Lab_Three_Salameh

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Part 3 - Data Analysis

```
setwd("~/Downloads/Machine_Learning/Lab_Three_Salameh")

library(tidyverse)

## Warning: package 'ggplot2' was built under R version 4.1.2

## Warning: package 'tibble' was built under R version 4.1.2

## Warning: package 'tidyr' was built under R version 4.1.2

## Warning: package 'readr' was built under R version 4.1.2

## Warning: package 'purrr' was built under R version 4.1.2

## Warning: package 'dplyr' was built under R version 4.1.2

## Warning: package 'stringr' was built under R version 4.1.2

library(gbm)

## Warning: package 'gbm' was built under R version 4.1.2

library(ISLR)
library(tree)

## Warning: package 'tree' was built under R version 4.1.2

library(glmnet)

## Warning: package 'glmnet' was built under R version 4.1.2

library(leaps)

Covid_df <- read.csv("CovidData.csv")
```

Question 1:

The “VariableDescription.xlsx” spreadsheet contains a list of variables that we’ll use for our analyses. Note that this is not a full list of all the variables in the dataset, although it’s close (we ignoring a few perfectly co-linear predictors). Filter the full set of variables in the

dataset down to the Opportunity Insights and PM COVID variables listed in the spreadsheet along with 'county', 'state' and 'deathspc'.

```
Covid_df <- Covid_df[, c(
  "state", "deathspc", "intersects_msa", "cur_smoke_q1", "cur_smoke_q2",
"cur_smoke_q3", "cur_smoke_q4", "bmi_obese_q1", "bmi_obese_q2",
"bmi_obese_q3", "bmi_obese_q4", "exercise_any_q1",
  "exercise_any_q2", "exercise_any_q3", "exercise_any_q4", "brfss_mia",
"puninsured2010", "reimb_penroll_adj10", "mort_30day_hosp_z",
"adjmortmeas_amiall30day", "adjmortmeas_chfall30day", "med_prev_qual_z",
"primcarevis_10", "diab_hemotest_10", "diab_eyeexam_10", "diab_lipids_10",
"mammogram_10", "cs00_seg_inc", "cs00_seg_inc_pov25", "cs00_seg_inc_aff75",
"cs_race_theil_2000", "gini99", "poor_share", "inc_share_1perc",
  "frac_middleclass", "scap_ski90pcm", "rel_tot", "cs_frac_black",
"cs_frac_hisp", "unemp_rate", "cs_labforce", "cs_elf_ind_man",
"cs_born_foreign", "mig_inflow", "mig_outflow", "pop_density",
"frac_traveltime_lt15", "hhinc00", "median_house_value", "ccd_exp_tot",
"score_r", "cs_fam_wkidsinglemom", "subcty_exp_pc", "taxrate",
"tax_st_diff_top20", "pm25", "pm25_mia",
  "summer_tmmx", "summer_rmax", "winter_tmmx", "winter_rmax", "bmcruderate"
)]
```

Question 2:

Compute descriptive (summary) statistics for the subset of Opportunity Insights and PM COVID variables you filtered in previous question.

```
summary(Covid_df)
```

```
##     state              deathspc        intersects_msa    cur_smoke_q1
##  Length:3107        Min.   :   0.000   Min.   :0.0000   Min.   :0.0000
##  Class :character   1st Qu.:   0.000   1st Qu.:0.0000   1st Qu.:0.0000
##  Mode  :character   Median :   3.802   Median :1.0000   Median :0.2500
##                     Mean   :  23.790   Mean   :0.5967   Mean   :0.2127
##                     3rd Qu.:  21.462   3rd Qu.:1.0000   3rd Qu.:0.3109
##                     Max.   :2279.611   Max.   :1.0000   Max.   :1.0000
##
##   cur_smoke_q2     cur_smoke_q3     cur_smoke_q4      bmi_obese_q1
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.00000   Min.   :0.00000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0.08013
##  Median :0.1987   Median :0.1429   Median :0.09653   Median :0.27208
##  Mean   :0.1710   Mean   :0.1345   Mean   :0.09832   Mean   :0.23917
##  3rd Qu.:0.2500   3rd Qu.:0.2000   3rd Qu.:0.14872   3rd Qu.:0.33553
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.00000   Max.   :1.00000
##
##   bmi_obese_q2     bmi_obese_q3     bmi_obese_q4    exercise_any_q1
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.3125
##  Median :0.2416   Median :0.2231   Median :0.1941   Median :0.5666
```

```
##  Mean   :0.2146   Mean   :0.2096   Mean   :0.1867   Mean   :0.4560
##  3rd Qu.:0.3043   3rd Qu.:0.2972   3rd Qu.:0.2667   3rd Qu.:0.6415
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##
##  exercise_any_q2  exercise_any_q3  exercise_any_q4    brfss_mia
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.4444   1st Qu.:0.3542   1st Qu.:0.4000   1st Qu.:0.0000
##  Median :0.7071   Median :0.7784   Median :0.8333   Median :0.0000
##  Mean   :0.5557   Mean   :0.6038   Mean   :0.6387   Mean   :0.2494
##  3rd Qu.:0.7692   3rd Qu.:0.8418   3rd Qu.:0.8905   3rd Qu.:0.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##
##  puninsured2010   reimb_penroll_adj10 mort_30day_hosp_z
adjmortmeas_amiall30day
##  Min.   : 3.625   Min.   : 3664       Min.   :-7.7780   Min.   :0.0000
##  1st Qu.:14.410   1st Qu.: 8159       1st Qu.:-0.2559   1st Qu.:0.1453
##  Median :18.147   Median : 9194       Median : 0.4001   Median :0.1627
##  Mean   :18.469   Mean   : 9303       Mean   : 0.4578   Mean   :0.1655
##  3rd Qu.:21.961   3rd Qu.:10285       3rd Qu.: 1.1478   3rd Qu.:0.1834
##  Max.   :41.366   Max.   :18443       Max.   : 8.4727   Max.   :0.4447
##                   NA's   :4           NA's   :1         NA's   :1
##  adjmortmeas_chfall30day med_prev_qual_z    primcarevis_10
diab_hemotest_10
##  Min.   :0.0000          Min.   :-4.85385   Min.   :18.33   Min.   : 16.91
##  1st Qu.:0.0963          1st Qu.:-0.61559   1st Qu.:78.80   1st Qu.: 81.11
##  Median :0.1072          Median :-0.09023   Median :82.20   Median : 84.78
##  Mean   :0.1090          Mean   :-0.14855   Mean   :80.87   Mean   : 83.71
##  3rd Qu.:0.1202          3rd Qu.: 0.44443   3rd Qu.:84.96   3rd Qu.: 87.68
##  Max.   :0.3445          Max.   : 3.47852   Max.   :95.67   Max.   :100.00
##                          NA's   :95         NA's   :9       NA's   :38
##  diab_eyeexam_10 diab_lipids_10   mammogram_10    cs00_seg_inc
##  Min.   :31.37   Min.   :19.66   Min.   :30.00   Min.   :-0.013363
##  1st Qu.:61.26   1st Qu.:75.00   1st Qu.:57.94   1st Qu.: 0.005047
##  Median :65.98   Median :79.76   Median :63.62   Median : 0.013647
##  Mean   :66.08   Mean   :78.31   Mean   :63.11   Mean   : 0.025892
##  3rd Qu.:70.91   3rd Qu.:83.34   3rd Qu.:68.91   3rd Qu.: 0.036453
##  Max.   :90.00   Max.   :94.48   Max.   :95.24   Max.   : 0.438241
##  NA's   :53      NA's   :50      NA's   :78
##  cs00_seg_inc_pov25  cs00_seg_inc_aff75  cs_race_theil_2000     gini99
##  Min.   :-0.019502   Min.   :-0.001993   Min.   :0.00000    Min.   :0.1610
##  1st Qu.: 0.004164   1st Qu.: 0.003455   1st Qu.:0.01559    1st Qu.:0.3175
##  Median : 0.013136   Median : 0.012577   Median :0.04719    Median :0.3700
##  Mean   : 0.024278   Mean   : 0.026463   Mean   :0.07540    Mean   :0.3790
##  3rd Qu.: 0.034737   3rd Qu.: 0.037337   3rd Qu.:0.10451    3rd Qu.:0.4295
##  Max.   : 0.749106   Max.   : 0.196959   Max.   :0.71201    Max.   :1.0914
##                                                             NA's   :99
##    poor_share      inc_share_1perc   frac_middleclass scap_ski90pcm
##  Min.   :0.00000   Min.   :0.01857   Min.   :0.2156   Min.   :-4.258739
##  1st Qu.:0.09538   1st Qu.:0.06258   1st Qu.:0.4919   1st Qu.:-0.964225
##  Median :0.12962   Median :0.08360   Median :0.5598   Median :-0.091105
```

```
##  Mean   :0.14174   Mean   :0.09481   Mean   :0.5542   Mean   : 0.000182
##  3rd Qu.:0.17528   3rd Qu.:0.11357   3rd Qu.:0.6228   3rd Qu.: 0.818039
##  Max.   :0.56917   Max.   :0.73477   Max.   :0.8750   Max.   : 9.911112
##                    NA's   :99        NA's   :1
##     rel_tot         cs_frac_black      cs_frac_hisp        unemp_rate
##  Min.   :  1.816   Min.   : 0.0000   Min.   : 0.08203   Min.   :0.01609
##  1st Qu.: 39.670   1st Qu.: 0.2645   1st Qu.: 0.91724   1st Qu.:0.03742
##  Median : 51.329   Median : 1.6911   Median : 1.78344   Median :0.04691
##  Mean   : 53.225   Mean   : 8.7445   Mean   : 6.20919   Mean   :0.04987
##  3rd Qu.: 64.787   3rd Qu.:10.0310   3rd Qu.: 5.10768   3rd Qu.:0.05874
##  Max.   :164.527   Max.   :85.9651   Max.   :97.53905   Max.   :0.17699
##  NA's   :1
##   cs_labforce     cs_elf_ind_man    cs_born_foreign     mig_inflow
##  Min.   :0.3192   Min.   :0.00000   Min.   : 0.0000   Min.   :0.00000
##  1st Qu.:0.5670   1st Qu.:0.08864   1st Qu.: 0.8985   1st Qu.:0.01650
##  Median :0.6166   Median :0.14939   Median : 1.7273   Median :0.02443
##  Mean   :0.6093   Mean   :0.15912   Mean   : 3.4420   Mean   :0.02868
##  3rd Qu.:0.6580   3rd Qu.:0.21993   3rd Qu.: 3.9221   3rd Qu.:0.03632
##  Max.   :0.8609   Max.   :0.48554   Max.   :50.9357   Max.   :0.16867
##                                                       NA's   :90
##   mig_outflow       pop_density       frac_traveltime_lt15    hhinc00
##  Min.   :0.00000   Min.   :    0.10   Min.   :0.09988      Min.   :10512
##  1st Qu.:0.01877   1st Qu.:   17.48   1st Qu.:0.29993      1st Qu.:28734
##  Median :0.02511   Median :   43.13   Median :0.38582      Median :32235
##  Mean   :0.02752   Mean   :  244.33   Mean   :0.40380      Mean   :32854
##  3rd Qu.:0.03304   3rd Qu.:  104.99   3rd Qu.:0.49909      3rd Qu.:36039
##  Max.   :0.15326   Max.   :66940.08   Max.   :0.81764      Max.   :77943
##  NA's   :90
##  median_house_value  ccd_exp_tot        score_r
cs_fam_wkidsinglemom
##  Min.   :      0    Min.   : 3.032   Min.   :-38.68714   Min.   :0.02479
##  1st Qu.:  77047    1st Qu.: 5.027   1st Qu.: -4.96963   1st Qu.:0.15244
##  Median : 100775    Median : 5.785   Median :  0.83494   Median :0.18247
##  Mean   : 112180    Mean   : 6.093   Mean   :  0.07735   Mean   :0.19460
##  3rd Qu.: 128501    3rd Qu.: 6.735   3rd Qu.:  5.99018   3rd Qu.:0.22158
##  Max.   :1333001    Max.   :53.258   Max.   : 32.98522   Max.   :0.54388
##                     NA's   :27       NA's   :38
##  subcty_exp_pc      taxrate        tax_st_diff_top20      pm25
##  Min.   :    0   Min.   :0.00000   Min.   :0.0000    Min.   : 0.000
##  1st Qu.: 1510   1st Qu.:0.01499   1st Qu.:0.0000    1st Qu.: 6.310
##  Median : 1936   Median :0.02034   Median :0.0000    Median : 8.785
##  Mean   : 2119   Mean   :0.02309   Mean   :0.7756    Mean   : 8.372
##  3rd Qu.: 2505   3rd Qu.:0.02716   3rd Qu.:1.0000    3rd Qu.:10.484
##  Max.   :20542   Max.   :0.20991   Max.   :7.2200    Max.   :15.786
##                                    NA's   :1
##     pm25_mia        summer_tmmx     summer_rmax     winter_tmmx
##  Min.   :0.00000   Min.   :290.5   Min.   :31.64   Min.   :264.7
##  1st Qu.:0.00000   1st Qu.:300.8   1st Qu.:88.05   1st Qu.:275.1
##  Median :0.00000   Median :303.3   Median :91.32   Median :280.2
##  Mean   :0.00354   Mean   :303.1   Mean   :88.97   Mean   :280.4
```

```
##  3rd Qu.:0.00000   3rd Qu.:305.8   3rd Qu.:94.81   3rd Qu.:285.5
##  Max.   :1.00000   Max.   :313.9   Max.   :99.78   Max.   :298.3
##
##   winter_rmax     bmcruderate
##  Min.   :58.16   Min.   : 189.3
##  1st Qu.:85.09   1st Qu.: 864.3
##  Median :88.03   Median :1036.3
##  Mean   :87.47   Mean   :1029.2
##  3rd Qu.:90.75   3rd Qu.:1194.1
##  Max.   :97.67   Max.   :1978.6
##
```

```
apply(Covid_df, 2, sd, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x),
na.rm =
## na.rm): NAs introduced by coercion
```

```
##                   state                deathspc           intersects_msa
##                      NA            6.785215e+01            4.906356e-01
##            cur_smoke_q1            cur_smoke_q2            cur_smoke_q3
##            1.493481e-01            1.281304e-01            1.321812e-01
##            cur_smoke_q4            bmi_obese_q1            bmi_obese_q2
##            1.101103e-01            1.659285e-01            1.532368e-01
##            bmi_obese_q3            bmi_obese_q4         exercise_any_q1
##            1.758494e-01            1.672267e-01            2.738741e-01
##         exercise_any_q2         exercise_any_q3         exercise_any_q4
##            3.223363e-01            3.578608e-01            3.769216e-01
##               brfss_mia          puninsured2010     reimb_penroll_adj10
##            4.327567e-01            5.536651e+00            1.590926e+03
##       mort_30day_hosp_z adjmortmeas_amiall30day adjmortmeas_chfall30day
##            1.206493e+00            3.940837e-02            2.356548e-02
##         med_prev_qual_z          primcarevis_10        diab_hemotest_10
##            8.638807e-01            7.401457e+00            6.594153e+00
##         diab_eyeexam_10          diab_lipids_10            mammogram_10
##            7.598549e+00            7.854145e+00            8.397699e+00
##            cs00_seg_inc      cs00_seg_inc_pov25      cs00_seg_inc_aff75
##            3.057628e-02            3.075727e-02            3.292040e-02
##      cs_race_theil_2000                  gini99              poor_share
##            8.413111e-02            8.667691e-02            6.545970e-02
##         inc_share_1perc        frac_middleclass           scap_ski90pcm
##            5.063134e-02            9.309948e-02            1.347960e+00
##                 rel_tot           cs_frac_black            cs_frac_hisp
##            1.850252e+01            1.448372e+01            1.205040e+01
##              unemp_rate             cs_labforce          cs_elf_ind_man
##            1.773790e-02            7.039307e-02            9.086221e-02
##         cs_born_foreign              mig_inflow             mig_outflow
##            4.836270e+00            1.903371e-02            1.378019e-02
##             pop_density    frac_traveltime_lt15                 hhinc00
##            1.676096e+03            1.372145e-01            6.975837e+03
```

```
##      median_house_value             ccd_exp_tot               score_r
##            6.318905e+04            2.103573e+00            9.007980e+00
##    cs_fam_wkidsinglemom           subcty_exp_pc                 taxrate
##            6.782804e-02            9.998335e+02            1.384751e-02
##       tax_st_diff_top20                    pm25                pm25_mia
##            1.470989e+00            2.565927e+00            5.940534e-02
##             summer_tmmx             summer_rmax             winter_tmmx
##            3.173951e+00            9.689271e+00            6.597855e+00
##             winter_rmax              bmcruderate
##            4.811207e+00            2.483818e+02
```

Question 3:

Note that some variables have missing values. This causes problems when estimating the models. Normally we'd impute missing values by replacing them with their mean or median value, but to keep things simple, given the size of our data, you should drop all observations (rows) with missing values.

```
Covid_df <- na.omit(Covid_df)
```

Question 4:

Create a separate dummy variable for each of the 48 states and the District of Columbia in the dataset (so you'll create 49 dummy variables in total).

```
states <- unique(Covid_df$state)

dummy_states <- sapply(states, function(x) as.numeric(Covid_df$state == x))

colnames(dummy_states) <- states

Covid_df <- cbind(Covid_df, dummy_states)

Covid_df$state <- NULL

Covid_df$county <- NULL
```

Question 5:

Split the sample into training (80% of the data) and test (20% of the data) sets. Be sure to set a seed so you can replicate your work.

```
set.seed(123)

n_obs <- nrow(Covid_df)
```

```r
split_index <- sample(seq_len(n_obs),
  size = floor(0.8 * n_obs),
  replace = FALSE
)

train_data <- Covid_df[split_index, ]

test_data <- Covid_df[-split_index, ]
```

Question 6

Using the training data, estimate the relationship between COVID-19 deaths per capita (y = deathspc) and the Opportunity Insights and PM COVID predictors listed in the spreadsheet, as well as state-level fixed effects (the state dummy variables) using OLS.

Part A:

Based on those estimates, calculate and report the MSE and R2 in both the training and test sets.

```r
OLS_model_train <- lm(deathspc ~ ., data = train_data)

Train_prediction <- predict(OLS_model_train, newdata = test_data)
```

```
## Warning in predict.lm(OLS_model_train, newdata = test_data): prediction
from a
## rank-deficient fit may be misleading
```

```r
MSE_Train <- mean((test_data$deathspc - Train_prediction)^2)

output_1 <- paste("The MSE for the Training Data", MSE_Train)

print(output_1)
```

```
## [1] "The MSE for the Training Data 1589.29241323927"
```

```r
train_r2 <- 1 - MSE_Train / var(train_data$deathspc)

train_r2
```

```
## [1] 0.4346467
```

```r
summary(OLS_model_train)
```

```
##
## Call:
## lm(formula = deathspc ~ ., data = train_data)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -171.18  -16.13   -4.89    6.66  575.15
##
## Coefficients: (2 not defined because of singularities)
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               8.285e+01  2.362e+02   0.351 0.725836
## intersects_msa            1.803e+00  2.434e+00   0.740 0.459076
## cur_smoke_q1             -9.603e-01  9.762e+00  -0.098 0.921653
## cur_smoke_q2             -3.979e+00  9.812e+00  -0.406 0.685117
## cur_smoke_q3             -1.650e+00  7.899e+00  -0.209 0.834559
## cur_smoke_q4              4.634e+00  9.262e+00   0.500 0.616861
## bmi_obese_q1             -6.549e+00  9.331e+00  -0.702 0.482848
## bmi_obese_q2              5.910e+00  9.245e+00   0.639 0.522745
## bmi_obese_q3             -1.361e+01  6.656e+00  -2.045 0.040997 *
## bmi_obese_q4             -1.883e+00  6.740e+00  -0.279 0.779994
## exercise_any_q1          -6.936e+00  8.311e+00  -0.835 0.404011
## exercise_any_q2           1.756e+01  8.205e+00   2.140 0.032480 *
## exercise_any_q3          -1.953e+00  6.879e+00  -0.284 0.776569
## exercise_any_q4          -2.514e+00  7.464e+00  -0.337 0.736236
## brfss_mia                -5.528e-01  8.559e+00  -0.065 0.948513
## puninsured2010           -7.011e-01  4.562e-01  -1.537 0.124449
## reimb_penroll_adj10      -1.269e-03  1.054e-03  -1.203 0.228936
## mort_30day_hosp_z         1.466e+00  2.055e+00   0.713 0.475716
## adjmortmeas_amiall30day -2.032e+01  4.759e+01  -0.427 0.669402
## adjmortmeas_chfall30day  1.506e+01  7.902e+01   0.191 0.848876
## med_prev_qual_z           8.752e+00  5.430e+00   1.612 0.107138
## primcarevis_10           -3.094e-01  1.981e-01  -1.562 0.118540
## diab_hemotest_10         -1.014e+00  2.889e-01  -3.511 0.000456 ***
## diab_eyeexam_10          -9.248e-02  2.477e-01  -0.373 0.708965
## diab_lipids_10           -2.283e-01  2.539e-01  -0.899 0.368518
## mammogram_10             -2.599e-01  2.245e-01  -1.158 0.246942
## cs00_seg_inc              1.302e+03  4.955e+02   2.629 0.008631 **
## cs00_seg_inc_pov25       -8.462e+02  2.611e+02  -3.241 0.001211 **
## cs00_seg_inc_aff75       -5.217e+02  2.523e+02  -2.068 0.038785 *
## cs_race_theil_2000        1.309e+01  1.536e+01   0.852 0.394196
## gini99                   -3.896e+01  2.733e+01  -1.426 0.154084
## poor_share               -1.654e+00  3.983e+01  -0.042 0.966880
## inc_share_1perc          -2.858e+00  3.425e+01  -0.083 0.933501
## frac_middleclass         -6.995e+01  2.277e+01  -3.072 0.002152 **
## scap_ski90pcm            -5.109e+00  1.449e+00  -3.526 0.000430 ***
## rel_tot                   1.453e-01  8.095e-02   1.795 0.072806 .
## cs_frac_black             7.869e-01  1.649e-01   4.772 1.94e-06 ***
## cs_frac_hisp             -3.714e-02  1.631e-01  -0.228 0.819908
## unemp_rate               -1.824e+02  8.576e+01  -2.127 0.033536 *
## cs_labforce              -5.657e+01  2.849e+01  -1.986 0.047183 *
## cs_elf_ind_man            3.556e+01  1.602e+01   2.220 0.026527 *
## cs_born_foreign           1.357e+00  4.069e-01   3.335 0.000867 ***
## mig_inflow               -2.024e+01  1.100e+02  -0.184 0.854070
## mig_outflow              -2.464e+02  1.476e+02  -1.669 0.095297 .
## pop_density               9.793e-03  7.006e-04  13.977  < 2e-16 ***
```

```
## frac_traveltime_lt15    -1.226e+01  1.332e+01  -0.921 0.357322
## hhinc00                  7.630e-04  3.852e-04   1.981 0.047713 *
## median_house_value      -7.727e-06  3.422e-05  -0.226 0.821368
## ccd_exp_tot              1.460e+00  7.025e-01   2.078 0.037779 *
## score_r                  2.253e-01  1.741e-01   1.294 0.195646
## cs_fam_wkidsinglemom     1.622e+01  3.820e+01   0.425 0.671209
## subcty_exp_pc           -9.642e-04  1.247e-03  -0.773 0.439521
## taxrate                 -5.663e+01  1.231e+02  -0.460 0.645595
## tax_st_diff_top20        4.347e+01  5.431e+01   0.800 0.423508
## pm25                    -4.063e-01  1.034e+00  -0.393 0.694267
## pm25_mia                 5.855e+00  2.461e+01   0.238 0.811968
## summer_tmmx              1.754e-01  9.537e-01   0.184 0.854077
## summer_rmax             -2.974e-01  3.506e-01  -0.848 0.396277
## winter_tmmx              6.531e-01  7.130e-01   0.916 0.359797
## winter_rmax             -5.724e-01  4.110e-01  -1.393 0.163849
## bmcruderate             -3.748e-05  8.352e-03  -0.004 0.996421
## Alabama                 -6.936e+00  1.478e+01  -0.469 0.638918
## Arizona                 -9.399e+01  8.805e+01  -1.067 0.285864
## Arkansas                -5.720e+01  4.636e+01  -1.234 0.217376
## California              -3.076e+02  3.372e+02  -0.912 0.361739
## Colorado                 2.359e+01  1.166e+01   2.023 0.043235 *
## Connecticut              9.915e+01  2.248e+01   4.411 1.08e-05 ***
## Delaware                -1.106e+00  4.281e+01  -0.026 0.979386
## Florida                 -1.259e+01  1.563e+01  -0.805 0.420641
## Georgia                  1.610e+01  1.434e+01   1.122 0.261774
## Idaho                   -1.393e+01  2.026e+01  -0.688 0.491805
## Illinois                 1.424e+01  1.317e+01   1.081 0.279805
## Indiana                  4.650e+01  1.341e+01   3.468 0.000534 ***
## Iowa                    -1.057e+02  1.446e+02  -0.731 0.464767
## Kansas                   1.062e+00  8.783e+00   0.121 0.903739
## Kentucky                 3.394e+00  9.426e+00   0.360 0.718801
## Louisiana               -9.664e+01  2.092e+02  -0.462 0.644245
## Maine                    2.574e+00  1.836e+01   0.140 0.888520
## Maryland                -4.232e+01  4.573e+01  -0.925 0.354930
## Massachusetts            8.683e+01  2.018e+01   4.302 1.76e-05 ***
## Michigan                 3.780e+01  1.316e+01   2.872 0.004114 **
## Minnesota               -9.329e+01  1.245e+02  -0.750 0.453587
## Mississippi              1.250e+01  1.443e+01   0.866 0.386497
## Missouri                 6.245e+00  1.278e+01   0.489 0.625201
## Montana                  2.071e+01  1.253e+01   1.652 0.098599 .
## Nebraska                -5.848e+01  8.446e+01  -0.692 0.488704
## Nevada                  -1.373e+01  1.721e+01  -0.798 0.425148
## `New Hampshire`          1.055e+01  1.918e+01   0.550 0.582550
## `New Mexico`            -1.496e+01  1.443e+01  -1.037 0.299856
## `New York`               5.055e+01  1.380e+01   3.663 0.000255 ***
## `North Carolina`        -5.577e+01  4.589e+01  -1.215 0.224370
## `North Dakota`          -1.290e+02  1.760e+02  -0.733 0.463766
## Ohio                    -9.408e+01  1.345e+02  -0.699 0.484395
## Oklahoma                 5.152e+00  1.336e+01   0.386 0.699736
## Oregon                   5.921e+00  1.345e+01   0.440 0.659832
```

```
## Pennsylvania             2.102e+01  1.375e+01   1.529 0.126393
## `Rhode Island`          -2.725e+02  3.250e+02  -0.839 0.401836
## `South Carolina`        -2.321e+01  1.558e+01  -1.489 0.136534
## `South Dakota`           1.994e+01  1.364e+01   1.463 0.143688
## Tennessee               -8.117e-02  1.397e+01  -0.006 0.995364
## Texas                   -1.173e+01  1.369e+01  -0.857 0.391369
## Utah                    -6.362e+00  1.504e+01  -0.423 0.672255
## Vermont                 -2.554e+02  3.097e+02  -0.824 0.409790
## Virginia                -1.491e+01  1.360e+01  -1.096 0.273074
## Washington               1.787e+01  1.342e+01   1.331 0.183349
## `West Virginia`         -1.006e+02  1.261e+02  -0.798 0.425131
## Wisconsin                       NA         NA      NA       NA
## Wyoming                         NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 41.22 on 2226 degrees of freedom
## Multiple R-squared:  0.4227, Adjusted R-squared:  0.3955
## F-statistic: 15.52 on 105 and 2226 DF,  p-value: < 2.2e-16

OLS_model_test <- lm(deathspc ~ ., data = test_data)

Test_prediction <- predict(OLS_model_test, newdata = train_data)

## Warning in predict.lm(OLS_model_test, newdata = train_data): prediction
from a
## rank-deficient fit may be misleading

MSE_Test <- mean((train_data$deathspc - Test_prediction)^2)

output_2 <- paste("The MSE for the Test Data", MSE_Test)

print(output_2)

## [1] "The MSE for the Test Data 2176.75559766276"

test_r2 <- 1 - MSE_Test / var(test_data$deathspc)

test_r2

## [1] 0.08504075

summary(OLS_model_test)

##
## Call:
## lm(formula = deathspc ~ ., data = test_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -101.244  -18.845   -3.507   11.401  258.585
```

```
##
## Coefficients: (3 not defined because of singularities)
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -6.535e+02  5.147e+02  -1.270 0.204831
## intersects_msa           4.904e+00  4.949e+00   0.991 0.322224
## cur_smoke_q1            -1.134e-01  2.228e+01  -0.005 0.995942
## cur_smoke_q2            -1.460e+01  2.409e+01  -0.606 0.544741
## cur_smoke_q3             7.828e+00  1.875e+01   0.418 0.676446
## cur_smoke_q4            -1.663e+01  1.782e+01  -0.933 0.351212
## bmi_obese_q1             8.176e+00  1.572e+01   0.520 0.603117
## bmi_obese_q2             7.954e+00  2.158e+01   0.369 0.712637
## bmi_obese_q3            -2.525e+01  1.378e+01  -1.833 0.067395 .
## bmi_obese_q4             2.721e+01  1.400e+01   1.943 0.052552 .
## exercise_any_q1          4.769e+00  1.540e+01   0.310 0.756873
## exercise_any_q2          1.920e+01  1.807e+01   1.063 0.288480
## exercise_any_q3         -5.667e+00  1.760e+01  -0.322 0.747587
## exercise_any_q4         -2.306e+01  1.251e+01  -1.844 0.065812 .
## brfss_mia               -1.725e+01  2.113e+01  -0.816 0.414691
## puninsured2010           2.755e-01  9.912e-01   0.278 0.781196
## reimb_penroll_adj10     -1.063e-03  2.228e-03  -0.477 0.633540
## mort_30day_hosp_z       -2.826e+00  4.469e+00  -0.632 0.527468
## adjmortmeas_amiall30day  7.238e+01  1.069e+02   0.677 0.498704
## adjmortmeas_chfall30day -3.803e+01  1.773e+02  -0.214 0.830275
## med_prev_qual_z         -6.200e-01  1.053e+01  -0.059 0.953069
## primcarevis_10           2.557e-01  4.062e-01   0.630 0.529261
## diab_hemotest_10        -4.832e-01  6.623e-01  -0.730 0.466011
## diab_eyeexam_10          1.101e-02  5.453e-01   0.020 0.983899
## diab_lipids_10          -2.287e-01  5.460e-01  -0.419 0.675513
## mammogram_10             4.749e-01  4.723e-01   1.005 0.315235
## cs00_seg_inc            -8.661e+01  9.376e+02  -0.092 0.926441
## cs00_seg_inc_pov25      -3.352e+02  4.932e+02  -0.680 0.497131
## cs00_seg_inc_aff75       4.551e+02  4.757e+02   0.957 0.339196
## cs_race_theil_2000      -2.449e+01  3.035e+01  -0.807 0.419993
## gini99                  -3.275e+01  6.057e+01  -0.541 0.588931
## poor_share               2.231e+02  8.294e+01   2.690 0.007390 **
## inc_share_1perc          2.205e+01  7.189e+01   0.307 0.759236
## frac_middleclass        -4.317e+01  4.641e+01  -0.930 0.352758
## scap_ski90pcm           -1.597e+00  2.911e+00  -0.549 0.583441
## rel_tot                  1.121e-01  1.557e-01   0.720 0.471831
## cs_frac_black            9.702e-01  3.369e-01   2.880 0.004152 **
## cs_frac_hisp             2.402e-03  4.216e-01   0.006 0.995457
## unemp_rate              -1.471e+02  1.662e+02  -0.885 0.376473
## cs_labforce              1.017e+01  5.885e+01   0.173 0.862839
## cs_elf_ind_man           8.885e+01  3.355e+01   2.648 0.008357 **
## cs_born_foreign         -9.943e-01  1.123e+00  -0.886 0.376208
## mig_inflow              -1.284e+02  2.213e+02  -0.580 0.562052
## mig_outflow             -2.173e+01  3.035e+02  -0.072 0.942959
## pop_density              3.729e-03  3.943e-03   0.946 0.344773
## frac_traveltime_lt15    -1.892e+01  2.565e+01  -0.737 0.461268
## hhinc00                  1.322e-03  8.157e-04   1.621 0.105767
```

```
## median_house_value       1.075e-04  1.161e-04   0.927 0.354649
## ccd_exp_tot              -8.155e-01  2.259e+00  -0.361 0.718243
## score_r                   1.605e-01  3.787e-01   0.424 0.671879
## cs_fam_wkidsinglemom     -6.885e+01  7.760e+01  -0.887 0.375383
## subcty_exp_pc             6.480e-03  3.108e-03   2.085 0.037632 *
## taxrate                   1.833e+02  2.739e+02   0.669 0.503684
## tax_st_diff_top20        -3.566e+00  1.027e+01  -0.347 0.728660
## pm25                      3.401e-02  2.030e+00   0.017 0.986639
## pm25_mia                  1.180e+01  3.418e+01   0.345 0.730166
## summer_tmmx               3.279e-01  2.022e+00   0.162 0.871252
## summer_rmax              -1.662e+00  7.811e-01  -2.128 0.033855 *
## winter_tmmx               2.076e+00  1.465e+00   1.416 0.157281
## winter_rmax               1.141e+00  8.390e-01   1.360 0.174478
## bmcruderate              -2.740e-04  1.746e-02  -0.016 0.987486
## Alabama                  -3.480e+01  2.756e+01  -1.263 0.207230
## Arizona                  -6.416e+01  5.321e+01  -1.206 0.228444
## Arkansas                 -3.977e+01  2.077e+01  -1.915 0.056106 .
## California               -5.255e+01  5.770e+01  -0.911 0.362886
## Colorado                 -3.181e+01  3.110e+01  -1.023 0.306817
## Connecticut               1.035e+02  2.846e+01   3.636 0.000306 ***
## Delaware                  4.122e+01  4.272e+01   0.965 0.335118
## Florida                  -4.520e+01  3.324e+01  -1.360 0.174559
## Georgia                   1.509e+01  2.758e+01   0.547 0.584596
## Idaho                    -1.750e+01  2.811e+01  -0.623 0.533906
## Illinois                  1.567e+01  1.890e+01   0.829 0.407540
## Indiana                   1.970e+01  2.011e+01   0.980 0.327733
## Iowa                      2.818e+01  2.635e+01   1.069 0.285493
## Kansas                   -1.850e+01  2.188e+01  -0.846 0.398228
## Kentucky                  1.528e+00  2.063e+01   0.074 0.941013
## Louisiana                 2.994e+01  3.299e+01   0.908 0.364577
## Maine                     1.990e+01  2.273e+01   0.876 0.381671
## Maryland                  1.981e+01  2.333e+01   0.849 0.396261
## Massachusetts             1.222e+02  2.492e+01   4.906 1.28e-06 ***
## Michigan                  1.773e+01  1.641e+01   1.081 0.280335
## Minnesota                 1.801e+01  2.546e+01   0.707 0.479758
## Mississippi              -2.916e+01  2.921e+01  -0.998 0.318637
## Missouri                 -1.397e+01  2.107e+01  -0.663 0.507528
## Montana                  -2.649e+01  2.524e+01  -1.049 0.294514
## Nebraska                  4.995e+00  1.928e+01   0.259 0.795673
## Nevada                   -6.329e+01  4.578e+01  -1.383 0.167448
## `New Hampshire`          -1.050e+01  3.265e+01  -0.322 0.747920
## `New Mexico`             -1.636e+01  3.535e+01  -0.463 0.643756
## `New York`                1.276e+01  1.861e+01   0.686 0.493055
## `North Carolina`         -2.673e+01  1.932e+01  -1.383 0.167282
## `North Dakota`            3.318e+01  3.413e+01   0.972 0.331424
## Ohio                      8.121e+00  2.243e+01   0.362 0.717423
## Oklahoma                 -1.800e+01  2.677e+01  -0.673 0.501546
## Oregon                   -2.808e+01  3.351e+01  -0.838 0.402450
## Pennsylvania              2.753e+01  1.909e+01   1.442 0.149898
## `Rhode Island`            2.425e+01  5.837e+01   0.415 0.677980
```

```
## `South Carolina`        -4.789e+01  3.012e+01  -1.590 0.112415
## `South Dakota`          -5.162e+00  2.089e+01  -0.247 0.804958
## Tennessee               -2.176e+01  2.268e+01  -0.959 0.337817
## Texas                   -3.780e+01  2.924e+01  -1.293 0.196690
## Utah                    -8.722e+01  4.767e+01  -1.830 0.067942 .
## Vermont                  4.738e+01  5.744e+01   0.825 0.409896
## Virginia                -2.714e+01  2.326e+01  -1.167 0.243873
## Washington              -2.706e+01  3.110e+01  -0.870 0.384820
## `West Virginia`                 NA         NA      NA       NA
## Wisconsin                       NA         NA      NA       NA
## Wyoming                         NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 39.25 on 478 degrees of freedom
## Multiple R-squared:  0.4683, Adjusted R-squared:  0.3526
## F-statistic: 4.047 on 104 and 478 DF,  p-value: < 2.2e-16
```

The MSE for the Training data is equal to `1589.29241323927`

The R^2 for the Training data is equal to `0.4346467`

The MSE for the Test data is equal to `2176.75559766276`

The R^2 for the Test data is equal to `0.08504075`

`MSE Difference = 587`

Part B:

Is there any evidence of overfitting? Briefly explain

Yes, there is evidence of overfitting when the training model performs significantly better than the test model. The mean squared error (MSE) for the training model was much lower than that of the test model, indicating that the model is fitting the noise in the training data too closely instead of the underlying pattern. This leads to high variance and low bias, resulting in a failure to generalize well to new data. Ultimately, this creates a model that performs well on the training data but poorly on new, unseen data. We also know that the MSE continues to decrease as the model becomes more complex (adding more predicting variables). However, the MSE for the test data will decrease initially, but then increase overtime as we continue to add more co-variates.

Question 7

Use the training set to estimate Ridge Regression and the Lasso analogs to the OLS model in the previous question. For each, you should report a plot of the cross-validation estimates of the test error as a function of the value of the hyperparameter (λ) that indicates the

tuned value of λ. Hint: to do so you should be sure standardize your predictors and tune the hyperparameter by:

a. Calculating each model for a grid or range of values of λ. You'll want to adjust the values you use based on the data, but start by using 100 values of λ from 0.01 to 100.

b. Using 10-fold cross-validation (10FCV) (on the training set) to estimate the test error for each model at the given value of λ.

c. Plotting the cross-validation estimates of the test error as a function of the value of λ.

d. Choosing the optimal value of λ.

e. Re-estimating your model using that optimal value of λ

Question 7 Ridge Regression

Part A:

```
library(glmnet)

set.seed(321)

# Standardize predictors

stndrd_ridge1 <- model.matrix(OLS_model_train)

# Set up grid of lambda values

a1 <- seq(-2, 2, by = 1/25)

r1 <- 10^a1

# Fit Ridge Regression model for each value of lambda

ridge_model1 <- glmnet(stndrd_ridge1,
  train_data$deathspc,
  alpha = 0,
  lambda = r1
)
```

Part B:

Perform 10-fold cross-validation to estimate test error

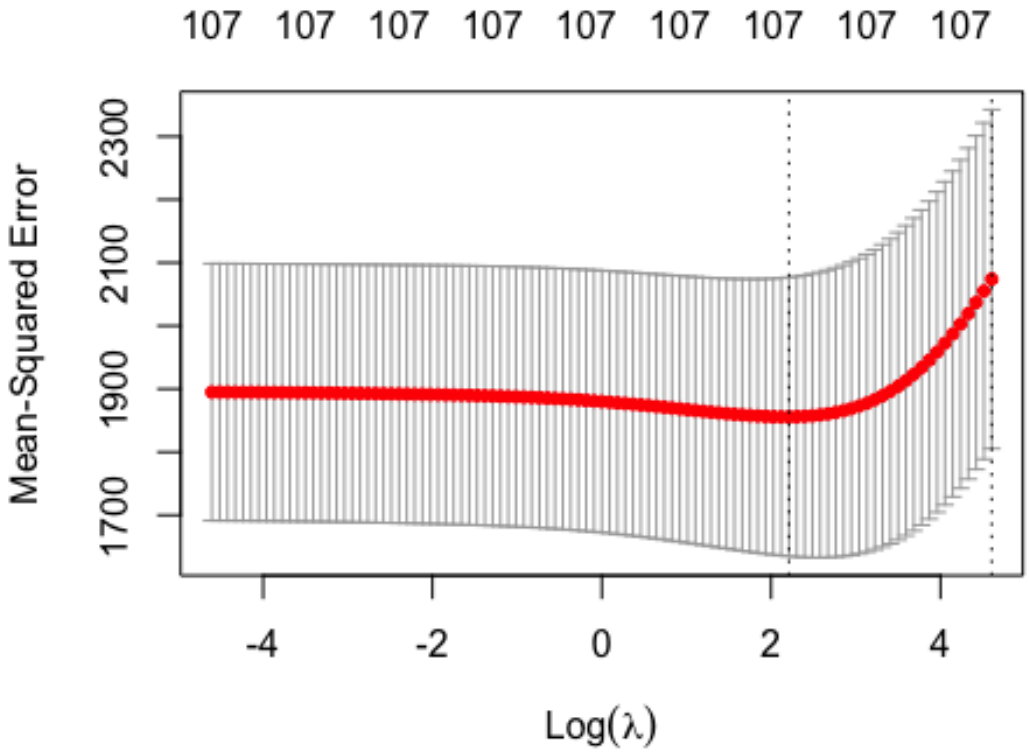
```
cv_ridge1 <- cv.glmnet(stndrd_ridge1,
  train_data$deathspc,
```

```
  alpha = 0,
  lambda = r1,
  nfolds = 10
)
```

Part C:

Plot cross-validation estimates of test error

```
plot(cv_ridge1)
```



Part D:

Choose optimal value of lambda

```
opt_lambda1 <- cv_ridge1$lambda.min

output_3 <- paste("The optimal value of lambda for the ridge regression is",
opt_lambda1)

print(output_3)
```

```
## [1] "The optimal value of lambda for the ridge regression is
9.1201083935591"
```

Part: E

Re-estimate model using optimal value of lambda

```
ridge_model_opt1 <- glmnet(stndrd_ridge1,
  train_data$deathspc,
  alpha = 0,
  lambda = opt_lambda1
)
```

Question 7 Lasso Regression:

Part A:

```
library(glmnet)

set.seed(321)

# Standardize predictors

stndrd_lasso2 <- model.matrix(OLS_model_train)

# Set up grid of lambda values

a2 <- seq(-2, 2, by = 1 / 25)

l2 <- 10^a2

# Fit Lasso Regression model for each value of lambda

lasso_model2 <- glmnet(stndrd_lasso2,
  train_data$deathspc,
  alpha = 1,
  lambda = l2
)
```

Part B:

Perform 10-fold cross-validation to estimate test error

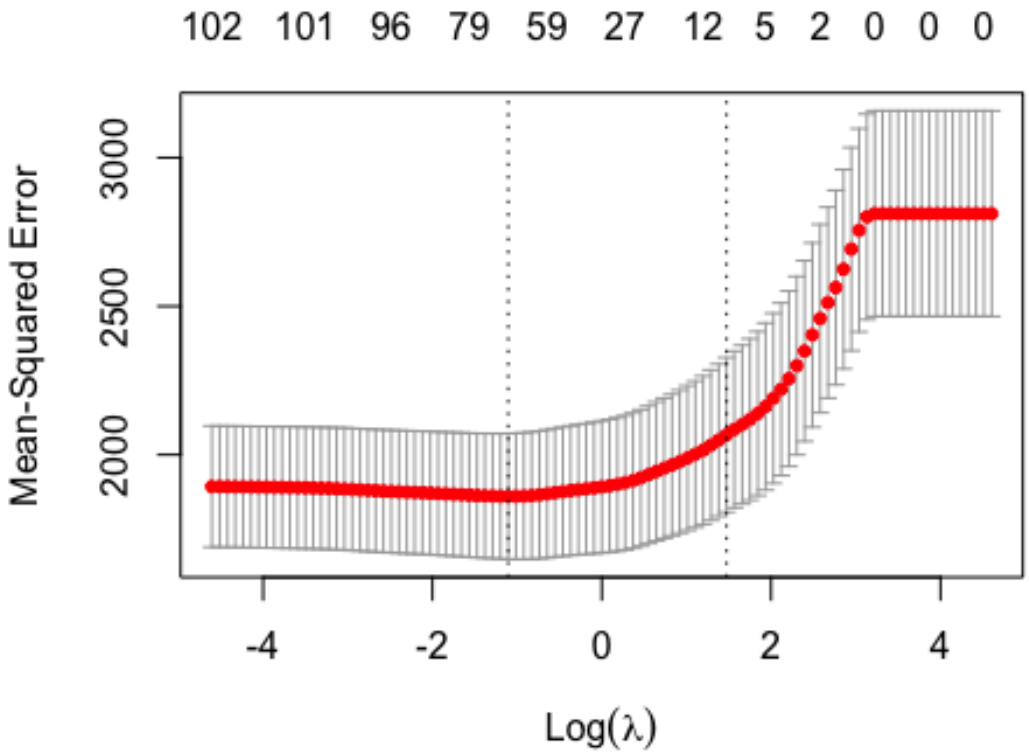
```
cv_lasso2 <- cv.glmnet(stndrd_lasso2,
  train_data$deathspc,
  alpha = 1,
```

```
  lambda = 12,
  nfolds = 10
)
```

Part C:

Plot cross-validation estimates of test error

```
plot(cv_lasso2)
```



Part D:

Choose optimal value of lambda

```
lambda_opt2 <- cv_lasso2$lambda.min

output_4 <- paste("The optimal value of lambda for the lasso regression is",
lambda_opt2)

print(output_4)
```

```
## [1] "The optimal value of lambda for the lasso regression is
0.331131121482591"
```

Part E:

Re-estimate model using optimal value of lambda

```
lasso_model_opt2 <- glmnet(stndrd_lasso2,
  train_data$deathspc,
  alpha = 1,
  lambda = lambda_opt2
)
```

Question 8:

Using the optimal values of λ you found for Ridge Regression and the Lasso in the previous question, calculate and report the training- and test-set prediction errors (MSE & R2) for each model. Did Ridge Regression and/or the Lasso mitigate overfitting? Briefly explain your results.

Ridge Regression Training Set

```
stndrd_ridge3 <- model.matrix(OLS_model_test)

ridge_train_pred <- predict(ridge_model_opt1, newx = stndrd_ridge3)

ridge_train_mse <- mean((test_data$deathspc - ridge_train_pred)^2)

ridge_train_mse

## [1] 1603.056

ridge_train_r2 <- 1 - ridge_train_mse / var(train_data$deathspc)

ridge_train_r2

## [1] 0.4297505
```

Ridge Regression Test Set

```
stndrd_ridge3 <- model.matrix(OLS_model_test)

# Set up grid of lambda values

a3 <- seq(-2, 2, by = 1 / 25)

r3 <- 10^a1
```

```r
# Fit Ridge Regression model for each value of lambda

ridge_model3 <- glmnet(stndrd_ridge3,
  test_data$deathspc,
  alpha = 0,
  lambda = r3
)

cv_ridge3 <- cv.glmnet(stndrd_ridge3,
  test_data$deathspc,
  alpha = 0,
  lambda = r3,
  nfolds = 10
)

opt_lambda3 <- cv_ridge3$lambda.min

ridge_model_opt3 <- glmnet(stndrd_ridge3,
  test_data$deathspc,
  alpha = 0,
  lambda = opt_lambda3
)

ridge_test_pred <- predict(ridge_model_opt3, newx = stndrd_ridge1)

ridge_test_mse <- mean((train_data$deathspc - ridge_test_pred)^2)

ridge_test_mse
```

```
## [1] 2093.761
```

```r
ridge_test_r2 <- 1 - ridge_test_mse / var(test_data$deathspc)

ridge_test_r2
```

```
## [1] 0.119926
```

The MSE for the Ridge Regression Training data is equal to `1603.056`

The R^2 for the Ridge Regression Training data is equal to `0.4297505`

The MSE for the Ridge Regression Test data is equal to `2093.761`

The R^2 for the Ridge Regression Test data is equal to `0.119926`

`MSE Difference = 490`

Lasso Regression Training Set

```
stndrd_lasso4 <- model.matrix(OLS_model_test)

lasso_train_pred <- predict(lasso_model_opt2,
  newx = stndrd_lasso4
)

lasso_train_mse <- mean((test_data$deathspc - lasso_train_pred)^2)

lasso_train_mse

## [1] 1594.639

lasso_train_r2 <- 1 - lasso_train_mse / var(train_data$deathspc)

lasso_train_r2

## [1] 0.4327447
```

Lasso Regression Test Set

```
stndrd_lasso4 <- model.matrix(OLS_model_test)

a4 <- seq(-2, 2, by = 1 / 25)

l4 <- 10^a2

# Fit Lasso Regression model for each value of lambda

lasso_model4 <- glmnet(stndrd_lasso4,
  test_data$deathspc,
  alpha = 1,
  lambda = l4
)

cv_lasso4 <- cv.glmnet(stndrd_lasso4,
  test_data$deathspc,
  alpha = 1,
  lambda = l4,
  nfolds = 10
)

lambda_opt4 <- cv_lasso4$lambda.min

lasso_model_opt4 <- glmnet(stndrd_lasso4,
```

```
  test_data$deathspc,
  alpha = 1,
  lambda = lambda_opt4
)

lasso_test_pred <- predict(lasso_model_opt4,
  newx = stndrd_lasso2
)

lasso_test_mse <- mean((train_data$deathspc - lasso_test_pred)^2)

lasso_test_mse

## [1] 2154.324

lasso_test_r2 <- 1 - lasso_test_mse / var(test_data$deathspc)

lasso_test_r2

## [1] 0.09446952
```

The MSE for the Lasso Regression Training data is equal to `1594.639`

The R^2 for the Lasso Regression Training data is equal to `0.4327447`

The MSE for the Lasso Regression Test data is equal to `2154.324`

The R^2 for the Lasso Regression Test data is equal to `0.09446952`

`MSE Difference = 560`

Both Lasso and Ridge Regression are effective in reducing overfitting by minimizing the difference between the mean squared error (MSE) of the training and test datasets, compared to the original Ordinary Least Squares (OLS) model. However, Ridge Regression is more effective than Lasso in reducing the MSE difference to a greater extent. Therefore, in this example, Ridge Regression is generally considered to be the preferred method for reducing overfitting.