

# *On a theoretical property of the Bhattacharyya coefficient as a feature evaluation criterion*

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*Abstract:* In the context of evaluation of features in a two-class pattern recognition problem it is shown that, irrespective of the values of the a priori probabilities of the two classes, the maximum difference between the existing lower and upper bounds to Bayesian probability of error in terms of the Bhattacharyya coefficient is approximately equal to 0.2071.

*Key words:* Bhattacharyya coefficient, Bayesian probability of error, pattern recognition, feature evaluation, error bounds.

## 1. Introduction

The Bayesian probability of error ( $P_e$ ) is an optimum measure of effectiveness of a set of features selected for the purpose of pattern recognition. Owing to the difficulty involved in computation (or estimation) of  $P_e$ , various indirect measures of feature effectiveness have been suggested in the past. The Bhattacharyya coefficient ( $\rho$ ), which was originally defined as a measure of overlap between two probability distributions [1], has become a popular feature evaluation criterion in pattern recognition [2-12]. The two main reasons behind the popularity of  $\rho$  as a feature evaluation criterion are that (a) lower and upper bounds to  $P_e$  exist in terms of  $\rho$  [13-14] and that (b) closed-form expressions are available for  $\rho$  in the case of the exponential family of distributions, a few special cases of the family being the Gaussian distribution, the Multinomial distribution and the Poisson distribution [2]. It is worth noting that both the upper and the lower bounds to  $P_e$  in terms of a measure are indicative of how closely the measure approximates  $P_e$ . If the resulting upper bound is sufficiently low, then the pattern recognition system under consideration is

'acceptable'. On the other hand a sufficiently high lower bound leads to a 'rejection' decision. Difference between the upper bound and the lower bound is an indicator of the overall closeness of a measure to  $P_e$ . In this letter it is shown that the maximum difference between the existing upper bound and the Hudimoto lower bound to  $P_e$  in terms of  $\rho$  remains the same for all values of the a priori probabilities and this maximum difference is  $(\sqrt{2} - 1)/2$ .

## 2. Derivation of the span between error bounds

Suppose the a priori probabilities of the two classes  $\omega_1$  and  $\omega_2$  are  $\pi_1$  and  $\pi_2$ , respectively ( $0 < \pi_1, \pi_2 < 1$ ,  $\pi_1 + \pi_2 = 1$ ). Let  $p(x|\omega_1)$  and  $p(x|\omega_2)$  be the class-conditional probability density functions of the feature vector  $X$ , assumed to be continuous, in the two classes  $\omega_1$  and  $\omega_2$ , respectively. Then the Bayesian error probability [15] is given by

$$\rho_e = \int_{\Omega_x} \min[\pi_1 p(x|\omega_1), \pi_2 p(x|\omega_2)] dx \quad (1)$$

and the Bhattacharyya coefficient [1] is defined by

$$\rho = \int_{\Omega_x} [p(x|\omega_1)p(x|\omega_2)]^{1/2} dx \quad (2)$$

where  $\Omega_x$  denotes the sample space of  $X$ .

Clearly,  $0 \leq \rho \leq 1$ .

Hudimoto [13,14] showed that  $P_e$  is bounded above and below by the following relationships:

$$\frac{1}{2} - \frac{1}{2}\sqrt{1 - 4\pi_1\pi_2\rho^2} \leq P_e \leq \sqrt{\pi_1\pi_2}\rho. \quad (3)$$

These are the tightest bounds to  $P_e$  in terms of  $\rho$  available in the literature.

The span between the above upper and lower bounds to  $P_e$  (i.e., the difference between them) is given by

$$\delta = \sqrt{\pi_1\pi_2}\rho - \frac{1}{2} + \frac{1}{2}\sqrt{1 - 4\pi_1\pi_2\rho^2}. \quad (4)$$

In the following theorem the maximum value of  $\delta$  is determined which is found to be independent of the value of  $\pi_1$  (and so  $\pi_2$ ).

**Theorem.** *Whatever be the value of the a priori probability  $\pi_1$ , (i) the maximum value of  $\delta$  is  $\frac{1}{2}(\sqrt{2} - 1)$  and (ii) this maximum can be attained for  $\pi_1$ -values (and so  $\pi_2$ -values) lying inside the interval*

$$\left[ \frac{2 - \sqrt{2}}{4}, \frac{2 + \sqrt{2}}{4} \right].$$

**Proof.** (i) Taking the first derivative of  $\delta$  with respect to  $\rho$  one gets

$$\frac{d\delta}{d\rho} = \sqrt{\pi_1\pi_2} - \frac{2\pi_1\pi_2\rho}{\sqrt{1 - 4\pi_1\pi_2\rho^2}}.$$

Equating the above expression to 0 leads to

$$\rho = \frac{1}{\sqrt{8\pi_1\pi_2}}. \quad (5)$$

The second derivative of  $\delta$  with respect to  $\rho$  is

$$\frac{d^2\delta}{d\rho^2} = -\frac{2\pi_1\pi_2}{(1 - 4\pi_1\pi_2\rho^2)^{3/2}}. \quad (6)$$

It is easy to see that

$$\frac{d^2\delta}{d\rho^2} < 0. \quad (7)$$

Thus, the maximum value of  $\delta$  is attained at the value of  $\rho$  given in equation (5). Substituting this value of  $\rho$  in equation (4) gives,

$$\begin{aligned} \delta_{\max} &= \sqrt{\pi_1\pi_2} \cdot \frac{1}{\sqrt{8\pi_1\pi_2}} - \frac{1}{2} \\ &\quad + \frac{1}{2}\sqrt{1 - 4\pi_1\pi_2 \cdot \frac{1}{8\pi_1\pi_2}} \\ &= \frac{1}{\sqrt{8}} - \frac{1}{2} + \frac{1}{2}\sqrt{1 - \frac{1}{2}} \\ &= \frac{1}{2}(\sqrt{2} - 1). \end{aligned}$$

Hence the first part of the theorem is proved.

(ii) The above mentioned maximum value occurs at

$$\rho = \frac{1}{\sqrt{8\pi_1\pi_2}}.$$

But  $\rho$  is restricted by the condition  $\rho \leq 1$ . Substitution of the above value of  $\rho$  in the inequality  $\rho \leq 1$  leads to the desired result.

In Figures 1 to 4 the  $P_e$  bounds for different values of  $\pi_1$ , namely,  $\pi_1 = 0.500, 0.625, 0.750$  and  $0.875$ , are shown. It can be seen from these figures that the value of  $\rho$ , for which the maximum value of  $\delta$  ( $= \frac{1}{2}(\sqrt{2} - 1) \simeq 0.2071$ ) is attained, gets shifted towards the right with increases in the value of  $\pi_1$ . For values of  $\pi_1 > (2 + \sqrt{2})/4$  the maximum would occur at a value of  $\rho$  outside its range (Figure 4). The same situation would arise for  $\pi_1 < (2 - \sqrt{2})/4$ .

### 3. Conclusion

For all values of the a priori probabilities of the two classes in the range  $(2 - \sqrt{2})/4$  to  $(2 + \sqrt{2})/4$  the maximum difference between the existing tightest lower and upper bounds to  $P_e$  in terms of the Bhattacharyya coefficient ( $\rho$ ) is the same and it is

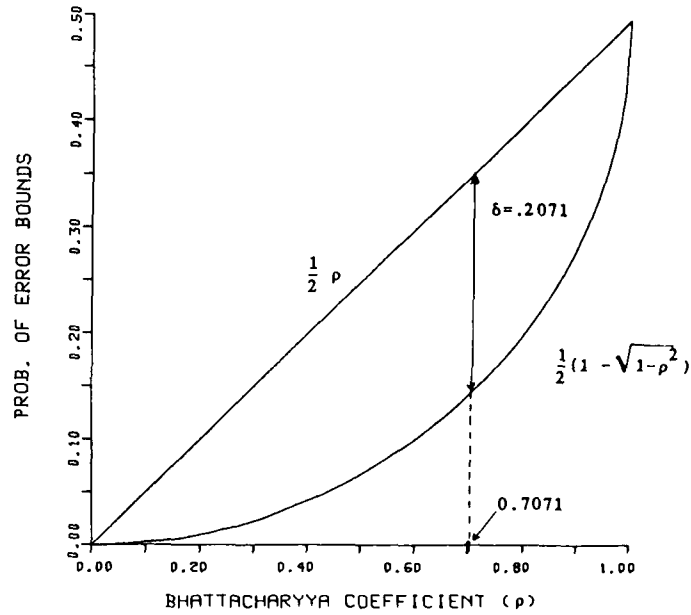


Figure 1. Probability of error ( $P_e$ ) bounds in terms of the Bhattacharyya coefficient ( $\rho$ ) for  $\pi_1 = \pi_2 = 0.500$

equal to  $(\sqrt{2} - 1)/2$ . In other words, irrespective of the values of the two a priori probabilities, the span of the two  $P_e$  bounds in terms of the Bhattacharyya coefficient cannot exceed 0.2071 (approximately).

The span is smaller for a priori probabilities outside the range mentioned above. This result would give further insight into the applicability of Bhattacharyya coefficient as a feature evaluation criterion.

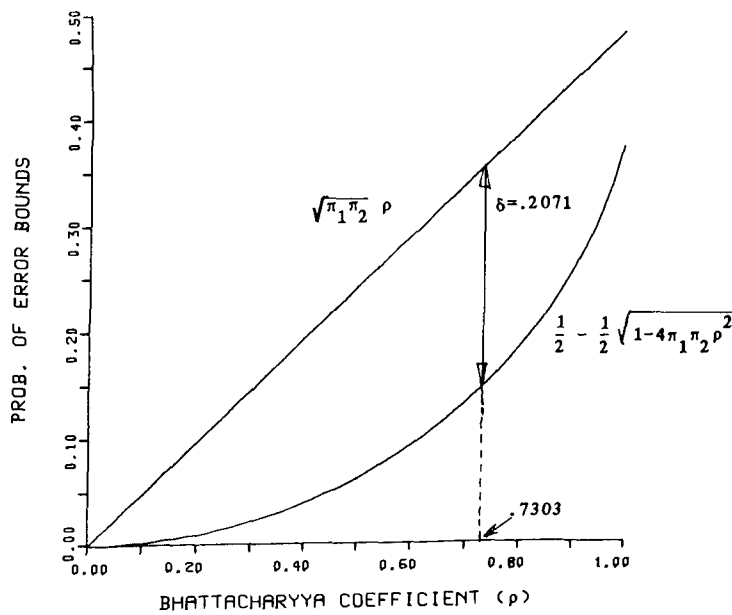


Figure 2. Probability of error ( $P_e$ ) bounds in terms of the Bhattacharyya coefficient ( $\rho$ ) for  $\pi_1 = 0.625, \pi_2 = 0.375$

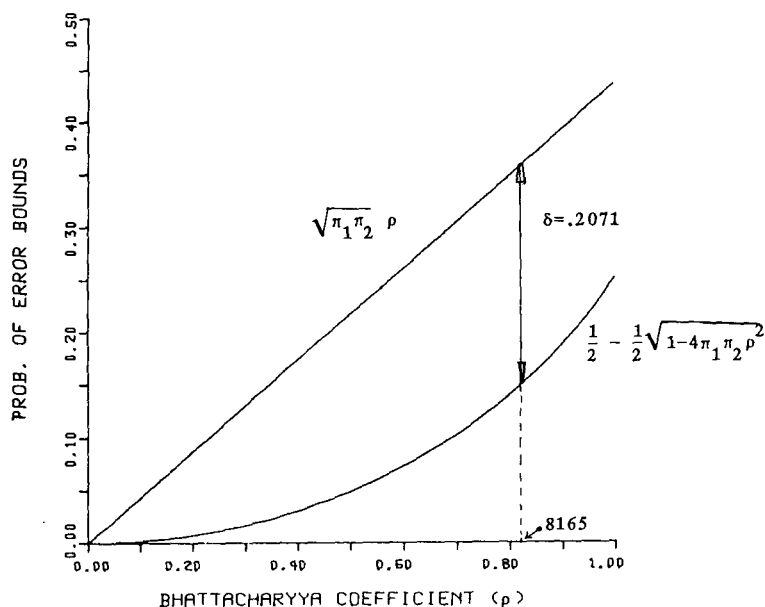


Figure 3. Probability of error ( $P_e$ ) bounds in terms of the Bhattacharyya coefficient ( $\rho$ ) for  $\pi_1 = 0.750$  and  $\pi_2 = 0.250$ .

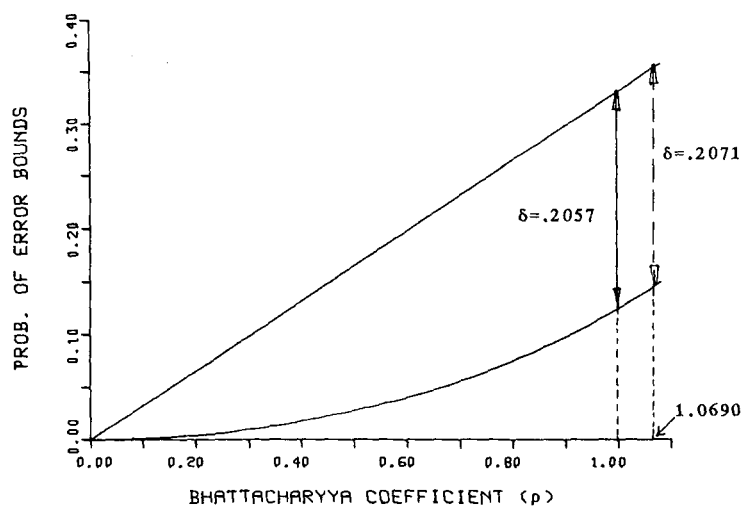


Figure 4. Probability of error ( $P_e$ ) bounds in terms of the Bhattacharyya coefficient ( $\rho$ ) for  $\pi_1 = 0.875$  and  $\pi_2 = 0.125$ .

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