

## Useful distance functions for machine learning

### Topics we'll cover

- 1  $L_p$  norms
- 2 Metric spaces

## Measuring distance in $\mathbb{R}^m$

Usual choice: **Euclidean distance**:

$$\|x - z\|_2 = \sqrt{\sum_{i=1}^m (x_i - z_i)^2}.$$

$\ell_p$  distance between 2 vectors  $x$  &  $z$ ,

For  $p \geq 1$ , here is  $\ell_p$  **distance**:

$$\|x - z\|_p = \left( \sum_{i=1}^m |x_i - z_i|^p \right)^{1/p}$$

- $p = 2$ : Euclidean distance

- $\ell_1$  distance:  $\|x - z\|_1 = \sum_{i=1}^m |x_i - z_i|$   $v + y$

- $\ell_\infty$  distance:  $\|x - z\|_\infty = \max_i |x_i - z_i|$   $y$



difference along  
each coordinate

$$x = (1, 1, \dots, 1)$$

### Example 1

Consider the all-ones vector  $(1, 1, \dots, 1)$  in  $\mathbb{R}^d$ .

What are its  $\ell_2$ ,  $\ell_1$ , and  $\ell_\infty$  length?

$$\begin{aligned} \|x\|_2 & \quad \ell_2 \text{ norm} \\ &= \sqrt{1^2 + 1^2 + \dots + 1^2} \\ &= \sqrt{d} \end{aligned}$$

$$\begin{aligned} \|x\|_1 & \quad \ell_1 \text{ norm} \\ &= |x_1| + \dots + |x_d| \\ &= d \end{aligned}$$

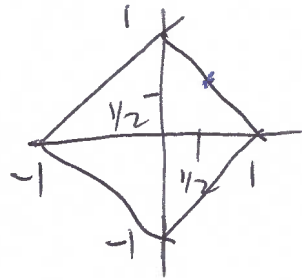
$$\|x\|_\infty = 1$$

## Example 2

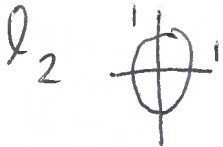
In  $\mathbb{R}^2$ , draw all points with:

- ①  $\ell_2$  length 1
- ②  $\ell_1$  length 1
- ③  $\ell_\infty$  length 1

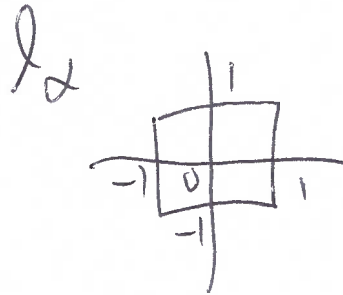
$$\ell_1: \{(x_1, x_2) : |x_1| + |x_2| = 1\}$$



unit ball for  $\ell_1$



$$\{(x_1, x_2) : \sqrt{x_1^2 + x_2^2} = 1\}$$



## Metric spaces

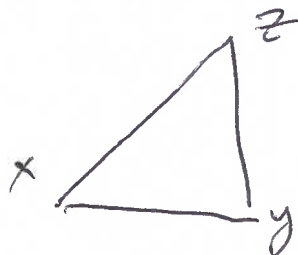
$$d(x, x') = 3.6$$

data

Let  $\mathcal{X}$  be the space in which data lie.

A distance function  $d : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$  is a **metric** if it satisfies these properties:

- ✓  $d(x, y) \geq 0$  (nonnegativity)
- ✓  $d(x, y) = 0$  if and only if  $x = y$
- ✓  $d(x, y) = d(y, x)$  (symmetry)
- ✓  $d(x, z) \leq d(x, y) + d(y, z)$  (triangle inequality)



## Example 1

$$d(x, y) = \sum_{i=1}^m |x_i - y_i|$$

$\mathcal{X} = \mathbb{R}^m$  and  $d(x, y) = \|x - y\|_p$

Check:

- $d(x, y) \geq 0$  (nonnegativity) ✓
- $d(x, y) = 0$  if and only if  $x = y$  ✓
- $d(x, y) = d(y, x)$  (symmetry) ✓
- $d(x, z) \leq d(x, y) + d(y, z)$  (triangle inequality) ✓

$$|x_i - z_i| \leq |x_i - y_i| + |y_i - z_i|$$

Sum over all  $i$

$d_1$  satisfies metric distance 4 properties

## Example 2

$\mathcal{X} = \{\text{strings over some alphabet}\}$  and  $d = \text{edit distance}$

Check:

- $d(x, y) \geq 0$  (nonnegativity)
- $d(x, y) = 0$  if and only if  $x = y$
- $d(x, y) = d(y, x)$  (symmetry)
- $d(x, z) \leq d(x, y) + d(y, z)$  (triangle inequality)

$$x = \{A, C, G, T\}^*$$

$$x = A C C G T$$

$$y = C C G T$$

edit distance

$d(x, y) = \#$  of insertions, deletions, substitutions  
to get from  $x$  to  $y$

$$d(x, y) \geq 0$$

$$d(x, y) = 0 \iff x = y$$

$$d(x, y) = d(y, x)$$

triangle inequality

## A non-metric distance function

$d \rightarrow$  distance

$d(p, q)$  distance between  $p$  &  $q$

Let  $p, q$  be probability distributions on some set  $\mathcal{X}$ .

The **Kullback-Leibler divergence** or **relative entropy** between  $p, q$  is:

$$d(p, q) = \sum_{x \in \mathcal{X}} p(x) \log \frac{p(x)}{q(x)}.$$

$$p = \left(\frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{8}\right)$$

$$q = \left(\frac{1}{6}, \frac{1}{3}, \frac{1}{3}, \frac{1}{6}\right)$$

we can compute  $I_1, I_2$  but

the choice  
is always  
KL div

$$d(p, q) = \frac{1}{2} \log \frac{1/2}{1/6} + \frac{1}{4} \log \frac{1/4}{1/3} + \frac{1}{8} \log \frac{1/8}{1/3} + \frac{1}{8} \log \frac{1/8}{1/6}$$

w/c is  $d(p, q)$