International Journal of Basic Science and Technology
March, Volume 8, Number 3, Page 92 - 100
ISSN 2488-8648
http://www.ijbst.fuotuoke.edu.ng/

Construction of Discriminant and Classification Function For the Separation of Two Periwinkle Types (Rough and Smooth)

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Article Information
Article # 08014
Received: 12th July 2022
1st Revision: 15th August 2022
2nd Revision: 27th Sept. 2022
Acceptance: 28th Sept. 2022
Available online:
30th Sept. 2022

Key Words
Linear discriminant, Periwinkle, Probability, Morphological measurement

Abstract

The aim of the project is to develop a linear discriminant and classification function that using morphological measures, can most effectively distinguish between rough and smooth periwinkle forms. I employed a secondary data set that included measurements for weight, shell length, shell width, aperture length, and aperture width for 12 rough and 12 smooth type periwinkles. The data set was subjected to discriminant and classification analysis after justifying the assumption of distinct group mean and equality of covariance matrices. The linear discriminant that best separated the two groups is $Z = 1.013x_1 - 0.683x_2 - 1.814x_3 - 5.142x_4 - 5.200$ while the classicification ; assign y to rough if Z > 5.2009 and to smooth if Z < 5.2009. The apparent error rate in the classification obtained from the re-substitution method was 0.208. The minimized error rate was 0.0763.This shows that about 7.63% of the objects were incorrectly allocated to one population

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Introduction

Discriminant analysis and classification are multivariate techniques concerned with separating distinct sets of objects and allocating new objects to previously defined groups. As a separation procedure, it is often employed on a one-time basis to investigate observed frequencies.

As usual relationships are not well understood. Discriminant function Analysis has been used extensively in the past to derive optimal combinations of variables to different groups because of its computational simplicity. However Discriminant function Analysis assumes that the predictors have a multivariate normal distribution along with homogenous variance-covariance matrices Harrell (2001). Discriminant analysis as a general research technique can be very useful in the investigation of various aspects of a multivariate research problem. It is sometimes preferable to logistic regression especially when the sample size is very small and the assumptions are met. Application of it to the failed industry in Nigeria shows that the derived model appeared to outperform the previous model build since the model can exhibit true ex-ante predictive ability for about 3 years subsequent to Alayande and Bashiru (2015).

Periwinkle is a univalve, prosobranch gastropod found in the intertidal zone of brackish ecosystems in Niger-Delta and other parts of West African coastal waters such as mangrove swamps, creeks, lagoons, and estuaries. Periwinkles have been described by Badmus *et al* (2007) as small marine snails with spinal – cone, shaped shells having a round opening and dull interior. The genus *T.s fuscatus* comprises a single species that has two varieties; *Tympanotonus fuscatus var fuscatus* and *T. fuscatus var radula*. *T.fuscatus var fuscatus* is characterized by turreted, glandular and spiny shells with tapering ends, Jambo and Chinda (2009) and inhabits the mudflats of the Lagos Lagoon system which is a large expanse of shallow waters extending from the republic of Benin in the west to the Niger Delta in the East, Hill, and Webb (2008), Yoloye (2002), Fagade (2005). *T,fuscatus* var radula has an elongated shell with regular increasing whorls, weakly curved ribs, and much fine striation with blackish brown stripes on the shell. The loss of apex or last whorl is common among adults and a protective operculum in the aperture is used to seal the snail in case of any disturbance Moruf (2015).

They usually inhabit soft substratum or mudflats rich in decaying organic matter and detritus Jamabo and Chinda (2010). When in their habitat, they migrate to the coastal edge and usually aggregate under the breathing roots of mangrove plant species such as *Avicenia nitida, Rhizophora mangle*, and *Nypa palm* for protection from the direct heat of the sun Cariton and Cohen (2002). They provide a livelihood and nutrition for the vast majority of people and constitute a major food item or delicacy of a large number of people living in the Niger – Delta. Jamabo and Chinda (2010).

Millions of *T, fuscatus* are transported in jute bags daily to the markets for sale. They can remain in these bags for weeks without water. During the transportation to the markets, the periwinkles are subjected to high temperatures in addition to a lack of food and water. Thermal tolerance has been used to examine the thermal capacities of marine invertebrates to tolerate their environment Egonmwan (2007).

According to Asunkkwari and Archibong (2011), periwinkles have a very high protein content of 10.2mg/ml. It is a relatively cheap source of animal protein and its shell is commonly used as a a source of calcium and phosphate in livestock feed and as ornaments Jamabo *et al*. (2009). This species has some medicinal value, the flesh is edible and also used as bait by fishermen Bob-Manuel (2012).

Methods

Box's M Test

In discriminant analysis, we assume that the individual group covariance matrices are equal (homogeneity across groups). In this case, we use the Box's M statistic. The statistic M is a modification of the likelihood ratio and varies between 0 and 1 in which we fail to accept the null hypothesis (H_0) when its value tends toward 0 and otherwise if the value tends toward 1. The chi-squared (χ^2) and F-test approximation for the distribution of M, either of these test approximations is referred to as Boxes' M-test

$$H_0 : \Sigma_1 = \Sigma_2 = \cdots = \Sigma_p \quad vs \quad H_1 : \Sigma_1 \neq \Sigma_2 \neq \cdots \neq \Sigma_p$$

And suppose that $S_1 \cdots S_p$ are sample covariance matrices from the n populations where each S_i is based on n_i independent observation each consisting of a kx1 column vector (or a 1xk row vector).

We denote S as pooled covariance matrix.

$$S = \frac{1}{n-p}\sum_{i=1}^{p}(n_i - 1)\ln|S_i| \quad (1)$$

$$M = (n-p)|S| - (n_i - 1)|S_i| \quad (2)$$

$$C_1 = \left[\frac{2k^2 + 3k - 1}{6(k+1)(p-1)}\right]\left[\sum_{i=1}^{p}\frac{1}{n_i - 1} - \frac{1}{n-p}\right] \quad (3)$$

$$U = -2(1 - C_1)\ln M \text{ is approximately } \chi^2\left[\frac{1}{2}(p-1)k(k+1)\right] \quad (4)$$

$$\ln M = \frac{1}{2}\left(\sum_{i=1}^{p} n_i - p\right)\ln|S_i| = \frac{1}{2}\left(\sum_{i=1}^{p} n_i - p\right)\ln|S_{pl}| \quad (5)$$

We reject the null hypothesis (H_0) if $U > \chi^2_\alpha$ (Or p-value < α)

This estimate works well provided n_i >20, $p \leq 5$ and $k \leq 5$.

Group Two Classification

A simple procedure for classification can be based on our discriminant function,

$$Z = a'y = (\bar{y}_1 - \bar{y}_2)' S_{pl}^{-1} y \quad (6)$$

Where; y is the vector of measurements on the new sampling unit that we wish to classify into one of the groups (population). To determine whether y is closer to $\bar{y}_1$ or $\bar{y}_2$ we check to see if Z n (20) is closer to the transformed mean $\bar{Z}_1$ or $\bar{Z}_2$. We evaluate (20) for each observation y_{ii} from the first sample and obtain $Z_{11}, Z_{12}, \ldots, Z_{1n1}$ from which

$$\bar{Z}_1 = \frac{\sum_{i=1}^{n_1} z_{1i}}{n_1} = a'\bar{y}_1 = (\bar{y}_1 - \bar{y}_2)S_{pl}^{-1}\bar{y}_1 \quad (7)$$

similarly,

$$\bar{Z}_2 = a'\bar{y}_2 = (\bar{y}_1 - \bar{y}_2)S_{pl}^{-1}\bar{y}_2 . \quad (8)$$

Denotes the two groups G_1 *and* G_2, Fisher's (1936) linear classification assigns y to G_1 if $Z = a'y$ is closer to $\bar{Z}_1$ than $\bar{Z}_2$ and assigns y to G_2 if Z is closer to $\bar{Z}_2$.

In general, Z is closer to $\bar{Z}_1$ if Z> $\frac{1}{2}\left(\bar{Z}_1 + \bar{Z}_2\right)$

Because $\bar{Z}_1$ is always greater than $\bar{Z}_2$. This can easily be shown as follows

$$\bar{Z}_1 - \bar{Z}_2 = a'\left(\bar{y}_1 - \bar{y}_2\right) = \left(\bar{y}_1 - \bar{y}_2\right)' S_{pl}^{-1}\left(\bar{y}_1 - \bar{y}_2\right) > 0 \tag{9}$$

Because S_{pl}^{-1} is positive definite. Thus, since $\frac{1}{2}\left(\bar{Z}_1 + \bar{Z}_2\right)$ is the midpoint $Z > \left(\bar{Z}_1 + \bar{Z}_2\right)$ implies that Z is closer to $\bar{Z}_1$. By (2.4) the distance from $\bar{Z}_1$ to $\bar{Z}_2$ is the same as $\bar{y}_1$ to $\bar{y}_2$. To express the classification rule in terms of y, we first write $\frac{1}{2}\left(\bar{Z}_1 + \bar{Z}_2\right)$ in the form

$$\frac{1}{2}\left(\bar{Z}_1 + \bar{Z}_2\right) = \frac{1}{2}\left(\bar{y}_1 - \bar{y}_2\right)' S_{pl}^{-1}\left(\bar{y}_1 + \bar{y}_2\right) \tag{10}$$

then the classification rule becomes; assign y to G_1

$$\text{if } a'y = \left(\bar{y}_1 - \bar{y}_2\right)' S_{pl}^{-1} y > \frac{1}{2}\left(\bar{y}_1 - \bar{y}_2\right)' S_{pl}^{-1}\left(\bar{y}_1 + \bar{y}_2\right) \tag{11}$$

And assign y to G_2 if

$$a'y = \left(\bar{y}_1 - \bar{y}_2\right)' S_{pl}^{-1} y < \frac{1}{2}\left(\bar{y}_1 - \bar{y}_2\right)' S_{pl}^{-1}\left(\bar{y}_1 + \bar{y}_2\right) \tag{12}$$

Prior Probability of Classification

Let P_1 be the prior probability of π_1 and P_2 be the prior probability of π_2 where $P_1 + P_2 = 1$. The overall probabilities of correctly or incorrectly classifying objects can be derived as the product of the prior and conditional classification probabilities:

(i) P(correctly classified as π^1) = P(observation from π^1 and is correctly classified as π^1)

= P(xƐR^1/π^1)P(π^1) = p(1/1) P^1 (13)

(ii) P(misclassified as G_1) = P(observation from G_2 and is misclassified as G_1)

= P(xƐR^1/G_2)P(G_2) = P(1/2) P^2 (14)

(iii) P(correctly classified as G_2) = P(observations from G_2 and is correctly classified as

(G_2) = P(xƐR_2/G_2)P(G_2) = P(2/2) P_2 (15)

(iv) P(misclassification as G_2) = P(observation from G_1 and is classified as

G_2= P(xƐR^2 / G_1)P(G_1) = P(2/1) P_1 (16)

Total Probability of Misclassification (TPM)

The criteria other than the expected cost of misclassification can be used to derive optimal classification procedures. The cost of misclassification might be ignored and R_1 and R_2 can be chosen to minimize the total probability of misclassification (TPM).

TPM = P (misclassifying a G_1 observation or misclassifying a G_2 observation) = P (observation from G_1 and is misclassified) + P(observation from G_2 and is misclassified = $P_1 \int_{R_2} f_1(x)dx + P_2 \int_{R_1} f_2(x)dx$ (17)

Results and Discussion

The data for this work comprises five morphological measurements taken from 12 rough (G_1) and 12 smooth (G_2) shelled periwinkle samples. Special features such as weight(x_1), shell length (x_2), shell width(x_3), aperture length(x_4), and aperture width(x_5), were measured from both periwinkle samples. Morphological measurements can be used to increase the consistency of individuals in a population and the separation of individuals between populations Gwaza *et al.* (2013).

Table 1: The Morphological Measurements of Rough (G_1) Periwinkle

S/N	Weight	Shell Length	Shell Width	Aperture Length	Aperture Width
1	4.6	5.2	2.11	0.81	0.73
2	3.8	5.0	1.83	0.71	0.63
3	3.8	4.42	1.72	0.61	0.60
4	3.0	3.76	1.53	0.63	0.61
5	3.8	4.10	1.83	0.74	0.71
6	3.0	3.82	1.43	0.83	0.71
7	3.6	3.83	1.78	0.82	0.81
8	3.4	4.23	1.51	0.71	0.63
9	3.3	3.62	1.82	0.52	0.51
10	3.0	3.83	1.81	0.63	0.61
11	3.0	3.72	1.42	0.54	0.51
12	3.4	3.82	0.71	0.63	0.52

Table 2: The Morphological Measurements of Smooth (G_2) Periwinkle

S/N	Weight	Shell length	Shell width	Aperture length	Aperture width
1	3.9	4.83	1.62	0.64	0.52
2	2.4	3.71	1.43	0.53	0.48
3	3.6	4.10	1.52	0.53	0.51
4	4.2	4.31	1.57	0.51	0.47
5	3.5	4.42	1.72	0.53	0.50
6	2.8	4.62	1.61	0.51	0.50
7	2.6	3.73	1.41	0.51	0.50
8	3.0	3.62	1.62	0.63	0.61
9	3.2	3.91	1.71	0.63	0.61
10	3.6	4.12	1.82	0.53	0.51
11	2.9	3.91	1.81	0.62	0.61
12	3.0	3.83	1.71	0.63	0.61

Table 3: Tests Of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Weight	.939	1.431	1	22	.044
Shell_length	.999	.012	1	22	.015
Shell_width	1.000	.001	1	22	.070
Aperture_length	.665	11.103	1	22	.003
Aperture_width	.707	9.138	1	22	.006

Table 3 provides statistical evidence of significant differences between means of smooth and rough periwinkles.

Table 4: Box's M-Test for Equality of Covariance Matrices

	Box's M	25.485
F	Approx.	1.274
	df1	15
	df2	1948.737
	Sig.	.210

From table 4, the p-value 0.210 is greater than 0.05, therefore, we do not reject the null hypothesis (H_0) and conclude that the covariance matrices do not differ between the groups

Table 5: Eigen values of Rough And Smooth Periwinkle Types

Function	Eigen value	% of Variance	Cumulative %	Canonical Correlation
1	.658[a]	100.0	100.0	.786

a. First 1 canonical discriminant function was used in the analysis.

From Table 5, a canonical correlation of 0.786 suggest the model explains 61.78% of the variation in the grouping variables. That is whether periwinkle is smooth or rough.

Table 6: Wilks' Lambda Test

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.378	9.855	5	.03

Wilk's Lambda test indicates the significance of the discriminant function. The table shows a significant function ($P < 0.05$) and provides the proportion of the total variability not explained . Therefore 37.8 % variability is unexplained.

Table 7: Standardize Canonical Discriminant Function Coefficient

	Function
	1
Weight	.519
Shell_length	-.311
Shell_width	-.483
Aperture_length	.435
Aperture_width	.579

Table 7 provides an index of the importance of each predictor like the standardized regression coefficient (beta') did in regression. The sign indicates the direction of the relationship. Aperture width is the strongest predictor while shell width (- ve sign) is next in importance as a predictor. These two variables with large coefficients stand out as those that strongly predict allocation to the rough and smooth groups. Weight, shell length, and aperture length were less successful predictors.

	Function 1
Weight	1.013
Shell_length Shell_width Aperture_length Aperture_width Constant	-.683 -1.814 5.142 7.454 -5.200

unstandardized coefficients

The unstandardized coefficients from table 8 were used to create the discriminant function equation.

$$Z = 1.013x_1 - 0.683x_2 - 1.814x_3 + 5.142x_4 + 7.454x_5 - 5.200 \tag{18}$$

These coefficients indicate the partial contribution of each variable to the discriminant function controlling for all other variables in the equation. They provide information on the relative importance of each variable.

3.1 Classification Rule for Two Groups {rough (G_1) and smooth (G_2)}

The linear classification rule employs the same discriminant function $z = a'y$. Where; a' = (1.013, -0.683, -1.814, 5.142, 7.454). For the rough group (G_1) we find

$$\bar{z}_1 = a'\bar{y}_1 = 1.013(3.4750) - 0.683(4.1125) - 1.814(1.6250) + 5.142(0.6817) + 7.454(0.6317)$$

$= 5.9776$

Similarly for the smooth group (G_2);

$$\bar{z}_2 = a'\bar{y}_2 = 4.4242 \tag{19}$$

Thus we assign an observation vector y to G_1 if

$$z > \frac{1}{2}(\bar{z}_1 + \bar{z}_2) = 5.2009 \tag{20}$$

And assign y to G_2 if $z < 5.2009$

Table 9: Classification result table

			Predicted Group Membership		Total
			Rough	Smooth	
Original	Count	Rough	9	3	12
		Smooth	2	10	12
	%	Rough	75.0	25.0	100.0
		Smooth	16.7	83.3	100.0

G_2: Smooth	$n_{2m} = 2$	$n_{2c} = 10$
Predicted Membership		
Actual membership	G_1: Rough	G_2: Smooth
G_1: Rough	$n_{1c} = 9$	$n_{1m} = 3$

The apparent error rate expressed as a percentage is

$$\text{APER} = \left(\frac{n_{1m} + n_{2m}}{n_1 + n_2}\right) * 100\% = \left(\frac{3+2}{12+12}\right) * 100\% = \left(\frac{5}{24}\right) 100\% = 20.8\% \tag{21}$$

It has been observed from table 9 that 79.2% of the observations were correctly classified as rough and smooth periwinkle by the discriminant function. Smooth periwinkles were classified with better accuracy of 83.3% than rough periwinkles which has 75%. Out of the total of 24 observations that 12 were rough, 9 were correctly classified as rough, while 3 were misclassified as rough. Out of the 12 smooth periwinkles, 10 were correctly classified as smooth, while 2 were misclassified as smooth. The apparent error is 20.8%.

Then

$$\int_{R_2} f_1(x)dx = P(x\varepsilon R_2 /G_1) = P(2/1) = 0.8966 \quad (22)$$

That is, P(observations from G_1 and are misclassified)

$$\int_{R_1} f_2(x)dx = P(x\varepsilon R_1 /G_2) = P(1/2) = 0.7896 \quad (23)$$

That is, P (observations from G_2 and are misclassified)

3.2 Total Probability of Misclassification (TPM)

$$TPM = P_1 \int_{R_2} f_1(x)dx + P_2 \int_{R_1} f_2(x)dx$$

P_1 and P_2 are the prior probabilities for groups.

$$TPM = 0.50(0.8966) + 0.50(0.7896) = 0.8431 \quad (24)$$

This shows that the total probability of misclassification obtained is 0.8431, which indicates the chance of an object being misclassified.

Table 10: Prior Probabilities for Groups

Periwinkle	Prior	Cases Used in Analysis	
		Unweighted	Weighted
Rough	.500	12	12.000
Smooth	.500	12	12.000
Total	1.000	24	24.000

From Table 10, we can see that all the objects had an equal chance of being classified or misclassified.

3.4: Optimum Error Rate (OER) Of Misclassification

Recall

$$\Delta^2 = (\mu_1 - \mu_2)' \Sigma^{-1} (\mu_1 - \mu_2)$$

$$= \begin{bmatrix} 3.48-3.23 \\ 4.11-4.09 \\ 1.63-1.63 \\ 0.68-0.57 \\ 0.61-0.54 \end{bmatrix}' \begin{bmatrix} 0.262 & 0.166 & 0.052 & 0.011 & 0.006 \\ 0.166 & 0.207 & 0.048 & 0.010 & 0.003 \\ 0.052 & 0.048 & 0.071 & 0.006 & 0.010 \\ 0.011 & 0.010 & 0.006 & 0.007 & 0.006 \\ 0.006 & 0.003 & 0.010 & 0.006 & 0.006 \end{bmatrix}^{-1} \begin{bmatrix} 3.48-3.23 \\ 4.11-4.09 \\ 1.63-1.63 \\ 0.68-0.57 \\ 0.61-0.54 \end{bmatrix}$$

$$= \begin{bmatrix} 0.25 \\ 0.02 \\ 0.00 \\ 0.11 \\ 0.07 \end{bmatrix} \begin{bmatrix} 8.08 & -4.25 & -5.19 & -31.35 & 34.04 \\ -4.25 & 42.25 & -71.37 & -559.94 & 662.02 \\ -5.19 & -71.37 & 166.66 & 1192.15 & -1429.05 \\ -31.35 & -559.94 & 1192.15 & 9844.90 & -11520.50 \\ 34.04 & 662.02 & -1429.05 & -11520.50 & 13703.87 \end{bmatrix} [0.25 \ 0.02 \ 0.00 \ 0.11 \ 0.07]$$

$\Delta^2 = 8.193$

$\Delta = \sqrt{8.193}$

$= 2.862$ (25)

$$\text{Min TPM} = \text{OER} = \Phi\left(\frac{-\Delta}{2}\right) = \Phi(-1.431)$$

$= 0.0763$ (26)

The optimum error rate of misclassification was calculated and the result gave 0.0763. From the optimal classification rule, about 7.63% of the objects were incorrectly allocated to one population.

Conclusion

Based on the result obtained, we conclude that the linear discriminant function, will correctly classify periwinkle as either rough or smooth 79.2% and misclassify periwinkle as either rough or smooth 7.63% of the time.

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