

POM_681 Final Project

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```
# Load libraries
library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## vforcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr    1.3.1
## v purrr    1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
library(caret)

## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
## 
##     lift

library(e1071)
library(randomForest)

## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:dplyr':
## 
##     combine

## The following object is masked from 'package:ggplot2':
## 
##     margin

library(xgboost)

##
## Attaching package: 'xgboost'
##
```

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## The following object is masked from 'package:dplyr':
##
##     slice

library(ROCR)
library(pROC)

## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
##
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

library(smotefamily)
library(rpart)
library(rpart.plot)
library(corrplot)

## corrplot 0.95 loaded

library(cluster)
library(factoextra)

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
library(ggplot2)
library(patchwork)
library(ggcorrplot)
# Load dataset
hr <- read.csv("/Users/nandhinivijayakumar/Downloads/WA_Fn-UseC_-HR-Employee-Attrition.csv")
head(hr)

##   Age Attrition BusinessTravel DailyRate          Department
## 1  41      Yes    Travel_Rarely     1102             Sales
## 2  49      No     Travel_Frequently    279 Research & Development
## 3  37      Yes    Travel_Rarely     1373 Research & Development
## 4  33      No     Travel_Frequently    1392 Research & Development
## 5  27      No     Travel_Rarely      591 Research & Development
## 6  32      No     Travel_Frequently    1005 Research & Development
##   DistanceFromHome Education EducationField EmployeeCount EmployeeNumber
## 1                  1         2  Life Sciences           1              1
## 2                  8         1  Life Sciences           1              2
## 3                  2         2        Other            1              4
## 4                  3         4  Life Sciences           1              5
## 5                  2         1     Medical            1              7
## 6                  2         2  Life Sciences           1              8
##   EnvironmentSatisfaction Gender HourlyRate JobInvolvement JobLevel
## 1                      2 Female       94            3            2
## 2                      3 Male        61            2            2
## 3                      4 Male        92            2            1
## 4                      4 Female      56            3            1
## 5                      1 Male        40            3            1
## 6                      4 Male        79            3            1
##   JobRole JobSatisfaction MaritalStatus MonthlyIncome MonthlyRate
## 1 Sales Executive             4       Single      5993      19479

```

```
##          Age             Attrition           BusinessTravel
##          0                  0                      0
##          DailyRate          Department        DistanceFromHome
##          0                  0                      0
##          Education          EducationField      EmployeeCount
##          0                  0                      0
##          EmployeeNumber     EnvironmentSatisfaction Gender
##          0                  0                      0
##          HourlyRate          JobInvolvement      JobLevel
##          0                  0                      0
##          JobRole             JobSatisfaction    MaritalStatus
##          0                  0                      0
##          MonthlyIncome       MonthlyRate        NumCompaniesWorked
##          0                  0                      0
##          Over18              Overtime          PercentSalaryHike
##          0                  0                      0
```

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##          PerformanceRating RelationshipSatisfaction           StandardHours
##                      0                      0                         0
##          StockOptionLevel      TotalWorkingYears TrainingTimesLastYear
##                      0                      0                         0
##          WorkLifeBalance     YearsAtCompany    YearsInCurrentRole
##                      0                      0                         0
##  YearsSinceLastPromotion   YearsWithCurrManager
##                      0                      0

# Drop unnecessary columns (like EmployeeNumber, Over18, StandardHours, EmployeeCount - not useful)
hr <- hr %>% select(-c(EmployeeNumber, Over18, StandardHours, EmployeeCount))

hr <- hr %>% dplyr::mutate_if(is.character, as.factor)

# Make Attrition a factor
hr$Attrition <- as.factor(hr$Attrition)

# Check structure
str(hr)

## 'data.frame': 1470 obs. of 31 variables:
## $ Age : int 41 49 37 33 27 32 59 30 38 36 ...
## $ Attrition : Factor w/ 2 levels "No","Yes": 2 1 2 1 1 1 1 1 1 1 ...
## $ BusinessTravel : Factor w/ 3 levels "Non-Travel","Travel_Frequently",...: 3 2 3 2 3 2 3
## $ DailyRate : int 1102 279 1373 1392 591 1005 1324 1358 216 1299 ...
## $ Department : Factor w/ 3 levels "Human Resources",...: 3 2 2 2 2 2 2 2 2 2 ...
## $ DistanceFromHome : int 1 8 2 3 2 2 3 24 23 27 ...
## $ Education : int 2 1 2 4 1 2 3 1 3 3 ...
## $ EducationField : Factor w/ 6 levels "Human Resources",...: 2 2 5 2 4 2 4 2 2 4 ...
## $ EnvironmentSatisfaction : int 2 3 4 4 1 4 3 4 4 3 ...
## $ Gender : Factor w/ 2 levels "Female","Male": 1 2 2 1 2 2 1 2 2 2 ...
## $ HourlyRate : int 94 61 92 56 40 79 81 67 44 94 ...
## $ JobInvolvement : int 3 2 2 3 3 3 4 3 2 3 ...
## $ JobLevel : int 2 2 1 1 1 1 1 1 3 2 ...
## $ JobRole : Factor w/ 9 levels "Healthcare Representative",...: 8 7 3 7 3 3 3 3 5 1
## $ JobSatisfaction : int 4 2 3 3 2 4 1 3 3 3 ...
## $ MaritalStatus : Factor w/ 3 levels "Divorced","Married",...: 3 2 3 2 2 3 2 1 3 2 ...
## $ MonthlyIncome : int 5993 5130 2090 2909 3468 3068 2670 2693 9526 5237 ...
## $ MonthlyRate : int 19479 24907 2396 23159 16632 11864 9964 13335 8787 16577 ...
## $ NumCompaniesWorked : int 8 1 6 1 9 0 4 1 0 6 ...
## $ Overtime : Factor w/ 2 levels "No","Yes": 2 1 2 2 1 1 2 1 1 1 ...
## $ PercentSalaryHike : int 11 23 15 11 12 13 20 22 21 13 ...
## $ PerformanceRating : int 3 4 3 3 3 3 4 4 4 3 ...
## $ RelationshipSatisfaction: int 1 4 2 3 4 3 1 2 2 2 ...
## $ StockOptionLevel : int 0 1 0 0 1 0 3 1 0 2 ...
## $ TotalWorkingYears : int 8 10 7 8 6 8 12 1 10 17 ...
## $ TrainingTimesLastYear : int 0 3 3 3 3 2 3 2 2 3 ...
## $ WorkLifeBalance : int 1 3 3 3 3 2 2 3 3 2 ...
## $ YearsAtCompany : int 6 10 0 8 2 7 1 1 9 7 ...
## $ YearsInCurrentRole : int 4 7 0 7 2 7 0 0 7 7 ...
## $ YearsSinceLastPromotion : int 0 1 0 3 2 3 0 0 1 7 ...
## $ YearsWithCurrManager : int 5 7 0 0 2 6 0 0 8 7 ...

#.....EDA (Exploratory Data Analysis).....
```

```

# Attrition distribution(checking data imbalance)
table(hr$Attrition)

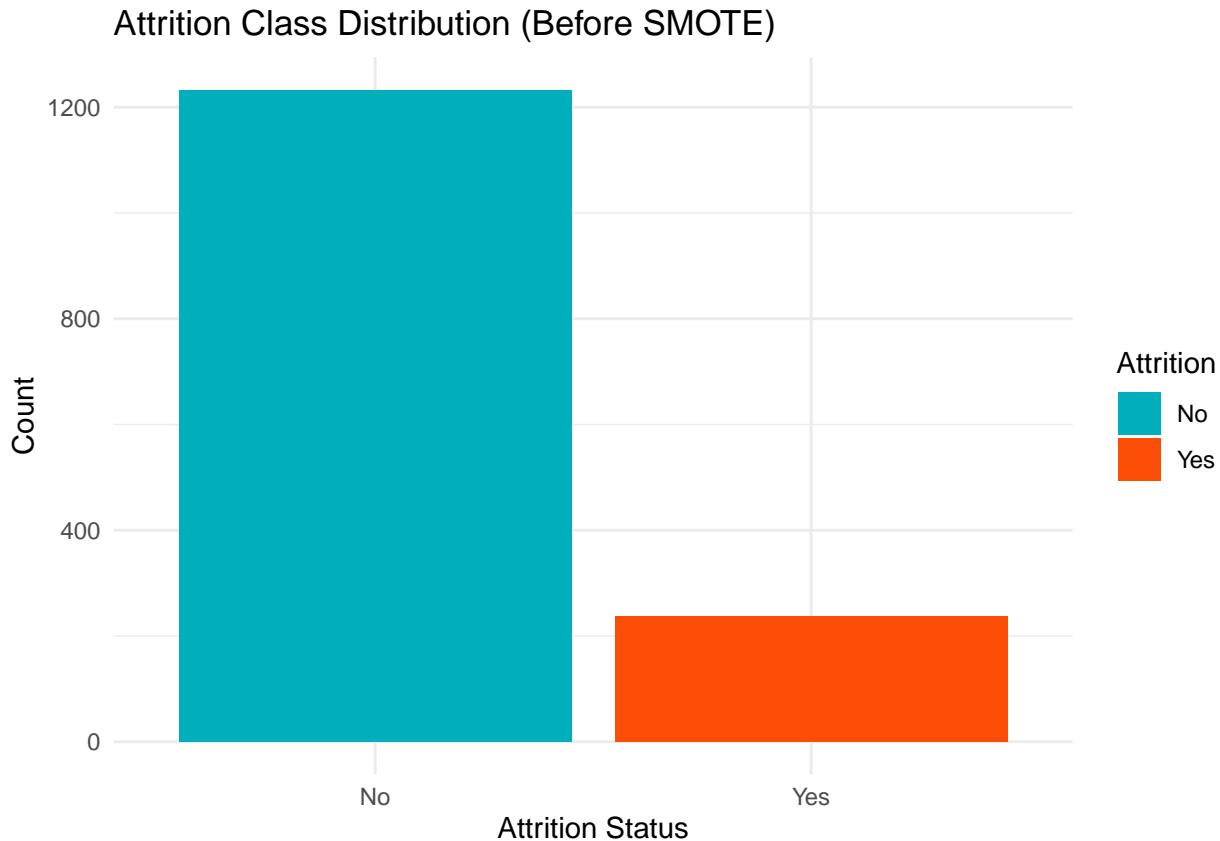
##
##    No   Yes
## 1233  237

prop.table(table(hr$Attrition))

##
##          No        Yes
## 0.8387755 0.1612245

# Plot 1: Attrition Class Distribution (Before SMOTE)
ggplot(hr, aes(x=Attrition, fill=Attrition)) +
  geom_bar() +
  ggtitle("Attrition Class Distribution (Before SMOTE)") +
  theme_minimal() +
  labs(x="Attrition Status", y="Count") +
  scale_fill_manual(values=c("#00AFBB", "#FC4E07"))

```



```

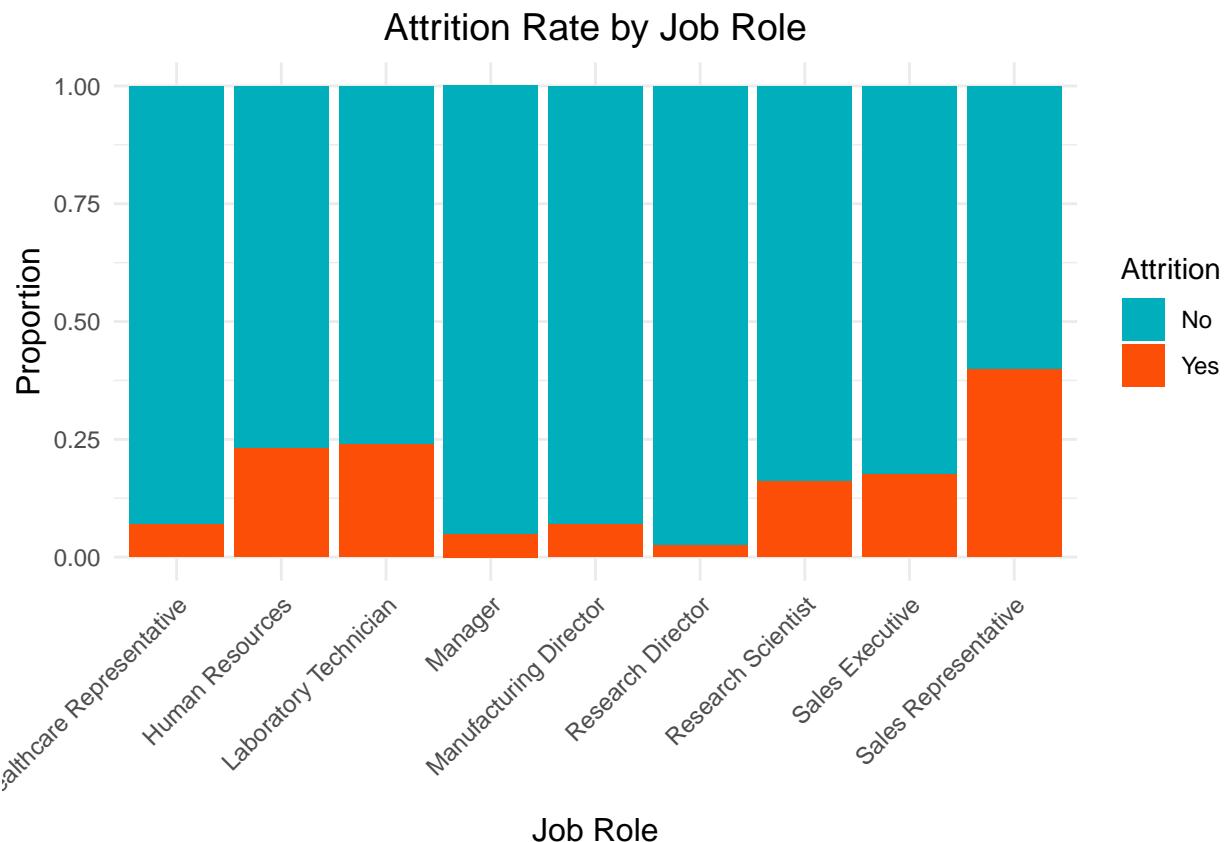
# Visualize Attrition by JobRole
# Visualize Attrition by JobRole (fixed overlapping labels)
ggplot(hr, aes(x = JobRole, fill = Attrition)) +
  geom_bar(position = "fill") +
  labs(title = "Attrition Rate by Job Role", x = "Job Role", y = "Proportion") +
  theme_minimal() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),

```

```

    plot.title = element_text(hjust = 0.5, size = 14),
    axis.title = element_text(size = 12)
) +
scale_fill_manual(values = c("#00AFBB", "#FC4E07"))

```



```

# Create Age Groups
hr$AgeGroup <- cut(hr$Age,
                     breaks = c(18, 25, 35, 45, 55, 65),
                     labels = c("18-25", "26-35", "36-45", "46-55", "56-65"),
                     right = FALSE)

```

```

# Plot 2: Age Group vs Attrition
p1 <- ggplot(hr, aes(x=AgeGroup, fill=Attrition)) +
  geom_bar(position="fill") +
  scale_y_continuous(labels=scales::percent) +
  labs(title="Age Group vs Attrition", x="Age Group", y="Proportion") +
  scale_fill_manual(values=c("#00AFBB", "#FC4E07")) +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5, size=14),
        axis.title = element_text(size=12),
        axis.text = element_text(size=10))

```

```

# Plot 3: Marital Status vs Attrition
p2 <- ggplot(hr, aes(x=MaritalStatus, fill=Attrition)) +
  geom_bar(position="fill") +
  scale_y_continuous(labels=scales::percent) +
  labs(title="Marital Status vs Attrition", x="Marital Status", y="Proportion") +

```

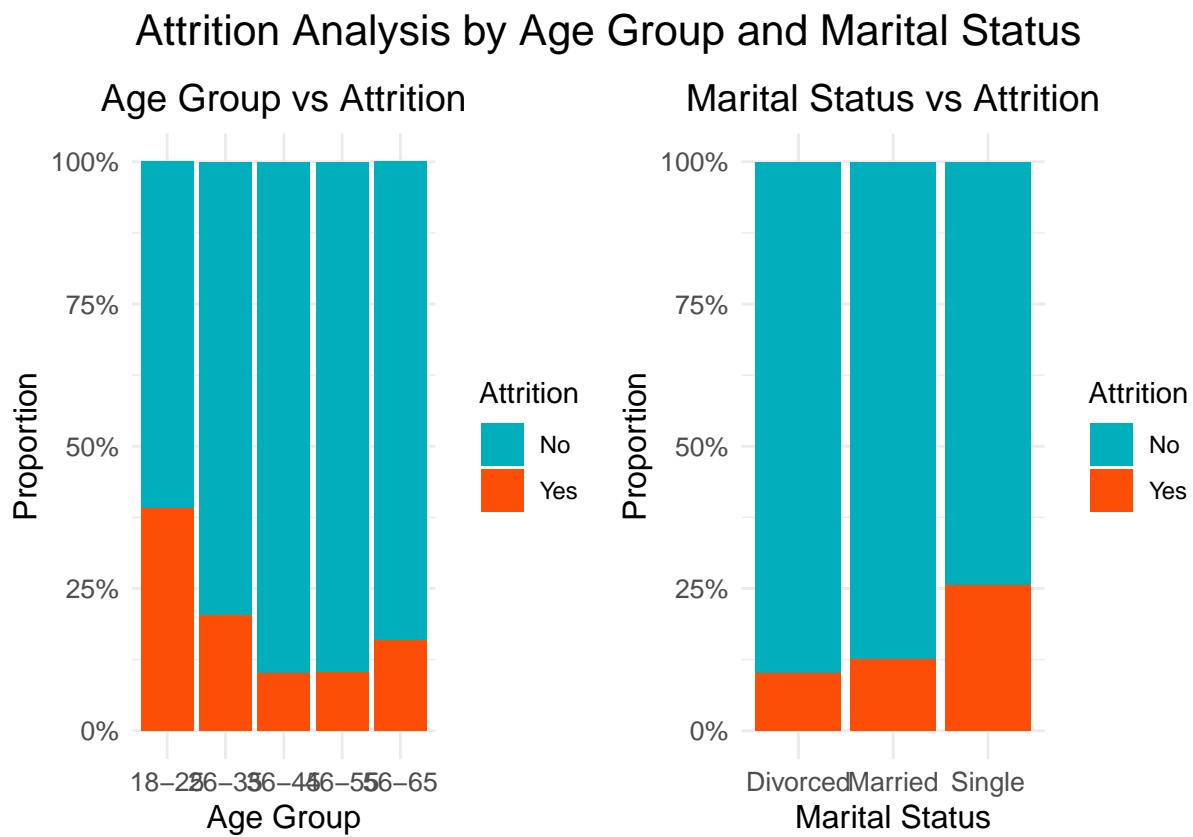
```

scale_fill_manual(values=c("#00AFBB", "#FC4E07")) +
theme_minimal() +
theme(plot.title = element_text(hjust = 0.5, size=14),
      axis.title = element_text(size=12),
      axis.text = element_text(size=10))

# Combine side-by-side using patchwork
combined_plot <- (p1 | p2) +
  plot_annotation(title = "Attrition Analysis by Age Group and Marital Status",
                  theme = theme(plot.title = element_text(hjust = 0.5, size=16)))

print(combined_plot)

```



```

##correlation matrix

library(dplyr)
library(ggcorrplot)

# Select only numeric columns and remove constant columns
nums <- hr %>%
  select_if(is.numeric) %>%
  select(where(~ var(.x, na.rm = TRUE) != 0))

# Compute correlation matrix
corr <- round(cor(nums, use = "complete.obs"), 1)

# Plot correlation matrix using ggcorrplot

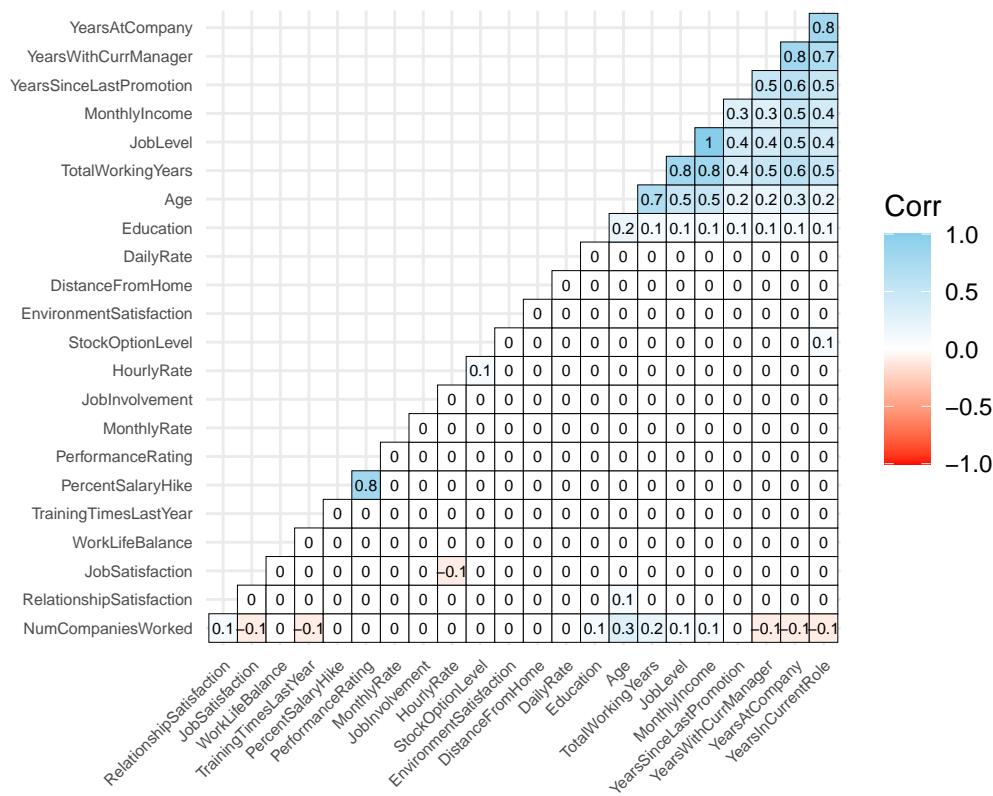
```

```

ggcorrplot(corr,
            type = "lower",
            lab = TRUE,
            lab_size = 2,
            method = "square",
            colors = c("red", "white", "skyblue"),
            title = "Correlation Matrix: Employee Attrition",
            hc.order = TRUE,
            hc.method = "complete",
            tl.cex = 6,
            outline.color = "black",
            ggtheme = theme_minimal() +
              theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1)))

```

Correlation Matrix: Employee Attrition



#.....Feature Engineering.....

```

# Create bins for DistanceFromHome
hr$DistanceGroup <- cut(hr$DistanceFromHome,
                        breaks = c(0, 5, 15, 30),
                        labels = c("Near", "Medium", "Far"))

# Create bins for MonthlyIncome
hr$IncomeGroup <- cut(hr$MonthlyIncome,
                      breaks = quantile(hr$MonthlyIncome, probs=c(0, 0.33, 0.66, 1)),
                      labels = c("Low", "Medium", "High"),
                      include.lowest = TRUE)

```

```

#.....Data Preprocessing.....
# Prepare X and y
# Data Preprocessing: Encode categorical variables
#dummies <- dummyVars(Attrition ~ ., data = hr, fullRank = TRUE)
#hr_transformed <- data.frame(predict(dummies, newdata = hr))
#hr_transformed$Attrition <- ifelse(hr$Attrition == "Yes", 1, 0)
#hr_transformed$Attrition <- as.factor(hr_transformed$Attrition)

# ----- Split Data -----
set.seed(999)
trainIndex <- createDataPartition(hr$Attrition, p = 0.8, list = FALSE)
train <- hr[trainIndex, ]
test <- hr[-trainIndex, ]

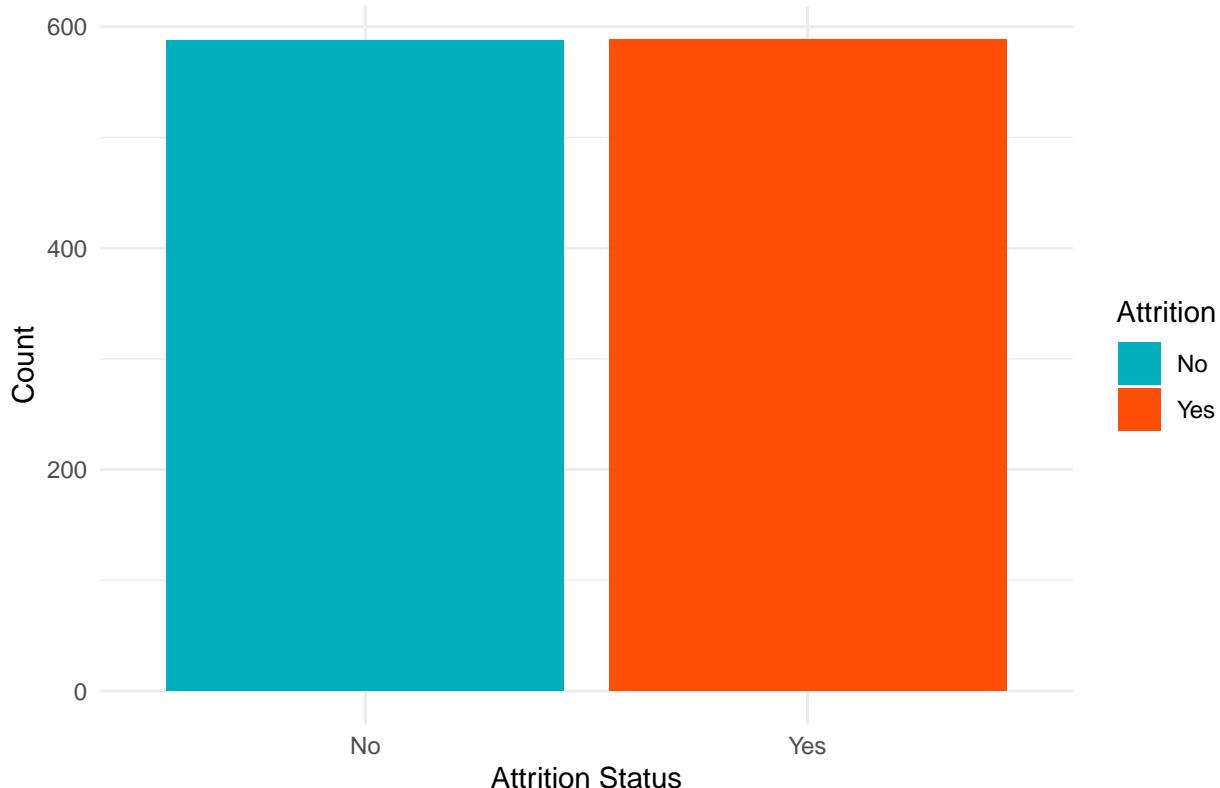
# ----- SMOTE on Training Only -----
library(ROSE)

## Loaded ROSE 0.0-4
train_new <- ROSE(Attrition ~ ., data = train, seed = 999)$data
# Train/test split
#train <- hr_balanced
#X_train <- train %>% select(-Attrition)
#y_train <- train$Attrition
#smote_output <- SMOTE(X_train, y_train, K = 5)
hr_balanced <- train_new

# Bar plot - After SMOTE
ggplot(hr_balanced, aes(x=Attrition, fill=Attrition)) +
  geom_bar() +
  ggtitle("Attrition Class Distribution (After SMOTE)") +
  theme_minimal() +
  labs(x="Attrition Status", y="Count") +
  scale_fill_manual(values=c("#00AFBB", "#FC4E07"))

```

Attrition Class Distribution (After SMOTE)



```
#..... [Logistic Regression] .....
```

```
# Fit the logistic regression model
model_logit <- glm(Attrition ~ ., data=hr_balanced, family="binomial")
summary(model_logit)

##
## Call:
## glm(formula = Attrition ~ ., family = "binomial", data = hr_balanced)
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.118e+01  5.437e+02 -0.021 0.983587
## Age                  -1.972e-02  1.106e-02 -1.784 0.074444 .
## BusinessTravelTravel_Frequently 1.786e+00  3.321e-01  5.377 7.59e-08 ***
## BusinessTravelTravel_Rarely    9.295e-01  2.926e-01  3.177 0.001488 **
## DailyRate             -5.048e-05 1.584e-04 -0.319 0.750011
## DepartmentResearch & Development 1.681e+01  5.437e+02  0.031 0.975339
## DepartmentSales        1.520e+01  5.437e+02  0.028 0.977700
## DistanceFromHome       1.891e-02  1.192e-02  1.587 0.112596
## Education             1.314e-01  6.674e-02  1.969 0.048896 *
## EducationFieldLife Sciences -2.799e+00  8.821e-01 -3.173 0.001509 **
## EducationFieldMarketing -2.432e+00  9.171e-01 -2.652 0.008006 **
## EducationFieldMedical   -2.674e+00  8.746e-01 -3.057 0.002237 **
## EducationFieldOther      -2.180e+00  9.299e-01 -2.344 0.019075 *
## EducationFieldTechnical Degree -1.427e+00  8.940e-01 -1.596 0.110526
## EnvironmentSatisfaction -2.843e-01  5.811e-02 -4.892 9.97e-07 ***
```

```

## GenderMale           -6.336e-02  1.689e-01 -0.375  0.707613
## HourlyRate          -2.085e-03  3.180e-03 -0.656  0.512122
## JobInvolvement      -2.592e-01  8.709e-02 -2.977  0.002914 **
## JobLevel             8.517e-02  9.292e-02  0.917  0.359370
## JobRoleHuman Resources 1.618e+01  5.437e+02  0.030  0.976262
## JobRoleLaboratory Technician 9.186e-01  4.138e-01  2.220  0.026416 *
## JobRoleManager        2.566e-01  5.298e-01  0.484  0.628101
## JobRoleManufacturing Director -6.924e-01  4.576e-01 -1.513  0.130278
## JobRoleResearch Director -1.692e+00  7.317e-01 -2.313  0.020742 *
## JobRoleResearch Scientist -7.193e-02  4.281e-01 -0.168  0.866589
## JobRoleSales Executive   3.005e+00  7.778e-01  3.864  0.000112 ***
## JobRoleSales Representative 2.472e+00  8.627e-01  2.866  0.004163 **
## JobSatisfaction       -2.153e-01  5.950e-02 -3.619  0.000296 ***
## MaritalStatusMarried   3.199e-01  2.329e-01  1.373  0.169635
## MaritalStatusSingle    1.371e+00  2.765e-01  4.957  7.15e-07 ***
## MonthlyIncome          -2.522e-05  2.462e-05 -1.025  0.305482
## MonthlyRate            -2.055e-05  9.026e-06 -2.277  0.022815 *
## NumCompaniesWorked    6.337e-02  2.669e-02  2.374  0.017603 *
## OverTimeYes            2.009e+00  1.827e-01 10.997 < 2e-16 ***
## PercentSalaryHike     -4.848e-02  2.010e-02 -2.412  0.015886 *
## PerformanceRating     -1.043e-02  2.121e-01 -0.049  0.960793
## RelationshipSatisfaction -1.326e-01  6.086e-02 -2.179  0.029317 *
## StockOptionLevel       -1.133e-01  9.006e-02 -1.258  0.208392
## TotalWorkingYears      -7.542e-03  1.162e-02 -0.649  0.516260
## TrainingTimesLastYear -2.350e-01  5.212e-02 -4.508  6.53e-06 ***
## WorkLifeBalance        -2.390e-01  8.371e-02 -2.855  0.004301 **
## YearsAtCompany          8.575e-03  1.373e-02  0.625  0.532254
## YearsInCurrentRole     -6.703e-02  2.404e-02 -2.788  0.005309 **
## YearsSinceLastPromotion 7.419e-02  2.396e-02  3.096  0.001963 **
## YearsWithCurrManager   -4.150e-02  2.225e-02 -1.865  0.062190 .
## AgeGroup26-35           -5.497e-01  3.353e-01 -1.639  0.101126
## AgeGroup36-45           -9.339e-01  3.910e-01 -2.389  0.016909 *
## AgeGroup46-55           -7.237e-01  4.996e-01 -1.449  0.147422
## AgeGroup56-65           -2.292e-01  6.351e-01 -0.361  0.718149
## DistanceGroupMedium    1.952e-01  2.156e-01  0.905  0.365257
## DistanceGroupFar        4.549e-01  3.126e-01  1.455  0.145675
## IncomeGroupMedium       -1.347e+00  2.780e-01 -4.846  1.26e-06 ***
## IncomeGroupHigh          -3.072e-01  4.128e-01 -0.744  0.456679
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 1631.7 on 1176 degrees of freedom
## Residual deviance: 1026.5 on 1124 degrees of freedom
## AIC: 1132.5
##
## Number of Fisher Scoring iterations: 14
# Get predictions as probabilities (type = "response")
probabilities_rf <- predict(model_logit, newdata = test, type = "response")

# Convert probabilities to binary predictions (using threshold 0.5)
predictions_rf_class <- ifelse(probabilities_rf > 0.5, "Yes", "No")

```

```

# Ensure both 'predictions_rf_class' and 'test$Attrition' are factors with the same levels
test$Attrition <- factor(test$Attrition, levels = c("No", "Yes"))
predictions_rf_class <- factor(predictions_rf_class, levels = c("No", "Yes"))

# Create confusion matrix (indicating positive class as 'Yes')
library(caret)
conf_logit <- confusionMatrix(predictions_rf_class, test$Attrition, positive = 'Yes')

# Print confusion matrix
conf_logit

## Confusion Matrix and Statistics
##
##             Reference
## Prediction   No  Yes
##       No    195   16
##       Yes    51   31
##
##             Accuracy : 0.7713
##                 95% CI : (0.7189, 0.8182)
##       No Information Rate : 0.8396
##       P-Value [Acc > NIR] : 0.9991
##
##             Kappa : 0.3476
##
##   Mcnemar's Test P-Value : 3.271e-05
##
##             Sensitivity : 0.6596
##             Specificity  : 0.7927
##       Pos Pred Value : 0.3780
##       Neg Pred Value : 0.9242
##             Prevalence  : 0.1604
##       Detection Rate : 0.1058
##       Detection Prevalence : 0.2799
##       Balanced Accuracy : 0.7261
##
##       'Positive' Class : Yes
##

# Create ROC object
roc_logit <- roc(test$Attrition, probabilities_rf)

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

# Prepare data
df_logit <- data.frame(
  fpr = 1 - roc_logit$specificities,
  tpr = roc_logit$sensitivities
)

# Plot
ggplot(df_logit, aes(x=fpr, y=tpr)) +
  geom_line(color="blue", size=1.2) +

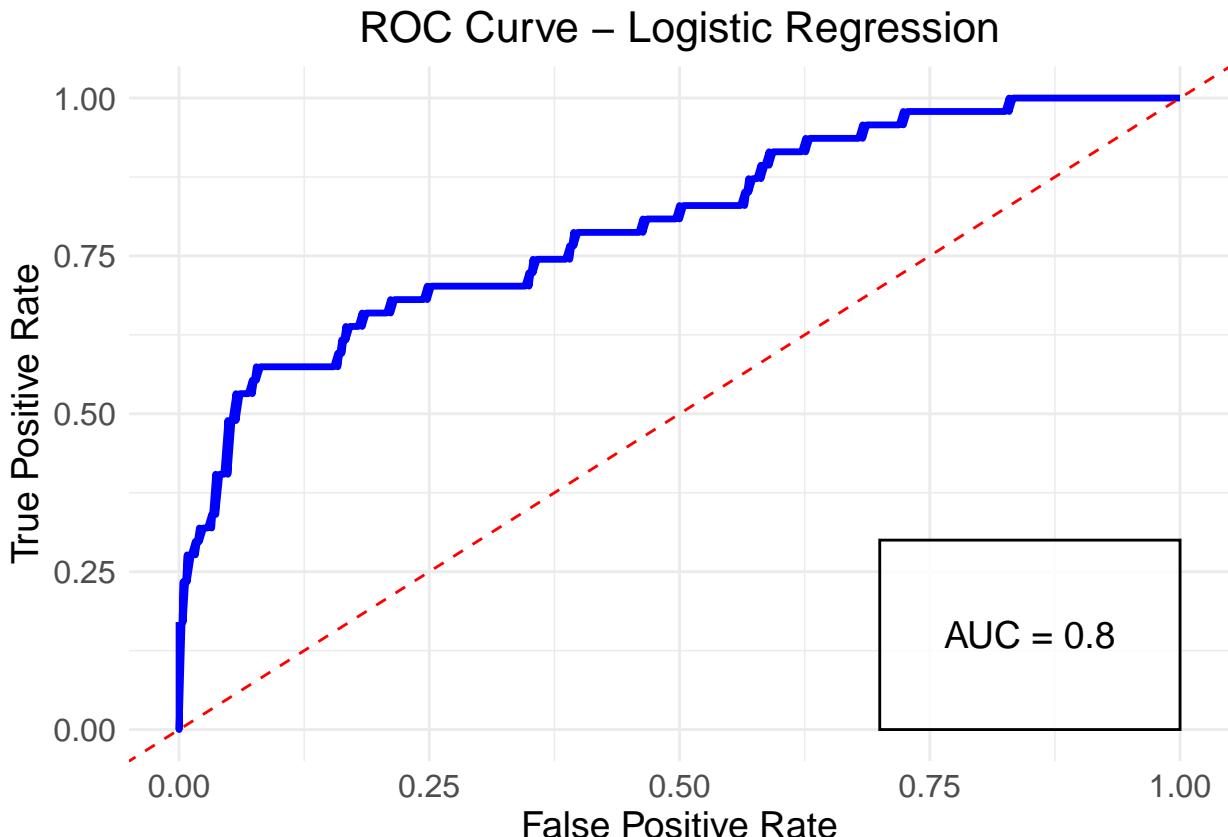
```

```

geom_abline(intercept=0, slope=1, linetype="dashed", color="red") +
  labs(title="ROC Curve - Logistic Regression",
       x="False Positive Rate", y="True Positive Rate") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5, size = 16),
        axis.title = element_text(size = 14),
        axis.text = element_text(size = 12)) +
  annotate("rect", xmin = 0.7, xmax = 1, ymin = 0, ymax = 0.3,
           fill = "white", color = "black", alpha = 0.8) +
  annotate("text", x = 0.85, y = 0.15,
           label = paste("AUC =", round(auc(roc_logit), 3)), size = 5)

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

```



```

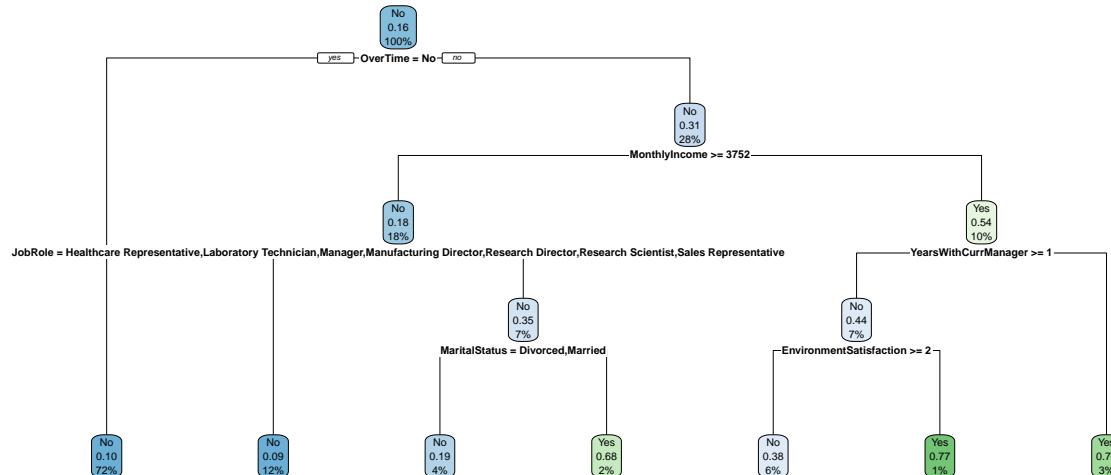
conf_tree <- confusionMatrix(as.factor(predict(model_tree, newdata=test, type="class")), as.factor(test$Attrition))

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  No Yes
##           No 188 17
##           Yes  58 30
##
##           Accuracy : 0.744
##                 95% CI : (0.69, 0.793)
##   No Information Rate : 0.8396
##   P-Value [Acc > NIR] : 1
##
##           Kappa : 0.2975
##
## McNemar's Test P-Value : 3.86e-06
##
##           Sensitivity : 0.7642
##           Specificity : 0.6383
##   Pos Pred Value : 0.9171
##   Neg Pred Value : 0.3409
##           Prevalence : 0.8396
##           Detection Rate : 0.6416
##   Detection Prevalence : 0.6997
##   Balanced Accuracy : 0.7013
##
## 'Positive' Class : No
##

# Build a new tree
model_tree_simple <- rpart(Attrition ~ ., data=train, method="class", control=control)

# Plot the simpler tree
rpart.plot(model_tree_simple, extra = 106, fallen.leaves = TRUE)

```



```

# Create ROC object
roc_tree <- roc(test$Attrition, prob_tree)

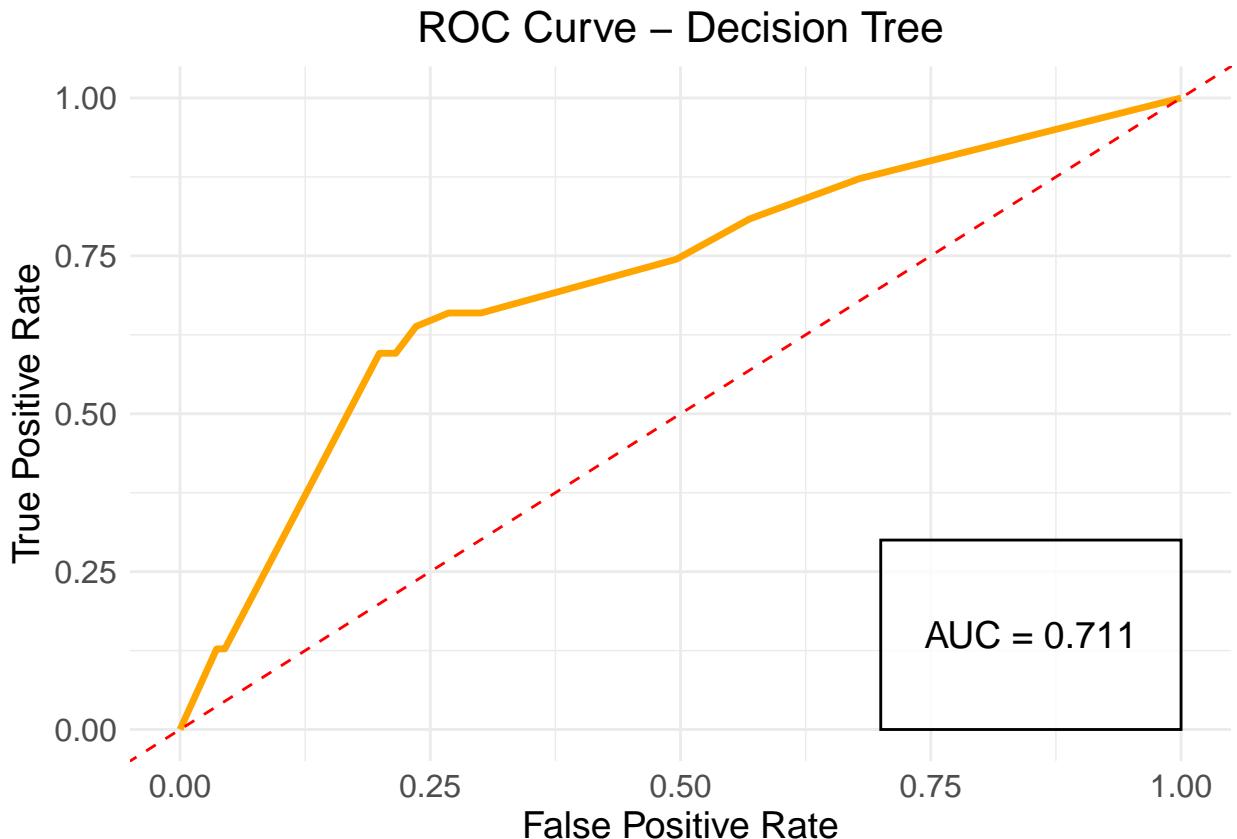
```

```

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
# Prepare data
df_tree <- data.frame(
  fpr = 1 - roc_tree$specificities,
  tpr = roc_tree$sensitivities
)

# Plot
ggplot(df_tree, aes(x=fpr, y=tpr)) +
  geom_line(color="orange", size=1.2) +
  geom_abline(intercept=0, slope=1, linetype="dashed", color="red") +
  labs(title="ROC Curve - Decision Tree",
       x="False Positive Rate", y="True Positive Rate") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5, size = 16),
        axis.title = element_text(size = 14),
        axis.text = element_text(size = 12)) +
  annotate("rect", xmin = 0.7, xmax = 1, ymin = 0, ymax = 0.3,
           fill = "white", color = "black", alpha = 0.8) +
  annotate("text", x = 0.85, y = 0.15,
           label = paste("AUC =", round(auc(roc_tree), 3)), size = 5)

```



```

#.....[SVM].....
model_svm <- svm(as.factor(Attrition) ~ ., data=hr_balanced, kernel="linear", probability=TRUE)
summary(model_svm)

```

```

## 
## Call:
## svm(formula = as.factor(Attrition) ~ ., data = hr_balanced, kernel = "linear",
##       probability = TRUE)
##
## 
## Parameters:
##   SVM-Type: C-classification
##   SVM-Kernel: linear
##   cost: 1
##
## Number of Support Vectors: 598
##
## ( 297 301 )
##
## 
## Number of Classes: 2
##
## Levels:
## No Yes

# Predict classes
pred_svm <- predict(model_svm, newdata=test, probability=TRUE)

# Confusion Matrix
conf_svm <- confusionMatrix(as.factor(pred_svm), as.factor(test$Attrition))
conf_svm

## Confusion Matrix and Statistics
## 
##             Reference
## Prediction  No Yes
##           No 196 16
##           Yes 50 31
##
##                 Accuracy : 0.7747
##                           95% CI : (0.7225, 0.8213)
##   No Information Rate : 0.8396
##   P-Value [Acc > NIR] : 0.9985
##
##                 Kappa : 0.353
##
##   Mcnemar's Test P-Value : 4.865e-05
##
##                 Sensitivity : 0.7967
##                 Specificity : 0.6596
##   Pos Pred Value : 0.9245
##   Neg Pred Value : 0.3827
##                 Prevalence : 0.8396
##                 Detection Rate : 0.6689
##   Detection Prevalence : 0.7235
##   Balanced Accuracy : 0.7282
##
##   'Positive' Class : No
##

```

```

# Get probabilities
prob_svm <- attr(predict(model_svm, newdata=test, probability=TRUE), "probabilities")[,2]

# ROC Curve
# Create ROC object
roc_svm <- roc(test$Attrition, prob_svm)

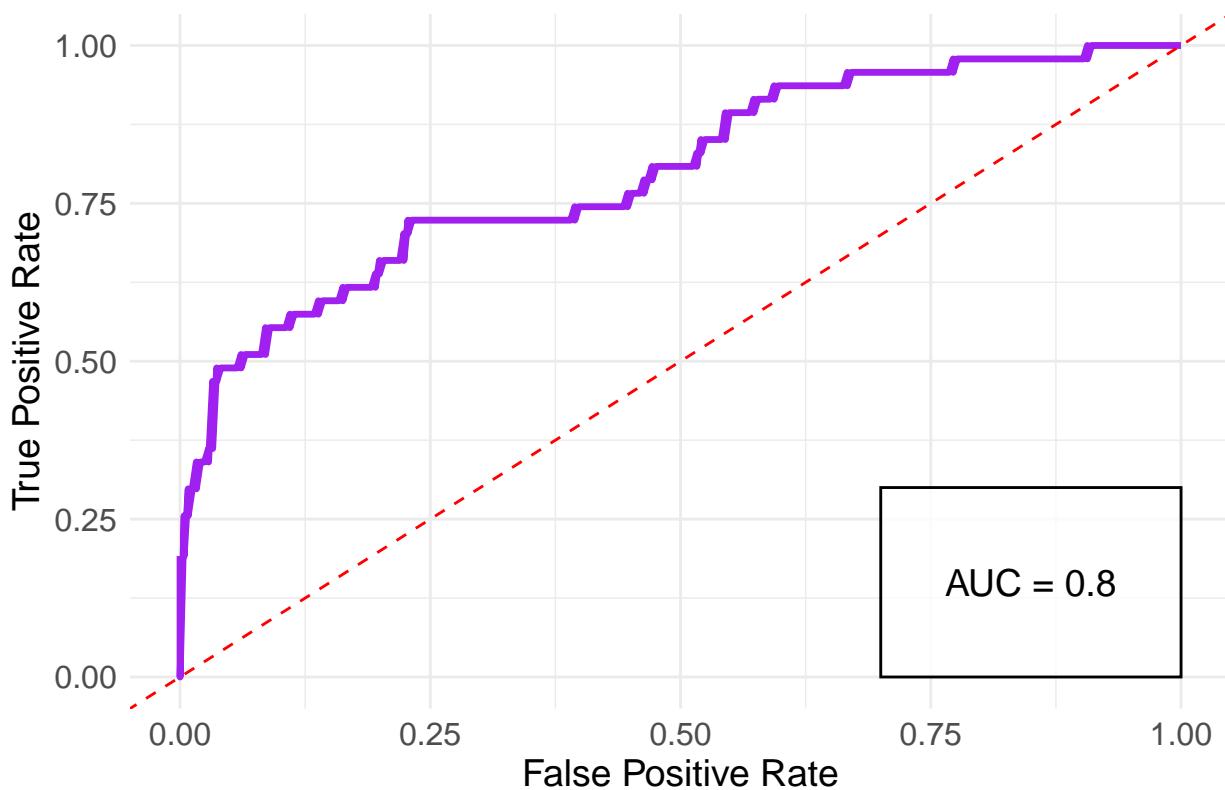
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases

# Prepare data
df_svm <- data.frame(
  fpr = 1 - roc_svm$specificities,
  tpr = roc_svm$sensitivities
)

# Plot
ggplot(df_svm, aes(x=fpr, y=tpr)) +
  geom_line(color="purple", size=1.2) +
  geom_abline(intercept=0, slope=1, linetype="dashed", color="red") +
  labs(title="ROC Curve - SVM",
       x="False Positive Rate", y="True Positive Rate") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5, size = 16),
        axis.title = element_text(size = 14),
        axis.text = element_text(size = 12)) +
  annotate("rect", xmin = 0.7, xmax = 1, ymin = 0, ymax = 0.3,
           fill = "white", color = "black", alpha = 0.8) +
  annotate("text", x = 0.85, y = 0.15,
           label = paste("AUC =", round(auc(roc_svm), 3)), size = 5)

```

ROC Curve – SVM



```
#.....[Random Forest].....
library(caret)
library(randomForest)
library(dplyr)
library(ggplot2)

table(train$Attrition)

##
##  No Yes
## 987 190

# Set up training control
train_control <- trainControl(method = "cv", number = 5)

# Train model using caret with method = 'rf'
model_rf <- train(as.factor(Attrition) ~ .,
                    data = hr_balanced,
                    method = "rf",
                    trControl = train_control)

# Get variable importance
importance_rf <- varImp(model_rf)$importance

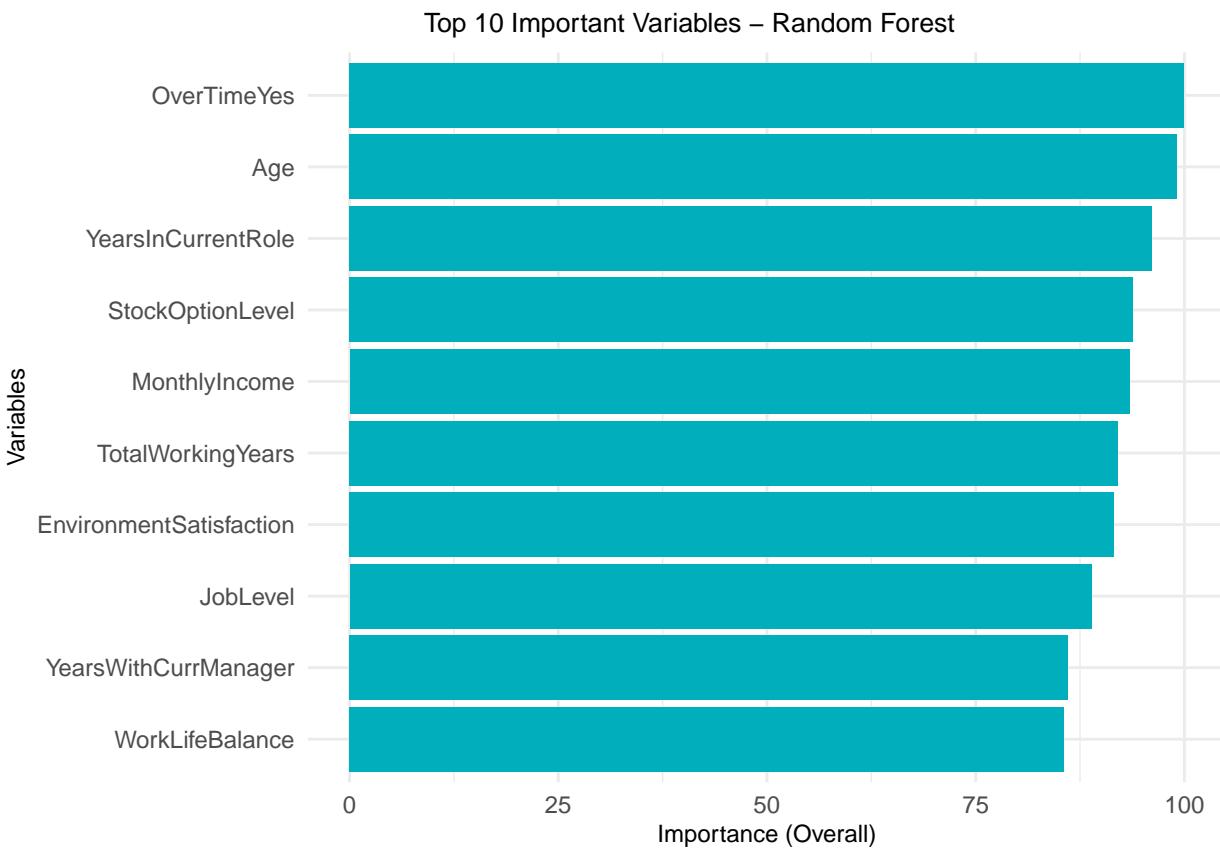
# Convert rownames to a proper column for plotting
importance_rf <- importance_rf %>%
  mutate(Variable = rownames(.)) %>%
  arrange(desc(Overall)) %>%
```

```

top_n(10, Overall) # Optional: top 10 variables

# Plot variable importance
ggplot(importance_rf, aes(x = reorder(Variable, Overall), y = Overall)) +
  geom_col(fill = "#00AFBB") +
  coord_flip() +
  labs(title = "Top 10 Important Variables - Random Forest",
       x = "Variables", y = "Importance (Overall)") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.3, size = 10),
        axis.title = element_text(size = 9),
        axis.text = element_text(size = 9))

```



```

# Predict Probabilities for Random Forest
prob_rf <- predict(model_rf, newdata=test %>% select(-Attrition), type="prob") [,2]
pred_rf <- predict(model_rf, newdata=test %>% select(-Attrition))
conf_rf <- confusionMatrix(as.factor(pred_rf), as.factor(test$Attrition))
conf_rf

```

```

## Confusion Matrix and Statistics
##
##             Reference
## Prediction   No  Yes
##       No    206   25
##       Yes     40   22
##
##             Accuracy : 0.7782

```

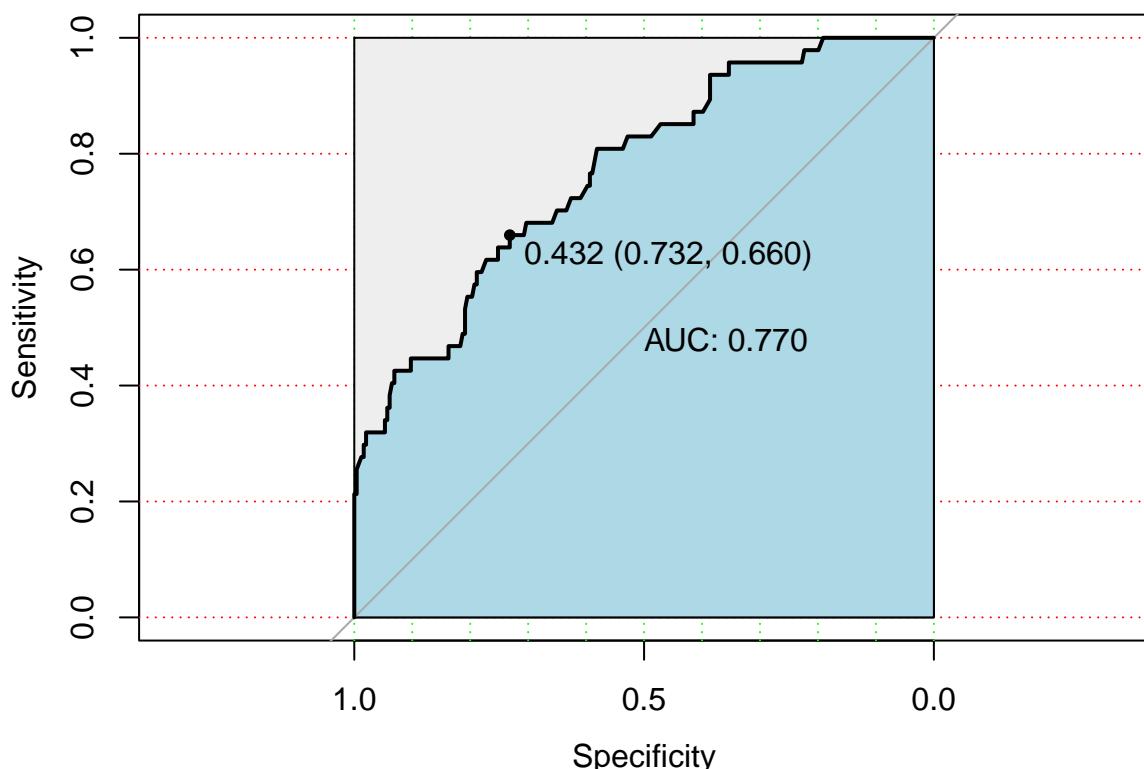
```

##                               95% CI : (0.7262, 0.8244)
##      No Information Rate : 0.8396
##      P-Value [Acc > NIR] : 0.99766
##
##                          Kappa : 0.2706
##
##  Mcnemar's Test P-Value : 0.08248
##
##                          Sensitivity : 0.8374
##                          Specificity : 0.4681
##      Pos Pred Value : 0.8918
##      Neg Pred Value : 0.3548
##                          Prevalence : 0.8396
##                          Detection Rate : 0.7031
##      Detection Prevalence : 0.7884
##      Balanced Accuracy : 0.6527
##
##      'Positive' Class : No
##
# ROC Curve for Random Forest
prob_rf <- predict(model_rf, test, type = "prob")[, 2] # Probability of 'Yes'
roc_rf <- roc(test$Attrition, prob_rf, percent = FALSE)

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
plot.roc(roc_rf,
          print.auc = TRUE,
          auc.polygon = TRUE,
          grid = c(0.1, 0.2),
          grid.col = c("green", "red"),
          max.auc.polygon = TRUE,
          auc.polygon.col = "lightblue",
          print.thres = TRUE,
          main = 'ROC Curve - Random Forest')

```

ROC Curve – Random Forest



```
# ..... [XGBoost] .....
```

```
# Define cross-validation control
cvcontrol <- trainControl(
  method = "repeatedcv",
  number = 5,
  repeats = 1,
  classProbs = TRUE,
  summaryFunction = twoClassSummary,
  search = "random"
)
# Replace invalid characters with underscores and ensure valid factor names
levels(train$Attrition) <- make.names(levels(train$Attrition))

# Perform Randomized Search with fewer hyperparameter combinations
set.seed(123)
model_xgb <- train(as.factor(Attrition) ~.,
  data = hr_balanced,
  method = "xgbTree",
  trControl = cvcontrol,
  tuneLength = 10,
  metric = "ROC"
)

# Print the best model parameters
print(model_xgb$bestTune)
```

```
##   nrounds max_depth      eta    gamma colsample_bytree min_child_weight
```

```

## 3      526      9 0.1742067 3.18181      0.4063891      4
##   subsample
## 3 0.6064874

# Plot the top 15 variable importance
var_imp <- varImp(model_xgb, scale = TRUE)
top_15_vars <- head(var_imp$importance, 15)

# Install or update lime package

library(lime)

## 
## Attaching package: 'lime'

## The following object is masked from 'package:dplyr':
## 
##     explain

library(xgboost)
library(caret)
library(tidyverse)
library(gridExtra)

## 
## Attaching package: 'gridExtra'

## The following object is masked from 'package:randomForest':
## 
##     combine

## The following object is masked from 'package:dplyr':
## 
##     combine

# Create the LIME explainer object
explainer_xgb <- lime::lime(hr_balanced[, -which(names(hr_balanced) == "Attrition")], model_xgb)

# Choose 4 different test samples (or rows from your test dataset)
test_samples <- test[1:2, -which(names(test) == "Attrition")]

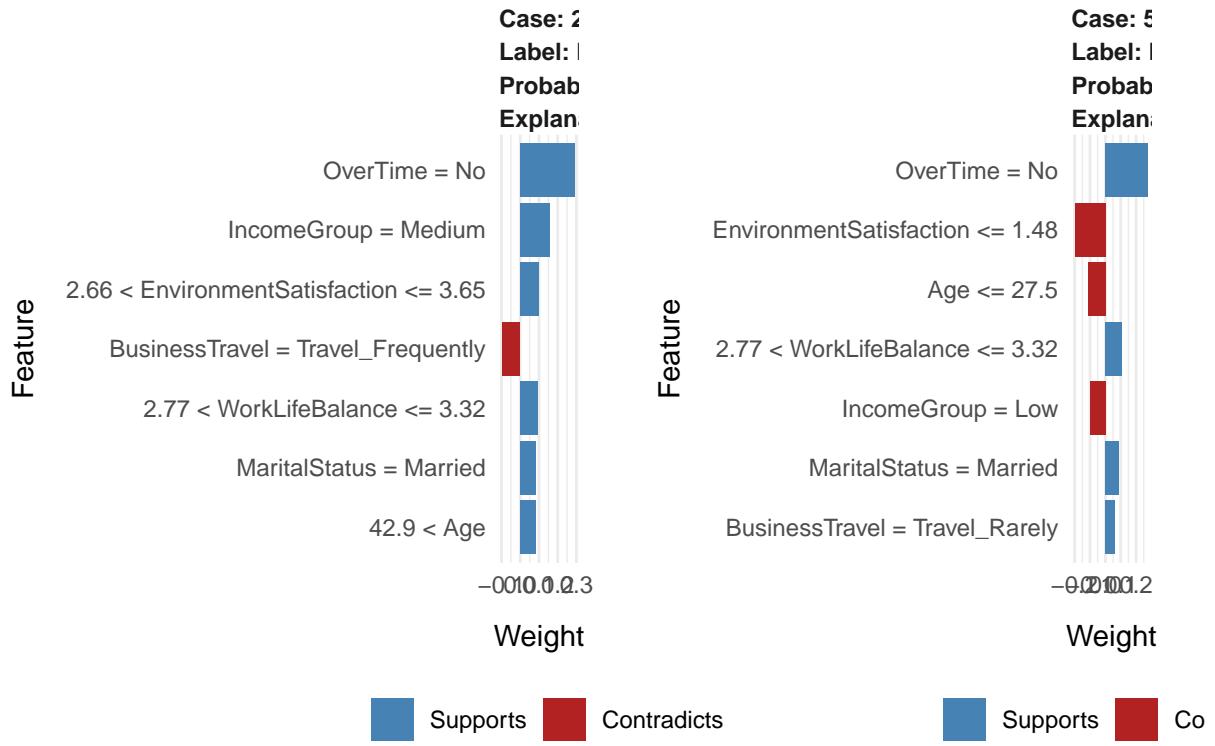
# Create the explanations for each of the 2 test samples
explanations <- lapply(1:2, function(i) {
  lime::explain(test_samples[i, , drop = FALSE], explainer_xgb, n_labels = 1, n_features = 7)
})

# Generate the LIME plots for feature importances
plots <- lapply(explanations, function(explanation) {
  lime::plot_features(explanation) # Make sure this generates the feature importance plot
})

plot1 <- lime::plot_features(explanations[[1]])
plot2 <- lime::plot_features(explanations[[2]])

combined_plots <- plot1 + plot2 + plot_layout(ncol = 2)
print(combined_plots)

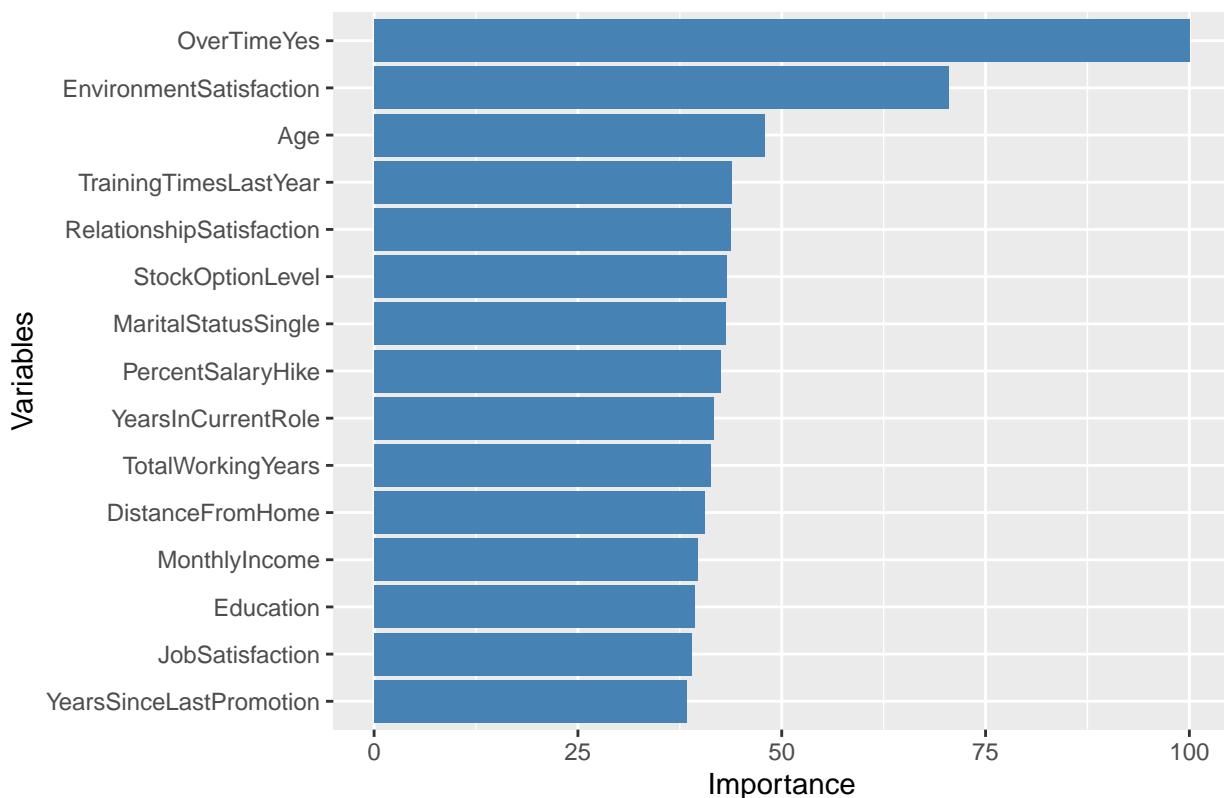
```



```
grid_plots <- wrap_plots(combined_plots, ncol = 1, nrow = 4)
```

```
# Plot variable importance
ggplot(top_15_vars, aes(x = reorder(rownames(top_15_vars), Overall), y = Overall)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  xlab("Variables") +
  ylab("Importance") +
  ggtitle("Top 15 Variable Importance")
```

Top 15 Variable Importance



```

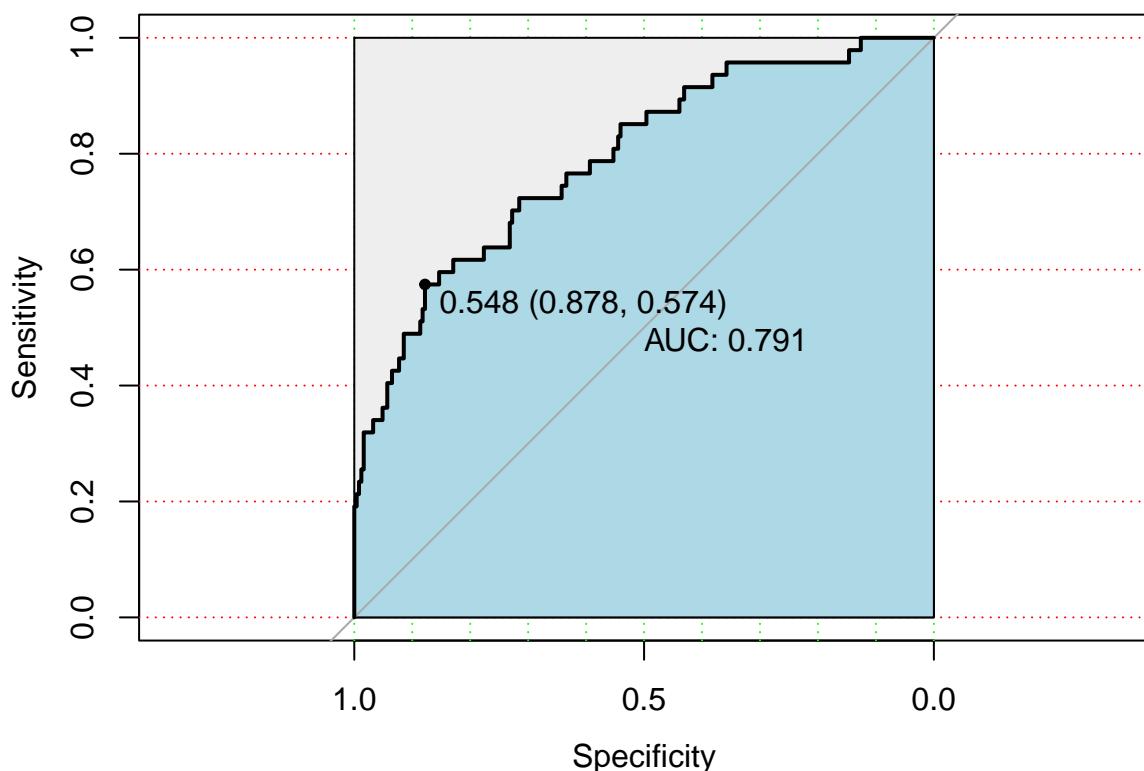
# Get the model predictions
prob_pred <- predict(model_xgb, newdata = test, type = "prob")[,2]

roc_xgb <- roc(test$Attrition, prob_pred, percent = FALSE)

## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
plot.roc(roc_xgb,
          print.auc = TRUE,
          auc.polygon = TRUE,
          grid = c(0.1, 0.2),
          grid.col = c("green", "red"),
          max.auc.polygon = TRUE,
          auc.polygon.col = "lightblue",
          print.thres = TRUE,
          main = 'ROC Curve - XGBoost')

```

ROC Curve – XGBoost



```
# Predict Probabilities for XGB
prob_xgb <- predict(model_xgb, newdata=test, type="prob")[,2]
pred_xgb <- predict(model_xgb, newdata=test )
conf_xgb <- confusionMatrix((pred_xgb), (test$Attrition))
conf_xgb

## Confusion Matrix and Statistics
##
##             Reference
## Prediction  No Yes
##       No    209   19
##       Yes     37   28
##
##                   Accuracy : 0.8089
##                           95% CI : (0.7591, 0.8523)
##   No Information Rate : 0.8396
##   P-Value [Acc > NIR] : 0.9321
##
##                   Kappa : 0.3856
##
##   Mcnemar's Test P-Value : 0.0231
##
##                   Sensitivity : 0.8496
##                   Specificity  : 0.5957
##   Pos Pred Value  : 0.9167
##   Neg Pred Value : 0.4308
##   Prevalence      : 0.8396
##   Detection Rate  : 0.7133
```



```
##                               Model AUC Accuracy Sensitivity Specificity Balanced_Accuracy
## 1      Random Forest 0.770    0.778        0.837     0.468          0.653
## 2 Logistic Regression 0.800   0.771        0.660     0.793          0.726
## 3           XGBoost 0.791   0.809        0.850     0.596          0.723
## 4             SVM 0.800   0.775        0.797     0.660          0.728
## 5      Decision Tree 0.711   0.744        0.764     0.638          0.701
```