BENCHMARKING FOR THE FUTURE

by

Robert Benjamin Ceyanes

A Thesis submitted in Partial Fulfillment

of the Requirements for the Degree

Quantitative Educational Research and Assessment

Major Subject: Mathematics

West Texas A&M University

Canyon, Tx

May 2015

Approved:

Thesis Committee Chairman | Date

Thesis Committee Member | Date

Department Head | Date

Graduate School Dean | Date

ABSTRACT

This paper examines the benchmarking system currently in place for education in the United States of America and attempts to correct the disconnect educators and researchers feel toward the process. Studies and administrators claim that benchmarks are necessary to identify students at risk. Studies also show that teachers disagree. This study attempts to use statistical methods to allow educators to better utilize the benchmark data. The research identifies several limitations to current benchmark analyses and suggests recommendations to enhance them. The data indicates that a single multiple choice test is not an accurate measure of student knowledge. More information is needed to better predict student success on state mandated examinations.

ACKNOWLEDGEMENTS

The author would like to thank Pam Lockwood, Kristina Gill, and Daniel Seth for their contributions to this work. The author also expresses his unyielding love for his wife, Elena Ceyanes, and two daughters, Sara Moore and Allison Ceyanes. Without their support and encouragement this work would never have been completed.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

The “No Child Left Behind” Act became law in 2001. Since that time educators have worked diligently to effectively assess ongoing strategies to best educate all students. Considering the diverse levels of education that can be present in a classroom of students these goals are a challenge to achieve. The mainstreaming of students with disabilities as well as the introduction of state mandated assessments designed to close achievement gaps have enhanced the challenges to raise as many students as possible to the test level.

Educators have worked hard to respond to the resulting pressure. The U.S. teacher often experiences the strain of the urgency created by the public and subsequently politicians in charge of educational policy (Strauss, 2014). Administrators and teachers bear the burden of blame when a school system is deemed failing by the state. The typical state school system feels pressure as the state mandated testing window approaches. Strauss (2014) suggests that the “morale in the teaching profession is at a 20-year low.” The consequences of the testing are such that all campus personnel become involved in preparation for the state assessment to avoid the failing identification by the state. One of the responsibilities assigned to the classroom teacher is to identify students who may need additional assistance outside of the classroom to successfully pass the state assessment. Fluctuating state curriculum guidelines for essential knowledge and skills create a challenge in the development of "benchmark" examinations helpful in identifying students in need of assistance to meet the required standards. In Texas, a link to the "Subject Area Review" can be found at www. tea.texas.gov/curriculum/teks. State committees continuously review and update these guidelines for different grade levels. As a result, the author of this study, as an experienced teacher, has had to turn to the internet to acquire benchmark examinations from school districts in other states, despite slightly differing curriculum standards. The result can be ineffective or irrelevant assessment questions on an administered benchmark examination impacting the identification of challenged students. In other situations the administered benchmark may be well developed and provide useful information but not be fully utilized by the classroom teacher as a means of identifying deficient students (Bancroft, 2010). As the intended identifier for students in need of remediation, a benchmark examination provides segments of scores into which the instructor can categorize each student's performance. Inherent in this process is a struggle to select cutoff percentage scores that will provide the administration with a suggested list of students needing intervention.

Corporations world-wide currently and successfully use statistical and data mining strategies to predict customer buying habits using data obtained from surveys and logs of internet usage. One article in The New York Times quotes a Target employee's "hypothetical example. A fictional Target shopper, named Jenny Ward, is 23, lives in Atlanta and in March bought cocoa-butter lotion, a purse large enough to double as a diaper bag, zinc and magnesium supplements and a bright blue rug. Based on the company's statistical analysis there is an 87% chance that she is pregnant and that her delivery date is sometime in late August" (Duhigg, 2012, para. 49). The article recounts how the Target marketing team knew before the girls' father that she was pregnant.

If a business can use statistics to identify pregnant young women from a shopping list, can educators use the same techniques to identify students who are in danger of failing mandated state-wide examinations of required knowledge and skills? The research presented here will develop a logistic regression model to identify students for intervention purposes. Educational systems focus on currently developing more precise examinations; however, a more effective strategy may be stronger analysis of the currently used assessment tools. Targeting students for remediation utilizing a percentage score on a single examination is unlikely to be an optimal strategy. This is especially true given the impact of a limitless number of demographic and socio-economic variables over an ever shifting foundation of knowledge.

In this research, cohort groups of students in mathematics are administered the same unit and benchmark examinations throughout the academic year. Student responses to each administered question are considered the predictive variables. The response variable is whether or not a student passes the state examination on the first attempt. A predictive logistic regression model is developed to identify which questions from the administered examinations are relevant in a model to predict student success on a mandatory state assessment examination. This model is then tested for its predictive ability on a second year cohort of students. The developed model will be compared to the traditional percentage score only model currently in use to assess the feasibility of this method. The model will be deemed successful if it predicts student failure while identifying a set of questions and concepts key to student success. The expected outcome of a successful model is the reduction of class instructional time and the number of personnel dedicated to identification and remediation of at risk students.

CHAPTER 2

REVIEW OF THE LITERATURE

Standardized testing has been a hot topic since the No Child Left Behind Act (NCLB) of 2001 (Public Law 107-110, 2002). This law compels state-mandated testing throughout the country. Based on this testing, schools receive ratings and the associated negative stigma attached to a below standard rating. In response to the pressure politicians have placed on the school systems, educational administrations have implemented various techniques to avoid a failing label. One of these techniques is to use multiple benchmarks to gauge student progress and place students into interventions where necessary.

Standardized testing and the benchmark testing engendered by them are no strangers to criticism. The introduction of Common Core State Standards Initiative (CCSSI) in 2009 heightened the associated concerns. Of the forty-five states that originally participated in CCSSI, at least 8 have filed for repeals or conducted votes on the matter (Parker, 2013). A current look at the website corestandards.org officially indicates that Texas, Virginia, Alaska, Nebraska, Minnesota, Indiana, Oklahoma, and South Carolina are nonparticipants in CCSSI. Organizations such as fairtesting.org have started grass roots initiatives to campaign against the use of standardized exams. In addition to the political battles raging in town halls and state capitals across the nation, there is evidence that the scope of the problem is not limited to the United States. One study examines comparable issues between the United States and Namibia (Zeichner & Ndimande, 2008). Another study investigates the effects of nationally-mandated educational standards to England (Berliner, 2011).

Although few studies and scholarly publications have focused on the criticisms, there is no shortage of strong opinions. Though politicians who fight against the CCSSI focus on the constitutionality of the federal government dictating educational goals to states and the lack of public input allowed into the standards, the teachers and parents focus on the exams themselves. Valerie Strauss (2014) summarizes various issues in her article: "11 Problems Created by the Standardized Testing Obsession." Leading her list of concerns are instructional time lost, teaching to the test, test anxiety, narrowing the curriculum, and the issues associated with multiple choice tests (Strauss, 2014). The opinions are so strong that studies and surveys have been conducted on changing attitudes and the intensity of those attitudes against the CCSSI (Johnson J. , 2013: Aydeniz & Southerland, 2012: Barksdale-Ladd & Thomas, 2000). Berliner (2011) focuses on the issue of the narrowed curriculum. He laments that "most notable is the clear evidence that a great deal of the curriculum deemed desirable for our schools by a broad spectrum of citizens is instead curtailed in high stakes environments." Further he argues that "the test themselves are also not demanding of higher cognitive processes" (p. 299). With the focus on high-stakes standardized testing the effectiveness of the school systems' response through use of multiple benchmarks to identify interventions and direct curriculum does not seem to be adequately addressed.

Several studies did investigate this issue somewhat from 2001 – 2007, although most of the studies focused on fluency tests and reading (Good, Simmons, & Kame'enui, 2001: Stage & Jacobsen, 2001: Silbertglitt & Hintze, 2007). One study focused on math curriculum based measures (CBM) noted that "fewer studies have examined the relation between statewide achievement tests and math, especially math concepts and applications" (Keller-Margulis, Shapiro, & Hintze, 2008, p. 377). Keller-Margulis, Shapiro and Hintze (2008) demonstrated a positive correlation between curriculum based measures and student success on state-mandated assessments 1 and 2 years later. However, the authors did not address the issue of identifying student success for the current school year. One current study on the use of a math CBM to predict current year success used a measure of computational ability instead of problem based or standard based benchmarks (Shapiro, Keller, & Lutz, 2006).

In the face of this finding comes another study with opposite findings. Bancroft (2010) uses interviews with teachers and administrators to evaluate the productiveness of using benchmarks to improve scores on state assessments. This study concludes that "teachers viewed the benchmark tests as an interruption to their classroom instruction and as an inadequate means of measuring their students' progress." Further he argues that "ultimately, even the administration found the tests an inadequate assessment for their purposes" (Bancroft, 2010, p. 1). These views coincide with the observation that "an assessment anchored by benchmarks, in either sense of the word, should not be expected to yield a predictable curve of results … it is possible that very few products or performances - or even none at all – will match the benchmark performance" (Wiggins & McTighe, 2005, p. 338).

It is instructive to consider the disparity between conclusions of statistical studies and observations of teachers and administrators. Statistical evaluations of benchmarks produce a positive correlation to performances on future state-mandated tests while experienced teachers, administrators, and instructional methods experts claim they do not. An explanation may lie in the limitations found in the Keller-Margulis, Shapiro and Hintze (2008) study, in which the authors acknowledge that "the use of ROC curves, although offering a high degree of flexibility to the researcher also provide complete control of the levels of diagnostic accuracy desired and introduces some level of subjectivity into the selection of these cut scores" (p. 387). Indeed, both studies that identified statistical correlations between benchmark scores and future state-mandated assessment success adjusted the cut scores to determine the optimal statistical results. The disconnect between statistical findings and implementation is implied by these ideas. In particular, teachers are not afforded the opportunity to know in advance what these optimal cut scores should be while researchers looking in hindsight may be able to manipulate the situation to bolster their claims.

CHAPTER 3

METHODOLOGY

The study is comprised of four distinct segments. 1.) As seen in Table 1 (page 21) where only a portion of the testing is observed, cohorts of students preparing for a state mandated end of year examination will take numerous unit and benchmark tests throughout the year in preparation. This research will identify a single examination that provides the best list of questions to predict the student outcome on the high stakes state examination. 2.) A logistic regression model will then be developed from a single student cohort to predict the student outcome on the state examination with question data provided from the selected test. 3.) The logistic regression model developed will then be tested on data from a second cohort of students. The results of the Study Model are compared to the traditional method of using percentile based scores from the test to designate students for intervention. 4.) Conclusions will then be drawn from the comparative results. Various strategies are employed for each segment of this study. An overview of these methodologies is summarized in the remainder of this chapter.

School districts seek to identify students early in the academic year in need of additional assistance in order to successfully complete a high stakes state examination. Identifying a single examination that provides the greatest information on student outcomes would be ideal, rather than attempting to combine information from numerous tests. However, the test selected will need to provide the most complete information regarding a student's knowledge and likelihood to successfully pass a state examination. Several options are available to investigate which examinations provide the best predictor questions. Two competing options are 1.) a question by question investigation, utilizing a two-sample z test for the difference between two proportions; and 2.) a question by question examination of information gain provided by the question.

Generally preferred by statisticians, the two-sample z test determines if there exists for each question a statistically significant difference in the proportion of successes and failures. Proportions that are meaningful to compare in this setting are considering only the students who answered the predictor examination question correctly, the proportion of students who successfully passed the state examination versus the proportion who did not pass. This two-sample z test compares the proportion of students where the question accurately predicted a passing score on the state-wide examination versus the proportion where the question missed indicates failures on the examination. The assumptions for the two-sample z test are that data is from a random sample, is normally distributed, and the observations are independent. Using a two-sample z test for the difference between two proportions, with a pooled estimator for the proportion P_c, presumption of equal variances, has the form

$$z = \frac{(\hat{P}_1 - \hat{P}_2) - 0}{\sqrt{\frac{\hat{P}_C * (1 - \hat{P}_C)}{n_1} + \frac{\hat{P}_C * (1 - \hat{P}_C)}{n_2}}} . \tag{1}$$

A z statistic of 1.65 or higher will correspond to a p-value of .05. This value has been the hallmark value of significance for over 90 years since R. A. Fisher first employed the method. Although, Valen Johnson from Texas A&M disputes this value in favor of a stronger (lower) p-value in his recent paper "Revised Standards for Statistical Evidence" (Johnson V. E., 2013). However, when multiple tests are run, a stronger p-value is consistently recommended. The Bonferroni correction is widely used to adjust for multiple tests. This method which simply divides the relative p-score by the number of tests conducted was first advocated statistically by Olive Jean Dunn in 1961 (Dunn, 1961). Using a range of Z statistics helps to categorize the significance levels of questions on multiple tests. Tests can then be evaluated by how many questions they possess with z statistic of over 1.65 or any other determined score a researcher believes will help distinguish one test from another.

Entropy is another method to consider for distinguishing tests with stronger predictor questions. This procedure generally favored by computer scientists and data miners, determines information gain from each of the considered predictor variables. First introduced by Claude E. Shannon, the father of information theory, in a landmark paper published in 1948 by The Bell System Technical Journal, entropy uses logarithms to rate how much information is gained from the variable (Shannon, 1948). Shannon, influenced by Alan Turing and George Boole, discovered while working in communications, that Boolean logic, specifically a base 2 logarithm can be used to separate a signal from the underlying noise. The mathematics behind the algorithm forms the basis for information theory. How much of the information received is the actual message and how much is noise can be applied to any information gained. If you have a piece of information (a predictor variable), information entropy separates out how often that information points to the outcome (the message) and separates out the false positives (the noise). Shannon explains "The logarithmic measure is more convenient for various reasons:

1. It is practically more useful. Parameters of engineering importance … tend to vary linearly with the logarithm of the number of possibilities…

2. It is nearer to our intuitive feeling as to the proper measure…

3. It is mathematically more suitable. Many of the limiting operations are simple in terms of the logarithm …" (Shannon, 1948, p. 379).

Another advantage to use of logarithms is the property that transforms complex operations into addition and subtraction. Thus, each new piece of information (predictor variable) adds information into the system. The first step is to find the entropy weight when the predictor points true with

$$(2) \qquad -\left[\frac{\text{True positive}}{\text{predictor true}}\log_2\frac{\text{True positive}}{\text{predictor true}}+\frac{\text{False positive}}{\text{predictor true}}\log_2\frac{\text{False positive}}{\text{predictor true}}\right].$$

Next, find the entropy weight when the predictor points false

$$(3) \qquad -\left[\frac{\text{false negative}}{\text{predictor false}}\log_2\frac{\text{false negative}}{\text{predictor false}}+\frac{\text{true negative}}{\text{predictor false}}\log_2\frac{\text{true negative}}{\text{predictor false}}.\right]$$

The results from equations (2) and (3) are used to provide a total weighted entropy,

$$(4) \qquad -\left[\frac{predictor\ true}{total\ sample} * result\ equation\ (2) + \frac{predictor\ false}{total\ sample} *\right.$$

$$\left. result\ equation\ 3. \right]$$

Next we find the possible information gain for the entire system from

$$(5) \qquad -\left[\frac{all\ positives}{total\ sample}\log_2\frac{all\ positives}{total\ sample} + \frac{all\ negatives}{total\ sample}\log_2\frac{all\ negatives}{total\ sample}\right].$$

The final step is to subtract the total weighted entropy, equation (4), from the total information gained, equation (5) to find the information gained by the single question. (Shannon, 1948, pp. 11-12)

The two-sample Z test and the information entropy method often, but not always, provide the same results. This is an example of two distinct disciplines, statistics and computer science, examining the same problem, yet formulating two completely different approaches that largely determine at the same result. This is a nice example of the beauty and elegance of mathematics. The information from both of these methods will assist this study in determining which of the many cohort examinations are likely to provide meaningful data, thus simulating an unbiased experiment. This methodology will drive the selection of the examination which will be used to construct a predictive logistic regression model.

Following determination of the examination that provides the best student information, the work moves to the development of a predictive logistic regression model for the examination results of a selected student cohort. The set of initial predictive variables for this model are identified for the previously selected examination. The outcome variable for the model will be the student result, pass or fail, on a state mandated high stakes examination. The specific score a student earns on a state mandated test is irrelevant to the scope of this research. The outcome variable takes on only one of two values – pass or fail. Logistic models evaluate discrete binary outcomes from continuous or discrete predictor variables. This characteristic is the primary reason this methodology was selected.

The logistic regression model is based on the logit function and its inverse

(6) $$\mathrm{logit}^{-1}(\mathrm{x}) = \frac{\mathrm{e}^{\mathrm{x}}}{1+\mathrm{e}^{\mathrm{x}}}.$$

The model presumes that the logit of the probability distribution function of a binary outcome variable Y can be estimated by a linear function of its predictor variables:

(7) $$\mathrm{P(Y|X)} = \mathrm{logit}^{-1}(\beta_0 + \beta_1 x_1 + \cdots \beta_n x_n) = \frac{e^{\beta_0+\beta_1 x_1 \cdots \beta_n x_n}}{1+e^{\beta_0+\beta_1 x_1 \cdots \beta_n x_n}},$$

where $X = (x_1, x_2, \dots, x_n)$ is the vector of predictor variables (Hosmer & Lemeshow, 2000).

The predictor variables are assumed to be independent in this model. The logistic model development for this research was completed with the software platform R and its use of the generalized linear model package under the binary family logit subcommand. This program uses iterations of the log likelihood function to estimate the coefficients for the linear function of the predictor variables based on values of the outcome and predictor variables found in the data. The program outputs values of the coefficients, the standard deviation of these coefficients, the z score and the p-value associated with significance of the predictive variable.

Initially, a univariate logistic regression model for the outcome is completed for each predictor variable. This helps to eliminate predictor variables with low association to the outcome, as indicated with a high p-value or low level of statistical significance. A logistic regression model is then developed with all the variables determined to have a good association with the outcome variable from the univariate analysis. A three step systematic elimination of predictor variables is then conducted to determine the set of variables present in the final model. The procedure removes the variable with the largest p-value, and model formed again with this variable eliminated. The residuals or errors reported by the program and the coefficients on the remaining variables are then examined. The residuals should follow a chi-squared probability function with one degree of freedom for each variable removed from the model. The coefficients on the remaining variables should not change by more than 25% from their values in the previous model. If a deviation is observed from either of these stipulations, the eliminated variable should be returned to the model. The procedure is repeated until the remaining variables are significant to a p-value of less than 0.05 or one of the other conditions is true. The predictive variables that remain after this process is complete and the resulting model that is developed form the Study Model.

Once the logistic model to predict student performance on a high stakes state-wide examination is developed, this Study Model will be used to predict student scores on the state-wide examination for a 2nd cohort of students. The SAS System and its

Classification procedure will be utilized to calculate these predictions on student performance (Hosmer & Lemeshow, 2000, p. 162). The SAS Classification procedure runs a developed statistical model and compares the predicted outcome against the actual results to determine if the model makes accurate predictions for the outcome variable using all available cutoff scores. Various models can be compared with the SAS Classification procedure to determine which model makes the most accurate predictions.

Additional methodology is also used to assess the fit of the developed logistic regression models. The Akaike Information Criteria (AIC) value for comparing the models results is an output of the R generalize linear regression package. This statistic developed by Akaike and Sugiura was introduced for comparing linear regression models in 1978 (Sugiura, 1978) . The AIC statistic is a balance between improving goodness of fit and including too many variables. The statistic rewards a model for fitting the data well, but also penalizes it for including too many parameters. The lower the value of the AIC statistic, the better the model conservatively fits the data. Another diagnostic for comparing binary outcome models advocated by Spackman is the Receiver Operation Characteristic (ROC) curve. The ROC curve visually displays the true positive rate of the model, termed *sensitivity*, to the false positive rate of the model, 1 – *specificity*. Points above the diagonal of the ROC plot indicate a good classification by the developed model. Points below the diagonal indicate poor classifications by the model (Spackman, 1989). R squared statistics in general select the best fit model by examining the portion of the variance in the outcome variable explained by the model; therefore the higher the value, the better the model fits the data (Starnes, Yates, & Moore, 2012). Allison recommends the use “all of these GOF tests” (Goodness of Fit) that can be applied using his recommended algorithm provided in “Measures of Fit for Logistic Regression” (Allison, 2014). Since there is a lack of consensus of agreement in the literature regarding the best measures of Goodness of Fit, each of these methods will be applied and examined for the developed logistic regression model.

Each question on the selected examination becomes a possible candidate to be a predictive variable. The predictive variables are coded in the database with a 0 for an incorrect response and a 1 for a correct response. The freeware software program R is used to construct the logistic regression model. The R database recognizes the outcome variable as a factor with only two possibilities. All other information needs to be deleted leaving no identification marks. Students who miss either the predictive test or the state assessment are left out of the study.

CHAPTER 4

SELECTION OF SUBJECTS

The original study population is a convenience sample of students at an independent school district in the Texas Panhandle region. The available data to the researcher includes both freshman and sophomore high school cohorts and 4th grade students at the elementary level. The participating curriculum directors agreed to give the same benchmark to those grade levels for two consecutive years. Under the belief that this strategy will be successful for any age group whose cohorts operate within similar environments, the three classes were subjected to the treatment with the hopes that at least one environment will provide a suitable research setting and subsequent data for analysis. This tactic proves to be invaluable as examined later in the chapter.

The four elementary schools in the study ISD are feeders to the Junior High school, which is the sole feeder to the High school. Of the four elementary schools, three are designated Title 1 by the federal government. A Title 1 school is a school who qualifies to receive federal funds because they are deemed higher than average poverty by their participation in the free and reduced lunch program. The High school also qualifies for Title 1 designation by virtue of the Junior High status; although the school recently opted out of this designation due to lack of free and reduced lunch participation. The Junior

High has a 58% free and reduced lunch rate for the student population. The district demographics show a population of 55% White, 39% Hispanic, 4% Black, 1% American Indian, and 0 % Asian (Greatschools.org).

Applying Methods for Exam Selection

Although this research utilizes a convenience sample, the model mitigates the lurking variables by using successive cohort groups who are administered the same examinations and are instructed in the same environment. The available data on the High school population includes four examinations from Algebra I and five examinations from Geometry administered at the study ISD. The elementary level population of fourth graders has data available on five mathematics tests from fourth grade administered at the ISD. All the tests are administered during the 2012-2013 and 2013-2014 school years.

The outcome variable of this study is the binary student outcome, success or failure, on the State of Texas Assessments of Academic Readiness (STAAR) or the End of Course (EOC) mathematics test for each student. The predictive variables are the questions on the benchmark or unit examinations. The premise of this research is that the questions administered on the benchmark or unit examinations can predict student outcome on the STAAR or EOC. Should the hypothesis prove to be true, these examinations administered earlier in the academic year will allow schools ample opportunity to select students for intervention and intervene in a timely manner.

The data is originally recorded in an excel spreadsheet. The data is then used to evaluate the question data provided by each examination in order to determine the optimal examination instrument. The methodology for determining the optimal testing instrument was previously discussed in Chapter 3. Initially a two sample proportion Z-test is utilized to examine all questions on each testing instrument. For each examination question, students who successfully answered the question and successfully passed the state examination, comparing the proportion of these students who then are compared to those that successfully answered the question but did not pass the state examination. Therefore, the calculated Z-scores effectively rate each question for its ability to predict whether a student passes the EOC administered in April 2013. Table 1 below displays the outcomes of the two-sample z-score analysis. Included are, in the last three columns, the number of questions on each exam with Z-scores above 1.65, 3.0, and 3.5, respectively. Henceforth in this document, the fourth grade state mandated examination will be referred to as the STAAR and the Geometry and Algebra I state mandated examinations as the Geometry and Algebra EOCs. This terminology is consistent with that used by the State of Texas educational system. Appendix 1 contains the data spreadsheets for reference. Closer examination of the set of predictor test questions versus the STAAR/EOC student outcome data indicate that the standard significance level of 0.05 with an associated Z-score of 1.65 does not supply the predictive power needed for the research goal. Ideally, each included math question should have some significance in relation to whether a student passes the STAAR/EOC; however, the research goal is to identify exam questions which indicate strongly which students will pass the STAAR/EOC. A Z-score of over 3.5 provides a much better predictor variable. Additional evidence for favoring a 3.5 Z-score comes from utilizing the Bonferroni

Table 1 : Evaluating Test Questions

Algebra I	**Pass, fail, absent, total**	**% of Students Question Incorrect**	**Number of questions**	**% of questions Z score above 1.65**	**% of questions Z score above 3.0**	**% of questions Z score above 3.5**
Unit 1 test	121, 27 13, 148	18.2%	6	84.3% (5/6)	16.6% (1/6)	0% (0/6)
Unit 3 test	113,24 12,137	17.5%	22	0% (0/22)	0% (0/7)	0% (0/7)
Unit 4 test	38,14 7,152	26.9%	9	11.1% (1/7)	0% (0/7)	0% (0/7)
Semester test	124,22 12,146	15.1%	30	30% (9/30)	3% (1/30)	0% (0/30)
Geometry	**Pass, fail, absent, total**	**% of Students Question Incorrect**	**Number of questions**	**% of questions Z score above 1.65**	**% of questions Z score above 3.0**	**% of questions Z score above 3.5**
Unit 1 test	153,16 36,169	9.5%	15	0% (0/15)	0% (0/15)	0% (0/15)
Unit 2 test	142, 17 20,159	10.7%	30	70% (21/30)	33% (20/30)	17% (5/30)
Unit 4 test	119,12 19,131	9.2%	16	50% (8/16)	6% (1/16)	6% (1/16)
Unit 5 test	80,8 8,88	9.1%	12	58% (7/12)	25% (3/12)	17% (2/12)
Semester test	164,22 23,186	11.8%	35	60% (21/35)	17% (6/35)	11% (4/35)
4th Grade	**Pass, fail, absent, total**	**% of Students Question Incorrect**	**Number of questions**	**% of questions Z score above 1.65**	**% of questions Z score above 3.0**	**% of questions Z score above 3.5**
Unit 1 test	177,79 19,256	30.9%	35	82.9% (29/35)	62.9% (22/35)	54.3% (19/35)
2nd 6 wks test	175, 84 19,259	32.4%	20	65% (13/20)	45% (9/20)	40% (8/20)
Unit 6 test	89,48 11,137	35%	14	14.3% (2/14)	0% (0/14)	0% (0/14)
Unit 7 test	89,49 9,138	35.5%	27	25.9% (7/27)	3.7% (1/27)	0% (0/27)
Feb Benchmark	174,85 5,259	32.8%	48	67% (32/48)	33% (16/48)	31.2% (15/48)

correction. There are a total of 319 examination questions. The Bonferroni correction in this case would justify a significance level of 0.05/319 = .000157.

The information gain found through Shannon's entropy process is included in the full examination question summary table found in Appendix 1. The study herein chooses to use the two-sample z-statistic to categorize questions and rank the tests for two reasons. The thesis audience (non-engineering and science experts) will more likely recognize the z-statistic over the more technical information gain statistic. In addition, information gain from entropy did not add any new information to the selection process. Indeed, investigation of the entropy collaborates the results. A personal motivation for incorporating the separate methods is to celebrate the beauty of two separate disciplines that resolve the same problem with very similar results. Questions that have an information gain lower than 0.01 are generally not significant at the 1.65 z-statistic level. The questions containing an information gain between 0.01 and 0.026 typically have a z-value between 1.65 and 3.0, while those questions with a higher than 0.033 information gained correspond to questions with a z-value greater than 3.5. Although the scale slides slightly with the number of questions in the corresponding tests, the rankings have few exceptions. This is nothing short of remarkable.

The Table 1 summary statistics of examination data suggest the elimination of several examinations from consideration while also indicating sources of bias in the study. All four of the Algebra examinations appear dramatically subpar when compared to the Geometry and 4th grade examinations, suggesting further investigation into the reasons for the difference. The administration of the Algebra I examinations excluded a subpopulation of the Algebra I cohort. The students deemed likely to fail the Algebra I EOC, based on their academic performance the previous year, were enrolled in a foundations class. These students were not administered the same examinations as the remainder of the Algebra I cohort. This strategy led to a significant bias in the results. A similar concern was identified in the Geometry student cohort. The examination results omit a subpopulation of honors students who did not participate in the unit examinations. The fourth grade examinations labeled Unit 6 Test and Unit 7 Test exhibited similar patterns of lack of significance. Upon investigation it was found that two of the schools in the lower income part of the district did not record their results for these exams.

Resulting Population and Variables

The preliminary analysis of the 4th grade data reveals three exams with significant questions. The 4th grade and Geometry data reveal examinations with questions providing quality information gain, giving us the ability to rule out that this modeling approach will only work for a certain grade level or a particular school. High school and Elementary can both benefit from the process. A preliminary conclusion that results from the analysis in this study follows: in order for this methodology to provide accurate predictions of student STAAR/EOC results based on benchmark or unit examinations, <u>all</u> students must take the unit and benchmark examinations and have their results included in the data.

In this research setting the study ISD committed to requiring all students enrolled in 4th grade mathematics, Geometry, and Algebra I to complete the same unit and benchmark examinations. However, as the study was conducted, subpopulation groups were exempt from the examinations providing the data. The researcher has observed this practice as a classroom teacher. The administration then unknowing uses incomplete results to form judgments regarding which students need remediation, based on what seems to be solid rational. Higher level students obviously will not need the interventions and the low level students obviously will. However, removal of the top and bottom deciles the population studied removes crucial data from the model. The model is now unable to identify the critical questions that the top decile of student understands that the lower does not. In summary, the research to this point seems to indicate that questions can be used as predictors for STAAR/EOC success in different age groups in different settings. However meaningful predictions require the condition that no sub-groups in the cohort are exempt from providing data to the study.

Further investigation based on the two-sample Z-score analysis of all examinations reveal the only tests administered to the full grade level cohort are: the Geometry semester test, Fourth Grade Unit One test, Fourth Grade 2nd Six Weeks test, and the Fourth Grade February benchmark. However, legislative changes during the conduct of this research further limited the diversity of the study population. The Texas Legislature decided to eliminate the EOC test in Geometry as a requirement for high school graduation in 2013. The third phase of this study will be to test of the developed logistic regression model on a second cohort of students. Students taking the EOC in Geometry the following year would know it was no longer a requirement for graduation, leading to an uncontrollable confounding variable. In addition, communication with the elementary math coordinators at the study ISD indicated the second six weeks test would not be administered to fourth graders in the second year cohort. The Fourth Grade Unit One examination, mislabeled by the testing coordinator, was actually a fall benchmark given the week before Thanksgiving. This examination was administered on both years, at the same point in the semester. All of the questions on the examination except questions #4 and #20 were the same with no changes. The Fourth Grade Fall Benchmark examination included 34 questions and was indicated by the two-sample z-score and information gain strategies as the highest ranked examination administered to the initial study cohorts. With many of the possible external variables held constant by the educational environment, this examination is an optimal choice for the study.

CHAPTER 5

THE TRADITIONAL MODEL

Traditional models for identifying students at risk of not successfully completing state mandated standardized examinations rely upon school districts administering benchmark examinations throughout the academic year. The goal of benchmark examinations is to identify at risk students by setting a cutoff examination score. All students scoring at or below the cutoff benchmark score are classified as at risk for failing the statewide examination. This method of identifying at risk students has limitations. How do school districts determine the cutoff score on the benchmark? The problem goes beyond the state of Texas as other states such as Florida and North Carolina are adopting new programs to use instead of Benchmark examinations (Parker, 2013). Recently, many of the states who have adopted the Common Core standards are choosing against the use of the benchmarks provided, as these states face the first round of Common Core testing scheduled for the 2014-2015 school year (Parker, 2013). A percentage score of 70 is typically used as a cutoff score on benchmark and standardized exams. The Texas Education Agency (TEA) determines passing level on the statewide assessment based on a scaled student score. The State of Texas does not publish the method used to determine these scaled scores. In the past, when new state standards and assessments are implemented, the passing scores are gradually increased over a few years. With the current edition of standardized testing (grade-level STAAR and EOC), the passing scores were to go through three phases starting in consecutive years. There has been much political strife as parents and school districts question the rigor and validity of the state assessments being implemented. In the 2014-2015 school year, this resulted in the TEA continuing to use the phase one standards for a fourth consecutive year. In addition, each grade level STAAR or EOC is evaluated at a different level. For example, Phase one for Algebra I is equivalent to approximately 37 percent or 20 out of 54 questions correct necessary to pass. Meanwhile in fourth grade, the standard stands at approximately 60 percent, or 29 out of 48 questions correct required to earn a passing score. Justification provided by the TEA states that, "the final recommended standards are the values that resulted from meetings with hundreds of Texas educators … During the process of making these recommendations, Texas educators considered empirical data related to STAAR and other tests, as well as the goal of preparing students for success beyond high school" (Texas Education Agency, 2013).

This lack of consistency and seeming randomness of scaled scores creates a dilemma for many teachers. As they choose benchmark cutoff scores, they must factor in which students they perceive, based on their own assessment, need interventions, while excluding those that they perceive do not. This decided modification is the only option other than the 70% standard that this experienced teacher was able to see.

Table 2 below shows results from the research setting ISD using the traditional benchmark testing method with a set percent score as the cutoff. All teachers are expected to identify struggling students with the preferred 70% cutoff score, but no stringent across the board system was implemented. Since a standardized score and/or method was not used, there is likely a variance between each teacher's preferred cutoff score or use of a cutoff score at all. This fact illustrates a complication to the evaluation of the benchmark process. Ethics prevents requiring the teachers to not perform any interventions for the study cohorts. These interventions continue throughout the process of this research and undoubtedly present a lurking variable that cannot ethically be eliminated by this study. By comparing models under the same conditions with different cohorts we mitigate this conflict, but do not completely eliminate it.

Sub-tables in Table 2 were constructed with specified cut-scores to evaluate the traditional model under various cut-score conditions. Simple predict and table commands in the R program calculates the results displayed in the table. The highlighted numbers on the chart are the number of failures correctly identified and the total number of students needed to be assigned to remediation based on this process. In order to identify 75 out of the 79 failing students, a cutoff score of 70% would need to be utilized, assigning 173 out of the 256 students (67.6%) to remediation. The cut-score of 65 improves the number of affected students at a cost of correctly identifying only 66 out of 79 failures (83.5%) while assigning to remediation 120 of the 256 students (46.9%). As the cut-score drops to 60, 55, and 50, the number of students assigned to remediation enters acceptable levels, but at a cost of only correctly identifying 76.0%, 65.8%, and 43.0%, of students at risk of not successfully completing state-wide examinations, respectively. An additional limitation and challenge of the traditional method of identifying at risk students is the cost of remediation to the school district. A usual rate for tutoring is $30 an hour which

Table 2 : Cutoff Scores

EOC result	Failed Benchmark at 50%	Passed Benchmark at 50%	Total EOC Results
Failed	**34**	45	79
Passed	11	166	177
Total	**45**	**211**	**256**
Intervention?	**Yes**	**No**	

EOC result	Failed Benchmark at 55%	Passed Benchmark at 55%	Total EOC Results
Failed	**52**	27	79
Passed	25	152	177
Total	**77**	**179**	**256**
Intervention?	**Yes**	**No**	

EOC result	Failed Benchmark at 60%	Passed Benchmark at 60%	Total EOC Results
Failed	**60**	19	79
Passed	43	134	177
Total	**103**	**153**	**256**
Intervention?	**Yes**	**No**	

EOC result	Failed Benchmark at 65%	Passed Benchmark at 65%	Total EOC Results
Failed	**66**	13	79
Passed	54	123	177
Total	**120**	**136**	**256**
Intervention?	**Yes**	**No**	

EOC result	Failed Benchmark at 70%	Passed Benchmark at 70%	Total EOC Results
Failed	**75**	4	79
Passed	98	79	177
Total	**173**	**83**	**256**
Intervention?	**Yes**	**No**	

may be a concern for school districts in less fortunate populations. Limited school funding and the unknown factor of how many students will require remediation make it difficult for school districts to allocate resources. A school district would need to determine, prior to the academic year, the number of students the budget can afford to serve as well as allocate an individual instructor either during normal hours or after school. The impact is a limit on the number of students recommended to remediation.

There are philosophies concerning which students are recommended to remediation and which students are not. A "bubble kid" philosophy states that the limited available resources should be allocated to students that have the best chance to pass the exam. A new cut-score is selected to identify those students that fall into the "bubble kids" group. The students who score below the upper "passing" score, but above the lower "bubble" score should have a better chance to pass the exam than those below the "bubble score".

The formerly mentioned bias created by the ISD instructors selecting individual cut-off scores for remediation identification or hand selecting students can be exasperated by the "bubble kid" theology. For example, consider a hypothetical case where a uniform system was in place with the above data. Of the 173 students that did not earn a percent score of 70 on the benchmark, 77 learners who scored lower than a 55 will not be classified as "bubble kids" and will be left off the intervention rosters. The final number for intervention becomes a manageable 96 spread among the 4 elementary schools.

Another philosophy is one where the school district remediates until the resources are expended. The district looks at the resources it possesses, and provides assistance to as many students as it has resources working from the bottom up. Once the resources are exhausted, the remaining students are left out of the intervention process. By using the traditional cut-score model, a school district limits itself to two unattractive choices. If a school system only has resources to service 40% of the students in special interventions, the choice in this set of data is to set a cut score of 60 and miss 24.1% (19 out of 79) of the failures, or to use a bubble group scheme where two cutoff scores are employed. One cutoff score decides who needs intervention, and one decides who is beyond help and not worth expending resources. The “bubble” group scenario most likely utilized by the study ISD shows that 23 of the 96 students with the interventions failed anyway, and 25 of the 77 students denied interventions passed regardless of the omission. This type of inconsistency fuels the motivation for this study. This research seeks to develop a model that will accurately identify students in need of remediation so that institutional resources are not expended on those who do not need the remediation.

CHAPTER 6

MODEL CONSTRUCTION

Logistic regression will be used in this chapter to develop a statistical model that predicts a student successfully passing the STAAR Examination in 4th grade mathematics. The outcome variable of this model is whether or not a student in the course passes the STAAR. This is a binary random variable, a value of 0 indicating a student did not pass and a value of 1 indicating a student passing the STAAR. Logistic regression is the appropriate model for a binary outcome variable.

The predictor variables for this model are questions from the Unit 1 benchmark examination identified in Chapter 4 as the optimal examination after applying data mining techniques to all administered examinations. Each will be binary in nature coded as 0 if a student incorrectly answered the question and 1 if the student answered the question correctly. The goal of this research is to find the model that correctly predicts failures on the STAAR examination while limiting the number of incorrectly predicted student failures. As expressed in Chapter 4, the Fourth Grade Unit 1 Benchmark test provides the study with the best predictive questions. Weaknesses of the traditional model for identifying students at risk for failing a state-mandated test were indicated in Chapter 5 with the example analysis results from this model displayed in Table 2. A new model is sought using statistical tools that will more accurately predict student failure.

Chapter 4 discussed the challenges to the new study methodology. One such challenge was changes made to the administered examinations from one year to the next based on curriculum changes or determination by classroom teachers that a question was not effective. Questions 4 and 20 are removed from the list of available predictors provided by the Unit 1 Benchmark examination because these two questions were changed from Year 1 to Year 2. Ambiguity in the questions informed the decision by the classroom instructors to alter these questions. A model for the first year could still be crafted, but it will be invalidated for the Year 2 cohort group if these two questions are included. For the questions remaining on the Unit 1 Benchmark, consistent from Year 1 to Year 2 a univariate test is performed.

The univariate analysis of each predictor question indicates the questions' relationship to the outcome variable of the study. The results of this univariate analysis for all predictive questions considered are shown in Appendix 3. Question 15 and question 12 are the first prediction questions to be removed from consideration based on the univariate analysis results. Most of the questions exhibit a p-value below 0.000001, a few scored between 0.01 and 0.20, and questions 15 and 12 are the exceptions with p-values of 0.848 and 0.309 respectively. Table 3 below represents the output from the summary procedure in the R programming language after running a generalized linear model (glm) with the logistics model selection using the remaining questions on the 2013 cohort group.

The model development then continues through a step wise procedure removing the predictor question with the highest p-score (lowest correlation) and rerunning the general

Table 3 : Original Model Question Analysis

Coefficients: Question	Estimate	Standard error	Z value	P-value
Intercept	-6.19517	1.50810	-4.108	.0000399
Question 1	0.33691	0.51553	0.654	0.51553
Question 2	1.36876	0.45553	3.005	0.00266
Question 3	-0.66586	0.46787	-1.423	0.15469
Question 5	0.77830	0.45978	1.693	0.09050
Question 6	0.53330	0.51288	1.040	0.29842
Question 7	0.81595	0.43164	1.890	0.05871
Question 8	0.41816	0.45407	0.921	0.35710
Question 9	-0.44505	0.46578	-0.955	0.33933
Question 10	0.53407	0.52842	1.011	0.31216
Question 11	0.39487	0.72159	0.547	0.58423
Question 13	0.73939	0.41725	1.772	0.07638
Question 14	0.53074	0.43271	1.227	0.21999
Question 16	-0.26947	0.70497	-0.382	0.70228
Question 17	0.99605	0413306.	2.411	0.01589
Question 18	0.92953	0.63650	1.460	0.14419
Question 19	-0.16957	0.50644	-0.335	0.73775
Question 21	0.49989	0.67029	0.746	0.45580
Question 22	0.83416	0.92232	0.904	0.36577
Question 23	-0.01251	0.497300	-0.025	0..97993
Question 24	0.41606	0.53550	0.777	0.43719
Question 25	0.65679	0.44154	1.488	0.13688
Question 26	0.32520	0.52733	0.617	0.53744
Question 27	-0.62367	0.43928	-1.420	0.15568
Question 28	0.61859	0.45549	1.358	0.17444
Question 29	0.31114	0.44030	0.707	0.47978
Question 30	-0.36460	0.42700	-0.854	0.39318
Question 31	1.46355	0.49931	2.931	0.00338
Question 32	0.27667	0.50917	0.543	0.58686
Question 33	-0.37208	0.42063	-0.885	0.37638
Question 34	-0.16839	0.44725	-0.377	0.70654
Null deviance	**Df**	**Residual deviance**	**Df**	**AIC**
316.40	255	183.74	225	245.74

* Chi squared p-value for 183.27 with 224 degrees of freedom is .02035031

linear model and the corresponding summary procedure. The reduced model is then checked for significance by subtracting the new residual deviance from the residual deviance of the previous model and running a new chi-squared test with degree of freedom equal to one. If the corresponding p-value is greater than .20, indicating the reduced model did not eliminate any valuable information, the procedure continues. The model coefficients are next considered against the Full Model to ensure that the predictor coefficients do not change by more than around twenty five percent. The process is repeated moving on to consideration of the predictive question with the next highest p-score. Following questions are removed in order until the process reaches one of three concluding states. The process terminates when the remaining questions exhibiting a p-value of less than 0.05. Other states of termination are when the chi-square test of fit or coefficient change conditions are violated. The order of question removal is as follows: 23, 19, 34, 16, 11, 32, 29, 9, 1, 24, 26, 21, 33, 22, 30, 8, 10, 3, 6, 27, 25, 18, 7, and 5.

Table 4 : Study Model Question Analysis

Coefficients: Question	Estimate	Standard Error	Z-score	P-value
Intercept	-3.8871	0.6898	-5.635	1.75 e-08
Question 2	1.3557	0.3768	3.598	0.000321
Question 13	0.8240	0.3692	2.232	0.025609
Question 14	0.6677	0.3769	1.771	0.076522
Question 17	0.9116	0.3703	2.462	0.013819
Question 28	0.7095	0.3927	1.807	0.070817
Question 31	1.2740	0.3975	3.205	0.001349
Question 5	0.6804	0.4048	1.681	0.092755
Question 7	0.6733	0.3869	1.749	0.080308
Question 18	0.8673	0.5429	1.598	0.110132
Null deviance	Df	Residual deviance	Df	AIC
316.40	255	198.98	246	218.98

* Chi squared p-value for 198.98 with 246 degrees of freedom is .01248981

Questions 2, 13, 14, 17, 28, 31, 5, 7 and 18 remain as predictive variables to produce the results displayed in Table 4. Obvious from the p-values displayed in Table 4, the predictive variable selection method did not conclude with all the p-values under the target 0.05. The procedure finished with the violation of the coefficient change condition. Table 5 illustrates a violation of a 30.38% change in predictive variable 14 at the removal of question 18. The marked change over 25% causes the process to end..

Table 5 : Coefficient analysis

Question	Original	Study Model	Study Model without question18 (% difference)	Study Model without questions 18 & 7 (% difference)	Reduced Model (% difference)
2	1.3688	1.3557 (0.96%)	1.3506 (1.33%)	1.2703 (7.20%)	1.4022 (2.44%)
13	0.7394	0.8240 (11.44)	0.8735 (18.14%)	0.8631 (16.73%)	0.9731 (31.6%)
14	0.5307	0.6677 (25.8%)	0.6919 (30.38%)	0.8703 (64.00%)	0.8914 (67.97%)
17	0.9961	0.9116 (8.48%)	0.9397 (5.66%)	0.8846 (11.19%)	0.9222 (7.42%)
28	0.6186	0.7095 (14.69%)	0.7241 (17.05%)	0.9054 (46.36%)	1.0045 (62.38%)
31	1.4636	1.2740 (11.59%)	1.2713 (13.14%)	1.2940 (11.59%)	1.2779 (12.68%)
5	0.7783	0.6804 (12.58%)	0.7358 (5.46%)	0.7680 (1.32%)	
7	0.8160	0.6766 (17.08%)	0.6917 (15.23%)		
18	0.9295	0.8673 (6.69%)			

Throughout the process the coefficients and Akaike Information Criteria (AIC) scores monitored lead to the following observations. The removal of questions 29 and 10 cause questions 9 and 3 respectively to break the 25% change in coefficient barrier, but only just before the latter questions are removed due to high p-values. The removal of questions 26 and 6 cause the coefficient of question 14 to slide slightly over 25% (25.8% and 26.65% respectively). In both instances, when the removal of the next question with the highest p-value occurs, the violating coefficients return to levels below 25%.

Question 6 is returned to the Study Model for reconsideration due to its interaction with the coefficient on question 14.

Table 6 displays some of the descriptive statistics for measuring the fit of logistic models and compares them for six competing models. The Score Only Model corresponds to using the total score received on the benchmark as the predictive variable with no question predictive variables. The Study Model column displays statistics for the model

Table 6 : Model Comparison

	Score Only Model	Study Model without question 18	Study Model	Study Model with 25	Study Model with 6	All
Residual (DF)	205.41 (227)	201.58 (247)	198.98 (246)	197.43 (245)	197.74 (245)	183.74 (225)
Chi-square test of fit			.1069	.2131	.2655	.7605
P value	0.1549	0.0156	0.0125	.0114	.01312	0.0215
R^2 values***	.5705	.5260	.6223	.5980	.4768	.1598
AIC	263.41	219.58	218.98	219.43	219.74	247.27
ROC	.8418	.8806	.8815	.8863	.8839	.8992

* R^2 scores are the average of the Osius, McCullagh, IM, and RSS tests reported by SAS in Appendix 3.

with predictor questions 2, 13, 14, 17, 28, 31, 5, 7, and 18. The All column uses all the questions except for 4, 20, 15, and 12. The output procedures in R and SAS can be found in Appendix 3.

The model p-value and AIC model scores illustrate that the Study Model is the best model available. The AIC compares two different models, the lowest value being the better model of those under consideration. But it does not identify the quality of the models. They might in fact both be bad models. The fact that the Study Model also has a strong p-value score validates the model. Table 7 displays that the Study Model correctly predicts the highest number of students in comparison to the remaining models under consideration. The predictive ability of these models displayed in Table 7 results from classification tables generated from the SAS logistic program. The classification tables follow the advice of Homer and Lemeshow that although logistic theory dictates that a zero outcome should follow a model's result of less than .51, using different cutoff points has certain advantages (Hosmer & Lemeshow, 2000). By optimizing the cutoff point to provide the model a balance of sensitivity and specificity, the results created containing a higher percentage of positive predictions to false positive errors - a result beneficial to the task of intervention identification. These tables are found at the end of Appendix 3. The chart reports the correct model cutoff percentage for three hypothetical levels of determination. An administrator wishing to correctly identify either 75%, 80%, or 85% of the failures on the statewide assessment using the Study Model will need to use a cutoff percentage for the model at 0.67, 0.76, or 0.82 respectively. The resulting identification of 60, 65, and 70 students meets or surpasses the goals of 60, 64, and 68 students of the 79 total failures. The specificity of the procedure is measured by the number of students pulled for intervention with the lower number the most desirable. The Study Model example provided pulls the 60, 65, and 70 failures at the cost of pulling a total of 95, 114, and 134 students respectively. In the second subsection of the table, the administrator planning for a set number of

Table 7 : Model Comparison by Predictions

Predictions*	Score Only Model	Study Model without question 18	Study Model	Study Model with question 25	All	Study Model with question 6
Pred 85%:68 (Cutoff %)	68/137 (.78)	69/134 (.84)	70/134 (.82)	68/130 (.83)	68/159 (.86)	68/127 (.80)
Pred 80%:64 (Cutoff %)	66/120 (.73)	65/118 (.78)	65/114 (.76)	64/108 (.74)	64/126 (.82)	64/106 (.74)
Pred 75%:60 (Cutoff %)	60/103 (.67)	60/96 (.68)	60/95 (.67)	60/93 (.67)	60/107 (.75)	61/97 (.67)
Student tot**						
Pred 55%:141 (Cutoff %)	68/137 (.78)	69/134 (.84)	70/134 (.85)	68/131 (.84)	68/139 (.86)	70/141 (.86)
Pred 50% :128 (Cutoff %)	66/120 (.73)	67/125 (.83)	68/124 (.83)	66/121 (.82)	64/126 (.82)	68/127 (.80)
Pred 45% :116 (Cutoff %)	60/103 (.67)	63/113 (.77)	65/114 (.76)	66/112 (.78)	61/114 (.77)	66/116 (.77)

* The Predictions tables determine the results of the model given you want to be sure to get a certain number of failures – 85% of the 79 failures is 68 the least number to identify in that row

**The Student tot tables determine the results of the model given you only have resources to pull a certain number of the total students – 55% of the 255 is 141, the most number to pull for intervention in that row

interventions is taken into consideration. From this viewpoint, a total amount of interventions drive the cutoff percentages. The administrator with the resources to help the three hypothetical values of 45%, 50%, or 55% of the students in the cohort should use the model percentage values of 0.76, 0.83, and 0.85 respectively if the Study Model is employed. The goals along with the number of successful predictions are also reported.

Conclusions

The results listed in Table 6 and 7 suggest the selection of the model that includes questions 2, 13, 14, 17, 28, 31, 5, 7, and 18. This study will refer to this model as the "Study Model" henceforth. Although adding questions 25 or 6 does reduce the change in the question 14 coefficient, they fail the Chi squared test of fit test along with sporting a lower R square value and a larger AIC value. Table 7 confirms the decision to leave these two questions out of the model as they successfully predict less students for interventions (the intended goal). Taking question 18 out of the Study Model not only violates the change in coefficient condition, but the statistics show its inferiority in each of the test of fit categories.

The Study Model on paper greatly improves on the Score Only Model. The residual squared errors drop 6.43 while actually increasing the degrees of freedom by 19. The Study Model outperforms the Score Only Model in every measure, including (the most important) prediction measure. Correctly predicting 0 – 2 more failures while pulling 3 – 8 less students gives the study model an advantage over the Score Only Model. The Score Only Model is an improvement over the traditional model, previously discussed, in that the traditional model uses cut scores determined without statistics while the Score Only Model uses the total score of the previous year to make future predictions. With the Study Model out predicting the Score Only Model on Cohort 1, the study continues with the hope of improving the prediction power for a second cohort of students.

CHAPTER 7

TESTING THE STUDY MODEL WITH A SECOND COHORT

The primary goal of this research is to implement the developed Study Model to predict future student failure of the STAAR examination. Whether the statistical patterns identified in the Study Model from a single year of data hold for the following year is important. It is valuable to make accurate predictions from the patterns. The crucial question is if the model effectively predicts student outcomes before they have completed the state-wide assessment so that any necessary interventions may be prescribed in advance?

Businesses that use statistics to predict behavior rarely use one simple data collection to make their forecast. They often use demographics, past histories, and any information that can be correlated to their outcome. In this chapter evidence is provided to determine if a single test, without all the other information, may be used to make accurate predictions?

The four elementary schools used to devise the Study Model administered the same Benchmark test the next year. Questions 4 and 20 were removed from both the Study Model and the Year 2 Best Fit Model due to inconsistencies in utilization between the two years. Appropriate reporting of the Benchmark scores were also found to be inconsistent across the faculty. Unfortunately, difficulties arose in reporting scores of five teachers in two different schools. This resulted in the loss of around 90 student scores. However, the students were randomly assigned to teachers and therefore no detectable skewing of the data presents itself. Students absent on the day of the STAAR examination further contribute to a loss of data, as do students absent from the benchmark. Ultimately 143 subjects had complete data in the second year compared to 256 in the first year. Thirty nine of these subjects failed the STAAR examination.

The results from the benchmark were entered into the Score Only Model and the Study Model to determine which of the models lead to a more precise forecast. The role of a school administrator leads to consideration of two comparative viewpoints. Viewpoint "A" uses the idea that administrators want to assist 85% of the students at risk of failing. Table 7 found in Chapter 5 provides the researcher with the appropriate values to use to make predictions. When creating our model with the first cohort, the logistic procedure in SAS determines the classification table located in Appendix 3. As reported in Table 7, the probability value on this table that accurately predicts 85% of the failures is 0.78 for the Score Only Model and 0.82 for the Study Model. These values are used to make predictions for the second cohort since at these values that the models reach the 85% threshold. Viewpoint "B" uses the idea that the school can only provide assistance to 45% of the students and want to select the model that will assist as many students as possible under this restriction. Under this viewpoint consulting Table 7 to identify where the probability found in the classification table for the two models reaches the appropriate threshold is unnecessary. Unlike viewpoint A where the number of future failures is unknown, forty five percent of the total students is computable. The second cohort has 143 students, so in viewpoint B the school will intervene with no more than 64 students. Seen from the classification table SAS generates in Appendix 4 the threshold will be met at probability level of .82 for both models.

Table 8 below compares the results for viewpoints A and B. For viewpoint A the Score Only Model correctly identifies 34 out of the 39 failures while the Study Model only identifies 30 of them. Although the probability level changes slightly for the Score Only Model, there is no difference in the result for viewpoint B.

Table 8 : Results

	Score Only Model (Correct/pulled) % correctly identified	Study Model (Correct/pulled) % correctly identified	Difference
Viewpoint A	.78 (34/61) 87.2%	.82 (30/63) 76.9%	-4
Viewpoint B	.82 (34/61) 87.2%	.82 (30/63) 76.9%	-4

The Score Only Model outperforms the Study Model in the second cohort group. To determine whether the Score Only Model outperforms the Study Model created by the cohort 1 data, or if it betters all possible models in this second year, the cohort 2 data is analyzed to create new models. The Year 2 Best Fit Model is constructed in a manner similar to the development of the Study Model devised for Year 1. When the univariate tests are run on cohort 2, questions 4,5,10,12,15,16,20,21,23,32 fail at the .20 level. This model then deletes questions with the highest p-value one by one, while continuing the same residual, p-value, and coefficient checks as administered when creating the Study

Model in Chapter 6. The order of question deletion through this process is 6, 25, 31, 30, 19, 7, 28, 14, 29, and 8. When question 29 is removed, the coefficient for question 8 falls outside parameters, but the AIC continues to fall from 105.0 to 104.77 and the residuals hold well with a G-score of .1831 (1.772 with df=1). As documented in Table 9, when

Table 9 : Coefficient Analysis for Year 2 Best Fit Model

Question	Full Model	Year 2 Best Fit Model (% change)	Without #8 (% change)	Without #27 (% change)	Without #8, & #27 (% change)
1	5.83567	4.8053 (17.66%)	4.2509 (27.16%)	4.7454 (18.68%)	4.2292 (27.53%)
2	1.47224	1.2384 (15.88%)	1.3024 (11.54%)	1.1191 (23.99%)	1.2256 (16.75%)
3	1.89754	1.6097 (15.17%)	1.4108 (25.65%)	1.5643 (17.56%)	1.3712 (27.74%)
9	1.76690	1.3881 (21.44%)	1.3851 (21.61%)	1.4274 (19.21%)	1.4130 (20.03%)
11	3.70767	3.1648 (14.64%)	2.9389 (20.73%)	3.6557 (1.40%)	3.5206 (5.05%)
13	2.41663	2.3259 (3.75%)	2.2806 (5.63%)	2.1588 (10.67%)	2.1230 (12.15%)
17	2.25126	2.1474 (4.61%)	2.4754 (9.96%)	1.6321 (27.50%)	1.9751 (12.27%)
18	2.23382	2.3160 (3.68%)	2.1832 (2.26%)	2.4280 (8.69%)	2.3660 (5.92%)
22	-7.01003	-6.3374 (9.60%)	-6.3806 (8.98%)	-5.9356 (15.36%)	-6.0846 (13.20%)
24	2.54192	2.0372 (19.86%)	1.6241 (36.11%)	1.9877 (21.74%)	1.5541 (38.86%)
26	2.30948	2.0064 (13.12%)	1.7559 (23.97%)	2.3380 (1.23%)	2.0816 (9.87%)
33	-3.09795	-2.7823 (10.19%)	-2.6622 (14.07%)	-2.5085 (19.03%)	-2.4382 (21.30%)
34	2.35655	2.0894 (11.34%)	2.1864 (7.22%)	2.0604 (12.57%)	2.1866 (7.21%)
27	1.23633	1.0360 (16.20%)	1.0991 (11.10%)		
8	1.68614	1.0483 (37.83%)		1.1186 (33.66%)	

question 8 is deleted from the model, 3 coefficients have a percent change that exceeds the 25% barrier. If question 8 is retained and question 27 removed, the coefficient for question 8 closes on the original value, but it does not remedy the situation. With a slightly better AIC and p-value, the decision is made to keep both 8 and 27 in the new model. Table 9 shows the relevant coefficient changes. The new model (Year 2 Best Fit Model) utilizes questions 1, 2, 3, 8, 9, 11, 13, 17, 18, 22, 24, 26, 27, 33, and 34. Recall the Study Model developed in Chapter 6 and tested here was based on questions 2, 13, 14, 17, 28, 31, 5, 7, and 18.

Table 10 : Year 2 Best Fit Model

Coefficients: Question	Estimate	Standard Error	Z-score	P-value
Intercept	-9.9052	2.8226	-3.509	4.49 e-4
Question 1	4.8053	1.4103	3.407	6.56 e-4
Question 2	1.2384	0.6828	1.814	0.0697
Question 3	1.6097	0.7264	2.216	0.0267
Question 8	1.0483	0.7841	1.337	0.1812
Question 9	1.3881	0.6705	2.070	0.0384
Question 11	3.1648	1.5601	2.029	0.0425
Question 13	2.3259	0.8914	2.609	0.0091
Question 17	2.1474	0.9042	2.375	0.0176
Question 18	-2.3160	0.9358	2.475	0.0133
Question 22	-6.3374	2.4027	-2.638	0.0085
Question 24	2.0372	1.0396	1.960	0.0501
Question 26	2.0064	0.8927	2.247	0.0246
Question 27	1.0360	0.7471	1.387	0.1655
Question 33	-2.7823	1.0388	-2.731	0.0063
Question 34	2.0894	0.7598	2.750	0.0060
Null deviance	Df	Residual deviance	Df	AIC
167.582	142	72.771	127	104.77

The Year 2 Best Fit Model not surprisingly outperforms the Score Only Model for Year 2 as seen in Table 11. The residuals are lower, driving the lower p-value. The lower AIC value is complemented by the higher ROC score. All of these indicators point to the Year 2 Best Fit Model as superior to the Score Only Model for Year 2. Recall the

Table 11 : Cohort 2 Model Comparison

	Score Only Model Year 2	Study Model	Year 2 Best Fit Model
Residual	101.84	119.00	72.771
DF	(121)	(133)	(127)
P value	.1038	.1979	2.94 e-5
AIC	145.84	139.00	104.77
ROC	.8656	.8550	.9477

observations from Table 8 that the Score Only Model makes better predictions than the Study Model. The summary data of Table 11 provides statistical evidence that the Score Only Model is preferred. With a higher p-value and lower ROC score, the Study Model's only advantage is in the lower AIC score. Table 12 observes that the Study Model

Table 12 : Cohort 2 Model Comparison by Predictions

Predictions*	Score Intercept Only	Study Model	Year 2 Best Fit Model
Pred 85% 34	(.78) 34/61	(.90) 36/94	(.92) 34/71
Pred 80% 32	(.71) 33/55	(.88) 33/85	(.83) 32/53
Pred 75% 30	(.64) 30/45	(.82) 30/63	(.76) 30/48
Student tot**			
Pred 55% 78	(.84) 35/71	(.87) 31/74	(.96) 35/76
Pred 50% 71	(.84) 35/71	(.84) 31/67	(.92) 34/71
Pred 45% 64	(.78) 34/61	(.82) 30/63	(.89) 32/63

* The Predictions tables determine the results of the model given you want to be sure to get a certain number of failures – 85% of the 39 failures is 34 the least number to identify in that row

**The Student tot tables determine the results of the model given you only have resources to pull a certain number of the total students – 55% of the 143 is 78, the most number to pull for intervention in that row continues to lag behind the other two models. Just as the case in Table 7, Table 12 seeks to find the balance or sensitivity and specificity by using various cutoff percentages found in parenthesis. The number of correctly identified students failing the state assessment and the number of total students pulled for interventions are listed for each of the same hypothetical goals from Table 7. The goals being the identical, it is noteworthy that although the Year 2 Best Fit Model statistically outshines the Score Only Model, the Score Only Model maintains an advantage when making predictions. The surprising result is that comparatively few of the questions in the Year 2 constructed model are the same as the Study Model. The Year 2 Best Fit Model utilizes questions 1, 2, 3, 8, 9, 11, 13, 17, 18, 22, 24, 26, 27, 33 and 34 whereas the Study Model from Year 1 utilizes questions 2, 13, 14, 17, 28, 31, 5, 7, and 18. Only 4 questions overlap in the 20 questions utilized by both models. Table 13 presents the comparative p-values for each question for cohort 1 and cohort 2. The univariate columns record the result of running the generalized linear model logistically for each question by itself on its ability to predict EOC success. The "All questions" columns refer to the p-value on the question variable when it was included in the Full Model with all qualified questions included, for cohort 1 and cohort 2, respectively. The average distance between the two years in the all questions column is .328864. Questions 2, 17 and 31 are particularly troublesome. Of the 12 questions with a p-value of under 0.15 in the cohort 2 analysis with all questions included, 6 of them have a p-value of over .40 with cohort 1. Questions 23, 24, 26, and 34 give pause in this direction. The result is a seemingly lurking variable or uninvestigated interaction.

Table 13 : Question Comparison by Cohort

Coefficients: Question	Cohort 1 Univariate p-value	Cohort 2 Univariate p-value	Cohort 1 All questions P-value	Cohort 2 All questions P-value	Difference Univariate/ All questions
Question 1	.0000839	.000604	.52260	.00642	.00052/.51618
Question 2	1.66 e-10	.00152	.00273	.34419	.00152/.34146
Question 3	.000161	.0163	.15101	.07973	.01614/.07128
Question 5	1.39 e-6	.35705	.08952	.41397	.35705/.32445
Question 6	.0571	.1383	.30024	.51729	.0812/.21705
Question 7	7.96 e-6	.00249	.62417	.30275	.00248/.32142
Question 8	.00313	.00151	.38351	.13862	.00162/.24489
Question 9	.000583	.0000829	.33986	.01514	.0005/.32472
Question 10	3.68 e-6	.318	.30405	.34225	.318/.0382
Question 11	.0000125	.00354	.54761	.40033	.00353/.14728
Question 12	.309	.5197	.49718	.05737	.2107/.43981
Question 13	1.82 e-7	.00594	.09145	.24611	.00594/.15466
Question 14	1.93 e-8	.00579	.19738	.03537	.00579/.16201
Question 15	.848	.360978	.95509	.64761	.48702/.30748
Question 16	.00441	.521	.72545	.68865	.51659/.0368
Question 17	.000268	.000378	.01978	.35866	.00011/.33888
Question 18	.000348	.00293	.14604	.03446	.00258/.11158
Question 19	.00212	.0606	.69646	.12240	.05848/.57406
Question 21	.0122	.352	.47833	.35983	.3398/.1185
Question 22	.000787	.166	.34617	.45718	.16521/.11101
Question 23	2.44 e-6	.7842	.99162	.15727	.78420/.83435
Question 24	.00473	.0107	.44344	.01618	.00597/.42726
Question 25	3.37 e-6	8.86 e-6	.12270	.19126	5 e-6/.06856
Question 26	.0000661	.000293	.51954	.00878	.00023/.51076
Question 27	.180335	.00827	.19672	.76749	.17207/.57077
Question 28	1.3 e-8	.0000329	.18997	.40055	.00003/.21058
Question 29	.00165	.00222	.41569	.17809	.00057/.2376
Question 30	.196591	.09621	.44103	.81095	.10038/.36992
Question 31	1.32 e-9	.00277	.00455	.97281	.00277/.96826
Question 32	.0247	.572109	.58761	.38394	.54741/.20367
Question 33	.110755	.1225	.38895	.05971	.01175/.32924
Question 34	.00313	8.59 e-5	.69838	.02420	.00304/.67418
	Univariate	Average Difference	All questions	Average Difference	
		.131355		.328864	

Conclusion

The Study Model when applied to Year 2 did not improve on the Score Only Model as anticipated. But the point remains that just because the Study Model does not improve on the Score Only Model in Year 2, a model that does improve on the Score Only Model does exist for cohort 2. The breakdown does not reside in the question type regression model. The failure comes from the identification of significant questions beforehand. The fact that the Score Only Model out predicts the fitted model on STAAR results brings the experiment to a halt; however, interesting results were found.

The logistic regression models presented in this chapter for the year 2 data indicate that logistic models of good fit can be developed to model the student outcome on the STAAR examination. However, the questions identified as statistically significant in the Year 1 and Year 2 models of best fit presented are considerably different. This finding presents an added complexity. Both groups of students completed the same examination, and yet completely different questions are found to be significant in each group. The conclusion of this research is therefore that Benchmark examinations cannot accurately and consistently predict student performance on an end of year examination by themselves.

CHAPTER 8

THE FUTURE OF BENCHMARKS

This research looked for evidence to determine if benchmark examination questions could accurately predict whether or not a student successfully makes a passing score on a statewide assessment. After examination of the convenience samples of high school freshman, sophomores and fourth graders from a Texas panhandle region school district, the study population of two cohort groups of 4th grade students was selected. The students attended the 4th grade in the back to back school years of 2012-2013 and 2013-2014. A logistic regression model was developed from the Year 1 data on cohort 1. The Year 2 data received an analysis based on this model and it is compared to the model based entirely on scores. Further examination of the year 2 data provides background to research by developing a logistic regression model on the cohort 2 data. A question by question comparison between the two cohort groups concludes the research.

Discussion

The outcome of the study is problematic for the state of Texas school system where the benchmark system is so prevalent that a law (HB 5 of the 2013 Texas legislation session) was passed to limit the number of benchmarks a school can give each year to two. The Texas American Federation of Teachers questions “whether school districts will comply with the letter and spirit of this new law or will try to play games to evade it – for instance, by relabeling their test prep tests as something other than "benchmark" tests" (Texas AFT, 2013, para. 4). The question no longer seems to be whether schools use benchmarks as much as how many benchmarks do they use? With this practice so commonplace that it attracts the attention of lawmakers, what is the impact of the discovery that benchmarks cannot accurately predict the STAAR results? One fact finding group estimates that students spend 7-9 days in actual benchmark testing (Owen, 2012). This number can be easily doubled if the teacher performs a review before and a review after the test. The use of benchmarks seemingly results in less actual days of instruction and more hours of interventions that focus on the wrong students. Districts that pay up to $30 an hour for teachers and staff to conduct these interventions may be able to save these funds and apply them towards an intervention strategy that has better success. This study sheds light on a practice exploding in popularity.

A big question that surrounds this research is why. It only makes sense that a benchmark designed to test the same information as the STAAR would be able to predict the outcome. Many issues come into play. One such issue is the apparent overuse of benchmarks. Children are smart. It does not take them very long to figure out which examinations really count, and which are for practice. A large portion of fourth graders still want to please their teacher, but another subpopulation of students will only try when it really counts.

Another factor is instruction. While this study pointed out that the instruction does not change substantially in a single year, over time instructional holes can deviate results from a baseline. Mathematics is a subject that builds on itself. A cohort that experiences a substandard teacher will be behind the next year. Several bad (or several good) instructional years can change a group of students knowledge of mathematics as a whole in comparison to other cohorts.

People have good days, and people have bad days. Students are no different. A difficulty in making predictions derives from the snapshot nature of testing. A benchmark is given on a certain day, and the STAAR is given on a certain day. It is unreasonable to believe that each student will be in the same emotional state on both days. Whether the student is just not feeling themselves that day, or whether they are going through a major life changing event, some days are just better than others. Take for example the child who finds out his parents are getting divorce just before the STAAR or the benchmark. There is no doubt that these kinds of things do happen, and they do change the results.

Another concern for the students who are close to the passing score is the kind of test that is administered. With the pass or fail mentality of this test, a multiple choice test can literally come down to luck. True, it is statistically improbable that a student can reach a passing score completely by luck. But there is something to be said for the students who misses or passes by a couple of questions. These two groups of students may simply be separated by whether they guess right or wrong on several crucial items. There is no way to predict which student will guess right, and which will guess wrong. A deeper look at the data brings us to a final troubling thought. The Score Only Model out predicts the Study Model. The Score Only Model grades students on the mathematical information the student possesses in whole. The Study Model uses specific questions which in turn are pointed at specific mathematical skills. The results of this study indicate that the STAAR favors the student with general mathematic knowledge rather than the students with specific knowledge of certain skills. Using a multiple choice snapshot examination to determine knowledge acquired over years of instruction contains many drawbacks, very few of which the work is able to address

Challenges to the Methodology

Tracking students creates difficulties for this methodology. In the case of this research, the freshman Algebra I teachers prevent the students with the lowest previous state examination scores from participating in the same benchmark as the remainder of the cohort. The geometry students with the highest previous state examination score did not participate in the same benchmark as the rest of the cohort. Both extremes produce undesirable results. When the higher student group is removed, valuable data about what the students should know to pass the state examination disappears resulting in a benchmark that contains very few statistically significant questions to build a prediction model. Only when school districts are willing to administer the same benchmark exam to the entire cohort will the information needed to build predictive models exist. This is a hard sell for some teachers. Although a school district may declare officially that using benchmarks to evaluate teachers performance and practices is not condoned, it has been known to happen. These methods of evaluation build barriers to process.

Another limitation comes from the outside. Politicians still struggle with the implementation of the state assessment. Resistance from teachers and parents produce a system that is instable at the least, and may be described as chaotic. Changing standards, graduation requirements, and passing percentage levels form a few of these challenges. This study was impacted by the change of requirement for a passing Geometry EOC score in order to graduate high school. Cohort 1 is under the impression that they must pass the Geometry EOC to graduate. Cohort 2 is told that they do not need to pass, and eventually the EOC test is not administered. As long as the fluctuation between the requirements, the standards, and the percentage levels continue, finding cohorts under the same conditions remains difficult.

Collecting data remains another issue. Whenever a computer is involved, there is the possibility of technological barriers. There is also the human element. Teachers who fear judgment from their posted scores may conveniently forget to run the scores, while others may even go as far as tampering with scores, having the students correct the tests prior to entering the scores into the computer for example. In this study, the scores from 90 students were lost in what appears to be honest technological errors.

Limitations of the Study

Despite the careful design of this project, there are limitations to this study. The population of students is a single rural school district in the Texas Panhandle. Additional studies on various populations are needed to make larger inferences more stable. Analysis of different courses and grade levels were originally planned; however, inconsistency in data for all students in these populations, required the study be limited to a single course and grade, namely fourth grade mathematics. A single year of student benchmark data was used to develop the model for both Year 1 and Year 2. Using more than one year of previous data along with various other known demographic indicators may have impacted the study. Due to the educational process and ethical responsibilities, the school district continued to remediate students they felt were at risk in preparation for the STAAR examination while this study was underway. This remediation may have impacted the student outcome variable. Fluidity at the teaching positions makes it impossible to ascertain whether the two cohort groups received the same level of education. Foundational skills in earlier grade levels may have been better developed in one group over the other. This would create gaps that influence the performance of each cohort.

Conclusion

The results of this study support that it is unlikely to be able to predict a student outcome on a statewide assessment based on student benchmark examination scores using a single year of data. Using the analogy of businesses that use data mining techniques to analyze the shopping habits of their customers, a synonymous business analysis would depend on a single shopping experience alone to make decisions regarding marketing. Several shopping experiences, demographics, and numerous other data points are taken into consideration when companies make marketing decisions. In our example of the pregnant girl in Chapter 1, surely Target would not determine a 75 year old male was pregnant given the same shopping occurrence. However, in education, the system limits itself to benchmark testing results alone.

This study provides evidence for the inadequacy of this benchmark system alone in determining student outcome on state-wide 4th Grade Mathematics STAAR examinations. In order to identify 85% of students who need remediation, between 49.7% and 67.6% of population students must be targeted for remediation. To be certain those students are identified, a benchmark score of over 70% (refer Table 2 and Appendix 4) must be used as the cutoff value to identify this target population. The resulting environment is one where school systems are forced to give up on some students and concentrate on those "bubble kids" who school districts feel are the most likely to be successful under remediation, due to the financial investment. In Year 1, of students who scored below the 50 percentile mark, therefore being identified by the study school district as not a good risk, received no intervention, 24.4% (11/45) passed the STAAR. A similar result of 25% (2/8) passed the STAAR in the second cohort.

In summary, this study identifies four concerns to using benchmarks as identifiers of students in danger of failing a state-wide examination. First, for accurate predictions, the entire cohort must take the same benchmark test. Failure to do so removes valuable information from the data and skews the results. Second, the "bubble kid" model leaves out students who have the opportunity to pass. With 25% of both cohorts passing <u>even without interventions</u>, the students who fall in this group may have a better chance of passing than teachers give them credit. Third, more information is needed. Information from prior testing, demographics, gender, economic status, and other types of evaluations must be factored into the equation. A single test on a single day does not paint a true picture of a students' mathematical knowledge. Fourth, with the Score Only Model out predicting the question based model, the current STAAR test in Texas may measure a student's mathematical general knowledge rather than targeting specific knowledge base.

Further study should be conducted which includes variables such as past test experience, gender, race, age in days compared to the mean for that grade, economic status, English as a second language status, and many other factors that have been predicted to influence end of course grades. All of these factors should be utilized in a further study to confirm or deny the profitability of administering benchmark examinations and determining student remediation based on these scores. This kind of study across many grade levels and districts would prove beneficial to the understanding of how to correctly identify at risk students.

REFERENCES

Allison, P. D. (2014). *Paper 1485-2014.* Retrieved April 22, 2014, from SAS Global Forum: http://support.sas.com/resources/papers/proceedings14/1485-2014.pdf

Aydeniz, M., & Southerland, S. A. (2012). A National Survey of Middle and High School Science Teachers' Responses to Standardized Testing; Is Science Being Devalued in Schools? *Journal of Science Teacher Education* , 233-257.

Bancroft, K. (2010). Implementing the mandate: the limitations of benchmark tests. *Educational Assessment, Evaluation and Accountability* , 53-72.

Barksdale-Ladd, M. A., & Thomas, K. F. (2000). What's at Stake in High-Stakes Testing: Teachers and Parents Speak Out. *Journal of Teacher Education* , 384-397.

Berliner, D. (2011). Rational Responses to High Stakes Testing: the Case of Curriculum Narrowing and the Harm that Follows. *Cambridge Journal of Education* , 287-302.

Duhigg, C. (2012, February 16). *How Companies Learn Your Secrets.* Retrieved 12 19, 2014, from The New York Times: NTTimes.com

Dunn, O. J. (1961). Multiple Comparisons Among Means. *Journal of the American Statistical Association* , *56* (No. 293), 52-64.

Good, R. H., Simmons, D. C., & Kame'enui, E. J. (2001). The importance and decisino-making utility of a continuum of fluency-based indicators of foundational reading skills for third-grade high-stakes outcome. *Scientific Studies of Reading* , 257-288.

Greatschools.org. (n.d.). Retrieved 4 3, 2015, from Greatschools.org: http://www.greatschools.org/texas/pampa/5284-Pampa-High-School/details/#Students

Hosmer, D. W., & Lemeshow, S. (2000). *Applied Logistic Regression.* John Wiley and Sons Inc.

Johnson, J. (2013). The Human Factor. *Educational Leadership* , 16-21.

Johnson, V. E. (2013, November 26). *Revised Standards for Statisical Evidence.* Retrieved April 24, 2015, from Proceedings of the National Academy of Sciences of the United States of America: www.pnas.org/content/110/48/19313.full.

Keller-Margulis, M. A., Shapiro, E. S., & Hintze, J. M. (2008). Long-Term Diagnostic Accuracy of Curriculum-Based Measure in Reading and MAthematics. *School Psychology Review* , 374-390.

Owen, S. (2012, August 29). *PolitiFact Check.* Retrieved April 18, 2015, from http://www.politifact.com/texas/statements/2012/aug/29/ted-lyon/ted-lyon-says-most-texas-schools-spend-45-days-man/

Parker, S. (2013, May 28). *Common Core Standards : Why States Are Now Saying 'No Thank You'.* Retrieved April 25, 2015, from www.takepart.com/article/2013/05/28/common-core-standards-why-states-are-now-saying-no-thank-you

Public Law 107-110. (2002, January 8). Retrieved April 24, 2015, from www2.ed.gov/policy/elsed/leg/esea02/107-110.pdf

Shannon, C. E. (1948). A Mathematical Theory of Communication. *The Bell System Technical Journal , 27* (No. 3), 379-423.

Shapiro, E. S., Keller, M. A., & Lutz, J. G. (2006). Curriculum-Based Measures and Performance on State Assessment and Standardized Tests. *Journal of Psychoeducational Assessment* , 19-35.

Silbertglitt, B., & Hintze, J. (2007). How much growth can we expect? A conditional analysis of R-CBM growth rates by level of performance. *Exceptional Children* , 71-84.

Spackman, K. A. (1989). Signal Detection Theory: Valuagble Tools for Evaluating Inductive Learning. In *Machine Learning Proceedings* (pp. 160-163). Morgan Kaugmann Publishers.

Stage, S. A., & Jacobsen, M. D. (2001). Predicting student success on a state-mandated performance-based assessment using oral reading fluency. *School Psychology Review* , 407-419.

Starnes, D. S., Yates, D. S., & Moore, D. S. (2012). *The Practice of Statistics for AP* 4th ed.* New York, New York: W. H. Freeman and Company.

Strauss, V. (2014, April 22). *11 Problems Created by the Standardized Testing Obsession.* Retrieved April 24, 2015, from The Washington Post: www.washingtonpost.com/blogs/answer-sheet/wp/2014/04/22/11-problems-created-by-the-standarized-testing-obssession/

Sugiura, N. (1978). Further Analysis of the Data by Akaike's Information Criterion and the Finite Corrections. *Communications in Statistics , a(7)*, 13-26.Texas AFT. (2013, December 11). *New Limit on Benchmark Testing: Will Districts Honor or Evade It?* Retrieved 4 18, 2015, from www.texasaft.org/new-limit-on-benchmark-testing-will-districts-honor-or-evade-it/

Texas Education Agency. (2013, July). *State of Texas Assessments of Academic Readiness (STAAR) Progress Measure Questions and Answers.* Retrieved March 2, 2015, from http://www.psptexas.net/docs/STAAR-ProMeasureQA.pdf.

Wiggins, G., & McTighe, J. (2005). *Understanding by Design.* Alexandria: Association for Supervision and Curriculum Development.

Zeichner, K., & Ndimande, B. (2008). Contradictions and Tensions in the Place of Teachers in Educational Reform: Reflections on Teacher Preparation in the USA and Namibia. *Teachers and Teaching: Theory and Practice* , 331-343

APPENDIX 1

CHAPTER 4 DATA

Algebra Unit 1 test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain*	z-score**
1	148	105	91	14	43	30	13	0.026582672	2.4168625
2	148	0	0	0	148	121	27	#DIV/0!	#DIV/0!
3	148	87	79	8	61	42	19	0.056150377	3.4037501
4	148	0	0	0	148	121	27	#DIV/0!	#DIV/0!
5	148	62	54	8	86	67	19	0.010258563	1.4282601
6	148	88	77	11	60	44	16	0.022990327	2.1909927
7	148	66	59	7	82	62	20	0.023726791	2.1583219
8	148	27.001	27	0.001	121	94	27	0.059117455	2.7141728

Algebra Unit 3 test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	Z-score
1	137	69	60	9	67	52	15	0.021330903	1.42903
2	137	0	0	0	0	0	0	#DIV/0!	#DIV/0!
3	137	69	60	9	67	52	15	0.021330903	1.42903
4	137	50	40	10	86	72	14	0.012057718	-0.54968
5	137	86	73	13	50	39	11	0.015804942	1.01273
6	137	106	90	16	30	22	8	0.021003651	1.454623
7	137	86	71	15	50	41	9	0.010527702	0.082113
8	137	0	0	0	137	113	24	#DIV/0!	#DIV/0!
9	137	0	0	0	137	113	24	#DIV/0!	#DIV/0!
10	137	0	0	0	137	113	24	#DIV/0!	#DIV/0!
11	137	47	37	10	89	75	14	0.013846619	-0.80827
12	137	0	0	0	137	113	24	#DIV/0!	#DIV/0!
13	137	73	63	10	63	49	14	0.019382127	1.299485
14	137	67	55	12	69	57	12	0.010525283	-0.07941
15	137	0	0	0	137	113	24	#DIV/0!	#DIV/0!
16	137	40	32	8	96	80	16	0.01160756	-0.46562
17	137	81	64	17	55	48	7	0.018857156	-1.23808

Algebra Unit 4 test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	52	43	32	11	9	6	3	0.003045226	0.476773
2	52	23	18	5	29	20	9	0.007912586	0.750541
3	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
4	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
5	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
6	52	9	5	4	43	33	10	0.02180517	-1.30318
7	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
8	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
9	52	34	29	5	18	9	9	0.100307763	2.729756
10	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
11	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
12	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
13	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
14	52	18	14	4	34	24	10	0.004377196	0.556061
15	52	0	0	0	52	38	14	#DIV/0!	#DIV/0!
16	52	22	17	5	30	21	9	0.004787252	0.584138
17	52	19	13	6	33	25	8	0.00451766	-0.57434
18	52	26	19	7	26	19	7	0	0
19	52	12	10	2	40	28	12	0.012437421	0.913283
20	52	20	14	6	32	24	8	0.002152557	-0.39546

Algebra Semester test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	146	103	92	11	43	32	11	0.024128797	2.294274
2	146	92	80	12	54	44	10	0.003856111	0.892755
3	146	77	68	9	69	56	13	0.007193058	1.206057
4	146	71	65	6	75	59	16	0.024196733	2.174796
5	146	105	91	14	41	33	8	0.004167281	0.937884
6	146	98	87	11	48	37	11	0.016165322	1.855168
7	146	72	65	7	74	59	15	0.016007462	1.781183
8	146	99	86	13	47	38	9	0.004312478	0.949611
9	146	89	82	7	57	42	15	0.044677951	3.040169
10	146	85	78	7	61	46	15	0.036393197	2.72443
11	146	72	62	10	75	63	12	-0.00097135	0.358633
12	146	70	60	10	76	64	12	0.000318575	0.25374
13	146	65	60	5	81	64	17	0.026128315	2.231789
14	146	62	54	8	84	70	14	0.001975465	0.628311
15	146	48	42	6	98	82	16	0.001870917	0.607146
16	146	54	44	10	92	80	12	0.003856111	-0.89276
17	146	135	117	18	11	7	4	0.016476033	2.053133
18	146	82	70	12	64	54	10	0.000135962	0.166058
19	146	53	45	8	93	79	14	2.14543E-07	-0.00659
20	146	8	6	2	138	118	20	0.002810885	-0.80766
21	146	120	102	18	26	22	4	1.21498E-05	0.0497
22	146	93	81	12	53	43	10	0.004527806	0.968773
23	146	89	77	12	57	47	10	0.002182274	0.669097
24	146	48	39	9	98	85	13	0.003635207	-0.87024
25	146	113	101	12	33	23	10	0.033571469	2.7807
26	146	66	55	11	80	69	11	0.001183256	-0.4903
27	146	96	82	14	50	42	8	0.00025276	0.227061
28	146	83	75	8	63	49	14	0.021745155	2.105091
29	146	118	102	16	28	22	6	0.005023187	1.046424
30	146	66	55	11	80	69	11	0.001183256	-0.4903

Geometry Unit 1 Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	169	65	57	8	104	96	8	0.004140693	-0.99705
2	169	48	44	4	121	109	12	0.000439442	0.317185
3	169	42	42	0	127	111	16	#NUM!	2.417578
4	169	121	114	7	48	39	9	0.025849649	2.596087
5	169	107	101	6	62	52	10	0.020724421	2.251673
6	169	29	25	4	140	128	12	0.002977327	-0.8742
7	169	92	86	6	77	67	10	0.008720839	1.429762
10	169	105	95	10	64	58	6	4.38998E-06	-0.03205
12	169	42	36	6	127	117	10	0.005958734	-1.23037
13	169	60	56	4	109	97	12	0.003820882	0.922714
14	169	65	60	5	104	93	11	0.001699643	0.623159
15	169	63	57	6	106	96	10	1.58737E-06	-0.01929
16	169	132	123	9	37	30	7	0.01819703	2.221965
20	169	33	23	10	136	130	6	0.06915461	-4.5574
22	169	75	69	6	94	84	10	0.00146413	0.582044

Geometry Unit 2 Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	159	107	101	6	52	41	11	0.037359198	2.976134
2	159	126	116	10	33	26	7	0.018887722	2.196983
3	159	114	104	10	45	38	7	0.006618373	1.246954
4	159	65	55	10	10	5	5	0.174450239	1.761599
5	159	113	107	6	46	35	11	0.048168263	3.442217
6	159	93	85	8	66	57	9	0.004578206	1.01222
7	159	104	97	7	55	45	10	0.021211422	2.222661
8	159	125	119	6	34	23	11	0.077920881	4.609909
9	159	130	120	10	29	22	7	0.025240871	2.591498
10	159	97	92	5	67	50	17	-0.03248473	3.763859
11	159	124	115	9	35	27	8	0.027011484	2.637386
12	159	112	106	6	47	36	11	0.046216317	3.360436
13	159	103	92	11	34	28	6	0.029253461	0.966271
14	159	47	46	1	67	53	14	0.135033848	3.147828
15	159	61	58	3	98	84	14	0.017335258	1.858831
16	159	94	89	5	65	53	12	0.031203903	2.636482
17	159	104	99	5	55	43	12	0.046803749	3.301754
18	159	83	77	6	76	65	11	0.009979001	1.476727
19	159	121	112	9	38	30	8	0.02234923	2.369298
20	159	83	81	2	76	61	15	0.062470777	3.531866
21	159	89	86	3	70	56	14	0.05368456	3.368571
22	159	26	26	0	45	34	11	0.263457402	3.572252
23	159	35	31	4	124	111	13	0.000114124	-0.15972
24	159	129	123	6	30	19	11	0.091483186	5.111469
25	159	106	99	7	53	43	10	0.023676312	2.359165
26	159	69	63	6	90	79	11	0.002347808	0.713228
27	159	91	84	7	68	58	10	0.008987244	1.415939
28	159	55	51	4	104	91	13	0.004941111	1.014619
29	159	100	90	10	59	52	7	0.000605542	0.367533
30	159	65	60	5	94	82	12	0.00486831	1.01782

Geometry Unit 4 Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	r							#VALUE!	#VALUE!
2	131	54	52	2	77	67	10	0.020146433	1.813078
3	r							#VALUE!	#VALUE!
4	r							#VALUE!	#VALUE!
5	131	45	43	2	86	76	10	0.011256088	1.353508
6	r							#VALUE!	#VALUE!
7	131	51	50	1	80	69	11	0.034827131	2.280797
8	131	55	51	4	76	68	8	0.0022858	0.637122
9	r							#VALUE!	#VALUE!
10	r							#VALUE!	#VALUE!
11	r							#VALUE!	#VALUE!
12	r							#VALUE!	#VALUE!
13	131	68	65	3	63	54	9	0.021843408	1.957434
14	131	66	63	3	65	56	9	0.019514145	1.845083
15	131	76	72	4	55	47	8	0.0180042	1.81767
16	r							#VALUE!	#VALUE!
17	131	95	90	5	36	29	7	0.030773427	2.511888
18	131	63	58	5	68	61	7	0.001209475	0.467378
19	r							#VALUE!	#VALUE!
20	131	60	56	4	71	63	8	0.004660908	0.909542
21	131	84	83	1	47	36	11	0.100416263	4.22749
22	131	62	57	5	69	62	7	0.000940592	0.412137
23	131	72	68	4	59	51	8	0.013787595	1.580004
24	131	82	79	3	49	40	9	0.042713878	2.823931
25	r							#VALUE!	#VALUE!
26	r							#VALUE!	#VALUE!
27	r							#VALUE!	#VALUE!
28	131	75	71	4	56	48	8	0.016889446	1.757255
29	131	92	85	7	39	34	5	0.004658427	0.945555
30	r							#VALUE!	#VALUE!

* r designates a free response question not graded by the computer

Geometry Unit 5 Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	88	54	49	5	34	31	3	3.94215E-05	-0.06923
2	88	20	19	1	68	61	7	0.004849824	0.72396
3	88	61	57	4	27	23	4	0.011766483	1.242635
4	r							#VALUE!	#VALUE
5	88	55	54	1	33	26	7	0.077986215	3.063767
6	r							#VALUE!	#VALUE
7	r							#VALUE!	#VALUE
8	88	33	33	0	55	47	8	#NUM!	2.297825
9	88	63	59	4	25	21	4	0.015060235	1.420217
10	88	62	61	1	26	19	7	0.107286542	3.768157
11	88	42	39	3	46	41	5	0.003061362	0.607408
12	88	58.001	58	0	30	22	8	0.154082342	4.124279
13	r							#VALUE!	#VALUE
14	r							#VALUE!	#VALUE
15	r							#VALUE!	#VALUE
16	88	41	40	1	47	40	7	0.038138167	2.027317
17	88	48	47	1	40	33	7	0.055711107	2.504912
18	88	68	64	4	20	16	4	0.026019315	1.930559

Geometry Semester Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	186	185	163	22	1.0001	1	0	0.000971269	-0.36698
2	186	129	117	12	57	47	10	0.009417457	1.604588
3	186	99	91	8	87	73	14	0.011099994	1.688088
4	186	171	155	16	15	9	6	0.033977195	3.523725
5	186	109	96	13	77	68	9	9.53811E-06	-0.04957
6	186	108	103	5	78	61	17	0.050157698	3.57711
7	186	95	87	8	91	77	14	0.008459872	1.470067
8	186	13	11	2	173	153	20	0.000611637	-0.41174
9	186	167	151	16	19	13	6	0.023456354	2.813478
10	186	138	126	12	48	38	10	0.017635948	2.242947
11	186	84	77	7	102	87	15	0.007144932	1.339295
12	186	100	94	6	86	70	16	0.027871316	2.654014
13	186	164	149	15	22	15	7	0.028525817	3.092027
14	186	148	134	14	38	30	8	0.013348436	1.974005
15	186	128	120	8	58	44	14	0.043652948	3.49947
16	186	137	124	13	49	40	9	0.009778733	1.651624
17	186	132	121	11	54	43	11	0.018994072	2.30742
18	186	60	56	4	126	108	18	0.009597765	1.504128
19	186	159	142	17	27	22	5	0.004705685	1.164346
20	186	109	100	9	77	64	13	0.012276988	1.794333
21	186	126	115	11	60	49	11	0.013152915	1.895828
22	186	166	149	17	20	15	5	0.01181927	1.930858
23	186	165	148	17	21	16	5	0.010490807	1.805167
24	186	127	121	6	59	43	16	0.069463605	4.401364
25	186	78	73	5	108	91	17	0.015652178	1.944404
26	186	153	139	14	33	25	8	0.01948576	2.434868
27	186	151	138	13	35	26	9	0.02600184	2.823379
28	186	175	158	17	11	6	5	0.032932603	3.560379
29	186	161	144	17	34	29	5	-0.00681012	0.77251
30	186	128	115	13	58	49	9	0.004095679	1.048787
31	186	165	146	19	21	18	3	0.000506608	0.370291
32	186	95	89	6	91	75	16	0.022598772	2.378481
33	186	137	123	14	49	41	8	0.004721624	1.136184
34	186	144	131	13	42	33	9	0.016502382	2.18967
35	186	77	70	7	109	94	15	0.003757345	0.971518

Fourth Grade Unit 1 (Benchmark)

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	256	212	158	54	44	19	25	0.044020788	4.096405
2	256	170	141	29	86	36	50	0.124407069	6.720962
3	256	149	117	32	107	60	47	0.041225959	3.835275
4	256	148	116	32	108	61	47	0.03935406	3.745805
5	256	115	98	17	141	79	62	0.075055958	5.029188
6	256	209	150	59	47	27	20	0.009963562	1.920843
7	256	145	117	28	111	60	51	0.059038662	4.572227
8	256	110	87	23	146	90	56	0.025890031	2.99168
9	256	175	133	42	81	44	37	0.033359395	3.492375
10	256	216	161	55	40	16	24	0.049194593	4.343719
11	256	230	170	60	26	7	19	0.062238267	4.916721
12	256	228	160	68	28	17	11	0.002839305	1.022846
13	256	171	137	34	85	40	45	0.079682711	5.392693
14	256	167	136	31	89	41	48	0.093863713	5.834512
15	256	95	65	30	161	112	49	0.000103116	-0.19146
16	256	234	168	66	22	9	13	0.023190152	2.998456
17	256	135	107	28	121	70	51	0.038941368	3.702166
18	256	229	167	62	27	10	17	0.037579867	3.818365
19	256	205	151	54	51	26	25	0.026245718	3.13754
20	256	137	112	25	119	65	54	0.062732103	4.687087
21	256	232	166	66	24	11	13	0.017540896	2.596649
22	256	242	174	68	14	3	11	0.04060759	3.975065
23	256	193	149	44	63	28	35	0.06376656	4.887437
24	256	211	154	57	45	23	22	0.022105856	2.88409
25	256	138	113	25	118	64	54	0.065029048	4.773586
26	256	79	69	10	177	108	69	0.055444466	4.211972
27	256	123	90	33	133	87	46	0.005097692	1.342465
28	256	136	116	20	120	61	59	0.102846076	5.956691
29	256	169	128	41	87	49	38	0.02793785	3.185832
30	256	106	78	28	150	99	51	0.00476592	1.294102
31	256	198	157	41	58	20	38	0.111853622	6.497451
32	256	66	53	13	190	124	66	0.015501624	2.278834
33	256	113	84	29	143	93	50	0.007281273	1.599822
34	256	110	87	23	146	90	56	0.025890031	2.99168

Fourth Grade Second Six Weeks Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	256	236	164	72	23	11	12	-0.0051401	0.417527
2	256	217	157	60	42	18	24	0.019984711	2.622461
3	256	191	144	47	68	31	37	0.037936519	3.71229
4	256	113	65	48	146	110	36	0.008936562	-3.57751
5	256	6	3	3	253	172	81	-0.01472107	-1.02712
6	256	207	157	50	52	18	34	0.068708516	4.773444
7	256	170	133	37	89	42	47	0.053875014	4.429165
8	256	170	135	35	89	40	49	0.070467089	5.002115
9	256	194	142	52	65	33	32	0.013274824	2.484749
10	256	106	80	26	153	95	58	-0.00231115	1.843505
11	256	44	21	23	215	154	61	0.008389194	-3.37911
12	256	144	116	28	115	59	56	0.053915565	4.483377
13	256	153	127	26	106	48	58	0.098277224	5.853765
14	256	98	74	24	161	101	60	-0.00392323	1.737621
15	256	165	138	27	94	37	57	0.133170771	6.761163
16	256	150	115	35	109	60	49	0.020777252	3.101124
17	256	195	140	55	64	35	29	0.000526335	1.643817
18	256	206	147	59	53	28	25	0.000838345	1.559865
19	256	243	169	74	16	6	10	0.001293685	0.609068
20	256	164	132	32	95	43	52	0.077815836	5.247781

Fourth Grade Unit 6 Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	137	131	87	44	6	2	4	0.013684724	-2.36325
2	137	80	53	27	57	36	21	0.000734702	-0.6348
3	137	124	85	39	13	4	9	0.036818265	-0.33906
4	137	95	72	23	42	17	25	0.082175938	1.853634
5	137	72	57	15	65	32	33	0.072018304	1.956048
6	137	119	82	37	18	7	11	0.030979761	-0.11108
7	137	57	41	16	80	48	32	0.011100539	0.436428
8	137	83	59	24	54	30	24	0.018106422	0.446699
9	137	44	30	14	93	59	34	0.001565858	-0.12225
10	137	126	81	45	11	8	3	0.001730138	-3.04586
11	137	106	76	30	31	13	18	0.047341908	0.87665
12	137	80	58	22	57	31	26	0.025144914	0.73775
13	137	75	53	22	62	36	26	0.012455178	0.31113
14	137	73	49	24	64	40	24	0.001684915	-0.39938

Fourth Grade Unit 7 Test

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	138	132	88	44	6	1	5	0.03188502	-2.16672
2	138	105	72	33	33	17	16	0.016239177	-0.18958
3	138	57	44	13	81	45	36	0.036841545	1.261296
4	138	114	79	35	24	10	14	0.033134712	0.064144
5	138	100	71	29	38	18	20	0.034196805	0.563215
6	138	69	61	8	69	28	41	0.192604999	3.59726
7	138	122	84	38	16	5	11	0.043512025	-0.14858
8	138	75	60	15	63	29	34	0.091719279	2.212402
9	138	77	47	30	61	42	19	0.004769018	-1.69963
10	138	108	70	38	30	19	11	0.000117221	-1.53256
11	138	113	77	36	25	12	13	0.01828855	-0.3966
12	138	127	85	42	11	4	7	0.020475798	-1.4031
13	138	96	67	29	42	22	20	0.019833823	0.183789
14	138	110	76	34	28	13	15	0.025254449	-0.0184
15	138	90	69	21	48	20	28	0.086533998	1.924271
16	138	124	81	43	14	8	6	0.001876925	-2.12171
17	138	79	64	15	59	25	34	0.116769555	2.565143
18	138	107	75	32	31	14	17	0.032967414	0.330542
19	138	73	59	14	65	30	35	0.096483688	2.311503
20	138	88	63	25	50	26	24	0.027594913	0.606976
21	138	78	56	22	60	33	27	0.021788755	0.565083
22	138	95	69	26	43	20	23	0.045143168	0.968881
23	138	118	76	42	20	13	7	1.37621E-05	-2.14703
24	138	96	73	23	42	16	26	0.094145913	1.94816
25	138	29	21	8	109	68	41	0.005417017	0.315248
26	138	52	43	9	86	46	40	0.067053379	1.967635
27	138	23	20	3	115	69	46	0.036286401	1.487721

Fourth Grade February Benchmark

#	total	count y	y passed	y fail	count n	n passed	n fail	info gain	z-score
1	259	94	73	21	165	101	64	0.021172393	2.253344
2	259	189	143	46	70	31	39	0.061102481	3.754906
3	259	124	95	29	135	79	56	0.027107286	2.50967
4	259	232	167	65	27	7	20	0.060509522	2.919619
5	259	109	84	25	150	90	60	0.023781221	2.367061
6	259	151	126	25	108	48	60	0.122321597	5.926876
7	259	228	157	71	31	17	14	0.006491429	-0.26704
8	259	86	65	21	173	109	64	0.011807573	1.591415
9	259	198	141	57	61	33	28	0.016670948	1.307891
10	259	53	43	10	206	131	75	0.017654581	2.13155
11	259	123	100	23	136	74	62	0.060795299	4.052686
12	259	251	171	80	8	3	5	0.008482904	-1.98874
13	259	128	106	22	131	68	63	0.08064752	4.736058
14	259	97	74	23	162	100	62	0.016690991	1.938361
15	259	227	163	64	32	11	21	0.046299401	2.487958
16	259	72	59	13	187	115	72	0.029446706	2.784226
17	259	218	151	67	41	23	18	0.007284942	0.101358
18	259	250	171	79	9	3	6	0.012446618	-1.36794
19	259	233	162	71	26	12	14	0.015159881	0.406281
20	259	241	167	74	18	7	11	0.018151995	0.197451
21	259	31	26	5	228	148	80	0.013816057	1.903469
22	259	155	127	28	104	47	57	0.106359981	5.473993
23	259	223	158	65	36	16	20	0.025694204	1.492693
24	259	190	141	49	69	33	36	0.04286496	2.948298
25	259	191	152	39	68	22	46	0.136114222	6.132029
26	259	160	132	28	99	42	57	0.123884835	5.951797
27	259	161	130	31	98	44	54	0.098187584	5.212595
28	259	228	162	66	31	12	19	0.033667278	1.81717
29	259	141	121	20	118	53	65	0.140189319	6.387831
30	259	83	61	22	176	113	63	0.006278155	1.047673
31	259	148	120	28	111	54	57	0.084846157	4.83181
32	259	148	121	27	111	53	58	0.093477936	5.105228
33	259	204	147	57	55	27	28	0.027597917	1.969555
34	259	160	119	41	99	55	44	0.027030384	2.331991
35	259	60	42	18	199	132	67	0.000792258	0.165368
36	259	220	165	55	39	9	30	0.106591188	4.876968
37	259	120	95	25	139	79	60	0.041575562	3.264617
38	259	145	122	23	114	52	62	0.122091065	5.927402

39	259	108	91	17	151	83	68	0.07230853	4.4808
40	259	242	166	76	17	8	9	0.008724087	-0.72138
41	259	114	70	44	145	104	41	0.008559206	-2.40418
42	259	147	107	40	112	67	45	0.013447178	1.464814
43	259	172	137	35	87	37	50	0.098560663	5.179038
44	259	231	164	67	28	10	18	0.036553737	1.867245
45	259	191	141	50	68	33	35	0.039019425	2.749503
46	259	56	43	13	203	131	72	0.008710409	1.407175
47	259	232	163	69	27	11	16	0.024841775	1.148476
48	259	137	111	26	122	63	59	0.071578251	4.412278

APPENDIX 2

CHAPTER 5 DATA

```
> table(totunit1c$Passed,totunit1c$cutoff50)

    f   p
a   0   0
f  34  45
p  11 166
```

```
> table(totunit1c$Passed,totunit1c$cutoff55)

    f   p
a   0   0
f  52  27
p  25 152
```

```
> table(totunit1c$Passed,totunit1c$cutoff60)

    f   p
a   0   0
f  60  19
p  43 134
```

```
> table(totunit1c$Passed,totunit1c$cutoff65)

    f   p
a   0   0
f  66  13
p  54 123
```

```
> table(totunit1c$Passed,totunit1c$cutoff70)

   f  p
a  0  0
f 75  4
p 98 79
```

APPENDIX 3

CHAPTER 6 DATA

Univariate Testing for each question on cohort one

```
> q1lm <- glm(Passed~X1,data=totunit1c,family=binomial(logit))
> summary(q1lm)

Call:
glm(formula = Passed ~ X1, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.6539  -1.0633     0.7668   0.7668   1.2960

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)  -0.2744      0.3044   -0.902     0.367
X11           1.3480      0.3428    3.933  8.39e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 300.78  on 254  degrees of freedom
AIC: 304.78

Number of Fisher Scoring iterations: 4
```

```
> q2lm <- glm(Passed~X2,data=totunit1c,family=binomial(logit))
> summary(q2lm)

Call:
glm(formula = Passed ~ X2, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.8807  -1.0415    0.6116   0.6116   1.3197

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.3285     0.2186  -1.503    0.133
X21           1.9100     0.2989   6.390 1.66e-10 ***
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 272.25  on 254  degrees of freedom
AIC: 276.25

Number of Fisher Scoring iterations: 4
```

```
> q3lm <- glm(Passed~X3,data=totunit1c,family=binomial(logit))
> summary(q3lm)

Call:
glm(formula = Passed ~ X3, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.7540  -1.2827    0.6954   0.6954   1.0756

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2442     0.1948   1.254 0.209973
X31           1.0522     0.2788   3.774 0.000161 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 301.77  on 254  degrees of freedom
AIC: 305.77

Number of Fisher Scoring iterations: 4
```

```
> q4lm <- glm(Passed~X4,data=totunit1c,family=binomial(logit))
> summary(q4lm)

Call:
glm(formula = Passed ~ X4, family = binomial(logit), data = totunit1c)

Deviance Residuals:
   Min      1Q       Median      3Q     Max
-1.750  -1.290       0.698   0.698   1.069

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)   0.2607     0.1941     1.343    0.179161
X41           1.0271     0.2785     3.689    0.000226 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 302.43  on 254  degrees of freedom
AIC: 306.43

Number of Fisher Scoring iterations: 4


> q5lm <- glm(Passed~X5,data=totunit1c,family=binomial(logit))
> summary(q5lm)

Call:
glm(formula = Passed ~ X5, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q       Median      3Q      Max
-1.9554  -1.2819      0.5656   1.0764   1.0764

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)   0.2423     0.1697     1.428    0.153
X51           1.5094     0.3128     4.826    1.39e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 289.76  on 254  degrees of freedom
AIC: 293.76

Number of Fisher Scoring iterations: 4
```

```
> q6lm <- glm(Passed~X6,data=totunit1c,family=binomial(logit))
> summary(q6lm)

Call:
glm(formula = Passed ~ X6, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.5905  -1.3072     0.8145   0.8145   1.0529

Coefficients:
            Estimate    Std. Error  z value    Pr(>|z|)
(Intercept)  0.3001     0.2950      1.017      0.3090
X61          0.6330     0.3326      1.903      0.0571 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 312.87  on 254  degrees of freedom
AIC: 316.87

Number of Fisher Scoring iterations: 4
```

```
> q7lm <- glm(Passed~X7,data=totunit1c,family=binomial(logit))
> summary(q7lm)

Call:
glm(formula = Passed ~ X7, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.8136  -1.2472     0.6551   0.6551   1.1092

Coefficients:
            Estimate    Std. Error  z value    Pr(>|z|)
(Intercept)  0.1625     0.1905      0.853      0.393
X71          1.2675     0.2838      4.466      7.96e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 295.45  on 254  degrees of freedom
AIC: 299.45

Number of Fisher Scoring iterations: 4
```

```
> q8lm <- glm(Passed~X8,data=totunit1c,family=binomial(logit))
> summary(q8lm)

Call:
glm(formula = Passed ~ X8, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7692  -1.3844   0.6849   0.9837   0.9837

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4745     0.1702   2.788  0.00531 **
X81           0.8560     0.2897   2.954  0.00313 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 307.21  on 254  degrees of freedom
AIC: 311.21

Number of Fisher Scoring iterations: 4
```

```
> q9lm <- glm(Passed~X9,data=totunit1c,family=binomial(logit))
> summary(q9lm)

Call:
glm(formula = Passed ~ X9, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6894  -1.2518   0.7409   0.7409   1.1048

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1733     0.2231   0.777 0.437273
X91           0.9794     0.2848   3.440 0.000583 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 304.56  on 254  degrees of freedom
AIC: 308.56

Number of Fisher Scoring iterations: 4
```

```
> q10lm <- glm(Passed~X10,data=totunit1c,family=binomial(logit))
> summary(q10lm)

Call:
glm(formula = Passed ~ X10, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q      Median       3Q      Max
-1.6541  -1.0108     0.7667   0.7667   1.3537

Coefficients:
            Estimate    Std. Error  z value    Pr(>|z|)
(Intercept)  -0.4055    0.3227      -1.256     0.209
X101          1.4795    0.3586       4.126     3.68e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 298.94  on 254  degrees of freedom
AIC: 302.94

Number of Fisher Scoring iterations: 4


> q11lm <- glm(Passed~X11,data=totunit1c,family=binomial(logit))
> summary(q11lm)

Call:
glm(formula = Passed ~ X11, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q      Median       3Q      Max
-1.6394  -0.7920     0.7775   0.7775   1.6200

Coefficients:
            Estimate    Std. Error  z value    Pr(>|z|)
(Intercept)  -0.9985    0.4421      -2.258     0.0239 *
X111          2.0400    0.4669       4.369     1.25e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 294.31  on 254  degrees of freedom
AIC: 298.31

Number of Fisher Scoring iterations: 4
```

```
> q12lm <- glm(Passed~X12,data=totunit1c,family=binomial(logit))
> summary(q12lm)

Call:
glm(formula = Passed ~ X12, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5555  -1.5555   0.8416   0.8416   0.9990

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4353     0.3870   1.125    0.261
X121          0.4203     0.4131   1.017    0.309

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 315.39  on 254  degrees of freedom
AIC: 319.39

Number of Fisher Scoring iterations: 4
```

```
> q13lm <- glm(Passed~X13,data=totunit1c,family=binomial(logit))
> summary(q13lm)

Call:
glm(formula = Passed ~ X13, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7974  -1.1278   0.6659   0.6659   1.2278

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1178     0.2173  -0.542    0.588
X131          1.5114     0.2897   5.217 1.82e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 288.12  on 254  degrees of freedom
AIC: 292.12

Number of Fisher Scoring iterations: 4
```

```
> q14lm <- glm(Passed~X14,data=totunit1c,family=binomial(logit))
> summary(q14lm)

Call:
glm(formula = Passed ~ X14, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8352  -1.1113   0.6408   0.6408   1.2450

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1576     0.2127  -0.741    0.459
X141          1.6363     0.2913   5.618 1.93e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 283.09  on 254  degrees of freedom
AIC: 287.09

Number of Fisher Scoring iterations: 4


> q15lm <- glm(Passed~X15,data=totunit1c,family=binomial(logit))
> summary(q15lm)

Call:
glm(formula = Passed ~ X15, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5425  -1.5183   0.8519   0.8712   0.8712

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.82668    0.17128   4.826 1.39e-06 ***
X151        -0.05349    0.27938  -0.191    0.848
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 316.36  on 254  degrees of freedom
AIC: 320.36

Number of Fisher Scoring iterations: 4
```

```
> q16lm <- glm(Passed~X16,data=totunit1c,family=binomial(logit))
> summary(q16lm)

Call:
glm(formula = Passed ~ X16, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q      Median      3Q      Max
-1.5910  -1.5910      0.8141   0.8141   1.3370

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)  -0.3677    0.4336      -0.848    0.39643
X161         1.3020     0.4573      2.847     0.00441 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 308.17  on 254  degrees of freedom
AIC: 312.17

Number of Fisher Scoring iterations: 4
```

```
> q17lm <- glm(Passed~X17,data=totunit1c,family=binomial(logit))
> summary(q17lm)

Call:
glm(formula = Passed ~ X17, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q      Median      3Q      Max
-1.7737  -1.3145      0.6818   1.0462   1.0462

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)   0.3167    0.1841      1.720     0.085419 .
X171         1.0240     0.2810      3.644     0.000268 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 302.58  on 254  degrees of freedom
AIC: 306.58

Number of Fisher Scoring iterations: 4
```

```
> q18lm <- glm(Passed~X18,data=totunit1c,family=binomial(logit))
> summary(q18lm)

Call:
glm(formula = Passed ~ X18, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.6165  -0.9619    0.7946   0.7946   1.4094

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.5306     0.3985  -1.331 0.183033
X181          1.5215     0.4254   3.577 0.000348 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 303.06  on 254  degrees of freedom
AIC: 307.06

Number of Fisher Scoring iterations: 4


> q19lm <- glm(Passed~X19,data=totunit1c,family=binomial(logit))
> summary(q19lm)

Call:
glm(formula = Passed ~ X19, family = binomial(logit), data = totunit1c)

Deviance Residuals:
   Min      1Q   Median      3Q     Max
-1.633  -1.194    0.782   0.782   1.161

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.03922    0.28011   0.140  0.88864
X191         0.98908    0.32187   3.073  0.00212 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 307.09  on 254  degrees of freedom
AIC: 311.09

Number of Fisher Scoring iterations: 4
```

```
> q21lm <- glm(Passed~X21,data=totunit1c,family=binomial(logit))
> summary(q21lm)

Call:
glm(formula = Passed ~ X21, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5856  -1.5856   0.8182   0.8182   1.2491

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1671     0.4097  -0.408   0.6834
X211          1.0894     0.4348   2.506   0.0122 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 310.18  on 254  degrees of freedom
AIC: 314.18

Number of Fisher Scoring iterations: 4
```

```
> q22lm <- glm(Passed~X22,data=totunit1c,family=binomial(logit))
> summary(q22lm)

Call:
glm(formula = Passed ~ X22, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5934  -1.5934   0.8123   0.8123   1.7552

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.2993     0.6513  -1.995 0.046066 *
X221          2.2388     0.6669   3.357 0.000787 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 301.99  on 254  degrees of freedom
AIC: 305.99

Number of Fisher Scoring iterations: 4
```

```
> q23lm <- glm(Passed~X23,data=totunit1c,family=binomial(logit))
> summary(q23lm)

Call:
glm(formula = Passed ~ X23, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7196  -1.0842   0.7194   0.7194   1.2735

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.2231     0.2535  -0.880    0.379
X231          1.4429     0.3061   4.713 2.44e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 293.77  on 254  degrees of freedom
AIC: 297.77

Number of Fisher Scoring iterations: 4


> q24lm <- glm(Passed~X24,data=totunit1c,family=binomial(logit))
> summary(q24lm)

Call:
glm(formula = Passed ~ X24, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6179  -1.1963   0.7936   0.7936   1.1586

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.04445    0.29822   0.149  0.88151
X241         0.94945    0.33611   2.825  0.00473 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 308.56  on 254  degrees of freedom
AIC: 312.56

Number of Fisher Scoring iterations: 4
```

```
> q25lm <- glm(Passed~X25,data=totunit1c,family=binomial(logit))
> summary(q25lm)

Call:
glm(formula = Passed ~ X25, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.8484  -1.2504    0.6322   0.7507   1.1062

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1699     0.1848   0.919    0.358
X251          1.3386     0.2881   4.647 3.37e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 293.32  on 254  degrees of freedom
AIC: 297.32

Number of Fisher Scoring iterations: 4


> q26lm <- glm(Passed~X26,data=totunit1c,family=binomial(logit))
> summary(q26lm)

Call:
glm(formula = Passed ~ X26, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-2.0332  -1.3726    0.5203   0.9940   0.9940

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4480     0.1541   2.907  0.00365 **
X261          1.4835     0.3718   3.990 6.61e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 296.72  on 254  degrees of freedom
AIC: 300.72

Number of Fisher Scoring iterations: 4
```

```
> q27lm <- glm(Passed~X27,data=totunit1c,family=binomial(logit))
> summary(q27lm)

Call:
glm(formula = Passed ~ X27, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6221  -1.4572   0.7904   0.9214   0.9214

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.6373     0.1823   3.496 0.000473 ***
X271          0.3660     0.2732   1.340 0.180335
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 314.59  on 254  degrees of freedom
AIC: 318.59

Number of Fisher Scoring iterations: 4
```

```
> q28lm <- glm(Passed~X28,data=totunit1c,family=binomial(logit))
> summary(q28lm)

Call:
glm(formula = Passed ~ X28, family = binomial(logit), data = totunit1c)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.958  -1.192   0.564   0.564   1.163

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.03334    0.18260   0.183    0.855
X281         1.72452    0.30325   5.687  1.3e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.4  on 255  degrees of freedom
Residual deviance: 279.9  on 254  degrees of freedom
AIC: 283.9

Number of Fisher Scoring iterations: 4
```

```
> q29lm <- glm(Passed~X29,data=totunit1c,family=binomial(logit))
> summary(q29lm)

Call:
glm(formula = Passed ~ X29, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.6830  -1.2871     0.7455   0.7455   1.0715

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2542     0.2162   1.176  0.23953
X291          0.8842     0.2809   3.147  0.00165 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 306.49  on 254  degrees of freedom
AIC: 310.49

Number of Fisher Scoring iterations: 4


> q30lm <- glm(Passed~X30,data=totunit1c,family=binomial(logit))
> summary(q30lm)

Call:
glm(formula = Passed ~ X30, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.6317  -1.4689     0.7832   0.9116   0.9116

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.6633     0.1724   3.848  0.000119 ***
X301          0.3612     0.2797   1.291  0.196591
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 314.71  on 254  degrees of freedom
AIC: 318.71

Number of Fisher Scoring iterations: 4
```

```
> q31lm <- glm(Passed~X31,data=totunit1c,family=binomial(logit))
> summary(q31lm)

Call:
glm(formula = Passed ~ X31, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.7747  -0.9196    0.6812   0.6812   1.4592

Coefficients:
            Estimate  Std. Error  z value   Pr(>|z|)
(Intercept)  -0.6419   0.2763     -2.323    0.0202 *
X311          1.9845   0.3272      6.065    1.32e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 276.71  on 254  degrees of freedom
AIC: 280.71

Number of Fisher Scoring iterations: 4


> q32lm <- glm(Passed~X32,data=totunit1c,family=binomial(logit))
> summary(q32lm)

Call:
glm(formula = Passed ~ X32, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.8026  -1.4542    0.6624   0.9238   0.9238

Coefficients:
            Estimate  Std. Error  z value   Pr(>|z|)
(Intercept)   0.6306   0.1524      4.139    3.49e-05 ***
X321          0.7747   0.3450      2.246    0.0247 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.4  on 255  degrees of freedom
Residual deviance: 310.9  on 254  degrees of freedom
AIC: 314.9

Number of Fisher Scoring iterations: 4
```

```
> q33lm <- glm(Passed~X33,data=totunit1c,family=binomial(logit))
> summary(q33lm)

Call:
glm(formula = Passed ~ X33, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6493  -1.4497   0.7702   0.9276   0.9276

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.6206     0.1754   3.539 0.000402 ***
X331          0.4429     0.2777   1.595 0.110755
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 313.82  on 254  degrees of freedom
AIC: 317.82

Number of Fisher Scoring iterations: 4


> q34lm <- glm(Passed~X34,data=totunit1c,family=binomial(logit))
> summary(q34lm)

Call:
glm(formula = Passed ~ X34, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7692  -1.3844   0.6849   0.9837   0.9837

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4745     0.1702   2.788  0.00531 **
X341          0.8560     0.2897   2.954  0.00313 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 307.21  on 254  degrees of freedom
AIC: 311.21

Number of Fisher Scoring iterations: 4
```

General Linear Models (Residuals, AIG, and P-values)

GLM Logistics for Reduced Model

(Table 5 only)

```
> thesislm <- glm(Passed~X2+X13+X14+X17+X28+X31,data=totunit1c,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X2 + X13 + X14 + X17 + X28 + X31, family = binomial(logit),
    data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-2.6672  -0.5128     0.3719   0.6061   2.4473

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)  -2.9434   0.4860     -6.056   1.39e-09 ***
X21           1.4022   0.3591      3.905   9.42e-05 ***
X131          0.9731   0.3551      2.740   0.006136 **
X141          0.8914   0.3545      2.515   0.011907 *
X171          0.9222   0.3577      2.578   0.009932 **
X281          1.0045   0.3678      2.731   0.006314 **
X311          1.2779   0.3873      3.300   0.000968 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 208.74  on 249  degrees of freedom
AIC: 222.74

Number of Fisher Scoring iterations: 5
```

P-value for Reduced Model

```
> pchisq(208.74,249)
[1] 0.02996081
```

GLM Logistics for Study Model without Questions 18 and 7

(Table 5 only)

```
> thesislm <- glm(Passed~X2+X13+X14+X17+X28+X31+X5,data=totunit1c,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X2 + X13 + X14 + X17 + X28 + X31 + X5,
    family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-2.7833  -0.5721     0.3134   0.5863   2.4705

Coefficients:
            Estimate   Std. Error  z value  Pr(>|z|)
(Intercept)  -3.0033   0.4886      -6.147   7.89e-10 ***
X21           1.2703   0.3657       3.474   0.000513 ***
X131          0.8631   0.3620       2.385   0.017099 *
X141          0.8703   0.3574       2.435   0.014884 *
X171          0.8846   0.3619       2.444   0.014519 *
X281          0.9054   0.3728       2.429   0.015156 *
X311          1.2940   0.3918       3.303   0.000956 ***
X51           0.7680   0.3941       1.948   0.051364 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 204.86  on 248  degrees of freedom
AIC: 220.86

Number of Fisher Scoring iterations: 5
```

P-value for Study Model without Questions 18 and 7

```
> pchisq(204.86,248)
[1] 0.02107943
```

GLM Logistics for Score Only Model

```
> thesislm <- glm(Passed~Score,data=totunit1c,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ Score, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q      Median      3Q      Max
-2.32725  -0.00013   0.37146  0.66805  1.73440

Coefficients:
            Estimate      Std. Error   z value   Pr(>|z|)
(Intercept) -1.857e+01    6.523e+03    -0.003    0.998
Score18     -4.282e-08    9.224e+03    0.000     1.000
Score21     -4.264e-08    7.989e+03    0.000     1.000
Score24     -4.275e-08    7.989e+03    0.000     1.000
Score26     -4.236e-08    9.224e+03    0.000     1.000
Score29     -4.255e-08    7.145e+03    0.000     1.000
Score32     -4.259e-08    7.532e+03    0.000     1.000
Score35     -4.255e-08    7.989e+03    0.000     1.000
Score38      1.787e+01    6.523e+03    0.003     0.998
Score41      1.857e+01    6.523e+03    0.003     0.998
Score44      1.897e+01    6.523e+03    0.003     0.998
Score47      1.731e+01    6.523e+03    0.003     0.998
Score50      1.821e+01    6.523e+03    0.003     0.998
Score53      1.843e+01    6.523e+03    0.003     0.998
Score56      1.926e+01    6.523e+03    0.003     0.998
Score59      1.948e+01    6.523e+03    0.003     0.998
Score62      1.917e+01    6.523e+03    0.003     0.998
Score65      2.058e+01    6.523e+03    0.003     0.997
Score68      1.938e+01    6.523e+03    0.003     0.998
Score71      2.105e+01    6.523e+03    0.003     0.997
Score74      1.995e+01    6.523e+03    0.003     0.998
Score76      2.105e+01    6.523e+03    0.003     0.997
Score79      2.121e+01    6.523e+03    0.003     0.997
Score82      3.713e+01    6.684e+03    0.006     0.996
Score85      2.087e+01    6.523e+03    0.003     0.997
Score88      3.713e+01    6.973e+03    0.005     0.996
Score91      3.713e+01    6.973e+03    0.005     0.996
Score94      2.051e+01    6.523e+03    0.003  0.997
Score97      3.713e+01    7.989e+03    0.005  0.996

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 205.41  on 227  degrees of freedom
AIC: 263.41
```

P-value for Score Only Model

```
> pchisq(205.41,227)
[1] 0.1548737
```

GLM Logistics for Study Model without Question 18

```
> thesislm <- glm(Passed~X2+X13+X14+X17+X28+X31+X5+X7,data=totunit1c,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X2 + X13 + X14 + X17 + X28 + X31 + X5 +
    X7, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8587  -0.5403   0.2833   0.5788   2.5492

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)  -3.2096   0.5119    -6.270   3.62e-10 ***
X21           1.3506   0.3738     3.614   0.000302 ***
X131          0.8735   0.3656     2.389   0.016885 *
X141          0.6919   0.3732     1.854   0.063756 .
X171          0.9397   0.3673     2.558   0.010517 *
X281          0.7241   0.3889     1.862   0.062586 .
X311          1.2713   0.3945     3.223   0.001268 **
X51           0.7358   0.3995     1.842   0.065506 .
X71           0.6917   0.3824     1.809   0.070460 .

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 201.58  on 247  degrees of freedom
AIC: 219.58

Number of Fisher Scoring iterations: 5
```

P-value for Study Model without questions 18

```
> pchisq(201.58,247)
[1] 0.0156299
```

GLM Logistics for Study Model

```
> thesislm <- glm(Passed~X2+X13+X14+X17+X28+X31+X5+X7+X18,data=totunit1c
,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X2 + X13 + X14 + X17 + X28 + X31 + X5 +
    X7 + X18, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-2.8624  -0.4934     0.2780   0.5554   2.4769

Coefficients:
            Estimate   Std. Error  z value    Pr(>|z|)
(Intercept)  -3.8871   0.6898      -5.635     1.75e-08 ***
X21          1.3557    0.3768      3.598      0.000321 ***
X131         0.8240    0.3692      2.232      0.025609 *
X141         0.6677    0.3769      1.771      0.076522 .
X171         0.9116    0.3703      2.462      0.013819 *
X281         0.7095    0.3927      1.807      0.070817 .
X311         1.2740    0.3975      3.205      0.001349 **
X51          0.6804    0.4048      1.681      0.092755 .
X71          0.6766    0.3869      1.749      0.080308 .
X181         0.8673    0.5429      1.598      0.110132
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 198.98  on 246  degrees of freedom
AIC: 218.98
```

P-value for the Study Model

```
> pchisq(198.98,246)
[1] 0.01248981
```

GLM Logistics for Study Model with Question 25

```
> thesislm <- glm(Passed~X2+X13+X14+X17+X28+X31+X5+X7+X18+X25,data=totunit1c,
family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X2 + X13 + X14 + X17 + X28 + X31 + X5 +
    X7 + X18 + X25, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median      3Q     Max
-2.9040  -0.5264    0.2657  0.5500  2.3232


Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -3.8989     0.6934  -5.623 1.87e-08 ***
X21           1.3018     0.3805   3.421 0.000624 ***
X131          0.8269     0.3705   2.232 0.025641 *
X141          0.6761     0.3801   1.779 0.075240 .
X171          0.8752     0.3722   2.351 0.018703 *
X281          0.5978     0.4044   1.478 0.139293
X311          1.2466     0.3980   3.132 0.001737 **
X51           0.6219     0.4116   1.511 0.130798
X71           0.6844     0.3911   1.750 0.080108 .
X181          0.7895     0.5527   1.428 0.153198
X251          0.4804     0.3846   1.249 0.211596

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 197.43  on 245  degrees of freedom
AIC: 219.43

Number of Fisher Scoring iterations: 5
```

P-value for Study Model with Question 25

```
> pchisq(197.43,245)
[1] 0.01143234
```

Study Model with Question 6

```
> thesislm <- glm(Passed~X2+X5+X7+X13+X14+X17+X18++X26+X28+X31+X6,
data=totunit1c,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X2 + X5 + X7 + X13 + X14 + X17 + X18 +
    +X26 + X28 + X31 + X6, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q     Median      3Q      Max
-2.9674  -0.4682     0.2629  0.6193   2.4134

Coefficients:
            Estimate    Std. Error  z value  Pr(>|z|)
(Intercept)  -4.3715    0.8214      -5.322   1.03e-07 ***
X21          1.2958     0.3841      3.374    0.000741 ***
X51          0.7444     0.4112      1.810    0.070267 .
X71          0.6870     0.3917      1.754    0.079440 .
X131         0.7415     0.3750      1.977    0.048005 *
X141         0.6019     0.3789      1.589    0.112117
X171         0.9053     0.3728      2.429    0.015148 *
X181         0.9929     0.5571      1.782    0.074693 .
X261         0.3498     0.4717      0.742    0.458312
X281         0.6410     0.3970      1.615    0.106365
X311         1.2801     0.4012      3.191    0.001420 **
X61          0.5222     0.4607      1.133    0.257013
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 197.18  on 244  degrees of freedom
AIC: 221.18

Number of Fisher Scoring iterations: 5
```

P-value for Study Model with Question 6

```
> pchisq(198.45,245)
[1] 0.01312434
```

GLM Logistics for All Model (without 4, 12, 15, and 20)

```
> thesislm <- glm(Passed~X1+X2+X3+X5+X6+X7+X8+X9+X10+X11+X13+X14+X16+
X17+X18+X19+X21+X22+X23+X24+X25+X26+X27+X28+X29+X30+X31+X32+X33+
X34,data=totunit1c,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X1 + X2 + X3 + X5 + X6 + X7 + X8 + X9 +
    X10 + X11 + X13 + X14 + X16 + X17 + X18 + X19 + X21 + X22 +
    X23 + X24 + X25 + X26 + X27 + X28 + X29 + X30 + X31 + X32 +
    X33 + X34, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-3.1445  -0.3830    0.2126   0.5644   2.1430

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -6.19517    1.50810  -4.108 3.99e-05 ***
X11          0.33691    0.51553   0.654  0.51343
X21          1.36876    0.45553   3.005  0.00266 **
X31         -0.66586    0.46787  -1.423  0.15469
X51          0.77830    0.45978   1.693  0.09050 .
X61          0.53330    0.51288   1.040  0.29842
X71          0.81595    0.43164   1.890  0.05871 .
X81          0.41816    0.45407   0.921  0.35710
X91         -0.44505    0.46578  -0.955  0.33933
X101         0.53407    0.52842   1.011  0.31216
X111         0.39487    0.72159   0.547  0.58423
X131         0.73939    0.41725   1.772  0.07638 .
X141         0.53074    0.43271   1.227  0.21999
X161        -0.26947    0.70497  -0.382  0.70228
X171         0.99605    0.41306   2.411  0.01589 *
X181         0.92953    0.63650   1.460  0.14419
X191        -0.16957    0.50644  -0.335  0.73775
X211         0.49989    0.67029   0.746 0 .45580
X221         0.83416    0.92232   0.904  0.36577
X231        -0.01251    0.49730  -0.025  0.97993
X241         0.41606    0.53550   0.777  0.43719
X251         0.65679    0.44154   1.488  0.13688
X261         0.32520    0.52733   0.617  0.53744
X271        -0.62367    0.43928  -1.420  0.15568
X281         0.61859    0.45549   1.358  0.17444
X291         0.31114    0.44030   0.707  0.47978
X301        -0.36460    0.42700  -0.854  0.39318
X311         1.46355    0.49931   2.931  0.00338 **
X321         0.27667    0.50917   0.543  0.58686
X331        -0.37208    0.42063  -0.885  0.37638
X341        -0.16839    0.44725   -0.377  0.70654
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 183.74  on 225  degrees of freedom
AIC: 245.74
```

P-value for All Model

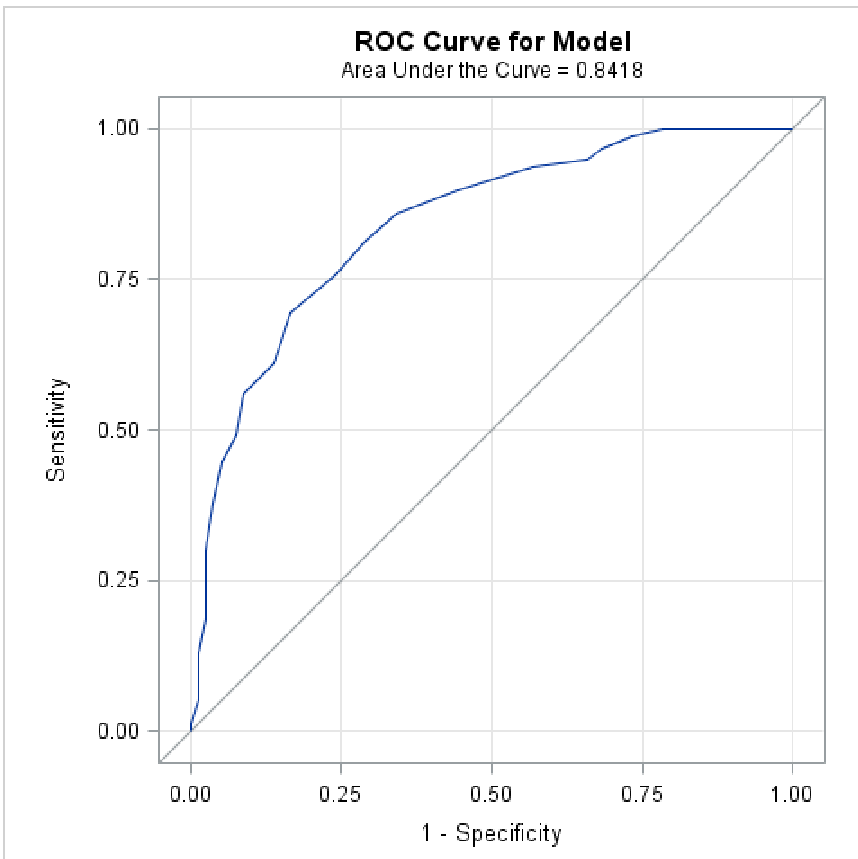
```
> pchisq(183.74,225)
[1] 0.02035031
```

SAS Output - ROC Curves

Sample of Complete SAS program Utilized for ROC Curves

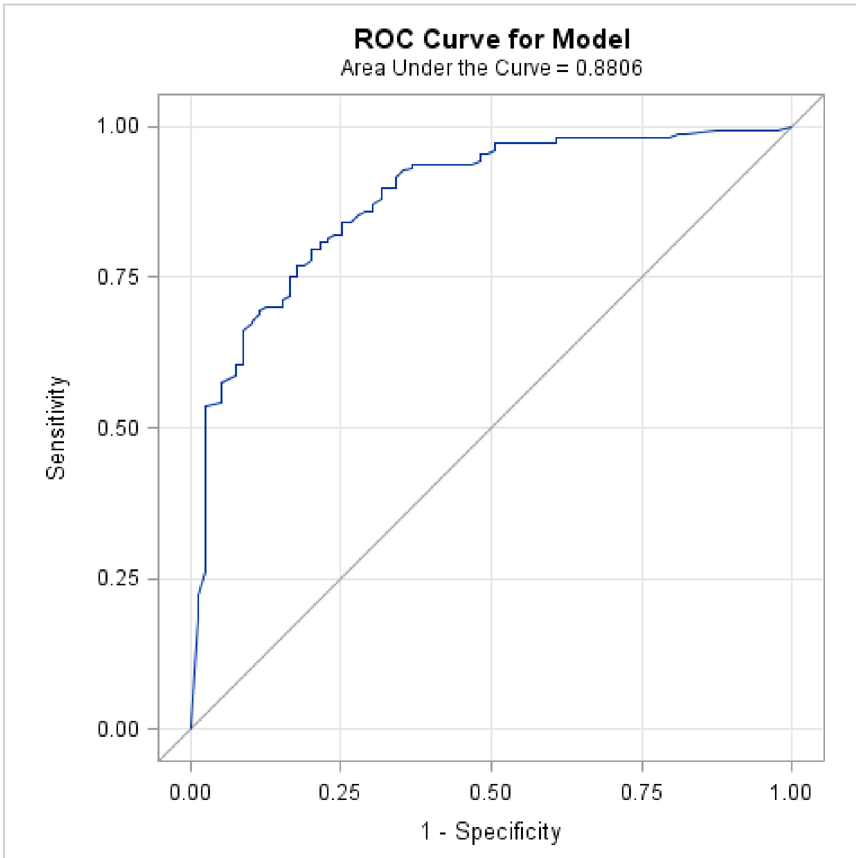
```
proc logistic data=WORK.TH desc;
 model Passed = Score
 / outroc=roc1;
run;
data roc2;
 set roc1;
 spec = 1-_1mspec_;
run;
symbol1 i=join v=none ;
proc gplot data=roc2;
 plot _sensit_*_PROB_=1 spec*_PROB_=1 / overlay haxis=0 to 1 by .25 vaxis=0 to 1 by .1 ;
run;
quit;
```

ROC Curve for Score Only Model – Year 1



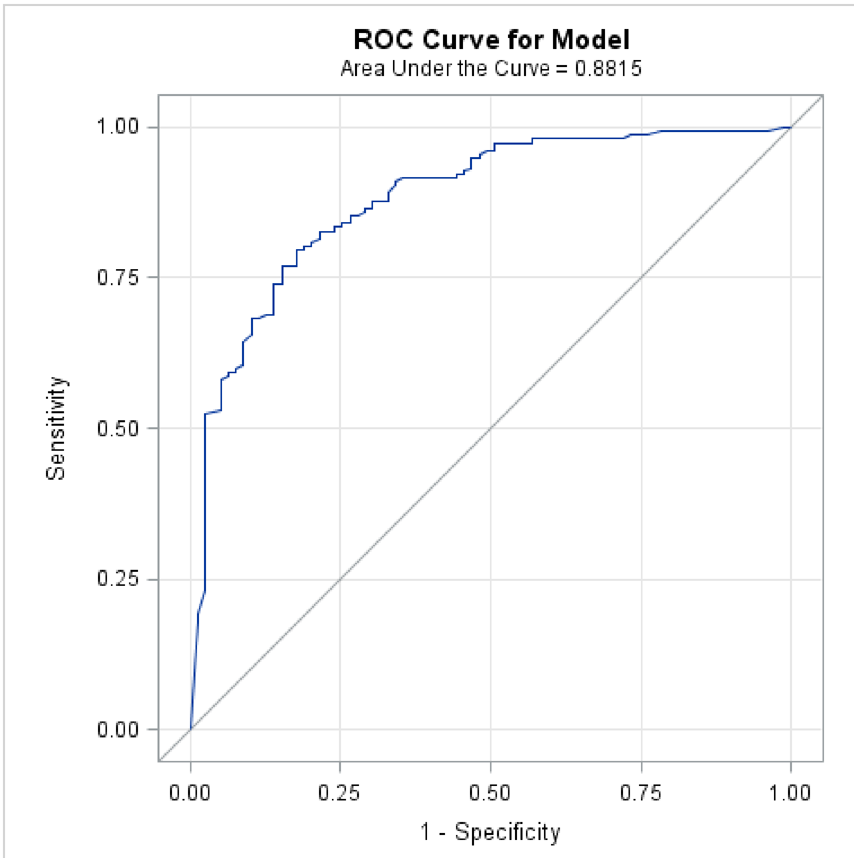
ROC Curve for Study Model without Question 18

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7
 / outroc=roc1;
run;
```



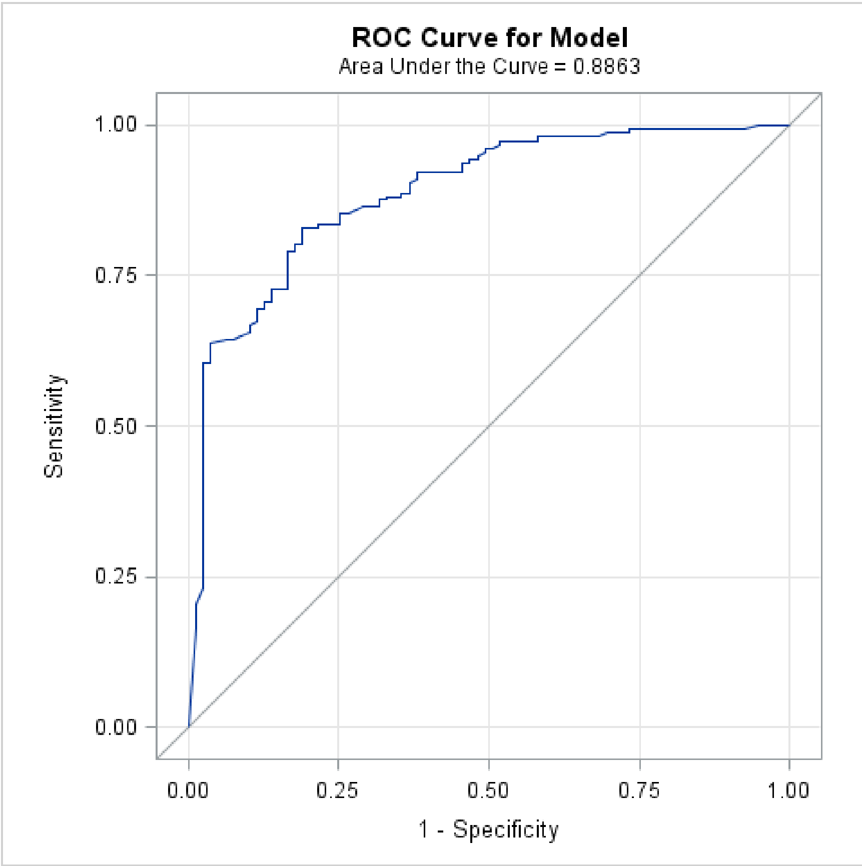
ROC Curve for the Study Model

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7 X18
 / outroc=roc1;
run;
```



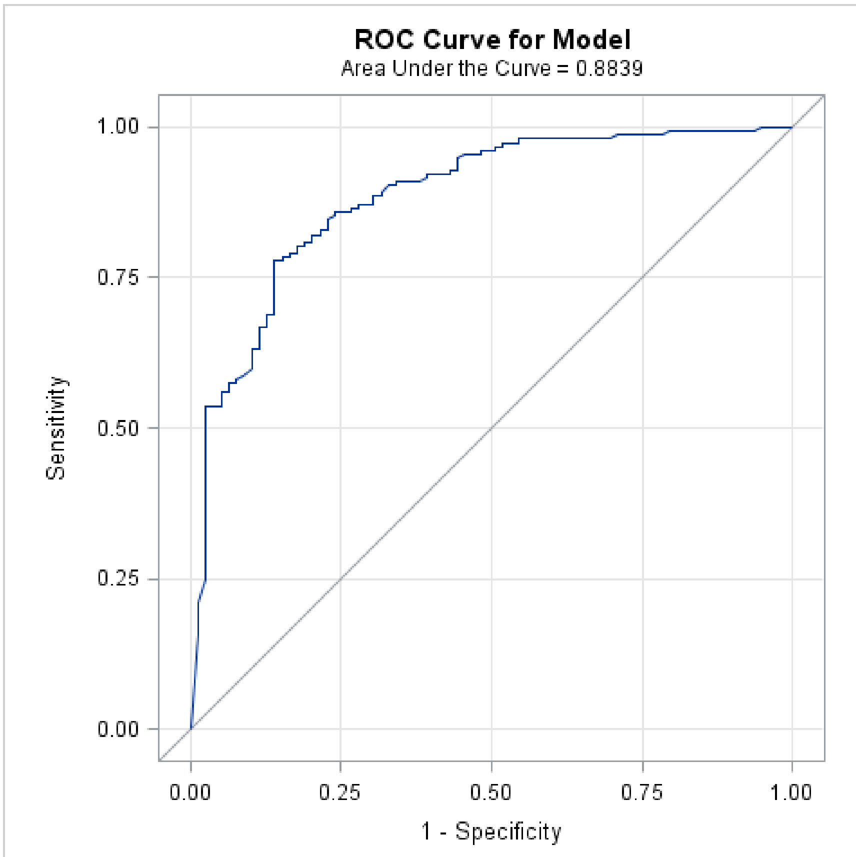
ROC Curve for Study Model with Question 25

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7 X18 X25
 / outroc=roc1;
run;
```



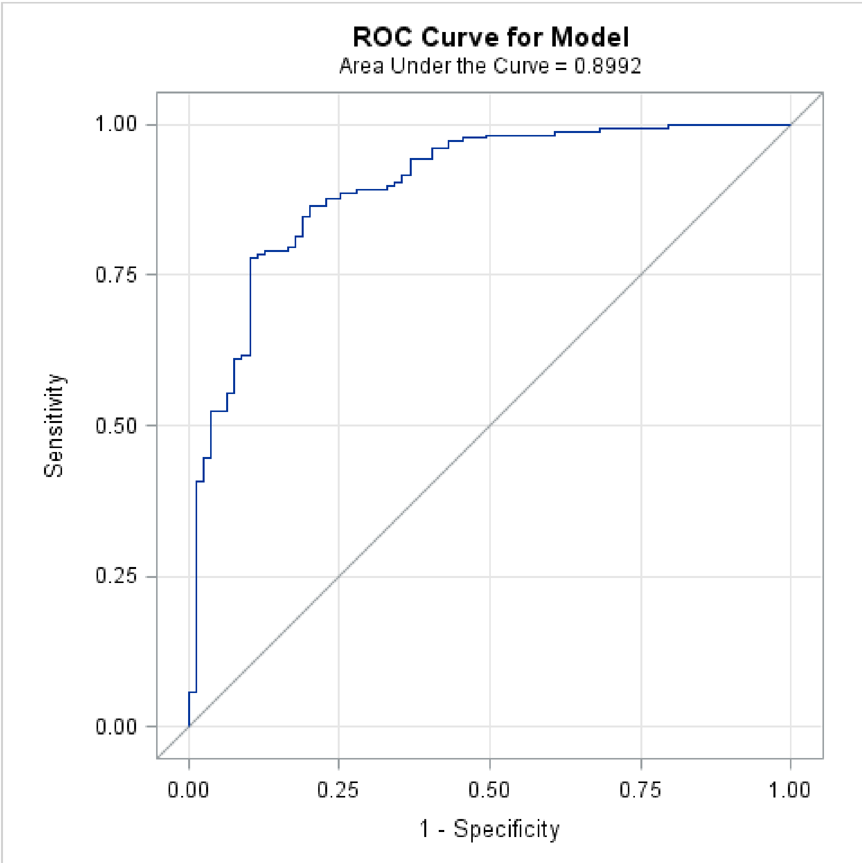
ROC Curve for Study Model with Question 6

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7 X18 X6
 / outroc=roc1;
run;
```



ROC Curve for All Questions Model –Year 1

```
proc logistic data=WORK.TH desc;
 model Passed = X1 X2 X3 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X16 X17 X18 X19 X21 X22 X23
X24 X25 X26 X27 X28 X29 X30 X31 X32 X33 X34
/ outroc=roc1; run;
```



Classification Tables for Predictions

Classification Table for Score Only Model

```
proc logistic data=WORK.TH desc;
 model Passed = Score
 / ctable pprob = (.67 to .85 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.670	134	60	19	43	75.8	75.7	75.9	12.4	41.7
0.680	134	60	19	43	75.8	75.7	75.9	12.4	41.7
0.690	134	60	19	43	75.8	75.7	75.9	12.4	41.7
0.700	134	60	19	43	75.8	75.7	75.9	12.4	41.7
0.710	134	60	19	43	75.8	75.7	75.9	12.4	41.7
0.720	134	60	19	43	75.8	75.7	75.9	12.4	41.7
0.730	123	66	13	54	73.8	69.5	83.5	9.6	45.0
0.740	123	66	13	54	73.8	69.5	83.5	9.6	45.0
0.750	123	66	13	54	73.8	69.5	83.5	9.6	45.0
0.760	123	66	13	54	73.8	69.5	83.5	9.6	45.0
0.770	123	66	13	54	73.8	69.5	83.5	9.6	45.0
0.780	108	68	11	69	68.8	61.0	86.1	9.2	50.4
0.790	108	68	11	69	68.8	61.0	86.1	9.2	50.4
0.800	108	68	11	69	68.8	61.0	86.1	9.2	50.4
0.810	108	68	11	69	68.8	61.0	86.1	9.2	50.4
0.820	99	68	11	78	65.2	55.9	86.1	10.0	53.4
0.830	99	72	7	78	66.8	55.9	91.1	6.6	52.0
0.840	99	72	7	78	66.8	55.9	91.1	6.6	52.0
0.850	99	72	7	78	66.8	55.9	91.1	6.6	52.0

Classification Table for Study Model without Question 18

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7
 / ctable pprob = (.67 to .85 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.670	143	59	20	34	78.9	80.8	74.7	12.3	36.6
0.680	141	60	19	36	78.5	79.7	75.9	11.9	37.5
0.690	141	61	18	36	78.9	79.7	77.2	11.3	37.1
0.700	141	61	18	36	78.9	79.7	77.2	11.3	37.1
0.710	140	61	18	37	78.5	79.1	77.2	11.4	37.8
0.720	136	61	18	41	77.0	76.8	77.2	11.7	40.2
0.730	133	62	17	44	76.2	75.1	78.5	11.3	41.5
0.740	132	62	17	45	75.8	74.6	78.5	11.4	42.1
0.750	130	62	17	47	75.0	73.4	78.5	11.6	43.1
0.760	130	62	17	47	75.0	73.4	78.5	11.6	43.1
0.770	127	63	16	50	74.2	71.8	79.7	11.2	44.2
0.780	124	65	14	53	73.8	70.1	82.3	10.1	44.9
0.790	123	65	14	54	73.4	69.5	82.3	10.2	45.4
0.800	122	66	13	55	73.4	68.9	83.5	9.6	45.5
0.810	122	66	13	55	73.4	68.9	83.5	9.6	45.5
0.820	119	66	13	58	72.3	67.2	83.5	9.8	46.8
0.830	119	67	12	58	72.7	67.2	84.8	9.2	46.4
0.840	112	69	10	65	70.7	63.3	87.3	8.2	48.5
0.850	103	70	9	74	67.6	58.2	88.6	8.0	51.4

Classification Table for Study Model

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7 X18
 / ctable pprob = (.67 to .85 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.670	142	60	19	35	78.9	80.2	75.9	11.8	36.8
0.680	142	60	19	35	78.9	80.2	75.9	11.8	36.8
0.690	142	61	18	35	79.3	80.2	77.2	11.3	36.5
0.700	141	62	17	36	79.3	79.7	78.5	10.8	36.7
0.710	139	63	16	38	78.9	78.5	79.7	10.3	37.6
0.720	139	63	16	38	78.9	78.5	79.7	10.3	37.6
0.730	139	63	16	38	78.9	78.5	79.7	10.3	37.6
0.740	135	63	16	42	77.3	76.3	79.7	10.6	40.0
0.750	132	63	16	45	76.2	74.6	79.7	10.8	41.7
0.760	128	65	14	49	75.4	72.3	82.3	9.9	43.0
0.770	128	65	14	49	75.4	72.3	82.3	9.9	43.0
0.780	128	65	14	49	75.4	72.3	82.3	9.9	43.0
0.790	122	65	14	55	73.0	68.9	82.3	10.3	45.8
0.800	120	67	12	57	73.0	67.8	84.8	9.1	46.0
0.810	120	67	12	57	73.0	67.8	84.8	9.1	46.0
0.820	120	68	11	57	73.4	67.8	86.1	8.4	45.6
0.830	120	68	11	57	73.4	67.8	86.1	8.4	45.6
0.840	116	68	11	61	71.9	65.5	86.1	8.7	47.3
0.850	113	70	9	64	71.5	63.8	88.6	7.4	47.8

Classification Table for Study Model with Question 25

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7 X18 X25
 / ctable pprob = (.67 to .85 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.670	144	60	19	33	79.7	81.4	75.9	11.7	35.5
0.680	142	61	18	35	79.3	80.2	77.2	11.3	36.5
0.690	142	61	18	35	79.3	80.2	77.2	11.3	36.5
0.700	142	61	18	35	79.3	80.2	77.2	11.3	36.5
0.710	137	61	18	40	77.3	77.4	77.2	11.6	39.6
0.720	135	63	16	42	77.3	76.3	79.7	10.6	40.0
0.730	134	63	16	43	77.0	75.7	79.7	10.7	40.6
0.740	133	64	15	44	77.0	75.1	81.0	10.1	40.7
0.750	132	64	15	45	76.6	74.6	81.0	10.2	41.3
0.760	129	65	14	48	75.8	72.9	82.3	9.8	42.5
0.770	129	65	14	48	75.8	72.9	82.3	9.8	42.5
0.780	129	66	13	48	76.2	72.9	83.5	9.2	42.1
0.790	126	66	13	51	75.0	71.2	83.5	9.4	43.6
0.800	124	66	13	53	74.2	70.1	83.5	9.5	44.5
0.810	124	66	13	53	74.2	70.1	83.5	9.5	44.5
0.820	122	66	13	55	73.4	68.9	83.5	9.6	45.5
0.830	115	68	11	62	71.5	65.0	86.1	8.7	47.7
0.840	114	68	11	63	71.1	64.4	86.1	8.8	48.1
0.850	114	68	11	63	71.1	64.4	86.1	8.8	48.1

Study Model with Question 6

```
proc logistic data=WORK.TH desc;
 model Passed = X2 X13 X14 X17 X28 X31 X5 X7 X18 X6
 / ctable pprob = (.67 to .85 by .01);
run;
```

Classification Table

Prob Level	Correct Event	Correct Non-Event	Incorrect Event	Incorrect Non-Event	Percentages Correct	Percentages Sensi-tivity	Percentages Speci-ficity	Percentages False POS	Percentages False NEG
0.650	143	58	21	34	78.5	80.8	73.4	12.8	37.0
0.660	142	58	21	35	78.1	80.2	73.4	12.9	37.6
0.670	141	61	18	36	78.9	79.7	77.2	11.3	37.1
0.680	140	61	18	37	78.5	79.1	77.2	11.4	37.8
0.690	140	61	18	37	78.5	79.1	77.2	11.4	37.8
0.700	139	62	17	38	78.5	78.5	78.5	10.9	38.0
0.710	138	63	16	39	78.5	78.0	79.7	10.4	38.2
0.720	138	63	16	39	78.5	78.0	79.7	10.4	38.2
0.730	138	63	16	39	78.5	78.0	79.7	10.4	38.2
0.740	135	64	15	42	77.7	76.3	81.0	10.0	39.6
0.750	133	65	14	44	77.3	75.1	82.3	9.5	40.4
0.760	130	65	14	47	76.2	73.4	82.3	9.7	42.0
0.770	127	66	13	50	75.4	71.8	83.5	9.3	43.1
0.780	125	66	13	52	74.6	70.6	83.5	9.4	44.1
0.790	123	67	12	54	74.2	69.5	84.8	8.9	44.6
0.800	118	68	11	59	72.7	66.7	86.1	8.5	46.5
0.810	113	68	11	64	70.7	63.8	86.1	8.9	48.5
0.820	112	68	11	65	70.3	63.3	86.1	8.9	48.9
0.830	111	68	11	66	69.9	62.7	86.1	9.0	49.3
0.840	111	68	11	66	69.9	62.7	86.1	9.0	49.3
0.850	110	68	11	67	69.5	62.1	86.1	9.1	49.6
0.860	106	70	9	71	68.8	59.9	88.6	7.8	50.4
0.870	102	70	9	75	67.2	57.6	88.6	8.1	51.7
0.880	99	70	9	78	66.0	55.9	88.6	8.3	52.7

Classification Table for All Model Year 1

```
proc logistic data=WORK.TH desc;
 model Passed = X1 X2 X3 X5 X6 X7 X8 X9 X10 X11 X12 X13 X14 X16 X17 X18 X19 X21 X22 X23
X24 X25 X26 X27 X28 X29 X30 X31 X32 X33 X34
 / ctable pprob = (.74 to .90 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.740	133	59	20	44	75.0	75.1	74.7	13.1	42.7
0.750	130	60	19	47	74.2	73.4	75.9	12.8	43.9
0.760	129	61	18	48	74.2	72.9	77.2	12.2	44.0
0.770	124	61	18	53	72.3	70.1	77.2	12.7	46.5
0.780	121	61	18	56	71.1	68.4	77.2	12.9	47.9
0.790	120	62	17	57	71.1	67.8	78.5	12.4	47.9
0.800	118	63	16	59	70.7	66.7	79.7	11.9	48.4
0.810	117	63	16	60	70.3	66.1	79.7	12.0	48.8
0.820	115	64	15	62	69.9	65.0	81.0	11.5	49.2
0.830	115	64	15	62	69.9	65.0	81.0	11.5	49.2
0.840	113	65	14	64	69.5	63.8	82.3	11.0	49.6
0.850	107	66	13	70	67.6	60.5	83.5	10.8	51.5
0.860	106	68	11	71	68.0	59.9	86.1	9.4	51.1
0.870	103	68	11	74	66.8	58.2	86.1	9.6	52.1
0.880	103	70	9	74	67.6	58.2	88.6	8.0	51.4
0.890	99	70	9	78	66.0	55.9	88.6	8.3	52.7
0.900	97	70	9	80	65.2	54.8	88.6	8.5	53.3

R Squared Tests

Example of Partial SAS Program Used to Find R Squared Values

```
proc logistic data=WORK.TH;
model Passed(desc) = Score;
output out=a xbeta=xb;
data b;
set a;
za=xb**2*(xb>=0);
zb=xb**2*(xb<0);
num=1;
proc logistic data=b;
model Passed(desc) = Score;
test za=0,zb=0;
run;
```

(Using macro goflogit Procedure in SAS)

Score Only Model

	TEST	Value	p-Value
Results from the Goodness-of-Fit Tests	Standard Pearson Test	270.499	0.228
	Standard Deviance	224.982	0.905
	Osius-Test	0.644	0.260
	McCullagh-Test	0.687	0.246
	Farrington-Test	0.000	1.000
	IM-Test	0.416	0.812
	RSS-Test	36.407	0.964

For Study Model without Question 18

	TEST	Value	p-Value
Results from the Goodness-of-Fit Tests	Standard Pearson Test	278.332	0.083
	Standard Deviance	201.579	0.984
	Osius-Test	0.709	0.239
	McCullagh-Test	0.634	0.263
	Farrington-Test	0.000	1.000
	IM-Test	3.623	0.934
	RSS-Test	31.671	0.668

For the Study Model

	TEST	Value	p-Value
Results from the Goodness-of-Fit Tests	Standard Pearson Test	273.473	0.110
	Standard Deviance	198.980	0.988
	Osius-Test	0.557	0.289
	McCullagh-Test	0.465	0.321
	Farrington-Test	0.000	1.000
	IM-Test	3.971	0.949
	RSS-Test	31.423	0.930

For Study Model with Question 25

	TEST	Value	p-Value
Results from the Goodness-of-Fit Tests	Standard Pearson Test	276.276	0.083
	Standard Deviance	197.426	0.989
	Osius-Test	0.596	0.276
	McCullagh-Test	0.489	0.312
	Farrington-Test	0.000	1.000
	IM-Test	3.675	0.978
	RSS-Test	31.328	0.826

For Study Model with Question 6

	TEST	Value	p-Value
Results from the Goodness-of-Fit Tests	Standard Pearson Test	283.520	0.046
	Standard Deviance	197.738	0.988
	Osius-Test	0.828	0.204
	McCullagh-Test	0.735	0.231
	Farrington-Test	0.000	1.000
	IM-Test	5.777	0.888
	RSS-Test	30.996	0.584

APPENDIX 4

CHAPTER 7 DATA

Score Only Model
Year 2

```
proc logistic data=WORK.THESIS desc;
  model passed = score
  / ctable pprob = (.75 to .90 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.750	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.760	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.770	77	33	6	27	76.9	74.0	84.6	7.2	45.0
0.780	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.790	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.800	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.810	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.820	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.830	68	34	5	36	71.3	65.4	87.2	6.8	51.4
0.840	68	35	4	36	72.0	65.4	89.7	5.6	50.7
0.850	68	35	4	36	72.0	65.4	89.7	5.6	50.7
0.860	60	35	4	44	66.4	57.7	89.7	6.3	55.7
0.870	60	36	3	44	67.1	57.7	92.3	4.8	55.0
0.880	60	36	3	44	67.1	57.7	92.3	4.8	55.0
0.890	60	36	3	44	67.1	57.7	92.3	4.8	55.0
0.900	48	36	3	56	58.7	46.2	92.3	5.9	60.9

Study Model
Year 2

```
proc logistic data=WORK.THESIS desc;
  model passed = q2 q13 q14 q17 q28 q31 q5 q7 q18
  / ctable pprob = (.75 to .90 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.750	76	27	12	27	72.5	73.8	69.2	13.6	50.0
0.760	75	27	12	28	71.8	72.8	69.2	13.8	50.9
0.770	75	27	12	28	71.8	72.8	69.2	13.8	50.9
0.780	74	27	12	29	71.1	71.8	69.2	14.0	51.8
0.790	74	28	11	29	71.8	71.8	71.8	12.9	50.9
0.800	71	28	11	32	69.7	68.9	71.8	13.4	53.3
0.810	71	28	11	32	69.7	68.9	71.8	13.4	53.3
0.820	70	30	9	33	70.4	68.0	76.9	11.4	52.4
0.830	68	30	9	35	69.0	66.0	76.9	11.7	53.8
0.840	67	31	8	36	69.0	65.0	79.5	10.7	53.7
0.850	62	31	8	41	65.5	60.2	79.5	11.4	56.9
0.860	60	31	8	43	64.1	58.3	79.5	11.8	58.1
0.870	60	31	8	43	64.1	58.3	79.5	11.8	58.1
0.880	51	33	6	52	59.2	49.5	84.6	10.5	61.2
0.890	49	33	6	54	57.7	47.6	84.6	10.9	62.1
0.900	45	36	3	58	57.0	43.7	92.3	6.3	61.7

Cohort 2 Data

Univariate testing for the second cohort group

```
> thesislm <- glm(passed~q1,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median      3Q      Max
-1.7277  -0.8203    0.7136  0.7136   1.5829

Coefficients:
            Estimate    Std. Error  z value    Pr(>|z|)
(Intercept)  -0.9163    0.5916     -1.549      0.121426
q11           2.1542    0.6281      3.430      0.000604 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 154.25  on 141  degrees of freedom
AIC: 158.25

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q2,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q2, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median      3Q      Max
-1.8170  -1.2557   0.6528   0.6528   1.1010

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1823     0.3028   0.602  0.54705
q21           1.2553     0.3960   3.170  0.00152 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 157.45  on 141  degrees of freedom
AIC: 161.45
```

```
> thesislm <- glm(passed~q3,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q3, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median      3Q     Max
-1.7610  -1.3370    0.6905  0.6905  1.0258

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)   0.3677    0.3066    1.199    0.2304
q31           0.9445    0.3930    2.403    0.0163 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 161.85  on 141  degrees of freedom
AIC: 165.85

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q5,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q5, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median      3Q     Max
-1.6894  -1.5330    0.7409  0.8595  0.8595

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)   0.8056    0.2625    3.069    0.00215 **
q51           0.3471    0.3768    0.921    0.35705
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 166.73  on 141  degrees of freedom
AIC: 170.73

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q6,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q6, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.7125  -1.4566    0.7244   0.7244   0.9218

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.6360     0.2915   2.182   0.0291 *
q61           0.5680     0.3832   1.482   0.1383
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 165.40  on 141  degrees of freedom
AIC: 169.4

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q7,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q7, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.7692  -1.2033    0.6849   0.6849   1.1518

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.06062    0.34832   0.174  0.86183
q71          1.26979    0.41988   3.024  0.00249 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 158.52  on 141  degrees of freedom
AIC: 162.52

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q8,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q8, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9886  -1.3824   0.5460   0.9854   0.9854

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4700     0.2327   2.019  0.04344 *
q81           1.3581     0.4279   3.174  0.00151 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 156.22  on 141  degrees of freedom
AIC: 160.22

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q9,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q9, family = binomial(logit), data = testdata)

Deviance Residuals:
   Min      1Q  Median     3Q    Max
-1.837  -1.105   0.640  0.640  1.251

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.1719     0.3393  -0.506    0.613
q91           1.6535     0.4201   3.936 8.29e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 151.76  on 141  degrees of freedom
AIC: 155.76

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q10,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q10, family = binomial(logit), data = testdata)

Deviance Residuals:
   Min       1Q        Median      3Q      Max
-1.6459  -1.4132       0.7726   0.7726   0.9587

Coefficients:
            Estimate    Std. Error  z value     Pr(>|z|)
(Intercept)   0.5390    0.4756      1.133       0.257
q101          0.5171    0.5180      0.998       0.318

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 166.62  on 141  degrees of freedom
AIC: 170.62

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q11,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q11, family = binomial(logit), data = testdata)

Deviance Residuals:
   Min       1Q        Median      3Q      Max
-1.6924  -0.7090       0.7387   0.7387   1.7344

Coefficients:
            Estimate    Std. Error  z value     Pr(>|z|)
(Intercept)  -1.2528    0.8018      -1.562      0.11818
q111          2.4120    0.8270      2.917       0.00354 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 156.85  on 141  degrees of freedom
AIC: 160.85

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q12,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q12, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q      Median       3Q      Max
-1.6394  -1.5066      0.7775   0.7775   0.8806

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)   0.7472    0.4047     1.847    0.0648 .
q121          0.2942    0.4570     0.644    0.5197
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 167.18  on 141  degrees of freedom
AIC: 171.18

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q13,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q13, family = binomial(logit), data = testdata)

Deviance Residuals:
   Min      1Q      Median      3Q     Max
-1.750  -1.231      0.698   0.698   1.125

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)   0.1252    0.3542     0.353   0.72385
q131          1.1627    0.4227     2.751   0.00594 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 160.14  on 141  degrees of freedom
AIC: 164.14

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q14,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q14, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q            Median       3Q      Max
-1.7420  -1.2068          0.7036   0.7036   1.1483

Coefficients:
            Estimate      Std. Error  z value      Pr(>|z|)
(Intercept)  0.06899      0.37161     0.186        0.85271
q141         1.20077      0.43512     2.760        0.00579 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 160.10  on 141  degrees of freedom
AIC: 164.1

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q15,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q15, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q            Median       3Q      Max
-1.7090  -1.5542          0.7268   0.8427   0.8427

Coefficients:
            Estimate      Std. Error  z value      Pr(>|z|)
(Intercept)   0.8528      0.2342      3.641        0.000272 ***
q151          0.3435      0.3937      0.872        0.383029
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 166.81  on 141  degrees of freedom
AIC: 170.81

Number of Fisher Scoring iterations: 4
```

```
> thesislm<- glm(passed~q16,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q16, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6225  -1.6225   0.7901   0.7901   1.0108

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4055     0.9129   0.444    0.657
q161          0.5987     0.9329   0.642    0.521

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 167.19  on 141  degrees of freedom
AIC: 171.19

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q17,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q17, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8607  -1.2322   0.6243   0.6243   1.1236

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1278     0.2923   0.437 0.661896
q171          1.4084     0.3962   3.555 0.000378 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 154.62  on 141  degrees of freedom
AIC: 158.62

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q18,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q18, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7034  -1.0108   0.7308   0.7308   1.3537

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.4055     0.5270  -0.769  0.44171
q181          1.5892     0.5668   2.804  0.00505 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 159.58  on 141  degrees of freedom
AIC: 163.58

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q19,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q19, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6799  -1.2637   0.7478   0.7478   1.0935

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2007     0.4495   0.446   0.6553
q191          0.9307     0.4961   1.876   0.0606 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 164.19  on 141  degrees of freedom
AIC: 168.19

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q21,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q21, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.6304  -1.4661    0.7842   0.7842   1.0579

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.2877     0.7638   0.377    0.706
q211          0.7340     0.7881   0.931    0.352

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 166.76  on 141  degrees of freedom
AIC: 170.76

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q22,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q22, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.6314  -1.6314    0.7835   0.7835   1.4823

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.6931     1.2247  -0.566    0.571
q221          1.7170     1.2397   1.385    0.166

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 165.52  on 141  degrees of freedom
AIC: 169.52

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q23,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q23, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.6171  -1.5829    0.7942   0.7942   0.8203

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)  0.91629   0.48305     1.897    0.0578 .
q231         0.07584   0.52428     0.145    0.8850
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 167.56  on 141  degrees of freedom
AIC: 171.56

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q24,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q24, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median       3Q      Max
-1.7047  -1.1330    0.7299   0.7299   1.2225

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept) -0.1054    0.4595     -0.229    0.8186
q241         1.2919    0.5061      2.553    0.0107 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 161.18  on 141  degrees of freedom
AIC: 165.18

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q25,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q25, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8692  -1.0302   0.6189   0.6189   1.3321

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -0.3567     0.3485  -1.024    0.306
q251          1.9120     0.4303   4.443 8.86e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 146.93  on 141  degrees of freedom
AIC: 150.93

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q26,data=testdata,family=binomial(logit))
> summary(thesislm)


Call:
glm(formula = passed ~ q26, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0255  -1.3336   0.5246   1.0288   1.0288

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.3600     0.2379   1.513 0.130191
q261          1.5536     0.4291   3.621 0.000293 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 152.58  on 141  degrees of freedom
AIC: 156.58

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q27,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q27, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median      3Q     Max
-1.8365  -1.3777    0.6400  0.9895  0.9895

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4595     0.2607   1.762  0.07799 .
q271          1.0221     0.3870   2.641  0.00827 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 160.39  on 141  degrees of freedom
AIC: 164.39

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q28,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q28, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q    Median      3Q     Max
-1.9214  -1.1774    0.5863  0.5863  1.1774

Coefficients:
              Estimate  Std. Error  z value  Pr(>|z|)
(Intercept) -3.400e-15   2.887e-01    0.000         1
q281         1.674e+00   4.031e-01    4.153  3.29e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 149.41  on 141  degrees of freedom
AIC: 153.41

Number of Fisher Scoring iterations: 3
```

```
> thesislm <- glm(passed~q29,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q29, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.7520  -1.1461     0.6967   0.6967   1.2090

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept) -0.07411   0.38516     -0.192    0.84742
q291         1.36609   0.44648      3.060    0.00222 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 158.31  on 141  degrees of freedom
AIC: 162.31

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q30,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q30, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.7578  -1.4724     0.6927   0.9087   0.9087

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)   0.6712   0.2563       2.618    0.00883 **
q301          0.6338   0.3810       1.664    0.09621 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 164.77  on 141  degrees of freedom
AIC: 168.77

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q31,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q31, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q       Median      3Q      Max
-1.7080  -0.9400       0.7276  0.7276   1.4350

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)  -0.5878    0.5578     -1.054    0.29197
q311          1.7817    0.5954      2.992    0.00277 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 158.18  on 141  degrees of freedom
AIC: 162.18

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q32,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q32, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q       Median      3Q      Max
-1.6765  -1.5759       0.7502  0.8257   0.8257

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)   0.9008    0.2326      3.873    0.000107 ***
q321          0.2231    0.3950      0.565    0.572109
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 167.26  on 141  degrees of freedom
AIC: 171.26

Number of Fisher Scoring iterations: 4
```

```
> thesislm <- glm(passed~q33,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q33, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q     Median       3Q      Max
-1.7105  -1.4408     0.7258   0.7258   0.9351

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)   0.6008     0.3018      1.991     0.0465 *
q331          0.5986     0.3876      1.544     0.1225
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 165.22  on 141  degrees of freedom
AIC: 169.22

Number of Fisher Scoring iterations: 4


> thesislm <- glm(passed~q34,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q34, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0828  -1.3088   0.4927   1.0515   1.0515

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.3037     0.2368   1.283      0.2
q341          1.7440     0.4441   3.927 8.59e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 149.29  on 141  degrees of freedom
AIC: 153.29

Number of Fisher Scoring iterations: 4
```

General Linear Models (Residuals, AIG, and P-values)

GLM Logistics for Full Model minus
4,5,10,12,15,16,20,21,23,32 (univariate rejects) Year 2

```
> thesislm <- glm(passed~q1+q2+q3+q6+q7+q8+q9+q11+q13+q14+q17+q18+q19+q22+q24+q25+q26+q27+q28+q29+q30+q31+q33+q34,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1 + q2 + q3 + q6 + q7 + q8 + q9 + q11 +
    q13 + q14 + q17 + q18 + q19 + q22 + q24 + q25 + q26 + q27 +
    q28 + q29 + q30 + q31 + q33 + q34, family = binomial(logit),
    data = testdata)

Deviance Residuals:
     Min        1Q     Median       3Q      Max
-2.23396  -0.04016   0.03502  0.29590  2.26611

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -13.48702    4.17639  -3.229 0.001241 **
q11           5.83567    1.75521   3.325 0.000885 ***
q21           1.47224    0.88152   1.670 0.094899 .
q31           1.89754    0.93344   2.033 0.042069 *
q61          -0.06835    0.75155  -0.091 0.927541
q71          -0.62736    0.90048  -0.697 0.485994
q81           1.68614    1.04193   1.618 0.105603
q91           1.76690    0.85749   2.061 0.039345 *
q111          3.70767    2.01465   1.840 0.065716 .
q131          2.41663    1.09892   2.199 0.027872 *
q141          0.93389    0.89751   1.041 0.298093
q171          2.25126    1.13824   1.978 0.047947 *
q181          2.23382    1.11971   1.995 0.046042 *
q191          0.50741    1.09611   0.463 0.643425
q221         -7.01003    3.19182  -2.196 0.028074 *
q241          2.54192    1.25732   2.022 0.043207 *
q251          0.16050    0.97470   0.165 0.869203
q261          2.30948    1.02234   2.259 0.023883 *
q271          1.23633    0.90764   1.362 0.173155
q281         -0.65901    0.84258  -0.782 0.434135
q291          1.03241    0.87952   1.174 0.240462
q301          0.33529    0.76807   0.437 0.662445
q311          0.30961    1.08436   0.286 0.775245
q331         -3.09795    1.22574  -2.527 0.011491 *
q341          2.35655    0.92954   2.535 0.011239 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.582  on 142  degrees of freedom
Residual deviance:  67.409  on 118  degrees of freedom
AIC: 117.41
```

GLM Logistics for Year 2 Best Fit Model without Question 8

```
> thesislm <- glm(passed~q1+q2+q3+q9+q11+q13+q17+q18+q22+q24+q26+q27+q33+q34,
data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1 + q2 + q3 + q9 + q11 + q13 + q17 +
    q18 + q22 + q24 + q26 + q27 + q33 + q34, family = binomial(logit),
    data = testdata)

Deviance Residuals:
     Min        1Q      Median       3Q      Max
-2.41987  -0.13562   0.08652  0.41323  1.98419

Coefficients:
            Estimate  Std. Error  z value  Pr(>|z|)
(Intercept)  -8.5081  2.2893      -3.716   0.000202 ***
q11          4.2509   1.2299      3.456    0.000548 ***
q21          1.3024   0.6578      1.980    0.047701 *
q31          1.4108   0.6670      2.115    0.034433 *
q91          1.3851   0.6670      2.077    0.037832 *
q111         2.9389   1.5357      1.914    0.055652 .
q131         2.2806   0.8769      2.601    0.009299 **
q171         2.4754   0.8764      2.825    0.004733 **
q181         2.1832   0.9233      2.365    0.018045 *
q221         -6.3806  2.3722      -2.690   0.007150 **
q241         1.6241   0.9358      1.736    0.082641 .
q261         1.7559   0.7996      2.196    0.028092 *
q271         1.0991   0.7299      1.506    0.132107
q331         -2.6622  0.9832      -2.708   0.006778 **
q341         2.1864   0.7635      2.864    0.004187 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.582  on 142  degrees of freedom
Residual deviance:  74.723  on 128  degrees of freedom
AIC: 104.72

Number of Fisher Scoring iterations: 7
```

GLM Logistics for Year 2 Best Fit Model without Question 27

```
> thesislm <- glm(passed~q1+q2+q3+q8+q9+q11+q13+q17+q18+q22+q24+q26+q33+q34,data=testdata,fa
mily=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1 + q2 + q3 + q8 + q9 + q11 + q13 + q17 +
    q18 + q22 + q24 + q26 + q33 + q34, family = binomial(logit),
    data = testdata)

Deviance Residuals:
     Min        1Q          Median        3Q        Max
-2.62794  -0.10517    0.07663   0.39678   1.89379

Coefficients:
            Estimate    Std. Error  z value     Pr(>|z|)
(Intercept) -10.0724    2.8016      -3.595      0.000324 ***
q11         4.7454      1.3598      3.490       0.000484 ***
q21         1.1191      0.6749      1.658       0.097285 .
q31         1.5643      0.7090      2.206       0.027358 *
q81         1.1186      0.7698      1.453       0.146203
q91         1.4274      0.6575      2.171       0.029940 *
q111        3.6557      1.6173      2.260       0.023800 *
q131        2.1588      0.8509      2.537       0.011175 *
q171        1.6321      0.8022      2.035       0.041896 *
q181        2.4280      0.9011      2.694       0.007051 **
q221        -5.9356     2.4016      -2.472      0.013454 *
q241        1.9877      1.0355      1.920       0.054910 .
q261        2.3380      0.8596      2.720       0.006530 **
q331        -2.5085     0.9776      -2.566      0.010288 *
q341        2.0604      0.7534      2.735       0.006238 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.582  on 142  degrees of freedom
Residual deviance:  74.777  on 128  degrees of freedom
AIC: 104.78

Number of Fisher Scoring iterations: 7
```

GLM Logistics for Year 2 Best Fit Model without Questions 8 and 27

```
> thesislm <- glm(passed~q1+q2+q3+q9+q11+q13+q17+q18+q22+q24+q26+q33+q34
,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1 + q2 + q3 + q9 + q11 + q13 + q17 +
   q18 + q22 + q24 + q26 + q33 + q34, family = binomial(logit),
   data = testdata)

Deviance Residuals:
   Min      1Q          Median     3Q      Max
-2.6255  -0.1327        0.1161   0.3862   1.9381

Coefficients:
            Estimate    Std. Error  z value     Pr(>|z|)
(Intercept)  -8.6967    2.3354      -3.724      0.000196 ***
q11          4.2292     1.1996      3.526       0.000423 ***
q21          1.2256     0.6483      1.890       0.058715 .
q31          1.3712     0.6542      2.096       0.036087 *
q91          1.4130     0.6512      2.170       0.030014 *
q111         3.5206     1.6339      2.155       0.031183 *
q131         2.1230     0.8448      2.513       0.011976 *
q171         1.9751     0.7765      2.544       0.010969 *
q181         2.3660     0.8912      2.655       0.007934 **
q221         -6.0846    2.4326      -2.501      0.012374 *
q241         1.5541     0.9288      1.673       0.094272 .
q261         2.0816     0.7668      2.715       0.006636 **
q331         -2.4382    0.9639      -2.530      0.011418 *
q341         2.1866     0.7615      2.872       0.004084 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

   Null deviance: 167.582  on 142  degrees of freedom
Residual deviance:  77.103  on 129  degrees of freedom
AIC: 105.1

Number of Fisher Scoring iterations: 7
```

GLM Logistics for Score Only Model
Year 2

```
> thesislm <- glm(passed~score,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ score, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min        1Q     Median       3Q      Max
-2.26493  -0.60386   0.00008  0.57802  1.89302

Coefficients:
             Estimate   Std. Error  z value  Pr(>|z|)
(Intercept)  1.957e+01  1.075e+04   0.002    0.999
score26%    -3.913e+01  1.521e+04  -0.003    0.998
score29%    -3.913e+01  1.521e+04  -0.003    0.998
score41%    -2.026e+01  1.075e+04  -0.002    0.998
score47%    -2.026e+01  1.075e+04  -0.002    0.998
score50%    -1.997e+01  1.075e+04  -0.002    0.999
score53%    -2.066e+01  1.075e+04  -0.002    0.998
score56%    -2.066e+01  1.075e+04  -0.002    0.998
score59%    -1.957e+01  1.075e+04  -0.002    0.999
score62%    -2.008e+01  1.075e+04  -0.002    0.999
score65%    -2.118e+01  1.075e+04  -0.002    0.998
score68%    -1.872e+01  1.075e+04  -0.002    0.999
score71%    -1.796e+01  1.075e+04  -0.002    0.999
score74%    -1.737e+01  1.075e+04  -0.002    0.999
score76%    -1.749e+01  1.075e+04  -0.002    0.999
score79%    -1.708e+01  1.075e+04  -0.002    0.999
score82%    -1.786e+01  1.075e+04  -0.002    0.999
score85%    -2.327e-07  1.128e+04   0.000    1.000
score88%    -2.343e-07  1.242e+04   0.000    1.000
score91%    -2.342e-07  1.113e+04   0.000    1.000
score94%    -2.344e-07  1.162e+04   0.000    1.000
score97%    -2.341e-07  1.242e+04   0.000    1.000

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 101.84  on 121  degrees of freedom
AIC: 145.84

Number of Fisher Scoring iterations: 18
```

P-value for Score Only Model
Year 2

```
> pchisq(101.84,121)
[1] 0.1038434
```

GLM Logistics for Study Model
Year 2

```
> thesislm <- glm(passed~q2+q13+q14+q17+q28+q31+q5+q7+q18,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q2 + q13 + q14 + q17 + q28 + q31 + q5 +
    q7 + q18, family = binomial(logit), data = testdata)

Deviance Residuals:
    Min       1Q        Median      3Q      Max
-2.4855  -0.4464        0.3054   0.5704   2.0354

Coefficients:
            Estimate   Std. Error  z value   Pr(>|z|)
(Intercept)  -4.6957   1.1448      -4.102    4.1e-05 ***
q21          1.2470    0.4995      2.496     0.01254 *
q131         1.3278    0.5479      2.423     0.01538 *
q141         0.4699    0.5293      0.888     0.37460
q171         0.9078    0.4960      1.830     0.06722 .
q281         1.2003    0.5078      2.364     0.01809 *
q311         1.9811    0.7625      2.598     0.00937 **
q51         -0.2106    0.4977      -0.423    0.67221
q71          0.1724    0.5357      0.322     0.74755
q181         0.6423    0.6947      0.925     0.35513
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.58  on 142  degrees of freedom
Residual deviance: 119.00  on 133  degrees of freedom
AIC: 139

Number of Fisher Scoring iterations: 5
```

P-value for Study Model
Year 2

```
> pchisq(119,133)
[1] 0.1978711
```

GLM Logistics for Year 2 Best Fit Model

```
> thesislm <- glm(passed~q1+q2+q3+q8+q9+q11+q13+q17+q18+q22+q24+q26+q27
+q33+q34,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1 + q2 + q3 + q8 + q9 + q11 + q13 + q17 +
   q18 + q22 + q24 + q26 + q27 + q33 + q34, family = binomial(logit),
   data = testdata)

Deviance Residuals:
    Min        1Q          Median      3Q      Max
-2.38173  -0.09655     0.06427   0.40531   2.16275

Coefficients:
             Estimate    Std. Error  z value    Pr(>|z|)
(Intercept)  -9.9052     2.8226      -3.509     0.000449 ***
q11          4.8053      1.4103      3.407      0.000656 ***
q21          1.2384      0.6828      1.814      0.069702 .
q31          1.6097      0.7264      2.216      0.026696 *
q81          1.0483      0.7841      1.337      0.181235
q91          1.3881      0.6705      2.070      0.038434 *
q111         3.1648      1.5601      2.029      0.042496 *
q131         2.3259      0.8914      2.609      0.009075 **
q171         2.1474      0.9042      2.375      0.017550 *
q181         2.3160      0.9358      2.475      0.013326 *
q221         -6.3374     2.4027      -2.638     0.008349 **
q241         2.0372      1.0396      1.960      0.050050 .
q261         2.0064      0.8927      2.247      0.024609 *
q271         1.0360      0.7471      1.387      0.165527
q331         -2.7823     1.0188      -2.731     0.006313 **
q341          2.0894     0.7598      2.750      0.005962 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 167.582  on 142  degrees of freedom
Residual deviance:  72.771  on 127  degrees of freedom
AIC: 104.77

Number of Fisher Scoring iterations: 7
```

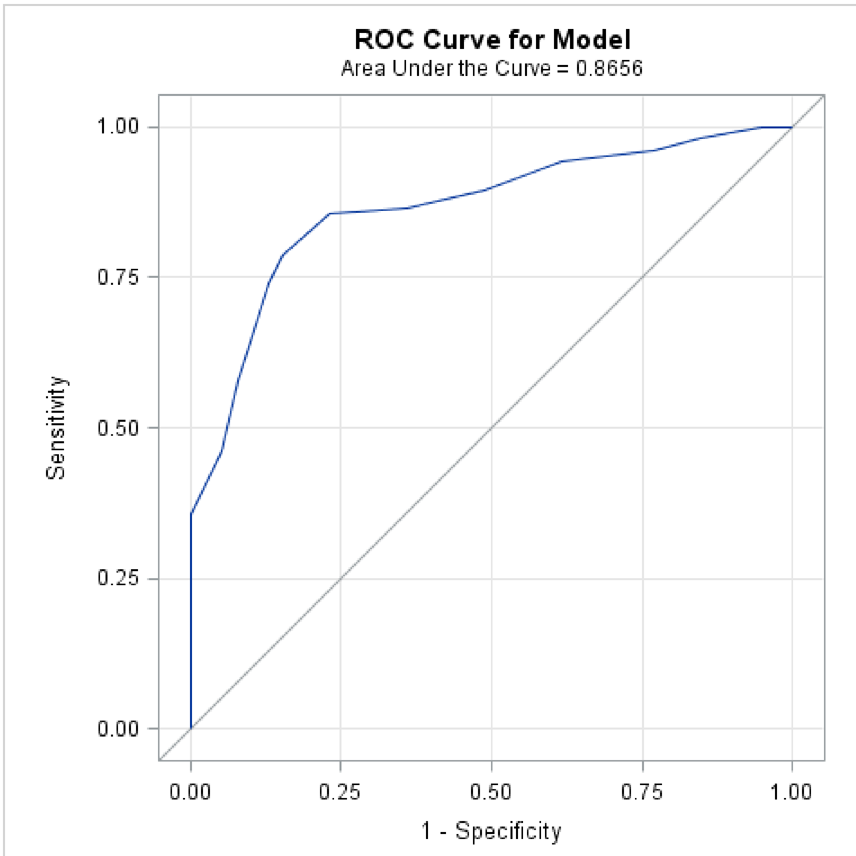
P-value for Year 2 Best Fit Model

```
> pchisq(72.771,127)
[1] 2.939287e-05
```

SAS Output - ROC Curves
Year 2

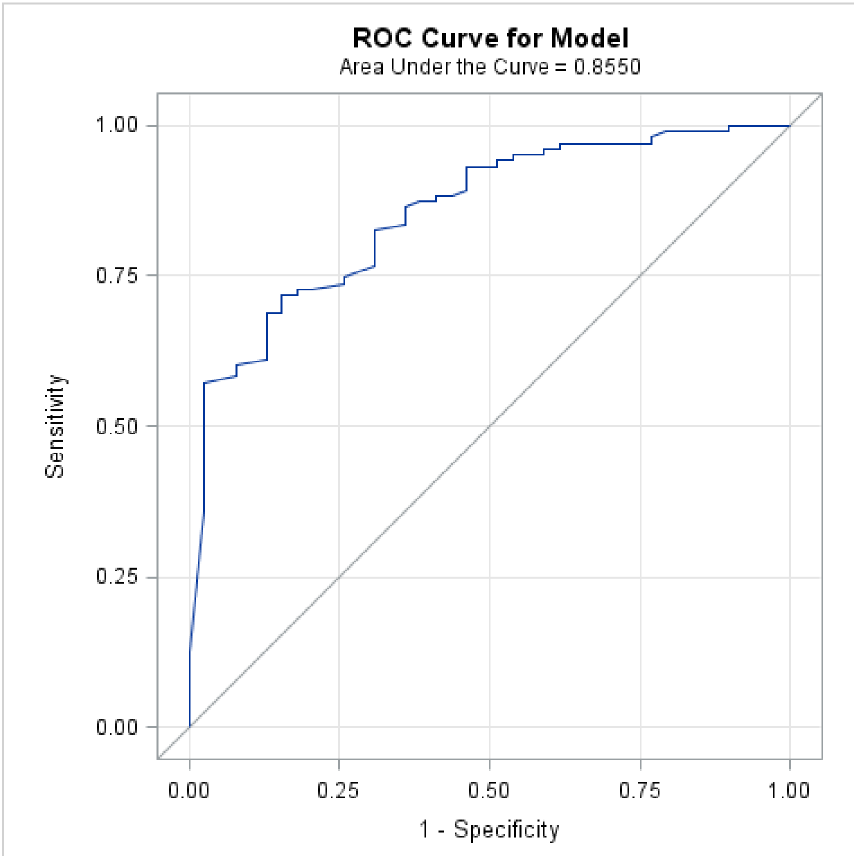
```
proc logistic data=WORK.THESIS desc;
 model Passed = score
 / outroc=roc1;
run;
```

ROC Curve for Score Only Model – Year 2



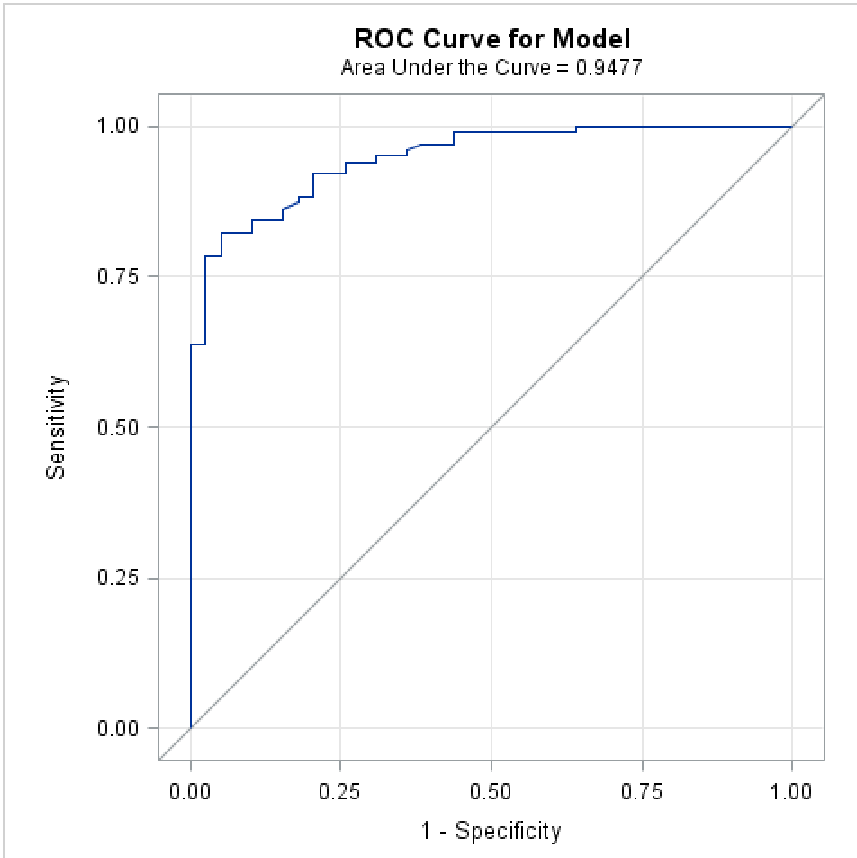
ROC Curve for Study Model on Year 2

```
proc logistic data=WORK.THESIS desc;
 model Passed = q2 q13 q14 q17 q28 q31 q5 q7 q18
 / outroc=roc1;
run;
```



ROC Curve for the Year 2 Best Fit Model

```
proc logistic data=WORK.THESIS desc;
 model Passed = q1 q2 q3 q8 q9 q11 q13 q17 q118 q22 q24 q26 q27 q33 q34
 / outroc=roc1;
run;
```



Classification Tables for Predictions

Classification Table for Score Only Model
Year 2

```
proc logistic data=WORK.THESIS desc;
 model passed = score
 / ctable pprob = (.62 to .87 by .01);
run;
```

Classification Table

Prob Level	Correct Event	Correct Non-Event	Incorrect Event	Incorrect Non-Event	Percentages Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.620	89	25	14	15	79.7	85.6	64.1	13.6	37.5
0.630	89	25	14	15	79.7	85.6	64.1	13.6	37.5
0.640	89	30	9	15	83.2	85.6	76.9	9.2	33.3
0.650	89	30	9	15	83.2	85.6	76.9	9.2	33.3
0.660	89	30	9	15	83.2	85.6	76.9	9.2	33.3
0.670	89	30	9	15	83.2	85.6	76.9	9.2	33.3
0.680	89	30	9	15	83.2	85.6	76.9	9.2	33.3
0.690	89	30	9	15	83.2	85.6	76.9	9.2	33.3
0.700	82	30	9	22	78.3	78.8	76.9	9.9	42.3
0.710	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.720	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.730	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.740	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.750	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.760	82	33	6	22	80.4	78.8	84.6	6.8	40.0
0.770	77	33	6	27	76.9	74.0	84.6	7.2	45.0
0.780	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.790	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.800	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.810	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.820	77	34	5	27	77.6	74.0	87.2	6.1	44.3
0.830	68	34	5	36	71.3	65.4	87.2	6.8	51.4
0.840	68	35	4	36	72.0	65.4	89.7	5.6	50.7

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.850	68	35	4	36	72.0	65.4	89.7	5.6	50.7
0.860	60	35	4	44	66.4	57.7	89.7	6.3	55.7
0.870	60	36	3	44	67.1	57.7	92.3	4.8	55.0

Classification Table for Study Model
Year 2

```
proc logistic data=WORK.THESIS desc;
 model Passed = q2 q13 q14 q17 q28 q31 q5 q7 q18
 / ctable pprob = (.80 to .92 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.740	76	27	12	27	72.5	73.8	69.2	13.6	50.0
0.750	76	27	12	27	72.5	73.8	69.2	13.6	50.0
0.760	75	27	12	28	71.8	72.8	69.2	13.8	50.9
0.770	75	27	12	28	71.8	72.8	69.2	13.8	50.9
0.780	74	27	12	29	71.1	71.8	69.2	14.0	51.8
0.790	74	28	11	29	71.8	71.8	71.8	12.9	50.9
0.800	71	28	11	32	69.7	68.9	71.8	13.4	53.3
0.810	71	28	11	32	69.7	68.9	71.8	13.4	53.3
0.820	70	30	9	33	70.4	68.0	76.9	11.4	52.4
0.830	68	30	9	35	69.0	66.0	76.9	11.7	53.8
0.840	67	31	8	36	69.0	65.0	79.5	10.7	53.7
0.850	62	31	8	41	65.5	60.2	79.5	11.4	56.9
0.860	60	31	8	43	64.1	58.3	79.5	11.8	58.1
0.870	60	31	8	43	64.1	58.3	79.5	11.8	58.1
0.880	51	33	6	52	59.2	49.5	84.6	10.5	61.2
0.890	49	33	6	54	57.7	47.6	84.6	10.9	62.1
0.900	45	36	3	58	57.0	43.7	92.3	6.3	61.7
0.910	45	36	3	58	57.0	43.7	92.3	6.3	61.7
0.920	41	38	1	62	55.6	39.8	97.4	2.4	62.0
0.930	41	38	1	62	55.6	39.8	97.4	2.4	62.0
0.940	39	38	1	64	54.2	37.9	97.4	2.5	62.7
0.950	37	38	1	66	52.8	35.9	97.4	2.6	63.5
0.960	13	38	1	90	35.9	12.6	97.4	7.1	70.3

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.970	0	39	0	103	27.5	0.0	100.0	.	72.5
0.980	0	39	0	103	27.5	0.0	100.0	.	72.5
0.990	0	39	0	103	27.5	0.0	100.0	.	72.5

Classification Table Year 2 Best Fit Model

```
proc logistic data=WORK.THESIS desc;
  model passed = q1 q2 q3 q8 q9 q11 q13 q17 q18 q22 q24 q26 q27 q33 q34
  / ctable pprob = (.62 to .87 by .01);
run;
```

Classification Table

Prob Level	Correct		Incorrect		Percentages				
	Event	Non-Event	Event	Non-Event	Correct	Sensi-tivity	Speci-ficity	False POS	False NEG
0.740	84	29	10	18	80.1	82.4	74.4	10.6	38.3
0.750	84	29	10	18	80.1	82.4	74.4	10.6	38.3
0.760	84	30	9	18	80.9	82.4	76.9	9.7	37.5
0.770	83	30	9	19	80.1	81.4	76.9	9.8	38.8
0.780	83	30	9	19	80.1	81.4	76.9	9.8	38.8
0.790	83	30	9	19	80.1	81.4	76.9	9.8	38.8
0.800	83	30	9	19	80.1	81.4	76.9	9.8	38.8
0.810	81	30	9	21	78.7	79.4	76.9	10.0	41.2
0.820	81	31	8	21	79.4	79.4	79.5	9.0	40.4
0.830	81	32	7	21	80.1	79.4	82.1	8.0	39.6
0.840	81	32	7	21	80.1	79.4	82.1	8.0	39.6
0.850	79	32	7	23	78.7	77.5	82.1	8.1	41.8
0.860	78	32	7	24	78.0	76.5	82.1	8.2	42.9
0.870	77	32	7	25	77.3	75.5	82.1	8.3	43.9
0.880	73	32	7	29	74.5	71.6	82.1	8.8	47.5
0.890	73	33	6	29	75.2	71.6	84.6	7.6	46.8
0.900	70	33	6	32	73.0	68.6	84.6	7.9	49.2
0.910	68	33	6	34	71.6	66.7	84.6	8.1	50.7
0.920	65	34	5	37	70.2	63.7	87.2	7.1	52.1
0.930	65	35	4	37	70.9	63.7	89.7	5.8	51.4
0.940	63	35	4	39	69.5	61.8	89.7	6.0	52.7
0.950	61	35	4	41	68.1	59.8	89.7	6.2	53.9
0.960	60	35	4	42	67.4	58.8	89.7	6.3	54.5
0.970	56	37	2	46	66.0	54.9	94.9	3.4	55.4

Classification Table									
Prob Level	**Correct**		**Incorrect**		**Percentages**				
	Event	**Non-Event**	**Event**	**Non-Event**	**Correct**	**Sensi-tivity**	**Speci-ficity**	**False POS**	**False NEG**
0.980	55	38	1	47	66.0	53.9	97.4	1.8	55.3
0.990	47	39	0	55	61.0	46.1	100.0	0.0	58.5

GLM Logistics for Year 1 All Questions Model for Table 13

```
> thesislm <- glm(Passed~X1+X2+X3+X5+X6+X7+X8+X9+X10+X11+X12+X13+X14+X15+X16+X17
+X18+X19+X21+X22+X23+X24+X25+X26+X27+X28+X29+X30+X31+X32+X33+X34,data=totunit1c,f
amily=binomial(logit))
> summary(thesislm)

Call:
glm(formula = Passed ~ X1 + X2 + X3 + X5 + X6 + X7 + X8 + X9 +
    X10 + X11 + X12 + X13 + X14 + X15 + X16 + X17 + X18 + X19 +
    X21 + X22 + X23 + X24 + X25 + X26 + X27 + X28 + X29 + X30 +
    X31 + X32 + X33 + X34, family = binomial(logit), data = totunit1c)

Deviance Residuals:
    Min       1Q          Median       3Q      Max
-3.1502  -0.4011         0.2110   0.5538   2.1386

Coefficients:
             Estimate   Std. Error  z value     Pr(>|z|)
(Intercept) -5.818943  1.575369   -3.694      0.000221 ***
X11          0.332547  0.520138    0.639      0.522599
X21          1.371807  0.457839    2.996      0.002733 **
X31         -0.671287  0.467480   -1.436      0.151011
X51          0.780039  0.459410    1.698      0.089524 .
X61          0.529928  0.511548    1.036      0.300235
X71          0.808455  0.433878    1.863      0.062417 .
X81          0.396492  0.454988    0.871      0.383518
X91         -0.447417  0.468777   -0.954      0.339864
X101         0.564253  0.548995    1.028      0.304047
X111         0.433265  0.720485    0.601      0.547606
X121        -0.503284  0.741287   -0.679      0.497180
X131         0.713066  0.422484    1.688      0.091450 .
X141         0.573189  0.444660    1.289      0.197381
X151        -0.024118  0.428302   -0.056      0.955094
X161        -0.249918  0.711640   -0.351      0.725448
X171         0.967952  0.415330    2.331      0.019776 *
X181         0.918234  0.631666    1.454      0.146037
X191        -0.198516  0.508888   -0.390      0.696464
X211         0.477509  0.673498    0.709      0.478325
X221         0.881231  0.935442    0.942      0.346168
X231        -0.005255  0.500196   -0.011      0.991618
X241         0.407575  0.531802    0.766      0.443436
X251         0.686277  0.444616    1.544      0.122703
X261         0.341087  0.529596    0.644      0.519543
X271        -0.577853  0.447617   -1.291      0.196720
X281         0.601797  0.459153    1.311      0.189970
X291         0.364078  0.447309    0.814      0.415685
X301        -0.333579  0.432959   -0.770      0.441025
X311         1.425621  0.502445    2.837      0.004549 **
X321         0.279017  0.514507    0.542      0.587612
X331        -0.366188  0.425043   -0.862      0.388946
X341        -0.173844  0.448617   -0.388      0.698378
---
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 316.40  on 255  degrees of freedom
Residual deviance: 183.26  on 223  degrees of freedom
AIC: 249.26

Number of Fisher Scoring iterations: 6
```

GLM Logistics for Year 2 All Questions Model for Table 13

```
> thesislm <- glm(passed~q1+q2+q3+q5+q6+q7+q8+q9+q10+q11+q12+q13+q14+q15+
q16+q17+q18+q19+q21+q22+q23+q24+q25+q26+q27+q28+q29+q30+q31+q32+q33
+q34,data=testdata,family=binomial(logit))
> summary(thesislm)

Call:
glm(formula = passed ~ q1 + q2 + q3 + q5 + q6 + q7 + q8 + q9 +
    q10 + q11 + q12 + q13 + q14 + q15 + q16 + q17 + q18 + q19 +
    q21 + q22 + q23 + q24 + q25 + q26 + q27 + q28 + q29 + q30 +
    q31 + q32 + q33 + q34, family = binomial(logit), data = testdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.66722  -0.00633   0.01340   0.20197   2.43519

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -19.50105   9.01568  -2.163  0.03054 *
q11           7.85093   2.88069   2.725  0.00642 **
q21           1.11008   1.17356   0.946  0.34419
q31           2.20449   1.25808   1.752  0.07973 .
q51          -0.93292   1.14200  -0.817  0.41397
q61          -0.67278   1.03901  -0.648  0.51729
q71           1.43286   1.39037   1.031  0.30275
q81           2.00169   1.35162   1.481  0.13862
q91           3.76284   1.54912   2.429  0.01514 *
q101         -1.19190   1.25499  -0.950  0.34225
q111          1.93572   2.30163   0.841  0.40033
q121         -2.56766   1.35108  -1.900  0.05737 .
q131          1.89846   1.63682   1.160  0.24611
q141          3.17396   1.50848   2.104  0.03537 *
q151         -0.50139   1.09694  -0.457  0.64761
q161          2.11497   5.27836   0.401  0.68865
q171          1.29901   1.41517   0.918  0.35866
q181          3.66143   1.73142   2.115  0.03446 *
q191          2.30873   1.49454   1.545  0.12240
q211         -3.16273   3.45395  -0.916  0.35983
q221         -3.40133   4.57478  -0.743  0.45718
q231         -2.13112   1.50683  -1.414  0.15727
q241          4.56441   1.89800   2.405  0.01618 *
q251          1.72671   1.32125   1.307  0.19126
q261          4.85188   1.85155   2.620  0.00878 **
q271          0.34309   1.16041   0.296  0.76749
q281         -0.96905   1.15275  -0.841  0.40055
q291          1.69514   1.25878   1.347  0.17809
q301          0.24611   1.02885   0.239  0.81095
q311          0.04328   1.26954   0.034  0.97281
q321         -0.89868   1.03218  -0.871  0.38394
q331         -3.42479   1.81888  -1.883  0.05971 .
q341          2.56756   1.13916   2.254  0.02420 *
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 166.298  on 140  degrees of freedom
Residual deviance:  52.212  on 108  degrees of freedom
  (2 observations deleted due to missingness)
AIC: 118.21

Number of Fisher Scoring iterations: 9
```

Traditional Cutoff Score Tables for Year 2

```
> View(testdata)
> table(testdata$passed,testdata$cutoff50)

     f   p
  f   6  33
  p   2 102

> table(testdata$passed,testdata$cutoff55)

    f  p
  f 12 27
  p  5 99

> table(testdata$passed,testdata$cutoff60)

    f  p
  f 20 19
  p 11 93

> table(testdata$passed,testdata$cutoff65)

    f  p
  f 25 14
  p 14 90

> table(testdata$passed,testdata$cutoff70)

    f  p
  f 33  6
  p 22 82

> table(testdata$passed,testdata$cutoff75)

    f  p
  f 35  4
  p 36 68
```