

Support Vector Machine (SVM) with Linear kernel

Replication-based stagewise additive modeling (RSAM)

Simulation-based settings

Article: Lizbeth Naranjo, Carlos J. Perez, Daniel F. Merino (2025). A data ensemble-based approach for detecting vocal disorders using replicated acoustic biomarkers from electroglottography. *Sensing and Bio-Sensing Research Journal*, vol, num, pages.

Data

```
## read data
datos2 <- read.csv(paste0(address,"data_simulated.csv"),
                  sep = ";",header=TRUE, dec=".")

archivo = "RSAM_crossval_strata_SVM_linear_simula" ## name of the files to save results
```

```
dim(datos2)
```

```
[1] 900 24
```

```
summary(datos2)
```

V1	V2	V3	V4
Min. :-2.46818	Min. :-2.8869	Min. :-2.3041	Min. :-2.23859
1st Qu.: -0.64472	1st Qu.: -0.4958	1st Qu.: -0.1822	1st Qu.: 0.05472
Median : 0.02661	Median : 0.2384	Median : 0.6347	Median : 1.09540
Mean :-0.01209	Mean : 0.2109	Mean : 0.6358	Mean : 1.05924
3rd Qu.: 0.60494	3rd Qu.: 0.9120	3rd Qu.: 1.3916	3rd Qu.: 1.98603
Max. : 2.62886	Max. : 2.9954	Max. : 4.0518	Max. : 4.75694

V5	V6	V7	V8
Min. :-2.9530	Min. :-2.1113	Min. :-3.0853	Min. :-2.236
1st Qu.: 0.2255	1st Qu.: 0.6053	1st Qu.: 0.9834	1st Qu.: 1.317
Median : 1.2606	Median : 1.8159	Median : 2.4098	Median : 2.774
Mean : 1.4013	Mean : 1.9805	Mean : 2.5094	Mean : 2.689
3rd Qu.: 2.4265	3rd Qu.: 3.3161	3rd Qu.: 3.9536	3rd Qu.: 3.962
Max. : 7.2912	Max. : 7.2158	Max. : 8.0646	Max. : 7.362

V9	V10	V11	V12
Min. :-2.530	Min. :-1.322	Min. :-1.068	Min. :-0.9634
1st Qu.: 1.402	1st Qu.: 1.986	1st Qu.: 2.123	1st Qu.: 1.8628
Median : 2.667	Median : 3.055	Median : 3.296	Median : 2.9238
Mean : 2.573	Mean : 3.064	Mean : 3.388	Mean : 2.9824

V13		V14		V15		V16	
3rd Qu.:	3.817	3rd Qu.:	4.127	3rd Qu.:	4.546	3rd Qu.:	4.0124
Max. :	7.988	Max. :	7.115	Max. :	7.231	Max. :	7.0910
Min. :	-1.885	Min. :	-2.079	Min. :	-2.269	Min. :	-2.1259
1st Qu.:	1.655	1st Qu.:	1.313	1st Qu.:	1.112	1st Qu.:	0.5982
Median :	3.038	Median :	2.747	Median :	2.537	Median :	1.9031
Mean :	2.805	Mean :	2.623	Mean :	2.648	Mean :	1.9893
3rd Qu.:	4.087	3rd Qu.:	3.928	3rd Qu.:	4.098	3rd Qu.:	3.3091
Max. :	6.597	Max. :	6.704	Max. :	8.223	Max. :	7.2479

V17		V18		V19		V20	
Min. :	-3.18364	Min. :	-2.7850	Min. :	-3.8817	Min. :	-2.7783
1st Qu.:	-0.01008	1st Qu.:	-0.1074	1st Qu.:	-0.1600	1st Qu.:	-0.2862
Median :	1.08517	Median :	0.8566	Median :	0.6810	Median :	0.4368
Mean :	1.25594	Mean :	0.9245	Mean :	0.6666	Mean :	0.3959
3rd Qu.:	2.51669	3rd Qu.:	1.9699	3rd Qu.:	1.5111	3rd Qu.:	1.1143
Max. :	6.44674	Max. :	5.6873	Max. :	4.1971	Max. :	4.0928

V21		ID		rep		status	
Min. :	-2.43443	Min. :	1.00	Min. :	1	Min. :	1
1st Qu.:	-0.67873	1st Qu.:	75.75	1st Qu.:	1	1st Qu.:	1
Median :	0.06097	Median :	150.50	Median :	2	Median :	2
Mean :	0.01474	Mean :	150.50	Mean :	2	Mean :	2
3rd Qu.:	0.67792	3rd Qu.:	225.25	3rd Qu.:	3	3rd Qu.:	3
Max. :	3.26405	Max. :	300.00	Max. :	3	Max. :	3

```
head(datos2)
```

	V1	V2	V3	V4	V5	V6	V7
1	1.1541136	1.206173	-0.9686025	0.02312405	2.3165891	-0.3054029	-1.61019789
2	1.1541136	1.485269	-0.4104103	0.86041236	3.4329735	1.0900776	0.06437873
3	1.1541136	1.485269	-0.4104103	0.86041236	3.4329735	0.3691737	-1.37742906
4	-0.6443284	-1.553137	-1.5977095	1.80509752	-0.4816474	1.3936230	2.15860994
5	-0.6443284	-1.326381	-1.1441960	2.48536784	0.4253797	2.5274069	3.51915059
6	-0.6443284	-1.326381	-1.1441960	2.48536784	0.4253797	1.7541637	1.97266414

	V8	V9	V10	V11	V12	V13	V14	V15
1	2.0685608	2.6366958	5.544770	4.434717	4.987851	3.720234	3.668854	3.077667
2	3.4640413	3.7530802	6.102962	4.434717	4.429659	2.603849	2.273374	1.403090
3	1.3013296	0.8694646	3.219346	1.551101	2.987851	2.603849	3.715182	4.286706
4	2.1574187	3.9048461	6.289806	7.142163	6.178932	4.254271	3.944702	2.582941
5	3.2912026	4.8118732	6.743320	7.142163	5.725419	3.347244	2.810918	1.222400
6	0.9714729	1.7189003	3.650347	4.049190	4.178932	3.347244	4.357404	4.315373

	V16	V17	V18	V19	V20	V21	ID	rep	status
1	-0.3964881	1.5892168	0.48317124	1.863786	-0.8284375	-0.1784143	1	1	1
2	-1.7919686	0.4728324	-0.35411707	1.305594	-1.1075336	-0.1784143	2	1	2
3	1.0916470	3.3564480	1.80859462	2.747402	-0.3866297	-0.1784143	3	1	3
4	0.2449769	2.6747610	0.70607137	1.582024	-2.1536013	-1.0602656	1	2	1
5	-0.8888070	1.7677339	0.02580105	1.128511	-2.3803581	-1.0602656	2	2	2
6	2.2041659	4.8607067	2.34553072	2.674997	-1.6071148	-1.0602656	3	2	3

```
datos2 <- as.data.frame(datos2)
datos2$ID_fact = as.factor(datos2$ID)    ## categorical ID of the subject
datos2$STATUS_fact = as.factor(datos2$status)    ## categorical response variable
table(datos2$STATUS_fact)
```

1 2 3

300 300 300

```
## data set  
trainc <- datos2 %>% select(-status,-ID)
```

Crossvalidation

Training and testing data subsets

```
## Select data: 75% training & 25% testing stratified per category
SIM = 100  ## repeat N times the cross-validation process
N = 300  ## sample size
Nfit = 225  ## sample size for training subset
Ntest = 75  ## sample size for testing subset
Ncat = 100  ## sample size per category
Ncatfit = 75  ## training per category
Ncattest = 25  ## testing per category
FIT <- matrix(0,SIM,Nfit)  ## training subsets
TEST <- matrix(0,SIM,Ntest)  ## testing subsets

categoria = trainc %>% filter(rep==1) %>% select(STATUS_fact)
categoria = as.numeric(categoria$STATUS_fact)
id = 1:N
set.seed(12345)
for(si in 1:SIM){
  for(j in 1:3){
    idcat = id[categoria==j]  ## stratified per category j
    ran0 = sample(idcat, size=Ncatfit, replace=FALSE)

    FIT[si,(j-1)*Ncatfit+1:Ncatfit] <- sort(ran0)
    TEST[si,(j-1)*Ncattest+1:Ncattest] <- setdiff(idcat,ran0)
  } }
```

Classification metrics for models predicting nominal outcomes

```
## Functions to compute classification metrics
## Ytrue = true response variable
## Ypred = predicted outcome
## cat = category
## TP = true positive
## TN = true negative
## FP = false positive
## FN = false negative

## Function to compute the precision per class=cat
fn_precision_class <- function(Ytrue,Ypred,cat){
  TP = sum(Ypred[Ytrue==cat]==cat)
  FP = sum(Ypred[Ytrue!=cat]==cat)
  precision = TP/(TP+FP)
  return(precision)
}

## Function to compute the recall per class=cat
fn_recall_class <- function(Ytrue,Ypred,cat){ ## cat==category
  TP = sum(Ypred[Ytrue==cat]==cat)
  FN = sum(Ypred[Ytrue==cat]!=cat)
  recall = TP/(TP+FN)
  return(recall)
}

## Function to compute the F1-score per class=cat
fn_f1score_class <- function(Ytrue,Ypred,cat){ ## cat==category
  TP = sum(Ypred[Ytrue==cat]==cat)
  FP = sum(Ypred[Ytrue!=cat]==cat)
  FN = sum(Ypred[Ytrue==cat]!=cat)
  precision = TP/(TP+FP)
  recall = TP/(TP+FN)
  f1score = 2*(precision*recall)/(precision+recall)
  return(f1score)
}

## To save classification metrics
## Fitxxx: metric for training subset. Testxxx: metric for testing subset
FitAccuracy = TestAccuracy <- array(NA,dim=c(SIM,4)) ## Accuracy Rate
FitPrecisionClass = TestPrecisionClass <- array(NA,dim=c(SIM,4,3)) ## Precision per class
FitRecallClass = TestRecallClass <- array(NA,dim=c(SIM,4,3)) ## Recall per class
FitF1ScoreClass = TestF1ScoreClass <- array(NA,dim=c(SIM,4,3)) ## F1-score per class
FitPrecisionMacroAve = TestPrecisionMacroAve <- array(NA,dim=c(SIM,4)) ## Precision Macro Average
FitRecallMacroAve = TestRecallMacroAve <- array(NA,dim=c(SIM,4)) ## Recall Macro Average
FitF1ScoreMacroAve = TestF1ScoreMacroAve <- array(NA,dim=c(SIM,4)) ## F1-score Macro Average
```

Model estimation

```
##-----
for(sim in 1:SIM){ ## BEGIN sim
##-----
my_fit = FIT[sim,]    ## training subset
my_test = TEST[sim,]  ## testing subset

## Training data subset
train1 <- trainc %>% filter(ID_fact%in%my_fit, rep==1) ## repetition=1
train2 <- trainc %>% filter(ID_fact%in%my_fit, rep==2) ## repetition=2
train3 <- trainc %>% filter(ID_fact%in%my_fit, rep==3) ## repetition=3

Yc = train1$STATUS_fact    ## categorical response variable for training
n = length(Yc)
G = 3 # classes

## Testing data subset
test1 <- trainc %>% filter(ID_fact%in%my_test, rep==1) ## repetition=1
test2 <- trainc %>% filter(ID_fact%in%my_test, rep==2) ## repetition=2
test3 <- trainc %>% filter(ID_fact%in%my_test, rep==3) ## repetition=3

Yc.new = test1$STATUS_fact    ## categorical response variable for testing
n.new = length(Yc.new)

## Delete variables which are not used
train1 <- train1 %>% select(-c(rep,ID_fact))
train2 <- train2 %>% select(-c(rep,ID_fact))
train3 <- train3 %>% select(-c(rep,ID_fact))
test1 <- test1 %>% select(-c(rep,ID_fact,STATUS_fact))
test2 <- test2 %>% select(-c(rep,ID_fact,STATUS_fact))
test3 <- test3 %>% select(-c(rep,ID_fact,STATUS_fact))

##-----
## Algorithm RSAM
## Replication-based stagewise additive modeling
##-----

## Algo1: Initialize the observation weights $w_i=1/n$, $i=1,...,n$
w1 = rep(1/n,n)

## Algo2: BEGIN for replication j=1 to J do:

## REPLICATION j=1:
## Algo3: Fit a classifier $T(x_j,z)$ to the training data using weights $w_i$
mod1 <- tune( "svm", STATUS_fact ~ . ,
              data = train1,
              weights = w1,
              kernel = "linear",
              ranges = list(cost=c(0.01,0.1,0.5,1,5,10,20,50)) )
## summary(mod1)
mejor_mod1 <- mod1$best.model
## Predictions
```

```

pred1 <- predict(mejor_mod1, newdata = train1)

## Algo4: Compute $err = \sum wi I[Y != T(xj,z)] / \sum wi$
err1 <- (sum(wi1*(Yc!=pred1))) / sum(wi1)
## Algo5: Compute $alpha = log (1-err)/err +log(G-1)$
alp1 <- log((1-err1)/err1) + log(G-1)
alp1 <- ifelse(is.finite(alp1), alp1, log(G-1))
## Algo6: Set wi = wi* exp(alpha*I[Y \neq T(xj,z)])
wi2 = wi1*exp(alp1*(Yc!=pred1))
## Algo7: Re-normalize wi
wi2 = c(wi2/sum(wi2))

##-----
## REPLICATION j=2:
## Algo3: Fit a classifier $T(xj,z)$ to the training data using weights $wi$
mod2 <- tune( "svm", STATUS_fact ~ . ,
              data = train2,
              weights = wi2,
              kernel = "linear",
              ranges = list(cost=c(0.01,0.1,0.5,1,5,10,20,50)) )
## summary(mod2)
mejor_mod2 <- mod2$best.model
## Predictions
pred2 <- predict(mejor_mod2, newdata = train2)

## Algo4: Compute $err = \sum wi I[Y != T(xj,z)] / \sum wi$
err2 <- (sum(wi2*(Yc!=pred2))) / sum(wi2)
## Algo5: Compute $alpha = log (1-err)/err +log(G-1)$
alp2 <- log((1-err2)/err2) + log(G-1)
alp2 <- ifelse(is.finite(alp2), alp2, log(G-1))
## Algo6: Set wi = wi* exp(alpha*I[Y \neq T(xj,z)])
wi3 = wi2*exp(alp2*(Yc!=pred2))
## Algo7: Re-normalize wi
wi3 = c(wi3/sum(wi3))

##-----
## REPLICATION j=3:
## Algo3: Fit a classifier $T(xj,z)$ to the training data using weights $wi$
mod3 <- tune( "svm", STATUS_fact ~ . ,
              data = train3,
              weights = wi3,
              kernel = "linear",
              ranges = list(cost=c(0.01,0.1,0.5,1,5,10,20,50)) )
## summary(mod3)
mejor_mod3 <- mod3$best.model
## Predictions
pred3 <- predict(mejor_mod3, newdata = train3)

## Algo4: Compute $err = \sum wi I[Y != T(xj,z)] / \sum wi$
err3 <- (sum(wi3*(Yc!=pred3))) / sum(wi3)
## Algo5: Compute $alpha = log (1-err)/err +log(G-1)$
alp3 <- log((1-err3)/err3) + log(G-1)
alp3 <- ifelse(is.finite(alp3), alp3, log(G-1))

```

```

## Algo6: Set  $w_i = w_i \cdot \exp(\alpha \cdot I[Y \neq T(x_j, z)])$ 
wi4 = wi3*exp(alp3*(Yc!=pred3))
## Algo7: Re-normalize  $w_i$ 
wi4 = c(wi4/sum(wi4))

## Algo8: End for replication  $j=1$  to  $J$ 
##-----

## Algo9: Output  $T^*(x, z) = \arg \max_G \sum_j \alpha \cdot I[T(x_j, z)=G]$ 

pred = cbind(pred1,pred2,pred3)
alpha = c(alp1,alp2,alp3)

argclase = matrix(NA,n,3)
clase = rep(NA,n)
for(i in 1:n){
  argclase[i,1] = sum(alpha*(pred[i,]==1))
  argclase[i,2] = sum(alpha*(pred[i,]==2))
  argclase[i,3] = sum(alpha*(pred[i,]==3))
  clase[i] = which(argclase[i,]==max(argclase[i,]))
}

##-----
## Predict new subjects for testing subsets
pred1.new <- predict(mejor_mod1, newdata = test1)
pred2.new <- predict(mejor_mod2, newdata = test2)
pred3.new <- predict(mejor_mod3, newdata = test3)

pred.new = cbind(pred1.new,pred2.new,pred3.new)

argclase.new = matrix(NA,n.new,3)
clase.new = rep(NA,n.new)
for(i in 1:n.new){
  argclase.new[i,1] = sum(alpha*(pred.new[i,]==1))
  argclase.new[i,2] = sum(alpha*(pred.new[i,]==2))
  argclase.new[i,3] = sum(alpha*(pred.new[i,]==3))
  clase.new[i] = which(argclase.new[i,]==max(argclase.new[i,]))
}

##-----
## End RSAM
##-----
## Classification Metrics for models predicting nominal outcomes

## Accuracy Rate
FitAccuracy[sim,] = c(sum(Yc==pred1)/n,
                      sum(Yc==pred2)/n,
                      sum(Yc==pred3)/n,
                      sum(Yc==clase)/n)

TestAccuracy[sim,] = c(sum(Yc.new==pred1.new)/n.new,
                       sum(Yc.new==pred2.new)/n.new,
                       sum(Yc.new==pred3.new)/n.new,
                       sum(Yc.new==clase.new)/n.new)

```



```

## Precision
for(cate in 1:3){
  FitPrecisionClass[sim,1, cate] = fn_precision_class(Yc, pred1, cate)
  FitPrecisionClass[sim,2, cate] = fn_precision_class(Yc, pred2, cate)
  FitPrecisionClass[sim,3, cate] = fn_precision_class(Yc, pred3, cate)
  FitPrecisionClass[sim,4, cate] = fn_precision_class(Yc, clase, cate)

  TestPrecisionClass[sim,1, cate] = fn_precision_class(Yc.new, pred1.new, cate)
  TestPrecisionClass[sim,2, cate] = fn_precision_class(Yc.new, pred2.new, cate)
  TestPrecisionClass[sim,3, cate] = fn_precision_class(Yc.new, pred3.new, cate)
  TestPrecisionClass[sim,4, cate] = fn_precision_class(Yc.new, clase.new, cate)
}
for(rep in 1:4){
  FitPrecisionMacroAve[sim, rep] = mean(FitPrecisionClass[sim, rep,])
  TestPrecisionMacroAve[sim,rep] = mean(TestPrecisionClass[sim,rep,])
}

## Recall
for(cate in 1:3){
  FitRecallClass[sim,1, cate] = fn_recall_class(Yc, pred1, cate)
  FitRecallClass[sim,2, cate] = fn_recall_class(Yc, pred2, cate)
  FitRecallClass[sim,3, cate] = fn_recall_class(Yc, pred3, cate)
  FitRecallClass[sim,4, cate] = fn_recall_class(Yc, clase, cate)

  TestRecallClass[sim,1, cate] = fn_recall_class(Yc.new, pred1.new, cate)
  TestRecallClass[sim,2, cate] = fn_recall_class(Yc.new, pred2.new, cate)
  TestRecallClass[sim,3, cate] = fn_recall_class(Yc.new, pred3.new, cate)
  TestRecallClass[sim,4, cate] = fn_recall_class(Yc.new, clase.new, cate)
}
for(rep in 1:4){
  FitRecallMacroAve[sim, rep] = mean(FitRecallClass[sim, rep,])
  TestRecallMacroAve[sim,rep] = mean(TestRecallClass[sim,rep,])
}

## F1-Score
for(cate in 1:3){
  FitF1ScoreClass[sim,1, cate]= fn_f1score_class(Yc, pred1, cate)
  FitF1ScoreClass[sim,2, cate]= fn_f1score_class(Yc, pred2, cate)
  FitF1ScoreClass[sim,3, cate]= fn_f1score_class(Yc, pred3, cate)
  FitF1ScoreClass[sim,4, cate]= fn_f1score_class(Yc, clase, cate)

  TestF1ScoreClass[sim,1, cate] = fn_f1score_class(Yc.new, pred1.new, cate)
  TestF1ScoreClass[sim,2, cate] = fn_f1score_class(Yc.new, pred2.new, cate)
  TestF1ScoreClass[sim,3, cate] = fn_f1score_class(Yc.new, pred3.new, cate)
  TestF1ScoreClass[sim,4, cate] = fn_f1score_class(Yc.new, clase.new, cate)
}
for(rep in 1:4){
  FitF1ScoreMacroAve[sim, rep] = mean(FitF1ScoreClass[sim, rep,])
  TestF1ScoreMacroAve[sim,rep] = mean(TestF1ScoreClass[sim,rep,])
}
##-----
}## END sim
##-----

```

Results

Accuracy Rate

```
columna = c("rep1","rep2","rep3","ensemble")
renglon = c("fit_mean","fit_sd","test_mean","test_sd")

summary(FitAccuracy)
```

##	V1	V2	V3	V4
## Min.	:0.8000	Min. :0.8667	Min. :0.8489	Min. :0.9156
## 1st Qu.:	0.8622	1st Qu.:0.8967	1st Qu.:0.8800	1st Qu.:0.9689
## Median	:0.8933	Median :0.9378	Median :0.9089	Median :0.9822
## Mean	:0.8943	Mean :0.9331	Mean :0.9072	Mean :0.9793
## 3rd Qu.:	0.9167	3rd Qu.:0.9656	3rd Qu.:0.9244	3rd Qu.:0.9911
## Max.	:1.0000	Max. :1.0000	Max. :0.9956	Max. :1.0000

```
apply(FitAccuracy,2,"sd")
```

```
## [1] 0.04459047 0.03853600 0.03329452 0.01580805
```

```
summary(TestAccuracy)
```

##	V1	V2	V3	V4
## Min.	:0.6267	Min. :0.7733	Min. :0.7467	Min. :0.7867
## 1st Qu.:	0.7333	1st Qu.:0.8133	1st Qu.:0.8133	1st Qu.:0.8933
## Median	:0.7733	Median :0.8400	Median :0.8400	Median :0.9200
## Mean	:0.7724	Mean :0.8425	Mean :0.8384	Mean :0.9100
## 3rd Qu.:	0.8000	3rd Qu.:0.8567	3rd Qu.:0.8667	3rd Qu.:0.9333
## Max.	:0.8533	Max. :0.9600	Max. :0.9200	Max. :0.9867

```
apply(TestAccuracy,2,"sd")
```

```
## [1] 0.04368051 0.03356525 0.03810459 0.04003926
```

```
RESaccuracy <- rbind(apply(FitAccuracy,2,"mean"), apply(FitAccuracy,2,"sd"),
                     apply(TestAccuracy,2,"mean"),apply(TestAccuracy,2,"sd"))
colnames(RESaccuracy) = columna
rownames(RESaccuracy) = renglon
write.csv(RESaccuracy, file=paste0(archivo,"_accuracy",".csv"))
```

Precision Macro Average

```
summary(FitPrecisionMacroAve)
```

##	V1	V2	V3	V4
## Min.	:0.8135	Min. :0.8760	Min. :0.8701	Min. :0.9163
## 1st Qu.	:0.8661	1st Qu.:0.9003	1st Qu.:0.8934	1st Qu.:0.9713
## Median	:0.8934	Median :0.9378	Median :0.9119	Median :0.9823
## Mean	:0.8972	Mean :0.9354	Mean :0.9142	Mean :0.9799
## 3rd Qu.	:0.9172	3rd Qu.:0.9658	3rd Qu.:0.9248	3rd Qu.:0.9912
## Max.	:1.0000	Max. :1.0000	Max. :0.9956	Max. :1.0000

```
apply(FitPrecisionMacroAve,2,"sd")
```

```
## [1] 0.04176334 0.03601308 0.02841511 0.01505234
```

```
summary(TestPrecisionMacroAve)
```

##	V1	V2	V3	V4
## Min.	:0.6272	Min. :0.7806	Min. :0.7542	Min. :0.7873
## 1st Qu.	:0.7514	1st Qu.:0.8289	1st Qu.:0.8291	1st Qu.:0.8959
## Median	:0.7877	Median :0.8516	Median :0.8541	Median :0.9220
## Mean	:0.7823	Mean :0.8497	Mean :0.8525	Mean :0.9142
## 3rd Qu.	:0.8159	3rd Qu.:0.8692	3rd Qu.:0.8777	3rd Qu.:0.9373
## Max.	:0.8601	Max. :0.9600	Max. :0.9284	Max. :0.9872

```
apply(TestPrecisionMacroAve,2,"sd")
```

```
## [1] 0.04356581 0.03267145 0.03727543 0.03903139
```

```
RESprecision <- rbind(apply(FitPrecisionMacroAve,2,"mean"), apply(FitPrecisionMacroAve,2,"sd"),  
                      apply(TestPrecisionMacroAve,2,"mean"), apply(TestPrecisionMacroAve,2,"sd"))  
colnames(RESprecision) = columna  
rownames(RESprecision) = renglon  
write.csv(RESprecision, file=paste0(archivo,"_precision",".csv"))
```

Recall Macro Average

```
summary(FitRecallMacroAve)
```

##	V1	V2	V3	V4
## Min.	:0.8000	Min. :0.8667	Min. :0.8489	Min. :0.9156
## 1st Qu.	:0.8622	1st Qu.:0.8967	1st Qu.:0.8800	1st Qu.:0.9689
## Median	:0.8933	Median :0.9378	Median :0.9089	Median :0.9822
## Mean	:0.8943	Mean :0.9331	Mean :0.9072	Mean :0.9793
## 3rd Qu.	:0.9167	3rd Qu.:0.9656	3rd Qu.:0.9244	3rd Qu.:0.9911
## Max.	:1.0000	Max. :1.0000	Max. :0.9956	Max. :1.0000

```
apply(FitRecallMacroAve,2,"sd")
```

```
## [1] 0.04459047 0.03853600 0.03329452 0.01580805
```

```
summary(TestRecallMacroAve)
```

##	V1	V2	V3	V4
## Min.	:0.6267	Min. :0.7733	Min. :0.7467	Min. :0.7867
## 1st Qu.	:0.7333	1st Qu.:0.8133	1st Qu.:0.8133	1st Qu.:0.8933
## Median	:0.7733	Median :0.8400	Median :0.8400	Median :0.9200
## Mean	:0.7724	Mean :0.8425	Mean :0.8384	Mean :0.9100
## 3rd Qu.	:0.8000	3rd Qu.:0.8567	3rd Qu.:0.8667	3rd Qu.:0.9333
## Max.	:0.8533	Max. :0.9600	Max. :0.9200	Max. :0.9867

```
apply(TestRecallMacroAve,2,"sd")
```

```
## [1] 0.04368051 0.03356525 0.03810459 0.04003926
```

```
RESrecall <- rbind(apply(FitRecallMacroAve,2,"mean"), apply(FitRecallMacroAve,2,"sd"),  
                  apply(TestRecallMacroAve,2,"mean"), apply(TestRecallMacroAve,2,"sd"))  
colnames(RESrecall) = c(columna  
rownames(RESrecall) = renglon  
write.csv(RESrecall, file=paste0(archivo,"_recall",".csv"))
```

F1-Score Macro Average

```
summary(FitF1ScoreMacroAve)
```

##	V1	V2	V3	V4
##	Min. :0.7963	Min. :0.8630	Min. :0.8450	Min. :0.9153
##	1st Qu.:0.8622	1st Qu.:0.8949	1st Qu.:0.8775	1st Qu.:0.9688
##	Median :0.8932	Median :0.9376	Median :0.9078	Median :0.9822
##	Mean :0.8938	Mean :0.9324	Mean :0.9060	Mean :0.9792
##	3rd Qu.:0.9165	3rd Qu.:0.9655	3rd Qu.:0.9238	3rd Qu.:0.9911
##	Max. :1.0000	Max. :1.0000	Max. :0.9956	Max. :1.0000

```
apply(FitF1ScoreMacroAve,2,"sd")
```

```
## [1] 0.04521401 0.03934139 0.03422739 0.01602530
```

```
summary(TestF1ScoreMacroAve)
```

##	V1	V2	V3	V4
##	Min. :0.6198	Min. :0.7747	Min. :0.7354	Min. :0.7828
##	1st Qu.:0.7344	1st Qu.:0.8130	1st Qu.:0.8112	1st Qu.:0.8933
##	Median :0.7737	Median :0.8405	Median :0.8384	Median :0.9195
##	Mean :0.7708	Mean :0.8413	Mean :0.8363	Mean :0.9093
##	3rd Qu.:0.8014	3rd Qu.:0.8571	3rd Qu.:0.8617	3rd Qu.:0.9333
##	Max. :0.8520	Max. :0.9597	Max. :0.9207	Max. :0.9867

```
apply(TestF1ScoreMacroAve,2,"sd")
```

```
## [1] 0.04466944 0.03395305 0.03928180 0.04055799
```

```
RESf1score <- rbind(apply(FitF1ScoreMacroAve,2,"mean"), apply(FitF1ScoreMacroAve,2,"sd"),  
                    apply(TestF1ScoreMacroAve,2,"mean"),apply(TestF1ScoreMacroAve,2,"sd"))  
colnames(RESf1score) = columna  
rownames(RESf1score) = renglon  
write.csv(RESf1score, file=paste0(archivo,"_f1score",".csv"))
```