

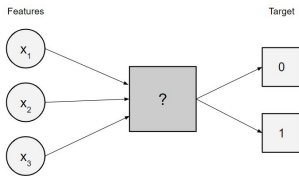
# **Introduction to Machine Learning**

## **Introduction: Data**

[compstat-lmu.github.io/lecture\\_i2ml](https://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.



Features $x$				Target $y$
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
4.3	3.0	1.1	0.1	setosa
5.0	3.3	1.4	0.2	setosa
7.7	3.8	6.7	2.2	virginica
5.5	2.5	4.0	1.3	versicolor

# DATA LABELS

- We distinguish two basic forms our data may come in:
  - For **labeled** data we have already observed the target values (*labels*).
  - For **unlabeled** data these remain unknown.
- It is easy to see how labeled data are vastly more informative.
- In practice, however, we will much more frequently encounter the unlabeled sort.

		Features $x$				Target $y$
		Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
labeled data	{	4.3	3.0	1.1	0.1	setosa
		5.0	3.3	1.4	0.2	setosa
		7.7	3.8	6.7	2.2	virginica
		5.5	2.5	4.0	1.3	versicolor
unlabeled data	{	5.9	3.0	5.1	1.8	?
		4.4	3.2	1.3	0.2	?

# 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  $y$ .
- It is important to understand that the true distribution is essentially **unknown** to us.

# DATA-GENERATING PROCESS

- Usually we assume the data to be drawn *i.i.d.* from the joint probability density function (pdf) / probability mass function (pmf)  $p(\mathbf{x}, y)$ .
  - i.i.d. stands for independent and identically distributed.
  - We presuppose that all samples are drawn from the same distribution and are mutually independent – the  $i$ -th realization does not depend on the previous  $i - 1$  ones.
  - It is a strong yet crucial assumption that is precondition to many theoretical implications (e.g., the Central Limit Theorem).
- **FIGURE**

# 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  $\theta$  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  $p(\mathbf{x}; \theta)$ .