





Introduction to Data Mining

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Outline

-  Introduction
-  Big Data
-  Data mining processing
-  Data types

Introduction

What is data mining?

The study of collecting, cleaning, processing, analyzing, and gaining useful insights from data.

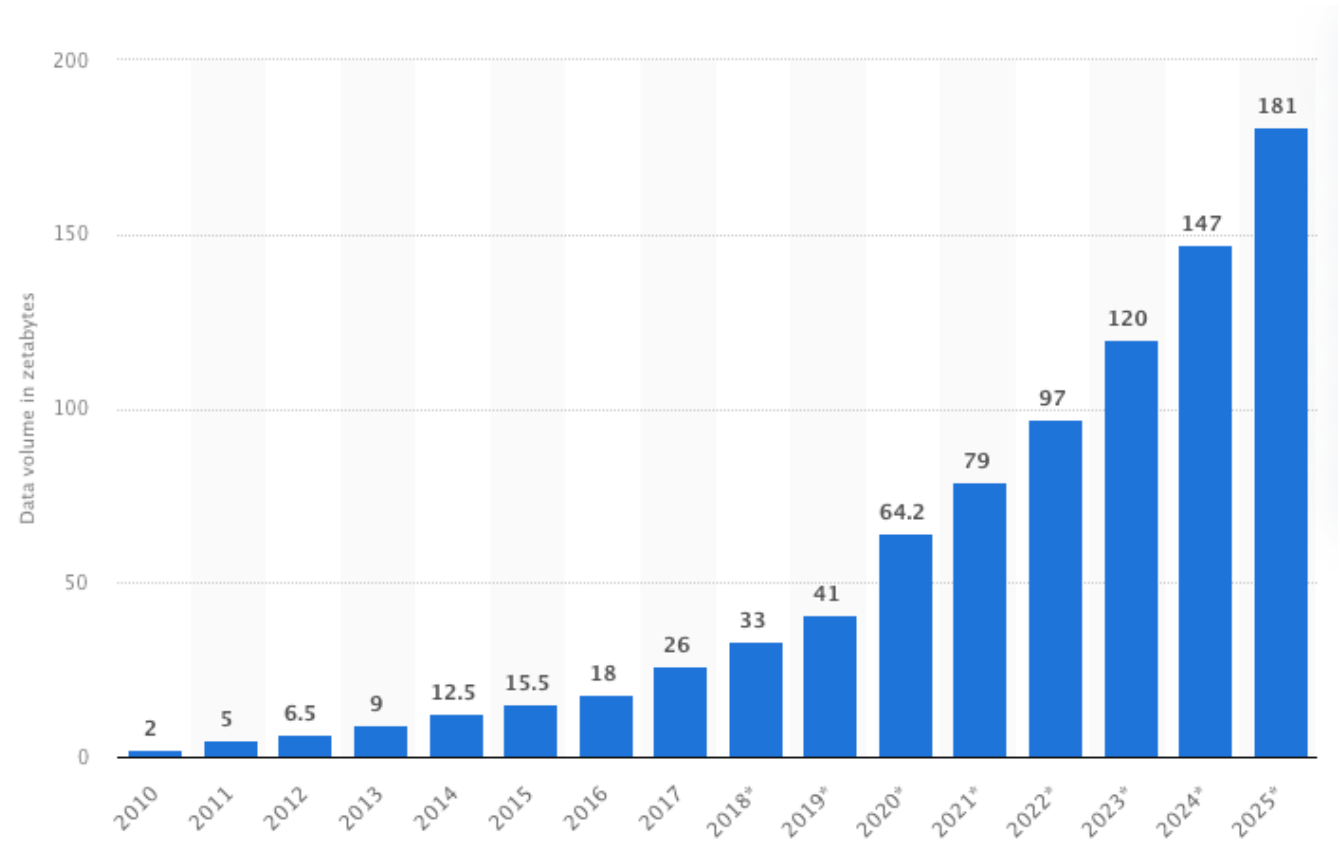
Why data is so important?

*We are in the Era of Big Data,
and big, is not just an adjective*

Introduction

Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2020, with forecasts from 2021 to 2025

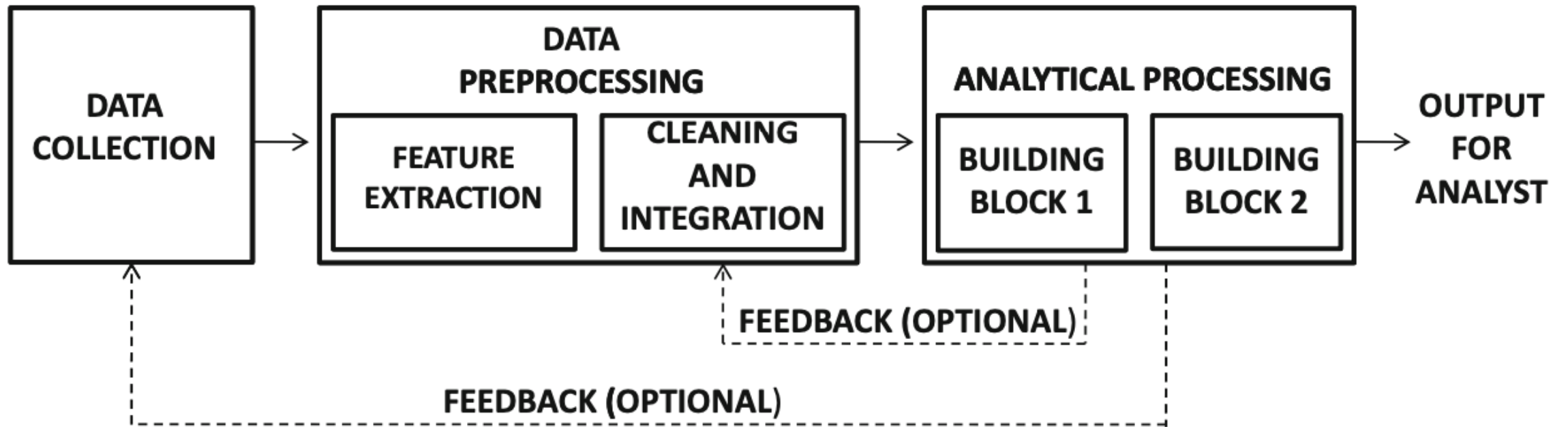
1 Zb = 1e9 TB = 1e12 GB



Big Data

- Volume in terms of memory of the data
- Velocity (speed) of data's production and update
- Variety, internal organization and structure of data
- Veracity, truthfulness of the produced data
- Value, actual value of raw or aggregated data

Data mining process



Data mining process – Data collection

- Data can be extracted from heterogeneous sources: sensors, system logs, documental corpora, biomedical data ...
- Managing structured or semi-structured data
- Volume and truthfulness of collected data
- Data storage: database, datawarehouse, data lake, HDFS and database NoSQL

Data mining process – Data preprocessing

- Feature extraction
 - Feature is a valuable characteristics of data (field of interest in a record)
 - Most important feature identification
 - Transformation from raw data to a suitable format for analysis algorithms (multi-dimensional vectors, time series, binary or categorical data)

Data mining process – Data preprocessing

- Data cleaning and integration
 - Handle missing and erroneous values
 - Integrate data from multiple sources
 - Horizontal and vertical operation on data and data field
 - This process can be done relying on problem-related knowledge
 - Cured data are stored accordingly

Data mining process – Analytical processing

Cured data are organized in a database \mathcal{D} with n records and d features, that can be represented by a data matrix \mathcal{X} with n row vectors $\mathbf{x} \in \mathbb{R}^d$

d columns/attributes

n rows/records

Data Matrix

$$\begin{bmatrix} 1 & 0 & \cdots & 2 \\ 0 & 3 & \cdots & 5 \\ 3 & 0 & \cdots & 8 \\ 7 & 0 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 2 & \cdots & 1 \end{bmatrix} \in \mathbb{R}^{n \times d}$$

Data mining process – Analytical processing

We can look for:

- Relations among \mathcal{X} columns
 - Recurrent structures among features of single data point that are correlated with another (target) feature
 - e.g. Association pattern mining, Data classification
- Relations among \mathcal{X} rows
 - Similarity among data points, thus making some data points more similar to other with respect to some criteria
 - e.g. Clustering, Outlier analysis

Data mining process – Analytical processing

- Association Pattern Mining

- Originally defined in the context of *sparse binary databases*

- e.g. customer transactional database

each column in the data matrix corresponds to an item, and a customer transaction represents a row, $x_{i,j}$ is 1, if customer transaction i contains item j as one of the items that was bought.

$$\begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \in \{0,1\}^{5 \times 4}$$

Data mining process – Analytical processing

- Frequent Pattern Mining

Given a binary $n \times d$ data matrix D , determine all subsets of columns such that all the values in these columns take on the value of 1 for at least a fraction s of the rows in the matrix.

- Relative frequency of a pattern is referred to as its support, s is the minimum support, and patterns that satisfy the minimum support requirement, are frequent patterns or itemset

Minimum support	Frequent patterns	Support
2/5	{2,3}	3/5
	{1,4}	2/5

$$\begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \in \{0,1\}^{5 \times 4}$$

Data mining process – Analytical processing

- Frequent Pattern Mining

- Frequent Pattern Mining is a class of association patterns.
- Other definitions of relevant association patterns are possible that do not use absolute frequencies but use other statistical quantifications such as the χ^2 measure.
- These measures often lead to generation of more interesting rules from a statistical perspective.
- Association pattern mining was originally proposed in the context of association rule mining, where confidence of the rule is considered

Data mining process – Analytical processing

- Confidence of the rule

- $\text{conf}(A \Rightarrow B)$ is the fraction of transactions containing A , which also contains B .
- Confidence is obtained by dividing the support of the pattern $A \cup B$ with the support of pattern A

$$\text{conf}(A \Rightarrow B) = \frac{\text{supp}(A \cup B)}{\text{supp}(A)}$$

If A appears, then B also appears

Data mining process – Analytical processing

- Association Rules

- Let A and B be two sets of items. The rule $A \Rightarrow B$ is said to be valid at support level s and confidence level c , if the following two conditions are satisfied:

1. The support of the item set A is at least s

$$\text{supp}(A) \geq s$$

2. The confidence of $A \Rightarrow B$ is at least c

$$\text{conf}(A \Rightarrow B) \geq c$$

Data mining process – Analytical processing

- Classification

- Prediction of a discrete label (particular feature) for a given data point
- Supervised approach, labels are known for the training data set
- Predict the correct label for new data, by learning the relationships of the provided features in the data with respect to the label

Data mining process – Analytical processing

- Clustering

- Looking for similarity groups among data
- Unsupervised approach, groups are not known (numbers or structure)
- e.g. customer segmentation, data summarization

Data mining process – Analytical processing

- Outlier analysis

- Outlier can be identified as a data point that highly differs from the others, and it can arise a suspect that it may be generated differently
- Outliers can be detected via clustering analysis
- Relevant example can be:
 - Intrusion detection
 - Financial Fraud detection
 - Unexpected patterns from sensors (failure prevention)
 - Unusual patterns in medical imaging (disease)
 - Weather and environmental forecasts

Data types

Dependency is a feature related to the origin of the observed phenomenon from which data are collected

- Nondependency-oriented Data
 - Data records do not have any specified dependencies between either the data items or the attributes
 - e.g. set of demographics records
- Dependency-oriented Data
 - Implicit or explicit relationships may exist between data items
 - e.g. social networks data or time series

Nondependency-oriented Data

- Multidimensional Data (vectors)

- A multidimensional data set \mathcal{D} is a set of n records, $\overline{X}_1, \dots, \overline{X}_n$ such that each record \overline{X}_i contains a set of d features denoted by (x_i^1, \dots, x_i^d)

Name	Age	Gender	Race	ZIP code
John S.	45	M	African American	05139
Manyona L.	31	F	Native American	10598
Sayani A.	11	F	East Indian	10547
Jack M.	56	M	Caucasian	10562
Wei L.	63	M	Asian	90210

Nondependency-oriented Data

- Multidimensional Data (vectors)
 - \overline{X}_i is a record, data point, instance, example, transaction, entity, tuple, object, feature-vector (sample)
 - x_i^k is a field, attribute, dimension, feature.

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Nondependency-oriented Data

- Quantitative Multidimensional Data
 - Numerical in the sense that they have a natural ordering
 - Continuous, numeric, or quantitative
 - Convenient for analytical processing (mean, variance, ...)

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Nondependency-oriented Data

- Categorical Data
 - Take on discrete unordered values
 - Unordered discrete-valued Data

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Nondependency-oriented Data

- Mixed Attribute Data
 - Combination of categorical and numeric attributes
- Binary Data
 - A special case of multidimensional categorical data, where each categorical attribute may take on one of at most two discrete values
 - A special case of multidimensional quantitative data, where an ordering exists between the two values
 - Setwise data if attribute is treated as a set element indicator

Nondependency-oriented Data

- Text Data

- Generally referred to string, that have an order

BUT

- Text can be represented in a vector-space representation in terms of frequencies of the words in a document, thus creating a *document-term matrix* $n \times d$ with n documents and d terms.
 - In this configuration textual data can be analyzed by distance measures (Latent Semantic Analysis)

Dependency-oriented Data

- Implicit dependencies
 - Known dependencies related to data's domain
 - Data values may be related to each other temporally or spatially
- Explicit dependencies
 - An explicitly dependencies is reported
 - Graph or network data where edges are used to specify relationships

Dependency-oriented Data

- Time-Series Data

- Series of values generated by continuous measurement over time.
- *Contextual attributes*
 - Define the context on the basis of which the implicit dependencies occur in the data
 - e.g. time stamp
- *Behavioral attributes*
 - Represent the values that are measured in a particular context
 - e.g. actual value of interest

Dependency-oriented Data

- Multivariate Time-Series

- A time series of length n and dimensionality d contains d *numeric features* at each of n time stamps
- $(t_1; \overline{Y}_1), \dots, (t_n; \overline{Y}_n)$, where $\overline{Y}_i = (y_i^1, \dots, y_i^d)$

- Multivariate Discrete Sequence Data

- Discrete sequence of length n and dimensionality d contains d *discrete features* at each of n time stamps
- $(t_1; \overline{Y}_1), \dots, (t_n; \overline{Y}_n)$, where $\overline{Y}_i = (y_i^1, \dots, y_i^d)$

Dependency-oriented Data

- Textual Data
 - A multivariate discrete sequence with $d = 1$
 - Text is represented as vectors called *word embeddings*
 - *Noncontextual word embeddings*
 - *Contextual word embeddings*

Dependency-oriented Data

- Spatial Data

- A d -dimensional spatial data record contains d behavioral attributes and one or more contextual attributes containing the spatial location.
- A set of n locations associated with corresponding d behavioral attributes
- $(L_1; \overline{X}_1), \dots, (L_n; \overline{X}_n)$, where $\overline{X}_i = (x_i^1, \dots, x_i^d)$

- Spatiotemporal Data

- Both spatial and temporal attributes are contextual
- The temporal attribute is contextual, whereas the spatial attributes are behavioral (e.g. trajectory analysis)

Dependency-oriented Data

- Network and Graph Data

- A network $G = (N, A)$ contains a set of nodes N and a set of edges A , where the edges in A represent the relationships between the nodes. In some cases, an attribute set \overline{X}_i may be associated with node i , or an attribute set \overline{Y}_{ij} may be associated with edge (i, j) .
- $(L_1; \overline{X}_1), \dots, (L_n; \overline{X}_n)$, where $\overline{X}_i = (x_i^1, \dots, x_i^d)$
- e.g. Web Graph, Social Networks, Chemical compound databases