



BITS Pilani

Pilani | Dubai | Goa | Hyderabad

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Data Pre-processing



- *The slides presented here are obtained from the authors of the books and from various other contributors. I hereby acknowledge all the contributors for their material and inputs.*
- *I have added and modified a few slides to suit the requirements of the course.*

Data Preprocessing Concepts

Preprocessing Objectives

- To improve data quality
- To modify data to better fit specific data mining technique

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 compression
- **Data transformation and data discretization**
 - Normalization
 - Concept hierarchy generation

Data Quality: Multidimensional View

- 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?

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

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 attribute values, lacking certain attributes 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 attributes, 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 attribute 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 attribute mean
 - the attribute mean for all samples belonging to the same class: smarter
 - the most probable value: inference-based such as Bayesian formula or decision tree

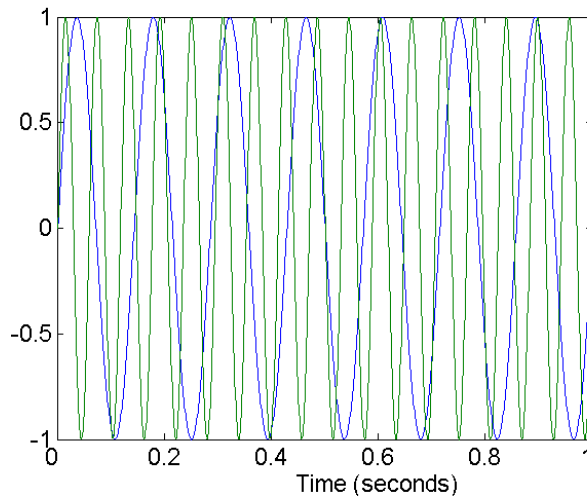
Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute 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

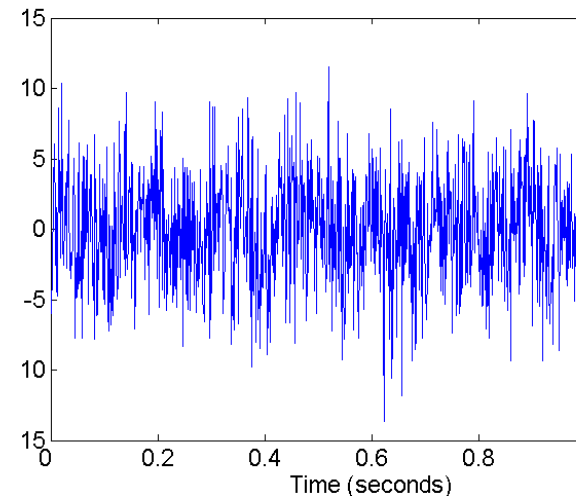
Noise

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

How to Handle Noisy Data?

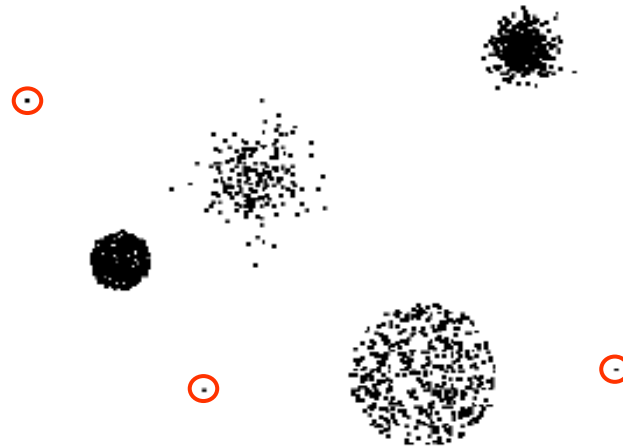
- Binning (also used for discretization)
 - first sort data and partition into (equal-frequency) bins
 - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
 - Binning methods smooth a sorted data value by consulting its "neighborhood," that is, the values around it, i.e. they perform *local* smoothing.
- Regression
 - smooth by fitting the data into regression functions
- Clustering
 - detect and remove outliers
- Combined computer and human inspection
 - detect suspicious values and check by human (e.g., deal with possible outliers)

Duplicate Data

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

Outliers

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



Data Cleaning as a Process

- Data discrepancy detection
 - Use metadata (e.g., domain, range, dependency, distribution)
 - Check field overloading
 - Check uniqueness rule, consecutive rule and null rule
 - Use commercial tools
 - Data scrubbing: use simple domain knowledge (e.g., postal code, spell-check) to detect errors and make corrections
 - Data auditing: by analyzing data to discover rules and relationship to detect violators (e.g., correlation and clustering to find outliers)
- Data migration and integration
 - Data migration tools: allow transformations to be specified
 - ETL (Extraction/Transformation/Loading) tools: allow users to specify transformations through a graphical user interface
- Integration of the two processes
 - Iterative and interactive (e.g., Potter's Wheels)



Data Preprocessing Techniques

Major Tasks in Data Preprocessing

- **Data cleaning**
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- **Data integration**
 - Integration of multiple databases, data cubes, or files
- **Data reduction**
 - Dimensionality reduction
 - Numerosity reduction
 - Data compression
- **Data transformation and data discretization**
 - Normalization
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Data Integration

- **Data integration:** Combines data from multiple sources into a coherent store
 - Schema integration: e.g., $A.cust-id \equiv B.cust-\#$
 - Integrate metadata from different sources
 - Entity identification problem:
 - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton
 - Detecting and resolving data value conflicts
 - For the same real world entity, attribute values from different sources are different
 - Possible reasons: different representations, different scales, e.g., metric vs. British units

Any problems with the Data?

Name	Age	DateOfFirstBuy	Profession	DateOfBirth
Bill Gates	34	15-Jan-2015	MGR	Feb 24, 1981
John	38	27-Jan-2015		Mar 11, 1982
William Gates	34	15-Jan-2015	MGR	Feb 24, 1981
Kennedy	37	30-Jan-2015	DOC	Nov 03,1982

Any problems with the Data?

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- 1) *Missing values in Profession column*
- 2) *Format of DateOfFirstBuy and DateOfBirth are different, needs standardization*
- 3) *Row 1 and Row 3 are potentially duplicate data.*
- 4) *Both Age and DateOfBirth are stored. Age is derived attribute.*
- 5) *Inconsistent format for name, missing first or last names*
- 6) *Entity identification issues*

Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
 - *Object identification*: The same attribute or object may have different names in different databases
 - *Derivable data*: One attribute may be a “derived” attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by *correlation analysis* and *covariance analysis*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Correlation Analysis (Nominal Data)

- χ^2 (chi-square) test

$$\chi^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}}$$

- The larger the χ^2 (chi-square) value, the more likely the variables are related
- The cells that contribute the most to the χ^2 value are those whose actual count is very different from the expected count
- Correlation does not imply causality
 - # of hospitals and # of car-theft in a city are correlated
 - Both are causally linked to the third variable: population

Chi-Square Calculation: An Example

	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- χ^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93$$

- It shows that like_science_fiction and play_chess are correlated in the group

Correlation Analysis (Numeric Data)

- Correlation coefficient (also called **Pearson's product moment coefficient**)

$$r_{A,B} = \frac{\sum_{i=1}^n (a_i - \bar{A})(b_i - \bar{B})}{n\sigma_A\sigma_B} = \frac{\sum_{i=1}^n (a_i b_i) - n\bar{A}\bar{B}}{n\sigma_A\sigma_B}$$

where n is the number of tuples, \bar{A} and \bar{B} are the respective means of A and B , σ_A and σ_B are the respective standard deviation of A and B , and $\sum(a_i b_i)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A 's values increase as B 's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{AB} < 0$: negatively correlated

Correlation (viewed as linear relationship)

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

$$a'_k = (a_k - \text{mean}(A)) / \text{std}(A)$$

$$b'_k = (b_k - \text{mean}(B)) / \text{std}(B)$$

$$\text{correlation}(A, B) = A' \bullet B'$$

Covariance (Numeric Data)

- Covariance is similar to correlation

$$Cov(A, B) = E((A - \bar{A})(B - \bar{B})) = \frac{\sum_{i=1}^n (a_i - \bar{A})(b_i - \bar{B})}{n}$$

Correlation coefficient: $r_{A,B} = \frac{Cov(A, B)}{\sigma_A \sigma_B}$

where n is the number of tuples, \bar{A} and \bar{B} are the respective mean or **expected values** of A and B , σ_A and σ_B are the respective standard deviation of A and B

- **Positive covariance:** If $Cov_{A,B} > 0$, then A and B both tend to be larger than their expected values
- **Negative covariance:** If $Cov_{A,B} < 0$ then if A is larger than its expected value, B is likely to be smaller than its expected value
- **Independence:** $Cov_{A,B} = 0$

Co-Variance: An Example

- It can be simplified in computation as

$$Cov(A, B) = E((A - \bar{A})(B - \bar{B})) = \frac{\sum_{i=1}^n (a_i - \bar{A})(b_i - \bar{B})}{n}$$

- Suppose two stocks A and B have the following values in one week: (2, 5), (3, 8), (5, 10), (4, 11), (6, 14).

$$Cov(A, B) = E(A \cdot B) - \bar{A}\bar{B}$$

- Question: If the stocks are affected by the same industry trends, will their prices rise or fall together?
 - $E(A) = (2 + 3 + 5 + 4 + 6) / 5 = 20 / 5 = 4$
 - $E(B) = (5 + 8 + 10 + 11 + 14) / 5 = 48 / 5 = 9.6$
 - $Cov(A, B) = (2 \times 5 + 3 \times 8 + 5 \times 10 + 4 \times 11 + 6 \times 14) / 5 - 4 \times 9.6 = 4$
- Thus, A and B rise together since $Cov(A, B) > 0$.

Normalization

- **Min-max normalization:** to $[new_min_A, new_max_A]$

$$v' = \frac{v - min_A}{max_A - min_A} (new_max_A - new_min_A) + new_min_A$$

- Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to $\frac{73,600 - 12,000}{98,000 - 12,000} (1.0 - 0) + 0 = 0.716$

- **Z-score normalization** (μ : mean, σ : standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

- Ex. Let $\mu = 54,000$, $\sigma = 16,000$. Then $\frac{73,600 - 54,000}{16,000} = 1.225$

- **Normalization by decimal scaling**

$$v' = \frac{v}{10^j} \quad \text{Where } j \text{ is the smallest integer such that } \text{Max}(|v'|) < 1$$

Discretization

- Three types of attributes
 - Nominal—values from an unordered set, e.g., color, profession
 - Ordinal—values from an ordered set, e.g., military or academic rank
 - Numeric—real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
 - Interval labels can then be used to replace actual data values
 - Reduce data size by discretization
 - Supervised vs. unsupervised
 - Split (top-down) vs. merge (bottom-up)
 - Discretization can be performed recursively on an attribute
 - Prepare for further analysis, e.g., classification

Data Discretization Methods

- Typical methods: All the methods can be applied recursively
 - Binning
 - Top-down split, unsupervised
 - Histogram analysis
 - Top-down split, unsupervised
 - Clustering analysis (unsupervised, top-down split or bottom-up merge)
 - Decision-tree analysis (supervised, top-down split)
 - Correlation (e.g., χ^2) analysis (unsupervised, bottom-up merge)

Simple Discretization: Binning

- **Equal-width** (distance) partitioning
 - Divides the range into N intervals of equal size: uniform grid
 - if A and B are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
 - The most straightforward, but outliers may dominate presentation
 - Skewed data is not handled well
- **Equal-depth** (frequency) partitioning
 - Divides the range into N intervals, each containing approximately same number of samples
 - Good data scaling
 - Managing categorical attributes can be tricky

Binning Methods for Data Smoothing

Sorted data for *price* (in dollars): 4, 8, 15, 21, 21, 24, 25, 28, 34

Partition into (equal-frequency) bins:

Bin 1: 4, 8, 15

Bin 2: 21, 21, 24

Bin 3: 25, 28, 34

Smoothing by bin means:

Bin 1: 9, 9, 9

Bin 2: 22, 22, 22

Bin 3: 29, 29, 29

Smoothing by bin boundaries:

Bin 1: 4, 4, 15

Bin 2: 21, 21, 24

Bin 3: 25, 25, 34

Discretization by Classification & Correlation Analysis

- Classification (e.g., decision tree analysis)
 - Supervised: Given class labels, e.g., cancerous vs. benign
 - Using *entropy* to determine split point (discretization point)
 - Top-down, recursive split
 - Details to be covered in Chapter “Classification”
- Correlation analysis (e.g., Chi-merge: χ^2 -based discretization)
 - Supervised: use class information
 - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low χ^2 values) to merge
 - Merge performed recursively, until a predefined stopping condition

Data Reduction Strategies

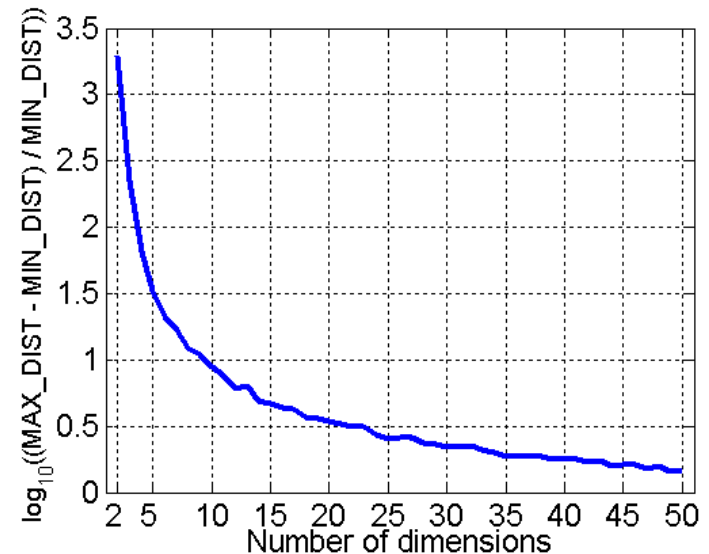
- **Data reduction:** Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.
- Data reduction strategies
 - Dimensionality reduction, e.g., remove unimportant attributes
 - 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

Data Reduction : 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)

Curse of Dimensionality

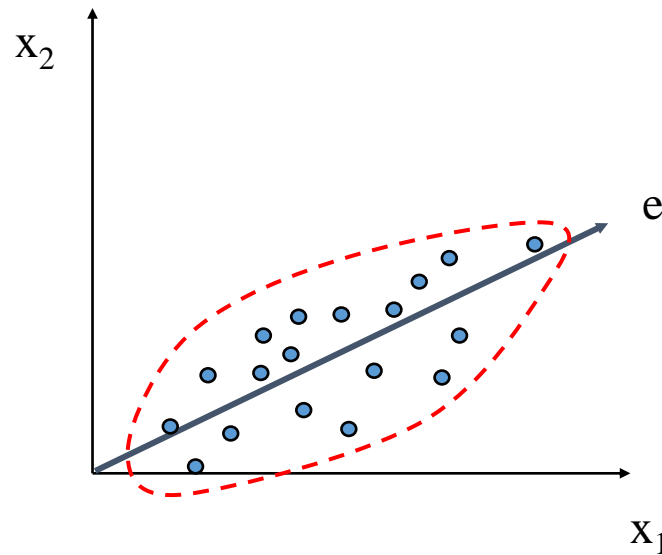
- When dimensionality increases, data becomes increasingly sparse in the space that it occupies
- Definitions of density and distance between points, which are critical for clustering and outlier detection, become less meaningful



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

Principal Component Analysis (PCA)

Find a projection that captures the largest amount of variation in data
The original data are projected onto a much smaller space, resulting in dimensionality reduction.



Principal Component Analysis (Steps)

- Given N data vectors from n -dimensions, find $k \leq n$ orthogonal vectors (*principal components*) that can be best used to represent data
 - Normalize input data: Each attribute falls within the same range
 - Compute k orthonormal (unit) vectors, i.e., *principal components*
 - Each input data (vector) is a linear combination of the k principal component vectors
 - The principal components are sorted in order of decreasing “significance” or strength
 - Since the components are sorted, the size of the data can be reduced by eliminating the *weak components*, i.e., those with low variance (i.e., using the strongest principal components, it is possible to reconstruct a good approximation of the original data)
- Works for numeric data only

Attribute Subset Selection

- Another way to reduce dimensionality of data
- Redundant attributes
 - Duplicate much or all of the information contained in one or more other attributes
 - E.g., purchase price of a product and the amount of sales tax paid
- Irrelevant attributes
 - 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

Heuristic Search in Attribute Selection

- There are 2^d possible attribute combinations of d attributes
- Typical heuristic attribute selection methods:
 - Best single attribute under the attribute independence assumption: choose by significance tests
 - Best step-wise feature selection:
 - The best single-attribute is picked first
 - Then next best attribute condition to the first, ...
 - Step-wise attribute elimination:
 - Repeatedly eliminate the worst attribute
 - Best combined attribute selection and elimination
 - Optimal branch and bound:
 - Use attribute elimination and backtracking

Attribute Creation (Feature Generation)

- Create new attributes (features) that can capture the important information in a data set more effectively than the original ones
- Three general methodologies
 - Attribute extraction
 - Domain-specific
 - Mapping data to new space (see: data reduction)
 - E.g., Fourier transformation, wavelet transformation
 - Attribute construction
 - Combining features
 - Data discretization

Data Reduction: Numerosity Reduction

- Reduce data volume by choosing alternative, *smaller forms* of data representation
- **Parametric methods** (e.g., regression)
 - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
 - Ex.: Log-linear models—obtain value at a point in m -D space as the product on appropriate marginal subspaces
- **Non-parametric methods**
 - Do not assume models
 - Major families: histograms, clustering, sampling, ...

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

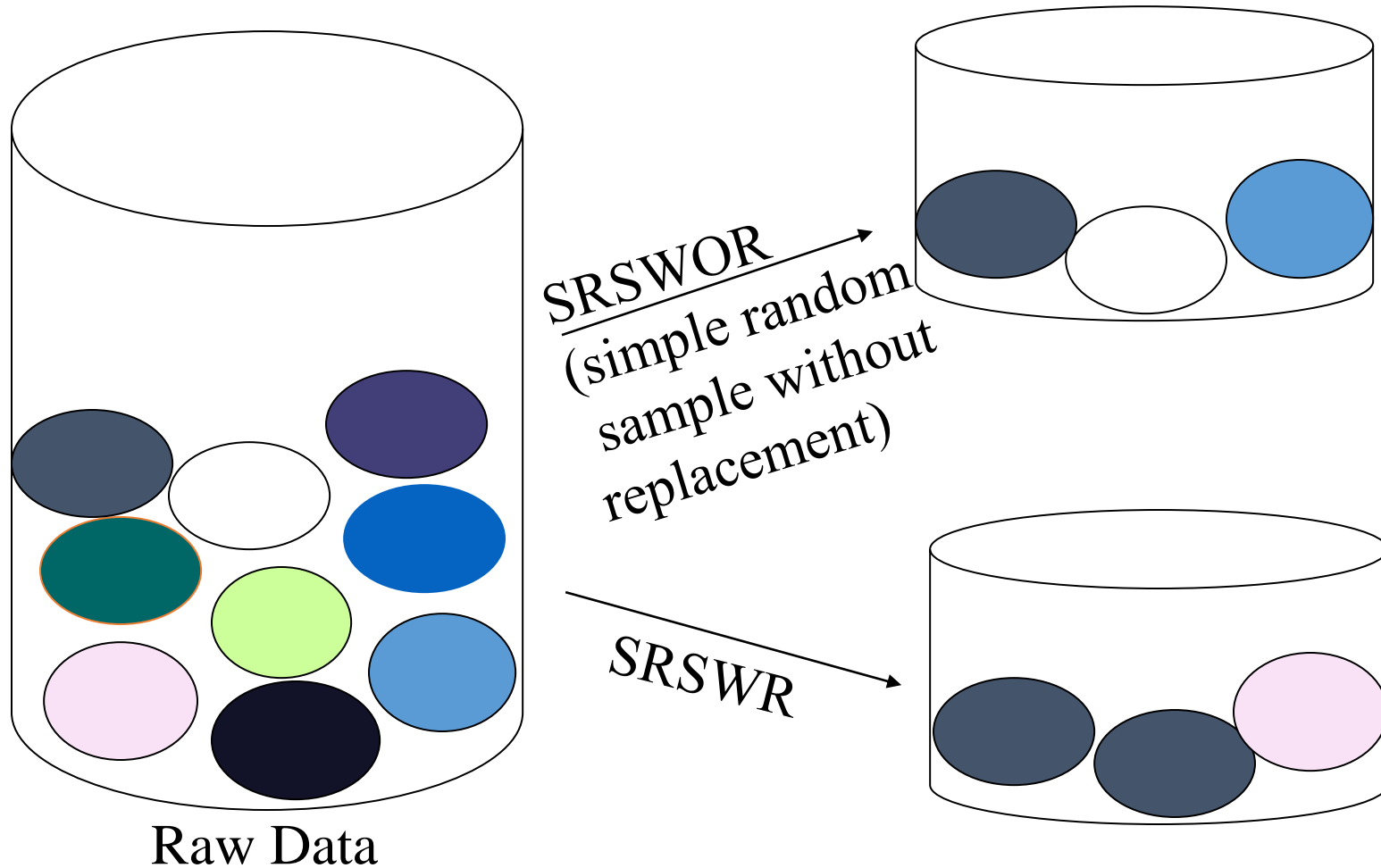
Sampling with replacement

- 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



Text Books

	Author(s), Title, Edition, Publishing House
T1	Tan P. N., Steinbach M & Kumar V. "Introduction to Data Mining" Pearson Education
T2	Data Mining: Concepts and Techniques, Third Edition by Jiawei Han, Micheline Kamber and Jian Pei Morgan Kaufmann Publishers
R1	Predictive Analytics and Data Mining: Concepts and Practice with RapidMiner by Vijay Kotu and Bala Deshpande Morgan Kaufmann Publishers

Thank You