- Student name : 정석규 - Major : 전기공학과 - Student id : 201724570 **Table of Contents** 1. Introduction 2. Problem 1 3. Problem 2 4. Problem 3 5. Problem 4 6. Problem 5 Introduction Open the data set OJ in the R package ISLR. THe data information is available with ?OJ. Let us begin with the following R commands data(OJ) y < -0J[, 1]x <- scale(0J[, -c(1, 11:14, 17)])A matrix x consists of n = 1,070 and p = 12, and a binary response y has either CH or MM. Let us regard CH as "negative" and MM as "positive". Next randomly generate training, validation and tests samples using the following R commands. set.seed(1111) $M \leftarrow sample(rep(c(-1, 0, 1), c(600, 370, 100)))$ The vector M constists of 600 training samples (-1), 370 validation sample(0) and 100 test samples (1). In order to asses classification performance, consider 3 different scores which are accuracy(ACC), F1 score and Matthews correlation coefficieint(MCC). They are $ACC = rac{TP + TN}{TP + FP + TN + FN}$, $F_1 = rac{2TP}{2TP + FP + FN}$ and $MCC = rac{TP imes TN - FP imes FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$ respectively. Note that MCC = 0 if the denominator is equal to 0. library(dplyr) library(ISLR) data(OJ) y <- 0J[, 1] $x \leftarrow scale(0J[, -c(1, 11:14, 17)])$ set.seed(1111) $M \leftarrow sample(rep(c(-1, 0, 1), c(600, 370, 100)))$ # Train-Validation-Test sets split train <- M==-1; valid <- M==0; test <- M==1 # Factor matching of "CH", "MM" : 1, 2 # Our positive target of this problem is "MM" # Functions of evaluation metrics : ACC, F1, MCC calc.tp <- function(preds, actual) {</pre> res <- sum(preds[actual=='MM'] == 'MM')</pre> return(res) calc.tn <- function(preds, actual) {</pre> res <- sum(preds[actual=='CH'] == 'CH') return(res) calc.fp <- function(preds, actual) {</pre> res <- sum(preds[actual=='CH'] == 'MM') return(res) calc.fn <- function(preds, actual) {</pre> res <- sum(preds[actual=='MM'] == 'CH') return(res) cfx.res <- function(preds, actual) {</pre> tp <- calc.tp(preds, actual)</pre> tn <- calc.tn(preds, actual)</pre> fp <- calc.fp(preds, actual)</pre> fn <- calc.fn(preds, actual)</pre> return(list(tp, tn, fp, fn)) score.acc <- function(preds, actual) {</pre> cfx <- cfx.res(preds, actual)</pre> tp <- cfx[[1]]; tn <- cfx[[2]]; fp <- cfx[[3]]; fn <- cfx[[4]] res <- (tp + tn) / (tp + fp + tn + fn)return(res) score.f1 <- function(preds, actual) {</pre> cfx <- cfx.res(preds, actual)</pre> tp <- cfx[[1]]; tn <- cfx[[2]]; fp <- cfx[[3]]; fn <- cfx[[4]] res <- (2 * tp) / ((2 * tp) + fp + fn) return(res) score.mcc <- function(preds, actual) {</pre> cfx <- cfx.res(preds, actual)</pre> tp <- cfx[[1]]; tn <- cfx[[2]]; fp <- cfx[[3]]; fn <- cfx[[4]]</pre> **if** $(sqrt((tp + fp)*(tp + fn)*(tn + fp)*(tn + fn)) == 0) {$ res <- 0 } **else** { res <- ((tp * tn) - (fp * fn)) / sqrt((tp + fp)*(tp + fn)*(tn + fp)*(tn + fn))return(res) Problem 1 Apply a logistic regression(LR) for the training samples and then predict the class labels of validation samples, where the prediction probability of 'y=MM' P(y=MM|x)>cindicates $\hat{y}=MM$; otherwise $\hat{y}=CH$. The threshold c starts from 0 to 1 increased by 0.001. Based on the validation samples, find 3 optimal thresholds $\hat{c_1}, \hat{c_2}, \hat{c_3}$ that maximize ACC, F_1 , and MCC, respectively. If multiple thresholds have the same largest score, the optimal threshold should be the average of the multiple thresholds. Provide a single plot with 3 line respresenting ACC, F_1 , and MCC, respectively. In the plot, the thresholds are on the x-axis and the scores are on the y-axis. Also, include the numerical values of $\hat{c_1},\hat{c_2},\hat{c_3}$. # The things need to consider : Logistic regression(LR), threshold <- (0, 1, 0.001) # Required outputs : # 1. Finding 3 optimal thresholds c1, c2, c3 that maximize ACC, F1, MCC # 2. Provide a single plot with 3 lines representing ACC, F1 and MCC(including the numerical values of c1, c2, # Workflows of problem 1 : # 1. Initialize thresholds and performance result matrix of length(thresholds) x 4 # 1.1 thresholds <- seq(0, 1, 0.001) # 1.2 res <- matrix(NA, length(thresholds), 4)</pre> # 2. Fitting model Logistic regression with training set. # 3. Predict probability of validation set. # 4. (Iterating in threshold) Predicting the class labels of the validation samples based on thresholds c. # 4.1 Initialize yhat storing CH as negative # 4.2 Convert CH into MM which value is higher than thresholds[i] # 4.3 Calculate ACC, F1, MCC and store into res matrix # 5. Extract 3 optimal thresholds c1, c2, c3 that maximize ACC, F1, MCC respectively. # 5.1 Extract thresholds of maximum scores from metrics # 5.2 Calculate the average of the multiple thresholds # Make grids of thresholds and evaluation metrics thresholds < seq(0, 1, 0.001) res <- matrix(NA, length(thresholds), 4)</pre> res[, 1] <- thresholds colnames(res) <- c('thresholds', 'ACC', 'F1', 'MCC')</pre> # Training model Logistic Regressions g1 <- glm(y ~ x, family="binomial", subset=train) pred <- predict(g1, data.frame(x), type="response")[valid]</pre> for (i in 1:length(thresholds)) { yhat <- rep("CH", length(pred))</pre> yhat[pred > thresholds[i]] <- "MM"</pre> res[i, 2] <- score.acc(yhat, y[valid])</pre> res[i, 3] <- score.f1(yhat, y[valid])</pre> res[i, 4] <- score.mcc(yhat, y[valid])</pre> # Result matrix res %>% head(3) thresholds ACC F1 MCC ## [1,] 0.000 0.3810811 0.5518591 0 ## [2,] 0.001 0.3810811 0.5518591 0 ## [3,] 0.002 0.3810811 0.5518591 0 # Find 3 optimal thresholds c1, c2, c3 that maximize ACC, F1, MCC respectively $c1 \leftarrow mean(res[which(res[, 2] == max(res[, 2])), 1])$ $c2 \leftarrow mean(res[which(res[, 3] == max(res[, 3])), 1])$ $c3 \leftarrow mean(res[which(res[, 4] == max(res[, 4])), 1])$ # numerical values of c1, c2, c3 cbind(c1, c2, c3)c1 c2 ## [1,] 0.5405 0.3835 0.3835 # Visualization of problem1 matplot(x=res[, 1], y=res[, c(2:4)], type='l', pch=0.3, col=c(1:3),xlab="thresholds", ylab='Score metrics', main="Figure of Problem1") legend("center", legend=c("ACC", "F1", "MCC"), col=c(1:3), lty=1:2, cex=0.5) points(x=c1, y=0, pch="x", col=1) points(x=c2, y=0, pch="x", col=2) points(x=c3, y=0.05, pch="x", col=3) Figure of Problem1 0.8 9.0 0.4 0.2 0.0 0.0 0.2 0.4 0.6 8.0 1.0 thresholds Problem 2 With $\hat{c_1},\hat{c_2},\hat{c_3}$ obtained by Q1, find ACC, F_1 and MCC of the test samples, LR should be applied to compute ACC of the test samples with $\hat{c_1}$, F_1 score of the test samples with $\hat{c_2}$, and MCC of the test samples with $\hat{c_3}$. # The things need to consider : c1, c2, c3 obtained by Q1, Logistic Regression should be applied. # Required outputs : # 1. Finding ACC, F1, MCC of the test samples # 2. ACC of the test samples with c1, F1 score of the test samples with c2, MCC of the test samples with c3. # Workflows of Problem2 : # 1. Predict probability of test set. # 2. Calculate ACC by c1 threshold, F1 by c2 threshold, MCC by c3 threshold. # 3. Return result pred <- predict(g1, data.frame(x), type="response")[test]</pre> # ACC by c1 threshold yhat <- rep("CH", length(pred))</pre> yhat[pred > c1] <- "MM"acc <- score.acc(yhat, y[test])</pre> # F1 by c2 threshold yhat <- rep("CH", length(pred))</pre> yhat[pred > c2] <- "MM"f1 <- score.f1(yhat, y[test])</pre> # MCC by c3 threshold yhat <- rep("CH", length(pred))</pre> yhat[pred > c3] <- "MM" mcc <- score.mcc(yhat, y[test])</pre> cbind(acc, f1, mcc) f1 acc ## [1,] 0.87 0.7901235 0.6688529 Problem 3 Repeat Q1 and Q2 with linear discriminant analysis(LDA), quadratic discriminant analysis(QDA), and naive Bayes(NB) classification methods. Note that the prediction probability is equivalent of the posterior probability of 3 methods. You don't need to provide a line plot and the optimal thresholds here. For each classification method, just find the ACC, F_1 score and MCC of the test samples. # The things need to consider : Repeat Q1 and Q2 with LDA, QDA, NB. Find the ACC, F1, MCC of test samples. # Required outputs : # 1. Repeat Q1 and Q2 with LDA, QDA, NB. # 2. Find the ACC, F1, MCC of test samples. # Workflows of Problem3 : # 1. Importing library # 2. Training model with training set applying LDA, QDA, NB. # 3. Initialize 3 x 3 matrix, rows : (ACC, F1, MCC) and cols : (LDA, QDA, NB) # 4. For each model, repeat Q1 and Q2. # 5. Store result of (ACC, F1, MCC) in result matrix # Importing library library(MASS) library(e1071) # Training model with training set applying LDA, QDA, NB $g1 <- lda(y \sim x, subset=train)$ $g2 <- qda(y \sim x, subset=train)$ g3 <- naiveBayes(x, y, subset=train)</pre> thresholds < seq(0, 1, 0.001) # Initialize 3 x 3 matrix model.err <- matrix(0, 3, 3)rownames(model.err) <- c('ACC', 'F1', 'MCC'); colnames(model.err) <- c('LDA', 'QDA', 'NB')</pre> # Repeat Q1 and Q2 for each model for (k in 1:3) { # Part : Question1 # Call model LDA, QDA, NB g <- get(paste("g", k, sep="")) # Evaluation matrix by thresholds by each model res <- matrix(NA, length(thresholds), 4)</pre> res[, 1] <- thresholds colnames(res) <- c('thresholds', 'ACC', 'F1', 'MCC')</pre> # Make prediction of validation set **if** (k==1 || k==2) { valid.pred <- predict(g, data.frame(x))\$posterior[valid, 2]</pre> } else { valid.pred <- predict(g, data.frame(x), type="raw")[valid, 2]</pre> for (i in 1:length(thresholds)) { yhat <- rep("CH", length(valid.pred))</pre> yhat[valid.pred > thresholds[i]] <- "MM"</pre> res[i, 2] <- score.acc(yhat, y[valid])</pre> res[i, 3] <- score.f1(yhat, y[valid])</pre> res[i, 4] <- score.mcc(yhat, y[valid])</pre> # Find 3 optimal thresholds c1, c2, c3 that maximize ACC, F1, MCC respectively $c1 \leftarrow mean(res[which(res[, 2] == max(res[, 2])), 1])$ $c2 \leftarrow mean(res[which(res[, 3] == max(res[, 3])), 1])$ $c3 \leftarrow mean(res[which(res[, 4] == max(res[, 4])), 1])$ # Part : Question2 # Make prediction of test set **if** (k==1 || k==2) { test.pred <- predict(g, data.frame(x))\$posterior[test, 2]</pre> } else { test.pred <- predict(g, data.frame(x), type="raw")[test, 2]</pre> # ACC by c1 threshold yhat <- rep("CH", length(test.pred))</pre> yhat[test.pred > c1] <- "MM"</pre> model.err[1, k] <- score.acc(yhat, y[test])</pre> # F1 by c2 threshold yhat <- rep("CH", length(test.pred))</pre> yhat[test.pred > c2] <- "MM"</pre> model.err[2, k] <- score.f1(yhat, y[test])</pre> # MCC by c3 threshold yhat <- rep("CH", length(test.pred))</pre> yhat[test.pred > c3] <- "MM"</pre> model.err[3, k] <- score.mcc(yhat, y[test])</pre> model.err ## ACC 0.8500000 0.7400000 0.7700000 ## F1 0.7804878 0.7042254 0.7073171 ## MCC 0.6378677 0.5416138 0.4803845 Problem 4 Repeat Q1 and Q2 with a K-nearest neighbor (KNN) classification methods, where K = 1, 3, 6, ..., 197, 199. First, find the optimal K values that maximizes ACC, F_1 score and MCC of the validation samples respectively. If multiple K values have the same largest score, the optimal K should be the smallest one among them. Provide a single plot with 3 lines representing ACC, F_1 and MCC, respectively. In the plot, the values of K are on the x-axis and the scores are on the y-axis. Finally, find ACC, F_1 and MCC of the test samples, using the corresponding optimal thresholds. # ============ Problem 4 ========== # The things need to consider : # 1. Repeat Q1 and Q2 with KNN classification method. # 2. Find the optimal K values that maximize metrics. # 3. If multiple K values have the same largest score, the optimal K should be smallest one among them. # Required outputs : # 1. Provide a single plot with 3 lines # 2. In the plot, the value of K are on the x-axis and the scores are on the y-axis. # 3. find ACC, F1, MCC of the test samples, using the optimal thresholds # Workflows of Problem4 : # 1. Import library class # 2. Set Hyper parameter grids : thresholds, K # 3. Initialize Error matrix length(K) \times 3. # 4. Find the optimal K values that maximize ACC, F1 score and MCC of the validation samples. # Importing library for KNN library(class) # Hyper-parameter grids : thresholds, K thresholds \leftarrow seq(0, 1, 0.001) K < - seq(1, 199, 2)# Initialize Error matrix 3 x length(K) matrix model.err <- matrix(0, length(K), 3)</pre> colnames(model.err) <- c('ACC', 'F1', 'MCC'); rownames(model.err) <- K</pre> for (i in 1:length(K)) { # First, find the optimal K values that maximize ACC, F1 score and MCC of the validation samples, respectively. # Make prediction of validation set valid.preds <- knn(x[train,], x[valid,], y[train], k=K[i])</pre> model.err[i, 1] <- score.acc(valid.preds, y[valid])</pre> model.err[i, 2] <- score.f1(valid.preds, y[valid])</pre> model.err[i, 3] <- score.mcc(valid.preds, y[valid])</pre> # Optimal K values that maximize ACC, F1 score, MCC, respectively. wm.acc <- which.min(model.err[, 1])</pre> wm.f1 <- which.min(model.err[, 2])</pre> wm.mcc <- which.min(model.err[, 3])</pre> cbind(wm.acc, wm.f1, wm.mcc) wm.acc wm.f1 wm.mcc # Visualization of problem1 matplot(x=K, y=model.err, type='l', pch=0.3, col=c(1:3), xlab="thresholds", ylab='Score metrics', main="Figure of Problem4") legend("bottom", legend=c("ACC", "F1", "MCC"), col=c(1:3), lty=1:2, cex=0.5) Figure of Problem4 0.80 0.70 0.60 0.50 150 50 200 100 thresholds # Find ACC, F1, and MCC of the test samples test.preds <- knn(x[train,], x[test,], y[train], k=98)</pre> p4.res <- cbind(score.acc(test.preds, y[test]), score.f1(test.preds, y[test]), score.mcc(test.preds, y[test])) colnames(p4.res) <- c('ACC', 'F1', 'MCC')</pre> ACC F1 ## [1,] 0.8 0.6969697 0.5507826 Problem 5 Next, randomly generate training, validation and test samples 100 times, using the following R commands. set.seed(1234) $M \leftarrow rep(c(-1, 0, 1), c(600, 370, 100))$ M <- apply(matrix(M, length(M), 100), 2, sample)</pre> For each column of the matrix M, 1,070 samples consist of 600 training samples (-1), 370 validation samples(0) and 100 test samples(1). Since we have 100 different training, validation and test samples, you need to compute ACC, F_1 score and MCC of test sets 100 times. That is to say, you have to repeat Q1-Q4 for each set, where 5 classification methods such as LR, LDA, QDA, NB and KNN should be applied. Note that the optimal threshold or K can be determined using the validation set. For each method, find the average ACC, average F_1 score and average MCC of the test samples over 100 different sets. Summarize your answer using the following table. (test) LR LDA QDA NB KNN ACC F_1 MCC Which method is a winner? # The things need to consider : Repeat Q1-Q4 for each set, where 5 classification methods such as LR, LDA, QDA, N # Required outputs : Find the average ACC, average F1 score and average MCC of the test samples over 100 differen t sets. # Workflows of Problem5 : # 1. Initialize result matrix with 3 x 5. (rows for test metrics, cols for models) # 2. Initialize five result matrix with 100 x 3 (This will store test score of LR, LDA, QDA, NB, KNN) # 2. Repeat the steps 100 times # 2.1 Indexes of training/valid/test sets is stored in M[, i]==-1, M[, i]==0, M[, i]==1# 2.2 Repeat Q1 - Q4 # Randomly generate training, validation and test sample 100 times set.seed(1234) $M \leftarrow rep(c(-1, 0, 1), c(600, 370, 100))$ M <- apply(matrix(M, length(M), 100), 2, sample) # Initialize 100 times test score matrix of each model lr.score <- matrix(0, 100, 3) $lda.score \leftarrow matrix(0, 100, 3)$ qda.score \leftarrow matrix(0, 100, 3) nb.score \leftarrow matrix(0, 100, 3) knn.score \leftarrow matrix(0, 100, 3) # Initialize problem5 result matrix 3 x 5 p5.res <- matrix(0, 3, 5)rownames(p5.res) <- c('ACC', 'F1', 'MCC'); colnames(p5.res) <- c('LR', 'LDA', 'QDA', 'NB', 'KNN') for (i in 1:100){ train <- M[,i]==-1; valid <- M[,i]==0; test <- M[,i]==1# Problem1 - 2 p1.res <- matrix(NA, length(thresholds), 4)</pre> p1.res[, 1] <- thresholds colnames(res) <- c('thresholds', 'ACC', 'F1', 'MCC')</pre> $g1 \leftarrow glm(y \sim x, family="binomial", subset=train)$ pred <- predict(g1, data.frame(x), type="response")[valid]</pre> for (j in 1:length(thresholds)) { yhat <- rep("CH", length(pred))</pre> yhat[pred > thresholds[j]] <- "MM"</pre> p1.res[j, 2] <- score.acc(yhat, y[valid])</pre> p1.res[j, 3] <- score.f1(yhat, y[valid])</pre> p1.res[j, 4] <- score.mcc(yhat, y[valid])</pre> $c1 \leftarrow mean(p1.res[which(p1.res[, 2] == max(p1.res[, 2])), 1])$ $c2 \leftarrow mean(p1.res[which(p1.res[, 3] == max(p1.res[, 3])), 1])$ $c3 \leftarrow mean(p1.res[which(p1.res[, 4] == max(p1.res[, 4])), 1])$ pred <- predict(g1, data.frame(x), type="response")[test]</pre> # ACC by c1 threshold yhat <- rep("CH", length(pred))</pre> yhat[pred > c1] <- "MM"</pre> lr.score[i, 1] <- score.acc(yhat, y[test])</pre> # F1 by c2 threshold yhat <- rep("CH", length(pred))</pre> yhat[pred > c2] <- "MM" lr.score[i, 2] <- score.f1(yhat, y[test])</pre> # MCC by c3 threshold yhat <- rep("CH", length(pred))</pre> yhat[pred > c3] <- "MM" lr.score[i, 3] <- score.mcc(yhat, y[test])</pre> # Problem3 : LDA, QDA, NB # Training model with training set applying LDA, QDA, NB $g1 <- lda(y \sim x, subset=train)$ $g2 <- qda(y \sim x, subset=train)$ g3 <- naiveBayes(x, y, subset=train)</pre> thresholds \leftarrow seq(0, 1, 0.001) # Initialize 3 x 3 matrix model.err <- matrix(0, 3, 3)rownames(model.err) <- c('ACC', 'F1', 'MCC'); colnames(model.err) <- c('LDA', 'QDA', 'NB')</pre> # Repeat Q1 and Q2 for each model for (k in 1:3) { # Part : Question1 # Call model LDA, QDA, NB g <- get(paste("g", k, sep="")) # Evaluation matrix by thresholds by each model res <- matrix(NA, length(thresholds), 4)</pre> res[, 1] <- thresholds colnames(res) <- c('thresholds', 'ACC', 'F1', 'MCC')</pre> # Make prediction of validation set **if** (k==1 || k==2) { valid.pred <- predict(g, data.frame(x))\$posterior[valid, 2]</pre> } else { valid.pred <- predict(g, data.frame(x), type="raw")[valid, 2]</pre> for (l in 1:length(thresholds)) { yhat <- rep("CH", length(valid.pred))</pre> yhat[valid.pred > thresholds[1]] <- "MM"</pre> res[1, 2] <- score.acc(yhat, y[valid])</pre> res[l, 3] <- score.f1(yhat, y[valid])</pre> res[1, 4] <- score.mcc(yhat, y[valid])</pre> # Find 3 optimal thresholds c1, c2, c3 that maximize ACC, F1, MCC respectively $c1 \leftarrow mean(res[which(res[, 2] == max(res[, 2])), 1])$ $c2 \leftarrow mean(res[which(res[, 3] == max(res[, 3])), 1])$ $c3 \leftarrow mean(res[which(res[, 4] == max(res[, 4])), 1])$ # Part : Question2 # Make prediction of test set **if** (k==1 || k==2) { test.pred <- predict(g, data.frame(x))\$posterior[test, 2]</pre> } else { test.pred <- predict(g, data.frame(x), type="raw")[test, 2]</pre> # ACC by c1 threshold yhat <- rep("CH", length(test.pred))</pre> yhat[test.pred > c1] <- "MM"</pre> model.err[1, k] <- score.acc(yhat, y[test])</pre> # F1 by c2 threshold yhat <- rep("CH", length(test.pred))</pre> yhat[test.pred > c2] <- "MM"</pre> model.err[2, k] <- score.f1(yhat, y[test])</pre> # MCC by c3 threshold yhat <- rep("CH", length(test.pred))</pre> yhat[test.pred > c3] <- "MM"</pre> model.err[3, k] <- score.mcc(yhat, y[test])</pre> lda.score[i,] <- model.err[, 1]</pre> qda.score[i,] <- model.err[, 2]</pre> nb.score[i,] <- model.err[, 3]</pre> # Problem4 : KNN # Initialize Error matrix 3 x length(K) matrix model.err <- matrix(0, length(K), 3)</pre> colnames(model.err) <- c('ACC', 'F1', 'MCC'); rownames(model.err) <- K</pre> for (m in 1:length(K)) { # First, find the optimal K values that maximize ACC, F1 score and MCC of the validation samples, respectivel # Make prediction of validation set valid.preds <- knn(x[train,], x[valid,], y[train], k=K[m])</pre> model.err[m, 1] <- score.acc(valid.preds, y[valid])</pre> model.err[m, 2] <- score.f1(valid.preds, y[valid])</pre> model.err[m, 3] <- score.mcc(valid.preds, y[valid])</pre> # Optimal K values that maximize ACC, F1 score, MCC, respectively. wm.acc <- which.min(model.err[, 1])</pre> wm.f1 <- which.min(model.err[, 2])</pre> wm.mcc <- which.min(model.err[, 3])</pre> test.preds1 <- knn(x[train,], x[test,], y[train], k=wm.acc)</pre> test.preds2 <- knn(x[train,], x[test,], y[train], k=wm.f1)</pre> test.preds3 <- knn(x[train,], x[test,], y[train], k=wm.mcc)</pre> knn.score[i, 1] <- score.acc(test.preds1, y[test])</pre> knn.score[i, 2] <- score.f1(test.preds2, y[test])</pre> knn.score[i, 3] <- score.mcc(test.preds3, y[test])</pre> # Calculate average value of 100 times iteration and store into p5.res matrix p5.res[, 1] <- apply(lr.score, 2, mean) p5.res[, 2] <- apply(lda.score, 2, mean)</pre> p5.res[, 3] <- apply(qda.score, 2, mean) p5.res[, 4] <- apply(nb.score, 2, mean)</pre> p5.res[, 5] <- apply(knn.score, 2, mean) # View problem5 result matrix p5.res LDA ## ACC 0.8222000 0.8176000 0.7885000 0.7836000 0.7762000 ## F1 0.7719514 0.7721626 0.7383222 0.7139288 0.6958412 ## MCC 0.6263166 0.6204818 0.5544242 0.5327633 0.5301608

Score metrics

Homework2

Jeong Seok Gyu

Student information

2022-11-02

c3)

Score metrics