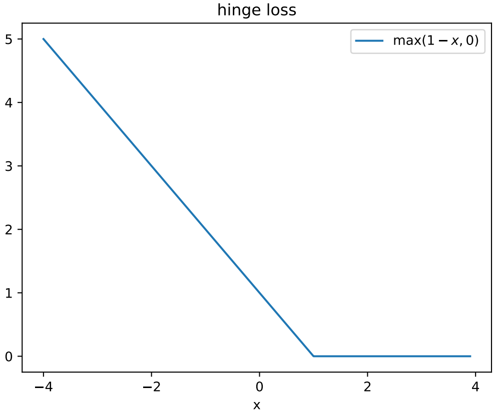
Machine learning II, unsupervised learning and agents: metrics



Metrics

Let $D = \{x_1, \ldots, x_n\} \subset \mathcal{X}$ be a dataset of n samples, with labels $\{y_1, \ldots, y_n\} \subset \mathcal{Y}$.
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 to elements of a set (for instance of a linear space).

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

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**.

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

$$l(y, z) = (y - z)^2 \tag{2}$$

absolute loss for **regression**.

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

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

In **unsupervised learning**, there is notion of **output space**!

Metrics in input space

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

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- weighted L_1 : $\sum_{k=1}^{p} w_k |x_k - y_k|$
- $||x - y||_\infty$: $\max(|x_i - y_i|, i \in [1, n])$ (infinity norm distance, Chebyshev distance)

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

Choice of the metric

In some contexts, some usual metrics such as $L2$ might not be meaningful !

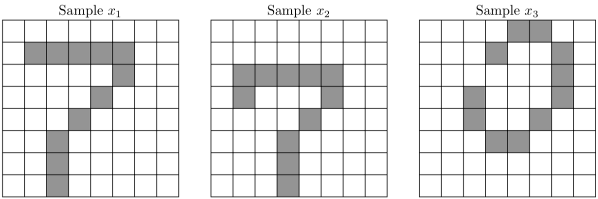

Figure – In $\mathbb{R}^{64}$, those three points form an equilateral triangle, [Fix et al., ,]

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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- 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 is $\mathcal{X}$ is a dataset of texts.

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

Example : cosine similarity

The **cosine similarity** may be used to compare texts.
If u and v are vectors,

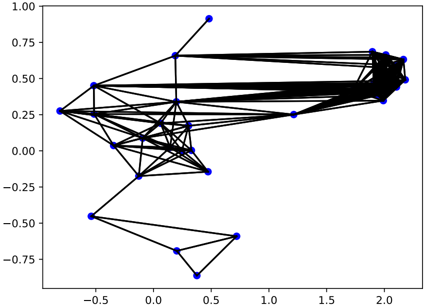
$$S_C(u, v) = \frac{(u|v)}{||u||||v||} \tag{4}$$

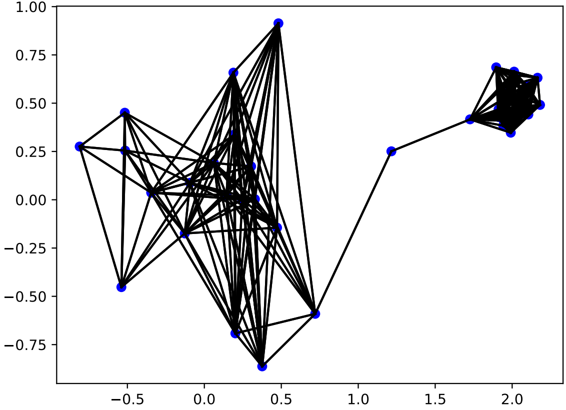
- the **bag of words representation** allows us to build a vector from a text (one hot encoding).
- **cosine_similarity/scraper.py**
- **cosine_similarity/similarity.py**

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.)

Exercice 1 : Using **metrics/geometric_data/build_graph_2.py**, choose the metric and the threshold so that this graph (and the ones on the next slides) are built.

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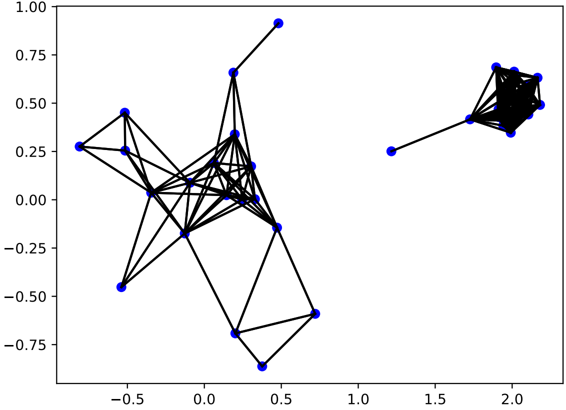
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References I

Fix, J., Frezza-Buet, H., Geist, M., and Pennerath, F.
Machine Learning.pdf.