Data Preprocessing

1. Data cleaning.

Data cleaning routines attempt to fill in missing values, smooth out noise while identifying outliers, and correct inconsistencies in the data.

(i). Missing values

1. **Ignore the tuple**: This is usually done when the class label is missing (assuming the mining task involves classification or description). This method is not very effective, unless the tuple contains several attributes with missing values. It is especially poor when the percentage of missing values per attribute varies considerably.

2. **Fill in the missing value manually:** In general, this approach is time-consuming and may not be feasible given a large data set with many missing values.

3. **Use a global constant to fill in the missing value:** Replace all missing attribute values by the same constant, such as a label like “Unknown". If missing values are replaced by, say, “Unknown", then the mining program may mistakenly think that they form an interesting concept, since they all have a value in common - that of “Unknown". Hence, although this method is simple, it is not recommended.

4. **Use the attribute mean to fill in the missing value:** For example, suppose that the average income of All Electronics customers is $28,000. Use this value to replace the missing value for income.

5. **Use the attribute mean for all samples belonging to the same class as the given tuple:** For example, if classifying customers according to credit risk, replace the missing value with the average income value for customers in the same credit risk category as that of the given tuple.

6. **Use the most probable value to fill in the missing value:** This may be determined with inference-based tools using a Bayesian formalism or decision tree induction. For example, using the other customer attributes in your data set, you may construct a decision tree to predict the missing values for income.

(ii). Noisy data

Noise is a random error or variance in a measured variable.

1. Binning methods:

Binning methods smooth a sorted data value by consulting the ”neighborhood", or values around it. The sorted values are distributed into a number of 'buckets', or bins. Because binning methods consult the neighborhood of values, they perform local smoothing. Figure illustrates some binning techniques.

In this example, the data for price are first sorted and partitioned into equi-depth bins (of depth 3). In smoothing by bin means, each value in a bin is replaced by the mean value of the bin. For example, the mean of the values 4, 8, and 15 in Bin 1 is 9. Therefore, each original value in this bin is replaced by the value 9. Similarly, smoothing by bin medians can be employed, in which each bin value is replaced by the bin median. In smoothing by bin boundaries, the minimum and maximum values in a given bin are identified as the bin boundaries. Each bin value is then replaced by the closest boundary value.

(i).Sorted data for price (in dollars): 4, 8, 15, 21, 21, 24, 25, 28, 34

(ii).Partition into (equi-width) bins:

- Bin 1: 4, 8, 15
- Bin 2: 21, 21, 24
- Bin 3: 25, 28, 34

(iii).Smoothing by bin means:

- Bin 1: 9, 9, 9,
- Bin 2: 22, 22, 22
- Bin 3: 29, 29, 29

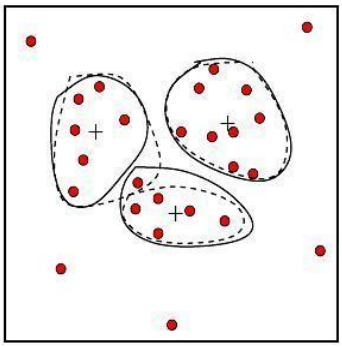
(iv).Smoothing by bin boundaries:

- Bin 1: 4, 4, 15
- Bin 2: 21, 21, 24
- Bin 3: 25, 25, 34

2. Clustering:

Outliers may be detected by clustering, where similar values are organized into groups or “clusters”. Intuitively, values which fall outside of the set of clusters may be considered outliers.

Figure: Outliers may be detected by clustering analysis.



3. **Combined computer and human inspection:** Outliers may be identified through a combination of computer and human inspection. In one application, for example, an information-theoretic measure was used to help identify outlier patterns in a handwritten character database for classification. The measure's value reflected the “surprise" content of the predicted character label with respect to the known label. Outlier patterns may be informative or “garbage". Patterns whose surprise content is above a threshold are output toa list. A human can then sort through the patterns in the list to identify the actual garbage ones

4. **Regression:** Data can be smoothed by fitting the data to a function, such as withregression. Linear regression involves finding the “best" line to fit two variables, so that one variable can be used to predict the other. Multiple linear regression is an extension of linear regression, where more than two variables are involved and the data are fit to a multidimensional surface.

(iii). Inconsistent data

There may be inconsistencies in the data recorded for some transactions. Some data inconsistencies may be corrected manually using external references. For example, errors made at data entry may be corrected by performing a paper trace. This may be coupled with routines designed to help correct the inconsistent use of codes. Knowledge engineering tools may also be used to detect the violation of known data constraints. For example, known functional dependencies between attributes can be used to find values contradicting the functional constraints.

2. Data transformation.

In data transformation, the data are transformed or consolidated into forms appropriate for mining. Data transformation can involve the following:

1. **Normalization,** where the attribute data are scaled so as to fall within asmall specified range, such as -1.0 to 1.0, or 0 to 1.0.

There are three main methods for data normalization : **min-max normalization, z- score normalization, and normalization by decimal scaling.**

(i).Min-max normalization performs a linear transformation on the original data. Suppose that minA and maxA are the minimum and maximum values of an attribute A. Min-max normalization maps a value v of A to v0 in the range [new minA; new maxA] by computing

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

(ii).z-score normalization (or zero-mean normalization), the values for an attribute A are normalized based on the mean and standard deviation of A. A value v of A is normalized to v0 by computing where mean A and stand dev A are the mean and standard deviation, respectively, of attribute A. This method of normalization is useful when the actual minimum and maximum of attribute A are unknown, or when there are outliers which dominate the min-max normalization.

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

(iii). **Normalization by decimal scaling** normalizes by moving the decimal point of values of attribute A. The number of decimal points moved depends on the maximum absolute value of
A. A value v of A is normalized to v0by computing where j is the smallest integer such that

$Max(|v'|) < 1.$

2. **Smoothing,** which works to remove the noise from data? Such techniques include binning, clustering, and regression.

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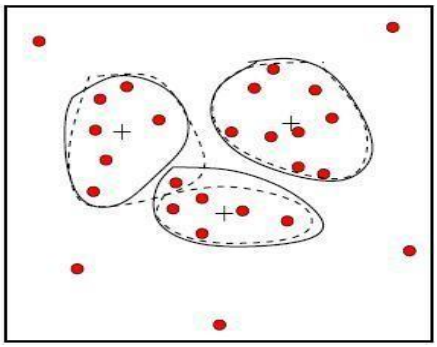

3. **Aggregation,** where summary or aggregation operations are applied to the data. For example, the daily sales data may be aggregated so as to compute monthly and annual total amounts.

4. **Generalization of the data**, where low level or 'primitive' (raw) data are replaced by higher level concepts through the use of concept hierarchies. For example, categorical attributes, like street, can be generalized to higher level concepts, like city or county.

3. Data reduction.

Data reduction techniques can be applied to obtain a reduced representation of the data set that is much smaller in volume, yet closely maintains the integrity of the original data. That is, mining on the reduced data set should be more efficient yet produce the same (or almost the same) analytical results.

Strategies for data reduction include the following.

1. **Data cube aggregation,** where aggregation operations are applied to the data in the construction of a data cube.

2. **Dimension reduction**, where irrelevant, weakly relevant or redundant attributes or dimensions may be detected and removed.

3. **Data compression**, where encoding mechanisms are used to reduce the data set size.

4. **Numerosity reduction,** where the data are replaced or estimated by alternative, smaller data representations such as parametric models (which need store only the model parameters instead of the actual data), or nonparametric methods such as clustering, sampling, and the use of histograms.

5. **Discretization and concept hierarchy generation,** where raw data values for attributes are replaced by ranges or higher conceptual levels. Concept hierarchies allow the mining of data at multiple levels of abstraction, and are a powerful tool for data mining.

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
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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:

Step-wise forward selection: The procedure starts with an empty set of attributes. The best of the original attributes is determined and added to the set. At each subsequent iteration or step, the best of the remaining original attributes is added to the set.