

FA6

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```
data <- read.csv("D:/FEU/3RD YR 2ND SEM/EDA/customer_segmentation.csv")
head(data)
```

### Data Exploration

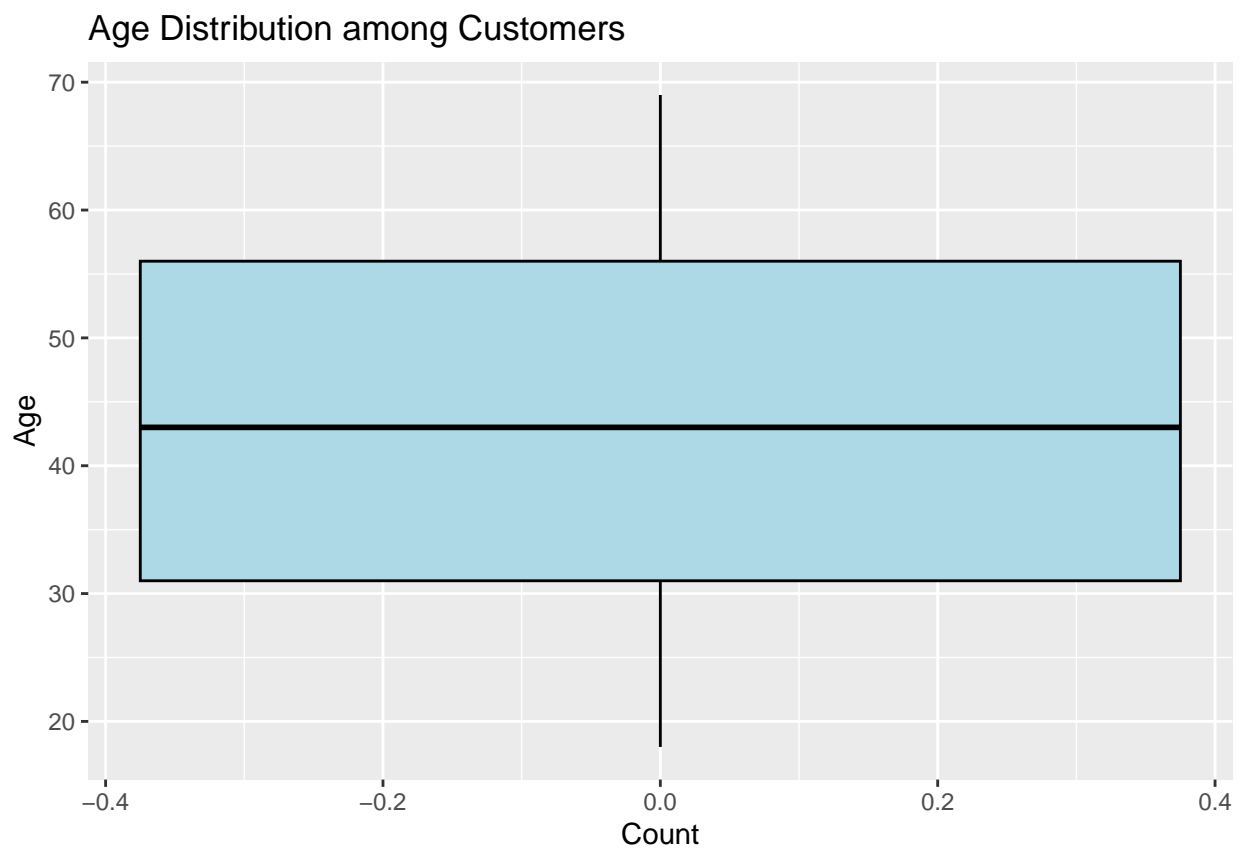
```
## Customer.ID Age Annual.Income..K.. Gender Product.Category.Purchased
## 1          1  56                106 Female                Fashion
## 2          2  69                66 Female                Home
## 3          3  46                110  Male                Fashion
## 4          4  32                50  Male                Electronics
## 5          5  60                73 Female                Others
## 6          6  25                48  Male                Home
## Average.Spend.per.Visit.... Number.of.Visits.in.Last.6.Months
## 1          163.4528                16
## 2          163.0205                31
## 3          104.5413                29
## 4          110.0646                26
## 5          142.2546                38
## 6          106.7621                22
## Customer.Segment
## 1 Premium Shopper
## 2 Budget Shopper
## 3 Budget Shopper
## 4 Regular Shopper
## 5 Regular Shopper
## 6 Budget Shopper
```

```
summary(data)
```

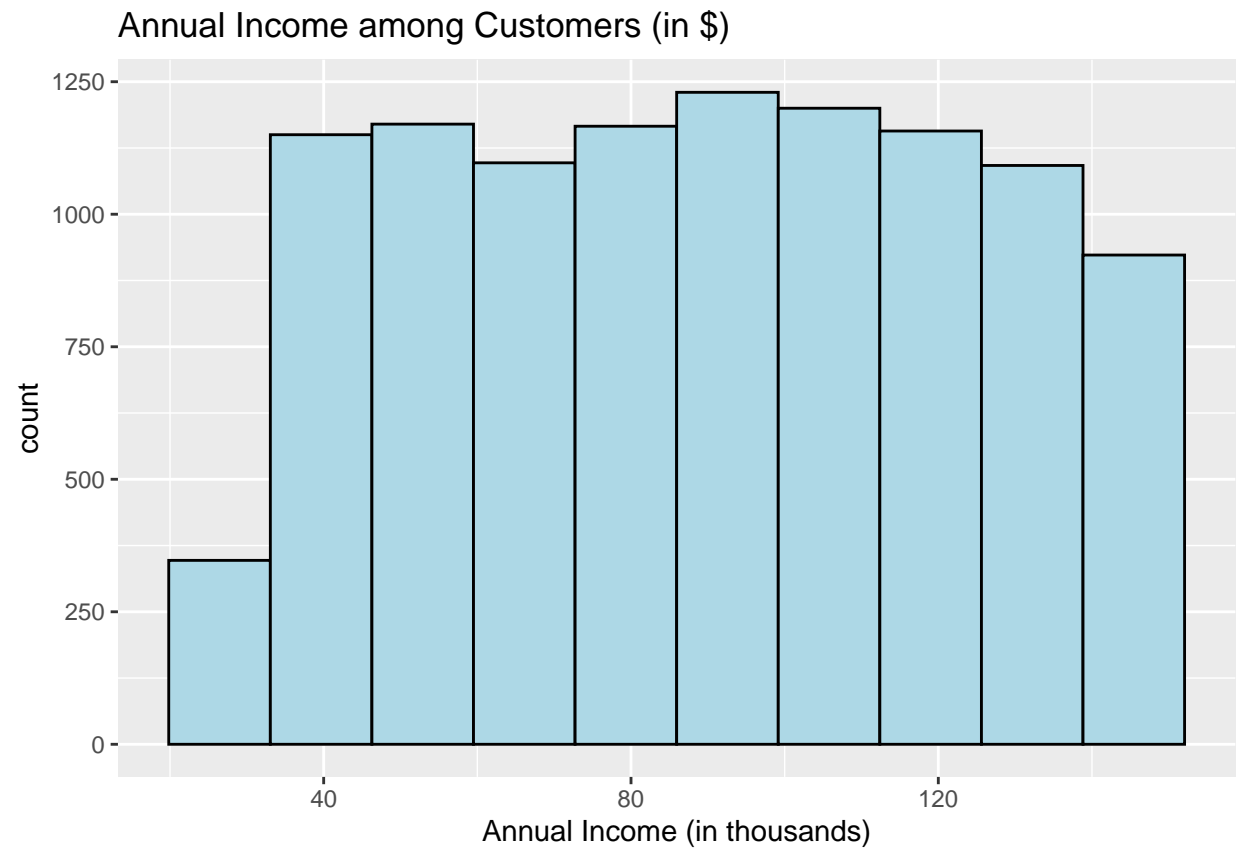
```
## Customer.ID          Age          Annual.Income..K..          Gender
## Min.   :    1   Min.   :18.00   Min.   : 30.00   Length:10532
## 1st Qu.: 2634   1st Qu.:31.00   1st Qu.: 59.00   Class :character
## Median : 5266   Median :43.00   Median : 89.00   Mode  :character
## Mean   : 5266   Mean   :43.59   Mean   : 89.18
## 3rd Qu.: 7899   3rd Qu.:56.00   3rd Qu.:118.00
## Max.   :10532   Max.   :69.00   Max.   :149.00
## Product.Category.Purchased Average.Spend.per.Visit....
## Length:10532                Min.   : 10.00
## Class :character            1st Qu.: 56.71
```

```
## Mode :character      Median :104.69
##                      Mean   :104.30
##                      3rd Qu.:150.89
##                      Max.   :199.96
## Number.of.Visits.in.Last.6.Months Customer.Segment
## Min.    : 5.00      Length:10532
## 1st Qu.:13.00      Class :character
## Median :22.00      Mode  :character
## Mean   :21.92
## 3rd Qu.:31.00
## Max.   :39.00
```

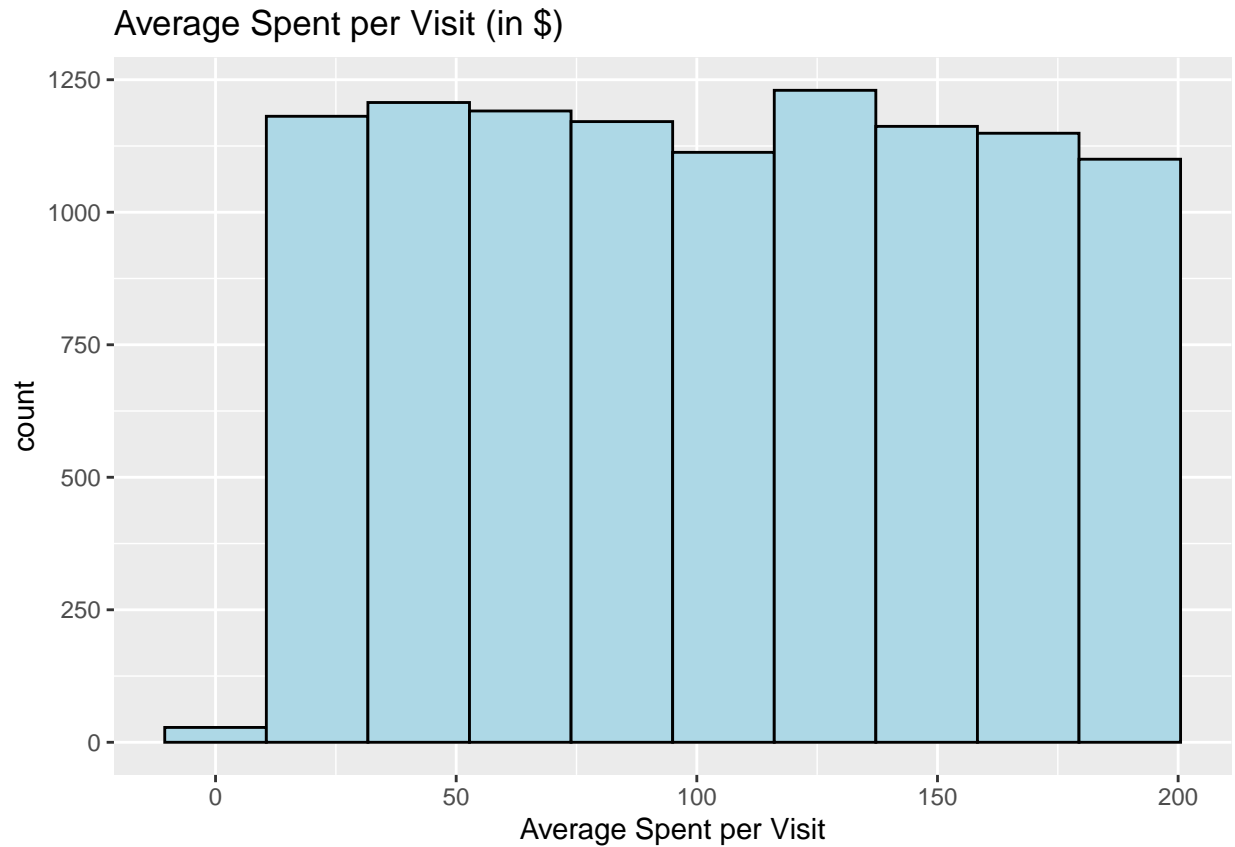
```
library(ggplot2)
ggplot(data = data, mapping = aes(y = Age)) +
  geom_boxplot( fill = "lightblue", color = "black") +
  labs(title = "Age Distribution among Customers", x = "Count")
```



```
library(ggplot2)
ggplot(data = data, mapping = aes(x = Annual.Income..K..)) +
  geom_histogram( fill = "lightblue", color = "black", bins = 10)+
  labs(title = "Annual Income among Customers (in $)", x = "Annual Income (in thousands)")
```



```
ggplot(data = data, mapping = aes(x =Average.Spend.per.Visit...)) +  
  geom_histogram( fill = "lightblue", color = "black", bins = 10)+  
  labs(title = "Average Spent per Visit (in $)", x = "Average Spent per Visit")
```

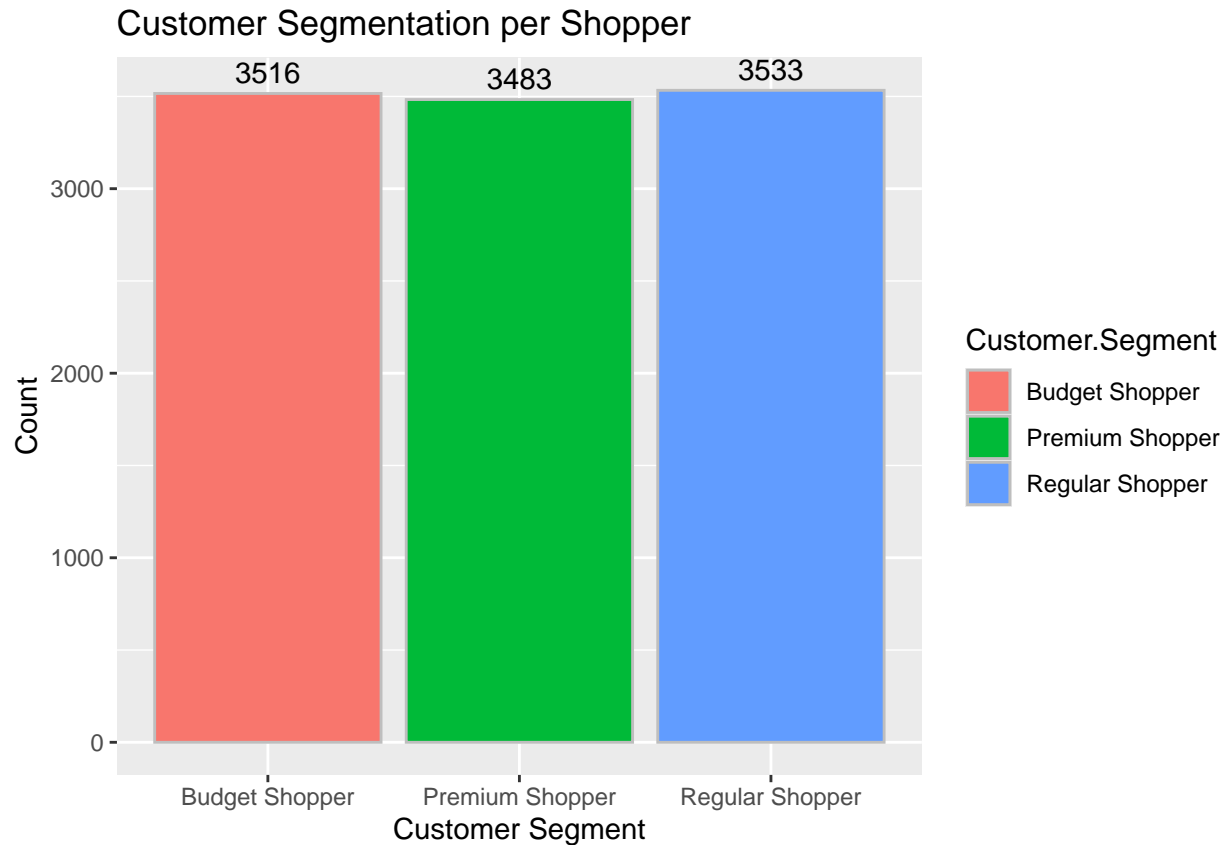


```
colSums(is.na(data))
```

```
##           Customer.ID           Age
##           0           0
##       Annual.Income..K..           Gender
##           0           0
## Product.Category.Purchased Average.Spend.per.Visit....
##           0           0
## Number.of.Visits.in.Last.6.Months Customer.Segment
##           0           0
```

There are no missing values.

```
ggplot(data = data, mapping = aes(x = Customer.Segment, fill = Customer.Segment )) +
  geom_bar(color = "gray") +
  geom_text(stat = "count", aes(label = after_stat(count)), vjust = -0.5) +
  labs(title= "Customer Segmentation per Shopper", x = "Customer Segment", y = "Count")
```



The three types of customer are about equal but the highest one is the regular shopper, having 50 more than the lowest (premium shopper). The one in the middle is the budget shoppers, tallying at 3516. Nevertheless, all of them are high.

```
library("caret")
```

### Data Reprocessing

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

```
library(dplyr)
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
## filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
## intersect, setdiff, setequal, union
```

```

dummy <- dummyVars("~Product.Category.Purchased", data = data)
prod_dummy <- data.frame(predict(dummy, newdata = data))
data_OH<-cbind(data, prod_dummy)
data_OH$Product.Category.Purchased<- NULL
head(data_OH)

```

```

## Customer.ID Age Annual.Income..K.. Gender Average.Spend.per.Visit....
## 1          1  56                    106 Female                163.4528
## 2          2  69                    66 Female                163.0205
## 3          3  46                    110 Male                 104.5413
## 4          4  32                    50 Male                 110.0646
## 5          5  60                    73 Female                142.2546
## 6          6  25                    48 Male                 106.7621
## Number.of.Visits.in.Last.6.Months Customer.Segment
## 1                                16 Premium Shopper
## 2                                31 Budget Shopper
## 3                                29 Budget Shopper
## 4                                26 Regular Shopper
## 5                                38 Regular Shopper
## 6                                22 Budget Shopper
## Product.Category.PurchasedBooks Product.Category.PurchasedElectronics
## 1                                0                                0
## 2                                0                                0
## 3                                0                                0
## 4                                0                                1
## 5                                0                                0
## 6                                0                                0
## Product.Category.PurchasedFashion Product.Category.PurchasedHome
## 1                                1                                0
## 2                                0                                1
## 3                                1                                0
## 4                                0                                0
## 5                                0                                0
## 6                                0                                1
## Product.Category.PurchasedOthers
## 1                                0
## 2                                0
## 3                                0
## 4                                0
## 5                                1
## 6                                0

```

```

data_OH$Gender_Label <- ifelse(data_OH$Gender == "Male", 1, 0)
data_OH$Gender <- NULL
data_OH$Customer.ID <- NULL

df <- data_OH
df <- df%>%rename(Gender = Gender_Label)

head(df)

```

```

## Age Annual.Income..K.. Average.Spend.per.Visit....
## 1  56                    106                163.4528

```

```
## 2 69 66 163.0205
## 3 46 110 104.5413
## 4 32 50 110.0646
## 5 60 73 142.2546
## 6 25 48 106.7621
## Number.of.Visits.in.Last.6.Months Customer.Segment
## 1 16 Premium Shopper
## 2 31 Budget Shopper
## 3 29 Budget Shopper
## 4 26 Regular Shopper
## 5 38 Regular Shopper
## 6 22 Budget Shopper
## Product.Category.PurchasedBooks Product.Category.PurchasedElectronics
## 1 0 0
## 2 0 0
## 3 0 0
## 4 0 1
## 5 0 0
## 6 0 0
## Product.Category.PurchasedFashion Product.Category.PurchasedHome
## 1 1 0
## 2 0 1
## 3 1 0
## 4 0 0
## 5 0 0
## 6 0 1
## Product.Category.PurchasedOthers Gender
## 1 0 0
## 2 0 0
## 3 0 1
## 4 0 1
## 5 1 0
## 6 0 1
```

```
continuous_vars <- c("Age", "Annual.Income..K..", "Average.Spend.per.Visit....")
df[continuous_vars] <- scale(df[continuous_vars])

head(df)
```

```
##      Age Annual.Income..K.. Average.Spend.per.Visit....
## 1 0.8323972 0.4886923 1.083217431
## 2 1.7046295 -0.6737348 1.075302088
## 3 0.1614492 0.6049350 0.004477697
## 4 -0.7778779 -1.1387056 0.105615627
## 5 1.1007764 -0.4703100 0.695052913
## 6 -1.2475415 -1.1968270 0.045143784
## Number.of.Visits.in.Last.6.Months Customer.Segment
## 1 16 Premium Shopper
## 2 31 Budget Shopper
## 3 29 Budget Shopper
## 4 26 Regular Shopper
## 5 38 Regular Shopper
## 6 22 Budget Shopper
## Product.Category.PurchasedBooks Product.Category.PurchasedElectronics
```

```
## 1 0 0
## 2 0 0
## 3 0 0
## 4 0 1
## 5 0 0
## 6 0 0
## Product.Category.PurchasedFashion Product.Category.PurchasedHome
## 1 1 0
## 2 0 1
## 3 1 0
## 4 0 0
## 5 0 0
## 6 0 1
## Product.Category.PurchasedOthers Gender
## 1 0 0
## 2 0 0
## 3 0 1
## 4 0 1
## 5 1 0
## 6 0 1
```

```
library(caret)
library(dplyr)
set.seed(600)
trIndex <- createDataPartition(df$Customer.Segment, p = 0.8, list = FALSE)

train_data <- df[trIndex, ]
test_data <- df[-trIndex, ]

train_data$Customer.Segment <- as.factor(train_data$Customer.Segment)
test_data$Customer.Segment <- as.factor(test_data$Customer.Segment)

cat("\nTraining data rows:", nrow(train_data),
    "\nTest data rows:", nrow(test_data),
    "\nClass distribution in training set:\n")
```

```
##
## Training data rows: 8427
## Test data rows: 2105
## Class distribution in training set:
```

```
print(table(train_data$Customer.Segment))
```

```
##
## Budget Shopper Premium Shopper Regular Shopper
## 2813 2787 2827
```

```
library(nnet)
segment_mlr <- multinom(Customer.Segment ~ ., data = train_data)
```

```
## # weights: 36 (22 variable)
## initial value 9258.005757
```



```
## iter 10 value 9248.948137
## iter 20 value 9246.986594
## final value 9246.582703
## converged
```

```
summary(segment_mlr)
```

```
## Call:
## multinom(formula = Customer.Segment ~ ., data = train_data)
##
## Coefficients:
## (Intercept) Age Annual.Income..K..
## Premium Shopper 0.06239558 -0.002531114 -0.004037751
## Regular Shopper 0.09614614 0.029310277 -0.013686390
## Average.Spend.per.Visit.... Number.of.Visits.in.Last.6.Months
## Premium Shopper -0.03229190 -0.003489528
## Regular Shopper -0.05849034 -0.003156629
## Product.Category.PurchasedBooks
## Premium Shopper -0.10962215
## Regular Shopper -0.08548282
## Product.Category.PurchasedElectronics
## Premium Shopper 0.02838115
## Regular Shopper 0.02325285
## Product.Category.PurchasedFashion
## Premium Shopper 0.1295403
## Regular Shopper 0.1252064
## Product.Category.PurchasedHome Product.Category.PurchasedOthers
## Premium Shopper 0.001907183 0.01218914
## Regular Shopper -0.028865774 0.06203545
## Gender
## Premium Shopper -0.008107097
## Regular Shopper -0.078946806
##
## Std. Errors:
## (Intercept) Age Annual.Income..K..
## Premium Shopper 0.05827820 0.02680783 0.02677545
## Regular Shopper 0.05798534 0.02672753 0.02668951
## Average.Spend.per.Visit.... Number.of.Visits.in.Last.6.Months
## Premium Shopper 0.02685104 0.002651785
## Regular Shopper 0.02676879 0.002643341
## Product.Category.PurchasedBooks
## Premium Shopper 0.05387690
## Regular Shopper 0.05349586
## Product.Category.PurchasedElectronics
## Premium Shopper 0.05588146
## Regular Shopper 0.05584757
## Product.Category.PurchasedFashion
## Premium Shopper 0.05649986
## Regular Shopper 0.05646343
## Product.Category.PurchasedHome Product.Category.PurchasedOthers
## Premium Shopper 0.05478646 0.05314039
## Regular Shopper 0.05504375 0.05255361
## Gender
## Premium Shopper 0.05352182
```

```
## Regular Shopper 0.05335506
##
## Residual Deviance: 18493.17
## AIC: 18533.17
```

The only thing noticeable on the customer segmentation is that the age and annual income slightly has an influence on being a premium shopper, but in terms of shopping behavior, it is obvious that being a premium shopper would make you spend a higher average every visit, which is true on the analysis. We can also see that being a premium shopper also shows a tendency to lean on fashion products.

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-8
```

```
library(caret)
library(ggplot2)

set.seed(123)
train_data_balanced <- upSample(
  x = train_data[, -which(names(train_data) == "Customer.Segment")],
  y = train_data$Customer.Segment,
  yname = "Customer.Segment"
)
X <- model.matrix(Customer.Segment ~ ., data = train_data_balanced)[, -1]
y <- train_data_balanced$Customer.Segment

cv_fit <- cv.glmnet(X, y, family = "multinomial", alpha = 0.5,
  type.measure = "class", nfolds = 5, standardize = TRUE)

best_lambda <- cv_fit$lambda.min
cat("Best lambda:", best_lambda, "\n")
```

```
## Best lambda: 0.009726015
```

```
final_model <- glmnet(X, y, family = "multinomial", alpha = 0.5, lambda = best_lambda, standardize = TRUE)

test_X <- model.matrix(Customer.Segment ~ ., data = test_data)[, -1]

pred_probs <- predict(final_model, newx = test_X, type = "response")[,1] # 3D array
pred_labels <- colnames(pred_probs)[max.col(pred_probs)]

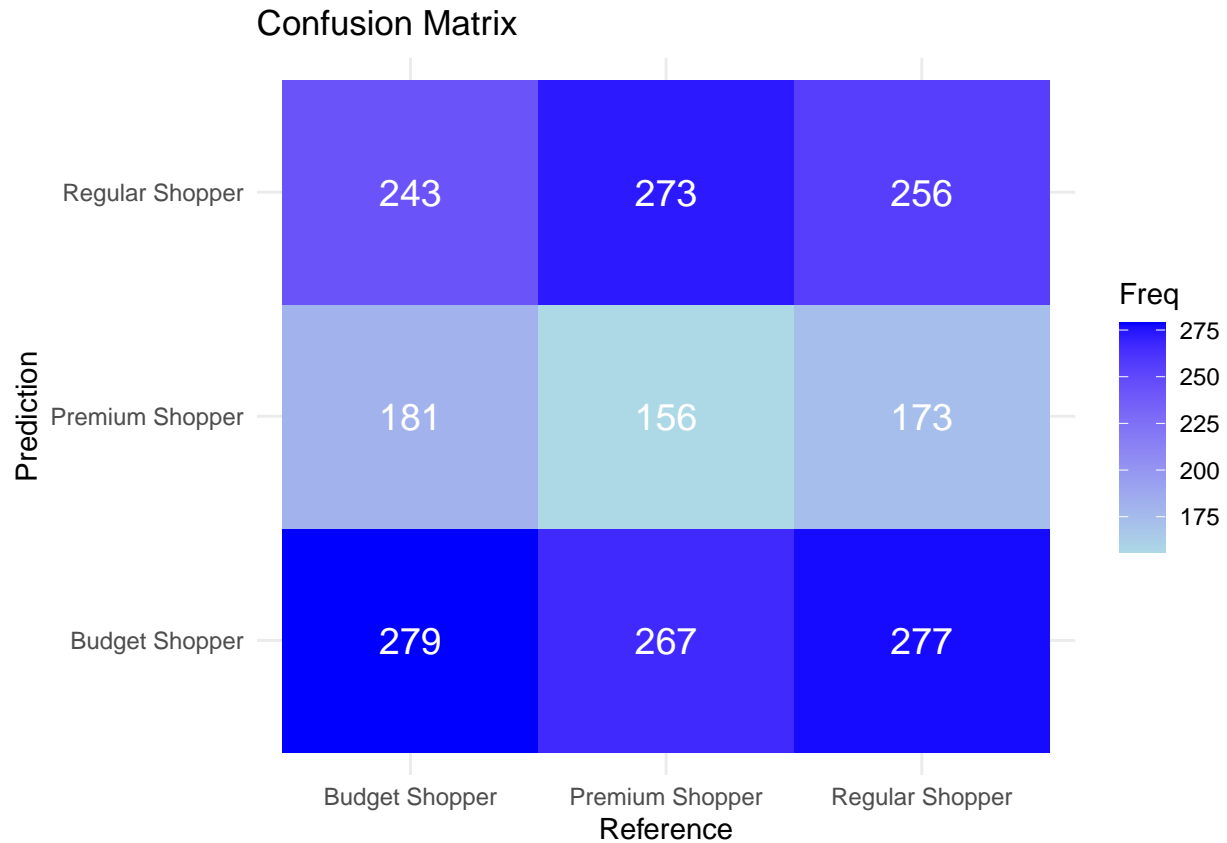
class_levels <- levels(train_data$Customer.Segment)
pred_labels <- factor(pred_labels, levels = class_levels)
true_labels <- factor(test_data$Customer.Segment, levels = class_levels)

conf_matrix <- confusionMatrix(pred_labels, true_labels)
print(conf_matrix)
```

```
## Confusion Matrix and Statistics
```

```
##
##               Reference
## Prediction      Budget Shopper Premium Shopper Regular Shopper
##   Budget Shopper           279           267           277
##   Premium Shopper          181           156           173
##   Regular Shopper          243           273           256
##
## Overall Statistics
##
##               Accuracy : 0.3283
##               95% CI : (0.3082, 0.3488)
##   No Information Rate : 0.3354
##   P-Value [Acc > NIR] : 0.7625
##
##               Kappa : -0.0081
##
## McNemar's Test P-Value : 6.067e-09
##
## Statistics by Class:
##
##               Class: Budget Shopper Class: Premium Shopper
## Sensitivity           0.3969           0.22414
## Specificity           0.6120           0.74876
## Pos Pred Value        0.3390           0.30588
## Neg Pred Value        0.6693           0.66144
## Prevalence            0.3340           0.33064
## Detection Rate        0.1325           0.07411
## Detection Prevalence  0.3910           0.24228
## Balanced Accuracy     0.5044           0.48645
##
##               Class: Regular Shopper
## Sensitivity           0.3626
## Specificity           0.6312
## Pos Pred Value        0.3316
## Neg Pred Value        0.6624
## Prevalence            0.3354
## Detection Rate        0.1216
## Detection Prevalence  0.3667
## Balanced Accuracy     0.4969
```

```
ggplot(as.data.frame(conf_matrix$table),
       aes(Reference, Prediction, fill = Freq)) +
  geom_tile() +
  geom_text(aes(label = Freq), color = "white", size = 5) +
  scale_fill_gradient(low = "lightblue", high = "blue") +
  theme_minimal() +
  labs(title = "Confusion Matrix")
```



**Reporting** The customer segmentation model was built using multinomial logistic regression with elastic net regularization. It classified shoppers into three (budget, regular, premium) groups based on their age, income, spending habits, and history. The model achieved 32.6 accuracy, which is worse than random guessing, even though there are already feature scaling and cross-validation. The confusion matrix showed frequent misclassifications particularly for premium shoppers, although we can see that the age and annual income slightly has an influence on being a premium shopper. This suggests that the model lack predictive power for clear segmentation. For future improvements, analysts should focus on testing advanced nonlinear models like XGBoost (Extreme Gradient Boosting).