Data cleaning and Data preprocessing

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This presentation was prepared on the basis of the following public materials:

1. Jiawei Han and Micheline Kamber, „Data mining, concept and techniques" http://www.cs.sfu.ca
2. Gregory Piatetsky-Shapiro, „kdnuggest", http://www.kdnuggets.com/data_mining_course/

Outline

- Introduction
- 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
  - noisy: containing errors or outliers
  - inconsistent: containing discrepancies in codes or names
- No quality data, no quality mining results!
  - Quality decisions must be based on quality data
  - Data warehouse needs consistent integration of quality data


Data Understanding: Relevance

- What data is available for the task?
- Is this data relevant?
- Is additional relevant data available?
- How much historical data is available?
- Who is the data expert ?

Data Understanding: Quantity

- Number of instances (records, objects)
  - *Rule of thumb: 5,000 or more desired*
  - if less, results are less reliable; use special methods (boosting, …)
- Number of attributes (fields)
  - *Rule of thumb: for each attribute, 10 or more instances*
  - If more fields, use feature reduction and selection
- Number of targets
  - *Rule of thumb: >100 for each class*
  - if very unbalanced, use stratified sampling

Multi-Dimensional Measure of Data Quality

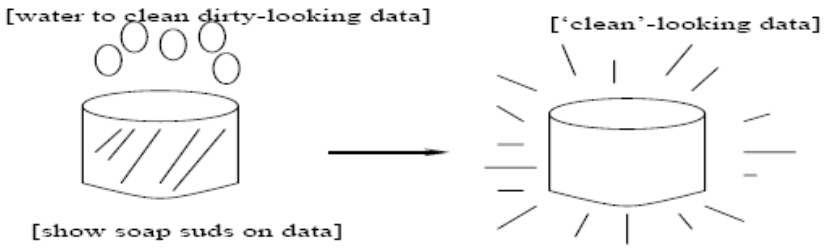
- A well-accepted multidimensional view:
  - Accuracy
  - Completeness
  - Consistency
  - Timeliness
  - Believability
  - Value added
  - Interpretability
  - Accessibility
- Broad categories:
  - intrinsic, contextual, representational, and accessibility.

Major Tasks in Data Preprocessing

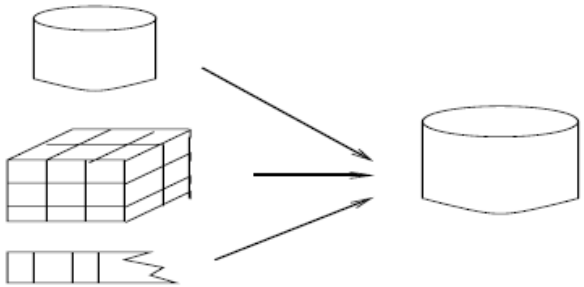
- Data cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration
  - Integration of multiple databases, data cubes, or files
- Data transformation
  - Normalization and aggregation
- Data reduction
  - Obtains reduced representation 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

Data Cleaning



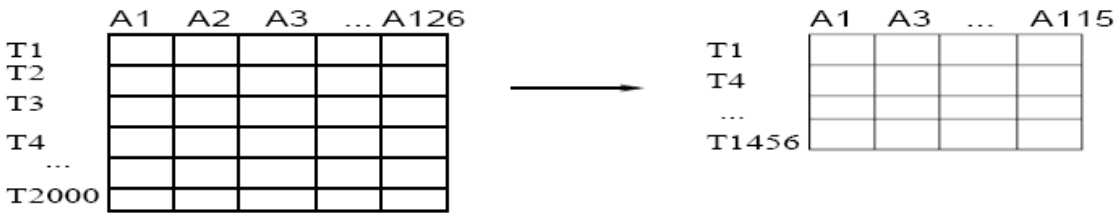
Data Integration



Data Transformation

-2, 32, 100, 59, 48 → -0.02, 0.32, 1.00, 0.59, 0.48

Data Reduction



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Data Cleaning

- Data cleaning tasks
  - Data acquisition and metadata
  - Fill in missing values
  - Unified date format
  - Converting nominal to numeric
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data


Data Cleaning: Acquisition

- Data can be in DBMS
  - ODBC, JDBC protocols
- Data in a flat file
  - Fixed-column format
  - Delimited format: tab, comma "," , other
  - E.g. C4.5 and Weka "arff" use comma-delimited data
  - Attention: Convert field delimiters inside strings
- Verify the number of fields before and after


Data Cleaning: Example

- **Original data (fixed column format)**

000000000130.06.19971979-10-3080145722 #000310 111000301.01.000100000000004
0000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.0000
00000000000. 000000000000000.000000000000000.0000000......
000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.00
0000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.0000
00000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000000000000.000000
000000000.000000000000000.000000000000000.000000000000000.00 000000000300.00 000000000300.00

- **Clean data**

0000000001,199706,1979.833,8014,5722 , ,#000310 ….
,111,03,000101,0,04,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0300,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0300,0300.00

Data Cleaning: Metadata

- **Field types:**
  - **binary, nominal (categorical), ordinal, numeric, …**
  - **For nominal fields: tables translating codes to full descriptions**
- **Field role:**
  - input : inputs for modeling
  - target : output
  - id/auxiliary : keep, but not use for modeling
  - ignore : don't use for modeling
  - weight : instance weight
  - …
- **Field descriptions**

Data Cleaning: Reformatting

Convert data to a standard format (e.g. arff or csv)

- Missing values
- Unified date format
- Binning of numeric data
- Fix errors and outliers
- Convert nominal fields whose values have order to numeric.
  - ***Q: Why?*** A: to be able to use “>” and “<“ comparisons on these fields)


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?
- **Use a global constant to fill in the missing value**: e.g., "unknown", a new class?!
- **Imputation**: Use the attribute mean to fill in the missing value, or use the attribute mean for all samples belonging to the same class to fill in the missing value: smarter
- Use the most probable value to fill in the missing value: inference-based such as Bayesian formula or decision tree


Data Cleaning: Unified Date Format

- We want to transform all dates to the same format internally
- Some systems accept dates in many formats
  - e.g. "Sep 24, 2003" , 9/24/03, 24.09.03, etc
  - dates are transformed internally to a standard value
- Frequently, just the year (YYYY) is sufficient
- For more details, we may need the month, the day, the hour, etc
- Representing date as YYYYMM or YYYYMMDD can be OK, but has problems
- ***Q: What are the problems with YYYYMMDD dates?***
  - A: Ignoring for now the Looming Y10K (year 10,000 crisis …)
  - YYYYMMDD does not preserve intervals:
  - 20040201 - 20040131 /= 20040131 – 20040130
  - This can introduce bias into models

Unified Date Format Options

- To preserve intervals, we can use
  - Unix system date: Number of seconds since 1970
  - Number of days since Jan 1, 1960 (SAS)
- Problem:
  - values are non-obvious
  - don't help intuition and knowledge discovery
  - harder to verify, easier to make an error


KSP Date Format

$$\text{KSP Date} = \text{YYYY} + \frac{\text{days\_starting\_Jan\_1} - 0.5}{365 + 1\_\text{if\_leap\_year}}$$

- Preserves intervals (almost)
- The year and quarter are obvious
  - Sep 24, 2003 is 2003 + (267-0.5)/365= 2003.7301 (round to 4 digits)
- Consistent with date starting at noon
- Can be extended to include time

Y2K issues: 2 digit Year

- 2-digit year in old data – legacy of Y2K
- E.g. Q: Year 02 – is it 1902 or 2002 ?
  - A: Depends on context (e.g. child birthday or year of house construction)
  - Typical approach: CUTOFF year, e.g. 30
  - if YY < CUTOFF , then 20YY, else 19YY

Conversion: Nominal to Numeric

- Some tools can deal with nominal values internally
- Other methods (neural nets, regression, nearest neighbor) require only numeric inputs
- To use nominal fields in such methods need to convert them to a numeric value
  - Q: Why not ignore nominal fields altogether?
  - A: They may contain valuable information
- Different strategies for binary, ordered, multi-valued nominal fields

Conversion: Binary to Numeric

- Binary fields
  - E.g. Gender=M, F
- Convert to Field_0_1 with 0, 1 values
  - e.g. Gender = M → Gender_0_1 = 0
  - Gender = F → Gender_0_1 = 1

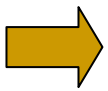
Conversion: Ordered to Numeric

- Ordered attributes (e.g. Grade) can be converted to numbers preserving *natural* order, e.g.
  - A → 4.0
  - A- → 3.7
  - B+ → 3.3
  - B → 3.0
- Q: Why is it important to preserve *natural* order?
- A: To allow meaningful comparisons, e.g. Grade > 3.5

Conversion: Nominal, Few Values

- Multi-valued, unordered attributes with small (*rule of thumb* < *20*) no. of values
  - e.g. Color=Red, Orange, Yellow, …, Violet
  - for each value *v* create a binary "flag" variable C_*v* , which is 1 if Color=*v*, 0 otherwise

ID	Color	…
371	red	
433	yellow	



ID	C_red	C_orange	C_yellow	…
371	1	0	0	
433	0	0	1	

Conversion: Nominal, Many Values

- Examples:
  - US State Code (50 values)
  - Profession Code (7,000 values, but only few frequent)
- Q: How to deal with such fields ?
- A: Ignore ID-like fields whose values are unique for each record
- For other fields, group values "naturally":
  - e.g. 50 US States → 3 or 5 regions
  - Profession – select most frequent ones, group the rest
- Create binary flag-fields for selected values


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
- Other data problems which requires data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

How to Handle Noisy Data?

- Binning method:
  - first sort data and partition into (equi-depth) bins
  - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
- Clustering
  - detect and remove outliers
- Combined computer and human inspection
  - detect suspicious values and check by human
- Regression
  - smooth by fitting the data into regression functions

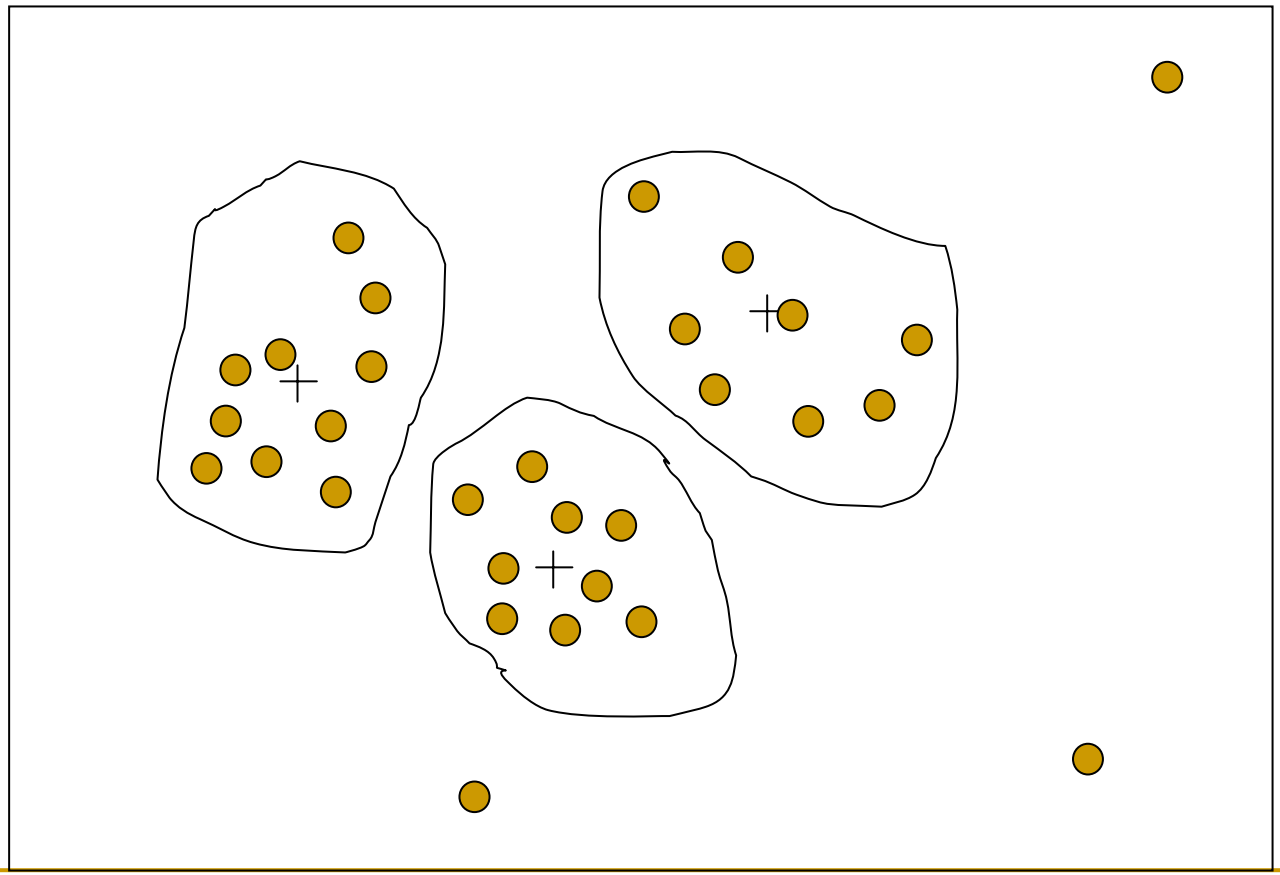

Simple Discretization Methods: Binning

- Equal-width (distance) partitioning:
  - It 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: $W = (B\text{-}A)/N$.
  - The most straightforward
  - But outliers may dominate presentation
  - Skewed data is not handled well.
- Equal-depth (frequency) partitioning:
  - It divides the range into N intervals, each containing approximately same number of samples
  - Good data scaling
  - Managing categorical attributes can be tricky.

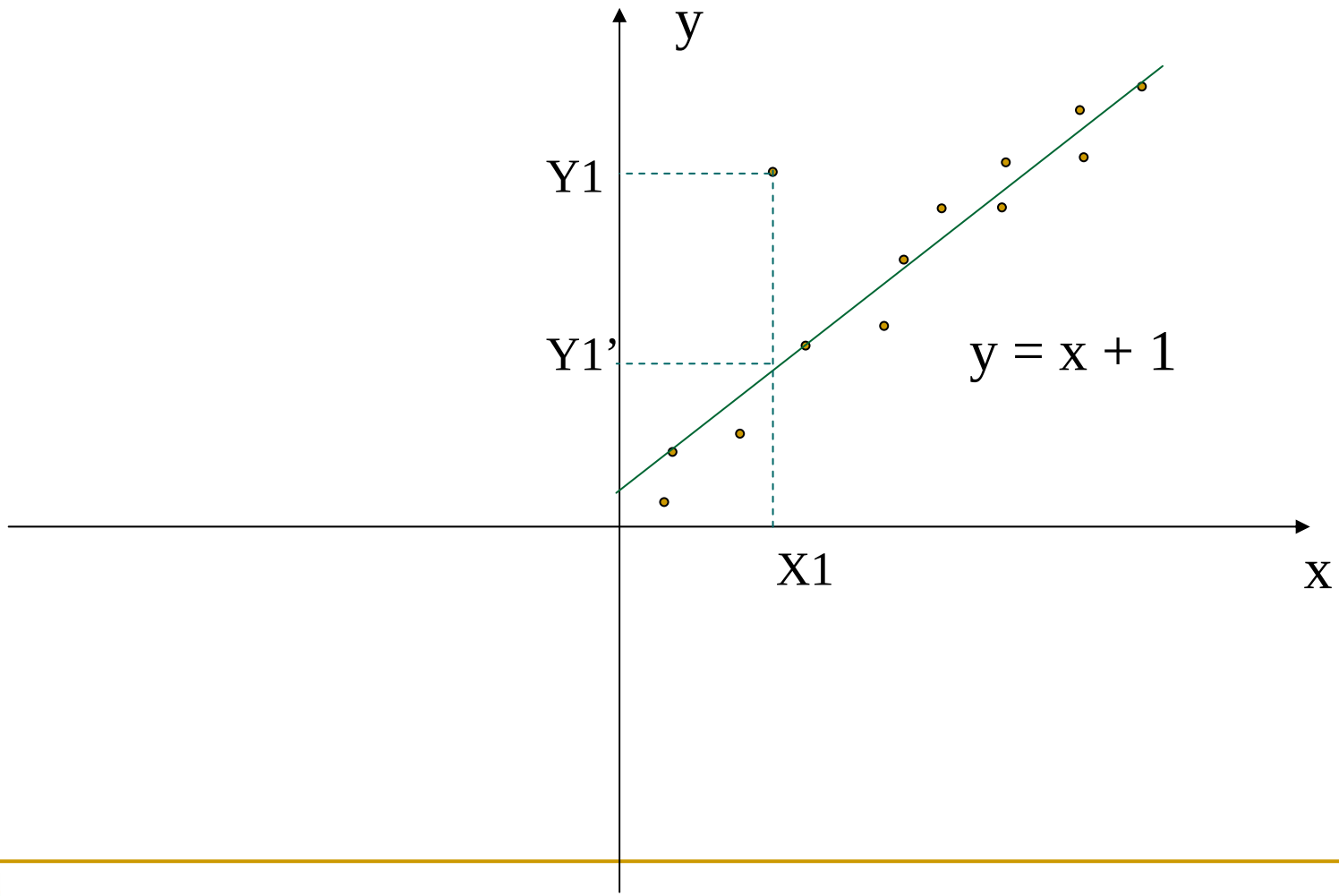
Binning Methods for Data Smoothing

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



Regression



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Data Integration

- Data integration:
  - combines data from multiple sources into a coherent store
- Schema integration
  - integrate metadata from different sources
  - Entity identification problem: identify real world entities from multiple data sources, e.g., A.cust-id ≡ B.cust-#
- 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 Redundant Data in Data Integration

- Redundant data occur often when integration of multiple databases
  - The same attribute may have different names in different databases
  - One attribute may be a "derived" attribute in another table, e.g., annual revenue
- Redundant data may be able to be detected by correlational analysis
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Data Transformation

- Smoothing: remove noise from data
- Aggregation: summarization, data cube construction
- 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

Data Transformation: Normalization

- min-max normalization

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

- z-score normalization

$$v' = \frac{v - mean_A}{stand\_dev_A}$$

- normalization by decimal scaling

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

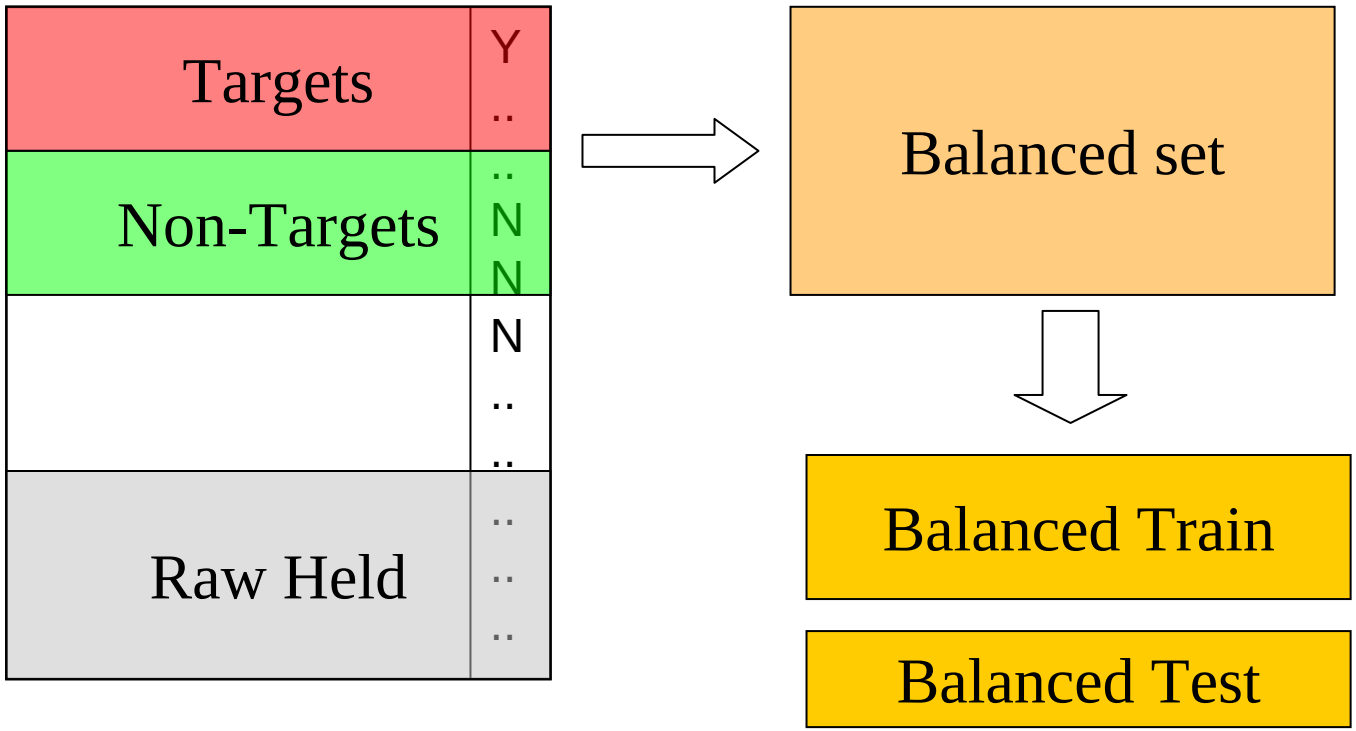
Unbalanced Target Distribution

- Sometimes, classes have very unequal frequency
  - Attrition prediction: 97% stay, 3% attrite (in a month)
  - medical diagnosis: 90% healthy, 10% disease
  - eCommerce: 99% don't buy, 1% buy
  - Security: >99.99% of Americans are not terrorists
- Similar situation with multiple classes
- Majority class classifier can be 97% correct, but useless


Handling Unbalanced Data

- With two classes: let positive targets be a minority
- Separate raw held-aside set (e.g. 30% of data) and raw train
  - put aside raw held-aside and don't use it till the final model
- Select remaining positive targets (e.g. 70% of all targets) from raw train
- Join with equal number of negative targets from raw train, and randomly sort it.
- Separate randomized balanced set into balanced train and balanced test

Building Balanced Train Sets



Learning with Unbalanced Data

- Build models on balanced train/test sets
- Estimate the final results (lift curve) on the raw held set

- Can generalize "balancing" to multiple classes
  - stratified sampling
  - Ensure that each class is represented with approximately equal proportions in train and test

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Data Reduction Strategies

- Warehouse may store terabytes of data: Complex data analysis/mining may take a very long time to run on the complete data set
- Data reduction
  - Obtains a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Data reduction strategies
  - Data cube aggregation
  - Dimensionality reduction
  - Numerosity reduction
  - Discretization and concept hierarchy generation


Data Cube Aggregation

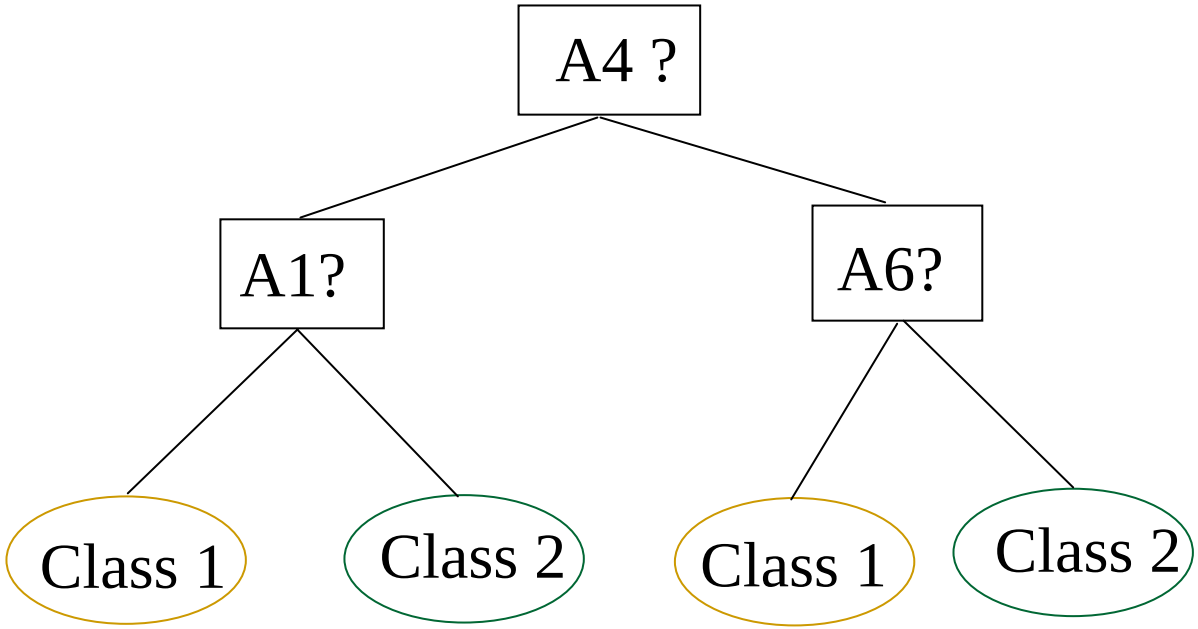
- The lowest level of a data cube
  - the aggregated data for an individual entity of interest
  - e.g., a customer in a phone calling data warehouse.
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible


Dimensionality Reduction

- Feature selection (i.e., attribute subset selection):
  - Select a minimum set of features such that the probability distribution of different classes given the values for those features is as close as possible to the original distribution given the values of all features
  - reduce # of patterns in the patterns, easier to understand
- Heuristic methods (due to exponential # of choices):
  - step-wise forward selection
  - step-wise backward elimination
  - combining forward selection and backward elimination
  - decision-tree induction


Example of Decision Tree Induction

Initial attribute set:
{A1, A2, A3, A4, A5, A6}



-------> Reduced attribute set: {A1, A4, A6}

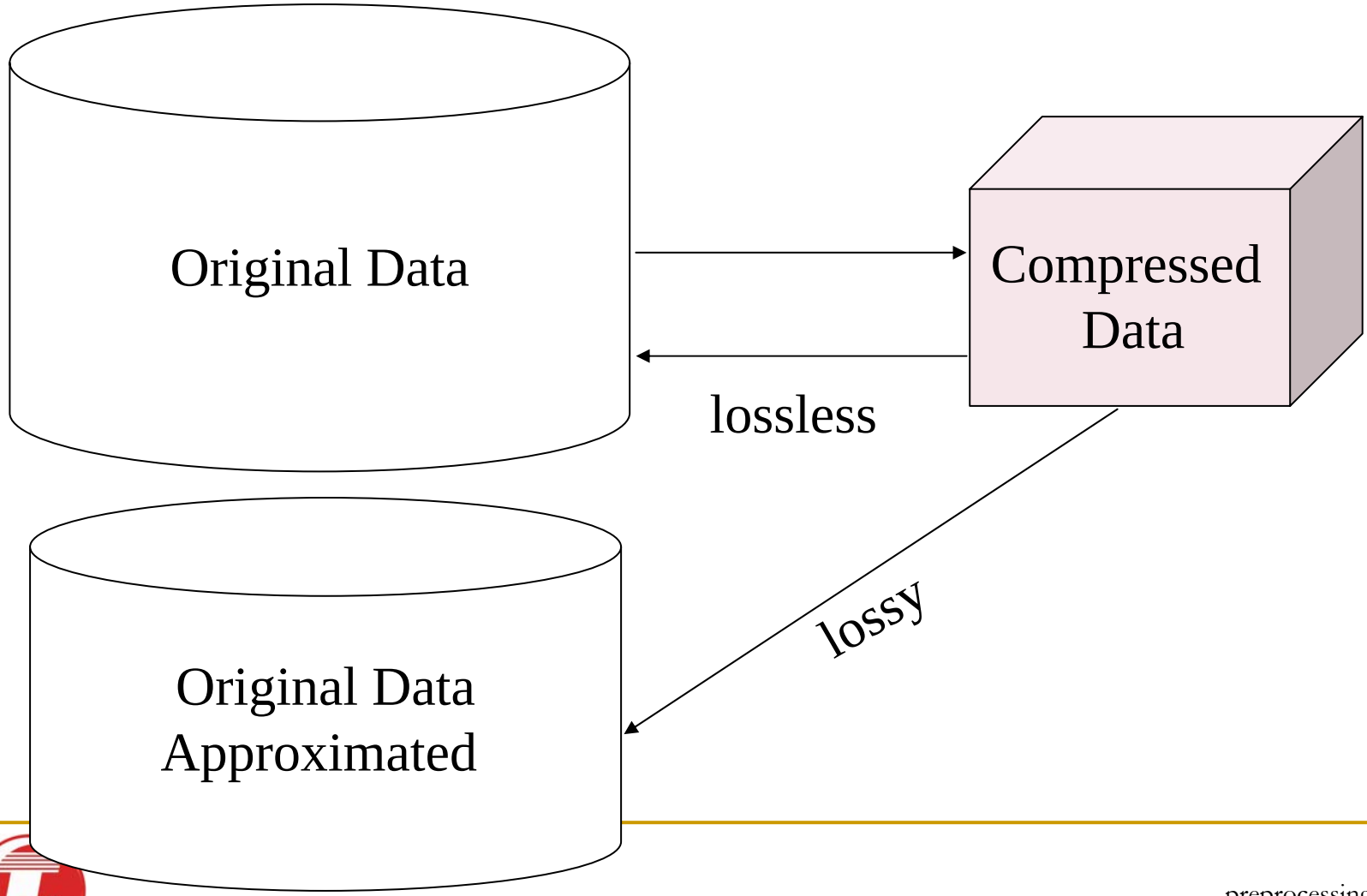
Attribute Selection

- There are 2^d possible sub-features of d features
- First: Remove attributes with no or little variability
  - Examine the number of distinct field values
    - *Rule of thumb: remove a field where almost all values are the same (e.g. null), except possibly in minp % or less of all records.*
    - *minp* could be 0.5% or more generally less than 5% of the number of targets of the smallest class
- What is good N?
  - Rule of thumb -- keep top 50 fields

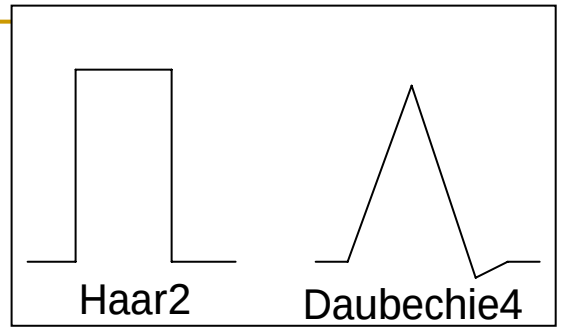
Data Compression

- 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



Wavelet Transforms

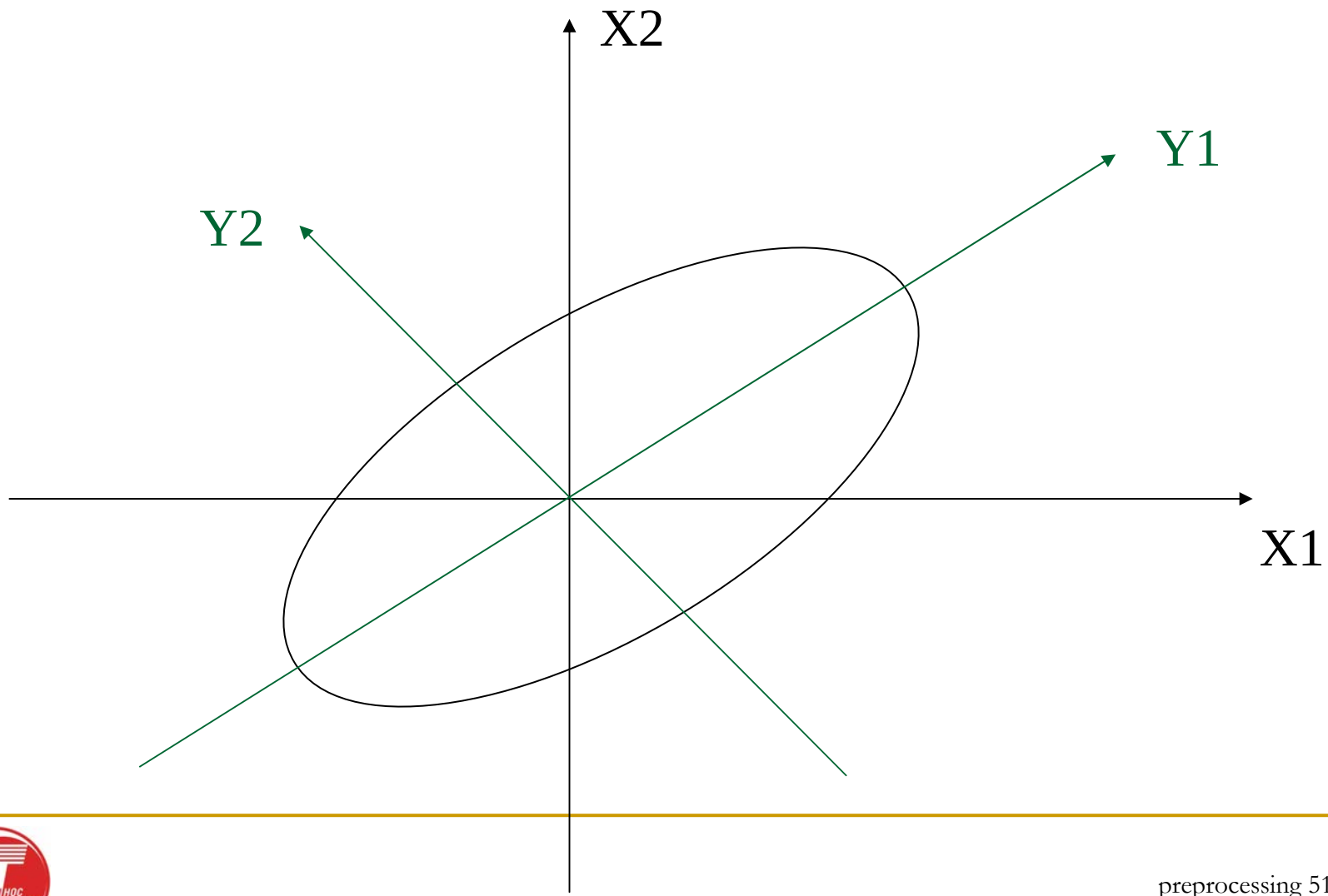


- Discrete wavelet transform (DWT): linear signal processing
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients
- Similar to discrete Fourier transform (DFT), but better lossy compression, localized in space
- Method:
  - Length, L, must be an integer power of 2 (padding with 0s, when necessary)
  - Each transform has 2 functions: smoothing, difference
  - Applies to pairs of data, resulting in two set of data of length L/2
  - Applies two functions recursively, until reaches the desired length

Principal Component Analysis

- Given *N* data vectors from *k*-dimensions, find *c* <= *k* orthogonal vectors that can be best used to represent data
  - The original data set is reduced to one consisting of N data vectors on c principal components (reduced dimensions)
- Each data vector is a linear combination of the *c* principal component vectors
- Works for numeric data only
- Used when the number of dimensions is large

Principal Component Analysis



Numerosity Reduction

- Parametric methods
  - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
  - 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


Regression and Log-Linear Models

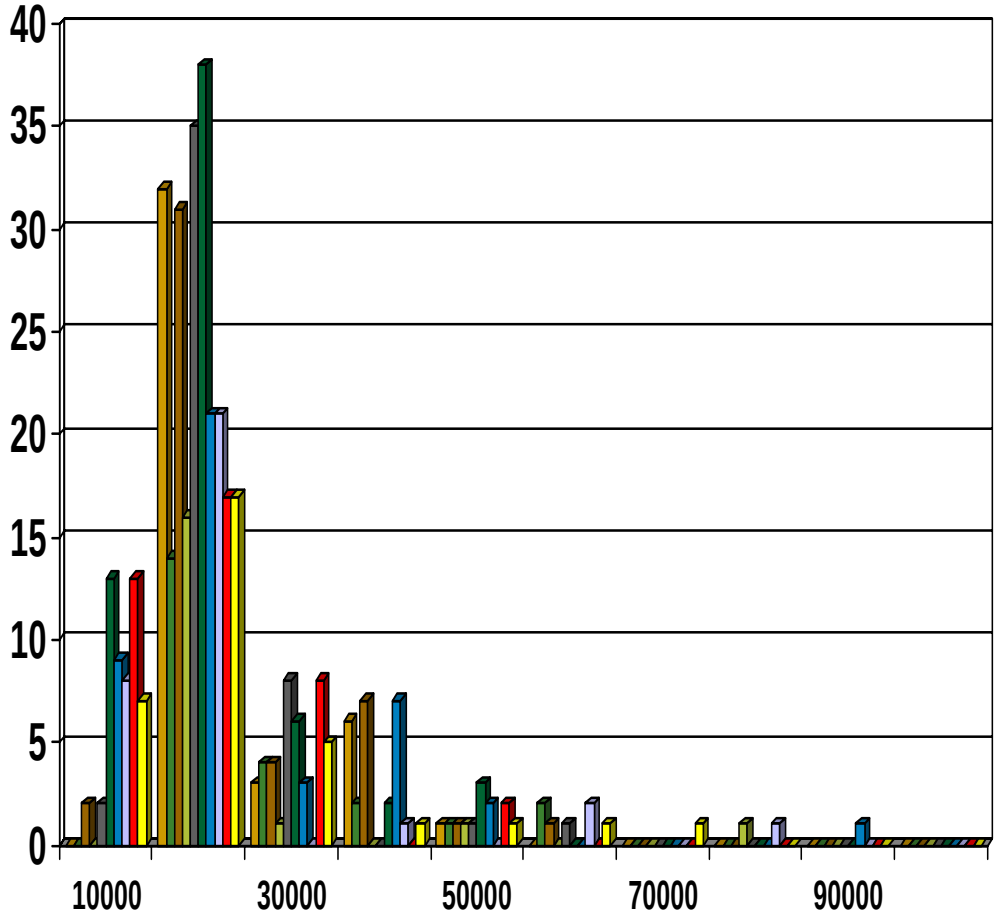
- Linear regression: Data are modeled to fit a straight line
  - Often uses the least-square method to fit the line
- Multiple regression: allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- Log-linear model: approximates discrete multidimensional probability distributions


Regress Analysis and Log-Linear Models

- Linear regression: $Y = \alpha + \beta X$
  - Two parameters , α and β specify the line and are to be estimated by using the data at hand.
  - using the least squares criterion to the known values of $Y_1, Y_2, \ldots$, $X_1, X_2, \ldots$.
- Multiple regression: $Y = b0 + b1\ X1 + b2\ X2$.
  - Many nonlinear functions can be transformed into the above.
- Log-linear models:
  - The multi-way table of joint probabilities is approximated by a product of lower-order tables.
  - Probability: $p(a, b, c, d) = \alpha_{ab}\ \beta_{ac} \chi_{ad}\ \delta_{bcd}$

Histograms

- A popular data reduction technique
- Divide data into buckets and store average (sum) for each bucket
- Can be constructed optimally in one dimension using dynamic programming
- Related to quantization problems.



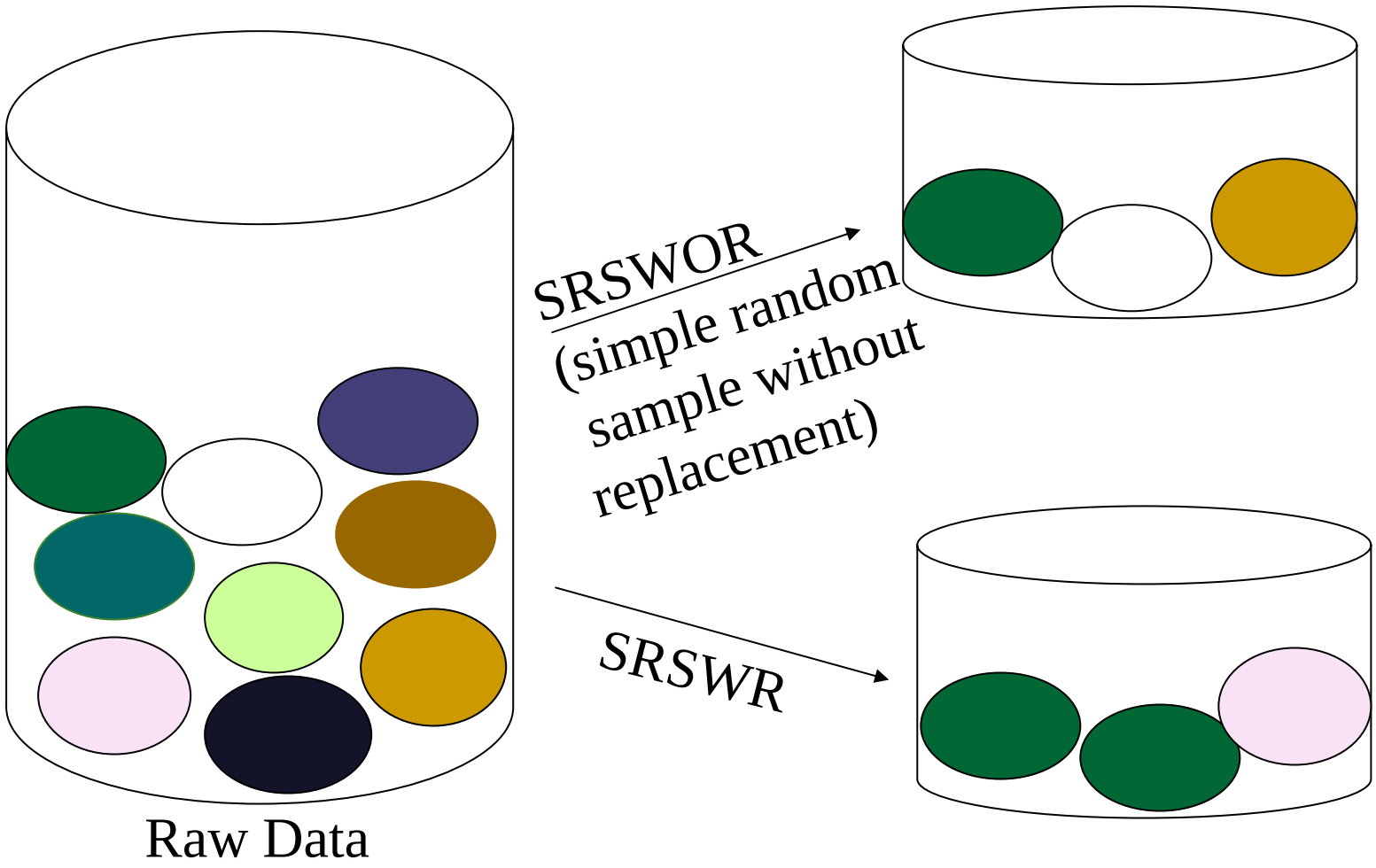
Clustering

- Partition data set into clusters, and one can store cluster representation 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, further detailed in Chapter 8


Sampling

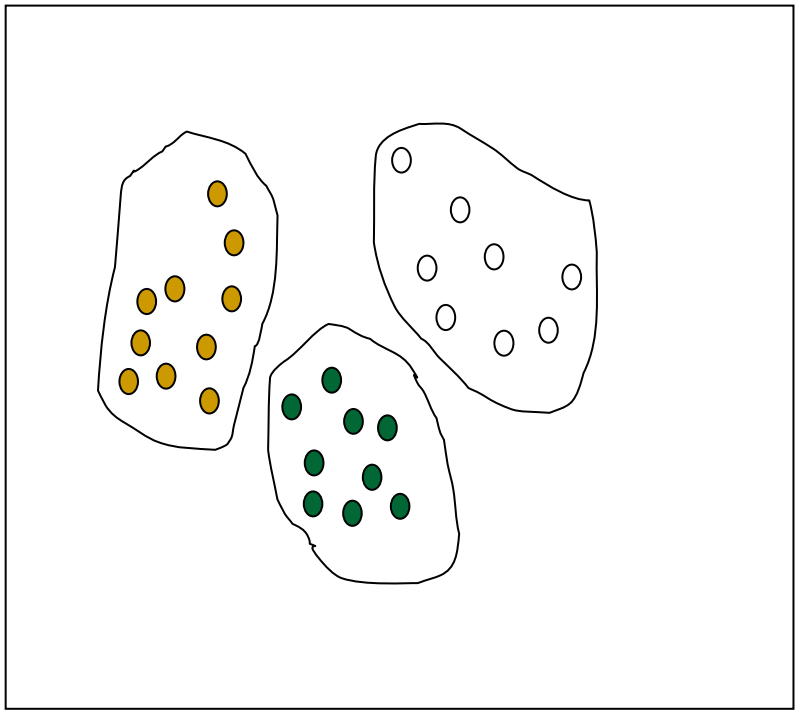
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
- Develop adaptive sampling methods
  - Stratified sampling:
    - Approximate the percentage of each class (or subpopulation of interest) in the overall database
    - Used in conjunction with skewed data
- Sampling may not reduce database I/Os (page at a time).

Sampling

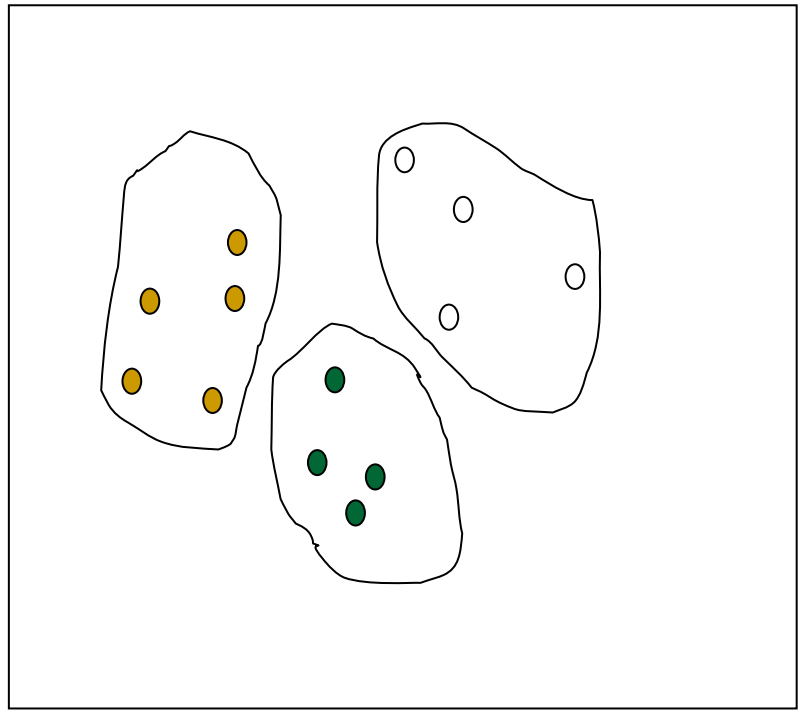

SRSWOR
(simple random
sample without
replacement)
SRSWR
Raw Data

Sampling

Raw Data



Cluster/Stratified Sample



Hierarchical Reduction

- Use multi-resolution structure with different degrees of reduction
- Hierarchical clustering is often performed but tends to define partitions of data sets rather than "clusters"
- Parametric methods are usually not amenable to hierarchical representation
- Hierarchical aggregation
  - An index tree hierarchically divides a data set into partitions by value range of some attributes
  - Each partition can be considered as a bucket
  - Thus an index tree with aggregates stored at each node is a hierarchical histogram

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Discretization

- Three types of attributes:
  - Nominal — values from an unordered set
  - Ordinal — values from an ordered set
  - Continuous — real numbers
- 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 and Concept hierachy

- 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.
- Concept hierarchies
  - reduce the data by collecting and replacing low level concepts (such as numeric values for the attribute age) by higher level concepts (such as young, middle-aged, or senior).

Discretization and concept hierarchy generation for numeric data

- Binning (see sections before)
- Histogram analysis (see sections before)
- Clustering analysis (see sections before)
- Entropy-based discretization
- Segmentation by natural partitioning

Entropy-Based Discretization

- Given a set of samples S, if S is partitioned into two intervals S1 and S2 using boundary T, the entropy after partitioning is

$$E(S,T) = \frac{|S_1|}{|S|} Ent(S_1) + \frac{|S_2|}{|S|} Ent(S_2)$$

- The boundary that minimizes the entropy function over all possible boundaries is selected as a binary discretization.
- The process is recursively applied to partitions obtained until some stopping criterion is met, e.g.,

$$Ent(S) - E(T,S) > \delta$$

- Experiments show that it may reduce data size and improve classification accuracy


Segmentation by natural partitioning

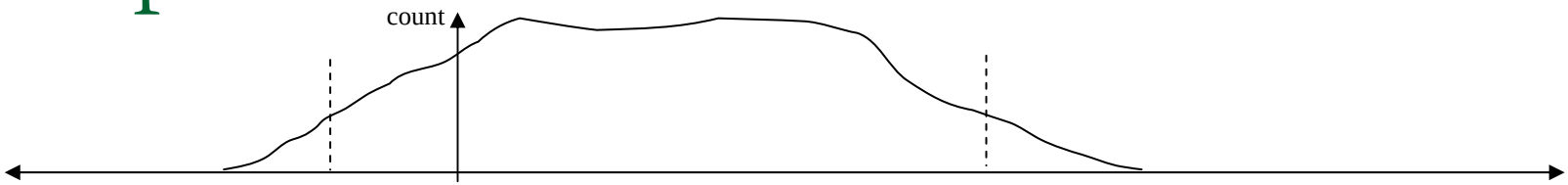
3-4-5 rule can be used to segment numeric data into relatively uniform, "natural" intervals.

* If an interval covers 3, 6, 7 or 9 distinct values at the most significant digit, partition the range into 3 equi-width intervals

* If it covers 2, 4, or 8 distinct values at the most significant digit, partition the range into 4 intervals

* If it covers 1, 5, or 10 distinct values at the most significant digit, partition the range into 5 intervals

Example of 3-4-5 rule

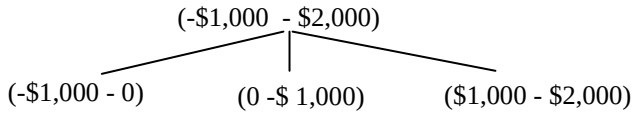


Step 1: -$351 -$159 profit $1,838 $4,700

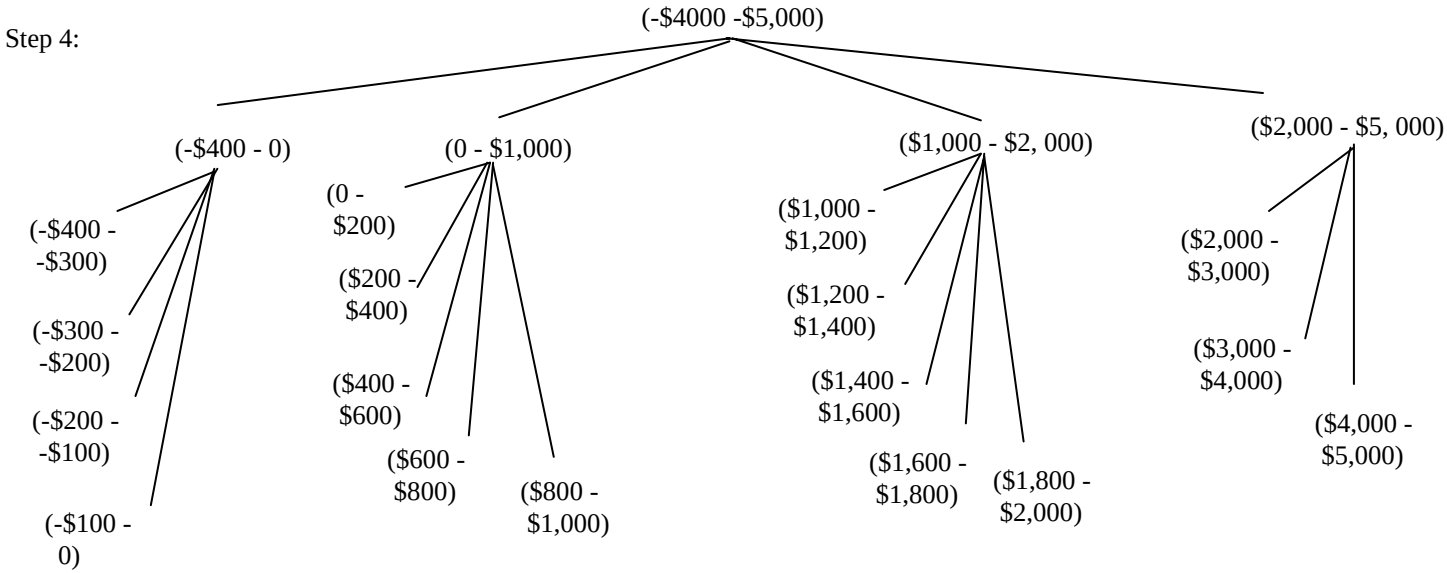
Min Low (i.e, 5%-tile) High(i.e, 95%-0 tile) Max

Step 2: msd=1,000 Low=-$1,000 High=$2,000

Step 3:



Step 4:

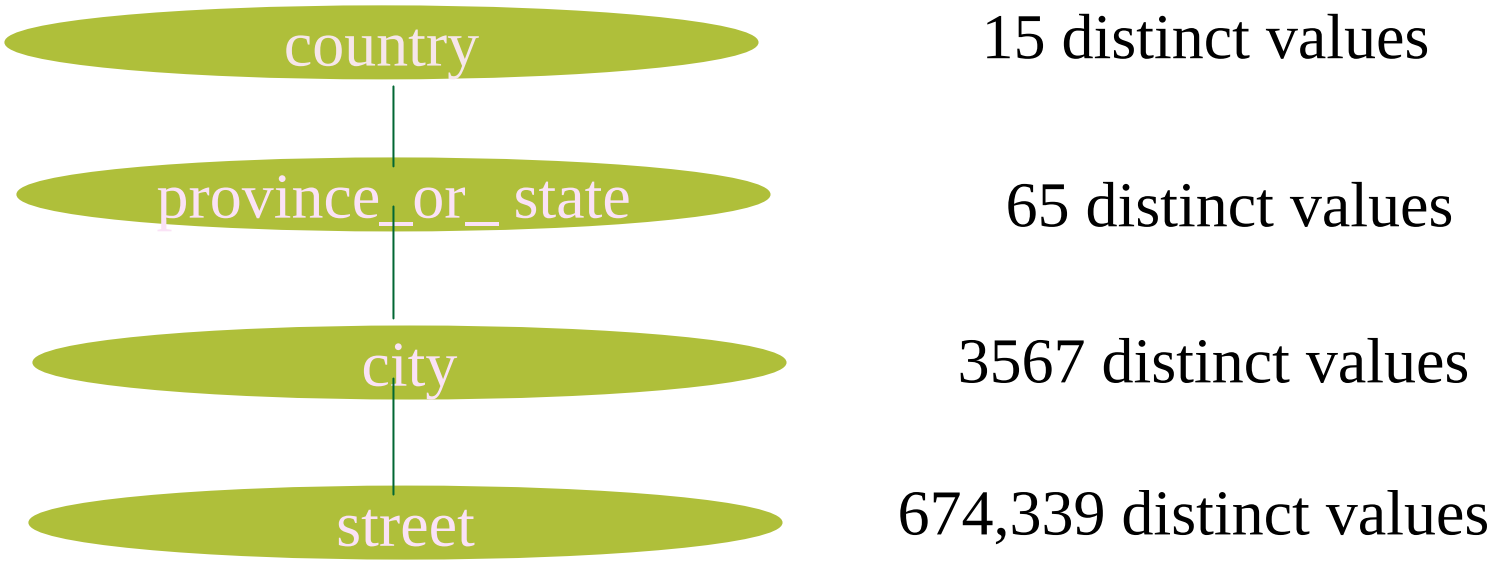


Concept hierarchy generation for categorical data

- Specification of a partial ordering of attributes explicitly at the schema level by users or experts
- Specification of a portion of a hierarchy by explicit data grouping
- Specification of a set of attributes, but not of their partial ordering
- Specification of only a partial set of attributes

Specification of a set of attributes

Concept hierarchy can be automatically generated based on the number of distinct values per attribute in the given attribute set. The attribute with the most distinct values is placed at the lowest level of the hierarchy.



Outline

- Introduction
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization and concept hierarchy generation
- Summary


Summary

- Data preparation is a big issue for both warehousing and mining
- Data preparation includes
  - Data cleaning and data integration
  - Data reduction and feature selection
  - Discretization
- A lot a methods have been developed but still an active area of research


Good data preparation is key to producing valid and reliable models