

# xgboost with crossvalidation in R

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*January 4, 2017*

Setting the seed so that we get the same results each time we run the model

```
set.seed(123)
```

Importing the library mlbench for sonar dataset

```
library(mlbench)
```

```
## Warning: package 'mlbench' was built under R version 3.2.2
```

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.2.3
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
## Warning: package 'ggplot2' was built under R version 3.2.5
```

Storing the data set named “Sonar” into DataFrame named “DataFrame”

```
data("Sonar")
DataFrame <- Sonar
```

Type help(“Sonar”) to know about the data set

```
help("Sonar")
```

```
## starting httpd help server ...
```

```
## done
```

Check the dimension of this data frame

```
dim(DataFrame)
```

```
## [1] 208 61
```

Check first 3 rows

```
head(DataFrame,3)
```

```
##      V1      V2      V3      V4      V5      V6      V7      V8      V9      V10
## 1 0.0200 0.0371 0.0428 0.0207 0.0954 0.0986 0.1539 0.1601 0.3109 0.2111
## 2 0.0453 0.0523 0.0843 0.0689 0.1183 0.2583 0.2156 0.3481 0.3337 0.2872
## 3 0.0262 0.0582 0.1099 0.1083 0.0974 0.2280 0.2431 0.3771 0.5598 0.6194
##      V11      V12      V13      V14      V15      V16      V17      V18      V19      V20
## 1 0.1609 0.1582 0.2238 0.0645 0.0660 0.2273 0.3100 0.2999 0.5078 0.4797
## 2 0.4918 0.6552 0.6919 0.7797 0.7464 0.9444 1.0000 0.8874 0.8024 0.7818
## 3 0.6333 0.7060 0.5544 0.5320 0.6479 0.6931 0.6759 0.7551 0.8929 0.8619
##      V21      V22      V23      V24      V25      V26      V27      V28      V29      V30
## 1 0.5783 0.5071 0.4328 0.5550 0.6711 0.6415 0.7104 0.8080 0.6791 0.3857
## 2 0.5212 0.4052 0.3957 0.3914 0.3250 0.3200 0.3271 0.2767 0.4423 0.2028
## 3 0.7974 0.6737 0.4293 0.3648 0.5331 0.2413 0.5070 0.8533 0.6036 0.8514
##      V31      V32      V33      V34      V35      V36      V37      V38      V39      V40
## 1 0.1307 0.2604 0.5121 0.7547 0.8537 0.8507 0.6692 0.6097 0.4943 0.2744
## 2 0.3788 0.2947 0.1984 0.2341 0.1306 0.4182 0.3835 0.1057 0.1840 0.1970
## 3 0.8512 0.5045 0.1862 0.2709 0.4232 0.3043 0.6116 0.6756 0.5375 0.4719
##      V41      V42      V43      V44      V45      V46      V47      V48      V49      V50
## 1 0.0510 0.2834 0.2825 0.4256 0.2641 0.1386 0.1051 0.1343 0.0383 0.0324
## 2 0.1674 0.0583 0.1401 0.1628 0.0621 0.0203 0.0530 0.0742 0.0409 0.0061
## 3 0.4647 0.2587 0.2129 0.2222 0.2111 0.0176 0.1348 0.0744 0.0130 0.0106
##      V51      V52      V53      V54      V55      V56      V57      V58      V59      V60
## 1 0.0232 0.0027 0.0065 0.0159 0.0072 0.0167 0.0180 0.0084 0.0090 0.0032
## 2 0.0125 0.0084 0.0089 0.0048 0.0094 0.0191 0.0140 0.0049 0.0052 0.0044
## 3 0.0033 0.0232 0.0166 0.0095 0.0180 0.0244 0.0316 0.0164 0.0095 0.0078
##      Class
## 1      R
## 2      R
## 3      R
```

Check the summary of data

```
summary(DataFrame)
```

```
##      V1      V2      V3      V4
## Min.   :0.00150  Min.   :0.00060  Min.   :0.00150  Min.   :0.00580
## 1st Qu.:0.01335  1st Qu.:0.01645  1st Qu.:0.01895  1st Qu.:0.02438
## Median :0.02280  Median :0.03080  Median :0.03430  Median :0.04405
## Mean   :0.02916  Mean   :0.03844  Mean   :0.04383  Mean   :0.05389
## 3rd Qu.:0.03555  3rd Qu.:0.04795  3rd Qu.:0.05795  3rd Qu.:0.06450
## Max.   :0.13710  Max.   :0.23390  Max.   :0.30590  Max.   :0.42640
##      V5      V6      V7      V8
## Min.   :0.00670  Min.   :0.01020  Min.   :0.0033  Min.   :0.00550
## 1st Qu.:0.03805  1st Qu.:0.06703  1st Qu.:0.0809  1st Qu.:0.08042
## Median :0.06250  Median :0.09215  Median :0.1070  Median :0.11210
## Mean   :0.07520  Mean   :0.10457  Mean   :0.1217  Mean   :0.13480
## 3rd Qu.:0.10028  3rd Qu.:0.13412  3rd Qu.:0.1540  3rd Qu.:0.16960
## Max.   :0.40100  Max.   :0.38230  Max.   :0.3729  Max.   :0.45900
##      V9      V10      V11      V12
## Min.   :0.00750  Min.   :0.0113  Min.   :0.0289  Min.   :0.0236
## 1st Qu.:0.09703  1st Qu.:0.1113  1st Qu.:0.1293  1st Qu.:0.1335
```

##	Median :0.15225	Median :0.1824	Median :0.2248	Median :0.2490
##	Mean :0.17800	Mean :0.2083	Mean :0.2360	Mean :0.2502
##	3rd Qu.:0.23342	3rd Qu.:0.2687	3rd Qu.:0.3016	3rd Qu.:0.3312
##	Max. :0.68280	Max. :0.7106	Max. :0.7342	Max. :0.7060
##	V13	V14	V15	V16
##	Min. :0.0184	Min. :0.0273	Min. :0.0031	Min. :0.0162
##	1st Qu.:0.1661	1st Qu.:0.1752	1st Qu.:0.1646	1st Qu.:0.1963
##	Median :0.2640	Median :0.2811	Median :0.2817	Median :0.3047
##	Mean :0.2733	Mean :0.2966	Mean :0.3202	Mean :0.3785
##	3rd Qu.:0.3513	3rd Qu.:0.3862	3rd Qu.:0.4529	3rd Qu.:0.5357
##	Max. :0.7131	Max. :0.9970	Max. :1.0000	Max. :0.9988
##	V17	V18	V19	V20
##	Min. :0.0349	Min. :0.0375	Min. :0.0494	Min. :0.0656
##	1st Qu.:0.2059	1st Qu.:0.2421	1st Qu.:0.2991	1st Qu.:0.3506
##	Median :0.3084	Median :0.3683	Median :0.4350	Median :0.5425
##	Mean :0.4160	Mean :0.4523	Mean :0.5048	Mean :0.5630
##	3rd Qu.:0.6594	3rd Qu.:0.6791	3rd Qu.:0.7314	3rd Qu.:0.8093
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	V21	V22	V23	V24
##	Min. :0.0512	Min. :0.0219	Min. :0.0563	Min. :0.0239
##	1st Qu.:0.3997	1st Qu.:0.4069	1st Qu.:0.4502	1st Qu.:0.5407
##	Median :0.6177	Median :0.6649	Median :0.6997	Median :0.6985
##	Mean :0.6091	Mean :0.6243	Mean :0.6470	Mean :0.6727
##	3rd Qu.:0.8170	3rd Qu.:0.8320	3rd Qu.:0.8486	3rd Qu.:0.8722
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	V25	V26	V27	V28
##	Min. :0.0240	Min. :0.0921	Min. :0.0481	Min. :0.0284
##	1st Qu.:0.5258	1st Qu.:0.5442	1st Qu.:0.5319	1st Qu.:0.5348
##	Median :0.7211	Median :0.7545	Median :0.7456	Median :0.7319
##	Mean :0.6754	Mean :0.6999	Mean :0.7022	Mean :0.6940
##	3rd Qu.:0.8737	3rd Qu.:0.8938	3rd Qu.:0.9171	3rd Qu.:0.9003
##	Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000
##	V29	V30	V31	V32
##	Min. :0.0144	Min. :0.0613	Min. :0.0482	Min. :0.0404
##	1st Qu.:0.4637	1st Qu.:0.4114	1st Qu.:0.3456	1st Qu.:0.2814
##	Median :0.6808	Median :0.6071	Median :0.4904	Median :0.4296
##	Mean :0.6421	Mean :0.5809	Mean :0.5045	Mean :0.4390
##	3rd Qu.:0.8521	3rd Qu.:0.7352	3rd Qu.:0.6420	3rd Qu.:0.5803
##	Max. :1.0000	Max. :1.0000	Max. :0.9657	Max. :0.9306
##	V33	V34	V35	V36
##	Min. :0.0477	Min. :0.0212	Min. :0.0223	Min. :0.0080
##	1st Qu.:0.2579	1st Qu.:0.2176	1st Qu.:0.1794	1st Qu.:0.1543
##	Median :0.3912	Median :0.3510	Median :0.3127	Median :0.3211
##	Mean :0.4172	Mean :0.4032	Mean :0.3926	Mean :0.3848
##	3rd Qu.:0.5561	3rd Qu.:0.5961	3rd Qu.:0.5934	3rd Qu.:0.5565
##	Max. :1.0000	Max. :0.9647	Max. :1.0000	Max. :1.0000
##	V37	V38	V39	V40
##	Min. :0.0351	Min. :0.0383	Min. :0.0371	Min. :0.0117
##	1st Qu.:0.1601	1st Qu.:0.1743	1st Qu.:0.1740	1st Qu.:0.1865
##	Median :0.3063	Median :0.3127	Median :0.2835	Median :0.2781
##	Mean :0.3638	Mean :0.3397	Mean :0.3258	Mean :0.3112
##	3rd Qu.:0.5189	3rd Qu.:0.4405	3rd Qu.:0.4349	3rd Qu.:0.4244
##	Max. :0.9497	Max. :1.0000	Max. :0.9857	Max. :0.9297
##	V41	V42	V43	V44

```
## Min.      :0.0360   Min.      :0.0056   Min.      :0.0000   Min.      :0.0000
## 1st Qu.:0.1631   1st Qu.:0.1589   1st Qu.:0.1552   1st Qu.:0.1269
## Median :0.2595   Median :0.2451   Median :0.2225   Median :0.1777
## Mean    :0.2893   Mean    :0.2783   Mean    :0.2465   Mean    :0.2141
## 3rd Qu.:0.3875   3rd Qu.:0.3842   3rd Qu.:0.3245   3rd Qu.:0.2717
## Max.    :0.8995   Max.    :0.8246   Max.    :0.7733   Max.    :0.7762
##      V45      V46      V47      V48
## Min.      :0.00000   Min.      :0.00000   Min.      :0.00000   Min.      :0.00000
## 1st Qu.:0.09448   1st Qu.:0.06855   1st Qu.:0.06425   1st Qu.:0.04512
## Median :0.14800   Median :0.12135   Median :0.10165   Median :0.07810
## Mean    :0.19723   Mean    :0.16063   Mean    :0.12245   Mean    :0.09142
## 3rd Qu.:0.23155   3rd Qu.:0.20037   3rd Qu.:0.15443   3rd Qu.:0.12010
## Max.    :0.70340   Max.    :0.72920   Max.    :0.55220   Max.    :0.33390
##      V49      V50      V51      V52
## Min.      :0.00000   Min.      :0.00000   Min.      :0.000000   Min.      :0.000800
## 1st Qu.:0.02635   1st Qu.:0.01155   1st Qu.:0.008425   1st Qu.:0.007275
## Median :0.04470   Median :0.01790   Median :0.013900   Median :0.011400
## Mean    :0.05193   Mean    :0.02042   Mean    :0.016069   Mean    :0.013420
## 3rd Qu.:0.06853   3rd Qu.:0.02527   3rd Qu.:0.020825   3rd Qu.:0.016725
## Max.    :0.19810   Max.    :0.08250   Max.    :0.100400   Max.    :0.070900
##      V53      V54      V55
## Min.      :0.000500   Min.      :0.001000   Min.      :0.00060
## 1st Qu.:0.005075   1st Qu.:0.005375   1st Qu.:0.00415
## Median :0.009550   Median :0.009300   Median :0.00750
## Mean    :0.010709   Mean    :0.010941   Mean    :0.00929
## 3rd Qu.:0.014900   3rd Qu.:0.014500   3rd Qu.:0.01210
## Max.    :0.039000   Max.    :0.035200   Max.    :0.04470
##      V56      V57      V58
## Min.      :0.000400   Min.      :0.00030   Min.      :0.000300
## 1st Qu.:0.004400   1st Qu.:0.00370   1st Qu.:0.003600
## Median :0.006850   Median :0.00595   Median :0.005800
## Mean    :0.008222   Mean    :0.00782   Mean    :0.007949
## 3rd Qu.:0.010575   3rd Qu.:0.01043   3rd Qu.:0.010350
## Max.    :0.039400   Max.    :0.03550   Max.    :0.044000
##      V59      V60      Class
## Min.      :0.000100   Min.      :0.000600   M:111
## 1st Qu.:0.003675   1st Qu.:0.003100   R: 97
## Median :0.006400   Median :0.005300
## Mean    :0.007941   Mean    :0.006507
## 3rd Qu.:0.010325   3rd Qu.:0.008525
## Max.    :0.036400   Max.    :0.043900
```

Lets check the data set again

```
str(DataFrame)
```

```
## 'data.frame':   208 obs. of  61 variables:
## $ V1      : num  0.02 0.0453 0.0262 0.01 0.0762 0.0286 0.0317 0.0519 0.0223 0.0164 ...
## $ V2      : num  0.0371 0.0523 0.0582 0.0171 0.0666 0.0453 0.0956 0.0548 0.0375 0.0173 ...
## $ V3      : num  0.0428 0.0843 0.1099 0.0623 0.0481 ...
## $ V4      : num  0.0207 0.0689 0.1083 0.0205 0.0394 ...
## $ V5      : num  0.0954 0.1183 0.0974 0.0205 0.059 ...
## $ V6      : num  0.0986 0.2583 0.228 0.0368 0.0649 ...
```

```

## $ V7 : num 0.154 0.216 0.243 0.11 0.121 ...
## $ V8 : num 0.16 0.348 0.377 0.128 0.247 ...
## $ V9 : num 0.3109 0.3337 0.5598 0.0598 0.3564 ...
## $ V10 : num 0.211 0.287 0.619 0.126 0.446 ...
## $ V11 : num 0.1609 0.4918 0.6333 0.0881 0.4152 ...
## $ V12 : num 0.158 0.655 0.706 0.199 0.395 ...
## $ V13 : num 0.2238 0.6919 0.5544 0.0184 0.4256 ...
## $ V14 : num 0.0645 0.7797 0.532 0.2261 0.4135 ...
## $ V15 : num 0.066 0.746 0.648 0.173 0.453 ...
## $ V16 : num 0.227 0.944 0.693 0.213 0.533 ...
## $ V17 : num 0.31 1 0.6759 0.0693 0.7306 ...
## $ V18 : num 0.3 0.887 0.755 0.228 0.619 ...
## $ V19 : num 0.508 0.802 0.893 0.406 0.203 ...
## $ V20 : num 0.48 0.782 0.862 0.397 0.464 ...
## $ V21 : num 0.578 0.521 0.797 0.274 0.415 ...
## $ V22 : num 0.507 0.405 0.674 0.369 0.429 ...
## $ V23 : num 0.433 0.396 0.429 0.556 0.573 ...
## $ V24 : num 0.555 0.391 0.365 0.485 0.54 ...
## $ V25 : num 0.671 0.325 0.533 0.314 0.316 ...
## $ V26 : num 0.641 0.32 0.241 0.533 0.229 ...
## $ V27 : num 0.71 0.327 0.507 0.526 0.7 ...
## $ V28 : num 0.808 0.277 0.853 0.252 1 ...
## $ V29 : num 0.679 0.442 0.604 0.209 0.726 ...
## $ V30 : num 0.386 0.203 0.851 0.356 0.472 ...
## $ V31 : num 0.131 0.379 0.851 0.626 0.51 ...
## $ V32 : num 0.26 0.295 0.504 0.734 0.546 ...
## $ V33 : num 0.512 0.198 0.186 0.612 0.288 ...
## $ V34 : num 0.7547 0.2341 0.2709 0.3497 0.0981 ...
## $ V35 : num 0.854 0.131 0.423 0.395 0.195 ...
## $ V36 : num 0.851 0.418 0.304 0.301 0.418 ...
## $ V37 : num 0.669 0.384 0.612 0.541 0.46 ...
## $ V38 : num 0.61 0.106 0.676 0.881 0.322 ...
## $ V39 : num 0.494 0.184 0.537 0.986 0.283 ...
## $ V40 : num 0.274 0.197 0.472 0.917 0.243 ...
## $ V41 : num 0.051 0.167 0.465 0.612 0.198 ...
## $ V42 : num 0.2834 0.0583 0.2587 0.5006 0.2444 ...
## $ V43 : num 0.282 0.14 0.213 0.321 0.185 ...
## $ V44 : num 0.4256 0.1628 0.2222 0.3202 0.0841 ...
## $ V45 : num 0.2641 0.0621 0.2111 0.4295 0.0692 ...
## $ V46 : num 0.1386 0.0203 0.0176 0.3654 0.0528 ...
## $ V47 : num 0.1051 0.053 0.1348 0.2655 0.0357 ...
## $ V48 : num 0.1343 0.0742 0.0744 0.1576 0.0085 ...
## $ V49 : num 0.0383 0.0409 0.013 0.0681 0.023 0.0264 0.0507 0.0285 0.0777 0.0092 ...
## $ V50 : num 0.0324 0.0061 0.0106 0.0294 0.0046 0.0081 0.0159 0.0178 0.0439 0.0198 ...
## $ V51 : num 0.0232 0.0125 0.0033 0.0241 0.0156 0.0104 0.0195 0.0052 0.0061 0.0118 ...
## $ V52 : num 0.0027 0.0084 0.0232 0.0121 0.0031 0.0045 0.0201 0.0081 0.0145 0.009 ...
## $ V53 : num 0.0065 0.0089 0.0166 0.0036 0.0054 0.0014 0.0248 0.012 0.0128 0.0223 ...
## $ V54 : num 0.0159 0.0048 0.0095 0.015 0.0105 0.0038 0.0131 0.0045 0.0145 0.0179 ...
## $ V55 : num 0.0072 0.0094 0.018 0.0085 0.011 0.0013 0.007 0.0121 0.0058 0.0084 ...
## $ V56 : num 0.0167 0.0191 0.0244 0.0073 0.0015 0.0089 0.0138 0.0097 0.0049 0.0068 ...
## $ V57 : num 0.018 0.014 0.0316 0.005 0.0072 0.0057 0.0092 0.0085 0.0065 0.0032 ...
## $ V58 : num 0.0084 0.0049 0.0164 0.0044 0.0048 0.0027 0.0143 0.0047 0.0093 0.0035 ...
## $ V59 : num 0.009 0.0052 0.0095 0.004 0.0107 0.0051 0.0036 0.0048 0.0059 0.0056 ...
## $ V60 : num 0.0032 0.0044 0.0078 0.0117 0.0094 0.0062 0.0103 0.0053 0.0022 0.004 ...

```

```
## $ Class: Factor w/ 2 levels "M","R": 2 2 2 2 2 2 2 2 2 2 ...
```

Lets create the train and test data set.Target variable is Class

```
library(caTools)
library(caret)
ind = createDataPartition(DataFrame$Class, p = 2/3, list = FALSE)
trainDF<-DataFrame[ind,]
testDF<-DataFrame[-ind,]
```

We will be using the caret package for crossvalidation.Function named train in caret package is used for crossvalidation. Let's choose the paramters for the train function in caret number = 5(It means we are using 5 fold cross-validation) method="cv"(Means we are using cross-validation.You can also choose other like LOOCV or repeated CV,etc.) classProbs=TRUE(It will give the probabilities for each class.Not just the class labels)

```
ControlParamteres <- trainControl(method = "cv",
                                   number = 5,
                                   savePredictions = TRUE,
                                   classProbs = TRUE
)
```

We will put the above paramter in the model below in trControl argument

Following are the Tuning parameters which one can tune for xgboost model in caret:

1. nrounds (# Boosting Iterations) It is the number of iterations the model runs before it stops.With higher value of nrounds model will take more time and vice-versa.
2. max\_depth (Max Tree Depth) Higher value of max\_depth will create more deeper trees or we can say it will create more complex model.Higher value of max\_depth may create overfitting and lower value of max\_depth may create underfitting.All depends on data in hand.Default value is 6. range: [1,infinity]
3. eta (Shrinkage) It is learning rate which is step size shrinkage which actually shrinks the feature weights. With high value of eta,model will run fast and vice versa.With higher eta and lesser nrounds,model will take lesser time to run.With lower eta and higher nrounds model will take more time. range: [0,1]
4. gamma (Minimum Loss Reduction) It is minimum loss reduction required to make a further partition on a leaf node of the tree. The larger value will create more conservative model. One can play with this parameter also but mostly other parameters are used for model tuning. range: [0,infinity]
5. colsample\_bytree (Subsample Ratio of Columns) Randomly choosing the number of columns out of all columns or variables at a time while tree building process.You can think of mtry paramter in random forest to begin understanding more about this.Higher value may create overfitting and lower value may create underfitting.One needs to play with this value. range: (0,1]
6. min\_child\_weight (Minimum Sum of Instance Weight) You can try to begin with thinking of min bucket size in decision tree( rpart).It is like number of observations a terminal node.If the tree partition step results in a leaf node with the sum of instance weight less than min\_child\_weight, then the building process will give up further partitioning. In linear regression mode, this simply corresponds to minimum number of instances needed to be in each node range: [0,infinity]

Why do we need model tuning? As we have already seen there are lot of parameters in xgboost model like eta, colsample\_bytree, etc. You do not know which values of each parameters would give you the best predictive model. So you need to create a grid of several combinations of parameters which you think that can deliver best results. You can start by your intuition and later on keep on modifying the parameters till you are satisfied with the results. Here, for demonstration purpose I'm only choosing two values of colsample\_bytree and two values of max\_depth. For rest of the parameters single value is taken.

```
parametersGrid <- expand.grid(eta = 0.1,
                             colsample_bytree=c(0.5,0.7),
                             max_depth=c(3,6),
                             nrounds=100,
                             gamma=1,
                             min_child_weight=2
                             )
```

To check how this grid looks like type as below. It gives four combinations of parameters. You can choose more combinations if you need or want.

```
parametersGrid

##   eta colsample_bytree max_depth nrounds gamma min_child_weight
## 1 0.1                0.5        3     100      1                2
## 2 0.1                0.7        3     100      1                2
## 3 0.1                0.5        6     100      1                2
## 4 0.1                0.7        6     100      1                2
```

Let's now do the 5-fold crossvalidation for the xgboost model with the chosen parameters grid using train function. We will put the parametersGrid in the tuneGrid argument and controlParameters in trControl argument of train function. To know more about the train function type and run ?train in the console

```
modelxgboost <- train(Class~.,
                      data = trainDF,
                      method = "xgbTree",
                      trControl = ControlParameters,
                      tuneGrid=parametersGrid)
```

```
## Loading required package: xgboost
```

```
## Warning: package 'xgboost' was built under R version 3.2.5
```

```
## Loading required package: plyr
```

```
## Warning: package 'plyr' was built under R version 3.2.5
```

Let's check the crossvalidation results for parameters tuning for xgboost model. We can easily see that there are four rows with each having the combination and their corresponding accuracy and kappa, etc. For max\_depth=3 and colsample\_bytree=0.5 (rest values are fixed as we choose), the value of accuracy and kappa is 0.8203 and 0.6375 (approx) respectively. As the max\_depth=3 and colsample\_bytree=0.7 gives the best accuracy, the final model is chosen for [nrounds = 100, max\_depth = 3, eta = 0.1, gamma = 1, colsample\_bytree = 0.7 and min\_child\_weight = 2]. You can choose any customized metric other than accuracy. You have to put that in trainControl function.

```
modelxgboost
```

```
## eXtreme Gradient Boosting
##
## 139 samples
## 60 predictor
## 2 classes: 'M', 'R'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 111, 111, 112, 111, 111
## Resampling results across tuning parameters:
##
##  max_depth  colsample_bytree  Accuracy  Kappa  Accuracy SD
##  3           0.5               0.8211640  0.6387160  0.10367114
##  3           0.7               0.8066138  0.6087258  0.09566611
##  6           0.5               0.8423280  0.6826879  0.10234625
##  6           0.7               0.7994709  0.5956444  0.11664837
##  Kappa SD
##  0.2096112
##  0.1942108
##  0.2064117
##  0.2360170
##
## Tuning parameter 'nrounds' was held constant at a value of 100
##
## Tuning parameter 'gamma' was held constant at a value of 1
##
## Tuning parameter 'min_child_weight' was held constant at a value of 2
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were nrounds = 100, max_depth = 6,
## eta = 0.1, gamma = 1, colsample_bytree = 0.5 and min_child_weight = 2.
```

Let's check the predictions on the test data set

```
predictions<-predict(modelxgboost,testDF)
```

Let's check the confusion matrix

```
t<-table(predictions=predictions,actual=testDF$Class)
t
```

```
##           actual
## predictions  M  R
##           M 33  6
##           R  4 26
```