Data Preprocessing

Data Preprocessing

- Why preprocess the data?
- Descriptive data summarization
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization
- Summary

Why Data Preprocessing?

- Data in the real world is dirty
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., occupation=“ ”
  - noisy: containing errors or outliers
    - e.g., Salary=“-10”
  - inconsistent: containing discrepancies in codes or names
    - e.g., Age=“42” Birthday=“03/07/1997”
    - e.g., Was rating “1,2,3”, now rating “A, B, C”
    - e.g., discrepancy between duplicate records

Why Is Data Dirty?

- Incomplete data may come from
  - “Not applicable” data value when collected
  - Different considerations between the time when the data was collected and when it is analyzed.
  - Human/hardware/software problems
- Noisy data (incorrect values) may come from
  - Faulty data collection instruments
  - Human or computer error at data entry
  - Errors in data transmission
- Inconsistent data may come from
  - Different data sources
  - Functional dependency violation (e.g., modify some linked data)
- Duplicate records also need data cleaning

Why Is Data Preprocessing Important?

- No quality data, no quality mining results!
  - Quality decisions must be based on quality data
    - e.g., duplicate or missing data may cause incorrect or even misleading statistics.
  - Data warehouse needs consistent integration of quality data
- Data extraction, cleaning, and transformation comprises the majority of the work of building a data warehouse

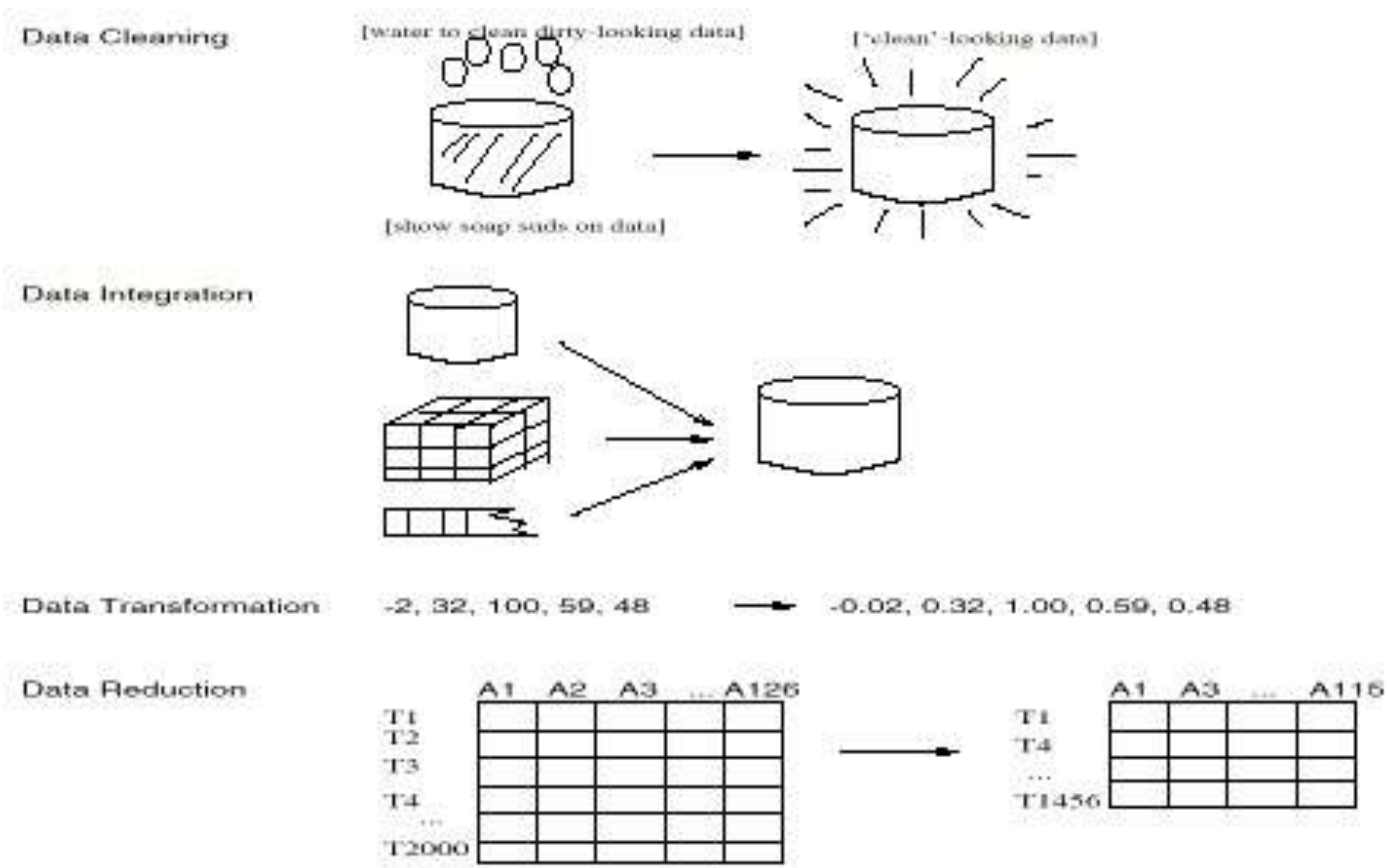
Multi-Dimensional Measure of Data Quality

- A well-accepted multidimensional view:
  - Accuracy
  - Completeness
  - Consistency
  - Timeliness
  - Believability
  - Value added
  - Interpretability
  - Natural,
  - Representational
  - Accessibility

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 transformation**
  - Normalization and aggregation
- **Data reduction**
  - Obtains reduced representation in volume but produces the same or similar analytical results
- **Data discretization**
  - Part of data reduction but with particular importance, especially for numerical data

Forms of Data Preprocessing



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Mining Data Descriptive Characteristics

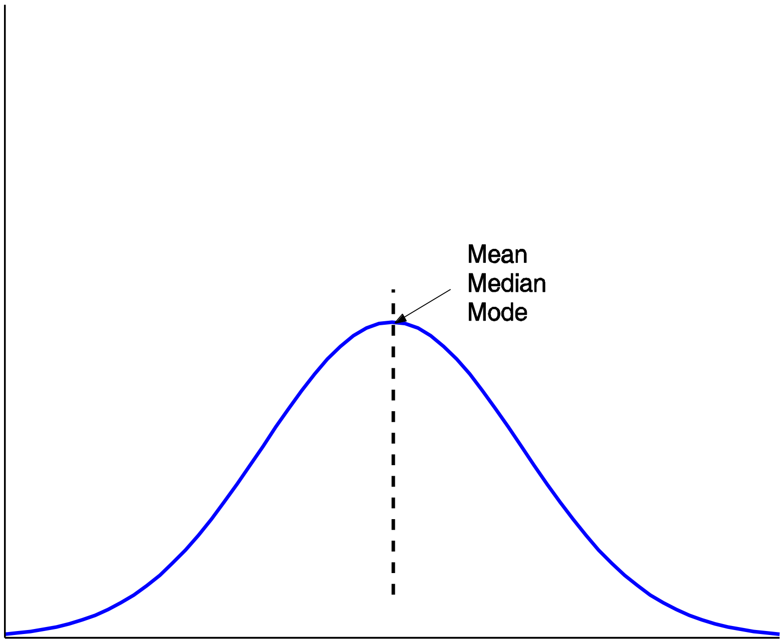
- Motivation
  - To better understand the data: central tendency, variation and spread
- Data dispersion characteristics
  - median, max, min, quantiles, outliers, variance, etc.
- Numerical dimensions correspond to sorted intervals
  - Data dispersion: analyzed with multiple granularities of precision
  - Boxplot or quantile analysis on sorted intervals
- Dispersion analysis on computed measures
  - Folding measures into numerical dimensions
  - Boxplot or quantile analysis on the transformed cube

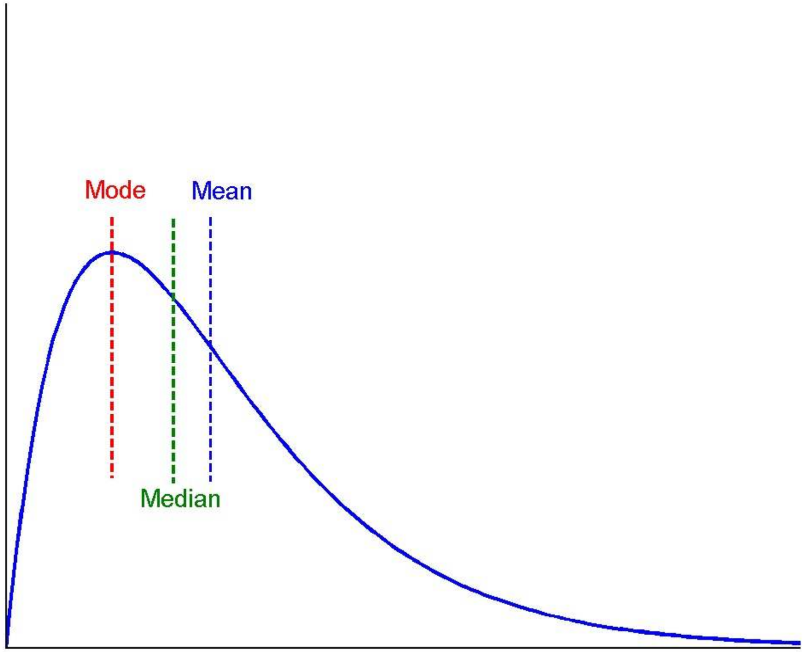
Measuring the Central Tendency

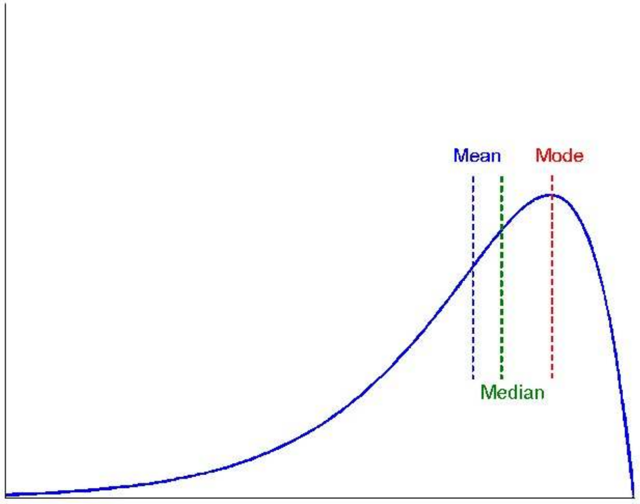
- Mean (algebraic measure) (sample vs. population): $\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$ $\mu = \frac{\sum x}{N}$
  - Weighted arithmetic mean: $\bar{x} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$
  - Trimmed mean: chopping extreme values
- Median: A holistic measure
  - Middle value if odd number of values, or average of the middle two values otherwise
- Mode
  - Value that occurs most frequently in the data
  - Unimodal, bimodal, trimodal

Symmetric vs. Skewed Data

- Median, mean and mode of symmetric, right and left skewed data(tail's direction)







Measuring the Dispersion of Data

- Quartiles, outliers and boxplots
  - Quartiles: Q_1 (25th percentile), Q_3 (75th percentile)
  - Inter-quartile range: IQR = $Q_3 - Q_1$
  - Five number summary: min, Q_1, M, Q_3, max
  - Boxplot: ends of the box are the quartiles, median is marked, whiskers, and plot outlier individually
  - Outlier: usually, a value higher/lower than 1.5 x IQR
- Variance and standard deviation (*sample: s, population: σ)*
  - Variance: (algebraic, scalable computation)

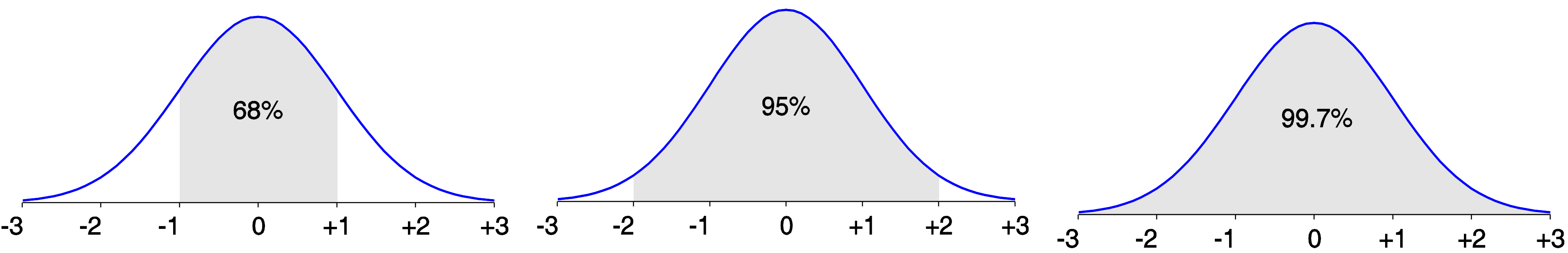
$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{n}(x_i - \mu)^2 = \frac{1}{N}\sum_{i=1}^{n}x_i^2 - \mu^2$$

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 = \frac{1}{n-1}[\sum_{i=1}^{n}x_i^2 - \frac{1}{n}(\sum_{i=1}^{n}x_i)^2]$$

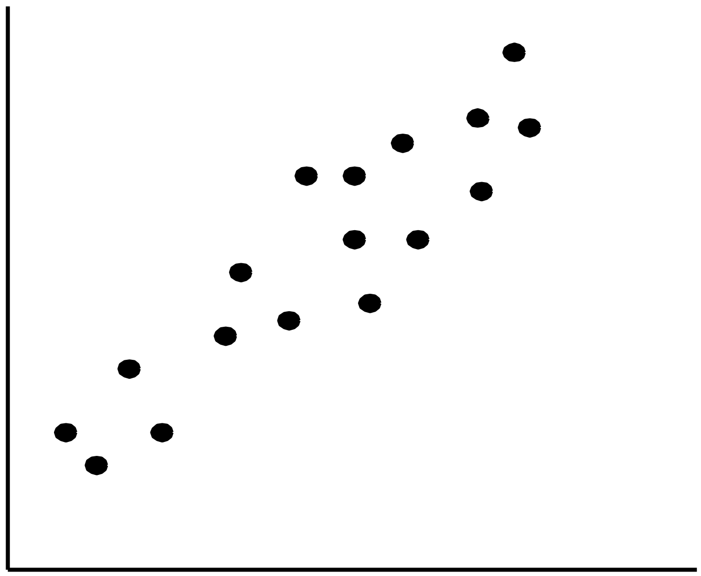
  - Standard deviation *s (or σ)* is the square root of variance *s^2 (or σ^2)*

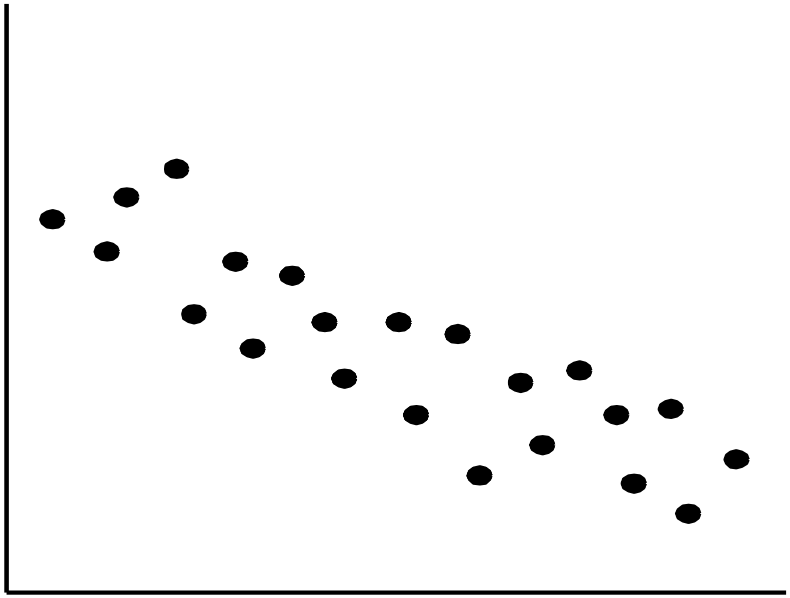
Properties of Normal Distribution Curve

- The normal (distribution) curve
  - From μ–σ to μ+σ: contains about 68% of the measurements (μ: mean, σ: standard deviation)
  - From μ–2σ to μ+2σ: contains about 95% of it
  - From μ–3σ to μ+3σ: contains about 99.7% of it

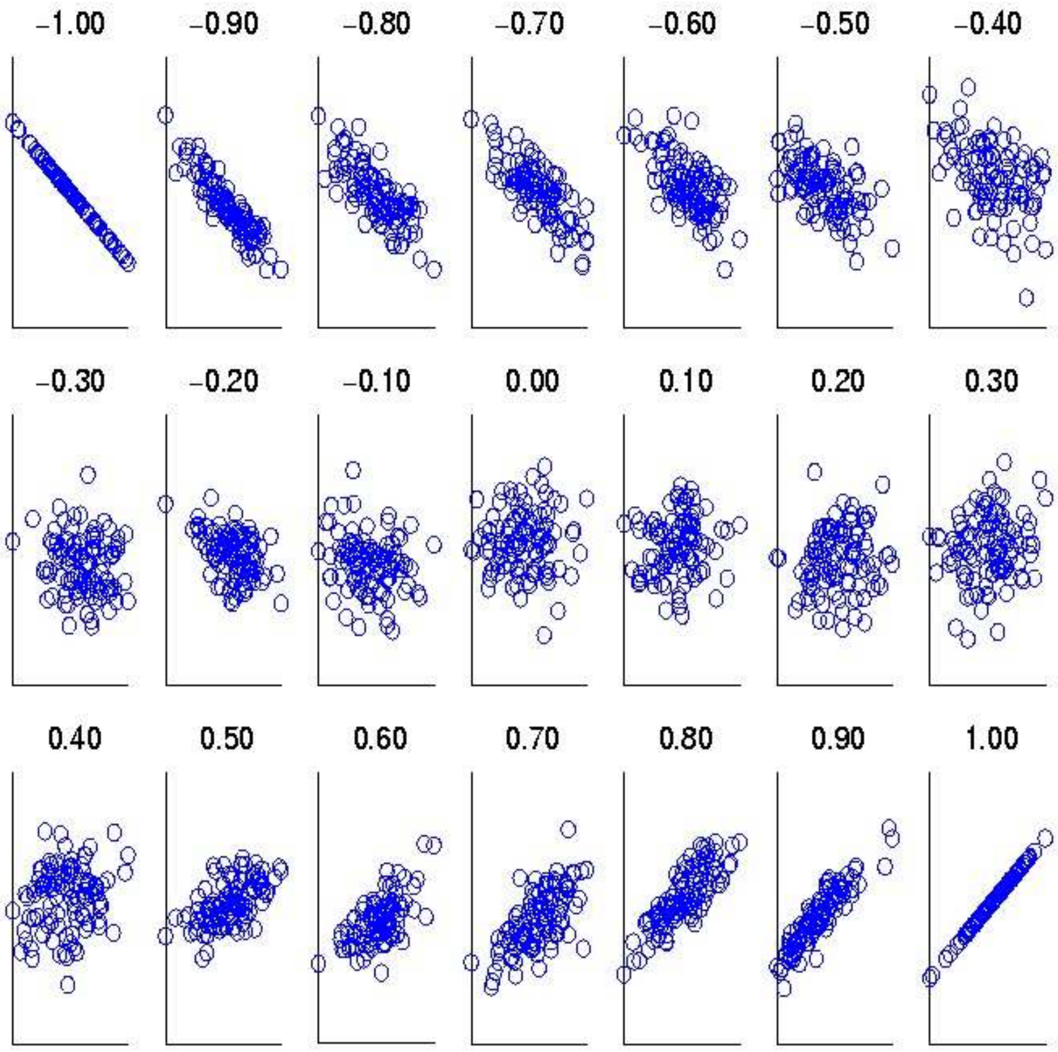


Positively and Negatively Correlated Data





Korelasyonu görsel değerlendirme



Scatter plots showing the similarity from

–1 to 1.

Korelasyon(Correlation)

- Korelasyon, objeler arasındaki lineer ilişki ölçütlerini ifade eder.

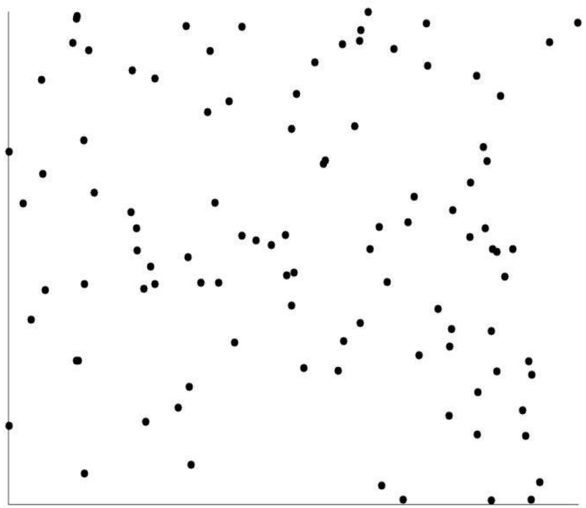
- Korelasyonu hesaplamak için, p ve q data objelerini standardize edip dot product alırız.

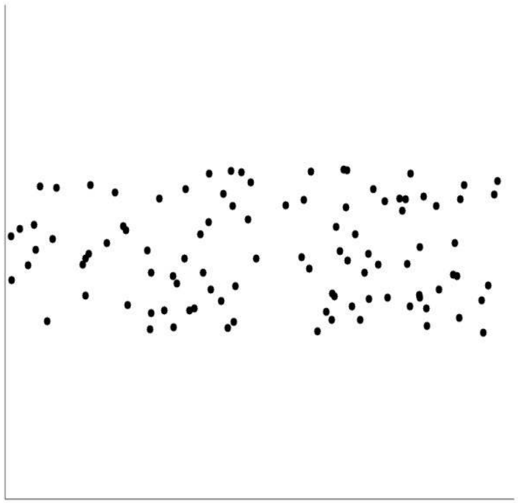
$$p'_k = (p_k - mean(p)) / std(p)$$

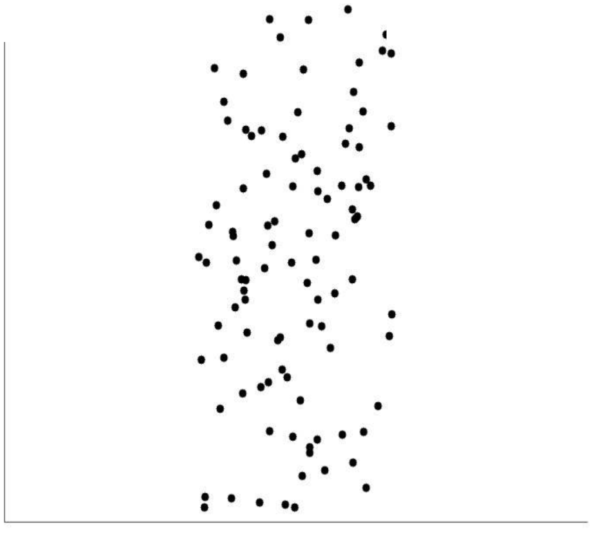
$$q'_k = (q_k - mean(q)) / std(q)$$

$$correlation(p, q) = p' \bullet q'$$

Not Correlated Data







Benzerlik(Similarity)

- Benzerlik(Similarity)
  - İki objenin benzerliğinin sayısal değeri
  - Yüksek değer daha çok benzerlik ifade eder
  - Genellikle [0,1] aralık değerlerindedir
  - Farklılık(Dissimilarity) tam tersini ifade eder

Basit Attributeler için Similarity/Dissimilarity

p ve *q* veri iki objesi için attribute değerlerdir.

Attribute Type	Dissimilarity	Similarity
Nominal	$d = \begin{cases} 0 & \text{if } p = q \\ 1 & \text{if } p \neq q \end{cases}$	$s = \begin{cases} 1 & \text{if } p = q \\ 0 & \text{if } p \neq q \end{cases}$
Ordinal	$d = \frac{\lvert p-q \rvert}{n-1}$ (values mapped to integers 0 to $n-1$, where n is the number of values)	$s = 1 - \frac{\lvert p-q \rvert}{n-1}$
Interval or Ratio	$d = \lvert p - q \rvert$	$s = -d$, $s = \frac{1}{1+d}$ or $s = 1 - \frac{d - min\_d}{max\_d - min\_d}$

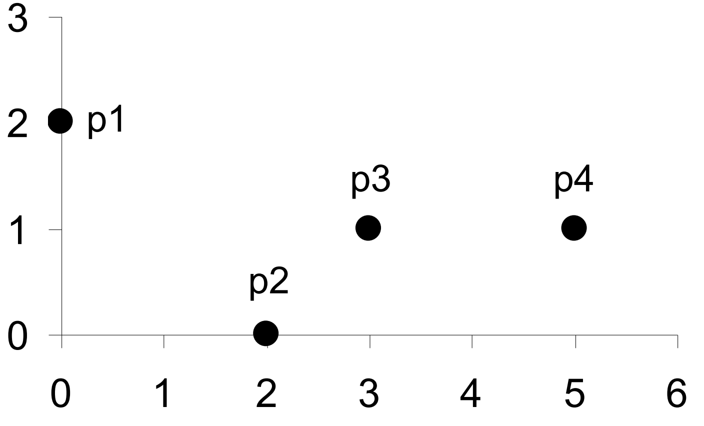
Benzerlik Ölçüleri

- Öklit uzaklığı(Euclidean distance)

$$dist = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2}$$

  – n boyut(attribute) sayısını, pk ve qk sırasıyla, p ve q objelerinin k'ninci değerlerini ifade eder.

Öklit uzaklığı
(Euclidean Distance)



point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

	p1	p2	p3	p4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
p3	3.162	1.414	0	2
p4	5.099	3.162	2	0

Uzaklık Matrisi

Minkovski uzaklığı

- Minkovski uzaklığı, Öklit uzaklığının genelleştirilmiş versiyonudur.

$$dist = \left(\sum_{k=1}^{n} | p_k - q_k |^r \right)^{\frac{1}{r}}$$

– r bir parametre olsun, n boyut(attribute) sayısını, pk ve qk sırasıyla, p ve q objelerinin k'ninci değerlerini ifade eder.

Minkovski uzaklığı

- r = 1. City block(Manhattan, taxicab, L_1 norm) distance.
  - Hamming distance bunun genel kullanım örneklerindendir, iki binary vektör arası uzaklığı bulur.

- r = 2. Euclidean distance

- $r \to \infty$. “supremum” (L_{max} norm, L_∞ norm) distance.
  - Bu vektörlerin değerleri arasındaki maksimum farkı ifade eder

- r ile n karıştırılmamalıdır, bütün bu uzaklıklar tüm boyutlar için tanımlanmıştır.

Minkovski uzaklığı

point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

L1	p1	p2	p3	p4
p1	0	4	4	6
p2	4	0	2	4
p3	4	2	0	2
p4	6	4	2	0

L2	p1	p2	p3	p4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
p3	3.162	1.414	0	2
p4	5.099	3.162	2	0

L_∞	p1	p2	p3	p4
p1	0	2	3	5
p2	2	0	1	3
p3	3	1	0	2
p4	5	3	2	0

Uzaklık Matrisi

Uzaklıkların Ortak özellikleri

Öklit uzaklığı gibi uzaklıkların bazı temel özellikleri vardır:

1. $d(p, q) \geq 0$ tüm *p* ve *q* için ve $d(p, q) = 0$ sadece $p = q$. (Positive definiteness)
2. $d(p, q) = d(q, p)$ tüm *p* ve *q* için. (Symmetry)
3. $d(p, r) \leq d(p, q) + d(q, r)$ tüm *p, q*, ve *r noktaları için*. (Triangle Inequality)

d(p, q), p ve *q* noktaları(veri objeleri) için uzaklık değeridir.

Bu özellikleri sağlayan tüm uzaklık değerlerine metrik(metric) denir.

Binary Vektörler arası benzerlik

- *p* ve *q* objelerinin binary attributeler içeren vektörler olarak ifade edilmesi yaygındır.
- Bu değerlerin benzerlikleri hesaplansın

  M_{01} = p'nin 0 ve q'nun 1 olduğu değerlerin sayısı olsun

  M_{10} = p'nin 1 ve q'nun 0 olduğu değerlerin sayısı olsun

  M_{00} = p'nin 0 ve q'nun 0 olduğu değerlerin sayısı olsun

  M_{11} = p'nin 1 ve q'nun 1 olduğu değerlerin sayısı olsun

- Simple Matching ve Jaccard Coefficients

  SMC = number of matches / number of attributes

  $= (M_{11} + M_{00}) / (M_{01} + M_{10} + M_{11} + M_{00})$

  Jaccard = number of 11 matches / number of not-both-zero attributes values

  $= (M_{11}) / (M_{01} + M_{10} + M_{11})$

SMC ve Jaccard Örneği

p = 1 0 0 0 0 0 0 0 0 0
q = 0 0 0 0 0 0 1 0 0 1

$M_{01} = 2$ (p'nin 0 ve q'nun 1 olduğu değerlerin sayısı)
$M_{10} = 1$ (p'nin 1 ve q'nun 0 olduğu değerlerin sayısı)
$M_{00} = 7$ (p'nin 0 ve q'nun 0 olduğu değerlerin sayısı)
$M_{11} = 0$ (p'nin 1 ve q'nun 1 olduğu değerlerin sayısı)

$SMC = (M_{11} + M_{00})/(M_{01} + M_{10} + M_{11} + M_{00}) = (0+7) / (2+1+0+7) = 0.7$

$J = (M_{11}) / (M_{01} + M_{10} + M_{11}) = 0 / (2 + 1 + 0) = 0$

Cosine Benzerliği

d_1 ve d_2 iki doküman vektörü olsun

$$\cos(d_1, d_2) = (d_1 \bullet d_2) / ||d_1||\ ||d_2||\ ,$$

Vektörler areası dot product demektir. $|| d ||$ d vektörü uzunluğunu ifade eder.

örnek:

$d_1 =$ **3 2 0 5 0 0 0 2 0 0**

$d_2 =$ **1 0 0 0 0 0 0 1 0 2**

$d_1 \bullet d_2 = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5$

$||d_1|| = (3*3+2*2+0*0+5*5+0*0+0*0+0*0+2*2+0*0+0*0)^{\mathbf{0.5}} = (42)^{\mathbf{0.5}} = 6.481$

$||d_2|| = (1*1+0*0+0*0+0*0+0*0+0*0+0*0+1*1+0*0+2*2)^{\mathbf{0.5}} = (6)^{\mathbf{0.5}} = 2.245$

$\cos(d_1, d_2) = 0.3150$

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Data Cleaning

- Importance
  – Data cleaning is one of the biggest problems in data analysis
- Data cleaning tasks
  – Fill in missing values
  – Identify outliers and smooth out noisy data
  – Correct inconsistent data
  – Resolve redundancy caused by data integration

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 (assuming the tasks in classification—not effective when the percentage 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 requires 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)

Simple Discretization Methods: 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: $W = (B - A)/N$.
  - 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

Then, partition into equal-frequency (equi-depth) bins:

- Bin 1: 4, 8, 9, 15
- Bin 2: 21, 21, 24, 25
- Bin 3: 26, 28, 29, 34

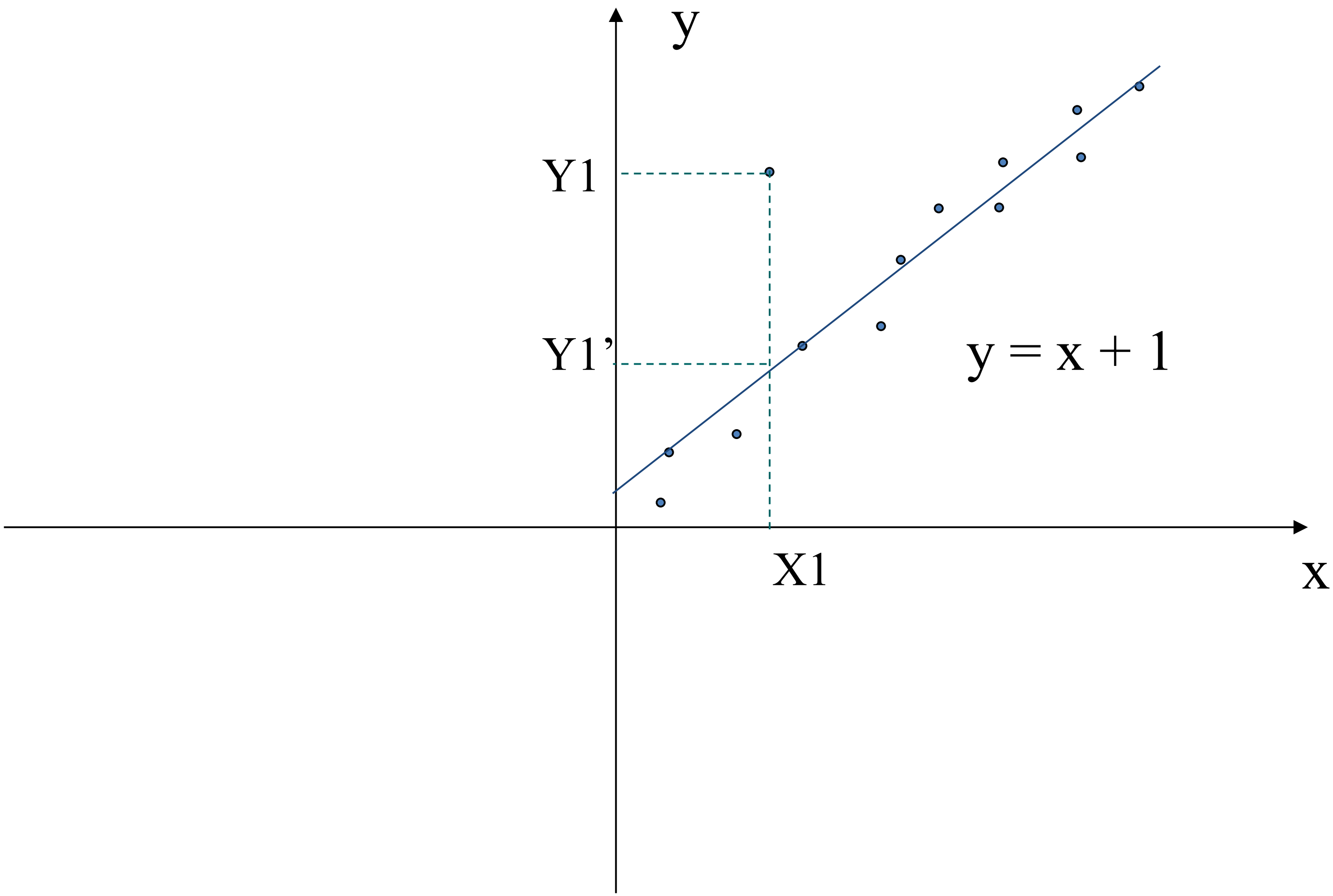
* Smoothing by bin means:

- Bin 1: 9, 9, 9, 9
- Bin 2: 23, 23, 23, 23
- Bin 3: 29, 29, 29, 29

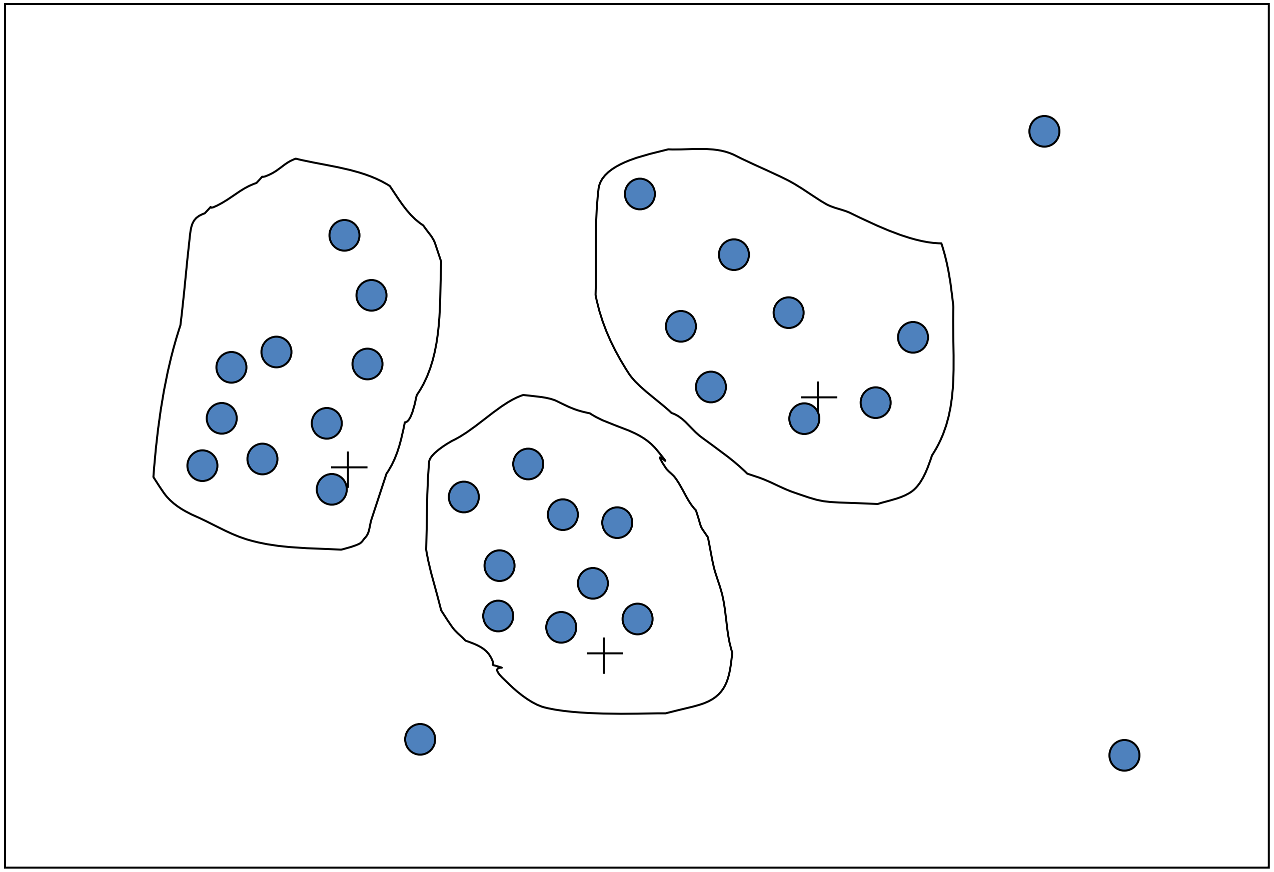
* Smoothing by bin boundaries:

- Bin 1: 4, 4, 4, 15
- Bin 2: 21, 21, 25, 25
- Bin 3: 26, 26, 26, 34

Regression



Cluster Analysis



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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 able to be detected by *correlation analysis*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Data Transformation

- Smoothing: remove noise from data
- Aggregation: summarization
- Generalization: concept hierarchy climbing
- Normalization: scaled to fall within a small, specified range
  - min-max normalization
  - z-score normalization
  - normalization by decimal scaling
- Attribute/feature construction
  - New attributes constructed from the given ones

Data Transformation: 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 \$73,000 is mapped to $\frac{73,000-12,000}{98,000-12,000}(1.0-0)+0=0.709$

- Z-score normalization (μ: mean, σ: standard deviation): $v' = \frac{v - \mu_A}{\sigma_A}$

  – Ex. Let μ = 54,000, σ = 16,000. Then $\frac{73,000-54,000}{16,000} = 1.188$

- Normalization by decimal scaling

$$v' = \frac{v}{10^j}$$ Where j is the smallest integer such that Max(|ν'|) < 1

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Data Reduction Strategies

- Why data reduction?
  - You may need to process terabytes of data
  - Complex data analysis/mining may take a very long time to run on the complete data set
- Data reduction
  - Obtain a reduced representation of the data set that is much smaller in volume but yet produce the same (or almost the same) analytical results
- **Data reduction strategies**
  - Data cube aggregation:
  - Dimensionality reduction — e.g., remove unimportant attributes
  - Data Compression
  - Numerosity reduction — e.g., fit data into models
  - Discretization and concept hierarchy generation

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Discretization

- Discretization
  - Reduce the number of values for a given continuous attribute by dividing the range of the attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Reduce data size by discretization
  - Also, some classification algorithms only accept categorical attributes.

Discretization and Concept Hierarchy

- Concept hierarchy formation
  - Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for age) by higher level concepts (such as young, middle-aged, or senior)