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## A Discriminant Approach for Allocating Newly Admitted Candidates into the Appropriate Course of Study in Federal Polytechnic Nekede, Owerri

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### **Abstract:**

*This paper demonstrates the use of linear discriminant analysis (LDA) in the admission processes of a higher education in Nigeria. Joint Admission and Matriculation Board (JAMB) and Post Unified Tertiary Matriculation Examination (PUTME) scores of candidates applying for admissions into Science and Laboratory Technology (SLT) and Statistics (STA) departments, since the two departments has the same admission requirements, in 2013/2014 from Federal Polytechnic Nekede, Nigeria was used to derive the linear classification rule after assumption justifications corroborate the case of multivariate normality and equal covariance matrices. Based on this LDA rule, an Apparent Error Rate (APER) of 32% was obtained. This suggests a relatively high rate of misclassification in the admission procedure as could be depicted from a partition plot and a predicted classification scores plot. A possible reason for the high APER could be that JAMB and PUTME may not be the only factors needed to discriminate and classify a student into SLT or STA departments. Other factors like the student's choice may be valuable. Meanwhile, the set rules were used to classify a sample of five new entrants into their appropriate course of study.*

**Keywords:** Discriminant Function, Mahalanobis Distance,  $T^2$ , Q-Q Plots, Multivariate Normality

### **1. Introduction**

As the year goes by, candidates seeking admission into tertiary institutions in Nigeria increased drastically more than the tertiary institutions can absorb and as a result candidates are doing all sort of things such as examination malpractices just to pass JAMB. Even before the JAMB examinations are conducted, some candidates make arrangements on ways of cheating. They even bring impersonators and expo into the examination halls. A frightening dimension is the involvement of parents, guardians and examination officials in this unwholesome act.

The spate of misconduct during JAMB examination in Nigeria coupled with the fact that most of the students who had spurious JAMB scores could not cope with their undergraduate courses occasioned calls by the University of Lagos in the year 2005 for a Post Universities Matriculation Examination (Post UME). The essence of the post UME (now Post UTME) is to screen potential students before admission using aptitude test, oral interviews etc.

The Federal Polytechnic Nekede officially began its Post UTME in the year 2008. To allow prospective candidates apply, those who earlier applied to JAMB, wrote the 2008 JAMB for Polytechnics, and attained the prescribed national minimum score were invited to apply to Federal Polytechnic Nekede, provided they meet the minimum entry requirements. The Post-Jamb screening test conducted that year revealed that many candidates who scored very high in JAMB examination performed badly in the Post Jamb test. The results of the two examinations were averaged to determine the eligible candidates for admissions. The most challenging problem was that those candidates admitted under this guideline performed poorly at their respective undergraduate courses and this prompted the institution to rely solely on the Post Jamb tests for admissions provided the candidates obtained the national minimum JAMB requirement for Polytechnics.

### **2. The Admission Problem**

According to Nze (2013), every year, the Federal Polytechnic Nekede conducts a Post Jamb screening test for admitting candidates into various programmes available in her institution. Usually, a large number of candidates pass the screening test than the Polytechnic can absorb. The task of selecting the best candidates on the basis of the screening test scores is not always easy. It has been observing that some of the qualified candidates are shifted into departments they did not apply for so that they are not denied admission. One

consequence of this shifting is that those candidates may or may not graduate successfully from those departments. It is against this backdrop that this study was initiated with a view to statistically derive a rule that will best allocate candidates into their appropriate course of study. The above problems present us with two indicative problems: 1) to find discriminants whose numerical values or scores are such that the collections are separated as much as possible and 2) to sort objects (student's post UTME scores) into two groups or more labeled classes. In the latter case, the emphasis would be on deriving a rule that can be used to optimally assign new objects to the labeled classes.

Thus, this study would aim at first, discriminating or separating the candidates into specific courses and then, predicting and allocating the suitable course of study for the candidates applying for admission on the basis of their scores at JAMB and Post-UTME using the Discriminant Analysis approach as summarized by Johnson and Wichern (2007).

This is not far from what is obtainable in the literature. Okpara (2001) applied the method of discriminant analysis in analyzing the scores of candidates admitted in the school of physical sciences, Nnamdi Azikiwe University Awka in 2000/2001 session and constructed a discriminant function that successfully discriminates between those admitted and those not admitted.

Mahbub (2011) carried out a study on an application of discriminant analysis on university Matriculation Examination scores for candidates admitted into Anambra State University. The study focused on the candidates admitted in the Department of Industrial Chemistry for 2009/2010 session with the aim of using discriminate function to achieve a sharper discrimination between those "Accepted" and those "Not Accepted". The data for the study were collected at the admissions office of Anambra State University and were analyzed using average scores, Hotelling's  $T^2$  distribution and discriminant analysis. The result of the analysis showed that the

average scores of those candidates accepted is higher compared to the average scores of not accepted candidates. Hotelling's  $T^2$  distribution used showed that the population mean vectors of the two groups (accepted and not accepted candidates) are different. Finally, discriminant function found for "Accepted" and "Not Accepted" candidates and classification rule also showed that some candidates were wrongly classified or misclassified.

Audu and Usman (2013) derived an expression for the discriminant rule in the situation of two groups. The derived expression was used to identify the relative contributions of the subjects to the separation of the groups. Group dependent Fisher discriminant analysis was employed in classifying students into various departments on the basis of their cumulative results for one-year foundation programme (Preliminary Degree Programme in Federal University of Technology, Minna). The discriminant scores for each department was predicted with probability of correct classification of 0.796 and apparent error rate of 0.204.

### 3. Methodology

#### 3.1. Data Collection

Data for this study is from a secondary source. The data were collected from Admissions Department of the Federal Polytechnic Nekede, Owerri. The data are scores obtained by each candidate who sat for the 2013/2014 Jamb and Post UTME for Science Laboratory Technology (SLT) and Statistics (STA) departments respectively. A simple random sample of 60 candidates was selected from the Department of Statistics (STA) while a simple random sample of 100 candidates was selected from Department of Science Laboratory Technology (SLT), both in School of Industrial and Applied Sciences (SIAS) of the Polytechnic. Since the method of analysis assumes that research data must come from a normal distribution, we made a choice of sample size that is at least 30, which is usually the case for normal population. The R software (R-3.2.1, 2015) will be used throughout this work.

#### 3.2. Statistical Approach - Discriminant Analysis

Discriminant Analysis is a multivariate technique that is concerned with separating distinct set of objects and with allocating new objects into previously defined groups (Johnson & Wichern, 2007). Discriminant Analysis is a powerful statistical tool that is concerned with the problem of classification. This problem of classification arises when an investigator makes a number of measurements on an individual and wishes to classify the individual into one of the several population groups on the basis of these measurements (Morrison, 1967.)

Either Linear or Quadratic rules may be used to derive classification equations in discriminant analysis for the purpose of predicting group membership. Generally, the decision about which rule to use is governed by the degree to which the separate group covariance matrices are unequal (Young, 1993).

#### 3.3. Assumptions

Once a Discriminant Analysis is contemplated, it may be important to check whether the research data satisfy the assumptions of a Discriminant Analysis. Some of the assumptions to be examined include no outliers, normality assumption and equality of variance covariance matrices.

#### 3.4. Multivariate Normality and Outlier Detection

Discriminant Analysis assumes that data for the independent variables represent a sample from a multivariate normal distribution. Many statistical tests and graphical approaches are available to check the multivariate normality assumption. Burdinski (2000) reviewed several statistical and practical approaches, including the Q-Q plot, box-plot, stem and leaf plot, Shapiro-Wilk and Kolmogorov-Smirnov tests to evaluate the univariate normality, contour and perspective plots for assessing bivariate normality, and the chi-square Q-Q plot to check the multivariate normality. In addition, Mardia (1970), Henze and Zirkler (1990), and Royston

(1992) proposed various tests for multivariate normality. Holgersson (2006) stated the importance of graphical procedures and presented a simple graphical tool, which is based on the scatter plot of two correlated variables to assess whether the data belong to a multivariate normal distribution or not. For a bivariate data (although could also be used for all  $P \geq 2$ ), a somewhat more formal way for judging the joint normality of a data set is based on the squared generalized distances

$$d_i^2 = (X_i - \bar{X})^T S^{-1} (X_i - \bar{X}) \quad i = 1, 2, \dots, n \quad (1)$$

Specifically, the values of  $d_i^2, i = 1, 2, \dots, n$  are compared with the  $\chi^2$  quantiles with  $P$  degrees of freedom. In the decision,  $P$ -variate normality is indicated if roughly half of the  $d_i^2$  are less than or equal to  $q_{c,p}(.50) = 10.6$  where  $q_{c,p}((i - \frac{1}{2})/n)$  is the  $100((i - \frac{1}{2})/n)$  quantile of the chi-square ( $\chi^2$ ) distribution. Likewise, with the  $d_{(1)}^2 \leq d_{(2)}^2 \leq \dots \leq d_{(n)}^2$  ordered, the graphical approach also graphs the pairs  $(q_{c,p}((i - \frac{1}{2})/n), d_{(i)}^2)$ , producing a straight line that passes through the origin with slope 1. Figure 1 (left and right panel) shows the chi-square plot of the students groups 1 and 2 respectively.

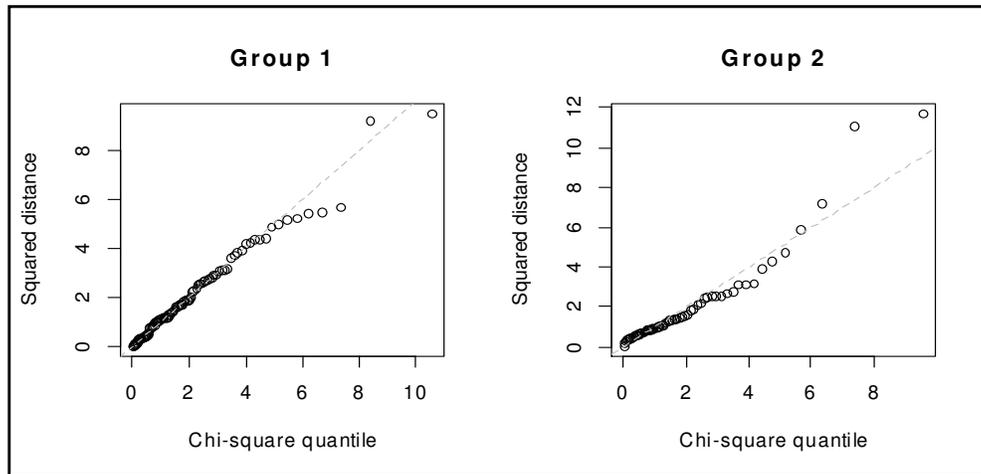


Figure 1: Chi-Square Q-Q Plot for Group 1 (Left panel) and Group 2 (Right panel)

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> d_i^2 for Student Group1 (Upper panel)
[1] 2.94316084 1.00753301 0.35469720 5.01474634 0.80526443 3.12528520 1.42493004
[8] 0.14114643 0.07587800 1.73991450 1.72998339 1.41312967 1.01650990 1.16994545
[15] 2.25959033 0.99180315 1.15445754 5.22614465 0.30212056 0.27029446 0.76456697
[22] 1.48623723 2.02656887 9.54163151 0.43214834 1.09561264 0.17804256 0.29581068
[29] 0.02711121 0.20919287 9.21365448 4.87834399 2.60432815 0.54410298 4.24593458
[36] 0.26745683 1.10379633 3.16755840 0.39876061 1.22747853 0.77883352 0.01626887
[43] 0.46707772 4.21148332 1.87084978 2.36865835 1.61636713 1.16104311 2.70231632
[50] 1.88452275 1.74548558 3.94427013 5.47111112 0.85658014 1.93175265 1.39787944
[57] 0.11541065 0.40072533 1.08620452 4.40960122 1.17450873 2.25056357 5.72428582
[64] 0.32721649 0.74050916 0.45126114 0.36545804 1.01354575 3.64950600 1.03890555
[71] 0.08879884 4.40254563 2.80705043 1.83128115 1.87985906 1.31095852 2.73548436
[78] 2.94444462 3.82329411 1.65212912 1.67800880 5.50113034 0.54648305 3.15174071
[85] 0.82870087 2.81350864 3.76707771 2.61556523 0.28639127 5.25710321 2.56779584
[92] 3.08224436 1.12008261 2.55884999 1.31483833 0.42047757 4.47005567 1.18554009
[99] 0.12602251 0.18546262

> d_i^2 for Student Group2 (lower panel)
[1] 0.8490002 11.0882098 0.40315830.72129687.22555503.10543361.5567779
[8] 0.93909152.69234410.47205380.73837820.36330101.07024143.9322894
[15] 0.03580462.41968980.87288161.22653404.74635220.86796830.4327291
[22] 0.66849591.03696961.11608372.60044640.66153311.44627802.1454229
[29] 1.04022412.49386891.24680490.73338410.76929021.36808380.5352963
[36] 1.40728013.14949384.32372850.2777354 11.7344294 2.57621360.8950785
[43] 3.19201260.35854591.30575370.61105011.83914202.19217591.6407195
[50] 1.34504712.59873371.87090490.82344081.53088890.23499730.5767845
[57] 0.83649440.38583602.75309795.9191432
    
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Table 1: Squared distances ( $d_i^2$ ) for the student's jamb and putme scores

While the left panel of Figure 1 suggests a multivariate normality (validated by the Mardia’s MVN test with non-significant Skewness and Kurtures *p-values* of 0.142 and 0.492 respectively at 5% significant levels), the right panel seems to suggest otherwise. A possible reason could be the presence of outliers. Multivariate outliers are the common reason for violating multivariate normality assumption. In other words, multivariate normality assumption requires the absence of multivariate outliers. Depending upon the nature of the outlier and the objectives of the investigators, outliers may be deleted or appropriately “weighted” in a subsequent analysis. To check for the existence of outliers, a scatter plot showing configuration of the points as displayed in Figure 2 could be applied (Critchley, 1985).

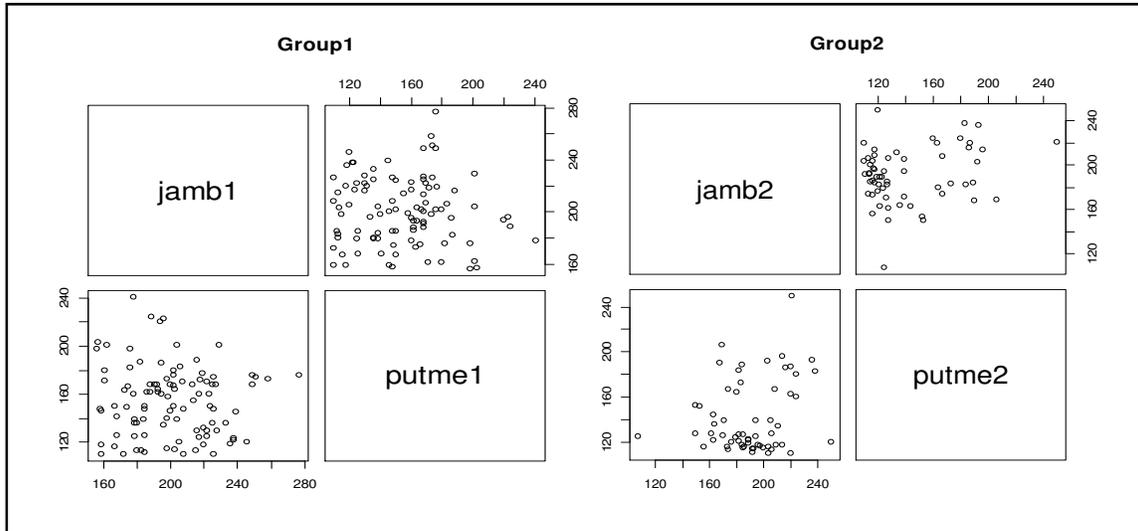


Figure 2: Multivariate plot of the students’ Group 1 (left panel) and Group 2 (right panel) data sets

Some steps in outlier detection are to make a dot plot for each variable; to make a scatter plot for each pair of variables; and calculating/examining how large or small the standardized values,  $z_{ik} = (x_{ik} - \bar{x}_k) / \sqrt{s_{kk}}$  for  $i = 1, 2, \dots, n$  and each column of  $k = 1, 2, \dots, p$  are as summarized by Johnson and Wichern (2007). Furthermore, a fourth step of outlier detection procedure, which integrates the other steps calculates the  $d_i^2$  given in (1) and then examining these distances for usually large values. In a  $\chi^2$  plot, the outliers would be the points farthest from the origin, implying values that are greater than the  $q_{c,p}(.50) = 10.60$ . Table 1 (Upper and Lower Panel) shows the  $d_i^2$  values of the First and Second student groups respectively.

It is evident that outliers may be depicted for Group2 data set due to large  $d_i^2$  values ( $d_i^2 > 10.60$ ) spotted at the second and fortieth values (i.e. at  $n = 2, 40$ ) of Table 1. An R pairs plot showing the multivariate scatter displayed in Figure 2 really showcases the scenario. Observe that two points are spotted lying far from the other clusters in the right panel of Figure 2. This may have greatly contributed to its non-compliance to the Mardia’s normality test.

Figure 3 shows a reconstructed  $\chi^2$  Q-Q plot ignoring these points (outliers). Observe that Figure 3 suggests an approximate cleaned situation with all the  $d_i^2 < 10.60$ . In addition, the Mardia’s MVN test conducted on the cleaned data set showed non-significant Skewness and Kurtures *p-values* of 0.063 and 0.386 respectively at 5% significant levels. Consequently, the cleaned Group 2 data set would be used for further analysis in this work.

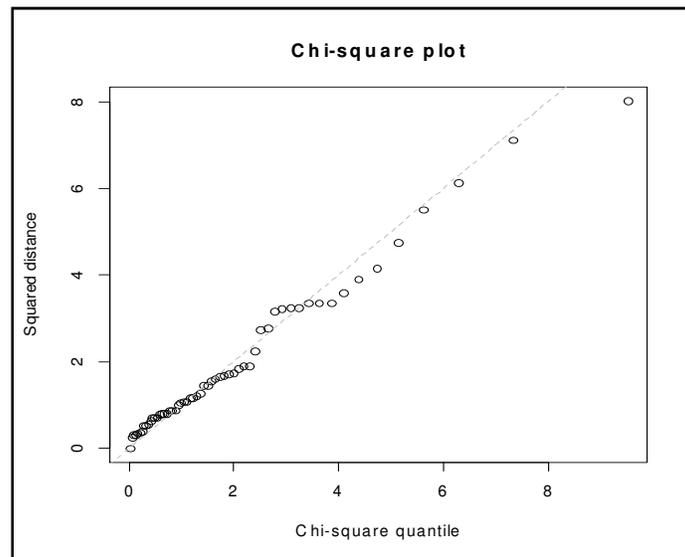


Figure 3: Chi-Square Q-Q Plot for Cleaned Group 2 data set

3.5. Equality of Covariance Matrices Using the Box’s M Test

Fisher’s Linear Discriminant Function assumes that the population covariance matrices across the groups are equal because a pooled estimate of the common covariance matrix is used. To determine whether the covariance matrices for the groups under study are equal, the Box’s M test will be used (Box, 1949). The hypotheses:  $H_0 : \Sigma_1 = \Sigma_2$  against  $H_1 : \Sigma_1 \neq \Sigma_2$  needs to be tested. The test statistic is given by

$$C = (1-u) \left\{ \sum_k (n_k - 1) \ln |S_{pooled}| - \sum_k (n_k - 1) \ln |S_k| \right\} \tag{2}$$

$$u = \frac{2p^2 + 3p - 1}{6(p+1)(k-1)} \left[ \sum_k \frac{1}{(n_k - 1)} - \frac{1}{\sum_k (n_k - 1)} \right]$$

where  $k$  is the number of groups, At significance level  $\alpha$ , It is important to note that Box’s M test is very sensitive to non-normality, such that a significant value indicates either unequal covariance matrices or non-normality or both. Hence, it is necessary to establish multivariate normality before using Box M test (Box, 1949). Meanwhile,  $H_0$  for the Student grade data considered in this work is not rejected since  $C = (4.61)$  is less than  $\chi^2_{p(p+1)(k-1)/2} (\alpha) = 7.81$ .

3.6. Equality of Group Mean Vectors (For Two Samples)

In Discriminant analysis it is worthwhile to first test whether or not the mean vectors of the groups under study are equal. If the two groups differ in their mean vectors, it then means that we can construct a discriminant function which hopefully will enable us to distinguish members of one group from those of another group. Conducting such test is usually performed using the Hotellings’ T<sup>2</sup> test under the assumption that the covariance matrices are equal  $\Sigma_1 = \Sigma_2$ . However, in the case of the unequal variances where  $\Sigma_1 \neq \Sigma_2$ , Tamae and Takashi (2010) adjusted the degrees of freedom of the  $F$  - distribution to accommodate the test for the mean vectors with unequal variances.

Given the hypothesis of the inequality of means, the Hotellings’ T<sup>2</sup> test statistic for two sample groups  $X_1$  and  $X_2$  with respective

sample numbers  $n_1 = 100$ ,  $n_2 = 58$ , the group means are  $\bar{X}_1 = \begin{pmatrix} 200.59 \\ 154.63 \end{pmatrix}$ ,  $\bar{X}_2 = \begin{pmatrix} 191.45 \\ 140.41 \end{pmatrix}$  respectively. Also, the group

sample covariance matrices are given as  $S_1 = \begin{pmatrix} 670.08 & -45.53 \\ -45.53 & 854.60 \end{pmatrix}$ ,  $S_2 = \begin{pmatrix} 515.48 & 112.27 \\ 112.27 & 833.30 \end{pmatrix}$  while the pooled covariance matrix is  $S = \frac{(n_1 - 1)S_1 + (n_2 - 1)S_2}{n_1 + n_2 - 2} = \begin{pmatrix} 613.59 & 12.13 \\ 12.13 & 846.82 \end{pmatrix}$ . Also, the F value is given by

$$F = \frac{n_1 + n_2 - p - 1}{p(n_1 + n_2 - 2)} T^2 = \frac{100 + 58 - 2 - 1}{2(100 + 58 - 2)} \times 13.54 = 6.73 \tag{3}$$

where

$$T^2 = (\bar{X}_1 - \bar{X}_2)^T S^{-1} (\bar{X}_1 - \bar{X}_2) \tag{4}$$

We shall reject the null hypothesis ( $H_0$ ) of equality of mean vectors at a significance level,  $\alpha$ , if  $F > F_{\alpha, P, n_1 + n_2 - P - 1}$ , Otherwise do not reject. In this paper, since,  $F = 6.73 > F_{\alpha, P, n_1 + n_2 - P - 1} = 3.072$  we therefore reject the null hypothesis,  $H_0$ , and conclude that there is a significant difference between the mean vectors of the scores of SLT and Statistics candidates at  $\alpha = 0.05$ .

#### 4. Results and Discussions

The Fisher’s Linear Discriminant function (FLDF) as discussed in Rencher (2002) is given by:

$$y = (\bar{X}_1 - \bar{X}_2)^T S^{-1} X_1 = \hat{a}^T X = (9.14 \quad 14.22) \frac{1}{519453.2469} \begin{pmatrix} 846.82 & -12.13 \\ -12.13 & 613.59 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = 0.0146X_1 + 0.0166X_2$$

The mean discriminant function for the SLT candidates is therefore

$$\bar{y}_1 = \hat{a} \bar{X}_1 = (\bar{X}_1 - \bar{X}_2)^T S^{-1} \bar{X}_1 = (9.14 \quad 14.22) \frac{1}{519453.2469} \begin{pmatrix} 846.82 & -12.13 \\ -12.13 & 613.59 \end{pmatrix} \begin{pmatrix} 200.59 \\ 154.63 \end{pmatrix} = 5.49$$

Also, the mean discriminant function for STA candidates is:

$$\bar{y}_2 = \hat{a} \bar{X}_2 = (\bar{X}_1 - \bar{X}_2)^T S^{-1} \bar{X}_2 = (9.14 \quad 14.22) \frac{1}{519453.2469} \begin{pmatrix} 846.82 & -12.13 \\ -12.13 & 613.59 \end{pmatrix} \begin{pmatrix} 191.45 \\ 140.41 \end{pmatrix} = 5.12$$

The critical value of the Fisher’s linear discriminant function is given by

$$\hat{y}_{critical} = \frac{\bar{y}_1 + \bar{y}_2}{2} = \frac{5.49 + 5.12}{2} = 5.31$$

##### 4.1. Classification Rule

Classify the candidates whose discriminant scores are greater than or equal to the critical value (5.31) into SLT and those whose discriminant scores are less than the critical value (5.31) into STA.

Using prior probabilities proportional to the sample sizes ( $SLT = c = 0.37, STA = s = 0.63$ ), the confusion matrix is presented in Table 2.

Actual Membership	Predicted Membership		Total
	To SLT = c ( $\pi_1$ )	To STA = s ( $\pi_2$ )	
From SLT = c ( $\pi_1$ )	68	32	100
From STA = s ( $\pi_2$ )	19	39	58

Table 2: Confusion matrix

$$APER = \frac{n_{1,miss} + n_{2,miss}}{n_1 + n_2} = \frac{32 + 19}{158} = \frac{51}{158} = 0.32$$

The apparent error rate is then given as

$$\frac{n_{1.miss}}{n_1} = \frac{32}{100} = 0.32$$

Observe that the probability of misclassification of SLT candidates = and the probability of misclassification of

$$\frac{n_{2.miss}}{n_2} = \frac{19}{58} = 0.33$$

STA candidates=

A partition plot for the linear discriminant analysis uses the R klaR package by Weihs et. al (2005). Maintaining the proportions of the data sets as the prior probabilities, it is observable that there is a clear distinction of the two discriminated populations. The error due to misclassification is calculated to be around 32%.

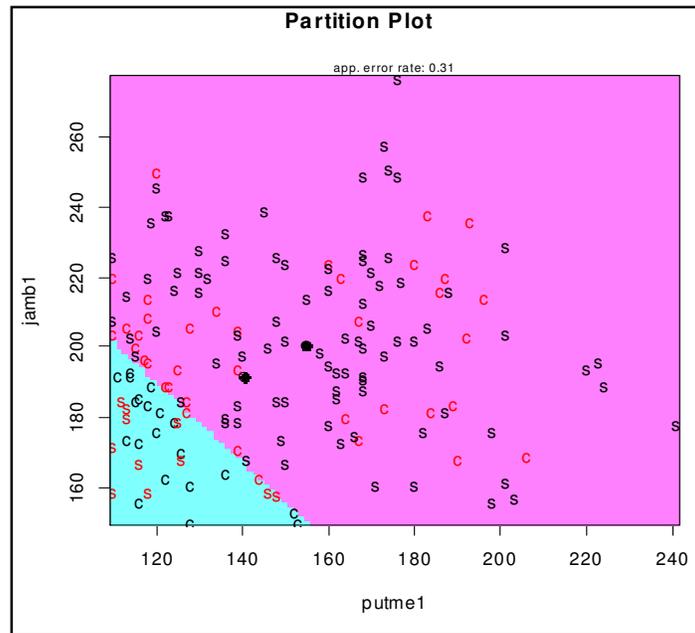


Figure 4: Partition plot of the Student Grades with prior probability using LDA (c=0.37, s=0.63)

The overall probability of misclassification is (0.32 or 32%). This is an indication that the discriminant function derived in this study has the capability of correctly allocating about 68% of the candidates applying for admission into their appropriate courses of study. Although the overall error rate of 32% may be low, there is unfairness here. It is less likely that more Statistics (STA) candidates will be misclassified as Science Laboratory Technology (SLT) candidates, rather than vice versa. This is evident from the group probabilities of misclassification, where out of 100 candidates admitted into SLT, about 68 were correctly admitted whereas 32 were wrongly admitted. Similarly, out of 58 candidates admitted into STA, about 39 were correctly admitted whereas 19 were wrongly admitted. This therefore, shows that SLT has about 32% chance of being misclassified whereas STA has about 33% chance of being misclassified. The Fisher Linear Discriminant Function indicated that about 32% of the candidates were misclassified into their courses of study. The LDA1 values of 8.425736 for SLT and 9.033104 for STA, which are quite close supports the high level of the APER value. A possible cause of the close LDA1 values leading to high APER value may be the non-presence of another factor which would be able to help discriminate the students as much as possible. For instance, such factor may have been the choices of students to the two departments irrespective of their scores and other factors like the existence of quota of admission into a particular department if any. The partition plot of Figure 4 and predicted classification scores plot displayed in Figure 5 brings this argument to limelight as many SLT and STA scores crossed the region of each other. With the group centroids closer together within, high error rate is inevitable. This is also supported by the expected unbiased actual error rate of 0.3228 using the Lachenbruch predicted membership approach (Lachenbruch, 1975).

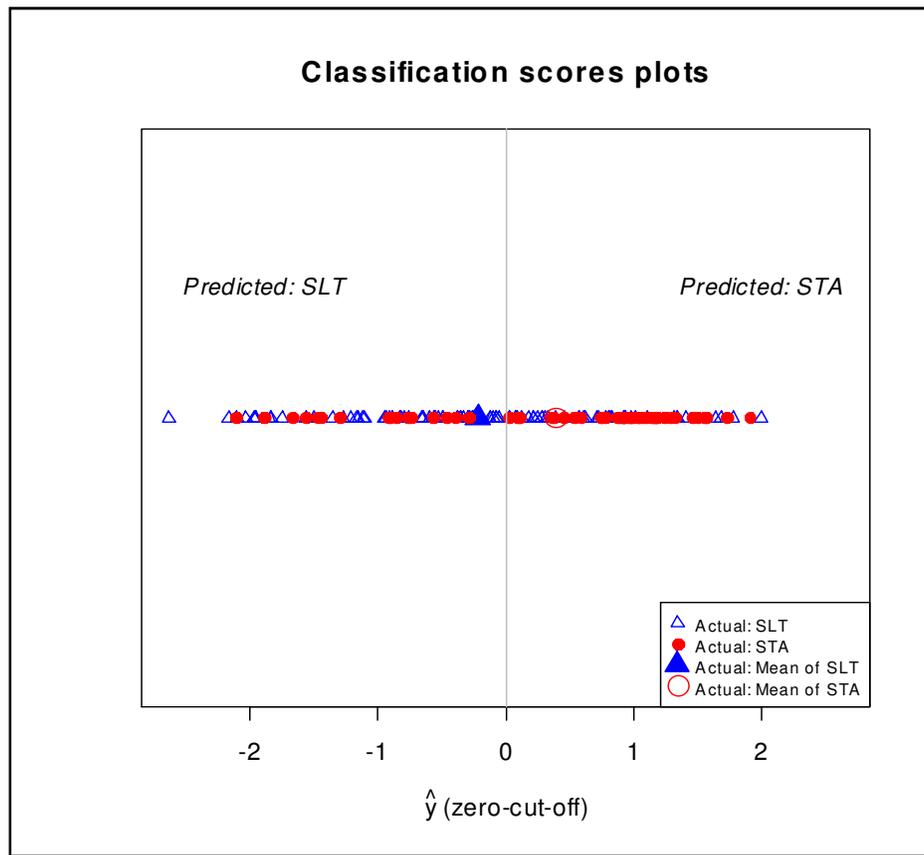


Figure 5: Predicted classification scores plot of the Student Grades

4.2. Allocation of New Students

The classification rule for allocating candidates into their appropriate course of study can be given as follows:

Allocate a new candidate  $(x_0)$  to SLT Department  $(\pi_1)$  if  $\hat{y}_0 = \hat{a}x_0 \geq \hat{y}_{Critical} (= 5.31)$  (5)

Allocate a new candidate  $(x_0)$  to STA Department  $(\pi_2)$  if  $\hat{y}_0 = \hat{a}x_0 < \hat{y}_{Critical} (= 5.31)$  (6)

Using the LDA1 values, this implies that we then allocate an observation to the SLT group if  $(\hat{y} - 8.425736)^2$  is smaller than  $(\hat{y} - 9.033104)^2$ ; we allocate an observation to the STA group if  $(\hat{y} - 9.033104)^2$  is smaller than  $(\hat{y} - 8.425736)^2$ .

	Student1	Student2	Student3	Student4	Student5
<b>jamb</b>	192	189	220	249	164
<b>putme</b>	114	122	180	168	136

Table 3: New students' scores for 2015 session

Table 3 shows five samples of the 2015 session JAMB and PUTME scores randomly selected for people looking for admission into the SLT and STA departments of the Federal Polytechnics, Nekede Owerri.

Applying the classification rules (5) and (6), Table 4 shows the appropriate departments the students need to be admitted into.

	Student1	Student2	Student3	Student4	Student5
$\hat{y}_0$	4.69	4.78	6.19	6.41	4.64
<b>department</b>	SLT	SLT	STA	STA	SLT

Table 4: New students' scores allocation using (5) and (6)

#### 4.3. Recommendations

The management of Federal Polytechnic Nekede should adopt this predictive model in its admission process as it will help them minimize the rate of misclassification during any admission period.

This study focused on two departments only and the result of the discriminant analysis cannot be extended to the entire departments within the institution. We therefore recommend that future research be carried out to accommodate all the departments so that the institution would have a better knowledge of the classification rules for placing all candidates into their appropriate courses of study. This recommendation certainly calls for a multiple discriminant analysis.

The discriminant function derived in this paper is able to correctly classify about 68% of all the candidates into their appropriate courses of study, but could not do same for those candidates that were denied admissions. So, we recommend that future research be carried out in order to derive a classification rule that can be used to place those candidates who were qualified for admission but were denied admission due to inadequate admission space. In addition, a future discriminant analysis may look into such factors like the students' choice in correctly discriminating the departments the student is admitted into.

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