Assignment: 10.3 Final Project Step 3

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Introduction.

Credit score cards are a common risk control method in the financial industry.

It uses personal information and data submitted by credit card applicants to predict the probability of future defaults and credit card borrowings.

The bank is able to decide whether to issue a credit card to the applicant. Credit scores can objectively quantify the magnitude of risk.

I want to perform EDA on the top of credit card application data

split out the data and try to found the correlation , dependent variables, independent variables

outliers and biased for the given data set. this will help me researches on the best variables which the credit

card company give more importance while issuing new card to new card member

The problem statement you addressed.

1) usually credit card companies are considering the historical credit report to analysis new card applicant financial strength

under this research i would like to find other variables like house, kids , family , education infromation of applicant

will add more weight in the favour of an applicant.

2) as usual credit card companies mostly checking the credit scores for last 6 month to decide the applicant , under this

research i am predecting instead of verifying hostory credit trails, is it better to consider the current credit liabilites of applicant

How you addressed this problem statement

1) Data used

https://www.kaggle.com/rikdifos/credit-card-approval-prediction?select=credit_record.csv

https://www.kaggle.com/rikdifos/credit-card-approval-prediction?select=application_record.csv

2) my approach is focused on below lsited three points

1 Getting a better understanding of data

2 Identifying various data patterns

3 Getting a better understanding of the problem statement

3) Performed below steps to address above points

1) Checked the Introductory Details About Data variables

2) Descriping data – Data Profiling

3) Data cleaning steps

4) Checking Duplicates

5) Data Visualization – By using plots

6) Multi-Variate analysis Various Plots

7) Analyse the regression and plots outcomes and find out the dependent and multiple independent varibales

8) which is going to help me in identifying the closes fit independent variable

9) create the trainging & test data models and find out the accuracy of applicant based on recent credit rating type

```
library(ggplot2)
theme_set(theme_minimal())
library(readxl)
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
```

```
## v tibble  3.1.2     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.1
## v purrr   0.3.4
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(dplyr)
library(QuantPsyc)
```

```
## Loading required package: boot
```

```
## Loading required package: MASS
```

```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
##
##     select
```

```
##
## Attaching package: 'QuantPsyc'
```

```
## The following object is masked from 'package:base':
##
##     norm
```

```
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'
```

```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
library(car)
```

```
## Loading required package: carData
```

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:boot':
##
##     logit
```

```
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
## The following object is masked from 'package:purrr':
##
##     some
```

```
library(PerformanceAnalytics)
```

```
## Loading required package: xts
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
##
## Attaching package: 'xts'
```

```
## The following objects are masked from 'package:dplyr':
##
##     first, last
```

```
##
## Attaching package: 'PerformanceAnalytics'
```

```
## The following object is masked from 'package:graphics':
##
##     legend
```

```
library(GGally)
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

Analyse the correlation among variables

merge application and credit report for current month

perform EDA by using R programming

What types of plots and tables will help you to illustrate the findings to your questions?

import and clean my data

```
### Set the working directory to the root of your DSC 520 directory
setwd("D:/MS_DataScience/DSC 520-Datastatiics.pdf/dsc520")
### Load card data `data/credit_record.csv` to DF
credit_df <- read.csv("data/credit_record.csv")
### Cleaning records, by filtering out old records and keep current credit record
credit_val <- filter(credit_df, MONTHS_BALANCE==0)
head(credit_val)
```

```
##        ID MONTHS_BALANCE STATUS
## 1 5001711              0      X
## 2 5001712              0      C
## 3 5001713              0      X
## 4 5001714              0      X
## 5 5001715              0      X
```

```
## 6 5001717              0      C
```

```
### Load credit card application data `data/application_record.csv` to DF
appl_df <- read.csv("data/application_record.csv")
### Join the credit data with application data and find out current credit status
card_df <- merge(x = appl_df, y = credit_val, by = "ID", all.x = TRUE)
head(card_df)
```

```
##        ID CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY CNT_CHILDREN
## 1 5008804           M            Y               Y            0
## 2 5008805           M            Y               Y            0
## 3 5008806           M            Y               Y            0
## 4 5008808           F            N               Y            0
## 5 5008809           F            N               Y            0
## 6 5008810           F            N               Y            0
##   AMT_INCOME_TOTAL     NAME_INCOME_TYPE            NAME_EDUCATION_TYPE
## 1           427500              Working               Higher education
## 2           427500              Working               Higher education
## 3           112500              Working Secondary / secondary special
## 4           270000 Commercial associate Secondary / secondary special
## 5           270000 Commercial associate Secondary / secondary special
## 6           270000 Commercial associate Secondary / secondary special
##     NAME_FAMILY_STATUS NAME_HOUSING_TYPE DAYS_BIRTH DAYS_EMPLOYED FLAG_MOBIL
## 1       Civil marriage  Rented apartment     -12005         -4542          1
## 2       Civil marriage  Rented apartment     -12005         -4542          1
## 3              Married House / apartment     -21474         -1134          1
## 4 Single / not married House / apartment     -19110         -3051          1
## 5 Single / not married House / apartment     -19110         -3051          1
## 6 Single / not married House / apartment     -19110         -3051          1
##   FLAG_WORK_PHONE FLAG_PHONE FLAG_EMAIL OCCUPATION_TYPE CNT_FAM_MEMBERS
## 1               1          0          0                              2
## 2               1          0          0                              2
## 3               0          0          0  Security staff              2
## 4               0          1          1     Sales staff              1
## 5               0          1          1     Sales staff              1
## 6               0          1          1     Sales staff              1
##   MONTHS_BALANCE STATUS
## 1              0      C
## 2              0      C
## 3              0      C
## 4              0      0
## 5             NA   <NA>
## 6              0      C
```

```
### fixing missing value,defaulting the missed month balance & status as 0
card_df$MONTHS_BALANCE <- factor(ifelse( is.na(card_df$MONTHS_BALANCE), 0, card_df$MONTHS_BALANCE))
card_df$STATUS <- factor(ifelse( is.na(card_df$STATUS), 0, card_df$STATUS))
### factoring variables
card_df$CODE_GENDER <- factor(card_df$CODE_GENDER)
card_df$FLAG_OWN_CAR <- factor(card_df$FLAG_OWN_CAR)
card_df$FLAG_OWN_REALTY <- factor(card_df$FLAG_OWN_REALTY)
card_df$NAME_EDUCATION_TYPE <- factor(card_df$NAME_EDUCATION_TYPE)
```

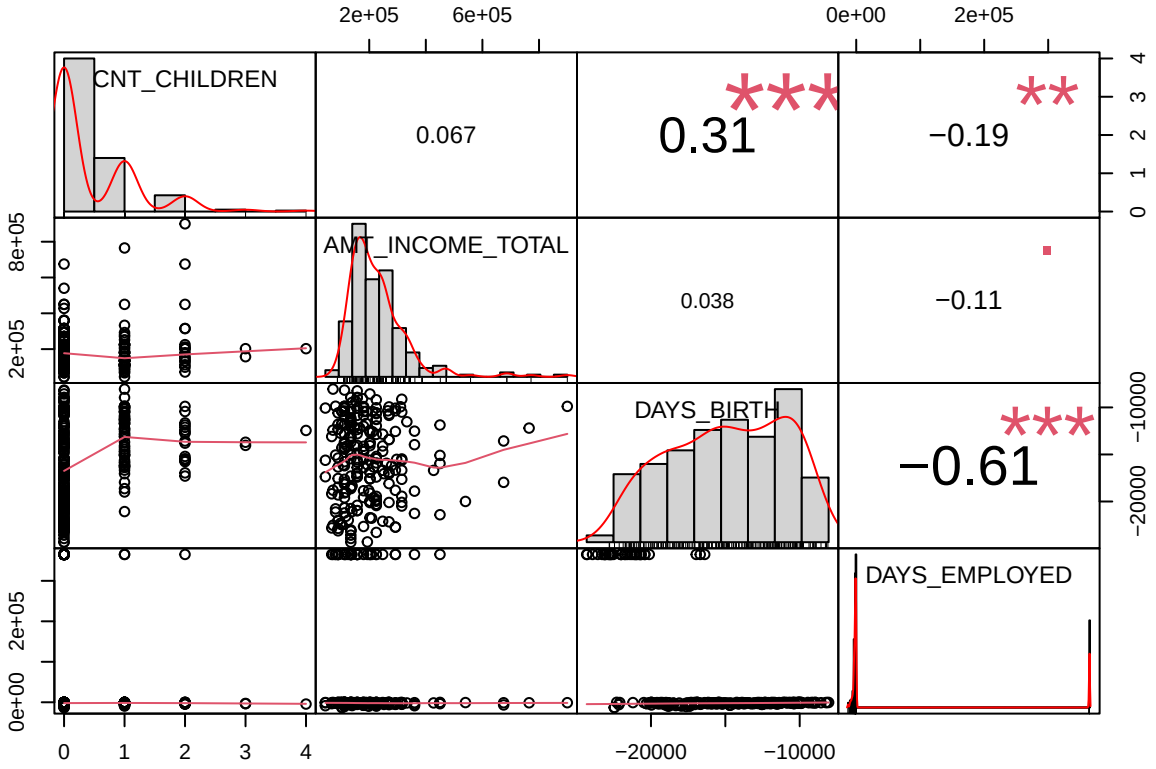
slice and dice the dataset

```
card_df1 <- dplyr::select(card_df, ID, CNT_CHILDREN, AMT_INCOME_TOTAL, DAYS_BIRTH, DAYS_EMPLOYED, STATUS
card_df2 <- filter(card_df1, STATUS==1)
card_df3 <- dplyr::select(card_df2, CNT_CHILDREN, AMT_INCOME_TOTAL, DAYS_BIRTH, DAYS_EMPLOYED)
dim(card_df3)
```

```
## [1] 236   4
```

Correlation Matrix

```
chart.Correlation(card_df3, histogram=TRUE, pch=19)
```



Analysis : In the above plot: ### The distribution of each variable is shown on the diagonal. ### On the bottom of the diagonal : the bivariate scatter plots with a fitted line are displayed ### On the top of the diagonal : the value of the correlation plus the significance level as stars ### Each significance level is associated to a symbol : p-values(0, 0.001, 0.01, 0.05, 0.1, 1) <=> symbols(???***???***, ***???***, ??????, ???.???, " ???)

correlation

```
res <- cor(card_df3)
round(res, 2)
```

```
##                  CNT_CHILDREN AMT_INCOME_TOTAL DAYS_BIRTH DAYS_EMPLOYED
## CNT_CHILDREN             1.00              0.07       0.31         -0.19
## AMT_INCOME_TOTAL         0.07              1.00       0.04         -0.11
```

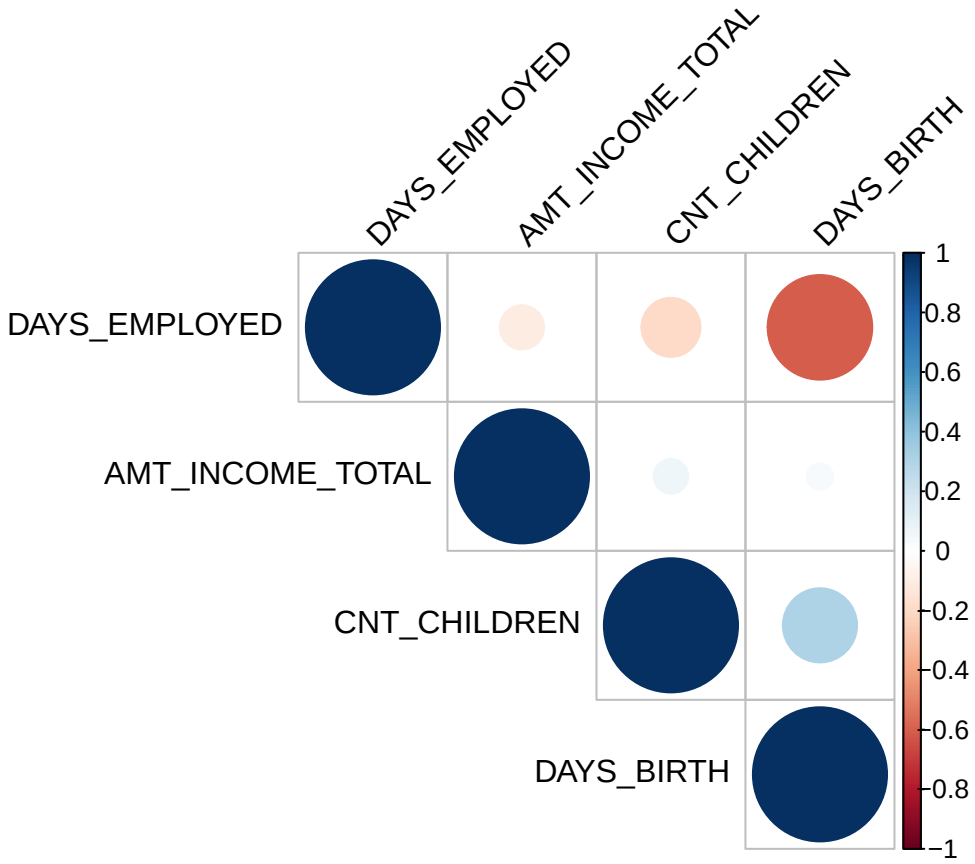
```
## DAYS_BIRTH              0.31             0.04       1.00         -0.61
## DAYS_EMPLOYED          -0.19            -0.11      -0.61          1.00
```

corrplot

```
library(corrplot)
```

```
## corrplot 0.90 loaded
```

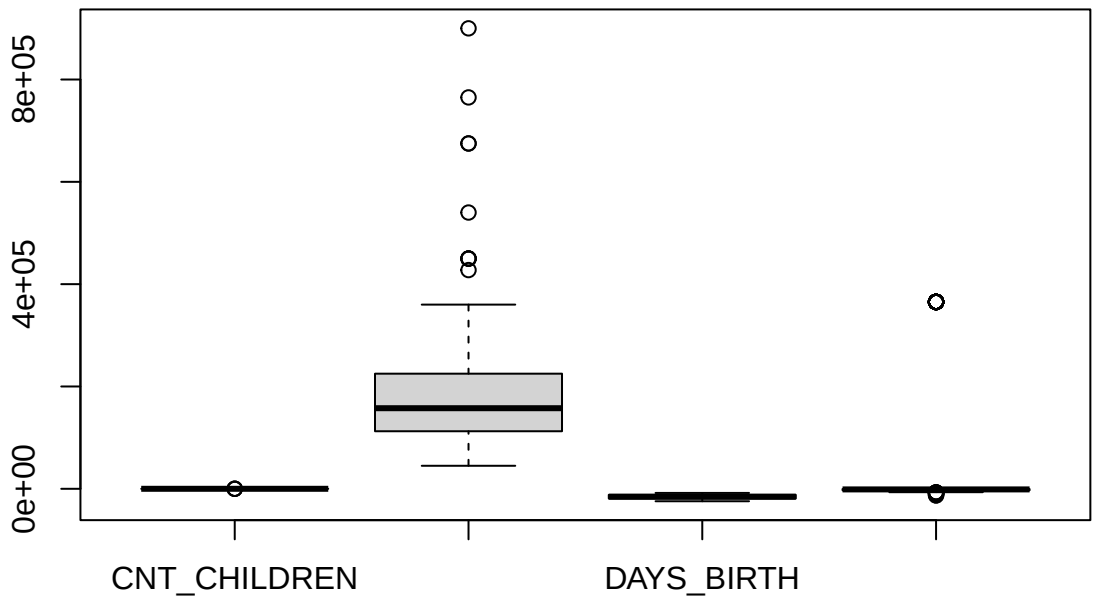
```
corrplot(res, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)
```



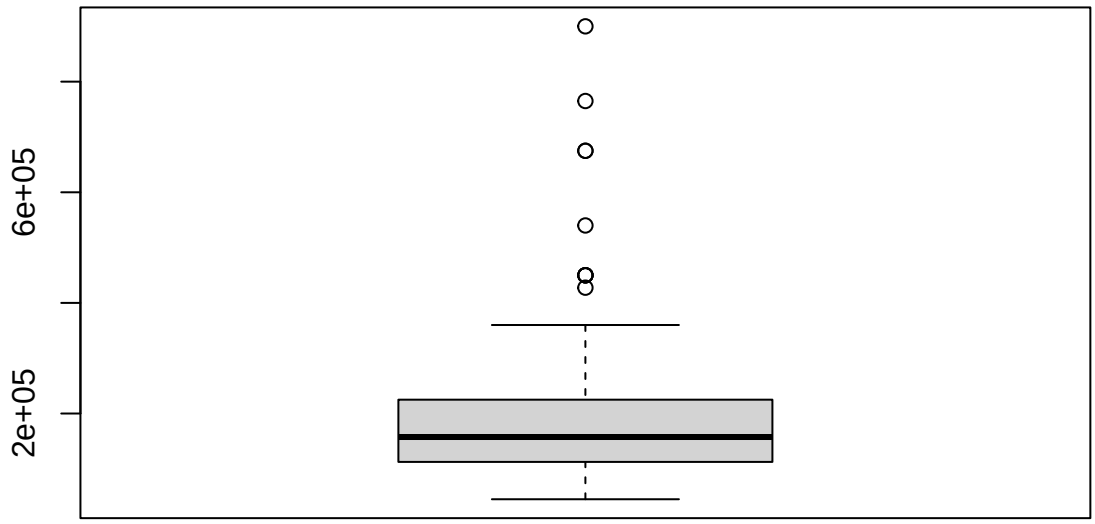
Positive correlations are displayed in blue and negative correlations in red color. ### Color intensity and the size of the circle are proportional to the correlation coefficients. ### In the right side of the correlogram, the legend color shows the correlation coefficients and the corresponding colors.

boxplot to find out outlier and removed outlier value from my dataset

```
boxplot(card_df3)
```




```
boxplot(card_df3$AMT_INCOME_TOTAL)
```



assign the outlier values into a vector

```
outliers_AMT_INCOME_TOTAL <- boxplot(card_df3$AMT_INCOME_TOTAL, plot=FALSE)$out
### finding the rows which contains outliers
card_df3[which(card_df3$AMT_INCOME_TOTAL %in% outliers_AMT_INCOME_TOTAL),]
```

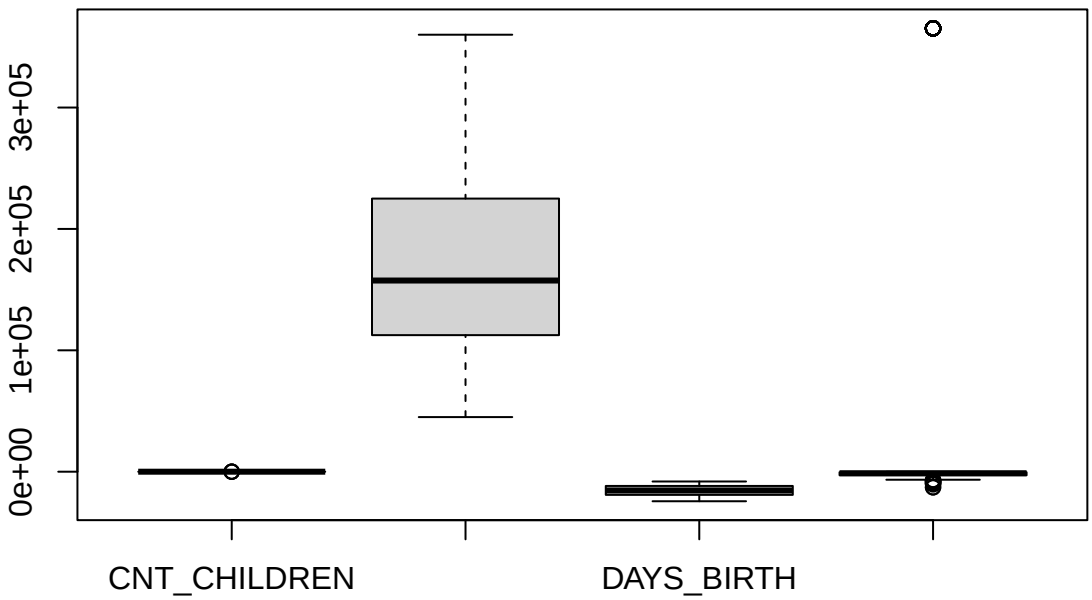
```
##     CNT_CHILDREN AMT_INCOME_TOTAL DAYS_BIRTH DAYS_EMPLOYED
## 2              1           765000     -12197         -1194
## 34             0           540000     -19996          -691
## 58             2           450000     -11870          -221
## 97             0           675000     -17964         -6594
## 99             2           675000     -13567         -1175
## 112            2           900000      -9889         -1000
## 164            1           450000     -15098         -1562
## 193            0           427500     -16691         -1565
## 203            0           450000     -21406        365243
## 215            0           450000     -15960         -3574
```

```
card_df4 <- card_df3[-which(card_df3$AMT_INCOME_TOTAL %in% outliers_AMT_INCOME_TOTAL),]
```

clean data after removing outlies records

Now boxplot is showing no outliers , you will notice that those pesky outliers are gone

```
boxplot(card_df4)
```



Anaysing the multiple variables by using scatter plots, pair plots, regression fit models

Scatter plots with multiple groups

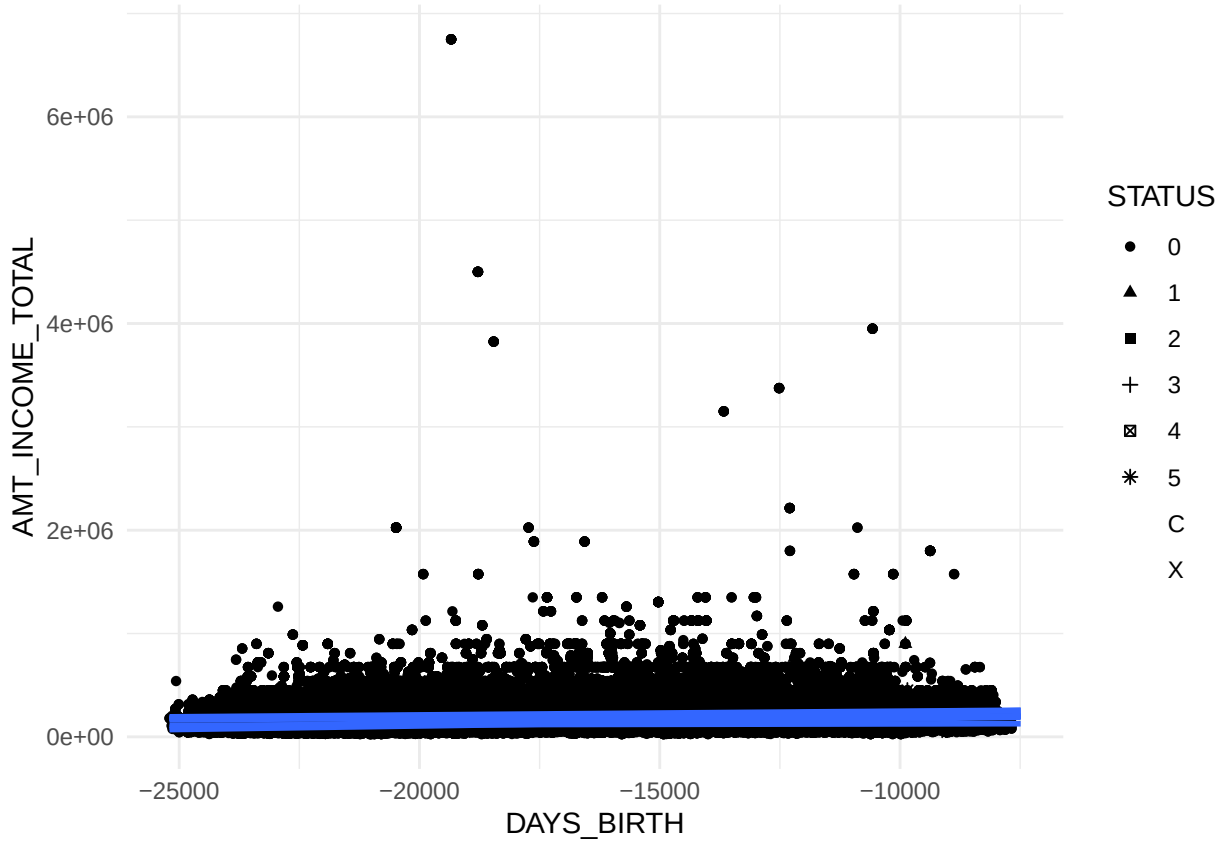
Change point shapes by the levels of STATUS

```
ggplot(card_df1, aes(x=DAYS_BIRTH, y=AMT_INCOME_TOTAL, shape=STATUS)) +
  geom_point() + geom_smooth(method=lm, se=FALSE, fullrange=TRUE)
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```
## Warning: The shape palette can deal with a maximum of 6 discrete values because
## more than 6 becomes difficult to discriminate; you have 8. Consider
## specifying shapes manually if you must have them.
```

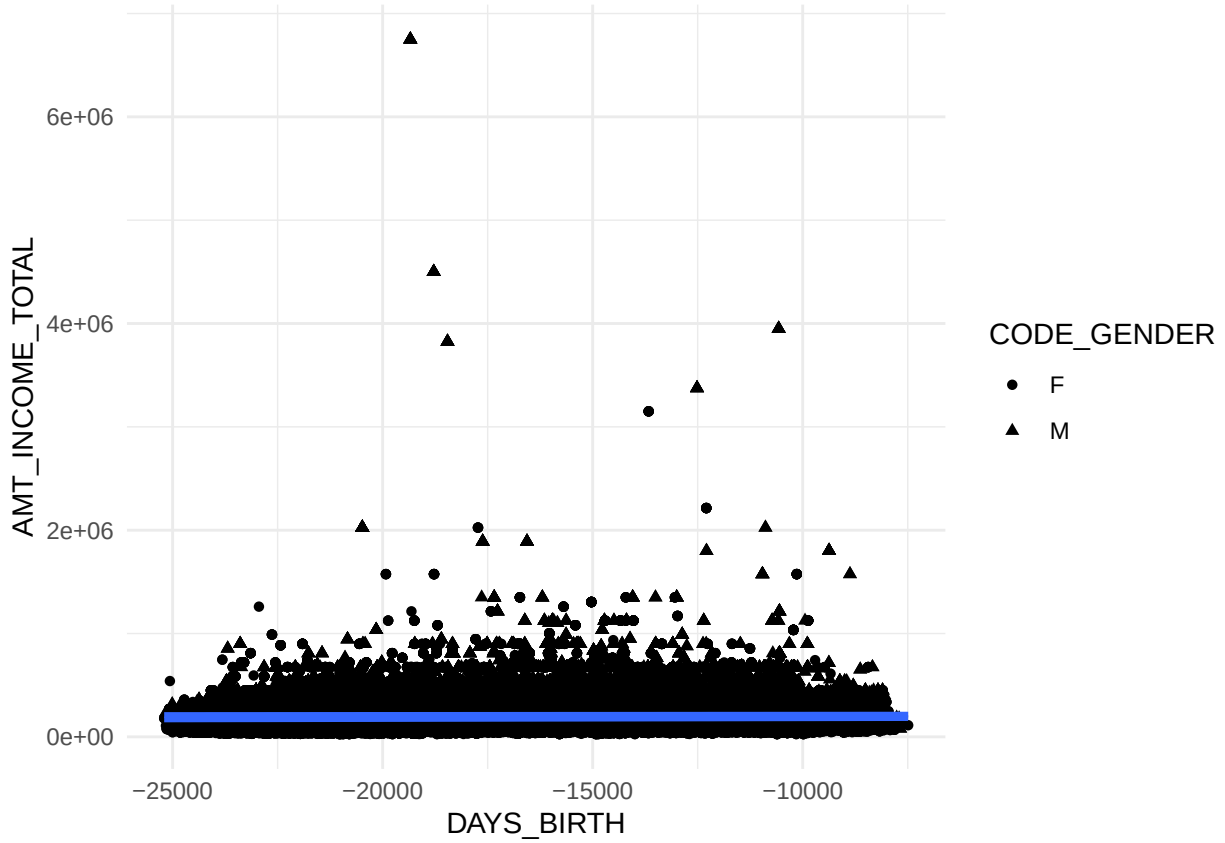
```
## Warning: Removed 17461 rows containing missing values (geom_point).
```



Change point shapes by the levels of STATUS

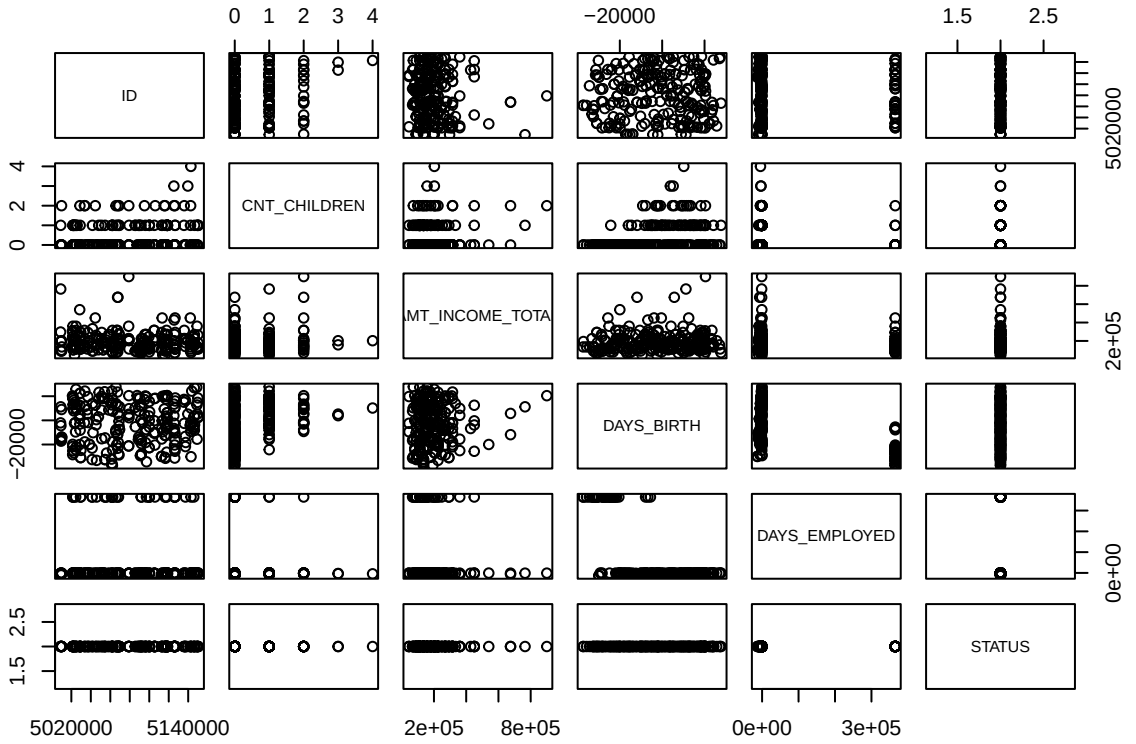
```
ggplot(card_df, aes(x=DAYS_BIRTH, y=AMT_INCOME_TOTAL, shape=CODE_GENDER)) +
  geom_point() + geom_smooth(method=lm, se=FALSE, fullrange=TRUE)
```

```
## `geom_smooth()` using formula 'y ~ x'
```



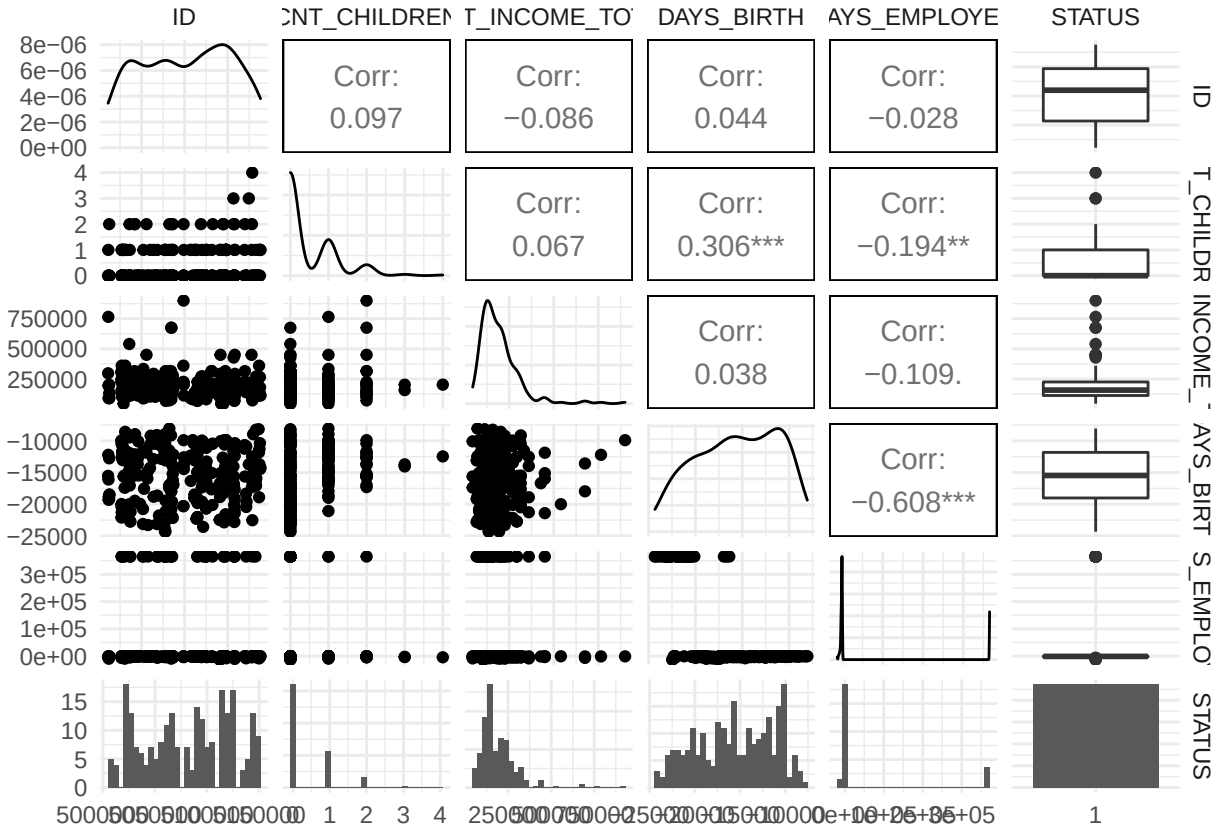
Pairplot

```
pairs(card_df2)
```

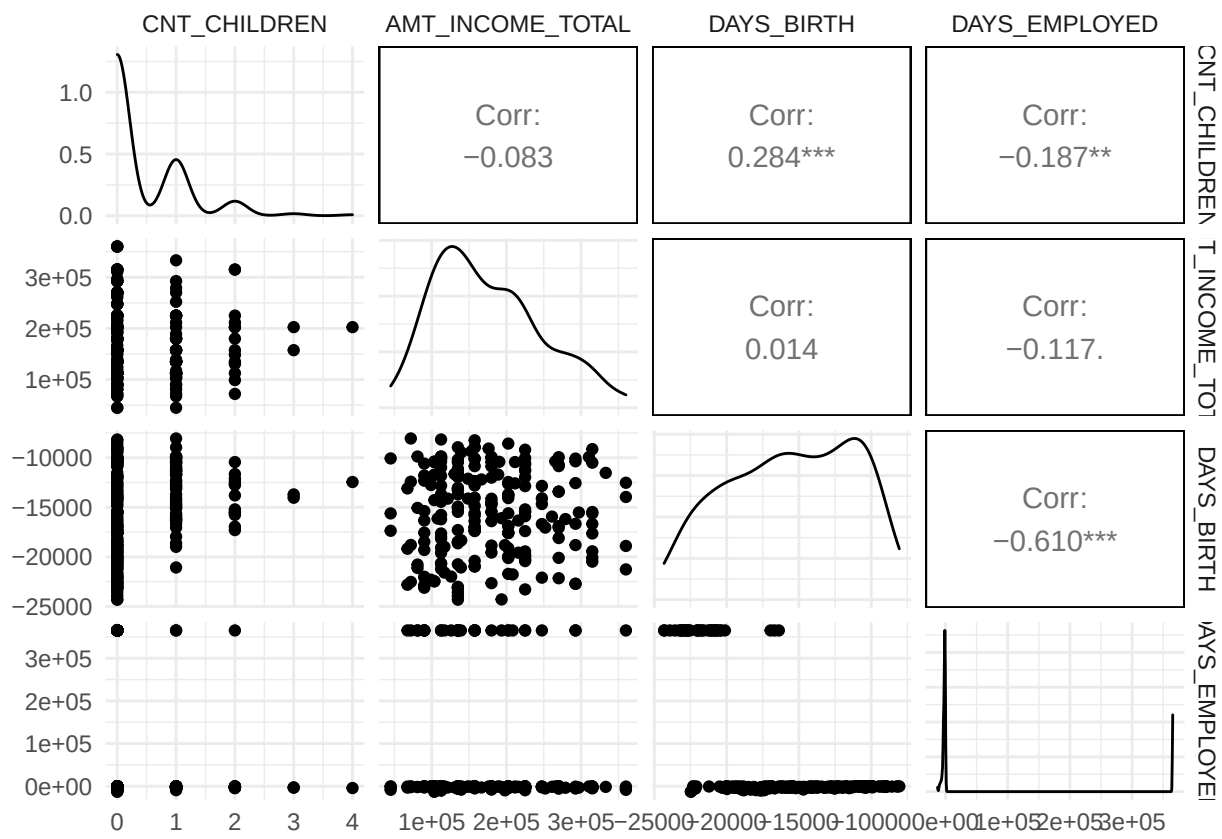



```
ggpairs(card_df2)
```

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




```
ggpairs(card_df4)
```



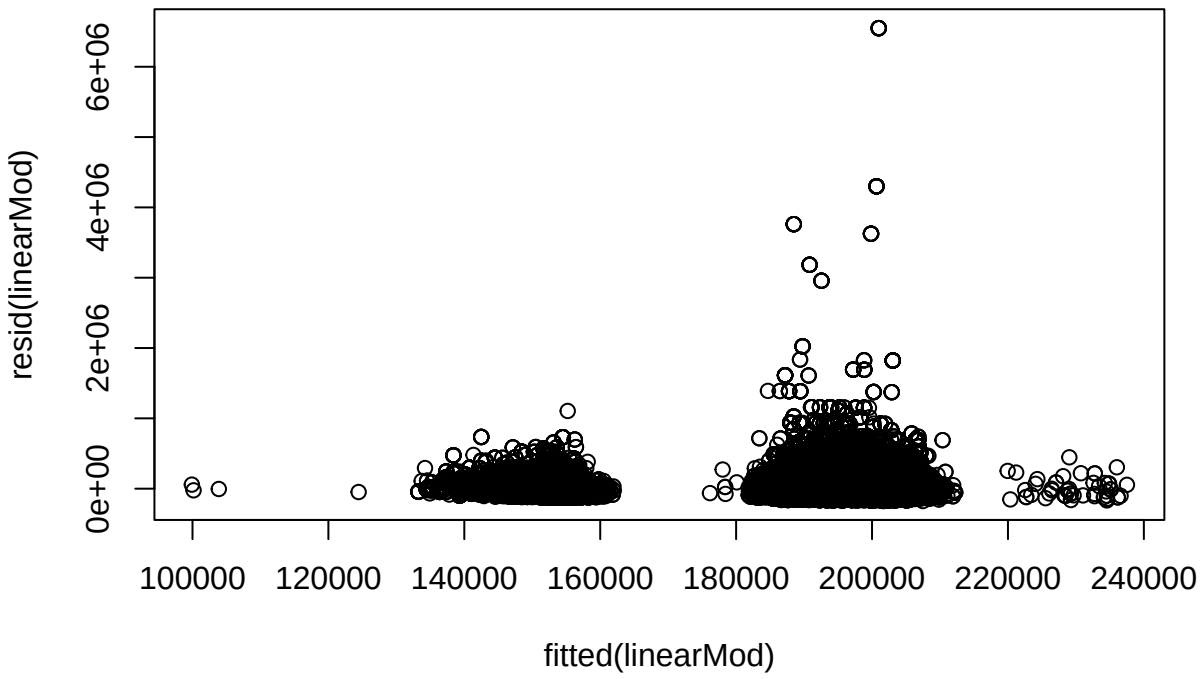
fit liner model

```
linearMod <- lm(AMT_INCOME_TOTAL ~ STATUS + CNT_CHILDREN +DAYS_BIRTH + DAYS_EMPLOYED, data=card_df1)
summary(linearMod)
```

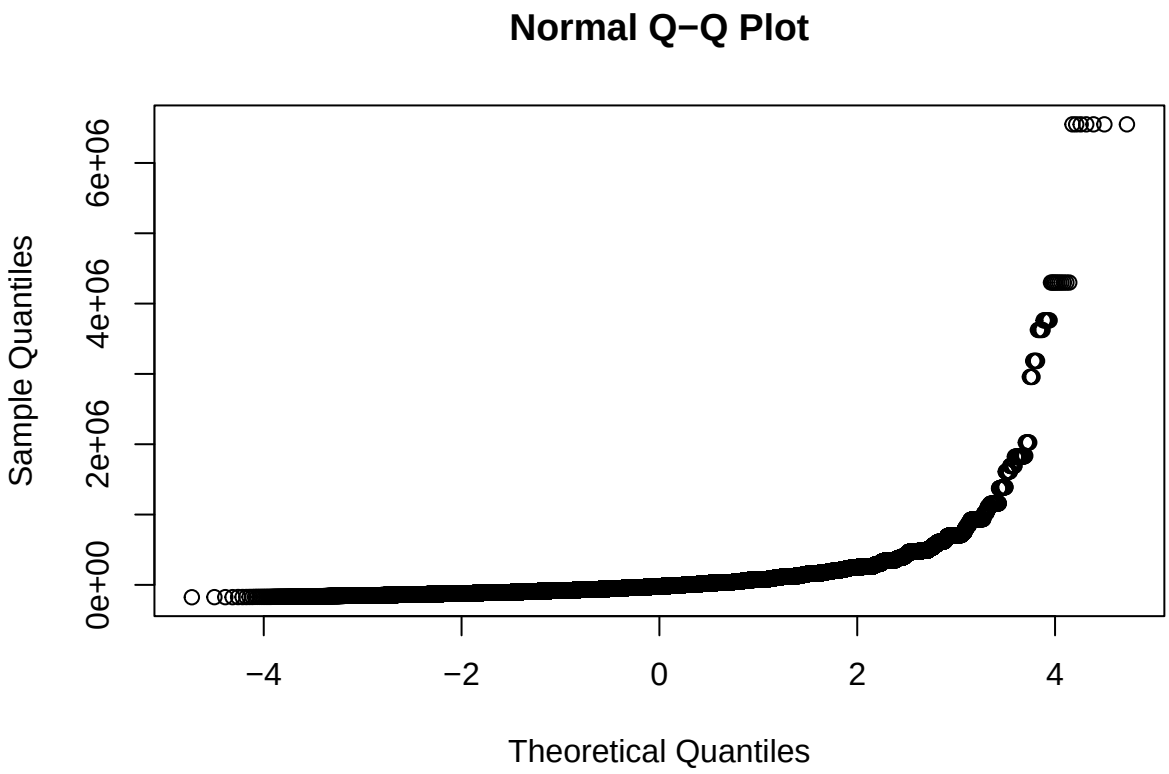
```
##
## Call:
## lm(formula = AMT_INCOME_TOTAL ~ STATUS + CNT_CHILDREN + DAYS_BIRTH +
##     DAYS_EMPLOYED, data = card_df1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -175987  -63822  -19786   34324 6549013
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.741e+05  8.307e+02 209.573  < 2e-16 ***
## STATUS1        4.863e+03  7.089e+03   0.686  0.49275
## STATUS2       -1.015e+04  2.498e+04  -0.407  0.68436
## STATUS3       -5.366e+04  4.445e+04  -1.207  0.22740
## STATUS4       -3.201e+04  4.869e+04  -0.657  0.51099
## STATUS5        3.410e+04  1.418e+04   2.405  0.01616 *
## STATUSC       -3.108e+03  9.705e+02  -3.202  0.00136 **
## STATUSX        3.573e+03  1.634e+03   2.187  0.02877 *
## CNT_CHILDREN  -7.124e+02  2.422e+02  -2.942  0.00327 **
## DAYS_BIRTH    -1.387e+00  5.177e-02 -26.798  < 2e-16 ***
## DAYS_EMPLOYED -1.388e-01  1.508e-03 -92.075  < 2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 108900 on 438546 degrees of freedom
## Multiple R-squared:  0.02185,    Adjusted R-squared:  0.02183
## F-statistic: 979.8 on 10 and 438546 DF,  p-value: < 2.2e-16
```

```
plot(fitted(linearMod), resid(linearMod))
```




```
qqnorm(resid(linearMod))
```



categorical variables- fit log model

```
logMod <- glm(STATUS ~ AMT_INCOME_TOTAL + CNT_CHILDREN +DAYS_BIRTH + DAYS_EMPLOYED, data=card_df, family
summary(logMod)
```

```
##
## Call:
## glm(formula = STATUS ~ AMT_INCOME_TOTAL + CNT_CHILDREN + DAYS_BIRTH +
##     DAYS_EMPLOYED, family = binomial(link = "logit"), data = card_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.2960  -0.2910  -0.2878  -0.2843   2.5949
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -3.157e+00  4.059e-02 -77.781   <2e-16 ***
## AMT_INCOME_TOTAL -1.076e-07  7.322e-08  -1.470   0.1416
## CNT_CHILDREN     -2.867e-02  1.144e-02  -2.506   0.0122 *
## DAYS_BIRTH       -2.264e-06  2.401e-06  -0.943   0.3456
## DAYS_EMPLOYED    -1.821e-07  7.110e-08  -2.561   0.0104 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 148852  on 438556  degrees of freedom
```

```
## Residual deviance: 148838  on 438552  degrees of freedom
## AIC: 148848
##
## Number of Fisher Scoring iterations: 6
```

```
logMod2 <- glm(CODE_GENDER ~ AMT_INCOME_TOTAL + CNT_CHILDREN +DAYS_BIRTH + DAYS_EMPLOYED, data=card_df,
summary(logMod2)
```

```
##
## Call:
## glm(formula = CODE_GENDER ~ AMT_INCOME_TOTAL + CNT_CHILDREN +
##     DAYS_BIRTH + DAYS_EMPLOYED, family = binomial(link = "logit"),
##     data = card_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.4857  -0.9221  -0.7129   1.2723   2.2252
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -1.330e-01  1.716e-02  -7.751  9.1e-15 ***
## AMT_INCOME_TOTAL  3.559e-06  3.488e-08 102.025  < 2e-16 ***
## CNT_CHILDREN      5.757e-02  4.638e-03  12.411  < 2e-16 ***
## DAYS_BIRTH        7.870e-05  1.036e-06  75.945  < 2e-16 ***
## DAYS_EMPLOYED    -1.198e-06  3.502e-08 -34.195  < 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: 555384  on 438556  degrees of freedom
## Residual deviance: 524391  on 438552  degrees of freedom
## AIC: 524401
##
## Number of Fisher Scoring iterations: 4
```

```
logMod3 <- glm(FLAG_OWN_REALTY ~ AMT_INCOME_TOTAL + CNT_CHILDREN +DAYS_BIRTH + DAYS_EMPLOYED, data=card
summary(logMod3)
```

```
##
## Call:
## glm(formula = FLAG_OWN_REALTY ~ AMT_INCOME_TOTAL + CNT_CHILDREN +
##     DAYS_BIRTH + DAYS_EMPLOYED, family = binomial(link = "logit"),
##     data = card_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.3812  -1.4075   0.7837   0.8768   1.1055
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -3.635e-01  1.733e-02 -20.972  < 2e-16 ***
## AMT_INCOME_TOTAL  7.223e-07  3.417e-08  21.140  < 2e-16 ***
## CNT_CHILDREN      1.299e-01  4.872e-03  26.661  < 2e-16 ***
## DAYS_BIRTH       -6.209e-05  1.034e-06 -60.053  < 2e-16 ***
```

```
## DAYS_EMPLOYED     1.350e-07  3.189e-08   4.235 2.29e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 540647  on 438556  degrees of freedom
## Residual deviance: 534394  on 438552  degrees of freedom
## AIC: 534404
##
## Number of Fisher Scoring iterations: 4
```

```
logMod4 <- glm(FLAG_OWN_REALTY ~ STATUS + CNT_CHILDREN +DAYS_BIRTH + DAYS_EMPLOYED, data=card_df, family
summary(logMod4)
```

```
##
## Call:
## glm(formula = FLAG_OWN_REALTY ~ STATUS + CNT_CHILDREN + DAYS_BIRTH +
##     DAYS_EMPLOYED, family = binomial(link = "logit"), data = card_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0007  -1.4101   0.7864   0.8753   1.4623
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -2.303e-01  1.627e-02 -14.154  < 2e-16 ***
## STATUS1       -3.506e-01  1.346e-01  -2.605  0.00918 **
## STATUS2       -6.977e-01  4.643e-01  -1.503  0.13289
## STATUS3       -2.404e-01  8.734e-01  -0.275  0.78312
## STATUS4       -1.080e+00  9.253e-01  -1.167  0.24325
## STATUS5        3.203e-01  3.076e-01   1.041  0.29778
## STATUSC       -1.650e-01  1.896e-02  -8.699  < 2e-16 ***
## STATUSX       -1.991e-01  3.169e-02  -6.284  3.3e-10 ***
## CNT_CHILDREN   1.288e-01  4.868e-03  26.459  < 2e-16 ***
## DAYS_BIRTH    -6.301e-05  1.033e-06 -61.009  < 2e-16 ***
## DAYS_EMPLOYED  3.775e-08  3.156e-08   1.196  0.23171
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 540647  on 438556  degrees of freedom
## Residual deviance: 534748  on 438546  degrees of freedom
## AIC: 534770
##
## Number of Fisher Scoring iterations: 4
```

Implications

the conclusion that can be drawn from something although it is not explicitly stated.

1) Most of the dependent variables likes gender tyep, flat own reality are deciding factors for approving new cards to applicant

2) initial data summary looks good , but during EDA analysis i foud we have outliars in dataset

3) some of the variables are having good corelations , like applicant age, kids counts, current credit rating

4) seems the current credit status is not much dependant on annual income of applican and i got no correlation between credit status and annual income of applicant

5)GENDER should be one the deciding factors, i found the good correlations of its amoungs multiple variables

so it shows genders factors is also important for new appliant

Limitations

I havent found much OF free data in web related to credit card transactions and and i believe the used credit score DATASET

might be near to the truth , so here in this research i have colcluded most of the finding bases on

two data sets, however i believe , i need some more types of datasets for research like past trasnsactions, ### multiple cards reports etc.

time constrants-> in depth alaysis need some more time and research

Concluding Remarks

past credit history is not good enough to decide about the new credit card applicant. seems the other factors like age of applicant, gender, kids counts and home owner are the other variables whihc need to give some additional points while deciding the new applicant fit.

Total Annual income of applicant should not give much waitage for new card applicant