Weekly Assignment 05

Xiang Li

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```
library(glmnet)

## Loading required package: Matrix

## Loaded glmnet 4.1-8

train = readRDS("masq_train.Rda")
test = readRDS("masq_test.Rda")
```

 \mathbf{a}

```
cor(train[, 12:100], use = "complete.obs")[1:10, 1:10]
```

```
##
             MASQ01
                          MASQ02
                                      MASQ03
                                                 MASQ04
                                                           MASQ05
                                                                     MASQ06
## MASQ01 1.0000000
                     0.261353159
                                  0.26580128 0.3799619 0.3334452 0.4776699
## MASQ02 0.2613532
                     1.000000000
                                  0.60885594 0.4719651 0.1793683 0.4386177
## MASQ03 0.2658013
                     0.608855943
                                  1.00000000 0.5002626 0.2046107 0.3881681
## MASQ04 0.3799619
                     0.471965131
                                  0.50026256 1.0000000 0.2092146 0.5627482
                                  0.20461071 0.2092146 1.0000000 0.2786777
## MASQ05 0.3334452
                     0.179368348
                                  0.38816815 0.5627482 0.2786777 1.0000000
## MASQ06 0.4776699
                     0.438617714
## MASQ07 0.3162404 -0.003336177 -0.03074847 0.1139440 0.1427528 0.1127332
## MASQ08 0.4787031
                     0.402560583
                                  0.38046996 0.5191725 0.2464122 0.6417347
## MASQ09 0.1795725
                     0.294294617
                                  0.32506414 0.2929352 0.1664870 0.2591377
## MASQ11 0.5246302
                     0.200081494
                                  0.21396668 0.2795097 0.2325892 0.3399698
##
                MASQ07
                          MASQ08
                                     MASQ09
                                                MASQ11
## MASQ01 0.316240354 0.4787031 0.17957253 0.5246302
## MASQ02 -0.003336177 0.4025606 0.29429462 0.2000815
## MASQ03 -0.030748474 0.3804700 0.32506414 0.2139667
          0.113943990 0.5191725 0.29293518 0.2795097
## MASQ04
## MASQ05
           0.142752789 0.2464122 0.16648703 0.2325892
## MASQ06
           0.112733188 0.6417347 0.25913770 0.3399698
## MASQ07
           1.000000000 0.1167942 0.04063244 0.3327615
## MASQO8
           0.116794186 1.0000000 0.24678531 0.3394676
## MASQ09
           0.040632436 0.2467853 1.00000000 0.1491871
## MASQ11
           0.332761545 0.3394676 0.14918709 1.0000000
```

We can see that there are some highly correlated relationships among predictors, so we need use variable selection. The performance of these three models could be elastic net regression > lasso regression > ridge regression.

b

Choice elastic net (with $\alpha = 0.5$), lasso and relaxed lasso.

 \mathbf{c}

```
train_X = model.matrix(D_DEPDYS ~ . - 1, data = train)
train_y = train$D_DEPDYS
test_X = model.matrix(D_DEPDYS ~ . - 1, data = test)
test_y = test$D_DEPDYS
set.seed(519)
lasso_cv_model = cv.glmnet(x = train_X, y = train_y, family = "binomial", alpha = 1)
lasso_cv_model
##
## Call: cv.glmnet(x = train_X, y = train_y, family = "binomial", alpha = 1)
##
## Measure: Binomial Deviance
##
       Lambda Index Measure
                                  SE Nonzero
## min 0.01140
                  34 1.028 0.02357
                                          38
## 1se 0.03482
                  22 1.050 0.01725
                                          18
set.seed(519)
elanet_cv_model = cv.glmnet(x = train_X, y = train_y, family = "binomial", alpha = 0.5)
elanet cv model
##
## Call: cv.glmnet(x = train_X, y = train_y, family = "binomial", alpha = 0.5)
## Measure: Binomial Deviance
##
##
        Lambda Index Measure
                                  SE Nonzero
## min 0.02078
                  35
                       1.027 0.02341
                                          43
## 1se 0.06346
                  23
                      1.048 0.01756
                                          24
set.seed(519)
rlasso_cv_model = cv.glmnet(x = train_X, y = train_y, family = "binomial", alpha = 1,
    relax = TRUE)
rlasso_cv_model
## Call: cv.glmnet(x = train_X, y = train_y, relax = TRUE, family = "binomial",
                                                                                      alpha = 1)
## Measure: Binomial Deviance
##
##
       Gamma Index Lambda Index Measure
                                              SE Nonzero
## min 1.00
                5 0.01140
                              34 1.028 0.02357
                 2 0.06679
## 1se 0.25
                              15 1.050 0.02062
                                                      12
```

Based on the binomial deviance, the best model is elastic net ($\alpha = 0.5$).

d

```
elanet_y = predict(elanet_cv_model, newx = test_X, s = "lambda.min", type = "response")
elanet_y = (elanet_y > 0.5) * 1
elanet_MCR = mean(elanet_y != test_y)
elanet_MCR
```

[1] 0.2291435

The MCR of elastic net model on test set is 0.2291.

 \mathbf{e}

```
coef mat = coef(elanet cv model, s = "lambda.min")
coef result = coef mat[coef mat[, 1] != 0, 1]
coef result
##
    (Intercept)
                    GENDERm
                                 GENDERv
                                            Leeftijd
                                                          DEMOG26
                                                                       DEMOG32
  -5.459473825 -0.034368564
##
                            0.028060897
                                         0.007358254 -0.353841681
                                                                   0.071558718
       DEMOG34
                   DEMOG3NA
                                 DEMOG53
                                             DEMOG55
                                                          DEMOG62
                                                                       DEMOG72
  -0.019574423 -0.209533000 -0.181904110
                                                                  0.022965398
##
                                         0.130540152 0.228083585
##
        MASQ01
                     MASQ02
                                 MASQ03
                                              MASQ04
                                                           MASQ05
                                                                       MASQ13
##
   0.170351729 -0.071314371 -0.037831392
                                         0.004491825 0.011420746
                                                                  0.058926040
##
        MASQ14
                     MASQ16
                                 MASQ18
                                              MASQ21
                                                           MASQ22
                                                                        MASQ24
##
   0.041945595
                                         0.036592390 0.101300266
                                                                  0.032626889
##
        MASQ29
                     MASQ30
                                 MASQ31
                                              MASQ33
                                                           MASQ37
                                                                       MASQ38
   0.002027648 0.112532564
                             0.045704211
                                         0.008858013
                                                      0.103909663
##
                                                                   0.030143268
                                                                       MASQ59
##
        MASQ41
                     MASQ43
                                 MASQ44
                                              MASQ50
                                                           MASQ54
   0.134000912 0.060017828
##
                             0.009045107
                                         0.005053763
                                                      0.018096950 -0.052972139
##
        MASQ60
                     MASQ62
                                 MASQ70
                                              MASQ76
                                                           MASQ78
                                                                        MASQ83
##
   0.050538144
                0.074037505
                             ##
                     MASQ90
        MASQ89
   0.145667618 0.076646625
select_predictors = c("GENDER", "Leeftijd", "DEMOG2", "DEMOG3", "DEMOG5", "DEMOG6",
    "DEMOG7", "MASQ01", "MASQ02", "MASQ03", "MASQ04", "MASQ05", "MASQ13", "MASQ14",
    "MASQ16", "MASQ18", "MASQ21", "MASQ22", "MASQ24", "MASQ29", "MASQ30", "MASQ31",
    "MASQ33", "MASQ37", "MASQ38", "MASQ41", "MASQ43", "MASQ44", "MASQ50", "MASQ54",
   "MASQ59", "MASQ60", "MASQ62", "MASQ70", "MASQ76", "MASQ78", "MASQ83", "MASQ89",
select_predictors_id = which(colnames(train) %in% select_predictors) - 1
AD_id = c(1, 14, 18, 21, 23, 26, 27, 30, 33, 35, 36, 39, 40, 44, 49, 53, 58, 66,
   72, 78, 86, 89)
AA_id = c(3, 19, 25, 45, 48, 52, 55, 57, 61, 67, 69, 73, 75, 79, 85, 87, 88)
GDD id = c(6, 8, 10, 13, 16, 22, 24, 42, 47, 56, 64, 74)
```

```
GDA_id = c(2, 9, 12, 15, 20, 59, 63, 65, 77, 81, 82)
GDM_id = c(4, 5, 17, 29, 31, 34, 37, 50, 51, 70, 76, 80, 83, 84, 90)
print(sum(select_predictors_id %in% AD_id))

## [1] 9

print(sum(select_predictors_id %in% AA_id))

## [1] 6

print(sum(select_predictors_id %in% GDD_id))

## [1] 5

print(sum(select_predictors_id %in% GDA_id))

## [1] 6

print(sum(select_predictors_id %in% GDA_id))

## [1] 4
```

The Anhedonic Depression subscale.