

Data Mining: Concepts and Techniques

Chapter 2: Getting to Know Your Data

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

Types of Data Sets

- Record
 - Relational records
 - Data matrix, e.g., numerical matrix, crosstabs
 - Document data: text documents: term-frequency vector
 - Transaction data
- Graph and network
 - World Wide Web
 - Social or information networks
 - Molecular Structures
- Ordered
 - Video data: sequence of images
 - Temporal data: time-series
 - Sequential Data: transaction sequences
 - Genetic sequence data
- Spatial, image and multimedia:
 - Spatial data: maps
 - Image data:
 - Video data:

	team	coach	play	ball	score	game	win	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

<i>TID</i>	<i>Items</i>
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Important Characteristics of Structured Data

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

So, what is Data?

Attributes

- Collection of data **objects** and their **attributes**
- An attribute is a property or characteristic of an object
 - Examples: eye color of a person, temperature, etc.
 - Attribute is also known as **variable, field, characteristic, or feature**
- A collection of attributes describe an object
 - Object is also known as **record, point, case, sample, entity, or instance**

Objects

<i>Tid</i>	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Size: Number of objects

Dimensionality: Number of attributes

Sparsity: Number of populated object-attribute pairs⁵

Data Objects

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

Attributes

- **Attribute (or dimensions, features, variables):** a data field, representing a characteristic or feature of a data object.
 - *E.g., customer_ID, name, address*
- Types:
 - Nominal
 - Binary
 - Numeric: quantitative
 - Interval-scaled
 - Ratio-scaled

Attribute Types

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

Numeric Attribute Types

- Quantity (integer or real-valued)
- **Interval**
 - Measured on a scale of **equal-sized units**
 - Values have order
 - E.g., *temperature in C° or F°, calendar dates*
 - No true zero-point
- **Ratio**
 - Inherent **zero-point**
 - We can speak of values as being an order of magnitude larger than the unit of measurement (10 K° is twice as high as 5 K°).
 - e.g., *temperature in Kelvin, length, counts, monetary quantities*

Categorical Data

- Data that consists of a collection of records, each of which consists of a **fixed set** of **categorical** attributes

<i>Tid</i>	<u>Refund</u>	Marital Status	Taxable Income	Cheat
1	Yes	Single	High	No
2	No	Married	Medium	No
3	No	Single	Low	No
4	Yes	Married	High	No
5	No	Divorced	Medium	Yes
6	No	Married	Low	No
7	Yes	Divorced	High	No
8	No	Single	Medium	Yes
9	No	Married	Medium	No
10	No	Single	Medium	Yes

Document Data

- Each document becomes a 'term' vector,
 - each term is a component (attribute) of the vector,
 - the value of each component is the number of times the corresponding term occurs in the document.
 - **Bag-of-words** representation – no ordering

	team	coach	play	ball	score	game	win	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

Transaction Data

- Each record (transaction) is a **set of items**.

<i>TID</i>	<i>Items</i>
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

- A set of items can also be represented as a **binary vector**, where each attribute is an item.
- A document can also be represented as a **set of words** (no counts)

Sparsity: average number of products bought

Ordered Data

- Genomic **sequence** data

```
GGTTC CGCCTTCAGCCCCGCGCC  
CGCAGGGCCCGCCCCGCGCCGTC  
GAGAAGGGCCCGCCTGGCGGGCG  
GGGGGAGGCGGGGCCGCCCGAGC  
CCAACCGAGTCCGACCAGGTGCC  
CCCTCTGCTCGGCCTAGACCTGA  
GCTCATTAGGCGGCAGCGGACAG  
GCCAAGTAGAACACGCGAAGCGC  
TGGGCTGCCTGCTGCGACCAGGG
```

- Data is a long **ordered** string

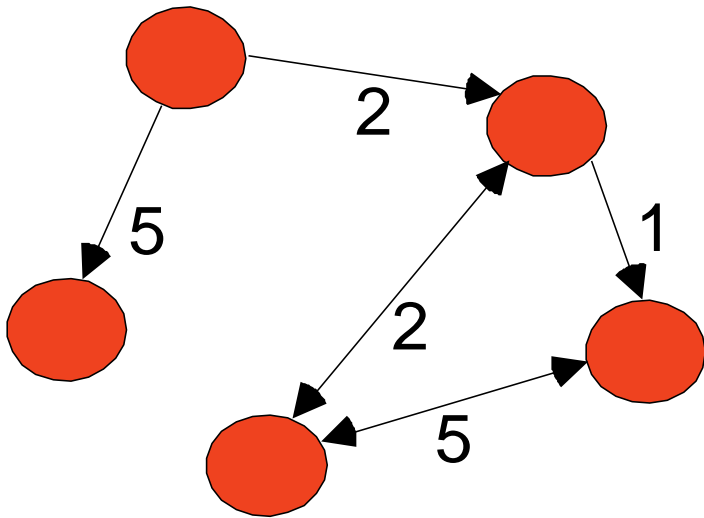
Ordered Data

- Time series
 - Sequence of ordered (over “time”) numeric



Graph Data

- Examples: Web graph and HTML Links



```
<a href="papers/papers.html#bbbb">  
Data Mining </a>
```

```
<li>
```

```
<a href="papers/papers.html#aaaa">  
Graph Partitioning </a>
```

```
<li>
```

```
<a href="papers/papers.html#aaaa">  
Parallel Solution of Sparse Linear System of Equations </a>
```

```
<li>
```

```
<a href="papers/papers.html#ffff">  
N-Body Computation and Dense Linear System Solvers
```

Attribute		Type Description	Examples	Operations
Categorical (Qualitative)	Nominal	The values of a nominal attribute are just different names; i.e., nominal values provide only enough information to distinguish one object from another. ($=$, \neq)	zip codes, employee ID numbers, eye color, gender	mode, entropy, contingency correlation, χ^2 test
	Ordinal	The values of an ordinal attribute provide enough information to order objects. ($<$, $>$)	hardness of minerals, {good, better, best}, grades, street numbers	median, percentiles, rank correlation, run tests, sign tests
Numerical (Quantitative)	Interval	For interval attributes, the differences between values are meaningful, i.e., a unit of measurement exists. ($+$, $-$)	calendar dates, temperature in Celsius or Fahrenheit	mean, standard deviation, Pearson's correlation, t and F tests
	Ratio	For ratio variables, both differences and ratios are meaningful. ($*$, $/$)	temperature in Kelvin, monetary quantities, counts, age, mass, length, electrical current	geometric mean, harmonic mean, percent Variation

	Attribute Type	Transformation	Comments
Categorical Qualitative	Nominal	Any permutation of values	If all employee ID numbers were reassigned, would it make any difference?
	Ordinal	An order preserving change of values, i.e., $new_value = f(old_value)$ where f is a monotonic function	An attribute encompassing the notion of good, better best can be represented equally well by the values {1, 2, 3} or by { 0.5, 1, 10}.
Numeric Quantitative	Interval	$new_value = a * old_value + b$ where a and b are constants	Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree).
	Ratio	$new_value = a * old_value$	Length can be measured in meters or feet.

Discrete vs. Continuous Attributes

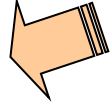
■ Discrete Attribute

- Has only a finite or countably infinite set of values
 - E.g., zip codes, profession, or the set of words in a collection of documents
- Sometimes, represented as integer variables
- Note: Binary attributes are a special case of discrete attributes

■ Continuous Attribute

- Has real numbers as attribute values
 - E.g., temperature, height, or weight
- Practically, real values can only be measured and represented using a finite number of digits
- Continuous attributes are typically represented as floating-point variables

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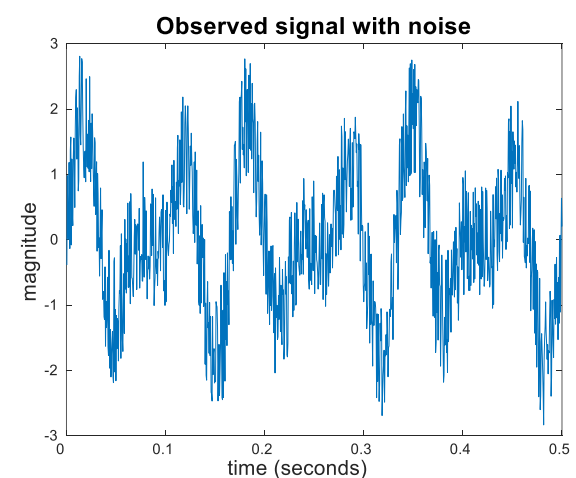
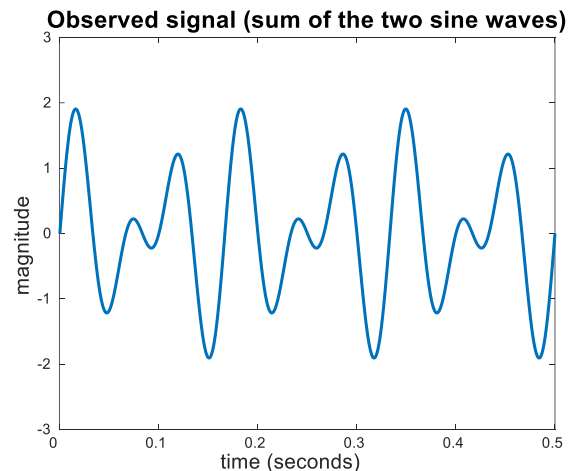
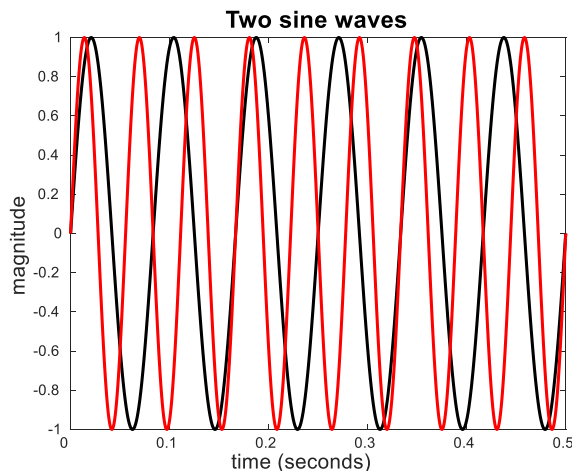
Data Quality

- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?

- Examples of data quality problems:
 - Noise and outliers
 - Wrong data
 - Fake data
 - Missing values
 - Duplicate data

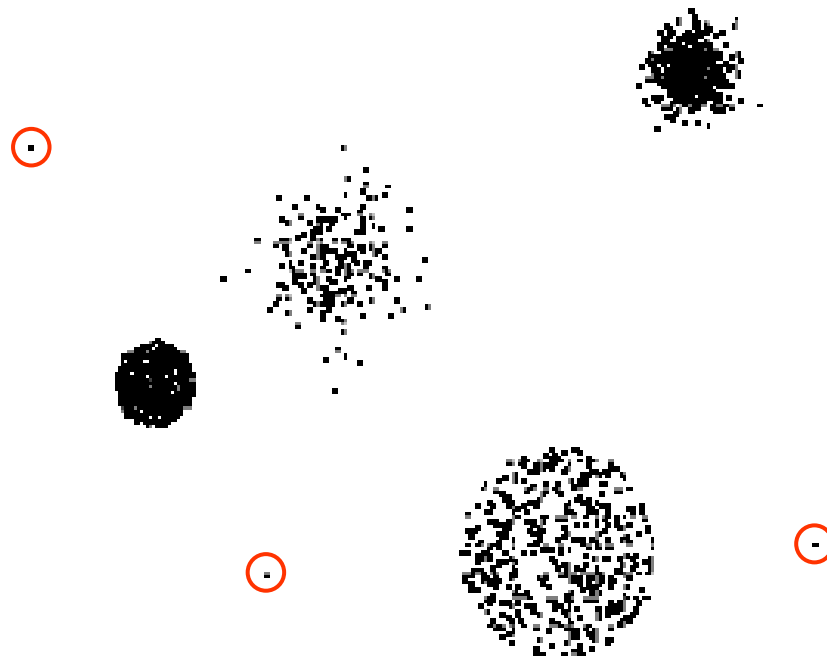
Noise

- **For objects, noise is an extraneous object**
- **For attributes, noise refers to modification of original values**
 - **Examples: distortion of a person's voice when talking on a poor phone and "snow" on television screen**
 - **The figures below show two sine waves of the same magnitude and different frequencies, the waves combined, and the two sine waves with random noise**
 - **The magnitude and shape of the original signal is distorted**



Outliers

- **Outliers** are data objects with characteristics that are considerably different than most of the other data objects in the data set
 - **Case 1:** Outliers are noise that interferes with data analysis
 - **Case 2:** Outliers are the goal of our analysis
 - Credit card fraud
 - Intrusion detection
- Causes?



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, etc.
- 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

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

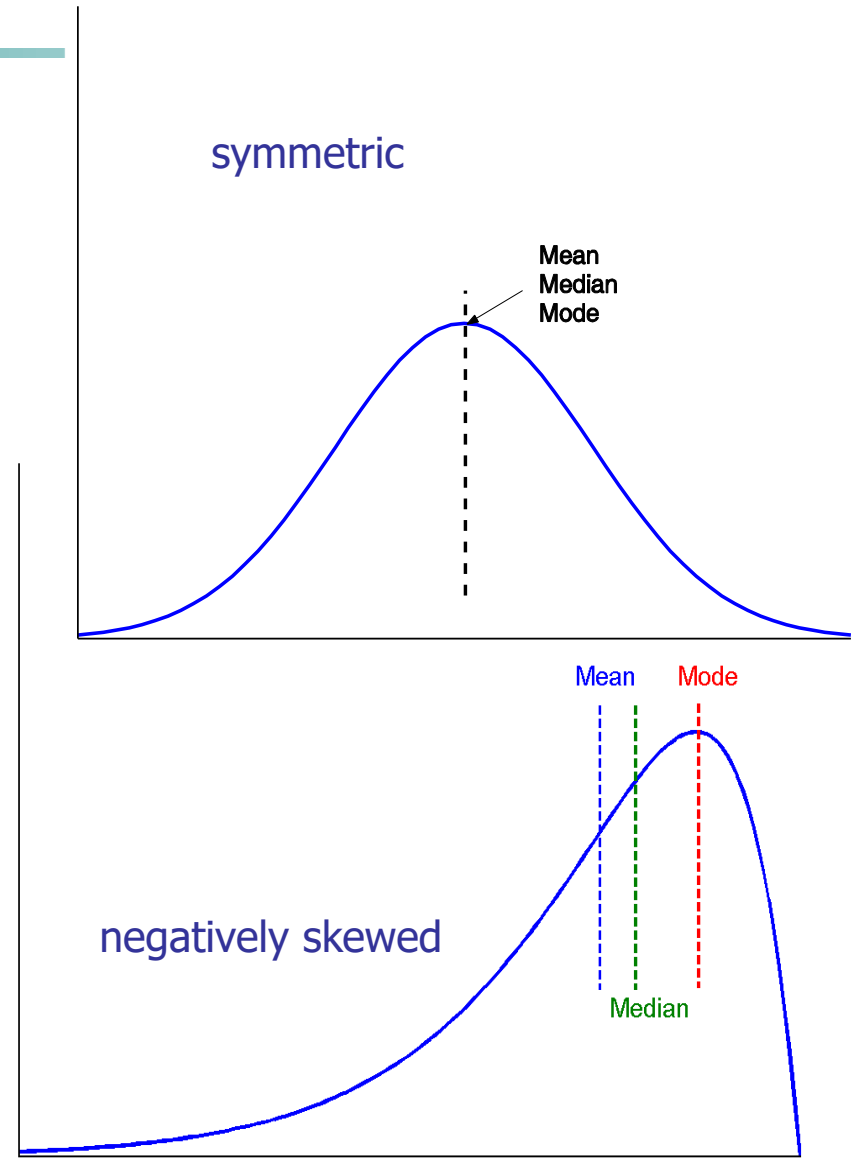
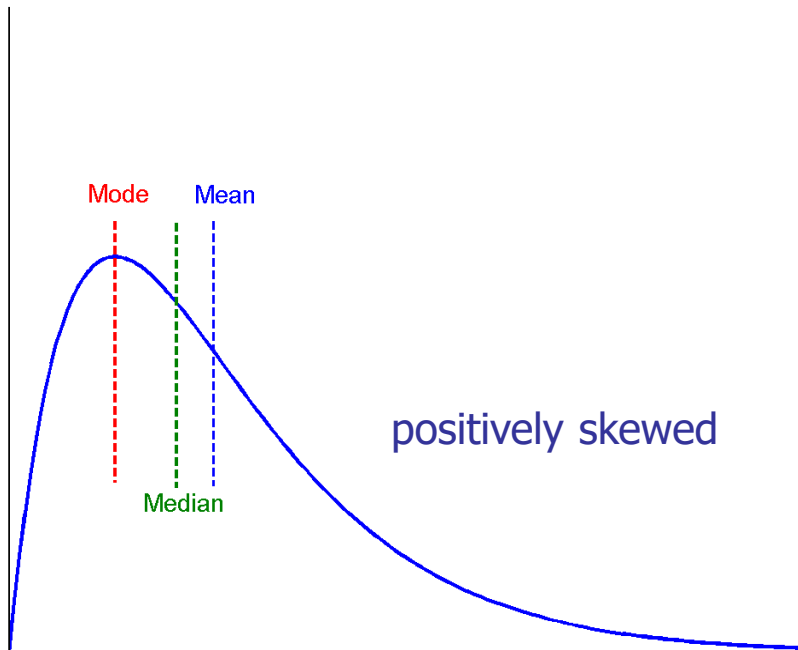
$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad \mu = \frac{\sum x}{N}$$

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

 - Weighted arithmetic mean:
 - Trimmed mean: chopping extreme values
$$\bar{x} = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}$$
- Median:
 - Middle value if odd number of values, or average of the middle two values otherwise
 - Estimated by interpolation (for *grouped data*):
$$median = L_1 + \left(\frac{n/2 - (\sum freq)l}{freq_{median}} \right) width$$
- Mode
 - Value that occurs most frequently in the data
 - Unimodal, bimodal, trimodal
 - Empirical formula: $mean - mode = 3 \times (mean - median)$

Symmetric vs. Skewed Data

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



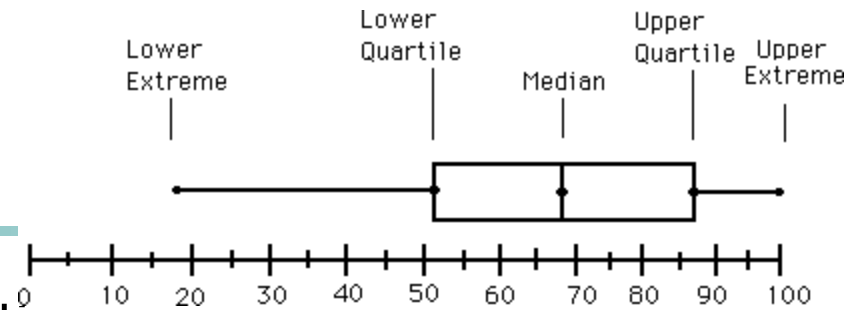
Measuring the Dispersion of Data

- Quartiles, outliers and boxplots
 - **Quartiles:** Q_1 (25th percentile), Q_3 (75th percentile)
 - **Inter-quartile range:** $IQR = Q_3 - Q_1$
 - **Five number summary:** min, Q_1 , median, Q_3 , max
 - **Boxplot:** ends of the box are the quartiles; median is marked; add whiskers, and plot outliers individually
 - **Outlier:** usually, a value higher/lower than $1.5 \times IQR$
- Variance and standard deviation (*sample: s , population: σ*)
 - **Variance:** (algebraic, scalable computation)

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

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

Boxplot Analysis

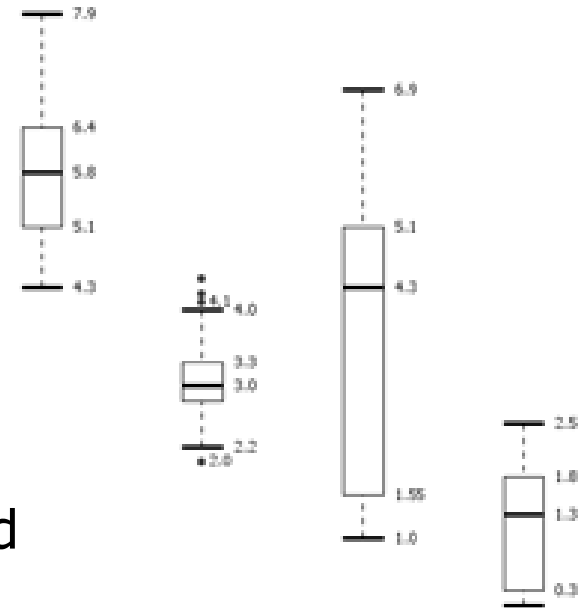


- **Five-number summary** of a distribution

- Minimum, Q1, Median, Q3, Maximum

- **Boxplot**

- Data is represented with a box
- The ends of the box are at the first and third quartiles, i.e., the height of the box is IQR
- The median 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

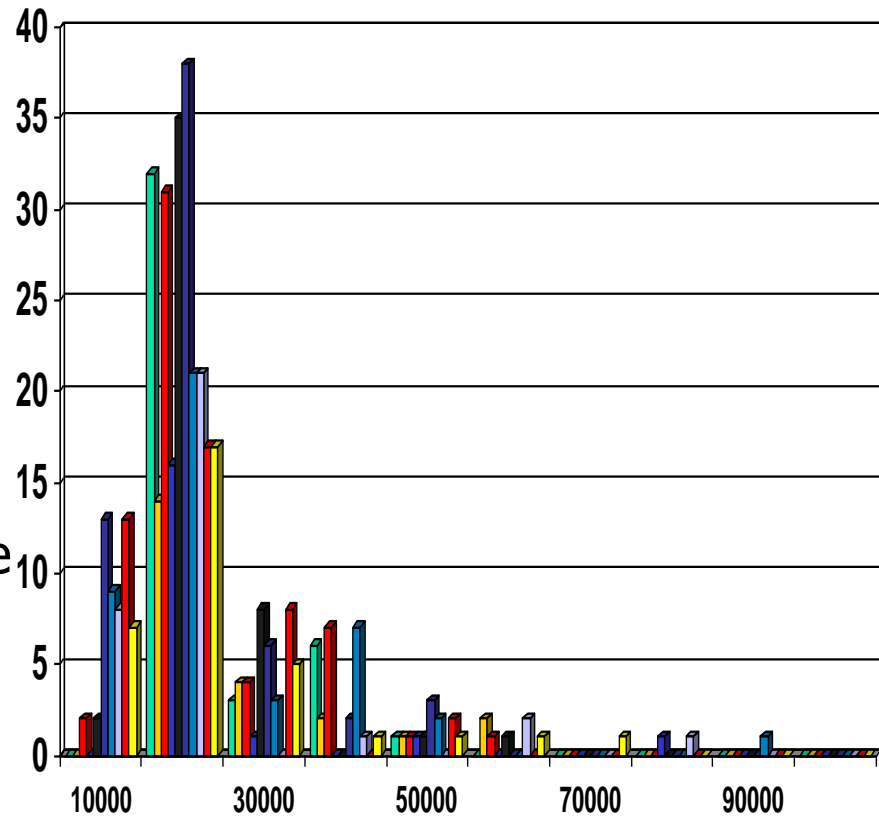


Graphic Displays of Basic Statistical Descriptions

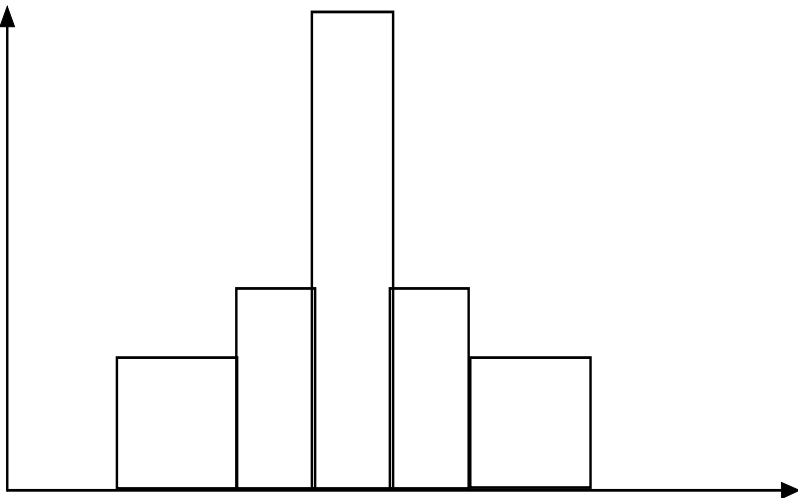
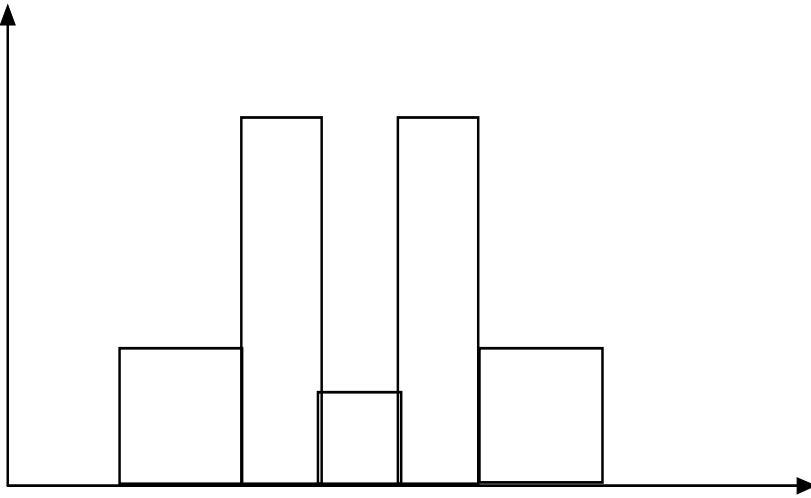
- **Boxplot:** graphic display of five-number summary
- **Histogram:** x-axis are values, y-axis repres. frequencies
- **Scatter plot:** each pair of values is a pair of coordinates and plotted as points in the plane

Histogram Analysis

- Histogram: Graph display of tabulated frequencies, shown as bars
- It shows what proportion of cases fall into each of several categories
- 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
- The categories are usually specified as non-overlapping intervals of some variable. The categories (bars) must be adjacent



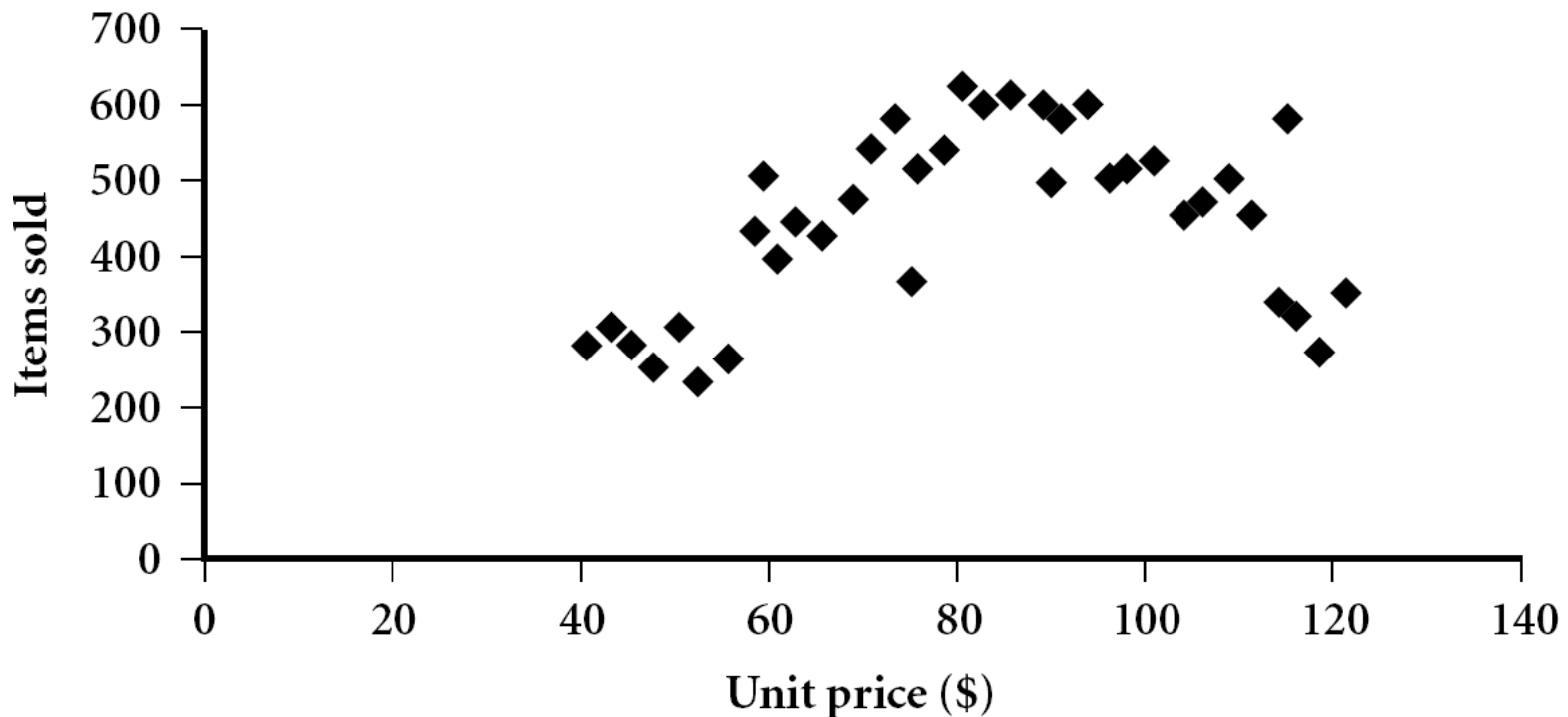
Histograms Often Tell More than Boxplots



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

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



Similarity and Dissimilarity Measures

- Similarity measure
 - Numerical measure of how alike two data objects are.
 - Is higher when objects are more alike.
 - Often falls in the range $[0,1]$
- Dissimilarity measure
 - Numerical measure of how different two data objects are
 - Lower when objects are more alike
 - Minimum dissimilarity is often 0
 - Upper limit varies
- **Proximity** refers to a similarity or dissimilarity

Proximity Measure for Nominal Attributes

- Can take 2 or more states, e.g., red, yellow, blue, green (generalization of a binary attribute)
- 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

Proximity Measure for Binary Attributes

- A contingency table for binary data

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

- Distance measure for symmetric binary variables:

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

- Distance measure for asymmetric binary variables:

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

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

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

- Note: Jaccard coefficient is the same as "coherence":

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

Dissimilarity between Binary Variables

- Example

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

- Gender is a symmetric attribute
- The remaining attributes are asymmetric binary
- Let the values Y and P be 1, and the value N 0

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

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

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

Similarity/Dissimilarity for Simple Attributes

- The following table shows the similarity and dissimilarity between two objects, x and y , with respect to a single, simple attribute.

Attribute Type	Dissimilarity	Similarity
Nominal	$d = \begin{cases} 0 & \text{if } x = y \\ 1 & \text{if } x \neq y \end{cases}$	$s = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{if } x \neq y \end{cases}$
Ordinal	$d = x - y / (n - 1)$ (values mapped to integers 0 to $n-1$, where n is the number of values)	$s = 1 - d$
Interval or Ratio	$d = x - y $	$s = -d, s = \frac{1}{1+d}, s = e^{-d},$ $s = 1 - \frac{d - \min_d}{\max_d - \min_d}$

Euclidean Distance

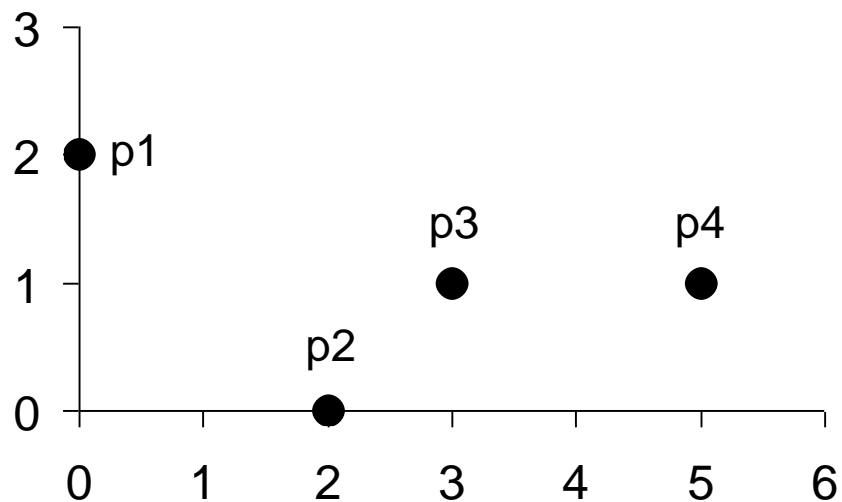
- Euclidean Distance

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{k=1}^n (x_k - y_k)^2}$$

where n is the number of dimensions (attributes) and x_k and y_k are, respectively, the k^{th} attributes (components) or data objects \mathbf{x} and \mathbf{y} .

- Standardization is necessary, if scales differ.

Euclidean Distance



point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

	p1	p2	p3	p4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
p3	3.162	1.414	0	2
p4	5.099	3.162	2	0

Minkowski Distance

- Minkowski Distance is a generalization of Euclidean Distance

$$d(\mathbf{x}, \mathbf{y}) = \left(\sum_{k=1}^n |x_k - y_k|^r \right)^{1/r}$$

Where r is a parameter, n is the number of dimensions (attributes) and x_k and y_k are, respectively, the k^{th} attributes (components) or data objects x and y .

Minkowski Distance: Examples

- $r = 1$. City block (Manhattan, taxicab, L_1 norm) distance.
 - A common example of this for binary vectors is the Hamming distance, which is just the number of bits that are different between two binary vectors
- $r = 2$. Euclidean distance
- $r \rightarrow \infty$. “supremum” (L_{\max} norm, L_{∞} norm) distance.
 - This is the maximum difference between any component of the vectors
- Do not confuse r with n , i.e., all these distances are defined for all numbers of dimensions.

Minkowski Distance

point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

L1	p1	p2	p3	p4
p1	0	4	4	6
p2	4	0	2	4
p3	4	2	0	2
p4	6	4	2	0

L2	p1	p2	p3	p4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
p3	3.162	1.414	0	2
p4	5.099	3.162	2	0

L_∞	p1	p2	p3	p4
p1	0	2	3	5
p2	2	0	1	3
p3	3	1	0	2
p4	5	3	2	0

Similarity Between Binary Vectors

- Common situation is that objects, \mathbf{x} and \mathbf{y} , have only binary attributes

- Compute similarities using the following quantities

f_{01} = the number of attributes where \mathbf{x} was 0 and \mathbf{y} was 1

f_{10} = the number of attributes where \mathbf{x} was 1 and \mathbf{y} was 0

f_{00} = the number of attributes where \mathbf{x} was 0 and \mathbf{y} was 0

f_{11} = the number of attributes where \mathbf{x} was 1 and \mathbf{y} was 1

- Simple Matching and Jaccard Coefficients

SMC = number of matches / number of attributes

$$= (f_{11} + f_{00}) / (f_{01} + f_{10} + f_{11} + f_{00})$$

J = number of 11 matches / number of non-zero attributes

$$= (f_{11}) / (f_{01} + f_{10} + f_{11})$$

SMC versus Jaccard: Example

$$\mathbf{x} = 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$$

$$\mathbf{y} = 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 1$$

$f_{01} = 2$ (the number of attributes where \mathbf{x} was 0 and \mathbf{y} was 1)

$f_{10} = 1$ (the number of attributes where \mathbf{x} was 1 and \mathbf{y} was 0)

$f_{00} = 7$ (the number of attributes where \mathbf{x} was 0 and \mathbf{y} was 0)

$f_{11} = 0$ (the number of attributes where \mathbf{x} was 1 and \mathbf{y} was 1)

$$\begin{aligned}\text{SMC} &= (f_{11} + f_{00}) / (f_{01} + f_{10} + f_{11} + f_{00}) \\ &= (0+7) / (2+1+0+7) = 0.7\end{aligned}$$

$$\text{J} = (f_{11}) / (f_{01} + f_{10} + f_{11}) = 0 / (2 + 1 + 0) = 0$$

Correlation measures the linear relationship between objects ⁴⁹

$$\text{corr}(\mathbf{x}, \mathbf{y}) = \frac{\text{covariance}(\mathbf{x}, \mathbf{y})}{\text{standard_deviation}(\mathbf{x}) * \text{standard_deviation}(\mathbf{y})} = \frac{s_{xy}}{s_x s_y}, \quad (2.11)$$

where we are using the following standard statistical notation and definitions

$$\text{covariance}(\mathbf{x}, \mathbf{y}) = s_{xy} = \frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y}) \quad (2.12)$$

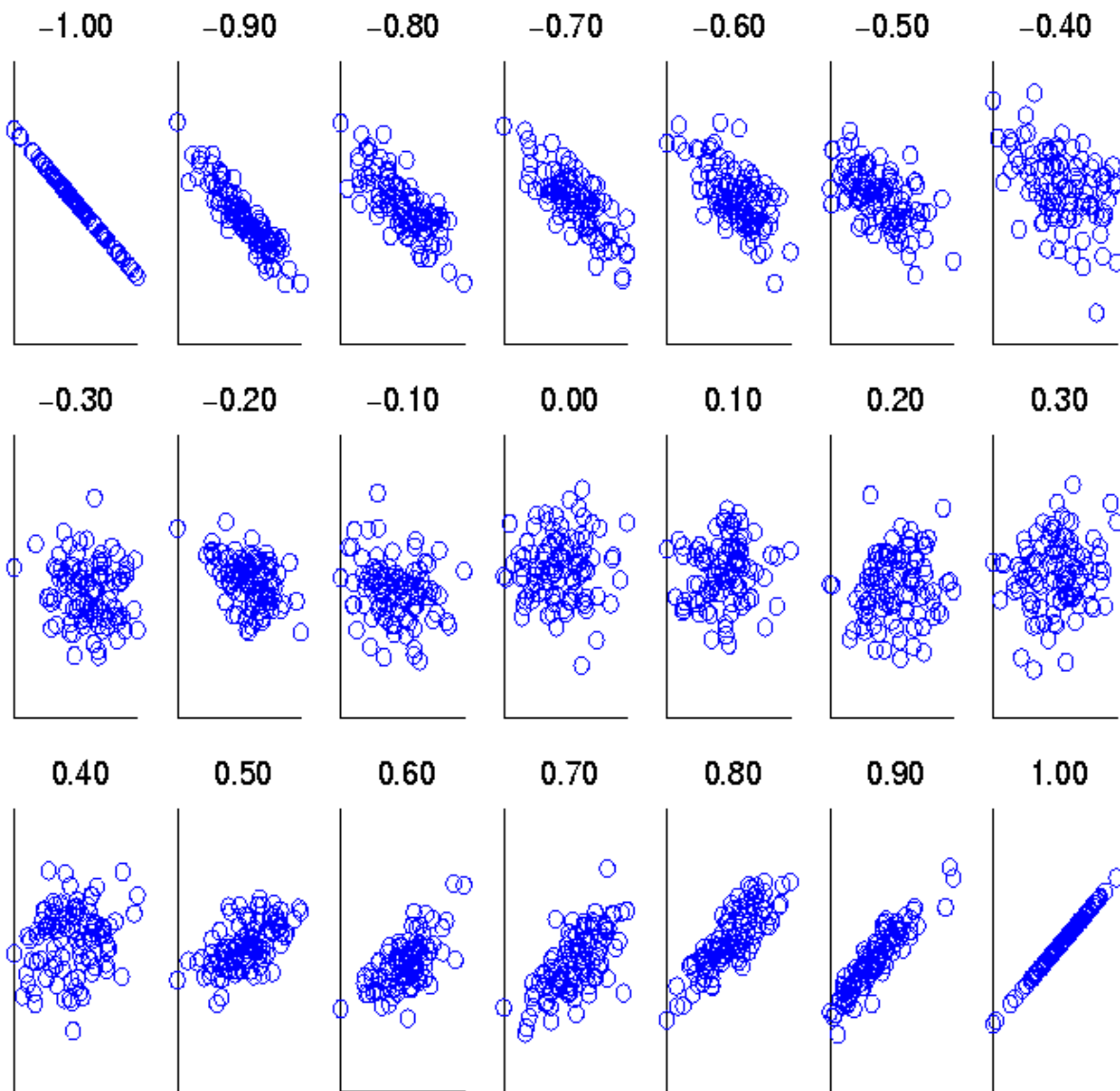
$$\text{standard_deviation}(\mathbf{x}) = s_x = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{x})^2}$$

$$\text{standard_deviation}(\mathbf{y}) = s_y = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (y_k - \bar{y})^2}$$

$$\bar{x} = \frac{1}{n} \sum_{k=1}^n x_k \text{ is the mean of } \mathbf{x}$$

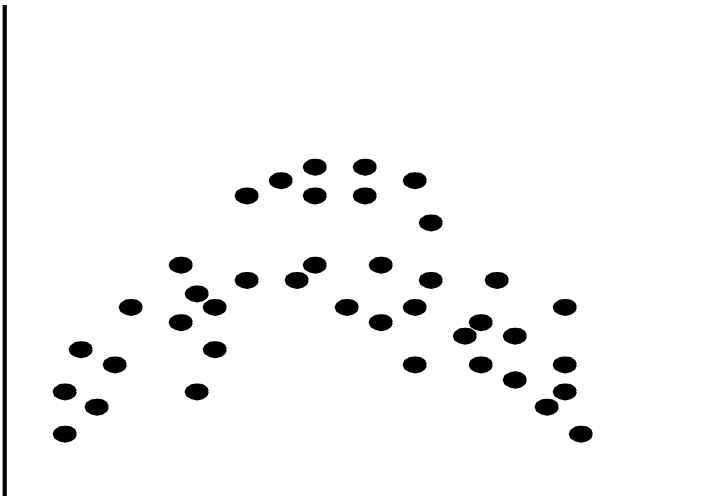
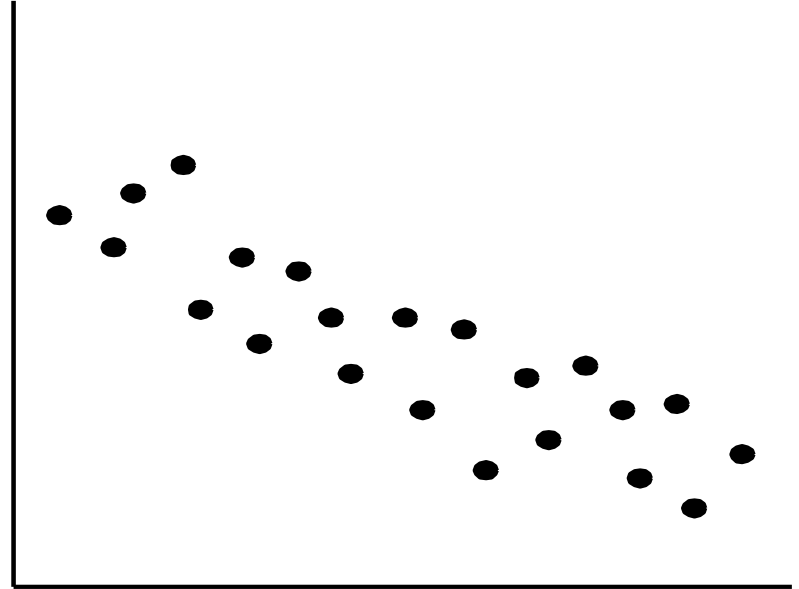
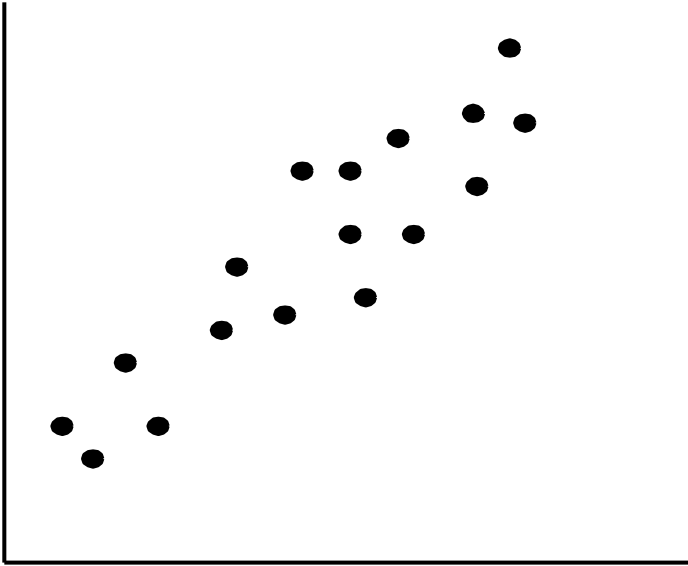
$$\bar{y} = \frac{1}{n} \sum_{k=1}^n y_k \text{ is the mean of } \mathbf{y}$$

Visually Evaluating Correlation



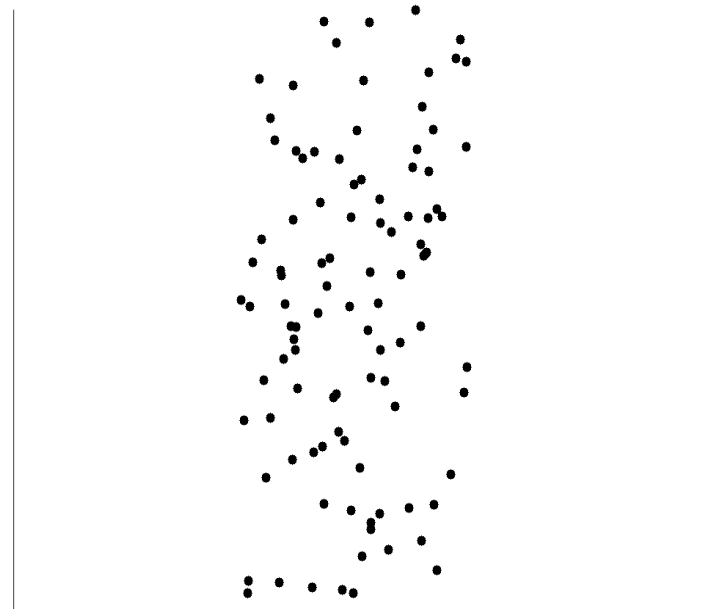
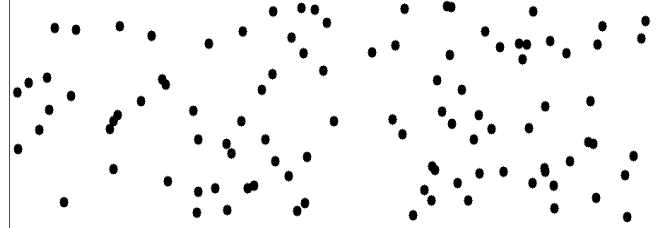
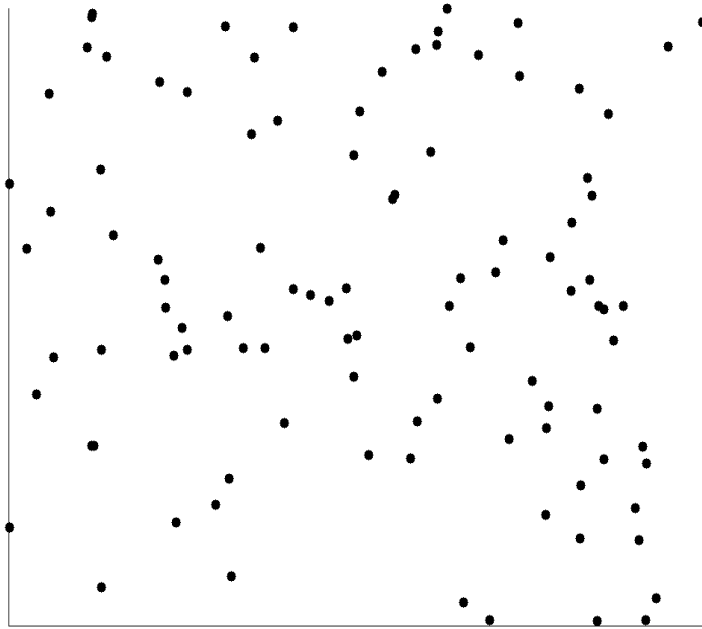
Scatter plots showing the similarity from -1 to 1.

Positively and Negatively Correlated Data



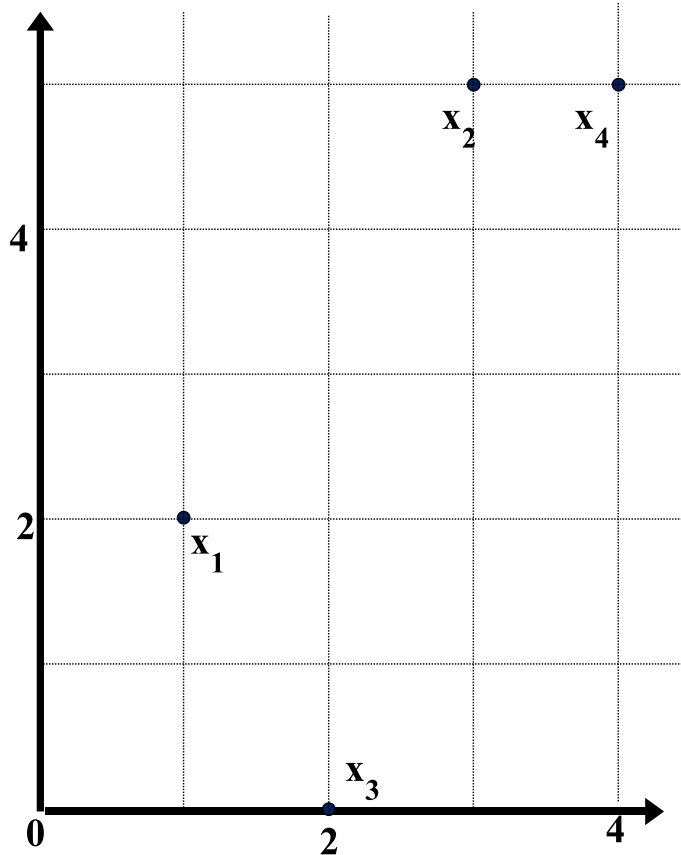
- The left half fragment is positively correlated
- The right half is negative correlated

Uncorrelated Data



Example:

Data Matrix and Dissimilarity Matrix



Data Matrix

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

Dissimilarity Matrix
(with **Euclidean Distance**)

	$x1$	$x2$	$x3$	$x4$
$x1$	0			
$x2$	3.61	0		
$x3$	5.1	5.1	0	
$x4$	4.24	1	5.39	0

Example: Minkowski Distance

Dissimilarity Matrices

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

Manhattan (L_1)

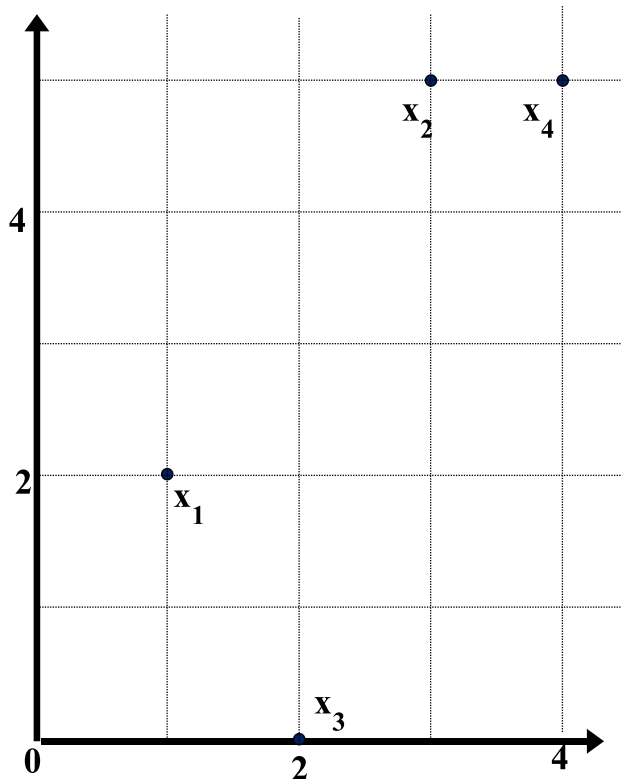
L	x1	x2	x3	x4
x1	0			
x2	5	0		
x3	3	6	0	
x4	6	1	7	0

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_∞	x1	x2	x3	x4
x1	0			
x2	3	0		
x3	2	5	0	
x4	3	1	5	0



Cosine Similarity

- A **document** can be represented by thousands of attributes, each recording the *frequency* of a particular word (such as keywords) or phrase in the document.

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

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

$$\cos(d_1, d_2) = (d_1 \bullet d_2) / (||d_1|| ||d_2||),$$

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

Example: Cosine Similarity

- $\cos(d_1, d_2) = (d_1 \bullet d_2) / (||d_1|| ||d_2||)$,
where \bullet indicates vector dot product, $||d||$: the length of vector d
- Ex: Find the **similarity** between documents 1 and 2.

$$d_1 = (5, 0, 3, 0, 2, 0, 0, 2, 0, 0)$$

$$d_2 = (3, 0, 2, 0, 1, 1, 0, 1, 0, 1)$$


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

$$||d_1|| = (5*5 + 0*0 + 3*3 + 0*0 + 2*2 + 0*0 + 0*0 + 2*2 + 0*0 + 0*0)^{0.5} = (42)^{0.5} \\ = 6.481$$

$$||d_2|| = (3*3 + 0*0 + 2*2 + 0*0 + 1*1 + 1*1 + 0*0 + 1*1 + 0*0 + 1*1)^{0.5} = (17)^{0.5} \\ = 4.12$$

$$\cos(d_1, d_2) = 0.94$$

Chapter 2: Getting to Know Your Data

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

Summary

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

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