

# 1600 to 2400 and back: Examining *College Board's* SAT redesign

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## Introduction

The SAT – scholastic assessment test – is a standardized exam offered by the *College Board* – a private, non-profit organization in the United States. Notorious among high school upperclassmen and ubiquitous among college admissions committees, the SAT is considered one of the many hurdles a high school student must clear before applying to colleges. Split into three sections – Math, Critical Reading, and Writing – the SAT claims to assess a student's readiness for college and quantify said readiness on a 2400-point scale (where each individual section is scored out of 800 points).

Despite its commitment to providing a fair exam for all students, the SAT has endured numerous criticisms regarding its academic fairness and contributing to the achievement gap between the rich – who can afford private tutors and preparation resources – and the poor. In 2015 – due largely to criticisms that pointed to the SAT's academic irrelevance in a modern academic landscape – the *College Board* finally dropped behind the ACT with regards to the number of test-takers. In response, the *College Board* has announced that the Writing section is now optional, and as such they will restore a 1600-point “total score”. While the *College Board* has given their own public reasons for dropping the Writing section – including its poor representation of academic proficiency – it might be expected that an exam with two sections devoted to the humanities (Writing, Critical Reading) cannot equally compare a strong humanities student with a strong mathematically-minded student. Therein lies our question: **Are students who are naturally more adept at mathematics at a disadvantage in relation to students who are adept within the humanities?**

## Problem

With two sections pertaining to material that is overwhelmingly considered to be within the same field – English and the humanities – it is evident that a student would strive to maximize their SAT score by favoring the material tested within the Writing and Critical Reading sections. Our assertion, then, is that the separate Critical Reading and Writing sections on the SAT result in

similar scores that do not accurately represent individual reading and writing comprehension skills, and instead serve as a detriment to the standardized exam. This problem is important due to the SAT's omnipresence within numerous dimensions of the socio-educational system and ability to influence social progress: if rich students can afford tutors and improve a single "major" skill (English language skills), they are able to more efficiently game the SAT's weaknesses and further contribute to the national achievement gap.

## Model Definition

We can assert that the SAT was unable to **independently** test writing and critical reading skills if for any Critical Reading score we can closely approximate a Writing score. Therefore, we represent our assertion through a simple linear regression model:

$$\text{Average writing score} = \beta_0 + \beta_1 \times \text{Average critical reading score} + \text{random error}$$

Furthermore, we note that since the appropriateness of our assertion's model follows a  $\beta_0 = 0$  and  $\beta_1 = 1$  – where there is no significant  $\beta_0$  due to our desire to express average writing score as a function of average critical reading score – we can simplify our model such that average critical reading and average writing scores are consistent with one another:

$$\text{Average writing score} = \text{Average critical reading score} + \text{random error}$$

## Data Sourcing and Cleaning

I sourced my data by using NYC's new data initiative, NYC Open Data, which allowed me to access datasets pertaining to different public sectors – including education – who have released license-free data to the public. My dataset ([data.cityofnewyork.us/Education/SAT-Results/f9bf-2cp4/](https://data.cityofnewyork.us/Education/SAT-Results/f9bf-2cp4/)) reported 2012 SAT scores broken down by the scores pertaining to the critical reading, mathematics, and writing sections. Each observation was a high school, with the reported scores resulting from the mean SAT scores from all 2012 college-bound seniors at that particular high school. The NYC Open Data portal provides a simple "Export" to CSV, and so obtaining the data was straightforward.

## Variables

For each observation, the CSV contained six features: school code, school name, number of SAT test takers, critical reading average, math average, and writing average scores (averaged across the  $n$  number of SAT test takers at that particular school). Note that this analysis does not weigh a school more favorably for having more test-taking students or having higher average scores per

section, since there are factors unrelated to this analysis that may be influencing the number of seniors that take the SAT at any particular school or influence how well they perform (systemic social, financial, and educational accessibility deficiencies being particularly notable).

## Regression Validation

Before approaching a dataset with the mindset of performing a linear regression, it was necessary to validate that the conditions for performing a regression analysis of our data was an appropriate route.

1.  $E(\epsilon_i) = 0 \forall i$ : Although our dataset does sample from numerous different high schools where different socioeconomic influences may be impacting the results returned from each high school, we are interested in the intra-observational relationship between critical reading and writing. In other words, we do not care to compare two schools from completely different socioeconomic backgrounds — rather, we wish to compare a school's average critical reading score to its own average writing score.
2.  $V(\epsilon_i) = 0 \forall i$ : We note that the homoscedasticity within this dataset is referring to the equal playing field for all high school students to achieve a possible 800/800 on any particular section of the SAT. It is **not** the case that the (critical reading)/(writing) relationship is stronger for some schools than for others.
3.  $\epsilon_i$  and  $\epsilon_j$  are not correlated with each other for  $i \neq j$ : This is fundamentally assured due to the randomness of our dataset: it would be impossible to assert that knowing observation 283's expected value will tell us anything about observation 284's (or 285's, 286's, etc.) expected value. The only such case where knowing observation  $i$ 's expected value would be able to tell us anything about observation  $j$ 's expected value would be if the same set of seniors that were counted in observation  $i$ 's expected value were counted towards observation  $j$ 's expected value. No expected values within our dataset are correlated because it would not be possible for (a senior/group of seniors) enrolled into the school on observation  $i$  to also be enrolled into the school on observation  $j$ . Therefore, there cannot be a correlation between expected values when  $i \neq j$ .
4.  $\epsilon_i \sim N(0, \sigma^2)$ : Given that our data contains a large number of observations with scores ranging across the score spectrum and an evident clustering of scores towards the mean, we can assume that our data represents a normal distribution.

Because we can show that these assumptions hold, we know that least squares regression is the proper regression to use.

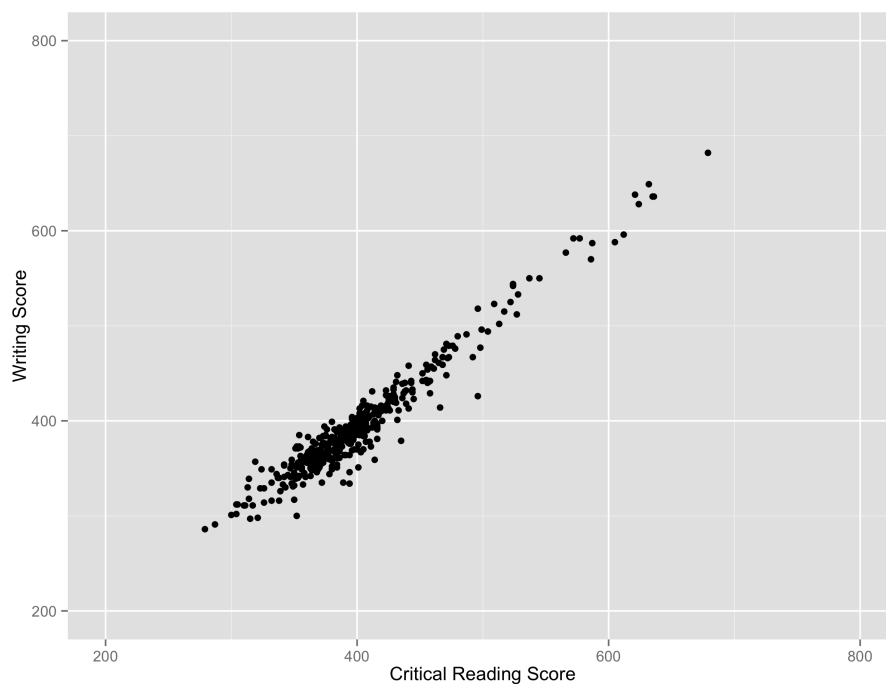
## Data Validation

Upon obtaining the data, I noticed that high schools that were not able to report more than 5 seniors' scores had their entire observation suppressed, leaving the "s" character in place of each of their features. This required a line of code within my R script in order to filter out rows where the number of test takers was equal to the string "s". Furthermore, the SAT section scores were encoded as character strings, and so my R script also converted each feature into its numerical value.

## Exploratory Data Analysis

First, let's take a quick look at our data through a scatterplot:

Figure 1: Scatterplot of our high schools' reported scores



At first glance, there seems to be a very strong linear relationship between average critical reading score and average writing score. We also note that, while most datapoints are centered at the 350 ~ 450 point range (with a thorough range of scores – ranging from high 200s to low 600s), we have a particularly notable outlier whose averaged scores are at the 680 range while its position is still aligned with our regression line. After utilizing R's *identify* function, we discover that this school is actually *Stuyvesant High School*, an extremely competitive and well-performing public high school in New York City.

Moving on, we perform a least squares regression with average writing score as our dependent (target) variable, and average critical reading score as our independent (predicting) variable:

Residuals:

```

+-----+-----+-----+-----+-----+
|  Min   |  1Q   | Median |  3Q   |  Max   |
+-----+-----+-----+-----+-----+
| -63.292 | -7.206 | 0.851  | 8.866  | 44.999  |
+-----+-----+-----+-----+-----+

```

Coefficients:

```

+-----+-----+-----+-----+-----+
| Estimate Std. | Error | t value | Pr(>|t|) |
+-----+-----+-----+-----+-----+
| (Intercept) | -7.52321 | 4.93528 | -1.524 | 0.128 . |
+-----+-----+-----+-----+-----+
| CR_Score | 1.00164 | 0.01219 | 82.166 | <2e-16 *** |
+-----+-----+-----+-----+-----+

```

```

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

Residual standard error: 14.19 on 419 degrees of freedom

Multiple R-squared: 0.9416, Adjusted R-squared: 0.9414

F-statistic: 6751 on 1 and 419 DF, p-value: < 2.2e-16

We observe that, in accordance with R's summary, our regression equation becomes:

$$\text{Average writing score} = -7.52321 + 1.00164 \times \text{Average critical reading score}$$

We note that our regression is very strong, with an  $R^2$  of 94.16%, an adjusted  $R^2$  of 94.14%, and a very significant F-statistic of 6751. We also note that the intercept coefficient ( $\beta_0$ ) is not relevant to our findings, because by default the SAT is structured such that the lowest score you can obtain on any section is 200. Our slope coefficient ( $\beta_1$ ), however, signifies that a one point increase in mean critical reading score is associated with an estimated expected 1.00164 point increase in our mean writing score.

## Testing the Null Hypothesis

Our t-statistic given in the output for our linear regression's output in `CR_Score` examines the null hypothesis of  $\beta_1 = 0$ , which is strongly rejected. Despite the strong rejection of the null hypothesis, we can clearly observe a relationship between our critical reading scores and writing scores. That said, if we refer back to our original assertion, it states that our model would support a  $\beta_1 = 1$ . Furthermore, our original assertion states that  $\beta_0 = 0$  because of our interest in whether average critical reading scores can directly – and independently – predict average writing scores.

Furthermore, the t-statistic for our average writing score can be calculated manually (assuming our model corresponds to a  $\beta_1 = 1$ ):

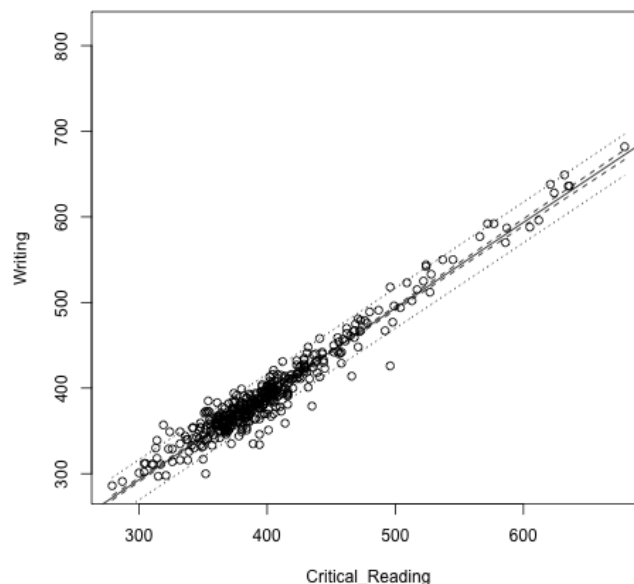
$$t = \frac{1.00164 - 1}{14.19} \approx 0.0001$$

Factoring in our reported standard error of the estimate of 3.76 allows us to observe that this model shows signs of extreme relevance, providing a prediction of writing score to within  $\pm 7.52$  points approximately 95% of the time.

## Confidence and Prediction Intervals

We can observe our 95% confidence and prediction intervals on a scatterplot:

Figure 2: 95% confidence and prediction intervals for our regression model, plotted.



We notice that our confidence interval (short, dashed lines) is nearly overlapping our regression

line while our prediction interval (pointwise lines) has a much wider margin in relation to our regression line and confidence interval, simply due to the prediction interval's incorporation of our writing score's variability (whereas our confidence interval does not).

## Interpreting Unusual Data

Figure 2 also highlights a number of points within the dataset that fall far outside of the 95% prediction interval – one of the most notable being “GED PLUS s CITYWIDE”, a GED program whose college-bound students averaged a 496 on the critical reading section and a 426 on the writing section. A potential explanation for this deviation from the regression line – aside from the educational impact of GED students often having to balance work and GED fulfillment classes – is that only 8 seniors had their grades averaged, and so using the mean of 8 data points may be a misleading measurement of central tendency due to the sparse data. We can further observe any unusual data points through diagnostic plots, which can tell us more about whether our assumptions of least squares regressions hold for this particular data. The following plots represent our data's residuals and our residual values versus fitted values:

Figure 3: A normality plot with a significant amount of low outliers, potentially indicating right skewness within the dataset

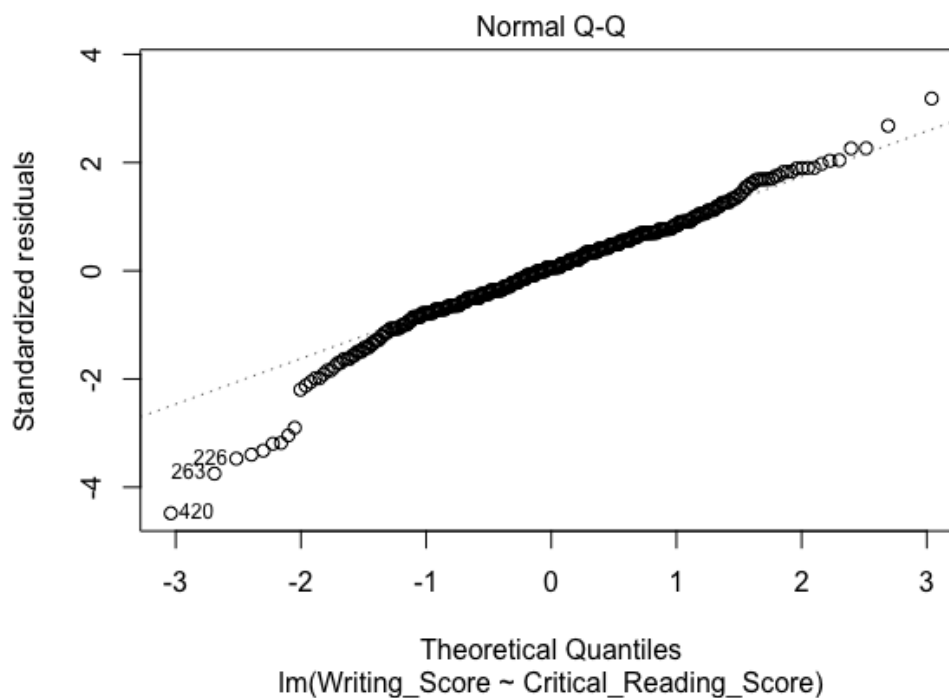
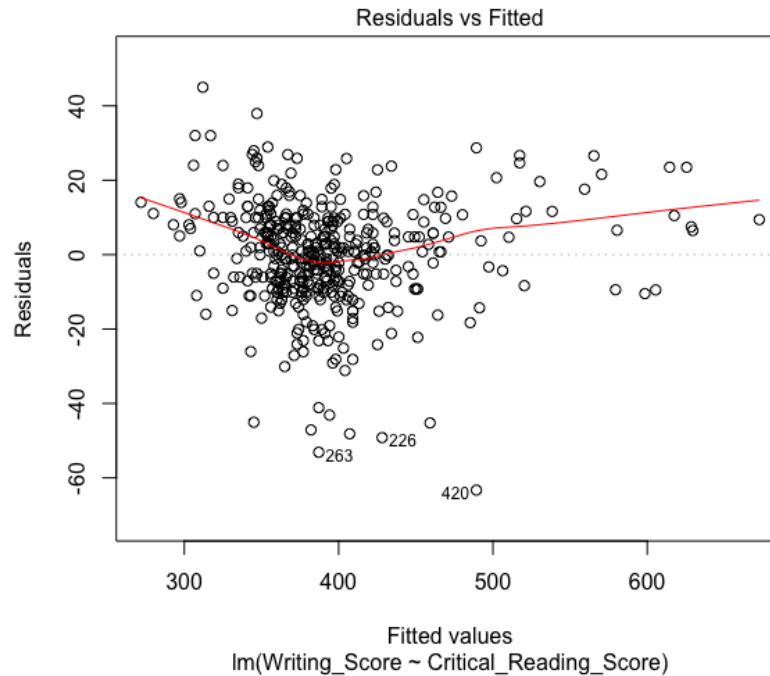


Figure 4: A residuals vs fitted plot where we can see a rough horizontal band around the 0 line, if not a partial positive skew



Through our plots, we note that observations 226, 263, and 420 are particularly unusual. Whereas observations 226 (“Bronx Aerospace High School”) and 263 (“Juan Morel Campos Secondary School”) did not show outstanding residual values – with Bronx Aerospace scoring 388 and 382 while Juan Morel scoring 365 and 369 on critical reading and writing scores, respectively – observation 420 (“Queens Satellite High School for Opportunity”) reported an average score of 403 on critical reading and 367 on writing.

One can speculate – given the lack of documented history – regarding “Queens Satellite High School for Opportunity” that the exceptional residual can be traced back to the dataset’s method of aggregating scores: the mean. By its design, the mean of any dataset can provide a useful statistic for measuring central tendency, however, one main disadvantage is that the mean is particularly susceptible to the influence of outliers. Given that the school just barely met the criteria for not suppressing their score – with 6 high school seniors representing the high school – if would be possible for one or more of the seniors to perform exceptionally poorly on the writing section while performing at the average, expected level for the critical reading section (given the SATs history with complaints regarding its writing section’s scoring criteria, this seems more likely than the case where the seniors did poorly on the critical reading section). These below-expected scores can dramatically shift our mean, and as such will influence our regression model by contributing a notable lower outlier to our data set.



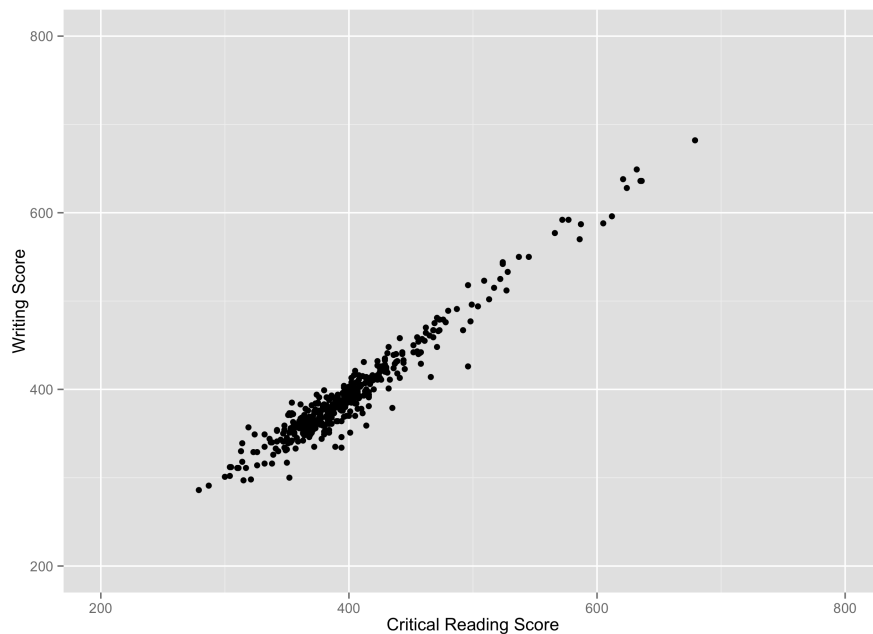
## Outlier Omission

### Omitting $o_1$

In order to understand the effect of including the outlier “Queens Satellite High School for Opportunity” in our regression, we will examine our regression model after removing the outlier. In order to omit this particular school, I modified my R script such that our dataframe `df` was assigned the rows of `df` where the `SCHOOL.NAME` field was not equal to “QUEENS SATELLITE HIGH SCHOOL FOR OPPORTUNITY”.

The scatterplot, without our outlier, is as follows:

Figure 5: Scatterplot of our high schools’ reported scores, one outlier removed ( $o_1$ )



We still note a few unusual points (including “GED PLUS s CITYWIDE”) as marginally unusual. Looking to R’s regression output:

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Residuals:

```
+-----+-----+-----+-----+-----+
|  Min  |  1Q  | Median |  3Q  |  Max  |
+-----+-----+-----+-----+-----+
| -63.366 | -7.240 | 0.784 | 8.797 | 44.934 |
+-----+-----+-----+-----+-----+
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-7.47240	4.91626	-1.52	0.129 .
CR_Score	1.00169	0.01214	82.49	<2e-16 ***

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

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Residual standard error: 14.14 on 418 degrees of freedom

Multiple R-squared: 0.9421, Adjusted R-squared: 0.942

F-statistic: 6804 on 1 and 418 DF, p-value: < 2.2e-16

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$$\text{Average writing score} = -7.4724 + 1.00169 \times \text{Average critical reading score}$$

While the regression relationship is still very strong, our  $\beta_1$  coefficient is almost insignificantly farther away from our hypothesized value of  $\beta_1 = 1$ . Looking to our prediction/confidence and diagnostic plots, we note that our confidence interval is still missing a few egregious data points, especially the observation "GED PLUS s CITYWIDE":

Figure 6: Confidence and prediction interval plot for our regression model with a removed lower outlier ( $o_1$ )

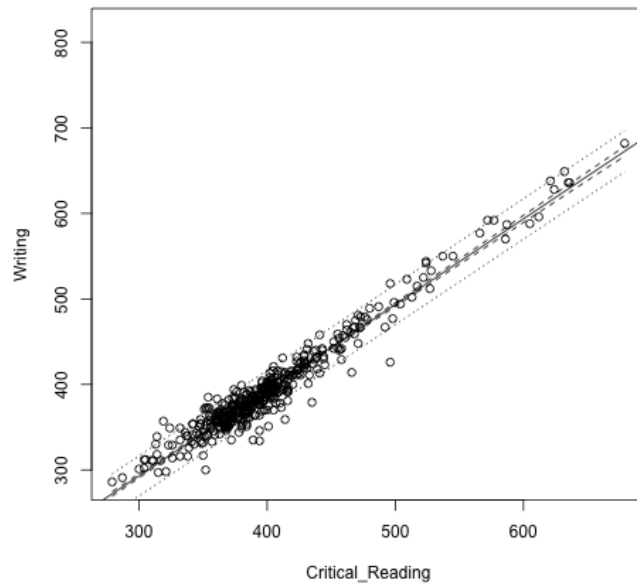


Figure 7: Normality plot with a removed lower outlier ( $o_1$ )

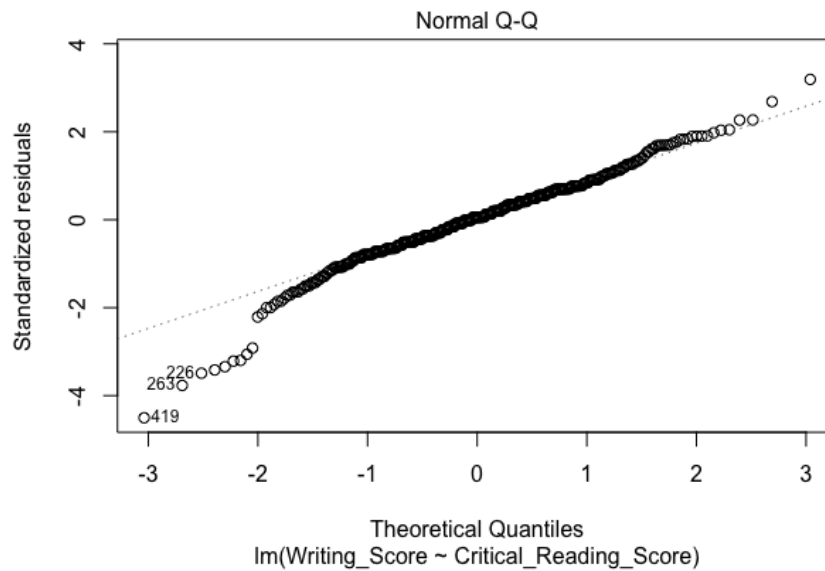
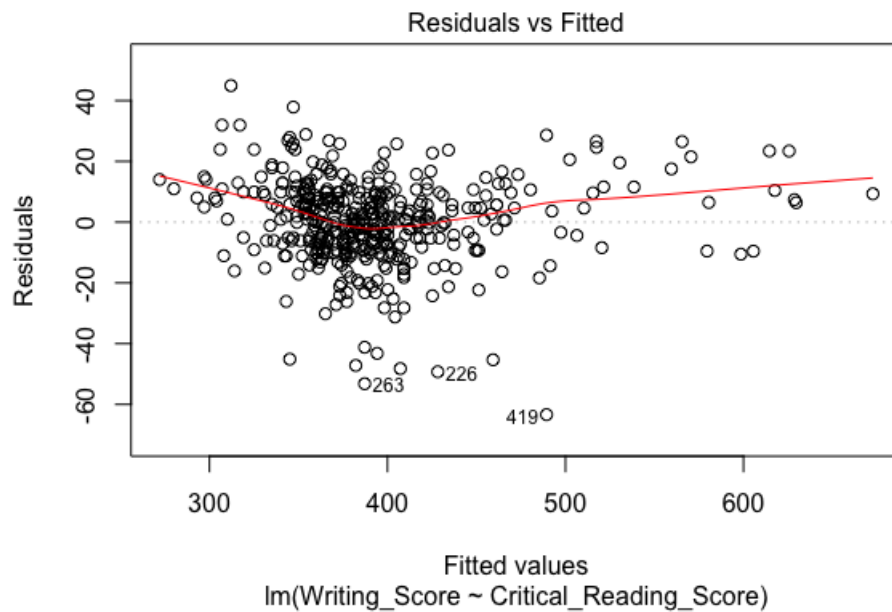


Figure 8: Residuals vs fitted plot with a removed lower outlier ( $o_1$ )

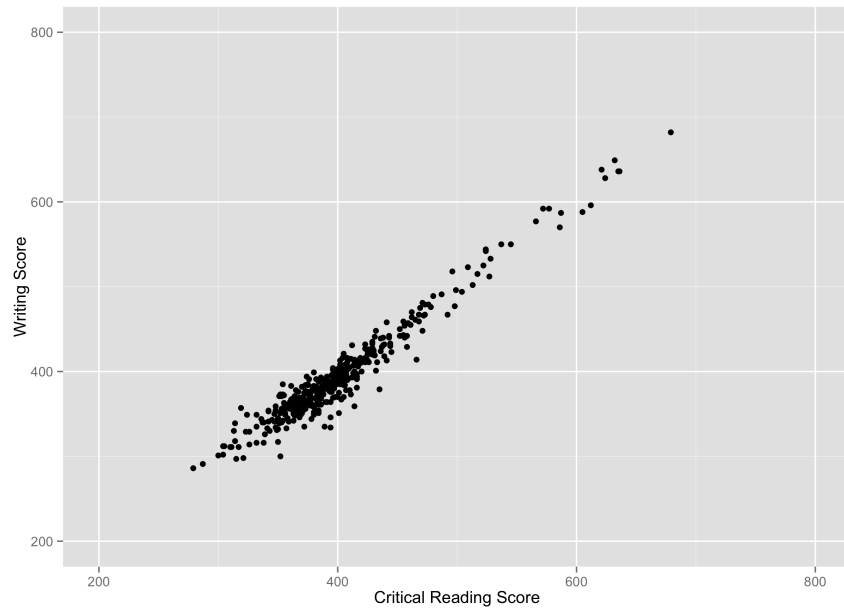


### Omitting $o_2$

Unfortunately, we can still observe outliers – particularly within our prediction and confidence interval plot. What if were to re-add our previous outlier and instead remove the “GED PLUS s CITYWIDE” outlier from our regression? In order to omit this particular school, I modified my R script such that our dataframe `df` was assigned the rows of `df` where the `SCHOOL.NAME` field was not equal to “GED PLUS s CITYWIDE”.

Here’s the scatterplot:

Figure 9: Scatterplot of our reported scores, second outlier ( $o_2$ ) removed, first outlier ( $o_1$ ) intact



And summary statistics from our regression:

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Residuals:

Min	1Q	Median	3Q	Max
-53.245	-7.414	0.672	8.704	45.214

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-9.16912	4.83471	-1.897	0.0586 .
CR_Score	1.00613	0.01195	84.200	<2e-16 ***

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

Residual standard error: 13.86 on 418 degrees of freedom  
Multiple R-squared: 0.9443, Adjusted R-squared: 0.9442  
F-statistic: 7090 on 1 and 418 DF, p-value: < 2.2e-16

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$$\text{Average writing score} = -9.16912 + 1.00613 \times \text{Average critical reading score}$$

We notice that removing “GED PLUS s CITYWIDE” had a more dramatic effect than removing “Queens Satellite High School for Opportunity”, but our omission actually brings our  $\beta_1$  away from its ideal value of 1 moreso than omitting “Queens Satellite High School for Opportunity” did. Thus, we note that the strength of the relationship between average writing score and average critical reading score has weakened. Let’s look at the 95% confidence/prediction interval plots and the diagnostic plots:

Figure 10: Confidence and prediction interval plot for our regression model with a removed lower outlier ( $o_2$ ); previous outlier ( $o_1$ ) intact

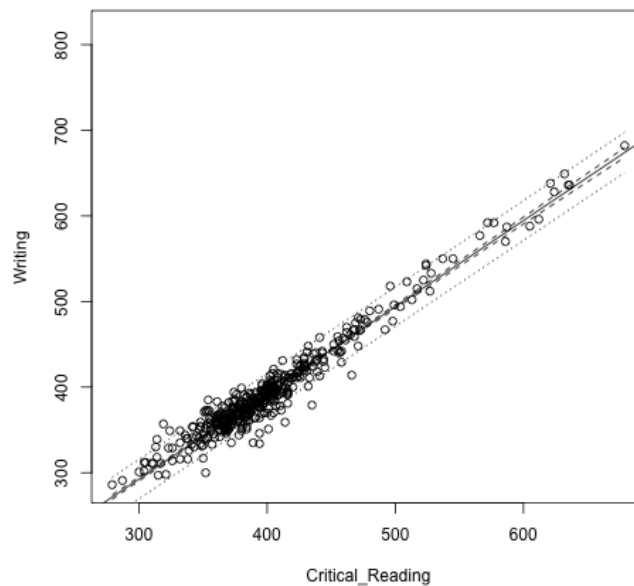


Figure 11: Normality plot with a removed lower outlier ( $o_2$ ); previous outlier ( $o_1$ ) intact

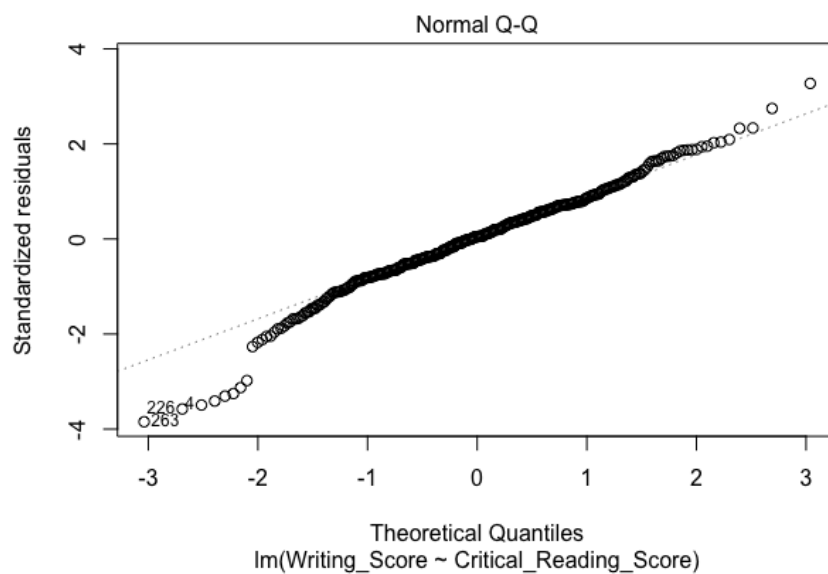
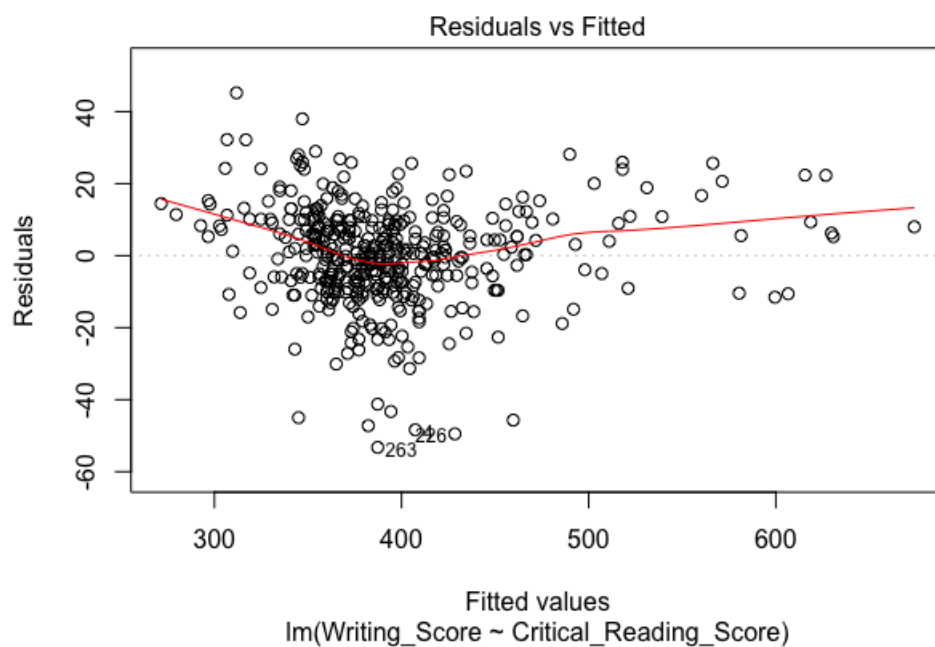


Figure 12: Residuals vs fitted plot with a removed lower outlier ( $o_2$ ); previous outlier ( $o_1$ ) intact



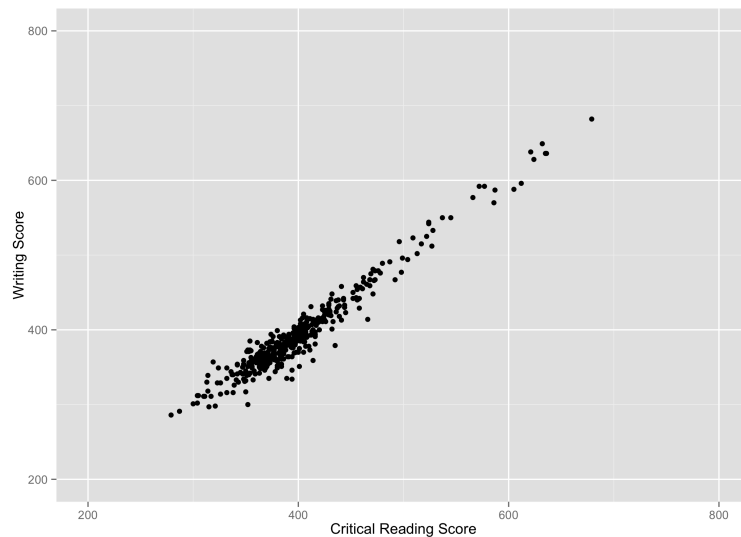
Given  $o_2$ 's more drastic influence upon our dataset, we arrive at the question: what happens to our linear regression if we remove both notable outliers?

## Omitting $o_1$ and $o_2$

Lastly, we're curious in what will happen to our regression line when we omit both outliers. In order to omit both observations, I modified my R script such that both previous one-line modifications were applied onto my dataframe `df`.

Ideally, the omission of both outliers would provide a  $\beta_1$  coefficient that is closer to our ideal value of 1, and so we first look at our general scatterplot:

Figure 13: Scatterplot of our reported scores both outliers ( $o_1, o_2$ ) removed



Followed by R's summary statistics:

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Residuals:

```
+-----+-----+-----+-----+-----+
|  Min  |  1Q  | Median |  3Q  |  Max  |
+-----+-----+-----+-----+-----+
| -53.315 | -7.417 | 0.611  | 8.639 | 45.149 |
+-----+-----+-----+-----+-----+
```



Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-9.1200	4.8146	-1.894	0.0589 .
CR_Score	1.0062	0.0119	84.558	<2e-16 ***

---

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

---

Residual standard error: 13.81 on 417 degrees of freedom

Multiple R-squared: 0.9449, Adjusted R-squared: 0.9448

F-statistic: 7150 on 1 and 417 DF, p-value: < 2.2e-16

The summary of our linear regression results in the following regression equation:

$$\text{Average writing score} = -9.1200 + 1.0062 \times \text{Average critical reading score}$$

We note a strong  $R^2$  of 94.49%, adjusted  $R^2$  of 94.48%, and very significant F-statistic of 7150. As usual, our  $\beta_0$  does not hold much significance to our regression model due to the minimum score on each section being a 200. Our slope coefficient ( $\beta_1$ ), however, implies that a one point increase in mean critical reading score is associated with an estimated expected 1.0062 point increase in our mean writing score.

Lastly, let's take a look at our prediction/confidence interval and diagnostic plots:

Figure 14: Fitted line plot of our reported scores where both outliers ( $o_1, o_2$ ) have been removed

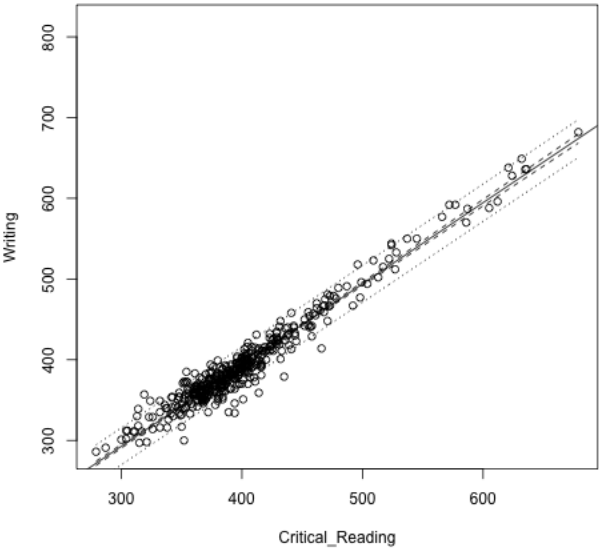


Figure 15: Scatterplot of our reported scores both outliers ( $o_1, o_2$ ) removed

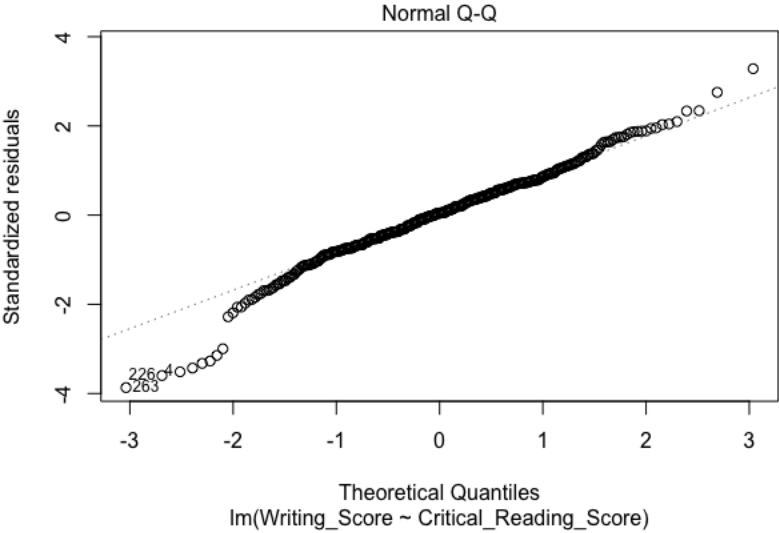
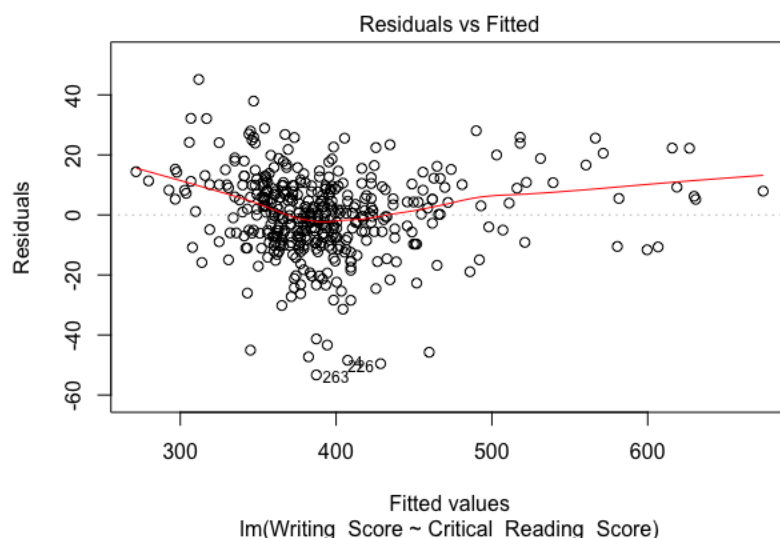


Figure 16: Scatterplot of our residuals vs our fitted line plot where both outliers ( $o_1, o_2$ ) are removed



We note that the confidence interval is narrower than in previous iterations, mostly due to the removal of two of the dataset's outliers. The Q-Q plot is much closer to showing an ideal distribution, with a slightly persistent left skew. Lastly, our plot of fitted values with regards to residuals is getting closer and closer to having the slope center around 0. Our dataset contained a reasonable number of observations, although due to our particular analysis of the data – our decision to base our writing score model around our critical reading score – there aren't too many more paths to follow with regards to analyzing this dataset.

## Summary

There seems to be a strong case in support of my assertion that the *College Board* unfairly weighs the humanities on the SAT. Despite removing two outstanding outliers, our final regression model is incredibly close to our ideal model. With regards to our real-world problem, we can safely say that the SAT should restructure their exam in order to ensure an equal weighing of sections with respect to the other sections.

Understanding the weaknesses of a nationally-recognized standardized exam is vital to test-takers, educators, and the broader educational community. Should the *College Board* consider redesigning their SAT exam, it would be sensible to consider adopting a subject structure that is more varied – like the ACT's, whose four test sections (Science, Mathematics, English, Reading) not only span a wider variety of topics, but are also committed to evaluating a student equally between the more numerical/analytical and creative/humanities sections.

Despite our model's relative simplicity, I do feel that a simple linear regression model that utilizes critical reading score is more representative of an SAT test taker's performance on the writing section than a more involved, complex linear regression model that includes the mathematics section and other auxiliary features. Ideally, our results would have been more transparent if the dataset did not contain the averaged score of all college-bound seniors per observation – rather, if each row contained a college-bound senior's scores, I strongly believe our data would have avoided any influences stemming from the mean. Furthermore, it would have been more ideal if our dataset had scores distributed across the past few years in order to be sure that the 2012 SAT exam was not just an anomaly within the history of SAT exams but that also would have proven much more difficult for a simple linear regression.

From this analysis, I've learned both peripheral skills and more directly-applied skills. Peripherally, the data collection and exploration phases of the analysis were useful in building data extraction and interpretation skills. While validating and cleaning my data in R, however, I gained more directly-applied skills with regards to programming, file I/O, and data visualization. During the data analysis and statistical reporting phase, there were instances where I was unsure as to how I should have approached this problem and, on numerous occasions, I considered restarting my analysis with a modified regression model or different dataset altogether. Ultimately, I learned more about statistical reporting and the data modeling/analysis process (going from question → data → model → analysis → results).

## Resources

All files pertaining to this statistical report, including the R data analysis script, dataset, plots, and this PDF write-up are open to the public and hosted on GitHub ([github.com/dannyfig/multivariate/problem\\_set\\_1](https://github.com/dannyfig/multivariate/problem_set_1)).

## Data

Below is a slice of the 2012 SAT Result dataset I utilized for this statistical analysis. Note that some high school names were truncated in order to fit on the page. Furthermore, some feature names were shortened in order to fit — originally, the feature names were: DBN, SCHOOL NAME, Num of SAT Test Takers, SAT Critical Reading Avg., Score SAT Math Avg. Score, SAT Writing Avg. Score.

DBN	SCHOOL NAME	# of test takers	Critical Reading	Math	Writing
01M292	HENRY STREET SCHOOL FOR ...	29	355	404	363
01M448	UNIVERSITY NEIGHBORHOOD ...	91	383	423	366
01M450	EAST SIDE COMMUNITY SCHOOL	70	377	402	370
01M458	FORSYTH SATELLITE ACADEMY	7	414	401	359
:	:	:	:	:	:
:	:	:	:	:	:
02M376	NYC ISCHOOL	92	473	483	479
02M392	MANHATTAN BUSINESS ACADEMY	s	s	s	s
02M393	BUSINESS OF SPORTS SCHOOL	s	s	s	s
02M394	EMMA LAZARUS HIGH SCHOOL	79	319	512	357
:	:	:	:	:	:
:	:	:	:	:	:
79M645	SCHOOL FOR COOPERATIVE ...	s	s	s	s
79Q950	GED PLUS s CITYWIDE	8	496	400	426
79X490	PHOENIX ACADEMY	9	367	370	360