Data Preprocessing (Chapter 3)

Outline

- Why preprocess the data?
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization and concept hierarchy generation
- Summary

Why Data Preprocessing?

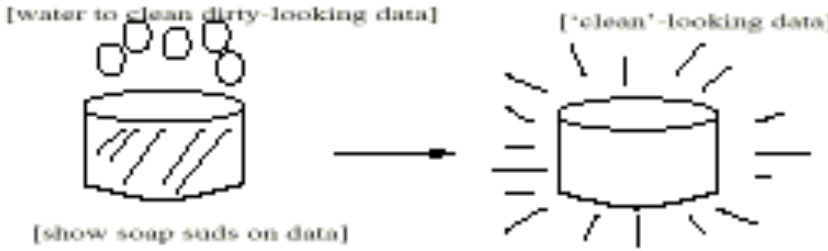
- Data in the real world is dirty
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
  - noisy: containing errors or outliers
  - inconsistent: containing discrepancies in codes or names
- No quality data, no quality mining results!
  - Quality decisions must be based on quality data
  - Data warehouse needs consistent integration of quality data

Major Tasks in Data Preprocessing

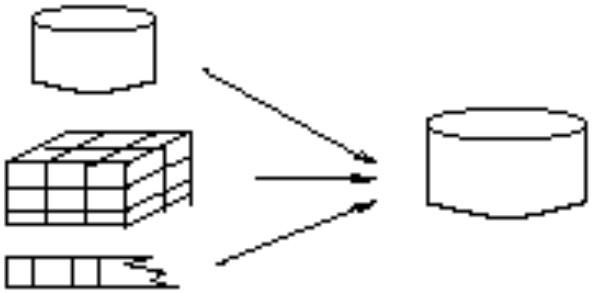
- Data cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration
  - Integration of multiple databases, data cubes, or files
- Data transformation
  - Normalization and aggregation
- Data reduction
  - Obtains reduced representation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



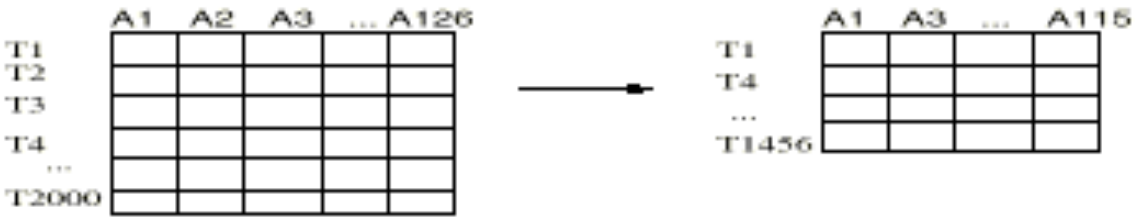
Data Integration



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
  - Fill in missing values
  - Identify outliers and smooth out noisy data
  - Correct inconsistent data

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?!
- Use the attribute mean to fill in the missing value
- 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

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

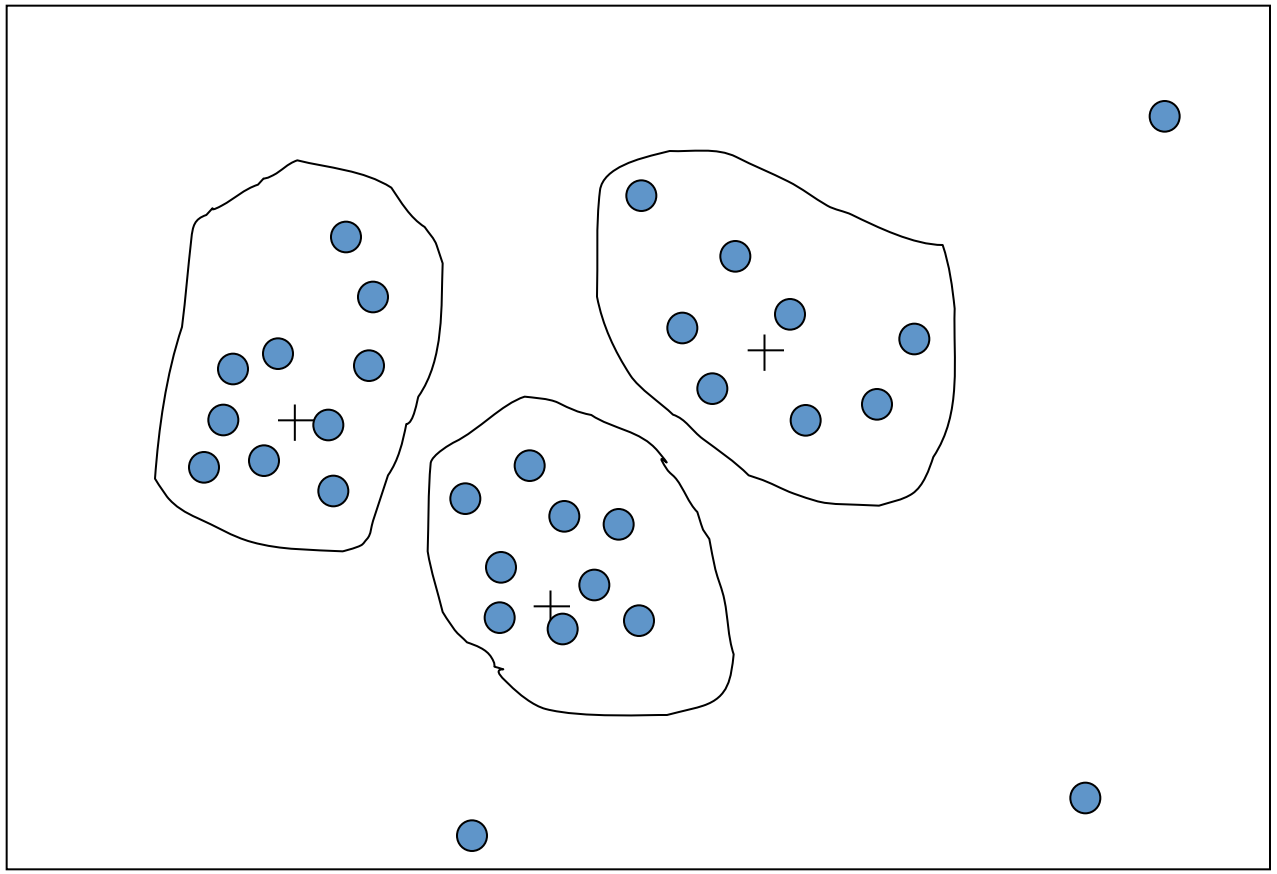
Binning Methods

- 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: $W = (B-A)/N$.
  - 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.

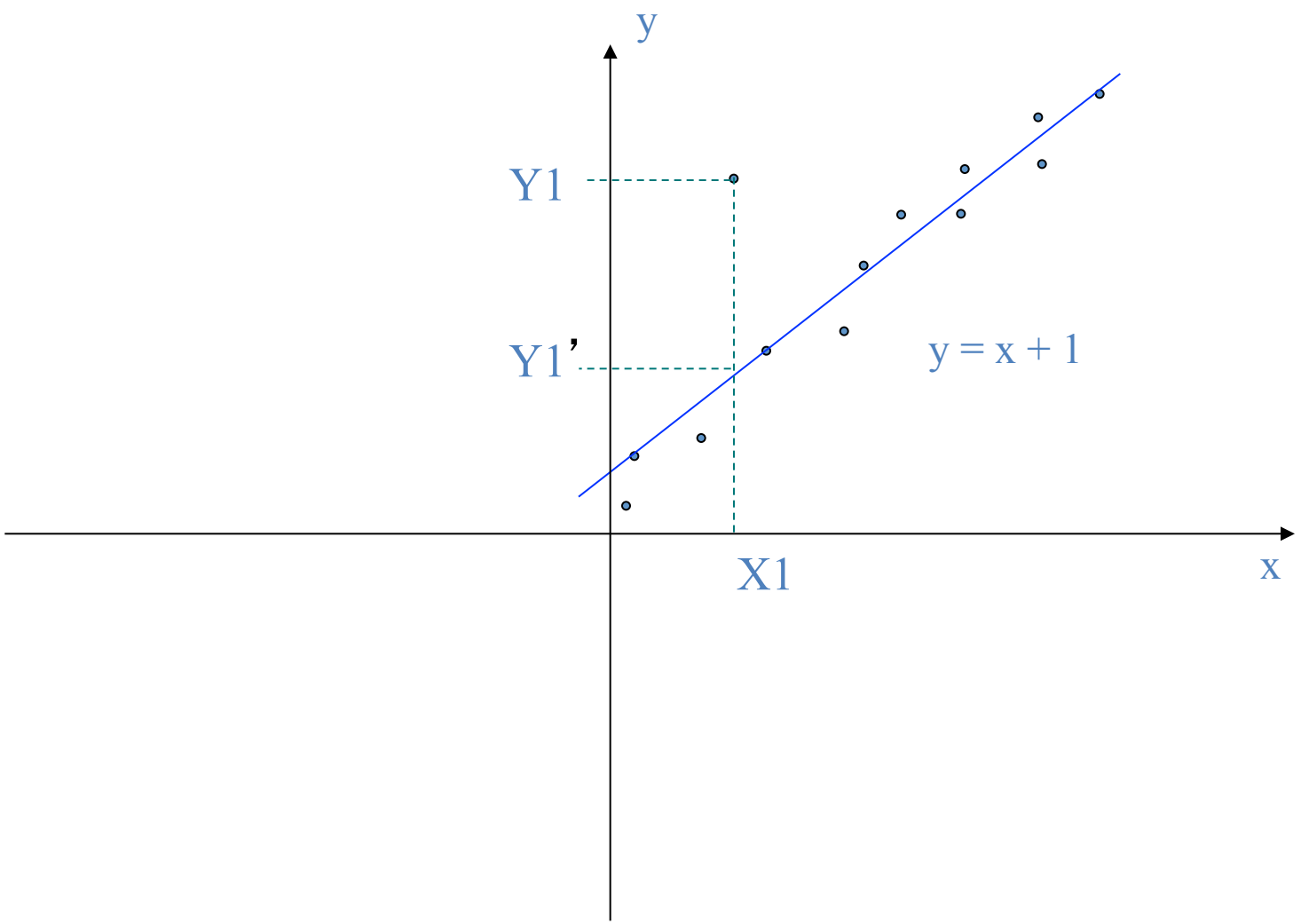
Binning Methods for Data Smoothing

* 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 (database, data cubes, flat files, etc.) into a coherent store
- 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
- Schema integration
  - Entity identification problem: identify real world entities from multiple data sources, e.g., A.cust-id ≡ B.cust-number
  - integrate metadata from different sources
- Metadata keeps the details of:
  - meaning of the attribute, attribute name, type, value range, etc.

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
  - Correlation analysis can help determine how strongly one attribute implies the other attribute
  - Pearson Correlation
  - Chi-squared test
- 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

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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
  - Dimensionality reduction
  - Data compression
  - Numerosity reduction
  - Discretization and concept hierarchy generation

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

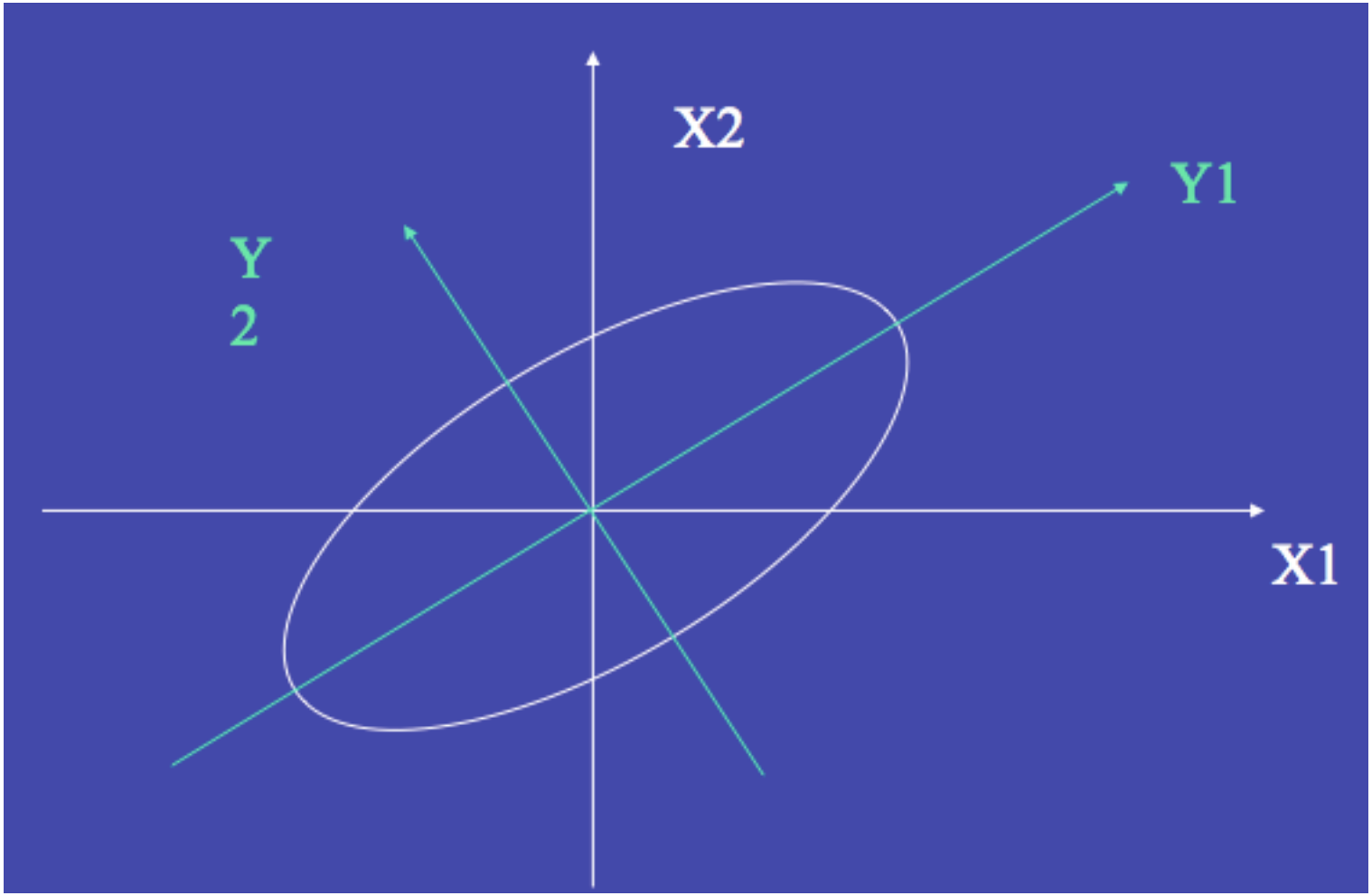
Heuristic Feature Selection Methods

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

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

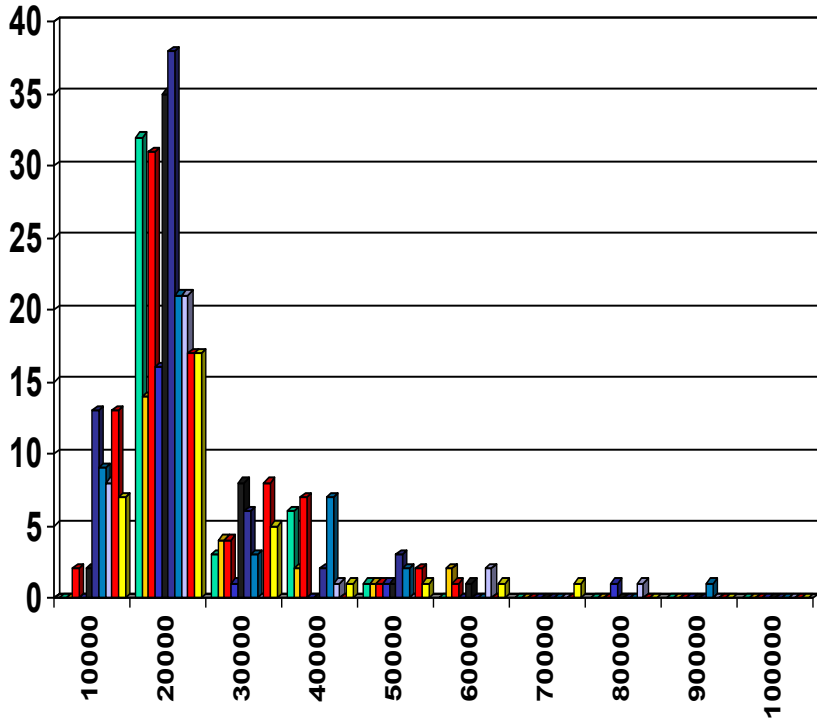
- Parametric methods
  - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
- Non-parametric methods
  - Do not assume models
  - Major families: histograms, clustering, sampling

Regression

- 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.

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
- Partitioning rules:
  - Equal-width
  - Equal-depth (equal frequency)
  - V-optimal: with the least histogram variance (weighted sum of the original values that each bucket represents)
  - Maxdiff: set bucket boundary between each pair for pairs have the β-1 largest differences



V-optimal

Given: 1, 3, 4, 7, 2, 8, 3, 6, 3, 6, 8, 2, 1, 6, 3, 5, 3, 4, 7, 2, 6, 7, 2

- Histogram (value-count):

(1, 2), (2, 4), (3, 5), (4, 2), (5, 1), (6, 4), (7, 3), (8, 2)

Option 1:

Bucket 1 contains values 1 through 4.

Bucket 2 contains values 5 through 8.

- Bucket 1:
  - Average frequency 3.25
  - Weighted variance 2.28
- Bucket 2:
  - Average frequency 2.5
  - Weighted variance 2.19
- Sum of Weighted Variance 4.47

Option 2:

Bucket 1 contains values 1 through 2.

Bucket 2 contains values 3 through 8.

- Bucket 1:
  - Average frequency 3
  - Weighted variance 1.41
- Bucket 2:
  - Average frequency 2.83
  - Weighted variance 3.29
- Sum of Weighted Variance 4.7

Which choice is better?

MaxDiff

TABLE II. COMPUTING THE SPREAD, AREA AND Δ AREA

Value	180	250	260	270	320	345	380	410	450	490	550
Frequency	2	1	1	2	1	1	1	1	3	1	1
Spread	70	10	10	50	25	35	35	40	40	60	-
Area	140	10	10	100	25	35	35	40	120	60	-
Δ Area	130	0	90	75	10	0	5	80	60	-	-

TABLE III. Max-diff Histogram

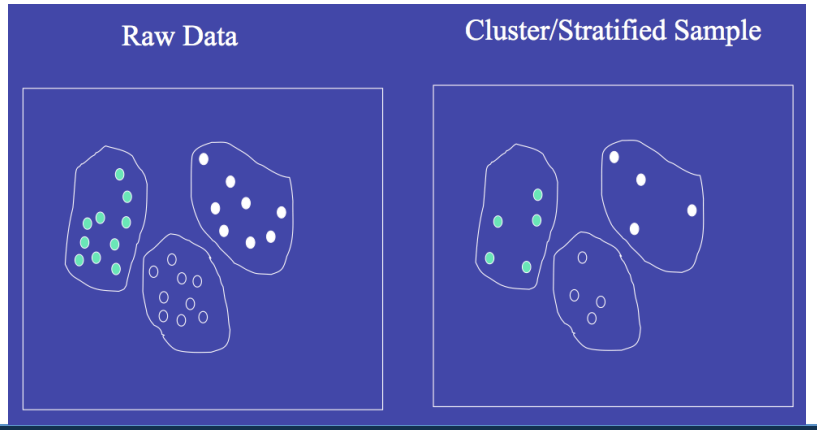
Bucket	Frequency
[100-180]	2
[200-260]	2
[270-300]	2
[320-400]	3
[410-460]	4
[480-600]	2

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

- 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



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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.,

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

  Where

$$Ent(S_1) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

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

Example on Entropy based discretization

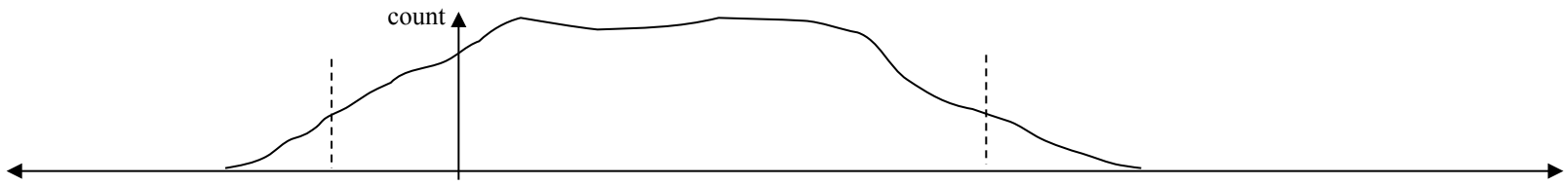
	attribute I	class
Data1	13	good
Data2	13	good
Data3	17	bad
Data4	18	bad
Data5	22	good
Data6	22	good
Data7	25	good
Data8	30	good

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 equal width intervals
* If it covers 2, 4, or 8 distinct values at the most significant digit, partition the range into 4 equal width intervals
* If it covers 1, 5, or 10 distinct values at the most significant digit, partition the range into 5 equal width intervals

Example of 3-4-5 rule

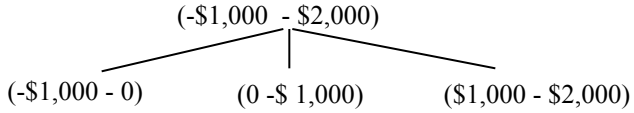


Step 1: -$351 -$159 profit $1,838 $4,700

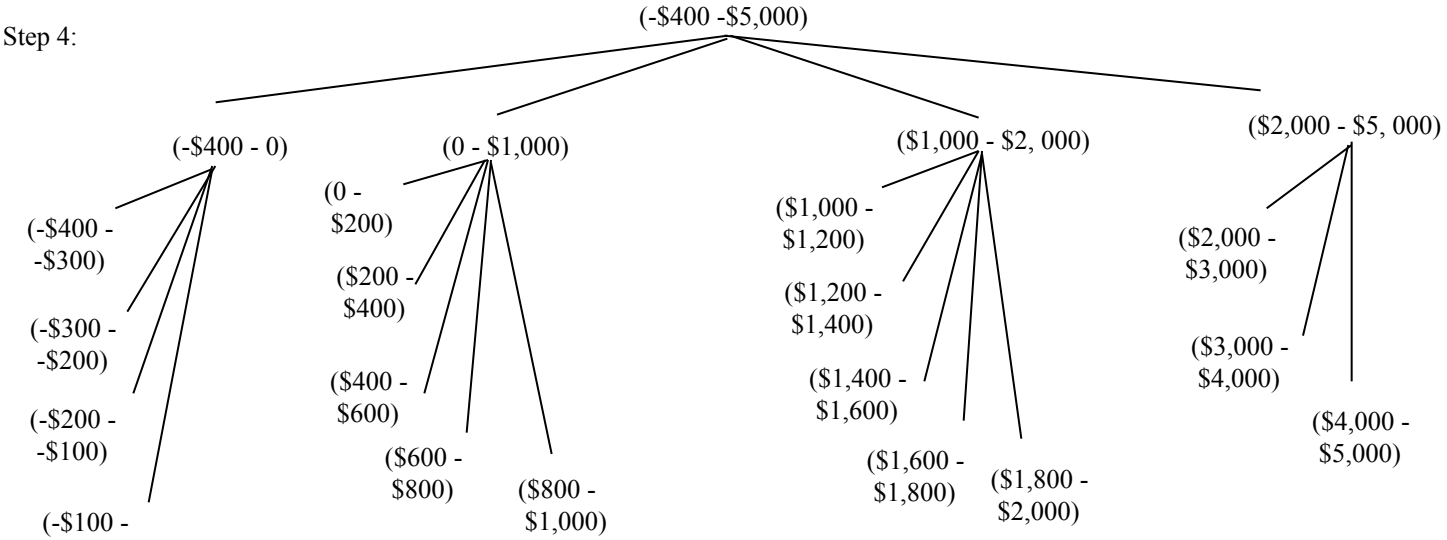
Min Low (i.e, 5%-tile) High(i.e, 95%-0 tile) Max

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 (job categories, geographical locations, etc.
  - street < city < state < country ;
  - professor < department < college < Univ.
- Specification of a portion of a hierarchy by explicit data grouping
  - {Biology, Chemistry, Math, Physics, Computer Science} < Computational Sciences PhD program
- Specification of a set of attributes, but not of their partial ordering
- Specification of only a partial set of attributes
  - Only street < city, not others

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.

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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