

Data Mining:

Concepts and Techniques

(3rd ed.)

— Chapter 3 —

By: Jiawei Han, Micheline Kamber, and Jian Pei

Lecturer: Mohammed L. Mahmood



Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
 - Data Quality
 - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary

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 compression

- **Data transformation and data discretization**

- Normalization
- Concept hierarchy generation

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/concluded

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 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

How to Handle Noisy Data?

- Binning
 - 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.
- 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)

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

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)

- **X² (chi-square) test**

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

- The larger the X² value, the more likely the variables are related
- The cells that contribute the most to the X² value are those whose actual count is very different from the expected count

Chi-Square Calculation: An Example

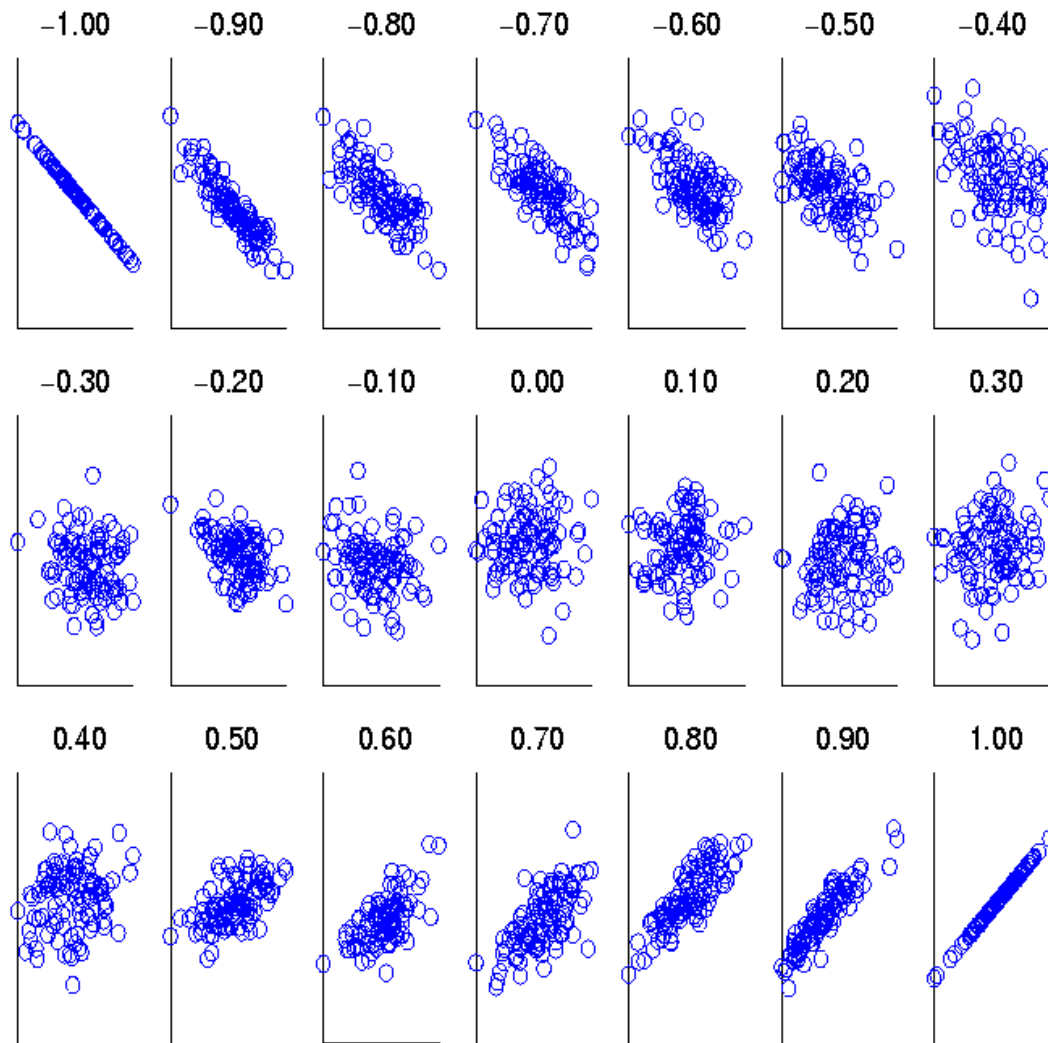
	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- 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

Visually Evaluating Correlation



**Scatter plots
showing the
similarity from
-1 to 1.**

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
 - clustering, sampling
 - **Data compression**

Data Reduction 1: 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**

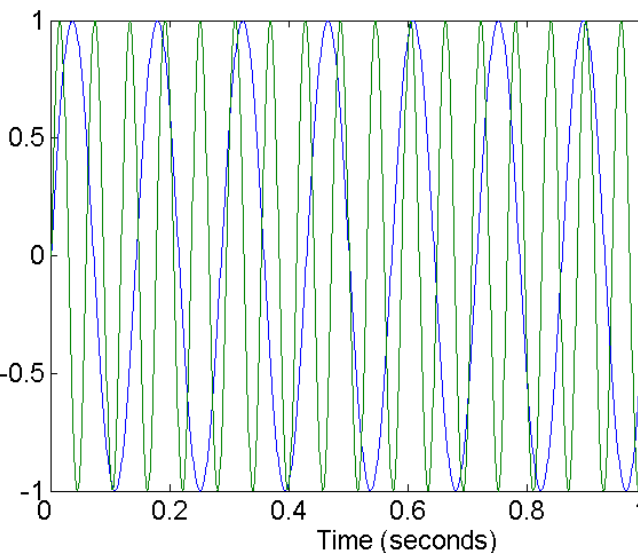
- Avoid the curse of dimensionality
- Help eliminate irrelevant features and reduce noise
- Reduce time and space required in data mining
- Allow easier visualization

- **Dimensionality reduction techniques**

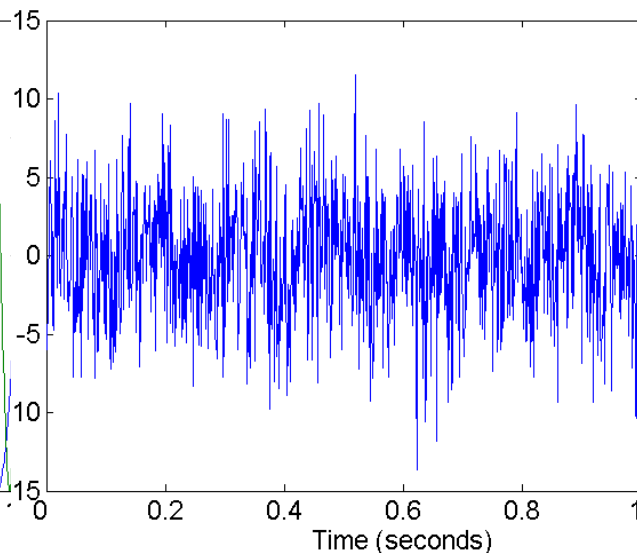
- Wavelet transforms
- Principal Component Analysis
- Supervised and nonlinear techniques (e.g., feature selection)

Mapping Data to a New Space

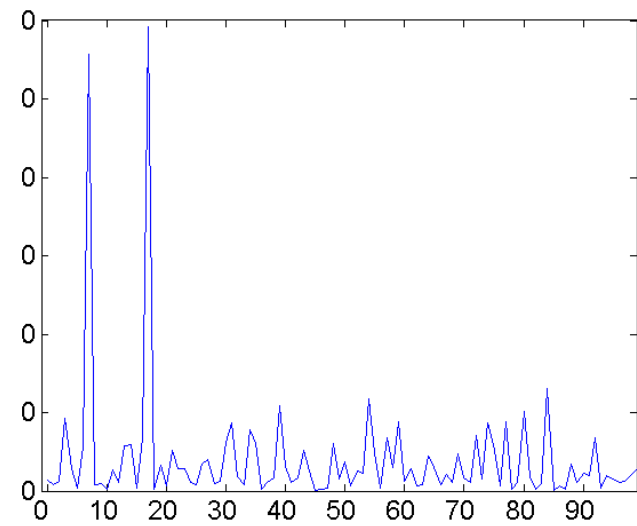
- **Fourier transform**
- **Wavelet transform**



Two Sine Waves



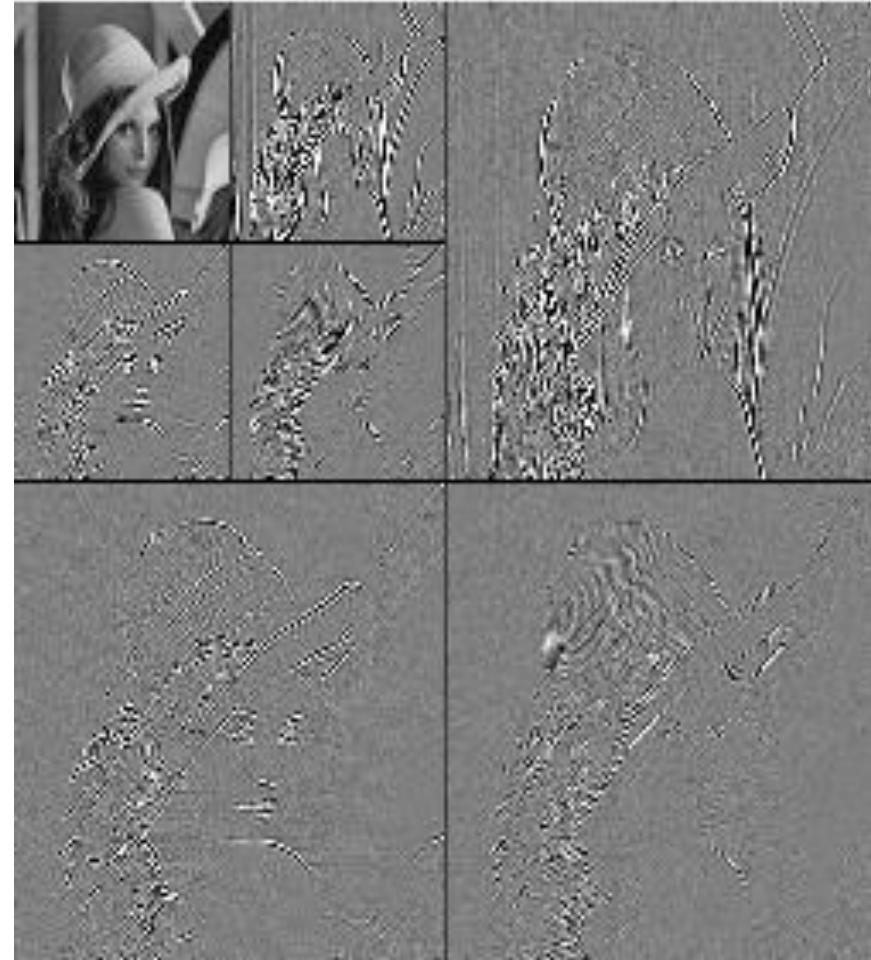
Two Sine Waves + Noise



Frequency

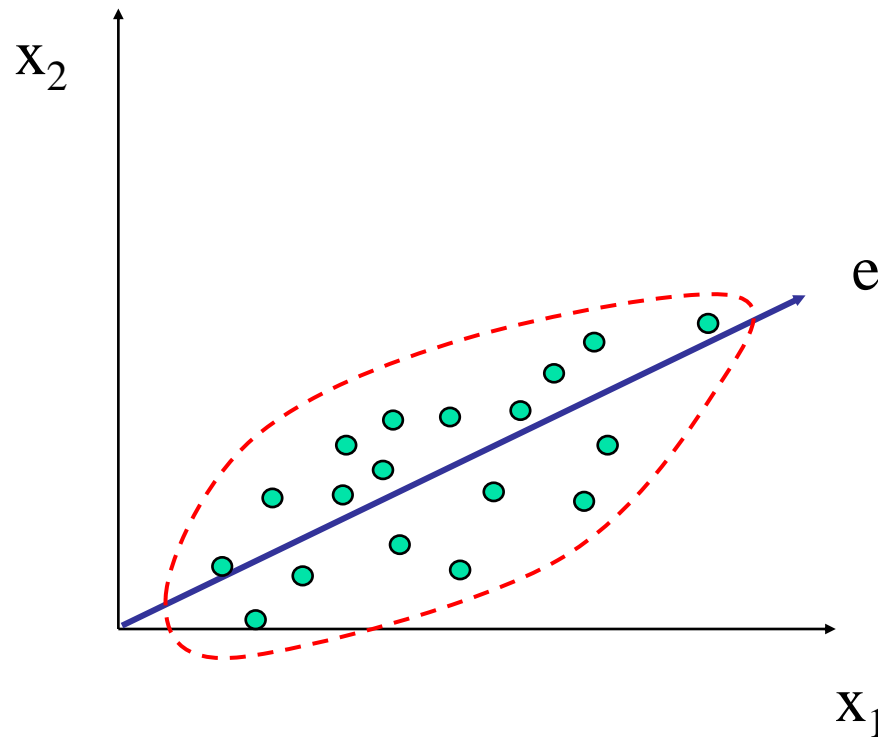
What Is Wavelet Transform?

- Decomposes a signal into different frequency subbands
 - Applicable to n-dimensional signals
- Data are transformed to preserve relative distance between objects at different levels of resolution
- Allow natural clusters to become more distinguishable
- Used for image compression



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. We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space



Attribute Subset Selection

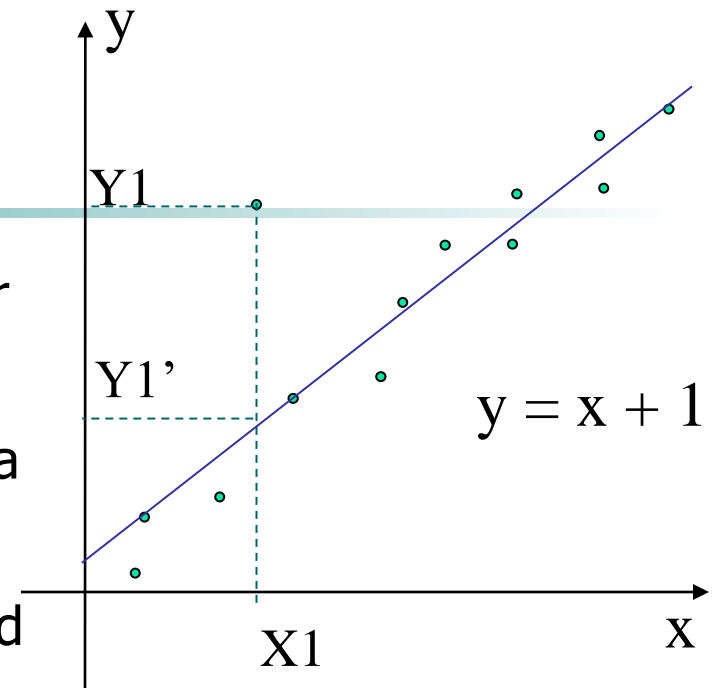
- Another way to reduce dimensionality of data
- Redundant attributes
 - Duplicate much or all of the information contained in one or more other attributes
 - E.g., purchase price of a product and the amount of sales tax paid
- Irrelevant attributes
 - Contain no information that is useful for the data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

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, manifold approaches (not covered)
 - Attribute construction
 - Combining features (see: discriminative frequent patterns in Chapter 7)
 - Data discretization

Regression Analysis

- Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a ***dependent variable*** (also called ***response variable*** or *measurement*) and of one or more *independent variables* (aka. ***explanatory variables*** or ***predictors***)
- The parameters are estimated so as to give a "**best fit**" of the data
- Most commonly the best fit is evaluated by using the ***least squares method***, but other criteria have also been used
- Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships



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

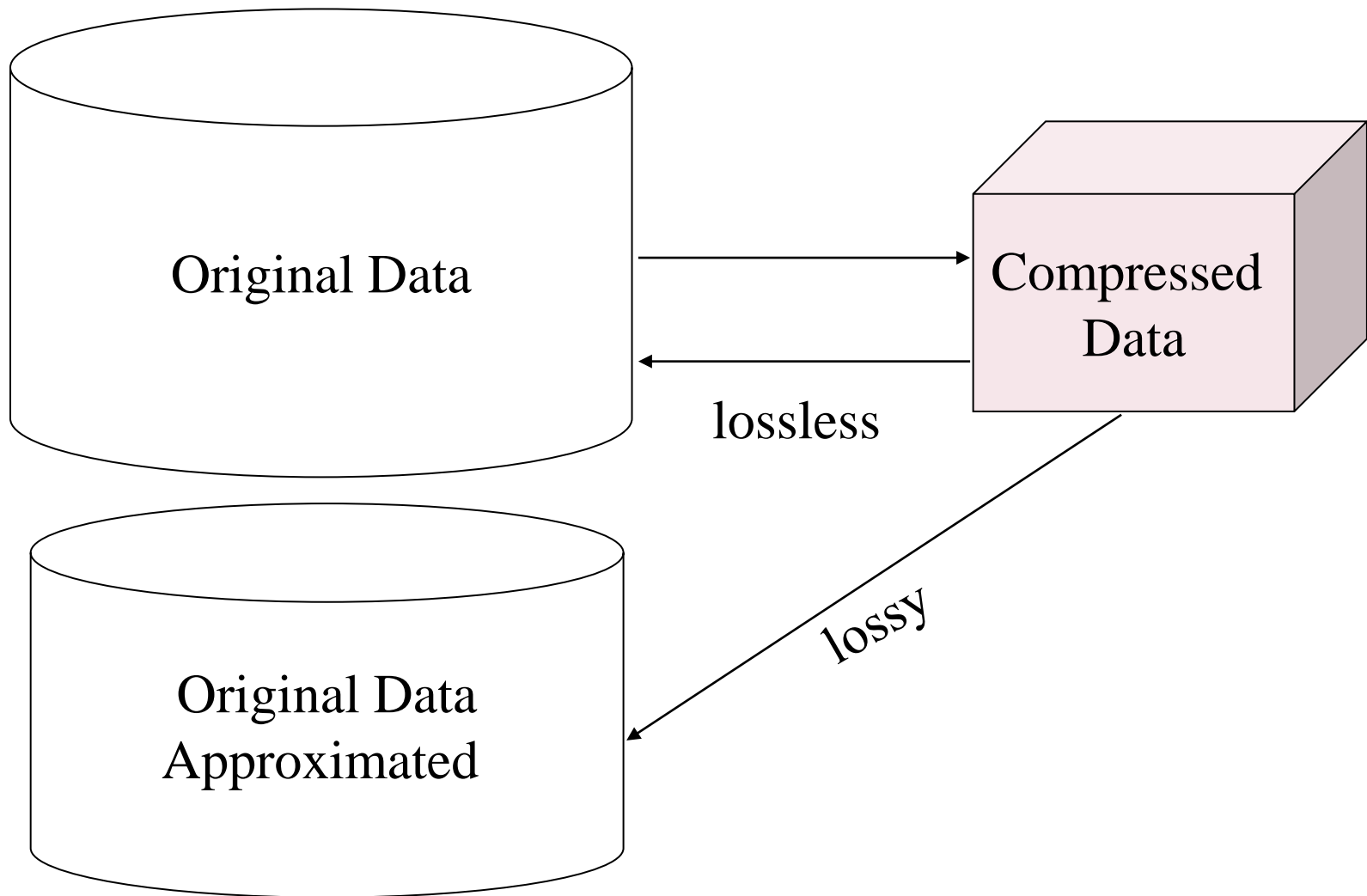
Sampling

- 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:

Data Reduction 3: Data Compression

- String compression
 - There are extensive theories and well-tuned algorithms
 - Typically lossless, but only limited manipulation is possible without expansion
- Audio/video compression
 - Typically lossy compression, with progressive refinement
 - Sometimes small fragments of signal can be reconstructed without reconstructing the whole

Data Compression



Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods
 - Smoothing: Remove noise from data
 - Attribute/feature construction
 - New attributes constructed from the given ones
 - Aggregation: Summarization, data cube construction
 - Normalization: Scaled to fall within a smaller, specified range
 - min-max normalization
 - z-score normalization
 - normalization by decimal scaling
 - Discretization: Concept hierarchy climbing

Normalization

- **Min-max normalization:** to $[\text{new_min}_A, \text{new_max}_A]$
- **Z-score normalization** (μ : mean, σ : standard deviation)
- **Normalization by decimal scaling**

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)

Summary

- **Data quality:** accuracy, completeness, consistency, timeliness, believability, interpretability
- **Data cleaning:** e.g. missing/noisy values, outliers
- **Data integration** from multiple sources:
 - Entity identification problem
 - Remove redundancies
 - Detect inconsistencies
- **Data reduction**
 - Dimensionality reduction
 - Numerosity reduction
 - Data compression
- **Data transformation and data discretization**
 - Normalization
 - Concept hierarchy generation

References

- D. P. Ballou and G. K. Tayi. Enhancing data quality in data warehouse environments. *Comm. of ACM*, 42:73-78, 1999
- A. Bruce, D. Donoho, and H.-Y. Gao. Wavelet analysis. *IEEE Spectrum*, Oct 1996
- T. Dasu and T. Johnson. *Exploratory Data Mining and Data Cleaning*. John Wiley, 2003
- J. Devore and R. Peck. *Statistics: The Exploration and Analysis of Data*. Duxbury Press, 1997.
- H. Galhardas, D. Florescu, D. Shasha, E. Simon, and C.-A. Saita. Declarative data cleaning: Language, model, and algorithms. *VLDB'01*
- M. Hua and J. Pei. Cleaning disguised missing data: A heuristic approach. *KDD'07*
- H. V. Jagadish, et al., *Special Issue on Data Reduction Techniques*. *Bulletin of the Technical Committee on Data Engineering*, 20(4), Dec. 1997
- H. Liu and H. Motoda (eds.). *Feature Extraction, Construction, and Selection: A Data Mining Perspective*. Kluwer Academic, 1998
- J. E. Olson. *Data Quality: The Accuracy Dimension*. Morgan Kaufmann, 2003
- D. Pyle. *Data Preparation for Data Mining*. Morgan Kaufmann, 1999
- V. Raman and J. Hellerstein. *Potters Wheel: An Interactive Framework for Data Cleaning and Transformation*, *VLDB'2001*
- T. Redman. *Data Quality: The Field Guide*. Digital Press (Elsevier), 2001
- R. Wang, V. Storey, and C. Firth. A framework for analysis of data quality research. *IEEE Trans. Knowledge and Data Engineering*, 7:623-640, 1995