Decision Tree

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2023-05-11

```
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
```

```
data <- read.csv("BankChurners.csv") #dataset menggunakan data Problem Churner Kartu Kredit di sebuah Bank
head(data)
```

```
##   CLIENTNUM    Attrition_Flag Customer_Age Gender Dependent_count
## 1 768805383 Existing Customer           45      M               3
## 2 818770008 Existing Customer           49      F               5
## 3 713982108 Existing Customer           51      M               3
## 4 769911858 Existing Customer           40      F               4
## 5 709106358 Existing Customer           40      M               3
## 6 713061558 Existing Customer           44      M               2
##   Education_Level Marital_Status Income_Category Card_Category Months_on_book
## 1     High School        Married     $60K - $80K          Blue             39
## 2        Graduate         Single  Less than $40K          Blue             44
## 3        Graduate        Married    $80K - $120K          Blue             36
## 4     High School        Unknown  Less than $40K          Blue             34
## 5      Uneducated        Married     $60K - $80K          Blue             21
## 6        Graduate        Married     $40K - $60K          Blue             36
##   Total_Relationship_Count Months_Inactive_12_mon Contacts_Count_12_mon
## 1                        5                      1                     3
## 2                        6                      1                     2
## 3                        4                      1                     0
## 4                        3                      4                     1
## 5                        5                      1                     0
## 6                        3                      1                     2
##   Credit_Limit Total_Revolving_Bal Avg_Open_To_Buy Total_Amt_Chng_Q4_Q1
## 1        12691                 777           11914                1.335
## 2         8256                 864            7392                1.541
## 3         3418                   0            3418                2.594
## 4         3313                2517             796                1.405
## 5         4716                   0            4716                2.175
## 6         4010                1247            2763                1.376
##   Total_Trans_Amt Total_Trans_Ct Total_Ct_Chng_Q4_Q1 Avg_Utilization_Ratio
## 1            1144             42               1.625                 0.061
## 2            1291             33               3.714                 0.105
## 3            1887             20               2.333                 0.000
## 4            1171             20               2.333                 0.760
## 5             816             28               2.500                 0.000
## 6            1088             24               0.846                 0.311
##   Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inacti
ve_12_mon_1
## 1
9.3448e-05
```

```
## 2
5.6861e-05
## 3
2.1081e-05
## 4
1.3366e-04
## 5
2.1676e-05
## 6
5.5077e-05
##   Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inacti
ve_12_mon_2
## 1
0.99991
## 2
0.99994
## 3
0.99998
## 4
0.99987
## 5
0.99998
## 6
0.99994
```

```
data <- read.csv("BankChurners.csv")
#mengubah kolom tertentu ke faktor dan numerik
data<- data%>% select(-CLIENTNUM,-Avg_Open_To_Buy,-Avg_Utilization_Ratio,-Total_Trans_Amt, -Total_Trans_Ct)
data$Customer_Age <- as.numeric(data$Customer_Age)
data$Gender <- as.factor(data$Gender)
data$Dependent_count <- as.numeric(data$Dependent_count)
data$Education_Level <- as.factor(data$Education_Level)
data$Income_Category <- as.factor(data$Income_Category)
data$Marital_Status <- as.factor(data$Marital_Status)
data$Card_Category <- as.factor(data$Card_Category)
data$Months_on_book <- as.numeric(data$Months_on_book)
data$Total_Relationship_Count <- as.numeric(data$Total_Relationship_Count)
data$Months_Inactive_12_mon <- as.numeric(data$Months_Inactive_12_mon)
data$Contacts_Count_12_mon <- as.numeric(data$Contacts_Count_12_mon)
head(data)
```

```
##      Attrition_Flag Customer_Age Gender Dependent_count Education_Level
## 1 Existing Customer           45      M               3     High School
## 2 Existing Customer           49      F               5        Graduate
## 3 Existing Customer           51      M               3        Graduate
## 4 Existing Customer           40      F               4     High School
## 5 Existing Customer           40      M               3      Uneducated
## 6 Existing Customer           44      M               2        Graduate
##   Marital_Status Income_Category Card_Category Months_on_book
## 1        Married     $60K - $80K          Blue             39
## 2         Single  Less than $40K          Blue             44
## 3        Married    $80K - $120K          Blue             36
## 4        Unknown  Less than $40K          Blue             34
## 5        Married     $60K - $80K          Blue             21
## 6        Married     $40K - $60K          Blue             36
##   Total_Relationship_Count Months_Inactive_12_mon Contacts_Count_12_mon
## 1                        5                      1                     3
## 2                        6                      1                     2
## 3                        4                      1                     0
## 4                        3                      4                     1
## 5                        5                      1                     0
## 6                        3                      1                     2
##   Credit_Limit Total_Revolving_Bal Total_Amt_Chng_Q4_Q1 Total_Ct_Chng_Q4_Q1
## 1        12691                 777                1.335                1.625
## 2         8256                 864                1.541                3.714
## 3         3418                   0                2.594                2.333
## 4         3313                2517                1.405                2.333
## 5         4716                   0                2.175                2.500
## 6         4010                1247                1.376                0.846
##   Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inacti
ve_12_mon_1
## 1
9.3448e-05
## 2
5.6861e-05
## 3
2.1081e-05
## 4
1.3366e-04
## 5
```

```
2.1676e-05
## 6
5.5077e-05
##   Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inacti
ve_12_mon_2
## 1
0.99991
## 2
0.99994
## 3
0.99998
## 4
0.99987
## 5
0.99998
## 6
0.99994
```

```
nrow(data)
```

```
## [1] 10127
```

```
ncol(data)-1
```

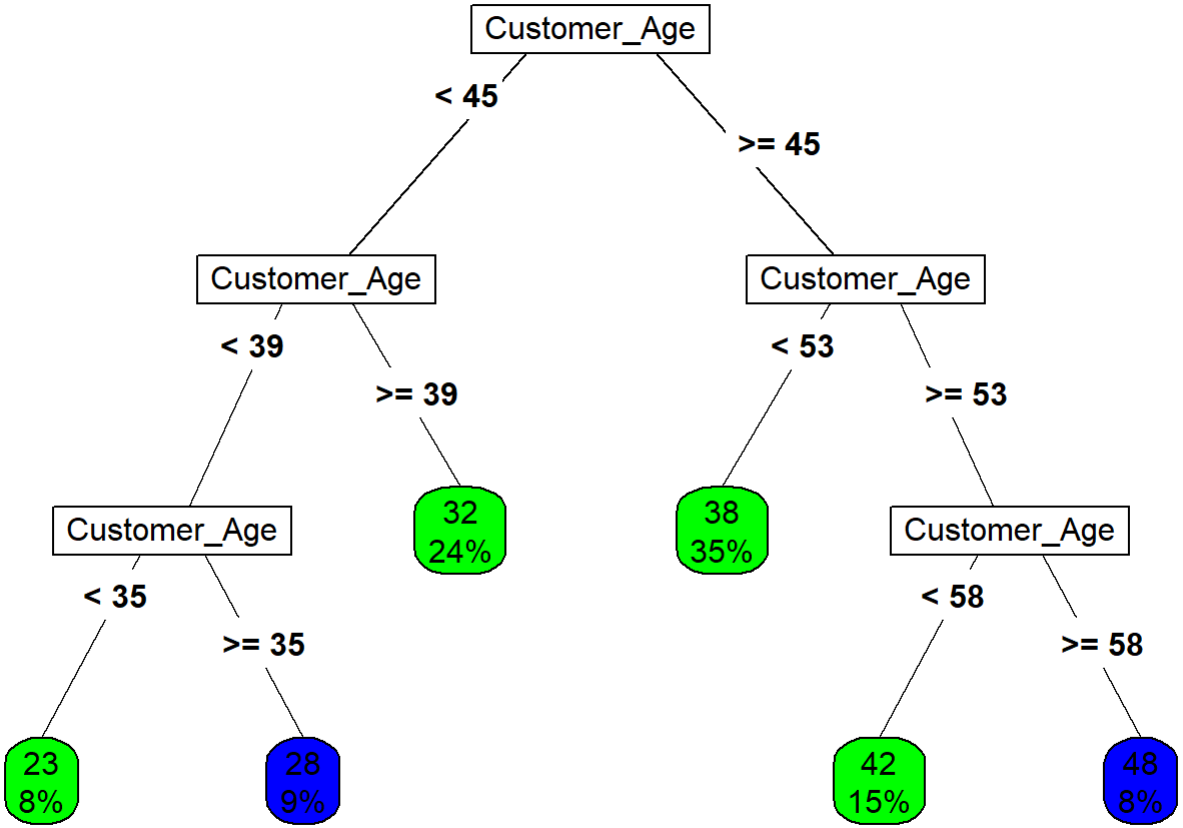
```
## [1] 17
```

```
sum(is.na(data)) #check data missing value
```

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

```
#membagi data training & data testing
set.seed(145)
train <- sample(1:nrow(data), .4*nrow(data))
data.train = data[train, ]
data.test = data[-train, ]
```

```
#Decision tree untuk target pada Month on Book Kasus Churn kartu Kredit di Bank
library(rpart)
library(rpart.plot)

# membuat model decision tree
fit <- rpart(Months_on_book ~ ., data = data.train)

# membuat plot pohon keputusan
rpart.plot(fit,type = 5, box.col = c("blue", "green"), fallen.leaves = FALSE)
```




```
#MSE regression tree
pred.data <- predict(fit, data.test)
MSETR <- mean((data.test$Months_on_book - pred.data)^2)
paste("Test MSE of tree model = ", MSETR)
```

```
## [1] "Test MSE of tree model =  26.9164662744249"
```

```
summary(fit) #ringkasan cart pada target months_on_book
```

```
## Call:
## rpart(formula = Months_on_book ~ ., data = data.train)
##   n= 4050
##
##           CP nsplit rel error    xerror        xstd
## 1 0.42058934      0 1.0000000 1.0013158 0.024187821
## 2 0.09389959      1 0.5794107 0.5802897 0.012409949
## 3 0.05833847      2 0.4855111 0.4879206 0.010217086
## 4 0.02235797      3 0.4271726 0.4327800 0.009000161
## 5 0.01519624      4 0.4048146 0.4139315 0.008864005
## 6 0.01000000      5 0.3896184 0.3979826 0.008843957
##
## Variable importance
##         Customer_Age      Dependent_count Total_Amt_Chng_Q4_Q1
##                   90                    7                    2
##  Total_Ct_Chng_Q4_Q1
##                    1
##
## Node number 1: 4050 observations,    complexity param=0.4205893
##   mean=35.87605, MSE=64.6755
##   left son=2 (1672 obs) right son=3 (2378 obs)
##   Primary splits:
##       Customer_Age           < 44.5        to the left,  improve=0.420589300, (0 missing)
##       Dependent_count        < 1.5         to the right, improve=0.009159007, (0 missing)
##       Months_Inactive_12_mon < 3.5         to the left,  improve=0.008223545, (0 missing)
##       Total_Amt_Chng_Q4_Q1   < 0.6205      to the right, improve=0.005690824, (0 missing)
##       Marital_Status         splits as  LRLL, improve=0.003406310, (0 missing)
##   Surrogate splits:
##       Total_Amt_Chng_Q4_Q1 < 1.146       to the right, agree=0.591, adj=0.010, (0 split)
##       Total_Ct_Chng_Q4_Q1  < 0.1775      to the left,  agree=0.588, adj=0.001, (0 split)
##
## Node number 2: 1672 observations,    complexity param=0.05833847
##   mean=29.6561, MSE=39.27946
##   left son=4 (696 obs) right son=5 (976 obs)
##   Primary splits:
##       Customer_Age
< 38.5        to the left,  improve=0.232674100, (0 missing)
##       Dependent_count
< 1.5         to the left,  improve=0.081141320, (0 missing)
```

```
##       Marital_Status
splits as  LRLR, improve=0.010405120, (0 missing)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_2 < 0.006055    to the right, improve=0.006281008, (0 missing)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_1 < 0.993945    to the left,  improve=0.006281008, (0 missing)
##   Surrogate splits:
##       Dependent_count       < 1.5         to the left,  agree=0.704, adj=0.289, (0 split)
##       Total_Amt_Chng_Q4_Q1  < 1.0175      to the right, agree=0.611, adj=0.066, (0 split)
##       Contacts_Count_12_mon < 3.5         to the right, agree=0.599, adj=0.037, (0 split)
##       Income_Category       splits as  RRRRRL, agree=0.590, adj=0.014, (0 split)
##       Education_Level       splits as  RRRRLRR, agree=0.586, adj=0.004, (0 split)
##
## Node number 3: 2378 observations,    complexity param=0.09389959
##   mean=40.24937, MSE=36.20401
##   left son=6 (1431 obs) right son=7 (947 obs)
##   Primary splits:
##       Customer_Age    < 52.5        to the left,  improve=0.285686700, (0 missing)
##       Dependent_count < 1.5         to the right, improve=0.102613000, (0 missing)
##       Marital_Status  splits as  LRRL, improve=0.009849039, (0 missing)
##       Credit_Limit    < 17010.5     to the right, improve=0.007834934, (0 missing)
##       Income_Category splits as  LRLLRL, improve=0.005686279, (0 missing)
##   Surrogate splits:
##       Dependent_count
< 1.5         to the right, agree=0.692, adj=0.226, (0 split)
##       Total_Amt_Chng_Q4_Q1
< 0.4965      to the right, agree=0.613, adj=0.027, (0 split)
##       Total_Ct_Chng_Q4_Q1
< 1.1645      to the left,  agree=0.610, adj=0.020, (0 split)
##       Months_Inactive_12_mon
< 5.5         to the left,  agree=0.604, adj=0.006, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_1 < 2.06045e-05 to the right, agree=0.604, adj=0.006, (0 split)
##
## Node number 4: 696 observations,    complexity param=0.01519624
##   mean=26.07615, MSE=44.89219
##   left son=8 (312 obs) right son=9 (384 obs)
##   Primary splits:
##       Customer_Age
```

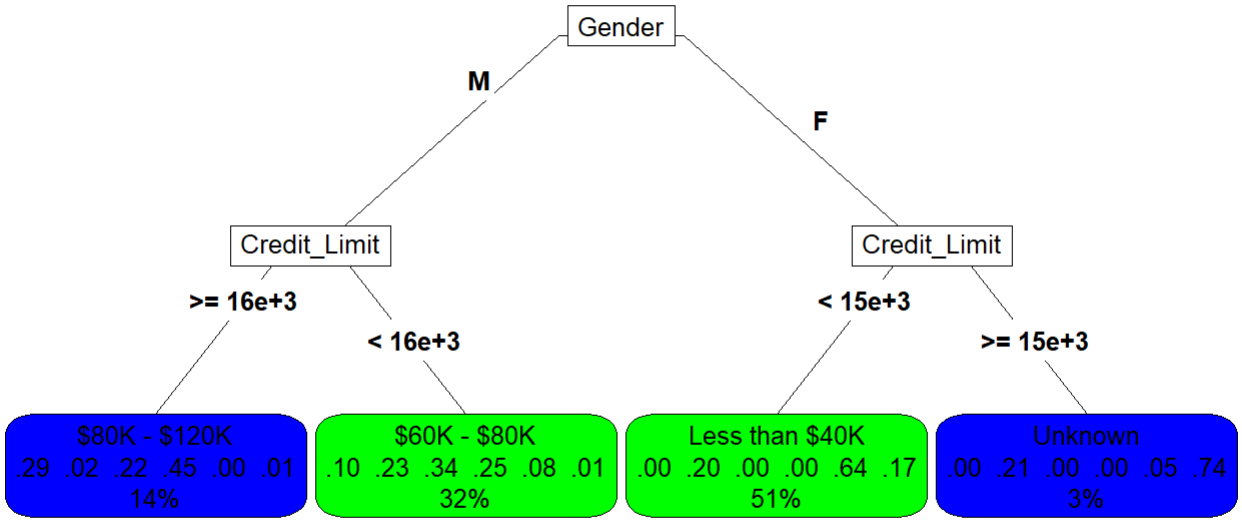
```
< 34.5        to the left,  improve=0.12739450, (0 missing)
##       Dependent_count
< 1.5         to the left,  improve=0.03703222, (0 missing)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_2 < 0.003558315 to the right, improve=0.02067505, (0 missing)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_1 < 0.99644     to the left,  improve=0.02067505, (0 missing)
##       Months_Inactive_12_mon
< 2.5         to the left,  improve=0.01079876, (0 missing)
##   Surrogate splits:
##       Dependent_count     < 1.5         to the left,  agree=0.677, adj=0.279, (0 split)
##       Total_Ct_Chng_Q4_Q1 < 0.4825      to the left,  agree=0.572, adj=0.045, (0 split)
##       Marital_Status      splits as  LRRR, agree=0.570, adj=0.042, (0 split)
##       Card_Category       splits as  RL-L, agree=0.565, adj=0.029, (0 split)
##       Education_Level     splits as  RRRRLRR, agree=0.559, adj=0.016, (0 split)
##
## Node number 5: 976 observations
##   mean=32.20902, MSE=19.62025
##
## Node number 6: 1431 observations
##   mean=37.63312, MSE=16.75359
##
## Node number 7: 947 observations,    complexity param=0.02235797
##   mean=44.20275, MSE=39.6231
##   left son=14 (621 obs) right son=15 (326 obs)
##   Primary splits:
##       Customer_Age           < 57.5        to the left,  improve=0.156073400, (0 missing)
##       Dependent_count        < 1.5         to the right, improve=0.055345210, (0 missing)
##       Income_Category        splits as  LRLLLL, improve=0.020332490, (0 missing)
##       Months_Inactive_12_mon < 4.5         to the left,  improve=0.009997846, (0 missing)
##       Total_Amt_Chng_Q4_Q1   < 0.3975      to the left,  improve=0.006560102, (0 missing)
##   Surrogate splits:
##       Dependent_count
< 0.5         to the right, agree=0.758, adj=0.298, (0 split)
##       Total_Ct_Chng_Q4_Q1
< 0.229       to the right, agree=0.661, adj=0.015, (0 split)
##       Total_Amt_Chng_Q4_Q1
< 0.2785      to the right, agree=0.660, adj=0.012, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
```

```
active_12_mon_1 < 0.99815     to the left,  agree=0.660, adj=0.012, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_2 < 0.00159847  to the right, agree=0.660, adj=0.012, (0 split)
##
## Node number 8: 312 observations
##   mean=23.42308, MSE=51.16716
##
## Node number 9: 384 observations
##   mean=28.23177, MSE=29.42805
##
## Node number 14: 621 observations
##   mean=42.40097, MSE=26.52361
##
## Node number 15: 326 observations
##   mean=47.63497, MSE=46.61215
```

```
# Menghitung akurasi model
threshold <- 40 # threshold untuk mengklasifikasikan hasil prediksi

pred_class <- ifelse(pred.data < threshold, "0", "1")

actual_class <- ifelse(data.test$Months_on_book < threshold, "0", "1")

accuracy <- sum(pred_class == actual_class) / length(actual_class)

print(paste0("Akurasi model: ", round(accuracy, 2)))
```

```
## [1] "Akurasi model: 0.82"
```

```r
#Decision tree untuk target pada Income Category Kasus Churn kartu Kredit di Bank
library(rpart)
library(rpart.plot)

# membuat model decision tree
fit <- rpart(Income_Category ~ ., data = data.train)

# membuat plot pohon keputusan
rpart.plot(fit,type = 5, box.col = c("blue", "green"), fallen.leaves = FALSE)
```



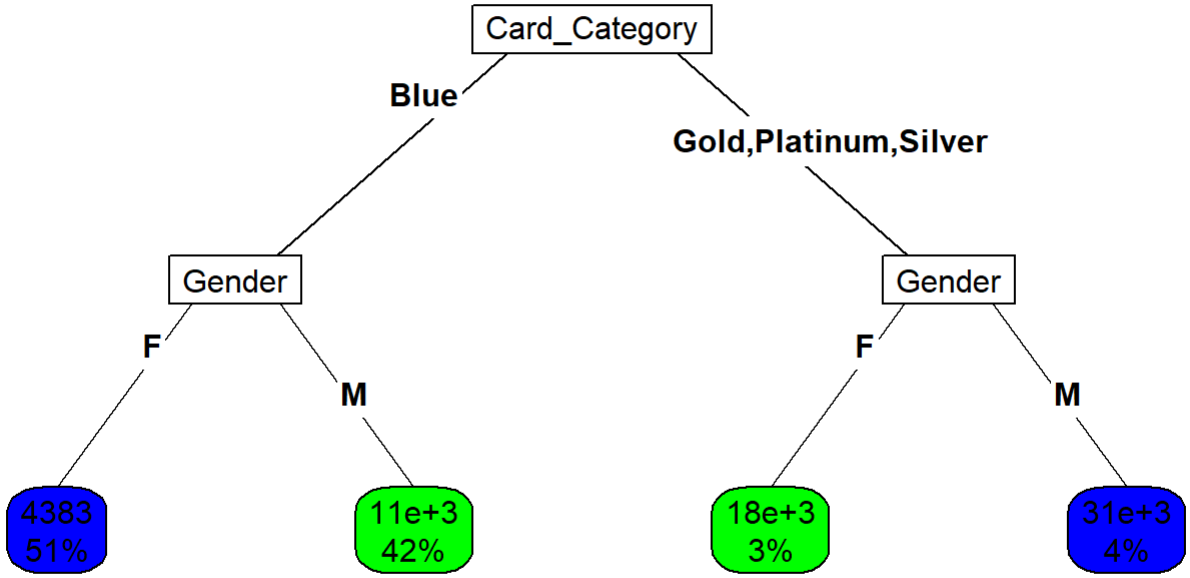

```r
summary(fit) #ringkasan cart pada target Income_Category
```

```
## Call:
## rpart(formula = Income_Category ~ ., data = data.train)
##   n= 4050
##
##           CP nsplit rel error    xerror       xstd
## 1 0.18085106      0 1.0000000 1.0000000 0.01153367
## 2 0.04255319      1 0.8191489 0.8191489 0.01206427
## 3 0.03305471      2 0.7765957 0.7830547 0.01208768
## 4 0.01000000      3 0.7435410 0.7610182 0.01208888
##
## Variable importance
##                Gender          Credit_Limit         Card_Category
##                    58                    34                     5
##   Total_Ct_Chng_Q4_Q1  Total_Amt_Chng_Q4_Q1 Contacts_Count_12_mon
##                     1                     1                     1
##
## Node number 1: 4050 observations,    complexity param=0.1808511
##   predicted class=Less than $40K  expected loss=0.6498765  P(node) =1
##     class counts:   296   735   562   581  1418   458
##    probabilities: 0.073 0.181 0.139 0.143 0.350 0.113
##   left son=2 (1867 obs) right son=3 (2183 obs)
##   Primary splits:
##       Gender          splits as  RL, improve=550.979000, (0 missing)
##       Credit_Limit    < 9687.5     to the right, improve=213.645800, (0 missing)
##       Customer_Age    < 63.5       to the left,  improve=  7.482250, (0 missing)
##       Card_Category   splits as  RLLL, improve=  6.657424, (0 missing)
##       Dependent_count < 1.5        to the right, improve=  5.781067, (0 missing)
##   Surrogate splits:
##       Credit_Limit          < 7663.5     to the right, agree=0.698, adj=0.344, (0 split)
##       Card_Category         splits as  RLRL, agree=0.555, adj=0.035, (0 split)
##       Total_Ct_Chng_Q4_Q1   < 0.4395     to the left,  agree=0.548, adj=0.020, (0 split)
##       Total_Amt_Chng_Q4_Q1  < 0.9405     to the right, agree=0.547, adj=0.018, (0 split)
##       Contacts_Count_12_mon < 4.5        to the right, agree=0.545, adj=0.013, (0 split)
##
## Node number 2: 1867 observations,    complexity param=0.04255319
##   predicted class=$80K - $120K    expected loss=0.6888056  P(node) =0.4609877
##     class counts:   296   304   562   581   105    19
##    probabilities: 0.159 0.163 0.301 0.311 0.056 0.010
##   left son=4 (578 obs) right son=5 (1289 obs)
```

```
##   Primary splits:
##       Credit_Limit        < 15624.5    to the right, improve=55.477880, (0 missing)
##       Customer_Age        < 63.5       to the left,  improve=15.365210, (0 missing)
##       Dependent_count     < 0.5        to the right, improve=10.294330, (0 missing)
##       Months_on_book      < 51.5       to the left,  improve= 8.130918, (0 missing)
##       Total_Ct_Chng_Q4_Q1 < 0.2945     to the left,  improve= 2.754293, (0 missing)
##   Surrogate splits:
##       Card_Category
splits as  RLLL, agree=0.767, adj=0.247, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_1 < 1.9004e-05 to the left,  agree=0.691, adj=0.003, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_2 < 0.0008535  to the left,  agree=0.691, adj=0.003, (0 split)
##       Total_Ct_Chng_Q4_Q1
< 1.866      to the right, agree=0.691, adj=0.002, (0 split)
##
## Node number 3: 2183 observations,    complexity param=0.03305471
##   predicted class=Less than $40K  expected loss=0.3985341  P(node) =0.5390123
##     class counts:     0   431     0     0  1313   439
##    probabilities: 0.000 0.197 0.000 0.000 0.601 0.201
##   left son=6 (2057 obs) right son=7 (126 obs)
##   Primary splits:
##       Credit_Limit
< 14571.5    to the left,  improve=79.615020, (0 missing)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_2 < 0.00299343 to the left,  improve= 5.117774, (0 missing)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_1 < 0.997005   to the right, improve= 4.895387, (0 missing)
##       Months_on_book
< 45.5       to the right, improve= 4.058076, (0 missing)
##       Customer_Age
< 32.5       to the right, improve= 2.691338, (0 missing)
##   Surrogate splits:
##       Card_Category splits as  LRRL, agree=0.95, adj=0.135, (0 split)
##
## Node number 4: 578 observations
##   predicted class=$80K - $120K    expected loss=0.5484429  P(node) =0.142716
##     class counts:   169    13   130   261     0     5
##    probabilities: 0.292 0.022 0.225 0.452 0.000 0.009
```

```
##
## Node number 5: 1289 observations
##   predicted class=$60K - $80K     expected loss=0.6648565  P(node) =0.3182716
##     class counts:   127   291   432   320   105    14
##    probabilities: 0.099 0.226 0.335 0.248 0.081 0.011
##
## Node number 6: 2057 observations
##   predicted class=Less than $40K  expected loss=0.3646087  P(node) =0.5079012
##     class counts:     0   404     0     0  1307   346
##    probabilities: 0.000 0.196 0.000 0.000 0.635 0.168
##
## Node number 7: 126 observations
##   predicted class=Unknown         expected loss=0.2619048  P(node) =0.03111111
##     class counts:     0    27     0     0     6    93
##    probabilities: 0.000 0.214 0.000 0.000 0.048 0.738
```

```
#Decision tree untuk target pada Credit Limit Kasus Churn kartu Kredit di Bank
fit <- rpart(Credit_Limit~ .-Income_Category, data = data.train)
# membuat plot pohon keputusan dengan kotak-kotak berwarna
rpart.plot(fit,type = 5, box.col = c("blue", "green"), fallen.leaves = FALSE)
```




```
summary(fit) #ringkasan cart pada target Credit_Limit
```

```
## Call:
## rpart(formula = Credit_Limit ~ . - Income_Category, data = data.train)
##   n= 4050
##
##           CP nsplit rel error    xerror       xstd
## 1 0.27032445      0 1.0000000 1.0003917 0.03087604
## 2 0.12004317      1 0.7296755 0.7303960 0.02495747
## 3 0.03007386      2 0.6096324 0.6107377 0.01934606
## 4 0.01000000      3 0.5795585 0.5809953 0.01954203
##
## Variable importance
##        Card_Category               Gender  Total_Ct_Chng_Q4_Q1
##                   63                   35                     1
## Total_Amt_Chng_Q4_Q1
##                    1
##
## Node number 1: 4050 observations,    complexity param=0.2703245
##   mean=8604.584, MSE=8.231369e+07
##   left son=2 (3773 obs) right son=3 (277 obs)
##   Primary splits:
##       Card_Category            splits as  LRRR, improve=0.270324500, (0 missing)
##       Gender                   splits as  LR, improve=0.178192000, (0 missing)
##       Total_Relationship_Count < 2.5         to the right, improve=0.008711110, (0 missing)
##       Dependent_count          < 1.5         to the left,  improve=0.005346975, (0 missing)
##       Marital_Status           splits as  RLRR, improve=0.004447622, (0 missing)
##
## Node number 2: 3773 observations,    complexity param=0.1200432
##   mean=7326.454, MSE=5.75931e+07
##   left son=4 (2077 obs) right son=5 (1696 obs)
##   Primary splits:
##       Gender                splits as  LR, improve=0.184165100, (0 missing)
##       Dependent_count       < 0.5         to the left,  improve=0.004688497, (0 missing)
##       Total_Amt_Chng_Q4_Q1  < 0.9155      to the left,  improve=0.004516374, (0 missing)
##       Contacts_Count_12_mon < 3.5         to the left,  improve=0.003859603, (0 missing)
##       Customer_Age          < 37.5        to the left,  improve=0.003366444, (0 missing)
##   Surrogate splits:
##       Total_Amt_Chng_Q4_Q1
< 0.9515      to the left,  agree=0.557, adj=0.015, (0 split)
##       Total_Ct_Chng_Q4_Q1
```

```
< 0.4455      to the right, agree=0.557, adj=0.015, (0 split)
##       Contacts_Count_12_mon
< 4.5         to the left,  agree=0.556, adj=0.012, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_1 < 0.9982      to the left,  agree=0.553, adj=0.005, (0 split)
##       Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_In
active_12_mon_2 < 0.001802605 to the right, agree=0.553, adj=0.005, (0 split)
##
## Node number 3: 277 observations,    complexity param=0.03007386
##   mean=26013.92, MSE=9.369492e+07
##   left son=6 (106 obs) right son=7 (171 obs)
##   Primary splits:
##       Gender          splits as  LR, improve=0.38629620, (0 missing)
##       Dependent_count < 1.5         to the left,  improve=0.05269036, (0 missing)
##       Customer_Age    < 33.5        to the left,  improve=0.04262481, (0 missing)
##       Card_Category   splits as  -RRL, improve=0.04162684, (0 missing)
##       Months_on_book  < 51.5        to the right, improve=0.03305434, (0 missing)
##   Surrogate splits:
##       Total_Ct_Chng_Q4_Q1  < 1.122       to the right, agree=0.632, adj=0.038, (0 split)
##       Dependent_count      < 1.5         to the left,  agree=0.628, adj=0.028, (0 split)
##       Customer_Age         < 33.5        to the left,  agree=0.625, adj=0.019, (0 split)
##       Education_Level      splits as  RLRRRRR, agree=0.625, adj=0.019, (0 split)
##       Total_Amt_Chng_Q4_Q1 < 1.407       to the right, agree=0.625, adj=0.019, (0 split)
##
## Node number 4: 2077 observations
##   mean=4383.499, MSE=1.519539e+07
##
## Node number 5: 1696 observations
##   mean=10930.53, MSE=8.591928e+07
##
## Node number 6: 106 observations
##   mean=18372.69, MSE=7.144288e+07
##
## Node number 7: 171 observations
##   mean=30750.59, MSE=4.885854e+07
```