term-frequency matrix of text documents

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| Kyrie Irving | G | 41 | 42 | 15 | 22 | 68.2 | 4 | 7 | 57.1 | 8 | 9 | 88.9 | 0 | 3 | 3 | 4 |
| Richard Jefferson | | 6 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 |
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| Kyle Korver | | 20 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 3 | 3 | 4 |
| Iman Shumpert | | 10 | 5 | 2 | 2 | 100 | 1 | 1 | 100 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0 |

| | PLAYER | TEAM | AGE | GP | W | L | MIN | PTS | FGM | FGA | FG% |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Russell Westbrook | OKC | 28 | 81 | 46 | 35 | 34.6 | 31.6 | 10.2 | 24.0 | 42.5 |
| 2 | James Harden | HOU | 27 | 81 | 54 | 27 | 36.4 | 29.1 | 8.3 | 18.9 | 44.0 |
| 3 | Isaiah Thomas | BOS | 28 | 76 | 51 | 25 | 33.8 | 28.9 | 9.0 | 19.4 | 46.3 |
| 4 | Anthony Davis | NOP | 24 | 75 | 31 | 44 | 36.1 | 28.0 | 10.3 | 20.3 | 50.5 |
| 5 | DeMar DeRozan | TOR | 27 | 74 | 47 | 27 | 35.4 | 27.3 | 9.7 | 20.9 | 46.7 |
| 6 | Damian Lillard | POR | 26 | 75 | 38 | 37 | 35.9 | 27.0 | 8.8 | 19.8 | 44.4 |
| 7 | DeMarcus Cousins | NOP | 26 | 72 | 30 | 42 | 34.2 | 27.0 | 9.0 | 19.9 | 45.2 |
| 8 | LeBron James | CLE | 32 | 74 | 51 | 23 | 37.8 | 26.4 | 9.9 | 18.2 | 54.8 |

# Data Objects

- Data sets are made up of data objects.
- A **data object** represents an entity.
- Examples:
  - Sales database: customers, store items, sales.
  - Medical database: patients, treatments.
  - University database: students, professors, courses.
- Also called *samples, examples, instances, data points, objects, tuples.*
- Data objects are described by **attributes.**
- Database rows → data objects; columns → attributes.

# Attributes

- **Attribute (**or **dimensions, features, variables**)
  - A data field, representing a characteristic or feature of a data object
- Types:
  - Nominal (e.g., red, blue)
  - Binary (e.g., {true, false})
  - Ordinal (e.g., {freshman, sophomore, junior, senior})
  - Numeric: quantitative
    - Interval-scaled: 100°C is interval scales
    - Ratio-scaled: 100°K is ratio scaled since it is twice as high as 50 °K

# Attribute Types

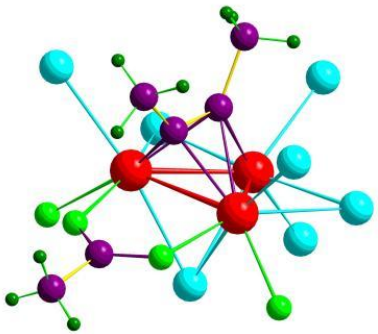
- **Nominal:** categories, states, or "names of things"
  - *Hair_color* = {*auburn, black, blond, brown, grey, red, white*}
  - marital status, occupation, ID numbers, zip codes
- **Binary**
  - Nominal attribute with only 2 states (0 and 1)
  - Symmetric binary: both outcomes equally important
    - e.g., gender
  - Asymmetric binary: outcomes not equally important.
    - e.g., medical test (positive vs. negative)
    - Convention: assign 1 to most important outcome (e.g., HIV positive)
- **Ordinal**
  - Values have a meaningful order (ranking) but magnitude between successive values is not known
  - *Size* = {*small, medium, large*}, grades, army rankings

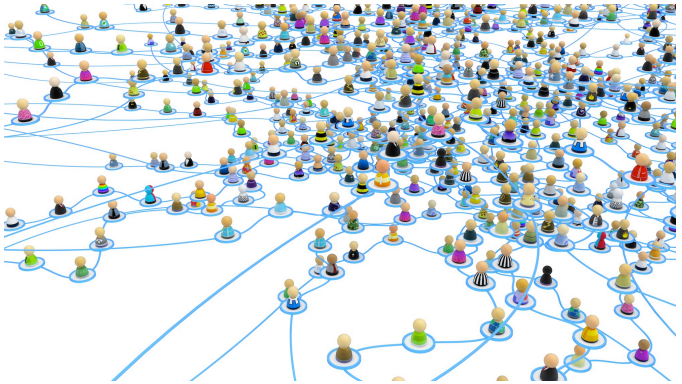
# Discrete vs Continuous Attributes

- **Discrete Attribute**
  - Has only a finite or countable 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

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

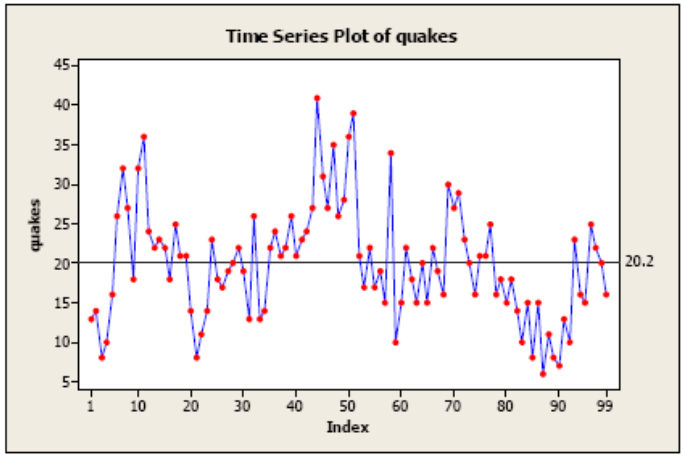
- Transportation networks
- World Wide Web
- Molecular structures
- Social or information networks





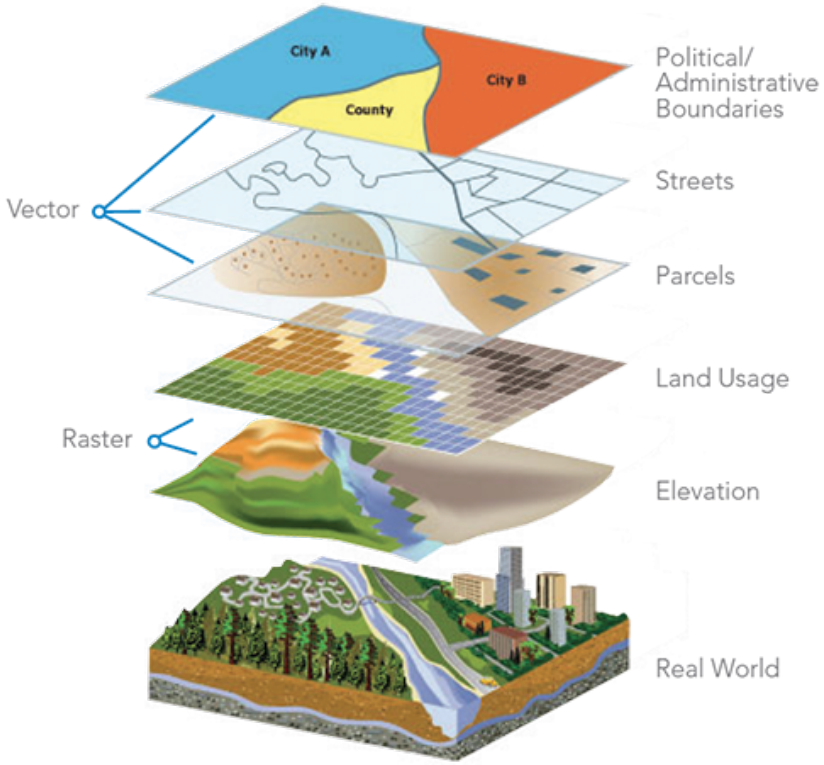
# Types of Data Sets: (3) Ordered Data

- Video data: sequence of images
- Temporal data: time-series
- Sequential Data: transaction sequences
- Genetic sequence data




# Other Types of Data Sets

- Spatial data
- Image and multimedia data




# Characterisitcs of Structured Data

- Dimensionality
  - Curse of dimensionality
- Sparsity
  - Only presence counts
- Resolution
  - Patterns depend on the scale
- Distribution
  - Centrality and dispersion

# Chapter 2. Getting to Know Your Data

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

# Basic Statistical Descriptions of Data

- Motivation: to better understand the data
- 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.

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

- 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):

Finding the **median** from a grouped frequency table

**Example: Parcels**

Calculate an **estimate of the median** weight, shown to the nearest gram, in the following grouped frequency table:

| Weight (g) | 1-10 | 11-20 | 21-30 | 31-40 | 41-50 |
|---|---|---|---|---|---|
| Frequency | 10 | 13 | 28 | 15 | 9 |

**Which interval does the median lie?**

***Cumulative frequency***

# Finding the median from a grouped frequency table

| Weight (g) | 1-10 | 11-20 | 21-30 | 31-40 | 41-50 |
|---|---|---|---|---|---|
| Frequency | 10 | 13 | 28 | 15 | 9 |
| Cumulative Frequency | 10 | 23 | 51 | 66 | 75 |

The median lies in the ½ (75) = 37.5 therefore:

38th position

Therefore the **median** lies in the **21 – 30** class.

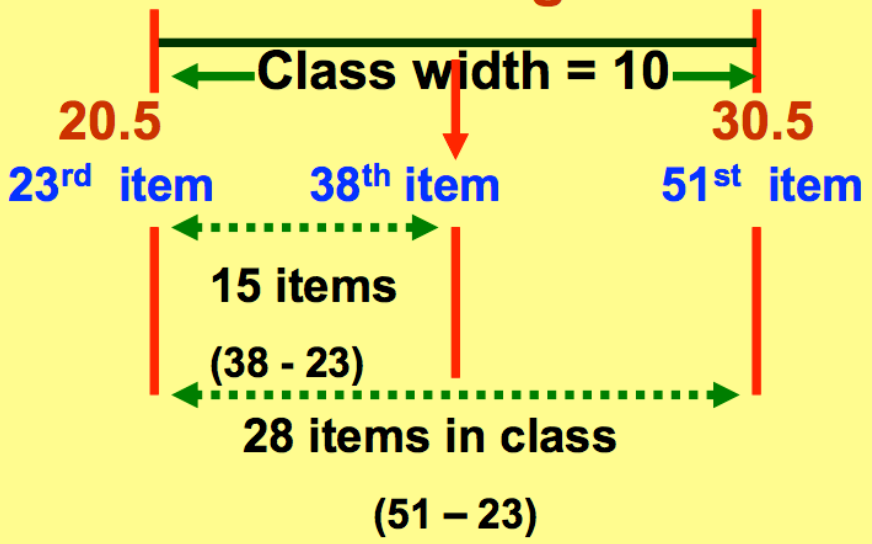
BUT

Remember it was rounded:

**ACTUAL CLASS BOUNDARY: 20.5 – 30.5**

Lower class boundary + number of items up to median x class width
Number of items in the class

**Useful diagram:**




**Assumption:**

data are evenly spread over each class interval

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

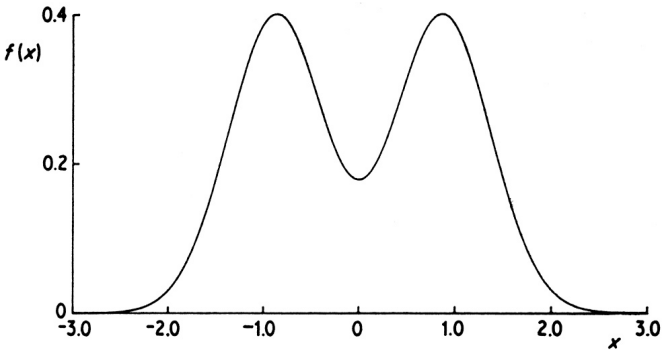
$$20.5 + \frac{15}{28} \times 10$$

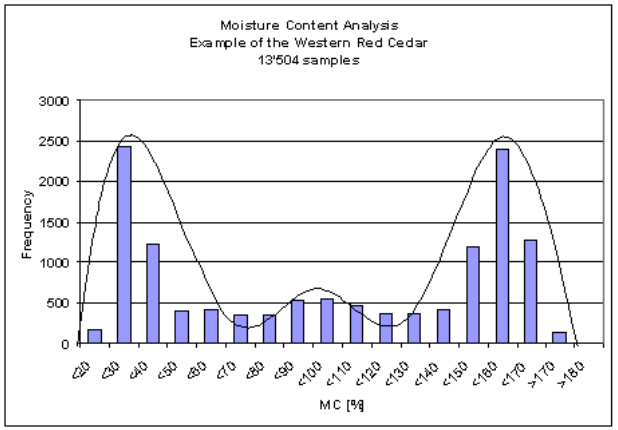
$$= 25.85714....$$

$$= 25.9(1d.p.)$$

# Measuring the Central Tendency: (3) Mode

- Mode: Value that occurs most frequently in the data
- Multi-modal
  - Bimodal
  - Trimodal

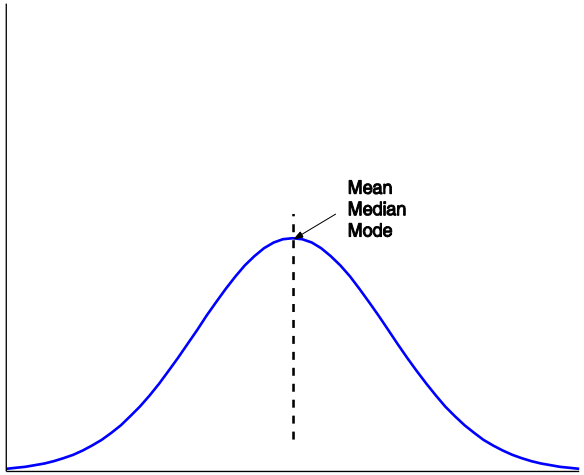


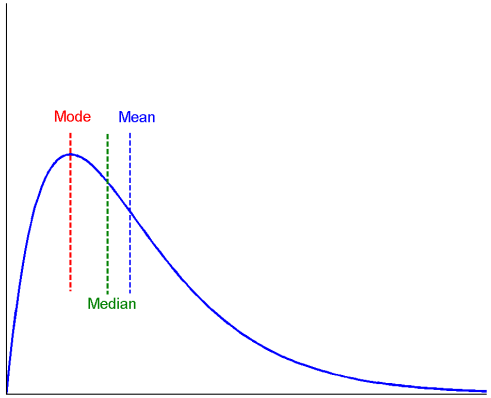



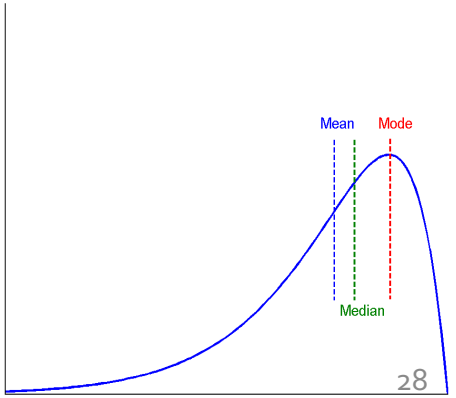

Symmetric data

Positively skewed data

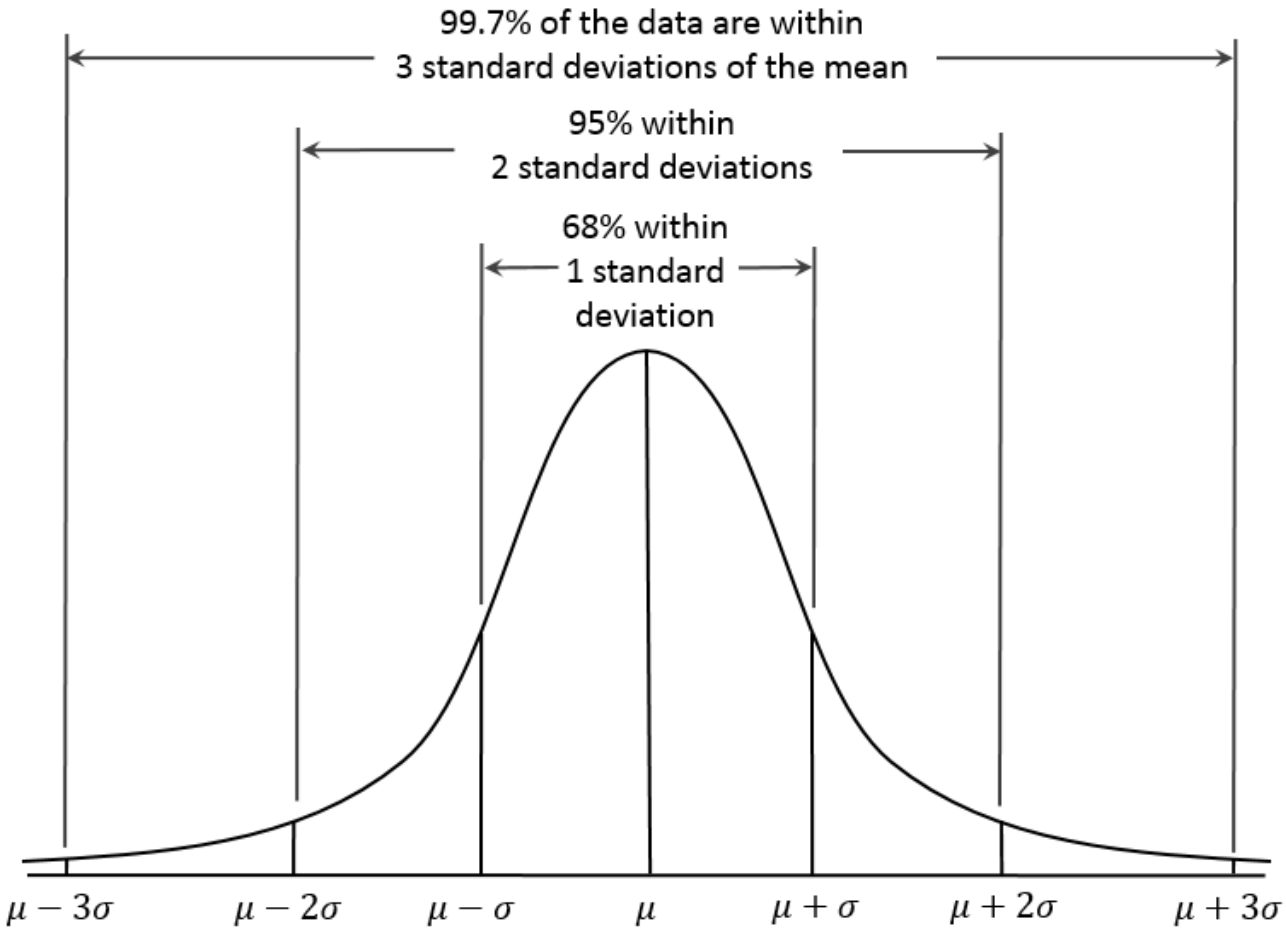
Negatively skewed data



# Properties of Normal Distribution Curve



# 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?

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

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

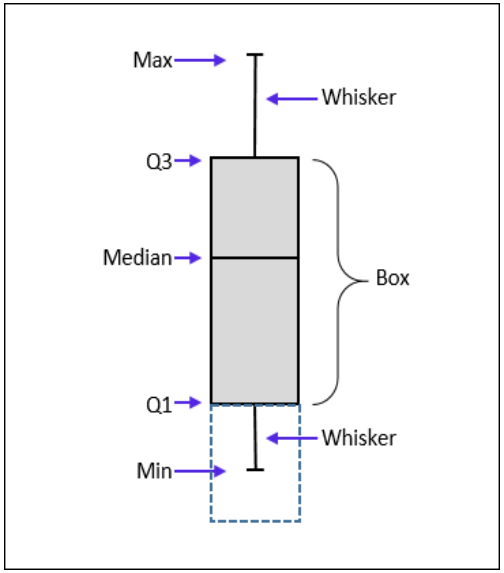
- Standard deviation s (or σ) is the **square root** of variance $s^2$ (or $\sigma^2$)

# Graphic Displays of Basic Statistical Descriptions

- **Boxplot**: graphic display of five-number summary
- **Histogram**: x-axis are values, y-axis repres. frequencies
- **Quantile plot**: each value $x_i$ is paired with $f_i$ indicating that approximately $100\, f_i$% of data are $\leq x_i$
- **Quantile-quantile (q-q) plot**: graphs the quantiles of one univariant distribution against the corresponding quantiles of another
- **Scatter plot**: each pair of values is a pair of coordinates and plotted as points in the plane

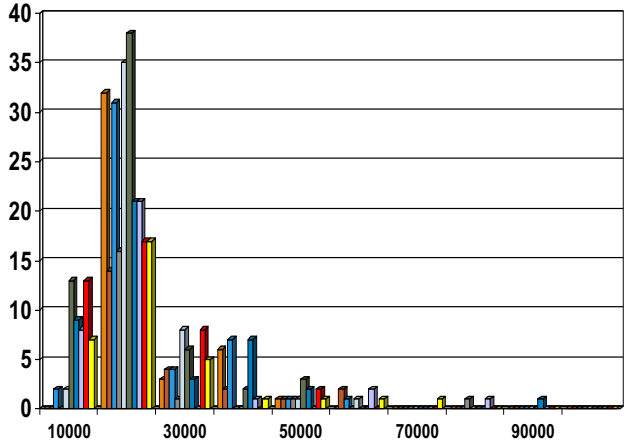
# Measuring the Dispersion of Data: (1) Quartiles & Boxplots

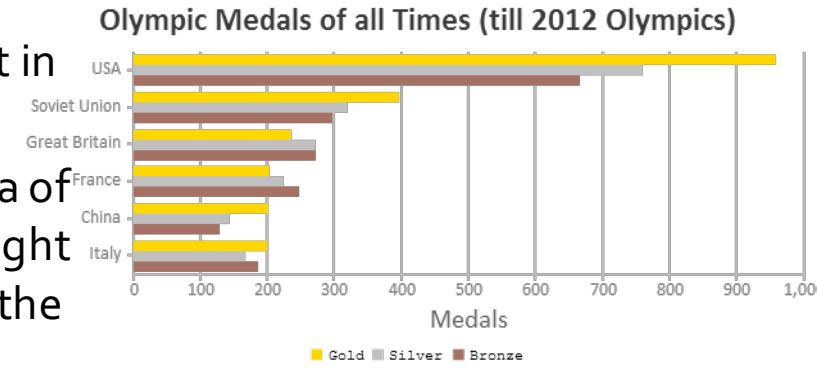
- **Quartiles**: $Q_1$ ($25^{th}$ percentile), $Q_3$ ($75^{th}$ percentile)
- **Inter-quartile range**: $IQR = Q_3 - Q_1$
- **Five number summary**: min, $Q_1$, median, $Q_3$, max
- **Boxplot**: Data is represented with a box
  - $Q_1$, $Q_3$, IQR: The ends of the box are at the first and third quartiles, i.e., the height of the box is IQR
  - Median ($Q_2$) is marked by a line within the box
  - Whiskers: two lines outside the box extended to Minimum and Maximum
  - Outliers: points beyond a specified outlier threshold, plotted individually
    - Outlier: usually, a value higher/lower than 1.5 x IQR



# (2) Histogram Analysis

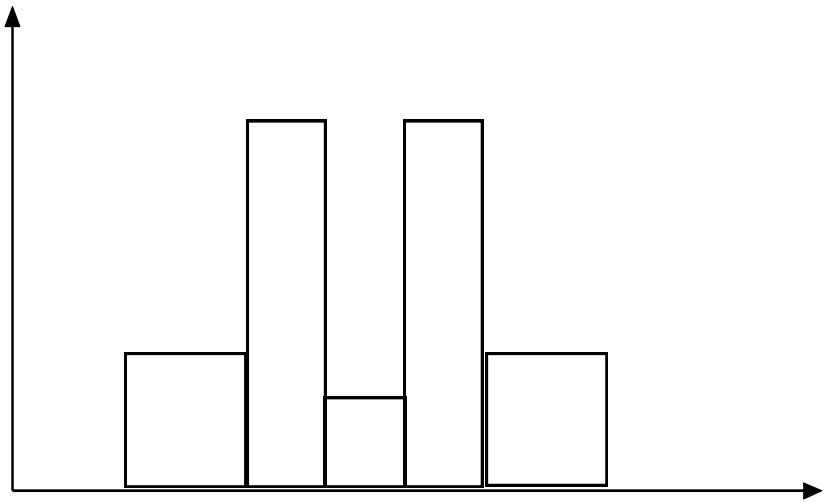
- Histogram: Graph display of **tabulated frequencies**, shown as bars
- Between histograms and bar charts
  - Histograms are used to show distributions of variables while bar charts are used to compare variables
  - Histograms plot **binned quantitative data** while bar charts plot **categorical data**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

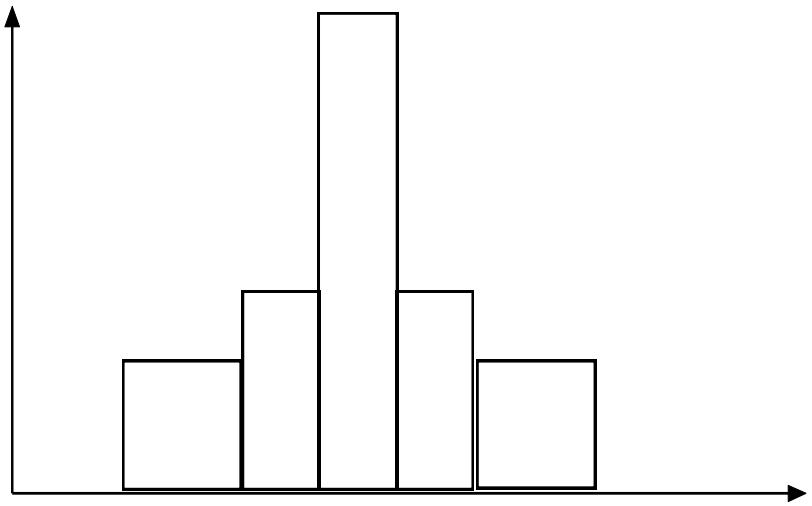


# Histograms Often Tell More than Boxplots

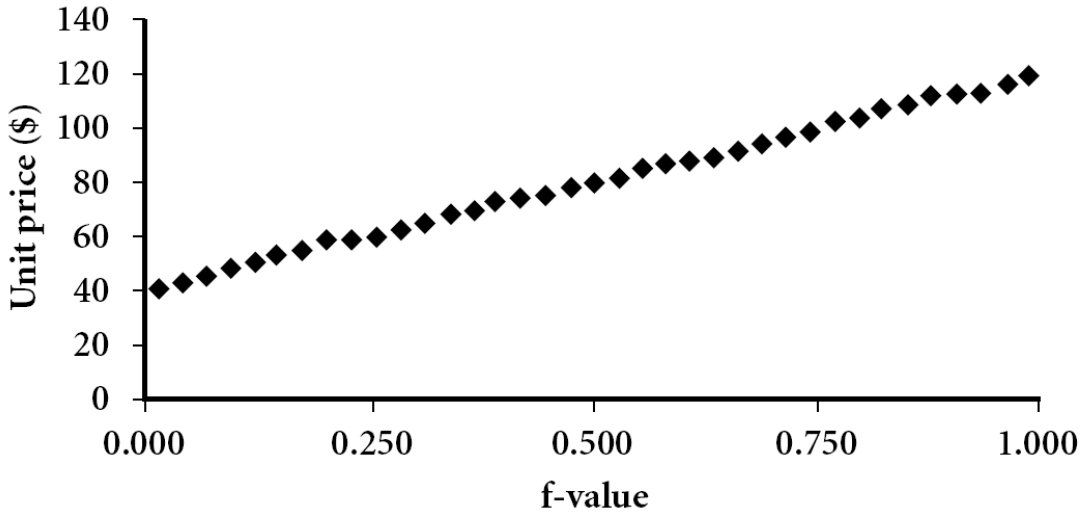
- The two histograms may have the same boxplot
  - The same values for: min, Q1, median, Q3, max
- But they have rather different data distributions





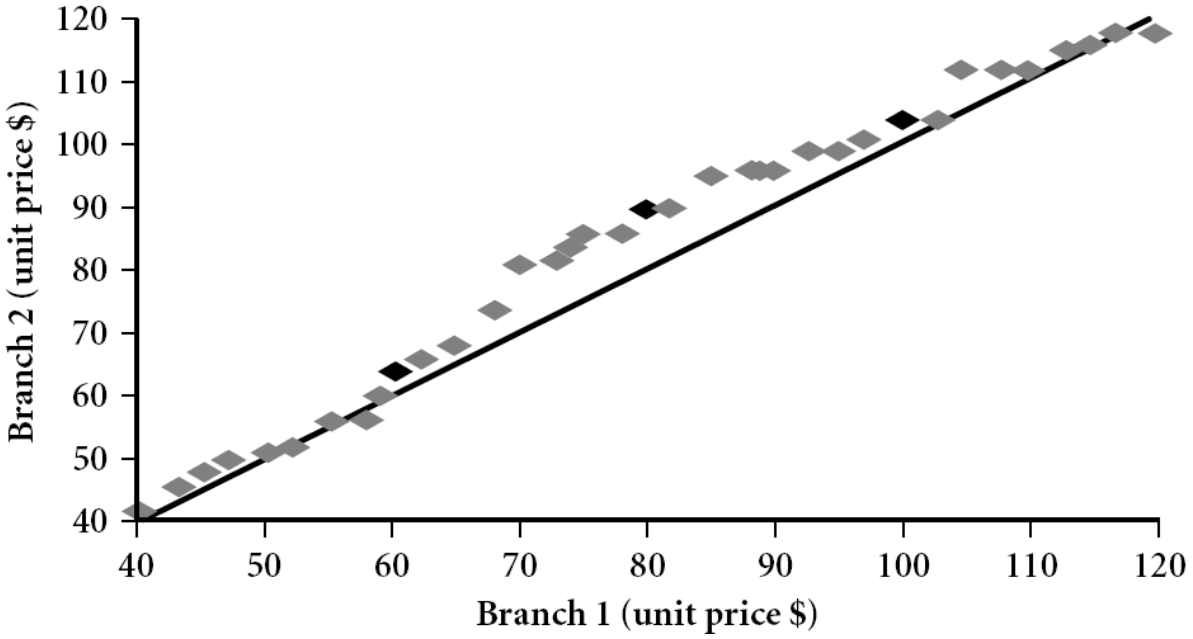
# (3) Quantile Plot

- 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 $x_i$



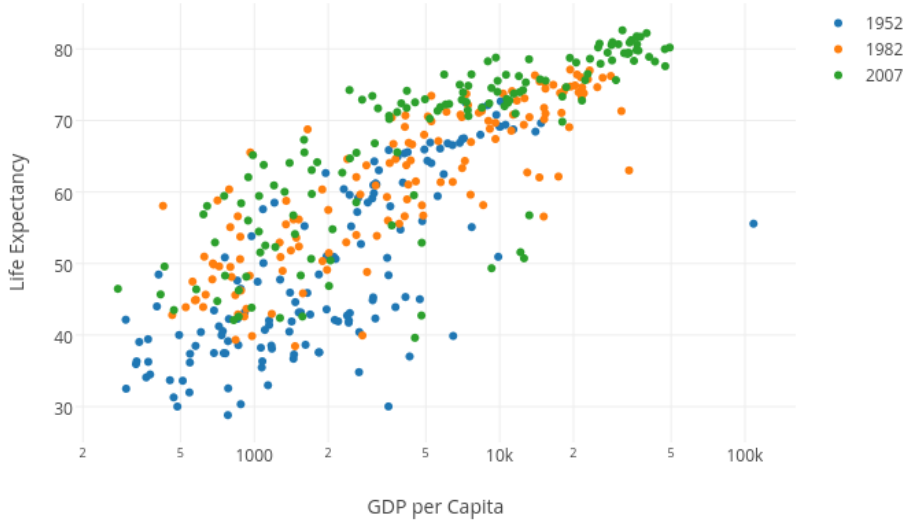
# (4) Quantile-Quantile (Q-Q) Plot

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

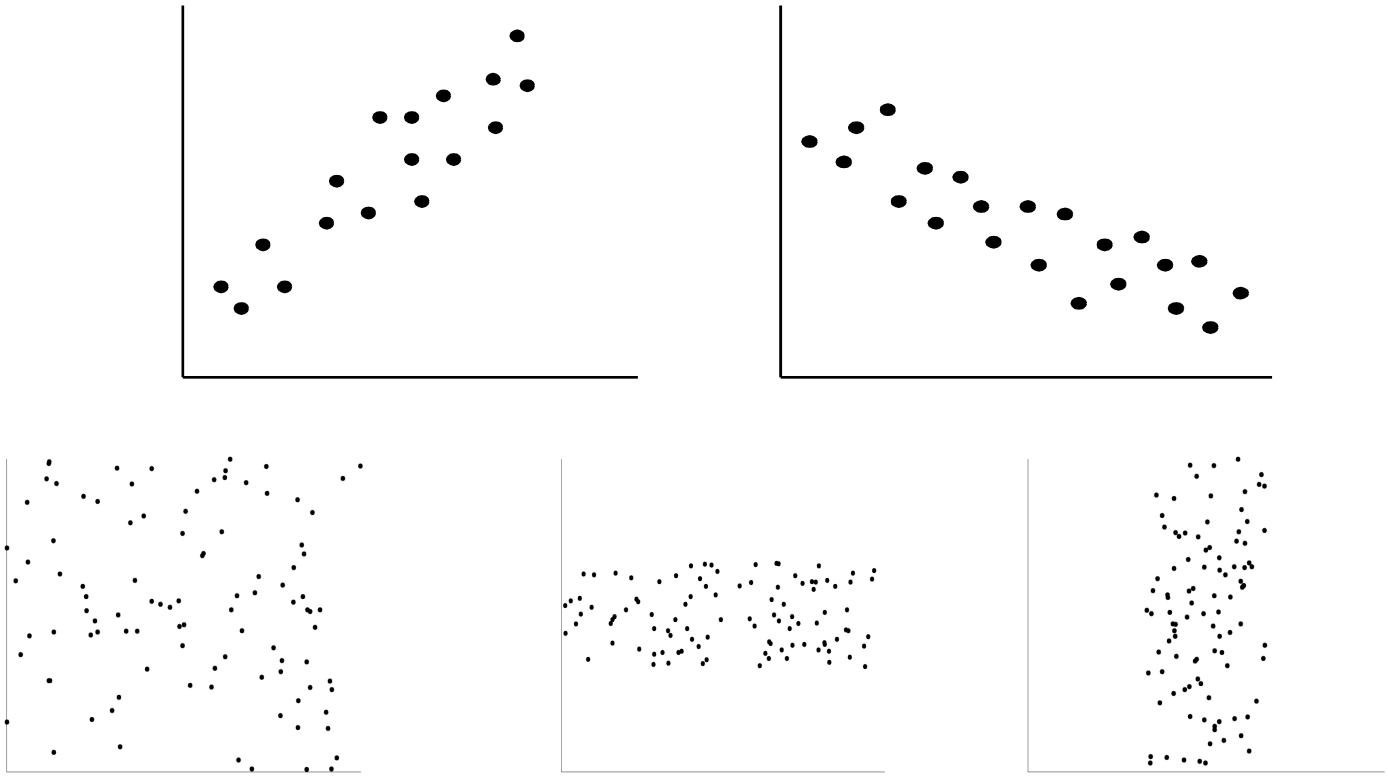


# (5) Scatter plot

- 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, Negatively Correlated, and Uncorrelated Data




# Chapter 2. Getting to Know Your Data

Meng Jiang

CS412 Summer 2017:

Introduction to Data Mining

# Review: Lecture 2

- Data objects, attributes, and attribute types
- Statistical descriptions
  - min, Q1, median, Q3, max; mean, variance, standard deviation; mode
  - sample (s) vs population (σ)

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2 \qquad \bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

Why?

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

# Biased Sample Variance

$$\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2 = \frac{1}{n}\sum_{i=1}^{n}\left[(X_i - \mu) + (\mu - \bar{X})\right]^2$$

**Biased**

$$= \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2 + \frac{2}{n}\sum_{i=1}^{n}(X_i - \mu)(\mu - \bar{X}) + \frac{1}{n}\sum_{i=1}^{n}(\mu - \bar{X})^2$$

$$= \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2 + 2(\bar{X} - \mu)(\mu - \bar{X}) + (\mu - \bar{X})^2$$

$$= \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2 - (\mu - \bar{X})^2$$

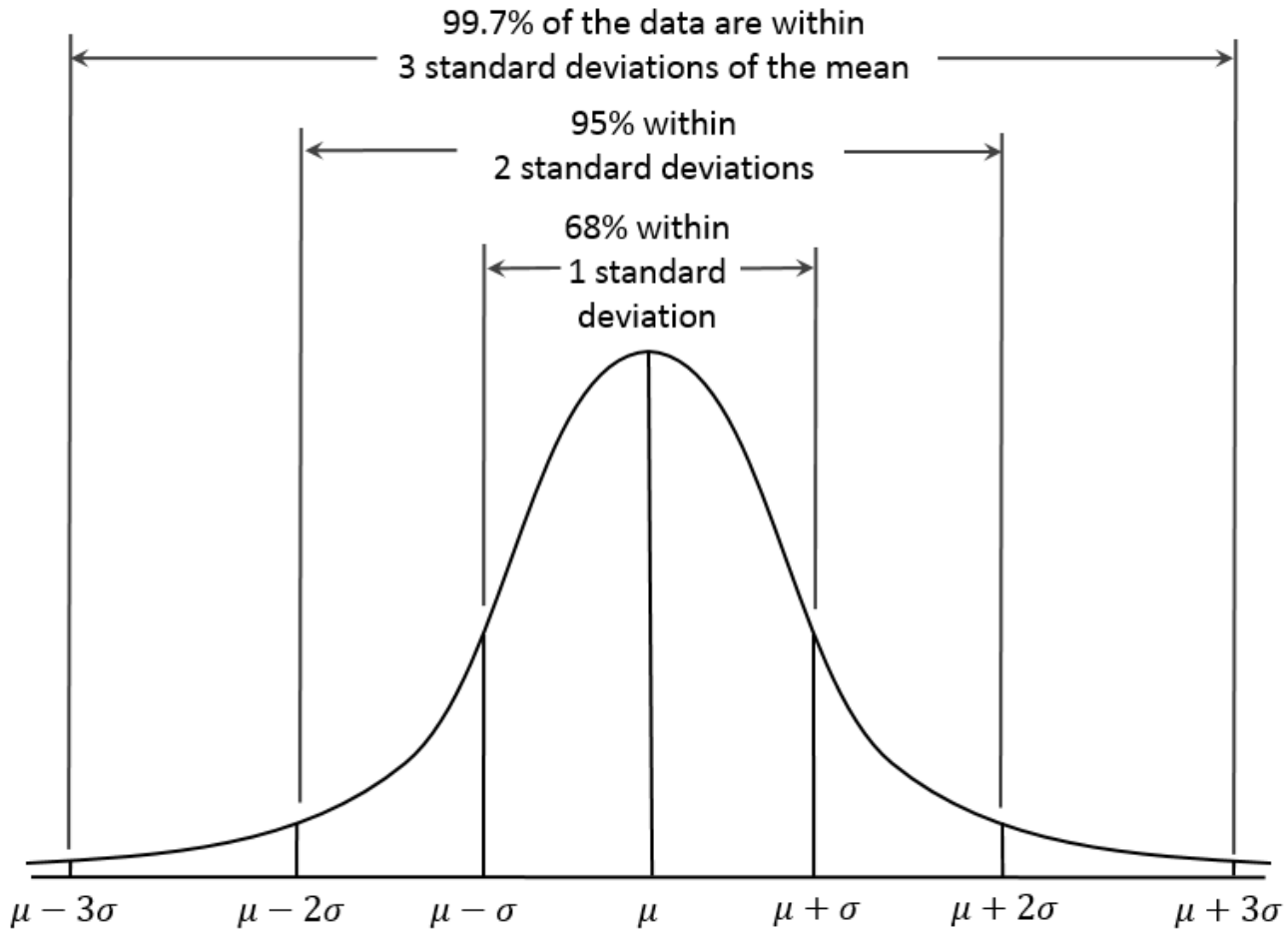
**Unbiased**

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$$

Bessel's Correction: 3 alternative proofs of correctness

# Z-score in Normal Distribution

Z-score: The distance between the raw score and the population mean in the unit of the standard deviation




| Z-score | -3 | -2 | -1 | 0 | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|

# Z-score Normalization

- The normalized value of $X_i$ is calculated as:

$$Z_i = \frac{X_i - \bar{X}}{s}$$

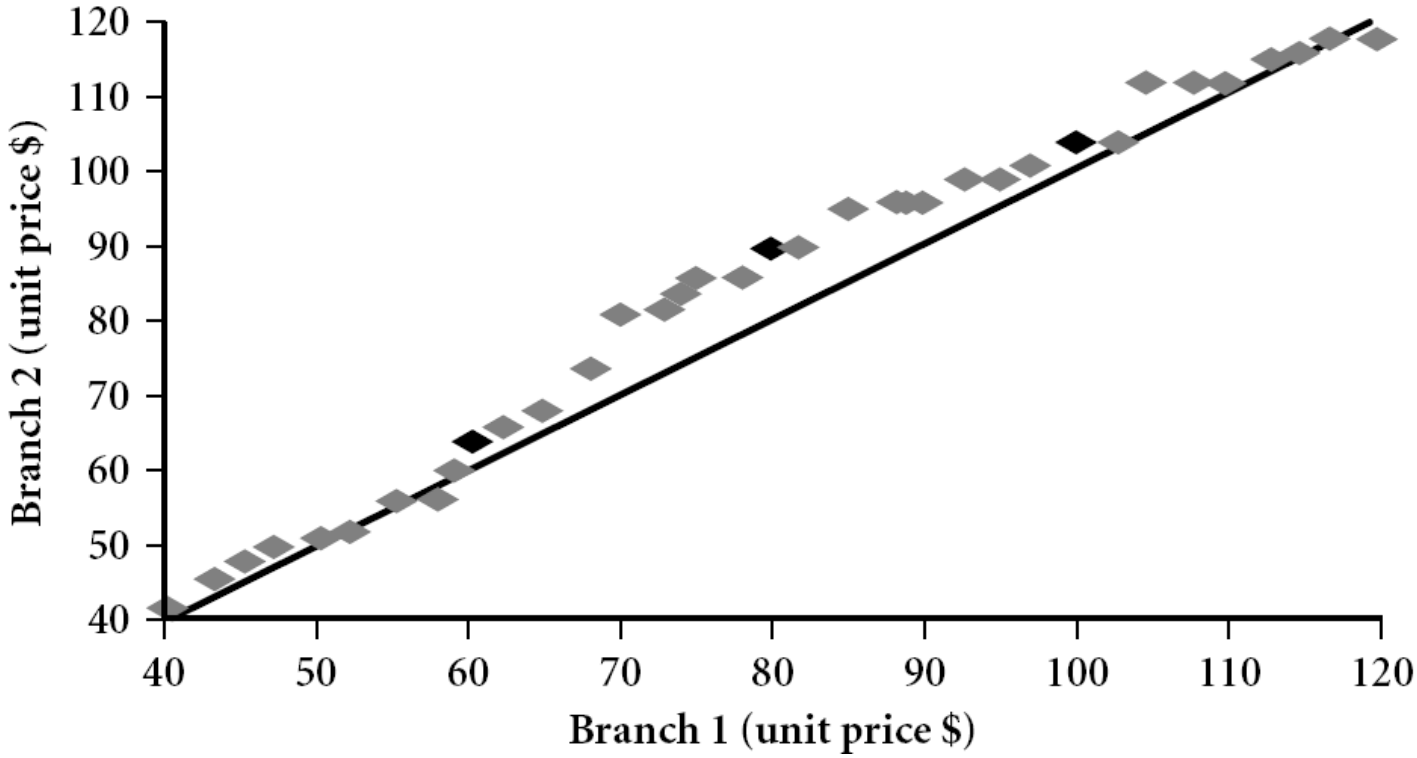
$$\mathbf{y} = \begin{bmatrix} 35 \\ 36 \\ 46 \\ 68 \\ 70 \end{bmatrix}$$

$$\begin{aligned} s &= \sqrt{\frac{(35-51)^2 + (36-51)^2 + (46-51)^2 + (68-51)^2 + (70-51)^2}{5-1}} \\ &= \frac{1}{2}\sqrt{(-16)^2 + -15^2 + (-5)^2 + 17^2 + 19^2} \\ &= 17\,. \end{aligned}$$

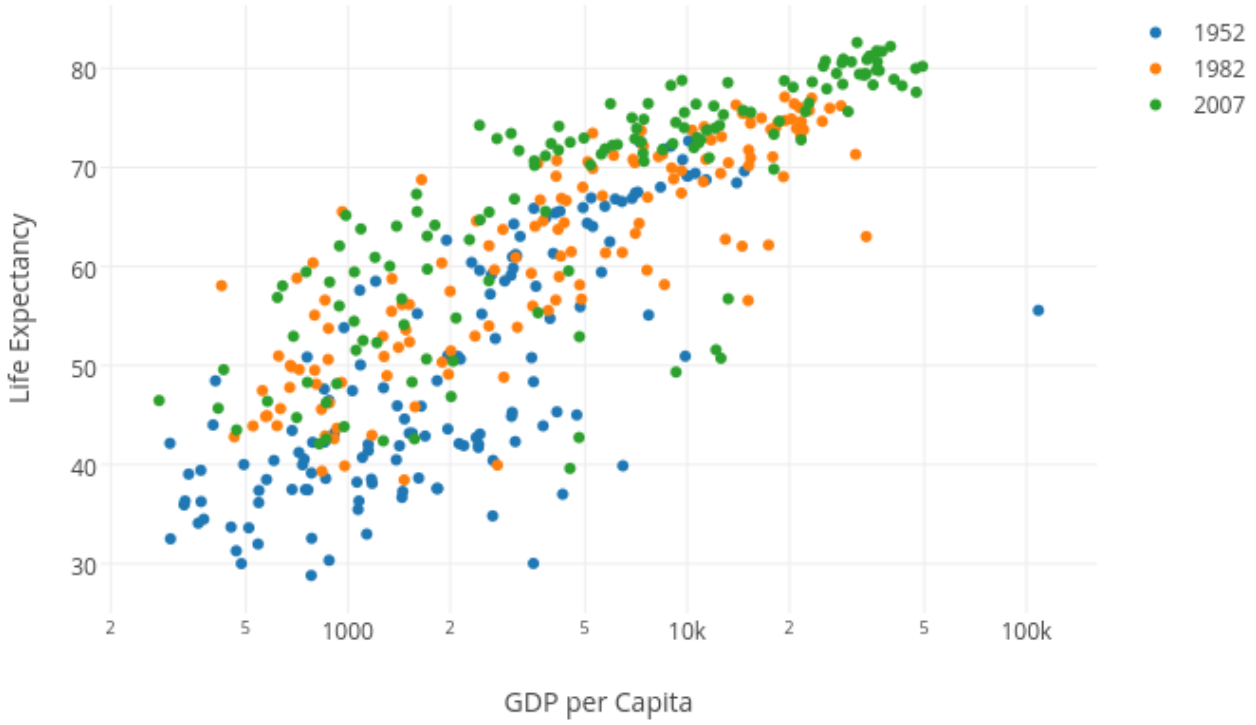
$$\mathbf{z} = \begin{bmatrix} \frac{35-51}{17} \\ \frac{36-51}{17} \\ \frac{46-51}{17} \\ \frac{68-51}{17} \\ \frac{70-51}{17} \end{bmatrix} = \begin{bmatrix} -\frac{16}{17} \\ -\frac{15}{17} \\ -\frac{5}{17} \\ \frac{17}{17} \\ \frac{19}{17} \end{bmatrix} = \begin{bmatrix} -0.9412 \\ -0.8824 \\ -0.2941 \\ 1.0000 \\ 1.1176 \end{bmatrix}$$

# Review: Lecture 2

- Q-Q plot



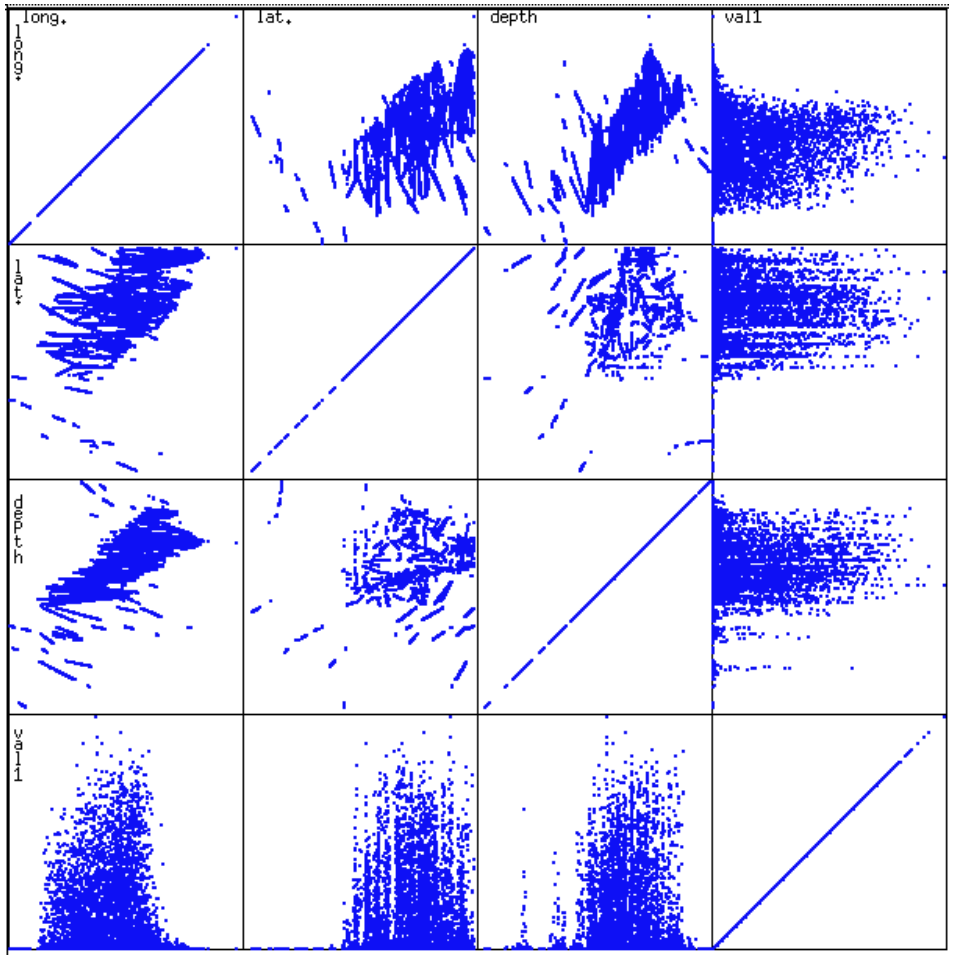
# Review: Scatter Plot



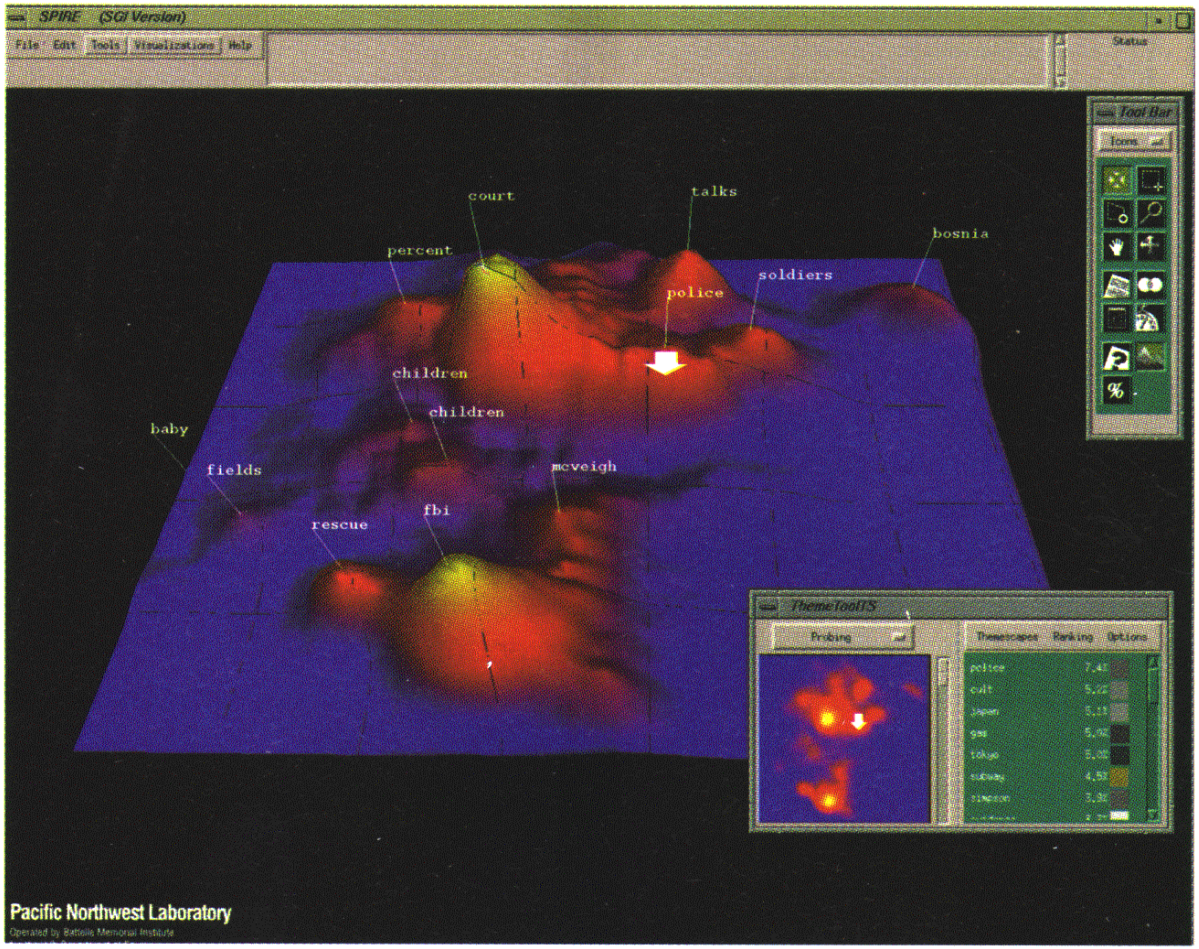
# Chapter 2. Getting to Know Your Data

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

# Scatterplot Matrices



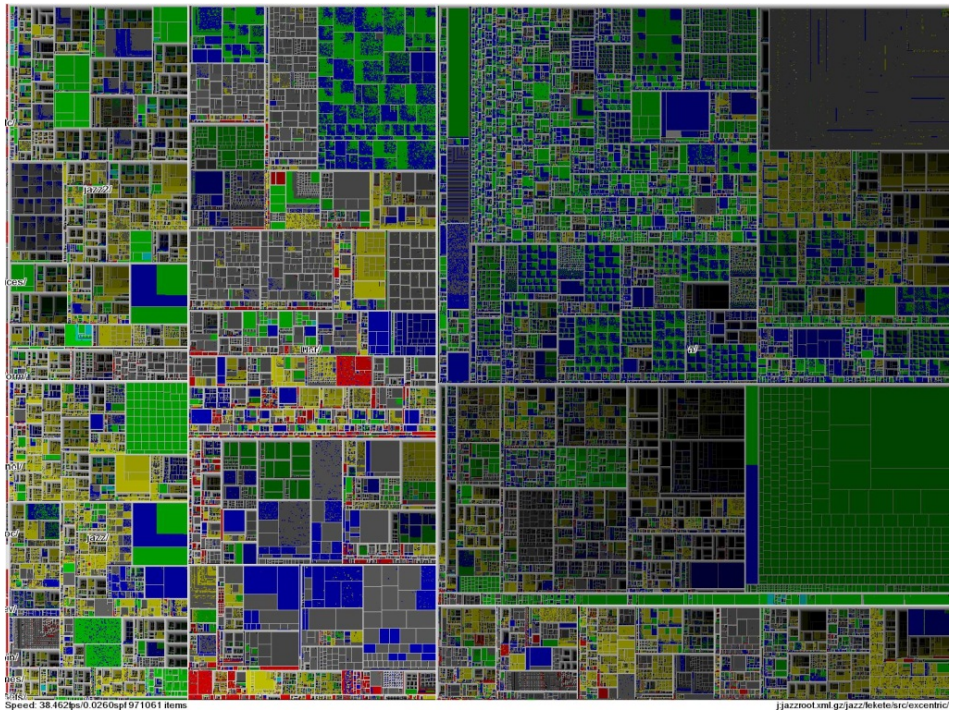
# Landscapes




news articles visualized as a landscape

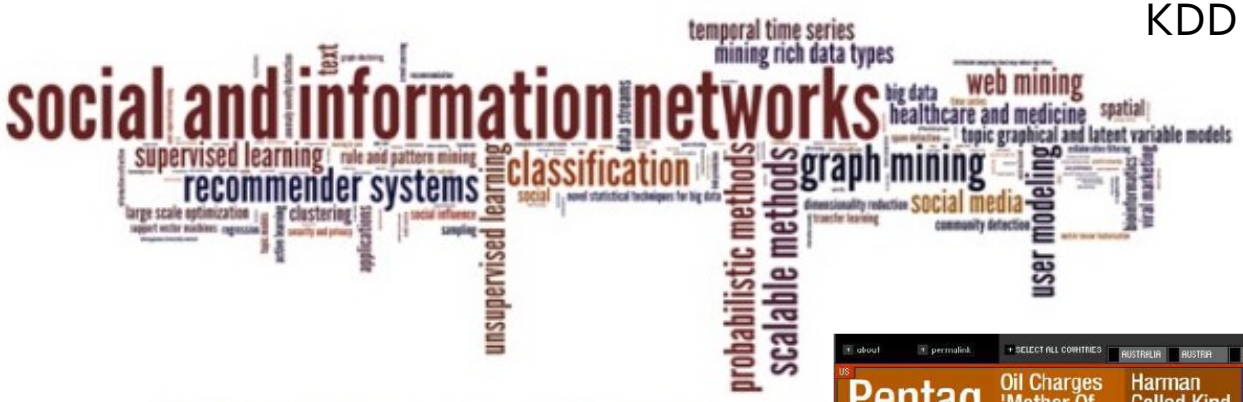
# Tree-Map

- 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)

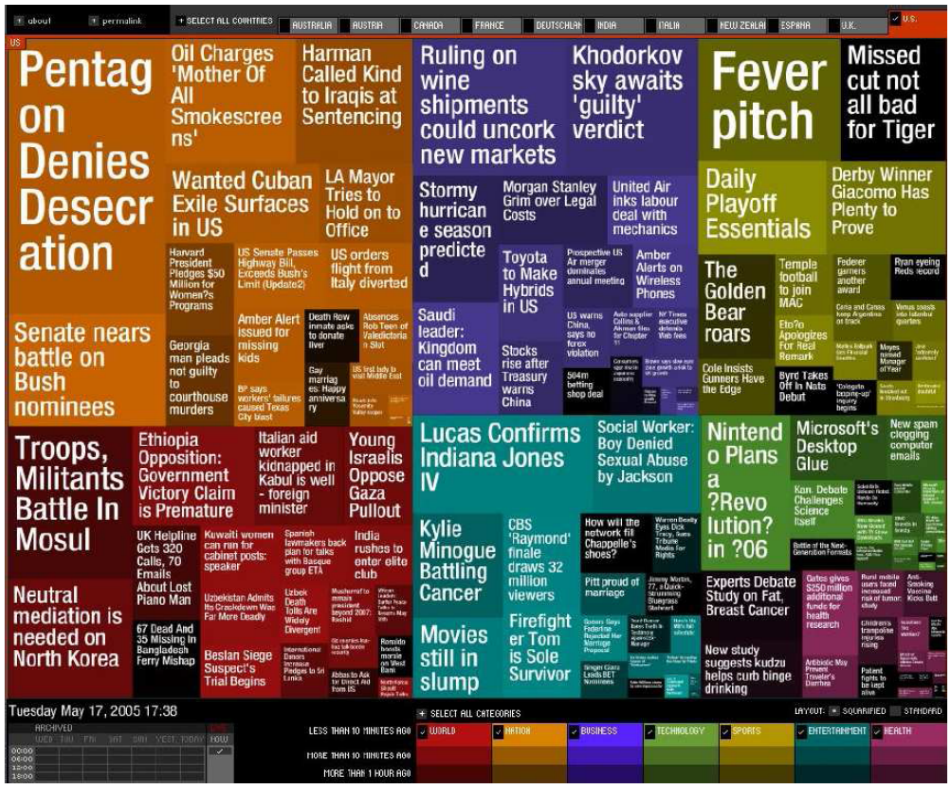


# Tag Cloud

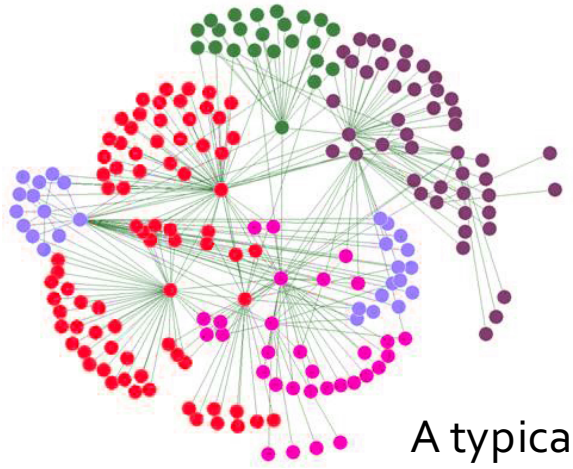
KDD 2013 Research Paper Title



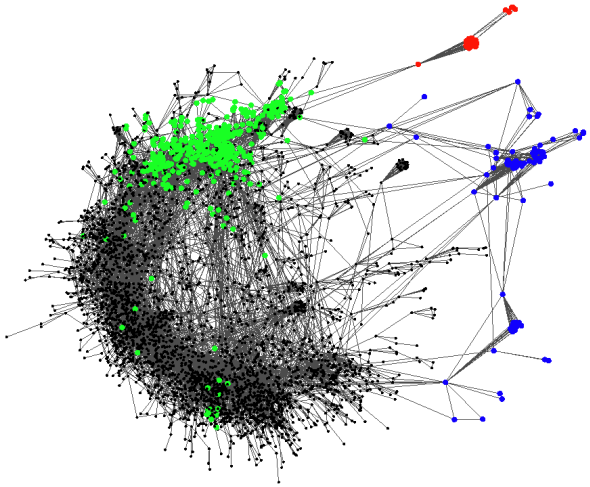

Newsmap: Google News Stories in 2005



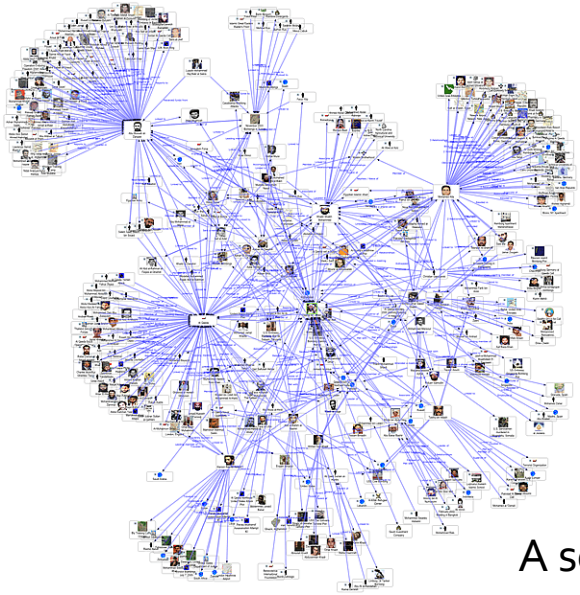
# Networks



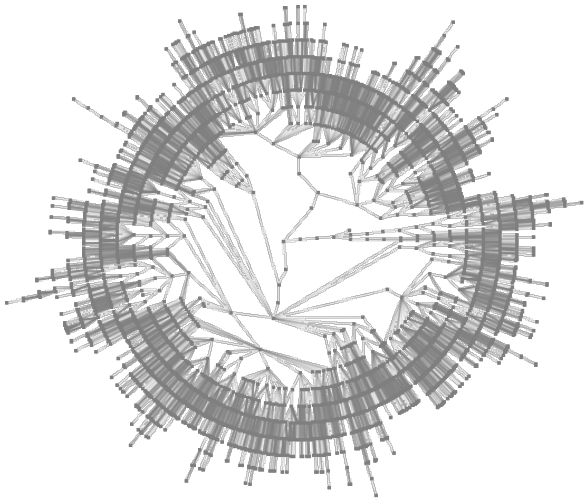
A typical network structure



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, 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, ∞) , depending on the definition
- **Proximity** usually refers to either similarity or dissimilarity

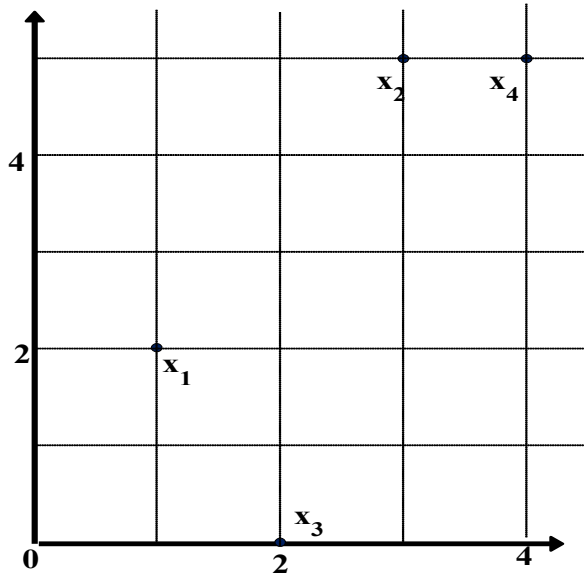
# Data Matrix and Dissimilarity Matrix

- 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)
  - 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

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

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

# Example: Euclidean Distance




Data Matrix

| point | attribute | attribute |
|---|---|---|
| *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 |

# Minkowski Distance

- Minkowski distance: A popular distance measure

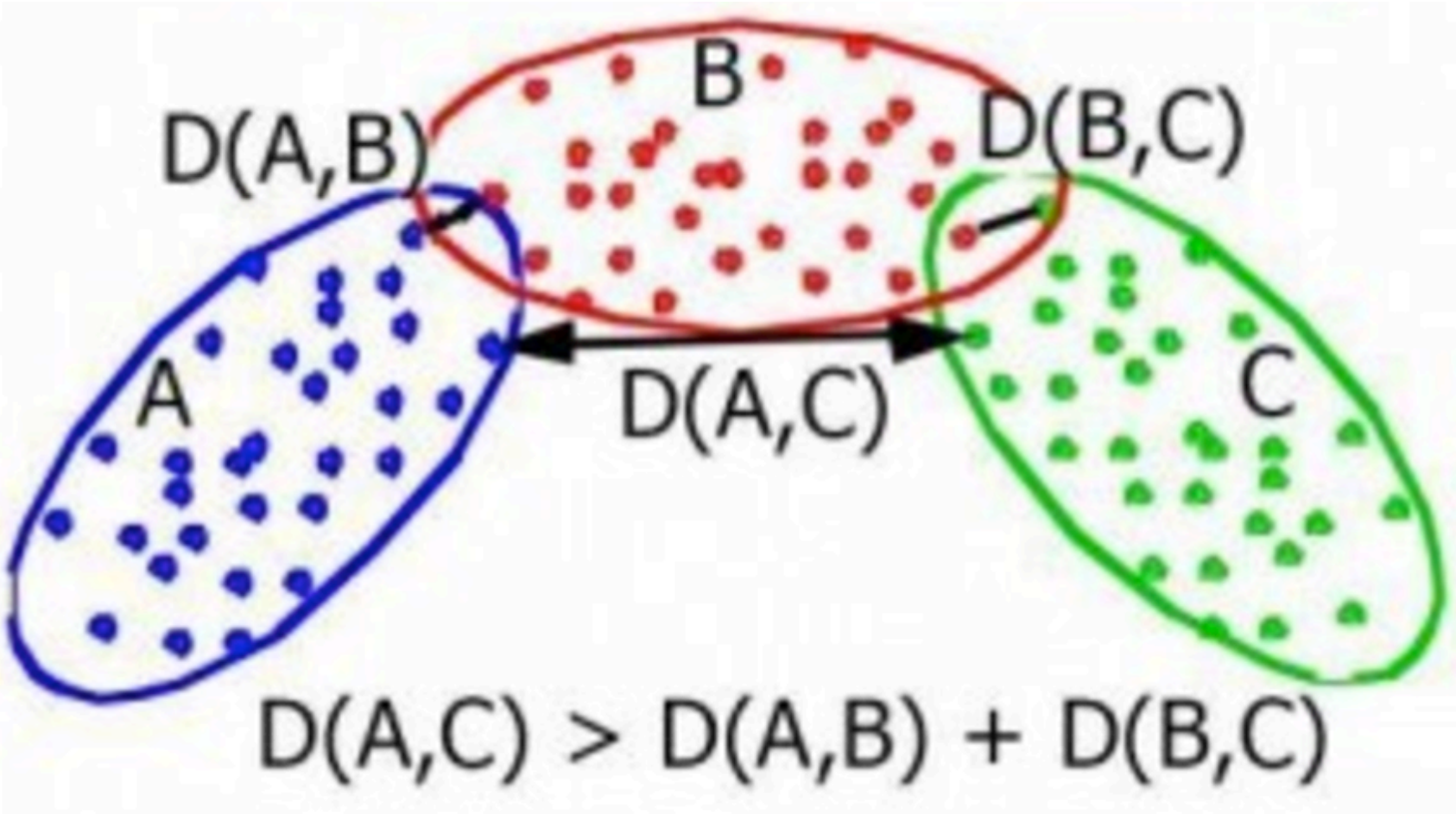
$$d(i, j) = \sqrt[p]{| x_{i1} - x_{j1} |^p + | x_{i2} - x_{j2} |^p + \ldots + | x_{il} - x_{jl} |^p}$$

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

**or L-*h* norm**

- Properties
  - d(i, j) > o if i ≠ j, and d(i, i) = o (Positivity)
  - d(i, j) = d(j, i) (**Symmetry**)
  - d(i, j) ≤ d(i, k) + d(k, j) (**Triangle Inequality**)
- A distance that satisfies these properties is a metric
- 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

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

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

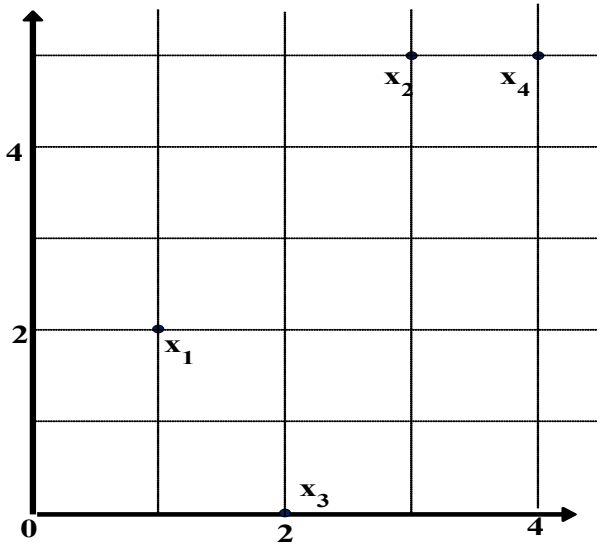
$$d(i, j) = \sqrt{| x_{i1} - x_{j1} |^2 + | x_{i2} - x_{j2} |^2 + \cdots + | x_{il} - x_{jl} |^2}$$

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

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

# Example: Minkowski Distance at Special Cases

| point | attribute 1 | attribute 2 |
|---|---|---|
| x1 | 1 | 2 |
| x2 | 3 | 5 |
| x3 | 2 | 0 |
| x4 | 4 | 5 |




Manhattan ($L_1$)

| L | x1 | x2 | x3 | x4 |
|---|---|---|---|---|
| x1 | 0 | | | |
| x2 | 5 | 0 | | |
| x3 | 3 | 6 | 0 | |
| x4 | 6 | 1 | 7 | 0 |

Euclidean ($L_2$)

| L2 | x1 | x2 | x3 | x4 |
|---|---|---|---|---|
| x1 | 0 | | | |
| x2 | 3.61 | 0 | | |
| x3 | 2.24 | 5.1 | 0 | |
| x4 | 4.24 | 1 | 5.39 | 0 |

Supremum ($L_\infty$)

| L∞ | 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* \ Object *j* | 1 | 0 | sum |
|---|---|---|---|
| 1 | $q$ | $r$ | $q+r$ |
| 0 | $s$ | $t$ | $s+t$ |
| sum | $q+s$ | $r+t$ | $p$ |

- Distance measure for symmetric binary variables:

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

- 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 "coherence":

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

# 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(freshman, senior) = 1, d(junior, senior) = 1/3
  - Compute the dissimilarity using methods for interval-scaled variables

# Attributes of Mixed Types

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

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

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

# Cosine Similarity of Two Vectors

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

| *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 |

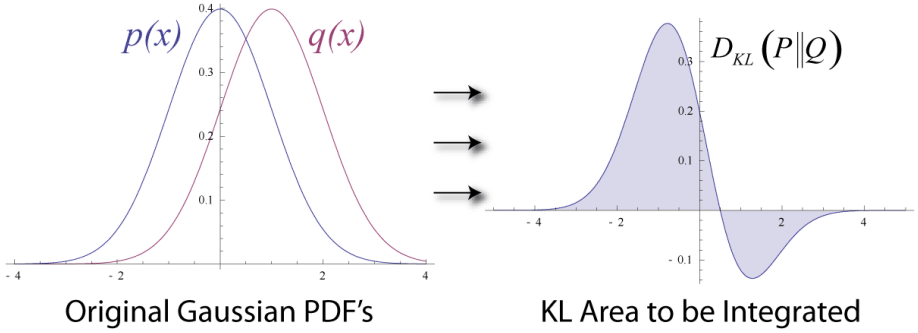
- Other vector objects: Gene features in micro-arrays
- Applications: Information retrieval, biologic taxonomy, gene feature mapping, etc.
- **Cosine measure:** If $d_1$ and $d_2$ are two vectors (e.g., term-frequency vectors), then

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

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

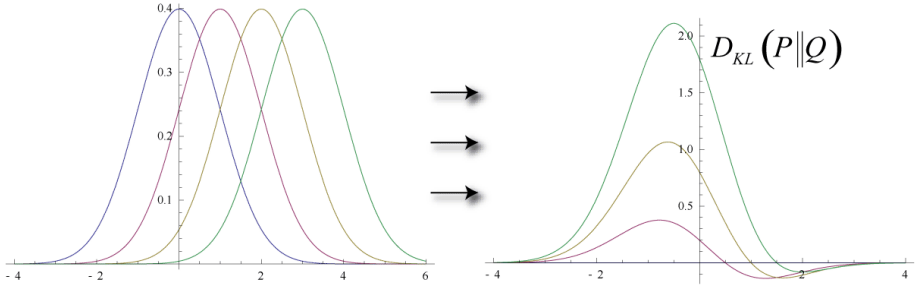
# KL Divergence: Comparing Two Probability Distributions

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




Original Gaussian PDF's

KL Area to be Integrated




Discrete form

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

Continuous form

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

# 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

# Announcement

- Assignment 1 is out!
- Due date: June 15th.
- Compass
- TAs: Xuan Wang (xwang174@illinois.edu) and Sheng Wang (swang141@illinois.edu)

# $4^{th}$ Credit Project

- **Project goal:**
  - Given a real dataset, (1) conduct data preprocessing and data cleaning, (2) define at least three data mining tasks, and (3) design and implement data mining methods: the project should go through the Knowledge Discovery in Databases (KDD) process.
- **Data sets:**
  - KDD 2015-2016 papers: PDF files and TXT files.
    - 224 KDD'15 papers and 206 KDD'16 papers.

# Evaluation

- Project organization: It contains all the steps of the KDD process: data preprocessing, data cube construction, data mining task definition, data mining method design, model evaluation, discussions and future work. (5%)
- Data preprocessing and cube construction: How is the raw dataset transformed into an understandable format? How are the **dimensions and values** extracted from the dataset? Are basic data cube operations doable on the cube? (30%)
- Task definition: Define at least **three different** data mining tasks (**frequent pattern mining, classification, clustering, prediction, recommendation, outlier detection, etc.**) with input and output as "Given … (concrete description of task-relevant data), find/classify/recommend/detect …". (10% * 3 = 30%)
- Data mining method design and model evaluation. (30%)
- Discussions on how to use knowledge that has been discovered in real life and future work. (5%)

# Large-Scale Distributed Bayesian Matrix Factorization using Stochastic Gradient MCMC

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## ABSTRACT

Despite having various attractive qualities such as high prediction accuracy and the ability to quantify uncertainty and avoid overfitting, Bayesian Matrix Factorization has not been widely adopted because of the prohibitive cost of inference. In this paper, we propose a scalable distributed Bayesian matrix factorization algorithm using stochastic gradient MCMC. Our algorithm, based on Distributed Stochastic Gradient Langevin Dynamics, can not only match the prediction accuracy of standard MCMC methods like Gibbs sampling, but at the same time is as fast and simple as stochastic gradient descent. In our experiments, we show that our algorithm can achieve the same level of prediction accuracy as Gibbs sampling an order of magnitude faster. We also show that our method reduces the prediction error as fast as distributed stochastic gradient descent, achieving a 4.1% improvement in RMSE for the Netflix dataset and an 1.8% for the Yahoo music dataset.

## Categories and Subject Descriptors

G.4 [**Mathematical Software**]: Algorithm design and analysis; Parallel and vector implementations

## Keywords

Large-Scale, Distributed, Matrix Factorization, MCMC, Stochastic Gradient, Bayesian Inference

## 1. INTRODUCTION

Recommender systems have become a pervasive tool in industry to understand customers and their interests in products. Examples range between music recommendation (Pandora), book recommendation (Amazon), movie recommendation (Netflix), news recommendation (Yahoo) to partner recommendation (eHarmony). Recommender systems represent a personalized technology that can help filter at an individual level the enormous amounts of information that is available to us. Given the exponential growth of data, recommender systems are likely to play an increasingly important role to manage our information streams.

During 2006-2011 Netflix [6] ran a competition where teams around the world could develop and test new recommender technology on Netflix movie rating data. A few valuable lessons were learnt from that exercise. First, matrix factorization methods work very well compared to nearest neighbor type models. Second, averaging over many different models pays off in terms of prediction accuracy. One particularly effective model was Bayesian probabilistic matrix factorization (BPMF) [26] where predictions are averaged over samples from the posterior distribution. Besides improved prediction accuracy, a full Bayesian analysis also comes with additional advantages such as probabilities over models, confidence intervals, robustness against overfitting, and incorporating prior knowledge and side-information [2, 23].

Unfortunately, since the number of user-product interactions can easily run into the billions, posterior inference is usually too ex-

# Tip 1: Dimension and Value Extraction

| Paper | Dimension | Value | Paper | Dimension | Value |
|---|---|---|---|---|---|
| kdd15-p9 | PROBLEM | prediction | kdd15-p9 | DATASET | netflix |
| kdd15-p9 | METRIC | prediction accuracy | kdd15-p9 | DATASET | yahoo music |
| kdd15-p9 | PROBLEM | uncertainty | kdd15-p9 | PROBLEM | recommender systems |
| kdd15-p9 | PROBLEM | over-fitting | kdd15-p9 | PROBLEM | music recommendation |
| kdd15-p9 | METHOD | Bayesian matrix factorization | kdd15-p9 | PROBLEM | book recommendation |
| kdd15-p9 | PROBLEM | prohibitive cost of inference | kdd15-p9 | PROBLEM | movie recommendation |
| kdd15-p9 | METHOD | scalable distributed Bayesian matrix factorization | kdd15-p9 | PROBLEM | news recommendation |
| kdd15-p9 | METHOD | stochastic gradient mcmc | kdd15-p9 | PROBLEM | partner recommendation |
| kdd15-p9 | METHOD | distributed stochastic gradient langevin dynamics | kdd15-p9 | PROBLEM | recommender systems |
| kdd15-p9 | METHOD | mcmc | kdd15-p9 | DATASET | netflix |
| kdd15-p9 | METHOD | gibbs sampling | kdd15-p9 | PROBLEM | recommender |
| kdd15-p9 | METHOD | stochastic gradient descent | kdd15-p9 | DATASET | netflix movie rating |
| kdd15-p9 | PROBLEM | prediction | kdd15-p9 | METHOD | bayesian probabilistic matrix factorization |
| kdd15-p9 | METRIC | accuracy | kdd15-p9 | METHOD | posterior distribution |
| kdd15-p9 | METHOD | gibbs sampling | kdd15-p9 | METHOD | bayesian analysis |
| kdd15-p9 | METRIC | prediction error | kdd15-p9 | METRIC | confidence intervals |
| kdd15-p9 | METHOD | distributed stochastic gradient descent | kdd15-p9 | METRIC | robustness |
| kdd15-p9 | METRIC | rmse | | | |

# Tip 2: Data Mining Tasks

- Given a table of Paper-Problem and a table of Paper-Method, find association rules like Problem→Method or frequent (Problem, Method) pairs/itemsets; categorized as "frequent pattern mining".
- Given a table of Paper-Author and a table of Paper-Problem, for a specific problem, classify authors into "experts" or "non-experts"; categorized as "binary classification".
- Given a table of Paper-Author, Paper-Problem, and Paper-Method, group papers into K clusters by different metrics of paper-paper similarity and compare the results.

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