8. Appendix for R Code

Table of Contents

1. Preprocessing

```
# load the csv data
library(tidyverse)
HRdata <- read_csv("aug_train.csv")

# Check if there is any missing value (number of missing values = 20733)
sum(is.na(HRdata))
```

```
## [1] 20733
```

```
# Check nrows and ncols
dim(HRdata)
```

```
## [1] 19158    14
```

1.1 Handling Missing Values

```
# Function na.omit removes observation with missing values
HRdata <- na.omit(HRdata)
dim(HRdata)
```

```
## [1] 8955   14
```

1.2 Drop enrollee_id and city

```
HRdata <- subset(HRdata, select = -c(enrollee_id, city))
dim(HRdata)
```

```
## [1] 8955   12
```

1.3 Change predictor: experience to numeric

```
HRdata <- HRdata %>%
  mutate(experience = case_when(experience==">20" ~ "21",
                                experience=="<1" ~ "0",
                                TRUE ~ as.character(experience)))
HRdata$experience <- as.numeric(HRdata$experience)
```

1.4 Define Baseline for Categorical Variables -> Factor Type

```
HRdata$gender <- factor(HRdata$gender)
HRdata$relevent_experience <- factor(HRdata$relevent_experience)
HRdata$enrolled_university <- factor(HRdata$enrolled_university)
HRdata$education_level <- factor(HRdata$education_level)
HRdata$major_discipline <- factor(HRdata$major_discipline)
HRdata$company_size <- factor(HRdata$company_size)
HRdata$company_type <- factor(HRdata$company_type)
HRdata$last_new_job <- factor(HRdata$last_new_job)

#HRdata$target <- factor(HRdata$target, levels=c(0, 1), labels=c("No","Yes"))
HRdata$target <- factor(HRdata$target, levels=c(0, 1), labels=c("0","1"))

# Check the data type to see the changes
glimpse(HRdata)
```

```
## Rows: 8,955
## Columns: 12
## $ city_development_index <dbl> 0.776, 0.767, 0.762, 0.920, 0.920, 0.913, 0.926~
## $ gender                 <fct> Male, Male, Male, Male, Male, Male, Male, Male,~
## $ relevent_experience    <fct> No relevent experience, Has relevent experience~
## $ enrolled_university    <fct> no_enrollment, no_enrollment, no_enrollment, no~
## $ education_level        <fct> Graduate, Masters, Graduate, Graduate, Graduate~
## $ major_discipline       <fct> STEM, STEM, STEM, STEM, STEM, STEM, STEM, STEM,~
## $ experience             <dbl> 15, 21, 13, 7, 5, 21, 16, 11, 11, 0, 18, 21, 19~
## $ company_size           <fct> 50-99, 50-99, <10, 50-99, 5000-9999, 1000-4999,~
## $ company_type           <fct> Pvt Ltd, Funded Startup, Pvt Ltd, Pvt Ltd, Pvt ~
## $ last_new_job           <fct> >4, 4, >4, 1, 1, 3, >4, 1, 2, 1, 2, 3, >4, >4, ~
## $ training_hours         <dbl> 47, 8, 18, 46, 108, 23, 18, 68, 50, 65, 68, 40,~
## $ target                 <fct> 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,~
```

2. Exploratory Data Analysis

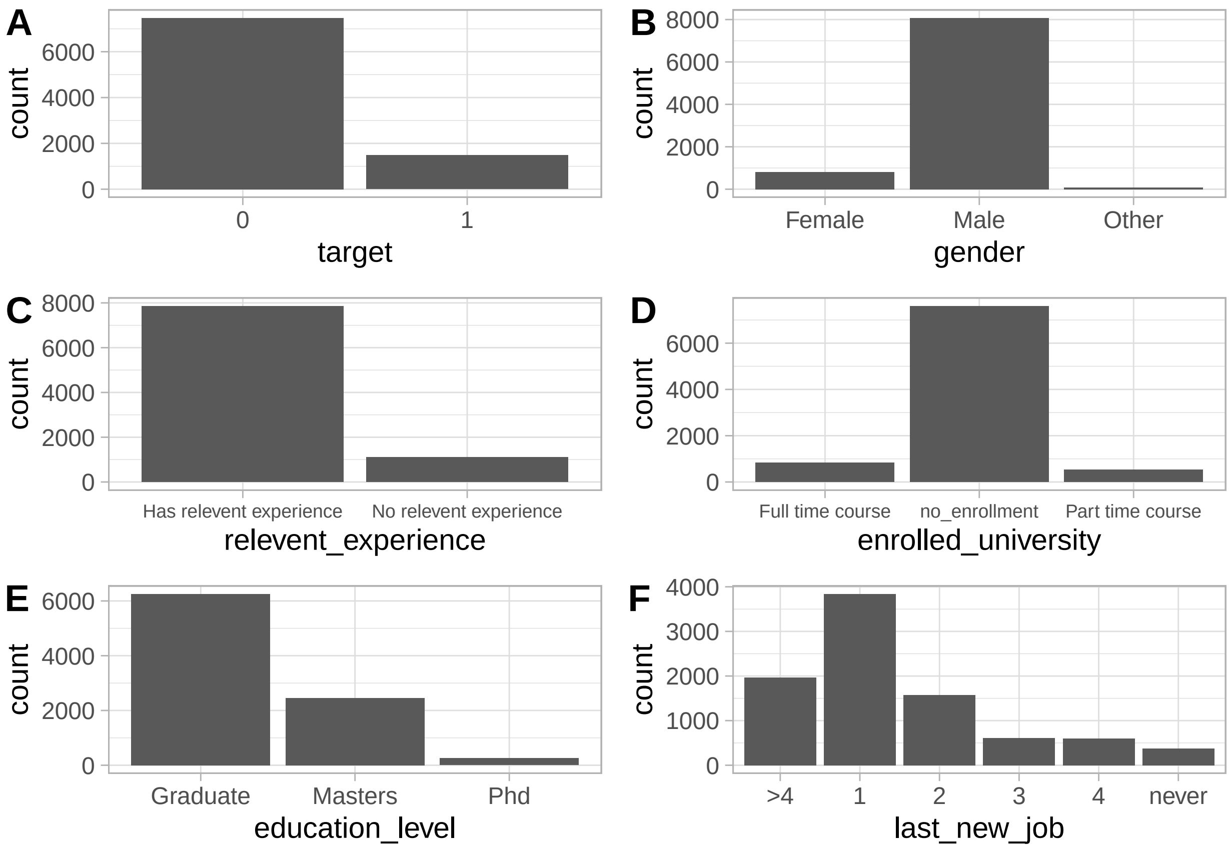
```r
# Generate summary statistics
summary(HRdata)
```

```
##  city_development_index   gender                   relevent_experience
##  Min.   :0.4480         Female: 804   Has relevent experience:7851
##  1st Qu.:0.7940         Male  :8073   No relevent experience :1104
##  Median :0.9100         Other :  78
##  Mean   :0.8446
##  3rd Qu.:0.9200
##  Max.   :0.9490
##
##       enrolled_university education_level       major_discipline
##  Full time course: 832     Graduate:6252   Arts           : 129
##  no_enrollment   :7594     Masters :2449   Business Degree: 170
##  Part time course: 529     Phd     : 254   Humanities     : 378
##                                            No Major       : 112
##                                            Other          : 177
##                                            STEM           :7989
##
##    experience      company_size             company_type  last_new_job
##  Min.   : 0.00   50-99    :1986   Early Stage Startup: 385   >4   :1965
##  1st Qu.: 6.00   100-500  :1814   Funded Startup     : 784   1    :3838
##  Median :10.00   10000+   :1449   NGO                : 356   2    :1570
##  Mean   :11.64   10/49    : 951   Other              :  72   3    : 610
##  3rd Qu.:18.00   1000-4999: 930   Public Sector      : 564   4    : 599
##  Max.   :21.00   <10      : 840   Pvt Ltd            :6794   never: 373
##                  (Other)  : 985
##  training_hours   target
##  Min.   :  1.00   0:7472
##  1st Qu.: 23.00   1:1483
##  Median : 47.00
##  Mean   : 65.07
##  3rd Qu.: 88.00
##  Max.   :336.00
##
```

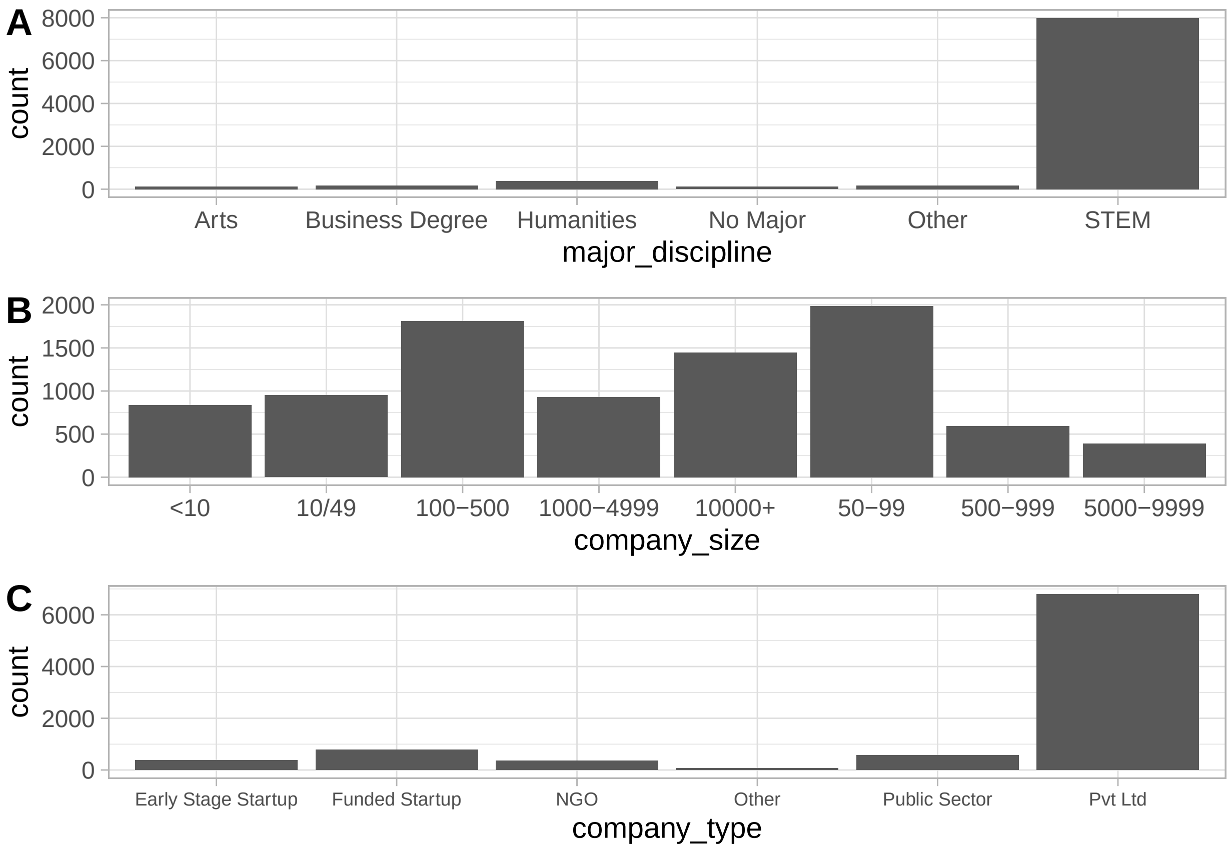
2.1 Categorical Variable Distributions

```r
# target
target <- HRdata %>%
  ggplot(aes(x = target)) + geom_bar() + theme_light()

# gender
gender <- HRdata %>%
  ggplot(aes(x = gender)) + geom_bar() + theme_light()

# relevent_experience
relevent_experience <- HRdata %>%
  ggplot(aes(x = relevent_experience)) + geom_bar() + theme_light() +
```

```r
  theme(axis.text.x = element_text(size = 7))

# enrolled_university
enrolled_university <- HRdata %>%
  ggplot(aes(x = enrolled_university)) + geom_bar() + theme_light() +
  theme(axis.text.x = element_text(size = 7))

# education_level
education_level <- HRdata %>%
  ggplot(aes(x = education_level)) + geom_bar() + theme_light()

# major_discipline
major_discipline <- HRdata %>%
  ggplot(aes(x = major_discipline)) + geom_bar() + theme_light()

# company_size
company_size <- HRdata %>%
  ggplot(aes(x = company_size)) + geom_bar() + theme_light()

# company_type
company_type <- HRdata %>%
  ggplot(aes(x = company_type)) + geom_bar() + theme_light() +
  theme(axis.text.x = element_text(size = 7))

# last_new_job
last_new_job <- HRdata %>%
  ggplot(aes(x = last_new_job)) + geom_bar() + theme_light()


# library allows clear labels and save plot as pdf
suppressMessages(library(cowplot))
(p_cat_1 <- plot_grid(target, gender, relevent_experience, enrolled_university,
                      education_level,last_new_job, labels = "AUTO", ncol=2,
                      rel_widths=20, rel_heights=50))
```




```
(p_cat_2 <- plot_grid(major_discipline, company_size,
                      company_type, labels = "AUTO", ncol=1,
                      rel_widths=20, rel_heights=50))
```



Categorical Variable Description:

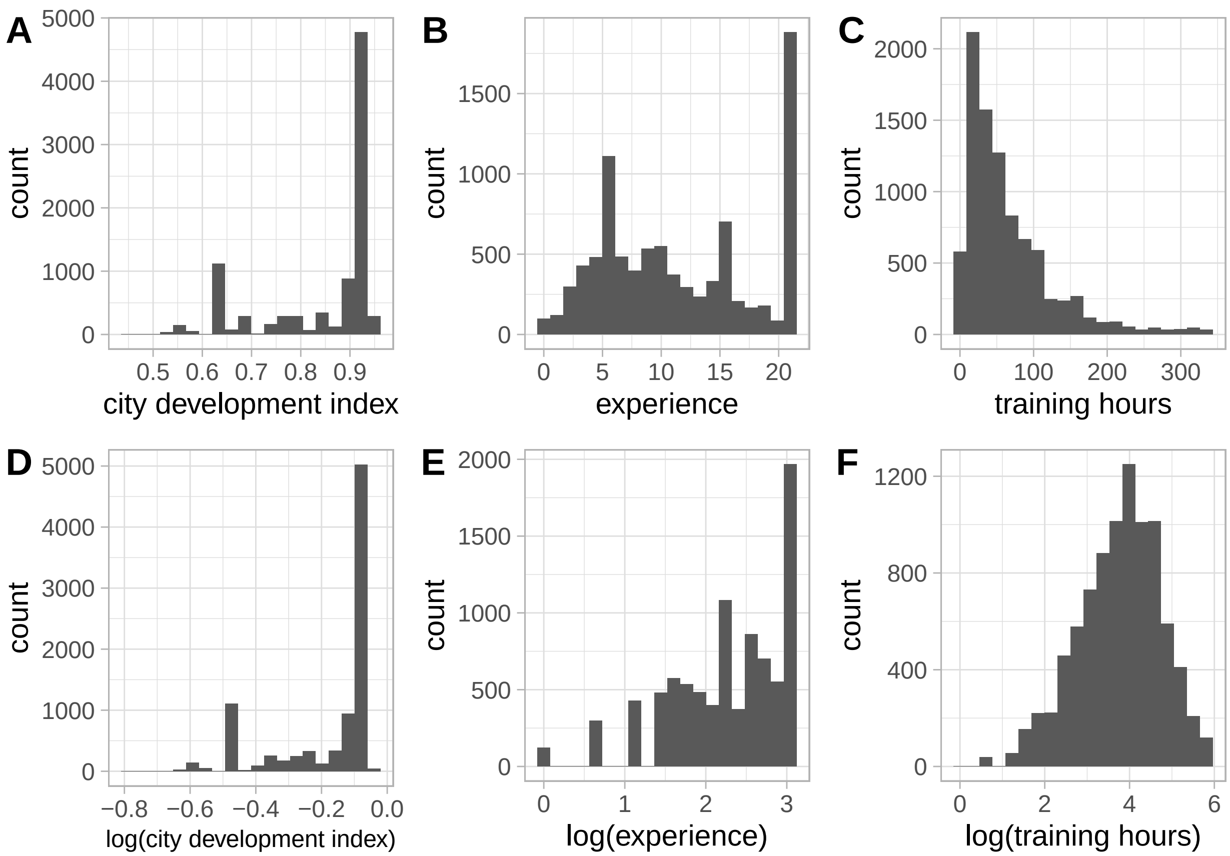
- target: 0 – Not looking for job change, 1 – Looking for a job change
- gender: Gender of candidate
- relevent_experience: Relevant experience of candidate
- enrolled_university: Type of University course enrolled if any
- education_level: Education level of candidate
- lastnewjob: Difference in years between previous job and current job
- major_discipline :Education major discipline of candidate
- company_size: No of employees in current employer's company
- company_type : Type of current employer

2.2 Continuous Variable Distributions

```
# city_development_index
city_development_index <- HRdata %>%
  ggplot(aes(x = city_development_index)) + geom_histogram(bins=20) +
  labs(x = "city development index") + theme_light()

# experience
experience <- HRdata %>%
  ggplot(aes(x = experience)) + geom_histogram(bins=20) + labs(x = "experience") +
  theme_light()

# training_hours
```

```r
training_hours <- HRdata %>%
  ggplot(aes(x = training_hours)) + geom_histogram(bins=20) + labs(x = "training hours") +
  theme_light()

# Distributions are skewed -> Taking the log
# city_development_index
log_city_development_index <- HRdata %>%
  ggplot(aes(x = log(city_development_index))) + geom_histogram(bins=20) +
  labs(x = "log(city development index)") + theme_light() +
  theme(axis.title.x = element_text(size = 9))

# experience
log_experience <- HRdata %>%
  ggplot(aes(x = log(experience))) + geom_histogram(bins=20) +
  labs(x = "log(experience)") + theme_light()

# training_hours
log_training_hours <- HRdata %>%
  ggplot(aes(x = log(training_hours))) + geom_histogram(bins=20) +
  labs(x = "log(training hours)") + theme_light()

(p_con_1 <- plot_grid(city_development_index, experience, training_hours,
                      log_city_development_index, log_experience, log_training_hours,
                      labels = "AUTO", ncol=3))
```

```
## Warning: Removed 97 rows containing non-finite values (stat_bin).
```



Continuous Variable Description:

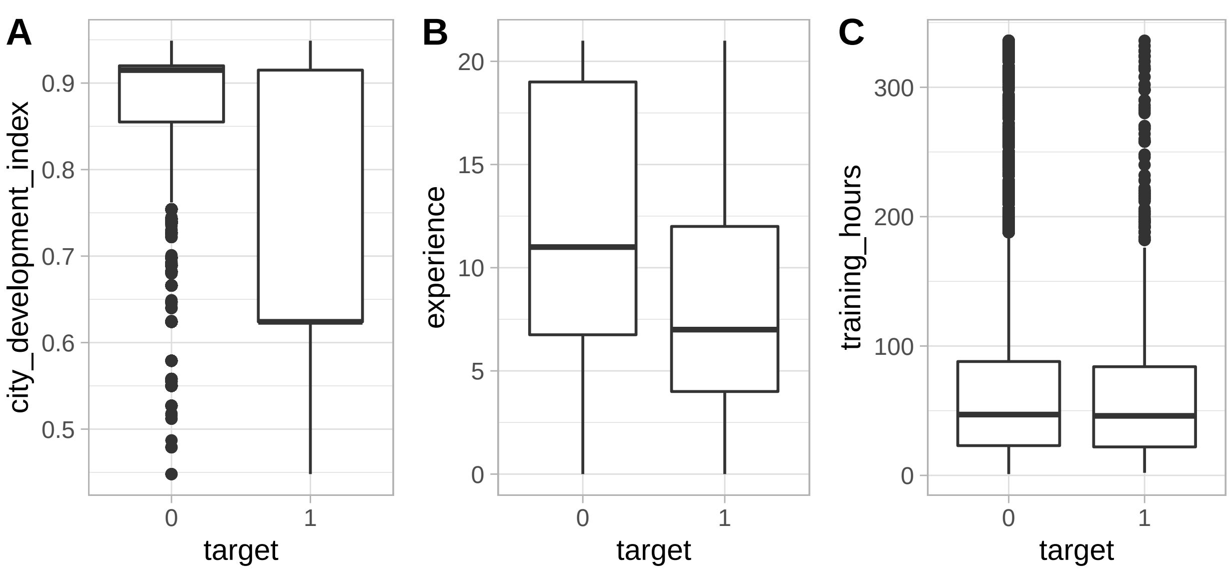
- city_ development _index : Developement index of the city (scaled)
- experience: Candidate total experience in years
- training_hours: training hours completed

Insights from above transformation:

- We can see that only the **training hours** has significant effect (approximately follow normal distribution) after taking the log.
- We can use log(training_hours) instead of training_hours in our model.

2.3 2D plot

```r
# city_development_index and target
box1 <- HRdata %>%
  ggplot(aes(x=target, y=city_development_index)) + geom_boxplot() + theme_light()

# experience and target
box2 <- HRdata %>%
  ggplot(aes(x=target, y=experience)) + geom_boxplot() + theme_light()

# training_hours and target
box3 <- HRdata %>%
  ggplot(aes(x=target, y=training_hours)) + geom_boxplot() + theme_light()

plot_grid(box1, box2, box3, labels = "AUTO", ncol=3)
```



3. Data Modelling

3.1 Data Spliting

```r
# Let's first split the data into training and test data (80/20)
library(caret)
set.seed(414)
idx_tr <- createDataPartition(HRdata$target, p=0.8, list=FALSE)

# Define training and test data
train <- HRdata[idx_tr,]
test  <- HRdata[-idx_tr,]

nrow(train)
```

```
## [1] 7165
```

```r
nrow(test)
```

```
## [1] 1790
```

```r
# proportion of target = 1 in whole dataset
summary(HRdata$target)[2]/sum(summary(HRdata$target))
```

```
##         1
## 0.1656058
```

```r
# proportion of target = 1 in train dataset
summary(train$target)[2]/sum(summary(train$target))
```

```
##         1
## 0.1656664
```

```r
# proportion of target = 1 in test dataset
summary(test$target)[2]/sum(summary(test$target))
```

```
##         1
## 0.1653631
```

- The distribution of target variable stay the same in training and testing datasets.

3.2 Model1: Logistic Regression

Using all the 11 features

```r
model1_LR <- glm(target ~ ., family=binomial, data=train)

# GOF (Hosmer-Lemeshow) -> p-value < 0.05, lack of fit
suppressMessages(library(ResourceSelection))
hoslem.test(model1_LR$y,fitted(model1_LR),g=10)
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  model1_LR$y, fitted(model1_LR)
## X-squared = 34, df = 8, p-value = 4.062e-05
```

Feature selection using AIC

```r
suppressMessages(library(faraway))
# Feature selection using AIC
model1_LR_small <- step(model1_LR, trace=0)
sumary(model1_LR_small)
```

```
##                                              Estimate  Std. Error  z value
## (Intercept)                                5.07220180  0.27659360  18.3381
## city_development_index                    -7.90843974  0.28303647 -27.9414
## relevent_experienceNo relevent experience  0.22758258  0.10482851   2.1710
## enrolled_universityno_enrollment          -0.34307101  0.10611573  -3.2330
## enrolled_universityPart time course       -0.53907907  0.17320185  -3.1124
## experience                                -0.03173049  0.00642043  -4.9421
## company_size10/49                          0.26131118  0.15850507   1.6486
## company_size100-500                        0.09322330  0.14964724   0.6230
## company_size1000-4999                      0.26282677  0.17159843   1.5316
## company_size10000+                         0.43859155  0.15324665   2.8620
## company_size50-99                          0.08985473  0.14449178   0.6219
## company_size500-999                        0.03347894  0.19219371   0.1742
## company_size5000-9999                      0.24302615  0.21570564   1.1267
## company_typeFunded Startup                 0.16814256  0.20949170   0.8026
## company_typeNGO                            0.18636766  0.25507380   0.7306
## company_typeOther                          1.08451663  0.38128408   2.8444
## company_typePublic Sector                  0.44302151  0.22563213   1.9635
## company_typePvt Ltd                        0.17298040  0.17707036   0.9769
## training_hours                            -0.00107045  0.00060317  -1.7747
##                                              Pr(>|z|)
## (Intercept)                               < 2.2e-16
## city_development_index                    < 2.2e-16
## relevent_experienceNo relevent experience  0.029931
## enrolled_universityno_enrollment           0.001225
## enrolled_universityPart time course        0.001856
## experience                                7.728e-07
## company_size10/49                          0.099230
## company_size100-500                        0.533315
## company_size1000-4999                      0.125612
## company_size10000+                         0.004210
## company_size50-99                          0.534029
## company_size500-999                        0.861713
## company_size5000-9999                      0.259888
## company_typeFunded Startup                 0.422193
## company_typeNGO                            0.464998
## company_typeOther                          0.004450
## company_typePublic Sector                  0.049592
## company_typePvt Ltd                        0.328618
## training_hours                             0.075948
```

```
##
## n = 7165 p = 19
## Deviance = 5219.29583 Null Deviance = 6433.42182 (Difference = 1214.12598)
```

```
# GOF: p-value < 0.05, lack of fit
hoslem.test(model1_LR_small$y,fitted(model1_LR_small),g=10)
```

```
##
##  Hosmer and Lemeshow goodness of fit (GOF) test
##
## data:  model1_LR_small$y, fitted(model1_LR_small)
## X-squared = 37.5, df = 8, p-value = 9.31e-06
```

Likelihood Ratio Test: compare smaller and larger model

$$H_0 : \text{Smaller model selected by AIC is adequate} \quad vs. \quad H_a : \text{Larger model is adequate}$$

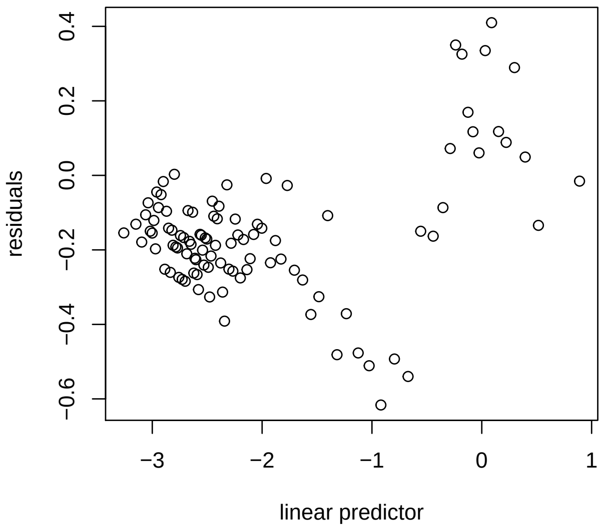
```
anova(model1_LR_small, model1_LR, test = "Chi")
```

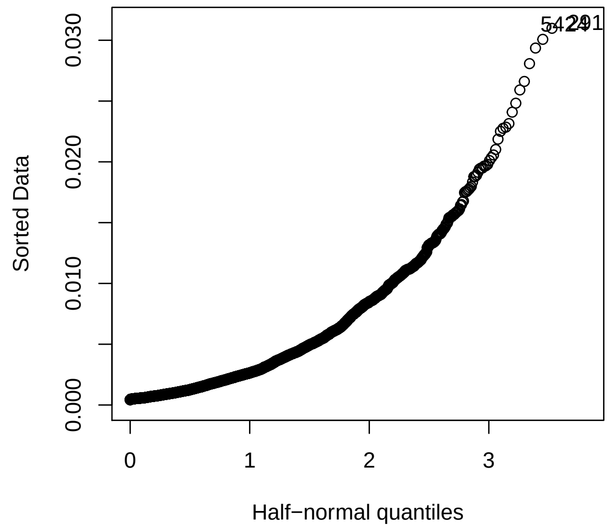
```
## Analysis of Deviance Table
##
## Model 1: target ~ city_development_index + relevent_experience + enrolled_university +
##     experience + company_size + company_type + training_hours
## Model 2: target ~ city_development_index + gender + relevent_experience +
##     enrolled_university + education_level + major_discipline +
##     experience + company_size + company_type + last_new_job +
##     training_hours
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      7146     5219.3
## 2      7132     5201.3 14   18.004   0.2066
```

- LRT: Deviance = 18.004, follow χ^2_{14}
- The p-value is 0.2066, which is larger than 0.05, we fail to reject the null hypothesis. Thus, we prefer the smaller model selected by AIC.

Model Diagnostics

```
# Deviance Residuals plot
par(mfrow = c(1, 2))
train_assumption <- mutate(train, residuals=residuals(model1_LR_small),
                           linpred=predict(model1_LR_small))
gdf <- group_by(train_assumption, cut(linpred,
                                      breaks=c(min(linpred),
                                               unique(quantile(linpred, (1:100)/101)),
                                               max(linpred)),include.lowest = TRUE))
diagdf <- summarise(gdf, residuals=mean(residuals), linpred=mean(linpred), .groups = 'drop')

plot(residuals ~ linpred, diagdf, xlab="linear predictor")

# half-normal plot
halfnorm(hatvalues(model1_LR_small))
```





3.3 Model2: LDA

use the 7 features selected by AIC in Model 1 with log(training_hours)

```
suppressMessages(library(MASS))
model2_LDA = lda(target ~ city_development_index + relevent_experience +
                 enrolled_university + experience + company_size +
                 company_type + log(training_hours), data=train)
```

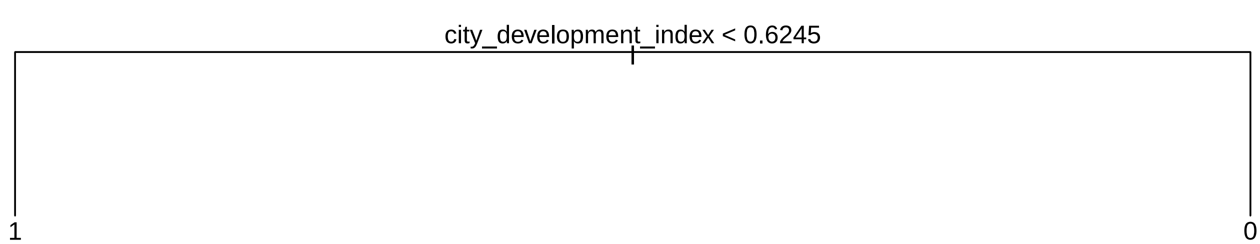
3.4 Model3: QDA

use the 7 features selected by AIC in Model 1 with log(training_hours)

```
model3_QDA = qda(target ~ city_development_index + relevent_experience +
                 enrolled_university + experience + company_size +
                 company_type + log(training_hours), data=train)
```

3.5 Model4: Classification Tree

```
suppressMessages(library(tree))
set.seed(108)
model4_tree <- tree(target ~ ., data=train)
plot(model4_tree); text(model4_tree, pretty=0)
```



```r
summary(model4_tree)
```

```
##
## Classification tree:
## tree(formula = target ~ ., data = train)
## Variables actually used in tree construction:
## [1] "city_development_index"
## Number of terminal nodes:  2
## Residual mean deviance:  0.7127 = 5105 / 7163
## Misclassification error rate: 0.1369 = 981 / 7165
```

```r
# no need to prune the tree
```

3.6 Model5: Bagging

```r
suppressMessages(library(randomForest))
set.seed(108)
model5_bagging <- randomForest(target ~ ., data=train, ntree=500,
                        mtry=11, importance=TRUE)
model5_bagging
```

```
##
## Call:
##  randomForest(formula = target ~ ., data = train, ntree = 500,      mtry = 11, importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 11
##
##         OOB estimate of  error rate: 14.7%
## Confusion matrix:
##      0   1 class.error
## 0 5656 322  0.05386417
## 1  731 456  0.61583825
```

3.7 Model6: Random Forest

```r
set.seed(108)
model6_rf <- randomForest(target ~ ., data=train, ntree=500,
                        mtry=sqrt(11), importance=TRUE)
model6_rf
```

```
##
## Call:
##  randomForest(formula = target ~ ., data = train, ntree = 500,      mtry = sqrt(11), importance = TRU
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 3
##
```

```
##         OOB estimate of  error rate: 14.36%
## Confusion matrix:
##      0   1 class.error
## 0 5667 311  0.05202409
## 1  718 469  0.60488627
```

3.8 Model7: Boosting

```r
suppressMessages(library(gbm))
set.seed(108)

# gbm need character type response instead of factor
train_boost <- train
train_boost$target <- as.character(train_boost$target)
test_boost <- test
test_boost$target <- as.character(test_boost$target)


model7_boosting <- gbm(target ~ ., data=train_boost, distribution="bernoulli",
                n.trees=500, shrinkage=0.3)
model7_boosting
```

```
## gbm(formula = target ~ ., distribution = "bernoulli", data = train_boost,
##     n.trees = 500, shrinkage = 0.3)
## A gradient boosted model with bernoulli loss function.
## 500 iterations were performed.
## There were 11 predictors of which 11 had non-zero influence.
```

4. Model Selection using ROC Analysis

```r
suppressMessages(library(pROC))

# Create matrix to store the evaluation metrics for each model
eva_metrics = matrix(0, nrow=7, ncol=5)

# phat
phat1 <- predict(model1_LR_small, newdata=test, type="response")
phat2 <- predict(model2_LDA, newdata=test)$posterior[,2]
phat3 <- predict(model3_QDA, newdata=test)$posterior[,2]
phat4 <- predict(model4_tree, newdata=test)[,2]
phat5 <- predict(model5_bagging, newdata=test, type="prob")[,2]
phat6 <- predict(model6_rf, newdata=test, type="prob")[,2]
phat7 <- predict(model7_boosting, newdata=test_boost, type="response")

# create roc object
roc_obj1 <- roc(response=test$target, predictor=phat1)
roc_obj2 <- roc(response=test$target, predictor=phat2)
roc_obj3 <- roc(response=test$target, predictor=phat3)
roc_obj4 <- roc(response=test$target, predictor=phat4)
roc_obj5 <- roc(response=test$target, predictor=phat5)
roc_obj6 <- roc(response=test$target, predictor=phat6)
roc_obj7 <- roc(response=test$target, predictor=phat7)

# calculate AUC
AUC1 <- auc(roc_obj1)
AUC2 <- auc(roc_obj2)
AUC3 <- auc(roc_obj3)
AUC4 <- auc(roc_obj4)
AUC5 <- auc(roc_obj5)
AUC6 <- auc(roc_obj6)
AUC7 <- auc(roc_obj7)

# show the performance matric
roc_1 <- c(coords(roc_obj1, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC1)
eva_metrics[1,] <- t(roc_1)

roc_2 <- c(coords(roc_obj2, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC2)
eva_metrics[2,] <- t(roc_2)

roc_3 <- c(coords(roc_obj3, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC3)
eva_metrics[3,] <- t(roc_3)

roc_4 <- c(coords(roc_obj4, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC4)
eva_metrics[4,] <- t(roc_4)

roc_5 <- c(coords(roc_obj5, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC5)
```

```r
eva_metrics[5,] <- t(roc_5)

roc_6 <- c(coords(roc_obj6, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC6)
eva_metrics[6,] <- t(roc_6)

roc_7 <- c(coords(roc_obj7, "b", ret=c("threshold","se","sp","accuracy"),
                         best.method="youden", transpose=TRUE), AUC7)
eva_metrics[7,] <- t(roc_7)

# Create metrics df
metrics <- as.data.frame(eva_metrics)
colnames(metrics) = c("Threshold","Sensitivity","Specificity","Accuracy","AUC")
rownames(metrics) = c("Logistic Regression","LDA","QDA","Tree","Bagging","RF","Boosting")
metrics
```

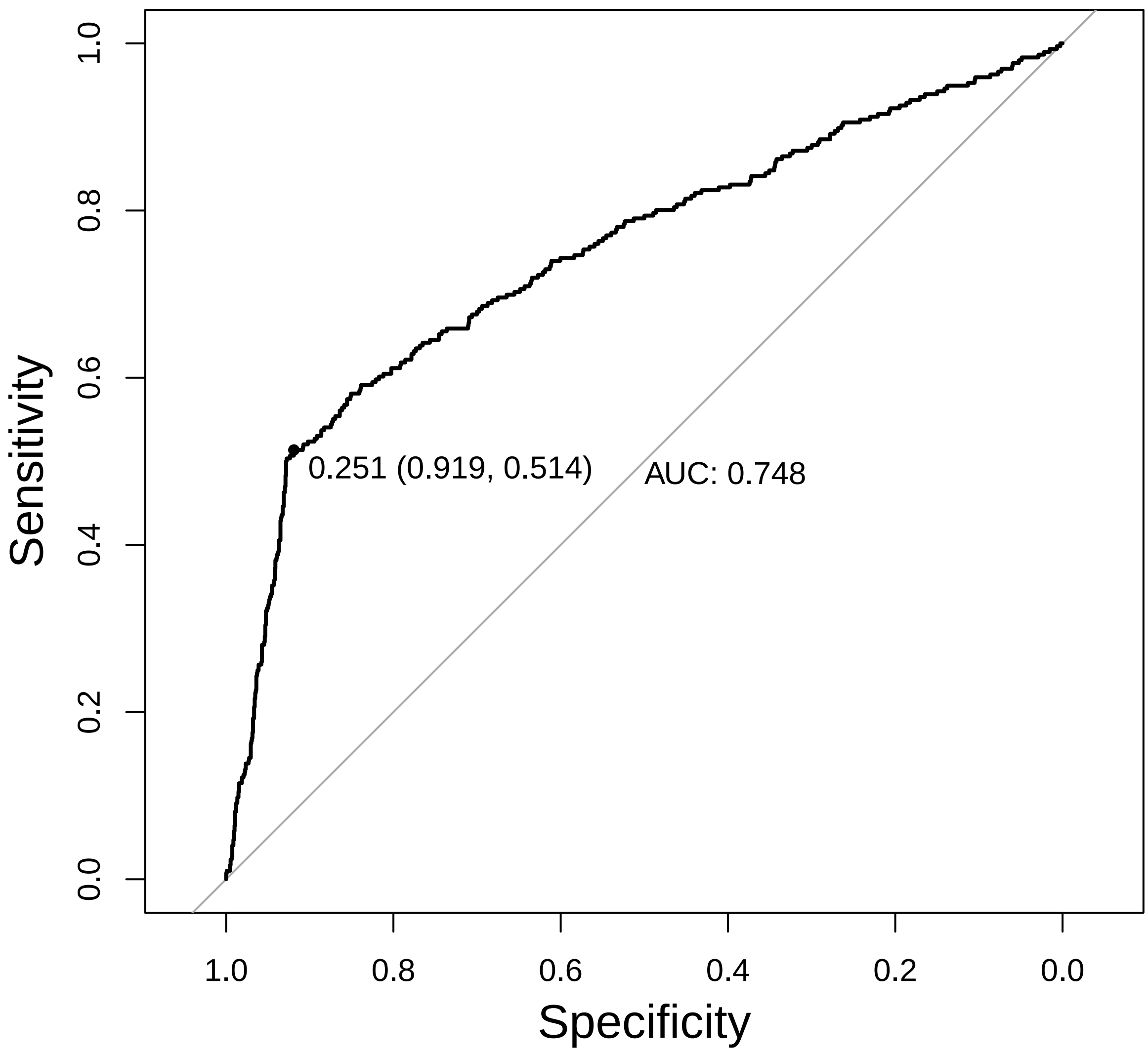
```
##                     Threshold Sensitivity Specificity  Accuracy       AUC
## Logistic Regression 0.3509160   0.5202703   0.9149933 0.8497207 0.7362988
## LDA                 0.4368809   0.5236486   0.9136546 0.8491620 0.7363350
## QDA                 0.2258706   0.5743243   0.8159304 0.7759777 0.7114675
## Tree                0.3411479   0.4966216   0.9243641 0.8536313 0.7104929
## Bagging             0.3270000   0.5000000   0.9022758 0.8357542 0.7410735
## RF                  0.2670000   0.5202703   0.9049531 0.8413408 0.7430703
## Boosting            0.2514782   0.5135135   0.9190094 0.8519553 0.7479411
```

- The best model based on the highest AUC is Boosting, the AUC = 0.7479411.

5. Analyze the Best Performing Model - Boosting

5.1 Boosting ROC Analysis

```
# produce ROC Curve
plot(roc_obj7,legacy.axes=F,print.auc=T,print.thres=T,cex.lab=1.5)
```



5.2 Boosting Confusion Matrix using Best Threshold

```
# make prediction cutoff=0.2514782
# Obtain Y_hat values for the data observation (cutoff=0.2514782)
proba_hat <- predict(model7_boosting, newdata=test_boost, type="response")

n = nrow(test); y_hat = rep(0,n)
cutoff = 0.2514782; idx = which(proba_hat > cutoff)
y_hat[idx] = 1
```

```r
# confusion matrix at cutoff=0.2514782
(conf_mat = table(predicted = y_hat, actual = test$target))
```

```
##          actual
## predicted    0    1
##         0 1373  144
##         1  121  152
```

```r
# sensitivity/recall
conf_mat[2, 2] / sum(conf_mat[, 2])
```

```
## [1] 0.5135135
```

```r
# precision/positive predictive value
conf_mat[2, 2] / sum(conf_mat[2, ])
```

```
## [1] 0.5567766
```

```r
# specificity
conf_mat[1, 1] / sum(conf_mat[, 1])
```

```
## [1] 0.9190094
```

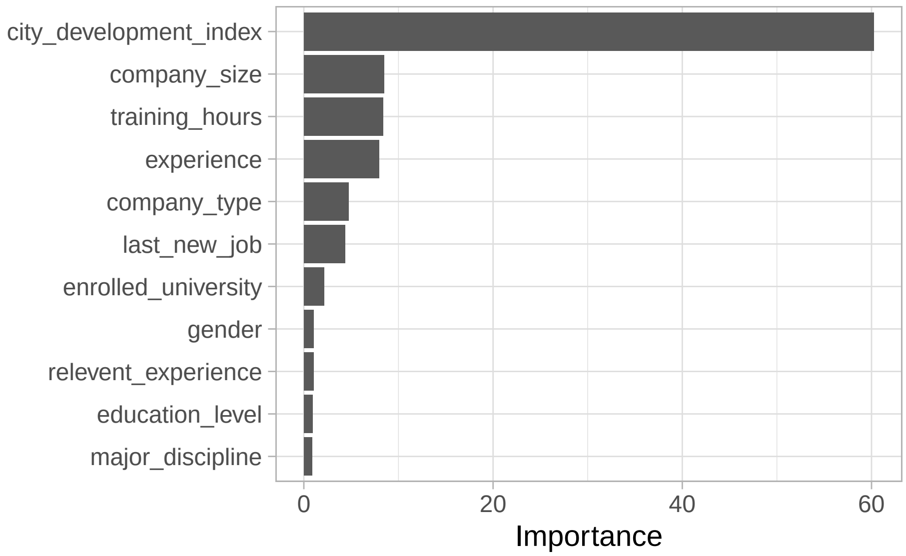
	Summary Metrics for Boosting
Sensitivity/Recall	0.5135135
Precision/Positive Predictive Value	0.5567766
Specificity	0.9190094
Accuracy	0.8519553
AUC	0.7479411

5.3 Boosting Summary and Feature Importance

```r
summary(model7_boosting, las=1, plotit=F)
```

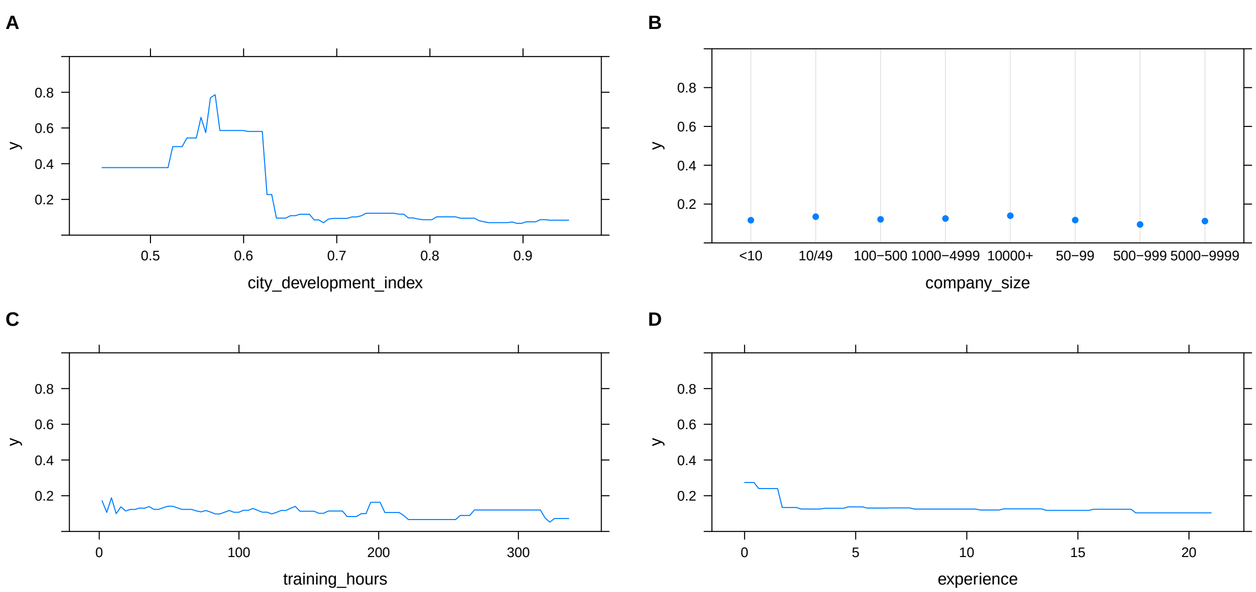
```
##                                           var    rel.inf
## city_development_index city_development_index 60.2531637
## company_size                     company_size  8.4526089
## training_hours                 training_hours  8.3464673
## experience                         experience  7.9438939
## company_type                     company_type  4.7450783
## last_new_job                     last_new_job  4.3622290
## enrolled_university       enrolled_university  2.1210473
## gender                                 gender  1.0072945
## relevent_experience       relevent_experience  1.0043377
## education_level               education_level  0.9018400
## major_discipline             major_discipline  0.8620393
```

```r
vip::vip(model7_boosting, num_features=11) + theme_light()
```



Probability of Success vs the Top 4 Most Important Feature - Same Scale

```r
city <- plot.gbm(model7_boosting, 1, type="response", ylim=range(0:1))
company <- plot.gbm(model7_boosting, 8, type="response", ylim=range(0:1))
training <- plot.gbm(model7_boosting, 11, type="response", ylim=range(0:1))
experience <- plot.gbm(model7_boosting, 7, type="response", ylim=range(0:1))

plot_grid(city, company, training, experience,
          labels = "AUTO", ncol=2)
```



Probability of Success vs the Top 4 Most Important Feature - Different Scale

```r
city <- plot.gbm(model7_boosting, 1, type="response")
company <- plot.gbm(model7_boosting, 8, type="response")
training <- plot.gbm(model7_boosting, 11, type="response")
experience <- plot.gbm(model7_boosting, 7, type="response")

plot_grid(city, company, training, experience,
          labels = "AUTO", ncol=2)
```