Hyperparameter Tuning

Team Rho

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```
#libraries

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

```
#reading data

# data_GTrends <- read_excel("C:/data_science/DSE6311OM_/week3_Exploratory Data Analysis/googleTrendsMH
# acs_data <- load("C:\\data_science\\DSE6311OM_\\Week4_Pre-processing and Feature Engineering\\ACS_for
# Replace with this code to allow quick access regardless of download location
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
```

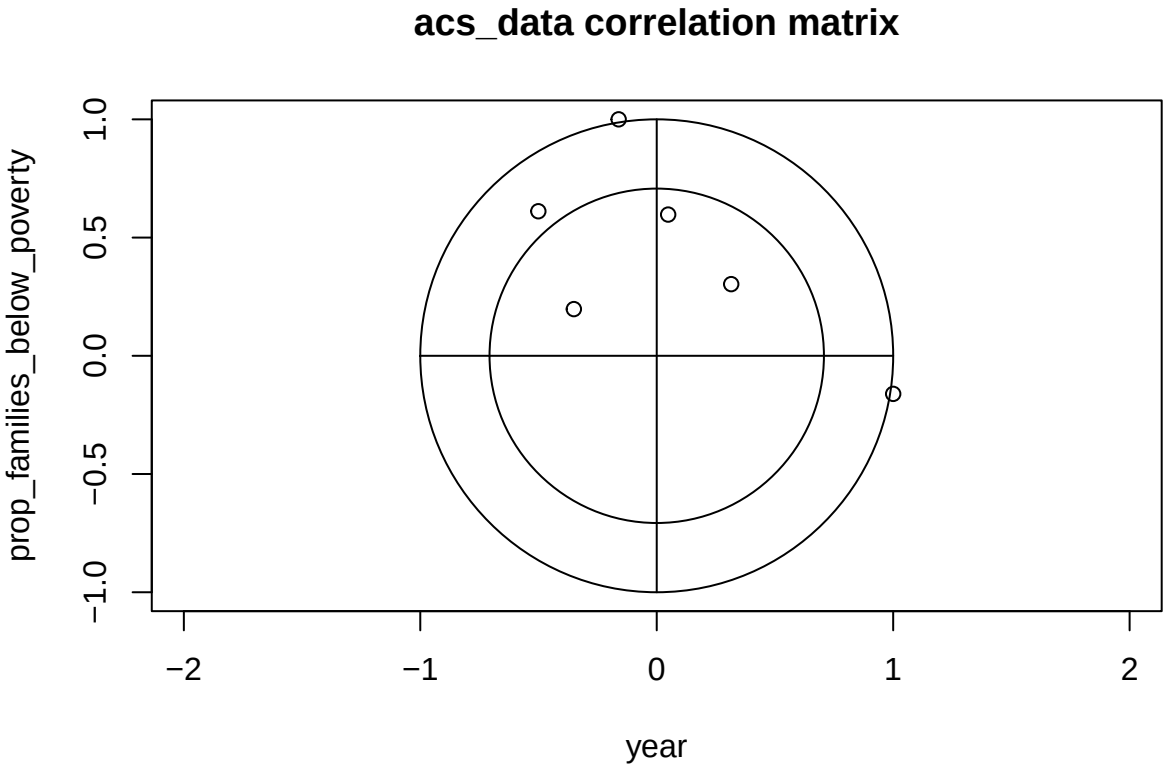
```
##CORRELATION MATRIX FOR acs_data

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
```

updated code

```
#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))])
```

testing GitHub

```
#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
```

```r
#joining both datasets acs_data and data_GTrends

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

```r
#testing correlation


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()

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
```

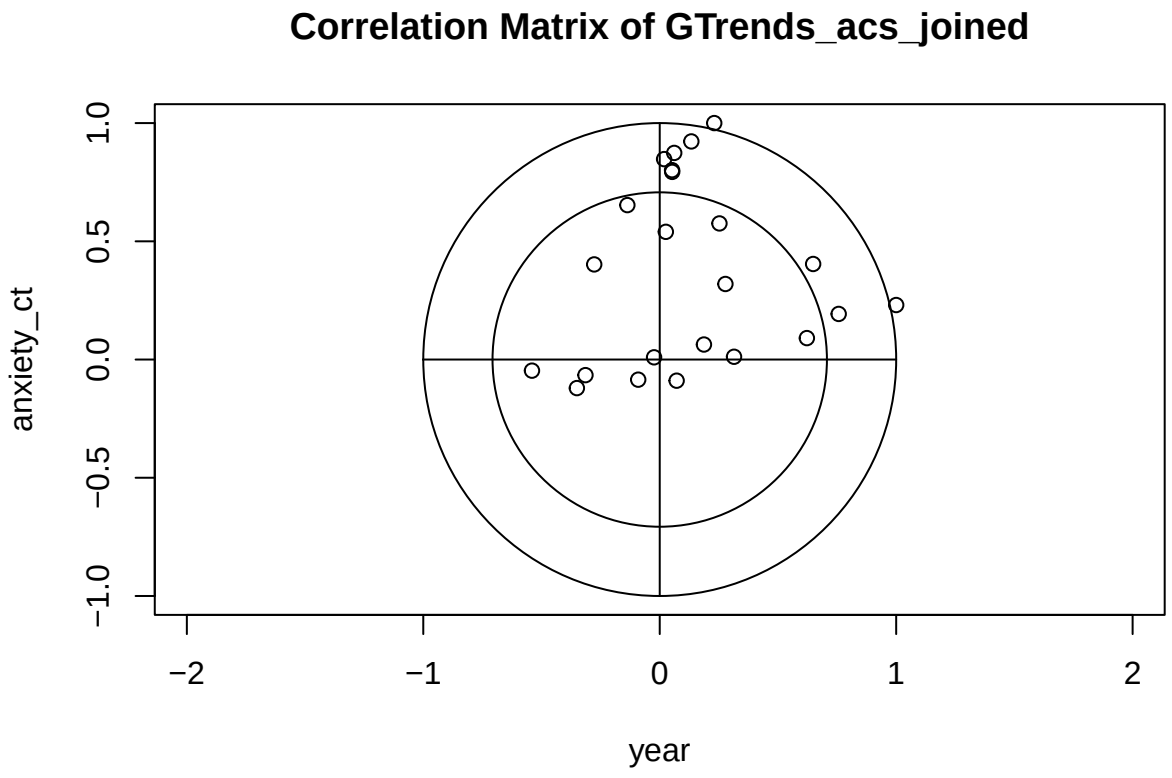
```
## mean_psychiatrists_near_me                                -0.02069818
## mean_psychologist_near_me                                 -0.18536934
## anxiety_prop                                              -0.24439237
## adhd_prop                                                 -0.06381305
## bipolar_prop                                               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
```

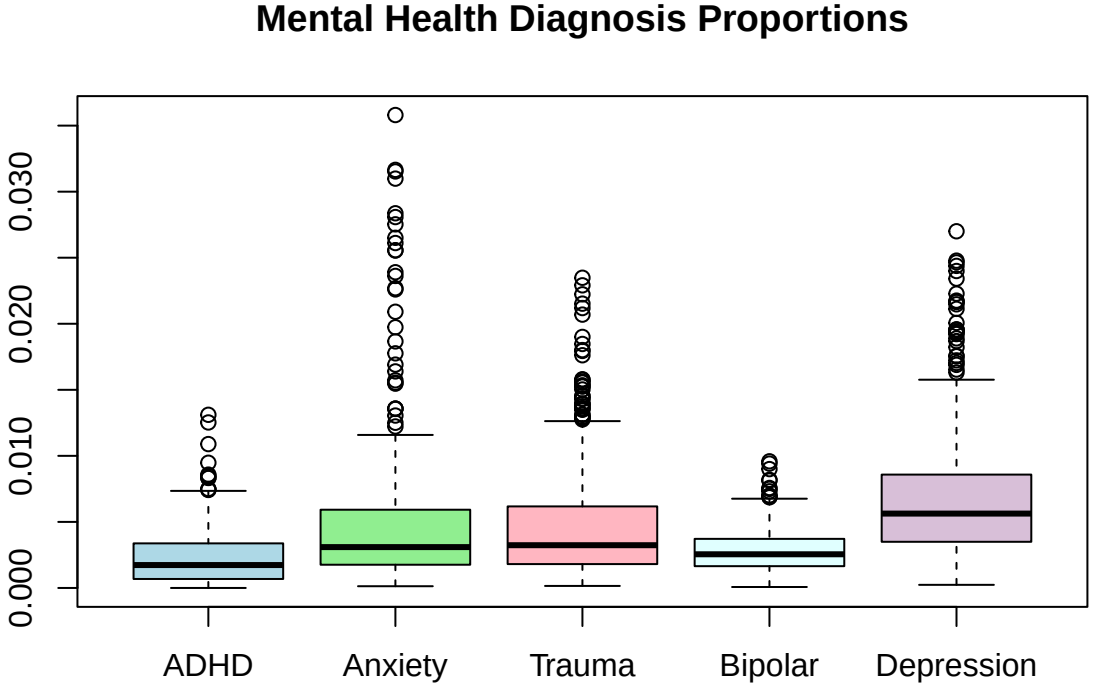
high correlation variables

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.
2. 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

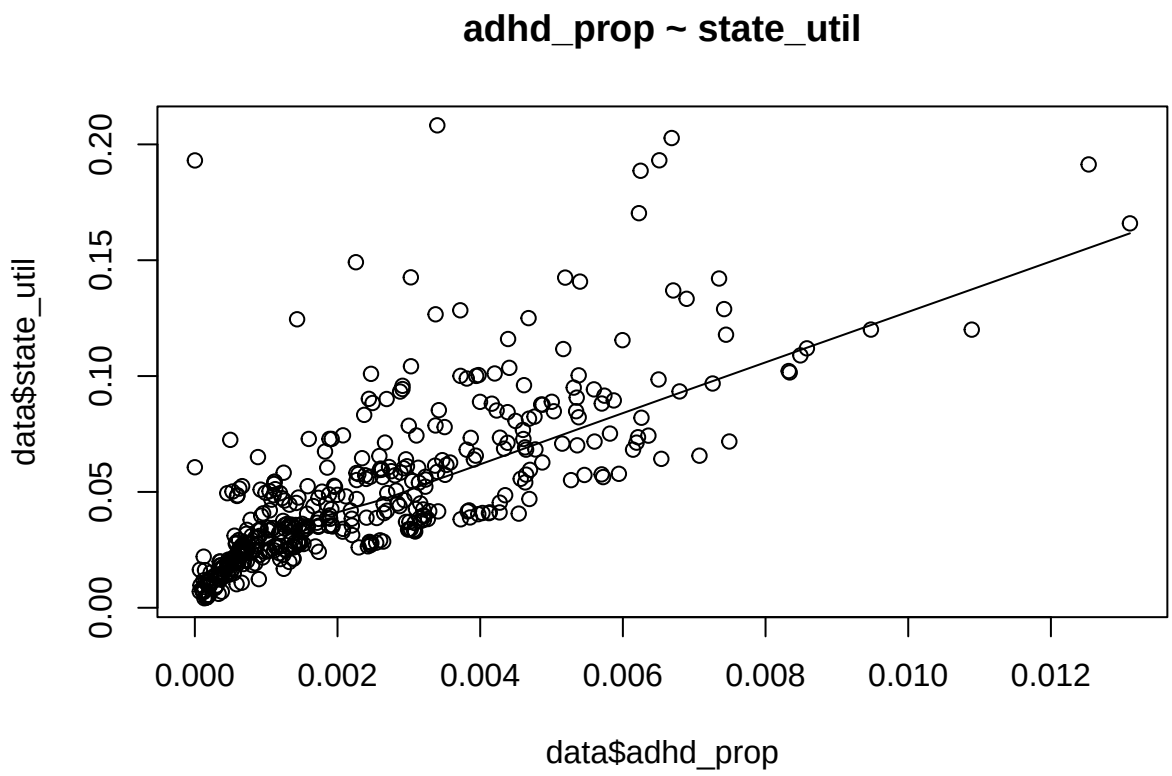
```
#correlation matrix

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))
```



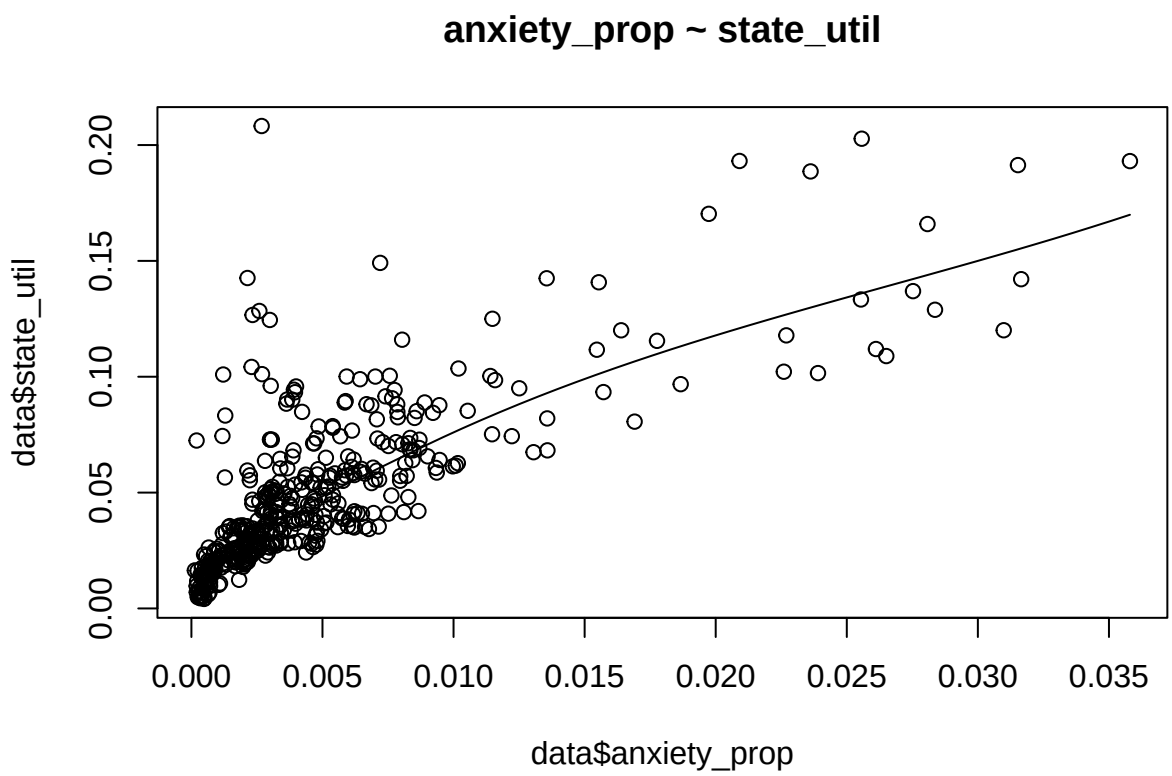
```r
data <- data_GTrends
data$adhd_prop= data$adhd_ct/data$population_est
data$anxiety_prop = data$anxiety_ct/data$population_est
data$bipolar_prop = data$bipolar_ct/data$population_est
data$depression_prop = data$depression_ct/data$population_est
data$trauma_prop = data$trauma_stress_ct/data$population_est
data$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" ))
```



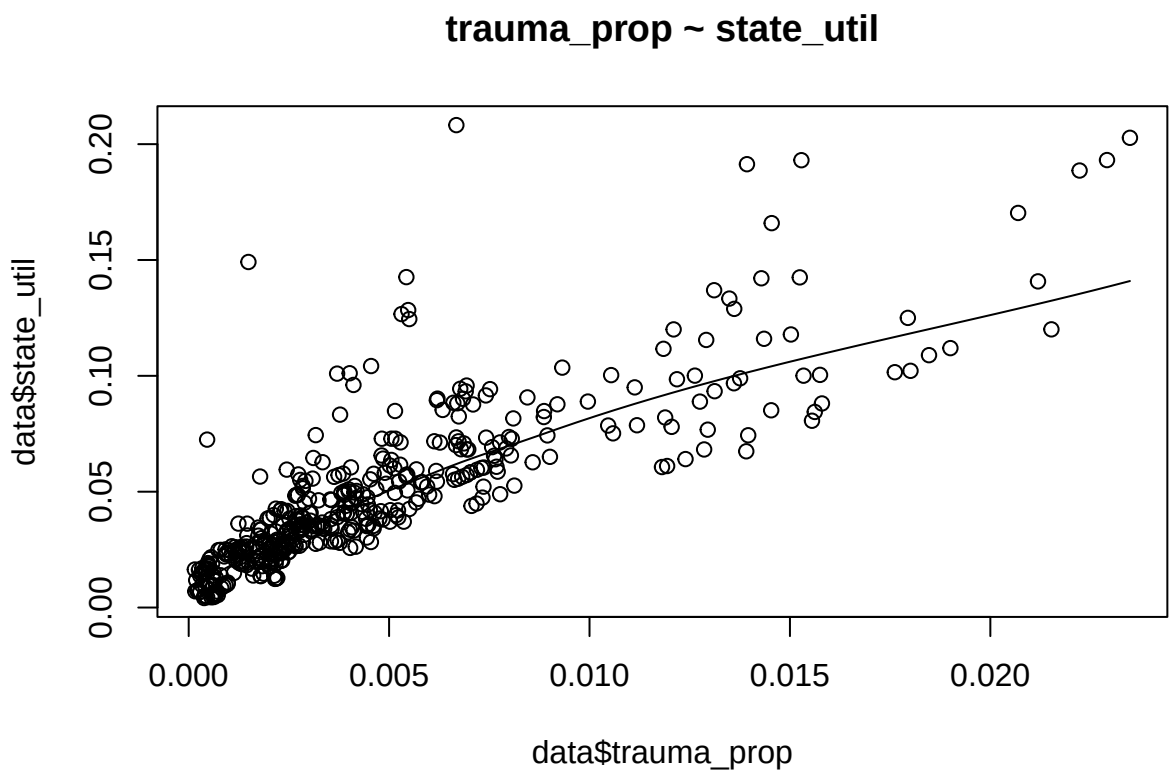

```r
par(mfrow=c(1,1))  # divide graph area in 2 columns
scatter.smooth(x=data$adhd_prop, y=data$state_util, main="adhd_prop ~ state_util")
```



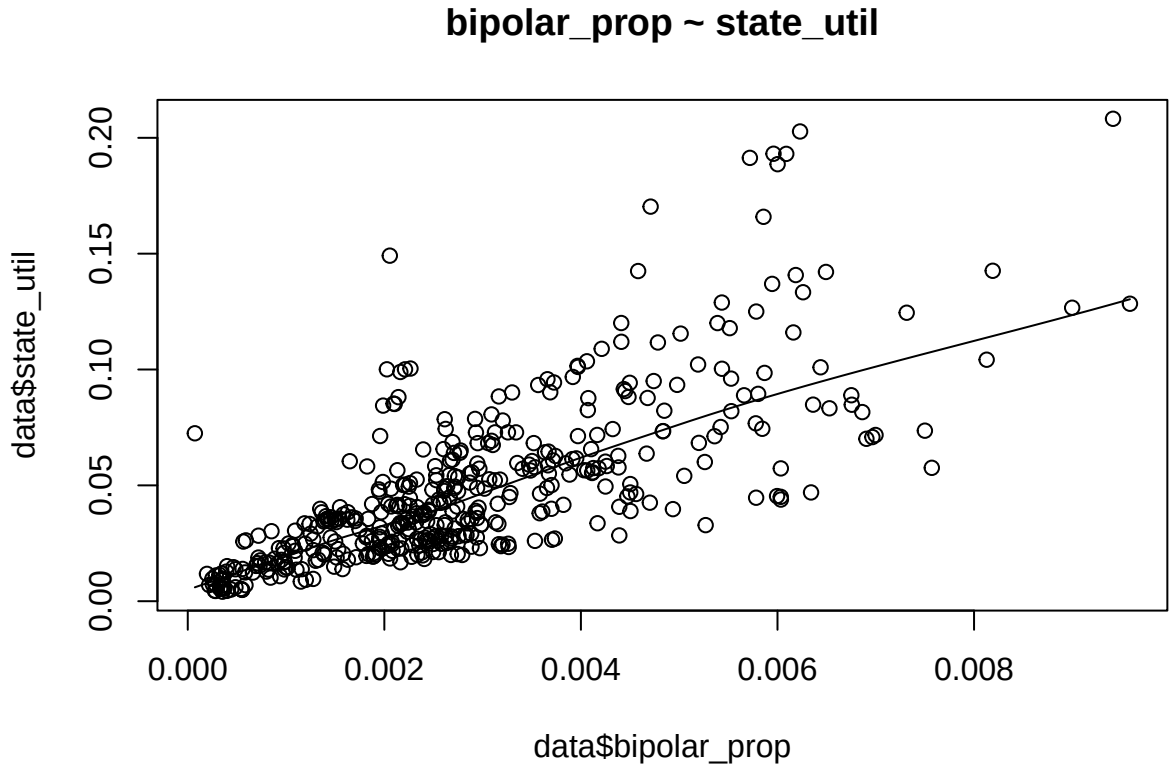

```
scatter.smooth(x=data$anxiety_prop, y=data$state_util, main="anxiety_prop ~ state_util")
```



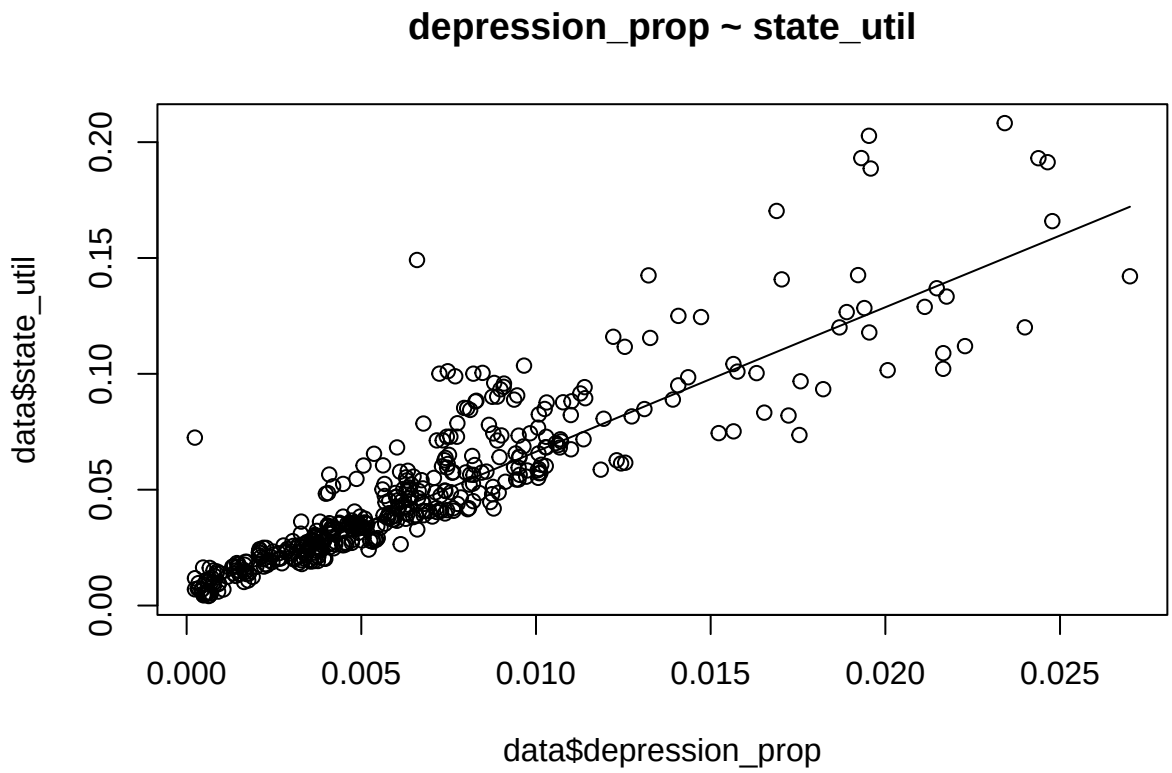
```r
scatter.smooth(x=data$trauma_prop, y=data$state_util, main="trauma_prop ~ state_util")
```




```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")
```

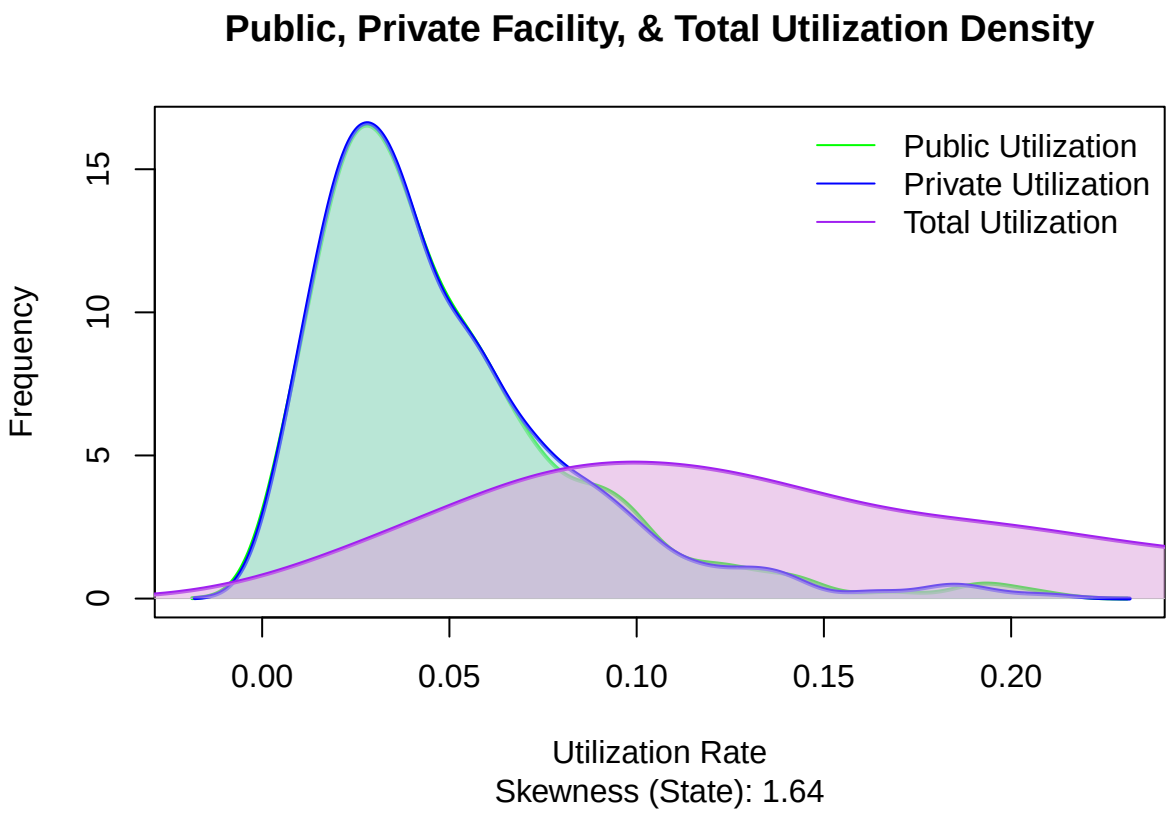



```r
library(e1071)
```

```
## 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)
```

```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,
         -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  25
```

```
names(clean_GTrends_acs_joined)
```

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

```
# 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] "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"
```

```
#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)
```

```
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  18
```

```
dim(test_set)
```

```
## [1] 97 18
```

TARGET ENCODING OF STATE BY Njagi

```
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"
```

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

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

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

     class(GTrend_training_set$state)
```

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

```
    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"
```

```
# 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) / (

   #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



            test_set$state <- factor(test_set$state)

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

```
dim(test_set_f)
```

```
## [1] 97 18
```

```
#center and scale

# 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))

state_util_index <-
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
```

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

head(GTrend_training_set_f)
```

```
## # A tibble: 6 x 18
##    year mean_adhd mean_ptsd mean_bipolar mean_depression mean_mental_hospital
##   <dbl>     <dbl>     <dbl>        <dbl>           <dbl>                <dbl>
## 1 -1.55    -0.349   -1.77          0.914          -1.15                -0.196
## 2 -1.55    -0.725   -1.03          0.711          -0.671               -0.242
## 3 -1.55    -0.551   -0.998         0.863           0.127               -0.247
## 4 -1.55    -0.927   -0.897         0.457          -1.35                 0.223
## 5 -1.55    -0.276   -1.74          2.59           -0.221               -2.20
## 6 -1.55    -0.569   -0.0217       -0.508          -0.311               -1.97
## # i 12 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>, state_encoded <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: 18 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 mean_adhd                 nume~                      0                    205
##  4 mean_ptsd                 nume~                      0                    114
##  5 mean_bipolar              nume~                      0                     97
##  6 mean_depression           nume~                      0                    230
##  7 mean_mental_hospital      nume~                      0                    272
##  8 mean_psychiatrists_near_~ nume~                      0                     59
##  9 mean_psychologist_near_me nume~                      0                    153
## 10 state_mentalhealth_util   nume~                      0                    433
## 11 anxiety_prop              nume~                      0                    433
## 12 adhd_prop                 nume~                      0                    433
## 13 bipolar_prop              nume~                      0                    433
## 14 prop_families_below_pove~ nume~                      0                    433
```

```
## 15 prop_adults_without_heal~ nume~                      0                   433
## 16 prop_unemployed_in_labor~ nume~                      0                   433
## 17 prop_without_internet_ac~ nume~                      0                   433
## 18 prop_adult_disability     nume~                      0                   433
## # i abbreviated names: 1: `Number of Missing Values`,
## #   2: `Number of Unique Values`
```

```
codebook$variable
```

```
##  [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"
```

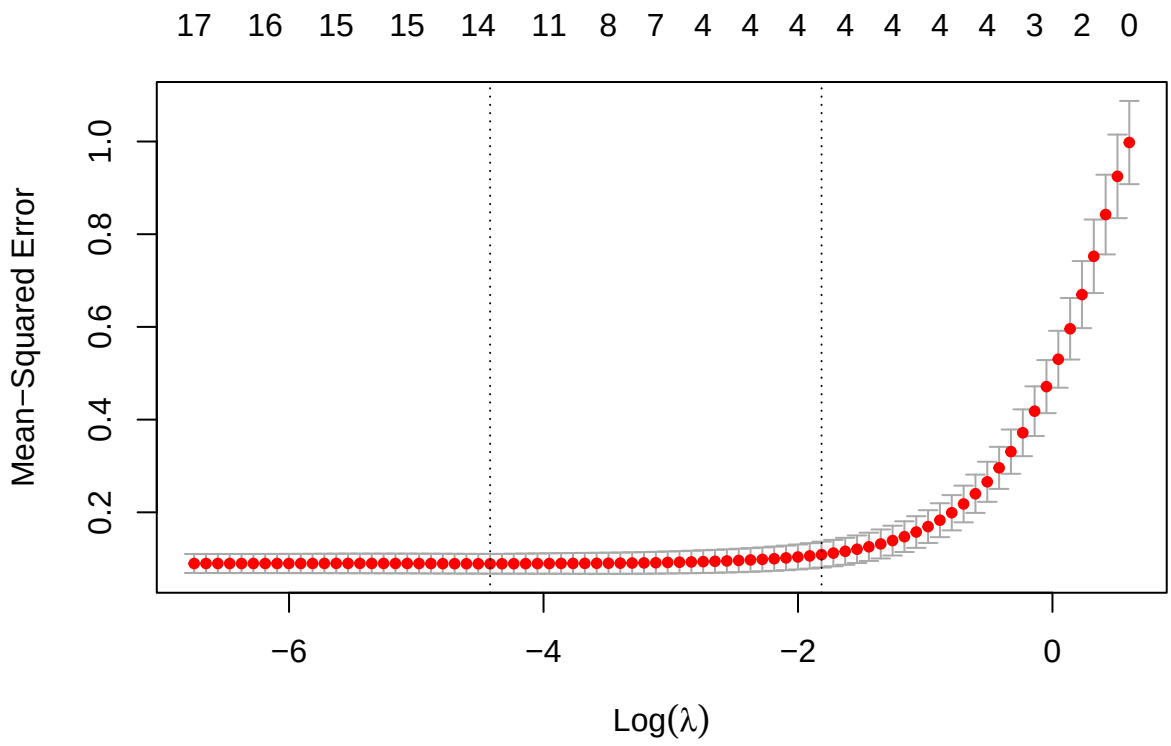
```
# Create an empty dataframe with three fields store storing model train and test RMSE values.
mse_df <- tibble(
  Model = character(),
  Train_MSE = numeric(),
  Test_MSE = numeric()
)

# 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)

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

```r
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 matrx

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
```

```r
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))
```

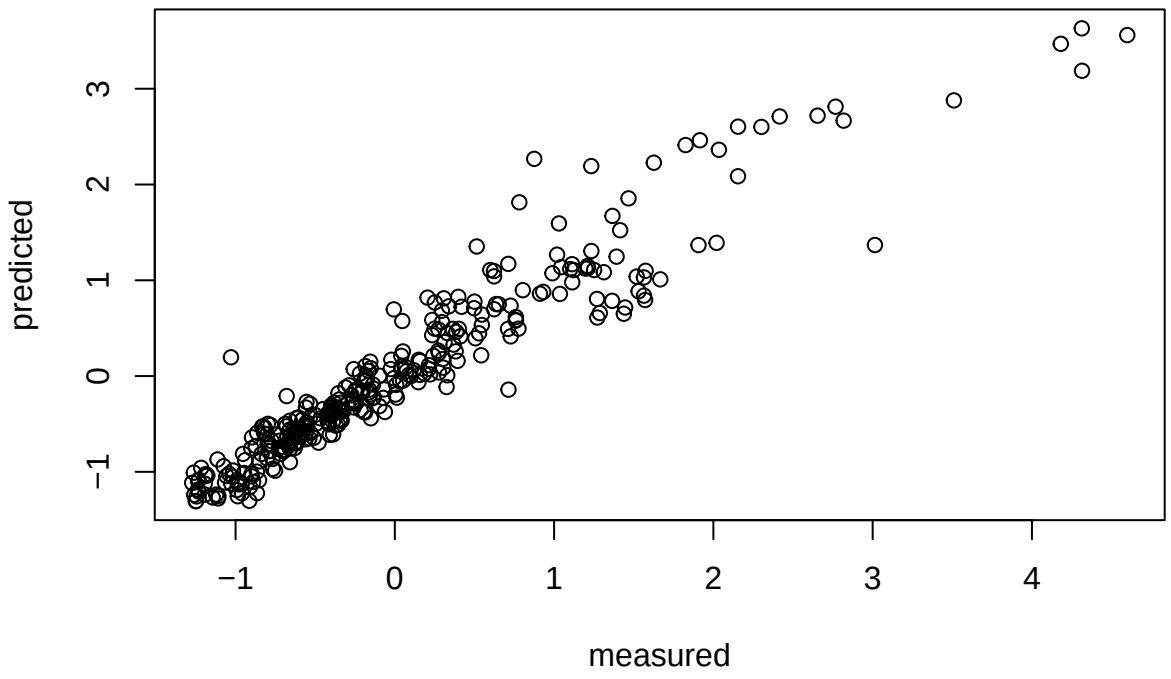
```
## [1] "MSE (MIN): 0.0915275070471097"
```

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

```
## [1] "MSE (1SE): 0.106943694036694"
```

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)
```

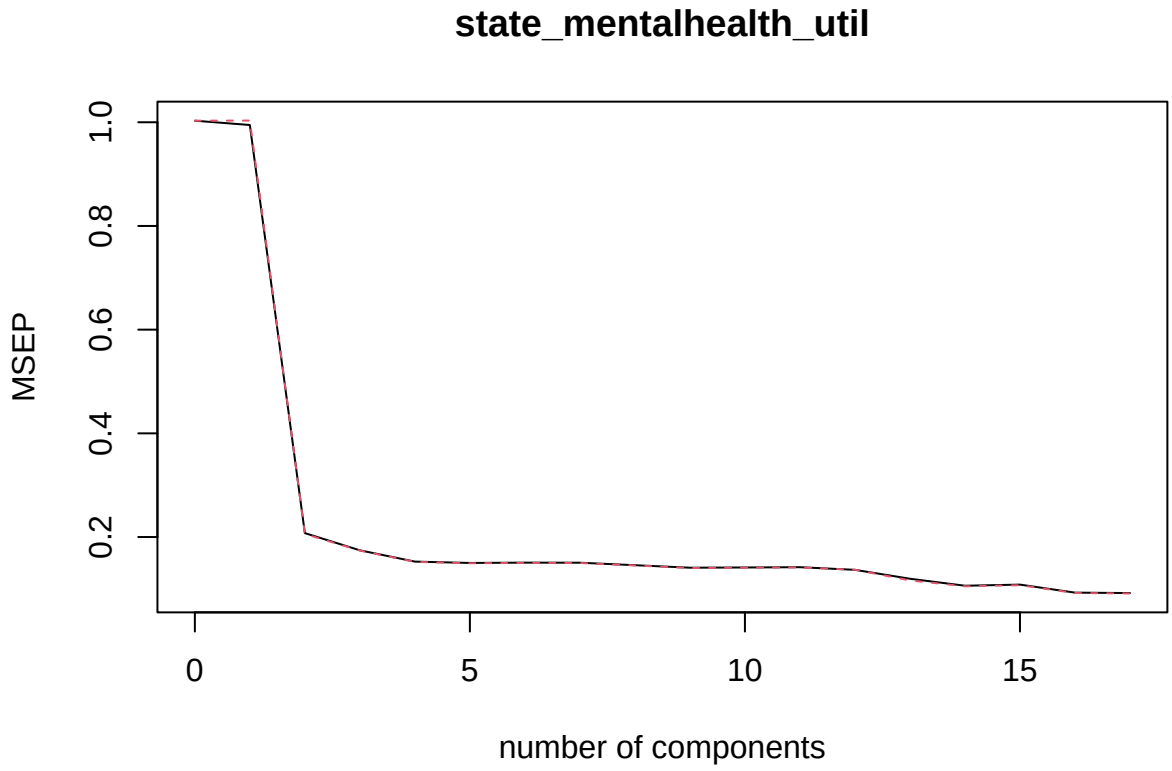



```
# Show the summary of the PCR fit.
summary(pcr_fit)
```

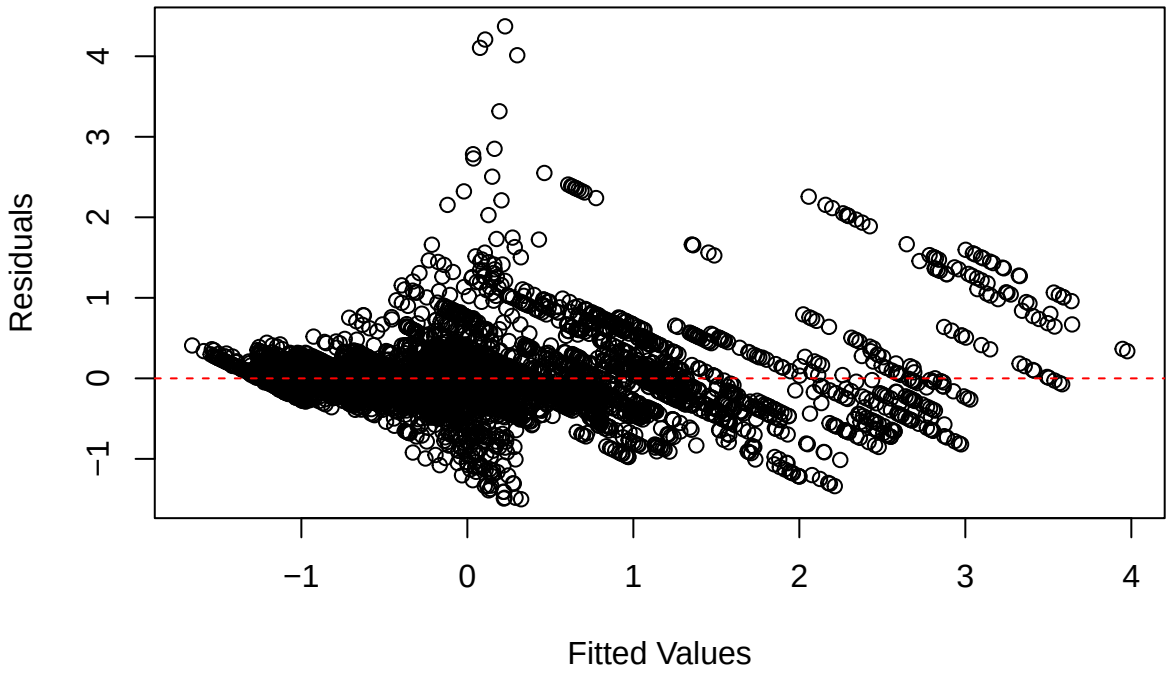
```
## Data:    X dimension: 336 17
##  Y dimension: 336 1
## Fit method: svdpc
## Number of components considered: 17
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           1.001   0.9974   0.4556   0.4176   0.3907   0.3873   0.3881
## adjCV        1.001   1.0016   0.4537   0.4170   0.3901   0.3866   0.3875
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV      0.3879   0.3817   0.3753    0.3759    0.3766    0.3698    0.3458
## adjCV   0.3872   0.3811   0.3745    0.3754    0.3760    0.3700    0.3412
##        14 comps  15 comps  16 comps  17 comps
## CV       0.3257    0.3290    0.3046    0.3032
## adjCV    0.3241    0.3273    0.3034    0.3020
##
## TRAINING: % variance explained
##                           1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                          22.313    42.08    55.58    66.24    73.67    80.57
## state_mentalhealth_util     3.124    79.83    83.12    85.35    85.63    85.72
##                           7 comps  8 comps  9 comps  10 comps  11 comps
## X                           84.69    88.07    91.02     92.88     94.56
## state_mentalhealth_util     85.92    86.29    86.92     87.05     87.21
##                           12 comps  13 comps  14 comps  15 comps  16 comps
## X                            95.97     97.06     98.08     98.92     99.65
```

```
## state_mentalhealth_util     87.83     90.18     91.33     91.37     92.02
##                           17 comps
## X                           100.00
## state_mentalhealth_util     92.14
```

```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 0.965872049277168"
```

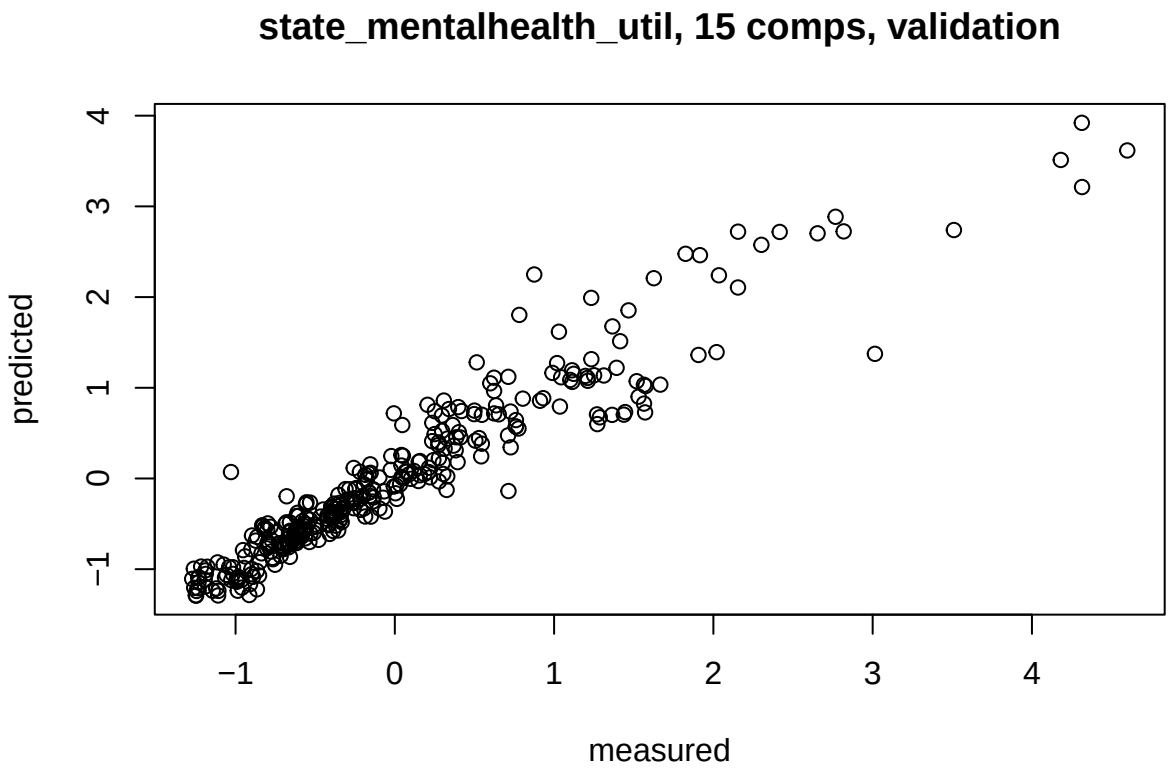
```
paste("PCR Test MSE for M Selected:",pcr_m_selected,"is", pcr_test_mse)
```

```
## [1] "PCR Test MSE for M Selected: 1 is 0.0344761154335153"
```

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)
```

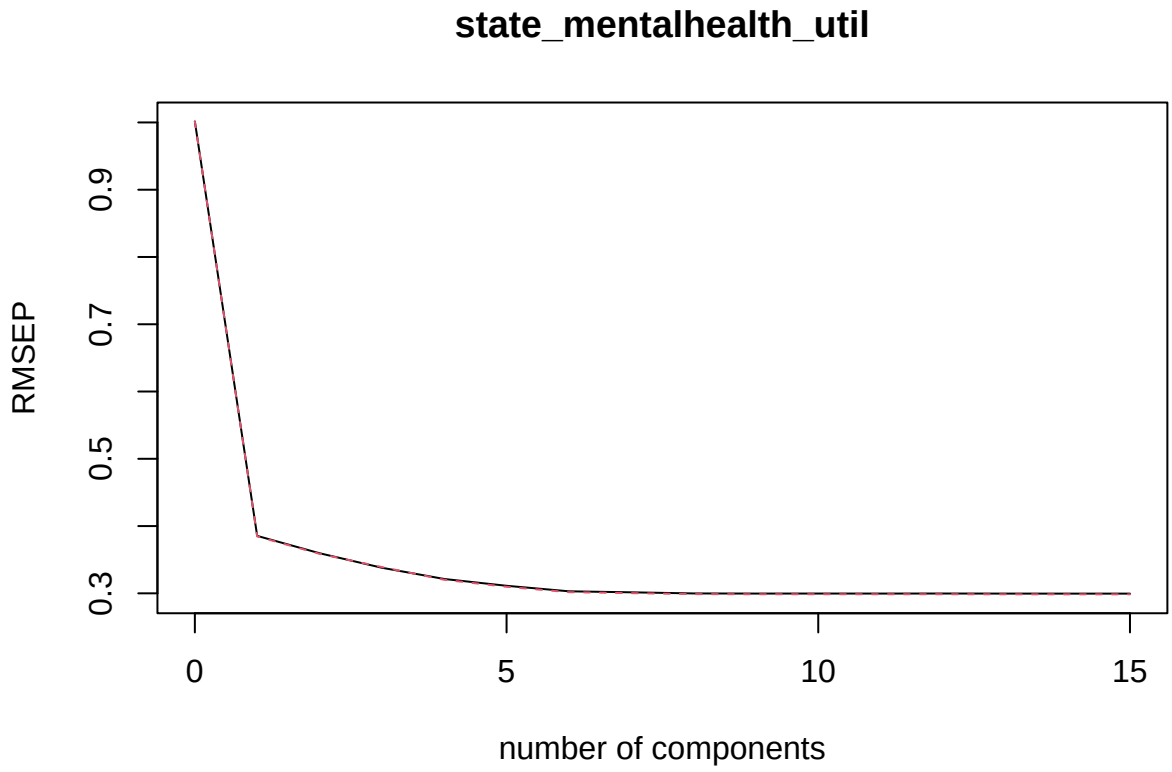



```r
# print the summary of the partial least square regression fit.
summary(plsr_fit)
```

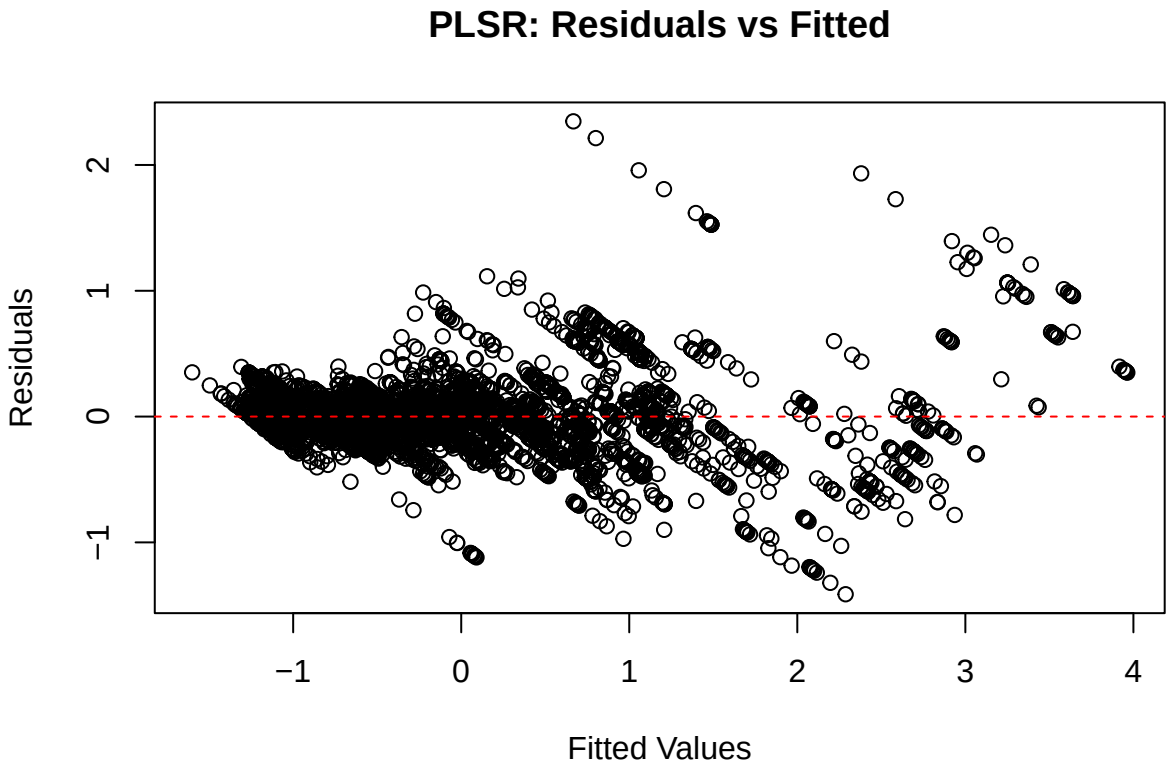
```
## Data:    X dimension: 336 17
##  Y dimension: 336 1
## Fit method: kernelpls
## Number of components considered: 15
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           1.001   0.3854   0.3596   0.3380   0.3214   0.3112   0.3030
## adjCV        1.001   0.3846   0.3587   0.3391   0.3202   0.3097   0.3017
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV      0.3015   0.2999   0.2997    0.2997    0.2997    0.2997    0.2996
## adjCV   0.3003   0.2988   0.2986    0.2987    0.2986    0.2987    0.2986
##        14 comps  15 comps
## CV       0.2996    0.2996
## adjCV    0.2985    0.2985
##
## TRAINING: % variance explained
##                           1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                           19.69    32.49    46.09    56.53    65.47    71.48
## state_mentalhealth_util     85.66    87.98    89.62    91.13    91.68    92.00
##                           7 comps  8 comps  9 comps  10 comps  11 comps
```

```
## X                          77.58    80.53    84.28     89.14     91.17
## state_mentalhealth_util    92.08    92.11    92.13     92.13     92.14
##                          12 comps  13 comps  14 comps  15 comps
## X                           93.56     95.04     96.43     97.86
## state_mentalhealth_util     92.14     92.14     92.14     92.14
```

```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 0.0783454038310351"
```

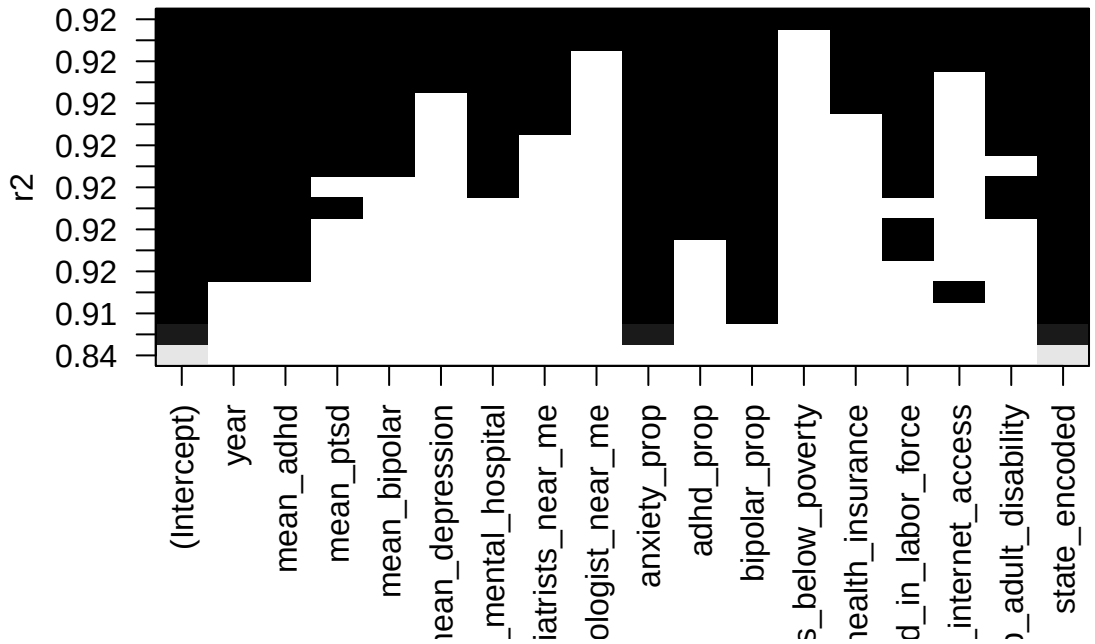
```
paste("PLSR Test MSE for M Selected:",plsr_M_selected,"is", plsr_test_mse)
```

```
## [1] "PLSR Test MSE for M Selected: 15 is 1.79020333893143"
```

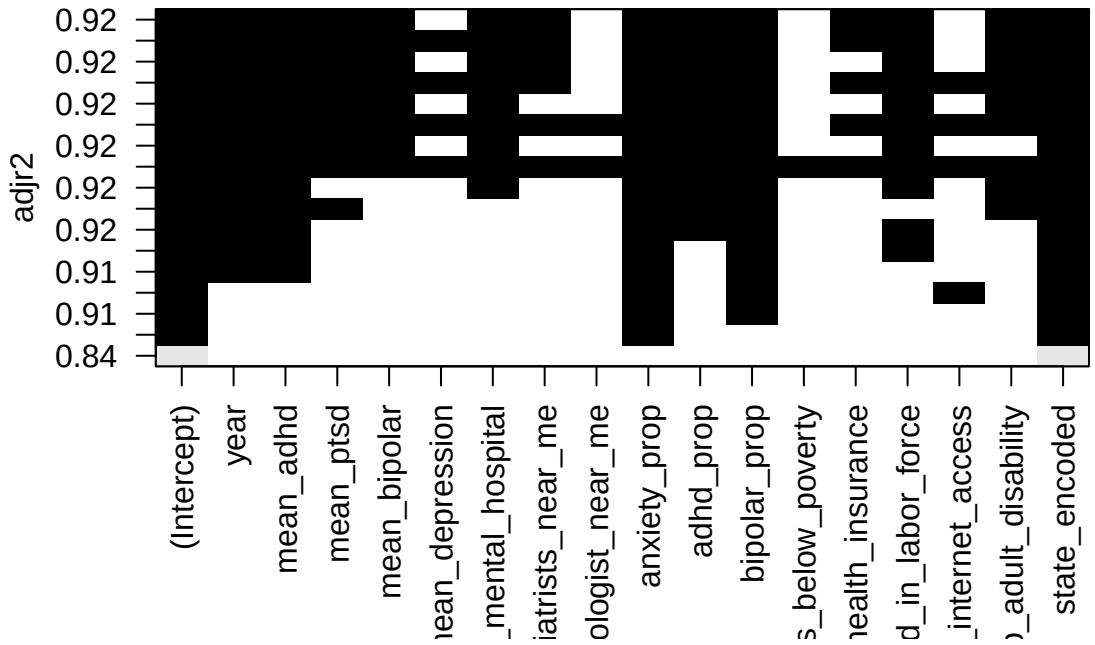
Best Subset Selection

```
# 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.
```

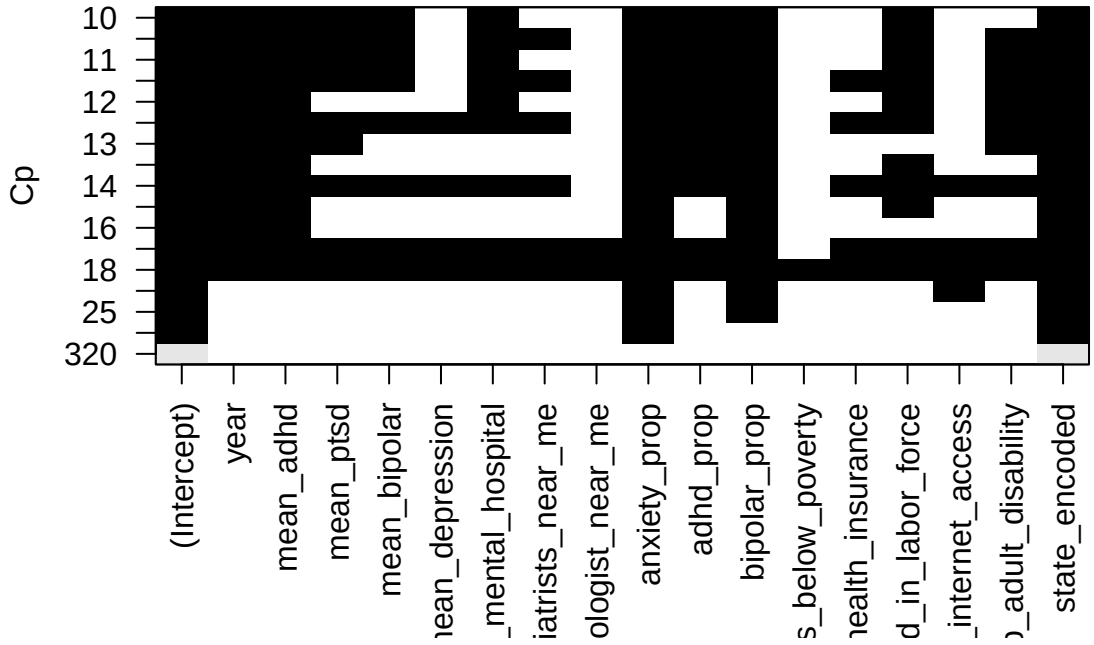
```
reg_fit_train <- regsubsets(state_mentalhealth_util ~ ., data=GTrend_training_set_f, nvmax=23)

plot(reg_fit_train, scale="r2")
```



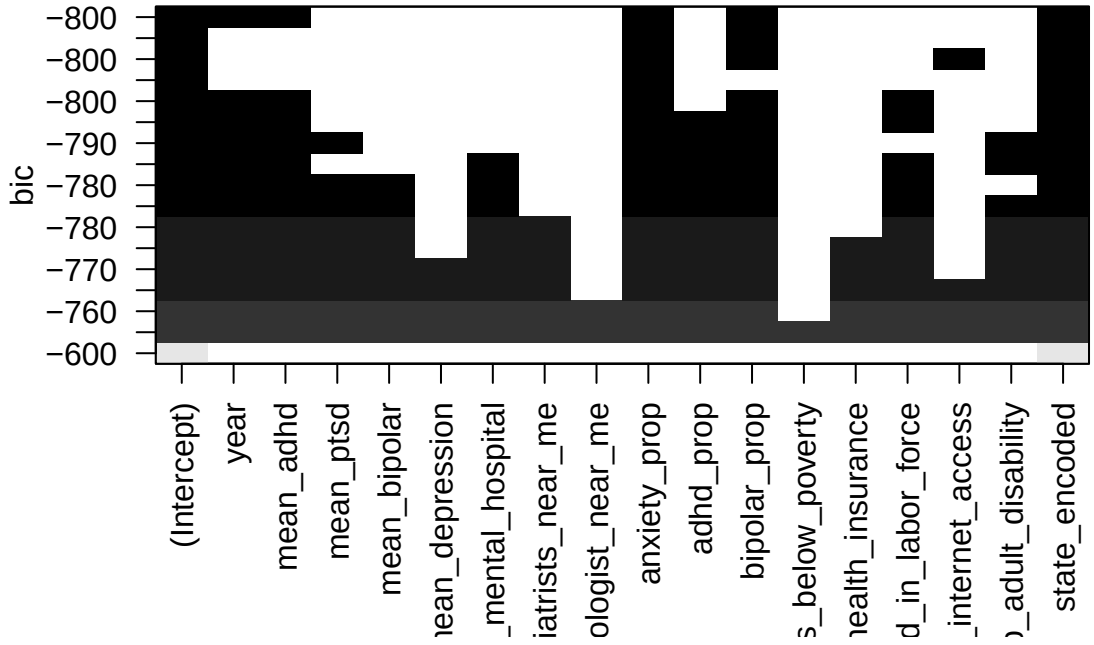

```
plot(reg_fit_train, scale="adjr2")
```




```
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)
```

```
## Subset selection object
## Call: regsubsets.formula(state_mentalhealth_util ~ ., data = GTrend_training_set_f,
##     nvmax = 23)
## 17 Variables  (and intercept)
##                                    Forced in Forced out
```

```
## year                                    FALSE      FALSE
## mean_adhd                               FALSE      FALSE
## mean_ptsd                               FALSE      FALSE
## mean_bipolar                            FALSE      FALSE
## mean_depression                         FALSE      FALSE
## mean_mental_hospital                    FALSE      FALSE
## mean_psychiatrists_near_me              FALSE      FALSE
## mean_psychologist_near_me               FALSE      FALSE
## anxiety_prop                            FALSE      FALSE
## adhd_prop                               FALSE      FALSE
## bipolar_prop                            FALSE      FALSE
## prop_families_below_poverty             FALSE      FALSE
## prop_adults_without_health_insurance    FALSE      FALSE
## prop_unemployed_in_labor_force          FALSE      FALSE
## prop_without_internet_access            FALSE      FALSE
## prop_adult_disability                   FALSE      FALSE
## state_encoded                           FALSE      FALSE
## 1 subsets of each size up to 17
## Selection Algorithm: exhaustive
##           year mean_adhd mean_ptsd mean_bipolar mean_depression
## 1  ( 1 )  " "  " "       " "       " "          " "
## 2  ( 1 )  " "  " "       " "       " "          " "
## 3  ( 1 )  " "  " "       " "       " "          " "
## 4  ( 1 )  " "  " "       " "       " "          " "
## 5  ( 1 )  "*"  "*"       " "       " "          " "
## 6  ( 1 )  "*"  "*"       " "       " "          " "
## 7  ( 1 )  "*"  "*"       " "       " "          " "
## 8  ( 1 )  "*"  "*"       "*"       " "          " "
## 9  ( 1 )  "*"  "*"       " "       " "          " "
## 10  ( 1 ) "*"  "*"       "*"       "*"          " "
## 11  ( 1 ) "*"  "*"       "*"       "*"          " "
## 12  ( 1 ) "*"  "*"       "*"       "*"          " "
## 13  ( 1 ) "*"  "*"       "*"       "*"          " "
## 14  ( 1 ) "*"  "*"       "*"       "*"          "*"
## 15  ( 1 ) "*"  "*"       "*"       "*"          "*"
## 16  ( 1 ) "*"  "*"       "*"       "*"          "*"
## 17  ( 1 ) "*"  "*"       "*"       "*"          "*"
##           mean_mental_hospital mean_psychiatrists_near_me
## 1  ( 1 )  " "                  " "
## 2  ( 1 )  " "                  " "
## 3  ( 1 )  " "                  " "
## 4  ( 1 )  " "                  " "
## 5  ( 1 )  " "                  " "
## 6  ( 1 )  " "                  " "
## 7  ( 1 )  " "                  " "
## 8  ( 1 )  " "                  " "
## 9  ( 1 )  "*"                  " "
## 10  ( 1 ) "*"                  " "
## 11  ( 1 ) "*"                  " "
## 12  ( 1 ) "*"                  "*"
## 13  ( 1 ) "*"                  "*"
## 14  ( 1 ) "*"                  "*"
## 15  ( 1 ) "*"                  "*"
## 16  ( 1 ) "*"                  "*"
```

```
## 17  ( 1 ) "*"                  "*"
##           mean_psychologist_near_me anxiety_prop adhd_prop bipolar_prop
## 1  ( 1 )  " "                       " "          " "        " "
## 2  ( 1 )  " "                       "*"          " "        " "
## 3  ( 1 )  " "                       "*"          " "        "*"
## 4  ( 1 )  " "                       "*"          " "        "*"
## 5  ( 1 )  " "                       "*"          " "        "*"
## 6  ( 1 )  " "                       "*"          " "        "*"
## 7  ( 1 )  " "                       "*"          "*"        "*"
## 8  ( 1 )  " "                       "*"          "*"        "*"
## 9  ( 1 )  " "                       "*"          "*"        "*"
## 10  ( 1 ) " "                       "*"          "*"        "*"
## 11  ( 1 ) " "                       "*"          "*"        "*"
## 12  ( 1 ) " "                       "*"          "*"        "*"
## 13  ( 1 ) " "                       "*"          "*"        "*"
## 14  ( 1 ) " "                       "*"          "*"        "*"
## 15  ( 1 ) " "                       "*"          "*"        "*"
## 16  ( 1 ) "*"                       "*"          "*"        "*"
## 17  ( 1 ) "*"                       "*"          "*"        "*"
##           prop_families_below_poverty prop_adults_without_health_insurance
## 1  ( 1 )  " "                         " "
## 2  ( 1 )  " "                         " "
## 3  ( 1 )  " "                         " "
## 4  ( 1 )  " "                         " "
## 5  ( 1 )  " "                         " "
## 6  ( 1 )  " "                         " "
## 7  ( 1 )  " "                         " "
## 8  ( 1 )  " "                         " "
## 9  ( 1 )  " "                         " "
## 10  ( 1 ) " "                         " "
## 11  ( 1 ) " "                         " "
## 12  ( 1 ) " "                         " "
## 13  ( 1 ) " "                         "*"
## 14  ( 1 ) " "                         "*"
## 15  ( 1 ) " "                         "*"
## 16  ( 1 ) " "                         "*"
## 17  ( 1 ) "*"                         "*"
##           prop_unemployed_in_labor_force prop_without_internet_access
## 1  ( 1 )  " "                            " "
## 2  ( 1 )  " "                            " "
## 3  ( 1 )  " "                            " "
## 4  ( 1 )  " "                            "*"
## 5  ( 1 )  " "                            " "
## 6  ( 1 )  "*"                            " "
## 7  ( 1 )  "*"                            " "
## 8  ( 1 )  " "                            " "
## 9  ( 1 )  "*"                            " "
## 10  ( 1 ) "*"                            " "
## 11  ( 1 ) "*"                            " "
## 12  ( 1 ) "*"                            " "
## 13  ( 1 ) "*"                            " "
## 14  ( 1 ) "*"                            " "
## 15  ( 1 ) "*"                            "*"
## 16  ( 1 ) "*"                            "*"
```

```
## 17  ( 1 ) "*"                           "*"
##           prop_adult_disability state_encoded
## 1  ( 1 )  " "                   "*"
## 2  ( 1 )  " "                   "*"
## 3  ( 1 )  " "                   "*"
## 4  ( 1 )  " "                   "*"
## 5  ( 1 )  " "                   "*"
## 6  ( 1 )  " "                   "*"
## 7  ( 1 )  " "                   "*"
## 8  ( 1 )  "*"                   "*"
## 9  ( 1 )  "*"                   "*"
## 10  ( 1 ) " "                   "*"
## 11  ( 1 ) "*"                   "*"
## 12  ( 1 ) "*"                   "*"
## 13  ( 1 ) "*"                   "*"
## 14  ( 1 ) "*"                   "*"
## 15  ( 1 ) "*"                   "*"
## 16  ( 1 ) "*"                   "*"
## 17  ( 1 ) "*"                   "*"
```

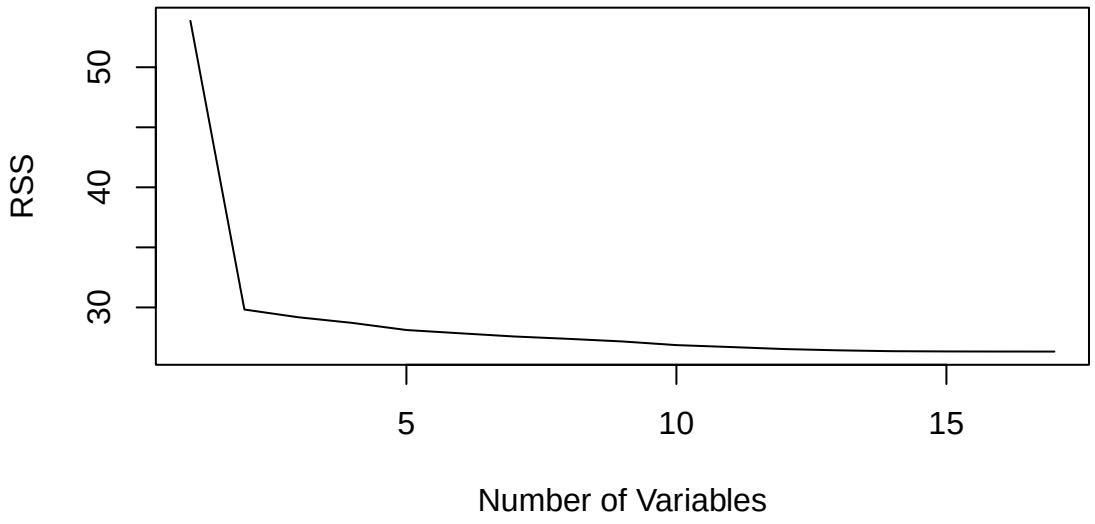
```
names(reg.summary)
```

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

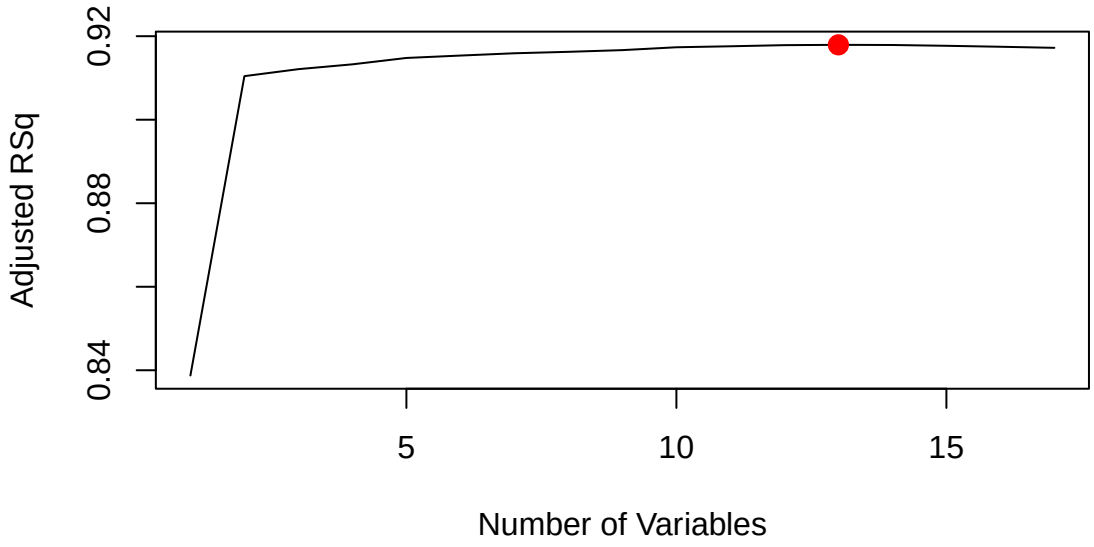
```
#Print the R^2 statistic
reg.summary$rsq
```

```
##  [1] 0.8392261 0.9109725 0.9128931 0.9142993 0.9160618 0.9168802 0.9176724
##  [8] 0.9182612 0.9189085 0.9198194 0.9202972 0.9207971 0.9211178 0.9213264
## [15] 0.9213864 0.9214142 0.9214207
```

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



```
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)
```



Random Forest

```
library(randomForest)
```

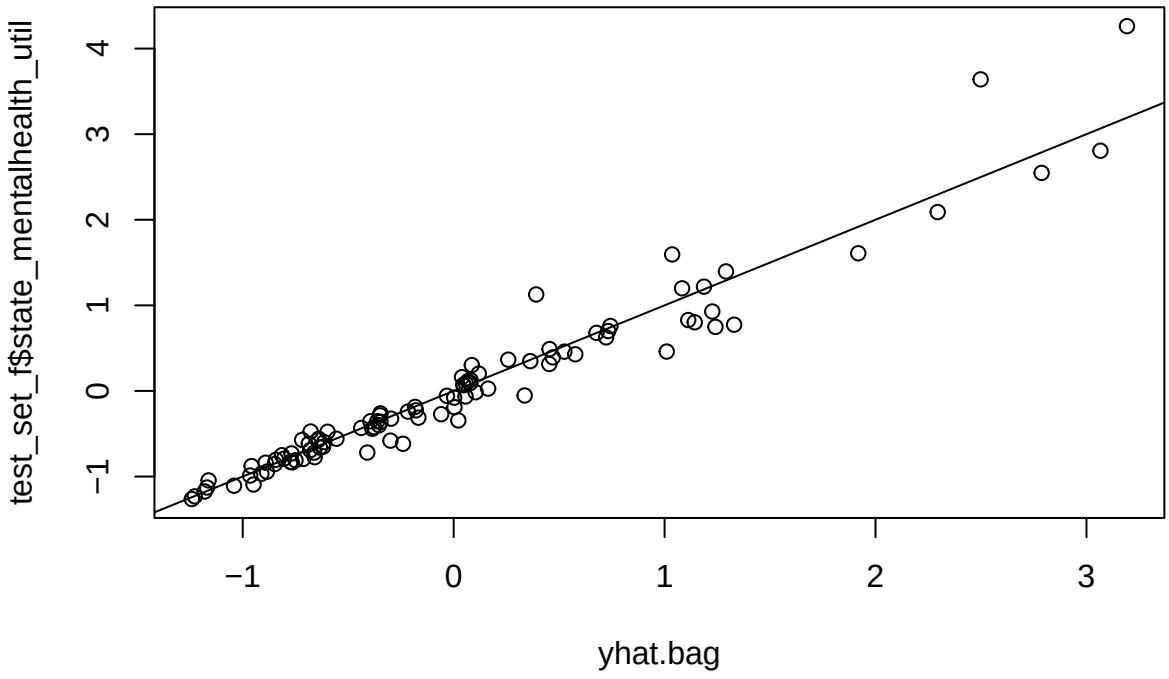
```
## randomForest 4.7-1.2

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

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

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
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: 17
##
##           Mean of squared residuals: 0.09194341
##                     % Var explained: 90.78
```

```
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: 0.0604315303625464"
```

```
# 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: 0.09078431
##                     % Var explained: 90.89
```

```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: = 1.76591530123137"
```

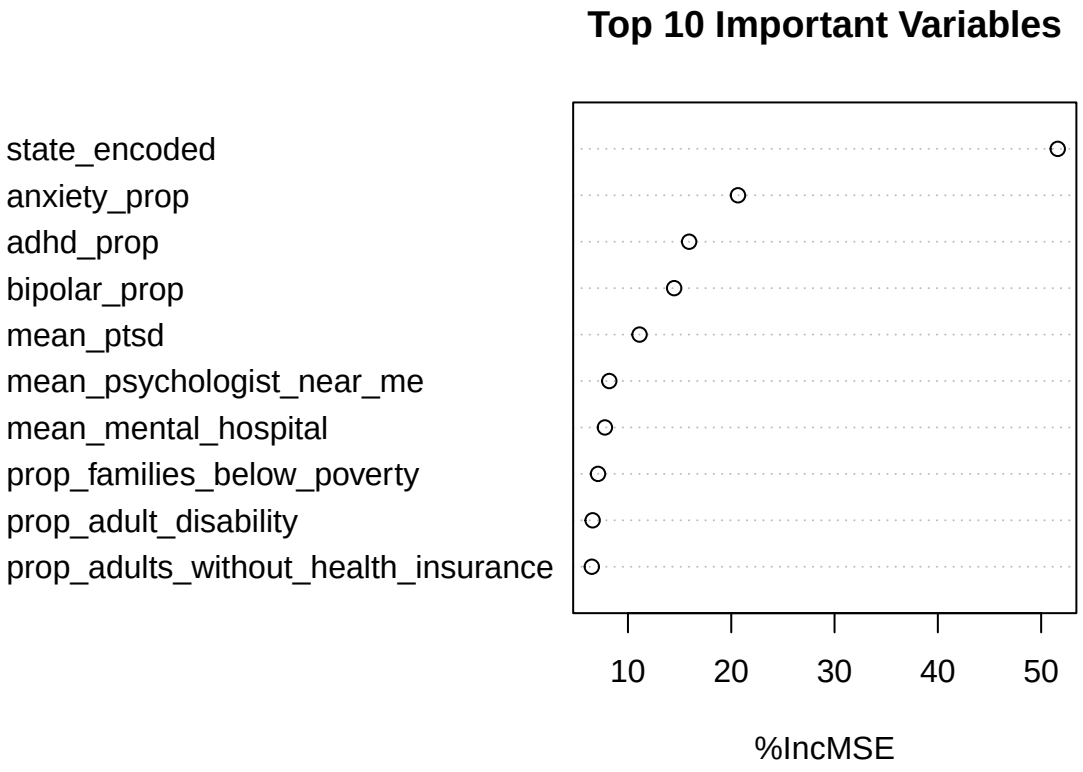
```r
paste("Test MSE associated with the Random Forest is: =", rf_test_mse)
```

```
## [1] "Test MSE associated with the Random Forest is: = 0.0622744273933698"
```

```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 51.606691    197.065536
## anxiety_prop                               anxiety_prop 20.651969     67.892737
## adhd_prop                                     adhd_prop 15.925081     27.838683
## bipolar_prop                               bipolar_prop 14.473929     12.213798
## mean_ptsd                                     mean_ptsd 11.122421      7.150023
## mean_psychologist_near_me mean_psychologist_near_me  8.193055      2.335012
```

```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"
)
```

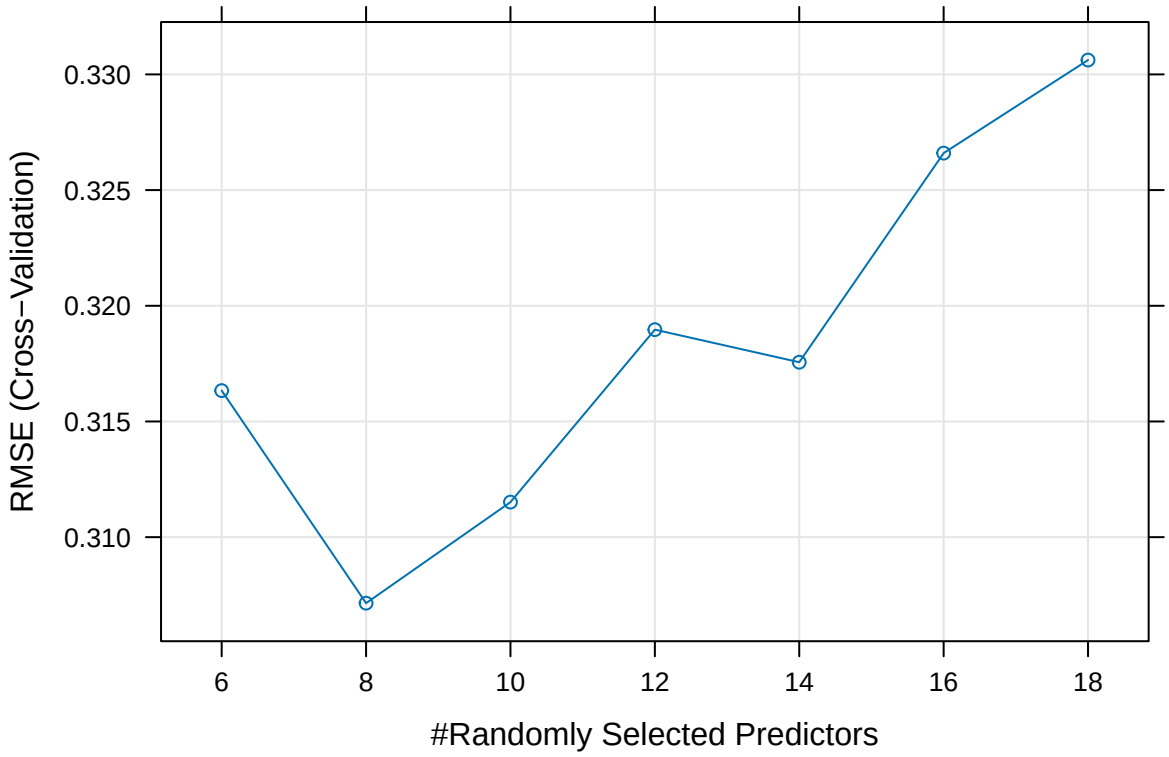



```r
set.seed(42)

# 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
##  17 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    0.3163335  0.9120426  0.1646418
##    8    0.3071460  0.9158553  0.1561582
##   10    0.3115143  0.9111749  0.1579116
##   12    0.3189678  0.9058795  0.1608917
##   14    0.3175611  0.9066239  0.1602527
##   16    0.3265981  0.9007171  0.1638053
##   18    0.3306210  0.8978363  0.1672510
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 8.
```

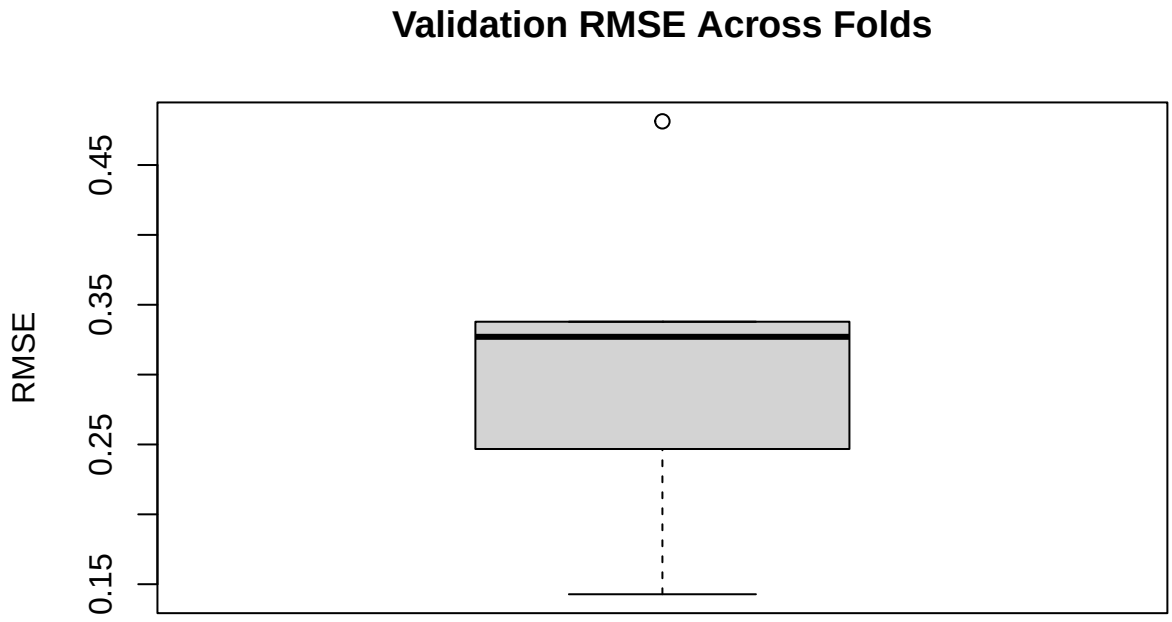
```r
# Show validation plot
plot(rf_cv_model)
```



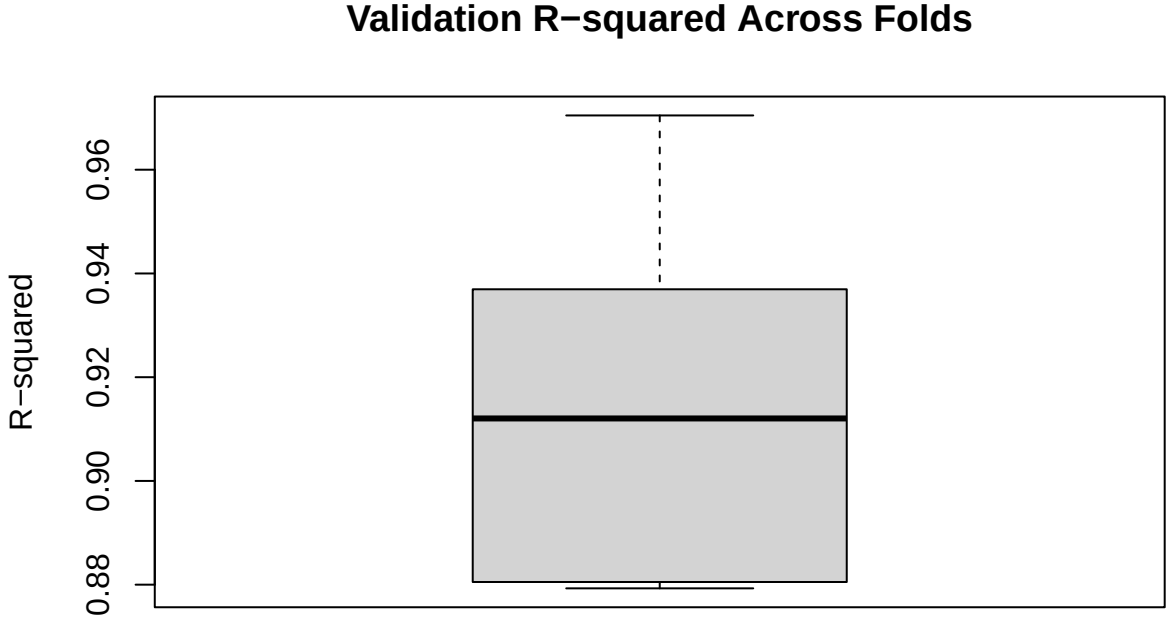

```r
names(rf_cv_model)
```

```
##  [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")
```

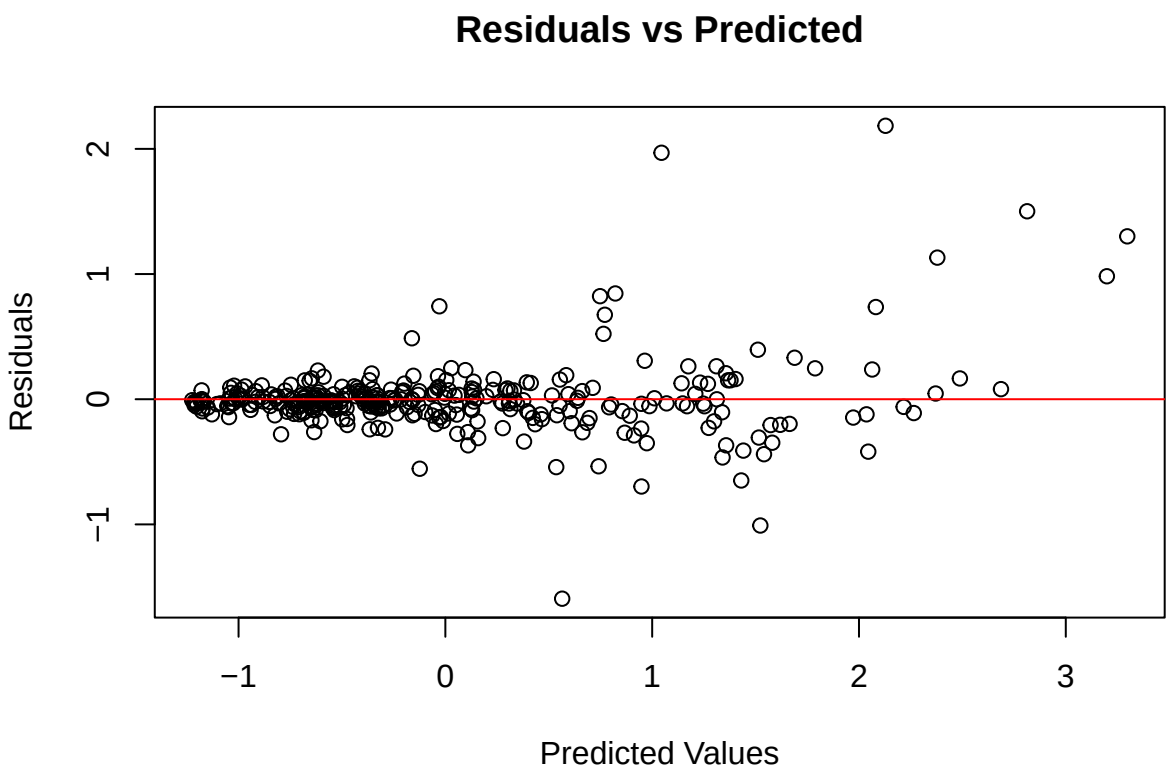



```
# Show R squared across folds with na.omit() as above.
boxplot(na.omit(rf_cv_model$resample$Rsquared),
        main = "Validation R-squared Across Folds",
        ylab = "R-squared")
```




```
# 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")
```




```
mse_df
```

```
## # A tibble: 3 x 3
##   Model                              Train_MSE Test_MSE
##   <chr>                                  <dbl>    <dbl>
## 1 Principal Component Regression      0.966    0.0345
## 2 Partial Least Squares Regression    0.0783   1.79
## 3 Random Forest                       1.77     0.0623
```

```
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] "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, i
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 10
##
##           Mean of squared residuals: 0.08418735
##                     % Var explained: 91.56
```

```
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: = 1.76672358261379"
```

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

```
## [1] "Test MSE associated with the Random Forest is: = 0.0587883005613294"
```

```
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 43.884187    173.952897
## anxiety_prop                                  anxiety_prop 20.954153     72.208143
## adhd_prop                                        adhd_prop 16.854960     38.769934
## bipolar_prop                                  bipolar_prop 12.263089     14.908929
## mean_ptsd                                        mean_ptsd 11.724616      7.222497
## prop_families_below_poverty prop_families_below_poverty  8.947283      2.304902
```

```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"
)
```