

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

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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



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

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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	n	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



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

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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



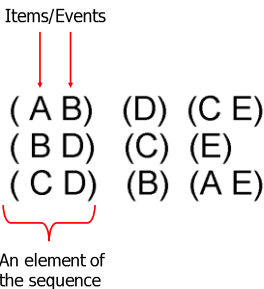
From: Tan,Steinbach, Kumar, Introduction to Data Mining, McGraw Hill 2006

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Ordered Data

- Sequences of transactions




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

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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




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

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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.




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

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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




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

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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)




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

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Important Characteristics of Structured Data

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




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

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Data Preprocessing

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




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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




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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




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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




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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




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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

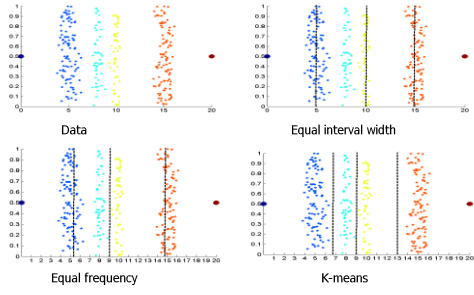


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Discretization



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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
$$v' = \frac{v - \min_i}{\max_i - \min_i} (new_max_i - new_min_i) + new_min_i$$
 - z-score normalization
$$v' = \frac{v - mean_i}{stand_dev_i}$$
 - decimal scaling
$$v' = \frac{v}{10^j} \quad j \text{ is the smallest integer such that } \max(|v'|) < 1$$

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




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

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SMC versus Jaccard: Example

$$p = 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$$
$$q = 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 1$$
$$M_{01} = 2 \quad (\text{the number of attributes where } p \text{ was 0 and } q \text{ was 1})$$
$$M_{10} = 1 \quad (\text{the number of attributes where } p \text{ was 1 and } q \text{ was 0})$$
$$M_{00} = 7 \quad (\text{the number of attributes where } p \text{ was 0 and } q \text{ was 0})$$
$$M_{11} = 0 \quad (\text{the number of attributes where } p \text{ was 1 and } q \text{ was 1})$$
$$SMC = (M_{11} + M_{00}) / (M_{01} + M_{10} + M_{11} + M_{00}) = (0+7) / (2+1+0+7) = 0.7$$
$$J = (M_{11}) / (M_{01} + M_{10} + M_{11}) = 0 / (2 + 1 + 0) = 0$$




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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:
$$d_1 = 3\ 2\ 0\ 5\ 0\ 0\ 0\ 2\ 0\ 0$$
$$d_2 = 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 2$$
$$d_1 \bullet d_2 = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5$$
$$||d_1|| = (3^2 + 2^2 + 0^2 + 5^2 + 0^2 + 0^2 + 0^2 + 2^2 + 0^2 + 0^2)^{0.5} = (42)^{0.5} = 6.481$$
$$||d_2|| = (1^2 + 0^2 + 0^2 + 0^2 + 0^2 + 0^2 + 0^2 + 1^2 + 0^2 + 2^2)^{0.5} = (6)^{0.5} = 2.245$$
$$\cos(d_1, d_2) = .3150$$




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Combining Similarities

- Sometimes attributes are of many different types, but an overall similarity is needed.
 - For the k^{th} attribute, compute a similarity, s_k , in the range $[0, 1]$.
 - Define an indicator variable, δ_k , for the k_{th} attribute as follows:
$$\delta_k = \begin{cases} 0 & \text{if the } k^{th} \text{ attribute is a binary asymmetric attribute and both objects have a value of 0, or if one of the objects has a missing values for the } k^{th} \text{ attribute} \\ 1 & \text{otherwise} \end{cases}$$
 - 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

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