Analysis of Student success and fairness in General Education Program for Undergraduates

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Abstract

Carnegie Mellon University's Dietrich College is interested in assessing student achievement and fairness in its new general education program. By using the data of 91 students' artifacts from freshmen statistics in 2019, this study aims to evaluate the achievement and the fairness of the program. From the histograms and summary statistics for the ratings of different rubrics and raters, it appeared that the rating distributions of different raters and rubrics are sometimes significantly different. Then, two approaches(intraclass correlation, proportions of agreements) were used to analyze the agreements of different raters for each rubric and found that the raters usually disagree with each other in three rubrics. Also, according to the results of the fitted linear mixed-effects models, we found that raters, semester, and rubrics could be significant variables influencing the ratings of each rubric. Further, by exploratory data analysis, a significant bias was found for different semesters within the rating processes.

1 Introduction

The success of students and the fairness of the ratings are always important topics for an education program. Now, Dietrich College at Carnegie Mellon University is currently establishing a new undergraduate "General Education" program. This program outlines a collection of courses and experiences that all students must take, and the institution hopes to grade student work in each of the "Gen Ed" courses each year to see whether the new program is a success or not. Recently, the college has been experimenting with rating work in Freshman Statistics, using raters from across the college. We want to know the students success and the fairness in this rating processes in Dietrich College at CMU. From the next section, we will answer the following four questions by statistical approaches. [1]

[1] The statistical methods in this paper were from [**?**].

1, **Rating Distributions under different raters and rubrics** Is the distribution of ratings for each rubrics pretty much indistinguishable from the other rubrics, or are there rubrics that tend to get especially high or low rating? Is the distribution of ratings given by each rater pretty much indistinguishable from the other raters, or are there raters that tend to give especially high or low ratings?

2, **The Agreement of Different Raters** For each rubric, do the raters generally agree on their scores? If not, is there one rater who disagrees with the others? Or do they all disagree?

3, **The Factors that Influencing the Rating** More generally, how are the various factors in this experiment (Rater, Semester, Sex, Repeated, Rubric) related to the ratings? Do the factors interact in any interesting ways?

4, **Rating Distributions under different gender and semesters** Is the distribution of ratings for each semester pretty much indistinguishable from the other semester, or are there semesters that tend to get especially high or low rating? Is the distribution of ratings given by each gender pretty much indistinguishable from another gender, or is there gender that tend to have especially high or low ratings?

2 Data

The dataset we are using for this study comes from an experiment conducted by Dietrich College at CMU. In this recent experiment, 91 project papers—referred to as "artifacts"—were randomly sampled from a Fall and Spring section of Freshman Statistics in 2019([**?**]). Three raters from three different departments were asked to rate these artifacts on seven rubrics, as shown in Table 1. The rating scale for the 7 rubrics is shown in Table 2. The raters did not know which class or which students produced the artifacts that they rated. Thirteen of the 91 artifacts were rated by all three raters; each of the remaining 78 artifacts were rated by only rater. The variables available for analysis are defined in Table 3.

In order to make our analysis easier, our dataset has two formats. The first format of our data is the file "ratings.csv", which is just like the format in table 3. The other format is in the csv file "tall.csv". It is almost the same with the first one, however with the ratings in one column. Table 4 is the summary statistics of the ratings for each rubric using the full dataset. According to the table, we find that the mean of the ratings for rubrics CritDes and SelMeth are significantly lower than the other rubrics. Table 5 is the summary statistics of the ratings for each rater using the full dataset. According to this table, we find that the mean ratings for all three raters are similar. Given the ratings' standard deviations for different raters are also similar, the rating distribution for each rater is similar too.

Short Name	Full Name	Description
RsrchQ	Research Question	Given a scenario, the student generates, critiques or evaluates a relevant empirical research question.
CritDes	Critique Design	Given an empirical research question, the student critiques or evaluates to what extent a study design convincingly answer that question.
InitEDA	Initial EDA	Given a data set, the student appropriately describes the data and provides initial Exploratory Data Analysis.
SelMeth	Select Method(s)	Given a data set and a research question, the student selects appropriate method(s) to analyze the data.
InterpRes	Interpret Results	The student appropriately interprets the results of the selected method(s).
VisOrg	Visual Organization	The student communicates in an organized, coherent and effective fashion with visual elements (charts, graphs, tables, etc.).
TxtOrg	Text Organization	The student communicates in an organized, coherent and effective fashion with text elements (words, sentences, paragraphs, section and subsection titles, etc.).

Table 1: Rubrics for rating Freshman Statistics projects

Rating	Meaning
1	Student does not generate any relevant evidence.
2	Student generates evidence with significant flaws.
3	Student generates competent evidence; no flaws, or only minor ones.
4	Student generates outstanding evidence; comprehensive and sophisticated.

Table 2: Rating scale used for all rubrics

Variable Name	Values	Description
(X)	$1, 2, 3, \ldots$	Row number in the data set
Rater	1,2 or 3	Which of the three raters gave a rating
(Sample)	$1, 2, 3, \ldots$	Sample number
(Overlap)	$1, 2, \ldots, 13$	Unique identifier for artifact seen by all 3 raters
Semester	Fall or Spring	Which semester the artifact came from
Sex	M or F	Sex or gender of student who created the artifact
RsrchQ	$1, 2, 3$ or 4	Rating on Research Question
CritDes	$1, 2, 3$ or 4	Rating on Critique Design
InitEDA	$1, 2, 3$ or 4	Rating on Initial EDA
SelMeth	$1, 2, 3$ or 4	Rating on Select Method(s)
InterpRes	$1, 2, 3$ or 4	Rating on Interpret Results
VisOrg	$1, 2, 3$ or 4	Rating on Visual Organization
TxtOrg	$1, 2, 3$ or 4	Rating on Text Organization
Artifact	(text labels)	Unique identifier for each artifact
Repeated	0 or 1	1 = this is one of the 13 artifacts seen by all 3 raters

Table 3: Variables in the Dataset

	Min.	1_{st} Quantile	Median	Mean	3_{rd} Quantile	Max.	SD
RsrchQ	1	2	2	2.35	3	4	0.59
CritDes	1	1	2	1.87	2	4	0.84
InitEDA	1	2	2	2.44	3	4	0.70
SelMeth	1	2	2	2.07	2	3	0.49
InterpRes	1	2	3	2.49	3	4	0.61
TxtOrg	1	2	3	2.60	3	4	0.70
VisOrg	1	2	2	2.41	3	4	0.67

Table 4: Summary Statistics of the ratings for each Rubric using all the ratings for each rubrics

	Min.	1_{st} Quantile	Median	Mean	3_{rd} Quantile	Max.	SD
Rater 1	1	2	2	2.35	3	4	0.70
Rater 2	1	1	2	2.43	3	4	0.70
Rater 3	1	1	2	2.18	3	4	0.69

Table 5: Summary Statistics of the ratings for each Rater using all the ratings for each rubrics

3 Method

In this paper, we used different methods to solve the questions mentioned in the introduction section.

3.1 Rating Distributions under different raters and rubrics

In order to solve the first research question, we focused on the distributions of ratings for all the seven rubrics and three raters. To be more specific, by using histograms and some summary statistics, we analyzed the distributions for each rubric and rater. Our analysis was performed both on the full dataset and its subset(contains only 13 artifacts that were rated by all three raters). In the end, we compared the results and got our results.

3.2 The Agreement of Different Raters

After examining the distributions of the ratings, our second research goal is to investigate the rating agreement between different raters and to find the very rubrics that the raters usually disagree with. In this section, we used two different approaches to obtain a thorough and convincing result. Firstly, we evaluated the agreement by computing the intraclass correlation(ICC) for each rubric. ICC is a measure that evaluates the average correlation between levels within a specific data group. To be more specific, the procedure of calculating the ICC requires fitting different simple mixed models for each artifact. We expected to see a strong positive correlation in each rubric, which could be a sign of agreement for raters. Then, we evaluated the percentage of the number of agreements(two raters agree with each other if they had the same rating for an artifact) for each pair of raters. We calculated this kind of percentage by using a two-way table for every pairs of raters. Then, we evaluated the agreement by the percentage calculated before. In the end, we summarized the two approaches and obtained our conclusion.

3.3 The Factors that Influencing the Rating

This research question asked us to evaluate the relationships between the ratings and some of the factors that were used in the experiment.

In general, to solve this question, we evaluated different random-intercept models by adding fixed effects for Rater, Semester, Sex, and/or Repeated to the random intercept models using the full data set as well as using the dataset with 13 artifacts only. And we tried interactions and new random effects for the seven rubric-specific models using all the data. In the end, we tried to add fixed effects, interactions, and new random effects to the "combined" model using all the data. Based on the final model result, we found the relationship between ratings and the various factors.

To be more specific, we started from a null model with only an intercept for all seven rubrics. Then we tried to add all the variables except "Rubric" to our null model to see whether these variables are significant or not. Specifically, we tried to add the fixed effects sex, semester, and repeated by using ANOVA tests (method for anova()), backward elimination (method for fitLMER.fnc()) and likelihood ratio test (method for exactRLRT()). After all the fixed effects were added to the model, we began to evaluate the interaction terms. We tried all the possible interaction terms(the combinations of existing fixed effects) for the models of the seven rubrics by evaluating each temporary model by using the ANOVA table and LRT.

Our last step of solving this question was trying to add all fixed effects(including rubrics), interactions, new random effects to a "combined" model using all the data to find the most significant variables for ratings.

As a result, we obtained our final model for each rubric as well as a combined model. After that, we evaluated the summary for each model and summarized the significant variables and interaction terms.

3.4 Rating Distributions under different genders and semesters

To solve this problem, we did more EDA(including visualization and summary statistics) on the rating distributions of different genders and semesters. To be more specific, we evaluated the histograms of the ratings for each gender and semester. In the end, we compared the results and got our conclusion.

4 Result

4.1 Rating Distributions under different raters and rubrics

Firstly, we try to examine this question on the dataset containing only 13 artifacts. According to figure 1, we found that the distribution of the rubrics InitEDA, RsrchQ, VisOrg, SelMeth are similar with the greatest number of the rating 2. The rubrics TxtOrg, InterpRes are also similar in that they all have the rating 3 as the highest frequency rating. Also, these rubrics stated above all have a very low number of the ratings 1 and 4. However, the rubric CritDes is significantly different from other rubrics, it has the rating 1 as the highest frequency rating, and the distribution of the ratings in this rubric shows that it might be a totally different rubric compared with other rubrics. Thus, we find that not all the distributions of the rubrics are identical, some of them are not the same, especially for the rubric CritDes, whose distribution is very different from other rubrics. The rubric CritDes seems to have especially low ratings for the artifacts. Also, the ratings for the rubric CritDes are seriously right-skewed.

Then, according to Figure 2 and the summary statistics in Table 4, we find that the distribution of ratings for each rubric in the full dataset are very similar to the distributions shown in Figure 2. Thus, we

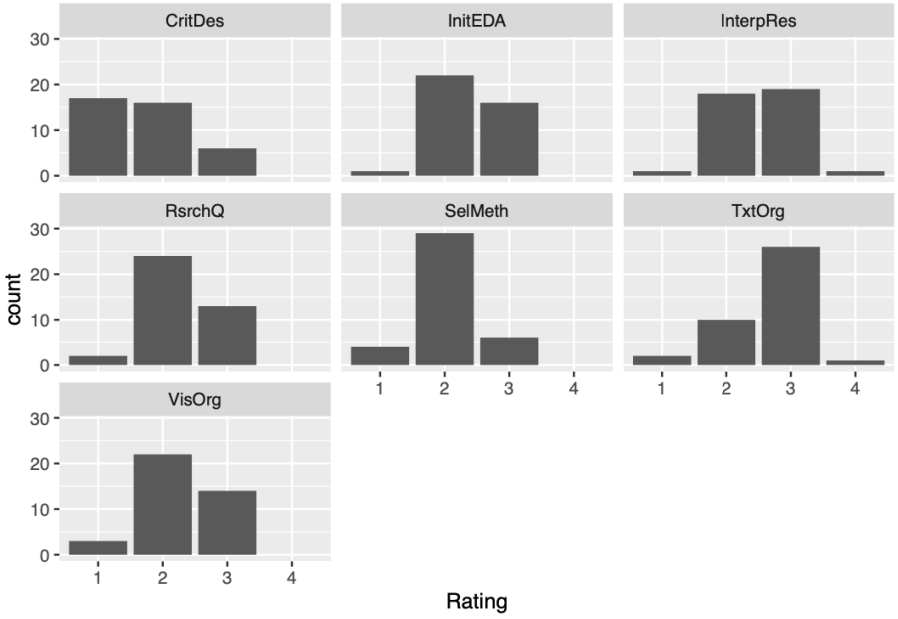


Figure 1: Distribution of ratings for each rubric for the 13 artifacts

can conclude that the rating distributions are identical for the rubrics in full dataset and the subset with only 13 artifacts.

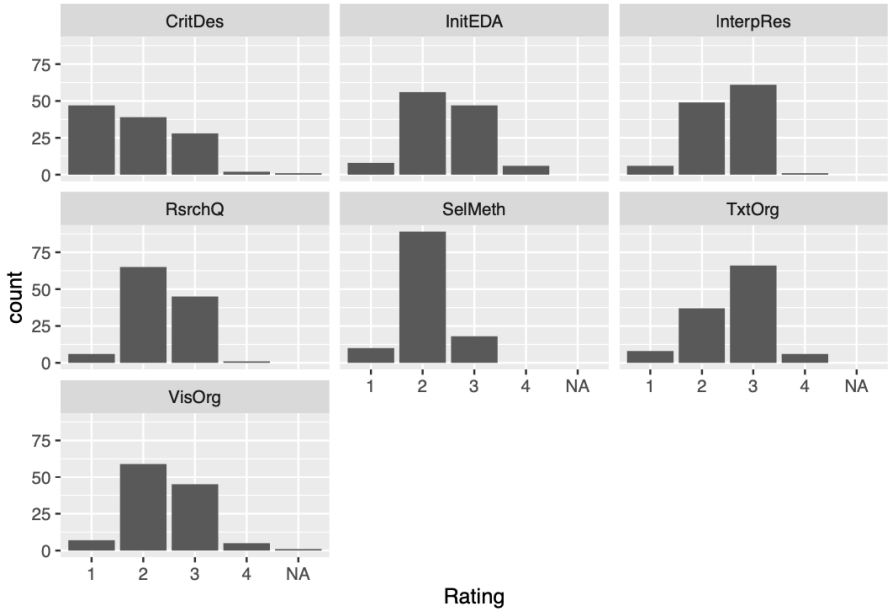


Figure 2: Distribution of ratings for each rubric for the full dataset

Also, we find that in the 13 artifacts data, the ratings distribution for the three raters are similar.

However, the rater 3 tend to give the greatest number of rating 2 and greatest number of rating 1.

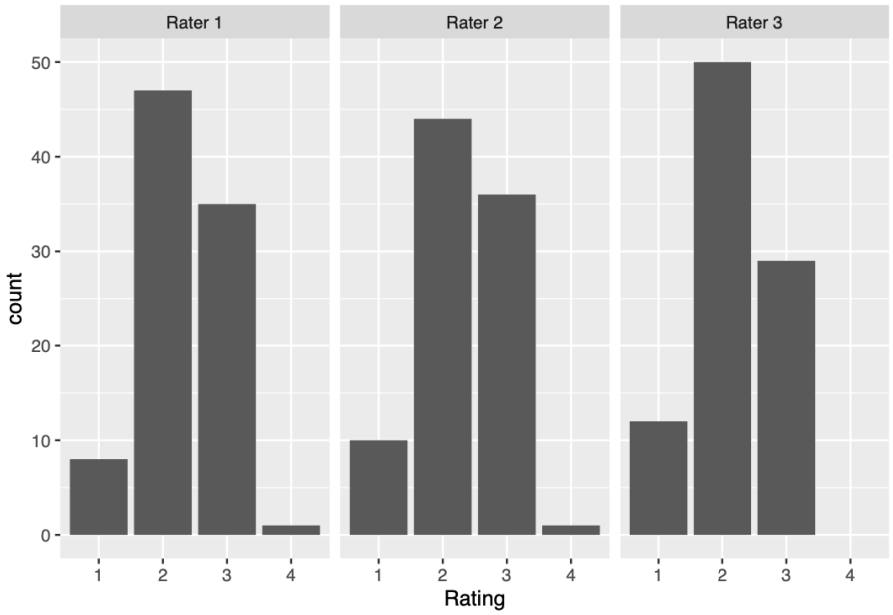


Figure 3: Distribution of ratings for each rater for the 13 artifacts

According to figure 4, we find that the distributions are similar to the distributions in figure 3, however, rater 1 and rater 2 are more likely to have similar number of rating 2 and 3. And for rater 3, it seems he/she gave more rating 2(in percentage). But we can find that the distribution of the ratings for each raters are not that distinguishable, all of them are not tend to give especially high or low score.

4.2 The Agreement of Different Raters

As we mentioned in the method section, we used two approach to solve this question. And all the result of the two approach could be found in Figure 5.

4.2.1 ICC

According to the second column in the Figure 5 below, which is the intraclass correlation(ICC) of the 7 rubrics in the sub-dataset, we find strong positive ICCs in the rubrics of CritDes, VisOrg, SelMeth and

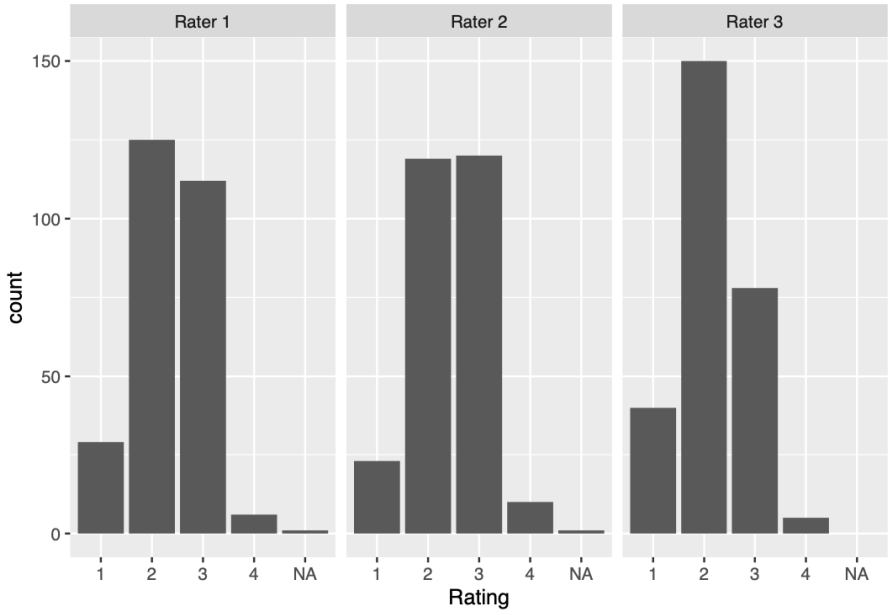


Figure 4: Distribution of ratings for each rater for the full dataset

InitEDA. It means that the raters usually agree with each other in these rubrics. However, relatively low ICCs are found in the rest of the rubrics, showing that the raters usually disagree with each other in the rubrics RsrchQ, InterpRes, TxtOrg. The lowest ICC in the sub-dataset is 0.14(Rubric TxtOrg), is means that raters hardly agree with each other in this rubric.

4.2.2 Proportions of Agreement

Our second approach for this question could give us a more detailed result with respect to this question. According to the last three columns in Figure 5, which are the proportions of the agreement for each pair of raters(e.g.: a12 means the proportion of the agreement of rater1 and rater 2), we find,

RsrchQ For rubric RsrchQ, rater 1 and rater 2 agree with each other in 38% of the artifacts, which means for this rubric, rater 1 and rater 2 do not usually agree with each other.

CritDes For rubric CritDes, all the pairs of raters agree with each other in some moderate proportions.

InitEDA For rubric InitEDA, rater 2 and rater 3 agree with each other for almost all the artifacts, and the rest of the pairs agree with each other in some moderate proportions.

SelMeth For rubric SelMeth, rater 1 and rater 2 agree with each other for almost all the artifacts, and the rest of the pairs agree with each other in some moderate proportions.

InterpRes For rubric InterpRes, all the pairs of raters agree with each other in some moderate proportions.

VisOrg For rubric VisOrg, rater 1 and rater 2 agree with each other in a moderate proportion, the rest of the pairs agree with each other in high proportions.

TxtOrg For rubric TxtOrg, all the pairs of raters agree with each other in some moderate proportions.

According to the first column of Figure 5, we find that by using the full dataset, we can get a similar result comparing with the second column of Figure 5 that the three raters roughly agree with each other for the rubrics CritDes, InitEDA, SelMeth and VisOrg. They usually disagree with each other for the rubrics InterpRes, TxtOrg and RsrchQ. In sum, considering the results obtained by the two approaches

```
##           ICC.alldata ICC.common        a12  a23  a13
## CritDes          0.67       0.57       0.54 0.69 0.62
## InitEDA          0.69       0.49       0.69 0.85 0.54
## InterpRes        0.22       0.23       0.62 0.62 0.54
## RsrchQ           0.21       0.19       0.38 0.54 0.77
## SelMeth          0.47       0.52       0.92 0.69 0.62
## TxtOrg           0.19       0.14       0.69 0.54 0.62
## VisOrg           0.66       0.59       0.54 0.77 0.77
```

Figure 5: The ICC for each rubric, full data

above, we find that in most of the case, we can roughly say that the three raters agree with other in most of the rubrics. However, for some rubrics RsrchQ, TxtOrg and InterpRes the ICCs are very low and there are at least one raters usually disagree with other two raters.

4.3 The Factors that Influencing the Rating

4.3.1 Fixed Effects

In this part, we found the most important factors related to the ratings. Firstly, we added the fixed effects to the seven rubric-specific models using just the data from the 13 common artifacts that all three raters saw. As a result, we failed to add any fixed effects to the model for each rubric by using the 13 artifacts. We then tried to add the fixed effects to the model fitted by the full dataset. We found that we should not add any fixed effects to the models for rubrics InitEDA, RsrchQ and TxtOrg. And we should add Rater as a fixed effect to the model for rubrics CritDes, InterpRes, SelMeth, it showed that different Raters could significantly influence the Ratings for these rubrics. In the end, we find that for rubric SelMeth, we should add the variables Rater and Semester to its model, it meant that for this rubric, different Raters and different semesters could be influential for the final ratings.

4.3.2 Interaction Terms and Random Effects for Models of the 7 Rubrics

Then, we considered the fixed effects of the interaction terms. For the models with intercept only, we did not need to examine the interaction terms. For the rubric SelMeth, we found our previous model makes sense given the t value of each variable is greater than 1.96 that they are all significant. After adding the interaction between Semester and Rater, we found that there was no evidence that we should add this interaction to the model. For random effects, since we should only try the effects that appeared in the fixed effect, we tried Rater and Semester as the random effects, after fitting these models, we found that we do not need to add any random effects to the model(details please refer to the appendix). Thus we obtained our final model, with random effects group by each artifact and fixed effects Rater and Semester. It showed that for each artifact rated by rubric SelMeth, different Raters and Semesters are significant factors influencing the Ratings.

For the rubric CritDes, we did a similar thing, since Rater is the only fixed effect we included in the model, we only test the Rater as a random effect. And we also find we did not need to add Rater as a random effect here too. It showed that group by each artifact rated by rubric CritDes, different Raters is the only significant fixed effect influencing the Ratings, Different Raters could have different rating for the rubric CritDes for each artifact.

Similarly, for the rubric InterpRes and VisOrg, we did the same thing, and found interaction terms and random effects are also not needed in the models of this two rubrics.

In summation, by using the full data set, we found that we do not need to add any random effects for any rubrics. For fixed effects, rubrics InitEDA, RsrchQ, and TxtOrg do not need any fixed effect. The fixed effect Rater could be significant for the rubrics SelMeth, CritDes, InterpRes and VisOrg. And the fixed effect Semester could be influential for the rubric SelMeth. According to Table 6, which is the model summary of the 7 models, we can find the estimated value of each parameters of the models. Thus, we found that the rubrics CritDes, VisOrg and the InitEDA have more variation across the artifacts.

	CritDes	SelMeth	InterpRes	VisOrg	RsrchQ	TxtOrg	InitEDA
Intercept					2.35	2.59	2.44
Rater 1	1.69	2.25	2.70	2.38			
Rater 2	2.11	2.23	2.59	2.65			
Rater 3	1.89	2.03	2.14	2.28			
SemesterS19		−0.36					

Table 6: Model Summary for the 7 Rubrics

Further, according to Table 7, we can find that τ^2 and σ^2 of the models. Roughly speaking, the random effect says how much the ratings vary across artifacts, from the prediction made by the fixed effects, in our models, the bigger τ^2 is for each random effect, the bigger the variation across artifacts.

	CritDes	SelMeth	InterpRes	VisOrg	RsrchQ	TxtOrg	InitEDA
τ^2	0.43	0.09	0.06	0.28	0.07	0.09	0.37
σ^2	0.24	0.10	0.25	0.14	0.28	0.40	0.17

Table 7: τ^2 and σ^2 for the 7 Rubrics

4.3.3 Combined model

In the end, we fitted a combined model by adding the fixed effects and the random effects into a model with intercept only using the similar procedure in Section 4.3.1 and 4.3.2. By evaluating the ANOVA table and LRT of the models, we find that our final model could be represented as follows,

$$Rating \sim (0 + Rubric|Artifact) + (0 + Rater|Artifact) + Rater + Semester + Rubric + Rater : Rubric.$$

We can interpret the final model as follows. Firstly, for the variable Rater$(((0+Rater|Artifact)+Rater))$, which is a fixed effect as well as a random effect, it shows that different raters could rate the same artifact differently. Secondly, for the variable Rubric$(((0+Rubric|Artifact)+Rubric))$, which is also a fixed effect as well as a random effect, it shows that the same artifact could have different ratings with respect to different rubrics. For the interaction term$(Rater : Rubric)$, it shows that there is also an interaction effect between the variables Rater and Rubric. It means that each pair of rater and rubric could have different interpretation of the same artifact. According to the model summary in figure 6 we find that most of the variables are statistically significant. The model summary of our combined model could be found in Figure 6, and it could be interpreted as follows, for example, the average rating of the artifacts would be 0.159 lower if the semester is S19. All the variables could be explained in this kind of way.

The most important thing for our model is that the rating of each artifact could be influenced by Sex, Semester, Rubric and Rater. Moreover, interactions exist in these variables.

4.4 Rating Distributions under different genders and semesters

4.4.1 Gender

According to the histogram by using the 13 artifacts(figure 7), we find that the distributions of the Ratings for Male and Female are almost identical, no bias was found from this plot. Similarly, we also did not find any bias in Ratings for Male and Female populations. (figure 8)

	Estimate	Std. Error	t value
(Intercept)	1.7575545	0.11404151	15.4115336
as.factor(Rater)2	0.3660542	0.13918252	2.6300297
as.factor(Rater)3	0.1959088	0.12966636	1.5108686
SemesterS19	-0.1591805	0.07647529	-2.0814634
RubricInitEDA	0.7394940	0.12996076	5.6901329
RubricInterpRes	0.9915148	0.12770767	7.7639406
RubricRsrchQ	0.7261869	0.11793023	6.1577676
RubricSelMeth	0.4106797	0.12470498	3.2932102
RubricTxtOrg	1.0157815	0.12999540	7.8139797
RubricVisOrg	0.6542506	0.13353098	4.8996162
as.factor(Rater)2:RubricInitEDA	-0.2998076	0.15609075	-1.9207264
as.factor(Rater)3:RubricInitEDA	-0.2947319	0.15635201	-1.8850532
as.factor(Rater)2:RubricInterpRes	-0.5132297	0.15348482	-3.3438467
as.factor(Rater)3:RubricInterpRes	-0.7148433	0.15363960	-4.6527283
as.factor(Rater)2:RubricRsrchQ	-0.4874137	0.14722146	-3.3107521
as.factor(Rater)3:RubricRsrchQ	-0.3223799	0.14726517	-2.1891116
as.factor(Rater)2:RubricSelMeth	-0.3863739	0.15030941	-2.5705236
as.factor(Rater)3:RubricSelMeth	-0.3871581	0.14961457	-2.5877033
as.factor(Rater)2:RubricTxtOrg	-0.5510439	0.15646043	-3.5219379
as.factor(Rater)3:RubricTxtOrg	-0.4448937	0.15673122	-2.8385772
as.factor(Rater)2:RubricVisOrg	-0.1048994	0.15861081	-0.6613632
as.factor(Rater)3:RubricVisOrg	-0.2752130	0.15884865	-1.7325485

Figure 6: The Summary of the Final Model

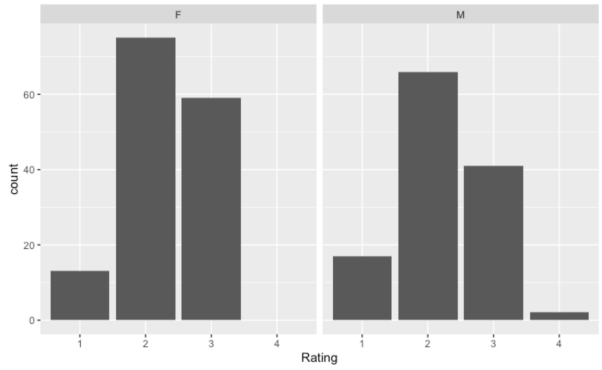


Figure 7: Histograms of Sex and Ratings, 13 artifacts

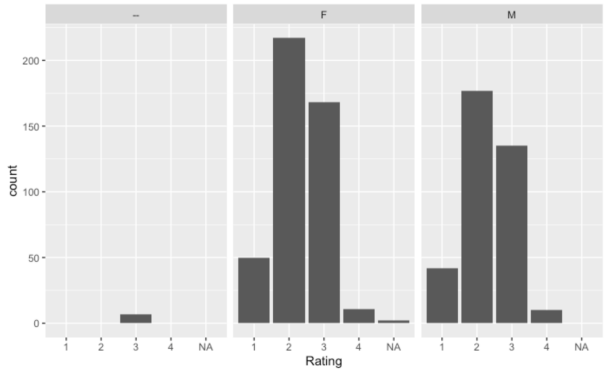


Figure 8: Histograms of Sex and Ratings, full dataset

4.4.2 Semester

According to the histogram by using the 13 artifacts(figure 9), we find that the distributions of the Ratings for Semester F19 and S19 were quite different. Generally, we find that there was a gap of the total number of the ratings. The number of the ratings in F19 was two times more than the number of the ratings in S19, however, they have similar number of the rating 1. This result showed that the distributions of the ratings in this two semesters were significantly different from each other. It was likely that in S19 raters tend to give a much lower ratings for some artifacts. Similarly, we found similar difference using

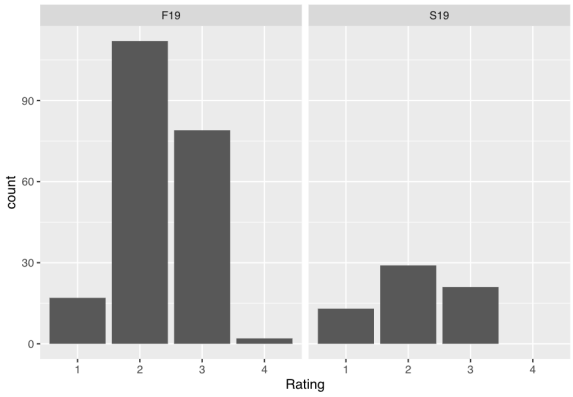


Figure 9: Histograms of Semester and Ratings, 13 artifacts

the full dataset. (figure 8) The result shows that ratings for different genders have similar distribution,

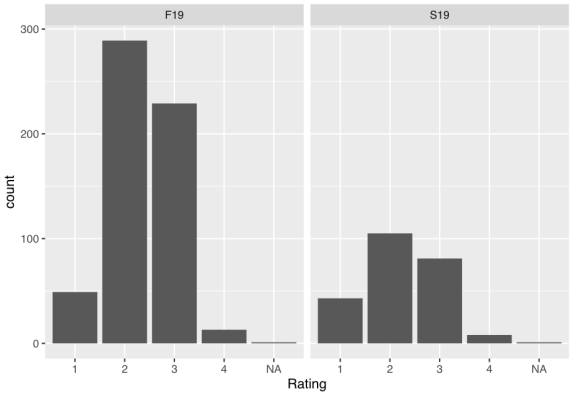


Figure 10: Histograms of Semester and Ratings, full dataset

however, the ratings in different semesters have significantly different distribution that in S19, we have a much higher proportion of low ratings.

5 Discussion

5.1 Rating Distributions under different raters and rubrics

According to the result of question 1, we found that most of the rubrics have the similar distribution of the Ratings, however, rubric CritDes seemed to be very different from other rubrics. It might because of the rule of rating for the rubric CritDes is different from the rest of the rubrics. It seemed to be a much more strict rubric that more than half of the artifacts got rating 1 in this rubric. I think it is a good thing to have rubrics with different distribution that if all the rubrics are the same, we do not need that many rubrics anymore. Different rubrics, which could evaluate the different aspects of an artifact are we really need. And for different raters, we can say they roughly agree with each other when rating, however, rater 3 seems to be more extreme, since he/she are more likely to give a lower rating(1, 2), it might be a factor of unfairness.

5.2 The Agreement of Different Raters

According to the result of question 2, we find that for most of the artifacts and for most of the rubrics, raters are quite likely to give similar or identical ratings, and thus have high ICCs, but for some rubrics(InterpRes, RsrchQ, VisOrg), the ICCs are low, which means, for these rubrics, the raters do not usually agree with each others. For the same artifacts, it could be really weird to have raters disagree with each other and give significantly different ratings. From my perspective, it might because these specific rubrics are more subjective and thus different raters could have more different results. This pattern is not good for a rubric, since if the raters usually disagree with each other in a specific rubric, this rubric might not be a good one, and could possibly entail some unfair ratings.

5.3 The Factors that Influencing the Rating

Form the result of this question, we find that there are three final models(for rubrics InitEDA, RsrchQ and TxtOrg), who only have intercept. It seems that the fairness are guaranteed for these rubrics. And for the rest of the rubrics, it seems that the rating for each rubric are related to different raters, which is, it seems that it is not so fair to use these rubric, especially when not all three raters are rating a specific artifact. Moreover, we find that different semesters is also a significant variable for the rubric SelMeth, it means that the fairness for this rubric could be very poor. The rubric we want should be objective and uniform.

According to the result of the combined model, we find that the ratings are influenced by many factors and there interactions. This model result shows us that the rating processes might not be fair. Different

raters, Semesters and Rubric all could lead to different ratings. From my perspective, it would be better if the program could set up a uniform rating standard to make the rating processes fairer.

5.4 Rating Distributions under different genders and semesters

For the result of this question, we find that sex is not a significant factor that influencing the rating. It means that the bias of sex does not exist in the Rating processes . However, for different semesters, we find a significant disparity in the distributions of ratings. This result shows that the rating process might be different in the two semester(F19, S19). This is a sign of unfairness in the rating processes, since the rating of an artifact should not be different in two semesters. This kind of bias is not good for the students' success, since it might impact students' enthusiasm for learning.

In summation, our results of the previous questions show that there are some defects in the fairness of this education program. Depending on our results and conclusions, the program manager should find out the detailed reasons of this kind of biases and try to fix it as soon as possible.

5.5 Limitation and Possible Improvement

There are some limitations in our analysis, firstly, in our analysis, we used either 91 samples dataset or 13 samples dataset, however, the sample size might be too small to reach a convincing result. Secondly, we only found out the significant factors for the ratings in each rubric and rater, but we can hardly give a specific reason for the result. Finally, we only used one approach to fit the model, which is the lmer model, thus the result might not be so comprehensive and convincing.

For improvement, most importantly, a much larger dataset is needed to obtain a more convincing result. Then, we can also try to fit other models like some generalized linear models and etc., which might provide useful insights and better results. Also, to make a more reasonable inference, we need more background information about this education program.

References

Junker, B. W. (2021), *Project 02 assignment sheet and data for 36-617: Applied Regression Analysis*, Department of Statistics and Data Science, Carnegie Mellon University, Pittsburgh PA, Accessed Nov 08, 2021 from https://canvas.cmu.edu/courses/25337/files/folder/Project02.

Sheather, S. J. (2009), *A Modern Approach to Regression*, Springer.

Technical Appendix

11/29/2021

Package and Data Preparation

```
library(lme4)
```

```
## Loading required package: Matrix
```

```
library(arm)
```

```
## Loading required package: MASS
```

```
##
## arm (Version 1.12-2, built: 2021-10-15)
```

```
## Working directory is /Users/wyc
```

```
library(ggplot2)
ratings <- read.csv("/Users/wyc/ratings.csv",header=T)
rating = ratings
tall <-  read.csv("/Users/wyc/tall.csv",header=T)
tall$Rating <- factor(tall$Rating,levels=1:4)
for (i in unique(tall$Rubric)) {
  ratings[,i] <- factor(ratings[,i],levels=1:4)
}
tall$Sex[nchar(tall$Sex)==0] <- "--"

##
## Extract the reduced data set with the 13 artifacts that all 3 raters saw...
ratings.13 <- ratings[grep("O",ratings$Artifact),]
tall.13 <-  tall[grep("O",tall$Artifact),]
```

Missing value

```
colSums(is.na(tall))
```

```
##        X    Rater Artifact Repeated Semester      Sex   Rubric   Rating
##        0        0        0        0        0        0        0        2
```

There are 2 NAs in Rating.

Question 1, Is the distribution of ratings for each rubrics pretty much indistinguishable from the other rubrics, or are there rubrics that tend to get especially high or low ratings? Is the distribution of ratings given by each rater pretty much indistinguishable from the other raters, or are there raters that tend to give especially high or low ratings?

```
summary(rating)
```

```
##        X            Rater       Sample          Overlap     Semester
##  Min.   :  1   Min.   :1   Min.   :  1.00   Min.   : 1   Length:117
##  1st Qu.: 30   1st Qu.:1   1st Qu.: 31.00   1st Qu.: 4   Class :character
##  Median : 59   Median :2   Median : 60.00   Median : 7   Mode  :character
##  Mean   : 59   Mean   :2   Mean   : 59.89   Mean   : 7
##  3rd Qu.: 88   3rd Qu.:3   3rd Qu.: 89.00   3rd Qu.:10
##  Max.   :117   Max.   :3   Max.   :118.00   Max.   :13
##                                             NA's   :78
##      Sex                RsrchQ        CritDes         InitEDA
##  Length:117         Min.   :1.00   Min.   :1.000   Min.   :1.000
##  Class :character   1st Qu.:2.00   1st Qu.:1.000   1st Qu.:2.000
##  Mode  :character   Median :2.00   Median :2.000   Median :2.000
##                     Mean   :2.35   Mean   :1.871   Mean   :2.436
##                     3rd Qu.:3.00   3rd Qu.:3.000   3rd Qu.:3.000
##                     Max.   :4.00   Max.   :4.000   Max.   :4.000
##                                    NA's   :1
##     SelMeth        InterpRes         VisOrg          TxtOrg
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000
##  1st Qu.:2.000   1st Qu.:2.000   1st Qu.:2.000   1st Qu.:2.000
##  Median :2.000   Median :3.000   Median :2.000   Median :3.000
##  Mean   :2.068   Mean   :2.487   Mean   :2.414   Mean   :2.598
##  3rd Qu.:2.000   3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.:3.000
##  Max.   :3.000   Max.   :4.000   Max.   :4.000   Max.   :4.000
##                                  NA's   :1
##    Artifact            Repeated
##  Length:117         Min.   :0.0000
##  Class :character   1st Qu.:0.0000
##  Mode  :character   Median :0.0000
##                     Mean   :0.3333
##                     3rd Qu.:1.0000
##                     Max.   :1.0000
##
```

```
summary(as.numeric(tall[tall$Rater == 1,]$Rating))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   1.000   2.000   2.000   2.349   3.000   4.000       1
```

```
summary(as.numeric(tall[tall$Rater == 2,]$Rating))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    1.00    2.00    2.00    2.43    3.00    4.00       1
```

```
summary(as.numeric(tall[tall$Rater == 3,]$Rating))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   2.000   2.176   3.000   4.000
```

```r
sd(rating$RsrchQ)
```

```
## [1] 0.5918446
```

```r
sd(rating$CritDes,na.rm=TRUE)
```

```
## [1] 0.8395669
```

```r
sd(rating$InitEDA)
```

```
## [1] 0.6995641
```

```r
sd(rating$SelMeth)
```

```
## [1] 0.486481
```

```r
sd(rating$InterpRes)
```

```
## [1] 0.6104744
```

```r
sd(rating$VisOrg,na.rm=TRUE)
```

```
## [1] 0.67333
```

```r
sd(rating$TxtOrg)
```

```
## [1] 0.6955503
```

```r
sd(as.numeric(tall[tall$Rater == 1,]$Rating),na.rm=TRUE)
```

```
## [1] 0.6974383
```

```r
sd(as.numeric(tall[tall$Rater == 2,]$Rating),na.rm=TRUE)
```

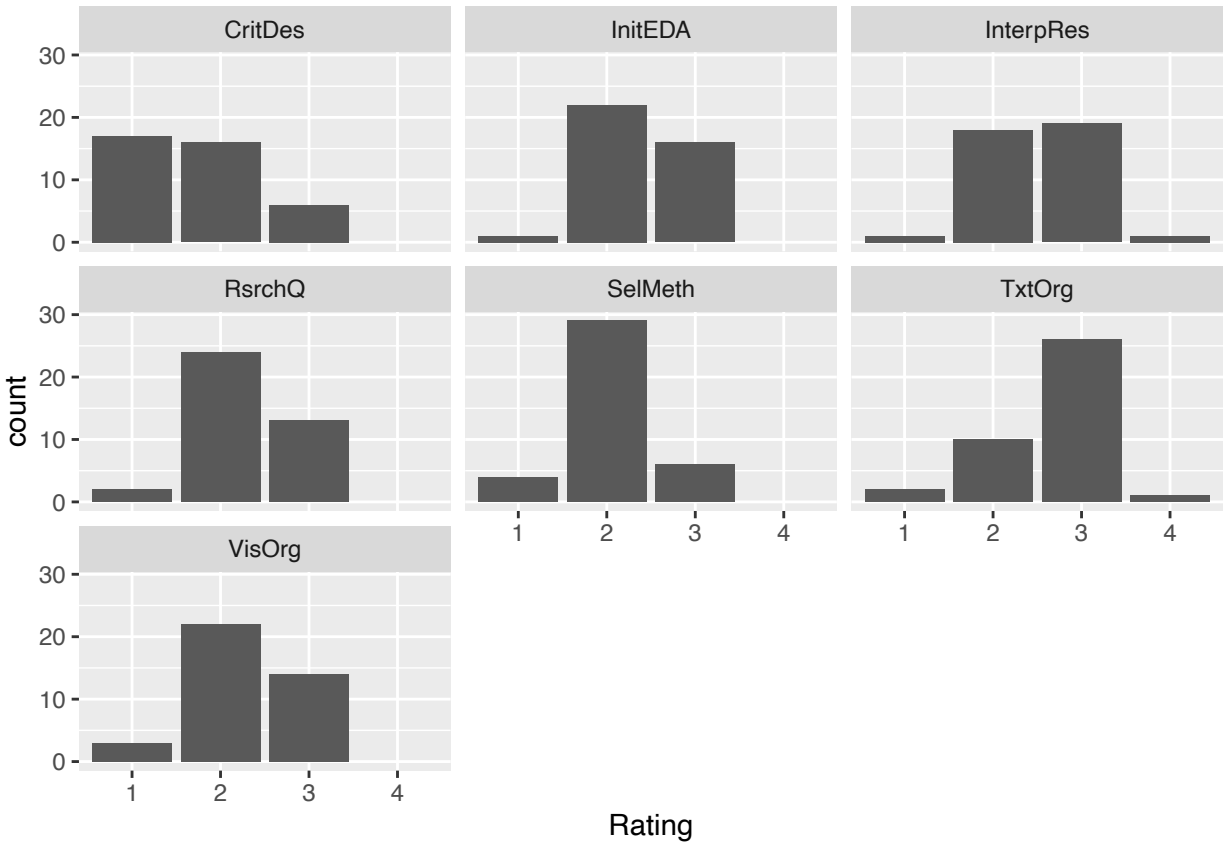
```
## [1] 0.699691
```

```r
sd(as.numeric(tall[tall$Rater == 3,]$Rating),na.rm=TRUE)
```

```
## [1] 0.6901631
```

```r
g <- ggplot(tall.13,aes(x = Rating)) +
  facet_wrap( ~ Rubric) +
  geom_bar()

g
```



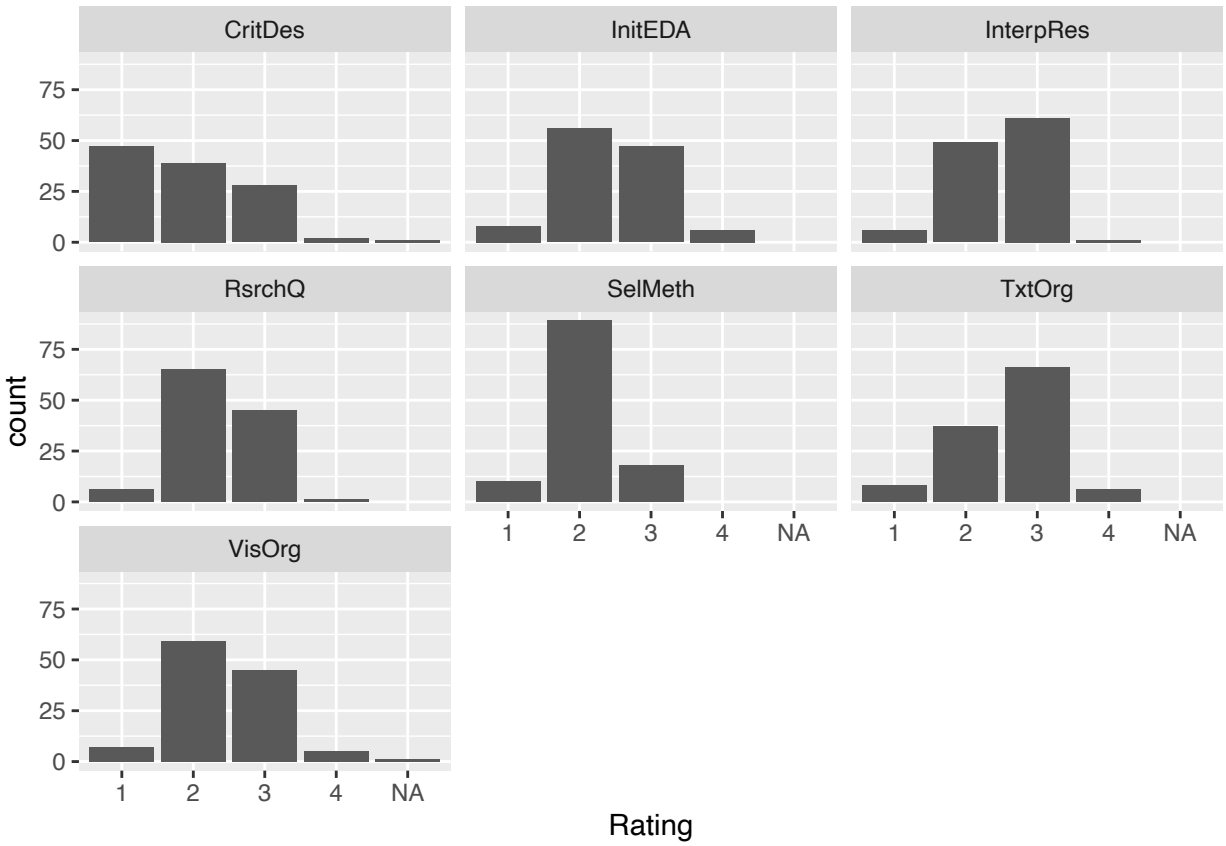

```
tmp <- data.frame(lapply(split(tall.13$Rating,tall.13$Rubric),summary))
row.names(tmp) <- paste("Rating",1:4)

tmp
```

```
##          CritDes InitEDA InterpRes RsrchQ SelMeth TxtOrg VisOrg
## Rating 1      17       1         1      2       4      2      3
## Rating 2      16      22        18     24      29     10     22
## Rating 3       6      16        19     13       6     26     14
## Rating 4       0       0         1      0       0      1      0
```

```
g <- ggplot(tall,aes(x = Rating)) +
  facet_wrap( ~ Rubric) +
  geom_bar()

g
```




```
tmp0 <- lapply(split(tall$Rating,tall$Rubric),summary)
tmp <- data.frame(matrix(0,nrow=5,ncol=7))
names(tmp) <- names(tmp0)
row.names(tmp) <- c(paste("Rating",1:4),"<NA>")
for (i in names(tmp0)) {
  tmp[,i] <- tmp[,i] + c(tmp0[[i]],0)[1:5]
}

tmp
```

```
##          CritDes InitEDA InterpRes RsrchQ SelMeth TxtOrg VisOrg
## Rating 1      47       8         6      6      10      8      7
## Rating 2      39      56        49     65      89     37     59
## Rating 3      28      47        61     45      18     66     45
## Rating 4       2       6         1      1       0      6      5
## <NA>           1       0         0      0       0      0      1
```

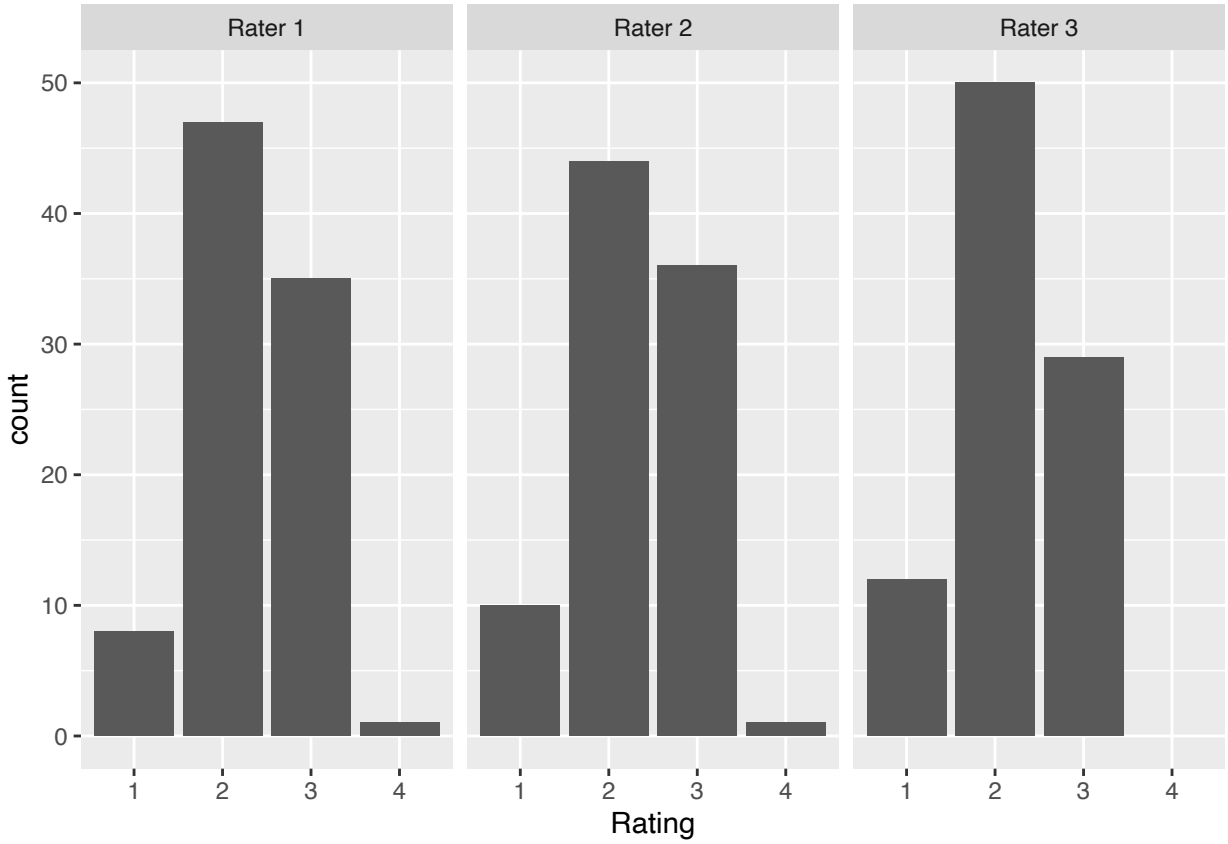
The plot shows that different number of ratings for each rubric, and we can find the distribution information of the ratings in this plot.

In order to solve the first research question, we focused on the distributions of ratings for all the seven rubrics and three raters. To be more specific, by using histograms and some summary statistics, we analyzed the distributions for each rubric and rater. Our analysis was performed both on the full dataset and its subset(contains only 13 artifacts that were rated by all three raters). In the end, we compared the results and got our results.

```
rater.name <- function(x) { paste("Rater",x) }
```

```
g <- ggplot(tall.13,aes(x = Rating)) +
  facet_wrap( ~ Rater, labeller=labeller(Rater=rater.name)) +
  geom_bar()

g
```



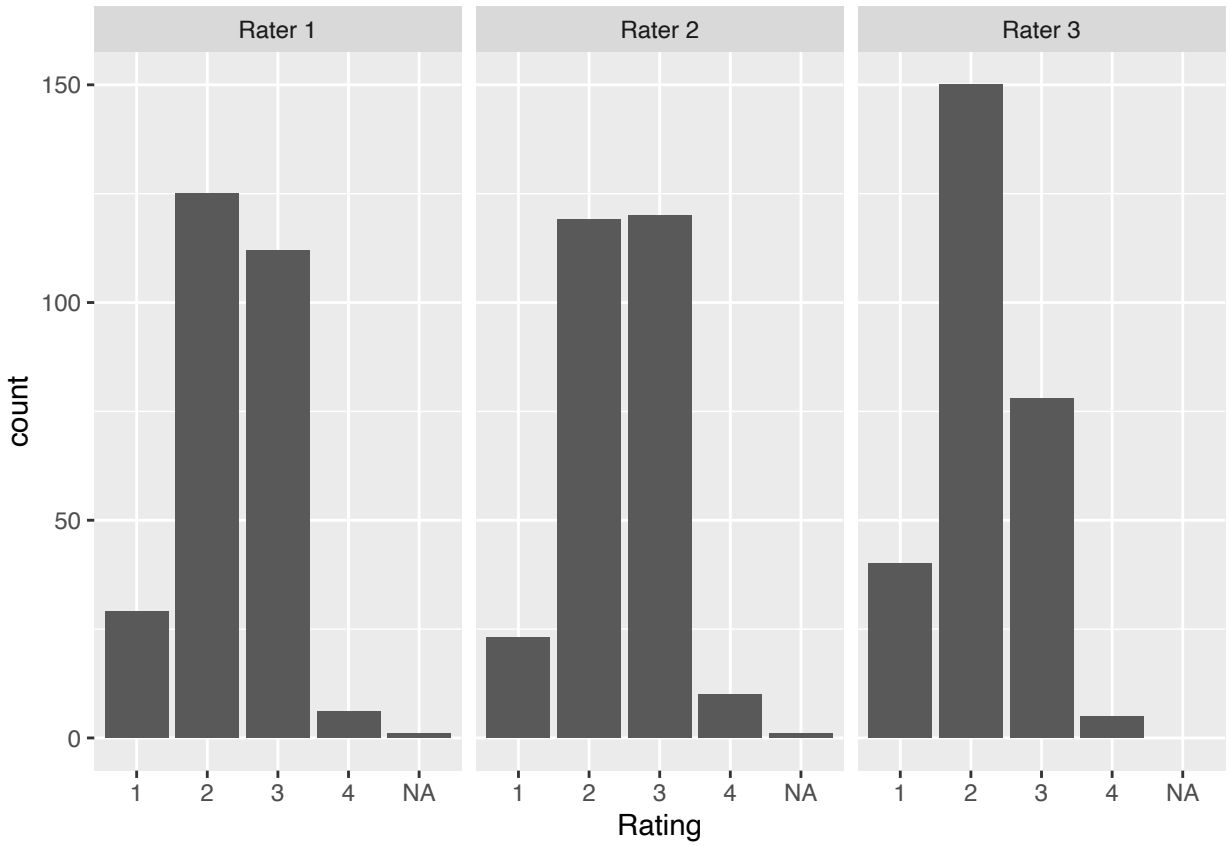

```
tmp <- data.frame(lapply(split(tall.13$Rating,tall.13$Rater),summary))
row.names(tmp) <- paste("Rating",1:4)
names(tmp) <- paste("Rater",1:3)

tmp
```

```
##          Rater 1 Rater 2 Rater 3
## Rating 1       8      10      12
## Rating 2      47      44      50
## Rating 3      35      36      29
## Rating 4       1       1       0
```

```
g <- ggplot(tall,aes(x = Rating)) +
  facet_wrap( ~ Rater, labeller=labeller(Rater=rater.name)) +
  geom_bar()

g
```




```
tmp0 <- lapply(split(tall$Rating,tall$Rater),summary)
tmp <- data.frame(matrix(0,nrow=5,ncol=3))  ## three raters...
names(tmp) <- names(tmp0)
row.names(tmp) <- c(paste("Rating",1:4),"<NA>")
for (i in names(tmp0)) {
  tmp[,i] <- tmp[,i] + c(tmp0[[i]],0)[1:5]
}
names(tmp) <- paste("Rater",1:3)
tmp
```

```
##          Rater 1 Rater 2 Rater 3
## Rating 1      29      23      40
## Rating 2     125     119     150
## Rating 3     112     120      78
## Rating 4       6      10       5
## <NA>           1       1       0
```

The plot shows that different number of ratings for each rater, and we can find the distribution information of the ratings in this plot.

We try to examine this question on the dataset containing only 13 artifacts. According to figure above, we found that the distribution of the rubrics InitEDA, RsrchQ, VisOrg, SelMeth are similar with the greatest number of the rating 2. The rubrics TxtOrg, InterpRes are also similar in that they all have the rating 3 as the highest frequency rating. Also, these rubrics stated above all have a very low number of the ratings 1 and 4. However, the rubric CritDes is significantly different from other rubrics, it has the rating 1 as the highest frequency rating, and the distribution of the ratings in this rubric shows that it might be a totally different rubric compared with other rubrics. Thus, we find that not all the distributions of the rubrics are identical, some of them are not the same, especially for the rubric CritDes, whose distribution is very different from

other rubrics. The rubric CritDes seems to have especially low ratings for the artifacts. Also, the ratings for the rubric CritDes are seriously right-skewed.

```
tall[apply(tall,1,function(x){any(is.na(x))}),]
```

```
##       X Rater Artifact Repeated Semester Sex  Rubric Rating
## 161 161     2       45        0      S19   F CritDes   <NA>
## 684 684     1      100        0      F19   F  VisOrg   <NA>
```

```
ratings[ratings$Sex=="--",]
```

```
##   X Rater Sample Overlap Semester Sex RsrchQ CritDes InitEDA SelMeth InterpRes
## 5 5     3      5      NA     Fall  --      3       3       3       3         3
##   VisOrg TxtOrg Artifact Repeated
## 5      3      3        5        0
```

We find that there are two NA in our dataset.

Question 2 For each rubric, do the raters generally agree on their scores? If not, is there one rater who disagrees with the others? Or do they all disagree?

```
Rubric.names <- sort(unique(tall$Rubric))



ICC.vec <- NULL
for (i in Rubric.names) {

  tmp <- lmer(as.numeric(Rating) ~ 1 + (1|Artifact), data=tall.13[tall.13$Rubric==i,])
  sig2 <- summary(tmp)$sigma^2
  tau2 <- attr(summary(tmp)$varcor[[1]],"stddev")^2
  ICC <- tau2 / (tau2 + sig2)
  ICC.vec <- c(ICC.vec,ICC)
}
names(ICC.vec) <- Rubric.names

agreement.results <- cbind(ICC.common=ICC.vec,"       a12"=0,a23=0,a13=0)

agreement.tables <- as.list(rep(NA,7))
names(agreement.tables) <- Rubric.names

for (i in Rubric.names) {
  r12 <- data.frame(r1=factor(ratings.13[ratings.13$Rater==1,i],levels=1:4),
                    r2=factor(ratings.13[ratings.13$Rater==2,i],levels=1:4),
                    a1=ratings.13[ratings.13$Rater==1,"Artifact"],
                    a2=ratings.13[ratings.13$Rater==2,"Artifact"])
  if(any(r12[,3]!=r12[,4])) { stop(paste("Rater 1-2 Artifact mismatch on rubric",i)) }
  a12 <- mean(r12[,1]==r12[,2])
  r12 <- table(r12[,1:2])

  r23 <- data.frame(r2=factor(ratings.13[ratings.13$Rater==2,i],levels=1:4),
                    r3=factor(ratings.13[ratings.13$Rater==3,i],levels=1:4),
                    a2=ratings.13[ratings.13$Rater==2,"Artifact"],
                    a3=ratings.13[ratings.13$Rater==3,"Artifact"])
```

```
  if(any(r23[,3]!=r23[,4])) { stop(paste("Rater 2-3 Artifact mismatch on rubric",i)) }
  a23 <- mean(r23[,1]==r23[,2])
  r23 <- table(r23[,1:2])

  r13 <- data.frame(r1=factor(ratings.13[ratings.13$Rater==1,i],levels=1:4),
                    r3=factor(ratings.13[ratings.13$Rater==3,i],levels=1:4),
                    a1=ratings.13[ratings.13$Rater==1,"Artifact"],
                    a3=ratings.13[ratings.13$Rater==3,"Artifact"])
  if(any(r13[,3]!=r13[,4])) { stop(paste("Rater 1-3 Artifact mismatch on rubric",i)) }
  a13 <- mean(r13[,1]==r13[,2])
  r13 <- table(r13[,1:2])

  agreement.results[i,2:4] <- c(a12,a23,a13)

  agreement.tables[[i]] <- list(r12,r23,r13)

}
round(agreement.results,2)
```

```
##           ICC.common        a12  a23  a13
## CritDes         0.57       0.54 0.69 0.62
## InitEDA         0.49       0.69 0.85 0.54
## InterpRes       0.23       0.62 0.62 0.54
## RsrchQ          0.19       0.38 0.54 0.77
## SelMeth         0.52       0.92 0.69 0.62
## TxtOrg          0.14       0.69 0.54 0.62
## VisOrg          0.59       0.54 0.77 0.77
```

```
##

if (F) { print(agreement.tables) }


ICC.vec <- NULL
for (i in Rubric.names) {

  tmp <- lmer(as.numeric(Rating) ~ 1 + (1|Artifact), data=tall[tall$Rubric==i,])
  sig2 <- summary(tmp)$sigma^2
  tau2 <- attr(summary(tmp)$varcor[[1]],"stddev")^2
  ICC <- tau2 / (tau2 + sig2)
  ICC.vec <- c(ICC.vec,ICC)
}
names(ICC.vec) <- Rubric.names

agreement.results <- cbind(ICC.alldata=ICC.vec,agreement.results)

round(agreement.results,2)
```

```
##           ICC.alldata ICC.common        a12  a23  a13
## CritDes          0.67       0.57       0.54 0.69 0.62
## InitEDA          0.69       0.49       0.69 0.85 0.54
## InterpRes        0.22       0.23       0.62 0.62 0.54
## RsrchQ           0.21       0.19       0.38 0.54 0.77
## SelMeth          0.47       0.52       0.92 0.69 0.62
```

```
## TxtOrg           0.19       0.14       0.69 0.54 0.62
## VisOrg           0.66       0.59       0.54 0.77 0.77
```

By calculating the tau2 and sigma2, we can find that ICCs for each rubrics. Further, we used a two way table to show the proportion of agreements.

Firstly, we evaluated the agreement by computing the intraclass correlation(ICC) for each rubric. ICC is a measure that evaluates the average correlation between levels within a specific data group. To be more specific, the procedure of calculating the ICC requires fitting different simple mixed models for each artifact. We expected to see a strong positive correlation in each rubric, which could be a sign of agreement for raters. Then, we evaluated the percentage of the number of agreements(two raters agree with each other if they had the same rating for an artifact) for each pair of raters. We calculated this kind of percentage by using a two-way table for every pairs of raters. Then, we evaluated the agreement by the percentage calculated before. In the end, we summarized the two approaches and obtained our conclusion.

Question 3 More generally, how are the various factors in this experiement (Rater, Semester, Sex, Repeated, Rubric) related to the ratings? Do the factors interact in any interesting ways?

Question 3 (i): Adding fixed effects to the seven rubric-specific models using just the data from the 13 common artifacts that al three raters saw

```
library(LMERConvenienceFunctions)
library(RLRsim)

tmp <- lmer(as.numeric(Rating) ~ -1 + as.factor(Rater) +
              Semester + Sex + (1|Artifact),
            data=tall.13[tall.13$Rubric=="RsrchQ",],REML=FALSE)

tmp.back_elim <- fitLMER.fnc(tmp,set.REML.FALSE = TRUE,log.file.name = FALSE)
```

```
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.7355 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.279 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
```

```
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
```

```
formula(tmp.back_elim)
```

```
## as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
```

```
tmp.int_only <- update(tmp.back_elim, . ~ . + 1 - as.factor(Rater))

anova(tmp.int_only,tmp.back_elim)
```

```
## Data: tall.13[tall.13$Rubric == "RsrchQ", ]
## Models:
## tmp.int_only: as.numeric(Rating) ~ (1 | Artifact)
## tmp.back_elim: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##               npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## tmp.int_only     3 69.457 74.447 -31.728   63.457
## tmp.back_elim    5 72.018 80.335 -31.009   62.018 1.4391  2      0.487
```

```
anova(tmp.int_only,tmp.back_elim)$"Pr(>Chisq)"[2]
```

```
## [1] 0.4869707
```

```
Rubric.names <- sort(unique(tall$Rubric))

model.formula.13 <- as.list(rep(NA,7))
names(model.formula.13) <- Rubric.names


for (i in Rubric.names) {


  rubric.data <- tall.13[tall.13$Rubric==i,]
  tmp <- lmer(as.numeric(Rating) ~ -1 + as.factor(Rater) +
              Semester + Sex + (1|Artifact),
            data=rubric.data,REML=FALSE)


  tmp.back_elim <- fitLMER.fnc(tmp,set.REML.FALSE = TRUE,log.file.name = FALSE)


  tmp.single_intercept <- update(tmp.back_elim, . ~ . + 1 - as.factor(Rater))
  pval <- anova(tmp.single_intercept,tmp.back_elim)$"Pr(>Chisq)"[2]


  if (pval<=0.05) {
    tmp_final <- tmp.back_elim
  } else {
    tmp_final <- tmp.single_intercept
  }


  model.formula.13[[i]] <- formula(tmp_final)
```

```
}
```

```
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.2229 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Semester" = 0.1826 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.8137 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.6429 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
```

```
## ============================================================
## ===              backfitting fixed effects             ===
## ============================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.8294 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.2947 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===            forwardfitting random effects          ===
## ============================================================
##  ===       random slopes       ===
## ============================================================
## ===            re-backfitting fixed effects           ===
## ============================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===              backfitting fixed effects             ===
## ============================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.7355 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.279 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===            forwardfitting random effects          ===
## ============================================================
##  ===       random slopes       ===
## ============================================================
## ===            re-backfitting fixed effects           ===
## ============================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===              backfitting fixed effects             ===
```

```
## ============================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.9383 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Semester" = 0.4287 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===            forwardfitting random effects       ===
## ============================================================
##  ===       random slopes       ===
## ============================================================
## ===            re-backfitting fixed effects        ===
## ============================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===              backfitting fixed effects         ===
## ============================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.5358 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.1319 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===            forwardfitting random effects       ===
## ============================================================
##  ===       random slopes       ===
## ============================================================
## ===            re-backfitting fixed effects        ===
## ============================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===              backfitting fixed effects         ===
## ============================================================
## processing model terms of interaction level 1
```

```
##   iteration 1
##     p-value for term "Semester" = 0.1922 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.1078 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
```

```
model.formula.13
```

```
## $CritDes
## as.numeric(Rating) ~ (1 | Artifact)
##
## $InitEDA
## as.numeric(Rating) ~ (1 | Artifact)
##
## $InterpRes
## as.numeric(Rating) ~ (1 | Artifact)
##
## $RsrchQ
## as.numeric(Rating) ~ (1 | Artifact)
##
## $SelMeth
## as.numeric(Rating) ~ (1 | Artifact)
##
## $TxtOrg
## as.numeric(Rating) ~ (1 | Artifact)
##
## $VisOrg
## as.numeric(Rating) ~ (1 | Artifact)
```

We found the most important factors related to the ratings. Firstly, we added the fixed effects to the seven rubric-specific models using just the data from the 13 common artifacts that all three raters saw. As a result, we failed to add any fixed effects to the model for each rubric by using the 13 artifacts.

Question 3 (ii): Adding fixed effects to the seven rubric-specific models using all the data

```
Rubric.names <- sort(unique(tall$Rubric))
```

```
tall[c(161,684),]
```

```
##       X Rater Artifact Repeated Semester Sex  Rubric Rating
## 161 161     2       45        0      S19   F CritDes   <NA>
## 684 684     1      100        0      F19   F  VisOrg   <NA>
```

```
tall.nonmissing <- tall[-c(161,684),]


tall.nonmissing[tall.nonmissing$Sex=="--",]
```

```
##       X Rater Artifact Repeated Semester Sex    Rubric Rating
## 5     5     3        5        0      F19  --    RsrchQ      3
## 122 122     3        5        0      F19  --   CritDes      3
## 239 239     3        5        0      F19  --   InitEDA      3
## 356 356     3        5        0      F19  --   SelMeth      3
## 473 473     3        5        0      F19  -- InterpRes      3
## 590 590     3        5        0      F19  --    VisOrg      3
## 707 707     3        5        0      F19  --    TxtOrg      3
```

```
tall.nonmissing <- tall.nonmissing[tall.nonmissing$Sex!="--",]

model.formula.alldata <- as.list(rep(NA,7))
names(model.formula.alldata) <- Rubric.names


for (i in Rubric.names) {


  rubric.data <- tall.nonmissing[tall.nonmissing$Rubric==i,]
  tmp <- lmer(as.numeric(Rating) ~ -1 + as.factor(Rater) +
              Semester + Sex + (1|Artifact),
            data=rubric.data,REML=FALSE)

  tmp.back_elim <- fitLMER.fnc(tmp,set.REML.FALSE = TRUE,log.file.name = FALSE)


  tmp.single_intercept <- update(tmp.back_elim, . ~ . + 1 - as.factor(Rater))
  pval <- anova(tmp.single_intercept,tmp.back_elim)$"Pr(>Chisq)"[2]


  if (pval<=0.05) {
    tmp_final <- tmp.back_elim
  } else {
    tmp_final <- tmp.single_intercept
  }


  model.formula.alldata[[i]] <- formula(tmp_final)

}
```

```
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
```

```
## ========================================================
## ===               backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.7154 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.5297 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===             forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===             re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
## ========================================================
## ===               backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.8802 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.7402 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===             forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===             re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
```

```
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.608 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Semester" = 0.5312 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.6166 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Semester" = 0.3987 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
```

```
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.1935 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.5041 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Semester" = 0.205 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
```

```
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
## Warning in fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE): Argument "ran.effects" is
## TRUE
## ========================================================
## ===              backfitting fixed effects         ===
## ========================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Semester" = 0.2158 >= 0.05
##     not part of higher-order interaction
##     removing term
##   iteration 2
##     p-value for term "Sex" = 0.3523 >= 0.05
##     not part of higher-order interaction
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
## pruning random effects structure ...
##   nothing to prune
## refitting model(s) with ML (instead of REML)
```

```
model.formula.alldata
```

```
## $CritDes
## as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##
## $InitEDA
## as.numeric(Rating) ~ (1 | Artifact)
##
## $InterpRes
```

```
## as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##
## $RsrchQ
## as.numeric(Rating) ~ (1 | Artifact)
##
## $SelMeth
## as.numeric(Rating) ~ as.factor(Rater) + Semester + (1 | Artifact) -
##     1
##
## $TxtOrg
## as.numeric(Rating) ~ (1 | Artifact)
##
## $VisOrg
## as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
```

And if we use all the data, we find that we should add Rater as a fixed effect in the rubrics SelMeth, VisOrg, CritDes, InterpRes, and should add Semester as a fixed effect in the rubric SelMeth. ### Question 3 (iii): Trying interactions and new random effects for the seven rubric specific models using all the data

```
fla <- formula(model.formula.alldata[["SelMeth"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="SelMeth",])
round(summary(tmp)$coef,2)  ## fixed effects and their t-values
```

```
##                   Estimate Std. Error t value
## as.factor(Rater)1     2.25       0.08   29.99
## as.factor(Rater)2     2.23       0.07   29.99
## as.factor(Rater)3     2.03       0.08   27.03
## SemesterS19          -0.36       0.10   -3.66
```

```
tmp.single_intercept <- update(tmp, . ~ . + 1 - as.factor(Rater))
anova(tmp.single_intercept,tmp)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing[tall.nonmissing$Rubric == "SelMeth", ]
## Models:
## tmp.single_intercept: as.numeric(Rating) ~ Semester + (1 | Artifact)
## tmp: as.numeric(Rating) ~ as.factor(Rater) + Semester + (1 | Artifact) - 1
##                      npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## tmp.single_intercept    4 145.07 156.08 -68.534   137.07
## tmp                     6 142.05 158.58 -65.027   130.05 7.0146  2    0.02998 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tmp.fixed_interactions <- update(tmp, . ~ . + as.factor(Rater)*Semester - Semester)
anova(tmp,tmp.fixed_interactions)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing[tall.nonmissing$Rubric == "SelMeth", ]
## Models:
## tmp: as.numeric(Rating) ~ as.factor(Rater) + Semester + (1 | Artifact) - 1
## tmp.fixed_interactions: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) + as.factor(Rater):Se
##                         npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## tmp                        6 142.05 158.58 -65.027   130.05
## tmp.fixed_interactions     8 143.46 165.49 -63.731   127.46 2.592  2     0.2736
```

```
m0 <- tmp                                          ## Null hypothesis
mA <- update(m0, . ~ . + (Semester|Artifact))      ## Alternative hypotheses
```

```
## Error: number of observations (=116) <= number of random effects (=180) for term (Semester | Artifac
```

```
m  <- update(mA, . ~ . - (1|Artifact))             ## Model with only the new R.E.
```

```
## Error in h(simpleError(msg, call)): error in evaluating the argument 'object' in selecting a method
```

```
exactRLRT(m0=m0,mA=mA,m=m)
```

```
## Error in exactRLRT(m0 = m0, mA = mA, m = m): object 'm' not found
```

```
m0 <- tmp                                          ## Null hypothesis
mA <- update(m0, . ~ . + (as.factor(Rater)|Artifact))   ## Alternative hypotheses
```

```
## Error: number of observations (=116) <= number of random effects (=270) for term (as.factor(Rater) |
```

```
m  <- update(mA, . ~ . - (1|Artifact))             ## Model with only the new R.E.
```

```
## Error in h(simpleError(msg, call)): error in evaluating the argument 'object' in selecting a method
```

```
exactRLRT(m0=m0,mA=mA,m=m)
```

```
## Error in exactRLRT(m0 = m0, mA = mA, m = m): object 'm' not found
```

```
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ as.factor(Rater) + Semester + (1 | Artifact) -
##     1
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "SelMeth", ]
##
## REML criterion at convergence: 143.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0480 -0.3923 -0.0551  0.2674  2.5827
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.08973  0.2996
##  Residual             0.10842  0.3293
## Number of obs: 116, groups:  Artifact, 90
##
## Fixed effects:
##                   Estimate Std. Error t value
## as.factor(Rater)1  2.25037    0.07503  29.992
## as.factor(Rater)2  2.22653    0.07424  29.991
## as.factor(Rater)3  2.03316    0.07521  27.033
## SemesterS19       -0.35860    0.09796  -3.661
##
## Correlation of Fixed Effects:
##             a.(R)1 a.(R)2 a.(R)3
## as.fctr(R)2  0.285
## as.fctr(R)3  0.287  0.280
## SemesterS19 -0.413 -0.391 -0.394
```

```
fla <- formula(model.formula.alldata[["CritDes"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="CritDes",])
round(summary(tmp)$coef,2)
```

```
##                   Estimate Std. Error t value
## as.factor(Rater)1     1.69       0.12   13.98
## as.factor(Rater)2     2.11       0.12   17.34
## as.factor(Rater)3     1.89       0.12   15.51
```

```
tmp.single_intercept <- update(tmp, . ~ . + 1 - as.factor(Rater))
anova(tmp.single_intercept,tmp)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing[tall.nonmissing$Rubric == "CritDes", ]
## Models:
## tmp.single_intercept: as.numeric(Rating) ~ (1 | Artifact)
## tmp: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##                      npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## tmp.single_intercept    3 277.68 285.91 -135.84   271.68
## tmp                     5 273.62 287.35 -131.81   263.62 8.0535  2    0.01783 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m0 <- tmp                                       ## Null hypothesis
mA <- update(m0, . ~ . + (as.factor(Rater)|Artifact))   ## Alternative hypotheses
```

```
## Error: number of observations (=115) <= number of random effects (=267) for term (as.factor(Rater) |
```

```
m  <- update(mA, . ~ . - (1|Artifact))          ## Model with only the new R.E.
```

```
## Error in h(simpleError(msg, call)): error in evaluating the argument 'object' in selecting a method
```

```
exactRLRT(m0=m0,mA=mA,m=m)
```

```
## Error in exactRLRT(m0 = m0, mA = mA, m = m): object 'm' not found
```

```
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "CritDes", ]
##
## REML criterion at convergence: 271
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.55495 -0.50027 -0.08228  0.64663  1.60935
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.4349   0.6595
##  Residual             0.2473   0.4972
## Number of obs: 115, groups:  Artifact, 89
##
## Fixed effects:
##                   Estimate Std. Error t value
## as.factor(Rater)1   1.6863     0.1207   13.98
```

```
## as.factor(Rater)2   2.1129     0.1219   17.34
## as.factor(Rater)3   1.8908     0.1219   15.51
##
## Correlation of Fixed Effects:
##             a.(R)1 a.(R)2
## as.fctr(R)2 0.244
## as.fctr(R)3 0.244  0.246
```

```
fla <- formula(model.formula.alldata[["InterpRes"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="InterpRes",])
round(summary(tmp)$coef,2)
```

```
##                   Estimate Std. Error t value
## as.factor(Rater)1     2.70       0.09   30.34
## as.factor(Rater)2     2.59       0.09   29.01
## as.factor(Rater)3     2.14       0.09   23.70
```

```
tmp.single_intercept <- update(tmp, . ~ . + 1 - as.factor(Rater))
anova(tmp.single_intercept,tmp)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing[tall.nonmissing$Rubric == "InterpRes", ]
## Models:
## tmp.single_intercept: as.numeric(Rating) ~ (1 | Artifact)
## tmp: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##                      npar    AIC    BIC   logLik deviance  Chisq Df Pr(>Chisq)
## tmp.single_intercept    3 218.53 226.79 -106.263   212.53
## tmp                     5 200.66 214.43  -95.331   190.66 21.864  2  1.787e-05
##
## tmp.single_intercept
## tmp                  ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m0 <- tmp                                       ## Null hypothesis
mA <- update(m0, . ~ . + (as.factor(Rater)|Artifact))   ## Alternative hypotheses
```

```
## Error: number of observations (=116) <= number of random effects (=270) for term (as.factor(Rater) |
```

```
m  <- update(mA, . ~ . - (1|Artifact))          ## Model with only the new R.E.
```

```
## Error in h(simpleError(msg, call)): error in evaluating the argument 'object' in selecting a method
```

```
exactRLRT(m0=m0,mA=mA,m=m)
```

```
## Error in exactRLRT(m0 = m0, mA = mA, m = m): object 'm' not found
```

```
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "InterpRes", ]
##
## REML criterion at convergence: 199.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5317 -0.7627  0.2635  0.6614  2.6535
```

```
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.06224  0.2495
##  Residual             0.25250  0.5025
## Number of obs: 116, groups:  Artifact, 90
##
## Fixed effects:
##                   Estimate Std. Error t value
## as.factor(Rater)1  2.70421    0.08912   30.34
## as.factor(Rater)2  2.58574    0.08912   29.01
## as.factor(Rater)3  2.13918    0.09027   23.70
##
## Correlation of Fixed Effects:
##             a.(R)1 a.(R)2
## as.fctr(R)2 0.061
## as.fctr(R)3 0.062  0.062
```

```
fla <- formula(model.formula.alldata[["VisOrg"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="VisOrg",])
round(summary(tmp)$coef,2)
```

```
##                   Estimate Std. Error t value
## as.factor(Rater)1     2.38        0.1   24.62
## as.factor(Rater)2     2.65        0.1   27.70
## as.factor(Rater)3     2.28        0.1   23.64
```

```
tmp.single_intercept <- update(tmp, . ~ . + 1 - as.factor(Rater))
anova(tmp.single_intercept,tmp)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing[tall.nonmissing$Rubric == "VisOrg", ]
## Models:
## tmp.single_intercept: as.numeric(Rating) ~ (1 | Artifact)
## tmp: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##                      npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## tmp.single_intercept    3 227.21 235.44 -110.60   221.21
## tmp                     5 220.82 234.54 -105.41   210.82 10.392  2   0.005539
##
## tmp.single_intercept
## tmp                  **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m0 <- tmp                                          ## Null hypothesis
mA <- update(m0, . ~ . + (as.factor(Rater)|Artifact))   ## Alternative hypotheses
```

```
## Error: number of observations (=115) <= number of random effects (=267) for term (as.factor(Rater) |
```

```
m  <- update(mA, . ~ . - (1|Artifact))          ## Model with only the new R.E.
```

```
## Error in h(simpleError(msg, call)): error in evaluating the argument 'object' in selecting a method
```

```
exactRLRT(m0=m0,mA=mA,m=m)
```

```
## Error in exactRLRT(m0 = m0, mA = mA, m = m): object 'm' not found
```

```r
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ as.factor(Rater) + (1 | Artifact) - 1
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "VisOrg", ]
##
## REML criterion at convergence: 219.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.5004 -0.3365 -0.2483  0.3841  1.8552
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.2907   0.5392
##  Residual             0.1467   0.3830
## Number of obs: 115, groups:  Artifact, 89
##
## Fixed effects:
##                   Estimate Std. Error t value
## as.factor(Rater)1  2.37794    0.09658   24.62
## as.factor(Rater)2  2.64891    0.09564   27.70
## as.factor(Rater)3  2.28355    0.09658   23.64
##
## Correlation of Fixed Effects:
##             a.(R)1 a.(R)2
## as.fctr(R)2 0.263
## as.fctr(R)3 0.265  0.263
```

```r
fla <- formula(model.formula.alldata[["RsrchQ"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="RsrchQ",])
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ (1 | Artifact)
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "RsrchQ", ]
##
## REML criterion at convergence: 209.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.2694 -0.5285 -0.3736  0.9743  2.4770
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.07276  0.2697
##  Residual             0.27825  0.5275
## Number of obs: 116, groups:  Artifact, 90
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  2.35169    0.05794   40.59
```

```r
fla <- formula(model.formula.alldata[["TxtOrg"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="TxtOrg",])
```

```r
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ (1 | Artifact)
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "TxtOrg", ]
##
## REML criterion at convergence: 247.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3557 -0.7550  0.3834  0.5302  2.4132
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.09371  0.3061
##  Residual             0.39573  0.6291
## Number of obs: 116, groups:  Artifact, 90
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  2.58745    0.06821   37.93
```

```r
fla <- formula(model.formula.alldata[["InitEDA"]])
tmp <- lmer(fla,data=tall.nonmissing[tall.nonmissing$Rubric=="InitEDA",])
summary(tmp)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ (1 | Artifact)
##    Data: tall.nonmissing[tall.nonmissing$Rubric == "InitEDA", ]
##
## REML criterion at convergence: 239
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.8889 -0.3391 -0.1427  0.4276  1.6035
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Artifact (Intercept) 0.3651   0.6042
##  Residual             0.1655   0.4068
## Number of obs: 116, groups:  Artifact, 90
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  2.44226    0.07537    32.4
```

According to the result above, we could get all the 7 final models and there coefficients, tau2 and sigma2.

We then tried to add the fixed effects to the model fitted by the full dataset. We found that we should not add any fixed effects to the models for rubrics InitEDA, RsrchQ and TxtOrg. And we should add Rater as a fixed effect to the model for rubrics CritDes, InterpRes, SelMeth, it showed that different Raters could significantly influence the Ratings for these rubrics. In the end, we find that for rubric SelMeth, we should add the variables Rater and Semester to its model, it meant that for this rubric, different Raters and different semesters could be influential for the final ratings.

Then, we considered the fixed effects of the interaction terms. For the models with intercept only, we did not

need to examine the interaction terms. For the rubric SelMeth, we found our previous model makes sense given the t value of each variable is greater than 1.96 that they are all significant. After adding the interaction between Semester and Rater, we found that there was no evidence that we should add this interaction to the model. For random effects, since we should only try the effects that appeared in the fixed effect, we tried Rater and Semester as the random effects, after fitting these models, we found that we do not need to add any random effects to the model(details please refer to the appendix). Thus we obtained our final model, with random effects group by each artifact and fixed effects Rater and Semester. It showed that for each artifact rated by rubric SelMeth, different Raters and Semesters are significant factors influencing the Ratings.

And we did similar thing to all the rubrics.

2(c)(iv): Trying to add fixed effects, interactions, and new random effects to the "combined" model Rating ~ 1 + (0 + Rubric|Artifact), using all the data.

```
comb.0 <- lmer(as.numeric(Rating) ~ 1 + (0 + Rubric | Artifact),
               data=tall.nonmissing)
```

```
## boundary (singular) fit: see ?isSingular
```

```
summary(comb.0)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ 1 + (0 + Rubric | Artifact)
##    Data: tall.nonmissing
##
## REML criterion at convergence: 1471.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0218 -0.4940 -0.0753  0.5271  3.7759
##
## Random effects:
##  Groups   Name            Variance Std.Dev. Corr
##  Artifact RubricCritDes   0.64070  0.8004
##           RubricInitEDA   0.38288  0.6188   0.26
##           RubricInterpRes 0.25658  0.5065   0.00 0.79
##           RubricRsrchQ    0.17398  0.4171   0.38 0.50 0.74
##           RubricSelMeth   0.09619  0.3102   0.56 0.37 0.41 0.26
##           RubricTxtOrg    0.40425  0.6358   0.03 0.69 0.80 0.64 0.24
##           RubricVisOrg    0.31878  0.5646   0.17 0.78 0.76 0.60 0.29 0.79
##  Residual                 0.19477  0.4413
## Number of obs: 810, groups:  Artifact, 90
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  2.23210    0.04013   55.63
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
```

```
comb.full <- update(comb.0, . ~ . + as.factor(Rater) + Semester +
                      Sex + Repeated + Rubric)

summary(comb.full)
```

```
## Linear mixed model fit by REML ['lmerMod']
```

```
## Formula: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Sex + Repeated + Rubric
##    Data: tall.nonmissing
##
## REML criterion at convergence: 1429.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.1091 -0.5065 -0.0178  0.5242  3.7932
##
## Random effects:
##  Groups   Name            Variance Std.Dev. Corr
##  Artifact RubricCritDes   0.55311  0.7437
##           RubricInitEDA   0.35239  0.5936   0.47
##           RubricInterpRes 0.17512  0.4185   0.23 0.75
##           RubricRsrchQ    0.16997  0.4123   0.58 0.44 0.71
##           RubricSelMeth   0.06816  0.2611   0.39 0.60 0.74 0.41
##           RubricTxtOrg    0.26339  0.5132   0.34 0.62 0.70 0.56 0.67
##           RubricVisOrg    0.25809  0.5080   0.35 0.73 0.68 0.52 0.41 0.76
##  Residual                 0.18916  0.4349
## Number of obs: 810, groups:  Artifact, 90
##
## Fixed effects:
##                     Estimate Std. Error t value
## (Intercept)         2.013748   0.109103  18.457
## as.factor(Rater)2   0.001977   0.054887   0.036
## as.factor(Rater)3  -0.174867   0.055045  -3.177
## SemesterS19        -0.175017   0.087850  -1.992
## SexM                0.010506   0.081271   0.129
## Repeated           -0.073586   0.098522  -0.747
## RubricInitEDA       0.547054   0.095710   5.716
## RubricInterpRes     0.587091   0.100893   5.819
## RubricRsrchQ        0.460875   0.087516   5.266
## RubricSelMeth       0.164863   0.094265   1.749
## RubricTxtOrg        0.692880   0.099523   6.962
## RubricVisOrg        0.530182   0.099136   5.348
##
## Correlation of Fixed Effects:
##             (Intr) a.(R)2 a.(R)3 SmsS19 SexM   Repetd RbIEDA RbrcIR RbrcRQ
## as.fctr(R)2 -0.245
## as.fctr(R)3 -0.237  0.499
## SemesterS19 -0.361  0.008  0.000
## SexM        -0.398 -0.026 -0.035  0.302
## Repeated    -0.154  0.001 -0.003  0.079  0.009
## RubrcIntEDA -0.552 -0.001  0.000 -0.001  0.000  0.007
## RbrcIntrpRs -0.660 -0.001  0.000 -0.001  0.000 -0.009  0.734
## RubrcRsrchQ -0.626 -0.001  0.000 -0.001  0.000 -0.039  0.585  0.756
## RubricSlMth -0.689 -0.001  0.000 -0.001  0.000 -0.088  0.659  0.777  0.689
## RubrcTxtOrg -0.611 -0.001  0.000 -0.001  0.000  0.005  0.674  0.751  0.682
## RubricVsOrg -0.607 -0.001 -0.001 -0.002 -0.001 -0.021  0.715  0.745  0.668
##             RbrcSM RbrcTO
## as.fctr(R)2
## as.fctr(R)3
## SemesterS19
```

```
## SexM
## Repeated
## RubrcIntEDA
## RbrcIntrpRs
## RubrcRsrchQ
## RubricSlMth
## RubrcTxtOrg  0.725
## RubricVsOrg  0.680  0.750
```

```
comb.back_elim <- fitLMER.fnc(comb.full, log.file.name = FALSE)
```

```
## Warning in fitLMER.fnc(comb.full, log.file.name = FALSE): Argument "ran.effects" is empty, which mea
## TRUE
```

```
## ============================================================
## ===              backfitting fixed effects             ===
## ============================================================
## processing model terms of interaction level 1
##   iteration 1
##     p-value for term "Sex" = 0.887 >= 0.05
##     not part of higher-order interaction
```

```
## boundary (singular) fit: see ?isSingular
```

```
##     removing term
##   iteration 2
##     p-value for term "Repeated" = 0.0919 >= 0.05
##     not part of higher-order interaction
```

```
## boundary (singular) fit: see ?isSingular
```

```
##     removing term
## pruning random effects structure ...
##   nothing to prune
## ============================================================
## ===            forwardfitting random effects           ===
## ============================================================
##  ===       random slopes       ===
## ============================================================
## ===            re-backfitting fixed effects            ===
## ============================================================
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE
```

```
## boundary (singular) fit: see ?isSingular
```

```
## pruning random effects structure ...
##   nothing to prune
```

```
summary(comb.back_elim)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Rubric
##    Data: tall.nonmissing
##
## REML criterion at convergence: 1424.1
##
```

```
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.1200 -0.5125 -0.0173  0.5302  3.7752
##
## Random effects:
##  Groups   Name            Variance Std.Dev. Corr
##  Artifact RubricCritDes   0.55495  0.7449
##           RubricInitEDA   0.35064  0.5921   0.47
##           RubricInterpRes 0.16892  0.4110   0.23 0.75
##           RubricRsrchQ    0.16777  0.4096   0.59 0.44 0.70
##           RubricSelMeth   0.06499  0.2549   0.40 0.60 0.74 0.40
##           RubricTxtOrg    0.25615  0.5061   0.33 0.61 0.69 0.55 0.66
##           RubricVisOrg    0.25894  0.5089   0.35 0.73 0.68 0.52 0.41 0.75
##  Residual                 0.18934  0.4351
## Number of obs: 810, groups:  Artifact, 90
##
## Fixed effects:
##                      Estimate Std. Error t value
## (Intercept)         2.0084130  0.0987610  20.336
## as.factor(Rater)2   0.0003231  0.0547446   0.006
## as.factor(Rater)3 -0.1771062  0.0548892  -3.227
## SemesterS19       -0.1730357  0.0826927  -2.093
## RubricInitEDA      0.5474747  0.0957148   5.720
## RubricInterpRes    0.5864544  0.1008618   5.814
## RubricRsrchQ       0.4584082  0.0874179   5.244
## RubricSelMeth      0.1590770  0.0937771   1.696
## RubricTxtOrg       0.6930033  0.0995479   6.962
## RubricVisOrg       0.5289027  0.0990973   5.337
##
## Correlation of Fixed Effects:
##             (Intr) a.(R)2 a.(R)3 SmsS19 RbIEDA RbrcIR RbrcRQ RbrcSM RbrcTO
## as.fctr(R)2 -0.281
## as.fctr(R)3 -0.277  0.499
## SemesterS19 -0.264  0.017  0.011
## RubrcIntEDA -0.610 -0.001  0.000 -0.002
## RbrcIntrpRs -0.735 -0.001  0.000  0.000  0.734
## RubrcRsrchQ -0.701 -0.001  0.000  0.002  0.586  0.756
## RubricSlMth -0.782  0.000  0.000  0.006  0.662  0.779  0.688
## RubrcTxtOrg -0.679 -0.001  0.000 -0.001  0.674  0.751  0.682  0.728
## RubricVsOrg -0.675 -0.001 -0.001  0.000  0.715  0.745  0.667  0.681  0.750
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
```

```
comb.inter <- update(comb.back_elim, . ~ . + as.factor(Rater)*Semester*Rubric)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00431172 (tol = 0.002, component 1)
```

```
ss <- getME(comb.inter,c("theta","fixef"))
comb.inter.u<- update(comb.inter,start=ss,
             control=lmerControl(optimizer="bobyqa",
                                 optCtrl=list(maxfun=2e5)))
```

```
## boundary (singular) fit: see ?isSingular
```

```r
summary(comb.inter.u)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Rubric + as.factor(Rater):Semester + as.factor(Rater):Rubric +
##     Semester:Rubric + as.factor(Rater):Semester:Rubric
##    Data: tall.nonmissing
## Control: lmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))
##
## REML criterion at convergence: 1424.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9141 -0.5141 -0.0653  0.5023  3.6609
##
## Random effects:
##  Groups   Name            Variance Std.Dev. Corr
##  Artifact RubricCritDes   0.48550  0.6968
##           RubricInitEDA   0.35257  0.5938   0.42
##           RubricInterpRes 0.14619  0.3824   0.32 0.80
##           RubricRsrchQ    0.16444  0.4055   0.66 0.43 0.72
##           RubricSelMeth   0.06297  0.2509   0.45 0.64 0.78 0.49
##           RubricTxtOrg    0.25441  0.5044   0.44 0.65 0.67 0.60 0.62
##           RubricVisOrg    0.25527  0.5052   0.35 0.73 0.68 0.57 0.35 0.76
##  Residual                 0.18839  0.4340
## Number of obs: 810, groups:  Artifact, 90
##
## Fixed effects:
##                                            Estimate Std. Error t value
## (Intercept)                                1.739538   0.136568  12.738
## as.factor(Rater)2                          0.302995   0.155107   1.953
## as.factor(Rater)3                          0.237851   0.155863   1.526
## SemesterS19                               -0.129077   0.250318  -0.516
## RubricInitEDA                              0.765215   0.165241   4.631
## RubricInterpRes                            0.979228   0.162160   6.039
## RubricRsrchQ                               0.710427   0.147386   4.820
## RubricSelMeth                              0.462750   0.155274   2.980
## RubricTxtOrg                               1.011251   0.160899   6.285
## RubricVisOrg                               0.647869   0.166603   3.889
## as.factor(Rater)2:SemesterS19              0.268014   0.303883   0.882
## as.factor(Rater)3:SemesterS19             -0.072789   0.301026  -0.242
## as.factor(Rater)2:RubricInitEDA           -0.325018   0.204108  -1.592
## as.factor(Rater)3:RubricInitEDA           -0.374190   0.205354  -1.822
## as.factor(Rater)2:RubricInterpRes         -0.469281   0.201051  -2.334
## as.factor(Rater)3:RubricInterpRes         -0.711515   0.202316  -3.517
## as.factor(Rater)2:RubricRsrchQ            -0.447050   0.189326  -2.361
## as.factor(Rater)3:RubricRsrchQ            -0.474411   0.190681  -2.488
## as.factor(Rater)2:RubricSelMeth           -0.301450   0.193678  -1.556
## as.factor(Rater)3:RubricSelMeth           -0.365656   0.194970  -1.875
## as.factor(Rater)2:RubricTxtOrg            -0.449164   0.200927  -2.235
## as.factor(Rater)3:RubricTxtOrg            -0.407754   0.202209  -2.016
## as.factor(Rater)2:RubricVisOrg             0.009042   0.205059   0.044
## as.factor(Rater)3:RubricVisOrg            -0.287443   0.206299  -1.393
## SemesterS19:RubricInitEDA                 -0.050212   0.301475  -0.167
```

```
## SemesterS19:RubricInterpRes                     0.127813   0.295706   0.432
## SemesterS19:RubricRsrchQ                        0.133874   0.267750   0.500
## SemesterS19:RubricSelMeth                      -0.089616   0.282837  -0.317
## SemesterS19:RubricTxtOrg                        0.166097   0.293176   0.567
## SemesterS19:RubricVisOrg                        0.146845   0.302496   0.485
## as.factor(Rater)2:SemesterS19:RubricInitEDA     0.020326   0.392376   0.052
## as.factor(Rater)3:SemesterS19:RubricInitEDA     0.252422   0.389961   0.647
## as.factor(Rater)2:SemesterS19:RubricInterpRes -0.266618   0.385390  -0.692
## as.factor(Rater)3:SemesterS19:RubricInterpRes -0.152392   0.383354  -0.398
## as.factor(Rater)2:SemesterS19:RubricRsrchQ    -0.217348   0.360414  -0.603
## as.factor(Rater)3:SemesterS19:RubricRsrchQ     0.354319   0.357388   0.991
## as.factor(Rater)2:SemesterS19:RubricSelMeth   -0.401035   0.370200  -1.083
## as.factor(Rater)3:SemesterS19:RubricSelMeth   -0.192670   0.367887  -0.524
## as.factor(Rater)2:SemesterS19:RubricTxtOrg    -0.542267   0.385011  -1.408
## as.factor(Rater)3:SemesterS19:RubricTxtOrg    -0.316395   0.382614  -0.827
## as.factor(Rater)2:SemesterS19:RubricVisOrg    -0.603626   0.392909  -1.536
## as.factor(Rater)3:SemesterS19:RubricVisOrg    -0.186749   0.390759  -0.478
##
## Correlation matrix not shown by default, as p = 42 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
## optimizer (bobyqa) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
comb.inter_elim <- fitLMER.fnc(comb.inter.u, log.file.name = FALSE)
## Warning in fitLMER.fnc(comb.inter.u, log.file.name = FALSE): Argument "ran.effects" is empty, which r
## TRUE
## ============================================================
## ===              backfitting fixed effects             ===
## ============================================================
## processing model terms of interaction level 3
##   iteration 1
##     p-value for term "as.factor(Rater):Semester:Rubric" = 0.5526 >= 0.05
##     not part of higher-order interaction
## boundary (singular) fit: see ?isSingular
##     removing term
## processing model terms of interaction level 2
##   iteration 2
##     p-value for term "as.factor(Rater):Semester" = 0.598 >= 0.05
##     not part of higher-order interaction
## boundary (singular) fit: see ?isSingular
##     removing term
##   iteration 3
##     p-value for term "Semester:Rubric" = 0.0761 >= 0.05
##     not part of higher-order interaction
## boundary (singular) fit: see ?isSingular
##     removing term
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
```

```
## pruning random effects structure ...
##   nothing to prune
## ========================================================
## ===            forwardfitting random effects       ===
## ========================================================
##  ===       random slopes       ===
## ========================================================
## ===            re-backfitting fixed effects        ===
## ========================================================
## processing model terms of interaction level 2
##   all terms of interaction level 2 significant
## processing model terms of interaction level 1
##   all terms of interaction level 1 significant
## resetting REML to TRUE

## boundary (singular) fit: see ?isSingular

## pruning random effects structure ...
##   nothing to prune
summary(comb.inter_elim)

## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Rubric + as.factor(Rater):Rubric
##    Data: tall.nonmissing
## Control: lmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 2e+05))
##
## REML criterion at convergence: 1419.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9280 -0.5122 -0.0447  0.4827  3.5854
##
## Random effects:
##  Groups   Name            Variance Std.Dev. Corr
##  Artifact RubricCritDes   0.50348  0.7096
##           RubricInitEDA   0.35480  0.5956   0.44
##           RubricInterpRes 0.15192  0.3898   0.35 0.82
##           RubricRsrchQ    0.17953  0.4237   0.63 0.44 0.72
##           RubricSelMeth   0.06727  0.2594   0.42 0.60 0.74 0.36
##           RubricTxtOrg    0.26069  0.5106   0.42 0.64 0.67 0.55 0.64
##           RubricVisOrg    0.25491  0.5049   0.34 0.71 0.68 0.51 0.38 0.77
##  Residual                 0.18519  0.4303
## Number of obs: 810, groups:  Artifact, 90
##
## Fixed effects:
##                                 Estimate Std. Error t value
## (Intercept)                      1.75945    0.11785  14.929
## as.factor(Rater)2                0.36537    0.13296   2.748
## as.factor(Rater)3                0.21421    0.13297   1.611
## SemesterS19                     -0.17780    0.08228  -2.161
## RubricInitEDA                    0.74625    0.13676   5.457
## RubricInterpRes                  1.01453    0.13479   7.527
## RubricRsrchQ                     0.74926    0.12419   6.033
## RubricSelMeth                    0.42672    0.13040   3.272
```

```
## RubricTxtOrg                        1.04967    0.13551   7.746
## RubricVisOrg                        0.68354    0.13947   4.901
## as.factor(Rater)2:RubricInitEDA    -0.30843    0.17249  -1.788
## as.factor(Rater)3:RubricInitEDA    -0.29522    0.17282  -1.708
## as.factor(Rater)2:RubricInterpRes -0.53674    0.17008  -3.156
## as.factor(Rater)3:RubricInterpRes -0.75247    0.17049  -4.414
## as.factor(Rater)2:RubricRsrchQ     -0.50157    0.16151  -3.106
## as.factor(Rater)3:RubricRsrchQ     -0.37068    0.16179  -2.291
## as.factor(Rater)2:RubricSelMeth    -0.39602    0.16467  -2.405
## as.factor(Rater)3:RubricSelMeth    -0.41324    0.16504  -2.504
## as.factor(Rater)2:RubricTxtOrg     -0.58380    0.17141  -3.406
## as.factor(Rater)3:RubricTxtOrg     -0.48649    0.17177  -2.832
## as.factor(Rater)2:RubricVisOrg     -0.14444    0.17442  -0.828
## as.factor(Rater)3:RubricVisOrg     -0.33380    0.17481  -1.910

##
## Correlation matrix not shown by default, as p = 22 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

## optimizer (bobyqa) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
```

```
formula(comb.inter.u)
```

```
## as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Rubric + as.factor(Rater):Semester + as.factor(Rater):Rubric +
##     Semester:Rubric + as.factor(Rater):Semester:Rubric
```

```
formula(comb.inter_elim)
```

```
## as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Rubric + as.factor(Rater):Rubric
```

```
formula(comb.back_elim)
```

```
## as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) +
##     Semester + Rubric
```

```
summary(comb.inter.u)$varcor
```

```
##  Groups   Name            Std.Dev. Corr
##  Artifact RubricCritDes   0.69678
##           RubricInitEDA   0.59378  0.416
##           RubricInterpRes 0.38235  0.324 0.800
##           RubricRsrchQ    0.40551  0.655 0.430 0.723
##           RubricSelMeth   0.25094  0.446 0.639 0.784 0.488
##           RubricTxtOrg    0.50439  0.436 0.649 0.667 0.604 0.622
##           RubricVisOrg    0.50524  0.349 0.727 0.675 0.567 0.346 0.757
##  Residual                 0.43404
```

```
summary(comb.inter_elim)$varcor
```

```
##  Groups   Name            Std.Dev. Corr
##  Artifact RubricCritDes   0.70956
##           RubricInitEDA   0.59565  0.445
##           RubricInterpRes 0.38977  0.354 0.815
##           RubricRsrchQ    0.42371  0.631 0.440 0.716
##           RubricSelMeth   0.25937  0.424 0.601 0.737 0.364
```

```
##           RubricTxtOrg    0.51058  0.417 0.637 0.675 0.547 0.636
##           RubricVisOrg    0.50489  0.339 0.715 0.677 0.512 0.376 0.772
##  Residual                 0.43034
```

```
summary(comb.back_elim)$varcor
```

```
##  Groups   Name            Std.Dev. Corr
##  Artifact RubricCritDes   0.74495
##           RubricInitEDA   0.59215  0.467
##           RubricInterpRes 0.41100  0.230 0.749
##           RubricRsrchQ    0.40960  0.588 0.436 0.704
##           RubricSelMeth   0.25493  0.399 0.603 0.736 0.397
##           RubricTxtOrg    0.50612  0.335 0.614 0.691 0.551 0.656
##           RubricVisOrg    0.50886  0.350 0.731 0.679 0.516 0.414 0.752
##  Residual                 0.43513
```

```
anova(comb.back_elim,comb.inter_elim,comb.inter.u)
```

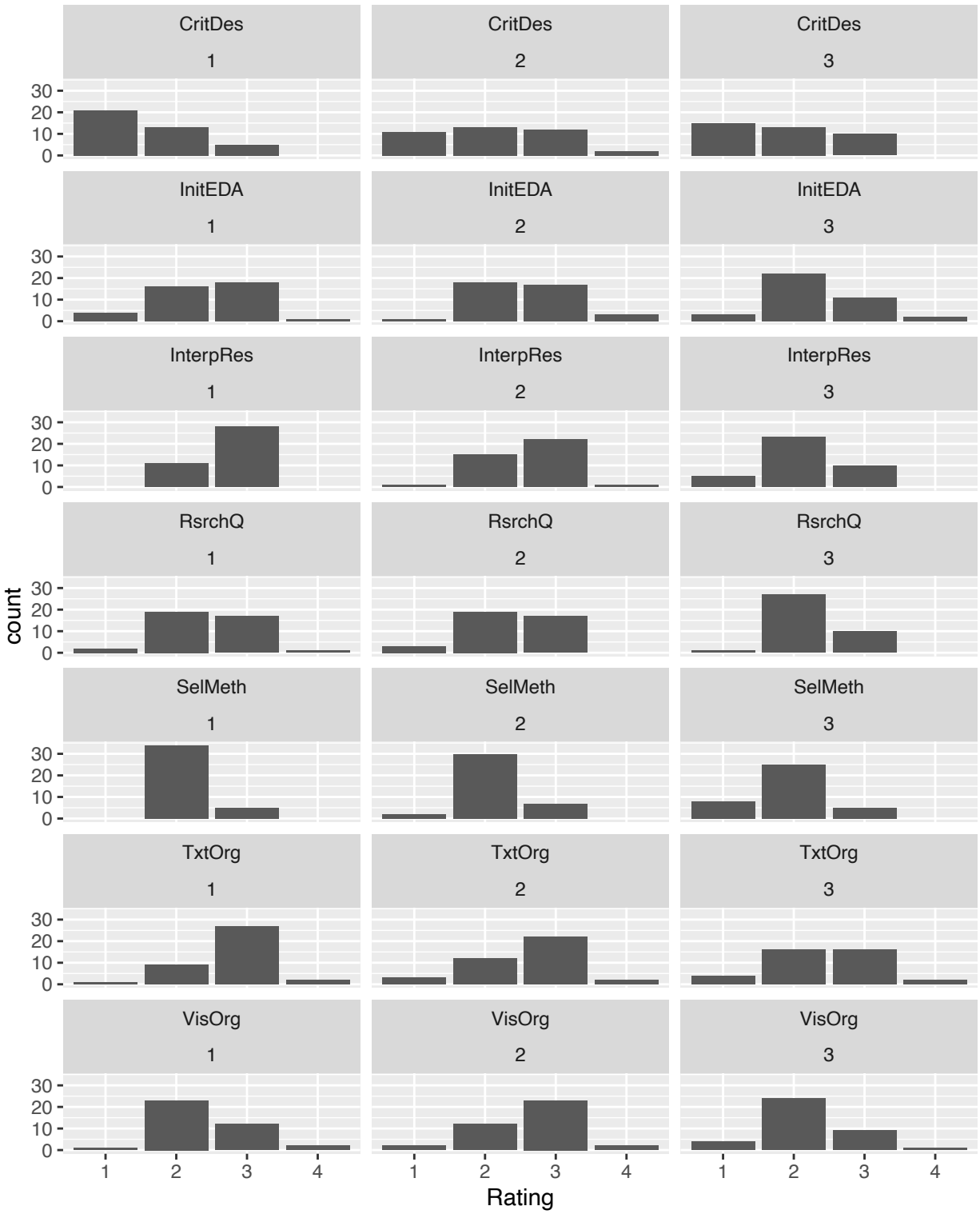
```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing
## Models:
## comb.back_elim: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) + Semester + Rubric
## comb.inter_elim: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) + Semester + Rubric
## comb.inter.u: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) + Semester + Rubric + a
##                 npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## comb.back_elim    39 1464.0 1647.2 -693.02   1386.0
## comb.inter_elim   51 1454.5 1694.1 -676.26   1352.5 33.526 12   0.000801 ***
## comb.inter.u      71 1471.4 1804.8 -664.68   1329.4 23.161 20   0.280962
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Here we use ANOVA table and stepwise method to find the final combined model.

```
g <- ggplot(tall.nonmissing, aes(x=Rating)) +
  geom_bar() +
  facet_wrap( ~ Rubric + Rater, nrow=7)

g
```




```
m0 <- comb.inter_elim
mA <- lmer(as.numeric(Rating) ~ (0 + Rubric | Artifact) +
             (0 + as.factor(Rater) | Artifact) + as.factor(Rater) +
             Semester + Rubric + as.factor(Rater):Rubric, data=tall.nonmissing)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
```

```
## Model failed to converge with max|grad| = 0.00347545 (tol = 0.002, component 1)
```

```
anova(m0,mA)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Warning in commonArgs(par, fn, control, environment()): maxfun < 10 *
## length(par)^2 is not recommended.
```

```
## Data: tall.nonmissing
## Models:
## m0: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) + Semester + Rubric + as.factor(
## mA: as.numeric(Rating) ~ (0 + Rubric | Artifact) + (0 + as.factor(Rater) | Artifact) + as.factor(Rat
##    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m0   51 1454.5 1694.1 -676.26   1352.5
## mA   57 1415.9 1683.6 -650.94   1301.9 50.647  6  3.487e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
m0 <- comb.inter_elim
mA <- lmer(as.numeric(Rating) ~ (0 + Rubric | Artifact) +
             (0 + Semester | Artifact) + as.factor(Rater) +
             Semester + Rubric + as.factor(Rater):Rubric, data=tall.nonmissing)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## unable to evaluate scaled gradient
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge: degenerate Hessian with 1 negative eigenvalues
```

```
anova(m0,mA)
```

```
## refitting model(s) with ML (instead of REML)
```

```
## Data: tall.nonmissing
## Models:
## m0: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) + Semester + Rubric + as.factor(
## mA: as.numeric(Rating) ~ (0 + Rubric | Artifact) + (0 + Semester | Artifact) + as.factor(Rater) + Se
##    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m0   51 1454.5 1694.1 -676.26   1352.5
## mA   54 1458.4 1712.0 -675.18   1350.4 2.1534  3     0.5412
```

```
m0 <- comb.inter_elim
mA <- lmer(as.numeric(Rating) ~ (0 + Rubric | Artifact) +
             (0 + as.factor(Rater) | Artifact) +
             (0 + as.factor(Rater):Rubric | Artifact) + as.factor(Rater) +
             Semester + Rubric + as.factor(Rater):Rubric, data=tall.nonmissing)
```

```
## Error: number of observations (=810) <= number of random effects (=1890) for term (0 + as.factor(Rat
```

```
comb.final <- lmer(as.numeric(Rating) ~ (0 + Rubric | Artifact) +
             (0 + as.factor(Rater) | Artifact) + as.factor(Rater) +
             Semester + Rubric + as.factor(Rater):Rubric, data=tall.nonmissing)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00347545 (tol = 0.002, component 1)
```

```
formula(comb.final)
```

```
## as.numeric(Rating) ~ (0 + Rubric | Artifact) + (0 + as.factor(Rater) |
##     Artifact) + as.factor(Rater) + Semester + Rubric + as.factor(Rater):Rubric
```

```
summary(comb.final)$varcor
```

```
##  Groups     Name              Std.Dev. Corr
##  Artifact   RubricCritDes     0.70456
##             RubricInitEDA     0.56385   0.318
##             RubricInterpRes   0.31953   0.142  0.674
##             RubricRsrchQ      0.42309   0.500  0.194  0.538
##             RubricSelMeth     0.19564   0.145  0.227  0.376 -0.240
##             RubricTxtOrg      0.50029   0.268  0.437  0.364  0.305  0.213
##             RubricVisOrg      0.48201   0.175  0.504  0.445  0.276 -0.160
##  Artifact.1 as.factor(Rater)1 0.11309
##             as.factor(Rater)2 0.33421  -0.488
##             as.factor(Rater)3 0.30670   0.330  0.663
##  Residual                     0.36700
##
##
##
##
##
##
##
##   0.537
##
##
##
##
```

```
summary(comb.final)$coef
```

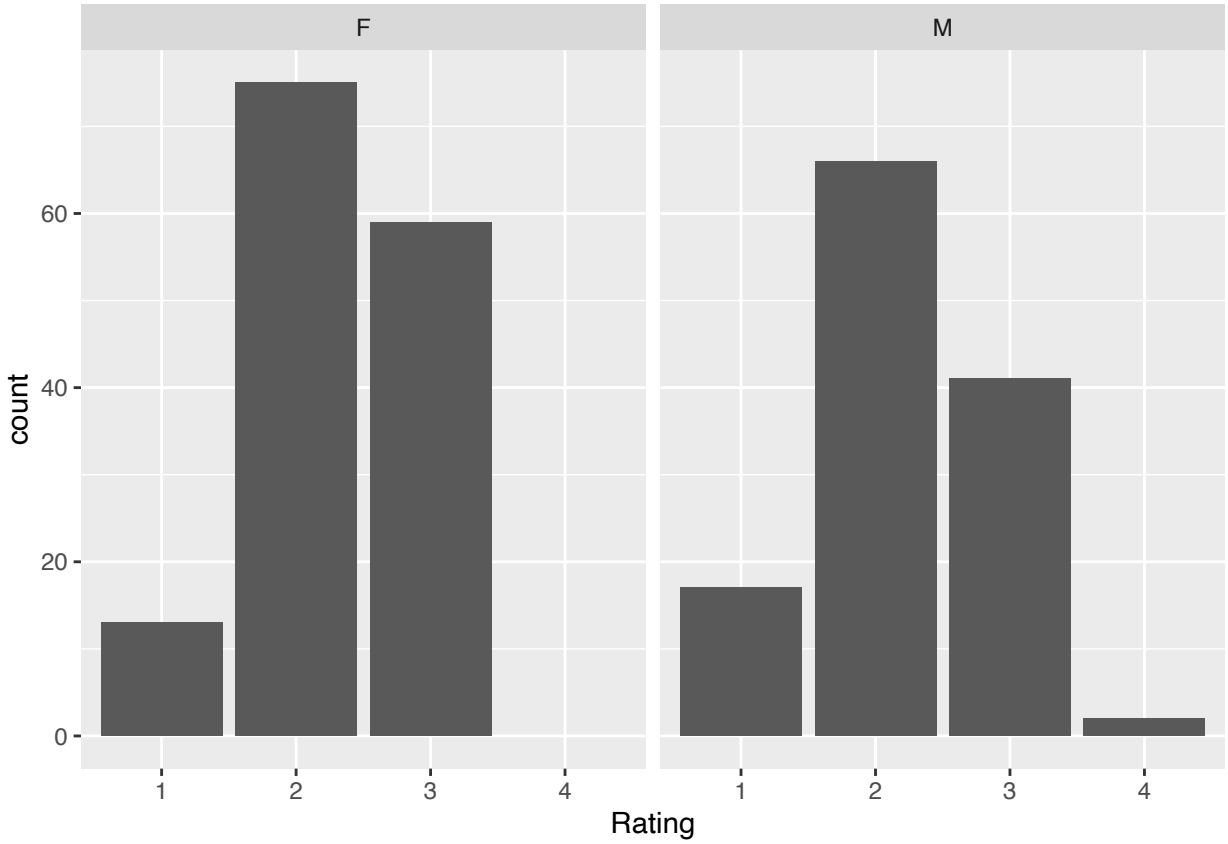
```
##                                    Estimate Std. Error    t value
## (Intercept)                       1.7575675 0.11403884 15.4120075
## as.factor(Rater)2                 0.3660512 0.13918262  2.6300063
## as.factor(Rater)3                 0.1958650 0.12967617  1.5104163
## SemesterS19                      -0.1591929 0.07647446 -2.0816477
## RubricInitEDA                     0.7394806 0.12996198  5.6899761
## RubricInterpRes                   0.9915166 0.12771096  7.7637555
## RubricRsrchQ                      0.7261861 0.11792862  6.1578445
## RubricSelMeth                     0.4106681 0.12470221  3.2931906
## RubricTxtOrg                      1.0157886 0.12999521  7.8140465
## RubricVisOrg                      0.6542550 0.13353206  4.8996095
## as.factor(Rater)2:RubricInitEDA  -0.2997977 0.15609303 -1.9206348
## as.factor(Rater)3:RubricInitEDA  -0.2946987 0.15635429 -1.8848136
## as.factor(Rater)2:RubricInterpRes -0.5132368 0.15349003 -3.3437796
## as.factor(Rater)3:RubricInterpRes -0.7148456 0.15364513 -4.6525755
## as.factor(Rater)2:RubricRsrchQ   -0.4874143 0.14722200 -3.3107438
## as.factor(Rater)3:RubricRsrchQ   -0.3223763 0.14726598 -2.1890751
## as.factor(Rater)2:RubricSelMeth  -0.3863680 0.15031029 -2.5704694
## as.factor(Rater)3:RubricSelMeth  -0.3871301 0.14961676 -2.5874779
## as.factor(Rater)2:RubricTxtOrg   -0.5510564 0.15646236 -3.5219741
## as.factor(Rater)3:RubricTxtOrg   -0.4448931 0.15673326 -2.8385369
## as.factor(Rater)2:RubricVisOrg   -0.1049122 0.15861363 -0.6614326
## as.factor(Rater)3:RubricVisOrg   -0.2752225 0.15885162 -1.7325758
```

The summary of the final model could be find here.

Question 4 Is the sex a influential factor in this experiment?

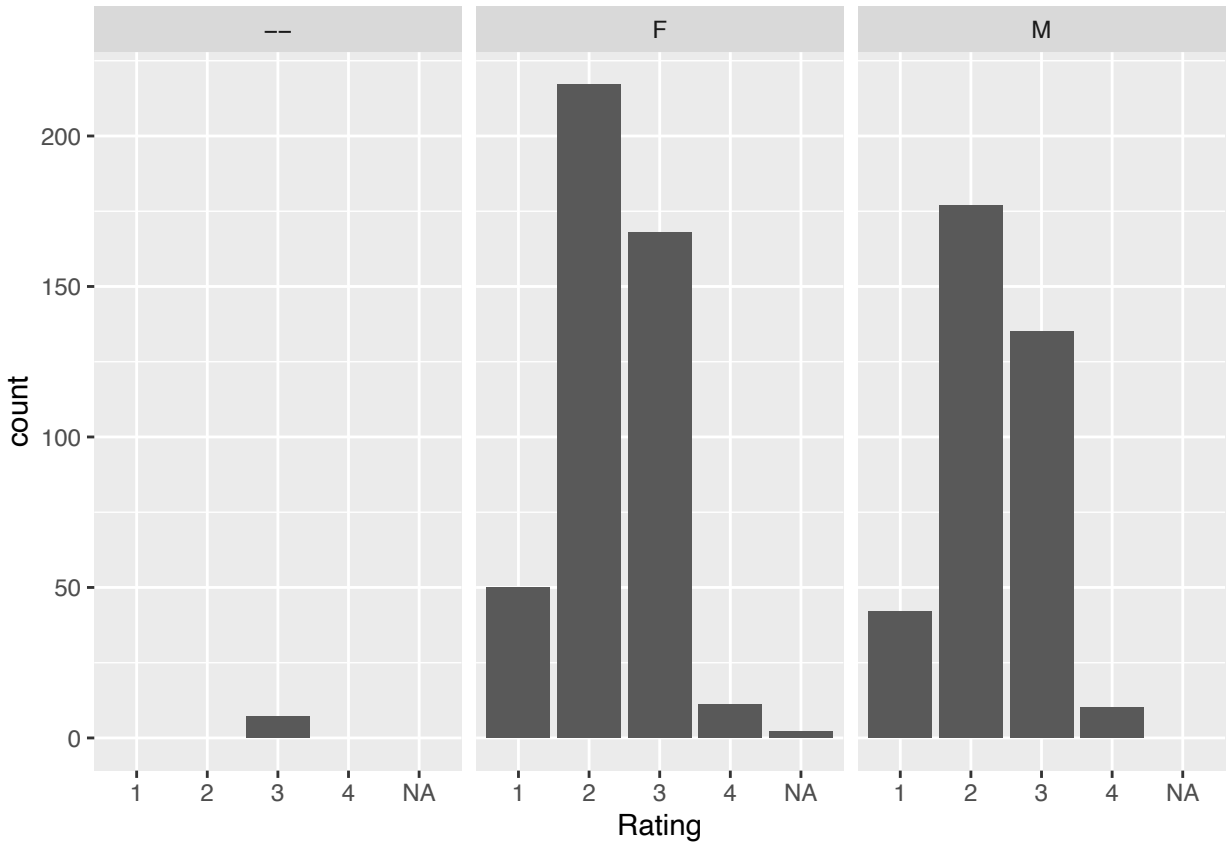
```
g <- ggplot(tall.13,aes(x = Rating)) +
  facet_wrap( ~ Sex) +
  geom_bar()

g
```



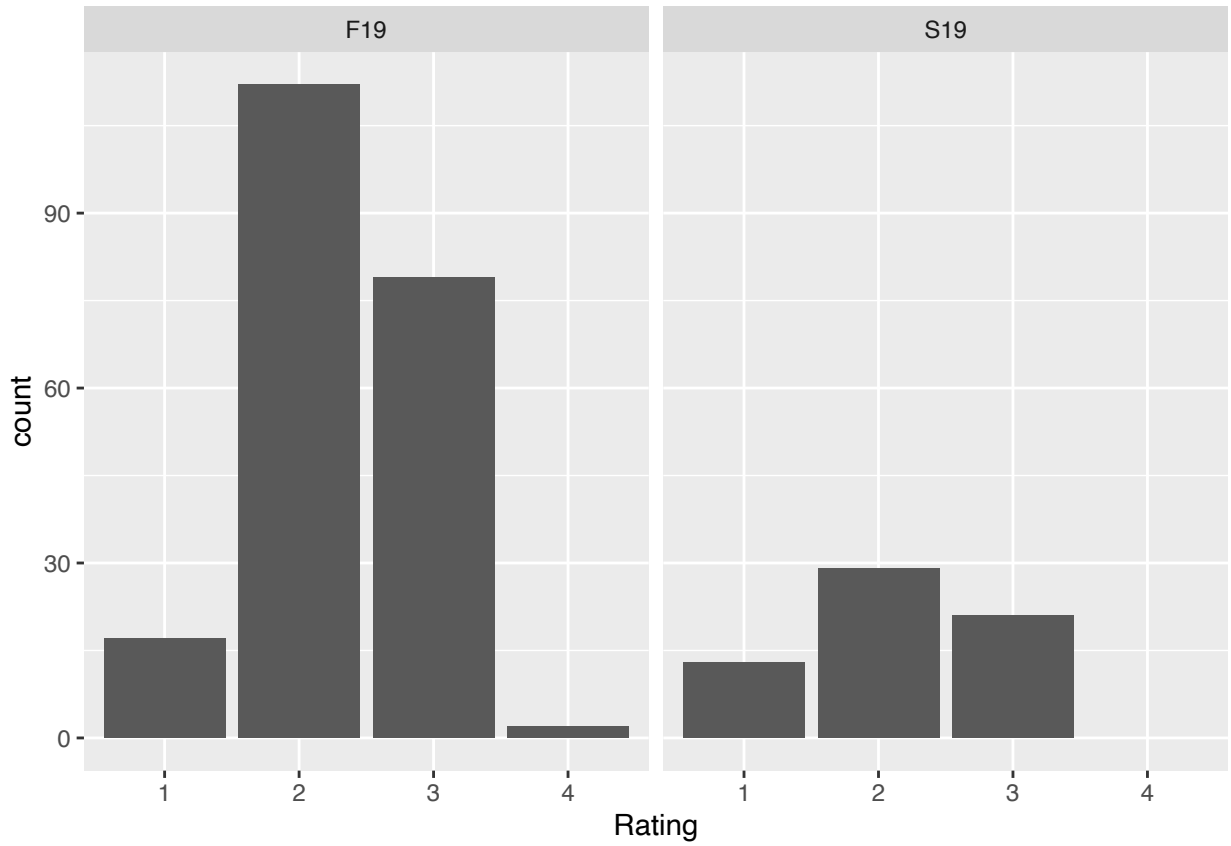

```
##
## Barplots for full data set
g <- ggplot(tall,aes(x = Rating)) +
  facet_wrap( ~ Sex) +
  geom_bar()

g
```



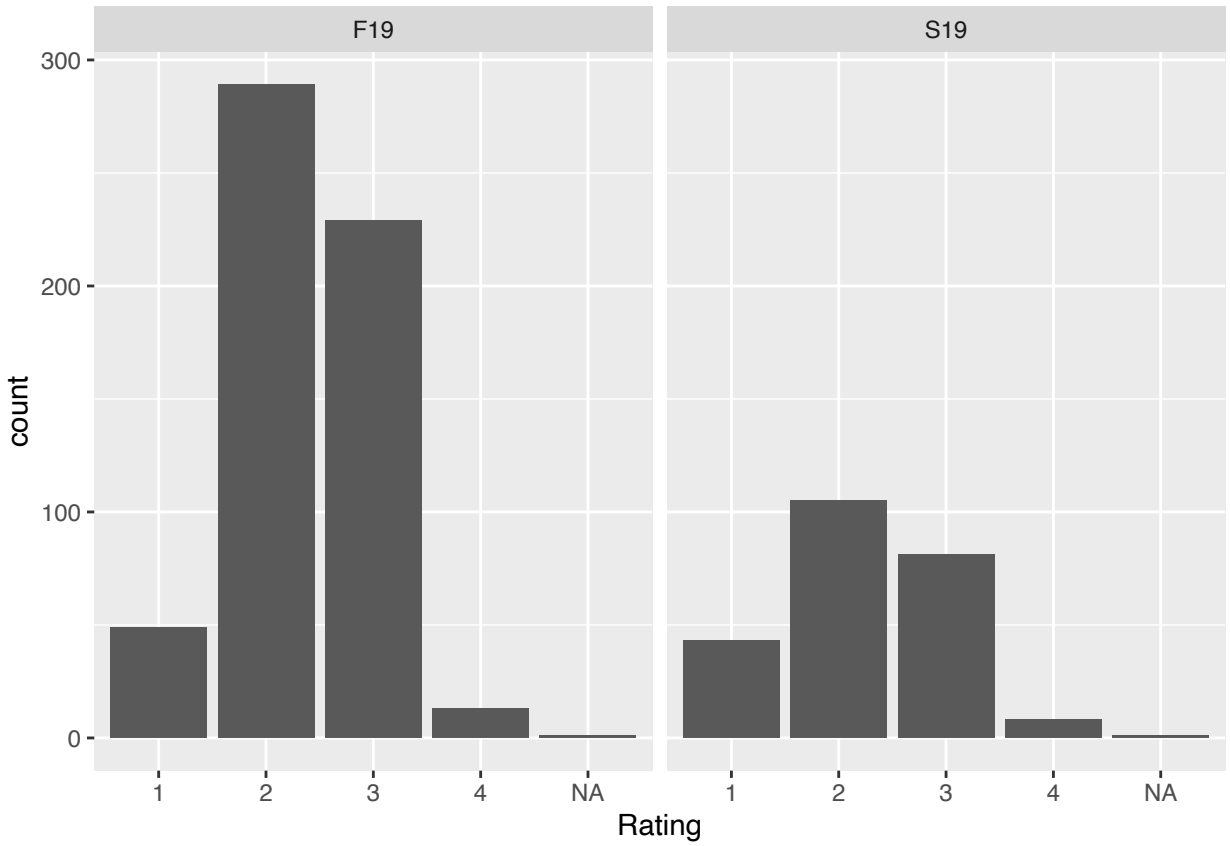

```
g <- ggplot(tall.13,aes(x = Rating)) +
  facet_wrap( ~ Semester) +
  geom_bar()

g
```




```
##
## Barplots for full data set
g <- ggplot(tall,aes(x = Rating)) +
  facet_wrap( ~ Semester) +
  geom_bar()

g
```



In this question, we plotted the ratings distribution for each gender and Semester.

According to the histogram by using the 13 artifacts, we find that the distributions of the Ratings for Male and Female are almost identical, no bias was found from this plot.

According to the histogram by using the 13 artifacts, we find that the distributions of the Ratings for Semester F19 and S19 were quite different. Generally, we find that there was a gap of the total number of the ratings. The number of the ratings in F19 was two times more than the number of the ratings in S19, however, they have similar number of rating 1. This result showed that the distributions of the ratings in this two semesters were significantly different from each other. It was likely that in S19 raters tend to give a much lower ratings for some artifacts.