

# Credit Card Fraud Detection

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## Introduction

Project ini bertujuan untuk membuat model yang dapat mengklasifikasikan apakah sebuah transaksi termasuk fraud atau tidak. Kebanyakan fitur dalam dataset sudah discaled nilainya dan tidak ditunjukkan nama fiturnya untuk alasan privasi. Namun, kita tetap bisa membangun model menggunakan fitur-fitur tersebut untuk melakukan klasifikasi.

## Tujuan Project

1. Memahami distribusi data transaksi yang bersifat fraud dan tidak.
2. Membuat sub-dataframe dengan rasio transaksi fraud dan tidak fraud yang tidak terlalu jauh agar model tidak overfitting.
3. Menentukan algoritma klasifikasi mana yang memberikan hasil yang terbaik.

## Referensi

1. Kaggle
2. Machinelearningplus.com

## Packages yang Digunakan

```
# library untuk mengolah data  
library(utils)  
library(tidyr)  
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
```

```
# library untuk memplot data
library(corrplot)
```

```
## corrplot 0.84 loaded
```

```
library(ggplot2)
```

```
# library untuk membangun model
library(caret)
```

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

```
# library untuk directory
library(here)
```

```
## here() starts at D:/R/Project/Portofolio/Credit Fraud Detection
```

## Datasets

Dataset transaksi kartu kredit berasal dari kaggle. Data berisi 28 variabel yang tidak diketahui nama kolomnya dan sudah di scaled oleh pemilik data, variabel waktu transaksi, dan variabel jumlah uang pertransaksi.

```
# Import data csv
df <- read.csv(here("creditcard.csv"))
```

```
# melihat ringkasan dataframe
str(df)
```

```
## 'data.frame': 284807 obs. of 31 variables:
## $ Time : num 0 0 1 1 2 2 4 7 7 9 ...
## $ V1 : num -1.36 1.192 -1.358 -0.966 -1.158 ...
## $ V2 : num -0.0728 0.2662 -1.3402 -0.1852 0.8777 ...
## $ V3 : num 2.536 0.166 1.773 1.793 1.549 ...
## $ V4 : num 1.378 0.448 0.38 -0.863 0.403 ...
## $ V5 : num -0.3383 0.06 -0.5032 -0.0103 -0.4072 ...
## $ V6 : num 0.4624 -0.0824 1.8005 1.2472 0.0959 ...
## $ V7 : num 0.2396 -0.0788 0.7915 0.2376 0.5929 ...
## $ V8 : num 0.0987 0.0851 0.2477 0.3774 -0.2705 ...
## $ V9 : num 0.364 -0.255 -1.515 -1.387 0.818 ...
## $ V10 : num 0.0908 -0.167 0.2076 -0.055 0.7531 ...
## $ V11 : num -0.552 1.613 0.625 -0.226 -0.823 ...
## $ V12 : num -0.6178 1.0652 0.0661 0.1782 0.5382 ...
## $ V13 : num -0.991 0.489 0.717 0.508 1.346 ...
## $ V14 : num -0.311 -0.144 -0.166 -0.288 -1.12 ...
## $ V15 : num 1.468 0.636 2.346 -0.631 0.175 ...
## $ V16 : num -0.47 0.464 -2.89 -1.06 -0.451 ...
## $ V17 : num 0.208 -0.115 1.11 -0.684 -0.237 ...
## $ V18 : num 0.0258 -0.1834 -0.1214 1.9658 -0.0382 ...
## $ V19 : num 0.404 -0.146 -2.262 -1.233 0.803 ...
## $ V20 : num 0.2514 -0.0691 0.525 -0.208 0.4085 ...
```

```
## $ V21 : num -0.01831 -0.22578 0.248 -0.1083 -0.00943 ...
## $ V22 : num 0.27784 -0.63867 0.77168 0.00527 0.79828 ...
## $ V23 : num -0.11 0.101 0.909 -0.19 -0.137 ...
## $ V24 : num 0.0669 -0.3398 -0.6893 -1.1756 0.1413 ...
## $ V25 : num 0.129 0.167 -0.328 0.647 -0.206 ...
## $ V26 : num -0.189 0.126 -0.139 -0.222 0.502 ...
## $ V27 : num 0.13356 -0.00898 -0.05535 0.06272 0.21942 ...
## $ V28 : num -0.0211 0.0147 -0.0598 0.0615 0.2152 ...
## $ Amount: num 149.62 2.69 378.66 123.5 69.99 ...
## $ Class : int 0 0 0 0 0 0 0 0 0 0 ...
```

```
summary(df)
```

```
##      Time      V1      V2      V3
## Min.      : 0 Min.    :-56.40751 Min.    :-72.71573 Min.    :-48.3256
## 1st Qu.: 54202 1st Qu.: -0.92037 1st Qu.: -0.59855 1st Qu.: -0.8904
## Median : 84692 Median :  0.01811 Median :  0.06549 Median :  0.1799
## Mean   : 94814 Mean   :  0.00000 Mean   :  0.00000 Mean   :  0.0000
## 3rd Qu.:139321 3rd Qu.:  1.31564 3rd Qu.:  0.80372 3rd Qu.:  1.0272
## Max.    :172792 Max.    :  2.45493 Max.    : 22.05773 Max.    :  9.3826
##      V4      V5      V6      V7
## Min.    :-5.68317 Min.    :-113.74331 Min.    :-26.1605 Min.    :-43.5572
## 1st Qu.: -0.84864 1st Qu.: -0.69160 1st Qu.: -0.7683 1st Qu.: -0.5541
## Median : -0.01985 Median : -0.05434 Median : -0.2742 Median :  0.0401
## Mean   : 0.00000 Mean   :  0.00000 Mean   :  0.0000 Mean   :  0.0000
## 3rd Qu.: 0.74334 3rd Qu.:  0.61193 3rd Qu.:  0.3986 3rd Qu.:  0.5704
## Max.    :16.87534 Max.    : 34.80167 Max.    : 73.3016 Max.    :120.5895
##      V8      V9      V10     V11
## Min.    :-73.21672 Min.    :-13.43407 Min.    :-24.58826 Min.    :-4.79747
## 1st Qu.: -0.20863 1st Qu.: -0.64310 1st Qu.: -0.53543 1st Qu.: -0.76249
## Median :  0.02236 Median : -0.05143 Median : -0.09292 Median : -0.03276
## Mean   :  0.00000 Mean   :  0.00000 Mean   :  0.00000 Mean   :  0.00000
## 3rd Qu.:  0.32735 3rd Qu.:  0.59714 3rd Qu.:  0.45392 3rd Qu.:  0.73959
## Max.    : 20.00721 Max.    : 15.59500 Max.    : 23.74514 Max.    :12.01891
##      V12     V13     V14     V15
## Min.    :-18.6837 Min.    :-5.79188 Min.    :-19.2143 Min.    :-4.49894
## 1st Qu.: -0.4056 1st Qu.: -0.64854 1st Qu.: -0.4256 1st Qu.: -0.58288
## Median :  0.1400 Median : -0.01357 Median :  0.0506 Median :  0.04807
## Mean   :  0.0000 Mean   :  0.00000 Mean   :  0.0000 Mean   :  0.00000
## 3rd Qu.:  0.6182 3rd Qu.:  0.66251 3rd Qu.:  0.4931 3rd Qu.:  0.64882
## Max.    :  7.8484 Max.    :  7.12688 Max.    : 10.5268 Max.    :  8.87774
##      V16     V17     V18
## Min.    :-14.12985 Min.    :-25.16280 Min.    :-9.498746
## 1st Qu.: -0.46804 1st Qu.: -0.48375 1st Qu.: -0.498850
## Median :  0.06641 Median : -0.06568 Median : -0.003636
## Mean   :  0.00000 Mean   :  0.00000 Mean   :  0.000000
## 3rd Qu.:  0.52330 3rd Qu.:  0.39968 3rd Qu.:  0.500807
## Max.    : 17.31511 Max.    :  9.25353 Max.    :  5.041069
##      V19     V20     V21
## Min.    :-7.213527 Min.    :-54.49772 Min.    :-34.83038
## 1st Qu.: -0.456299 1st Qu.: -0.21172 1st Qu.: -0.22839
## Median :  0.003735 Median : -0.06248 Median : -0.02945
## Mean   :  0.000000 Mean   :  0.00000 Mean   :  0.00000
## 3rd Qu.:  0.458949 3rd Qu.:  0.13304 3rd Qu.:  0.18638
```

```
## Max. : 5.591971 Max. : 39.42090 Max. : 27.20284
## V22 V23 V24
## Min. :-10.933144 Min. :-44.80774 Min. :-2.83663
## 1st Qu.: -0.542350 1st Qu.: -0.16185 1st Qu.: -0.35459
## Median : 0.006782 Median : -0.01119 Median : 0.04098
## Mean : 0.000000 Mean : 0.00000 Mean : 0.00000
## 3rd Qu.: 0.528554 3rd Qu.: 0.14764 3rd Qu.: 0.43953
## Max. : 10.503090 Max. : 22.52841 Max. : 4.58455
## V25 V26 V27
## Min. :-10.29540 Min. :-2.60455 Min. :-22.565679
## 1st Qu.: -0.31715 1st Qu.: -0.32698 1st Qu.: -0.070840
## Median : 0.01659 Median : -0.05214 Median : 0.001342
## Mean : 0.00000 Mean : 0.00000 Mean : 0.000000
## 3rd Qu.: 0.35072 3rd Qu.: 0.24095 3rd Qu.: 0.091045
## Max. : 7.51959 Max. : 3.51735 Max. : 31.612198
## V28 Amount Class
## Min. :-15.43008 Min. : 0.00 Min. :0.000000
## 1st Qu.: -0.05296 1st Qu.: 5.60 1st Qu.:0.000000
## Median : 0.01124 Median : 22.00 Median :0.000000
## Mean : 0.00000 Mean : 88.35 Mean :0.001728
## 3rd Qu.: 0.07828 3rd Qu.: 77.17 3rd Qu.:0.000000
## Max. : 33.84781 Max. :25691.16 Max. :1.000000
```

```
# cek jumlah data kosong dan data na
sum(is.null(df))
```

```
## [1] 0
```

```
sum(is.na(df))
```

```
## [1] 0
```

```
# melihat perbandingan data fraud dan non frauds
p_f <- round(sum(df$Class==1)/nrow(df)*100,2)
p_nf <- round(sum(df$Class==0)/nrow(df)*100,2)
sprintf("Persentase data yang bersifat frauds adalah %g persen",p_f)
```

```
## [1] "Persentase data yang bersifat frauds adalah 0.17 persen"
```

```
sprintf("Persentase data yang bersifat non-frauds adalah %g persen",p_nf)
```

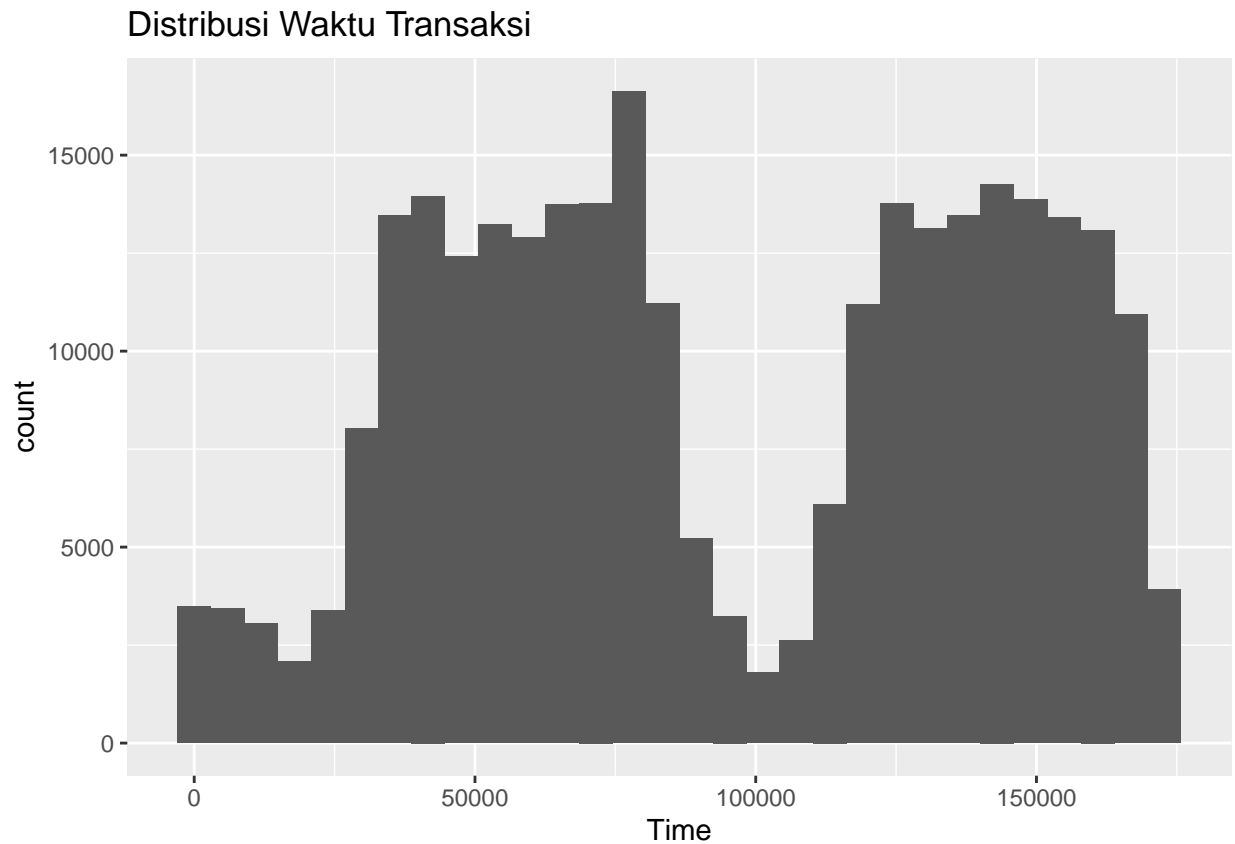
```
## [1] "Persentase data yang bersifat non-frauds adalah 99.83 persen"
```

## Exploration Data Analysis

Berdasarkan eksplorasi data diatas, tidak terdapat nilai NULL atau nilai NA pada dataset. Dataset juga sangat tidak seimbang, persentase observasi yang termasuk non-frauds jauh lebih besar dibandingkan yang termasuk frauds.

```
#memplot distribusi waktu dan jumlah per transaksi
ggplot(df,aes(x=Time))+
  geom_histogram()+
  labs(title = "Distribusi Waktu Transaksi")
```

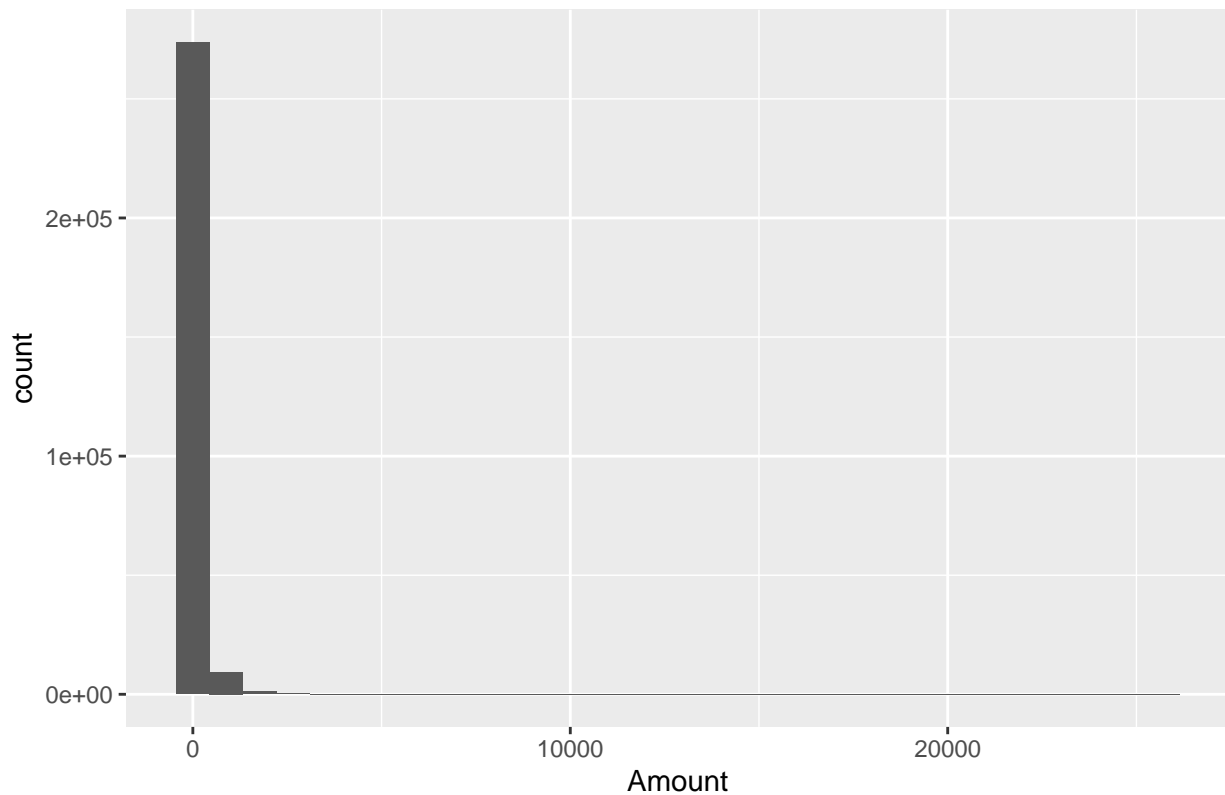
## 'stat\_bin()' using 'bins = 30'. Pick better value with 'binwidth'.



```
ggplot(df,aes(x=Amount))+
  geom_histogram()+
  labs(title = "Distribusi Jumlah Transaksi")
```

## 'stat\_bin()' using 'bins = 30'. Pick better value with 'binwidth'.

## Distribusi Jumlah Transaksi



Dilihat dari distribusi waktu transaksi diketahui bahwa terdapat dua waktu puncak yang terjadi jumlah transaksi terbanyak. Dilihat dari distribusi jumlah transaksi diketahui bahwa jumlah transaksi di dataset ini mayoritas adalah transaksi berjumlah kecil.

#Pre-processing

### Scaling Variabel

Semua variabel kecuali “Time” dan “Amount” sudah di scaled, oleh karena itu kita scaled variabel “Time” dan “Amount”.

```
#membuat dataset baru tanpa kolom time dan amount untuk sampling
new_df<- subset(df,select = -c(Time,Amount))

#membuat skala kolom time dan amount agar ternormalisasi di dataset baru
new_df$scale_time <- scale(df$Time)
new_df$scale_amount <- scale(df$Amount)
```

### Undersampling

Perbandingan persentase data yang fraud (0.17) dan data yang non-fraud ('r p\_nf') sangat tidak seimbang. Oleh karena itu perlu diperlakukan teknik sampling undersampling atau oversampling agar model yang dihasilkan tidak overfitting kearah non-fraud. Pada project ini akan digunakan random undersampling.

```

#membuat dataset baru tanpa kolom time dan amount untuk sampling
data<- subset(df,select = -c(Time,Amount))

#membuat skala kolom time dan amount agar ternormalisasi di dataset baru
data$scale_time <- scale(df$Time)
data$scale_amount <- scale(df$Amount)

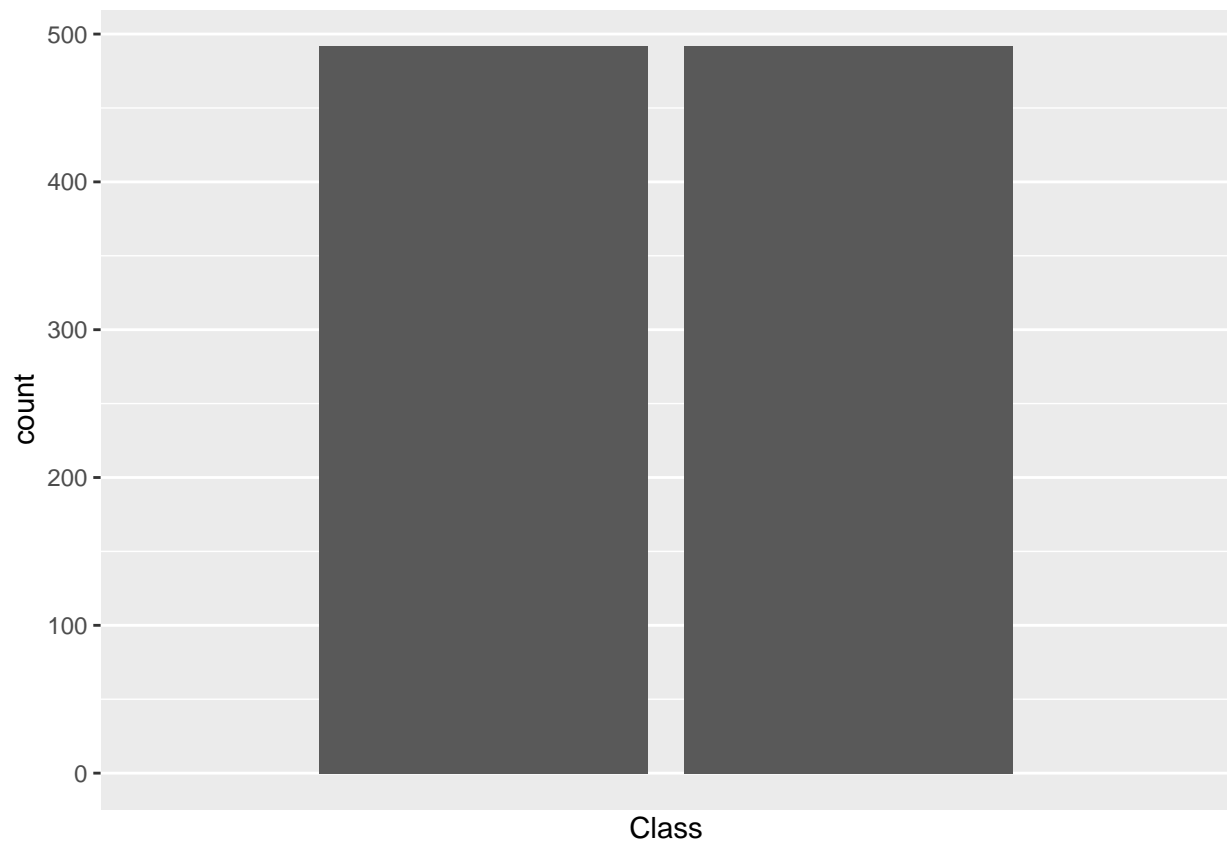
#membuat dataset baru untuk yang fraud dan non fraud
fraud_df <- filter(data,Class==1)
nfraud_df <- filter(data,Class==0)

#Melakukan undersampling
set.seed(50)
sample_num <- sample(nrow(nfraud_df),nrow(fraud_df))
under_sampling <- nfraud_df[sample_num,]

#membuat dataset baru hasil undersampling
new_df <- rbind(fraud_df,under_sampling)

#plot hasil undersampling
ggplot(new_df,aes(x=Class))+
  geom_bar()+
  scale_x_discrete(labels=c('non-fraud','fraud'))

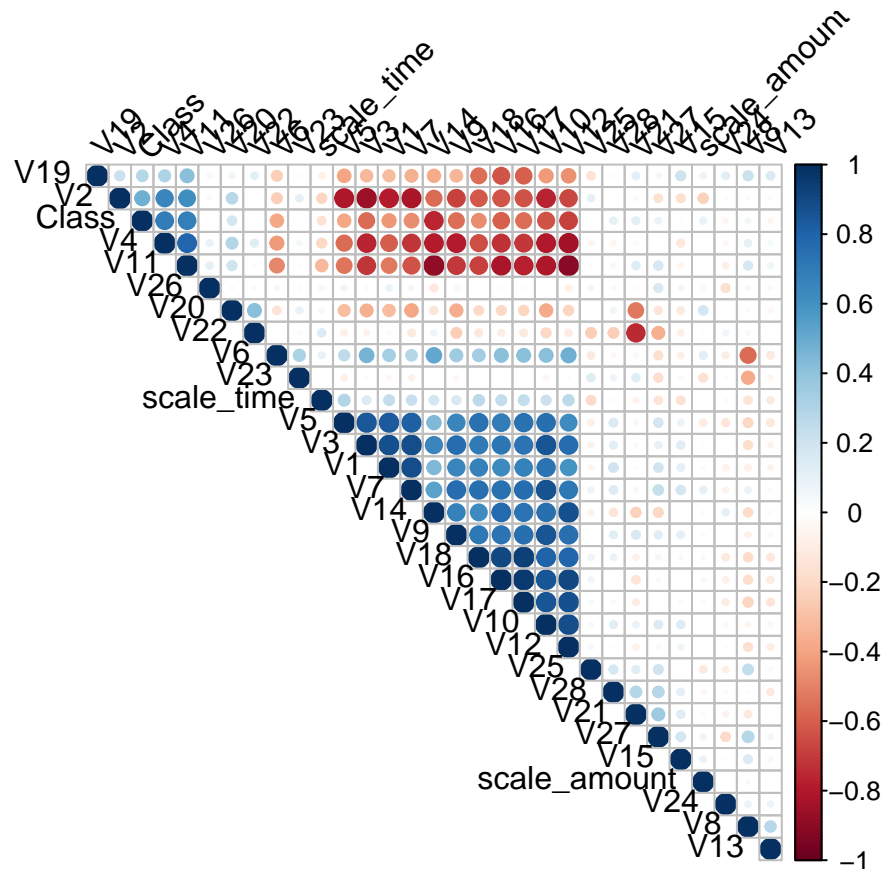
```



## Correlation Matrix

Setelah semua data di scaled, kita lihat bagaimana korelasi antar semua variabel dengan memplot correlation matrix.

```
#melihat korelasi matrix antar variabel
cor_mat <- cor(new_df)
corrplot(cor_mat, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)
```



```
#Melihat mana yang korelasi paling berpengaruh ke Class
matrix <- cor_mat[, "Class"]
```

```
# 5 korelasi positif tertinggi terhadap variabel Class
print(tail(sort(matrix), 5, decreasing=TRUE))
```

```
##          V19          V2          V11          V4          Class
## 0.2862293 0.4867436 0.6846938 0.6952337 1.0000000
```

```
# 5 korelasi negatif tertinggi terhadap variabel Class
print(head(sort(matrix), 5, decreasing=TRUE))
```

```
##          V14          V12          V10          V16          V3
## -0.7533102 -0.6819162 -0.6319585 -0.5941377 -0.5671144
```



Dari correlation matrix diatas didapatkan variabel yang paling berpengaruh terhadap variabel “Class” adalah V14,V4,V11,V12, dan V10.

## Outlier Removal

Selanjutnya kita menghilangkan data-data outlier data-data outlier berdasarkan V14,V4,V11,V12, dan V10. Namun, karena label yang diutamakan untuk dideteksi adalah berlabel fraud, maka kita lebih mengutamakan menghapus nilai outlier dari data-data yang berlabel fraud.

```
#menghapus data outlier berdasarkan v14,v4,v11,v12,v10
```

```
##Mendapatkan nilai yg fraud di V14
```

```
v14_fraud <- new_df%>%  
  filter(Class==1)
```

```
v14_q25 <- quantile(v14_fraud$V14,0.25)  
sprintf("kuartil 25 v14 adalah %g",v14_q25)
```

```
## [1] "kuartil 25 v14 adalah -9.69272"
```

```
v14_q75 <- quantile(v14_fraud$V14,0.75)  
sprintf("kuartil 75 v14 adalah %g",v14_q75)
```

```
## [1] "kuartil 75 v14 adalah -4.28282"
```

```
v14_iqr <- v14_q75 - v14_q25  
sprintf("Jarak Interkuartil v14 adalah %g",v14_iqr)
```

```
## [1] "Jarak Interkuartil v14 adalah 5.4099"
```

```
v14_upper <- v14_q75 + v14_iqr*1.5  
sprintf("V14 Upper : %g",v14_upper)
```

```
## [1] "V14 Upper : 3.83203"
```

```
v14_lower <- v14_q25 - v14_iqr*1.5  
sprintf("V14 Lower : %g",v14_lower)
```

```
## [1] "V14 Lower : -17.8076"
```

```
outlier_v14 <- which(v14_fraud$V14<v14_lower|v14_fraud$V14>v14_upper)  
data_outlier_v14 <- v14_fraud[outlier_v14,"V14"]  
print(data_outlier_v14)
```

```
## [1] -19.21433 -18.82209 -18.49377 -18.05000
```

```
length(data_outlier_v14)
```

```
## [1] 4
```

```
#menghilangkan data outlier dari dataset  
if(length(outlier_v14)>0){  
  new_df <- new_df[-outlier_v14,]  
} else print("Tidak ada data outlier")
```

```
##Mendapatkan nilai yg fraud di V4  
v4_fraud <- new_df%>%  
  filter(Class==1)
```

```
v4_q25 <- quantile(v4_fraud$V4,0.25)  
sprintf("kuartil 25 v4 adalah %g",v4_q25)
```

```
## [1] "kuartil 25 v4 adalah 2.35158"
```

```
v4_q75 <- quantile(v4_fraud$V4,0.75)  
sprintf("kuartil 75 v4 adalah %g",v4_q75)
```

```
## [1] "kuartil 75 v4 adalah 6.31302"
```

```
v4_iqr <- v4_q75 - v4_q25  
sprintf("Jarak Interkuartil v4 adalah %g",v4_iqr)
```

```
## [1] "Jarak Interkuartil v4 adalah 3.96143"
```

```
v4_upper <- v4_q75 + v4_iqr*1.5  
sprintf("V4 Upper : %g",v4_upper)
```

```
## [1] "V4 Upper : 12.2552"
```

```
v4_lower <- v4_q25 - v4_iqr*1.5  
sprintf("V4 Lower : %g",v4_lower)
```

```
## [1] "V4 Lower : -3.59057"
```

```
outlier_v4 <- which(v4_fraud$V4<v4_lower|v4_fraud$V4>v4_upper)  
data_outlier_v4 <- v4_fraud[outlier_v4,"V4"]  
print(data_outlier_v4)
```

```
## numeric(0)
```

```
length(data_outlier_v4)
```

```
## [1] 0
```

```
#menghilangkan data outlier dari dataset  
if(length(outlier_v4)>0){  
  new_df <- new_df[-outlier_v4,]  
} else print("Tidak ada data outlier")
```

```
## [1] "Tidak ada data outlier"
```

```
##Mendapatkan nilai yg fraud di V11  
v11_fraud <- new_df%>%  
  filter(Class==1)  
  
v11_q25 <- quantile(v11_fraud$V11,0.25)  
sprintf("kuartil 25 v11 adalah %g",v11_q25)
```

```
## [1] "kuartil 25 v11 adalah 1.96515"
```

```
v11_q75 <- quantile(v11_fraud$V11,0.75)  
sprintf("kuartil 75 v11 adalah %g",v11_q75)
```

```
## [1] "kuartil 75 v11 adalah 5.2669"
```

```
v11_iqr <- v11_q75 - v11_q25  
sprintf("Jarak Interkuartil v11 adalah %g",v11_iqr)
```

```
## [1] "Jarak Interkuartil v11 adalah 3.30175"
```

```
v11_upper <- v11_q75 + v11_iqr*1.5  
sprintf("V11 Upper : %g",v11_upper)
```

```
## [1] "V11 Upper : 10.2195"
```

```
v11_lower <- v11_q25 - v11_iqr*1.5  
sprintf("V11 Lower : %g",v11_lower)
```

```
## [1] "V11 Lower : -2.98748"
```

```
outlier_v11 <- which(v11_fraud$V11<v11_lower|v11_fraud$V11>v11_upper)  
data_outlier_v11 <- v11_fraud[outlier_v11,"V11"]  
print(data_outlier_v11)
```

```
## [1] 10.85301 10.44685 11.27792 11.15249 11.02706 10.54526 10.27777
```

```
length(data_outlier_v11)
```

```
## [1] 7
```

```
#menghilangkan data outlier dari dataset
```

```
if(length(outlier_v11)>0){  
  new_df <- new_df[-outlier_v11,]  
} else print("Tidak ada data outlier")
```

```
##Mendapatkan nilai yg fraud di V12
```

```
v12_fraud <- new_df%>%  
  filter(Class==1)
```

```
v12_q25 <- quantile(v12_fraud$V12,0.25)  
sprintf("kuartil 25 v12 adalah %g",v12_q25)
```

```
## [1] "kuartil 25 v12 adalah -8.57676"
```

```
v12_q75 <- quantile(v12_fraud$V12,0.75)  
sprintf("kuartil 75 v12 adalah %g",v12_q75)
```

```
## [1] "kuartil 75 v12 adalah -2.85428"
```

```
v12_iqr <- v12_q75 - v12_q25  
sprintf("Jarak Interkuartil v12 adalah %g",v12_iqr)
```

```
## [1] "Jarak Interkuartil v12 adalah 5.72249"
```

```
v12_upper <- v12_q75 + v12_iqr*1.5  
sprintf("V12 Upper : %g",v12_upper)
```

```
## [1] "V12 Upper : 5.72945"
```

```
v12_lower <- v12_q25 - v12_iqr*1.5  
sprintf("V12 Lower : %g",v12_lower)
```

```
## [1] "V12 Lower : -17.1605"
```

```
outlier_v12 <- which(v12_fraud$V12<v12_lower|v12_fraud$V12>v12_upper)  
data_outlier_v12 <- v12_fraud[outlier_v12,"V12"]  
print(data_outlier_v12)
```

```
## [1] -18.04760 -18.68371 -18.55370 -18.43113 -17.18292 -17.18292
```

```
length(data_outlier_v12)
```

```
## [1] 6
```

```
#menghilangkan data outlier dari dataset  
if(length(outlier_v12)>0){  
  new_df <- new_df[-outlier_v12,]  
} else print("Tidak ada data outlier")
```

```
##Mendapatkan nilai yg fraud di V10  
v10_fraud <- new_df%>%  
  filter(Class==1)
```

```
v10_q25 <- quantile(v10_fraud$V10,0.25)  
sprintf("kuartil 25 v10 adalah %g",v10_q25)
```

```
## [1] "kuartil 25 v10 adalah -7.10147"
```

```
v10_q75 <- quantile(v10_fraud$V10,0.75)  
sprintf("kuartil 75 v10 adalah %g",v10_q75)
```

```
## [1] "kuartil 75 v10 adalah -2.47154"
```

```
v10_iqr <- v10_q75 - v10_q25  
sprintf("Jarak Interkuartil v10 adalah %g",v10_iqr)
```

```
## [1] "Jarak Interkuartil v10 adalah 4.62993"
```

```
v10_upper <- v10_q75 + v10_iqr*1.5  
sprintf("V10 Upper : %g",v10_upper)
```

```
## [1] "V10 Upper : 4.47335"
```

```
v10_lower <- v10_q25 - v10_iqr*1.5  
sprintf("V10 Lower : %g",v10_lower)
```

```
## [1] "V10 Lower : -14.0464"
```

```
outlier_v10 <- which(v10_fraud$V10<v10_lower|v10_fraud$V10>v10_upper)  
data_outlier_v10 <- v10_fraud[outlier_v10,"V10"]  
print(data_outlier_v10)
```

```
## [1] -14.67647 -15.12416 -14.22670 -14.11018 -14.55716 -16.64963 -18.27117  
## [8] -15.23996 -15.23996 -14.92465 -14.92465 -15.56379 -15.56379 -14.53316  
## [15] -16.74604 -15.34610 -15.12375 -22.18709 -22.18709 -22.18709 -22.18709  
## [22] -17.14151 -16.30354 -16.25561 -16.60120 -15.23183 -18.91324 -20.94919  
## [29] -19.83615 -23.22825 -24.40318 -24.58826
```

```
length(data_outlier_v10)
```

```
## [1] 32
```

```
#menghilangkan data outlier dari dataset
```

```
if(length(outlier_v10)>0){  
  new_df <- new_df[-outlier_v10,]  
} else print("Tidak ada data outlier")
```

```
#mengubah variabel Class menjadi factor N= Non-fraud dan F= Frauds
```

```
new_df$Class <- factor(new_df$Class,levels = c(0,1),labels = c("N","F"))
```

## Membangun Model

### Membuat Hypertuning Parameter Obyek untuk Semua Model

```
set.seed(50)  
mycontrol <- trainControl(method = "cv",  
                           number = 10,  
                           summaryFunction = twoClassSummary,  
                           classProbs = TRUE,  
                           verboseIter = TRUE)
```

### Membuat Model untuk klasifikasi

Project ini menggunakan 5 algoritma klasifikasi untuk dibandingkan hasil akhirnya, yaitu : Random Forest, glmnet atau logistic regression, Extreme Gradient Boost(XGBdart),Support Vector Machine(SVM), dan K Nearest Neighbor. Cross Validation juga dilakukan dengan jumlah fold = 10.

```
#Membuat model dengan caret beserta cv
```

```
##membuat object hypertuning parameter
```

```
set.seed(50)  
mycontrol <- trainControl(method = "cv",  
                           number = 10,  
                           summaryFunction = twoClassSummary,  
                           classProbs = TRUE,  
                           verboseIter = TRUE)
```

```
##membuat model klasifikasi dengan random forest
```

```
model_rf <- train( Class ~ .,  
                  data = new_df,  
                  tuneLength=3,  
                  metric = "ROC",  
                  method = "ranger",  
                  trControl = mycontrol)
```

[illegible]





```
## + Fold10: mtry= 2, min.node.size=1, splitrule=gini
## - Fold10: mtry= 2, min.node.size=1, splitrule=gini
## + Fold10: mtry=16, min.node.size=1, splitrule=gini
## - Fold10: mtry=16, min.node.size=1, splitrule=gini
## + Fold10: mtry=30, min.node.size=1, splitrule=gini
## - Fold10: mtry=30, min.node.size=1, splitrule=gini
## + Fold10: mtry= 2, min.node.size=1, splitrule=extratrees
## - Fold10: mtry= 2, min.node.size=1, splitrule=extratrees
## + Fold10: mtry=16, min.node.size=1, splitrule=extratrees
## - Fold10: mtry=16, min.node.size=1, splitrule=extratrees
## + Fold10: mtry=30, min.node.size=1, splitrule=extratrees
## - Fold10: mtry=30, min.node.size=1, splitrule=extratrees
## Aggregating results
## Selecting tuning parameters
## Fitting mtry = 30, splitrule = extratrees, min.node.size = 1 on full training set
```

```
print(model_rf)
```

```
## Random Forest
##
## 935 samples
## 30 predictor
## 2 classes: 'N', 'F'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 841, 842, 841, 841, 842, 842, ...
## Resampling results across tuning parameters:
##
##   mtry  splitrule  ROC      Sens      Spec
##   2     gini      0.9774144 0.9796735 0.8799495
##   2     extratrees 0.9801792 0.9897959 0.8665657
##   16    gini      0.9792485 0.9614694 0.9003535
##   16    extratrees 0.9804884 0.9796735 0.8912626
##   30    gini      0.9790612 0.9635102 0.8935354
##   30    extratrees 0.9806969 0.9776735 0.8957576
##
## Tuning parameter 'min.node.size' was held constant at a value of 1
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were mtry = 30, splitrule = extratrees
## and min.node.size = 1.
```

```
max(model_rf[["results"]][["ROC"]])
```

```
## [1] 0.9806969
```

```
##membuat model klasifikasi dengan glmnet
model_glmnet <- train( Class ~ .,
  data = new_df,
  tuneLength=3,
  metric = "ROC",
  method = "glmnet",
  trControl = mycontrol)
```

[illegible]

```
## + Fold10: alpha=0.10, lambda=0.07679
## - Fold10: alpha=0.10, lambda=0.07679
## + Fold10: alpha=0.55, lambda=0.07679
## - Fold10: alpha=0.55, lambda=0.07679
## + Fold10: alpha=1.00, lambda=0.07679
## - Fold10: alpha=1.00, lambda=0.07679
## Aggregating results
## Selecting tuning parameters
## Fitting alpha = 0.1, lambda = 0.0768 on full training set
```

```
print(model_glmnet)
```

```
## glmnet
##
## 935 samples
## 30 predictor
## 2 classes: 'N', 'F'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 842, 841, 840, 842, 842, 841, ...
## Resampling results across tuning parameters:
##
##  alpha  lambda      ROC      Sens      Spec
##  0.10   0.0007678963  0.9756767  0.9816735  0.9078788
##  0.10   0.0076789629  0.9782398  0.9837143  0.8854545
##  0.10   0.0767896290  0.9795788  1.0000000  0.8379293
##  0.55   0.0007678963  0.9760417  0.9816735  0.9078788
##  0.55   0.0076789629  0.9781154  0.9796735  0.8899495
##  0.55   0.0767896290  0.9735616  0.9959184  0.8447980
##  1.00   0.0007678963  0.9764418  0.9796735  0.9123232
##  1.00   0.0076789629  0.9767506  0.9817143  0.8876768
##  1.00   0.0767896290  0.9685201  0.9959184  0.8380808
##
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were alpha = 0.1 and lambda = 0.07678963.
```

```
max(model_glmnet[["results"]][["ROC"]])
```

```
## [1] 0.9795788
```

```
##membuat model klasifikasi dengan xgbDart
model_xgbdart <- train( Class ~ .,
                        data = new_df,
                        tuneLength=3,
                        metric = "ROC",
                        method = "xgbDART",
                        trControl = mycontrol)
```

```
## + Fold01: max_depth=1, eta=0.3, rate_drop=0.01, skip_drop=0.05, min_child_weight=1, subsample=0.50,
## - Fold01: max_depth=1, eta=0.3, rate_drop=0.01, skip_drop=0.05, min_child_weight=1, subsample=0.50,
## + Fold01: max_depth=1, eta=0.3, rate_drop=0.01, skip_drop=0.05, min_child_weight=1, subsample=0.50,
```

[illegible]

[illegible]



[illegible]

[illegible]







[illegible]



[illegible]





[illegible]













[illegible]



[illegible]













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[illegible]







[illegible]



[illegible]



```

## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.05, min_child_weight=1, subsample=1.00,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.05, min_child_weight=1, subsample=1.00,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.05, min_child_weight=1, subsample=1.00,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.50,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.50,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.50,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.50,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.75,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.75,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.75,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=0.75,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=1.00,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=1.00,
## + Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=1.00,
## - Fold10: max_depth=3, eta=0.4, rate_drop=0.50, skip_drop=0.95, min_child_weight=1, subsample=1.00,
## Aggregating results
## Selecting tuning parameters
## Fitting nrounds = 50, max_depth = 2, eta = 0.3, gamma = 0, subsample = 1, colsample_bytree = 0.6, ra

```

```
print(model_xgbdart)
```

```

## eXtreme Gradient Boosting
##
## 935 samples
## 30 predictor
## 2 classes: 'N', 'F'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 840, 842, 842, 841, 842, 841, ...
## Resampling results across tuning parameters:
##
##  max_depth  eta  rate_drop  skip_drop  subsample  colsample_bytree  nrounds
##  1           0.3  0.01      0.05      0.50      0.6              50
##  1           0.3  0.01      0.05      0.50      0.6              100
##  1           0.3  0.01      0.05      0.50      0.6              150
##  1           0.3  0.01      0.05      0.50      0.8              50
##  1           0.3  0.01      0.05      0.50      0.8              100
##  1           0.3  0.01      0.05      0.50      0.8              150
##  1           0.3  0.01      0.05      0.75      0.6              50
##  1           0.3  0.01      0.05      0.75      0.6              100
##  1           0.3  0.01      0.05      0.75      0.6              150
##  1           0.3  0.01      0.05      0.75      0.8              50
##  1           0.3  0.01      0.05      0.75      0.8              100
##  1           0.3  0.01      0.05      0.75      0.8              150
##  1           0.3  0.01      0.05      1.00      0.6              50
##  1           0.3  0.01      0.05      1.00      0.6              100
##  1           0.3  0.01      0.05      1.00      0.6              150
##  1           0.3  0.01      0.05      1.00      0.8              50
##  1           0.3  0.01      0.05      1.00      0.8              100
##  1           0.3  0.01      0.05      1.00      0.8              150
##  1           0.3  0.01      0.95      0.50      0.6              50
##  1           0.3  0.01      0.95      0.50      0.6              100
##  1           0.3  0.01      0.95      0.50      0.6              150

```

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 150 |

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.50 | 0.6 | 150 |

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 1 | 0.4 | 0.50 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 1 | 0.4 | 0.50 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 150 |

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 150 |

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 2 | 0.4 | 0.50 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 2 | 0.4 | 0.50 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.50 | 0.6 | 150 |

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.01 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.50 | 0.6 | 150 |

|    |   |     |      |      |      |     |     |
|----|---|-----|------|------|------|-----|-----|
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 3 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 3 | 0.3 | 0.50 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.50 | 0.6 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.50 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.75 | 0.6 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 0.75 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 1.00 | 0.6 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.05 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.50 | 0.6 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.50 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.75 | 0.6 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 0.75 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 1.00 | 0.6 | 150 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 50  |
| ## | 3 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 100 |
| ## | 3 | 0.4 | 0.01 | 0.95 | 1.00 | 0.8 | 150 |
| ## | 3 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 50  |
| ## | 3 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 100 |
| ## | 3 | 0.4 | 0.50 | 0.05 | 0.50 | 0.6 | 150 |



|    |           |           |           |      |      |     |     |
|----|-----------|-----------|-----------|------|------|-----|-----|
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.50 | 0.8 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.50 | 0.8 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.50 | 0.8 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.75 | 0.6 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.75 | 0.6 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.75 | 0.6 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.75 | 0.8 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.75 | 0.8 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 0.75 | 0.8 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 1.00 | 0.6 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.05 | 1.00 | 0.6 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 1.00 | 0.6 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 1.00 | 0.8 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.05 | 1.00 | 0.8 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.05 | 1.00 | 0.8 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.50 | 0.6 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.50 | 0.6 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.50 | 0.6 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.50 | 0.8 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.50 | 0.8 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.50 | 0.8 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.75 | 0.6 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.75 | 0.6 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.75 | 0.6 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.75 | 0.8 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.75 | 0.8 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 0.75 | 0.8 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 1.00 | 0.6 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.95 | 1.00 | 0.6 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 1.00 | 0.6 | 150 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 1.00 | 0.8 | 50  |
| ## | 3         | 0.4       | 0.50      | 0.95 | 1.00 | 0.8 | 100 |
| ## | 3         | 0.4       | 0.50      | 0.95 | 1.00 | 0.8 | 150 |
| ## | R0C       | Sens      | Spec      |      |      |     |     |
| ## | 0.9756693 | 0.9695510 | 0.9007576 |      |      |     |     |
| ## | 0.9788786 | 0.9695510 | 0.9053535 |      |      |     |     |
| ## | 0.9769995 | 0.9716327 | 0.9053535 |      |      |     |     |
| ## | 0.9786650 | 0.9715510 | 0.9029798 |      |      |     |     |
| ## | 0.9814711 | 0.9695102 | 0.9030303 |      |      |     |     |
| ## | 0.9810430 | 0.9654286 | 0.9142929 |      |      |     |     |
| ## | 0.9794199 | 0.9755918 | 0.9008081 |      |      |     |     |
| ## | 0.9811665 | 0.9735918 | 0.9008081 |      |      |     |     |
| ## | 0.9807137 | 0.9715102 | 0.8963131 |      |      |     |     |
| ## | 0.9812099 | 0.9735918 | 0.9052525 |      |      |     |     |
| ## | 0.9820987 | 0.9695510 | 0.9098485 |      |      |     |     |
| ## | 0.9799269 | 0.9735918 | 0.9030808 |      |      |     |     |
| ## | 0.9808652 | 0.9797143 | 0.8962626 |      |      |     |     |
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| ## | 0.9772551 | 0.9655102 | 0.9008081 |      |      |     |     |
| ## | 0.9777101 | 0.9797143 | 0.9075758 |      |      |     |     |

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| ## | 0.9813899 | 0.9634286 | 0.9120707 |
| ## | 0.9825195 | 0.9654694 | 0.9120202 |
| ## | 0.9819832 | 0.9654694 | 0.9120202 |
| ## | 0.9782938 | 0.9695102 | 0.9098485 |
| ## | 0.9792593 | 0.9654694 | 0.9098485 |
| ## | 0.9807158 | 0.9695102 | 0.9120707 |
| ## | 0.9788905 | 0.9674694 | 0.9030808 |
| ## | 0.9788382 | 0.9674286 | 0.9030808 |
| ## | 0.9777350 | 0.9674286 | 0.9030808 |
| ## | 0.9780407 | 0.9736327 | 0.8985354 |
| ## | 0.9803687 | 0.9655102 | 0.9053535 |
| ## | 0.9795472 | 0.9675102 | 0.9075758 |
| ## | 0.9811222 | 0.9695102 | 0.9031818 |
| ## | 0.9808971 | 0.9756327 | 0.9054040 |
| ## | 0.9815522 | 0.9756327 | 0.9054040 |
| ## | 0.9808043 | 0.9695510 | 0.9121212 |
| ## | 0.9817647 | 0.9695102 | 0.9143434 |
| ## | 0.9815473 | 0.9695102 | 0.9143434 |
| ## | 0.9802426 | 0.9674694 | 0.9052525 |
| ## | 0.9804281 | 0.9695102 | 0.9142929 |
| ## | 0.9805106 | 0.9674694 | 0.9097980 |
| ## | 0.9795834 | 0.9674694 | 0.9075253 |
| ## | 0.9804032 | 0.9695102 | 0.9097980 |
| ## | 0.9804978 | 0.9695102 | 0.9097980 |
| ## | 0.9753521 | 0.9817143 | 0.8713636 |
| ## | 0.9759140 | 0.9756327 | 0.8894444 |
| ## | 0.9772032 | 0.9715102 | 0.8985354 |
| ## | 0.9731738 | 0.9776327 | 0.8847980 |
| ## | 0.9753779 | 0.9817143 | 0.8893434 |
| ## | 0.9749331 | 0.9735510 | 0.8938889 |
| ## | 0.9758608 | 0.9817143 | 0.8758081 |
| ## | 0.9748295 | 0.9796735 | 0.8916667 |
| ## | 0.9778129 | 0.9755918 | 0.8917172 |
| ## | 0.9743175 | 0.9776327 | 0.8939394 |
| ## | 0.9761571 | 0.9695102 | 0.8916667 |
| ## | 0.9769366 | 0.9715510 | 0.8916667 |
| ## | 0.9756766 | 0.9796327 | 0.8826768 |
| ## | 0.9751491 | 0.9775918 | 0.8849495 |
| ## | 0.9740340 | 0.9735510 | 0.8962121 |
| ## | 0.9730985 | 0.9796327 | 0.8804040 |
| ## | 0.9748440 | 0.9775918 | 0.8872222 |
| ## | 0.9767340 | 0.9735510 | 0.8894949 |
| ## | 0.9770725 | 0.9634694 | 0.9098485 |
| ## | 0.9779706 | 0.9634286 | 0.9097980 |

|    |           |           |           |
|----|-----------|-----------|-----------|
| ## | 0.9788824 | 0.9654694 | 0.9097980 |
| ## | 0.9782550 | 0.9614286 | 0.9098485 |
| ## | 0.9800596 | 0.9613878 | 0.9076263 |
| ## | 0.9805527 | 0.9593878 | 0.9053535 |
| ## | 0.9814383 | 0.9695102 | 0.9030808 |
| ## | 0.9811432 | 0.9735918 | 0.9053535 |
| ## | 0.9826002 | 0.9715510 | 0.9076263 |
| ## | 0.9800372 | 0.9695102 | 0.9143939 |
| ## | 0.9808468 | 0.9674694 | 0.9121212 |
| ## | 0.9811187 | 0.9674694 | 0.9098485 |
| ## | 0.9764192 | 0.9654694 | 0.9120707 |
| ## | 0.9774861 | 0.9633878 | 0.9188384 |
| ## | 0.9780989 | 0.9633878 | 0.9188384 |
| ## | 0.9776586 | 0.9654286 | 0.9097980 |
| ## | 0.9793567 | 0.9674694 | 0.9075253 |
| ## | 0.9798702 | 0.9674694 | 0.9053030 |
| ## | 0.9822971 | 0.9634694 | 0.9098485 |
| ## | 0.9829280 | 0.9675510 | 0.9098485 |
| ## | 0.9824374 | 0.9735918 | 0.9120707 |
| ## | 0.9789752 | 0.9593061 | 0.9076263 |
| ## | 0.9801205 | 0.9675102 | 0.9008586 |
| ## | 0.9800558 | 0.9655102 | 0.9030808 |
| ## | 0.9810387 | 0.9695510 | 0.9054040 |
| ## | 0.9815951 | 0.9776735 | 0.9054040 |
| ## | 0.9812232 | 0.9756327 | 0.9098485 |
| ## | 0.9784156 | 0.9695510 | 0.9053030 |
| ## | 0.9813914 | 0.9715918 | 0.9098485 |
| ## | 0.9816207 | 0.9715918 | 0.9097980 |
| ## | 0.9798811 | 0.9674286 | 0.9097980 |
| ## | 0.9814034 | 0.9633878 | 0.9120202 |
| ## | 0.9828678 | 0.9654286 | 0.9075253 |
| ## | 0.9802799 | 0.9634286 | 0.9142424 |
| ## | 0.9817162 | 0.9695102 | 0.9165657 |
| ## | 0.9823678 | 0.9674694 | 0.9142929 |
| ## | 0.9779465 | 0.9635510 | 0.9075758 |
| ## | 0.9779440 | 0.9655510 | 0.9120707 |
| ## | 0.9773697 | 0.9635102 | 0.9120707 |
| ## | 0.9777887 | 0.9695102 | 0.9008081 |
| ## | 0.9779436 | 0.9756327 | 0.9142929 |
| ## | 0.9795870 | 0.9756327 | 0.9097980 |
| ## | 0.9798013 | 0.9675510 | 0.9030303 |
| ## | 0.9797277 | 0.9634694 | 0.9143434 |
| ## | 0.9800495 | 0.9695510 | 0.9120202 |
| ## | 0.9798425 | 0.9715510 | 0.9120707 |
| ## | 0.9804086 | 0.9797143 | 0.9075758 |
| ## | 0.9803509 | 0.9817143 | 0.9075758 |
| ## | 0.9806404 | 0.9634286 | 0.9098990 |
| ## | 0.9800874 | 0.9654286 | 0.9097980 |
| ## | 0.9798563 | 0.9654286 | 0.9097980 |
| ## | 0.9802840 | 0.9695510 | 0.9120202 |
| ## | 0.9811095 | 0.9634286 | 0.9097475 |
| ## | 0.9814714 | 0.9613878 | 0.9097475 |
| ## | 0.9767316 | 0.9837551 | 0.8939394 |
| ## | 0.9792585 | 0.9796735 | 0.9030303 |



```
## 0.9785464 0.9776327 0.8939899
## 0.9768799 0.9756327 0.8871717
## 0.9778648 0.9735510 0.8893434
## 0.9781293 0.9694694 0.8984343
## 0.9750130 0.9777143 0.8826768
## 0.9785662 0.9797143 0.8917172
## 0.9778981 0.9736327 0.8962626
## 0.9744678 0.9735102 0.8849495
## 0.9771475 0.9694694 0.8871212
## 0.9768510 0.9654286 0.8939394
## 0.9766666 0.9857551 0.8871717
## 0.9781572 0.9816735 0.8939394
## 0.9791405 0.9817143 0.8962626
## 0.9759596 0.9796735 0.8939394
## 0.9773485 0.9735918 0.9007071
## 0.9769343 0.9755918 0.9007071
## 0.9802463 0.9614286 0.9052525
## 0.9814356 0.9654694 0.9052020
## 0.9810713 0.9655102 0.9052020
## 0.9794157 0.9675102 0.9165657
## 0.9789608 0.9593061 0.9142424
## 0.9784555 0.9613878 0.9097475
## 0.9802664 0.9776327 0.9097980
## 0.9798986 0.9776735 0.9052525
## 0.9799841 0.9776735 0.9052525
## 0.9778655 0.9695102 0.9120202
## 0.9781230 0.9695102 0.9142929
## 0.9796910 0.9735918 0.9120707
## 0.9775792 0.9715510 0.9121212
## 0.9796012 0.9675102 0.9143434
## 0.9793708 0.9715510 0.9165657
## 0.9776371 0.9715510 0.9097475
## 0.9785120 0.9715510 0.9120202
## 0.9794294 0.9695102 0.9142929
##
## Tuning parameter 'gamma' was held constant at a value of 0
## Tuning
## parameter 'min_child_weight' was held constant at a value of 1
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were nrounds = 50, max_depth = 2, eta
## = 0.3, gamma = 0, subsample = 1, colsample_bytree = 0.6, rate_drop =
## 0.01, skip_drop = 0.05 and min_child_weight = 1.
```

```
max(model_xgbdart[["results"]][["ROC"]])
```

```
## [1] 0.9835582
```

```
##membuat model klasifikasi dengan SVM
model_svm <- train( Class ~ .,
                    data = new_df,
                    tuneLength=3,
                    metric = "ROC",
                    method = "svmRadial",
                    trControl = mycontrol)
```

```
## + Fold01: sigma=0.04285, C=0.25
## - Fold01: sigma=0.04285, C=0.25
## + Fold01: sigma=0.04285, C=0.50
## - Fold01: sigma=0.04285, C=0.50
## + Fold01: sigma=0.04285, C=1.00
## - Fold01: sigma=0.04285, C=1.00
## + Fold02: sigma=0.04285, C=0.25
## - Fold02: sigma=0.04285, C=0.25
## + Fold02: sigma=0.04285, C=0.50
## - Fold02: sigma=0.04285, C=0.50
## + Fold02: sigma=0.04285, C=1.00
## - Fold02: sigma=0.04285, C=1.00
## + Fold03: sigma=0.04285, C=0.25
## - Fold03: sigma=0.04285, C=0.25
## + Fold03: sigma=0.04285, C=0.50
## - Fold03: sigma=0.04285, C=0.50
## + Fold03: sigma=0.04285, C=1.00
## - Fold03: sigma=0.04285, C=1.00
## + Fold04: sigma=0.04285, C=0.25
## - Fold04: sigma=0.04285, C=0.25
## + Fold04: sigma=0.04285, C=0.50
## - Fold04: sigma=0.04285, C=0.50
## + Fold04: sigma=0.04285, C=1.00
## - Fold04: sigma=0.04285, C=1.00
## + Fold05: sigma=0.04285, C=0.25
## - Fold05: sigma=0.04285, C=0.25
## + Fold05: sigma=0.04285, C=0.50
## - Fold05: sigma=0.04285, C=0.50
## + Fold05: sigma=0.04285, C=1.00
## - Fold05: sigma=0.04285, C=1.00
## + Fold06: sigma=0.04285, C=0.25
## - Fold06: sigma=0.04285, C=0.25
## + Fold06: sigma=0.04285, C=0.50
## - Fold06: sigma=0.04285, C=0.50
## + Fold06: sigma=0.04285, C=1.00
## - Fold06: sigma=0.04285, C=1.00
## + Fold07: sigma=0.04285, C=0.25
## - Fold07: sigma=0.04285, C=0.25
## + Fold07: sigma=0.04285, C=0.50
## - Fold07: sigma=0.04285, C=0.50
## + Fold07: sigma=0.04285, C=1.00
## - Fold07: sigma=0.04285, C=1.00
## + Fold08: sigma=0.04285, C=0.25
## - Fold08: sigma=0.04285, C=0.25
## + Fold08: sigma=0.04285, C=0.50
## - Fold08: sigma=0.04285, C=0.50
## + Fold08: sigma=0.04285, C=1.00
## - Fold08: sigma=0.04285, C=1.00
## + Fold09: sigma=0.04285, C=0.25
## - Fold09: sigma=0.04285, C=0.25
## + Fold09: sigma=0.04285, C=0.50
## - Fold09: sigma=0.04285, C=0.50
```

```
## + Fold09: sigma=0.04285, C=1.00
## - Fold09: sigma=0.04285, C=1.00
## + Fold10: sigma=0.04285, C=0.25
## - Fold10: sigma=0.04285, C=0.25
## + Fold10: sigma=0.04285, C=0.50
## - Fold10: sigma=0.04285, C=0.50
## + Fold10: sigma=0.04285, C=1.00
## - Fold10: sigma=0.04285, C=1.00
## Aggregating results
## Selecting tuning parameters
## Fitting sigma = 0.0429, C = 1 on full training set
```

```
print(model_svm)
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 935 samples
## 30 predictor
## 2 classes: 'N', 'F'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 842, 841, 842, 840, 842, 841, ...
## Resampling results across tuning parameters:
##
##      C      ROC      Sens      Spec
## 0.25 0.9725519 0.9491020 0.8890909
## 0.50 0.9753924 0.9552245 0.9004545
## 1.00 0.9777837 0.9633878 0.9049495
##
## Tuning parameter 'sigma' was held constant at a value of 0.04285383
## ROC was used to select the optimal model using the largest value.
## The final values used for the model were sigma = 0.04285383 and C = 1.
```

```
max(model_svm[["results"]][["ROC"]])
```

```
## [1] 0.9777837
```

```
##membuat model klasifikasi dengan KNN
model_knn <- train( Class ~ .,
                    data = new_df,
                    tuneLength=3,
                    metric = "ROC",
                    method = "knn",
                    trControl = mycontrol)
```

```
## + Fold01: k=5
## - Fold01: k=5
## + Fold01: k=7
## - Fold01: k=7
## + Fold01: k=9
## - Fold01: k=9
```

## + Fold02: k=5  
## - Fold02: k=5  
## + Fold02: k=7  
## - Fold02: k=7  
## + Fold02: k=9  
## - Fold02: k=9  
## + Fold03: k=5  
## - Fold03: k=5  
## + Fold03: k=7  
## - Fold03: k=7  
## + Fold03: k=9  
## - Fold03: k=9  
## + Fold04: k=5  
## - Fold04: k=5  
## + Fold04: k=7  
## - Fold04: k=7  
## + Fold04: k=9  
## - Fold04: k=9  
## + Fold05: k=5  
## - Fold05: k=5  
## + Fold05: k=7  
## - Fold05: k=7  
## + Fold05: k=9  
## - Fold05: k=9  
## + Fold06: k=5  
## - Fold06: k=5  
## + Fold06: k=7  
## - Fold06: k=7  
## + Fold06: k=9  
## - Fold06: k=9  
## + Fold07: k=5  
## - Fold07: k=5  
## + Fold07: k=7  
## - Fold07: k=7  
## + Fold07: k=9  
## - Fold07: k=9  
## + Fold08: k=5  
## - Fold08: k=5  
## + Fold08: k=7  
## - Fold08: k=7  
## + Fold08: k=9  
## - Fold08: k=9  
## + Fold09: k=5  
## - Fold09: k=5  
## + Fold09: k=7  
## - Fold09: k=7  
## + Fold09: k=9  
## - Fold09: k=9  
## + Fold10: k=5  
## - Fold10: k=5  
## + Fold10: k=7  
## - Fold10: k=7  
## + Fold10: k=9  
## - Fold10: k=9

```
## Aggregating results
## Selecting tuning parameters
## Fitting k = 7 on full training set
```

```
print(model_knn)
```

```
## k-Nearest Neighbors
##
## 935 samples
## 30 predictor
## 2 classes: 'N', 'F'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 842, 841, 842, 841, 842, 842, ...
## Resampling results across tuning parameters:
##
##  k  ROC          Sens          Spec
##  5  0.9612901  0.9816735  0.8691414
##  7  0.9676789  0.9898367  0.8690909
##  9  0.9672594  0.9938776  0.8646465
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was k = 7.
```

```
max(model_knn[["results"]][["ROC"]])
```

```
## [1] 0.9676789
```

## Membandingkan Performa Model

Kelima model yang digunakan dalam project ini dibandingkan menggunakan metrik berupa ROC karena dataset yang digunakan dalam project ini sangat tidak berimbang proposinya, sehingga ROC lebih cocok untuk mengukur performa model.

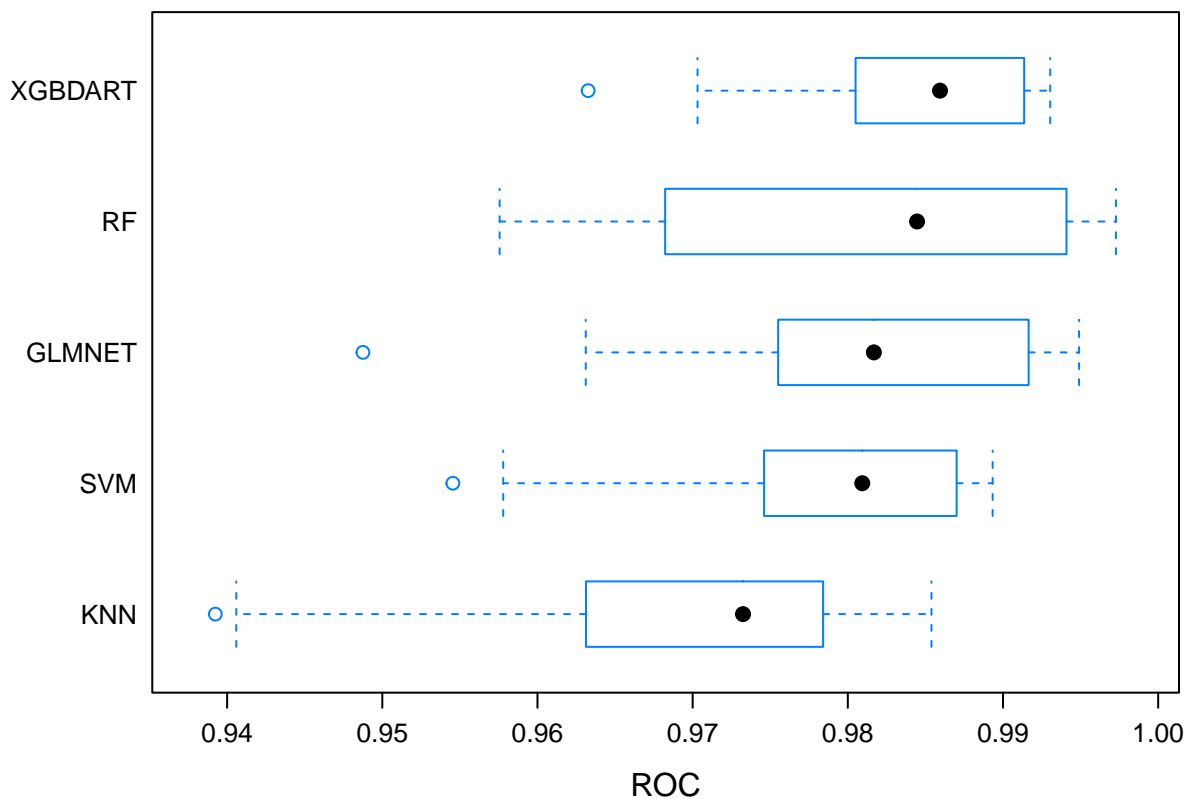
```
#membuat list model yang digunakan
list_model <- list(RF=model_rf, GLMNET=model_glmnet, XGBDART=model_xgbdart, SVM=model_svm, KNN=model_knn)

#membandingkan semua model
model_compare <- resamples(list_model)
summary(model_compare)
```

```
##
## Call:
## summary.resamples(object = model_compare)
##
## Models: RF, GLMNET, XGBDART, SVM, KNN
## Number of resamples: 10
##
## ROC
```

```
##           Min.    1st Qu.    Median      Mean    3rd Qu.      Max. NA's
## RF      0.9575603 0.9707290 0.9844620 0.9806969 0.9916837 0.9972789    0
## GLMNET  0.9487528 0.9758349 0.9816790 0.9795788 0.9906702 0.9948980    0
## XGBDART 0.9632653 0.9814317 0.9859412 0.9835582 0.9908558 0.9930427    0
## SVM     0.9545455 0.9757344 0.9809297 0.9777837 0.9866651 0.9893333    0
## KNN     0.9392393 0.9642857 0.9732444 0.9676789 0.9779678 0.9853896    0
##
## Sens
##           Min.    1st Qu.    Median      Mean    3rd Qu. Max. NA's
## RF      0.9591837 0.9593878 0.9795918 0.9776735 0.9950000    1    0
## GLMNET  1.0000000 1.0000000 1.0000000 1.0000000 1.0000000    1    0
## XGBDART 0.9387755 0.9591837 0.9693878 0.9735918 1.0000000    1    0
## SVM     0.9387755 0.9591837 0.9591837 0.9633878 0.9746939    1    0
## KNN     0.9591837 0.9796939 1.0000000 0.9898367 1.0000000    1    0
##
## Spec
##           Min.    1st Qu.    Median      Mean    3rd Qu.      Max. NA's
## RF      0.7954545 0.8636364 0.8977273 0.8957576 0.9329545 0.9777778    0
## GLMNET  0.7333333 0.8045455 0.8522727 0.8379293 0.8806818 0.9090909    0
## XGBDART 0.8409091 0.8863636 0.9103535 0.9075253 0.9488636 0.9555556    0
## SVM     0.8636364 0.8863636 0.8977273 0.9049495 0.9272727 0.9555556    0
## KNN     0.8181818 0.8492424 0.8636364 0.8690909 0.8833333 0.9318182    0
```

```
scales <- list(x=list(relation="free"), y=list(relation="free"))
bwplot(model_compare, scales=scales, metric = "ROC")
```



Berdasarkan boxplot diatas, didapatkan bahwa model yang paling bagus performanya adalah XGBDart.

### #Kesimpulan

Dataset credit card fraud yang digunakan dalam project ini mengandung ketidakseimbangan yang sangat jauh antara data berlabel fraud dan non-fraud. Random Undersampling digunakan untuk mengatasi ketidakseimbangan data ini. Variabel yang paling berpengaruh terhadap nilai di variabel “Class” adalah variabel V14,V11,V12,V4,dan V10. Sehingga data outlier dihilangkan berdasarkan variabel-variabel tersebut. Di antara lima model yang digunakan untuk klasifikasi credit card fraud didapatkan bahwa model XGBDart memiliki ROC yang paling bagus senilai 0.981844.