Home Credit: Final Report

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Introduction

Assessing the Problem

Traditionally, borrowing costs have been tied to creditors' assessment of credit default risk based on simple, but broad financial criteria. Unfortunately, this leaves many potential borrowers out of the market, or paying higher interest rates. Conversely, these same criteria may not always be sufficient to redudce default risk by clients who may meet the criteria, but may eventually default because of other, potentially forseeable, reasons not sufficiently accounted for in the criteria.

Client Solution

Using historical client credit data, I will create a Machine Laerning model capable of predicting, as accurately as possible, an individual applicants's liklihood of defaulting. This model can then be used by Home Creidt to make more refined decisions as to whom they offer loans, the types of loans offered and the interest terms.

Steps Taken

1. Cleaned and merged the "train" data to get a single data frame for incorporation in ML algorythms;
2. Examined the data using P-tests to determine signifant features for incorporation into the ML algorhythms;
3. Reserved 80% of the training data for training the algorythms and 20% for testing
4. Using Caret package, trained several different models:
    a. General Linear Model, using 100% of the apportioned train data
    b. Naive Bayes model, using 100% of the apportioned train data
    c. K Nearest Neighbor Model, using 100% of the apportioned train data
    d. Random Forest Model, with the data segmented into 5%, 10%, 20%, 30%, 60% and 80% groups for comparision, and as a check against overfitting
5. Used visualization tools to deomonstrate these correlations and the accuracy of the model.

Data Cleanup and Feature Selection

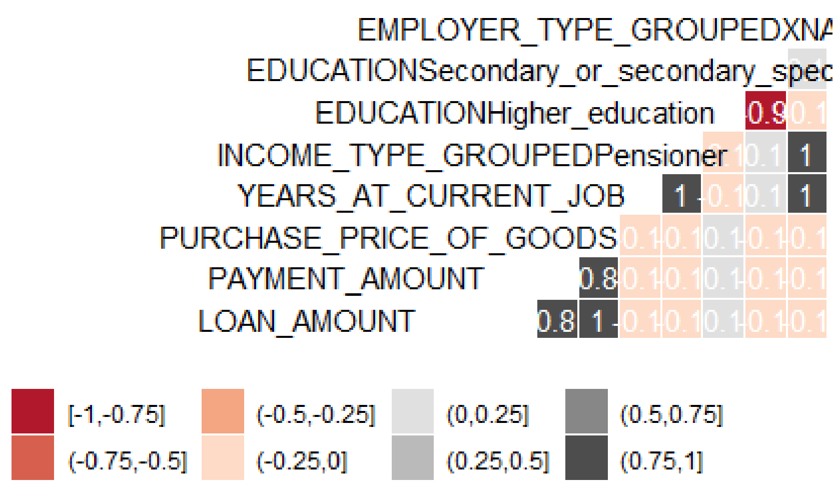
1) I examined P values for each potential feature vs. TARGET to assist in determining its releavance and significance for use in ML models;
2) I used a correlation chart to determine highly correlated (and therefore redundant) features for removal so that they won't be overrepresenated in the ML trainers at later steps;
3) I supplied a plot for each variable that demonstrates simple counts for each categorical variable or binned continuous variable;
4) I supplied a plot demonstrating the significance of each variable to the TARGET variable;
5) I supplied summary statistical information for each variable;

- for continuous features, I used the Shapiro-Wilks Test (shapiro.test())to test for distributive normality;
- upon finding that my continous features are not normally distriubted, I applied the Wilcoxon Rank Sum Test (wilcox.test()) as the t-test assumption of normality is not met.

Correlation matrix with ONLY correlation values > .6

The full correlation matrix for the features of this data set is too large to legibly display. Therefore a simplified correlation matrix follows, which displays ONLY correlation values between features that are greater than 0.6.

Based on this correlation matrix, I removed three features from the model: INCOME_TYPE_GROUPEDPensioner, EMPLOYER_TYPE_GROUPEDXNA, and EDUCATIONHigher_education



Summary of P values for each feature

The following table of p values will be used for final feature selection in our ML models. Of particular note are the "Signif. codes: `0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1`" which demonstrate the significance of the feature based on is P-value.

```
##
## Call:
## glm(formula = TARGET ~ ., family = "binomial", data = results_train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6034  -0.4391  -0.3328  -0.2487   3.2870
##
```

```
## Coefficients:
##                                        Estimate Std. Error z value
## (Intercept)                          -1.976e+00  6.090e-01  -3.244
## SK_ID_CURR                           -4.553e-08  6.635e-08  -0.686
## LOAN_TYPERevolving loans             -3.389e-01  2.879e-02 -11.773
## AGE                                  -8.499e-03  8.860e-04  -9.593
## GENDERM                               3.612e-01  1.553e-02  23.251
## GENDERXNA                            -6.500e+00  3.500e+01  -0.186
## OWNS_CARY                            -3.862e-01  2.066e-02 -18.688
## AGE_OF_CAR                            6.053e-03  9.512e-04   6.363
## OWNS_REALTYY                          4.839e-02  1.539e-02   3.145
## CHILDREN                             -7.783e-03  1.008e-02  -0.772
## TOTAL_INCOME                          1.362e-08  1.829e-08   0.745
## LOAN_AMOUNT                           2.276e-06  1.265e-07  17.998
## PAYMENT_AMOUNT                        1.011e-05  1.351e-06   7.478
## PURCHASE_PRICE_OF_GOODS              -2.898e-06  1.219e-07 -23.784
## RATIO_LOAN_TO_ANNUITY                 4.653e-04  2.136e-03   0.218
## EDUCATIONHigher education             1.194e+00  5.903e-01   2.022
## EDUCATIONIncomplete higher            1.357e+00  5.912e-01   2.295
## EDUCATIONLower secondary              1.732e+00  5.925e-01   2.924
## EDUCATIONSecondary / secondary special  1.597e+00  5.901e-01   2.706
## MARITAL_STATUSMarried                -1.629e-01  2.220e-02  -7.336
## MARITAL_STATUSSeparated              -2.428e-02  3.357e-02  -0.723
## MARITAL_STATUSSingle / not married   -5.724e-02  2.626e-02  -2.180
## MARITAL_STATUSUnknown                -8.218e+00  5.087e+01  -0.162
## MARITAL_STATUSWidow                  -1.487e-01  4.134e-02  -3.596
## HOUSING_STATUSHouse / apartment       3.332e-02  1.141e-01   0.292
## HOUSING_STATUSMunicipal apartment     1.771e-01  1.192e-01   1.485
## HOUSING_STATUSOffice apartment       -1.728e-01  1.397e-01  -1.237
## HOUSING_STATUSRented apartment        1.811e-01  1.225e-01   1.478
## HOUSING_STATUSWith parents            8.831e-02  1.170e-01   0.755
## YEARS_AT_CURRENT_JOB                 -3.329e-02  1.566e-03 -21.267
## YEARS_SINCE_GETTING_IDENTITY_DOCUMENT  -5.066e-03  8.003e-04  -6.330
## REGION_AND_CITY_RATING                1.757e-01  1.432e-02  12.271
## External.Score.1                      2.317e-03  2.393e-02   0.097
## External.Score.2                     -2.239e+00  3.436e-02 -65.146
## External.Score.3                     -1.145e+00  2.570e-02 -44.541
## MAX_DAYS_LATE_BUREAU                  1.015e-04  7.516e-05   1.350
## INCOME_TYPE_GROUPEDOther              1.042e-01  7.555e-01   0.138
## INCOME_TYPE_GROUPEDPensioner         -2.756e+00  8.834e-01  -3.120
## INCOME_TYPE_GROUPEDState servant     -6.391e-02  3.648e-02  -1.752
## INCOME_TYPE_GROUPEDWorking            1.276e-01  1.743e-02   7.318
## EMPLOYER_TYPE_GROUPEDBank            -4.612e-01  1.153e-01  -4.000
## EMPLOYER_TYPE_GROUPEDBusiness Entity -7.900e-02  6.944e-02  -1.138
## EMPLOYER_TYPE_GROUPEDEducation       -2.483e-01  7.596e-02  -3.269
## EMPLOYER_TYPE_GROUPEDElectricity     -2.934e-01  1.507e-01  -1.947
## EMPLOYER_TYPE_GROUPEDGovt Services   -2.546e-01  7.559e-02  -3.368
## EMPLOYER_TYPE_GROUPEDHousing          2.960e-02  7.643e-02   0.387
## EMPLOYER_TYPE_GROUPEDIndustry        -1.897e-01  7.479e-02  -2.536
## EMPLOYER_TYPE_GROUPEDMedicine        -1.920e-01  7.908e-02  -2.428
```

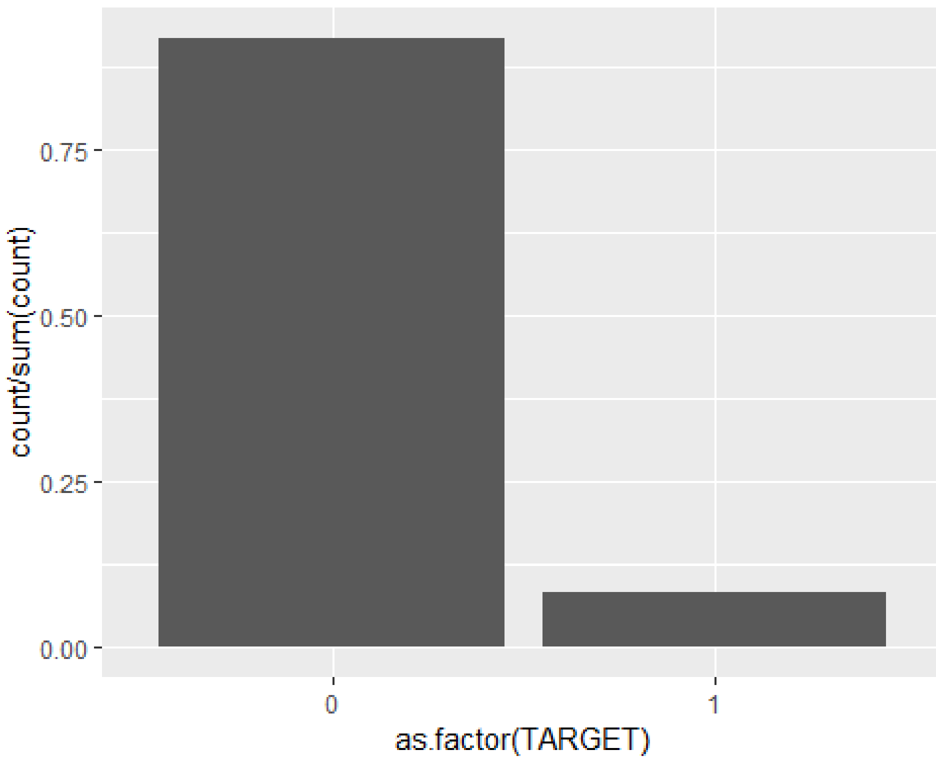
```
## EMPLOYER_TYPE_GROUPEDOther             -1.397e-01  7.458e-02  -1.873
## EMPLOYER_TYPE_GROUPEDSelf-employed      2.126e-02  7.048e-02   0.302
## EMPLOYER_TYPE_GROUPEDService           -1.604e-01  7.565e-02  -2.121
## EMPLOYER_TYPE_GROUPEDTrade             -1.171e-01  7.483e-02  -1.564
## EMPLOYER_TYPE_GROUPEDTransport         -4.745e-02  7.761e-02  -0.611
## EMPLOYER_TYPE_GROUPEDXNA                3.554e+01  1.787e+00  19.886
##                                        Pr(>|z|)
## (Intercept)                            0.001179 **
## SK_ID_CURR                             0.492578
## LOAN_TYPERevolving loans                < 2e-16 ***
## AGE                                     < 2e-16 ***
## GENDERM                                 < 2e-16 ***
## GENDERXNA                              0.852673
## OWNS_CARY                               < 2e-16 ***
## AGE_OF_CAR                             1.98e-10 ***
## OWNS_REALTYY                           0.001659 **
## CHILDREN                               0.439990
## TOTAL_INCOME                           0.456509
## LOAN_AMOUNT                             < 2e-16 ***
## PAYMENT_AMOUNT                         7.55e-14 ***
## PURCHASE_PRICE_OF_GOODS                 < 2e-16 ***
## RATIO_LOAN_TO_ANNUITY                  0.827594
## EDUCATIONHigher education              0.043168 *
## EDUCATIONIncomplete higher             0.021708 *
## EDUCATIONLower secondary               0.003455 **
## EDUCATIONSecondary / secondary special 0.006816 **
## MARITAL_STATUSMarried                  2.20e-13 ***
## MARITAL_STATUSSeparated                0.469508
## MARITAL_STATUSSingle / not married     0.029275 *
## MARITAL_STATUSUnknown                  0.871674
## MARITAL_STATUSWidow                    0.000323 ***
## HOUSING_STATUSHouse / apartment        0.770330
## HOUSING_STATUSMunicipal apartment      0.137599
## HOUSING_STATUSOffice apartment         0.216014
## HOUSING_STATUSRented apartment         0.139517
## HOUSING_STATUSWith parents             0.450204
## YEARS_AT_CURRENT_JOB                    < 2e-16 ***
## YEARS_SINCE_GETTING_IDENTITY_DOCUMENT  2.45e-10 ***
## REGION_AND_CITY_RATING                  < 2e-16 ***
## External.Score.1                       0.922857
## External.Score.2                        < 2e-16 ***
## External.Score.3                        < 2e-16 ***
## MAX_DAYS_LATE_BUREAU                   0.177062
## INCOME_TYPE_GROUPEDOther               0.890308
## INCOME_TYPE_GROUPEDPensioner           0.001808 **
## INCOME_TYPE_GROUPEDState servant       0.079727 .
## INCOME_TYPE_GROUPEDWorking             2.52e-13 ***
## EMPLOYER_TYPE_GROUPEDBank              6.34e-05 ***
## EMPLOYER_TYPE_GROUPEDBusiness Entity   0.255276
## EMPLOYER_TYPE_GROUPEDEducation         0.001078 **
```

```
## EMPLOYER_TYPE_GROUPEDElectricity       0.051515 .
## EMPLOYER_TYPE_GROUPEDGovt Services     0.000757 ***
## EMPLOYER_TYPE_GROUPEDHousing           0.698551
## EMPLOYER_TYPE_GROUPEDIndustry          0.011197 *
## EMPLOYER_TYPE_GROUPEDMedicine          0.015178 *
## EMPLOYER_TYPE_GROUPEDOther             0.061041 .
## EMPLOYER_TYPE_GROUPEDSelf-employed     0.762938
## EMPLOYER_TYPE_GROUPEDService           0.033954 *
## EMPLOYER_TYPE_GROUPEDTrade             0.117726
## EMPLOYER_TYPE_GROUPEDTransport         0.540877
## EMPLOYER_TYPE_GROUPEDXNA                < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 172443  on 307383  degrees of freedom
## Residual deviance: 157879  on 307330  degrees of freedom
##   (127 observations deleted due to missingness)
## AIC: 157987
##
## Number of Fisher Scoring iterations: 8
```

Distribution of the Dependent Variable "Target"

The following plot displays a simple distribution of our TARGET values. TARGET = 1 means that the sample had some problem repaying their load. TARGET = 0 means that the sample successfully repaid their load without issue.

Note that because the TARGET data is highly unbalanced, I downsampled the data sets when training each model.

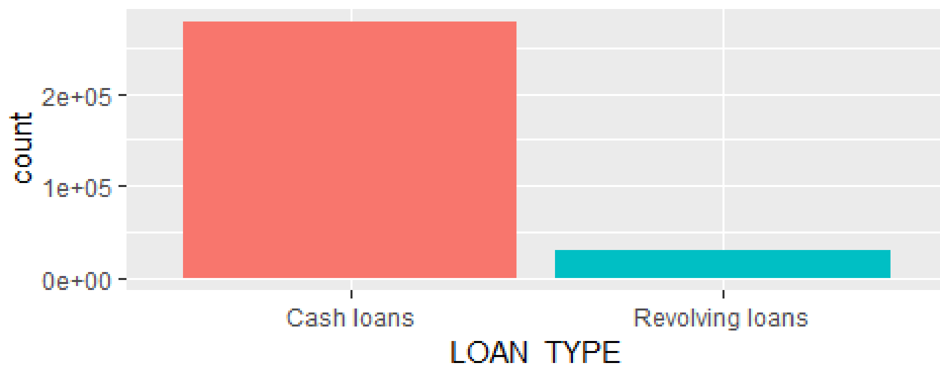


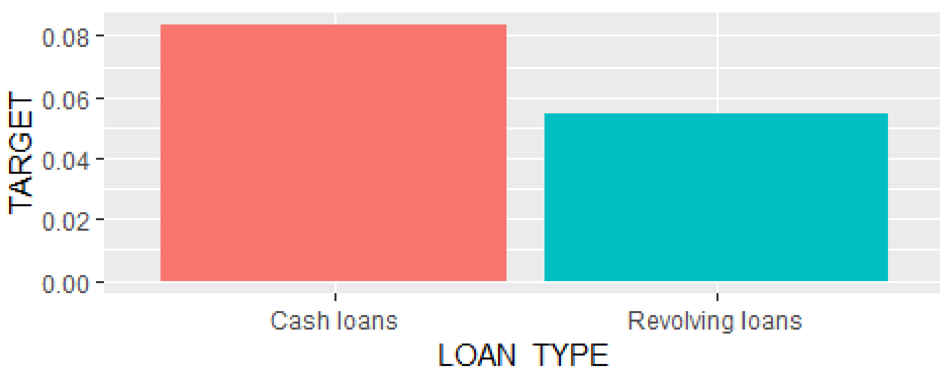

```
# A tibble: 2 x 2
  TARGET      n
   <int>  <int>
1      0 282686
2      1  24825
```

Feature Significance

The following statistics and plots demonstrate both simple counts for each feature, as well as the significance of each feature to our ML models.

Loan Type and Loan Type v. Target

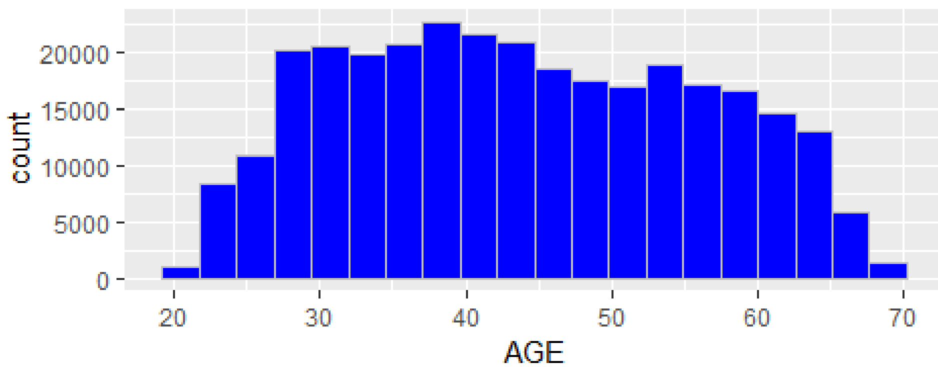


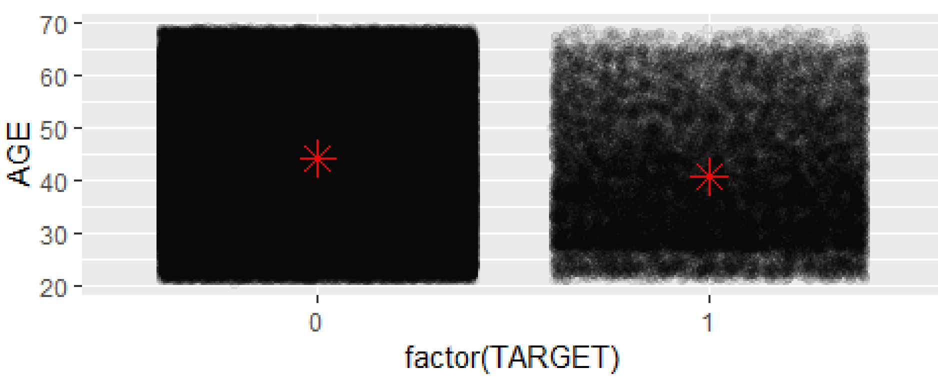



```
# A tibble: 2 x 2
  LOAN_TYPE            n
  <chr>            <int>
1 Cash loans      278232
2 Revolving loans  29279


Call:
glm(formula = TARGET ~ LOAN_TYPE, family = "binomial", data = results_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4175  -0.4175  -0.4175  -0.4175   2.4101

Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)              -2.396250   0.006855  -349.6   <2e-16 ***
LOAN_TYPERevolving loans -0.451779   0.026581   -17.0   <2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 172217  on 307509  degrees of freedom
AIC: 172221

Number of Fisher Scoring iterations: 5
```

Age and Age v. Target



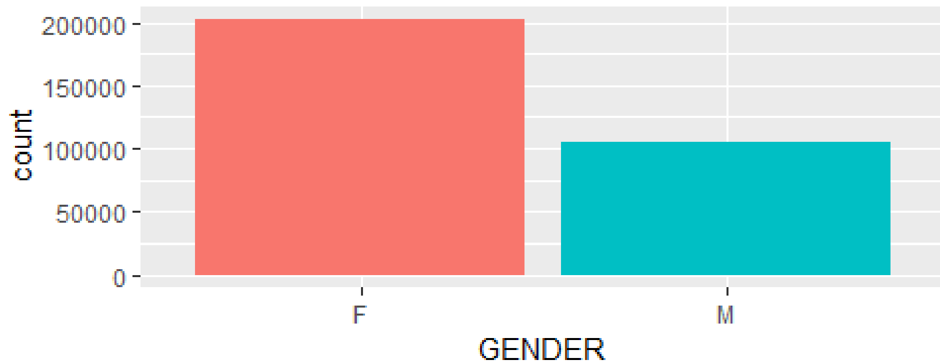


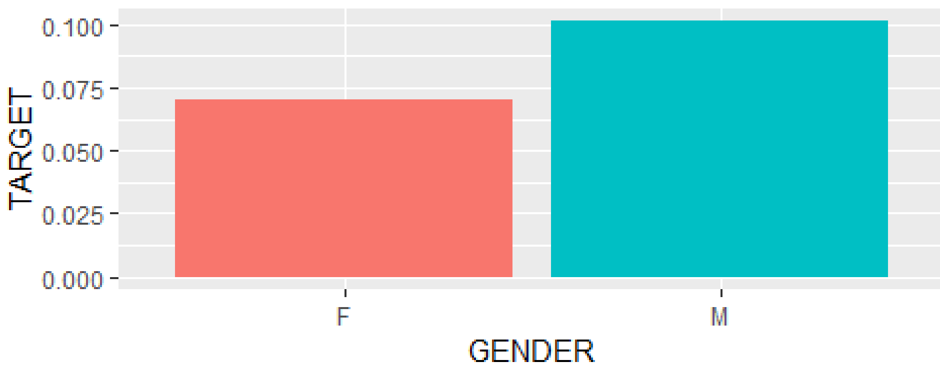

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  20.50   33.98   43.12   43.91   53.89   69.07 


    Anderson-Darling normality test

data:  results_train$AGE
A = 2381, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  AGE by TARGET
```

```
W = 4091300000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

Gender and Gender v. Target

Note that, becsuse the number of XNA values for gender was extermely low (total count of 4), they have been removed in the following.

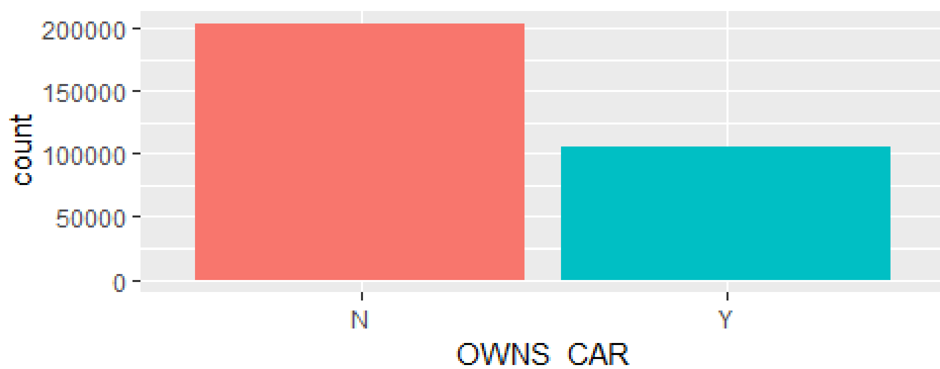


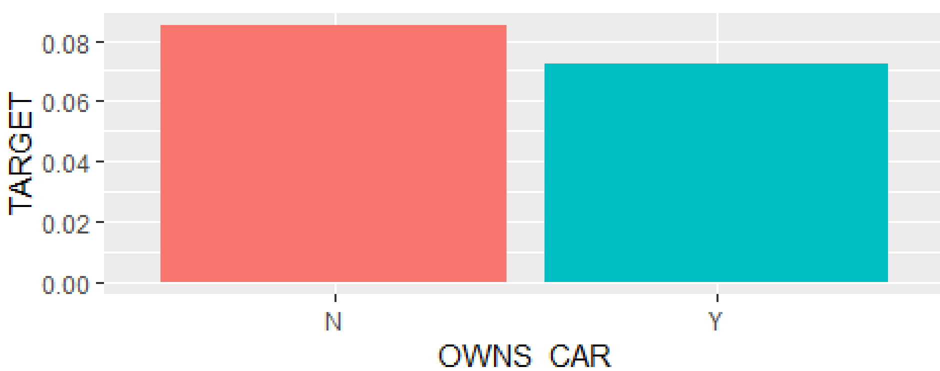



```
# A tibble: 2 x 2
  GENDER      n
  <fct>   <int>
1 F      202373
2 M      105007


Call:
glm(formula = TARGET ~ GENDER, family = "binomial", data = results_train,
    na.action = na.omit)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4625  -0.4625  -0.3810  -0.3810   2.3062

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.586793   0.008711 -296.95   <2e-16 ***
GENDERM      0.405238   0.013429   30.18   <2e-16 ***
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172541  on 307506  degrees of freedom
Residual deviance: 171649  on 307505  degrees of freedom
  (4 observations deleted due to missingness)
AIC: 171653

Number of Fisher Scoring iterations: 5
```

Owns a car? and Owns Car v. Target

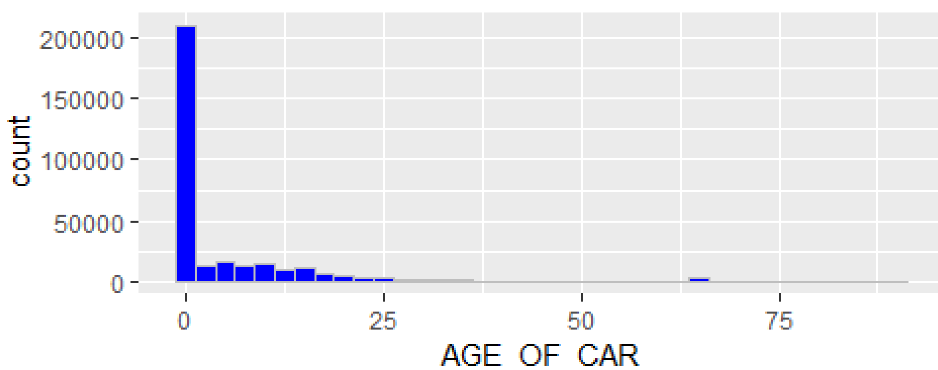


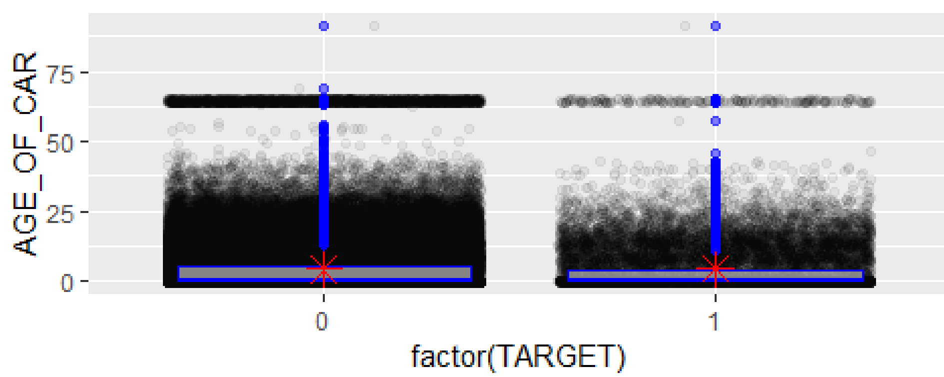



```
# A tibble: 2 x 2
  OWNS_CAR       n
  <chr>      <int>
1 N         202924
2 Y         104587


Call:
glm(formula = TARGET ~ OWNS_CAR, family = "binomial", data = results_train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
```

```
-0.4215  -0.4215  -0.4215  -0.3878   2.2913

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.37624    0.00796 -298.53   <2e-16 ***
OWNS_CARY   -0.17359    0.01434  -12.11   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 172393  on 307509  degrees of freedom
AIC: 172397

Number of Fisher Scoring iterations: 5
```

Age of car and Age of Car v. Target

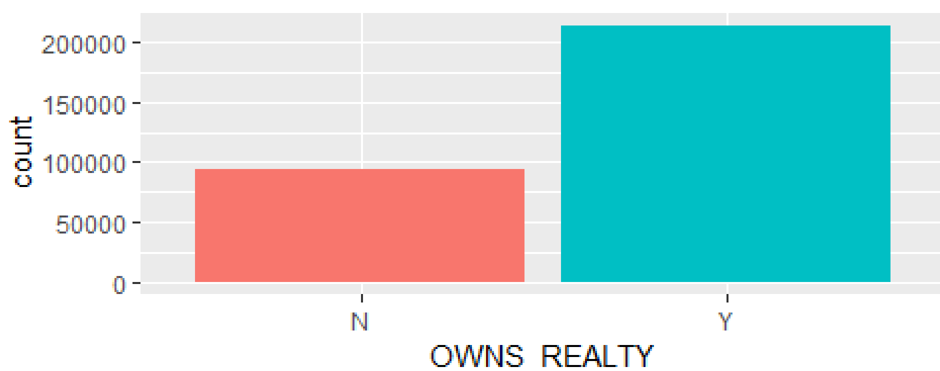


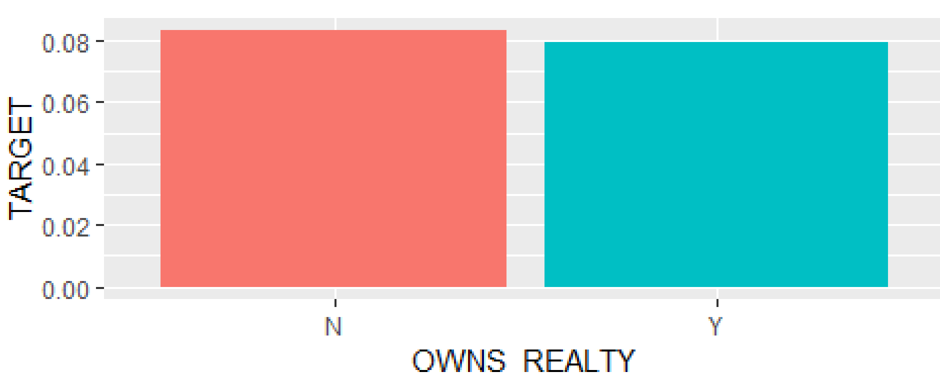



```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   0.000   0.000   4.102   5.000  91.000 

# A tibble: 62 x 2
   `factor(AGE_OF_CAR)`       n
   <fct>                  <int>
 1 0                     205063
```

```
 2 1                       5280
 3 2                       5852
 4 3                       6370
 5 4                       5557
 6 5                       3595
 7 6                       6382
 8 7                       7424
 9 8                       5887
10 9                       5020
# ... with 52 more rows


    Anderson-Darling normality test

data:  results_train$AGE_OF_CAR
A = 50400, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  AGE_OF_CAR by TARGET
W = 3595300000, p-value = 1.451e-14
alternative hypothesis: true location shift is not equal to 0
```

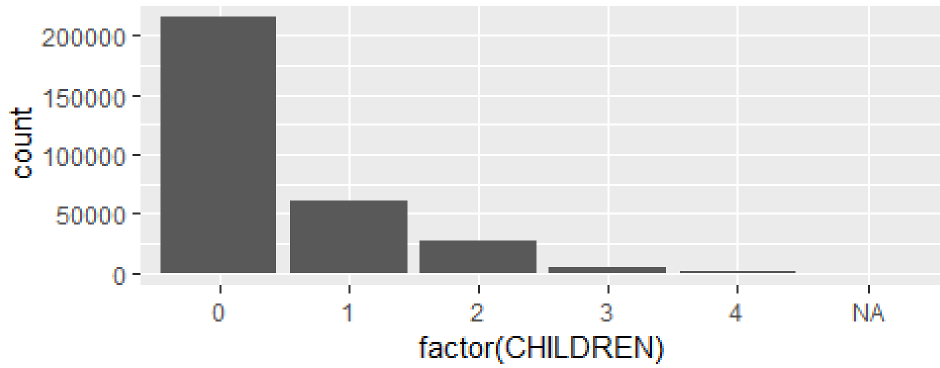
Owns Real Estate? and Owns RE v. Target

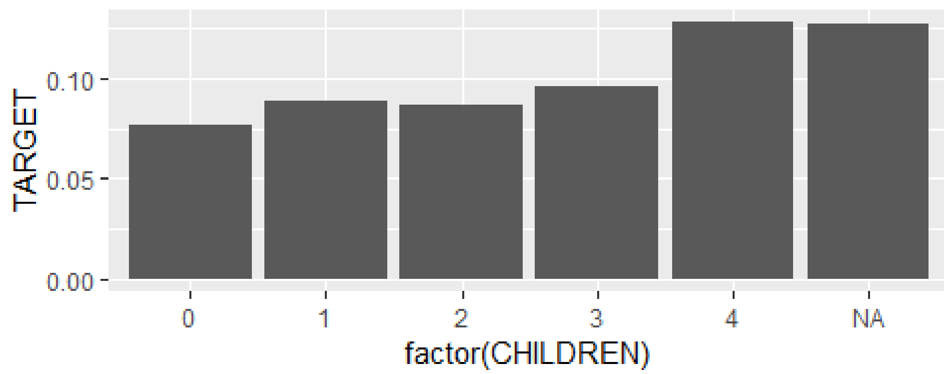




```
# A tibble: 2 x 2
  OWNS_REALTY      n
  <chr>        <int>
1 N            94199
2 Y           213312


Call:
glm(formula = TARGET ~ OWNS_REALTY, family = "binomial", data =
results_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4169  -0.4169  -0.4073  -0.4073   2.2497

Coefficients:
             Estimate Std. Error  z value Pr(>|z|)
(Intercept)  -2.39900    0.01179 -203.408  < 2e-16 ***
OWNS_REALTYY -0.04858    0.01425   -3.409 0.000651 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 172530  on 307509  degrees of freedom
AIC: 172534

Number of Fisher Scoring iterations: 5
```

Number of Children and Number of Children v. Target

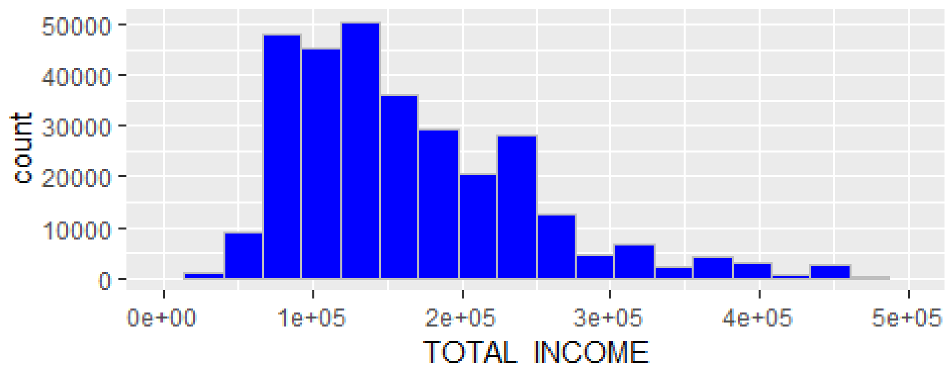


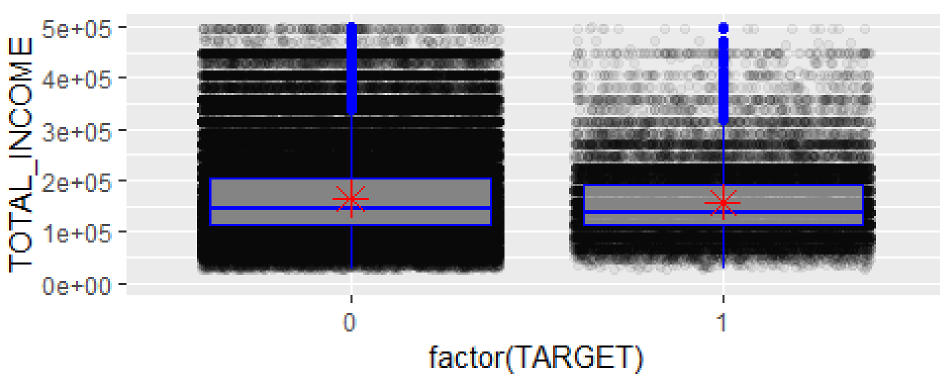



```
# A tibble: 6 x 2
  CHILDREN      n
     <int>  <int>
1        0 215371
2        1  61119
3        2  26749
4        3   3717
5        4    429
6       NA    126


Call:
glm(formula = TARGET ~ CHILDREN, family = "binomial", data = results_train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.4804  -0.4207  -0.4024  -0.4024   2.2602  

Coefficients:
             Estimate Std. Error z value Pr(>|z|)    
(Intercept) -2.473205   0.007764 -318.54   <2e-16 ***
CHILDREN     0.093030   0.008893   10.46   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172443  on 307384  degrees of freedom
Residual deviance: 172337  on 307383  degrees of freedom
  (126 observations deleted due to missingness)
AIC: 172341

Number of Fisher Scoring iterations: 5
```

Total Income and Total Income v. Target

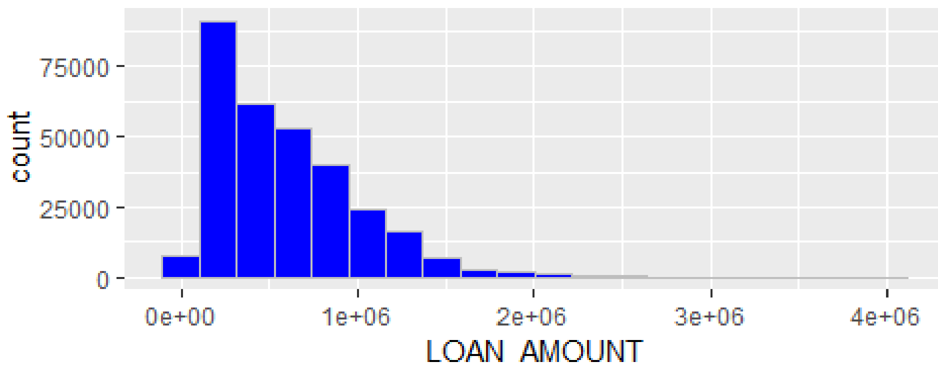


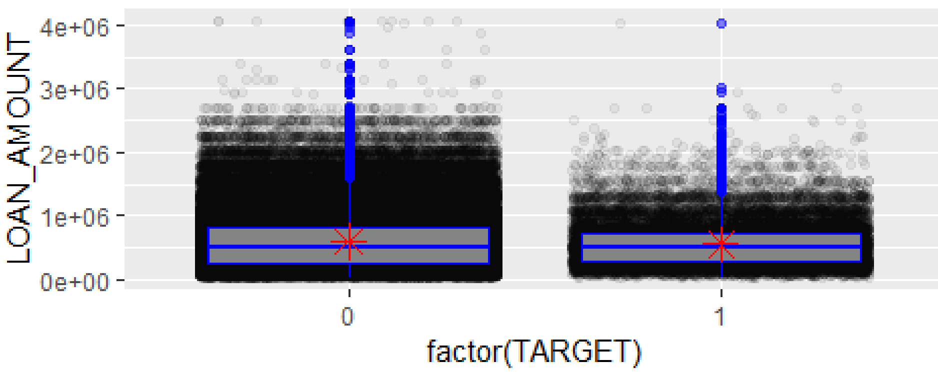



```
    Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
   25650    112500    147150    168798    202500 117000000


    Anderson-Darling normality test

data:  results_train$TOTAL_INCOME
A = 49822, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  TOTAL_INCOME by TARGET
```

```
W = 3643100000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

Amount of Loan and Amount of Loan v. Target

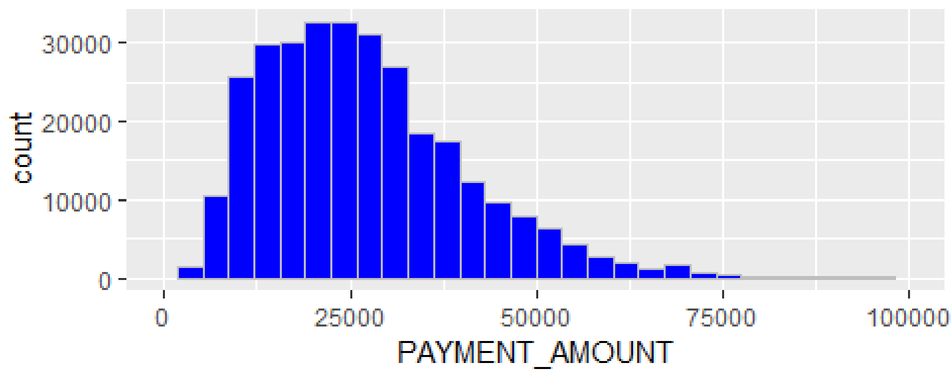


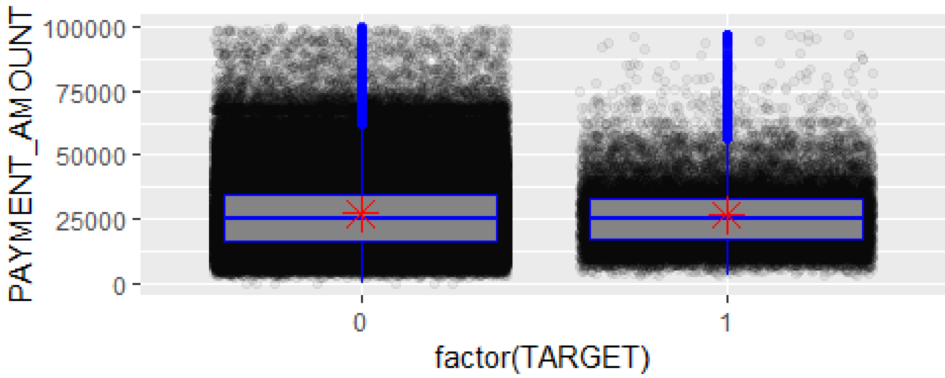



```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  45000  270000  513531  599026  808650 4050000 


    Anderson-Darling normality test

data:  results_train$LOAN_AMOUNT
A = 7249.4, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  LOAN_AMOUNT by TARGET
W = 3639200000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

Monthly Payment and Monthly Payment v. Target

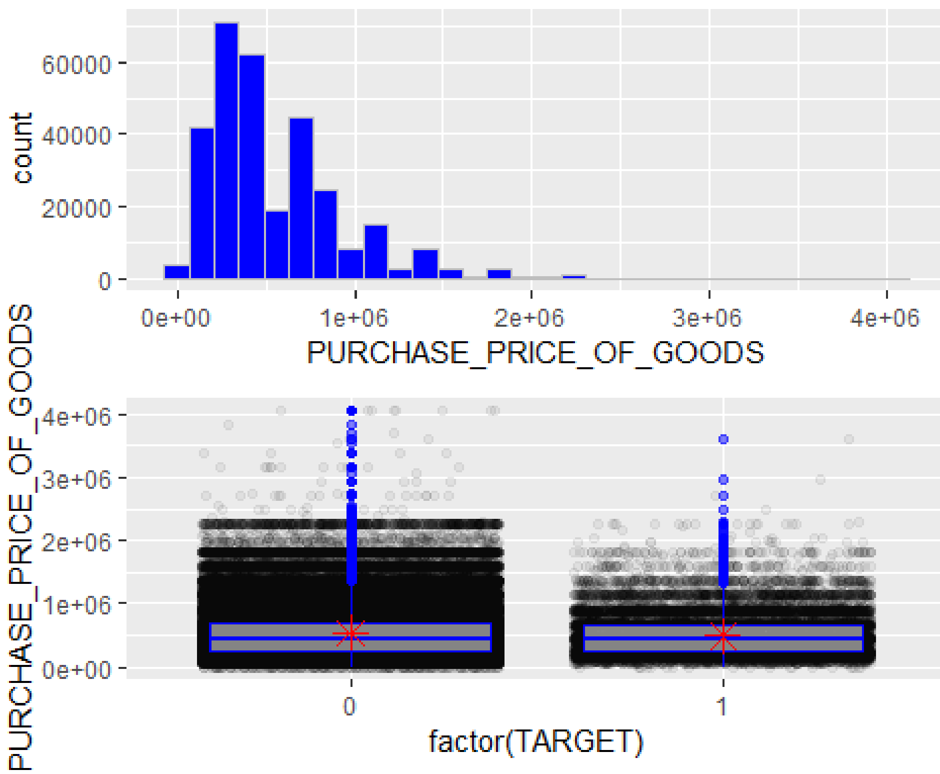
```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```






```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
      0   16524   24903   27108   34596  258026 


    Anderson-Darling normality test

data:  results_train$PAYMENT_AMOUNT
A = 4118.6, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  PAYMENT_AMOUNT by TARGET
W = 3509200000, p-value = 0.9764
alternative hypothesis: true location shift is not equal to 0
```

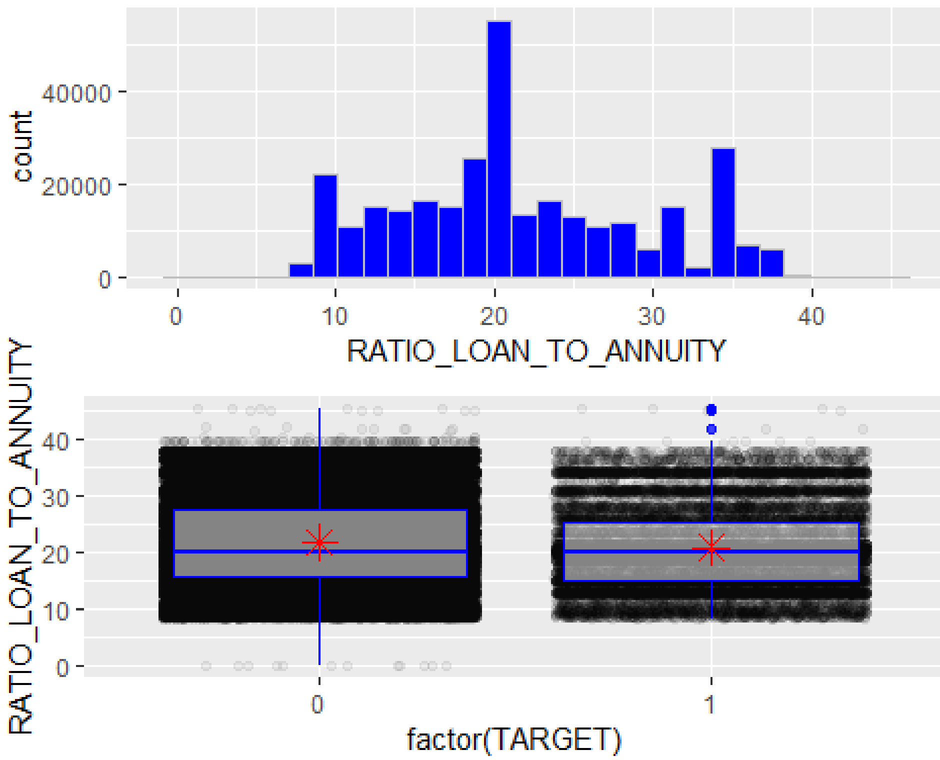
Price of Goods Purchased with the Loan and Price v. Target




```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
      0  238500  450000  537909  679500 4050000 


    Anderson-Darling normality test

data:  results_train$PURCHASE_PRICE_OF_GOODS
A = 8872.1, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  PURCHASE_PRICE_OF_GOODS by TARGET
W = 3742200000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

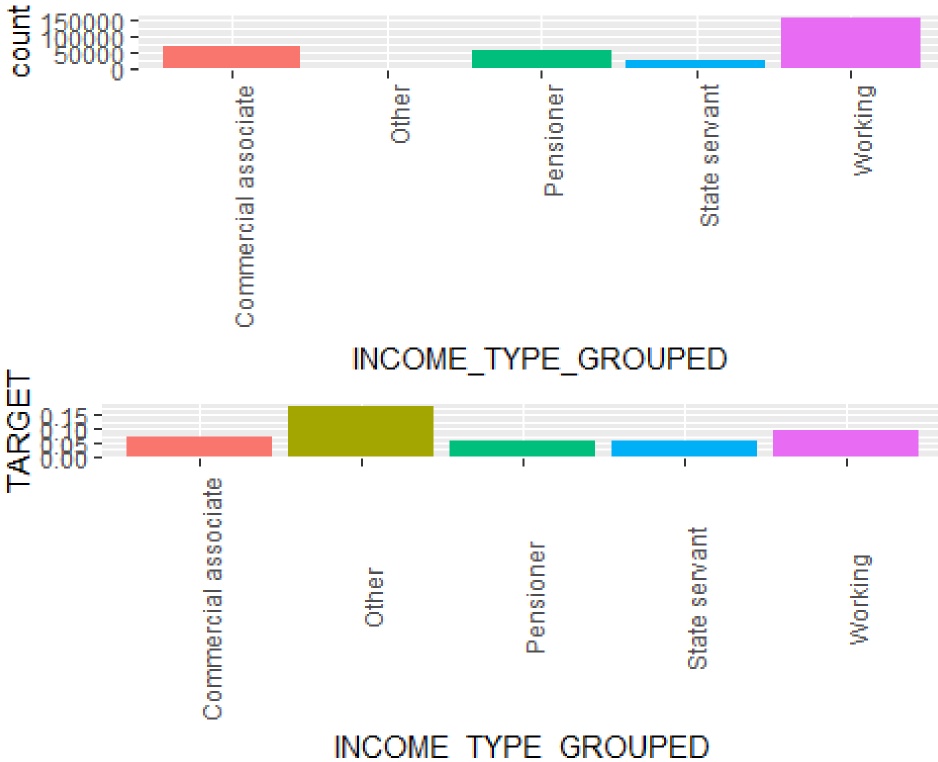
Ratio of Loan to Payment Amount and Ratio v. Target

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   0.00   15.61   20.00   21.61   27.10   45.31 


	Anderson-Darling normality test

data:  results_train$RATIO_LOAN_TO_ANNUITY
A = 3810.3, p-value < 2.2e-16


	Wilcoxon rank sum test with continuity correction

data:  RATIO_LOAN_TO_ANNUITY by TARGET
W = 3733600000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

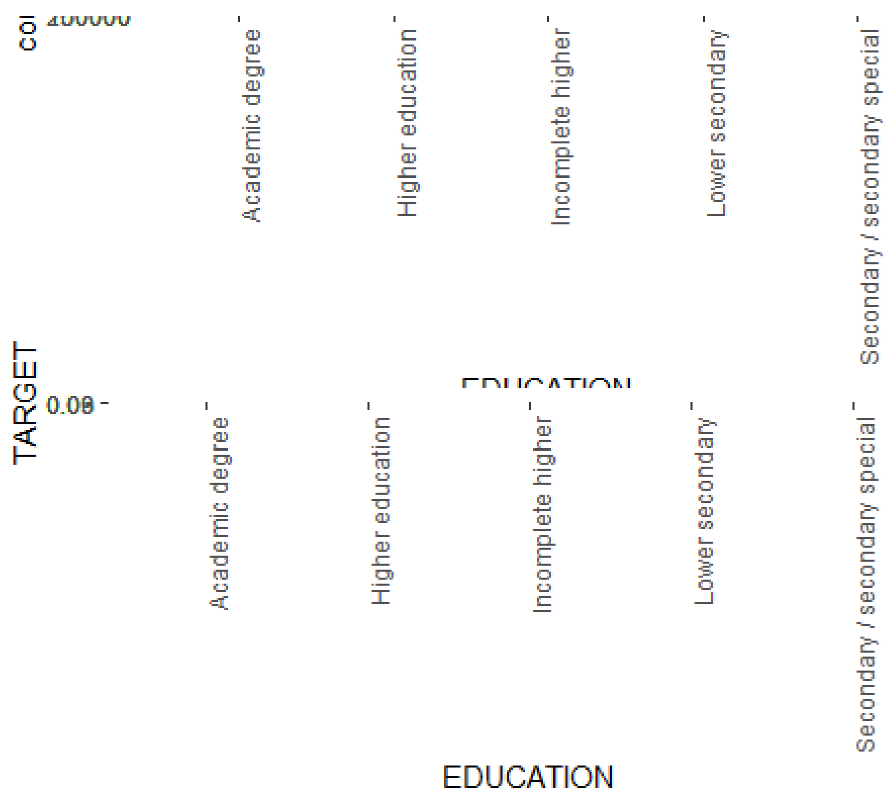
Type of Income and Type of Income v. Target




```
# A tibble: 5 x 2
  INCOME_TYPE_GROUPED       n
  <chr>                 <int>
1 Commercial associate  71617
2 Other                    55
3 Pensioner             55362
4 State servant         21703
5 Working              158774


Call:
glm(formula = TARGET ~ INCOME_TYPE_GROUPED, family = "binomial", 
    data = results_train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.6335  -0.4490  -0.3944  -0.3328   2.4171  

Coefficients:
                                 Estimate Std. Error  z value Pr(>|z|)    
(Intercept)                      -2.51458    0.01420 -177.074  < 2e-16 ***
INCOME_TYPE_GROUPEDOther          1.01050    0.34989    2.888  0.00388 ** 
INCOME_TYPE_GROUPEDPensioner     -0.35135    0.02358  -14.900  < 2e-16 ***
INCOME_TYPE_GROUPEDState servant -0.28126    0.03242   -8.675  < 2e-16 ***
```

```
INCOME_TYPE_GROUPEDWorking        0.27077    0.01656   16.348  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 171258  on 307506  degrees of freedom
AIC: 171268

Number of Fisher Scoring iterations: 5
```

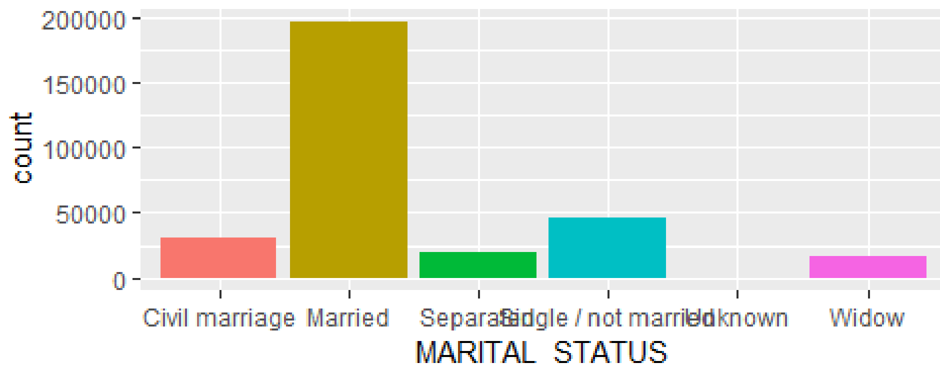
Education Level and Education Level v. Target

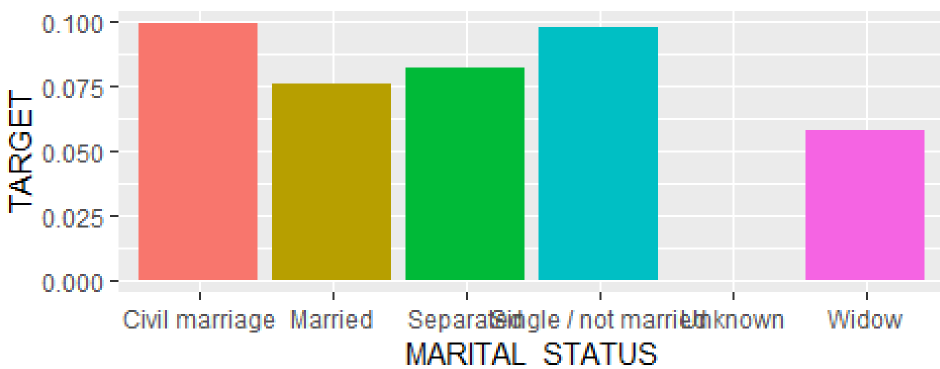



```
# A tibble: 5 x 2
  EDUCATION                          n
  <chr>                          <int>
1 Academic degree                  164
2 Higher education               74863
3 Incomplete higher              10277
4 Lower secondary                 3816
5 Secondary / secondary special 218391


Call:
glm(formula = TARGET ~ EDUCATION, family = "binomial", data = results_train)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4811  -0.4328  -0.4328  -0.3318   2.8288

Coefficients:
                                       Estimate Std. Error z value
(Intercept)                             -3.9826     0.5765  -6.908
EDUCATIONHigher education                1.1105     0.5767   1.925
EDUCATIONIncomplete higher               1.6043     0.5776   2.778
EDUCATIONLower secondary                 1.8844     0.5788   3.255
EDUCATIONSecondary / secondary special   1.6616     0.5766   2.882
                                       Pr(>|z|)
(Intercept)                            4.91e-12 ***
EDUCATIONHigher education               0.05417 .
EDUCATIONIncomplete higher              0.00548 **
EDUCATIONLower secondary                0.00113 **
EDUCATIONSecondary / secondary special  0.00395 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 171437  on 307506  degrees of freedom
AIC: 171447

Number of Fisher Scoring iterations: 5
```

Marital Status and Marital Status v. Target

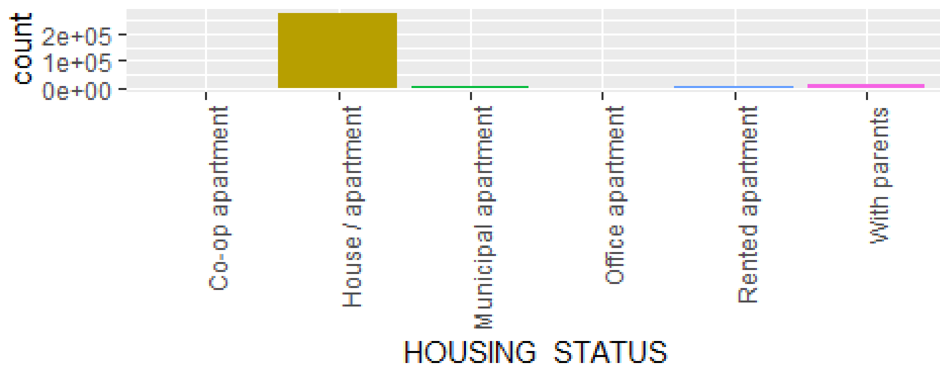


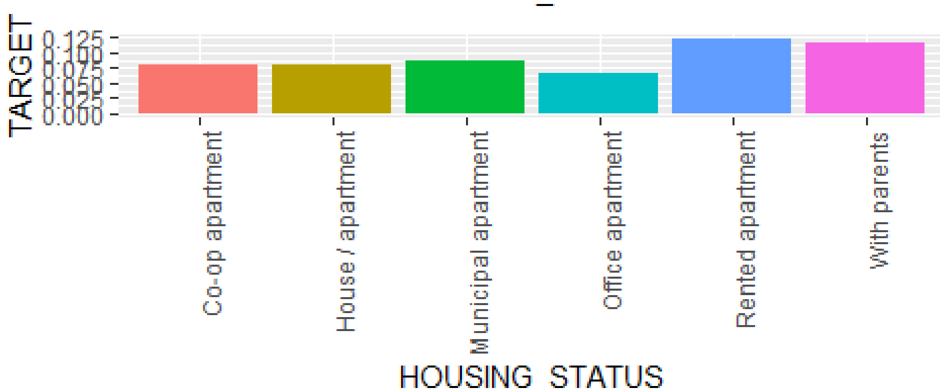



```
# A tibble: 6 x 2
  MARITAL_STATUS            n
  <chr>                 <int>
1 Civil marriage        29775
2 Married              196432
3 Separated             19770
4 Single / not married  45444
5 Unknown                   2
6 Widow                 16088


Call:
glm(formula = TARGET ~ MARITAL_STATUS, family = "binomial", data =
results_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4577  -0.4135  -0.3965  -0.3965   2.3846

Coefficients:
                                  Estimate Std. Error  z value Pr(>|z|)
(Intercept)                       -2.20340    0.01937 -113.780  < 2e-16
MARITAL_STATUSMarried             -0.30031    0.02116  -14.190  < 2e-16
MARITAL_STATUSSeparated           -0.21285    0.03236   -6.577 4.81e-11
```

```
MARITAL_STATUSSingle / not married -0.01538    0.02498   -0.616    0.538
MARITAL_STATUSUnknown              -6.36237   31.08014   -0.205    0.838
MARITAL_STATUSWidow                -0.57974    0.03884  -14.928  < 2e-16

(Intercept)                        ***
MARITAL_STATUSMarried              ***
MARITAL_STATUSSeparated            ***
MARITAL_STATUSSingle / not married
MARITAL_STATUSUnknown
MARITAL_STATUSWidow                ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 172045  on 307505  degrees of freedom
AIC: 172057

Number of Fisher Scoring iterations: 7
```

Housing Status and Housing Status v. Target

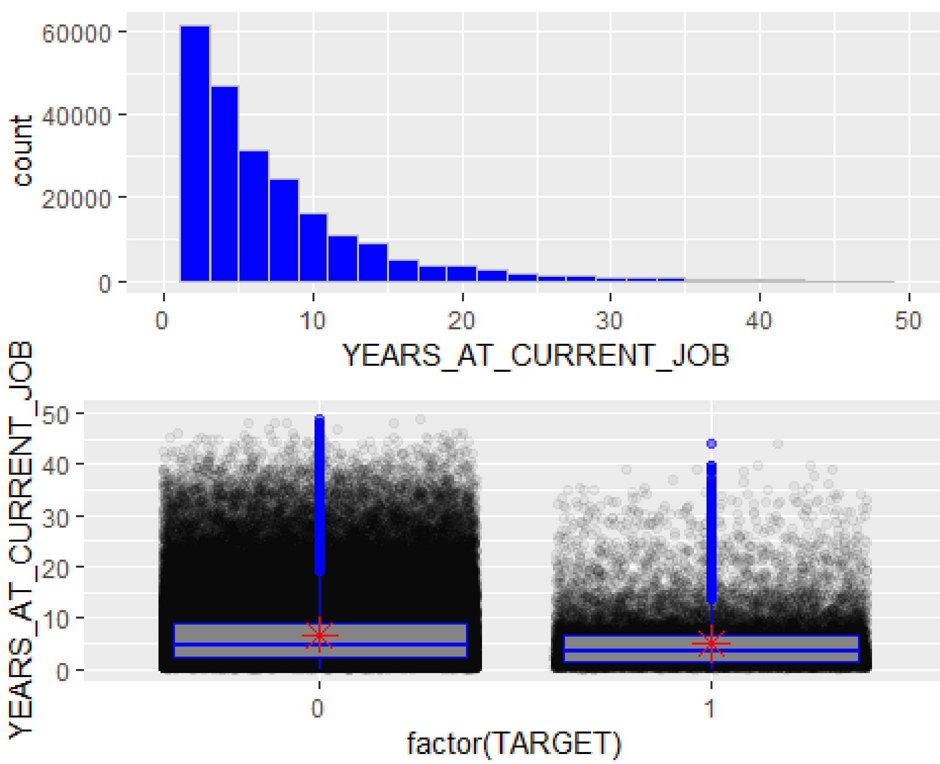





```
# A tibble: 6 x 2
  HOUSING_STATUS           n
  <chr>                <int>
1 Co-op apartment       1122
2 House / apartment   272868
3 Municipal apartment  11183
4 Office apartment      2617
5 Rented apartment      4881
6 With parents         14840


Call:
glm(formula = TARGET ~ HOUSING_STATUS, family = "binomial", data = 
results_train)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-0.5126  -0.4029  -0.4029  -0.4029   2.3334  

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)    
(Intercept)                       -2.45159    0.11047 -22.192  < 2e-16 ***
HOUSING_STATUSHouse / apartment   -0.01885    0.11070  -0.170 0.864815    
HOUSING_STATUSMunicipal apartment  0.08041    0.11554   0.696 0.486434    
```

```
HOUSING_STATUSOffice apartment    -0.20272    0.13575  -1.493 0.135338    
HOUSING_STATUSRented apartment     0.48847    0.11875   4.113  3.9e-05 ***
HOUSING_STATUSWith parents         0.43025    0.11339   3.795 0.000148 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 172165  on 307505  degrees of freedom
AIC: 172177

Number of Fisher Scoring iterations: 5
```

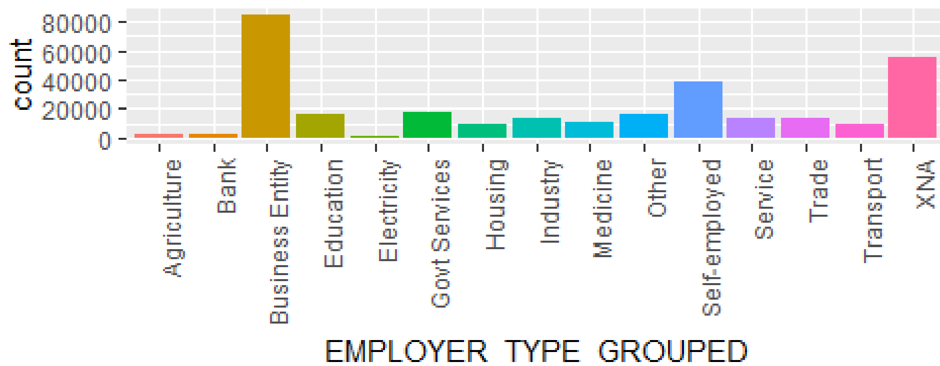
Years at Current Job and Years v. Target

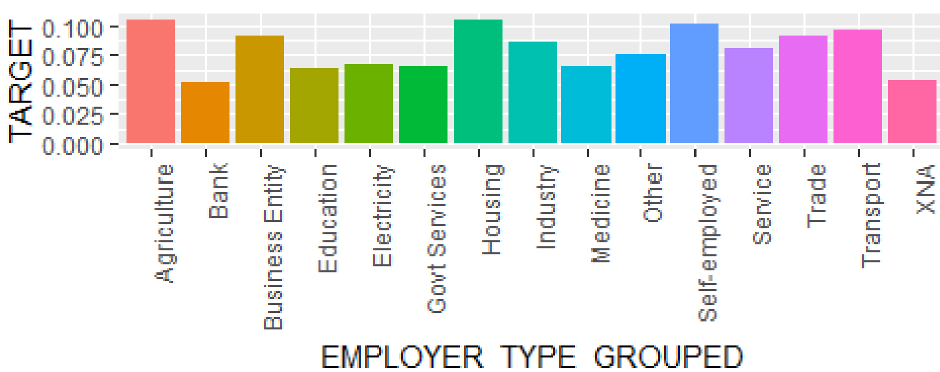



```
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
   0.000    2.554    6.075  185.420   15.625  999.981 


    Anderson-Darling normality test

data:  results_train$YEARS_AT_CURRENT_JOB
A = 82723, p-value < 2.2e-16
```

```
    Wilcoxon rank sum test with continuity correction

data:  YEARS_AT_CURRENT_JOB by TARGET
W = 4150800000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

Employer Organization Type and Type v. Target





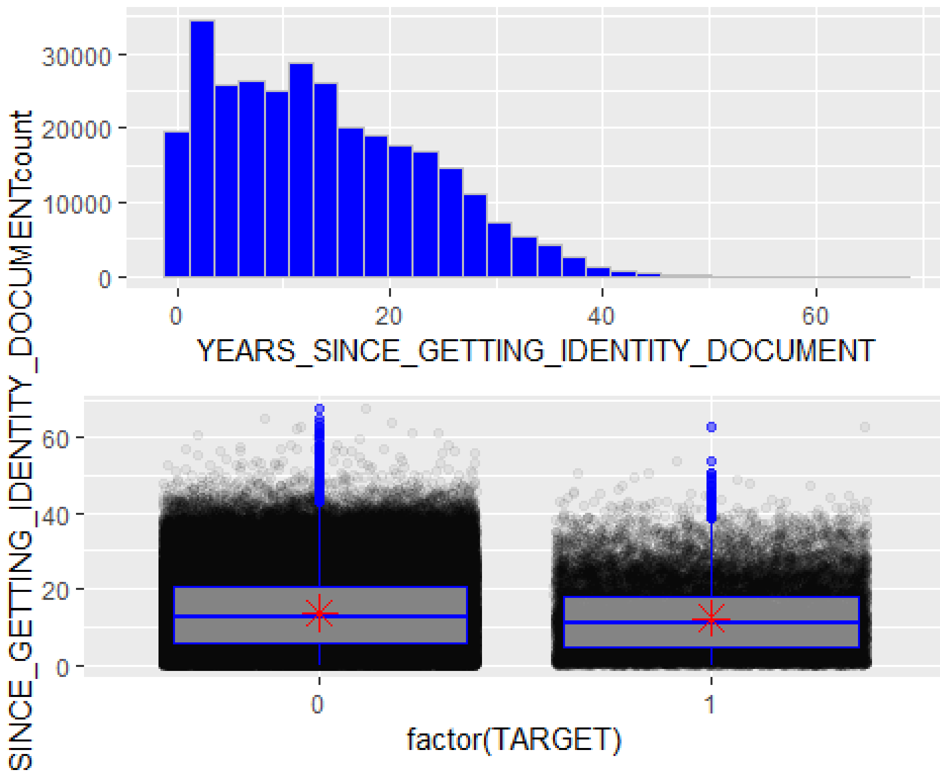

```
# A tibble: 15 x 2
   EMPLOYER_TYPE_GROUPED      n
   <chr>                  <int>
 1 Agriculture             2454
 2 Bank                    2507
 3 Business Entity        84529
 4 Education              17100
 5 Electricity              950
 6 Govt Services          17536
 7 Housing                 9679
 8 Industry               14311
 9 Medicine               11193
10 Other                  16683
11 Self-employed          38412
12 Service                13478
13 Trade                  14315
```

```
14 Transport              8990
15 XNA                   55374


Call:
glm(formula = TARGET ~ EMPLOYER_TYPE_GROUPED, family = "binomial",
    data = results_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4719  -0.4374  -0.4241  -0.3332   2.4328

Coefficients:
                                     Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -2.145772   0.065926 -32.548  < 2e-16
EMPLOYER_TYPE_GROUPEDBank           -0.760288   0.111618  -6.812 9.66e-12
EMPLOYER_TYPE_GROUPEDBusiness Entity -0.153162   0.067000  -2.286 0.022253
EMPLOYER_TYPE_GROUPEDEducation      -0.556057   0.073067  -7.610 2.74e-14
EMPLOYER_TYPE_GROUPEDElectricity    -0.498938   0.146104  -3.415 0.000638
EMPLOYER_TYPE_GROUPEDGovt Services  -0.501625   0.072590  -6.910 4.83e-12
EMPLOYER_TYPE_GROUPEDHousing         0.006975   0.073771   0.095 0.924668
EMPLOYER_TYPE_GROUPEDIndustry       -0.217486   0.072353  -3.006 0.002648
EMPLOYER_TYPE_GROUPEDMedicine       -0.506571   0.076149  -6.652 2.88e-11
EMPLOYER_TYPE_GROUPEDOther          -0.346169   0.072079  -4.803 1.57e-06
EMPLOYER_TYPE_GROUPEDSelf-employed  -0.032278   0.068052  -0.474 0.635281
EMPLOYER_TYPE_GROUPEDService        -0.273849   0.073043  -3.749 0.000177
EMPLOYER_TYPE_GROUPEDTrade          -0.158813   0.072062  -2.204 0.027535
EMPLOYER_TYPE_GROUPEDTransport      -0.089093   0.074967  -1.188 0.234664
EMPLOYER_TYPE_GROUPEDXNA            -0.717556   0.068555 -10.467  < 2e-16

(Intercept)                         ***
EMPLOYER_TYPE_GROUPEDBank           ***
EMPLOYER_TYPE_GROUPEDBusiness Entity *
EMPLOYER_TYPE_GROUPEDEducation      ***
EMPLOYER_TYPE_GROUPEDElectricity    ***
EMPLOYER_TYPE_GROUPEDGovt Services  ***
EMPLOYER_TYPE_GROUPEDHousing
EMPLOYER_TYPE_GROUPEDIndustry       **
EMPLOYER_TYPE_GROUPEDMedicine       ***
EMPLOYER_TYPE_GROUPEDOther          ***
EMPLOYER_TYPE_GROUPEDSelf-employed
EMPLOYER_TYPE_GROUPEDService        ***
EMPLOYER_TYPE_GROUPEDTrade          *
EMPLOYER_TYPE_GROUPEDTransport
EMPLOYER_TYPE_GROUPEDXNA            ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 171260  on 307496  degrees of freedom
AIC: 171290

Number of Fisher Scoring iterations: 5
```

Years Since Getting Current Identity Documnent and Years v. Target

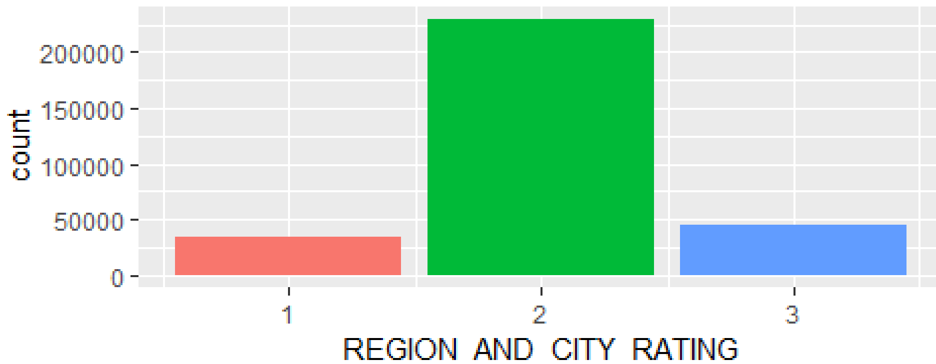
```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

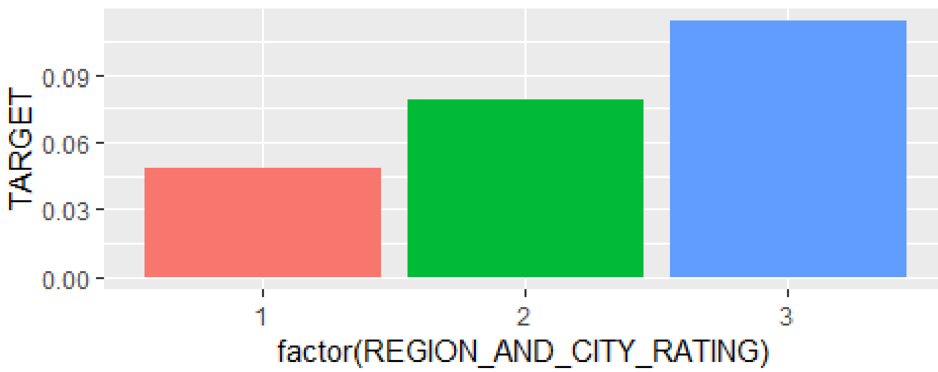



```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   5.503  12.331  13.651  20.478  67.548 


    Anderson-Darling normality test

data:  results_train$YEARS_SINCE_GETTING_IDENTITY_DOCUMENT
A = 3532.2, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  YEARS_SINCE_GETTING_IDENTITY_DOCUMENT by TARGET
W = 3807600000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

Rating of Region and Rating v. Target

The meaning of this variable is not reported in the materials made available by HOME CREDIT. It may relate to population density, per capita welath of the region, but this information is not supplied.

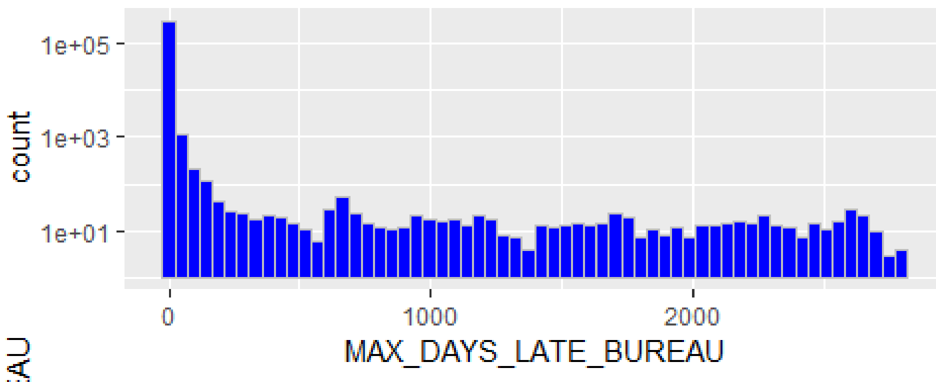


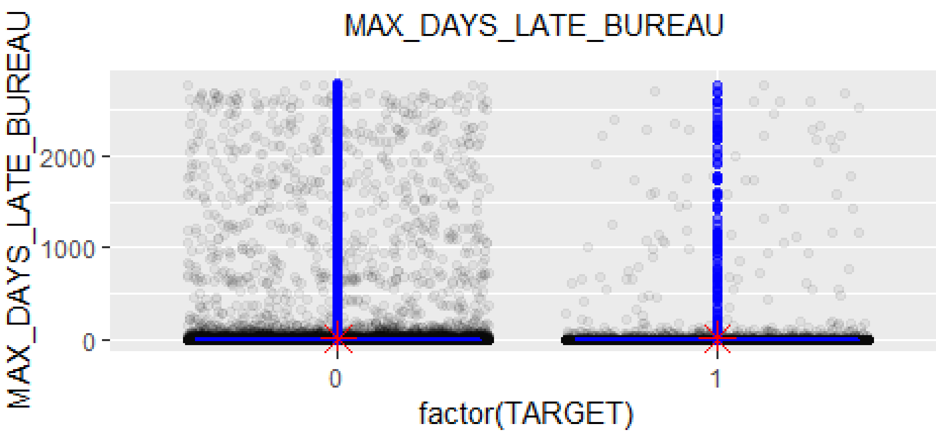



```
# A tibble: 3 x 2
  REGION_AND_CITY_RATING      n
                   <int>  <int>
1                      1  34167
2                      2 229484
3                      3  43860


Call:
glm(formula = TARGET ~ REGION_AND_CITY_RATING, family = "binomial",
    data = results_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.4979  -0.4035  -0.4035  -0.4035   2.4340

Coefficients:
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)            -3.35108    0.02859 -117.20   <2e-16 ***
REGION_AND_CITY_RATING  0.44198    0.01309   33.77   <2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 172542  on 307510  degrees of freedom
Residual deviance: 171406  on 307509  degrees of freedom
AIC: 171410

Number of Fisher Scoring iterations: 5
```

Maximum dates late payment as reprted to HOME CREDIT by and outside credit bureau






```
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's
   0.000    0.000    0.000    4.086    0.000 2792.000        1


    Anderson-Darling normality test

data:  results_train$MAX_DAYS_LATE_BUREAU
A = 116840, p-value < 2.2e-16


    Wilcoxon rank sum test with continuity correction

data:  MAX_DAYS_LATE_BUREAU by TARGET
```

```
W = 3468100000, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
```

Findings and Recommendations

The Area Under ROC Curve was used as the primary statistic for evaluating model performance. The most successful model was the Random Forest model, trained on 80% of the data, with an AUC score of 0.7297.

The following table summarizes the overall performance of the different models.

Pct of train data used and model type	Training time in seconds	Sensitivity: TP/(TP+FN)	Accuracy: (TP+TN)/N	AUC Score	Specificity: (TN/N)	Precision: TP/(TP+FP)	Comment
100% GLM	51.71	0.6402820	0.6677669	0.7110466	0.9549854	0.1456520	Downsampled training set
100% Naive Bayes	2304.37	0.5268882	0.2640890	0.7110466	0.8529577	0.0574604	Downsampled training set
100% KNN	15074.17	0.3822759	0.3465741	0.6844597	0.8635919	0.0486442	Downsampled training set
5% Random Forest	665.32	0.6580060	0.6561087	0.7108947	0.9562179	0.1438003	Downsampled training set
10% Random Forest	1554.28	0.6374622	0.6721245	0.7139183	0.9549685	0.1470042	Downsampled training set
20% Random Forest	3440.52	0.6501511	0.6765146	0.7220000	0.9567006	0.1509399	Downsampled training set
30% Random Forest	5852.06	0.6539778	0.6761569	0.7268011	0.9571100	0.1514035	Downsampled training set
60% Random Forest	17222.51	0.6547835	0.6782381	0.7285197	0.9573377	0.1524430	Downsampled training set
80% Random Forest	65159.25	0.6521652	0.6829534	0.7297375	0.9573496	0.1541171	Downsampled training set

Specific Statistics for Each Model with AUC Graphs

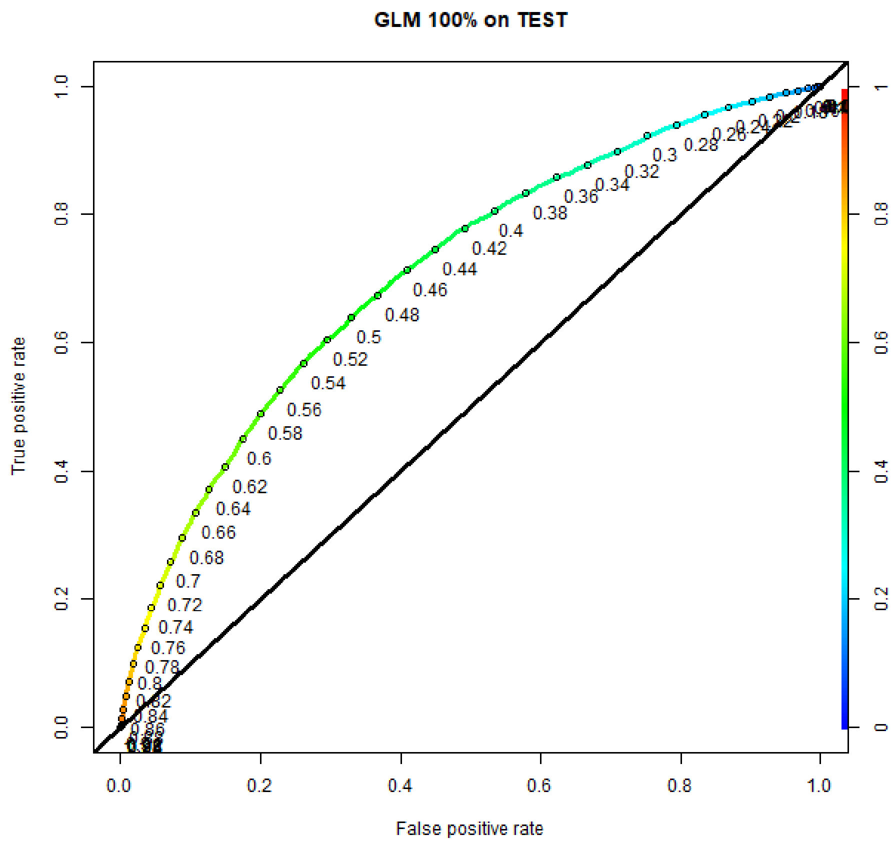
More detiled statistical analysis for the performance of each model is given below, accompanied by a graphs deonstrating the AUC performance of each mode. Again, overall, the Random Forest model trained on 80% of the data perfored best overall. It's overall Accuracy, measured as True Positives + True Negatives / Total Negatives was the highest, at 0.6829. Its Specificity (TN/N) was also highest overall at 0.9573. Its Precision (TP/TP+FP) 0.1541 was also the highest of the model tested here.

The specifics for the performance of each model follow:

Using a Generalized Linear Model

Trained on 100% of the train data

Area under ROC Curve = 0.7110466



Confusion Matrix

```
##            Predicted 1 Predicted 0
## Actual 1          3179        1786
## Actual 0         18647       37890
```

Sensitivity: TP/(TP+FN) = 0.640282

Specificity: TN/N = 0.6701806

Precision: TP/(TP+FP) = 0.145652

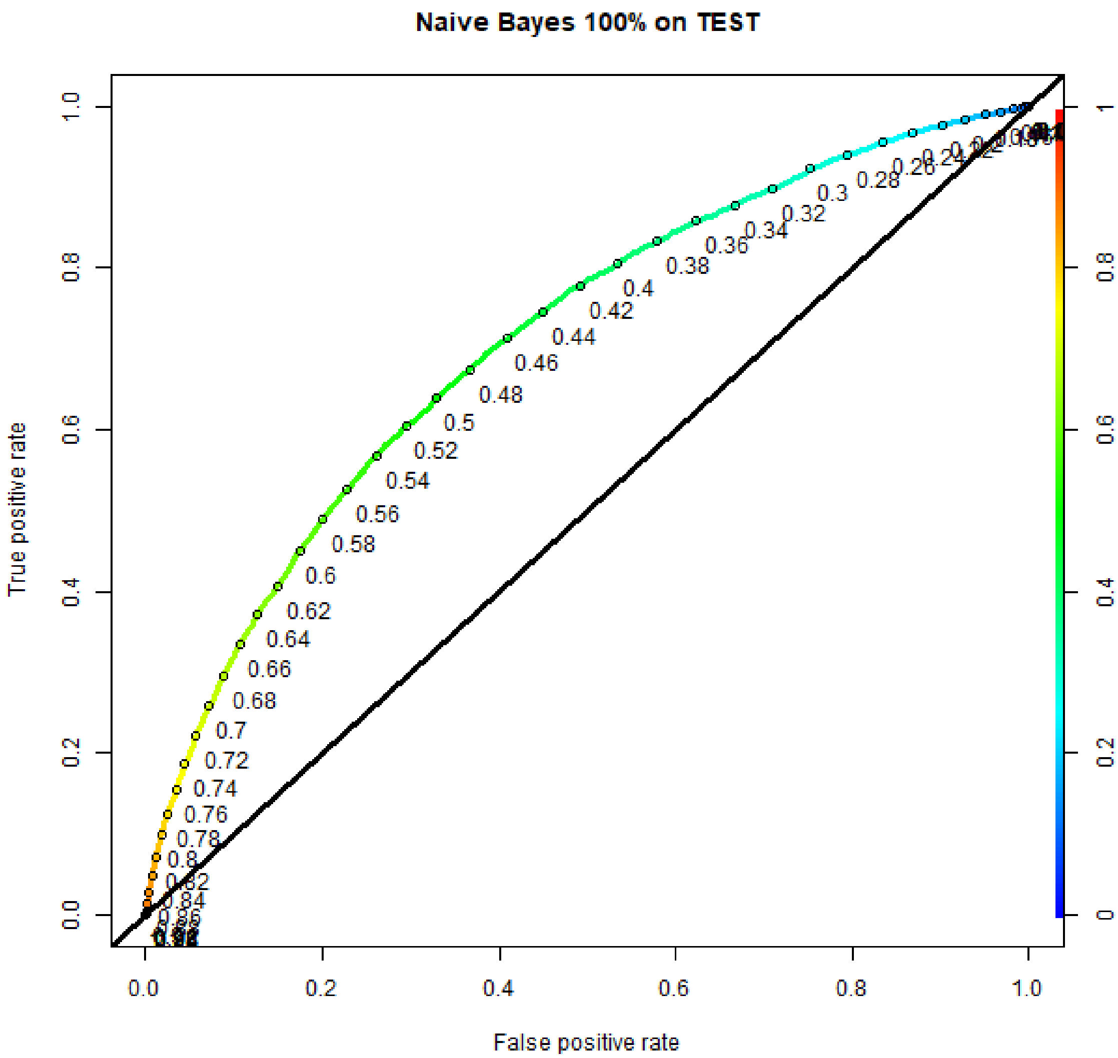
Accuracy = 3179.6160775

AUC Score = 0.7110466

Using a Naive Bayes Model

Trained on 100% of the train data

Area under ROC Curve = 0.7110466



Confusion Matrix

```
##             Predicted 1 Predicted 0
## Actual 1          2616        2349
## Actual 0         42911       13626
```

Sensitivity: TP/(TP+FN) = 0.5268882

Specificity: TN/N = 0.2410103

Precision: TP/(TP+FP) = 0.0574604

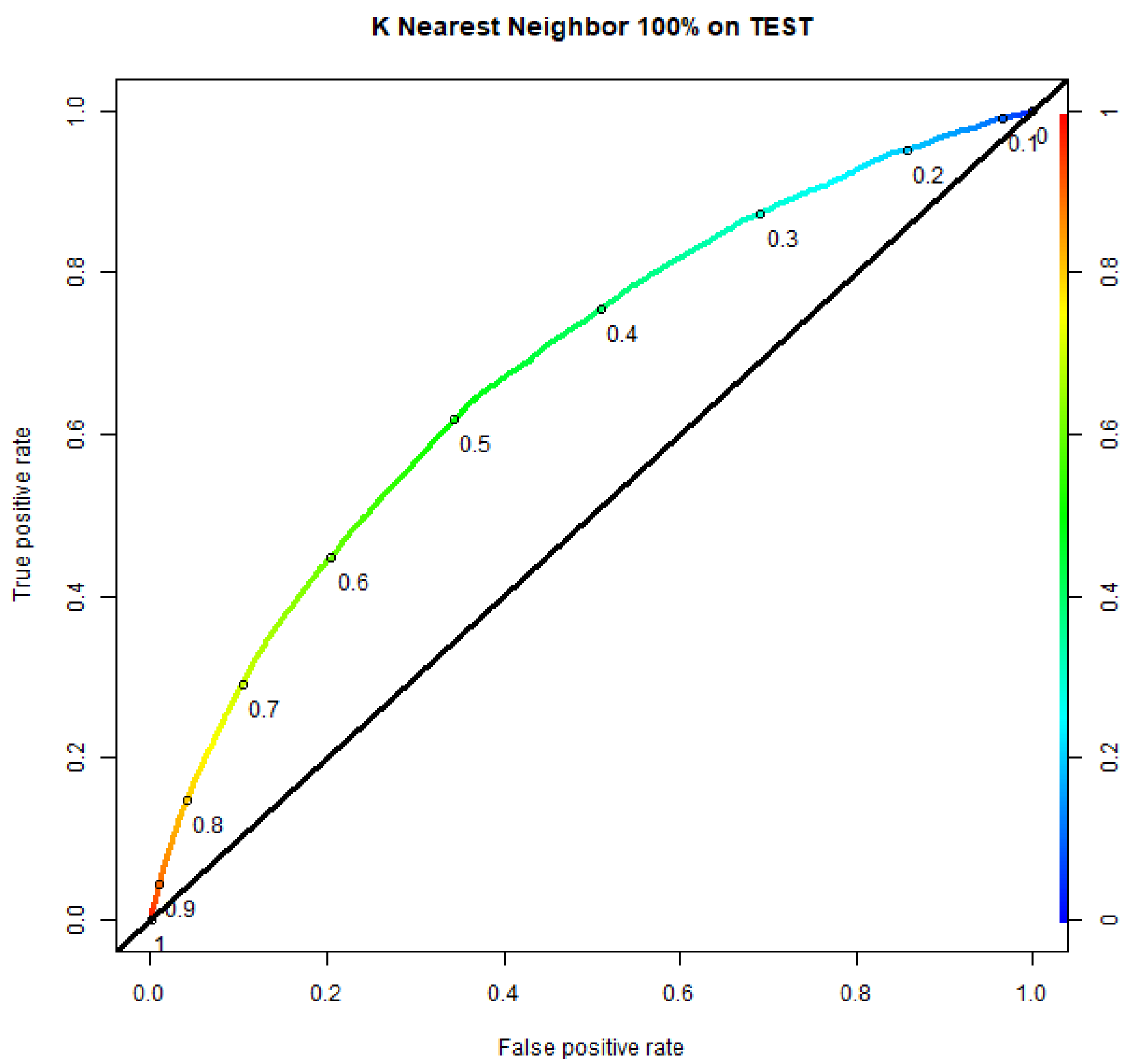
Accuracy = 2616.2215538

AUC Score = 0.7110466

Using a K Nearest Neighbor Model

Trained on 100% of the train data

Area under ROC Curve = 0.6844597



Confusion Matrix

```
##            Predicted 1 Predicted 0
## Actual 1         1898        3067
## Actual 0        37120       19417
```

Sensitivity: TP/(TP+FN) = 0.3822759

Specificity: TN/N = 0.3434388

Precision: TP/(TP+FP) = 0.0486442

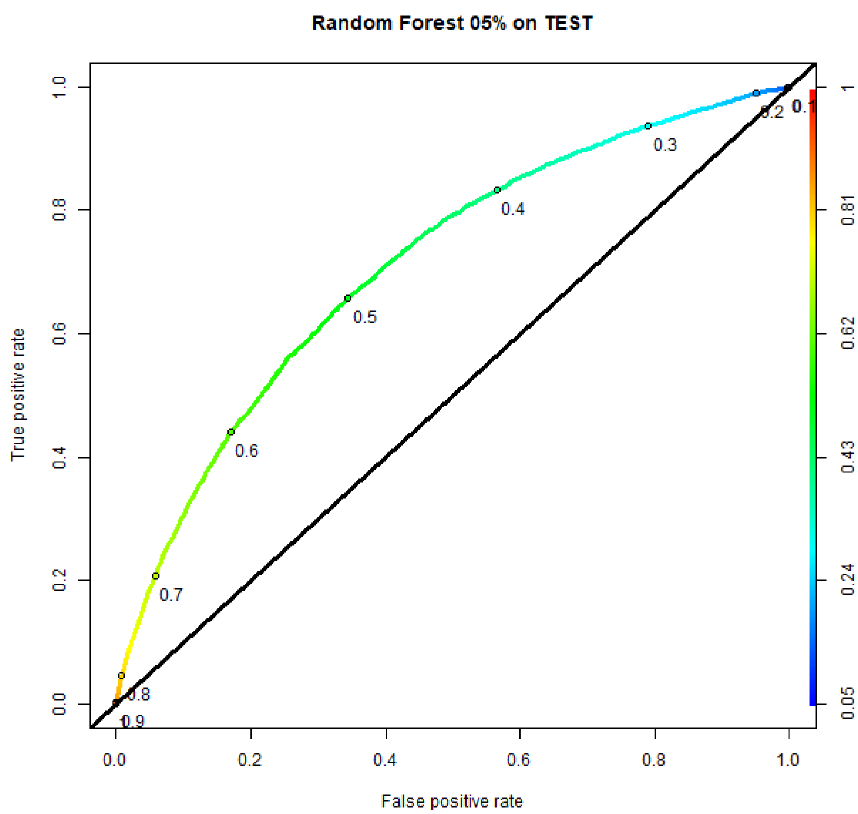
Accuracy = 1898.3157133

AUC Score = 0.6844597

Using a Random Forest Model

Trained on 5% of the train data

Area under ROC Curve = 0.7108947



Confusion Matrix

```
##           Predicted 1 Predicted 0
## Actual 1         3267        1698
## Actual 0        19452       37085
```

Sensitivity: TP/(TP+FN) = 0.658006

Specificity: TN/N = 0.6559421

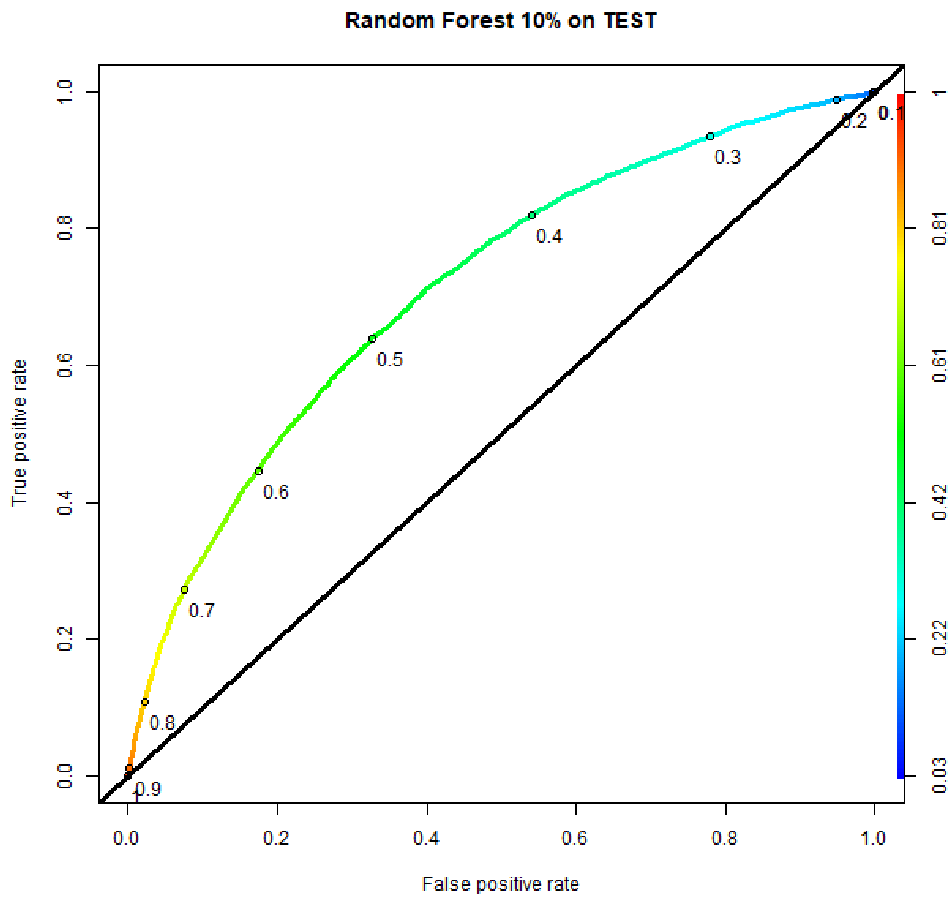
Precision: TP/(TP+FP) = 0.1438003

Accuracy = 3267.6029885

AUC Score = 0.7108947

Trained on 10% of the train data

Area under ROC Curve = 0.7139183



Confusion Matrix

```
##            Predicted 1 Predicted 0
## Actual 1          3165        1800
## Actual 0         18365       38172
```

Sensitivity: TP/(TP+FN) = 0.6374622

Specificity: TN/N = 0.6751685

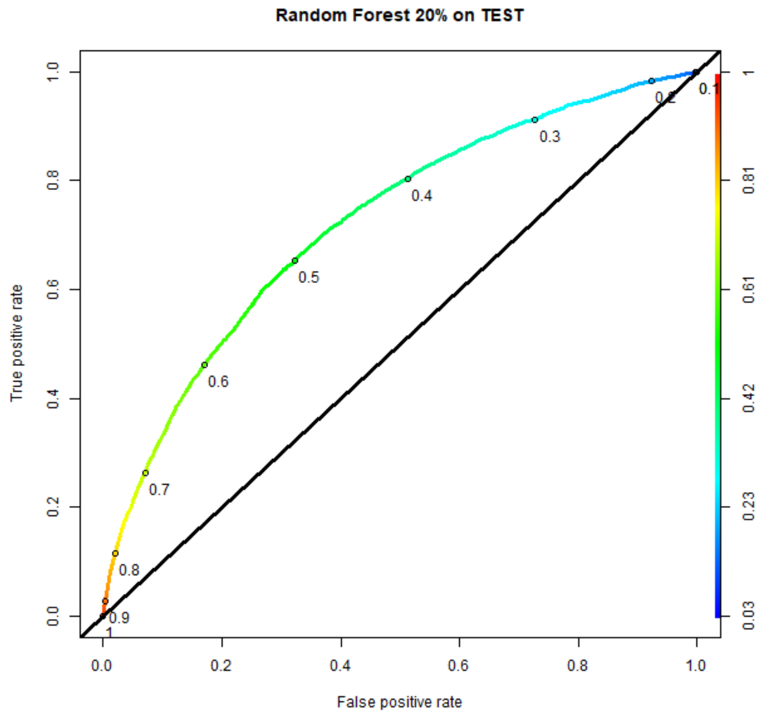
Precision: TP/(TP+FP) = 0.1470042

Accuracy = 3165.6206627

AUC Score = 0.7139183

Trained on 20% of the train data

Area under ROC Curve = 0.722



Confusion Matrix

```
##           Predicted 1 Predicted 0
## Actual 1         3228        1737
## Actual 0        18158       38379
```

Sensitivity: TP/(TP+FN) = 0.6501511

Specificity: TN/N = 0.6788298

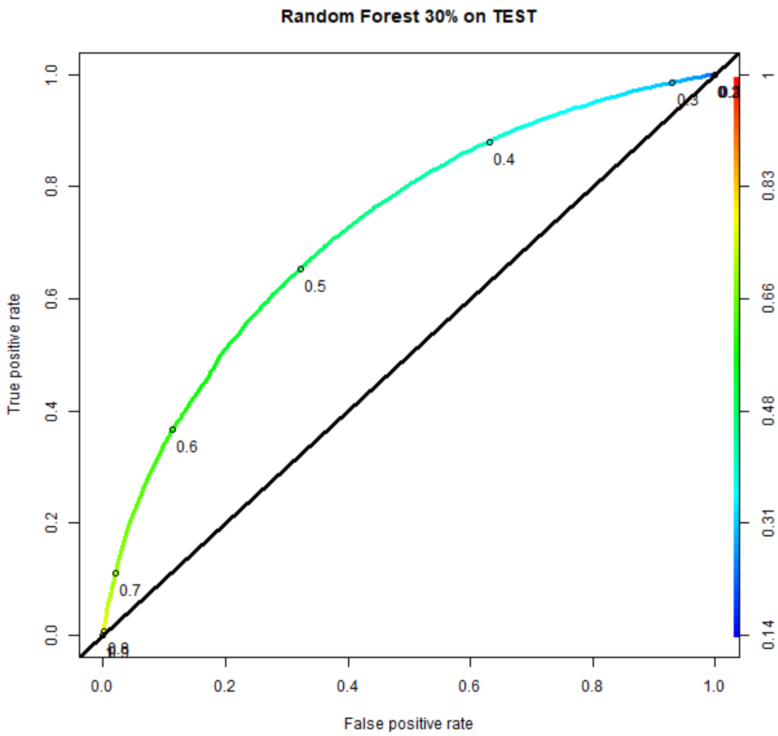
Precision: TP/(TP+FP) = 0.1509399

Accuracy = 3228.6240285

AUC Score = 0.722

Trained on 30% of the train data

Area under ROC Curve = 0.7268011



Confusion Matrix

```
##            Predicted 1 Predicted 0
## Actual 1         3247        1718
## Actual 0        18199       38338
```

Sensitivity: TP/(TP+FN) = 0.6539778

Specificity: TN/N = 0.6781046

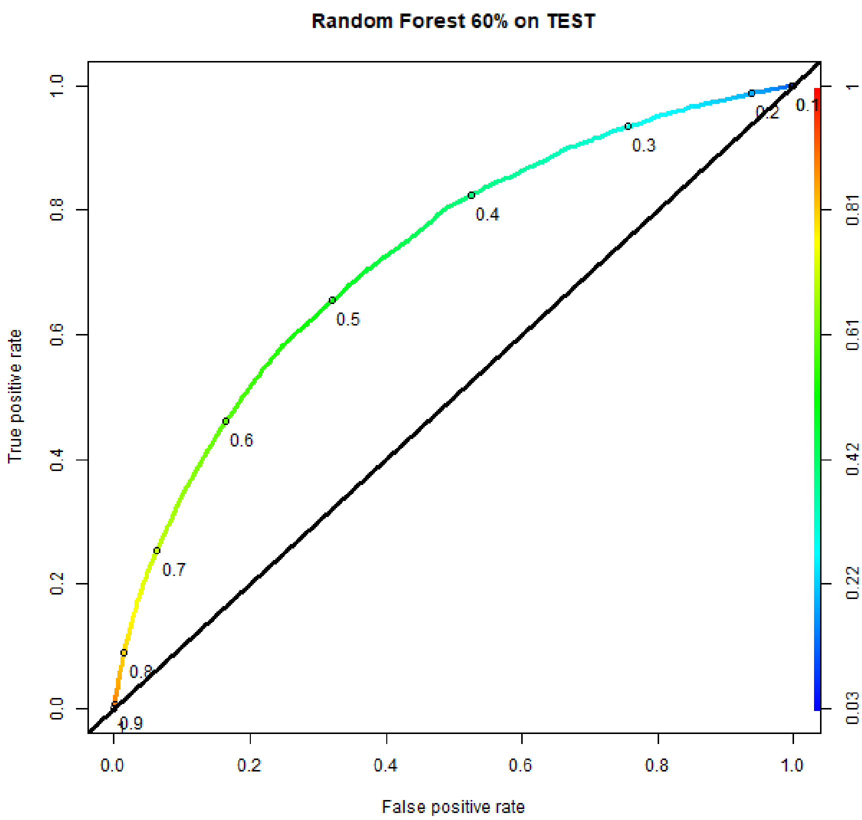
Precision: TP/(TP+FP) = 0.1514035

Accuracy = 3247.6233618

AUC Score = 0.7268011

Trained on 60% of the train data

Area under ROC Curve = 0.7285197



Confusion Matrix

```
##          Predicted 1 Predicted 0
## Actual 1        3251        1714
## Actual 0       18075       38462
```

Sensitivity: TP/(TP+FN) = 0.6547835

Specificity: TN/N = 0.6802979

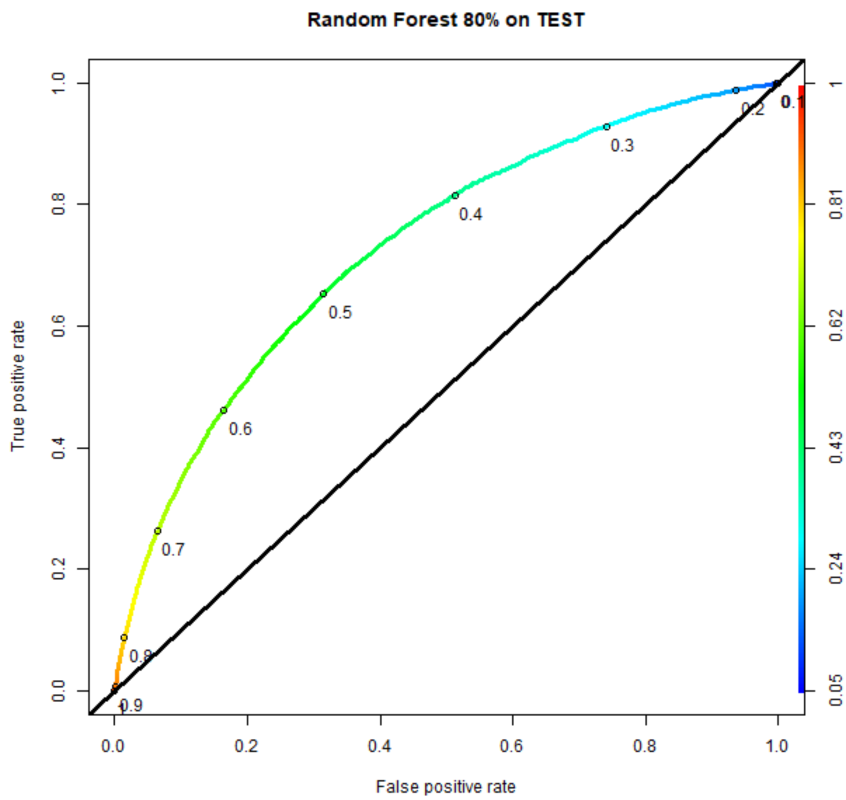
Precision: TP/(TP+FP) = 0.152443

Accuracy = 3251.625378

AUC Score = 0.7285197

Trained on 80% of the train data

Area under ROC Curve = 0.7297375



Confusion Matrix

```
##            Predicted 1 Predicted 0
## Actual 1          3238        1727
## Actual 0         17772       38765
```

Sensitivity: TP/(TP+FN) = 0.6521652

Specificity: TN/N = 0.6856572

Precision: TP/(TP+FP) = 0.1541171

Accuracy = 3238.6303047

AUC Score = 0.7297375

Conclusion and Suggestions

As one might anticipate, accurately predicting the liklihood of a client defaulting or struggling to repay debt is challenging. Changing life circumstanes, changing environmental or politcal conditions can significantly alter overall outcomes.

Area Under a ROC Curve is a useful measurement of a model's performance vs. random selection however. Given that random selection would typically yield an AUC score of .5, the Random Forest model trained on 80% of the data is a significan improvement upon this. With a AUC score of 0.7297 this model would be best used in combination with Home Credit's current decision processes to decrease risk and maximize profits.