Data preprocessing

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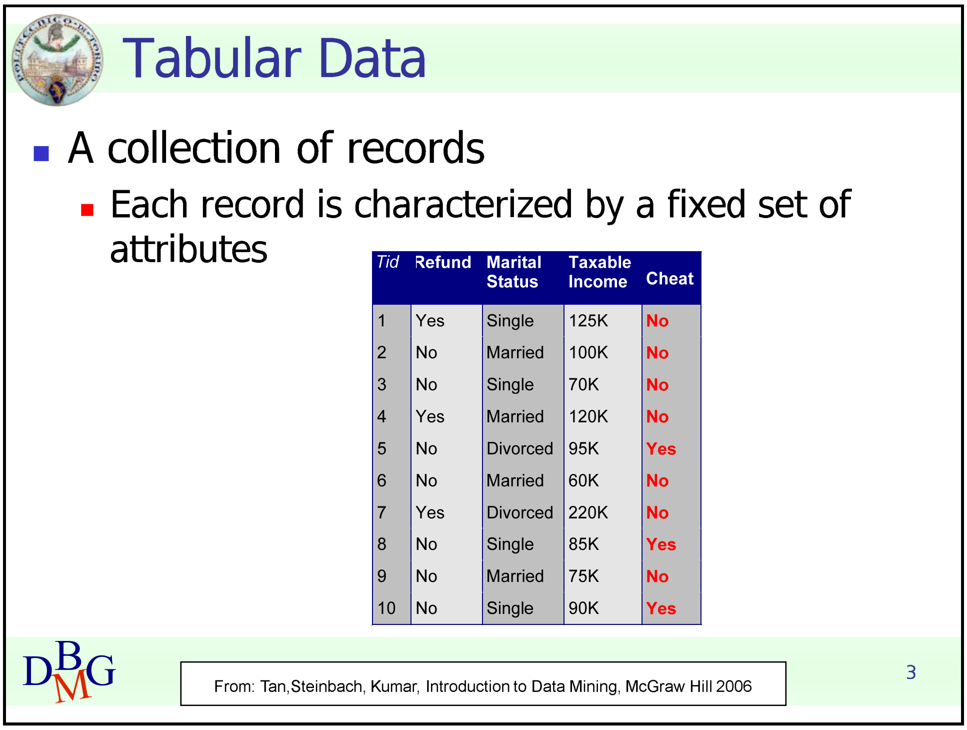
Data set types

- Record
  - Tables
  - Document Data
  - Transaction Data
- Graph
  - World Wide Web
  - Molecular Structures
- Ordered
  - Spatial Data
  - Temporal Data
  - Sequential Data
  - Genetic Sequence Data

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006



Tabular Data

- A collection of records
  - Each record is characterized by a fixed set of attributes

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**

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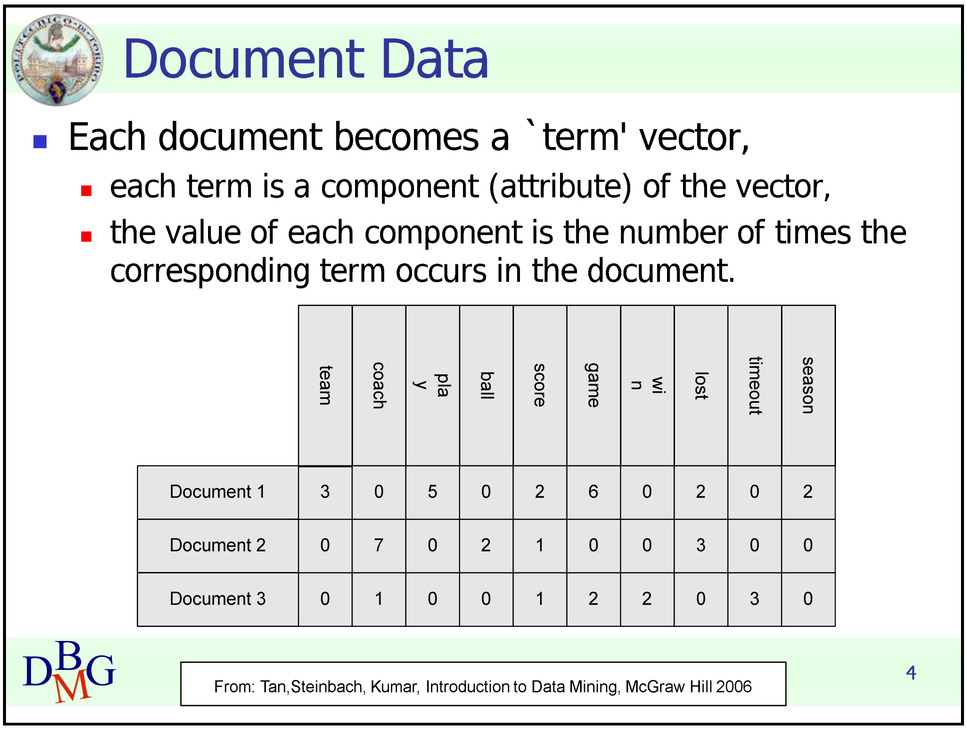

Document Data

- 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

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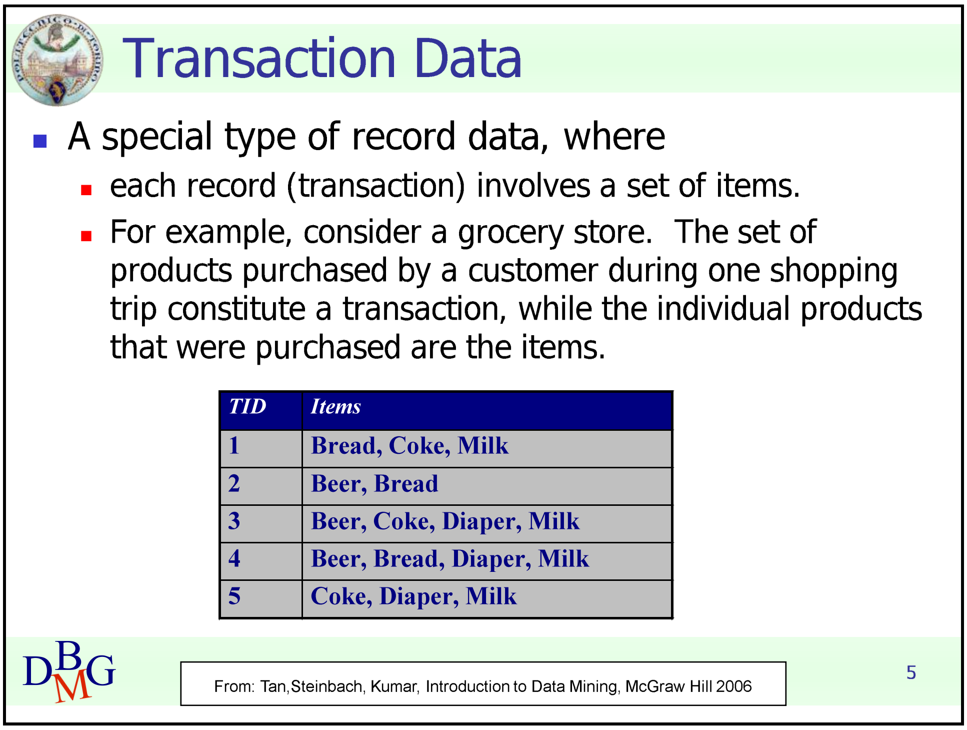

Transaction Data

- 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.

TID	*Items*
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

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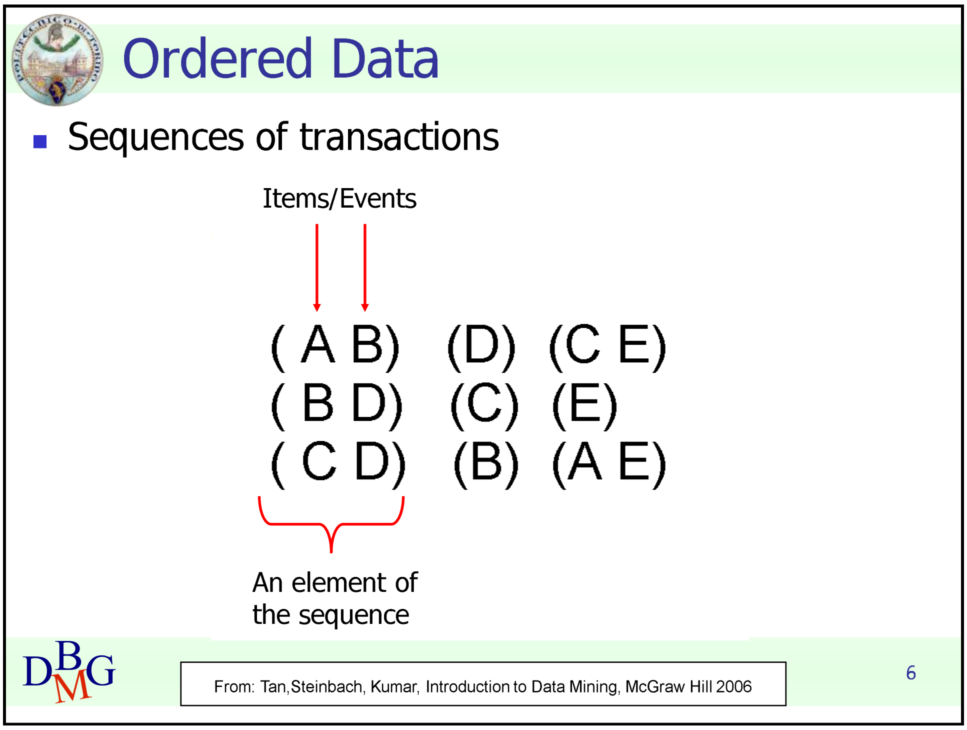

Ordered Data

- Sequences of transactions

Items/Events

(A B) (D) (C E)
(B D) (C) (E)
(C D) (B) (A E)

An element of the sequence

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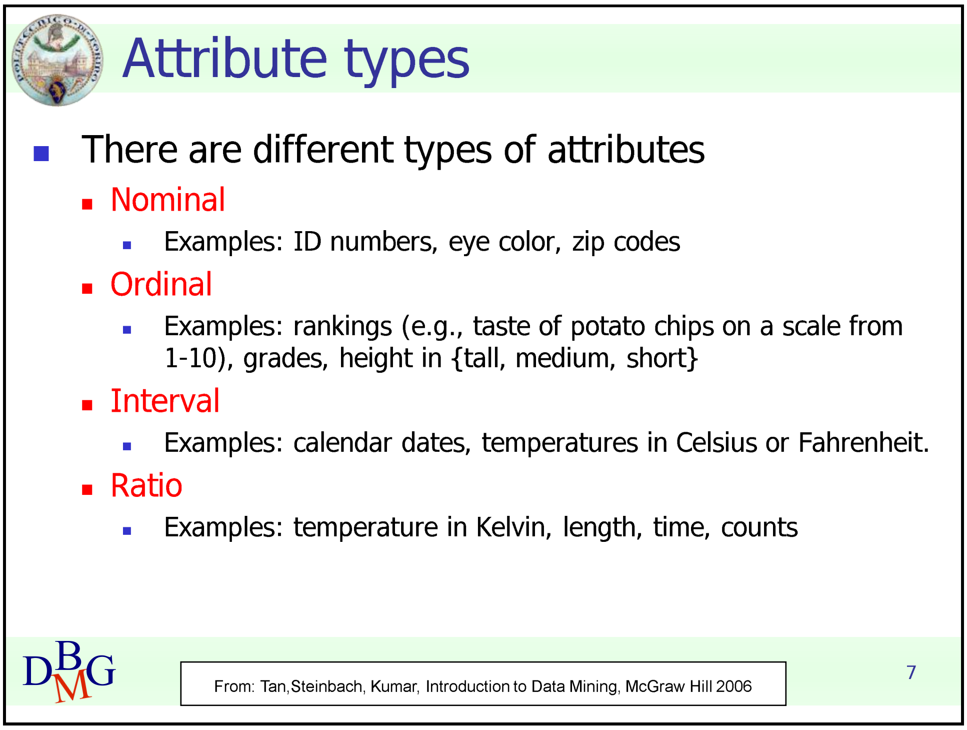

Attribute types

- 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

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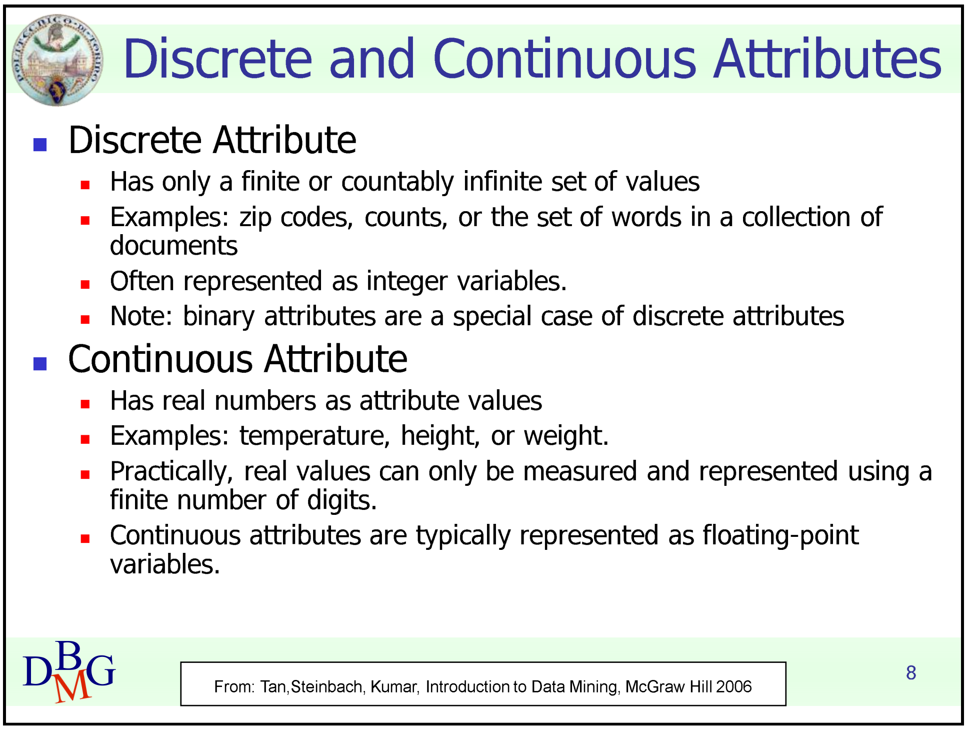

Discrete and Continuous Attributes

- 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.

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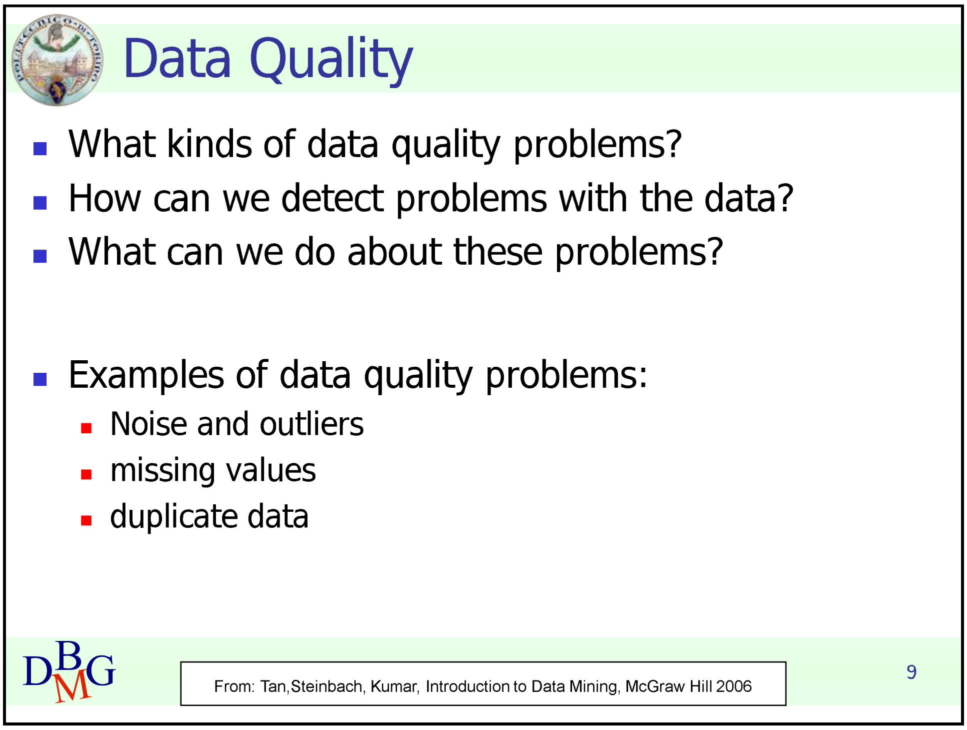

Data Quality

- 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
  - missing values
  - duplicate data

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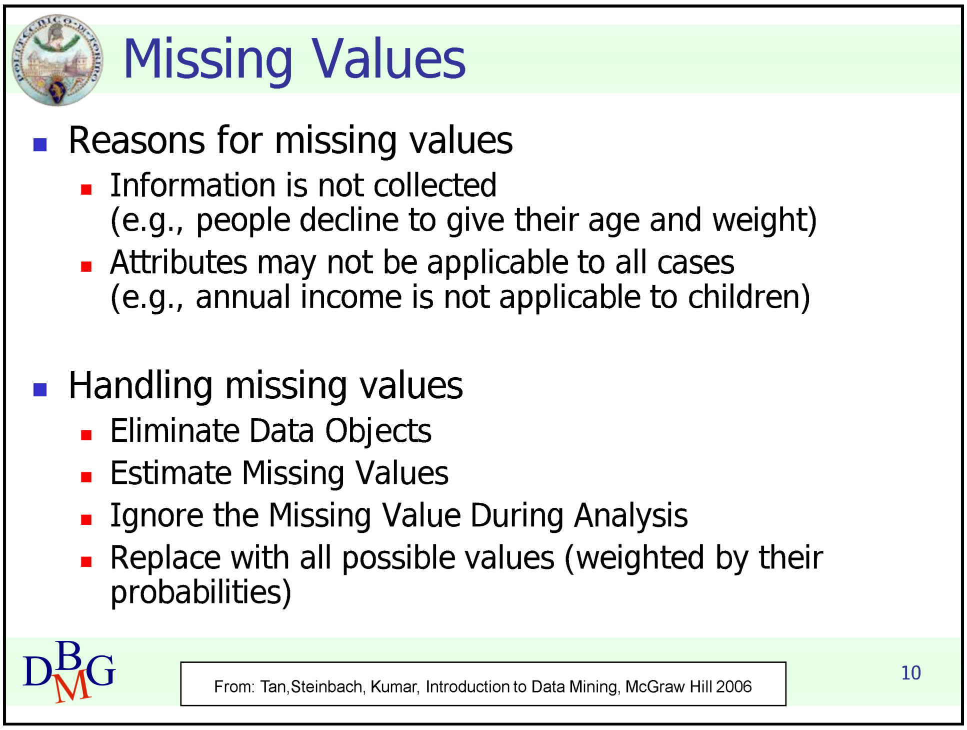

Missing Values

- 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)

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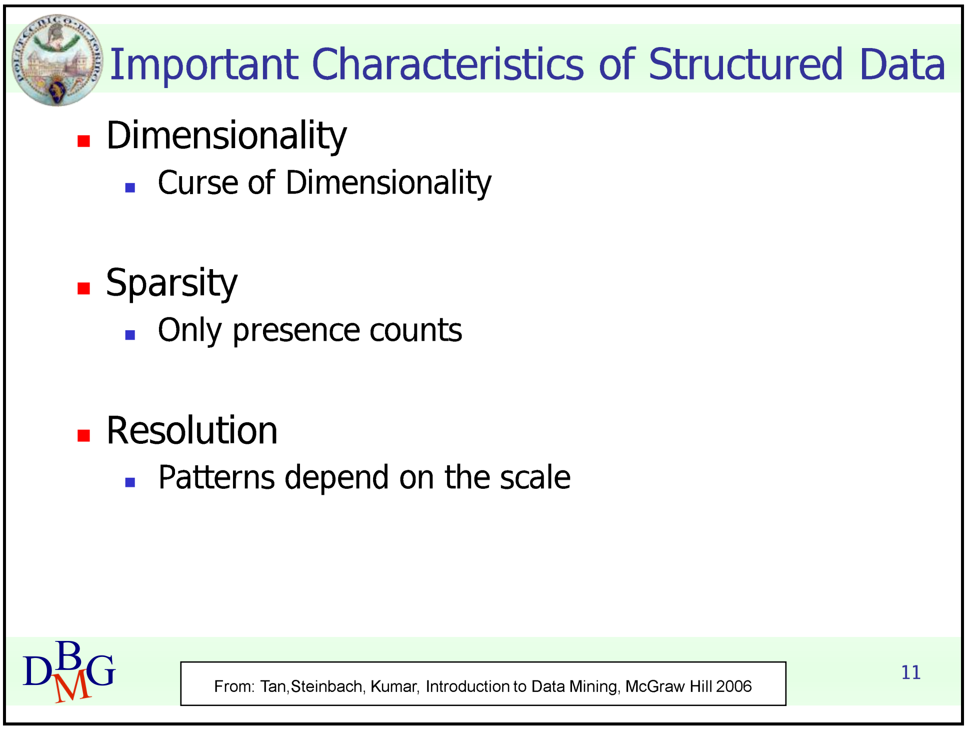

Important Characteristics of Structured Data

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

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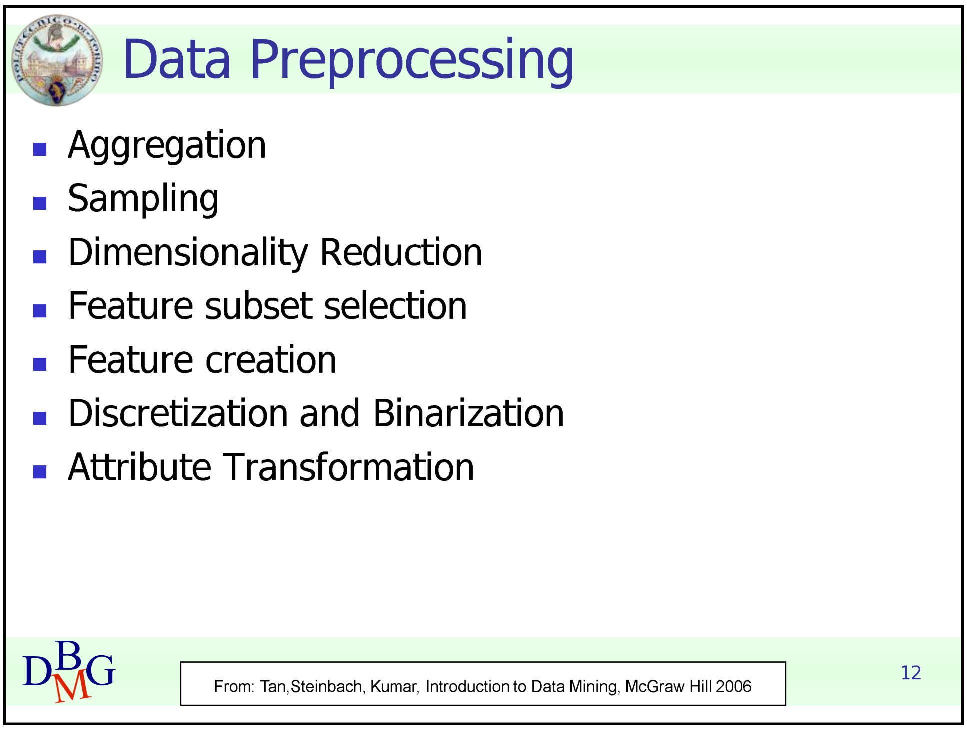
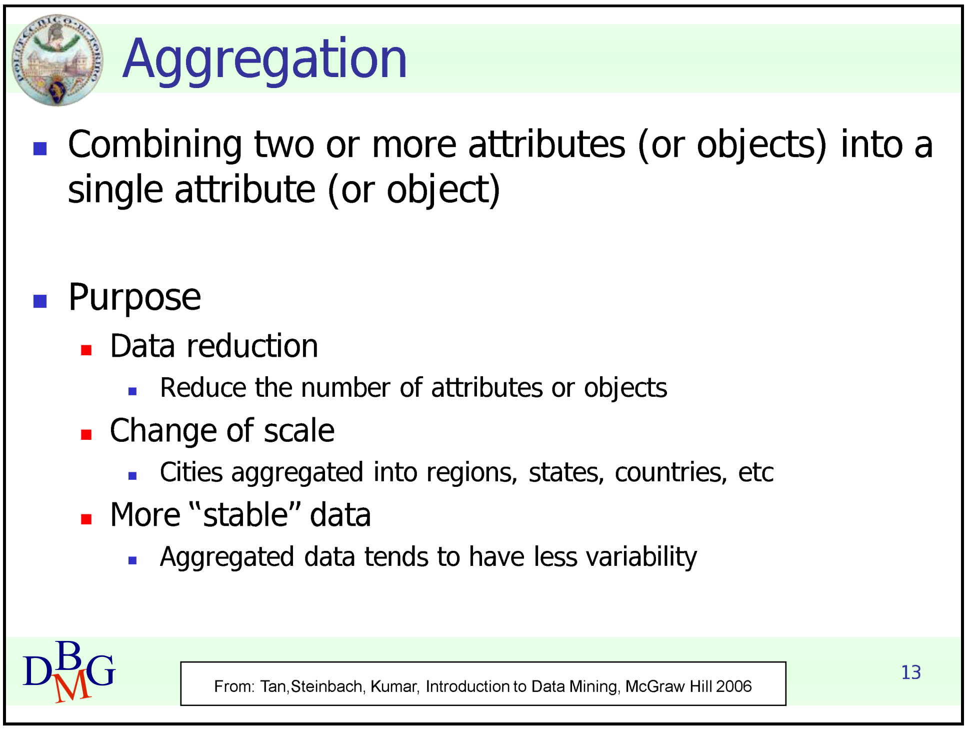


Data Preprocessing

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

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006



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

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

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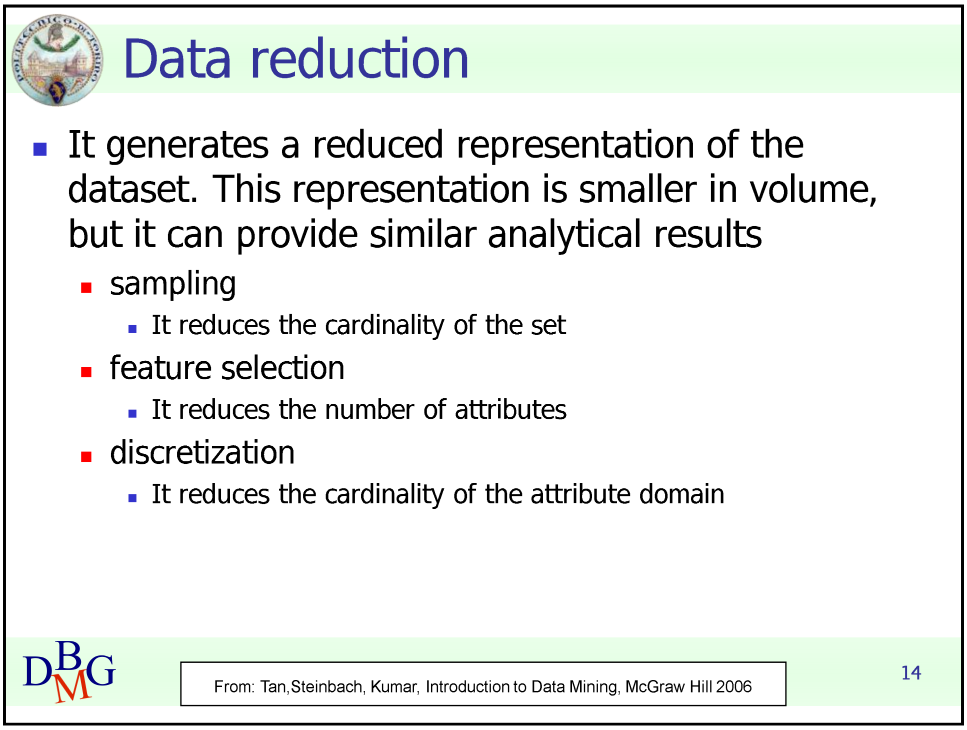

Data reduction

- It generates a reduced representation of the dataset. This representation is smaller in volume, but it can provide similar analytical results
  - sampling
    - It reduces the cardinality of the set
  - feature selection
    - It reduces the number of attributes
  - discretization
    - It reduces the cardinality of the attribute domain

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

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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

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

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

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

Dimensionality Reduction

- Purpose:
  - 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

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

Discretization

- It splits the domain of a continuous attribute in a set of intervals
  - It reduces the cardinality of the attribute domain
- Techniques
  - N intervals with the same width $W=(v_{max} – v_{min})/N$
    - Easy to implement
    - It can be badly affected by outliers and sparse data
    - Incremental approach
  - N intervals with (approximately) the same cardinality
    - It better fits sparse data and outliers
    - Non incremental approach
  - clustering
    - It well fits sparse data and outliers

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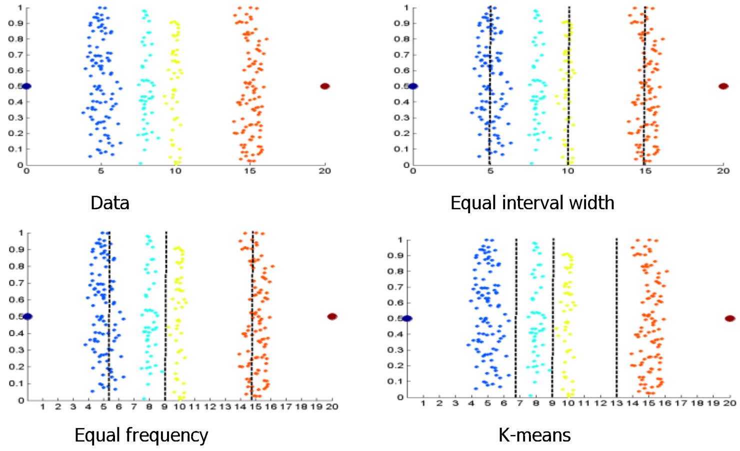
Discretization



Data

Equal interval width

Equal frequency

K-means

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Normalization

- It is a type of data transformation
  - The values of an attribute are scaled so as to fall within a small specified range, typically (-1,+1) or (0,+1)
- Techniques
  - min-max normalization

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

  - z-score normalization $v' = \frac{v - mean_A}{stand\_dev_A}$
  - decimal scaling

$$v' = \frac{v}{10^j}$$

j is the smallest integer such that max(|v'|)< 1

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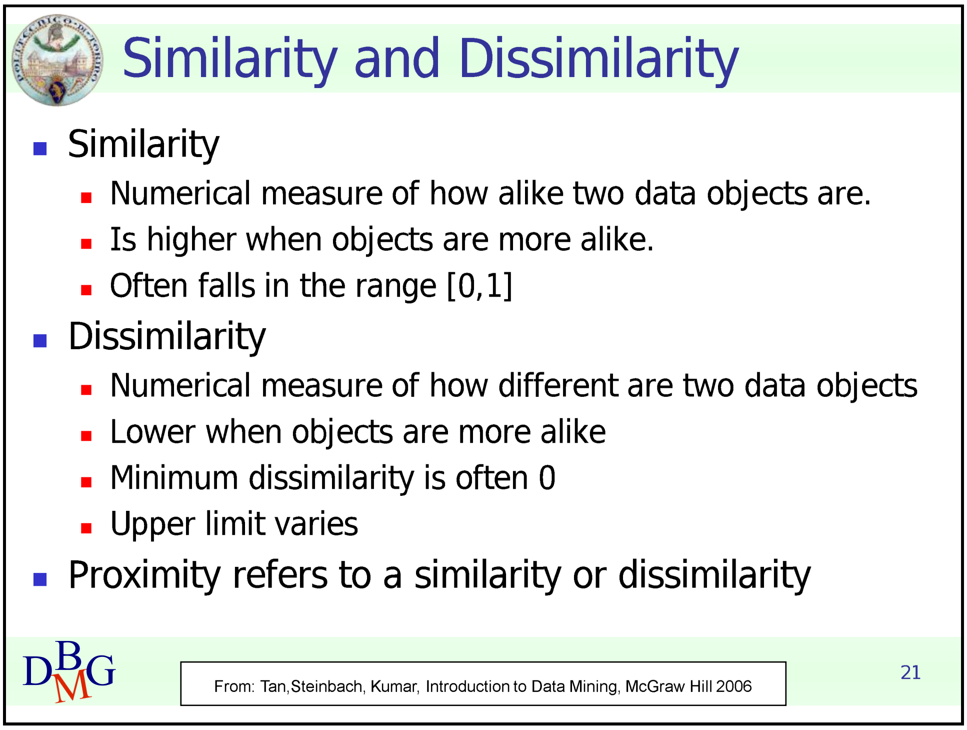

Similarity and Dissimilarity

- 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

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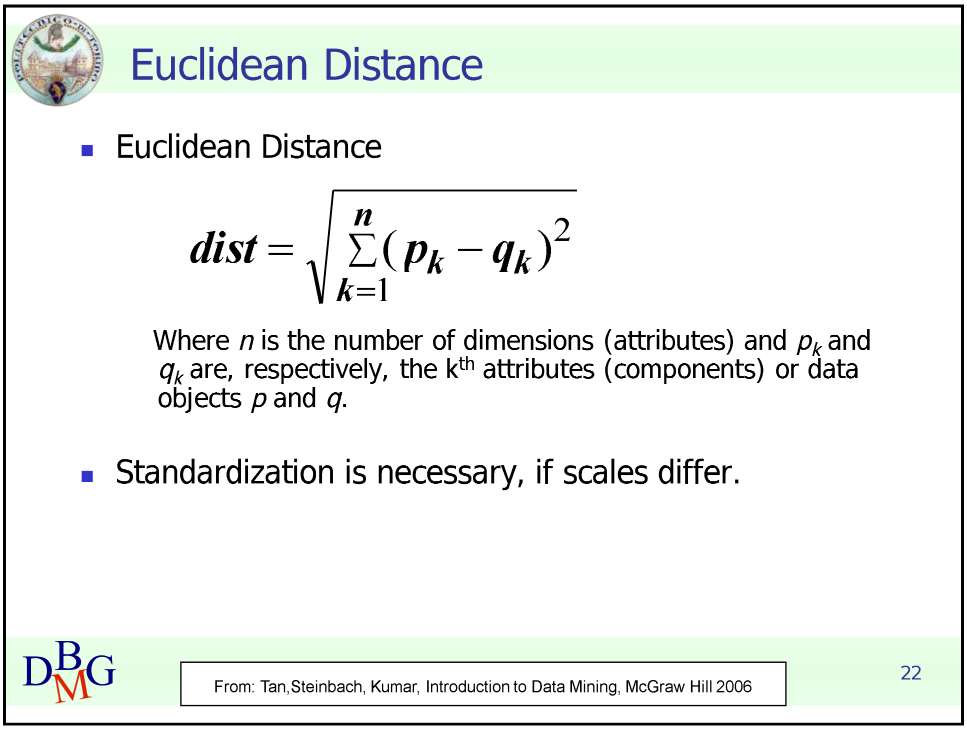

Euclidean Distance

- 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 kth attributes (components) or data objects p and q.

- Standardization is necessary, if scales differ.

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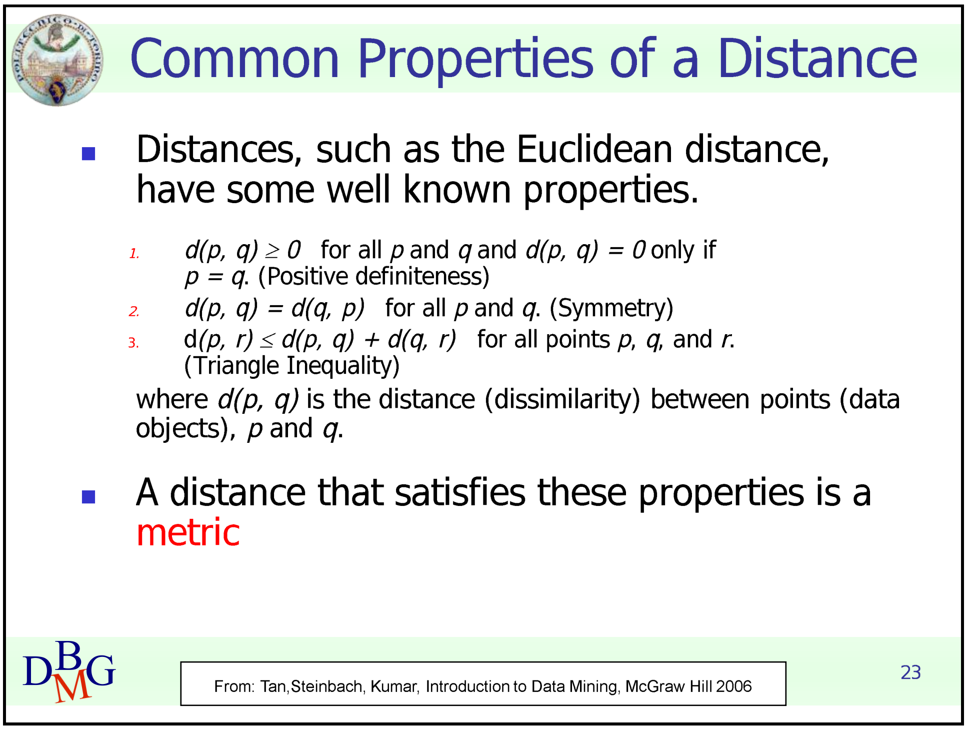

Common Properties of a Distance

- 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

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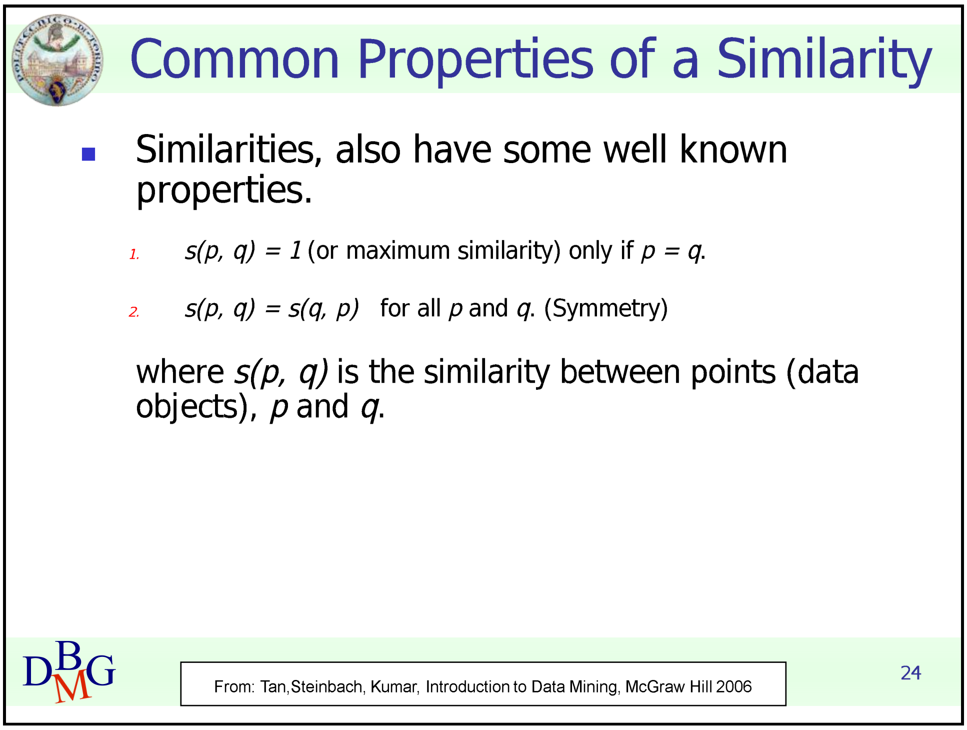

Common Properties of a Similarity

- 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*.

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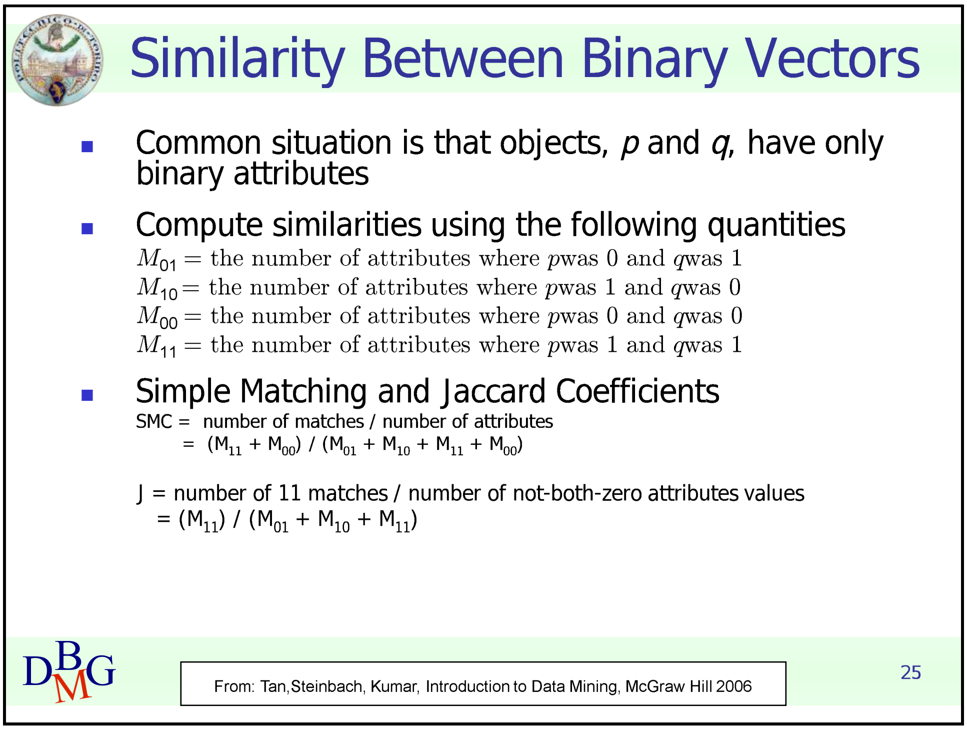

Similarity Between Binary Vectors

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

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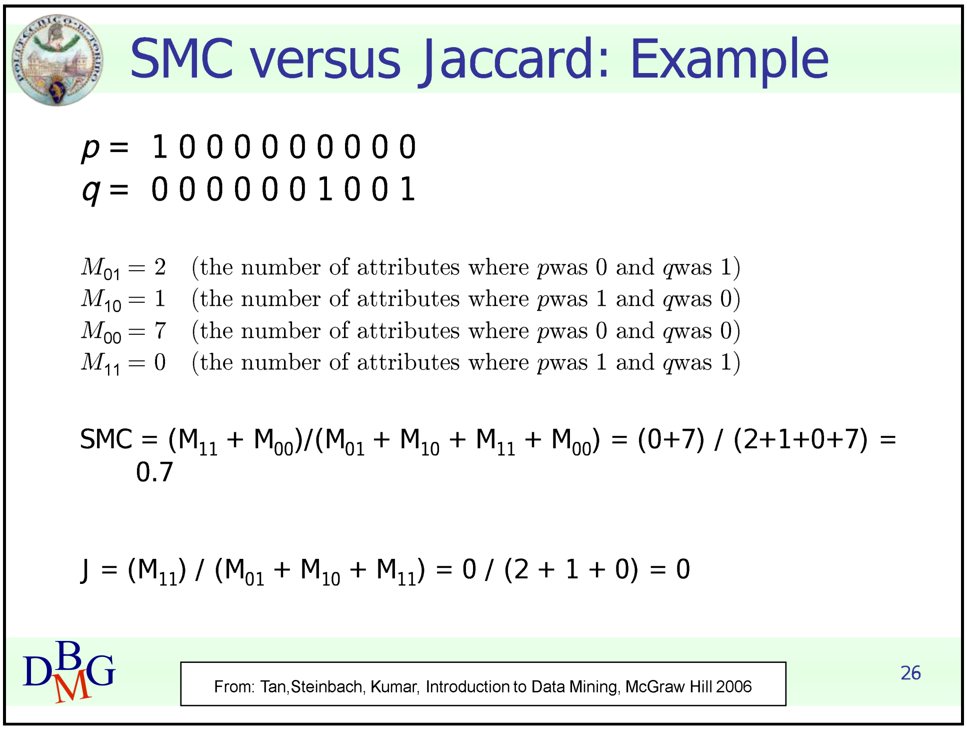

SMC versus Jaccard: Example

p = 1 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)

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

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

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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*3+2*2+0*0+5*5+0*0+0*0+0*0+2*2+0*0+0*0)$^{0.5}$ = (42) $^{0.5}$ =
6.481
$||d_2||$ = (1*1+0*0+0*0+0*0+0*0+0*0+0*0+1*1+0*0+2*2) $^{0.5}$ = (6) $^{0.5}$ = 2.245

cos(d_1, d_2) = .3150

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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:

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

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

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

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Combining Weighted Similarities

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

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

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

From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006