

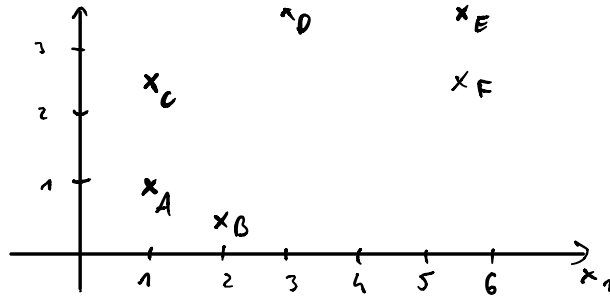
## kNN Classification

**Problem 1:** You are given the following dataset, with points of two different classes:

Name	$x_1$	$x_2$	class
A	1.0	1.0	1
B	2.0	0.5	1
C	1.0	2.5	1
D	3.0	3.5	2
E	5.5	3.5	2
F	5.5	2.5	2

We perform 1-NN classification with leave-one-out cross validation on the data in the plot.

- Compute the distance between each point and its nearest neighbor using  $L_1$ -norm as distance measure.
- Compute the distance between each point and its nearest neighbor using  $L_2$ -norm as distance measure.
- What can you say about classification if you compare the two distance measures?



a)  $L_1$ -Norm:  $\|x\|_1 = \sum_{i=1}^n |x_i|$        $d_1(x_1, x_2) = |x_1 - x_2| = \sum_{i=1}^n |x_{1i} - x_{2i}|$

$d_1(A, B) = 1.5$      $d_1(B, A) = 1.5$      $d_1(C, A) = 1.5$

$d_1(D, E) = 2.5$      $d_1(E, F) = 1$      $d_1(F, E) = 1$

b)  $L_2$ -Norm:  $\|x\|_2 = \sqrt{\sum_{i=1}^n |x_i|^2}$        $d_2(x_1, x_2) = \sqrt{|x_1 - x_2|^2} = \sqrt{\sum_{i=1}^n |x_{1i} - x_{2i}|^2}$

$d_2(A, B) \approx 1.12$      $d_2(B, A) \approx 1.12$      $d_2(C, A) \approx 1.5$

$d_2(D, E) \approx 2.2$      $d_2(E, F) = 1$      $d_2(F, E) = 1$

- c) The classes are the same but for D. Here the  $L_1$  distance is smallest to point E whereas with  $L_2$  the closest point is C.

L<sub>1</sub>

A

$$B: |(1,1) - (2,0.5)| = 1 + 0.5 = 1.5$$

$$C: |(1,1) - (1,2.5)| = 0 + 1.5 = 1.5$$

$$D: |(1,1) - (3,0.5)| = 2 + 2.5 = 4.5$$

$$E: |(1,1) - (5.5,3.5)| = 4.5 + 2.5 = 7$$

$$F: |(1,1) - (5.5,2.5)| = 4.5 + 1.5 = 6$$

C

$$D: |(1,2.5) - (3,3.5)| = 2 + 1 = 3$$

$$E: |(1,2.5) - (5.5,3.5)| = 4.5 + 1 = 5.5$$

$$F: |(1,2.5) - (5.5,2.5)| = 4.5 + 0 = 4.5$$

E

$$F: |(5.5,3.5) - (5.5,2.5)| = 0 + 1 = 1$$

B

$$C: |(2,0.5) - (1,2.5)| = 1 + 2 = 3$$

$$D: |(2,0.5) - (3,3.5)| = 1 + 3 = 4$$

$$E: |(2,0.5) - (5.5,3.5)| = 3.5 + 3 = 6.5$$

$$F: |(2,0.5) - (5.5,2.5)| = 3.5 + 2 = 6.5$$

D

$$E: |(3,3.5) - (5.5,3.5)| = 2.5 + 0 = 2.5$$

$$F: |(3,3.5) - (5.5,2.5)| = 2.5 + 1 = 3.5$$

Q2

A

$$B: |(1,1) - (2,0.5)|^2 = \sqrt{1^2 + 0.5^2} \approx 1.12$$

$$C: |(1,1) - (1,2.5)|^2 = \sqrt{0^2 + 1.5^2} \approx 1.5$$

$$D: |(1,1) - (3,3.5)|^2 = \sqrt{2^2 + 2.5^2} \approx 3.4$$

$$E: |(1,1) - (5.5, 3.5)|^2 = \sqrt{4.5^2 + 2.5^2} \approx 5.1$$

$$F: |(1,1) - (5.5, 2.5)|^2 = \sqrt{4.5^2 + 1.5^2} \approx 4.8$$

B

$$C: |(2,0.5) - (1,2.5)|^2 \approx 2.4$$

$$D: |(2,0.5) - (3,3.5)|^2 \approx 3.3$$

$$E: |(2,0.5) - (5.5, 3.5)|^2 \approx 4.7$$

$$F: |(2,0.5) - (5.5, 2.5)|^2 \approx 4.2$$

C

$$D: |(1,2.5) - (3,3.5)|^2 \approx 2.2$$

$$E: |(1,2.5) - (5.5, 3.5)|^2 \approx 4.7$$

$$F: |(1,2.5) - (5.5, 2.5)|^2 \approx 4.6$$

D

$$E: |(3,3.5) - (5.5, 3.5)|^2 \approx 2.5$$

$$F: |(3,3.5) - (5.5, 2.5)|^2 \approx 2.7$$

E

$$F: |(5.5, 3.5) - (5.5, 2.5)|^2 \approx 1$$

**Problem 2:** Consider a dataset with 3 classes  $\mathcal{C} = \{A, B, C\}$ , with the following class distribution  $N_A = 16, N_B = 32, N_C = 64$ . We use unweighted  $k$ -NN classifier, and set  $k$  to be equal to the number of data points, i.e.  $k = N_A + N_B + N_C =: N$ .

- What can we say about the prediction for a new point  $x_{new}$ ?
- How about if we use the weighted (by distance) version of  $k$ -Nearest Neighbors?

$$N = 16 + 32 + 64 = 112 = k$$

$$a) \quad p(y = A | x, N) = \frac{16}{112}$$

$$p(y = B | x, N) = \frac{32}{112}$$

$$p(y = C | x, N) = \frac{64}{112} \quad \leftarrow \text{ } x \text{ will be classified as } C \text{ since it is the largest class.}$$

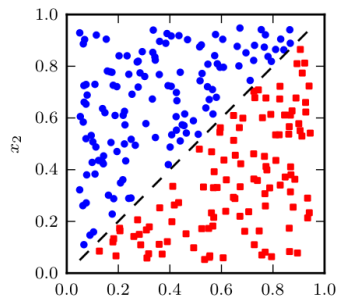
$$b) \quad z = \sum_{i \in \mathcal{N}_k(x)} \frac{1}{d(x, x_i)} \quad p(y = c | x, N) = \frac{1}{z} \sum_{i \in \mathcal{N}_k(x)} \frac{1}{d(x, x_i)} \mathbb{I}(y_i = c)$$

$$p(y = A | x, N)$$

$x_{new}$  will be predicted as  $C$  as well we consider all 112 nearest neighbors. The distance does not play a role when  $k = N$ .

Classification is based on the weights. Since those are not given we cannot make any class label prediction

**Problem 3:** The plot below shows data of two classes that can easily be separated by a single (diagonal) line. Does there exist a decision tree of depth 1 that classifies this dataset with 100% accuracy? Justify your answer.



The data cannot be split diagonally but only vertically and horizontally.  
A diagonal cut touches both the  $x_1$  and  $x_2$  dimension.  
With this data, a cut can only be accomplished with a zig-zag pattern

**Problem 4:** You are developing a model to classify games at which machine learning will beat the world champion within five years. The following table contains the data you have collected.

No.	$x_1$ (Team or Individual)	$x_2$ (Mental or Physical)	$x_3$ (Skill or Chance)	$y$ (Win or Lose)
1	T	M	S	W
2	I	M	S	W
3	T	P	S	W
4	I	P	C	W
5	T	P	C	L
6	I	M	C	L
7	T	M	S	L
8	I	P	S	L
9	T	P	C	L
10	I	P	C	L

a) Calculate the entropy  $i_H(y)$  of the class labels  $y$ .

b) Build the optimal decision tree of depth 1 using entropy as the impurity measure.

$$i_H(f) = - \sum_{c \in C} \pi_c \log \pi_c \quad \left( \lim_{x \rightarrow 0^+} x \log x = 0 \right) \quad \pi_c = p(y=c | t)$$

$$C = \{W, L\} \quad p(y=W) = \frac{4}{10} \quad p(y=L) = \frac{6}{10}$$

$$\begin{aligned} a) \quad i_H(y) &= p(y=W) \log p(y=W) + p(y=L) \log p(y=L) \\ &= - \left( \frac{4}{10} \cdot \log \frac{4}{10} + \frac{6}{10} \cdot \log \frac{6}{10} \right) \\ &\approx 0.673012 \end{aligned}$$

b) Split on  $x_1$ :

$$p(y=W | x_1=T) = \frac{2}{3} \quad p(y=W | x_1=I) = \frac{2}{5}$$

$$i_H(x_1=T) = i_H(x_1=I) = \frac{2}{3} \cdot \log \frac{2}{3} + \frac{1}{3} \cdot \log \frac{1}{3} \approx 0.673$$

$$\Delta_{x_1} = 1 - \frac{3}{10} \cdot 0.673 - \frac{5}{10} \cdot 0.673 \approx 0.327$$

Split on  $x_2$ :

$$p(y=W | x_2=M) = \frac{2}{4} \quad p(y=W | x_2=P) = \frac{2}{6}$$

$$i_H(x_2=M) = \frac{2}{4} \log \frac{2}{4} + \frac{2}{4} \log \frac{2}{4} \approx 0.693$$

$$i_H(x_2=P) = \frac{2}{6} \log \frac{2}{6} + \frac{4}{6} \log \frac{4}{6} \approx 0.637$$

$$\Delta_{x_2} = 1 - \frac{4}{10} \cdot 0.693 - \frac{6}{10} \cdot 0.637 = 0.340$$

Split on  $x_3$ :

$$p(y=W | x_3=5) = \frac{3}{5} \quad p(y=W | x_3=6) = \frac{1}{5}$$

$$i_H(x_3=5) = \frac{3}{5} \cdot \log \frac{3}{5} + \frac{2}{5} \cdot \log \frac{2}{5} = i_H(x_3=7) \approx 0.673$$

$$i_H(x_3=6) = \frac{1}{5} \cdot \log \frac{1}{5} + \frac{4}{5} \cdot \log \frac{4}{5} \approx 0.5$$

$$\Delta_{x_3} = 1 - \frac{4}{10} \cdot 0.673 - \frac{6}{10} \cdot 0.5 \approx 0.431$$

Split on  $x_3$  (highest value)!

### Programming Task

**Problem 5:** Load the notebook `exercise_02_notebook.ipynb` from Piazza. Fill in the missing code and run the notebook. Convert the evaluated notebook to HTML using `nbconvert` and add it to your submission.

*Note: We suggest that you use Anaconda for installing Python and Jupyter, as well as for managing packages. We recommend that you use Python 3.*

*For more information on Jupyter notebooks, consult the Jupyter documentation. Instructions for converting the Jupyter notebooks to PDF are provided within the notebook.*