```
Load Packages
 library(readr)
 library(MASS)
 library(class)
 library(caret)
 ## Loading required package: lattice
 ## Loading required package: ggplot2
 library(e1071)
 library(ISLR)
 library(leaps)
 library(glmnet)
 ## Loading required package: Matrix
 ## Loaded glmnet 4.1-1
 library(readr)
Read the File
 national history date switch <- read csv('national2.csv')</pre>
 ##
 ## - Column specification -
 ## cols(
```

```
.default = col double(),
##
##
   date = col character(),
   deathDirection = col character(),
##
    deathDirection1 = col_character(),
##
##
    deathDirection2 = col character(),
    deathDirection3 = col_character(),
##
##
    deathDirection4 = col character()
## )
## i Use `spec()` for the full column specifications.
```

```
Covid <- national_history_date_switch
Covid[is.na(Covid)] <- 0
Covid <- Covid[, -c(1:2)]</pre>
```

```
# Split the Data
set.seed(1)
train=sample(nrow(Covid), size=0.5*nrow(Covid))
test=-(train)
dim(Covid[train,])
```

```
## [1] 210 20
```

```
dim(Covid[test,])
```

```
## [1] 210 20
```

```
training=Covid[train,]
testing=Covid[-train,]
```

# BIC

```
regfit=regsubsets(deathIncrease~.,data=Covid[train,],nvmax=15)
summary(regfit)
```

```
## Subset selection object
## Call: regsubsets.formula(deathIncrease ~ ., data = Covid[train, ],
##
       nvmax = 15)
## 19 Variables (and intercept)
##
                             Forced in Forced out
## deathDirectionUp
                                 FALSE
                                            FALSE
## deathDirection1Up
                                 FALSE
                                            FALSE
## deathDirection2Up
                                 FALSE
                                            FALSE
## deathDirection3Up
                                 FALSE
                                            FALSE
## deathDirection4Up
                                 FALSE
                                            FALSE
## inIcuCumulative
                                 FALSE
                                            FALSE
## inIcuCurrently
                                 FALSE
                                            FALSE
## hospitalizedIncrease
                                 FALSE
                                            FALSE
## hospitalizedCurrently
                                 FALSE
                                            FALSE
## hospitalizedCumulative
                                 FALSE
                                            FALSE
## negative
                                 FALSE
                                            FALSE
## negativeIncrease
                                 FALSE
                                            FALSE
## onVentilatorCumulative
                                 FALSE
                                            FALSE
## onVentilatorCurrently
                                 FALSE
                                            FALSE
## positive
                                 FALSE
                                            FALSE
## positiveIncrease
                                 FALSE
                                            FALSE
## states
                                 FALSE
                                            FALSE
## totalTestResults
                                 FALSE
                                            FALSE
## totalTestResultsIncrease
                                 FALSE
                                             FALSE
## 1 subsets of each size up to 15
## Selection Algorithm: exhaustive
##
             deathDirectionUp deathDirection1Up deathDirection2Up
                               ## 1
      (1)
             " "
                               ## 2
     (1)
## 3
      (1)
## 4
      (1)
             " "
                               " * "
## 5
      (1)
## 6
       1
             11 11
## 7
      (1)
## 8
      (1)
## 9
      (1)
## 10
       (1)
             " * "
## 11
       (1)
             " * "
       (1)
## 12
                               " * "
       (1)
             " * "
## 13
             " * "
                               " * "
       (1)
## 14
       (1)
                               " 4 "
                                                  .....
## 15
             " * "
##
             deathDirection3Up deathDirection4Up inIcuCumulative inIcuCurrently
## 1
      (1)
                                .. ..
## 2
      (1)
             " "
                                .. ..
                                                                    .. ..
## 3
      (1)
             " "
## 4
      (1)
## 5
      (1)
## 6
      (1)
      (1)
## 7
      (1
## 8
             " "
                                                                    .. ..
## 9
      (1)
      (1)
## 10
```

```
. .
                                                     " * "
       (1)""
## 11
##
   12
       (1)
                                                     " * "
  13
##
       (1)
##
       (1)
  14
       (1)
## 15
##
              hospitalizedIncrease hospitalizedCurrently hospitalizedCumulative
##
   1
        1)
              " * "
      (1)
##
              " * "
##
   3
      (1)
                                     .. ..
              " * "
##
  4
      (1)
##
  5
              " * "
      (1)
## 6
      (1)
   7
##
      (1)
##
   8
        1)
              " * "
##
   9
      (1)
##
  10
       (1)
##
  11
       (1)
  12
##
       (1)
       (1)
##
  13
##
   14
       (1)
##
  15
       (1)
##
              negative negativeIncrease onVentilatorCumulative
##
  1
      (1)
##
   2
      (1)
##
        1)
              11 11
##
      (1)
## 5
      (1)
##
  6
        1)
##
   7
        1)
##
  8
        1)
   9
##
      (1)
##
  10
       (1)
##
  11
       (1)
## 12
       (1)
## 13
       (1)
## 14
       (1)
              " "
                                          " * "
       (1)"*"
## 15
                                          " * "
##
              onVentilatorCurrently positive positiveIncrease states
                                                . .
##
  1
      (1)
                                      " * "
                                                " "
##
   2
      (1)
                                      " * "
##
        1)
                                      " * "
##
      (1)
##
  5
        1)
                                      11 .......
## 6
        1)
##
  7
        1)
                                      " * "
##
        1)
  8
  9
        1)
##
## 10
       (1)
                                                                   " * "
## 11
       (1)
                                                                   " * "
## 12
       (1)
                                      " 4 "
                                                                   " + "
##
  13
       (1)
       (1)
                                      " * "
                                                                   " * "
##
  14
                                      " * "
                                                                  " * "
       (1)
##
  15
##
              totalTestResults totalTestResultsIncrease
```

```
## 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)
            " * "
      (1)"*"
                             " * "
## 14
      (1)"*"
                             " * "
## 15
```

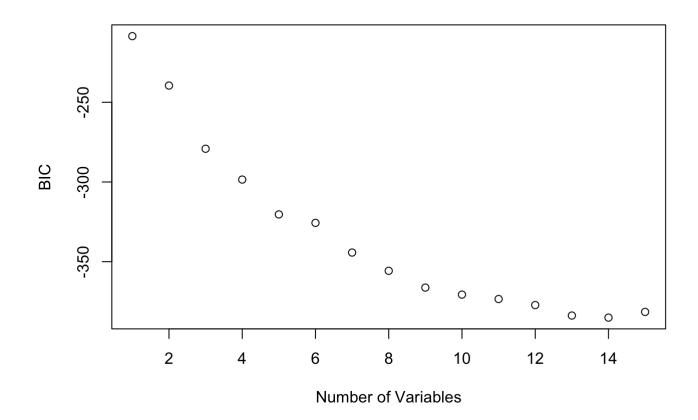
```
reg.summary=summary(regfit)
names(reg.summary)
```

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

```
reg.summary$bic
```

```
## [1] -208.5291 -239.5195 -279.1536 -298.4901 -320.3459 -325.6457 -344.2646
## [8] -355.7169 -366.2271 -370.6329 -373.4050 -377.2007 -383.7695 -385.0738
## [15] -381.4951
```

plot(reg.summary\$bic,xlab="Number of Variables",ylab="BIC") ### BIC indicates the best m
odel has 9 variables



best\_n=which.min(reg.summary\$bic) #find the model with the lowest BIC
best\_n # Model with 9 regressors is the best

## [1] 14

coef(regfit,id=best\_n)

##	(Intercept)	deathDirectionUp	deathDirection1Up
##	4.050117e+01	4.238685e+02	2.941449e+02
##	deathDirection2Up	inIcuCumulative	hospitalizedIncrease
##	1.489491e+02	-7.279764e-01	1.065176e-01
##	${\tt hospitalizedCurrently}$	$hospitalized {\tt Cumulative}$	${\tt onVentilatorCumulative}$
##	-2.248521e-02	1.991649e-02	2.659858e+00
##	${\tt onVentilatorCurrently}$	positive	positiveIncrease
##	3.143235e-01	5.170688e-04	7.336796e-03
##	states	totalTestResults	${\tt totalTestResultsIncrease}$
##	-1.350200e+01	-2.883831e-05	9.402354e-04

Stepwise

```
##
## Call:
## NULL
##
## Deviance Residuals:
                     Median
##
      Min
                1Q
                                 3Q
                                         Max
## -1144.3
          -178.1
                      13.5
                              153.5
                                      2010.4
##
## Coefficients:
##
                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                           4.050e+01 7.421e+01 0.546 0.585827
## deathDirectionUp
                           4.239e+02 6.153e+01 6.889 7.56e-11 ***
                           2.941e+02 5.718e+01 5.144 6.52e-07 ***
## deathDirection1Up
## deathDirection2Up
                           1.489e+02 5.946e+01 2.505 0.013063 *
## inIcuCumulative
                          -7.280e-01 8.329e-02 -8.740 1.07e-15 ***
## hospitalizedIncrease
                          1.065e-01 2.868e-02 3.714 0.000266 ***
## hospitalizedCurrently
                          -2.249e-02 4.262e-03 -5.275 3.51e-07 ***
## hospitalizedCumulative 1.992e-02 2.983e-03 6.678 2.47e-10 ***
## onVentilatorCumulative
                           2.660e+00 5.473e-01 4.860 2.41e-06 ***
## onVentilatorCurrently
                          3.143e-01 3.286e-02 9.565 < 2e-16 ***
                           5.171e-04 8.565e-05 6.037 7.78e-09 ***
## positive
## positiveIncrease
                           7.337e-03 1.997e-03 3.674 0.000309 ***
## states
                          -1.350e+01 2.823e+00 -4.784 3.39e-06 ***
## totalTestResults
                          -2.884e-05 8.259e-06 -3.492 0.000594 ***
## totalTestResultsIncrease 9.402e-04 2.112e-04
                                                4.453 1.43e-05 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 121822)
##
##
      Null deviance: 217767172 on 209 degrees of freedom
## Residual deviance: 23755296 on 195 degrees of freedom
## AIC: 3071.6
##
## Number of Fisher Scoring iterations: 2
```

#### **BIC-KNN**

```
set.seed(276)
trControl=trainControl(method = "cv", number = 10)
knn.fit <- train(deathIncrease ~ inIcuCumulative + hospitalizedIncrease + hospitalizedCu
rrently + hospitalizedCumulative + onVentilatorCumulative + onVentilatorCurrently + posi
tive + positiveIncrease + totalTestResults, #label
                 method
                            = "knn", #the algorithm you select
                 tuneGrid
                            = expand.grid(k = 1:10), #grid for hyperparameter
                 preProcess = c("center", "scale"), #standardize input data
                 trControl = trControl,
                            = "RMSE",
                 metric
                 data
                            = training) #specify data
knn.fit
```

```
## k-Nearest Neighbors
##
## 210 samples
##
     9 predictor
##
## Pre-processing: centered (9), scaled (9)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 190, 188, 188, 188, 190, 190, ...
## Resampling results across tuning parameters:
##
##
    k
        RMSE
                  Rsquared
                             MAE
        461.6705 0.8218257 290.0006
##
##
     2 377.8041 0.8622227 242.4938
##
     3 371.7473 0.8656514 240.0481
     4 362.5517 0.8724488 236.5830
##
     5 378.2021 0.8630004 245.9442
##
     6 398.7493 0.8537993 257.7555
##
##
     7 417.2677 0.8398895 266.8665
     8 432.6498 0.8259419 280.0156
##
##
     9 446.6365 0.8148695 282.5174
##
    10 450.4789 0.8158246 284.6154
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 4.
```

```
test_pred = predict(knn.fit,newdata=testing)
mean(testing$deathIncrease-test_pred)^2
```

```
## [1] 0.140625
```

Stepwise-KNN

```
set.seed(4)
trControl=trainControl(method = "cv", number = 10)
knn.fit1 <- train(deathIncrease ~ inIcuCumulative + hospitalizedIncrease + hospitalized
Currently +hospitalizedCumulative + onVentilatorCurrently + positive + positiveIncrease
+ totalTestResults, #label
                 method
                            = "knn", #the algorithm you select
                 tuneGrid
                            = expand.grid(k = 1:10), #grid for hyperparameter
                 preProcess = c("center", "scale"), #standardize input data
                 trControl = trControl,
                            = "RMSE",
                 metric
                 data
                            = training) #specify data
knn.fit1
```

```
## k-Nearest Neighbors
##
## 210 samples
##
    8 predictor
##
## Pre-processing: centered (8), scaled (8)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 190, 189, 189, 187, 190, 190, ...
## Resampling results across tuning parameters:
##
##
    k
        RMSE
                  Rsquared
                             MAE
     1 459.6968 0.8080517 290.4959
##
##
     2 376.8940 0.8585859 245.9989
     3 371.5678 0.8592665 234.7110
##
     4 363.2277 0.8629891 237.1163
##
     5 363.0526 0.8632598 240.4549
##
     6 395.0507 0.8452910 258.7481
##
##
     7 412.1755 0.8349530 265.5719
     8 424.8777 0.8256935 271.2260
##
     9 432.7406 0.8172640 271.2023
##
    10 441.6840 0.8119456 276.7707
##
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 5.
```

```
test_pred1 = predict(knn.fit1,newdata=testing)
mean(testing$deathIncrease-test_pred1)^2
```

```
## [1] 39.08036
```

RandomForest-KNN

```
set.seed(8)
trControl=trainControl(method = "cv", number = 10)
knn.fit2 <- train(deathIncrease ~ hospitalizedIncrease + totalTestResultsIncrease + onVe
ntilatorCurrently + hospitalizedCumulative + negativeIncrease + positiveIncrease + inIcu
Currently + totalTestResults, #label
                 method
                            = "knn", #the algorithm you select
                 tuneGrid
                            = expand.grid(k = 1:10), #grid for hyperparameter
                 preProcess = c("center", "scale"), #standardize input data
                 trControl = trControl,
                            = "RMSE",
                 metric
                 data
                            = training) #specify data
knn.fit2
```

```
## k-Nearest Neighbors
##
## 210 samples
##
    8 predictor
##
## Pre-processing: centered (8), scaled (8)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 189, 190, 189, 186, 189, 189, ...
## Resampling results across tuning parameters:
##
##
    k
        RMSE
                  Rsquared
                             MAE
     1 395.4247 0.8711760 265.9511
##
##
     2 356.4656 0.8884258 232.8458
     3 361.9817 0.8845384 229.8780
##
     4 374.3533 0.8799502 241.4025
##
     5 376.0296 0.8758882 247.8460
##
     6 380.8519 0.8737664 248.9728
##
##
     7 401.9446 0.8568702 261.7475
     8 408.1159 0.8496633 267.9392
##
##
     9 413.9170 0.8472182 270.7794
    10 424.5275 0.8397886 275.2314
##
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 2.
```

```
test_pred2 = predict(knn.fit2,newdata=testing)
mean(testing$deathIncrease-test_pred2)^2
```

```
## [1] 1292.916
```

```
{\it\# hospitalizedIncrease + totalTestResultsIncrease + onVentilatorCurrently + hospitalized} \\ {\it Cumulative + negativeIncrease + positiveIncrease + inIcuCurrently + totalTestResults} \\
```

Based on KNN results, BIC model have the lowest model when K=3; Stepwise and Random Forest model has lowest test error when k=2. BIC model has the lowest test error which is 1.286809e-05.

```
set.seed(8)
```

tune.out=tune(svm, deathIncrease ~ inIcuCumulative + hospitalizedIncrease + hospitalized Currently + hospitalizedCumulative + onVentilatorCumulative + onVentilatorCurrently + positive + positiveIncrease + totalTestResults , data=training, ranges = list(epsilon = seq(0.1,0.2), cost =  $2^{(2:8)}$ 

summary(tune.out)

```
##
## Parameter tuning of 'svm':
##
##
    sampling method: 10-fold cross validation
##
##
  - best parameters:
##
    epsilon cost
##
        0.2
              16
##
##
  - best performance: 137517.9
##
##
  - Detailed performance results:
##
      epsilon cost
                       error dispersion
## 1
          0.0
                  4 137864.7
                              114345.22
##
  2
          0.2
                  4 138396.4
                              116433.76
## 3
          0.4
                  4 171088.4
                              130308.62
                  4 237699.7
## 4
          0.6
                              123857.75
## 5
          0.8
                  4 364131.1
                              115462.12
## 6
          1.0
                  4 530373.5
                              122138.92
## 7
          0.0
                  8 143014.4
                              122625.87
          0.2
## 8
                  8 144417.1
                              115249.80
## 9
          0.4
                  8 166117.9
                              121109.39
## 10
          0.6
                  8 229999.9
                              109848.50
## 11
          0.8
                  8 345332.9
                              103761.18
## 12
          1.0
                  8 519519.2
                              110913.02
## 13
          0.0
                16 163914.4
                              146347.50
## 14
          0.2
                16 137517.9
                              105384.67
## 15
          0.4
                16 159133.2
                              109729.40
## 16
          0.6
                16 221272.9
                                94767.11
## 17
          0.8
                16 338879.4
                                92121.96
## 18
          1.0
                16 502148.3
                              119634.85
## 19
          0.0
                32 184172.6
                              172289.05
## 20
          0.2
                32 144604.1 114190.67
## 21
          0.4
                32 157251.2
                                94648.91
## 22
          0.6
                32 214530.1
                                80588.04
## 23
          0.8
                32 331149.6
                                92424.82
                32 482911.2
## 24
          1.0
                             123592.77
## 25
          0.0
                 64 214800.4
                              210998.32
## 26
          0.2
                 64 161419.1
                              119219.14
## 27
          0.4
                 64 154584.1
                                85387.24
## 28
          0.6
                 64 216129.9
                                79716.01
                 64 339685.7
## 29
          0.8
                                95599.43
## 30
          1.0
                 64 480880.8
                              127660.17
          0.0
               128 253234.4
                              264474.76
## 31
## 32
          0.2
               128 183135.2
                              145427.32
          0.4
               128 156885.8
## 33
                                79377.70
## 34
               128 183646.8
          0.6
                                92642.20
## 35
          0.8
               128 348761.9
                                90402.51
## 36
          1.0
               128 474918.0
                              125913.34
## 37
          0.0
               256 284327.3
                              289913.57
## 38
          0.2
               256 204302.9
                              172602.47
## 39
          0.4
               256 157958.3
                                75439.42
## 40
          0.6
               256 197847.5
                                88709.04
```

```
## 41 0.8 256 364056.1 79558.73
## 42 1.0 256 471615.0 123662.38
```

```
test_pred=predict(tune.out$best.model,newdata=testing)
mean(testing$deathIncrease-test_pred)^2
```

```
## [1] 1675.671
```

```
\#\#\# Best BIC model with SVM has epison 0 and cost 8 and test error 0.0009420781
```

## Stpewise-SVM

```
set.seed(9)

tune.out1=tune(svm, deathIncrease ~ inIcuCumulative + hospitalizedIncrease + hospitaliz
edCurrently +hospitalizedCumulative + onVentilatorCurrently + positive + positiveIncreas
e + totalTestResults ,data=training,ranges = list(epsilon = seq(0,1,0.2), cost = 2^(2:8
)))

summary(tune.out1)
```

```
##
## Parameter tuning of 'svm':
##
##
    sampling method: 10-fold cross validation
##
##
  - best parameters:
##
    epsilon cost
##
          0
##
##
  - best performance: 130740.1
##
##
  - Detailed performance results:
##
      epsilon cost
                       error dispersion
## 1
          0.0
                  4 130740.1
                              127473.09
##
  2
          0.2
                  4 133266.7
                              121474.27
## 3
          0.4
                  4 162223.7
                              114435.40
                  4 224028.2
## 4
          0.6
                              102882.92
## 5
          0.8
                  4 350151.1
                               88262.35
## 6
          1.0
                  4 520893.3
                               97854.04
## 7
          0.0
                 8 146096.9
                             136436.54
          0.2
## 8
                  8 139863.0
                              125957.82
                              104722.10
## 9
          0.4
                 8 159682.5
## 10
          0.6
                 8 217478.3
                               96448.65
## 11
          0.8
                 8 339146.7
                               89376.44
## 12
          1.0
                 8 515073.8
                              104451.00
## 13
          0.0
                16 165939.0
                              161712.31
## 14
          0.2
                16 143866.3
                              128278.20
## 15
          0.4
                16 160171.2 104570.29
## 16
          0.6
                16 213625.8
                               94900.96
## 17
          0.8
                16 336838.9
                               92577.33
## 18
          1.0
                16 489934.4
                             119438.96
## 19
          0.0
                32 188508.5
                              187742.25
## 20
          0.2
                32 151610.0
                              130145.23
## 21
          0.4
                32 158713.1 101684.58
## 22
          0.6
                32 212753.8
                               87601.62
## 23
          0.8
                32 343234.1
                             105053.98
                32 492486.0
## 24
          1.0
                              135313.67
## 25
          0.0
                 64 207462.9
                              217271.94
## 26
          0.2
                 64 161583.6
                             122706.08
## 27
          0.4
                 64 158820.6
                               90603.72
## 28
          0.6
                 64 217752.2
                               85122.40
                 64 348948.3
## 29
          0.8
                               94413.78
## 30
          1.0
                 64 485531.9
                             127092.17
          0.0
               128 228116.7
                              239270.77
## 31
## 32
          0.2
               128 177802.5
                              116976.05
          0.4
               128 158530.2
## 33
                               73368.51
               128 195446.5
## 34
          0.6
                              105412.31
## 35
          0.8
               128 358597.8
                               99713.52
## 36
          1.0
               128 482955.7
                              120812.42
## 37
          0.0
               256 261935.1
                             268060.52
## 38
          0.2
               256 195395.2
                              121585.70
## 39
          0.4
               256 186357.2
                               92319.25
## 40
          0.6
               256 211173.4 120013.88
```

```
## 41 0.8 256 366061.4 128516.45
## 42 1.0 256 482779.3 120860.46
```

test\_pred1=predict(tune.out1\$best.model,newdata=testing)
mean(testing\$deathIncrease-test\_pred1)^2

```
## [1] 156.6271
```

### Best Stepwise model with SVM has epison 0 and cost 4 and test error 0.001162792

#### RandomForest-SVM

```
##
## Parameter tuning of 'svm':
##
##
    sampling method: 10-fold cross validation
##
##
  - best parameters:
##
    epsilon cost
##
        0.2
              16
##
##
  - best performance: 118330.5
##
##
  - Detailed performance results:
##
      epsilon cost
                       error dispersion
## 1
          0.0
                  4 128184.6
                              105671.22
##
  2
          0.2
                  4 122779.9
                              109460.80
## 3
          0.4
                  4 158121.1
                              113023.61
                  4 218294.6
## 4
          0.6
                              109584.73
## 5
          0.8
                  4 351150.6
                              118686.37
## 6
          1.0
                  4 527292.6
                              144155.55
## 7
          0.0
                  8 138403.8
                              100253.74
          0.2
                  8 121680.7
## 8
                              105564.44
## 9
          0.4
                  8 153430.0
                              100523.87
## 10
          0.6
                  8 218492.5
                                99773.71
## 11
          0.8
                  8 355318.3
                              123379.72
## 12
          1.0
                  8 526169.7
                              159923.30
## 13
          0.0
                16 151661.3
                              102761.04
## 14
          0.2
                16 118330.5
                                82969.86
## 15
          0.4
                16 146518.1
                                78956.57
## 16
          0.6
                16 228738.1
                             101830.48
                16 368546.2
## 17
          0.8
                              126038.56
## 18
          1.0
                 16 540192.1
                              159994.49
## 19
          0.0
                32 163329.9
                              109023.57
## 20
          0.2
                32 123094.8
                               71209.77
## 21
          0.4
                32 159441.5
                                83567.35
## 22
          0.6
                32 247877.0
                              110550.02
## 23
          0.8
                32 389761.6
                              128493.78
## 24
          1.0
                32 544597.6
                              155839.44
## 25
          0.0
                 64 172446.6
                              124006.53
## 26
          0.2
                 64 131822.4
                                69549.73
## 27
          0.4
                 64 187701.2
                              104290.59
## 28
          0.6
                 64 289138.4
                              159755.27
                 64 417511.5
## 29
          0.8
                              161710.96
## 30
          1.0
                 64 544597.6
                              155839.44
          0.0
               128 194150.7
## 31
                              159346.33
## 32
          0.2
               128 169193.8
                                79151.93
          0.4
               128 231817.8
## 33
                             153663.84
## 34
               128 299111.6
          0.6
                              199422.28
## 35
          0.8
               128 416697.2
                              163446.69
## 36
          1.0
               128 544597.6
                              155839.44
## 37
          0.0
               256 232474.0
                              210083.75
## 38
          0.2
               256 217157.9
                              112216.22
## 39
          0.4
               256 294106.1
                              286622.21
## 40
          0.6
               256 310697.9
                              204578.46
```

```
## 41 0.8 256 416697.2 163446.69
## 42 1.0 256 544597.6 155839.44
```

test\_pred2=predict(tune.out2\$best.model,newdata=testing)
mean(testing\$deathIncrease-test\_pred2)^2

```
## [1] 795.2648
```

### Best Random Forest model with SVM has epison 0 and cost 4 and test error 0.09970952

Based on SVM results, the BIC model has lowest test error which is 0.0009420781 and it has epison = 0, cost = 8 Later, we use Ridge & Lasso regression to control the model complexity which is selected by BIC method

#### BIC-Lasso/Ridge

```
# Split the Data
x.train=model.matrix(deathIncrease~inIcuCumulative + hospitalizedIncrease + hospitalized
Currently + hospitalizedCumulative + onVentilatorCumulative + onVentilatorCurrently + po
sitive + positiveIncrease + totalTestResults,Covid[train,])[,-1] #put regressors from tr
aining set into a matrix
y.train=Covid[train,]$deathIncrease #label for training set
x.test=model.matrix(deathIncrease~inIcuCumulative + hospitalizedIncrease + hospitalizedC
urrently + hospitalizedCumulative + onVentilatorCumulative + onVentilatorCurrently + pos
itive + positiveIncrease + totalTestResults,Covid[test,])[,-1] #put regressors from test
set into a matrix
y.test=Covid[test,]$deathIncrease #label for test set
```

### **BIC-Ridge**

```
ridge.mod=glmnet(x.train,y.train,alpha=0) #build a ridge regression: alpha=0
cv.out=cv.glmnet(x.train,y.train,alpha=0) # use 10 fold cv to select shrinkage parameter
bestlam_r=cv.out$lambda.min #find the best shrinkage parameter
bestlam_r # The lamda value
```

```
## [1] 79.30512
```

```
ridge.pred=predict(ridge.mod,s=bestlam_r,newx=x.test) #making prediction using the best
    shrinkage parameter
ridge.err=mean((ridge.pred-y.test)^2) #calculate MSE
ridge.err
```

```
## [1] 359824.4
```

```
out=glmnet(x.train,y.train,alpha=0)
predict(out,type="coefficients",s=bestlam_r)[1:9,]
```

```
##
                                  inIcuCumulative
              (Intercept)
                                                     hospitalizedIncrease
##
             4.774864e+00
                                    -2.241493e-03
                                                             2.405351e-01
##
    hospitalizedCurrently hospitalizedCumulative onVentilatorCumulative
##
             1.596318e-03
                                     2.673234e-04
                                                            -1.103210e-01
##
    onVentilatorCurrently
                                         positive
                                                         positiveIncrease
             1.268782e-01
##
                                     4.008362e-05
                                                            -1.132331e-03
```

#### **BIC-Lasso**

lasso.mod=glmnet(x.train,y.train,alpha=1) #build a LASSO regression
cv.out=cv.glmnet(x.train,y.train,alpha=1) # use 10 fold cv to select shrinkage parameter
bestlam\_l=cv.out\$lambda.min #find the best shrinkage parameter
bestlam\_l

```
## [1] 0.08703727
```

```
lasso.pred=predict(lasso.mod,s=bestlam_l,newx=x.test) #making prediction using the best
    shrinkage parameter
lasso.err=mean((lasso.pred-y.test)^2) #calculate MSE
lasso.err
```

```
## [1] 270132.7
```

```
out=glmnet(x.train,y.train,alpha=1)
predict(out,type="coefficients",s=bestlam_1)[1:9,]
```

```
##
              (Intercept)
                                  inIcuCumulative
                                                    hospitalizedIncrease
##
            -22.962776574
                                     -0.555649432
                                                              0.220680237
##
   hospitalizedCurrently hospitalizedCumulative onVentilatorCumulative
##
             -0.024432851
                                      0.014433354
                                                              2.540117172
##
   onVentilatorCurrently
                                                        positiveIncrease
                                         positive
##
              0.237051087
                                      0.000524686
                                                              0.010961965
```

Lasso regression has lower test error 0.1969 than ridge regression 0.2744617 based on model selected with BIC. Moreover, Lasso regreesion indicates variables 'inlcuCumulative', 'hospitalizedCumulative', 'onVentilatorCumulative' and 'postive' have more explanatory power than other variables.

#### Elastic Net

```
Elastic.mod=glmnet(x.train,y.train,alpha=0.5) #build a ridge regression: alpha=0 cv.out=cv.glmnet(x.train,y.train,alpha=0.5) # use 10 fold cv to select shrinkage paramet er bestlam_e=cv.out$lambda.min #find the best shrinkage parameter bestlam_e # The lamda value
```

```
## [1] 0.1586102
```

```
Elastic.pred=predict(Elastic.mod,s=bestlam_e,newx=x.test) #making prediction using the b
est shrinkage parameter
Elastic.err=mean((Elastic.pred-y.test)^2) #calculate MSE
Elastic.err
```

```
## [1] 282265.5
```

```
out=glmnet(x.train,y.train,alpha=0.5)
predict(out,type="coefficients",s=bestlam_e)[1:9,]
```

```
##
                                  inIcuCumulative
                                                     hospitalizedIncrease
              (Intercept)
##
            -1.751208e+01
                                    -4.618553e-01
                                                             2.307667e-01
##
   hospitalizedCurrently hospitalizedCumulative onVentilatorCumulative
##
            -2.198059e-02
                                     1.275897e-02
                                                             1.940482e+00
                                                         positiveIncrease
##
   onVentilatorCurrently
                                         positive
             2.240305e-01
                                     4.471337e-04
                                                             9.713347e-03
##
```

The test error of models with singular independent variable

```
library(randomForest)
```

```
## randomForest 4.6-14
```

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

```
##
## Attaching package: 'randomForest'
```

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

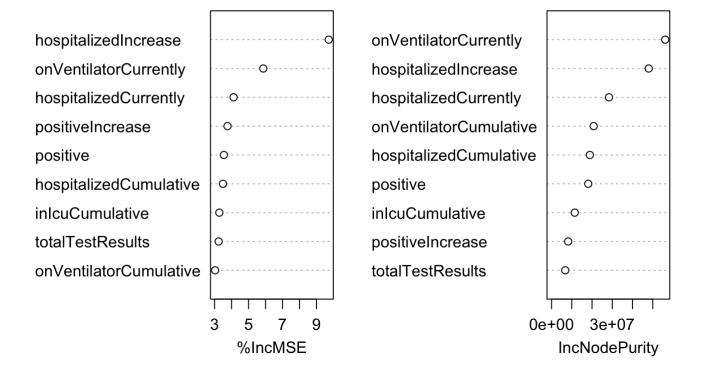
```
rf.covid_x=randomForest(deathIncrease~inIcuCumulative + hospitalizedIncrease + hospitali
zedCurrently + hospitalizedCumulative + onVentilatorCumulative + onVentilatorCurrently +
positive + positiveIncrease + totalTestResults ,data=Covid, subset=train,mtry=5,importan
ce=TRUE,ntree=25)
```

```
importance(rf.covid x)
```

```
##
                            %IncMSE IncNodePurity
## inIcuCumulative
                           3.280396
                                          11440692
## hospitalizedIncrease
                           9.719619
                                          48011024
## hospitalizedCurrently
                           4.119324
                                          28371601
## hospitalizedCumulative 3.493907
                                          18928649
## onVentilatorCumulative 3.028475
                                          20787939
## onVentilatorCurrently
                           5.865249
                                          56164792
## positive
                           3.547225
                                          18106988
## positiveIncrease
                           3.760331
                                           8215223
## totalTestResults
                           3.239679
                                           6769504
```

```
varImpPlot(rf.covid_x)
```

# rf.covid x



```
model <- lm(deathIncrease~., data = Covid)
car::vif(model)</pre>
```

deathDirection2	deathDirection1	deathDirection	##
1.526813	1.503656	1.590445	##
inIcuCumulative	deathDirection4	deathDirection3	##
3917.879775	1.552630	1.528459	##
hospitalizedCurrently	hospitalizedIncrease	${\tt inIcuCurrently}$	##
96.843462	2.130408	141.692596	##
negativeIncrease	negative	hospitalizedCumulative	##
4.018872	3452.370738	1234.006119	##
positive	${\tt onVentilatorCurrently}$	${\tt onVentilatorCumulative}$	##
930.373484	60.615614	2981.453260	##
totalTestResults	states	positiveIncrease	##
2151.488265	5.305762	34.060342	##
		totalTestResultsIncrease	##
		43.499864	##