Further Analysis and Tuning

Team Rho

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```
#libraries

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

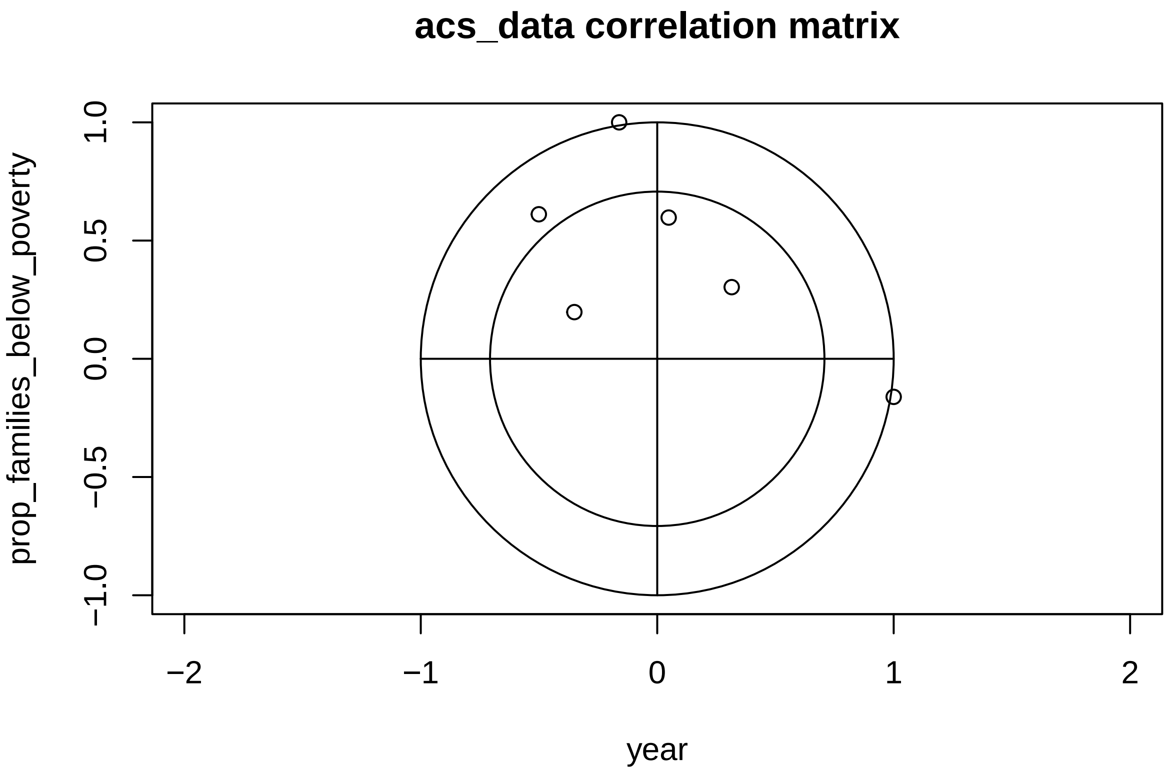
```
#reading data
data_GTrends <- read_excel("~/GitHub/DSE6311OM_SP2025R2_Data-Science-Capstone/Data/googleTrendsMH.xlsx"
    sheet = "googleTrendsMH")
acs_data <- load("~/GitHub/DSE6311OM_SP2025R2_Data-Science-Capstone/Data/ACS_for_MHGoogleTrends.Rdata")

acs_data <- ACS_data
ACS_data <- NULL
```

```
##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
```

```
#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
```

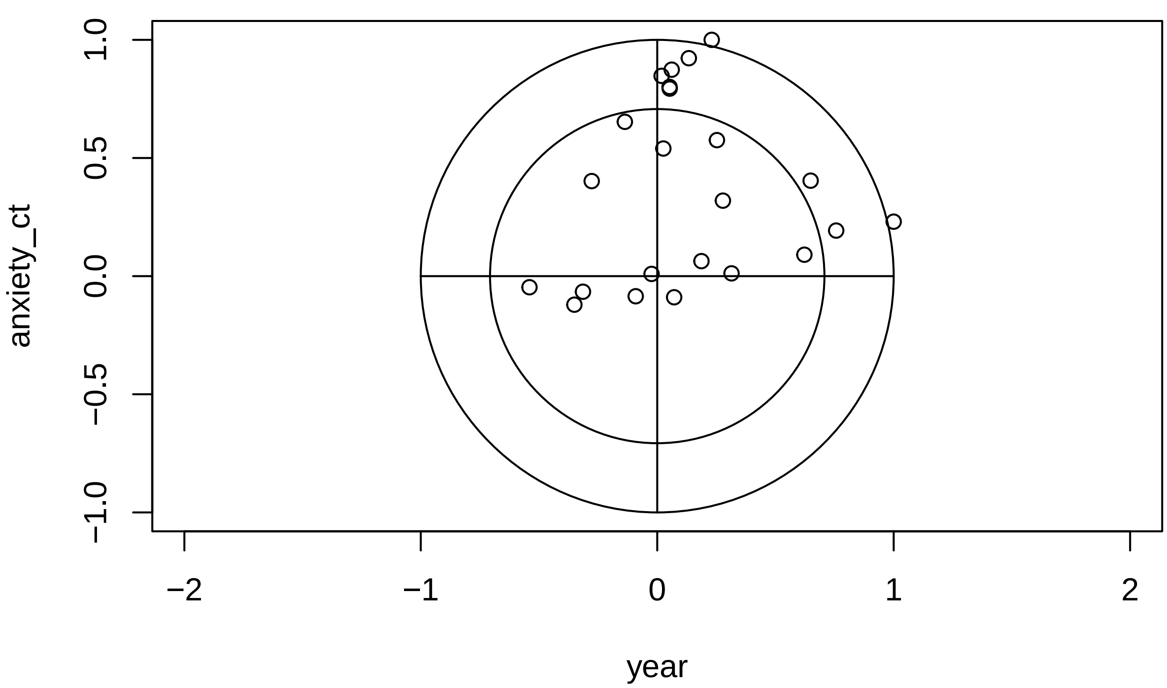
```
## prop_unemployed_in_labor_force                              1.00000000
## prop_without_internet_access                               -0.34452758
## prop_adult_disability                                       0.06756309
##                                      prop_without_internet_access
## year                                                     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

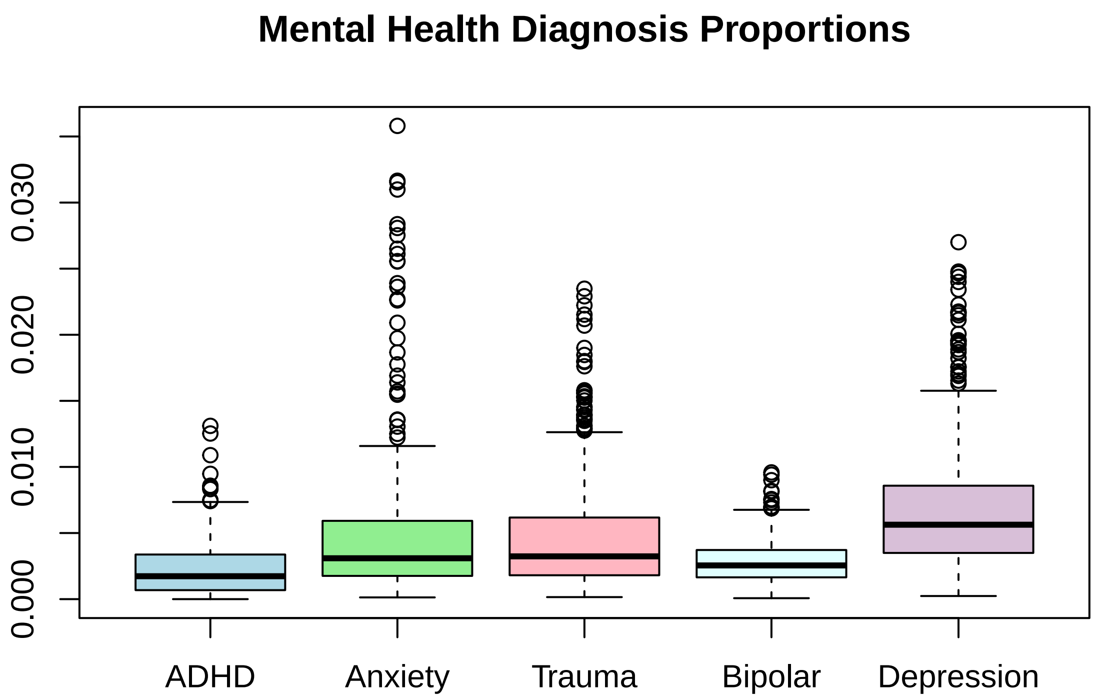
```
#correlation matrix

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

Correlation Matrix of GTrends_acs_joined

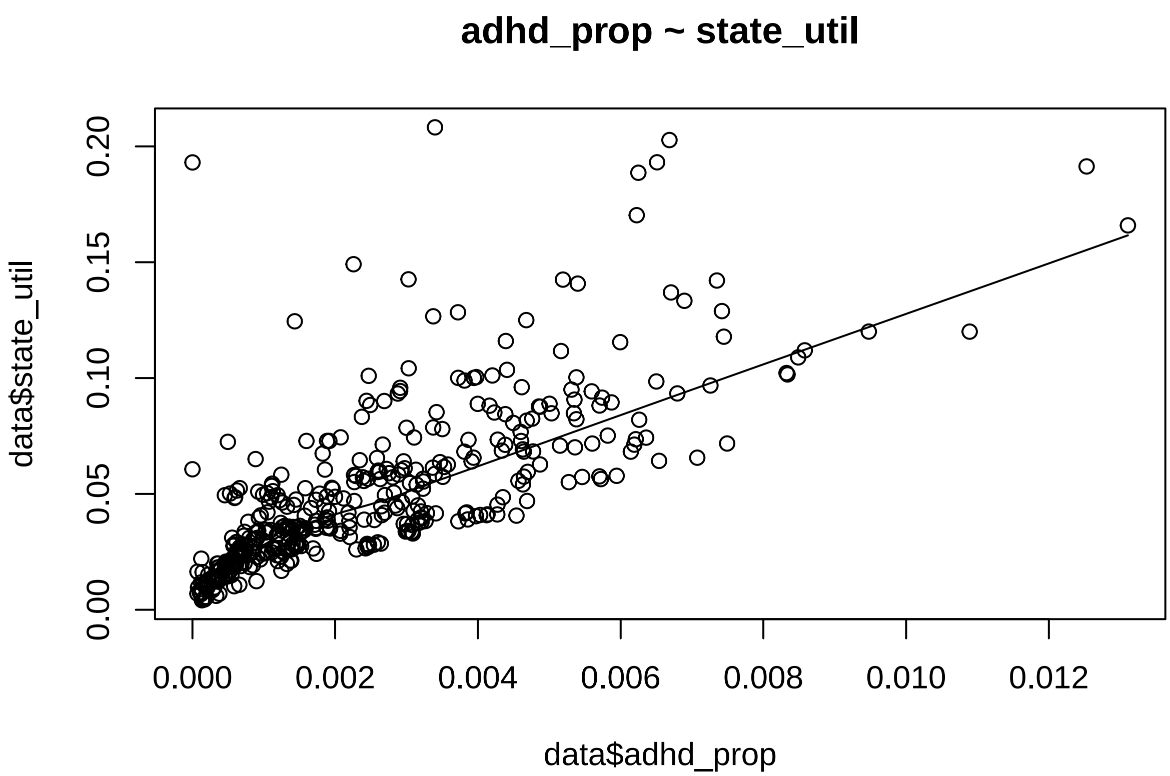



```
data <- data_GTrends
data$adhd_prop= data$adhd_ct/data$population_est
data$anxiety_prop = data$anxiety_ct/data$population_est
data$bipolar_prop = data$bipolar_ct/data$population_est
```

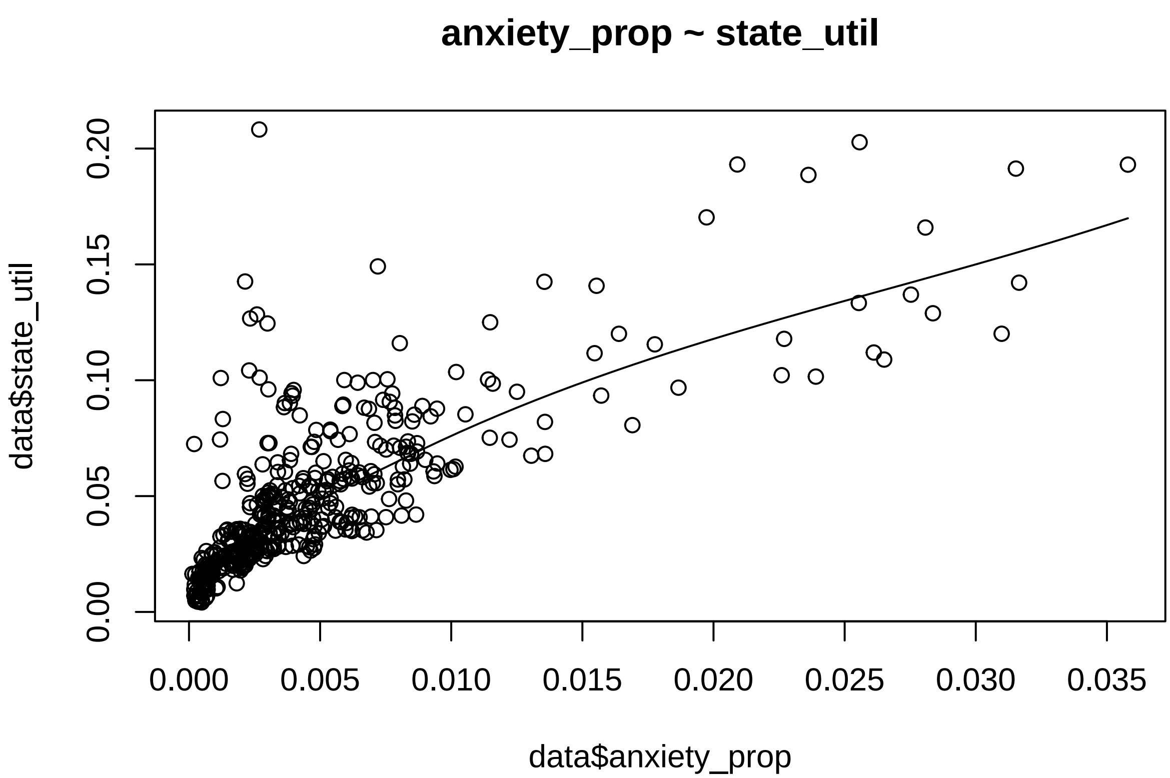
```r
data$depression_prop = data$depression_ct/data$population_est
data$trauma_prop = data$trauma_stress_ct/data$population_est
data$state_util = data$state_psych_care/data$population_est
data$private_util = data$private_psych_care/data$population_est
data$diff_util = data$total_util-(data$state_util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



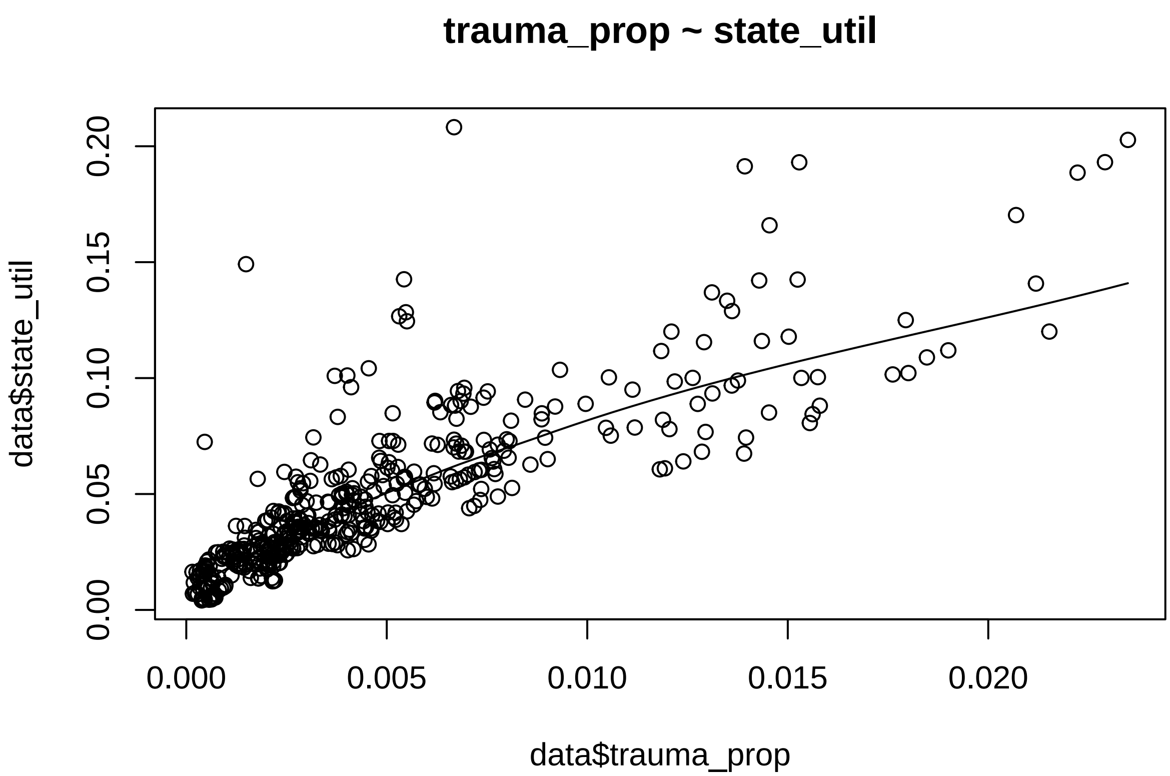

```r
par(mfrow=c(1,1))  # divide graph area in 2 columns
scatter.smooth(x=data$adhd_prop, y=data$state_util, main="adhd_prop ~ state_util")
```



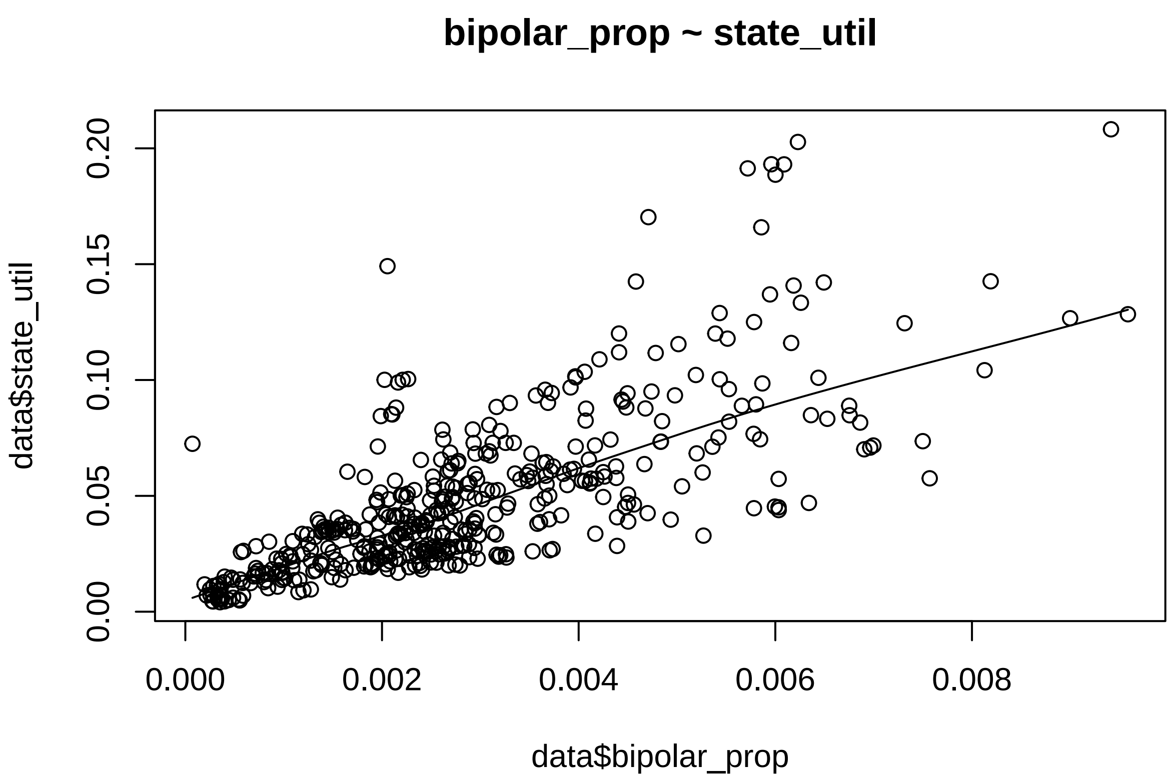

```
scatter.smooth(x=data$anxiety_prop, y=data$state_util, main="anxiety_prop ~ state_util")
```



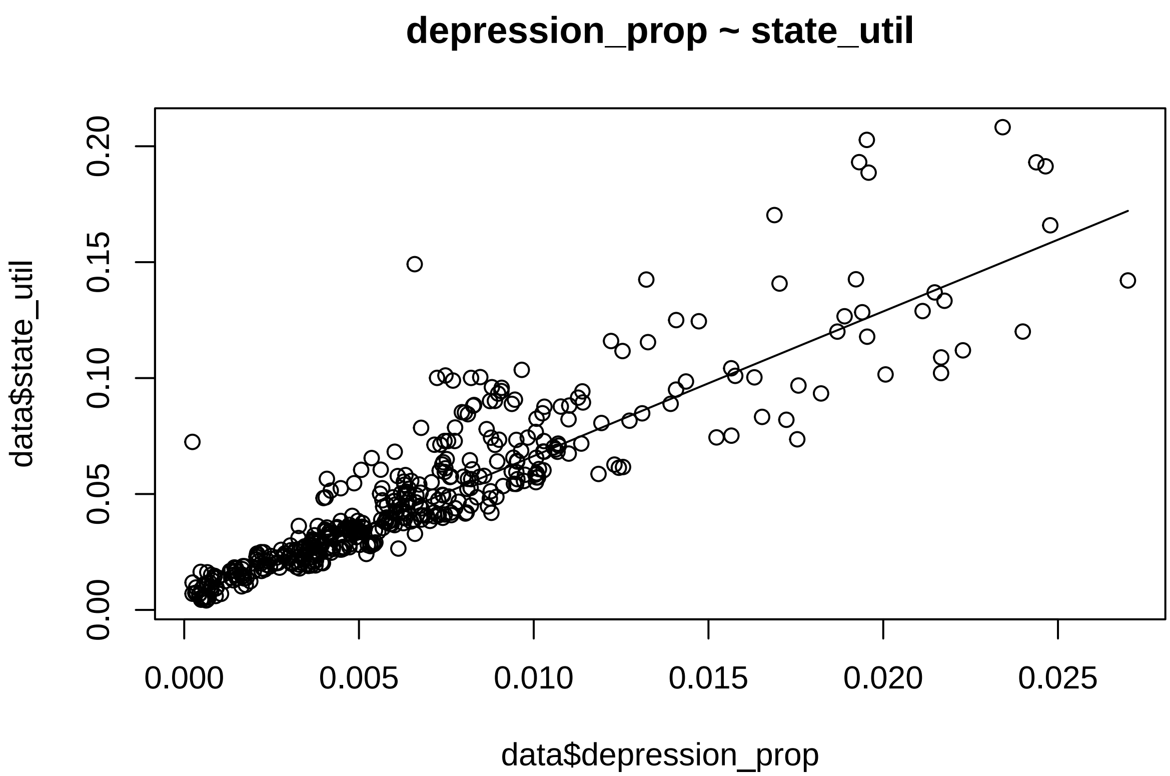
```r
scatter.smooth(x=data$trauma_prop, y=data$state_util, main="trauma_prop ~ state_util")
```




```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")
```

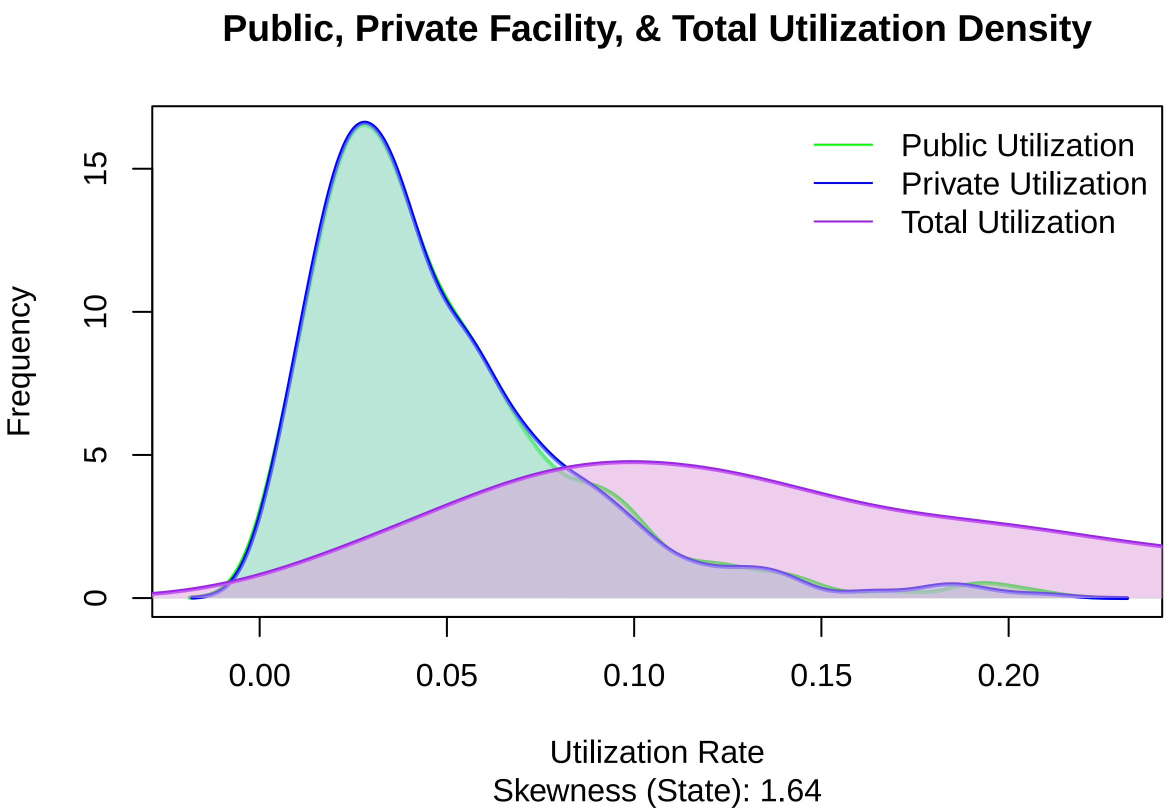



```r
library(e1071)
```

```
## 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)
```

```
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")
```




```
#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 AL    South             23.5      8.75         22.3            59
## 2  2013 CT    Atlantic          21.2      9.67         22.1            60.1
## 3  2013 FL    South             20.2      8            22              49
## 4  2013 LA    South             23.7      8.08         21.7            53.7
## 5  2013 NM    West Pacific      22.5     17            23.2            71.6
## 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 -1.61    -0.717  -1.10           0.744          -0.685               -0.286
## 2 -1.61    -0.546  -1.07           0.893           0.137               -0.292
## 3 -1.61    -0.950  -1.84          -0.645          -1.63                 0.320
## 4 -1.61    -0.914  -0.957          0.496          -1.39                 0.202
## 5 -1.61    -0.277  -1.88           2.58           -0.221               -2.34
## 6 -1.61    -0.564  -0.00262       -0.446          -0.313               -2.10
## # 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"
```

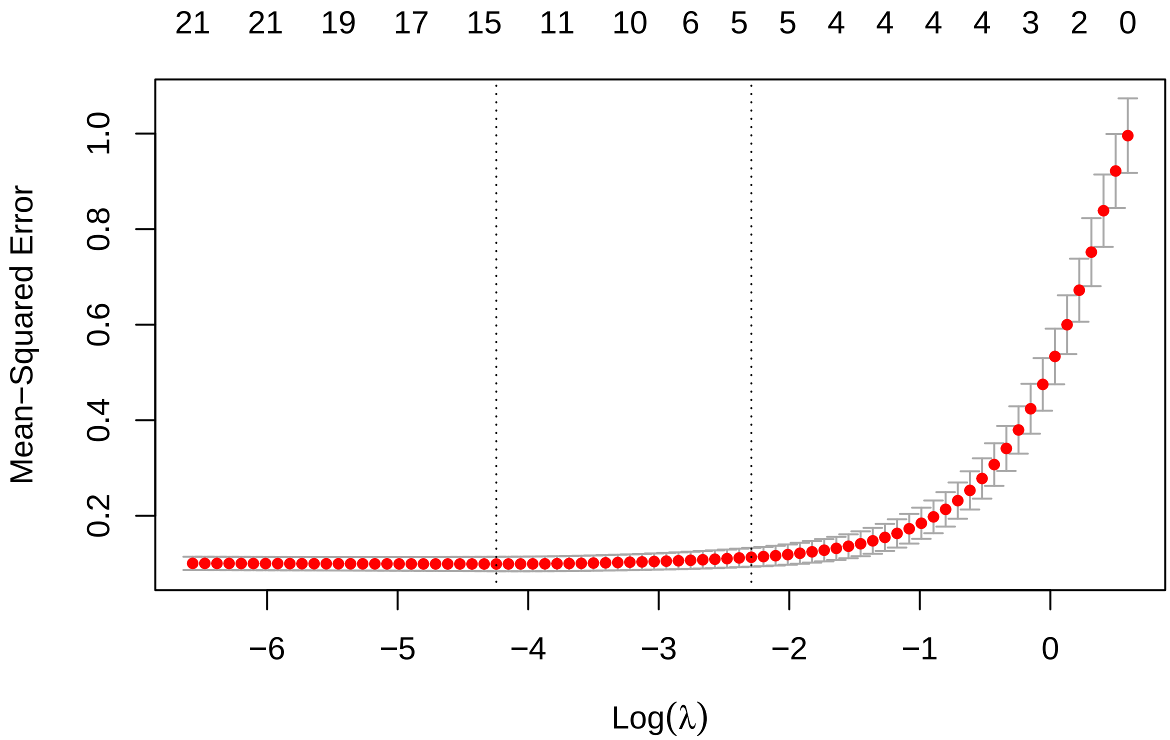
```
##  [7] "mean_depression"
##  [8] "mean_mental_hospital"
##  [9] "mean_psychiatrists_near_me"
## [10] "mean_psychologist_near_me"
## [11] "state_mentalhealth_util"
## [12] "anxiety_prop"
## [13] "adhd_prop"
## [14] "bipolar_prop"
## [15] "prop_families_below_poverty"
## [16] "prop_adults_without_health_insurance"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

```r
# 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()
)

# 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
  )
  updated_df <- bind_rows(df, new_row)
  return(updated_df)
}
```

INITIAL MODELS BY Njagi

1. LINEAR REGRESSION (ELASTIC NET REGULARIZATION)

```r
# DEVELOPING THE MODEL (LR. ENR)

x <- model.matrix(state_mentalhealth_util ~ ., data = GTrend_training_set_f, intercept = FALSE)

y <- GTrend_training_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, y, alpha = 0.5, family = "gaussian", nfolds = 5)

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




```r
#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, y, alpha = 0.5, lambda = best_lambda, family = "gaussian")
model_lambda_1se <- glmnet(x, y, 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), colnames(x_test))
x <- x[, common_columns]
x_test <- x_test[, common_columns]

# 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))
```

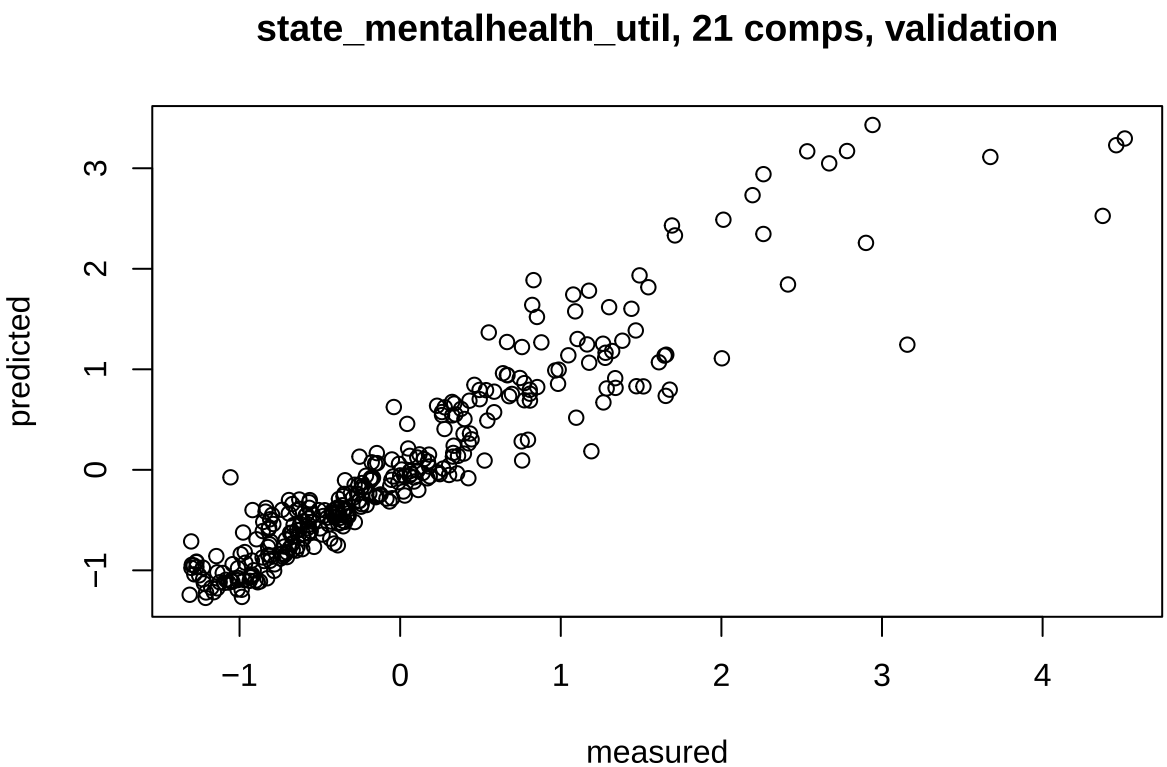
```
## [1] "MSE (MIN): 0.200069501840115"
```

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

```
## [1] "MSE (1SE): 0.257735684065944"
```

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)
```

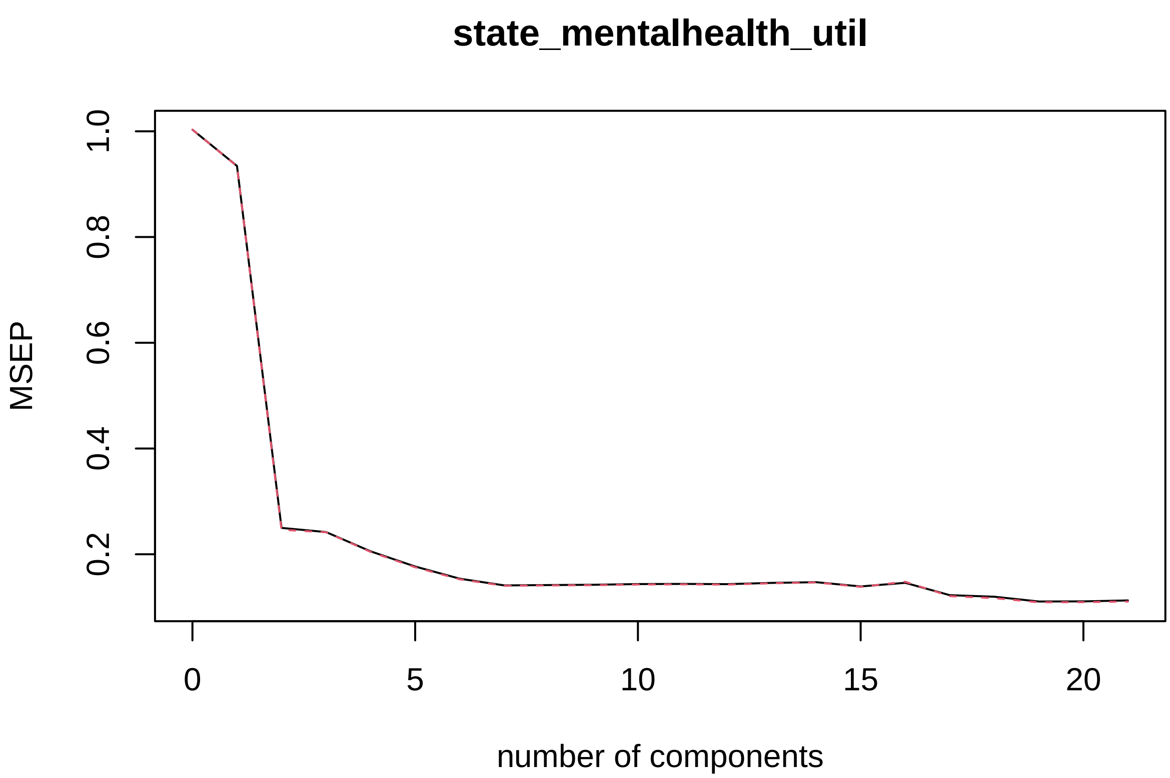



```r
# Show the summary of the PCR fit.
summary(pcr_fit)
```

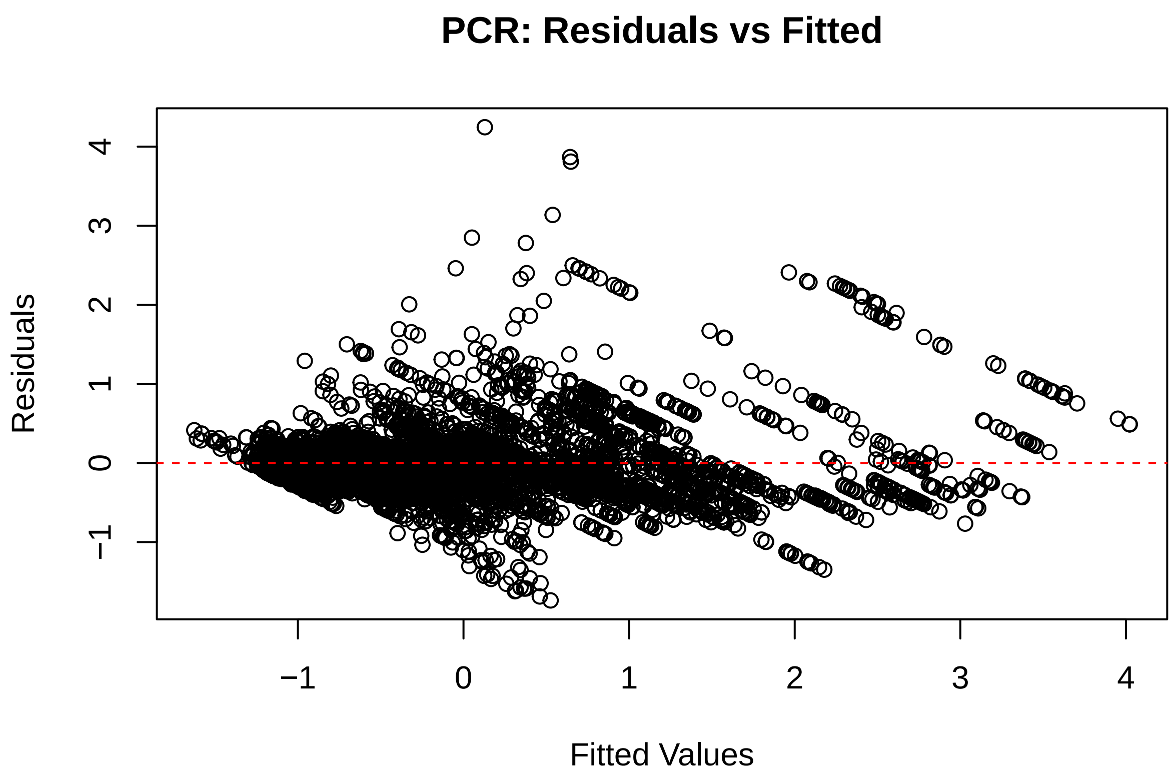
```
## Data:    X dimension: 336 21
##  Y dimension: 336 1
## Fit method: svdpc
## Number of components considered: 21
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           1.001   0.9666   0.4999   0.4919   0.4533   0.4205   0.3921
## adjCV        1.001   0.9664   0.4963   0.4916   0.4522   0.4188   0.3907
```

```
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV      0.3756   0.3765   0.3772    0.3790    0.3794    0.3788    0.3819
## adjCV   0.3746   0.3755   0.3762    0.3778    0.3782    0.3776    0.3809
##        14 comps  15 comps  16 comps  17 comps  18 comps  19 comps  20 comps
## CV       0.3837    0.3730    0.3821    0.3502    0.3459    0.3326    0.3330
## adjCV    0.3829    0.3719    0.3847    0.3476    0.3420    0.3304    0.3307
##        21 comps
## CV       0.3356
## adjCV    0.3326
##
## TRAINING: % variance explained
##                           1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                           18.80    35.10    48.37    58.36    66.57    74.12
## state_mentalhealth_util     10.46    76.26    76.82    80.97    83.49    85.88
##                           7 comps  8 comps  9 comps  10 comps  11 comps
## X                           79.88    84.20    87.72     90.16     92.13
## state_mentalhealth_util     86.96    86.97    86.97     87.00     87.14
##                           12 comps  13 comps  14 comps  15 comps  16 comps
## X                            93.53      94.8     95.97     96.97     97.83
## state_mentalhealth_util      87.30      87.3     87.46     88.48     88.48
##                           17 comps  18 comps  19 comps  20 comps  21 comps
## X                            98.60     99.22     99.74    100.00    100.00
## state_mentalhealth_util      91.09     91.43     91.47     91.47     91.47
```

```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)
```




```r
# 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 0.892746569104939"
```

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

```
## [1] "PCR Test MSE for M Selected: 1 is 0.107292869659061"
```

Partial Least Squares Regression (PLSR)

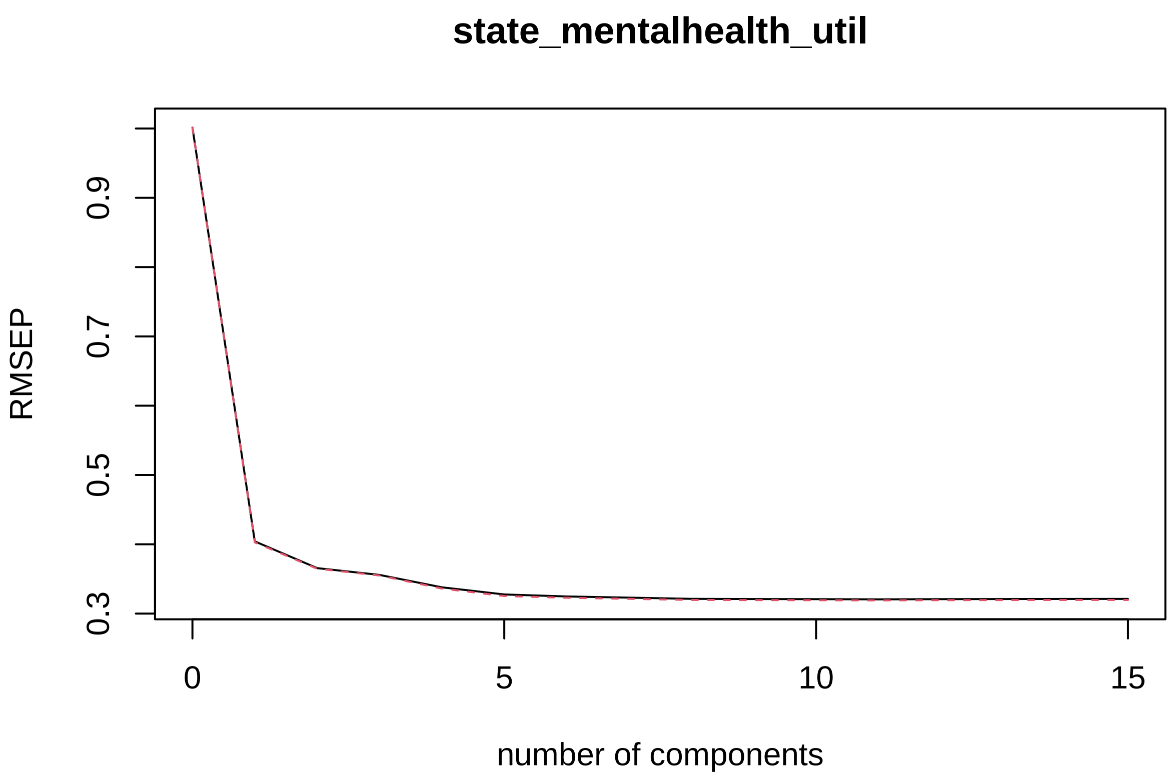
```r
# Set the PLS M selected value.
plsr_M_selected <- 15

# 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)

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


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

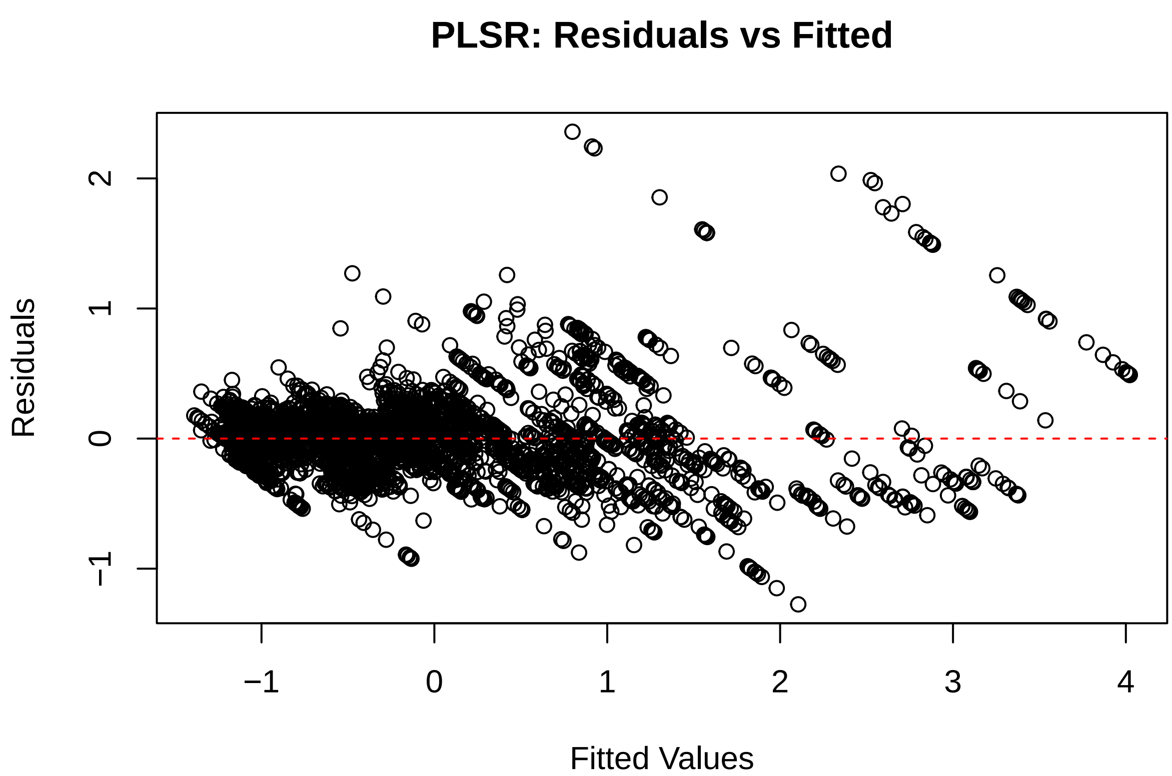
```
## Data:    X dimension: 336 21
##  Y dimension: 336 1
## Fit method: kernelpls
## Number of components considered: 15
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           1.001   0.4042   0.3656   0.3558   0.3379   0.3276   0.3247
## adjCV        1.001   0.4028   0.3648   0.3550   0.3361   0.3254   0.3228
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV      0.3230   0.3213   0.3210    0.3208    0.3206    0.3208    0.3210
## adjCV   0.3213   0.3197   0.3194    0.3193    0.3191    0.3193    0.3195
##        14 comps  15 comps
```

```
## CV        0.3211    0.3212
## adjCV     0.3196    0.3196
##
## TRAINING: % variance explained
##                           1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                           16.45    28.16    41.96    47.35    54.00    63.47
## state_mentalhealth_util     84.80    87.87    88.78    90.46    91.25    91.36
##                           7 comps  8 comps  9 comps  10 comps  11 comps
## X                           71.02    74.83    80.56     84.22     87.37
## state_mentalhealth_util     91.42    91.46    91.46     91.47     91.47
##                           12 comps  13 comps  14 comps  15 comps
## X                            89.71     92.21     94.33     95.79
## state_mentalhealth_util      91.47     91.47     91.47     91.47
```

```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 0.0850717416253914"
```

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

```
## [1] "PLSR Test MSE for M Selected: 15 is 2.29151161913794"
```

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

```
## Reordering variables and trying again:
```

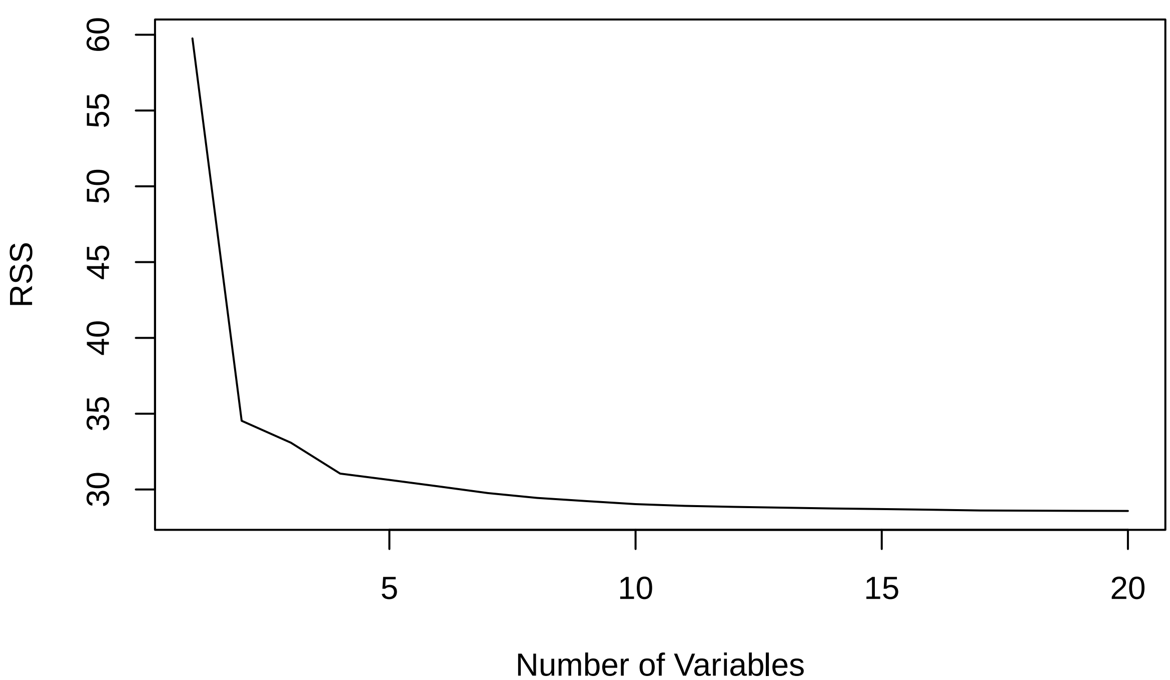
```r
# plot(reg_fit_train, scale="r2")
# plot(reg_fit_train, scale="adjr2")
# plot(reg_fit_train, scale="Cp")
# plot(reg_fit_train, scale="bic")
# The summary() command outputs the best set of variables for each model size.
reg.summary <- summary(reg_fit_train)
#print(reg.summary)
names(reg.summary)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

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

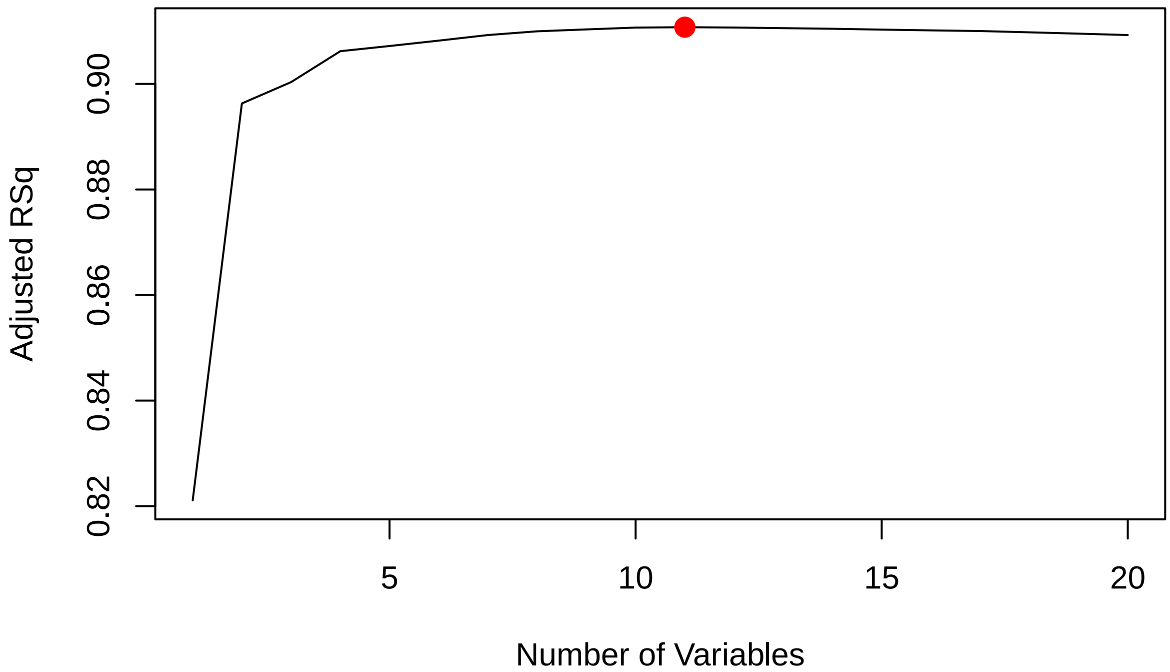
```r
#Print the R^2 statistic
reg.summary$rsq
```

```
##  [1] 0.8216182 0.8969173 0.9012360 0.9073183 0.9085616 0.9098450 0.9111532
##  [8] 0.9121123 0.9127341 0.9133318 0.9136722 0.9138754 0.9140330 0.9141863
## [15] 0.9143022 0.9144344 0.9145826 0.9146204 0.9146535 0.9146743
```

```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)
```

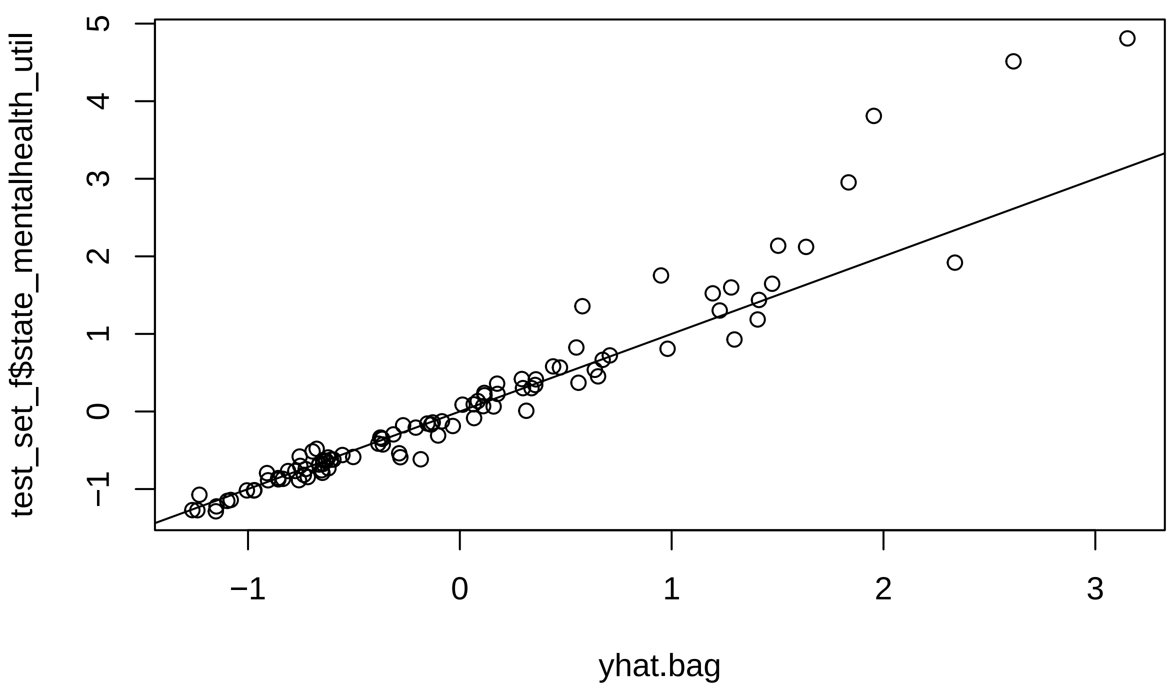
```
##  [1] "year"
##  [2] "mean_adhd"
##  [3] "mean_ptsd"
##  [4] "mean_bipolar"
##  [5] "mean_depression"
##  [6] "mean_mental_hospital"
##  [7] "mean_psychiatrists_near_me"
##  [8] "mean_psychologist_near_me"
##  [9] "state_mentalhealth_util"
## [10] "anxiety_prop"
## [11] "adhd_prop"
## [12] "bipolar_prop"
## [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"
## [22] "state_encoded"
```

Random Forest

```r
library(randomForest)
set.seed(42)
# Bagging
bag.data <- randomForest(state_mentalhealth_util ~ ., data=GTrend_training_set_f, mtry=24, importance=TI
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: 21
##
##           Mean of squared residuals: 0.09183399
##                     % Var explained: 90.79
```

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

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




```r
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: 0.151401340033868"
```

```r
# 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: 0.09492429
##                     % Var explained: 90.48
```

```r
yhat_train_rf <- predict(rf_model, newdata = GTrend_training_set_f)
yhat_test_rf <- predict(rf_model, newdata = test_set_f)
rf_train_mse <- mean((yhat_train_rf-test_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: = 2.26626436930369"
```

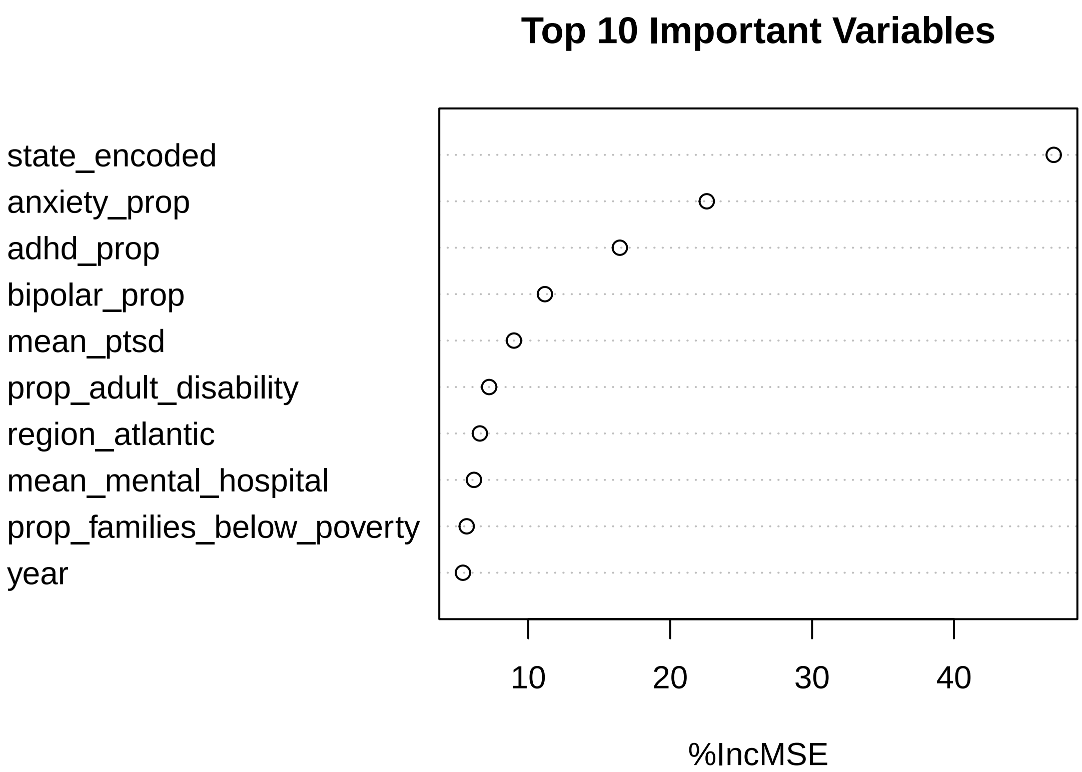
```r
paste("Test MSE associated with the Random Forest is: =", rf_test_mse)
```

```
## [1] "Test MSE associated with the Random Forest is: = 0.150106524105354"
```

```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
## state_encoded                 state_encoded 47.032269    177.389091
## anxiety_prop                   anxiety_prop 22.580920     77.544338
## adhd_prop                         adhd_prop 16.453825     32.996645
## bipolar_prop                   bipolar_prop 11.174085     16.529628
## mean_ptsd                         mean_ptsd  8.991949      3.546010
## prop_adult_disability prop_adult_disability  7.245363      1.928612
```

```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"
)
```

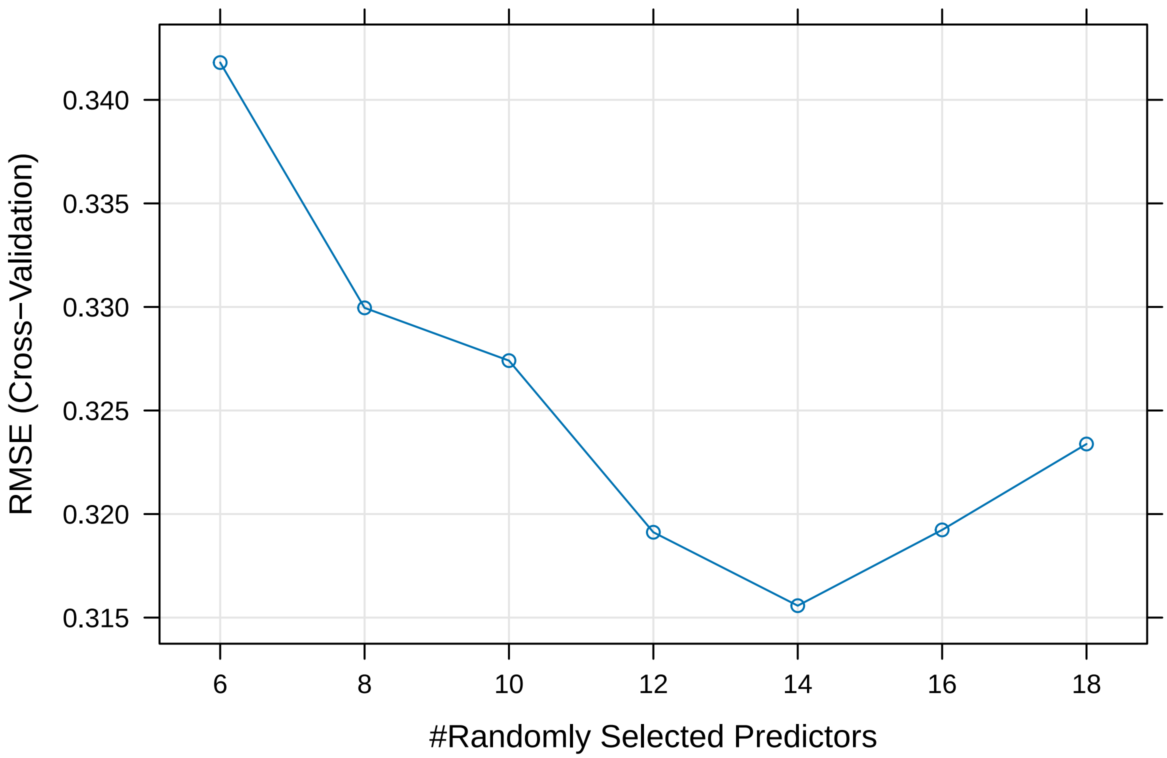



```r
set.seed(42)

# 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
##  21 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    0.3418021  0.8907334  0.1726882
##    8    0.3299568  0.8959366  0.1622307
##   10    0.3274096  0.8958886  0.1598377
##   12    0.3191213  0.9011913  0.1560467
##   14    0.3155763  0.9032903  0.1565676
##   16    0.3192357  0.9010482  0.1575305
##   18    0.3233829  0.8987259  0.1609650
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 14.
```

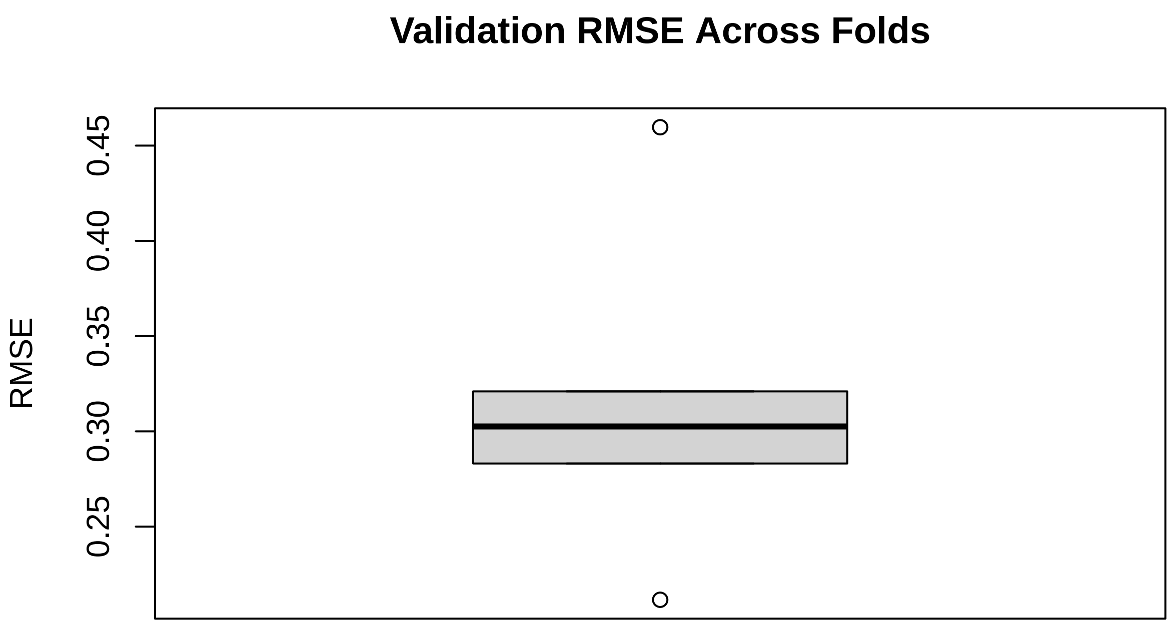
```
# Show validation plot
plot(rf_cv_model)
```



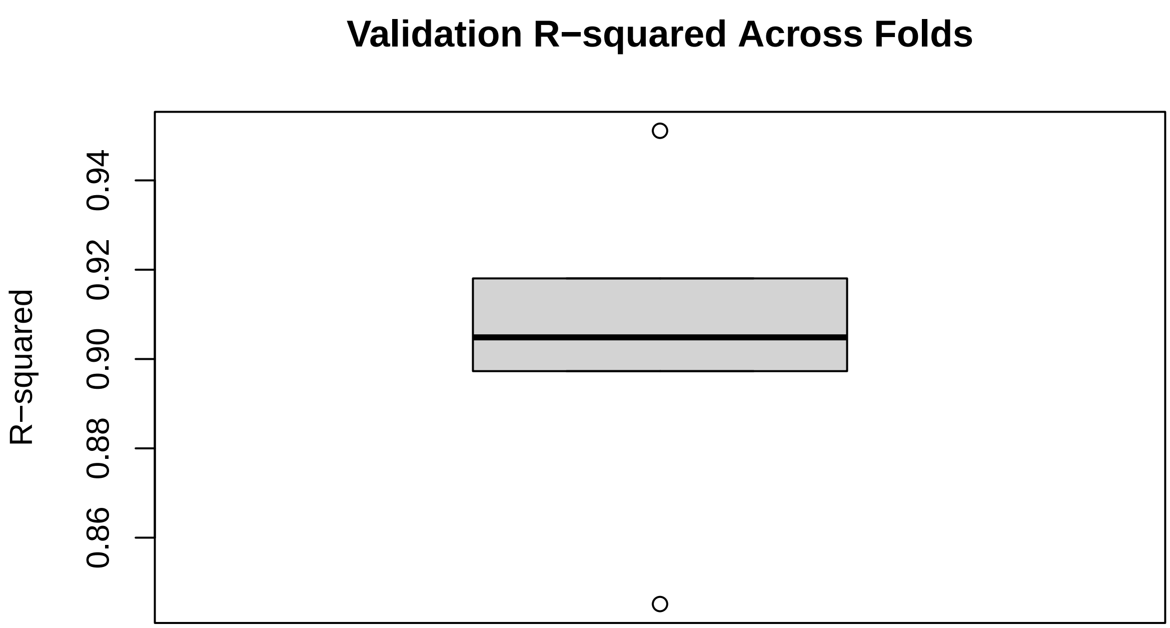

```
names(rf_cv_model)
```

```
##  [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"
```

```
# 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")
```

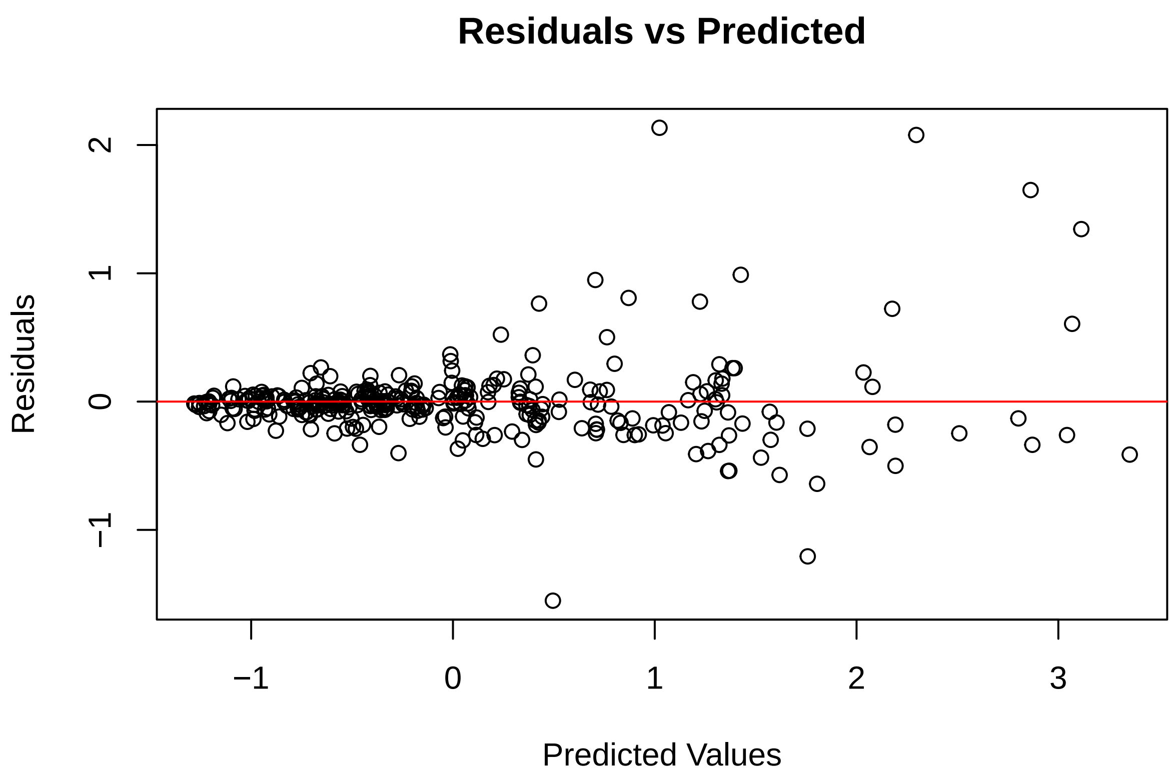



```r
# Show R squared across folds with na.omit() as above.
boxplot(na.omit(rf_cv_model$resample$Rsquared),
        main = "Validation R-squared Across Folds",
        ylab = "R-squared")
```




```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",
```

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




```r
mse_df
```

```
## # A tibble: 3 x 3
##   Model                              Train_MSE Test_MSE
##   <chr>                                  <dbl>    <dbl>
## 1 Principal Component Regression      0.893     0.107
## 2 Partial Least Squares Regression    0.0851    2.29
## 3 Random Forest                       2.27      0.150
```

```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"
## [22] "state_encoded"
```

Tune MRTRY Hyperparameter to 10 from 12*

```
# 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, in
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 10
##
##           Mean of squared residuals: 0.09003624
##                     % Var explained: 90.97
```

```
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)
rf_train_mse_mtry_10 <- mean((yhat_train_rf_mtry_10-test_set_f$state_mentalhealth_util)^2)
rf_test_mse_mtry_10 <- mean((yhat_test_rf_mtry_10-test_set_f$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: = 2.26245322753598"
```

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

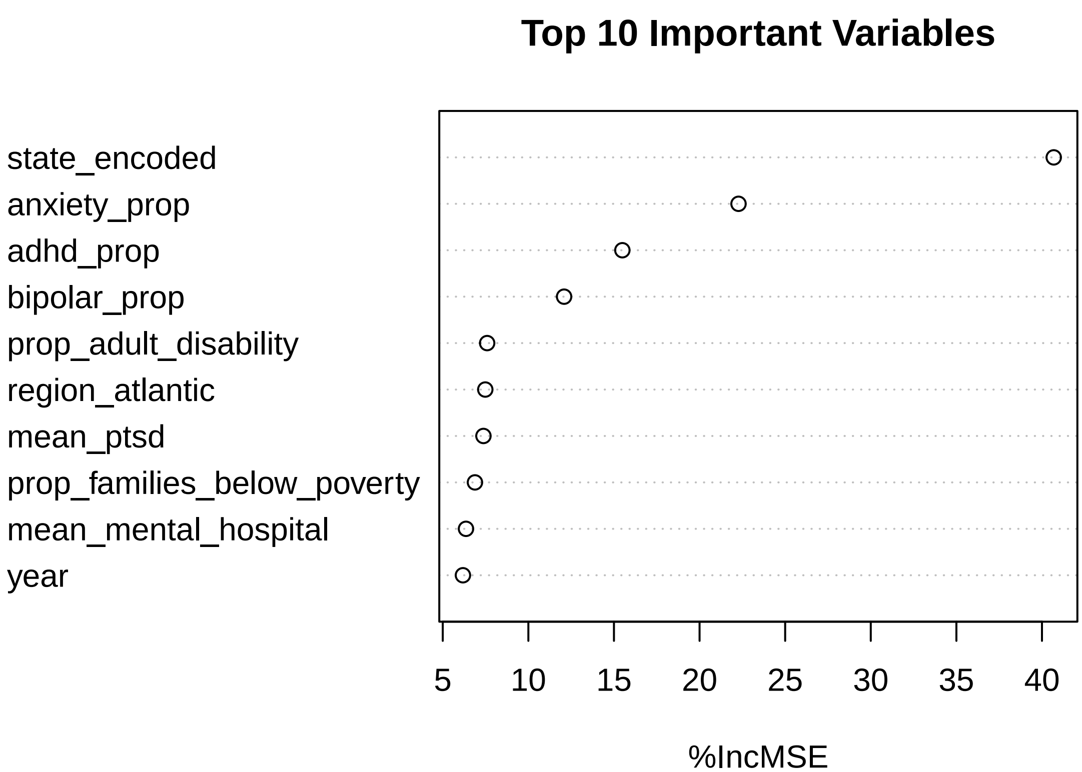
```
## [1] "Test MSE associated with the Random Forest is: = 0.137602601588164"
```

```
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
## state_encoded                  state_encoded 40.687225    160.316950
```

```
## anxiety_prop                         anxiety_prop 22.275688     74.115050
## adhd_prop                               adhd_prop 15.490461     38.837544
## bipolar_prop                         bipolar_prop 12.087581     23.893660
## prop_adult_disability prop_adult_disability  7.592323      3.273373
## region_atlantic                   region_atlantic  7.483596      1.274988
```

```
# 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"
)
```




```
print(mse_df)
```

```
## # A tibble: 4 x 3
##   Model                           Train_MSE Test_MSE
##   <chr>                               <dbl>    <dbl>
## 1 Principal Component Regression     0.893     0.107
## 2 Partial Least Squares Regression   0.0851    2.29
## 3 Random Forest                      2.27      0.150
## 4 Random Forest -MTRY=10             2.26      0.138
```

```
set.seed(42)
```

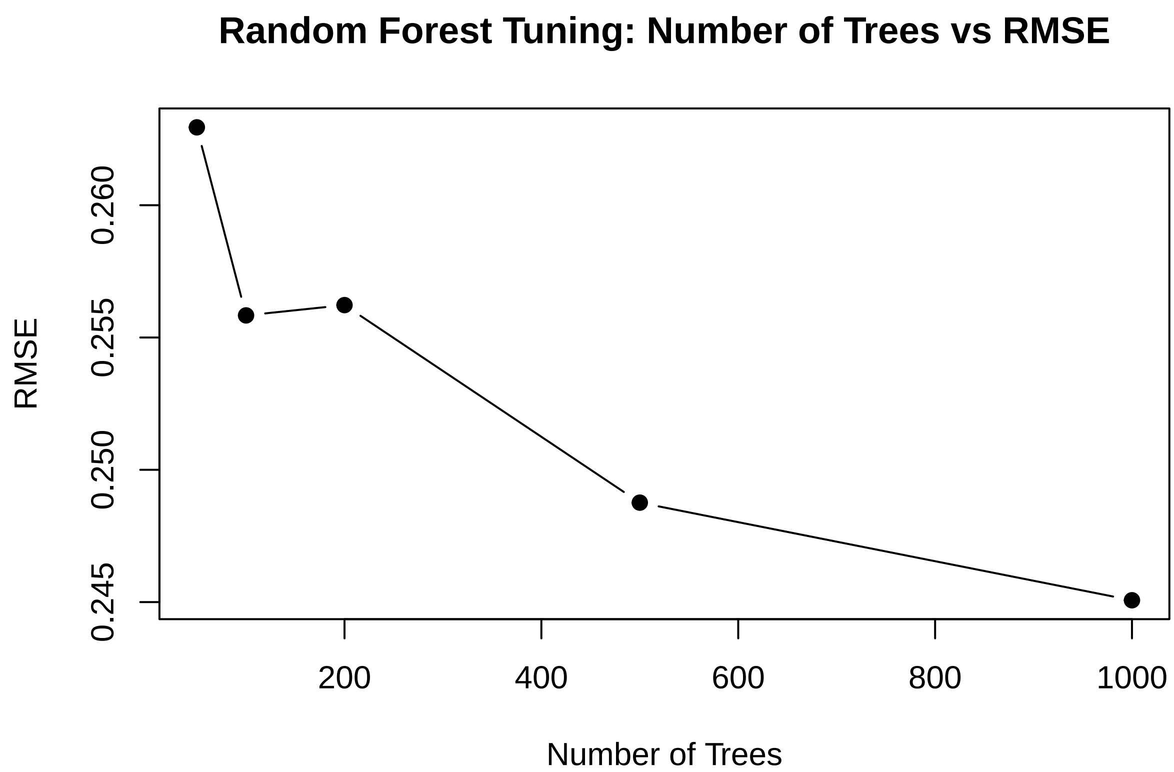
```r
rf_data <- GTrend_training_set_f[, c(-10)]
rf_label <- GTrend_training_set_f$state_mentalhealth_util

ntree_grid <- c(50, 100, 200, 500, 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 0.2629426
## 2   100 0.2558351
## 3   200 0.2562250
## 4   500 0.2487590
## 5  1000 0.2450700
```

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

```
## [1] "Best number of trees: 1000"
```

```r
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
0.245
0.250
0.255
0.260
200
400
600
800
1000
Number of Trees