

## PREDICTION COMPETITION 5

Q1

Training data : Error estimation using 10 fold cross validation : 0.1779548

Test data : Error estimation of 'svm' using 10-fold cross validation: 0.2038239

```
1 library(readr)
2 dat <- read.csv("Desktop/aug_train (1).csv", header = TRUE)
3 dat2<- dat
4 library(e1071)
5 library(dplyr)
6
7 ### data cleaning :
8 dat$city = as.factor(dat$city)
9 dat$city_development_index = as.factor(dat$city_development_index)
10 dat$gender = as.factor(dat$gender)
11 dat$relevent_experience = as.factor(dat$relevent_experience)
12 dat$enrolled_university = as.factor(dat$enrolled_university)
13 dat$education_level = as.factor(dat$education_level)
14 dat$major_discipline = as.factor(dat$major_discipline)
15 dat$experience= as.factor(dat$experience)
16 dat$company_size = as.factor(dat$company_size)
17 dat$company_type = as.factor(dat$company_type)
18 dat$last_new_job = as.factor(dat$last_new_job)
19 dat$city<- factor(dat$city,levels = c("city_103","city_21","city_16","city_114","city_160"))
20 dat$enrollee_id = as.factor(dat$enrollee_id)
21 ### creating a data frame for easier use ::
22 frame<- tbl_df(dat)
23 ### dealing with missing values to reduce the imbalance in the data::
24 frame$gender[frame$gender == ""] <- NA
25 frame$enrolled_university[frame$enrolled_university == ""] <- NA
26 frame$education_level[frame$education_level == ""] <- NA
27 frame$major_discipline[frame$major_discipline == ""] <- NA
28 frame$company_size[frame$company_size == ""] <- NA
29 frame$company_type[frame$company_type == ""] <- NA
30 frame$last_new_job[frame$last_new_job == ""] <- NA
31
32
```

```

33 train <- sample(1:nrow(frame),1000)
34 training <- frame[train,]
35 testing <- frame[-train,]
36 ##### creating a SVM function using target to see whether one is a potential
37 ##### candidate or not.
38
39 svmf = svm(target~., data = frame[train,], kernel="radial",cost=1, gamma= 5.177323e-05)
40 ##### tuning out :::
41 tune.out <- tune(svm , target~., data = frame[train,] , kernel = "linear",cost = 0.001)
42
43 xtest <- frame[-train,]
44 ytest<- frame$target
45 bestmod<- tune.out$best.model
46 ypred <- predict(bestmod,xtest)
47 ytest<- ytest[c(1:length(ypred))]
48 testdat<- data.frame(x = xtest,y= as.factor(ytest))
49 pred = predict(bestmod,newdata = frame[-train,])
50 prediction_model = predict(bestmod,newdata = frame[train,])
51
52

```

```
> summary(tune.out$best.model)
```

Call:

```
best.tune(method = svm, train.x = target ~ ., data = frame[train, ], kernel = "linear",
  cost = 0.001)
```

Parameters:

```

  SVM-Type:  eps-regression
  SVM-Kernel: linear
      cost:  0.001
    gamma:  5.177323e-05
  epsilon:  0.1

```

Number of Support Vectors: 147

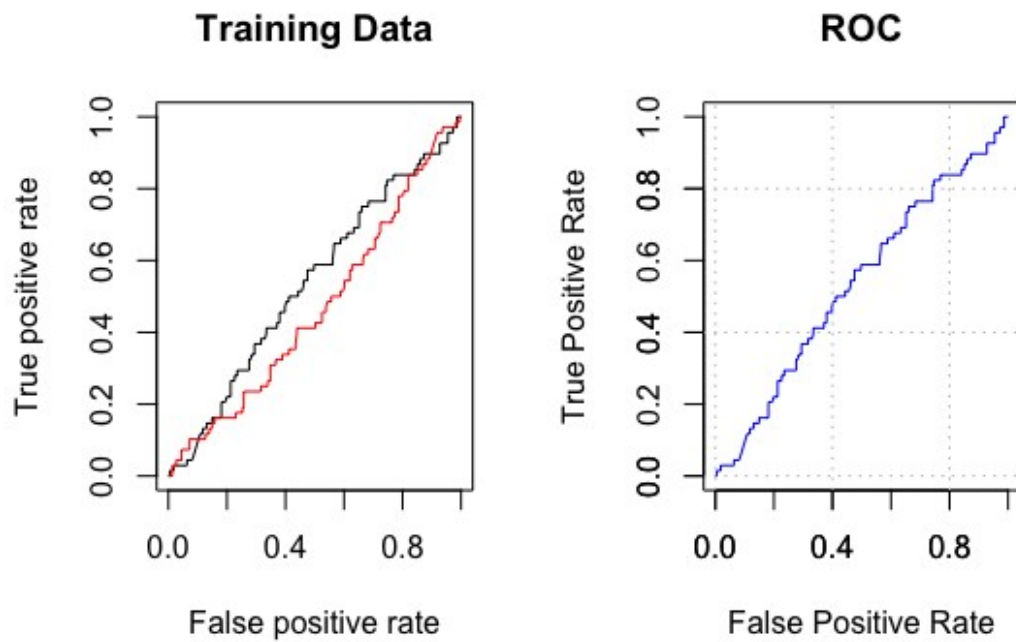
```
> summary(tune.out)
```

Error estimation of 'svm' using 10-fold cross validation: 0.1779548

1

Q2  
A)

```
53
54 ##### QUESTION 2 :::
55 rocplot <- function(pred , truth , ...) {
56   predob <- prediction(pred , truth)
57   perf <- performance(predob , "tpr", "fpr")
58   plot(perf , ...)
59 }
60
61 library(ROCR)
62 svmfit.opt <- svm(target~.,data=frame[train,],kernel="radial",cost = 1, gamma=5, decision.values= T)
63 fitted<- attributes(predict(svmfit.opt,frame[train,],decision.values = TRUE))$decision.values
64 par(mfrow=c(1,2))
65 var <- frame[train,"target"]
66 len_f <- length(fitted)
67 rocplot(fitted,var[1:len_f,1], main = "Training Data")
68 rocplot(-fitted , var[1:len_f,1], add = T, col = "red")
69
70
71 ### ROC :::
72 rocplot(fitted, var[1:len_f,1], type = "l", col = "blue", xlab = "False Positive Rate"
73         | ylab = "True Positive Rate", main = "ROC")
74 axis(1, seq(0.0,1.0,0.4))
75 axis(2, seq(0.0,1.0,0.4))
76 abline(h=seq(0.0,1.0,0.4), v=seq(0.0,1.0,0.4), col="gray", lty=3)
77
```



B)

Calculating the AUC using glm and the pROC package to get the auc.

```

78 ### Calculating the AUC :::
79 glm.fit = glm(target~., data = training, family="binomial")
80 predicted <- predict(glm.fit,data = frame[-train,],type= "response")
81 library(pROC)
82 testing <- frame[-train,]
83 AUC <- auc(testing$target[1:len_f],predicted) |
84

```

```

> AUC
Area under the curve: 0.5655
>

```

D)

Calculating the variable importance using the gbm method and boosting ::

```
86 ##### part d)
87 boosting <- gbm(target~.-city_development_index-enrollee_id, data= testing,
88                 distribution = "gaussian", n.trees= 1000, interaction.depth = 4, shrinkage = 0.01)
89 summary(boosting)
90
91
```

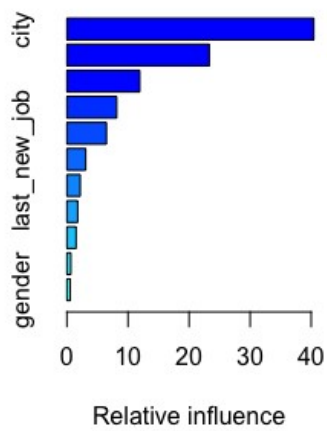
```
> summary(boosting)
```

	var	rel.inf
city	city	40.4247585
company_size	company_size	23.3045664
experience	experience	11.9304117
education_level	education_level	8.1528005
company_type	company_type	6.4705238
last_new_job	last_new_job	3.0812341
major_discipline	major_discipline	2.1827220
enrolled_university	enrolled_university	1.7676838
training_hours	training_hours	1.4975057
relevent_experience	relevent_experience	0.6497003
gender	gender	0.5380932

The most important variables are as follows from the training data^  
However, the testing data gives a better importance :

```
> summary(boosting)
```

	var	rel.inf
experience	experience	35.0245521
city	city	19.0175342
company_size	company_size	16.6230017
last_new_job	last_new_job	8.4786199
company_type	company_type	5.7174332
education_level	education_level	5.5987691
training_hours	training_hours	3.9712284
enrolled_university	enrolled_university	2.7384052
major_discipline	major_discipline	1.9324182
gender	gender	0.6377761
relevent_experience	relevent_experience	0.2602621



(training data variable

importance)

Confusion matrix using the best model prediction and the target which determines whether a potential candidate or not.

```
> table(predict= ypred, candidate= ytest)
```

predict	candidate	
	0	1
0.0396450554191474	0	1
0.0400642377264664	0	1
0.0401501786651821	1	0
0.0401992322490509	0	1
0.0402438334891641	0	1
0.0404269597208246	1	0