

C5: Description on Data (Chapter 2 in Vipin's book)

October 30, 2019

Tentative Class Agenda

- Class 8 – (10/30) Introduction to data
- Class 9 – (11/6) More on data, OLAP (HW#4)
- Class 10 – (11/13) Introduction to data mining, Classification
- Class 11 – (11/20) Association (HW#5)
- Class 12 – (11/27) Clustering and others
- Class 13 – (12/4) R (HW#6)
- Class 14 – (12/11) Exam (in class, closed book)
- Class 15 – (12/18) Project presentation I
- Class 16 – (12/25) Project presentation II

Data

Recap: Procedure of Data Mining

- Obtain and look over the data
- Decide your goal (usually a stretched and reachable one)
- Data cleaning/cleansing
- Choose data granularity, feature selection
- Apply mining methods
- Decide what to output and in what form
- Interpret your results (may have iterative refinements); convince your receiver/boss



What is Data?

- 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

Attributes

Objects

Tid	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

Attribute Values

- Attribute values are numbers or symbols assigned to an attribute
 - Data granularity
- Distinction between attributes and attribute values
 - Same attribute can be mapped to different attribute values
 - ◆ Example: height can be measured in feet or meters
 - Different attributes can be mapped to the same set of values
 - ◆ Example: Attribute values for ID and age are integers
 - ◆ But properties of attribute values can be different

Types of Attributes

- There are different types of attributes
 - **Nominal**
 - ◆ Examples: ID numbers, eye color, zip codes
 - **Ordinal**
 - ◆ Examples: rankings (e.g., taste of potato chips on a scale from 1-10), grades, height in {tall, medium, short}
 - **Interval**
 - ◆ Examples: calendar dates, temperatures in Celsius or Fahrenheit.
 - **Ratio**
 - ◆ Examples: temperature in Kelvin, length, time, counts

Properties of Attribute Values

- The type of an attribute depends on which of the following properties it possesses:
 - Distinctness: $= \neq$
 - Order: $< >$
 - Addition: $+ -$
 - Multiplication: $* /$
 - Nominal attribute: distinctness
 - Ordinal attribute: distinctness & order
 - Interval attribute: distinctness, order & addition
 - Ratio attribute: all 4 properties

Discrete and Continuous Attributes

- Discrete Attribute
 - Has only a finite or countably infinite set of values
 - Examples: zip codes, counts, or the set of words in a collection of documents
 - Often represented as integer variables.
 - Note: binary attributes are a special case of discrete attributes
- Continuous Attribute
 - Has real numbers as attribute values
 - Examples: 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

- **Record**

- Data Matrix
- Document Data
- Transaction Data

- **Graph**

- World Wide Web
- Molecular Structures

- **Ordered**

- Spatial Data
- Temporal Data
- Sequential Data
- Genetic Sequence Data

Important Characteristics of Structured Data

- **Dimensionality**
 - ◆ Curse of Dimensionality
- **Sparsity**
 - ◆ Only presence counts
- **Resolution**
 - ◆ Patterns depend on the scale

Record Data

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

<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

Data Matrix

- If data objects have the same fixed set of numeric attributes, then the data objects can be thought of as points in a multi-dimensional space, where each dimension represents a distinct attribute
- Such data set can be represented by an m by n matrix, where there are m rows, one for each object, and n columns, one for each attribute

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.

	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

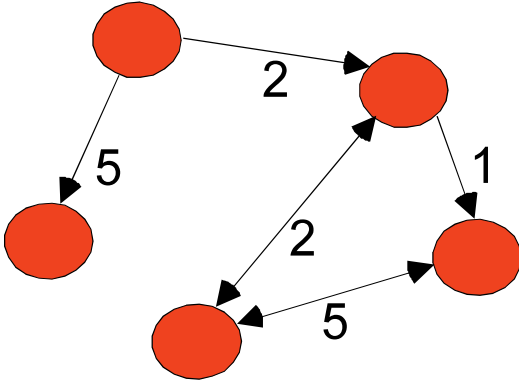
Transaction Data

- A special type of record data, where
 - each record (transaction) involves a set of items.
 - For example, consider a grocery store. The set of products purchased by a customer during one shopping trip constitute a transaction, while the individual products that were purchased are the 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

Graph Data

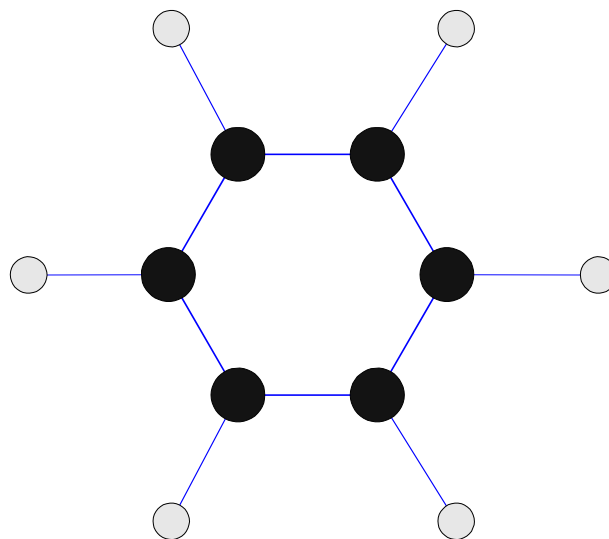
- Examples: Generic graph and HTML Links



```
<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
```

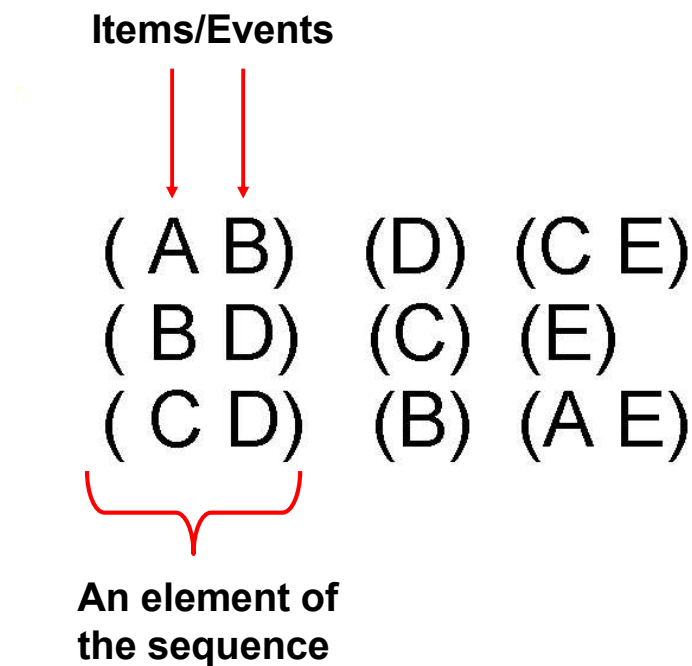
Chemical Data

- Benzene Molecule: C_6H_6



Ordered Data

- Sequences of transactions

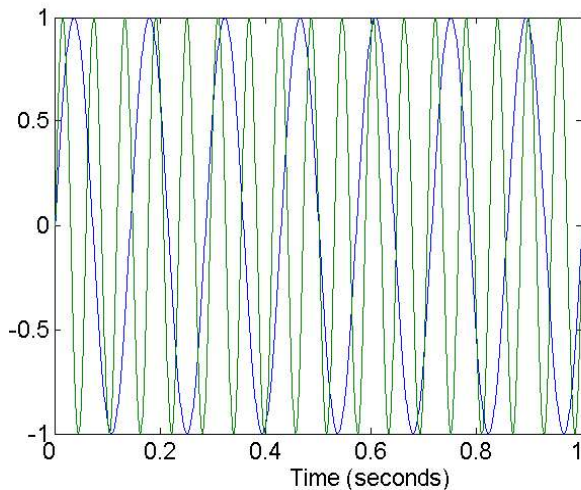


Data Quality

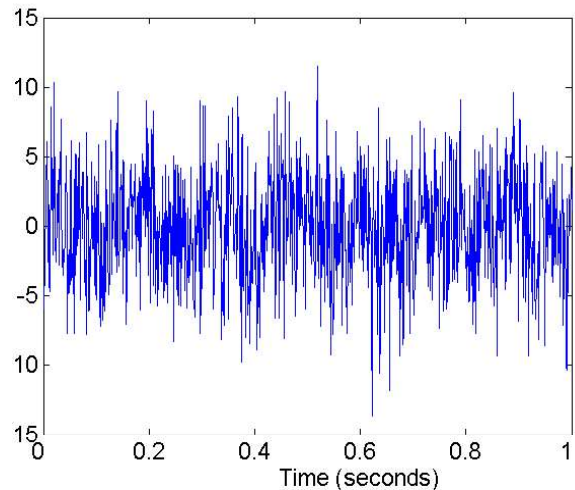
- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?
- Examples of data quality problems:
 - Noise and outliers
 - missing values
 - duplicate data

Noise

- 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



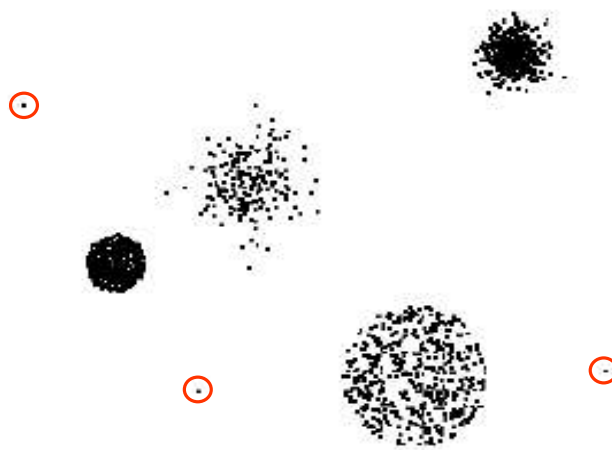
Two Sine Waves



Two Sine Waves + Noise

Outliers

- Outliers are data objects with characteristics that are considerably different than most of the other data objects in the data set



Missing Values

- Reasons for missing values
 - Information is not collected (e.g., people decline to give their age and weight)
 - Attributes may not be applicable to all cases (e.g., annual income is not applicable to children)
- Handling missing values
 - Eliminate Data Objects
 - Estimate Missing Values
 - Ignore the Missing Value During Analysis
 - Replace with all possible values (weighted by their probabilities)

Duplicate Data

- Data set may include data objects that are duplicates, or almost duplicates of one another
 - Major issue when merging data from heterogeneous sources
- Examples:
 - Same person with multiple email addresses
- Data cleaning
 - Process of dealing with duplicate (missing, erroneous, etc) data issues

Data Preprocessing

Data Preprocessing

- Aggregation
- Sampling
- Dimensionality Reduction
- Feature subset selection
- Feature creation
- Discretization and Binarization
- Attribute Transformation

Aggregation

- Combining two or more attributes (or objects) into a single attribute (or object)
- Purpose
 - Data reduction
 - ◆ Reduce the number of attributes or objects
 - Change of scale
 - ◆ Cities aggregated into regions, states, countries, etc
 - More “stable” data
 - ◆ Aggregated data tends to have less variability

Sampling

- **Sampling is the main technique employed for data selection.**
 - It is often used for both the preliminary investigation of the data and the final data analysis.
- **Statisticians sample because **obtaining** the entire set of data of interest is too expensive or time consuming.**
- **Sampling is used in data mining because **processing** the entire set of data of interest is too expensive or time consuming.**

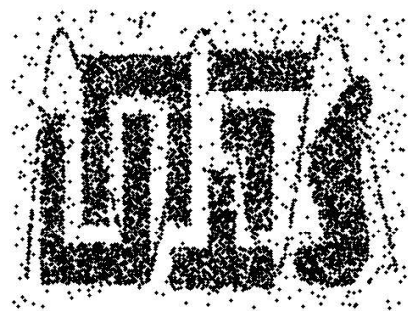
Sampling ...

- The key principle for effective sampling is the following:
 - using a sample will work almost as well as using the entire data sets, if the sample is representative
 - A sample is representative if it has approximately the same property (of interest) as the original set of data

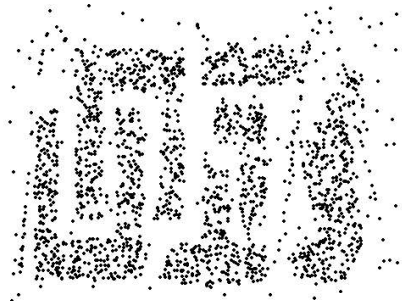
Types of Sampling

- Simple Random Sampling
 - There is an equal probability of selecting any particular item
- Sampling without replacement
 - As each item is selected, it is removed from the population
- Sampling with replacement
 - Objects are not removed from the population as they are selected for the sample.
 - ◆ In sampling with replacement, the same object can be picked up more than once
- Stratified sampling
 - Split the data into several partitions; then draw random samples from each partition (e.g., poll)

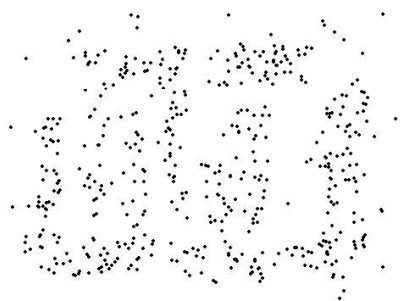
Sample Size



8000 points



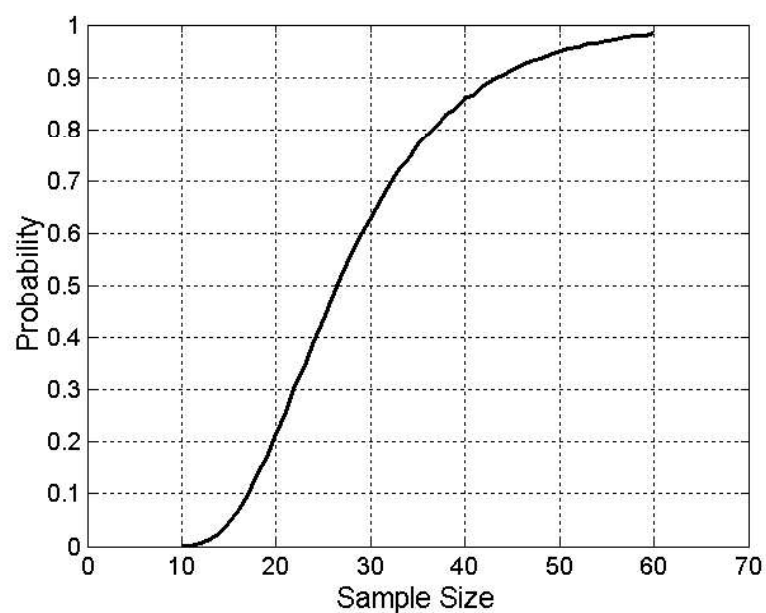
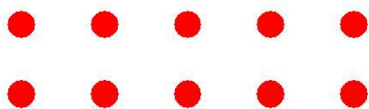
2000 Points



500 Points

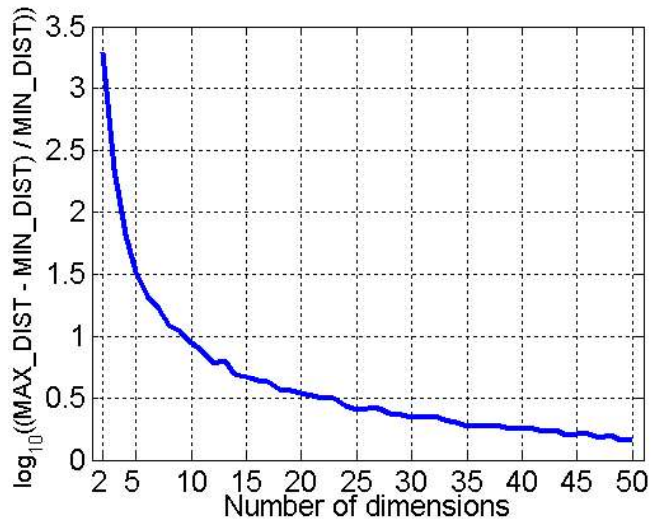
Sample Size

- What sample size is necessary to get at least one object from each of 10 groups (with replacement)



Curse of Dimensionality

- When dimensionality increases, data becomes increasingly sparse in the space that it occupies
- Definitions of density and distance between points, which is critical for clustering and outlier detection, become less meaningful



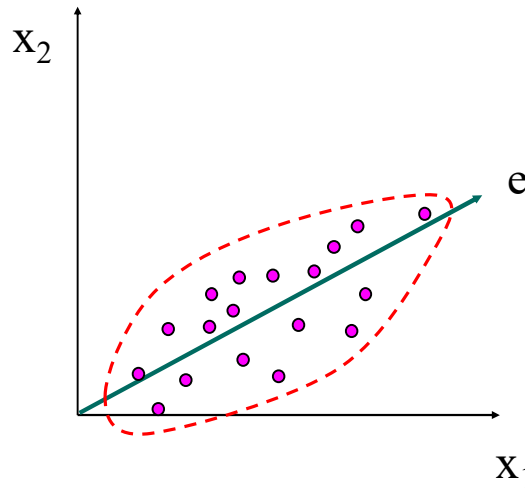
- Randomly generate 500 points
- Compute difference between max and min distance between any pair of points

Dimensionality Reduction

- Purpose:
 - Avoid curse of dimensionality
 - Reduce amount of time and memory required by data mining algorithms
 - Allow data to be more easily visualized
 - May help to eliminate irrelevant features or reduce noise
- Techniques
 - Principle Component Analysis
 - Singular Value Decomposition
 - Others: supervised and non-linear techniques

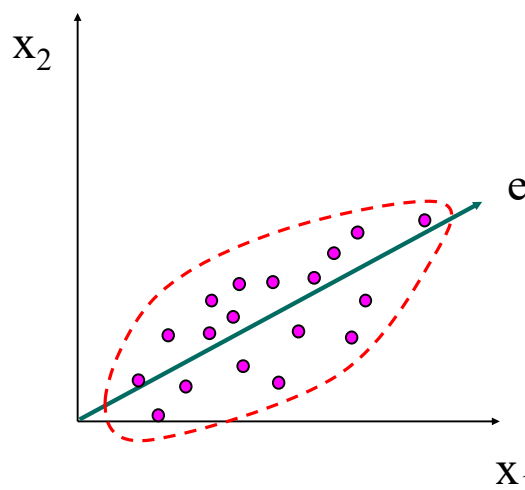
Dimensionality Reduction: PCA

- Goal is to find a projection that captures the largest amount of variation in data



Dimensionality Reduction: PCA

- Find the eigenvectors of the covariance matrix
- The eigenvectors define the new space

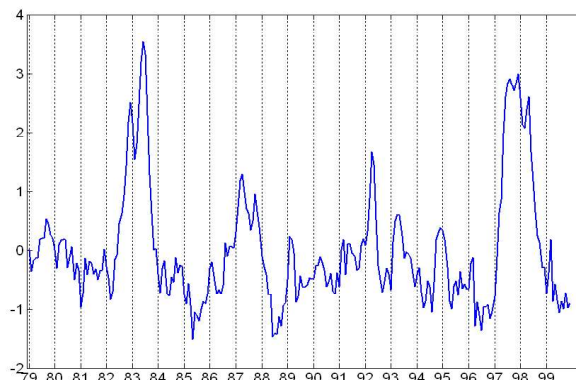


Feature Subset Selection

- Another way to reduce dimensionality of data
- Redundant features
 - duplicate much or all of the information contained in one or more other attributes
 - Example: purchase price of a product and the amount of sales tax paid
- Irrelevant features
 - contain no information that is useful for the data mining task at hand
 - Example: students' ID is often irrelevant to the task of predicting students' GPA

Attribute Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values such that each old value can be identified with one of the new values
 - Simple functions: x^k , $\log(x)$, e^x , $|x|$
 - Standardization and Normalization



On Data Similarity/Dissimilarity (Distance)

Example use: Clustering

Similarity and Dissimilarity

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

Similarity/Dissimilarity for Simple Attributes

p and q are the attribute values for two data objects.

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

Table 5.1. Similarity and dissimilarity for simple attributes

Euclidean Distance

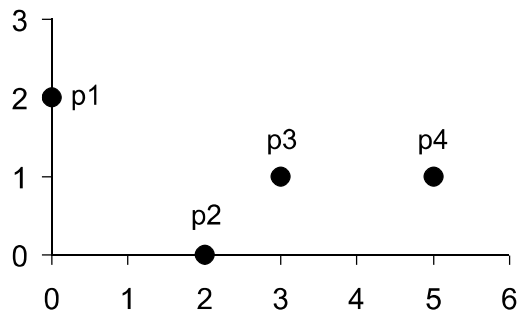
- Euclidean Distance

$$dist = \sqrt{\sum_{k=1}^n (p_k - q_k)^2}$$

Where n is the number of dimensions (attributes) and p_k and q_k are, respectively, the k^{th} attributes (components) or data objects p and q .

- 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

Distance Matrix

Minkowski Distance

- Minkowski Distance is a generalization of Euclidean Distance

$$dist = \left(\sum_{k=1}^n |p_k - q_k|^r \right)^{\frac{1}{r}}$$

Where r is a parameter, n is the number of dimensions (attributes) and p_k and q_k are, respectively, the k th attributes (components) or data objects p and q .

Minkowski Distance: Examples

- $r = 1$. City block (Manhattan, taxicab, L_1 norm) distance.
 - A common example of this 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

Distance Matrix

Common Properties of a Distance

- Distances, such as the Euclidean distance, have some well known properties.

1. $d(p, q) \geq 0$ for all p and q and $d(p, q) = 0$ only if $p = q$. (Positive definiteness)
2. $d(p, q) = d(q, p)$ for all p and q . (Symmetry)
3. $d(p, r) \leq d(p, q) + d(q, r)$ for all points p, q , and r . (Triangle Inequality)

where $d(p, q)$ is the distance (dissimilarity) between points (data objects), p and q .

- A distance that satisfies these properties is a **metric**

Common Properties of a Similarity

- Similarities, also have some well known properties.

1. $s(p, q) = 1$ (or maximum similarity) only if $p = q$.
2. $s(p, q) = s(q, p)$ for all p and q . (Symmetry)

where $s(p, q)$ is the similarity between points (data objects), p and q .

Similarity Between Binary Vectors

- Common situation is that objects, p and q , have only binary attributes

- Compute similarities using the following quantities

M_{01} = the number of attributes where p was 0 and q was 1

M_{10} = the number of attributes where p was 1 and q was 0

M_{00} = the number of attributes where p was 0 and q was 0

M_{11} = the number of attributes where p was 1 and q was 1

- Simple Matching and Jaccard Coefficients

SMC = number of matches / number of attributes

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

J = number of 11 matches / number of not-both-zero attributes values

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

SMC versus Jaccard: Example

$p = 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$

$q = 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 1$

$M_{01} = 2$ (the number of attributes where p was 0 and q was 1)

$M_{10} = 1$ (the number of attributes where p was 1 and q was 0)

$M_{00} = 7$ (the number of attributes where p was 0 and q was 0)

$M_{11} = 0$ (the number of attributes where p was 1 and q was 1)

$$\text{SMC} = (M_{11} + M_{00}) / (M_{01} + M_{10} + M_{11} + M_{00}) = (0 + 7) / (2 + 1 + 0 + 7) = 0.7$$

$$J = (M_{11}) / (M_{01} + M_{10} + M_{11}) = 0 / (2 + 1 + 0) = 0$$

Cosine Similarity

- If d_1 and d_2 are two document vectors, then

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

where \bullet indicates vector dot product and $\|d\|$ is the length of vector d .

- Example:

$$d_1 = 3 \ 2 \ 0 \ 5 \ 0 \ 0 \ 0 \ 2 \ 0 \ 0$$

$$d_2 = 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 2$$

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

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

$$\|d_2\| = (1^2 + 0^2 + 0^2 + 0^2 + 0^2 + 0^2 + 0^2 + 1^2 + 0^2 + 2^2)^{0.5} = (6)^{0.5} = 2.245$$

$$\cos(d_1, d_2) = .3150$$

Correlation

- Correlation measures the linear relationship between objects
- To compute correlation, we standardize data objects, p and q , and then take their dot product

$$p'_k = (p_k - \text{mean}(p)) / \text{std}(p)$$

$$q'_k = (q_k - \text{mean}(q)) / \text{std}(q)$$

$$\text{correlation}(p, q) = p' \bullet q'$$

General Approach for Combining Similarities

- Sometimes attributes are of many different types, but an overall similarity is needed.

1. For the k^{th} attribute, compute a similarity, s_k , in the range $[0, 1]$.
2. Define an indicator variable, δ_k , for the k^{th} attribute as follows:

$$\delta_k = \begin{cases} 0 & \text{if the } k^{th} \text{ attribute is a binary asymmetric attribute and both objects have} \\ & \text{a value of 0, or if one of the objects has a missing value for the } k^{th} \text{ attribute} \\ 1 & \text{otherwise} \end{cases}$$

3. Compute the overall similarity between the two objects using the following formula:

$$similarity(p, q) = \frac{\sum_{k=1}^n \delta_k s_k}{\sum_{k=1}^n \delta_k}$$

Using Weights to Combine Similarities

- May not want to treat all attributes the same.
 - Use weights w_k which are between 0 and 1 and sum to 1.

$$similarity(p, q) = \frac{\sum_{k=1}^n w_k \delta_k s_k}{\sum_{k=1}^n \delta_k}$$

$$distance(p, q) = \left(\sum_{k=1}^n w_k |p_k - q_k|^r \right)^{1/r}$$

Density

- Density-based clustering require a notion of density
- Examples:
 - Euclidean density
 - ◆ Euclidean density = number of points per unit volume
 - Probability density
 - Graph-based density

Euclidean Density – Cell-based

- Simplest approach is to divide region into a number of rectangular cells of equal volume and define density as # of points the cell contains

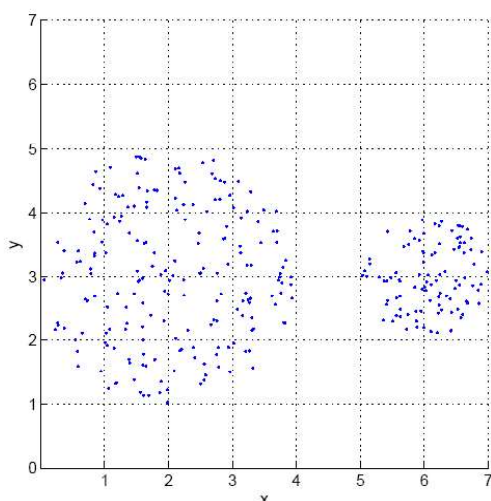


Figure 7.13. Cell-based density.

0	0	0	0	0	0	0
0	0	0	0	0	0	0
4	17	18	6	0	0	0
14	14	13	13	0	18	27
11	18	10	21	0	24	31
3	20	14	4	0	0	0
0	0	0	0	0	0	0

Table 7.6. Point counts for each grid cell.

Euclidean Density – Center-based

- Euclidean density is the number of points within a specified radius of the point

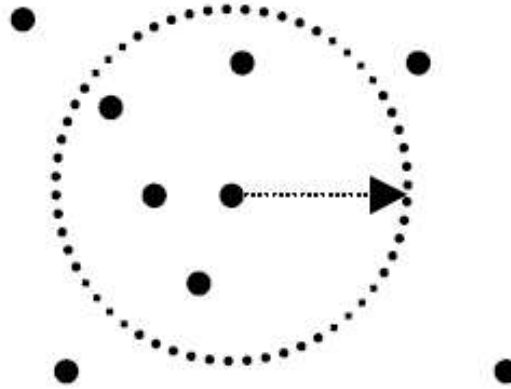


Figure 7.14. Illustration of center-based density.