CS699
Lecture 3
Data Preprocessing

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

Data Cleaning

- Data in the Real World Is Dirty: Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, transmission error
  - <u>incomplete</u>: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation*="" (missing data)
  - <u>noisy</u>: containing noise, errors, or outliers
    - e.g., *Salary*="−10" (an error)
  - <u>inconsistent</u>: 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
  - <u>Intentional</u> (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 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 (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”
  - 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

How to Handle Noisy Data?

- Binning
  - first sort data and partition into 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)

Binning Methods for Data Smoothing

- 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: 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 36
- Partition into equal-width bins: (36 – 4) / 3 = 10.67
- Bin intervals are: [4, 14.67), [14.67, 25.34), [25.34, 36]

  - Bin 1: 4, 8, 9

  - Bin 2: 15, 21, 21, 24, 25

  - Bin 3: 26, 28, 29, 36
- Smoothing by **bin means**:

  - Bin 1: 7, 7, 7

  - Bin 2: 21.2, 21.2, 21.2, 21.2, 21.2

  - Bin 3: 29.75, 29.75, 29.75, 29.75
- Smoothing by **bin boundaries**:

  - Bin 1: 4, 9, 9

  - Bin 2: 15, 25, 25, 25, 25

  - Bin 3: 26, 26, 26, 36

Binning Methods for Data Smoothing

- Sorted data: 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 36
- Partition into equal-depth bins:

  - Bin 1: 4, 8, 9, 15

  - Bin 2: 21, 21, 24, 25

  - Bin 3: 26, 28, 29, 36
- Smoothing by **bin means**:

  - Bin 1: 9, 9, 9, 9

  - Bin 2: 22.75, 22.75, 22.75, 22.75

  - Bin 3: 29.75, 29.75, 29.75, 29.75
- Smoothing by **bin boundaries**:

  - Bin 1: 4, 4, 4, 15

  - Bin 2: 21, 21, 25, 25

  - Bin 3: 26, 26, 26, 36

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 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 (X^2 test is a hypothesis test and we will discuss this in more detail later)
- 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

Example – Compute Expected Values first

	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

- Calculation of expected count of entry (A_i, B_j):

$$e_{ij} = \frac{count(A = a_i) \times count(B = b_j)}{n}$$

- Example:

$$e_{12} = \frac{count(Like\ SF) \times count(Not\ \ play\ chess)}{n} = \frac{450 \times 1200}{1500} = 360$$

Example – Compute Expected Values first

	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

- Calculation of expected count of entry (A_i, B_j):

$$e_{ij} = \frac{count(A = a_i) \times count(B = b_j)}{n}$$

- Example:

$$e_{21} = \frac{count(Not\ Like\ SF) \times count(Not\ \ play\ chess)}{n} = \frac{1050 \times 1200}{1500} = 840$$

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)

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

- The chi-square statistic is *too high*, so we conclude that like_science_fiction and play_chess are correlated.
- We will revisit this and will discuss *how high is too high* later.

Correlation Analysis (Numeric Data)

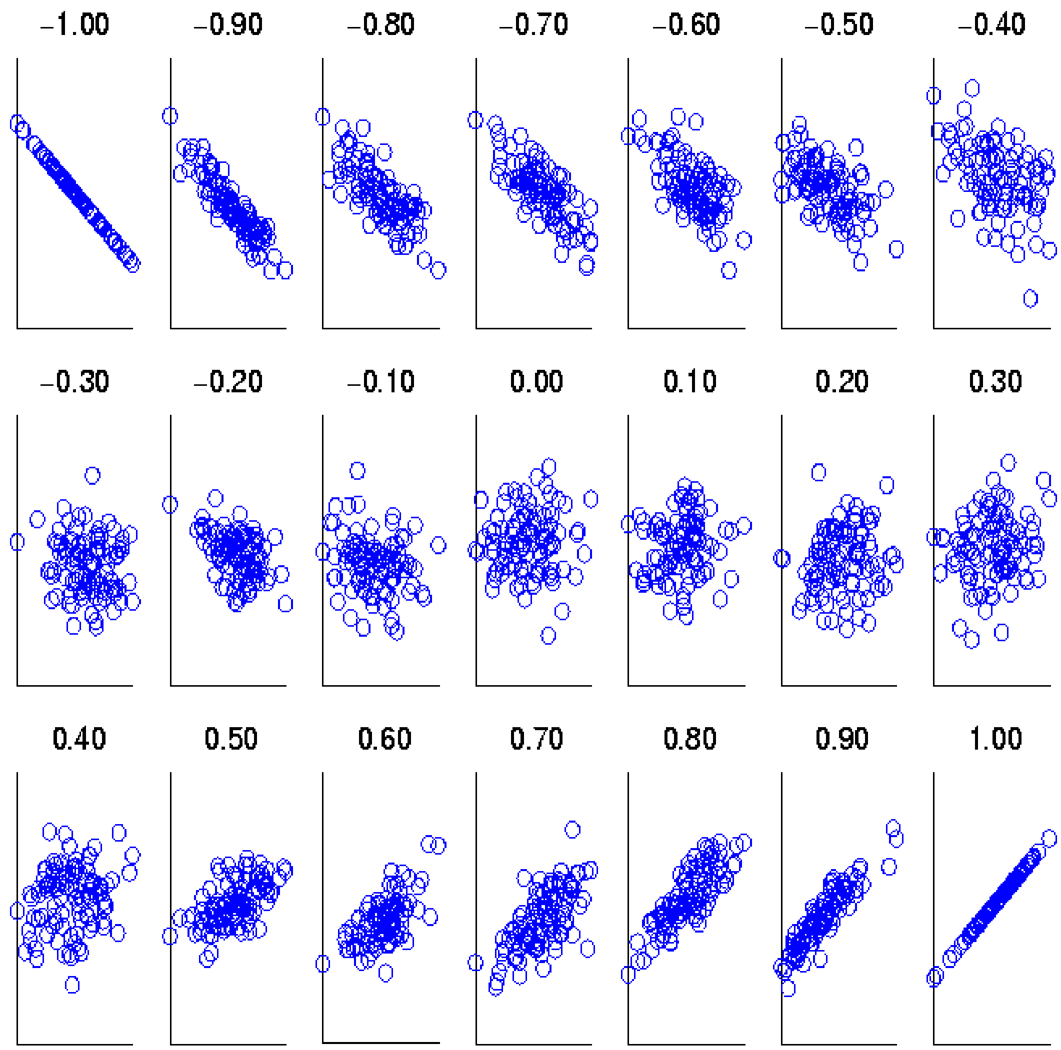
- Correlation coefficient (also called Pearson's product moment coefficient)

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

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 $\Sigma(a_i b_i)$ 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
- Note: In the book, *n* is used in the denominator. We use *n* – 1 for a sample and we use *n* for the population.

Visually Evaluating Correlation



Scatter plots showing the similarity from –1 to 1.

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? — 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
  - Attribute subset selection

Data Reduction: Numerosity Reduction

- **Sampling**
  - Simple random sample without replacement (SRSWOR)
  - Simple random sample with replacement (SRSWR)
  - Cluster sample
  - Stratified sample

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

- **Normalization by decimal scaling**

$$v' = \frac{v}{10^j}$$

Where j is the smallest integer such that Max(|v'|) < 1

- Example
  - Suppose the values of attribute *income* are: \$35,000, \$50,000, \$80,000, \$150,000. Then, j = 6.
  - 35,000 is normalized to 35,000 / 10^6 = 0.035
  - 50,000 is normalized to 50,000 / 10^6 = 0.05
  - 80,000 is normalized to 80,000 / 10^6 = 0.08
  - 150,000 is normalized to 150,000 / 10^6 = 0.15

Discretization

- 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)
  - Using entropy (supervised)
  - Etc.

References

- Han, J., Kamber, M., Pei, J., “Data mining: concepts and techniques,” 3rd Ed., Morgan Kaufmann, 2012
- http://www.cs.illinois.edu/~hanj/bk3/