Further Analysis and Tuning

Team Rho

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```r
#libraries

library(readxl)
library(caret)
library(tidyr)
library(dplyr)
library(corrplot)
library(rvest)
library(glmnet)
library(pls)
library(fastDummies)
library(randomForest)
library(janitor)
```

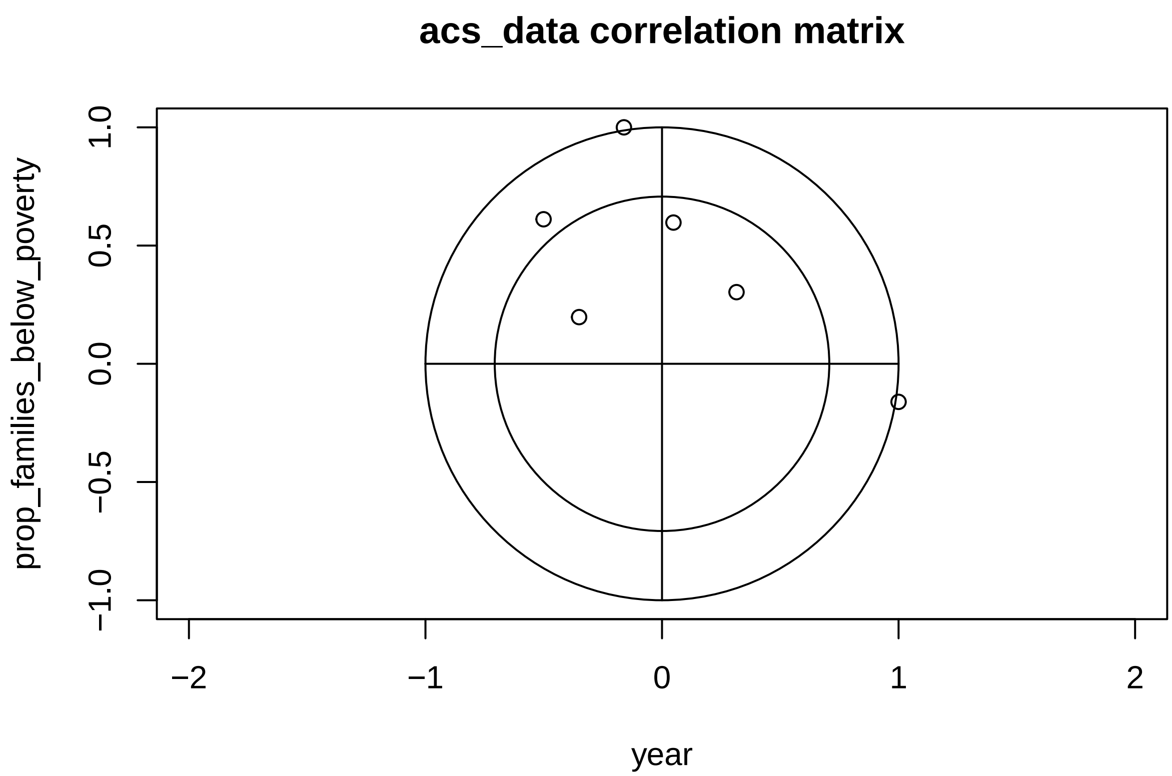
```r
#reading data
data_GTrends <- read_excel("~/GitHub/DSE6311OM_SP2025R2_Data-Science-Capstone/Data/googleTrendsMH.xlsx"
    sheet = "googleTrendsMH")
acs_data <- load("~/GitHub/DSE6311OM_SP2025R2_Data-Science-Capstone/Data/ACS_for_MHGoogleTrends.Rdata")

acs_data <- ACS_data
ACS_data <- NULL
```

```r
##CORRELATION MATRIX FOR acs_data

acs_correlation_matrix <- acs_data %>%
  select_if(is.numeric) %>%
  select(-prop_persons_below_poverty_threshold, -prop_veterans_disability) %>%
  cor()

print(acs_correlation_matrix)
```

```
##                                             year prop_families_below_poverty
## year                                  1.00000000                  -0.1610309
## prop_families_below_poverty          -0.16103094                   1.0000000
## prop_adults_without_health_insurance -0.35051348                   0.1974453
## prop_unemployed_in_labor_force       -0.50071692                   0.6113240
## prop_without_internet_access          0.31496819                   0.3030755
## prop_adult_disability                 0.04834553                   0.5972604
##                                      prop_adults_without_health_insurance
## year                                                           -0.3505135
## prop_families_below_poverty                                     0.1974453
```

```
## prop_adults_without_health_insurance                            1.0000000
## prop_unemployed_in_labor_force                                  0.2889701
## prop_without_internet_access                                   -0.1226758
## prop_adult_disability                                           0.1945398
##                                     prop_unemployed_in_labor_force
## year                                                    -0.5007169
## prop_families_below_poverty                              0.6113240
## prop_adults_without_health_insurance                     0.2889701
## prop_unemployed_in_labor_force                           1.0000000
## prop_without_internet_access                            -0.1705119
## prop_adult_disability                                    0.1723363
##                                     prop_without_internet_access
## year                                                  0.3149682
## prop_families_below_poverty                           0.3030755
## prop_adults_without_health_insurance                 -0.1226758
## prop_unemployed_in_labor_force                       -0.1705119
## prop_without_internet_access                          1.0000000
## prop_adult_disability                                 0.3494365
##                                     prop_adult_disability
## year                                           0.04834553
## prop_families_below_poverty                    0.59726036
## prop_adults_without_health_insurance           0.19453980
## prop_unemployed_in_labor_force                 0.17233629
## prop_without_internet_access                   0.34943653
## prop_adult_disability                          1.00000000
```

```r
#presenting correlation matrix in graphic format

acs_correlation_matrix <- acs_data %>%
  select_if(is.numeric) %>%
  select(-prop_persons_below_poverty_threshold, -prop_veterans_disability) %>%
  cor() %>%
  corrplot( diag = F,
           tl.cex = 0.7,
           tl.col = "black",
           main = "acs_data correlation matrix",
           mar = c(0,0,1,0))
```




```
#removing correlated features
acs_data_clean <- acs_data %>%
  select(-prop_persons_below_poverty_threshold, -prop_veterans_disability)
# convert state names into abbreviation to match state in data_GTrends

acs_data_clean$state <- toupper(state.abb[match(tolower(acs_data_clean$state), tolower(state.name))])
```

```
#data transformations ct variables
#creating response variable => state_mentalhealth_utili = state_psych_care / population_est
#state_mentalhealth_utili <- data_GTrends$state_psych_care / data_GTrends$population_est

data_GTrends <- data_GTrends %>%
  mutate(state_mentalhealth_util = state_psych_care/population_est,
         anxiety_prop = anxiety_ct/ population_est,
         trauma_stress_prop = trauma_stress_ct/population_est,
         adhd_prop = adhd_ct/population_est,
         bipolar_prop = bipolar_ct/population_est,
         depression_prop = depression_ct/population_est)

#data_GTrends <- data_GTrends %>%
  #select(-state_psych_care, -anxiety_ct, -trauma_stress_ct, -adhd_ct, -bipolar_ct, -depression_ct) all
```

```
#joining both datasets acs_data and data_GTrends

GTrends_acs_joined <- inner_join(data_GTrends, acs_data_clean, by = c("year", "state"))
```

```
#testing correlation
```

```r
correlation_matrix <- GTrends_acs_joined %>%
  select_if(is.numeric) %>%
  select(-fips, -population_est,-private_psych_care, -total_util, -outpatient_util, -mean_anxiety, -res
        -total_util) %>%
cor()

print(correlation_matrix)
```

```
##                                              year   anxiety_ct trauma_stress_ct
## year                                   1.00000000  0.230563501       0.13366856
## anxiety_ct                             0.23056350  1.000000000       0.92240079
## trauma_stress_ct                       0.13366856  0.922400795       1.00000000
## adhd_ct                                0.01851770  0.847645702       0.87161036
## bipolar_ct                            -0.13690754  0.653131435       0.75571956
## depression_ct                          0.06120702  0.873780027       0.94087338
## comm_psych_care                        0.05264059  0.793626073       0.89977194
## state_psych_care                       0.05220254  0.800842275       0.90248691
## mean_adhd                              0.75682637  0.192811841       0.08958471
## mean_ptsd                              0.62228218  0.090669189       0.04475684
## mean_bipolar                          -0.09097469 -0.085128361      -0.08423315
## mean_depression                       -0.02390143  0.009319898      -0.02136263
## mean_mental_hospital                   0.27777930  0.319455125       0.28112091
## mean_psychiatrists_near_me             0.18697534  0.063526502       0.09919989
## mean_psychologist_near_me              0.64878930  0.404062943       0.38356349
## anxiety_prop                           0.25256530  0.575638687       0.40794338
## adhd_prop                              0.02582844  0.540119606       0.44884626
## bipolar_prop                          -0.27713846  0.402247684       0.39406527
## prop_families_below_poverty           -0.31411265 -0.065951520      -0.02266406
## prop_adults_without_health_insurance  -0.35036488 -0.120820100      -0.08943951
## prop_unemployed_in_labor_force        -0.54031845 -0.047006409       0.07676369
## prop_without_internet_access           0.31423583  0.011777977      -0.03506000
## prop_adult_disability                  0.07154859 -0.089418168      -0.12802032
##                                           adhd_ct  bipolar_ct depression_ct
## year                                   0.018517704 -0.13690754    0.06120702
## anxiety_ct                             0.847645702  0.65313144    0.87378003
## trauma_stress_ct                       0.871610355  0.75571956    0.94087338
## adhd_ct                                1.000000000  0.83440163    0.90823233
## bipolar_ct                             0.834401629  1.00000000    0.88673220
## depression_ct                          0.908232333  0.88673220    1.00000000
## comm_psych_care                        0.874225711  0.87090215    0.95667411
## state_psych_care                       0.884006979  0.87166405    0.95701158
## mean_adhd                             -0.007745775 -0.10866030    0.02253769
## mean_ptsd                             -0.124707857 -0.22821302   -0.08131642
## mean_bipolar                          -0.082850695 -0.03030126   -0.08659302
## mean_depression                       -0.026389005 -0.09361394   -0.02884011
## mean_mental_hospital                   0.220054198  0.21655455    0.28147786
## mean_psychiatrists_near_me             0.086212620  0.06521304    0.09221333
## mean_psychologist_near_me              0.316683082  0.20732437    0.35169600
## anxiety_prop                           0.306023903  0.03211950    0.27306557
## adhd_prop                              0.557691198  0.19368296    0.36224924
## bipolar_prop                           0.458390120  0.36562312    0.36378200
## prop_families_below_poverty            0.091452450  0.21421452    0.06093810
## prop_adults_without_health_insurance   0.001121328  0.24369742    0.03448441
```

```
## prop_unemployed_in_labor_force        0.124358517  0.28278587    0.13217179
## prop_without_internet_access          0.010097643 -0.11859483   -0.03027184
## prop_adult_disability                -0.041620397 -0.11618594   -0.11834226
##                                      comm_psych_care state_psych_care
## year                                      0.05264059       0.05220254
## anxiety_ct                                0.79362607       0.80084228
## trauma_stress_ct                          0.89977194       0.90248691
## adhd_ct                                   0.87422571       0.88400698
## bipolar_ct                                0.87090215       0.87166405
## depression_ct                             0.95667411       0.95701158
## comm_psych_care                           1.00000000       0.99936080
## state_psych_care                          0.99936080       1.00000000
## mean_adhd                                 0.01154550       0.01301038
## mean_ptsd                                -0.09505592      -0.09409334
## mean_bipolar                             -0.06243299      -0.06269307
## mean_depression                          -0.04094749      -0.04237320
## mean_mental_hospital                      0.24373032       0.24415647
## mean_psychiatrists_near_me                0.13571311       0.13354197
## mean_psychologist_near_me                 0.36100819       0.35825438
## anxiety_prop                              0.18813746       0.20049138
## adhd_prop                                 0.28982510       0.30527377
## bipolar_prop                              0.30483675       0.31814831
## prop_families_below_poverty               0.06341390       0.06303851
## prop_adults_without_health_insurance      0.02920460       0.02820942
## prop_unemployed_in_labor_force            0.16815934       0.16554652
## prop_without_internet_access             -0.03609294      -0.03484673
## prop_adult_disability                    -0.15530682      -0.14673191
##                                         mean_adhd   mean_ptsd mean_bipolar
## year                                  0.756826372  0.62228218 -0.090974692
## anxiety_ct                            0.192811841  0.09066919 -0.085128361
## trauma_stress_ct                      0.089584712  0.04475684 -0.084233146
## adhd_ct                              -0.007745775 -0.12470786 -0.082850695
## bipolar_ct                           -0.108660303 -0.22821302 -0.030301260
## depression_ct                         0.022537693 -0.08131642 -0.086593022
## comm_psych_care                       0.011545502 -0.09505592 -0.062432992
## state_psych_care                      0.013010379 -0.09409334 -0.062693072
## mean_adhd                             1.000000000  0.42495384  0.179510680
## mean_ptsd                             0.424953840  1.00000000  0.193509244
## mean_bipolar                          0.179510680  0.19350924  1.000000000
## mean_depression                      -0.245750075  0.41128942  0.308755245
## mean_mental_hospital                  0.287677009  0.09702821  0.232486981
## mean_psychiatrists_near_me            0.042769431  0.05674090 -0.005280538
## mean_psychologist_near_me             0.415735545  0.23433255 -0.080183845
## anxiety_prop                          0.222753634  0.30520691 -0.005956554
## adhd_prop                             0.028590323  0.09085592 -0.010212770
## bipolar_prop                         -0.159049076 -0.04663275  0.157398435
## prop_families_below_poverty          -0.208577621 -0.20391856  0.293106346
## prop_adults_without_health_insurance -0.186412427 -0.24473889  0.233057761
## prop_unemployed_in_labor_force       -0.327758496 -0.43653037  0.157300589
## prop_without_internet_access         -0.126520915  0.33393361 -0.090016482
## prop_adult_disability                 0.109982033  0.10629585  0.222236769
##                                      mean_depression mean_mental_hospital
## year                                    -0.023901425           0.27777930
## anxiety_ct                               0.009319898           0.31945513
```

```
## trauma_stress_ct                     -0.021362629         0.28112091
## adhd_ct                              -0.026389005         0.22005420
## bipolar_ct                           -0.093613944         0.21655455
## depression_ct                        -0.028840113         0.28147786
## comm_psych_care                      -0.040947486         0.24373032
## state_psych_care                     -0.042373199         0.24415647
## mean_adhd                            -0.245750075         0.28767701
## mean_ptsd                             0.411289416         0.09702821
## mean_bipolar                          0.308755245         0.23248698
## mean_depression                       1.000000000        -0.10548867
## mean_mental_hospital                 -0.105488666         1.00000000
## mean_psychiatrists_near_me            0.001374564         0.15614239
## mean_psychologist_near_me            -0.098056483         0.41633384
## anxiety_prop                          0.050429764         0.02664347
## adhd_prop                             0.069487449        -0.06288825
## bipolar_prop                          0.026384149        -0.09485722
## prop_families_below_poverty          -0.077146712         0.21535926
## prop_adults_without_health_insurance -0.062380502        -0.02688604
## prop_unemployed_in_labor_force       -0.348426242         0.10886182
## prop_without_internet_access          0.385215253         0.07508085
## prop_adult_disability                -0.081676556         0.16483923
##                                      mean_psychiatrists_near_me
## year                                                0.186975337
## anxiety_ct                                          0.063526502
## trauma_stress_ct                                    0.099199887
## adhd_ct                                             0.086212620
## bipolar_ct                                          0.065213036
## depression_ct                                       0.092213328
## comm_psych_care                                     0.135713106
## state_psych_care                                    0.133541968
## mean_adhd                                           0.042769431
## mean_ptsd                                           0.056740904
## mean_bipolar                                       -0.005280538
## mean_depression                                     0.001374564
## mean_mental_hospital                                0.156142388
## mean_psychiatrists_near_me                          1.000000000
## mean_psychologist_near_me                           0.466711912
## anxiety_prop                                       -0.104990533
## adhd_prop                                          -0.105489672
## bipolar_prop                                       -0.156142069
## prop_families_below_poverty                        -0.185544042
## prop_adults_without_health_insurance               -0.257450224
## prop_unemployed_in_labor_force                     -0.020698183
## prop_without_internet_access                        0.051130358
## prop_adult_disability                              -0.239770625
##                                      mean_psychologist_near_me anxiety_prop
## year                                                0.64878930  0.252565296
## anxiety_ct                                          0.40406294  0.575638687
## trauma_stress_ct                                    0.38356349  0.407943378
## adhd_ct                                             0.31668308  0.306023903
## bipolar_ct                                          0.20732437  0.032119498
## depression_ct                                       0.35169600  0.273065574
## comm_psych_care                                     0.36100819  0.188137462
## state_psych_care                                    0.35825438  0.200491380
```

```
## mean_adhd                                          0.41573555  0.222753634
## mean_ptsd                                          0.23433255  0.305206913
## mean_bipolar                                      -0.08018385 -0.005956554
## mean_depression                                   -0.09805648  0.050429764
## mean_mental_hospital                               0.41633384  0.026643466
## mean_psychiatrists_near_me                         0.46671191 -0.104990533
## mean_psychologist_near_me                          1.00000000  0.018713136
## anxiety_prop                                       0.01871314  1.000000000
## adhd_prop                                         -0.02192663  0.772593545
## bipolar_prop                                      -0.20102389  0.592973858
## prop_families_below_poverty                       -0.16397365 -0.139411004
## prop_adults_without_health_insurance              -0.20618180 -0.202330161
## prop_unemployed_in_labor_force                    -0.18536934 -0.244392365
## prop_without_internet_access                       0.15990322  0.090420463
## prop_adult_disability                             -0.08569762  0.099264075
##                                        adhd_prop bipolar_prop
## year                                  0.02582844  -0.27713846
## anxiety_ct                            0.54011961   0.40224768
## trauma_stress_ct                      0.44884626   0.39406527
## adhd_ct                               0.55769120   0.45839012
## bipolar_ct                            0.19368296   0.36562312
## depression_ct                         0.36224924   0.36378200
## comm_psych_care                       0.28982510   0.30483675
## state_psych_care                      0.30527377   0.31814831
## mean_adhd                             0.02859032  -0.15904908
## mean_ptsd                             0.09085592  -0.04663275
## mean_bipolar                         -0.01021277   0.15739843
## mean_depression                       0.06948745   0.02638415
## mean_mental_hospital                 -0.06288825  -0.09485722
## mean_psychiatrists_near_me           -0.10548967  -0.15614207
## mean_psychologist_near_me            -0.02192663  -0.20102389
## anxiety_prop                          0.77259354   0.59297386
## adhd_prop                             1.00000000   0.73676449
## bipolar_prop                          0.73676449   1.00000000
## prop_families_below_poverty           0.06474605   0.24288704
## prop_adults_without_health_insurance -0.10333794   0.15947980
## prop_unemployed_in_labor_force       -0.06381305   0.17824936
## prop_without_internet_access          0.10675502  -0.09079816
## prop_adult_disability                 0.20587109   0.24830497
##                                      prop_families_below_poverty
## year                                                 -0.31411265
## anxiety_ct                                           -0.06595152
## trauma_stress_ct                                     -0.02266406
## adhd_ct                                               0.09145245
## bipolar_ct                                            0.21421452
## depression_ct                                         0.06093810
## comm_psych_care                                       0.06341390
## state_psych_care                                      0.06303851
## mean_adhd                                            -0.20857762
## mean_ptsd                                            -0.20391856
## mean_bipolar                                          0.29310635
## mean_depression                                      -0.07714671
## mean_mental_hospital                                  0.21535926
## mean_psychiatrists_near_me                           -0.18554404
```

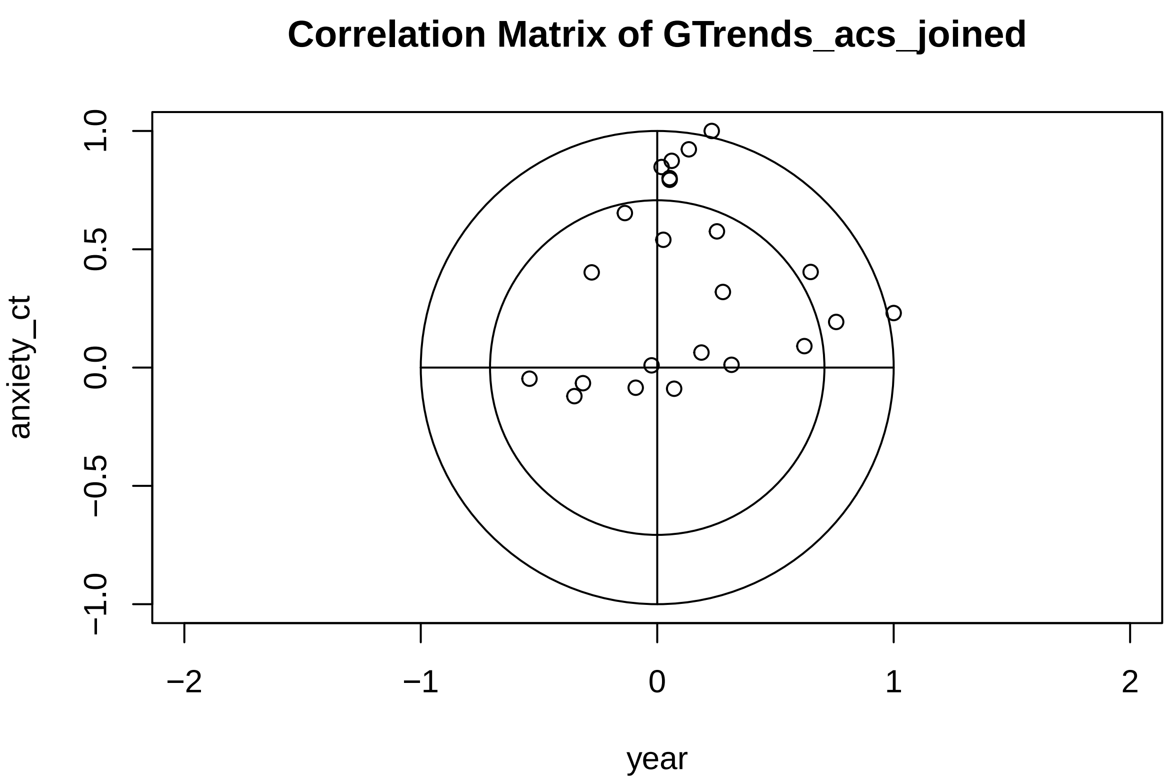
```
## mean_psychologist_near_me                        -0.16397365
## anxiety_prop                                     -0.13941100
## adhd_prop                                         0.06474605
## bipolar_prop                                      0.24288704
## prop_families_below_poverty                       1.00000000
## prop_adults_without_health_insurance              0.60329043
## prop_unemployed_in_labor_force                    0.52364772
## prop_without_internet_access                      0.12312374
## prop_adult_disability                             0.65543780
##                                      prop_adults_without_health_insurance
## year                                                         -0.350364883
## anxiety_ct                                                   -0.120820100
## trauma_stress_ct                                             -0.089439512
## adhd_ct                                                       0.001121328
## bipolar_ct                                                    0.243697423
## depression_ct                                                 0.034484408
## comm_psych_care                                               0.029204600
## state_psych_care                                              0.028209419
## mean_adhd                                                    -0.186412427
## mean_ptsd                                                    -0.244738889
## mean_bipolar                                                  0.233057761
## mean_depression                                              -0.062380502
## mean_mental_hospital                                         -0.026886042
## mean_psychiatrists_near_me                                   -0.257450224
## mean_psychologist_near_me                                    -0.206181798
## anxiety_prop                                                 -0.202330161
## adhd_prop                                                    -0.103337943
## bipolar_prop                                                  0.159479797
## prop_families_below_poverty                                   0.603290434
## prop_adults_without_health_insurance                          1.000000000
## prop_unemployed_in_labor_force                                0.409465887
## prop_without_internet_access                                 -0.106556672
## prop_adult_disability                                         0.289928013
##                                      prop_unemployed_in_labor_force
## year                                                    -0.54031845
## anxiety_ct                                              -0.04700641
## trauma_stress_ct                                         0.07676369
## adhd_ct                                                  0.12435852
## bipolar_ct                                               0.28278587
## depression_ct                                            0.13217179
## comm_psych_care                                          0.16815934
## state_psych_care                                         0.16554652
## mean_adhd                                               -0.32775850
## mean_ptsd                                               -0.43653037
## mean_bipolar                                             0.15730059
## mean_depression                                         -0.34842624
## mean_mental_hospital                                     0.10886182
## mean_psychiatrists_near_me                              -0.02069818
## mean_psychologist_near_me                               -0.18536934
## anxiety_prop                                            -0.24439237
## adhd_prop                                               -0.06381305
## bipolar_prop                                             0.17824936
## prop_families_below_poverty                              0.52364772
## prop_adults_without_health_insurance                     0.40946589
```

```
## prop_unemployed_in_labor_force                               1.00000000
## prop_without_internet_access                                -0.34452758
## prop_adult_disability                                        0.06756309
##                                       prop_without_internet_access
## year                                                      0.31423583
## anxiety_ct                                                0.01177798
## trauma_stress_ct                                         -0.03506000
## adhd_ct                                                   0.01009764
## bipolar_ct                                               -0.11859483
## depression_ct                                            -0.03027184
## comm_psych_care                                          -0.03609294
## state_psych_care                                         -0.03484673
## mean_adhd                                                -0.12652092
## mean_ptsd                                                 0.33393361
## mean_bipolar                                             -0.09001648
## mean_depression                                           0.38521525
## mean_mental_hospital                                      0.07508085
## mean_psychiatrists_near_me                                0.05113036
## mean_psychologist_near_me                                 0.15990322
## anxiety_prop                                              0.09042046
## adhd_prop                                                 0.10675502
## bipolar_prop                                             -0.09079816
## prop_families_below_poverty                               0.12312374
## prop_adults_without_health_insurance                     -0.10655667
## prop_unemployed_in_labor_force                           -0.34452758
## prop_without_internet_access                              1.00000000
## prop_adult_disability                                     0.30396009
##                                       prop_adult_disability
## year                                               0.07154859
## anxiety_ct                                        -0.08941817
## trauma_stress_ct                                  -0.12802032
## adhd_ct                                           -0.04162040
## bipolar_ct                                        -0.11618594
## depression_ct                                     -0.11834226
## comm_psych_care                                   -0.15530682
## state_psych_care                                  -0.14673191
## mean_adhd                                          0.10998203
## mean_ptsd                                          0.10629585
## mean_bipolar                                       0.22223677
## mean_depression                                   -0.08167656
## mean_mental_hospital                               0.16483923
## mean_psychiatrists_near_me                        -0.23977062
## mean_psychologist_near_me                         -0.08569762
## anxiety_prop                                       0.09926407
## adhd_prop                                          0.20587109
## bipolar_prop                                       0.24830497
## prop_families_below_poverty                        0.65543780
## prop_adults_without_health_insurance               0.28992801
## prop_unemployed_in_labor_force                     0.06756309
## prop_without_internet_access                       0.30396009
## prop_adult_disability                              1.00000000
```

high correlation variables

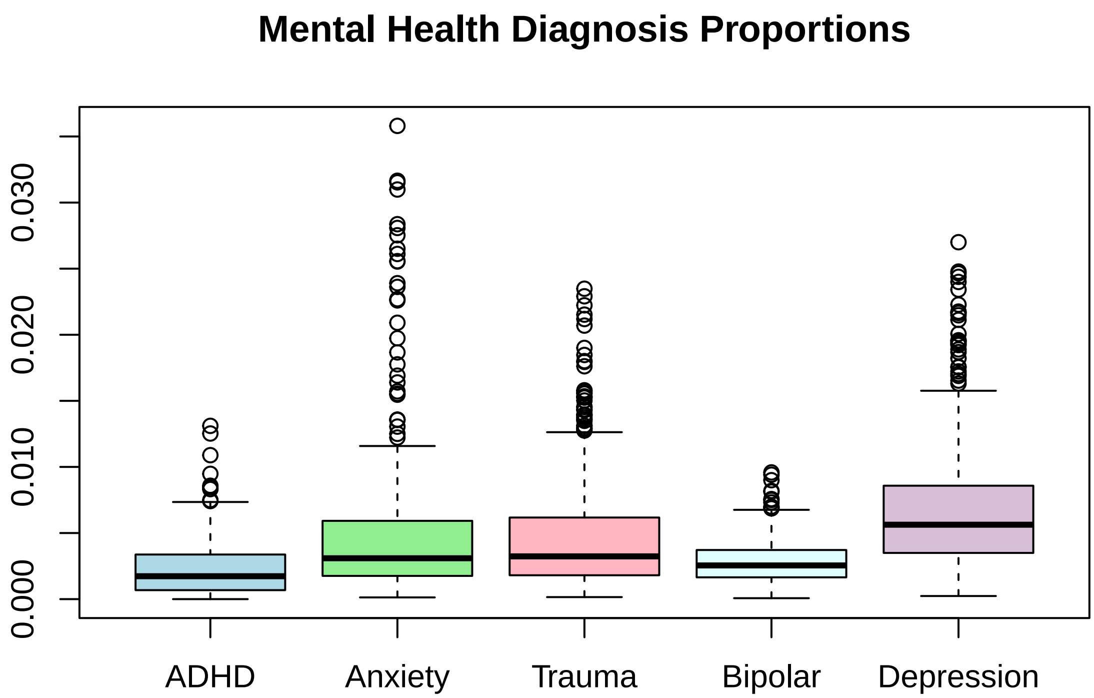
1. private, reside and comm__psych__care,
2. inpatient__util vs outpatient__util (i already have state__mentalhealth__util)
3. mean__therapist near__me vs mean__psychiatrist and mean__psychologist
4. mean__alltrend vs mean__adhd, mean__ptsd, mean__anxiety, mean__mentalhospital.
5. mean__anxiety vs year, mean__adhd & ptsd
6. outpatient__util vs total__util, adhd, bipolar & depression
7. total__util
8. depression prob vs adhd. ptsd, bipolar and trauma__stress__prop
9. trauma__stress__prop vs adhd, anxiety__prop and state__mentalhealth__util 10.state__mentalhealth__util vs adhd, ptsd, bipolar

```
#correlation matrix

GTrends_acs_joined %>%
  select_if(is.numeric) %>%
  select(-fips, -population_est,-private_psych_care, -total_util, -outpatient_util, -mean_anxiety, -resi
         -total_util) %>%
  cor() %>%

corrplot(diag = F,
         tl.cex = 0.7,
         tl.col = "black",
         main = "Correlation Matrix of GTrends_acs_joined",
         mar = c(0, 0, 1, 0))
```

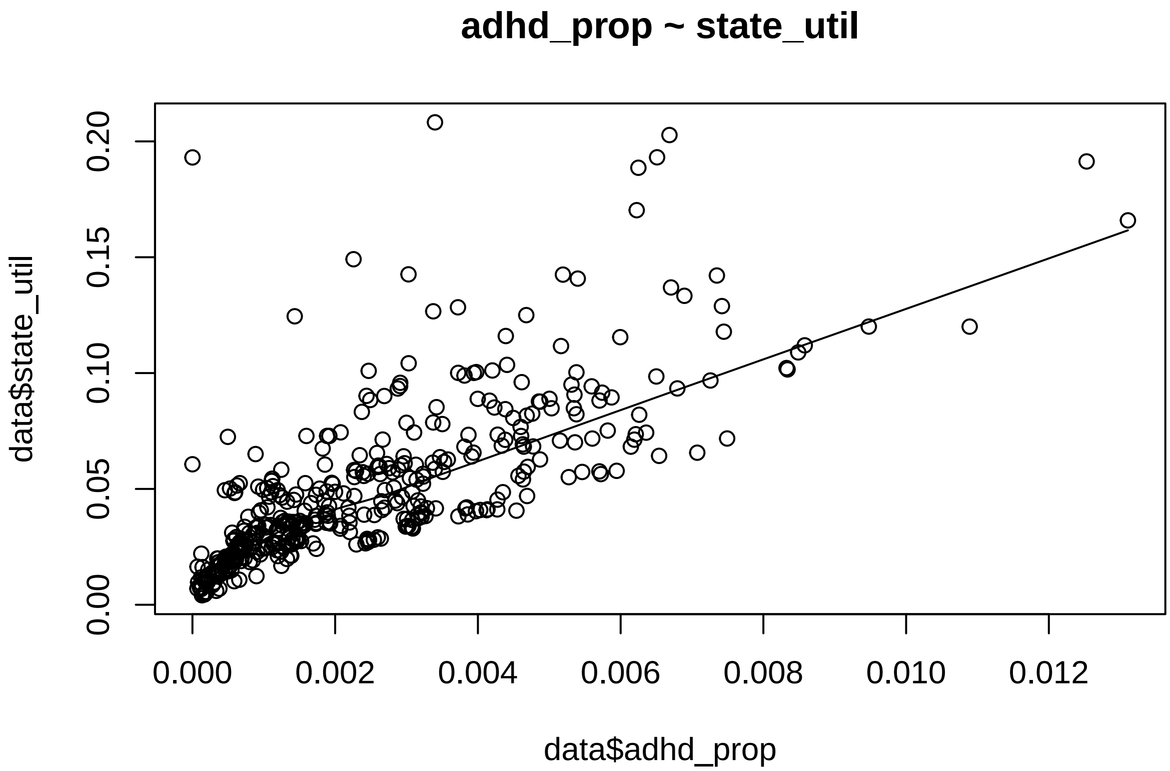



```
data <- data_GTrends
data$adhd_prop= data$adhd_ct/data$population_est
data$anxiety_prop = data$anxiety_ct/data$population_est
data$bipolar_prop = data$bipolar_ct/data$population_est
```

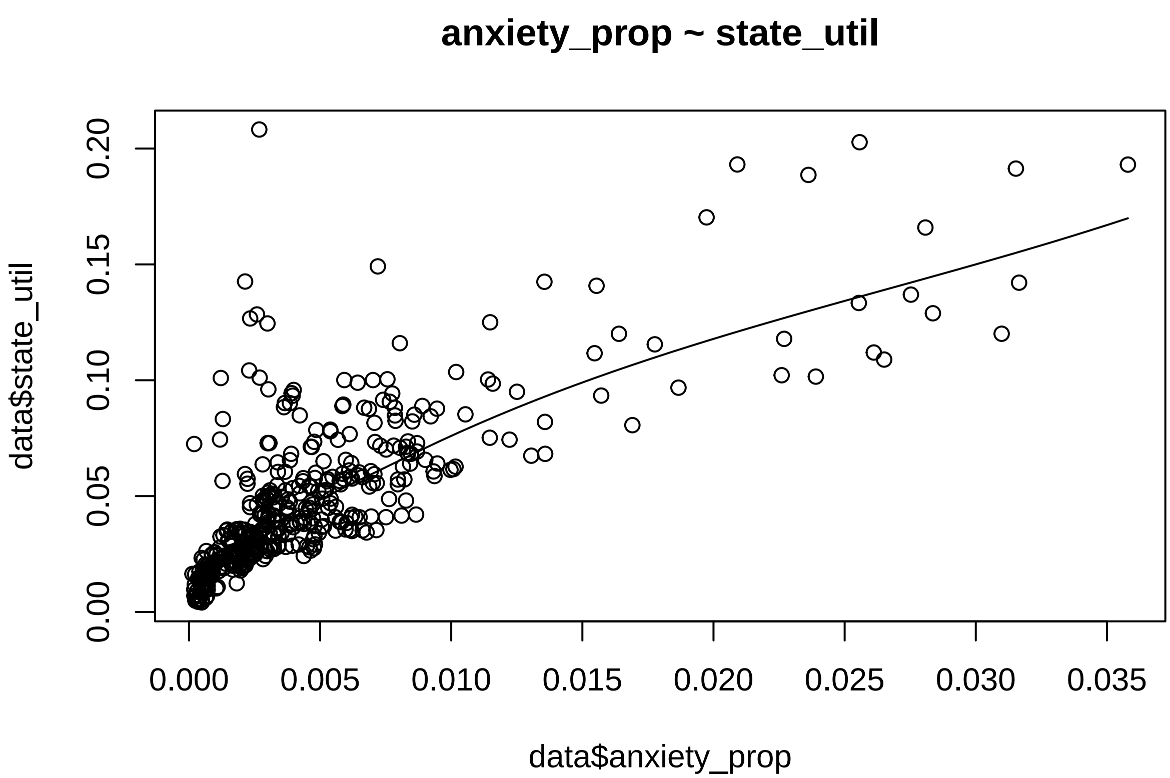
```r
data$depression_prop = data$depression_ct/data$population_est
data$trauma_prop = data$trauma_stress_ct/data$population_est
data$state_util = data$state_psych_care/data$population_est
data$private_util = data$private_psych_care/data$population_est
data$diff_util = data$total_util-(data$state_util + data$private_util)

boxplot(data[c("adhd_prop", "anxiety_prop", "trauma_prop", "bipolar_prop",  "depression_prop")],
        main = "Mental Health Diagnosis Proportions",
        names = c("ADHD", "Anxiety", "Trauma", "Bipolar", "Depression"),
        col = c("lightblue", "lightgreen", "lightpink", "lightcyan","thistle" ))
```



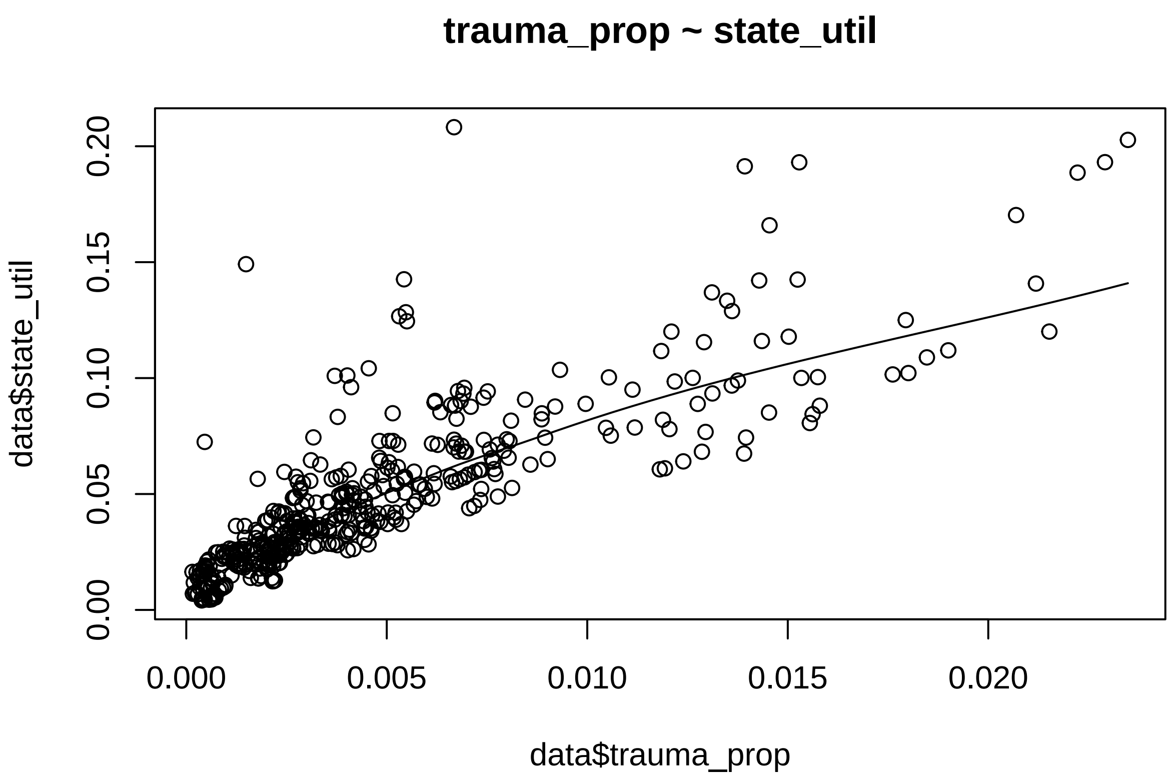

```r
par(mfrow=c(1,1))  # divide graph area in 2 columns
scatter.smooth(x=data$adhd_prop, y=data$state_util, main="adhd_prop ~ state_util")
```



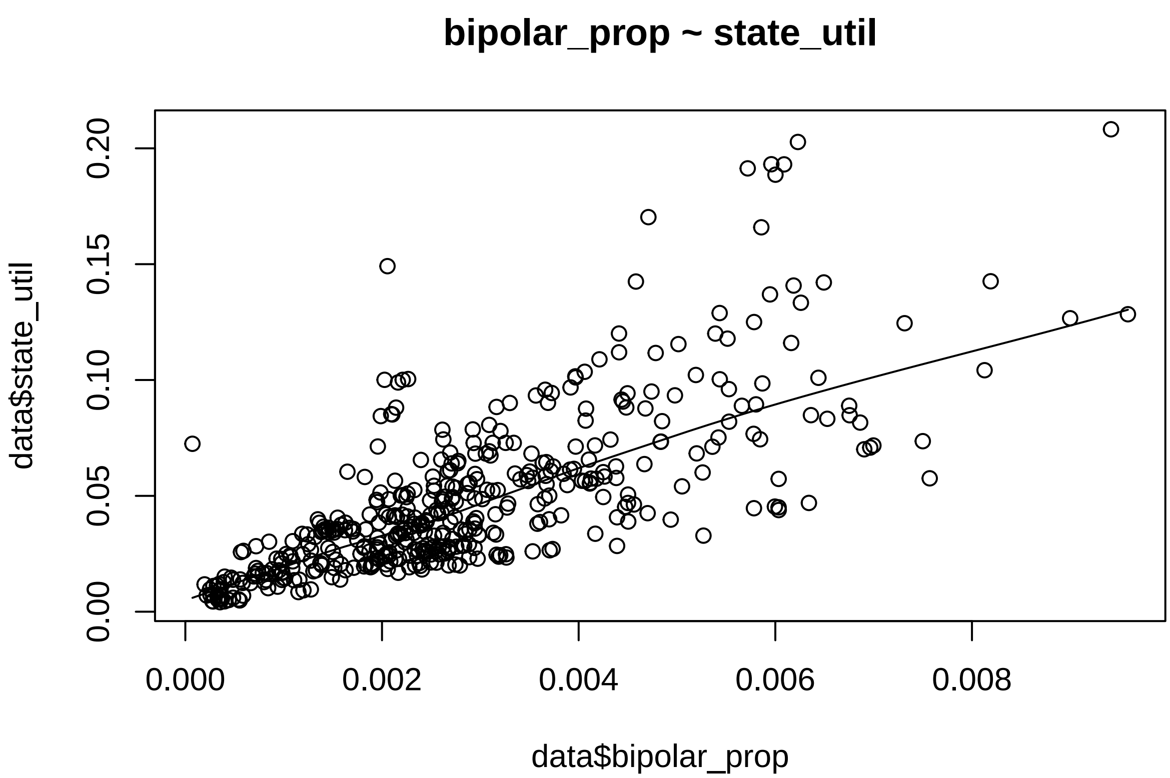

```r
scatter.smooth(x=data$anxiety_prop, y=data$state_util, main="anxiety_prop ~ state_util")
```



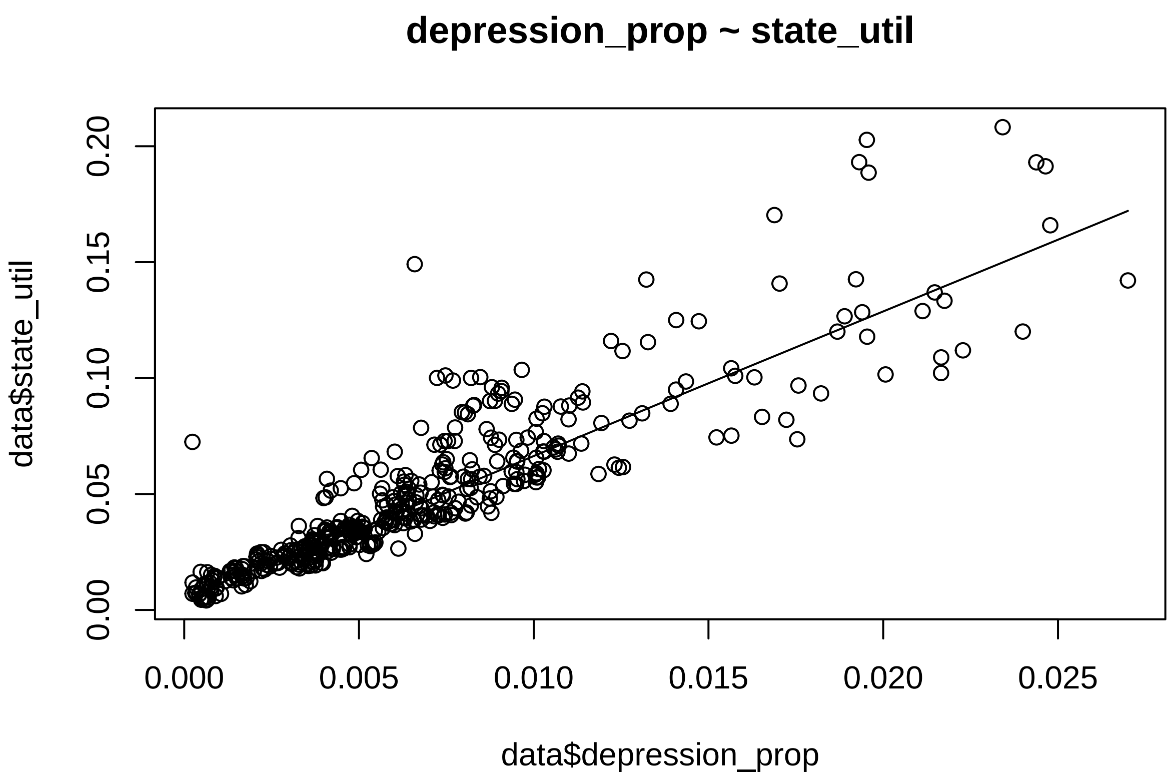
```r
scatter.smooth(x=data$trauma_prop, y=data$state_util, main="trauma_prop ~ state_util")
```




```r
scatter.smooth(x=data$bipolar_prop, y=data$state_util, main="bipolar_prop ~ state_util")
```



```r
scatter.smooth(x=data$depression_prop, y=data$state_util, main="depression_prop ~ state_util")
```

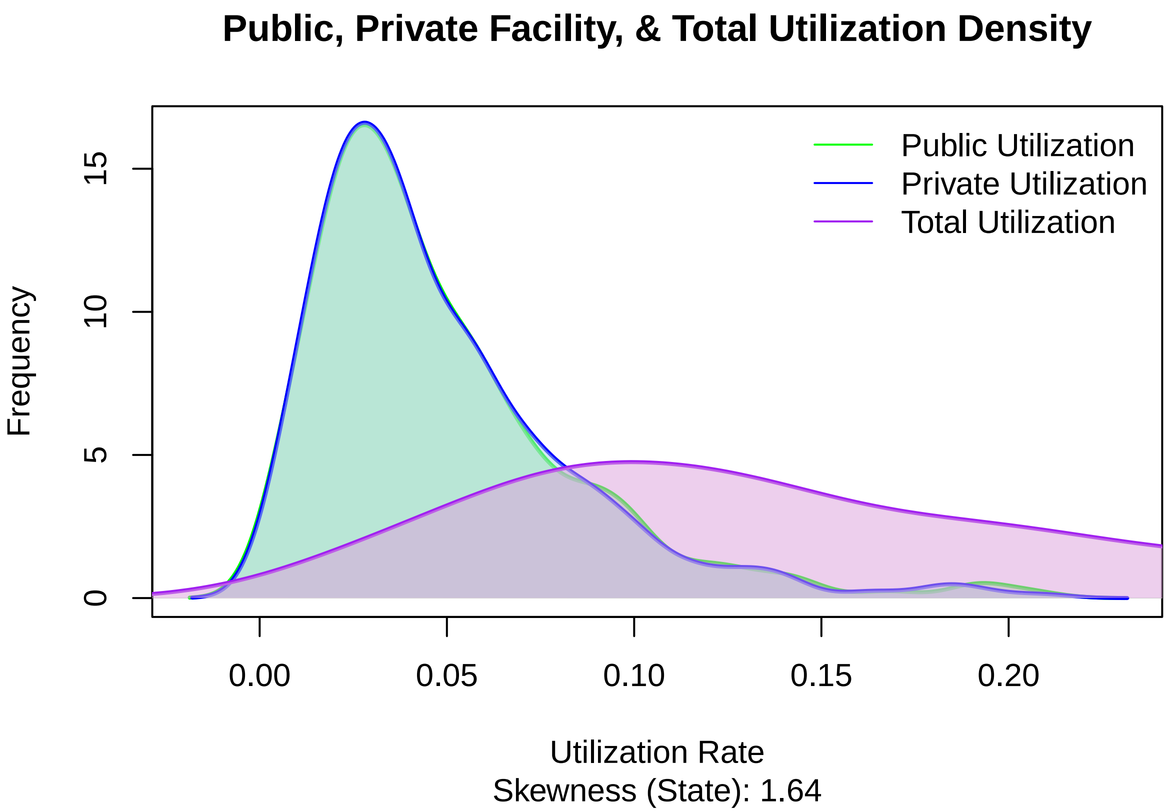



```r
library(e1071)
```

```
## Warning: package 'e1071' was built under R version 4.3.3
```

```r
par(mfrow=c(1, 1))

# Create a density plot that shows public, private, and total mental healthcare utilization rate
# frequency
plot(density(data$state_util),
     main = "Public, Private Facility, & Total Utilization Density",
     ylab = "Frequency",
     xlab = "Utilization Rate",
     col = "green",
     lwd = 2,
     sub = paste("Skewness (State):", round(e1071::skewness(data$state_util), 2)))

# Fill the first density with polygon
polygon(density(data$state_util), col = adjustcolor("lightgreen", alpha.f = 0.5), border = NA)

# Add second density line
lines(density(data$private_util), col = "blue", lwd = 2)
polygon(density(data$private_util), col = adjustcolor("lightblue", alpha.f = 0.5), border = NA)

# Add third density line
lines(density(data$total_util), col = "purple", lwd = 2)
```

```r
polygon(density(data$total_util), col = adjustcolor("plum", alpha.f = 0.5), border = NA)

# Add legend
legend("topright", legend = c("Public Utilization", "Private Utilization", "Total Utilization "),
       col = c("green", "blue", "purple"), lwd = 1, bty = "n")
```




```r
#data split: train and test dataset

clean_GTrends_acs_joined <- GTrends_acs_joined %>%
  select(-fips, -population_est,-private_psych_care, -total_util,
         # Comment the next line out and replace it to include region
         #-outpatient_util, -region, -mean_anxiety, -resid_psych_care,
         -outpatient_util, -mean_anxiety, -resid_psych_care,
         -mean_all_trends, -mean_therapist_near_me, -depression_prop,
         -trauma_stress_prop, -inpatient_util,
         -contains(c("median", "total")), -total_util) #i have added region as part of eliminated featu

test_n <- (1/sqrt(19))*nrow(clean_GTrends_acs_joined)
test_prop <- round((1/sqrt(19))*nrow(clean_GTrends_acs_joined)/nrow(clean_GTrends_acs_joined), 2)
train_prop <- 1-test_prop

paste("The ideal split ratio is", train_prop, ":", test_prop, " training : testing")
```

```
## [1] "The ideal split ratio is 0.77 : 0.23  training : testing"
```

```r
# Show the dimensions of the dataframe and the column names.
dim(clean_GTrends_acs_joined)
```

```
## [1] 433  26
```

```r
names(clean_GTrends_acs_joined)
```

```
##  [1] "year"
##  [2] "state"
##  [3] "region"
##  [4] "anxiety_ct"
##  [5] "trauma_stress_ct"
##  [6] "adhd_ct"
##  [7] "bipolar_ct"
##  [8] "depression_ct"
##  [9] "comm_psych_care"
## [10] "state_psych_care"
## [11] "mean_adhd"
## [12] "mean_ptsd"
## [13] "mean_bipolar"
## [14] "mean_depression"
## [15] "mean_mental_hospital"
## [16] "mean_psychiatrists_near_me"
## [17] "mean_psychologist_near_me"
## [18] "state_mentalhealth_util"
## [19] "anxiety_prop"
## [20] "adhd_prop"
## [21] "bipolar_prop"
## [22] "prop_families_below_poverty"
## [23] "prop_adults_without_health_insurance"
## [24] "prop_unemployed_in_labor_force"
## [25] "prop_without_internet_access"
## [26] "prop_adult_disability"
```

```r
# Remove some fields used in the calculation of the proportions
cols_to_exclude = c("anxiety_ct",
                    "trauma_stress_ct",
                    "adhd_ct","bipolar_ct",
                    "depression_ct",
                    "comm_psych_care",
                    "state_psych_care")
clean_GTrends_acs_joined <- clean_GTrends_acs_joined[,!(names(clean_GTrends_acs_joined)
                                                        %in% cols_to_exclude)]
names(clean_GTrends_acs_joined)
```

```
##  [1] "year"
##  [2] "state"
##  [3] "region"
##  [4] "mean_adhd"
##  [5] "mean_ptsd"
##  [6] "mean_bipolar"
##  [7] "mean_depression"
```

```
##  [8] "mean_mental_hospital"
##  [9] "mean_psychiatrists_near_me"
## [10] "mean_psychologist_near_me"
## [11] "state_mentalhealth_util"
## [12] "anxiety_prop"
## [13] "adhd_prop"
## [14] "bipolar_prop"
## [15] "prop_families_below_poverty"
## [16] "prop_adults_without_health_insurance"
## [17] "prop_unemployed_in_labor_force"
## [18] "prop_without_internet_access"
## [19] "prop_adult_disability"
```

```r
#write the merged dataframe to a CSV file with a time stamp in the  name.
# This way we don't overwrite the file in case someone else is working on the file.
# TimeStamp <- format(Sys.time(), "%Y%m%d_%H%M%S")
# file_name <- paste("~/GitHub/DSE6311OM_SP2025R2_Data-Science-Capstone/Data/clean_GTrends_acs_joined_"
# write.csv(clean_GTrends_acs_joined, file_name, row.names = FALSE)
```

```r
train <- createDataPartition(clean_GTrends_acs_joined$state_mentalhealth_util,
                             p = 0.77,
                             list = FALSE,
                             times = 1)


GTrend_training_set <- clean_GTrends_acs_joined[train, ]


test_set <- clean_GTrends_acs_joined[-train, ]

dim(GTrend_training_set)
```

```
## [1] 336  19
```

```r
dim(test_set)
```

```
## [1] 97 19
```

```r
head(test_set)
```

```
## # A tibble: 6 x 19
##    year state region       mean_adhd mean_ptsd mean_bipolar mean_depression
##   <dbl> <chr> <chr>            <dbl>     <dbl>        <dbl>           <dbl>
## 1  2013 AZ    West Pacific      20.1     10.6          22              62.1
## 2  2013 DE    Atlantic          24.2      8.83         25.1            65
## 3  2013 LA    South             23.7      8.08         21.7            53.7
## 4  2013 MT    West Pacific      20.1     13.1          24.3            65.6
## 5  2013 NE    Central           23.4      9.42         22.8            64.4
## 6  2013 NY    Atlantic          19.8      7.92         22.1            57.8
## # i 12 more variables: mean_mental_hospital <dbl>,
## #   mean_psychiatrists_near_me <dbl>, mean_psychologist_near_me <dbl>,
```

```
## #   state_mentalhealth_util <dbl>, anxiety_prop <dbl>, adhd_prop <dbl>,
## #   bipolar_prop <dbl>, prop_families_below_poverty <dbl>,
## #   prop_adults_without_health_insurance <dbl>,
## #   prop_unemployed_in_labor_force <dbl>, prop_without_internet_access <dbl>,
## #   prop_adult_disability <dbl>
```

```r
## One-hot encoding using fastDummies
train_encoded <- dummy_cols(GTrend_training_set,
                            select_columns = "region",
                            remove_first_dummy = FALSE, ## TRUE for true dummy encoding
                            remove_selected_columns = TRUE) ## Drops original columns

# Sanitize column names by replacing spaces in column names with underscores
train_encoded <- clean_names(train_encoded)

## Repeat to make test_encoded!
test_encoded <- dummy_cols(test_set,
                            select_columns = "region",
                            remove_first_dummy = FALSE, ## TRUE for true dummy encoding
                            remove_selected_columns = TRUE) ## Drops original columns

# Sanitize column names by replacing spaces in column names with underscores
test_encoded <- clean_names(test_encoded)

## Align test set with training set columns (IF NEEDED)
missingFeatures <- setdiff(names(train_encoded), names(test_encoded))

test_encoded[missingFeatures] <- 0
test_encoded <- test_encoded[, names(train_encoded)]
names(test_encoded)
```

```
##  [1] "year"
##  [2] "state"
##  [3] "mean_adhd"
##  [4] "mean_ptsd"
##  [5] "mean_bipolar"
##  [6] "mean_depression"
##  [7] "mean_mental_hospital"
##  [8] "mean_psychiatrists_near_me"
##  [9] "mean_psychologist_near_me"
## [10] "state_mentalhealth_util"
## [11] "anxiety_prop"
## [12] "adhd_prop"
## [13] "bipolar_prop"
## [14] "prop_families_below_poverty"
## [15] "prop_adults_without_health_insurance"
## [16] "prop_unemployed_in_labor_force"
## [17] "prop_without_internet_access"
## [18] "prop_adult_disability"
## [19] "region_atlantic"
## [20] "region_central"
## [21] "region_south"
## [22] "region_west_pacific"
```

```r
# Assign the encoded training set and test set
GTrend_training_set <- train_encoded
test_set <- test_encoded
```

TARGET ENCODING OF STATE BY Njagi

```r
unique(clean_GTrends_acs_joined$state)
```

```
##  [1] "AL" "AZ" "AR" "CA" "CO" "CT" "DE" "FL" "HI" "ID" "IL" "IN" "IA" "KS" "KY"
## [16] "LA" "MA" "MS" "MO" "MT" "NE" "NV" "NJ" "NM" "NY" "NC" "ND" "OH" "OK" "OR"
## [31] "PA" "RI" "SC" "SD" "TN" "TX" "UT" "VT" "VA" "WA" "WI" "WY" "MN" "MI" "AK"
## [46] "GA"
```

```r
is.factor(clean_GTrends_acs_joined$state) #checking whether region is a factor = false
```

```
## [1] FALSE
```

```r
GTrend_training_set$state <- factor(GTrend_training_set$state)

class(GTrend_training_set$state)
```

```
## [1] "factor"
```

```r
levels(GTrend_training_set$state)
```

```
##  [1] "AK" "AL" "AR" "AZ" "CA" "CO" "CT" "DE" "FL" "GA" "HI" "IA" "ID" "IL" "IN"
## [16] "KS" "KY" "LA" "MA" "MI" "MN" "MO" "MS" "MT" "NC" "ND" "NE" "NJ" "NM" "NV"
## [31] "NY" "OH" "OK" "OR" "PA" "RI" "SC" "SD" "TN" "TX" "UT" "VA" "VT" "WA" "WI"
## [46] "WY"
```

```r
# we are going to apply target encoding (state_mentalhealth_util). To avoid overfitting we are going to
#smoothed version of target encoding

main_mean <- mean(GTrend_training_set$state_mentalhealth_util)

smoothing_factor <- 10

#calculating the smoothed state means from the training set
state_encoded_by_smoothedmean <- GTrend_training_set %>%
  group_by(state) %>%
  summarise(state_encoded = (mean(state_mentalhealth_util) * n() + main_mean * smoothing_factor) / (n()

#merging the smoothed encoded state means with the training set

GTrend_training_set_f <- GTrend_training_set %>%
  left_join(state_encoded_by_smoothedmean, by = "state") %>%
  select(-state)


#merging smoothed encoded state means with the test_set
```

```r
test_set$state <- factor(test_set$state)

test_set_f <- test_set%>%
  left_join(state_encoded_by_smoothedmean, by = "state") %>%
  select(-state)

names(GTrend_training_set_f)
```

```
##  [1] "year"
##  [2] "mean_adhd"
##  [3] "mean_ptsd"
##  [4] "mean_bipolar"
##  [5] "mean_depression"
##  [6] "mean_mental_hospital"
##  [7] "mean_psychiatrists_near_me"
##  [8] "mean_psychologist_near_me"
##  [9] "state_mentalhealth_util"
## [10] "anxiety_prop"
## [11] "adhd_prop"
## [12] "bipolar_prop"
## [13] "prop_families_below_poverty"
## [14] "prop_adults_without_health_insurance"
## [15] "prop_unemployed_in_labor_force"
## [16] "prop_without_internet_access"
## [17] "prop_adult_disability"
## [18] "region_atlantic"
## [19] "region_central"
## [20] "region_south"
## [21] "region_west_pacific"
## [22] "state_encoded"
```

```r
state_util_index <- 10
test_set_f[, c(-10)] <- scale(test_set_f[, c(-10)],
                            center = apply(GTrend_training_set_f[, c(-10)], 2, mean),
                            scale = apply(GTrend_training_set_f[, c(-10)], 2, sd))
#(-10) is the state_mentalhealth_util, i want to exclude it from center and scale since its already a p


GTrend_training_set_f[, -10] <- scale(GTrend_training_set_f[, -10])

head(GTrend_training_set_f)
```

```
## # A tibble: 6 x 22
##    year mean_adhd mean_ptsd mean_bipolar mean_depression mean_mental_hospital
##   <dbl>     <dbl>     <dbl>        <dbl>           <dbl>                <dbl>
## 1 -1.57    -0.305    -1.77         0.932           -1.14               -0.237
## 2 -1.57    -0.512    -0.985        0.882            0.125              -0.290
## 3 -1.57    -0.935    -1.70        -0.674           -1.57                0.317
## 4 -1.57    -0.898    -0.883        0.480           -1.34                0.200
## 5 -1.57    -0.559    -1.39         0.781           -0.972               0.163
## 6 -1.57    -0.681    -2.07         0.731           -2.67               -0.370
## # i 16 more variables: mean_psychiatrists_near_me <dbl>,
```

```
## #   mean_psychologist_near_me <dbl>, state_mentalhealth_util <dbl>,
## #   anxiety_prop <dbl>, adhd_prop <dbl>, bipolar_prop <dbl>,
## #   prop_families_below_poverty <dbl>,
## #   prop_adults_without_health_insurance <dbl>,
## #   prop_unemployed_in_labor_force <dbl>, prop_without_internet_access <dbl>,
## #   prop_adult_disability <dbl>, region_atlantic <dbl>, ...
```

```r
#generating codebook

library(tibble)

codebook <- tibble(
  variable = names(clean_GTrends_acs_joined),
  class = sapply(clean_GTrends_acs_joined, class),
  "Number of Missing Values" = sapply(clean_GTrends_acs_joined, function(x) sum(is.na(x))),
  "Number of Unique Values" = sapply(clean_GTrends_acs_joined, function(x) length(unique(x)))
)

print(codebook)
```

```
## # A tibble: 19 x 4
##    variable                  class Number of Missing Va~1 Number of Unique Val~2
##    <chr>                     <chr>                  <int>                  <int>
##  1 year                      nume~                      0                     10
##  2 state                     char~                      0                     46
##  3 region                    char~                      0                      4
##  4 mean_adhd                 nume~                      0                    205
##  5 mean_ptsd                 nume~                      0                    114
##  6 mean_bipolar              nume~                      0                     97
##  7 mean_depression           nume~                      0                    230
##  8 mean_mental_hospital      nume~                      0                    272
##  9 mean_psychiatrists_near_~ nume~                      0                     59
## 10 mean_psychologist_near_me nume~                      0                    153
## 11 state_mentalhealth_util   nume~                      0                    433
## 12 anxiety_prop              nume~                      0                    433
## 13 adhd_prop                 nume~                      0                    433
## 14 bipolar_prop              nume~                      0                    433
## 15 prop_families_below_pove~ nume~                      0                    433
## 16 prop_adults_without_heal~ nume~                      0                    433
## 17 prop_unemployed_in_labor~ nume~                      0                    433
## 18 prop_without_internet_ac~ nume~                      0                    433
## 19 prop_adult_disability     nume~                      0                    433
## # i abbreviated names: 1: `Number of Missing Values`,
## #   2: `Number of Unique Values`
```

```r
codebook$variable
```

```
##  [1] "year"
##  [2] "state"
##  [3] "region"
##  [4] "mean_adhd"
##  [5] "mean_ptsd"
##  [6] "mean_bipolar"
```

```
##  [7] "mean_depression"
##  [8] "mean_mental_hospital"
##  [9] "mean_psychiatrists_near_me"
## [10] "mean_psychologist_near_me"
## [11] "state_mentalhealth_util"
## [12] "anxiety_prop"
## [13] "adhd_prop"
## [14] "bipolar_prop"
## [15] "prop_families_below_poverty"
## [16] "prop_adults_without_health_insurance"
## [17] "prop_unemployed_in_labor_force"
## [18] "prop_without_internet_access"
## [19] "prop_adult_disability"
```

```
# Create an empty dataframe with three fields store storing model train and test RMSE values.
mse_df <- tibble(
  Model = character(),
  Train_MSE = numeric(),
  Test_MSE = numeric(),
  Delta_MSE = numeric()
)

# Function to add rows to the mse_df
add_rmse_row <- function(df, model_name, train_mse, test_mse) {
  new_row <- tibble(
    Model = model_name,
    Train_MSE = train_mse,
    Test_MSE = test_mse,
    Delta_MSE = train_mse-test_mse
  )
  updated_df <- bind_rows(df, new_row)
  return(updated_df)
}
```

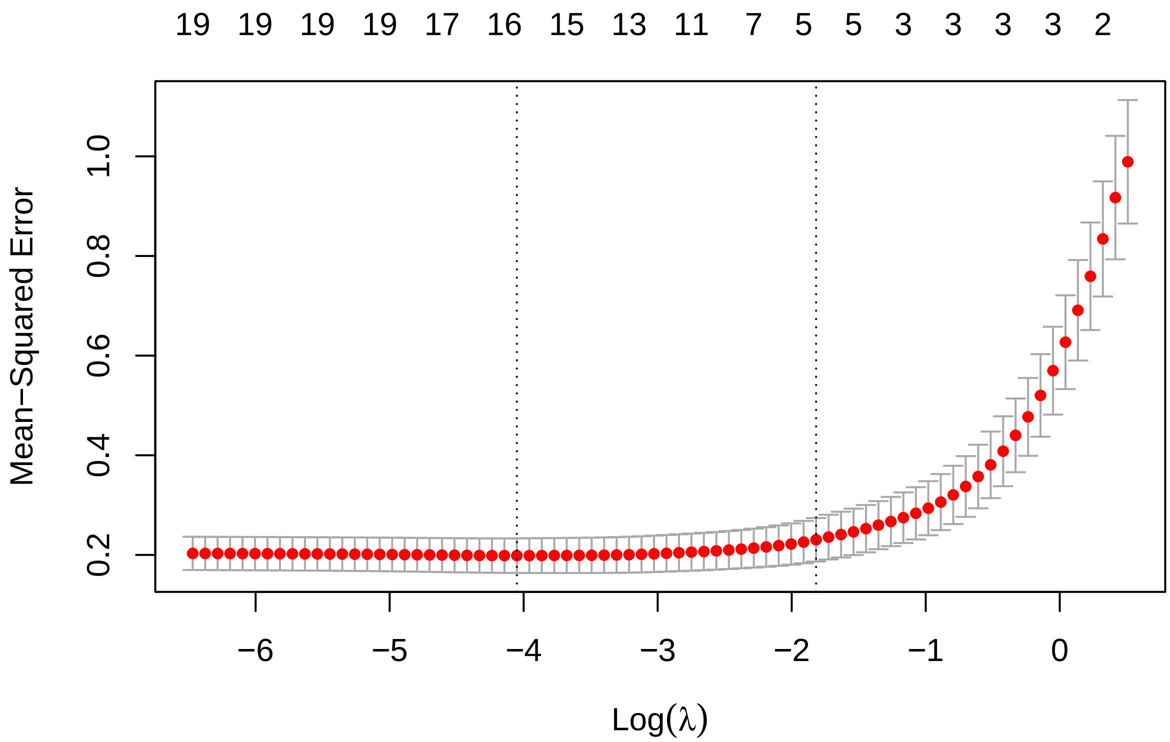
```
GTrend_training_set_f<- subset(GTrend_training_set_f, select = -state_encoded)
test_set_f <- subset(test_set_f, select = -state_encoded)
```

INITIAL MODELS BY Njagi

1. LINEAR REGRESSION (ELASTIC NET REGULARIZATION)

```
# DEVELOPING THE MODEL (LR. ENR)
#preparing the train set into matrix
x_train <- model.matrix(state_mentalhealth_util ~ ., data = GTrend_training_set_f, intercept = FALSE)
y_train <- GTrend_training_set_f$state_mentalhealth_util

#preparing the test set into matrix
x_test <- model.matrix(state_mentalhealth_util ~ ., data = test_set_f, intercept = FALSE)
y_test <- test_set_f$state_mentalhealth_util

#Performing cross_validation to find the best lambda

set.seed(123) # for consistent and replicable results
```

```
cv_model <- cv.glmnet(x_train, y_train, alpha = 0.5, family = "gaussian", nfolds = 5)

plot(cv_model) #plotting cross-validation curve
```




```
train_preds <- predict(cv_model, newx=x_train)
test_preds <- predict(cv_model, newx=x_test)

elastic_net_train_mse <- mean((train_preds-y_train)^2)
elastic_net_test_mse <- mean((test_preds-y_test)^2)
#add the test and train RMSEs to the mse_df
mse_df <-  add_rmse_row(mse_df, "Elastic Net", elastic_net_train_mse, elastic_net_test_mse)
```

```
#getting the best/ optimal lambda
best_lambda <- cv_model$lambda.min
best_lambda_1se <- cv_model$lambda.1se


#developing the model using the best lambda
model_min <- glmnet(x_train, y_train, alpha = 0.5, lambda = best_lambda, family = "gaussian")
model_lambda_1se <- glmnet(x_train, y_train, alpha = 0.5, lambda = best_lambda_1se, family = "gaussian")

#preparing the test set into matrix
x_test <- model.matrix(state_mentalhealth_util ~ ., data = test_set_f, intercept = FALSE)
y_test <- test_set_f$state_mentalhealth_util

#ensure x and x_test have the same number of columns. its a good practise after using model.matrix
common_columns <- intersect(colnames(x_train), colnames(x_test))
x_train <- x_train[, common_columns]
x_test <- x_test[, common_columns]
```

```r
# use test set to make predictions, use lambda min and lambda_1se
y_pred_min <- predict(model_min, newx = x_test)
y_pred_1se <- predict(model_lambda_1se, newx = x_test)

#calculate the mean squared error
mse_min <- mean((y_test - y_pred_min)^2)
mse_1se <- mean((y_test - y_pred_1se)^2)


print(paste("MSE (MIN):", mse_min))
```

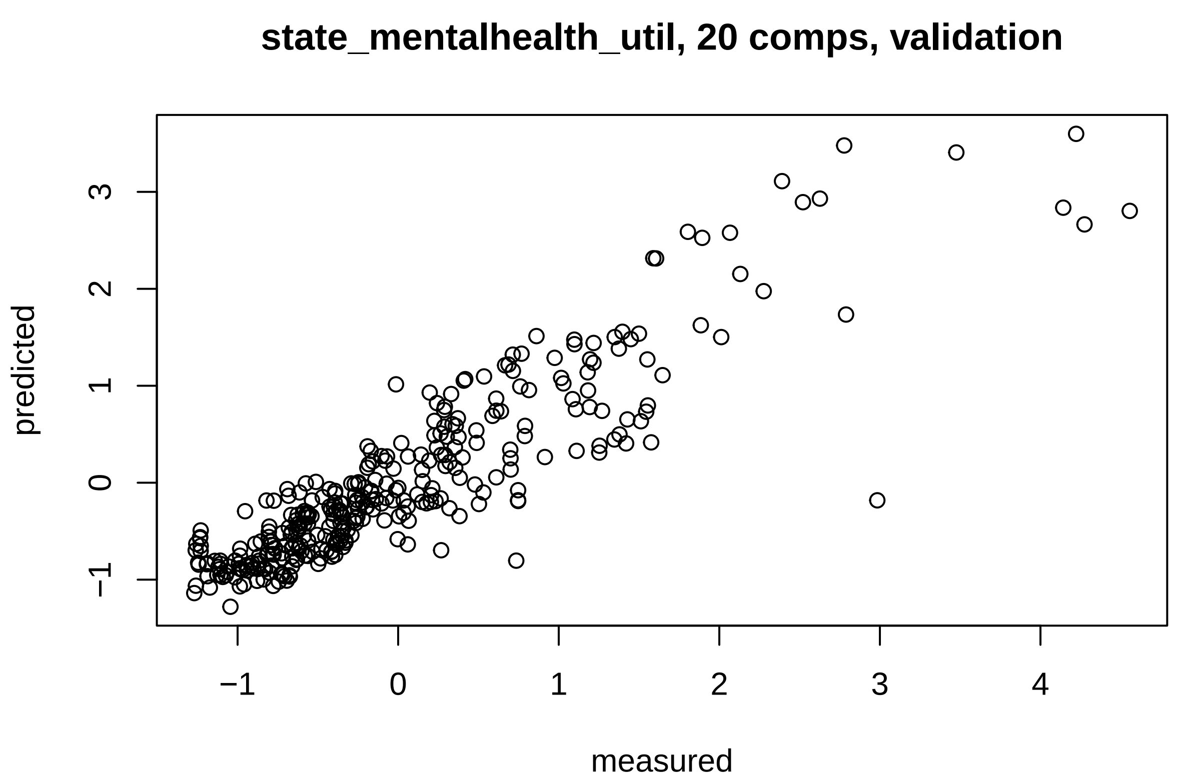
```
## [1] "MSE (MIN): 0.156000549003981"
```

```r
print(paste("MSE (1SE):", mse_1se))
```

```
## [1] "MSE (1SE): 0.217409251822564"
```

Principal Component Regression (PCR)

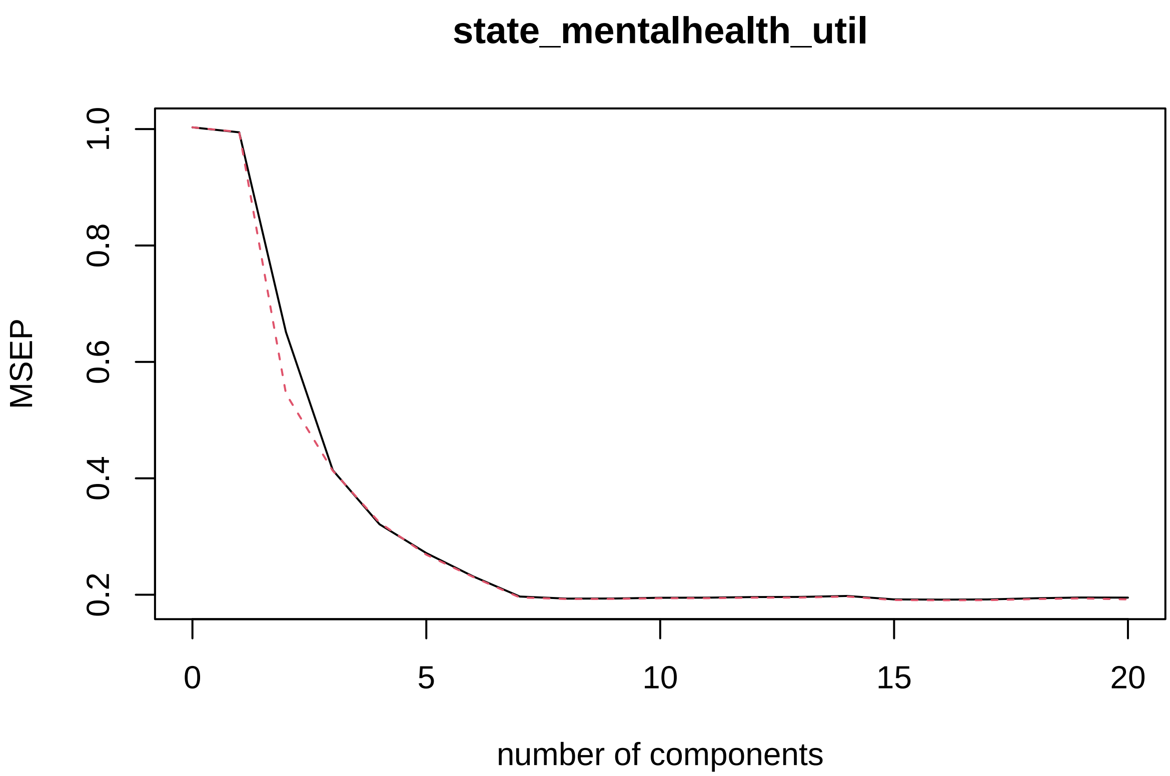
```r
pcr_m_selected <- 1

# Get the PCR fit for the training data set
pcr_fit <- pcr(state_mentalhealth_util ~ ., data =GTrend_training_set_f ,
               scale=TRUE, validation="CV")
# plot the PCR fit
plot(pcr_fit)
```



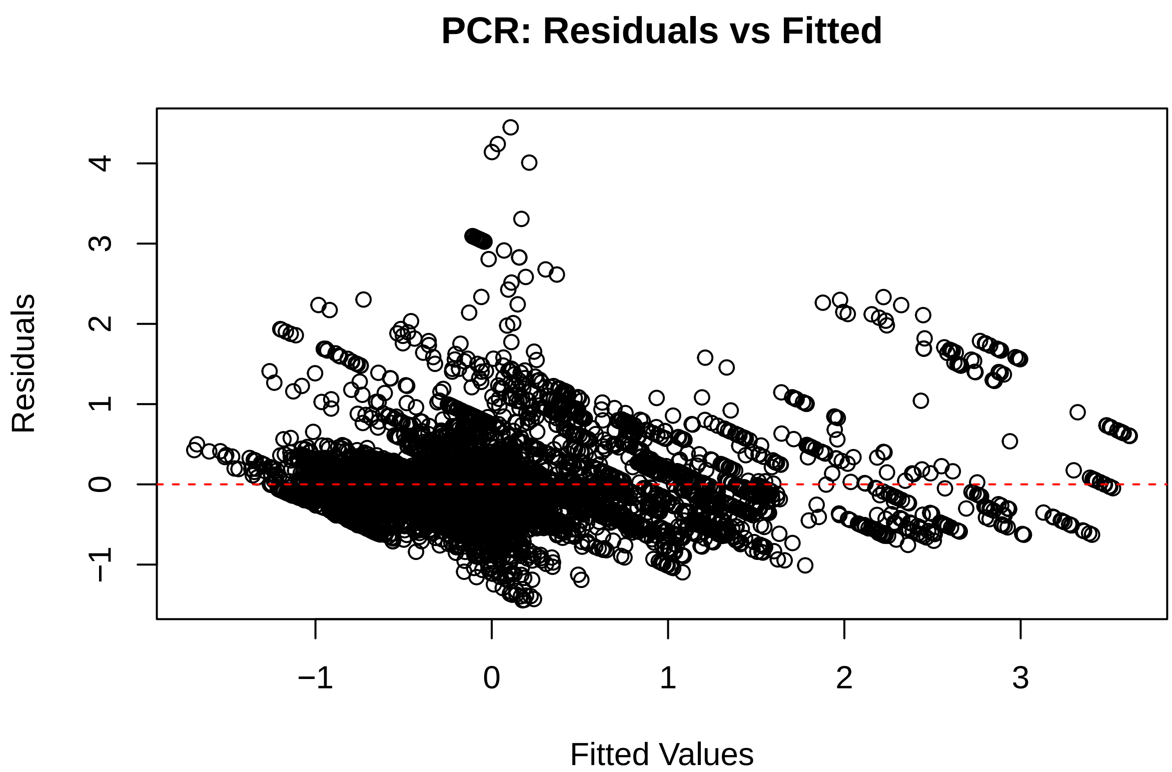
```r
# Show the summary of the PCR fit.
summary(pcr_fit)
```

```
## Data:    X dimension: 336 20
##  Y dimension: 336 1
## Fit method: svdpc
## Number of components considered: 20
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           1.001   0.9972   0.8069   0.6434   0.5666   0.5211   0.4812
## adjCV        1.001   0.9975   0.7384   0.6427   0.5690   0.5185   0.4801
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV      0.4437   0.4397   0.4399    0.4413    0.4416    0.4427    0.4430
## adjCV   0.4420   0.4389   0.4392    0.4405    0.4405    0.4416    0.4418
##        14 comps  15 comps  16 comps  17 comps  18 comps  19 comps  20 comps
## CV       0.4449    0.4381    0.4377    0.4381    0.4404    0.4418    0.4416
## adjCV    0.4437    0.4369    0.4365    0.4367    0.4388    0.4402    0.4381
##
## TRAINING: % variance explained
##                          1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                         19.517    34.06    48.08    58.03    66.69    74.26
## state_mentalhealth_util    2.094    52.96    60.48    69.31    74.44    78.56
##                          7 comps  8 comps  9 comps  10 comps  11 comps
## X                           79.9     84.5    88.17     90.90     92.87
## state_mentalhealth_util     81.6     81.7    81.70     81.71     82.12
##                          12 comps  13 comps  14 comps  15 comps  16 comps
## X                           94.48     95.82      96.9     97.87     98.62
## state_mentalhealth_util     82.20     82.20      82.2     82.73     82.78
##                          17 comps  18 comps  19 comps  20 comps
## X                           99.24     99.72    100.00    100.00
## state_mentalhealth_util     83.01     83.01     83.05     83.14
```

```r
# Show the validation plot.
validationplot(pcr_fit, val.type="MSEP")
```




```r
# Plot the residuals vs the fitted values.
pcr_fitted_vals <- as.vector(fitted(pcr_fit, ncomp=5))
pcr_residuals <- as.vector(residuals(pcr_fit, ncomp=5))
plot(pcr_fitted_vals, pcr_residuals,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "PCR: Residuals vs Fitted")
abline(h = 0, col = "red", lty = 2)
```




```
# Get the predictions
pcr_preds_train <- predict(pcr_fit, data=GTrend_training_set_f, ncomp=pcr_m_selected)
pcr_preds_test <- predict(pcr_fit, data=test_set, ncomp=pcr_m_selected)

# Store and print the pcr mean square error for M_selected.
pcr_train_mse <- mean((pcr_preds_train-GTrend_training_set_f$state_mentalhealth_util)^2)
pcr_test_mse <- mean((pcr_preds_test-test_set$state_mentalhealth_util)^2)

#add the test and train RMSEs to the mse_df
mse_df <-  add_rmse_row(mse_df, "Principal Component Regression", pcr_train_mse, pcr_test_mse)

paste("PCR Train MSE for M Selected:",pcr_m_selected,"is", pcr_train_mse)
```

```
## [1] "PCR Train MSE for M Selected: 1 is 0.976150288333769"
```

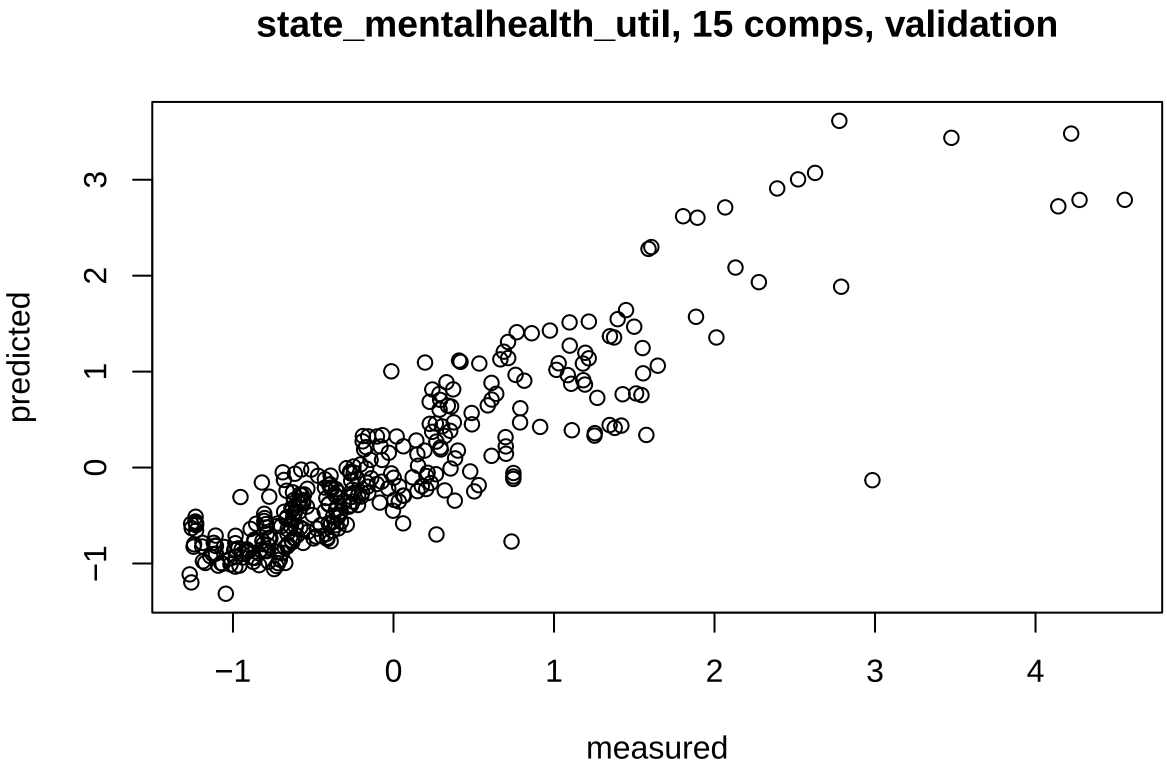
```
paste("PCR Test MSE for M Selected:",pcr_m_selected,"is", pcr_test_mse)
```

```
## [1] "PCR Test MSE for M Selected: 1 is 0.0237374704623666"
```

Partial Least Squares Regression (PLSR)

```
# Set the PLS M selected value.
plsr_M_selected <- 15

# Get the PCR fit for the training data set
plsr_fit <- plsr(state_mentalhealth_util ~ ., data=GTrend_training_set_f ,
                 scale=TRUE, validation="CV", ncomp=plsr_M_selected)
```

```r
# Plot the PLSR fit
plot(plsr_fit)
```

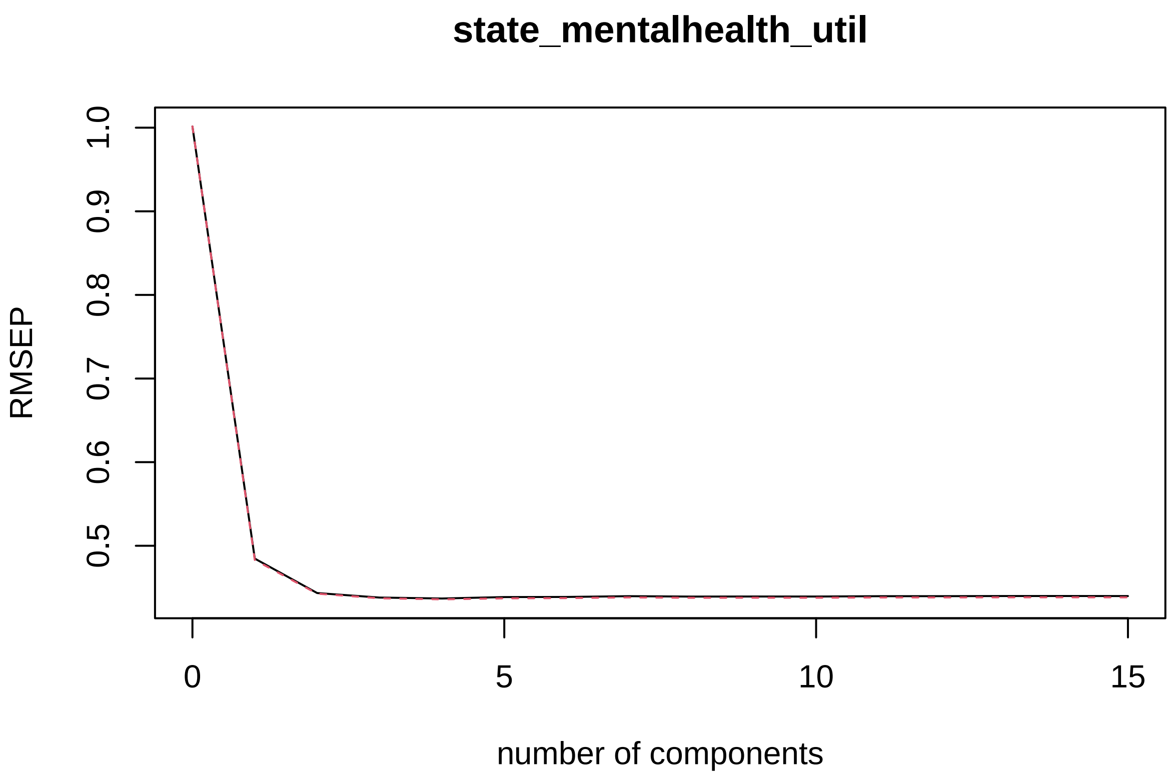



```r
# print the summary of the partial least square regression fit.
summary(plsr_fit)
```

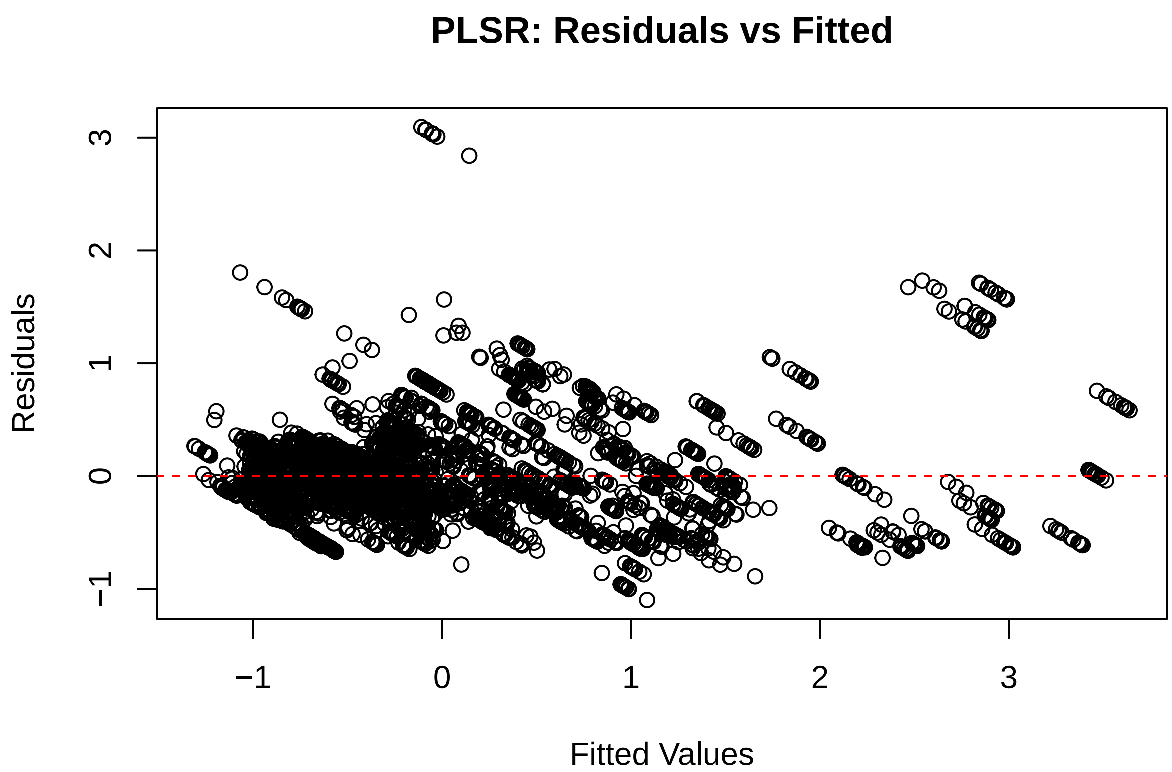
```
## Data:    X dimension: 336 20
##  Y dimension: 336 1
## Fit method: kernelpls
## Number of components considered: 15
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           1.001   0.4847   0.4434   0.4381   0.4370   0.4386   0.4388
## adjCV        1.001   0.4830   0.4427   0.4372   0.4359   0.4372   0.4374
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV      0.4397   0.4393   0.4393    0.4393    0.4397    0.4397    0.4399
## adjCV   0.4382   0.4378   0.4379    0.4378    0.4382    0.4382    0.4384
##        14 comps  15 comps
## CV       0.4399    0.4398
## adjCV    0.4384    0.4383
##
## TRAINING: % variance explained
##                         1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                         14.16    26.30    41.04    48.19    53.53    62.84
## state_mentalhealth_util   78.08    81.69    82.29    82.63    82.89    82.96
##                         7 comps  8 comps  9 comps  10 comps  11 comps
```

```
## X                           71.56    75.14    81.99     85.40     87.93
## state_mentalhealth_util     83.00    83.03    83.04     83.04     83.04
##                           12 comps  13 comps  14 comps  15 comps
## X                           90.28     92.28     94.21     96.34
## state_mentalhealth_util     83.05     83.05     83.05     83.05
```

```r
# Show the validation plot
validationplot(plsr_fit)
```




```r
# Plot the residuals vs the fitted values.
plsr_fitted_vals <- as.vector(fitted(plsr_fit, ncomp=5))
plsr_residuals <- as.vector(residuals(plsr_fit, ncomp=5))
plot(plsr_fitted_vals, plsr_residuals,
     xlab = "Fitted Values",
     ylab = "Residuals",
     main = "PLSR: Residuals vs Fitted")
abline(h = 0, col = "red", lty = 2)
```




```
# Get the predictions
plsr_train_preds <- predict(plsr_fit, data=GTrend_training_set_f, ncomp=plsr_M_selected)
plsr_test_preds <- predict(plsr_fit, data=test_set_f, ncomp=plsr_M_selected)

# Store and print the MSE value for the PLSR
plsr_train_mse <- mean((plsr_train_preds-GTrend_training_set_f$state_mentalhealth_util)^2)
plsr_test_mse <- mean((plsr_test_preds-test_set_f$state_mentalhealth_util)^2)

#add the test and train RMSEs to the mse_df
mse_df <-  add_rmse_row(mse_df, "Partial Least Squares Regression", plsr_train_mse, plsr_test_mse)

paste("PLSR Train MSE for M Selected:",plsr_M_selected,"is", plsr_train_mse)
```

```
## [1] "PLSR Train MSE for M Selected: 15 is 0.169030339951674"
```

```
paste("PLSR Test MSE for M Selected:",plsr_M_selected,"is", plsr_test_mse)
```

```
## [1] "PLSR Test MSE for M Selected: 15 is 1.68050161028894"
```

Best Subset Selection

```
# Load library needed for regsubsets() function
library(leaps)

# The regsubsets() function (part of the leaps library) performs best sub- set selection
# by identifying the best model that contains a given number of predictors, where best
# is quantified using RSS.
```

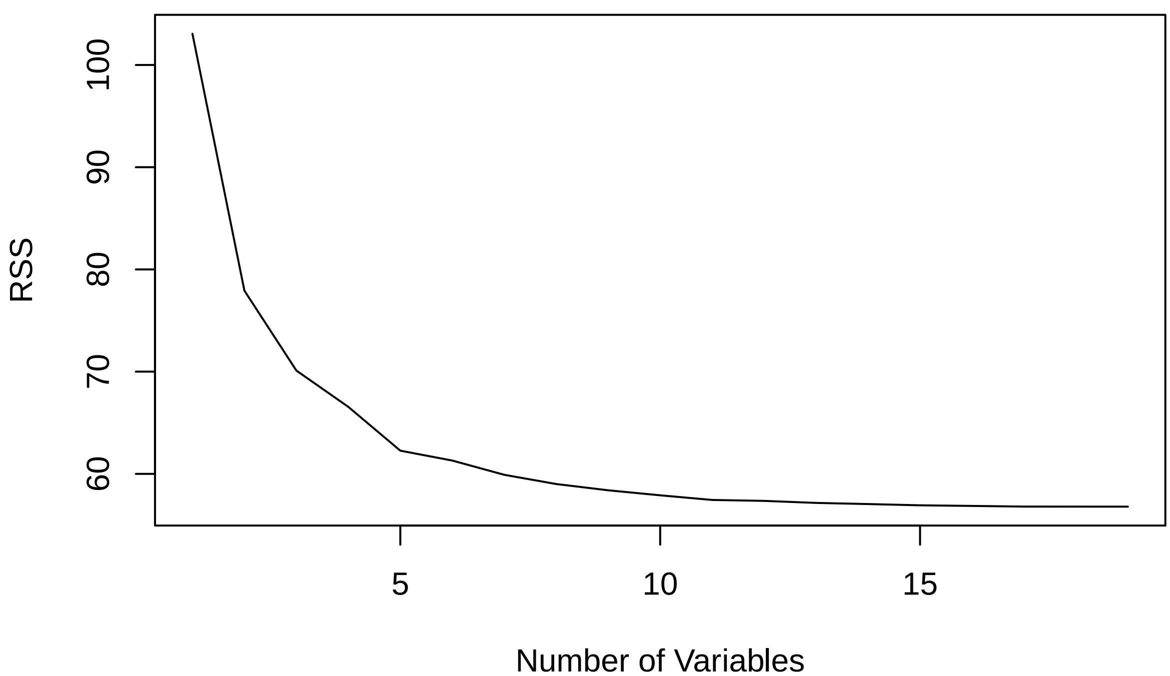
```r
reg_fit_train <- regsubsets(state_mentalhealth_util ~ ., data=GTrend_training_set_f, nvmax=23)

# plot(reg_fit_train, scale="r2")
# plot(reg_fit_train, scale="adjr2")
# plot(reg_fit_train, scale="Cp")
# plot(reg_fit_train, scale="bic")
# The summary() command outputs the best set of variables for each model size.
reg.summary <- summary(reg_fit_train)
#print(reg.summary)
names(reg.summary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

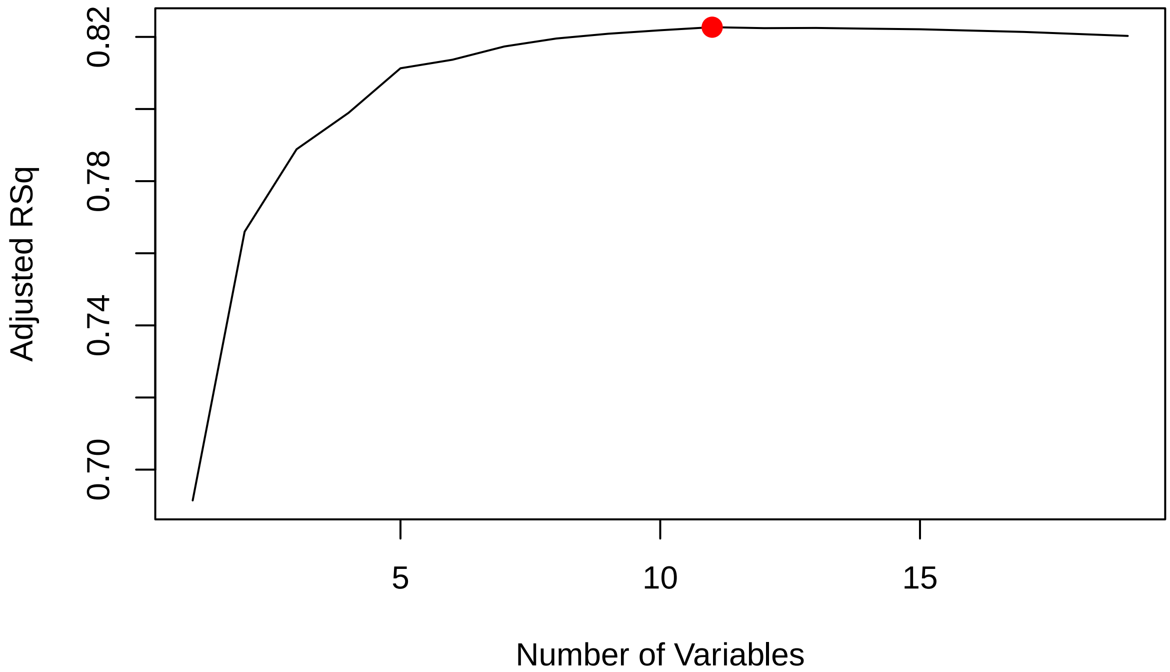
```r
#Print the R^2 statistic
reg.summary$rsq
```

```
##  [1] 0.6923734 0.7673893 0.7907310 0.8013363 0.8141220 0.8170127 0.8211679
##  [8] 0.8238626 0.8256914 0.8271587 0.8285138 0.8287855 0.8293753 0.8297109
## [15] 0.8300799 0.8302590 0.8304507 0.8304579 0.8304651
```

```r
#par(mfrow=c(1,2))
plot(reg.summary$rss, xlab="Number of Variables", ylab="RSS", type="l")
```




```r
plot(reg.summary$adjr2 , xlab = "Number of Variables",ylab = "Adjusted RSq", type = "l")

# which.max(reg.summary$adjr2)
plot(reg.summary$adjr2 , xlab = "Number of Variables", ylab = "Adjusted RSq", type = "l")
points(which.max(reg.summary$adjr2), reg.summary$adjr2[which.max(reg.summary$adjr2)],
       col = "red", cex = 2, pch = 20)
```




```r
names(GTrend_training_set_f)
```

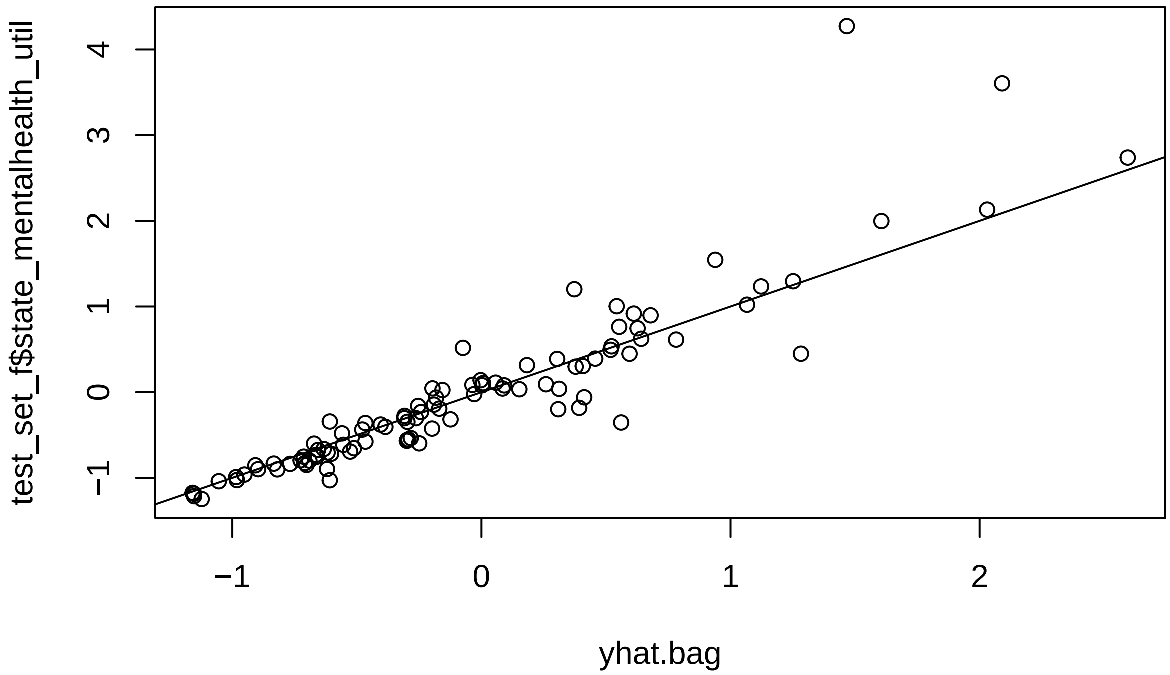
```
##  [1] "year"
##  [2] "mean_adhd"
##  [3] "mean_ptsd"
##  [4] "mean_bipolar"
##  [5] "mean_depression"
##  [6] "mean_mental_hospital"
##  [7] "mean_psychiatrists_near_me"
##  [8] "mean_psychologist_near_me"
##  [9] "state_mentalhealth_util"
## [10] "anxiety_prop"
## [11] "adhd_prop"
## [12] "bipolar_prop"
## [13] "prop_families_below_poverty"
## [14] "prop_adults_without_health_insurance"
## [15] "prop_unemployed_in_labor_force"
## [16] "prop_without_internet_access"
## [17] "prop_adult_disability"
## [18] "region_atlantic"
## [19] "region_central"
## [20] "region_south"
## [21] "region_west_pacific"
```

Random Forest

```r
library(randomForest)
set.seed(42)
# Bagging
bag.data <- randomForest(state_mentalhealth_util ~ ., data=GTrend_training_set_f, mtry=24, importance=T
bag.data
```

```
##
## Call:
##  randomForest(formula = state_mentalhealth_util ~ ., data = GTrend_training_set_f,      mtry = 24, i
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 20
##
##           Mean of squared residuals: 0.1349072
##                     % Var explained: 86.47
```

```
yhat.bag <- predict(bag.data, newdata=test_set_f)

plot(yhat.bag, test_set_f$state_mentalhealth_util)
abline(0,1)
```




```
bagged_mse <- mean((yhat.bag - test_set_f$state_mentalhealth_util)^2)
paste ("Test MSE associated with the bagged regression is:", bagged_mse)
```

```
## [1] "Test MSE associated with the bagged regression is: 0.164275815686234"
```

```
# Random Forest
rf_model <- randomForest(state_mentalhealth_util ~ .,
                         data=GTrend_training_set_f,
                         mtry = 12,
                         importance = TRUE)
print(rf_model)
```

```
##
## Call:
##  randomForest(formula = state_mentalhealth_util ~ ., data = GTrend_training_set_f,      mtry = 12, i
```

```
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 12
##
##           Mean of squared residuals: 0.1310277
##                     % Var explained: 86.86
```

```r
yhat_train_rf <- predict(rf_model, newdata = GTrend_training_set_f)
yhat_test_rf <- predict(rf_model, newdata = test_set_f)

# Calculate the train and test mean square errors
rf_train_mse <- mean((yhat_train_rf - GTrend_training_set_f$state_mentalhealth_util)^2)
rf_test_mse <- mean((yhat_test_rf - test_set_f$state_mentalhealth_util)^2)

#add the test and train RMSEs to the mse_df
mse_df <- add_rmse_row(mse_df, "Random Forest", rf_train_mse, rf_test_mse)

paste("Train MSE associated with the Random Forest is: =", rf_train_mse)
```

```
## [1] "Train MSE associated with the Random Forest is: = 0.0214065566108363"
```

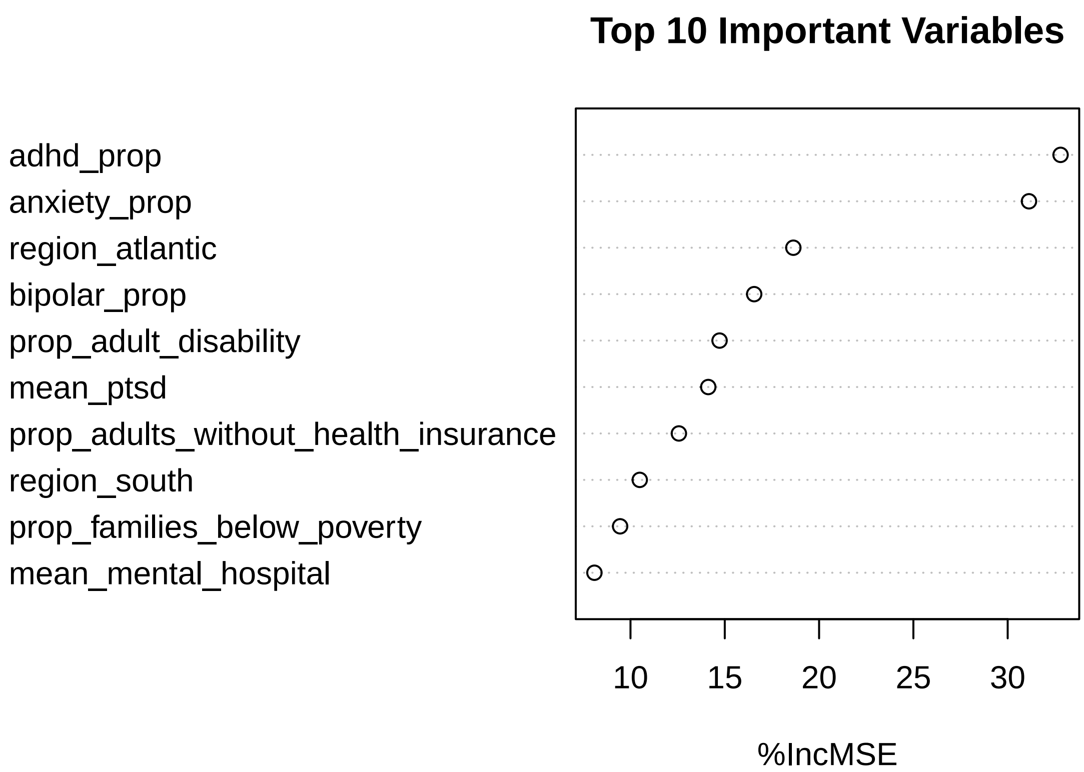
```r
paste("Test MSE associated with the Random Forest is: =", rf_test_mse)
```

```
## [1] "Test MSE associated with the Random Forest is: = 0.156521361326391"
```

```r
imp <- importance(rf_model)
# Let's sort the output of the importance() function
imp_df <- data.frame(Variable = rownames(imp), imp)
imp_sorted <- imp_df[order(-imp_df$X.IncMSE), ]
head(imp_sorted)
```

```
##                                    Variable X.IncMSE IncNodePurity
## adhd_prop                         adhd_prop 32.80460    110.787783
## anxiety_prop                   anxiety_prop 31.12953    126.817498
## region_atlantic             region_atlantic 18.63535      6.027650
## bipolar_prop                   bipolar_prop 16.55793     33.678015
## prop_adult_disability prop_adult_disability 14.72331      9.269517
## mean_ptsd                         mean_ptsd 14.12375     11.387996
```

```r
# Show the importance plot
#varImpPlot(rf_model)
varImpPlot(
  x = rf_model,     # trained random forest
  sort = TRUE,      # sort by importance
  n.var = 10,       # show top 10 variables
  type = 1,         # mean decrease in accuracy
  main = "Top 10 Important Variables"
)
```

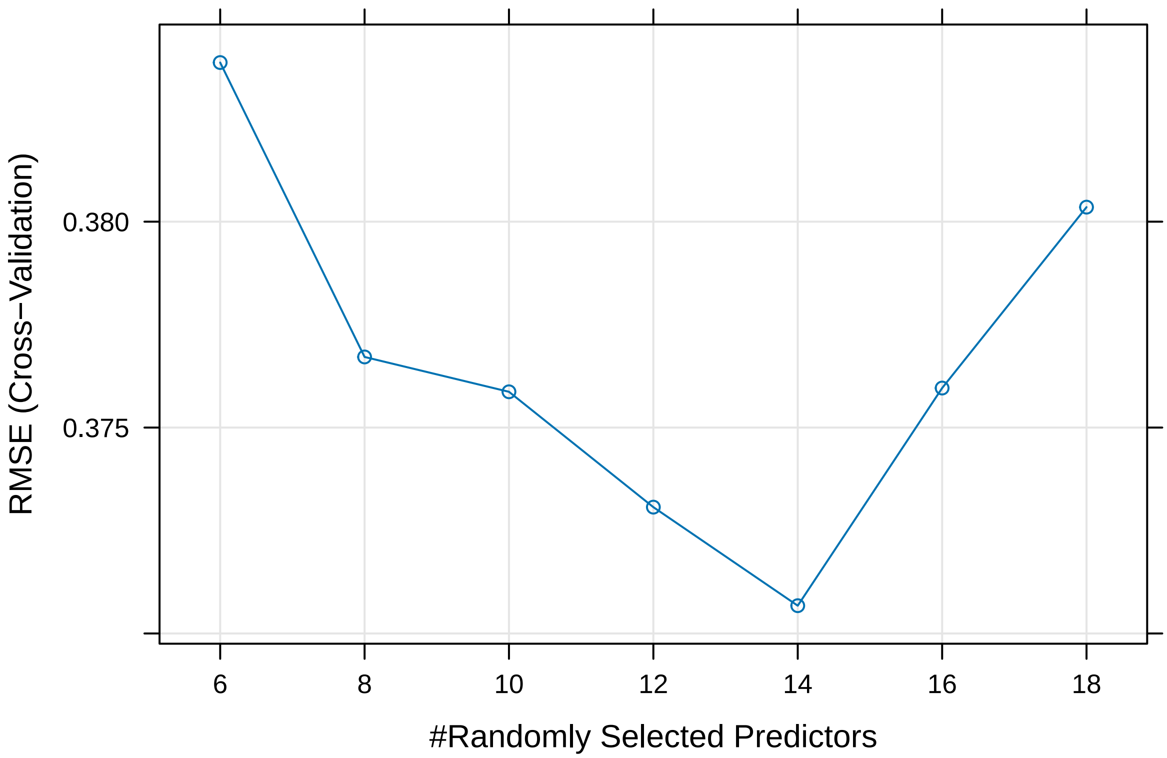



```r
set.seed(42)

# Set up a 5 fold cross-vlidation for the random forest model.
rf_control <- trainControl(method="cv", number=5)

# Define the tuning grid with values for mtry at 8, 10, 12, or 14.
tune_grid <- expand.grid(.mtry = c(6, 8, 10, 12, 14, 16, 18))

# Train the random forest model using k-fold cross validation
rf_cv_model <- train(state_mentalhealth_util ~ .,
                     data = GTrend_training_set_f,
                     method = "rf",
                     trControl = rf_control,
                     tuneGrid = tune_grid,
                     importance = TRUE)
# Print the results
print(rf_cv_model)
```

```
## Random Forest
##
## 336 samples
##  20 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 268, 269, 269, 269, 269
## Resampling results across tuning parameters:
##
##   mtry  RMSE       Rsquared   MAE
```

```
##    6     0.3838649  0.8632106  0.2297460
##    8     0.3767151  0.8648211  0.2243657
##   10     0.3758689  0.8632626  0.2233623
##   12     0.3730673  0.8645190  0.2229596
##   14     0.3706746  0.8652485  0.2208448
##   16     0.3759599  0.8608161  0.2237057
##   18     0.3803534  0.8571591  0.2257979
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 14.
```

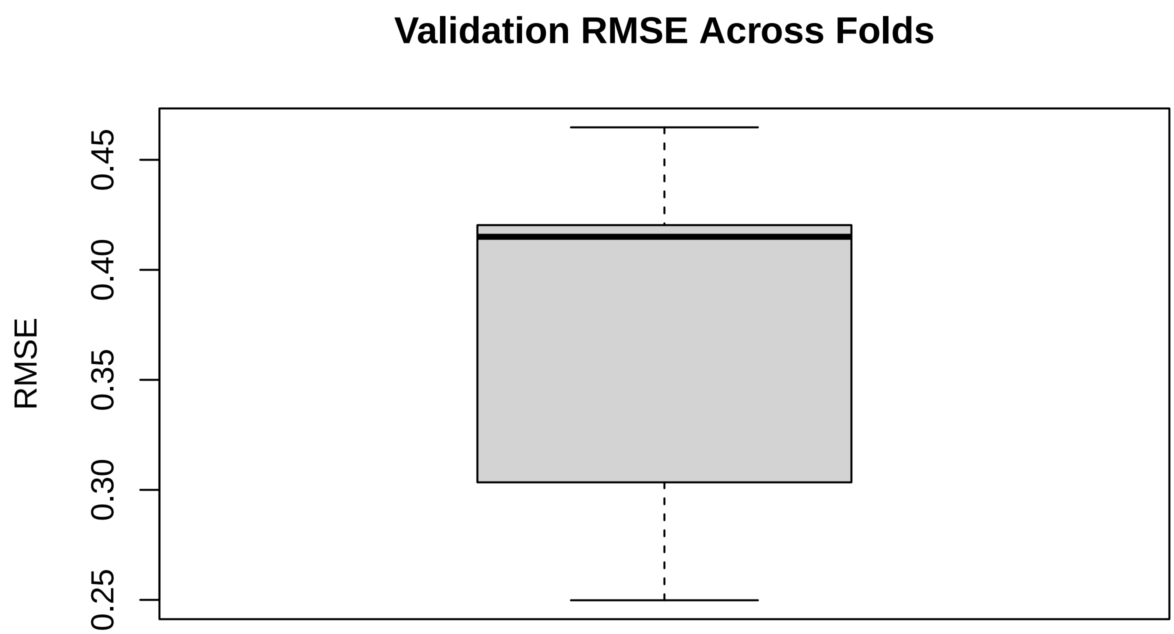
```r
# Show validation plot
plot(rf_cv_model)
```



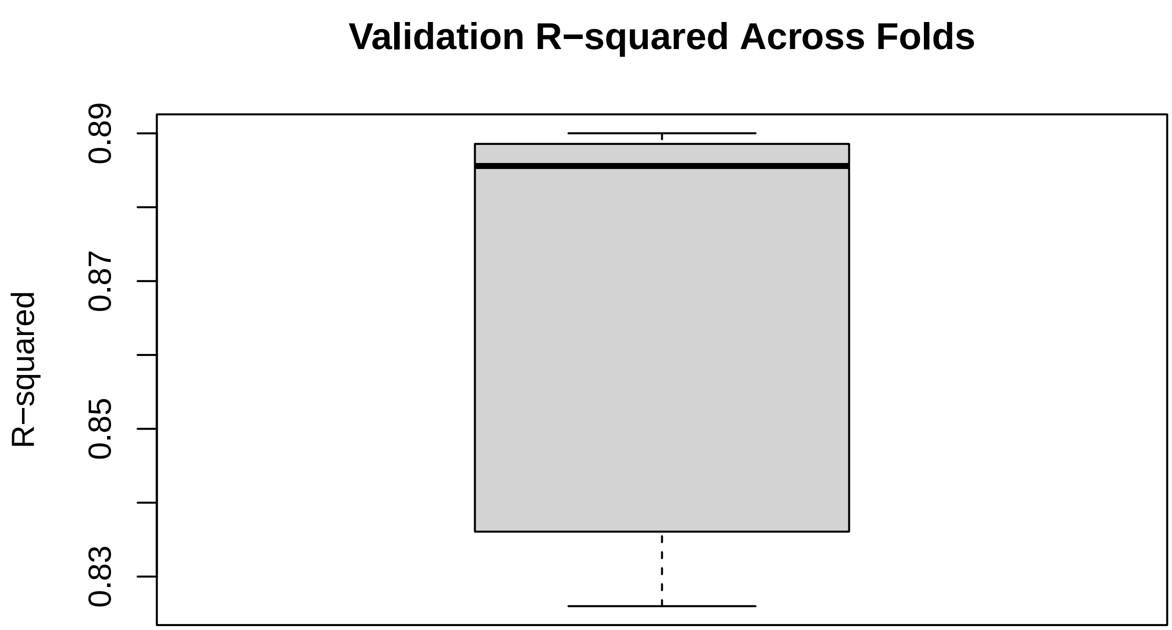

```r
names(rf_cv_model)
```

```
##  [1] "method"       "modelInfo"    "modelType"    "results"      "pred"
##  [6] "bestTune"     "call"         "dots"         "metric"       "control"
## [11] "finalModel"   "preProcess"   "trainingData" "ptype"        "resample"
## [16] "resampledCM"  "perfNames"    "maximize"     "yLimits"      "times"
## [21] "levels"       "terms"        "coefnames"    "xlevels"
```

```r
# Show RMSE across folds while using na.omit to remove null values before plotting
boxplot(na.omit(rf_cv_model$resample$RMSE),
        main = "Validation RMSE Across Folds",
        ylab = "RMSE")
```

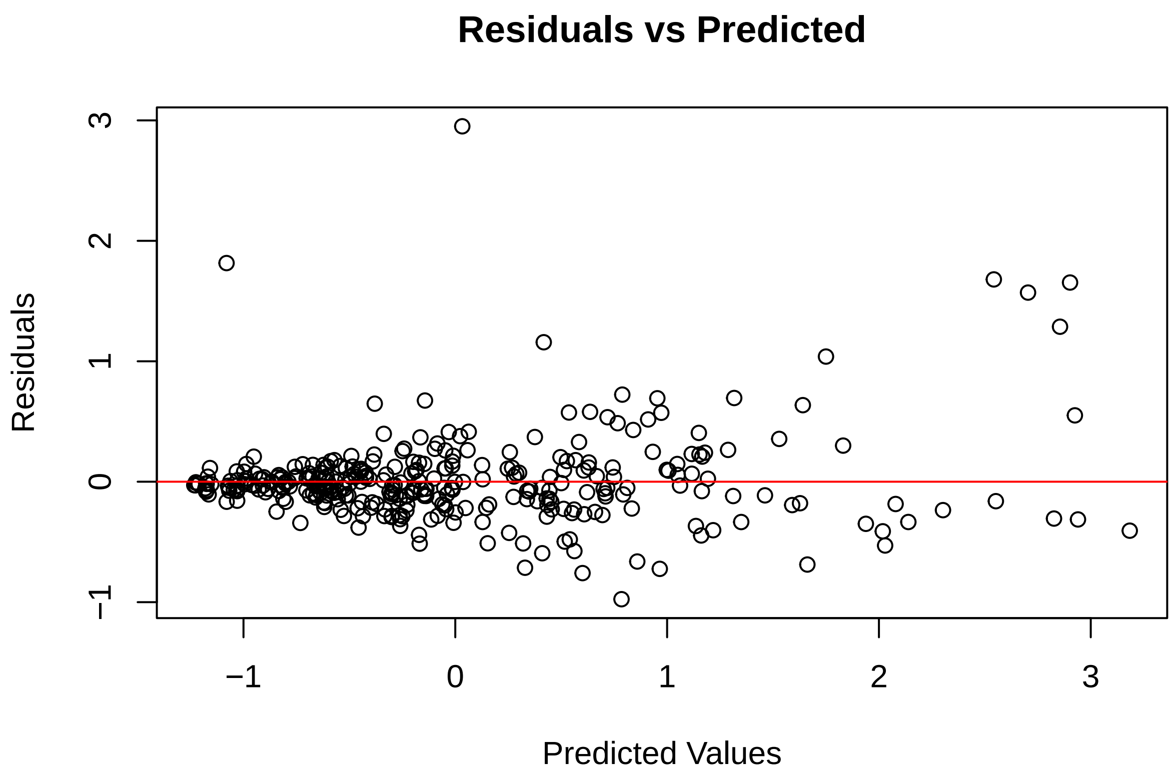



```r
# Show R squared across folds with na.omit() as above.
boxplot(na.omit(rf_cv_model$resample$Rsquared),
        main = "Validation R-squared Across Folds",
        ylab = "R-squared")
```




```r
# Show the residuals plot
# Residuals
residuals <- rf_cv_model$finalModel$y - rf_cv_model$finalModel$predicted

# Plot residuals vs fitted
plot(rf_cv_model$finalModel$predicted, residuals,
      xlab = "Predicted Values",
      ylab = "Residuals",
```

```
      main = "Residuals vs Predicted")
abline(h = 0, col = "red")
```



Tune MRTRY Hyperparameter to 10 from 12* Let's do some hyperparameter tuning. We have the opportunity to reset the mtry value from 12 to 10 here, calculate and collect the MSE for comparison with other MSE values from the other models. We can also tune the number tree using some specific values.

```
# Random Forest with MTRY=10
rf_model_mtry_10 <- randomForest(state_mentalhealth_util ~ .,
                                 data=GTrend_training_set_f,
                                 mtry = 10, importance = TRUE)
print(rf_model_mtry_10)
```

```
##
## Call:
##  randomForest(formula = state_mentalhealth_util ~ ., data = GTrend_training_set_f,      mtry = 10, i
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 10
##
##           Mean of squared residuals: 0.1266968
##                     % Var explained: 87.29
```

```
yhat_train_rf_mtry_10 <- predict(rf_model_mtry_10, newdata = GTrend_training_set_f)
yhat_test_rf_mtry_10 <- predict(rf_model_mtry_10, newdata = test_set_f)

# Calculate the test and train mean square errors
rf_train_mse_mtry_10 <- mean((yhat_train_rf_mtry_10 - GTrend_training_set_f$state_mentalhealth_util)^2)
```

```r
rf_test_mse_mtry_10 <- mean((yhat_test_rf_mtry_10 - test_set_f$state_mentalhealth_util)^2)

#add the test and train RMSEs to the mse_df
mse_df <- add_rmse_row(mse_df, "Random Forest -MTRY=10", rf_train_mse_mtry_10, rf_test_mse_mtry_10)

paste("Train MSE associated with the Random Forest is: =", rf_train_mse_mtry_10)
```

```
## [1] "Train MSE associated with the Random Forest is: = 0.0217853563419011"
```

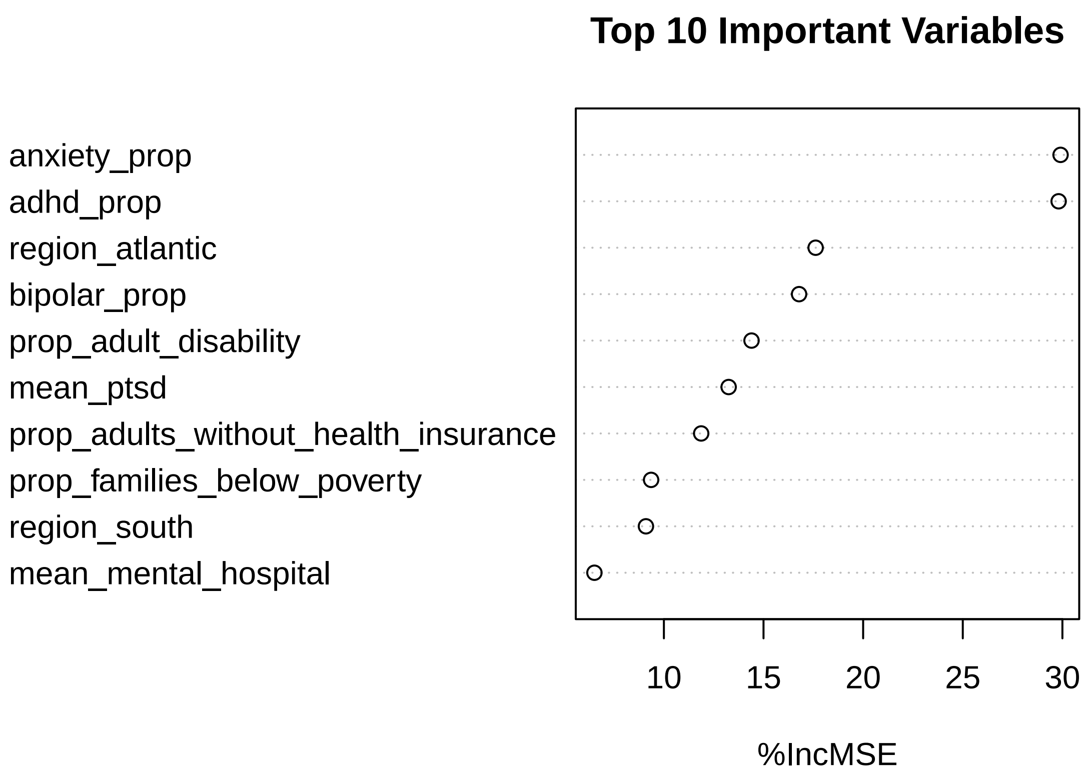
```r
paste("Test MSE associated with the Random Forest is: =", rf_test_mse_mtry_10)
```

```
## [1] "Test MSE associated with the Random Forest is: = 0.157264958833439"
```

```r
imp <- importance(rf_model_mtry_10)
# Let's sort the output of the importance() function
imp_df <- data.frame(Variable = rownames(imp), imp)
imp_sorted <- imp_df[order(-imp_df$X.IncMSE), ]
head(imp_sorted)
```

```
##                                       Variable X.IncMSE IncNodePurity
## anxiety_prop                      anxiety_prop 29.90768    118.215839
## adhd_prop                            adhd_prop 29.81074    103.058168
## region_atlantic                region_atlantic 17.61606      5.225390
## bipolar_prop                      bipolar_prop 16.78480     41.085289
## prop_adult_disability prop_adult_disability 14.39946      9.069914
## mean_ptsd                            mean_ptsd 13.25021     14.419896
```

```r
# Show the importance plot
#varImpPlot(rf_model)
varImpPlot(
  x = rf_model_mtry_10,    # trained random forest
  sort = TRUE,      # sort by importance
  n.var = 10,       # show top 10 variables
  type = 1,         # mean decrease in accuracy
  main = "Top 10 Important Variables"
)
```




```
mse_df
```

```
## # A tibble: 5 x 4
##   Model                               Train_MSE Test_MSE Delta_MSE
##   <chr>                                   <dbl>    <dbl>     <dbl>
## 1 Elastic Net                            0.215    0.217   -0.00289
## 2 Principal Component Regression         0.976    0.0237   0.952
## 3 Partial Least Squares Regression       0.169    1.68    -1.51
## 4 Random Forest                          0.0214   0.157   -0.135
## 5 Random Forest -MTRY=10                 0.0218   0.157   -0.135
```

```
set.seed(42)

rf_data <- GTrend_training_set_f[, c(-10)]
rf_label <- GTrend_training_set_f$state_mentalhealth_util

ntree_grid <- c(50, 100, 200, 300, 400, 500,600, 700, 800, 900, 1000)
control <- trainControl(method = "cv", number = 5)

results <- data.frame(ntree = integer(), Accuracy = numeric())

for (nt in ntree_grid) {
  set.seed(12)
  rf_model <- train(x = rf_data,
    y = rf_label,
    method = "rf",
    metric = "RMSE",
    tuneGrid = expand.grid(mtry = sqrt(ncol(rf_data))),
    trControl = control,
```

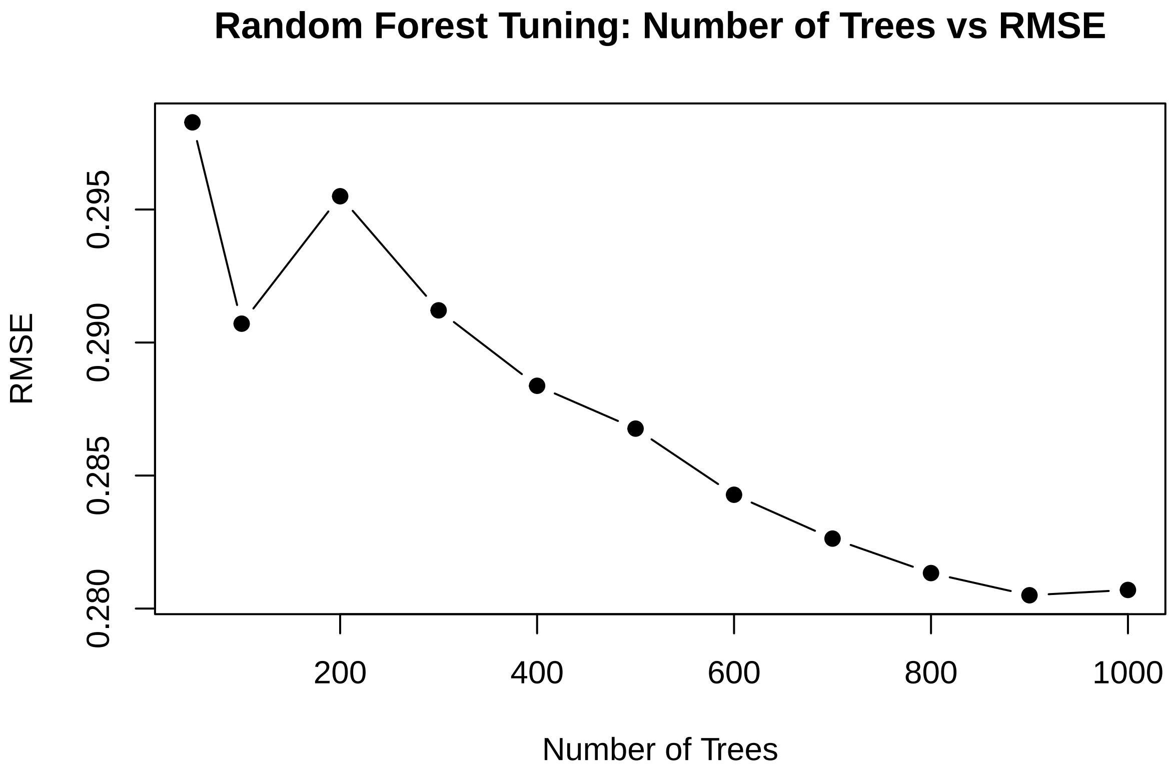
```
    ntree = nt
  )

  results <- rbind(results, data.frame(ntree = nt, RMSE = min(rf_model$results$RMSE)))
}

print(results)
```

```
##    ntree      RMSE
## 1     50 0.2982767
## 2    100 0.2907091
## 3    200 0.2954989
## 4    300 0.2912103
## 5    400 0.2883744
## 6    500 0.2867641
## 7    600 0.2842781
## 8    700 0.2826304
## 9    800 0.2813344
## 10   900 0.2805009
## 11  1000 0.2807005
```

```
best_ntree <- results$ntree[which.min(results$RMSE)]
paste("Best number of trees:", best_ntree)
```

```
## [1] "Best number of trees: 900"
```

```
plot(
  results$ntree, results$RMSE,
  type = "b",
  xlab = "Number of Trees",
  ylab = "RMSE",
  main = "Random Forest Tuning: Number of Trees vs RMSE",
  pch = 19
)
```


Random Forest Tuning: Number of Trees vs RMSE
RMSE
0.280
0.285
0.290
0.295
200
400
600
800
1000
Number of Trees