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Technical Note

Some Remarks on the Gaussian Discriminant

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MASSACHUSETTS INSTITUTE OF TECHNOLOGY

LINCOLN LABORATORY

SOME REMARKS ON THE GAUSSIAN DISCRIMINANT

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ABSTRACT

We comment on the performance of the Gaussian discriminant function with (possibly) non-Gaussian underlying distributions. An asymptotic expression for the probability of error for the Gaussian case is given with a formal convergence proof.

I. INTRODUCTION

For many practical problems in two class pattern recognition, one has (reliable estimates of) the first two moments of each class (mean vectors in R^n - M_1, M_2 and covariance matrices -Σ_1, Σ_2). Whether or not the underlying distributions are indeed Gaussian, one proceeds to apply the standard Gaussian hypothesis test to classify new data. More precisely, one uses the Gaussian discriminant function $h(X) = \log \frac{p_2(X)}{p_1(X)}$, where p_1, p_2 are multivariate normal with the same first two moments as the underlying distributions. Applying an affine transformation to our problem (which has no effect on the discriminant h) that simultaneously diagonalizes Σ_1 and Σ_2 ($\Sigma_1 \to I$, $\Sigma_2 \to \Lambda$, $M_2 \to \vec{0}$, $M_1 \to (d_1, d_2, .., d_n)$ with $d_\ell \geq 0$), we have

$$(1) \quad h(X) = \tfrac{1}{2} \sum_{\ell=1}^{n} \left[(x_\ell - d_\ell)^2 - x_\ell^2/\lambda_\ell + \ln(1/\lambda_\ell) \right]$$

In this correspondence, we first present some elementary inequalities in h, valid regardless of the class distributions; and then we demonstrate the asymptotic result:

$$(2) \quad P_{error} \approx \frac{1}{\sqrt{2\pi}} \int_{\frac{\sqrt{J}}{2}}^{\infty} e^{-\frac{1}{2}x^2}\, dx \quad \begin{pmatrix}\text{with } J \text{ the divergence} \\ \text{of } p_1,\ p_2\end{pmatrix}$$

for the case of equal priors, Gaussian distributions, and all λ_ℓ close to 1. We note that the above does not follow from the elementary fact that, for fixed n, $h(X) \to$ a linear function as all $\lambda_\ell \to 1$; for all λ_ℓ may be close to 1 but the quadratic part of $h = \frac{1}{2}\sum_1^n x_\ell^2 \left(1-\frac{1}{\lambda_\ell}\right)$ may not approach 0 if n becomes large.

II. THE GAUSSIAN DISCRIMINANT FOR ARBITRARY CLASS DISTRIBUTIONS

Calculating the first moments of h under each hypothesis, we have, regardless of the underlying distributions:

$$(3) \quad E_1(h) = \frac{1}{2}\sum_{\ell=1}^{n}\left[\left(1-\frac{1}{\lambda_\ell}\right) - \frac{d_\ell^2}{\lambda_\ell} + \ln(1/\lambda_\ell)\right]$$

$$(4) \quad E_2(h) = \frac{1}{2}\sum_{\ell=1}^{n}\left[(\lambda_\ell-1) + d_\ell^2 + \ln(1/\lambda_\ell)\right]$$

Since $Z-1 + \ln(1/Z) \geq 0$ for all $Z > 0$, we see immediately that

$$(5) \quad E_2(h) \geq \frac{1}{2}\sum_1^n d_\ell^2 = \frac{1}{2} D^2 .$$

Noting that the maximum value of $f(Z) = 1-\frac{1}{Z} - \frac{\gamma^2}{Z} + \ln(1/Z)$ for $Z > 0$ occurs at $Z = 1+\gamma^2$, we have $f(Z) \leq 1 - \frac{1}{1+\gamma^2} + \ln\left(\frac{1}{1+\gamma^2}\right) - \frac{\gamma^2}{1+\gamma^2} \leq -\frac{\gamma^2}{1+\gamma^2}$. Hence

$$(6) \quad E_1(h) \le -\tfrac{1}{2} \sum_{1}^{n} d_\ell^2/1+d_\ell^2$$

which is $\approx -\tfrac{1}{2}D^2$ if each component d_ℓ is small. Therefore, in many practical problems $E_2(h) - E_1(h) \gtrapprox D^2 = \sum_{1}^{n} d_\ell^2$. D^2 is then a first order measure of the performance of h. If n is large, the λ_ℓ are close to one, the d_ℓ are small, and the sequence of random variables x_ℓ is k dependent for small k, then we could apply the central limit theorem and obtain estimates of the error probability of h by calculating $VAr_1(h)$ and $VAr_2(h)$ from sample data.

III. ASYMPTOTIC APPROXIMATION TO ERROR PROBABILITY

To justify the claim in I, we state and prove the following theorem:

Theorem : Let a sequence of decision problems, with underlying Gaussian distributions described by means D^i, $\vec{0}$ in R^{n_i} and covariances I, Λ^i, be given. Then, if $\max_{i \le \ell \le n_i} |\lambda_\ell^i - 1| \to 0$ as $i \to \infty$,

$$\left| P^i_{error} - \frac{1}{\sqrt{2\pi}} \int_{\frac{\sqrt{J^i}}{2}} e^{-\frac{1}{2}x^2}\, dx \right| \to 0$$

for the equal prior case.

<u>Proof:</u> We shall apply a central limit theorem for arrays of random variables and use the first two moments of h^i to obtain an asymptotic expression for the error probability. Calculating the variances under each hypothesis of h^i, we obtain

$$(7) \quad \mathrm{VAr}_1(h^i) = \tfrac{1}{2}\sum_{1}^{n_i}\left[\left(1-\frac{1}{\lambda_\ell^i}\right)^2 + \frac{2\left(d_\ell^i\right)^2}{\lambda_\ell}\right]$$

$$(8) \quad \mathrm{VAr}_2(h^i) = \tfrac{1}{2}\sum_{1}^{n_i}\left[\left(\lambda_\ell^i-1\right)^2 + 2\lambda_\ell^i \left(d_\ell^i\right)^2\right]$$

Using (3), (4), (7) and (8), and noting by elementary calculus that

$$\frac{\left(1-1/\lambda_\ell^i\right)^2}{1-1/\lambda_\ell^i + \ln\left(1/\lambda_\ell^i\right)} \longrightarrow \frac{-2\left(1-1/\lambda_\ell^i\right)}{\left(\lambda_\ell^i-1\right)} \longrightarrow -2$$

$$\frac{\left(\lambda_\ell^i-1\right)^2}{\lambda_\ell^i-1 + \ln\left(1/\lambda_\ell^i\right)} \longrightarrow \frac{2\left(\lambda_\ell^i-1\right)}{\left(1-\lambda_\ell^i\right)} = +2$$

$$\frac{2\left(d_\ell^i\right)^2}{\lambda_\ell^i} \Bigg/ \frac{-\left(d_\ell^i\right)^2}{\lambda_\ell^i} = -2$$

$$\frac{2\lambda_\ell^i\left(d_\ell^i\right)^2}{\left(d_\ell^i\right)^2} \longrightarrow +2\ ,$$

we have

$$\mathrm{VAr}_1(h^i) \Big/ 2E_1(h^i) \longrightarrow -1$$

and $$\mathrm{VAr}_2(h^i) \Big/ 2E_2(h^i) \longrightarrow +1 \quad .$$

Futhermore

$$-\left(d_\ell^i\right)^2 \Big/ \frac{\left(d_\ell^i\right)^2}{\lambda_\ell^i} \longrightarrow -1$$

and $$\frac{\left(\lambda_\ell^i-1\right) + \ln\left(1/\lambda_\ell^i\right)}{\left(1-\frac{1}{\lambda_\ell^i}\right) + \ln\left(1/\lambda_\ell^i\right)} \longrightarrow \frac{1-1/\lambda_\ell^i}{1/\left(\lambda_\ell^i\right)^2 - 1/\lambda_\ell^i} \longrightarrow -1$$

imply that

$$\frac{E_2(h^i)}{E_1(h^i)} \longrightarrow -1$$

or equivalently

$$E_2(h^i)/J^i \longrightarrow +\tfrac{1}{2}$$

$$E_1(h^i)/J^i \longrightarrow -\tfrac{1}{2} \quad .$$

We now proceed with the main proof. We may assume (by passing to subsequences if necessary) that both J^i and P^i_{error} are convergent sequences (possibly to $+\infty$ in the case of J^i). We divide the argument into several cases:

CASE (1) $J^i \to 0$

It suffices to show that $P^i_{error} \to \frac{1}{2}$. This is actually true in general. Consider any 2 positive density functions, p,q , on some probability space. Then, if for some real $\delta > 0$, there is no measureable set whose q measure is greater than δ and such that on this set $q/p > 1+\delta$, it follows that

$$P_{error} = \frac{1}{2}\left[\int_{q \le p} q + \int_{q>p} p\right] =$$

$$\frac{1}{2}\left[\int_{q\le p} q + \int_{q/p>1+\delta} p + \int_{1<q/p<1+\delta} p\right] \ge$$

$$\frac{1}{2}\left[\int_{q\le p} q + \int_{1<q/p\le 1+\delta} (p/q)\, q\right] >$$

$$\frac{1}{2}\left[\frac{1}{1+\delta}\int_{q\le p} q + \frac{1}{1+\delta}\left(\int_{q/p>1} q - \int_{q/p>1+\delta} q\right)\right]$$

$\ge \frac{1-\delta}{2(1+\delta)}$. Hence if P^i_{error} does not approach $\frac{1}{2}$, such a δ exits. But then the divergence $J^i(p,q)$ =

$$\int_{p\ge q} \ln(p/q)(p-q) + \int_{q>p} \ln(q/p)(q-p)$$

$$\geq \left[\ln(1+\delta)\right] \left[\left(1-\frac{1}{1+\delta}\right)\delta\right] = \frac{\delta^2 \ln(1+\delta)}{1+\delta} > 0 .$$

CASE (2) $J^i \rightarrow J \neq 0$

Let's rewrite

$$h^i(X) = \tfrac{1}{2} \sum_{1}^{n_i} \left[(x_\ell^i)^2 \left[1 - 1/\lambda_\ell^i\right] - 2x_\ell^i \, d_\ell^i \right] + K_i$$

where we reorder the d_ℓ^i such that

$$d_\ell^i \geq d_{\ell+1}^i .$$

Subcase (a) $\sup_i \left(\sum_{1}^{n_i} (d_\ell^i)^2 \right) = +\infty$.

Clearly from (5) $J = +\infty$. Consider the (sub-optimal) discriminants $g^i = \sum_{1}^{n_i} x_\ell^i \, d_\ell^i$. These are normally distributed with means, $\sum_{1}^{n_i} (d_\ell^i)^2$ and 0, and standard deviations, $\sqrt{\sum_{1}^{n_i} (d_\ell^i)^2}$ and $\sqrt{\sum_{1}^{n_i} \lambda_\ell^i \, (d_\ell^i)^2}$. One can then find arbitrarily large i for which g^i has arbitrarily small error probability. Since h^i is optimal, it has arbitrarily small error for these i and hence, $P_{error}^i \rightarrow 0$.

Subcase (b) $\sup_i \left(\sum_1^{n_i} (d_\ell^i)^2 \right) < +\infty$.

We first note that $\mathrm{VAr}(h^i) \to J \neq 0$ under either hypothesis. Let us rewrite $h^i = \frac{1}{2} \sum_1^{\overline{n_i}} \left[(x_\ell^i)^2 \left[1 - 1/\lambda_\ell^i \right] - 2x_\ell^i \, d_\ell^i \right]$

$$+ \frac{1}{2} \sum_{\overline{n_i}+1}^{n_i} \left[(x_\ell^i)^2 \left[1 - 1/\lambda_\ell^i \right] - 2x_\ell^i \, d_\ell^i \right] + K_i = F_1^i + F_2^i + K_i \text{ with}$$

$\overline{n_i}$ chosen such that $\overline{n_i} \to \infty$ but that $\sum_1^{\overline{n_i}} |1 - 1/\lambda_\ell^i| \to 0$. We may now apply a central limit theorem, for instance Corollary 4.2 on page 232 of [1]: F or any $\beta > 0$, either F_2^i has variance $< \beta$, or F_2^i becomes normal in distribution for large i. This follows from the central limit theorem for arrays mentioned above, provided the variances of the terms in the summand of F_2^i become arbitrarily small and this follows if $\sup_i \left\{ d_\ell^i ; \ell > \overline{n_i} \right\} \to 0$. But if this were not the case, $d_{\overline{n_i}+1}^i \geq \gamma > 0$ for infinitely many i and hence, since $\overline{n_i} \to \infty$, $\sum_1^{n_i} (d_\ell^i)^2 \geq \overline{n_i} \, \gamma^2$ contradicts our initial assumption. Further, F_1^i either has variance $< \beta$ or approaches a normal random variable in distribution since its linear part is normal and its nonlinear part has variance approaching 0. Since β was arbitrary, $J > 0$, and F_1^i is independent of F_2^i ; h^i approaches a normal random variable in distribution and we obtain the asymptotic error formula (2).

Finally we note that, in (2), we could replace J by 8B where B is the Bhattacharyya distance. This follows from the simply verified fact that $\frac{8B}{J} \longrightarrow 1$ as all $\lambda_{\ell} \longrightarrow 1$.

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