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# MACHINE LEARNING AND PATTERN RECOGNITION

Project task

## Laboratory 2 – Loading and visualization

1. For each feature, both classes exhibit a unimodal distribution with Normal shape, and they overlap in the central part of their domain:
   * the mean values are the same (approximately 0) for both features and their respective classes.
   * the variances are different:
     + approximately 0.6 for the fake class of feature 1 and the genuine class of feature 2.
     + approximately 1.4 for the genuine class of feature 1 and the fake class of feature 2.

We observe that, for each feature, the class with the lower variance exhibits the highest modal frequency (peak value).

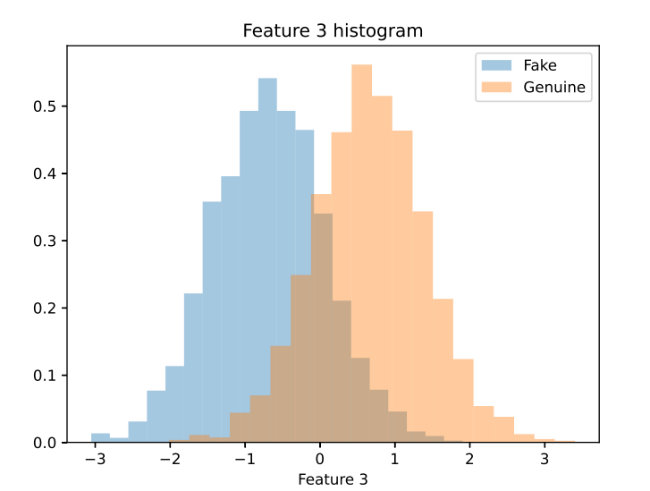
Immagine che contiene diagramma, schermata, testo, Diagramma

Descrizione generata automaticamenteImmagine che contiene diagramma, schermata

Descrizione generata automaticamente

1. For each feature, both classes demonstrate a unimodal distribution with Normal shape, and they overlap on their respective sides; for each pair of classes within each feature:
   * the mean values are opposite but nearly equal in magnitude (between 0.6 and 0.7).
   * the variances are nearly equal (between 0.5 and 0.6).

We observe that, for each feature, the classes display the similar modal frequencies.

Immagine che contiene diagramma, testo, schermata, Diagramma

Descrizione generata automaticamente

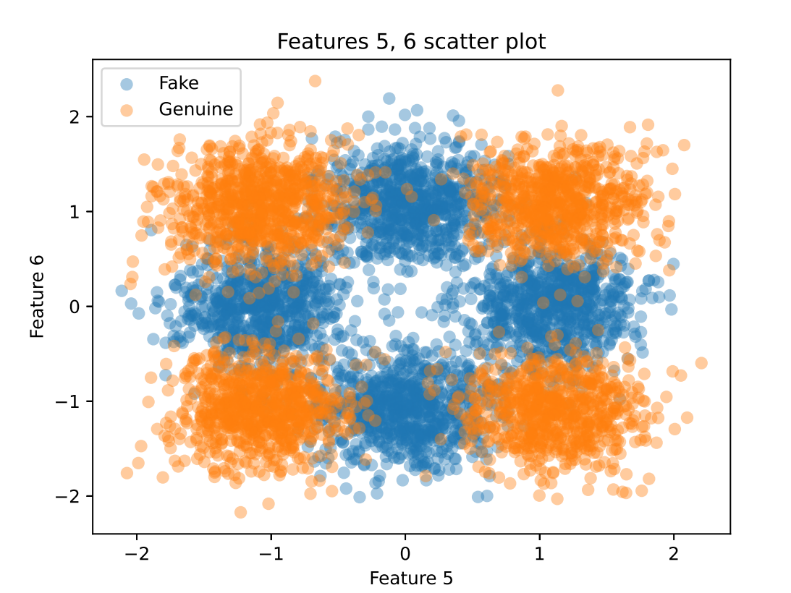
1. For each feature, the fake class displays a unimodal distribution, while the genuine class exhibits a bimodal distribution:
   * for the fake class, the modal values are opposite.
   * for the genuine class, the modal value is approximately 0.

We observe that they overlap around the modal values of the fake class distribution, while the overlapping is minimal in the central part of the domain.

Immagine che contiene testo, diagramma, schermata, Diagramma

Descrizione generata automaticamenteImmagine che contiene testo, diagramma, schermata, Diagramma

Descrizione generata automaticamenteFurthermore, the scatter plots highlight the presence of four clusters for each class.



## Laboratory 3 – Dimensionality reduction

1. By applying PCA, we get these histograms of the six different projected features, in descending order of explained variance:Immagine che contiene testo, schermata, diagramma, Diagramma

   Descrizione generata automaticamenteImmagine che contiene testo, diagramma, schermata, Diagramma

   Descrizione generata automaticamenteImmagine che contiene testo, diagramma, schermata, mappa

   Descrizione generata automaticamenteImmagine che contiene testo, schermata, diagramma, Diagramma

   Descrizione generata automaticamenteImmagine che contiene schermata, diagramma, testo, Diagramma

   Descrizione generata automaticamenteImmagine che contiene schermata, diagramma, Diagramma, testo

   Descrizione generata automaticamente

We observe that these dimensions still present histograms with a significant overlapping, except for the first one, where the class distribution are more distinguishable. Moreover, these plots show that, despite the strong overlapping, all the features have a Gaussian distribution, which could lead to an advantage in classification stage.

The scatterplots do not highlight the presence of clusters among reduced features, differently by some of the original ones.

1. By applying 1-dimensional LDA, we get the following histogram, which refers to the class distribution of the projected feature:

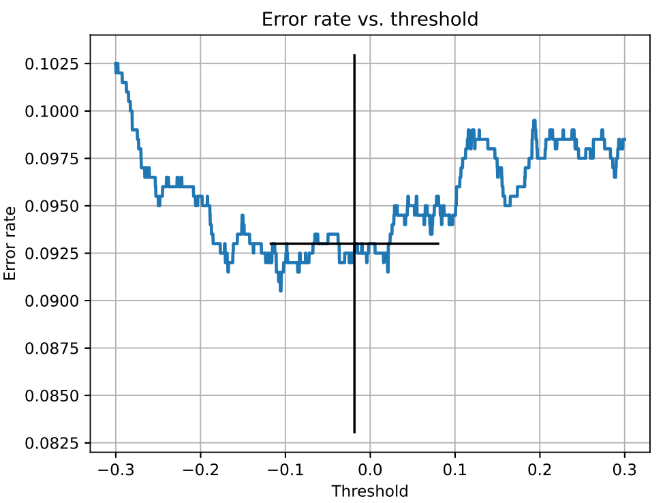
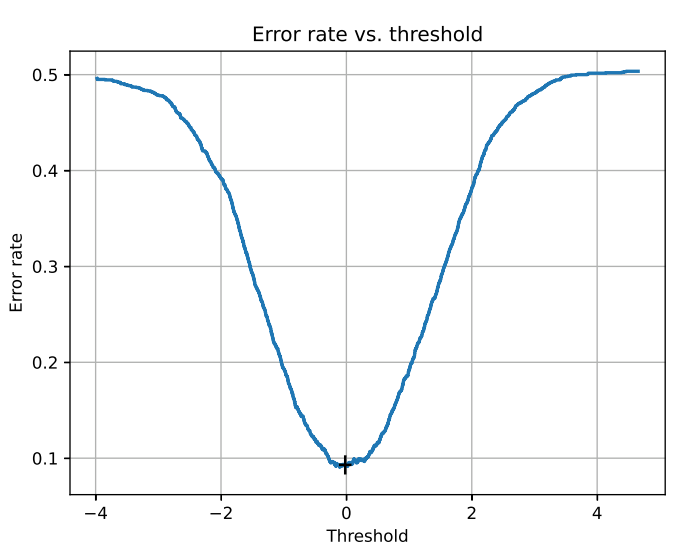
Immagine che contiene testo, schermata, diagramma, Diagramma

Descrizione generata automaticamente

We can observe that a significant overlapping is still present, but:

* This overlapping is less than the one observed in the original features: it’s comparable with the one obtained in the first PCA feature;
* both the class distributions are bell-shaped, as after applying PCA.

thus, the LDA direction is better than the original features and it’s more suitable to be used in a classification task.

1. By applying LDA as a classifier, the dataset is split randomly into training and validation set, with a dimension of 2/3 and 1/3 with respect to the original dataset, respectively. The threshold is computed as the mean of the mean values per class, working only on the training set: its value is about -0.02, as it’s possible to notice in the plots at point 4. The error rate obtained is 0.093 (9.3 %): the accuracy is greater than 90%, thus the classifier could be considered as a good one, in particular if we consider its simplicity.
2. Changing the threshold in a wide range, delimited by the minimum and maximum value in the validation set with a step of about 10-4; the goal is to find the value that minimizes the error rate, just by performing the prediction stage with different values of the threshold. The results are showed in the following plots:

The right plot offers a global view: we can observe that the error rate has a minimum around a point (denoted by the black cross), which represents the optimal value of the threshold; it is not far from the computed one at the previous point. In fact, by zooming in (left plot), we can notice that the minimum value for the error rate is about 0.09 (9 %) and it corresponds to a threshold value near to -0.1, while the computed one is about -0.02: this is coherent with the error rate obtained as the previous point (0.093), which is near to the optimal one.

Therefore, the accuracy can be improved by a little quantity, but the error rate computed at the previous point is higher than the minimum one by less than 1%.

1. Applying PCA as a preprocessing stage means to:

* Select the number of PCA dimensions *m*, to keep after PCA transformation; in particular, the *m* values that explain the higher variance will be kept;
* Apply 1-dimensional LDA on the dataset, but projected over the *m* PCA features;
* Use LDA as a classifier, comparing the results obtained for different values of *m*.

This task has been implemented by iterating over valid (and meaningful) values of *m*, such as from 2 to 5 (included):

* with *m* = 1 LDA would become irrelevant, since it would not perform a dimensionality reduction;
* with *m* = 6 PCA would become irrelevant, since it would not perform a dimensionality reduction, but only a projection over other directions than the original ones.

The results obtained are the following:

|  |  |  |
| --- | --- | --- |
| PCA dimensions (*m*) | Error rate | Error rate (%) |
| 5 | 0.0930 | 9.30 |
| 4 | 0.0925 | 9.25 |
| 3 | 0.0925 | 9.25 |
| 2 | 0.0895 | 8.95 |

Therefore, we can observe that PCA preprocessing is beneficial for LDA classification in almost all cases, with an accuracy improvement for each value of *m*, except for 5. Moreover, the optimal configuration consists in performing a PCA preprocessing by selecting the two projected directions with the higher variance, then applying LDA classification on them.

## Laboratory 4 – Gaussian density estimation

To perform Gaussian estimation, original dataset is taken and split in two parts (by class), for each feature; then, the best Gaussian fitting is estimated by computing mean and variance with the maximum likelihood method and then by plotting the corresponding Gaussian distribution over the feature histogram. The results obtained are the following:

Immagine che contiene schermata, testo, diagramma, Diagramma

Descrizione generata automaticamenteImmagine che contiene testo, diagramma, schermata, Diagramma

Descrizione generata automaticamenteImmagine che contiene testo, diagramma, schermata, Diagramma

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Descrizione generata automaticamenteImmagine che contiene testo, schermata, Diagramma, diagramma

Descrizione generata automaticamente

Immagine che contiene schermata, testo, Diagramma, diagramma

Descrizione generata automaticamente