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Multiple Regression Analysis of the Impact of Senior Secondary School Certificate Examination (SSCE) Scores on the final Cumulative Grade Point Average(CGPA) of Students of Tertiary Institutions in Ghana.

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Abstract

The purpose of the research was to determine if SSCE scores, session and sex of students imparts negatively or positively on each student FCGPA score at the tertiary level. Data were compiled from the student records of various departments. The information sought were on gender, the session (morning or evening), the cumulative grade points average and the Senior Secondary School Certificate Examination(SSCE) scores of the 2006 to 2009 year group of students. The multiple linear regression with interaction was used to analysis the data. It was found that students who to attend the morning session on the average obtain higher FCGPA than their evening counterparts. It was also identified that there is no relation between a student's sex and his or her cumulative grade points average (CGPA) at 5% significance level. Also a student who enters Koforidua Polytechnic with the "best SSCE" scores obtains the highest cumulative grade point average (CGPA).

Keywords: multiple linear regression, CGPA, student performance, examination scores

1. Introduction

Measuring academic performance of student is challenging since student performance is a product of socio-economic (e.g. financial constraints, community violence), psychological (e.g. student's ability, motivation, quality of secondary obtained, childhood training and experience) and environmental factors (e.g. available of learning materials, proximity). In Ghana the SSCE examination is required for admission into a tertiary Institution. This examination has played an increasingly important role in admissions not only into the Universities in Ghana but also into country's ten Polytechnics.

Roughly over 95% of Koforidua Polytechnic students are admitted using their SSCE exam score. Two main streams of students are admitted. Those that attend the morning session and those that attend evening session. It is needless to say that Koforidua polytechnic students like any other group of students are from diverse socio-economic and environmental backgrounds, with different psychological problems.

1.1. Objectives and Research Questions

The primary objective of this study was to determining whether or not there is a ''causal" effect of SSCE scores on FCGPA in tertiary Institutions. The study also answers the following questions:

1. Is a student sex related to his or her cumulative grade point average (FCGPA)?
2. On the average, do the morning session students have higher cumulative grade point average GPAs than their counterparts in the evening session?

2. Study Population

The population of study comprises students who completed the polytechnic in the year 2006. The data used for this study were mainly secondary. Data were compiled from the student records of various departments. The data consists of information on the gender, the session (morning or evening) , the cumulative grade point average (C.G.P.A) and the Senior Secondary School Examination (S.S.S.E) of the 2006 year group students. In total 686 data points were used in this study.

3. Statistical Methods

Multiple linear regression was employed in answering the key research questions. Multiple linear regression (MLR) is the appropriate method of analysis when the research problem involves a single metric dependent variable presumed to be related to two or more metric independent variables. Multiple linear regression are useful for testing theories about relationships between two or more variables.

Several assumptions about the relationships between the dependent and independent variables that affect the statistical procedure used for multiple linear regression are made. The assumptions to be examined are in four areas: (1) Linearity of the phenomenon measured. The linearity of the relationship between dependent and independent variables represent the degree to which the change in the dependent variable is associated with the independent variable. The concept of correlation is based on a linear relationship.

Corrective actions can be taken if the linearity assumption is violated. For example, transforming the data values (logarithm, square root among others) of one or more independent variables to achieve linearity. Directly including the nonlinear relationships in the regression model, such as through the creation of polynomial terms. (2) Constant variance of the error terms. The presence of unequal variances (heteroscedasticity) is one of the most common assumption violations. Diagnosis is made with residual plots or simple statistical tests. (3) Independence of the error terms. It is assumed in regression that each predicted value is independent, which means that the predicted value is not related to any other prediction. Data transformations, such as first differences in a time series model, inclusion of indicator variables, or specially formulated regression models can address violation if it occurs. (4) Normality of the error term distribution. The assumption violation is non-normality of the independent or dependent variable or both.

Normal probability plots can be used to remedy the assumption violation. The linear additive model for relating a dependent variable to p independent variables is

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip+} + \varepsilon_i \text{..................}(1)$$

The subscript i denotes the observational unit from which the observations on Y and the p independent variables were taken. The second subscript designates the independent variable. The sample size is denoted with n, i = 1, . . . , n, and p denotes the number of independent variables. There are (p + 1) parameters βj, j = 0, . . . , p to be estimated when the linear model includes the intercept β_0. For convenience, we use $p^/ = (p+1)$. In this study we assume that $n > p^/$**.** Four matrices are needed to express the linear model in matrix notation:

1. Y : the n×1 column vector of observations on the dependent variable Y_i;
2. X: the n × $p^/$ matrix consisting of a column of ones, which is labeled **1**, followed by the p column vectors of the observations on the independent variables;
3. β: the $p^/$ × 1 vector of parameters to be estimated; and
4. the n × 1 vector of random errors.

With these definitions, the linear model can be written as

$$Y = X\beta + \varepsilon \text{..................}(2)$$

or

$$\underset{(n \times 1)}{\begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ \cdot \\ Y_p \end{pmatrix}} = \underset{(n \times p^/)}{\begin{bmatrix} 1 & X_{11} & \cdot & \cdot & X_{1p} \\ 1 & X_{21} & \cdot & \cdot & X_{2p} \\ & & & & \cdot \\ \vdots & \vdots & \vdots & \vdots & \cdot \\ 1 & X_{n1} & \cdot & \cdot & X_{np} \end{bmatrix}} \underset{(p^/ \times 1)}{\begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \cdot \\ \beta_p \end{pmatrix}} + \underset{(n \times 1)}{\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \cdot \\ \varepsilon_n \end{pmatrix}}$$

Each column of X contains the values for a particular independent variable. The elements of a particular row of X, say row r, are the coefficients on the corresponding parameters in β that give E(Yr). Notice that $\beta 0$ has the constant multiplier 1 for all observations; hence, the column vector 1 is the first column of X. Multiplying the first row of X by β, and adding the first element of ε confirms that the model for the first observation is

$$Y_1 = \beta_0 + \beta_1 X_{11} + \beta_2 X_{12} + \cdots + \beta_p X_{1p+} + \varepsilon_1 \text{..................}(3)$$

The vectors Y and ε are random vectors; the elements of these vectors are random variables. The matrix **X** is considered to be a matrix of known constants. A model for which **X** is of full column rank is called a full-rank model.

The vector β is a vector of unknown constants to be estimated from the data. Each element β_j is a partial regression coefficient reflecting the change in the dependent variable per unit change in the j^{th} independent variable, assuming all other independent variables are held constant. The definition of each partial regression coefficient is dependent on the set of independent variables in the model. Whenever clarity demands, the subscript notation on βj is expanded to identify explicitly both the independent variable to which the coefficient applies and the other independent variables in the model. For example, $\beta_{2.13}$ would designate the partial regression coefficient for X_2 in a model that contains X_1, X_2, and X_3. It is common to assume that ε_i are independent and identically distributed(i.i.d) as normal random variables with mean zero and variance σ^2. Since ε_i are assumed to be independent of each other, the covariance between ε_i and ε_j is zero for any $\mathbf{i \neq j}$. The joint probability density function of $\varepsilon_2, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_n$ is

$$\prod_{i=1}^{n}[(2\pi)^{-1/2}\sigma^{-1}e^{\varepsilon_i^2/2\sigma^2}] - (2\pi)^{-n/2}e^{\sum_{i=1}^{n}\varepsilon_i^2/2\sigma^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(4)$$

The random vector $\boldsymbol{\varepsilon}$ is a vector $(\varepsilon_2, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_n)'$ consisting of random variables ε_i. Since the elements of X and β are assumed to be constants, the Xβ term in the model is a vector of constants. Thus, Y is a random vector that is the sum of the constant vector Xβ and the random vector $\boldsymbol{\varepsilon}$. Since ε_i are assumed to be independent $N(0, \sigma^2)$ random variables, we have that

1. Y_i is a normal random variable with mean $\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+\cdots+\beta_pX_{ip}$ and variance σ^2;
2. Y_i are independent of each other.

The covariance between Y_i and Y_j is zero for $\mathbf{i \neq j}$. j. The joint probability density function of

$Y_1, \ldots, Y_n$ is $(2\pi)^{-n/2}\sigma^{-n}e^{-[Yi-(\beta0+\beta1Xi1+\cdots+\beta pXip)]2/2\sigma2}$. (5)

The conventional tests of hypotheses and confidence interval estimates of the parameters are based on the assumption that the estimates are normally distributed. Thus, the assumption of normality of the ε_i is critical for these purposes. However, normality is not required for least squares estimation. Even in the absence of normality, the least squares estimates are the best linear unbiased estimates (b.l.u.e.). They are best in the sense of having minimum variance among all linear unbiased estimators. If normality does hold, the maximum likelihood estimators are derived using the criterion of finding those values of the parameters that would have maximized the probability of obtaining the particular sample, called the likelihood function. Maximizing the likelihood function in equation 5 with respect to $\beta = (\beta_0\ \beta_1\ \cdot\ \cdot\ \cdot\ \beta_p\ )^{/}$ is equivalent to minimizing the sum of squares in the exponent, and hence the least squares estimates coincide with maximum likelihood estimates.

3.1. Maximum Likelihood Estimates

Once a model is specified with its parameters, and data have been collected, we are now in a position to evaluate its goodness of fit. That is, we want to find out how well it fits the observed data. The Goodness of fit is assessed by finding parameter values of a model that best fits the data. This procedure is called parameter estimation(Myung, 2001; Rubin, Hinton, & Wenzel, 1999; Lamberts, 2000; Usher & McClelland, 2001)).

The idea behind maximum likelihood parameter estimation is to determine the parameters that maximize the probability (likelihood) of the sample data methodology is presented next. The principle of maximum likelihood estimation (MLE), states that the desired probability distribution is the one that makes the observed data "most likely," which means that we must seek the value of the parameter vector that maximizes the likelihood function. If *x* is a continuous random variable with probability density function (pdf):

$$f(x;\theta_1,\theta_2,\dots,\theta_k)$$

where $(\theta_1,\theta_2,\dots,\theta_k)$are *k* unknown constant parameters which need to be estimated, and we conduct an experiment and obtain *N* independent observations, x_1, x_2,...,x_N. Then the likelihood function is given by the following product:

$$L(x_1,x_2,\dots,x_N|\theta_1,\theta_2,\dots,\theta_k)=L=\prod_{i=1}^{N} f(x_i;\theta_1,\theta_2,\dots,\theta_k)$$

$$i = 1,2,\dots,N \qquad (23)$$

The logarithmic likelihood function is given by:

$$\Lambda = \ln L = \sum_{i=1}^{N} \ln f(x_i;\theta_1,\theta_2,\dots,\theta_k)$$

The maximum likelihood estimators (MLE) of $\theta_1, \theta_2, \dots, \theta_k$ are obtained by maximizing *L* or Λ. By maximizingΛ, which is much easier to work with than *L*, the maximum likelihood estimators (MLE) of $\theta_1, \theta_2, \dots, \theta_k$ are the simultaneous solutions of *k* equations such that:

$$\frac{\partial(\Lambda)}{\partial\theta_j} = 0, \;\; j = 1, 2, ..., k$$

To estimate $\hat{\lambda}$, for a sample of *n* units , first obtain the likelihood function:

$$\begin{aligned} L(\lambda | t_1, t_2, ..., t_n) &= \prod_{i=1}^{n} f(t_i) \\ &= \prod_{i=1}^{n} \lambda e^{-\lambda t_i} \\ &= \lambda^n \cdot e^{-\lambda \sum_{i=1}^{N} t_i} \end{aligned}$$

Take the natural log of both sides. The log-likelihood links the data, unknown model parameters and assumptions and allows rigorous, statistical inferences:

$$\Lambda = \ln(L) = n \; \ln(\lambda) - \lambda \sum_{i=1}^{n} t_i$$

Obtain $\frac{\partial\Lambda}{\partial\lambda}$, and set it equal to zero:

$$\frac{\partial\Lambda}{\partial\lambda} - \frac{n}{\lambda} - \sum_{i=1}^{n} t_i - 0$$

Solving for $\hat{\lambda}$

$$\hat{\lambda} = \frac{n}{\sum_{i=1}^{n} t_i}$$

Note that the value of λ is an estimate because it will vary from sample to sample. For example, if we take another sample from the same population and re-estimate λ, this value may differ from the one previously calculated. In the language of statistics, we say $\hat{\lambda}$ is an estimate of the true value of λ.

3.2. Coefficient of Determination

The coefficient of determination is the proportion of the total variation in the dependent variable, Y that is explained by the dependent variable, $X_1, X_2, \ldots \ldots X_k$. The coefficient of determination is usually denoted by R^2 and is given by

$$R^2 = \frac{SS_{yy} - SSE}{S_{yy}},$$

where

$$SS_{yy} - \sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}$$

and $$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

By definition, R^2 lies between 0 and 1 or between 0% and 100%. A high value of R^2 indicate a reliable regression equation for prediction. If the independent variables are mutually uncorrelated, then

$$R^2 = r_{YX_1}^2 + r_{YX_2}^2 + \cdots \ldots \ldots \ldots \ldots \ldots + r_{YX_k}^2$$

On the other hand, if the independent variables are correlated or collinear, then the contribution of X_i's to the variation of Y is such that

$$R^2 < r_{YX_1}^2 + r_{YX_2}^2 + \cdots \ldots \ldots \ldots \ldots \ldots + r_{YX_k}^2$$

Thus, collinearity is not a desirable property in regression because it makes it difficult to separate the contribution of each (collinear) variable to the variation in the dependent variable. Making Inference in Multiple Linear Regression Analysis: The standard error The multiple standard error of estimate is given by

$$s = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n-k-1}}$$

We need the standard error to find confidence intervals on regression coefficients, perform hypothesis tests for these coefficients as well as make inferences concerning $\mathbf{E(Y)}$ and $\mathbf{Y}$.

3.3. Confidence intervals on regression coefficients.

A $100(1-\alpha)\%$ confidence interval on the regression coefficient β_j, is given by

$$b_j \pm t_{\alpha/2} s \ ,$$

Where b_j is the estimated value of β_j; $t_{\alpha/2}$ has a t – value with degrees of freedom $n-k-1$

and s is the standard error.

3.4. Tests for individual regression coefficients

The dependence of Y on $X_j$can be assessed testing the significance of β_j. The hypotheses are

$$H_0 : \beta_j = 0$$

$$H_1 : \beta_j \neq 0 \text{ (or } \beta_j > 0 \text{ } or \text{ } \beta_j < 0)$$

The test statistic is

$$t = \frac{\hat{\beta}_j}{\sqrt{\beta}},$$

which has student t distribution with $n-k-1$ degrees of freedom.

If $\mathbf{H_0}$ is rejected, it means that $\boldsymbol{X_j}$ significantly explains the variation in Y and so it has to be maintained in the equation. On the other hand, if we fail to reject $\mathbf{H_0}$, then $\mathbf{X_j}$ does not significantly contribute to Y and so it is unimportant.

3.5. Test for a set of regression coefficients

The overall ability of a set of independent variables (or all the independent variables) to explain the variation in the dependent variable can be tested simultaneously. Suppose in the model

$$E(y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k$$

we wish to test whether $X_{g+1}, X_{g+2};.............., X_k$ (k > g) significantly contribute to the variation in Y. This is equivalent to testing whether the associated regression coefficients, $\beta_{g+1}, \beta_{g+2};.............., \beta_k$, are equal to 0. The hypothesis, therefore, are:

$H_0 : \beta_{g+1} = \beta_{g+2} = ... = \beta_k = 0$

H_0 :At least one of the βs is not equal to 0.

The test statistics is F, given by

$$F = \frac{[SS_E(\mathrm{Re}\,ducedModel) - SS_E(FullModel]/g}{SS_E(FullModel)/(n-k-1)},$$

and F has degrees of freedom $\mathbf{g}$ and $\mathbf{n-k-1}$.

The term $\mathbf{SS_E}$ denotes the error sum of squares. Thus $\boldsymbol{SS_E}$ (Full model) denotes denote the error sum of square of the full model

$$E(y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k$$

and $\mathbf{SS_E}$ (Reduced model) denotes the error sum of squares of the reduced model

$$E(y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_g X_g$$

Note that $\mathbf{k-g}$ is the number of coefficients equated to zero in the null hypothesis, k the number of independent variables and $\mathbf{n}$ the number of observations.

4. Data Analysis and Results

The table 1 above represents the total number of students who successfully completed Koforidua polytechnic in the year 2006. It can be observed from the table 1 that male students (69.5%) are more than female students (30.5%). The table 2 above represents the distribution of students by session (morning or evening). It can be observed from table 2 that majority of the students (85.6%) attend morning session and minority of the students (14.4%) attend the evening session.

Table 3 present the regression results. The results indicate that Senior Secondary Certificate Examination (SSCE) score is associated with the cumulative grade point average (FCGPA) at 1% significance level. That is student who enters Koforidua polytechnic with the "best" SSCE score tend to obtain the highest cumulative grade point average (FCGPA).There appears to be no relation between a student's sex and his or her cumulative grade point average (FCGPA) at 5% significance level.

However there is some significant relationship between session and FCGPA, that is students who tend to attend the morning session tend to on the average obtain higher FCGPA than their evening counterparts. It is also important to note that a unit decrease in SSCE score tend to be related with an increment of FCGPA of -0.13485, all other variables remaining constant. From table 3, the estimated multiple linear regression with interaction may be written as:

$$y = 5.3730174 82 - 0.134852056x_1 - 0.547266894\,x_3 + 0.03454177x_1 * x_3$$

………………… (3)

Where y: Cumulative Grade Point Average (C.G.P.A)

x_1 : Senior Secondary Certificate Examination (SSCE)

x_3 : Session (Morning or Evening)

Since SSCE scores is a continuous variable, it is differentiable. Note that x_3 is a dummy variable defined by

$$X_3 = \begin{cases} & \text{If a student attends morning session} \\ & \text{otherwise} \end{cases}$$

0

Differentiating y with respect to X_1 gives

Now $\frac{\partial y}{\partial x_1}\Big|_{X_{3=0}} = \beta_1 = -0.134852056$

$Thus, \beta_1 =$ -0.134852056 measures the impact of the student SSCE score of each evening student on their final C.G.P.A.

Now $= \beta_1 + \beta_3 = -0.134852056 + 0.03454177 = -0.1$

$Again, here\ \beta_1 + \beta_3 = -0.1$ measures the impact of the student SSCE score of each Morning student on their final C.G.P.A. The model can be written as follows using the conditional expectations

$$E\left(Y\big|_{X_1X_3}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_3 + \beta_3 X_1 X_3$$

Thus; $E\left(Y\big|_{X_1X_3=0}\right) = \beta_0 + \beta_1 X_1$

And ; $E\left(Y\big|_{X_1,X_3=1}\right) = \beta_0 + \beta_1 X_1 + \beta_2 + \beta_3 X_1$

$Hence,\ E\left(Y\big|_{X_1,X_3=1}\right) - E\left(Y\big|_{X_1,X_3=0}\right) - \beta_0 + \beta_1 X_1 + \beta_2 + \beta_3 X_1 - (\beta_0 + \beta_1 X_1)$

$$= \beta_0 + \beta_1 X_1 + \beta_2 + \beta_3 X_1 - \beta_0 - \beta_1 X_1$$

$$= \beta_2 + \beta_3 X_1$$

where

$E\left(Y\big|_{X_1,X_3=0}\right) = \beta_0 + \beta_1 X_1$ is the expected C.G.P.A score giving that the student is in the Evening Session.

$E\left(Y\big|_{X_1,X_3=1}\right) = \beta_0 + \beta_1 X_1 + \beta_2 + \beta_3 X_1$ is the expected C.G.P.A score giving that the student is in the Morning Session.

$$E\left(Y\big|_{X_1,X_3=1}\right) - E\left(Y\big|_{X_1,X_3=0}\right) = \beta_2 + \beta_3 X_1$$

Now if $X_1 = 0$, it means that a student's SSCE score is equal to zero which obviously cannot be possible. It implies that β_3 is equal to -0.547266894 has no practical interpretation.

4.1. Findings

The major findings of this research include the following: It was revealed that SSCE score is associated with the cumulative grade point average at 1% significant level, thus a student who enters Koforidua polytechnic with the best SSCE score tend to obtain the highest cumulative grade point average.

The estimated multiple linear regression with interaction, $y = 5.373017482 - 0.134852056x_1 - 0.547266894x_3 + 0.03454177x_1 * x_3$ shows that a unit decrease in SSCE score tend to be related with an increment of FCGPA of – 0.13485, all other variables remaining constants. The study also revealed that students who tend to attend the morning session tend to on the average obtain higher FCGPA than their evening counterparts.

5. Conclusion

The FCGPA of a student depends on a number of socio – economic, cultural, educational factors. In this study SSCE scores and "session" were found to be significantly related to students final cumulative grade point average (FCGPA). There may be other factors which may have direct effect on student FCGPA. This requires an elaborate study of the FCGPA of the students with multiple socio – economic factors by application of multiple regression analysis as suggested by Bickel (2007).

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Table 1: Distribution of the sex of the 2006 year group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	209	30.5	30.5	30.5
	M	477	69.5	69.5	100.0
	Total	686	100.0	100.0	

Table 2: Distribution of the "Session"of the attendance of the 2006 year group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	99	14.4	14.4	14.4
	M	587	85.6	85.6	100.0
	Total	686	100.0	100.0	

Table 3: Estimated Model

Parameter	Estimate	Standard Error	t Value	Pr > $\lvert t \rvert$
intercepts	5.373017482	0.29233067	18.38	<.0001
SSCE	-0.134852056	0.01560956	-8.64	<.0001
SEX	-0.227491610	0.22537258	-1.01	0.3131
session 1	-0.547266894	0.27685247	-1.98	0.0485
SSCE *sex	0.010373141	0.01136616	0.91	0.3618
SSCE*session 1	0.034574177	0.01461658	2.37	0.0183
sex*session 1	0.002869375	0.09108131	0.03	0.9749

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