BUAN4310 Group Project 1

Shayla Nguyen

2024-10-25

```
library(caret)

## Loading required package: ggplot2

## Loading required package: lattice

library(ROSE)

## Loaded ROSE 0.0-4

library(pROC)

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

library(readr)

# Load the credit31 data
credit31 <- read_csv("credit_31.csv")

## New names:
## • `` -> `...1`

## Rows: 30000 Columns: 68
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr (12): NAME_CONTRACT_TYPE, CODE_GENDER, FLAG_OWN_CAR, FLAG_OWN_REALTY, NA...
## dbl (56): ...1, SK_ID_CURR, TARGET, CNT_CHILDREN, AMT_INCOME_TOTAL, AMT_CRED...
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.

# Add new fields into data frame to improve model accuracy
credit31$Income_Credit_Ratio <- credit31$AMT_INCOME_TOTAL / credit31$AMT_CRED
```

```
IT
credit31$Annuity_Income_Ratio <- credit31$AMT_ANNUITY / credit31$AMT_INCOME_T
OTAL
credit31$Credit_As_Percentage <- credit31$AMT_CREDIT / credit31$AMT_INCOME_TO
TAL
credit31$Percent_Days_Employed <- credit31$DAYS_EMPLOYED / credit31$DAYS_BIRT
H
credit31$Income_Per_Person <- credit31$AMT_INCOME_TOTAL / credit31$CNT_FAM_ME
MBERS

# Remove XNA from CODE_GENDER variable and convert to factor
credit31 <- credit31[credit31$CODE_GENDER != "XNA", ]
credit31$CODE_GENDER <- factor(credit31$CODE_GENDER)

# Explore data
names(credit31)

##  [1] "...1"                        "SK_ID_CURR"
##  [3] "TARGET"                      "NAME_CONTRACT_TYPE"
##  [5] "CODE_GENDER"                 "FLAG_OWN_CAR"
##  [7] "FLAG_OWN_REALTY"             "CNT_CHILDREN"
##  [9] "AMT_INCOME_TOTAL"            "AMT_CREDIT"
## [11] "AMT_ANNUITY"                 "AMT_GOODS_PRICE"
## [13] "NAME_TYPE_SUITE"             "NAME_INCOME_TYPE"
## [15] "NAME_EDUCATION_TYPE"         "NAME_FAMILY_STATUS"
## [17] "NAME_HOUSING_TYPE"           "DAYS_BIRTH"
## [19] "DAYS_EMPLOYED"               "DAYS_REGISTRATION"
## [21] "DAYS_ID_PUBLISH"             "OWN_CAR_AGE"
## [23] "FLAG_MOBIL"                  "FLAG_EMP_PHONE"
## [25] "FLAG_WORK_PHONE"             "FLAG_CONT_MOBILE"
## [27] "FLAG_PHONE"                  "FLAG_EMAIL"
## [29] "OCCUPATION_TYPE"             "CNT_FAM_MEMBERS"
## [31] "REGION_RATING_CLIENT"        "REGION_RATING_CLIENT_W_CITY"
## [33] "WEEKDAY_APPR_PROCESS_START"  "HOUR_APPR_PROCESS_START"
## [35] "REG_REGION_NOT_LIVE_REGION"  "REG_REGION_NOT_WORK_REGION"
## [37] "LIVE_REGION_NOT_WORK_REGION" "REG_CITY_NOT_LIVE_CITY"
## [39] "REG_CITY_NOT_WORK_CITY"      "LIVE_CITY_NOT_WORK_CITY"
## [41] "ORGANIZATION_TYPE"           "DAYS_LAST_PHONE_CHANGE"
## [43] "FLAG_DOCUMENT_2"             "FLAG_DOCUMENT_3"
## [45] "FLAG_DOCUMENT_4"             "FLAG_DOCUMENT_5"
## [47] "FLAG_DOCUMENT_6"             "FLAG_DOCUMENT_7"
## [49] "FLAG_DOCUMENT_8"             "FLAG_DOCUMENT_9"
## [51] "FLAG_DOCUMENT_10"            "FLAG_DOCUMENT_11"
## [53] "FLAG_DOCUMENT_12"            "FLAG_DOCUMENT_13"
## [55] "FLAG_DOCUMENT_14"            "FLAG_DOCUMENT_15"
## [57] "FLAG_DOCUMENT_16"            "FLAG_DOCUMENT_17"
## [59] "FLAG_DOCUMENT_18"            "FLAG_DOCUMENT_19"
## [61] "FLAG_DOCUMENT_20"            "FLAG_DOCUMENT_21"
## [63] "AMT_REQ_CREDIT_BUREAU_HOUR"  "AMT_REQ_CREDIT_BUREAU_DAY"
## [65] "AMT_REQ_CREDIT_BUREAU_WEEK"  "AMT_REQ_CREDIT_BUREAU_MON"
```

```
## [67] "AMT_REQ_CREDIT_BUREAU_QRT"   "AMT_REQ_CREDIT_BUREAU_YEAR"
## [69] "Income_Credit_Ratio"         "Annuity_Income_Ratio"
## [71] "Credit_As_Percentage"        "Percent_Days_Employed"
## [73] "Income_Per_Person"
```

```r
str(credit31)
```

```
## tibble [30,000 × 73] (S3: tbl_df/tbl/data.frame)
##  $ ...1                      : num [1:30000] 284834 161354 132607 199508
99768 ...
##  $ SK_ID_CURR                : num [1:30000] 429876 287055 253803 331291
215821 ...
##  $ TARGET                    : num [1:30000] 0 0 1 0 0 0 0 0 0 0 ...
##  $ NAME_CONTRACT_TYPE        : chr [1:30000] "Cash loans" "Cash loans" "C
ash loans" "Cash loans" ...
##  $ CODE_GENDER               : Factor w/ 2 levels "F","M": 1 2 2 1 1 2 1
1 1 1 ...
##  $ FLAG_OWN_CAR              : chr [1:30000] "N" "Y" "N" "Y" ...
##  $ FLAG_OWN_REALTY           : chr [1:30000] "N" "Y" "Y" "N" ...
##  $ CNT_CHILDREN              : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ AMT_INCOME_TOTAL          : num [1:30000] 103500 81000 112500 225000 6
7500 ...
##  $ AMT_CREDIT                : num [1:30000] 675000 808650 423000 646920
135000 ...
##  $ AMT_ANNUITY               : num [1:30000] 21776 26217 28269 25065 1615
0 ...
##  $ AMT_GOODS_PRICE           : num [1:30000] 675000 675000 423000 540000
135000 ...
##  $ NAME_TYPE_SUITE           : chr [1:30000] "Family" "Family" "Spouse, p
artner" "Unaccompanied" ...
##  $ NAME_INCOME_TYPE          : chr [1:30000] "State servant" "Working" "W
orking" "Working" ...
##  $ NAME_EDUCATION_TYPE       : chr [1:30000] "Higher education" "Secondar
y / secondary special" "Secondary / secondary special" "Higher education" ...
##  $ NAME_FAMILY_STATUS        : chr [1:30000] "Separated" "Married" "Marri
ed" "Married" ...
##  $ NAME_HOUSING_TYPE         : chr [1:30000] "House / apartment" "House /
apartment" "House / apartment" "House / apartment" ...
##  $ DAYS_BIRTH                : num [1:30000] -14211 -17884 -14629 -12894
-16825 ...
##  $ DAYS_EMPLOYED             : num [1:30000] -2875 -2192 -984 -1994 -1087
...
##  $ DAYS_REGISTRATION         : num [1:30000] -4018 -7442 -741 -1278 -8220
...
##  $ DAYS_ID_PUBLISH           : num [1:30000] -4693 -1428 -1747 -3897 -367
...
##  $ OWN_CAR_AGE               : num [1:30000] NA 1 NA 1 18 NA NA NA NA NA
...
##  $ FLAG_MOBIL                : num [1:30000] 1 1 1 1 1 1 1 1 1 1 ...
##  $ FLAG_EMP_PHONE            : num [1:30000] 1 1 1 1 1 1 1 0 1 0 ...
```

```
##  $ FLAG_WORK_PHONE            : num [1:30000] 1 1 0 1 0 0 0 0 0 0 ...
##  $ FLAG_CONT_MOBILE           : num [1:30000] 1 1 1 1 1 1 1 1 1 1 ...
##  $ FLAG_PHONE                 : num [1:30000] 0 1 0 1 0 0 0 0 0 0 ...
##  $ FLAG_EMAIL                 : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ OCCUPATION_TYPE            : chr [1:30000] "Laborers" "Security staff"
"Laborers" "Laborers" ...
##  $ CNT_FAM_MEMBERS            : num [1:30000] 1 2 2 2 2 1 2 2 1 2 ...
##  $ REGION_RATING_CLIENT       : num [1:30000] 2 2 2 2 2 2 2 2 2 3 ...
##  $ REGION_RATING_CLIENT_W_CITY: num [1:30000] 2 2 2 2 2 2 2 2 2 3 ...
##  $ WEEKDAY_APPR_PROCESS_START : chr [1:30000] "SUNDAY" "TUESDAY" "MONDAY"
"SATURDAY" ...
##  $ HOUR_APPR_PROCESS_START    : num [1:30000] 11 11 8 10 9 12 14 11 11 11
...
##  $ REG_REGION_NOT_LIVE_REGION : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ REG_REGION_NOT_WORK_REGION : num [1:30000] 0 0 1 0 0 0 0 0 0 0 ...
##  $ LIVE_REGION_NOT_WORK_REGION: num [1:30000] 0 0 1 0 0 0 0 0 0 0 ...
##  $ REG_CITY_NOT_LIVE_CITY     : num [1:30000] 0 0 0 0 0 1 0 0 0 0 ...
##  $ REG_CITY_NOT_WORK_CITY     : num [1:30000] 0 1 1 0 1 1 1 0 0 0 ...
##  $ LIVE_CITY_NOT_WORK_CITY    : num [1:30000] 0 1 1 0 1 0 1 0 0 0 ...
##  $ ORGANIZATION_TYPE          : chr [1:30000] "Postal" "Business Entity Ty
pe 3" "Industry: type 9" "Business Entity Type 1" ...
##  $ DAYS_LAST_PHONE_CHANGE     : num [1:30000] -1735 0 -570 -1748 -1204 ...
##  $ FLAG_DOCUMENT_2            : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_3            : num [1:30000] 1 1 1 1 1 1 1 0 0 0 ...
##  $ FLAG_DOCUMENT_4            : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_5            : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_6            : num [1:30000] 0 0 0 0 0 0 0 0 0 1 ...
##  $ FLAG_DOCUMENT_7            : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_8            : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_9            : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_10           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_11           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_12           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_13           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_14           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_15           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_16           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_17           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_18           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_19           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_20           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ FLAG_DOCUMENT_21           : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ AMT_REQ_CREDIT_BUREAU_HOUR : num [1:30000] 0 0 0 1 0 0 0 0 0 0 ...
##  $ AMT_REQ_CREDIT_BUREAU_DAY  : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ AMT_REQ_CREDIT_BUREAU_WEEK : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ AMT_REQ_CREDIT_BUREAU_MON  : num [1:30000] 0 0 0 1 0 0 0 0 1 1 ...
##  $ AMT_REQ_CREDIT_BUREAU_QRT  : num [1:30000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ AMT_REQ_CREDIT_BUREAU_YEAR : num [1:30000] 2 2 0 2 1 1 2 5 0 2 ...
##  $ Income_Credit_Ratio        : num [1:30000] 0.153 0.1 0.266 0.348 0.5 ..
.
```

```
##  $ Annuity_Income_Ratio       : num [1:30000] 0.21 0.324 0.251 0.111 0.239
...
##  $ Credit_As_Percentage       : num [1:30000] 6.52 9.98 3.76 2.88 2 ...
##  $ Percent_Days_Employed      : num [1:30000] 0.2023 0.1226 0.0673 0.1546
0.0646 ...
##  $ Income_Per_Person          : num [1:30000] 103500 40500 56250 112500 33
750 ...
```

```r
summary(credit31$TARGET)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1949  0.0000  1.0000
```

```r
# Convert education type to factor with levels across education
credit31$NAME_EDUCATION_TYPE <- factor(credit31$NAME_EDUCATION_TYPE, levels =
c(
  "Secondary / secondary special",
  "Higher education",
  "Lower secondary",
  "Incomplete higher",
  "Academic degree"))

# Set Target variable as factor
credit31$TARGET <- as.factor(credit31$TARGET)

# Variable list
# Percent_Days_Employed, NAME_EDUCATION_TYPE, REGION_RATING_CLIENT_W_CITY, AM
T_GOODS_PRICE, CODE_GENDER, DAYS_BIRTH, AMT_CREDIT, AMT_ANNUITY, DAYS_EMPLOYE
D, DAYS_REGISTRATION, DAYS_ID_PUBLISH, Annuity_Income_Ratio

# Remove unused variables
credit31 <- credit31[ , -c(1:2, 4, 6:9, 13:14, 16:17, 22:31, 33:69, 71, 73)]
names(credit31)
```

```
##  [1] "TARGET"                      "CODE_GENDER"
##  [3] "AMT_CREDIT"                  "AMT_ANNUITY"
##  [5] "AMT_GOODS_PRICE"             "NAME_EDUCATION_TYPE"
##  [7] "DAYS_BIRTH"                  "DAYS_EMPLOYED"
##  [9] "DAYS_REGISTRATION"           "DAYS_ID_PUBLISH"
## [11] "REGION_RATING_CLIENT_W_CITY" "Annuity_Income_Ratio"
## [13] "Percent_Days_Employed"
```

```r
# Training - Validation split
set.seed(666)
train_index <- sample(1:nrow(credit31), 0.7 * nrow(credit31))
valid_index <- setdiff(1:nrow(credit31), train_index)
train_df <- credit31[train_index, ]
valid_df <- credit31[valid_index, ]

# Double check
nrow(train_df)
```

```
## [1] 21000
```

```r
nrow(valid_df)
```

```
## [1] 9000
```

```r
head(train_df)
```

```
## # A tibble: 6 × 13
##   TARGET CODE_GENDER AMT_CREDIT AMT_ANNUITY AMT_GOODS_PRICE NAME_EDUCATION
_TYPE
##   <fct>  <fct>            <dbl>       <dbl>           <dbl> <fct>
## 1 0      M               956574      38066.          855000 Secondary / se
conda…
## 2 0      F              1633473      45050.         1363500 Secondary / se
conda…
## 3 1      F               279000      15134.          279000 Secondary / se
conda…
## 4 0      F               405000      20250           405000 Higher educati
on
## 5 1      M               279000      22041           279000 Secondary / se
conda…
## 6 0      F               808650      26217           675000 Secondary / se
conda…
## # ℹ 7 more variables: DAYS_BIRTH <dbl>, DAYS_EMPLOYED <dbl>,
## #   DAYS_REGISTRATION <dbl>, DAYS_ID_PUBLISH <dbl>,
## #   REGION_RATING_CLIENT_W_CITY <dbl>, Annuity_Income_Ratio <dbl>,
## #   Percent_Days_Employed <dbl>
```

```r
head(valid_df)
```

```
## # A tibble: 6 × 13
##   TARGET CODE_GENDER AMT_CREDIT AMT_ANNUITY AMT_GOODS_PRICE NAME_EDUCATION
_TYPE
##   <fct>  <fct>            <dbl>       <dbl>           <dbl> <fct>
## 1 0      M               808650      26217           675000 Secondary / se
conda…
## 2 1      M               423000      28269           423000 Secondary / se
conda…
## 3 0      M               450000      30074.          450000 Secondary / se
conda…
## 4 0      F               202500      10125           202500 Secondary / se
conda…
## 5 0      F               269550      12002.          225000 Secondary / se
conda…
## 6 0      F              1125000      36292.         1125000 Secondary / se
conda…
## # ℹ 7 more variables: DAYS_BIRTH <dbl>, DAYS_EMPLOYED <dbl>,
## #   DAYS_REGISTRATION <dbl>, DAYS_ID_PUBLISH <dbl>,
## #   REGION_RATING_CLIENT_W_CITY <dbl>, Annuity_Income_Ratio <dbl>,
## #   Percent_Days_Employed <dbl>
```

```r
str(train_df)
```

```
## tibble [21,000 × 13] (S3: tbl_df/tbl/data.frame)
##  $ TARGET                     : Factor w/ 2 levels "0","1": 1 1 2 1 2 1 1
1 1 1 ...
##  $ CODE_GENDER                : Factor w/ 2 levels "F","M": 2 1 1 1 2 1 2
2 1 2 ...
##  $ AMT_CREDIT                 : num [1:21000] 956574 1633473 279000 405000
279000 ...
##  $ AMT_ANNUITY                : num [1:21000] 38066 45050 15134 20250 2204
1 ...
##  $ AMT_GOODS_PRICE            : num [1:21000] 855000 1363500 279000 405000
279000 ...
##  $ NAME_EDUCATION_TYPE        : Factor w/ 5 levels "Secondary / secondary
special",..: 1 1 1 2 1 1 1 2 1 1 ...
##  $ DAYS_BIRTH                 : num [1:21000] -14523 -13597 -21630 -14352
-23121 ...
##  $ DAYS_EMPLOYED              : num [1:21000] -926 -247 -14068 -4132 36524
3 ...
##  $ DAYS_REGISTRATION          : num [1:21000] -8452 -7709 -5517 -10 -935 .
..
##  $ DAYS_ID_PUBLISH            : num [1:21000] -4476 -4795 -5024 -2199 -445
0 ...
##  $ REGION_RATING_CLIENT_W_CITY: num [1:21000] 2 3 2 2 2 2 2 2 2 2 ...
##  $ Annuity_Income_Ratio       : num [1:21000] 0.169 0.222 0.108 0.15 0.109
...
##  $ Percent_Days_Employed      : num [1:21000] 0.0638 0.0182 0.6504 0.2879
-15.797 ...
```

```r
str(valid_df)
```

```
## tibble [9,000 × 13] (S3: tbl_df/tbl/data.frame)
##  $ TARGET                     : Factor w/ 2 levels "0","1": 1 2 1 1 1 1 2
1 1 1 ...
##  $ CODE_GENDER                : Factor w/ 2 levels "F","M": 2 2 2 1 1 1 1
1 1 2 ...
##  $ AMT_CREDIT                 : num [1:9000] 808650 423000 450000 202500 2
69550 ...
##  $ AMT_ANNUITY                : num [1:9000] 26217 28269 30074 10125 12002
...
##  $ AMT_GOODS_PRICE            : num [1:9000] 675000 423000 450000 202500 2
25000 ...
##  $ NAME_EDUCATION_TYPE        : Factor w/ 5 levels "Secondary / secondary
special",..: 1 1 1 1 1 1 4 1 1 1 ...
##  $ DAYS_BIRTH                 : num [1:9000] -17884 -14629 -9655 -21512 -2
2485 ...
##  $ DAYS_EMPLOYED              : num [1:9000] -2192 -984 -2940 -1874 365243
...
##  $ DAYS_REGISTRATION          : num [1:9000] -7442 -741 -8153 -10778 -1454
4 ...
```

```
##  $ DAYS_ID_PUBLISH            : num [1:9000] -1428 -1747 -2298 -4811 -4620
...
##  $ REGION_RATING_CLIENT_W_CITY: num [1:9000] 2 2 2 2 3 2 2 2 1 2 ...
##  $ Annuity_Income_Ratio       : num [1:9000] 0.324 0.251 0.122 0.113 0.133
...
##  $ Percent_Days_Employed      : num [1:9000] 0.1226 0.0673 0.3045 0.0871 -
16.2439 ...
```

```r
# Use ROSE to balance model
train_df_rose <- ROSE(TARGET ~ Percent_Days_Employed + NAME_EDUCATION_TYPE +
REGION_RATING_CLIENT_W_CITY + AMT_GOODS_PRICE + CODE_GENDER + DAYS_BIRTH + AM
T_CREDIT + AMT_ANNUITY + DAYS_EMPLOYED + DAYS_REGISTRATION + DAYS_ID_PUBLISH
+ Annuity_Income_Ratio,
                      data = train_df, seed = 666)$data

table(train_df_rose$TARGET)
```

```
##
##     0     1
## 10339 10642
```

```r
# Normalization algorithm
train_norm <- train_df_rose
valid_norm <- valid_df

norm_values <- preProcess(train_df_rose[, -c(1)],
                          method = c("center", "scale"))
train_norm[, -c(1)] <- predict(norm_values,
                               train_df_rose[, -c(1)])

# Apply to validation set
valid_norm[, -c(1)] <- predict(norm_values,
                               valid_df[, -c(1)])

# Drop missing values
library(tidyr)
valid_norm <- drop_na(valid_norm)

# Train logistic regression model
logistic_model <- glm(TARGET ~ Percent_Days_Employed + NAME_EDUCATION_TYPE +
REGION_RATING_CLIENT_W_CITY + AMT_GOODS_PRICE + CODE_GENDER + DAYS_BIRTH + AM
T_CREDIT + AMT_ANNUITY + DAYS_EMPLOYED + DAYS_REGISTRATION + DAYS_ID_PUBLISH
+ Annuity_Income_Ratio,
                      data = train_norm, family = binomial)

# Prediction on training set
logistic_pred_train <- predict(logistic_model, newdata = train_norm, type = "
response")
logistic_pred_train_class <- ifelse(logistic_pred_train > 0.5, 1, 0)
```

```r
# Prediction on validation set
logistic_pred_valid <- predict(logistic_model, newdata = valid_norm, type = "
response")
logistic_pred_valid_class <- ifelse(logistic_pred_valid > 0.5, 1, 0)

# Confusion matrix on training set
confusionMatrix(as.factor(logistic_pred_train_class), as.factor(train_norm$TA
RGET), positive = "1")
```

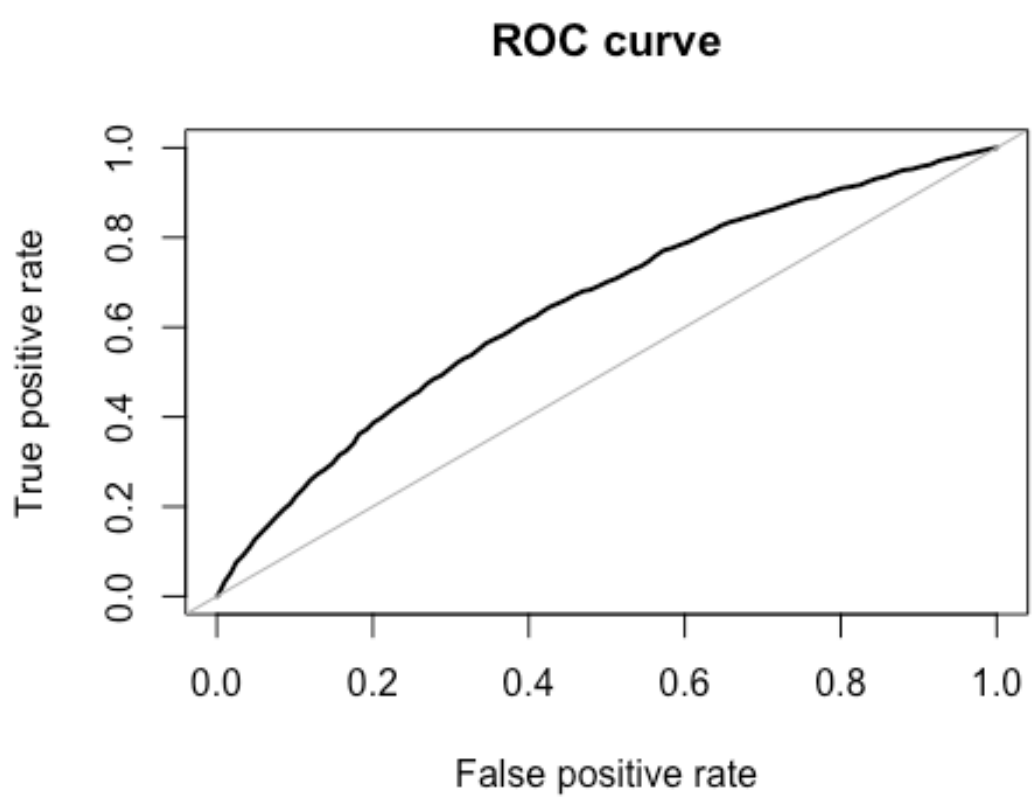
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5773 3900
##          1 4566 6742
##
##                Accuracy : 0.5965
##                  95% CI : (0.5898, 0.6031)
##     No Information Rate : 0.5072
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.1921
##
##  Mcnemar's Test P-Value : 4.923e-13
##
##             Sensitivity : 0.6335
##             Specificity : 0.5584
##          Pos Pred Value : 0.5962
##          Neg Pred Value : 0.5968
##              Prevalence : 0.5072
##          Detection Rate : 0.3213
##    Detection Prevalence : 0.5390
##       Balanced Accuracy : 0.5959
##
##        'Positive' Class : 1
##
```

```r
# Confusion matrix on validation set
confusionMatrix(as.factor(logistic_pred_valid_class), as.factor(valid_norm$TA
RGET), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 4027  600
##          1 3198 1165
##
##                Accuracy : 0.5775
##                  95% CI : (0.5672, 0.5878)
```

```
##     No Information Rate : 0.8037
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1397
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.6601
##             Specificity : 0.5574
##          Pos Pred Value : 0.2670
##          Neg Pred Value : 0.8703
##              Prevalence : 0.1963
##          Detection Rate : 0.1296
##    Detection Prevalence : 0.4853
##       Balanced Accuracy : 0.6087
##
##        'Positive' Class : 1
##
```

```r
# Model Evaluation
library(ROSE)
ROSE::roc.curve(valid_norm$TARGET, logistic_pred_valid)
```



```
## Area under the curve (AUC): 0.646

# Load new customer data
new_customers <- read_csv("credit_test_31.csv")

## New names:
## Rows: 5 Columns: 67
## ── Column specification
## ──────────────────────────────────────────────────────── Delimiter: "," ch
r
## (12): NAME_CONTRACT_TYPE, CODE_GENDER, FLAG_OWN_CAR, FLAG_OWN_REALTY, NA..
. dbl
## (55): ...1, SK_ID_CURR, CNT_CHILDREN, AMT_INCOME_TOTAL, AMT_CREDIT, AMT_..
.
## ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ
## Specify the column types or set `show_col_types = FALSE` to quiet this mes
sage.
## • `` -> `...1`

# Preprocess new customer data
new_customers$Income_Credit_Ratio <- new_customers$AMT_INCOME_TOTAL / new_cus
tomers$AMT_CREDIT
new_customers$Annuity_Income_Ratio <- new_customers$AMT_ANNUITY / new_custome
rs$AMT_INCOME_TOTAL
new_customers$Credit_As_Percentage <- new_customers$AMT_CREDIT / new_customer
s$AMT_INCOME_TOTAL
new_customers$Percent_Days_Employed <- new_customers$DAYS_EMPLOYED / new_cust
omers$DAYS_BIRTH
new_customers$Income_Per_Person <- new_customers$AMT_INCOME_TOTAL / new_custo
mers$CNT_FAM_MEMBERS

# Remove XNA from CODE_GENDER variable and convert to factor
new_customers <- new_customers[new_customers$CODE_GENDER != "XNA", ]
new_customers$CODE_GENDER <- factor(new_customers$CODE_GENDER)

# Convert education type to factor with levels across education
new_customers$NAME_EDUCATION_TYPE <- factor(new_customers$NAME_EDUCATION_TYPE
, levels = c(
  "Secondary / secondary special",
  "Higher education",
  "Lower secondary",
  "Incomplete higher",
  "Academic degree"))

# Normalize new customer data using the same scaling as the training data
new_customers_norm <- predict(norm_values, new_customers[, -c(1)])

# Predict risk of new customers
new_customer_predictions <- predict(logistic_model, newdata = new_customers_n
```

```r
orm, type = "response")
new_customer_predictions_class <- ifelse(new_customer_predictions > 0.5, 1, 0
)

# Display predictions for new customers
new_customer_results <- data.frame(new_customers, Predicted_Risk = new_custom
er_predictions_class)
head(new_customer_results)
```

```
##   ...1 SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REA
LTY
## 1    1     402254         Cash loans           M            N
Y
## 2    2     440463         Cash loans           F            N
Y
## 3    3     242185         Cash loans           F            N
N
## 4    4     235118         Cash loans           M            Y
Y
## 5    5     407346         Cash loans           F            N
Y
##   CNT_CHILDREN AMT_INCOME_TOTAL AMT_CREDIT AMT_ANNUITY AMT_GOODS_PRICE
## 1            0           247500     746280     59094.0          675000
## 2            0           112500     589500     32107.5          589500
## 3            1           112500     272520     16803.0          225000
## 4            0           157500     533313     37246.5          472500
## 5            2           112500     283500     22527.0          283500
##   NAME_TYPE_SUITE     NAME_INCOME_TYPE           NAME_EDUCATION_TYPE
## 1   Unaccompanied              Working Secondary / secondary special
## 2   Unaccompanied Commercial associate             Incomplete higher
## 3   Unaccompanied              Working Secondary / secondary special
## 4   Unaccompanied              Working               Higher education
## 5   Unaccompanied              Working Secondary / secondary special
##   NAME_FAMILY_STATUS NAME_HOUSING_TYPE DAYS_BIRTH DAYS_EMPLOYED
## 1          Separated House / apartment      -9889         -2077
## 2            Married House / apartment      -9843         -2772
## 3            Married House / apartment     -10208          -853
## 4            Married House / apartment     -21121         -3561
## 5     Civil marriage House / apartment     -19354         -5103
##   DAYS_REGISTRATION DAYS_ID_PUBLISH OWN_CAR_AGE FLAG_MOBIL FLAG_EMP_PHONE
## 1              -417           -1342          NA          1              1
## 2              -524           -2523          NA          1              1
## 3             -1893           -1946          NA          1              1
## 4             -7328           -3506           3          1              1
## 5             -9478           -2873          NA          1              1
##   FLAG_WORK_PHONE FLAG_CONT_MOBILE FLAG_PHONE FLAG_EMAIL OCCUPATION_TYPE
## 1               0                1          0          0        Laborers
## 2               0                1          0          0   Cooking staff
## 3               1                1          0          0     Sales staff
## 4               0                1          0          1         Drivers
```

```
## 5               0                 1          0          0        Laborers
##   CNT_FAM_MEMBERS REGION_RATING_CLIENT REGION_RATING_CLIENT_W_CITY
## 1               1                    3                           3
## 2               2                    2                           2
## 3               3                    2                           2
## 4               2                    2                           2
## 5               4                    2                           2
##   WEEKDAY_APPR_PROCESS_START HOUR_APPR_PROCESS_START REG_REGION_NOT_LIVE_R
EGION
## 1                    TUESDAY                       9
0
## 2                   THURSDAY                      12
0
## 3                   THURSDAY                      13
0
## 4                    TUESDAY                      17
0
## 5                     FRIDAY                      13
0
##   REG_REGION_NOT_WORK_REGION LIVE_REGION_NOT_WORK_REGION REG_CITY_NOT_LIVE
_CITY
## 1                          0                           0
0
## 2                          0                           0
1
## 3                          0                           0
0
## 4                          0                           0
0
## 5                          0                           0
1
##   REG_CITY_NOT_WORK_CITY LIVE_CITY_NOT_WORK_CITY      ORGANIZATION_TYPE
## 1                      0                       0                  Other
## 2                      1                       0 Business Entity Type 2
## 3                      1                       1          Trade: type 3
## 4                      0                       0 Business Entity Type 3
## 5                      1                       0 Business Entity Type 3
##   DAYS_LAST_PHONE_CHANGE FLAG_DOCUMENT_2 FLAG_DOCUMENT_3 FLAG_DOCUMENT_4
## 1                   -785               0               1               0
## 2                   -202               0               0               0
## 3                  -1474               0               1               0
## 4                   -618               0               1               0
## 5                   -510               0               1               0
##   FLAG_DOCUMENT_5 FLAG_DOCUMENT_6 FLAG_DOCUMENT_7 FLAG_DOCUMENT_8
## 1               0               0               0               0
## 2               0               0               0               1
## 3               0               0               0               0
## 4               0               0               0               0
## 5               0               0               0               0
##   FLAG_DOCUMENT_9 FLAG_DOCUMENT_10 FLAG_DOCUMENT_11 FLAG_DOCUMENT_12
```

```
## 1                0                 0                 0                 0
## 2                0                 0                 0                 0
## 3                0                 0                 0                 0
## 4                0                 0                 0                 0
## 5                0                 0                 0                 0
##   FLAG_DOCUMENT_13 FLAG_DOCUMENT_14 FLAG_DOCUMENT_15 FLAG_DOCUMENT_16
## 1                0                0                0                0
## 2                0                0                0                0
## 3                0                0                0                0
## 4                0                0                0                0
## 5                0                0                0                0
##   FLAG_DOCUMENT_17 FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20
## 1                0                0                0                0
## 2                0                0                0                0
## 3                0                0                0                0
## 4                0                0                0                0
## 5                0                0                0                0
##   FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY
## 1                0                           0                          0
## 2                0                           0                          0
## 3                0                          NA                         NA
## 4                0                           0                          0
## 5                0                           0                          0
##   AMT_REQ_CREDIT_BUREAU_WEEK AMT_REQ_CREDIT_BUREAU_MON
## 1                          0                         0
## 2                          0                         0
## 3                         NA                        NA
## 4                          0                         0
## 5                          0                         0
##   AMT_REQ_CREDIT_BUREAU_QRT AMT_REQ_CREDIT_BUREAU_YEAR Income_Credit_Ratio
## 1                         1                          3           0.3316450
## 2                         0                          2           0.1908397
## 3                        NA                         NA           0.4128137
## 4                         0                          0           0.2953238
## 5                         0                          3           0.3968254
##   Annuity_Income_Ratio Credit_As_Percentage Percent_Days_Employed
## 1            0.2387636             3.015273            0.21003135
## 2            0.2854000             5.240000            0.28162146
## 3            0.1493600             2.422400            0.08356191
## 4            0.2364857             3.386114            0.16859997
## 5            0.2002400             2.520000            0.26366643
##   Income_Per_Person Predicted_Risk
## 1            247500              1
## 2             56250              1
## 3             37500              1
## 4             78750              0
## 5             28125              0
```

```
new_customer_results <- data.frame(
  Customer_ID = new_customers$SK_ID_CURR,  # Replace with the actual identifi
```

```r
er column if different
  Prediction = new_customer_predictions_class,
  Probability = new_customer_predictions
)

# Format and display top results for clarity
head(new_customer_results[order(-new_customer_results$Probability), ])  # Top
predictions with high probability

##   Customer_ID Prediction Probability
## 1      402254          1   0.7369819
## 3      242185          1   0.5901293
## 2      440463          1   0.5713890
## 5      407346          0   0.4692277
## 4      235118          0   0.4174471

# Calculate accuracy for training set
train_accuracy <- mean(logistic_pred_train_class == train_norm$TARGET) * 100

# Calculate accuracy for validation set
valid_accuracy <- mean(logistic_pred_valid_class == valid_norm$TARGET) * 100

# Print accuracy results
cat("Training Accuracy:", round(train_accuracy, 2), "%\n")

## Training Accuracy: 59.65 %

cat("Validation Accuracy:", round(valid_accuracy, 2), "%\n")

## Validation Accuracy: 57.75 %

# Load required libraries
library(caret)

# Confusion matrix for training set
train_conf_matrix <- confusionMatrix(as.factor(logistic_pred_train_class), as
.factor(train_norm$TARGET), positive = "1")
cat("Training Confusion Matrix:\n")

## Training Confusion Matrix:

print(train_conf_matrix)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 5773 3900
##          1 4566 6742
##
##                Accuracy : 0.5965
```

```
##                  95% CI : (0.5898, 0.6031)
##     No Information Rate : 0.5072
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.1921
##
##  Mcnemar's Test P-Value : 4.923e-13
##
##             Sensitivity : 0.6335
##             Specificity : 0.5584
##          Pos Pred Value : 0.5962
##          Neg Pred Value : 0.5968
##              Prevalence : 0.5072
##          Detection Rate : 0.3213
##    Detection Prevalence : 0.5390
##       Balanced Accuracy : 0.5959
##
##        'Positive' Class : 1
##
```

```r
# Calculate F1 score for training set
train_precision <- train_conf_matrix$byClass["Pos Pred Value"]
train_recall <- train_conf_matrix$byClass["Sensitivity"]
train_f1 <- 2 * ((train_precision * train_recall) / (train_precision + train_
recall))
cat("Training F1 Score:", round(train_f1, 2), "\n")
```

```
## Training F1 Score: 0.61
```

```r
# Confusion matrix for validation set
valid_conf_matrix <- confusionMatrix(as.factor(logistic_pred_valid_class), as
.factor(valid_norm$TARGET), positive = "1")
cat("\nValidation Confusion Matrix:\n")
```

```
##
## Validation Confusion Matrix:
```

```r
print(valid_conf_matrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 4027  600
##          1 3198 1165
##
##                Accuracy : 0.5775
##                  95% CI : (0.5672, 0.5878)
##     No Information Rate : 0.8037
##     P-Value [Acc > NIR] : 1
##
```

```
##                   Kappa : 0.1397
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.6601
##             Specificity : 0.5574
##          Pos Pred Value : 0.2670
##          Neg Pred Value : 0.8703
##              Prevalence : 0.1963
##          Detection Rate : 0.1296
##    Detection Prevalence : 0.4853
##       Balanced Accuracy : 0.6087
##
##        'Positive' Class : 1
##
```

```r
# Calculate F1 score for validation set
valid_precision <- valid_conf_matrix$byClass["Pos Pred Value"]
valid_recall <- valid_conf_matrix$byClass["Sensitivity"]
valid_f1 <- 2 * ((valid_precision * valid_recall) / (valid_precision + valid_
recall))
cat("Validation F1 Score:", round(valid_f1, 2), "\n")
```

```
## Validation F1 Score: 0.38
```