Data Warehousing and Data Mining

Unit-1 part(b) Data Preprocessing:

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Outline

- Why to preprocess data?
- Mean, median, mode & range
- Attribute types
- Data preprocessing tasks
  - ✓ Data cleaning
  - ✓ Data integration
  - ✓ Data transformation
  - ✓ Data reduction
- Discretization and Concept Hierarchy Generation.
- Applications

Why to preprocess data?

- Real world data are generally "**dirty**"
  - **Incomplete**: Missing attribute values, lack of certain attributes of interest, or containing only aggregate data.
    - **E.g.** Department=" "
    - **E.g.** Occupation =" "
  - **Noisy**: Containing errors or outliers.
    - **E.g.** Salary="**abcxy**"
    - **E.g.** Salary="-**1**"
  - **Inconsistent**: Containing similarity in codes or names.
    - **E.g.** "" &**Gujarat** "**Gujrat**" (Common mistakes like **spelling, grammar, articles**)
    - **E.g.** "**Age=42**" & "**DOB:19/08/1980**" (Common s like **discrepancies in code**)

Data Layout

X1	X2	X3	X4	Y
78.5	67	1	0.2	73.2
78.5	67	0	0.2	69.2
78.5	67	0	0.2	69
78.5	67	0	0.2	69
75.5	66.5	1	0.2	73.5
75.5	66.5	1	0.4	72.5
75.5	66.5	0	0.3	65.5
75.5	66.5	0	0.2	65.5
75	64	1	0.2	71
75	64	0	0.1	68
75	64	1	0.2	70.5

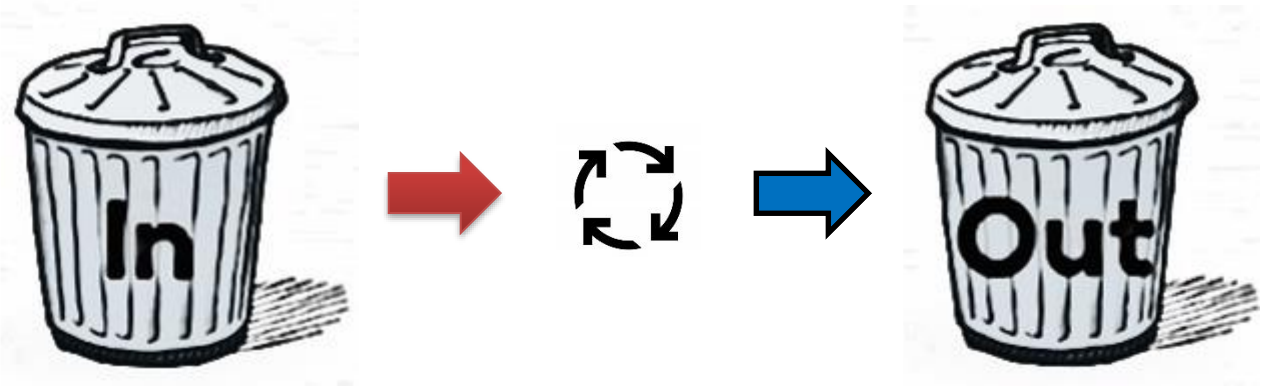
Missing Data

X1	X2	X3	X4	Y
78.5	67	1	0.2	73.2
78.5	67	0	0.2	69.2
78.5	67	0	0.2	69
78.5		0	0.2	69
75.5	66.5	1	0.2	73.5
75.5	66.5	1	0.4	
75.5	66.5	0	0.3	65.5
75.5	66.5	0	0.2	65.5
75		1		71
75	64	0	0.1	68
75	64	1	0.2	70.5

Why data preprocessing is important?

"No quality data, No quality results"

- It looks like **Garbage In Garbage Out (GIGO)**.



- Quality decisions must be based on **quality data**.
- Duplicate or missing data may cause incorrect or even misleading statistics.
- **Data preparation, cleaning and transformation are the majority task in data mining. (could be as high as 90%).**
- Data preprocessing **prepares** raw data for **further processing**.

Garbage in → Garbage out

Inaccurate Labels

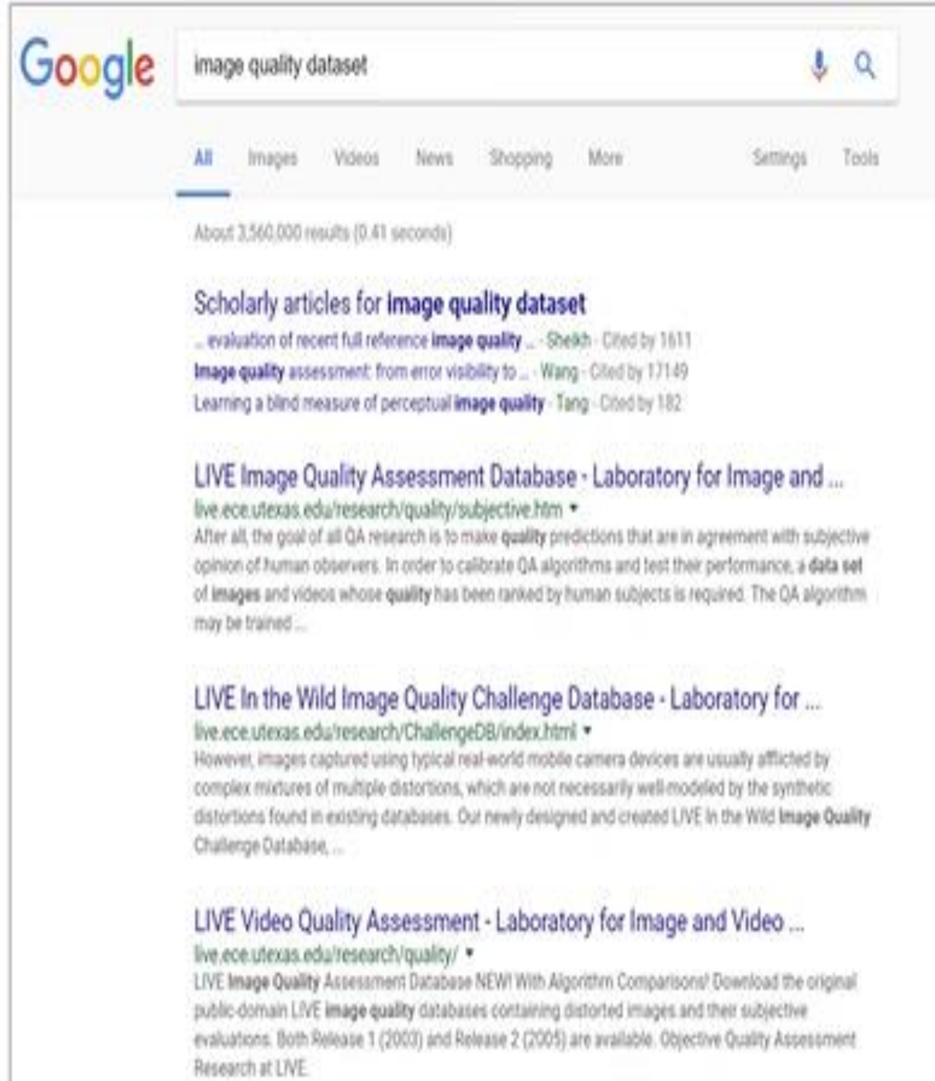
Cat

Dog

Inaccurate and Missing Values

Age	Annual Income
0	$115k
43	$198k
-	$140k
26	$120k
18	$24k
24	$76k
20	-

Public Datasets



The Internet
as a source of data

→ NLP models

Image classifiers

Article Talk Read Edit View history

List of dog breeds

From Wikipedia, the free encyclopedia

Dogs have been selectively bred for thousands of years, sometimes by inbreeding dogs from the same ancestral lines, sometimes by mixing dogs from very different lines.[1] The process continues today, resulting in a widening in appearance without speciation, "from the Chihuahua to the Great Dane."[2]

The following list uses a wide interpretation of "breed." Breeds are usually categorized by the functional type from which the breed was developed. The basic types are companion dogs, guard dogs, hunting dogs, herding dogs, and working dogs, although there are many other types and subtypes. Breeds listed here may be traditional breeds with long histories as registered breeds, rare breeds with their own registries, or new breeds that may still be under development.

In some cases, a breed's origin overlaps the boundaries of two or more countries; the dog is normally listed only in the country with which it is most commonly associated; for example, by its designated country according to the Fédération Cynologique Internationale (FCI). Some dogs, such as the Löwchen, have an uncertain origin and are listed under several countries.

List with classification and standards [edit]

A · B · C · D · E · F · G · H · I · J · K · L · M · N · O · P · Q · R · S · T · U · V · W · X · Y · Z

Breed	Origin	Fédération Cynologique Internationale	American Kennel Club	Australian National Kennel Council	Canadian Kennel Club	The Kennel Club	New Zealand Kennel Club	United Kennel Club

Samoyed

Golden Retriever

Missing Data

Age	Annual Income
	~~$115k~~
43	$198k
	~~$140k~~
26	$120k
18	$24k
24	$76k
~~20~~	~~-~~

Age	Annual Income	Height
25	$115k	
43	$198k	6′
30	$140k	
26	$120k	5′ 10″
18	$24k	
24	$76k	
20	$35k	

Data Imputation

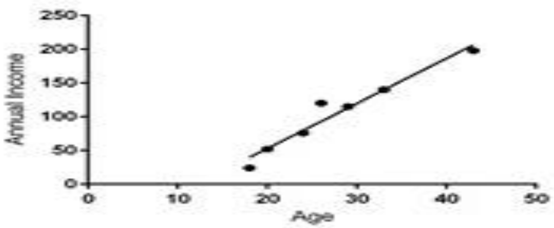
Stock Prices								
Company A	116.4	117.0	116.1	114.5	115.2			118.0
Company B	65.2	66.1	64.9		63.8	65.1	65.4	65.7

Stock Prices								
Company A	116.4	117.0	116.1	114.5	115.2	115.2	115.2	118.0
Company B	65.2	66.1	64.9	64.9	63.8	65.1	65.4	65.7

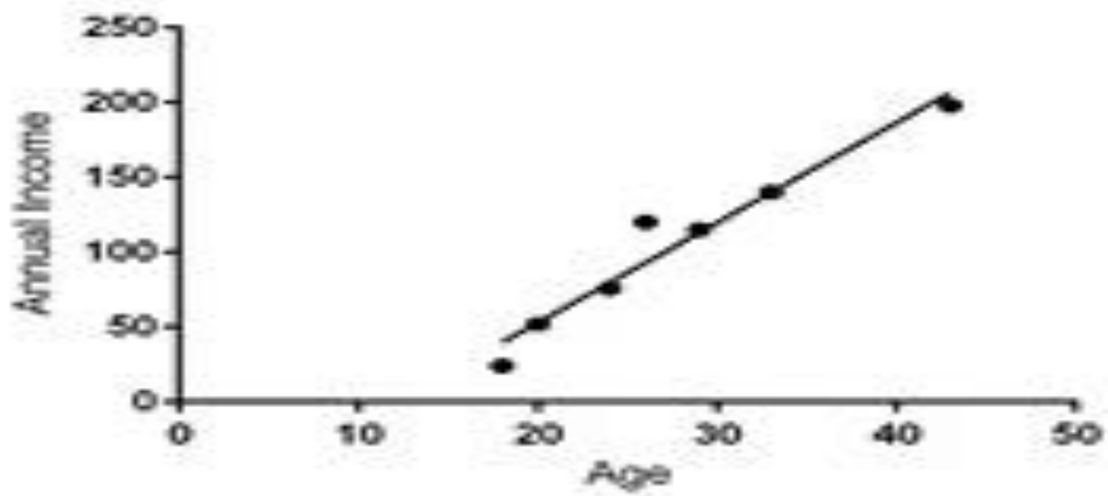
Age	Annual Income
26.2	$115k
43	$198k
26.2	$140k
26	$120k
18	$24k
24	$76k
20	$112k

Mean age: 26.2
Mean income: $112k

Age	Annual Income
29	$115k
43	$198k
33	$140k
26	$120k
18	$24k
24	$76k
20	$52k



Age	Annual Income
29	$115k
43	$198k
33	$140k
26	$120k
18	$24k
24	$76k
20	$52k



Data imputation

- Caveat :data might not be missing at random

Gender	Likes
M	Cats
M	Dogs
F	Missing
M	Cats
F	Dogs
F	Dogs
F	Cats

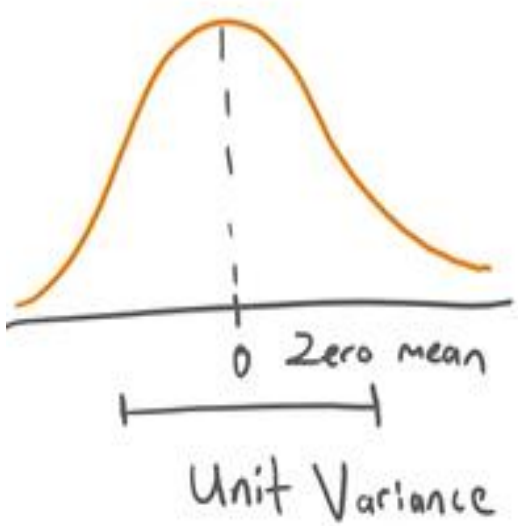
Classes
Cats
Dogs
Missing

Feature of scaling

Variable	Range of values
Age	0 - 100+
Annual income	0 - 1,000,000+
Years of experience	0 - 40+

Range of values
0 - 1
0 - 1
0 - 1

Standardization



$$\hat{X} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

$$\hat{age} = \frac{age - 18}{99 - 18}$$

$$\hat{X} = \frac{X - \mu}{\sigma}$$

Mean

- Mean is the **average** of a dataset.
- To find the mean, calculate the sum of all the data and then divide by the total number of data.
- Example
  - ✔ Find out mean for **12, 15, 11, 11, 7, 13**

First, find the **sum of the data**.

12 + 15 +11 + 11 + 7 + 13 = **69**

Then **divide by the total number of data**.

69 / 6 = **11.5** ⟸ **Mean**

Median

- Median is the **middle number** in a dataset when the data is arranged in numerical order (Sorted Order).

If count is **Odd** then **middle number** is **Median**

If count is **Even** then take **average of middle two numbers** that is **Median**

Median - Odd (Cont..)

- Example
  - ✓ Find out Median for 12, 15, 11, 11, 7, 13, 15

In above example, count of data is **7**. (Odd)

First, arrange the **data** in **ascending order**.

7, 11, 11, 12, 13, 15, 15

Partitioning data into equal halfs

7, 11, 11, $\boxed{12,}$ 13, 15, 15

12 ⇦ Median

Median - Even (Cont..)

- Example
  - ✓ Find out median for 12, 15, 11, 11, 7, 13

In above example, count of data is **6**. (Even)

First, arrange the **data** in **ascending order**.

7, 11, 11, 12, 13, 15

Calculate an **average** of the **two numbers** in the **middle**.

7, 11, $\boxed{11, 12,}$ 13, 15

(11 + 12)/2 = **11.5** ⟸ **Median**

Mode

- The mode is the **number that occurs most often** within a set of numbers.
- <u>Example</u>

1

Find mode.

12, 15, 11, 11, 7, 13

11 ⇐ **Mode** **(Unimodal)**

2

Find mode.

12, 15, 11, 11, 7, 12, 13

11, 12 ⇐ **Mode** **(Bimodal)**

Mode (Cont..)

- Example

3

Find mode.

12, 12 15, 11, 11, 7, 13, 7

7, 11, 12 ⇐ Mode (Trimodal)

4

Find mode.

12, 15, 11, 10, 7, 14, 13

No Mode

Range

- The range of a set of data is the **difference** between the **largest and the smallest number in the set**.
- <u>Example</u>
  - ✓ Find range for given data 40, 30, 43, 48, 26, 50, 55, 40, 34, 42, 47, 50

First, arrange the **data** in **ascending order**.
26, 30, 34, 40, 40, 42, 43, 47, 48, 50, 50, 55

- In our example **largest number is 55**, and subtract the **smallest number is 26**.

$$\boxed{55 - 26 = 29 \Leftarrow \text{Range}}$$

Standard deviation

- The Standard Deviation is a measure of **how spread out any data are**.
- Its symbol is **σ** (the Greek letter sigma).
- $Sample\ variance : (s)^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x - mean)^2$
- Standard Deviation is **Square root of sample variance**.

Standard deviation (Cont..)

- The **Variance** is defined as:

The average of the **squared** differences from the Mean.

To calculate the variance follow these steps:

1. Calculate the mean**, x**.
2. Write a table that subtracts the mean from each observed value.
3. Square each of the differences, add this column.
4. Divide by **n -1** where **n** is the number of items in the **sample**, this is the **variance** (In actual case take n).
5. To get the **standard deviation** we take the **square root** of the variance.

Standard deviation - example

- The owner of the Indian restaurant is interested in how much people spend at the restaurant.
- He examines **10** randomly selected receipts for parties and writes down the following data.

44, 50, 38, 96, 42, 47, 40, 39, 46, 50

1. Find out Mean (1st step)
   - ✓ Mean is **49.2**
2. Write a table that subtracts the mean from each observed value. (2nd step)

Standard deviation – example (Cont..)

Step : 3

X	X – Mean	(X – Mean)^2
44	-5.2	27.04
50	0.8	0.64
38	11.2	125.44
96	46.8	2190.24
42	-7.2	51.84
47	-2.2	4.84
40	-9.2	84.64
39	-10.2	104.04
46	-3.2	10.24
50	0.8	0.64
	Total	**2600.4**

Step : 4

$$= \frac{2600.4}{10 - 1}$$

$S^2 = 288.7$ ~ 289

Step : 5

$$S = \sqrt{289}$$

$S = 17$

Standard deviation – example (Cont..)

- Standard deviation can be thought of measuring **how far the data values lie from the mean**, we take the mean and move on standard deviation in either direction.
- The **mean** for this example is **49.2** and the **standard deviation** is **17**.
- Now, 49.2 - 17 = 32.2 and 49.2 + 17 = 66.2
- This means that most of the data probably spend between **32.2** and **66.2**.
- If all data are same then variance & standard deviation is 0 (zero).

Example (Try it)

- Calculate Mean, Median, Mode, Range, Variance & Standard deviation .

  13, 18, 13, 14, 13, 16, 14, 21, 13

- Mean is **15**.
- Median is **14**.
- Mode is **13 & 14 (Bimodal)**.
- Range is **8**.
- Variance is :**64.**
- Standard deviation is **2 root 2.**

Attribute Types

- An attribute is a **property of the object.**
- It also represents different **features of the object**.
  - **E.g.** Person → $\boxed{\text{Name, Age, Qualification etc.}}$
- Attribute types can be divided into four categories.

1. **Nominal**
2. **Ordinal**
3. **Interval**
4. **Ratio**

1) Nominal Attribute

- Nominal attributes are **named** attributes which can be **separated into discrete (individual) categories** which do not overlap.
- Nominal attributes values also called as **distinct values**.
- Example

What is your gender?
Male
Female
Other

What is your hair color?
Black
Brown
Gray
Blonde
Other

2) Ordinal Attribute

- Ordinal attribute is the **order of the values,** that's important and significant, but the differences between each one is not really known.
- Example
  - **Rankings** → 1st, 2nd, 3rd
  - **Ratings** → ★ ★ ★ , ★ ★ ★ ★ ★
- We know that a 5 star is better than a 2 star or 3 star, but we don't know and cannot quantify–how much better it is?

3) Interval Attribute

Attribute Types

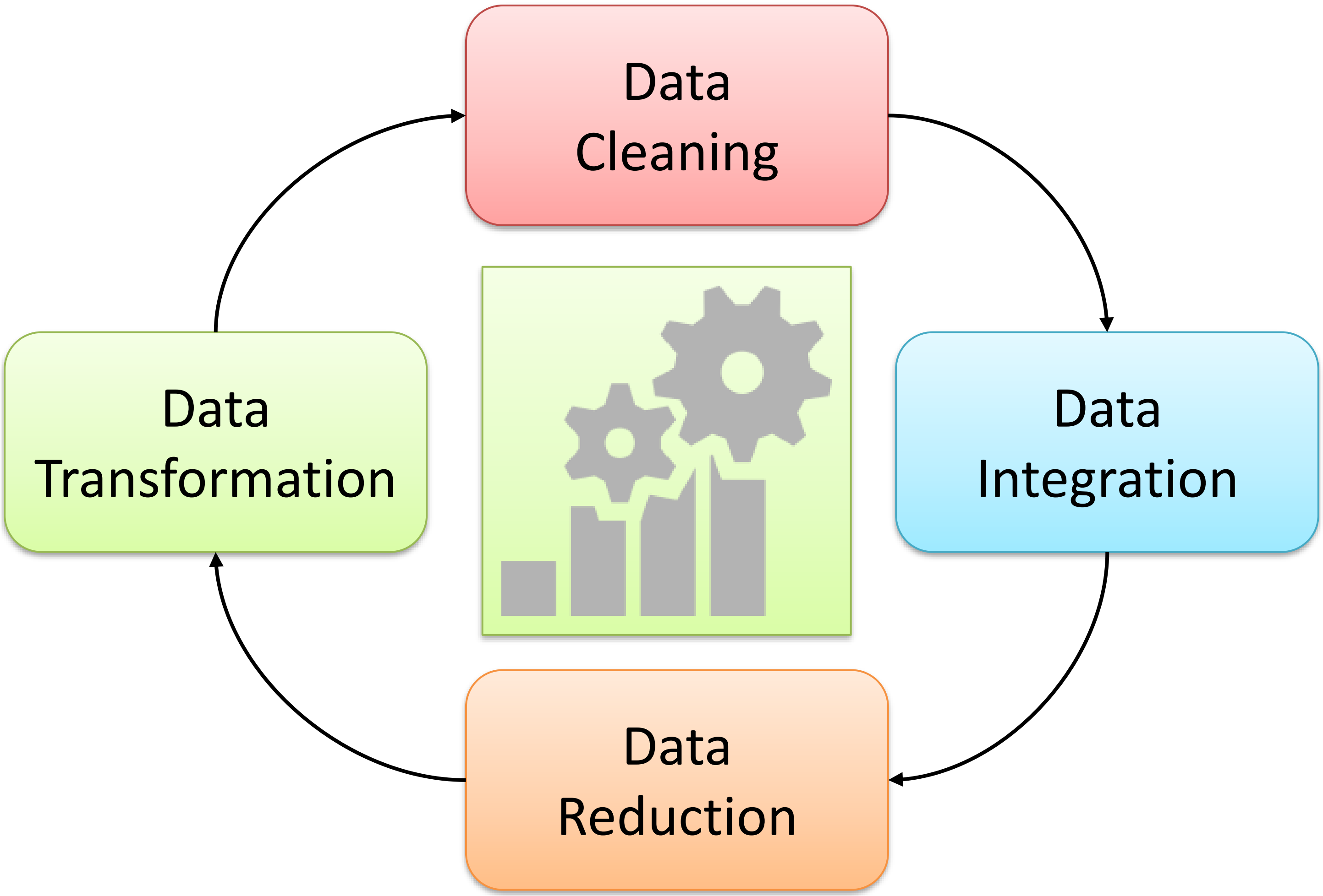
- Interval attribute comes in the form of a **numerical value** where the **difference** between points is **meaningful**.
- Example
  - **Temperature** → 10°-20°, 30°-50°, 35°-45°
  - **Calendar Dates** → 15th – 22nd, 10th – 30th
- We can not find true zero (absolute) value with interval attributes.

4) Ratio Attribute

Attribute Types

- Ratio attribute is looks **like interval attribute**, but it **must have** a **true zero (absolute)** value.
- It tells us about the order and the exact value between units or data.
- Example
  - **Age Group** → 10-20, 30-50, 35-45 (In years)
  - **Mass** → 20-30 kg, 10-15 kg
- It does have a true zero (absolute) so, it is possible to compute ratios.

Data Preprocessing Tasks



1) Data Cleaning

1. **Fill in missing values**
    1. Ignore the tuple
    2. Fill missing value manually
    3. Fill in the missing value automatically
    4. Use a global constant to fill in the missing value
2. **Identify outliers and smooth out noisy data**
    1. Binning Method
    2. Clustering
3. **Correct inconsistent data**
4. **Resolve redundancy caused by data integration**

1) Fill missing values

Data Cleaning

- **Ignore the tuple (record/row):**
  - Usually done when **class label is missing**.
  - **Example**
    - The task is to distinguish between two types of emails, “spam” and “non-spam” (Ham).
    - Spam & non-spam are called as class label.
    - If an email comes to you, in which class label is missing then it is discarded.
- **Fill missing value manually:**
  - Use the **attribute mean (average)** to **fill in the missing value** and **also use the attribute mean (average)** for **all samples belonging to the same class**.

1) Fill missing values (Cont..)

Data Cleaning

- **Fill in the missing value automatically**:
  - **Predict** the **missing value** by using a **learning algorithm**:
    - Consider the attribute with the missing value as a dependent variable and run a learning algorithm (usually Naive Bayes or Decision tree) to predict the missing value.
- **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"***.

2) Identify outliers and smooth out noisy data

Data Cleaning

1. **Binning method**
2. **Clustering**

1) Binning method

- Data binning or **bucketing** is a data pre-processing technique used to **reduce the effects of minor observation errors**.
- The original data values which fall in a given small interval called **as a bin** are **replaced by a value which represents that interval**, often called the central value.
- **Steps of Binning method**

  1. **Sort the attribute values** and **partition** them into **bins**.

  2. Then smooth by **bin means, bin median** or **bin boundaries**.

Binning method - Example

- Given data: **4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34**
- <u>Step: 1</u>
- Partition into **equal-depth [n=4]**:

  Bin 1: 4, 8, 9, 15

  Bin 2: 21, 21, 24, 25

  Bin 3: 26, 28, 29, 34

$(4 + 8 + 9 + 15)/4 = \mathbf{9}$

$(21 + 21 + 24 + 25)/4 = \mathbf{23}$

$(26 + 28 + 29 + 34)/4 = \mathbf{29}$

- <u>Step: 2</u>
  - Smoothing by **bin means**:

    Bin 1: 9, 9, 9, 9

    Bin 2: 23, 23, 23, 23

    Bin 3: 29, 29, 29, 29

Binning method - Example (Cont..)

- Given data: $\boxed{4, 8, 9, 15,}$ $\boxed{21, 21, 24, 25,}$ $\boxed{26, 28, 29, 34}$

- Step: 1
- Partition into **equal-depth [n=4]**:

  Bin 1: 4, 8, 9, 15

  Bin 2: 21, 21, 24, 25

  Bin 3: 26, 28, 29, 34

- Step: 2
  - Smoothing by **bin boundaries**:

    Bin 1: **4**, **4**, **4**, **15**

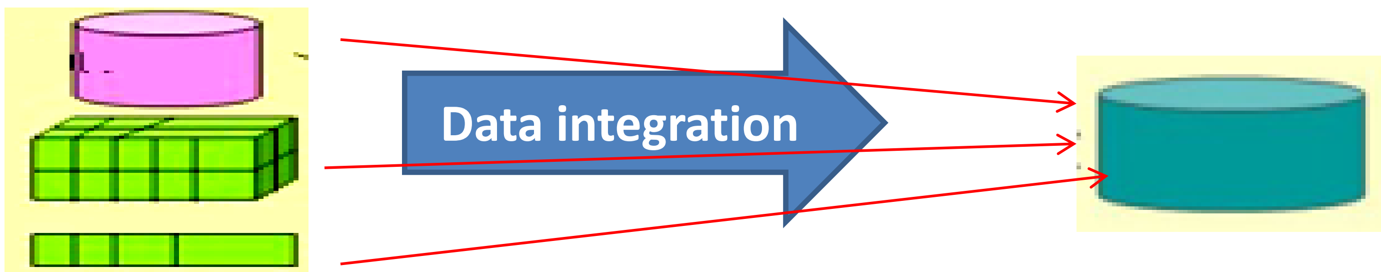
    Bin 2: **21**, **21**, **25**, **25**

    Bin 3: **26**, **26**, **26**, **34**

1) Binning method (Cont..)

- Binning method is a **top-down splitting technique** based on a **specified number of bins**.
- It is also used as **discretization method** for data reduction and concept hierarchy generation.
- For example, attribute values can be discretized (separated) by applying equal-width or equal-frequency binning, and then replacing each value by the bin mean or median.
- It can be applied **recursively to the resulting partitions** to **generate concept hierarchies**.
- It **does not use class information**, therefore it is an **unsupervised discretization technique**.

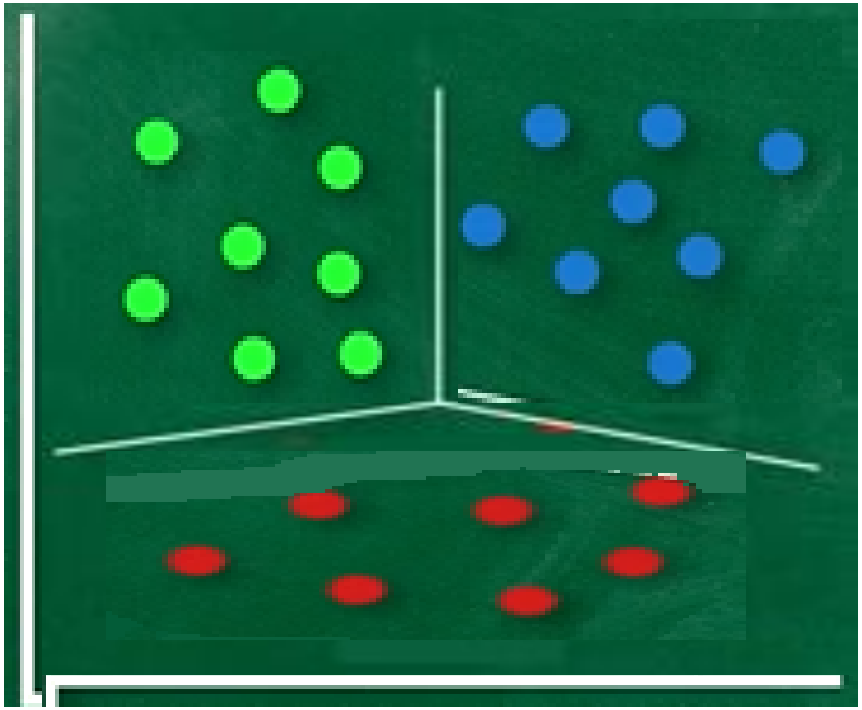
Form of data preprocessing



Data transformation -2,32,100,59,48 → -0.02,0.32,100.0,0.59,0.48

2) Clustering

- Clustering is a process of **partitioning a set of data** (or objects) into a **set of meaningful sub-classes**, called clusters.
- It enables the abstraction of **large amounts data** by forming **meaningful groups or categories of objects**.
- In clustering, objects in the same cluster are similar to each other and those in different clusters are dissimilar.
- **Example**
  - Library (Group of Books based on different categories)
  - Cloths (By size S, M, L, XL, XXL etc.)



3) Correct inconsistent data

Data Cleaning

- If you have inconsistencies in your data, it can cause major problems later on.
- But with larger datasets, it can be difficult to find all of the inconsistencies.
- **It contains similarity in codes or names.**
- We can manually solve common mistakes like spelling, grammar, articles or use other tools for it.

Financial

Employee	Salary
John	1000

Employee → Salary

Human Resources

Employee	Salary
John	2000
Mary	3000

Employee → Salary

Target Database

Employee	Salary
John	**1000**
John	**2000**
Mary	3000

Employee → Salary

Mapping

$\text{Financial}(e,s) \subseteq \text{Global}(e,s)$

$\text{HumanRes}(e,s) \subseteq \text{Global}(e,s)$

4) Resolve redundancy caused by data integration

Data Cleaning

- Data redundancy occurs in database systems **which have a field that is repeated in two or more tables**.
- When customer data is duplicated and attached with each product bought, then redundancy of data is known as **inconsistency**.
- So, the entity "customer" **might appear with different values**.
- Database **normalization** prevents redundancy and makes the best possible usage of storage.
- The proper use of **foreign keys** can minimize data redundancy and reduce the chance of destructive anomalies appearing.

Example - Problem Of Data Redundancy In Single Tabale Database

Employee Number	First Name	Last Name	Date of Birth	Department Code	Department Name	Department Head
1001	Steave	Jakson	25-09-1985	SA001	Sales	Paul Colgan
1002	Kitty	Mathew	06-04-1998	ACC008	Accounts	Jerry Mathew
1003	Meena	Patel	11-05-1992	SA001	Sales	Paul Colgan
1004	Nancy	Samual	02-12-1996	ACC008	Accounts	Jerry Mathew
1005	Michael	Smith	28-03-1995	SA001	Sales	Paul Colgan
1006	James	Garcia	22-01-1994	SA002	Sales	David Smith
1007	Nancy	Samual	11-02-1996	ACC008	Accounts	Charles Williams

Redundant Data In Table

SA001	Sales	Paul Colgan

ACC008	Accounts	Jerry Mathew

Data Integration

- Data integration involves **combining data residing in different sources** and providing users with a **unified view** of these all data.
- In relational databases we also combine schemas like A.CustomerID = B.CustomerID.
- In real world, attribute values from different sources are different.
- Data Integration may involve inconsistent data and therefore **needs data cleaning** also.

Data Transformation

- Data transformation is the process of **converting data from one form to another form**.
- Data often resides in different locations across the storage and also differs in format.
- Data transformation is necessary to ensure that data from one application or database is understandable to other applications and databases also.

Data Transformation (Cont..)

- Data transformation strategies includes the following:
    1. **Smoothing**
    2. **Attribute construction**
    3. **Aggregation**
    4. **Normalization**
    5. **Discretization**
    6. **Concept hierarchy generation for nominal data**

Data Transformation (Cont..)

1. **Smoothing**
   - It works to **remove noise from the data**.
   - It is a form of data cleaning where users specify transformations to correct data inconsistencies.
   - Such techniques include **binning, regression and clustering**.
2. **Attribute construction**
   - It is referred as **new attributes are constructed** and added from the given set of attributes to help the mining process.
3. **Aggregation**
   - In this, **summary or aggregation operations** are applied to the data.
   - **E.g.** Daily sales data are aggregated at individual source so sales manager can compute monthly and annually total amounts.

Data Transformation (Cont..)

4. Normalization

- Normalization is **scaling technique** or a **mapping technique**.
- With normalization, we can find **new range from an existing range**.
- There are three techniques for normalization.

1. **Min-Max Normalization**
   - This is a simple normalization technique in which we fit given data in a pre-defined boundary, or a pre-defined interval [0,1].
2. **Decimal scaling**
   - In this technique we move the decimal point of values of the attribute.

1) Min-max normalization

- Min max is a technique that helps to **normalizing the data**.
- It will **scale the data between 0 and 1**.
- Example

Age
16
20
30
40

1) Min-max normalization (Cont..)

- Min : Minimum value = 16
- Max : Maximum value = 40
- V = Respective value of attributes. In our example V_1= 16, V_2=20, V_3=30 & V_4=40.
- NewMax = 1
- NewMin = 0

$$\boxed{\textbf{Formula} : V' = \frac{v - Min_A}{Max_A - Min_A}(NewMax_A - NewMin_A) + NewMin_A}$$

1) Min-max normalization (Cont..)

Formula : $V' = \frac{v - Min_A}{Max_A - Min_A}(NewMax_A - NewMin_A) + NewMin_A$

For Age 16 :

MinMax (v') = (16 – 16)/(40-16) * (1 – 0) + 0
= 0 / 24 * 1
= **0**

For Age 20 :

MinMax (v') = (20 – 16)/(40-16) * (1 – 0) + 0
= 4 / 24 * 1
= **0.16**

1) Min-max normalization (Cont..)

For Age 30 :

MinMax (v') = (30 – 16)/(40-16) * (1 – 0) + 0
= 14 / 24 * 1
= **0.58**

For Age 40 :

MinMax (v') = (40 – 16)/(40-16) * (1 – 0) + 0
= 24 / 24 * 1
= **1**

Age	After Min-max normalization
16	0
20	0.16
30	0.58
40	1

2) Decimal scaling

- In this technique we move the decimal point of values of the attribute.
- This movement of decimal points totally depends on the **maximum value among all values** in the attribute.
- Value V of attribute A can be normalized by the following formula

Normalized value of attribute = $\mathbf{(v^i / 10^j)}$

Decimal scaling - Example

CGPA	Formula	After Decimal Scaling
2	2 / 10	**0.2**
3	3 / 10	**0.3**

- We will check maximum value among our attribute CGPA.
- Maximum value is 3 so, we can convert it into decimal by dividing with 10. why 10?
- We will count total digits in our maximum value and then put 1.
- After 1 we can put zeros equal to the length of maximum value.
- Here 3 is maximum value and total digits in this value is only 1 so, we will put one zero after 1.

Decimal scaling (Try it!)

Bonus	Formula	After Decimal Scaling
400	400/1000	**0.4**
310	310/1000	**0.31**

Salary	Formula	After Decimal Scaling
40,000	40000/100000	**0.4**
31,000	31000/100000	**0.31**

Data Transformation (Cont..)

5. Discretization

- Discretization techniques can be categorized based on **how the separation is performed**, such as whether it uses class information or which direction it proceeds (top-down or bottom-up).
- The raw values of a numeric attribute (e.g. age) are replaced by interval labels (e.g. 0-10, 11-20 etc.) or conceptual labels (e.g. youth, adult, senior).

6. Concept hierarchy generation for nominal data

- In this, attributes such as address can be **generalized to higher-level concepts**, like street or city or state or country.
- Many hierarchies for nominal attributes are implicit within the database schema.
- **E.g.** city, country or state table in RDBMS.

Data Reduction

- **Reducing the number of attributes**
  - **Data cube aggregation**: applying roll-up, slice or dice operations.
  - **Removing irrelevant attributes**: attribute selection, searching the attribute space
- **Reducing the number of attribute values**
  - **Binning**: Reducing the number of attributes by grouping them into intervals (bins).
  - **Clustering**: Grouping similar values in a clusters.
  - Aggregation or Generalization
- **Reducing the number of tuples**
  - Sampling : Only sample data are used for mining purpose.

Data mining task primitives

- A data mining task can be specified in the form of a **data mining query**, which is input to the data mining system.
- A data mining **query** is defined in terms of data mining task primitives.
- These primitives **allow the user to inter-actively communicate** with the **data mining system** during discovery of knowledge.

Data mining task primitives (Cont..)

- The data mining task primitives includes the following:
  - Task-relevant data
  - Kind of knowledge to be mined
  - Background knowledge
  - Interestingness measurement
  - Presentation for visualizing the discovered patterns

Data mining task primitives (Cont..)

- **Task-relevant data**
  - This specifies the **portions of the database or the dataset** of data in which the **user is interested**.
  - This includes the **database attributes** or data warehouse dimensions of interest (referred to as the relevant attributes or dimensions).
- **The kind of knowledge to be mined**
  - This specifies the data mining functions to be performed.
  - Such as **characterization, discrimination, association or correlation analysis, classification, prediction, clustering, outlier analysis**, or evolution analysis.

Data mining task primitives (Cont..)

- **The background knowledge to be used in the discovery process**
  - The **knowledge** about the **domain** is useful for **guiding the knowledge discovery process** for evaluating the interesting patterns.
  - **Concept hierarchies** are a **popular form of background knowledge**, which allow data to be mined at multiple levels of abstraction.
  - An example of a concept hierarchy for the attribute (or dimension) age is shown in **user beliefs** regarding relationships in the data are another form of background knowledge.

Data mining task primitives (Cont..)

- **The interestingness measures and thresholds for pattern evaluation**
  - **Different kinds of knowledge** may have **different interestingness measures**.
  - For example, interestingness measures for association rules include support and confidence.
  - Rules whose support and confidence values are below **user-specified thresholds are considered uninteresting**.
- **The expected representation for visualizing the discovered patterns**
  - It refers to the **discovered patterns** are **to be displayed**, which may **include rules, tables, charts, graphs, decision trees, and cubes**.
  - A data mining query language can be designed to incorporate these primitives, **allowing users** to **flexibly interact with data mining systems**.

Thank you!

13 18, 13, 14, 13, 16, 14, 21, 13

order	13	13	13	13	14	14	16	18	21				
	13	-2	-2	4									
	18	3	3	9				2089	9	232.1111			
	13	-2	-2	4									
	14	-1	-1	1									
	13	-2	-2	4									
	16	1	1	1						64	8	8	
	14	-1	-1	1									
	21	6	6	36									
	13	-2	-2	4									
	135	0	0	64							21	13	8
				mean	135	9	15						
				mode	13	14							