Data Mining and Predictive Modelling

Data Preprocessing

- Data Preprocessing
  - Data Quality
  - Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization

Data Quality (Measures)

- 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?

Tasks in Data Preprocessing

- Data Cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data Integration
  - Integration of multiple databases, data cubes, or files
- Data reduction
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- Data transformation and data discretization
  - Normalization
  - Concept hierarchy generation

Data Cleaning

- The real-world data is highly dirty such as:
  - Incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - E.g., Profession=“ ” (missing data)
  - Noisy: containing noise, errors, or outliers
    - E.g., salary= ‘-10’ (an error)
  - Inconsistent: containing discrepancies in codes or names, e.g.,
    - Discrepancy between duplicate records
    - Was rating “1,2,3”, given rating “A,B,C”
  - Intentional (e.g., disguised missing data)
    - Jan. 1 as everyone’s birthday?

Incomplete (Missing) Data

Data is not always available

- E.g., many tuples have no recorded value for several attributes, such as customer income in sales data

Missing data may be due to

- Equipment malfunction
- Inconsistent with other recorded data and thus deleted
- Data not entered due to misunderstanding
- Certain data my not be considered important at the time of entry
- Not register history or changes of the data

Missing data may need to be inferred

Handling missing data

- Ignore the tuple, usually done when class label is missing (when doing classification)—not effective when the % of missing values per attribute varies considerably
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
  - a global constant : e.g., “unknown”, a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree

Noisy Data

Noise: random error or variance in a measured variable

Incorrect attribute values may be due to

- faulty data collection instruments
- data entry problems
- data transmission problems
- technology limitation
- inconsistency in naming convention

Other data problems which require data cleaning

- duplicate records
- incomplete data
- inconsistent data

Handling Noisy Data

Binning

- first sort data and partition into (equal-frequency) bins
- then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.

Regression

- smooth by fitting the data into regression functions

Clustering

- detect and remove outliers

Combined computer and human inspection

- detect suspicious values and check by human (e.g., deal with possible outliers)

Data 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

Data Integration

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
- Detecting and resolving data value conflicts
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g., metric vs. British units

Handling Redundancy in Data Integration

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

Correlation Analysis (Nominal Data)

- **X^2 (chi-square) test**

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

- 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

Correlation Analysis (Numeric Data)

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

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

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

Covariance (Numeric Data)

- Covariance is similar to correlation

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

Correlation coefficient: $$r_{A,B} = \frac{Cov(A,B)}{\sigma_A \sigma_B}$$

where n is the number of tuples, $\bar{A}$ and $\bar{B}$ are the respective mean or **expected values** of A and B, σ_A and σ_B are the respective standard deviation of A and B.

- **Positive covariance**: If $Cov_{A,B} > 0$, then A and B both tend to be larger than their expected values.
- **Negative covariance**: If $Cov_{A,B} < 0$ then if A is larger than its expected value, B is likely to be smaller than its expected value.
- **Independence**: $Cov_{A,B} = 0$ but the converse is not 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) does a covariance of 0 imply independence

Data Reduction

- **Data reduction**: Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.
- Data reduction strategies
  - Dimensionality reduction, e.g., remove unimportant attributes
    - Wavelet transforms
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation
  - Numerosity reduction (some simply call it: Data Reduction)
    - Regression and Log-Linear Models
    - Histograms, clustering, sampling
    - Data cube aggregation
  - Data compression

Data Reduction: Dimensionality Reduction

Curse of dimensionality

- When dimensionality increases, data becomes increasingly sparse
- Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
- The possible combinations of subspaces will grow exponentially

Dimensionality reduction

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

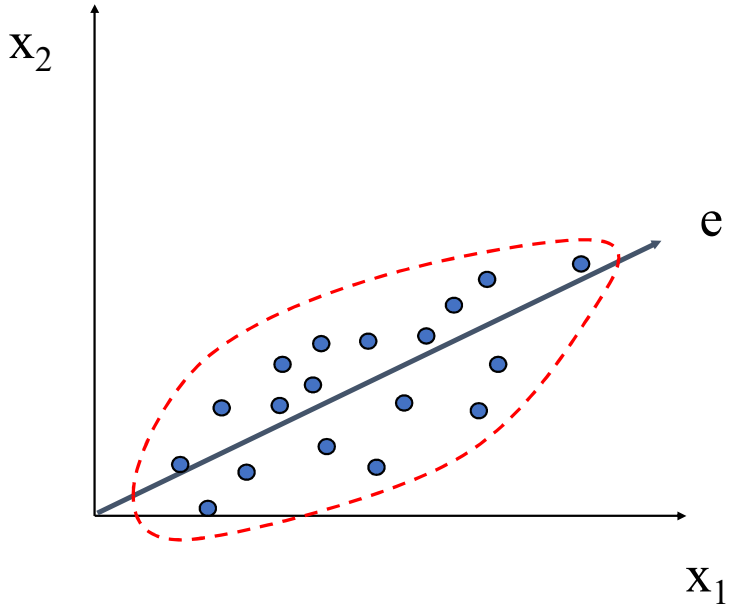
Dimensionality reduction techniques

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

Data Reduction: Principal Component Analysis

Find a projection that captures the largest amount of variation in data

The original data are projected onto a much smaller space, resulting in dimensionality reduction. We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space



Data Reduction: Attribute Subset Selection

Another way to reduce dimensionality of data

Redundant attributes

- Duplicate much or all of the information contained in one or more other attributes
- E.g., purchase price of a product and the amount of sales tax paid

Irrelevant attributes

- Contain no information that is useful for the data mining task at hand
- E.g., students' ID is often irrelevant to the task of predicting students' GPA

Thank You