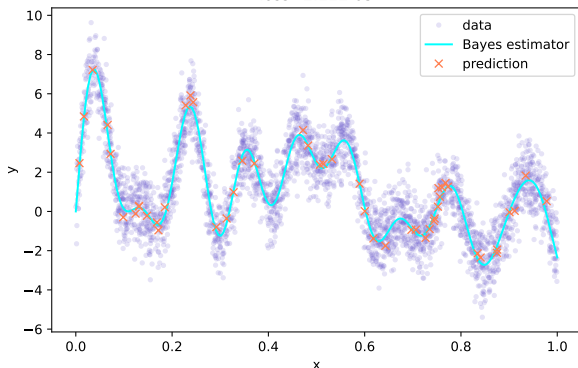


Machine learning I, supervised learning: metrics

kNN regression
10 neighbors, 100000 samples
loss=2.11E-05



Metrics

Let $D = \{x_1, \dots, x_n\} \subset \mathcal{X}$ be a dataset of n samples, with labels $\{y_1, \dots, y_n\} \subset \mathcal{Y}$.

There is a metric in the input space \mathcal{X} and in the output space \mathcal{Y} .

- ▶ The **metric** in \mathcal{X} determines to what extent two samples x_i and x_j should be considered similar or dissimilar.
- ▶ The **metric** in \mathcal{Y} determines to what extent two labels y_i and y_j should be considered similar or dissimilar.

This is very important during the complete processing of the data.

Metrics in output space

A **loss function** l is a map that measures the discrepancy between two elements of a set (for instance of a linear space).

$$l : \begin{cases} \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R}_+ \\ (y, z) \mapsto l(y, z) \end{cases}$$

Typically, z can represent our prediction for a given input x , $z = \tilde{f}(x)$, and y the correct label.

"0-1" loss for **binary** classification.

$\mathcal{Y} = \{0, 1\}$ or $\mathcal{Y} = \{-1, 1\}$.

$$l(y, z) = 1_{y \neq z} \tag{1}$$

square loss for **regression**.

$$\mathcal{Y} = \mathbb{R}.$$

$$l(y, z) = (y - z)^2 \quad (2)$$

absolute loss for **regression**.

$$\mathcal{Y} = \mathbb{R}.$$

$$l(y, z) = |y - z| \tag{3}$$

Cross entropy loss (more advanced)

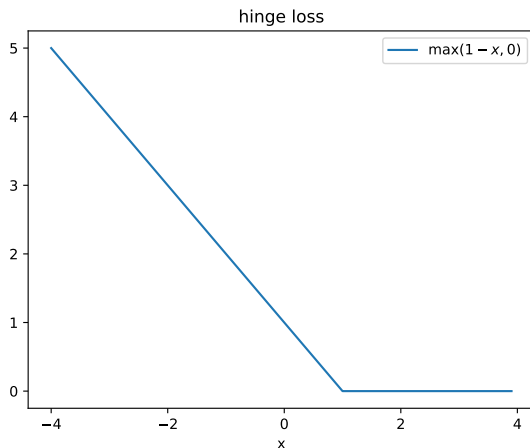
- ▶ $\mathcal{Y} = \{0, 1\}$



$$l(z, y) = y \log(1 + e^{-z}) + (1 - y) \log(1 + e^z) \quad (4)$$

- ▶ typically used for logistic regression or neural networks (note that sometimes $\mathcal{Y} = \{-1, 1\}$, and then the writing is different).

Other losses exist and are relevant in some contexts, such as the hinge loss.



Metrics in input space

Often, $\mathcal{X} = \mathbb{R}^p$ (input space). In this case, **geometric** metrics are used.

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- ▶ weighted L1 : $\sum_{k=1}^p w_k |x_k - y_k|$
- ▶ L_∞ : $\max(x_1, \dots, x_n)$ (infinity norm distance, Chebyshev distance)

<https://www.geogebra.org/geometry?lang=fr>

Non-geometric data

Not all data are geometric !

Hamming distance

- ▶ $\#\{x_i \neq y_i\}$ (Hamming distance)
- ▶ Levenshtein distance for strings (allows deletions and additions)

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- ▶ **separate the values** : $\forall x, y, d(x, y) = 0 \Leftrightarrow x = y$
- ▶ respect the **triangular inequality**
 $\forall x, y, z, d(x, y) \leq d(x, z) + d(y, z)$

General definition of a distance

We could verify that :

- ▶ L2 is a distance
- ▶ Hamming is a distance

Similarities

Sometimes, it is not possible to define a proper **distance** in the input space \mathcal{X} ! This may happen for instance if \mathcal{X} is a dataset of texts.

- ▶ When distances are unavailable, we can use **Similarities** or **Dissimilarity** to compare points.
- ▶ Dissimilarities are more general and don't always abide by the distance axioms.
- ▶ Other examples : Adjacency in an oriented graph, Custom aggregated score to compare data.

Example : cosine similarity

The **cosine similarity** may be used to compare texts.

If u and v are vectors,

$$S_C(u, v) = \frac{(u|v)}{||u|| ||v||} \quad (5)$$

- ▶ the **bag of words representation** allows us to build a vector from a text (one hot encoding).
- ▶ `cosine_similarity/scrapper.py`
- ▶ `cosine_similarity/similarity.py`

Hybrid data

Sometimes each sample contains both numerical data and non-numerical data (text, categorical data.)

See **hybrid_data/**

This is often the case in machine learning applications! (database of customers, database of cars, etc.)