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Erratum

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EFFECTS OF SAMPLE SIZE RATIO ON THE PERFORMANCE OF THE QUADRATIC DISCRIMINANT FUNCTION

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ABSTRACT

This study investigated the performance of the heteroscedastic discriminant function under the non-optimal condition of unbalanced group representation in the populations. The asymptotic performance of the classification function with respect to increased Mahalanobis' distance (under this condition) was considered. Results obtained have shown that the misclassification of observations from the smaller group escalates when the sample size ratio 1:2 is exceeded (for small sample sizes). Results also show more sensitivity to sample size than the distance function when the data set is balanced, while the performance of the function in the classification of the underrepresented group improved by increasing the distance function. More robustness with unbalanced data was also observed with the Quadratic Function than the Linear Discriminant Function.

Keywords: Heteroscedastic, Unbalanced data, Discriminant function, prior probabilities, Misclassification
2000 Mathematics Subject Classification: 62H30, 62C05, 00A72.

INTRODUCTION

In this study we restrict ourselves to the two group classification problem when the covariance structures and mean vectors are unequal. We define two groups R_1 and R_2 with Multivariate Normal density functions $f_1(x)$ and $f_2(x)$ respectively. $R_1 \sim N_p(\mu_1, \Sigma_1)$ and $R_2 \sim N_p(\mu_2, \Sigma_2)$ where $\mu_i \in \Re^{p\times p}$ and $\Sigma_i \in \Re^{p\times p}$. The i^{th} group conditional density $f_i(X_i, \theta_i)$ is given by

$$f_i(X_i, \theta_i) = \varphi(X; \mu_i, \Sigma_i)$$

$$= (2\pi)^{\frac{p}{2}} |\Sigma|^{-\frac{1}{2}} \exp\left\{\left(-\frac{1}{2}\right)(X - \mu_i)^{\Sigma_i^{-1}}(X - \mu_i)\right\} \quad \text{...(1)}$$

and θ_i consists of the elements of μ_i and the $(1/2)P(P + 1)$ distinct elements of Σ_i (i =1, ..., g). It is assumed that each Σ_i is nonsingular. The elements of the vector P of the mixing proportions for the populations sum up to 1.

and θi consists of the elements of $\boldsymbol{\mu i}$ and the $(1/2)P(P + 1)$ distinct elements of Σi (i =1, ..., g). It is assumed that each Σi is nonsingular. The elements of the vector P of the mixing proportions for the populations sum up to 1.
Observations from these groups constitute the training sample. A classification function will be constructed using the training sample on the basis of which future observations (of unknown group memberships) will be classified. This is done by comparing the function to a predetermined cut-off value. The procedure is often utilized (but not limited to) the Social Sciences, Medical sciences, Education and Psychology.

$$Q(X) = \log f_1(X)/\log f_2(X) \tag{2.1}$$

This reduces to

$$Q(X) = \left(\frac{1}{2}\right)\left[(x-\mu_2)'\Sigma_2^{-1}(x-\mu_2) - (x-\mu_1)'\Sigma_1^{-1}(x-\mu_1)\right] + \left(\frac{1}{2}\right)\log|\Sigma_2|/|\Sigma_1| \tag{2.2}$$

This is a quadratic classification function here after referred to as the Quadratic Discriminant
Function (QDF). This function contains population parameters and the sample estimates will be obtained from the training data. $Q(X)$ is the general equation. Equation (2.2) above can be written as

$$Q(x) = x' Ax + b' x + c \tag{2.3}$$

Where

$$A = \left(\frac{1}{2}\right)(\Sigma_2^{-1} - \Sigma_1^{-1})$$

$$b = \Sigma_1^{-1}\mu_1 - \Sigma_2^{-1}\mu_2 \tag{2.4}$$

$$c = \left(\frac{1}{2}\right)\log\frac{|\Sigma_2|}{|\Sigma_1|} + \left(\frac{1}{2}\right)(\mu_2'\Sigma_2^{-1}\mu_2 - \mu_1'\Sigma_1^{-1}\mu_1)$$

The quadratic

$$\delta(x;\mu_i,\Sigma_i)' = (x-\mu_i)'\,\Sigma_i^{-1}(x-\mu_i) \tag{2.5}$$

$$= D_i^2(x)$$

is the squared Mahalanobis' distance between x and μi with respect to Σ.
The cut-off point is determined by the log ratios of the costs of misclassification and prior probabilities. We define $C(i|j)\ i \neq j$ as the cost of misclassifying an observed vector as belonging to group Ri when it actually belongs to Rj and $C(j|i)$ as the converse.

Consequently, $C(i|i) = C(j|j) = 0$. Also, the assumption $C(j|i) = C(i|j)$ is the exception and not the norm in practice. This rule is however regularly applied when the misclassification costs are unknown.

Let P_i i=1, 2 be the prior probability of an observation belonging to group R_i and this information is often obtained from the training sample composition. An observed P-variate vector x is assigned to R_1 if

$$Q(x) > \log\left[\frac{C(1|2)P_2}{C(2|1)P_1} = \eta\right] \tag{2.6}$$

The total probability of misclassification (TPM) gives a measure of the performance of the function. This is a proportion of misclassified observations from the training sample and is given as

$$TPM = P_1P[Q(x) < \eta|x \in R_1] + P_2P[Q(x) > \eta|x \in R_2] \tag{2.7}$$

Denote $R_0 = (R_1^0, R_2^0)$, where R_1^0 and R_2^0 are the distributions that generated the training samples, the TPM using the QDF will be represented as

$$Q(x;R^0) = x'A(R^0)x + b(R^0)'x + c(R^0) \tag{2.8}$$

where

$$A(R^0) = (1/2)[C_2(R^0)^{-1} - C_1(R^0)^{-1}] \tag{2.9}$$

$$b(R^0) = C_1(R^0)^{-1}T_1(R^0)^{-1} - C_2(R^0)^{-1}T_2(R^0)^{-1} \tag{2.10}$$

$$c(R^0) = (1/2)\log(|C_2(R^0)||C_1(R^0)| + (1/2)(T_2(R^0)'C_2(R^0)^{-1}T_2(R^0) - T_1(R^0)'C_1(R^0)^{-1}T_1(R^0)) \tag{2.11}$$

This is analogous to the quadratic function and equations 2.9 to 2.11 are the values of a location function T at the distributions R_1^0 and R_2^0.

That is, $T_1(R^0) = E_{R_1^0}(X)$ and $T_2(R^0) = E_{R_2^0}(X)$. Similarly, $C_1(R^0)$ and $C_2(R^0)$ are the values of the covariance matrix function C at the distributions R_1^0 and R_2^0.

Thus, $C_1(R^0) = Cov_{R_1^0}(X)$ and $C_2(R^0) = Cov_{R_1^0}(X)$ when the data follows a normal distribution,
$T_1(R^0) = \mu_1$, $T_2(R^0) = \mu_2$, $C_1(R^0) = \Sigma_1$ and $C_2(R^0) = \Sigma_2$ (Joossens[5]).
McFarland and Richards[7] have provided exact misclassification probabilities for the finite sample from a normal distribution. The future data is supposed to be a normal mixture of

the training data and the observations of unknown group membership. This gives a TPM for the mixture as

$TPM(R^0, R) = P_1\, C(2|1)(R^0, R) + P2C(1|2)(R^0, R)$ (2.12)

The theoretical derivations have been provided by Jossens[5], McFarlan and Richards [7] and McLachlan [8].

The Simulation Experiment

We consider two populations $R_1 \sim (\mu_4, \Sigma_{4\times4})$ and $R_2 \sim (\mu_4, \Sigma_{4\times4})$ with μ_1 =[0,0,0,0] and μ_2 = [δ,0,0,0], Σ_1 =I and Σ_2 = kI. For our case we set k = 6 (Adebanji and Nokoe[1]) and δ = 1, 2, 3 and 4. Different values of δ are considered to see if there is any observable change in the performance of the functions from very close samples to well separated samples. Twenty one sample sizes (ranging from 25 to 500) are generated for R_1 and the number of corresponding observations generated from R_2 is determined by the sample size ratio composition under consideration. We consider $n_1 : n_2$ = 1:1, 1:2, 1:3 and 1:4; that is from balanced to extremely unbalanced data sets. The large sample sizes are considered in order to enable us observe the performance of the QDF when the population parameters are known.

The four sample size ratio combinations were considered for every value of δ under consideration. Random samples are generated and 100 replications of each sample specification is generated using SAS V(8) (1996). The large number of replications minimizes between sample variability. The QDF is constructed and the leave-one-out error rate estimation procedure (Lachembruch and Mickey[6])is used for estimating the TPM.

Results of Simulation

In the results, the total probability of misclassification (averaged over 100 replications) is denoted as decimals, and the associated standard deviations (SD) are also denoted as decimals. The coefficient of variation (CV) (denoted as percentages) are presented. Results are also presented for different values of δ and sample size ratio combinations.

Scheme 1: Equal Sample sizes ($n_1 : n_2$ =1:1)

When the sample size ratios are equal, the performance of the function for group G_1 with an identity covariance structure is slightly better than that for G_2 with the covariance structure $\Sigma = kI$ though not significantly different in values. Higher reduction in error rates and SD was observed for increased sample sizes than for increase in the δ value. The results

stabilized around sample size 1200 beyond which no significant improvement was recorded in the performance of the function.

Scheme 2: Unequal Sample sizes ($n_1 : n_2$ =1:2)

The ratio of the error rates for $G_2 : G_1$ was 1:5 and this increased to 1:10 when the sample size 1200 was attained for δ=1. This high misclassification of the under-represented group underscored the improvement in the performance of the function as can be observed from the total error rates. The SD shows a steady decline to sample size 900 at which it stabilizes. The CV reduces more gradually to sample size 1200 and remained stable afterwards. For δ=2, the ratio was 1:3 for smaller sample sizes and 1:6 when the sample size 1200 was attained. For δ=3, the ratio increased to 1:4 and similar results was observed for δ=4. The group error rates for this scheme are presented in table 4.1.

Table 1: Group Error for δ = 1, 2, 3 and 4($n_1 : n_2$ = 1 : 2)

		δ = 1		δ = 2		δ = 3		δ = 4	
n1	Sample Size	G1	G2	G1	G2	G1	G2	G1	G2
25	75	0.306	0.065	0.231	0.086	0.146	0.082	0.115	0.053
50	225	0.305	0.047	0.230	0.047	0.151	0.048	0.114	0.031
75	225	0.305	0.032	0.225	0.043	0.151	0.047	0.114	.029
100	300	0.304	0.033	0.228	0.044	0.170	0.037	0.113	0.030
200	600	0.303	0.029	0.228	0.042	0.148	0.046	0.113	0.027
300	900	0.302	0.026	0.227	0.040	0.168	0.036	0.113	0.028
400	1200	0.301	0.027	0.225	0.040	0.157	0.039	0.112	0.027

Scheme 3: Unequal Sample sizes

($n_1 : n_2$ =1:3)

The ratio of the error rates $G_2 : G_1$ for δ = 1 increased from 1:9 to 1:26 at sample size 1200, for δ = 2, it rose from 1:4 to 1:9. At δ = 3, the change was from 1:4 to 1:6 and 1:2 to 1:4 for δ = 4. The high error rate for the smaller group further underscores the performance of the function. There was a steady reduction in the SD until sample size 800 beyond which it remained relatively constant. A similar pattern was observed for the CV which recorded only a slight improvement beyond sample size 800. Refer to table 4.2 below for the group error rates.

Table 2: Group Error for δ = 1, 2, 3 and 4($n_1 : n_2$ =1:3)

		δ = 1		δ = 2		δ = 3		δ = 4	
n1	Sample Size	G1	G2	G1	G2	G1	G2	G1	G2
25	100	0.412	0.043	0.279	0.065	0.193	0.054	0.139	0.046
50	200	0.412	0.027	0.283	0.045	0.195	0.054	0.135	0.033
75	300	0.411	0.018	0.284	0.042	0.195	0.044	0.133	0.029
100	400	0.410	0.020	0.299	0.036	0.205	0.038	0.127	0.032
200	800	0.410	0.016	0.280	0.040	0.193	0.039	0.125	0.032
300	1200	0.409	0.016	0.297	0.031	0.204	0.035	0.122	0.031
400	1600	0.409	0.016	0.288	0.035	0.198	0.034	0.084	0.044

Scheme 4: Unequal Sample sizes ($n_1 : n_2$ =1:4)

The widening in the gap of the ratio $G_2 : G_1$ was not as rapid as had earlier been observed. For δ = 1 the increase was from 1:9 to 1:11, while for δ = 2, 3 and 4 the recorded values were 1:4 to 1:7, 1:6 to 1:8 and 1:5 to 1:9 respectively. See table 4.3 below for details of change in error rates.

Table 3: Group Error for δ = 1, 2, 3 and 4($n_1 : n_2$=1:4)

		δ = 1		δ = 2		δ = 3		δ = 4	
n1	Sample Size	G1	G2	G1	G2	G1	G2	G1	G2
25	125	0.426	0.049	0.351	0.047	0.105	0.018	0.179	0.036
50	250	0.423	0.048	0.348	0.034	0.098	0.017	0.178	0.027
75	375	0.427	0.048	0.351	0.033	0.091	0.017	0.178	0.027
100	500	0.442	0.046	0.363	0.027	0.093	0.012	0.178	0.022
200	1000	0.424	0.047	0.348	0.030	0.089	0.016	0.169	0.025
300	1500	0.440	0.047	0.361	0.025	0.087	0.016	0.177	0.020
400	2000	0.432	0.047	0.355	0.028	0.087	0.015	0.177	0.020

Figures

The graphs for the total (mean) error rates, standard deviation (SD) and coefficient of variation are presented in a series of figures 1.1 to 4.3. Figures 1.1, 1.2 and 1.3 are the graphs of the mean error rates, SD and CV for the balanced data set. Figures 2.1, 2.2 and 2.3 represent the mean error rates, SD and CV for sample size composition $n_1 : n_2$ =1:2. The graphs for sample size ratios 1:3 and 1:4 are presented in figures 3.1 to 3.3 and 4.1 to 4.3 respectively.

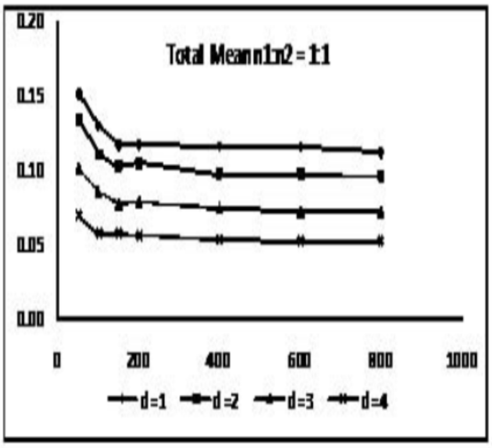

figure 1.1

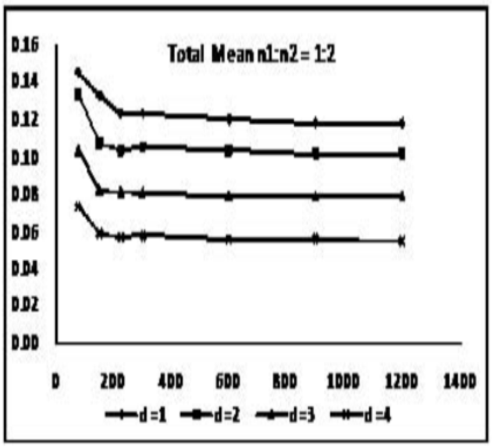

figure 2.1

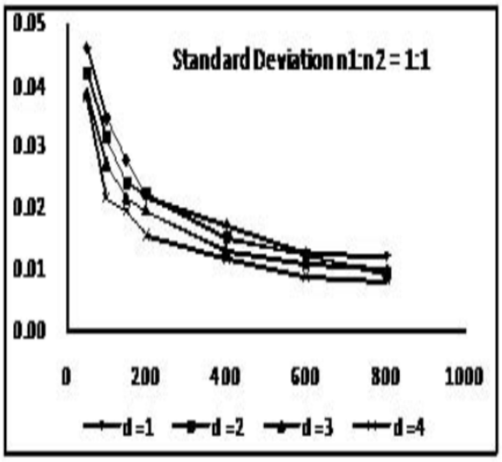

figure 1.2

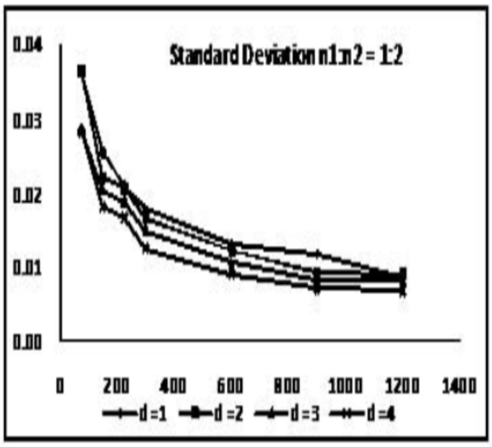

figure 2.2

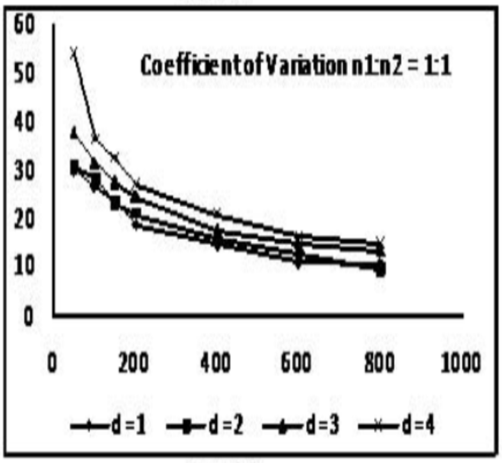

figure 1.3

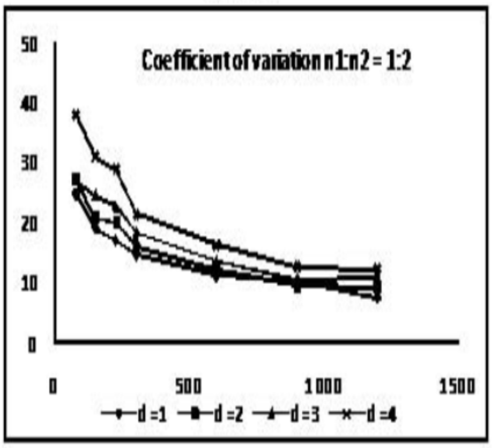

figure 2.3

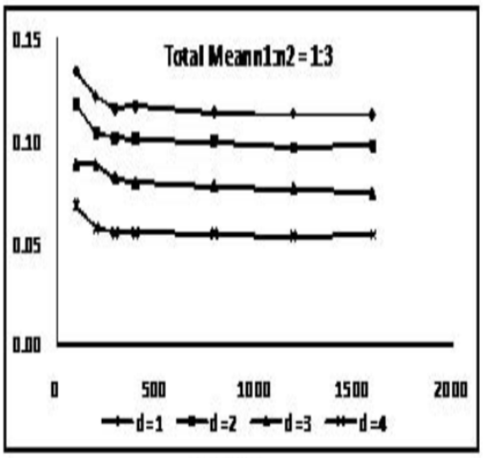

figure 3.1

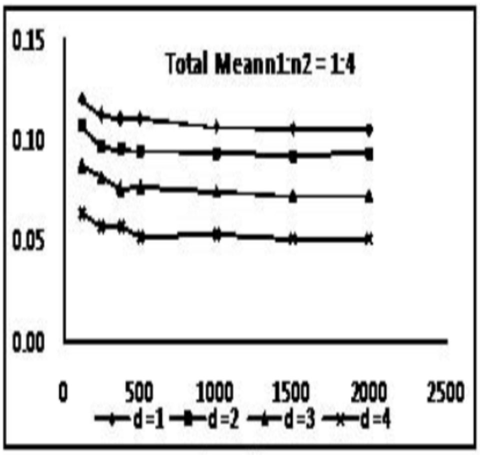

figure 4.1

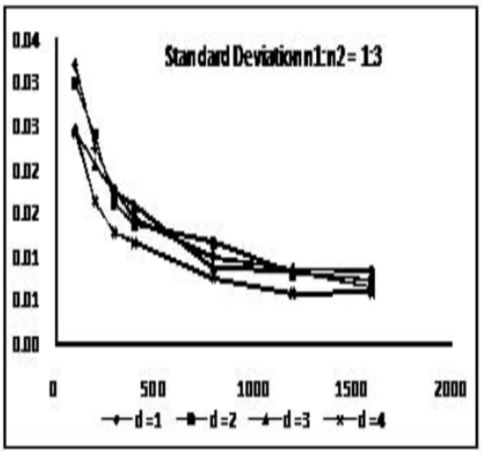

figure 3.2

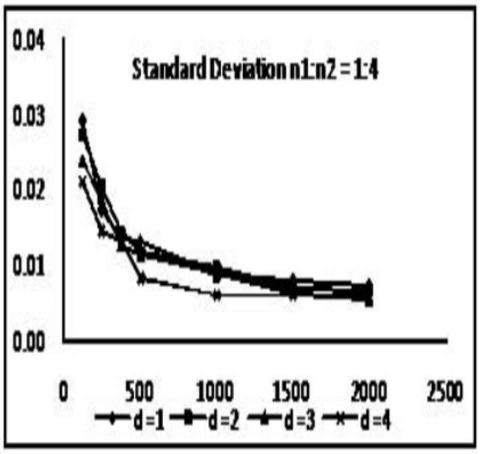

figure 4.2

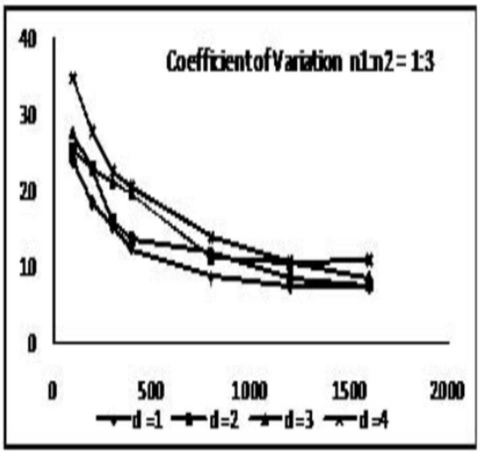

figure 3.3

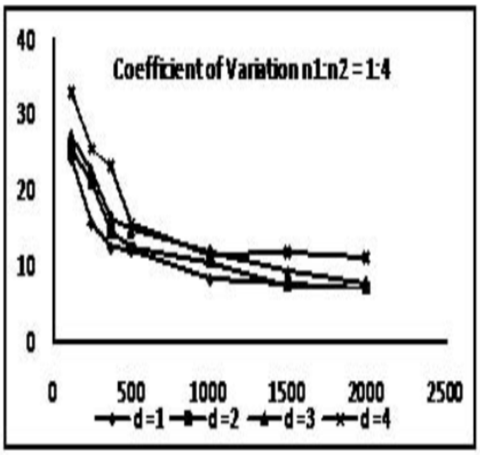

figure 4.3

DISCUSSION

When the data set is balanced, the QDF benefits more from increase in sample size than increase in the distance function. More robustness was also observed in using the function for unbalanced data over the linear discriminant function (Adebanji et al) [2].
The performance of the function in classifying unbalanced data also improved significantly when the between group squared distance is relatively large (i.e. data sets are well separated). The performance however deteriorates in classifying the smaller group when the total sample size is large.

CONCLUSION

In conclusion, using of the QDF for the classification of unbalanced data will not be recommended beyond sample size ratio 1:2 when the data sets are relatively close, and ratio 1:3 when the observations are well separated (subject to moderate sample size).

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