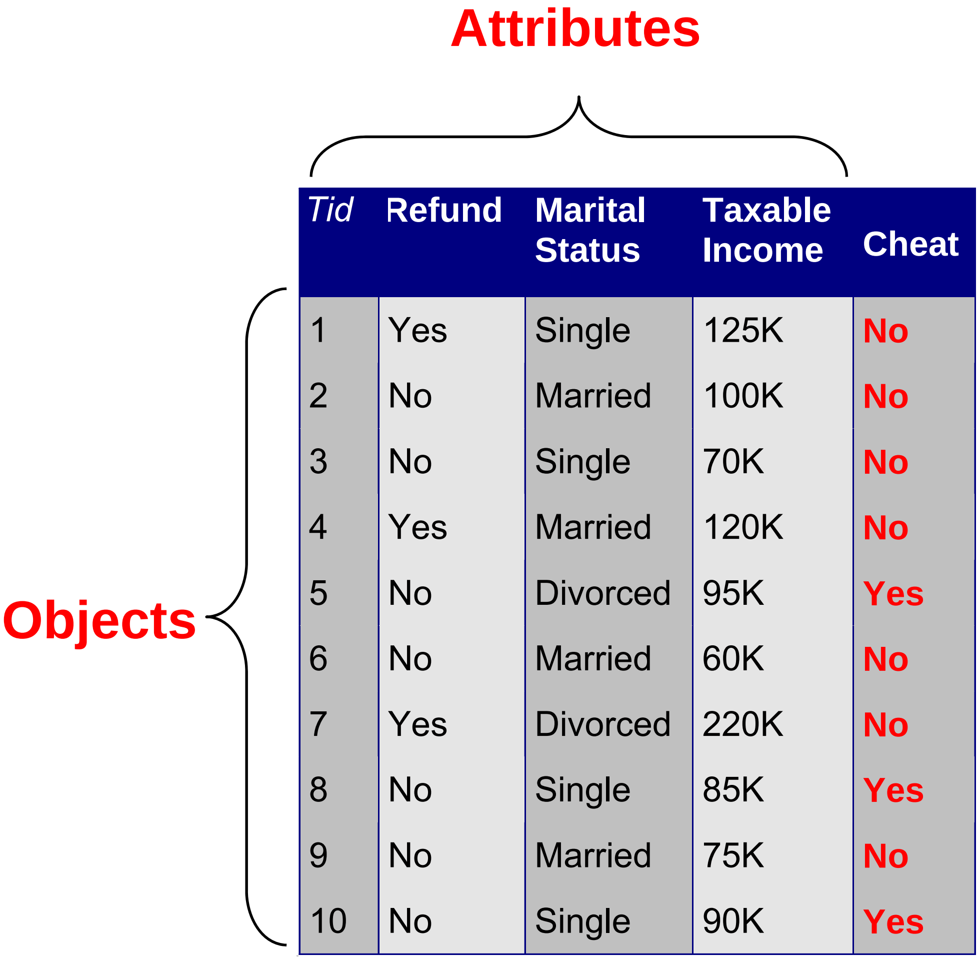
Data Mining: Data Preprocessing

I211: Information infrastructure II

What is Data?

- Collection of data objects and their attributes
- An attribute is a property or characteristic of an object
  - Examples: eye color of a person, temperature, etc.
  - Attribute is also known as variable, field, characteristic, or feature
- A collection of attributes describe an object
  - Object is also known as record, point, case, sample, entity, or instance



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

Data Preprocessing

- Why preprocess the data?
- Descriptive data summarization (covered!)
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization and concept hierarchy generation
- Summary

Why Data Preprocessing?

- Data in the real world is dirty
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., occupation=“ ”
  - noisy: containing errors or outliers
    - e.g., Salary=“-10”
  - inconsistent: containing discrepancies in codes or names
    - e.g., Age=“42” Birthday=“03/07/1997”
    - e.g., Was rating “1,2,3”, now rating “A, B, C”
    - e.g., discrepancy between duplicate records

Why Is Data Dirty?

- Incomplete data may come from
  - “Not applicable” data value when collected
  - Different considerations between the time when the data was collected and when it is analyzed.
  - Human/hardware/software problems
- Noisy data (incorrect values) may come from
  - Faulty data collection instruments
  - Human or computer error at data entry
  - Errors in data transmission
- Inconsistent data may come from
  - Different data sources
  - Functional dependency violation (e.g., modify some linked data)
- Duplicate records also need data cleaning

Why Is Data Preprocessing Important?

- No quality data, no quality mining results!
  - Quality decisions must be based on quality data
    - e.g., duplicate or missing data may cause incorrect or even misleading statistics.
  - Data warehouse needs consistent integration of quality data
- Data extraction, cleaning, and transformation comprises the majority of the work of building a data mining system

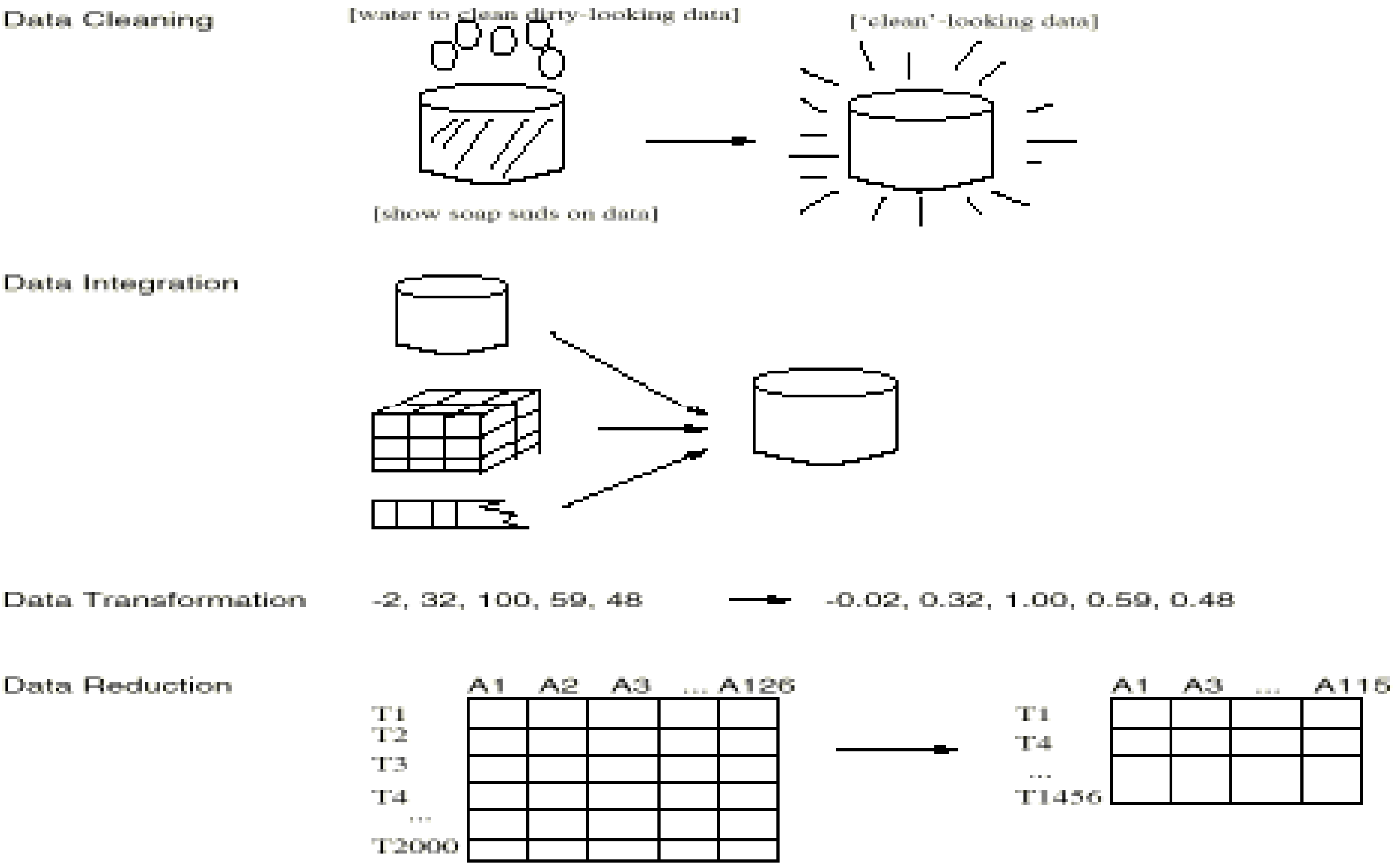
Multi-Dimensional Measure of Data Quality

- A well-accepted multidimensional view:
  - Accuracy
  - Completeness
  - Consistency
  - Timeliness
  - Believability
  - Value added
  - Interpretability
  - Accessibility

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 or files
- Data transformation
  - Normalization and aggregation
- Data reduction
  - Obtains reduced representation in volume but produces the same or similar analytical results
- Data discretization
  - Part of data reduction but with particular importance, especially for numerical data

Forms of Data Preprocessing



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Data Cleaning

- Importance
  - garbage in garbage out principle (GIGO)

- Data cleaning tasks
  - Fill in missing values
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data
  - Resolve redundancy caused by data integration

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 (assuming the tasks in classification—not effective when the percentage 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 data points 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 due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention
- Class label noise is hard to deal with
  - sometimes we don’t know whether the class label is correct or it is simply unexpected
- Noise demands robustness in training algorithms, that is, training should not be sensitive to noise

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)

Simple Discretization Methods: 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 data points
  - 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

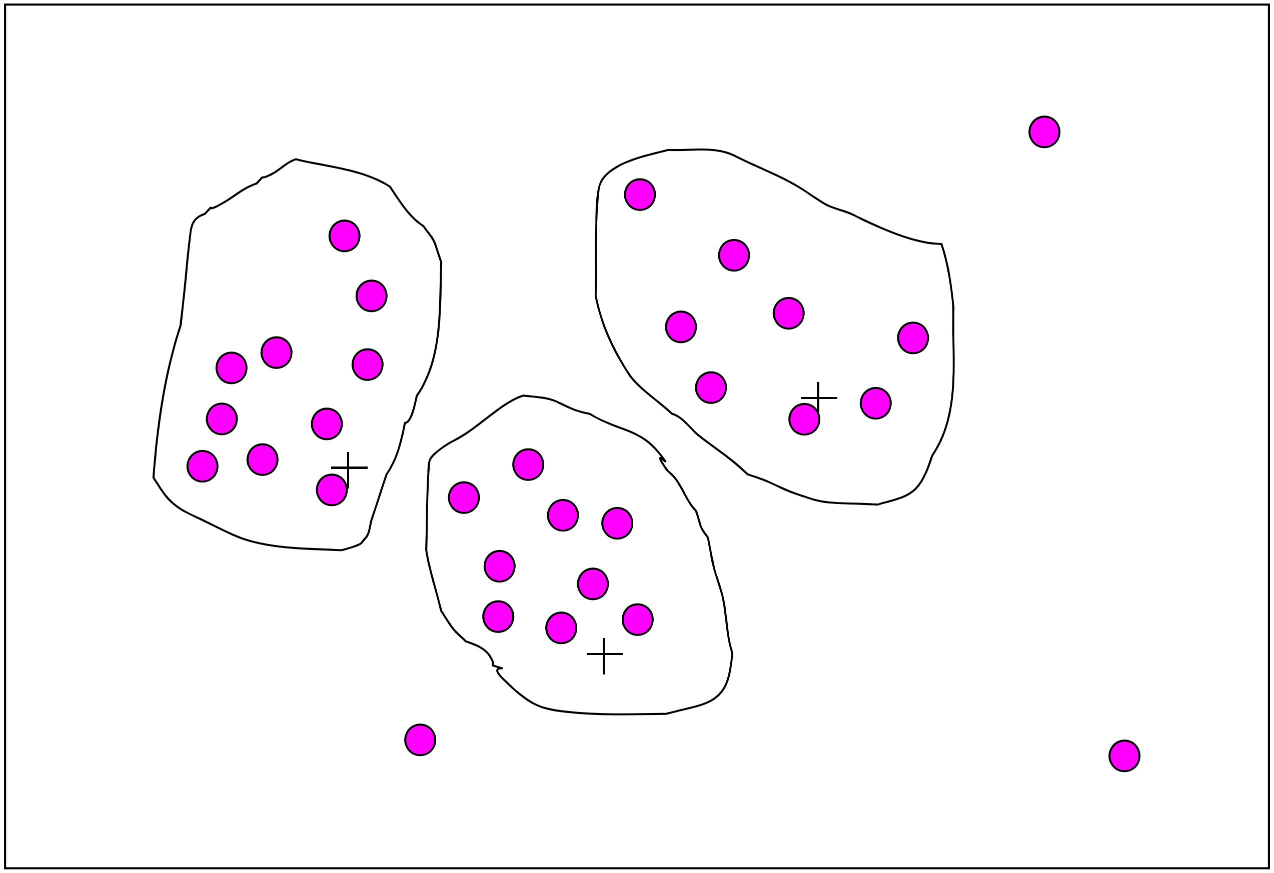
* Smoothing by bin means:

  - 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

Cluster Analysis as Binning



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)

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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 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*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Correlation Analysis (Numerical Data)

- Correlation coefficient (Pearson’s correlation coefficient)

$$r_{A,B} = \frac{\sum (A-\overline{A})(B-\overline{B})}{(n-1)\sigma_A \sigma_B} = \frac{\sum (AB) - n\overline{A}\overline{B}}{(n-1)\sigma_A \sigma_B}$$

where n is the number of tuples, $\overline{A}$ and $\overline{B}$ are the respective means of *A* and *B*, σ_A and σ_B are the respective standard deviation of *A* and *B*, and Σ(*AB*) 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.
- $r_{A,B} = 0$: uncorrelated; $r_{A,B} < 0$: negatively correlated

Correlation Analysis (Categorical Data)

- X^2 (chi-square) test

$$\chi^2_{n-1} = \sum_{i=1}^{n} \frac{(Observed_i - Expected_i)^2}{Expected_i}$$

- *n* is the number of possible values
- 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-Square Calculation: An Example

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

Probability to play chess: P(chess) = 300/1500 = 0.2

Probability to like science fiction: P(SciFi) = 450/1500 = 0.3

If science fiction and chess playing are independent attributes, then the probability to like SciFi AND play chess is

P(SciFi, chess) = P(SciFi) · P(chess) = 0.06

That means, we expect 0.06 · 1500 = 90 such cases (if they are independent)

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 expected counts calculated based on the data distribution in the two categories)

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

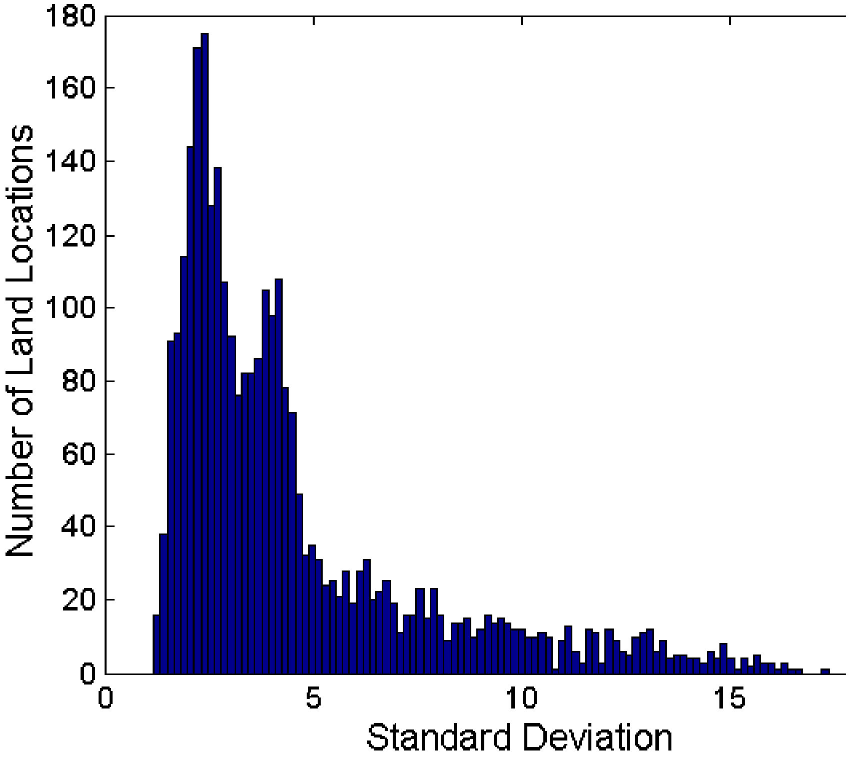
- It shows that like_science_fiction and play_chess are correlated in the group

Data Transformation

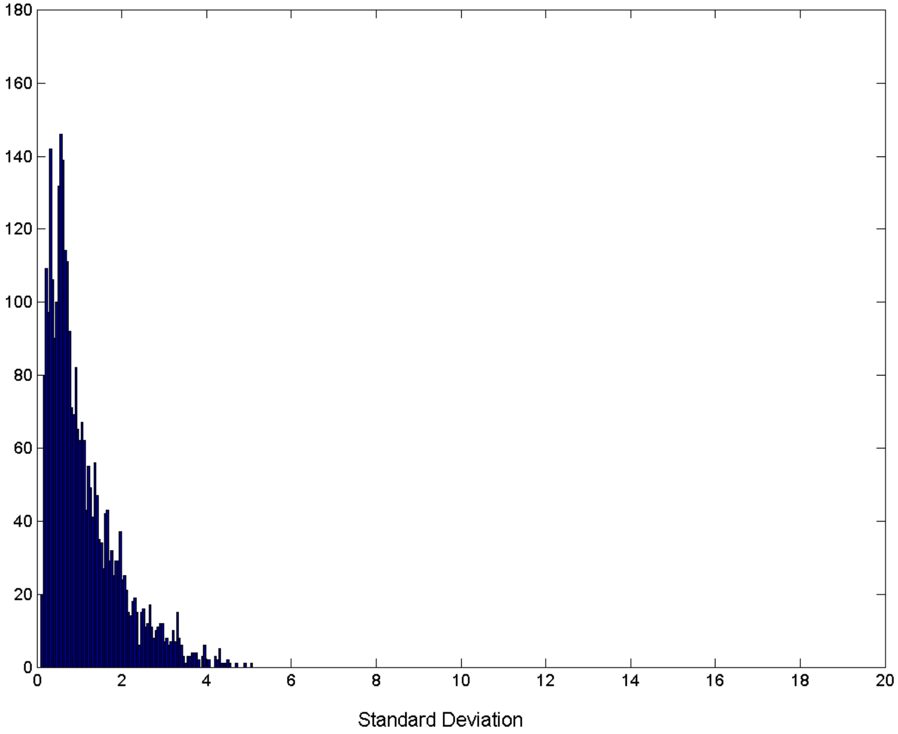
- Smoothing: remove noise from data
- Aggregation: summarization
- Generalization: concept hierarchy climbing
- Normalization: scaled to fall within a small, specified range
  - min-max normalization
  - z-score normalization
  - normalization by decimal scaling
- Attribute/feature construction
  - New attributes constructed from the given ones

Aggregation

Variation of Precipitation in Australia



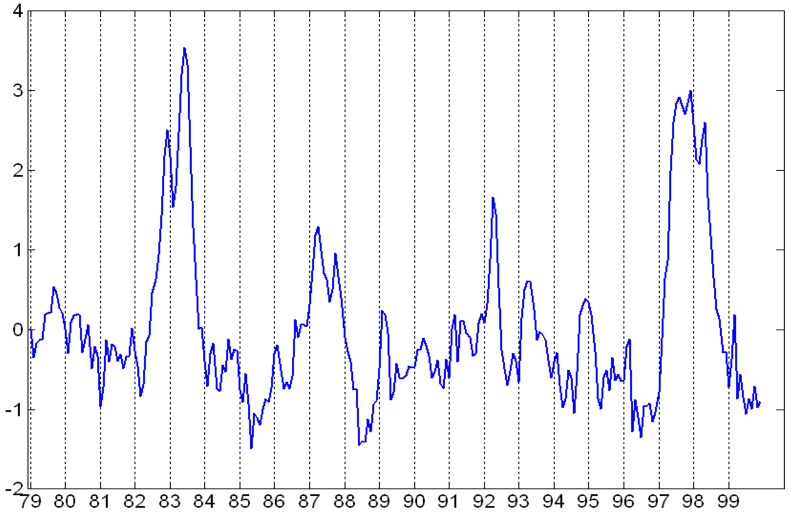
Standard Deviation of Average Monthly Precipitation



Standard Deviation of Average Yearly Precipitation

Attribute Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values such that each old value can be identified with one of the new values
  - Simple functions: x^k, $\log(x)$, e^x, $|x|$
  - Standardization and Normalization



Attribute 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 μ = 54,000, σ = 16,000. Then

$$\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$$

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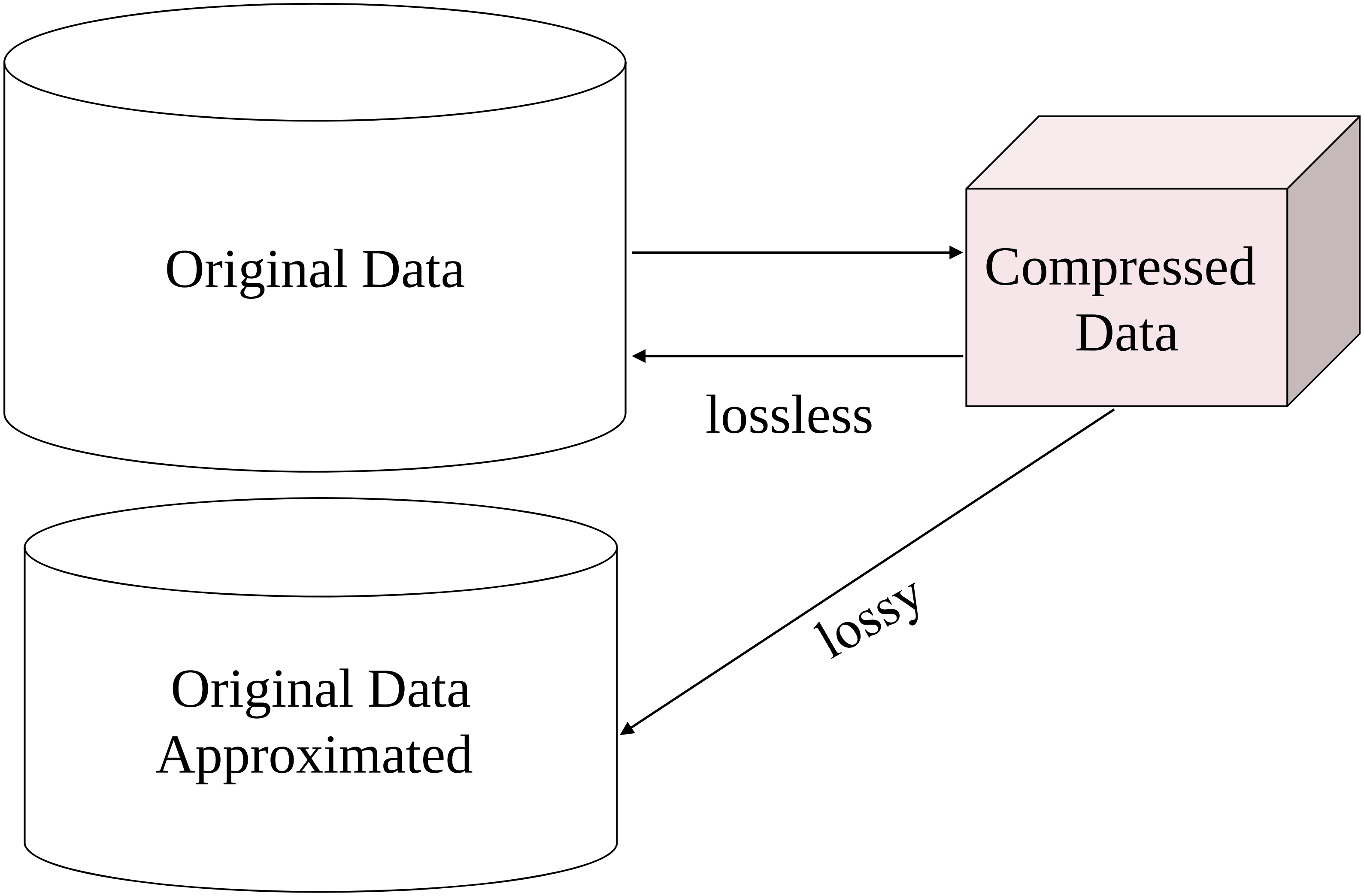
Data Reduction Strategies

- Why data reduction?
  - A database may store terabytes of data
  - Complex data analysis/mining may take a very long time to run on the complete data set
- Data reduction
  - Obtain a reduced representation of the data set that is much smaller in volume but yet produce the same (or almost the same) analytical results
- Data reduction strategies
  - Data Compression
  - Sampling
  - Discretization and concept hierarchy generation
  - Dimensionality reduction — e.g. remove unimportant attributes

Data Compression

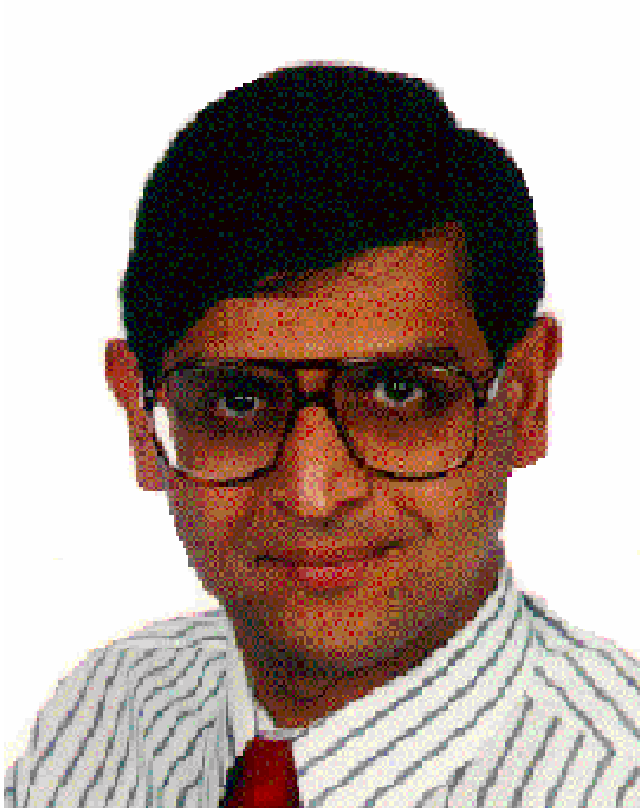
- String compression
  - There are extensive theories and well-tuned algorithms
  - Typically lossless
  - But only limited manipulation is possible without expansion
- Audio/video compression
  - Typically lossy compression, with progressive refinement
  - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
  - Typically short and vary slowly with time

Data Compression



Data Compression (via PCA)

Dimensions = 206



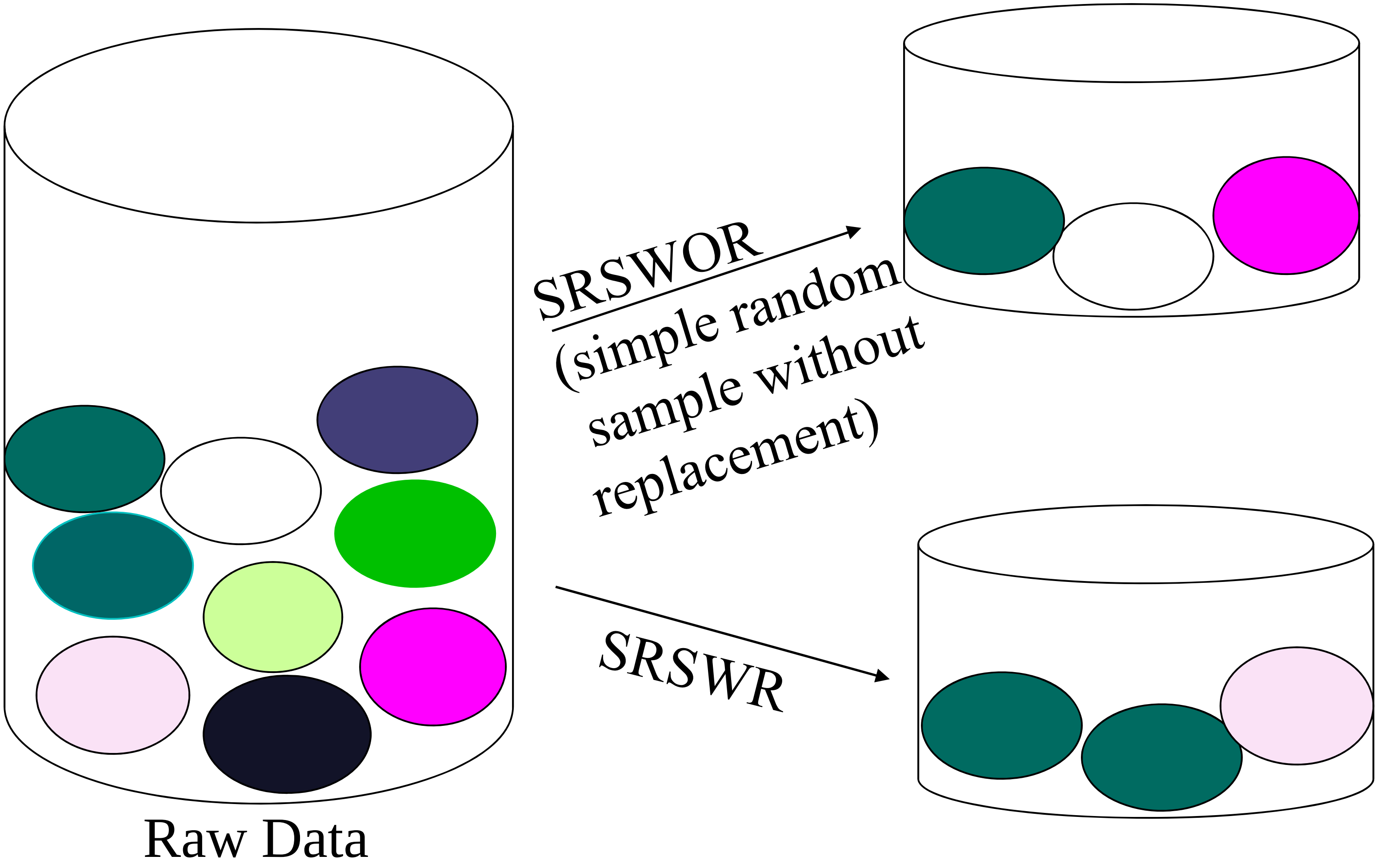
Data Reduction Method: Sampling

- 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
- Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
- Develop adaptive sampling methods
  - Stratified sampling:
    - Approximate the percentage of each class (or subpopulation of interest) in the overall database
    - Used in conjunction with skewed data

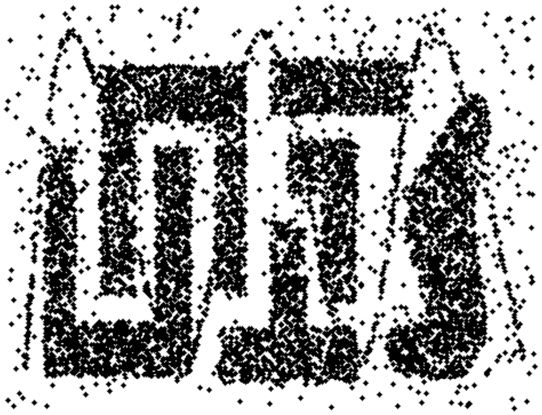
Types of Sampling

- 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

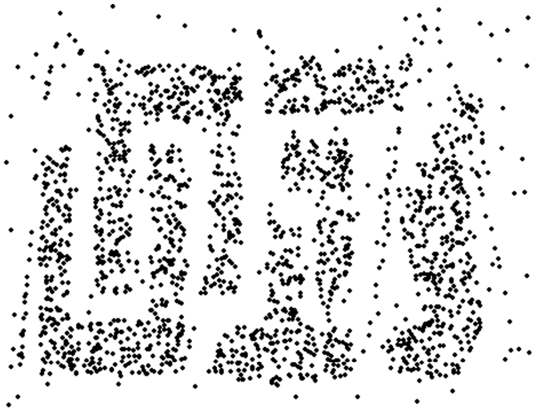
Sampling: with or without Replacement



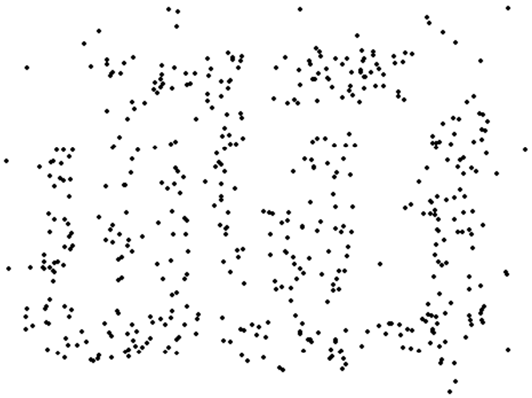
Sample Size



8000 points



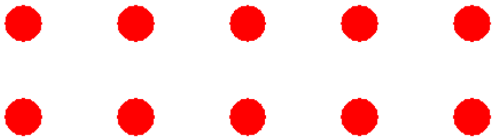
2000 Points

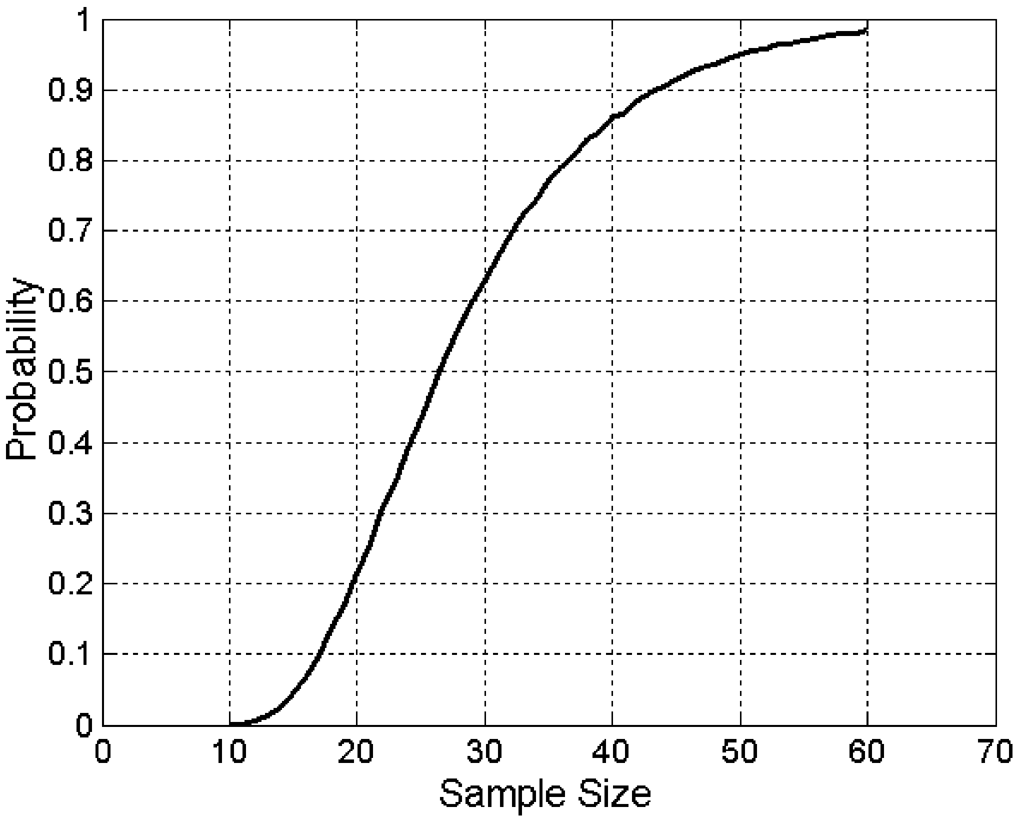


500 Points

Sample Size

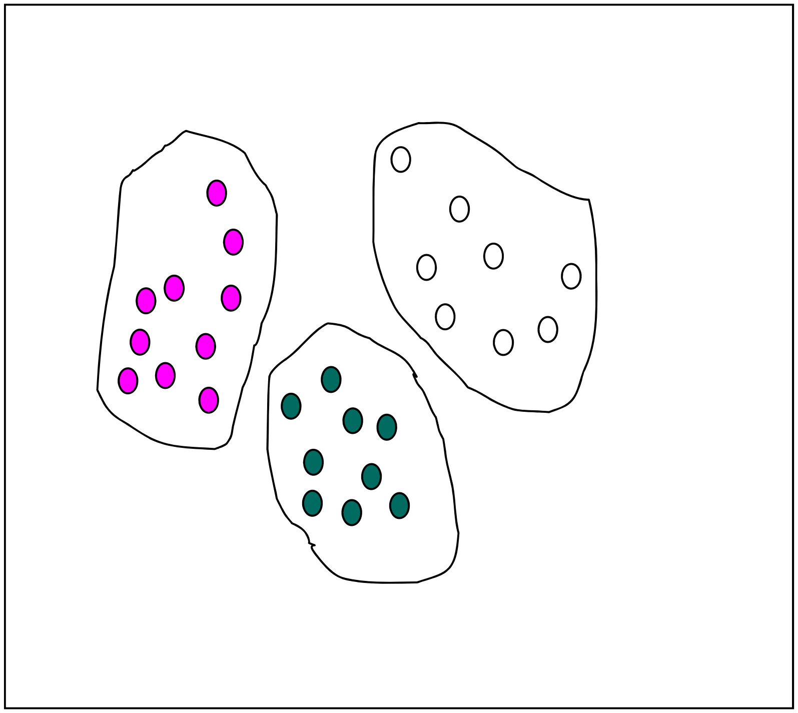
- What sample size is necessary to get at least one object from each of 10 groups.



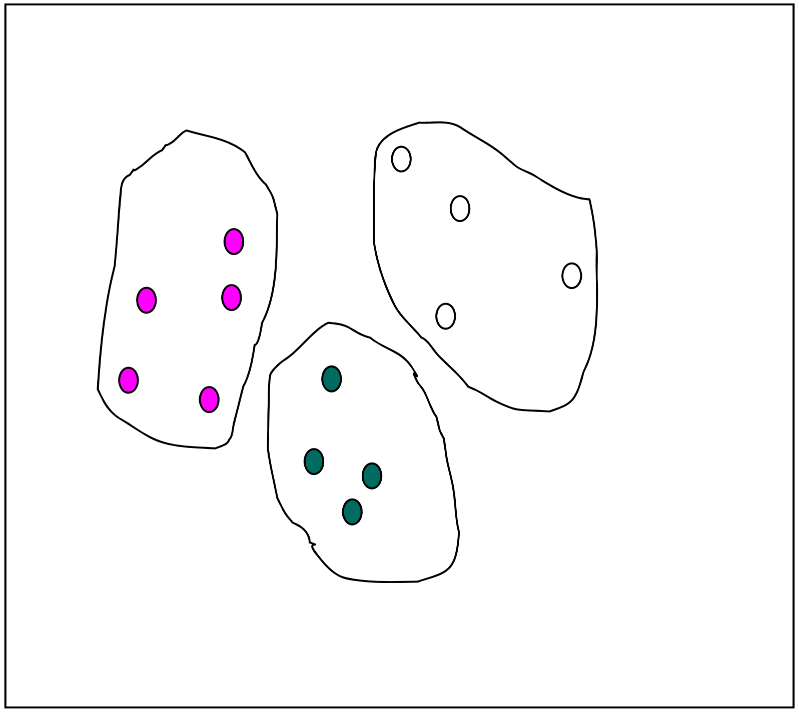


Sampling: Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample



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 attributes
  - Example: 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
  - Example: students' ID is often irrelevant to the task of predicting students' GPA

Feature Subset Selection

- Techniques:
  - Brute-force approach:
    - Try all possible feature subsets as input to data mining algorithm
  - Embedded approaches:
    - Feature selection occurs naturally as part of the data mining algorithm
  - Filter approaches:
    - Features are selected before data mining algorithm is run
  - Wrapper approaches:
    - Use the data mining algorithm as a black box to find best subset of attributes

Feature Creation

- Create new attributes that can capture the important information in a data set much more efficiently than the original attributes

- Methodologies:
  - Mapping Data to New Space
    - Feature construction by combining features

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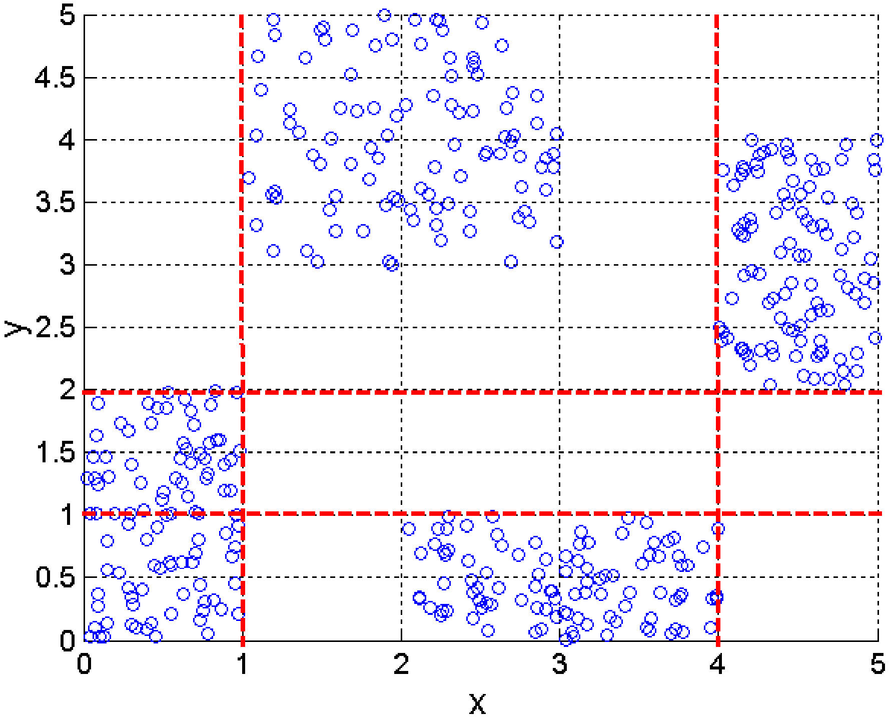
Discretization

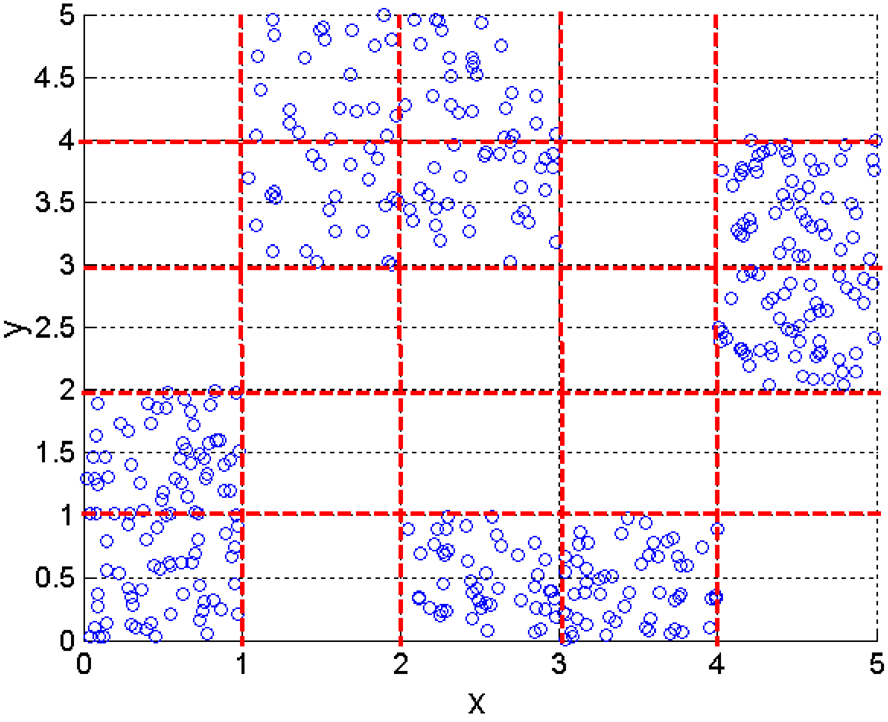
- Three types of attributes:
  - Nominal — values from an unordered set, e.g., color, profession
  - Ordinal — values from an ordered set, e.g., military or academic rank
  - Continuous — real numbers, e.g., integer or real numbers (here we aggregated interval and ratio attributes into *continuous*)
- Discretization:
  - Divide the range of a continuous attribute into intervals
  - Some classification algorithms only accept categorical attributes.
  - Reduce data size by discretization
  - Prepare for further analysis

Discretization Using Class Labels

- **Entropy based approach**

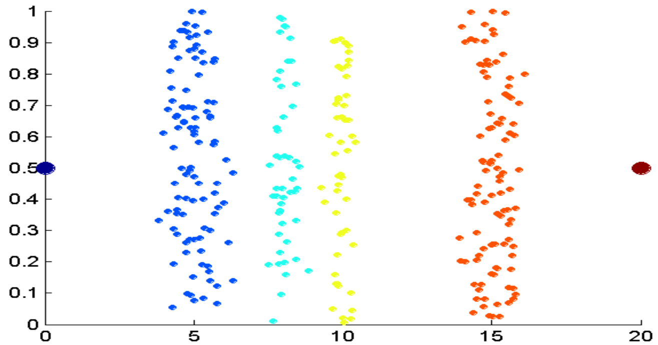


3 categories for both x and y

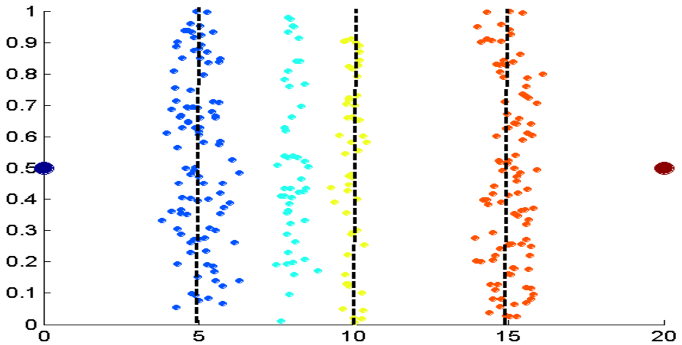


5 categories for both x and y

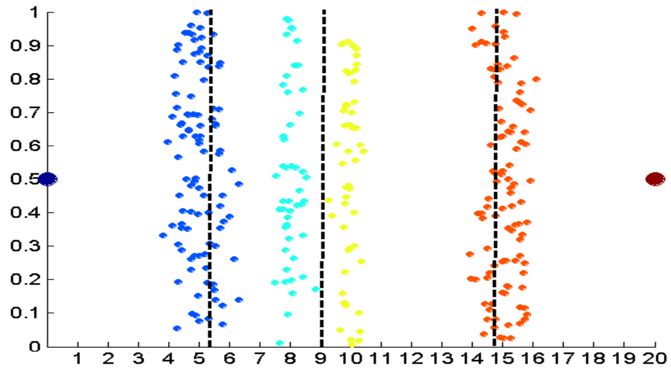
Discretization Without Using Class Labels



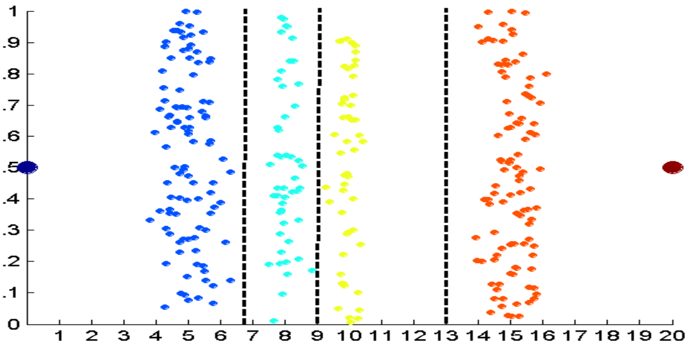
Data



Equal interval width



Equal frequency



K-means

Discretization and Concept Hierarchy

- Discretization
  - Reduce the number of values for a given continuous attribute by dividing the range of the attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Supervised vs. unsupervised (use class or don’t use class variable)
  - Split (top-down) vs. merge (bottom-up)

- 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 young, middle-aged, or senior)

Discretization and Concept Hierarchy Generation for Numeric Data

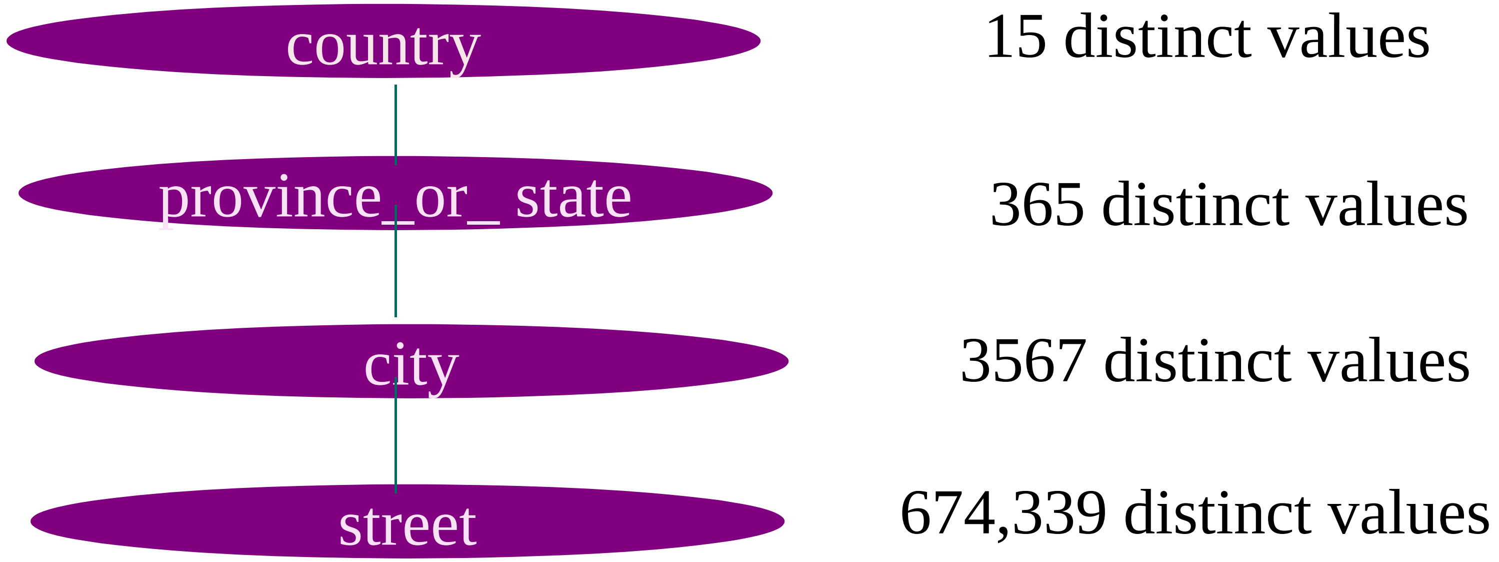
- Typical methods: All the methods can be applied recursively
  - Binning (covered earlier)
    - Top-down split, unsupervised,
  - Histogram analysis (covered earlier)
    - Top-down split, unsupervised
  - Clustering analysis (covered earlier and in more detail later)
    - Either top-down split or bottom-up merge, unsupervised
  - Entropy-based discretization: supervised, top-down split
  - Interval merging by χ^2 Analysis: unsupervised, bottom-up merge
  - Segmentation by natural partitioning: top-down split, unsupervised

Concept Hierarchy Generation for Categorical 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
  - {Urbana, Champaign, Chicago} < Illinois
- Specification of only a partial set of attributes
  - E.g., only street < city, not others
- 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



country — 15 distinct values

province_or_ state — 365 distinct values

city — 3567 distinct values

street — 674,339 distinct values

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Summary

- Data preparation or preprocessing is a big issue for data mining
- Descriptive data summarization is need for quality data preprocessing
- Data preparation includes
  - Data cleaning and data integration
  - Data reduction and feature selection
  - Discretization
- A lot a methods have been developed but data preprocessing still an active area of research