



# Residual Analysis

#### To evaluate assumptions:

- Constant variance & uncorrelated errors
  - Response variable or fitted values vs residuals
- Linearity
  - Predicting variables vs residuals
- Normality
  - Histogram and QQ normal plot

#### To evaluate outliers:

· Cook's distance plots

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## Residual Analysis

```
## Residual analysis for the reduced model
```

```
res = stdres(reduced.line)

cook = cooks.distance(reduced.line)

par(mfrow = c(2,3))

plot(sat, res, xlab = "SAT Score", ylab = "Residuals", pch = 19)

abline(h = 0)

plot(takers, res, xlab = "Percent of Students Tested", ylab = "Residuals", pch = 19)

abline(h = 0)

plot(rank, res, xlab = "Median Class Ranking Percentile", ylab = "Residuals", pch = 19)

abline(h = 0)

hist(res, xlab = "Residuals", main = "Histogram of Residuals")

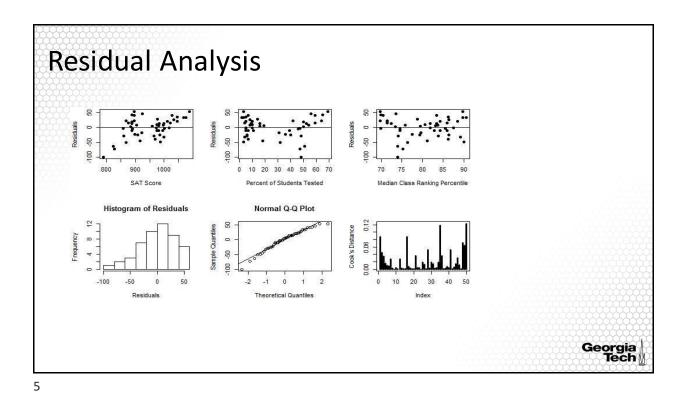
qqnrom(res)

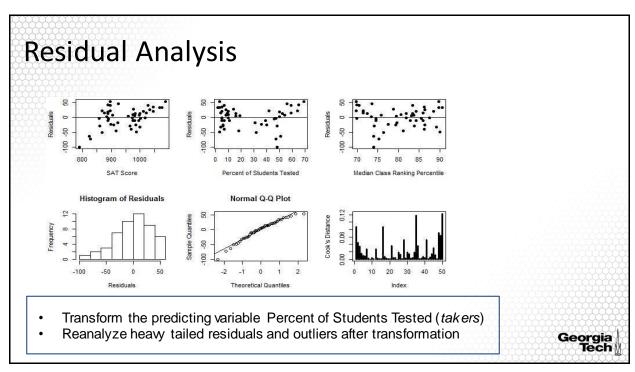
qqline(res)

plot(cook,type="h",lwd=3, ylab = "Cook's Distance")
```

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### Linear Regression Analysis in R

regression.line = Im(sat ~ log(takers)+rank+income+years+public+expend) summary(regression.line)

Estimate Std. Error t value Pr(>|t|)(Intercept) 407.53990 282.76325 1.441 0.15675 log(takers) -38.43758 15.95214 -2.410 0.02032 \* rank 4.11427 2.50166 1.645 0.10734 income -0.03588 0.13011 -0.276 0.78407 years 17.21811 6.32007 2.724 0.00928 \*\* public -0.11301 0.56239 -0.201 0.84168 2.56691 0.80641 3.183 0.00271 \*\* expend

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

Residual standard error: 24.86 on 43 degrees of freedom Multiple R-squared: 0.8919, Adjusted R-squared: 0.8769

F-statistic: 59.15 on 6 and 43 DF, p-value: < 2.2e-16

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Coefficients:

# Linear Regression Analysis in R

regression.line <- Im(sat ~ log(takers)+rank+income+years+public+expend) summary(regression.line)
Coefficients:

Estimate Std. Error t value (Intercept) 407.53990 282.76325 1.441 0.15675 log(takers) -38.43758 15.95214 -2.410 0.02032 \* rank 4.11427 2.50166 1.645 0.10734 income -0.03588 0.13011 -0.276 0.78407 17.21811 6.32007 2.724 0.00928 \*\* years public -0.11301 0.56239 -0.201 0.84168 3.183 0.00271 \*\* expend 2.56691 0.80641

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

Residual standard error: 24.86 on 43 degrees of freedom

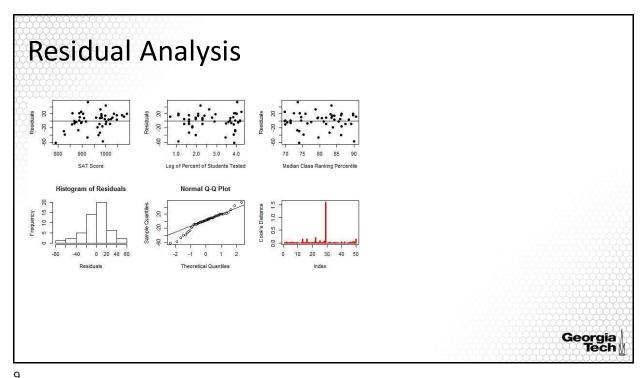
Multiple R-squared: 0.8919, Adjusted R-squared: 0.8769

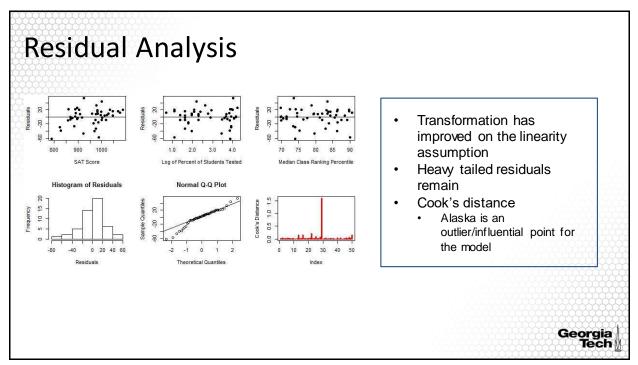
F-statistic: 59.15 on 6 and 43 DF, p-value: < 2.2e-16

Test for statistical significance:

 $\widehat{\sigma}$  = 24.86, df = *n*-*p*-1 = 43 R<sup>2</sup> ≈ 0.892 ⇒ 89.2% of variability explained

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## State SAT Performance: Findings

- Given all other predictors in the model:
  - Percent of students taking SAT from a public school and family income of test takers are not statistically significantly associated to SAT score
  - A \$100,000 increase in the expenditure on secondary schools results in a 2.56-point increase in the SAT score
  - One additional year that test takers had in social sciences, natural sciences, and humanities leads to a 17.2-point increase in the SAT score
- The predictors in the model explain close to 90% of the variability in SAT score
- We find that the relationship between state average SAT score and the percent of students taking SAT to be nonlinear
- Ranking changes after controlling for the bias selection factors
  - For example, Connecticut moves from 35<sup>th</sup> to 1<sup>st</sup>, Massachusetts from 41<sup>st</sup> to 4<sup>th</sup>, and New York from 36<sup>th</sup> to 5<sup>th</sup>

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# Summary



