

STATISTICAL ANALYSIS OF PERFORMANCE
OF LEARNING DISABLED STUDENTS

by

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ABSTRACT

Learning disabilities and attention-deficit/hyperactivity disorder are characterized to be the most common problems seen by child neurologists, neuropsychologists and developmental pediatricians, comprising a major percentage of referrals from parents and teachers. College students with learning disabilities and attention-deficit/hyperactivity have average or above levels of intellectual functioning despite the inability to learn specific academic skills. For learners of different needs tutoring proves to be the most beneficial with the individualization it offers. Peer tutoring has proved to be such technique providing educational benefits to both the tutor and the tutee. Regression analysis proves to be an effective technique to determine the combined effects of parameters affecting the performance of college students.

The study involves cognitive analysis of students' accomplishment in academics with documented learning disability and/or attention deficit/hyperactivity disorder from Texas Tech University. Performance parameters are considered over four consecutive semesters concentrating on long semesters of fall and spring.

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CHAPTER I
LITERATURE REVIEW

1.1 Learning Disability

A Learning Disability (LD) is an inherent disorder presumed to be of the neurological kind. In a conventional environment, children with a learning disability may have difficulty in reading, writing, reasoning, spelling, organizing and recalling information but they can be as sharp as their peers. A learning disability is incurable; however, children with learning disabilities can succeed with the right support and guidance. Individuals with a learning disability are from a heterogeneous group who are unable to learn specific academic skills often despite having normal or above normal intelligence (Frances and Milne, 1996).

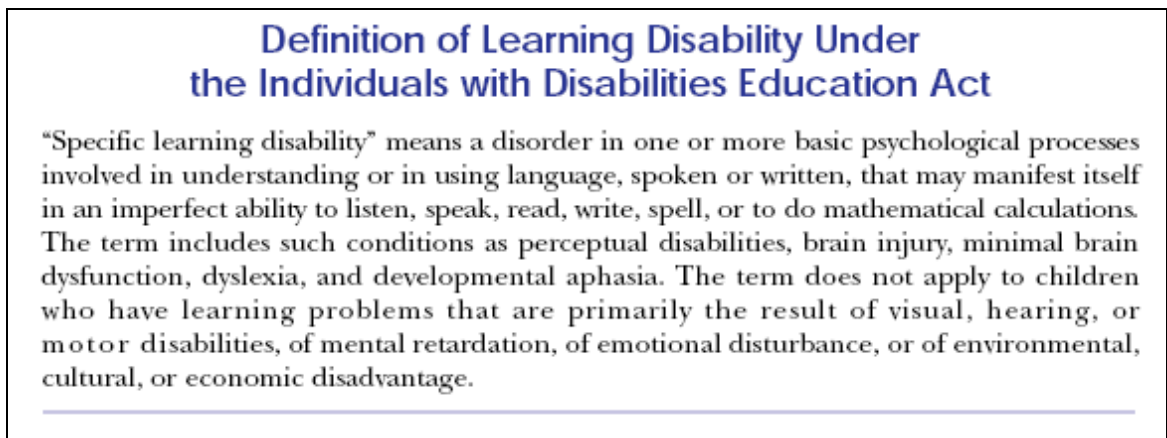


Figure 1.0: Definition of Learning Disability

Source: Code of Federal Regulations, Title 34, Subtitle B, Chapter III, Section 300.7(b) (10).

The definition mentioned under Individuals with Disabilities Education Act (IDEA) concentrates on the difference between a child’s academic accomplishment and his or her evident capacity and opportunity to learn. Thus, “learning disabilities reflect unexpected learning problems in a seemingly capable child” (Lyon, 1996).

Learning disability is classified into the following disorders:

- ◆ Dyslexia – reading disorder
The person has trouble understanding written words and cannot identify different word sounds.
- ◆ Dyscalculia – arithmetic disorder
The person has trouble solving arithmetic problems and grasping mathematical concepts.
- ◆ Dysgraphia – writing disorder
The person has trouble forming letters or writing within a defined space and creating meaningful sentences.
- ◆ Articulation disorder – speech disorder
The person has trouble pronouncing certain alphabets or words.
- ◆ Receptive Language Disorder
The person has trouble understanding language. He hears the words, but is not able to process the words correctly.
- ◆ Expressive Language Disorder
The person has trouble with verbalization.
- ◆ Nonverbal Learning Disorder
The person has trouble with spatial, visual, organizational, intuitive, motor, sensory, social, evaluative and holistic processing functions.
- ◆ Dyspraxia
The person has trouble with fine motor tasks.

These different types of learning disabilities often occur together with specific emotional or behavioral disorders such as attention deficit disorder. Although, much of the available information pertaining to learning disabilities is associated with reading disorders, and the majority of cases of LD have their primary deficits in reading (Lyon, 1995) LD should not be misinterpreted as dyslexia (Lyon, 1989; Lyon, 1995).

A learning disability is often unexposed. It may not appear to a casual observer that difficulty in processing information can cause a person to get along differently from others in learning and living situations. An individual who thinks logically and clearly

may be physically unable to write a simple paragraph. In fact, one of the attributes of students with learning disabilities is inconsistent performance. The characteristic of disability is such that it does not often become apparent in academic settings. Its affect increases as more demands are placed on these skills. Still, adults with learning disabilities having normal or above normal intelligence devise extraordinary coping mechanisms to hide or overcome the disability (Hartman and Krulwich, 1984). The attributes of learning disabled students may include poor memory skills, trouble with summarization, lack of processing skills, continuous spelling mistakes, severe aptitude achievement discrepancies, slow working habits, inability to grasp concepts completely, either paying too detailed or no attention to facts, and adjustment problems.

1.2 Attention Deficit / Hyperactivity Disorder

Attention Deficit/Hyperactivity Disorder (ADHD) previously Attention Deficit Disorder (ADD) is characterized by consistent inattention, over activity, or impulsiveness according to the criteria listed in the Diagnostic and Statistical Manual of Mental Disorders (3rd ed., DSM-III; American Psychiatric Association, 1980, and DSM III, rev. [DSM-III-R], 1987). (Barkley, et. al., 1990) ADHD is a behavioral disorder as perceived by the child's parents and teachers. (Shaywitz, et. al., 1995) ADD is still used for inattentive children whereas ADHD for hyperactive as well as inattentive kids. Officially, all are required to use ADHD.

The Diagnostic and Statistical Manual of Diseases - Fourth Revision (DSM-IV) have classified ADHD into the following types:

- ◆ Predominantly Inattentive

The person has trouble organizing or completing a task, is inattentive to details and is easily distracted.

- ◆ Hyperactive/Impulsive

The person is restless, impatient, talks constantly, has constant mood swings and is unable to deal with anxiety and impulsivity.

◆ Combined

The person shows predominant symptoms of both the types mentioned above for at least six months. (Hale, et. al., 2000)

A standard is also mentioned for adolescents and adults with ADHD in Partial Remission in DSM-IV, who show only some symptoms but are otherwise suffering from significant functional damage. Inattentiveness and lack of control of impulsiveness is regarded as the foremost defects than is hyperactivity.

After diagnoses and classification, the person is assessed for learning disabilities and other neurological disorders. The probability of an ADHD person having learning disability is 0.3 to 0.4. (Kidd, 2000) ADHD is very different from learning disability. LD makes the person incapacitate to understanding in the regular way, requiring mediate strategies for grasping whereas ADHD makes the person barely available for comprehension because of the over activity, inattention, and impulsivity.

1.3 Linear Regression

A model describes reality in a simple way providing a hypothetical approximation of a complex process. Models can be mathematically expressed as deterministic or probabilistic. Deterministic models have precisely defined responses by a group of equations. For example Mass Energy Equivalence ($E = mc^2$), Newton Second Law of Motion ($F = ma$). Probabilistic models have variable responses because of the randomness (in terms of elements) associated with them.

The equation for the probabilistic linear model is given by

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k + \mathcal{E} \quad (1.1)$$

where y is the response variable, x_1, x_2, \dots, x_k are the regressor variables, $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ are the unknown parameters and \mathcal{E} is the random error term. The regressor variables are also called as covariates or predictors. The response y is a linear function of the unknown regression coefficients $\beta_0, \beta_1, \beta_2, \dots, \beta_k$. Equation (1.1) is also called as linear regression model or first order linear model. Assuming that on average the errors balance out the

error term \mathcal{E} has an expected value of zero. The expected value of the response y in the linear regression model becomes

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \quad (1.2)$$

Linear models have their responses as a linear function of the unknown parameters $\beta_0, \beta_1, \beta_2, \dots, \beta_k$. (Myers et. al., 2002) Linear models can be of different sorts. For example, an interaction model with two variables where,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \mathcal{E} \quad (1.3)$$

or a second order model with two variables where,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \mathcal{E} \quad (1.4)$$

Regression Analysis is used for modeling the relationship between the response (dependent or predicted) variable and the predictors (independent) variables, for determining the magnitude of the relationships between them and for making predictions based on them. Linear models incorporate both systematic and normally distributed random error components. The ordinary least squares (OLS) estimation technique used for analysis assumes only one error component whereas multiple errors are usually associated with designed experiments and survey data. (Nelder and Wedderburn, 1972) The error (residual) in the OLS prediction of the observed value y , is defined as the difference between the observed value y and the fitted value \hat{y} , given as

$$e = y - \hat{y} \quad (1.5)$$

The basic idea in OLS is to choose such regression coefficients that will minimize the sum of square residuals.

Although being descriptive the least square fitting procedure has a sound justification if assumptions are made on data generation. The experimenter does not have much control over the treatment variables which are experimental but so is not the case always with independent variables in a social science application. The error term represents the effect of all omitted variables. In an experiment, the omitted factors causing disturbance and the treatment variables are ensured to be uncorrelated by randomizing the independent treatment variables; thereby simplifying inference. Experimental controls must be replaced by assumptions for independent, non-

experimental research. This signifies the importance of assumptions in non-experimental research. The following are the Gauss Markov assumptions.

- ◆ Error, ε has an expected value of zero.
- ◆ If repeated samples are taken by fixing the independent variables at a specific value, the variables will be known to become independent of the disturbance. Hence, it is assumed independent variables are not random. Along with this assumption, for non-experimental work it also assumed that they have finite variances.
- ◆ The regressor variables are linearly independent. They cannot be expressed as a linear combination of the other regressor variables. If multicollinearity occurs, it becomes difficult to know the effects of the presumed independent variables.
- ◆ Variance of the error, ε for each observation is same.
- ◆ Errors, ε associated with each observation are not correlated.

The regression coefficients will be unbiased if the first three assumptions are fulfilled. If we draw more than one sample, the average value of the least square estimator of each sample will reflect the true value of β . For the variance of the sampling distribution to be an important indicator of the estimates obtained, we usually consider a single sample. The variance of the estimator is given by

$$\text{Var}(b) = \sigma^2 (X' X)^{-1} \quad (1.6)$$

if all assumptions are satisfied, where

b = OLS estimator of β

X = ($n \times p$) matrix of the levels of the independent variables

$$\hat{\sigma}^2 = \sum_{i=1}^n e_i^2 / (n-p) = \text{Standard error of regression}$$

= Standard deviation of the residuals, e_i

In case of high correlation between independent variables the matrix $X' X$ will become approximately singular whereas the elements of the inverse matrix will be very large giving imprecise estimates of beta. The least square estimates being sensitive should always adhere to the assumptions as they can be greatly influenced by outliers.

The coefficient of determination, R^2_{adjusted} , is used to measure the amount of

variation in the dependent variable accounted by the variation in the independent predictor variables. R^2 is the percent of variation that is explained by the regression equation. The total variation is split into two parts, the part that can be explained by the regression equation and the part that cannot be explained by the regression equation. The ratio of the explained variation to the total variation is a measure of how good the regression line is. If the regression line passes through every point on the scatter plot, it can explain all of the variation. The further the line is from the points, the less it is able to explain all variation in the model. The value of R^2 lies between 0 and 1. Greater the R^2 , greater is the variation explained in the response, by the model. An adjusted R-squared, takes the size of the sample into consideration. It is used while comparing the results of models with different number of observations or independent variables, or to restrain suspect results of analysis due to a small number of observations. Accordingly, smaller sample size decreases R-square value and vice versa. According to Vinsnes et. al., (2001), “In many situations, the outcome will depend on more than one explanatory variable. This leads to multiple regression, in which the dependent variable is predicted by a linear combination of the possible explanatory variables.”

1.4 Peer Tutoring

According to K.J. Topping, “Peer tutoring is defined as more able students helping less able students to learn in co-operative working pairs or small groups carefully organized by a professional teacher”. It represents a very effective and economical way of approaching LD students’ needs for increased opportunity to read and get individual attention (Limbrick, et. al., 1985). In olden times, a peer tutor was seen as a substitute teacher. Later the interaction was defined to be qualitatively different when compared to a teacher and a student. Peer tutoring came to be seen with lot many dimensions not only from able to less able transaction. Both tutor and tutee gain from peer tutoring. The different variables contributing to the type of peer tutoring are place, time, ability, type of tutor and tutee, year of study, objectives, number of tutees, course content and role continuity. (Topping, 1996) The place where tutoring is done plays an important role. Tutoring may be scheduled after class or during regular classroom sessions or both. The

tutor could be of either the same ability as the tutee, or same ability with more specific knowledge in the subject area, or higher ability with subject experience. It is better to have average (or less) performing students as tutors to make it a demanding effort for both the sides in terms of knowledge. Otherwise, the tutoring task could prove to be less challenging. (Fantuzzo et.al., 1989) Learning and behavior disabled students have also been employed in schools as tutors to get benefits of peer tutoring. (Scruggs and Osguthorpe, 1990) Tutoring may be done for all tutees or a specific group. They could be failure, minority, or brighter students, etc. The tutor and the tutee can be from same or different years of study. Peer tutoring has a broad scope and can be done in all subjects. The course content varies from knowledge accumulation to skill application. Tutoring can be done either in dyads or in groups. Sometimes two tutors can also tutor a group together. The roles of tutor and tutee can change over the course of tutoring thereby introducing innovation and raising self-esteem of all. The objective of peer tutoring could be reducing dropout from classes, increasing performance, gains in terms of better attitude, social and emotional changes in behavior patterns, conceptual gains and self-image gains, or a combination of any of these.

Tutors carry out various teaching functions such as presenting information and giving corrective feedback (Delquadri, et. al., 1988). One of the possible benefits of tutoring is the customization that different learners can receive (Harrison, 1976). Peer tutoring increases the time students spend in relevant academic behaviors as compared to teacher directed instruction (Greenwood, et. al., 1988). Teachers can also aid in providing individual attention without immolating the needs of other class members. It allows the teacher to move forward with lessons for students who are ready. That way the less able students are forced to partake responsibility for their own learning. Thus, it promotes cooperation, empathy and increased comprehension among students involved in peer tutoring activities (Scruggs and Richter, 1985). Peer tutoring streamlines LD students into regular classes by allowing them to work together on a one to one basis with other students. It helps them to gain self-respect and inculcate a cooperative attitude with others. It also decreases the pressure on teacher time (Christoplus, 1974). Other reported benefits include increased opportunities to respond, giving additional practice, increasing

time on-task by reducing independent work time, gaining on feedback and including ongoing performance monitoring (Simmons, et. al., 1995).

CHAPTER II ANALYSIS

The study involves analysis of performance of students diagnosed as either learning disabled or having attention deficit/hyperactivity disorder. These students were enrolled for an optional supplemental academic enhancement service at Texas Tech University, Lubbock. This service is provided by Techniques Center here. Performance parameters are considered for four consecutive semesters of Fall and Spring. The analysis is carried out using the software R. The version used is 2.2.1. R is a language and environment for statistical computing and graphics, which is easily extended via packages. (Department of Statistics and Mathematics, Wirtschafts University, 2006)

2.1 Fitted Models

2.1.1 Semester Wise Regression Analysis

Fitting a second order multiple linear regression model to the available data using equation (1.4). Considering eight variables equation (1.4) becomes

$$\begin{aligned}
 \hat{y} = & \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \beta_4x_4 + \beta_5x_5 + \beta_6x_6 + \beta_7x_7 + \beta_8x_8 \\
 & + \beta_{11}x_1^2 + \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + \beta_{14}x_1x_4 + \beta_{15}x_1x_5 + \beta_{16}x_1x_6 + \beta_{17}x_1x_7 + \beta_{18}x_1x_8 \\
 & + \beta_{22}x_2^2 + \beta_{23}x_2x_3 + \beta_{24}x_2x_4 + \beta_{25}x_2x_5 + \beta_{26}x_2x_6 + \beta_{27}x_2x_7 + \beta_{28}x_2x_8 \\
 & + \beta_{33}x_3^2 + \beta_{34}x_3x_4 + \beta_{35}x_3x_5 + \beta_{36}x_3x_6 + \beta_{37}x_3x_7 + \beta_{38}x_3x_8 \\
 & + \beta_{44}x_4^2 + \beta_{45}x_4x_5 + \beta_{46}x_4x_6 + \beta_{47}x_4x_7 + \beta_{48}x_4x_8 \\
 & + \beta_{55}x_5^2 + \beta_{56}x_5x_6 + \beta_{57}x_5x_7 + \beta_{58}x_5x_8 \\
 & + \beta_{66}x_6^2 + \beta_{67}x_6x_7 + \beta_{68}x_6x_8 \\
 & + \beta_{77}x_7^2 + \beta_{78}x_7x_8 \\
 & + \beta_{88}x_8^2
 \end{aligned} \tag{2.0}$$

where,

y = semester GPA

x₁ = Number of no shows to a tutor

x₂ = Ethnicity

- White - 0

- Black, No data, Other Hispanic American, Asian /Pacific Islander, Other - 1

x_3 = Cumulative number of hours completed by end of the semester

x_4 = Attention Deficit Disorder

- No, Multiple, No Disability Information - 0

- Yes - 1

x_5 = Learning Disability

- No, ADD, No Disability Information, Multiple - 0

- Yes - 1

x_6 = Number of Disabilities

- No Disability Information / One Disability - 0

- Multiple - 1

x_7 = Total number of hours tutored

x_8 = Number of attempted credit hours in the semester

2.1.1.1 Semester I

The second order fitted model for the available data for Semester I is given by the following equation.

$$\hat{y} = - 2.57929 + 0.73102 x_1 - 25.12837 x_2 + 0.01437 x_3 + 2.39064 x_4 + 4.12505 x_5 - 7.27713 x_6 + 0.03055 x_7 + 0.19632 x_8 - 0.00656 x_1x_3 - 0.48430 x_1x_4 + 0.39410 x_1x_6 + 0.30947 x_2x_3 - 0.01978 x_3x_5 + 0.03477 x_3x_6 - 0.03316 x_4x_7 - 0.04768 x_5x_7 + 0.06539 x_6x_7 \quad (2.1)$$

```

lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + (x1 *
  x3) + (x1 * x4) + (x1 * x6) + (x2 * x3) + (x3 * x5) + (x3 *
  x6) + (x4 * x7) + (x5 * x7) + (x6 * x7))

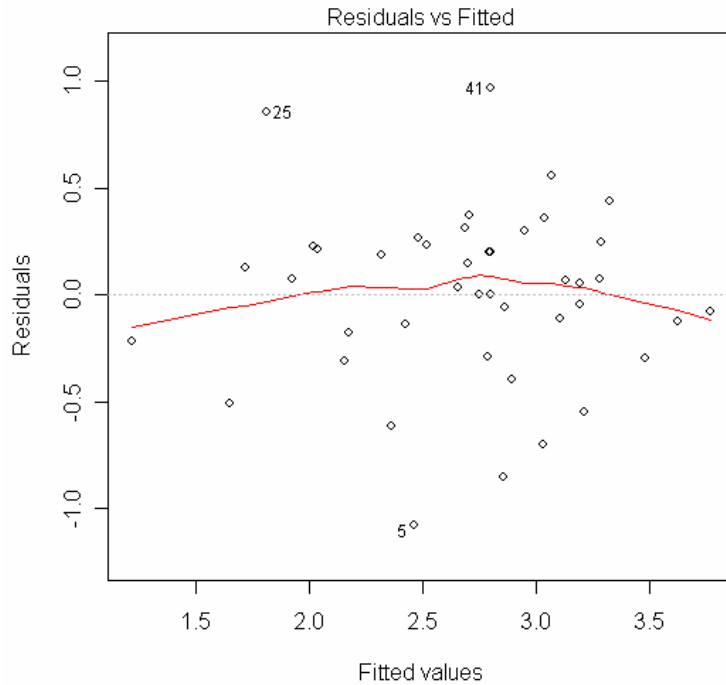
Residuals:
  Min    1Q  Median    3Q   Max
-1.07646 -0.19564  0.05717  0.23109  0.96707

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.579291   1.446013  -1.784  0.086613 .
x1             0.731022   0.240954   3.034  0.005566 **
x2            -25.128373   7.385056  -3.403  0.002252 **
x3             0.014370   0.008888   1.617  0.118467
x4             2.390641   0.856819   2.790  0.009937 **
x5             4.125051   1.288334   3.202  0.003699 **
x6             7.277127   1.587583  -4.584  0.000110 ***
x7             0.030551   0.018596   1.643  0.112921
x8             0.196324   0.069254   2.835  0.008946 **
x1:x3         -0.006560   0.002260  -2.903  0.007614 **
x1:x4         -0.484300   0.126492  -3.829  0.000768 ***
x1:x6         0.394100   0.124155   3.174  0.003958 **
x2:x3         0.309469   0.090056   3.436  0.002070 **
x3:x5        -0.019775   0.009063  -2.182  0.038721 *
x3:x6         0.034766   0.009997   3.478  0.001867 **
x4:x7        -0.033155   0.018669  -1.776  0.087913 .
x5:x7        -0.047679   0.018872  -2.526  0.018225 *
x6:x7         0.065394   0.019575   3.341  0.002626 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

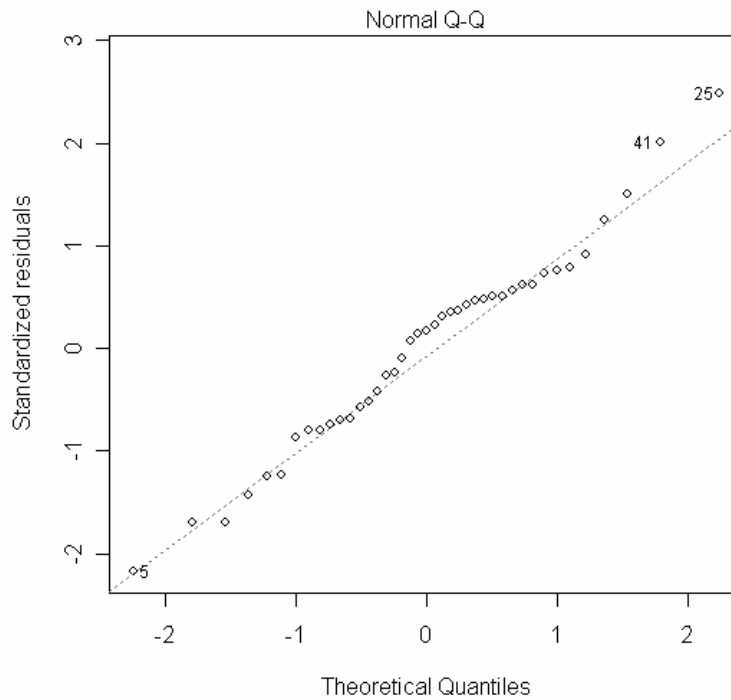
Residual standard error: 0.5277 on 25 degrees of freedom
Multiple R-Squared: 0.651,    Adjusted R-squared: 0.4137
F-statistic: 2.743 on 17 and 25 DF, p-value: 0.01083

```

Figure 2.0: t test summary for final second order analysis of Semester I



$\text{lm}(y \sim x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + (x1 * x3) + (x1 * x4) + (x1 \dots$
Figure 2.1: Plot of Residual vs. Fitted values for Semester I



$\text{lm}(y \sim x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + (x1 * x3) + (x1 * x4) + (x1 \dots$
Figure 2.2: Normal Probability Plot for Semester I

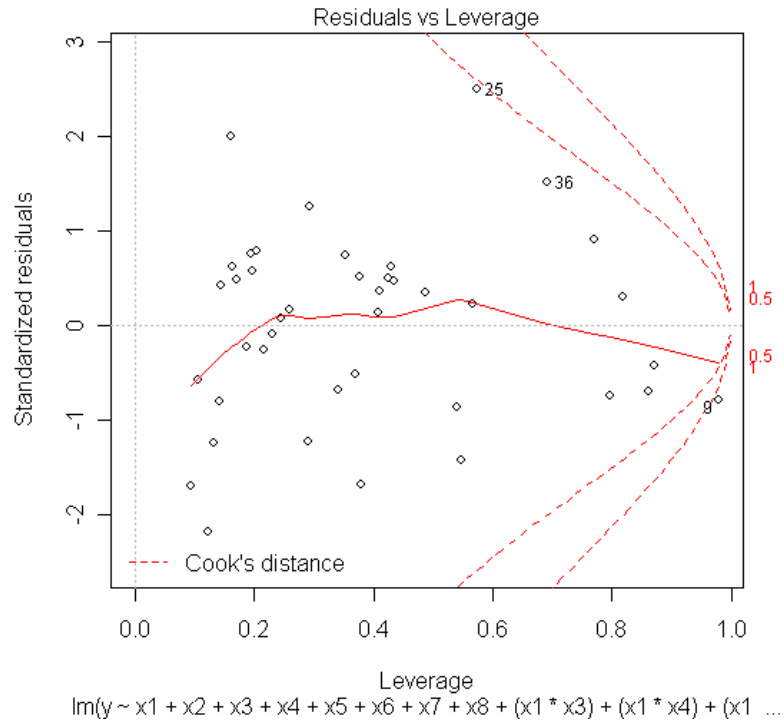


Figure 2.3: Plot of Cook's Distance for Semester I

From the above plots, it can be concluded that the normality assumption is approximately satisfied which could be attributed to the presence of three outliers. The randomness in the residual versus fitted plot indicates that the constant variance assumption for all values of the response is also satisfied.

2.1.1.2 Semester II

The second order fitted model for the available data for Semester II is given by the following equation.

$$\hat{y} = 3.908834 - 0.095161 x_1 - 0.815885 x_4 - 0.810124 x_5 - 0.032247 x_7 + 0.033025 x_4 x_7 + 0.027294 x_5 x_7 \quad (2.2)$$

```
lm(formula = y ~ x1 + x4 + x5 + x7 + (x4 * x7) + (x5 * x7))
Residuals:
    Min       1Q   Median       3Q      Max
-1.37663 -0.24283 -0.03283  0.23920  1.05749
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Interce)  3.908834    0.284057  13.761 < 2e-16 ***
x1         -0.095161    0.024170  -3.937  0.000238 ***
x4         -0.815885    0.275855  -2.958  0.004592 **
x5         -0.810124    0.287826  -2.815  0.006801 **
x7         -0.032247    0.008700  -3.707  0.000496 ***
x4:x7      0.033025    0.009116   3.623  0.000645 ***
x5:x7      0.027294    0.009294   2.937  0.004868 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5095 on 54 degrees of freedom
Multiple R-Squared:  0.3703,    Adjusted R-squared:  0.3003
F-statistic: 5.293 on 6 and 54 DF,  p-value: 0.000237
```

Figure 2.4: t test summary for final second order analysis of Semester II

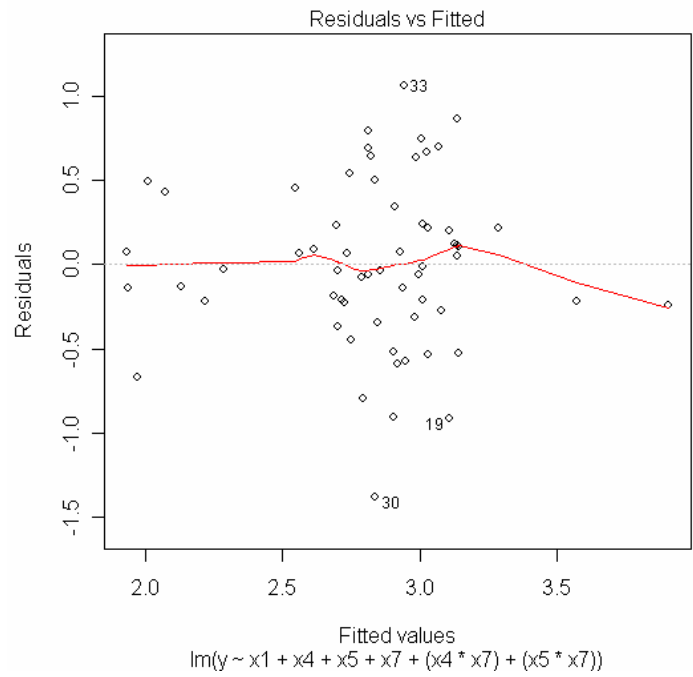


Figure 2.5: Plot of Residual vs. Fitted values for Semester II

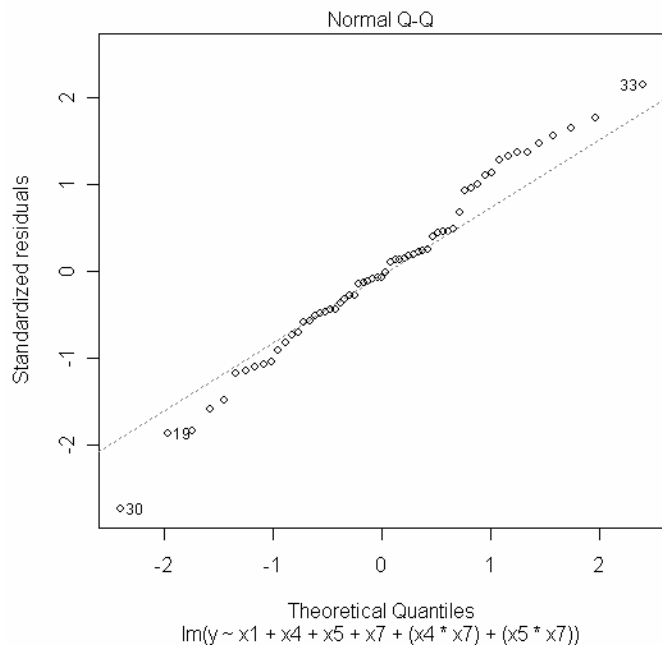


Figure 2.6: Normal Probability Plot for Semester II

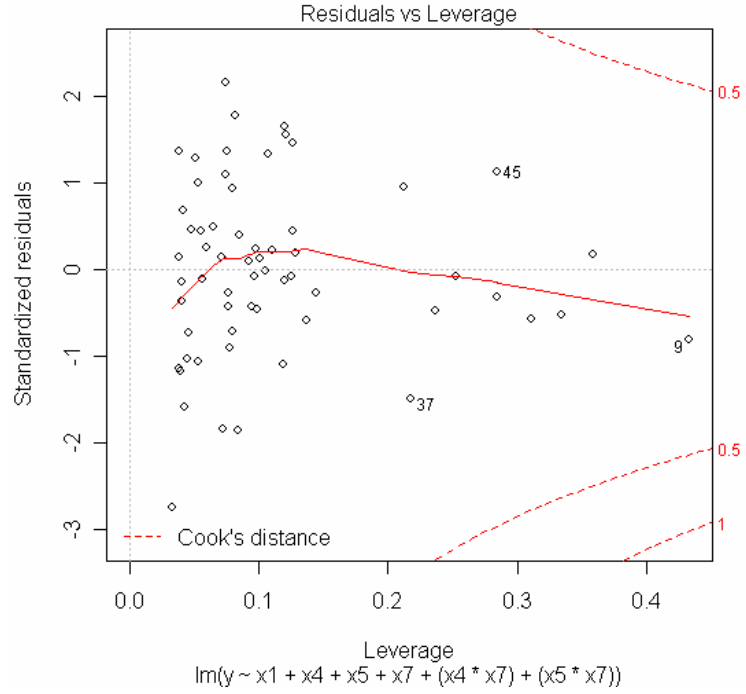


Figure 2.7: Plot of Cook's Distance for Semester II

From the above plots, it can be concluded that the normality assumption is approximately satisfied. The pattern in the residual versus fitted plot indicates slight non variance.

2.1.1.3 Semester III

The second order fitted model for the available data for Semester III is given by the following equation.

$$\hat{y} = 5.596954 - 0.246546 x_1 - 0.624747 x_2 - 0.009153 x_3 - 2.476096 x_4 - 4.512250 x_5 - 0.017842 x_7 - 0.051292x_8 + 0.199627 x_1x_4 + 0.227247 x_1x_5 + 0.016219 x_3x_4 + 0.019572 x_4x_7 + 0.016887 x_5x_7 + 0.244716 x_5x_8 \quad (2.3)$$

```
lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x7 + x8 + (x1 * x4) +
  (x1 * x5) + (x3 * x4) + (x4 * x7) + (x5 * x7) + (x5 * x8))

Residuals:
    Min     1Q   Median     3Q     Max
-1.18086 -0.29792  0.06493  0.34789  1.01317

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.596954  1.092863   5.121 3.87e-06 ***
x1          -0.246546  0.100029  -2.465  0.01680 *
x2          -0.624747  0.302996  -2.062  0.04387 *
x3          -0.009153  0.003643  -2.512  0.01490 *
x4          -2.476096  0.661415  -3.744  0.00043 ***
x5          -4.512250  1.367355  -3.300  0.00169 **
x7          -0.017842  0.009231  -1.933  0.05832 .
x8          -0.051292  0.064745  -0.792  0.43158
x1:x4         0.199627  0.097390   2.050  0.04508 *
x1:x5         0.227247  0.096468   2.356  0.02202 *
x3:x4         0.016219  0.005111   3.173  0.00245 **
x4:x7         0.019572  0.009933   1.970  0.05375 .
x5:x7         0.016887  0.009544   1.769  0.08227 .
x5:x8         0.244716  0.087376   2.801  0.00699 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5604 on 56 degrees of freedom
Multiple R-Squared:  0.3568,    Adjusted R-squared:  0.2075
F-statistic: 2.389 on 13 and 56 DF, p-value: 0.01244
```

Figure 2.8: t test summary for final second order analysis of Semester III

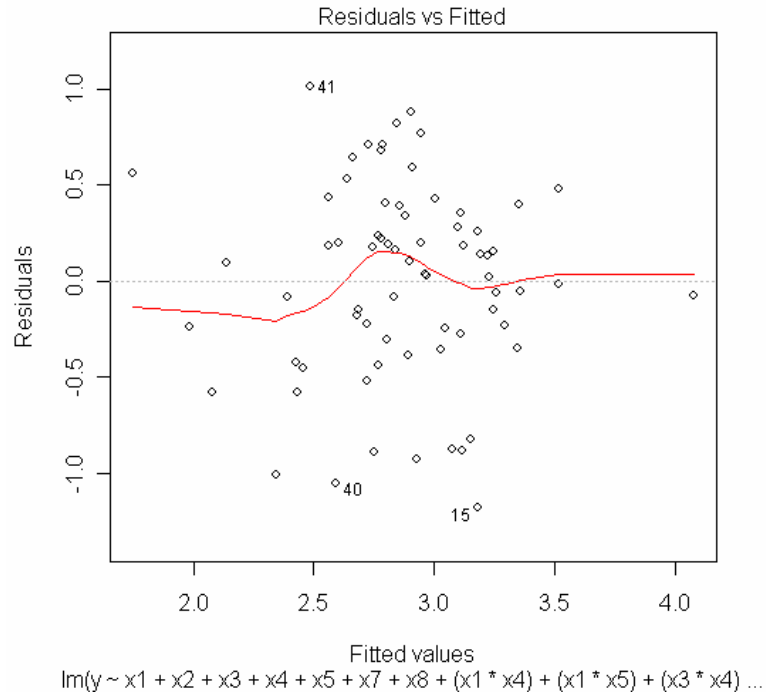


Figure 2.9: Plot of Residual vs. Fitted values for Semester III

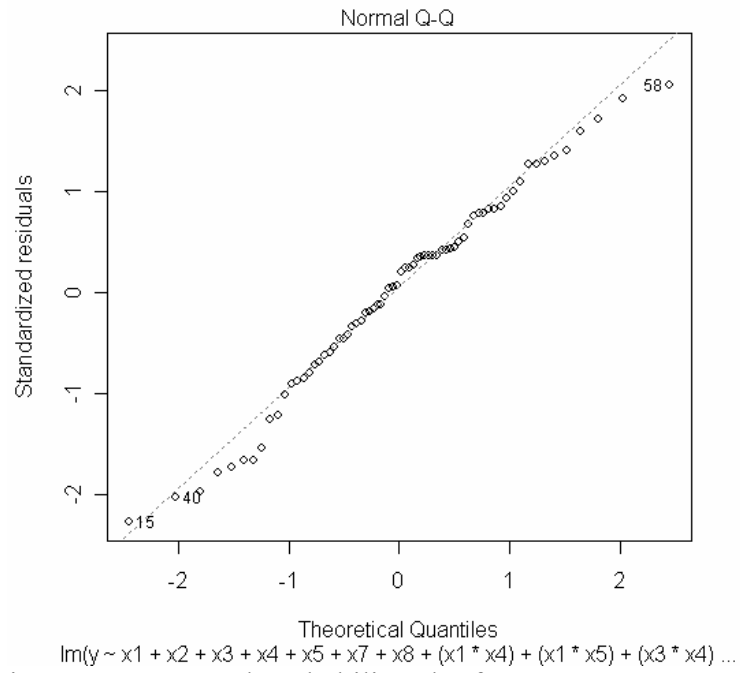


Figure 2.10: Normal Probability Plot for Semester III

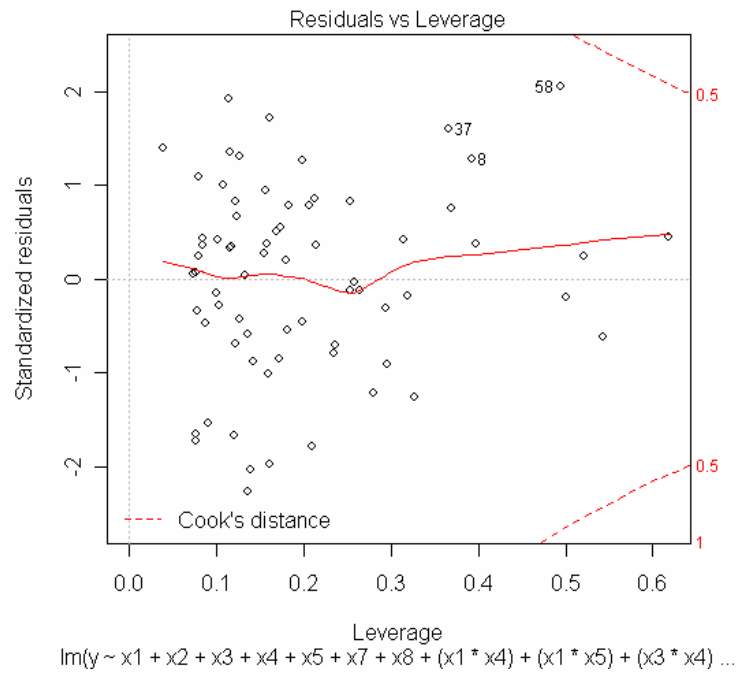


Figure 2.11: Plot of Cook's Distance for Semester III

From the above plots, it can be concluded that the normality assumption is satisfied. The randomness in the residual versus fitted plots indicate that the constant variance assumption for all values of the response is also satisfied. Thus the model is adequate.

2.1.1.4 Semester IV

The second order fitted model for the available data for Semester IV is given by the following equation.

$$\hat{y} = -1.538651 - 0.095081x_1 + 0.043007 x_3 + 2.967059 x_4 - 0.844815 x_6 + 0.003174 x_7 + 0.316449 x_8 - 0.002915 x_3x_8 - 0.219097 x_4x_8 + 0.021118 x_6x_7 \quad (2.4)$$

```
lm(formula = y ~ x1 + x3 + x4 + x6 + x7 + x8 + (x3 * x8) + (x4 *
x8) + (x6 * x7))

Residuals:
    Min       1Q   Median       3Q      Max
-1.692426 -0.318086  0.008267  0.434576  1.433602

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.538651   1.185378  -1.298 0.197749
x1          -0.095081   0.029752  -3.196 0.001951 **
x3           0.043007   0.018101   2.376 0.019726 *
x4           2.967059   1.144166   2.593 0.011174 *
x6          -0.844815   0.340017  -2.485 0.014906 *
x7           0.003174   0.004866   0.652 0.515973
x8           0.316449   0.089906   3.520 0.000693 ***
x3:x8       -0.002915   0.001350  -2.159 0.033622 *
x4:x8       -0.219097   0.086147  -2.543 0.012771 *
x6:x7        0.021118   0.010453   2.020 0.046471 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6292 on 86 degrees of freedom
Multiple R-Squared:  0.3137,    Adjusted R-squared:  0.2419
F-statistic: 4.368 on 9 and 86 DF,  p-value: 0.0001033
```

Figure 2.12: t test summary for final second order analysis of Semester IV

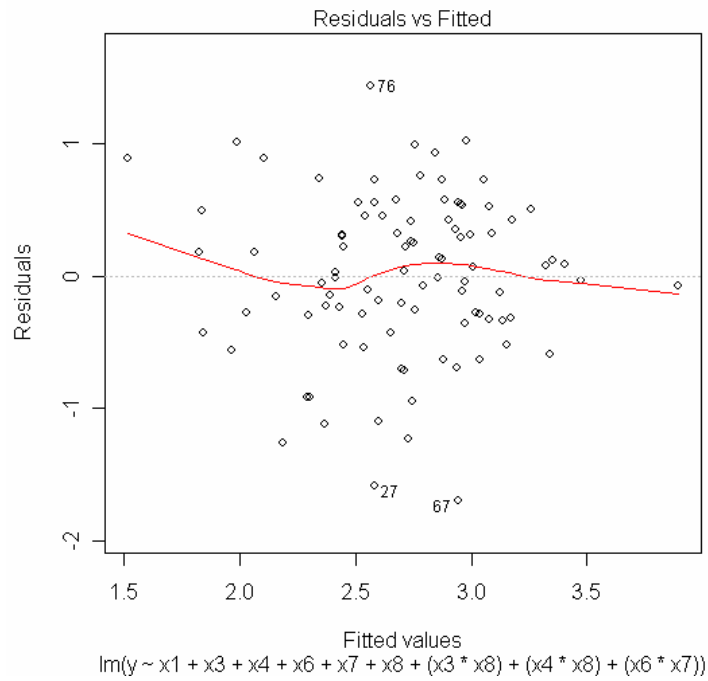


Figure 2.13: Plot of Residual vs. Fitted values for Semester IV

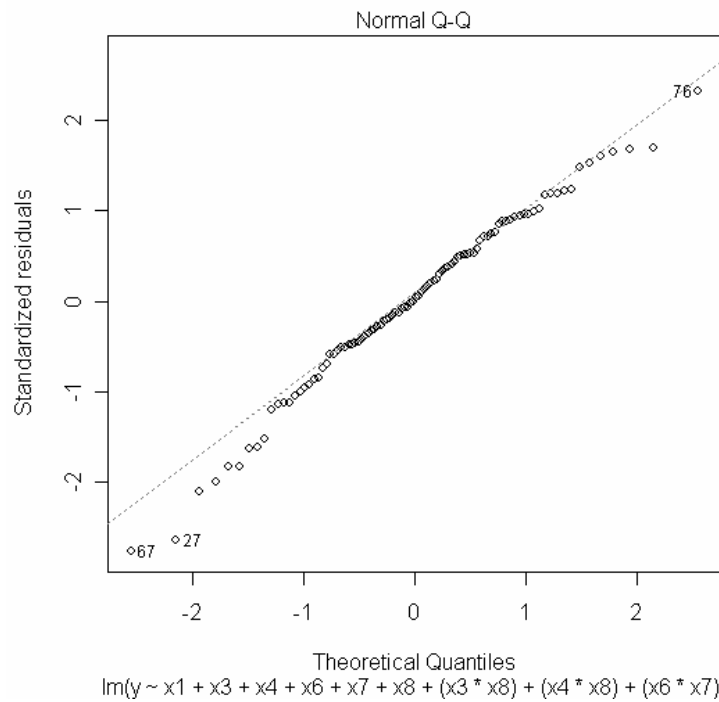


Figure 2.14: Normal Probability Plot for Semester IV

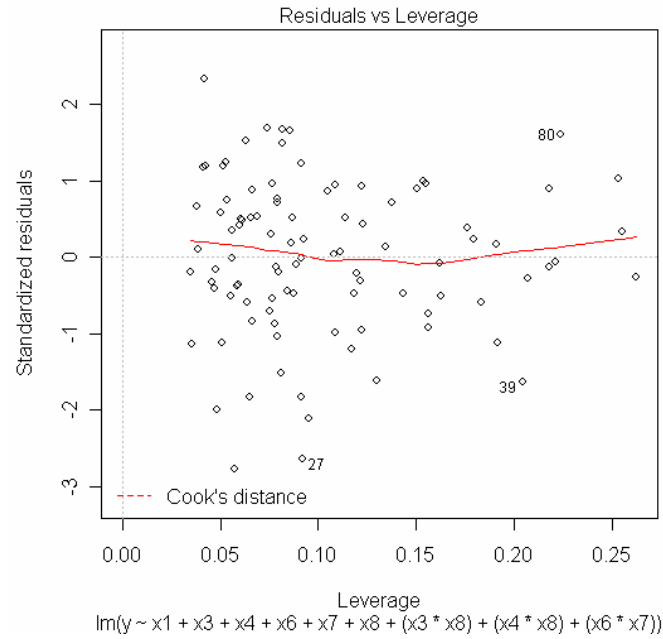


Figure 2.15: Plot of Cook's Distance for Semester IV

From the above plots, it can be concluded that the normality assumption is satisfied. The randomness in the residual versus fitted plots indicate that the constant variance assumption for all values of the response is also satisfied. Thus the model is adequate.

2.1.2 Selective Regression Analysis

The following analysis is carried out for students continuing for all four semesters. Fitting a second order multiple linear regression model to selected data using equation (1.4). Considering eight variables equation (1.4) becomes

$$\begin{aligned}
 \Delta \hat{y} = & \beta_0 + \beta_1 \Delta x_1 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 \Delta x_7 + \beta_8 \Delta x_8 \\
 & + \beta_{11} \Delta x_1^2 + \beta_{14} \Delta x_1 x_4 + \beta_{15} \Delta x_1 x_5 + \beta_{16} \Delta x_1 x_6 + \beta_{17} \Delta x_1 \Delta x_7 + \beta_{18} \Delta x_1 \Delta x_8 \\
 & + \beta_{44} x_4^2 + \beta_{45} x_4 x_5 + \beta_{46} x_4 x_6 + \beta_{47} x_4 \Delta x_7 + \beta_{48} x_4 \Delta x_8 \\
 & + \beta_{55} x_5^2 + \beta_{56} x_5 x_6 + \beta_{57} x_5 \Delta x_7 + \beta_{58} x_5 \Delta x_8 \\
 & + \beta_{66} x_6^2 + \beta_{67} x_6 \Delta x_7 + \beta_{68} x_6 \Delta x_8 \\
 & + \beta_{77} \Delta x_7^2 + \beta_{78} \Delta x_7 \Delta x_8 \\
 & + \beta_{88} \Delta x_8^2 \\
 & + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11}
 \end{aligned} \tag{2.5}$$

where,

Δy = Difference in semester GPA between 2 consecutive semesters

Δx_1 = Difference of number of no shows to a tutor between 2 consecutive semesters

x_4 = Attention Deficit Disorder

- No, Multiple, No Disability Information - 0

- Yes - 1

x_5 = Learning Disability

- No, ADD, No Disability Information, Multiple - 0

- Yes - 1

x_6 = Number of Disabilities

- No Disability Information / One Disability - 0

- Multiple - 1

Δx_7 = Difference of total number of hours tutored between two consecutive semesters

Δx_8 = Difference of number of attempted credit hours in the semester between two consecutive semesters

x_9 = Data from Semester I and Semester II

- No - 0

- Yes - 1

x_{10} = Data from Semester II and Semester III

- No - 0

- Yes - 1

x_{11} = Data from Semester III and Semester IV

- No - 0

- Yes - 1

```
lm(formula = y ~ x1 + x4 + x7 + x10 + (x4 * x7))
Residuals:
Min    1Q  Median    3Q    Max
-1.19551 -0.49916 -0.06417  0.43037  2.17052

Coefficients:
Estimate Std. Error t value Pr(> |t|)
(Intercept) -0.193039  0.145516  -1.327  0.19056
x1          -0.063409  0.025681  -2.469  0.01693 *
x4           0.113652  0.206282   0.551  0.58407
x7          -0.021507  0.007165  -3.002  0.00415 **
x10          0.408122  0.212584   1.920  0.06048 .
x4:x7        0.027050  0.010123   2.672  0.01009 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7114 on 51 degrees of freedom
Multiple R-Squared: 0.2366,    Adjusted R-squared: 0.1618
F-statistic: 3.162 on 5 and 51 DF,  p-value: 0.01461
```

Figure 2.16: t test summary for selective second order analysis

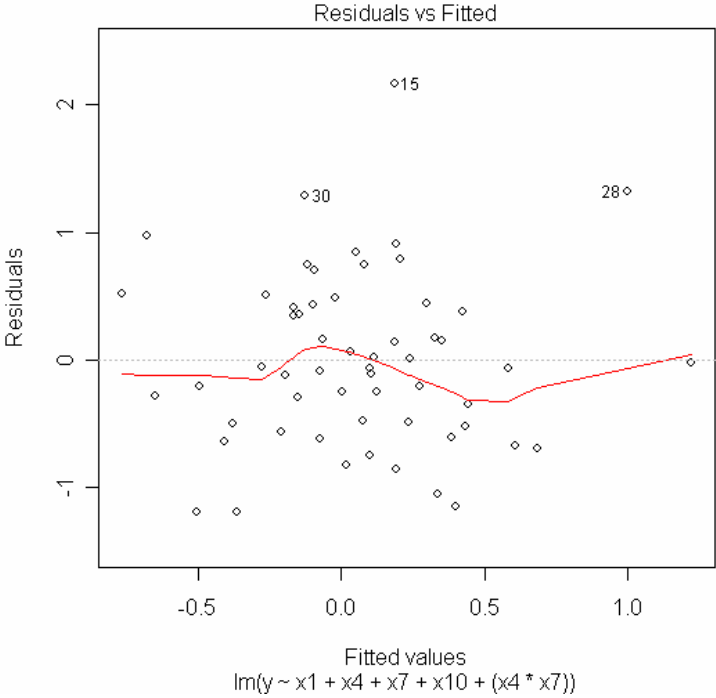


Figure 2.17: Plot of residual vs. fitted values

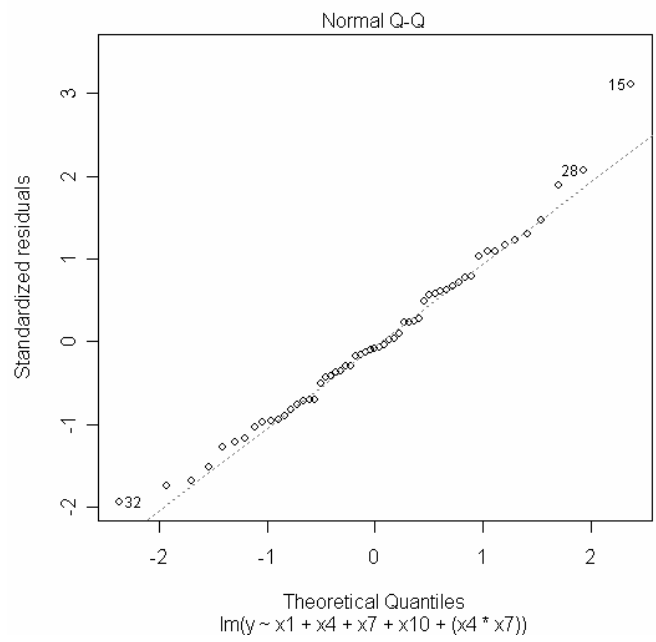


Figure 2.18: Normal probability plot

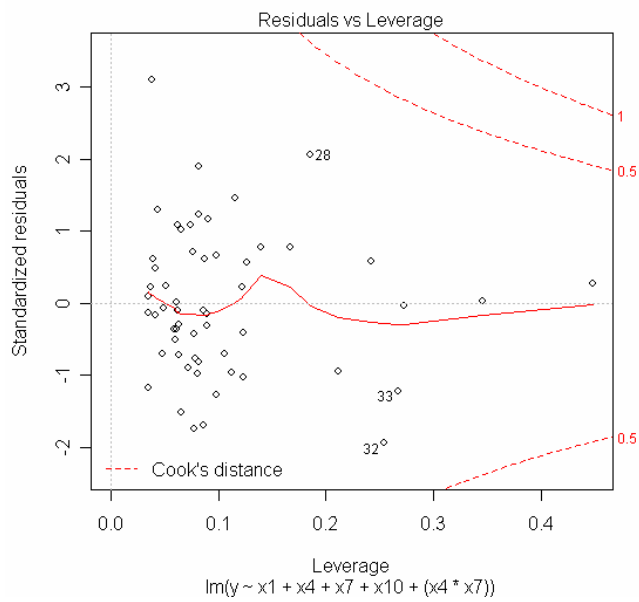


Figure 2.19: Plot of Cook's Distance

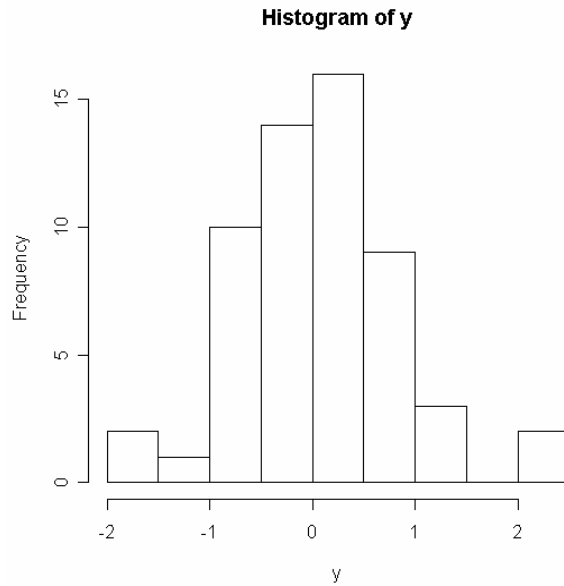


Figure 2.20: Histogram of difference in semester GPA

From the above plots, it can be concluded that the normality assumption is satisfied. The randomness in the residual versus fitted plots indicate that the constant variance assumption for all values of the response is also satisfied. There are no outliers. Thus the model is adequate.

2.2 Interpretation of Statistical Findings

2.2.1 Semester I

Significant variables from first order analysis: x3 - cumulative number of hours completed by spring 2004 and second order analysis: x1, x2, x3, x4, x5, x6, x7, x8.

Table 2.0: Interactions present in second order analysis of Semester I data

Variables	x1	x2	x3	x4	x5	x6	x7	x8
x1			-	-		+		
x2			+					
x3					-	+		
x4							-	
x5							-	
x6							+	
x7								
x8								

In semester I it can be seen from the analysis that the negative correlation of

- ◆ x1 and x3 signifies decrease in performance if the student does not show up to a tutor inspite of having increased pressure due the number of courses taken since.
- ◆ x1 and x4 shows decrease in performance of ADD students not attending tutoring sessions.
- ◆ x3 and x5 shows decrease in performance if a student having LD takes too many classes since the beginning.
- ◆ x4 and x7 shows decrease in performance if a student being tutored has ADD
- ◆ x5 and x7 shows decrease in performance if a student being tutored has LD

The positive correlation of

- ◆ x6 and x7 shows improvement in performance if a disabled student gets tutored
- ◆ x3 and x6 shows improvement in performance with increased cumulative hours and multiple disabilities.
- ◆ x2 and x3 shows improvement in performance for whites having higher numbers of cumulative hours.
- ◆ x1 and x6 shows improvement in performance for disabled students not attending to tutoring.

2.2.2 Semester II

Significant variables from first order analysis: x1 – number of no shows to a tutor and second order analysis: x1, x4, x5, x7.

Table 2.1: Interactions present in second order analysis of Semester II data

Variables	x1	x2	x3	x4	x5	x6	x7	x8
x1	■	■	■	■	■	■	■	■
x2	■	■	■	■	■	■	■	■
x3	■	■	■	■	■	■	■	■
x4	■	■	■	■	■	■	+	■
x5	■	■	■	■	■	■	+	■
x6	■	■	■	■	■	■	■	■
x7	■	■	■	■	■	■	■	■
x8	■	■	■	■	■	■	■	■

In semester II it can be seen from the analysis that the positive correlation of x4 and x7; and x5 and x7 shows increase in performance if a student having ADD or LD is tutored.

2.2.3 Semester III

Significant variables from first order analysis: x2 – ethnicity and second order analysis: x1, x2, x3, x4, x5, x7, x8.

Table 2.2: Interactions present in second order analysis of Semester III data

Variables	x1	x2	x3	x4	x5	x6	x7	x8
x1				+	+			
x2								
x3				+				
x4							+	
x5							+	+
x6								
x7								
x8								

- In Semester III it can be seen from the analysis that that the positive correlation of
- ◆ x1 and x4 shows increase in performance of a student having ADD and not attending to tutoring facilities regularly .
 - ◆ x1 and x5 shows increase in performance of a student having LD and not attending to tutoring facilities regularly.
 - ◆ x3 and x4 shows increase in performance of a student having ADD has more number of cumulative hours.
 - ◆ x4 and x7 shows increase in performance if a student having ADD is tutored .
 - ◆ x5 and x7 shows increase in performance if a student having LD is tutored .
 - ◆ x5 and x8 shows increase in performance if a student having LD takes less number of classes.

2.2.4 Semester IV

Significant variables from first order analysis: x1- number of no shows to a tutor and
 Second order analysis: x1, x3, x4, x6, x7, x8.

Table 2.3: Interactions present in second order analysis of Semester IV data

Variables	x1	x2	x3	x4	x5	x6	x7	x8
x1								
x2								
x3								-
x4								-
x5								
x6							+	
x7								
x8								

In semester IV it can be seen from the analysis that the interaction of x4(ADD) and x8(number of attempted credit hours) is negatively associated with y (GPA), which implies that a student having ADD taking increased number of courses will negatively affect the GPA. The positive interaction of x6 (number of disabilities) and x7(total number of hours tutored) implies that a student’s performance improves on tutoring inspite of having multiple disabilities. The negative interaction of x3(cumulative hours) and x8(Attempted credit hours in the current semester) signifies that too many credit hours has a negative effect on performance.

2.2.5 Selective Regression Analysis of All Semesters

Significant Variables from second order analysis of selected variables: $\Delta x1$, x4, $\Delta x7$, x10.

Table 2.4: Interactions present in second order analysis of Semester data

Variables	$\Delta x1$	x4	x5	x6	$\Delta x7$	$\Delta x8$
$\Delta x1$						
x4					+	
x5						
x6						
$\Delta x7$						
$\Delta x8$						

From selective regression analysis, it can be seen that the positive correlation of x_4 and x_7 shows increase in performance of an ADD student adding more hours to tutoring sessions while moving from Spring to Fall. This could be accounted to variable x_{10} being significant as for the fact that when a student moves from Fall to Spring, he has much less time to lose touch with his studies as compared to the transition from Spring to Fall, where the students have a long summer break. The above semesters essentially concentrate on spring and fall sessions, the first semester being spring and so on.

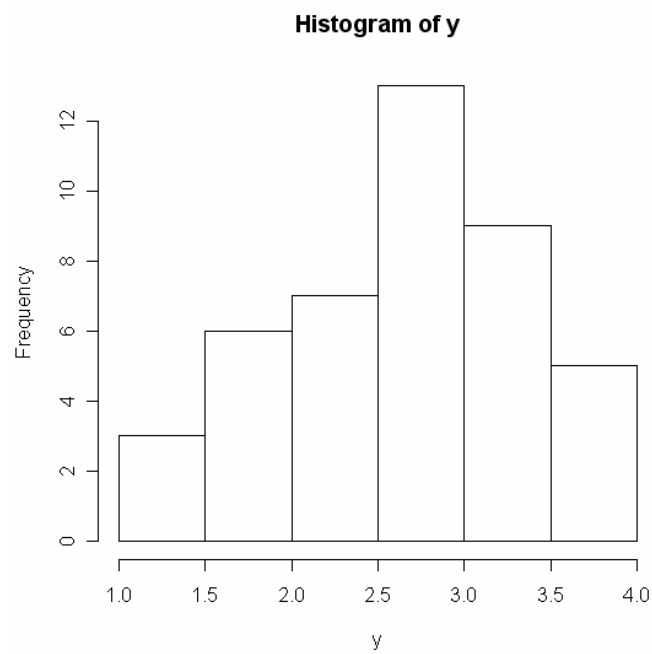


Figure 2.21: Histogram of semester I GPA

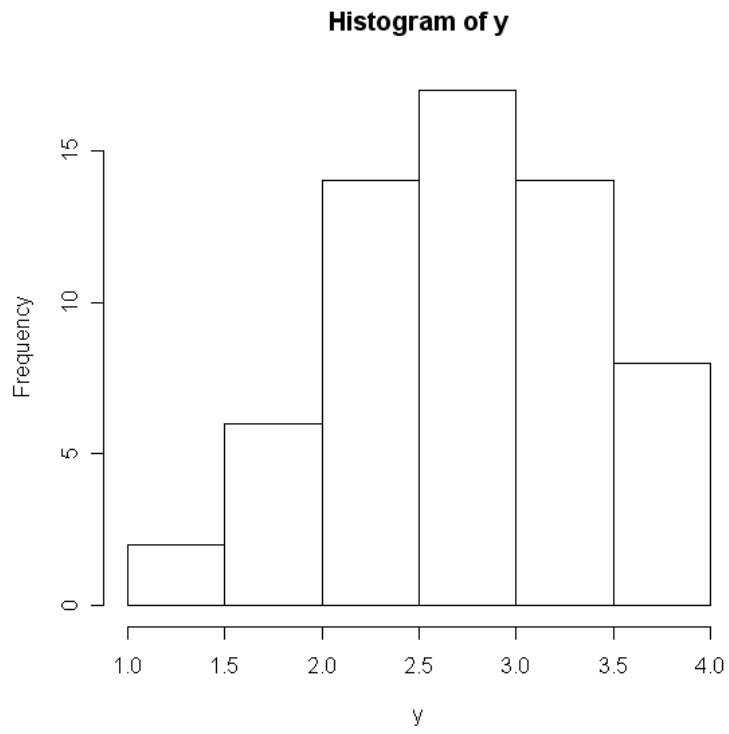


Figure 2.22: Histogram of semester II GPA

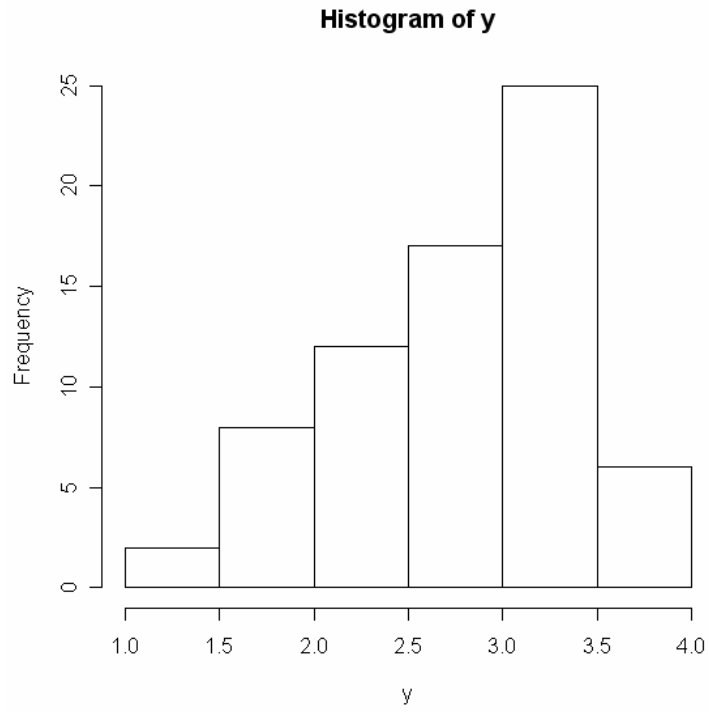


Figure 2.23: Histogram of semester III GPA

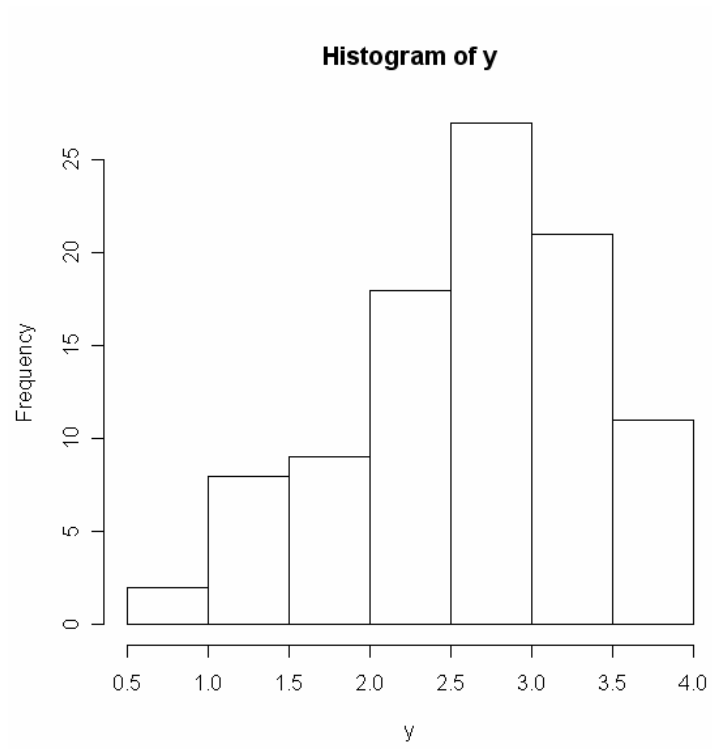


Figure 2.24: Histogram of semester IV GPA

CHAPTER III DISCUSSION AND CONCLUSION

Evidence shows that in terms of intellectual functioning LD and ADHD students are comparable with non-disabled students. However, the performance of disabled students may be more variable. Analyzing the intellectual activity of disabled (LD or ADHD) students, as a group is not helpful in diagnosing a learning disability in college students. It can be effectively concluded that on an average learning-disabled students do get an academic advantage when compared to those not being tutored. Thus, effective tutoring results in an increase in the Grade Point Average. The study led to the following conclusions to improve performance

- ◆ ADD students should be encouraged to tutoring sessions
- ◆ Balance course load for ADD students to avoid ending up with more credit hours during the last semesters of junior and senior years
- ◆ Increase hours of tutoring for ADD students
- ◆ Provide more hours of tutoring for students with more than one disability
- ◆ Students with Attention Deficit Disorder perform better in Spring as compared to Fall so could be advised to take more number or difficult courses in Spring.

This study could be further utilized and/or extended for the following purposes.

- ◆ Prediction of performances of students
- ◆ Determination of minimum and maximum hours of tutoring needed by enrolled students and tutors to be employed by the institution using Statistical Process Control
- ◆ Estimating number of hours of tutoring needed for a student depending on disability type
- ◆ An analysis could also be carried out based on tutor- tutee compatibility affected by the ethnicity of tutee
- ◆ Estimate the capacity of institution to enroll disabled students

REFERENCES

- Barkley, R.A., DuPaul, G.J., McMurray, M.B. "Comprehensive evaluation of attention deficit disorder with and without hyperactivity as defined by research criteria", *Journal of consulting and clinical psychology* (1990) 58:775-789.
- Christoplus, F. "Keeping exceptional children in regular classes", *Exceptional children* (1974) 39:569-572.
- Delquadri, J., Greenwood, C.R., Wharton, D.Carta, J.J. and Hall, R.V. "Classwide peer tutoring", *Exceptional children* (1986) 52:535-542.
- Fantuzzo, J.W., Riggio, R.W., Connelly, S. and Dimeff, L. "Effects of reciprocal peer tutoring on academic achievement and psychological adjustment: a component analysis", *Journal of educational psychology* (1989) 81:173-177.
- Greenwood, C.R., Carta, J.J. and Hall, R.V. "The use of peer tutoring strategies in classroom management and educational instruction", *School psychology review* (1988) 17:258- 275.
- Hale, T.S., Hariri, A.R., McCracken, J.T. "Attention deficit/hyperactivity disorder: perspectives from neuroimaging", *Mental retardation and developmental disabilities research reviews* (2000) 6:214-19.
- Harrison, G.V. "Structured tutoring: Antidote for low achievement", V.L. Allen (Ed.), *Children as teachers*, New York: academic press, (1976) 169-176.
- Hartman, R.C. and Krulwich, M.T. "Learning disabled adults in postsecondary education", *U.S. Department of education* (1984) (No. 300-80-0857), Washington D.C.: Higher Education and the Handicapped Resource Center (HEATH).
- Kidd, P.M. "Attention deficit/hyperactivity disorder (ADHD) in children: Rationale for its integrative management", *Alternative medicine review* (2000) 5:402-428.
- Limbrick, E., McNaughton, S. and Glynn, T. "Reading gains for underachieving tutors and tutees in a cross-age tutoring programme" *Journal of child psychology and psychiatry*, (1985) 26:939-953.
- Lyon, G.R. "IQ is irrelevant to the definition of learning disabilities: A position in search of logic and data", *Journal of learning disabilities* (1989) 22:504-519.
- Lyon, G.R. "Learning disabilities", *The Future of children: Special education for students with disabilities* (1996) 6:54-76.

Lyon, G.R. "Research initiatives and discoveries in learning disabilities", *Journal of child neurology* (1995) 10:120-126.

Lyon, G.R. "Toward a definition of dyslexia", *Annals of dyslexia* (1995) 45:3-27.

Myers, R.H., Montgomery, D.C., Vining, G.G. "Generalized linear models: With applications in the engineering and the sciences", *Wiley-interscience*, 1st ed., (2002).

Nelder, J.A., Wedderburn, R.W.M. "Generalized linear models", *Journal of the royal statistical society* (1972) 3:370-384.

Scruggs, T.E., Richter, L. "Tutoring learning disabled students: A critical review", *Learning disability quarterly* (1985) 8:286-298.

Scruggs, T.E., Osguthorpe, R.T. "Tutoring interventions within special education settings: a comparison of cross-age and peer tutoring", *Psychology in the schools* (1986) 23: 187-193.

Shaywitz, B.A., Fletcher, J.M., Shaywitz, S.E. "Defining and classifying learning disabilities and attention-deficit/hyperactivity disorder", *Journal of child neurology* (1995) 10:S50-57.

Simmons, D.C., Fuchs, L.S., Fuchs, D., Mathes, P., Hodge, J.P. "Effects of explicit teaching and peer tutoring on the reading achievement of learning-disabled and low-performing students in regular classrooms", *The elementary school journal* (1995) 95:387-408.

Stage, F.K., Milne, N.V. "Invisible scholars: Students with learning disabilities", *The journal of higher education* (1996) 67:426-445.

Topping, K.J. "The effectiveness of peer tutoring in further and higher education: A typology and review of the literature", *The journal of higher education* (1996) 32:321-345.

Vinsnes, A.G., Harkless, G.E., Haltbakk, J., Bohm, J., Hunskaar, S. "Healthcare personnel's attitudes towards patients with urinary incontinence", *Journal of clinical nursing* (2001) 10:455-462.

R Development Core Team (2005). R: A language and environment for statistical computing. Version 2.2.1. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-90005-07-0, URL <http://www.R-project.org>.

APPENDIX

A1. Semester I data used for analysis

y	x1	x2	x3	x4	x5	x6	x7	x8
3	1	0	109	1	1	1	43.5	12
3	1	0	142	0	1	0	25.75	13
3.2	1	0	36	1	0	0	58.5	15
2.5	0	0	87	0	1	0	37.5	12
1.384	1	0	96	1	1	1	27.75	13
2.333	1	0	93	1	0	0	40.5	12
1.75	2	0	101	1	1	1	28.25	12
2.666	0	0	94	0	1	0	56.25	16
2.8	1	0	69	0	0	1	59.5	15
3	0	0	102	0	1	0	25.5	13
3.357	1	0	125	1	1	1	25.25	14
2.75	0	0	105	0	1	0	49.75	12
3.4	2	0	129	0	1	0	30.5	15
3.25	2	0	97	0	1	0	36	12
2.25	4	0	134	1	0	0	50.5	15
3.5	2	0	91	0	1	0	37.5	15
3.153	0	0	97	0	1	0	22	13
1.846	0	0	58	0	0	0	29.75	13
2.5	4	0	80	1	1	1	32.25	12
3.076	0	0	86	0	1	0	54.25	13
2	4	0	142	1	1	1	10.25	12
3.538	3	0	104	1	1	1	37	16
3.692	10	0	82	0	0	1	12.25	13
2	1	0	95	0	1	0	37.5	12
2.666	1	0	80	1	1	1	8.75	13
2.25	5	0	122	0	0	1	20	12
2.5	0	0	104	0	1	0	49	14
2.692	3	0	65	1	0	0	39.25	13
2.8	7	1	86	1	0	0	24.25	13
1.142	3	0	164	0	1	0	42.25	14
2	1	0	127	0	0	1	24	15
2.75	7	1	73	0	1	0	33.5	15
1	4	0	116	0	0	1	16.25	12
2.75	1	0	126	0	1	0	35.5	12
2.285	7	0	70	1	0	0	18.25	16
3.769	0	0	72	1	0	0	27.25	13
3.187	0	0	113	1	1	1	24	16
1.846	0	0	67	1	1	1	25.75	16

A1. Continued

y	x1	x2	x3	4	x5	x6	x7	x8
3.25	0	0	63	0	1	0	21.5	12
3.625	1	0	110	0	1	0	60.25	16
3.769	1	0	107	1	1	1	33.75	13
2.846	4	0	116	0	1	0	38	13
3	1	0	89	0	1	0	45	12

A2. Semester II data used for analysis

Y	x1	x2	x3	x4	x5	x6	x7	x8
2.8	0	0	142	0	1	0	4.25	13
2.8	1	0	45	0	1	0	13.5	15
4	0	0	36	1	0	0	54	15
3.25	0	0	82	0	1	0	17.75	12
2.307	1	0	87	0	1	0	50.75	13
2	1	0	96	1	1	1	25.5	12
3.25	0	0	128	1	0	0	58.5	15
2.625	6	1	31	1	0	0	49.25	15
2.666	2	0	93	1	0	0	100.25	13
2.5	0	0	94	0	1	0	50.75	15
2	8	1	132	0	1	0	41.75	15
2	0	0	69	0	0	1	52.5	15
2.705	2	0	102	0	1	0	59.25	17
3.25	1	0	76	1	0	0	44.25	12
2.384	0	0	35	0	1	0	39.5	13
2.666	0	0	125	1	1	1	15	12
3.25	0	0	65	1	0	0	42	12
3.6	0	0	47	0	1	0	58	15
2.2	0	0	64	1	0	0	22.5	15
2.928	2	0	105	0	1	0	42.5	14
2.818	3	0	30	1	0	0	65	14
3.769	0	0	97	0	1	0	5.75	13
3.25	0	0	59	0	1	0	37.75	12
2.5	1	0	37	1	1	1	18.75	13
3.461	0	0	84	0	1	0	56	13
1.8	11	0	42	1	1	1	25	16
2.5	4	0	134	1	0	0	18	12
2.615	0	0	42	1	0	0	63.25	13
3	0	0	91	0	1	0	34.25	15
1.461	1	0	97	0	1	0	33.5	13
2.75	0	0	86	0	1	0	58	12
2.25	0	0	142	1	1	1	0	15
4	0	0	104	1	1	1	23.5	15
3.333	3	0	86	1	0	0	36.75	13
3.666	0	0	82	0	0	1	0	15
2.333	0	0	95	0	1	0	36	13
1.3	4	0	80	1	1	1	2.5	13
2.714	2	0	55	0	1	0	24	14
3	3	0	41	1	1	1	19.5	12
2	13	0	122	0	0	1	23	15
2	2	0	104	0	1	0	22.75	15

A2. Continued

Y	x1	x2	x3	x4	x5	x6	x7	x8
2.5	1	0	65	1	0	0	42.25	13
3.25	1	0	52	1	1	1	34	16
3.307	0	1	86	1	0	0	22.25	13
2.5	3	0	127	0	0	1	50	15
2.5	10	1	73	0	1	0	15.5	13
2.8	1	0	88	1	0	0	17.75	15
3.357	2	0	116	0	0	1	4.5	14
2.5	3	0	126	0	1	0	25.75	12
3.5	1	0	111	0	1	0	38.25	14
3	1	0	72	1	0	0	15.25	13
3.187	0	0	113	1	1	1	30.5	16
3.75	1	0	46	1	0	0	12	12
2.375	0	0	63	0	1	0	30	16
3.625	0	0	110	0	1	0	22.25	16
3.5	0	0	107	1	1	1	35.75	12
3.692	0	0	53	0	1	0	15	13
3.285	3	1	52	0	1	0	14	14
2.333	2	0	41	0	1	0	41.75	12
2.941	0	0	116	0	1	0	20.25	17
2.8	4	0	71	1	0	0	26.75	15

A3. Semester III data used for analysis

y	x1	x2	x3	x4	x5	x6	x7	x8
1.5	1	0	142	0	1	0	7.5	12
3.461	1	0	85	1	1	1	47	13
3.166	0	0	82	0	1	0	19.75	12
2	6	0	87	0	1	0	38.75	12
3.75	0	0	100	0	0	1	40	12
2.75	2	0	96	1	1	1	32	12
3.4	4	0	128	1	0	0	102.75	15
2.307	5	1	31	1	0	0	51.5	16
2.8	1	0	93	1	0	0	50.25	15
2.538	0	0	94	0	1	0	56	13
2.23	7	1	132	0	1	0	79.75	16
2.833	1	0	69	0	0	1	55.75	12
1.857	3	0	102	0	1	0	54.75	14
3.1	0	0	76	1	0	0	59	10
2	3	0	35	0	1	0	42	13
2	2	0	125	1	1	1	13.5	12
2	1	0	65	1	0	0	35.75	13
4	0	0	47	0	1	0	40	15
3.25	2	0	105	1	0	0	43.25	12
3.428	1	0	103	1	0	0	41.5	17
2.333	2	0	64	1	0	0	63.5	16
3	1	0	105	0	1	0	42.75	15
3	0	0	30	1	0	0	53.75	12
2.23	4	0	89	1	1	1	34.5	13
3.062	0	0	97	0	1	0	0	16
2.75	0	0	59	0	1	0	34	12
2.2	1	0	37	1	1	1	41.25	15
3.3	1	0	55	0	0	1	54.75	10
3.714	2	0	84	0	1	0	43.5	14
3.3	4	0	134	1	0	0	35	16
3.333	1	0	67	0	0	1	52	12
3.5	0	0	42	1	0	0	51.75	14
3.437	6	0	91	0	1	0	53.5	16
3.785	0	0	97	0	1	0	0	14
3	0	0	86	0	1	0	56.75	12
2.2	0	0	52	0	1	0	50.25	13
3.437	1	0	104	1	1	1	5.75	16
2.666	0	0	86	1	0	0	38.5	15
4	0	0	82	0	0	1	0	15
1.538	3	0	28	1	0	0	46.75	13
3.5	0	0	95	0	1	0	51.75	12

A3. Continued

Y	x1	x2	x3	x4	x5	x6	x7	x8
3.357	2	0	55	0	1	0	27.25	14
1.333	3	0	41	1	1	1	31.25	12
3.2	1	0	122	0	0	1	11.5	15
2.8	0	0	104	0	1	0	45.25	13
3.5	3	0	65	1	0	0	50.25	12
3.375	1	0	52	1	1	1	45.5	16
1.75	12	1	86	1	0	0	35	12
1.857	1	1	73	0	1	0	47.25	14
3	1	0	66	1	0	0	56.5	13
3.2	8	0	88	1	0	0	26.25	12
2.307	4	0	116	0	0	1	27.5	13
2.5	4	0	126	0	1	0	35.75	15
3	2	0	42	1	0	0	40.5	12
2.5	7	0	111	1	0	0	18.25	14
3.214	11	0	72	0	1	0	44.25	14
3	0	0	113	1	1	1	35	17
3.666	6	0	49	1	1	1	26.25	12
3.3	3	0	46	1	0	0	13.75	13
3	1	0	63	0	1	0	42.5	12
3.5	1	0	110	0	1	0	23.5	18
3.25	1	0	70	1	1	1	57	13
3	0	0	107	1	1	1	44.25	14
3.142	8	0	53	0	1	0	13.5	13
3	2	1	52	0	1	0	8.5	15
3.461	4	0	41	0	1	0	39.75	13
2.5	1	0	116	0	1	0	34.25	14
2.923	3	0	80	0	1	0	67	13
2.333	0	0	89	0	1	0	17.75	15
2.5	2	0	71	1	0	0	56.25	16

A4. Semester IV data used for analysis

Y	x1	x2	x3	x4	x5	x6	x7	x8
3	5	0	15	0	1	0	27.75	12
3.538	0	0	16	0	1	0	39	13
2.153	2	0	13	1	1	1	26.75	13
3.769	3	0	78	1	1	1	36.25	13
3.307	0	0	82	0	1	0	0	13
3.823	0	0	17	0	0	0	52.5	17
2.25	4	0	15	0	1	0	21.5	12
3.5	0	0	100	0	0	1	49	12
3	2	0	96	1	1	1	16.25	13
3.076	4	1	31	1	0	0	46	13
2.4	0	0	93	1	0	0	67.25	15
2	2	0	101	1	1	1	14	12
2.636	1	0	94	0	1	0	47	14
3	6	1	132	0	1	0	39.25	12
2.25	1	0	44	1	0	0	8	12
1.4	8	0	11	0	0	0	29.5	13
3.333	0	0	66	0	0	1	34.5	13
3	0	0	35	0	1	0	63.75	12
2	0	0	125	1	1	1	24	15
2.437	4	0	65	1	0	0	13.5	16
3	4	0	105	1	0	0	13	14
3.4	1	0	37	0	1	0	74.25	15
2.846	1	0	16	1	0	0	54.75	13
2.4	3	0	10	0	1	0	22.25	13
3	0	0	103	1	0	0	15	15
2	3	0	59	0	1	0	44.75	9
1	3	0	64	1	0	0	36.25	16
2.75	1	0	105	0	1	0	22.75	12
2.23	2	1	19	1	1	1	37	13
3.6	1	0	30	1	0	0	38	13
2.75	0	0	97	0	1	0	0	12
3.076	0	0	59	0	1	0	42.5	13
1.75	2	0	37	1	1	1	7	12
1.5	2	0	55	0	0	1	38.5	12
3.466	0	0	15	0	1	0	48.5	15
2.75	2	0	78	1	1	1	10.5	12
3.785	1	0	84	0	1	0	23.25	14
381.384	5	0	13	1	0	0	5.25	13
1.375	9	0	7	1	1	1	48.75	14
2	5	0	42	1	1	1	26	10
3.769	2	0	134	1	0	0	23	13

A4. Continued

Y	x1	x2	x3	x4	x5	x6	x7	x8
3.076	0	0	17	1	1	1	16.75	13
2.666	5	0	31	1	0	0	24.75	12
3.461	4	0	67	0	0	1	49.25	13
2.25	2	0	12	1	0	0	9.5	12
2.933	4	0	42	1	0	0	74.75	15
0.923	1	0	7	1	1	1	16.25	13
1.25	2	0	21	0	1	0	41	12
2.857	0	0	97	0	1	0	21.25	14
2	4	0	59	1	0	0	27.25	13
2.25	1	0	86	0	1	0	26.25	12
3.307	2	0	16	0	1	0	36	13
3.75	1	0	99	1	0	0	10.5	15
2.714	2	0	86	1	0	0	0.5	14
3	1	0	19	1	0	0	17.5	13
2.454	4	0	28	1	0	0	25.75	14
3	4	1	34	1	1	1	19	12
3.416	0	0	95	0	1	0	22.5	12
2.75	2	0	55	0	1	0	14	15
3.5	2	0	122	0	0	1	31	12
3.071	1	0	52	1	1	1	31.5	18
2.615	0	0	31	1	0	0	37.5	13
2.75	7	1	86	1	0	0	29.25	12
2.75	5	1	73	0	1	0	24	12
3.5	3	0	66	1	0	0	38.25	12
2.846	0	0	52	0	1	0	38.5	13
1.25	0	0	78	0	1	0	18.25	12
2	8	0	88	1	0	0	24.25	17
2.25	0	0	116	0	0	1	2	12
3.5	0	0	12	1	0	0	19.5	15
1.416	10	0	17	1	0	0	18.75	12
2.333	5	0	12	1	1	1	11.5	15
2.8	1	0	126	0	1	0	36	15
1.5	3	0	42	1	0	0	25	12
3	1	0	72	1	0	0	14	12
4	3	0	13	1	0	0	28.75	13
4	0	0	71	1	1	1	27	12
1.8	0	0	113	1	1	1	32.25	15
3.142	6	0	71	1	1	1	43.25	14
2.4	3	0	10	0	1	0	11.25	10
3.25	1	0	46	1	0	0	27.5	12
3.437	4	0	19	0	1	0	43.5	17

A4. Continued

Y	x1	x2	x3	x4	x5	x6	x7	x8
2.3	7	0	63	0	1	0	38.75	13
3.6	0	0	110	0	1	0	16	15
2.416	7	0	70	1	1	1	39.25	12
2.5	0	0	53	0	1	0	23	12
2.75	1	1	46	0	1	0	25	16
1.923	0	0	16	1	1	1	21.25	13
3.153	2	0	41	0	1	0	46	13
3	3	0	18	0	1	0	68.5	15
2.2	1	0	24	0	1	0	24.5	12
3.6	1	0	116	0	1	0	16.25	15
2.5	3	0	80	0	1	0	27	12
3.25	6	0	71	1	0	0	24.5	12
2.928	2	0	14	1	1	1	48.75	14
3.285	1	0	14	0	1	0	33.25	14

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