Title

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ABSTRACT

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I The goal of this study is to
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R
D

INTRODUCTION

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1.
2.
3.
4.

DATA

The data for this study comes from Dietrich College at Carnegie Mellon University. It contains the ratings (scores) of 91 statistics projects submitted in a freshmen "General Education" course. Each project is assigned a unique artifact and rated on 7 different rubrics, where each rubric's rating is an integer from 1 to 4. Three different raters from different departments rated all the projects.

The identities of the project authors were unknown to the raters. Thirteen of the projects were graded by all 3 raters, while the other 78 were only graded by 1 rater. The rubric scoring guide used by the raters is experimental and not typical of freshman statistics classes at CMU. Guides for assigning ratings are shown in the table below.

Table 1: Rating Guides

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.

A list of the variables contained in the dataset is shown below.

Table 2: Variable definitions

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

The following table describes the meaning of each rubric.

Table 3: Rubric descriptions

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

METHODS

1.

To answer the first research question, we mainly used exploratory data analysis. We looked at numerical summaries and plots of the distributions of ratings grouped by rubric and grouped by rater. We also subsetted the data to other just the 13 papers graded by all 3 graders and repeated the analyses on the reduced data set, to see if it was representative of the dataset as a whole.

2.

To explore this question, we first looked at the reduced dataset of 13 papers rated by each grader. We fit a random intercept model to predict rating for each of the 7 rubrics where the intercept randomly varied based on the artifact (unique paper) for that observation. So, each model had coefficients defining 13 different intercepts, where each intercept represented a cluster of 3 ratings.

For each of these 7 models, we found the intraclass correlation (ICC), which can be used as a metric for agreement between raters in a given model. High ICC for a given rubric means the raters tend to agree on the rating of that rubric. We also found the ICCs for the same models fitted on the whole dataset and compared.

Then, using the reduced data set again, we made two-way tables for each pair of raters and for each rubric (21 tables total) counting up the 13 ratings each rater assigned for that rubric. This allowed us to count the proportion of times out of 13 that two raters gave the same rating for a certain rubric. Using these seven measures of agreement for each pair of ratings, we could get an idea of how often any two raters were in agreement.

3.

[not done]

4.

[not done]

RESULTS

1. *Is the distribution of ratings for each rubric 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?*

Rubric distributions

Center and spread: The summary table showed that rubric score distributions have mostly similar centers except that CritDes (critical design) and to a lesser extent, SelMeth (select methods), are lower than the rest. The spreads of all rubrics are all comparable and range from about 0.5 to 0.85. (See Technical Appendix p. 2)

Shape: From the bar plots, InitEDA (initial EDA), InterpRes (interpret results), RsrchQ (research question), TxtOrg (text organization), and VisOrg (visual organization) are all similar. The distributions are all relatively symmetric with mostly 2 and 3 ratings. CritDes has many more 1 ratings than the rest and almost no 4s. It has a strictly decreasing shape with lower numbers of each subsequent score. rating SelMeth has a much higher percent of 2s than the others and a lower average rating than all the others except CritDes. It also is the only rubric with no papers scoring 4.

Rater distributions

Center and spread: [not done]

Shape: From the bar plots, Raters 1 and 2 distribute their ratings somewhat normally, while Rater 3

gives more irregular ratings. Raters 1 and 2 give mostly 2s and 3s by far, plus a few 1s and hardly any 4s. Rater 3 gives mostly 2s, with about half as many 3s, and about half as many 1s as that. Like the others, they give very few 4s. (See Tech. Appx p. 4)

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?*

Intraclass correlations

The intraclass correlations (ICC) for models based on the 13 papers graded by all graders show that for some rubrics (CritDes, InitEDA, SelMeth, and VisOrg), the correlation between is raters is average—in the 0.5 to 0.6 range. For the RsrchQ, InterpRes, and TxtOrg rubrics, the correlation is very low at around 0.2 or below (see Tech. Appx p. 6).

Based on all 117 papers in the data set, the ICCs were all close to the ICCs based on the reduced data set. For five rubrics, the difference was less than 0.1, while for CritDes, the full data set ICC was 0.1 higher, and for InitEDA, the full data set ICC was almost 0.2 higher.

Rater agreement

Based on the same set of papers, any pair of two raters gives the exact same score on the rubric for a certain paper around 63% to 67% of the time. The highest agreement rate, 67%, is between Raters 2 and 3, while the other two agreement rates are about 63%. (See Tech. Appx p. 8). These percentages are based on exact agreement. It is also notable that the raters only disagree by more than a point XXX [looks like it will be a low number] times in the whole dataset.

3. *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?*

[not done]

4. *Is there anything else interesting to say about this data?*

[hopefully]

DISCUSSION

1.

[not done]

2.

[not done]

3.

[not done]

4.

[not done]

REFERENCES

[none so far]

Project 2 - TECHNICAL APPENDIX - 1st draft

Zach Ohl

11/29/2021

```
library(lme4, quietly = T) #for lmer()

library(ggplot2)
library(tidyverse)
library(kableExtra)
library(performance)  #for icc
library(LMERConvenienceFunctions, quietly = T ) #for MLM var selection
library(GGally)
library(ggpubr)
library(RLRsim) # for exactRLRT test
```

```
#read  data
ratings <- read.csv(file = paste0("C:/Users/Zachary Ohl/Desktop/CMU courses/",
                                  "Applied Linear Models/project 2/ratings.csv"))
ratings_tall <- read.csv(file = paste0("C:/Users/Zachary Ohl/Desktop/CMU courses/",
                                       "Applied Linear Models/project 2/tall.csv"))
#Make non M/F sex values consinsent:
ratings_tall$Sex[ratings_tall$Sex==""] <- "--"

rubric_ratings <- ratings[, 7:13]

# Make sure all ratings run from 1 to 4,
ratings_tall$Rating <- factor(ratings_tall$Rating,levels=1:4)
for (i in unique(ratings_tall$Rubric)) {
  ratings[,i] <- factor(ratings[,i],levels=1:4)
}

#attach(ratings)
rubric_all3 <- ratings[ !is.na(ratings$Overlap), c(2, 7:13, 14)]
#includes rater(col 2) and artifact (col 14)
ratings_all3 <- ratings[ !is.na(ratings$Overlap), ] #includes all columns
ratings_tall_all3 <- ratings_tall[ ratings_tall$Repeated==1, ] #includes all columns
```

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?

Look at distributions of ratings by rubric

Look at mean and 5-number summaries of ratings by rubric:

```
temp_summary <- apply(rubric_ratings[, c(1, 3,4,5, 7)],2, function(x) c(summary(x),SD=sd(x))) %>%
  as.data.frame %>% t() %>% round(digits=2)
temp_summ_na <- apply(na.omit(rubric_ratings[, c(2, 6)]),2, function(x) c(summary(x),SD=sd(x))) %>%
  as.data.frame %>% t() %>% round(digits=2)

rbind(temp_summary, temp_summ_na) %>%
  kable(caption = "Summary tables of the numeric variables") %>%
  kable_styling(latex_options = "HOLD_position")
```

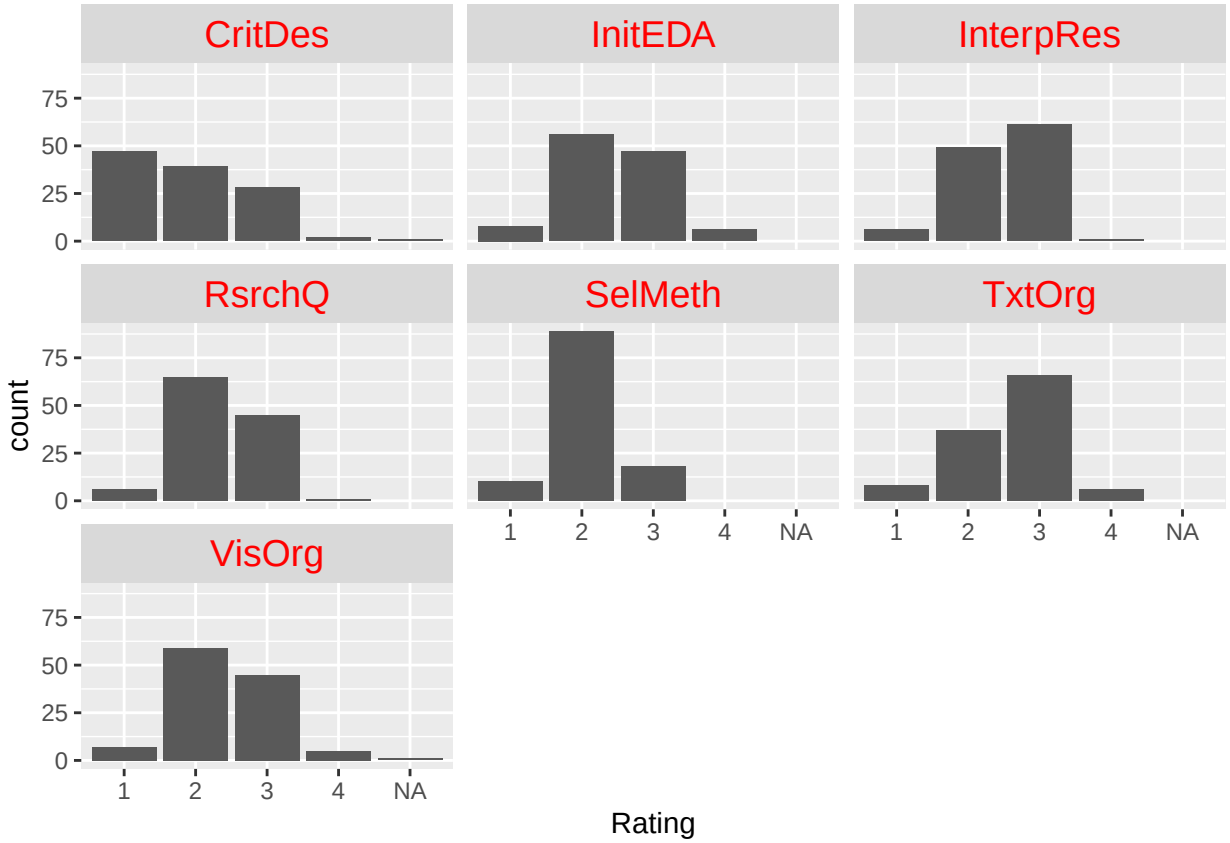
Table 1: Summary tables of the numeric variables

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
RsrchQ	1	2	2	2.35	3.0	4	0.59
InitEDA	1	2	2	2.44	3.0	4	0.70
SelMeth	1	2	2	2.07	2.0	3	0.49
InterpRes	1	2	3	2.49	3.0	4	0.61
TxtOrg	1	2	3	2.60	3.0	4	0.70
CritDes	1	1	2	1.86	2.5	4	0.84
VisOrg	1	2	2	2.42	3.0	4	0.68

The rubric score distributions are mostly similar except CritDes (critical design) and to a lesser extent, SelMeth (Method selection), are lower than the rest.

Look at the shapes of distributions of ratings by rubric:

```
## Bar plots for the whole data set. NAs dont show up?
ggplot(ratings_tall, aes(x = Rating)) +  facet_wrap( ~ Rubric) +  geom_bar() +
  theme(strip.text = element_text(size = 14, color = "red"))
```



InitEDA, InterpRes, RserchQ, TxtOrg, and VisOrg are all similar. CritDes has much more 1 ratings than the rest and almost no 4s. SelMeth has a much higher percent of 2s than the others and a lower average rating than all the others except CritDes.

Same plots but for only papers graded by all 3 raters:

```
## Bar plots for the reduced data set
ggplot(ratings_tall_all3, aes(x = Rating)) +  facet_wrap( ~ Rubric) +
  geom_bar() + theme(strip.text = element_text(size = 14, color = "red"))
```

The distributions look similar to the overall ratings.

Now look at distributions of ratings by rater:

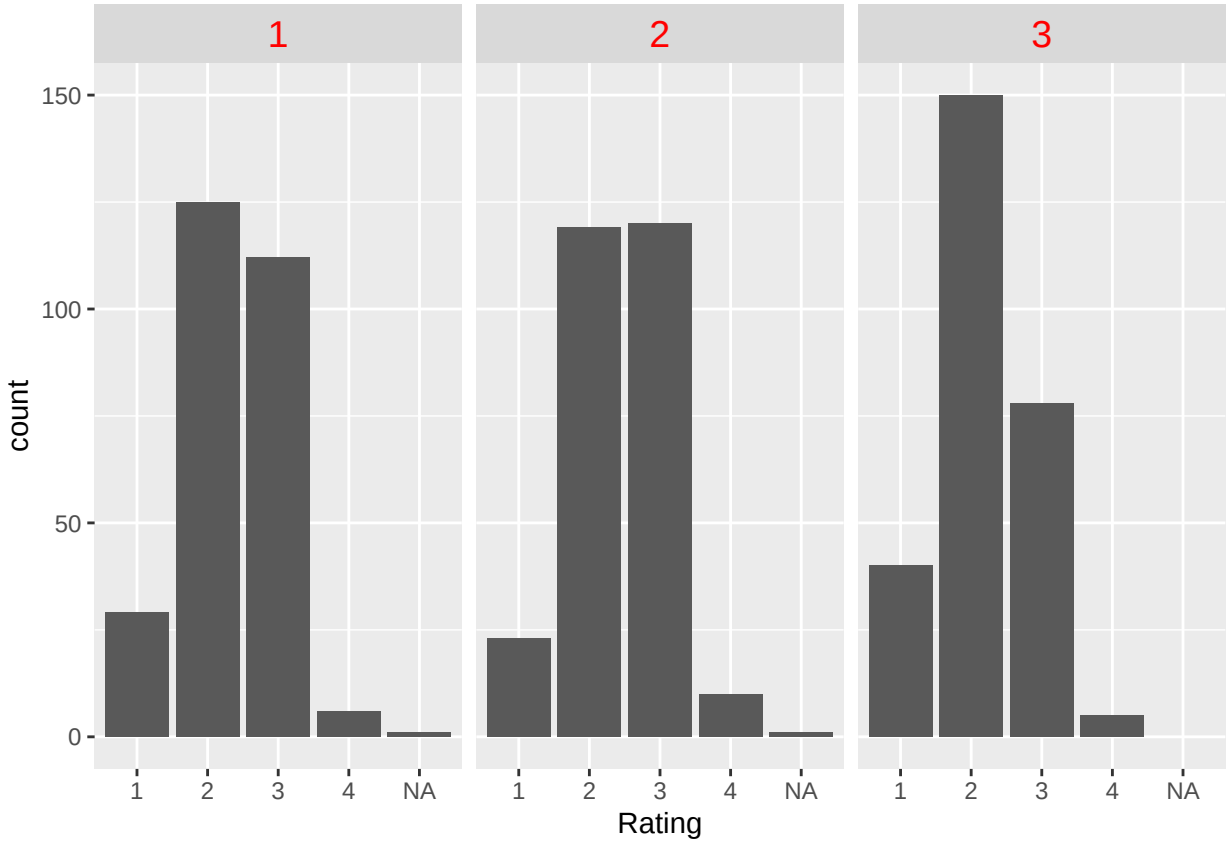
Look at mean and 5-number summaries of ratings by rubric: .....add later

```
#temp_summary <- apply(rubric_ratings[, c(1, 3,4,5, 7)],2,function(x) c(summary(x),SD=sd(x))) %>% as.da
#temp_summ_na <- apply(na.omit(rubric_ratings[, c(2, 6)]),2,function(x) c(summary(x),SD=sd(x))) %>% as.

#rbind(temp_summary, temp_summ_na) %>% kable(caption = "Summary tables of the numeric variables") %>%
```

Look at the shapes of distributions of ratings by rater:

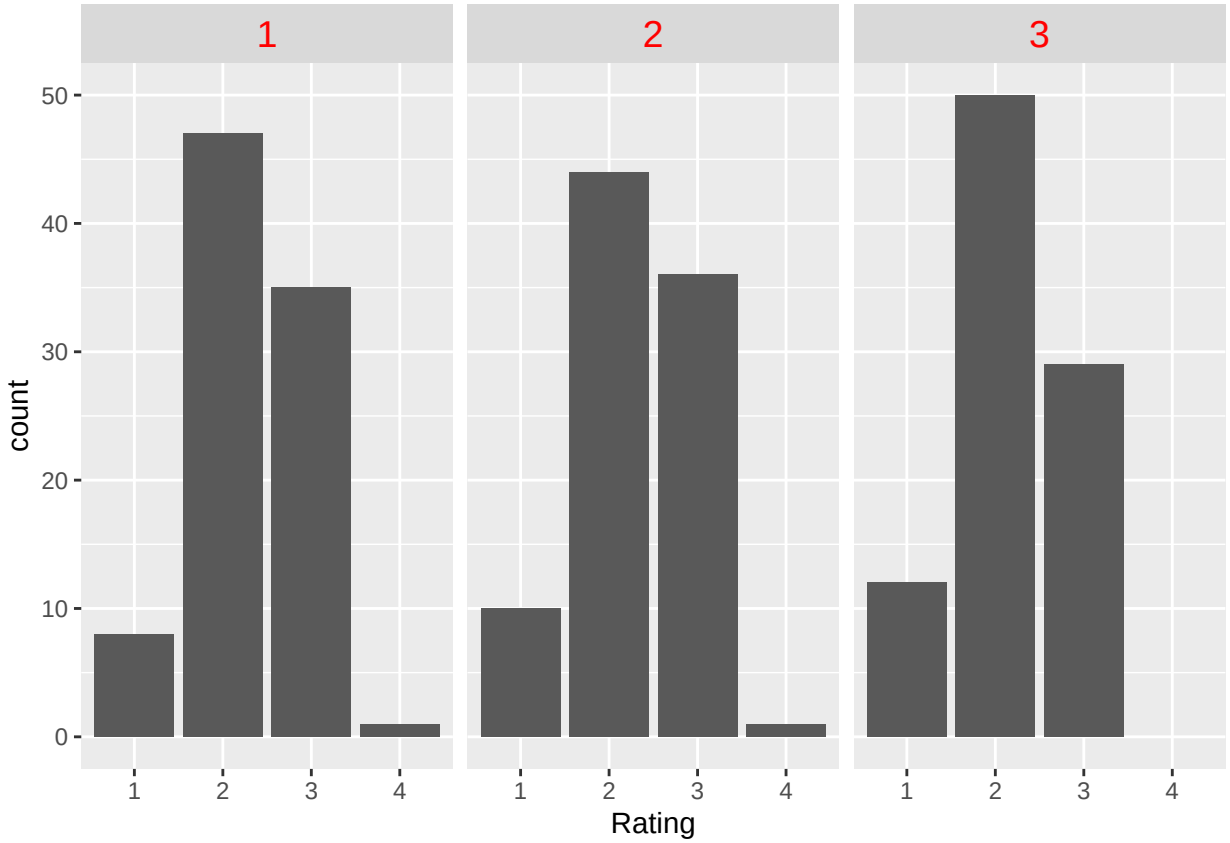
```
## Bar plots for the whole data set. NAs dont show up?
ggplot(ratings_tall, aes(x = Rating)) +  facet_wrap( ~ Rater) +  geom_bar() +
  theme(strip.text = element_text(size = 14, color = "red"))
```



From the distributions, it seems Raters 1 and 2 distribute their ratings somewhat normally, while Rater 3 gives more irregular ratings.

Same plots but for only papers graded by all 3 raters:

```
## Bar plots for the reduced data set
ggplot(ratings_tall_all3, aes(x = Rating)) +  facet_wrap( ~ Rater) +
  geom_bar() + theme(strip.text = element_text(size = 14, color = "red"))
```



The distributions look more similar between raters based on this smaller subset. Each rater gives the most 2s, followed by 3s, and then 1s.

Check for NAs:

```
#any(is.na(ratings_tall$Rating))  #True
ratings_tall[apply(ratings_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>
```

One NA score for CritDes and one for VisOrg. None are the in the data set of the 13 papers graded by all raters. Will need to drop these two observations of replace the NAs with values for models on the full data set, so R doesn't fit models to slightly different data sets depending on the rubric used.

Also, note the one missing or nonbinary sex value:

```
ratings_tall[ratings_tall$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
```

This artifact is also not in the set of 13 commonly graded papers.

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?

Use the 13 papers that were each rated by all 3 raters to fit seven random intercept models - one for each rubric: These models have 13 groups each - one for each artifact. #should i set REML = false for these??

```
randint_models = list()
#, REML = F
randint_models[[1]] <- lmer(as.numeric(RsrchQ) ~ 1 + (1 | Artifact), data = rubric_all3)
randint_models[[2]] <- lmer(as.numeric(CritDes) ~ 1 + (1 | Artifact), data = rubric_all3)
randint_models[[3]] <- lmer(as.numeric(InitEDA) ~ 1 + (1 | Artifact), data = rubric_all3)
randint_models[[4]] <- lmer(as.numeric(SelMeth) ~ 1 + (1 | Artifact), data = rubric_all3)
randint_models[[5]] <- lmer(as.numeric(InterpRes) ~ 1 + (1 | Artifact), data = rubric_all3)
randint_models[[6]] <- lmer(as.numeric(VisOrg) ~ 1 + (1 | Artifact), data = rubric_all3)
randint_models[[7]] <- lmer(as.numeric(TxtOrg) ~ 1 + (1 | Artifact), data = rubric_all3)
names(randint_models) <- c("RsrchQ", "CritDes", "InitEDA", "SelMeth", "InterpRes","VisOrg","TxtOrg")
```

Find the intraclass correlation (ICC) between raters for each rubric. This can be used as a measure of agreement between raters.

ICCs: Make sure *icc* function from *performance* library works:

```
#check:
artifact_RsrchQ_randint <- lmer(as.numeric(RsrchQ) ~ 1 + (1 | Artifact), data = rubric_all3)  #fit one
performance::icc(artifact_RsrchQ_randint)  #find icc using function
```

```
## # Intraclass Correlation Coefficient
##
##      Adjusted ICC: 0.189
##   Conditional ICC: 0.189
```

```
0.05983/(0.05983 + 0.25641)    #find icc using printed values and formula
```

```
## [1] 0.1891918
```

Both outputs from the *icc* function match the hand-calculated value.

Find all ICCs:

```
unlist(lapply(randint_models, FUN = performance::icc))[seq(from=2, to=14, by=2)]
```

```
##    RsrchQ.ICC_conditional   CritDes.ICC_conditional   InitEDA.ICC_conditional
##                 0.1891892                 0.5725594                 0.4929577
##   SelMeth.ICC_conditional InterpRes.ICC_conditional    VisOrg.ICC_conditional
##                 0.5212766                 0.2295720                 0.5924529
##    TxtOrg.ICC_conditional
##                 0.1428571
```

For the CritDes, InitEDA, SelMeth, and VisOrg rubrics, the correlation between is raters is average, at around 0.5 for all. For the RsrchQ, InterpRes, and TxtOrg rubrics, the correlation is very low at around 0.2. .....what counts as low/high?

For each of the 7 rubrics, make 3 two-way tables for cross-classification of ratings for each pair of raters:

```
#RsrchQ
RsrchQ_t12 <- table( "R1"=factor(rubric_all3$RsrchQ[rubric_all3$Rater==1], levels=1:4),
                     "R2"=factor(rubric_all3$RsrchQ[rubric_all3$Rater==2], levels=1:4) )
RsrchQ_t13 <- table( "R1"=factor(rubric_all3$RsrchQ[rubric_all3$Rater==1], levels=1:4),
                     "R2"=factor(rubric_all3$RsrchQ[rubric_all3$Rater==3], levels=1:4) )
RsrchQ_t23 <- table( "R2"=factor(rubric_all3$RsrchQ[rubric_all3$Rater==2], levels=1:4),
```

```
                    "R3"=factor(rubric_all3$RsrchQ[rubric_all3$Rater==3], levels=1:4) )

#CritDes
CritDes_t12 <- table( "R1"=factor(rubric_all3$CritDes[rubric_all3$Rater==1], levels=1:4),
                      "R2"=factor(rubric_all3$CritDes[rubric_all3$Rater==2], levels=1:4) )
CritDes_t13 <- table( "R1"=factor(rubric_all3$CritDes[rubric_all3$Rater==1], levels=1:4),
                      "R3"=factor(rubric_all3$CritDes[rubric_all3$Rater==3], levels=1:4) )
CritDes_t23 <- table( "R2"=factor(rubric_all3$CritDes[rubric_all3$Rater==2], levels=1:4),
                      "R3"=factor(rubric_all3$CritDes[rubric_all3$Rater==3], levels=1:4) )

#InitEDA
InitEDA_t12 <- table( "R1"=factor(rubric_all3$InitEDA[rubric_all3$Rater==1], levels=1:4),
                      "R2"=factor(rubric_all3$InitEDA[rubric_all3$Rater==2], levels=1:4) )
InitEDA_t13 <- table( "R1"=factor(rubric_all3$InitEDA[rubric_all3$Rater==1], levels=1:4),
                      "R3"=factor(rubric_all3$InitEDA[rubric_all3$Rater==3], levels=1:4) )
InitEDA_t23 <- table( "R2"=factor(rubric_all3$InitEDA[rubric_all3$Rater==2], levels=1:4),
                      "R3"=factor(rubric_all3$InitEDA[rubric_all3$Rater==3], levels=1:4) )
#SelMeth
SelMeth_t12 <- table( "R1"=factor(rubric_all3$SelMeth[rubric_all3$Rater==1], levels=1:4),
                      "R2"=factor(rubric_all3$SelMeth[rubric_all3$Rater==2], levels=1:4) )
SelMeth_t13 <- table( "R1"=factor(rubric_all3$SelMeth[rubric_all3$Rater==1], levels=1:4),
                      "R3"=factor(rubric_all3$SelMeth[rubric_all3$Rater==3], levels=1:4) )
SelMeth_t23 <- table( "R2"=factor(rubric_all3$SelMeth[rubric_all3$Rater==2], levels=1:4),
                      "R3"=factor(rubric_all3$SelMeth[rubric_all3$Rater==3], levels=1:4) )

#InterpRes
InterpRes_t12 <- table( "R1"=factor(rubric_all3$InterpRes[rubric_all3$Rater==1], levels=1:4),
                        "R2"=factor(rubric_all3$InterpRes[rubric_all3$Rater==2], levels=1:4) )
InterpRes_t13 <- table( "R1"=factor(rubric_all3$InterpRes[rubric_all3$Rater==1], levels=1:4),
                        "R3"=factor(rubric_all3$InterpRes[rubric_all3$Rater==3], levels=1:4) )
InterpRes_t23 <- table( "R2"=factor(rubric_all3$InterpRes[rubric_all3$Rater==2], levels=1:4),
                        "R3"=factor(rubric_all3$InterpRes[rubric_all3$Rater==3], levels=1:4) )

#VisOrg
VisOrg_t12 <- table( "R1"=factor(rubric_all3$VisOrg[rubric_all3$Rater==1], levels=1:4),
                     "R2"=factor(rubric_all3$VisOrg[rubric_all3$Rater==2], levels=1:4) )
VisOrg_t13 <- table( "R1"=factor(rubric_all3$VisOrg[rubric_all3$Rater==1], levels=1:4),
                     "R3"=factor(rubric_all3$VisOrg[rubric_all3$Rater==3], levels=1:4) )
VisOrg_t23 <- table( "R2"=factor(rubric_all3$VisOrg[rubric_all3$Rater==2], levels=1:4),
                     "R3"=factor(rubric_all3$VisOrg[rubric_all3$Rater==3], levels=1:4) )

#VisOrg
TxtOrg_t12 <- table( "R1"=factor(rubric_all3$TxtOrg[rubric_all3$Rater==1], levels=1:4),
                     "R2"=factor(rubric_all3$TxtOrg[rubric_all3$Rater==2], levels=1:4) )
TxtOrg_t13 <- table( "R1"=factor(rubric_all3$TxtOrg[rubric_all3$Rater==1], levels=1:4),
                     "R3"=factor(rubric_all3$TxtOrg[rubric_all3$Rater==3], levels=1:4) )
TxtOrg_t23 <- table( "R2"=factor(rubric_all3$TxtOrg[rubric_all3$Rater==2], levels=1:4),
                     "R3"=factor(rubric_all3$TxtOrg[rubric_all3$Rater==3], levels=1:4) )
```

.....actually show the 21 tables?

```
grid.arrange(
   tableGrob(RsrchQ_t12), tableGrob(RsrchQ_t13), tableGrob(RsrchQ_t23),
   tableGrob(CritDes_t12), tableGrob(CritDes_t13), tableGrob(CritDes_t23),
```

```
   #need to fix theme and add titles in somehow
  nrow=2, ncol=3
)
```

Find percent of times pairs of raters have exact agreement:

```
r1r2_percent_agree <- round(c(RsrchQ_t12 %>% diag%>%sum / RsrchQ_t12 %>% sum,
                          CritDes_t12 %>% diag%>%sum / CritDes_t12 %>% sum,
                          InitEDA_t12 %>% diag%>%sum / InitEDA_t12 %>% sum,
                          SelMeth_t12 %>% diag%>%sum / SelMeth_t12 %>% sum,
                          InterpRes_t12 %>% diag%>%sum / InterpRes_t12 %>% sum,
                          VisOrg_t12 %>% diag%>%sum / VisOrg_t12 %>% sum,
                          TxtOrg_t12 %>% diag%>%sum / TxtOrg_t12 %>% sum ), 3)

r1r3_percent_agree <- round(c(RsrchQ_t13 %>% diag%>%sum / RsrchQ_t13 %>% sum,
                          CritDes_t13 %>% diag%>%sum / CritDes_t13 %>% sum,
                          InitEDA_t13 %>% diag%>%sum / InitEDA_t13 %>% sum,
                          SelMeth_t13 %>% diag%>%sum / SelMeth_t13 %>% sum,
                          InterpRes_t13 %>% diag%>%sum / InterpRes_t13 %>% sum,
                          VisOrg_t13 %>% diag%>%sum / VisOrg_t13 %>% sum,
                          TxtOrg_t13 %>% diag%>%sum / TxtOrg_t13 %>% sum ), 3)

r2r3_percent_agree <- round(c(RsrchQ_t23 %>% diag%>%sum / RsrchQ_t23 %>% sum,
                          CritDes_t23 %>% diag%>%sum / CritDes_t23 %>% sum,
                          InitEDA_t23 %>% diag%>%sum / InitEDA_t23 %>% sum,
                          SelMeth_t23 %>% diag%>%sum / SelMeth_t23 %>% sum,
                          InterpRes_t23 %>% diag%>%sum / InterpRes_t23 %>% sum,
                          VisOrg_t23 %>% diag%>%sum / VisOrg_t23 %>% sum,
                          TxtOrg_t23 %>% diag%>%sum / TxtOrg_t23 %>% sum ), 3)

rater_percent_agree = data.frame("Rubric" = names(randint_models),
                                 "Raters 1 and 2 agreement" = r1r2_percent_agree,
                                 "Raters 1 and 3 agreement" = r1r3_percent_agree,
                                 "Raters 2 and 3 agreement" = r2r3_percent_agree)
```

Rater agreement for each rubric:

```
rater_percent_agree  %>%
  kable(caption = "Agreement between each pair of raters for each rubric") %>%
  kable_styling(latex_options = "HOLD_position")
```

Table 2: Agreement between each pair of raters for each rubric

Rubric	Raters.1.and.2.agreement	Raters.1.and.3.agreement	Raters.2.and.3.agreement
RsrchQ	0.385	0.769	0.538
CritDes	0.538	0.615	0.692
InitEDA	0.692	0.538	0.846
SelMeth	0.923	0.615	0.692
InterpRes	0.615	0.538	0.615
VisOrg	0.538	0.769	0.769
TxtOrg	0.692	0.615	0.538

. . . . . .possibly append this to above table? Average rater agreement:

```
round(summarize_all(rater_percent_agree[,2:4], mean), 3) %>%
  kable(caption = "Average agreement between each pair of raters") %>%
  kable_styling(latex_options = "HOLD_position")
```

Table 3: Average agreement between each pair of raters

Raters.1.and.2.agreement	Raters.1.and.3.agreement	Raters.2.and.3.agreement
0.626	0.637	0.67

Each pair of raters all agree with each around 2/3 of the time. Raters 2 and 3 agree the most by a small margin.

Find random intercept models with all ratings, not just papers commonly rated by all 3 raters: #should i set REML = false for these??

```
randint_models_all = list()
randint_models_all[[1]] <- lmer(as.numeric(RsrchQ) ~ 1 + (1 | Artifact), data = ratings)
randint_models_all[[2]] <- lmer(as.numeric(CritDes) ~ 1 + (1 | Artifact), data = ratings)
randint_models_all[[3]] <- lmer(as.numeric(InitEDA) ~ 1 + (1 | Artifact), data = ratings)
randint_models_all[[4]] <- lmer(as.numeric(SelMeth) ~ 1 + (1 | Artifact), data = ratings)
randint_models_all[[5]] <- lmer(as.numeric(InterpRes) ~ 1 + (1 | Artifact), data = ratings)
randint_models_all[[6]] <- lmer(as.numeric(VisOrg) ~ 1 + (1 | Artifact), data = ratings)
randint_models_all[[7]] <- lmer(as.numeric(TxtOrg) ~ 1 + (1 | Artifact), data = ratings)
names(randint_models_all) <- names(randint_models)
```

Find ICCs of above models:

```
unlist(lapply(randint_models_all, FUN = performance::icc))[seq(from=2, to=14, by=2)]
```

```
##    RsrchQ.ICC_conditional   CritDes.ICC_conditional   InitEDA.ICC_conditional
##                 0.2096214                 0.6730647                 0.6867210
##   SelMeth.ICC_conditional InterpRes.ICC_conditional    VisOrg.ICC_conditional
##                 0.4719014                 0.2200285                 0.6607372
##    TxtOrg.ICC_conditional
##                 0.1879927
```

Look at the ICCs of the two sets of models:

```
common_rated_ICCs <- round(unlist(lapply(randint_models,
                                         FUN = performance::icc))[seq(from=2, to=14, by=2)], 3)
all_rating_ICCs <- round(unlist(lapply(randint_models_all,
                                       FUN = performance::icc))[seq(from=2, to=14, by=2)], 3)

data.frame(common_rated_ICCs, all_rating_ICCs) %>%
  kable(caption = "Common correlation between raters for the commonly rated papers and for all papers, s
  kable_styling(latex_options = "HOLD_position")
```

Table 4: Common correlation between raters for the commonly rated papers and for all papers, shown for each rubric

	common_rated_ICCs	all_rating_ICCs
RsrchQ.ICC_conditional	0.189	0.210
CritDes.ICC_conditional	0.573	0.673
InitEDA.ICC_conditional	0.493	0.687
SelMeth.ICC_conditional	0.521	0.472
InterpRes.ICC_conditional	0.230	0.220
VisOrg.ICC_conditional	0.592	0.661
TxtOrg.ICC_conditional	0.143	0.188

The ICCs for all ratings are pretty close to the ICCs for only papers rated by all 3 raters. Most of the all-rating models have ICCs that are <= 0.1 bigger than the others. Only the SelMeth rubric has a smaller ICC and the InitEDA rubric an IDD almost 0.2 bigger. No single rater is disagreeing with the others more.

Question 3: 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?

Try adding fixed effects to 7 intercept models based on only the 13 commonly rated papers. Add three fixed effects (rater, semester, and sex) to each of the 7 intercept models. Eliminate variables using fitLMER.fnc() function. Test each rubric's models using ANOVA for whether Rating belongs in the model. Either way, save each preferred model in a list of length 7 called *model.formula.13*.

```
rubric.names <- sort(unique(ratings_tall$Rubric))

model.formula.13 <- list()
#

for (i in rubric.names) {

  ## fit each base model
  rubric.data <- ratings_tall_all3[ratings_tall_all3$Rubric==i,]
  tmp <- lmer(as.numeric(Rating) ~ -1 + as.factor(Rater) +
              Semester + Sex + (1|Artifact),
            data=rubric.data,REML=FALSE)

  ## do backwards elimination. Rater will always be kept in the model due to the intercept being remove
  tmp.back_elim <- fitLMER.fnc(tmp, set.REML.FALSE = TRUE, log.file.name = FALSE)

  ## check to see if the raters are significantly different from one another
  tmp.single_intercept <- update(tmp.back_elim, . ~ . + 1 - as.factor(Rater))
  pval <- anova(tmp.single_intercept,tmp.back_elim)$"Pr(>Chisq)"[2]

  ## choose the best model
  if (pval<=0.05) {
    tmp_final <- tmp.back_elim
  } else {
    tmp_final <- tmp.single_intercept
  }

  ## and add FORMULA to list:
```

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

}
```

Look at 7 chosen models:

```
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)
```

For all 7 rubrics, no fixed effects are deemed important, not even Rater.

Now try adding fixed effects to 7 intercept models based on all data. As before, add three fixed effects (rater, semester, and sex) to each of the 7 intercept models. Eliminate variables using fitLMER.fnc() function. Then test whether Rating belongs in each rubric's model using ANOVA. Either way, save each preferred model in a list called *model.formula.alldata*.

```
rubric.names <- sort(unique(ratings_tall$Rubric))

# Remove 2 observations with missing ratings so that we use the same data set for every model fit and m
ratings_tall[c(161,684),] ## Confirm from ealier code that these are the rows with missing ratings.
ratings_tall_noNA <- ratings_tall[-c(161,684),]


#Remove observation with sex non M/F sex, to ease interpretation of model if Sex variable is included:
ratings_tall_noNA[ratings_tall_noNA$Sex=="--",]  ## check which rows will be eliminated
ratings_tall_noNA <- ratings_tall_noNA[ratings_tall_noNA$Sex!="--",] ## remove Sex = '--' rows


model.formula.alldata <- list()
model.alldata <- list()


## There will be a lot of output from fitLMER.fnc() here... Sorry!

for (i in rubric.names) {
```

```
  ## fit each base model
  rubric.data <- ratings_tall_noNA[ratings_tall_noNA$Rubric==i,]
  tmp <- lmer(as.numeric(Rating) ~ -1 + as.factor(Rater) +
              Semester + Sex + (1|Artifact),
            data=rubric.data,REML=FALSE)

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

  ## check to see if the raters are significantly different from one another
  tmp.single_intercept <- update(tmp.back_elim, . ~ . + 1 - as.factor(Rater))
  pval <- anova(tmp.single_intercept,tmp.back_elim)$"Pr(>Chisq)"[2]

  ## choose the best model
  if (pval<=0.05) {
    tmp_final <- tmp.back_elim
  } else {
    tmp_final <- tmp.single_intercept
  }

  ## and add FORMULA to the list:
  model.formula.alldata[[i]] <- formula(tmp_final)
  #Plus add model to a list:
  model.alldata[[i]] <- tmp_final
}
```

Do

Look at 7 chosen models:

```
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
```

Three of the rubric's models (InitEDA, RsrchQ, TxtOrg) include none of the potential fixed effects, as with the models based on the reduced data. However, 3 rubric models (CritDes, InterpRes, VisOrg) include Rater

this time, and 1 rubric model (SelMeth) includes Rater AND Semester as FEs.

Try adding interactions and new random effects for the 7 rubric-models fit using all the data.

The InitEDA, RsrchQ and SelMeth models only include the random-intercept for artifact. Since we only add random effects that are also present as fixed effects, there is nothing to try for these three.
The CritDes, InterpRes, and VisOrg models include Rater as a lone fixed effect, so we'll try adding it as a random effect as well.

```
#null hypotheses (no new RE):
CritDes_rater_tmp0 <- model.alldata[[1]]
InterpRes_rater_tmp0 <- model.alldata[[3]]
VisOrg_rater_tmp0 <- model.alldata[[7]]

#alternate hypothese (1 new RE: Rater|Artifact)
CritDes_rater_tmpA <- update(model.alldata[[1]], .~. + (as.factor(Rater) | Artifact))
InterpRes_rater_tmpA <- update(model.alldata[[3]], .~. + (as.factor(Rater) | Artifact))
VisOrg_rater_tmpA <- update(model.alldata[[7]], .~. + (as.factor(Rater) | Artifact))

#models with just new RE (Rater|Artifact):
CritDes_rater_tmpN <- update(CritDes_rater_tmpA, .~. - (1 | Artifact))
InterpRes_rater_tmpN <- update(InterpRes_rater_tmpA, .~. - (1 | Artifact))
VisOrg_rater_tmpN <- update(VisOrg_rater_tmpA, .~. - (1 | Artifact))
```

Attempting to fit any of these models with the new RE (Rater|Artifact) results in a 'number of observations <= number of random effects' error, so testing for the new RE is not possible.

Now let's try to test new interactions and REs in the final rubric model for SelMeth. There are only two FE in the model, Rater and Semester, so we'll try adding their interaction:

```
#SelMeth
#original:
SelMeth_rater <- lmer(as.numeric(Rating) ~ as.factor(Rater) + Semester + (1 | Artifact) -
    1, data = ratings_tall_noNA[ratings_tall_noNA$Rubric=='SelMeth',])
#new interaction
SelMeth_rater_int <- lmer(as.numeric(Rating) ~ as.factor(Rater) + Semester + (1 | Artifact) -
    1 + as.factor(Rater)*Semester - Semester, data = ratings_tall_noNA[ratings_tall_noNA$Rubric=='SelMe
anova(SelMeth_rater, SelMeth_rater_int)
```

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

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

Based on the ANOVA test, the new interaction, Rater:Semester, does not improve the model.

Now try adding new random effects to the SelMeth model, if possible. Start by trying Semester as a new RE

```
#null hypotheses (no new RE):
SelMeth_rater_tmp0 <- model.alldata[[5]]

#alternate hypothese (1 new RE: Rater|Artifact)
SelMeth_rater_tmpA <- update(model.alldata[[5]], .~. + (Semester | Artifact))
```

```
#models with just new RE (Rater|Artifact):
SelMeth_rater_tmpN <- update(SelMeth_rater_tmpA, .~. - (1 | Artifact))
```

Once again, the attempt to add new REs results in a 'number of observations <= number of random effects' error, so the test is not possible. We saw with the attempts to add a new Rater RE to the models for CritDes, InterpRes, and VisOrg, that such an attempt would also cause the same error, since the Rater variable has even more levels than Semester.

Overall, no new random effects or new fixed effect interactions could be reasonably added to the seven rubric-specific models on the whole data set.

Try adding fixed effects, interactions, and new random effects to the combined model with only a random intercept for each Rubric depending on Artifact.

Intercept-only model on all data:

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

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

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

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: as.numeric(Rating) ~ 1 + (0 + Rubric | Artifact)
##    Data: ratings_tall_noNA
##
## 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
```

```
#coef(comb.0)
```

.....Add note on correlations here if relevant

Try adding all possible FEs to the intercept-only model and then running variable selection with fitLMER. fitLMER just does by backward elimination on fixed effects, since no aditional random effects are tested:

```
comb.full <- update(comb.0, . ~ . + as.factor(Rater) + Semester +
                    Sex + Repeated + Rubric)
#summary(comb.full)
comb.back_elim <- fitLMER.fnc(comb.full, log.file.name = FALSE)
```

Check resulting model:

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

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

Based on the T-tests performed by the fitLMER.fnc function, variables Sex and Repeated are determined to be unnecessary.

Try adding FE interactions, including 3-way and 2-way interactions between the variables Rater, Semester, and Rubric:

```
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| = 0.00371227 (tol = 0.002, component 1)
```

```
#fit produces warning. Try different optimizer/more iterations:

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

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

Now run variable selection on the model with FE interactions:

```
comb.inter_elim <- fitLMER.fnc(comb.inter.u, log.file.name = FALSE)
```

View model:

```
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: ratings_tall_noNA
## Control: lmerControl(optimizer = "Nelder_Mead", optCtrl = list(maxfun = 2e+05))
##
## REML criterion at convergence: 1419.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9187 -0.5122 -0.0439  0.4820  3.5875
##
## Random effects:
##  Groups   Name            Variance Std.Dev. Corr
##  Artifact RubricCritDes   0.50273  0.7090
##           RubricInitEDA   0.35392  0.5949   0.45
##           RubricInterpRes 0.15244  0.3904   0.35 0.81
##           RubricRsrchQ    0.17964  0.4238   0.63 0.44 0.72
##           RubricSelMeth   0.06729  0.2594   0.42 0.60 0.74 0.36
##           RubricTxtOrg    0.26145  0.5113   0.42 0.64 0.67 0.55 0.63
##           RubricVisOrg    0.25549  0.5055   0.34 0.71 0.67 0.51 0.38 0.77
##  Residual                 0.18501  0.4301
## Number of obs: 810, groups:  Artifact, 90
##
## Fixed effects:
```

```
##                                   Estimate Std. Error t value
## (Intercept)                        1.75956    0.11779  14.939
## as.factor(Rater)2                  0.36533    0.13290   2.749
## as.factor(Rater)3                  0.21397    0.13291   1.610
## SemesterS19                       -0.17781    0.08226  -2.162
## RubricInitEDA                      0.74601    0.13663   5.460
## RubricInterpRes                    1.01436    0.13483   7.523
## RubricRsrchQ                       0.74884    0.12424   6.028
## RubricSelMeth                      0.42655    0.13038   3.272
## RubricTxtOrg                       1.04956    0.13551   7.745
## RubricVisOrg                       0.68355    0.13943   4.902
## as.factor(Rater)2:RubricInitEDA   -0.30822    0.17235  -1.788
## as.factor(Rater)3:RubricInitEDA   -0.29485    0.17268  -1.707
## as.factor(Rater)2:RubricInterpRes -0.53661    0.17010  -3.155
## as.factor(Rater)3:RubricInterpRes -0.75212    0.17051  -4.411
## as.factor(Rater)2:RubricRsrchQ    -0.50122    0.16153  -3.103
## as.factor(Rater)3:RubricRsrchQ    -0.36993    0.16181  -2.286
## as.factor(Rater)2:RubricSelMeth   -0.39586    0.16464  -2.404
## as.factor(Rater)3:RubricSelMeth   -0.41292    0.16500  -2.502
## as.factor(Rater)2:RubricTxtOrg    -0.58390    0.17140  -3.407
## as.factor(Rater)3:RubricTxtOrg    -0.48627    0.17176  -2.831
## as.factor(Rater)2:RubricVisOrg    -0.14452    0.17437  -0.829
## as.factor(Rater)3:RubricVisOrg    -0.33347    0.17476  -1.908
```

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

```
## optimizer (Nelder_Mead) convergence code: 0 (OK)
## Model failed to converge with max|grad| = 0.039115 (tol = 0.002, component 1)
```

The only interaction kept in the model is that between Rater and Rubric.

. . . . . .posibly delete below Compare the three combined models fitted so far by their formulas:

```
cat("All possible FEs:\n")
```

```
## All possible FEs:
```

```
formula(comb.full)
```

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

```
cat("\nAbove model after variable selection:\n")
```

```
##
## Above model after variable selection:
```

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

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

```
cat("\nAll possible interactions between above model FEs added in:\n")
```

```
##
## All possible interactions between above model FEs added in:
```

```
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
```

```
cat("\nAbove model after variable selection:\n")
```

```
##
## Above model after variable selection:
```

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

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

Compare the three combined models fitted so far by the correlation between predictors: or don't? why

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

```
##  Groups   Name            Std.Dev. Corr
##  Artifact RubricCritDes   0.74372
##           RubricInitEDA   0.59362  0.466
##           RubricInterpRes 0.41847  0.232 0.750
##           RubricRsrchQ    0.41227  0.585 0.440 0.710
##           RubricSelMeth   0.26108  0.389 0.602 0.744 0.406
##           RubricTxtOrg    0.51321  0.338 0.618 0.702 0.563 0.671
##           RubricVisOrg    0.50803  0.347 0.732 0.678 0.516 0.411 0.756
##  Residual                 0.43492
```

```
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
```

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

```
##  Groups   Name            Std.Dev. Corr
##  Artifact RubricCritDes   0.69675
##           RubricInitEDA   0.59376  0.416
##           RubricInterpRes 0.38236  0.324 0.800
##           RubricRsrchQ    0.40550  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    0.50523  0.349 0.727 0.675 0.567 0.346 0.757
##  Residual                 0.43405
```

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

```
##  Groups   Name            Std.Dev. Corr
##  Artifact RubricCritDes   0.70903
##           RubricInitEDA   0.59491  0.445
```

```
##           RubricInterpRes 0.39044  0.352 0.814
##           RubricRsrchQ    0.42384  0.629 0.440 0.715
##           RubricSelMeth   0.25941  0.422 0.601 0.736 0.361
##           RubricTxtOrg    0.51132  0.416 0.636 0.669 0.547 0.634
##           RubricVisOrg    0.50546  0.339 0.715 0.674 0.513 0.376 0.770
##  Residual                 0.43013
```

Now compare the models using ANOVA and info criteria (not the original *comb.full*, because it is not nested within the others):

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

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

```
## Data: ratings_tall_noNA
## 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
```

The model *comb.inter_elim* with one interaction, Rater:Rubric, is preferred by the F-test and by AIC.

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

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

This model suggests Rating is affected by the Rater who graded the project, the Semester it was assigned, and the Rubric being graded, but that the Rubric affects the grade differently depending on Rater.

Look at coefficients for model FEs to see this varying effect :

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

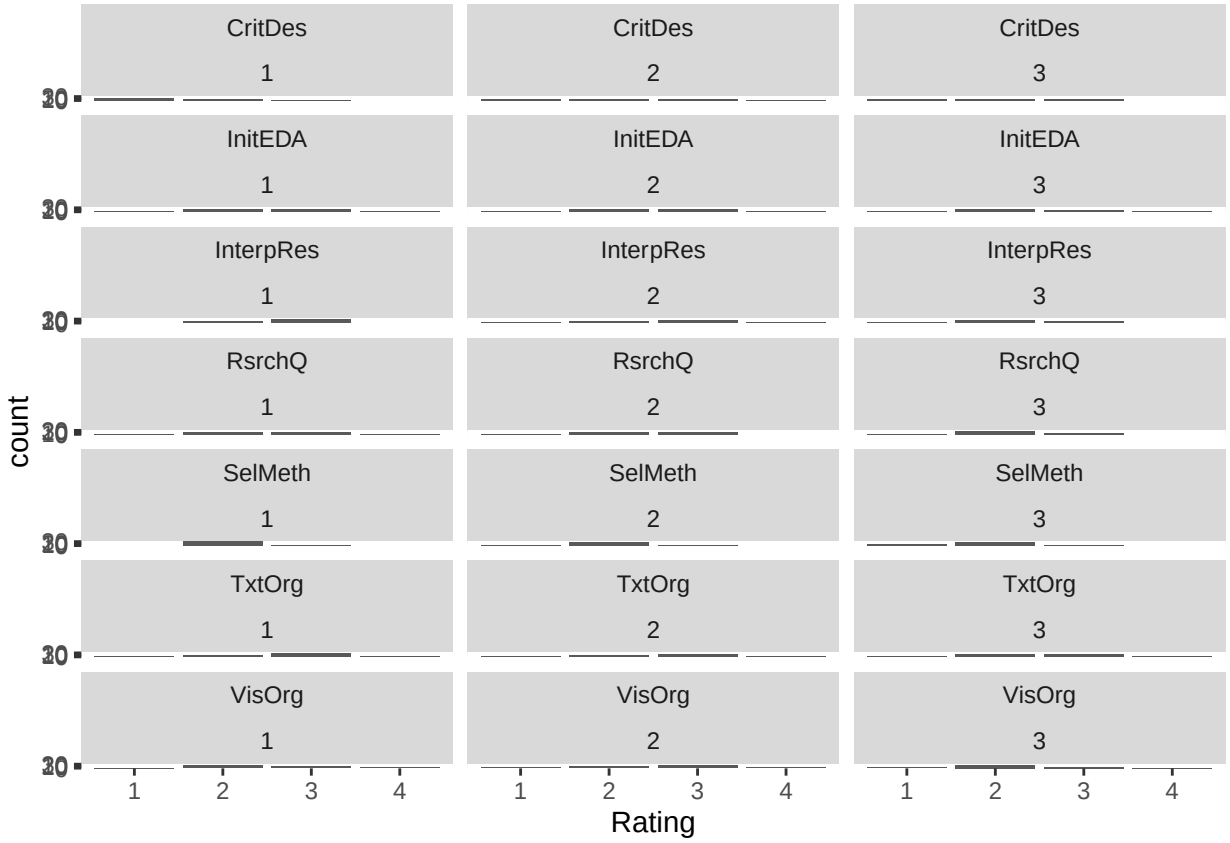
```
##                                   Estimate Std. Error    t value
## (Intercept)                      1.7595626 0.11778520 14.9387405
## as.factor(Rater)2                0.3653298 0.13289753  2.7489585
## as.factor(Rater)3                0.2139686 0.13291323  1.6098368
## SemesterS19                     -0.1778096 0.08225811 -2.1616056
## RubricInitEDA                    0.7460134 0.13662956  5.4601174
## RubricInterpRes                  1.0143629 0.13482598  7.5234971
## RubricRsrchQ                     0.7488442 0.12423680  6.0275554
## RubricSelMeth                    0.4265498 0.13038072  3.2715714
## RubricTxtOrg                     1.0495614 0.13551294  7.7451008
## RubricVisOrg                     0.6835512 0.13943106  4.9024310
## as.factor(Rater)2:RubricInitEDA -0.3082206 0.17235495 -1.7882900
## as.factor(Rater)3:RubricInitEDA -0.2948486 0.17268392 -1.7074467
## as.factor(Rater)2:RubricInterpRes -0.5366147 0.17009971 -3.1547068
## as.factor(Rater)3:RubricInterpRes -0.7521200 0.17050700 -4.4110799
## as.factor(Rater)2:RubricRsrchQ   -0.5012240 0.16152526 -3.1030688
## as.factor(Rater)3:RubricRsrchQ   -0.3699310 0.16181075 -2.2861953
## as.factor(Rater)2:RubricSelMeth  -0.3958571 0.16463537 -2.4044472
## as.factor(Rater)3:RubricSelMeth  -0.4129206 0.16500464 -2.5024787
```

```
## as.factor(Rater)2:RubricTxtOrg    -0.5838997 0.17139667 -3.4067157
## as.factor(Rater)3:RubricTxtOrg    -0.4862692 0.17175987 -2.8310989
## as.factor(Rater)2:RubricVisOrg    -0.1445162 0.17436925 -0.8287944
## as.factor(Rater)3:RubricVisOrg    -0.3334744 0.17475568 -1.9082321
```

There are a range of interaction coefficients that show the different in Rater's use of Rubrics. For example, Rater 2 tends to rate higher based on their coefficient alone, but Rater 2 rates the lowest for TxtOrg.

Also check for patterns using the plots :

```
ggplot(ratings_tall_noNA, aes(x=Rating)) +
geom_bar() + facet_wrap( ~ Rubric + Rater, nrow=7)
```



^.....graph labels taking up whole plot. fix later

These plots show how Raters' ratings for certain rubrics differ from each other.

Now try adding additional random effects to the model. THere are 3 fixed effects that can be tried as random effects: Rater, Semester, and the Rater:Rubric interaction.
First try adding Rater as a RE:

```
comb.inter_elim_RE1 <- lmer(as.numeric(Rating) ~ (0 + Rubric | Artifact) +
(0 + as.factor(Rater) | Artifact) + as.factor(Rater) +
Semester + Rubric + as.factor(Rater):Rubric, data = ratings_tall_noNA)
```

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

```
anova(comb.inter_elim, comb.inter_elim_RE1)
```

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

```
## Data: ratings_tall_noNA
## Models:
## comb.inter_elim: as.numeric(Rating) ~ (0 + Rubric | Artifact) + as.factor(Rater) + Semester + Rubric
## comb.inter_elim_RE1: as.numeric(Rating) ~ (0 + Rubric | Artifact) + (0 + as.factor(Rater) | Artifact
##                     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## comb.inter_elim       51 1454.5 1694.1 -676.26   1352.5
## comb.inter_elim_RE1   57 1415.9 1683.6 -650.94   1301.9 50.647  6  3.487e-09
##
## comb.inter_elim
## comb.inter_elim_RE1 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The ANOVA test, as well as AIC/BIC both suggest including this new random effect for Rater in the model.

Now try adding Semester as a RE:

```
comb.inter_elim_RE2 <- lmer(as.numeric(Rating) ~ (0 + Rubric | Artifact) +
(0 + as.factor(Rater) | Artifact) +
(0 + Semester | Artifact) + as.factor(Rater) +
Semester + Rubric + as.factor(Rater):Rubric, data = ratings_tall_noNA)
```

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

```
anova(comb.inter_elim_RE1, comb.inter_elim_RE2)
```

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

```
## Data: ratings_tall_noNA
## Models:
## comb.inter_elim_RE1: as.numeric(Rating) ~ (0 + Rubric | Artifact) + (0 + as.factor(Rater) | Artifact
## comb.inter_elim_RE2: as.numeric(Rating) ~ (0 + Rubric | Artifact) + (0 + as.factor(Rater) | Artifact
##                     npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## comb.inter_elim_RE1   57 1415.9 1683.6 -650.94   1301.9
## comb.inter_elim_RE2   60 1421.6 1703.4 -650.81   1301.6 0.252  3     0.9688
```

Neither the test or AIC/BIC want the new random effect for Semester in the model.

Now try adding the Rater:Rubric interaction as a RE:

```
comb.inter_elim_RE3 <- 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 = ratings_tall_noNA)
anova(comb.inter_elim_RE1, comb.inter_elim_RE3)
```

This causes an error as there are not enough observations in the data for the number of REs we are trying to add to the model.

So, the final model will include one additional random effect (Rater), as well as the fixed effect interaction betweeen Rater and Rubric. The model is:

```
formula(comb.inter_elim_RE1)
```

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

The model FE coefficients are:

```
summary(comb.inter_elim_RE1)$coef
```

```
##                                    Estimate Std. Error    t value
## (Intercept)                       1.7575480 0.11403819 15.4119246
## as.factor(Rater)2                 0.3660621 0.13918172  2.6301016
## as.factor(Rater)3                 0.1959097 0.12966534  1.5108870
## SemesterS19                      -0.1591742 0.07647418 -2.0814103
## RubricInitEDA                     0.7394970 0.12995957  5.6902082
## RubricInterpRes                   0.9915167 0.12770546  7.7640905
## RubricRsrchQ                      0.7261858 0.11793017  6.1577610
## RubricSelMeth                     0.4106840 0.12470160  3.2933335
## RubricTxtOrg                      1.0157794 0.12999510  7.8139821
## RubricVisOrg                      0.6542503 0.13353088  4.8996180
## as.factor(Rater)2:RubricInitEDA  -0.2998125 0.15608995 -1.9207676
## as.factor(Rater)3:RubricInitEDA  -0.2947318 0.15635120 -1.8850628
## as.factor(Rater)2:RubricInterpRes -0.5132350 0.15348360 -3.3439078
## as.factor(Rater)3:RubricInterpRes -0.7148439 0.15363842 -4.6527680
## as.factor(Rater)2:RubricRsrchQ   -0.4874138 0.14722146 -3.3107520
## as.factor(Rater)3:RubricRsrchQ   -0.3223752 0.14726517 -2.1890800
## as.factor(Rater)2:RubricSelMeth  -0.3863819 0.15030733 -2.5706125
## as.factor(Rater)3:RubricSelMeth  -0.3871584 0.14961257 -2.5877398
## as.factor(Rater)2:RubricTxtOrg   -0.5510453 0.15646042 -3.5219468
## as.factor(Rater)3:RubricTxtOrg   -0.4448837 0.15673124 -2.8385130
## as.factor(Rater)2:RubricVisOrg   -0.1049027 0.15861083 -0.6613842
## as.factor(Rater)3:RubricVisOrg   -0.2752089 0.15884872 -1.7325219
```

.....delete this? The RE coefficient values are shown (too many to list):

```
ranef(comb.inter_elim_RE1)[1:10]
```

```
## $Artifact
##     RubricCritDes RubricInitEDA RubricInterpRes RubricRsrchQ RubricSelMeth
## 100   0.799254427  -0.261024838    -0.121652629 -0.165076057   0.232376229
## 101  -0.496487528   0.434224814    -0.166227792 -0.741399207   0.032277197
## 102  -0.770637636  -0.332737858    -0.232329893 -0.744249801   0.048851503
## 103   0.139669409   0.330198946     0.098810078 -0.281592140   0.271543098
## 104  -0.576639438   0.308527575     0.091189508 -0.260811468   0.073418658
## 105  -0.590070680  -0.482686330    -0.340032335 -0.404172183  -0.097453016
## 106   0.204327384  -1.028883953    -0.399125707  0.233398883  -0.136307599
## 107  -0.559957851  -0.401608649     0.057206795  0.183134156  -0.102336429
## 111  -0.461603073  -0.351055688    -0.241463797 -0.311642336  -0.066937777
## 112  -0.499291170   0.322602196     0.271596738  0.197920492  -0.103867697
## 113  -0.586333414  -0.804706394    -0.145286443 -0.131179242   0.004220762
## 114  -0.448171831   0.440158218     0.189758047 -0.168281621   0.103933897
## 115  -0.370823564   0.454232839     0.370165276  0.290450339  -0.073352458
## 116  -0.588696034  -0.354273530    -0.287550231 -0.351685885  -0.123688575
## 117  -0.672337208  -0.136981915     0.011788252 -0.194733999  -0.104365858
## 118  -0.654134340  -0.212126192    -0.029465039 -0.208922753  -0.027825745
## 13    0.388204535  -0.746415810    -0.434670181  0.050610449  -0.158694230
## 15    0.688599423   0.476194361    -0.046966797 -0.110359209  -0.052055836
## 16    0.682592162   1.153695841     0.314120896 -0.008298752   0.186414900
## 17    0.335722581  -0.087916027     0.067039563  0.549517881  -0.199138172
## 21    0.775959601   1.090388721     0.451599362  0.434671629   0.085149958
## 22    0.730597615   0.381859393     0.248952158  0.430908625   0.090316590
## 23   -0.272029381  -0.723561310    -0.327004020 -0.010003856  -0.176380289
## 24    0.049051941  -0.202392191    -0.150283279 -0.130267442   0.068983982
## 25    1.160386392   0.007484406    -0.288600146  0.162946839  -0.130358471
```

```
## 26   -0.863325838  -0.484028339    -0.160023193 -0.518470516   0.112870050
## 27    0.101621683   0.386518050     0.006466788 -0.172809189   0.092091510
## 28   -0.298810862  -0.592028804    -0.413393496 -0.405015156  -0.059299014
## 32    0.660676549   0.404012104     0.250523950  0.407846922   0.001491722
## 33   -0.083936224   0.150252790    -0.059850296 -0.452438878   0.169479969
## 34    0.465688484  -0.311783603    -0.060504469 -0.201190616   0.261678796
## 35   -0.743816350  -0.254851355    -0.085370671 -0.283309904  -0.098077654
## 36    0.049051941  -0.202392191    -0.150283279 -0.130267442   0.068983982
## 37    0.775871813  -0.157021304    -0.206860449 -0.021694056   0.102486373
## 38   -0.016996478  -0.209480468    -0.141947841 -0.174736518  -0.064575263
## 39   -0.527958103   0.248599055     0.207286071  0.140180432  -0.087410199
## 40    0.105494330   0.357277062     0.013230435 -0.194216563   0.047357133
## 45    0.014660685  -0.241819859    -0.172285657 -0.089837830   0.049763027
## 46    0.149525211   0.324259400    -0.013546205 -0.141173524   0.032052349
## 47    1.130913925  -0.177627220    -0.049065979  0.677169620  -0.148596800
## 48    0.536956446   0.660643346     0.224703742  0.134774160   0.241950475
## 49   -0.903859261   0.215306545     0.273251512  0.159455304  -0.189834377
## 53    1.141774702   0.106548956     0.017115942  0.238983257   0.117982413
## 54   -0.662444940   0.383824093    -0.091935077 -0.662602135   0.147420999
## 55   -0.148685190  -0.372320725     0.070586894  0.317360372  -0.133655360
## 56    0.687791192  -0.264816882    -0.275989459 -0.060702569  -0.062069789
## 57   -0.769717846  -0.326314233    -0.169596192 -0.256439553  -0.084339398
## 6    -0.673895284  -0.277004067    -0.086942463 -0.260248201  -0.009252785
## 61    0.001538814   0.332842683    -0.079455720 -0.172069062   0.015992936
## 62    1.385202498   0.997741439     0.303261700  0.482991511  -0.052910156
## 63    0.682867532   0.348616818     0.206990349  0.445159596  -0.019000749
## 64    0.550893544  -0.162679319    -0.076524733  0.054788067   0.062473378
## 65    0.831967874  -0.452051603    -0.411612839  0.253164656  -0.217018183
## 66    0.741010208   0.910028221     0.371808631  0.382435120  -0.040223724
## 67   -0.816168926   0.144942635     0.292898045  0.146922110  -0.188097241
## 68    0.630981070  -0.239593320     0.050764537  0.488193481  -0.041945976
## 7    -0.621325541   0.311906175     0.069807605 -0.302789949   0.013854742
## 72   -0.056294130   0.416364668     0.192049401 -0.072221463   0.022353775
## 73   -0.746426401  -0.931290811    -0.323360413 -0.186557681  -0.017211085
## 74   -1.048639783   0.086000721     0.117160731 -0.493825375   0.092899126
## 75   -0.041412284   0.337817601     0.148248009 -0.088802210   0.098105036
## 76    0.037342687  -0.325731365    -0.216034999 -0.141568370  -0.005215155
## 77   -0.168476653  -0.233626097    -0.010439393 -0.072616310  -0.014913729
## 78    0.416148290   0.062400913     0.074608810  0.131269470   0.084763507
## 79   -0.309478122   0.018252870     0.132101679  0.023555683   0.051544602
## 8    -0.607309327  -0.208778680    -0.035853472 -0.212289120   0.006563547
## 84    0.308445851  -0.084163650     0.160689154  0.445180654  -0.061765352
## 85    1.073382862   0.376335653     0.315614108  0.876524405  -0.132031144
## 86    0.326648719  -0.159307927     0.119435862  0.430991900   0.014774761
## 87    0.204327384  -1.028883953    -0.399125707  0.233398883  -0.136307599
## 88    1.088096465   0.644180229     0.316282000  0.538699798  -0.077309776
## 9    -0.580527846  -0.340311186     0.050536003  0.182722180  -0.110517727
## 92   -0.540380336  -0.348340126     0.068435608  0.221431701  -0.052031876
## 93   -0.392335215  -0.163440961     0.178232959  0.352259092   0.028787916
## 94    1.037123761   1.033203354     0.338368009  0.394281236  -0.006580611
## 95    0.139669409   0.330198946     0.098810078 -0.281592140   0.271543098
## 96    0.239270278   0.380003753     0.224028454  0.314950845  -0.067576299
## O1   -0.501833135   0.422492400     0.120678820 -0.008547298  -0.092444312
## O10  -0.441620718  -0.001273012     0.155500759  0.049620157   0.036660616
```

```
## O11  -0.767149032  -0.330048966     0.328469563  0.512570342   0.013735953
## O12  -0.354418918  -0.488343083    -0.316167902 -0.338352508  -0.015400491
## O13   0.030664989   0.083217052    -0.316869316 -0.367351944  -0.071062643
## O2   -0.115962217   0.329821712     0.171346258  0.140222882  -0.072079827
## O3    0.283484440  -0.135250509    -0.012995229  0.231072663  -0.039719106
## O4   -0.111608085   0.044715167     0.203176133 -0.216903187   0.365019800
## O5    0.878801403  -0.426327177    -0.026091150  0.189637291   0.249949381
## O6   -0.897730628  -0.773057517    -0.419215540 -0.412698862  -0.112079073
## O7    0.137946203   0.206775492    -0.005709495 -0.013640063  -0.042674422
## O8    0.358956229  -0.209366221    -0.396311268 -0.311054388   0.029106551
## O9   -0.799406126   0.585057999     0.349324920 -0.190664552   0.074764753
##      RubricTxtOrg RubricVisOrg as.factor(Rater)1 as.factor(Rater)2
## 100 -0.4896793592  -0.44086319       0.034936568      -0.050188783
## 101  0.2892691284   0.46522893      -0.031032144       0.044579810
## 102 -1.1194088528  -0.43426972      -0.071722885       0.103034859
## 103  0.1091043260  -0.23982951       0.041764049      -0.059996930
## 104  0.0889463482  -0.11665635      -0.025624712       0.036811663
## 105 -0.5321703335  -0.35606582      -0.059281355       0.085161745
## 106  0.0172554445  -0.33465937      -0.022656943       0.032548258
## 107 -0.5131733071  -0.30985920      -0.011087353       0.015927745
## 111 -0.4110812031  -0.25279054      -0.035974074       0.051679232
## 112  0.2084053061   0.41592672       0.019756175      -0.028381105
## 113 -0.4728814134  -0.30644203      -0.016213573       0.023291914
## 114  0.2100354786  -0.01338107      -0.002317431       0.003329149
## 115  0.3294944365   0.51920199       0.043063456      -0.061863618
## 116  0.1298393248   0.27762843      -0.030969730       0.044490148
## 117  0.2258387455   0.84088523       0.010801963      -0.015517763
## 118  0.1276080694   0.31606861      -0.008677326       0.012465576
## 13  -0.7208355472  -0.62615682      -0.065719175      -0.387555964
## 15   0.4109255876   0.90084408       0.013941355       0.082214292
## 16   0.8983321370   0.58517698       0.020551785       0.121197001
## 17  -0.1152932168   0.03066764      -0.017999182      -0.106143914
## 21   0.9175021411   0.59118795       0.043496254       0.256504023
## 22   0.2103492050  -0.12229450       0.018247527       0.107608441
## 23  -0.6709941883  -0.56004326      -0.056913772      -0.335629164
## 24   0.2458067915  -0.13973909      -0.007466290      -0.044029849
## 25  -0.0007623467   0.07474060      -0.038408438      -0.226500397
## 26  -0.4701947997  -0.47160185       0.015712610       0.092659652
## 27   0.2990395462  -0.05305148      -0.006285748      -0.037068011
## 28  -0.6274025691  -0.51252569      -0.068990828      -0.406849402
## 32   0.2598320935   0.36094579       0.027330074       0.161169600
## 33  -0.4040417806  -0.39749927       0.018955163       0.111781475
## 34  -0.5023732572  -0.50591233       0.030230838       0.178275849
## 35  -0.2593062540   0.26606022      -0.004563978      -0.026914474
## 36   0.2458067915  -0.13973909      -0.007466290      -0.044029849
## 37   0.2587270560  -0.15232412      -0.005404281      -0.031869865
## 38  -0.2463859896   0.25347519      -0.002501969      -0.014754490
## 39  -0.2363863837  -0.12448150       0.010478486       0.061793227
## 40  -0.2426361233  -0.14307750      -0.010403973      -0.061353811
## 45   0.2993599871  -0.21570738       0.013972781      -0.084828503
## 46  -0.1862331518  -0.21911100       0.017905584      -0.108704483
## 47  -0.6837413431  -0.67097263       0.060711050      -0.368575702
## 48   0.6088839750  -0.35396522      -0.057928838       0.351684939
## 49   0.2597538164   0.72498630      -0.028115605       0.170689334
```

```
## 53   0.0731895763  -0.06274354      -0.066382216       0.403005249
## 54   0.3347476834  -0.11279192       0.048111314      -0.292082929
## 55  -0.3649965249   0.05817936      -0.010301114       0.062537877
## 56  -0.2393315344   0.11174846       0.019211956      -0.116635439
## 57   0.2765067671   0.22694723       0.019220334      -0.116686303
## 6   -0.3087891425  -0.21718008      -0.013646525      -0.080475634
## 61   0.8803198375   0.38765095       0.008576186      -0.052065873
## 62   0.4045615711   0.81896334      -0.054483093       0.330765888
## 63   0.2956495312   0.26735516      -0.036660224       0.222563567
## 64   0.2364079963   0.18588162      -0.001773938       0.010769546
## 65   0.3136067693   0.16069817       0.010823239      -0.065707688
## 66  -0.1911907522   0.26538362      -0.032412150       0.196773583
## 67  -0.8636321586   0.06975226      -0.003071244       0.018645465
## 68   0.2430608129   0.18121685      -0.034953085       0.212199557
## 7   -0.2555563878  -0.13049247      -0.012465983      -0.073513795
## 72  -0.2053946515   0.24592661      -0.010259031       0.062282394
## 73   0.1793900774  -0.33820540       0.034061407      -0.206786196
## 74  -0.4514453068  -0.05708319      -0.034017432       0.206519220
## 75  -0.3067556086  -0.28155979       0.018589867      -0.112858749
## 76  -0.2956548559  -0.35372140       0.035327686      -0.214473751
## 77  -0.3148163557   0.11131621       0.007163071      -0.043486875
## 78   0.0613942261  -0.04919909      -0.063400420       0.384902821
## 79   0.0495988760  -0.03565463      -0.060418625       0.366800392
## 8   -0.2460275192  -0.16365154      -0.002779113      -0.016388850
## 84   0.2939129506   0.42396437       0.044953934      -0.064579419
## 85   0.2776085260   0.41740124       0.054502535      -0.078296642
## 86   0.1956822745  -0.10085225       0.025474644      -0.036596080
## 87   0.0172554445  -0.33465937      -0.022656943       0.032548258
## 88   0.4757000508   1.03772669       0.071387507      -0.102553066
## 9   -0.2896191384  -0.21116911       0.009297944       0.054831388
## 92   0.0506056750  -0.20098157      -0.002255017       0.003239488
## 93   0.7354737876   0.01117134       0.029884599      -0.042931283
## 94   0.3159491992   0.50172646       0.031132840      -0.044724467
## 95   0.1091043260  -0.23982951       0.041764049      -0.059996930
## 96   0.2323927752   0.41278076       0.024178556      -0.034734159
## O1  -0.2365794802  -0.25844395      -0.212422212       0.271867968
## O10  0.1214373205   0.01136612       0.108526252      -0.367920428
## O11  0.3057043639  -0.26212604       0.052729231       0.052389292
## O12 -0.3628191000  -0.45355879       0.058315334      -0.016909001
## O13  0.2746815820   0.14800387      -0.008185723       0.048571895
## O2   0.1740665556   0.34225375       0.172176876      -1.028615066
## O3   0.2431308629   0.13200407      -0.038547653       0.159655530
## O4   0.1612199844  -0.27831215      -0.089503452       0.418557635
## O5  -0.0424660924  -0.48868914       0.030697279       0.059839532
## O6  -0.0545743949  -0.18315278      -0.050149497       0.116024369
## O7   0.1229848636   0.22421465       0.147803610       0.139018362
## O8  -0.5685054544  -0.90877683      -0.039475305      -0.248713156
## O9   0.3976758757   0.55919622       0.048179918       0.035280649
##     as.factor(Rater)3
## 100       0.031428653
## 101      -0.027916265
## 102      -0.064521325
## 103       0.037570599
## 104      -0.023051783
```

```
## 105      -0.053329026
## 106      -0.020382002
## 107      -0.009974093
## 111      -0.032361985
## 112       0.017772495
## 113      -0.014585599
## 114      -0.002084742
## 115       0.038739536
## 116      -0.027860118
## 117       0.009717358
## 118      -0.007806052
## 13       -0.536722039
## 15        0.113857679
## 16        0.167844409
## 17       -0.146997552
## 21        0.355229632
## 22        0.149025759
## 23       -0.464809179
## 24       -0.060976459
## 25       -0.313677937
## 26        0.128323345
## 27       -0.051335085
## 28       -0.563441313
## 32        0.223202027
## 33        0.154804949
## 34        0.246892285
## 35       -0.037273562
## 36       -0.060976459
## 37       -0.044136230
## 38       -0.020433333
## 39        0.085576768
## 40       -0.084968226
## 45       -0.051599354
## 46       -0.066122599
## 47       -0.224196674
## 48        0.213922386
## 49        0.103826651
## 53        0.245139427
## 54       -0.177667765
## 55        0.038040446
## 56       -0.070946830
## 57       -0.070977769
## 6        -0.111449830
## 61       -0.031670551
## 62        0.201197777
## 63        0.135380632
## 64        0.006550884
## 65       -0.039968574
## 66        0.119693139
## 67        0.011341636
## 68        0.129076428
## 7        -0.101808455
## 72        0.037885041
## 73       -0.125783597
```

```
## 74        0.125621200
## 75       -0.068649550
## 76       -0.130459771
## 77       -0.026452131
## 78        0.234128109
## 79        0.223116791
## 8        -0.022696740
## 84        0.040440194
## 85        0.049030038
## 86        0.022916784
## 87       -0.020382002
## 88        0.064219622
## 9         0.075935393
## 92       -0.002028595
## 93        0.026883943
## 94        0.028006850
## 95        0.037570599
## 96        0.021750833
## O1       -0.224083493
## O10      -0.112465388
## O11       0.174412982
## O12       0.118720019
## O13       0.029115529
## O2       -0.619306645
## O3        0.068657607
## O4        0.206836530
## O5        0.130611929
## O6       -0.001531173
## O7        0.481130258
## O8       -0.338167869
## O9        0.146890570
##
## $<NA>
## NULL
##
## $<NA>
## NULL
##
## $<NA>
## NULL
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## $<NA>
## NULL
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## $<NA>
## NULL
##
## $<NA>
## NULL
##
## $<NA>
```

```
## NULL
##
## $<NA>
## NULL
```

. . . .keep this? And the RE standard deviations and correlations are:

```
summary(comb.inter_elim_RE1)$varcor
```

```
##  Groups     Name              Std.Dev. Corr
##  Artifact   RubricCritDes     0.70457
##             RubricInitEDA     0.56379   0.318
##             RubricInterpRes   0.31947   0.142  0.674
##             RubricRsrchQ      0.42308   0.500  0.194  0.538
##             RubricSelMeth     0.19556   0.145  0.226  0.376 -0.241
##             RubricTxtOrg      0.50028   0.268  0.437  0.364  0.305  0.213
##             RubricVisOrg      0.48202   0.175  0.504  0.445  0.276 -0.161
##  Artifact.1 as.factor(Rater)1 0.11320
##             as.factor(Rater)2 0.33429  -0.486
##             as.factor(Rater)3 0.30682   0.332  0.663
##  Residual                     0.36699
##
##
##
##
##
##
##
##   0.537
##
##
##
##
```

Question 4: Is there anything else interesting to say about this data?

yes