8-2010

A Comparative Study between the Standards of Learning and In-Class Grades.

Randetta Lynn Fuller
East Tennessee State University

A Comparative Study Between the Standards of Learning and In-Class Grades

---

A thesis

presented to

the faculty of the Department of Mathematics

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Master of Science in Mathematical Sciences

---

by

Randetta Fuller

December 2010

Daryl Stephens, Ph.D., Chair

Michel Helfgott, Ed.D

Robert Price, Ph.D.

Keywords: Standards of Learning, Comparative, Statistics

ABSTRACT

A Comparative Study Between the Standards of Learning and In-Class Grades

by

Randetta Fuller

We examined the Standards of Learning mathematics scores and in-class grades for a rural Virginia county public school system. We looked at third, fourth, fifth, sixth, and seventh grades as well as Algebra I, Algebra II, and Geometry classes. The purpose of this was to determine whether or not there is a strong correlation between the Standards of Learning and the students' in-class grades. Had a strong enough correlation between the Standards of Learning and in-class grades been found we would have used only the in-class grades to predict the Standard of Learning test scores. However, we found that the students' in-class grades are not the only predictor of the Standards of Learning test scores. With the coefficient of determination ranging from 6.8% to 84.4%, this indicates that at best 84.4% of variation in the response is explained by the model for Algebra II and at worst only 6.8% for Algebra I.

DEDICATION

First, I would like to dedicate this thesis to my loving fiancé Matthew Shifflett. He has supported me and helped me follow my dreams no matter how strange they were since we met. I would also like to dedicate this to my parents Randy and Rebecca Fuller and my grandparents Harless and Narsie Fuller and Trula Sutherland. Without their love and support college wouldn't have been an option. Finally, I would like to dedicate this to all of friends who have stuck with me through the years and all of the complaining.

ACKNOWLEDGEMENTS

I would like to first thank my committee chair Dr. Daryl Stephens for helping me finish the thesis that began in high school in its own way. Next, I would like to thank Dr. Michel Helfgott and Dr. Robert Price for serving on my committee. Finally, I would like to thank Ms. Kristina Forster for proofreading all my work even if she didn’t understand all of it.

CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The purpose of this thesis was to determine whether or not there is a strong correlation between the Standards of Learning and the students' in-class grades. We examined the Standards of Learning scores and in-class grades for Russell County, a rural Virginia public school system. If there is a strong enough correlation between the Standards of Learning and in-class grades, we will use the in-class grades to predict Standard of Learning test scores. In the first section we discuss the background information. In the second section we introduce the definitions and terms used in this paper. In the third section we discuss the opinions of the guidance counselors and principals involved.

Background Information

In 2001 the No Child Left Behind Act was passed. As part of the act, states were required to issue statewide standardized tests as a method of determining what students know. Ideally, by 2014 all students would reach state standards in reading and mathematics. The purpose of this study is to use 2007-2008 Standards of Learning test scores and in-class grades for mathematics to determine whether or not standardized tests are giving a proper view of what students are learning.

It is not uncommon for students who do well in a class to barely pass or even fail the Standards of Learning Test. There are also a few cases where the student is failing a class and passes the Standards of Learning. In a few school systems this means that the student automatically passes the class; emphasis is placed on the Standards of Learning test instead of in-class grades. The Standards of Learning have come to be a high stakes test. If students do not pass a set number of them they do not graduate and if a school does not do well enough it does not receive accreditation.

According to Diane Ravitch, former United States Assistant Secretary of Education, standardized tests lay out clear expectations for students, teachers, and parents (Berube, 264-7). However, most standardized tests are not chosen because they best represent what students should know. Instead, like the state of Virginia, they are chosen because (1.) they are cheap, (2.) they are considered easy to read, and (3.) they are easy to grade (Berube, 264-7). Virginia's Standards of Learning is a multiple choice test that leaves no room for interpretation; the answer is either right or wrong.

Prior to No Child Left Behind being passed Virginia Standards of Learning were mandatory to take but not to pass. Teachers were able to focus more on what students struggle with but now they have to adhere to a strict countywide schedule. Russell County, the school system involved in our research, has its Pacing Guide online. All teachers in Russell County are supposed to follow this pacing guide.

Definitions and Terminology

The null hypothesis is a construct created for the purpose of statistical testing. It always says there is no difference or no relationship between variables. The research hypothesis is generally expressed in terms of what the researcher expects to find. It, like the null hypothesis, has a unique outcome. For example, if the null hypothesis says there is no relationship between two variables, the research hypothesis would say there is a positive relationship between the same two variables. If in this example the null hypothesis is rejected and the observed relationship is positive at the selected p-value, the research hypothesis would not be rejected.

However, if the observed relationship is negative, the research hypothesis would also be rejected. In this case both the null and research hypotheses would be rejected. The probability value, *p-value,* is the probability of obtaining a test statistic at least as extreme as the one that was actually observed. The smaller the p-value the more strongly we can reject the null hypothesis. Typically if the p-value is smaller than 0.05 we reject the null hypothesis. The *variance* of a random variable gives us an idea of how widely spread the data are. The larger the variance the more widespread. The *standard deviation*, σ, the square root of the variance, is the measure of the spread of the data. The *confidence interval* is an estimated range of values given a set of sample data. The *confidence level* lets us know how confident we can be in our confidence interval. The *prediction interval* is the range into which the response is expected to fall (Young, http://www.stats.gla.as.uk/steps/glossary/ index.html).

A *regression equation* allows us to express the relationship between our variables algebraically, where Y = response and X = predictor. The *coefficient of determination*, R^2, indicates how much variation in the response is explained by the equation. The higher the R^2 the better the equation fits the data. A *polynomial regression* is a form of linear regression in which the relationship between the *x* and the *y* is modeled as an *n*th order polynomial. *Weights* are a specific value for smoothing our parameters, in our case we used $1/S^2$ as our weight, where S is our sample variance (Young, http://www.stats.gla.as.uk/steps/glossary/ index.html).

Opinions

The opinions of the guidance counselors and principals vary from person to person. One elementary guidance counselor was "of the opinion that the SOLs, as they are given at this time, do reflect learning that takes place in the classroom." In contrast a high school guidance counselor says, “It is a great idea that everyone has the same standards, however they are not all age and developmentally appropriate. Also the funding and educational opportunities statewide cause slight difficulties. These tests are suppose to measure a child's knowledge of subject matter but does not allow for individual learning styles. It is a multiple choice test if you have trouble taking a multiple choice test you are in deep trouble. In some instances the test (for example Math) is more of a reading test instead of Math. I feel that if you want to measure what a child knows do not trick them as the point blank. Those trickery questions should be left to college students. We tend to teach the children how to take the test throughout the year. This limits problem solving, team work, higher critical thinking skills etc. A lot of emphasis is put on this test, pressure for the student, teacher, principal, school, division. You have to perform to get the funding and when you do well (having extra programs such as afterschool tutoring) those programs which are very helpful often get cut because ‘you are doing so well why do you need extra programs.’ Once again it could be a good program. I understand the reason for it, but modifications need to be made. And please do not forget our disabled students. Is this working for them? These are just a few concerns. I am sure that most of these have been addressed at some point or another. Some kind of test has to be given and even

> though I don't agree with all of the SOL's the next instrument could be even worse."

The previous two opinions sum up the opinions of most guidance counselors. Most are of the mind that the Standards of Learning are a decent enough test, but they should not be the only interpreter of what a student knows.

Karen Dorgan, an associate professor of education at Mary Baldwin College, sums up the opinions of teachers best: "In general, those new to teaching found such structure helpful, while some of the more experienced teachers expressed frustration at having to abandon previously constructed integrated units or to change the sequence of skills and concepts from that which had worked for them in the past" (Dorgan, 1203-28).

CHAPTER 2

LITERATURE REVIEW

Before the Virginia Board of Education adopted the Standards of Learning, math teachers across Virginia taught the same topics that they currently teach, but they taught them in a different order and with a different structure. Teachers used to be able to use hands-on activities and group exercises and they could take their time on areas that students struggled with. Since No Child Left Behind was passed and the Standards of Learning became a required test, teachers have had to adjust their teaching styles. Teachers now use more direct instruction and feel a greater pressure to stay on schedule. They have to go on with their lessons even if all the students don't understand the material. Teachers, for the most part, understand the need for accountability, but currently an administration that does not directly deal with students is making the decisions and the teachers have little to no say in what they need to teach and how they need to teach it (Pasi, 75-6). In Russell County, for example, there is a pacing guide on the internet that the teachers are to follow. It is laid out in a week-by-week lesson plan.

It must be kept in mind that having grade level goals is not an uncommon thing; most schools have always had them to make sure that students learn what they are supposed to before going on to the next class. However, the addition of standardized testing has caused some concern. In Virginia beginning with the graduating class of 2004 these tests determine whether or not a student graduates from high school and if the school receives state accreditation. In order for students to graduate from high school they have to pass six SOLs throughout their high school curriculum. In elementary school failing the Standards of Learning means the child either fails the grade or has to go to summer school. This means that the Standards of Learning is a high stakes test. According to Dorgan, "Virginia [is] placed in the hard-line category, both in constructing its state standards and in designing its assessment plan" (Dorgan, 1203-28). What Dorgan means by "hard-line category" is that the state standards are uncompromising.

Amber Winkler, the Research Director at the Thomas B. Fordham Institute, found in 2002 that new and veteran teachers view the Standards of Learning Test differently. New teachers see it in terms of what they gain from it, while veteran teachers see it in terms of what they lost. The differences don't just stop there however; experienced teachers were often perturbed by the Standards of Learning and felt that they had lost power in the classroom. The test was teaching the class. One of the biggest complaints that the teachers had was lack of flexibility to do activities that in the past they had done simply because there was no time for them in the pacing guide. According to Winkler, "Karen Mitchell's research echoes a similar sentiment: 85% of principals in a RAND study felt that standardized multiple-choice tests failed to address the knowledge, skills, and behaviors that innovative programs seek to promote" (Winkler, 219-25).

Inexperienced teachers, those with less than two years experience, say that the Standards of Learning help promote departmental collaboration and help give meaning to their teaching. They look forward to the department meetings. They say that sharing lessons and details of what they are doing in the classroom not only helps them but the students as well. It helps keep the lessons standardized. The inexperienced teachers say department meetings helped them be more organized and focused on the lessons (Winkler, 219-25).

Unfortunately, there are several variables that factor in to whether or not a child will do well on the Standards of Learning, but these factors are not considered when determining the percentage of students that have to pass the Standards of Learning. According to Raymond Pasi, a principal at Yorktown High, home, environment, and socioeconomic characteristics are key factors in how well a student will do (Pasi, 75-6). According to Clair Berube, Gary Orfield, a professor at the University of California, also states that high-stakes tests penalize low-income families and minorities (Berube, 264-7). Boards of Education do not consider this when setting the standards; poorer schools have to have the same pass rate as richer schools (Pasi, 75-6). They seem to believe that all students should be able to pass the Standards of Learning; however, as previously stated, they do not take into consideration that students differ, something that teachers seem to understand. Students have different background experience, home lives, natural ability, talents, learning styles, attitudes, economic background, and the list goes on, but the Board of Education doesn't seem to take this in to account (Dorgan, 1203-28).

Although the Standards of Learning is a high-stakes test, according to the Virginia Department of Education in 2004, Virginia's scores are going up. According to Clair Berube, a professor of education at Wagner College, Virginia chose the Standards of Learning for three main reasons, "because (1) it is cheap, (2) it is easy to read, and (3) it is simple to grade." Because the test is multiple-choice it is extremely objective and as said by Berube, "they really only test knowledge recall." While Berube was a sixth grade science teacher she conducted a study of her own students. A week after her students had taken the SOL she gave them her version of the SOL, the "Comprehension Measurement" tests. The only difference between the two tests was that she asked the students to explain their answers. What she found was rather surprising. It turns out that 71% of the students who had passed the SOL had failed her test, "They either could not explain their answers or gave bogus explanations. It seemed they could pass the SOL but did not understand the subject matter" (Berube, 264-7).

Berube used a multivariate analysis of variance (MANOVA) to determine whether the students who had constructivist teachers did better or those that had "drill and grill" teachers.

She discovered that the "drill and grill" students did better on the SOL, but several of those failed her test. The students with constructivist teachers did well on the SOL but had the lowest scores on Berube's test (Berube, 264-7).

It is not just the teachers who are affected by these tests. The students have more to lose and according to Pasi, "Schools are not equipped to help significantly; there are simply too many students for educators to provide individual instruction and monitoring... The great danger presented by the SOL tests is that we risk losing sight of the chief aims of teaching: to educate students as well as possible and to prepare them to think and to contribute effectively to society" (Pasi, 75-6). In 2001 Wendy Cole reported on how students in Roanoke Rapids, North Carolina feel about their standardized test. One fifth grader named Edward Lynch was one student with whom Cole spoke. He told her that at the beginning of the school year he wasn't concerned about the tests that he would have to take at the end of the school year, but two weeks before the big tests he was scared and having nightmares about his books squishing him and being stabbed by pencils (Cole, 61). In 2001 Cole reported that the Alliance for Childhood, a partnership of educators and health professionals, asked policymakers ... "to consider the toll taken by high-stakes testing of young kids, in ways that range from stomachaches to insomnia and depression" (Cole, 61).

In 2005 Beverly Hill looked at how differently learning styles in students affect how well they test on a standardized test. Teachers try to make sure that all students understand the material, but the standardized tests are in one format. According to Shelia Tobias, "Approximately 20 to 30 percent of the school-age population remember what is heard; 40 percent recall well visually the things that are seen or read; many must use their fingers in some manipulative way to help remember basic facts; and other people cannot internalize information or skills unless they use them in real-life activities such as actually writing a letter to learn correct format." It is not uncommon for up to half of the tactile-kinesthetic learners to fail the math portion of standardized tests. The Standard of Learning, however, does not take in to consideration all the differences (Hill, 27-30).

As mentioned, one obstacle that the students have with the SOL test is the readability of the math portion of the test. The math portion of the test is set up so that students solve real-world questions instead of just computation. Dorgan notes one teacher's take on this, "Yes, yes, reading is going to be our difficulty. That's, you know, understanding. Mine will come to me and say 'I don't know what they're asking me to do.' And some of that is terminology and some of that is their ability to break down what a problem is saying. They just need to develop better skills to do that" (Dorgan, 1203-28). Another problem isn't the test itself but how it is administered. During "SOL week," as most schools call it, the halls are silent, the classrooms are silent, and the teachers cannot help the students. This is not what most students are used to. The silence actually distracts some students.

According to Morse, a study released by the University of Virginia shows that although some schools have done better on the Standards of Learning things have had to be sacrificed. Schools have had to cancel field trips, pep rallies, dress-up days during homecoming week, and elective courses. Even before No Child Left Behind was proposed, let alone passed, Morse quoted Walt Haney, Senior Research Associate at Boston College's Center for the Study of Testing, Evaluation and Educational Policy, "Research shows that using test scores in combination with grades results in a more valid decision" (Morse, 34-38).

There are some schools that have embraced No Child Left Behind, schools in Norfolk, Virginia being among them. Norfolk goes even further than what No Child Left Behind asks.

They have regular assessments to track the progress of their students and they adjust their teaching practices accordingly. Norfolk has had a significant increase in students passing the Standards of Learning when compared to 1998, which was one of their worst years. They are however under scrutiny from critics who think they are improving their scores at the cost of a broader education (Butler, 54-6).

Over the past several years several studies have looked at the use of computers in classrooms. In 1985 and again in 1991 Kulik and associates found that students that use computers in the classroom as part of the instruction generally did better on achievement tests. However, according to Cuban, teachers are still the main factor in how well a student does. In 1996 Hogle claimed that computer games can be used to help motivate students, help them retain information, and improve their reasoning skills. Students tend to discuss computer games more than their homework. Computer games also help promote achievement. The students can see that they are accomplishing something by getting further in the game (McDonald, 459-72).

The Standards of Learning tests deal with recalling information instead of trying to get the students to develop more in-depth thinking skills. This is causing teachers to “teach the test,” and instead of having free time where the students can use the classroom computer to play an educational game, teachers are having to use the “free time” to administer practice tests and make sure that their students know how to take the test (McDonald, 459-72). Unfortunately, a lot of rural schools cannot afford a classroom computer for the students. Most classrooms involved with our research have a teacher’s computer that is not for student use, so the extra motivation that the students need is not available.

In 2004 the Virginia General Assembly released Review of Factors and Practices Associated with School Performance in Virginia, a report that examined whether or not schools were meeting their achievement goals and what was working best for schools that were meeting those goals. There were six major findings in the report: Standard of Learning pass rates had increased since their implementation, there is a relationship between the schools demographics and how well students did, students in schools with poor demographics did not necessarily do bad, division level support directly correlates to success of schools, overall schools believe that the SOLs have been beneficial, and there are still a number of challenges that need to be taken care of. The study found that teacher salaries are on average 13% lower in areas where there are a low number of college graduates (Christie, 565-7).

The study found nine practices that are advantageous to good SOL results: "strong principal leadership; an environment conducive to learning; an effective teaching staff; data-driven assessment of student weaknesses and teacher effectiveness; curriculum alignment, pacing, and resources; differentiation in teaching (altering content according to student needs and learning styles); academic remediation; teamwork, collaboration, and vertical integration; and the structure and intensity of the school day." It also found that a lack of parental support and student motivation are challenges that must be overcome (Christie, 565-7).

As previously mentioned, there are schools that are meeting standards even though they have low financial resources and the students come from low income families. The students and teachers at these schools work together and one school reports that it has math teachers lining up to teach in it because it has such a productive environment. Jo Boaler of Stanford University conducted a study at "Railside High" in California and found that even though the students scored lower on a standardized test given at the beginning of the year than their "wealthier" counterpart, "Railside High had a higher average score at the end of the year and by the second year "Railside" was doing significantly better. "Railside High" is not the real name of the school (Boaler, 502-6).

Although "Railside High" outperformed its wealthier counterpart for all three years that the test was given, the state decided that they were underperforming because they scored lower on the SAT-9. The standardized test that Boaler administered is easier to read than the SAT-9, it did not use long sentences that may confuse linguistic-minorities and low income students. The math portion of the SAT-9, along with other state issued standardized test, is more about reading comprehension than solving problems. Students must first understand what the question is asking before "solving for x" (Boaler, 502-6).

Boaler also found that when the students were told that women and minorities tend to score lower on these tests that is what happened, but when the students were not informed (the control group), there was not a significant difference between the groups. Typically if you tell students that they are low achievers they will be low achievers (Boaler, 502-6). In Virginia the students are labeled: Pass/Advanced, Pass/Proficient, Fail/Basic, and Fail/Below Basic.

In our culture it is common belief that males outperform females in mathematics. Ding et al. conducted a study to examine whether or not belief is true using standardized test scores. They found that the students' mathematical abilities develop at the same rate, but female students GPAs are significantly higher. There have been several factors suggested for the gender differences: biological factors, learning strategies, and socialization. Ding et al. seem to believe that socialization is the biggest factor (Ding, 279-95).

A large national sampling of students suggests that females do better than males in mathematics during elementary grades but by high schools they "fall behind" their male counterparts. Ding el al. found that females maintained a higher mathematics GPA during both middle school and high school. There data revealed three main results: both genders grow at the same rate over time, there is no significant difference in gender, and on average females have a higher mathematics GPA. Ding et al. suggested one explanation for females having a higher average mathematics GPA, "One explanation for the female advantage in mathematics performance as measured by GPA may be that much of what got factored into teachers' assigned grades was student effort rather than mathematical knowledge and skills. Thus, female students' higher GPAs might simply indicate their eagerness to please the teacher rather than their mathematical understanding. On the other hand, if GPA is considered a valid measure of mathematic learning to some degree, then our study suggests that female students can learn advanced mathematics content well and can maintain the advantage over males in mathematics performance as measured by classroom-based assessment" (Ding, 279-95).

As previously mentioned, the gender difference on standardized tests has decreased; however, research shows that the gender differences continue to exist in gifted students. Studies show that in gifted students males are still doing better than females in mathematics. During the 1970s research showed that males do better in mathematics than females beginning as early as third grade. This has often been attributed to the fact that males are encouraged in mathematics whereas females are encouraged to do well in language arts because these skills would help them with their future roles. Since then efforts have been made to close the gender gap and promote students doing well in all subjects no matter their gender, and currently the gender gap has narrowed significantly (Olszewki-Kubilius, 233-68).

Paula Olszewski-Kubilius, the Director at the Center for Talent Development at Northwestern University, found that gender differences are more often present in grades eighth through senior and in gifted students. Olszewski-Kubilius also found the way that students perceive themselves also has a lot to do with how well they do on standardized tests. Males tend to have a higher self-perception in mathematics, whereas females have a higher self-perception in verbal skills (Olszewki-Kubilius, 233-68).

CHAPTER 3

METHODS AND PROCEDURES

This study was designed to examine the Standards of Learning mathematics scores and in-class grades for a rural Virginia county public school system, Russell County. We looked at the third, fourth, fifth, sixth, and seventh grades as well as Algebra I, Algebra II, and Geometry classes. We used the in-class grades and Standards of Learning test scores for the 2007-2008 school year. Data collection for this study began by requesting a data set of individual student test scores and in-class grades from each school's guidance counselor(s), making sure that identifiable information was not included.

The third through seventh grade in-class grades were based on an A, B, C, D, or F grading scale. Because we were unable to use the letter grades, they were converted to a numerical scale: A=4, B=3, C=2, D=1, and F=0. The Algebra I, Algebra II, and Geometry in-class grades were based on a 94-100=A, 86-93=B, 78-85=C, 70-77=D, and below 70=F. We used the numerical grade as well as the aforementioned converted scale to determine whether or not this would skew the data any. Each class level had a different number of data points: third grade had 145 participating students, fourth had 100, fifth had 113, sixth had 110, seventh had 112, Algebra I had 155, Algebra II had 130, and Geometry had 139 participating students. These numbers are significantly lower than the number of students in Russell County because I only used the third through seventh grade and the high school math classes. There are several students who are unaccounted for because they were not required to take the mathematics portion of the SOLs. Because this was a voluntary participation study, there were also a couple of schools that declined to participate.

The purpose was to determine whether or not there is a strong correlation between the students' in-class grades and the Standards of Learning, H_A: A student's in-class grades can be used to accurately determine his or her score on the end-of-years Standards of Learning tests. Our null hypothesis is that the Standards of Learning and in-class grades have no bearing on one another. In order to determine whether or not we should reject or fail to reject our null hypothesis we used the Minitab Student Release 14 program. The results of the data analysis are presented in Chapter 4.

The null hypothesis was tested for each group by using a basic Regression plot with our $1/S^2$ weight, which determined the regression equation, estimated standard deviation, coefficient of determination, and p-value. The confidence interval and prediction interval were displayed with a 95% confidence level to show the range of test scores that students could attain given a specific in-class grade, these results were merely used to display our data. The histogram of residuals, normal plot of residuals, residuals versus fits, and residuals versus order were displayed to show the difference between the observed values and the predicted values. These results are discussed in depth in Chapter 4 for each class.

CHAPTER 4

RESULTS

The No Child Left Behind Act of 2001 required states to implement statewide standardized tests as a method of determining what students know. The purpose of this study is to use 2007-2008 Standards of Learning test scores and in-class grades for mathematics to determine whether or not standardized tests are giving a proper view of what students are learning. We looked at third, fourth, fifth, sixth, and seventh grades as well as Algebra I, Algebra II, and Geometry classes. Had a strong enough correlation between the Standards of Learning and in-class grades been found, we could have used only the in-class grades to predict the Standards of Learning test scores. However, we found that the students' in-class grades are not the only predictor of the Standards of Learning test scores. With the coefficient of determination ranging 6.8% to 84.4%, this indicates that at best 84.4% of variation in the response is explained by the model for Algebra II and at worst only 6.8% for Algebra I. In the following plots a weighted regression was used to determine the proper regression equation where our weights were our $1/S_i^2$, with S_i being our variance for each grade.

Third Grade Data Analysis

As previously mentioned, the third grade had 145 participating students. *Figure 1* shows the plot of third grade in-class grades (x) to SOL scores (y). A polynomial regression analysis of the third grade SOL scores versus third grade in-class grades with our $1/S_3^2$ weight being used determined the regression equation to be $y = 392 + 43.7 * x$, where y is the predicted SOL score and x is the in-class grade, with a p-value of 0.00 and a coefficient of determination of 32.5%. What this means is that although the in-class grades do help to determine what a student will make on the SOL, they are not the only factor. With a p-value of 0.00 we cannot reject our null hypothesis but our R^2=32.5%, this tells us that our in-class grades are a contributing factor. Given this, if a student made a B in math class then according to this equation the student would make a 523 on the SOL:

$$y = 392 + 43.7 * x$$

$$y = 392 + 43.7 * 3$$

$$y = 392 + 131.1$$

$$y = 523.1$$

A fitted line plot is displayed below in order to show our data. The confidence interval and prediction interval were displayed with a 95% confidence level to show the range of test scores that students could attain given a specific in-class grade.

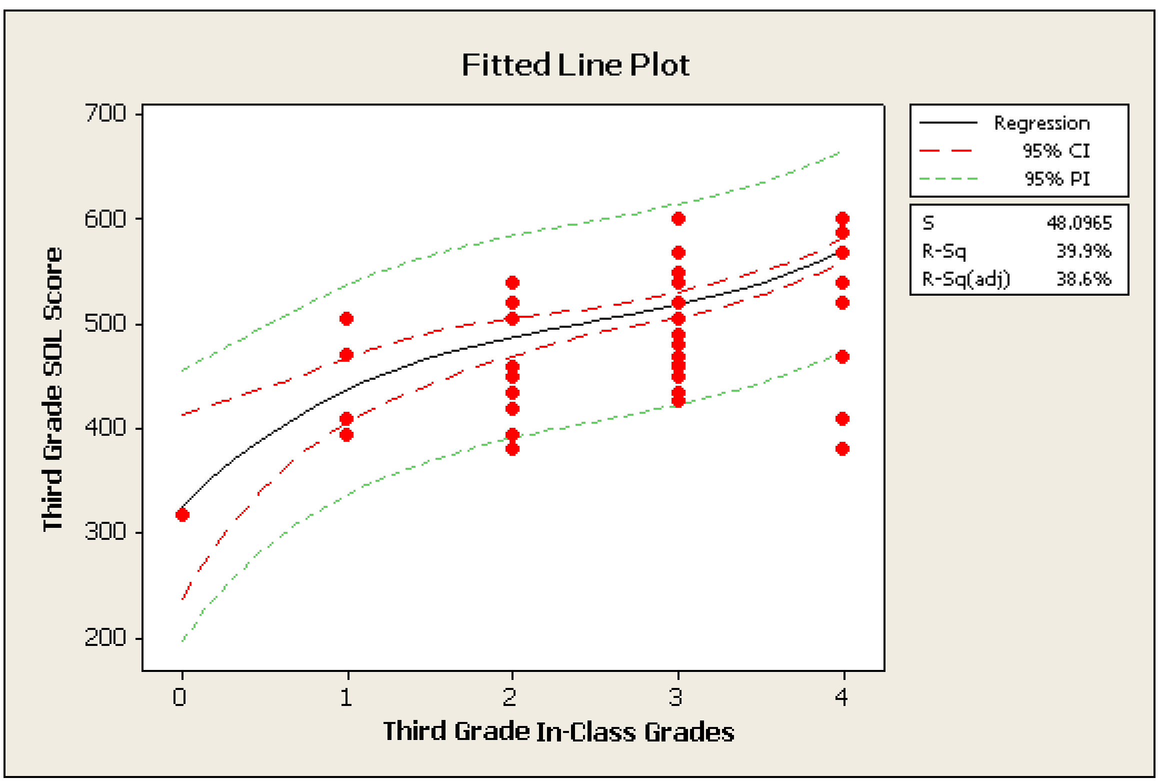


Figure 1: Fitted Plot for third grade in-class grades (x) to SOL scores (y)

With a normal plot of residuals, the points should generally form a straight line if the residuals are normally distributed. If they do not form a straight line, then the initial assumption may not be completely true. Our *Figure 2* shows the normal plot of residuals for the third grade group. As can be seen our data are not a perfectly straight line, but as previously mentioned this is due to there being factors that we have not considered.

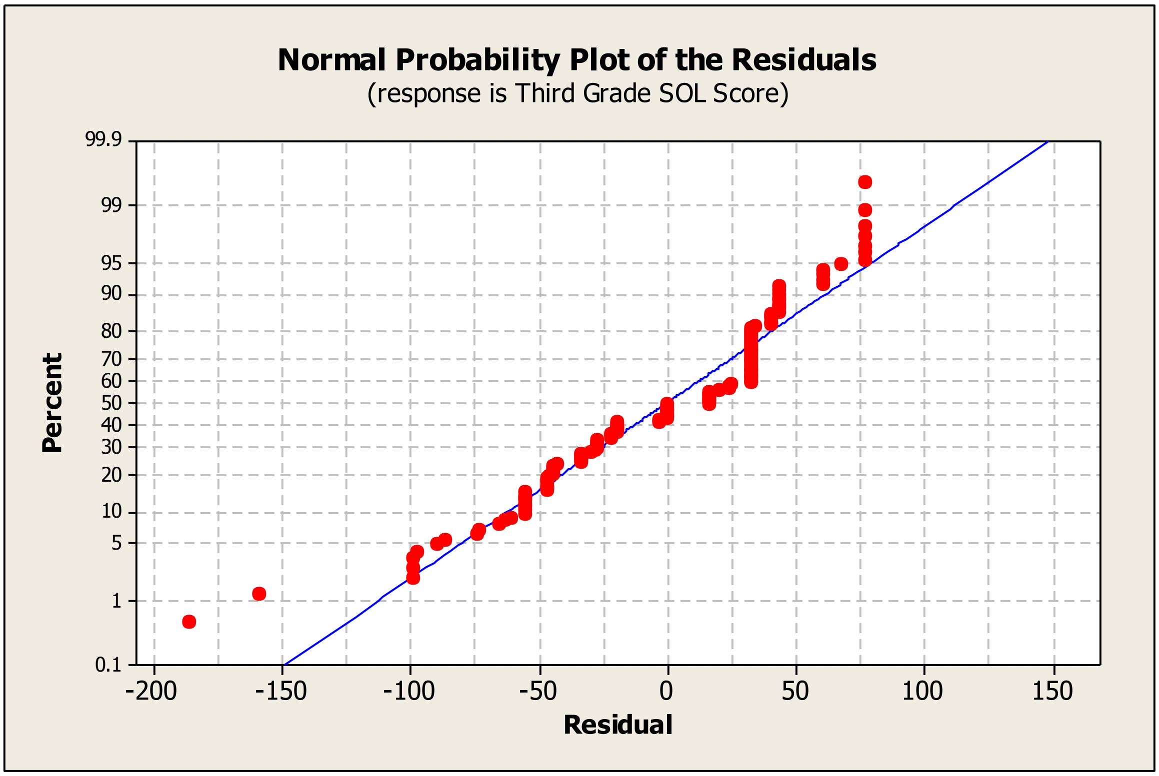


Figure 2: Normal Probability Plot of the Residuals for Third Grade SOL Score

Fourth Grade Data Analysis

The fourth grade had 100 participating students. *Figure 3* shows the plot of fourth grade in-class grades (x) to SOL scores (y). A polynomial regression analysis of the fourth grade SOL scores versus fourth grade in-class grades with our $1/S_4^2$ weight being used, determined the regression equation to be y = 317 + 54.3 * x, where y is the predicted SOL score and x is the in-class grade, with a p-value of 0.00 and a coefficient of determination of 50.1%. Again we can infer that the in-class grades help to determine the SOL score, but that is not the only factor. If a student made a C in math class, according to this equation the student would make a 425 on the SOL:

$$y = 317 + 54.3 * x$$

$$y = 317 + 54.3 * 2$$

$$y = 317 + 108.6$$

$$y = 425.6$$

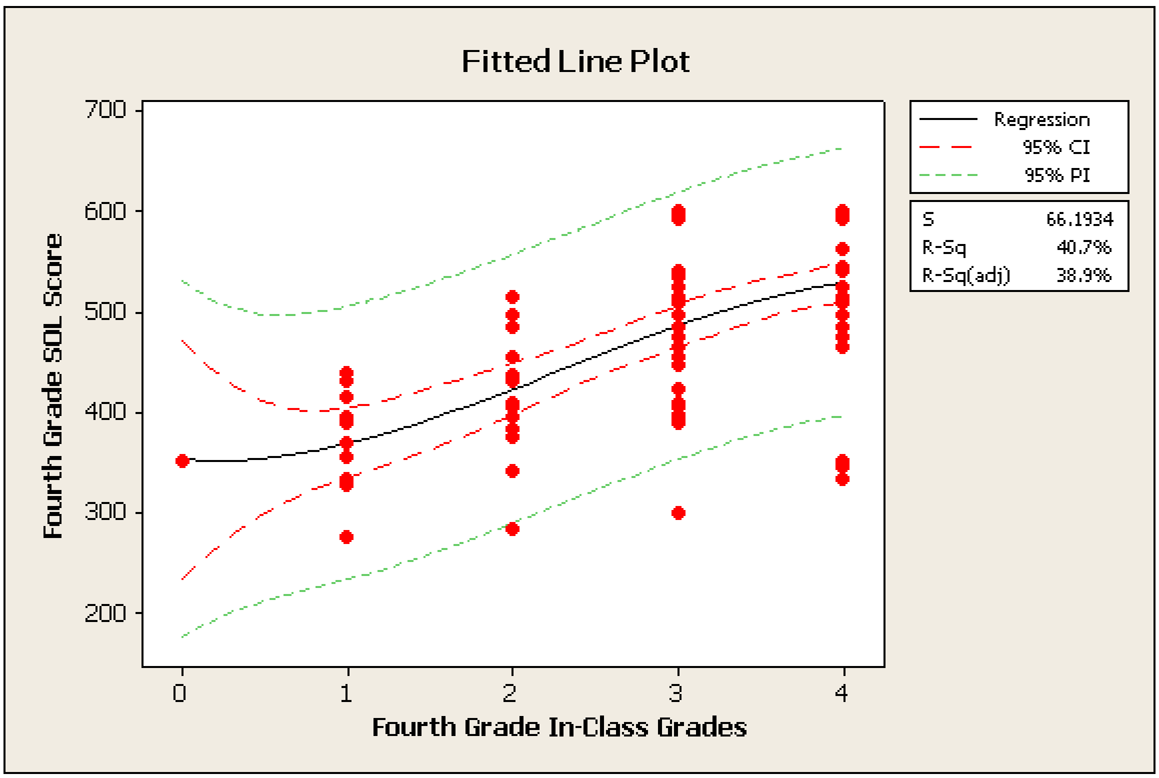


Figure 3: Fitted Line Plot for fourth grade in-class grades (x) to SOL scores (y)

With a residuals versus fits plot there should be a random pattern of residuals on both sides of 0. Our *Figure 4* shows the residual versus fits plot for the fourth grade group. Because we have a few points that lie far from the majority of points, the graph lets us know that we may have outliers. Because there isn't any recognizable pattern in the residual plot, we can assume that the data are random. This graph helps us visualize that our data are behaving the way that we expect them to; we can look at the original data and know that we have outliers because the data were supplied by Virginia guidance counselors. The other residual versus fits plots are not discussed, but they are included in the Appendix because they have similar attributes, so we can assume that all of our data have outliers and are random. Our *Figure 5* shows the normal plot of residual for the fourth grade group. As can be seen our data are again not a perfectly straight line.

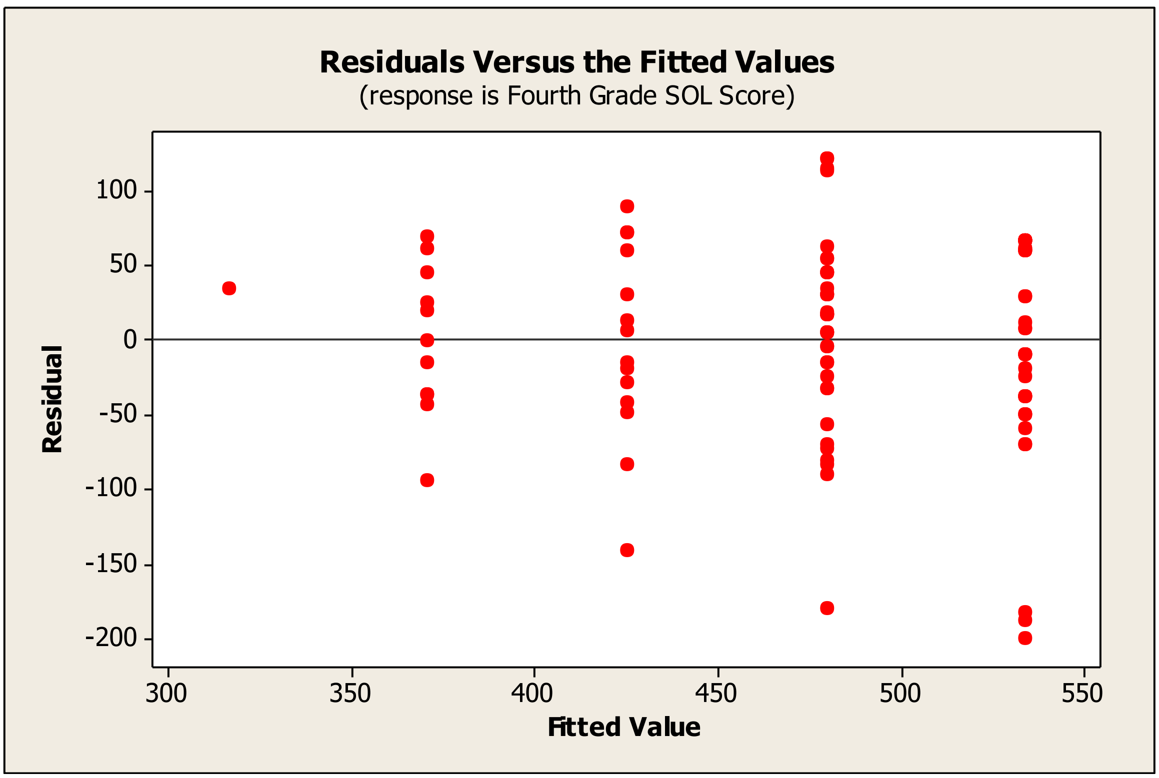


Figure 4: Residuals versus the Fitted Values for fourth grade SOL score

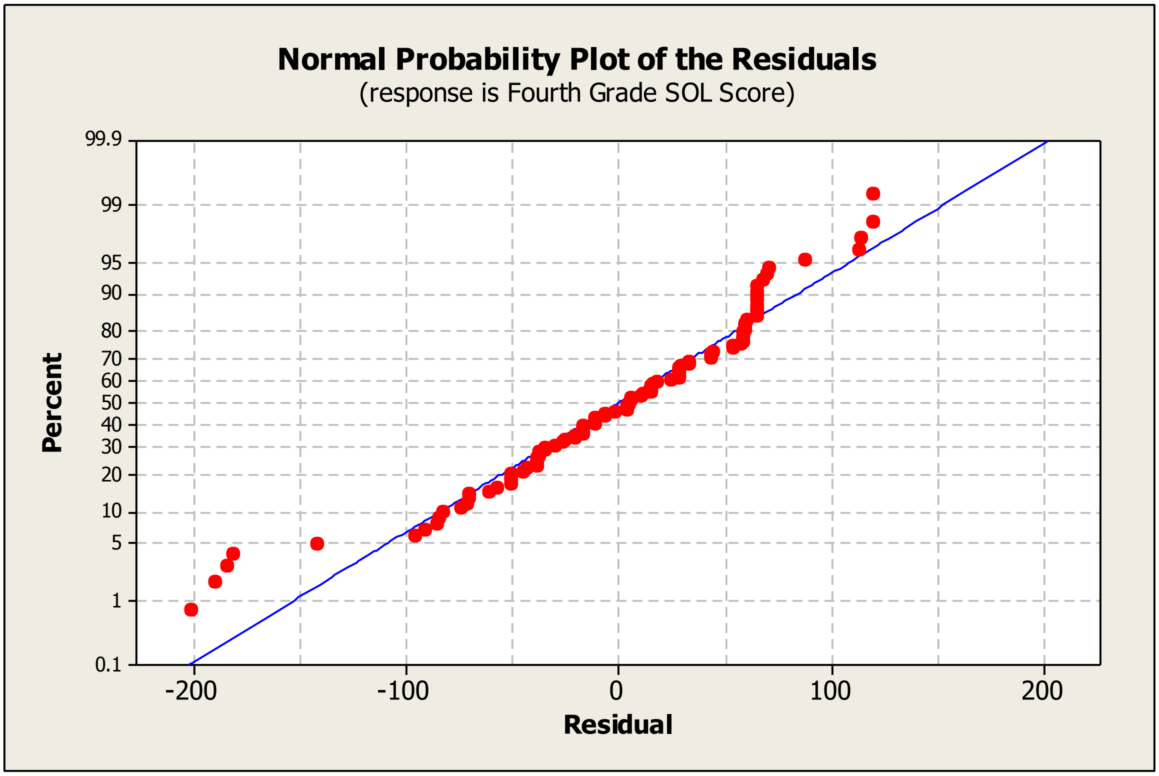


Figure 5: Normal Probability Plot of the Residuals for Fourth Grade SOL Score

Fifth Grade Data Analysis

The fifth grade had 113 participating students and a polynomial regression analysis of the fifth grade SOL scores versus fifth grade in-class grades with our $1/S_5^2$ weight being used, determined the regression equation to be y = 350 + 52.6 * x, with a p-value of 0.00 and a coefficient of determination of 50.4%. This lets us know that in the case of the fifth graders their in-class grades play a larger role in their SOL scores than in the other students we have looked at thus far. If a student made an A in math class then according to this equation the student would make a 560 on the SOL. The following graph, *Figure 6*, shows a fitted line plot of fifth grade in-class grades (x) to SOL scores (y) with a 95% confidence interval and prediction interval, again these are merely displayed in order to show our data.

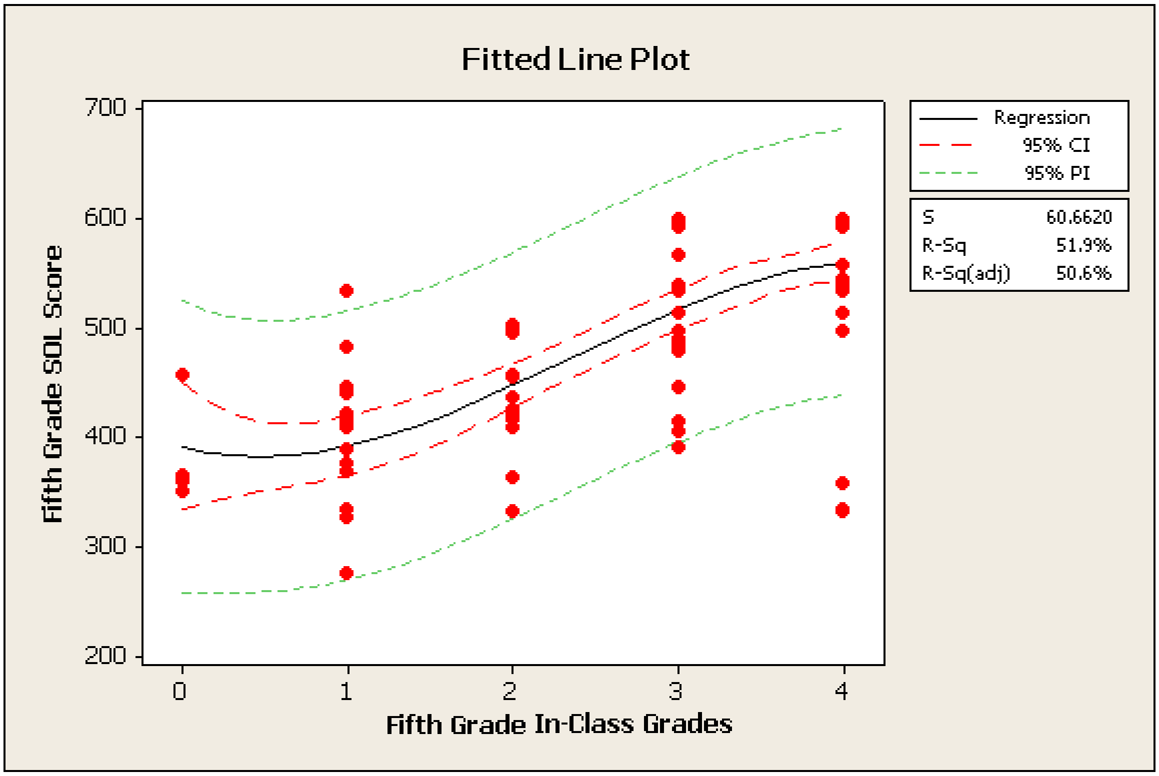


Figure 6: Fitted Line Plot for Fifth Grade SOL Score versus Fifth Grade In-Class

As mentioned before, with a normal plot of residual the points should generally form a straight line if the residuals are normally distributed. As our *Figure 7* shows, the normal plot of residual for the fifth grade group is not a straight line, but as previously mentioned this is likely because that there are other factors we have not considered.

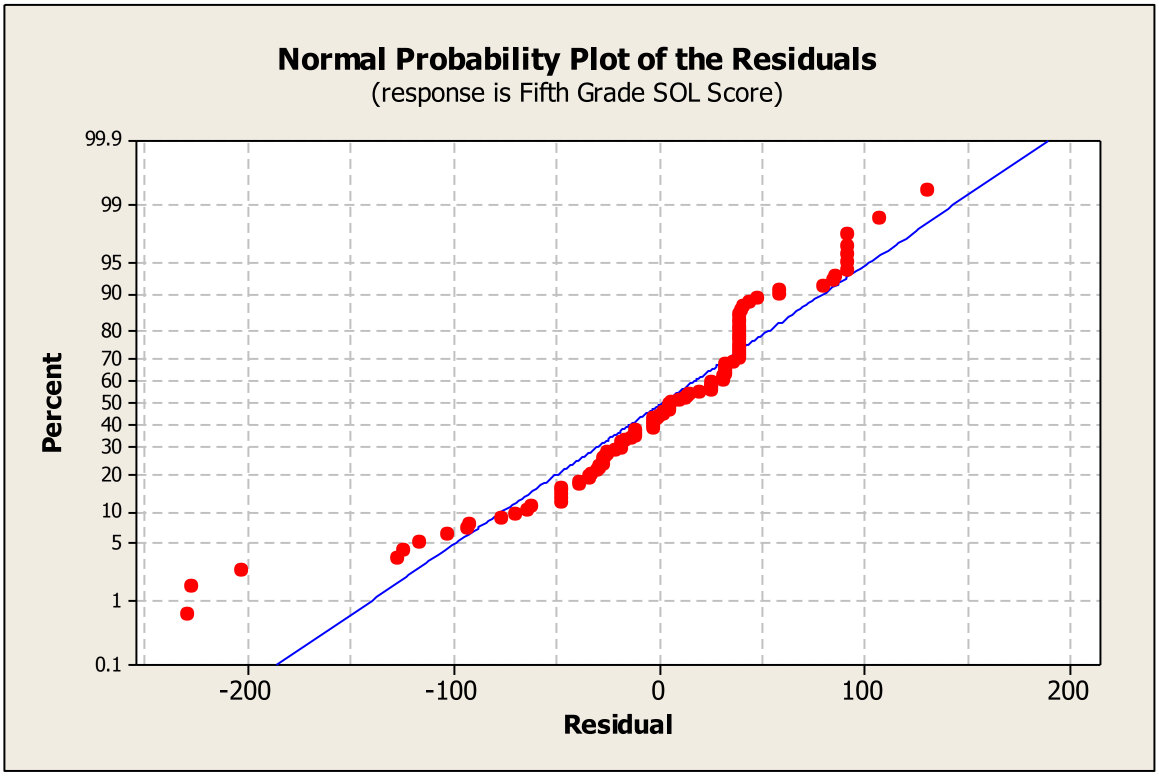


Figure 7: Normal Probability Plot of the Residuals for Fifth Grade SOL Score

Sixth Grade Data Analysis

The sixth grade had 110 participating students and a weighted polynomial regression analysis found the regression equation to be y = 279 + 63.7 * x, with a p-value of 0.00 and a coefficient of determination of 73.3%. This lets us know that in the case of the sixth graders their in-class grades play a role in their SOL scores, but again they are not the only factor. If a student made an A then according to this equation the student would make a 533 on the SOL. The following graph, *Figure 8*, shows the fitted line plot of sixth grade in-class grades (x) to SOL scores (y) with again a 95% confidence interval and prediction interval.

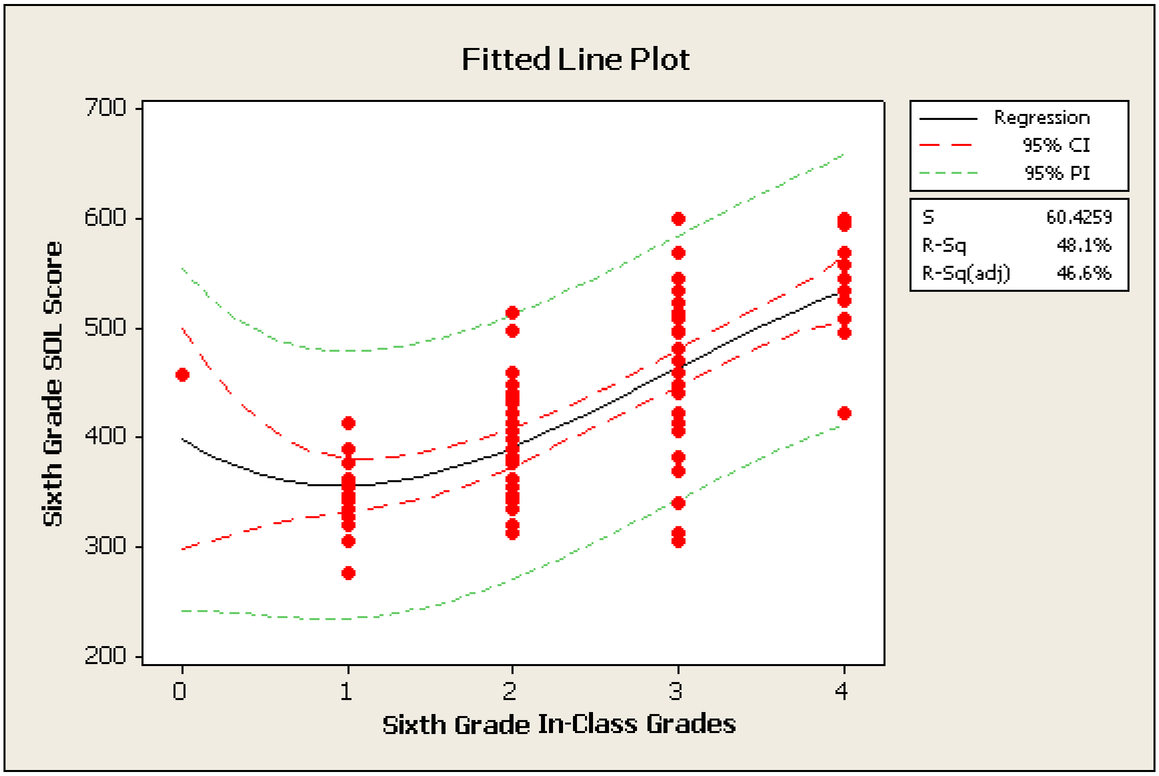


Figure 8: Fitted Line Plot for sixth grade in-class grades (x) to SOL scores (y)

As previously mentioned, with a normal plot of residual the points should generally form a straight line if the residuals are normally distributed. As our *Figure 9* shows, the normal plot of residual for the sixth grade group is almost a straight line, but not quite and as formerly mentioned this is likely because that there are other factors we have not considered.

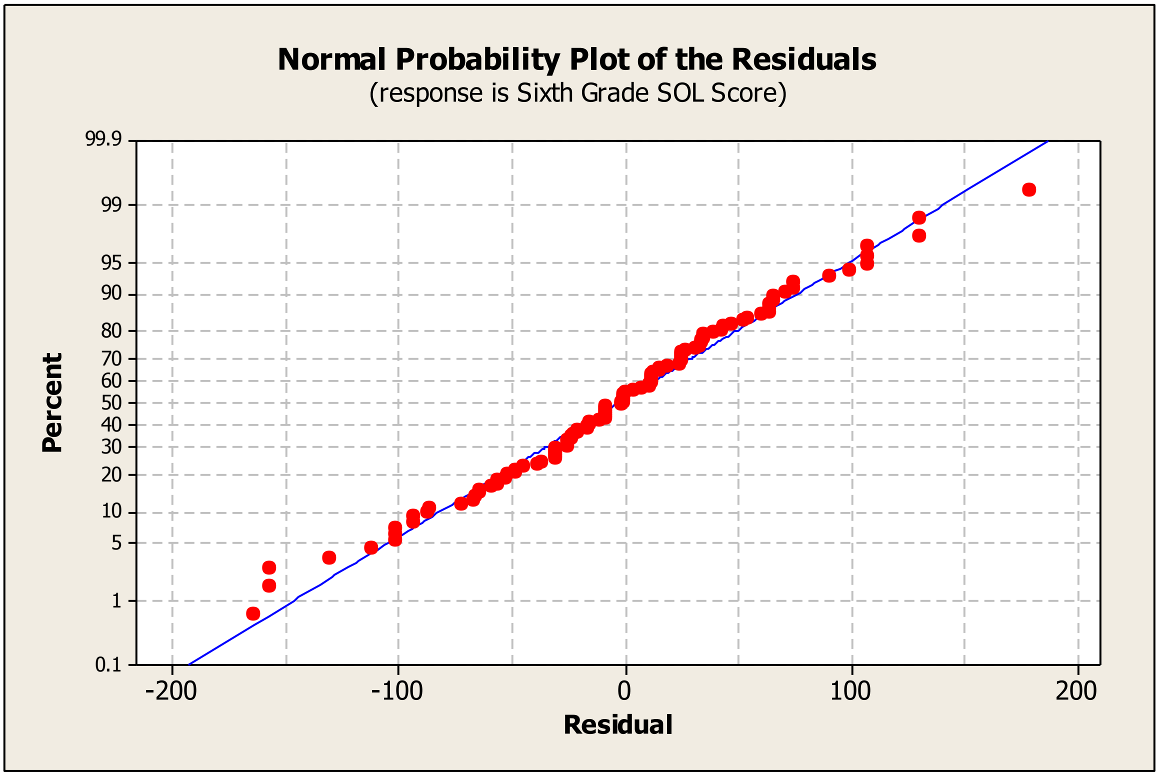


Figure 9: Normal Probability Plot of the Residuals for Sixth Grade SOL Score

Seventh Grade Data Analysis

The seventh grade had 112 participating students and a weighted polynomial regression analysis found the regression equation to be y = 371 + 35.7 * x, with a p-value of 0.00 and a coefficient of determination of 67.1%. If a student made a C then according to this equation the student would make a 442 on the SOL. As can be seen in the following graph, *Figure 10*, which again shows the fitted line plot of seventh grade in-class grades (x) to SOL scores (y), a respectable number of seventh graders with a C in their class fail the SOL.

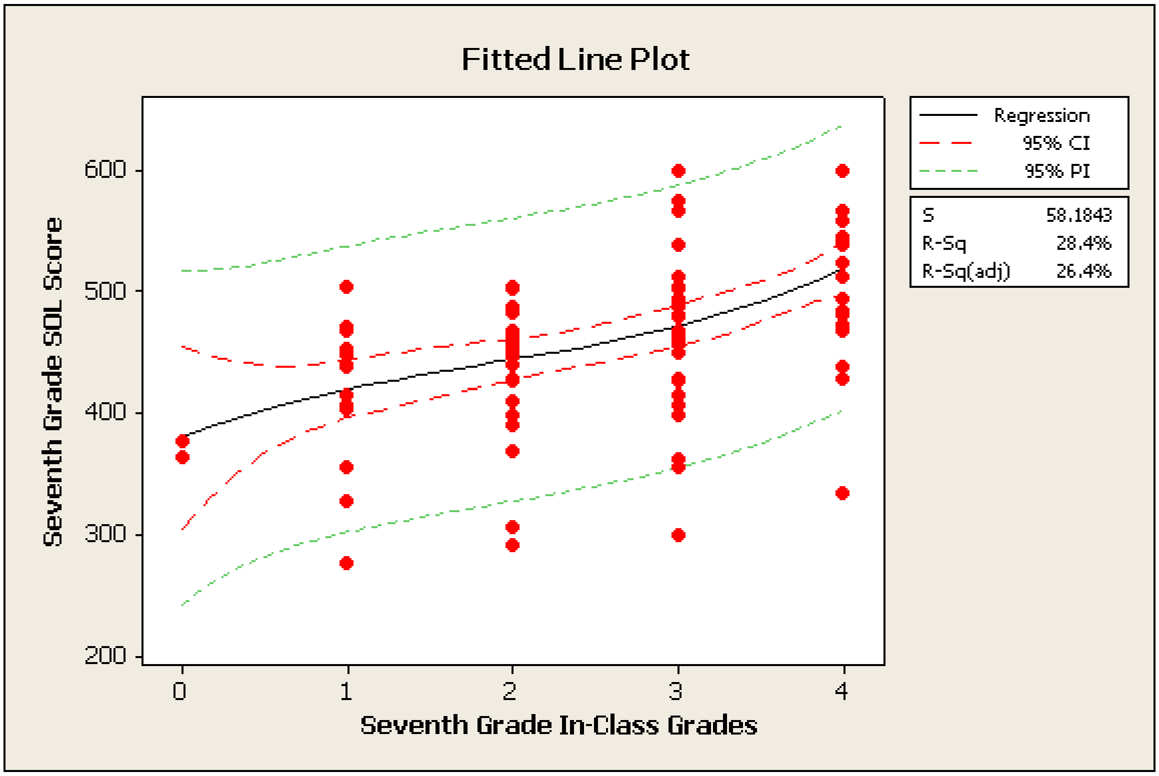


Figure 10: Fitted Line Plot for Seventh Grade SOL Score versus Seventh Grade In-Class

As our *Figure 11* shows, the normal plot of residual for the seventh grade group is not a straight line. As previously pointed out, this is because the seventh graders in-class grades do not play the only role in their SOL scores. Do not misinterpret this as proof that the in-class grades have no effect; there is an effect but other factors play a role.

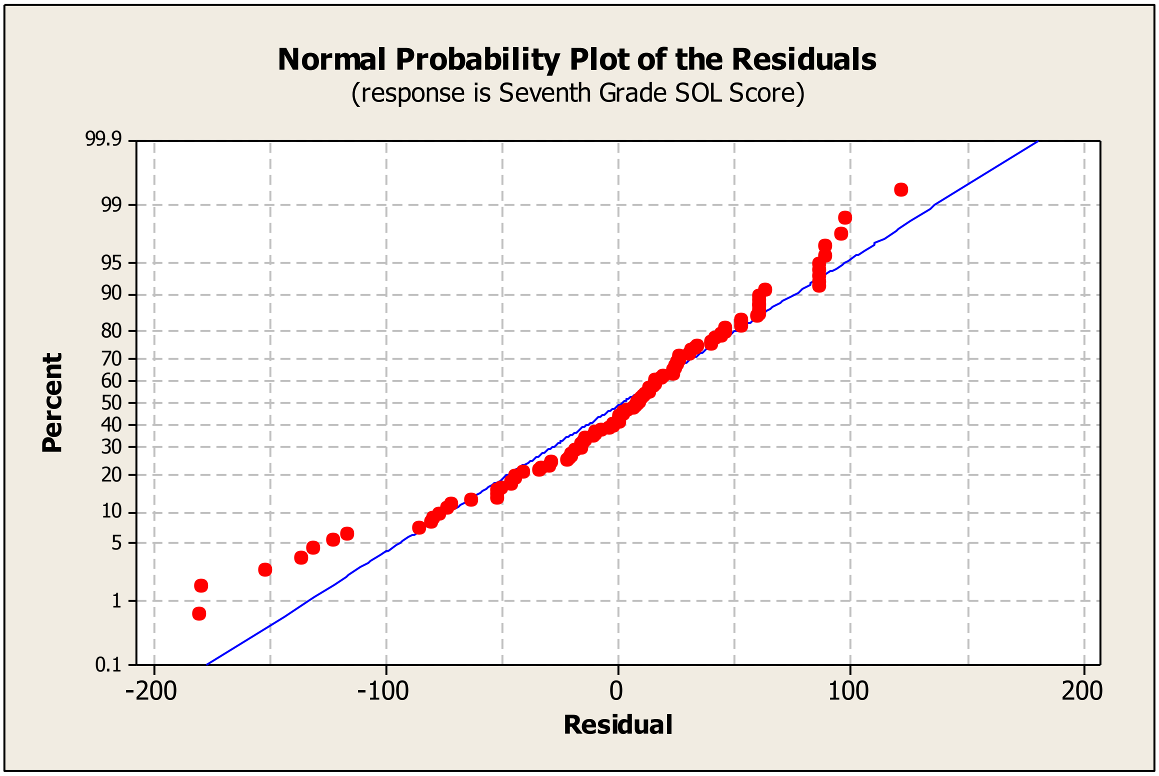


Figure 11: Normal Probability Plot of the Residuals for Seventh Grade SOL Score

Algebra I Data Analysis

As discussed, the Algebra I, Algebra II, and Geometry in-class grades were based on a 94-100=A, 86-93=B, 78-85=C, 70-77=D, and below 70=F. Both the numerical grade and the aforementioned converted scale (A=4, B=3, C=2, D=1, F=0) were used to determine whether or not this skewed the data for the elementary and middle school grades. We found that the data are skewed but not to the point that they are unusable, but we discuss this more in each section. The Algebra I class had 155 students enrolled in 2007-2008 school year. A weighted polynomial regression analysis for the numerical grade scale found the regression equation to be y = 395 + 0.765 * x, with a p-value of 0.00 and a coefficient of determination of 6.8%.

As a comparison using the same students, scores, and grades but changing the grades to our aforementioned scale the regression equation becomes y = 367 + 36.6 * x, with a p-value of

0.00 and a coefficient of determination of 84.1%. To better understand these equations, if a student made a C=82 then according to the “grade-equation” the student would make a 401 on the SOL and the same student would make a 440 on the “point-scale”.

This similarity can be seen in the follow graphs, *Figure 12* which shows the fitted line plot of Algebra I in-class grades (x) to SOL scores (y), and *Figure 13*, which shows the fitted line plot for the same students with the letter grades (x) to SOL scores (y). As can be seen, even though the data presentation looks different, there is a similar regression curve in each graph.

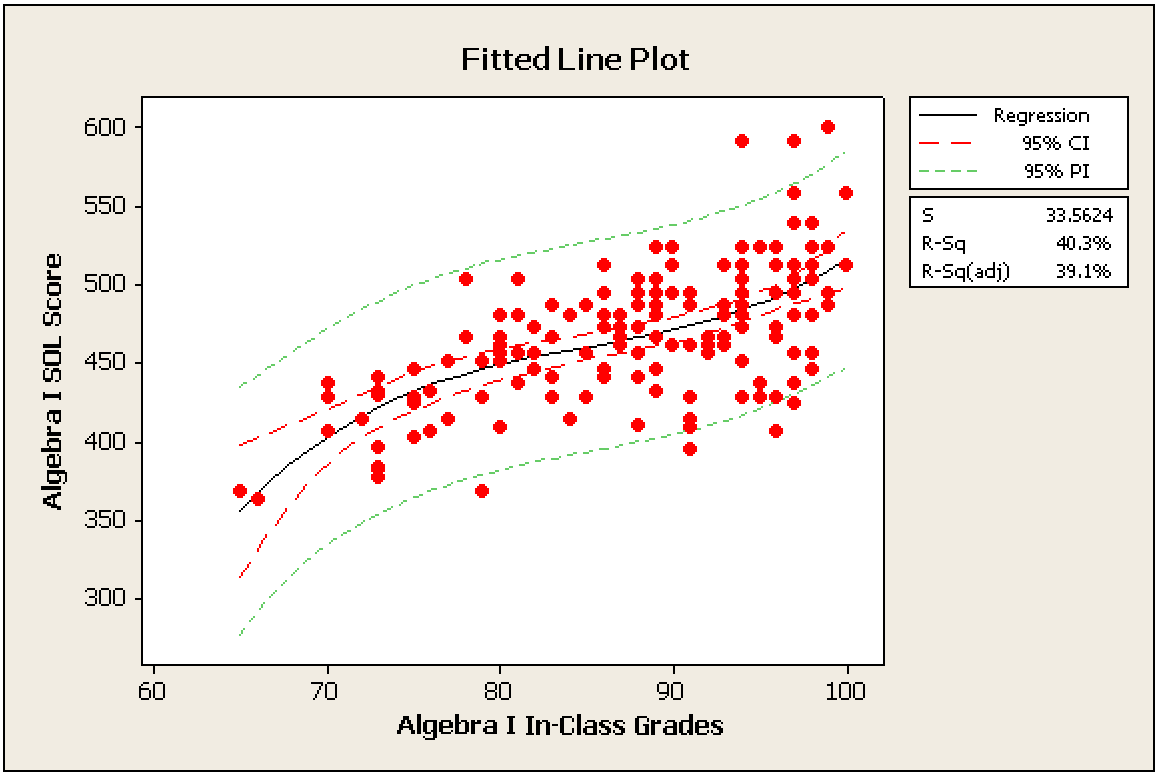


Figure 12: Fitted Line Plot for Algebra I SOL Score versus Algebra I Grade In-Class

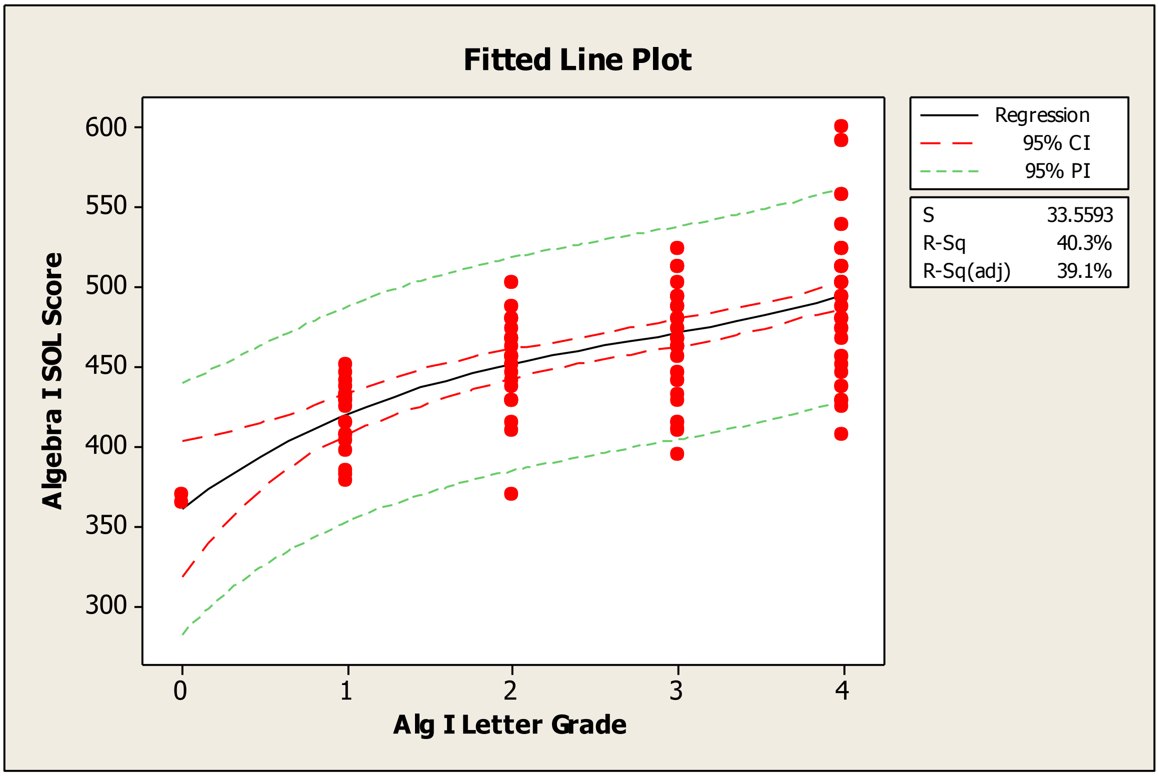


Figure 13: Fitted Line Plot for Algebra I SOL Score versus Algebra I Letter Grade

As our *Figure 14* shows, the normal plot of residuals for the Algebra I in-class grade group is not a straight line, neither is our *Figure 15* which is the normal plot of the residuals for the Algebra I letter grade group. Although the plots are similar, there is a slight difference. This helps us visualize how skewed our data are.

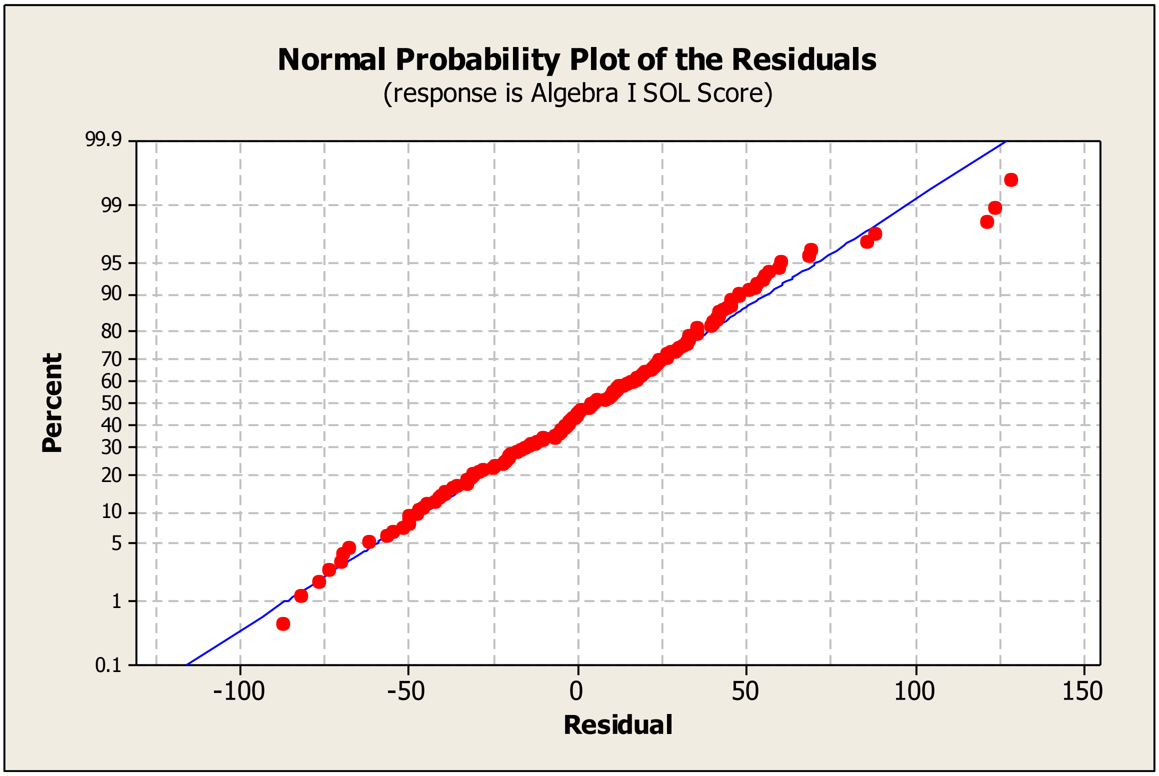


Figure 14: Normal Probability Plot of the Residuals for Algebra I In-Class Grade SOL Score

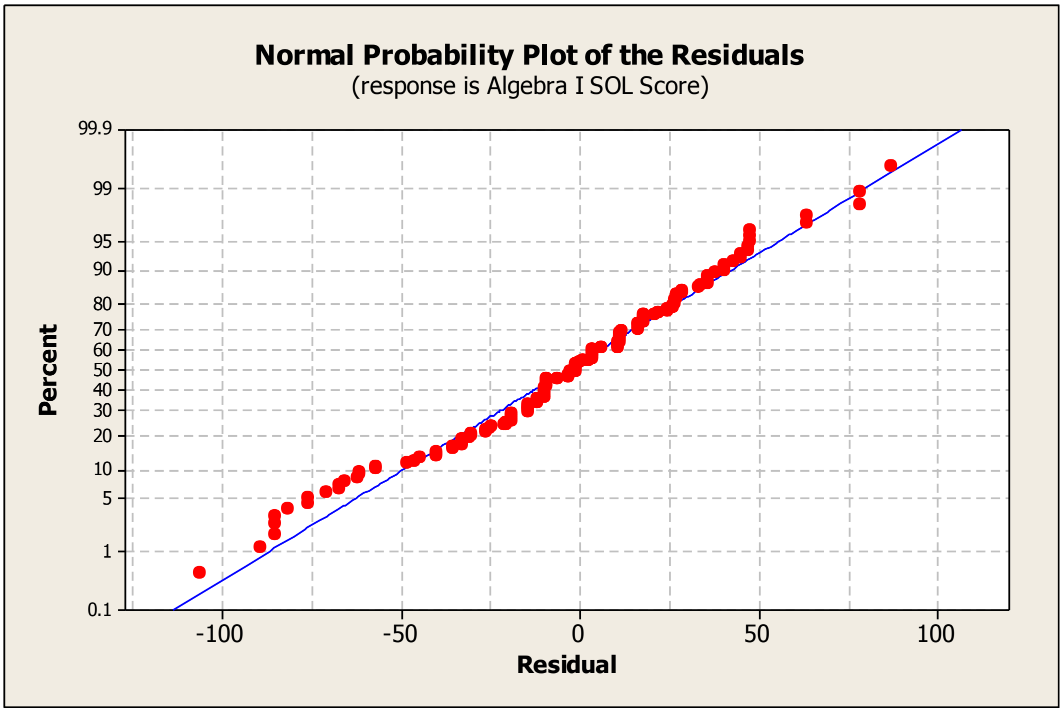


Figure 15: Normal Probability Plot of the Residuals for Algebra I Letter Grade SOL Score

Algebra II Data Analysis

The Algebra II class had 130 students enrolled in 2007-2008 school year. A weighted polynomial regression analysis for the numerical grade scale found the regression equation to be y = -140 + 8.13 * x, with a p-value of 0.00 and a coefficient of determination of 84.4%. As our previous results also indicate, we once again cannot discount the in-class grades as being a factor in determining the students SOL score, but they are still not the only factor.

To further our comparison we used the same data again, but changing the grades to our scale and the regression equation becomes y = 422 + 17.5 * x with a p-value of 0.00 and a coefficient of determination of 31.2%. If a student made a C=80, then according to the "grade-equation" the student would make a 510 on the SOL and the same student would make a 457 on the "point-scale". In this case the grade equation yields an advanced passing score, whereas the point-scale equation yields just a passing score.

Our *Figure 16* shows the fitted line plot of Algebra II in-class grades (x) to SOL scores (y), and *Figure 17* shows the fitted line plot for the same students with the letter grades (x) to SOL scores (y). Again there is a similar regression curve in each graph.

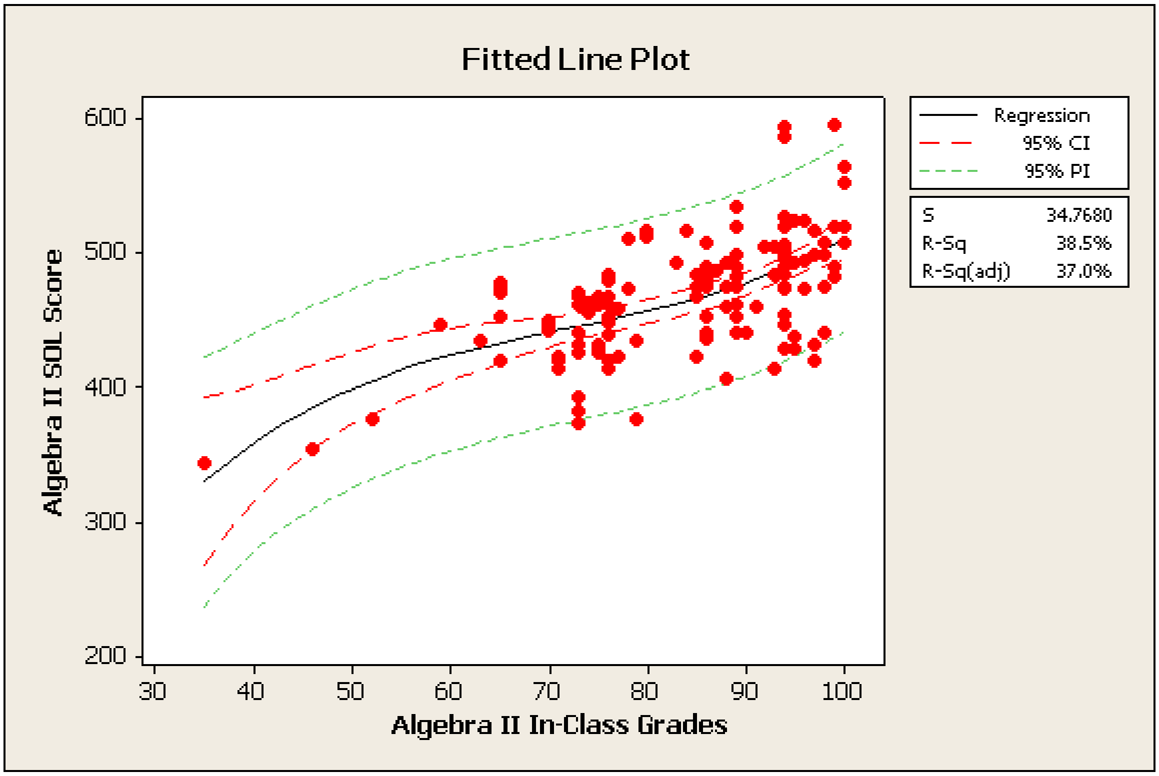


Figure 16: Fitted Line Plot for Algebra II in-class grades (x) to SOL scores (y)

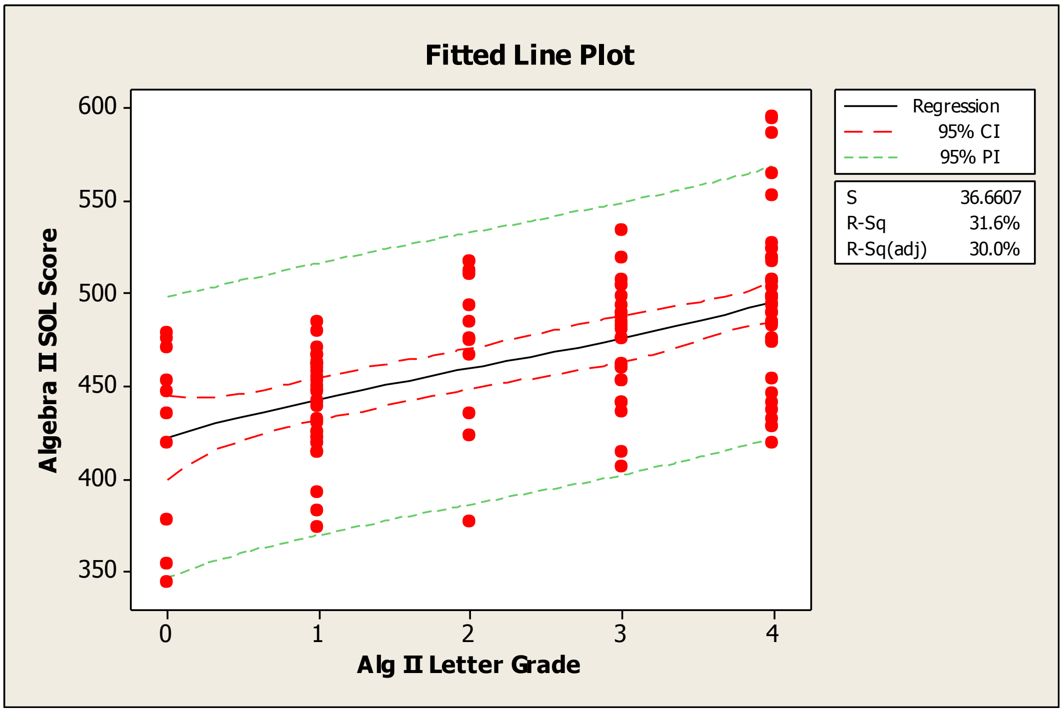


Figure 17: Fitted Line Plot for Algebra I letter grades (x) to SOL scores (y)

Our *Figure 18* shows the normal plot of residuals for the Algebra II in-class grade group and our *Figure 19* is the normal plot of the residual for the Algebra II letter grade group. Neither is a perfectly straight line. We again have similar plots with a slight difference.

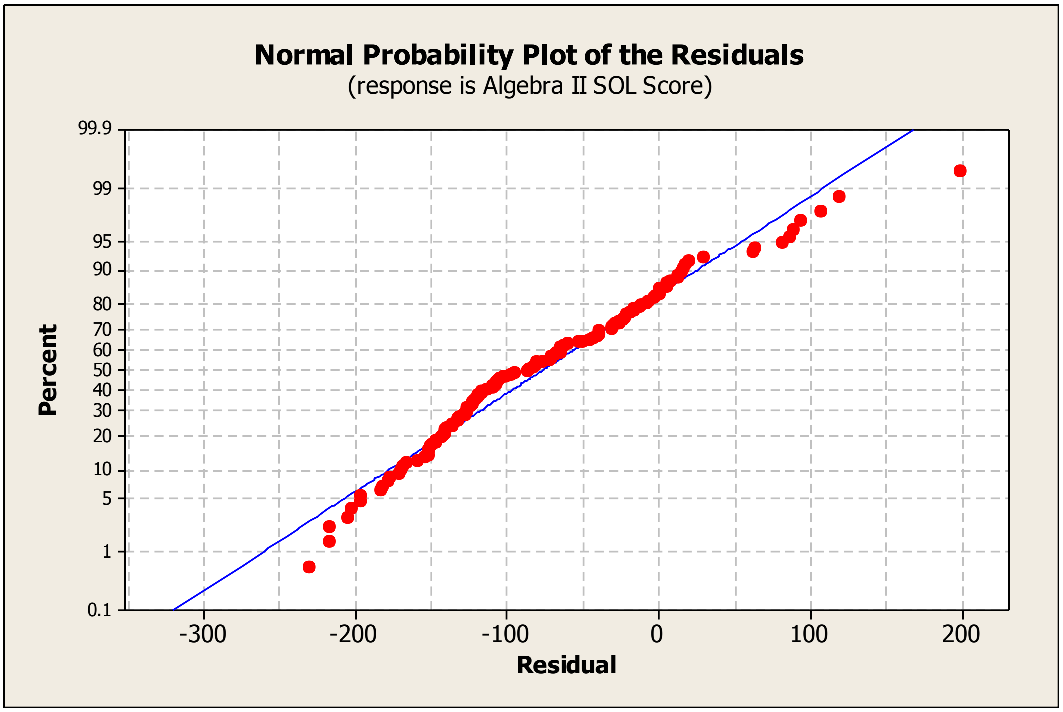


Figure 18: Normal Probability Plot of the Residuals for Algebra II In-Class Grade SOL Score

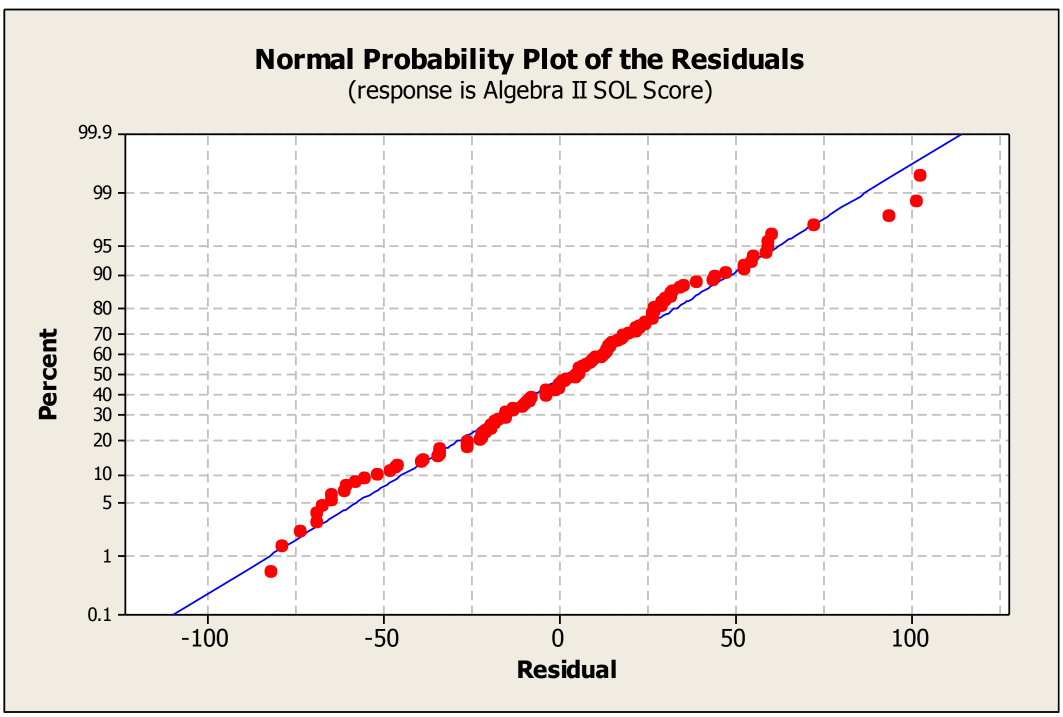


Figure 19: Normal Probability Plot of the Residuals for Algebra II Letter Grade SOL Score

Geometry Data Analysis

The Geometry class had 139 students enrolled. A weighted polynomial regression analysis for the numerical grade scale found the regression equation to be y = 1438 – 13.3 * x, with a p-value of 0.00 and a coefficient of determination of 66.0%. As all of our previous results have indicated, we cannot discount the in-class grades as being a factor in determining the students SOL score, but they are still not the only factor.

We used the same data again, but changing the grades to our scale the regression equation becomes y = 400 + 25.7 * x, with a p-value of 0.00 and a coefficient of determination of 20.9%. If a student made a C= 80 then our "grade-equation" has the student making a 374 on the SOL and the same student would make a 451on the "point-scale". In this case that is the difference between passing and failing.

Our, *Figure 20* shows the fitted line plot of Geometry in-class grades (x) to SOL scores (y), and *Figure 21* shows the fitted line plot for the same students with the letter grades (x) to SOL scores (y).

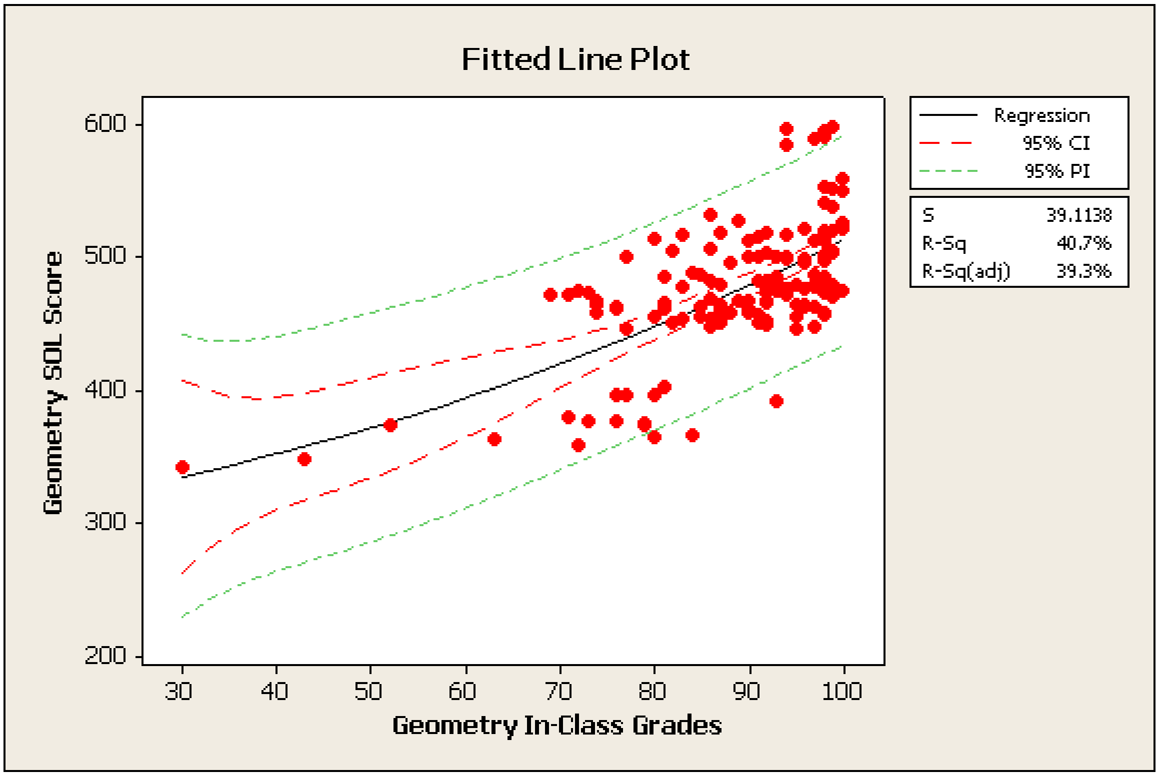


Figure 20: Fitted Line Plot for Geometry in-class grades (x) to SOL scores (y)

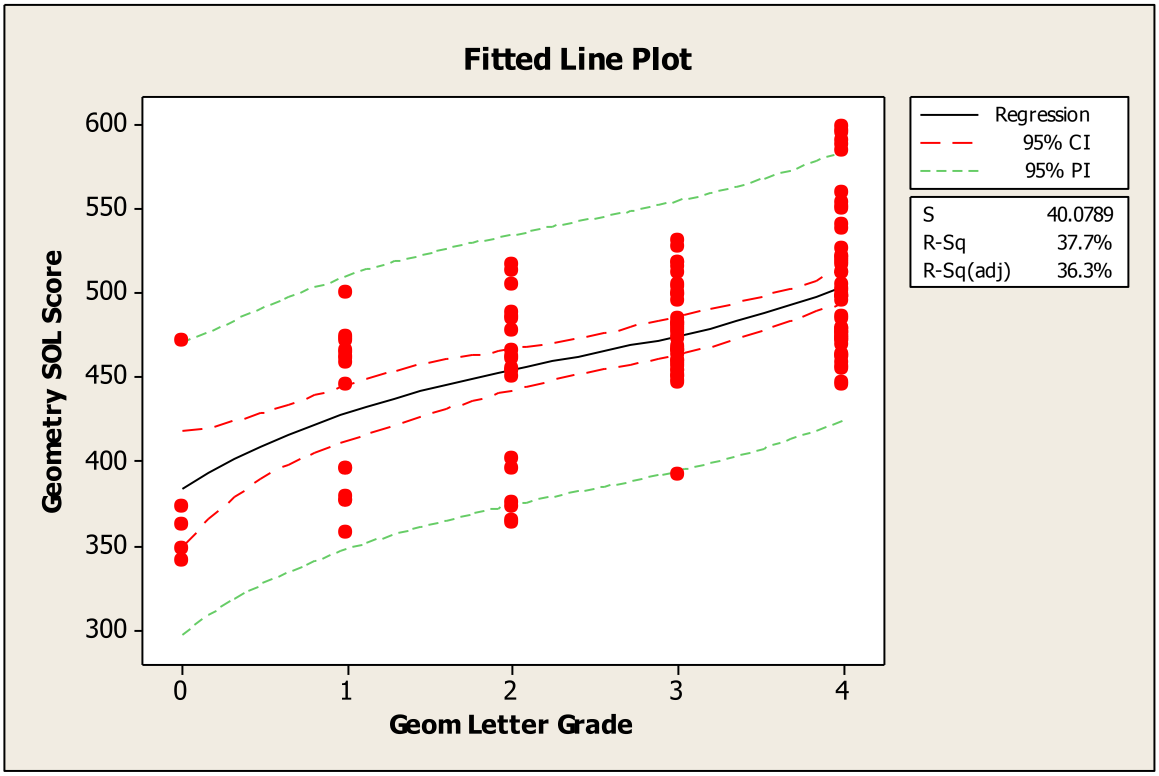


Figure 21: Fitted Line Plot for Geometry Letter grades (x) to SOL scores (y)

Our *Figure 22* shows the normal plot of residuals for the Geometry in-class grade group and our *Figure 23* is the normal plot of the residuals for the Geometry letter grade group, neither is a perfectly straight line. Our Geometry data are the most obviously skewed data that we have. The normal plot for the in-class grades has a distinctive curve that our letter grade data do not have.

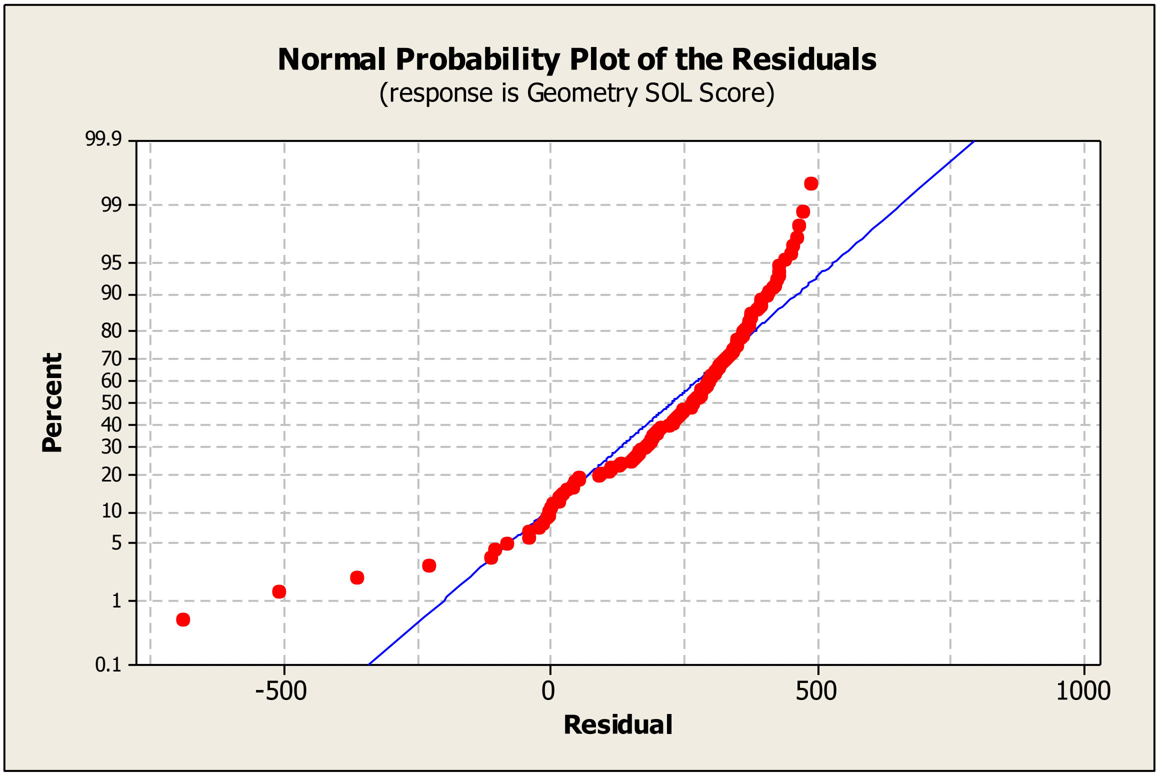


Figure 22: Normal Probability Plot of the Residuals for Geometry In-Class Grade SOL Score

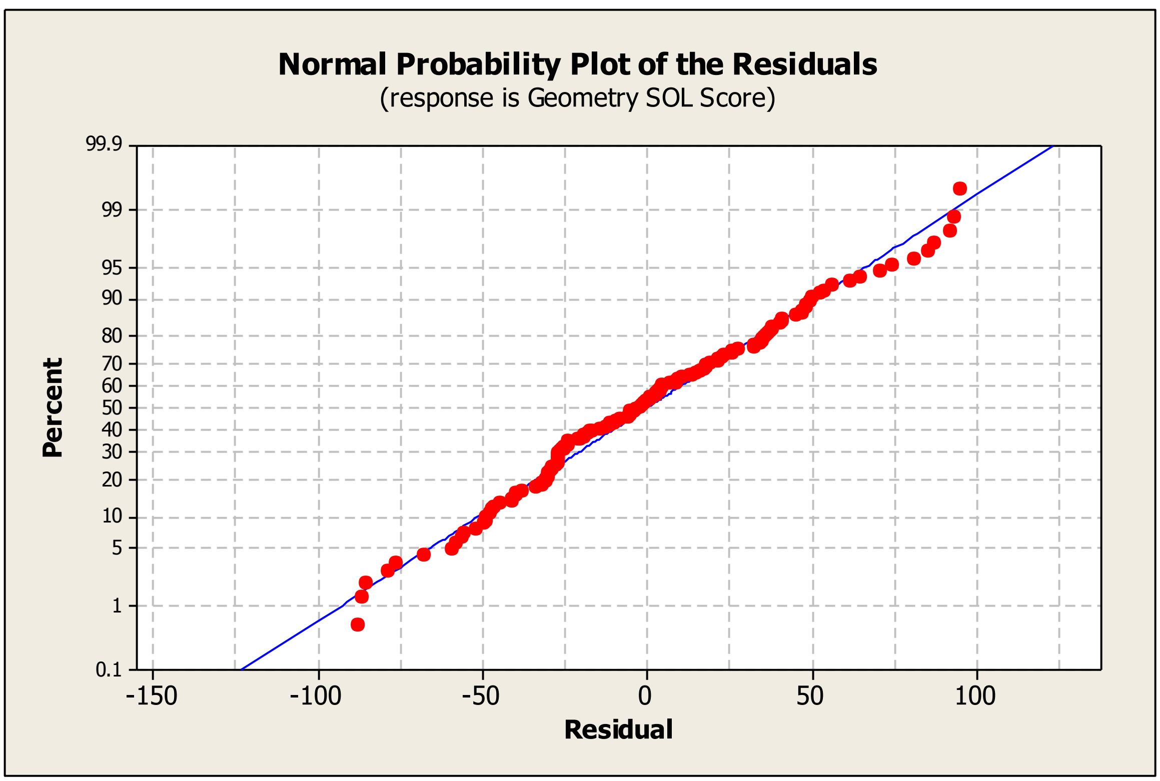


Figure 23: Normal Probability Plot of the Residuals for Geometry Letter Grade SOL Score

CHAPTER 5

CONCLUDING REMARKS

We examined the Standards of Learning mathematics scores and in-class grades for a rural Virginia county public school system, Russell County. The purpose of this was to determine whether or not there is a strong correlation between the Standards of Learning and the students' in-class grades. We looked at third, fourth, fifth, sixth, and seventh grades as well as Algebra I, Algebra II, and Geometry classes. Had a strong enough correlation between the Standards of Learning and in-class grades been found, we would have used only the in-class grades to predict the Standard of Learning test scores; however, we found that the students' in-class grades are not the only predictor of the Standards of Learning test scores. Unfortunately, there are several variables that factor into whether or not a child will do well on the Standards of Learning; we only examined how strongly the students' in-class grades influence the test scores. There are other factors that are not considered when determining the percentage of students that have to pass the Standards of Learning, such as background experience, economic background, home lives, natural ability, learning styles, attitudes, environment and socioeconomic characteristics. Because these factors are difficult to put in mathematical terms, we were unable to examine their actual influence on test scores.

With the coefficient of determination from 6.8% to 84.4%, this indicates that at best 84.4% of variation in the response is explained by the model for Algebra II and at worst only 6.8% for Algebra I. These results indicate that our remaining factors contribute significantly to the students' test results. As our data showed it is not unheard of for students who do well in a class to barely pass or even fail the Standards of Learning Test. There are also a few cases where the student is failing a class and passes the Standards of Learning. This may be because the students have difficulty with readability of the math portion of the test. The math portion of the test is set up so that students solve real-world questions instead of just computation, whereas most are accustomed to computations in the classroom.

WORKS CITED

Berube, C.T. "Are Standards Preventing Good Teaching?" *The Clearing House* 77.6 (2004): 264-7. Print.

Boaler, Jo. "When Learning No Longer Matters: Standardized Testing and the Creation of Inequality." *Phi Delta Kappan* 84.7 (2003): 502-6. Print.

Butler, Carolyn Kleiner "Success in the City [Norfolk Public School System Makes Huge Turnaround in Test Scores]." *U.S. News & World Report* 139.12 (2005): 54-6. Print.

Christie, Kathy. "Virginia's Excellent Adventure." *Phi Delta Kappan* 85.8 (2004): 565-7 Print.

Cole, Wendy. "Feeling Crushed by Tests at Age 11." *Time* 157.18 (2001): 61. Print.

Ding, Cody S., et. al. "Do Mathematical Gender Differences Continue? A Longitudinal Study of Gender Difference and Excellence in Mathematics Performance in the U.S. ." *Educational Studies (American Educational Studies Association)* 40.3 (2006): 279-95 Print.

Dorgan, Karen. "A Year in the Life of an Elementary School: One School's Experiences in Meeting New Mathematics Standards." *Teachers College Record* 106.6 (2004): 1203-28 Print.

Hill, Beverly. "Learning Styles and Standardized Test Scores: Is There a Connection?" *The Delta Kappa Gamma Bulletin* 71.3 (2005): 27-30. Print.

McDonald, Kathleen, et. al. "Using Web-Based Computer Games to Meet the Demands of Today's High-Stakes Testing: A Mixed Method Inquiry." *Journal of Research on Technology in Education* 35.4 (2003): 459-72 Print.

Morse, J. "Is That Your Final Answer? [Standardized Tests]." *Time* 155.25 (2000): 34-38. Print.

Olszewski-Kubilius, Paula, et. al. "Gender Differences among Elementary School-Aged Gifted Students in Achievement, Perceptions of Ability, and Subject Preference." *Journal for the Education of the Gifted* 25.3 (2002): 233-68. Print.

Pasi, Raymond. "The Sol: No Easy Answers." *Educational Leadership* 57.5 (2000): 75-6. Print.

Winkler, Amber. "Division in the Ranks: Standardized Testing Draws Lines between New and Veteran Teachers." *Phi Delta Kappan* 84.3 (2002): 219-25. Print.

Young, Stuart G. “Statistical Education Through Problem Solving.” United Kingdom, 1997. Statistics Glossary. Ed. Young, Stuart G. (2004): STEPS TLTP consortium. August 9, 2010. http://www.stats.gla.as.uk/steps/glossary/index.html.

APPENDIX: TEST RESULTS

```
MTB > Describe 'Third Grade SOL Score';
SUBC>   By 'Third Grade In Class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Third Grade SOL Score

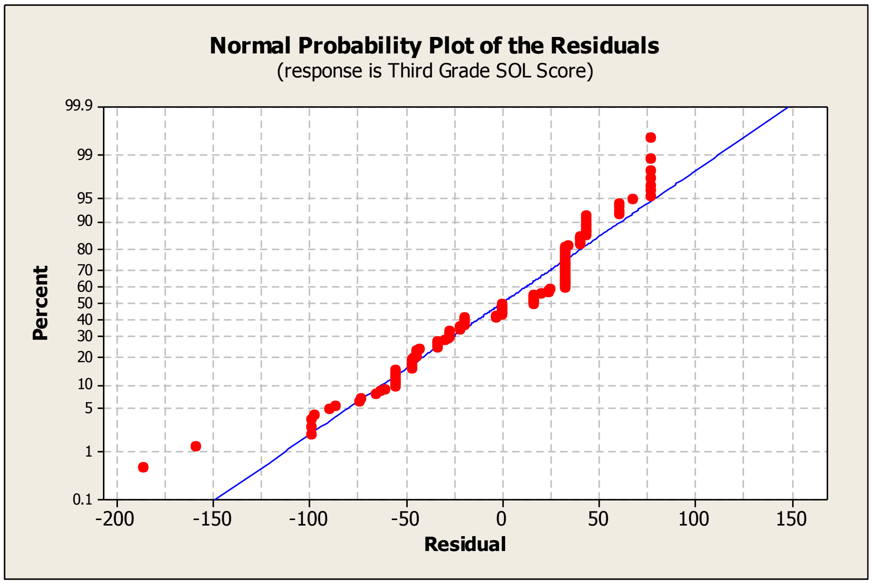
```
                  Third
                  Grade
                  In
Variable          Class   N  N*    Mean  SE Mean  StDev  Variance  CoefVar
Third Grade SOL   0       1   0  318.00        *      *         *        *
                  1       4   0   443.8     26.1   52.2    2724.3    11.76
                  2      21   0   484.8     10.9   49.8    2484.3    10.28
                  3      59   0  518.41     6.27  48.20   2322.76     9.30
                  4      60   0  569.03     6.13  47.51   2257.56     8.35

                  Third
                  Grade
                  In
Variable          Class  Minimum      Q1  Median      Q3  Maximum
Third Grade SOL   0       318.00       *  318.00       *   318.00
                  1        393.0   396.8   439.0   495.5    504.0
                  2        381.0   454.0   504.0   520.0    540.0
                  3       426.00  479.00  504.00  567.00   600.00
                  4       381.00  540.00  600.00  600.00   600.00

MTB > Let '1/S_3^2' = 1/(VARS3*VARS3)
Let '1/S_3^2' = 1/(VARS3*VARS3)
              J
* WARNING * Values out of bounds during operation at J
* WARNING * Missing returned 1 times

MTB > Regress 'Third Grade SOL Score' 1 'Third Grade In Class';
SUBC>   Weights '1/S^2';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

Regression Analysis: Third Grade SOL Score versus Third Grade In Class

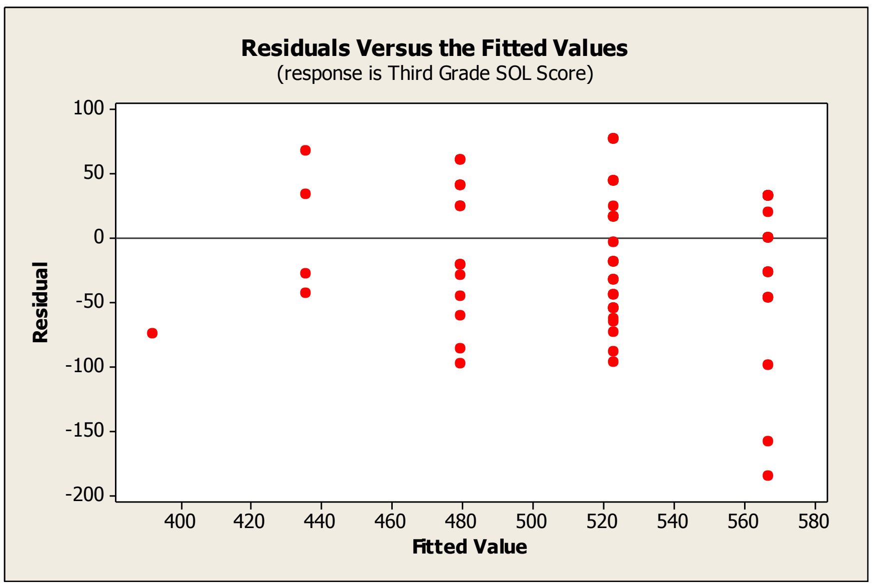
```
Weighted analysis using weights in 1/S_3^2
```

```
The regression equation is
Third Grade SOL Score = 392 + 43.7 Third Grade In Class


144 cases used, 1 cases contain missing values
                          or had zero weight


Predictor               Coef  SE Coef      T      P
Constant              391.95    17.74  22.10  0.000
Third Grade In Class  43.688    5.278   8.28  0.000


S = 0.0206740   R-Sq = 32.5%   R-Sq(adj) = 32.1%


Analysis of Variance

Source           DF        SS        MS      F      P
Regression        1  0.029282  0.029282  68.51  0.000
Residual Error  142  0.060693  0.000427
  Lack of Fit     2  0.000434  0.000217   0.50  0.605
  Pure Error    140  0.060259  0.000430
Total           143  0.089974


Unusual Observations

     Third    Third
     Grade    Grade
        In      SOL
Obs  Class    Score      Fit  SE Fit  Residual  St Resid
  2   1.00  504.000  435.642  12.651    68.358      1.25 X
  3   1.00  408.000  435.642  12.651   -27.642     -0.50 X
  4   1.00  470.000  435.642  12.651    34.358      0.63 X
  5   1.00  393.000  435.642  12.651   -42.642     -0.78 X
 37   3.00  426.000  523.018   4.257   -97.018     -2.03R
 90   4.00  468.000  566.706   5.544   -98.706     -2.13R
 96   4.00  468.000  566.706   5.544   -98.706     -2.13R
130   4.00  408.000  566.706   5.544  -158.706     -3.42R
136   4.00  381.000  566.706   5.544  -185.706     -4.01R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.

No evidence of lack of fit (P >= 0.1).
```

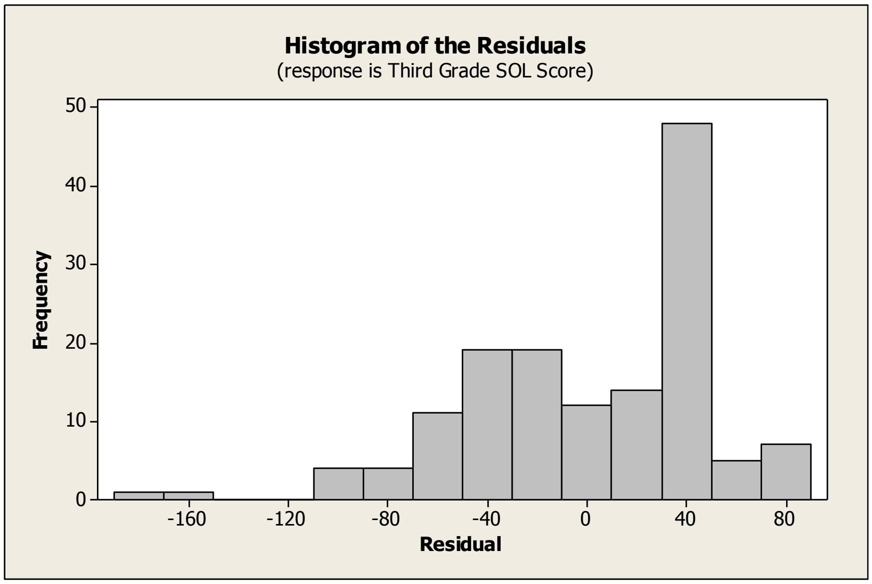
Normplot of Residuals for Third Grade SOL Score



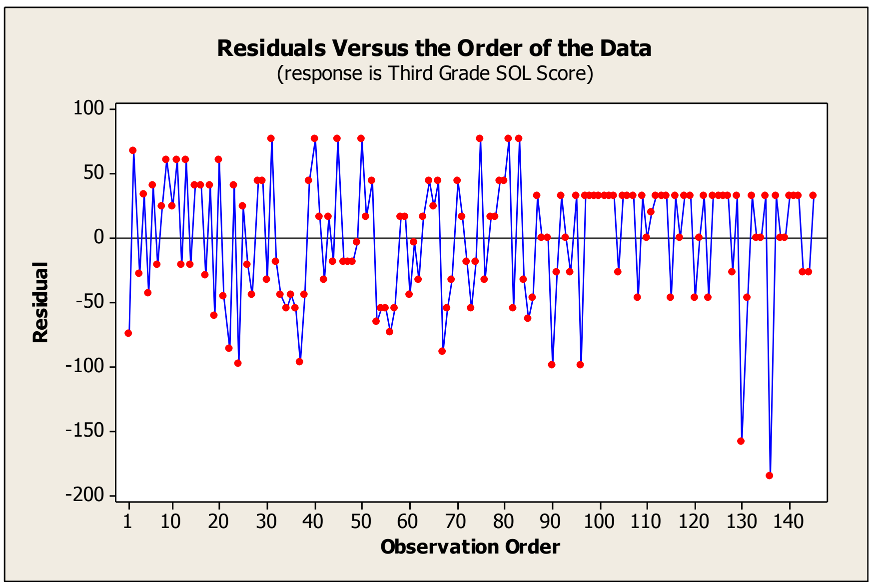
Residuals vs Fits for Third Grade SOL Score



Residual Histogram for Third Grade SOL Score



Residuals vs Order for Third Grade SOL Score



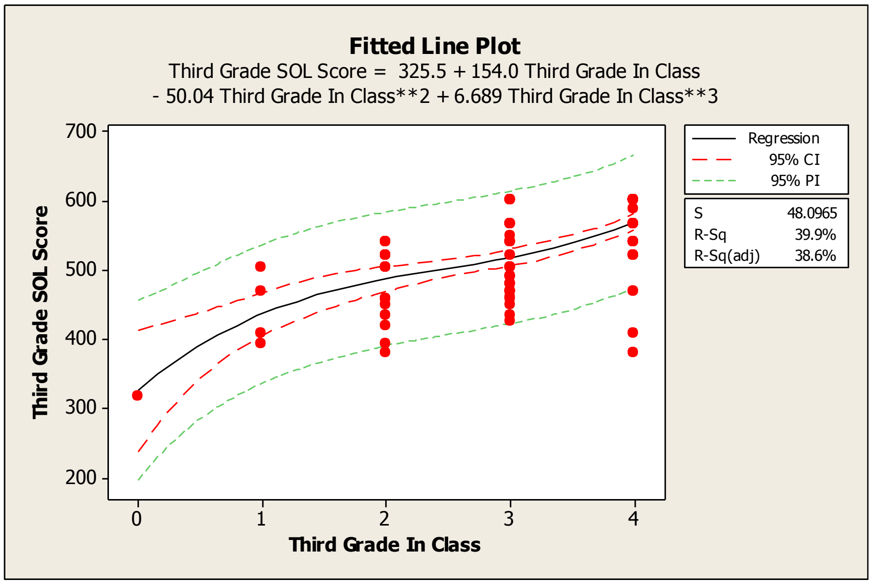

```
MTB > Fitline 'Third Grade SOL Score' 'Third Grade In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Third Grade SOL versus Third Grade In C

```
The regression equation is
Third Grade SOL Score = 325.5 + 154.0 Third Grade In Class
                        - 50.04 Third Grade In Class**2
                        + 6.689 Third Grade In Class**3


S = 48.0965   R-Sq = 39.9%   R-Sq(adj) = 38.6%


Analysis of Variance
```

```
Source        DF      SS       MS      F      P
Regression     3  216375  72125.1  31.18  0.000
Error        141  326171   2313.3
Total        144  542547


Sequential Analysis of Variance

Source      DF      SS      F      P
Linear       1  209224  89.76  0.000
Quadratic    1     195   0.08  0.774
Cubic        1    6956   3.01  0.085
```

Fitted Line: Third Grade SOL Score versus Third Grade In Class




```
MTB > Describe  'Fourth Grade SOL Score';
SUBC>   By  'Fourth Grade In Class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Fourth Grade SOL Score

Variable	Fourth Grade In Class	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Fourth Grade SOL	0	1	0	351.00	*	*	*	*
	1	11	0	369.9	15.2	50.3	2531.5	13.60
	2	14	0	422.1	17.4	65.1	4244.4	15.43

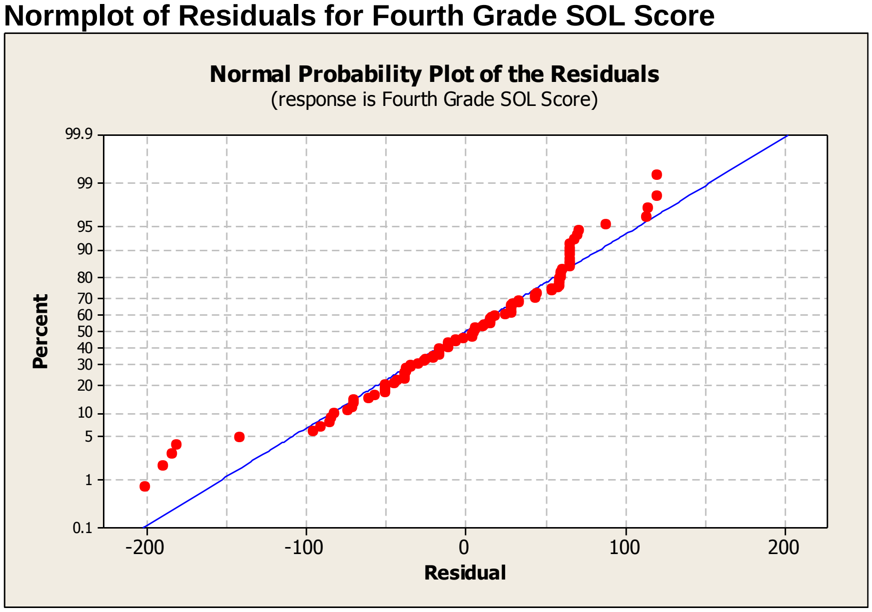
```
                  3       36   0   485.7     10.8   64.6    4168.8    13.29
                  4       38   0   528.9     11.8   72.5    5249.0    13.70

                  Fourth
                  Grade
                  In
Variable          Class   Minimum     Q1  Median     Q3  Maximum
Fourth Grade SOL  0        351.00      *  351.00      *   351.00
                  1         276.0  334.0   370.0  416.0    440.0
                  2         284.0  381.3   420.0  487.0    514.0
                  3         299.0  448.3   496.0  524.0    600.0
                  4         334.0  493.0   532.5  594.0    600.0

MTB > Let '1/S_4^2' = 1/(VARS4*VARS4)
Let '1/S_4^2' = 1/(VARS4*VARS4)
                 J
* WARNING * Values out of bounds during operation at J
* WARNING * Missing returned 1 times

MTB > Regress 'Fourth Grade SOL Score' 1  'Fourth Grade In Class';
SUBC>   Weights '1/S_4^2';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

Regression Analysis: Fourth Grade SOL Score versus Fourth Grade In Class

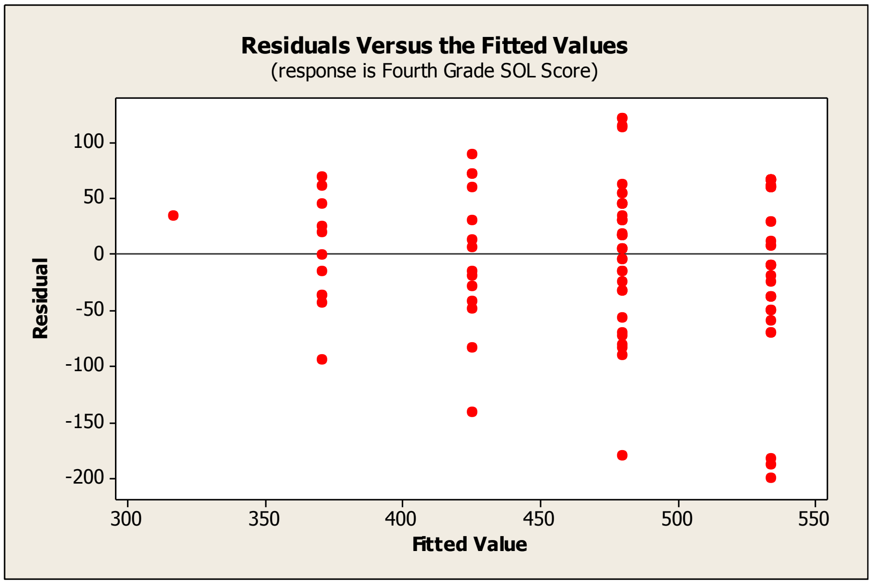
```
Weighted analysis using weights in 1/S_4^2


The regression equation is
Fourth Grade SOL Score = 317 + 54.3 Fourth Grade In Class


99 cases used, 1 cases contain missing values
                          or had zero weight


Predictor                Coef  SE Coef      T      P
Constant               316.92    15.24  20.79  0.000
Fourth Grade In Class  54.309    5.507   9.86  0.000


S = 0.0152566   R-Sq = 50.1%   R-Sq(adj) = 49.5%


Analysis of Variance

Source          DF        SS        MS      F      P
Regression       1  0.022634  0.022634  97.24  0.000
Residual Error  97  0.022578  0.000233
  Lack of Fit    2  0.000120  0.000060   0.25  0.776
  Pure Error    95  0.022458  0.000236
Total           98  0.045212
```

```
Unusual Observations

      Fourth    Fourth
       Grade     Grade
          In       SOL
Obs    Class     Score      Fit  SE Fit  Residual  St Resid
  2     1.00   396.000  371.234  10.468    24.766      0.67 X
  3     1.00   431.000  371.234  10.468    59.766      1.61 X
  4     1.00   416.000  371.234  10.468    44.766      1.20 X
  5     1.00   370.000  371.234  10.468    -1.234     -0.03 X
  6     1.00   327.000  371.234  10.468   -44.234     -1.19 X
  7     1.00   334.000  371.234  10.468   -37.234     -1.00 X
  8     1.00   390.000  371.234  10.468    18.766      0.50 X
  9     1.00   334.000  371.234  10.468   -37.234     -1.00 X
 10     1.00   440.000  371.234  10.468    68.766      1.85 X
 11     1.00   276.000  371.234  10.468   -95.234     -2.56RX
 12     1.00   355.000  371.234  10.468   -16.234     -0.44 X
 14     2.00   284.000  425.542   6.890  -141.542     -2.20R
 61     3.00   299.000  479.851   6.785  -180.851     -2.86R
 73     4.00   351.000  534.160  10.259  -183.160     -2.31R
 75     4.00   345.000  534.160  10.259  -189.160     -2.38R
 97     4.00   334.000  534.160  10.259  -200.160     -2.52R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.

No evidence of lack of fit (P >= 0.1).
```

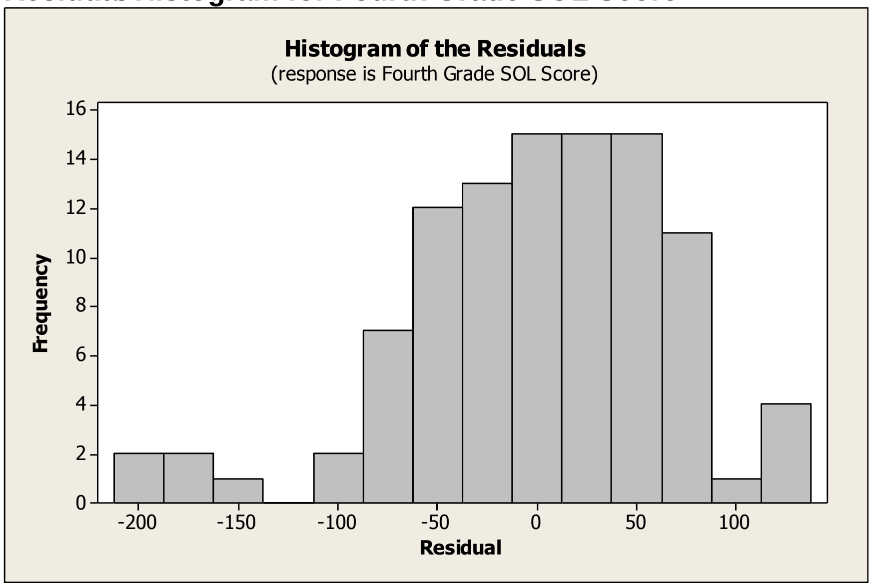
Normplot of Residuals for Fourth Grade SOL Score



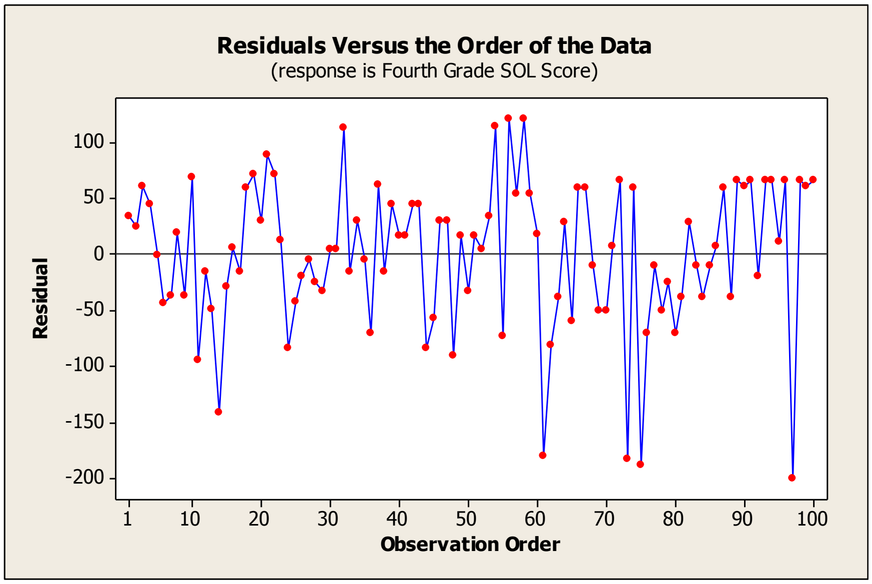
Residuals vs Fits for Fourth Grade SOL Score



Residual Histogram for Fourth Grade SOL Score



Residuals vs Order for Fourth Grade SOL Score

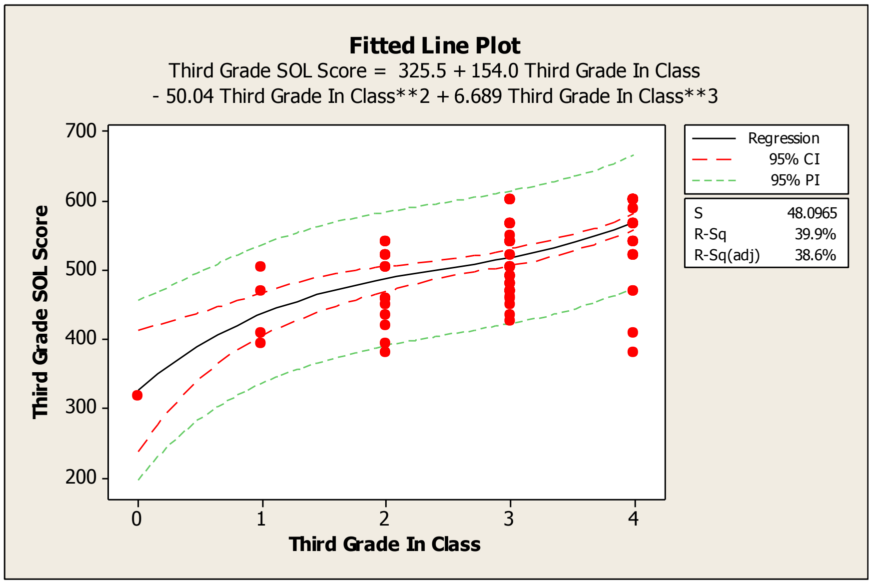



```
MTB > Fitline 'Third Grade SOL Score' 'Third Grade In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Third Grade SOL versus Third Grade In C

```
The regression equation is
Third Grade SOL Score = 325.5 + 154.0 Third Grade In Class
                        - 50.04 Third Grade In Class**2
                        + 6.689 Third Grade In Class**3


S = 48.0965   R-Sq = 39.9%   R-Sq(adj) = 38.6%


Analysis of Variance

Source       DF      SS       MS      F      P
Regression    3  216375  72125.1  31.18  0.000
Error       141  326171   2313.3
Total       144  542547


Sequential Analysis of Variance

Source     DF      SS      F      P
Linear      1  209224  89.76  0.000
Quadratic   1     195   0.08  0.774
Cubic       1    6956   3.01  0.085
```

Fitted Line: Third Grade SOL Score versus Third Grade In Class




```
MTB > Describe  'Fifth Grade SOL Score';
SUBC>   By  'Fifth Grade In Class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Fifth Grade SOL Score

Variable	Fifth Grade In Class	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Fifth Grade SOL	0	4	0	384.0	24.9	49.7	2472.7	12.95
	1	15	0	400.8	16.5	64.0	4095.5	15.97
	2	15	0	434.8	12.2	47.1	2217.0	10.83
	3	35	0	520.57	9.37	55.42	3071.02	10.65
	4	44	0	560.0	10.2	67.6	4574.5	12.08

Variable	Fifth Grade In Class	Minimum	Q1	Median	Q3	Maximum
Fifth Grade SOL	0	351.0	353.5	363.5	435.0	458.0
	1	276.0	370.0	409.0	440.0	534.0
	2	332.0	417.0	427.0	458.0	504.0
	3	392.00	490.00	514.00	567.00	600.00
	4	332.0	541.3	594.0	600.0	600.0

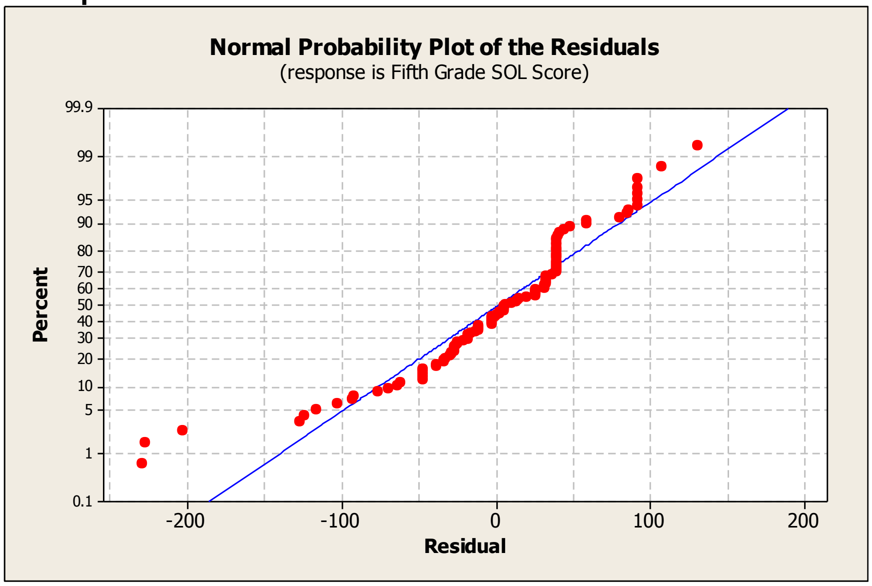
```
MTB > Let '1/S_5^2' = 1/(VARS5*VARS5)
MTB > Regress 'Fifth Grade SOL Score' 1  'Fifth Grade In Class';
SUBC>   Weights '1/S_5^2';
```

```
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

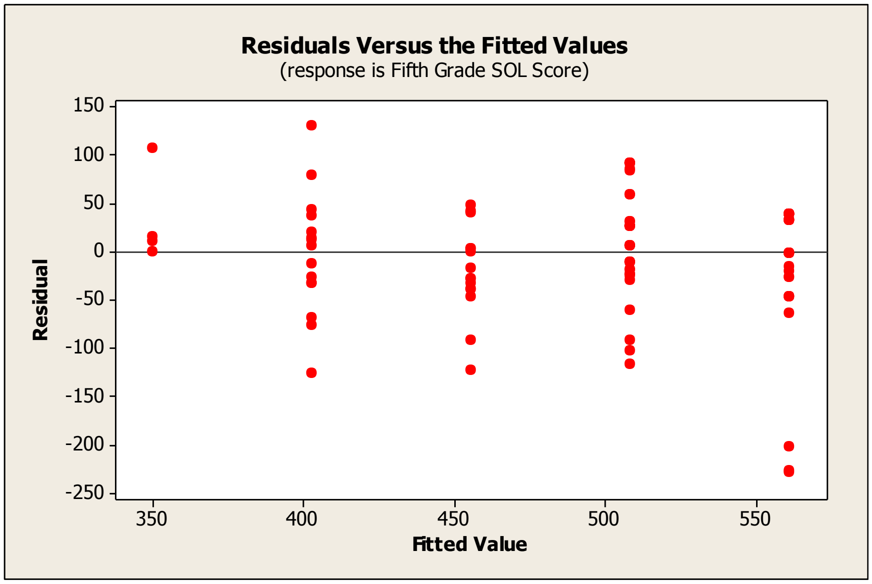
Regression Analysis: Fifth Grade SOL Score versus Fifth Grade In Class

```
Weighted analysis using weights in 1/S_5^2


The regression equation is
Fifth Grade SOL Score = 350 + 52.6 Fifth Grade In Class


Predictor               Coef  SE Coef      T      P
Constant              350.44    13.74  25.50  0.000
Fifth Grade In Class  52.616    4.954  10.62  0.000


S = 0.0175145   R-Sq = 50.4%   R-Sq(adj) = 50.0%


Analysis of Variance

Source           DF        SS        MS       F      P
Regression        1  0.034600  0.034600  112.79  0.000
Residual Error  111  0.034050  0.000307
  Lack of Fit     3  0.002632  0.000877    3.02  0.033
  Pure Error    108  0.031418  0.000291
Total           112  0.068650


Unusual Observations

     Fifth    Fifth
     Grade    Grade
        In      SOL
Obs  Class    Score      Fit  SE Fit  Residual  St Resid
  1   0.00  351.000  350.437  13.744     0.563      0.01 X
  2   0.00  366.000  350.437  13.744    15.563      0.38 X
  3   0.00  361.000  350.437  13.744    10.563      0.26 X
  4   0.00  458.000  350.437  13.744   107.563      2.62RX
 22   2.00  332.000  455.669   6.070  -123.669     -3.22R
 24   2.00  364.000  455.669   6.070   -91.669     -2.39R
 43   3.00  392.000  508.285   5.870  -116.285     -2.17R
 70   4.00  358.000  560.901   9.009  -202.901     -2.55R
 71   4.00  332.000  560.901   9.009  -228.901     -2.88R
107   4.00  334.000  560.901   9.009  -226.901     -2.85R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.


Lack of fit test
Possible curvature in variable Fifth Gr  (P-Value = 0.027 )

Overall lack of fit test is significant at P = 0.027
```

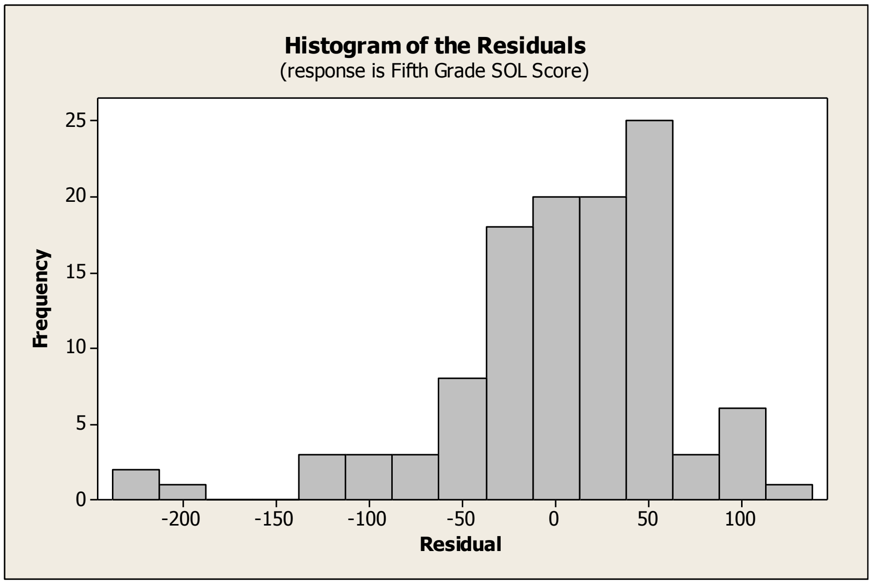
Normplot of Residuals for Fifth Grade SOL Score



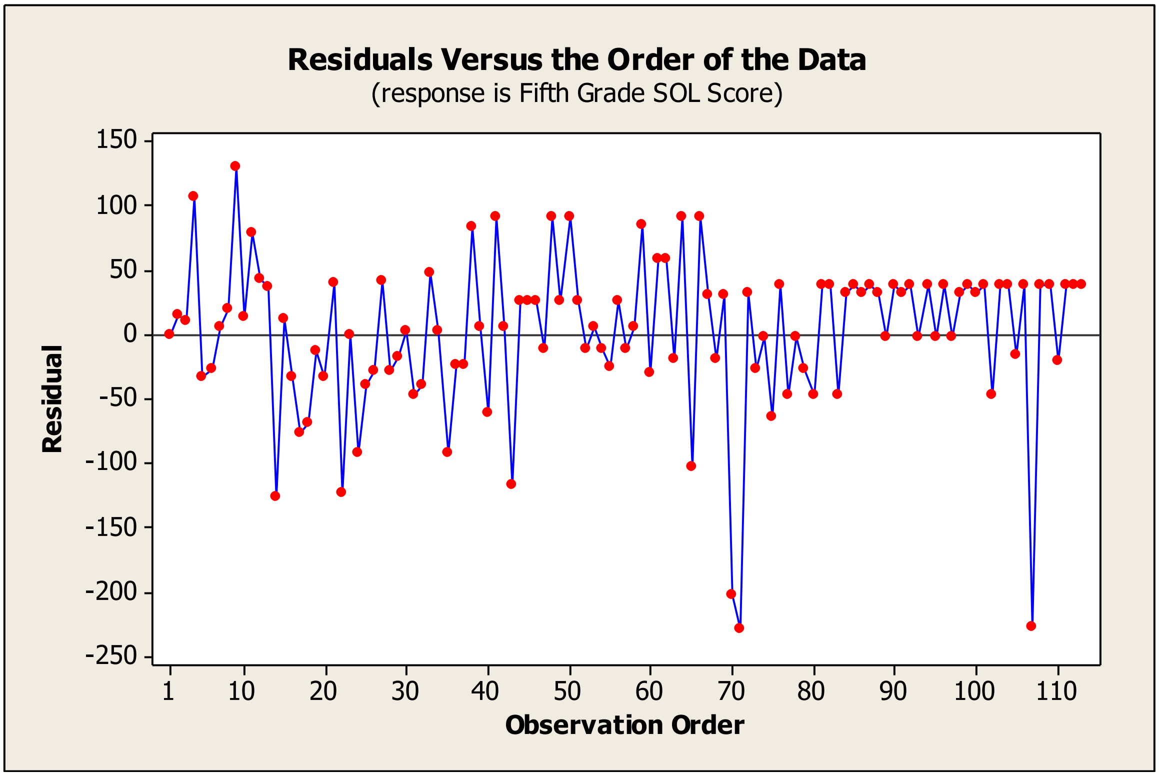
Residuals vs Fits for Fifth Grade SOL Score



Residual Histogram for Fifth Grade SOL Score



Residuals vs Order for Fifth Grade SOL Score



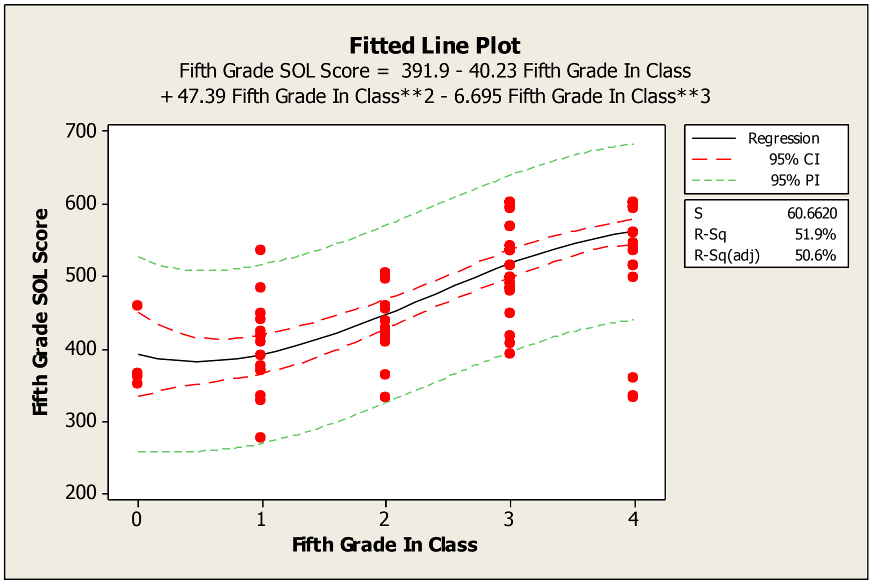

```
MTB > Fitline 'Fifth Grade SOL Score' 'Fifth Grade In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Fifth Grade SOL versus Fifth Grade In C

```
The regression equation is
Fifth Grade SOL Score = 391.9 - 40.23 Fifth Grade In Class
```

```
                         + 47.39 Fifth Grade In Class**2
                         - 6.695 Fifth Grade In Class**3


S = 60.6620   R-Sq = 51.9%   R-Sq(adj) = 50.6%


Analysis of Variance

Source       DF      SS      MS      F      P
Regression    3  432693  144231  39.19  0.000
Error       109  401106    3680
Total       112  833799


Sequential Analysis of Variance

Source     DF      SS       F      P
Linear      1  420748  113.07  0.000
Quadratic   1     935    0.25  0.618
Cubic       1   11010    2.99  0.087
```

Fitted Line: Fifth Grade SOL Score versus Fifth Grade In Class




```
MTB > Describe  'Sixth Grade SOL Score';
SUBC>   By  'Sixth Grade In Class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Sixth Grade SOL Score

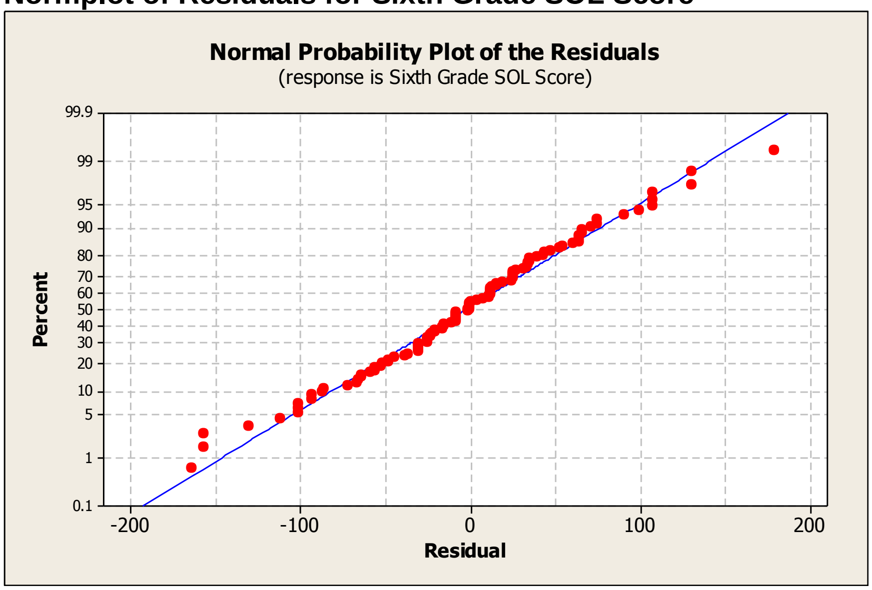
```
                  Sixth
                  Grade
                  In
Variable          Class   N  N*    Mean  SE Mean  StDev  Variance  CoefVar
Sixth Grade SOL   0       1   0  458.00        *      *         *        *
                  1      18   0  343.11     7.30  30.98    959.75     9.03
                  2      30   0   403.4     10.7   58.5    3424.7    14.51
                  3      46   0   458.9     10.5   71.1    5057.8    15.50
                  4      15   0   538.9     12.2   47.3    2234.6     8.77

                  Sixth
                  Grade
                  In
Variable          Class  Minimum      Q1  Median      Q3  Maximum
Sixth Grade SOL   0       458.00       *  458.00       *   458.00
                  1       276.00  327.00  337.50  359.00   414.00
                  2        313.0   354.8   398.0   440.0    514.0
                  3        306.0   414.0   470.0   500.0    600.0
                  4        422.0   509.0   545.0   569.0    600.0

MTB > Let '1/S_6^2' = 1/(VARS6*VARS6)
Let '1/S_6^2' = 1/(VARS6*VARS6)
                J
* WARNING * Values out of bounds during operation at J
* WARNING * Missing returned 1 times

MTB > Regress 'Sixth Grade SOL Score' 1  'Sixth Grade In Class';
SUBC>   Weights '1/S_6^2';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

Regression Analysis: Sixth Grade SOL Score versus Sixth Grade In Class

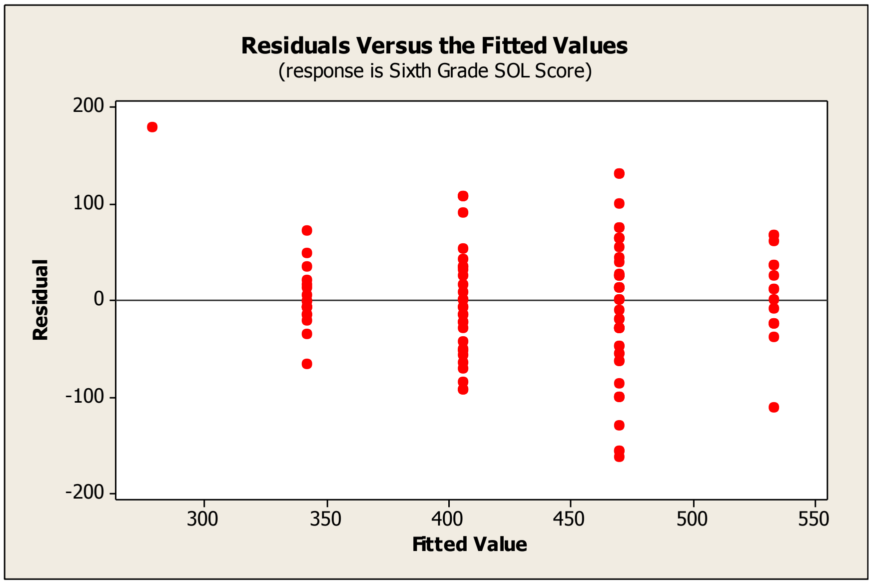
```
Weighted analysis using weights in 1/S_6^2


The regression equation is
Sixth Grade SOL Score = 279 + 63.7 Sixth Grade In Class


109 cases used, 1 cases contain missing values
                          or had zero weight


Predictor                Coef  SE Coef      T      P
Constant              278.798    6.943  40.15  0.000
Sixth Grade In Class   63.724    3.714  17.16  0.000


S = 0.0197353   R-Sq = 73.3%   R-Sq(adj) = 73.1%


Analysis of Variance
```

```
Source            DF       SS       MS       F      P
Regression         1  0.11466  0.11466  294.39  0.000
Residual Error   107  0.04167  0.00039
  Lack of Fit      2  0.00033  0.00017    0.42  0.657
  Pure Error     105  0.04134  0.00039
Total            108  0.15634


Unusual Observations

     Sixth     Sixth
     Grade     Grade
        In       SOL
Obs  Class     Score      Fit  SE Fit  Residual  St Resid
  6   1.00   390.000  342.522   4.343    47.478     2.58R
  9   1.00   276.000  342.522   4.343   -66.522    -3.61R
 15   1.00   414.000  342.522   4.343    71.478     3.88R
102   4.00   422.000  533.695   9.816  -111.695    -2.60R

R denotes an observation with a large standardized residual.

No evidence of lack of fit (P >= 0.1).
```

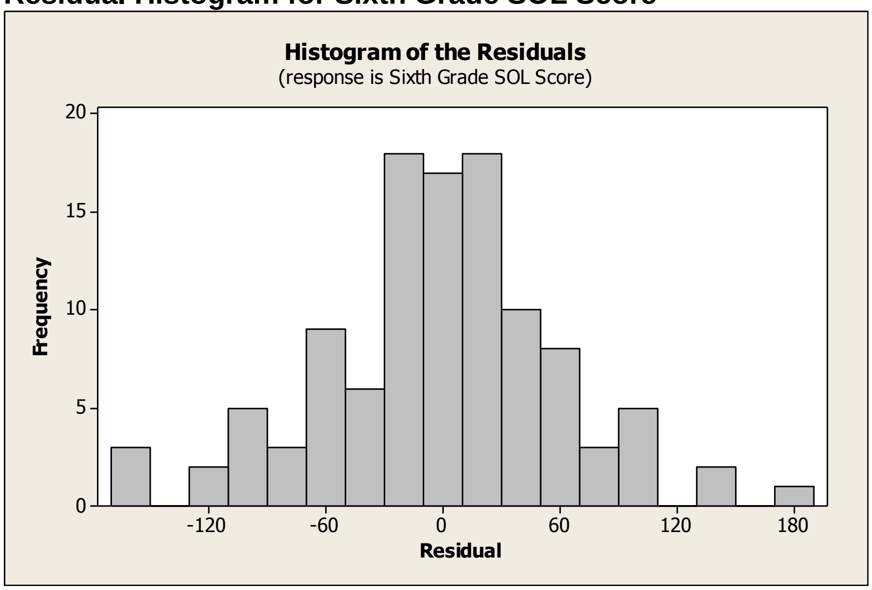
Normplot of Residuals for Sixth Grade SOL Score



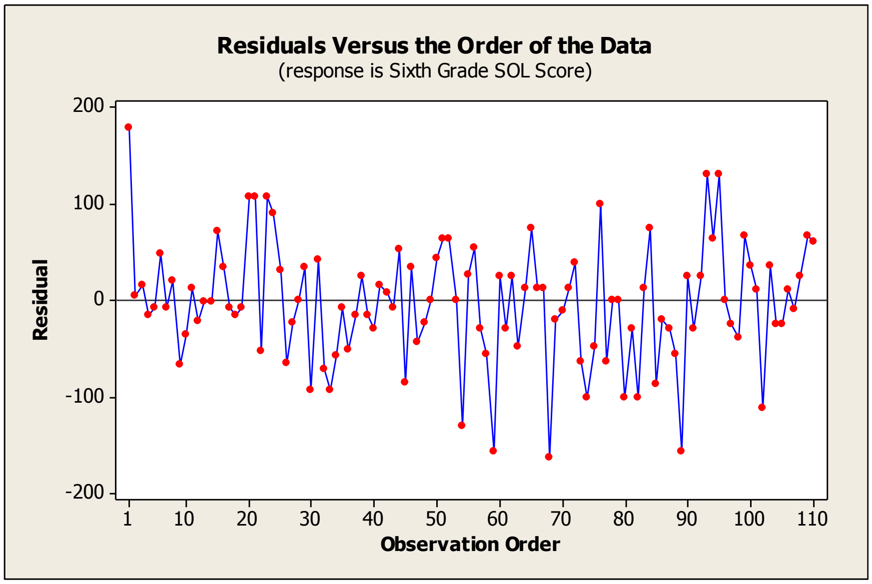
Residuals vs Fits for Sixth Grade SOL Score



Residual Histogram for Sixth Grade SOL Score



Residuals vs Order for Sixth Grade SOL Score

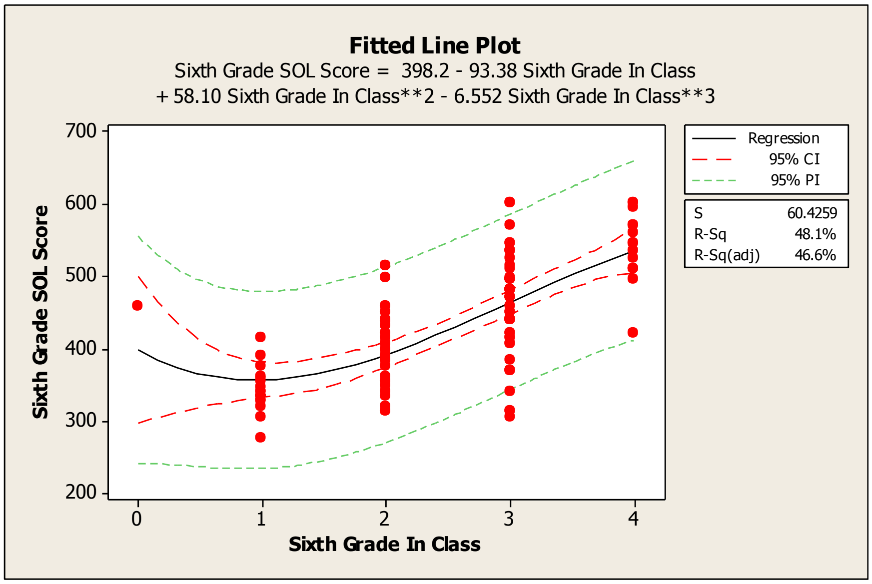



```
MTB > Fitline 'Sixth Grade SOL Score' 'Sixth Grade In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Sixth Grade SOL versus Sixth Grade In C

```
The regression equation is
Sixth Grade SOL Score = 398.2 - 93.38 Sixth Grade In Class
                        + 58.10 Sixth Grade In Class**2
                        - 6.552 Sixth Grade In Class**3


S = 60.4259   R-Sq = 48.1%   R-Sq(adj) = 46.6%


Analysis of Variance

Source       DF      SS      MS      F      P
Regression    3  358138  119379  32.70  0.000
Error       106  387036    3651
Total       109  745175


Sequential Analysis of Variance

Source     DF      SS      F      P
Linear      1  336292  88.83  0.000
Quadratic   1   15421   4.19  0.043
Cubic       1    6425   1.76  0.188
```

Fitted Line: Sixth Grade SOL Score versus Sixth Grade In Class




```
MTB > Describe  'Seventh Grade SOL Score';
SUBC>   By  'Seventh Grade In Class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Seventh Grade SOL Score

Variable	Seventh Grade In Class	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Seventh Grade SO	0	2	0	370.50	6.50	9.19	84.50	2.48
	1	17	0	423.6	14.0	57.9	3355.1	13.67
	2	26	0	439.5	10.5	53.7	2887.9	12.23
	3	39	0	472.92	9.41	58.77	3454.44	12.43
	4	28	0	518.6	11.9	63.0	3973.6	12.15

Variable	Seventh Grade In Class	Minimum	Q1	Median	Q3	Maximum
Seventh Grade SO	0	364.00	*	370.50	*	377.00
	1	276.0	405.0	440.0	467.0	504.0
	2	291.0	422.5	456.0	470.8	503.0
	3	299.00	456.00	479.00	502.00	600.00
	4	334.0	474.8	531.5	567.0	600.0

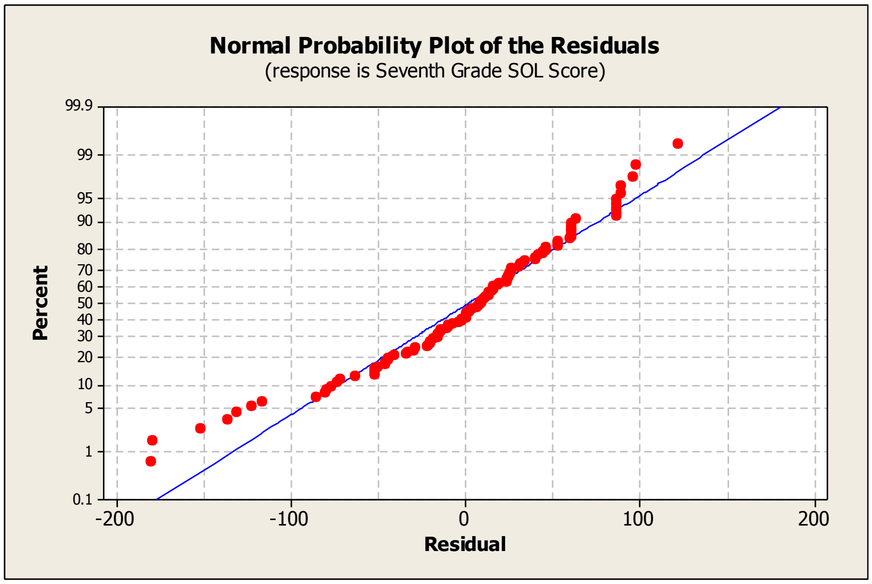
```
MTB > Let '1/S_7^2' = 1/(VARS7*VARS7)
MTB > Regress 'Seventh Grade SOL Score' 1  'Seventh Grade In Class';
SUBC>   Weights '1/S_7^2';
```

```
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

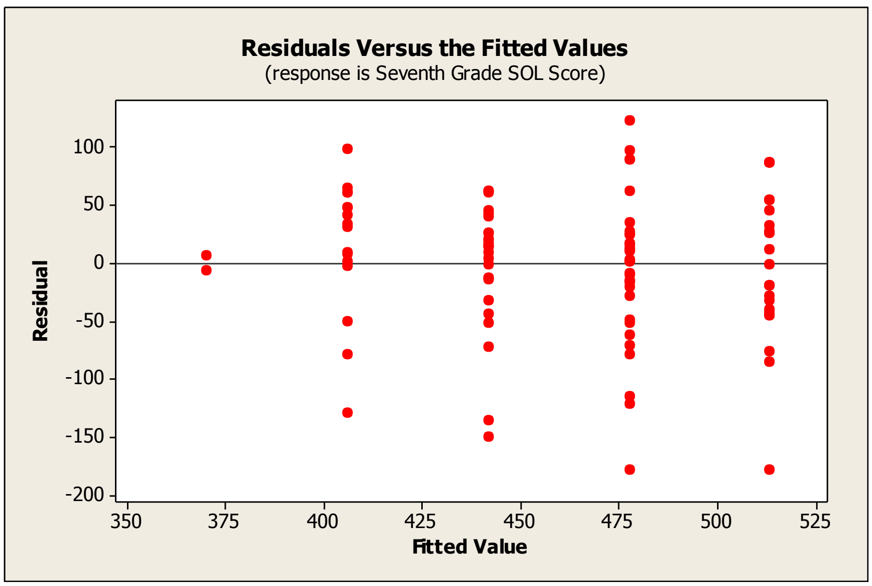
Regression Analysis: Seventh Grade SO versus Seventh Grade In

```
Weighted analysis using weights in 1/S_7^2


The regression equation is
Seventh Grade SOL Score = 371 + 35.7 Seventh Grade In Class


Predictor                  Coef  SE Coef       T      P
Constant                370.542    1.188  311.97  0.000
Seventh Grade In Class   35.730    2.387   14.97  0.000


S = 0.0199211   R-Sq = 67.1%   R-Sq(adj) = 66.8%


Analysis of Variance

Source            DF        SS        MS       F      P
Regression         1  0.088944  0.088944  224.12  0.000
Residual Error   110  0.043654  0.000397
  Lack of Fit      3  0.000598  0.000199    0.50  0.686
  Pure Error     107  0.043055  0.000402
Total            111  0.132597


Unusual Observations

     Seventh  Seventh
       Grade    Grade
          In      SOL
Obs    Class    Score      Fit  SE Fit  Residual  St Resid
  1     0.00  364.000  370.542   1.188    -6.542    -5.48RX
  2     0.00  377.000  370.542   1.188     6.458     5.41RX
 20     2.00  291.000  442.002   4.718  -151.002    -2.63R
 22     2.00  306.000  442.002   4.718  -136.002    -2.37R
 50     3.00  299.000  477.731   7.055  -178.731    -2.61R
 87     4.00  334.000  513.461   9.417  -179.461    -2.28R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.

No evidence of lack of fit (P >= 0.1).
```

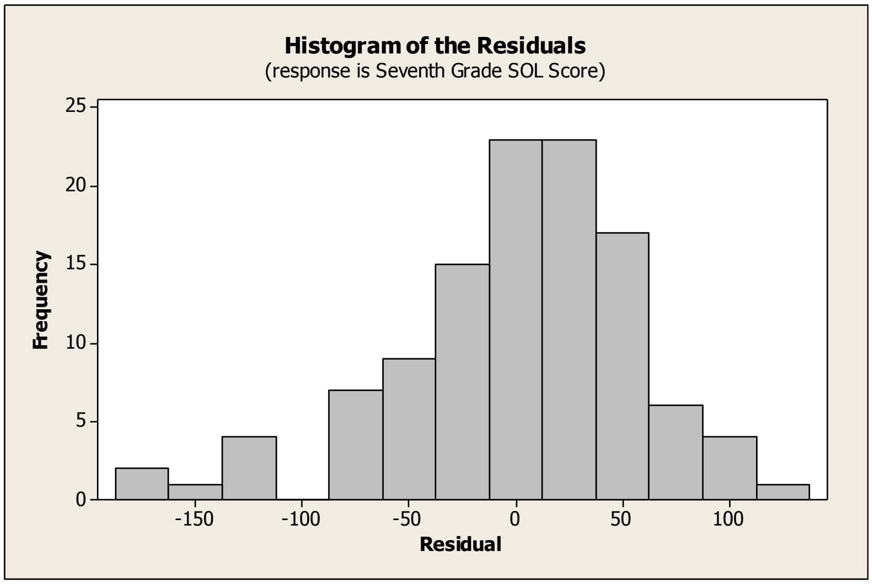
Normplot of Residuals for Seventh Grade SOL Score



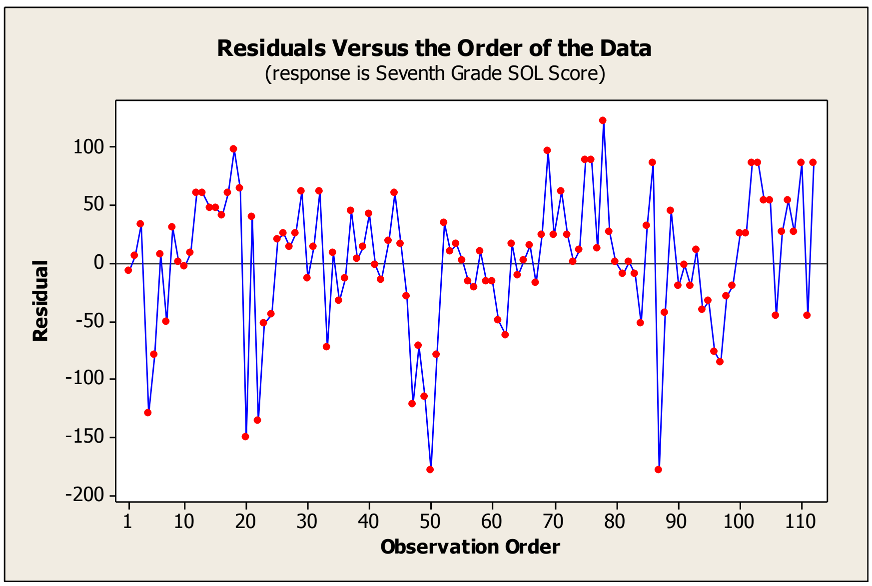
Residuals vs Fits for Seventh Grade SOL Score



Residual Histogram for Seventh Grade SOL Score



Residuals vs Order for Seventh Grade SOL Score




```
MTB > Fitline 'Seventh Grade SOL Score' 'Seventh Grade In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Seventh Grade SO versus Seventh Grade In

```
The regression equation is
Seventh Grade SOL Score = 379.7 + 53.25 Seventh Grade In Class
                          - 16.63 Seventh Grade In Class**2
                          + 3.011 Seventh Grade In Class**3


S = 58.1843   R-Sq = 28.4%   R-Sq(adj) = 26.4%
```

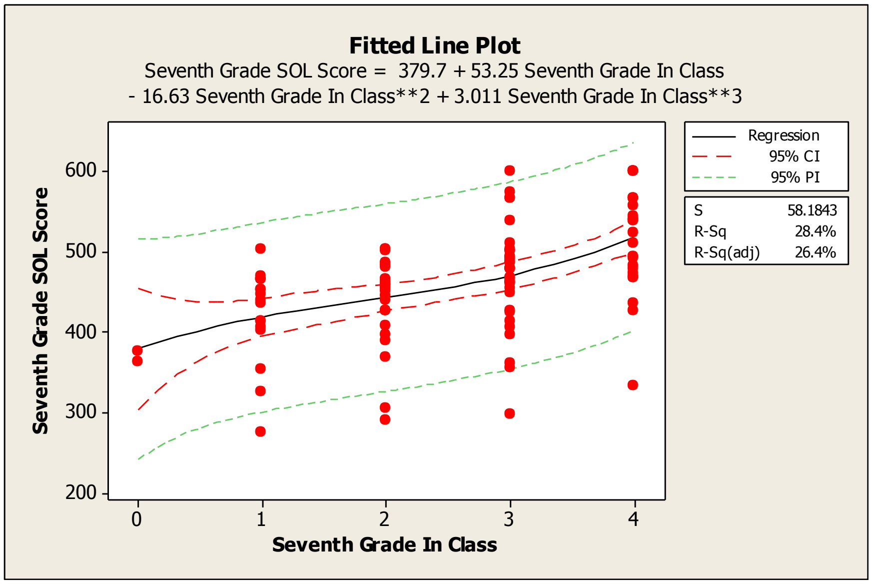
Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	145063	48354.5	14.28	0.000
Error	108	365625	3385.4		
Total	111	510688			

Sequential Analysis of Variance

Source	DF	SS	F	P
Linear	1	140339	41.68	0.000
Quadratic	1	2887	0.86	0.357
Cubic	1	1837	0.54	0.463

Fitted Line: Seventh Grade SOL Score versus Seventh Grade In Class




```
MTB > Describe  'Algebra I SOL Score';
SUBC>   By  'Algebra I In class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Algebra I SOL Score

Variable	Algebra I In class	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Algebra I SOL Sc	65	1	0	369.00	*	*	*	*
	66	1	0	364.00	*	*	*	*
	70	3	0	424.00	8.89	15.39	237.00	3.63

72	1	0	415.00	*	*	*	*
73	7	0	406.3	10.2	27.1	733.6	6.67
75	4	0	425.25	8.83	17.65	311.58	4.15
76	2	0	419.5	12.5	17.7	312.5	4.21
77	2	0	433.0	18.0	25.5	648.0	5.88
78	2	0	485.0	18.0	25.5	648.0	5.25
79	3	0	416.0	24.4	42.3	1789.0	10.17
80	6	0	454.17	9.91	24.28	589.37	5.35
81	4	0	469.0	14.3	28.7	823.3	6.12
82	4	0	457.75	5.60	11.21	125.58	2.45
83	4	0	455.8	13.2	26.4	696.9	5.79
84	2	0	447.5	32.5	46.0	2112.5	10.27
85	4	0	449.8	14.1	28.1	790.9	6.25
86	6	0	474.3	11.2	27.4	750.7	5.78
87	7	0	472.00	3.15	8.35	69.67	1.77
88	7	0	466.4	12.3	32.6	1065.3	7.00
89	9	0	477.78	9.47	28.42	807.94	5.95
90	4	0	498.0	13.5	27.0	728.0	5.42
91	8	0	438.1	13.3	37.7	1423.0	8.61
92	3	0	461.67	3.18	5.51	30.33	1.19
93	7	0	483.86	7.95	21.04	442.48	4.35
94	14	0	496.14	9.88	36.99	1367.98	7.45
95	3	0	463.0	30.6	53.0	2811.0	11.45
96	8	0	472.3	14.0	39.6	1567.9	8.38
97	14	0	499.4	12.0	44.7	1999.5	8.95
98	9	0	497.2	10.3	30.8	948.2	6.19
99	4	0	526.3	25.9	51.7	2674.9	9.83
100	2	0	535.0	23.0	32.5	1058.0	6.08

Variable	Algebra I In class	Minimum	Q1	Median	Q3	Maximum
Algebra I SOL Sc	65	369.00	*	369.00	*	369.00
	66	364.00	*	364.00	*	364.00
	70	407.00	407.00	428.00	437.00	437.00
	72	415.00	*	415.00	*	415.00
	73	378.0	382.0	397.0	432.0	441.0
	75	403.00	408.25	426.00	441.50	446.00
	76	407.0	*	419.5	*	432.0
	77	415.0	*	433.0	*	451.0
	78	467.0	*	485.0	*	503.0
	79	369.0	369.0	428.0	451.0	451.0
	80	409.00	440.50	459.00	470.25	480.00
	81	437.0	441.8	468.0	497.3	503.0
	82	446.00	448.50	456.00	468.75	473.00
	83	428.0	431.3	454.0	482.0	487.0
	84	415.0	*	447.5	*	480.0
	85	428.0	428.0	442.0	479.3	487.0
	86	441.0	444.8	476.5	498.5	512.0
	87	462.00	462.00	473.00	480.00	480.00
	88	411.0	441.0	473.0	494.0	503.0
	89	432.00	456.50	480.00	498.50	524.00
	90	462.0	470.0	503.0	521.0	524.0
	91	395.0	410.5	421.5	480.8	494.0
	92	456.00	456.00	462.00	467.00	467.00
	93	462.00	467.00	480.00	512.00	512.00
	94	428.00	478.25	498.50	505.25	591.00
	95	428.0	428.0	437.0	524.0	524.0
	96	407.0	437.8	473.0	507.5	524.0
	97	424.0	474.0	503.0	518.8	591.0
	98	446.0	468.0	503.0	518.0	539.0
	99	487.0	488.8	509.0	581.0	600.0
	100	512.0	*	535.0	*	558.0

```
MTB > Let '1/S_A1_C^2' = 1/('VARSA1_c'*'VARSA1_c')
Let '1/S_A1_C^2' = 1/('VARSA1_c'*'VARSA1_c')
                    J
* WARNING * Values out of bounds during operation at J
* WARNING * Missing returned 3 times

MTB > Regress 'Algebra I SOL Score' 1  'Algebra I In class';
SUBC>   Weights '1/S_A1_C^2';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

Regression Analysis: Algebra I SOL Score versus Algebra I In class

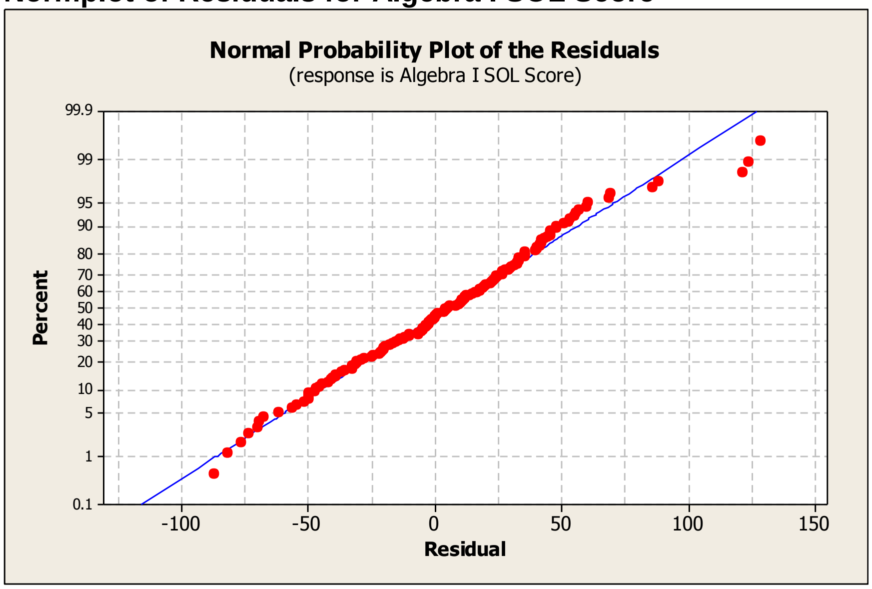
```
Weighted analysis using weights in 1/S_A1_C^2


The regression equation is
Algebra I SOL Score = 395 + 0.765 Algebra I In class


152 cases used, 3 cases contain missing values
                          or had zero weight


Predictor             Coef  SE Coef      T      P
Constant            395.26    20.66  19.14  0.000
Algebra I In class  0.7645   0.2304   3.32  0.001


S = 0.0675194   R-Sq = 6.8%   R-Sq(adj) = 6.2%


Analysis of Variance

Source           DF        SS        MS      F      P
Regression        1  0.050211  0.050211  11.01  0.001
Residual Error  150  0.683831  0.004559
  Lack of Fit    26  0.377049  0.014502   5.86  0.000
  Pure Error    124  0.306782  0.002474
Total           151  0.734042


Unusual Observations

     Algebra  Algebra
        I In    I SOL
Obs    class    Score      Fit  SE Fit  Residual  St Resid
  3       70  437.000  448.773   4.604   -11.773     -0.77 X
  4       70  407.000  448.773   4.604   -41.773     -2.73RX
  5       70  428.000  448.773   4.604   -20.773     -1.36 X
 14       75  403.000  452.596   3.484   -49.596     -2.39R
 18       76  407.000  453.360   3.262   -46.360     -2.22R
 37       82  456.000  457.948   1.978    -1.948     -0.24 X
 38       82  473.000  457.948   1.978    15.052      1.83 X
```

39	82	446.000	457.948	1.978	-11.948	-1.45 X
40	82	456.000	457.948	1.978	-1.948	-0.24 X
57	87	480.000	461.770	1.105	18.230	3.99RX
58	87	480.000	461.770	1.105	18.230	3.99RX
59	87	467.000	461.770	1.105	5.230	1.14 X
60	87	462.000	461.770	1.105	0.230	0.05 X
61	87	480.000	461.770	1.105	18.230	3.99RX
62	87	462.000	461.770	1.105	0.230	0.05 X
63	87	473.000	461.770	1.105	11.230	2.46RX
92	92	462.000	465.593	1.088	-3.593	-2.07RX
93	92	467.000	465.593	1.088	1.407	0.81 X
94	92	456.000	465.593	1.088	-9.593	-5.53RX

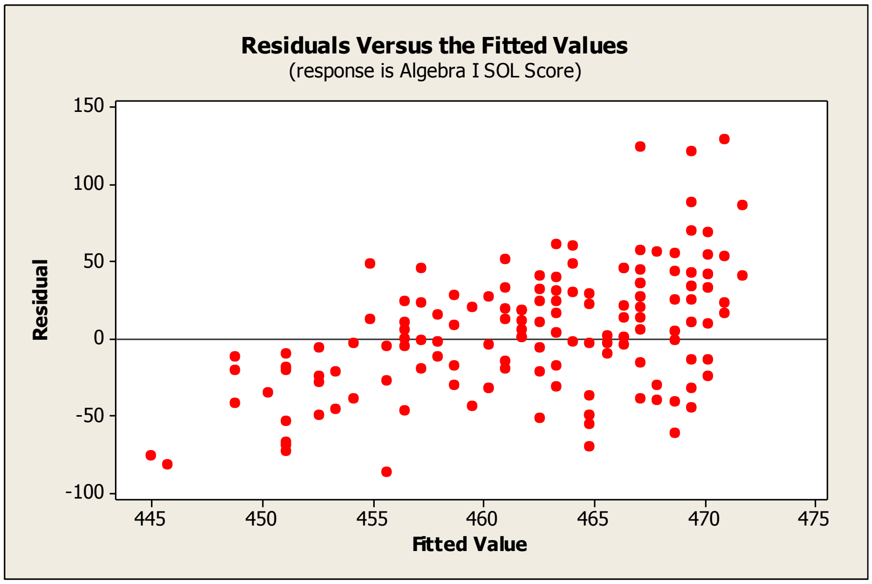
R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.

No evidence of lack of fit (P >= 0.1).

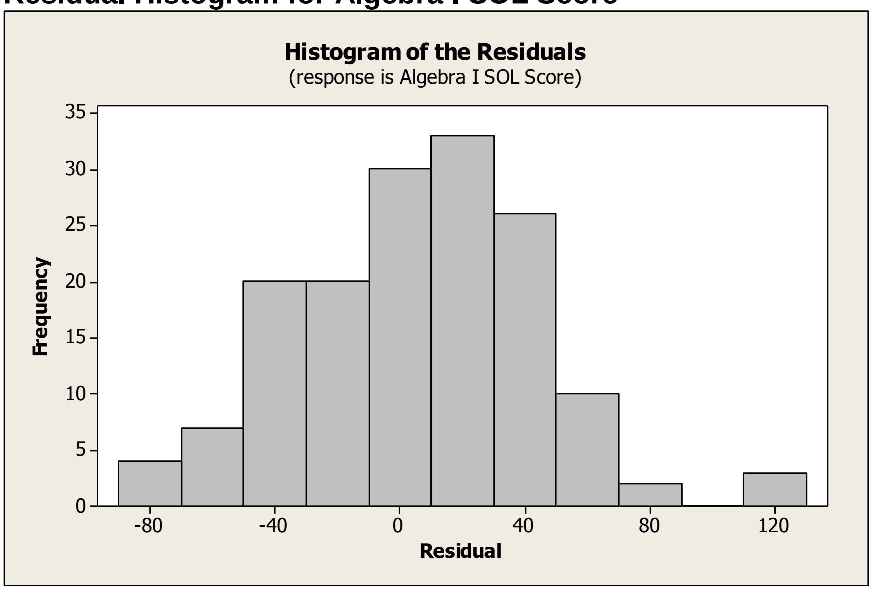
Normplot of Residuals for Algebra I SOL Score



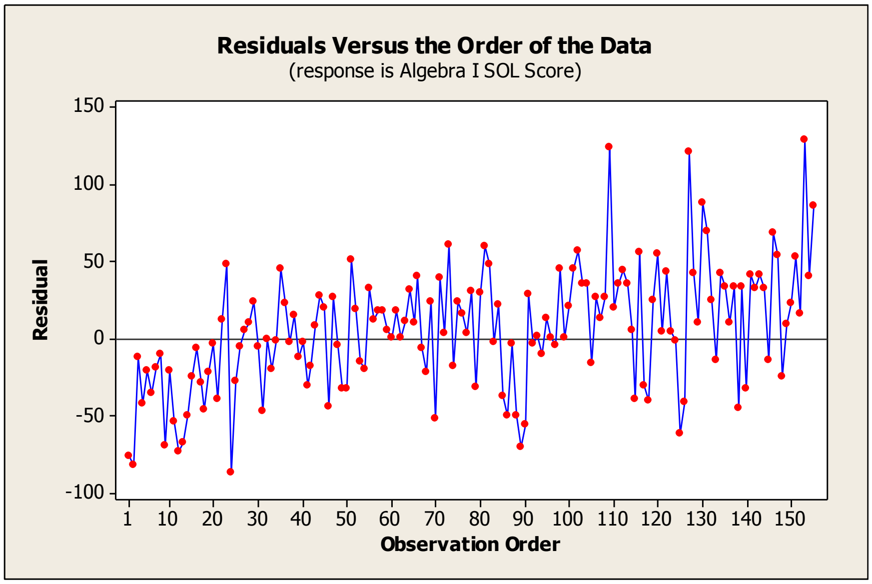
Residuals vs Fits for Algebra I SOL Score



Residual Histogram for Algebra I SOL Score



Residuals vs Order for Algebra I SOL Score

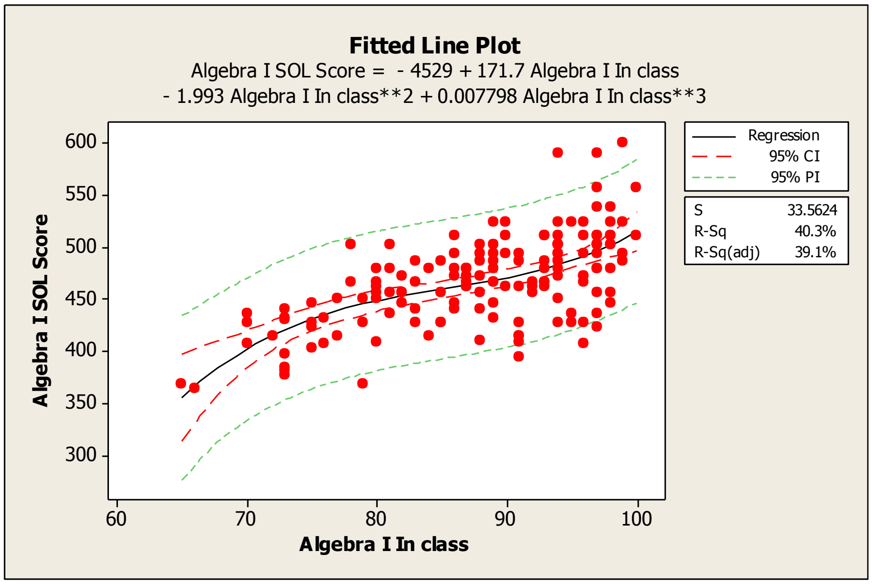



```
MTB > Fitline 'Algebra I SOL Score' 'Algebra I In class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Algebra I SOL Score versus Algebra I In class

```
The regression equation is
Algebra I SOL Score = - 4529 + 171.7 Algebra I In class
                      - 1.993 Algebra I In class**2
                      + 0.007798 Algebra I In class**3


S = 33.5624   R-Sq = 40.3%   R-Sq(adj) = 39.1%


Analysis of Variance

Source       DF      SS       MS      F      P
Regression    3  114814  38271.4  33.98  0.000
Error       151  170091   1126.4
Total       154  284906


Sequential Analysis of Variance

Source     DF      SS      F      P
Linear      1  110042  96.28  0.000
Quadratic   1     462   0.40  0.527
Cubic       1    4310   3.83  0.052
```

Fitted Line: Algebra I SOL Score versus Algebra I In class




```
MTB > Describe  'Algebra I SOL Score';
SUBC>   By 'Alg I Letter Grade';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Algebra I SOL Score

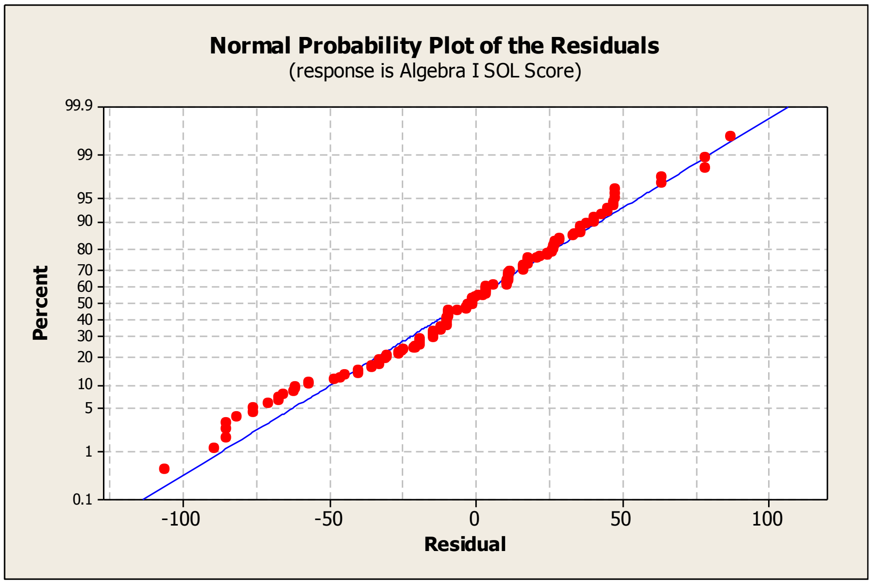
```
                  Alg I
                  Letter
Variable          Grade     N  N*    Mean  SE Mean  StDev  Variance  CoefVar
Algebra I SOL Sc  0         2   0  366.50     2.50   3.54     12.50     0.96
                  1        19   0  417.74     4.99  21.75    472.87     5.21
                  2        29   0  454.03     5.43  29.26    856.25     6.44
                  3        51   0  470.27     4.22  30.16    909.48     6.41
                  4        54   0  495.46     5.66  41.59   1729.95     8.39

                  Alg I
                  Letter
Variable          Grade   Minimum      Q1  Median      Q3  Maximum
Algebra I SOL Sc  0        364.00       *  366.50       *   369.00
                  1        378.00  403.00  424.00  432.00   451.00
                  2        369.00  432.50  456.00  476.50   503.00
                  3        395.00  456.00  473.00  494.00   524.00
                  4        407.00  473.00  503.00  512.00   600.00

MTB > Let '1/S_A1_g^2' = 1/('VARSA1_g'*'VARSA1_g')
MTB > Regress 'Algebra I SOL Score' 1 'Alg I Letter Grade';
SUBC>   Weights '1/S_A1_g^2';
SUBC>   GHistogram;
SUBC>   GNormalplot;
```

```
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

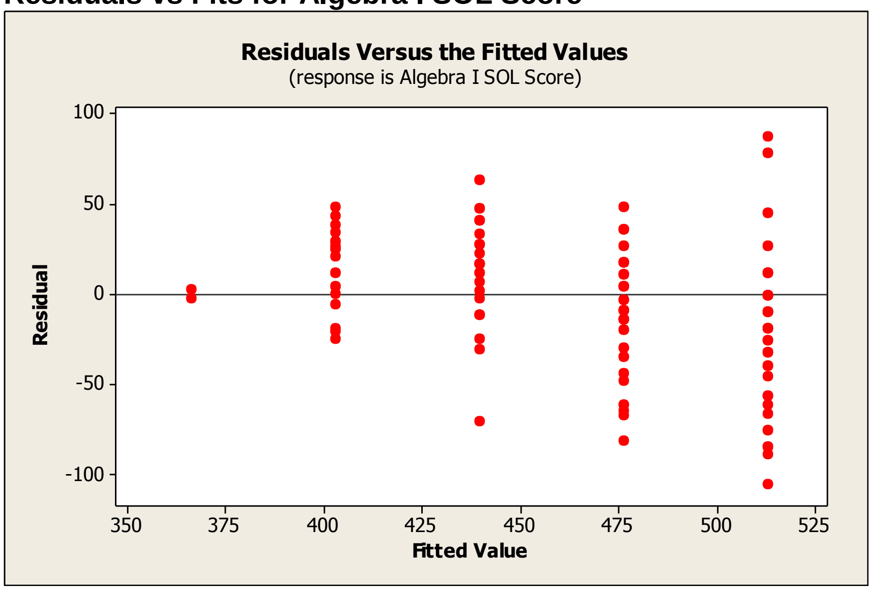
Regression Analysis: Algebra I SOL Score versus Alg I Letter Grade

```
Weighted analysis using weights in 1/S_A1_g^2


The regression equation is
Algebra I SOL Score = 367 + 36.6 Alg I Letter Grade


Predictor              Coef  SE Coef       T      P
Constant            366.587    0.371  988.25  0.000
Alg I Letter Grade   36.570    1.283   28.50  0.000


S = 0.0420347   R-Sq = 84.1%   R-Sq(adj) = 84.0%


Analysis of Variance

Source           DF      SS      MS       F      P
Regression        1  1.4352  1.4352  812.28  0.000
Residual Error  153  0.2703  0.0018
  Lack of Fit     3  0.0340  0.0113    7.18  0.000
  Pure Error    150  0.2364  0.0016
Total           154  1.7056


Unusual Observations

      Alg I  Algebra
     Letter    I SOL
Obs   Grade    Score      Fit  SE Fit  Residual  St Resid
  1    0.00  369.000  366.587   0.371     2.413     6.48RX
  2    0.00  364.000  366.587   0.371    -2.587    -6.95RX
 16    1.00  446.000  403.158   1.295    42.842     2.16R
 20    1.00  451.000  403.158   1.295    47.842     2.41R
 89    3.00  395.000  476.299   3.826   -81.299    -2.14R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.


Lack of fit test
Possible curvature in variable Alg I Le  (P-Value = 0.000 )

Overall lack of fit test is significant at P = 0.000
```

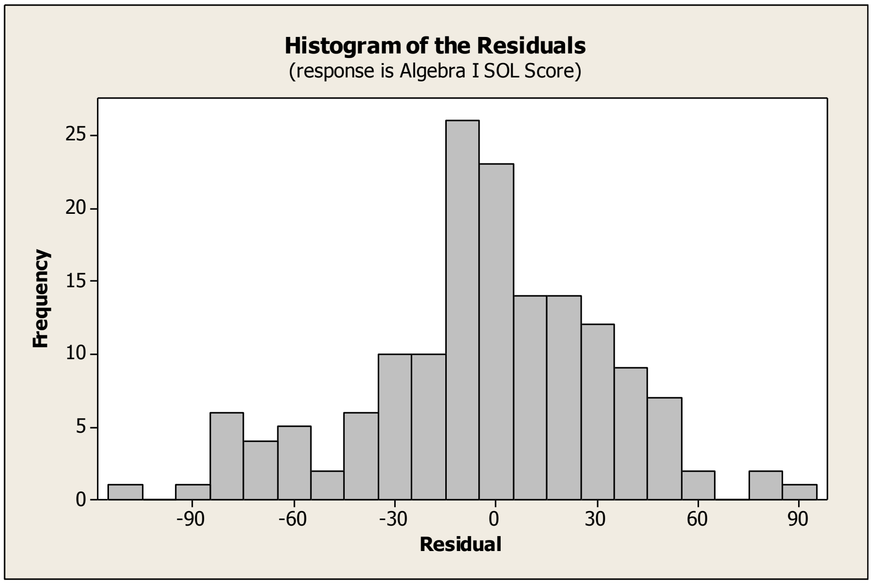
Normplot of Residuals for Algebra I SOL Score



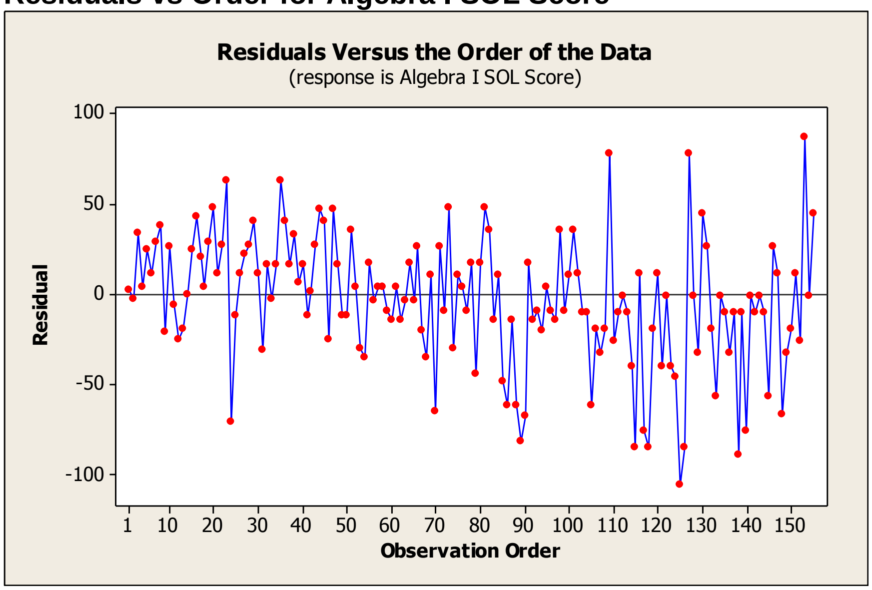
Residuals vs Fits for Algebra I SOL Score



Residual Histogram for Algebra I SOL Score



Residuals vs Order for Algebra I SOL Score



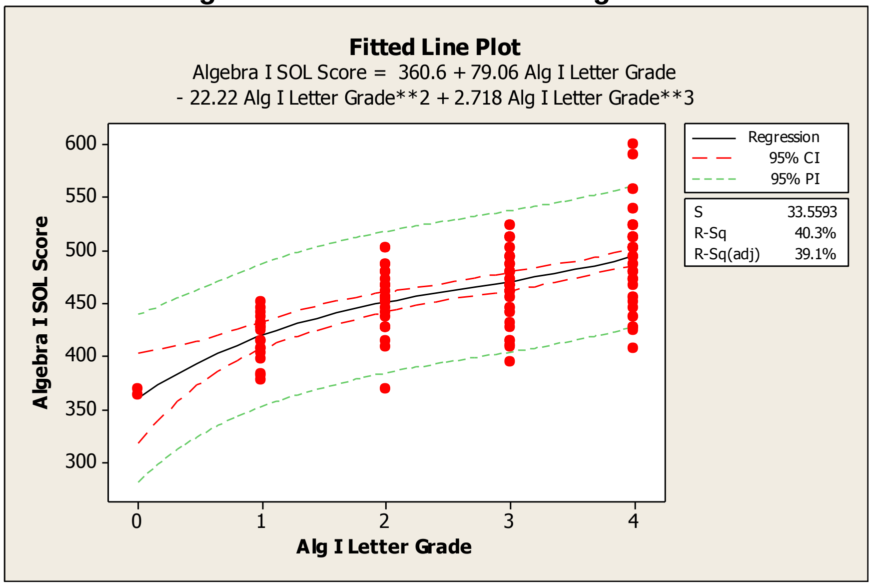

```
MTB > Fitline 'Algebra I SOL Score' 'Alg I Letter Grade';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Algebra I SOL Score versus Alg I Letter Grade

```
The regression equation is
Algebra I SOL Score = 360.6 + 79.06 Alg I Letter Grade
                      - 22.22 Alg I Letter Grade**2
                      + 2.718 Alg I Letter Grade**3


S = 33.5593   R-Sq = 40.3%   R-Sq(adj) = 39.1%
```

```
Analysis of Variance

Source        DF      SS       MS      F      P
Regression     3  114846  38281.8  33.99  0.000
Error        151  170060   1126.2
Total        154  284906


Sequential Analysis of Variance

Source      DF      SS      F      P
Linear       1  111413  98.25  0.000
Quadratic    1    1708   1.51  0.221
Cubic        1    1725   1.53  0.218
```

Fitted Line: Algebra I SOL Score versus Alg I Letter Grade




```
MTB > Describe  'Algebra II SOL Score';
SUBC>   By  'Algebra II In Class';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Algebra II SOL Score

```
                  Algebra
                  II In
Variable          Class      N  N*    Mean  SE Mean  StDev  Variance  CoefVar
Algebra II SOL S   35        1   0  344.00        *      *         *        *
                   46        1   0  354.00        *      *         *        *
                   52        1   0  377.00        *      *         *        *
```

59	1	0	447.00	*	*	*	*
63	1	0	435.00	*	*	*	*
65	5	0	459.0	10.9	24.4	593.5	5.31
70	3	0	446.33	2.33	4.04	16.33	0.91
71	3	0	418.33	2.33	4.04	16.33	0.97
73	9	0	427.1	12.4	37.2	1383.1	8.71
74	3	0	459.33	2.33	4.04	16.33	0.88
75	5	0	443.00	8.87	19.84	393.50	4.48
76	10	0	447.90	8.21	25.98	674.77	5.80
77	2	0	440.0	18.0	25.5	648.0	5.79
78	2	0	492.0	18.0	25.5	648.0	5.17
79	2	0	405.5	29.5	41.7	1740.5	10.29
80	2	0	514.50	2.50	3.54	12.50	0.69
83	1	0	493.00	*	*	*	*
84	1	0	517.00	*	*	*	*
85	4	0	462.3	13.5	27.1	732.9	5.86
86	8	0	466.75	8.81	24.92	620.79	5.34
87	1	0	487.00	*	*	*	*
88	4	0	458.5	18.8	37.5	1407.0	8.18
89	10	0	481.50	9.28	29.34	860.72	6.09
90	1	0	441.00	*	*	*	*
91	1	0	460.00	*	*	*	*
92	1	0	504.00	*	*	*	*
93	3	0	467.3	27.3	47.3	2233.3	10.11
94	21	0	496.95	8.43	38.63	1492.35	7.77
95	4	0	470.5	22.9	45.8	2099.0	9.74
96	3	0	497.0	14.8	25.6	657.0	5.16
97	4	0	466.5	24.1	48.3	2329.7	10.35
98	4	0	480.3	14.7	29.4	866.3	6.13
99	4	0	521.3	25.9	51.7	2674.9	9.92
100	4	0	536.0	13.7	27.4	753.3	5.12

Variable	Algebra II In Class	Minimum	Q1	Median	Q3	Maximum
Algebra II SOL S	35	344.00	*	344.00	*	344.00
	46	354.00	*	354.00	*	354.00
	52	377.00	*	377.00	*	377.00
	59	447.00	*	447.00	*	447.00
	63	435.00	*	435.00	*	435.00
	65	419.0	436.0	470.0	476.5	478.0
	70	442.00	442.00	447.00	450.00	450.00
	71	414.00	414.00	419.00	422.00	422.00
	73	373.0	387.0	432.0	464.5	470.0
	74	455.00	455.00	460.00	463.00	463.00
	75	425.00	427.50	431.00	464.50	467.00
	76	414.00	417.75	450.50	470.00	484.00
	77	422.0	*	440.0	*	458.0
	78	474.0	*	492.0	*	510.0
	79	376.0	*	405.5	*	435.0
	80	512.00	*	514.50	*	517.00
	83	493.00	*	493.00	*	493.00
	84	517.00	*	517.00	*	517.00
	85	423.0	434.0	471.0	481.8	484.0
	86	436.00	444.00	464.00	486.75	507.00
	87	487.00	*	487.00	*	487.00
	88	406.0	419.5	467.5	488.5	493.0
	89	441.00	459.75	478.50	503.25	534.00
	90	441.00	*	441.00	*	441.00
	91	460.00	*	460.00	*	460.00
	92	504.00	*	504.00	*	504.00
	93	414.0	414.0	484.0	504.0	504.0
	94	428.00	479.00	497.00	506.00	594.00

```
                 95        428.0   430.3   465.0   516.3    524.0
                 96        473.0   473.0   494.0   524.0    524.0
                 97        419.0   422.3   465.0   512.3    517.0
                 98        441.0   449.5   486.5   504.8    507.0
                 99        482.0   483.8   504.0   576.0    595.0
                100        507.0   510.0   536.0   562.0    565.0

MTB > Let '1/S_A2_c' = 1/('VARSA2_c'*'VARSA2_c')
Let '1/S_A2_c' = 1/('VARSA2_c'*'VARSA2_c')
                  J
* WARNING * Values out of bounds during operation at J
* WARNING * Missing returned 11 times

MTB > Regress 'Algebra II SOL Score' 1  'Algebra II In Class';
SUBC>   Weights '1/S_A2_c';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

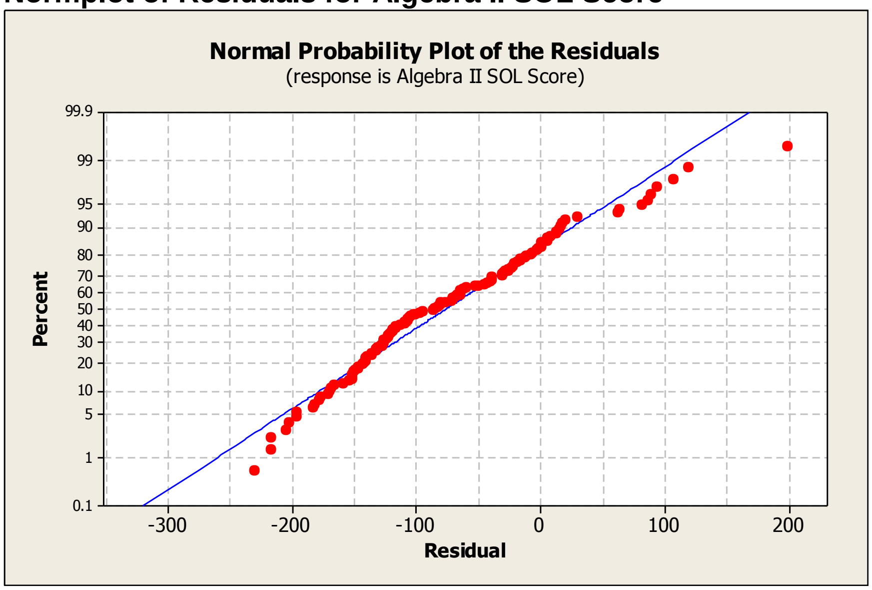
Regression Analysis: Algebra II SOL Score versus Algebra II In Class

```
Weighted analysis using weights in 1/S_A2_c


The regression equation is
Algebra II SOL Score = - 140 + 8.13 Algebra II In Class


119 cases used, 11 cases contain missing values
                          or had zero weight


Predictor               Coef  SE Coef      T      P
Constant             -140.39    23.99  -5.85  0.000
Algebra II In Class   8.1349   0.3237  25.13  0.000


S = 0.283607   R-Sq = 84.4%   R-Sq(adj) = 84.2%


Analysis of Variance

Source           DF      SS      MS       F      P
Regression        1  50.793  50.793  631.50  0.000
Residual Error  117   9.411   0.080
  Lack of Fit    21   8.864   0.422   74.16  0.000
  Pure Error     96   0.546   0.006
Total           118  60.204


Unusual Observations

     Algebra  Algebra
       II In   II SOL
Obs    Class    Score      Fit  SE Fit  Residual  St Resid
 11       70  447.000  429.054   1.840    17.946      4.22RX
```

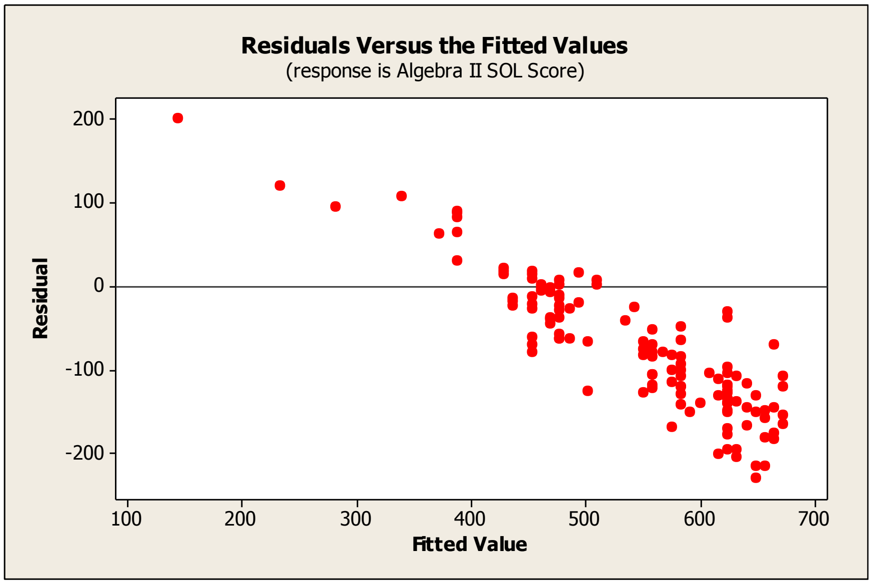
12	70	442.000	429.054	1.840	12.946	3.05RX
13	70	450.000	429.054	1.840	20.946	4.93RX
14	71	419.000	437.189	1.629	-18.189	-4.20RX
15	71	414.000	437.189	1.629	-23.189	-5.35RX
16	71	422.000	437.189	1.629	-15.189	-3.50RX
26	74	460.000	461.593	1.312	-1.593	-0.36 X
27	74	455.000	461.593	1.312	-6.593	-1.48 X
28	74	463.000	461.593	1.312	1.407	0.32 X
50	80	517.000	510.403	2.348	6.597	2.48RX
51	80	512.000	510.403	2.348	1.597	0.60 X

```
R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.


Lack of fit test
Possible curvature in variable Algebra   (P-Value = 0.004 )

Overall lack of fit test is significant at P = 0.004
```

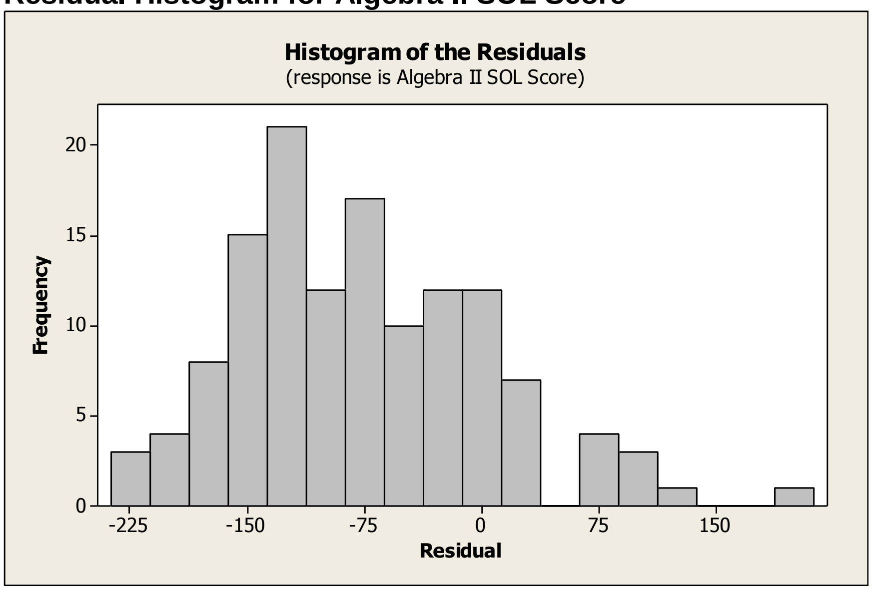
Normplot of Residuals for Algebra II SOL Score



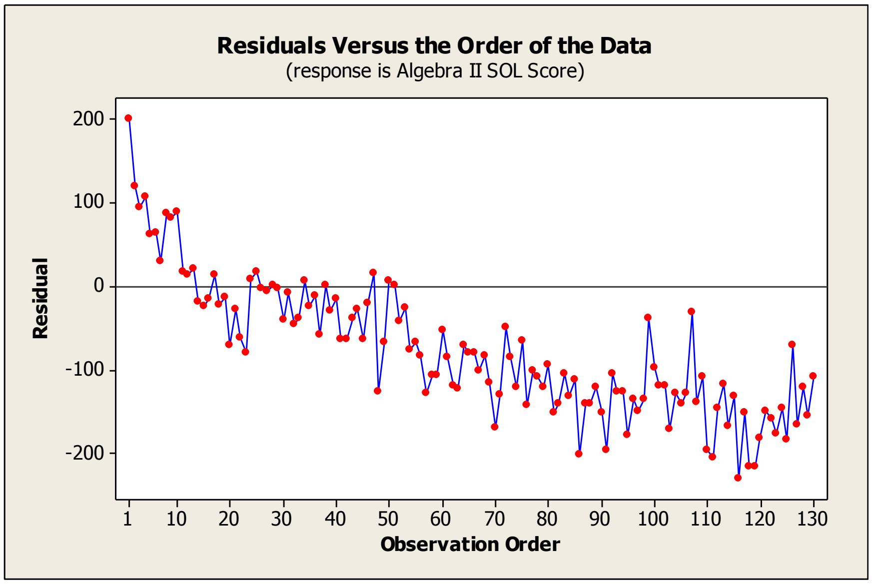
Residuals vs Fits for Algebra II SOL Score



Residual Histogram for Algebra II SOL Score



Residuals vs Order for Algebra II SOL Score

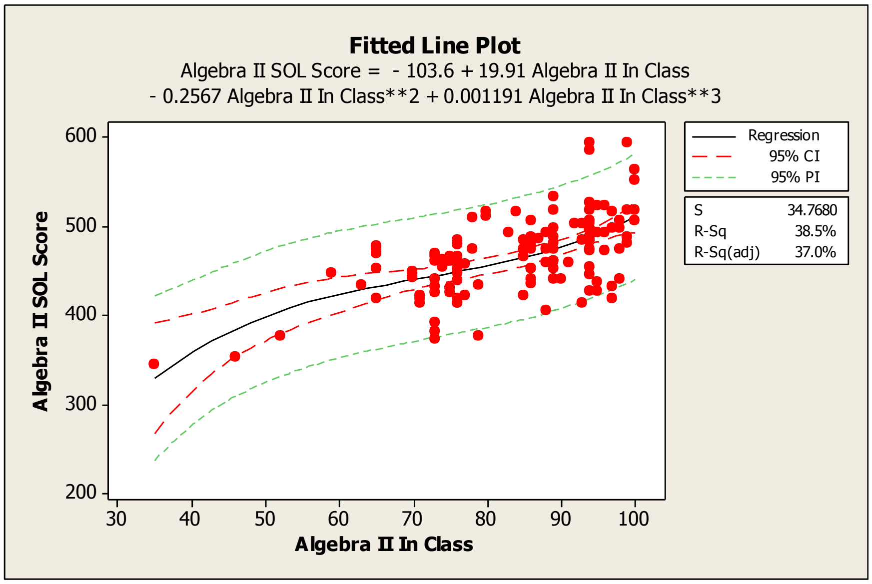



```
MTB > Fitline 'Algebra II SOL Score' 'Algebra II In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Algebra II SOL Score versus Algebra II In Class

```
The regression equation is
Algebra II SOL Score = - 103.6 + 19.91 Algebra II In Class
                       - 0.2567 Algebra II In Class**2
                       + 0.001191 Algebra II In Class**3


S = 34.7680   R-Sq = 38.5%   R-Sq(adj) = 37.0%


Analysis of Variance

Source       DF      SS       MS      F      P
Regression    3   95325  31774.9  26.29  0.000
Error       126  152311   1208.8
Total       129  247636


Sequential Analysis of Variance

Source     DF       SS      F      P
Linear      1  92659.3  76.53  0.000
Quadratic   1     19.0   0.02  0.901
Cubic       1   2646.5   2.19  0.141
```

Fitted Line: Algebra II SOL Score versus Algebra II In Class




```
MTB > Describe  'Algebra II SOL Score';
SUBC>   By  'Alg II Letter Grade';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Algebra II SOL Score

Variable	Alg II Letter Grade	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Algebra II SOL S	0	10	0	425.2	15.9	50.2	2516.0	11.80
	1	35	0	439.71	4.52	26.72	713.80	6.08
	2	12	0	473.6	12.5	43.4	1879.4	9.15
	3	29	0	471.62	5.55	29.91	894.53	6.34
	4	44	0	496.02	6.23	41.31	1706.44	8.33

Variable	Alg II Letter Grade	Minimum	Q1	Median	Q3	Maximum
Algebra II SOL S	0	344.0	371.3	441.0	471.3	478.0
	1	373.00	422.00	442.00	462.00	484.00
	2	376.0	443.0	479.5	511.5	517.0
	3	406.00	453.00	475.00	491.00	534.00
	4	419.00	475.00	497.00	518.50	595.00

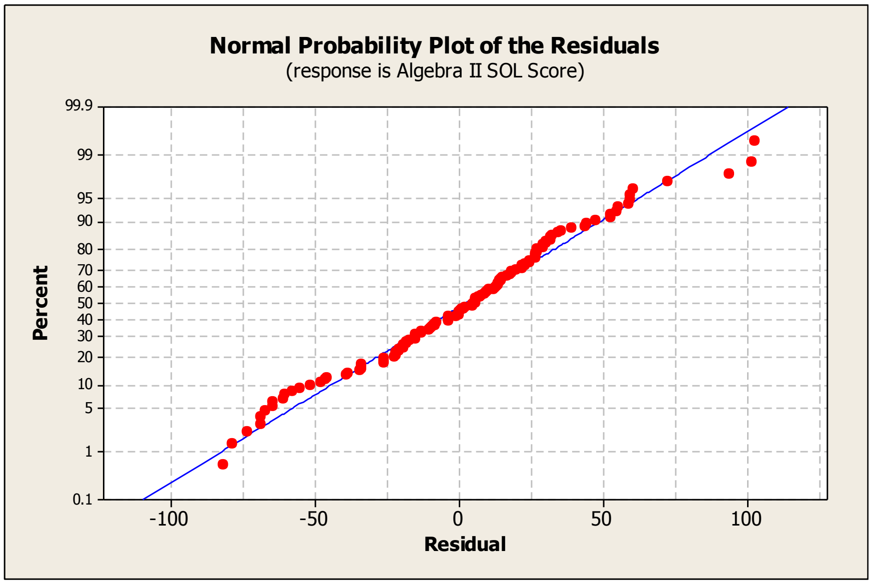
```
MTB > Let '1/S_A2_g' = 1/('VARSA2_g'*'VARSA2_g')
MTB > Regress 'Algebra II SOL Score' 1  'Alg II Letter Grade';
SUBC>   Weights '1/S_A2_g';
SUBC>   GHistogram;
SUBC>   GNormalplot;
```

```
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

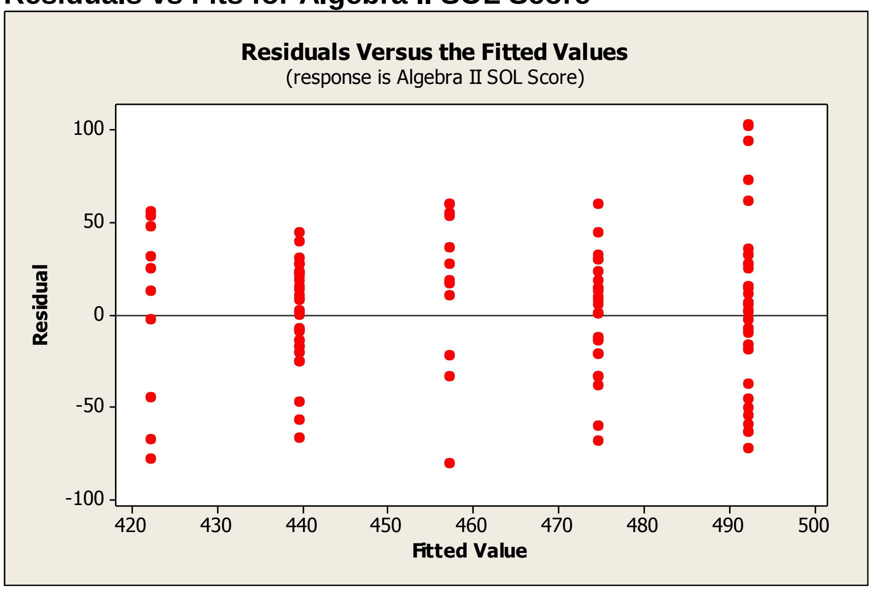
Regression Analysis: Algebra II SOL Score versus Alg II Letter Grade

```
Weighted analysis using weights in 1/S_A2_g


The regression equation is
Algebra II SOL Score = 422 + 17.5 Alg II Letter Grade


Predictor               Coef  SE Coef      T      P
Constant             422.331    5.221  80.88  0.000
Alg II Letter Grade   17.464    2.290   7.63  0.000


S = 0.0299807   R-Sq = 31.2%   R-Sq(adj) = 30.7%


Analysis of Variance

Source           DF        SS        MS      F      P
Regression        1  0.052293  0.052293  58.18  0.000
Residual Error  128  0.115052  0.000899
  Lack of Fit     3  0.001490  0.000497   0.55  0.651
  Pure Error    125  0.113562  0.000908
Total           129  0.167345


Unusual Observations

     Alg II  Algebra
     Letter   II SOL
Obs   Grade    Score      Fit  SE Fit  Residual  St Resid
 20    1.00  382.000  439.795   3.463   -57.795    -2.74R
 22    1.00  392.000  439.795   3.463   -47.795    -2.26R
 23    1.00  373.000  439.795   3.463   -66.795    -3.16R
 34    1.00  484.000  439.795   3.463    44.205     2.09R
 70    3.00  406.000  474.723   3.591   -68.723    -2.59R
 72    3.00  534.000  474.723   3.591    59.277     2.23R
 86    3.00  414.000  474.723   3.591   -60.723    -2.28R
107    4.00  594.000  492.186   5.392   101.814     2.00R
126    4.00  595.000  492.186   5.392   102.814     2.02R

R denotes an observation with a large standardized residual.

No evidence of lack of fit (P >= 0.1).
```

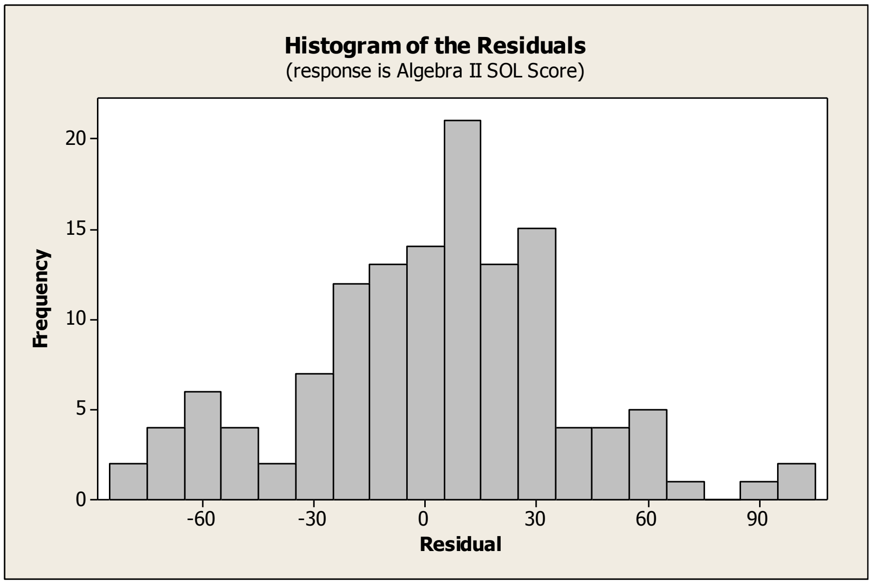
Normplot of Residuals for Algebra II SOL Score



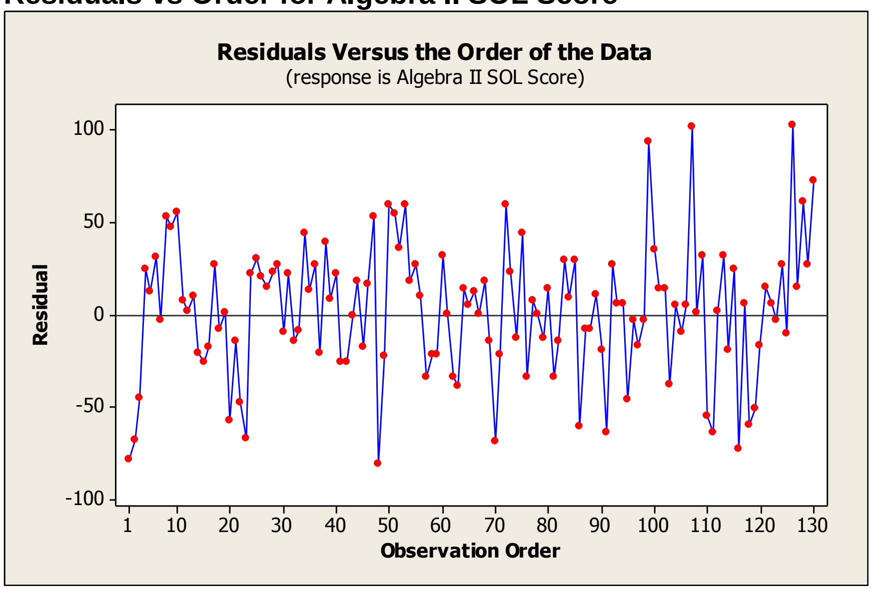
Residuals vs Fits for Algebra II SOL Score



Residual Histogram for Algebra II SOL Score



Residuals vs Order for Algebra II SOL Score



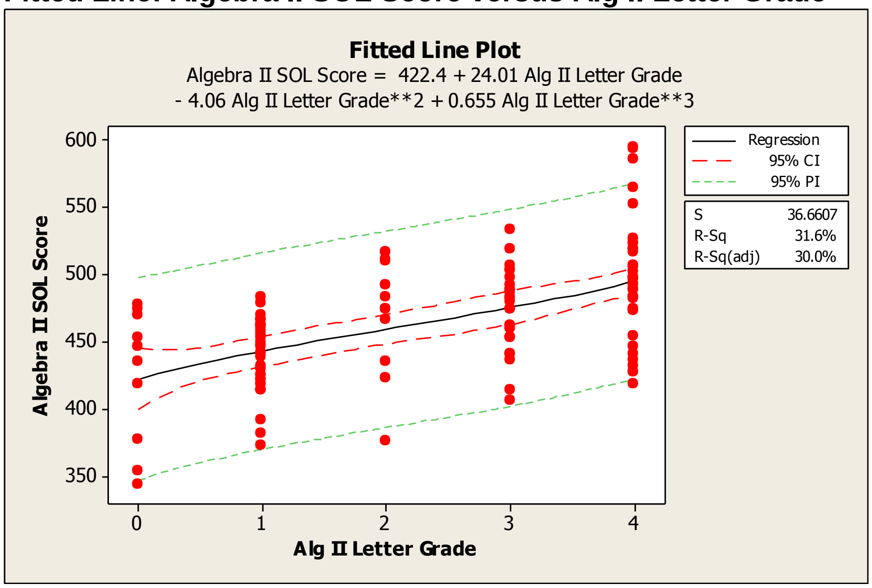

```
MTB > Fitline 'Algebra II SOL Score' 'Alg II Letter Grade';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Algebra II SOL Score versus Alg II Letter Grade

```
The regression equation is
Algebra II SOL Score = 422.4 + 24.01 Alg II Letter Grade
                       - 4.06 Alg II Letter Grade**2
                       + 0.655 Alg II Letter Grade**3


S = 36.6607   R-Sq = 31.6%   R-Sq(adj) = 30.0%
```

```
Analysis of Variance

Source        DF      SS       MS      F      P
Regression     3   78291  26097.1  19.42  0.000
Error        126  169344   1344.0
Total        129  247636


Sequential Analysis of Variance

Source      DF       SS      F      P
Linear       1  78124.2  58.99  0.000
Quadratic    1      2.2   0.00  0.968
Cubic        1    164.9   0.12  0.727
```

Fitted Line: Algebra II SOL Score versus Alg II Letter Grade




```
MTB > Describe  'Geometry SOL Score';
SUBC>    By  'Geometry In Class';
SUBC>    Mean;
SUBC>    SEMean;
SUBC>    StDeviation;
SUBC>    Variance;
SUBC>    CVariation;
SUBC>    QOne;
SUBC>    Median;
SUBC>    QThree;
SUBC>    Minimum;
SUBC>    Maximum;
SUBC>    N;
SUBC>    NMissing.
```

Descriptive Statistics: Geometry SOL Score

Variable	Geometry In Class	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Geometry SOL Sco	30	1	0	341.00	*	*	*	*
	43	1	0	348.00	*	*	*	*
	52	1	0	373.00	*	*	*	*
	63	1	0	362.00	*	*	*	*

69	1	0	471.00	*	*	*	*
71	2	0	425.0	46.0	65.1	4232.0	15.31
72	2	0	416.0	58.0	82.0	6728.0	19.72
73	2	0	425.0	48.0	67.9	4608.0	15.97
74	3	0	462.67	2.40	4.16	17.33	0.90
76	4	0	424.0	22.0	44.0	1935.3	10.38
77	3	0	447.0	30.0	52.0	2707.0	11.64
79	2	0	374.00	1.00	1.41	2.00	0.38
80	4	0	432.0	32.9	65.9	4336.7	15.24
81	4	0	453.0	17.7	35.4	1256.7	7.83
82	2	0	477.0	27.0	38.2	1458.0	8.00
83	3	0	482.0	18.4	31.8	1011.0	6.60
84	2	0	426.5	61.5	87.0	7564.5	20.39
85	3	0	467.33	9.61	16.65	277.33	3.56
86	7	0	481.0	11.1	29.4	864.3	6.11
87	6	0	470.2	10.4	25.4	645.4	5.40
88	2	0	476.0	19.0	26.9	722.0	5.64
89	2	0	496.5	30.5	43.1	1860.5	8.69
90	5	0	479.2	11.0	24.7	608.7	5.15
91	5	0	480.4	12.5	27.8	775.3	5.80
92	10	0	475.80	6.81	21.54	463.96	4.53
93	5	0	465.8	18.9	42.3	1787.2	9.08
94	8	0	514.4	17.4	49.2	2417.4	9.56
95	4	0	460.25	6.97	13.94	194.25	3.03
96	6	0	485.83	9.41	23.04	530.97	4.74
97	7	0	492.9	17.6	46.5	2165.5	9.44
98	15	0	511.1	11.1	43.1	1854.4	8.43
99	11	0	507.3	12.5	41.3	1709.0	8.15
100	5	0	526.0	14.8	33.1	1098.5	6.30

Variable	Geometry In Class	Minimum	Q1	Median	Q3	Maximum
Geometry SOL Sco	30	341.00	*	341.00	*	341.00
	43	348.00	*	348.00	*	348.00
	52	373.00	*	373.00	*	373.00
	63	362.00	*	362.00	*	362.00
	69	471.00	*	471.00	*	471.00
	71	379.0	*	425.0	*	471.0
	72	358.0	*	416.0	*	474.0
	73	377.0	*	425.0	*	473.0
	74	458.00	458.00	464.00	466.00	466.00
	76	377.0	381.8	428.5	461.8	462.0
	77	396.0	396.0	445.0	500.0	500.0
	79	373.00	*	374.00	*	375.00
	80	364.0	372.0	425.5	498.5	513.0
	81	402.0	416.8	463.0	479.3	484.0
	82	450.0	*	477.0	*	504.0
	83	453.0	453.0	477.0	516.0	516.0
	84	365.0	*	426.5	*	488.0
	85	454.00	454.00	462.00	486.00	486.00
	86	447.0	453.0	481.0	505.0	531.0
	87	450.0	452.3	461.0	488.0	518.0
	88	457.0	*	476.0	*	495.0
	89	466.0	*	496.5	*	527.0
	90	458.0	459.0	467.0	505.5	512.0
	91	450.0	453.0	481.0	507.5	515.0
	92	448.00	461.50	474.00	487.25	518.00
	93	392.0	433.0	480.0	491.5	499.0
	94	471.0	475.3	498.5	567.0	596.0
	95	445.00	447.50	459.00	474.25	478.00
	96	462.00	462.75	485.50	503.75	521.00
	97	447.0	462.0	478.0	512.0	588.0
	98	456.0	474.0	501.0	540.0	595.0

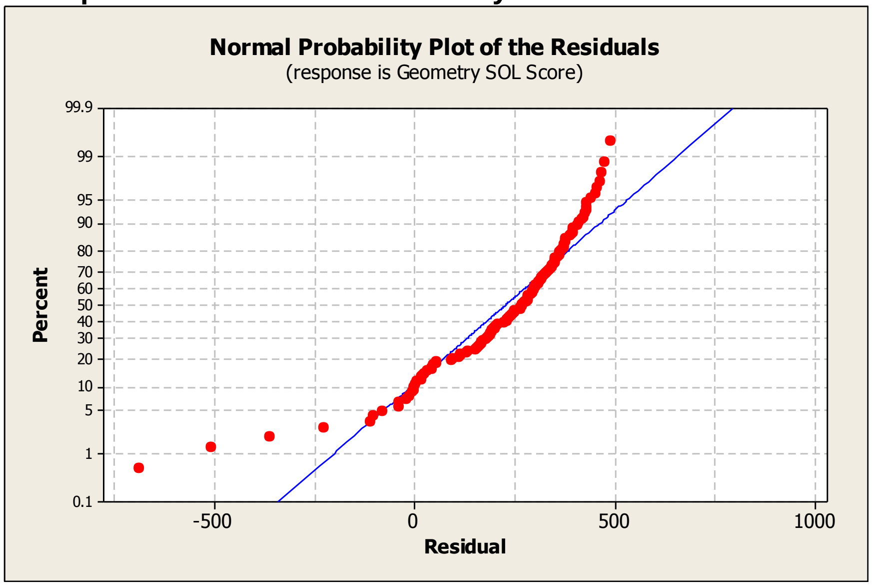
```
                  99         469.0   472.0   502.0   538.0    598.0
                 100         474.0   497.5   526.0   554.5    559.0

MTB > Let '1/S_G_c' = 1/('VARSG_c'*'VARSG_c')
Let '1/S_G_c' = 1/('VARSG_c'*'VARSG_c')
                 J
* WARNING * Values out of bounds during operation at J
* WARNING * Missing returned 5 times

MTB > Regress 'Geometry SOL Score' 1  'Geometry In Class';
SUBC>   Weights '1/S_G_c';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

Regression Analysis: Geometry SOL Score versus Geometry In Class

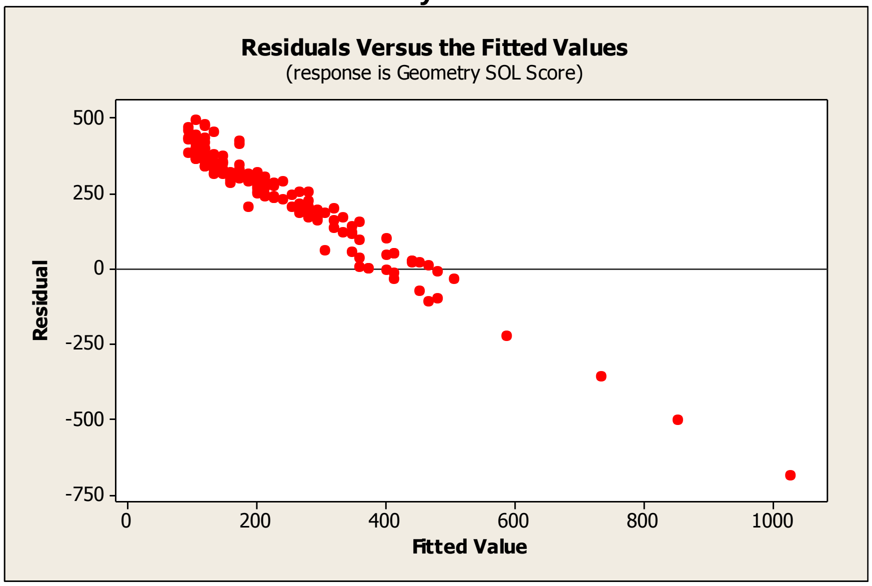
```
Weighted analysis using weights in 1/S_G_c


The regression equation is
Geometry SOL Score = 1428 - 13.3 Geometry In Class


134 cases used, 5 cases contain missing values
                          or had zero weight


Predictor               Coef  SE Coef       T      P
Constant             1427.71    65.67   21.74  0.000
Geometry In Class   -13.3307   0.8322  -16.02  0.000


S = 0.454887   R-Sq = 66.0%   R-Sq(adj) = 65.8%


Analysis of Variance

Source           DF      SS      MS       F      P
Regression        1  53.091  53.091  256.58  0.000
Residual Error  132  27.314   0.207
  Lack of Fit    26  26.585   1.022  148.68  0.000
  Pure Error    106   0.729   0.007
Total           133  80.405


Unusual Observations

               Geometry
     Geometry       SOL
Obs  In Class     Score      Fit  SE Fit  Residual  St Resid
 12        74   464.000  441.236   4.135    22.764      3.39RX
 13        74   466.000  441.236   4.135    24.764      3.69RX
 14        74   458.000  441.236   4.135    16.764      2.50RX
 22        79   375.000  374.582   0.641     0.418      0.65 X
 23        79   373.000  374.582   0.641    -1.582     -2.45RX
```

```
 92         95   478.000  161.290  13.406   316.710      3.63R
 93         95   455.000  161.290  13.406   293.710      3.36R
 94         95   463.000  161.290  13.406   301.710      3.45R
 95         95   445.000  161.290  13.406   283.710      3.25R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.


Lack of fit test
Possible curvature in variable Geometry  (P-Value = 0.000 )

Possible lack of fit at outer X-values (P-Value = 0.000)
Overall lack of fit test is significant at P = 0.000
```

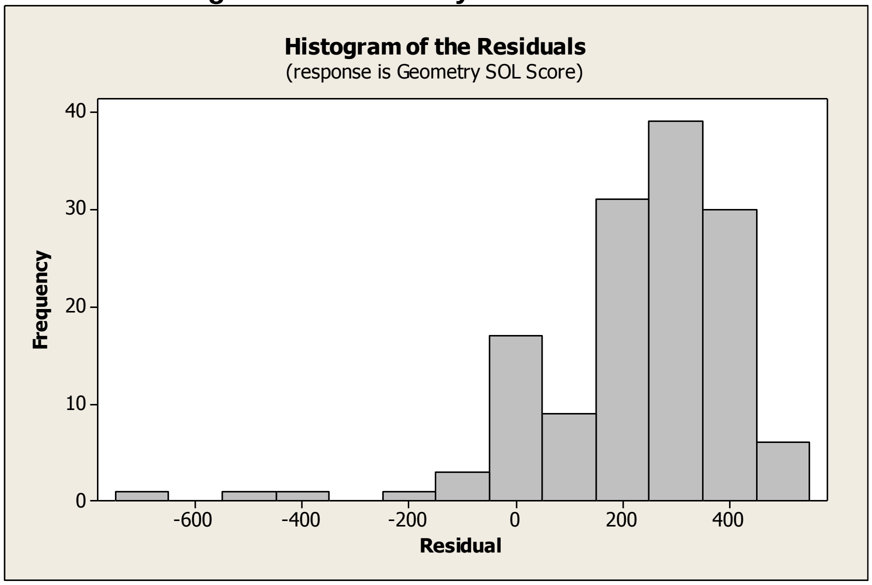
Normplot of Residuals for Geometry SOL Score



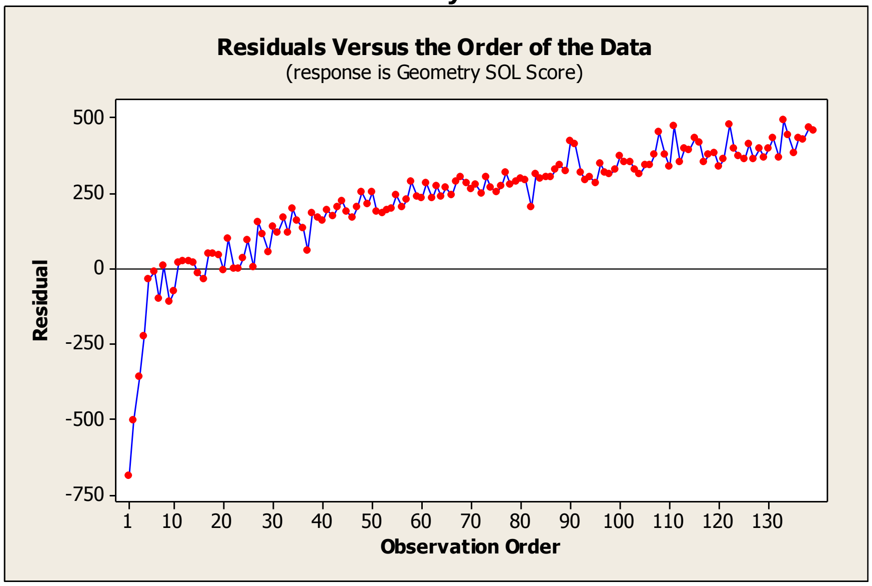
Residuals vs Fits for Geometry SOL Score



Residual Histogram for Geometry SOL Score



Residuals vs Order for Geometry SOL Score




```
MTB > Fitline 'Geometry SOL Score' 'Geometry In Class';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Geometry SOL Score versus Geometry In Class

```
The regression equation is
Geometry SOL Score = 302.5 + 0.63 Geometry In Class
                     + 0.0152 Geometry In Class**2
                     - 0.000006 Geometry In Class**3


S = 39.1138   R-Sq = 40.7%   R-Sq(adj) = 39.3%
```

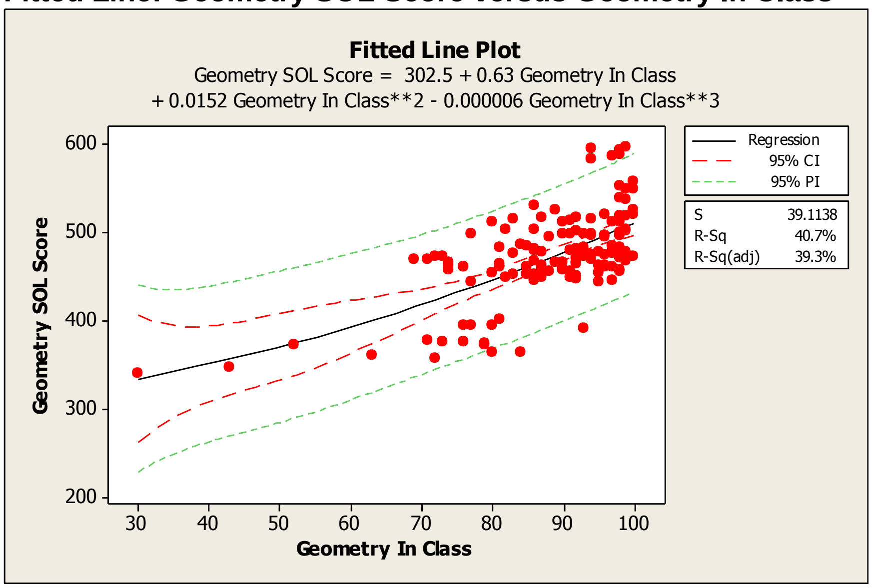
Analysis of Variance

Source	DF	SS	MS	F	P
Regression	3	141505	47168.2	30.83	0.000
Error	135	206535	1529.9		
Total	138	348039			

Sequential Analysis of Variance

Source	DF	SS	F	P
Linear	1	139732	91.90	0.000
Quadratic	1	1772	1.17	0.282
Cubic	1	0	0.00	0.994

Fitted Line: Geometry SOL Score versus Geometry In Class




```
MTB > Describe  'Geometry SOL Score';
SUBC>   By  'Geom Letter Grade';
SUBC>   Mean;
SUBC>   SEMean;
SUBC>   StDeviation;
SUBC>   Variance;
SUBC>   CVariation;
SUBC>   QOne;
SUBC>   Median;
SUBC>   QThree;
SUBC>   Minimum;
SUBC>   Maximum;
SUBC>   N;
SUBC>   NMissing.
```

Descriptive Statistics: Geometry SOL Score

Variable	Geom Letter Grade	N	N*	Mean	SE Mean	StDev	Variance	CoefVar
Geometry SOL Sco	0	5	0	379.0	23.7	52.9	2798.5	13.96

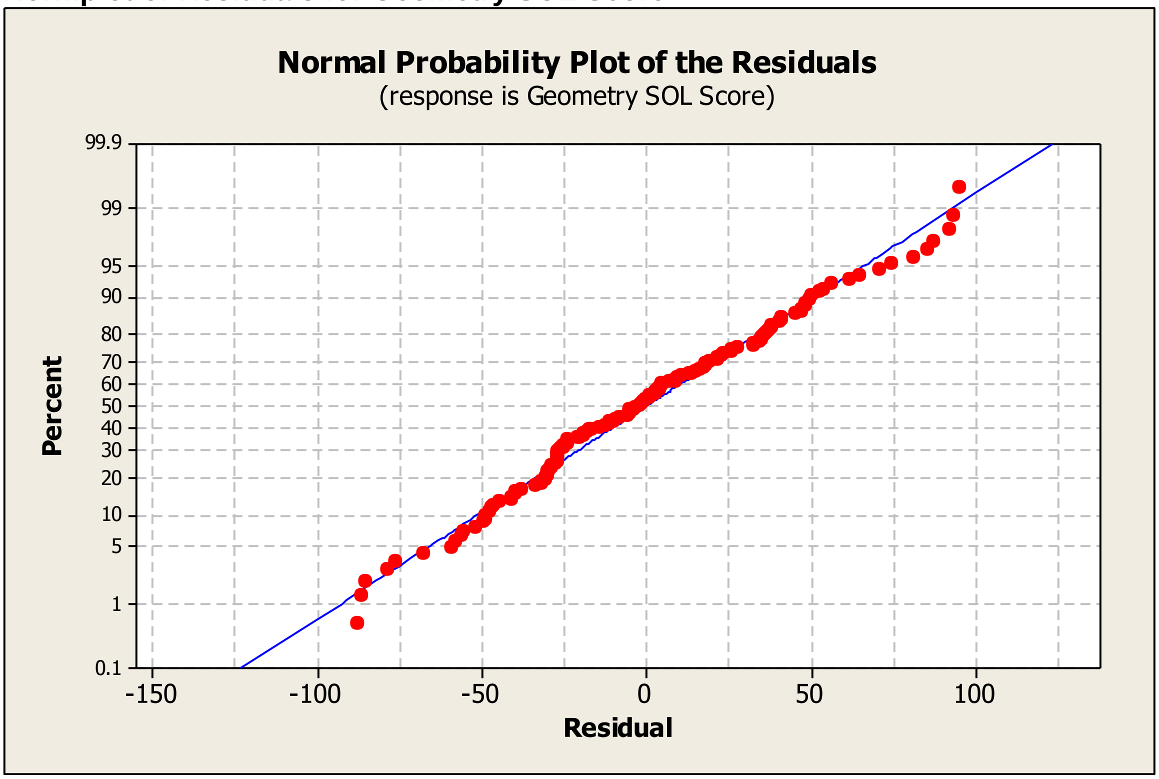
```
                 1       16   0   434.8     11.4   45.6    2077.1    10.48
                 2       20   0   447.2     11.2   50.1    2507.3    11.20
                 3       42   0  476.62     4.15  26.93    725.07     5.65
                 4       56   0  503.52     5.56  41.61   1731.60     8.26

                 Geom
                 Letter
Variable         Grade   Minimum      Q1  Median      Q3  Maximum
Geometry SOL Sco 0         341.0   344.5   362.0   422.0    471.0
                 1         358.0   383.3   459.5   469.8    500.0
                 2         364.0   397.5   458.0   485.5    516.0
                 3        392.00  457.75  475.00  499.00   531.00
                 4        445.00  472.50  497.00  521.00   598.00

MTB > Let '1/S_G_g' = 1/('VARSG_g'*'VARSG_g')
MTB > Regress 'Geometry SOL Score' 1  'Geom Letter Grade';
SUBC>   Weights '1/S_G_g';
SUBC>   GHistogram;
SUBC>   GNormalplot;
SUBC>   GFits;
SUBC>   GOrder;
SUBC>   NoDGraphs;
SUBC>   RType 1;
SUBC>   Constant;
SUBC>   Pure;
SUBC>   XLOF;
SUBC>   Brief 2.
```

Regression Analysis: Geometry SOL Score versus Geom Letter Grade

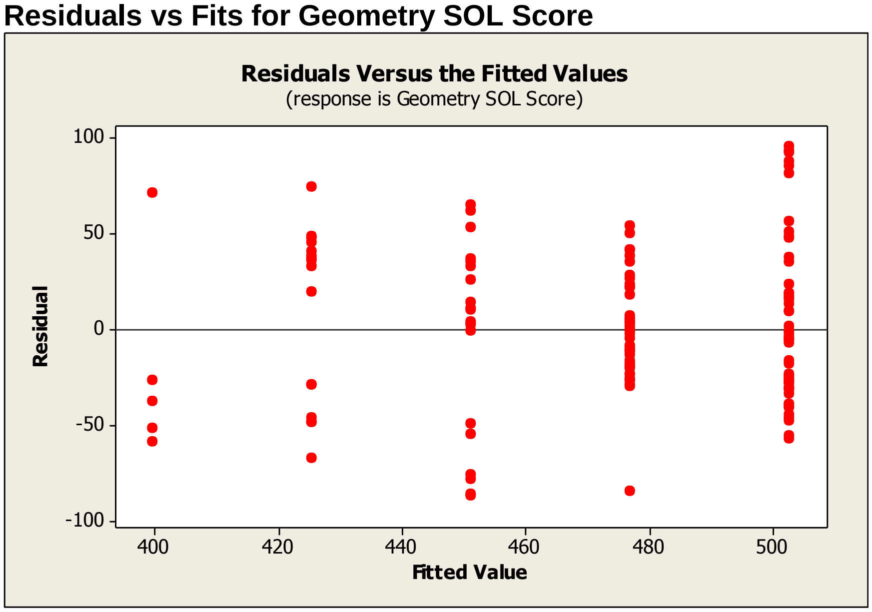
```
Weighted analysis using weights in 1/S_G_g


The regression equation is
Geometry SOL Score = 400 + 25.7 Geom Letter Grade


Predictor            Coef  SE Coef      T      P
Constant           399.78    13.34  29.97  0.000
Geom Letter Grade  25.715    4.272   6.02  0.000


S = 0.0277120   R-Sq = 20.9%   R-Sq(adj) = 20.3%


Analysis of Variance

Source           DF        SS        MS      F      P
Regression        1  0.027825  0.027825  36.23  0.000
Residual Error  137  0.105210  0.000768
  Lack of Fit     3  0.000672  0.000224   0.29  0.835
  Pure Error    134  0.104538  0.000780
Total           138  0.133035


Unusual Observations

       Geom  Geometry
     Letter       SOL
Obs   Grade     Score      Fit  SE Fit  Residual  St Resid
 48    3.00   531.000  476.928   2.702    54.072     2.72R
 50    3.00   518.000  476.928   2.702    41.072     2.06R
 58    3.00   527.000  476.928   2.702    50.072     2.51R
```

```
 77     3.00    518.000  476.928    2.702     41.072       2.06R
 82     3.00    392.000  476.928    2.702    -84.928      -4.27R

R denotes an observation with a large standardized residual.

No evidence of lack of fit (P >= 0.1).
```

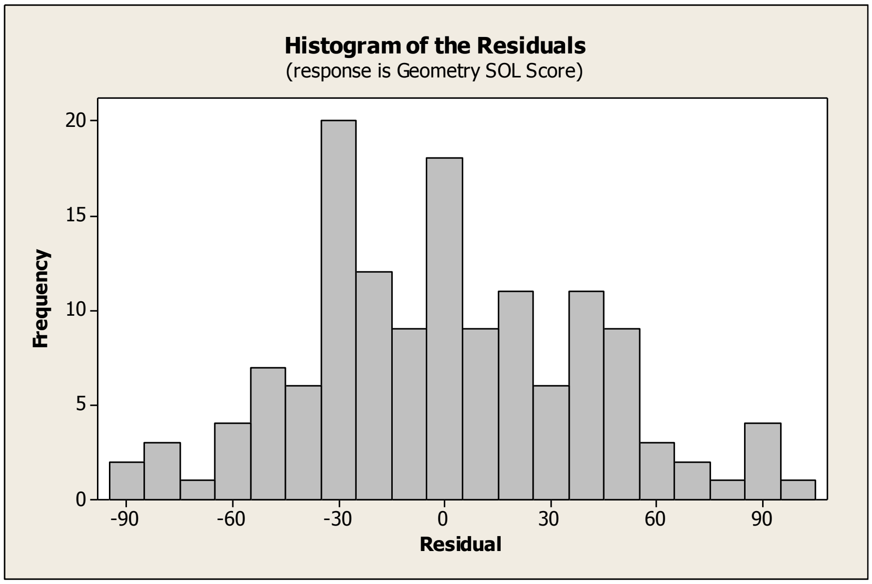
Normplot of Residuals for Geometry SOL Score



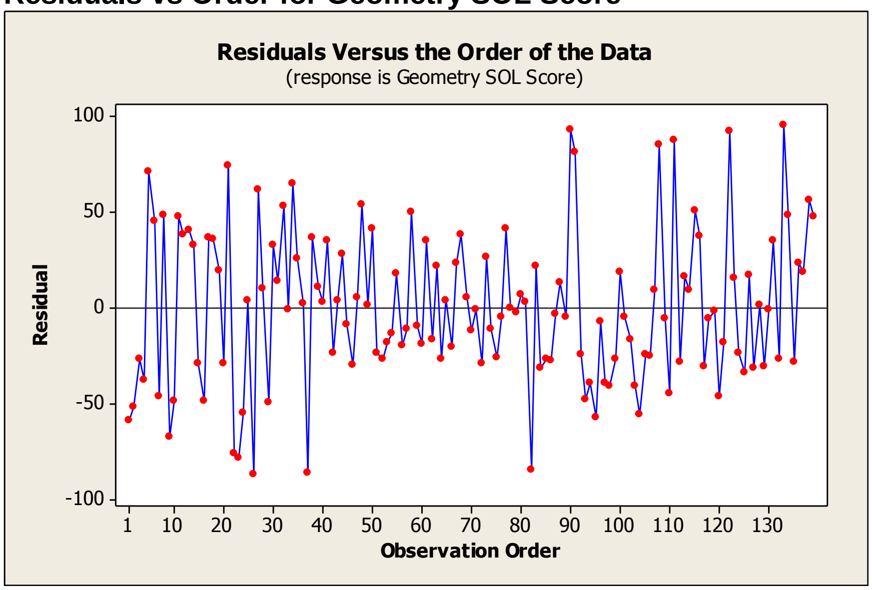
Residuals vs Fits for Geometry SOL Score



Residual Histogram for Geometry SOL Score



Residuals vs Order for Geometry SOL Score



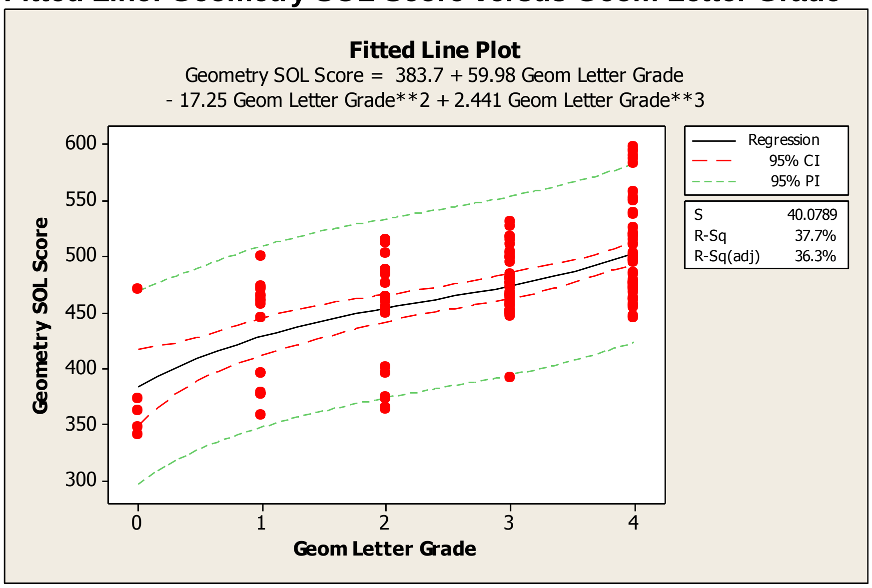

```
MTB > Fitline 'Geometry SOL Score' 'Geom Letter Grade';
SUBC>   Poly 3;
SUBC>   Confidence 95.0;
SUBC>   Ci;
SUBC>   Pi.
```

Polynomial Regression Analysis: Geometry SOL Score versus Geom Letter Grade

```
The regression equation is
Geometry SOL Score = 383.7 + 59.98 Geom Letter Grade
                     - 17.25 Geom Letter Grade**2 + 2.441 Geom Letter Grade**3


S = 40.0789   R-Sq = 37.7%   R-Sq(adj) = 36.3%


Analysis of Variance
```

```
Source        DF      SS       MS      F      P
Regression     3  131187  43729.0  27.22  0.000
Error        135  216852   1606.3
Total        138  348039


Sequential Analysis of Variance

Source      DF      SS      F      P
Linear       1  129272  80.95  0.000
Quadratic    1     171   0.11  0.745
Cubic        1    1744   1.09  0.299
```

Fitted Line: Geometry SOL Score versus Geom Letter Grade



VITA

RANDETTA L. FULLER

Personal Data:	Date of Birth: April 6, 1985 Place of Birth: Lebanon, Virginia
Education:	Southwest Virginia Community College, Richlands, Virginia; Associates in Applied Mathematics 2005
	Radford University, Radford, Virginia; Bachelor of Science in Applied Mathematics 2007
	East Tennessee State University, Johnson City, Tennessee Masters of Science in Mathematics Sciences 2010
Professional Experience:	Student Aide through Southwest Virginia Community College Teachers Aide, Honaker Elementary, Honaker, Virginia 2003
	Graduate Assistant East Tennessee State University, Johnson City, Tennessee 2007-2009