Webwork Pattern Final Report

Summary

Webwork is an useful tool for instructors to assign homework to students. It allows students to have instant feedback on their answers and to help students improve their learning. The purpose for the clients' study is to find out if any pattern of webwork use like student submitting time can be found, and if certain patterns of usage are related to better outcomes such as higher homework and exam grades.

In this study, identifiable patterns of students' Webwork submissions are found and the early submission pattern is correlated to higher final grades. The students have been clustered into 3 different groups with similar patterns of homework submission by k-means clustering method. Also, the result of ANOVA test shows earlier homework submissions are associated with higher final grades.

Introduction

The Webwork homework is available to students for an assigned time period. In the assigned time period, students may submit their assignments early or late. Early submissions could be interpreted as students start early and have more time to digest the course material. Late submission could be interpreted as the opposite. Therefore, different homework submission time patterns may result in differences in understanding the course material.

In order to test the relationship between students' submission time patterns and their course understanding, two research questions need to be answered: 1) whether the submission time of students' Webwork homework attempts have noticeable patterns; 2) whether there is a relationship between these patterns of homework submission time and the students' final grades.

Data Description

There are two datasets, the raw and processed, collected from two second-year mechanical engineering courses in 2017. The processed data are regarded as a reference for the process and analysis of raw data. The raw dataset contains four data files: attempts, grades, homework, and problem attributes, for the two courses separately.

AttemptData shows a timestamped student submission to a specific question in a specific problem set. There is also a column indicating the correctness of that attempt. A zero score means the answer submitted is wrong and a one score means the answer is correct. It is assumed that no attempts of a specific question occur after students obtain the right answer.

Grades represents weighted average of quizzes and final exams for each student in the course, which make up 75% of the course marks.

HWDates includes open and end dates of each Webwork homework set and the number of problems in each set.

Problem Attributes represents the homework set that each problem is corresponding to and the maximum number of attempts for each problem. The maximum number of attempts is 1, 2, or -1 for all the problems. The -1 maximum number of attempts means that the problem has an unlimited number of attempts. All problems with limited (1 or 2) attempts are removed, as a pattern is not able to be drawn based on just a few tries.

In the processed dataset, there are also sorted data files, such as UA__NS__1_1. The UA__NS __1_1 data table gives us details about the total number of submissions for each student and the submission times in three different periods: first 24hrs, last 24hrs and other times. Using this table, we could easily generate a graph and analyze the pattern of the attempts number and the submission time period.

Analysis

This section discusses the statistical methods used and the analyses performed on the data.

Data Transformation

The submission time of every attempt is quantified and normalized to a numeric value in the range [0,1]. For example, suppose the open time of a Webwork homework set is 2019/05/01 00:00:00 and close time is 2019/05/08 00:00:00. One attempt is made at 2019/05/04 00:00:00. The numeric representation of the submission time is calculated by (submission time - open time)/(close time - open time) (in hours). Therefore, the submission time of this attempt is transformed to 3/7.

For the next step, each student's attempts are extracted by searching through the **AttemptData** file. One vector is created to store all the normalized submission time data of the attempts that one student made.

Webwork Attempt Distribution Function

In order to identify the webwork usage patterns, a distribution function of a student's overall Webwork attempts is created. Since most homework has different available days, the data are normalized and put in the range [0,1]. In the distribution function, the x-axis is the scaled time passed since the homework released, and the y-axis is the fraction of data points that has a value smaller than the corresponding value. For example, Figure 1 below shows a student's overall webwork attempt distribution function, the red dot here represents that 22% of this student's overall webwork attempts have been done within 50 % of the available time.

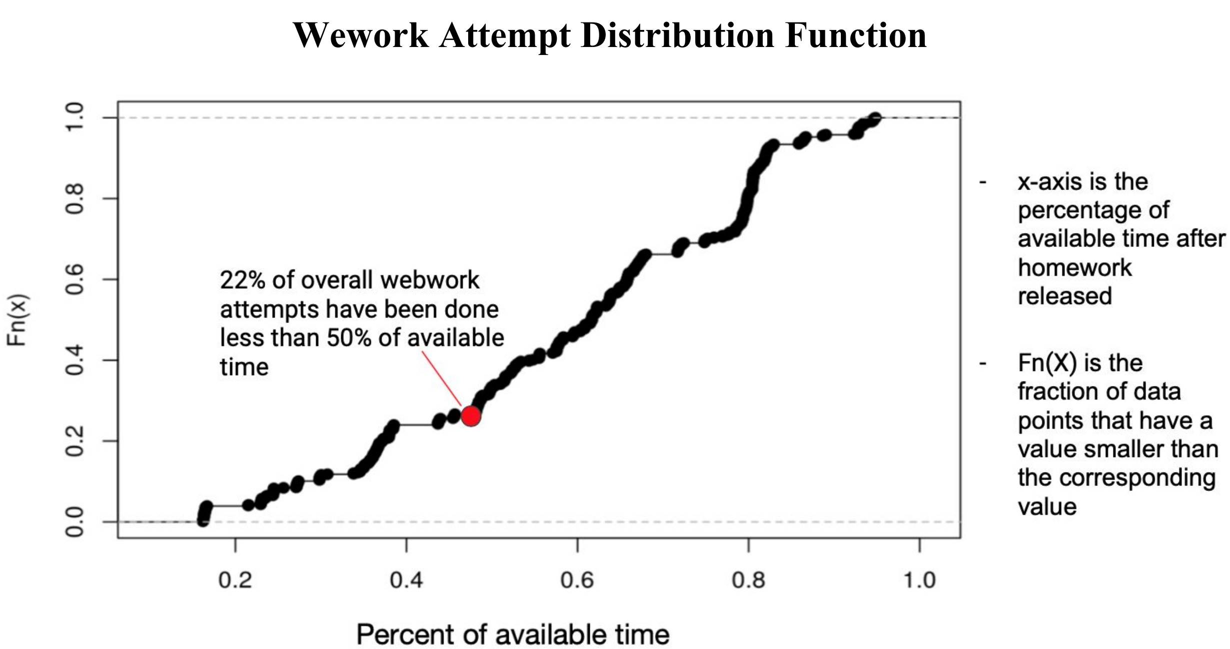

Figure 1. Webwork Attempt Distribution Function

Webwork Usage Patterns Vs Submission Time

Figure 2 below is the distribution functions for 20 students randomly picked from the whole population.The 25th,50th and 75th of students' final grades in Mech 221 are calculated, and those students are divided into 4 categories based on their final grades. For example, the red lines here show students who received final grades in the upper quartile and the green lines show students who received final grades in the lower quartile. From the graph, students who have higher final grades tend to start their homework earlier and students who have lower final grades tend to start their homework later than their peers.

Webwork Attempt Distribution Function for 20 Students from MECH221

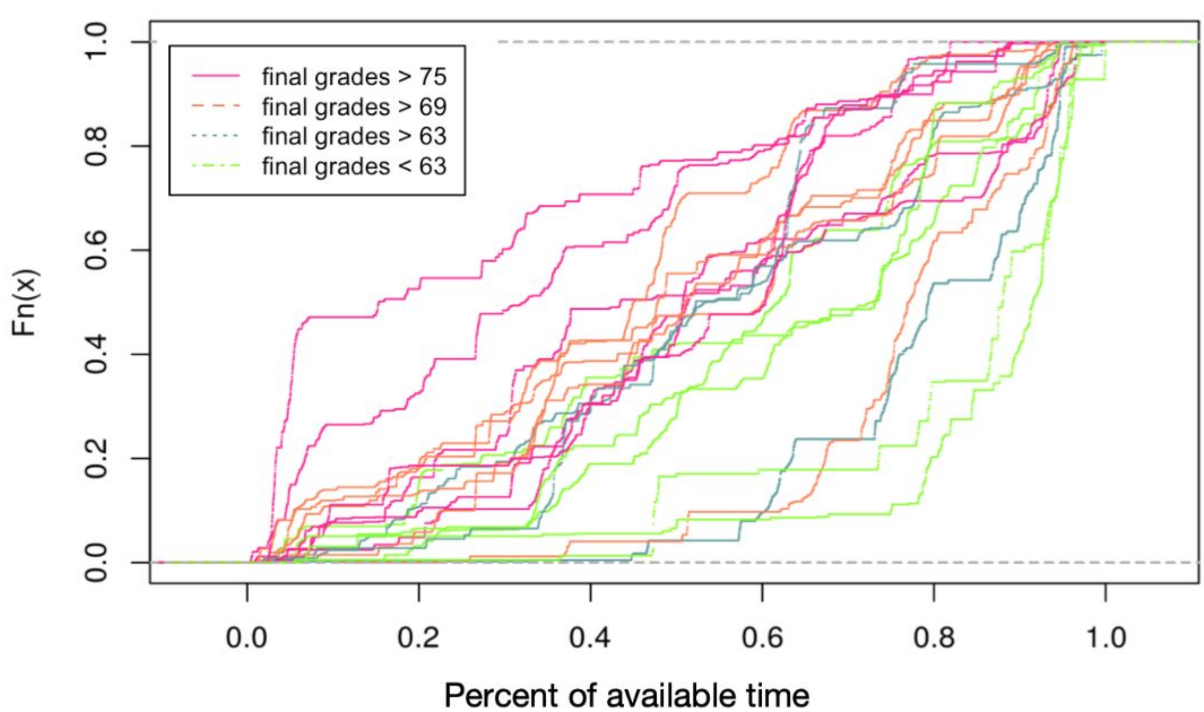

Figure 2. Webwork Usage Pattern for Mech 221 class

The same method is applied to Mech 222, with 20 students randomly picked from the cohort. The webwork usage pattern is very similar to the one for Mech 221. Figure 3 below shows students who have higher final grades tend to start their homework earlier and students who have lower final grades tend to start their homework later than their peers.

Webwork Attempt Distribution Function for 20 Students from MECH222

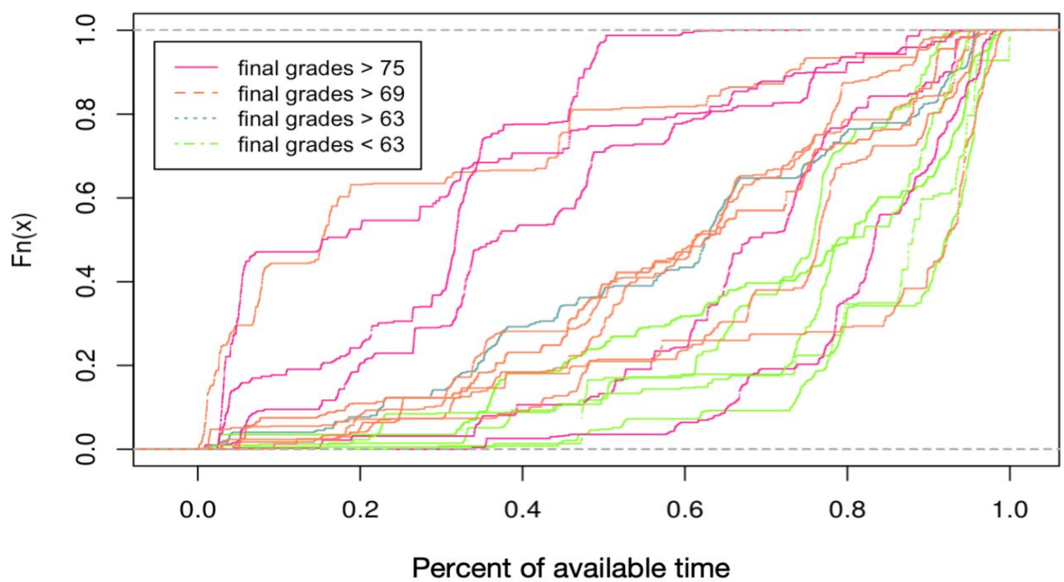

Figure 3. Webwork Usage Pattern for Mech 222 class

Clustering

The K-means algorithm is used for clustering. In K-means clustering, the numeric data matrix and the number of clusters need to be determined. The numeric data matrix includes samples and vectors of features for samples. For the sake of addressing students' submission time pattern hypothesis, "samples" refers to students and "features" refers to submission time. The number of clusters is set to be 3 according to the "elbow" method.

In order to have equal length vectors of features, the quantiles of the submission time vector, which is obtained from the previous data transformation process, is used as our features. There are two versions of clustering data matrix. For the actual clustering model, the data matrix contains 100 features, which are the 1 percent to the 100 percent quantile of the normalized submission time data vector. Precisely, each vector is divided into 100 percentiles, and the value at each percentile is a feature. For visualization purpose, the other version of data matrix has 2 features, which are the lower quartile and upper quartile of the normalized submission time vector.

Figure 4 below shows the visualization of clustering. Each data point that represents a student corresponds to two values, the lower quartile value and the upper quartile value. Each student belongs to one cluster. The green data points represent a cluster of students who have small lower and upper quartiles; the red data points represent a cluster of students who have large lower and upper quartiles; the blue data points represent a cluster of students who have lower and upper quartiles in-between.

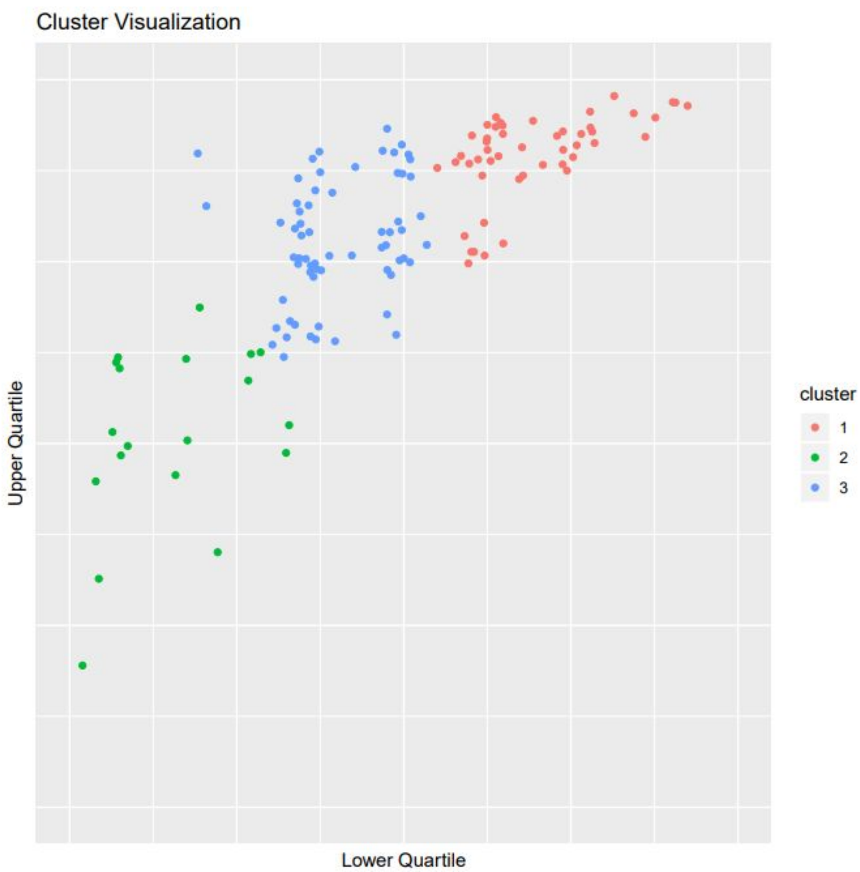

Figure 4. Scatter Plot of Clustering Consequence of Data Matrix with Two Features

Figure 5 below is the clusters selection method. The number of clusters selection is called k selection when clustering is introduced. This k selection is performed based on the 100-feature data matrix. In this figure, the independent variable is the number of clusters. The response variable is the residual of clustering, which is called within cluster sum of squares. Precisely, it is the sum of the squared distance from every point to its own cluster center.

For number of clusters selection, a reasonable k with acceptable clustering residual is necessary. According to the "elbow" method, the point that the increase of k will not result in large decrease of the residual should be selected. Therefore, the best cluster number k is selected to be 3 based on the data matrix.

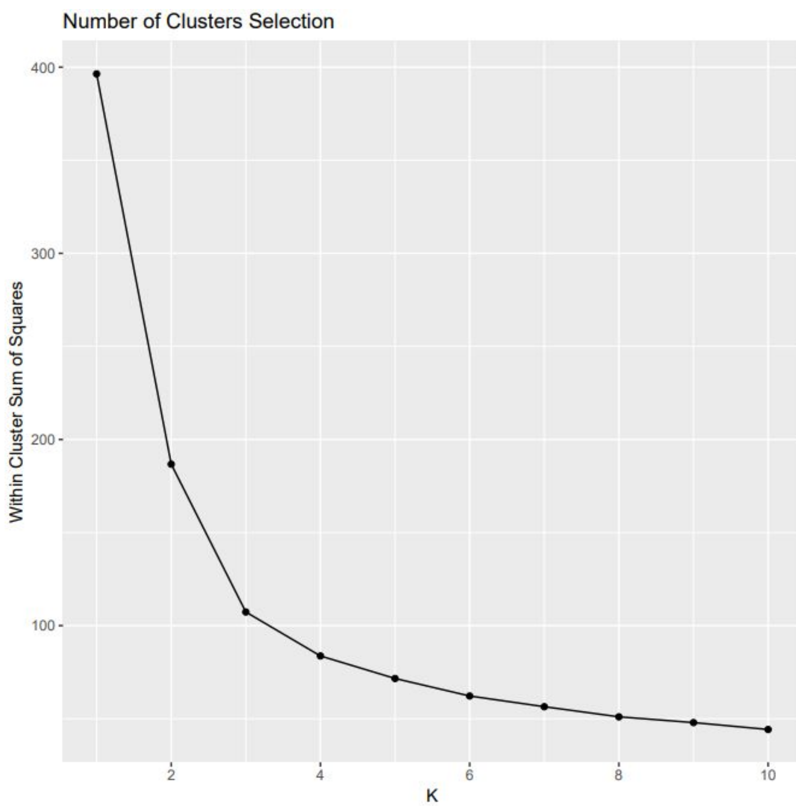

Figure 5. Line Graph of Number of Clusters versus Clustering Residual

ANOVA

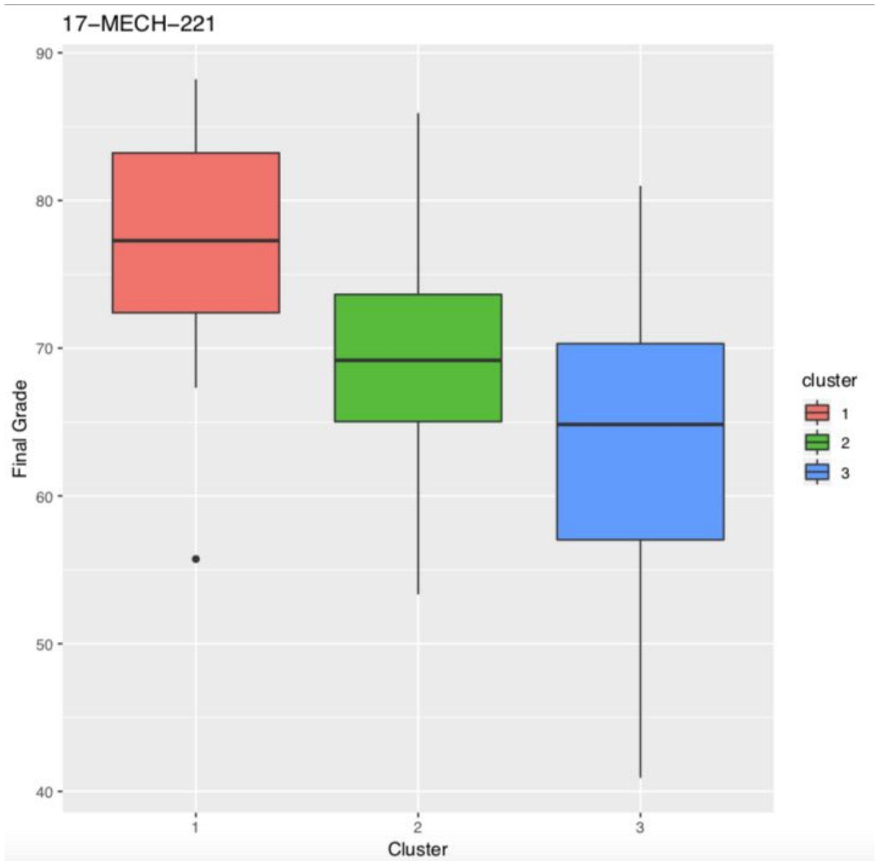

Figure 6. Boxplot of Final Grades versus Clusters for 17-MECH-221

Table 1. ANOVA table for 17-MECH-221

	Degrees of Freedom	Sum Square	Mean Square	F score	p-value
cluster	2	2690	1345.2	21.21	1.07e-08
Residuals	130	8246	63.4		

After determining the number of clusters, the box plot of final grades versus each clustering group can be drawn. It is clear to observe from Figure 6 that there may be much difference in the mean of final grades between the three clusters. The result of ANOVA test demonstrates an extremely small p-value of 1.07×10^{-8} indicating significant differences in final grades between students with different submission patterns.

The pattern of clusters can be recognized by calculating the mean of cluster submission time. The first cluster represents early submission pattern; similarly, the third cluster shows the late submission pattern. The second one is in-between. After comparing the clusters based on the final grades, statistically significant differences can be noticed in attempt patterns.

Table 2. ANOVA table for 17-MECH-222

	Degrees of Freedom	**Sum Square**	**Mean Square**	**F score**	**p-value**
cluster	2	1766	883	11.46	2.68e-05
Residuals	125	9628	77		

The same method is applied to the other course, MECH-222 and similar results are found. Table 2 shows that the p-value is 2.68×10^{-5}, indicating the same conclusion as that of MECH-221. Figure 7 below also shows a strong correlation between exam grades and patterns of online homework attempt, although the medium submission pattern suggests only limited disparity from the late one.

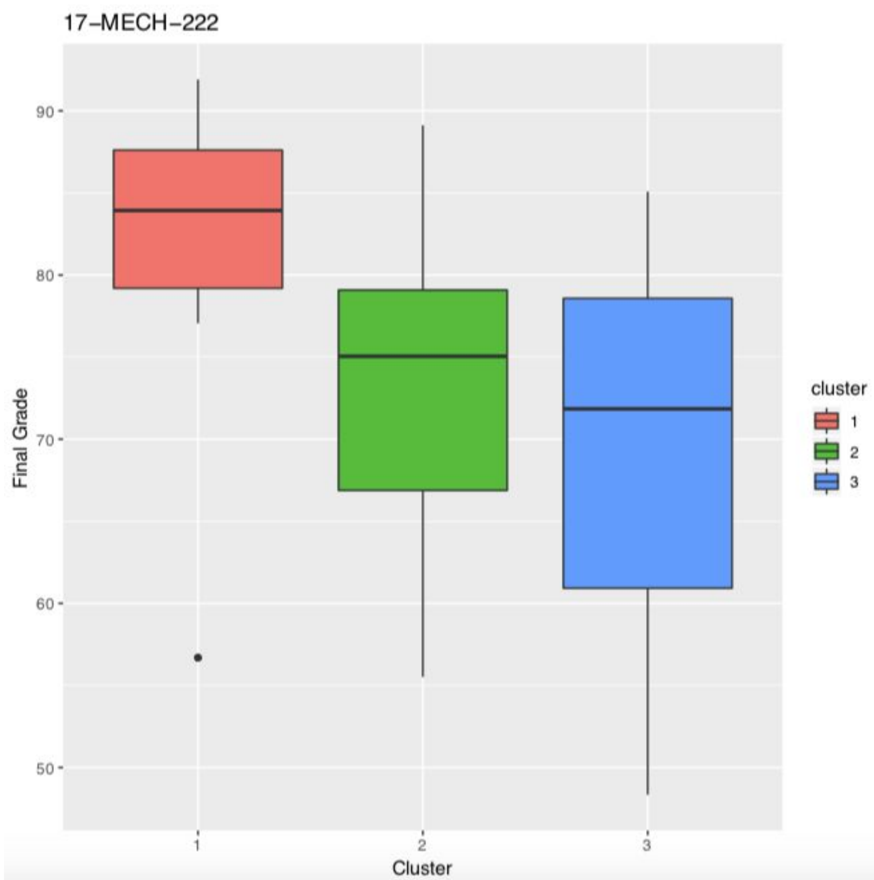

Figure 7. Boxplot of Final Grades versus Clusters for 17-MECH-222

Conclusions

Based on analysis, there are identifiable patterns of students' online homework attempts and the students can be clustered into three groups based on these patterns. From the result of Anova test, there is evidence to support the assumption that early homework usage behavior may be strongly correlated with higher final grades; late submission pattern may be associated with lower final grades.

Appendix

ANOVA Assumption Checks

Normality of the error term in this model is valid in our models. From Figure A 1.1, we can observe that the residuals of the fitted model do not show a pattern, which are randomly distributed and have constant variance. As all the points in the QQ-plot fall approximately along this reference line, we can assume normality of the error term in this model is valid in our models..

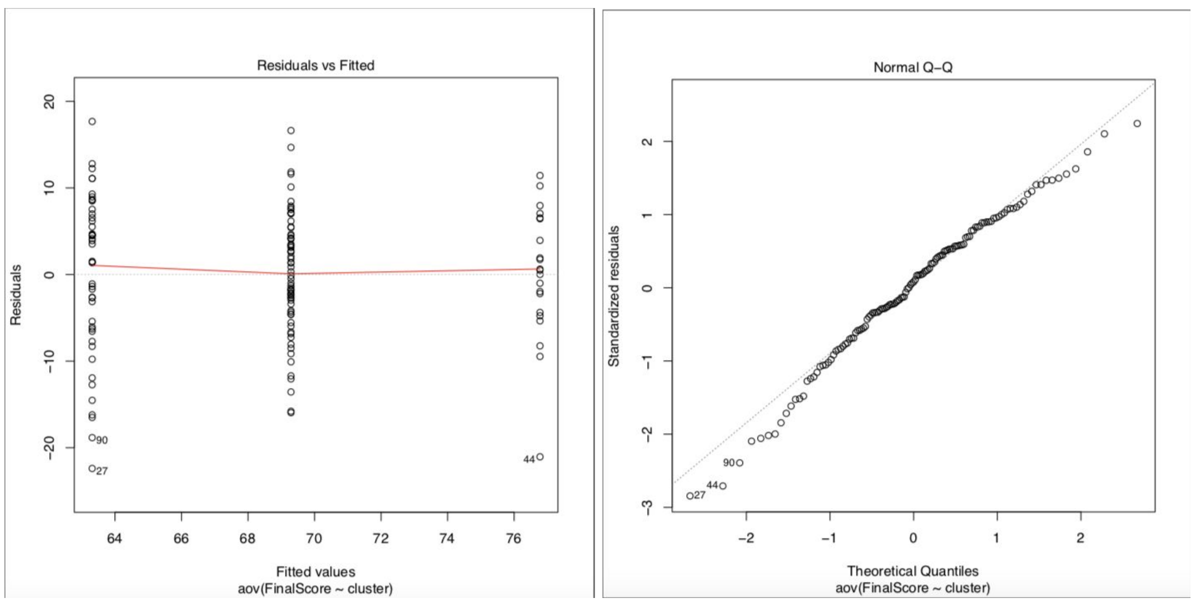

Figure A1. Residual vs Fitted plot and Q-Q plot of residuals against normal distribution.

Equal Variance Assumptions are checked by the Bartlett test as demonstrated below in Table 3. Since the p-value is not significant at the level of 5%, equal variance can be a validated assumption for the model.

Table 3. Bartlett Test of homogeneity of variances

K-squared	Degree of Freedom	p-value
5.1349	2	0.07673

For the fact that each student took their own individual final exams and the model is built by training every student in the course, independence is valid in this model.