Università degli Studi di Milano

Master Degree in Computer Science

Information Management course

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Data Mining: Concepts and Techniques

(3rd ed.)

— Chapter 3 —

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Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary

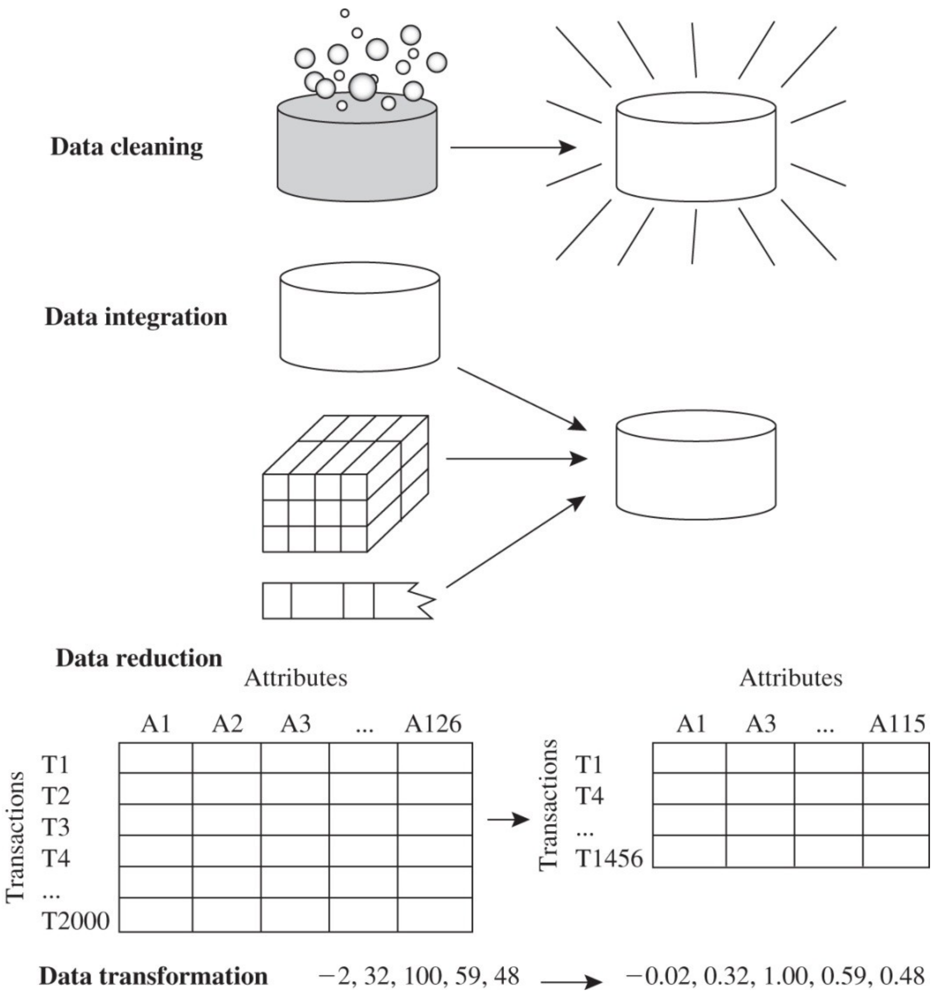
Data Quality: Why Preprocess the Data?

- 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

Major Tasks in Data Preprocessing



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Data Cleaning

- Data in the Real World Is Dirty (instrument faulty, human or computer error, transmission error …)
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation*=“ ” (missing data)
  - noisy: containing noise, errors, or outliers
    - e.g., *Salary*=“−10” (an error)
  - inconsistent: 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
  - Intentional (e.g., *disguised missing* data)
    - Jan. 1 as everyone’s birthday?

Incomplete (Missing) Data

- Data is not always available
  - E.g., 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

How to Handle Missing Data?

- Ignore the tuple (e.g. when class label is missing and doing classification) → simple, but loss of data
- Fill in the missing value manually
  → tedious + infeasible?
- Fill in it automatically with
  - global const (e.g., “unknown”) → a new class?!
  - the attribute mean or median
  - 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

How to Handle 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 knowledge about data → use **metadata** (e.g., domain, range, dependency, distribution) i.e. **know your data!**
  - 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) → already "data mining"
- Data migration and integration
  - Data migration tools: allow transformations to be specified
  - ETL (Extraction/Transformation/Loading) tools (GUI)
- Integration of the two processes
  - Iterative and interactive (e.g., Potter's Wheels)

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Data Integration

- **Data integration**:
  - Combines 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 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 able to be detected by *correlation analysis* and *covariance analysis*

Correlation Analysis (Nominal Data)

- **X^2 (chi-square) test**
  - Attribute A has c values (a_1 … a_c)
  - Attribute B has r values (b_1 … b_r)
  - Build a contingency table [o_{ij}], having 1 row for each a_i, one col for each b_j
  - o_{ij} is the observed frequency (number of tuples having value ai for A and bj for B)

$$e_{ij} = \frac{count(A=a_i) \times count(B=b_j)}{num.\ data\ tuples}$$

$$\chi^2 = \frac{\sum_i \sum_j (o_{ij} - e_{ij})^2}{e_{ij}}$$

Correlation Analysis (Nominal Data)

- 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

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

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 e_{ij})

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

- 2x2 table = 1 degree of freedom
- From chi-square distribution, the value for rejecting hypotesis of independency at 0.001 significance level is 10.828 → **strong correlation**

Covariance (Numeric Data)

- Covariance:
  - Attributes A and B
  - n → number of tuples
  - $\bar{A}$ and $\bar{B}$ → respective means of A and B
  - σ_A and σ_B → the respective standard deviation of A and B

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

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

Covariance (Numeric Data)

- Covariance:

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

- **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

Co-Variance: An Example

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

- It can be simplified in computation as

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

- Suppose two stocks A and B have the following values in one week: (2, 5), (3, 8), (5, 10), (4, 11), (6, 14).
- Question: If the stocks are affected by the same industry trends, will their prices rise or fall together?
  - E(A) = (2 + 3 + 5 + 4 + 6)/ 5 = 20/5 = 4
  - E(B) = (5 + 8 + 10 + 11 + 14) /5 = 48/5 = 9.6
  - Cov(A,B) = (2×5+3×8+5×10+4×11+6×14)/5 − 4×9.6= 4
- Thus, A and B rise together since Cov(A, B) > 0.

Correlation Analysis (Numeric Data)

- Correlation coefficient (also called Pearson's product moment coefficient)
  - Attributes A and B
  - n → number of tuples
  - $\overline{A}$ and $\overline{B}$ → respective means of A and B
  - σ_A and σ_B → the respective standard deviation of A and B

$$\rho_{X,Y} = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$$

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

Correlation Analysis (Numeric Data)

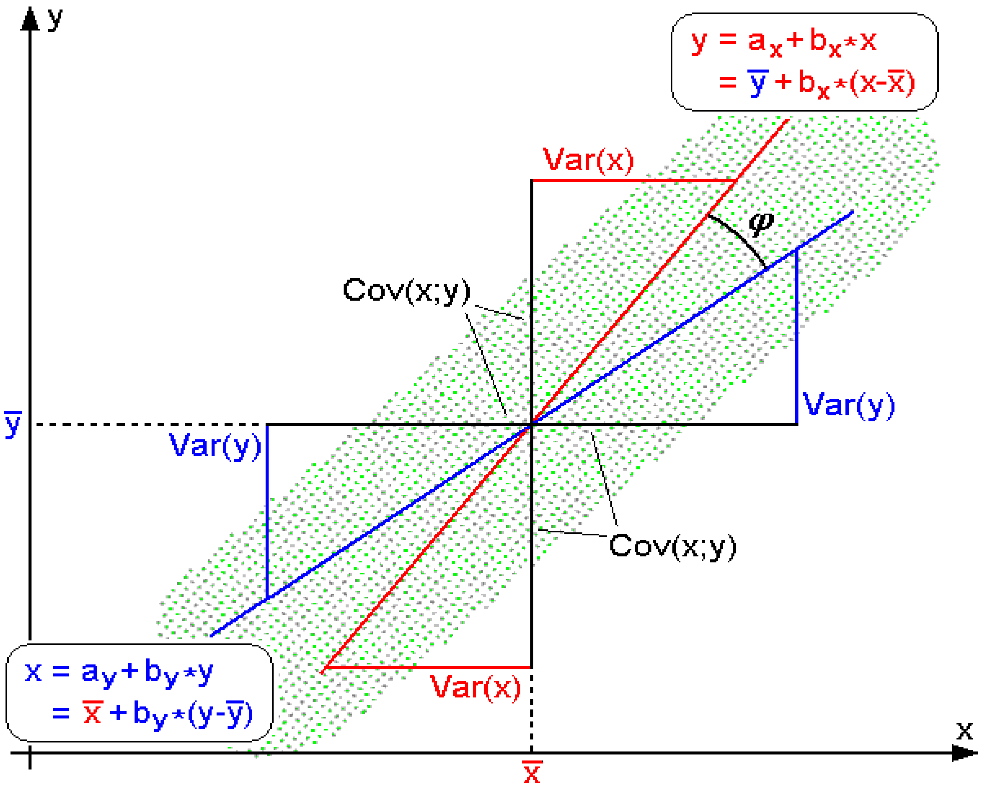
- Correlation coefficient (also called Pearson's product moment coefficient)

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

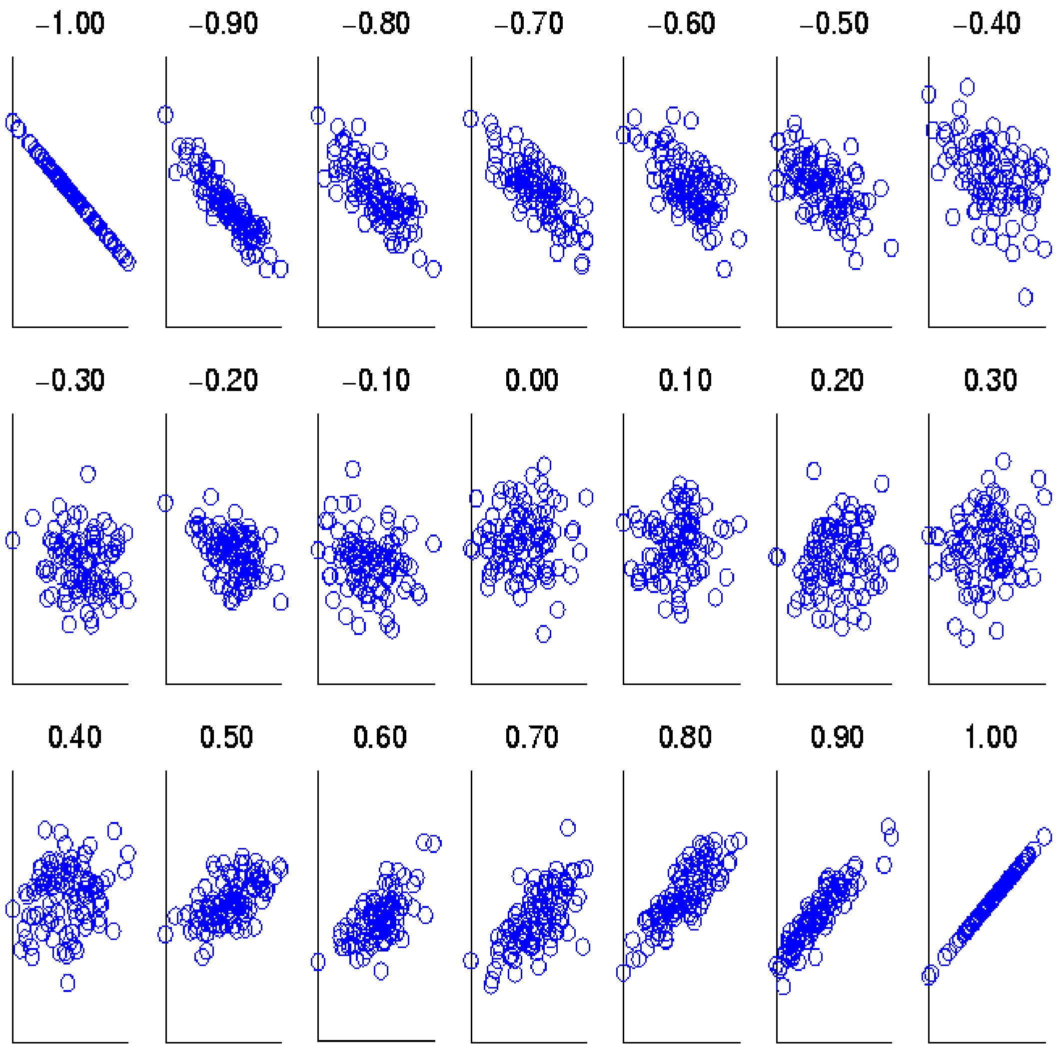
- If $r_{A,B} > 0$, A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{AB} < 0$: negatively correlated

Correlation Analysis (Numeric Data)

- Geometrically: the cosine of the angle between the two vectors, after centering (or possible regression lines)



Visually Evaluating Correlation



Scatter plots showing the similarity from –1 to 1.

Correlation (viewed as linear relationship)

- Correlation measures the linear relationship between objects
- To compute correlation, we standardize data objects, A and B, and then take their dot product

$$a'_k = (a_k - mean(A)) / std(A)$$

$$b'_k = (b_k - mean(B)) / std(B)$$

$$correlation(A, B) = A' \bullet B'$$

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Data Reduction Strategies

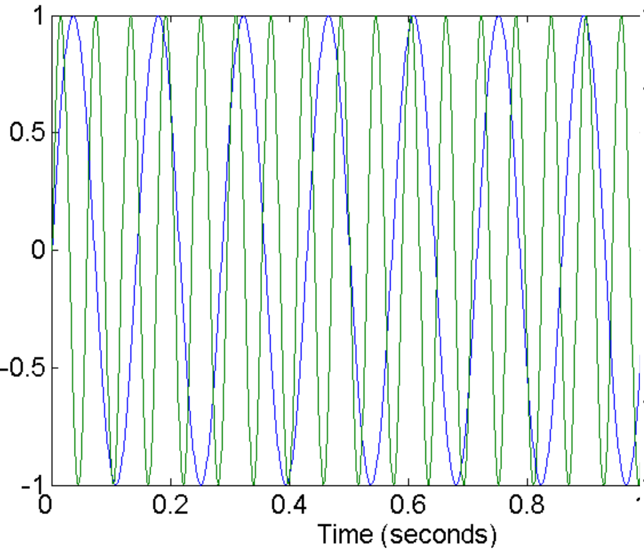
- **Data reduction**: Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction? Computational issues in big data!.
- Data reduction strategies
  - Dimensionality reduction, e.g., remove unimportant 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 1: Dimensionality Reduction

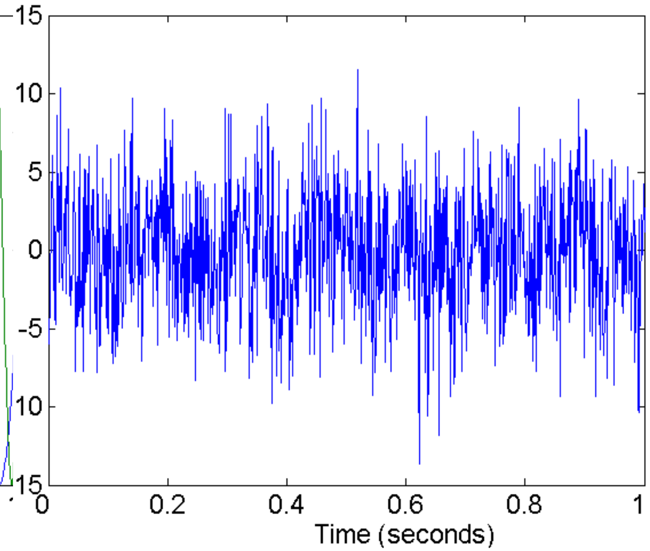
- **Curse of dimensionality**
  - When dimensionality increases, data becomes increasingly sparse
  - Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
  - The possible combinations of subspaces will grow exponentially
- **Dimensionality reduction**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

Mapping Data to a New Space

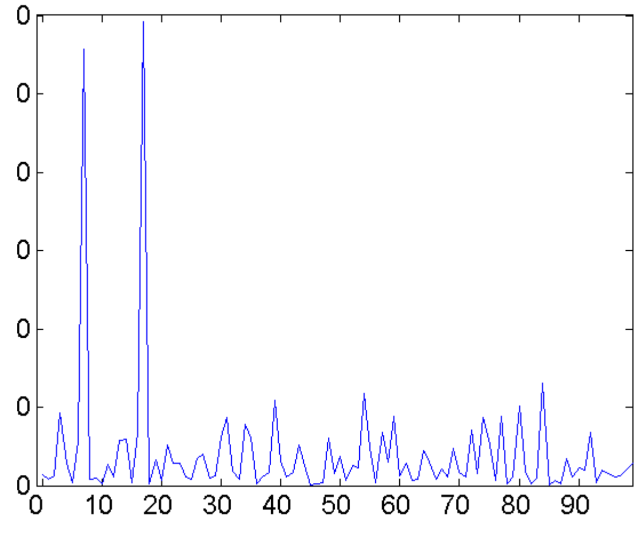
- **Fourier transform**
- **Wavelet transform**



Two Sine Waves



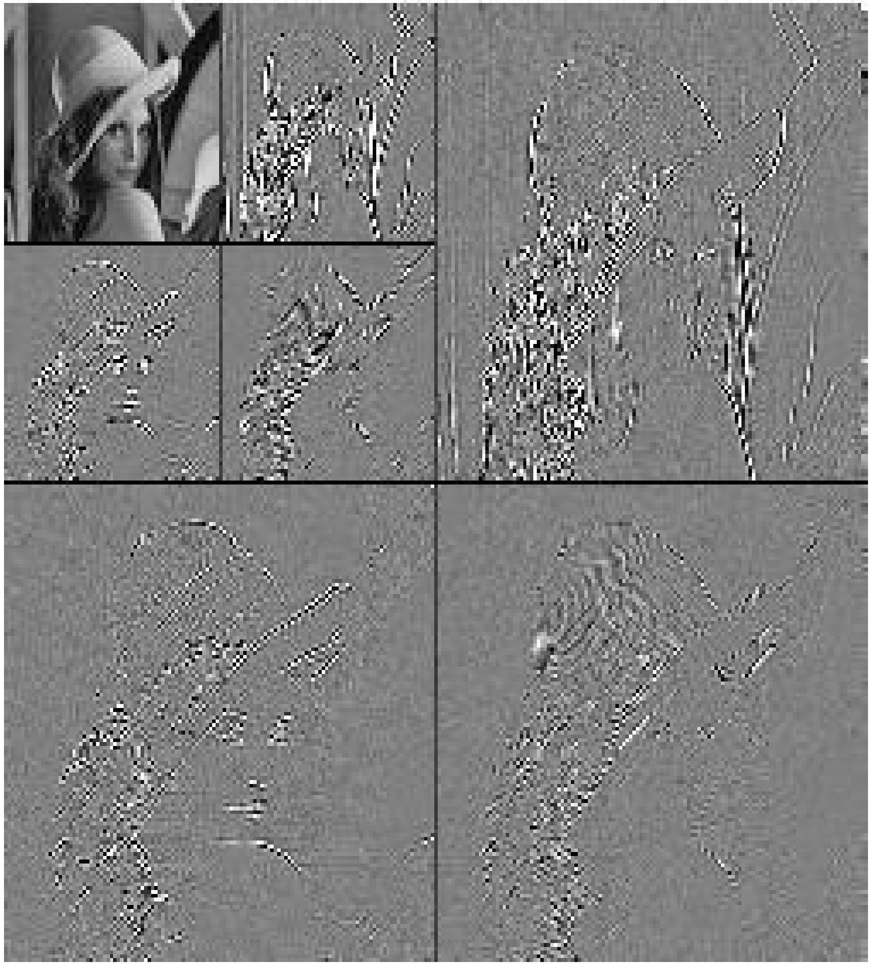
Two Sine Waves + Noise



Frequency

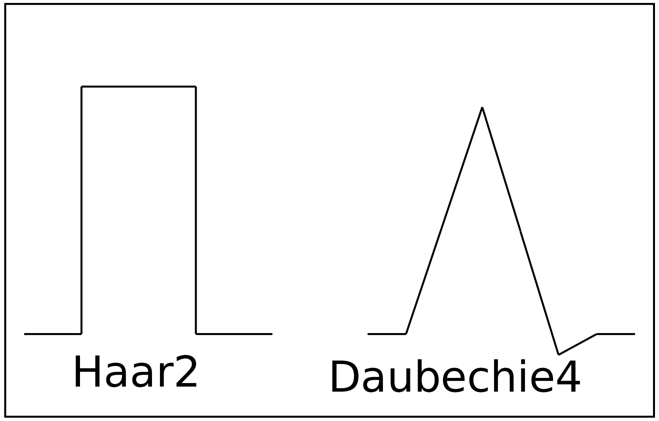
What Is Wavelet Transform?

- Decomposes a signal into different frequency subbands
  - Applicable to n-dimensional signals
- Data are transformed to preserve relative distance between objects at different levels of resolution
- Allow natural clusters to become more distinguishable



Wavelet Transformation

- Discrete wavelet transform (DWT) for linear signal processing, multi-resolution analysis
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients
- Similar to discrete Fourier transform (DFT), but better lossy compression, localized in space



Wavelet Transformation

- DWT Algorithm:
  - Length, L, must be an integer power of 2 (padding with 0’s, when necessary)
  - Each transform needs to apply 2 functions:
    smoothing (s()), difference (d())
  - Applies s() and d() to pairs of data (x_{2i}, x_{2i+1}) →
    two sets A and B of length L/2
  - Applies both s() and d() recursively
  - Until reaching the desired length (e.g. 2), obtaining L values
  - Select a few values to represent the wavelet coefficients

Wavelet Decomposition

- Wavelets: A math tool for space-efficient hierarchical decomposition of functions
- S = [2, 2, 0, 2, 3, 5, 4, 4] can be transformed to $S_{\wedge}$ = [$2^3/_4$, $-1^1/_4$, $^1/_2$, 0, 0, -1, -1, 0]
- s() = avg(); d() = diff / 2
- 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	$[2\frac{3}{4}]$	$[-1\frac{1}{4}]$

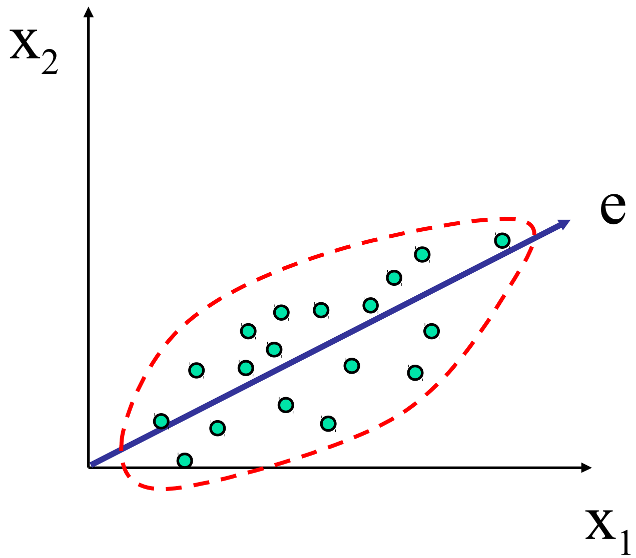
Why Wavelet Transform?

- Use hat-shape 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 O(N)
- Only applicable to low dimensional data

Principal Component Analysis (PCA)

- Find a projection that captures the largest amount of variation in data
- How?
  - find k (< n) orthogonal vectors that “best” represent data
  - project data into the space defined by these vectors
- Popular choice: eigenvectors



PCA Algorithm (Steps)

- Given *N* data vectors from *n*-dimensions, find $k \leq n$ orthogonal vectors (*principal components*) that can be best used to represent data
  - Normalize input data: Each attribute falls within the same range
  - Compute *k* orthonormal (unit) vectors, i.e., *principal components*
  - Each input data (vector) is a linear combination of the *k* principal component vectors
  - The principal components are sorted in order of decreasing "significance" or strength
  - Since the components are sorted, the size of the data can be reduced by eliminating the *weak components*, i.e., those with low variance

PCA Algorithm (remarks)

- Using the strongest principal components, it should be possible to rebuild a good approximation of original data
- Works for numeric data only
- unlike attribute subset selection, **new attributes are found**