

DDSAanalytics

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#DDSAanalytics Talent Management Report: Employee Attrition Analysis Introduction: DDSAnalytics, a leading analytics firm serving Fortune 100 companies, is embarking on a data science initiative to enhance talent management. Talent management encompasses workforce planning, employee development, and reducing attrition. Predicting employee turnover is the first focus area identified by the executive leadership.

This report, prepared by our data science team, analyzes existing employee data (CaseStudy2-data.csv) to identify the top factors contributing to attrition. Our evidence-based findings aim to inform strategies for mitigating attrition risks and improving workforce stability.

```
# Clean the global environment & load libraries
```

```
rm(list = ls())
```

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
```

```
## v dplyr      1.1.2      v readr      2.1.4
```

```
## v forcats    1.0.0      v stringr    1.5.0
```

```
## v ggplot2    3.4.3      v tibble     3.2.1
```

```
## v lubridate  1.9.2      v tidyr      1.3.0
```

```
## 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(dplyr)
```

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.3.2
```

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

```
##
```

```
## Attaching package: 'caret'
```

```
##
```

```
## The following object is masked from 'package:purrr':
```

```
##
```

```
## lift
```

```
library(e1071)
```

```
library(ggplot2)
```

```
library(ROSE)
```

```
## Warning: package 'ROSE' was built under R version 4.3.2
```

```
## Loaded ROSE 0.0-4
```

```
library(car)
```

```
## Warning: package 'car' was built under R version 4.3.2
```

```
## Loading required package: carData
```

```
##
```

```
## Attaching package: 'car'
```

```
##
```

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

```
##
```

```
##      recode
```

```
##
```

```
## The following object is masked from 'package:purrr':
```

```
##
```

```
##      some
```

#Employee Attrition Analysis: Identifying Top Factors and Model Development: Develop a model with one variable. Find the accuracy, specificity, sensitivity, using KNN, Naïve Bayes or Linear Regression.

```
#Data Reading and Initial Exploration
```

```
data <- read.csv("CaseStudy2-data.csv")
```

```
head(data)
```

```
##   ID Age Attrition   BusinessTravel DailyRate      Department
## 1  1  32        No   Travel_Rarely      117           Sales
## 2  2  40        No   Travel_Rarely    1308 Research & Development
## 3  3  35        No Travel_Frequently     200 Research & Development
## 4  4  32        No   Travel_Rarely     801           Sales
## 5  5  24        No Travel_Frequently     567 Research & Development
## 6  6  27        No Travel_Frequently     294 Research & Development
##   DistanceFromHome Education   EducationField EmployeeCount EmployeeNumber
## 1                13         4   Life Sciences             1             859
## 2                14         3       Medical             1            1128
## 3                18         2   Life Sciences             1            1412
## 4                 1         4       Marketing             1            2016
## 5                 2         1 Technical Degree             1            1646
## 6                10         2   Life Sciences             1             733
##   EnvironmentSatisfaction Gender HourlyRate JobInvolvement JobLevel
## 1                      2   Male         73              3         2
## 2                      3   Male         44              2         5
## 3                      3   Male         60              3         3
## 4                      3 Female         48              3         3
## 5                      1 Female         32              3         1
## 6                      4   Male         32              3         3
##   JobRole JobSatisfaction MaritalStatus MonthlyIncome
## 1   Sales Executive         4     Divorced         4403
## 2 Research Director         3       Single        19626
## 3 Manufacturing Director     4       Single         9362
## 4   Sales Executive         4     Married        10422
## 5 Research Scientist         4       Single         3760
```

	MonthlyRate	NumCompaniesWorked	Over18	OverTime	PercentSalaryHike
## 6 Manufacturing Director			1	Divorced	8793
## 1	9250	2	Y	No	11
## 2	17544	1	Y	No	14
## 3	19944	2	Y	No	11
## 4	24032	1	Y	No	19
## 5	17218	1	Y	Yes	13
## 6	4809	1	Y	No	21

	PerformanceRating	RelationshipSatisfaction	StandardHours	StockOptionLevel
## 1	3		3	80
## 2	3		1	80
## 3	3		3	80
## 4	3		3	80
## 5	3		3	80
## 6	4		3	80

	TotalWorkingYears	TrainingTimesLastYear	WorkLifeBalance	YearsAtCompany
## 1	8		3	2
## 2	21		2	4
## 3	10		2	3
## 4	14		3	3
## 5	6		2	3
## 6	9		4	2

	YearsInCurrentRole	YearsSinceLastPromotion	YearsWithCurrManager
## 1	2		0
## 2	7		4
## 3	2		2
## 4	10		5
## 5	3		1
## 6	7		1

```
#View(data)
str(data)
```

```
## 'data.frame': 870 obs. of 36 variables:
## $ ID : int 1 2 3 4 5 6 7 8 9 10 ...
## $ Age : int 32 40 35 32 24 27 41 37 34 34 ...
## $ Attrition : chr "No" "No" "No" "No" ...
## $ BusinessTravel : chr "Travel_Rarely" "Travel_Rarely" "Travel_Frequently" "Travel_Rarely" ...
## $ DailyRate : int 117 1308 200 801 567 294 1283 309 1333 653 ...
## $ Department : chr "Sales" "Research & Development" "Research & Development" "Sales" ...
## $ DistanceFromHome : int 13 14 18 1 2 10 5 10 10 10 ...
## $ Education : int 4 3 2 4 1 2 5 4 4 4 ...
## $ EducationField : chr "Life Sciences" "Medical" "Life Sciences" "Marketing" ...
## $ EmployeeCount : int 1 1 1 1 1 1 1 1 1 1 ...
## $ EmployeeNumber : int 859 1128 1412 2016 1646 733 1448 1105 1055 1597 ...
## $ EnvironmentSatisfaction : int 2 3 3 3 1 4 2 4 3 4 ...
## $ Gender : chr "Male" "Male" "Male" "Female" ...
## $ HourlyRate : int 73 44 60 48 32 32 90 88 87 92 ...
## $ JobInvolvement : int 3 2 3 3 3 3 4 2 3 2 ...
## $ JobLevel : int 2 5 3 3 1 3 1 2 1 2 ...
## $ JobRole : chr "Sales Executive" "Research Director" "Manufacturing Director" "Sales Executive" ...
## $ JobSatisfaction : int 4 3 4 4 4 1 3 4 3 3 ...
## $ MaritalStatus : chr "Divorced" "Single" "Single" "Married" ...
## $ MonthlyIncome : int 4403 19626 9362 10422 3760 8793 2127 6694 2220 5063 ...
```

```
## $ MonthlyRate      : int  9250 17544 19944 24032 17218 4809 5561 24223 18410 15332 ...
## $ NumCompaniesWorked : int  2 1 2 1 1 1 2 2 1 1 ...
## $ Over18           : chr  "Y" "Y" "Y" "Y" ...
## $ OverTime          : chr  "No" "No" "No" "No" ...
## $ PercentSalaryHike  : int  11 14 11 19 13 21 12 14 19 14 ...
## $ PerformanceRating  : int  3 3 3 3 3 4 3 3 3 3 ...
## $ RelationshipSatisfaction: int 3 1 3 3 3 3 1 3 4 2 ...
## $ StandardHours      : int  80 80 80 80 80 80 80 80 80 80 ...
## $ StockOptionLevel   : int  1 0 0 2 0 2 0 3 1 1 ...
## $ TotalWorkingYears  : int  8 21 10 14 6 9 7 8 1 8 ...
## $ TrainingTimesLastYear : int 3 2 2 3 2 4 5 5 2 3 ...
## $ WorkLifeBalance     : int  2 4 3 3 3 2 2 3 3 2 ...
## $ YearsAtCompany      : int  5 20 2 14 6 9 4 1 1 8 ...
## $ YearsInCurrentRole  : int  2 7 2 10 3 7 2 0 1 2 ...
## $ YearsSinceLastPromotion : int 0 4 2 5 1 1 0 0 0 7 ...
## $ YearsWithCurrManager : int  3 9 2 7 3 7 3 0 0 7 ...
```

```
summary(data)
```

```
##      ID      Age      Attrition      BusinessTravel
## Min.   : 1.0   Min.   :18.00   Length:870   Length:870
## 1st Qu.:218.2 1st Qu.:30.00   Class :character Class :character
## Median :435.5 Median :35.00   Mode  :character Mode  :character
## Mean   :435.5 Mean   :36.83
## 3rd Qu.:652.8 3rd Qu.:43.00
## Max.   :870.0 Max.   :60.00
##      DailyRate      Department      DistanceFromHome      Education
## Min.   : 103.0   Length:870   Min.   : 1.000   Min.   :1.000
## 1st Qu.: 472.5   Class :character 1st Qu.: 2.000   1st Qu.:2.000
## Median : 817.5   Mode  :character Median : 7.000   Median :3.000
## Mean   : 815.2   Mean   : 9.339   Mean   :2.901
## 3rd Qu.:1165.8   3rd Qu.:14.000   3rd Qu.:4.000
## Max.   :1499.0   Max.   :29.000   Max.   :5.000
##      EducationField      EmployeeCount      EmployeeNumber      EnvironmentSatisfaction
## Length:870   Min.   :1   Min.   : 1.0   Min.   :1.000
## Class :character 1st Qu.:1   1st Qu.: 477.2 1st Qu.:2.000
## Mode  :character Median :1   Median :1039.0 Median :3.000
## Mean   :1   Mean   :1029.8 Mean   :2.701
## 3rd Qu.:1   3rd Qu.:1561.5 3rd Qu.:4.000
## Max.   :1   Max.   :2064.0 Max.   :4.000
##      Gender      HourlyRate      JobInvolvement      JobLevel
## Length:870   Min.   : 30.00   Min.   :1.000   Min.   :1.000
## Class :character 1st Qu.: 48.00   1st Qu.:2.000   1st Qu.:1.000
## Mode  :character Median : 66.00   Median :3.000   Median :2.000
## Mean   : 65.61   Mean   :2.723   Mean   :2.039
## 3rd Qu.: 83.00   3rd Qu.:3.000   3rd Qu.:3.000
## Max.   :100.00   Max.   :4.000   Max.   :5.000
##      JobRole      JobSatisfaction      MaritalStatus      MonthlyIncome
## Length:870   Min.   :1.000   Length:870   Min.   : 1081
## Class :character 1st Qu.:2.000   Class :character 1st Qu.: 2840
## Mode  :character Median :3.000   Mode  :character Median : 4946
## Mean   :2.709   Mean   : 6390
## 3rd Qu.:4.000   3rd Qu.: 8182
## Max.   :4.000   Max.   :19999
```

```
## MonthlyRate NumCompaniesWorked Over18 OverTime
## Min. : 2094 Min. :0.000 Length:870 Length:870
## 1st Qu.: 8092 1st Qu.:1.000 Class :character Class :character
## Median :14074 Median :2.000 Mode :character Mode :character
## Mean :14326 Mean :2.728
## 3rd Qu.:20456 3rd Qu.:4.000
## Max. :26997 Max. :9.000
## PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours
## Min. :11.0 Min. :3.000 Min. :1.000 Min. :80
## 1st Qu.:12.0 1st Qu.:3.000 1st Qu.:2.000 1st Qu.:80
## Median :14.0 Median :3.000 Median :3.000 Median :80
## Mean :15.2 Mean :3.152 Mean :2.707 Mean :80
## 3rd Qu.:18.0 3rd Qu.:3.000 3rd Qu.:4.000 3rd Qu.:80
## Max. :25.0 Max. :4.000 Max. :4.000 Max. :80
## StockOptionLevel TotalWorkingYears TrainingTimesLastYear WorkLifeBalance
## Min. :0.0000 Min. : 0.00 Min. :0.000 Min. :1.000
## 1st Qu.:0.0000 1st Qu.: 6.00 1st Qu.:2.000 1st Qu.:2.000
## Median :1.0000 Median :10.00 Median :3.000 Median :3.000
## Mean :0.7839 Mean :11.05 Mean :2.832 Mean :2.782
## 3rd Qu.:1.0000 3rd Qu.:15.00 3rd Qu.:3.000 3rd Qu.:3.000
## Max. :3.0000 Max. :40.00 Max. :6.000 Max. :4.000
## YearsAtCompany YearsInCurrentRole YearsSinceLastPromotion
## Min. : 0.000 Min. : 0.000 Min. : 0.000
## 1st Qu.: 3.000 1st Qu.: 2.000 1st Qu.: 0.000
## Median : 5.000 Median : 3.000 Median : 1.000
## Mean : 6.962 Mean : 4.205 Mean : 2.169
## 3rd Qu.:10.000 3rd Qu.: 7.000 3rd Qu.: 3.000
## Max. :40.000 Max. :18.000 Max. :15.000
## YearsWithCurrManager
## Min. : 0.00
## 1st Qu.: 2.00
## Median : 3.00
## Mean : 4.14
## 3rd Qu.: 7.00
## Max. :17.00
```

```
sapply(data, class)
```

```
## ID Age Attrition
## "integer" "integer" "character"
## BusinessTravel DailyRate Department
## "character" "integer" "character"
## DistanceFromHome Education EducationField
## "integer" "integer" "character"
## EmployeeCount EmployeeNumber EnvironmentSatisfaction
## "integer" "integer" "integer"
## Gender HourlyRate JobInvolvement
## "character" "integer" "integer"
## JobLevel JobRole JobSatisfaction
## "integer" "character" "integer"
## MaritalStatus MonthlyIncome MonthlyRate
## "character" "integer" "integer"
## NumCompaniesWorked Over18 OverTime
## "integer" "character" "character"
```

```
##      PercentSalaryHike      PerformanceRating RelationshipSatisfaction
##      "integer"            "integer"            "integer"
##      StandardHours        StockOptionLevel      TotalWorkingYears
##      "integer"            "integer"            "integer"
##      TrainingTimesLastYear WorkLifeBalance      YearsAtCompany
##      "integer"            "integer"            "integer"
##      YearsInCurrentRole    YearsSinceLastPromotion YearsWithCurrManager
##      "integer"            "integer"            "integer"
```

```
colSums(is.na(data))
```

```
##      ID      Age      Attrition
##      0      0      0
##      BusinessTravel      DailyRate      Department
##      0      0      0
##      DistanceFromHome      Education      EducationField
##      0      0      0
##      EmployeeCount      EmployeeNumber      EnvironmentSatisfaction
##      0      0      0
##      Gender      HourlyRate      JobInvolvement
##      0      0      0
##      JobLevel      JobRole      JobSatisfaction
##      0      0      0
##      MaritalStatus      MonthlyIncome      MonthlyRate
##      0      0      0
##      NumCompaniesWorked      Over18      OverTime
##      0      0      0
##      PercentSalaryHike      PerformanceRating RelationshipSatisfaction
##      0      0      0
##      StandardHours      StockOptionLevel      TotalWorkingYears
##      0      0      0
##      TrainingTimesLastYear      WorkLifeBalance      YearsAtCompany
##      0      0      0
##      YearsInCurrentRole    YearsSinceLastPromotion YearsWithCurrManager
##      0      0      0
```

```
# Data Preprocessing
# Converting Attrition to a factor
data$Attrition <- factor(data$Attrition, levels = c("No", "Yes"))
str(data$Attrition)
```

```
## Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
```

```
# Identify continuous and categorical variables
continuous_vars <- c("Age", "DailyRate", "DistanceFromHome", "Education", "HourlyRate", "MonthlyIncome")

# Convert categorical variables to factors
categorical_vars <- c("BusinessTravel", "Department", "EducationField", "Gender", "JobInvolvement", "JobRole")

data[categorical_vars] <- lapply(data[categorical_vars], factor)

str(data[categorical_vars])
```

```
## 'data.frame': 870 obs. of 12 variables:
## $ BusinessTravel : Factor w/ 3 levels "Non-Travel","Travel_Frequently",...: 3 3 2 3 2 2 3 3 ...
## $ Department : Factor w/ 3 levels "Human Resources",...: 3 2 2 3 2 2 2 3 3 2 ...
## $ EducationField : Factor w/ 6 levels "Human Resources",...: 2 4 2 3 6 2 4 2 2 6 ...
## $ Gender : Factor w/ 2 levels "Female","Male": 2 2 2 1 1 2 2 1 1 2 ...
## $ JobInvolvement : Factor w/ 4 levels "1","2","3","4": 3 2 3 3 3 3 4 2 3 2 ...
## $ JobLevel : Factor w/ 5 levels "1","2","3","4",...: 2 5 3 3 1 3 1 2 1 2 ...
## $ JobRole : Factor w/ 9 levels "Healthcare Representative",...: 8 6 5 8 7 5 7 8 9 1 ...
## $ JobSatisfaction : Factor w/ 4 levels "1","2","3","4": 4 3 4 4 4 1 3 4 3 3 ...
## $ MaritalStatus : Factor w/ 3 levels "Divorced","Married",...: 1 3 3 2 3 1 2 1 2 2 ...
## $ OverTime : Factor w/ 2 levels "No","Yes": 1 1 1 1 2 1 2 2 2 1 ...
## $ WorkLifeBalance : Factor w/ 4 levels "1","2","3","4": 2 4 3 3 3 2 2 3 3 2 ...
## $ YearsSinceLastPromotion: Factor w/ 16 levels "0","1","2","3",...: 1 5 3 6 2 2 1 1 1 8 ...
```

```
# Final structure check
str(data)
```

```
## 'data.frame': 870 obs. of 36 variables:
## $ ID : int 1 2 3 4 5 6 7 8 9 10 ...
## $ Age : int 32 40 35 32 24 27 41 37 34 34 ...
## $ Attrition : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
## $ BusinessTravel : Factor w/ 3 levels "Non-Travel","Travel_Frequently",...: 3 3 2 3 2 2 2 3 3 ...
## $ DailyRate : int 117 1308 200 801 567 294 1283 309 1333 653 ...
## $ Department : Factor w/ 3 levels "Human Resources",...: 3 2 2 3 2 2 2 3 3 2 ...
## $ DistanceFromHome : int 13 14 18 1 2 10 5 10 10 10 ...
## $ Education : int 4 3 2 4 1 2 5 4 4 4 ...
## $ EducationField : Factor w/ 6 levels "Human Resources",...: 2 4 2 3 6 2 4 2 2 6 ...
## $ EmployeeCount : int 1 1 1 1 1 1 1 1 1 1 ...
## $ EmployeeNumber : int 859 1128 1412 2016 1646 733 1448 1105 1055 1597 ...
## $ EnvironmentSatisfaction : int 2 3 3 3 1 4 2 4 3 4 ...
## $ Gender : Factor w/ 2 levels "Female","Male": 2 2 2 1 1 2 2 1 1 2 ...
## $ HourlyRate : int 73 44 60 48 32 32 90 88 87 92 ...
## $ JobInvolvement : Factor w/ 4 levels "1","2","3","4": 3 2 3 3 3 3 4 2 3 2 ...
## $ JobLevel : Factor w/ 5 levels "1","2","3","4",...: 2 5 3 3 1 3 1 2 1 2 ...
## $ JobRole : Factor w/ 9 levels "Healthcare Representative",...: 8 6 5 8 7 5 7 8 9 1 ...
## $ JobSatisfaction : Factor w/ 4 levels "1","2","3","4": 4 3 4 4 4 1 3 4 3 3 ...
## $ MaritalStatus : Factor w/ 3 levels "Divorced","Married",...: 1 3 3 2 3 1 2 1 2 2 ...
## $ MonthlyIncome : int 4403 19626 9362 10422 3760 8793 2127 6694 2220 5063 ...
## $ MonthlyRate : int 9250 17544 19944 24032 17218 4809 5561 24223 18410 15332 ...
## $ NumCompaniesWorked : int 2 1 2 1 1 1 2 2 1 1 ...
## $ Over18 : chr "Y" "Y" "Y" "Y" ...
## $ OverTime : Factor w/ 2 levels "No","Yes": 1 1 1 1 2 1 2 2 2 1 ...
## $ PercentSalaryHike : int 11 14 11 19 13 21 12 14 19 14 ...
## $ PerformanceRating : int 3 3 3 3 3 4 3 3 3 3 ...
## $ RelationshipSatisfaction: int 3 1 3 3 3 3 1 3 4 2 ...
## $ StandardHours : int 80 80 80 80 80 80 80 80 80 80 ...
## $ StockOptionLevel : int 1 0 0 2 0 2 0 3 1 1 ...
## $ TotalWorkingYears : int 8 21 10 14 6 9 7 8 1 8 ...
## $ TrainingTimesLastYear : int 3 2 2 3 2 4 5 5 2 3 ...
## $ WorkLifeBalance : Factor w/ 4 levels "1","2","3","4": 2 4 3 3 3 2 2 3 3 2 ...
## $ YearsAtCompany : int 5 20 2 14 6 9 4 1 1 8 ...
## $ YearsInCurrentRole : int 2 7 2 10 3 7 2 0 1 2 ...
## $ YearsSinceLastPromotion : Factor w/ 16 levels "0","1","2","3",...: 1 5 3 6 2 2 1 1 1 8 ...
## $ YearsWithCurrManager : int 3 9 2 7 3 7 3 0 0 7 ...
```

```
summary(data)
```

```
##           ID           Age      Attrition      BusinessTravel
##  Min.      : 1.0    Min.      :18.00    No :730    Non-Travel      : 94
##  1st Qu.:218.2    1st Qu.:30.00    Yes:140    Travel_Frequently:158
##  Median :435.5    Median :35.00                      Travel_Rarely      :618
##  Mean   :435.5    Mean   :36.83
##  3rd Qu.:652.8    3rd Qu.:43.00
##  Max.   :870.0    Max.   :60.00
##
##      DailyRate           Department DistanceFromHome Education
##  Min.      : 103.0    Human Resources      : 35    Min.      : 1.000    Min.      :1.000
##  1st Qu.: 472.5    Research & Development:562    1st Qu.: 2.000    1st Qu.:2.000
##  Median : 817.5    Sales                  :273    Median : 7.000    Median :3.000
##  Mean   : 815.2                      Mean   : 9.339    Mean   :2.901
##  3rd Qu.:1165.8                      3rd Qu.:14.000    3rd Qu.:4.000
##  Max.   :1499.0                      Max.   :29.000    Max.   :5.000
##
##      EducationField EmployeeCount EmployeeNumber EnvironmentSatisfaction
##  Human Resources : 15    Min.      :1    Min.      : 1.0    Min.      :1.000
##  Life Sciences   :358    1st Qu.:1    1st Qu.: 477.2    1st Qu.:2.000
##  Marketing        :100    Median :1    Median :1039.0    Median :3.000
##  Medical          :270    Mean   :1    Mean   :1029.8    Mean   :2.701
##  Other            : 52    3rd Qu.:1    3rd Qu.:1561.5    3rd Qu.:4.000
##  Technical Degree: 75    Max.   :1    Max.   :2064.0    Max.   :4.000
##
##      Gender      HourlyRate      JobInvolvement JobLevel
##  Female:354    Min.      : 30.00    1: 47      1:329
##  Male :516    1st Qu.: 48.00    2:228      2:312
##                      Median : 66.00    3:514      3:132
##                      Mean   : 65.61    4: 81      4: 60
##                      3rd Qu.: 83.00    5: 37
##                      Max.   :100.00
##
##      JobRole      JobSatisfaction MaritalStatus MonthlyIncome
##  Sales Executive      :200    1:179      Divorced:191    Min.      : 1081
##  Research Scientist    :172    2:166      Married :410    1st Qu.: 2840
##  Laboratory Technician :153    3:254      Single  :269    Median : 4946
##  Manufacturing Director : 87    4:271                      Mean   : 6390
##  Healthcare Representative: 76                      3rd Qu.: 8182
##  Sales Representative   : 53                      Max.   :19999
##  (Other)                :129
##  MonthlyRate NumCompaniesWorked Over18      OverTime
##  Min.      : 2094    Min.      :0.000    Length:870    No :618
##  1st Qu.: 8092    1st Qu.:1.000    Class :character Yes:252
##  Median :14074    Median :2.000    Mode  :character
##  Mean   :14326    Mean   :2.728
##  3rd Qu.:20456    3rd Qu.:4.000
##  Max.   :26997    Max.   :9.000
##
##  PercentSalaryHike PerformanceRating RelationshipSatisfaction StandardHours
##  Min.      :11.0    Min.      :3.000    Min.      :1.000    Min.      :80
##  1st Qu.:12.0    1st Qu.:3.000    1st Qu.:2.000    1st Qu.:80
```

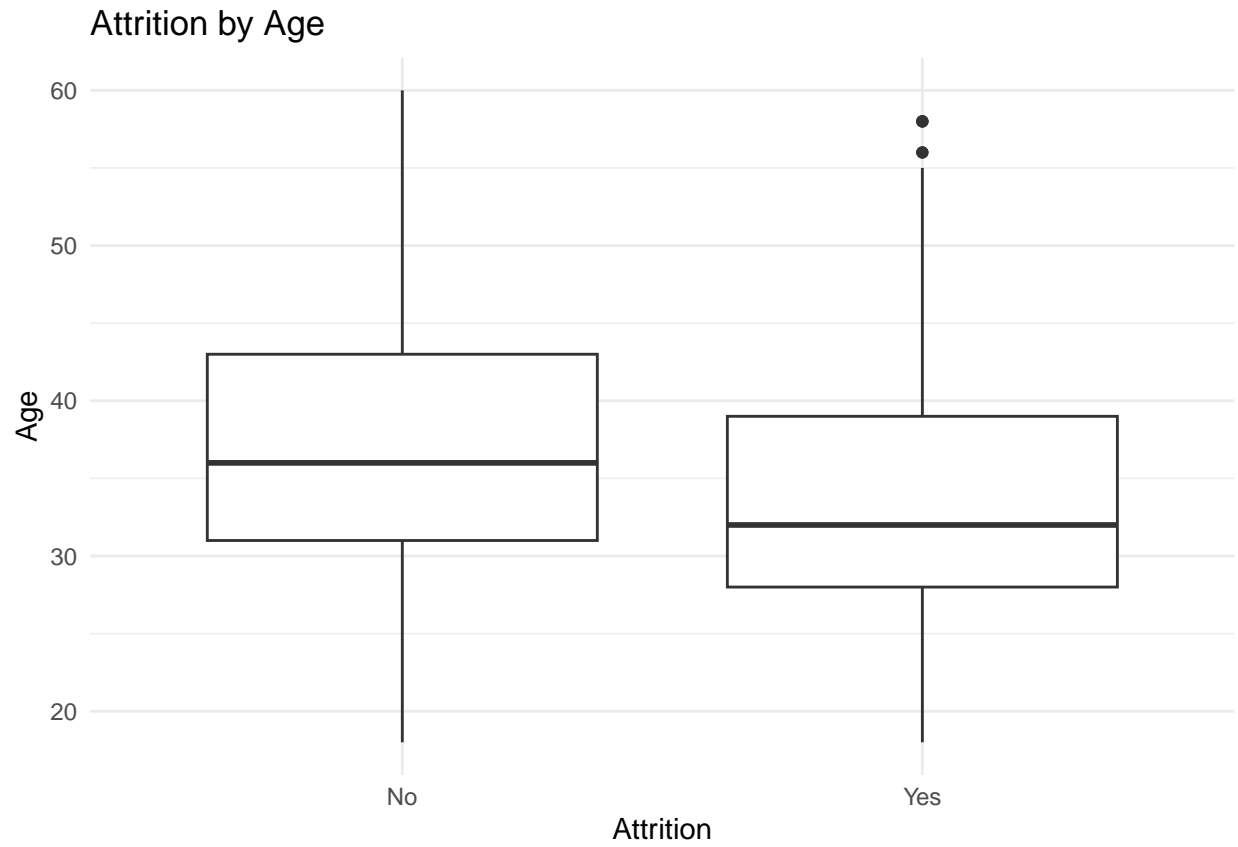


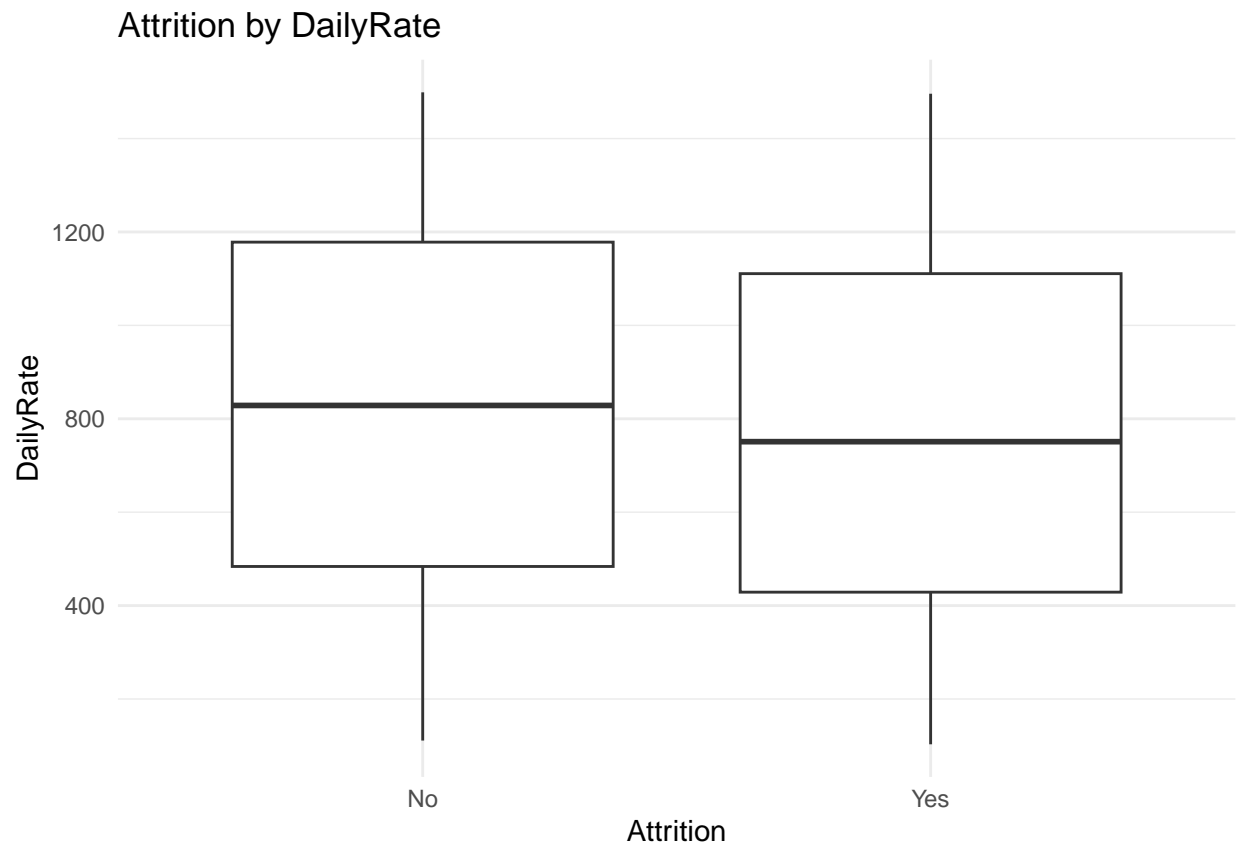
```
## Median :14.0      Median :3.000      Median :3.000      Median :80
## Mean    :15.2      Mean    :3.152      Mean    :2.707      Mean    :80
## 3rd Qu.:18.0      3rd Qu.:3.000      3rd Qu.:4.000      3rd Qu.:80
## Max.    :25.0      Max.    :4.000      Max.    :4.000      Max.    :80
##
## StockOptionLevel TotalWorkingYears TrainingTimesLastYear WorkLifeBalance
## Min.      :0.0000   Min.      : 0.00   Min.      :0.000    1: 48
## 1st Qu.:0.0000   1st Qu.: 6.00   1st Qu.:2.000    2:192
## Median :1.0000   Median :10.00   Median :3.000    3:532
## Mean    :0.7839   Mean    :11.05   Mean    :2.832    4: 98
## 3rd Qu.:1.0000   3rd Qu.:15.00   3rd Qu.:3.000
## Max.    :3.0000   Max.    :40.00   Max.    :6.000
##
## YearsAtCompany   YearsInCurrentRole YearsSinceLastPromotion
## Min.      : 0.000   Min.      : 0.000    0      :342
## 1st Qu.: 3.000   1st Qu.: 2.000    1      :214
## Median : 5.000   Median : 3.000    2       : 94
## Mean    : 6.962   Mean    : 4.205    7       : 41
## 3rd Qu.:10.000   3rd Qu.: 7.000    3       : 32
## Max.    :40.000   Max.    :18.000    4       : 32
##                                     (Other):115
## YearsWithCurrManager
## Min.      : 0.00
## 1st Qu.: 2.00
## Median : 3.00
## Mean    : 4.14
## 3rd Qu.: 7.00
## Max.    :17.00
##
```

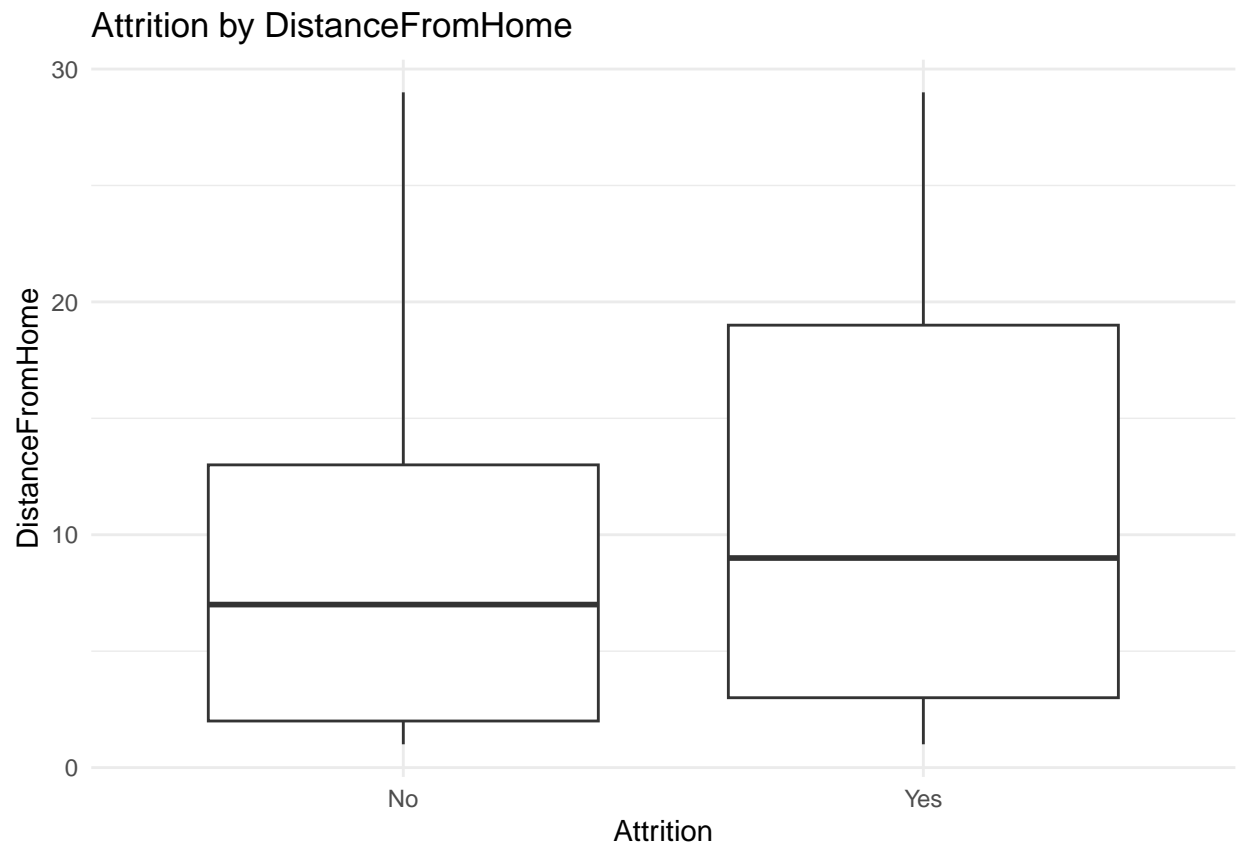
#DATA VIZ

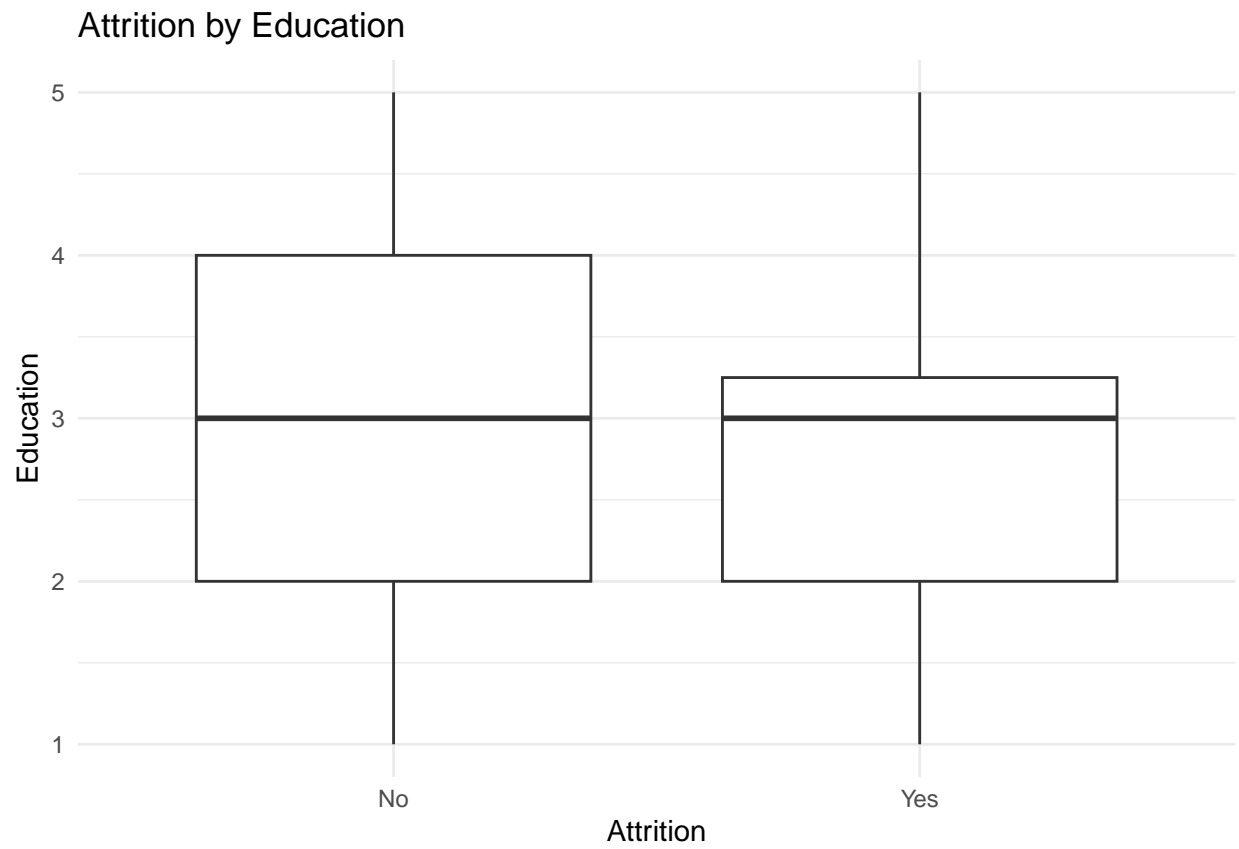
```
# Create box plots for continuous variables
for (var in continuous_vars) {
  p <- ggplot(data, aes_string(x = "Attrition", y = var)) +
    geom_boxplot() +
    labs(title = paste("Attrition by", var), y = var, x = "Attrition") +
    theme_minimal()
  print(p)
}
```

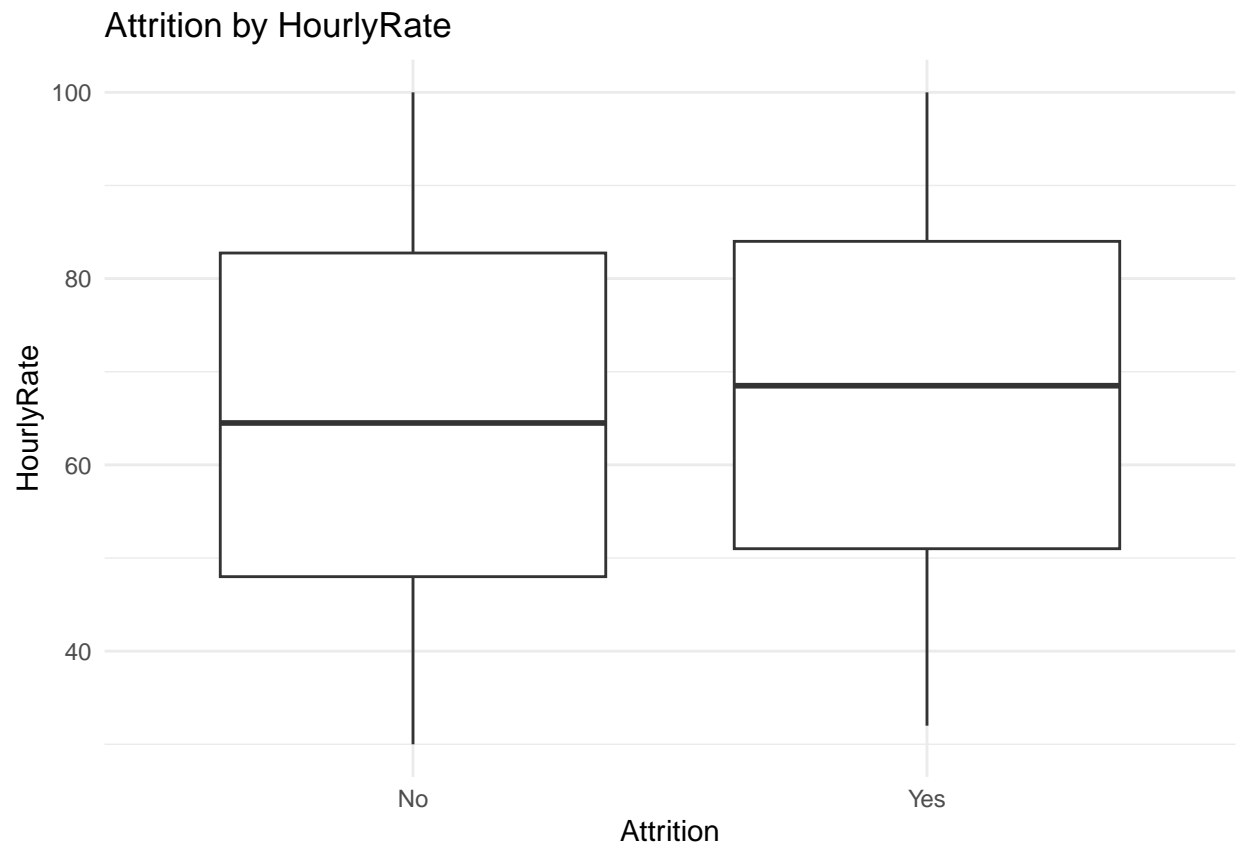
```
## Warning: 'aes_string()' was deprecated in ggplot2 3.0.0.
## i Please use tidy evaluation idioms with 'aes()'.
## i See also 'vignette("ggplot2-in-packages")' for more information.
## This warning is displayed once every 8 hours.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.
```

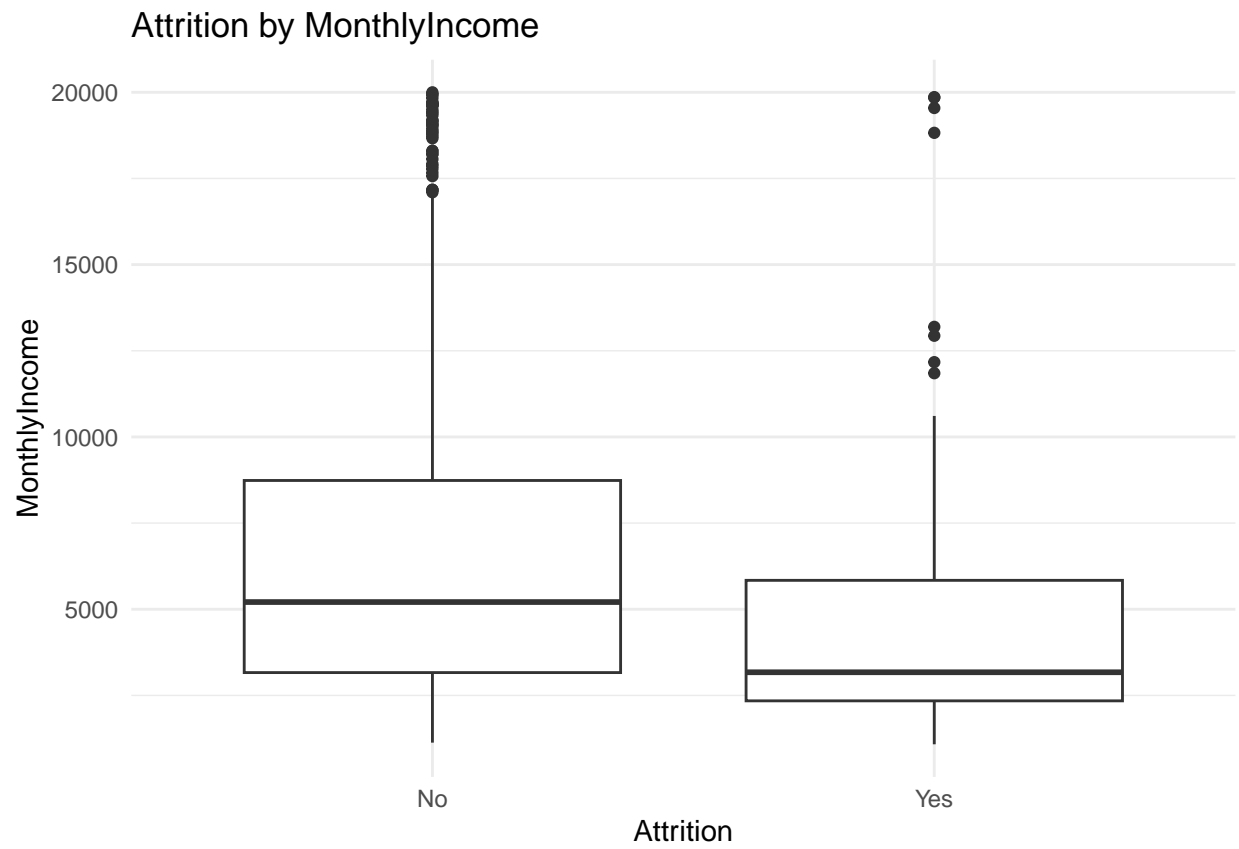


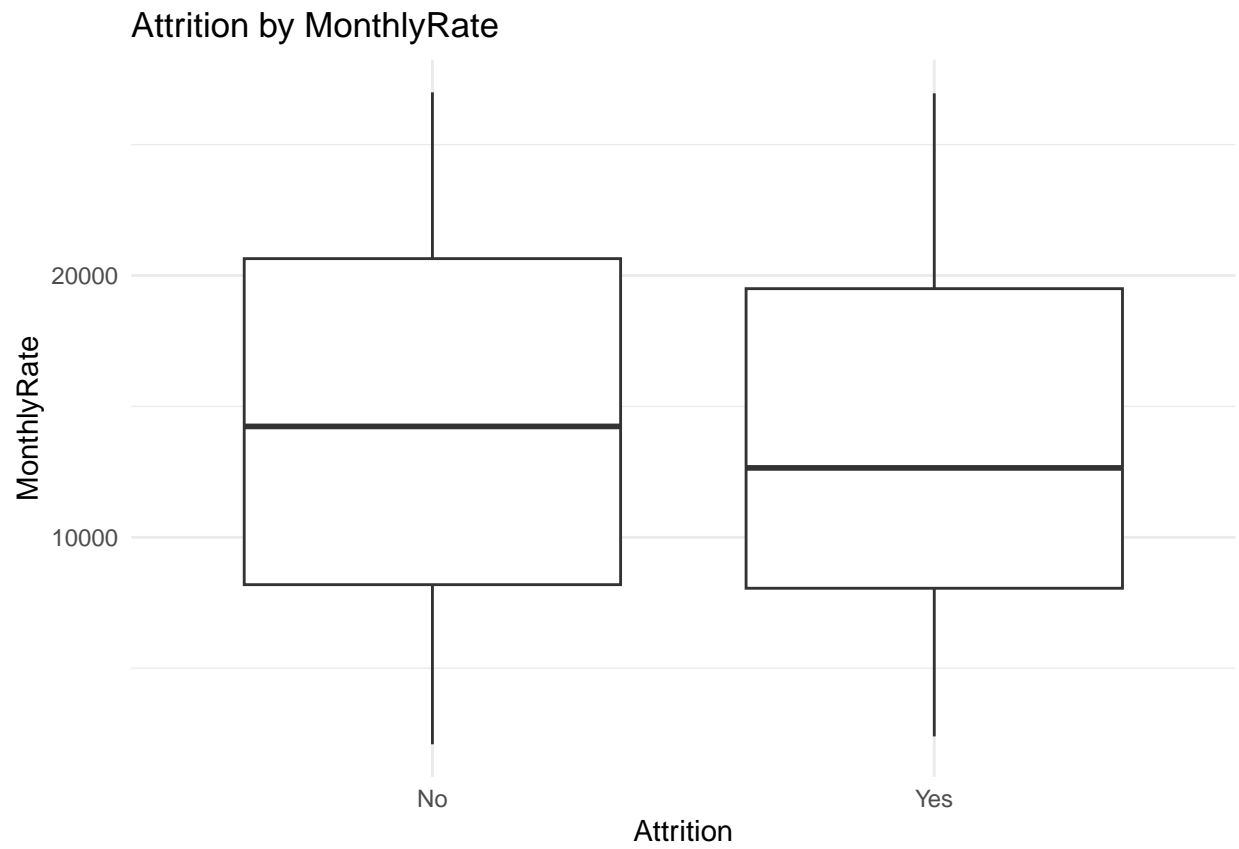


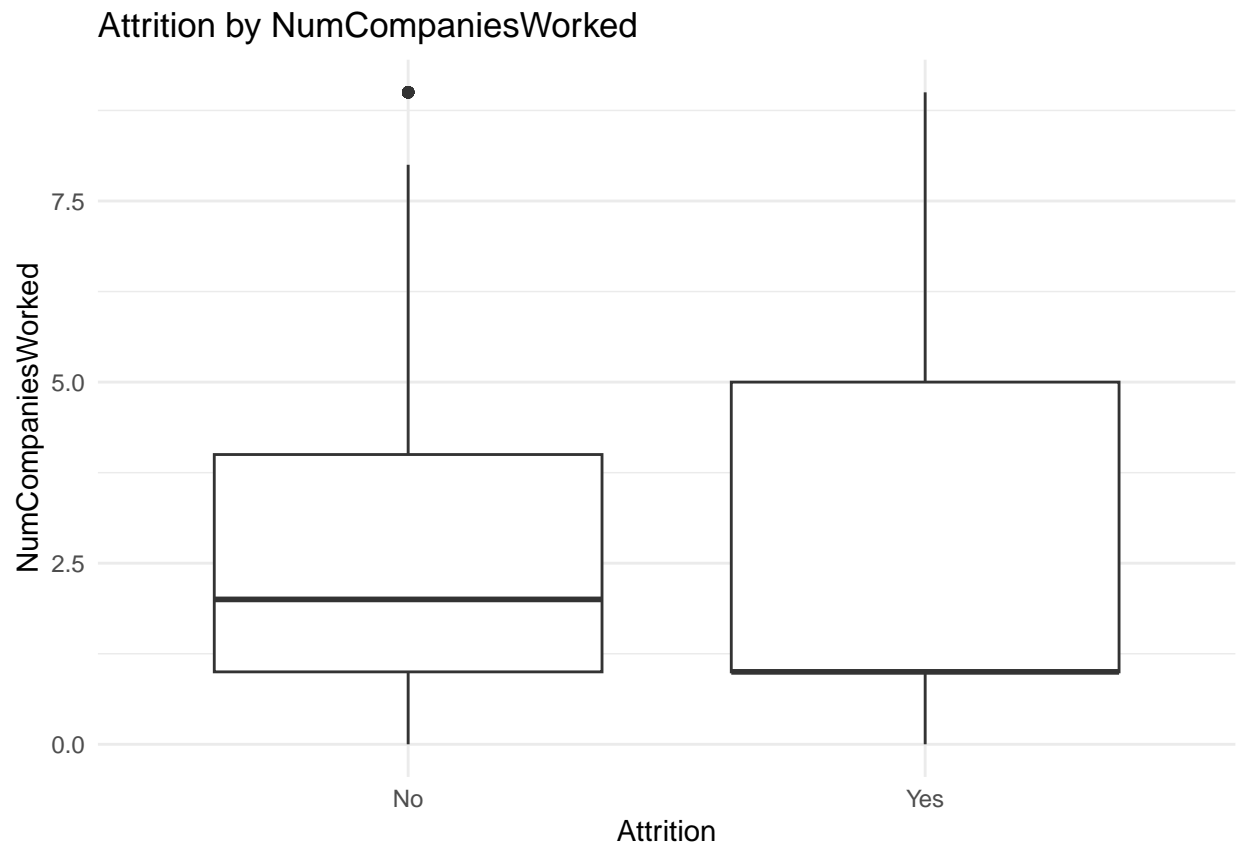


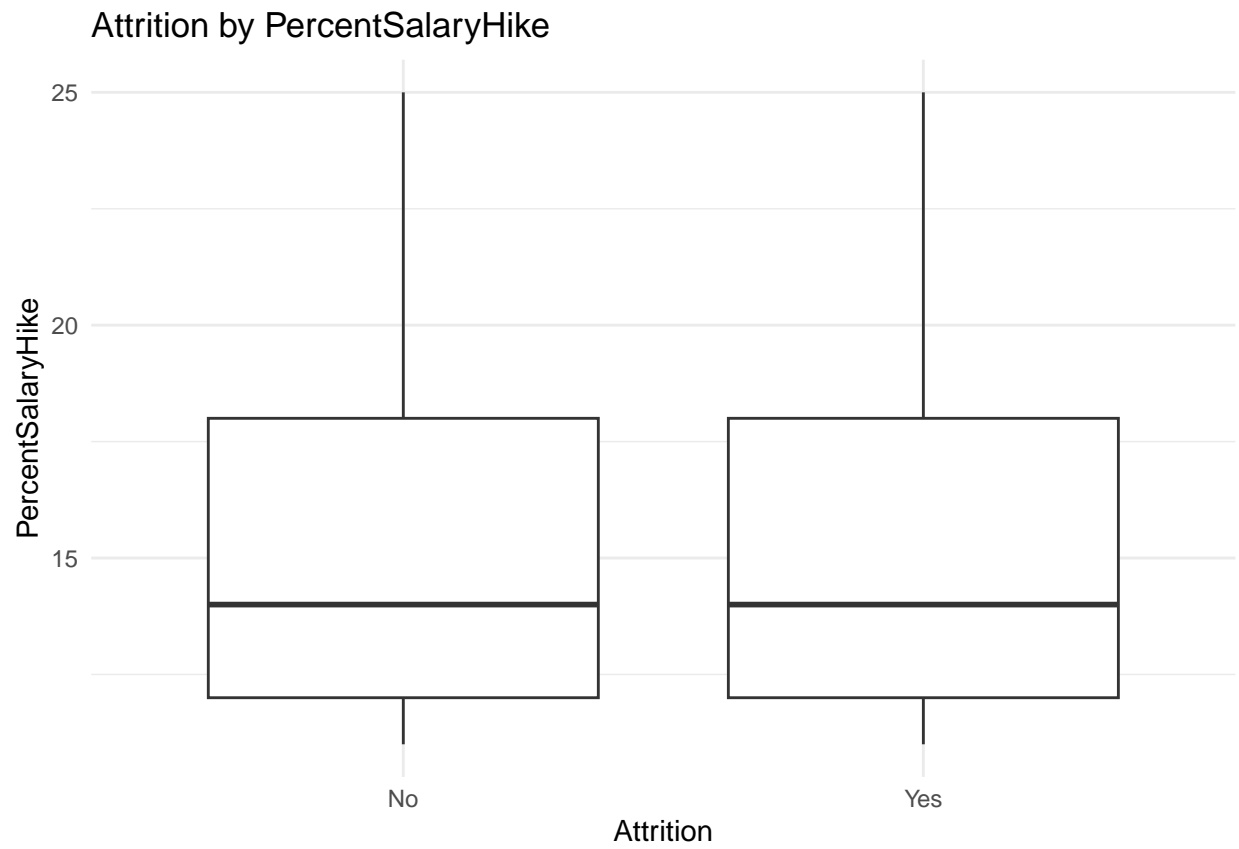


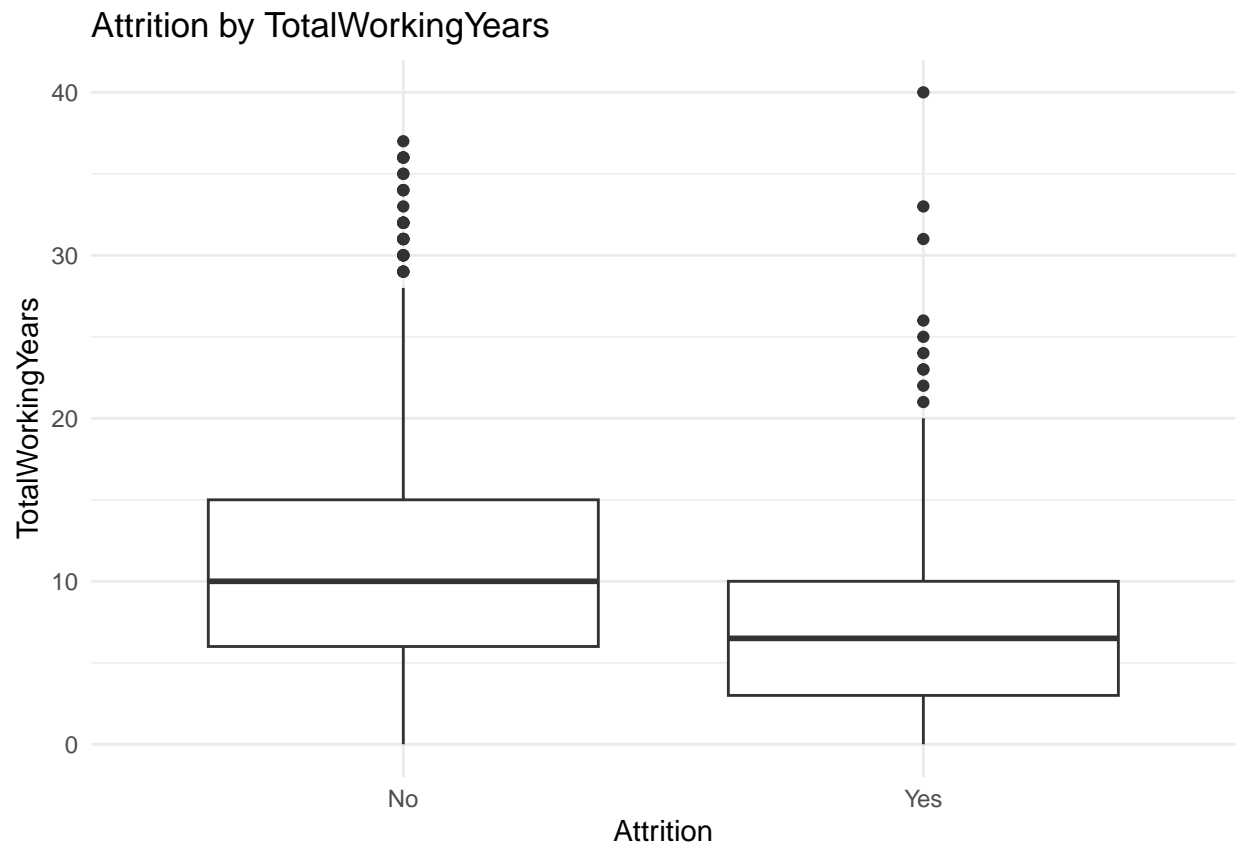


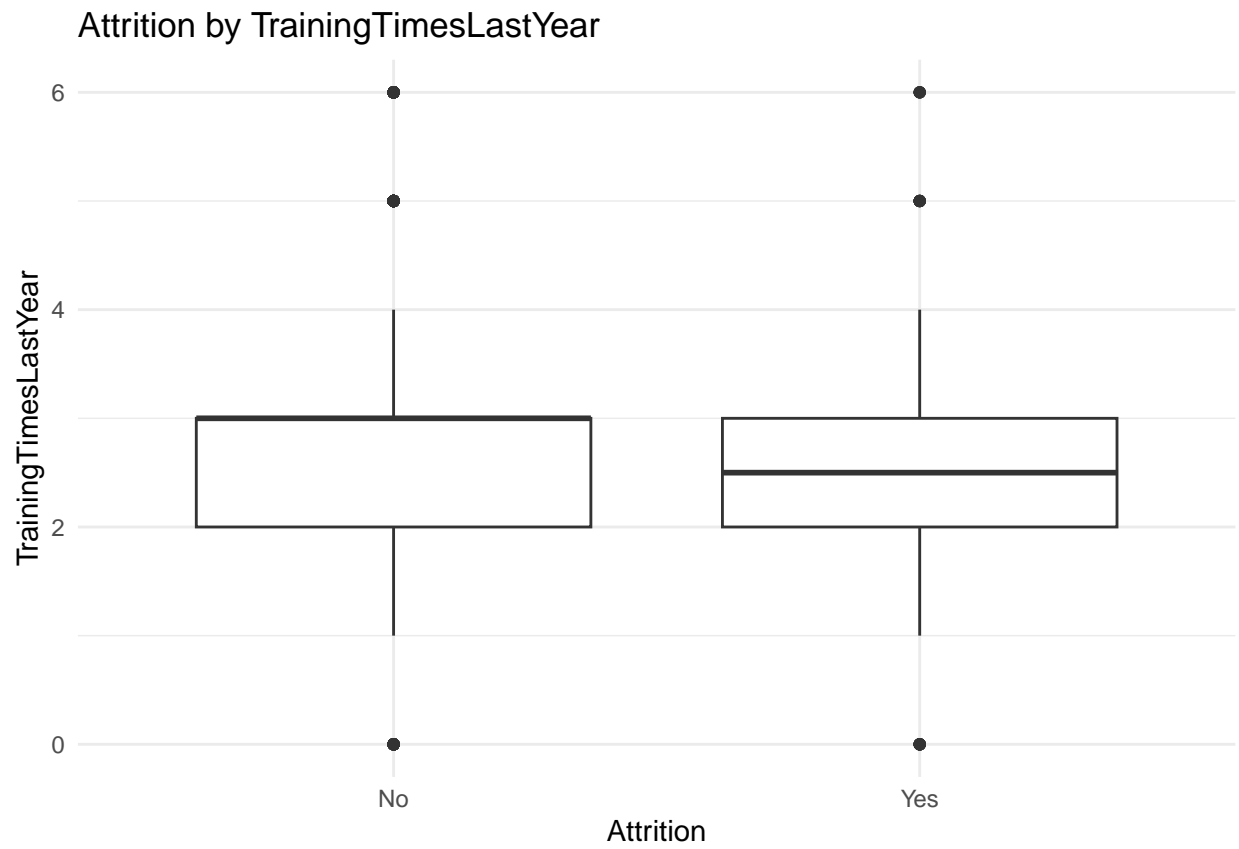


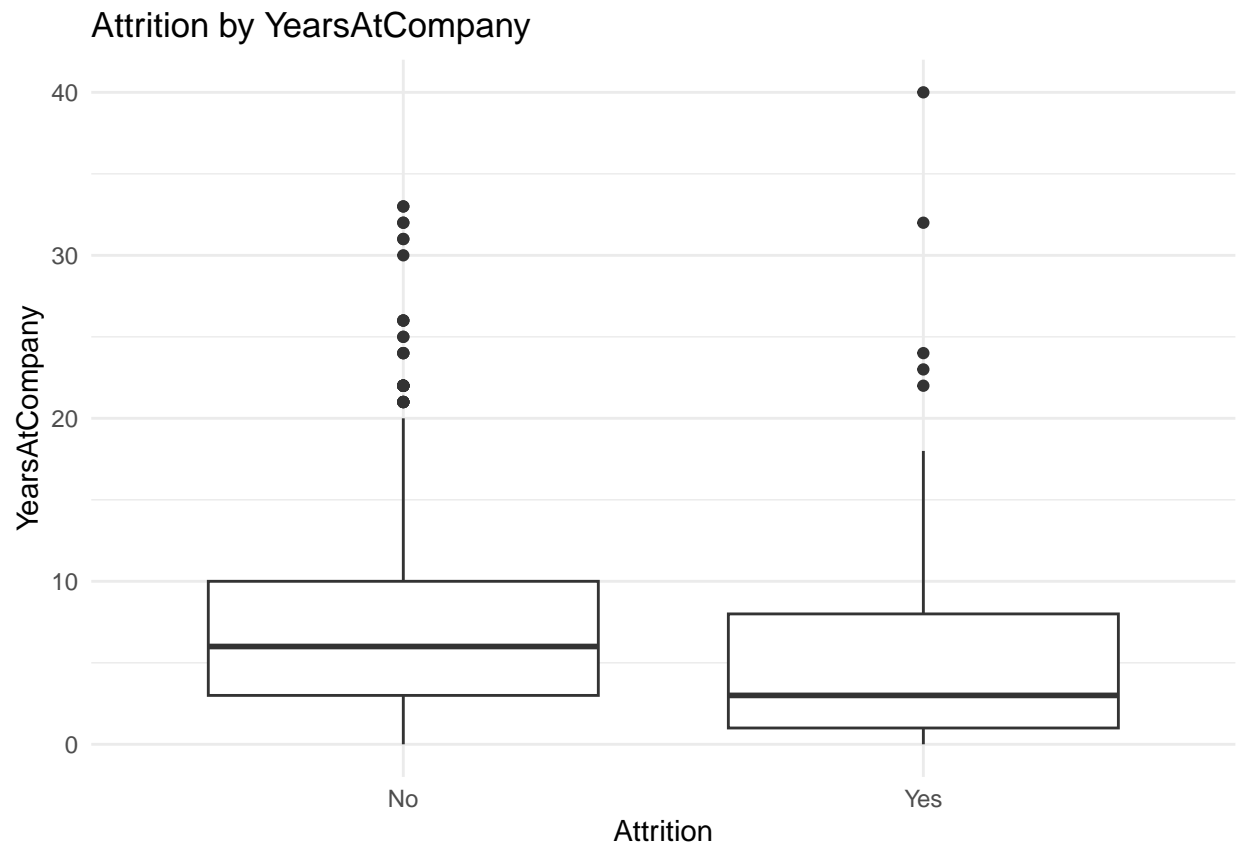


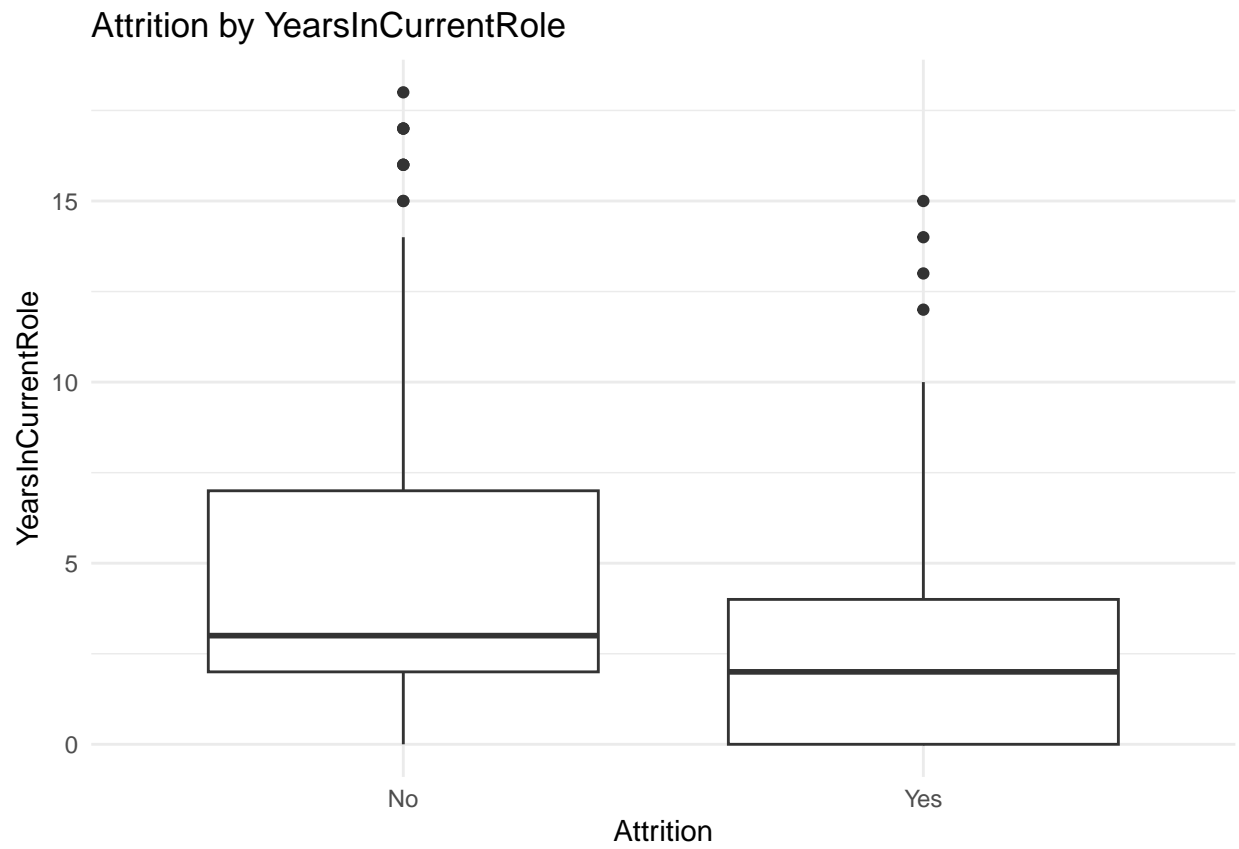


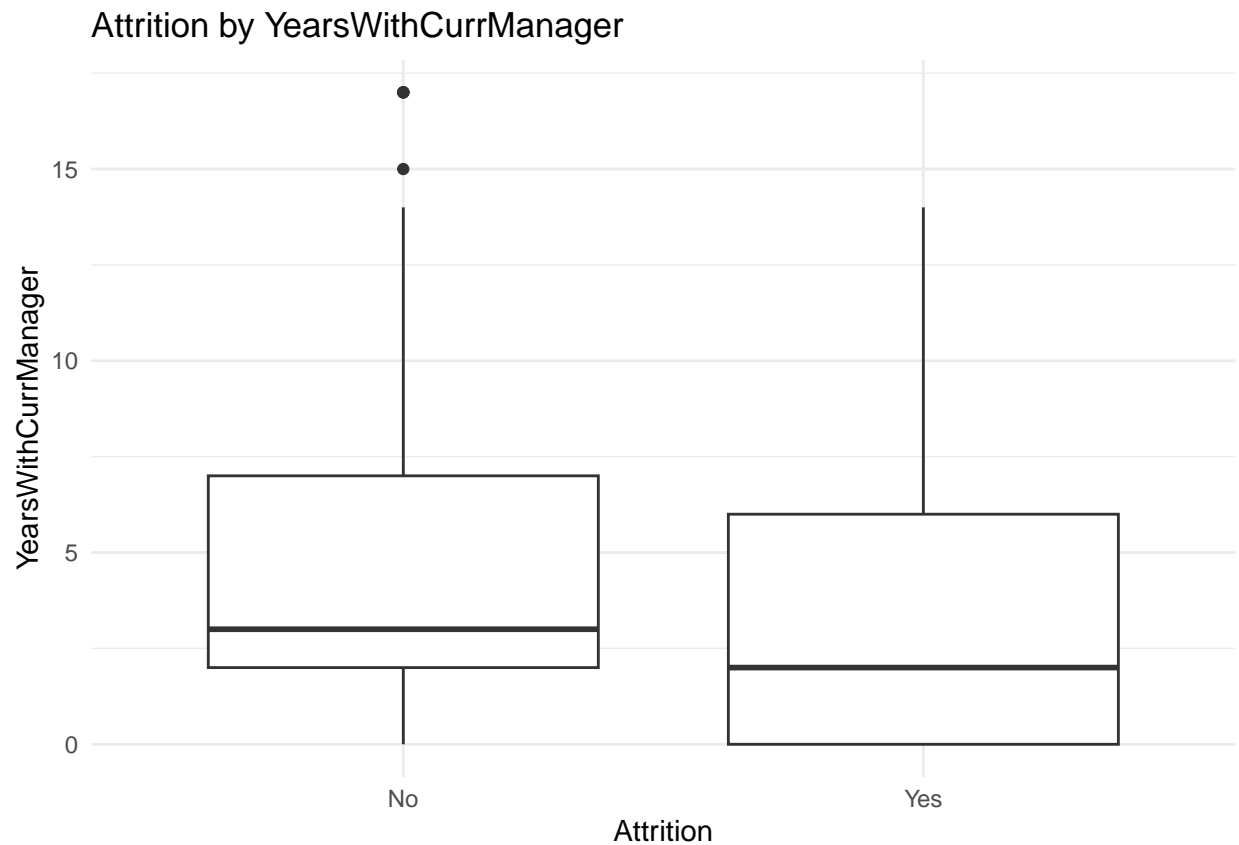




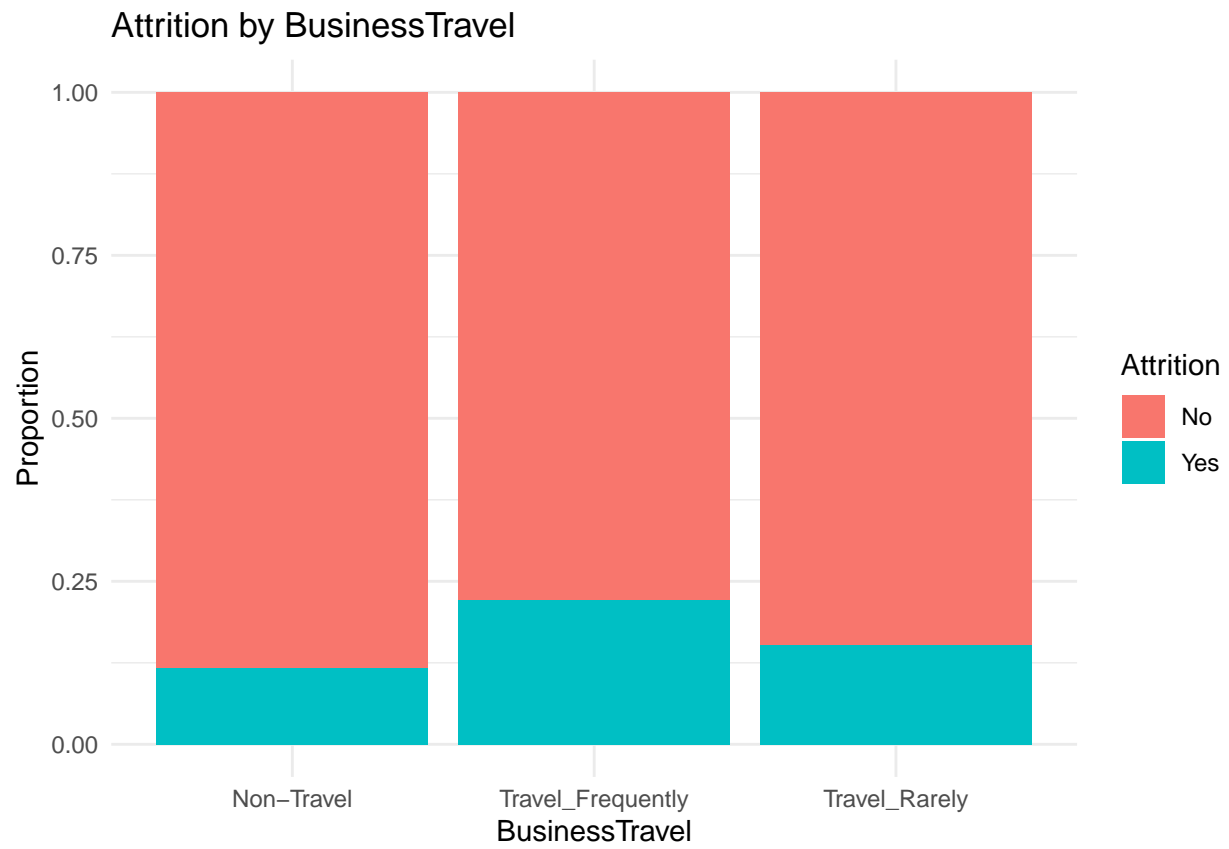


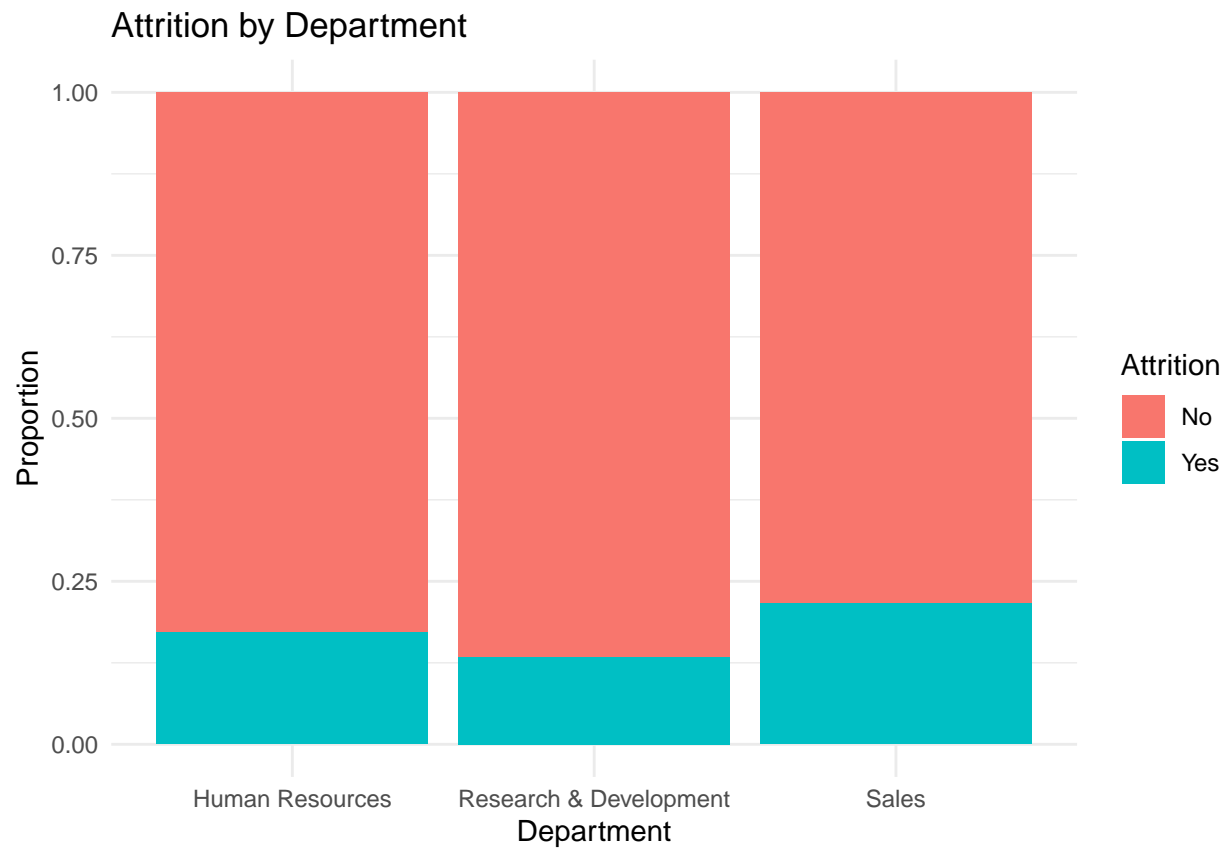


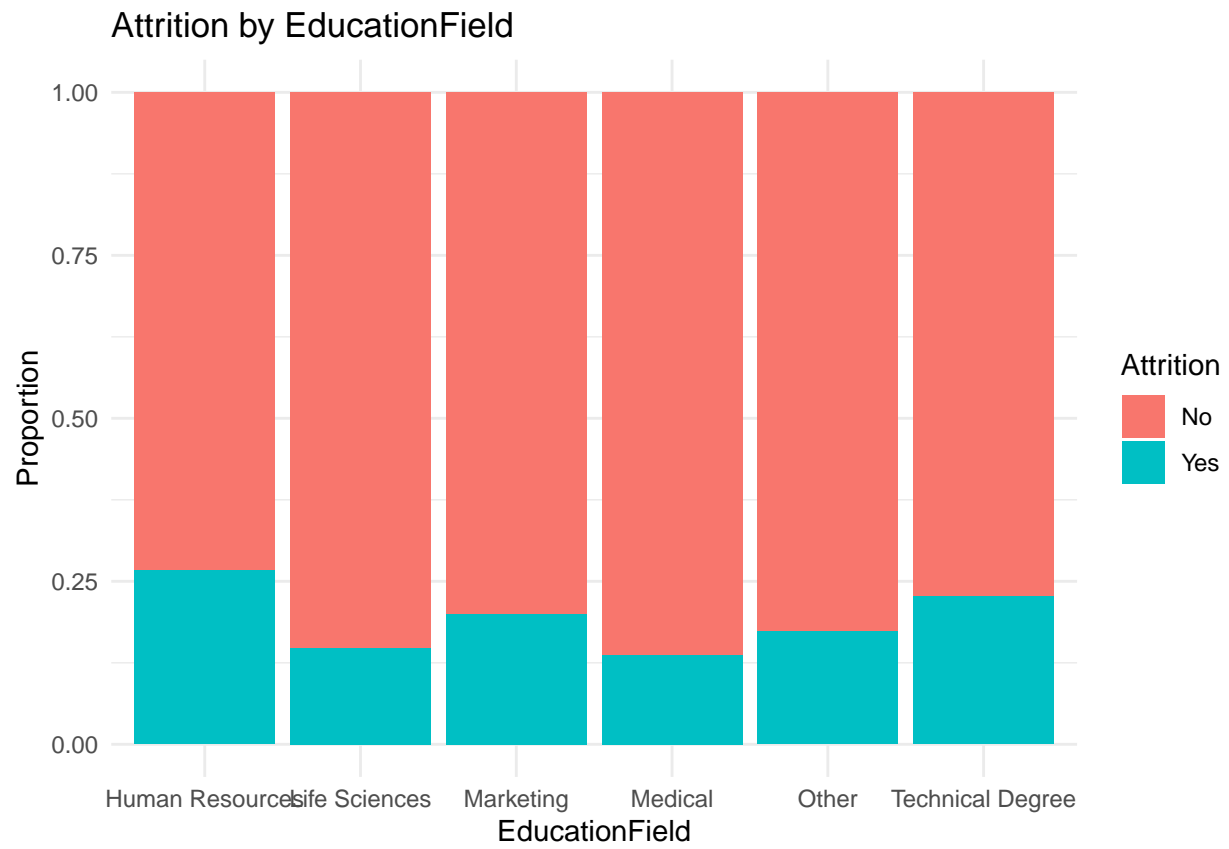


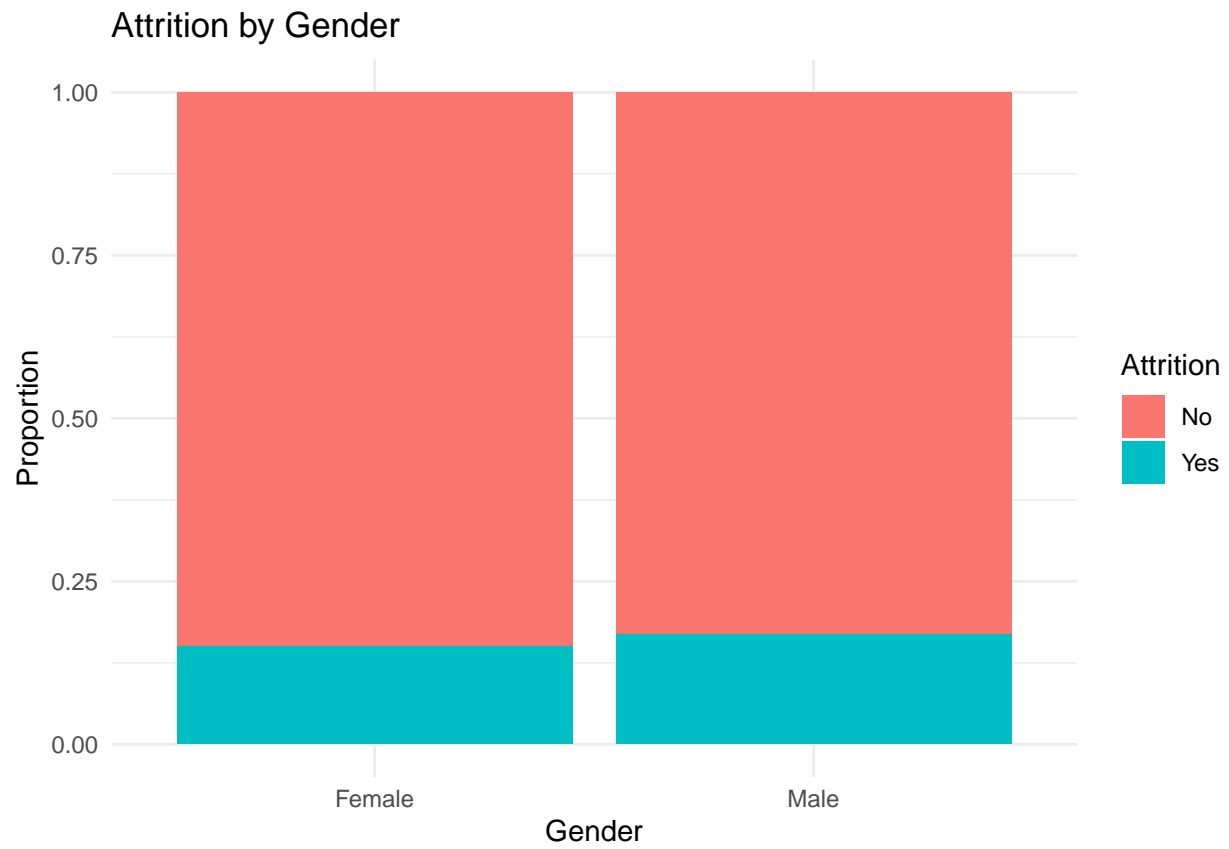


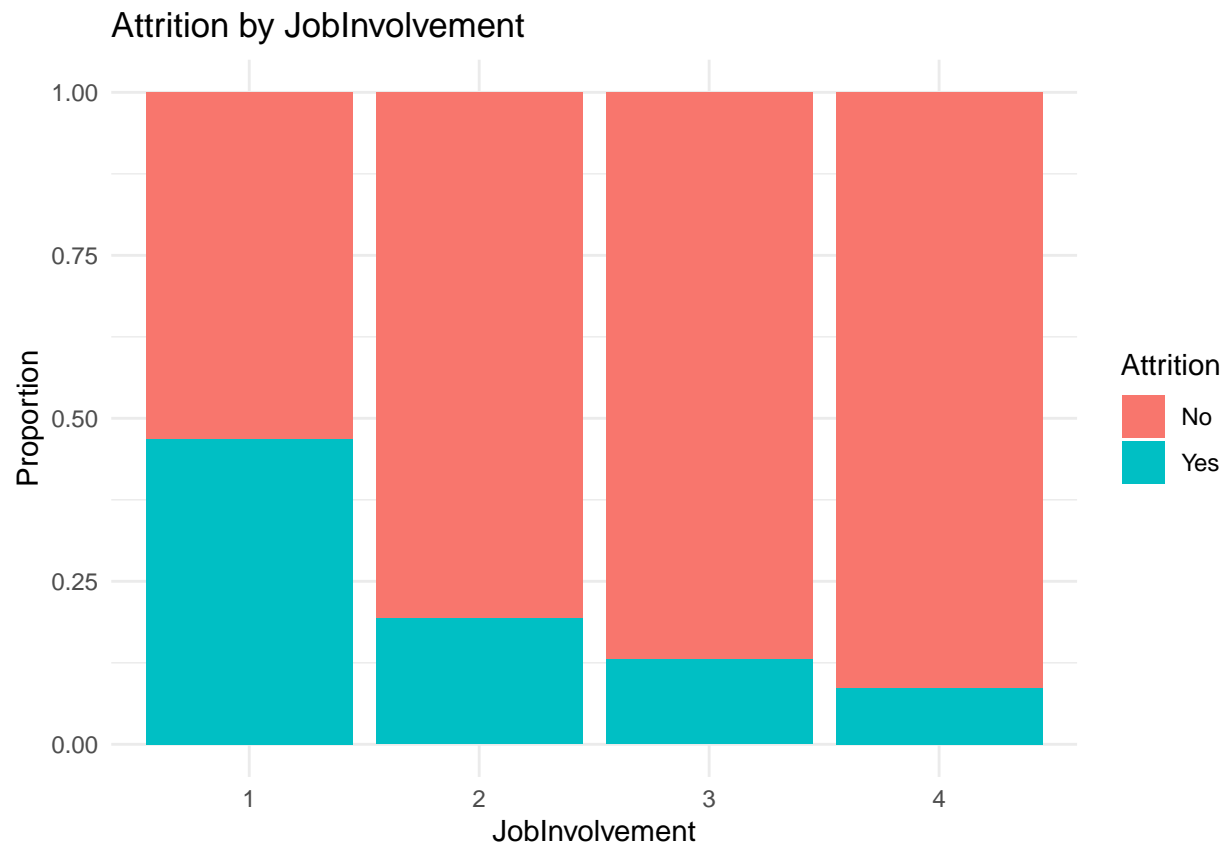
```
# Create bar plots for categorical variables
for (var in categorical_vars) {
  p <- ggplot(data, aes_string(x = var, fill = "Attrition")) +
    geom_bar(position = "fill") +
    labs(title = paste("Attrition by", var), y = "Proportion", x = var) +
    theme_minimal()
  print(p)
}
```

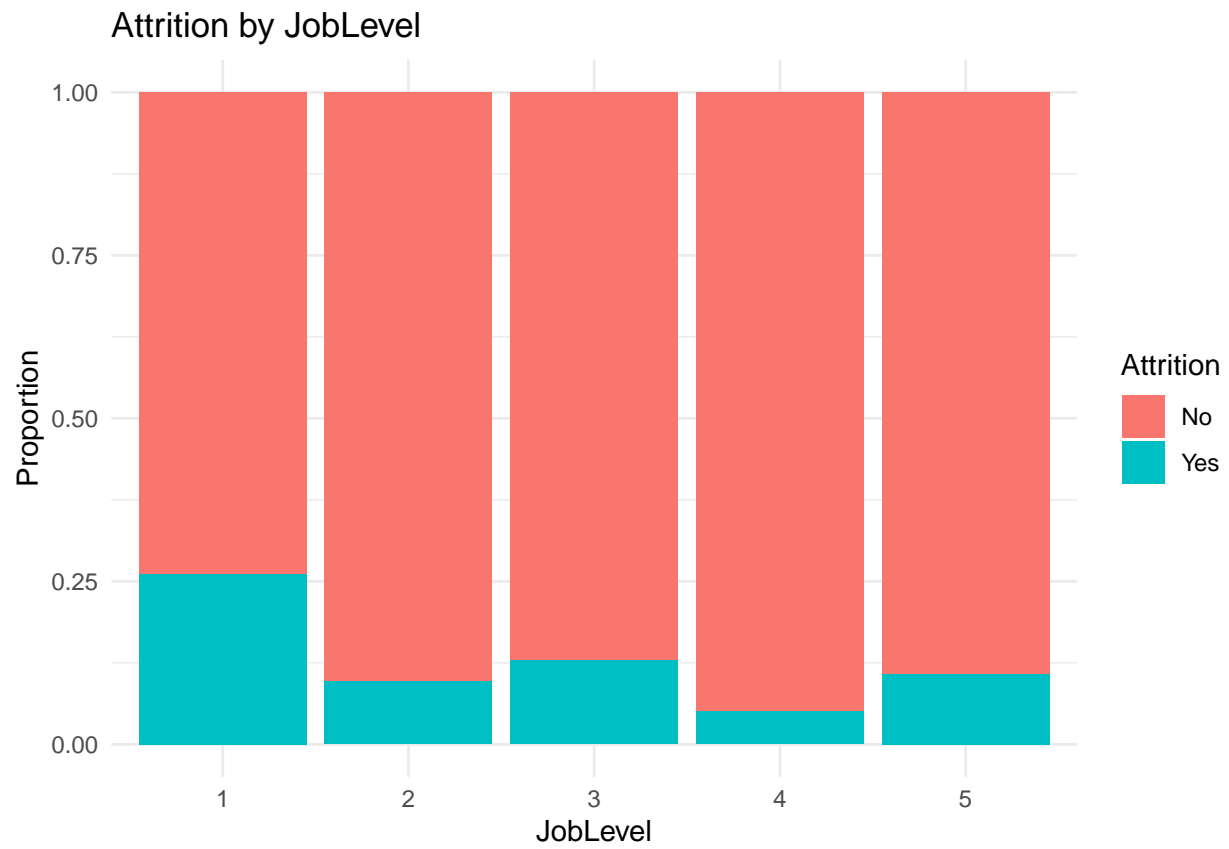


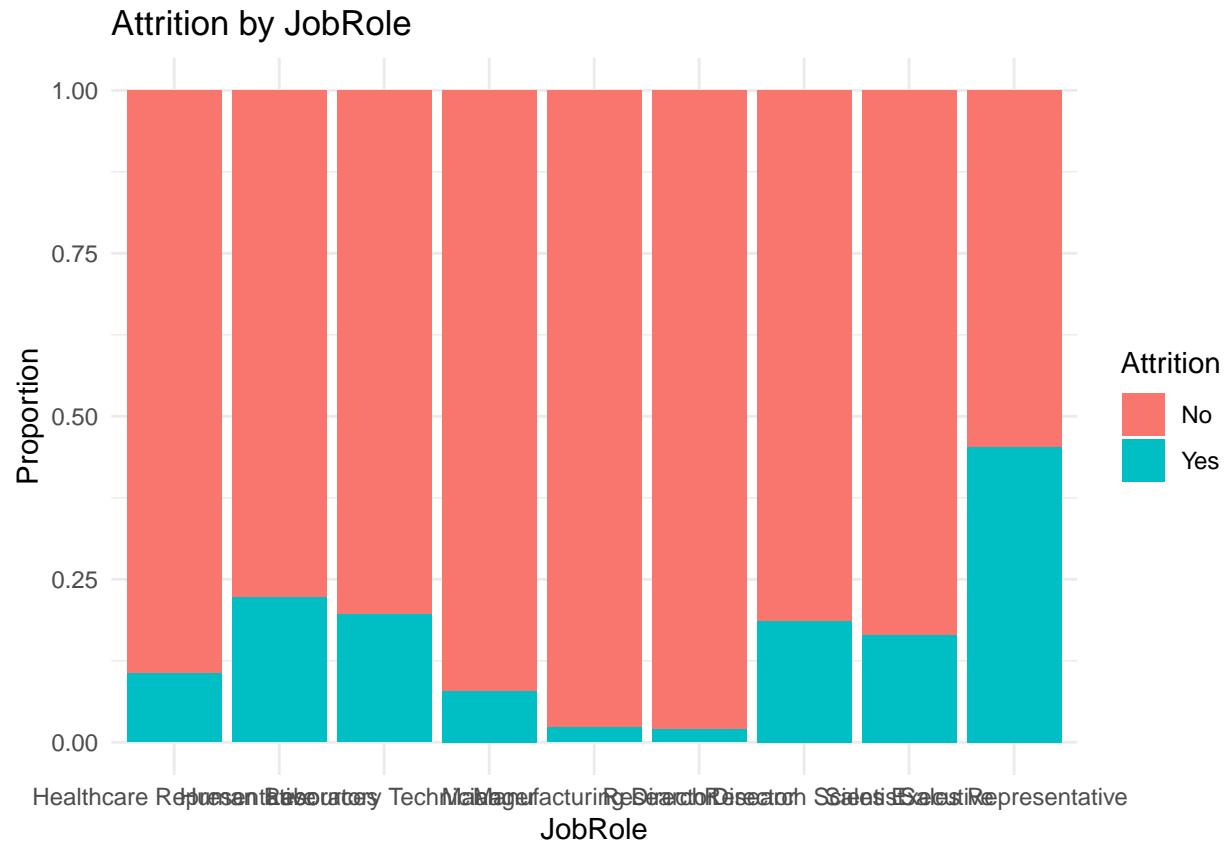


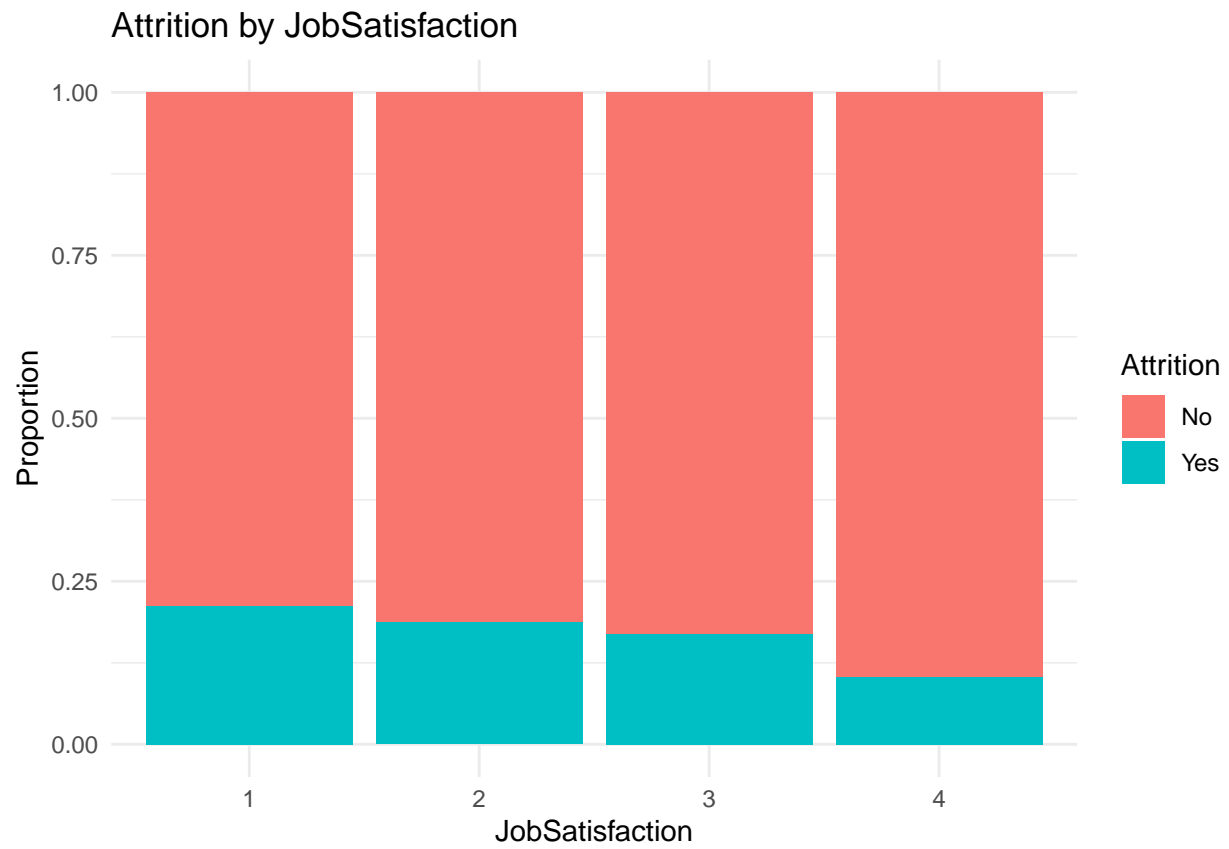


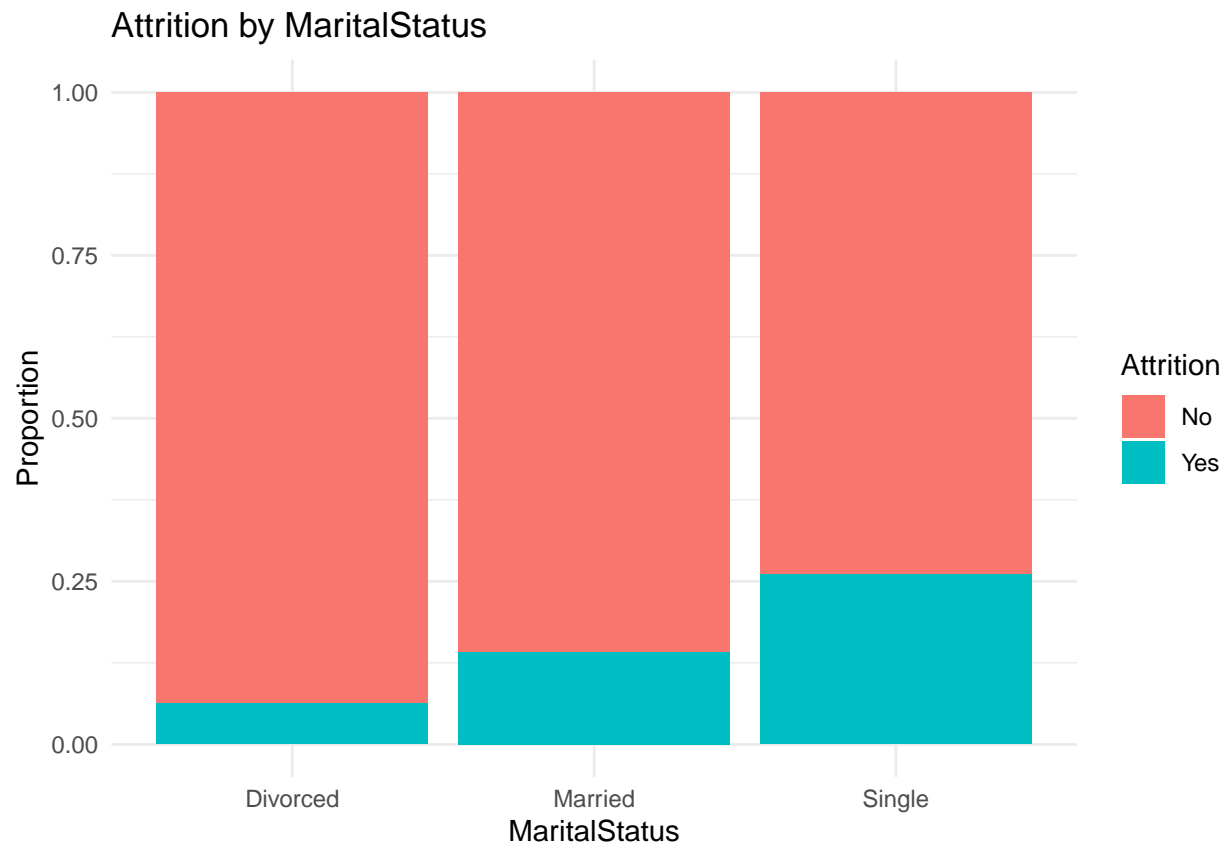


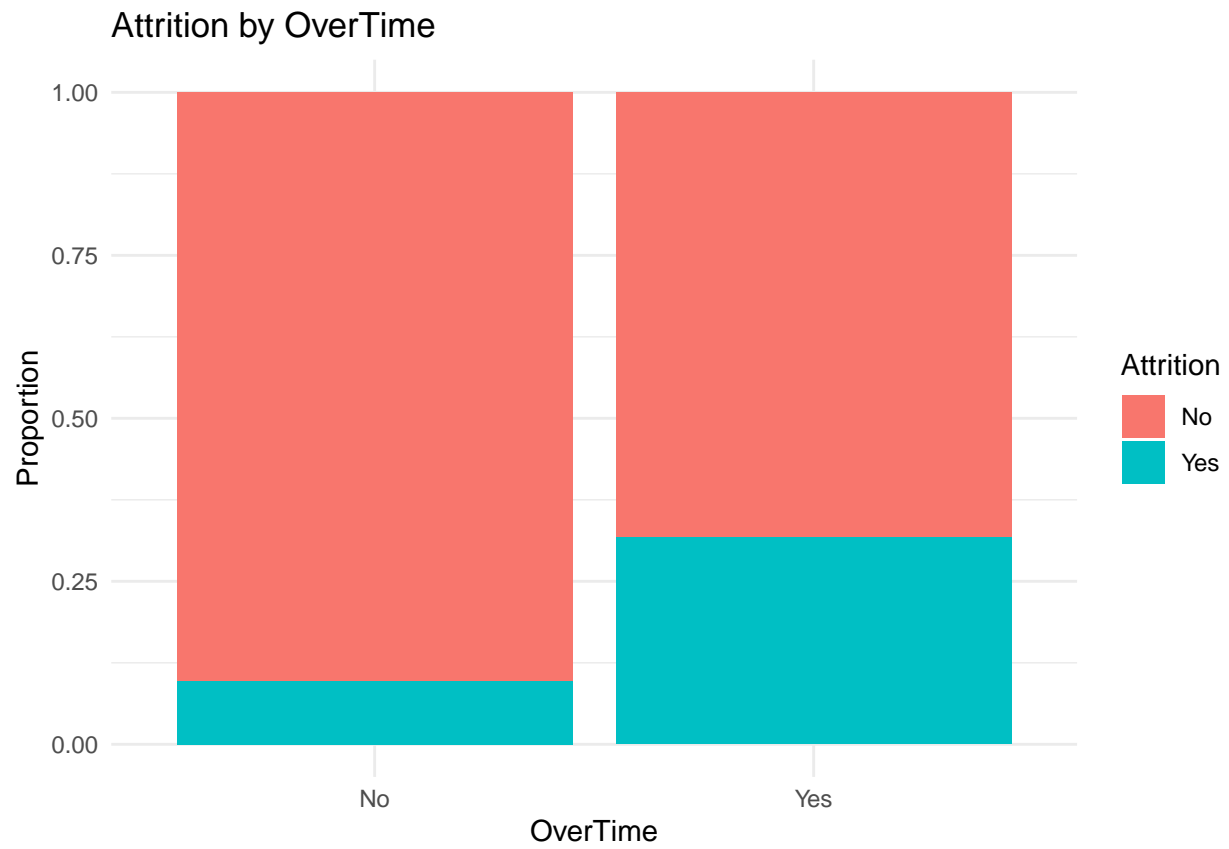


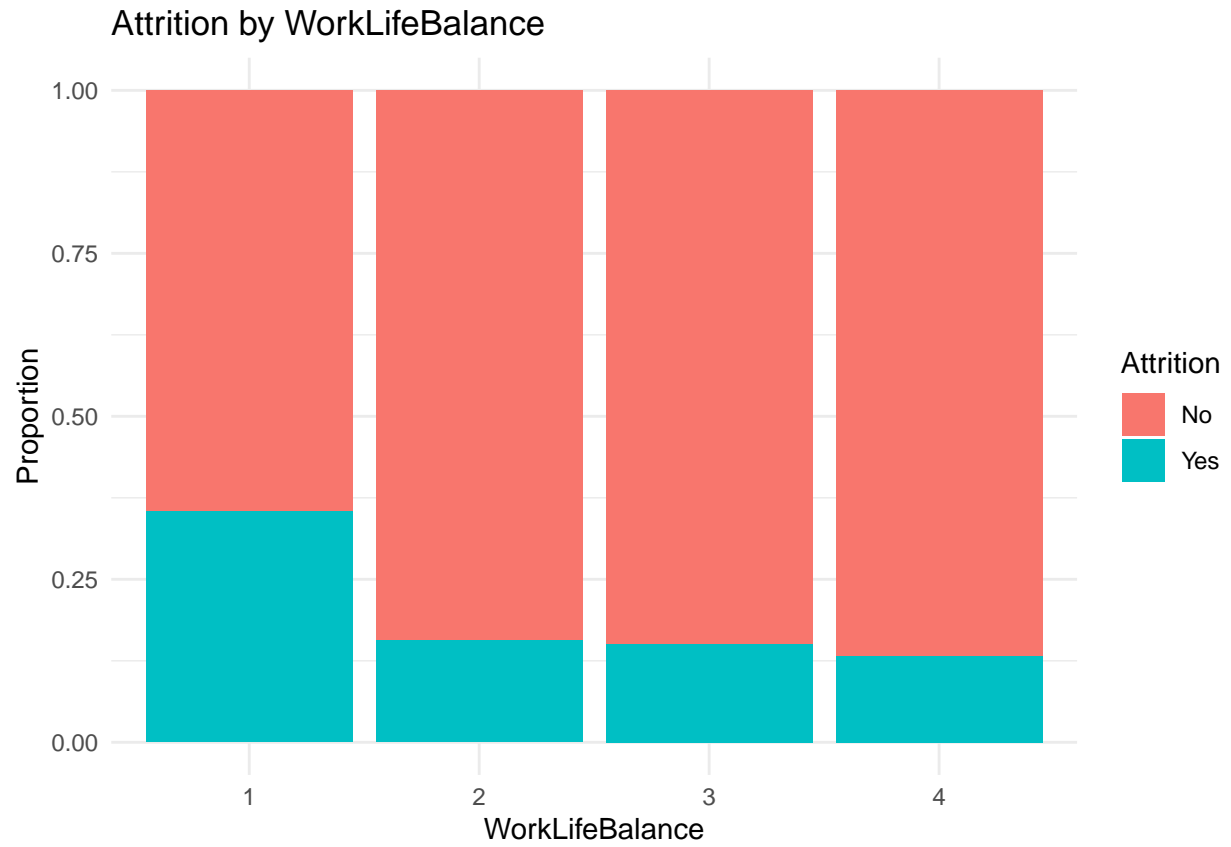


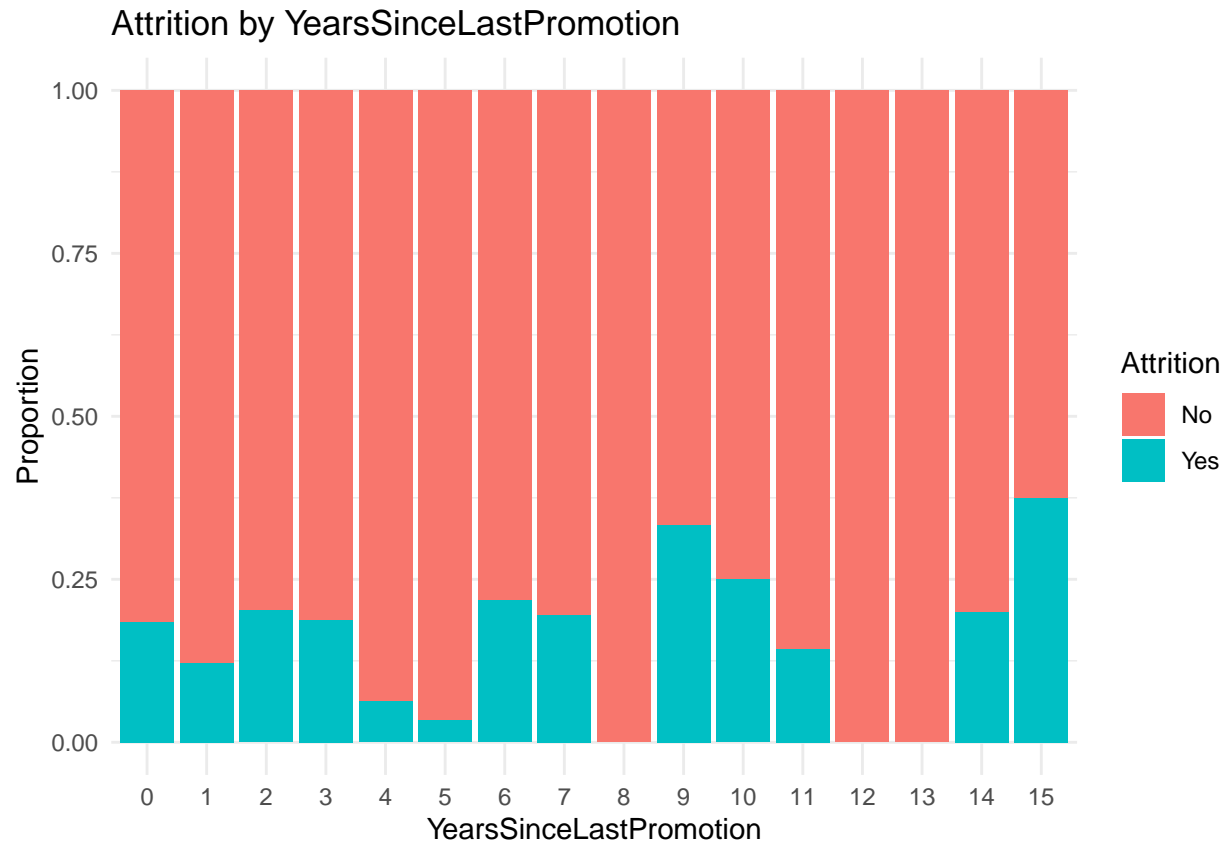




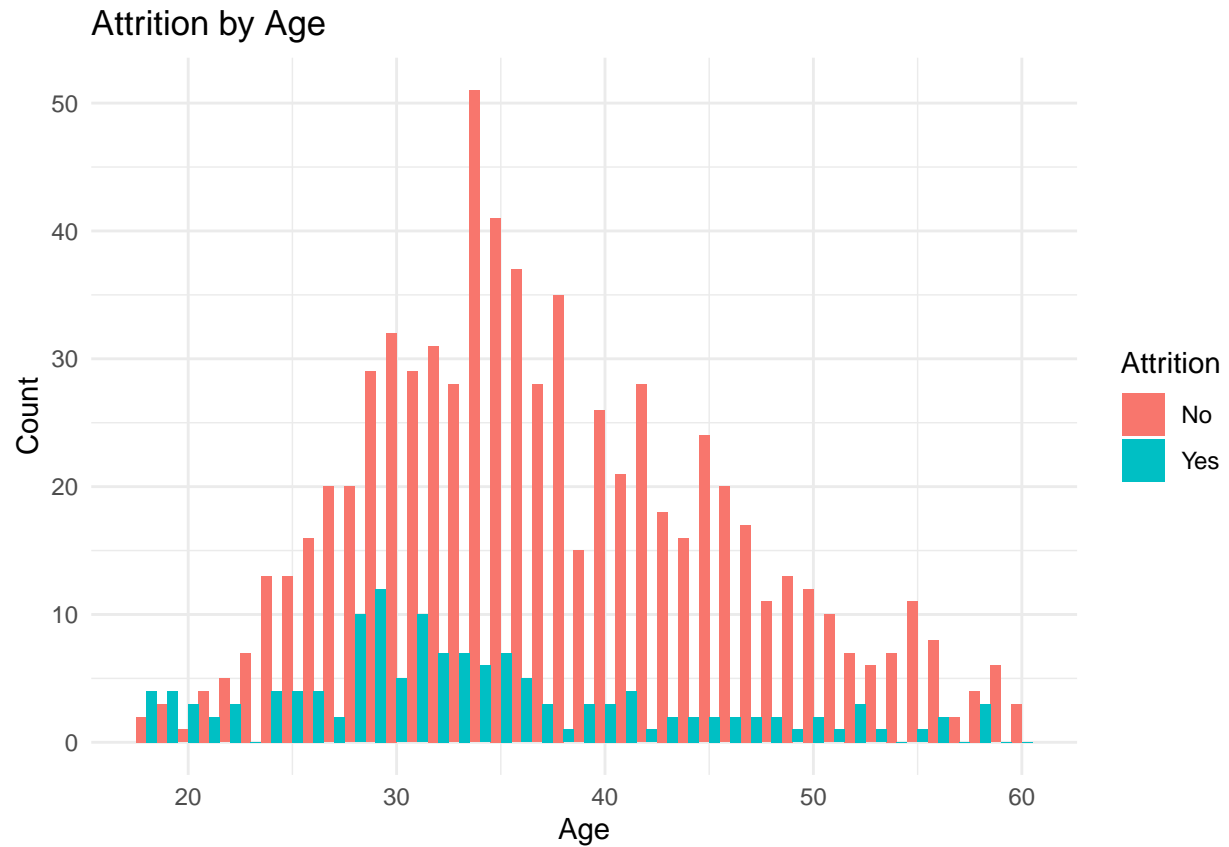




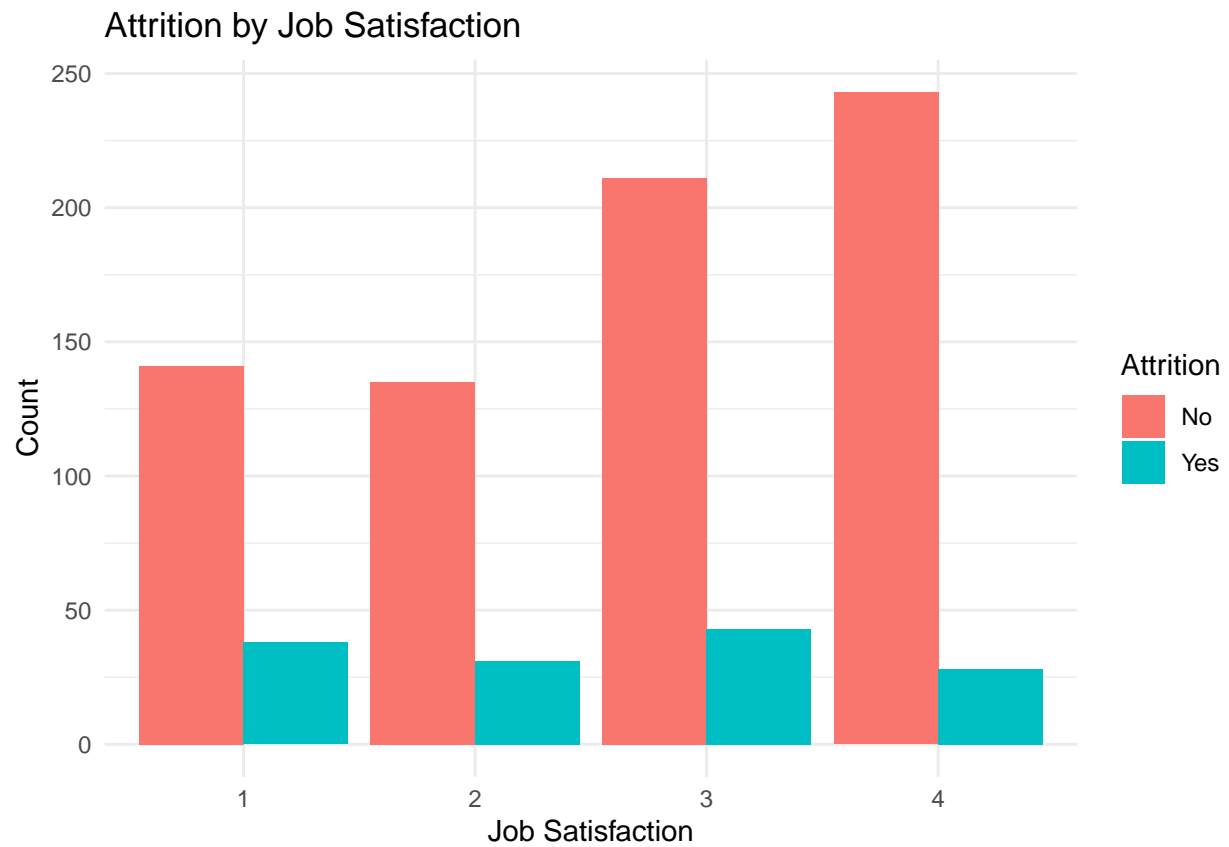




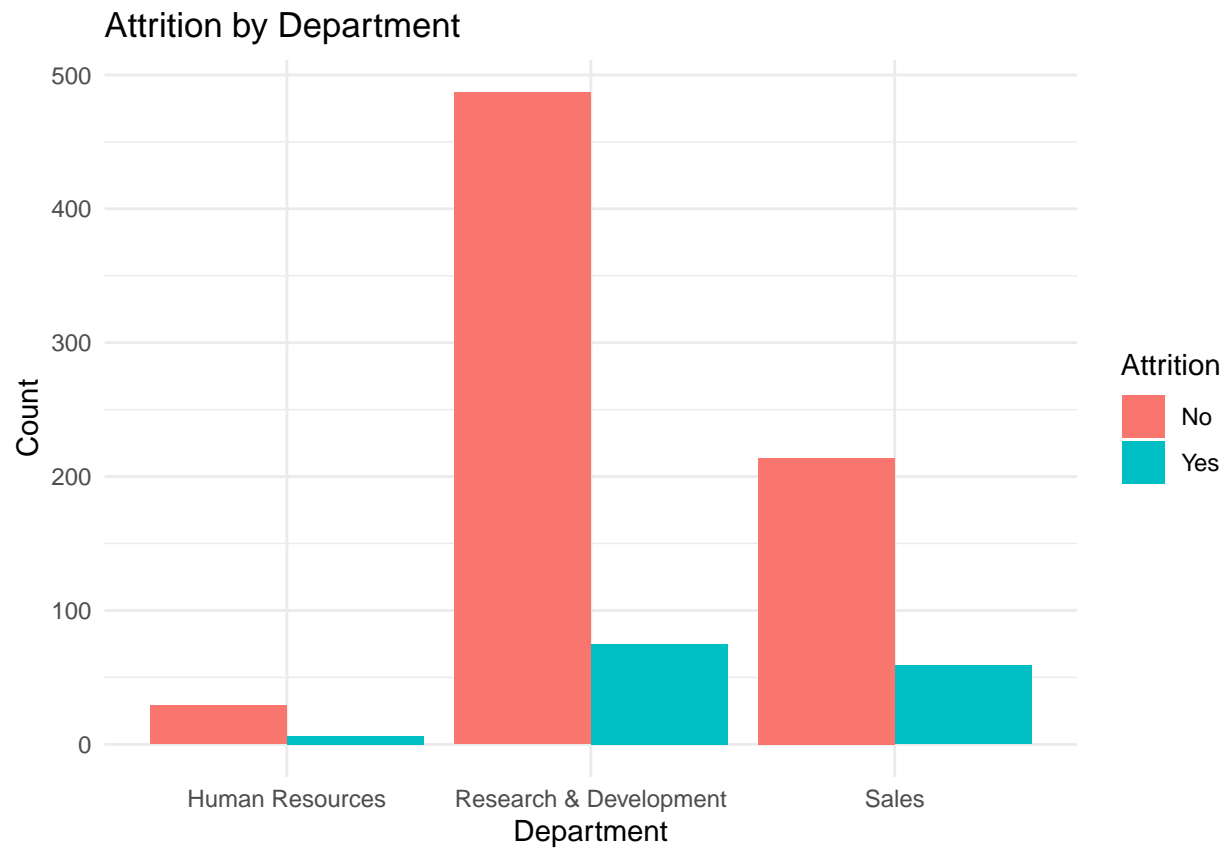
```
# Example: Visualize the relationship between Age and Attrition
ggplot(data, aes(x = Age, fill = Attrition)) +
  geom_histogram(binwidth = 1, position = "dodge") +
  labs(title = "Attrition by Age", x = "Age", y = "Count") +
  theme_minimal()
```



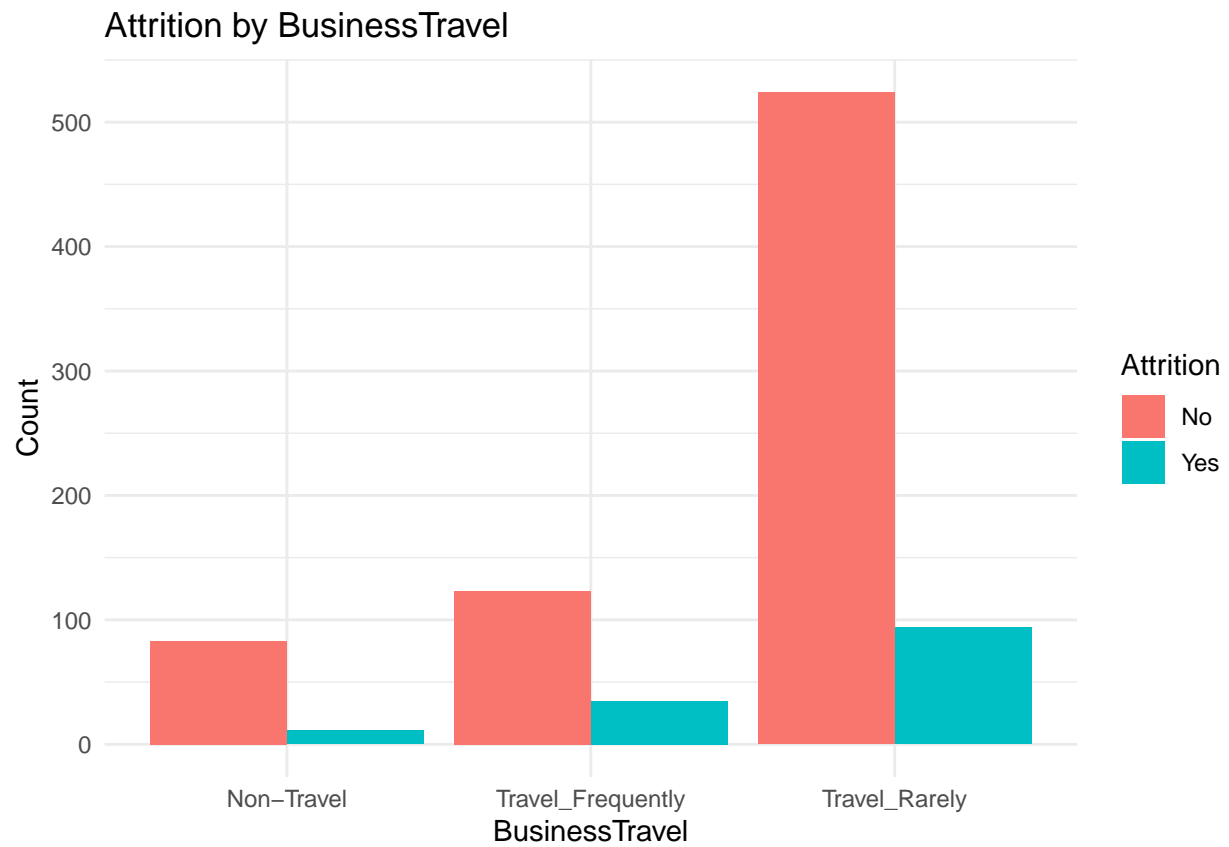
```
ggplot(data, aes(x = JobSatisfaction, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by Job Satisfaction", x = "Job Satisfaction", y = "Count") +  
  theme_minimal()
```



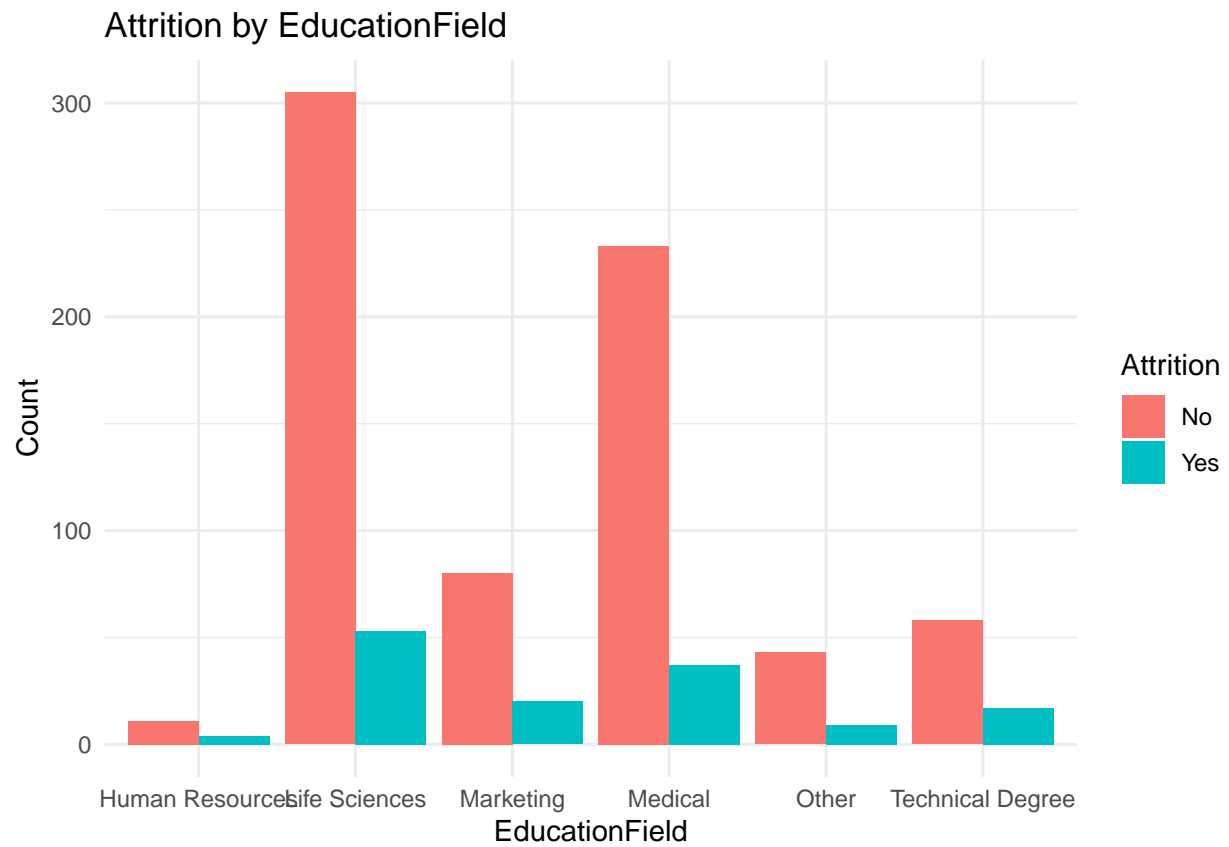
```
ggplot(data, aes(x = Department, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by Department", x = "Department", y = "Count") +  
  theme_minimal()
```



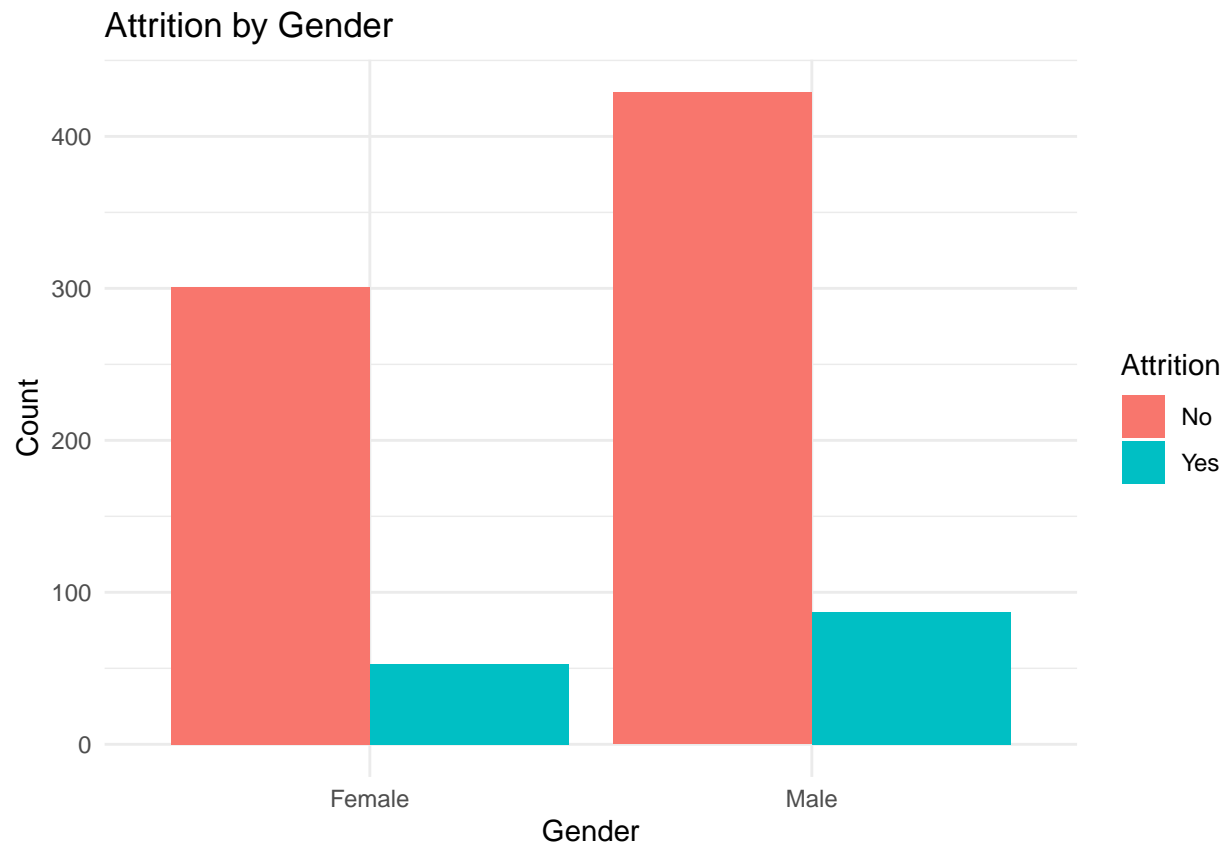
```
ggplot(data, aes(x = BusinessTravel, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by BusinessTravel", x = "BusinessTravel", y = "Count") +  
  theme_minimal()
```



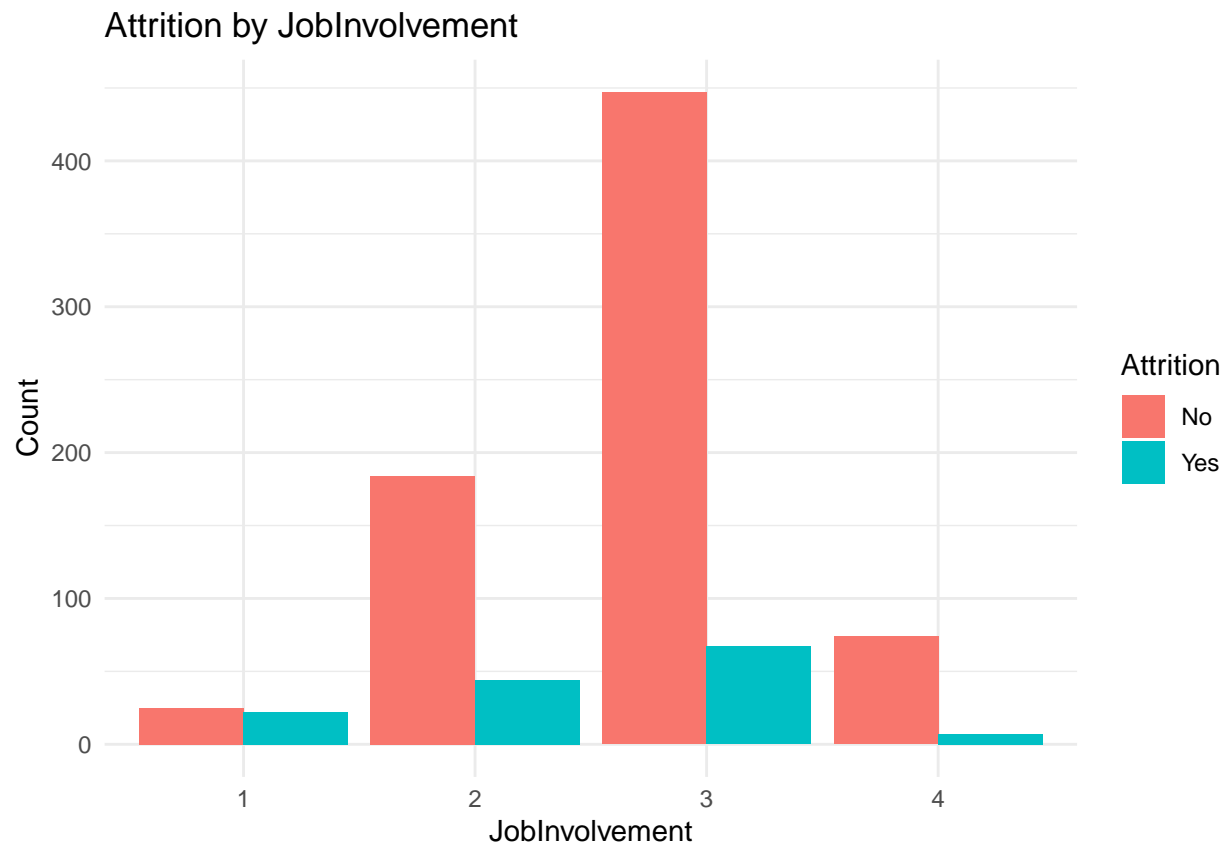
```
ggplot(data, aes(x = EducationField, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by EducationField", x = "EducationField", y = "Count") +  
  theme_minimal()
```



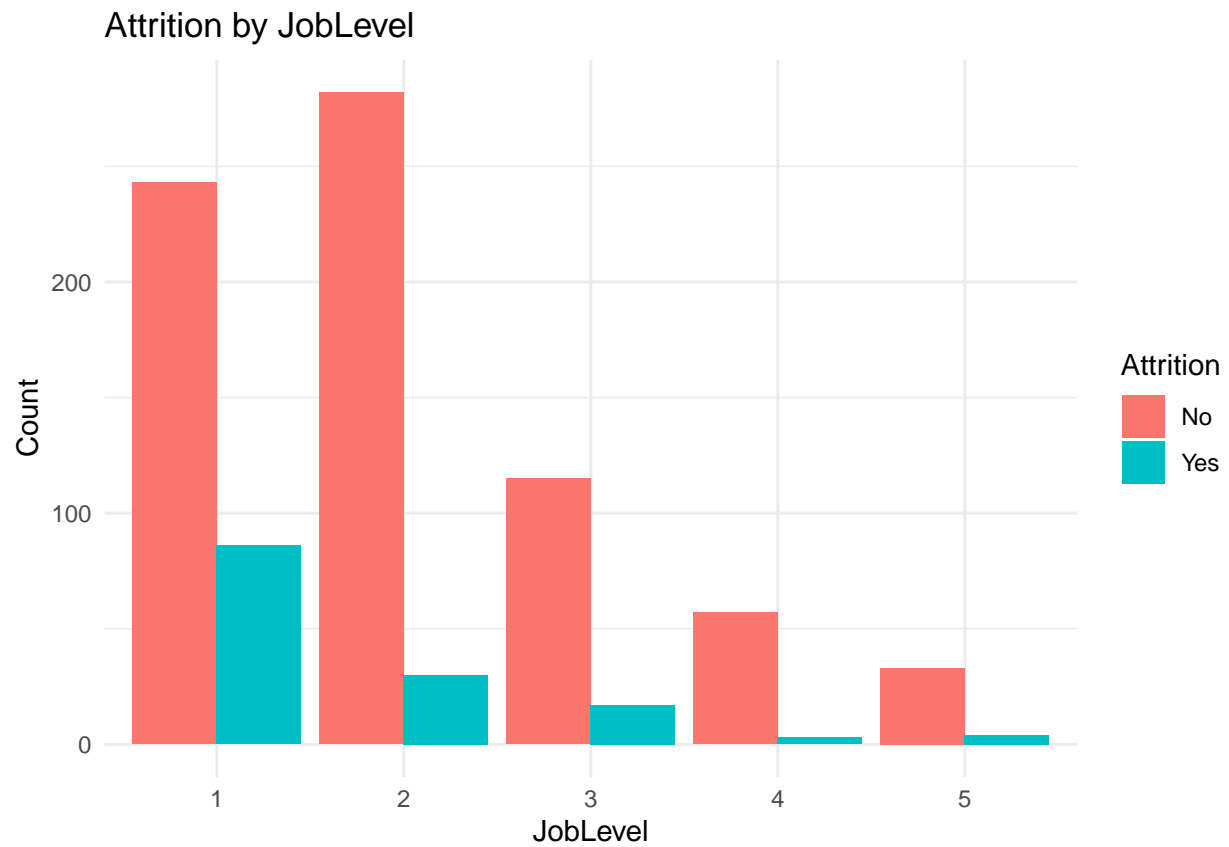
```
ggplot(data, aes(x = Gender, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by Gender", x = "Gender", y = "Count") +  
  theme_minimal()
```

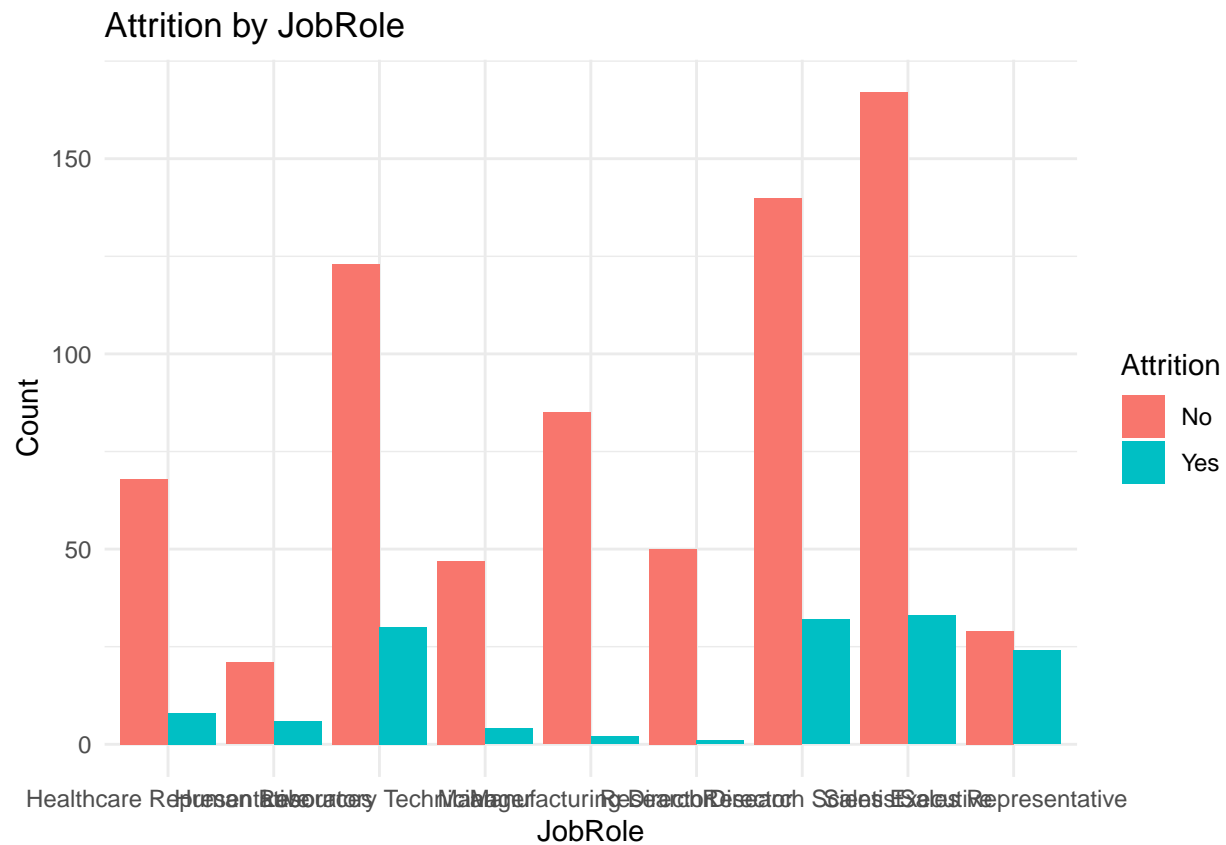
```
ggplot(data, aes(x = JobInvolvement, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by JobInvolvement", x = "JobInvolvement", y = "Count") +  
  theme_minimal()
```



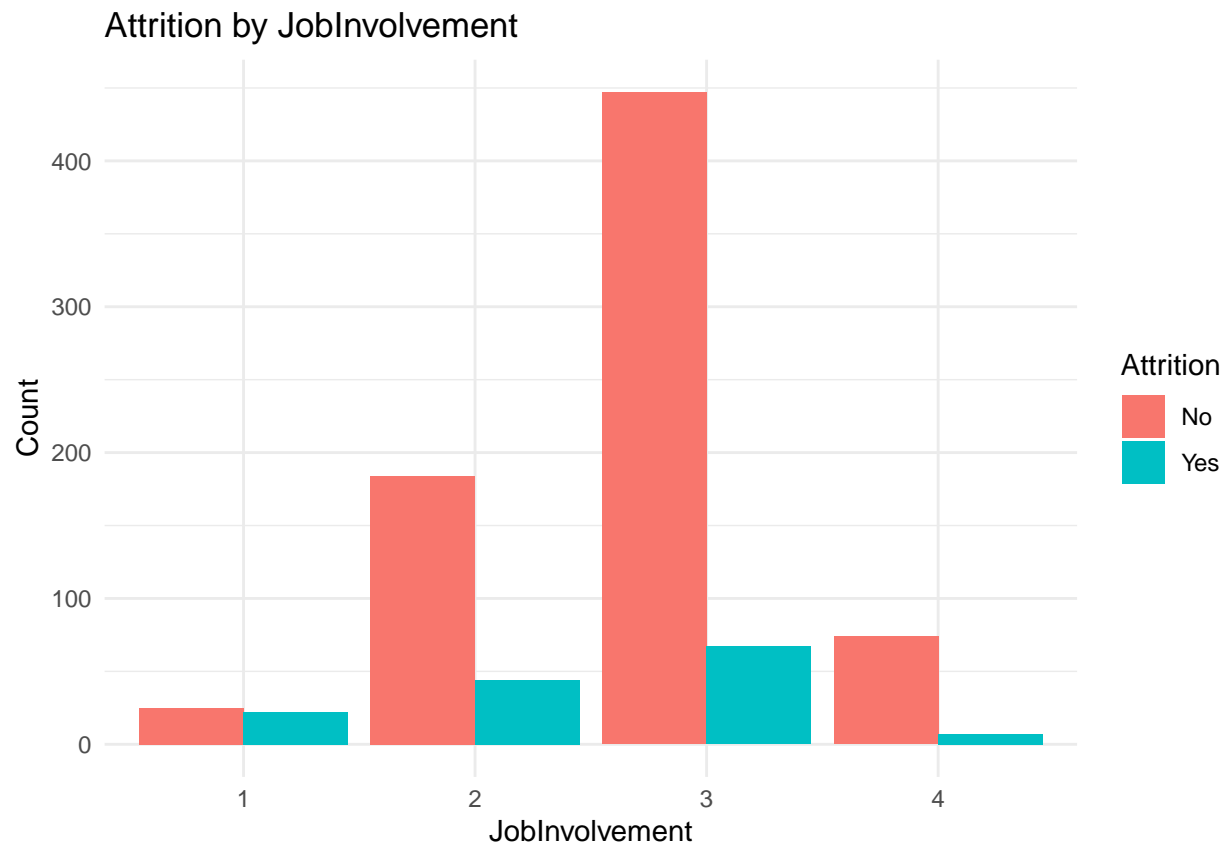
```
ggplot(data, aes(x = JobLevel, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by JobLevel", x = "JobLevel", y = "Count") +  
  theme_minimal()
```



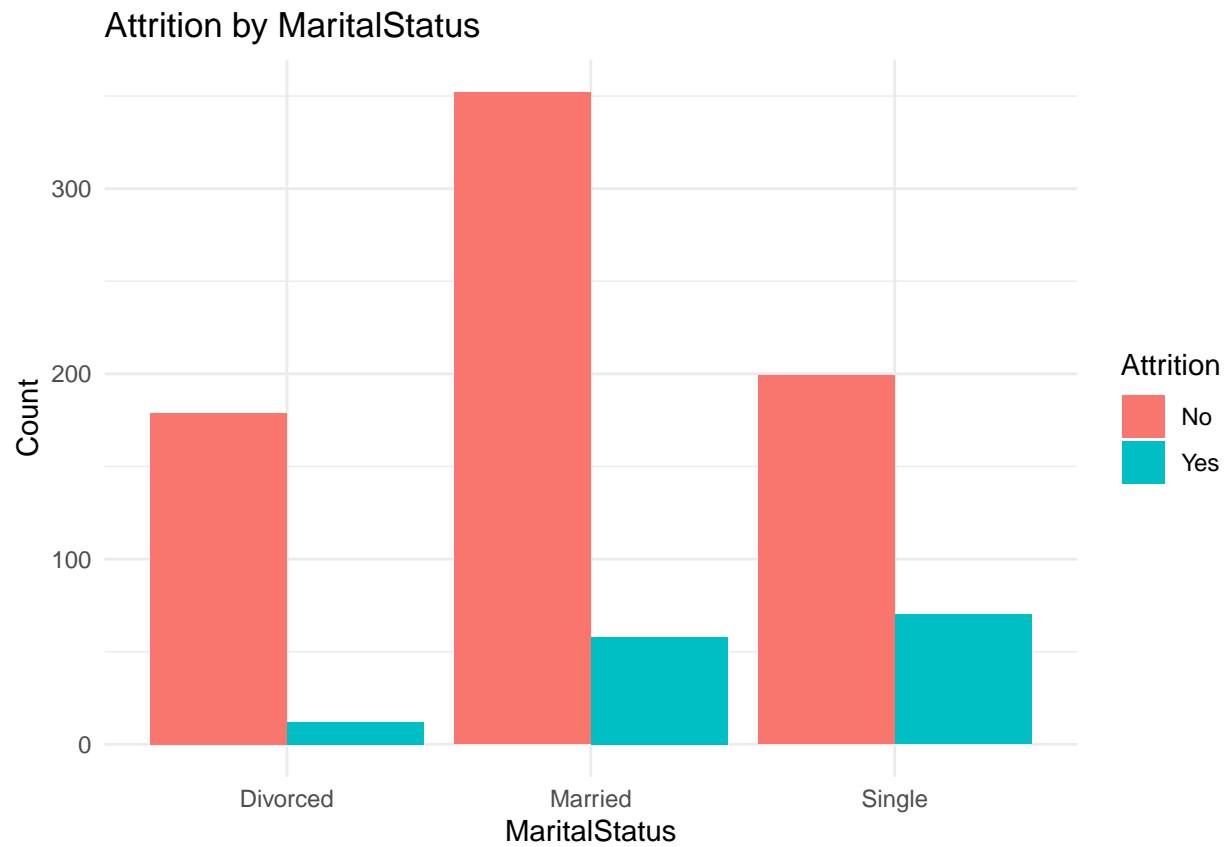
```
ggplot(data, aes(x = JobRole, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by JobRole", x = "JobRole", y = "Count") +  
  theme_minimal()
```



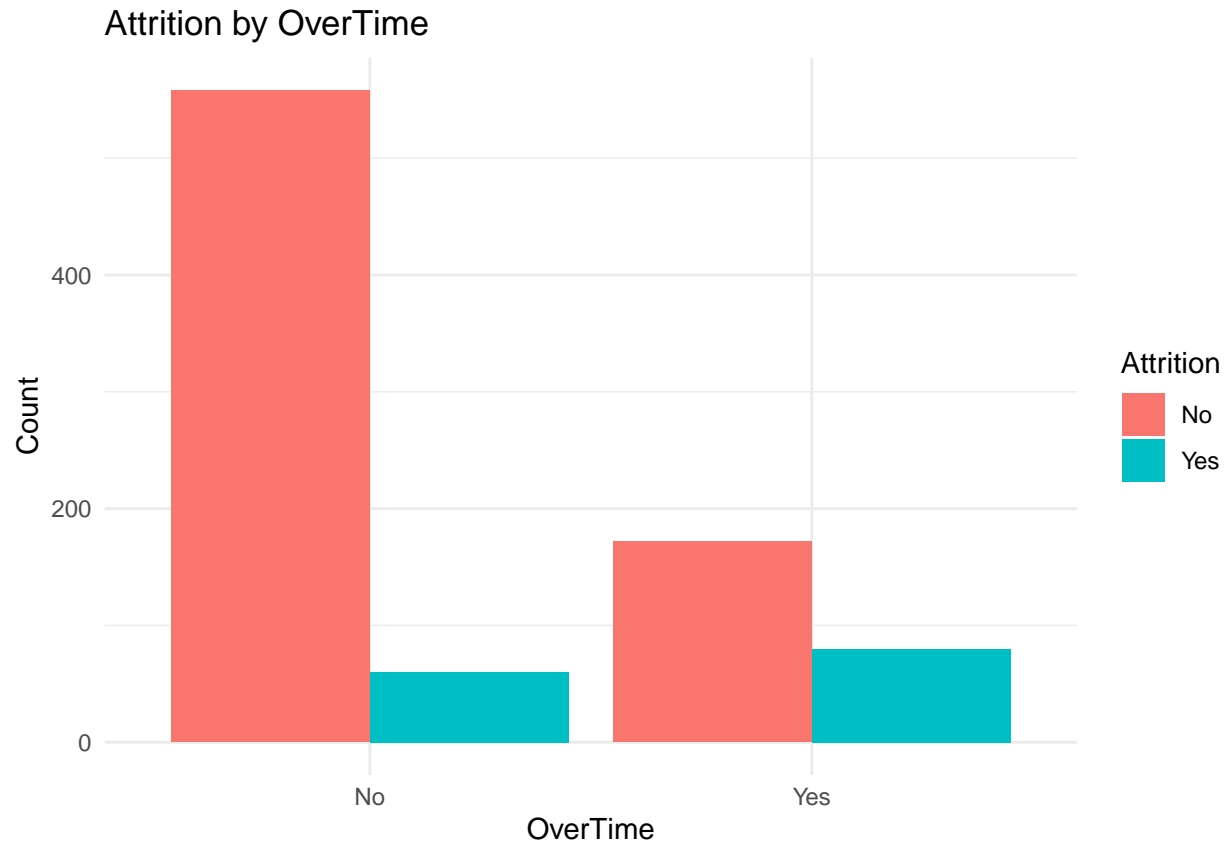
```
ggplot(data, aes(x = JobInvolvement, fill = Attrition)) +
  geom_bar(position = "dodge") +
  labs(title = "Attrition by JobInvolvement", x = "JobInvolvement", y = "Count") +
  theme_minimal()
```



```
ggplot(data, aes(x = MaritalStatus, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by MaritalStatus", x = "MaritalStatus", y = "Count") +  
  theme_minimal()
```



```
ggplot(data, aes(x = OverTime, fill = Attrition)) +  
  geom_bar(position = "dodge") +  
  labs(title = "Attrition by OverTime", x = "OverTime", y = "Count") +  
  theme_minimal()
```



Explore Job Role-Specific Trends: Examine trends related to specific job roles, such as variations in job satisfaction.

```
# Check data structure
str(data)
```

```
## 'data.frame': 870 obs. of 36 variables:
## $ ID : int 1 2 3 4 5 6 7 8 9 10 ...
## $ Age : int 32 40 35 32 24 27 41 37 34 34 ...
## $ Attrition : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
## $ BusinessTravel : Factor w/ 3 levels "Non-Travel","Travel_Frequently",...: 3 3 2 3 2 2 3 3 ...
## $ DailyRate : int 117 1308 200 801 567 294 1283 309 1333 653 ...
## $ Department : Factor w/ 3 levels "Human Resources",...: 3 2 2 3 2 2 2 3 3 2 ...
## $ DistanceFromHome : int 13 14 18 1 2 10 5 10 10 10 ...
## $ Education : int 4 3 2 4 1 2 5 4 4 4 ...
## $ EducationField : Factor w/ 6 levels "Human Resources",...: 2 4 2 3 6 2 4 2 2 6 ...
## $ EmployeeCount : int 1 1 1 1 1 1 1 1 1 1 ...
## $ EmployeeNumber : int 859 1128 1412 2016 1646 733 1448 1105 1055 1597 ...
## $ EnvironmentSatisfaction : int 2 3 3 3 1 4 2 4 3 4 ...
## $ Gender : Factor w/ 2 levels "Female","Male": 2 2 2 1 1 2 2 1 1 2 ...
## $ HourlyRate : int 73 44 60 48 32 32 90 88 87 92 ...
## $ JobInvolvement : Factor w/ 4 levels "1","2","3","4": 3 2 3 3 3 3 4 2 3 2 ...
```

```
## $ JobLevel          : Factor w/ 5 levels "1","2","3","4",...: 2 5 3 3 1 3 1 2 1 2 ...
## $ JobRole           : Factor w/ 9 levels "Healthcare Representative",...: 8 6 5 8 7 5 7 8 9 1
## $ JobSatisfaction   : Factor w/ 4 levels "1","2","3","4": 4 3 4 4 4 1 3 4 3 3 ...
## $ MaritalStatus     : Factor w/ 3 levels "Divorced","Married",...: 1 3 3 2 3 1 2 1 2 2 ...
## $ MonthlyIncome     : int  4403 19626 9362 10422 3760 8793 2127 6694 2220 5063 ...
## $ MonthlyRate       : int  9250 17544 19944 24032 17218 4809 5561 24223 18410 15332 ...
## $ NumCompaniesWorked : int   2 1 2 1 1 1 2 2 1 1 ...
## $ Over18            : chr   "Y" "Y" "Y" "Y" ...
## $ OverTime          : Factor w/ 2 levels "No","Yes": 1 1 1 1 2 1 2 2 2 1 ...
## $ PercentSalaryHike  : int   11 14 11 19 13 21 12 14 19 14 ...
## $ PerformanceRating  : int   3 3 3 3 3 4 3 3 3 3 ...
## $ RelationshipSatisfaction: int  3 1 3 3 3 3 1 3 4 2 ...
## $ StandardHours     : int   80 80 80 80 80 80 80 80 80 80 ...
## $ StockOptionLevel   : int   1 0 0 2 0 2 0 3 1 1 ...
## $ TotalWorkingYears  : int   8 21 10 14 6 9 7 8 1 8 ...
## $ TrainingTimesLastYear : int  3 2 2 3 2 4 5 5 2 3 ...
## $ WorkLifeBalance    : Factor w/ 4 levels "1","2","3","4": 2 4 3 3 3 2 2 3 3 2 ...
## $ YearsAtCompany     : int   5 20 2 14 6 9 4 1 1 8 ...
## $ YearsInCurrentRole  : int   2 7 2 10 3 7 2 0 1 2 ...
## $ YearsSinceLastPromotion : Factor w/ 16 levels "0","1","2","3",...: 1 5 3 6 2 2 1 1 1 8 ...
## $ YearsWithCurrManager : int   3 9 2 7 3 7 3 0 0 7 ...
```

```
# Convert factors to numeric
data$JobSatisfaction <- as.numeric(as.character(data$JobSatisfaction))
```

```
# Descriptive statistics
jobRoleTable <- table(data$JobRole)
jobSatisfactionSummary <- summary(data$JobSatisfaction)
```

```
# Descriptive Statistics by Job Role
job_satisfaction_by_role <- data %>%
  group_by(JobRole) %>%
  summarise(
    Count = n(),
    Mean = mean(JobSatisfaction, na.rm = TRUE),
    SD = sd(JobSatisfaction, na.rm = TRUE),
    Min = min(JobSatisfaction, na.rm = TRUE),
    Max = max(JobSatisfaction, na.rm = TRUE),
    Median = median(JobSatisfaction, na.rm = TRUE),
    IQR = IQR(JobSatisfaction, na.rm = TRUE)
  )
job_satisfaction_by_role
```

```
## # A tibble: 9 x 8
##   JobRole          Count Mean   SD   Min   Max Median   IQR
##   <fct>          <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 Healthcare Representative    76  2.83  1.15     1     4     3     2
## 2 Human Resources             27  2.56  1.05     1     4     3     1
## 3 Laboratory Technician      153  2.69  1.12     1     4     3     2
## 4 Manager                    51  2.51  1.12     1     4     2     1.5
## 5 Manufacturing Director      87  2.72  1.01     1     4     3     2
## 6 Research Director           51  2.49  1.10     1     4     3     1.5
## 7 Research Scientist         172  2.80  1.12     1     4     3     2
## 8 Sales Executive            200  2.72  1.16     1     4     3     2
```

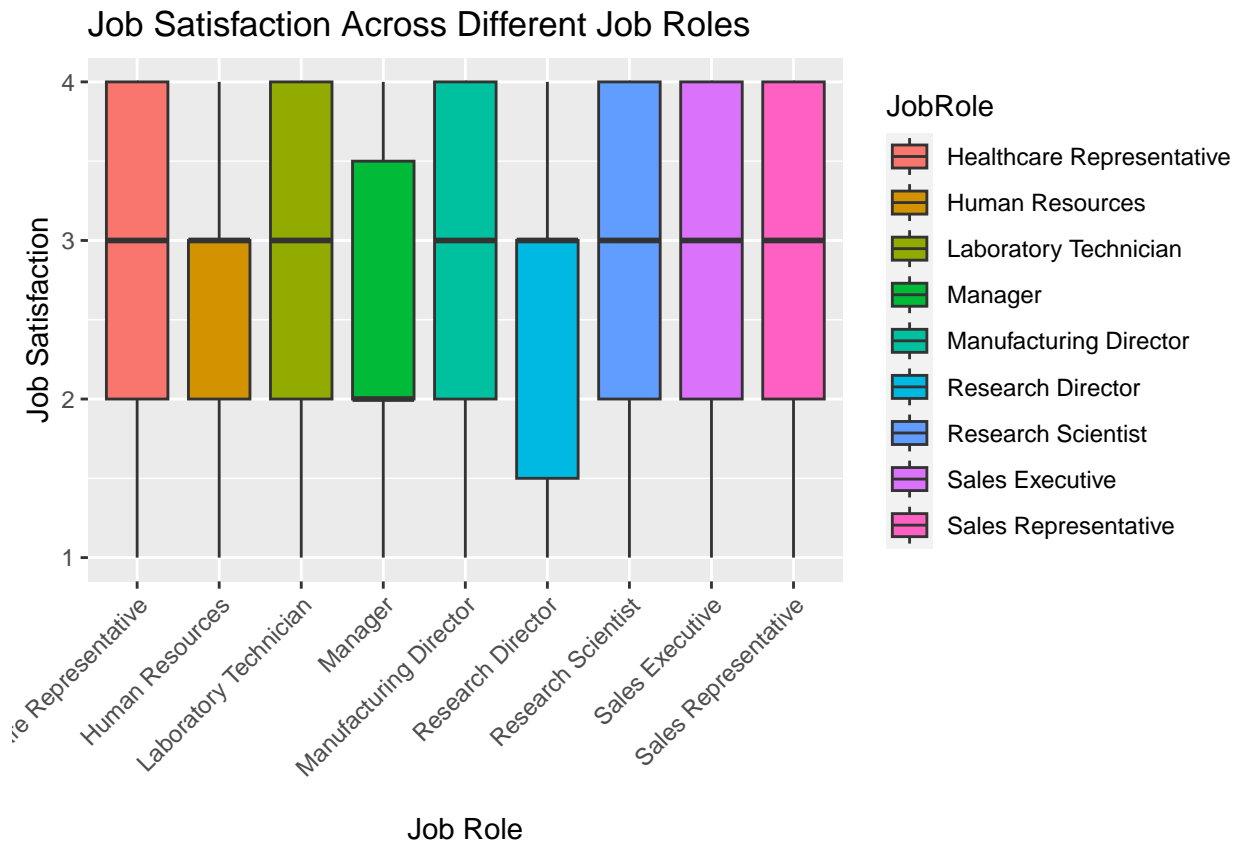


```
## 9 Sales Representative          53  2.70  1.08    1    4    3    2
```

```
#View(job_satisfaction_by_role)
```

```
# Visualization
```

```
ggplot(data, aes(x = JobRole, y = JobSatisfaction, fill = JobRole)) +  
  geom_boxplot() +  
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +  
  labs(title = "Job Satisfaction Across Different Job Roles", x = "Job Role", y = "Job Satisfaction")
```



```
# ANOVA Test
```

```
anova_result <- aov(JobSatisfaction ~ JobRole, data = data)
```

```
anova_summary <- summary(anova_result)
```

```
# LM
```

```
lm_model <- lm(JobSatisfaction ~ JobRole + WorkLifeBalance + YearsAtCompany + DistanceFromHome + Age + DailyRate + Gender + JobLevel, data = data)
```

```
summary(lm_model)
```

```
##
```

```
## Call:
```

```
## lm(formula = JobSatisfaction ~ JobRole + WorkLifeBalance + YearsAtCompany +  
##     DistanceFromHome + Age + DailyRate + Gender + JobLevel, data = data)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
```

```
## -2.0650 -0.7762 0.2255 1.1338 1.7337
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      2.740e+00  3.129e-01  8.757  <2e-16 ***
## JobRoleHuman Resources -2.958e-01  2.814e-01 -1.051  0.293
## JobRoleLaboratory Technician -1.912e-01  1.950e-01 -0.980  0.327
## JobRoleManager      -3.232e-01  2.649e-01 -1.220  0.223
## JobRoleManufacturing Director -9.529e-02  1.759e-01 -0.542  0.588
## JobRoleResearch Director  -2.523e-01  2.365e-01 -1.067  0.286
## JobRoleResearch Scientist  -9.843e-02  1.986e-01 -0.496  0.620
## JobRoleSales Executive   -1.014e-01  1.516e-01 -0.669  0.504
## JobRoleSales Representative -1.792e-01  2.464e-01 -0.727  0.467
## WorkLifeBalance2         2.799e-01  1.818e-01  1.540  0.124
## WorkLifeBalance3         6.822e-02  1.705e-01  0.400  0.689
## WorkLifeBalance4         1.431e-01  1.983e-01  0.721  0.471
## YearsAtCompany          1.309e-02  7.589e-03  1.725  0.085
## DistanceFromHome        -2.749e-03  4.695e-03 -0.585  0.558
## Age                     -3.997e-04  4.920e-03 -0.081  0.935
## DailyRate               -1.666e-05  9.515e-05 -0.175  0.861
## GenderMale              4.044e-02  7.801e-02  0.518  0.604
## JobLevel2               -4.380e-02  1.508e-01 -0.290  0.772
## JobLevel3               -2.531e-01  1.993e-01 -1.270  0.204
## JobLevel4               -1.244e-01  2.794e-01 -0.445  0.656
## JobLevel5               -2.049e-01  3.375e-01 -0.607  0.544
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.116 on 849 degrees of freedom
## Multiple R-squared:  0.02044, Adjusted R-squared:  -0.002635
## F-statistic: 0.8858 on 20 and 849 DF, p-value: 0.6059
```

#Visual analysis indicates that the job roles of Human Resources, Manager, and Research Director have lower than average levels of job satisfaction. However, the output from the linear model reveals that none of these job roles have a statistically significant impact on job satisfaction, as evidenced by p-values all exceeding the typical alpha level of 0.05.

#The residuals of the model, which measure the differences between observed and predicted values of job satisfaction, range from -2.0650 to 1.7337, with a median close to zero. This suggests that the model's predictions are not biased towards overestimating or underestimating job satisfaction.

#Regarding outliers, the range of residuals indicates individual cases where actual job satisfaction is much higher or lower than predicted by the model. Additionally, the model's low multiple R-squared value of 0.02044, indicating that only about 2% of the variability in job satisfaction is explained by all the combined predictors, suggests that job satisfaction is influenced by factors not included in this model.

#The overall F-statistic p-value of 0.6059 confirms that the model does not provide a statistically significant fit to the data, implying that the included variables do not have strong predictive power for job satisfaction.

#Additional study is recommended to explore other influencing factors.

#Build a model to predict employee attrition. The model should achieve at least 60% sensitivity and specificity (60 each = 120 total) for both the training and validation sets.

```
#LM model for predict employee attrition
```

```
#variables
```

```
continuous_vars <- c("Age", "DailyRate", "DistanceFromHome", "Education", "HourlyRate", "MonthlyIncome"
```

```
categorical_vars <- c("BusinessTravel", "Department", "EducationField", "Gender", "JobInvolvement", "Job"
```

```
#LM model with multiple variables
```

```
glmlog_model <- glm(Attrition ~ Age + DailyRate + DistanceFromHome + Education + HourlyRate + MonthlyIncome +  
summary(glmlog_model)
```

```
##
```

```
## Call:
```

```
## glm(formula = Attrition ~ Age + DailyRate + DistanceFromHome +  
## Education + HourlyRate + MonthlyIncome + MonthlyRate + NumCompaniesWorked +  
## PercentSalaryHike + TotalWorkingYears + TrainingTimesLastYear +  
## YearsAtCompany + YearsInCurrentRole + YearsWithCurrManager +  
## BusinessTravel + Department + EducationField + Gender + JobInvolvement +  
## JobLevel + JobRole + JobSatisfaction + MaritalStatus + OverTime +  
## WorkLifeBalance + YearsSinceLastPromotion, family = "binomial",  
## data = data)
```

```
##
```

```
## Coefficients:
```

	Estimate	Std. Error	z value	Pr(> z)
## (Intercept)	-1.442e+01	1.047e+03	-0.014	0.989005
## Age	-3.117e-02	1.963e-02	-1.588	0.112254
## DailyRate	-2.477e-04	3.276e-04	-0.756	0.449574
## DistanceFromHome	6.121e-02	1.657e-02	3.695	0.000220 ***
## Education	1.644e-02	1.326e-01	0.124	0.901298
## HourlyRate	1.546e-02	6.878e-03	2.248	0.024558 *
## MonthlyIncome	-7.851e-06	1.376e-04	-0.057	0.954499
## MonthlyRate	-1.721e-05	1.901e-05	-0.905	0.365374
## NumCompaniesWorked	2.317e-01	5.915e-02	3.917	8.97e-05 ***
## PercentSalaryHike	5.243e-03	3.647e-02	0.144	0.885695
## TotalWorkingYears	-8.041e-02	4.415e-02	-1.821	0.068588 .
## TrainingTimesLastYear	-2.953e-01	1.113e-01	-2.653	0.007980 **
## YearsAtCompany	1.077e-01	6.073e-02	1.773	0.076251 .
## YearsInCurrentRole	-1.878e-01	7.922e-02	-2.370	0.017785 *
## YearsWithCurrManager	-1.358e-01	6.885e-02	-1.972	0.048630 *
## BusinessTravelTravel_Frequently	1.802e+00	5.588e-01	3.225	0.001259 **
## BusinessTravelTravel_Rarely	9.453e-01	4.891e-01	1.933	0.053248 .
## DepartmentResearch & Development	1.672e+01	1.047e+03	0.016	0.987259
## DepartmentSales	1.749e+01	1.047e+03	0.017	0.986672
## EducationFieldLife Sciences	-9.661e-01	1.240e+00	-0.779	0.435875
## EducationFieldMarketing	-1.072e+00	1.307e+00	-0.820	0.412022
## EducationFieldMedical	-9.974e-01	1.229e+00	-0.811	0.417202
## EducationFieldOther	-1.167e+00	1.316e+00	-0.887	0.375072
## EducationFieldTechnical Degree	-2.748e-01	1.287e+00	-0.214	0.830919
## GenderMale	4.226e-01	2.712e-01	1.558	0.119145
## JobInvolvement2	-1.945e+00	5.127e-01	-3.794	0.000148 ***
## JobInvolvement3	-2.722e+00	4.975e-01	-5.471	4.48e-08 ***
## JobInvolvement4	-3.156e+00	6.932e-01	-4.553	5.29e-06 ***

```
## JobLevel2          -1.731e+00  6.788e-01 -2.550 0.010778 *
## JobLevel3          -3.348e-01  1.054e+00 -0.318 0.750703
## JobLevel4          -1.671e+00  1.756e+00 -0.951 0.341418
## JobLevel5           2.642e+00  2.258e+00  1.170 0.241990
## JobRoleHuman Resources  1.685e+01  1.047e+03  0.016 0.987156
## JobRoleLaboratory Technician -7.633e-02  7.767e-01 -0.098 0.921709
## JobRoleManager      -1.847e+00  1.628e+00 -1.135 0.256423
## JobRoleManufacturing Director -1.377e+00  9.253e-01 -1.488 0.136827
## JobRoleResearch Director -2.872e+00  1.847e+00 -1.555 0.119931
## JobRoleResearch Scientist -6.500e-01  7.952e-01 -0.817 0.413657
## JobRoleSales Executive  2.609e-01  1.558e+00  0.167 0.867026
## JobRoleSales Representative 3.320e-01  1.681e+00  0.197 0.843482
## JobSatisfaction      -4.817e-01  1.217e-01 -3.958 7.56e-05 ***
## MaritalStatusMarried  1.219e+00  4.223e-01  2.887 0.003893 **
## MaritalStatusSingle  2.158e+00  4.282e-01  5.041 4.64e-07 ***
## OverTimeYes          2.247e+00  2.859e-01  7.857 3.95e-15 ***
## WorkLifeBalance2     -1.441e+00  5.084e-01 -2.834 0.004592 **
## WorkLifeBalance3     -1.898e+00  4.752e-01 -3.994 6.50e-05 ***
## WorkLifeBalance4     -2.085e+00  6.350e-01 -3.284 0.001025 **
## YearsSinceLastPromotion1 -3.418e-01  3.508e-01 -0.975 0.329749
## YearsSinceLastPromotion2  2.427e-01  4.221e-01  0.575 0.565332
## YearsSinceLastPromotion3  9.876e-01  7.556e-01  1.307 0.191234
## YearsSinceLastPromotion4  3.722e-01  1.072e+00  0.347 0.728524
## YearsSinceLastPromotion5  2.579e-01  1.323e+00  0.195 0.845378
## YearsSinceLastPromotion6  2.961e+00  9.324e-01  3.176 0.001493 **
## YearsSinceLastPromotion7  1.444e+00  6.572e-01  2.198 0.027978 *
## YearsSinceLastPromotion8 -1.376e+01  9.098e+02 -0.015 0.987936
## YearsSinceLastPromotion9  2.899e+00  1.117e+00  2.596 0.009436 **
## YearsSinceLastPromotion10 3.445e+00  2.293e+00  1.503 0.132938
## YearsSinceLastPromotion11 1.559e+00  1.333e+00  1.170 0.242001
## YearsSinceLastPromotion12 -1.465e+01  1.484e+03 -0.010 0.992119
## YearsSinceLastPromotion13 -1.467e+01  1.441e+03 -0.010 0.991881
## YearsSinceLastPromotion14 1.810e+00  3.610e+00  0.501 0.616148
## YearsSinceLastPromotion15 4.925e+00  1.328e+00  3.710 0.000207 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
```

```
## Null deviance: 767.67 on 869 degrees of freedom
```

```
## Residual deviance: 427.77 on 808 degrees of freedom
```

```
## AIC: 551.77
```

```
##
```

```
## Number of Fisher Scoring iterations: 16
```

```
# stepwise to narrow down variables
```

```
stepwise_fit <- step(glmlog_model, direction = "both", trace = FALSE)
```

```
summary(stepwise_fit)
```

```
##
```

```
## Call:
```

```
## glm(formula = Attrition ~ Age + DistanceFromHome + HourlyRate +
```

```
## NumCompaniesWorked + TotalWorkingYears + TrainingTimesLastYear +
```

```
## YearsAtCompany + YearsInCurrentRole + YearsWithCurrManager +
```

```
##      BusinessTravel + Department + Gender + JobInvolvement + JobLevel +
##      JobSatisfaction + MaritalStatus + OverTime + WorkLifeBalance +
##      YearsSinceLastPromotion, family = "binomial", data = data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      1.500e+00  1.275e+00   1.176 0.239441
## Age              -3.381e-02  1.896e-02  -1.783 0.074573 .
## DistanceFromHome  6.097e-02  1.586e-02   3.845 0.000121 ***
## HourlyRate        1.470e-02  6.389e-03   2.302 0.021359 *
## NumCompaniesWorked 2.293e-01  5.571e-02   4.116 3.86e-05 ***
## TotalWorkingYears -8.256e-02  4.077e-02  -2.025 0.042883 *
## TrainingTimesLastYear -2.657e-01  1.072e-01  -2.478 0.013208 *
## YearsAtCompany     1.045e-01  5.267e-02   1.985 0.047190 *
## YearsInCurrentRole -1.863e-01  7.263e-02  -2.565 0.010311 *
## YearsWithCurrManager -1.340e-01  6.453e-02  -2.077 0.037831 *
## BusinessTravelTravel_Frequently 1.783e+00  5.358e-01   3.328 0.000876 ***
## BusinessTravelTravel_Rarely     9.299e-01  4.734e-01   1.964 0.049505 *
## DepartmentResearch & Development -6.522e-01  6.120e-01  -1.066 0.286569
## DepartmentSales      8.280e-01  6.396e-01   1.295 0.195479
## GenderMale          4.264e-01  2.604e-01   1.637 0.101542
## JobInvolvement2     -1.915e+00  4.919e-01  -3.893 9.90e-05 ***
## JobInvolvement3     -2.726e+00  4.798e-01  -5.681 1.34e-08 ***
## JobInvolvement4     -3.207e+00  6.680e-01  -4.801 1.58e-06 ***
## JobLevel2          -1.878e+00  3.735e-01  -5.027 4.97e-07 ***
## JobLevel3          -7.883e-01  5.053e-01  -1.560 0.118741
## JobLevel4          -2.563e+00  1.034e+00  -2.478 0.013217 *
## JobLevel5           8.200e-02  9.146e-01   0.090 0.928559
## JobSatisfaction     -4.888e-01  1.186e-01  -4.122 3.75e-05 ***
## MaritalStatusMarried  1.176e+00  4.046e-01   2.906 0.003664 **
## MaritalStatusSingle  2.124e+00  4.164e-01   5.100 3.40e-07 ***
## OverTimeYes         2.135e+00  2.720e-01   7.847 4.25e-15 ***
## WorkLifeBalance2    -1.506e+00  4.868e-01  -3.093 0.001982 **
## WorkLifeBalance3    -1.848e+00  4.493e-01  -4.113 3.91e-05 ***
## WorkLifeBalance4    -2.015e+00  6.033e-01  -3.340 0.000837 ***
## YearsSinceLastPromotion1 -3.187e-01  3.386e-01  -0.941 0.346686
## YearsSinceLastPromotion2  2.102e-01  4.039e-01   0.520 0.602780
## YearsSinceLastPromotion3  1.180e+00  7.347e-01   1.606 0.108340
## YearsSinceLastPromotion4  5.809e-01  9.802e-01   0.593 0.553421
## YearsSinceLastPromotion5  3.218e-01  1.228e+00   0.262 0.793245
## YearsSinceLastPromotion6  2.999e+00  8.984e-01   3.339 0.000842 ***
## YearsSinceLastPromotion7  1.496e+00  6.314e-01   2.369 0.017824 *
## YearsSinceLastPromotion8 -1.325e+01  9.818e+02  -0.013 0.989233
## YearsSinceLastPromotion9  3.153e+00  1.120e+00   2.816 0.004860 **
## YearsSinceLastPromotion10 1.812e+00  1.617e+00   1.121 0.262369
## YearsSinceLastPromotion11 2.056e+00  1.278e+00   1.609 0.107705
## YearsSinceLastPromotion12 -1.420e+01  1.485e+03  -0.010 0.992373
## YearsSinceLastPromotion13 -1.558e+01  1.411e+03  -0.011 0.991192
## YearsSinceLastPromotion14  1.697e+00  2.735e+00   0.620 0.535044
## YearsSinceLastPromotion15  5.436e+00  1.231e+00   4.418 9.98e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
## Null deviance: 767.67 on 869 degrees of freedom
## Residual deviance: 443.09 on 826 degrees of freedom
## AIC: 531.09
##
## Number of Fisher Scoring iterations: 16
```

```
stepwise_fit
```

```
##
## Call: glm(formula = Attrition ~ Age + DistanceFromHome + HourlyRate +
## NumCompaniesWorked + TotalWorkingYears + TrainingTimesLastYear +
## YearsAtCompany + YearsInCurrentRole + YearsWithCurrManager +
## BusinessTravel + Department + Gender + JobInvolvement + JobLevel +
## JobSatisfaction + MaritalStatus + OverTime + WorkLifeBalance +
## YearsSinceLastPromotion, family = "binomial", data = data)
##
## Coefficients:
## (Intercept) Age
## 1.50000 -0.03381
## DistanceFromHome HourlyRate
## 0.06097 0.01470
## NumCompaniesWorked TotalWorkingYears
## 0.22929 -0.08256
## TrainingTimesLastYear YearsAtCompany
## -0.26566 0.10452
## YearsInCurrentRole YearsWithCurrManager
## -0.18630 -0.13401
## BusinessTravelTravel_Frequently BusinessTravelTravel_Rarely
## 1.78286 0.92993
## DepartmentResearch & Development DepartmentSales
## -0.65223 0.82797
## GenderMale JobInvolvement2
## 0.42636 -1.91498
## JobInvolvement3 JobInvolvement4
## -2.72585 -3.20727
## JobLevel2 JobLevel3
## -1.87759 -0.78828
## JobLevel4 JobLevel5
## -2.56327 0.08200
## JobSatisfaction MaritalStatusMarried
## -0.48877 1.17564
## MaritalStatusSingle OverTimeYes
## 2.12355 2.13452
## WorkLifeBalance2 WorkLifeBalance3
## -1.50556 -1.84767
## WorkLifeBalance4 YearsSinceLastPromotion1
## -2.01505 -0.31868
## YearsSinceLastPromotion2 YearsSinceLastPromotion3
## 0.21020 1.17971
## YearsSinceLastPromotion4 YearsSinceLastPromotion5
## 0.58092 0.32179
## YearsSinceLastPromotion6 YearsSinceLastPromotion7
## 2.99929 1.49595
```

```
##      YearsSinceLastPromotion8      YearsSinceLastPromotion9
##      -13.24921                    3.15270
##      YearsSinceLastPromotion10     YearsSinceLastPromotion11
##      1.81215                      2.05640
##      YearsSinceLastPromotion12     YearsSinceLastPromotion13
##      -14.19661                    -15.58036
##      YearsSinceLastPromotion14     YearsSinceLastPromotion15
##      1.69659                      5.43586
##
## Degrees of Freedom: 869 Total (i.e. Null); 826 Residual
## Null Deviance: 767.7
## Residual Deviance: 443.1 AIC: 531.1
```

```
#choose variables: OverTime, YearsSinceLastPromotion, JobInvolvement, JobLevel
```

```
final_model <- glm(Attrition ~ OverTime + YearsSinceLastPromotion + JobInvolvement + JobLevel, data = data)
summary(final_model)
```

```
##
## Call:
## glm(formula = Attrition ~ OverTime + YearsSinceLastPromotion +
##      JobInvolvement + JobLevel, family = "binomial", data = data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.3236    0.4010   0.807 0.419583
## OverTimeYes       1.6737    0.2172   7.705 1.31e-14 ***
## YearsSinceLastPromotion1 -0.6352    0.2828  -2.246 0.024707 *
## YearsSinceLastPromotion2 -0.1959    0.3338  -0.587 0.557252
## YearsSinceLastPromotion3  0.3042    0.5734   0.531 0.595694
## YearsSinceLastPromotion4 -0.6829    0.7889  -0.866 0.386701
## YearsSinceLastPromotion5 -1.4109    1.0473  -1.347 0.177944
## YearsSinceLastPromotion6  0.7368    0.6053   1.217 0.223504
## YearsSinceLastPromotion7  0.4928    0.4757   1.036 0.300230
## YearsSinceLastPromotion8 -14.6954   635.5961 -0.023 0.981554
## YearsSinceLastPromotion9  1.1161    0.8741   1.277 0.201617
## YearsSinceLastPromotion10  0.6220    1.2132   0.513 0.608150
## YearsSinceLastPromotion11  0.8841    0.8642   1.023 0.306279
## YearsSinceLastPromotion12 -13.9264  1052.4651 -0.013 0.989443
## YearsSinceLastPromotion13 -15.0032   957.6984 -0.016 0.987501
## YearsSinceLastPromotion14  0.7927    1.3515   0.587 0.557532
## YearsSinceLastPromotion15  2.2151    0.8274   2.677 0.007428 **
## JobInvolvement2      -1.4706    0.4009  -3.668 0.000244 ***
## JobInvolvement3      -2.0301    0.3845  -5.280 1.29e-07 ***
## JobInvolvement4      -2.6456    0.5568  -4.752 2.02e-06 ***
## JobLevel2            -1.5685    0.2665  -5.886 3.95e-09 ***
## JobLevel3            -0.9899    0.3388  -2.922 0.003480 **
## JobLevel4            -2.7596    0.7426  -3.716 0.000202 ***
## JobLevel5            -1.3899    0.6175  -2.251 0.024384 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 767.67  on 869  degrees of freedom
```

```
## Residual deviance: 599.39 on 846 degrees of freedom
## AIC: 647.39
##
## Number of Fisher Scoring iterations: 15
```

#logistic regression model (glm) using the binomial family was developed to predict the probability of 'Attrition', utilizing various explanatory variables. #Several predictors have been identified as statistically significant ($p < 0.05$), suggesting they meaningfully contribute to the model in this dataset's context. Statistically significant coefficients were found for 'DistanceFromHome', 'HourlyRate', 'NumCompaniesWorked', 'TrainingTimesLastYear', 'YearsInCurrentRole', 'YearsWithCurrManager', 'BusinessTravel', 'JobInvolvement', 'JobLevel2', 'JobSatisfaction', 'MaritalStatus', 'OverTime', 'WorkLifeBalance', and 'YearsSinceLastPromotion'. These factors are predictive of attrition when controlling for other variables. Further research on these variables is recommended.

#Specifically, 'DistanceFromHome', 'NumCompaniesWorked', and 'OverTimeYes' exhibit positive coefficients, indicating that higher values of these predictors are associated with increased log odds of attrition. Conversely, 'JobSatisfaction' has a negative coefficient, suggesting that higher job satisfaction correlates with lower log odds of attrition. Similarly, higher levels of JobInvolvement (levels 2, 3, and 4) are associated with lower log odds of attrition compared to the baseline level. If focusing on retention, further study of this variable is recommended.

#The model's overall fit is reflected in the AIC value of 551.77. Generally, lower AIC values indicate a better-fitting model, suggesting that this model fits the data better than a model with no predictors.

#The stepwise logistic regression identifies several predictors as significant for the likelihood of attrition. 'DistanceFromHome', 'NumCompaniesWorked', 'TrainingTimesLastYear', 'YearsAtCompany', 'YearsInCurrentRole', and 'YearsWithCurrManager' show a significant relationship with attrition. Higher values of 'DistanceFromHome' and 'NumCompaniesWorked', frequent business travel ('BusinessTravelTravel_Frequently'), and 'OverTimeYes' are linked to increasing the odds of attrition. Marital status plays a role, with 'MaritalStatusSingle' increasing attrition odds compared to the baseline. Gender is also significant, with 'GenderMale' showing a relationship with attrition. Various levels of job involvement ('JobInvolvement2', 'JobInvolvement3', 'JobInvolvement4') and work-life balance ('WorkLifeBalance2', 'WorkLifeBalance3', 'WorkLifeBalance4'), along with years since the last promotion at certain levels ('YearsSinceLastPromotion6', 'YearsSinceLastPromotion7', 'YearsSinceLastPromotion9', 'YearsSinceLastPromotion15'), are identified as significant predictors, all influencing the likelihood of an employee leaving the organization.

#Moreover, higher 'TrainingTimesLastYear' and greater job satisfaction ('JobSatisfaction') lower the odds of attrition.

```
set.seed(123)
splitIndex <- createDataPartition(data$Attrition, p = 0.8, list = FALSE)
train_data <- data[splitIndex, ]
test_data <- data[-splitIndex, ]
```

#ran glm, Knn & NB without correcting for imbalance, none were predictive at required level. added code

```
# Calculate the number of 'Yes' and 'No' instances in the training data
yes_count <- nrow(train_data[train_data$Attrition == "Yes", ])
no_count <- nrow(train_data[train_data$Attrition == "No", ])
```

```
# Determine the desired number of 'Yes' instances after oversampling
oversampled_yes_count <- yes_count * 5
```

```
# Calculate the desired total size after oversampling
desired_size <- no_count + oversampled_yes_count
```



```

# if ..Apply Oversampling on the Training Set
if (desired_size > nrow(train_data)) {
  train_data_balanced <- ovun.sample(Attrition ~ ., data = train_data, method = "over", N = desired_size)
  table(train_data_balanced$Attrition)
} else {
  train_data_balanced <- train_data
}

```

```

##
## No Yes
## 584 560

```

```

# Inspect the first few rows of the balanced dataset
head(train_data_balanced)

```

```

## ID Age Attrition BusinessTravel DailyRate Department
## 1 2 40 No Travel_Rarely 1308 Research & Development
## 2 4 32 No Travel_Rarely 801 Sales
## 3 5 24 No Travel_Frequently 567 Research & Development
## 4 6 27 No Travel_Frequently 294 Research & Development
## 5 7 41 No Travel_Rarely 1283 Research & Development
## 6 8 37 No Travel_Rarely 309 Sales
## DistanceFromHome Education EducationField EmployeeCount EmployeeNumber
## 1 14 3 Medical 1 1128
## 2 1 4 Marketing 1 2016
## 3 2 1 Technical Degree 1 1646
## 4 10 2 Life Sciences 1 733
## 5 5 5 Medical 1 1448
## 6 10 4 Life Sciences 1 1105
## EnvironmentSatisfaction Gender HourlyRate JobInvolvement JobLevel
## 1 3 Male 44 2 5
## 2 3 Female 48 3 3
## 3 1 Female 32 3 1
## 4 4 Male 32 3 3
## 5 2 Male 90 4 1
## 6 4 Female 88 2 2
## JobRole JobSatisfaction MaritalStatus MonthlyIncome
## 1 Research Director 3 Single 19626
## 2 Sales Executive 4 Married 10422
## 3 Research Scientist 4 Single 3760
## 4 Manufacturing Director 1 Divorced 8793
## 5 Research Scientist 3 Married 2127
## 6 Sales Executive 4 Divorced 6694
## MonthlyRate NumCompaniesWorked Over18 OverTime PercentSalaryHike
## 1 17544 1 Y No 14
## 2 24032 1 Y No 19
## 3 17218 1 Y Yes 13
## 4 4809 1 Y No 21
## 5 5561 2 Y Yes 12
## 6 24223 2 Y Yes 14
## PerformanceRating RelationshipSatisfaction StandardHours StockOptionLevel
## 1 3 1 80 0
## 2 3 3 80 2

```

```
## 3          3          3          80          0
## 4          4          3          80          2
## 5          3          1          80          0
## 6          3          3          80          3
##   TotalWorkingYears TrainingTimesLastYear WorkLifeBalance YearsAtCompany
## 1          21          2          4          20
## 2          14          3          3          14
## 3           6          2          3           6
## 4           9          4          2           9
## 5           7          5          2           4
## 6           8          5          3           1
##   YearsInCurrentRole YearsSinceLastPromotion YearsWithCurrManager
## 1           7           4           9
## 2          10           5           7
## 3           3           1           3
## 4           7           1           7
## 5           2           0           3
## 6           0           0           0
```

```
# Convert Attrition to a factor if it's not already
data$Attrition <- as.factor(data$Attrition)

# Count the number of 'Yes' and 'No' in the Attrition column
attrition_counts_train <- table(train_data$Attrition)
# Output the counts
print(attrition_counts_train)
```

```
##
##   No Yes
## 584 112
```

```
# Count the number of 'Yes' and 'No' in the Attrition column after oversample
attrition_counts_balance <- table(train_data_balanced$Attrition)

# Output the counts
print(attrition_counts_balance)
```

```
##
##   No Yes
## 584 560
```

```
#LM model using stepwise selected variables
```

```
“{r{}} # Build the logistic regression model using stepwise selected variables #names(train_data) - go
through and change from train_data to train_data_balanced for train but not predict names(train_data_balanced)

final_model <- glm(Attrition ~ DistanceFromHome + NumCompaniesWorked + BusinessTravel + Over-
Time, data = train_data_balanced, family = “binomial”)

summary(final_model)
```

Predict and Evaluate on the test data

```
predictions <- predict(final_model, newdata = test_data, type = "response") predicted_classes <-  
ifelse(predictions > 0.5, "Yes", "No") predicted_classes <- factor(predicted_classes, levels = c("No",  
"Yes"))
```

Evaluate the model

```
conf_matrix <- confusionMatrix(predicted_classes, test_data$Attrition) conf_matrix  
#CHOOSE THIS MODEL #Sensitivity : 0.6781  
#Specificity : 0.6429
```

Save the logistic regression model to a file

```
saveRDS(final_model, "best_model.rds") # Load the saved logistic regression model #loaded_model <-  
readRDS("best_model.rds")
```

```
#before correct for imbalance  
Sensitivity : 1.00000  
Specificity : 0.03571  
#After correct for imbalance  
Sensitivity : 0.6781  
Specificity : 0.6429
```

```
```r  
KNN Model
set.seed(123)
train_control <- trainControl(method = "cv", number = 10)
knn_model <- train(Attrition ~ OverTime + YearsSinceLastPromotion + JobInvolvement + JobLevel, data = t

Model Evaluation
predictions_knn <- predict(knn_model, newdata = test_data)
conf_matrix_knn <- confusionMatrix(predictions_knn, test_data$Attrition)
conf_matrix_knn

Confusion Matrix and Statistics

Reference
Prediction No Yes
No 106 14
Yes 40 14

Accuracy : 0.6897
95% CI : (0.6152, 0.7575)
No Information Rate : 0.8391
P-Value [Acc > NIR] : 0.9999997
##
```

```
Kappa : 0.1644
##
Mcnemar's Test P-Value : 0.0006688
##
Sensitivity : 0.7260
Specificity : 0.5000
Pos Pred Value : 0.8833
Neg Pred Value : 0.2593
Prevalence : 0.8391
Detection Rate : 0.6092
Detection Prevalence : 0.6897
Balanced Accuracy : 0.6130
##
'Positive' Class : No
##
```

#BEFORE CORRECTING imbalance Sensitivity: 0.9726 Specificity: 0.3571

#AFTER CORRECT IMBALANCE WITH OVERSAMPLING Sensitivity: 0.7808 Specificity: 0.5000

```
Naive Bayes Model
set.seed(123)
nb_model <- train(Attrition ~ OverTime + YearsSinceLastPromotion + JobInvolvement + JobLevel, data = tr

Model Evaluation
predictions_nb <- predict(nb_model, newdata = test_data)
conf_matrix_nb <- confusionMatrix(predictions_nb, test_data$Attrition)
conf_matrix_nb
```

```
Confusion Matrix and Statistics
##
Reference
Prediction No Yes
No 26 2
Yes 120 26
##
Accuracy : 0.2989
95% CI : (0.2319, 0.3728)
No Information Rate : 0.8391
P-Value [Acc > NIR] : 1
##
Kappa : 0.0395
##
Mcnemar's Test P-Value : <2e-16
##
Sensitivity : 0.1781
Specificity : 0.9286
Pos Pred Value : 0.9286
Neg Pred Value : 0.1781
Prevalence : 0.8391
Detection Rate : 0.1494
Detection Prevalence : 0.1609
Balanced Accuracy : 0.5533
##
```

```
'Positive' Class : No
##
```

#BEFORE CORRECTING imbalance Sensitivity: 1.0000 (the model did not predict any 'Yes' cases) Specificity: 0.0000 (the model failed to correctly identify any of the 'Yes' cases)

#correct for imbalance Sensitivity : 0.1781  
Specificity : 0.9286

```
#Load the best model (lm)
```

```
loaded_model <- readRDS("best_model.rds")
```

```
Data Preprocessing test data -load and preprocess
```

```
Load the saved logistic regression model
```

```
loaded_model <- readRDS("best_model.rds")
```

```
Data Preprocessing test data -load and preprocess
```

```
Load test data
```

```
comp_data <- read.csv("CaseStudy2CompSet No Attrition.csv")
```

```
List of categorical variables
```

```
categorical_vars <- c("BusinessTravel", "Department", "EducationField", "Gender", "JobInvolvement", "JobLevel", "JobRole", "JobSatisfaction", "MaritalStatus", "OverTime", "WorkLifeBalance", "YearsSinceLastPromotion")
```

```
Apply factor levels to existing variables in test_data
```

```
comp_data[categorical_vars] <- lapply(comp_data[categorical_vars], factor)
```

```
str(comp_data[categorical_vars])
```

```
'data.frame': 300 obs. of 12 variables:
```

```
$ BusinessTravel : Factor w/ 3 levels "Non-Travel","Travel_Frequently",...: 3 3 3 3 3 2 1 3 ...
$ Department : Factor w/ 3 levels "Human Resources",...: 2 1 2 2 3 2 3 2 2 2 ...
$ EducationField : Factor w/ 6 levels "Human Resources",...: 2 1 4 2 2 4 2 4 4 2 ...
$ Gender : Factor w/ 2 levels "Female","Male": 2 2 2 1 2 1 2 2 1 2 ...
$ JobInvolvement : Factor w/ 4 levels "1","2","3","4": 4 3 3 3 2 2 3 3 2 3 ...
$ JobLevel : Factor w/ 5 levels "1","2","3","4",...: 2 1 1 4 2 3 1 2 2 3 ...
$ JobRole : Factor w/ 9 levels "Healthcare Representative",...: 3 2 3 4 8 1 9 5 1 1 ...
$ JobSatisfaction : Factor w/ 4 levels "1","2","3","4": 3 3 3 4 3 1 4 1 1 3 ...
$ MaritalStatus : Factor w/ 3 levels "Divorced","Married",...: 2 2 1 3 1 3 1 2 3 2 ...
$ OverTime : Factor w/ 2 levels "No","Yes": 1 1 1 2 1 1 1 1 1 1 ...
$ WorkLifeBalance : Factor w/ 4 levels "1","2","3","4": 2 3 2 3 3 2 2 3 3 3 ...
$ YearsSinceLastPromotion: Factor w/ 16 levels "0","1","2","3",...: 7 2 1 2 1 13 1 8 2 1 ...
```

```
Final structure and summary check for test data
```

```
str(comp_data)
```

```
'data.frame': 300 obs. of 35 variables:
```

```
$ ID : int 1171 1172 1173 1174 1175 1176 1177 1178 1179 1180 ...
$ Age : int 35 33 26 55 29 51 52 39 31 31 ...
$ BusinessTravel : Factor w/ 3 levels "Non-Travel","Travel_Frequently",...: 3 3 3 3 3 2 1 3 ...
$ DailyRate : int 750 147 1330 1311 1246 1456 585 1387 1062 534 ...
$ Department : Factor w/ 3 levels "Human Resources",...: 2 1 2 2 3 2 3 2 2 2 ...
$ DistanceFromHome : int 28 2 21 2 19 1 29 10 24 20 ...
$ Education : int 3 3 3 3 3 4 4 5 3 3 ...
```

```
$ EducationField : Factor w/ 6 levels "Human Resources",...: 2 1 4 2 2 4 2 4 4 2 ...
$ EmployeeCount : int 1 1 1 1 1 1 1 1 1 1 ...
$ EmployeeNumber : int 1596 1207 1107 505 1497 145 2019 1618 1252 587 ...
$ EnvironmentSatisfaction : int 2 2 1 3 3 1 1 2 3 1 ...
$ Gender : Factor w/ 2 levels "Female","Male": 2 2 2 1 2 1 2 2 1 2 ...
$ HourlyRate : int 46 99 37 97 77 30 40 76 96 66 ...
$ JobInvolvement : Factor w/ 4 levels "1","2","3","4": 4 3 3 3 2 2 3 3 2 3 ...
$ JobLevel : Factor w/ 5 levels "1","2","3","4",...: 2 1 1 4 2 3 1 2 2 3 ...
$ JobRole : Factor w/ 9 levels "Healthcare Representative",...: 3 2 3 4 8 1 9 5 1 1
$ JobSatisfaction : Factor w/ 4 levels "1","2","3","4": 3 3 3 4 3 1 4 1 1 3 ...
$ MaritalStatus : Factor w/ 3 levels "Divorced","Married",...: 2 2 1 3 1 3 1 2 3 2 ...
$ MonthlyIncome : int 3407 3600 2377 16659 8620 7484 3482 5377 6812 9824 ...
$ MonthlyRate : int 25348 8429 19373 23258 23757 25796 19788 3835 17198 22908 ...
$ NumCompaniesWorked : int 1 1 1 2 1 3 2 2 1 3 ...
$ Over18 : chr "Y" "Y" "Y" "Y" ...
$ OverTime : Factor w/ 2 levels "No","Yes": 1 1 1 2 1 1 1 1 1 1 ...
$ PercentSalaryHike : int 17 13 20 13 14 20 15 13 19 12 ...
$ PerformanceRating : int 3 3 4 3 3 4 3 3 3 3 ...
$ RelationshipSatisfaction: int 4 4 3 3 3 3 2 4 2 1 ...
$ StandardHours : int 80 80 80 80 80 80 80 80 80 80 ...
$ StockOptionLevel : int 2 1 1 0 2 0 2 3 0 0 ...
$ TotalWorkingYears : int 10 5 1 30 10 23 16 10 10 12 ...
$ TrainingTimesLastYear : int 3 2 0 2 3 1 3 3 2 2 ...
$ WorkLifeBalance : Factor w/ 4 levels "1","2","3","4": 2 3 2 3 3 2 2 3 3 3 ...
$ YearsAtCompany : int 10 5 1 5 10 13 9 7 10 1 ...
$ YearsInCurrentRole : int 9 4 1 4 7 12 8 7 9 0 ...
$ YearsSinceLastPromotion : Factor w/ 16 levels "0","1","2","3",...: 7 2 1 2 1 13 1 8 2 1 ...
$ YearsWithCurrManager : int 8 4 0 2 4 8 0 7 8 0 ...
```

```
Predict using the loaded model
comp_predictions <- predict(loaded_model, newdata = comp_data, type = "response")

Convert probabilities to class labels (assuming a threshold of 0.5)
comp_predictions_class <- ifelse(comp_predictions > 0.5, "Yes", "No")

Create a data frame to save the predictions
result_df <- data.frame(ID = comp_data$ID, Attrition = comp_predictions_class)

Write the predictions to a CSV file
write.csv(result_df, "Case2PredictionsMirzaAttrition.csv", row.names = FALSE)
```

#Develop a regression model to predict missing monthly incomes in another dataset. The model should achieve a Root Mean Square Error (RMSE) of less than \$3000 for both training and validation sets. Validation Requirement for Salary(RMSE < \$4000)

```
Read Training Data
train_data <- read.csv("CaseStudy2-data.csv")

Data Preprocessing
Convert categorical variables in the training data to factors
categorical_vars <- c("BusinessTravel", "Department", "EducationField", "Gender", "JobInvolvement",
 "JobLevel", "JobRole", "JobSatisfaction", "MaritalStatus", "OverTime",
 "WorkLifeBalance", "YearsSinceLastPromotion")
train_data[categorical_vars] <- lapply(train_data[categorical_vars], factor)
```

```

Log-transform the 'MonthlyIncome' variable
train_data$MonthlyIncome <- log(train_data$MonthlyIncome)

Check for and remove categorical variables with only one level
single_level_vars <- sapply(train_data, function(x) length(unique(x)) == 1)
train_data <- train_data[, !single_level_vars]

Split the data into training (70%) and validation (30%) sets
set.seed(123) # For reproducibility
train_index <- createDataPartition(train_data$MonthlyIncome, p = 0.7, list = FALSE)
train_set <- train_data[train_index,]
validation_set <- train_data[-train_index,]

Building a regression model on the training set
model <- train(MonthlyIncome ~ ., data = train_set, method = "lm", trControl = trainControl(method = "cv"))

Evaluate model performance on the validation set
validation_predictions <- predict(model, newdata = validation_set)

Reverse the log transformation for predictions and actual values
predicted_values_validation <- exp(validation_predictions)
actual_values_validation <- exp(validation_set$MonthlyIncome)

Calculate RMSE on the original scale
RMSE_train_original_scale <- sqrt(mean((exp(train_set$MonthlyIncome) - exp(predict(model, newdata = train_set)$predicted_values_validation))^2))
RMSE_validation_original_scale <- sqrt(mean((actual_values_validation - predicted_values_validation)^2))

Print RMSE on training and validation sets on the original scale
cat("RMSE on training data (original scale):", RMSE_train_original_scale, "\n")

RMSE on training data (original scale): 1029.428

cat("RMSE on validation data (original scale):", RMSE_validation_original_scale, "\n")

RMSE on validation data (original scale): 1118.905

Read the Dataset with Missing Monthly Incomes
comp_salary_data <- read.csv("CaseStudy2CompSet No Salary.csv")

Convert categorical variables in this dataset to factors
comp_salary_data[categorical_vars] <- lapply(comp_salary_data[categorical_vars], factor)

Apply the model to the competition data
comp_salary_predictions <- predict(model, newdata = comp_salary_data, type = "raw")
comp_salary_predictions <- exp(comp_salary_predictions) # Reverse log transformation

Create a data frame to save the predictions
result_df <- data.frame(ID = comp_salary_data$EmployeeNumber, PredictedSalary = comp_salary_predictions)

Write the predictions to a CSV file
write.csv(result_df, "Case2PredictionsMirzaSalary.csv", row.names = FALSE)

```