

Math 5365

Data Mining 1

Homework 16

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1. Load the fgl data set in the MASS library.

Split the data into 70% training and 30% testing data. Predict the glass types in the test data using the following three methods, and compare the classification accuracies of these methods.

- (a) Build an SVM and use the predict command.

Using the basic SVM command with no altered parameters, the accuracy is 73.4375%

- (b) Write a script implementing the one-against-rest approach with SVM's (much of the code you need is in the 'programming one-against-rest' section of chapter5.R)

The confusion matrix for this case is shown below.

		predy			
		Con	Head	WinF	WinNF
y	WinF	0	0	21	5
	WinNF	0	0	3	18
	Veh	0	0	3	0
	Con	2	0	0	1
	Tabl	0	0	1	0
	Head	0	9	1	0

- (c) Write a script implementing the one-against-one approach with SVM's.

The confusion matrix for this test is shown below.

		y					
		WinF	WinNF	Veh	Con	Tabl	Head
	WinF	16	10	0	0	0	0
	WinNF	2	19	0	0	0	0
predy	Veh	2	1	0	0	0	0
	Con	0	1	0	2	0	0
	Tabl	0	0	0	0	1	0
	Head	1	0	0	0	0	9

```

1 #Load the fgl data set in the MASS library.
2
3 library(e1071)
4 data(fgl,package='MASS')
5 source('~/.Dropbox/Tarleton/data_mining/class_notes/extras.R')
6 source('~/.Dropbox/Tarleton/data_mining/generic_functions/dataset_ops.R')
7
8 # Split the data into 70\% training and 30\% testing data.
9 # Predict the glass types in the test data using the following
10 # three methods, and compare the classification accuracies of
11 # these methods.
12
13 splitset <- splitdata(fgl,0.7,F)
14 train <- splitset$train
15
16 #(a) Build an SVM and use the predict command.
17
18 a_model <- svm(type~., fgl[train,])
19 a_pred <- predict(a_model,fgl[-train,])

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20 a_acc <- confmatrix(fgl$type[-train],a_pred)
21
22 #(b) Write a script implementing the one-against-rest approach
23 # with SVM's (much of the code you need is in the 'programming
24 # one-against-rest' section of chapter5.R)
25
26 one_against_rest <- function(dset, v_idx, train, my_pred){
27   tmpname <- names(dset)[v_idx]
28   names(dset)[v_idx] <- 'type'
29   levels_t <- levels(dset$type)
30
31   tmpdset <- dset[train,]
32   levels(tmpdset$type) <- c(levels_t, 'other')
33   tmptype <- dset$type[train]
34   preds <- list()
35   for(idx in 1:length(levels_t) ){
36     name <- levels_t[idx]
37
38     index_v <- (tmpdset$type != name) * 1
39     tmpdset$type[index_v == 1] <- 'other'
40
41     model <- svm(type~., tmpdset)
42     tmppred <- predict(model, dset[-train,])
43     preds[[idx]] <- tmppred
44     tmpdset$type <- tmptype
45     levels(tmpdset$type) <- c(levels_t,'other')
46   }

```

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47
48 votes <- matrix(0,
49                 nrow = (nrow(dset[-train,])),
50                 ncol = length(levels_t) )
51
52 for(idx in 1:length(levels_t)){
53   name <- levels_t[idx]
54   votes[,idx] <- (preds[[idx]] == name)
55   for(i in 1:length(levels_t)){
56     if(i != idx){
57       votes[,idx] <- votes[,idx] + ( preds[[i]] == 'other' )
58     }
59   }
60 }
61
62 one_against_rest_pred <- levels_t[apply(votes, 1 ,which.max)]
63 return(table(my_pred, one_against_rest_pred))
64 }
65
66 tab1 <- one_against_rest(fgl, ncol(fgl), train, fgl$type[-train])
67
68 #(c) Write a script implementing the one-against-one approach
69 #   with SVM's.
70
71 comp_preds <- function(idx1, idx2, var, train, dset){
72   tmpname <- names(dset)[var]
73   names(dset)[var] <- 'my_var_name'

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74   myvar <- dset[,var]
75
76   n1 <- levels(myvar)[idx1]
77   n2 <- levels(myvar)[idx2]
78
79   idx <- (((myvar == n1) | (myvar == n2) )) * 1
80   idx[-train] = 0
81
82   v1_v2_train <- dset[idx == 1,]
83   v1_v2_model <- svm(my_var_name~., v1_v2_train)
84   v1_v2_pred <- predict(v1_v2_model, dset[-train,], type='class')
85
86   names(dset)[var] <- tmpname
87
88   return(v1_v2_pred)
89 }
90
91 comp_votes <- function(preds, dset, v_idx){
92
93   nr = length(preds[[1]][[1]])
94   nc = length(levels(dset[,v_idx]))
95
96   votes <- matrix(0,nrow=nr, ncol=nc)
97   for(k in 1:nc){
98     name1 <- levels(dset[,v_idx])[k]
99
100    for(i in 1:nr){

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101     for(j in 1:nc){
102         if(j != i){
103             votes[,k] <- votes[,k] + (preds[[i]][[j]] == name1) * 1
104         }
105     }
106 }
107 }
108 return(votes)
109 }
110
111 one_against_one <- function(v_idx, dset, train, predicted){
112     tmpname <- (names(dset))[v_idx]
113     varname <- 'mytempname'
114     names(dset)[v_idx] <- 'mytempname'
115
116     list_of_preds <- list()
117     tmplist <- list()
118     acc <- matrix(-1, nrow = ncol(dset), ncol = ncol(dset))
119     len <- length( levels(dset$mytempname) )
120
121     for(i in 1:len ){
122         for(j in 1:len ){
123             if(i != j){
124                 tmplist[[j]] <- comp_preds(i, j, v_idx, train, dset)
125             }else{
126                 tmplist[[j]] = rep(-1, nrow(dset) - length(train))
127             }

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128     }
129     list_of_preds[[i]] <- tmplist
130 }
131 votes <- comp_votes(list_of_preds, dset, v_idx)
132 one_against_one_pred <- (levels(dset$mytempname))[apply(votes,1,which.max)]
133 return(table(predicted, one_against_one_pred))
134 }
135
136 data(fgl,package='MASS')
137 tab2 <- one_against_one(ncol(fgl), fgl, train, fgl$type[-train])

```