

## MACHINE LEARNING

LEIC IST-UL

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### RELATÓRIO - HOMEWORK 1

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#### **Grupo 10:**

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## Part I: Pen and paper

1. F1-measure of a kNN.

	P				N			
	x1	x2	x3	x4	x5	x6	x7	x8
x1	-	2	1	0	1	1	1	2
x2	2	-	1	2	1	1	1	0
x3	1	1	-	1	2	2	0	1
x4	0	2	1	-	1	1	1	2
x5	1	1	2	1	-	0	2	1
x6	1	1	2	1	0	-	2	1
x7	1	1	0	1	2	2	-	1
x8	2	0	1	2	1	1	1	-

Table 1: Hamming distance between observations

Thus with  $k = 5$ , and a leave-one-out evaluation schema, we use the closest 5 observations for each, excluding itself, to calculate the estimate using a weighted mode like so:

$$f(x_{new}) \leftarrow \operatorname{argmax}_{c \in \{P, N\}} \sum_i w_i \cdot \delta(c, f(x_i))$$

$$w_i = \begin{cases} \frac{1}{d(x_{new}, x_i)} & \text{if } x_{new} \neq x_i \\ 1 & \text{else} \end{cases}$$

In this case, because the relevant observations all have distances of either 0 or 1, the weight of each is the same:

	P				N						
	x1	x2	x3	x4	x5	x6	x7	x8	P	N	$f(x_{new})$
x1	-	-	1	0	1	1	1	-	2	3	N
x2	-	-	1	-	1	1	1	0	1	4	N
x3	1	1	-	1	-	-	0	1	3	2	P
x4	0	-	1	-	1	1	1	-	2	3	N
x5	1	1	-	1	-	0	-	1	3	2	P
x6	1	1	-	1	0	-	-	1	3	2	P
x7	1	1	0	1	-	-	-	1	4	1	P
x8	-	0	1	-	1	1	1	-	2	3	N

Table 2: leave-one-out evaluation kNN classifications

Now the confusion matrix:

	P	N
P	1	3
N	3	1

To calculate the F1-Measure we now need Precision and Recall:

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{1}{4}$$

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{1}{4}$$

**I.1 Solution:**

$$\text{F1 Score} = \frac{2}{\frac{1}{P} + \frac{1}{R}} = \frac{2}{\frac{1}{4} + \frac{1}{4}} = \frac{1}{2}$$

2. An example of a distance and  $k$  that will improve the F1-Measure by three fold is the following:

**I.2 Solution:**

$$d(x_1, x_2) = 2 \cdot d_{y_1}(x_1, x_2) + d_{y_2}(x_1, x_2)$$

$$k = 3$$

Where  $d_{y_j}(x_1, x_2)$  is the Hamming distance between  $x_1$  and  $x_2$  considering only the variable  $y_j$ .

To demonstrate the same process as previous but with the new distance measure and  $k$  value:

	P				N			
	x1	x2	x3	x4	x5	x6	x7	x8
x1	-	3	1	0	2	2	1	2
x2	3	-	2	3	1	1	2	0
x3	1	2	-	1	3	3	0	2
x4	0	3	1	-	2	2	1	2
x5	2	1	3	2	-	0	3	1
x6	2	1	3	2	0	-	3	1
x7	1	2	0	1	3	3	-	2
x8	3	0	2	3	1	1	2	-

Table 3: New distance between observations

	P				N				P	N	$f(x_{new})$
	x1	x2	x3	x4	x5	x6	x7	x8			
x1	-	-	1	0	-	-	1	-	2	1	P
x2	-	-	-	-	1	1	-	0	0	3	N
x3	1	-	-	1	-	-	0	-	2	1	P
x4	0	-	1	-	-	-	1	-	2	1	P
x5	-	1	-	-	-	0	-	1	1	2	N
x6	-	1	-	-	0	-	-	1	1	2	N
x7	1	-	0	1	-	-	-	-	3	0	P
x8	-	0	-	-	1	1	-	-	1	2	N

Table 4: leave-one-out evaluation with new metric

This metric performs better in this data set as can be seen in the confusion matrix:

	P	N
P	3	1
N	1	3

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{3}{4}$$

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{3}{4}$$

$$\text{F1 Score} = \frac{2}{\frac{1}{P} + \frac{1}{R}} = \frac{2}{\frac{4}{3} + \frac{4}{3}} = \frac{3}{4}$$

### 3. (a) Dataset:

$x$	$y_1$	$y_2$	$y_3$	Class
1	A	0	1.1	P
2	B	1	0.8	P
3	A	1	0.5	P
4	A	0	0.9	P
5	B	0	1.0	N
6	B	0	0.9	N
7	A	1	1.2	N
8	B	1	0.9	N
9	B	0	0.8	P

Table 5: Observed Values

### (b) Priors:

- For class Positive (P):

$$p(P) = \frac{5}{9}$$

- For class Negative (N):

$$p(N) = \frac{4}{9}$$

(c) **Class-conditional Probabilities:**

- Calculate the probabilities of the variable set  $\{y_1, y_2\}$  given each class.
- The values are calculated as follows:

$$p(y_1 = A, y_2 = 0) = \frac{2}{9}$$

$$p(y_1 = A, y_2 = 1) = \frac{2}{9}$$

$$p(y_1 = B, y_2 = 0) = \frac{2}{9}$$

$$p(y_1 = B, y_2 = 1) = \frac{3}{9}$$

$$p(y_1 = A, y_2 = 0|P) = \frac{2}{5}$$

$$p(y_1 = A, y_2 = 1|P) = \frac{1}{5}$$

$$p(y_1 = B, y_2 = 0|P) = \frac{1}{5}$$

$$p(y_1 = B, y_2 = 1|P) = \frac{1}{5}$$

$$p(y_1 = A, y_2 = 0|N) = 0$$

$$p(y_1 = A, y_2 = 1|N) = \frac{1}{4}$$

$$p(y_1 = B, y_2 = 0|N) = \frac{2}{4}$$

$$p(y_1 = B, y_2 = 1|N) = \frac{1}{4}$$

(d) **Mean and Standard Deviation of  $y_3$ :**

- For all observations:

$$\begin{aligned}\mu_{y_3} &= \frac{1.1 + 0.8 + 0.5 + 0.9 + 0.8 + 1.0 + 0.9 + 1.2 + 0.9}{9} \\ &= 0.9\end{aligned}$$

$$\begin{aligned}\sigma_{y_3} &= \sqrt{\frac{(1.1 - 0.9)^2 + (0.8 - 0.9)^2 + (0.5 - 0.9)^2 + (0.9 - 0.9)^2 + \dots}{9}} \\ &\approx 0.2\end{aligned}$$

- For Positive (P):

$$\mu_{y_3,P} = \frac{1.1 + 0.8 + 0.5 + 0.9 + 0.8}{5} = 0.82$$

$$\sigma_{y_3,P} = \sqrt{\frac{(1.1 - 0.82)^2 + (0.8 - 0.82)^2 + (0.5 - 0.82)^2 + \dots}{5}}$$

$$\approx 0.217$$

- For Negative (N):

$$\mu_{y_3,N} = \frac{1.0 + 0.9 + 1.2 + 0.9}{4} = 1.0$$

$$\sigma_{y_3,N} = \sqrt{\frac{(1.0 - 1.0)^2 + (0.9 - 1.0)^2 + (1.2 - 1.0)^2 + (0.9 - 1.0)^2}{4}}$$

$$\approx 0.1414$$

(e) **Prediction of Class:**

- To predict the class of a new observation  $(y_1, y_2, y_3)$ , we calculate the probability for both classes (Positive and Negative) and choose the class with the higher probability:

$$\text{Predicted Class} = \underset{h}{\operatorname{argmax}} p(h|y_1, y_2, y_3)$$

$$\text{where } p(h|y_1, y_2, y_3) = \frac{p(y_1, y_2, y_3|h) \cdot p(h)}{p(y_1, y_2, y_3)}$$

$$= \frac{p(y_1, y_2|h) \cdot p(y_3|h) \cdot p(h)}{p(y_1, y_2) \cdot p(y_3)}$$

$$\text{where } p(y_3|h) = \frac{1}{\sigma_h \sqrt{2\pi}} \exp\left(-\frac{(y_3 - \mu_h)^2}{2\sigma_h^2}\right)$$

$$\text{and } p(y_3) = \frac{1}{0.2\sqrt{2\pi}} \exp\left(-\frac{(y_3 - 0.9)^2}{2 \cdot 0.2^2}\right)$$

4. Under a MAP assumption we do not need to calculate the denominator, thus:

$$\text{Predicted Class} = \underset{h}{\operatorname{argmax}} \{p(y_1, y_2|h) \cdot p(y_3|h) \cdot p(h)\}$$

(a) For observation (A, 1, 0.8):

For class  $P$ :

$$\begin{aligned}
p(y_3 = 0.8|P) &= \frac{1}{0.217\sqrt{2\pi}} \exp\left(-\frac{(0.8 - 0.82)^2}{2 \cdot 0.217^2}\right) \\
&= 1.83 \\
p(y_3 = 0.8) &= \frac{1}{0.2\sqrt{2\pi}} \exp\left(-\frac{(0.8 - 0.9)^2}{2 \cdot 0.2^2}\right) \\
&= 1.76 \\
p(P) \cdot p(y_1 = A, y_2 = 1, y_3 = 0.8|P) &= \frac{5}{9} \cdot \frac{1}{5} \cdot 1.83 \\
&\approx 0.203
\end{aligned}$$

For class  $N$ :

$$\begin{aligned}
p(y_3 = 0.8|N) &= \frac{1}{0.1414\sqrt{2\pi}} \exp\left(-\frac{(0.8 - 1.0)^2}{2 \cdot 0.1414^2}\right) \\
&= 1.038 \\
p(N) \cdot p(y_1 = A, y_2 = 1, y_3 = 0.8|N) &= \frac{4}{9} \cdot \frac{1}{4} \cdot 1.038 \\
&\approx 0.115
\end{aligned}$$

**Since  $0.203 > 0.115$ , the predicted class is  $P$ .**

(b) For observation (B, 1, 1):

For class  $P$ :

$$\begin{aligned}
p(y_3 = 1|P) &= \frac{1}{0.217\sqrt{2\pi}} \exp\left(-\frac{(1 - 0.82)^2}{2 \cdot 0.217^2}\right) \\
&= 1.304 \\
p(y_3 = 1) &= \frac{1}{0.2\sqrt{2\pi}} \exp\left(-\frac{(1 - 0.9)^2}{2 \cdot 0.2^2}\right) \\
&= 1.76 \\
p(P) \cdot p(y_1 = B, y_2 = 1, y_3 = 1|P) &= \frac{5}{9} \cdot \frac{1}{5} \cdot 1.304 \\
&\approx 0.145
\end{aligned}$$

For class N:

$$\begin{aligned}
 p(y_3 = 1|N) &= \frac{1}{0.1414\sqrt{2\pi}} \exp\left(-\frac{(1-1.0)^2}{2 \cdot 0.1414^2}\right) \\
 &= 2.82 \\
 p(N) \cdot p(y_1 = B, y_2 = 1, y_3 = 1|N) &= \frac{4}{9} \cdot \frac{1}{4} \cdot 2.82 \\
 &\approx 0.313
 \end{aligned}$$

**Since  $0.145 < 0.313$ , the predicted class is N.**

(c) For observation (B, 0, 0.9):

For class P:

$$\begin{aligned}
 p(y_3 = 0.9|P) &= \frac{1}{0.217\sqrt{2\pi}} \exp\left(-\frac{(0.9-0.82)^2}{2 \cdot 0.217^2}\right) \\
 &= 1.72 \\
 p(y_3 = 0.9) &= \frac{1}{0.2\sqrt{2\pi}} \exp\left(-\frac{(0.9-0.9)^2}{2 \cdot 0.2^2}\right) \\
 &= 1.99 \\
 p(P) \cdot p(y_1 = B, y_2 = 0, y_3 = 0.9|P) &= \frac{5}{9} \cdot \frac{1}{5} \cdot 1.72 \\
 &\approx 0.191
 \end{aligned}$$

For class N:

$$\begin{aligned}
 p(y_3 = 0.9|N) &= \frac{1}{0.1414\sqrt{2\pi}} \exp\left(-\frac{(0.9-1.0)^2}{2 \cdot 0.1414^2}\right) \\
 &= 2.20 \\
 p(N) \cdot p(y_1 = B, y_2 = 0, y_3 = 0.9|N) &= \frac{4}{9} \cdot \frac{2}{4} \cdot 2.20 \\
 &\approx 0.489
 \end{aligned}$$

**Since  $0.191 < 0.489$ , the predicted class is N.**

**I.4 Solution:**

	(A, 1, 0.8)	(B, 1, 1)	(B, 0, 0.9)
Class	P	N	N



5. Class-conditional frequency of each word in the training vocabulary.

c	"Amazing"	"run"	"I"	"like"	"it"	"Too"	"tired"	"bad"	$N_c$	$V$
P	1	1	1	1	1	0	0	0	5	8
N	0	1	0	0	0	1	1	1	4	

Under a ML assumption, for the word  $w$ :

$$\begin{aligned}
 \text{Predicted Class} &= \underset{c}{\operatorname{argmax}} \{p(c|w)\} \\
 &= \underset{c}{\operatorname{argmax}} \left\{ \frac{p(w|c) \cdot p(c)}{p(w)} \right\} \\
 &= \underset{c}{\operatorname{argmax}} \left\{ \prod_i^i p(t_i|c) \right\}
 \end{aligned}$$

	"I"	"like"	"to"	"run"	$\prod_i^i p(t_i c)$
$\text{freq}(t_i P)$	1	1	0	1	$\frac{2^3 \cdot 1}{13^4} = 0.000280$
$p(t_i P)$	$\frac{1+1}{5+8}$	$\frac{1+1}{5+8}$	$\frac{0+1}{5+8}$	$\frac{1+1}{5+8}$	
$\text{freq}(t_i N)$	0	0	0	1	$\frac{2 \cdot 1^3}{12^4} = 0.000096$
$p(t_i P)$	$\frac{0+1}{4+8}$	$\frac{0+1}{4+8}$	$\frac{0+1}{4+8}$	$\frac{1+1}{4+8}$	

Since  $0.000280 > 0.000096$ , the predicted class is P.

**I.5 Solution:**

Since  $0.000280 > 0.000096$ , the predicted class is P.

## Part II: Programming

1. Solution to the programming questions here.

**End note:** do not forget to also submit your Jupyter notebook