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| GENDER SPEECH RECOGNITION  REPORT |
|  |
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Premises

# Task

The goal of the application is to build a model that best fits for the gender classification. We will discuss how they perform for the problem we have chosen, explaining pros and cons.

# Dataset

The dataset consists of synthetic speaker embeddings that represent the acoustic characteristics of a spoken utterance. Each row corresponds to a different speaker, and contains 12 features followed by the gender label (1 for female, 0 for male). The features do not have any particular interpretation. Speakers belong to four different age groups. The age information, however, is not available.

The training set consists of 3000 samples per class, whereas the test set contains 2000 samples per class.

Dimensionality Reduction Techniques

We have performed feature extraction within dimensionality reduction using PCA.

# PCA

In this part we’ve tested PCA for reducing the features, and we’ve empirically concluded that the best number of those to save is m=8. In fact, we can check that the error rate in the classification methods is quite similar for increasing values of m.

When we generate a plot scatter with this value, we can check that there are four different areas, one for each group age:

[METTERE FOTO]

# LDA

Text text …

Classification

# What we use…

* Generative models – Linear and Quadratic Classifiers
  + Multivariate Gaussian Classifier (**MGC**)
  + MGC + Naïve Bayes Classifier
  + MGC + Tied Covariance
  + MGC + Naïve Bayes Classifier with Tied Covariance
* Linear regression

# Expectation

Since this is the …, this should be the best for our goal..

# Results

Tables with results and combinations with pca and lda

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Classifier | Raw | PCA | LDA | PCA + LDA | PCA |
| MGC | 2.75% |  |  |  |  |
| MGC - Naïve | 29.5% |  |  |  |  |
| MGC - TC | 2.775% |  |  |  |  |
| MGC - Naïve + TC | 29.4% |  |  |  |  |

Table 1 - Error rates for Generative Models Classifiers and Dimensionality Reduction Techniques

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| λ | 0 | 0.000001 | 0.001 | 1 | 3 | Tied Gau |
| Raw | 2.75% | 2.75% | 2.725% | 3.7% | 5.325% | 2.775% |
| PCA |  |  |  |  |  |  |
| PCA |  |  |  |  |  |  |
| PCA + LDA |  |  |  |  |  |  |

Table 2 - Error rates for Linear Regression and Dimensionality Reduction Techniques and Comparison with Tied Cov

# Summary and Considerations

Dato che i risultati dei Naive sono scarsi, allora le features devono essere molto correlate tra di loro.

Validation

# K-Fold

Text Text

# Leave-One-Out

Text Text

# Holdout

Text Text