# ROBUSTNESS OF THE QUADRATIC DISCRIMINANT FUNCTION TO CORRELATED AND SKEWED TRAINING SAMPLES 



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KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF PHILOSOPHY

## Declaration

I hereby declare that this submission is my own work towards the Master of Philosophy (M.Phil.) and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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## Dedication


to $m y$

FAMILY
with love

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I am grateful and indebted to Most High God who is able to do immeasurable more in my life. Most especially for the life he has ushered me. I also wish to express my appreciation to my lovely parents for their support in my education and to Mr. Eric Takyi Atakorah for putting me on my toes. I am especially grateful to my supervisor, Dr. (Mrs.) A. O. Adebanji for the immense supervisory support I received from her. I have learnt a lot from the positive criticisms and the pressure she mounted on me. To all the lecturers in the Department of Mathematics, KNUST, I say thank you for the knowledge you imparted on me during my postgraduate studies. Last but not least, I appreciate every effort any of my postgraduate colleagues contributed to this work, most especially Philemon Baah.

## Abstract

This study investigates the asymptotic performance of Quadratic Discriminant Function and its robustness when the training samples are correlated normal or skewed. The scenarios considered were correlated normal, uncorrelated normal and skewed distributions. Three populations $\left(\Pi_{i}, i=1,2,3\right)$ with increasing group centroid separator function $(\delta=1,2,3,4,5)$ were considered. The number of predictor variables were 4,6 , and 8 with sample size ratios 1:1:1, 1:2:2 and 1:2:3. We simulated $N\left(\mu_{i}, \Sigma_{i}\right)$ of sample size $30,60,100$, $150,250,300,400,500,600,700$ and 2000 with MatLabR2009a for $p$ variables in $\Pi_{1}$. The sizes of $\Pi_{2}$ and $\Pi_{3}$ are determined by sample ratios at 1:1:1, 1:2:2 and 1:2:3 for $n_{1}: n_{2}: n_{3}$ and these ratios also determine the prior probabilities considered. The population means were $\mu_{1}=(0,0,0, \ldots, 0), \mu_{2}=(0,0,0, \ldots, \delta)$ and $\mu_{3}=(0,0,0, \ldots, 2 \delta)$ respectively. The covariance matrix $\Sigma_{i}$ has $\sigma_{k l}=0.7$ and $\sigma_{k}^{2}=i$ for $k \neq l, \quad i=1,2,3$. Reduction in error rates was more pronounced with increase in Mahalanobis distance than asymptotically. The coefficients of variation for sample size ratio 1:2:3 was more volatile under the three distributions considered. The optimal sample size ratio for the three distributions is 1:1:1. The results show the correlated normal distribution exhibits high coefficient of variation as $\delta$ increased. Further results show that the Quadratic Discriminant Function perform poorly when the training samples were skewed therefore, uncorrelated normal distribution was preferred

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## Chapter 1

## Introduction

### 1.1 Background of The Study

Discriminant analysis (DA) is a method used for finding out how a set of dependent/explanatory variables (DVs) is related to group membership, and particularly how they may be combined so as to enhance one's understanding of group differences. In more formal terms, DA aims at developing a rule for describing and subsequently predicting, if need be, group membership based on a given set of DVs. Once this rule becomes available, one may use it to make differential diagnosis, that is, group-membership prediction for particular subjects (Raykov and Marcoulides,2008).

Discriminant analysis as a topic in Multivariate Statistical Analysis has attracted much research interest over the years, with the evaluation of Discriminant Functions when the covariances matrices are unequal and the sample sizes are moderate being well explained by Wahl and Kronmal (1977). The following sections discuss some of the studies carried out on Discriminant Functions with unequal covariance matrices (Quadratic Discriminant Function).

In Scientific literatures, DA has many synonyms, such as classification, pattern recognition, character recognition, identification, prediction, and selection, depending on the type of scientific area in which it is used. The origin of DA is fairly old, and its development reflects the same broad phases as that of general statistical inferences in its applications (Giri, 2004). DA is essentially an adaptation of the regression analysis techniques for situation where the criterion variable is qualitative rather than quantitative. The assumptions for the data used in DA are that the data should be a random sample, normally distributed, homoscedastic, and uncorrelated among DVs. The terminology discrimination was introduced by Fisher (1936). In his early studies, Linear Function that maximizes the ratio of the between-samples variance to within-sample variances using two species (Iris Versicolor and Iris Setosa) out of the three species of the Iris data collected by Dr. E. Anderson was considered. Ever since his pioneering work, DA has been of great interest to statisticians, both theoretically and its application in other fields of study. Among them is Welch who derived the forms of Bayes rules for discriminating between two known multivariate populations with the same covariance matrix. (Rao, 1948).

Ideally, DA assumes the underlying populations to multivariate normality. In some classification problems, if there is evidence that the underlying distributions of the populations are multivariate normal, then Linear Discriminant Function (LDF) is optimum provided their covariance matrices are homogeneous. In the case of unequal covariance matrices of the normal populations, Quadratic Discriminant Function (QDF) is known to be optimum. Bahadur and Anderson (1962) considered the problem of discriminating between
two unknown multivariate normal populations with different covariance matrices by looking at the discriminant rules based on linear classification functions. Departures from the assumptions of linear discriminant function analysis were explored by Krzanowski (1977), where the effects of unequal covariances on the linear discriminant method are looked at. Marks and Dunn (1974) studied the problems in the situation of linear and Quadratic Discriminant Functions where the covariance matrices differ in an orderly manner while Lachenbruch (1979) discusses the sensitivity of quadratic discriminant analysis to initial misclassification of cases. Among the relationships governing the performance of Quadratic Discriminant Analysis, those that depend on the sample size and the number of variables used were studied by Wahl and Kronmal (1977). In the study of Adebanji and Nokoe (2004), they evaluated the quadratic classifier in which they found that cross-validation error estimation procedure to be more sensitive to increased separation of variance-covariance structure than resubstitution method. The assumption of the populations being normal is met in some of the fields of application of discriminant analysis. However, there are situations in which the populations that are non-normal or near-normal often arise. The data used for discrimination are also sometimes correlated. Lachenbruch et al.(1977) studied this case by looking at the effect of non-normality on quadratic discriminant function.

### 1.2 Problem Statement

LDF is commonly used by the researcher because of its simplicity of form and concept. In spite of theoretical evidence supporting the use of the QDF when covariances are heterogenous, its actual employment has been sporadic because there are unanswered questions regarding its performance in the practical situation where the discriminant function must be constructed using training samples that do not satisfy the classical assumption of the model.

In this study, we investigate the performance of classification functions when the underlying distributions are non-normal (skewed), when the covariance matrices are heterogeneous and when data of interest are correlated, sample size ratios are unequal, different number of variables and varying values of group centroid separator. Hence, the specific questions that are treated in this study are

- Under what conditions will we get least error rates using QDF classification with data having the features mentioned above
- Under which sample size ratio will misclassification of observation from a group rise?


### 1.3 Objectives

In this study the general objective is to examine the performance of QDF under nonnormality(positively skewed) and correlation within the data set by considering condition:

- Different sample size
- Varying the group centroid separator $(\delta=1,2,3,4,5)$
- Varying the number of variables (4, 6 and 8$)$


### 1.3.1 Specific Objective

The specific objectives of this study therefore are

- to examine the performance of QDF when the training samples are skewed
- to examine the asymptotic performance of QDF when the training samples are correlated.
- to determine the sample size ratio under which the performance of QDF deteriorate
- to conduct a Monte Carlo simulation to study the performance of QDF under the above mentioned conditions.


### 1.4 Methodology

Considering a three population case, we examine the effect of correlation, uncorrelation and skewness considering different sample size ratios, number of variables and varying group centroid separators $(\delta)$ on classification accuracy using simulated data from these three populations. The three populations differ with respect to their mean vector and
covariance matrices. This study examines the behaviour of QDF for observations from three multivariate normal populations. Sensitivity of the performance of the function to changes in

1. $\delta$ from 1 to 5 where $\delta$ is determined by the difference between the mean vectors,
2. Sample sizes are specified. Here 11 values of $n_{1}$ set at $30,60,100,150,250,300,400$, $500,600,700,2000$ and the sample size of $n_{2}$ and $n_{3}$ are determined by the sample ratios at 1:1:1, 1:2:2 and 1:2:3 and these ratios also determine the prior probabilities to be considered
3. The number of variables used were 4,6 and 8 for each case in (2)

MatLab R2009a is used to generate normal random data for all the populations and Minitab 16 for the graphs. The leave-one-out method is used to estimate the error rates (Lanchenbruch and Mickey, 1968) in all cases.

### 1.5 Justification of Problem

An enormous deal of study has been made since Fisher's (1936) original work on discriminant analysis. Some estimation methods have been proposed and some sampling properties derived. However, there is little investigation done on large sample properties of these functions. A considerable number of studies had been carried out on discriminant analysis but not much is done on the effect of non-normality and correlated data in classification with
respect to sample size ratios especially not on the QDF.

### 1.6 Organization of the Thesis

This thesis comprises of five chapters. Chapter 1 introduces the work by giving the background of the study, statement of the problem of this study, objectives of the study, methodology and justification of the problem of the study.

Framework of the study and literature are reviewed in Chapter 2. Quadratic discriminant function (QDF) as well as earlier related studies are discussed in this chapter. Chapter 3 talks about the methodology employed in our study. Chapter 4 presents and discusses the results obtained from the analysis and simulation. Finally summary of our findings, conclusion and recommendation for further research are presented in Chapter 5

## Chapter 2

## Literature Review

### 2.1 Selection of Variables in DA

In many applications of multivariate analysis, the statistician finds that he has data on very large number of variables which makes computation difficult. Murray (1977) studied the selection of variables in DA. He proposed that the procedure of selection of subset of variables were appealing from an intuitive point of view, but they produced rather disturbing results in practice. To estimate the magnitude of bias, he ran series of computer simulations in order to isolate the bias. $k$ independent normal random variables with unit variance and the means of two populations were specified. Since he was concerned with misclassification rates and parameters were known, the optimal discriminant rule was the likelihood ratio. Three different procedures were used to search through the subsets

1. $k=10$. Examine every subset.
2. $k=10$. Forward selection.
3. $k=50$. Forward selection up to ten variables.

Three different stopping procedure was also used to determine which subset to be used. They were

1. Choose the best subset of a given size.
2. Choose the best subset examined, irrespective of size.
3. Having found the best subset of size $r$, choose this unless the best subset of size $r+1$ gives strictly better classification

Sizes of data base used were 25,50 and 100 . The results indicated that for the stopping rule (1) and search procedure (1) and (2), as the number of variables increased, the best error rate did not decrease monotonically. He concluded that with data base size 25, only 4 variables were needed to the true error rates of all 50 variables. Also, for the stopping rules (2) and (3) with search procedures (1) and (2), the results indicated that neither of those stopping rules detected the increased discriminatory power of large subsets. He then concluded that the apparent error rate gave misleading estimates of the true error rates.

### 2.2 Unequal Covariance Matrices

The pioneering work on Quadratic Discrimination was by Smith (1947). He used Fisher's Iris data in his work. He provided a full expression for the QDF and his results showed the QDF outperforming the LDF when the homogeneity of variance covariance structure is violated. .

Anderson and Bahadur (1962) also studied a slightly different work on classification into two multivariate normal populations with different mean vectors and covariance matrices. If one attempts to use the LDF when in fact the covariance matrices are unequal, the performance on the LDF may be substantially affected. Marks and Dunn (1974) studied the performance of the LDF under this violation. Their intention was to find out whether sampling variability, arising from additional parameter estimation with increasing dimension size, reduces the quadratic's effectiveness to the point where a linear function with fewer parameters should be used instead. Their additional concern was the uncertainty about the behavior of the densities in the distribution tails which makes one reluctant to assign points far from the population means according to the quadratic. They approached these realistic problems by comparing the asymptotic and small sample performance of the QDF, best linear and Fisher's LDF for both proportional and non-proportional covariance differences under the assumption of normality and unequal covariance matrices. Two populations were used and sample sizes were from 10 to 100 . The number of variates were 2 and 10 . They employed the application of Monte Carlo simulation. Their results indicated that for small samples the QDF performed worse than the LDF when covariances were nearly equal and dimension was large (ie LDF was satisfactory when the covariance matrices were not too different). However, even for small samples, as covariance differences increased so did the performance of the QDF relative to Fisher's LDF. The best LDF appeared to offer little advantage in the situation where Fisher's function did better than the quadratic $d$ but did not match the performance of the quadratic when covariance inequality was greater. It
was also noted that when the means are widely separated the LDF generally do well. They concluded that for small sample sizes $\left(N_{1}, N_{2}<25\right)$ poor performances can be expected for QDF if the dimension size is moderately large $(k>6)$.

Wahl and Kronwal in 1977 extended the study of Marks and Dunn (1974). They observed that when the dimensions size and the covariance differences are large the QDF's performance is much better than Fisher's LDF provided the sample size is sufficient. For more than 100 observations, the asymptotic results are reached fairly quickly, thus favoring the QDF. They concluded that sample size is a critical factor in choosing between the QDF and LDF. It was therefore recommended that

1. For small covariance differences and small $d(d \leq 6)$ there is generally little to choose between the LDF and QDF.
2. For small samples $\left(n_{l}, n_{2}<25\right)$ and the covariance differences and/or d large, the LDF is preferred. However, when both covariance differences and d are large, the misclassification probabilities may be too large for practical use.
3. For large covariance differences and $d>6$, QDF is much better than LDF, provided that the samples sizes are sufficiently large.

### 2.3 DA Under Non-optimal Condition

In 1977, Kzarnowski studied the Fisher's Linear Discriminant Function under non-optimal conditions. He considered independent random samples, of sizes $n_{1}$ and $n_{2}$ respectively, from each of two $p$-variate distributions having mean vectors $\mu_{1}$ and $\mu_{2}$ and common covariance matrix $\Sigma$. He considered continuous and binary variables which were measured on each individual. Two populations were also looked at. They restricted their attention to when some or all the data are binary since the continuous non-normal case had already been tackled by Lachenbruch et al (1973). The specified parameters considered were the number of binary variables, means of the binary variables in the two populations, correlation between each pair of binary variables, means of continuous variables and Mahalanobis squared distances. His results indicated that in many instances the LDF may be satisfactory for classification but not for estimating risks of individuals belonging to a particular population. It was observed that the inflation of error rates for Fisher's LDF is generally greater in presence of moderate positive correlation among all the binary variables. Conversely, the largest differences in performance of Fisher's LDF between independent and correlated binary variables occur when the populations are widely separated, and it became intense as the number of binary variables were increasing. Agreement of LDF and QDF was adequate only for a moderate range constant multiple of group covariance matrix and with some amount of linear separation of populations. It becomes worse as the number of variables increase.

### 2.4 Evaluation of the Quadratic Classifier

Adebanji and Nokoe (2004) have considered evaluating the Quadratic classifier. They restricted their attention on two multivariate normal populations of independent variables. In addition to some theoretical result, in the case of known parameters, they conducted a Monte Carlo simulation in order to investigate the error rates. Results indicated that the total error rate computed showed that there was an increase in the error rate with re-substitution estimator for all $K$ values. On the other hand, there was a decline across $K$. The Cross-validation estimator showed a steady decline for and across all values $K$ and the recorded values showed a substantially low error rate estimates than re-substitution estimator for $K=4$ and $K=8$. The re-substitution estimator did not show high sensitivity in $K$ as it was in the cross-validation estimator even with increased sample size. They also looked at relative bias where re-substitution estimator recorded its highest bias at $K=8$ and lowest at $K=4$ while cross-validation estimator's highest and lowest bias were at $K=8$ and $K=2$ respectively. The distribution of error rates was found to be closer to Gamma than to Normal distribution. They concluded that the structure of the dispersion matrix could be informative considering the use of Quadratic classifier and also in deciding on the method of estimating misclassification rate.

### 2.5 Effect of Initial Misclassification on QDF

According to Lachenbruch (1974), the model assumed that the observations are randomly misclassified and that each observation had the same chance of being initially misclassified is clearly unrealistic. His study attempted to present two models of non-random initial misclassification, the complete separation model which was defined as for $x$ observation, calculate $\left(x-\mu_{1}\right)^{\prime}\left(x-\mu_{1}\right)=x^{\prime} x$ and $\left(x-\mu_{2}\right)^{\prime}\left(x-\mu_{2}\right)$ and assign the observation to whichever population with the smaller quantity. This amounted to assigning x to $\Pi_{1}$ if $x_{1}<\delta / 2$ and to $\Pi_{2}$ if otherwise. It was easy to show that this led to an initial misclassification rate of $\alpha_{i}=\phi(\delta / 2)$ in $\Pi_{1}$ and $\Pi_{2}$. The second model was the generalization of the first model. The same criterion was used, but, in addition, for an observation from $\Pi_{i}$ to be misclassified, $\left(x-\Pi_{i}\right)^{\prime}\left(x-\Pi_{i}\right)$ must be greater than a quantity, $V_{i}$. In these models, observations which were closer to the mean of the "wrong" population had a greater chance of being misclassified than others. He hoped these models were more realistic than the "equal chance" model. Monte Carlo experiments are used to evaluate the behavior of the LDF. His results indicated that (a) the actual error rates of the rules from samples with initial misclassification were only slightly affected, (b) the apparent error rates, obtained by resubstituting the observations into the calculated discriminant function, were drastically affected, and cannot be used, and (c) the Mahalanobis $D^{2}$ was greatly inflated.

Lachenbruch (1979) did a study on DA in which he considered the effects of initial misclassification on the QDF. In his simulation, a population of two with equal priori probabilities,
mean of 0 and 2 and number of variables, $2,4,8$ and a fraction of $\alpha_{i}$ of the $n_{i}$, which are actually from the other population, were considered. To determine the effects of initial misclassification, he generated the QDFs that would result from various values of the parameters and estimated the error. He found out that although initial misclassification is not a serious problem with LDFs if initial rates are about the same, it is with QDF. The severity of the problem increases with increasing differences in covariance matrices and with increasing initial misclassification rates. He then suggested that if initial misclassification is suspected, all sample points should be carefully checked and reassigned if needed.

### 2.6 DA with Correlated Training Samples

If one attempts to use the LDF or QDF when in fact the training samples are correlated, the performance on the LDF or QDF may be significantly affected. Lawoko (1988) studied the performance of the LDF and QDF under the assumption of correlated training samples. In his study consideration was given to the problem of allocating an object to one of two groups on the basis of measurements on the object. His attention was on Anderson's sample LDF (W) and QDF (Z) formed from the likelihood ratio criterion. The performance of the Z and W relative to each other under correlated training observations were studied. He found that their relative performance depends on the extent of the correlation among the training observations and the size of the separation between the classes. Z was recommended over W for positively correlated training observations which followed a moving average process
of order one on the basis asymptotic expansion of error rates. Under intraclass correlation model, he found that the discriminant functions formed under the model did not perform better than W and Z formed under the assumption of independent training observation. Asymptotic expected error rate for W under the model $\left(W_{m}\right)$ and W were equal when the training observations follow an autoregressive process but there was a slight improvement in the overall error rate when $W_{m}$ was used instead of $W$ for numerical evaluations of the asymptotic expansions. He concluded that the efficiency of the discriminant analysis estimator is generally lowered by positively correlated training observations.

Mardia et al (1979) reported that it might be thought that a linear combination of two variables would provide a better discriminator if they were correlated than when they were uncorrelated. However, this is not necessarily so. To show this they considered two bivariate populations $\Pi_{1}$ and $\Pi_{2}$. Supposing $\Pi_{1}$ is $N_{2}(0, \Sigma)$ and $\Pi_{2}$ is $N_{2}(\mu, \Sigma)$ where $\mu=\left(\mu_{1}, \mu_{2}\right)^{\prime}$ and $\Sigma=\left[\begin{array}{ll}1 & \rho \\ \rho & 1\end{array}\right]$. Now the Mahalanobis distance between the two populations is

$$
\Delta^{2}=\mu^{\prime} \Sigma^{-1} \mu^{\prime}=\left(\mu_{1}^{2}+\mu_{2}^{2}-2 \rho \mu_{1} \mu_{2}\right)\left(1-\rho^{2}\right)
$$

if the variables are uncorrelated then

$$
\Delta^{2}=\mu_{1}^{2}+\mu_{2}^{2}=\Delta_{0}^{2}
$$

Correlation then improves discrimination (i.e. reduce the probability of misclassification) if and only if $\Delta^{2}>\Delta_{0}^{2}$. This happens if and only if $\rho\left(1+f^{2}\right) \rho-2 f>0$ where $f=\mu_{2} / \mu_{1}$ In other words, discrimination is improved unless $\rho$ lies between zero and $2 f /\left(1+f^{2}\right)$ but
a small value of $\rho$ can actually harm discrimination. Note that if $\mu_{1}=\mu_{2}$ then any positive correlation reduces the power of discrimination.

### 2.7 Non-Normality

Several studies have been conducted on the effect of various types of non-normality on the QDF and LDF. Lachenbruch et al. (1973) considered the robustness of LDF. Three specific distributions and the case of independent variables were considered. These distributions were considered to be non-normal and generated from the normal distributions by using the Johnson system of transformations (log normal, inverse hyperbolic sine normal and logit normal distribution). The study indicated considerable decline in performance of the LDF (the log normal distribution used has extremely large skewness and kurtosis). They conducted Monte Carlo experiments to investigate robustness when parameters are estimated. Their results indicated that Fisher's LDF was greatly affected by non-normality in the population. Error rates for one population were greatly larger that the optimum values while the reverse was true in the other population. It was also noted that if error rates with LDF were greatly different in the two populations when a cut-off point is zero, then presence of non-normal data is indicated. They concluded that use of Fisher's LDF in non-normal situations could be badly misleading, and recommended that the data be transformed to approximate normality prior to use of the LDF and the error rates could be used as a check on the normality assumption.

Lachenbruch et al. (1977) studied the effect of non-normality on the QDF. They assumed that the data were transformable to normality, variables were independent and covariance matrices were proportional after transformation. In order to study the effect of non-normality on QDF, they generated random samples from non-normal distributions and the samples were transformed component by component by using Johnson's system of transformation. The data used represented rather mild departures from normality and the following are their observations:

1. In the computation of the overall sample standard deviation, the between sample variability of the individual error rates in the QDF on normal or non-normal distributions was quite large and for that instability of QDF is pronounced.
2. The actual error rates were considerably larger than the optimal rates in the case of zero mean difference (this is a very difficult problem in assignment)
3. The QDF for non-normal samples generally did not do substantially worse than when the QDF was applied to the normal samples which would be obtained after transformations;
4. In comparing the resubstitution method and the leave-one-out method, the resubstitution method had an unacceptably high bias. The leave-one-out method was far superior in respect of generally having a far lesser bias.
5. Attempting to obtain robust estimates of means and covariance was of little help unless the distribution was heavy-tailed or substantially skewed.

### 2.8 Error Rates

Evaluation of a classification procedure is by estimating the error rate. A good classification procedure should result in minimal error rates. Lachenbruch and Mickey (1968) did a study on estimation of these error rates. The discriminant function which was denoted as $W$ by Anderson was considered. They described eight techniques to estimate error and attempted to evaluate seven of them in which the holdout method was excluded since the number of hold-out cases in each group that are misclassified is binomially distributed. It was observed that none of the methods was uniformly best for all situations, although some methods performed better than the two methods which were in use at that time.

Krzanowski and Hand (1997) considered an assessment of error rate estimators paying special attention to the leave-one-out method. The leave-one-out rule seeks to overcome the drawback of resubstitution by a process of cross-validation. The estimator was investigated in a simulation study, both in absolute terms and in comparison with a popular bootstrap estimator. The Bayes' procedure was found to give unreliable estimates of the leave-outtwo which performed better than the leave-one-out. They compared the performance of the leave-one-out method with that of the 632 method, as measured by the incorrect and correct methods. They found that results leave-one-out method is even worse than had been expected. Motivated by this, extension of leave-one-out, the leave-two-out was looked at considering the varience.As expected, the leave-two-out method yields a slight variance reduction relative to the leave-one-out method, but not enough to make it a good competitor
for the 632 method.

In order to study the asymptotic error rates of Linear, Quadratic and Logistic rules Kakai and Pelz (2010) conducted a Monte Calor study in 2, 3 and 5-group discriminant analysis. The simulation study took into account the overlap of the populations $(e=0.05, e=0.1$, $e=1.5$ ), their common distribution (normal, chi-square with 4,8 and 12 df ) and their heteroscedasticity degree, $\Gamma$, measured by the value of the power function, $1-\beta$ of the homoscedasticity test related to $\Gamma(1-\beta=0.05,1-\beta=0.4,1-\beta=0.6,1-\beta=0.8)$.

The following observations were made

1. By considering the combination of the parameters the three rules gave similar error rates for normal homoscedastic populations.
2. For normal heteroscedastic population, the quadratic rule is theoretically Bayes rule and it presented lowest relative error irrespective of the number of groups.
3. For non-normal populations, quadratic rule still gave lowest relative error except for 2-group where logistic was the best
4. Quadratic and logistic rule were more influenced by the number of group irrespective of their lowest relative error
5. Also linear and quadratic were more influenced by non-normality

## Chapter 3

## Methodology

### 3.1 Concept of Discrimination and Classification

Discrimination and classification are multivariate techniques concerned with separating distinct sets of objects (or observations) and with allocating new objects (observations) to previously defined groups. Discriminant analysis is rather exploratory in nature. As a separative procedure, it is often employed on a one-time basis in order to investigate observed differences when causal relationships are not well understood. Classification procedures are less exploratory in the sense that they lead to well-defined rules, which can be used for assigning new objects. Classification ordinarily requires more problem structure than discrimination does. Discrimination is to describe, either graphically or algebraically, the differential features of objects (observations) from several known collections (populations). We try to find "discriminants" whose numerical values are such that the collections are separated as much as possible (separation). While classification is to sort objects (observations) into two or more labeled classes with the emphasis on deriving a rule that can be used to optimally assign new objects to the labeled classes (that is allocation). The idea
of discrimination and classification frequently overlap, and the distinction between separation and allocation becomes blurred but they are always applied together in discriminant analysis.

### 3.2 Discrimination and Classification of Two Population <br> 

Härdle and Simar (2012) used example, the detection of "fast" and "slow" consumers of a newly introduced product. Using a consumer's characteristics like education, income, family size, amount of previous brand switching, we want to classify each consumer into the two groups just identified. Let $f_{1}(\mathbf{x})$ and $f_{2}(\mathbf{x})$ be the probability density functions associated with the $p \times 1$ vector random variable $\mathbf{X}$ for the populations $\Pi_{1}$ and $\Pi_{2}$, respectively. An object with associated measurements $\mathbf{x}$ must be assigned to either $\Pi_{1}$ or $\Pi_{2}$. Let $\Omega$ be the sample space-that is, the collection of all possible observations $\mathbf{x}$. Let $R_{1}$ be that set of $\mathbf{x}$ values for which we classify objects as $\Pi_{1}$ and $R_{2}=\Omega-R_{1}$ be the remaining $\mathbf{x}$ values for which we classify objects as $\Pi_{2}$. Since every object must be assigned to one and only one of the two populations, the sets $R_{1}$ and $R_{2}$ are mutually exclusive and exhaustive. The main task of discriminant analysis is to find "good" regions $R_{j}$ where $j=1,2$ such that the error of misclassification is small. In the following we describe such rules when the population distributions are known. The conditional probability, $P(2 \mid 1)$, of classifying
an object as $\Pi_{2}$ when, in fact, it is from $\Pi_{1}$ is written as

$$
P(2 \mid 1)=P\left(X \in R_{2} \mid \Pi_{1}\right)=\int_{R_{2}=\Omega-R_{1}} f_{1}(\mathbf{x}) d \mathbf{x}
$$

Similarly, the conditional probability of classifying an object as $\Pi_{1}$ when, in fact, it is from $\Pi_{2}, P(1 \mid 2)$ is written as

$$
P(1 \mid 2)=P\left(X \in R_{1} \mid \Pi_{2}\right)=\int_{R_{1}} f_{2}(\mathbf{x}) d \mathbf{x}
$$

Where the individual integral signs represent the volume formed by the individual density functions over the region $R_{j}$.

### 3.3 Likelihood Ratio Discriminant Rule

It is suggested that $\mathbf{x}_{0}$ should be allocated to $\Pi_{1}$ whenever the probability of it coming from $\Pi_{1}$ is greater than probability of it from $\Pi_{2}$, to $\Pi_{2}$ whenever these probabilities are reversed, and by chanced to $\Pi_{1}$ or $\Pi_{2}$ whenever these probabilities are equal. By this argument, we define $R_{1}$ as the set of points for which $f_{1}(\mathbf{x}) \geq f_{2}(\mathbf{x})$, and $R_{2}$ as the set of points for which $f_{1}(\mathbf{x})<f_{2}(\mathbf{x})$. Rewriting the above slightly, the classification rule is as follows:

$$
\begin{equation*}
\text { Assign } \mathbf{x}_{0} \text { to } \Pi_{1} \text { if } \frac{f_{1}\left(\mathbf{x}_{0}\right)}{f_{1}\left(\mathbf{x}_{0}\right)} \geq 1 \tag{3.1}
\end{equation*}
$$

and to $\Pi_{2}$ when otherwise.
The allocation rule 3.1 is known as the likelihood ratio rule. This rule, however, fails to take into account some factors which may be important in practice. These factors are:
differential prior probabilities of observing individuals from the two populations and the differential costs of misclassification.

### 3.4 Prior Probability

An optimal classification rule should take into prior probabilities of occurrence into account. Let $p_{1}$ be the prior probability of $\Pi_{1}$ and $p_{2}$ be the prior probability of $\Pi_{2}$, where $p_{1}+p_{2}=1$. Then the overall probabilities of correctly or incorrectly classifying objects can be derived as the product of the prior and conditional classification probabilities:


$$
\begin{align*}
P\left(\text { observation is correctly classified as } \Pi_{2}\right)= & P\left(\text { observation comes from } \Pi_{2}\right. \\
& \text { and is correctly classified as } \left.\Pi_{2}\right) \\
P(2 \mid 2) p_{2}= & P\left(X \in R_{2} \mid \Pi_{2}\right) P\left(\Pi_{2}\right) \\
P\left(\text { observation is misclassified as } \Pi_{2}\right)= & P\left(\text { observation comes from } \Pi_{1}\right.  \tag{3.4}\\
& \text { and is misclassified as } \left.\Pi_{2}\right) \\
P(2 \mid 1) p_{1}= & P\left(X \in R_{2} \mid \Pi_{1}\right) P\left(\Pi_{1}\right)
\end{align*}
$$

### 3.5 Cost of Misclassification

According to Krzanowski (1988) another aspect of classification is cost. A rule that ignores costs may cause problems. The cost associated with each of these mistakes are $c(1 \mid 1), c(1 \mid 2), c(2 \mid 2)$ and $c(2 \mid 1)$ respectively. The costs are zero for correct classification, so the expected or average cost of misclassification is given by

$$
\begin{align*}
E C M & =c(2 \mid 1) P(2 \mid 1) p_{1}+c(1 \mid 2) P(1 \mid 2) p_{2} \\
& =c(2 \mid 1) p_{1} \int_{R_{2}} f_{1}(\mathbf{x}) d \mathbf{x}+c(1 \mid 2) p_{2} \int_{R_{1}} f_{2}(\mathbf{x}) d \mathbf{x} \tag{3.6}
\end{align*}
$$

The best classification rule is the one that yields minimum expected cost due to misclassification, and this rule will be obtained by finding the region $R_{1}$ and $R_{2}$ minimizing ECM
in 3.6 allocate $\mathbf{x}$

$$
\begin{gather*}
R_{1}: \frac{f_{1}(x)}{f_{2}(x)} \geq\left(\frac{c(1 \mid 2)}{c(2 \mid 1)}\right)\left(\frac{p_{2}}{p_{1}}\right)  \tag{3.7}\\
R_{2}: \frac{f_{1}(x)}{f_{2}(x)}<\left(\frac{c(1 \mid 2)}{c(2 \mid 1)}\right)\left(\frac{p_{2}}{p_{1}}\right) \tag{3.8}
\end{gather*}
$$

The right hand side of 3.7 and 3.8 known as the cut-off point is denoted by $\mathbf{k}$. It is clear from 3.6 that the implementation of the minimum ECM rule requires (1) the density function ratio evaluated at a new observation $\mathbf{x}_{\mathbf{0}}$, (2) the cost ratio, and (3) the prior probability ratio. The appearance of ratios in the definition of the optimal classification regions is significant (Johnson and Winchern, 2007).

The likelihood ratio discriminant rule 3.1 is thus a special case of the $E C M$ rule for equal misclassification costs and equal prior probabilities. Other special cases of Minimum Expected Cost Regions are:
(a) $p_{2} / p_{1}=1$ (equal prior probabilities); $k=c(1 \mid 2) / c(2 \mid 1)$

$$
R_{1}: \frac{f_{1}(\mathbf{x})}{f_{2}(\mathbf{x})} \geq \frac{c(1 \mid 2)}{c(2 \mid 1)} \quad R_{2}: \frac{f_{1}(\mathbf{x})}{f_{2}(\mathbf{x})}<\frac{c(1 \mid 2)}{c(2 \mid 1)}
$$

(b) $c(1 \mid 2) / c(2 \mid 1)=1$ (equal costs of misclassification); $k=p_{2} / p_{1}$

$$
R_{1}: \frac{f_{1}(\mathbf{x})}{f_{2}(\mathbf{x})} \geq \frac{p_{2}}{p_{1}} \quad R_{2}: \frac{f_{1}(\mathbf{x})}{f_{2}(\mathbf{x})}<\frac{p_{2}}{p_{1}}
$$

When the prior probabilities are unknown, they are often considered to be equal. Similarly, the costs of misclassification are also often taken to equal when they are unknown.

### 3.6 Total Probability of Misclassification

Criteria other than the ECM can be used to "optimal" classification procedures. One might ignore cost of misclassification and choose $R_{1}$ and $R_{2}$ to minimize the total probability of misclassification (TMP).

$$
\begin{aligned}
\mathrm{TMP}= & P\left(\text { misclassifying a } \Pi_{1} \text { observation or misclassifying a } \Pi_{2} \text { observation }\right) \\
= & P\left(\text { observation comes from } \Pi_{1} \text { and is misclassified }\right) \\
& +P\left(\text { observation comes from } \Pi_{2} \text { and is misclassified }\right) \\
= & p_{1} \int_{R_{2}} f_{1}(\mathbf{x}) d \mathbf{x}+p_{2} \int_{R_{1}} f_{2}(\mathbf{x}) d \mathbf{x}
\end{aligned}
$$

Mathematically, this problem equivalent to minimizing the expected/average cost of misclassification when the cost of misclassification are equal.

The rule (b) could have been derived equivalently by minimizing $T P M$, where

$$
\begin{equation*}
T P M=P(2 \mid 1) p_{1}+P(1 \mid 2) p_{2} \tag{3.9}
\end{equation*}
$$

is given by $E C M$ of (2.2) but with $c(2 \mid 1)$ and $c(1 \mid 2)$ removed. It is worth mention that the rule (b) is equivalent to the allocation rule derived by maximizing the posterior probability of population membership.

### 3.7 Bayes' Classification Rule

Let

$$
\begin{equation*}
P\left(\mathbf{x} \in \Pi_{i}\right)=p_{i}, i=1,2 \tag{3.10}
\end{equation*}
$$

be the prior probabilities that a randomly selected observation $\mathbf{x}=\mathbf{x}_{0}$ belongs to either $\Pi_{1}$ or $\Pi_{2}$. Suppose also that the conditional multivariate probability density of $\mathbf{x}$ for the $i$ th class is

$$
\begin{equation*}
P\left(\mathrm{x}=\mathbf{x}_{0} \mid \mathbf{x} \in \Pi_{i}\right)=f_{i}\left(\mathbf{x}_{0}\right), i=1,2 \tag{3.11}
\end{equation*}
$$

From 3.10 and 3.11, Bayes' theorem yields the posterior probability,

$$
\begin{equation*}
P\left(\Pi_{i} \mid \mathbf{x}\right)=P\left(\mathbf{x} \in \Pi_{i} \mid \mathbf{x}=\mathbf{x}_{0}\right)=\frac{f_{i}\left(\mathbf{x}_{0}\right) p_{i}}{f_{1}\left(\mathbf{x}_{0}\right) p_{1}+f_{2}\left(\mathbf{x}_{0}\right) p_{2}} \tag{3.12}
\end{equation*}
$$

that the observed $\mathbf{x}_{0}$ belongs to $\Pi_{i}, i=1,2$. For a given $\mathbf{x}_{0}$, a reasonable classification strategy is to assign $\mathbf{x}_{0}$ to the class with the higher posterior probability. This strategy is called the Bayes' classification rule. Since we are dealing with forced classification, the classification rule is

$$
\begin{equation*}
\operatorname{assign} \mathbf{x}_{0} \text { to } \Pi_{1} \text { if } \frac{P\left(\Pi_{1} \mid \mathbf{x}\right)}{P\left(\Pi_{2} \mid \mathbf{x}\right)} \geq 1 \tag{3.13}
\end{equation*}
$$

otherwise assign $\mathbf{x}_{0}$ to $\Pi_{2}$. The ratio $\frac{P\left(\Pi_{1} \mid \mathbf{x}\right)}{P\left(\Pi_{2} \mid \mathbf{x}\right)}$ is referred to as the "odds-ratio" that $\Pi_{1}$ rather than $\Pi_{2}$ is the correct class given the information in $\mathbf{x}_{0}$. Substituting 3.12 into 3.13, the Bayes' classification rule becomes

$$
\begin{equation*}
\operatorname{assign} \mathbf{x}_{0} \text { to } \Pi_{1} \text { if } \frac{f_{1}\left(\mathbf{x}_{0}\right)}{f_{2}\left(\mathbf{x}_{0}\right)} \geq \frac{p_{2}}{p_{1}} \tag{3.14}
\end{equation*}
$$

and to $\Pi_{2}$ otherwise.(Izenman, 2008).

### 3.8 Distance Based Classification

We now turn our attention to classification rules for several groups based on the distance between x and the discriminating groups. We consider the case where x is multivariate normal in $\Pi_{1}, i=1,2, \ldots, g$. The Mahalanobis squared distance between $x$ and $\Pi_{i}$ is defined as

$$
\begin{equation*}
\Delta_{i}^{2}=\left(\mathbf{x}-\mu_{i}\right)^{\prime} \Sigma^{-1}\left(\mathbf{x}-\mu_{i}\right) \tag{3.15}
\end{equation*}
$$

The allocation rule is allocate $x$ to the group for which $\Delta_{i}^{2}$ is smallest.

### 3.9 The Quadratic Classifier $\left(\Sigma_{1} \neq \Sigma_{2}\right)$

Suppose that the joint densities of $X^{\prime}=\left[X_{1}, X_{2}, \ldots, X_{p}\right]$ for population $\Pi_{1}$ and $\Pi_{2}$ are given by

$$
\begin{equation*}
f_{i}(\mathbf{x})=\frac{1}{(2 \pi)^{p / 2}\left|\Sigma_{i}\right|^{1 / 2}} \exp \left[-\frac{1}{2}\left(\mathbf{x}-\mu_{i}\right)^{\prime} \Sigma_{i}^{-1}\left(\mathbf{x}-\mu_{i}\right)\right] \tag{3.16}
\end{equation*}
$$

The covariance matrices as well as the mean vectors are different from one another for the two populations. The regions of minimum expected cost misclassification (ECM) and minimum total probability of misclassification (TPM) depends on the ratio of the densities, $\left(f_{1}(\mathbf{x})\right) /\left(f_{2}(\mathbf{x})\right.$, or equivalently, the natural logarithm of the density ratio, $\ln \left[\left(f_{1}(\mathbf{x}) /\left(f_{2}(\mathbf{x})\right]=\right.\right.$ $\ln \left[f_{1}(\mathbf{x})\right]-\ln \left[f_{2}(\mathbf{x})\right]$ when the multivariate normal densities have different covariance structures, the terms in the density ratio involving $\left|\Sigma_{i}^{1 / 2}\right|$ do not cancel as they do when we have equal covariance matrices and also the quadratic forms in the exponents of $f_{i}(\mathbf{x})$ do
not combine. Therefore substituting multivariate normal densities with different covariance matrices into 3.7 and 3.8 and after taking the natural logarithms and simplifying, the likelihood of the density ratios gives the quadratic function in $\mathbf{x} \in \Pi_{1}$ if

$$
-\frac{1}{2} \mathbf{x}^{\prime}\left(\Sigma_{1}^{-1}-\Sigma_{2}^{-1}\right) \mathbf{x}+\left(\mu_{1}^{\prime} \Sigma_{1}^{-1}-\mu_{2}^{\prime} \Sigma_{2}^{-1}\right) \mathbf{x}-k \geq \ln \left[\left(\frac{c(1 \mid 2)}{c(2 \mid 1)}\right)\left(\frac{p_{2}}{p_{1}}\right)\right]
$$

where

$$
\begin{equation*}
k=\frac{1}{2} \ln \left(\frac{\left|\Sigma_{1}\right|}{\left|\Sigma_{2}\right|}\right)+\frac{1}{2}\left(\mu_{1}^{\prime} \Sigma_{1}^{-1} \mu_{1}-\mu_{2}^{\prime} \Sigma_{2}^{-1} \mu_{2}\right) \tag{3.17}
\end{equation*}
$$

otherwise, $\mathbf{x} \in \Pi_{1}$. Considering the Mahalanobis distance, the function is sometimes written as

$$
\begin{equation*}
f(\mathbf{x})=D_{1}^{2}(\mathbf{x})-D_{2}^{2}(\mathbf{x})+\ln \left[\frac{\left|\Sigma_{1}\right|}{\left|\Sigma_{2}\right|}\right]-2 \ln \left(\frac{p_{1}}{p_{2}}\right) \tag{3.18}
\end{equation*}
$$

The quantity $D_{i}^{2}(\mathbf{x})=\left(\mathbf{x}-\mu_{i}\right)^{\prime} \Sigma^{-1}\left(\mathbf{x}-\mu_{i}\right)$ is the Mahalanobis Square Distance.
When $\Sigma_{1}=\Sigma_{2}$ the function reduces to linear classifier rule(Adebanji and Nokoe, 2004)
In many applications, the distributions of the populations of interest may not be multivariate normal.If the data are not multivariate normal, transformation of the data to more nearly normal and a test for equality of covariance matrix can be conducted to see whether the linear rule or the quadratic rule is appropriate. This transformation is done before testing is carried out.
we can also use the linear or quadratic rule without worrying about the form of the parent population and hope that it will work reasonably well. Studies have shown that there are non-normal cases where LDF performs poorly, even though the population covariance matrices are the same. The moral is to always check the performance of any classification
procedure (Johnson and Winchern, 2007).

### 3.10 Inferential Procedures In Discriminant Analysis

Several inferential procedures exists in discriminant function analysis. The basic ones are discussed here.

3.10.1 Test for $H_{0}: \mu_{1}=\mu_{2}$ When $\Sigma_{1}=\Sigma_{2}$ Using Hotelling's $T^{2}$-Test

In the multivariate case, we wish to compare the mean vectors from two populations. We assume that two independent random samples $\mathbf{y}_{11}, \mathbf{y}_{12}, \cdots, \mathbf{y}_{1 n_{1}}$ and $\mathbf{y}_{21}, \mathbf{y}_{22}, \cdots, \mathbf{y}_{2 n_{2}}$ are drawn from $N_{p}\left(\mu_{1}, \boldsymbol{\Sigma}_{1}\right)$ and $N_{p}\left(\mu_{2}, \boldsymbol{\Sigma}_{2}\right)$, respectively, where $\boldsymbol{\Sigma}_{1}$ and $\boldsymbol{\Sigma}_{2}$ are unknown. In order to obtain a $T^{2}$-test, we must assume that $\boldsymbol{\Sigma}_{1}=\boldsymbol{\Sigma}_{2}=\boldsymbol{\Sigma}$, say. From the two samples, we calculate $\overline{\mathbf{y}}_{1}, \overline{\mathbf{y}}_{2}, \mathbf{W}_{1}=\left(n_{1}-1\right) \mathbf{S}_{1}$, and $\mathbf{W}_{2}=\left(n_{2}-1\right) \mathbf{S}_{2}$. A pooled estimator of the covariance matrix is calculated as

$$
\mathbf{S}_{p l}=\frac{\mathbf{W}_{1}+\mathbf{W}_{2}}{n_{1}+n_{2}-2},
$$

for which $E\left(\mathbf{S}_{p l}\right)=\boldsymbol{\Sigma}$.

To test

$$
H_{0}: \mu_{1}=\mu_{2} \quad \text { versus } \quad H_{1}: \mu_{1} \neq \mu_{2},
$$

we use the test statistic

$$
T^{2}=\frac{n_{1} n_{2}}{n_{1}+n_{2}}\left(\overline{\mathbf{y}}_{1}-\overline{\mathbf{y}}_{2}\right)^{\prime} \mathbf{S}_{p l}^{-1}\left(\overline{\mathbf{y}}_{1}-\overline{\mathbf{y}}_{2}\right),
$$

which is distributed as $T_{p, n_{1}+n_{2}-2}^{2}$ when $H_{0}$ is true. We reject $H_{0}$ if $T^{2} \geq T_{\alpha, n_{1}+n_{2}-2}^{2}$.

### 3.10.2 Wilks's Likelihood Ratio Test

If $\mathbf{y}_{i j}, i=1,2, \cdots, g, j=1,2, \cdots, n$, are independently observed from $N_{p}\left(\mu_{i}, \boldsymbol{\Sigma}\right)$, then the likelihood ratio test statistic for $H_{0}: \mu_{1}=\mu_{2}=\cdots=\mu_{g}$ can be expressed as

$$
\begin{equation*}
\Lambda=\frac{|\mathbf{E}|}{|\mathbf{E}+\mathbf{H}|}, \tag{3.19}
\end{equation*}
$$

where $\mathbf{H}$ and $\mathbf{E}$ are defined as

$$
\mathbf{H}=n \sum_{i=1}^{g}\left(\overline{\mathbf{y}}_{i}-\overline{\mathbf{y}}\right)\left(\overline{\mathbf{y}}_{i}-\overline{\mathbf{y}} .\right)^{\prime}
$$

and

$$
\mathbf{E}=\sum_{i=1}^{g} \sum_{j=1}^{n}\left(\overline{\mathbf{y}}_{i j}-\overline{\mathbf{y}}_{i}\right)\left(\overline{\mathbf{y}}_{i j}-\overline{\mathbf{y}}_{i}\right)^{\prime}
$$

The test statistic 3.19 is distributed as the Wilks $\Lambda$-distribution. We reject $H_{0}: \mu_{1}=$ $\mu_{2}=\cdots=\mu_{g}$ if $\Lambda \leq \Lambda_{\alpha, p, \nu_{H}, \nu_{E}} \cdot p, \nu_{H}$ and $\nu_{E}$ is the dimension and degrees of freedom for hypothesis and error, respectively.

### 3.10.3 Box's M-Test

For a one-way MANOVA with $g$ groups $(g \geq 2)$, the assumption of equality of covariance matrices can be stated as a hypothesis to be tested:

$$
\begin{equation*}
H_{0}: \Sigma_{1}=\Sigma_{2}=\cdots=\Sigma_{g} \tag{3.20}
\end{equation*}
$$

versus $H_{1}$ : at least two $\boldsymbol{\Sigma}_{i}$ 's are unequal. Define $\mathbf{W}_{i}=\sum_{j=1}^{n_{i}}\left(\mathbf{y}_{i j}-\overline{\mathbf{y}}_{i}\right)\left(\mathbf{y}_{i j}-\overline{\mathbf{y}}_{i}\right)^{\prime}$, and

$$
\begin{equation*}
M=\frac{\left|\mathbf{S}_{1}\right|^{\nu_{1} / 2}\left|\mathbf{S}_{2}\right|^{\nu_{2} / 2} \cdots\left|\mathbf{S}_{g}\right|^{\nu_{g} / 2}}{\left|\mathbf{S}_{p l}\right|^{\sum_{i} \nu_{i} / 2}} \tag{3.21}
\end{equation*}
$$

where $\nu_{i}=n_{i}-1, \mathbf{S}_{i}=\mathbf{W}_{i} / \nu_{i}$ is the unbiased sample covariance matrix, and $\mathbf{S}_{p l}$ is the pooled sample covariance matrix,

$$
\mathbf{S}_{p l}=\frac{\sum_{i=1}^{g} \nu_{i} \mathbf{S}_{i}}{\sum_{i=1}^{g} \nu_{i}}=\frac{\mathbf{E}}{\nu_{E}}
$$

The statistic

$$
\begin{equation*}
u=-2\left(1-c_{1}\right) \ln M \tag{3.22}
\end{equation*}
$$

has an approximated $\chi^{2}$-distribution with $\frac{1}{2}(k-1) p(p+1)$ degrees of freedom, where

$$
c_{1}=\left[\sum_{i=1}^{g} \frac{1}{\nu_{i}}-\frac{1}{\sum_{i=1}^{g} \nu_{i}}\right]\left[\frac{2 p^{2}+3 p-1}{6(p+1)(k-1)}\right]
$$

We reject $H_{0}$ if $u>\chi_{\alpha}^{2}$.

### 3.11 Classification into Several Populations

In this section, generalization of classification procedure for more than two discriminating groups (ie from 2 to $g \geq 2$ ) is straight forward. However, not much is known about
the properties corresponding sample classification function, and in particular, their error rates have not been fully investigated. Therefore, we focus only on the Minimum ECM Classification with equal misclassification cost and Minimum TPM for multivariate normal population with unequal covariance matrices (Quadratic discriminant analysis).

### 3.12 Minimum ECM Classification with Equal Mis-

## classification Cost

Allocate $\mathbf{x}_{0}$ to $\Pi_{k}$ if

$$
\begin{equation*}
p_{k} f_{k}(\mathbf{x})>p_{i} f_{i}(\mathbf{x}) \quad \text { for all } i \neq k \tag{3.23}
\end{equation*}
$$

or, equivalently, Allocate $\mathbf{x}_{0}$ to $\Pi_{k}$ if

$$
\begin{equation*}
\ln p_{k} f_{k}(\mathbf{x})>\ln p_{i} f_{i}(\mathbf{x}) \quad \text { for all } i \neq k \tag{3.24}
\end{equation*}
$$

Note that the classification rule in 3.23 is identical to the one that maximizes the posterior probability $P\left(\Pi_{i} \mid \mathbf{x}\right)=\mathrm{P}\left(\mathbf{x}\right.$ comes from $\Pi_{i}$ given that $\mathbf{x}$ is observed $)$ where

$$
\begin{equation*}
P\left(\Pi_{i} \mid \mathbf{x}\right)=\frac{p_{k} f_{k}(\mathbf{x})}{\sum_{i=1}^{g} p_{i} f_{i}(\mathbf{x}}=\frac{(\text { prior }) \times(\text { likelihood })}{\sum[(\text { prior }) \times(\text { likelihood })]} \tag{3.25}
\end{equation*}
$$

Therefore, one should keep in mind that in general minimum ECM rule must have the prior probability, misclassification cost and density function before it can be implemented.

### 3.13 Minimum TPM Rule for Unequal-Covariance Nor-

## mal Populations

Suppose that the $\Pi_{i}$ are multivariate normal populations, with different mean vectors $\mu$ and covariance matrices $\boldsymbol{\Sigma}_{i} \quad(i=1, \ldots, g)$. An important special case occurs when the

$$
f_{i}(\mathbf{x})=\frac{1}{(2 \pi)^{p / 2}\left|\boldsymbol{\Sigma}_{i}\right|^{\frac{1}{2}}} \exp \left\{-\frac{1}{2}\left(\mathbf{x}-\mu_{i}\right)^{\prime} \boldsymbol{\Sigma}_{i}^{-1}\left(\mathbf{x}-\mu_{i}\right)\right\}
$$

with $c(i \mid i)=0, c(k \mid i)=1, k \neq i$ then

$$
\begin{align*}
\ln p_{k} f_{k}(\mathbf{x}) & =\ln p_{k}-\left(\frac{p}{2}\right) \ln \{(2 \pi)\}-\frac{1}{2} \ln \left|\boldsymbol{\Sigma}_{k}\right|-\frac{1}{2}\left(\mathbf{x}-\mu_{k}\right)^{\prime} \boldsymbol{\Sigma}_{k}^{-1}\left(\mathbf{x}-\mu_{k}\right) \\
& =\max _{i} \ln \left\{p_{i} f_{i}(\mathbf{x})\right\} \tag{3.26}
\end{align*}
$$

The constant $(p / 2) \ln (2 \pi)$ can be ignored in 3.26 , since it is the same for all population. Therefore, quadratic discriminant score for $i t h$ population is defined as

$$
\begin{equation*}
d_{i}^{Q}(\mathbf{x})=-\frac{1}{2} \ln \left|\Sigma_{i}\right|-\frac{1}{2}\left(\mathbf{x}-\mu_{i}\right)^{\prime} \boldsymbol{\Sigma}_{i}^{-1}\left(\mathbf{x}-\mu_{i}\right)+\ln p_{i} \tag{3.27}
\end{equation*}
$$

The quadratic score $d_{i}^{Q}(\mathbf{x})$ is composed of contributions from the generalized variance $\left|\boldsymbol{\Sigma}_{i}\right|$, the prior probability $p_{i}$, and the square of the distance from $x$ to the population mean $\mu_{i}$.

Allocate $x$ to $\Pi_{k}$ if the quadratic score

$$
\begin{equation*}
d_{k}^{Q}(\mathbf{x})=\text { largest of } d_{1}^{Q}(\mathbf{x}), d_{2}^{Q}(\mathbf{x}), \ldots, d_{g}^{Q}(\mathbf{x}) \tag{3.28}
\end{equation*}
$$

In practice, the $\mu_{i}$ and $\Sigma_{i}$ are unknown, but a training set of correctly classified observations if often available for the construction of estimates. The relevant sample quantities for
population $\Pi_{i}$ are the sample mean vector, $\bar{x}_{i}$, sample covariance matrix, $S_{i}$ and sample size, $n_{i}$. The estimate of the quadratic discriminant score 3.28 is then

$$
\begin{equation*}
\hat{d}_{i}^{Q}(\mathbf{x})=-\frac{1}{2} \ln \left|\mathbf{S}_{i}\right|-\frac{1}{2}\left(\mathbf{x}-\overline{\mathbf{x}}_{i}\right)^{\prime} \mathbf{S}_{i}^{-1}\left(\mathbf{x}-\overline{\mathbf{x}}_{i}\right)+\ln p_{i} \quad \text { for } \quad i=1,2, \ldots, g \tag{3.29}
\end{equation*}
$$

DA is relatively straight forward for known group-conditional densities. Generally, in practice, users of DA encounter the problem of their estimation from data. DA with other multivariate statistical techniques, has the assumptions of multivariate normality and spherical disturbance terms which provide a convenient way of specifying a parametric structure. However, in real life observations, some or all of these assumptions are sometimes violated. Therefore, it becomes necessary to use the Monte Carlo procedure with which data sets which resemble data obtained from controlled laboratory experiments and which are free of all the problems listed above are generated.

In this study, attention is focused on discrimination through the heteroscedastic normal model. Three mutually dependent normally distributed populations are considered.

### 3.14 Heteroscedastic Normal Model

Under a heteroscedastic normal model for the group-conditional distributions of the feature vector $\mathbf{X}$ on an entity, it is assumed that

$$
\begin{equation*}
\mathbf{X} \sim N\left(\mu_{i}, \Sigma_{i}\right) \quad \text { in } \quad G_{i} \quad \text { for } \quad i=1,2, \ldots, g \tag{3.30}
\end{equation*}
$$

where $\mu_{i}$ denote group means and $\Sigma_{i}$ denote group covariance matrix. The $i t h$ groupconditional density $f\left(\mathbf{X} ; \theta_{i}\right)$ is given by

$$
\begin{align*}
f_{i}\left(\mathbf{X} ; \theta_{i}\right) & =\phi\left(\mathbf{X} ; \mu_{i}, \Sigma_{i}\right)  \tag{3.31}\\
& =(2 \pi)^{-p / 2}\left|\boldsymbol{\Sigma}_{i}\right|^{-\frac{1}{2}} \exp \left\{-\frac{1}{2}\left(\mathbf{x}-\mu_{i}\right)^{\prime} \boldsymbol{\Sigma}_{i}^{-1}\left(\mathbf{x}-\mu_{i}\right)\right\} \tag{3.32}
\end{align*}
$$

where $\theta_{i}$ consists of the elements of $\mu_{i}$ and the $\frac{1}{2} P(1+P)$ distinct elements of $\Sigma_{i}$. It is assumed that each $\Sigma_{i}$ is non singular for the groups $\Pi_{1}, \ldots, \Pi_{g}$. If $p_{i}$ denote the prior probabilities of the groups then we let:

$$
\begin{align*}
\Psi_{U} & =\left(p_{1}, p_{2}, \ldots, \theta_{U}^{\prime}\right)^{\prime}  \tag{3.33}\\
& =\left(p^{\prime}, \theta_{U}^{\prime}\right)^{\prime} \tag{3.34}
\end{align*}
$$

where $\theta_{U}$ consists of the elements of $\mu_{1}, \ldots, \mu_{g}$ and the distinct elements of $\Sigma_{1}, \ldots, \Sigma_{g}$. The subscript "U" emphasizes that the group variance matrices are allowed to be unequal in the specification of the model 3.30. Let the posterior probability that an entity with feature vector $\mathbf{X}$ belongs to group $\Pi_{i}$ be denoted by $P_{i}\left((X) ; \Psi_{U}\right)$ for $i=1, \ldots, g$. We use the log ratios in estimating these posterior probabilities. Thus,

$$
\begin{align*}
\eta_{i g}\left((X) ; \Psi_{U}\right) & =\log \left(P_{i}\left((X) ; \Psi_{U}\right) / P_{g}\left((X) ; \Psi_{U}\right)\right)  \tag{3.35}\\
& =\log \left(P_{i} / P_{g}\right)+\xi_{i g}\left((X) ; \theta_{U}\right) \tag{3.36}
\end{align*}
$$

where $\xi_{i g}\left((X) ; \theta_{U}\right)=\log \left\{f_{i}\left(\mathbf{X} ; \theta_{i}\right) / f_{g}\left(\mathbf{X} ; \theta_{g}\right)\right\}$ for $(i=1, \ldots, g-1)$ corresponds to an arbitrary choice of $\Pi_{g}$ as the base group. Under the heteroscedastic normal model 3.30,

$$
\begin{equation*}
\xi_{i g}=-\frac{1}{2}\left\{\delta\left((X), \mu_{i} ; \Sigma_{i}\right)-\delta\left((X), \mu_{g} ; \Sigma_{g}\right)\right\}-\frac{1}{2}\left\{\log \left|\Sigma_{i}\right| /\left|\Sigma_{g}\right|\right\} \quad\left(i=1^{\prime} \ldots, g-1\right) \tag{3.37}
\end{equation*}
$$

where :

$$
\delta\left((X), \mu_{i} ; \Sigma_{i}\right)=\left(\mathbf{X}-\mu_{i}\right)^{\prime} \Sigma_{i}^{-1}\left(\mathbf{X}-\mu_{i}\right)
$$

is the squared Mahalanobis' distance between $\mathbf{X}$ and $\mu_{i}$ with respect to $\Sigma_{i}(i=1, \ldots, g)$. The optimal or Bayes rule $r_{0}\left(\mathbf{X} ; \Psi_{U}\right)$ assigns an entity with feature vector $\mathbf{X}$ to $\Pi_{g}$ if

$$
\eta_{i g}\left(\mathbf{X} ; \Psi_{U}\right) \leq 0 \quad(i=1, \ldots, g-1)
$$

is satisfied. Otherwise, the entity is assigned to $\Pi_{h}$ if

$$
\eta_{i g}\left(\mathbf{X} ; \Psi_{U}\right) \leq \eta_{h g}\left(\mathbf{X} ; \Psi_{U}\right) \quad(i=1, \ldots, g-1 ; i \neq h)
$$

holds.

In defining the Bayes rule, we take the costs of misclassification to be the same. However, unequal costs of misclassification can be incorporated into the formulation. In practice, $\theta_{U}$ is generally taken to be unknown and so must be estimated from the available training data.

### 3.15 Monte Carlo Studies

Monte Carlo method is a heuristic statistical technique for evaluation and simulation of intractable problems by probabilistic simulation. Its performance is similar to controlled laboratory experiments. The center in a Monte Carlo study usually is a test statistic or estimator that has unknown finite sample properties. A typical Monte Carlo study in
discriminant analysis involves the specification of the number of distributions of populations, sample sizes while the variable of interest is varied to investigate its effects on the asymptotic performance of the specific function of interest.

### 3.16 Simulation Design

Since we wish to evaluate the performance of QDF in case of correlated training samples and non-normality of distributions, we considered QDF. A Monte Carlo study was conducted. In the simulation procedure, multivariate normally correlated random data was generated for three populations with their mean vector $\mu_{1}=(0, \ldots, 0), \mu_{2}=(0, \ldots, \delta)$ and $\mu_{3}=$ $(0, \ldots, 2 \delta)$ respectively.

The covariance matrices, $\Sigma_{i}(\mathrm{i}=1,2,3)$. Where $k \neq l, \sigma_{k l}=0.7$ for all groups except the diagonal entries given as $\sigma_{k}^{2}=i$, for $i=1,2,3$. After this, the correlation in the generated data of the various populations was eliminated. Skewed data was generated from the exponent of the normally uncorrelated data (log-normal) in order to evaluate the performance of skewness on QDF. QDF was then performed in each case and the leave-one-out method was used to estimate the proportion of observations misclassified.

Factors consider in this study were

1. Mean vector separator which is set at $\delta$ from 1 to 5 where $\delta$ is determined by the difference between the mean vectors.
2. Sample sizes which are also specified. Here 14 values of $n_{1}$ set at $30,60,100,150$, $200,250,300,400,500,600,700,800,1000,2000$ and the sample size of $n_{2}$ and $n_{3}$ are determined by the sample ratios at 1:1:1, 1:2:2 and 1:2:3 and these ratios also determine the prior probabilities to be considered
3. The number of variables for this study is also specified. The number of variables are set at 4, 6 and 8 following Murray (1977) who considered this in selection of variables in Discriminant Analysis.

### 3.16.1 Subroutine for QDF

Series of subroutines were written in MatLab to perform the simulation and discrimination procedures on QDF. Below are the important ones.

### 3.16.1.1 Data Simulation

The subroutine below was used to generate correlated normal data.

```
%specifying the covariance matrices
for i = 1:3
    p(i).SIGMA = i*eye(nvar);
    for r = 1:nvar
        for c = 1:nvar
            if r }
                p(i).SIGMA(r,c) = p(i).SIGMA(r,c) + 0.7;%to ensure correlation
            end
        end
    end
end
    %normal correlated generated data
        p(i).rep(r).x = mvnrnd(p(i).mu,p(i).SIGMA,n(i));
        p(i).rep(r).x = single(p(i).rep(r).x); % converting to single precision to reduce memory usage
        p(i).rep(r).mu = mean(p(i).rep(r).x);%sample mean of group i
        p(i).rep(r).sigma = cov(p(i).rep(r).x);%sample covariance of group i
```

After QDF has been performed on the correlated normal data, the correlation in the data is then eliminated by the command Correlation_elimination(p(i).rep(r). $\mathrm{x}^{\prime}$ )

```
% eliminating correlation (uncorrelated normal data)
    [p(i).rep(r).z,p(i).rep(r).zmu,p(i).rep(r).zsigma] = Correlation_elimination(p(i).rep(r).x');
    p(i).rep(r).z = p(i).rep(r).z';
    for k = 1:n(i)
        p(i).rep(r).x(k,:) = p(i).rep(r).z(k,:)*(i*p(i).rep(r).zsigma)^(0.5)+p(i).mu;
    end
    p(i).rep(r).mu = mean(p(i).rep(r).x); p(i).rep(r).sigma = cov(p(i).rep(r).x);
    for k = 1:n(i)
```

We focussed our attention on positively skewed data. Therefore, after QDF has been performed on the uncorrelated normal data, the data is transformed to positively skewed data by finding the exponent of the uncorrelated normal data. The subroutine below was used

```
p(i).rep(r).x = exp(p(i).rep(r).x);
```


### 3.16.1.2 Discrimination Procedure

```
%quadratic discriminant score
    for i=1:3
    for k=1:n(i)
        for j=1:3
            if j==i
                p(i).rep(r).QDF{i,k}(j)= -1/2*log(det(p(i).rep(r).sigmaH{k}))...
                        -1/2*(p(i).rep(r).holdout(k,:)-p(i).rep(r).meanH{k})*inv(p(i).rep(r).sigmaH{k})...
                        *(p(i).rep(r).holdout(k,:)-p(i).rep(r).meanH{k})'+ log(prior(j));
            else
            p(i).rep(r).QDF{i,k}(j)= -1/2*log(det(p(j).rep(r).sigma))...
                        -1/2*(p(i).rep(r).holdout(k,:)-p(j).rep(r).mu)*inv(p(j).rep(r).sigma)...
                        *(p(i).rep(r).holdout(k,:)-p(j).rep(r).mu)'+ log(prior(j));
            end
        end
    end
```

\%finding the maximum and allocating it
for $r=1$ :nrep
rep(r).predict_label=[];
for $i=1: 3$
for $k=1: n(i)$

```
            rep(r).qmax(i,k)= max(p(i).rep(r).QDF{i,k});
            for j= 1:3
            if rep(r).qmax(i,k)== p(i).rep(r).QDF{i,k}(j)
                    p(i).rep(r).predict_label(k)= j;
            end
                end
            end
%developing the confusion matrix
for r = 1:nrep
    %rep(r).cm1=cfmatrix(rep(r).actual_label,rep(r).predict_label);
    rep(r).cm=cfmatrix(rep(r).actual_label,rep(r).predict_label,[1 2 3],1);
    %rep(r).pmc = 1-trace(rep(r).cm);% total proportion misclassified
end
%average confusion matrix
avgconfmat=zeros(3,3);
for j = 1:3
    for i = 1:3
        F = [];
        for r = 1:nrep
            F = horzcat(F,rep(r).cm(i,j));
        end
        avgconfmat(i,j) = mean(F);
    end
end
%average error rates for the different groups
for i = 1:3
    gp(i).err = [];
    for j = 1:3
        if j~=i
            gp(i).err = vertcat(gp(i).err,avgconfmat(j,i));
        end
    end
    QDA.totavg_gperr(:,i) = sum(gp(i).err);
end
```

[cor_out,norm_out,skew_out] = QuadDA(N,nratio, nvar, delta,nrep) is main command
used in the entire procedure. The hold-out observation is classified into one of the groups.
The leave-one-out error rates are computed using the cfmatrix command, which generates a confusion matrix. This is done for each replication within the cells and later averaged over replications.

## Chapter 4

## Simulation Results and Discussion

### 4.1 Introduction

This chapter contains the results of our investigation on the effects of correlation and skewness considering sample size ratio, number of variables and mean vector (group centroid) separator on the performance of QDF. The size of population1 $\left(n_{1}\right)$ is fixed throughout the study and the sizes of population 2 and population $3, n_{2}$ and $n_{3}$ respectively are determined by the sample size ratio under consideration. We first look at QDF when the training data are correlated and then when they are uncorrelated. Skewed distribution is applied afterwards. The summary of the 11 sample sizes for each value of $n_{1}$ and sample size ratio combination is presented in the table below.

Table 4.1: Sample Size Ratios

|  | Sample Size ( $n_{1}$ ) | 30 | 60 | 100 | 150 | 250 | $300$ | 400 | 500 | 600 | 700 | 2000 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| S.Size ( $N$ ) | 1:1:1 | 90 | 180 | 300 | 450 | 750 | 900 | 1200 | 1500 | 1800 | 2100 | 6000 |
|  | 1:2:2 | 150 | 300 | 500 | 750 | 1250 | 1500 | 2000 | 2500 | 3000 | 3500 | 10000 |
|  | 1:2:3 | 180 | 360 | 600 | 900 | 1500 | 1800 | 2400 | 3000 | 3600 | 4200 | 12000 |

These are the sample sizes for which we simulated the normal variate and alternate the
variables of interest as required.In this empirical study, the sensitivity of normal-based QDF classification models to correlated and skewed training samples is investigated, by considering sample size increment, varying of group centroid separator and varying number of variables. Three sample size ratios of population1 to population2 to population3 ( $n_{1}$ : $\left.n_{2}: n_{3}\right)$ considered are $1: 1: 1,1: 2: 2$ and $1: 2: 3$. Eleven sample sizes of population1 $n_{1}$ was set at $30,60,100,150,250,300,400,500,600,700,2000$ and the total sample size is determined by the sample ratios and these ratios also determine the prior probabilities to be considered. Multivariate normal data were generated for three $p$-variate situations $(p=4, \quad p=6$ and $p=8)$ for the QDF considering the three distributions. The sample size-ratio combination was repeated for each level of $\delta$ with each scenario being replicated 100 times. The results obtained are averaged over the number of replicates.

### 4.2 Discussion of Simulated Results

Discussion of simulated results is carried out in section 4.2 onwards. The results of the individual population error rates, their average error rates followed by their standard deviations and then their coefficients of variation with the various total sample sizes and sample size ratios of the distributions (correlated normal, uncorrelated normal and skewed) are presented. The summary of the results which consists of the average error rates of the distributions are first presented followed by their standard deviations and then their coefficient of variation in appendix A. Some of the graphs of the average error rates and coefficients of variation of
the distributions are displayed. The graphs show the total sample sizes on the horizontal axis and the average error rates or coefficients of variation on the vertical axis. Some of the results displayed in this chapter are for the various $\delta \mathrm{s}$, number of variables and sample size ratios. The remaining results (both tabular and graphical) are shown in the appendices. In all cases, the results were recorded to four decimal places.

### 4.3 Effect of Sample Size on QDF

In this section, we look at the asymptotic performance of the QDF in the cases where the training data are correlated, uncorrelated, and when they are skewed. Each subsection gives the performance of each distribution.

### 4.3.1 Correlated Normal Distribution

Evaluating the effect of sample size on QDF with respect to the correlated normal distribution for $\delta=1$ is present in figures 4.1 and the rest of the graphical representation of the results are shown in figure B. 1 to B.4. A bird's eye view of the tables and 15 graphs reveals that generally, an increased in the total sample size decreases the error rate of a particular $n_{1}$. It was observed that the average error rate for 4,6 , and 8 variables with $\delta=1$ were higher as compared to the other values of the $\delta$ and among the sample size ratios used, sample size ratio 1:1:1 gives the lowest average error rates as the sample size
increases asymptotically. Results also show that $n_{1}=30$ gave highest average error rates and lower average error rate are for $n_{1}=2000$ for variables 4,6 and 8 . There is a rapid decrease in the average error rate from total sample size of 90 to 180 of sample size ratio $(1: 1: 1)$ of 8 variables for all $\delta$. The results of 4 variables were higher the other number of variables. $\delta=5$ gave the lowest average error rates as the sample size increases. It was also observed that the average error rates of sample size ratio 1:1:1 and 1:2:2 were marginal for $\delta=1$. The difference between the ratios decreased as $\delta$ increased and with maintained total sample size and the average error rates decreased as the number of variables increased. In $\delta=5$ the performance of the three sample size ratios were marginal.


Figure 4.1: Average error rates of correlated normal distribution: $\delta=1$

The standard deviation of the error rate from table (4.2) with the remaining tables in appendix A for the correlated normal distribution reveals that as the sample size increases, standard deviation of the error rate for sample size ratio 1:1:1 exhibit low standard deviations for $\delta=1$ while sample size ratio 1:2:3 exhibits higher standard deviations. For a particular $\delta$, the standard deviation decreases as the number of variables also increases. From $\delta=2$ to $\delta=5$, the standard deviations decreases as the sample size increases asymptotically. There is a sharp decrease of the standard deviation of sample size ratio 1:1:1 of variable 6 and $8, \delta=4$ and of variable $8, \delta=5$ as compared with their counterparts in the same case.

Table 4.2: Standard Deviations for 4 variables and a sample size ratio of (1:1:1)


The coefficients of variation in correlated normal distribution in figure 4.2 and remaining graphs in figure B. 5 to B. 8 for $\delta=1$, variables 4 to 8 increased exponentially and then stabilized with averagely lower variations in sample size ratio 1:2:2 and with higher variations in sample size ratio 1:2:3 as the total sample size increases asymptotically. The variations also increased as $\delta$ increased. $\delta=3$ gives a steady coefficients of variation as the total sample size increased for variable 4 while it gave a little increase and then stabilized in variables 4 and 6 . There was a decline in the coefficients of variation for $\delta=4$ as the total sample size increased asymptotically in variable 4. The coefficients of variation increased from total sample size 150 to 500 and from 180 to 360 for sample size ratios 1:2:2 and 1:2:3 respectively for variables 6 and 8 and then decreased as the total sample size increased asymptotically. For $\delta=5$, there was a sharp decrease in the coefficients of variation in sample size ratio 1:1:1 for all number of variables as the total sample size increased.


Figure 4.2: Coefficients of Variation for Correlated Normal Distribution: $\delta=1$

### 4.3.2 Uncorrelated Normal Distribution

For the uncorrelated distribution the average error rate wa similar to the results obtained in the correlated normal distribution with the exception of the average error rate of sample size ratio 1:1:1 which decreased rapidly from total sample size of 90 to 180 for 8 variables in all $\delta$ s. The average error rate decreased as the total sample size increased asymptotically. And it reduced when $\delta$ also increased. The graphical representation of this result for $\delta=1$ in show in figure 4.3 with the rest in B. 9 to B. 12


Figure 4.3: Average error rates of uncorrelated normal distribution: $\delta=1$

The standard deviations for uncorrelated distribution decreased as the total sample size increased for $\delta=1$ for 4,6 and 8 variables. There was a rapid decrease (from 150 to 300 ) in the standard deviation of sample size ratio $1: 2: 2$ of 6 and 8 variables as the total sample size increases asymptotically. The sample size ratio 1:2:2 exhibited lower values of
standard deviations as the total sample size increases for $\delta=1$ and 2 . For $\delta=3,4$ and 5, sample size ratio 1:1:1 gave lower standard deviations. The standard deviation in this distribution decreased as the sample size increased asymptotically with increasing $\delta$. For $\delta=5$ the standard deviations of the various sample size ratios were marginal in all the number of variables

The coefficients of variation generally increased exponentially and stabilized with increasing total sample size and number of variables in $\delta=1$ exhibited lower variations as compared with the remaining $\delta \mathrm{s}$ as shown in figure 4.4 and figure B. 13 to B. 16 of appendix B.2. For $\delta=$ 4, the coefficients of variation in sample size ratio 1:1:1 decreased while the remaining ratios did not give any particular pattern for the 4 variable situation. For 4 variable situation with $\delta=5$, the coefficients of variation decreased as the total sample size increased. The coefficient of variation of the other 6 and 8 variables situations did not show any particular pattern as the total sample size increased.


Figure 4.4: Coefficients of Variation for Uncorrelated Normal Distribution: $\delta=1$

### 4.3.3 Skewed (Lognormal) Distribution

Unlike the already discussed distributions, there was an increase in the average error rates of the sample size ratios 1:2:2 and 1:2:3 as the total sample size increased asymptotically in the skewed distribution for $\delta=1$ to 3 in figures 4.5, 4.6 and 4.7 and in figures B. 17 and B. 18 of appendix B. 3 while the average error rates stabilized in the rest of the $\delta$ s. Sample size ratio 1:1:1 in this case gave lower average error rates. The average error rates for $\delta=5$ were the lowest as compared to the other $\delta$ s and they decreased as the total sample size increased.


Figure 4.5: Average error rates of skewed distribution: $\delta=1$


Figure 4.6: Average error rates of skewed distribution: $\delta=2$


Figure 4.7: Average error rates of skewed distribution: $\delta=3$

The standard deviations in this distribution happened to be large in $\delta=1$ they increased and stabilized as the total sample size increased asymptotically with sample size ratio 1:1:1 giving lower deviations in the situation of 4 and 8 variables for all $\delta$ s. In 6 variables case, the sample size ratio 1:1:1 and 1:2:2 reduced more than sample size ratio 1:2:3 by giving lower deviations for all giving $\delta \mathrm{s}$ as the total sample size increases.

The coefficients of variation in the skewed distribution increased exponentially with total sample size increased by exhibiting lower variabilities for all cases of variables used in $\delta=1$ as shown in figure 4.8 and rest of the graphical representation of the results in figure B. 19 to B.22. The coefficients of variation increased in $\delta=2$ and 3 but with higher variations and did not give any particular pattern in $\delta=4$ and 5 .


Figure 4.8: Coefficients of Variation for Skewed Distribution: $\delta=1$

### 4.4 Effect of Number of Variables on QDF

The effect of number of variables on the QDF under the three mentioned distributions are discussed in the subsections. The table of results used in this section are the same for the previous section. The graphical representation of the results are shown in figures C. 1 to C. 10 of appendix C.

$$
K N O
$$

### 4.4.1 Correlated Normal Distribution

The graphs of the results for sample size ratio 1:1:1 of the situations of 4,6 and 8 variables are shown in figure 4.9. It was observed that as the number of variables increased, the average error rate reduced in the correlated normal distribution. The rate at which it reduces in $\delta=1$ for ratio 1:1:1 is better than that of the other $\delta$ s. For increasing sample size ratio, as the number of variables increased, the decrease in the average error was marginal as $\delta$ increased.


Figure 4.9: Average Error Rate for Correlated Normal Distribution: $n_{1}: n_{2}: n_{3}=1: 1: 1$

The coefficients of variation in this distribution for ratio 1:1:1 in figure 4.10 reveals that as the number of variables increased the coefficients of variation increased for variables 4, 6 and 8 from $\delta=1$ to 3 except $\delta=4$ and 5 in which it reduced. Yet the in the case of 8 variables the variabilities exhibited were higher than the rest in this case. For ratio 1:2:2 the coefficients of variation increased from total sample size of 150 to 2000 and stabilized for all $\delta \mathrm{s}$ as the number of variables increased except $\delta=4$ which showed a decline in the coefficients of variation for the case of 4 and 6 variables. In $\delta=5$, there was declination in the coefficients of variation as the number of variables increased. Sample size ratio 1:2:3 gave similar result as ratio 1:2:2


Figure 4.10:
Coefficient of variation of correlated normal distribution: $n_{1}: n_{2}: n_{3}=$ 1:1:1

### 4.4.2 Uncorrelated Normal Distribution

The average error rate for the uncorrelated normal distribution was also looked at and it revealed that for 1:1:1, in figure 4.11, there was a sharp decline in the average error rate from total sample size 90 to 180 as the number of variables increase for all $\delta$ s. It also revealed that as the number of variables increased the average error rate reduced for all sample size ratios.

The coefficients of variation in this distribution for ratio 1:1:1 in figure 4.12 showed that the variabilities increased exponentially for all $\delta$ s with the exception of $\delta=4$ and 5 for which variable 4 declined. In the case of 8 variables, about $9.65 \%$ and $11.91 \%$ increase


Figure 4.11:
Average error rates of uncorrelated normal distribution: $n_{1}: n_{2}: n_{3}=$ $1: 1: 1$
in variations from total sample size of 90 to 180 for all $\delta=1$ and 2 . For $\delta=4$ and 5 , the coefficients of variation for variables 4 declined from total sample size of 90 to 6000 while variables 6 and 8 increased. For $\delta=5$, the coefficients of variations for 8 variables increased from 90 to 750 and declined to 6000. The coefficients of variation in general for this distribution increased as the number of variables increased.


Figure 4.12:
Coefficients of Variation for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 1: 1$

### 4.4.3 Skewed (Lognormal) Distribution

The skewed distribution performs differently with increasing number of variables. For sample size ratio 1:1:1, the average error rates of the variables reduced and curved upward as the total sample size increased for all $\delta \mathrm{s}$, as shown in figure 4.13. The average error rates of sample ratios 1:2:2 and 1:2:3 were different. Their average error rate increased as the total sample size increased and reduced with increasing number of variable for $\delta=1$ and 2. In $\delta=3$ and 4 of ratios 1:2:2 and 1:2:3, as the number of variables increased the average error rate dropped from the total sample size of 150 to 300 and increased as the sample size also increased respectively while that of $\delta=5$ decreased marginally. In general the average error rate increased as the number of variables increased with increasing $\delta$.


Figure 4.13: Average error rates of skewed distribution: $n_{1}: n_{2}: n_{3}=1: 1: 1$

The coefficients of variation in this distribution for ratio 1:1:1 in figure4.14reveals an in-
crease of variabilities in the individual number of variables as $\delta$ from 1 to 4 increased.

The variabilities also decreased as the number of variables increased with sharp increase in variabilities from total sample size of 90 to 180 . The variabilities also increased as the sample size ratio increased.


Figure 4.14: Coefficients of Variation for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 1: 1$

### 4.5 Effect of Group Centroid Separator on QDF

In this section, we present results of our investigation on the effect of the Mahalanobis distance on QDF for the three distributions. The graphs for these results are shown in figure 4.15 to D. 12 in appendix D.

### 4.5.1 Correlated Normal Distribution

Considering the correlated normal distribution in figure 4.15, it was observed that with increasing total sample size, the average error rate reduces as the $\delta$ increased and also reduced as the number of variables increased. It can be observed that there was about $2.37 \%$ drop in the average error rate from total sample size 90 to 180 for all $\delta=1$ s in the case of 8 variables. The average error rate reduced as the total sample size increased for all sample size ratios with increasing $\delta$.

Looking at the coefficients of variation of sample size ratio 1:1:1 with increasing total sample size in figure 4.16, uniform behavior of $\delta$ was not portrayed. As coefficients of variation for $\delta=5$ and 4 were declining, that of the rest of the $\delta$ s may be increasing or reducing depending on the particular sample size ratio. In a nutshell, the correlated normal distribution and the uncorrelated normal distribution give similar result with average error rates and coefficients of variation. Therefore, with increasing $\delta, \delta=5$ gives higher coefficients of variation.


Figure 4.15:
Average error rates of correlated normal distribution for $\delta: n_{1}: n_{2}$ : $n_{3}=1: 1: 1$


Figure 4.16: Coefficients of Variation for Correlated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 1: 1$

### 4.5.2 Uncorrelated Normal Distribution

We also looked the effect group centroid separator of uncorrelated on Quadratic Discriminant Function. The average error rate of the uncorrelated normal distribution for sample size ratio 1:1:1 in figure 4.17 revealed that the average error rates of the individual $\delta$ s reduce as the sample size increases. There was about $3.19 \%, 5.09 \%, 6.81 \%$ drop of the average error rate for $\delta=1$, variables 4,6 and 8 respectively. The average error rates of $\delta=2$ for variables 4 to 6 exhibited about $2.00 \% 3.99 \% 6.65 \%$ drop in the average error rates. In general, the average error rates decreased as $\delta$ increased irrespective of the number of variables and sample size ratios.


Figure 4.17:
Average error rates of uncorrelated normal distribution for $\delta: n_{1}: n_{2}$ : $n_{3}=1: 1: 1$

The coefficient of variation of this distribution of sample size ratio $1: 1: 1$ in figure 4.18 did not show any uniform pattern in the variabilities as $\delta$ increased but in general the as $\delta$
increased, the variabilities also increased.


Figure 4.18:
Coefficients of Variation for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 1: 1$

### 4.5.3 Skewed (Lognormal) Distribution

The average error rate of the skewed distribution for sample size ratio $1: 1: 1$ in figure 4.19 revealed that the average error rates of the individual $\delta$ s reduced and increased a little as the sample size increased except that of $\delta=$ which decreased as the total sample size increased. As the average error rates of $\delta=5$ reduced with increasing total sample size and sample size ratio, the rest of them increased with increasing total sample size. Whether the individual $\delta$ s increased or reduced, in a nut shell, it is observed that for the average error rates of $\delta$ reduced as the sample size increased.


Figure 4.19: Average error rates of skewed distribution for $\delta: n_{1}: n_{2}: n_{3}=1: 1: 1$

The coefficients of variation for sample size ratio $1: 1: 1$ in figure ?? showed that the variabilities increased exponentially as the total sample size and $\delta$ increased. $\delta=5$ gave lower variations in the case of 6 and 8 variables. For the rest of the sample size ratios, $\delta=4$ and 5 gave coefficients of variation above the rest of the $\delta$ s with $\delta=1$ producing lower coefficient of variations.


Figure 4.20: Coefficients of Variation for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 1: 1$

### 4.6 Comparison of Error Rates of Correlated Normal, Uncorrelated Normal and Skewed Distribution

We present the discussion on the comparison of error rates Correlated Normal, Uncorrelated Normal and Skewed Distribution under Quadratic Discriminant Function. We present graphs of the average error rates of misclassification and coefficient of variation for the three distributions in figure E. 1 to E. 12 of appendix F. However, observation made on sample size ratio 1:1:1 for 4 variable case in figure 4.21 showed the average error rates of skewed distribution were the highest with correlated normal distribution exhibiting least average error rates as delta increased with increasing sample size. It can also be observed that the average error rates of the distributions decreased as $\delta$ increased and the difference between the three distributions was also decreased marginally with increasing $\delta$. For sample size ratio 1:1:1 of variables 6 and 8 , there was $5.09 \%, 3.99 \%$ and $3.28 \%$ drop of the average error rates from total sample size 90 to 180 for $\delta=1,2$, and 3 respectively and $6.81 \%, 6.65 \%$ and $5.65 \%$ drop of the average error rates from total sample size 90 to 180 for $\delta=1,2$, and 3 respectively in the uncorrelated normal distribution. In general, for sample size ratio 1:1:1, the average error rate decreased with increasing sample size and $\delta$. To sum it up, as the average error rates of correlated normal and uncorrelated normal were decreasing, that of skewed distribution increased with higher average error rate for all number of variables and sample size ratios used with increasing sample size and $\delta$ followed by uncorrelated normal distribution.


Figure 4.21:
Average error rates of the three distributions for 4 variables: $n_{1}: n_{2}$ : $n_{3}=1: 1: 1$


Figure 4.22:
Average error rates of the three distributions for 6 variables: $n_{1}: n_{2}$ : $n_{3}=1: 1: 1$

Looking at figures 4.24 to 4.26 , the coefficients of variation for sample size ratio $1: 1: 1$ variable 4,6 and 8 showed that the skewed distribution gave higher variabilities for $\delta=1$


Figure 4.23:
Average error rates of the three distributions for 8 variables: $n_{1}: n_{2}$ : $n_{3}=1: 1: 1$
to 4 and it increased and stabilized with increasing sample size. The variabilities of correlated normal distribution increased as $\delta$ increased. In a nutshell, the skewed distribution exhibited the highest variabilities in all scenarios followed by the uncorrelated normal distribution.


Figure 4.24:
Coefficients of variation of the three distributions for 4 variables: $n_{1}$ : $n_{2}: n_{3}=1: 1: 1$


Figure 4.25:
Coefficients of variation of the three distributions for 6 variables: $n_{1}$ : $n_{2}: n_{3}=1: 1: 1$


Figure 4.26:
Coefficients of variation of the three distributions for 8 variables: $n_{1}$ : $n_{2}: n_{3}=1: 1: 1$ $\qquad$ $\square \square$

The coefficient of variation for correlated and uncorrelated normal distributions were lower as compared with the other distribution with increasing sample size and increases with increasing $\delta$. Yet correlated normal distribution gives higher variabilities when $\delta=5$. For all number of variables, the coefficients of variation for all the three distributions increases with increasing $\delta$ and they give very high variabilities when the sample size ratio is $1: 2: 3$.

The sample size ratio at which the performance the Quadratic Discriminant Function deteriorate was looked at. Figures F. 1 to F. 6 in appendix F showed how the average error rates and coefficients of variation of the individual distributions performed with increasing $\delta$ as the sample size increased.


Figure 4.27:
Average Error Rates for individual sample size ratios and distributions for $\delta=1$

It can be observed that as the sample size ratio increased the average error rates also decreased with increased with increasing number of variables as shown in figures 4.27 and


Figure 4.28:
Average Error Rates for individual sample size ratios and distributions for $\delta=5$
4.28. It was observed from figures 4.29 and 4.30 that for $\delta=1$, the variabilities increased and the stabilized as the sample size increased for all sample size ratios. The difference between the variabilities of a particular distribution from 4 variables to 8 variables was not much. In $\delta=5$, the variabilities for the correlated normal distributions and that of the uncorrelated normal distribution for 4 variables decreased and stabilized as the sample size increased while the rest increased and stabilized for all number of variables of all sample size ratios. In general, it is observed that the sample sample size ratio $1: 1: 1$ exhibited lower variabilities for all cases while sample size ratio $1: 2: 3$ exhibited high variabilities.


Figure 4.29:
Coefficients of Variation for individual sample size ratios and distributions for $\delta=1$


Figure 4.30:
Coefficients of Variation for individual sample size ratios and distributions for $\delta=5$

## Chapter 5

## Conclusion and Recommendations

### 5.1 Introduction

Summary of our findings from the simulation and some recommendation are made in this chapter. Below are the sections that cover them.

### 5.2 Findings and Conclusions

The summary of our Monte Carlo study focussed on the following:

1. The behaviour of the mean error rates and their stability as:

- The number of variables, $p$ increases from 4 to 6 and 8.
- The group centroid separator $\delta$ varies from 1 to 5 .
- The sample ratios vary from 1:1:1, 1:2:2 to 1:2:3 and varying sample size.

2. A comparison of the results in (1) above for correlated normal, uncorrelated normal and skewed distributions.

The following observations were made:

- The average error rates of the skewed distribution decreased as $\delta$ increased and also increased with unequal group prior probability. The coefficients of variation of this distribution increased up to total sample size of 2500 and 2400 after which it stabilized as the number of variables increased with increasing $\delta$ (from 1 to 3 ) for sample size ratios 1:2:2 and 1:2:3 respectively.
- The correlated normal distribution exhibited minimum misclassification error rates and high variability as the sample size increased asymptotically.
- The performance of the Quadratic Discriminant Function deteriorated when the sample size ratio was 1:2:3 for all the three distributions as $\delta$ increased with increasing sample size.
- An overview of the results shows that reduction in misclassification error rates is more pronounced as group centroid separator increases than as sample size increases.
- As the sample size increases (i.e. $n_{1}$ from 30 to 2000 ) the average error rate of the three distributions become almost the same at $\delta=5$ with little improvement in the performance by increasing sample size.
- For both correlated and uncorrelated normal distributions the average misclassification error rate decreased with increasing number of variables (from 4 to 8 ) and sample size ratio.
- The distributions exhibit increasing variations as $\delta$, number of variable and sample size ratios increases. The uncorrelated normal distribution exhibited the least variability in all cases. The results obtained from this study (skewed distribution) is in conformity with Lachenbruch et al. (1977). According to them if the underlying distributions are not normal, use of QDF is not necessarily optimal and may in fact be very bad.



### 5.3 Recommendations

Based on the findings from our work, the following recommendations are made for Quadratic Discriminant Function when the training samples are correlated or skewed for three population case.

- To use Quadratic Discriminant Function, it is recommended that sample sizes should be fairly large and the groups well separated.
- To use correlated normal distribution, one has to check the for degree of correlation.
- Sample size ratio $1: 1: 1$ is optimal for all distributions used in the case of coefficient of variation therefore, one should consider equal prior probabilities when using Quadratic Discriminant Function.
- Uncorrelated normal distribution should be preferred to correlated (positive) normal and skewed distributions since it has minimum coefficient of variation.

Due to minimal availability of the memory of the computer used for this study, we were restricted to some number of parameters. Therefore, the following recommendations are put across for further study with the help of much powerful computer:

- Increasing the sample size
- Increasing the group centroid separator (beyond 5)
- increasing number of variables.


## .

$\square$


The stability of the the error rates can then be well accessed.


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## Appendix A

## Table of Simulation Results

Table A.1: Error Rates for 4 variables and a sample ratio of (1:1:1)

| utions |  | corrNorm |  |  |  |  |  | UncorrNorm |  |  |  |  |  | wed |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | S. Size | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV |
| $\delta=1$ | 90 | 0.0633 | 0.1724 | 0.1361 | 0.1240 | 0.0530 | 0.4276 | 0.1160 | 0.2768 | 0.1938 | 0.1955 | 0.0681 | 0.3483 | 0.0538 | 0.2340 | 0.2311 | 0.1729 | 0.0875 | 0.5060 |
|  | 180 | 0.0465 | 0.1654 | 0.1334 | 0.1151 | 0.0536 | 0.4656 | 0.0884 | 0.2413 | 0.1611 | 0.1636 | 0.0641 | 0.3920 | 0.0396 | 0.2305 | 0.2411 | 0.1704 | 0.0942 | 0.5528 |
|  | 300 | 0.0405 | 0.1620 | 0.1334 | 0.1120 | 0.0543 | 0.4853 | 0.0799 | 0.2249 | 0.1517 | 0.1522 | 0.0603 | 0.3965 | 0.0328 | 0.2340 | 0.2434 | 0.1701 | 0.0983 | 0.5782 |
|  | 450 | 0.0378 | 0.1624 | 0.1347 | 0.1116 | 0.0547 | 0.4903 | 0.0741 | 0.2196 | 0.1481 | 0.1473 | 0.0603 | 0.4092 | 0.0302 | 0.2287 | 0.2495 | 0.1695 | 0.0998 | 0.5888 |
|  | 750 | 0.0359 | 0.1578 | 0.1330 | 0.1089 | 0.0534 | 0.4908 | 0.0715 | 0.2109 | 0.1425 | 0.1417 | 0.0575 | 0.4059 | 0.0257 | 0.2310 | 0.2532 | 0.1700 | 0.1031 | 0.6066 |
|  | 900 | 0.0365 | 0.1572 | 0.1311 | 0.1082 | 0.0526 | 0.4857 | 0.0710 | 0.2097 | 0.1422 | 0.1409 | 0.0573 | 0.4065 | 0.0254 | 0.2307 | 0.2526 | 0.1696 | 0.1030 | 0.6073 |
|  | 1200 | 0.0355 | 0.1545 | 0.1331 | 0.1077 | 0.0524 | 0.4868 | 0.0687 | 0.2069 | 0.1406 | 0.1387 | 0.1387 | 0.4096 | 0.0246 | 0.2274 | 0.2557 | 0.1692 | 0.1034 | 0.6110 |
|  | 1500 | 0.0354 | 0.1567 | 0.1320 | 0.1081 | 0.0529 | 0.4893 | 0.0686 | 0.2075 | 0.1402 | 0.1388 | 0.0571 | 0.4114 | 0.0238 | 0.2294 | 0.2589 | 0.1707 | 0.1051 | 0.6155 |
|  | 1800 | 0.0351 | 0.1551 | 0.1329 | 0.1077 | 0.0526 | 0.4881 | 0.0673 | 0.2053 | 0.1397 | 0.1374 | 0.0567 | 0.4123 | 0.0236 | 0.2289 | 0.2582 | 0.1702 | 0.1048 | 0.6159 |
|  | 2100 | 0.0346 | 0.1558 | 0.1337 | 0.1080 | 0.0531 | 0.4913 | 0.0670 | 0.2053 | 0.1399 | 0.1374 | 0.0567 | 0.4129 | 0.0227 | 0.2295 | 0.2598 | 0.1707 | 0.1057 | 0.6194 |
|  | 6000 | 0.0342 | 0.1541 | 0.1324 | 0.1069 | 0.0524 | 0.4898 | 0.0663 | 0.2028 | 0.1386 | 0.1359 | 0.0559 | 0.4116 | 0.0213 | 0.2293 | 0.2629 | 0.1712 | 0.1071 | 0.6258 |
| $\delta=2$ | 90 | 0.0377 | 0.1267 | 0.0997 | 0.0880 | 0.0447 | 0.5084 | 0.0754 | 0.1940 | 0.1268 | 0.1321 | 0.0524 | 0.3968 | 0.0459 | 0.1730 | 0.1877 | 0.1355 | 0.0680 | 0.5015 |
|  | 180 | 0.0266 | 0.1107 | 0.0939 | 0.0771 | 0.0402 | 0.5215 | 0.0574 | 0.1661 | 0.1096 | 0.1111 | 0.0469 | 0.4222 | 0.0324 | 0.1681 | 0.1947 | 0.1317 | 0.0741 | 0.5626 |
|  | 300 | 0.0234 | 0.1060 | 0.0910 | 0.0735 | 0.0384 | 0.5224 | 0.0538 | 0.1533 | 0.1039 | 0.1037 | 0.0421 | 0.4062 | 0.0275 | 0.1659 | 0.2059 | 0.1331 | 0.0781 | 0.5864 |
|  | 450 | 0.0199 | 0.1062 | 0.0912 | 0.0724 | 0.0394 | 0.5439 | 0.0486 | 0.1502 | 0.1005 | 0.0997 | 0.0424 | 0.4251 | 0.0238 | 0.1667 | 0.2069 | 0.1324 | 0.0800 | 0.6039 |
|  | 750 | 0.0212 | 0.1035 | 0.0899 | 0.0715 | 0.0370 | 0.5172 | 0.0466 | 0.1451 | 0.0993 | 0.0970 | 0.0409 | 0.4218 | 0.0216 | 0.1659 | 0.2125 | 0.1333 | 0.0822 | 0.6168 |
|  | 900 | 0.0202 | 0.1023 | 0.0905 | 0.0710 | 0.0370 | 0.5217 | 0.0448 | 0.1452 | 0.0986 | 0.0962 | 0.0415 | 0.4313 | 0.0214 | 0.1656 | 0.2124 | 0.1331 | 0.0821 | 0.6171 |
|  | 1200 | 0.0195 | 0.1021 | 0.0894 | 0.0703 | 0.0369 | 0.5249 | 0.0453 | 0.1426 | 0.0985 | 0.0955 | 0.0402 | 0.4209 | 0.0194 | 0.1653 | 0.2173 | 0.1340 | 0.0847 | 0.6318 |
|  | 1500 | 0.0198 | 0.1010 | 0.0911 | 0.0707 | 0.0367 | 0.5191 | 0.0446 | 0.1412 | 0.0973 | 0.0944 | 0.0398 | 0.4219 | 0.0192 | 0.1662 | 0.2180 | 0.1345 | 0.0850 | 0.6319 |
|  | 1800 | 0.0189 | 0.1017 | 0.0911 | 0.0706 | 0.0372 | 0.5265 | 0.0446 | 0.1418 | 0.0974 | 0.0946 | 0.0400 | 0.4230 | 0.0189 | 0.1661 | 0.2188 | 0.1346 | 0.0851 | 0.6325 |
|  | 2100 | 0.0192 | 0.1008 | 0.0906 | 0.0702 | 0.0367 | 0.5222 | 0.0440 | 0.1409 | 0.0972 | 0.0940 | 0.0399 | 0.4239 | 0.0194 | 0.1660 | 0.2216 | 0.1357 | 0.0860 | 0.6335 |
|  | 6000 | 0.0188 | 0.1008 | 0.0898 | 0.0698 | 0.0365 | 0.5234 | 0.0436 | 0.1396 | 0.0969 | 0.0934 | 0.0394 | 0.4223 | 0.0175 | 0.1665 | 0.2267 | 0.1369 | 0.0883 | 0.6454 |
| $\delta=3$ | 90 | 0.0180 | 0.0724 | 0.0586 | 0.0497 | 0.0300 | 0.6047 | 0.0454 | 0.1207 | 0.0807 | 0.0823 | 0.0345 | 0.4200 | 0.0362 | 0.1076 | 0.1356 | 0.0931 | 0.0489 | 0.5252 |
|  | 180 | 0.0121 | 0.0640 | 0.0564 | 0.0442 | 0.0264 | 0.5983 | 0.0325 | 0.1005 | 0.0719 | 0.0683 | 0.0296 | 0.4341 | 0.0276 | 0.0998 | 0.1392 | 0.0889 | 0.0493 | 0.5543 |
|  | 300 | 0.0095 | 0.0580 | 0.0561 | 0.0412 | 0.0245 | 0.5940 | 0.0283 | 0.0923 | 0.0677 | 0.0628 | 0.0277 | 0.4417 | 0.0226 | 0.0966 | 0.1434 | 0.0875 | 0.0522 | 0.5961 |
|  | 450 | 0.0089 | 0.0574 | 0.0552 | 0.0405 | 0.0239 | 0.5907 | 0.0263 | 0.0880 | 0.0654 | 0.0599 | 0.0263 | 0.4395 | 0.0209 | 0.0969 | 0.1469 | 0.0882 | 0.0535 | 0.6064 |
|  | 750 | 0.0087 | 0.0564 | 0.0554 | 0.0401 | 0.0232 | 0.5780 | 0.0257 | 0.0864 | 0.0636 | 0.0586 | 0.0256 | 0.4372 | 0.0180 | 0.0989 | 0.1598 | 0.0922 | 0.0601 | 0.6515 |
|  | 900 | 0.0085 | 0.0563 | 0.0551 | 0.0400 | 0.0230 | 0.5763 | 0.0253 | 0.0863 | 0.0641 | 0.0586 | 0.0257 | 0.4385 | 0.0174 | 0.0957 | 0.1586 | 0.0906 | 0.0593 | 0.6545 |
|  | 1200 | 0.0084 | 0.0558 | 0.0546 | 0.0396 | 0.0226 | 0.5708 | 0.0253 | 0.0864 | 0.0628 | 0.0581 | 0.0255 | 0.4393 | 0.0167 | 0.0951 | 0.1561 | 0.0893 | 0.0581 | 0.6507 |
|  | 1500 | 0.0081 | 0.0552 | 0.0548 | 0.0393 | 0.0225 | 0.5727 | 0.0250 | 0.0859 | 0.0625 | 0.0578 | 0.0253 | 0.4386 | 0.0169 | 0.0961 | 0.1587 | 0.0906 | 0.0589 | 0.6508 |
|  | 1800 | 0.0082 | 0.0552 | 0.0543 | 0.0393 | 0.0223 | 0.5682 | 0.0250 | 0.0844 | 0.0627 | 0.0573 | 0.0248 | 0.4330 | 0.0162 | 0.0977 | 0.1616 | 0.0918 | 0.0604 | 0.6579 |
|  | 2100 | 0.0080 | 0.0561 | 0.0545 | 0.0395 | 0.0226 | 0.5728 | 0.0248 | 0.0850 | 0.0623 | 0.0574 | 0.0250 | 0.4361 | 0.0165 | 0.0950 | 0.1619 | 0.0911 | 0.0606 | 0.6646 |
|  | 6000 | 0.0078 | 0.0550 | 0.0549 | 0.0393 | 0.0224 | 0.5698 | 0.0241 | 0.0841 | 0.0621 | 0.0568 | 0.0249 | 0.4380 | 0.0150 | 0.0955 | 0.1661 | 0.0922 | 0.0622 | 0.6741 |
| $\delta=4$ | 90 | 0.0077 | 0.0380 | 0.0341 | 0.0266 | 0.0200 | 0.7509 | 0.0230 | 0.0714 | 0.0512 | 0.0486 | 0.0236 | 0.4866 | 0.0347 | 0.0637 | 0.0774 | 0.0586 | 0.0252 | 0.4295 |
|  | 180 | 0.0042 | 0.0327 | 0.0294 | 0.0221 | 0.0159 | 0.7195 | 0.0154 | 0.0554 | 0.0427 | 0.0379 | 0.0189 | 0.4991 | 0.0243 | 0.0535 | 0.0845 | 0.0541 | 0.0296 | 0.5470 |
|  | 300 | 0.0036 | 0.0296 | 0.0313 | 0.0215 | 0.0144 | 0.6727 | 0.0140 | 0.0518 | 0.0403 | 0.0354 | 0.0173 | 0.4889 | 0.0200 | 0.0506 | 0.0836 | 0.0514 | 0.0286 | 0.5553 |
|  | 450 | 0.0027 | 0.0284 | 0.0308 | 0.0207 | 0.0139 | 0.6732 | 0.0127 | 0.0486 | 0.0388 | 0.0334 | 0.0160 | 0.4802 | 0.0174 | 0.0485 | 0.0878 | 0.0512 | 0.0307 | 0.5997 |
|  | 750 | 0.0027 | 0.0276 | 0.0312 | 0.0205 | 0.0135 | 0.6574 | 0.0119 | 0.0477 | 0.0384 | 0.0327 | 0.0158 | 0.4815 | 0.0156 | 0.0480 | 0.0943 | 0.0526 | 0.0348 | 0.6611 |
|  | 900 | 0.0027 | 0.0279 | 0.0302 | 0.0203 | 0.0131 | 0.6455 | 0.0120 | 0.0473 | 0.0377 | 0.0323 | 0.0153 | 0.4744 | 0.0159 | 0.0462 | 0.0948 | 0.0523 | 0.0344 | 0.6567 |
|  | 1200 | 0.0029 | 0.0272 | 0.0294 | 0.0198 | 0.0124 | 0.6286 | 0.0119 | 0.0469 | 0.0369 | 0.0319 | 0.0151 | 0.4725 | 0.0151 | 0.0464 | 0.0973 | 0.0529 | 0.0355 | 0.6709 |
|  | 1500 | 0.0027 | 0.0266 | 0.0303 | 0.0199 | 0.0126 | 0.6353 | 0.0117 | 0.0467 | 0.0371 | 0.0318 | 0.0151 | 0.4728 | 0.0144 | 0.0468 | 0.0963 | 0.0525 | 0.0351 | 0.6679 |
|  | 1800 | 0.0027 | 0.0277 | 0.0305 | 0.0203 | 0.0128 | 0.6301 | 0.0117 | 0.0459 | 0.0369 | 0.0315 | 0.0147 | 0.4660 | 0.0142 | 0.0456 | 0.1021 | 0.0540 | 0.0378 | 0.6998 |
|  | 2100 | 0.0025 | 0.0271 | 0.0306 | 0.0201 | 0.0128 | 0.6382 | 0.0116 | 0.0458 | 0.0370 | 0.0315 | 0.0147 | 0.4663 | 0.0138 | 0.0445 | 0.1015 | 0.0533 | 0.0374 | 0.7025 |
|  | 6000 | 0.0025 | 0.0271 | 0.0303 | 0.0200 | 0.0125 | 0.6284 | 0.0114 | 0.0456 | 0.0370 | 0.0313 | 0.0146 | 0.4656 | 0.0129 | 0.0444 | 0.1048 | 0.0540 | 0.0387 | 0.7165 |
| $\delta=5$ | 90 | 0.0029 | 0.0172 | 0.0177 | 0.0126 | 0.0123 | 0.9798 | 0.0114 | 0.0384 | 0.0281 | 0.0260 | 0.0156 | 0.5989 | 0.0306 | 0.0468 | 0.0361 | 0.0378 | 0.0158 | 0.4177 |
|  | 180 | 0.0011 | 0.0149 | 0.0163 | 0.0108 | 0.0094 | 0.8717 | 0.0071 | 0.0301 | 0.0244 | 0.0205 | 0.0121 | 0.5892 | 0.0217 | 0.0326 | 0.0420 | 0.0321 | 0.0145 | 0.4533 |
|  | 300 | 0.0008 | 0.0149 | 0.0150 | 0.0102 | 0.0084 | 0.8252 | 0.0060 | 0.0255 | 0.0208 | 0.0174 | 0.0098 | 0.5613 | 0.0180 | 0.0268 | 0.0418 | 0.0289 | 0.0128 | 0.4448 |
|  | 450 | 0.0007 | 0.0133 | 0.0160 | 0.0100 | 0.0078 | 0.7838 | 0.0055 | 0.0246 | 0.0218 | 0.0173 | 0.0093 | 0.5367 | 0.0160 | 0.0251 | 0.0449 | 0.0287 | 0.0159 | 0.5562 |
|  | 750 | 0.0006 | 0.0126 | 0.0153 | 0.0095 | 0.0071 | 0.7489 | 0.0044 | 0.0234 | 0.0210 | 0.0163 | 0.0090 | 0.5507 | 0.0137 | 0.0223 | 0.0454 | 0.0271 | 0.0152 | 0.5619 |
|  | 900 | 0.0006 | 0.0123 | 0.0150 | 0.0093 | 0.0069 | 0.7399 | 0.0049 | 0.0230 | 0.0205 | 0.0161 | 0.0085 | 0.5262 | 0.0135 | 0.0222 | 0.0472 | 0.0277 | 0.0162 | 0.5850 |
|  | 1200 | 0.0007 | 0.0128 | 0.0159 | 0.0098 | 0.0070 | 0.7158 | 0.0048 | 0.0231 | 0.0206 | 0.0162 | 0.0085 | 0.5260 | 0.0130 | 0.0216 | 0.0487 | 0.0278 | 0.0167 | 0.6027 |
|  | 1500 | 0.0007 | 0.0125 | 0.0147 | 0.0093 | 0.0066 | 0.7058 | 0.0046 | 0.0233 | 0.0203 | 0.0161 | 0.0085 | 0.5272 | 0.0127 | 0.0210 | 0.0486 | 0.0274 | 0.0164 | 0.5991 |
|  | 1800 | 0.0007 | 0.0123 | 0.0150 | 0.0093 | 0.0066 | 0.7016 | 0.0048 | 0.0232 | 0.0202 | 0.0160 | 0.0083 | 0.5182 | 0.0123 | 0.0211 | 0.0481 | 0.0272 | 0.0164 | 0.6034 |
|  | 2100 | 0.0006 | 0.0122 | 0.0152 | 0.0093 | 0.0065 | 0.7002 | 0.0045 | 0.0228 | 0.0203 | 0.0159 | 0.0083 | 0.5221 | 0.0122 | 0.0207 | 0.0481 | 0.0270 | 0.0165 | 0.6103 |
|  | 6000 | 0.0006 | 0.0123 | 0.0152 | 0.0094 | 0.0064 | 0.6843 | 0.0046 | 0.0226 | 0.0202 | 0.0158 | 0.0081 | 0.5109 | 0.0115 | 0.0194 | 0.0521 | 0.0277 | 0.0184 | 0.6653 |

Table A.2: Error Rates for 4 variables and a sample ratio of (1:2:2)

Table A.3: Error Rates for 4 variables and a sample ratio of (1:2:3)


|  |  | Table A. <br> CorrNorm |  |  |  |  |  | and a sample ratio of (1:1:1) |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Distributions |  |  |  |  |  |  |  | UncorrNorm |  |  |  |  |  | Skewed |  |  |  |  |  |
|  | S. Size | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV |
| $\delta=1$ | 90 | 0.0682 | 0.1578 | 0.1197 | 0.1152 | 0.0463 | 0.4022 | 0.1467 | 0.3009 | 0.2484 | 0.2320 | 0.0665 | 0.2867 | 0.0694 | 0.2343 | 0.2220 | 0.1753 | 0.0790 | 0.4508 |
|  | 180 | 0.0436 | 0.1484 | 0.1284 | 0.1068 | 0.0490 | 0.4585 | 0.1048 | 0.2599 | 0.1787 | 0.1811 | 0.0650 | 0.3586 | 0.0437 | 0.2284 | 0.2324 | 0.1682 | 0.0900 | 0.5350 |
|  | 300 | 0.0345 | 0.1401 | 0.1227 | 0.0991 | 0.0482 | 0.4868 | 0.0863 | 0.2322 | 0.1557 | 0.1581 | 0.0607 | 0.3841 | 0.0378 | 0.2203 | 0.2350 | 0.1644 | 0.0910 | 0.5535 |
|  | 450 | 0.0319 | 0.1359 | 0.1234 | 0.0971 | 0.0480 | 0.4944 | 0.0770 | 0.2169 | 0.1452 | 0.1464 | 0.0581 | 0.3970 | 0.0334 | 0.2223 | 0.2381 | 0.1646 | 0.0940 | 0.5712 |
|  | 750 | 0.0285 | 0.1309 | 0.1186 | 0.0926 | 0.0465 | 0.5016 | 0.0701 | 0.2049 | 0.1374 | 0.1374 | 0.0556 | 0.4046 | 0.0299 | 0.2211 | 0.2419 | 0.1643 | 0.0961 | 0.5848 |
|  | 900 | 0.0273 | 0.1297 | 0.1204 | 0.0925 | 0.0469 | 0.5073 | 0.0693 | 0.1997 | 0.1364 | 0.1351 | 0.0538 | 0.3984 | 0.0279 | 0.2201 | 0.2436 | 0.1639 | 0.0973 | 0.5937 |
|  | 1200 | 0.0258 | 0.1276 | 0.1190 | 0.0908 | 0.0467 | 0.5139 | 0.0669 | 0.1953 | 0.1328 | 0.1317 | 0.0528 | 0.4012 | 0.0264 | 0.2207 | 0.2480 | 0.1650 | 0.0993 | 0.6053 |
|  | 1500 | 0.0262 | 0.1276 | 0.1179 | 0.0905 | 0.0462 | 0.5099 | 0.0653 | 0.1948 | 0.1316 | 0.1306 | 0.0533 | 0.4078 | 0.0250 | 0.2232 | 0.2484 | 0.1655 | 0.1004 | 0.6066 |
|  | 1800 | 0.0254 | 0.1257 | 0.1189 | 0.0900 | 0.0462 | 0.5128 | 0.0650 | 0.1934 | 0.1322 | 0.1302 | 0.0527 | 0.4050 | 0.0254 | 0.2207 | 0.2494 | 0.1652 | 0.1001 | 0.6057 |
|  | 2100 | 0.0257 | 0.1255 | 0.1185 | 0.0899 | 0.0459 | 0.5105 | 0.0644 | 0.1906 | 0.1311 | 0.1287 | 0.0519 | 0.4031 | 0.0253 | 0.2203 | 0.2517 | 0.1658 | 0.1005 | 0.6065 |
|  | 6000 | 0.0244 | 0.1246 | 0.1182 | 0.0891 | 0.0459 | 0.5158 | 0.0622 | 0.1871 | 0.1294 | 0.1262 | 0.0512 | 0.4055 | 0.0227 | 0.2208 | 0.2566 | 0.1667 | 0.1032 | 0.6190 |
| $\delta=2$ | 90 | 0.0449 | 0.1110 | 0.0858 | 0.0806 | 0.0358 | 0.4450 | 0.1063 | 0.2296 | 0.1566 | 0.1642 | 0.0541 | 0.3296 | 0.0604 | 0.1774 | 0.1776 | 0.1385 | 0.0609 | 0.4397 |
|  | 180 | 0.0256 | 0.1015 | 0.0881 | 0.0717 | 0.0364 | 0.5074 | 0.0696 | 0.1831 | 0.1202 | 0.1243 | 0.0482 | 0.3876 | 0.0389 | 0.1713 | 0.1938 | 0.1347 | 0.0710 | 0.5273 |
|  | 300 | 0.0186 | 0.0931 | 0.0851 | 0.0656 | 0.0355 | 0.5416 | 0.0567 | 0.1606 | 0.1075 | 0.1083 | 0.0438 | 0.4047 | 0.0329 | 0.1632 | 0.1957 | 0.1306 | 0.0721 | 0.5520 |
|  | 450 | 0.0168 | 0.0909 | 0.0848 | 0.0642 | 0.0352 | 0.5492 | 0.0511 | 0.1518 | 0.1018 | 0.1016 | 0.0420 | 0.4138 | 0.0281 | 0.1636 | 0.2005 | 0.1308 | 0.0757 | 0.5786 |
|  | 750 | 0.0156 | 0.0863 | 0.0830 | 0.0616 | 0.0333 | 0.5408 | 0.0467 | 0.1407 | 0.0982 | 0.0952 | 0.0391 | 0.4109 | 0.0251 | 0.1664 | 0.2047 | 0.1321 | 0.0783 | 0.5929 |
|  | 900 | 0.0147 | 0.0854 | 0.0820 | 0.0607 | 0.0335 | 0.5513 | 0.0457 | 0.1388 | 0.0973 | 0.0939 | 0.0386 | 0.4110 | 0.0250 | 0.1618 | 0.2070 | 0.1313 | 0.0786 | 0.5985 |
|  | 1200 | 0.0146 | 0.0863 | 0.0819 | 0.0609 | 0.0334 | 0.5488 | 0.0444 | 0.1378 | 0.0942 | 0.0921 | 0.0387 | 0.4199 | 0.0233 | 0.1631 | 0.2133 | 0.1332 | 0.0812 | 0.6099 |
|  | 1500 | 0.0145 | 0.0846 | 0.0821 | 0.0604 | 0.0330 | 0.5469 | 0.0430 | 0.1356 | 0.0949 | 0.0911 | 0.0383 | 0.4202 | 0.0228 | 0.1622 | 0.2126 | 0.1325 | 0.0809 | 0.6108 |
|  | 1800 | 0.0137 | 0.0826 | 0.0832 | 0.0598 | 0.0330 | 0.5520 | 0.0430 | 0.1343 | 0.0941 | 0.0904 | 0.0377 | 0.4170 | 0.0225 | 0.1621 | 0.2123 | 0.1323 | 0.0809 | 0.6114 |
|  | 2100 | 0.0136 | 0.0821 | 0.0820 | 0.0593 | 0.0326 | 0.5505 | 0.0430 | 0.1332 | 0.0935 | 0.0899 | 0.0372 | 0.4136 | 0.0216 | 0.1634 | 0.2159 | 0.1336 | 0.0826 | 0.6185 |
|  | 6000 | 0.0133 | 0.0818 | 0.0817 | 0.0589 | 0.0324 | 0.5502 | 0.0410 | 0.1308 | 0.0926 | 0.0881 | 0.0369 | 0.4191 | 0.0201 | 0.1629 | 0.2202 | 0.1344 | 0.0845 | 0.6287 |
| $\delta=3$ | 90 | 0.0207 | 0.0738 | 0.0568 | 0.0504 | 0.0290 | 0.5753 | 0.0661 | 0.1567 | 0.1042 | 0.1090 | 0.0410 | 0.3762 | 0.0548 | 0.1208 | 0.1347 | 0.1034 | 0.0415 | 0.4017 |
|  | 180 | 0.0118 | 0.0574 | 0.0530 | 0.0407 | 0.0239 | 0.5878 | 0.0406 | 0.1130 | 0.0749 | 0.0762 | 0.0321 | 0.4212 | 0.0343 | 0.1089 | 0.1400 | 0.0944 | 0.0487 | 0.5156 |
|  | 300 | 0.0082 | 0.0511 | 0.0499 | 0.0364 | 0.0219 | 0.6019 | 0.0327 | 0.0976 | 0.0673 | 0.0659 | 0.0279 | 0.4230 | 0.0284 | 0.1008 | 0.1403 | 0.0898 | 0.0491 | 0.5463 |
|  | 450 | 0.0069 | 0.0514 | 0.0500 | 0.0361 | 0.0220 | 0.6095 | 0.0288 | 0.0907 | 0.0647 | 0.0614 | 0.0262 | 0.4259 | 0.0256 | 0.0980 | 0.1450 | 0.0896 | 0.0513 | 0.5727 |
|  | 750 | 0.0060 | 0.0485 | 0.0511 | 0.0352 | 0.0216 | 0.6124 | 0.0257 | 0.0866 | 0.0631 | 0.0585 | 0.0256 | 0.4383 | 0.0217 | 0.0995 | 0.1508 | 0.0907 | 0.0545 | 0.6009 |
|  | 900 | 0.0065 | 0.0482 | 0.0500 | 0.0349 | 0.0208 | 0.5957 | 0.0257 | 0.0853 | 0.0631 | 0.0580 | 0.0251 | 0.4325 | 0.0214 | 0.0995 | 0.1564 | 0.0924 | 0.0567 | 0.6133 |
|  | 1200 | 0.0059 | 0.0470 | 0.0504 | 0.0344 | 0.0208 | 0.6034 | 0.0246 | 0.0839 | 0.0623 | 0.0569 | 0.0249 | 0.4372 | 0.0204 | 0.1000 | 0.1606 | 0.0936 | 0.0587 | 0.6269 |
|  | 1500 | 0.0058 | 0.0464 | 0.0501 | 0.0341 | 0.0205 | 0.6027 | 0.0246 | 0.0825 | 0.0612 | 0.0561 | 0.0243 | 0.4330 | 0.0195 | 0.1002 | 0.1604 | 0.0934 | 0.0589 | 0.6308 |
|  | 1800 | 0.0057 | 0.0470 | 0.0492 | 0.0340 | 0.0204 | 0.6017 | 0.0240 | 0.0821 | 0.0610 | 0.0557 | 0.0243 | 0.4367 | 0.0192 | 0.0974 | 0.1608 | 0.0925 | 0.0591 | 0.6388 |
|  | 2100 | 0.0057 | 0.0465 | 0.0501 | 0.0341 | 0.0204 | 0.5991 | 0.0236 | 0.0815 | 0.0608 | 0.0553 | 0.0242 | 0.4379 | 0.0190 | 0.0980 | 0.1644 | 0.0938 | 0.0605 | 0.6448 |
|  | 6000 | 0.0053 | 0.0460 | 0.0497 | 0.0336 | 0.0202 | 0.6017 | 0.0227 | 0.0802 | 0.0600 | 0.0543 | 0.0239 | 0.4404 | 0.0175 | 0.0974 | 0.1665 | 0.0938 | 0.0614 | 0.6550 |
| $\delta=4$ | 90 | 0.0086 | 0.0431 | 0.0311 | 0.0207 | 0.0276 | 0.7506 | 0.0371 | 0.0988 | 0.0644 | 0.0668 | 0.0294 | 0.4404 | 0.0480 | 0.0834 | 0.0821 | 0.0712 | 0.0269 | 0.3777 |
|  | 180 | 0.0040 | 0.0309 | 0.0292 | 0.0214 | 0.0154 | 0.7193 | 0.0196 | 0.0646 | 0.0453 | 0.0431 | 0.0205 | 0.4743 | 0.0314 | 0.0647 | 0.0800 | 0.0590 | 0.0249 | 0.4212 |
|  | 300 | 0.0024 | 0.0275 | 0.0277 | 0.0192 | 0.0141 | 0.7321 | 0.0165 | 0.0542 | 0.0405 | 0.0371 | 0.0170 | 0.4571 | 0.0258 | 0.0577 | 0.0866 | 0.0567 | 0.0284 | 0.5000 |
|  | 450 | 0.0020 | 0.0252 | 0.0294 | 0.0189 | 0.0132 | 0.6980 | 0.0136 | 0.0499 | 0.0397 | 0.0344 | 0.0162 | 0.4711 | 0.0222 | 0.0553 | 0.0848 | 0.0541 | 0.0278 | 0.5150 |
|  | 750 | 0.0021 | 0.0255 | 0.0287 | 0.0187 | 0.0127 | 0.6789 | 0.0124 | 0.0480 | 0.0378 | 0.0327 | 0.0154 | 0.4722 | 0.0194 | 0.0532 | 0.0939 | 0.0555 | 0.0328 | 0.5910 |
|  | 900 | 0.0019 | 0.0237 | 0.0270 | 0.0175 | 0.0118 | 0.6766 | 0.0120 | 0.0464 | 0.0373 | 0.0319 | 0.0150 | 0.4696 | 0.0190 | 0.0508 | 0.0931 | 0.0543 | 0.0316 | 0.5827 |
|  | 1200 | 0.0018 | 0.0237 | 0.0276 | 0.0177 | 0.0119 | 0.6708 | 0.0115 | 0.0458 | 0.0372 | 0.0315 | 0.0149 | 0.4739 | 0.0175 | 0.0505 | 0.0986 | 0.0556 | 0.0352 | 0.6335 |
|  | 1500 | 0.0016 | 0.0232 | 0.0275 | 0.0175 | 0.0118 | 0.6736 | 0.0117 | 0.0455 | 0.0373 | 0.0315 | 0.0147 | 0.4667 | 0.0176 | 0.0497 | 0.0957 | 0.0543 | 0.0333 | 0.6123 |
|  | 1800 | 0.0017 | 0.0232 | 0.0280 | 0.0176 | 0.0118 | 0.6664 | 0.0109 | 0.0450 | 0.0364 | 0.0308 | 0.0147 | 0.4775 | 0.0171 | 0.0494 | 0.1010 | 0.0558 | 0.0363 | 0.6509 |
|  | 2100 | 0.0016 | 0.0232 | 0.0273 | 0.0173 | 0.0115 | 0.6659 | 0.0112 | 0.0443 | 0.0363 | 0.0306 | 0.0143 | 0.4667 | 0.0169 | 0.0492 | 0.0990 | 0.0550 | 0.0348 | 0.6322 |
|  | 6000 | 0.0017 | 0.0227 | 0.0273 | 0.0172 | 0.0113 | 0.6546 | 0.0108 | 0.0436 | 0.0360 | 0.0301 | 0.0141 | 0.4675 | 0.0154 | 0.0475 | 0.1066 | 0.0565 | 0.0384 | 0.6797 |
| $\delta=5$ | 90 | 0.0036 | 0.0238 | 0.0180 | 0.0151 | 0.0150 | 0.9928 | 0.0178 | 0.0554 | 0.0391 | 0.0374 | 0.0200 | 0.5345 | 0.0443 | 0.0600 | 0.0373 | 0.0472 | 0.0177 | 0.3757 |
|  | 180 | 0.0015 | 0.0161 | 0.0143 | 0.0106 | 0.0096 | 0.8996 | 0.0095 | 0.0344 | 0.0267 | 0.0235 | 0.0125 | 0.5305 | 0.0297 | 0.0423 | 0.0372 | 0.0364 | 0.0111 | 0.3050 |
|  | 300 | 0.0008 | 0.0133 | 0.0128 | 0.0090 | 0.0076 | 0.8421 | 0.0065 | 0.0284 | 0.0222 | 0.0191 | 0.0107 | 0.5632 | 0.0232 | 0.0351 | 0.0443 | 0.0342 | 0.0138 | 0.4039 |
|  | 450 | 0.0005 | 0.0121 | 0.0144 | 0.0090 | 0.0072 | 0.7999 | 0.0058 | 0.0248 | 0.0221 | 0.0176 | 0.0095 | 0.5404 | 0.0197 | 0.0311 | 0.0435 | 0.0314 | 0.0130 | 0.4131 |
|  | 750 | 0.0004 | 0.0115 | 0.0134 | 0.0084 | 0.0065 | 0.7699 | 0.0050 | 0.0239 | 0.0207 | 0.0165 | 0.0088 | 0.5347 | 0.0172 | 0.0277 | 0.0485 | 0.0311 | 0.0157 | 0.5030 |
|  | 900 | 0.0003 | 0.0109 | 0.0136 | 0.0083 | 0.0063 | 0.7539 | 0.0049 | 0.0239 | 0.0207 | 0.0165 | 0.0088 | 0.5330 | 0.0168 | 0.0279 | 0.0465 | 0.0304 | 0.0144 | 0.4757 |
|  | 1200 | 0.0003 | 0.0110 | 0.0130 | 0.0081 | 0.0060 | 0.7423 | 0.0048 | 0.0233 | 0.0203 | 0.0161 | 0.0085 | 0.5253 | 0.0159 | 0.0259 | 0.0504 | 0.0307 | 0.0170 | 0.5536 |
|  | 1500 | 0.0004 | 0.0109 | 0.0137 | 0.0083 | 0.0061 | 0.7380 | 0.0046 | 0.0222 | 0.0198 | 0.0155 | 0.0081 | 0.5226 | 0.0156 | 0.0248 | 0.0526 | 0.0310 | 0.0185 | 0.5959 |
|  | 1800 | 0.0003 | 0.0109 | 0.0139 | 0.0084 | 0.0061 | 0.7295 | 0.0045 | 0.0224 | 0.0205 | 0.0158 | 0.0083 | 0.5226 | 0.0152 | 0.0252 | 0.0492 | 0.0299 | 0.0155 | 0.5193 |
|  | 2100 | 0.0004 | 0.0106 | 0.0130 | 0.0080 | 0.0058 | 0.7208 | 0.0043 | 0.0224 | 0.0199 | 0.0155 | 0.0082 | 0.5275 | 0.0147 | 0.0244 | 0.0508 | 0.0300 | 0.0173 | 0.5766 |
|  | 6000 | 0.0004 | 0.0107 | 0.0137 | 0.0082 | 0.0058 | 0.7038 | 0.0044 | 0.0218 | 0.0198 | 0.0153 | 0.0079 | 0.5145 | 0.0141 | 0.0227 | 0.0533 | 0.0300 | 0.0173 | 0.5766 |

Table A.5: Error Rates for 6 variables and a sample ratio of (1:2:2)

Table A.6: Error Rates for 6 variables and a sample ratio of (1:2:3)


|  |  | Table A. <br> CorrNorm |  |  |  |  |  | and a sample ratio of (1:1:1) |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Distributions |  |  |  |  |  |  |  | UncorrNorm |  |  |  |  |  | Skewed |  |  |  |  |  |
|  | S. Size | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV | $\pi_{1}$ | $\pi_{2}$ | $\pi_{3}$ | G. Mean | SD | CV |
| $\delta=1$ | 90 | 0.0779 | 0.1623 | 0.1228 | 0.1210 | 0.0428 | 0.3540 | 0.1887 | 0.3240 | 0.3051 | 0.2726 | 0.0619 | 0.2269 | 0.0810 | 0.2360 | 0.2229 | 0.1800 | 0.0750 | 0.4169 |
|  | 180 | 0.0415 | 0.1368 | 0.1130 | 0.0971 | 0.0446 | 0.4593 | 0.1242 | 0.2827 | 0.2066 | 0.2045 | 0.0661 | 0.3234 | 0.0521 | 0.2218 | 0.2154 | 0.1631 | 0.0810 | 0.4967 |
|  | 300 | 0.0320 | 0.1266 | 0.1101 | 0.0896 | 0.0434 | 0.4851 | 0.0962 | 0.2416 | 0.1640 | 0.1673 | 0.0606 | 0.3624 | 0.0398 | 0.2152 | 0.2244 | 0.1598 | 0.0864 | 0.5403 |
|  | 450 | 0.0262 | 0.1229 | 0.1095 | 0.0862 | 0.0441 | 0.5122 | 0.0811 | 0.2188 | 0.1449 | 0.1483 | 0.0570 | 0.3845 | 0.0351 | 0.2146 | 0.2287 | 0.1595 | 0.0892 | 0.5590 |
|  | 750 | 0.0223 | 0.1114 | 0.1071 | 0.0803 | 0.0419 | 0.5220 | 0.0716 | 0.1995 | 0.1346 | 0.1352 | 0.0529 | 0.3911 | 0.0316 | 0.2114 | 0.2359 | 0.1596 | 0.0918 | 0.5749 |
|  | 900 | 0.0214 | 0.1119 | 0.1094 | 0.0809 | 0.0429 | 0.5308 | 0.0686 | 0.1951 | 0.1315 | 0.1318 | 0.0522 | 0.3963 | 0.0296 | 0.2150 | 0.2365 | 0.1603 | 0.0936 | 0.5835 |
|  | 1200 | 0.0206 | 0.1109 | 0.1070 | 0.0795 | 0.0423 | 0.5315 | 0.0651 | 0.1893 | 0.1286 | 0.1276 | 0.0511 | 0.4006 | 0.0289 | 0.2107 | 0.2395 | 0.1597 | 0.0938 | 0.5871 |
|  | 1500 | 0.0195 | 0.1097 | 0.1078 | 0.0790 | 0.0425 | 0.5382 | 0.0631 | 0.1859 | 0.1270 | 0.1253 | 0.0506 | 0.4034 | 0.0274 | 0.2109 | 0.2415 | 0.1599 | 0.0950 | 0.5940 |
|  | 1800 | 0.0190 | 0.1080 | 0.1070 | 0.0780 | 0.0421 | 0.5397 | 0.0622 | 0.1843 | 0.1252 | 0.1239 | 0.0501 | 0.4047 | 0.0267 | 0.2122 | 0.2421 | 0.1603 | 0.0957 | 0.5969 |
|  | 2100 | 0.0192 | 0.1078 | 0.1070 | 0.0780 | 0.0419 | 0.5372 | 0.0611 | 0.1820 | 0.1247 | 0.1226 | 0.0497 | 0.4051 | 0.0259 | 0.2128 | 0.2451 | 0.1613 | 0.0971 | 0.6020 |
|  | 6000 | 0.0179 | 0.1048 | 0.1068 | 0.0765 | 0.0416 | 0.5441 | 0.0577 | 0.1744 | 0.1224 | 0.1181 | 0.0479 | 0.4054 | 0.0236 | 0.2129 | 0.2502 | 0.1622 | 0.0995 | 0.6133 |
| $\delta=2$ | 90 | 0.0571 | 0.1252 | 0.0858 | 0.0894 | 0.0382 | 0.4273 | 0.1501 | 0.2679 | 0.2139 | 0.2106 | 0.0520 | 0.2467 | 0.0766 | 0.1887 | 0.1763 | 0.1472 | 0.0574 | 0.3898 |
|  | 180 | 0.0251 | 0.0996 | 0.0814 | 0.0687 | 0.0358 | 0.5210 | 0.0869 | 0.2091 | 0.1362 | 0.1441 | 0.0527 | 0.3658 | 0.0447 | 0.1739 | 0.1803 | 0.1330 | 0.0661 | 0.4972 |
|  | 300 | 0.0185 | 0.0879 | 0.0790 | 0.0618 | 0.0332 | 0.5378 | 0.0652 | 0.1714 | 0.1126 | 0.1164 | 0.0447 | 0.3843 | 0.0355 | 0.1619 | 0.1903 | 0.1292 | 0.0691 | 0.5350 |
|  | 450 | 0.0156 | 0.0826 | 0.0779 | 0.0587 | 0.0322 | 0.5478 | 0.0549 | 0.1540 | 0.1035 | 0.1041 | 0.0416 | 0.3992 | 0.0324 | 0.1612 | 0.1942 | 0.1293 | 0.0713 | 0.5515 |
|  | 750 | 0.0121 | 0.0780 | 0.0756 | 0.0552 | 0.0313 | 0.5668 | 0.0465 | 0.1398 | 0.0962 | 0.0942 | 0.0389 | 0.4128 | 0.0280 | 0.1601 | 0.2018 | 0.1300 | 0.0751 | 0.5778 |
|  | 900 | 0.0123 | 0.0756 | 0.0756 | 0.0545 | 0.0306 | 0.5622 | 0.0452 | 0.1368 | 0.0942 | 0.0921 | 0.0380 | 0.4127 | 0.0270 | 0.1618 | 0.2004 | 0.1298 | 0.0752 | 0.5798 |
|  | 1200 | 0.0112 | 0.0735 | 0.0755 | 0.0534 | 0.0304 | 0.5698 | 0.0432 | 0.1329 | 0.0934 | 0.0898 | 0.0372 | 0.4138 | 0.0253 | 0.1622 | 0.2065 | 0.1313 | 0.0780 | 0.5937 |
|  | 1500 | 0.0113 | 0.0740 | 0.0768 | 0.0540 | 0.0307 | 0.5683 | 0.0423 | 0.1308 | 0.0925 | 0.0885 | 0.0367 | 0.4140 | 0.0240 | 0.1613 | 0.2062 | 0.1305 | 0.0782 | 0.5990 |
|  | 1800 | 0.0103 | 0.0728 | 0.0761 | 0.0531 | 0.0306 | 0.5774 | 0.0413 | 0.1298 | 0.0918 | 0.0876 | 0.0366 | 0.4175 | 0.0240 | 0.1598 | 0.2103 | 0.1314 | 0.0794 | 0.6040 |
|  | 2100 | 0.0105 | 0.0725 | 0.0761 | 0.0530 | 0.0304 | 0.5737 | 0.0406 | 0.1276 | 0.0905 | 0.0862 | 0.0359 | 0.4167 | 0.0226 | 0.1609 | 0.2124 | 0.1319 | 0.0808 | 0.6122 |
|  | 6000 | 0.0099 | 0.0705 | 0.0756 | 0.0520 | 0.0300 | 0.5777 | 0.0388 | 0.1241 | 0.0891 | 0.0840 | 0.0352 | 0.4186 | 0.0208 | 0.1609 | 0.2183 | 0.1333 | 0.0833 | 0.6247 |
| $\delta=2$ | 90 | 0.0299 | 0.0849 | 0.0551 | 0.0566 | 0.0306 | 0.5399 | 0.1009 | 0.2013 | 0.1394 | 0.1472 | 0.0458 | 0.3109 | 0.0687 | 0.1382 | 0.1258 | 0.1109 | 0.0396 | 0.3570 |
|  | 180 | 0.0105 | 0.0587 | 0.0472 | 0.0388 | 0.0245 | 0.6303 | 0.0523 | 0.1329 | 0.0868 | 0.0907 | 0.0353 | 0.3893 | 0.0429 | 0.1117 | 0.1321 | 0.0955 | 0.0427 | 0.4465 |
|  | 300 | 0.0069 | 0.0525 | 0.0467 | 0.0353 | 0.0221 | 0.6259 | 0.0358 | 0.1068 | 0.0718 | 0.0714 | 0.0304 | 0.4260 | 0.0331 | 0.1057 | 0.1370 | 0.0919 | 0.0459 | 0.4993 |
|  | 450 | 0.0064 | 0.0467 | 0.0476 | 0.0335 | 0.0208 | 0.6191 | 0.0306 | 0.0947 | 0.0669 | 0.0641 | 0.0272 | 0.4248 | 0.0286 | 0.1037 | 0.1453 | 0.0925 | 0.0507 | 0.5485 |
|  | 750 | 0.0051 | 0.0436 | 0.0467 | 0.0318 | 0.0197 | 0.6218 | 0.0274 | 0.0872 | 0.0634 | 0.0594 | 0.0252 | 0.4245 | 0.0244 | 0.0998 | 0.1498 | 0.0913 | 0.0530 | 0.5798 |
|  | 900 | 0.0048 | 0.0429 | 0.0468 | 0.0315 | 0.0197 | 0.6261 | 0.0255 | 0.0830 | 0.0624 | 0.0570 | 0.0244 | 0.4279 | 0.0238 | 0.0994 | 0.1521 | 0.0918 | 0.0918 | 0.5926 |
|  | 1200 | 0.0046 | 0.0430 | 0.0461 | 0.0312 | 0.0194 | 0.6211 | 0.0241 | 0.0816 | 0.0615 | 0.0557 | 0.0243 | 0.4360 | 0.0226 | 0.0986 | 0.1532 | 0.0915 | 0.0547 | 0.5977 |
|  | 1500 | 0.0045 | 0.0413 | 0.0462 | 0.0307 | 0.0191 | 0.6215 | 0.0234 | 0.0811 | 0.0604 | 0.0550 | 0.0242 | 0.4401 | 0.0218 | 0.1011 | 0.1584 | 0.0937 | 0.0572 | 0.6106 |
|  | 1800 | 0.0043 | 0.0412 | 0.0455 | 0.0303 | 0.0189 | 0.6223 | 0.0233 | 0.0794 | 0.0594 | 0.0540 | 0.0235 | 0.4357 | 0.0211 | 0.0983 | 0.1592 | 0.0929 | 0.0576 | 0.6205 |
|  | 2100 | 0.0042 | 0.0407 | 0.0465 | 0.0305 | 0.0189 | 0.6216 | 0.0228 | 0.0790 | 0.0597 | 0.0539 | 0.0236 | 0.4375 | 0.0207 | 0.0986 | 0.1601 | 0.0931 | 0.0581 | 0.6239 |
|  | 6000 | 0.0038 | 0.0404 | 0.0463 | 0.0302 | 0.0189 | 0.6271 | 0.0212 | 0.0764 | 0.0584 | 0.0520 | 0.0231 | 0.4443 | 0.0187 | 0.0969 | 0.1660 | 0.0939 | 0.0607 | 0.6469 |
| $\delta=4$ | 90 | 0.0123 | 0.0494 | 0.0339 | 0.0319 | 0.0234 | 0.7332 | 0.0613 | 0.1327 | 0.0871 | 0.0937 | 0.0343 | 0.3658 | 0.0618 | 0.0964 | 0.0811 | 0.0798 | 0.0259 | 0.3246 |
|  | 180 | 0.0041 | 0.0309 | 0.0273 | 0.0208 | 0.0150 | 0.7233 | 0.0263 | 0.0779 | 0.0524 | 0.0522 | 0.0236 | 0.4515 | 0.0371 | 0.0729 | 0.0831 | 0.0644 | 0.0266 | 0.4135 |
|  | 300 | 0.0025 | 0.0268 | 0.0265 | 0.0186 | 0.0133 | 0.7180 | 0.0179 | 0.0607 | 0.0404 | 0.0424 | 0.0189 | 0.4675 | 0.0305 | 0.0634 | 0.0825 | 0.0588 | 0.0253 | 0.4309 |
|  | 450 | 0.0022 | 0.0253 | 0.0262 | 0.0179 | 0.0125 | 0.6998 | 0.0152 | 0.0533 | 0.0410 | 0.0365 | 0.0168 | 0.4608 | 0.0258 | 0.0579 | 0.0905 | 0.0581 | 0.0298 | 0.5132 |
|  | 750 | 0.0015 | 0.0213 | 0.0253 | 0.0160 | 0.0111 | 0.6914 | 0.0125 | 0.0477 | 0.0388 | 0.0330 | 0.0156 | 0.4730 | 0.0220 | 0.0548 | 0.0942 | 0.0570 | 0.0318 | 0.5569 |
|  | 900 | 0.0012 | 0.0228 | 0.0255 | 0.0165 | 0.0115 | 0.7013 | 0.0123 | 0.0467 | 0.0367 | 0.0319 | 0.0150 | 0.4695 | 0.0215 | 0.0532 | 0.0935 | 0.0561 | 0.0312 | 0.5571 |
|  | 1200 | 0.0014 | 0.0211 | 0.0258 | 0.0161 | 0.0110 | 0.6850 | 0.0117 | 0.0454 | 0.0364 | 0.0312 | 0.0146 | 0.4688 | 0.0198 | 0.0529 | 0.1022 | 0.0583 | 0.0366 | 0.6280 |
|  | 1500 | 0.0012 | 0.0210 | 0.0248 | 0.0157 | 0.0107 | 0.6840 | 0.0114 | 0.0439 | 0.0360 | 0.0304 | 0.0142 | 0.4659 | 0.0195 | 0.0521 | 0.0984 | 0.0567 | 0.0339 | 0.5987 |
|  | 1800 | 0.0012 | 0.0208 | 0.0244 | 0.0155 | 0.0105 | 0.6777 | 0.0109 | 0.0436 | 0.0358 | 0.0301 | 0.0143 | 0.4737 | 0.0191 | 0.0515 | 0.0999 | 0.0568 | 0.0346 | 0.6080 |
|  | 2100 | 0.0012 | 0.0213 | 0.0256 | 0.0160 | 0.0109 | 0.6811 | 0.0111 | 0.0439 | 0.0360 | 0.0303 | 0.0142 | 0.4684 | 0.0186 | 0.0506 | 0.1027 | 0.0573 | 0.0362 | 0.6311 |
|  | 6000 | 0.0011 | 0.0202 | 0.0248 | 0.0154 | 0.0104 | 0.6743 | 0.0103 | 0.0420 | 0.0349 | 0.0291 | 0.0137 | 0.4715 | 0.0169 | 0.0492 | 0.1052 | 0.0571 | 0.0371 | 0.6501 |
| $\delta=5$ | 90 | 0.0056 | 0.0316 | 0.0184 | 0.0185 | 0.0174 | 0.9418 | 0.0327 | 0.0828 | 0.0559 | 0.0571 | 0.0254 | 0.4441 | 0.0592 | 0.0757 | 0.0376 | 0.0575 | 0.0223 | 0.3884 |
|  | 180 | 0.0011 | 0.0166 | 0.0137 | 0.0105 | 0.0098 | 0.9369 | 0.0119 | 0.0430 | 0.0303 | 0.0284 | 0.0149 | 0.5262 | 0.0343 | 0.0501 | 0.0389 | 0.0411 | 0.0130 | 0.3153 |
|  | 300 | 0.0006 | 0.0138 | 0.0133 | 0.0092 | 0.0080 | 0.8672 | 0.0078 | 0.0313 | 0.0254 | 0.0215 | 0.0114 | 0.5304 | 0.0276 | 0.0406 | 0.0432 | 0.0371 | 0.0120 | 0.3246 |
|  | 450 | 0.0004 | 0.0126 | 0.0131 | 0.0087 | 0.0071 | 0.8201 | 0.0062 | 0.0277 | 0.0228 | 0.0189 | 0.0101 | 0.5356 | 0.0233 | 0.0369 | 0.0458 | 0.0353 | 0.0130 | 0.3670 |
|  | 750 | 0.0003 | 0.0106 | 0.0123 | 0.0077 | 0.0059 | 0.7595 | 0.0049 | 0.0244 | 0.0212 | 0.0168 | 0.0091 | 0.5413 | 0.0207 | 0.0318 | 0.0493 | 0.0339 | 0.0149 | 0.4385 |
|  | 900 | 0.0003 | 0.0104 | 0.0124 | 0.0077 | 0.0060 | 0.7813 | 0.0053 | 0.0242 | 0.0208 | 0.0168 | 0.0088 | 0.5253 | 0.0194 | 0.0303 | 0.0480 | 0.0325 | 0.0141 | 0.4329 |
|  | 1200 | 0.0003 | 0.0096 | 0.0121 | 0.0073 | 0.0055 | 0.7549 | 0.0048 | 0.0229 | 0.0202 | 0.0160 | 0.0083 | 0.5199 | 0.0186 | 0.0288 | 0.0495 | 0.0323 | 0.0151 | 0.4672 |
|  | 1500 | 0.0002 | 0.0100 | 0.0124 | 0.0075 | 0.0056 | 0.7423 | 0.0044 | 0.0226 | 0.0202 | 0.0157 | 0.0084 | 0.5309 | 0.0179 | 0.0286 | 0.0489 | 0.0318 | 0.0149 | 0.4685 |
|  | 1800 | 0.0003 | 0.0096 | 0.0122 | 0.0074 | 0.0054 | 0.7344 | 0.0046 | 0.0220 | 0.0198 | 0.0155 | 0.0080 | 0.5163 | 0.0171 | 0.0278 | 0.0509 | 0.0319 | 0.0158 | 0.4952 |
|  | 2100 | 0.0003 | 0.0098 | 0.0124 | 0.0075 | 0.0055 | 0.7332 | 0.0043 | 0.0219 | 0.0197 | 0.0153 | 0.0080 | 0.5248 | 0.0168 | 0.0270 | 0.0523 | 0.0320 | 0.0163 | 0.5082 |
|  | 6000 | 0.0002 | 0.0095 | 0.0123 | 0.0073 | 0.0052 | 0.7139 | 0.0041 | 0.0210 | 0.0194 | 0.0148 | 0.0077 | 0.5201 | 0.0154 | 0.0250 | 0.0544 | 0.0316 | 0.0174 | 0.5511 |

Table A.8: Error Rates for 8 variables and a sample ratio of (1:2:2)

Table A.9: Error Rates for 8 variables and a sample ratio of (1:2:3)










## Appendix B

## Graphs for Effect of Sample Size on Quadratic Discriminant Function

## B. 1 Graphs of Effect of Sample Size on Correlated Normal Distribution



Figure B.1: Average Error Rate for Correlated Normal Distribution: $\delta=2$


Figure B.2: Average Error Rate for Correlated Normal Distribution: $\delta=3$


Figure B.3: Average Error Rate for Correlated Normal Distribution: $\delta=4$


Figure B.4: Average Error Rate for Correlated Normal Distribution: $\delta=5$


Figure B.5: Coefficients of Variation for Correlated Normal Distribution: $\delta=2$


Figure B.6: Coefficients of Variation for Correlated Normal Distribution: $\delta=3$


Figure B.7: Coefficients of Variation for Correlated Normal Distribution: $\delta=4$


Figure B.8: Coefficients of Variation for Correlated Normal Distribution: $\delta=5$

## B. 2 Graphs of Effect of Sample Size on Uncorrelated Normal Distribution



Figure B.9: Average Error Rate for Uncorrelated Normal Distribution: $\delta=2$


Figure B.10: Average Error Rate for Uncorrelated Normal Distribution: $\delta=3$


Figure B.11: Average Error Rate for Uncorrelated Normal Distribution: $\delta=4$


Figure B.12: Average Error Rate for Uncorrelated Normal Distribution: $\delta=5$


Figure B.13: Coefficients of Variation for Uncorrelated Normal Distribution: $\delta=2$


Figure B.14: Coefficients of Variation for Uncorrelated Normal Distribution: $\delta=3$


Figure B.15: Coefficients of Variation for Uncorrelated Normal Distribution: $\delta=4$


Figure B.16: Coefficients of Variation for Uncorrelated Normal Distribution: $\delta=5$

## B. 3 Graphs of Effect of Sample Size on Skewed Distribution



Figure B.17: Average Error Rate for Skewed Distribution: $\delta=4$


Figure B.18: Average Error Rate for Skewed Distribution: $\delta=5$


Figure B.19: Coefficients of Variation for Skewed Distribution: $\delta=2$


Figure B.20: Coefficients of Variation for Skewed Distribution: $\delta=3$


Figure B.21: Coefficients of Variation for Skew Distribution: $\delta=4$


Figure B.22: Coefficients of Variation for Skewed Distribution: $\delta=5$

## Appendix C

# Graphs for Effect of Number of Variables on Quadratic Discriminant Function 

C. 1 Graphs of Effect of Number of Variable on Correlated Normal Distribution


Figure C.1: Average Error Rate for Correlated Normal Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 2$


Figure C.2: Average Error Rate for Correlated Normal Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 3$


Figure C.3:
Coefficients of Variation for Correlated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure C.4:
Coefficients of Variation for Correlated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$

## C. 2 Graphs of Effect of Number of Variables on Uncorrelated Normal Distribution



Figure C.5:
Average Error Rate for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure C.6:
Average Error Rate for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$


Figure C.7:
Coefficients of Variation for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure C.8:
Coefficients of Variation for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$

## C. 3 Graphs of Effect of Number of Variables on Skewed Distribution



Figure C.9: Average Error Rate for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 2$


Figure C.10: Average Error Rate for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 3$


Figure C.11: Coefficients of Variation for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 2$


Figure C.12: Coefficients of Variation for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 3$

## Appendix D

## Graphs for Effect of Group Centroid Separator on Quadratic Discriminant Function

D. 1 Graphs of Effect of Group Centroid Separator on Correlated Normal Distribution


Figure D.1: Average Error Rate for Correlated Normal Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 2$


Figure D.2:
Average Error Rate for Correlated Normal Distribution: $n_{1}: n_{2}: n_{3}==$ 1:2:3


Figure D.3:
Coefficients of Variation for Correlated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure D.4:
Coefficients of Variation for Correlated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$

## D. 2 Graphs of Effect of Group Centroid Separator on Uncorrelated Normal Distribution



Figure D.5:
Average Error Rate for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure D.6:
Average Error Rate for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$


Figure D.7:
Coefficients of Variation for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure D.8:
Coefficients of Variation for Uncorrelated Normal Distribution: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$

## D. 3 Graphs of Effect of Group Centroid Separator on Skewed Distribution



Figure D.9: Average Error Rate for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 2$


Figure D.10: Average Error Rate for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 3$


Figure D.11: Coefficients of Variation for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 2$


Figure D.12: Coefficients of Variation for Skewed Distribution: $n_{1}: n_{2}: n_{3}=1: 2: 3$

## Appendix E

## Graphs of Comparison of Error Rates of the Three Distributions

E. 1 Graphs of Comparison of Error Rates of the Three Distributions for Sample Size Ratio $n_{1}: n_{2}: n_{3}=$ 1:2:2


Figure E.1:
Average error rates of the three distributions for 4 variables: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure E.2:
Average error rates of the three distributions for 6 variables: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure E.3:
Average error rates of the three distributions for 8 variables: $n_{1}: n_{2}$ : $n_{3}=1: 2: 2$


Figure E.4:
Coefficients of Variation of the three distributions for 4 variables: $n_{1}$ : $n_{2}: n_{3}=1: 2: 2$


Figure E.5:
Coefficients of Variation of the three distributions for 6 variables: $n_{1}$ : $n_{2}: n_{3}=1: 2: 2$


Figure E.6:
Coefficients of Variation of the three distributions for 8 variables: $n_{1}$ : $n_{2}: n_{3}=1: 2: 2$

## E. 2 Graphs of Comparison of Error Rates of the Three Distributions for Sample Size Ratio $n_{1}: n_{2}: n_{3}=$ 1:2:3



Figure E.7:
Average error rates of the three distributions for 4 variables: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$


Figure E.8:
Average error rates of the three distributions for 6 variables: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$


Figure E.9:
Average error rates of the three distributions for 8 variables: $n_{1}: n_{2}$ : $n_{3}=1: 2: 3$


Figure E.10:
Coefficients of Variation of the three distributions for 4 variables: $n_{1}$ : $n_{2}: n_{3}=1: 2: 3$


Figure E.11:
Coefficients of Variation of the three distributions for 6 variables: $n_{1}$ : $n_{2}: n_{3}=1: 2: 3$


Figure E.12:
Coefficients of Variation of the three distributions for 8 variables: $n_{1}$ : $n_{2}: n_{3}=1: 2: 3$

## Appendix F

## Graphs of Comparison of Error Rates and Coefficients of Variation of the Three Distributions (Sample Size Ratio)



Figure F.1: $\quad$ Average Error Rates for individual sample size ratios and distributions for $\delta=2$


Figure F.2:
Average Error Rates for individual sample size ratios and distributions for $\delta=3$


Figure F.3:
Average Error Rates for individual sample size ratios and distributions for $\delta=4$


Figure F.4:
Coefficients of Variation for individual sample size ratios and distributions for $\delta=2$


Figure F.5:
Coefficients of Variation for individual sample size ratios and distributions for $\delta=3$


Figure F.6:
Coefficients of Variation for individual sample size ratios and distributions for $\delta=4$

