Comments from the peer reviewer

We received several suggestions from the peer reviews.

From the first peer, the peer advised that our paper should explain about the background of the model more deeply. We will partially accept this suggestion. Our intended readers already know what the Rasch model is, so we do not have to explain the basic backgrounds of the models, how bayesglm() and glm() functions are different. However, we shall distinguish the difference of the models more clearly in the paper. The peer claimed we should demonstrate on how to calculate AIC. We would not accept this because our intended audience have basic knowledge of statistics and regression modeling.

From the second peer, the peer suggested to move the description of the data to the method section. We will accept this advice. The peer also suggested to change the position of the table. We will accept this advice. The peer argued that we should add background knowledge about what MLE is and which MLE is the best. We would not accept this comment because, again, our intended audience are trained in basic statistics.

School security and student discipline practices youngwoo Kwon

Introduction

Security and strict disciplinary codes in high schools have been done to prevent, or discourage, adolescent students from his/her misconduct. Although adolescence is an important period greatly influenced by the environment and regulations are useful to preserve orderliness and safety, excessive regulations sometimes negatively affect students emotionally, or physically. Undoubtedly, that we need to study more about the school security for growing students and to analyze how school security affects the student, it is necessary to quantify the 'security measures' for each school. The goal of this paper is to make relative quantified security measurement scores for each school.

In 2014 Finn and Servos studied security and student discipline practice. The research examined the relationship among student misbehavior, suspensions, and security measures in a nationwide sample of high schools. From the data, Finn and Servos tried to identify the characteristics of schools that implemented the most invasive security measures, and examine the conditions related to racial/ ethnic and gender inequities in suspensions (Finn and Servos, p. 1). In this paper, we first reconstructed the model similar to the one used by Finn and Servos, and the variations of the model that might improve the model. Next, we compared those models and selected the recommended model. Finally, we created school indices from the original Finn and Servos model and the recommended model and analyzed how two models showed different results.

Method

The data Finn and Servos used is the Education Logistic Study of 2002 (ELS:2002) conducted by the National Center for Education Statistics. From twenty security-related data elements from the responses to the ELS:2002, Finn and Servos selected seven questions to construct their data; Q38c) Require students to pass through metal detectors each day; Q38d) Perform one or more random metal detector checks on students; Q38f) Use one or more random dog sniffs to check for drugs; Q38g) Perform one or more random sweeps for contraband (e.g., drugs or weapons) but not including dog sniffs; Q38h) Require drug testing for any students (e.g., athletes); Q38n) Use one or more security cameras to monitor the school; Q39a) Have a formal process to obtain parent input on policies related to school crime and discipline. In this paper, we first used the same data to replicate Finn and Servos's result, and selected the other 6 questions, overlapping with Finn and Servos's questions, to find a better dataset to analyze. In particular, we removed Q38d and Q39a from Finn and Servos's questions and add one another question; Q38j) Enforce a strict dress code. From now, we will call those two data sets 'Finn and Servos's data set' and 're-selected data set'.

We first modified the original data to construct Finn and Servos data set and our re-selected data set. We calculated the sum of the index of schools from the Finn and Servos's data and we fit the Rasch model by using the maximum likelihood and a penalized variant of maximum likelihood for the Finn and Servos data to replicate the Finn and Servos's result. We used Bayes Method to construct a penalized variant of maximum likelihood, a model fits a logistic model combining the same logistic likelihood as generalized linear model, but with a multivariate Cauchy prior distribution on the coefficients. Then we fit the same models, maximum likelihood, and penalized variant of maximum likelihood, for our re-selected data described above. To compare those four models, two for Finn and Servos and two for re-selected data, we compared the AIC and Deviance of the models and determined the best model among the four models.

To achieve our initial purpose, the quantification of the 'security measures', we scored each school's security for Finn and Servos's model and our determined best model. We indexed the schools in order of the security measurement scores and analyzed how the indices differ for the Finn and Servos's models and determined model. To deal with the large indices for the analysis, we constructed a visual graph that compares the indices of two models and calculated the correlation of the two models.

We also tried to replace the missing values in the data. We derived two models, one which replaced the missing values with the average of that variable for all data, and a model replaced the missing values by an average only from data with the same value for the determined independent variable. We used 'BYURBAN, a variable representing school urbanicity, as an independent variable since we determined this variable will be the most efficient variable to state the MAR.

Result

We first removed the rows that contained any missing data and calculated the sum of the index level of each school for Finn and Servos's data set by simply add the scores of each question selected for each school. As a result, we removed 44 school data out of 656 schools that contained the missing data and constructed a table of the sum of indices for each school. The result is described in Table 1.

Table 1. Table of sum of indices for each school, from Finn and Servos's data

Sum of indices	0	1	2	3	4	5	6	7
Number of schools	81	146	184	119	64	16	2	0

The AIC for model_0, maximum likelihood method model for the Finn and Servos's data set (which we also called as Finn and Servos's model), was 4471.554 and the Deviance for model_0 was 3235.554. The AIC for model_1, penalized variant for maximum likelihood method model for the Finn and Servos's data set, was 4846.643 and the Deviance for model_1 was 570.5367. The AIC for model_2, maximum likelihood method model for the re-selected data set, was 4245.643 and the Deviance for model_2 was 3011.735. Finally, the AIC for model_3, penalized variant for maximum likelihood method model for the re-selected data set, was 4628.027 and the Deviance was 528.6911. Overall, the model used penalized variant for maximum likelihood method showed higher AIC and lower Deviance than the model used maximum likelihood method. Also, the model from the re-selected data set showed lower AIC

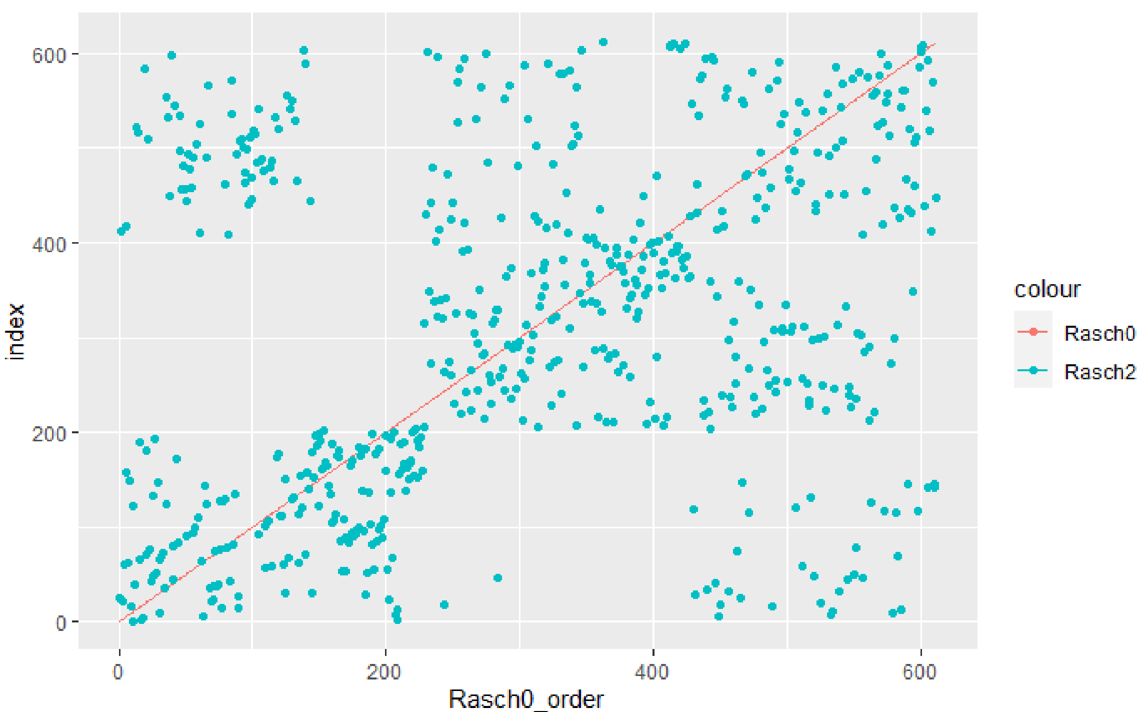


Figure 1. Rank of the model_0 verses rank of the model_2. Data are ordered in the rank of model_0 and the rank of the model_2 were described as blue dots. The blue dots showed four groups.

and lower Deviance than the model from the Finn and Servos's data set. Since we valued AIC more than Deviance for the model selection, we selected the model_2, maximum likelihood method model for the re-selected data set, as our recommended model.

We ranked the schools by the scores we provided from our recommended model and Finn and Servos's model, model_0. For the analysis of the ranks, Intuitive analysis was difficult due to a large number of schools. So, we visualized the data by rearranging them in the order of the rank of model_0 and comparing them with the rank of model_2.

For better visualization, we placed the rank of the model_0 as a red line and the rank of the model_2 as blue dots shown in the Figure 1. Unusually, the result of model_2 seemed to be divided into four groups. For the numerical analysis, the correlation of the rank of model_0 and model_2 was 0.3130.

We tried to replace the missing values. In our re-selected data set, there were 24 missing values. The first model replaced the missing values into the mean value of each questions. So, if the response of q38c is missed for the school "id3572", we replaced its value to the average of total q38c responses. The second model replaced the missing values into mean value of each questions calculated only from the data that has same 'BYURBAN' value, a value representing school urbanicity, with the school that has missing variables. For instance, if the 'BYURBAN' variable for the school "id3572" was 1, we replaced its missing value, the response of q38c, to the average of q38c responses from the data which have BYURBAN variable equals to 1.

Two model's AIC and deviance were almost equal. Their AIC were 4579.35 and 4579.40, and deviance were 3228.91 and 3228.98 Since we only replaced the missing variables and only 24 schools out of 656 schools had missing variables, AIC and deviance should not change much.

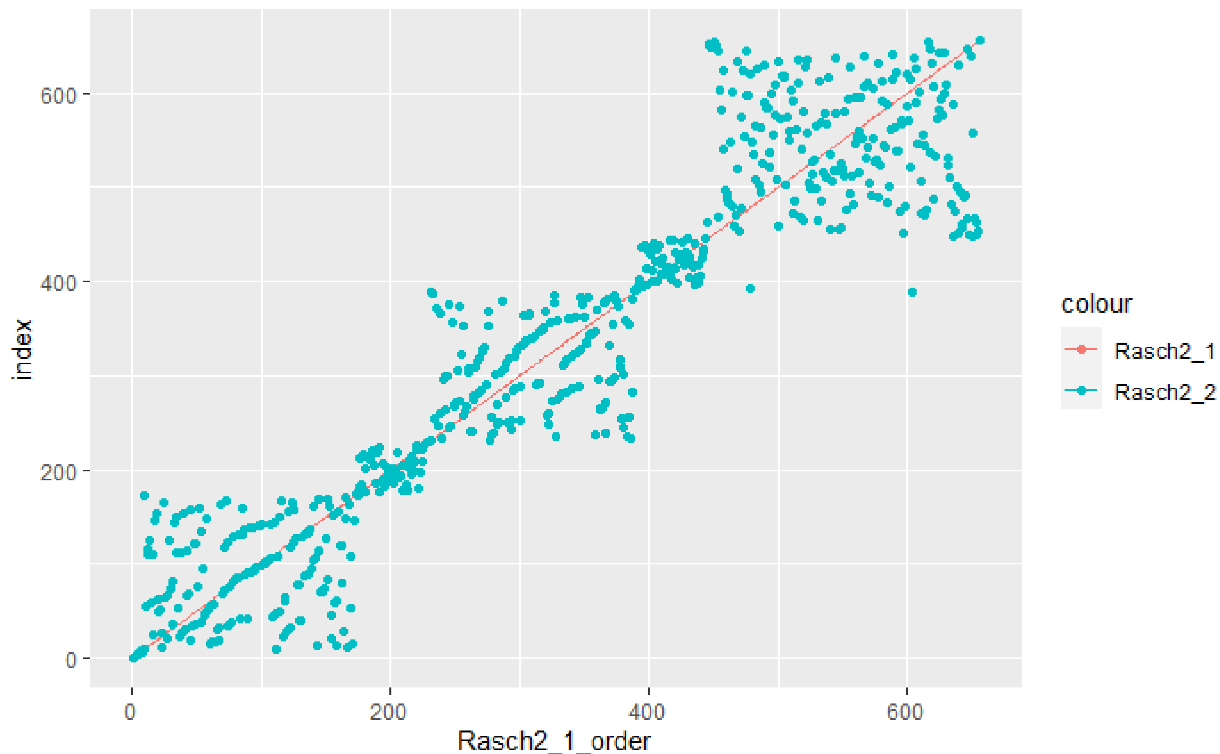


Figure 2. Rank of the Rasch2_1 model verses rank of the Rasch2_2. Data are ordered in the rank of Rasch 2_1 and the rank of the Rasch2_2 were described as blue dots.

Figure 2 shows the relationship between Rasch2_1 model, the model replaced the missing value from all data, and Rasch2_2 model, the model replaced the missing value from the data set that have same BYURBAN value. Two ranks seem highly related in the graph. We can also draw three groups for the blue dots. For numerical analysis, the correlation between the rank of two models were 0.9349.

Discussion

About the sum of indices model, this model is a very simple way to quantify the security measurement, but it had two problems. First, the importance of each question was not taken into account. It is hard to say that two schools with the same score really need to get the same score because the scores for all questions were weighted as 1. Second, there are too many schools which got the same score which makes this model meaningless. To create a more convincing and effective model, we used the Rasch model by using maximum likelihood and a penalized variant for maximum likelihood mentioned above. Since we used two data sets, we produced four models as a result.

Clearly, we stated that the re-selected data set is better than Finn and Servos's data set because it showed lower AIC and Deviance. The reason for this result is 1) Q38c and Q38d both ask about how much schools consider the material objects owned by students. Because there were only 16 schools that answered the question 'yes, it makes sense to remove Q38c from the data set. 2) Q38f and Q38g both ask about how much schools consider drugs. So, it makes sense to remove Q38f from the data set. 3) The question added in the re-selected data set, Q38j) Enforce a strict dress code, working positively at determining the score.

Among the four models, we selected model_2 because it showed the lowest AIC. Interestingly, the rank of the model_2 showed four groups compare to the model_0, the original model performed by Finn and Servos. Moreover, the model_0 data passed through the centers of the two groups that contained most of the model_2 data. One might say that this is a significant positive relationship, but we should remind that the 5 questions out of 6 or 7 were overlapped for the two data sets. Furthermore, model_0 and model_2 used the same analyzing method, the maximum likelihood method. From these points of view, we might interpret that the correction value of 0.3130, which we obtained, is rather low.

We also replaced the missing values. The two models, separated by reference to the BYURBAN variable or not, were highly related with a correlation of 0.9349. We cannot decide which model is more 'right' from the data because it is just our choice how to rank the schools, but this high correlation value was predicted that the two models would not be much different because there are only 24 of the 656 schools including missing values in the re-selected data set. We can also distinguish the rank of the second model into three groups, ordered by the rank of the first model.

For the further questions, we can analyze how important each question played in determining the score in each model. This will allow us to quantitatively analyze how the questions we removed and added from Finn and Servos's data played a major role in lowering AIC and lowering Deviance. In advance, we can expect that the added or removed questions had a significant effect, in good ways or bad ways, because we got a correction value that is lower than we expected from the number of overlapping questions.

We might also think about the reason why the rank data from model_2 was divided into four groups. Although the major of the data follows the positive relationship, some data groups showed low ranks in model_0 and high ranks in model_2, and low ranks in model_2, and high ranks in model_0. It would be good to analyze what differences these schools have and whether there are differences in overall other questions.

References

[1] Finn, Jeremy D. and Servoss, Timothy J. (2014) "Misbehavior, Suspensions, and Security Measures in High School: Racial/Ethnic and Gender Differences," Journal of Applied Research on Children: Informing Policy for Children at Risk: Vol. 5 : Iss. 2 , Article 11.

U3Paper_Option_B

youngwoo Kwon

2021 4 21

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(tidyr)
library(arm)
```

```
## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loading required package: lme4

##
## arm (Version 1.11-2, built: 2020-7-27)

## Working directory is C:/Users/FOS_15/Desktop/WS21/Stats 485/Paper3
```

```r
library(ggplot2)
library(matrixStats)
```

```
##
## Attaching package: 'matrixStats'

## The following object is masked from 'package:dplyr':
##
##     count
```

Summary : We analysed the $F. - S.$ model. We first reproduced their results with logistic regression using glm() and bayesglm(). Then, we used different variables to find a better model compare to the $F. - S.$'s model. As a result, we got a better model which showed lower AIC and lower deviance than the original model. We plotted the order of original model and preffered model and get the correlation value. Although two models have overlapping variables, the result states that the order of the models might be distinct from each other. We tried to replace the missing values. The first model replaced the missing value using mean value for the variable form whole data set, and the second model replaced the missing value using mean value for the variabl from the data set that has equal 'BYURBAN' value with the school contained missing value. Results are represented as visual graphs.

A : reconstruct measurement models similar to the one used by Finn and Servoss

```r
rawdata <- read.csv("http://dept.stat.lsa.umich.edu/~bbh/s485/data/security_wide.csv")
rawdata %>% complete.cases() %>% table()
```

```
## .
## FALSE  TRUE
##    44   612
```

We have to compare the result of the models later. To facilitate comparison (to avoid the absence of index on one side) I will remove missing values in advance.

```r
rawdata = rawdata %>% na.omit()
security <- rawdata[c(1,4,5,9,8,15,18,7)]
head(security)
```

```
##   school q38c q38d q38h q38g q38n q39a q38f
## 1 id1011    0    0    1    0    0    1    0
## 2 id1021    1    1    0    1    1    1    0
## 3 id1022    0    0    0    0    0    0    0
## 4 id1031    0    0    1    1    1    1    0
## 5 id1033    0    0    0    0    1    1    0
## 6 id1041    0    0    0    1    1    1    0
```

We don't have to worry about the missing datas now.

```r
sum_index <- security %>%
  dplyr::select(-school) %>% rowSums()
table(sum_index)
```

```
## sum_index
##   0   1   2   3   4   5   6
##  81 146 184 119  64  16   2
```

```r
col_index <- security %>%
  dplyr::select(-school) %>% colSums()
col_index
```

```
## q38c q38d q38h q38g q38n q39a q38f
##   16   65   95  141  289  344  269
```

```r
q_38c_data <- security %>% filter(q38c == 1)
sum(q_38c_data$q38d)/sum(q_38c_data$q38c)
```

```
## [1] 0.6875
```

```r
q_38f_data <- security %>% filter(q38f == 1)
sum(q_38f_data$q38g)/sum(q_38f_data$q38f)
```

```
## [1] 0.3457249
```

```r
security0 <- security %>% gather("item", "response", -school)
head(security0)
```

```
##   school item response
## 1 id1011 q38c        0
## 2 id1021 q38c        1
## 3 id1022 q38c        0
## 4 id1031 q38c        0
## 5 id1033 q38c        0
## 6 id1041 q38c        0
```

```r
rasch0 <- glm(response ~ item + school -1, family = "binomial", data = security0)
head(coef(rasch0), 10)
```

```
##     itemq38c     itemq38d     itemq38f     itemq38g     itemq38h     itemq38n
##  -4.24872351  -2.58132594  -0.14751400  -1.44274198  -2.05607672   0.03936898
##     itemq39a schoolid1021 schoolid1022 schoolid1031
##   0.56660141   2.73227774 -17.76083191   1.76881758
```

```r
rasch1 <- bayesglm(response ~ item + school - 1, data = security0)
```

```
## Warning in model.matrixBayes(object = mt, data = data, contrasts.arg =
## contrasts, : variable 'item' converted to a factor
```

```
head(coef(rasch1), 10)
```

```
##     itemq38c     itemq38d     itemq38f     itemq38g     itemq38h     itemq38n
##   0.02335348   0.10341088   0.43671255   0.22758172   0.15242565   0.46938940
##     itemq39a schoolid1021 schoolid1022 schoolid1031
##   0.55925101   0.42896082  -0.27934468   0.28724367
```

B : consider whether simple variations of the model specification might improve it

In a new data, I added the question Q38j 'Enforce a strict dress code'. Question 38c and 38d seem similar. So I removed the Q38d from the data. Q38f 'Use one or more random dog sniffs to check for drugs' did not make sense for me. So I removed Q38f.

```
security_new <- rawdata[c(1,4,9,8,15,18,11)]
head(security_new)
```

```
##   school q38c q38h q38g q38n q39a q38j
## 1 id1011    0    1    0    0    1    0
## 2 id1021    1    0    1    1    1    1
## 3 id1022    0    0    0    0    0    0
## 4 id1031    0    1    1    1    1    1
## 5 id1033    0    0    0    1    1    0
## 6 id1041    0    0    1    1    1    1
```

```
security_new0 <- security_new %>% gather("item", "response", -school)
head(security_new0)
```

```
##   school item response
## 1 id1011 q38c        0
## 2 id1021 q38c        1
## 3 id1022 q38c        0
## 4 id1031 q38c        0
## 5 id1033 q38c        0
## 6 id1041 q38c        0
```

```
rasch2 <- glm(response ~ item + school -1, family = "binomial", data = security_new0)
head(coef(rasch2), 10)
```

```
##      itemq38c      itemq38g      itemq38h      itemq38j      itemq38n
## -4.334269e+00 -1.522525e+00 -2.127519e+00  5.124067e-01 -9.160632e-02
##      itemq39a  schoolid1021  schoolid1022  schoolid1031  schoolid1033
##  4.014357e-01  3.669851e+00 -1.796160e+01  3.669851e+00  2.760727e-13
```

```
rasch3 <- bayesglm(response ~ item + school - 1, data = security_new0)
```

```
## Warning in model.matrixBayes(object = mt, data = data, contrasts.arg =
## contrasts, : variable 'item' converted to a factor
```

```r
head(coef(rasch3), 10)
```

```
##     itemq38c     itemq38g     itemq38h     itemq38j     itemq38n     itemq39a
##  0.022594494  0.226822488  0.151666517  0.578097352  0.468629760  0.558491173
## schoolid1021 schoolid1022 schoolid1031 schoolid1033
##  0.494106489 -0.331062465  0.494106489 -0.001039664
```

C : compare the alternative Rasch models you will have fit, arriving at a recommended model

```r
rasch0$aic
```

```
## [1] 4471.554
```

```r
rasch1$aic
```

```
## [1] 4846.643
```

```r
rasch2$aic
```

```
## [1] 4245.735
```

```r
rasch3$aic
```

```
## [1] 4628.027
```

The model Rasch2 shows the lowest AIC. Rasch0 shows the second lowest AIC.

```r
rasch0$deviance
```

```
## [1] 3235.554
```

```r
rasch1$deviance
```

```
## [1] 570.5367
```

```r
rasch2$deviance
```

```
## [1] 3011.735
```

```r
rasch3$deviance
```

```
## [1] 528.6911
```

Rasch4 has the lowest deviance. Rasch2 has the second lowest deviance. Comparing the results, it seems the second data set performs the better result. between glm() model and bayesglm() model, I choose the glm() model, the one with lower AIC, since I prefer AIC than deviance when selecting the model.

D : compare Finn and Servoss. The school security measurement to your preferred alternative.

```
rasch2_index <- as.vector(c(schoolid1011=0, coef(rasch2)[-(1:6)]))

rasch2_matrix <- matrix(c(as.vector(security$school), rasch2_index), ncol = 2)
head(rasch2_matrix)
```

```
##      [,1]     [,2]
## [1,] "id1011" "0"
## [2,] "id1021" "3.66985115967302"
## [3,] "id1022" "-17.9616040402437"
## [4,] "id1031" "3.66985115967313"
## [5,] "id1033" "2.76072654316916e-13"
## [6,] "id1041" "2.14003632437597"
```

```
rasch2_ordered0 <- rasch2_matrix[order(rasch2_matrix[,2]),]
head(rasch2_ordered0)
```

```
##      [,1]     [,2]
## [1,] "id1781" "-1.14468502860331"
## [2,] "id1661" "-1.14468502860333"
## [3,] "id2081" "-1.14468502860333"
## [4,] "id1702" "-1.14468502860334"
## [5,] "id1732" "-1.14468502860334"
## [6,] "id1791" "-1.14468502860334"
```

This is the order of the school using rasch2, glm() model with security new data.

```
rasch2_ordered1 = cbind(rasch2_ordered0, c(1:612))
rasch2_ordered2 = rasch2_ordered1[order(rasch2_ordered1[,1]),]
head(rasch2_ordered2)
```

```
##      [,1]     [,2]                   [,3]
## [1,] "id1011" "0"                    "205"
## [2,] "id1021" "3.66985115967302"     "609"
## [3,] "id1022" "-17.9616040402437"    "202"
## [4,] "id1031" "3.66985115967313"     "612"
## [5,] "id1033" "2.76072654316916e-13" "573"
## [6,] "id1041" "2.14003632437597"     "402"
```

The first column of this matrix is school names. The second column is their glm() coefficients. The third column is their order.

Let's repeat this procedure for the $F. - S.$ model, rasch0.

```
rasch0_index <- as.vector(c(schoolid1011=0, coef(rasch0)[-(1:7)]))
rasch0_matrix <- matrix(c(as.vector(security$school), rasch0_index), ncol = 2)
rasch0_ordered0 <- rasch0_matrix[order(rasch0_matrix[,2]),]
rasch0_ordered1 = cbind(rasch0_ordered0, c(1:612))
rasch0_ordered2 = rasch0_ordered1[order(rasch0_ordered1[,1]),]
head(rasch0_ordered2)
```

```
##       [,1]     [,2]                   [,3] 
## [1,] "id1011" "0"                    "228"
## [2,] "id1021" "2.73227773914541"     "412"
## [3,] "id1022" "-17.7608319146448"    "153"
## [4,] "id1031" "1.76881757903712"     "363"
## [5,] "id1033" "3.68920363618418e-13" "435"
## [6,] "id1041" "0.892167222603639"    "237"
```

Let's combine the order.

```
rasch_comp <- cbind(Rasch0 = as.numeric(rasch0_ordered2[,3]), Rasch2 = as.numeric(rasch2_ordered2[,3]))
rasch_comp1 <- as.data.frame(rasch_comp[order(rasch_comp[,1]),])
head(rasch_comp)
```

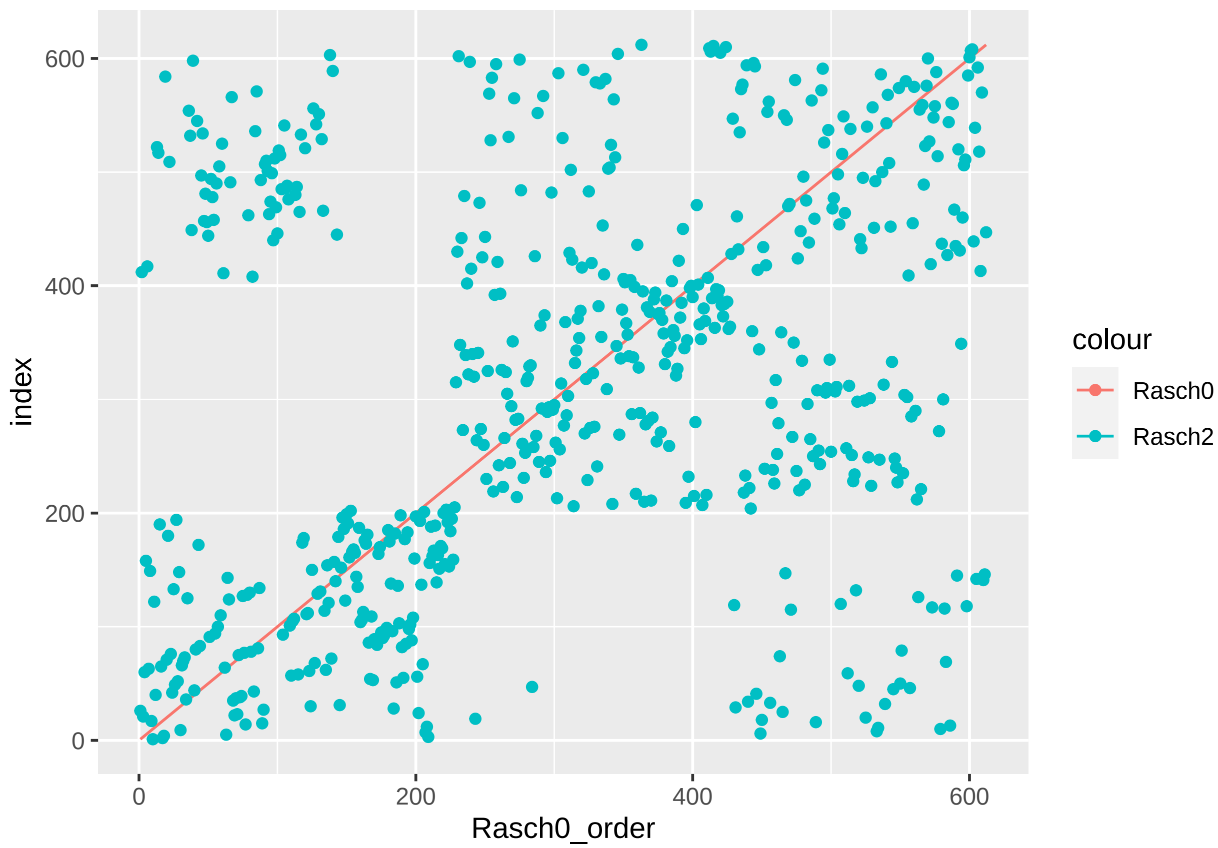
```
##      Rasch0 Rasch2
## [1,]    228    205
## [2,]    412    609
## [3,]    153    202
## [4,]    363    612
## [5,]    435    573
## [6,]    237    402
```

```
head(rasch_comp1)
```

```
##   Rasch0 Rasch2
## 1      1     26
## 2      2    412
## 3      3     21
## 4      4     60
## 5      5    158
## 6      6    417
```

The first row is index from the $F. - S.$ model and the second row is index from the fixed (preffered) model.

```
  ggplot(rasch_comp1, aes(x = Rasch0)) +
  geom_line(aes(y = Rasch0, colour = "Rasch0")) +
  geom_point(aes(y = Rasch2, colour = "Rasch2")) +
  labs(y = "index", x = "Rasch0_order")
```




```
cor(x = rasch_comp1$Rasch0, y = rasch_comp1$Rasch2)
```

```
## [1] 0.3130139
```

E : For the Version 2 of the paper

```
rawdata0 <- as.data.frame(read.csv("http://dept.stat.lsa.umich.edu/~bbh/s485/data/security_wide.csv"))
rawdata1 <- as.data.frame(read.csv("http://dept.stat.lsa.umich.edu/~bbh/s485/data/security_school_vars.c
```

```
rawdata0_new = rawdata0 %>% dplyr::left_join(rawdata1)
```

```
## Joining, by = "school"
```

```
head(rawdata0_new)
```

```
##   school q38a q38b q38c q38d q38e q38f q38g q38h q38i q38j q38k q38l q38m q38n
## 1 id1011    1    1    0    0    0    0    0    1    0    0    0    0    0    0
## 2 id1021    1    1    1    1    1    0    1    0    1    1    0    1    1    1
## 3 id1022    1    0    0    0    0    0    0    0    0    0    0    0    1    0
## 4 id1031    1    1    0    0    1    0    1    1    0    1    0    1    1    1
## 5 id1033    1    1    0    0    1    0    0    0    0    0    0    0    0    1
```

```
## 6 id1041    1    0    0    0    0    0    1    0    0    1    0    0    1    1
##   q38o q38p q39a q39b q39c q40a q40b q40c q40d q40e BYG10EP BYURBAN BYREGION
## 1    1    1    1    0    0    1    1    0    0    0       6       1        1
## 2    1    0    1    1    1    1    1    1    0    1       3       1        1
## 3    1    0    0    0    0    0    0    1    0    0       4       1        1
## 4    1    1    1    1    1    1    1    1    1    1       5       1        1
## 5    1    0    1    0    0    1    1    1    1    0       6       1        1
## 6    1    0    1    1    0    1    1    1    0    0       5       2        1
##   BYSPANP BY10FLP BYFTTP
## 1       3       5      6
## 2       3       7      6
## 3       3       3      6
## 4       3      -9      6
## 5       3       4      6
## 6       3       2      6
```

We can use new variables to estimate the missing values. We will now generate two models. The first model is similar to our preferred model. It uses the glm() for our new data set, but it replaces the missing varaibles to the mean value. (For example, if itemq38c is missed for some response, instead of just remove the data like rasch2 model, its itemq38c value would be total mean value of itemq38c).

```
rawdata0_new_df = as.data.frame(rawdata0_new[c(1,4,9,8,15,18,11)])
newdata_mean_1 <-  cbind(rawdata0_new[,1], as_tibble(sapply(rawdata0_new_df[,-1], function(x) ifelse(is

names(newdata_mean_1)[1] <- "school"
head(newdata_mean_1)
```

```
##   school q38c q38h q38g q38n q39a q38j
## 1 id1011    0    1    0    0    1    0
## 2 id1021    1    0    1    1    1    1
## 3 id1022    0    0    0    0    0    0
## 4 id1031    0    1    1    1    1    1
## 5 id1033    0    0    0    1    1    0
## 6 id1041    0    0    1    1    1    1
```

```
newdata_mean_2 <- newdata_mean_1 %>% gather("item", "response", -school)
head(newdata_mean_2)
```

```
##   school item response
## 1 id1011 q38c        0
## 2 id1021 q38c        1
## 3 id1022 q38c        0
## 4 id1031 q38c        0
## 5 id1033 q38c        0
## 6 id1041 q38c        0
```

```
nrow(rawdata0_new_df %>% na.omit())
```

```
## [1] 632
```

```r
nrow(newdata_mean_1 %>% na.omit())
```

```
## [1] 656
```

So there are 24 values that have been replaced into the mean value.

```r
select_na  <-  cbind(rawdata0_new[,1], as_tibble(sapply(rawdata0_new_df[,-1], function(x) ifelse(is.na(
names(select_na)[1] <- "school"
select_na  %>% gather("item", "response", -school) %>% filter(response == -20)
```

```
##    school item response
## 1  id3572 q38c      -20
## 2  id2241 q38h      -20
## 3  id3361 q38h      -20
## 4  id3572 q38h      -20
## 5  id3592 q38h      -20
## 6  id4251 q38h      -20
## 7  id1071 q38g      -20
## 8  id1452 q38g      -20
## 9  id1502 q38g      -20
## 10 id2342 q38g      -20
## 11 id2572 q38g      -20
## 12 id3361 q38g      -20
## 13 id3572 q38g      -20
## 14 id3592 q38g      -20
## 15 id1502 q38n      -20
## 16 id2372 q38n      -20
## 17 id2441 q38n      -20
## 18 id3181 q38n      -20
## 19 id3842 q38n      -20
## 20 id1182 q39a      -20
## 21 id1882 q39a      -20
## 22 id2991 q39a      -20
## 23 id3082 q39a      -20
## 24 id3151 q39a      -20
## 25 id1071 q38j      -20
## 26 id1621 q38j      -20
## 27 id2372 q38j      -20
## 28 id3243 q38j      -20
## 29 id3461 q38j      -20
## 30 id3521 q38j      -20
## 31 id3572 q38j      -20
## 32 id4261 q38j      -20
```

Those are the schools and items that had missing responses. There are 32 rows, because, some schools like id3572 had more than 2 items that are missing.

Now let's make an data set that replaces the the responses based on the additional independent variables. We will use urban as a new independent variable that to weaken the MAR assumption

```r
nrow(rawdata0_new %>% filter(BYURBAN == 1))
```

```
## [1] 207
```

```r
nrow(rawdata0_new %>% filter(BYURBAN == 2))
```

```
## [1] 322
```

```r
nrow(rawdata0_new %>% filter(BYURBAN == 3))
```

```
## [1] 127
```

```r
nrow(rawdata0_new %>% filter(BYURBAN != 1 & BYURBAN != 2 & BYURBAN != 3))
```

```
## [1] 0
```

So we can check that all the BYURBAN value in the dataset are 1,2 or 3.

We will seperate the data into three parts. One per BYURBAN value.

```r
data_urban1 = (rawdata0_new %>% filter(BYURBAN == 1))
data_urban2 = (rawdata0_new %>% filter(BYURBAN == 2))
data_urban3 = (rawdata0_new %>% filter(BYURBAN == 3))
```

And replace NA into mean values.

```r
data_urban1_df = as.data.frame(data_urban1)
data_urban1_mean <-  cbind(data_urban1[,1], as_tibble(sapply(data_urban1_df[,-1], function(x) ifelse(is
names(data_urban1_mean)[1] <- "school"
```

```r
data_urban2_df = as.data.frame(data_urban2)
data_urban2_mean <-  cbind(data_urban2[,1], as_tibble(sapply(data_urban2_df[,-1], function(x) ifelse(is
names(data_urban2_mean)[1] <- "school"
```

```r
data_urban3_df = as.data.frame(data_urban3)
data_urban3_mean <-  cbind(data_urban3[,1], as_tibble(sapply(data_urban3_df[,-1], function(x) ifelse(is
names(data_urban3_mean)[1] <- "school"
```

Combine them together

```r
newdata_mean_3 = rbind(data_urban1_mean[c(1,4,9,8,15,18,11)], data_urban2_mean[c(1,4,9,8,15,18,11)], da

newdata_mean_4 <- newdata_mean_3 %>% gather("item", "response", -school)
head(newdata_mean_4)
```

```
##   school item response
## 1 id1011 q38c        0
## 2 id1021 q38c        1
## 3 id1022 q38c        0
## 4 id1031 q38c        0
## 5 id1033 q38c        0
## 6 id1301 q38c        0
```

So now we have two data sets, newdatamean2 and newdatamean4.

Based on these data, we will generate models.

```r
rasch2_1 <- glm(response ~ item + school -1, family = "binomial", data = newdata_mean_2)
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```r
head(coef(rasch2_1), 10)
```

```
##      itemq38c      itemq38g      itemq38h      itemq38j      itemq38n
## -4.263466e+00 -1.480592e+00 -2.110410e+00  4.618481e-01 -6.524349e-02
##      itemq39a  schoolid1021  schoolid1022  schoolid1031  schoolid1033
##  3.869463e-01  3.627786e+00 -1.795240e+01  3.627786e+00  4.038911e-13
```

```r
rasch2_2 <- glm(response ~ item + school -1, family = "binomial", data = newdata_mean_4)
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```r
head(coef(rasch2_2), 10)
```

```
##      itemq38c      itemq38g      itemq38h      itemq38j      itemq38n
## -4.260922e+00 -1.480843e+00 -2.110476e+00  4.620121e-01 -6.545223e-02
##      itemq39a  schoolid1021  schoolid1022  schoolid1031  schoolid1033
##  3.870403e-01  3.626760e+00 -1.795244e+01  3.626760e+00  2.937097e-13
```

```r
rasch2_1$aic
```

```
## [1] 4579.353
```

```r
rasch2_2$aic
```

```
## [1] 4579.4
```

```r
rasch2_1$deviance
```

```
## [1] 3228.912
```

```r
rasch2_2$deviance
```

```
## [1] 3228.977
```

The only difference between two models is how we replaced the NA values. That is, most of the data are not affected. So the AIC and deviance between models are almost equal.

```r
rasch2_1_index <- as.vector(c(schoolid1011=0, coef(rasch2_1)[-(1:6)]))
rasch2_1_matrix <- matrix(c(as.vector(rawdata0_new$school), rasch2_1_index), ncol = 2)
rasch2_1_ordered0 <- rasch2_1_matrix[order(rasch2_1_matrix[,2]),]
rasch2_1_ordered1 = cbind(rasch2_1_ordered0, c(1:656))
rasch2_1_ordered2 = rasch2_1_ordered1[order(rasch2_1_ordered1[,1]),]
```

```r
rasch2_2_index <- as.vector(c(schoolid1011=0, coef(rasch2_2)[-(1:6)]))
rasch2_2_matrix <- matrix(c(as.vector(rawdata0_new$school), rasch2_2_index), ncol = 2)
rasch2_2_ordered0 <- rasch2_2_matrix[order(rasch2_2_matrix[,2]),]
rasch2_2_ordered1 = cbind(rasch2_2_ordered0, c(1:656))
rasch2_2_ordered2 = rasch2_2_ordered1[order(rasch2_2_ordered1[,1]),]
```

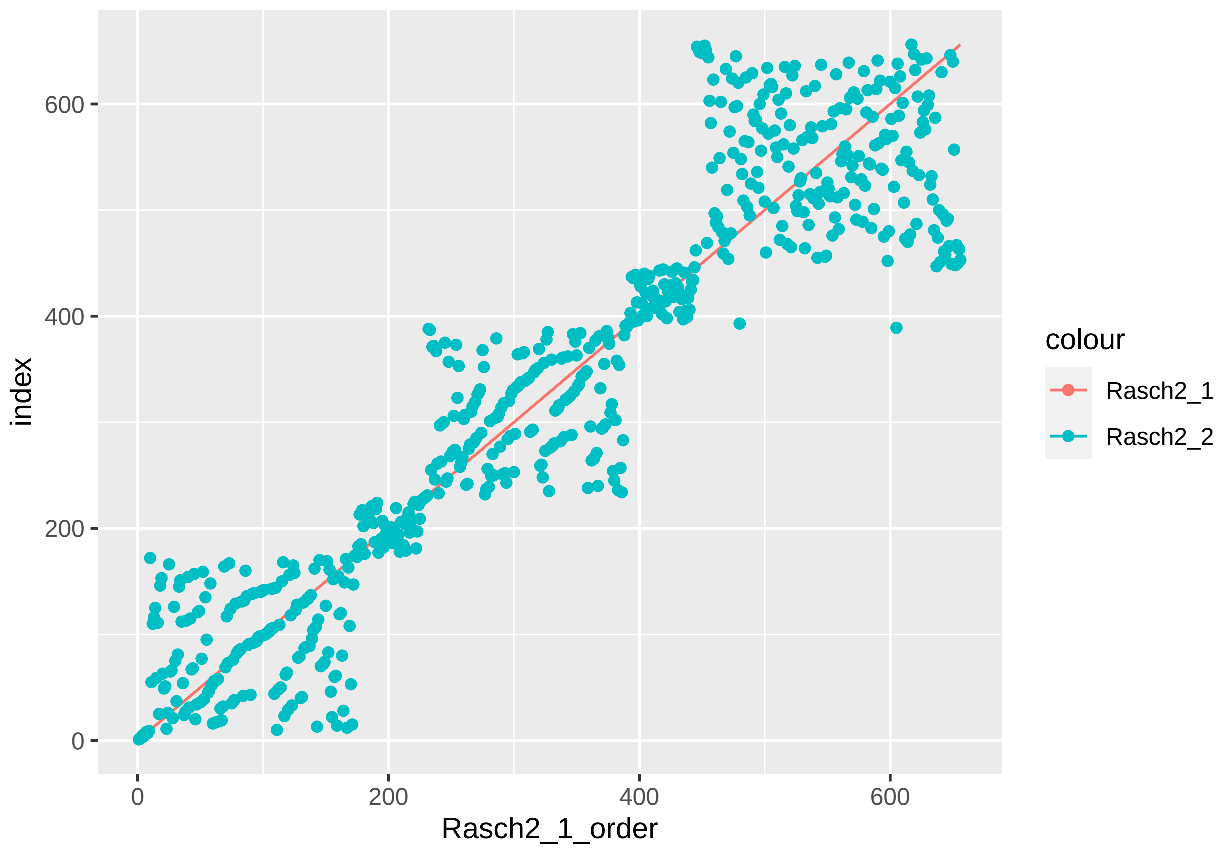
```r
rasch_comp2 <- cbind(Rasch2_1 = as.numeric(rasch2_1_ordered2[,3]), Rasch2_2 = as.numeric(rasch2_2_order
rasch_comp3 <- as.data.frame(rasch_comp2[order(rasch_comp2[,1]),])
head(rasch_comp2)
```

```
##      Rasch2_1 Rasch2_2
## [1,]      226      226
## [2,]      451      650
## [3,]      221      225
## [4,]      448      649
## [5,]      469      633
## [6,]      394      437
```

```r
head(rasch_comp3)
```

```
##   Rasch2_1 Rasch2_2
## 1        1        1
## 2        2        2
## 3        3        3
## 4        4        5
## 5        5        4
## 6        6        6
```

```r
ggplot(rasch_comp3, aes(x = Rasch2_1)) +
  geom_line(aes(y = Rasch2_1, colour = "Rasch2_1")) +
  geom_point(aes(y = Rasch2_2, colour = "Rasch2_2")) +
  labs(y = "index", x = "Rasch2_1_order")
```




```r
cor(x = rasch_comp3$Rasch2_1, y = rasch_comp3$Rasch2_2)
```

```
## [1] 0.9339474
```

```r
head(rawdata0_new %>% filter(school == "id2241"))
```

```
##   school q38a q38b q38c q38d q38e q38f q38g q38h q38i q38j q38k q38l q38m q38n
## 1 id2241    0    1    0    1    1    1    1   NA   NA    1    1    1    1    1
##   q38o q38p q39a q39b q39c q40a q40b q40c q40d q40e BYG10EP BYURBAN BYREGION
## 1    0    1    1    0    0    1    1    1    0    0       5       2        3
##   BYSPANP BY10FLP BYFTTP
## 1       3       3      6
```

```r
rasch2_1_ordered2 %>% as_tibble() %>% filter(rasch2_1_ordered2[,1] == "id2241")
```

```
## Warning: The `x` argument of `as_tibble.matrix()` must have unique column names if `.name_repair` is
## Using compatibility `.name_repair`.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_warnings()` to see where this warning was generated.
```

```
## # A tibble: 1 x 3
##   V1     V2               V3
##   <chr>  <chr>            <chr>
## 1 id2241 2.31568060796691 444
```

```r
rasch2_2_ordered2 %>% as_tibble() %>% filter(rasch2_1_ordered2[,1] == "id2241")
```

```
## # A tibble: 1 x 3
##   V1     V2               V3
##   <chr>  <chr>            <chr>
## 1 id2241 2.3073346343572 446
```

```r
rasch2_1_ordered2 %>% as_tibble() %>% filter(rasch2_1_ordered2[,1] == "id2342")
```

```
## # A tibble: 1 x 3
##   V1     V2                V3
##   <chr>  <chr>             <chr>
## 1 id2342 1.24940077595383 389
```

```r
rasch2_2_ordered2 %>% as_tibble() %>% filter(rasch2_1_ordered2[,1] == "id2342")
```

```
## # A tibble: 1 x 3
##   V1     V2                V3
##   <chr>  <chr>             <chr>
## 1 id2342 1.25347784380892 391
```