Chapter IV: Preprocessing

Knowledge Discovery in Databases

Luciano Melodia M.A.
Evolutionary Data Management, Friedrich-Alexander University Erlangen-Nürnberg
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Chapter III: Preprocessing

This is our agenda for this lecture:

- **Data preprocessing: an overview.**
  - Data quality.
  - Major tasks in data preprocessing.
- Data cleaning.
- Data integration.
- Data reduction.
- Data transformation and data discretization.
- Summary.

Data quality: why preprocess the data?

This is our agenda for this lecture:

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 refs, etc.
Timeliness: timely updated?
Believability: how trustworthy is it, that the data is correct?
Interpretability: how easily can the data be understood?
And even many more!

Major tasks in data preprocessing

Data cleaning:

- Fill in missing values.
- Smooth noisy data.
- Identify or remove outliers.
- 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.

Chapter IV: Preprocessing

Data preprocessing: an overview.

- Data quality.
- Major tasks in data preprocessing.

Data cleaning.

Data integration.

Data reduction.

Data transformation and data discretization.

Summary.

Data cleaning

Data in the real world is dirty. Lots of potentially incorrect data:

E.g. instrument faulty, human or computer error, transmission error.

Incomplete: lacking attributes, lacking certain attributes of interest or containing aggregate data.

E.g. occupation = "" (missing data).

Noisy: containing noise, errors or outliers.

Stochastic deviation, imprecision.
E.g. measurements.

Inconsistencies: containing discrepancies in codes or names.

E.g. age = "42", birthday = "03/07/2010".
Was rating "1,2,3" and now it is "A,B,C".
Discrepancy between duplicate records (e.g. address old and new).

Intentional (only default value, 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.
Examples are customer income in sales data.

Missing data may be due to:

Equipment malfunction.
Inconsistency 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 registered 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 percentage of missing values per attribute varies considerably.

Fill in the missing value manually.

Tedious or infeasible.

Fill in automatically with:

A global constant, e.g. "unkown", maybe a new class.
The attribute mean.
The attribute mean for all samples belonging to the same class.
The most probable value: Inference-based such as Bayesian formula or decision tree.

Noisy data?

Noise:

Random error or variance in a measured variable.
Stored value a little bit off the real value, up or down.
Leads to (slightly) incorrect attribute values.

May be due to:

Faulty or imprecise data-collection instruments.
Data-entry problems.
Data-transmission problems.
Technology limitation.
Inconsistency in naming conventions.

How to handle noisy data?

Beginning:

First sort data and partition into (equal-frequency) bins.
Then smooth by bin mean, by bin median or by bin boundaries.

Regression:

Smooth by fitting the data to 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 relationsships 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 (e.g. the Potter's Wheel tool).

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Data integration

Data integration:

Combine data from multiple sources into a coherent store.

Schema integration:

E.g. `A.cust-id` $\equiv$ `B.cust-#`.
Integrate metadata from different sources.

Entity-identification problem:

Identify the same 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 (coding).
- Different scales, e.g. metric vs. British units.

Handling redundancy in data integration

Redundant data often occur when integrating multiple databases.

Object (entity) 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:

Can be detected by **correlation analysis** and **covariance analysis**.

Careful integration of the data from multiple sources:

Helps to reduceavoid redundancies and inconsistencies and improve mining speed and quality.

Correlation analysis for nominal data (I)

Two attributes:

A has n distinct values: $A := \{a_1, a_2, \ldots, a_n\}$.
B has m distinct values: $B := \{b_1, b_2, \ldots, b_m\}$.

Contingency table:

Columns: the n values of A.
Rows: the m values of B.
Cells: counts of records with
$A' = \{a_i \in A \ : \ a_i = a_k \text{ for } a_k \in A\}$ and
$B' = \{b_j \in B \ : \ b_j = b_l \text{ for } b_l \in B\}$.

Expected count in cell (i, j):

$$e_{ij} = \frac{\#A' \cdot \#B'}{\#A + \#B}, \tag{1}$$

where $\#A + \#B$ is the total number of records.

Correlation analysis for nominal data (II)

χ^2-test:

$$\chi^2 = \sum_{i=1}^{N} \frac{(x_i - \hat{x}_i)^2}{\hat{x}_i}. \tag{2}$$

Summing over all cells of the contingency table.

No correlation (i.e. independence of attributes) yields χ^2 value of zero.

The larger the χ^2 value, the more likely the variables are related.

The cells that contribute the most to the χ^2 value are those whose actual count is very different from the expected count.

Correlation does not imply causality!

E.g. # of hospitals and # of car-thefts in a city are correlated.

Both are causally linked to the third variable: population.

χ^2 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 (column)	300	1200	1500

Numbers in parenthesis are expected counts calculated based on the data distribution in the two categories.

χ^2 calculation:

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93. \quad (3)$$

It shows that "like science fiction" and "play chess" are correlated in the group.

Correlation analysis of numerical data

Correlation coefficient:

Also called Pearson's product-moment coefficient

$$r_{A,B} = \frac{\sum_{i=1}^{N+M}(a_i - \mu_A)(b_i - \mu_B)}{(N+M-1)\sigma_A\sigma_B} = \frac{\sum_{i=1}^{N+M}(a_i b_i) - (N+M)\mu_A\mu_B}{(N+M-1)\sigma_A\sigma_B}. \tag{4}$$

where $N = \#A$, $M = \#B$, μ_A and μ_B are the means of A and B, respectively. σ_A and σ_B denote the corresponding standard deviations.

If $r_{A,B} > 0$, A and B are positively correlated (A's values increase with B's).
The higher, the stronger the correlation.

$r_{A,B} = 0$: independent.

$r_{A,B} < 0$: negatively correlated.

Visually evaluating correlation

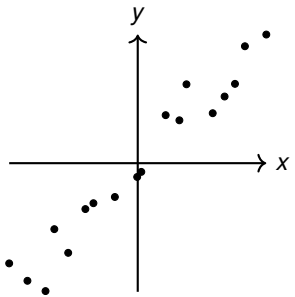

Figure: a) Positive correlation.

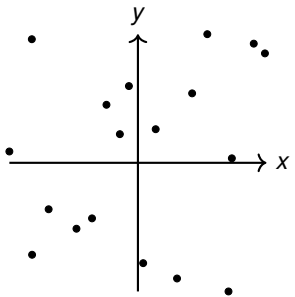

Figure: b) Uncorrelated/no correlation.

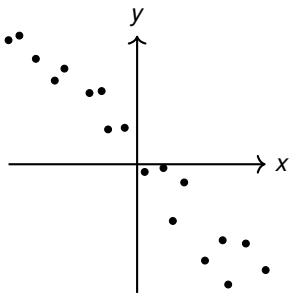

Figure: c) Negative correlation.

Covariance of numerical data (I)

Covariance is similar to correlation:

$$\mathrm{Cov}(A, B) = \frac{\sum_{i=1}^{n}(a_i - \overline{A})(b_i - \overline{B})}{n} \tag{5}$$

Pearson's correlation coefficient:

$$r = \frac{n\sum_{i=1}^{n} a_i b_i - \sum_{i=1}^{n} a_i \sum_{i=1}^{n} b_i}{\sqrt{\left(n\left(\sum_{i=1}^{n} a^2\right) - \left(\sum_{i=1}^{n} a_i\right)^2\right)\left(n\left(\sum_{i=1}^{n} b^2\right) - \left(\sum_{i=1}^{n} b_i\right)^2\right)}}, \tag{6}$$

where n is the number of tuples.

Covariance of numerical data (II)

Positive covariance:
If $\mathrm{Cov}(A, B) > 0$, then A and B tend to be either both larger or both smaller than their expected values.

Negative covariance:
If $\mathrm{Cov}(A, B) < 0$, then if A is larger than its expected value, B is likely to be smaller than its expected value and vice versa.

Independence:

$\mathrm{Cov}(A, B) = 0$.

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.

Covariance: an example (I)

Can be simplified in computation as:

$$\begin{aligned}
\mathrm{Cov}(A, B) &= E(A - E(A))(B - E(B)) && (7)\\
&= E(AB - AE(B) - E(A)B + E(A)E(B)) && (8)\\
&= E(AB) - E(A)E(B) - E(A)E(B) + E(A)E(B) && (9)\\
&= E(AB) - E(A)E(B). && (10)
\end{aligned}$$

Covariance: an example (II)

Suppose two stocks A and B have the following values within some time:
$(2, 5), (3, 8), (5, 10), (4, 11), (6, 14)$.

If the stocks are affected by the same industry trends, will their prices rise or fall together?

$$E(A) = \frac{2+3+5+4+6}{5} = \frac{20}{5} = 4. \tag{11}$$

$$E(B) = \frac{5+8+10+11+14}{5} = \frac{48}{5} = 9.6. \tag{12}$$

$$\mathrm{Cov}(A, B) = \frac{2\cdot 5+3\cdot 8+5\cdot 10+4\cdot 11+6\cdot 14}{5} - 4\cdot 9.6 = 4. \tag{13}$$

Thus, A and B rise together since $\mathrm{Cov}(A, B) > 0$.

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Data reduction I: dimensionality reduction

Curse of dimensionality:

When dimensionality increases data becomes increasingly sparse.
Density and distance between points, which are critical to clustering and outlier analysis become 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 strategies

Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) 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, i.e. remove unimportant attributes.
  - Wavelet transforms.
  - Principal component analysis.
  - Attribute subset selection or attribute creation.
- Numerosity reduction:
  - Regression and log-linear models.
  - Histograms, clustering and sampling.
  - Data cube aggregation.
- Data compression.

Mapping data to a new space

Fourier transform.

Wavelet transform.

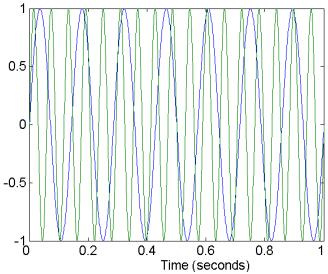


Figure: Two sine waves.

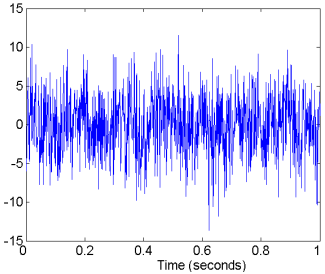


Figure: Two sine waves with noise.

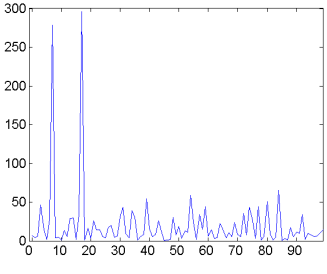


Figure: Frequencies.

What is wavelet transform?

Decomposes a signal into different frequency subbands.

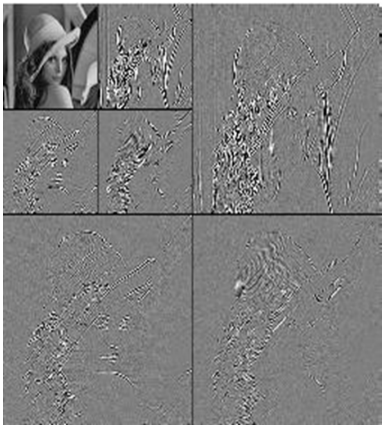
Applicable to *n*-dimensional signals.

Data transformed to preserve relative distance between objects at different levels of resolution.

Data transformed to preserve relative distance between objects at different levels of resolution.

Allow natural clusters to become more distinguishable.

Used for image compression.



Wavelet transformation

Discrete wavelet transform:
Transforms a vector X into a different vector X' of wavelet coefficients with the same length.

Compressed approximation:
Store only a small fraction of the strongest of the wavelet coefficients.

Similar to discrete fourier transform, but better lossy compression, localized in space.

Method:

The length of the vector must be an integer power of 2 (padding with 0's if necessary).
Each transform has two functions: smoothing and difference.
Applied to pairs of data, resulting in two sets of data with half the length.
The two functions are applied recursively until reaching the desired length.

Wavelet decomposition

Example:

$$X = (2, 2, 0, 2, 3, 5, 4, 4), \text{ can be transformed to} \tag{14}$$

$$X' = (2.75, -1.25, 0.5, 0, 0, -1, -1, 0). \tag{15}$$

Compression:
Many small detail coefficients can be replaced by 0's,
and only the significant coefficients are retained.

Resolution	Averages	Detail coefficients
8	$(2, 2, 0, 2, 3, 5, 4, 4)$	-
4	$(2, 1, 4, 4)$	$(0, -1, -1, 0)$
2	$(1\frac{1}{2}, 4)$	$(\frac{1}{2}, 0)$
1	$(2\frac{3}{4})$	$(1\frac{1}{4})$

Why wavelet transform?

Use hat-shaped filters:

Emphasize region where points cluster.
Suppress weaker information in their boundaries.

Effective removal of outliers:

Insensitive to noise, insensitive to input order.

Multi-resolution:

Detect arbitrary shaped clusters at different scales.

Efficient: Complexity $\mathcal{O}(N)$.

Principal component analysis (I)

Principal component analysis is a method of summarizing the properties of a set of multivariate data samples.

It is a **linear transformation** method that is often used for data analysis or data compression.

Principal component analysis is often also called **Karhunen-Loeve transformation**.

PCA is equivalent to maximization of the information at the output of a neural network with linear neurons.

The goal of the principal component analysis (PCA) is the identification of n **normed orthogonal vectors** $\{x_i \in \mathbb{R}^m \mid i = 1, 2, \ldots, n\}$ within the input space, which **represent most of the variance** of the data.

Principal component analysis: the problem (II)

Consider sample vectors $u_1, u_2, \ldots, u_n \in \mathbb{R}^m$ centered at zero and a complete orthonormal system $\{x_i \in \mathbb{R}^m \mid i = 1, 2, \ldots n\}$, such that:

$$\langle x \rangle = \int x p(x) d^m x = 0, \tag{16}$$

$$||u|| = 1, \tag{17}$$

$$\langle x^T u \rangle = 0, \tag{18}$$

where the Euclidean norm of the vector is given by

$$||u_i|| = \left(\sum_{i=1}^{m} u_i^2 \right)^{\frac{1}{2}}. \tag{19}$$

Goal: find u^* such that $\langle (x^T u^*)^2 \rangle$, the variance of the projections of x onto u^* becomes maximal according to the probability distribution $p(x)$.

Principal component analysis: optimization (III)

We seek for the maxima w^* of the following loss function, which represent the variance of the projections of x onto the new basis u:

$$L(w) := \langle (\frac{x^T w}{||w||})^2 \rangle = \langle (x^T u)^2 \rangle = u^T \langle x x^T \rangle = u^T \mathbf{C} u, \tag{20}$$

with

$$u^* = \frac{w^*}{||w^*||}, \tag{21}$$

because of the fact that

$$\langle (x^T w)^2 \rangle = \langle (x^T w)(x^T w) \rangle = w^T \langle x x^T \rangle w = w^T \mathbf{C} w, \tag{22}$$

and it holds that

$$L(w) = \frac{w^T \mathbf{C} w}{||w||^2}. \tag{23}$$

Principal component analysis: loss function (IV)

Extreme values of $L(w)$ correspond to the solution of the following equations:

$$\nabla_w L(w) = 0, \tag{24}$$

$$\frac{\mathbf{C}w||w||^2 - (w\mathbf{C}w)w}{||w||^4} = 0. \tag{25}$$

This yields the following eigenvalue problem:

$$\mathbf{C}w = \frac{w\mathbf{C}w}{||w||^2} \cdot w = L(w) \cdot w = \lambda \cdot w. \tag{26}$$

The above equation yields the eigenvalue problem, which solution is given by

$$w_i = a \cdot c_i, \;\; i = 1, 2, \ldots, n, \;\; a \in \mathbb{R}, \tag{27}$$

i.e. they are parallel to some eigenvector c_i of the correlation matrix $\mathbf{C} = \langle xx^T \rangle$.

Principal component analysis: principal components (V)

For a finite $a \in \mathbb{R}$, there exists a unique maximum with

$$w^* = a \cdot c_1. \tag{28}$$

The variance of the data becomes maximal for

$$u^* = u_1 = \pm c_1. \tag{29}$$

This procedure is iterated with the constraint of orthogonality:

$$w_k^T c_l = 0, \ \forall l < k. \tag{30}$$

Thus, the eigenvectors are sorted according to descending variance.

Principal component analysis: principal components (VI)

The first principal component corresponds to the eigenvector of the correlation matrix with the largest eigenvalue.

The **principal components of the data** x are given by the projection of the sample vector x onto the feature vectors u_i, such that:

$$x^T u_i, \;\; i = 1, 2, \ldots, m. \tag{31}$$

The kth component $x^T u_k$ is along the direction of the eigenvector u_k pointet to the kth biggest eigenvalue λ_k of the covariance matrix:

$$\mathrm{Cov}(x) = \langle (x - \mu)(x - \mu)^T \rangle, \text{ with } \mu = \langle x \rangle. \tag{32}$$

For centered data, which means if $\mu_k = 0$ then $\forall k$ it holds that the covariance matrix corresponds to the correlation matrix

$$\mathbf{C} = \langle x x^T \rangle. \tag{33}$$

Principal component analysis: principal components (VII)

Consider the variance of the kth component along a direction with unit vector u_k:

$$\sigma^2_{u_k} = \langle (x^T u_k)^2 \rangle \tag{34}$$
$$= \langle u_k^T x x^T u_k \rangle \tag{35}$$
$$= u_k^T \mathbf{C} u_k \tag{36}$$
$$= \sum_{\alpha=1}^{I} \lambda_\alpha u^2_{k\alpha}. \tag{37}$$

$u_{k\alpha}$ is the component of u_k along the eigenvector c_α of the matrix $\mathbf{C}$ to the eigenvalue λ_α.
Consider, that

$$\sigma^2_{u_k} = \lambda_k, \quad \text{if } u_k || c_k. \tag{38}$$

The eigenvalues of the covariance matrix correspond to the variance of the feature vector along the principal component u_i.

Attribute-subset selection

Another way to reduce dimensionality of data.

Redundant attributes:

Duplicate much or all of the information contained in 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.

Heuristic search in attribute selection

There are 2^d possible attribute combinations of d attributes.

Typical heuristic attribute-selection methods:

Best single attribute under the attribute-independence assumption:
choose by significance tests (e.g. t-test, see Chapter 6).

Best step-wise feature selection:

The best single attribute is picked first.

Then next best attribute condition to the first ...

Step-wise attribute elimination:

Repeatedly eliminate the worst attribute.

Best combined attribute selection and elimination.

Optimal branch and bound:

Use attribute elimination and backtracking.

Attribute creation (feature generation)

Create new attributes (features) that can capture the important information in a data set more effectively than the original ones.

Three general methodologies:

- Attribute extraction.
  - Domain-specific.
- Mapping data to new space (see: data reduction).
  - E.g. Fourier transformation, wavelet transformation, manifold approaches (not covered).
- Attribute construction:
  - Combining features (see: discriminative frequent patterns in Chapter 5).
  - Data discretization.

Data reduction (II): numerosity reduction

Reduce data volume by choosing alternative, smaller forms of data representation.

Parametric methods (e.g., regression):

- Assume the data fits some model (e.g. a function).
- Estimate model parameters.
- Store only the parameters.
- Discard the data (except possible outliers):
  - Ex. log-linear models-obtain value at a point in m-dimensional space as the product of appropriate marginal subspaces .

Non-parametric methods:

- Do not assume models.
- Major families: histograms, clustering, sampling, . . .

Parametric data reduction: regression and log-linear models

Linear regression:

Data modeled to fit a **straight line**.
Often uses the **least-square method** to fit the line.

Multiple regression:

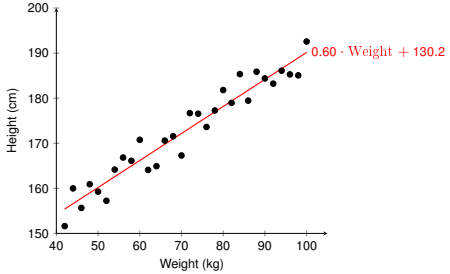
Allows a response random variable Y to be modeled as a linear function of a multidimensional feature vector $(x_1, x_2, \ldots, x_n)$.

Log-linear model:

Approximates discrete multidimensional probability distributions.

Regression analysis

A collective name for techniques for the modeling and analysis of numerical data consisting of values of a **dependent variable** (also called response variable or measurement) and of one or more **independent variables** (aka. explanatory variables or predictors).
The parameters are estimated so as to give a best fit of the data.
The **best fit** is evaluated by using the **least-squares method**, but other criteria have also been used.
Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships.



Regression analysis and log-linear models

Linear regression: $y = wx + b$.

Two regression coefficients, w and b,
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: $y = w_1 x_1 + w_2 x_2 + \ldots + w_n x_n + b$.

Many nonlinear functions can be transformed into the above.

Log-linear models:

Approximate discrete multidimensional probability distributions.
Estimate the probability of each point (tuple) in a multi-dimensional space for a set of discretized attributes, based on a smaller subset of dimensional combinations.
Useful also for dimensionality reduction and data smoothing.

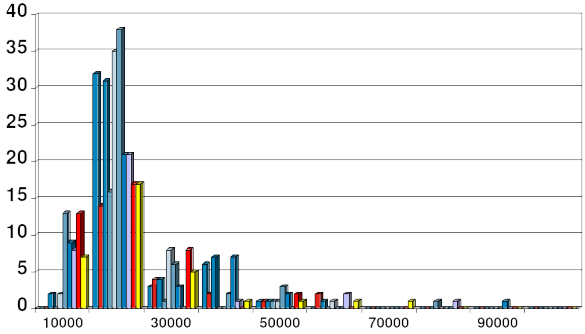
Histogram analysis

Divide data into buckets and store average (sum) or each bucket.

Partitioning rules:

Equal-width: equal bucket range.

Equal-frequency (or equal-depth).



Clustering

Partition data set into clusters based on similarity and store cluster representation (e.g., centroid and diameter) only.

Can be very effective if data points are close to each other under a certain norm and choice of space.

Can have hierarchical clustering and be stored in multidimensional index-tree structures.

There are many choices of clustering algorithms.

Cluster analysis will be studied in depth in Chapter 7.

Sampling

Obtain a small sample x to represent the whole data set X.

Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data.

Key principle: Choose a representative subset of the data.

Simple random sampling may have very poor performance in the presence of skew.
Develop adaptive sampling methods, e.g. stratified sampling.

Note: Sampling may not reduce database I/Os.

One page at a time.

Types of sampling

Simple random sampling.

There is an equal probability of selecting any particular item.

Sampling without repetition.

Once an object is selected, it is removed from the population.

Sampling with repetition.

A selected object is not removed from the population.

Stratified sampling:

Partition the data set and draw samples from each partition: Proportionally, i.e. approximately the same percentage of the data.
Used in conjunction with skewed data.

Data-cube aggregation

The lowest level of a data cube (base cuboid).

The aggregated data for an **individual entity of interest**.
E.g. a customer in a phone-calling data warehouse.
Number of calls per hour, day, or week.

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 the data cube, if possible.

Data reduction (III): 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 varies slowly with time.

Dimensionality and numerosity reduction may also be considered as forms of data compression.

Chapter IV: Preprocessing

Data transformations

Functions applied to a finite set of samples.

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 some interval $[\min, \max]$):

$$a_{\text{new}} = \frac{a - \min_A}{\max_A - \min_A}(\max - \min) + \min\,. \tag{39}$$

Example: let income range from \$12.000 to \$98.000 normalized to $[0, 1]$.
Then \$73.600 is mapped to $\frac{73.600-12.000}{98.000-12.000}(1-0)+0 = 0.716$.

Z-score normalization:

$$x_{\text{new}} := z = \frac{a - \mu_A}{\sigma_A},\ \text{with } \mu \text{ being the mean and } \sigma \text{ the standard deviation.} \tag{40}$$

Example: let $\mu = 54.000$ and $\sigma = 16.000$. Then $\frac{73.000-54.000}{16.000} = 1.225$.

Normalization by decimal scaling:

$$a_{\text{new}} = \frac{a}{10^k},\ \text{where } k \text{ is the smallest integer such that } \max(|a_{\text{new}}|) < 1. \tag{41}$$

Discretization

Three types of attributes:

Nominal – values from an unordered set, e.g. color, profession.
Ordinal – values from an ordered set, e.g. military or academic rank.
Numerical – numbers, e.g. integer or real numbers.

Divide the value 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:

Unsupervised, top-down split.

Histogram analysis:

Unsupervised, top-down split.

Clustering analysis:

Unsupervised, top-down split or bottom-up merge.

Decision-tree analysis:

Supervised, top-down split.

Correlation (e.g., χ^2) analysis:

Unsupervised, bottom-up merge.

Simple discretization: binning

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: $W = \frac{(B-A)}{N}$.

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 for price (in dollars):
4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34.

Partition into equal-frequency (equal-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.

Discretization without using class labels (binning vs. clustering)

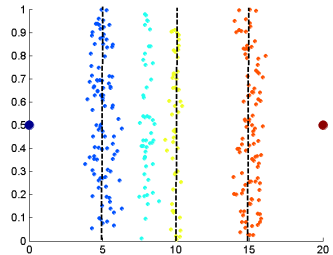


Figure: a) Equal interval width (binning).

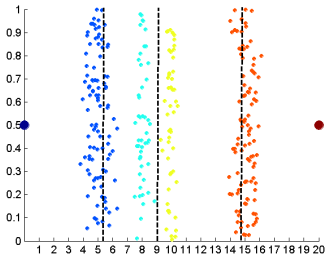


Figure: b) Equal frequency (binning).

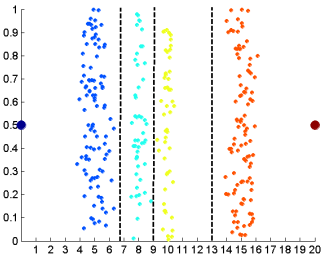


Figure: c) K-means clustering.

Discretization by classification & correlation analysis

Classification:

E.g. decision-tree analysis.
Supervised: Class labels given for training set e.g. cancerous vs. benign.
Using **entropy** to determine split point (discretization point).
Top-down, recursive split.
Details will be covered in Chapter 6.

Correlation analysis:

E.g. χ^2-merge: χ^2-based discretization.
Supervised: use class information.
Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low χ^2 values) to merge.
Merge performed recursively, until a predefined stopping condition.

Concept-hierarchy generation

Concept hierarchy:

Organizes concepts (i.e. attribute values) hierarchically.
Usually associated with each dimension in a data warehouse.
Facilitates **drilling and rolling** in data warehouses to view data at multiple granularity.

Concept-hierarchy formation:

Recursively reduce the data by collecting and replacing **low-level concepts** (such as numerical values for age) by **higher-level concepts** (such as youth, adult, or senior).
Can be explicitly specified by domain experts and/or data-warehouse designers.
Can be automatically formed for both numerical and nominal data.
For numerical data, use discretization methods shown.

Concept-hierarchy generation for nominal data

Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts.

$\#(\text{streets}) < \#(\text{city}) < \#(\text{state}) < \#(\text{country})$.

Specification of a hierarchy for a set of values by explicit data grouping.

$\#(\{\text{''}\textit{Urbana}\text{''}, \text{''}\textit{Champaign}\text{''}, \text{''}\textit{Chicago}\text{''}\}) < \#(\text{Illinois})$.

Specification of only a partial set of attributes.

Only $\#(\text{street}) < \#(\text{city})$, not others.

Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values.

E.g. for a set of attributes: $\{\text{street}, \text{city}, \text{state}, \text{country}\}$.
See on the next slides.

Automatic concept-hierarchy generation

Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute.

The attribute with the most distinct values is placed at the lowest level of the hierarchy.
Exceptions, e.g. weekday, month, quarter, year.

Example:

$$\#(\text{streets} = 674.339 > \#(\text{city}) = 3567, \tag{42}$$

$$\#(\text{city}) = 3567 > \#(\text{province or state}) = 356, \tag{43}$$

$$\#(\text{province or state}) = 356 > \#(\text{country}) = 15. \tag{44}$$

Chapter IV: Preprocessing

Summary

Data quality: Accuracy, completeness, consistency, timeliness, believability, interpretability.

Data cleaning: E.g. missing/noisy values, outliers.

Data integraiom from multiple sources:

- Entity identification problem.
- Remove redundancies.
- Detect inconsistencies.

Data reduction:

- Dimensionality reduction.
- Numerosity reduction.
- Data compression.

Data transformation and data discretization:

- Normalization.
- Concept-hierarchy generation.

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Thank you for your attention.
Any questions about the third chapter?

Ask them now, or again, drop me a line:
luciano.melodia@fau.de.