

Data Mining:


Concepts and Techniques

— Chapter 3 —

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Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview 
 - Data Quality
 - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Reduction


Data Quality: Why Preprocess the Data?

- Measures for data quality: A multidimensional view
 - Accuracy: correct or wrong, accurate or not
 - Completeness: not recorded, unavailable, ...
 - Consistency: some modified but some not, dangling, ...
 - Timeliness: timely update?
 - Believability: how trustable the data are correct?
 - Interpretability: how easily the data can be understood?

Major Tasks in Data Preprocessing

- **Data cleaning**
 - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
 - Integration of multiple databases, data cubes, or files
- **Data reduction**
 - Dimensionality reduction
 - Numerosity reduction
- **Data transformation and data discretization**
 - Normalization
 - ...

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Data Cleaning

- Data in the Real World Is Dirty: Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, transmission error
 - incomplete: lacking feature values, lacking certain features of interest, or containing only aggregate data
 - e.g., *Occupation*=" " (missing data)
 - noisy: containing noise, errors, or outliers
 - e.g., *Salary*="−10" (an error)
 - inconsistent: containing discrepancies in codes or names, e.g.,
 - *Age*="42", *Birthday*="03/07/2010"
 - Was rating "1, 2, 3", now rating "A, B, C"
 - discrepancy between duplicate records
 - Intentional (e.g., *disguised missing* data)
 - Jan. 1 as everyone's birthday?

Incomplete (Missing) Data

- Data is not always available
 - E.g., many tuples have no recorded value for several features, such as customer income in sales data
- Missing data may be due to
 - equipment malfunction
 - inconsistent with other recorded data and thus deleted
 - data not entered due to misunderstanding
 - certain data may not be considered important at the time of entry
 - not register history or changes of the data
- Missing data may need to be inferred


How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (when doing classification)—not effective when the % of missing values per feature varies considerably
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
 - a global constant : e.g., “unknown”, a new class?!
 - the feature mean
 - the feature mean for all samples belonging to the same class: smarter
 - the most probable value: inference-based such as Bayesian formula or decision tree

Noisy Data

- **Noise**: random error or variance in a measured variable
- **Incorrect feature values** may be due to
 - faulty data collection instruments
 - data entry problems
 - data transmission problems
 - technology limitation
 - inconsistency in naming convention
- **Other data problems** which require data cleaning
 - duplicate records
 - incomplete data
 - inconsistent data

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Data Reduction Strategies

- **Data reduction:** Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.
- Data reduction strategies
 - **Dimensionality reduction**, e.g., remove unimportant features
 - Wavelet transforms
 - Principal Components Analysis (PCA)
 - Feature subset selection, feature creation
 - **Numerosity reduction** (some simply call it: Data Reduction)
 - Regression and Log-Linear Models
 - Histograms, clustering, sampling
 - Data cube aggregation
 - **Data compression**

Dimensionality Reduction

- **Curse of dimensionality**

- When dimensionality increases, data becomes increasingly sparse
- Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
- The possible combinations of subspaces will grow exponentially

- **Dimensionality reduction**

- Avoid the curse of dimensionality
- Help eliminate irrelevant features and reduce noise
- Reduce time and space required in data mining
- Allow easier visualization

- **Dimensionality reduction techniques**

- Wavelet transforms
- Principal Component Analysis
- Supervised and nonlinear techniques (e.g., feature selection)

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 features
 - E.g., 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
 - E.g., students' ID is often irrelevant to the task of predicting students' GPA

feature Creation (Feature Generation)

- Create new features (features) that can capture the important information in a data set more effectively than the original ones
- Three general methodologies
 - feature extraction
 - Domain-specific
 - Mapping data to new space (see: data reduction)
 - E.g., Fourier transformation, wavelet transformation, manifold approaches (not covered)
 - feature construction
 - Combining features (see: discriminative frequent patterns in Chapter 7)
 - Data discretization

Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is “smeared”
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth in Chapter 10

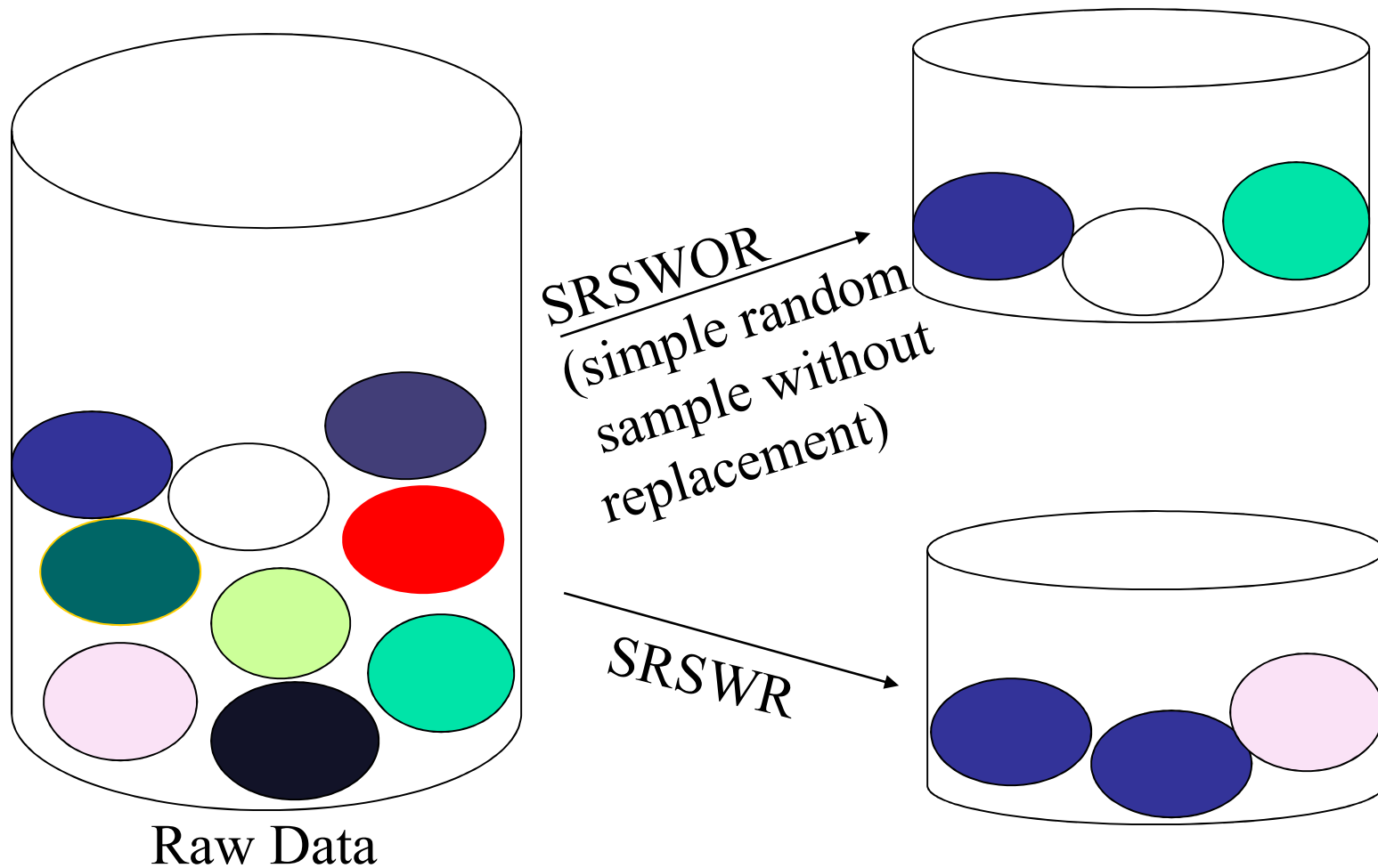
Sampling

- Sampling: obtaining a small sample s to represent the whole data set N
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Key principle: Choose a **representative** subset of the data
 - Simple random sampling may have very poor performance in the presence of skew
 - Develop adaptive sampling methods, e.g., stratified sampling:
- Note: Sampling may not reduce database I/Os (page at a time)

Types of Sampling

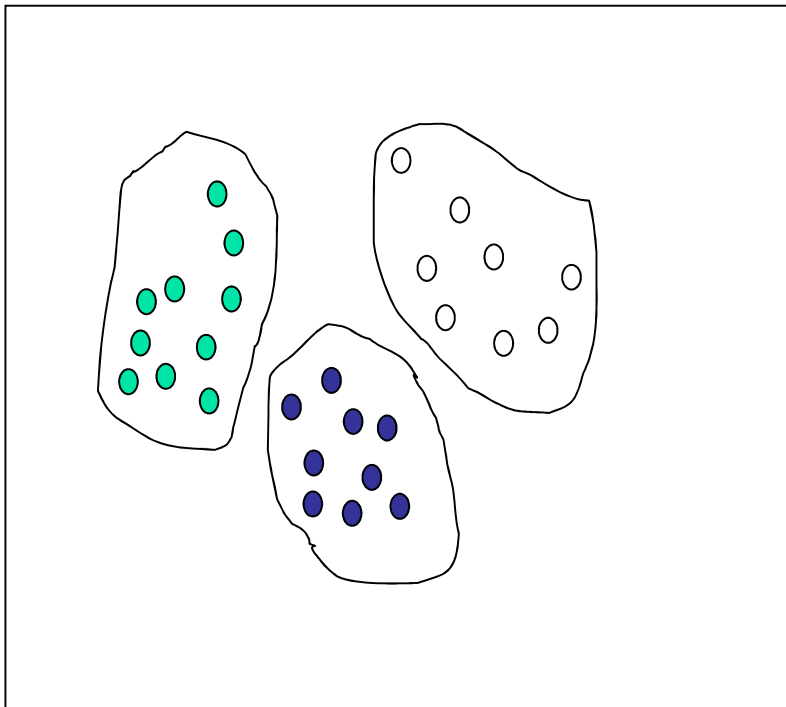
- **Simple random sampling**
 - There is an equal probability of selecting any particular item
- **Sampling without replacement**
 - Once an object is selected, it is removed from the population
- **Sampling with replacement**
 - A selected object is not removed from the population
- **Stratified sampling:**
 - Partition the data set, and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
 - Used in conjunction with skewed data

Sampling: With or without Replacement



Sampling: Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample

