Report on Prediction of Fraud (Supervised Learning)

March 29, 2024

1 Short Abstract

This report focuses on the prediction of fraud using supervised learning techniques. It delves into the analysis of various variables to determine their influence on the target variable, which indicates fraudulent transactions.

2 Statement of the Problem/Goal of the Analysis and Description of the Dataset(s)

The goal of this analysis is to identify the factors influencing fraudulent transactions. The dataset includes variables such as ID, date, target (indicating fraud), income, age, binary rule variables, and others. There are gaps and imbalances in the classes of the target variable, requiring preprocessing steps like filling gaps in non-binary characteristics.

3 List of Findings/Keypoints

1. There are gaps in non-binary characteristics, addressed by filling NA values using row sums of specific columns.
2. Initial hypotheses about transactional fraud include frequency of fraudulent transactions, discrepancies in card and passport data, and repeated transactions with similar yields. Statistically supported hypotheses involve identifying salary accounts based on age, amount, and weekend indicators, and detecting first transfers from external cards.
3. Models such as Logistic Regression and Random Forest achieved respective accuracies of 39.94% and 41.94%.

3.1 Theoretical Background of Used Methods

The methods employed in this analysis include logistic regression and random forest, which are commonly used for classification tasks in supervised learning. Logistic regression models the probability of a binary outcome, while random forest constructs an ensemble of decision trees to make predictions.

3.2 Conclusions

Through the analysis, it's evident that variables like income, age, and specific binary rule indicators play a role in predicting fraudulent transactions. Preprocessing steps like filling gaps and imputation are essential for handling missing data. Additionally, hypotheses generated from statistical analysis provide insights into potential patterns of fraudulent behavior. The models developed exhibit moderate predictive performance, suggesting further exploration and refinement may be necessary.

4 Prediction of fraud (supervised learning)

It is necessary to determine the influence of variables on target

Description of variables:

id - entity identifier
date - date
target - target variable
req_amt - income
age - age
rule_2_21 - rule 2_806 binary variables
rule_combi_1, rule_combi_2 binary variables in the form of combinations flags of the previous paragraph
rules_count - number of triggered flags
score - speed

There are gaps and pronounced imbalances in the classes of the target variable in the data.

[65]:
```
library("dplyr")
library("magrittr")
library(ggplot2)
options(warn=-1)
```

[2]:
```
df <- read.csv('Task DF Case 2.csv', sep=';')
```

[3]:
```
head(df, 5)
```

A data.frame: 5 × 28

	id	date	target	req_amt	age	rule_2_21	rule_2_22	rule_2
	<int>	<chr>	<int>	<dbl>	<int>	<dbl>	<dbl>	<dbl>
1	238687671	20.06.2019	0	689385	40	0	0	0
2	248689049	02.08.2019	0	450000	57	0	0	0
3	276054054	22.11.2019	0	500000	32	1	1	0
4	313767939	24.02.2020	0	730000	31	0	0	0
5	342351235	10.06.2020	0	1490000	68	0	0	0

[4]:
```
dim(df)
```

1. 100000 2. 28

[5]:
```
summary(df)
```

```
       id                date               target            req_amt
 Min.   :137175209   Length:100000      Min.   :0.00000   Min.   :  50000
 1st Qu.:220747368   Class :character   1st Qu.:0.00000   1st Qu.: 400000
 Median :263040542   Mode  :character   Median :0.00000   Median : 614900
```

```
 Mean   :280116429                     Mean   :0.00129   Mean   : 681123  
 3rd Qu.:337582833                     3rd Qu.:0.00000   3rd Qu.: 900000  
 Max.   :517283235                     Max.   :1.00000   Max.   :3000000  

      age           rule_2_21        rule_2_22        rule_2_23       rule_2_24   
 Min.   : 0.00   Min.   :0.000   Min.   :0.000   Min.   :0      Min.   :0      
 1st Qu.:34.00   1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0      1st Qu.:0      
 Median :41.00   Median :0.000   Median :0.000   Median :0      Median :0      
 Mean   :42.08   Mean   :0.158   Mean   :0.146   Mean   :0      Mean   :0      
 3rd Qu.:50.00   3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:0      3rd Qu.:0      
 Max.   :89.00   Max.   :1.000   Max.   :1.000   Max.   :0      Max.   :0      
                 NA's   :5777    NA's   :5777    NA's   :5777   NA's   :5777   
   rule_2_25        rule_2_26       rule_2_27        rule_2_31        rule_2_32    
 Min.   :0.000   Min.   :0      Min.   :0.000   Min.   :0.000   Min.   :0.000  
 1st Qu.:0.000   1st Qu.:0      1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.000  
 Median :0.000   Median :0      Median :1.000   Median :0.000   Median :0.000  
 Mean   :0.297   Mean   :0      Mean   :0.542   Mean   :0.068   Mean   :0.098  
 3rd Qu.:1.000   3rd Qu.:0      3rd Qu.:1.000   3rd Qu.:0.000   3rd Qu.:0.000  
 Max.   :1.000   Max.   :0      Max.   :1.000   Max.   :1.000   Max.   :1.000  
 NA's   :5777    NA's   :5777   NA's   :5777    NA's   :5777    NA's   :5777   
   rule_2_33        rule_2_34        rule_2_801       rule_2_802   
 Min.   :0.000   Min.   :0.000   Min.   :0.000   Min.   :0.000  
 1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.000  
 Median :0.000   Median :0.000   Median :0.000   Median :0.000  
 Mean   :0.125   Mean   :0.226   Mean   :0.408   Mean   :0.235  
 3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:1.000   3rd Qu.:0.000  
 Max.   :1.000   Max.   :1.000   Max.   :1.000   Max.   :1.000  
 NA's   :5777    NA's   :5777    NA's   :5777    NA's   :5777   
   rule_2_806     rule_combi_1     rule_combi_2       rules_count  
 Min.   :0.000   Min.   :0.000   Min.   :0.00000   Min.   :0.00  
 1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.00000   1st Qu.:0.00  
 Median :1.000   Median :0.000   Median :0.00000   Median :1.00  
 Mean   :0.629   Mean   :0.129   Mean   :0.06068   Mean   :1.66  
 3rd Qu.:1.000   3rd Qu.:0.000   3rd Qu.:0.00000   3rd Qu.:2.00  
 Max.   :1.000   Max.   :1.000   Max.   :1.00000   Max.   :8.00  
 NA's   :5777                                      NA's   :5777  
 score_bank_16   score_bank_50    score_nn_16       score_nn_50    
 Min.   :  0.0   Min.   :  0.0   Min.   :-1.000   Min.   :-1.000  
 1st Qu.:165.0   1st Qu.:167.0   1st Qu.: 0.114   1st Qu.: 0.116  
 Median :231.0   Median :234.0   Median : 0.125   Median : 0.124  
 Mean   :253.2   Mean   :256.5   Mean   : 0.054   Mean   : 0.052  
 3rd Qu.:316.0   3rd Qu.:321.0   3rd Qu.: 0.135   3rd Qu.: 0.131  
 Max.   :927.0   Max.   :936.0   Max.   : 0.338   Max.   : 0.347  
 NA's   :13472   NA's   :13472   NA's   :13472    NA's   :13472   
 score_bank_nn_16 score_bank_nn_50
 Min.   : 77.0    Min.   : 52.0   
 1st Qu.:188.0    1st Qu.:152.0   
 Median :237.0    Median :201.0   
```

```
 Mean   :258.5    Mean   :220.4
 3rd Qu.:313.0    3rd Qu.:271.0
 Max.   :895.0    Max.   :853.0
 NA's   :13472    NA's   :13472
```

[6]:
```
library(ggplot2)

# Convert target column to factor if it's not already
df$target <- as.factor(df$target)

# Calculate counts by target
counts <- as.data.frame(table(df$target))
max_count <- max(counts$Freq)

# Scale counts to 1
counts$Freq_scaled <- counts$Freq / max_count
```

[7]:
```
counts
```

A data.frame: 2 × 3

Var1 <fct>	Freq <int>	Freq_scaled <dbl>
0	99871	1.000000000
1	129	0.001291666

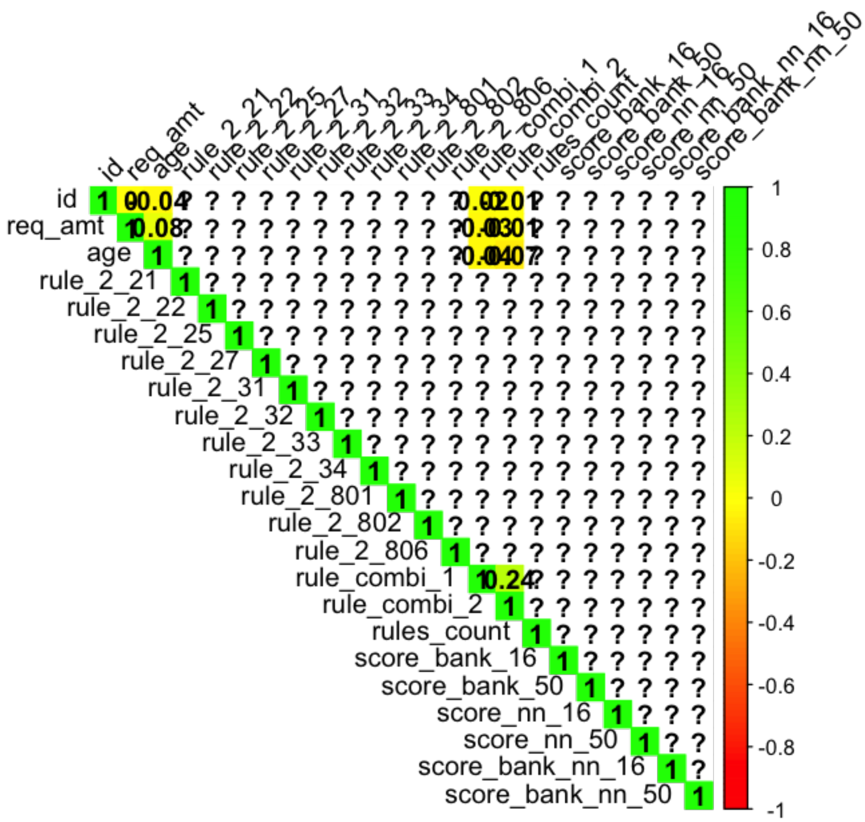
[8]:
```
# Uninformative features
print(table(df$rule_2_23, df$rule_2_24, df$rule_2_26))
# Drop rules with zeroes
df <- subset(df, select = -c(rule_2_23, rule_2_24, rule_2_26))
```

```
, ,  = 0


       0
  0 94223
```

[9]:
```
library(ggplot2)
library(corrplot)

# Select only numeric columns
numeric_df <- df[sapply(df, is.numeric)]

# Calculate Pearson correlation matrix
correlation_matrix <- cor(numeric_df)

# Plot heatmap
corrplot(correlation_matrix, method = "color", col = colorRampPalette(c("red",␣
 ↪"yellow", "green"))(100),
```

```
        type = "upper", order = "original", addCoef.col = "black", tl.col =␣
↪"black", tl.srt = 45)
```

```
corrplot 0.92 loaded
```



Multicollinear features don't exist

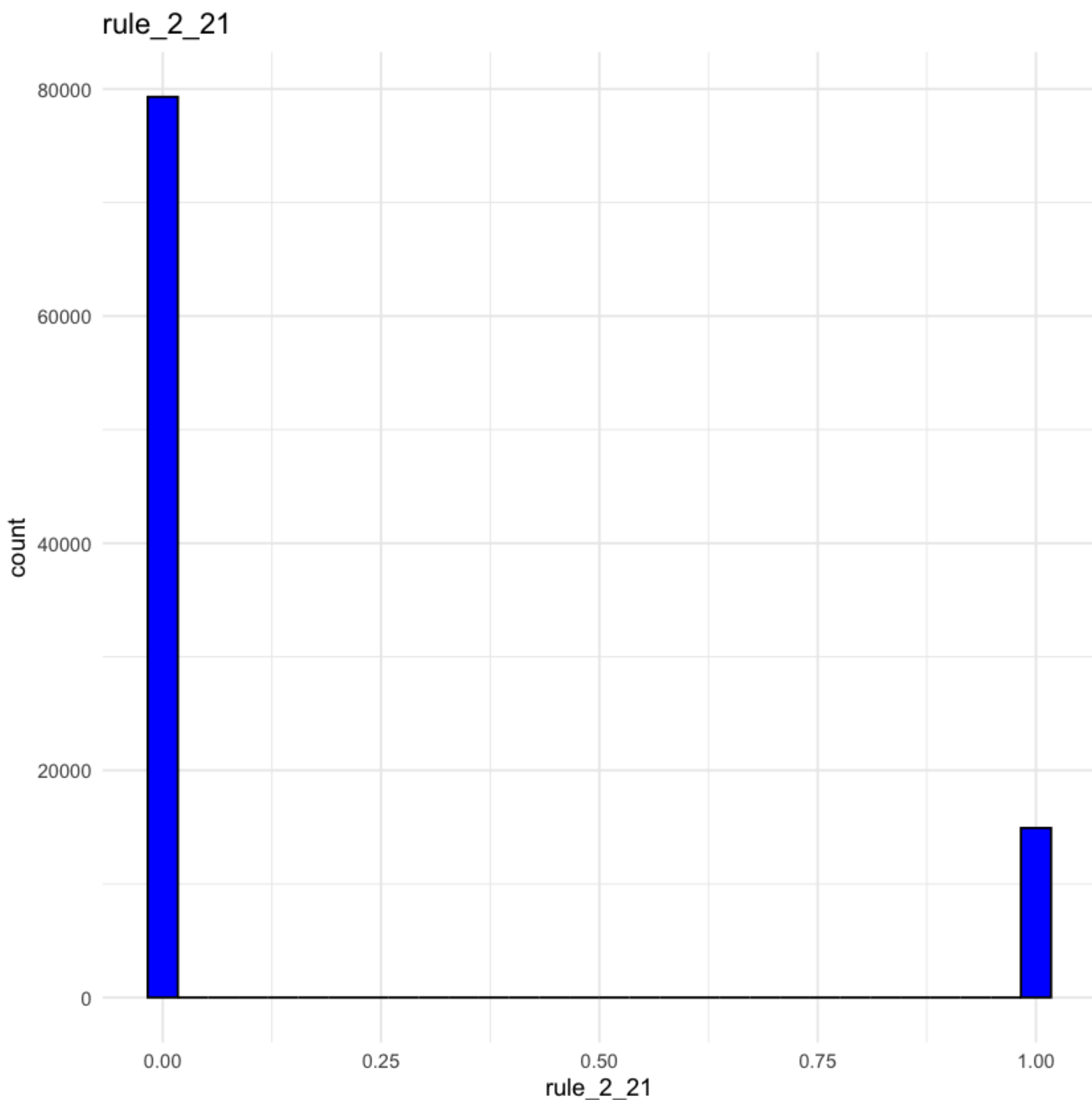
[10]:
```
# Print percentage of missing values
print("Percentage of missing values")
df$count_nulls <- 0
missing_percentage <- colSums(is.na(df)) / nrow(df) * 100
print(missing_percentage)
```

```
[1] "Percentage of missing values"
             id            date          target         req_amt
          0.000           0.000           0.000           0.000
            age       rule_2_21       rule_2_22       rule_2_25
          0.000           5.777           5.777           5.777
      rule_2_27       rule_2_31       rule_2_32       rule_2_33
          5.777           5.777           5.777           5.777
      rule_2_34      rule_2_801      rule_2_802      rule_2_806
          5.777           5.777           5.777           5.777
   rule_combi_1    rule_combi_2     rules_count   score_bank_16
          0.000           0.000           5.777          13.472
  score_bank_50     score_nn_16     score_nn_50 score_bank_nn_16
         13.472          13.472          13.472          13.472
score_bank_nn_50     count_nulls
         13.472           0.000
```

[11]:

```
# 1. Plotting a histogram of the 'rule_2_21' column
ggplot(df, aes(x = rule_2_21)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_21") +
  theme_minimal()

# 2. Calculating and printing the mode
# R does not have a built-in mode function, so we define one
getmode <- function(v) {
   uniqv <- unique(v)
   uniqv[which.max(tabulate(match(v, uniqv)))]
}
mode_rule_2_21 <- getmode(df$rule_2_21)
print(paste('mode:', mode_rule_2_21))

# 3. Printing summary statistics for 'rule_2_21'
print(summary(df$rule_2_21))

# 4. Filling missing values in 'rule_2_21' with its mode
df$rule_2_21[is.na(df$rule_2_21)] <- mode_rule_2_21
```

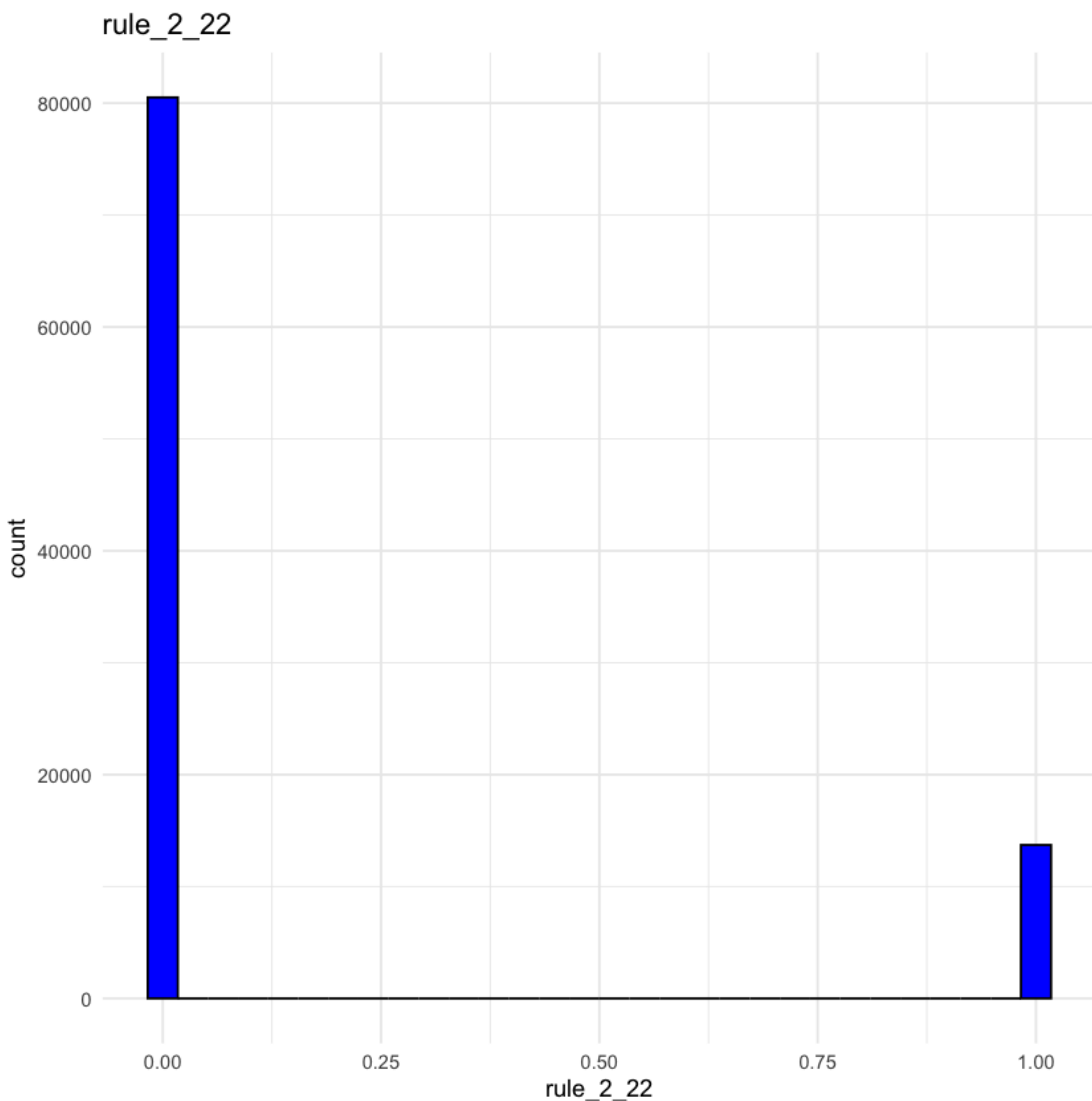
```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.158   0.000   1.000    5777
```



[12]:
```
# 1. Plotting a histogram of the 'rule_2_22' column
ggplot(df, aes(x = rule_2_22)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_22") +
  theme_minimal()

# 2. Calculating and printing the mode
# Using the previously defined getmode function
mode_rule_2_22 <- getmode(df$rule_2_22)
print(paste('mode:', mode_rule_2_22))

# 3. Printing summary statistics for 'rule_2_22'
print(summary(df$rule_2_22))
```

```
# 4. Filling missing values in 'rule_2_22' with its mode
df$rule_2_22[is.na(df$rule_2_22)] <- mode_rule_2_22
```

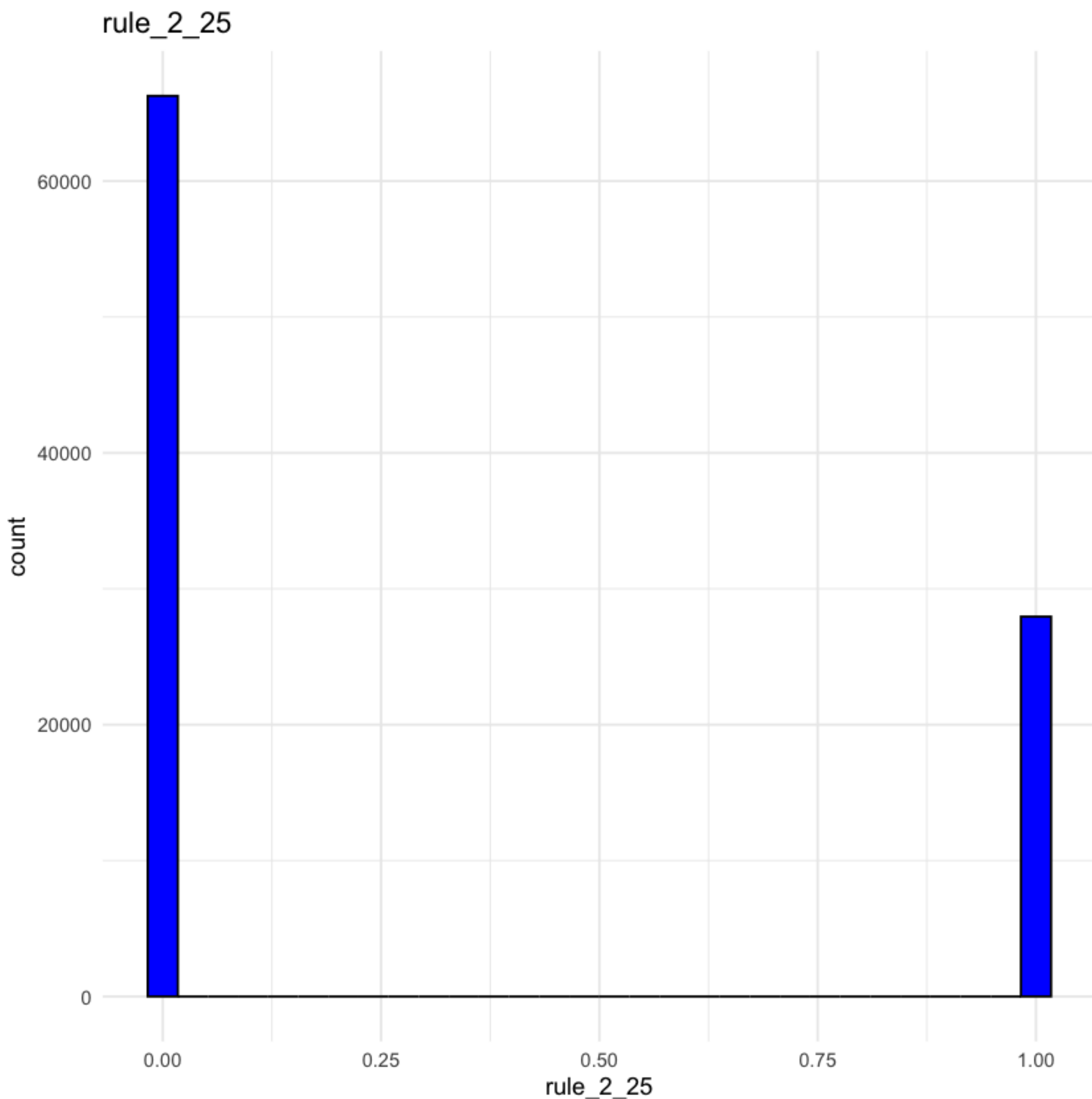
```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.146   0.000   1.000    5777
```



[13]:
```
# 1. Plotting a histogram of the 'rule_2_25' column
ggplot(df, aes(x = rule_2_25)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_25") +
  theme_minimal()
```

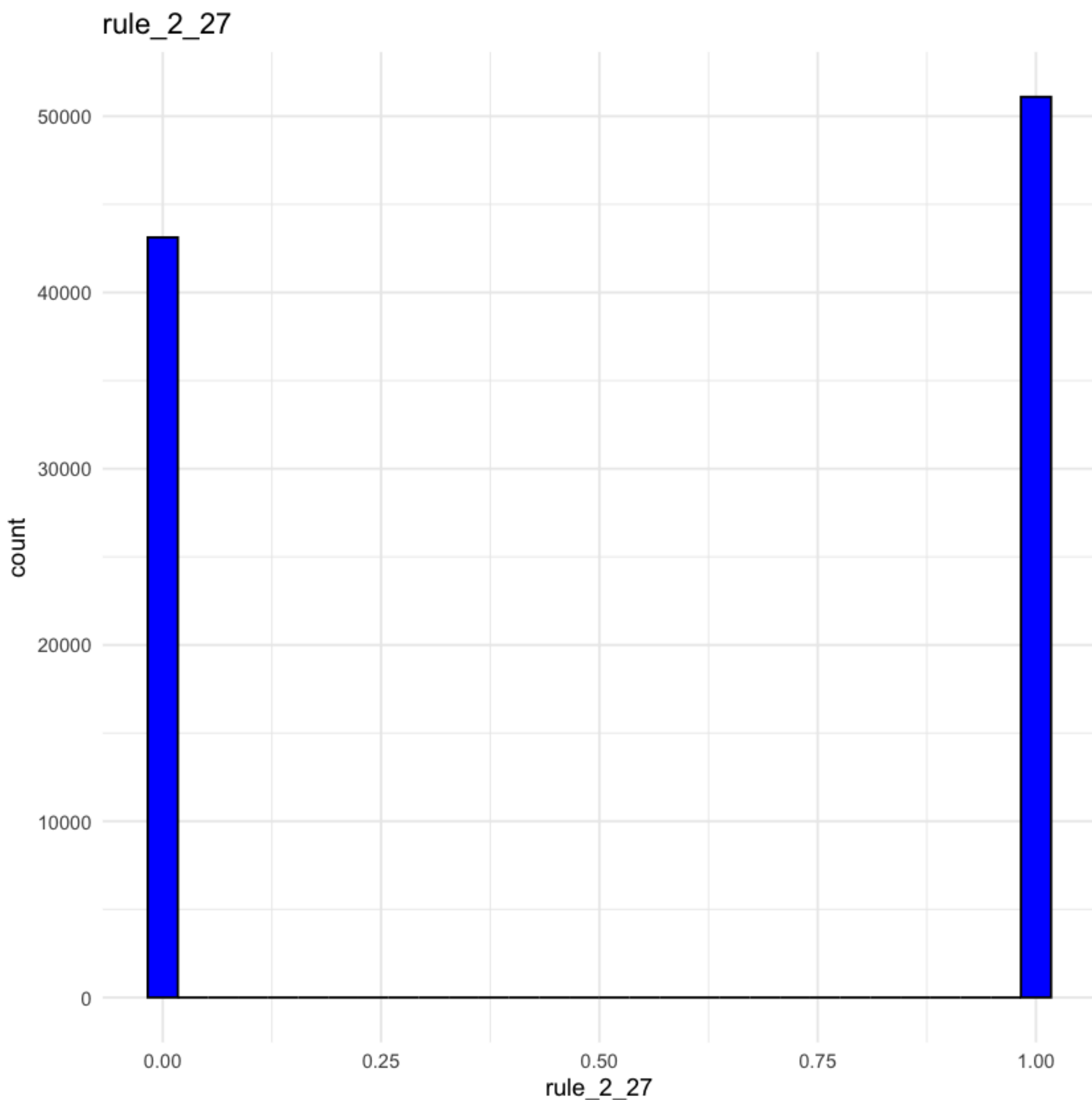
```r
# 2. Calculating and printing the mode
mode_rule_2_25 <- getmode(df$rule_2_25)
print(paste('mode:', mode_rule_2_25))

# 3. Printing summary statistics for 'rule_2_25'
print(summary(df$rule_2_25))

# 4. Filling missing values in 'rule_2_25' with its mode
df$rule_2_25[is.na(df$rule_2_25)] <- mode_rule_2_25
```

```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.297   1.000   1.000    5777
```



[14]:
```r
# 1. Plotting a histogram of the 'rule_2_27' column
ggplot(df, aes(x = rule_2_27)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_27") +
  theme_minimal()

# If you prefer a base R approach for histogram:
# hist(df_keys_2$rule_2_27, main = "rule_2_27", xlab = "rule_2_27", col = "blue")

# 2. Calculating and printing the mode
mode_rule_2_27 <- getmode(df$rule_2_27)
print(paste('mode:', mode_rule_2_27))

# 3. Printing summary statistics for 'rule_2_27'
print(summary(df$rule_2_27))

# 4. Filling missing values in 'rule_2_27' with its mode
df$rule_2_27[is.na(df$rule_2_27)] <- mode_rule_2_27
```

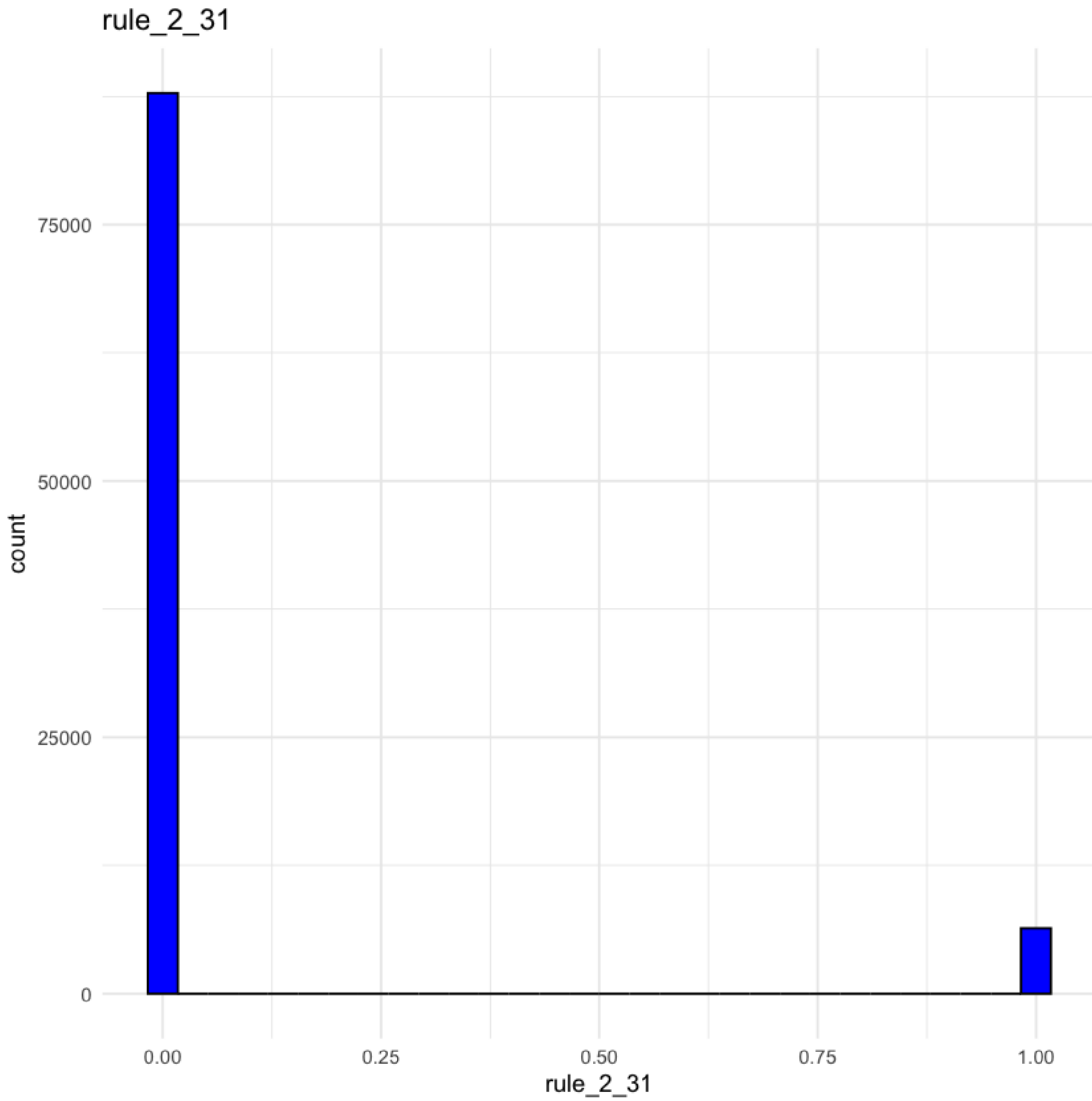
```
[1] "mode: 1"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
  0.000   0.000   1.000   0.542   1.000   1.000    5777 
```



[15]:
```
# Load necessary libraries
library(ggplot2)

# 1. Plotting a histogram of the 'rule_2_31' column
ggplot(df, aes(x = rule_2_31)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_31") +
  theme_minimal()

# 2. Calculating and printing the mode
mode_rule_2_31 <- getmode(df$rule_2_31)
print(paste('mode:', mode_rule_2_31))
```

```r
# 3. Printing summary statistics for 'rule_2_31'
print(summary(df$rule_2_31))

# 4. Filling missing values in 'rule_2_31' with its mode
df$rule_2_31[is.na(df$rule_2_31)] <- mode_rule_2_31
```

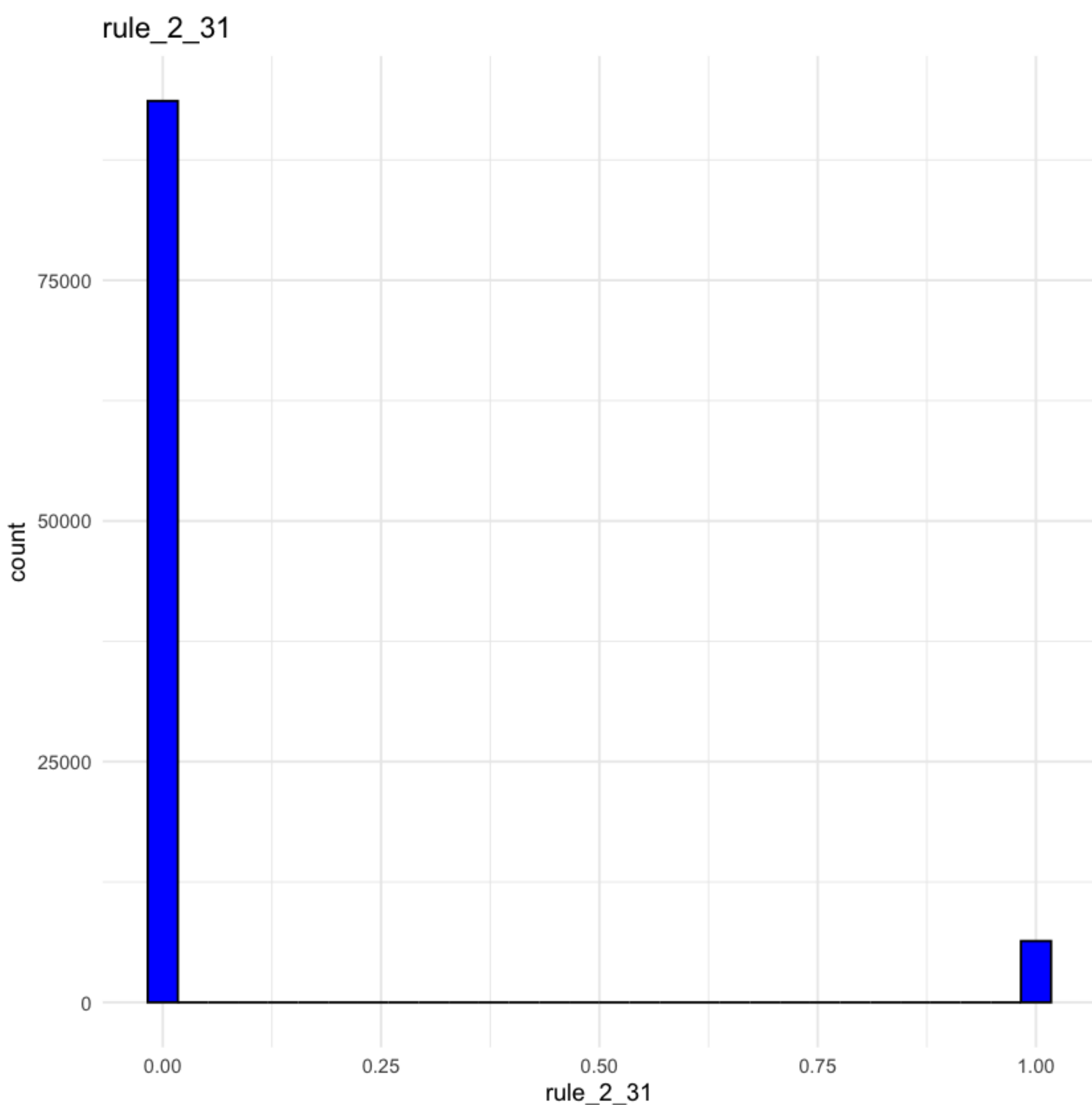
```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.068   0.000   1.000    5777
```



[16]:
```r
# 1. Plotting a histogram of the 'rule_2_31' column
ggplot(df, aes(x = rule_2_31)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
```

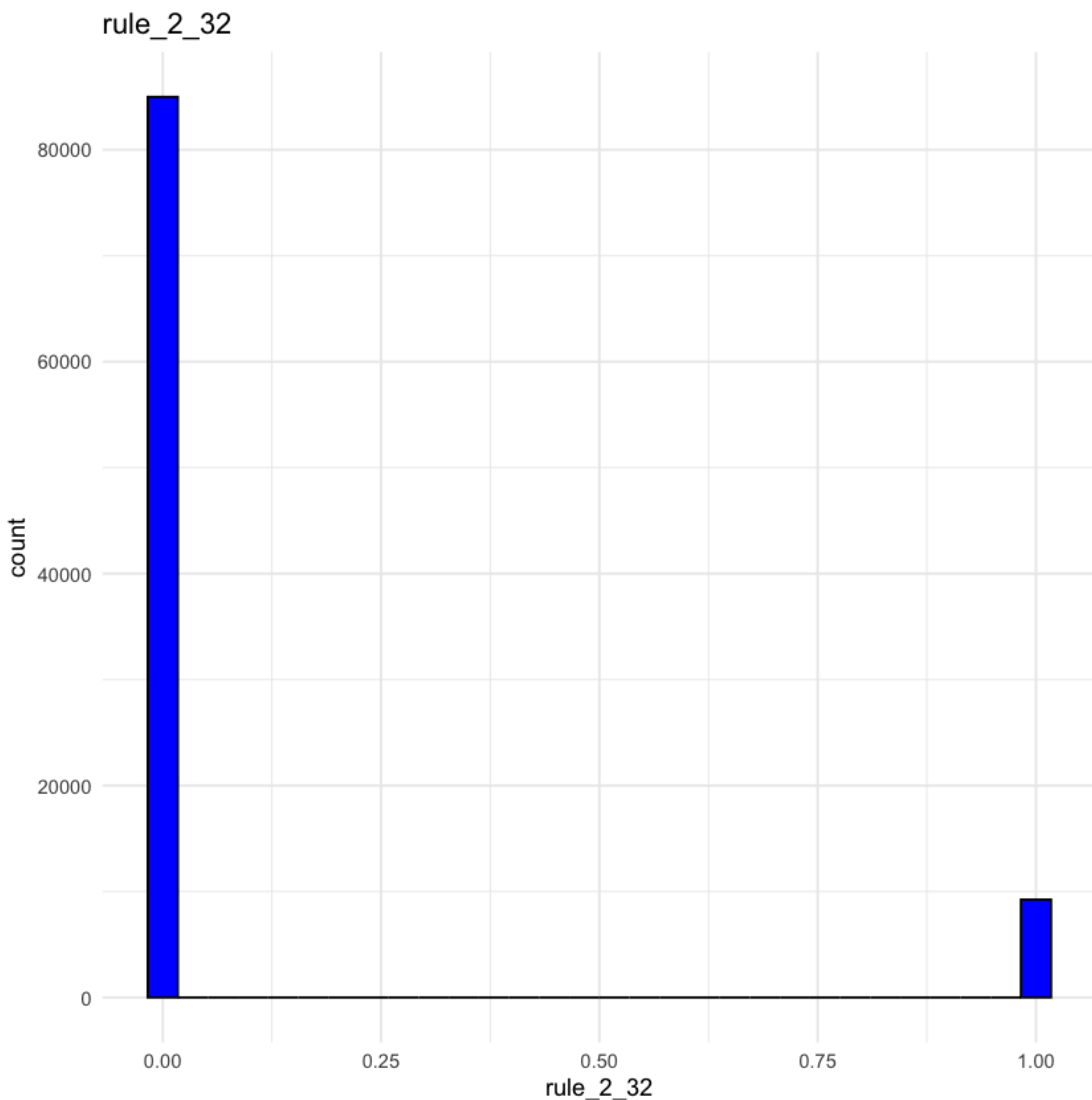
```r
  ggtitle("rule_2_31") +
  theme_minimal()

# 2. Calculating and printing the mode
mode_rule_2_31 <- getmode(df$rule_2_31)
print(paste('mode:', mode_rule_2_31))

# 3. Printing summary statistics for 'rule_2_31'
print(summary(df$rule_2_31))

# 4. Filling missing values in 'rule_2_31' with its mode
df$rule_2_31[is.na(df$rule_2_31)] <- mode_rule_2_31
```

```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.00000 0.00000 0.00000 0.06371 0.00000 1.00000 
```



[17]:
```r
# 1. Plotting a histogram of the 'rule_2_32' column
ggplot(df, aes(x = rule_2_32)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_32") +
  theme_minimal()

# 2. Calculating and printing the mode
mode_rule_2_32 <- getmode(df$rule_2_32)
print(paste('mode:', mode_rule_2_32))

# 3. Printing summary statistics for 'rule_2_32'
print(summary(df$rule_2_32))

# 4. Filling missing values in 'rule_2_32' with its mode
df$rule_2_32[is.na(df$rule_2_32)] <- mode_rule_2_32
```

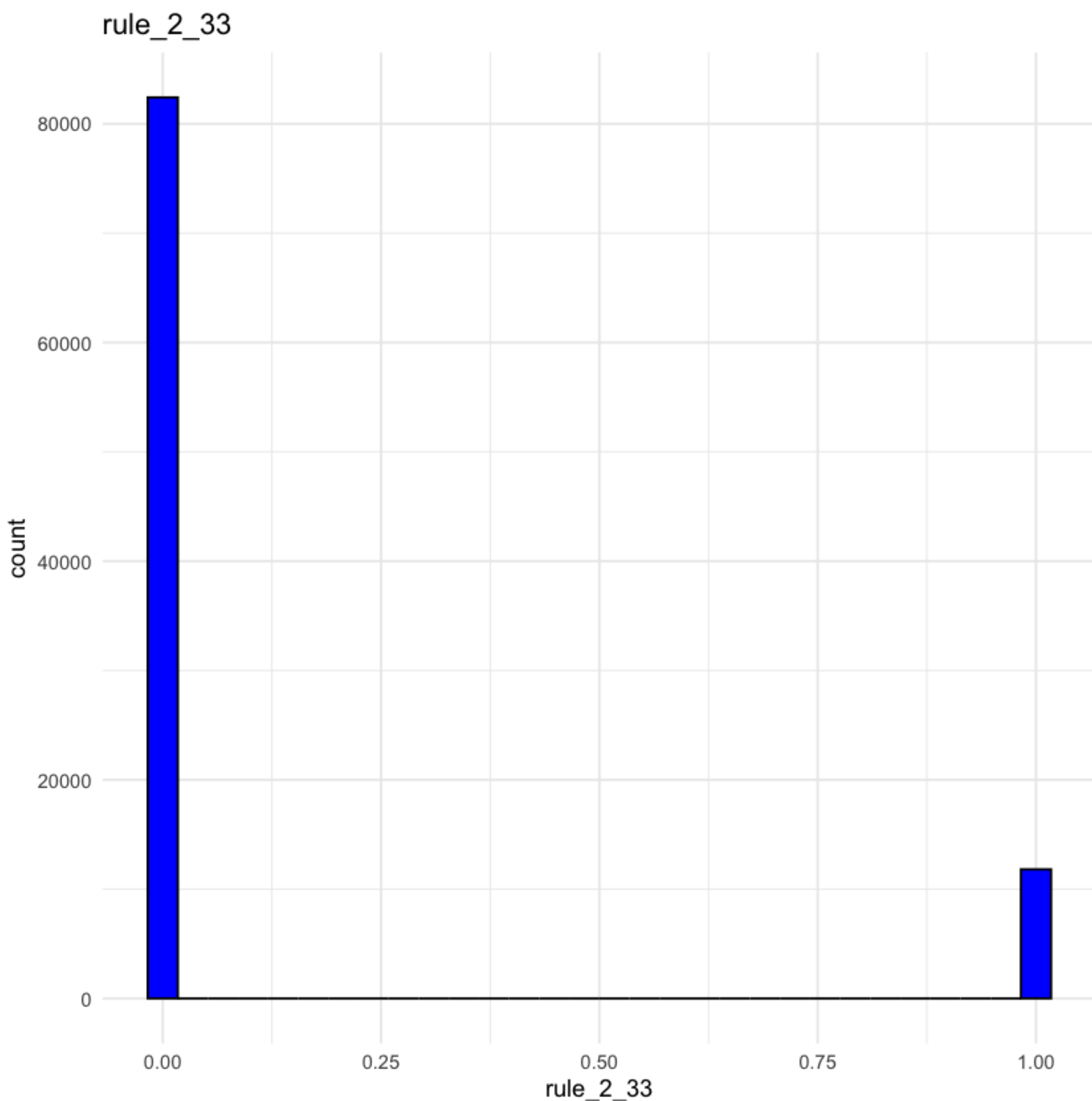
```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.098   0.000   1.000    5777
```



[18]:
```
# Plotting a histogram of the 'rule_2_33' column in 'df'
ggplot(df, aes(x = rule_2_33)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_33") +
  theme_minimal()

# Calculating the mode for 'rule_2_33'
mode_rule_2_33 <- df$rule_2_33[which.max(tabulate(match(df$rule_2_33,␣
↪unique(df$rule_2_33))))]
print(paste('mode:', mode_rule_2_33))

# Printing summary statistics for 'rule_2_33'
print(summary(df$rule_2_33))
```

```
# Filling missing values in 'rule_2_33' with its mode
df$rule_2_33[is.na(df$rule_2_33)] <- mode_rule_2_33
```

```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.125   0.000   1.000    5777
```

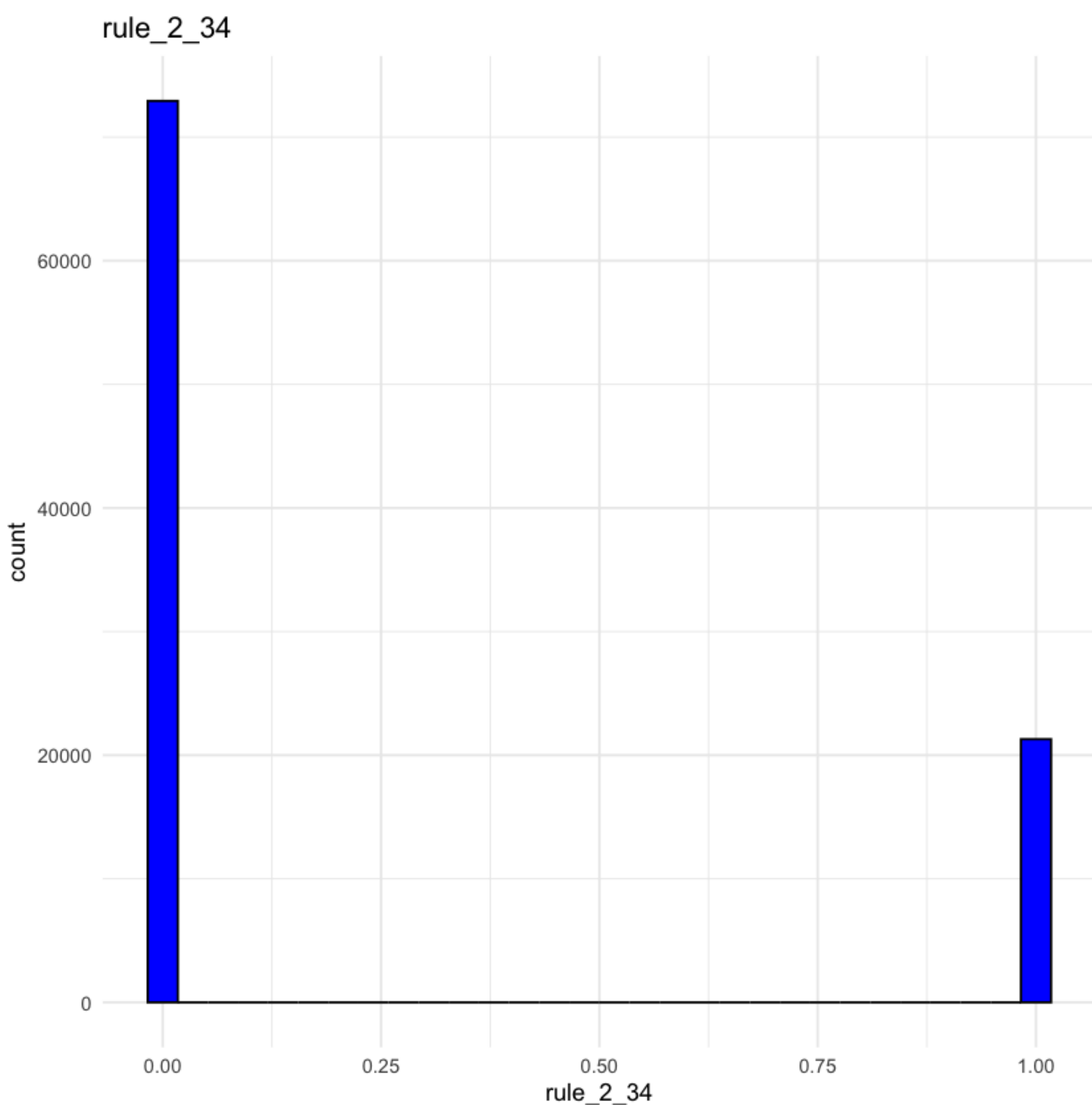


[19]:

```
# Plotting a histogram of the 'rule_2_34' column in 'df'
ggplot(df, aes(x = rule_2_34)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_34") +
  theme_minimal()
```

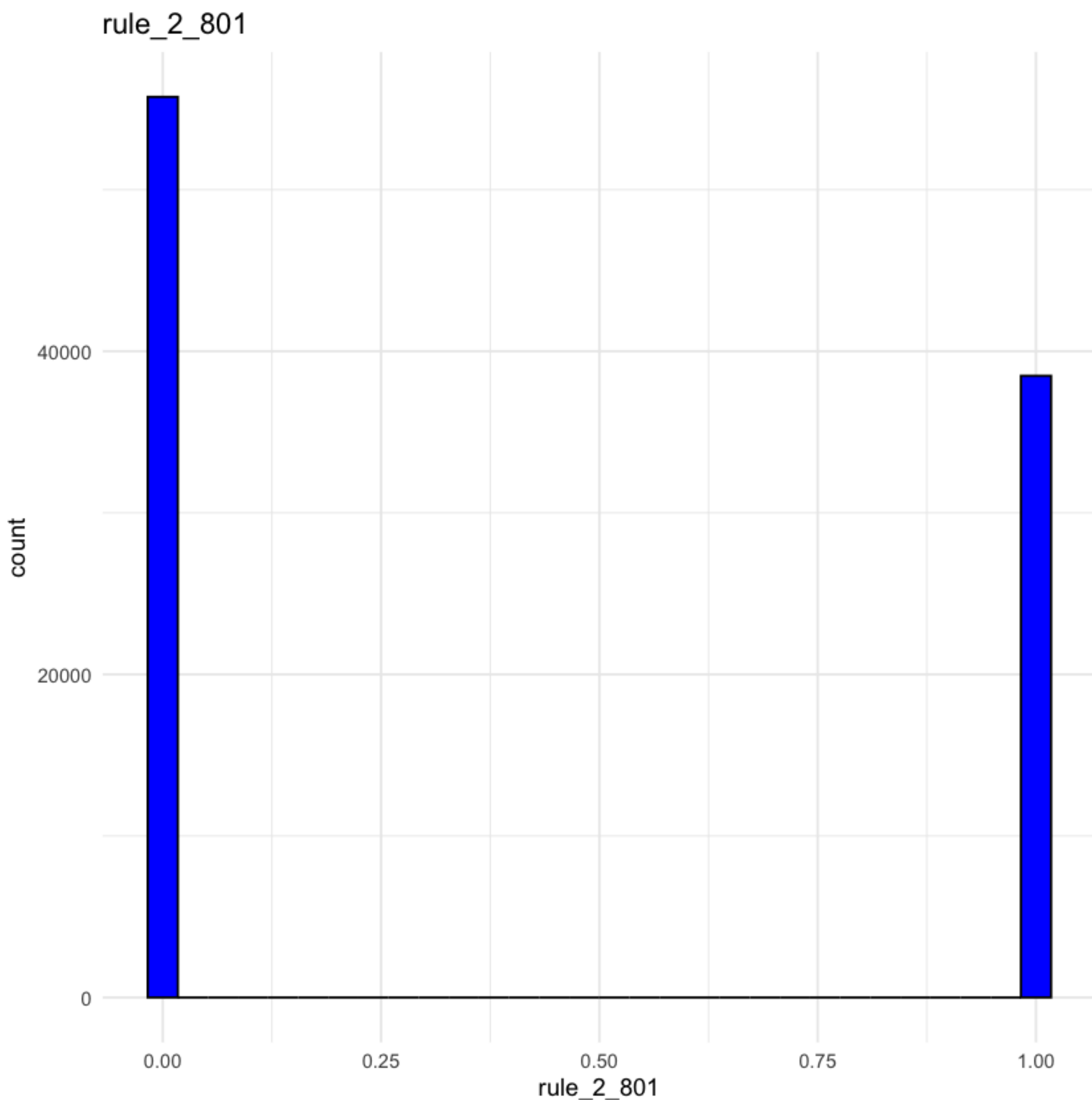
```r
# Calculating the mode for 'rule_2_34'
mode_rule_2_34 <- df$rule_2_34[which.max(tabulate(match(df$rule_2_34,
 ↪unique(df$rule_2_34))))]
print(paste('mode:', mode_rule_2_34))

# Printing summary statistics for 'rule_2_34'
print(summary(df$rule_2_34))

# Filling missing values in 'rule_2_34' with its mode
df$rule_2_34[is.na(df$rule_2_34)] <- mode_rule_2_34
```

```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.226   0.000   1.000    5777
```



[20]:
```
# Plotting a histogram of the 'rule_2_801' column in 'df'
ggplot(df, aes(x = rule_2_801)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_801") +
  theme_minimal()

# Calculating the mode for 'rule_2_801'
mode_rule_2_801 <- df$rule_2_801[which.max(tabulate(match(df$rule_2_801,
 ↪unique(df$rule_2_801))))]
print(paste('mode:', mode_rule_2_801))

# Printing summary statistics for 'rule_2_801'
print(summary(df$rule_2_801))

# Filling missing values in 'rule_2_801' with its mode
df$rule_2_801[is.na(df$rule_2_801)] <- mode_rule_2_801
```

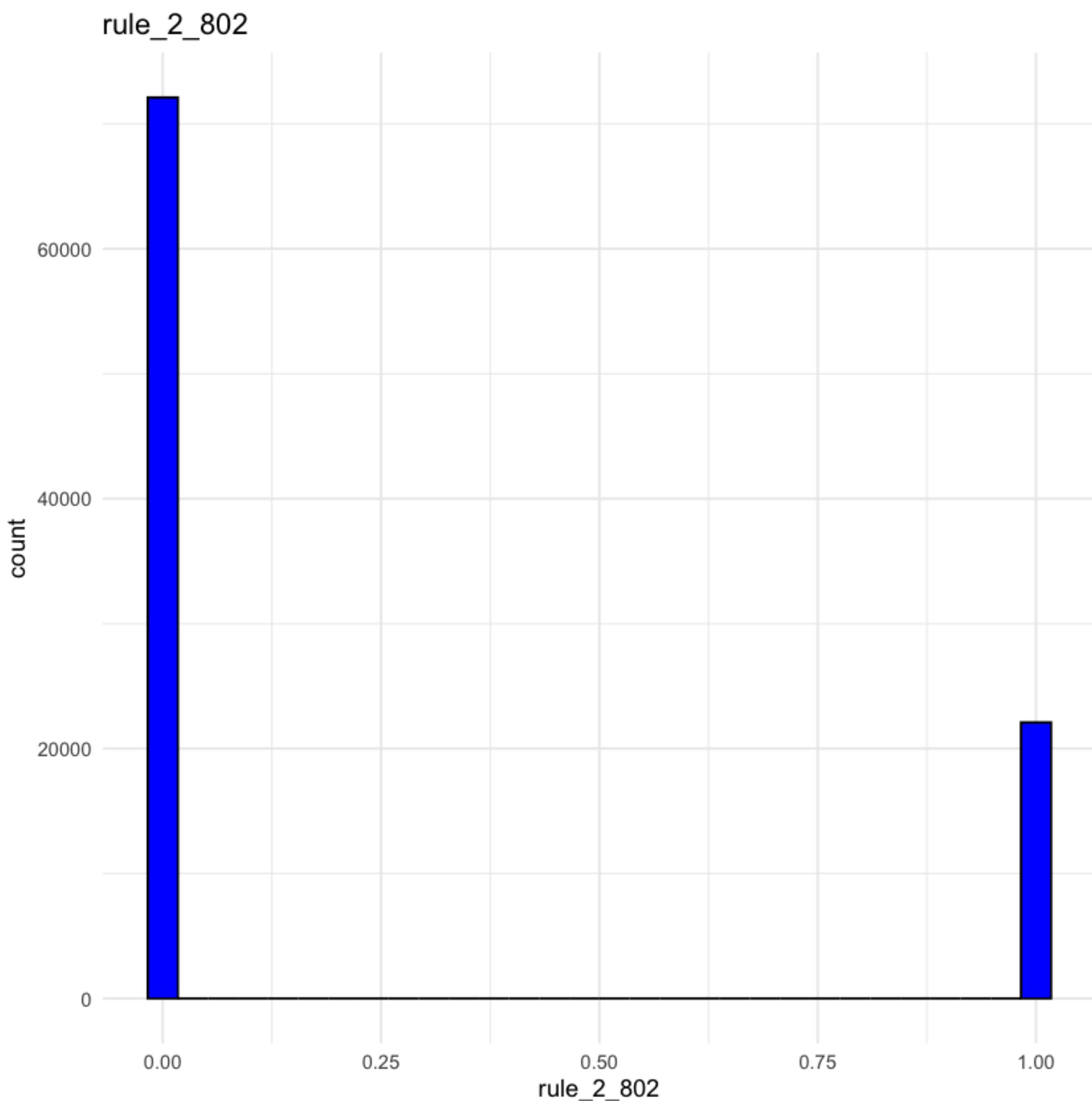
```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.408   1.000   1.000    5777
```




```
[21]: # Plotting a histogram of the 'rule_2_802' column in 'df'
ggplot(df, aes(x = rule_2_802)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_802") +
  theme_minimal()

# Calculating the mode for 'rule_2_802'
mode_rule_2_802 <- df$rule_2_802[which.max(tabulate(match(df$rule_2_802,␣
↪unique(df$rule_2_802))))]
print(paste('mode:', mode_rule_2_802))

# Printing summary statistics for 'rule_2_802'
print(summary(df$rule_2_802))
```

```
# Filling missing values in 'rule_2_802' with its mode
df$rule_2_802[is.na(df$rule_2_802)] <- mode_rule_2_802
```

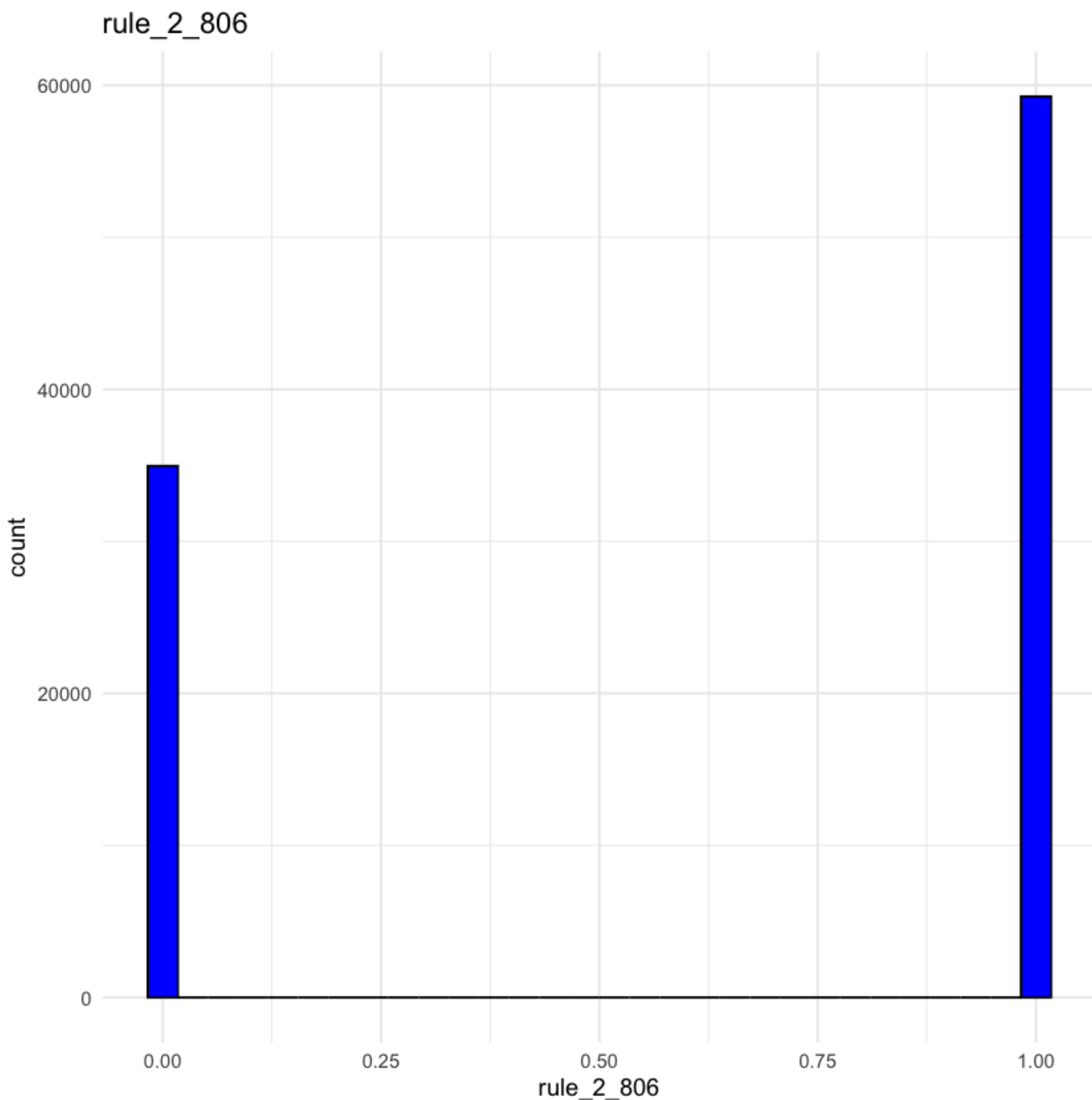
```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   0.000   0.235   0.000   1.000    5777
```



[22]:
```
# Plotting a histogram of the 'rule_2_806' column in 'df'
ggplot(df, aes(x = rule_2_806)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("rule_2_806") +
  theme_minimal()
```

```r
# Calculating the mode for 'rule_2_806'
mode_rule_2_806 <- df$rule_2_806[which.max(tabulate(match(df$rule_2_806,
 unique(df$rule_2_806))))]
print(paste('mode:', mode_rule_2_806))

# Printing summary statistics for 'rule_2_806'
print(summary(df$rule_2_806))

# Filling missing values in 'rule_2_806' with its mode
df$rule_2_806[is.na(df$rule_2_806)] <- mode_rule_2_806
```

```
[1] "mode: 0"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
  0.000   0.000   1.000   0.629   1.000   1.000    5777
```



Filling gaps in non-binary characteristics

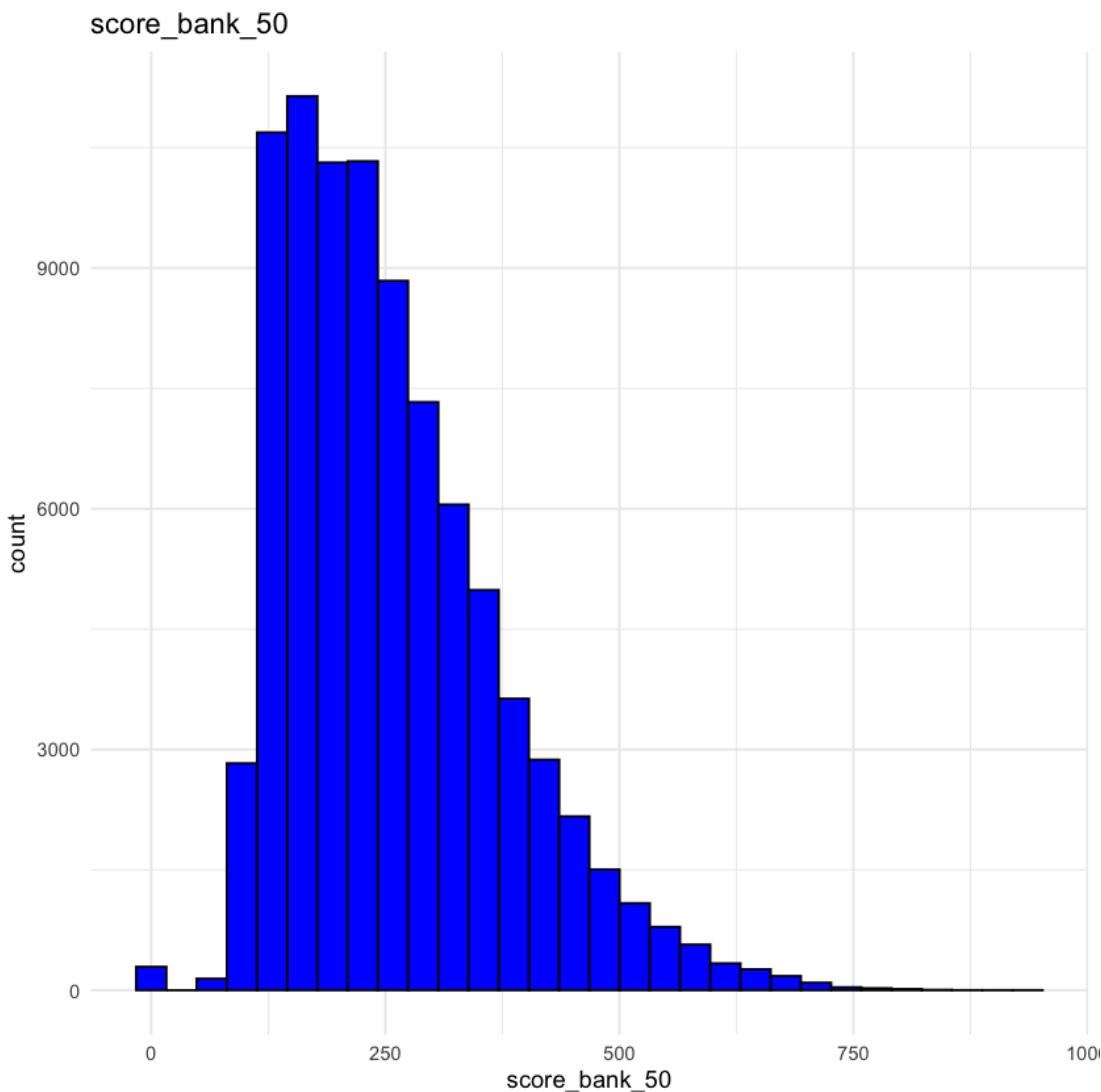
This R code does the following:

Checks for NA values in the rules_count column.
For rows with NA in rules_count, it calculates the sum of the specified columns.
It uses rowSums() to calculate the sum across the specified columns for each row. The na.rm = TRUE argument ensures that NA values are ignored in the summation.
The resulting sums are then used to fill in the NA values in the rules_count column.

[23]:
```
# Filling NA values in 'rules_count' with the sum of other specified columns
df$rules_count[is.na(df$rules_count)] <- rowSums(df[is.na(df$rules_count),␣
↪c('rule_2_21', 'rule_2_22', 'rule_2_25',
                                                                           ␣
↪'rule_2_27', 'rule_2_31', 'rule_2_32', 'rule_2_33', 'rule_2_34')], na.rm =␣
↪TRUE)
```

[24]:
```
# Plotting a histogram of the 'score_bank_50' column in 'df'
ggplot(df, aes(x = score_bank_50)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("score_bank_50") +
  theme_minimal()

# Calculating the mode for 'score_bank_50'
mode_score_bank_50 <- df$score_bank_50[which.
↪max(tabulate(match(df$score_bank_50, unique(df$score_bank_50))))]
print(paste('mode:', mode_score_bank_50))

# Printing summary statistics for 'score_bank_50'
print(summary(df$score_bank_50))

# Filling missing values in 'score_bank_50' with its mean
df$score_bank_50[is.na(df$score_bank_50)] <- mean(df$score_bank_50, na.rm = TRUE)
```

```
[1] "mode: NA"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
    0.0   167.0   234.0   256.5   321.0   936.0   13472
```

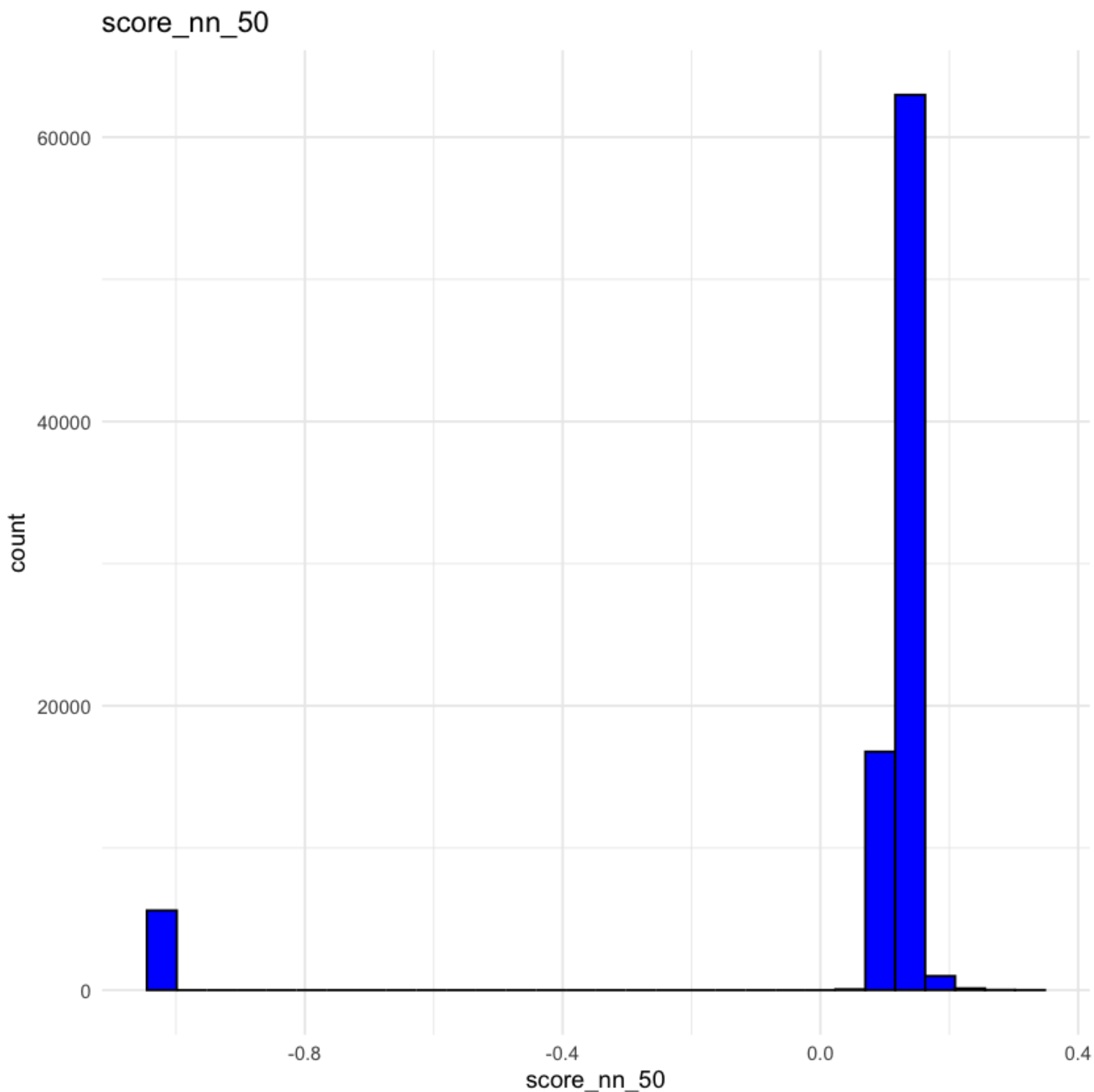


plot a histogram for the score_bank_50 column, calculate and print the mode, provide a summary of the column, and fill in missing values with the mean,

[25]:
```
# Plotting a histogram of the 'score_nn_50' column in 'df'
ggplot(df, aes(x = score_nn_50)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("score_nn_50") +
  theme_minimal()

# Calculating the mode for 'score_nn_50'
mode_score_nn_50 <- df$score_nn_50[which.max(tabulate(match(df$score_nn_50,
 ↪unique(df$score_nn_50))))]
print(paste('mode:', mode_score_nn_50))
```

```r
# Printing summary statistics for 'score_nn_50'
print(summary(df$score_nn_50))

# Filling missing values in 'score_nn_50' with its mode
df$score_nn_50[is.na(df$score_nn_50)] <- mode_score_nn_50
```

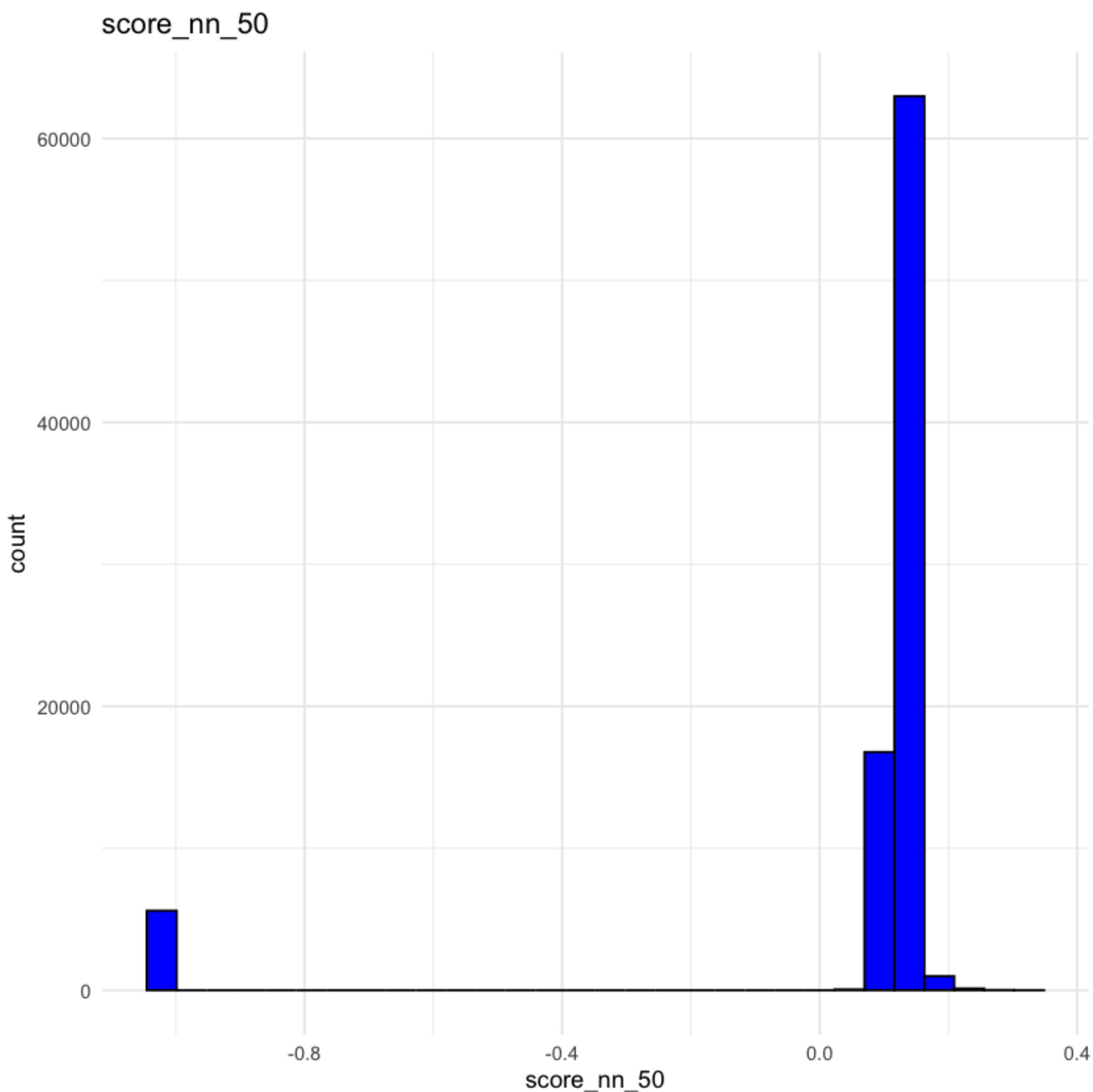
```
[1] "mode: NA"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
 -1.000   0.116   0.124   0.052   0.131   0.347   13472
```



[26]:
```r
# Plotting a histogram of the 'score_nn_50' column in 'df'
ggplot(df, aes(x = score_nn_50)) +
```

```r
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("score_nn_50") +
  theme_minimal()

# Calculating the mode for 'score_nn_50'
mode_score_nn_50 <- df$score_nn_50[which.max(tabulate(match(df$score_nn_50,
 ↪unique(df$score_nn_50))))]
print(paste('mode:', mode_score_nn_50))

# Printing summary statistics for 'score_nn_50'
print(summary(df$score_nn_50))

# Filling missing values in 'score_nn_50' with its mode
df$score_nn_50[is.na(df$score_nn_50)] <- mode_score_nn_50
```

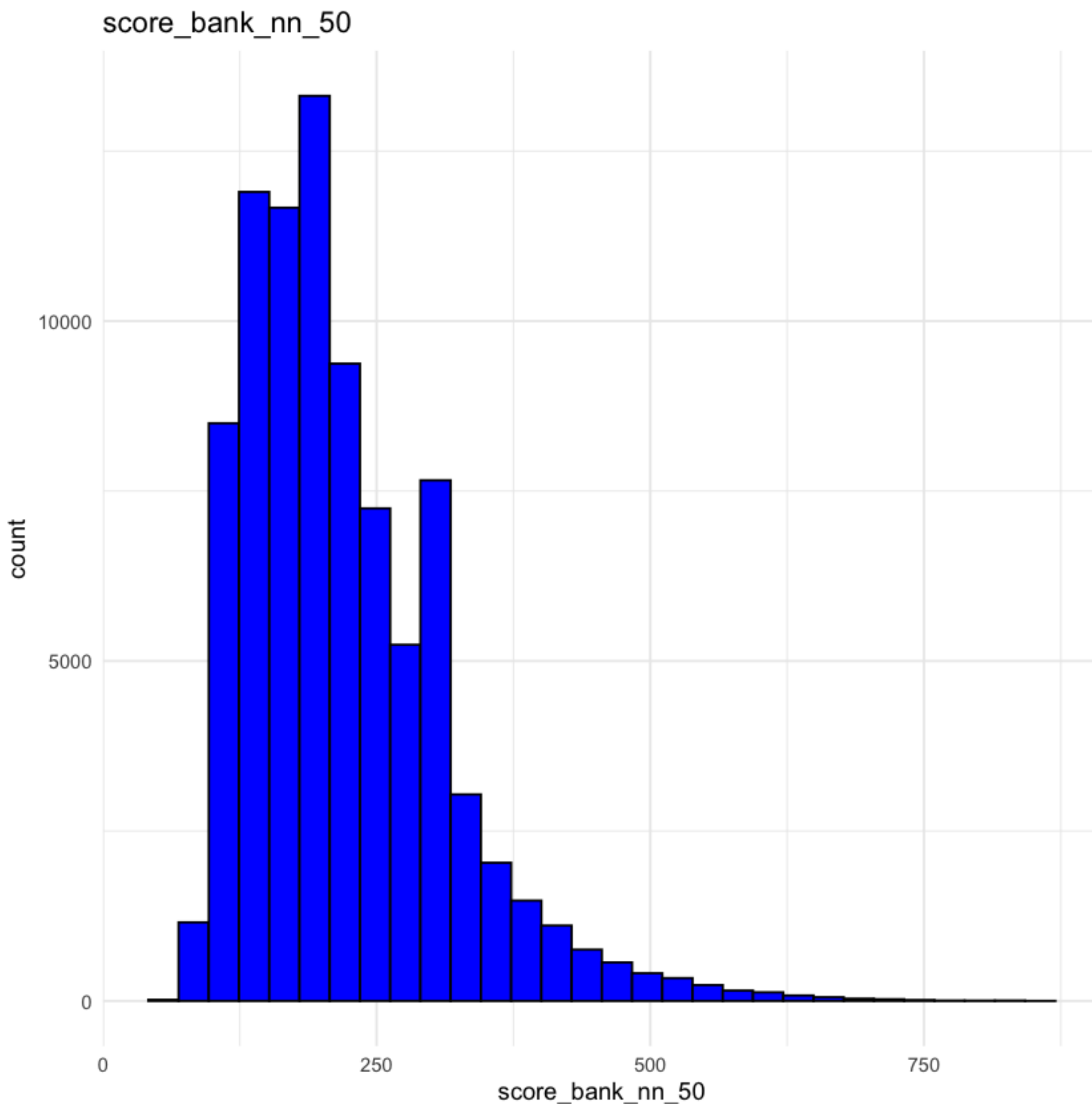
```
[1] "mode: NA"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
 -1.000   0.116   0.124   0.052   0.131   0.347   13472
```



[27]:
```
# Plotting a histogram of the 'score_bank_nn_50' column in 'df'
ggplot(df, aes(x = score_bank_nn_50)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  ggtitle("score_bank_nn_50") +
  theme_minimal()

# Calculating the mode for 'score_bank_nn_50' (for consistency, though mean is␣
↪used for imputation)
mode_score_bank_nn_50 <- df$score_bank_nn_50[which.
↪max(tabulate(match(df$score_bank_nn_50, unique(df$score_bank_nn_50))))]
print(paste('mode:', mode_score_bank_nn_50))
```

```r
# Printing summary statistics for 'score_bank_nn_50'
print(summary(df$score_bank_nn_50))

# Filling missing values in 'score_bank_nn_50' with its mean
df$score_bank_nn_50[is.na(df$score_bank_nn_50)] <- mean(df$score_bank_nn_50, na.
↪rm = TRUE)
```

```
[1] "mode: NA"
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
   52.0   152.0   201.0   220.4   271.0   853.0   13472
```



[28]:
```r
# Print the structure of the dataframe
str(df)
```

```r
# Get a summary of the number of non-NA values and basic statistics for each␣
↪column
summary(df)

# Print the dimensions of the dataframe
cat("Dimensions of dataframe: ", dim(df), "\n")

# Check for missing values in each column
sapply(df, function(x) sum(is.na(x)))

# Print the memory usage of the dataframe
print(object.size(df), units = "auto")
```

```
'data.frame':   100000 obs. of  26 variables:
 $ id               : int  238687671 248689049 276054054 313767939 342351235
241793622 349443099 310803433 489653217 315457381 ...
 $ date             : chr  "20.06.2019" "02.08.2019" "22.11.2019" "24.02.2020"
...
 $ target           : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ req_amt          : num  689385 450000 500000 730000 1490000 ...
 $ age              : int  40 57 32 31 68 38 67 40 40 38 ...
 $ rule_2_21        : num  0 0 1 0 0 0 0 0 0 0 ...
 $ rule_2_22        : num  0 0 1 0 0 0 0 0 0 0 ...
 $ rule_2_25        : num  1 0 1 0 0 0 0 1 0 0 ...
 $ rule_2_27        : num  1 0 1 1 0 1 0 1 0 1 ...
 $ rule_2_31        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ rule_2_32        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ rule_2_33        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ rule_2_34        : num  0 0 1 0 0 0 0 1 0 0 ...
 $ rule_2_801       : num  1 0 0 1 1 1 0 1 0 0 ...
 $ rule_2_802       : num  0 0 1 1 0 1 0 1 0 0 ...
 $ rule_2_806       : num  0 0 1 1 1 1 1 1 1 1 ...
 $ rule_combi_1     : int  1 0 0 0 0 0 0 0 0 0 ...
 $ rule_combi_2     : int  0 0 0 0 0 0 0 0 0 0 ...
 $ rules_count      : num  2 0 5 1 0 1 0 3 0 1 ...
 $ score_bank_16    : num  148 128 289 NA NA 210 NA NA NA 184 ...
 $ score_bank_50    : num  161 128 294 257 257 ...
 $ score_nn_16      : num  0.151 -1 0.126 NA NA ...
 $ score_nn_50      : num  0.124 -1 0.128 NA NA ...
 $ score_bank_nn_16: num  224 313 264 NA NA 157 NA NA NA 114 ...
 $ score_bank_nn_50: num  202 313 227 220 220 ...
 $ count_nulls      : num  0 0 0 0 0 0 0 0 0 0 ...

       id                  date              target        req_amt
 Min.   :137175209   Length:100000      0:99871   Min.   :  50000
 1st Qu.:220747368   Class :character   1:  129   1st Qu.: 400000
 Median :263040542   Mode  :character             Median : 614900
```

```
 Mean   :280116429                              Mean   : 681123
 3rd Qu.:337582833                              3rd Qu.: 900000
 Max.   :517283235                              Max.   :3000000

      age          rule_2_21         rule_2_22         rule_2_25     
 Min.   : 0.00   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000  
 1st Qu.:34.00   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000  
 Median :41.00   Median :0.0000   Median :0.0000   Median :0.0000  
 Mean   :42.08   Mean   :0.1492   Mean   :0.1371   Mean   :0.2795  
 3rd Qu.:50.00   3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:1.0000  
 Max.   :89.00   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000  

   rule_2_27        rule_2_31          rule_2_32          rule_2_33     
 Min.   :0.0000   Min.   :0.00000   Min.   :0.00000   Min.   :0.0000  
 1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.0000  
 Median :1.0000   Median :0.00000   Median :0.00000   Median :0.0000  
 Mean   :0.5688   Mean   :0.06371   Mean   :0.09235   Mean   :0.1181  
 3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.0000  
 Max.   :1.0000   Max.   :1.00000   Max.   :1.00000   Max.   :1.0000  

   rule_2_34        rule_2_801       rule_2_802      rule_2_806    
 Min.   :0.0000   Min.   :0.0000   Min.   :0.000   Min.   :0.0000  
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:0.0000  
 Median :0.0000   Median :0.0000   Median :0.000   Median :1.0000  
 Mean   :0.2129   Mean   :0.3848   Mean   :0.221   Mean   :0.5927  
 3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:0.000   3rd Qu.:1.0000  
 Max.   :1.0000   Max.   :1.0000   Max.   :1.000   Max.   :1.0000  

  rule_combi_1    rule_combi_2      rules_count    score_bank_16  
 Min.   :0.000   Min.   :0.00000   Min.   :0.000   Min.   :  0.0  
 1st Qu.:0.000   1st Qu.:0.00000   1st Qu.:0.000   1st Qu.:165.0  
 Median :0.000   Median :0.00000   Median :1.000   Median :231.0  
 Mean   :0.129   Mean   :0.06068   Mean   :1.622   Mean   :253.2  
 3rd Qu.:0.000   3rd Qu.:0.00000   3rd Qu.:2.000   3rd Qu.:316.0  
 Max.   :1.000   Max.   :1.00000   Max.   :8.000   Max.   :927.0  
                                                   NA's   :13472  
 score_bank_50    score_nn_16      score_nn_50     score_bank_nn_16
 Min.   :  0.0   Min.   :-1.000   Min.   :-1.000   Min.   : 77.0   
 1st Qu.:177.0   1st Qu.: 0.114   1st Qu.: 0.116   1st Qu.:188.0   
 Median :256.5   Median : 0.125   Median : 0.124   Median :237.0   
 Mean   :256.5   Mean   : 0.054   Mean   : 0.052   Mean   :258.5   
 3rd Qu.:305.0   3rd Qu.: 0.135   3rd Qu.: 0.131   3rd Qu.:313.0   
 Max.   :936.0   Max.   : 0.338   Max.   : 0.347   Max.   :895.0   
                 NA's   :13472    NA's   :13472    NA's   :13472   
 score_bank_nn_50  count_nulls
 Min.   : 52.0    Min.   :0   
 1st Qu.:160.0    1st Qu.:0   
 Median :216.0    Median :0   
```

```
 Mean   :220.4    Mean   :0  
 3rd Qu.:255.0    3rd Qu.:0  
 Max.   :853.0    Max.   :0  
```

```
Dimensions of dataframe:  100000 26
```

id 0 **date** 0 **target** 0 **req_amt** 0 **age** 0 **rule_2_21** 0 **rule_2_22** 0 **rule_2_25** 0 **rule_2_27** 0 **rule_2_31** 0 **rule_2_32** 0 **rule_2_33** 0 **rule_2_34** 0 **rule_2_801** 0 **rule_2_802** 0 **rule_2_806** 0 **rule_combi_1** 0 **rule_combi_2** 0 **rules_count** 0 **score_bank_16** 13472 **score_bank_50** 0 **score_nn_16** 13472 **score_nn_50** 13472 **score_bank_nn_16** 13472 **score_bank_nn_50** 0 **count_nulls** 0

```
18 Mb
```

5 Working with hypotheses

Based on the initial analysis of the data, it became clear that the data represents separate transactions. The main hypotheses regarding transactional fraud are:

- The frequency of fraudulent transactions from the card.
- The discrepancy between the card data and the passport data of its holder.

However, since the data is anonymized, decryption attempts are necessary.

Good hypotheses, based on statistics on the data, include:

- Repeated transactions with the same "yield" (repeated transactions within a short period of time).
- Identifying salary accounts based on the date of age and amount, with the introduction of an additional indicator for weekends (as wages are typically calculated on weekdays).
- One of the rules may involve detecting the first transfer from someone else's card.

[29]:
```r
# Split the 'date' column into separate columns for day, month, and year
date_components <- strsplit(as.character(df$date), "\\.")
df$day <- sapply(date_components, function(x) as.integer(x[1]))
df$month <- sapply(date_components, function(x) as.integer(x[2]))
df$year <- sapply(date_components, function(x) as.integer(x[3]))

# Check the first few rows to verify
head(df)
```

A data.frame: 6 × 29

	id	date	target	req_amt	age	rule_2_21	rule_2_22	rule_2
	<int>	<chr>	<fct>	<dbl>	<int>	<dbl>	<dbl>	<dbl>
1	238687671	20.06.2019	0	689385	40	0	0	1
2	248689049	02.08.2019	0	450000	57	0	0	0
3	276054054	22.11.2019	0	500000	32	1	1	1
4	313767939	24.02.2020	0	730000	31	0	0	0
5	342351235	10.06.2020	0	1490000	68	0	0	0
6	241793622	03.07.2019	0	564136	38	0	0	0

[30]:
```
# Subset the dataframe for rows where 'target' equals 1 and get a summary of the␣
↪'age' column
fraudster_age_summary <- summary(df[df$target == 1, 'age'])

# Print the summary
print(fraudster_age_summary)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  24.00   32.00   42.00   41.37   50.00   65.00
```

[31]:
```
library(dplyr)

df <- df %>%
  mutate(age_group = case_when(
    age >= 24 & age <= 24 ~ 1,
    age > 24 & age <= 42 ~ 2,
    age > 42 & age <= 65 ~ 3,
    age > 65 ~ 4,
    TRUE ~ 0  # Default case if none of the above conditions are met
  ))
```

[32]:
```
# Subset the dataframe for rows where 'target' equals 1 and get a summary of the␣
↪'req_amt' column
fraudster_req_amt_summary <- summary(df[df$target == 1, 'req_amt'])

# Print the summary
print(fraudster_req_amt_summary)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 370000  810000 1050000 1054612 1320000 1804800
```

[33]:
```
# Calculate the minimum 'req_amt' for rows where 'target' equals 1
min_fraud_amt_value <- min(df[df$target == 1, "req_amt"], na.rm = TRUE)

# Initialize the 'min_fraud_amt' column to 0
df$min_fraud_amt <- 0

# Update 'min_fraud_amt' to 1 where 'req_amt' is greater than the minimum fraud␣
↪'req_amt'
df$min_fraud_amt[df$req_amt > min_fraud_amt_value] <- 1
```

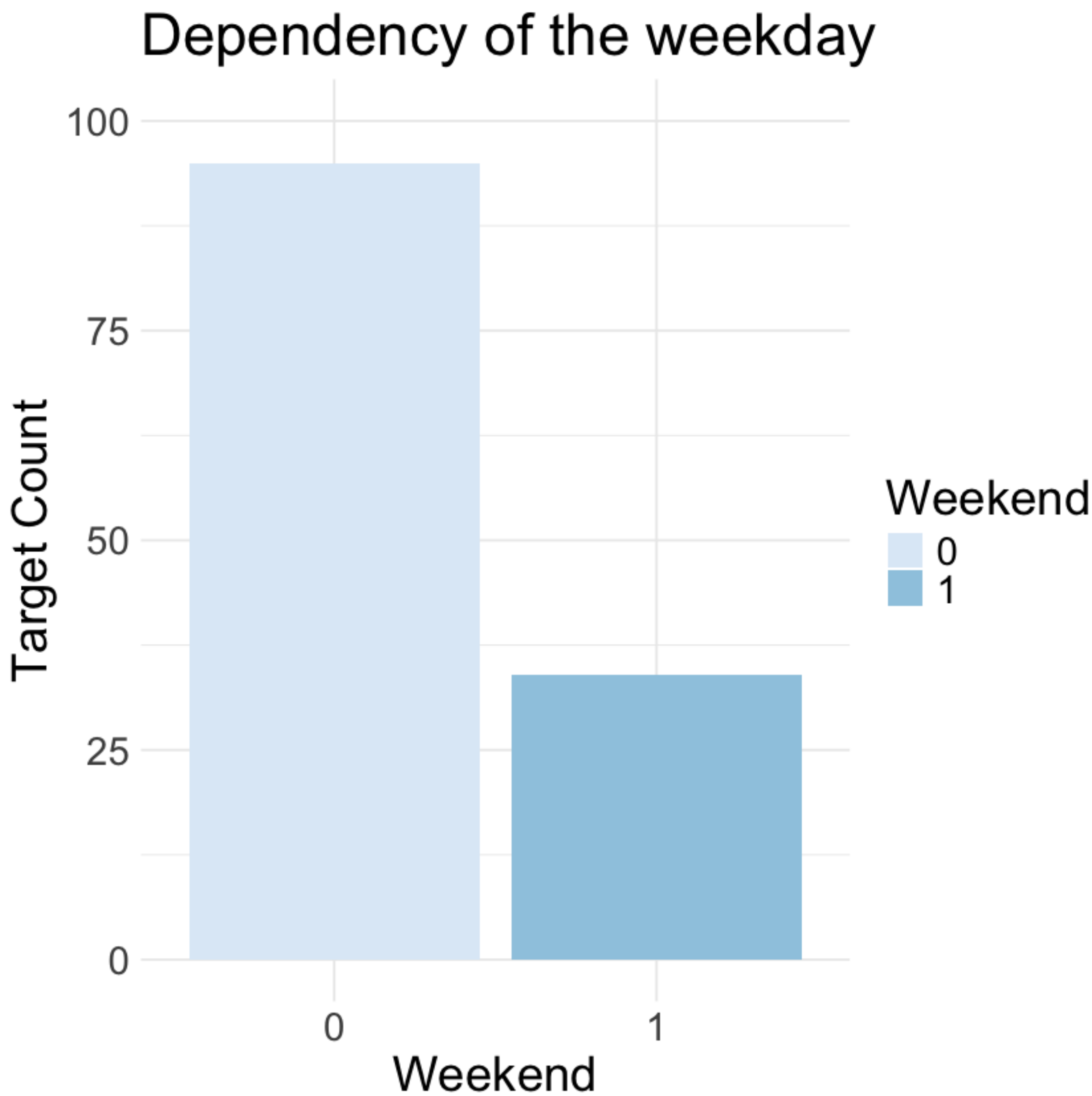
[66]:
```
library(dplyr)
library(lubridate)

df <- df %>%
  mutate(date = dmy(date), # Adjust the function dmy(), mdy(), ymd() based on␣
↪your date format
```

```
        weekend = if_else(wday(date) %in% c(1, 7), 1, 0)) # `wday()` defaults␣
↪to Sunday=1, Saturday=7
```

[35]:
```
# Adjust the date parsing function (ymd, dmy, mdy) based on your actual date␣
↪format
df$date <- ymd(df$date)

# Getting the number of the day with wday, setting week_start to define which␣
↪day is considered the start of the week
# By default, wday returns 1 = Sunday, 2 = Monday, ..., 7 = Saturday
df$number_of_day <- wday(df$date)
```

[36]:
```
# Assuming 'df' is your dataframe
df <- df %>%
  mutate(salary_card = 0) # Initialize 'salary_card' with 0

# Grouping and counting
salary <- df %>%
  filter(weekend == 0) %>%
  group_by(age, req_amt, day) %>%
  summarise(id_count = n(), .groups = 'drop') %>%
  filter(id_count >= 4) # Keeping groups with count >= 4

# Merging back to the original dataframe
df <- df %>%
  left_join(salary, by = c("age", "req_amt", "day")) %>%
  mutate(salary_card = ifelse(!is.na(id_count), 1, salary_card)) %>%
  select(-id_count) # Removing the extra 'id_count' column after merge
```

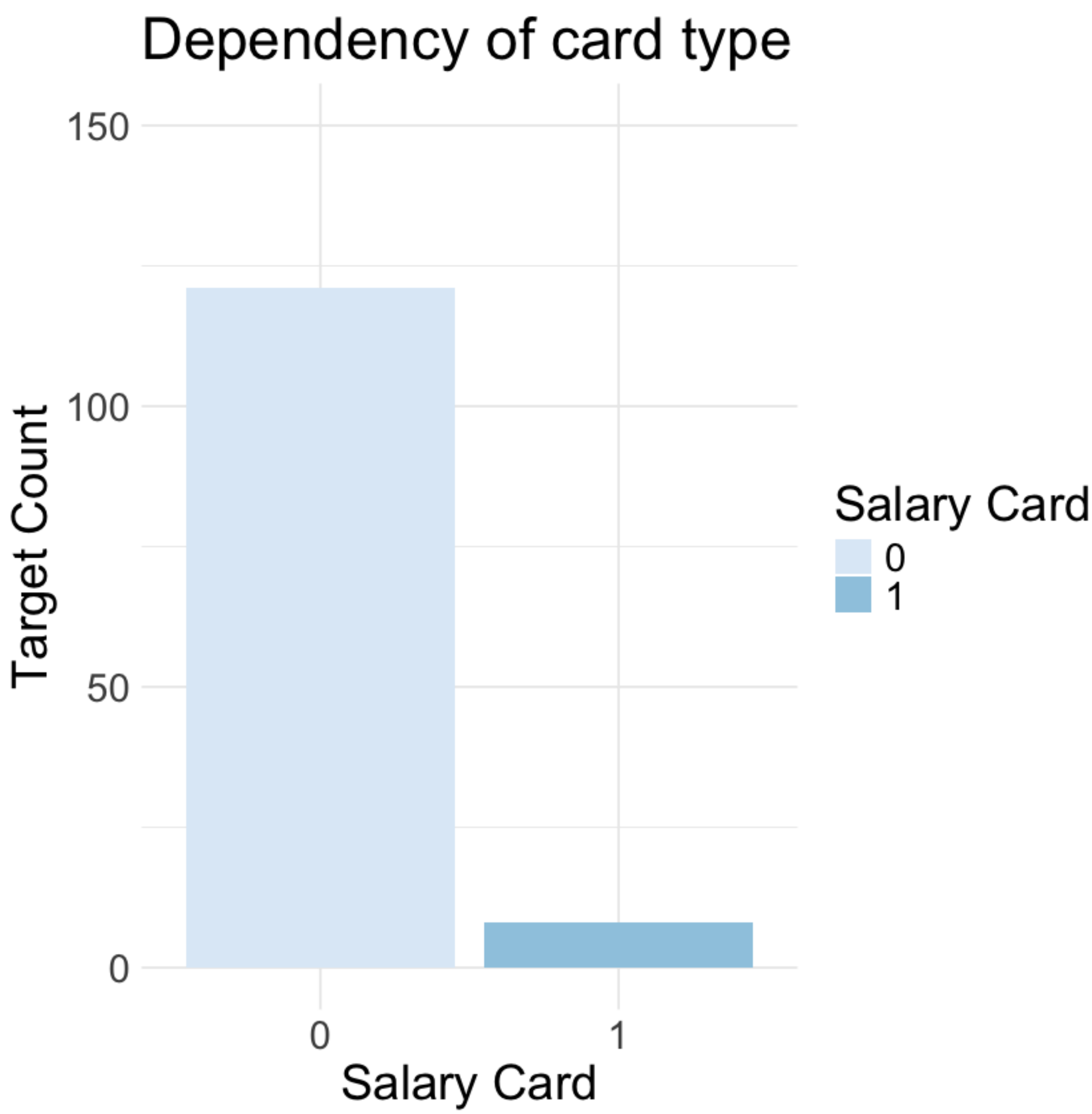
[37]:
```
# Filter for target == 1 and then count occurrences by 'weekend'
l <- df %>%
  filter(target == 1) %>%
  group_by(weekend) %>%
  summarise(target_count = n())

# Create the bar plot
ggplot(l, aes(x = as.factor(weekend), y = target_count, fill = as.
↪factor(weekend))) +
  geom_bar(stat = "identity", position = position_dodge()) +
  scale_fill_brewer(palette = "Blues", name = "Weekend") +
  labs(x = "Weekend", y = "Target Count", title = "Dependency of the weekday") +
  theme_minimal() +
  theme(text = element_text(size = 22)) +
  ylim(0, 100)
```



The dependence on the type of card is visible; on cards with periodic payments, fraud occurs much less

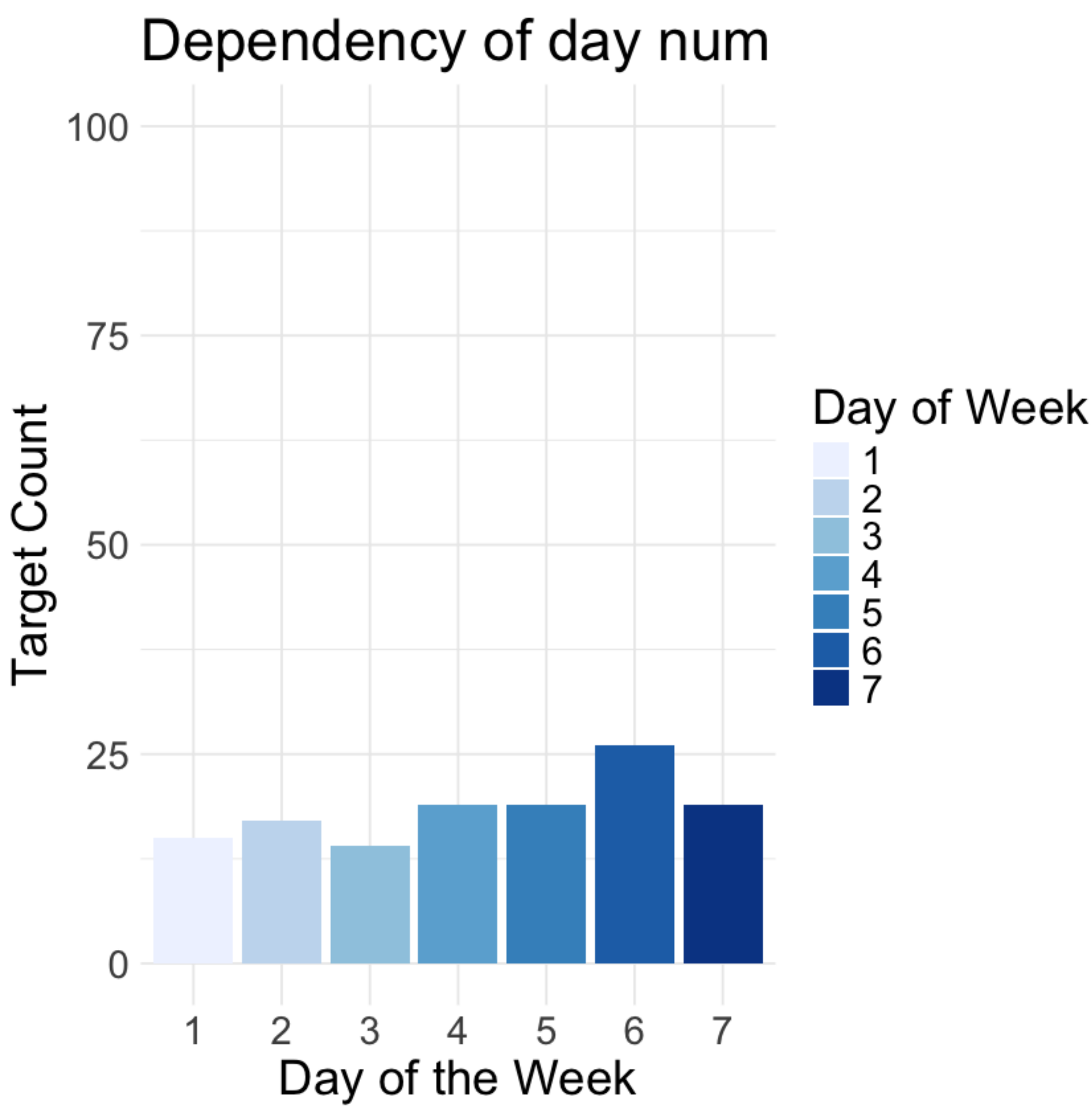
[38]:
```
# Prepare the data
l_salary <- df %>%
  filter(target == 1) %>%
  count(salary_card, target) %>%
  rename(target_count = n)

# Create the plot
ggplot(l_salary, aes(x = as.factor(salary_card), y = target_count, fill = as.
↪factor(salary_card))) +
  geom_bar(stat = "identity") +
```

```
  scale_fill_brewer(palette = "Blues", name = "Salary Card") +
  labs(x = "Salary Card", y = "Target Count", title = "Dependency of card type")␣
↪+
  theme_minimal() +
  theme(text = element_text(size = 22)) +
  ylim(0, 150)
```



[39]:
```
# Prepare the data
l_day <- df %>%
  filter(target == 1) %>%
  count(number_of_day, target) %>%
  rename(target_count = n)
```

```
# Create the plot
ggplot(l_day, aes(x = as.factor(number_of_day), y = target_count, fill = as.
↪factor(number_of_day))) +
  geom_bar(stat = "identity") +
  scale_fill_brewer(palette = "Blues", name = "Day of Week") +
  labs(x = "Day of the Week", y = "Target Count", title = "Dependency of day␣
↪num") +
  theme_minimal() +
  theme(text = element_text(size = 22)) +
  ylim(0, 100)
```



6 Fiting and prediction

Step 1: Data Preparation and Logistic Regression Model Fitting First, let's prepare the data and fit a logistic regression model:

[49]:
```
# Assuming 'df' and 'df_keys_2' are your dataframes
df_prep <- df[, !(names(df) %in% c('target', 'date', 'id', 'count_nulls'))] #␣
↪Exclude 'target', 'date', 'id'
target <- df$target

# Standard scaling
df_scaled <- scale(df_prep)

# Fit Logistic Regression Model
fit_lr <- glm(target ~ ., data = as.data.frame(df_scaled), family =␣
↪binomial(link = 'logit'))

# Extract and sort coefficients
coef_lr <- summary(fit_lr)$coefficients
sorted_coef_lr <- coef_lr[order(-abs(coef_lr[, "Estimate"])), ]
```

[50]:
```
sorted_coef_lr
```

A matrix: 30 × 4 of type dbl

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-12.525889555	66.47876302	-0.18841941	8.505479e-01
score_nn_16	9.839042114	3.14039583	3.13305794	1.729953e-03
min_fraud_amt	5.906455202	127.49183015	0.04632811	9.630487e-01
score_nn_50	-3.629514817	3.82343707	-0.94928065	3.424779e-01
score_bank_nn_50	1.334315672	0.28223257	4.72771682	2.270586e-06
score_bank_nn_16	-1.003122069	0.33910280	-2.95816507	3.094764e-03
year	-0.951570893	0.14146414	-6.72658715	1.736886e-11
score_bank_16	0.905169232	0.51838546	1.74613160	8.078809e-02
req_amt	0.813045037	0.09366984	8.67990244	3.961085e-18
rule_2_33	0.760446121	0.34253205	2.22007293	2.641382e-02
score_bank_50	-0.740444980	0.45093595	-1.64201806	1.005863e-01
rule_2_21	-0.695463969	0.38312695	-1.81523114	6.948840e-02
age_group	0.268534365	0.20456625	1.31270120	1.892837e-01
rule_2_31	0.215574041	0.12206164	1.76610798	7.737773e-02
rule_2_32	-0.210970387	0.16220483	-1.30064185	1.933811e-01
rule_2_25	0.189972914	0.15381781	1.23505148	2.168113e-01
weekend	-0.182683701	0.10594115	-1.72438845	8.463774e-02
age	-0.159646390	0.19389429	-0.82336818	4.102987e-01
rule_combi_1	0.130706350	0.13509655	0.96750326	3.332925e-01
rule_2_802	-0.117864448	0.14913227	-0.79033495	4.293322e-01
number_of_day	0.097100798	0.10651173	0.91164415	3.619561e-01
rule_combi_2	0.062441140	0.10554044	0.59163236	5.540968e-01
rule_2_22	-0.060003403	0.09817667	-0.61117779	5.410819e-01
day	0.052828755	0.09632188	0.54846056	5.833757e-01
rule_2_806	0.044955350	0.16164727	0.27810769	7.809297e-01
salary_card	0.040953489	0.04476529	0.91484910	3.602709e-01
month	-0.032631991	0.11058989	-0.29507211	7.679388e-01
rule_2_801	0.014972038	0.17021742	0.08795832	9.299098e-01
rule_2_27	-0.013774517	0.14428796	-0.09546546	9.239451e-01
rule_2_34	0.007341811	0.16637330	0.04412854	9.648019e-01

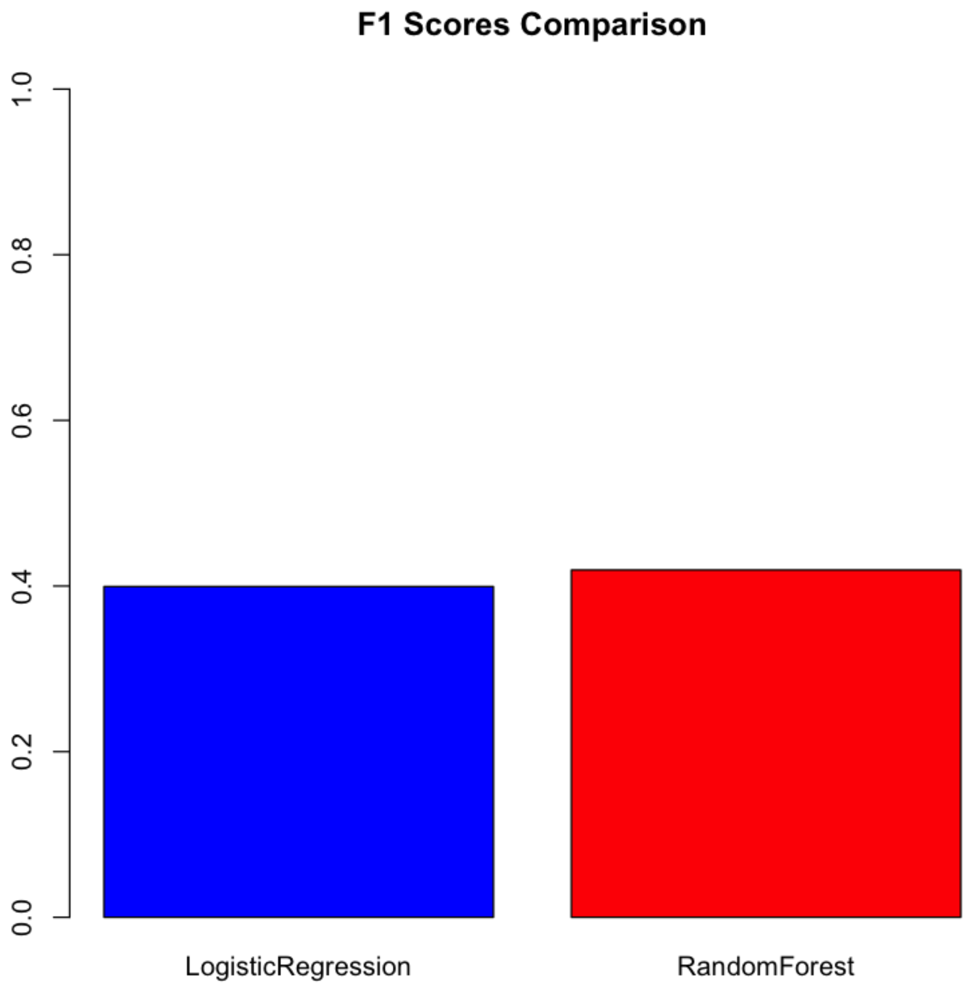
Step 2: Scoping Out Multiple Models and Comparing Them Based on F1 Score

[59]:
```
library(caret)

# Data partition
set.seed(123) # For reproducibility
index <- createDataPartition(target, p = .8, list = FALSE)  # This returns a
↪matrix, not a list
train_data <- df_scaled[index, , drop = FALSE]
train_target <- target[index]
test_data <- df_scaled[-index, , drop = FALSE]
test_target <- target[-index]

# Impute NA values in train_data and test_data with the median of each column
train_data <- apply(train_data, 2, function(x) ifelse(is.na(x), median(x, na.rm
↪= TRUE), x))
```

```
test_data <- apply(test_data, 2, function(x) ifelse(is.na(x), median(x, na.rm =␣
↪TRUE), x))

# Convert back to data frame if necessary
train_data <- as.data.frame(train_data)
test_data <- as.data.frame(test_data)

# Train a logistic regression model
ctrl <- trainControl(method = "none")
fit_lr_caret <- train(x = train_data, y = train_target, method = "glm", family =␣
↪"binomial", trControl = ctrl)

# Train a random forest model as an example
fit_rf <- train(x = train_data, y = train_target, method = "rf", trControl =␣
↪ctrl)

# Predict and calculate F1 score
predictions_lr <- factor(predictions_lr, levels = levels(test_target))
predictions_rf <- factor(predictions_rf, levels = levels(test_target))
```

[63]:

```
calculateF1Score <- function(predictions, actual) {
  cm <- table(actual, predictions)
  precision <- diag(cm) / rowSums(cm)
  recall <- diag(cm) / colSums(cm)
  f1 <- 2 * precision * recall / (precision + recall)
  return(mean(f1, na.rm = TRUE)) # Return the average F1 score if multiple␣
↪classes
}

f1_lr <- calculateF1Score(predictions_lr, test_target)
f1_rf <- calculateF1Score(predictions_rf, test_target)

# Comparing F1 scores
f1_scores <- c(LogisticRegression = f1_lr, RandomForest = f1_rf)
barplot(f1_scores, main = "F1 Scores Comparison", col = c("blue", "red"), names.
↪arg = names(f1_scores), ylim = c(0, 1))
```



[64]:
```
f1_scores
```

LogisticRegression 0.399374577840042 **RandomForest** 0.4193785222042