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Predicting the time until employment of graduates using a prognosis index in survival analysis

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Abstract
This research predicts the time until employment of graduates from Bayelsa State in Nigeria using the prognosis index in survival analysis. The Bayesian approach to inference which requires both the prior information and the observed data from unemployed graduates in different local government areas of Bayelsa state in the form of likelihood was used. The Metropolis - hasting within Gibbs was applied for simulation using the RJAGS software in R and convergence was checked using two chains. The trace plots of the parameters showed that the mixing was satisfactory. High values of the prognostic index indicated the best prognosis outcome for the event of interest (employment). The linear predictor was calculated in a range of 0 to 100 for some covariate vectors which showed that a female graduate with the same covariate vectors as a male graduate had a bit better chance of being employed. The prognosis index can be a reliable platform to help the government of Bayelsa state to strategize ways to tackle unemployment. It will also help individuals to effectively predicting the time until being employed and engage in strategic planning during the period of being unemployed.

Keywords: Prognostic index, unemployment, graduate, Bayesian, prior, posterior

Introduction

Unemployment is known to be one of the socioeconomic problems presently facing Nigeria as the labour force keep growing on a daily basis as a high number of young people graduate from either the Polytechnic or University. The rate of unemployment is measured or expressed as the percentage of the labour force that is currently actively seeking for employment but are without a job. There are several factors that contribute to the rise in the rate of unemployment in Nigeria. Some of which are labour market demands, the composition of the workforce's skills, the availability of job opportunities etc.

The challenge of unemployment in Nigeria has contributed to the widespread poverty, the diminishing economic growth, increased rate of social unrest etc. Unemployment has directly and indirectly affected the standard of living, the rate of poverty, crime rate, insecurity and other socio-political problems in Nigeria which is significant among the youth population [1] and [2]. It has caused more threats to the development and peaceful coexistence of people in Nigeria.

In the light of proffering solutions to the problems of unemployment, this research aims at analysing and predicting the time until employment of graduates in Bayelsa State, Nigeria using the prognosis index in survival analysis. It will help to understand the unemployment trends and inform or enable the government or policy makers to effectively create jobs for the teeming unemployed people. The adoption of a survival analysis approach will enable the assessment and prediction of a precise model which will enable individuals to effectively predicting the time until being employed and engage in strategic planning during the period of being unemployed.

Different researchers have investigated the prediction of unemployment rate using different statistical methods. For instance, [3] introduced the hybrid models for appraising Nigeria's unemployment rate using Time series and Machine learning techniques [4]. Proposed an ARIMA model in Times series for forecasting the rate of unemployment in Nigeria [5].

Also used the time series model of annual unemployment rates in Nigeria using Box-Jenkins methodology and examined the precision of forecast using this model [6]. Applied Neural Network model for forecasting unemployment while the study by [7] Karahan and Cetintas (2022) discussed the effectiveness of Artificial Neural Network model for predicting the future unemployment rate [8]. Aimed at identifying the potential determinants affecting unemployment in Nigeria using survival analysis. [9] Ugwu and Okonkwo (2025) developed an unemployment prediction system and employment tracking in Nigeria using a linear regression model and implemented the model using a trained on five years of data from the National Youth Service Corps (NYSC) covering graduates of Higher Education Institutions.

2.0 Materials and Methods

2.1 Study population and data collection

A set of data with 253 graduates from [8] was available for research. The study population was the unemployed graduates from different local government areas in Bayelsa State, Nigeria and the event of interest (survival time) was the time till first employment (duration of unemployment) after graduation from either polytechnics or universities. This is the time (approximately in months) from the date of passing out from the National Youths Service Corps (NYSC) of graduates below 30 years or date of receipt of the certificate exemption of NYSC of the graduates 30 years and above or date of receipt of OND certificate to the first day of employment. The data used for this research is right censored [10] and the censoring indicator was "1" for employed and "0" for censoring.

The explanatory variables used in this research were all grouped into categories. The variables were gender ("1" for male and "2" for female), age ("1" for less than or equal to 20 years, "2" for 20 - 25 years, "3" for 26 - 30 years, "4" for 31 - 35 years and "5" for 36 and above), marital status ("1" for single, "2" for married, "3" for divorced, "4" for widow or widower), education level ("1" for Ordinary National Diploma (OND), "2" for Higher National Diploma (HND) or Bachelors of Science (BSc.), "3" for Post Graduate Diploma (PGD) or Masters of Science (MSc.) and "4" for Doctors of Philosophy (PhD)), Cumulative Grade Point Average (CGPA) ("1" for less than 2.50, "2" for 2.50 - 2.99, "3" for 3.0 - 3.49, "4" for 3.5 and above), field or faculty of study ("1" for Education, "2" for Medical Science, "3" for Management Science, "4" for Arts, "5" for Sciences, "6" for Social Sciences, "7" for Environment Sciences and "8" for Others), residence lived by graduates ("1" for urban and "2" for rural), received training on job searching method ("1" for yes and "2" for no), Local Government Area ("1" for Brass, "2" for Ekeremor, "3" for Kolokuma, "4" for Nembe, "5" for Ogbia, "6" for Sagbama, "7" for Southern Ijaw and "8" for Yenagoa) and received training on field of study ("1" for yes and "2" for no).

2.2 Methodology

The Bayesian survival analysis approach will be used to analyse the data for which the event or survival time is the duration of unemployed. Bayesian inference requires the combination of prior experience (in the form of prior probability) and the observed data (in the form of a likelihood). It often involves calculations which are analytically intractable and are usually done using Markov chain Monte Carlo methods (MCMC) such as Metropolis and Metropolis - Hastings algorithm, Gibbs sampler and Metropolis within Gibbs algorithm [11] (Gilks *et al*., 1996). It is expected that the prior distribution should reflect the information about the parameters of the model. This is done by specifying prior information about the parameter of interest before looking at the data [12].

Bayesian inference will be applied to survival analysis using a Weibull model [13] in such a way that our prior beliefs about the unknown parameter of the survival analysis model are reflected. The proportional hazard model [14] which is mostly used by most researchers will be used for the analysis and the survival prediction by estimating the hazard ratios. The main product of the proportional hazard model is the prognostic index which is a linear predictor. This is also the logarithm of the hazard multiplier.

The probability density function of the Weibull distribution is given by

$$f(t) = \lambda\alpha t^{\alpha-1}e^{-\lambda t^{\alpha}}$$

where λ is the scale parameter which will be used to incorporate the explanatory variables and α is the shape parameter. The linear predictor or prognosis index of the i^{th}subject is given by

$$\eta_i = \underline{\beta}\ \underline{X_i}^T$$

where

$$\underline{X_i} = (1, x_{i,1}, x_{i,2}, x_{i,3}, \dots\dots\ x_{i,k})$$

is the vector of the explanatory variables for the i^{th}subject and $\underline{X_i}^T$ is the transpose.

and

$$\underline{\beta} = (\beta_0, \beta_1, \beta_2, \dots . \beta_k)^T$$

is the vector of the parameters of the model.

We have that

$$\lambda_i = e^{\{\eta_i\}} = e^{\{\underline{\beta}\ \underline{X_i}^T\}}$$

The survival function of the Weibull distribution [15] is given by

$$S_i(t) = e^{\{-\lambda_i t^{\alpha}\}}$$

and the hazard function of the Weibull distribution is given by

$$h_i(t) = \frac{f_i(t)}{S_i(t)} = \lambda_i\, h_0(t)$$

where $h_0(t)$ is the baseline hazard function.

The likelihood contribution [16] from the data can be simplified as

$$L(\beta, \alpha|D) = \left[\prod_{i\in E}\lambda_i\right]\alpha^{n_D}\left[\prod_{i\in E}t_i^{\alpha-1}\right]e^{\{-\sum_{i\in E\cup C}\lambda_i t^{\alpha}\}}$$

where C is the set of subjects that were censored, E is the set of subjects that had the event (employed) and n_D is the number of subjects that had the event. We will also note that the shape parameter accounts for additional possible hazard shapes.

We follow [12] to incorporate priors. We construct the prior distributions of the vector of parameters of explanatory We follow [12] to incorporate priors. We construct the prior distributions of the vector of parameters of explanatory variables $\underline{\beta} = (\beta_0, \beta_1, \beta_2, \dots . \beta_k)^T$ by giving them multivariate normal distribution with vector of means of parameters $\underline{\mu} = (\mu_0, \mu_1, \mu_2, \dots \dots \mu_k)^T$ and the vector of covariance matrix V. The multivariate normal distribution for the prior distribution is given by

$$\frac{1}{\sqrt{(2\pi)^k |V|}} e^{\{-\frac{1}{2}[(\underline{\beta}-\underline{\mu})^T V^{-1}(\underline{\beta}-\underline{\mu})]\}}$$

We will also give the shape parameter α, a gamma prior distribution given by

$$f(\alpha|a, b) = \frac{b^a}{\Gamma(a)} \alpha^{a-1} e^{\{-b\alpha\}}$$

which is approximately

$$\alpha^{a-1} e^{\{-b\alpha\}}$$

The posterior distribution is given by
$f(\beta, \alpha|D) \propto prior\ density \times likelihood\ density$
The joint posterior density will be simulated using Markov chain Monte Carlo (McMC) techniques via the JAGS program. The JAGS program which stands for Just another Gibbs sampler [17]. It is a program designed to work closely with the R language for the analysis of Bayesian models using McMC techniques. The RJAGS package can be used from within R to run JAGS [18].

3.0 Results and Discussions

We will apply the procedure discussed in Section 2.2 to the data set. The explanatory variables, categories and notations are given in Table 3.1.

Table 3.1: Explanatory variables and notations

Variables	Notation	Variables	Notation
Gender	x_1	Field of study (field)	x_6
Age	x_2	Resident where graduate stays (resid)	x_7
Educational level attained (Educat)	x_3	Received training for job search (rectraining)	x_8
LGA	x_4	Marital	x_9
CGPA	x_5	Received training on field of study (trainjob)	x_{10}

We will suppose that the overall survival lifetime is a Weibull distribution. All covariates are categorical variables. Gender, resid, rectraining and trainjob are 2-level categorical variables, Educat, CGPA and Marital are 4 level categorical variables, Age is a 5-level categorical variable, and LGA and field are 8 level categorical variables. The model will also include the constant β_0.
The prior values of the parameters are elicited following discussions in [12]. The construction of prior distributions of the parameters might involve elicitation of prior beliefs from either a person or analyst in the field of study. The elicitation also depends on the type of variable. A Weibull distribution is used for the survival time for the i^{th} individual which is given as Weibull(λ_i, α) where λ_i is the hazard multiplier which depends on the linear predictor η_i.
The linear predictor is given by

$$\eta_i = \beta_0 + \beta_1 x_{i,1} + \sum_{d=1}^{4} \beta_2 \delta_{i,2,d} + \sum_{d=1}^{3} \beta_3 \delta_{i,3,d} + \sum_{d=1}^{7} \beta_4 \delta_{i,4,d} + \sum_{d=1}^{3} \beta_5 \delta_{i,5,d} + \sum_{d=1}^{7} \beta_6 \delta_{i,6,d} + \beta_7 x_{i,7} + \beta_8 x_{i,8} + \sum_{d=1}^{3} \beta_9 x_{i,9,d} + \beta_{10} x_{i,10} \quad \dots\dots\dots 3.1$$

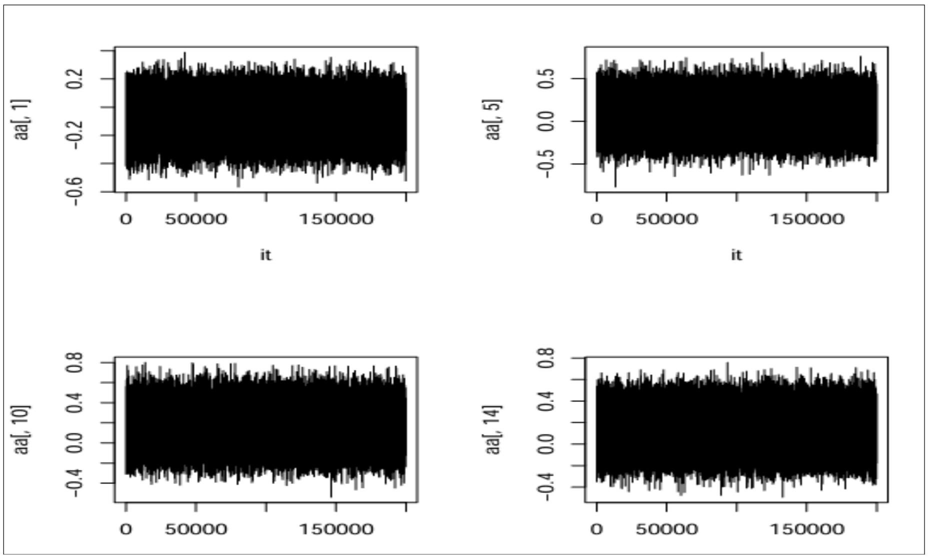
where $\delta_{i,j,d} = 1$ if $x_{i,1} = d$ and $\delta_{i,j,d} = 0$ otherwise for $j = 2, 3, 4, 5, 6, 9$.
The prior means and standard variances of the parameters of the model are given in Table 3.2.

Table 3.2: The prior means and variances of the parameters of model

Parameters	Prior means	Prior Variance	Parameters	Prior means	Prior Variance
Baseline parameter β_0	-1.5	0.16	CGPA $\delta_{5,1}$	0.000	0.140
Gender β_1	0.050	0.150	$\delta_{5,2}$	0.000	0.077
Age $\delta_{2,1}$	0.000	0.140	$\delta_{5,3}$	0.000	0.055
$\delta_{2,2}$	0.000	0.077	Field $\delta_{6,1}$	0.000	0.140
$\delta_{2,3}$	0.000	0.055	$\delta_{6,2}$	0.000	0.077
$\delta_{2,4}$	0.000	0.045	$\delta_{6,3}$	0.000	0.055
Educat $\delta_{3,1}$	0.000	0.150	$\delta_{6,4}$	0.000	0.045
$\delta_{3,2}$	0.000	0.140	$\delta_{6,5}$	0.000	0.140
$\delta_{3,3}$	0.000	0.055	$\delta_{6,6}$	0.000	0.077
LGA $\delta_{4,1}$	0.000	0.140	$\delta_{6,7}$	0.000	0.055
$\delta_{4,2}$	0.000	0.077	Resid β_7	0.000	0.173
$\delta_{4,3}$	0.000	0.055	Rectraining β_8	0.000	0.173
$\delta_{4,4}$	0.000	0.045	Marital $\delta_{9,1}$	0.000	0.140
$\delta_{4,5}$	0.000	0.140	$\delta_{9,2}$	0.000	0.077
$\delta_{4,6}$	0.000	0.077	$\delta_{9,3}$	0.000	0.055
$\delta_{4,7}$	0.000	0.055	Trainjob β_{10}	0.000	0.173
			Shape parameter α	1	0.5

It was not feasible to draw independent samples from the posterior distribution since the posterior was not be in a standard form. The Metropolis - hasting within Gibbs was applied for simulation using the RJAGS software in R. A burn-in of 5000 iterations of the sampler was used following 100000 iterations. The convergence was checked using two chains starting with different values. Visual inspection of the trace plots of the parameters of the model showed that the mixing was appeared very satisfactory as shown in figure 1.

Figure 1: Trace plot of the Baseline parameter β_0, $\beta_{2,1}(Age\ 1)$, $\beta_{5,1}(CGPA\ 1)$ and $\beta_{6,1}(Field\ 1)$.



The posterior means and standard deviations of the parameters of the model are given in Table 3.3.

Table 3.3: Table of Posterior means and standard deviation of the model parameters

Parameters	Posterior means	Posterior Standard deviation	Parameters	Posterior means	Posterior Standard deviation
Baseline parameter β_0	-1.81	0.115	$\beta_{6,1}(Field\ 1)$	0.140	0.143
$\beta_{1,1}$(Gender 1)	-0.0123	0.069	$\beta_{6,2}(Field\ 2)$	0.158	0.164
$\beta_{1,2}$(Gender 2)	0.0123	0.069	$\beta_{6,3}(Field\ 3)$	-0.0534	0.129
$\beta_{2,1}(Age\ 1)$	0.081	0.164	$\beta_{6,4}(Field\ 4)$	0.0234	0.143
$\beta_{2,2}(Age\ 2)$	-0.0191	0.128	$\beta_{6,5}(Field\ 5)$	0.0534	0.159
$\beta_{2,3}(Age\ 3)$	-0.0056	0.101	$\beta_{6,6}(Field\ 6)$	-0.187	0.260
$\beta_{2,4}(Age\ 4)$	-0.056	0.108	$\beta_{6,7}(Field\ 7)$	-0.137	0.203
$\beta_{2,5}(Age\ 5)$	0.158	0.165	$\beta_{6,8}(Field\ 8)$	0.0035	0.194
$\beta_{3,1}(Educat\ 1)$	-0.0821	0.109	$\beta_{7,1}(Resid\ 1)$	-0.0088	0.079
$\beta_{3,2}(Educat\ 2)$	-0.127	0.106	$\beta_{7,2}(Resid\ 2)$	0.0088	0.079
$\beta_{3,3}(Educat\ 3)$	0.103	0.144	$\beta_{8,1}(Rectraining\ 1)$	0.322	0.078
$\beta_{3,4}(Educat\ 4)$	0.106	0.16	$\beta_{8,2}(Rectraining\ 2)$	-0.322	0.078
$\beta_{4,1}(LGA\ 1)$	0.0679	0.130	$\beta_{9,1}(Marital\ 1)$	-0.0722	0.103
$\beta_{4,2}(LGA\ 2)$	0.121	0.141	$\beta_{9,2}(Marital\ 2)$	-0.126	0.109
$\beta_{4,3}(LGA\ 3)$	-0.047	0.15	$\beta_{9,3}(Marital\ 3)$	0.0898	0.145
$\beta_{4,4}(LGA\ 4)$	-0.0128	0.15	$\beta_{9,4}(Marital\ 4)$	0.108	0.16
$\beta_{4,5}(LGA\ 5)$	-0.0113	0.15	$\beta_{10,1}(Trainjob\ 1)$	0.351	0.075
$\beta_{4,6}(LGA\ 6)$	0.0625	0.30	$\beta_{10,2}(Trainjob\ 2)$	-0.351	0.075
$\beta_{4,7}(LGA\ 7)$	0.0518	0.185			
$\beta_{4,8}(LGA\ 8)$	-0.232	0.241			
$\beta_{5,1}(CGPA\ 1)$	0.1724	0.155			
$\beta_{5,2}(CGPA\ 2)$	0.0756	0.120			
$\beta_{5,3}(CGPA\ 3)$	-0.112	0.103			
$\beta_{5,4}(CGPA\ 4)$	-0.136	0.115			

Prognostic index

The prognostic index is calculated by substituting the posterior means of the parameters using Equation 3.1. The prognostic index will be used for predicting the duration of unemployment of graduates on the basis of their explanatory variables. It helps in planning and making decisions on the need of creation of jobs for the unemployed. It is known that high values of the prognostic index will indicate the best prognosis outcome for the event of interest (employment).

It might also be preferable to index the prognostic index in a range of 0 to 100 by finding the value $100\phi^{-1}\left(\frac{\eta_i - m}{s}\right)$ where ϕ^{-1} is the standard normal distribution function.

The values of m and s are the sample mean and standard deviation of the values of the linear predictor of all subjects in the data set using the posterior means in Table 3.2. The function to compute the linear predictor in a range of 0 to 100 is attached in the Appendix.

For instance, a graduate with covariate vector $X = (1,5,4,8,4,2,1,1,1,1)$ for the variables gender, age, education level, LGA, CGPA, field of study, place of residence, received training, marital status, received training on job respectively had an index of 80 on a scale from 0 to 100 of being employed. This indicates that a male graduate who is 36 years and above, has a PhD, from Yenagoa, in the field of Arts, resides in the urban area, who received training on job search, is single and received training in the field of jo search has an index of 80 of being employed.

A graduate with covariate vector $X = (1,3,2,1,3,3,1,1,1,1)$ for the variables gender, age, education level, LGA, CGPA, field of study, place of residence, received training, marital status, received training on job respectively had an index of 69 on a scale from 0 to 100 of being employed and a female graduate with similar covariate vector $X = (2,3,2,1,3,3,1,1,1,1)$ had an index of 71 of being employed. This indicates that a female graduate has a little bit better chance of being employed.

A graduate with covariate vector $X = (1,4,2,2,3,4,1,2,1,2)$ for the variables gender, age, education level, LGA, CGPA, field of study, place of residence, received training, marital status, received training on job respectively had an index of 67 on a scale from 0 to 100 of being employed and a female graduate with similar covariate vector $X = (2,4,2,2,3,4,1,2,1,2)$ had an index of 68 of being employed. Again, a female graduate has a little bit better chance of being employed.

A graduate with covariate vector $X = (1,3,3,4,4,5,1,1,2,1)$ for the variables gender, age, education level, LGA, CGPA, field of study, place of residence, received training, marital status, received training on job respectively had an index of 81 on a scale from 0 to 100 of being employed and a female graduate with similar covariate vector $X = (2,3,3,4,4,5,1,1,2,1)$ had an index of 82 of being employed. A female graduate has a little bit better chance of being employed.

4.0 Conclusion and Recommendations

4.1 Conclusion

This study presents the survival analysis approach to predicting the time until employment of a graduate in Bayelsa State, Nigeria. This research will be helpful for making inference, monitoring and controlling the rate of unemployment in Nigeria using the prognosis index in survival analysis. The prognosis index provides a reliable platform for predicting the time until employment of a graduate. This will help the government to strategize ways to tackle unemployment at all levels.

4.2 Recommendations

This research recommends the following

The government and private sector should make adequate solutions to increasing employment and reducing poverty by investment in agriculture, industrialization, diversification in the economy, modification in education curriculum among others have been identified in this research work. It is necessary that there should be significant policy interventions or changes in the economic structure to regulate the rate of unemployment in Bayelsa State and Nigeria at large. Hence, the Nigerian government should reduce reliance on a very few sectors such as oil and promote the growth or make adequate solutions such as investments in other sectors like agriculture, industrialization, technology and diversification in the economy.

The government should also modify the education curriculum to the enhancement of the quality of education and the alignment with the needs of the market to reduce the skills gap.

That the government should create an enabling environment for the private sector or businesses to thrive and so that new jobs employment can be created.

The government of Nigeria should also introduce skills development and entrepreneurship programs.

The government of Nigeria can intelligently detect the fraud in ministries by using an employee tracking system and also make the correct estimate of the rate of employment. This will enable them make effective plan to create jobs for the unemployed graduates.

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Appendix A

Function to compute the linear predictor in a range of 0 to 100

1. index<-function()
2. {#source("coefficientsweibnew.txt")
3. beta.gender <- c(-0.0123,0.0123)
4. beta.age <- c(0.081, -0.019, -0.006,-0.056,-0.00005)
5. beta.Educat <- c(-0.008, -0.127,0.103,0.105)
6. beta.lga <- c(0.0679,0.121, -0.047, -0.0128, -0.0113,0.0625,0.0518, -0.2322)
7. beta.cgpa <- c(0.172,0.076, -0.112,-0.136)
8. beta.field <- c(0.140,0.158, -0.0534,0.0234,0.0534, -0.187,-0.137,0.00354)
9. beta.resid <- c(-0.0088, 0.0088)
10. beta.rectraining <- c(0.322, -0.322)
11. beta.marital <- c(-0.0722,-0.1255, 0.0898,0.108)
12. beta.trainjob <- c(0.3510, -0.3510)
13. beta0<- -1.806
14. mean <- -2.27
15. std.dev <- 0.625
16. ############### GENDER
17. write(file="","Please enter the Gender of the graduate.
18. Enter 1 for male or 2 for female.")
19. gender<-scan(n=1)
20. # sex<-sex
21. ############### AGE Group
22. write(file="","Please enter the Age group of
23. the graduate (1, 2, 3, 4 or 5).")
24. age<-scan(n=1)
25. ############### Education level
26. write(file="","Please enter the Educational level
27. of the graduate (1, 2 or 3).")
28. Educat<-scan(n=1)
29. ################ LGA
30. write(file="","Please enter the LGA
31. for the graduate (1, 2, 3, 4, 5, 6, 7 or 8).")
32. lga<-scan(n=1)
33. ############### CGPA
34. write(file="","Please enter the CGPA of
35. the graduate (1, 2, 3, 4 or 5).")
36. cgpa<-scan(n=1)
37. ################ FIELD
38. write(file="","Please enter the field of study
39. for the graduate (1, 2, 3, 4, 5, 6, 7 or 8).")
40. field<-scan(n=1)
41. ############### AREA OF RESIDENCE
42. write(file="","Please enter the area of residence of the graduate.
43. Enter 1 for urban or 2 for rural.")
44. resid<-scan(n=1)
45. ############### RECEIVED TRAINING
46. write(file="","Please enter if the graduate has received training for job searching
47. Enter 1 for yes or 2 for no.")
48. rectraining<-scan(n=1)
49. ############### MARITAL STATUS
50. write(file="","Please enter the Marital status
51. of the graduate (1, 2 or 3).")
52. marital<-scan(n=1)
53. ############### TRAINING ON JOB
54. write(file="","Please enter if the graduate has received training for the field of job.
55. Enter 1 for yes or 2 for no.")
56. trainjob<-scan(n=1)
57. eta<-beta0 +beta.gender[gender]+beta.age[age]+beta.Educat[Educat]
58. +beta.lga[lga]+beta.cgpa[cgpa]+beta.field[field]+beta.resid[resid]+beta.rectraining[rectraining]
59. +beta.marital[marital]+beta.trainjob[trainjob]
60. ind<-100*pnorm(eta,mean,std.dev)
61. ind<-round(ind)
62. #ind<-c(mu,ind)
63. write(file="","Index value is")
64. write(ind,file="")
65. write(file="","The index is on a scale from 0 to 100,
66. Greater index values indicate greater chance of being employed.")