203105453 – Data Mining & Business Intelligence

Unit-4
Data Pre-processing

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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
- Data mining task primitives

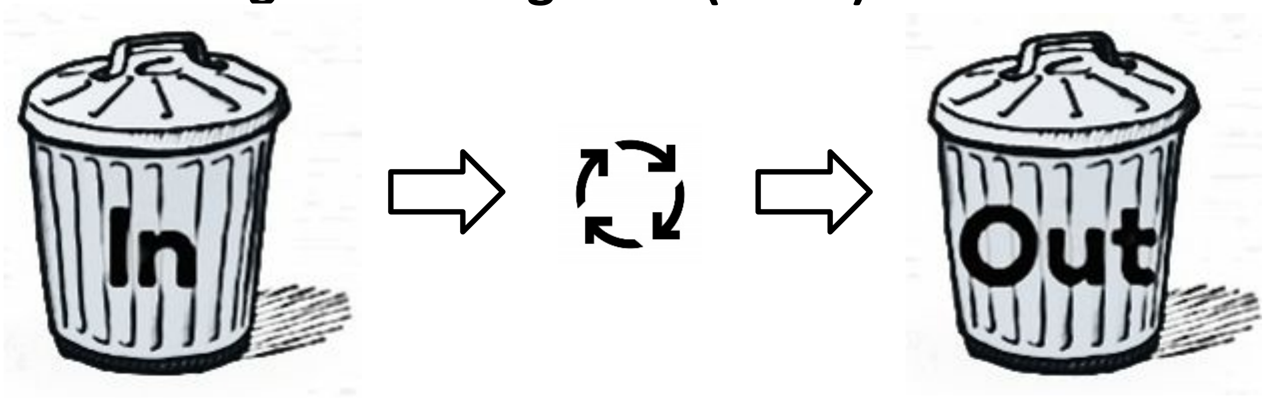
Why to preprocess data?

- Real world data are generally “**dirty**”
  - **Incomplete**: Missing attribute values, lack of certain attributes of interest, or containing only aggregate data.
    - **E.g.** Occupation=“ ”
  - **Noisy**: Containing errors or outliers.
    - **E.g.** Salary=“abcxy”
  - **Inconsistent**: Containing similarity in codes or names.
    - **E.g.** “Gujarat” & “Gujrat” (Common mistakes like **spelling, grammar, articles**)

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**.

Mean

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} x$$

- 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.
- <u>Example</u>
  - 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, 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, $\boxed{11, 11,}$ 7, 13

11 ⇐ Mode (Unimodal)

2

Find mode.

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

11, 12 ⇐ Mode (Bimodal)

Mode (Cont..)

- Example

3

Find mode.

$\boxed{12, 12}$ 15, $\boxed{11, 11,}$ 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**.

55 – 26 = 29 ⇐ 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

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

$\mathbf{S^2 = 288.7 \sim 289}$

Step : 5

$$S = \sqrt{289}$$

$\mathbf{S = 17}$

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 **289.**
- Standard deviation is **17**.

Attribute Types

- An attribute is a **property of the object.**
- It also represents different **features of the object**.
  - **E.g.** Person 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**.
- <u>Example</u>

What is your gender?
Male
Female
Other

What is your hair color?
Black
Brown
Gray
Blonde
Other

2) Ordinal Attribute

Attribute Types

- Ordinal attribute is the **order of the values**, that's important and significant, but the differences between each one is not really known.

- <u>Example</u>

  - **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?

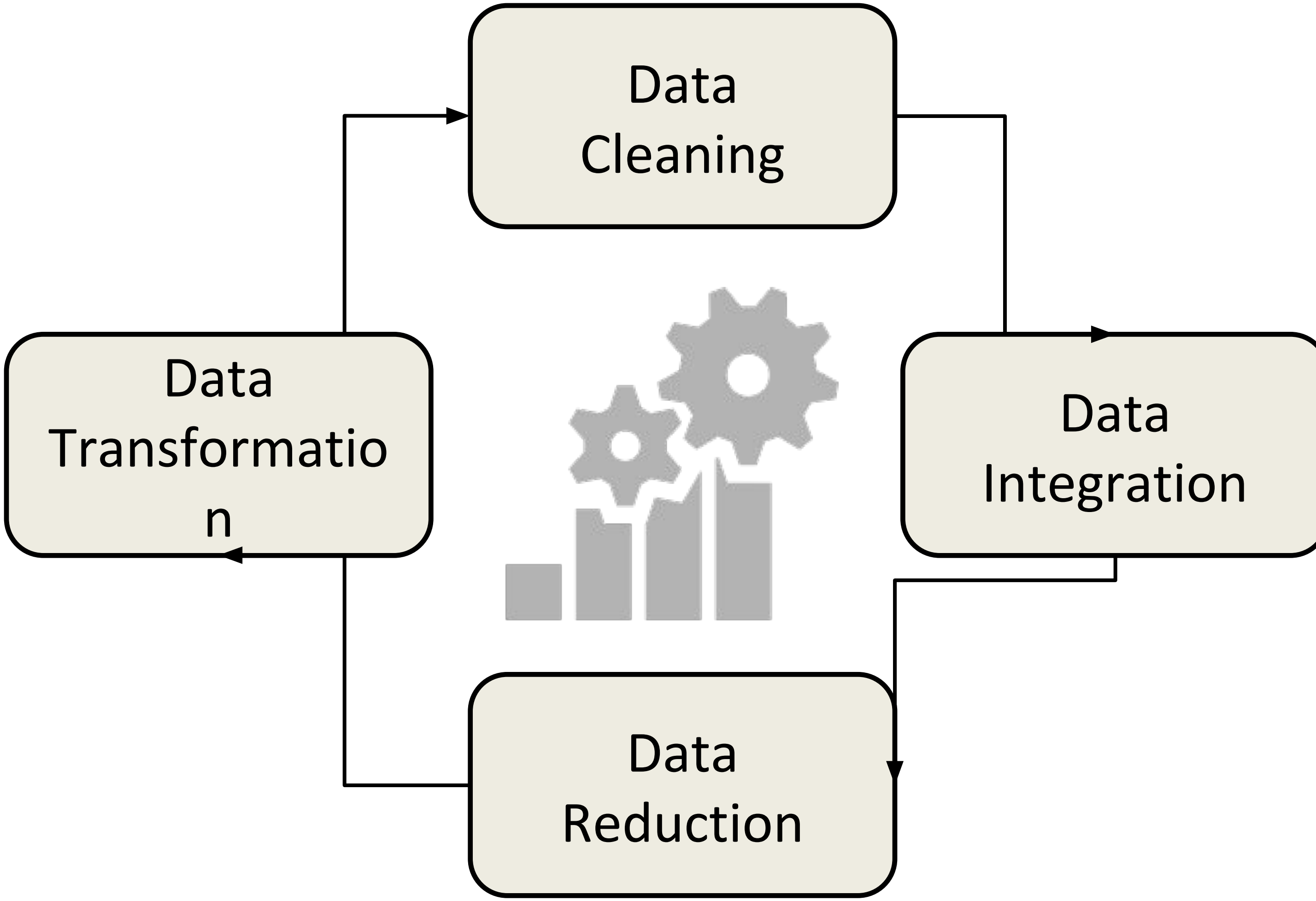
3) Interval Attribute

- 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

- 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

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**
- 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 means**:

(4 + 8 + 9 + 15)/4 = **9**

(21 + 21 + 24 + 25)/4 = **23**

(26 + 28 + 29 + 34)/4 = **29**

Bin 1: 9, 9, 9, 9

Bin 2: 23, 23, 23, 23

Bin 3: 29, 29, 29, 29

Binning method - Example (Cont..)

- Given data: **4, 8, 9, 15, 21, 21, 24, 25, 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**.

Binning method (Try it!)

0,4,12,16,16,18,24,26,28

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.

4) Resolve redundancy caused by data integration

- 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.

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 V1= 16, V2=20, V3=30 & V4=40.
- NewMax = 1
- NewMin = 0

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 = **(vi / 10j)**

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!