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# Application of discriminant analysis in modelling students' placement in colleges of education

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## ABSTRACT

This research designed a predictive model for the purpose of placing incoming students from the Pre-Nigerian Certificate of Education (Pre-NCE) programmes into courses of study based on the students' performance at the Pre-NCE level. A Discriminant function was constructed to each course combination. The classification model sought to assign students into courses of study through the analysis of subject scores at the Pre-NCE level using Discriminant analysis technique. The results obtained indicate different subjects in different courses as the strongest contributors for the placement of students into different subject combination.

**Keywords:** Predictive model, Classification model, discriminant analysis

## 1. INTRODUCTION

Discriminant analysis (DA) is a multivariate technique concerned with separating distinct sets of objects (observations) and with allocating new objects to previously defined groups (defined by a categorical variable) Johnson and Wichern (1982). The ideas associated with Discriminant analysis can be traced back to the 1920s and work completed by the English statistician Karl Pearson, and others, on intergroup distances, e.g., coefficient of racial likeness (CRL), (Huberty, 1994). In the 1930's, three different people – R.A. Fisher in UK, Hoteling in US and Mahalanobi is in India were trying to solve the same problem via three different approaches. Later their methods of Fisher linear Discriminant function, Hoteling's $T^2$ test and Mahalanobis $D^2$ distance were combined to devise what is today called Discriminant Analysis. Methodologists from Harvard University contributed much to the interest in application of discriminant analysis in education and psychology in the 1950s and 1960s (Huberty, 1994). Klecka (1980) provided several historical references that deal mostly with early applications of Discriminant Analysis.

The two types of discriminant analysis, i.e., Predictive Discriminant Analysis and Descriptive Discriminant Analysis, have different histories of development. According to Huberty (1994),

"Discriminant analysis for the first three or four decades focused on the prediction of group membership," Predictive Discriminant Analysis, whereas Descriptive Discriminant Analysis usage did not appear until the 1960s and "its use has been very limited in applied research settings over the past two decades." Predictive Discriminant Analysis and Descriptive Discriminant Analysis are multivariate analyses that have important differences in both their general application and when used in conjunction with stepwise methodology.

Researchers have used Discriminant analysis in a wide variety of settings: it was first developed by Fisher (1930), who was seeking to solve problems in physical anthropology and Biology. In other social sciences, some of the first application dealt with psychological and educational testing political scientists have found Discriminant analysis to be useful in studying citizen and court cases and it has also being used in educational interventions. The technique is especially useful, however, in analysis experimental data when assignment to a "treatment" group is presumed to effect scores on several criterion variables

In a study conducted by Fagoyinbo, Akinbo, and Ajibode, (2013), Discriminant analysis was used to classify students at risk in the department of Mathematics and Statistics, Federal Polytechnic, Ilaro and the study found out that 39 out of 51 students at risk were predicted at risk. Also, 14 out of 15 not at risk were predicted not at risk. The overall correct classification was 80.3%. Paliwal and Kumar (2008) have shown that when the results obtained by a Discriminant analysis were compared with those of neural networks in terms of the parameter academic performance on a categorical scale, no statistically significant differences were found.

Usoro (2006) carried out a study on classification of students into various departments on the basis of their cumulative results for a one year Foundation Programme otherwise known as Pre-National Diploma (PRE-ND) in Polytechnics system. Also, Erimafa et al (2009) carried out a study to predict the class of degree obtainable in a University system. Lohnes and McIntire (1967) reported on the use of Discriminant analysis to predict satisfactorily, the choice of programme to 9th and 10th grade students; college preparatory or non college preparatory programme, on the basis of six tests given by the educational testing service. The study concerns advising high school students regarding whether to choose a college preparatory course or non-college preparatory course. In their approach they used the means and pooled covariance matrix. When the Discriminant function was computed, the observations were re- substituted into the function and then classified. This method has a bias because the same observations were used to calculate the function and to evaluate it. It was suggested by Lachenbruch (1967) that to remove or reduce the biasness associated with such classification, a separate set of data be used and attempt to classify the new data set with the function. This normally results in smaller bias, but with smaller samples it can be fairly large. Lachenbruch (1968) and Glick (1972) both showed how as the sample size increases, the error rate (which is an indicator of bias) drops.

Iduseri and Edokpa (2011), carried out a research that compared the academic performances of students who majorly use Pidgin English and those who majorly use the conventional English, using Fisher's linear Discriminant analysis. The result of the analysis gave an extremely good separation between the two groups of students in terms of academic performance, with a measure of separation of 5.544. Records of the students' performance in their final school certificate examination gave 20% failure rate for students who majorly use conventional English and 56% failure rate for students who majorly use Pidgin English. Vandamme, Meskens and Superby (2007) used decision trees, neural networks and linear discriminant analysis for the early identification of three categories of students: low, medium and high-risk students. Some of the background information (demographics and academic history) of the first-year students in Belgian French-speaking universities were significantly related to academic success. Those were: previous education, number of hours of mathematics, financial independence, and age, while gender, parents' education and occupation, and marital status were not significantly related to the academic success. However, all three methods used to predict academic success did not perform well. Overall the correct classification rate was 40.63% using decision trees, 51.88% using neural networks and the best result was obtained with discriminant analysis with overall classification accuracy of 57.35%.

Michael (2004), used Discriminant analysis to illustrate how the technique can maximize the effectiveness and efficiency of screening procedures for identifying intellectually gifted children. In the study, it was discovered that the predictors of scores on an individually administered intelligence test, were group IQ and achievement tests, with high coefficients. Arithmetic ability (as an independent variable) recorded a negative coefficient: this was premised as an indication of suppressor effects. Since this variable's (with negative sign) zero order correlations with the criterion (dependent variable) are positive. He opined that it is best to removed these variables (with negative signs) and re-run the analysis to obtain robust results than can be more likely generalized.

Blazenka and Dijana (2009) used Discriminant analysis to analyze the effect of 30 variables upon the dependent variable, student success at the faculty of Organization and informatics, university of Zagreb. The model showed that eight variables out of the thirty variables contributed more. The eight variables are: first grade obtained at the Faculty, students' time management and goal centeredness, admission exam score, degree of students' personal responsibility and their interest in this Faculty, preparation for classes and in-class activity, and learning style. The remaining variables (22) were not included in the model because the contributed less. Talib et al (2011) used Step wise Discriminant analysis to investigate the effect of perceived stress, test competence, academic competence, time management, strategic studying and test anxiety on the academic performance of the university students in Pakistan as well as identifying whether these factors could distinguish differences among students based on academic performance. In the study, a sample of 250 university graduate and undergraduates students from Pakistan was selected. The step wise Discriminant analysis revealed that perceived stress followed by text anxiety and low academic competence significantly differed among the low and high GPA achievers. Perceived stress was found to be an important factor to discriminate among the students with low versus high academic performance.

## 2. TECHNIQUES USED IN DISCRIMINANT ANALYSIS

The two (2) techniques used in Discriminant analysis are:

1.Predictive Discriminant Analysis(PDA)

2.Descriptive Discriminant Analysis(DDA)

### 2.1. Predictive Discriminant Analysis

Predictive Discriminant analysis (PDA), or "classification" as it is sometimes called, generally includes "a set of predictor variables and one criterion variable, the latter being a grouping variable with two or more levels, that is, there are two or more groups" (Huberty & Barton, 1989). Predictive Discriminant analysis is similar to multiple regression analysis except that Predictive Discriminant Analysis is used when the criterion variable is categorical and nominally scaled. As in multiple regression, in Predictive Discriminant Analysis a set of rules is formulated which consists of as many linear combinations of predictors as there are categories, or groups (Huberty, 1994). The equation in Predictive Discriminant Analysis uses a person's scores on the predictor variables to predict the category to which the individual belongs (Gall, Borg, & Gall, 1996). In predictive Discriminant analysis, each object will have a single score on the Discriminant function in place of its scores on the various predictor variables. At the same time a cutoff score will be determined such that when the criterion groups are compared with respect to the discriminant scores the errors of classification are minimized (Kachigan, 1986).

### 2.2. Descriptive Discriminant Analysis

Descriptive Discriminant Analysis includes a collection of techniques involving two or more criterion variables and a set of one or more grouping variables, each with two or more levels, whose effects are assessed through Multivariate Analysis of Variance (MANOVA). "Whereas in Predictive Discriminant analysis (PDA) the multiple response variables play the role of predictor variables, in descriptive Discriminant analysis (DDA) they are viewed as outcome variables and the grouping variable(s) as the explanatory variable(s). That is, the roles of the two types of variables involved in a multivariate, multi-group setting in Descriptive Discriminant Analysis are reversed from the roles in Predictive Discriminant Analysis" (Huberty, 1994). In Descriptive Discriminant Analysis, the total "between-groups" association in Multivariate Analysis of Variance (MANOVA) is broken down into additive pieces through the use of uncorrelated linear combinations of the original variables (Discriminant functions) (Stevens, 1996).

Stevens (1996) described the distinction between Predictive Discriminant Analysis and Descriptive Discriminant Analysis in the following way; "in the predictive Discriminant analysis, the focus is on classifying subjects into one of several groups (or to predicate group membership),whereas in descriptive Discriminant analysis, the focus is on revealing major differences among the groups" .

### 2.3. Applications of Discriminant Analysis

Discriminant analysis has widespread application in situations in which the primary objective is to identify the group to which an object (e.g., person, firm, or product) belongs. Potential applications include predicting the success or failure of a new product, deciding whether a student should be admitted to graduate school, classifying students as to vocational interests, determining the category of credit risk for a person, or predicting whether a firm will be successful in each instance, the objects fall into groups, and the objective is to predict and explain bases for each object's group membership through a set of independent variables selected by the researcher, Joseph *et al.,* (2009).

### 2.4. The Discriminant Model

The elements of Discriminant model is given as:

$$Z_{jk} = a + W_1X_{1k} + W_2X_{2k} + \cdots + W_nX_{nk}$$

where $Z_{jk} =$ *discriminant Z score of Discriminant function j for object k*

$a =$ *intercept*

$W_i =$ *discriminant weight for independent variable i*

$X_{ik}$ = independent variable i for object k

### 2.5. Assumptions of Discriminant Function Analysis

As with any statistical technique, the proper use of the test requires that assumptions underlying the technique be observed (Klecka, 1980; Tabachnick & Fidell, 1989). The independent variables need to be interval while the dependent variable, the groups into which observations are classified, need to be nominal. Multivariate normality is assumed, but discriminant function analysis is robust to violations due to skewness rather than outliers (Tabachnick & Fidell, 1989). Discriminant function analysis does, however, include a technique that can be used to identify outliers, Mahalanobis distances, as a built-in option. Homogeneity of variance-covariance matrices is another assumption of Discriminant function analysis, but like multivariate normality, discriminant function analysis is robust to violations. Finally, violations of multicollinearity may make the underlying matrix calculations unstable and must be avoided but can be controlled with an option in the program. Generally, violations of these assumptions are conservative; that is, the power of the test is reduced, thereby lessening the chance of finding significance (Klecka, 1980). Discriminant function analysis produces functions that help define the groups; the maximum number of functions that can be defined is one less than the number of groups. The functions first seek to distinguish the first group from the others, then the second group from the rest, and so on. These are identified by the Eigen values on the output. The Eigen values also show what percent of variance is accounted for with each function. In addition, Wilk's lambda tests the significance of each function.

## 3. RESULTS AND DISCUSSIONS

The data for this study was the Pre-NCE student final score of the Kashim Ibrahim College of Education, Maiduguri, obtained from the average of the scores for the first and second semesters. In constructing the Discriminant function, all the subjects registered by a student in every course combination would be used.

### Assignment Rule

The table below gives the allocation rule for each of the subject combinations in the science based courses, Vocational and technical Education courses and Languages.

**Table 1** Assignment Rule

| S/N | Courses | $\lambda$ |
|---|---|---|
| 1 | Biology/Chemistry | 132.88 |
| 2 | Biology/Physics | 307.18 |
| 3 | Chemistry/Geography | 215.71 |
| 4 | Physics/Chemistry | 484.90 |
| 5 | Physical and Health Education | 112.20 |
| 6 | Agric Education | 110.24 |
| 7 | Home Economics | 138.33 |
| 8 | Fine and applied Art | 140.08 |

| | | |
|---|---|---|
| 9 | Business Education | 247.72 |
| 10 | English/Arabic | 74.78 |
| 11 | English/French | 123.05 |
| 12 | English/Hausa | 111.61 |

From the above table, assign candidate to a particular course combination if $D_i > \lambda$, reject candidate from a particular course combination if $D_i < \lambda$ and assign candidate conditionally if $D_i = \lambda$

Where $D_i =$ The score of a particular student in a particular course combination and $\lambda$ is the cut off point for a particular course combination.

## 4. DISCUSSION

Discriminant scores derived from the functions can be used in predicting the groupings of unclassified cases. The presence of negative coefficients in the Discriminant Function lowers the cutoff points and contributes less to the function, each course combination as a separate Discriminant function for the purpose of classification.

## 5. CONCLUSION

Using discriminant function analysis to classify data is very useful tool for researchers and college administrators. It can be utilized simultaneously to classify cases and the resultant model can be evaluated for usefulness relatively easily. The ability to develop a predictive model based on the model produced through the discriminant function analysis procedure increases its usefulness substantially. Colleges can utilize this dynamic and powerful procedure to target services and interventions to students who need it most, thereby utilizing their resources more effectively.

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