R Notebook: SOC 5800 Team Project

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## Introduction

This is an R Notebook for a study that examines how formerly incarcerated individuals who successfully reintegrated cope with barriers to re-entry. This study was conducted as a team project for the SOC 5800 Survey Design and Sampling course during the Fall 2019 semester at Saint Louis University.

## Project Set Up

The following code chunk enables the R Notebook to integrate seamlessly with the project organization format. This is normally included in the R Notebook to simplify file calls and enable file portability but it has been causing an error. To work around this problem, I’ve embedded the here() function where I enter a file path when necessary.

knitr::opts\_knit$set(root.dir = here::here())

## Load Dependencies

The following code chunk loads package dependencies required to perform the necessary tasks. Basic tasks include importing, reading, wrangling, and cleaning data; selecting a subset of the data; checking for unique observations; analyzing missing data; and performing various types of regression analyses.

library(tidyverse) # loads the basic R packages  
library(here) # enables file portability  
library(readr) # functions for reading data  
library(dplyr) # functions for data wrangling  
library(janitor) # functions for data cleaning  
library(naniar) # functions for analyzing missing data  
library(expss) # functions for calculating on values  
library(ggplot2) # functions for data visualizations  
library(boot) # functions for regression analysis  
library(ordinal) # functions for regression models for ordinal data  
library(MASS) # functions for ordered logistic or probit regression  
library(broom) # functions for tidying ordinal logistic regression models  
library(gvlma) # functions for global validation of linear model assumptions  
library(lmtest) # functions for testing linear regression models  
library(ltm) # functions for latent trait models under Item Response Theory  
library(leaps) # functions for regression subset selection  
library(car) # companion to applied regression  
library(aod) # functions to analyze overdispersed data counts and proportions  
library(pscl) # contains function for pseudo R2 measures for logistic regression  
library(ResourceSelection) # contains function for Hosmer-Lemeshow goodness of fit test  
library(psy) # functions for various procedures used in psychometry  
library(psych) #Procedures for Psychological, Psychometric, and Personality Research

## Load Raw Data

The following code chunk imports the raw data from the csv file.

dataRaw <- read.csv(here("Data","DataRaw","SOC5800\_Data\_NumericValues\_Raw\_CSV.csv"),   
 sep = ",", header = TRUE, fill = TRUE, dec = ".")

## Rename Variables

The following code chunk performs several actions to clean the raw data. It first renames the variables with descriptive camel case names. It then removes unused variables.

dataRaw %>%  
 rename(startDate = StartDate,  
 endDate = EndDate,  
 status = Status,  
 IPaddress = IPAddress,  
 progress = Progress,  
 sessionDuration = Duration..in.seconds.,  
 surveyCompleted = Finished,  
 surveyDate = RecordedDate,  
 responseID = ResponseId,  
 locationLat = LocationLatitude,  
 locationLong = LocationLongitude,  
 consent = Q43,  
 browserName = Q10\_Browser,  
 browserVersion = Q10\_Version,  
 opSyst = Q10\_Operating.System,  
 screenRes = Q10\_Resolution,  
 currentlyIncarcerated = Q1,  
 currentlyDetained = Q2,  
 residentialTreatment = Q3,  
 involCommitment = Q4,  
 gender = Q5,  
 genderSelfDescribe = Q5\_3\_TEXT,  
 transgender = Q7,  
 ethnicityRace = Q6,  
 primaryEthnicityRace = Q6\_10\_TEXT,  
 typeHometown = Q8,  
 religiousAffiliation = Q9,  
 ReligiousOther = Q9\_12\_TEXT,  
 ageNow = Q11,  
 ageRelease = Q13,  
 incarcerationYears = Q14.1\_1,  
 incarcerationMonths = Q14.2\_1,  
 educationLevels = Q15,  
 whenHighestEd = Q16,  
 relationshipStatus = Q17,  
 householdSize = Q18,  
 financialSupportInitial = Q19,  
 financialSupportGovt = Q19\_4\_TEXT,  
 financialSupportNonGovt = Q19\_5\_TEXT,  
 finanicalSupportOther = Q19\_6\_TEXT,  
 selfEmployment = Q20,  
 incomeInitial = Q21,  
 incomeLastYr = Q22,  
 financialStatus = Q23,  
 savings = Q24,  
 pssQ1 = Q41\_1,  
 pssQ2 = Q41\_2,  
 pssQ3 = Q41\_3,  
 pssQ4 = Q41\_4,  
 pssQ5 = Q41\_5,  
 pssQ6 = Q41\_6,  
 pssQ7 = Q41\_7,  
 pssQ8 = Q41\_8,  
 pssQ9 = Q41\_9,  
 pssQ10 = Q41\_10,  
 pssQ11 = Q41\_11,  
 pssQ12 = Q41\_12,  
 supportResidence = Q30\_1,  
 supportJob = Q30\_2,  
 supportAddiction = Q30\_3,  
 supportTransportation = Q30\_4,  
 supportFinancial = Q30\_5,  
 friendResidence = Q31\_1,  
 friendJob = Q31\_2,  
 friendAddiction = Q31\_3,  
 friendTransportation = Q31\_4,  
 friendFinancial = Q31\_5,  
 programsUsed = Q32,  
 importancePublicTrans = Q33\_1,  
 importanceHousing = Q33\_2,  
 importanceSNAP = Q33\_3,  
 importanceWIC = Q33\_4,  
 importanceTANF = Q33\_5,  
 importanceEITC = Q33\_6,  
 importanceJobTraining = Q33\_7,  
 importanceMedicare = Q33\_8,  
 importanceEducAid = Q33\_9,  
 aceQ1 = Q34\_1,  
 aceQ2 = Q34\_2,  
 aceQ3 = Q34\_3,  
 aceQ4 = Q34\_4,  
 aceQ5 = Q34\_5,  
 aceQ6 = Q34\_6,  
 aceQ7 = Q34\_7,  
 aceQ8 = Q34\_8,  
 aceQ9 = Q34\_9,  
 aceQ10 = Q34\_10,  
 helpDuring = Q35,  
 helpDuringType = Q33,  
 helpDuringOther = Q33\_8\_TEXT,  
 helpAfter = Q36,  
 helpAfterType = Q44,  
 helpAfterOther = Q44\_8\_TEXT,  
 gritQ1 = Q35\_1,  
 gritQ2 = Q35\_2,  
 gritQ3 = Q35\_3,  
 gritQ4 = Q35\_4,  
 gritQ5 = Q35\_5,  
 gritQ6 = Q35\_6,  
 gritQ7 = Q35\_7,  
 gritQ8 = Q35\_8,  
 stayInitial = Q36.1,  
 stayInitialOther = Q36\_6\_TEXT,  
 foodSecurityQ1 = Q37\_1,  
 foodSecurityQ2 = Q37\_2,  
 mostHelpful = Q38,  
 greatestObstacle = Q39,  
 helpKind = Q40,  
 justiceInteraction = Q41  
 ) -> dataRenamed  
  
dataRenamed %>%  
 dplyr::select (-c(status, progress, RecipientLastName, RecipientFirstName, RecipientEmail, ExternalReference)) -> dataAugmented

## Change Data Type

The following code chunk changes the data type for certain variables.

dataAugmented$pssQ1 <- as.numeric(dataAugmented$pssQ1)  
dataAugmented$pssQ2 <- as.numeric(dataAugmented$pssQ2)  
dataAugmented$pssQ3 <- as.numeric(dataAugmented$pssQ3)  
dataAugmented$pssQ4 <- as.numeric(dataAugmented$pssQ4)  
dataAugmented$pssQ5 <- as.numeric(dataAugmented$pssQ5)  
dataAugmented$pssQ6 <- as.numeric(dataAugmented$pssQ6)  
dataAugmented$pssQ7 <- as.numeric(dataAugmented$pssQ7)  
dataAugmented$pssQ8 <- as.numeric(dataAugmented$pssQ8)  
dataAugmented$pssQ9 <- as.numeric(dataAugmented$pssQ9)  
dataAugmented$pssQ10 <- as.numeric(dataAugmented$pssQ10)  
dataAugmented$pssQ11 <- as.numeric(dataAugmented$pssQ11)  
dataAugmented$pssQ12 <- as.numeric(dataAugmented$pssQ12)  
dataAugmented$aceQ1 <- as.numeric(dataAugmented$aceQ1)  
dataAugmented$aceQ2 <- as.numeric(dataAugmented$aceQ2)  
dataAugmented$aceQ3 <- as.numeric(dataAugmented$aceQ3)  
dataAugmented$aceQ4 <- as.numeric(dataAugmented$aceQ4)  
dataAugmented$aceQ5 <- as.numeric(dataAugmented$aceQ5)  
dataAugmented$aceQ6 <- as.numeric(dataAugmented$aceQ6)  
dataAugmented$aceQ7 <- as.numeric(dataAugmented$aceQ7)  
dataAugmented$aceQ8 <- as.numeric(dataAugmented$aceQ8)  
dataAugmented$aceQ9 <- as.numeric(dataAugmented$aceQ9)  
dataAugmented$aceQ10 <- as.numeric(dataAugmented$aceQ10)  
dataAugmented$gritQ1 <- as.numeric(dataAugmented$gritQ1)  
dataAugmented$gritQ2 <- as.numeric(dataAugmented$gritQ2)  
dataAugmented$gritQ3 <- as.numeric(dataAugmented$gritQ3)  
dataAugmented$gritQ4 <- as.numeric(dataAugmented$gritQ4)  
dataAugmented$gritQ5 <- as.numeric(dataAugmented$gritQ5)  
dataAugmented$gritQ6 <- as.numeric(dataAugmented$gritQ6)  
dataAugmented$gritQ7 <- as.numeric(dataAugmented$gritQ7)  
dataAugmented$gritQ8 <- as.numeric(dataAugmented$gritQ8)

## Adjust Value Assignments

The following code chunk adjusts the values assigned to fixed pre-determined response choices for select variables and recodes blanks with NA in the dataset.

dataAugmented$ageNow <- (as.numeric(dataAugmented$ageNow)+11)  
dataAugmented$ageRelease <- (as.numeric(dataAugmented$ageRelease)+11)  
dataAugmented[dataAugmented==""] <- NA

## Create Variables

The following code chunk creates additional variables needed for the study.

dataAugmented %>%  
 mutate (mspssScore = (pssQ1+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2+pssQ2)/12) %>%  
 mutate (aceScore = aceQ1+aceQ1+aceQ2+aceQ3+aceQ4+aceQ5+aceQ6+aceQ7+aceQ8+aceQ9+aceQ10) %>%  
 mutate (gritQ1R = 6-gritQ1, gritQ3R = 6-gritQ3, gritQ5R = 6-gritQ5, gritQ6R = 6-gritQ6) %>%  
 mutate (gritScore = (gritQ1R+gritQ2+gritQ3R+gritQ4+gritQ5R+gritQ6R+gritQ7+gritQ8)/8) %>%  
 mutate (incarcerationTime = (incarcerationYears\*12)+incarcerationMonths) %>%  
 mutate (povertyRatio = if(as.numeric(incomeLastYr) <= 6) {  
 (8070+(as.numeric(incomeLastYr)\*4420))/(8070+(as.numeric(householdSize)\*4420))  
 } else {  
 if(as.numeric(incomeLastYr) == 7) {  
 (34591/(8070+(as.numeric(householdSize)\*4420)))  
 } else {  
 if(as.numeric(incomeLastYr) == 8) {  
 (50001/(8070+(as.numeric(householdSize)\*4420)))  
 } else {  
 if(as.numeric(incomeLastYr) == 9) {  
 (75001/(8070+(as.numeric(householdSize)\*4420)))  
 } else {  
 if(as.numeric(incomeLastYr) == 10) {  
 (100001/(8070+(as.numeric(householdSize\*4420))))  
 } else {  
 (150000/(8070+(as.numeric(householdSize)\*4420)))  
 }  
 }  
 }  
 }  
 }  
 ) -> dataAugmented

## Select Cases

The following code chunk removes cases where the respondent was part of a protected population or did not provide informed consent.

dataAugmented <- dataAugmented[-c(1,2),]  
dataAugmented %>%  
 subset(currentlyIncarcerated=2) %>%  
 subset(currentlyDetained=2) %>%  
 subset(residentialTreatment=2) %>%  
 subset(involCommitment=2) -> dataClean

## Evaluate Missing Data

The following code chunk evaluates missing data.

miss\_var\_summary(dataClean, order = TRUE)

## # A tibble: 118 x 3  
## variable n\_miss pct\_miss  
## <chr> <int> <dbl>  
## 1 genderSelfDescribe 59 100   
## 2 incarcerationTime 59 100   
## 3 primaryEthnicityRace 56 94.9  
## 4 financialSupportNonGovt 54 91.5  
## 5 selfEmployment 54 91.5  
## 6 helpAfterOther 53 89.8  
## 7 finanicalSupportOther 51 86.4  
## 8 helpDuringOther 51 86.4  
## 9 ReligiousOther 49 83.1  
## 10 stayInitialOther 47 79.7  
## # ... with 108 more rows

miss\_case\_summary(dataClean, order = TRUE)

## # A tibble: 59 x 3  
## case n\_miss pct\_miss  
## <int> <int> <dbl>  
## 1 49 61 51.7  
## 2 50 61 51.7  
## 3 53 48 40.7  
## 4 56 46 39.0  
## 5 51 44 37.3  
## 6 58 23 19.5  
## 7 16 22 18.6  
## 8 57 20 16.9  
## 9 52 19 16.1  
## 10 55 18 15.3  
## # ... with 49 more rows

## Calculate Descriptive Statistics

The following code calculates descriptive statistics for select variables of interest.

print("Number of cases")

## [1] "Number of cases"

nrow(dataClean)

## [1] 59

print("gender; 1 - male, 2 - female, 3 - other, 4 - undisclosed")

## [1] "gender; 1 - male, 2 - female, 3 - other, 4 - undisclosed"

table(as.numeric(dataClean$gender))

##   
## 3 4   
## 31 26

print("ageNow")

## [1] "ageNow"

describe(as.numeric(dataClean$ageNow), na.rm = TRUE)

## vars n mean sd median trimmed mad min max range skew kurtosis se  
## X1 1 59 27.19 7.61 28 27.24 8.9 12 41 29 -0.01 -0.87 0.99

print("ageRelease")

## [1] "ageRelease"

describe(as.numeric(dataClean$ageRelease), na.rm = TRUE)

## vars n mean sd median trimmed mad min max range skew kurtosis se  
## X1 1 59 26.41 9.5 26 26.22 10.38 12 43 31 0.17 -1.14 1.24

print("selfEmployment; 1 - 0%, 2 - 1-25%, 3 - 26-50%, 4 - 51-75%, 5 - 75-99%, 6 - 100%")

## [1] "selfEmployment; 1 - 0%, 2 - 1-25%, 3 - 26-50%, 4 - 51-75%, 5 - 75-99%, 6 - 100%"

table(as.numeric(dataClean$selfEmployment))

##   
## 3 4 5 6   
## 1 1 1 2

## Compute Scale Reliabilities

The following code chunk evaluates the reliability for the MSPSS, ACE, and grit scales by calculating the Cronbach’s alpha for each variable.

reliabilityMSPSS <- cronbach (subset(dataClean, select=c(pssQ1, pssQ2, pssQ3, pssQ4, pssQ5, pssQ6, pssQ7, pssQ8, pssQ9, pssQ10, pssQ11, pssQ12)))  
print("Reliability for MPSS Scale")

## [1] "Reliability for MPSS Scale"

reliabilityMSPSS

## $sample.size  
## [1] 59  
##   
## $number.of.items  
## [1] 12  
##   
## $alpha  
## [1] 0.9587711

reliabilityACE <- cronbach (subset(dataClean, select=c(aceQ1, aceQ2, aceQ3, aceQ4, aceQ5, aceQ6, aceQ7, aceQ8, aceQ9, aceQ10)))  
print("Reliability for ACE Scale")

## [1] "Reliability for ACE Scale"

reliabilityACE

## $sample.size  
## [1] 59  
##   
## $number.of.items  
## [1] 10  
##   
## $alpha  
## [1] 0.9634455

reliabilityGrit <- cronbach (subset(dataClean, select=c(gritQ1, gritQ2, gritQ3, gritQ4, gritQ5, gritQ6, gritQ7, gritQ8)))  
print("Reliability for Short Grit Scale")

## [1] "Reliability for Short Grit Scale"

reliabilityGrit

## $sample.size  
## [1] 59  
##   
## $number.of.items  
## [1] 8  
##   
## $alpha  
## [1] 0.906496

## Perform Comparison of Means of Grit

The following code chunk performs calculations for comparison of means of the primary variables of interest.

# Comparison of means for gritScore grouped by various operationalizations of success using ANOVA  
# Coding for gritscore: values range from 1 (low grit) to 8 (high grit)  
# Null hypothesis: the means of the different groups are the same  
# Alternative hypothesis: the sample mean of at least one group is not equal to the others  
  
  
# Comparison of gritScore for cases grouped by incomeLastYr using ANOVA  
# Coding for incomeLastYr (Qualitrics Q22): ordinal ranging 1 - 10  
groupIncome <- group\_by(dataClean, incomeLastYr)  
  
groupIncome %>%  
 summarise(  
 count = n(),  
 mean = mean(gritScore, na.rm = TRUE),  
 sd = sd(gritScore, na.rm = TRUE)  
 )

## # A tibble: 12 x 4  
## incomeLastYr count mean sd  
## <fct> <int> <dbl> <dbl>  
## 1 1 13 3.16 0.596  
## 2 10 4 3.38 0.941  
## 3 11 2 2.12 0.884  
## 4 2 1 3 NaN   
## 5 3 3 3.38 0.760  
## 6 4 7 2.68 0.710  
## 7 5 3 2.75 0.331  
## 8 6 4 3.78 0.413  
## 9 7 8 2.86 0.398  
## 10 8 7 3.23 0.659  
## 11 9 3 3.67 0.191  
## 12 <NA> 4 3 0

aovGroupIncome <- aov(gritScore ~ as.numeric(incomeLastYr), data = groupIncome)  
summary(aovGroupIncome)

## Df Sum Sq Mean Sq F value Pr(>F)  
## as.numeric(incomeLastYr) 1 0.083 0.0829 0.185 0.669  
## Residuals 53 23.826 0.4495   
## 4 observations deleted due to missingness

# Comparison of gritScore for cases grouped by povertyLevel using ANOVA  
# Coding for povertyLevel (created variable): 1 - above, 2 - below  
dataClean %>%  
 mutate(povertyLevel = if (povertyRatio >1) {1} else {2})-> dataClean  
  
dataClean[dataClean==""] <- NA  
  
groupPoverty <- group\_by(dataClean, povertyLevel)  
  
groupPoverty %>%  
 summarise(  
 count = n(),  
 mean = mean(gritScore, na.rm = TRUE),  
 sd = sd(gritScore, na.rm = TRUE)  
 )

## # A tibble: 1 x 4  
## povertyLevel count mean sd  
## <dbl> <int> <dbl> <dbl>  
## 1 1 59 3.10 0.643

aovGroupPoverty <- aov(gritScore ~ as.numeric(povertyLevel), data = groupPoverty)  
summary(aovGroupPoverty)

## Df Sum Sq Mean Sq F value Pr(>F)  
## Residuals 58 23.95 0.4129

# Comparison of gritScore for cases grouped by financialStatus using ANOVA  
# Coding for financialStatus (Qualitrics Q23): 1 - not able, 2 - just able, 3 - comfortable no savings, 4 - comfortable and saving  
groupFinStat <- group\_by(dataClean, financialStatus)  
  
groupFinStat %>%  
 summarise(  
 count = n(),  
 mean = mean(gritScore, na.rm = TRUE),  
 sd = sd(gritScore, na.rm = TRUE)  
 )

## # A tibble: 5 x 4  
## financialStatus count mean sd  
## <fct> <int> <dbl> <dbl>  
## 1 1 12 3.07 0.602  
## 2 2 19 2.91 0.723  
## 3 3 15 3 0.582  
## 4 4 7 3.71 0.519  
## 5 <NA> 6 3.23 0.357

aovGroupFinStat <- aov(gritScore ~ as.numeric(financialStatus), data = groupFinStat)  
summary(aovGroupFinStat)

## Df Sum Sq Mean Sq F value Pr(>F)   
## as.numeric(financialStatus) 1 1.216 1.2159 2.822 0.0991 .  
## Residuals 51 21.975 0.4309   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 6 observations deleted due to missingness

# Comparison of gritScore for cases grouped by savings using ANOVA  
# Coding for savings (Qualitrics Q24): 1 - yes, 2 - no  
groupSavings <- group\_by(dataClean, savings)  
  
groupSavings %>%  
 summarise(  
 count = n(),  
 mean = mean(gritScore, na.rm = TRUE),  
 sd = sd(gritScore, na.rm = TRUE)  
 )

## # A tibble: 3 x 4  
## savings count mean sd  
## <fct> <int> <dbl> <dbl>  
## 1 1 15 3.55 0.551  
## 2 2 40 2.93 0.631  
## 3 <NA> 4 3 0

aovGroupSavings <- aov(gritScore ~ as.numeric(savings), data = groupSavings)  
summary(aovGroupSavings)

## Df Sum Sq Mean Sq F value Pr(>F)   
## as.numeric(savings) 1 4.134 4.134 11.08 0.00159 \*\*  
## Residuals 53 19.775 0.373   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 4 observations deleted due to missingness

## Perform Correlational Analysis

The following code chunk performs correlational analysis for the primary variables of interest.

dataClean %>%  
 dplyr::select(incomeLastYr, povertyRatio, povertyLevel, financialStatus, savings, ageNow, ageRelease, mspssScore, aceScore, gritScore) -> correlationDataset   
col\_names <- names(correlationDataset)  
correlationDataset[,col\_names] <- lapply(correlationDataset[,col\_names], as.numeric)  
correlation <- cor(correlationDataset, use="pairwise.complete.obs")  
correlation

## incomeLastYr povertyRatio povertyLevel financialStatus  
## incomeLastYr 1.00000000 0.07878926 NA 0.17463014  
## povertyRatio 0.07878926 1.00000000 NA -0.12702067  
## povertyLevel NA NA NA NA  
## financialStatus 0.17463014 -0.12702067 NA 1.00000000  
## savings -0.03251942 -0.06810200 NA -0.46516980  
## ageNow -0.04018701 0.15261350 NA -0.27436238  
## ageRelease 0.05583711 0.18136159 NA -0.09029268  
## mspssScore 0.18631487 0.13622780 NA 0.02088214  
## aceScore -0.04708187 0.09382109 NA 0.18032901  
## gritScore 0.05890139 0.06701438 NA 0.22898025  
## savings ageNow ageRelease mspssScore  
## incomeLastYr -0.032519423 -0.04018701 0.05583711 0.186314867  
## povertyRatio -0.068102000 0.15261350 0.18136159 0.136227802  
## povertyLevel NA NA NA NA  
## financialStatus -0.465169802 -0.27436238 -0.09029268 0.020882141  
## savings 1.000000000 0.05829047 -0.04001158 0.006858572  
## ageNow 0.058290466 1.00000000 0.35681341 0.221500986  
## ageRelease -0.040011576 0.35681341 1.00000000 0.047635687  
## mspssScore 0.006858572 0.22150099 0.04763569 1.000000000  
## aceScore -0.137134130 0.34336352 0.32248113 0.633053000  
## gritScore -0.415842618 0.08405773 0.08637535 0.187573493  
## aceScore gritScore  
## incomeLastYr -0.04708187 0.05890139  
## povertyRatio 0.09382109 0.06701438  
## povertyLevel NA NA  
## financialStatus 0.18032901 0.22898025  
## savings -0.13713413 -0.41584262  
## ageNow 0.34336352 0.08405773  
## ageRelease 0.32248113 0.08637535  
## mspssScore 0.63305300 0.18757349  
## aceScore 1.00000000 0.07753448  
## gritScore 0.07753448 1.00000000

## Perform Regression Analysis

The following code chunk performs a multiple regression using select variables of interest.

# Multiple regression using incomeLastYr as dependent variable  
regressionIncome <- lm(as.numeric(incomeLastYr) ~ as.numeric(ageNow) + as.numeric(ageRelease) + mspssScore + aceScore + gritScore,   
 data = dataClean, na.action = na.omit)  
summary(regressionIncome)

##   
## Call:  
## lm(formula = as.numeric(incomeLastYr) ~ as.numeric(ageNow) +   
## as.numeric(ageRelease) + mspssScore + aceScore + gritScore,   
## data = dataClean, na.action = na.omit)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -5.9238 -3.5354 0.1056 2.9196 6.0727   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 8.92690 4.85511 1.839 0.0720 .  
## as.numeric(ageNow) -0.03567 0.07120 -0.501 0.6186   
## as.numeric(ageRelease) 0.05221 0.05695 0.917 0.3638   
## mspssScore 0.42343 0.25219 1.679 0.0995 .  
## aceScore -0.12214 0.11779 -1.037 0.3049   
## gritScore 0.07734 0.76133 0.102 0.9195   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 3.62 on 49 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.06704, Adjusted R-squared: -0.02816   
## F-statistic: 0.7042 on 5 and 49 DF, p-value: 0.623

# Multiple regressiong using povertyRatio as dependent variable  
regressionPoverty <- lm(as.numeric(povertyRatio) ~ as.numeric(ageNow) + as.numeric(ageRelease) + mspssScore + aceScore + gritScore,   
 data = dataClean, na.action = na.omit)  
summary(regressionPoverty)

##   
## Call:  
## lm(formula = as.numeric(povertyRatio) ~ as.numeric(ageNow) +   
## as.numeric(ageRelease) + mspssScore + aceScore + gritScore,   
## data = dataClean, na.action = na.omit)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.0251 -0.5506 -0.1037 0.6112 2.3136   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.7992717 0.9335289 4.070 0.000188 \*\*\*  
## as.numeric(ageNow) 0.0097614 0.0191025 0.511 0.611851   
## as.numeric(ageRelease) 0.0174512 0.0158113 1.104 0.275582   
## mspssScore 0.0596084 0.0671626 0.888 0.379516   
## aceScore -0.0054573 0.0224945 -0.243 0.809413   
## gritScore -0.0008674 0.2022027 -0.004 0.996596   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9016 on 45 degrees of freedom  
## (8 observations deleted due to missingness)  
## Multiple R-squared: 0.06231, Adjusted R-squared: -0.04187   
## F-statistic: 0.5981 on 5 and 45 DF, p-value: 0.7015

# Multiple regression using financialStatus as dependent variable  
regressionFinStat <- lm(as.numeric(financialStatus) ~ as.numeric(ageNow) + as.numeric(ageRelease) + mspssScore + aceScore + gritScore,   
 data = dataClean, na.action = na.omit)  
summary(regressionFinStat)

##   
## Call:  
## lm(formula = as.numeric(financialStatus) ~ as.numeric(ageNow) +   
## as.numeric(ageRelease) + mspssScore + aceScore + gritScore,   
## data = dataClean, na.action = na.omit)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1.77400 -0.64404 0.04161 0.62059 1.79427   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.947574 1.258924 2.341 0.0235 \*  
## as.numeric(ageNow) -0.037400 0.018283 -2.046 0.0464 \*  
## as.numeric(ageRelease) -0.009505 0.014810 -0.642 0.5241   
## mspssScore -0.055092 0.065697 -0.839 0.4060   
## aceScore 0.049257 0.030414 1.620 0.1120   
## gritScore 0.372324 0.196693 1.893 0.0645 .  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9281 on 47 degrees of freedom  
## (6 observations deleted due to missingness)  
## Multiple R-squared: 0.1829, Adjusted R-squared: 0.09598   
## F-statistic: 2.104 on 5 and 47 DF, p-value: 0.08147

# Binary logistic regression using savings as dependent variable

dataClean %>% dplyr::select(incomeLastYr, povertyRatio, povertyLevel, financialStatus, savings, ageNow, ageRelease, mspssScore, aceScore, gritScore) %>% mutate(savingsBinary = 3-as.numeric(savings)) -> dataBinary dataCleansavingsBinary col\_names <- names(dataBinary) dataBinary[,col\_names] <- lapply(dataBinary[,col\_names], as.numeric)

logitSavings <- glm(savings ~ ageNow + ageRelease + mspssScore + aceScore + gritScore, data = dataBinary, family = binomial, na.action = na.omit) summary(logitSavings)

# Raise e to the coefficients

print(exp(coef(logitSavings)))

# Obtain various pseudo R-squared measures

print(pR2(logitSavings))

# Confidence intervals for the coefficients

print(exp(confint(logitSavings, level = 0.95)))

# Hosmer-Lemeshow Goodness of Fit Test

# Null hypothesis: the model is a good fit for the data

# Alternative hypothesis: the model is NOT a good fit for the data

HosLemLogitSavings <- hoslem.test(dataCleanexpected, HosLemLogitSavings$observed))

## Save Data

The following code chunk saves the cleaned data used for the analysis.

write.csv(dataClean, here("Data","DataClean","SOC5800\_Data\_NumericValues\_Clean\_CSV.csv"), append = FALSE)