

# Modeling\_ind\_0.R

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```
# Uncomment if packages not installed
## install.packages("psych")
## install.packages("caret")
## install.packages("randomForest")
## install.packages("MLmetrics")
## install.packages("doParallel")
## install.packages("kernlab")
## install.packages("glmnet")

# Load data
setwd('D:\\Yaxin\\HKBU BM\\Courses\\Sem 2\\ECON7860 Big Data Analytics for Business (S11)\\Group Project')
rawData <- read.csv2("HR_comma_sep.csv", sep = ',')

# Transform feature types
transform_feature <- function(X) {
  X$satisfaction_level <- as.numeric(X$satisfaction_level)
  X$last_evaluation <- as.numeric(X$last_evaluation)
  X$Work_accident <- as.factor(X$Work_accident)
  X$promotion_last_5years <- as.factor(X$promotion_last_5years)
  X$sales <- as.factor(X$sales)
  X$salary <- as.factor(X$salary)
  X$left <- factor(ifelse(X$left == 0, 'no', 'yes'), levels = c('yes', 'no'))
  return(X)
}

rawData <- transform_feature(rawData)
summary(rawData)
```

##	satisfaction_level	last_evaluation	number_project	average_monthly_hours
##	Min. :0.0900	Min. :0.3600	Min. :2.000	Min. : 96.0
##	1st Qu.:0.4400	1st Qu.:0.5600	1st Qu.:3.000	1st Qu.:156.0
##	Median :0.6400	Median :0.7200	Median :4.000	Median :200.0
##	Mean :0.6128	Mean :0.7161	Mean :3.803	Mean :201.1
##	3rd Qu.:0.8200	3rd Qu.:0.8700	3rd Qu.:5.000	3rd Qu.:245.0
##	Max. :1.0000	Max. :1.0000	Max. :7.000	Max. :310.0
##				
##	time_spend_company	Work_accident	left	promotion_last_5years
##	Min. : 2.000	0:12830	yes: 3571	0:14680

```
## 1st Qu.: 3.000      1: 2169      no :11428    1: 319
## Median : 3.000
## Mean   : 3.498
## 3rd Qu.: 4.000
## Max.   :10.000
##
##          sales      salary
## sales      :4140    high :1237
## technical  :2720    low  :7316
## support    :2229    medium:6446
## IT         :1227
## product_mng: 902
## marketing  : 858
## (Other)    :2923
```

```
## Partition the dataset by "time_over_5"
X <- rawData[rawData$time_spend_company < 6, -c(5)]
y <- X$left
tag <- colnames(X)
tag
```

```
## [1] "satisfaction_level" "last_evaluation" "number_project"
## [4] "average_monthly_hours" "Work_accident" "left"
## [7] "promotion_last_5years" "sales" "salary"
```

```
# Feature engineering
## Create dummy variables for "sales" and "salary"
library(psych)
```

```
## Warning: package 'psych' was built under R version 4.0.4
```

```
dummySales <- dummy.code(X$sales)
dummySalary <- dummy.code(X$salary)
colnames(dummySales)
```

```
## [1] "sales" "technical" "support" "IT" "product_mng"
## [6] "marketing" "RandD" "accounting" "hr" "management"
```

```
colnames(dummySalary)
```

```
## [1] "low" "medium" "high"
```

```
### Set "sales" and "low" as the default values respectively
dummySales <- dummySales[, -c(1)]
dummySalary <- dummySalary[, -c(1)]

X_dummy <- cbind(X[, -c(8, 9)], dummySales, dummySalary)
tag_dummy <- colnames(X_dummy)
tag_dummy
```

```
## [1] "satisfaction_level" "last_evaluation" "number_project"
## [4] "average_monthly_hours" "Work_accident" "left"
## [7] "promotion_last_5years" "technical" "support"
## [10] "IT" "product_mng" "marketing"
## [13] "RandD" "accounting" "hr"
## [16] "management" "medium" "high"
```

```
# Train(80%)-test(20%)-split (stratified as "left" is unbalanced)
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.0.4
```

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

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

```
##
## Attaching package: 'ggplot2'
```

```
## The following objects are masked from 'package:psych':
##
## %+%, alpha
```

```
## Set seed for replication purpose
set.seed(7860)
index <- createDataPartition(y, p = 0.8, list = FALSE)
X_train <- X[index, ]
X_test <- cbind(X[-index, 1 : 5], X[-index, 7 : length(X)])
y_test <- X[-index, 'left']
X_dummy_train <- X_dummy[index, ]
X_dummy_test <- cbind(X_dummy[-index, 1 : 5], X_dummy[-index, 7 : length(X_dummy)])
```

```
# Modeling with extracted factors, 5-fold nested CV with random search
models <- c('svmLinear', 'glmnet', 'rf', 'knn')
n_cluster <- 10 ## Please set the number of multiprocessing slaves accordingly
```

```
for (m in models) {
  assign(paste0(m, '_best'), list('model' = c(), 'f1_val' = c(),
                                   'confm' = c()))

  tune <- 15
  control <- trainControl(method = 'repeatedcv', number = 5, repeats = 2,
                          summaryFunction = prSummary, classProbs = TRUE,
                          search="random", verboseIter = TRUE)

  set.seed(7860)

  require(doParallel)
  cl <- makePSOCKcluster(n_cluster, outfile = '')
  registerDoParallel(cl)
```

```

if (m == 'rf') {
  m1 <- train(left ~ ., data = X_train, method = m,
              metric = 'F', tuneLength = tune, trControl = control)
  rf_best[['model']] <- m1
  rf_best[['f1_val']] <- F_meas(predict(m1, X_test), y_test)
  rf_best[['confm']] <- confusionMatrix(predict(m1, X_test), y_test)
} else if (m == 'glmnet') {
  m1 <- train(left ~ ., data = cbind(scale(X_dummy_train[ , 1 : 4]), X_dummy_train[ , 5 : length(X_dummy_train)]),
              method = m, family = 'binomial',
              metric = 'F', tuneLength = tune, trControl = control)
  glmnet_best[['model']] <- m1
  glmnet_best[['f1_val']] <- F_meas(predict(m1, cbind(scale(X_dummy_test[ , 1 : 4]), X_dummy_test[ , 5 : length(X_dummy_test)])), y_test)
  glmnet_best[['confm']] <- confusionMatrix(predict(m1, cbind(scale(X_dummy_test[ , 1 : 4]), X_dummy_test[ , 5 : length(X_dummy_test)])), y_test)
} else if (m == 'knn') {
  m1 <- train(left ~ ., data = cbind(scale(X_dummy_train[ , 1 : 4]), X_dummy_train[ , 5 : length(X_dummy_train)]),
              metric = 'F', tuneLength = tune, trControl = control, tuneGrid = expand.grid(k = c(2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30, 40, 50)))
  knn_best[['model']] <- m1
  knn_best[['f1_val']] <- F_meas(predict(m1, cbind(scale(X_dummy_test[ , 1 : 4]), X_dummy_test[ , 5 : length(X_dummy_test)])), y_test)
  knn_best[['confm']] <- confusionMatrix(predict(m1, cbind(scale(X_dummy_test[ , 1 : 4]), X_dummy_test[ , 5 : length(X_dummy_test)])), y_test)
} else {
  m1 <- train(left ~ ., data = cbind(scale(X_dummy_train[ , 1 : 4]), X_dummy_train[ , 5 : length(X_dummy_train)]),
              metric = 'F', tuneLength = tune, trControl = control)
  svmLinear_best[['model']] <- m1
  svmLinear_best[['f1_val']] <- F_meas(predict(m1, cbind(scale(X_dummy_test[ , 1 : 4]), X_dummy_test[ , 5 : length(X_dummy_test)])), y_test)
  svmLinear_best[['confm']] <- confusionMatrix(predict(m1, cbind(scale(X_dummy_test[ , 1 : 4]), X_dummy_test[ , 5 : length(X_dummy_test)])), y_test)
}

stopImplicitCluster()
stopCluster(cl)
}

```

```
## Loading required package: doParallel
```

```
## Warning: package 'doParallel' was built under R version 4.0.4
```

```
## Loading required package: foreach
```

```
## Warning: package 'foreach' was built under R version 4.0.4
```

```
## Loading required package: iterators
```

```
## Warning: package 'iterators' was built under R version 4.0.4
```

```
## Loading required package: parallel
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

```
## Aggregating results
```

```
## Selecting tuning parameters
```

```
## Fitting C = 12 on full training set
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

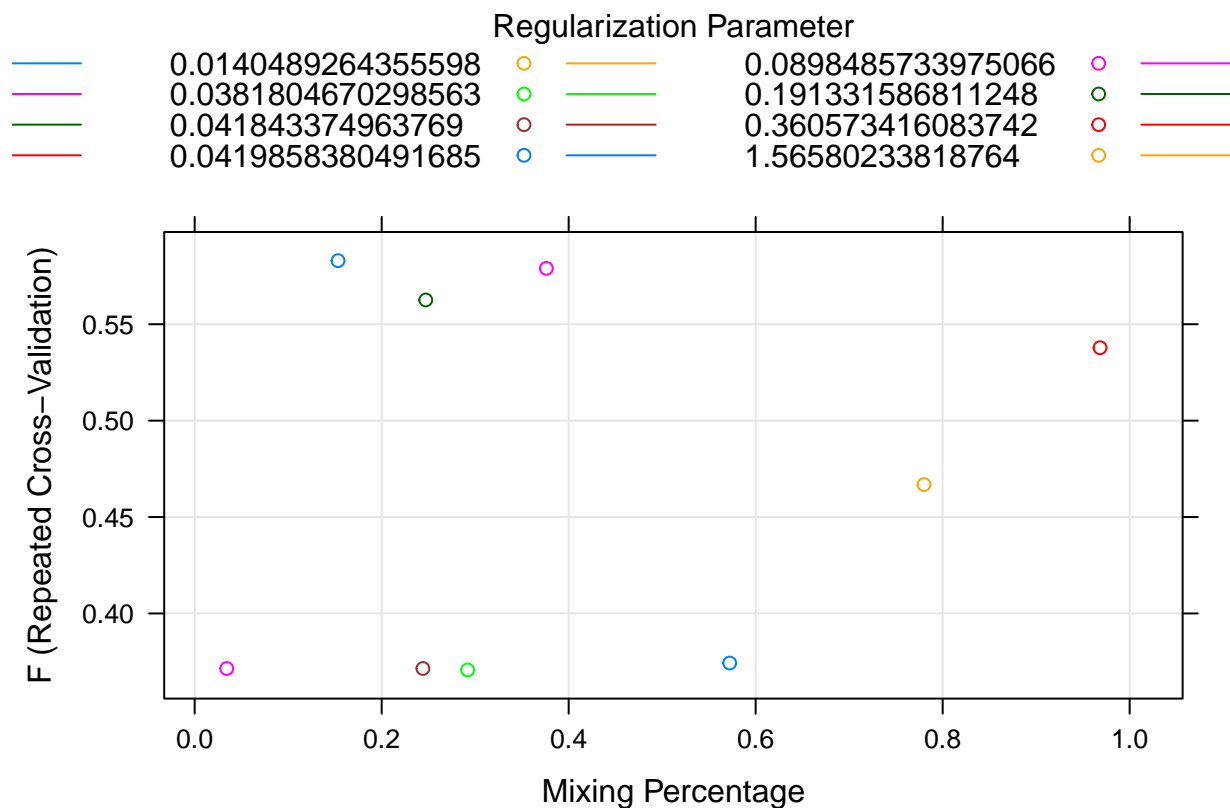
```
## Aggregating results
```

```
## Warning in train.default(x, y, weights = w, ...): missing values found in
## aggregated results
```

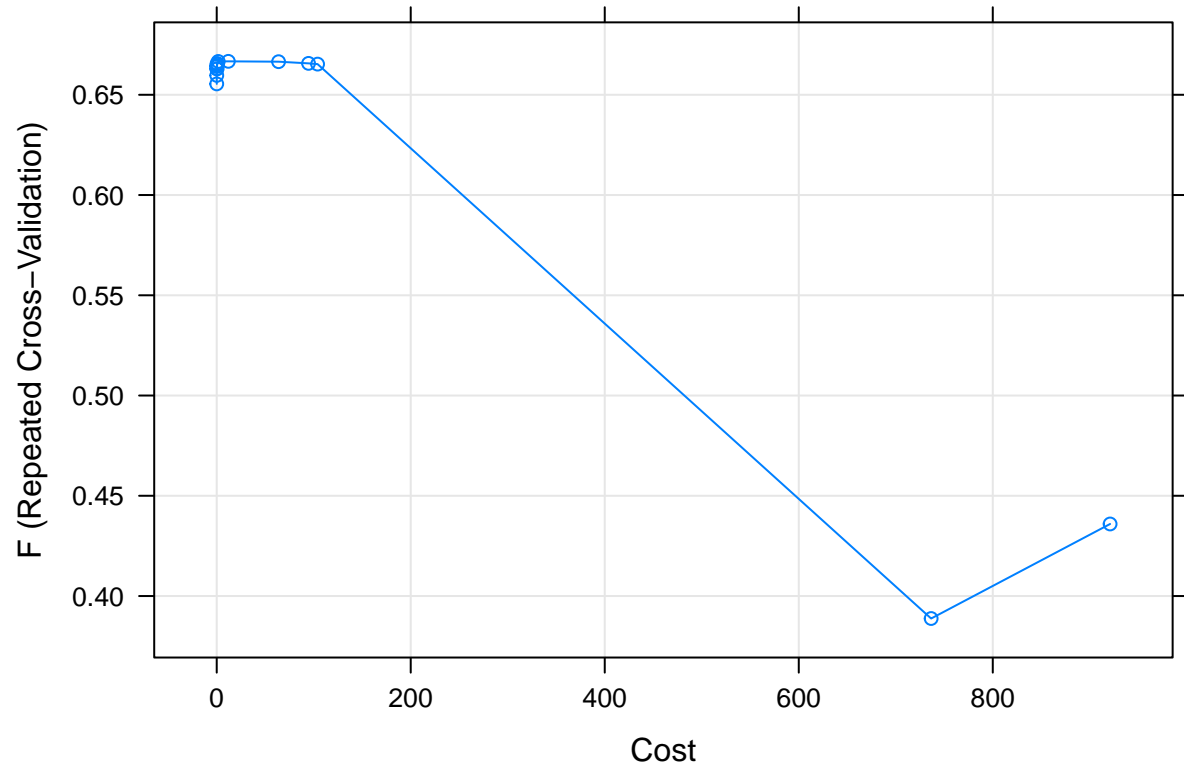
```
## Selecting tuning parameters
## Fitting alpha = 0.153, lambda = 0.00124 on full training set
## Aggregating results
## Selecting tuning parameters
## Fitting mtry = 7 on full training set
## Aggregating results
## Selecting tuning parameters
## Fitting k = 3 on full training set
```

```
results <- as.data.frame(cbind(glmnet_best, svmLinear_best, knn_best, rf_best))
```

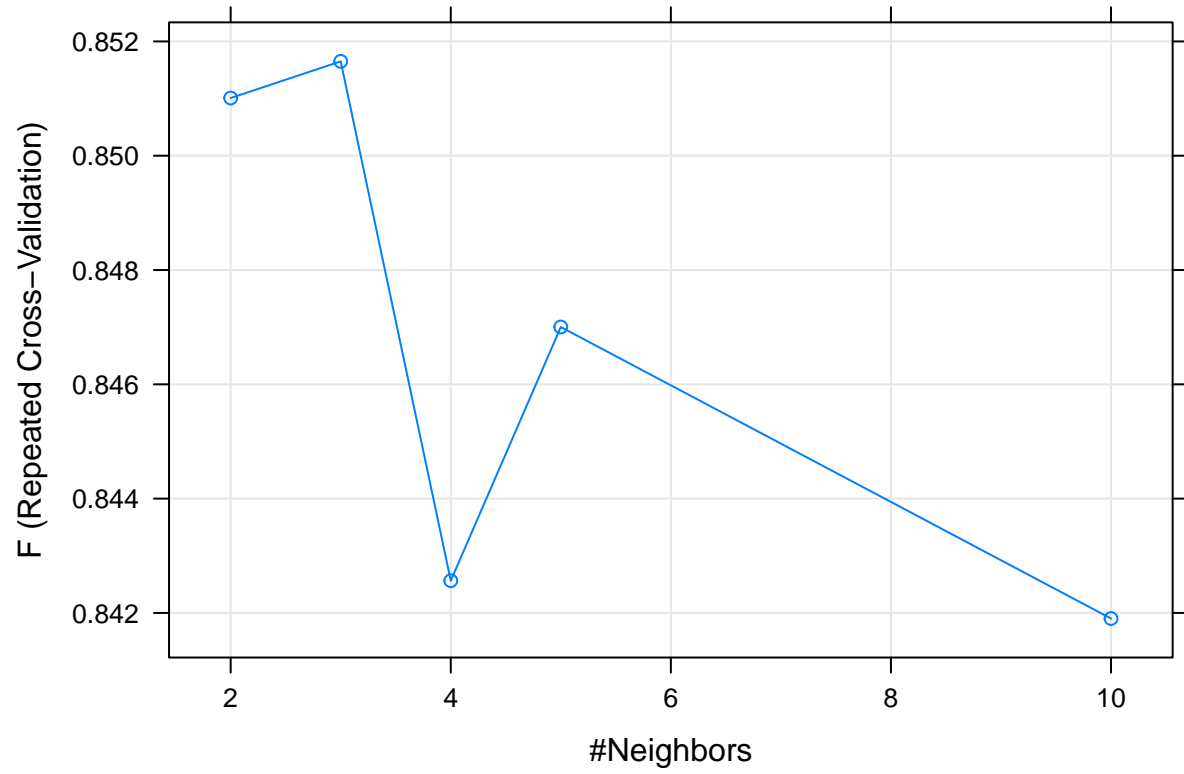
```
plot(results$glmnet_best$model)
```



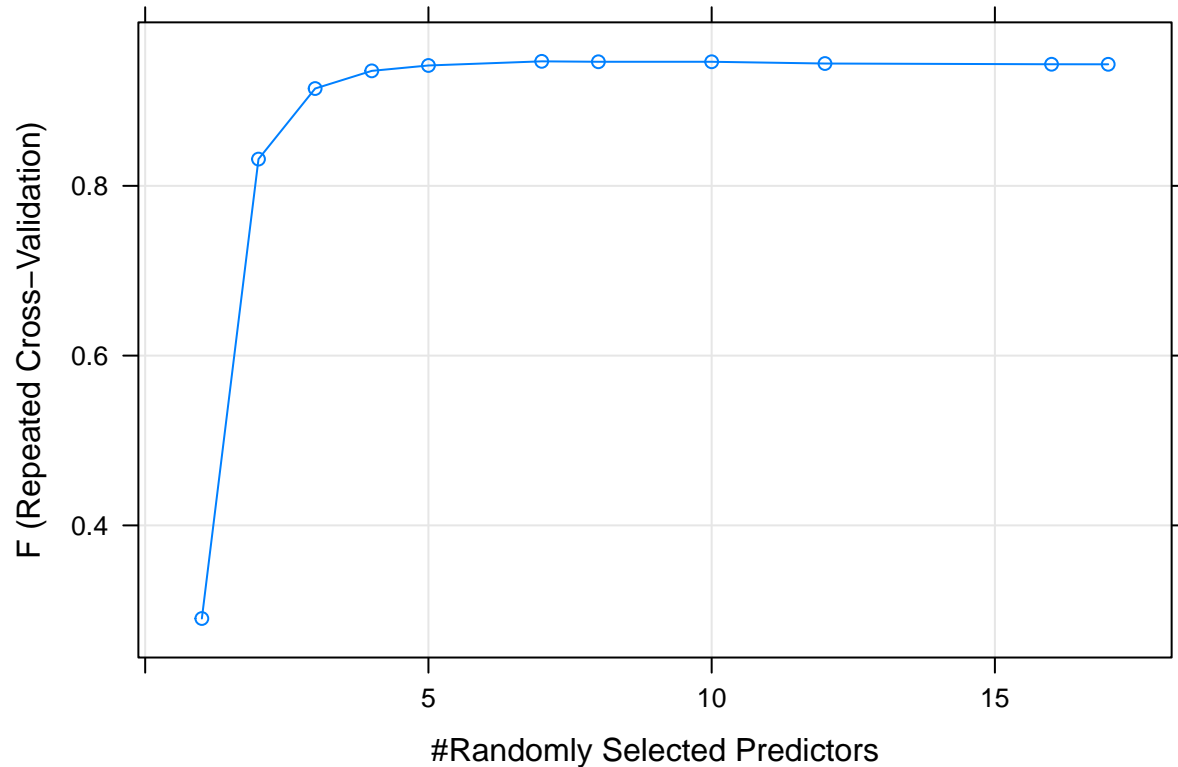
```
plot(results$svmLinear_best$model)
```



```
plot(results$kmn_best$model)
```



```
plot(results$rf_best$model)
```



```
for (i in 1 : 4) {
  cat(rep('\n', 3))
  print(results[[i]])
  cat(rep('\n', 3))
}
```

```
##
##
##
## $model
## glmnet
##
## 10974 samples
##    17 predictor
##    2 classes: 'yes', 'no'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 2 times)
## Summary of sample sizes: 8779, 8779, 8779, 8779, 8780, 8779, ...
## Resampling results across tuning parameters:
##
##  alpha      lambda      AUC      Precision  Recall      F
##  0.03431740  0.089848573  0.6354293  0.7564402  0.2462825  0.3714456
##  0.08249613  0.360573416  0.6007119      NaN  0.0000000      NaN
##  0.11032045  5.835644047  0.0000000      NaN  0.0000000      NaN
##  0.14298028  5.900723701  0.0000000      NaN  0.0000000      NaN
```



```

## 0.15333117 0.001237096 0.6132379 0.7074950 0.4960967 0.5829779
## 0.24414545 0.041843375 0.6328153 0.6459675 0.2607807 0.3714583
## 0.24717296 0.005363840 0.6159915 0.7076353 0.4671004 0.5625732
## 0.29186267 0.038180467 0.6322243 0.6393197 0.2611524 0.3707096
## 0.37615343 0.002088687 0.6142002 0.7077905 0.4901487 0.5789760
## 0.57222747 0.041985838 0.6372825 0.6462069 0.2635688 0.3742908
## 0.73301844 2.449870885 0.0000000 NaN 0.0000000 NaN
## 0.77100396 0.191331587 0.5770621 NaN 0.0000000 NaN
## 0.78001638 0.014048926 0.6241281 0.6653814 0.3596654 0.4668294
## 0.96830053 0.005986254 0.6184896 0.6953754 0.4386617 0.5378155
## 0.98979898 1.565802338 0.0000000 NaN 0.0000000 NaN
##
## F was used to select the optimal model using the largest value.
## The final values used for the model were alpha = 0.1533312 and lambda
## = 0.001237096.
##
## $f1_val
## [1] 0.5547703
##
## $confm
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##           yes  314 146
##           no   358 1925
##
##           Accuracy : 0.8163
##           95% CI : (0.8012, 0.8306)
##           No Information Rate : 0.755
##           P-Value [Acc > NIR] : 8.457e-15
##
##           Kappa : 0.4441
##
## Mcnemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.4673
##           Specificity : 0.9295
##           Pos Pred Value : 0.6826
##           Neg Pred Value : 0.8432
##           Prevalence : 0.2450
##           Detection Rate : 0.1145
##           Detection Prevalence : 0.1677
##           Balanced Accuracy : 0.6984
##
##           'Positive' Class : yes
##
##
##
##
##
##
##
##
##
##

```

```

## $model
## Support Vector Machines with Linear Kernel
##
## 10974 samples
##    17 predictor
##    2 classes: 'yes', 'no'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 2 times)
## Summary of sample sizes: 8779, 8779, 8779, 8779, 8780, 8779, ...
## Resampling results across tuning parameters:
##
##      C          AUC      Precision  Recall      F
##      0.04464867  0.6022223  0.7371450  0.5907063  0.6554272
##      0.07368128  0.6004907  0.7398197  0.5959108  0.6596572
##      0.09840031  0.5999223  0.7405653  0.6003717  0.6629115
##      0.13818800  0.5994605  0.7413602  0.6018587  0.6641282
##      0.15388959  0.5993138  0.7419980  0.6020446  0.6644928
##      0.39561848  0.5986093  0.7419756  0.5996283  0.6629700
##      0.40826969  0.5986001  0.7434283  0.6029740  0.6656199
##      0.64974256  0.5984318  0.7428439  0.6027881  0.6652099
##      1.56081702  0.5983204  0.7434946  0.6044610  0.6666199
##      11.98711010 0.5982231  0.7441789  0.6042751  0.6666691
##      63.79080326 0.5981868  0.7434881  0.6042751  0.6664944
##      94.68470164 0.5979691  0.7435708  0.6029740  0.6656624
##      103.98601383 0.5977665  0.7433567  0.6027881  0.6652898
##      736.48273800 0.4965342  0.4521771  0.4308550  0.3887858
##      920.95367219 0.5634040  0.4256875  0.3426270  0.4359383
##
## F was used to select the optimal model using the largest value.
## The final value used for the model was C = 11.98711.
##
## $f1_val
## [1] 0.6497129
##
## $confm
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##           yes  396 151
##           no   276 1920
##
##           Accuracy : 0.8443
##           95% CI : (0.8302, 0.8577)
##           No Information Rate : 0.755
##           P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.551
##
## Mcnemar's Test P-Value : 1.964e-09
##
##           Sensitivity : 0.5893
##           Specificity : 0.9271

```

```

##          Pos Pred Value : 0.7239
##          Neg Pred Value : 0.8743
##          Prevalence : 0.2450
##          Detection Rate : 0.1444
##          Detection Prevalence : 0.1994
##          Balanced Accuracy : 0.7582
##
##          'Positive' Class : yes
##
##
##
##
##
##
##
##
##
##
## $model
## k-Nearest Neighbors
##
## 10974 samples
##      17 predictor
##      2 classes: 'yes', 'no'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 2 times)
## Summary of sample sizes: 8779, 8779, 8779, 8779, 8780, 8779, ...
## Resampling results across tuning parameters:
##
##  k   AUC          Precision  Recall    F
##  2   0.1057112    0.8091698  0.8975836  0.8510093
##  3   0.1634299    0.8127667  0.8946097  0.8516513
##  4   0.1980941    0.8078878  0.8804833  0.8425641
##  5   0.2180272    0.8216192  0.8741636  0.8470031
## 10   0.2930483    0.8246629  0.8602230  0.8419024
##
## F was used to select the optimal model using the largest value.
## The final value used for the model was k = 3.
##
## $f1_val
## [1] 0.8521618
##
## $confm
## Confusion Matrix and Statistics
##
##          Reference
## Prediction  yes   no
##          yes  610  151
##          no   62 1920
##
##          Accuracy : 0.9223
##          95% CI : (0.9117, 0.9321)
##          No Information Rate : 0.755
##          P-Value [Acc > NIR] : < 2.2e-16
##

```

```

##                Kappa : 0.7991
##
## Mcnemar's Test P-Value : 1.643e-09
##
##                Sensitivity : 0.9077
##                Specificity : 0.9271
##                Pos Pred Value : 0.8016
##                Neg Pred Value : 0.9687
##                Prevalence : 0.2450
##                Detection Rate : 0.2224
##                Detection Prevalence : 0.2774
##                Balanced Accuracy : 0.9174
##
##                'Positive' Class : yes
##
##
##
##
##
##
##
## $model
## Random Forest
##
## 10974 samples
##      8 predictor
##      2 classes: 'yes', 'no'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 2 times)
## Summary of sample sizes: 8779, 8779, 8779, 8779, 8780, 8779, ...
## Resampling results across tuning parameters:
##
##  mtry  AUC      Precision Recall      F
##    1   0.8616727  0.9967071  0.1795539  0.2902993
##    2   0.9487339  0.9869695  0.7184015  0.8314906
##    3   0.9651951  0.9708307  0.8646840  0.9146202
##    4   0.8739066  0.9599272  0.9122677  0.9354524
##    5   0.6965537  0.9571933  0.9269517  0.9418093
##    7   0.4691848  0.9563755  0.9371747  0.9466568
##    8   0.4376008  0.9547790  0.9377323  0.9461573
##   10   0.3791470  0.9530556  0.9394052  0.9461679
##   12   0.3469535  0.9497937  0.9384758  0.9440835
##   16   0.3012814  0.9471755  0.9394052  0.9432464
##   17   0.2943130  0.9450048  0.9414498  0.9431920
##
## F was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 7.
##
## $f1_val
## [1] 0.9663426
##
## $confm

```

```

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##           yes  646   19
##           no   26 2052
##
##           Accuracy : 0.9836
##           95% CI : (0.9781, 0.988)
##           No Information Rate : 0.755
##           P-Value [Acc > NIR] : <2e-16
##
##           Kappa : 0.9555
##
## Mcnemar's Test P-Value : 0.3711
##
##           Sensitivity : 0.9613
##           Specificity : 0.9908
##           Pos Pred Value : 0.9714
##           Neg Pred Value : 0.9875
##           Prevalence : 0.2450
##           Detection Rate : 0.2355
##           Detection Prevalence : 0.2424
##           Balanced Accuracy : 0.9761
##
##           'Positive' Class : yes
##
##
##
##
##

```

```

save.image("D:/Yaxin/HKBU BM/Courses/Sem 2/ECON7860 Big Data Analytics for Business (S11)/Group Project.

```