

Loss and risk

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Exercise 1

We consider a tiny data set with 10 observations $(\mathbf{x}_i, y_i)_{1 \leq i \leq 10}$, with $\mathbf{x}_i \in \mathcal{X}$ et $y_i \in \{-1, 1\}$. Using different machine learning algorithms, two models are built from this data set: g_1 and g_2 . The outputs of the models on the learning data set are given by the following table:

$\mathbf{x}_i$	$g_1(\mathbf{x}_i)$	$g_2(\mathbf{x}_i)$	y_i
$\mathbf{x}_1$	1	1	1
$\mathbf{x}_2$	1	-1	1
$\mathbf{x}_3$	-1	1	1
$\mathbf{x}_4$	1	-1	1
$\mathbf{x}_5$	1	-1	1
$\mathbf{x}_6$	1	-1	-1
$\mathbf{x}_7$	-1	-1	-1
$\mathbf{x}_8$	-1	-1	-1
$\mathbf{x}_9$	-1	1	-1
$\mathbf{x}_{10}$	1	-1	-1

Question 1 Compute the confusion matrices of both models on the learning set.

Solution

g_1			
	-1	1	
-1	3	1	
1	2	4	

g_2			
	-1	1	
-1	4	3	
1	1	2	

Question 2 We use the loss function l_1 given by:

$l_1(p, t)$	$t = -1$	$t = 1$
$p = -1$	0	1
$p = 1$	3	0

where p is the predicted value and t the true value. Compute the empirical risk of both models on the learning set for l_1 .

Solution

The empirical risk for g_1 is 0.7 while it is 0.6 for g_2 .

Question 3 Determine the best model based on the available information using the loss function $l_0(p, t) = \mathbf{1}_{p \neq t}$.

Solution

We have only access to a data set and thus we need to rely on the empirical risk. The empirical risk of g_1 for l_0 is 0.3 while it is 0.4 for g_2 . The best model is therefore g_1 . However, this ranking as well as the performances might be misleading as we are using the same data set both to train the models and to evaluate them.

Exercise 2

In this exercise, we study a classification problem in which the target variable $\mathbf{Y}$ can take three different values in $\mathcal{Y} = \{A, B, C\}$. From a learning set $\mathcal{D}$, two models have been constructed g_1 and g_2 . Their predictions on a new set $\mathcal{D}'$ are summarized by the following confusion matrices (we use the convention that the predicted values are in rows while the true values are in columns):

g_1				g_2			
	A	B	C		A	B	C
A	44	0	0	A	44	4	5
B	5	62	1	B	2	64	3
C	1	8	54	C	4	2	47

Question 1 Using the confusion matrices, compute an estimation of the distribution of $\mathbf{Y}$, i.e. of the probabilities $\mathbb{P}(\mathbf{Y} = \mathbf{y})$ for $\mathbf{y} \in \mathcal{Y}$.

Solution

One simply needs to compute the frequencies of three possible values of $\mathbf{Y}$. This is done by summing the values by columns in either of the confusion matrices and then by dividing the quantities by the total number of examples. This gives:

	A	B	C
1	0.29	0.40	0.31

Question 2 What minimal consistency checks between $\mathcal{D}$ and $\mathcal{D}'$ should be done?

Solution

One should verify that the empirical distributions of $\mathbf{Y}$ are comparable on both sets.

Question 3 Compute the accuracy of each model on $\mathcal{D}'$ (the accuracy is the percentage of correct classification).

Solution

The accuracy is computed by summing the diagonal terms and dividing them by the total number of examples. This gives for g_1 0.9142857 and for g_2 0.8857143.

Question 4 Determine the best model between g_1 and g_2 according to the loss function $l_0(p, t) = \mathbf{1}_{p \neq t}$ using the empirical risk on $\mathcal{D}'$.

Solution

The best model is here the one with the largest accuracy as we are using the binary loss function. Thus the best model is g_1 .

Question 5 Is the selected model the best one according to the risk associated to l_0 ?

Solution

As the model is selected on a validation set, we can expect it to be better than the other model according to the true risk and not only the empirical risk.

Question 6 We define a new loss function l_2 as follows:

$l_2(p,t)$		t		
		A	B	C
p	A	0	2	1
	B	1	0	1
	C	2	1	0

We use the convention that p is the predicted value and t the true value. Compute the empirical risk of each model according to this loss function on $\mathcal{D}'$.

Solution

This is again a simple calculation. One can compute the term by term product of the loss matrix and of the confusion matrix, sum the obtained values and divide them by the total number of examples.

We get g_1 0.0914286 and for g_2 0.16. Therefore g_1 is the best model for the loss function l_2 .