Chapter DM:I (continued)

I. Introduction

- Data Mining Overview
- On Data

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On Data [Tan et al. 2005]

- An object $o \in O$ is described by a set of attributes.
  An object is also known as record, point, case, sample, entity, or instance.

- An attribute A is a property of an object.
  An attribute is also known as variable, field, characteristic, or feature.

- A measurement scale is a system (often a convention) of assigning a numerical or symbolic value to an attribute of an object.

Attributes

Objects

ID	Check	Status	Income	Risk
1	+	single	125 000	No
2	-	married	100 000	No
3	-	single	70 000	No
4	+	married	120 000	No
5	-	divorced	95 000	Yes
6	-	married	60 000	No
7	+	divorced	220 000	No
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- Attribute values may vary from one object to another or one time to another.
- The same attribute can be mapped to different attribute values.
  Example: height can be measured in feet or meters.
- Different attributes can be mapped to the same set of values.
  Example: attribute values for person ID and age are integers.

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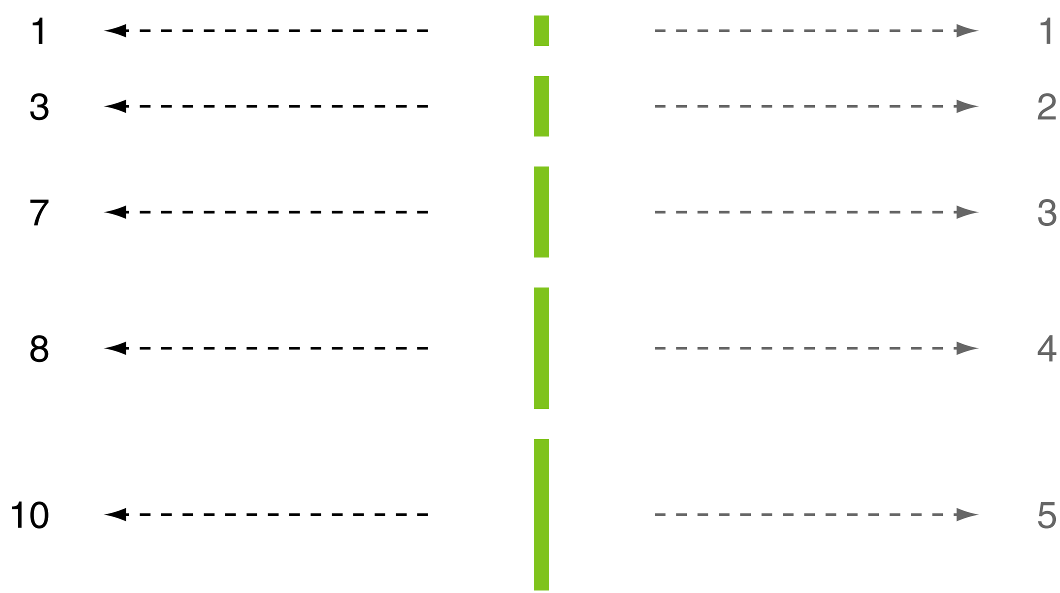
The way an attribute is measured may not match the attribute's properties:

Measuring lengths



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Types of Attributes

Type		Comparison	Statistics	Examples
categorical (qualitative)	nominal	values are names, only information to distinguish objects $= \quad \neq$	mode, entropy, contingency, correlation, χ^2 test	zip codes, employee IDs, eye color, gender: {male, female}

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numeric (quantitative)	interval	differences are meaningful, a unit of measurement exists $+ \quad -$	mean, standard deviation, Pearson's correlation, t-test, F-test	calendar dates, temperature in Celsius, temperature in Fahrenheit

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numeric (quantitative)	interval	differences are meaningful, a unit of measurement exists $+ \quad -$	mean, standard deviation, Pearson's correlation, t-test, F-test	calendar dates, temperature in Celsius, temperature in Fahrenheit
	ratio	differences and ratios are meaningful $* \quad /$	geometric mean, harmonic mean, percent variation	temperature in Kelvin, monetary quantities, counts, age, length, electrical current

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On Data [Tan et al. 2005]

Types of Attributes

Type		Permissible transformation	Comment
categorical (qualitative)	nominal	any one-to-one mapping, permutation of values	A reassignment of employee ID numbers will not make any difference.

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numeric (quantitative)	interval	$x \mapsto a \cdot x + b$, where a and b are constants	The Fahrenheit and Celsius temperature scales differ in terms of where their zero value is, as well as the size of a unit (degree).

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	ratio	$x \mapsto a \cdot x$, where a is a constant	Length can be measured in meters or feet.

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Remarks:

- Identifying, considering, and measuring an attribute A of an object O is the heart of model formation and always goes along with a sort of abstraction. Formally, this abstraction is operationalized by a model formation function $\alpha : O \rightarrow X$. [ML Introduction]

- The terms "attribute" and "feature" can be used synonymously. However, a slight distinction is the following: attributes are often associated with objects, O, while features usually designate the dimensions of the feature space, X.

- The type of an attribute is also referred to as the type of a *measurement scale* or *level of measurement*.

- We call a transformation of an attribute *permissible* if its meaning is unchanged after the transformation.

- Distinguish between *discrete* attributes and *continuous* attributes. The former can only take a finite or countably infinite set of values, the latter can be measured in infinitely small units. Be careful when deriving from this distinction an attribute's type.

- We will encode attributes of interval type or ratio type by real numbers. Note that attributes of nominal type and ordinal type can also be encoded by real numbers.

- Particular learning methods require particular attribute types.

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On Data [Tan et al. 2005]

Types of Data Sets

Data sets may not be a homogeneous collection of objects but come along with differently intricate characteristics:

1. Inhomogeneity of *attributes*:

2. Inhomogeneity of *objects*:

3. Inhomogeneity of *distributions*:

4. Curse of dimensionality:

5. Resolution:

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Types of Data Sets

Data sets may not be a homogeneous collection of objects but come along with differently intricate characteristics:

1. Inhomogeneity of *attributes*:
   Consider the combination of different attribute types within a single object.

2. Inhomogeneity of *objects*:
   Consider the combination of different objects in a single data set.

3. Inhomogeneity of *distributions*:
   The correlation between attributes varies in the sample space.

4. Curse of dimensionality:
   Attribute number and object density stand in exponential relation.

5. Resolution:
   The number of objects or attributes may be given at different resolutions.

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Types of Data Sets: Record Data

Collection of records, each of which consists of a fixed set of attributes:

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- If all elements in a data set have the same fixed set of numeric attributes, they can be thought of as points in a multi-dimensional space.
- Such data can be represented by a matrix, where each row stores an object and each column stores an attribute.
  Example: term-document matrices in information retrieval.

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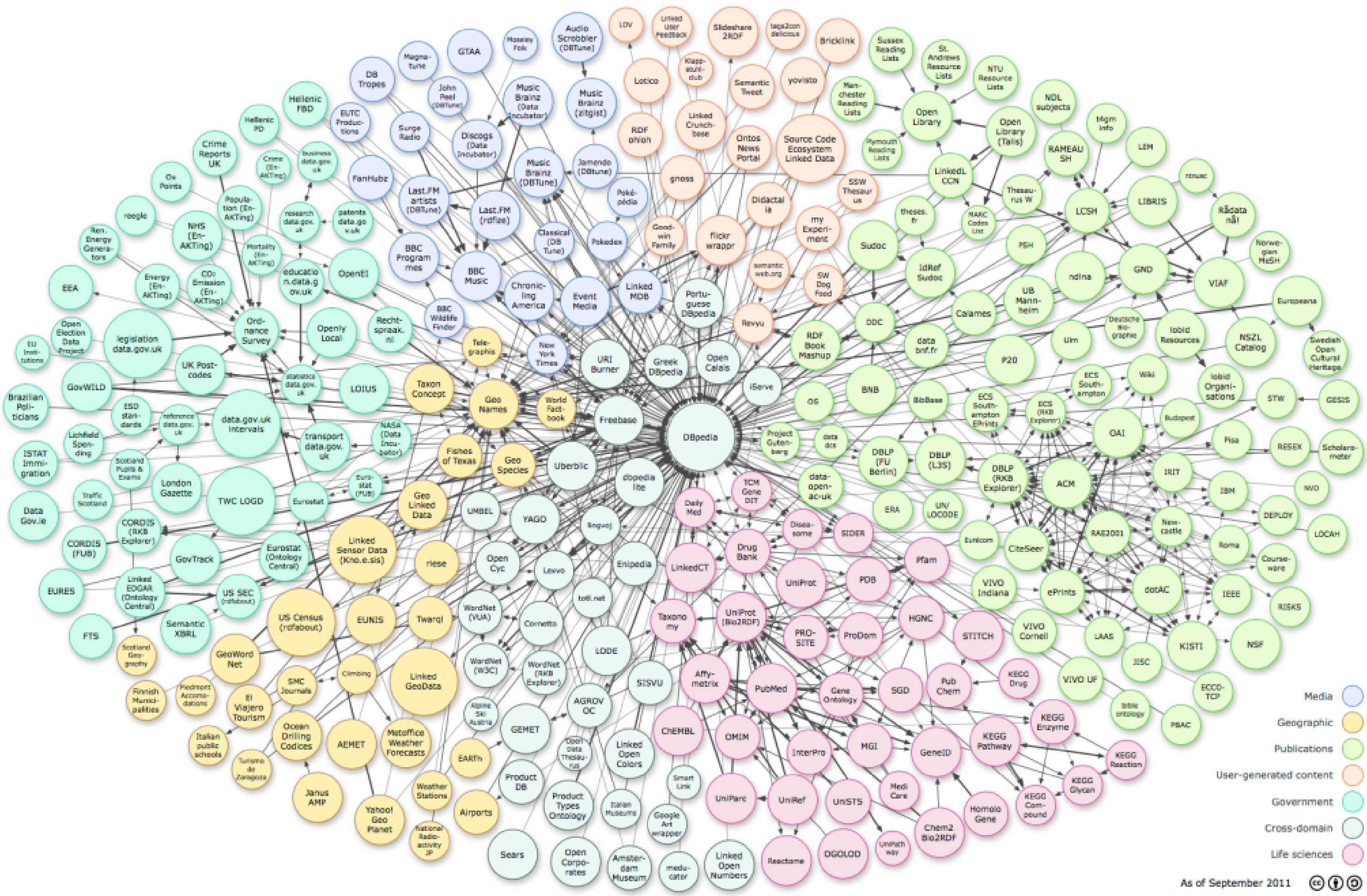
Types of Data Sets: Graph Data

Graph of the Linked Open Data cloud [lod-cloud.net] :



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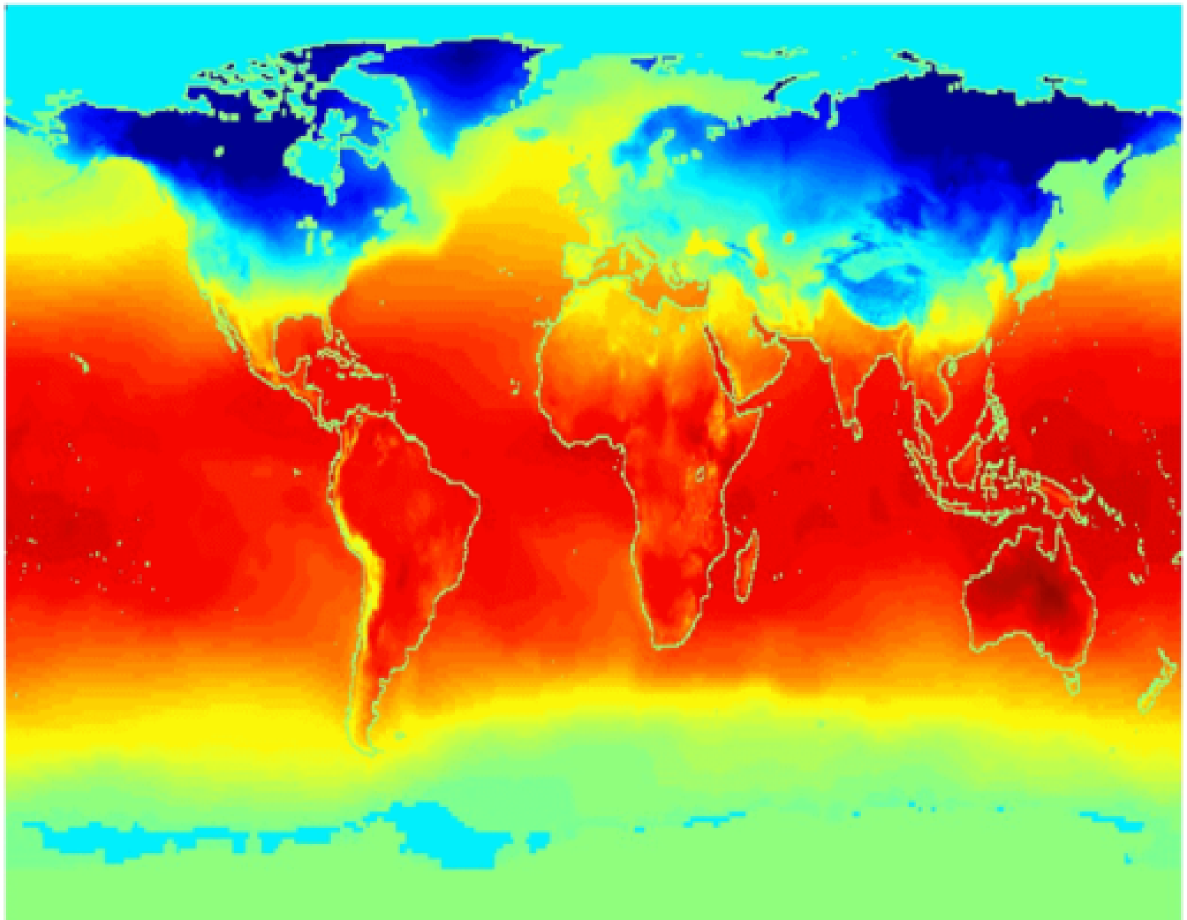
Types of Data Sets: Ordered Data

Average monthly temperature of land and ocean (= spatio-temporal data) :



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Data Quality

When repeating measurements of a quantity, measurement errors and data collection errors may occur during the measurement process. Questions:

1. What kinds of data quality problems exist?
2. How to detect data quality problems?
3. How to address data quality problems?

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Definition 1 (Precision, Bias, Accuracy)

Given a set of repeated measurements of the same quantity. Then, the closeness of the measurements to one another is called *precision*, a possible systematic variation is called *bias*, and the closeness to the true value is called *accuracy*.

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Examples for data quality problems:

- noise, artifacts, outliers
- missing values
- duplicate data

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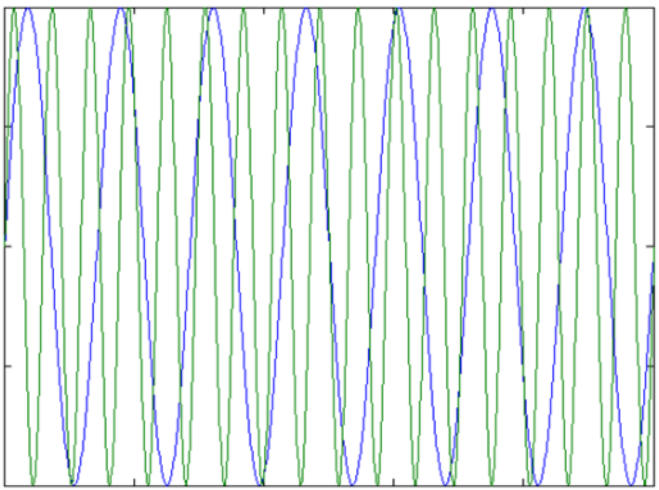
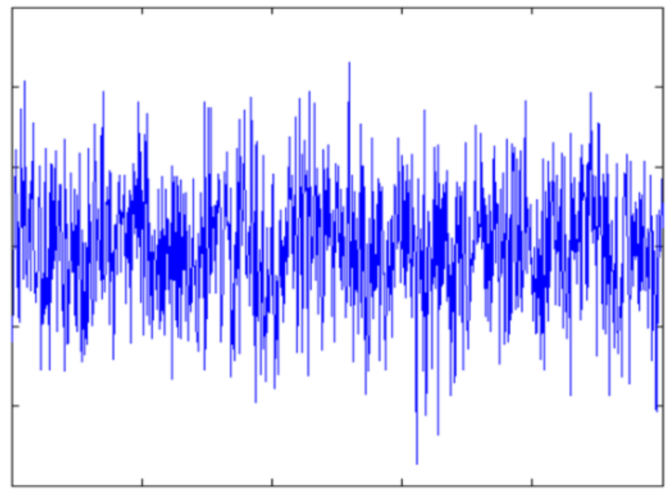
Data Quality: Noise

Noise refers to random modifications of attributes that often have a spatial or temporal characteristics:



sine waves



sine waves with noise

Noise represents the intrinsic variability of data. [Bishop 2006, p.47]

Artifacts refer to deterministic distortions of a measurement process.

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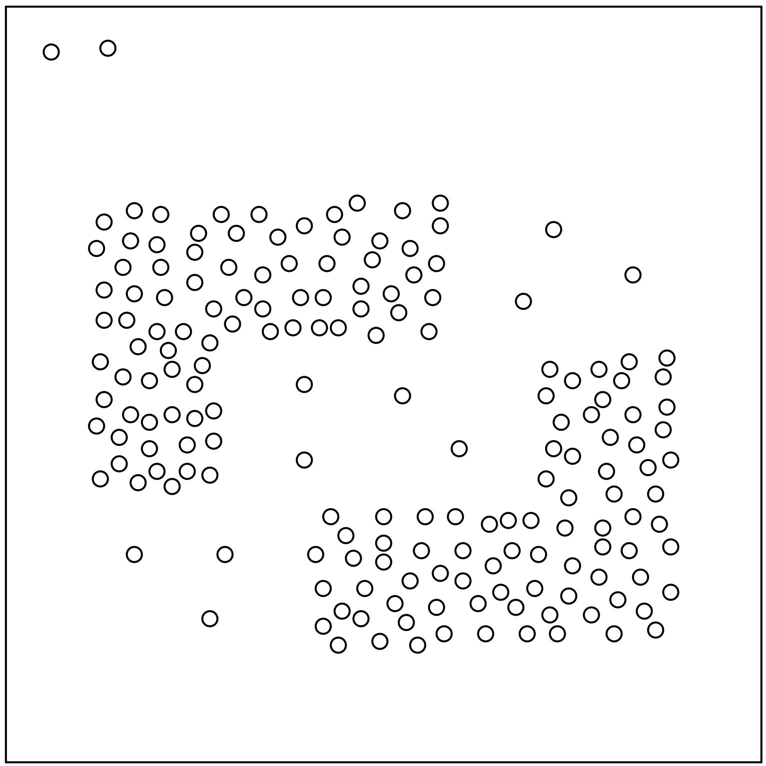
Data Quality: Outliers

Outliers are members in the data set with characteristics that are considerably different than most of the other elements:



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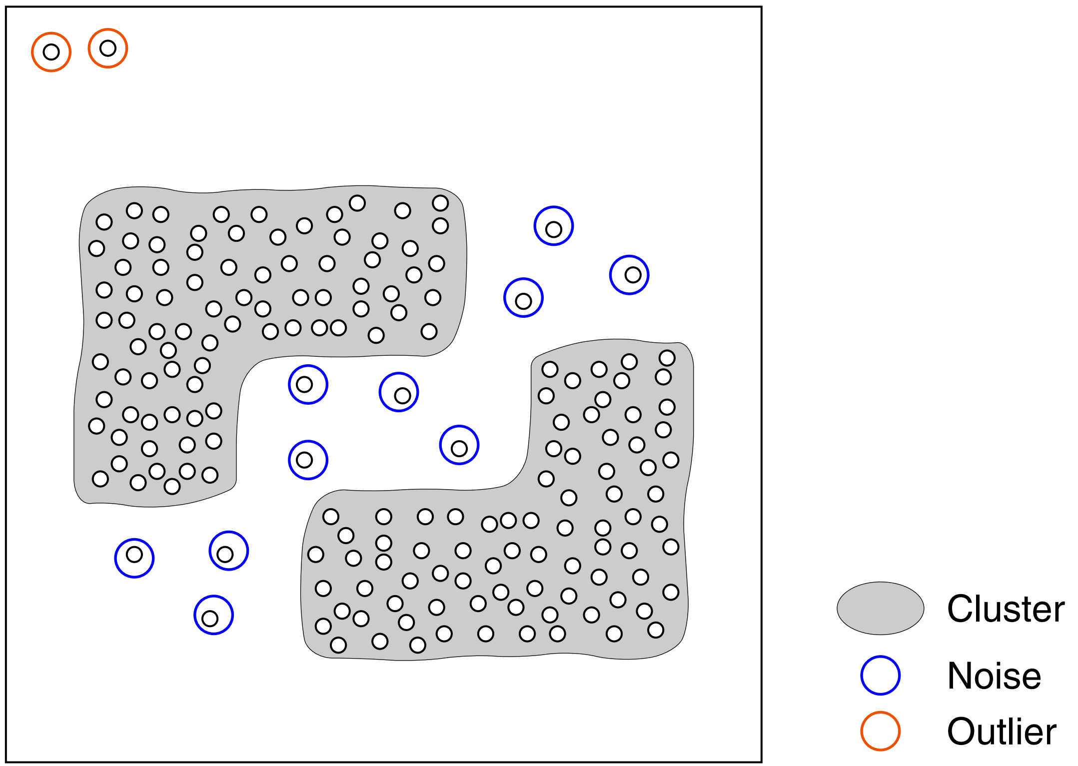

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On Data [Tan et al. 2005]

Data Quality: Missing Values

Main reasons for missing values:

1. Information is not collected.
   Example: people decline to give their age or weight.
2. Attributes may not be applicable to all elements in O.
   Example: annual income is not applicable to children.
3. Information is not trustworthy.
   Example: profile data on Facebook is intentionally misleading.

Strategies for handling missing values:

- eliminate members of the data
- estimate missing values
- ignore the missing value during analysis
- replace with all possible values weighted by their probabilities

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On Data [Tan et al. 2005]

Data Preprocessing

- sampling of object set O
- modeling of objects, $\alpha : O \rightarrow X$
- sampling of feature space X [ML Introduction]
- selection of attributes (features) [attributes versus features]
- transformation of attributes (features)
- discretization and binarization of attributes (features)
- dimensionality reduction of feature space X

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