

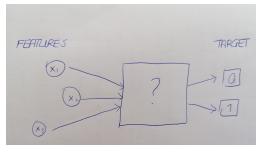
Introduction to Machine Learning

Introduction: Data

compstat-lmu.github.io/lecture_i2ml

DATA IN MACHINE LEARNING

- The data we deal with in machine learning usually consists of observations on different aspects of objects:
 - **Target** variable(s): the attribute(s) of interest
 - **Features**: measurable properties that provide a concise description of the object
 - Both features and target variables may be of different data types (categorical, numeric, ...).
- We assume some kind of relationship between the features and the target, in a sense that the value of the target variable can be explained by a combination of the features.



DATA IN MACHINE LEARNING

- For instance, it is reasonable to assume a relationship between certain features of a job-seeker, such as their field of expertise, academic qualifications and previous job experiences, and their salary.

Your skills impact your salary

Find Skills

Skill Name

Add

Related Skills

Value

⊕ Data science	+ 12%
⊕ Machine learning	+ 9%
⊕ SAS/MACROS	+ 7%
⊕ Clinical trials	+ 7%
⊕ Modeling	+ 6%
⊕ Business ...	+ 6%
⊕ Statistical models	+ 3%
⊕ Biostatistics	+ 3%
⊕ Marketing analytics	+ 3%
⊕ Pharmaceuticals	+ 3%

Statistician Salary Prediction

New York, NY

0 Years of Experience

Skills included in this prediction

R Data analysis SAS Statistics SQL

Does this salary look accurate? [Help us improve it!](#)

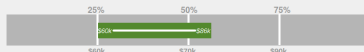
Your Salary Prediction ⓘ

\$60,500 - \$86,000

See how you compare to all other Statistician salaries nationwide

Statistician Range

Your Prediction ⓘ



- In practical applications we frequently encounter high-dimensional data, i.e., data with many features and/or observations.

NOTATION FOR DATA

In formal notation, the data sets we are given are of the following form:

$$\mathcal{D} = \left\{ \left(\mathbf{x}^{(1)}, y^{(1)} \right), \dots, \left(\mathbf{x}^{(n)}, y^{(n)} \right) \right\} \subset (\mathcal{X} \times \mathcal{Y})^n.$$

We call

- \mathcal{X} the input space with $p = \dim(\mathcal{X})$ (for now: $\mathcal{X} \subset \mathbb{R}^p$),
- \mathcal{Y} the output / target space,
- the tuple $(\mathbf{x}^{(i)}, y^{(i)}) \in \mathcal{X} \times \mathcal{Y}$ the i -th observation,
- $\mathbf{x}_j = \left(x_j^{(1)}, \dots, x_j^{(n)} \right)^T$ the j -th feature vector.

DATA-GENERATING PROCESS

- We assume the observed data \mathcal{D} to be generated by a process that can be characterized by some probability distribution

$$\mathbb{P}_{xy},$$

defined on $\mathcal{X} \times \mathcal{Y}$.

- Depending on the context, we denote the random variables following this distribution by \mathbf{x} and y .
- Usually we assume the data to be drawn i.i.d. from the joint probability density function (pdf) / probability mass function (pmf) $p(\mathbf{x}, y)$.

DATA-GENERATING PROCESS

Remarks:

- With a slight abuse of notation we write random variables, e.g., \mathbf{x} and y , in lowercase, as normal variables or function arguments. The context will make clear what is meant.
- Often, distributions are characterized by a parameter vector $\theta \in \Theta$. We then write $p(\mathbf{x}, y \mid \theta)$.
- This lecture mostly takes a frequentist perspective. Distribution parameters θ appear behind the \mid for improved legibility, not to imply that we condition on them in a probabilistic Bayesian sense. So, strictly speaking, $p(\mathbf{x} \mid \theta)$ should usually be understood to mean $p_\theta(\mathbf{x})$ or $p(\mathbf{x}, \theta)$ or $p(\mathbf{x}; \theta)$.