

#Libraries

```
library(tidyverse)
```

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

```
## v dplyr      1.1.4      v readr      2.1.5
```

```
## v forcats    1.0.0      v stringr   1.5.1
```

```
## v ggplot2     3.5.1      v tibble    3.2.1
```

```
## v lubridate   1.9.3      v tidyr     1.3.1
```

```
## v purrr       1.0.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()     masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(dplyr)
```

```
library(rpart)
```

```
library(partykit)
```

```
## Loading required package: grid
```

```
## Loading required package: libcoin
```

```
## Loading required package: mvtnorm
```

#Cleaning data for use

```
credit_data <- read.csv("credit_card.csv")
```

```
customer_data <- read.csv("customer.csv")
```

```
total_raw_data <- left_join(customer_data, credit_data, by = 'client_num')
```

```
client_data <- total_raw_data %>% select(-state_cd, -zipcode) %>%
```

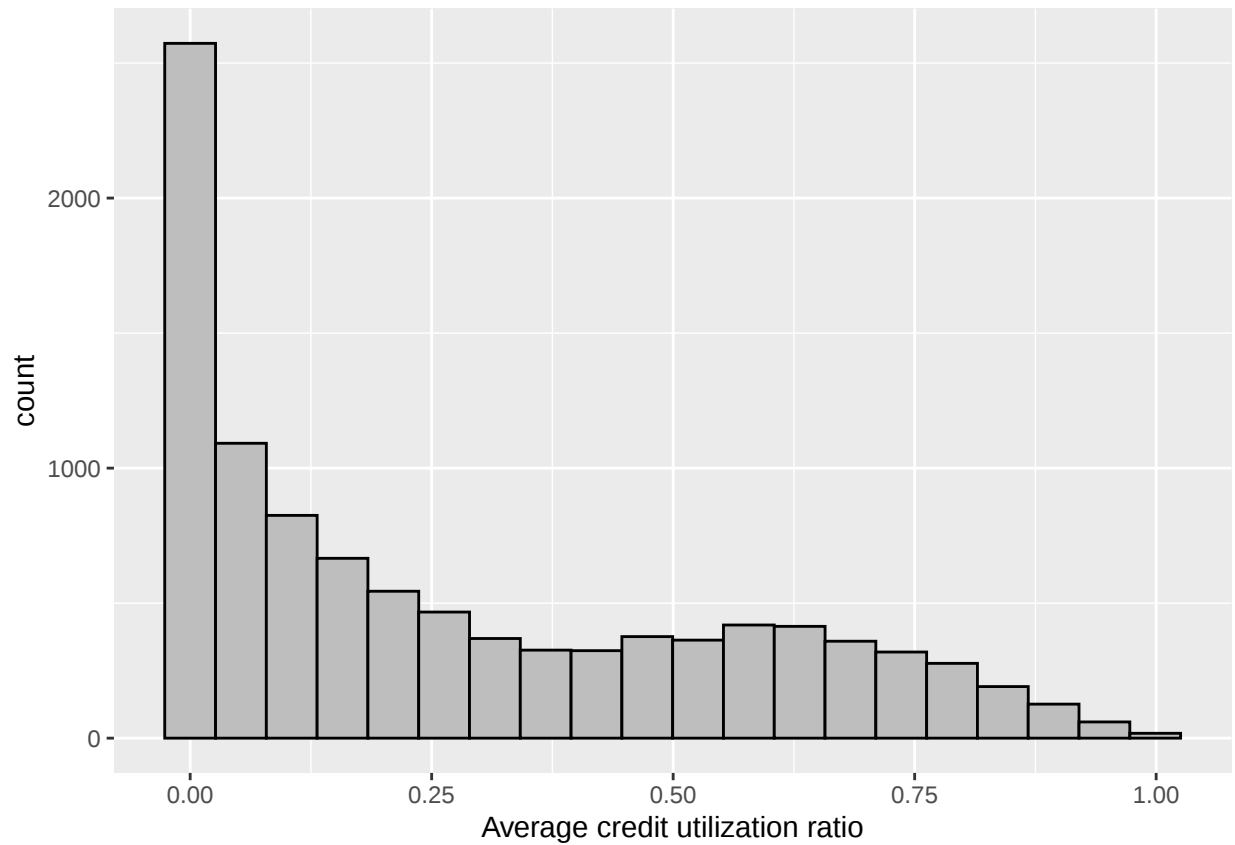
```
  mutate(ratio_usage = case_when(avg_utilization_ratio <= 0.3 ~ 'Low',  
                                 avg_utilization_ratio > 0.3 ~ 'High'))
```

#Visualizations

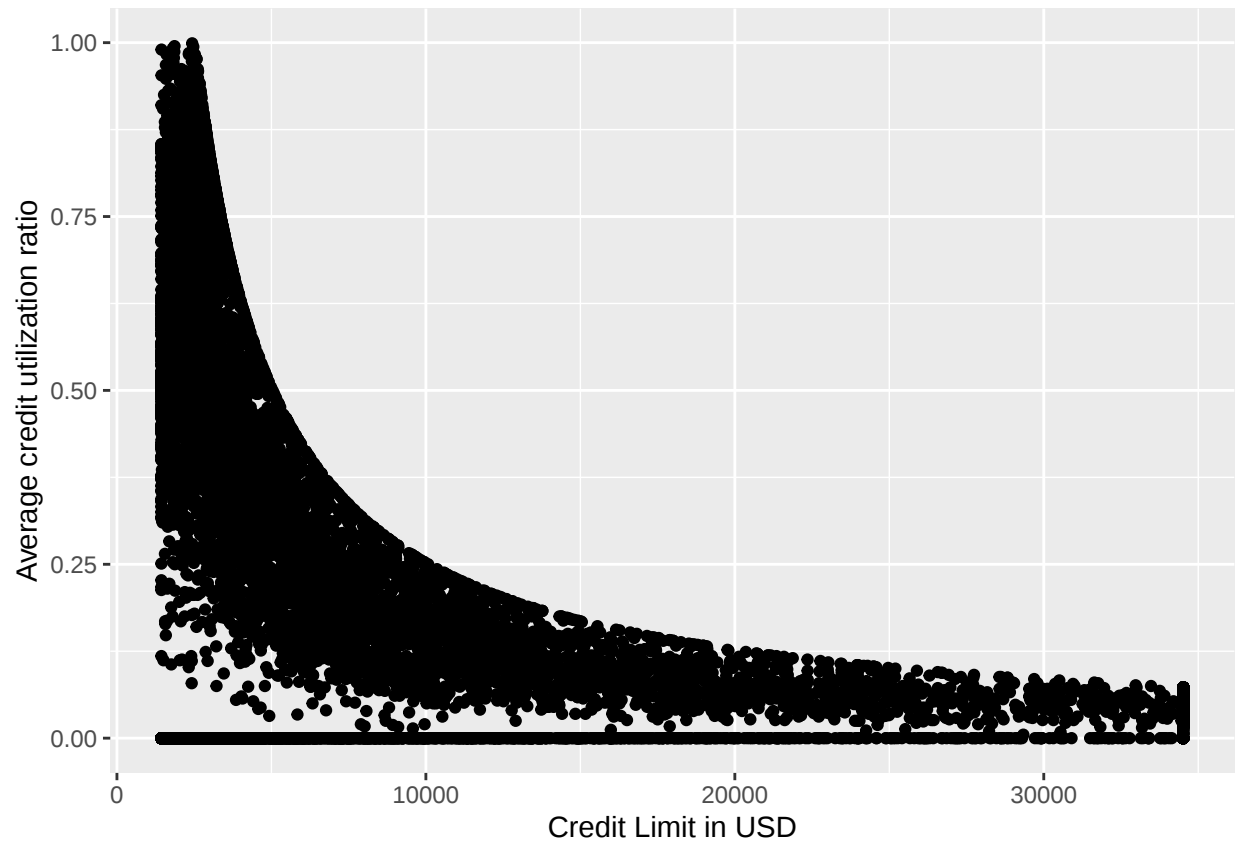
```
client_data %>% ggplot(aes(x = avg_utilization_ratio)) +
```

```
  geom_histogram(color = 'black', fill = 'grey', bins = 20) +
```

```
  labs(x = 'Average credit utilization ratio')
```



```
client_data %>% ggplot(aes(x = credit_limit, y = avg_utilization_ratio)) +  
  geom_point() +  
  labs(x = "Credit Limit in USD", y = "Average credit utilization ratio")
```



```
# Decision tree model to predict delinquency
```

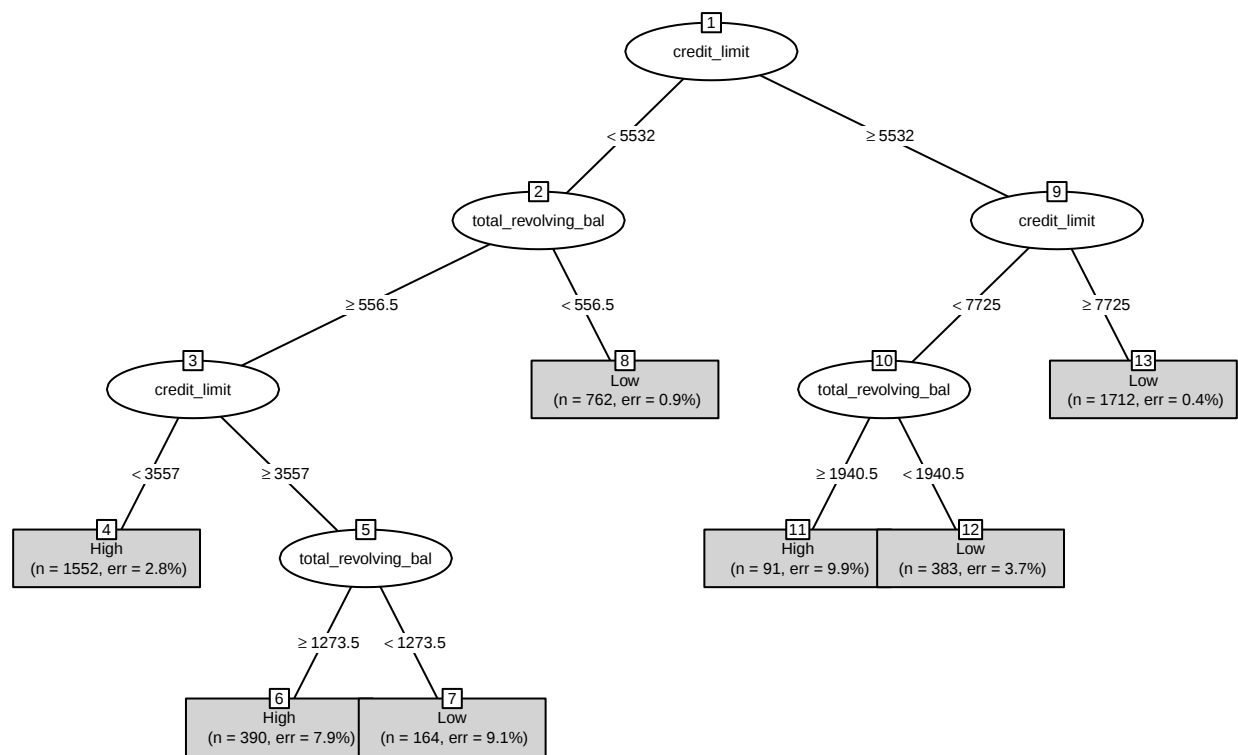
```
set.seed(172)
```

```
testing_data <- sample_n(client_data, size = round(0.5 * nrow(client_data)))
```

```
training_data <- anti_join(client_data, testing_data)
```

```
## Joining with 'by = join_by(client_num, customer_age, gender, dependent_count,
## education_level, marital_status, car_owner, house_owner, personal_loan,
## contact, customer_job, income, cust_satisfaction_score, card_category,
## annual_fees, activation_30_days, customer_acq_cost, week_start_date, week_num,
## qtr, current_year, credit_limit, total_revolving_bal, total_trans_amt,
## total_trans_vol, avg_utilization_ratio, use_chip, exp_type, interest_earned,
## delinquent_acc, ratio_usage)'
```

```
tree <- rpart(ratio_usage ~ total_revolving_bal + credit_limit + income +
              interest_earned + personal_loan, data = training_data)
plot(as.party(tree), gp = gpar(cex = 0.5), type = 'simple')
```



#Use tree for predictions

```
predictions <- predict(tree, newdata = testing_data, type = 'class')
confusion_matrix <- table(predictions, testing_data$ratio_usage)
confusion_matrix
```

```
##
## predictions High Low
##           High 1828 114
##           Low  46 3066
```

#Compute relevant rates

```
Accuracy <- (1828 + 3066) / (1828 + 114 + 46 + 3066)

Sensitivity <- 1828 / (1828 + 46)
Specificity <- 3066 / (3066 + 114)
FP_rate <- 114 / (114 + 3066)
FN_rate <- 46 / (1828 + 46)
```