# logistic

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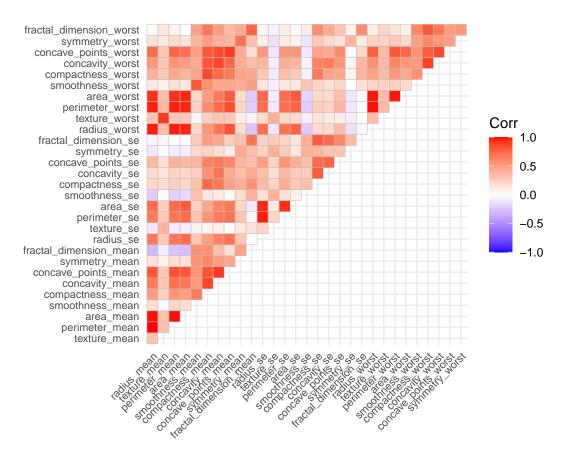
```
ggplot2::theme_set(theme_minimal() + theme(legend.position = "bottom"))
```

## data import and data clean

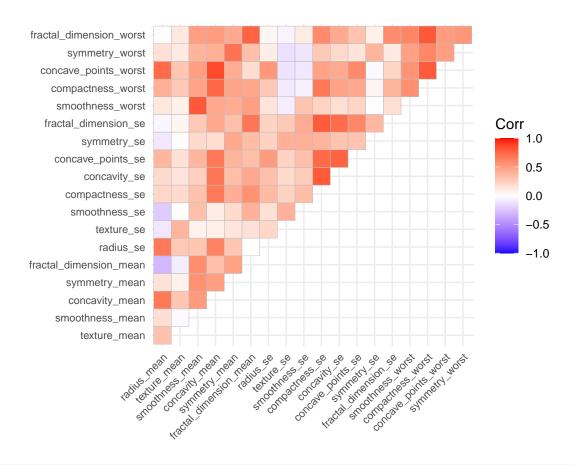
```
#load the data
breast = read.csv("breast-cancer.csv") %>%
    janitor::clean_names() %>%
    dplyr::select(-1, -33) %>% #drop id and NA columns
    mutate(diagnosis = recode(diagnosis, "M" = 1, "B" = 0))

#check collinearity
corr = breast[2:31] %>%
    cor()

ggcorrplot(corr, type = "upper", tl.cex = 8)
```



```
#remove some highly correlated variables
breast_dat <- breast %>% dplyr::select(-area_se, -perimeter_se, -area_worst, -perimeter_mean, -perimeter
corr1 = breast_dat[2:20] %>%
    cor()
ggcorrplot(corr1, type = "upper", tl.cex = 8)
```



```
#partition data into training and test data
trainRows <- createDataPartition(y = breast_dat$diagnosis, p = 0.8, list = FALSE)
breast_train <- breast_dat[trainRows, ]
breast_test <- breast_dat[-trainRows, ]
head(breast_dat, 5)</pre>
```

```
##
     diagnosis radius mean texture mean smoothness mean concavity mean
## 1
                                    10.38
                                                   0.11840
             1
                      17.99
                                                                    0.3001
## 2
                      20.57
                                    17.77
                                                   0.08474
                                                                    0.0869
             1
## 3
                      19.69
                                    21.25
                                                   0.10960
                                                                    0.1974
             1
## 4
             1
                      11.42
                                    20.38
                                                   0.14250
                                                                    0.2414
## 5
             1
                      20.29
                                    14.34
                                                   0.10030
                                                                    0.1980
     symmetry_mean fractal_dimension_mean radius_se texture_se smoothness_se
## 1
                                                1.0950
                                                           0.9053
                                                                        0.006399
            0.2419
                                    0.07871
## 2
            0.1812
                                    0.05667
                                                0.5435
                                                           0.7339
                                                                        0.005225
## 3
            0.2069
                                    0.05999
                                                0.7456
                                                           0.7869
                                                                        0.006150
## 4
            0.2597
                                    0.09744
                                                0.4956
                                                           1.1560
                                                                        0.009110
## 5
            0.1809
                                    0.05883
                                                0.7572
                                                           0.7813
                                                                        0.011490
##
     compactness_se concavity_se concave_points_se symmetry_se
## 1
            0.04904
                          0.05373
                                              0.01587
                                                          0.03003
## 2
                                              0.01340
                                                          0.01389
            0.01308
                          0.01860
## 3
            0.04006
                          0.03832
                                              0.02058
                                                          0.02250
## 4
            0.07458
                          0.05661
                                              0.01867
                                                          0.05963
## 5
            0.02461
                          0.05688
                                              0.01885
                                                          0.01756
     fractal_dimension_se smoothness_worst compactness_worst concave_points_worst
```

```
## 1
                 0.006193
                                     0.1622
                                                        0.6656
                                                                              0.2654
## 2
                 0.003532
                                     0.1238
                                                        0.1866
                                                                              0.1860
## 3
                                                        0.4245
                 0.004571
                                     0.1444
                                                                              0.2430
## 4
                                                                              0.2575
                 0.009208
                                     0.2098
                                                        0.8663
## 5
                 0.005115
                                     0.1374
                                                        0.2050
                                                                              0.1625
## symmetry_worst fractal_dimension_worst
## 1
             0.4601
                                     0.11890
             0.2750
## 2
                                     0.08902
## 3
             0.3613
                                     0.08758
## 4
             0.6638
                                     0.17300
## 5
             0.2364
                                     0.07678
r = dim(breast_dat)[1] #row number
c = dim(breast_dat)[2] #column number
var_names = names(breast_dat)[-c(1,2)] #variable names
standardize = function(col) {
  mean = mean(col)
  sd = sd(col)
  return((col - mean)/sd)
}
stand_df = breast_dat %>%
 dplyr::select(radius_mean:fractal_dimension_worst) %>%
  map_df(.x = ., standardize) #standardize
X = stand df #predictors
y = as.vector(ifelse(breast_dat[,2] == "M", 1, 0)) #response
x_train <- breast_train[2:20] #predictors</pre>
y_train <- breast_train[1] #response</pre>
x_train_stan <- cbind(rep(1, nrow(x_train)), scale(x_train))</pre>
x_test <- breast_test[2:20]</pre>
```

#### Full logistic model

x\_test\_stan <- cbind(rep(1, nrow(x\_test)), scale(x\_test))</pre>

```
Median
                   1Q
                                                 Max
                                  0.00000
## -1.56866 -0.00003
                        0.00000
                                             2.82897
##
## Coefficients:
##
                             Estimate Std. Error z value Pr(>|z|)
                             -85.8416
                                         36.2655 -2.367
## (Intercept)
                                                            0.0179 *
                                                    0.940
## radius mean
                               0.4828
                                          0.5136
                                                            0.3472
## texture_mean
                               1.2278
                                          0.4834
                                                    2.540
                                                            0.0111 *
                                         138.3795 -0.443
## smoothness mean
                             -61.2848
                                                            0.6579
## concavity_mean
                             277.1480
                                         130.0326
                                                    2.131
                                                            0.0331 *
## symmetry_mean
                            -174.8730
                                         92.2200 -1.896
                                                            0.0579 .
                                         380.8394 -0.705
                                                            0.4808
## fractal_dimension_mean
                            -268.5035
## radius_se
                              68.8555
                                         28.0557
                                                   2.454
                                                            0.0141 *
## texture_se
                              -0.4983
                                          2.0041 - 0.249
                                                            0.8036
                                                            0.0332 *
## smoothness_se
                            1374.2231
                                         645.1713
                                                    2.130
## compactness_se
                              42.7437
                                         215.7816
                                                    0.198
                                                            0.8430
                            -150.6774
## concavity_se
                                         83.3050 -1.809
                                                            0.0705 .
## concave_points_se
                             731.2978
                                         563.0794
                                                   1.299
                                                            0.1940
                                        653.0464 -2.004
                                                            0.0451 *
## symmetry_se
                           -1308.6896
## fractal dimension se
                           -6434.2765
                                       2965.7057 -2.170
                                                            0.0300 *
## smoothness_worst
                            -133.9879
                                         98.5470 -1.360
                                                            0.1739
                                          49.1751 -2.128
                                                            0.0334 *
## compactness_worst
                            -104.6221
                                                            0.0691 .
## concave_points_worst
                             161.9938
                                         89.1095
                                                    1.818
                                                    2.063
                                                            0.0391 *
## symmetry worst
                             180.8713
                                         87.6875
## fractal_dimension_worst
                             807.8439
                                         356.3095
                                                    2.267
                                                            0.0234 *
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 599.11 on 455 degrees of freedom
## Residual deviance: 27.13 on 436 degrees of freedom
## AIC: 67.13
##
## Number of Fisher Scoring iterations: 13
pred <- predict(glm.fit, newdata = breast_test, type = "response")</pre>
y_test <- factor(breast_test$diagnosis)</pre>
auc_full <- auc(y_test, pred)</pre>
auc_full
```

## Area under the curve: 0.9771

#### Newton-Raphson algorithm

coordinate-wise optimization of a logistic-lasso model

```
#soft threshold
sfxn <- function(beta, lambda) {
  if (abs(beta) > lambda) {
    return(sign(beta) * (abs(beta) - lambda))
```

```
}
else {
   return(0)
}
```

```
#coordinate-wise optimization function
coordwise_lasso <- function(lambda, x, y, betastart, tol = exp(-10), maxiter = 5000) {
  i <- 0
  n <- length(y)
  pnum <- length(betastart)</pre>
  betavec <- betastart
  loglik <- 0
  res <- c(0, loglik, betavec)
  prevloglik <- -Inf</pre>
  while (i < maxiter & abs(loglik - prevloglik) > tol & loglik < Inf) {</pre>
    i <- i + 1
    prevloglik <- loglik
    for (j in 1:pnum) {
      theta <- x %*% betavec
      p <- exp(theta) / (1 + exp(theta)) #probability of malignant cases
      w <- p*(1-p) #working weights
      w \leftarrow ifelse(abs(w-0) < 1e-5, 1e-5, w)
      z <- theta + (y - p)/w #working response
      zwoj \leftarrow x[, -j] \%*\% betavec[-j]
      \texttt{betavec[j]} \leftarrow \texttt{sfxn}(\texttt{sum}(\texttt{w*}(\texttt{x[,j]})*(\texttt{z - zwoj})), \texttt{ lambda}) \ / \ (\texttt{sum}(\texttt{w*x[,j]}*\texttt{x[,j]}))
    }
    theta <- x %*% betavec
    p <- exp(theta) / (1 + exp(theta)) #probability of malignant cases
    w <- p*(1-p) #working weights
    w \leftarrow ifelse(abs(w-0) < 1e-10, 1e-10, w)
    z \leftarrow theta + (y - p)/w
    loglik <- sum(w*(z - theta)^2) / (2*n) + lambda * sum(abs(betavec))</pre>
    res <- rbind(res, c(i, loglik, betavec))</pre>
  return(res)
}
\#coordwise\_res \leftarrow coordwise\_lasso(lambda = 0.006, x\_train\_stan, y\_train, betastart = rep(0, \#20))
#coordwise_res[nrow(coordwise_res), ]
```

We need to calculate lambdamax first to define a sequence of lambda.

```
x.matrix <- scale(x_train) %>% as.matrix()
y.matrix <- as.matrix(y_train)
lambdamax <- max(abs(t(x.matrix) %*% y.matrix)) #/ nrow(y.matrix)
lambda_seq1 <- exp(seq(log(lambdamax), -5, length = 50))
lambda_seq2 <- exp(seq(log(lambdamax), -5, length = 50))</pre>
```

```
#a path of solutions
pathwise <- function(x, y, lambda) {
   n <- length(lambda)
   betastart <- rep(0, 20)
   betas <- NULL</pre>
```

#### lambd&2 V3 V4 V5 V6 V7 V8 V9 V10 V11 V12 V13 V14 V15 V16 V17 V18 V19 V20 V21

- 50.48083960.619**4.5900**0.000 **0**00000 **0**00000 **0**0000 **0**0000 **0**0000 **0**0000 **0**0000 **0**0000 **0**0000

```
lamb d \bar{k} 2 \quad V3 \quad V4 \quad V5 \quad V6 \quad V7 \quad V8 \quad V9 \quad V10 \quad V11 \quad V12 \quad V13 \quad V14 \quad V15 \quad V16 \quad V17 \quad V18 \quad V19 \quad V20 \quad V21 \quad V20 \quad V20 \quad V21 \quad V20 \quad V
0.0102033 \ 1.582452979993 \ 17.3113466 - 14.75091253.570526931430 \ 3.4837598 -
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          8.4973.3790B6.57963981
                               0.7248177
                                                                                                                    0.6859605 3.724878686784 0.2534951
                                                                                                                                                                                                                                                                                                                                                                       3.7342582 8.38043141244343616014759
0.0082915 1.59462050775 17.9474420 - 15.22983663.68120851277 3.6558746 - - -
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                          8.7949.213382.6707050
                               0.7545704
                                                                                                                    0.7076959 3.882003248911 0.2601638
                                                                                                                                                                                                                                                                                                                                                                       3.8885088 8.72012858265947315324081
0.0067379 1.59384221886 17.9646426 - 15.26087743.6847.6632585 3.6591624 -
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 - 8.8229.6457922376605
                                                                                                                    0.7111196 3.8912782470599 0.2627046
                                                                                                                                                                                                                                                                                                                                                                       3.8906583 8.73134550269528612453739
                               0.7570750
```

#### cross-validation

```
set.seed(2022)
cv = function(data, lambda) {
  n <- nrow(data)</pre>
  data <- data[sample(n), ] #shuffle the data</pre>
 folds <- cut(seq(1, nrow(data)), breaks = 5, labels = FALSE) #Create 5 equal size folds
 # mse <- data.frame() #a data frame storing mse results</pre>
  #mse_lambda <- vector()</pre>
  #se <- vector() #a vector storing test errors</pre>
  res <- lambda
  #se <- vector() #a vectro storing test errors</pre>
    #Perform 5 fold cross validation
  for (i in 1:5) {
    #partition the data into train and test data
    testRows <- which(folds == i, arr.ind = TRUE)</pre>
    data test <- data[testRows, ]</pre>
    data_train <- data[-testRows, ]</pre>
    x_train <- data_train[2:20]</pre>
    x_train_stan <- cbind(rep(1, nrow(x_train)), scale(x_train))</pre>
    y_train <- data_train[1]</pre>
    x_test <- data_test[2:20]</pre>
    #standardized test data
    x_test_stan <- cbind(rep(1, nrow(x_test)), scale(x_test))</pre>
    y_test <- data_test %>% mutate(diagnosis = factor(diagnosis))
    y_test <- y_test$diagnosis</pre>
    #Use the test and train data partitions to perform lasso
    path_sol <- pathwise(x = x_train_stan,</pre>
                           y = y_train,
                           lambda = lambda)
    auc <- vector()</pre>
    for (j in 1:length(lambda)) {
      curbeta <- as.numeric(path_sol[j, 2:21])</pre>
      theta <- x_test_stan %*% curbeta
      p \leftarrow exp(theta) / (1 + exp(theta))
      auc[j] <- auc(y_test, p)</pre>
      #y.pred <- ifelse(p > 0.5, 1, 0)
      \#accuracy[j] \leftarrow mean(y.pred == y_test)
    }
    print(auc)
    res <- cbind(res, auc)
```

```
print(res)
      }
      return(res)
             #se[j] <- sqrt(var(error)/5)</pre>
      #cv.auc.lambda <- rowMeans(mse)</pre>
      #return(cv.auc.lambda)
}
cv_test = cv(data = breast_train, lambda_seq2)
           [1] 0.5000000 0.5000000 0.9931253 0.9931253 0.9931253 0.9920677 0.9910100
        [8] 0.9899524 0.9899524 0.9910100 0.9915389 0.9920677 0.9931253 0.9952406
## [15] 0.9957694 0.9962983 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.9968271 0.996827
## [22] 0.9968271 0.9962983 0.9962983 0.9957694 0.9957694 0.9957694 0.9952406
## [29] 0.9957694 0.9952406 0.9931253 0.9925965 0.9925965 0.9931253 0.9931253
## [36] 0.9936542 0.9931253 0.9920677 0.9920677 0.9915389 0.9894236 0.9894236
## [43] 0.9894236 0.9894236 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.974616 0.9746166 0.974616 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746166 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 0.9746160 
##
         [50] 0.9746166
##
                                                          res
        [1,] 1.752945e+02 0.5000000
## [2,] 1.424496e+02 0.5000000
## [3,] 1.157589e+02 0.9931253
## [4,] 9.406920e+01 0.9931253
## [5,] 7.644348e+01 0.9931253
## [6,] 6.212030e+01 0.9920677
## [7,] 5.048084e+01 0.9910100
## [8,] 4.102226e+01 0.9899524
## [9,] 3.333594e+01 0.9899524
## [10,] 2.708979e+01 0.9910100
## [11,] 2.201399e+01 0.9915389
## [12,] 1.788924e+01 0.9920677
## [13,] 1.453734e+01 0.9931253
## [14,] 1.181348e+01 0.9952406
## [15,] 9.599994e+00 0.9957694
## [16,] 7.801246e+00 0.9962983
## [17,] 6.339530e+00 0.9968271
## [18,] 5.151694e+00 0.9968271
## [19,] 4.186423e+00 0.9968271
## [20,] 3.402015e+00 0.9968271
## [21,] 2.764580e+00 0.9968271
## [22,] 2.246582e+00 0.9968271
## [23,] 1.825641e+00 0.9962983
## [24,] 1.483571e+00 0.9962983
## [25,] 1.205595e+00 0.9957694
## [26,] 9.797031e-01 0.9957694
## [27,] 7.961365e-01 0.9957694
## [28,] 6.469647e-01 0.9952406
## [29,] 5.257431e-01 0.9957694
## [30,] 4.272348e-01 0.9952406
## [31,] 3.471840e-01 0.9931253
## [32,] 2.821323e-01 0.9925965
## [33,] 2.292692e-01 0.9925965
## [34,] 1.863111e-01 0.9931253
```

```
## [35,] 1.514021e-01 0.9931253
## [36,] 1.230339e-01 0.9936542
## [37,] 9.998112e-02 0.9931253
## [38,] 8.124769e-02 0.9920677
## [39,] 6.602434e-02 0.9920677
## [40,] 5.365338e-02 0.9915389
## [41,] 4.360037e-02 0.9894236
## [42,] 3.543098e-02 0.9894236
## [43,] 2.879229e-02 0.9894236
## [44,] 2.339749e-02 0.9894236
## [45,] 1.901351e-02 0.9746166
## [46,] 1.545096e-02 0.9746166
## [47,] 1.255592e-02 0.9746166
## [48,] 1.020332e-02 0.9746166
## [49,] 8.291527e-03 0.9746166
## [50,] 6.737947e-03 0.9746166
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   [8] 0.9795699 0.9806452 0.9860215 0.9876344 0.9897849 0.9919355 0.9930108
## [15] 0.9935484 0.9940860 0.9940860 0.9946237 0.9946237 0.9962366 0.9962366
## [22] 0.9962366 0.9962366 0.9962366 0.9962366 0.9978495 0.9978495 0.9973118
## [29] 0.9978495 0.9973118 0.9967742 0.9967742 0.9951613 0.9946237 0.9935484
  [36] 0.9935484 0.9935484 0.9935484 0.9919355 0.9924731 0.9919355 0.9919355
   [43] \ \ 0.9919355 \ \ 0.9913978 \ \ 0.9913978 \ \ 0.9913978 \ \ 0.9913978 \ \ 0.9913978
##
   [50] 0.9919355
##
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    [2,] 1.424496e+02 0.5000000 0.5000000
   [3,] 1.157589e+02 0.9931253 0.9456989
   [4,] 9.406920e+01 0.9931253 0.9532258
   [5,] 7.644348e+01 0.9931253 0.9715054
##
   [6,] 6.212030e+01 0.9920677 0.9768817
   [7,] 5.048084e+01 0.9910100 0.9790323
  [8,] 4.102226e+01 0.9899524 0.9795699
  [9,] 3.333594e+01 0.9899524 0.9806452
## [10,] 2.708979e+01 0.9910100 0.9860215
## [11,] 2.201399e+01 0.9915389 0.9876344
## [12,] 1.788924e+01 0.9920677 0.9897849
## [13,] 1.453734e+01 0.9931253 0.9919355
## [14,] 1.181348e+01 0.9952406 0.9930108
## [15,] 9.599994e+00 0.9957694 0.9935484
## [16,] 7.801246e+00 0.9962983 0.9940860
## [17,] 6.339530e+00 0.9968271 0.9940860
## [18,] 5.151694e+00 0.9968271 0.9946237
## [19,] 4.186423e+00 0.9968271 0.9946237
## [20,] 3.402015e+00 0.9968271 0.9962366
## [21,] 2.764580e+00 0.9968271 0.9962366
## [22,] 2.246582e+00 0.9968271 0.9962366
## [23,] 1.825641e+00 0.9962983 0.9962366
## [24,] 1.483571e+00 0.9962983 0.9962366
## [25,] 1.205595e+00 0.9957694 0.9962366
## [26,] 9.797031e-01 0.9957694 0.9978495
## [27,] 7.961365e-01 0.9957694 0.9978495
## [28,] 6.469647e-01 0.9952406 0.9973118
## [29,] 5.257431e-01 0.9957694 0.9978495
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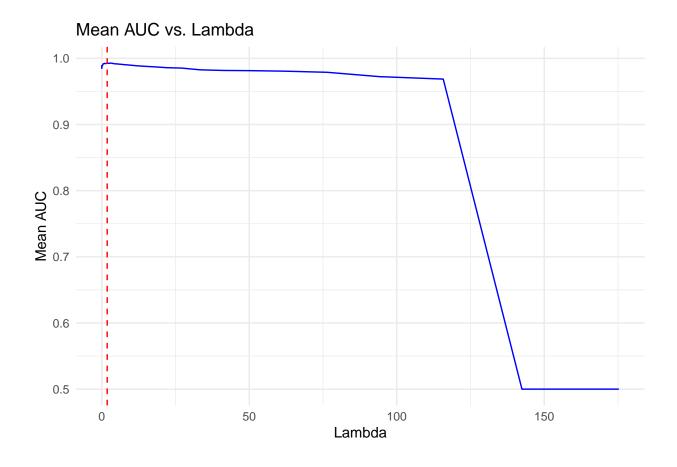
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## [31,] 3.471840e-01 0.9931253 0.9967742
## [32,] 2.821323e-01 0.9925965 0.9967742
## [33,] 2.292692e-01 0.9925965 0.9951613
## [34,] 1.863111e-01 0.9931253 0.9946237
## [35,] 1.514021e-01 0.9931253 0.9935484
## [36,] 1.230339e-01 0.9936542 0.9935484
## [37,] 9.998112e-02 0.9931253 0.9935484
## [38,] 8.124769e-02 0.9920677 0.9935484
## [39,] 6.602434e-02 0.9920677 0.9919355
## [40,] 5.365338e-02 0.9915389 0.9924731
## [41,] 4.360037e-02 0.9894236 0.9919355
## [42,] 3.543098e-02 0.9894236 0.9919355
## [43,] 2.879229e-02 0.9894236 0.9919355
## [44,] 2.339749e-02 0.9894236 0.9913978
## [45,] 1.901351e-02 0.9746166 0.9913978
## [46,] 1.545096e-02 0.9746166 0.9913978
## [47,] 1.255592e-02 0.9746166 0.9913978
## [48,] 1.020332e-02 0.9746166 0.9913978
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## [50,] 6.737947e-03 0.9746166 0.9919355
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   [8] 0.9636364 0.9641414 0.9681818 0.9702020 0.9742424 0.9757576 0.9767677
  [15] 0.9813131 0.9833333 0.9858586 0.9873737 0.9883838 0.9898990 0.9909091
  [22] 0.9904040 0.9898990 0.9868687 0.9858586 0.9848485 0.9843434 0.9833333
  [29] 0.9823232 0.9813131 0.9787879 0.9772727 0.9757576 0.9737374 0.9712121
   [36] 0.9696970 0.9681818 0.9666667 0.9676768 0.9676768 0.9671717 0.9671717
   [43] 0.9671717 0.9661616 0.9661616 0.9661616 0.9656566 0.9656566 0.9661616
##
   [50] 0.9661616
##
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                            auc
                                      auc
##
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    [3,] 1.157589e+02 0.9931253 0.9456989 0.9474747
##
   [4,] 9.406920e+01 0.9931253 0.9532258 0.9540404
    [5,] 7.644348e+01 0.9931253 0.9715054 0.9585859
   [6,] 6.212030e+01 0.9920677 0.9768817 0.9590909
##
   [7,] 5.048084e+01 0.9910100 0.9790323 0.9631313
   [8,] 4.102226e+01 0.9899524 0.9795699 0.9636364
   [9,] 3.333594e+01 0.9899524 0.9806452 0.9641414
## [10,] 2.708979e+01 0.9910100 0.9860215 0.9681818
## [11,] 2.201399e+01 0.9915389 0.9876344 0.9702020
## [12,] 1.788924e+01 0.9920677 0.9897849 0.9742424
## [13,] 1.453734e+01 0.9931253 0.9919355 0.9757576
## [14,] 1.181348e+01 0.9952406 0.9930108 0.9767677
## [15,] 9.599994e+00 0.9957694 0.9935484 0.9813131
## [16,] 7.801246e+00 0.9962983 0.9940860 0.9833333
## [17,] 6.339530e+00 0.9968271 0.9940860 0.9858586
## [18,] 5.151694e+00 0.9968271 0.9946237 0.9873737
## [19,] 4.186423e+00 0.9968271 0.9946237 0.9883838
## [20,] 3.402015e+00 0.9968271 0.9962366 0.9898990
## [21,] 2.764580e+00 0.9968271 0.9962366 0.9909091
## [22,] 2.246582e+00 0.9968271 0.9962366 0.9904040
## [23,] 1.825641e+00 0.9962983 0.9962366 0.9898990
## [24,] 1.483571e+00 0.9962983 0.9962366 0.9868687
```

```
## [25,] 1.205595e+00 0.9957694 0.9962366 0.9858586
## [26,] 9.797031e-01 0.9957694 0.9978495 0.9848485
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## [28,] 6.469647e-01 0.9952406 0.9973118 0.9833333
## [29,] 5.257431e-01 0.9957694 0.9978495 0.9823232
## [30,] 4.272348e-01 0.9952406 0.9973118 0.9813131
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## [45,] 1.901351e-02 0.9746166 0.9913978 0.9661616
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## [47,] 1.255592e-02 0.9746166 0.9913978 0.9656566
## [48,] 1.020332e-02 0.9746166 0.9913978 0.9656566
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## [15] 0.9798729 0.9793432 0.9793432 0.9793432 0.9798729 0.9804025 0.9804025
## [22] 0.9804025 0.9825212 0.9830508 0.9846398 0.9856992 0.9867585 0.9878178
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##
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##
                  res
                            auc
                                      auc
                                                auc
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##
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   [3,] 1.157589e+02 0.9931253 0.9456989 0.9474747 0.9700742
##
    [4,] 9.406920e+01 0.9931253 0.9532258 0.9540404 0.9708686
   [5,] 7.644348e+01 0.9931253 0.9715054 0.9585859 0.9772246
##
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   [7,] 5.048084e+01 0.9910100 0.9790323 0.9631313 0.9777542
##
   [8,] 4.102226e+01 0.9899524 0.9795699 0.9636364 0.9782839
  [9,] 3.333594e+01 0.9899524 0.9806452 0.9641414 0.9804025
## [10,] 2.708979e+01 0.9910100 0.9860215 0.9681818 0.9830508
## [11,] 2.201399e+01 0.9915389 0.9876344 0.9702020 0.9819915
## [12,] 1.788924e+01 0.9920677 0.9897849 0.9742424 0.9814619
## [13,] 1.453734e+01 0.9931253 0.9919355 0.9757576 0.9804025
## [14,] 1.181348e+01 0.9952406 0.9930108 0.9767677 0.9804025
## [15,] 9.599994e+00 0.9957694 0.9935484 0.9813131 0.9798729
## [16,] 7.801246e+00 0.9962983 0.9940860 0.9833333 0.9793432
## [17,] 6.339530e+00 0.9968271 0.9940860 0.9858586 0.9793432
## [18,] 5.151694e+00 0.9968271 0.9946237 0.9873737 0.9793432
## [19,] 4.186423e+00 0.9968271 0.9946237 0.9883838 0.9798729
```

```
## [20,] 3.402015e+00 0.9968271 0.9962366 0.9898990 0.9804025
## [21,] 2.764580e+00 0.9968271 0.9962366 0.9909091 0.9804025
## [22,] 2.246582e+00 0.9968271 0.9962366 0.9904040 0.9804025
## [23,] 1.825641e+00 0.9962983 0.9962366 0.9898990 0.9825212
## [24,] 1.483571e+00 0.9962983 0.9962366 0.9868687 0.9830508
## [25,] 1.205595e+00 0.9957694 0.9962366 0.9858586 0.9846398
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## [39,] 6.602434e-02 0.9920677 0.9919355 0.9676768 0.9899364
## [40,] 5.365338e-02 0.9915389 0.9924731 0.9676768 0.9920551
## [41,] 4.360037e-02 0.9894236 0.9919355 0.9671717 0.9931144
## [42,] 3.543098e-02 0.9894236 0.9919355 0.9671717 0.9931144
## [43,] 2.879229e-02 0.9894236 0.9919355 0.9671717 0.9936441
## [44,] 2.339749e-02 0.9894236 0.9913978 0.9661616 0.9931144
## [45,] 1.901351e-02 0.9746166 0.9913978 0.9661616 0.9931144
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## [47,] 1.255592e-02 0.9746166 0.9913978 0.9656566 0.9936441
## [48,] 1.020332e-02 0.9746166 0.9913978 0.9656566 0.9936441
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## [29] 0.9949950 0.9944945 0.9939940 0.9934935 0.9929930 0.9929930 0.9929930
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##
##
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                            auc
                                      auc
                                                auc
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##
##
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##
   [4,] 9.406920e+01 0.9931253 0.9532258 0.9540404 0.9708686 0.9904905
   [5,] 7.644348e+01 0.9931253 0.9715054 0.9585859 0.9772246 0.9939940
    [6,] 6.212030e+01 0.9920677 0.9768817 0.9590909 0.9788136 0.9959960
##
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   [8,] 4.102226e+01 0.9899524 0.9795699 0.9636364 0.9782839 0.9969970
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## [11,] 2.201399e+01 0.9915389 0.9876344 0.9702020 0.9819915 0.9979980
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```

```
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## [23,] 1.825641e+00 0.9962983 0.9962366 0.9898990 0.9825212 0.9984985
## [24,] 1.483571e+00 0.9962983 0.9962366 0.9868687 0.9830508 0.9979980
## [25,] 1.205595e+00 0.9957694 0.9962366 0.9858586 0.9846398 0.9979980
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## [49,] 8.291527e-03 0.9746166 0.9919355 0.9661616 0.9936441 1.0000000
## [50,] 6.737947e-03 0.9746166 0.9919355 0.9661616 0.9936441 1.0000000
cv_res <- as.data.frame(cv_test) #colnames(c("auc1", "auc2", "auc3", "auc4", "auc5"))</pre>
colnames(cv_res) <- c("res", "auc1", "auc2", "auc3", "auc4", "auc5")</pre>
cv_lambda <- cv_res[1]</pre>
mean_auc <- cv_res %>% dplyr::select(-1) %>% rowMeans()
cv_auc <- cbind(cv_lambda, mean_auc)</pre>
maxauc <- max(cv_auc$mean_auc)</pre>
bestlambda <- cv_auc[which(cv_auc$mean_auc == maxauc ),]$res
cv auc %>%
  ggplot(x = res, y = mean_auc) +
 geom\_line(aes(x = res, y = mean\_auc), col = "blue") +
  geom_vline(xintercept = bestlambda, linetype = "dashed", col = "red") +
  labs(title = "Mean AUC vs. Lambda",
       x = "Lambda",
```

v = "Mean AUC")



## Compare full model and lasso model

```
#corresponding betas of best lambda
lasso_beta <- pathwise_sol[which(pathwise_sol$lambda == bestlambda ),][2:21] %>% as.numeric()

#prediction performance function
predict <- function(x, y, betavec) {
   theta <- x %*% betavec
   p <- exp(theta) / (1 + exp(theta))
   auc <- auc(y, p)
}

auc_lasso <- predict(x_test_stan, y_test, lasso_beta)
auc_lasso

## Area under the curve: 0.9958

cbind(auc_full, auc_lasso) %>% knitr::kable()
```

auc_full	auc_lasso
0.9771242	0.9957516

### #coefficients of full and lasso models

glm\_beta <- glm.fit\$coefficients %>% as.vector()
coefnames <- rownames(coef(summary(glm.fit)))
cbind(coefnames, glm beta, lasso beta) %>% knitr::kable()

cbind(coeinames,	gim_beta,	lasso_beta)	%>% knitr::kable()

coefnames	glm_beta	lasso_beta
(Intercept)	-85.841618693509	-0.631891749918733
radius_mean	0.482809216338564	2.07950517324475
texture_mean	1.22782799498286	1.21495895057423
$smoothness\_mean$	-61.2848250472609	0
concavity_mean	277.147953900727	0.915894304171588
symmetry_mean	-174.873046711938	0
fractal_dimension_mean	-268.503538734735	0
radius_se	68.8555271776555	2.23661374208485
texture_se	-0.498284713431817	0
$smoothness\_se$	1374.2230814889	0
$compactness\_se$	42.7436942672398	-0.527415419852414
concavity_se	-150.677448596641	0
concave_points_se	731.297840302427	0
symmetry_se	-1308.68956822617	-0.385186799354295
fractal_dimension_se	-6434.27652769617	-0.421464230008035
$smoothness\_worst$	-133.987895735445	0.464232406689049
$compactness\_worst$	-104.622145944305	0
concave_points_worst	161.993778687915	2.1144068366775
symmetry_worst	180.871288833035	0.745540291717346
$\underline{fractal\_dimension\_worst}$	807.843869038758	0