Derogatory Credit Reports

The purpose of this report is to state the factors that could potentially contribute to derogatory reports on a credit card applicant's history. Since many variables affect the derogatory report, we will figure which variables are useful. We will also do the regression using those selected variables. We will try to use methods other than Poisson regression to get the relationship because too many individuals' history has zero derogatory reports than the usual Poisson condition. In conclusion, we will determine the most suitable model for the derogatory report and variables that effectively influence the derogatory reports.

The dataset consists of 12 variables with 1319 objects, with no missing data. In the dataset, the variable 'card' is determined by other variables in the dataset, such as reports, and 'share' is calculated from income and expenditure. To prevent potential confusions and interferences in the model, we will not use those two variables in our model. In Table 1, we checked the correlation between variables to see if any variables had a great influence on each other. We confirmed that two variables with particularly large correlations do not exist. We will fit the data into four assumptions, or models: Poisson, Gaussian, Quasi, and Negative binomial. And we will select the model that corresponds the most to the actual dataset.

We used the z-value, a value that represents how much the variable is useful to predict the response, to determine the effectivity of the variables. Four models both stated that expenditure, owner, and active are effective variables, and only Poisson stated that months is an effective variable also. So, we focused on the relationship between those four variables and a variable report.

In figure 1,2,3,4 below, we could find an association between expenditure or active and reports using graphs, but we could not check the intuitive relationship between owner or months and reports. Reports tended to increase when data had low expenditure or high active. Still, not having an intuitive association does not mean that there is no association, so we compared the four models using these four variables.

The Gaussian model and Quasi model showed the same estimate and standard error. So, we ignored the Quasi model and only considered the Gaussian model. We used AIC, a value that represents how much the model distribution is far from the real dataset distribution, to compare the three models, Poisson, Gaussian, and Negative binomial. AIC of Poisson was 2576.9, AIC of Negative binomial was 1994.2, and AIC of Gaussian model was 4429.4. So, we selected the Negative binomial which had the smallest AIC as our main model since it meant the distribution of the real dataset was closest to the Negative binomial distribution among the three models.

Table 2 below provides the estimates along with standard error and p-value. The model shows that there is a significant decrease in the number of derogatory reports with precision ($p < 0.001$); for each unit increase in expenditure, crossing decrease by a factor of 1.504 (variable 'expenditure'). Further, the model showed that applicants who owned their homes have lower derogatory reports with precision ($p < 0.001$) by a factor of 0.643 (variable 'owner2'). Moreover, the model showed that there is an increase in the number of derogatory reports with precision ($p < 0.02$); for each unit increase in months by factor 0.0027 (variable months). Lastly, the model showed that the applicant with a greater number of active credit accounts tends to have an increased number of derogatory reports with precision ($p < 0.001$) by a factor of 0.1240 (variable active).

In conclusion, we figured out that the number of derogatory reports is highly related to the expenditure, homeownership, months living at current address, and numbers of active credit accounts of the applicant. Applicants who spend more or owned house had a lower number of reports, and who did not change a current address for a long time or have many active credit accounts had a higher number of reports. We used Negative binomial model to predict the number of derogatory reports from variables.

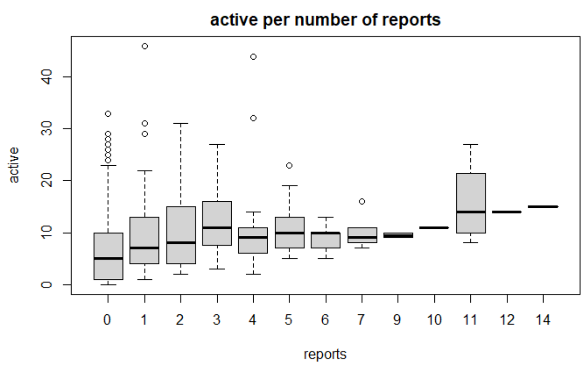


Figure 3. Active Credit Accounts per number of reports

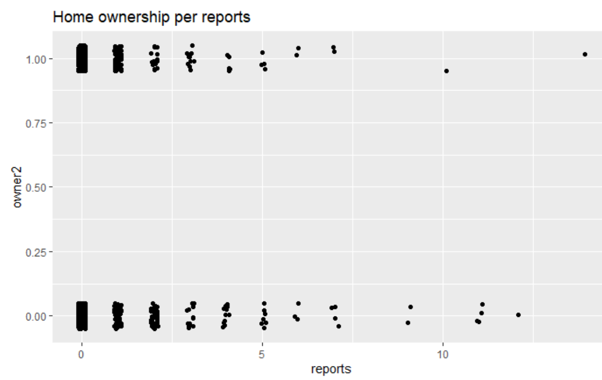


Figure 2. Home ownership per number of reports

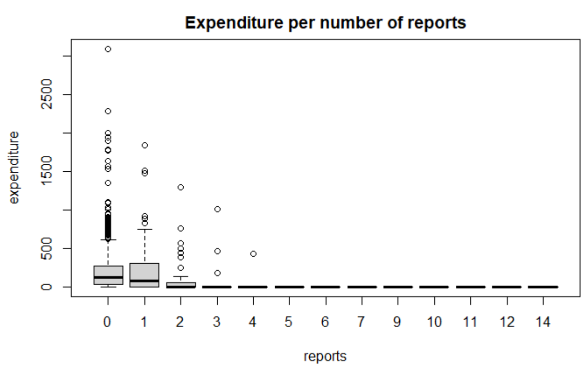


Figure 4. Expenditure per number of reports

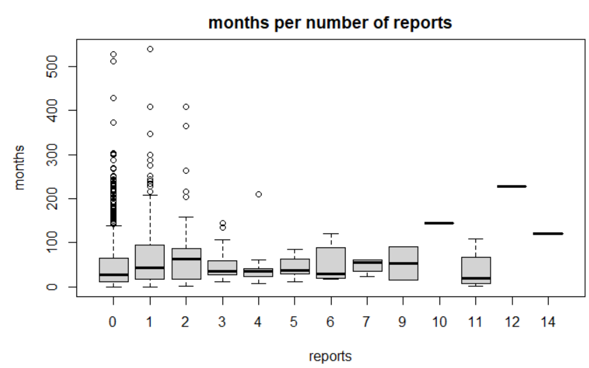


Figure 1. Months per number of reports

Table 1. Correlation between selected variables

	reports	age	income	share	expenditure	dependents	months	active	owner2	selfemp2	majorcards2
reports	1.000	0.044	0.011	-0.159	-0.137	0.020	0.049	0.208	-0.054	0.019	-0.007
age	0.044	1.000	0.325	-0.116	0.015	0.212	0.436	0.181	0.368	0.100	0.010
income	0.011	0.325	1.000	-0.054	0.281	0.318	0.130	0.181	0.325	0.112	0.107
share	-0.159	-0.116	-0.054	1.000	0.839	-0.083	-0.055	-0.023	-0.016	-0.079	0.051
expenditure	-0.137	0.015	0.281	0.839	1.000	0.053	-0.029	0.055	0.093	-0.036	0.078
dependents	0.020	0.212	0.318	-0.083	0.053	1.000	0.047	0.107	0.309	0.042	0.010
months	0.049	0.436	0.130	-0.055	-0.029	0.047	1.000	0.100	0.239	0.066	-0.041
active	0.208	0.181	0.181	-0.023	0.055	0.107	0.100	1.000	0.275	0.030	0.120
owner2	-0.054	0.368	0.325	-0.016	0.093	0.309	0.239	0.275	1.000	0.042	0.064
selfemp2	0.019	0.100	0.112	-0.079	-0.036	0.042	0.066	0.030	0.042	1.000	0.005
majorcards2	-0.007	0.010	0.107	0.051	0.078	0.010	-0.041	0.120	0.064	0.005	1.000

Table 2. Estimated value, Standard Error and p-value for each variable

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	-1.503575613	0.1407527227	1.230606e-26
expenditure	-0.002239835	0.0004247969	1.344162e-07
owner2	-0.642886284	0.1626833416	7.757701e-05
months	0.002663039	0.0010709985	1.290063e-02
active	0.123952861	0.0114319985	2.161801e-27

Assignment 1 Appendix

```
library(stats)
library(ggplot2)
library(MASS)
```

#1 Data skimming

```
dero = read.csv(file = 'C:/Users/krss9/Desktop/FS21/Stats 504/derogatory.csv')
head(dero)
```

```
##   card reports      age income       share expenditure owner selfemp dependents
## 1  yes       0 37.66667 4.5200 0.033269910  124.983300   yes      no          3
## 2  yes       0 33.25000 2.4200 0.005216942    9.854167    no      no          3
## 3  yes       0 33.66667 4.5000 0.004155556   15.000000   yes      no          4
## 4  yes       0 30.50000 2.5400 0.065213780  137.869200    no      no          0
## 5  yes       0 32.16667 9.7867 0.067050590  546.503300   yes      no          2
## 6  yes       0 23.25000 2.5000 0.044438400   91.996670    no      no          0
##   months majorcards active
## 1     54        yes     12
## 2     34        yes     13
## 3     58        yes      5
## 4     25        yes      7
## 5     64        yes      5
## 6     54        yes      1
```

#2 Converting categorical variables into numeric

```
dero$card2 <- ifelse(dero$card == 'yes', 1,0)
dero$owner2 <- ifelse(dero$owner == 'yes', 1, 0)
dero$selfemp2 <- ifelse(dero$selfemp == 'yes', 1, 0)
dero$majorcards2 <- ifelse(dero$majorcards == 'yes', 1, 0)
```

#3 glm with Poisson assumption

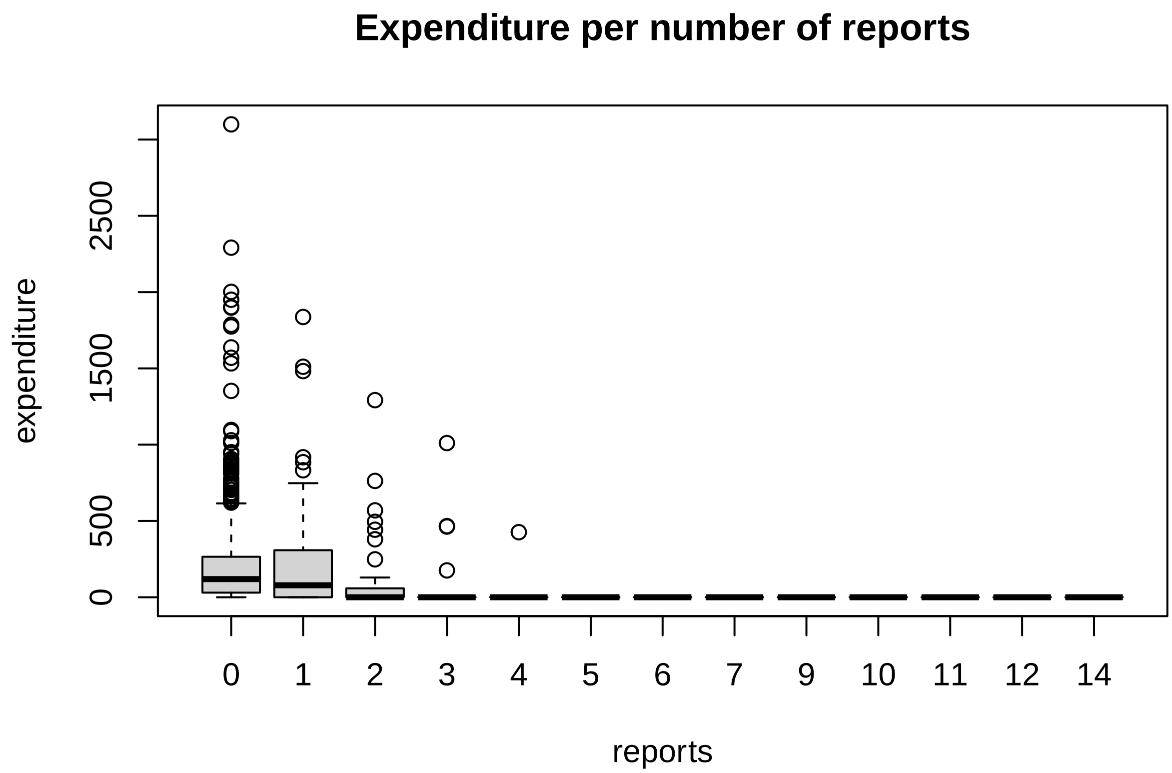
```
expr1 = 'reports ~ age + income + expenditure + owner2 + selfemp2 + dependents + months + majorcards2 +
model1_GLM = glm(expr1, family=poisson(), data=dero)
summary(model1_GLM)
```

```
##
## Call:
## glm(formula = expr1, family = poisson(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

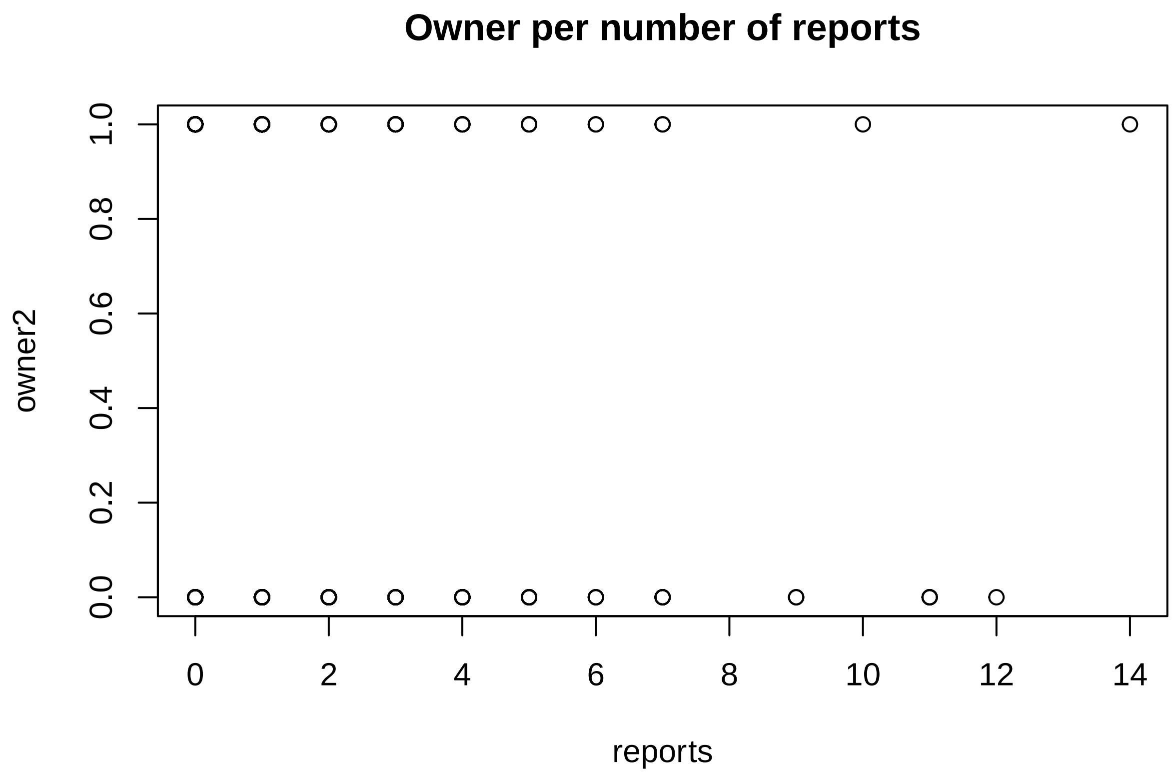
```
## -3.8691  -0.9467  -0.7081  -0.3476   7.3921
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.1794113  0.1763576  -6.688 2.27e-11 ***
## age          0.0018484  0.0047569   0.389 0.697598
## income       0.0655500  0.0264859   2.475 0.013327 *
## expenditure -0.0038243  0.0003674 -10.409  < 2e-16 ***
## owner2      -0.7866639  0.1027559  -7.656 1.92e-14 ***
## selfemp2    -0.0252848  0.1503499  -0.168 0.866447
## dependents   0.0881904  0.0355773   2.479 0.013181 *
## months       0.0023190  0.0006124   3.787 0.000153 ***
## majorcards2 -0.0298881  0.1052483  -0.284 0.776428
## active       0.0767950  0.0046391  16.554  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 2347.4  on 1318  degrees of freedom
## Residual deviance: 1901.0  on 1309  degrees of freedom
## AIC: 2570.5
##
## Number of Fisher Scoring iterations: 6
```

#4 Graphs of variables and reports

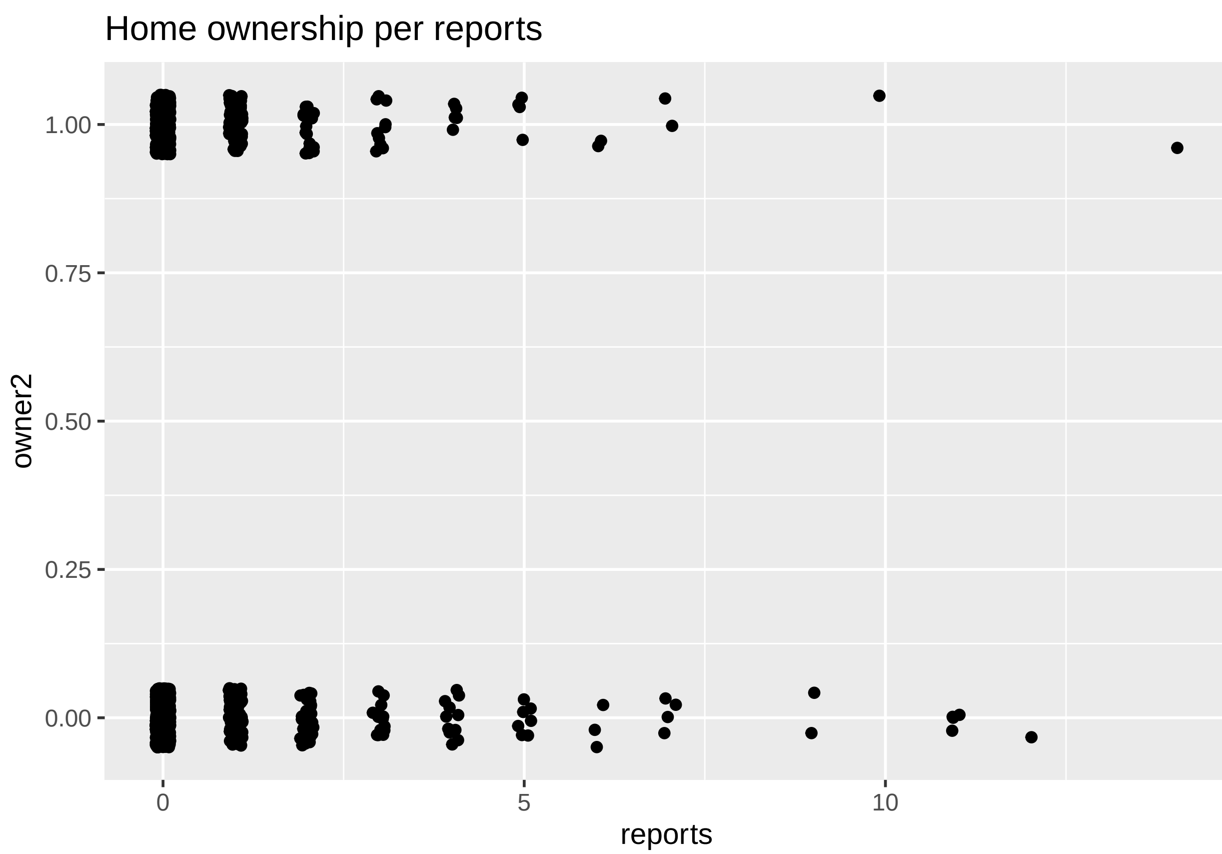
```
boxplot(expenditure ~ reports, data=dero, main ="Expenditure per number of reports")
```



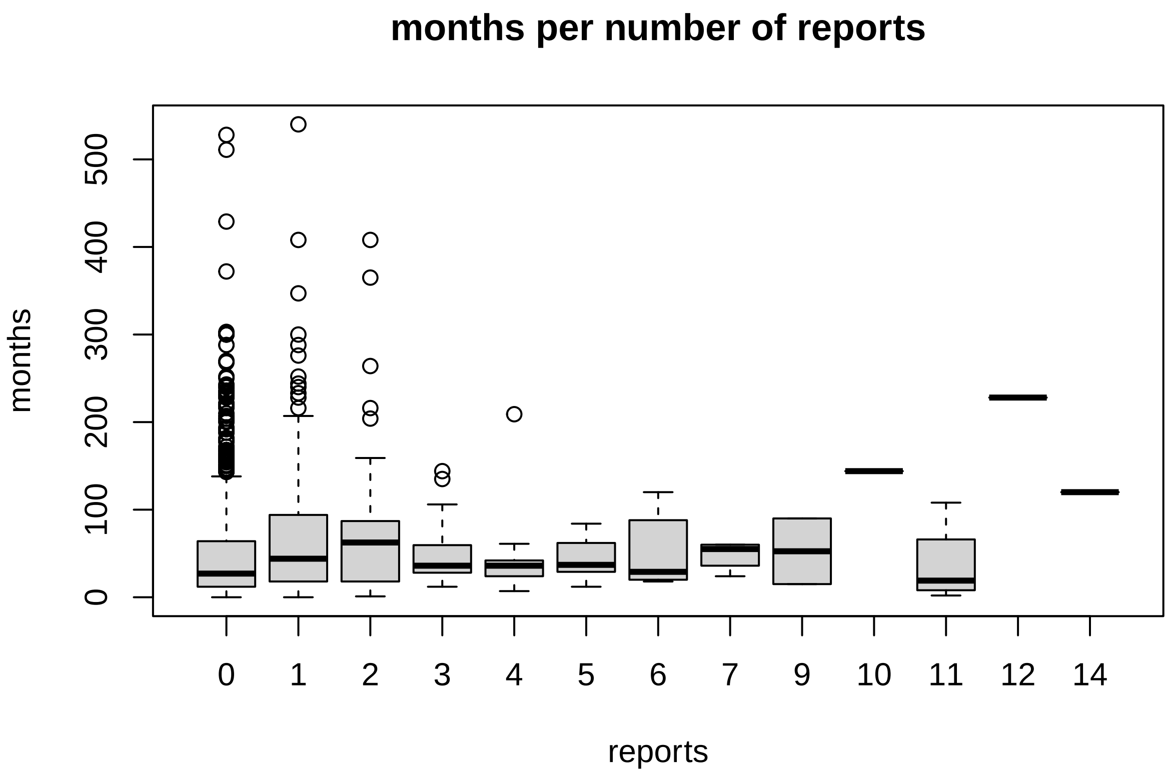

```
plot(owner2 ~ reports, data=dero, main ="Owner per number of reports")
```



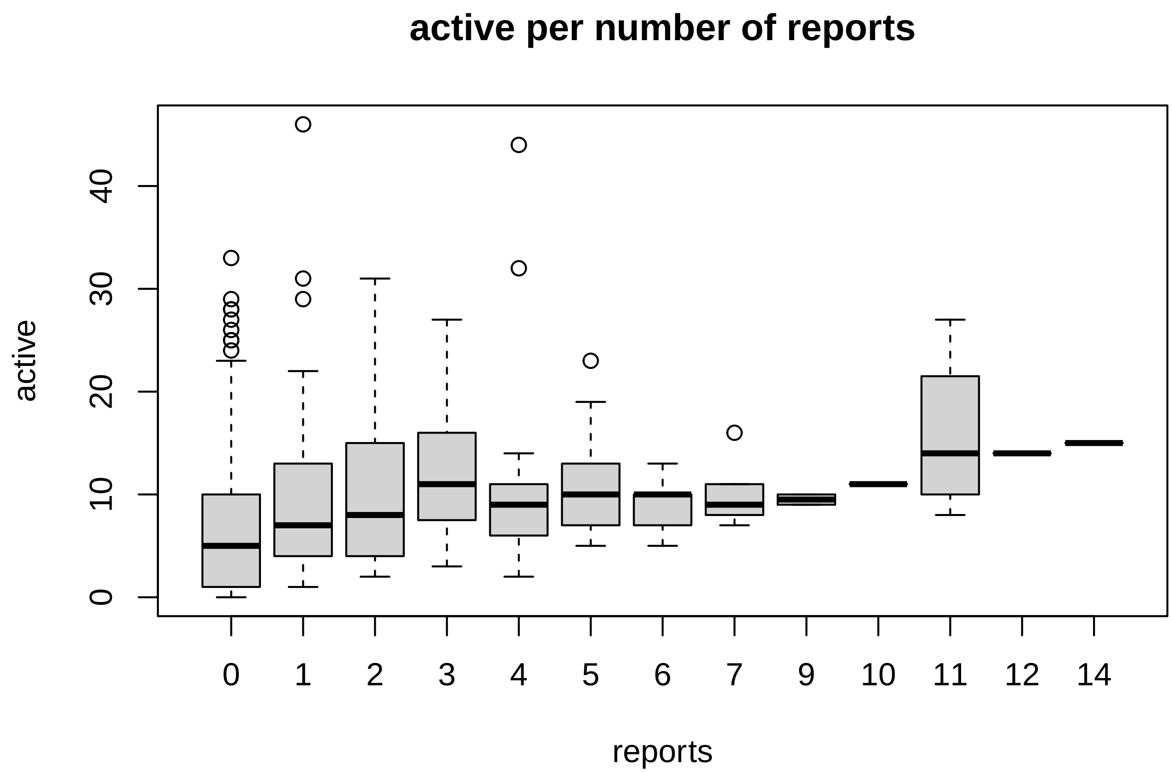

```
ggplot(data = dero, aes(x = reports, y = owner2))+
  geom_jitter(width = 0.1, height = 0.05) +
  ggtitle("Home ownership per reports")
```




```
boxplot(months ~ reports, data=dero, main ="months per number of reports")
```




```r
boxplot(active ~ reports, data=dero, main ="active per number of reports")
```



#5 Distribution of reports and missing values check

```
dero_rep0 = dero[which(dero$reports == 0),]
dim(dero_rep0)
```

```
## [1] 1060   16
```

```
dero_rep1 = dero[which(dero$reports == 1),]
dim(dero_rep1)
```

```
## [1] 137  16
```

```
dero_rep2 = dero[which(dero$reports > 1),]
dim(dero_rep2)
```

```
## [1] 122  16
```

```
which(is.na(dero))
```

```
## integer(0)
```

#6 glm with four assumptions _ Guassian, Poisson, NB, Quasi

```r
expr1 = 'reports ~ age + income + expenditure + owner2 + selfemp2 + dependents + months + majorcards2 +
model1_GLM = glm(expr1, family=poisson(), data=dero)
summary(model1_GLM)
```

```
##
## Call:
## glm(formula = expr1, family = poisson(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.8691  -0.9467  -0.7081  -0.3476   7.3921
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.1794113  0.1763576  -6.688 2.27e-11 ***
## age          0.0018484  0.0047569   0.389 0.697598
## income       0.0655500  0.0264859   2.475 0.013327 *
## expenditure -0.0038243  0.0003674 -10.409  < 2e-16 ***
## owner2      -0.7866639  0.1027559  -7.656 1.92e-14 ***
## selfemp2    -0.0252848  0.1503499  -0.168 0.866447
## dependents   0.0881904  0.0355773   2.479 0.013181 *
## months       0.0023190  0.0006124   3.787 0.000153 ***
## majorcards2 -0.0298881  0.1052483  -0.284 0.776428
## active       0.0767950  0.0046391  16.554  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 2347.4  on 1318  degrees of freedom
## Residual deviance: 1901.0  on 1309  degrees of freedom
## AIC: 2570.5
##
## Number of Fisher Scoring iterations: 6
```

```r
expr2 = 'reports ~ age + income + expenditure + owner2 + selfemp2 + dependents + months + majorcards2 +
model2_GLM = glm.nb(expr2, data=dero)
summary(model2_GLM)
```

```
##
## Call:
## glm.nb(formula = expr2, data = dero, init.theta = 0.2648349349,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4214  -0.6764  -0.5587  -0.3723   2.5341
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.9646475  0.3155450  -6.226 4.78e-10 ***
## age          0.0060381  0.0086661   0.697   0.4860
## income       0.0830533  0.0494830   1.678   0.0933 .
```

```
## expenditure -0.0023861  0.0004366  -5.465 4.63e-08 ***
## owner2      -0.8233963  0.1776964  -4.634 3.59e-06 ***
## selfemp2     0.0322711  0.2815948   0.115   0.9088
## dependents   0.0909177  0.0634911   1.432   0.1522
## months       0.0023967  0.0011723   2.044   0.0409 *
## majorcards2  0.0132247  0.1957436   0.068   0.9461
## active       0.1207594  0.0114787  10.520  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(0.2648) family taken to be 1)
##
##     Null deviance: 843.27  on 1318  degrees of freedom
## Residual deviance: 683.24  on 1309  degrees of freedom
## AIC: 1996.9
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  0.2648
##           Std. Err.:  0.0289
##
##  2 x log-likelihood:  -1974.9280
```

```
expr3 = 'reports ~ age + income + expenditure + owner2 + selfemp2 + dependents + months + majorcards2 +
model3_GLM = glm(expr3, family=gaussian(), data=dero)
summary(model3_GLM)
```

```
##
## Call:
## glm(formula = expr3, family = gaussian(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9799  -0.5228  -0.3066   0.0473  13.1757
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1928631  0.1490863   1.294    0.196
## age          0.0027089  0.0042444   0.638    0.523
## income       0.0284319  0.0247086   1.151    0.250
## expenditure -0.0007197  0.0001376  -5.231 1.96e-07 ***
## owner2      -0.3845987  0.0833708  -4.613 4.36e-06 ***
## selfemp2     0.0145824  0.1421554   0.103    0.918
## dependents   0.0303756  0.0311287   0.976    0.329
## months       0.0007878  0.0006040   1.304    0.192
## majorcards2 -0.0638952  0.0935942  -0.683    0.495
## active       0.0511610  0.0059530   8.594  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 1.674134)
##
##     Null deviance: 2385.2  on 1318  degrees of freedom
```

```
## Residual deviance: 2191.4  on 1309  degrees of freedom
## AIC: 4434.8
##
## Number of Fisher Scoring iterations: 2
```

```
expr4 = 'reports ~ age + income + expenditure + owner2 + selfemp2 + dependents + months + majorcards2 +
model4_GLM = glm(expr4, family=quasi(), data=dero)
summary(model4_GLM)
```

```
##
## Call:
## glm(formula = expr4, family = quasi(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9799  -0.5228  -0.3066   0.0473  13.1757
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.1928631  0.1490863   1.294    0.196
## age          0.0027089  0.0042444   0.638    0.523
## income       0.0284319  0.0247086   1.151    0.250
## expenditure -0.0007197  0.0001376  -5.231 1.96e-07 ***
## owner2      -0.3845987  0.0833708  -4.613 4.36e-06 ***
## selfemp2     0.0145824  0.1421554   0.103    0.918
## dependents   0.0303756  0.0311287   0.976    0.329
## months       0.0007878  0.0006040   1.304    0.192
## majorcards2 -0.0638952  0.0935942  -0.683    0.495
## active       0.0511610  0.0059530   8.594  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasi family taken to be 1.674134)
##
##     Null deviance: 2385.2  on 1318  degrees of freedom
## Residual deviance: 2191.4  on 1309  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 2
```

#7 Correlation table

```
res <- cor(dero[,c(2,3,4,5,6,9,10,12,14,15,16)])
as.data.frame(round(res, 3))
```

```
##             reports    age income  share expenditure dependents months active
## reports       1.000  0.044  0.011 -0.159      -0.137      0.020  0.049  0.208
## age           0.044  1.000  0.325 -0.116       0.015      0.212  0.436  0.181
## income        0.011  0.325  1.000 -0.054       0.281      0.318  0.130  0.181
## share        -0.159 -0.116 -0.054  1.000       0.839     -0.083 -0.055 -0.023
## expenditure  -0.137  0.015  0.281  0.839       1.000      0.053 -0.029  0.055
## dependents    0.020  0.212  0.318 -0.083       0.053      1.000  0.047  0.107
## months        0.049  0.436  0.130 -0.055      -0.029      0.047  1.000  0.100
```

```
## active        0.208  0.181  0.181 -0.023       0.055       0.107  0.100  1.000
## owner2       -0.054  0.368  0.325 -0.016       0.093       0.309  0.239  0.275
## selfemp2      0.019  0.100  0.112 -0.079      -0.036       0.042  0.066  0.030
## majorcards2  -0.007  0.010  0.107  0.051       0.078       0.010 -0.041  0.120
##             owner2 selfemp2 majorcards2
## reports     -0.054    0.019      -0.007
## age          0.368    0.100       0.010
## income       0.325    0.112       0.107
## share       -0.016   -0.079       0.051
## expenditure  0.093   -0.036       0.078
## dependents   0.309    0.042       0.010
## months       0.239    0.066      -0.041
## active       0.275    0.030       0.120
## owner2       1.000    0.042       0.064
## selfemp2     0.042    1.000       0.005
## majorcards2  0.064    0.005       1.000
```

#8 glm with fewer variables

```r
expr_fin = 'reports ~ expenditure + owner2 + months + active'
model5_GLM = glm(expr_fin, family = poisson(), data = dero)
model6_GLM = glm.nb(expr_fin, data = dero)
model7_GLM = glm(expr_fin, family = gaussian(), data = dero)
model8_GLM = glm(expr_fin, family = quasi(), data = dero)
```

```r
summary(model5_GLM)
```

```
##
## Call:
## glm(formula = expr_fin, family = poisson(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.4627  -0.9392  -0.7245  -0.3446   7.0969
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.9127446  0.0769756 -11.858  < 2e-16 ***
## expenditure -0.0037563  0.0003662 -10.258  < 2e-16 ***
## owner2      -0.6409897  0.0922590  -6.948 3.71e-12 ***
## months       0.0024628  0.0005512   4.468 7.89e-06 ***
## active       0.0775611  0.0045252  17.140  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 2347.4  on 1318  degrees of freedom
## Residual deviance: 1917.4  on 1314  degrees of freedom
## AIC: 2576.9
##
## Number of Fisher Scoring iterations: 6
```

```r
summary(model6_GLM)
```

```
##
## Call:
## glm.nb(formula = expr_fin, data = dero, init.theta = 0.2584495758,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4419  -0.6779  -0.5687  -0.3689   2.5203
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.5035756  0.1407527 -10.682  < 2e-16 ***
## expenditure -0.0022398  0.0004248  -5.273 1.34e-07 ***
## owner2      -0.6428863  0.1626833  -3.952 7.76e-05 ***
## months       0.0026630  0.0010710   2.487   0.0129 *
## active       0.1239529  0.0114320  10.843  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(0.2584) family taken to be 1)
##
##     Null deviance: 833.08  on 1318  degrees of freedom
## Residual deviance: 682.65  on 1314  degrees of freedom
## AIC: 1994.2
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  0.2584
##           Std. Err.:  0.0281
##
##  2 x log-likelihood:  -1982.2150
```

```r
summary(model7_GLM)
```

```
##
## Call:
## glm(formula = expr_fin, family = gaussian(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0421  -0.5351  -0.3142   0.0526  13.1192
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.3062669  0.0650670   4.707 2.78e-06 ***
## expenditure -0.0006785  0.0001317  -5.151 2.99e-07 ***
## owner2      -0.3233147  0.0768345  -4.208 2.75e-05 ***
## months       0.0009976  0.0005549   1.798   0.0724 .
## active       0.0518767  0.0058845   8.816  < 2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 1.673544)
##
##     Null deviance: 2385.2  on 1318  degrees of freedom
## Residual deviance: 2199.0  on 1314  degrees of freedom
## AIC: 4429.4
##
## Number of Fisher Scoring iterations: 2
```

```r
summary(model8_GLM)
```

```
##
## Call:
## glm(formula = expr_fin, family = quasi(), data = dero)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0421  -0.5351  -0.3142   0.0526  13.1192
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.3062669  0.0650670   4.707 2.78e-06 ***
## expenditure -0.0006785  0.0001317  -5.151 2.99e-07 ***
## owner2      -0.3233147  0.0768345  -4.208 2.75e-05 ***
## months       0.0009976  0.0005549   1.798   0.0724 .
## active       0.0518767  0.0058845   8.816  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasi family taken to be 1.673544)
##
##     Null deviance: 2385.2  on 1318  degrees of freedom
## Residual deviance: 2199.0  on 1314  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 2
```

#9 AIC comparison

```r
AIC(model5_GLM)
```

```
## [1] 2576.902
```

```r
AIC(model6_GLM)
```

```
## [1] 1994.215
```

```r
AIC(model7_GLM)
```

```
## [1] 4429.361
```

#10 Summary of the selected model

```r
summary(model6_GLM)
```

```
##
## Call:
## glm.nb(formula = expr_fin, data = dero, init.theta = 0.2584495758,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4419  -0.6779  -0.5687  -0.3689   2.5203
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.5035756  0.1407527 -10.682  < 2e-16 ***
## expenditure -0.0022398  0.0004248  -5.273 1.34e-07 ***
## owner2      -0.6428863  0.1626833  -3.952 7.76e-05 ***
## months       0.0026630  0.0010710   2.487   0.0129 *
## active       0.1239529  0.0114320  10.843  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(0.2584) family taken to be 1)
##
##     Null deviance: 833.08  on 1318  degrees of freedom
## Residual deviance: 682.65  on 1314  degrees of freedom
## AIC: 1994.2
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  0.2584
##           Std. Err.:  0.0281
##
##  2 x log-likelihood:  -1982.2150
```

```r
summary(model6_GLM)$coefficients[,c(1,2,4)]
```

```
##                 Estimate   Std. Error     Pr(>|z|)
## (Intercept) -1.503575613 0.1407527227 1.230606e-26
## expenditure -0.002239835 0.0004247969 1.344162e-07
## owner2      -0.642886284 0.1626833416 7.757701e-05
## months       0.002663039 0.0010709985 1.290063e-02
## active       0.123952861 0.0114319985 2.161801e-27
```