Università degli Studi di Milano

Master Degree in Computer Science

Information Management course

Teacher: Alberto Ceselli

Lecture 03 : 13/10/2015

Data Mining:

Concepts and Techniques

(3rd ed.)

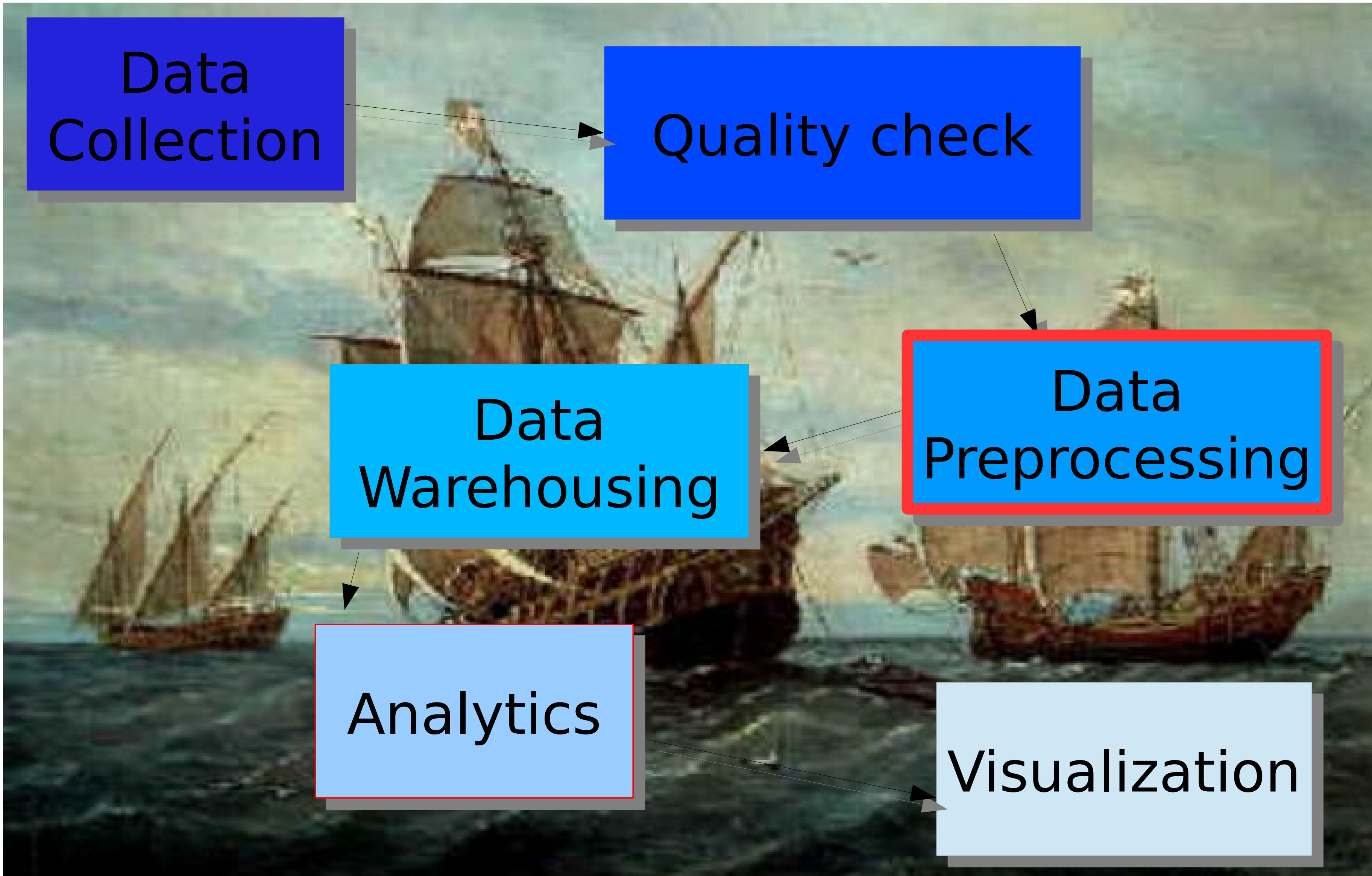
— Chapter 3 —

Jiawei Han, Micheline Kamber, and Jian Pei

University of Illinois at Urbana-Champaign &

Simon Fraser University

The Data Journey



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

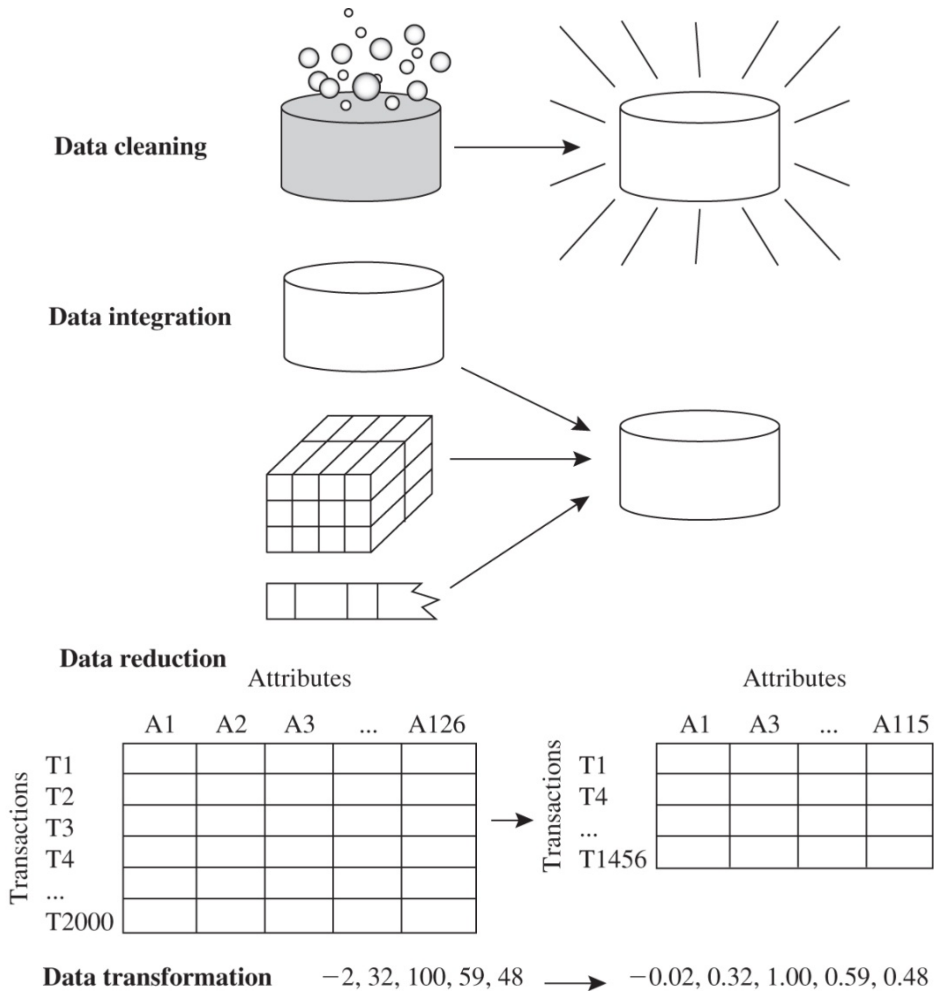
Data Quality: Why Preprocess the Data?

- 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

Major Tasks in Data Preprocessing



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 Cleaning

- Data in the Real World Is Dirty (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?

How to Handle Missing Data?

- Ignore the tuple (e.g. when class label is missing and doing classification) → simple, but loss of data
- Fill in the missing value manually → tedious + infeasible?
- Fill in it automatically with
  - global const (e.g., “unknown”) → a new class?!
  - the attribute mean or median
  - 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

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.
- Clustering
  - detect and remove outliers
- Regression
  - smooth by fitting the data into regression functions
- Filtering
  - Apply transforms (e.g whitening)
- Combined computer and human inspection

Data Cleaning as a Process

- Data discrepancy detection
  - Use knowledge about data → use **metadata** (e.g., domain, range, dependency, distribution) i.e. **know your data!**
  - 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) → already "data mining"
- Data migration and integration
  - Data migration tools: allow transformations to be specified
  - ETL (Extraction/Transformation/Loading) tools (GUI)
- Integration of the two processes
  - Iterative and interactive (e.g., Potter's Wheels)

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 Integration

- **Data integration**:
  - Combines data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ 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 integrating 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 detected by *correlation analysis* and *covariance analysis*

Correlation Analysis (Nominal Data)

- **X^2 (chi-square) test**
  - Attribute A has c values (a_1 … a_c)
  - Attribute B has r values (b_1 … b_r)
  - Build a contingency table [o_{ij}], having 1 row for each a_i, one col for each b_j
  - o_{ij} is the observed frequency (number of tuples having value ai for A and bj for B)

$$e_{ij} = \frac{count(A=a_i) \times count(B=b_j)}{num.\, data\, tuples}$$

$$\chi^2 = \sum_i \sum_j \frac{(o_{ij} - e_{ij})^2}{e_{ij}}$$

Correlation Analysis (Nominal Data)

- The larger the X^2 value, the more likely the variables are related
- The cells that contribute the most to the X^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

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

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

- X^2 (chi-square) calculation (numbers in parenthesis are e_{ij})

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

- K x K table → K categories → (K-1) degrees of freedom (1 in the example)
- From chi-square distribution, the value for rejecting hypotesis of independency at 0.001 significance level is 10.828 → **strong correlation**

Deg. freedom										
1	0.00	0.02	0.06	0.15	0.46	1.07	1.64	2.71	3.84	6.64	10.83
2	0.10	0.21	0.45	0.71	1.39	2.41	3.22	4.60	5.99	9.21	13.82
3	0.35	0.58	1.01	1.42	2.37	3.66	4.64	6.25	7.82	11.34	16.27
4	0.71	1.06	1.65	2.20	3.36	4.88	5.99	7.78	9.49	13.28	18.47
5	1.14	1.61	2.34	3.00	4.35	6.06	7.29	9.24	11.07	15.09	20.52
6	1.63	2.20	3.07	3.83	5.35	7.23	8.56	10.64	12.59	16.81	22.46
7	2.17	2.83	3.82	4.67	6.35	8.38	9.80	12.02	14.07	18.48	24.32
8	2.73	3.49	4.59	5.53	7.34	9.52	11.03	13.36	15.51	20.09	26.12
9	3.32	4.17	5.38	6.39	8.34	10.66	12.24	14.68	16.92	21.67	27.88
10	3.94	4.86	6.18	7.27	9.34	11.78	13.44	15.99	18.31	23.21	29.59
p-val	0.95	0.9	0.8	0.7	0.5	0.3	0.2	0.1	0.05	0.01	0.001

1 – Cum. Distr. Funct. = significance level

Covariance (Numeric Data)

- Covariance:
  - Attributes A and B
  - n → number of tuples
  - $\bar{A}$ and $\bar{B}$ → respective means of A and B
  - σ_A and σ_B → the respective standard deviation of A and B

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

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

Covariance (Numeric Data)

- Covariance:

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

- **Dep. w. positive correlation ← → positive covariance**
  If $Cov_{A,B} > 0$, then when A is larger (resp. smaller) than its expected value, B is larger (resp. smaller) as well
- **Dep. w. negative correlation ← → negative covariance**
  If $Cov_{A,B} < 0$, then when A is larger than its expected value, B is likely to be smaller than its expected value (and vice versa)

- **Independence →** $Cov_{A,B}=0$ (but the converse is not always true)
  - Some pairs of random variables may have a covariance of 0 but are not independent. Only under some additional assumptions (e.g., the data follow multivariate normal distributions) a covariance of 0 does imply independence

Co-Variance: An Example

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

- It can be simplified in computation as

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

- Suppose two stocks A and B have the following values in one week: (2, 5), (3, 8), (5, 10), (4, 11), (6, 14).
- 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) = (2×5+3×8+5×10+4×11+6×14)/5 − 4×9.6= 4
- Thus, A and B rise together since Cov(A, B) > 0.

Correlation Analysis (Numeric Data)

- Correlation coefficient (also called Pearson's product moment coefficient)
  - Attributes A and B
  - n → number of tuples
  - $\overline{A}$ and $\overline{B}$ → respective means of A and B
  - σ_A and σ_B → the respective standard deviation of A and B

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$$

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

Correlation Analysis (Numeric Data)

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

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

- 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

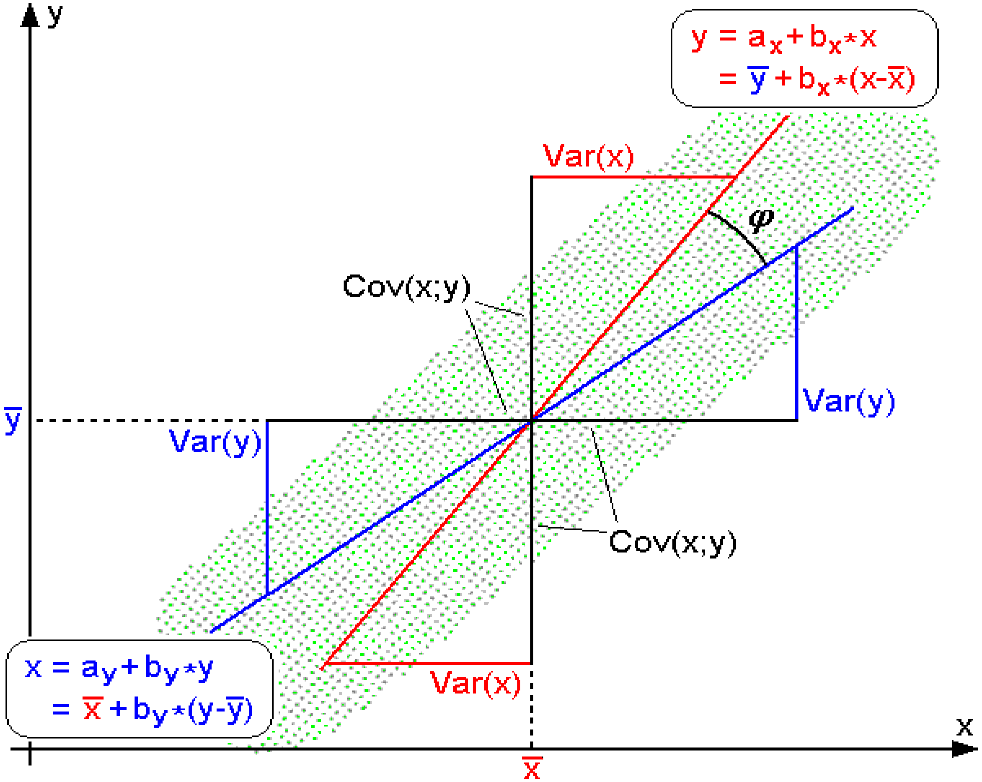
$$a'_k = (a_k - mean(A)) / std(A)$$

$$b'_k = (b_k - mean(B)) / std(B)$$

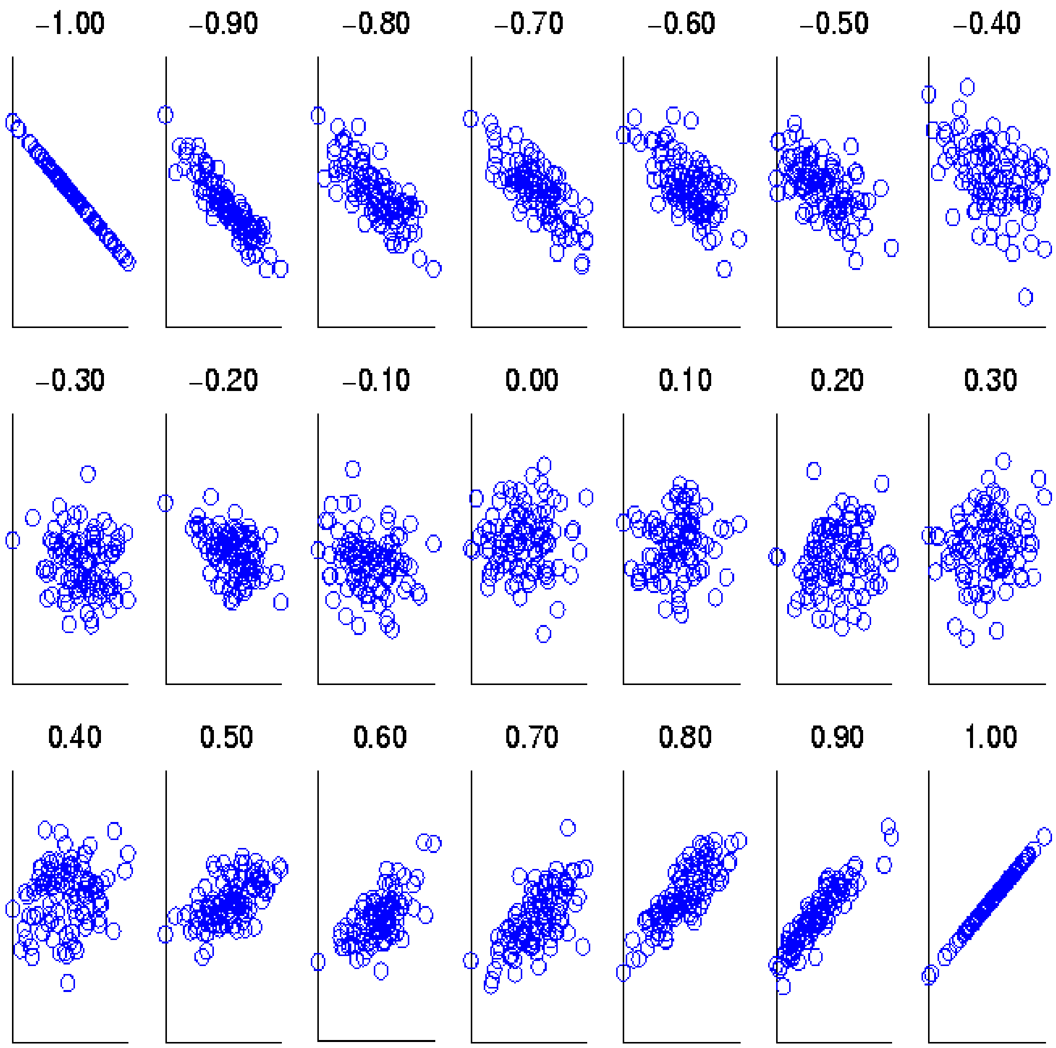
$$correlation(A, B) = A' \bullet B'$$

Correlation Analysis (Numeric Data)

- Geometrically: the cosine of the angle between the two vectors, after centering (or possible regression lines)



Visually Evaluating Correlation



Scatter plots showing the similarity from –1 to 1.

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 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? Computational issues in big data!
- Data reduction strategies
  - Numerosity reduction (or simply “Data Reduction” → red. the number of data objects)
    - Sampling
    - Histograms, clustering
    - Regression and Log-Linear Models
    - Data cube aggregation
  - Dimensionality reduction (→ red. the number of attributes)
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation
    - Transforms (Fourier, Wavelet, Whitening …)
  - Data compression

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? Computational issues in big data!
- Data reduction strategies
  - Numerosity reduction (or simply "Data Reduction" → red. the number of data objects)
    - Sampling
    - Histograms, clustering
    - Regression and Log-Linear Models
    - Data cube aggregation
  - Dimensionality reduction (→ red. the number of attributes)
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation
    - Transforms (Fourier, Wavelet, Whitening …)
  - Data compression

Numerosity Reduction: 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)

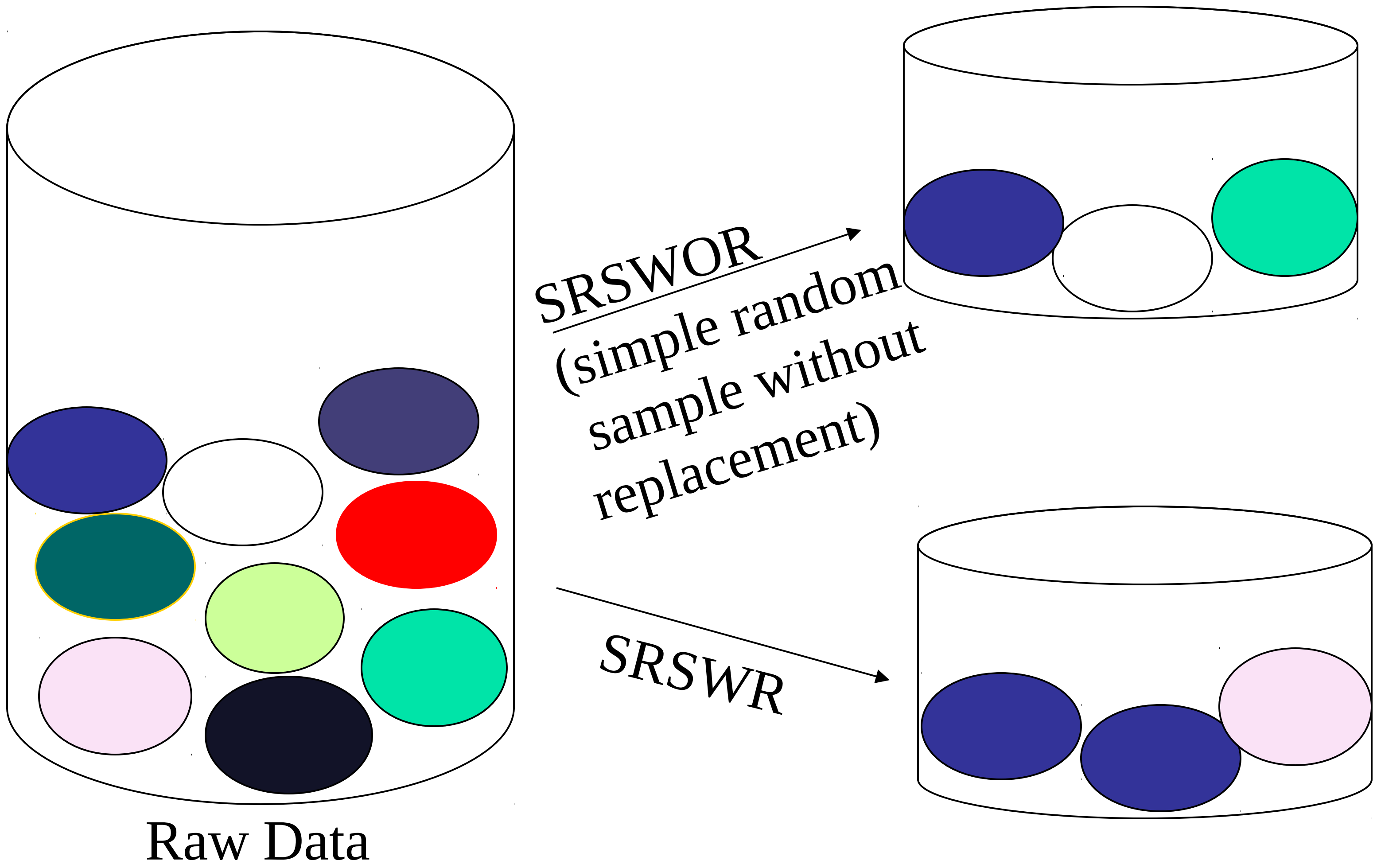
Sampling

- Beware! In general, sampling design (e.g. for surveys) is a serious issue:
  - Cochran, W.G. (1977). **Sampling techniques**, 3rd ed. New York: John Wiley & Sons
  - Lohr, S. (2009). **Sampling: Design and Analysis**. Duxbury Press
- in data sampling for automatic analyses we're more constrained (and therefore simplified)
- still we can exploit general techniques

Types of Sampling

- **Systematic sampling**
  - Choose equally-spaced data objects (or even contiguous elements to reduce I/O)
- **Simple random sampling**
  - There is an equal probability of selecting any particular item
- **Sampling without / with replacement**
  - Once an object is selected, it is removed (resp. 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

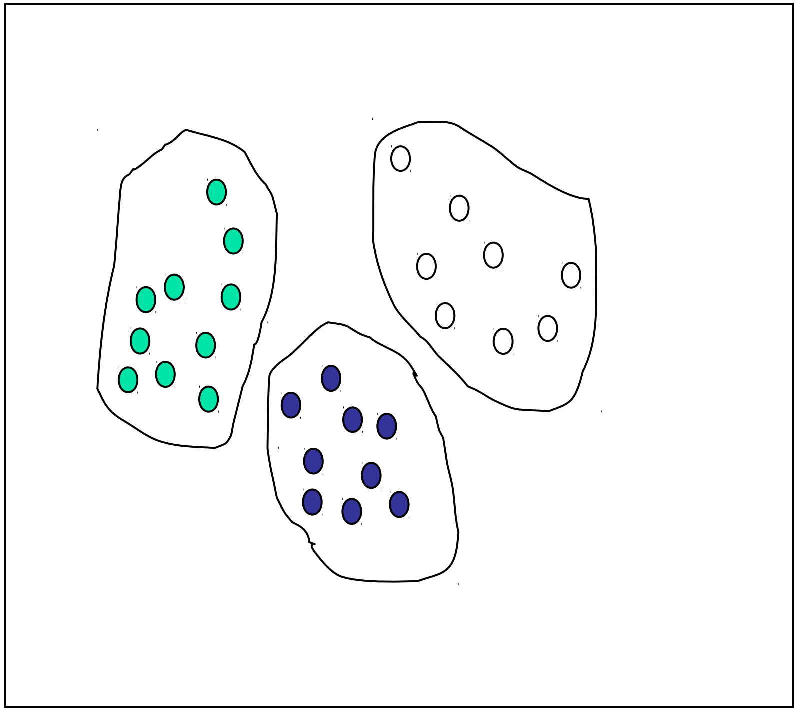


Types of Sampling

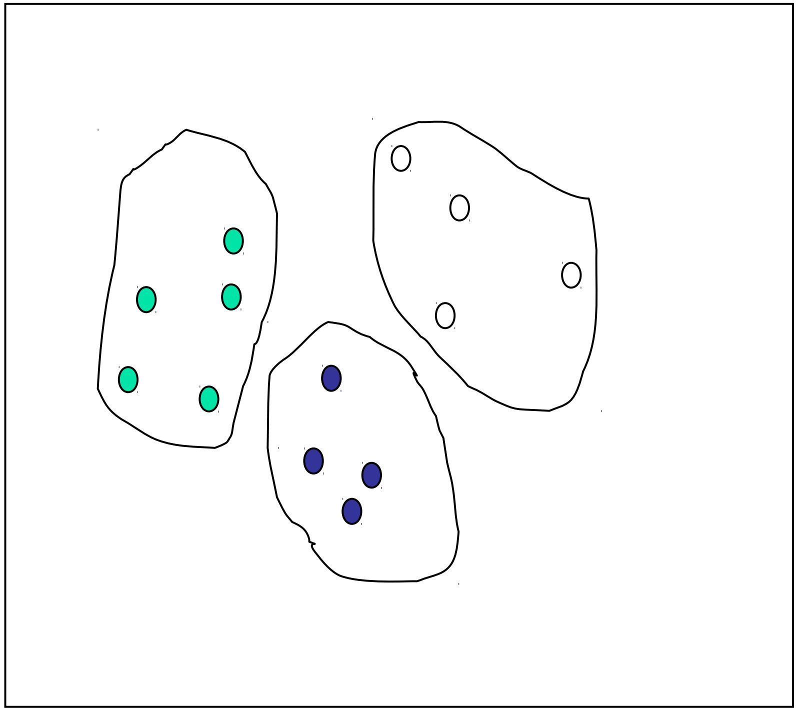
- **Stratified sampling:**
  - Choose a “category” attribute y
  - Partition the data set according to y values (strata)
  - Draw samples independently from each class (e.g. proportionally, i.e. approx. same % of data)
  - Better for skewed data
- **Clustered sampling:**
  - Cluster data, use cluster classes as category in a stratified sampling
- **Single stage / multi stage sampling:**
  - Perform hierarchical stratification or clustering
  - Sample recursively

Sampling: Cluster or Stratified Sampling

Raw Data

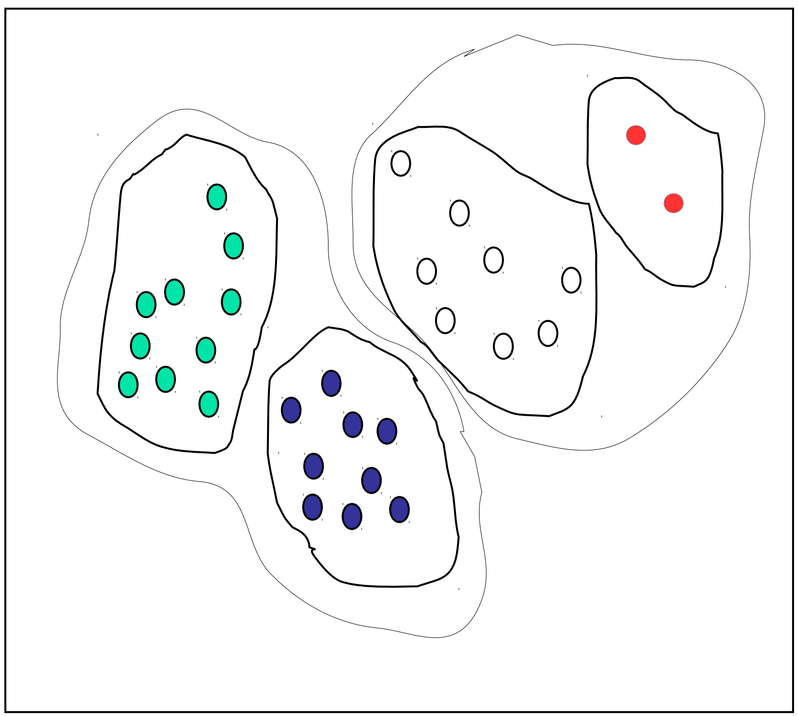


Cluster/Stratified Sample

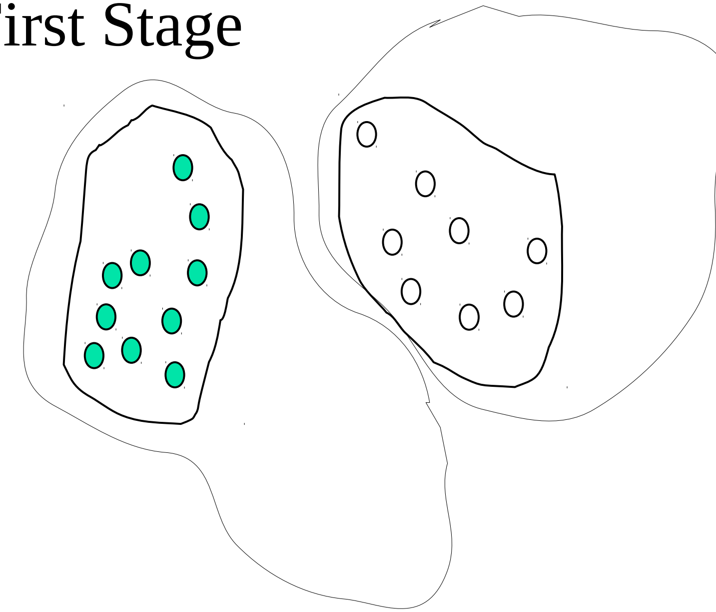


Sampling: Cluster or Stratified Sampling

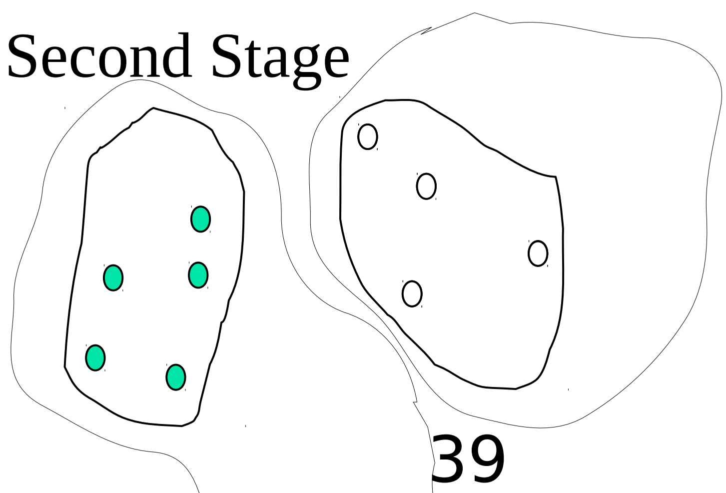
Raw Data



First Stage



Second Stage



Example: estimating sample size

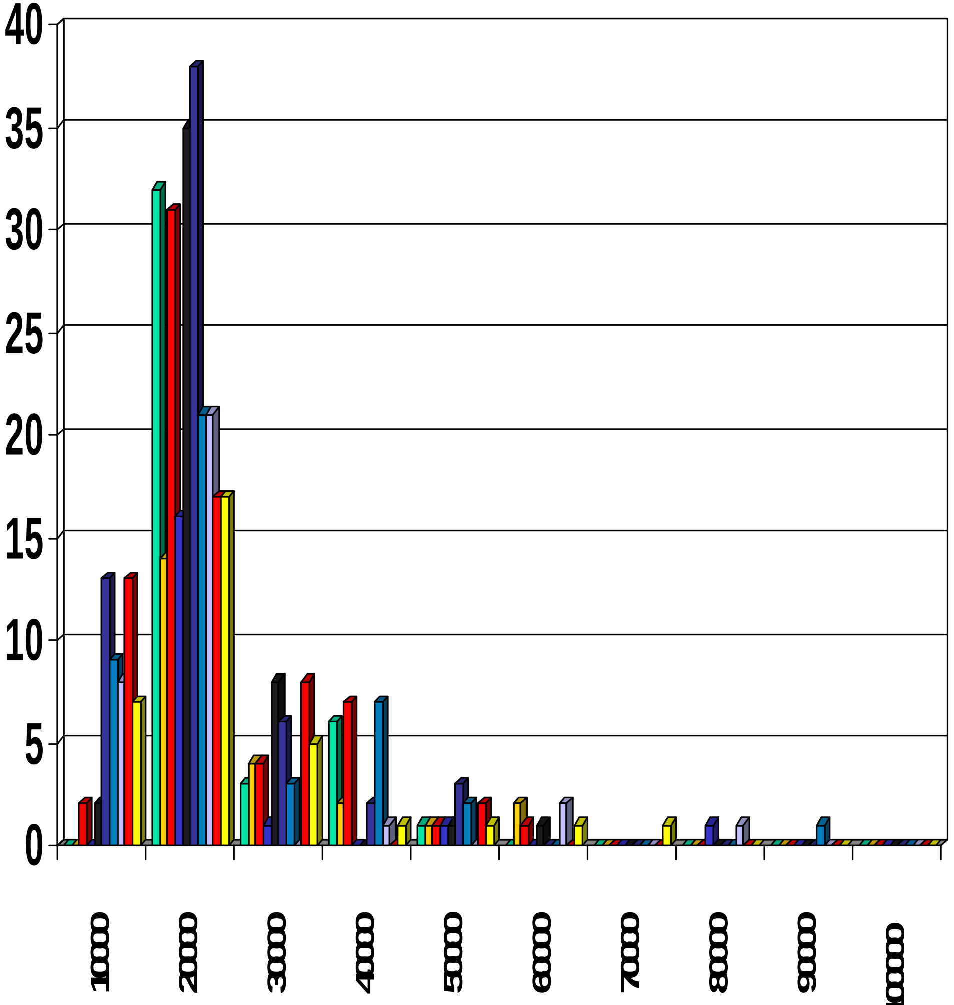
- Generally speaking: we want to select n data objects from N
  - to estimate the value P of a parameter of (the probability distribution of) an attribute
  - with a value p computed (by a consistent estimator) on the sample only
  - up to a given precision δ with a certain probability $(1-\alpha)$
  - **Then** $\Pr(|p - P| \geq \delta) \leq \alpha$
- If we assume our estimator to be asymptotically normal, and the attribute p.d.f. to have variance σ^2
  - z(x): value of the normal curve in x
  - $n_0 \geq z(\alpha/2)^2 \sigma^2 / \delta^2$; $n \geq n_0 / (1 + n_0 / N)$

Numerosity Reduction: change representation

- 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
- **Non-parametric** methods
  - Do not assume models
  - Major families: histograms, clustering, sampling, …

Histogram Analysis

- Divide data into buckets and store average (sum) for each bucket
- Partitioning rules:
  - Equal-width: equal bucket range
  - Equal-frequency (or equal-depth)



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
    - *We will have some dedicated lectures for clustering algorithms*

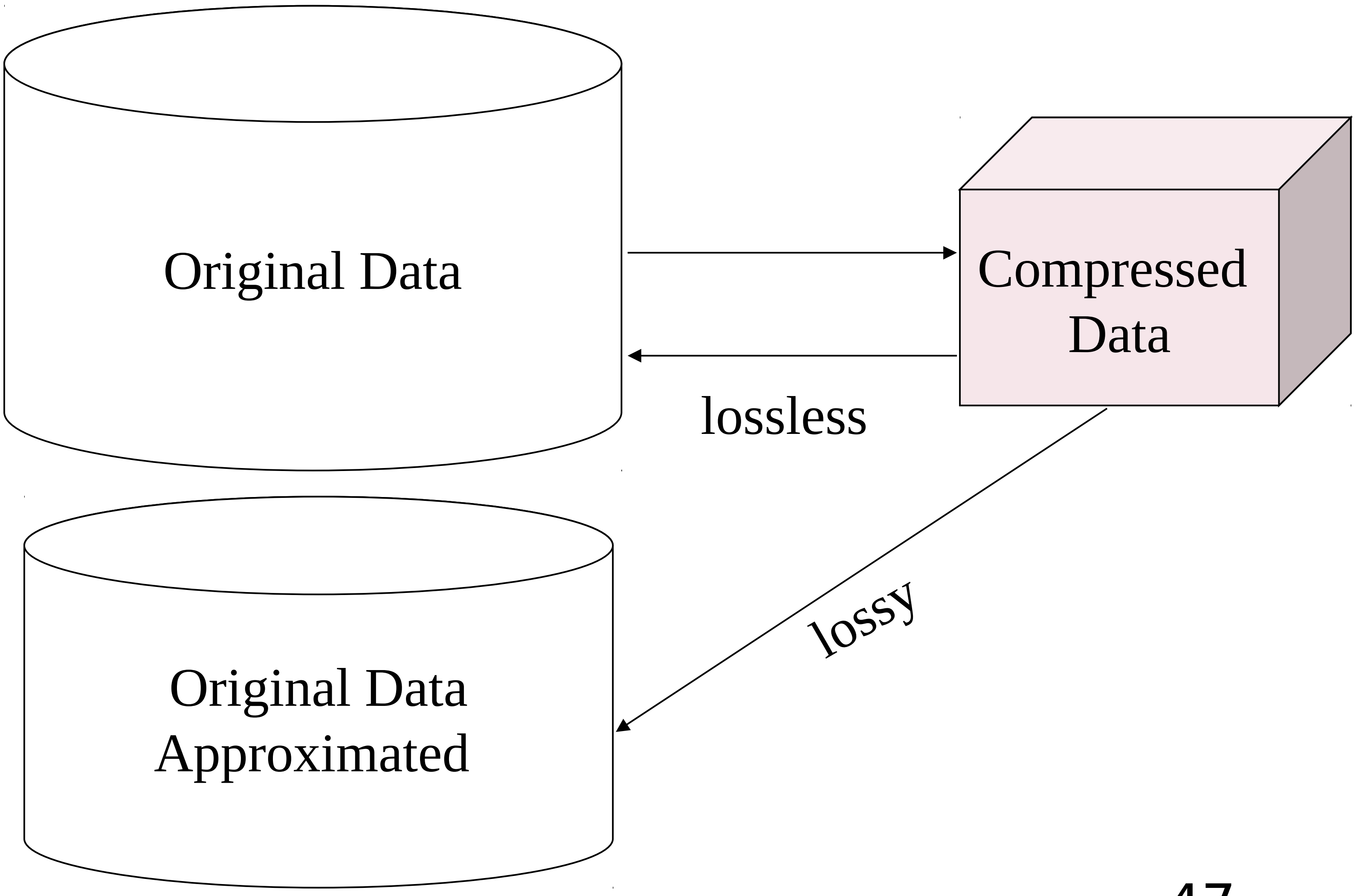
Data Reduction Strategies

- **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? Computational issues in big data!
- Data reduction strategies
  - Numerosity reduction (or simply "Data Reduction" → red. the number of data objects)
    - Sampling
    - Histograms, clustering
    - Regression and Log-Linear Models
    - Data cube aggregation
  - Dimensionality reduction (→ red. the number of attributes)
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation
    - Transforms (Fourier, Wavelet, Whitening …)
  - Data compression

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
- Time sequence is not audio
  - Typically short and vary slowly with time

Data Compression



Data Reduction Strategies

- Data reduction strategies
  - Numerosity reduction (or simply “Data Reduction” → red. the number of data objects)
    - Sampling
    - Histograms, clustering
    - Regression and Log-Linear Models
    - Data cube aggregation
  - Dimensionality reduction (→ red. the number of attributes)
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation
    - Transforms (Fourier, Wavelet, Whitening …)

      TOPIC OF THE NEXT SET OF LECTURES
  - Data compression

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 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 [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 \$73,600 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 μ = 54,000, σ = 16,000. Then $\frac{73,600 - 54,000}{16,000} = 1.225$
- **Normalization by decimal scaling**

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

Discretization

- Three types of attributes
  - Nominal—values from an unordered set, e.g. color
  - Ordinal—values from an ordered set, e.g. 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, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into equal-frequency (**equi-depth**) bins:

- Bin 1: 4, 8, 9, 15
- Bin 2: 21, 21, 24, 25
- Bin 3: 26, 28, 29, 34

* Smoothing by **bin means**:

- Bin 1: 9, 9, 9, 9
- Bin 2: 23, 23, 23, 23
- Bin 3: 29, 29, 29, 29

* Smoothing by **bin boundaries**:

- Bin 1: 4, 4, 4, 15
- Bin 2: 21, 21, 25, 25
- Bin 3: 26, 26, 26, 34

Binning Methods for Data Smoothing

- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into equal-frequency (**equi-depth**) bins:

- Bin 1: 4, 8, 9, 15
- Bin 2: 21, 21, 24, 25
- Bin 3: 26, 28, 29, 34

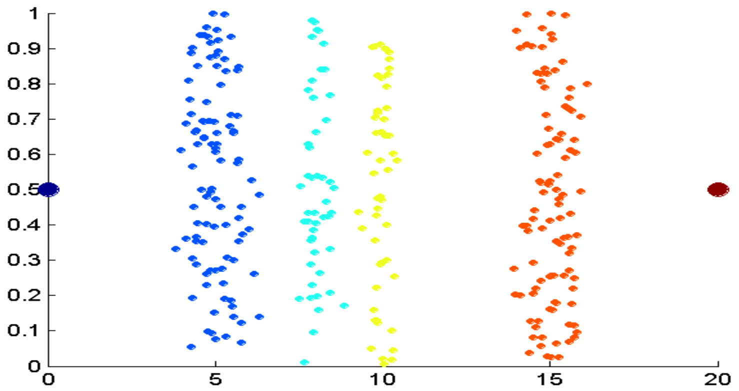
* Smoothing by **bin mean** **codes**:

- Bin 1: 1, 1, 1, 1
- Bin 2: 2, 2, 2, 2
- Bin 3: 3, 3, 3, 3

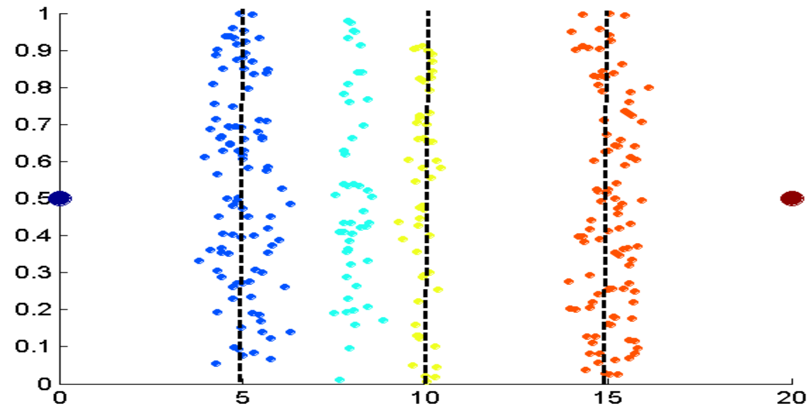
* Smoothing by **bin boundary** **codes**:

- Bin 1: 1l, 1l, 1l, 1r
- Bin 2: 2l, 2l, 2r, 2r
- Bin 3: 3l, 3l, 3l, 3r

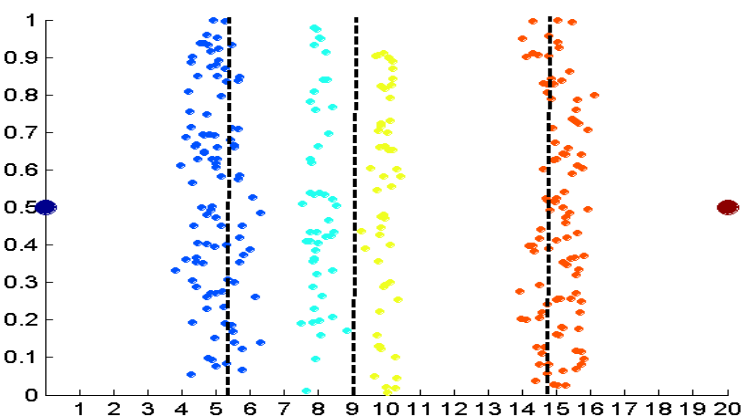
Discretization Without Using Class Labels (Binning vs. Clustering)



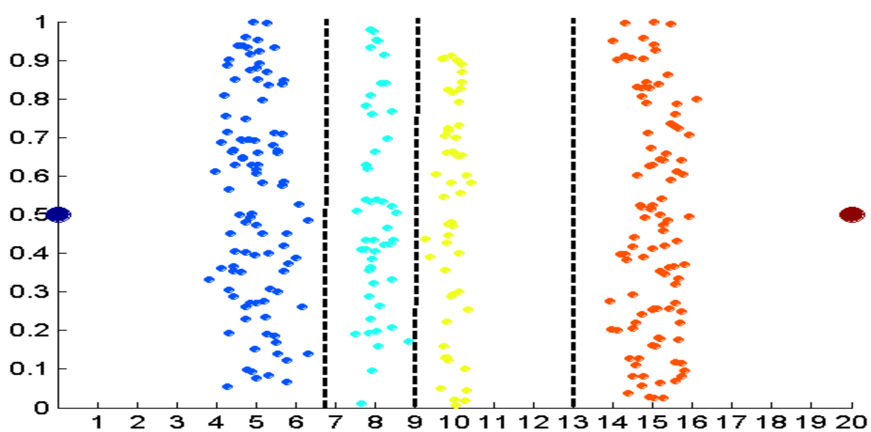
Data



Equal width (binning)



Equal frequency (binning)



K-means clustering leads to better results

Concept Hierarchy Generation

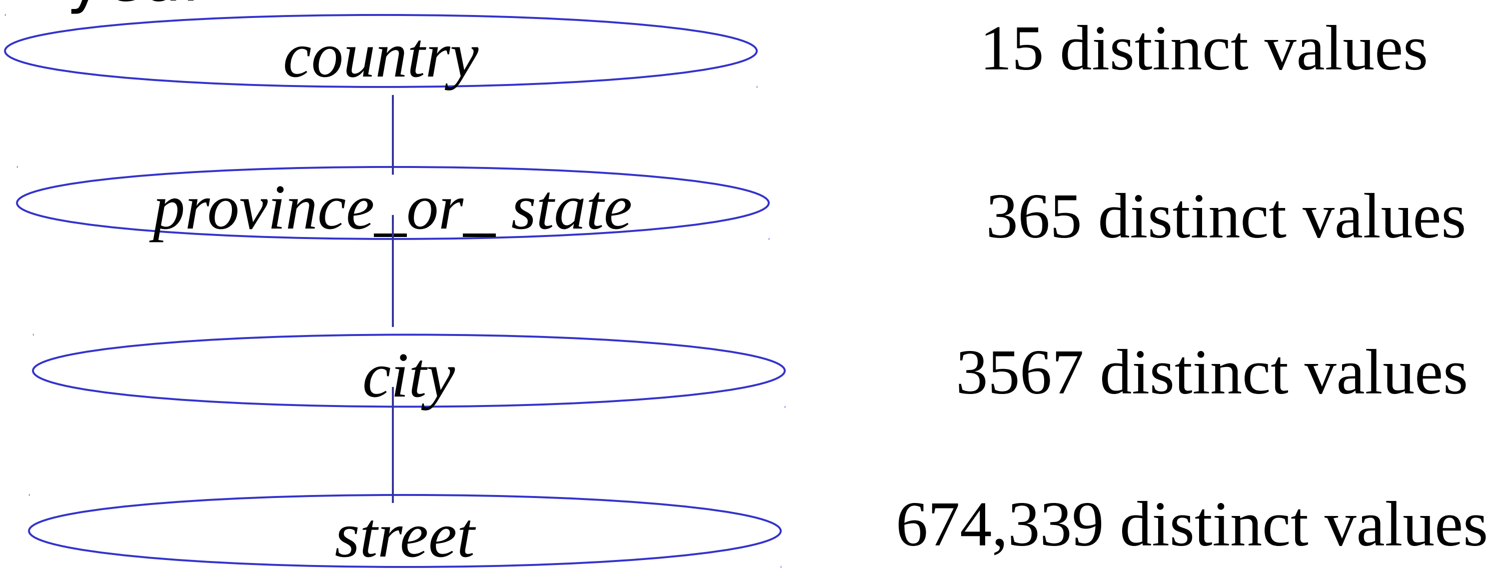
- **Concept hierarchy** organizes concepts (i.e., attribute values) hierarchically and is usually associated with each dimension in a data warehouse
- Concept hierarchies facilitate drilling and rolling in data warehouses to view data in multiple granularity
- Concept hierarchy formation: Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for *age*) by higher level concepts (such as *youth, adult*, or *senior*)
- Concept hierarchies can be explicitly specified by domain experts and/or data warehouse designers
- Concept hierarchy can be automatically formed for both numeric and nominal data. For numeric data, use discretization methods shown.

Concept Hierarchy Generation for Nominal Data

- Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts
  - *street* < *city* < *state* < *country*
- Specification of a hierarchy for a set of values by explicit data grouping
  - {Cremona, Lodi, Milano} < Lombardia
- Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values
  - E.g., for a set of attributes: {*street, city, state, country*}

Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
  - The attribute with the most distinct values is placed at the lowest level of the hierarchy
  - Exceptions, e.g., weekday, month, quarter, year



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

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