ML and PR Project Report – Part 8

For this part of the laboratory, we are going to analyze a new generative model, that should be able to offer much more fine-tuned descriptions of our data, that being the Gaussian Mixture Model.

# GMM – Standard and Diagonal

Let’s see how our model performs on the Fingerprints dataset, using different amounts of Mixture components, from 1 (merely Gaussian) to 32. To do that we are going to use DCF (minimum and actual) as metric. We are going to train the model using both the standard version, which uses complete covariance matrices, and a lighter one, which uses only diagonal matrices. The application of interest is the usual one with effective prior .

Immagine che contiene schermata, spazio, testo, nero

Descrizione generata automaticamente

For both versions of the model, the best results seems to come when using 8 components.

Surprisingly, the best performing model of all, is the diagonal version, with 8 components. It is not a surprise instead that the performance is improved compared to a simple MVG model, as we did observe that the last two features present 3 modalities each.

The reason for the models with too many components performing worse than the 4, 8, and 16 components ones may depend possibly overfitting. The latter may also be the reason why the diagonal model performs better, since as we had already hypothesized, when seeing a slightly better performance by the Naïve version of the MVG, that the data is not enough to allow a complete model not to become too fitting of the training population.

It may also be interesting to observe that, for the best performing models (e.g. diag with g=8 or 16), actual DCF is really close to the minimum one, meaning that the GMM description is able to yield calibrated scores too.

# Comparison with SVM and LR

The other best performing models we have found so far are **SVM with RBF kernel**, in particular that using and , and **Quadratic Logistic Regression**, with parameter **=0.0031**, with being a parameter promoting more rigid solutions, and C and parameters proportional to regularization ( directly, C inversely). For **GMM** instead, I’ll repeat that the **diagonal** model with is the best one.

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| --- | --- | --- | --- |
|  | **QLogistic** | **SVM** | **GMM** |
| minDCF | 0.243 | 0.182 | 0.1223 |
| actDCF | 0.292\* | 0.423 | 0.1295 |
| difference | +20.2%\* | +232% | +5.8% |

\* The actual DCF at λ=0.0031 is quite high, but QLR has similar minimum DCF results across many other λ values, and for the lower values of lambda, actual and minimum DCF almost overlap

The best performing model is the GMM, and it also seems to be decently well calibrated. Quadratic Logistic Regression is the worst of the three, and SVM is the most poorly calibrated one.

If we try the model on a wider range of applications instead, using Bayes Error Plots, we get the following results.

Immagine che contiene testo, diagramma, linea, Diagramma

Descrizione generata automaticamente

The ranking in terms of minimum DCF is consistent with the results of the previous table. The actual DCF follows the same pattern for low values in terms of prior log-odds magnitude , but soon the SVM shows signs of poorer calibration than the QLR model. GMM keeps the first place throughout all analyzed applications, and shows that it is able to maintain actual DCF values close to the minimum ones for a much wider range of priors than the other two models.

SVM has especially bad calibration, as the actual DCF deviates real quick from the minimum one.

# Conclusion

GMM seems to be the best model seen so far, both in terms of actual performance and good calibration. SVM is especially poorly calibrated.