Data Science Salaries

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2025-03-01

```
library(MASS)
library(car)
library(glmnet)
library(nnet)
library(leaps)
library(dplyr)
library(tidyverse)
library(Sleuth3)
library(logistf)
library(brglm2)
```

Abstract

The data set chosen for this report was Loan Approval Classification. There are 14 predictor variables and 45000 observations. These predictor variables are:

$

$

Objective

The objective of this analysis is to accurately predict whether or not a person given some information about them would be approved for a loan. A value of 0 indicates rejecton and a values of 1 indicates acceptance for a loan in loan status.

Predictors	Type
Age	Float
Gender	Categorical
Education	Categorical
Income	Float
Employment Years	Integer
Home Ownership	Categorical
Loan Amount	Float
Loan Intent	Categorical
Loan Interest Rate	Float
Loan Percent Income	Float
Credit History Length	Float
Credit Score	Integer
Previous Loans	Categorical
Loan Status	Integer

Data Clean Up

```
loan <- read.csv("./loan_data.csv")
loan <- as_tibble(loan)
loan <- loan |> mutate(
  person_gender = factor(person_gender,
    ordered = FALSE, levels = c("female", "male")
  ),
  person_education = factor(person_education,
    ordered = TRUE,
    levels = c("High School", "Associate", "Bachelor", "Master", "Doctorate")
  ),
  person_home_ownership = factor(person_home_ownership,
    ordered = FALSE,
    c("RENT", "OWN", "MORTGAGE", "OTHER")
  ),
  loan_intent = factor(loan_intent,
    ordered = FALSE,
    c(
      "PERSONAL", "MEDICAL", "EDUCATION",
      "VENTURE", "HOMEIMPROVEMENT", "DEBTCONSOLIDATION"
    )
  ),
  previous_loan_defaults_on_file = factor(previous_loan_defaults_on_file,
    ordered = FALSE, c("Yes", "No")
  )
)
set.seed(123) # reproducible
n <- nrow(loan) # 45 000
idx <- sample.int(n, size = 0.8 * n) # random 80 %
train <- loan[idx, ] # 36 000 rows
test <- loan[-idx, ] # 9 000 rows
predictors_numeric <- train |>
  select(where(is.numeric)) |>
  select(-loan_status)
test_model <- function(model) {
  pred_dist <- predict(firth_without_emp_exp, newdata = test, type = "response")
  likeif <- ifelse(pred_dist > 0.5, 1, 0)
  correct_response <- (likeif == test$loan_status)
  ratio <- mean(correct_response)
  ratio
}
```

Full Model vs Null Model

Full Model

This is the fitted model of all predictor variables that were left after data-clearning.

```
full_model <- glm(loan_status ~ .,
  data = train,
  family = binomial(link = "logit")
)
summary(full_model)
```

```
##
## Call:
## glm(formula = loan_status ~ ., family = binomial(link = "logit"),
##     data = train)
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -2.082e+01  1.146e+02  -0.182   0.8558
## person_age                       3.042e-02  1.223e-02   2.488   0.0128 *
## person_gendermale                2.433e-02  3.970e-02   0.613   0.5399
## person_education.L              -3.974e-02  1.076e-01  -0.369   0.7119
## person_education.Q              -2.797e-02  9.242e-02  -0.303   0.7622
## person_education.C              -6.312e-02  6.583e-02  -0.959   0.3377
## person_education^4              -5.586e-02  4.395e-02  -1.271   0.2037
## person_income                    4.409e-07  2.173e-07   2.029   0.0424 *
## person_emp_exp                  -2.269e-02  1.089e-02  -2.083   0.0372 *
## person_home_ownershipOWN        -2.131e+00  1.072e-01 -19.879  < 2e-16 ***
## person_home_ownershipMORTGAGE   -7.324e-01  4.494e-02 -16.298  < 2e-16 ***
## person_home_ownershipOTHER      -3.889e-01  3.569e-01  -1.090   0.2759
## loan_amnt                       -1.011e-04  4.403e-06 -22.961  < 2e-16 ***
## loan_intentMEDICAL               4.800e-01  6.519e-02   7.363 1.80e-13 ***
## loan_intentEDUCATION            -1.287e-01  6.730e-02  -1.912   0.0559 .
## loan_intentVENTURE              -4.740e-01  7.254e-02  -6.535 6.36e-11 ***
## loan_intentHOMEIMPROVEMENT       7.754e-01  7.563e-02  10.252  < 2e-16 ***
## loan_intentDEBTCONSOLIDATION     7.944e-01  6.737e-02  11.790  < 2e-16 ***
## loan_int_rate                    3.375e-01  7.379e-03  45.741  < 2e-16 ***
## loan_percent_income              1.589e+01  3.441e-01  46.179  < 2e-16 ***
## cb_person_cred_hist_length      -1.138e-02  1.010e-02  -1.126   0.2601
## credit_score                    -9.074e-03  4.587e-04 -19.781  < 2e-16 ***
## previous_loan_defaults_on_fileNo  2.038e+01  1.146e+02   0.178   0.8588
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 38136  on 35999  degrees of freedom
## Residual deviance: 15852  on 35977  degrees of freedom
## AIC: 15898
##
## Number of Fisher Scoring iterations: 19
```

```
# Statistics
AIC(full_model)
```

```
## [1] 15898.15
```

```
BIC(full_model)
```

```
## [1] 16093.45
```

```
mean((test$loan_status - predict(full_model, test, type = "response"))^2)
```

```
## [1] 0.07304491
```

Null Model

This is the model of only the intercept.

```r
null_model <- glm(
  loan_status ~ 1,
  data   = training,
  family = binomial(link = "logit")
)

anova(null_model, full_model, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: loan_status ~ 1
## Model 2: loan_status ~ person_age + person_gender + person_education +
##     person_income + person_emp_exp + person_home_ownership +
##     loan_amnt + loan_intent + loan_int_rate + loan_percent_income +
##     cb_person_cred_hist_length + credit_score + previous_loan_defaults_on_file
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     35999      38136
## 2     35977      15852 22    22284 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
AIC(null_model)
```

```
## [1] 38138.34
```

```r
BIC(null_model)
```

```
## [1] 38146.83
```

```r
mean((test$loan_status - predict(null_model, test, type = "response"))^2)
```

```
## [1] 0.1729012
```

Null Model vs. Full Model

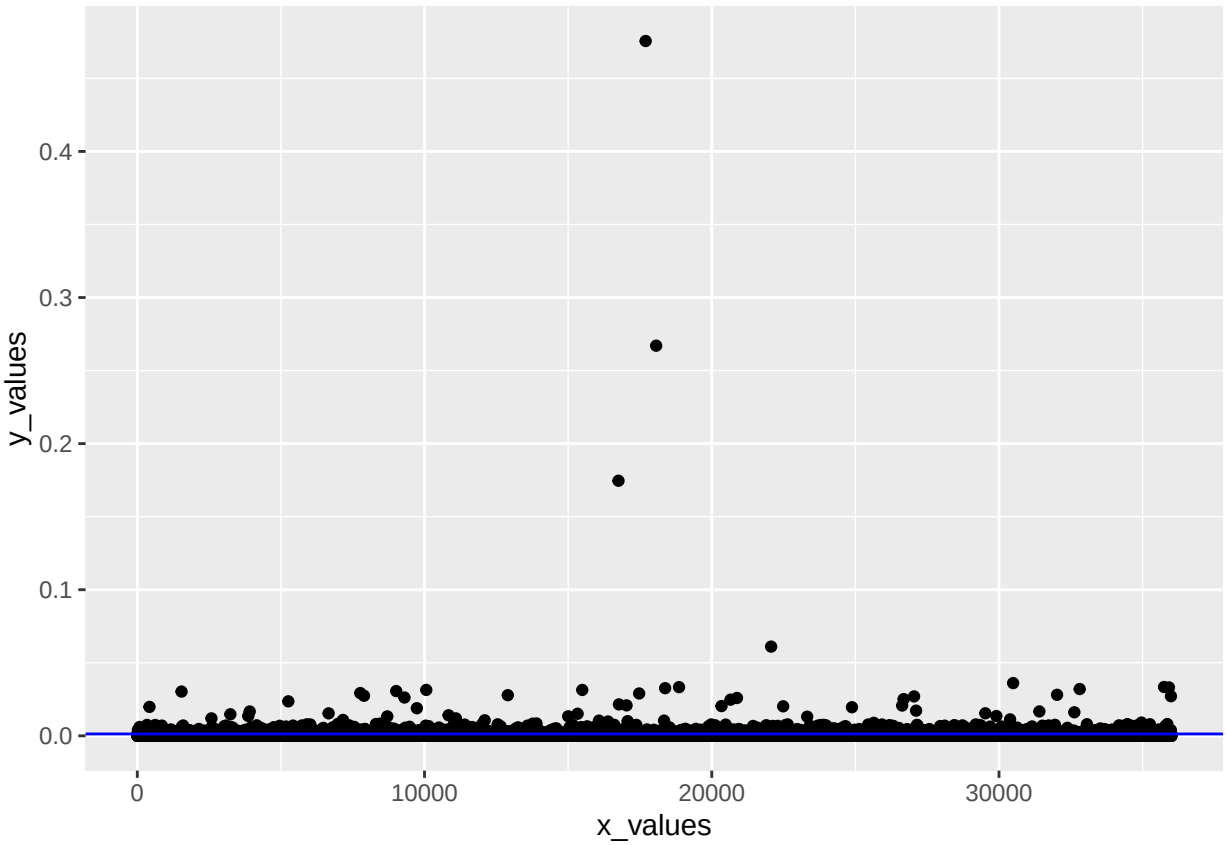
We can conclude from the statistics below that atleast one predictor variable is needed in our model as the we have gotten a very low p-value and the difference in AIC/BIC shows a very clear sign that we should not use the null model.

Problematic Sample Points

Leverage

We recieved around 5954 out of the 36000 oberservations that are considered high leverage.

```r
lev <- hatvalues(full_model)
cutoff <- (2 * length(coef(init_model))) / nrow(training)
lev_data <- data.frame(
  x_values = seq_along(lev),
  y_values = lev
)
ggplot(aes(x = x_values, y = y_values), data = lev_data) +
  geom_point() +
  geom_hline(yintercept = cutoff, col = "blue")
```




```
high_lev <- which(lev > cutoff)
head(high_lev)
```

```
## 19 21 22 36 39 43
## 19 21 22 36 39 43
```

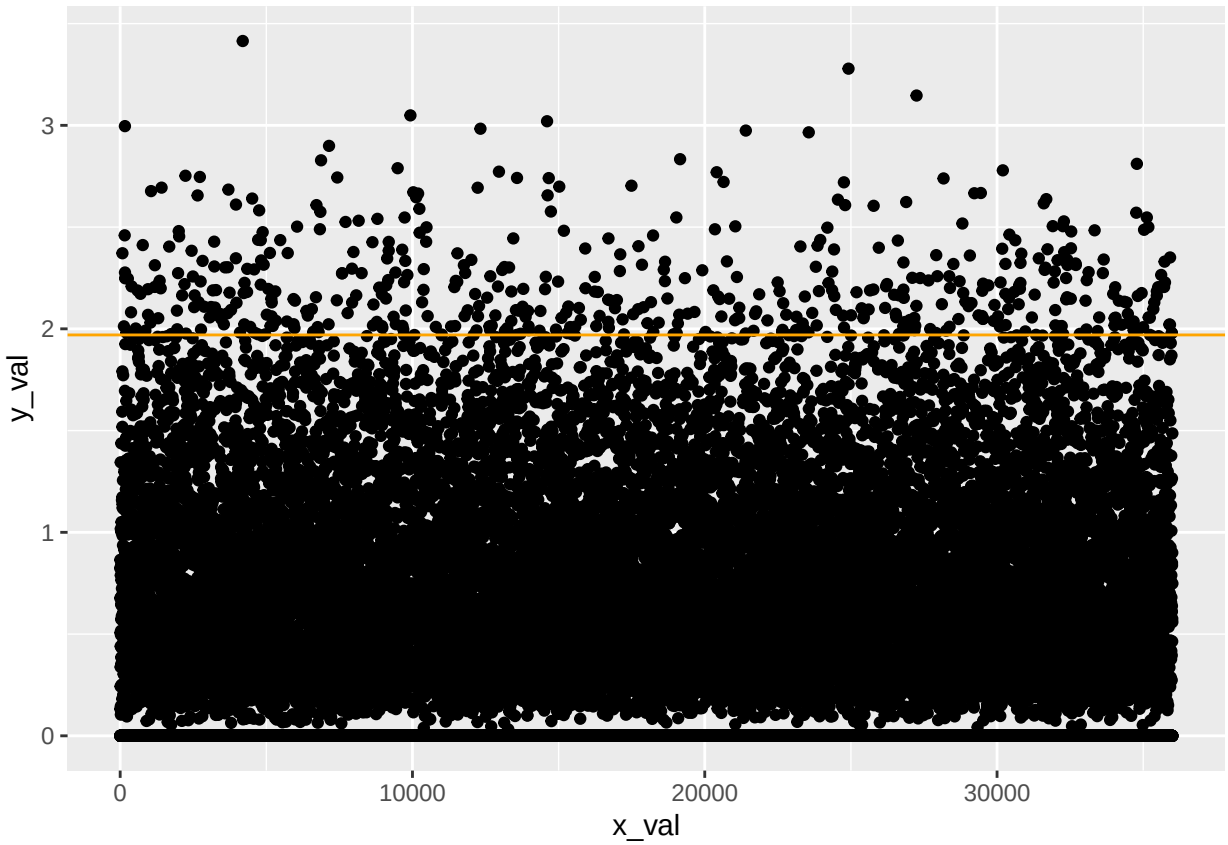
```
length(high_lev)
```

```
## [1] 5954
```

Outliers

We found 504 outliers within this data.

```
rstd <- rstudent(full_model)
outliers <- which(abs(rstd) >= 1.97)
ggplot(aes(x = x_val, y = y_val), data = data.frame(x_val = seq_along(rstd), y_val = abs(rstd))) +
  geom_point() +
  geom_hline(yintercept = 1.97, col = "orange")
```




```
head(outliers)
```

```
##  77 129 155 163 165 170
##  77 129 155 163 165 170
```

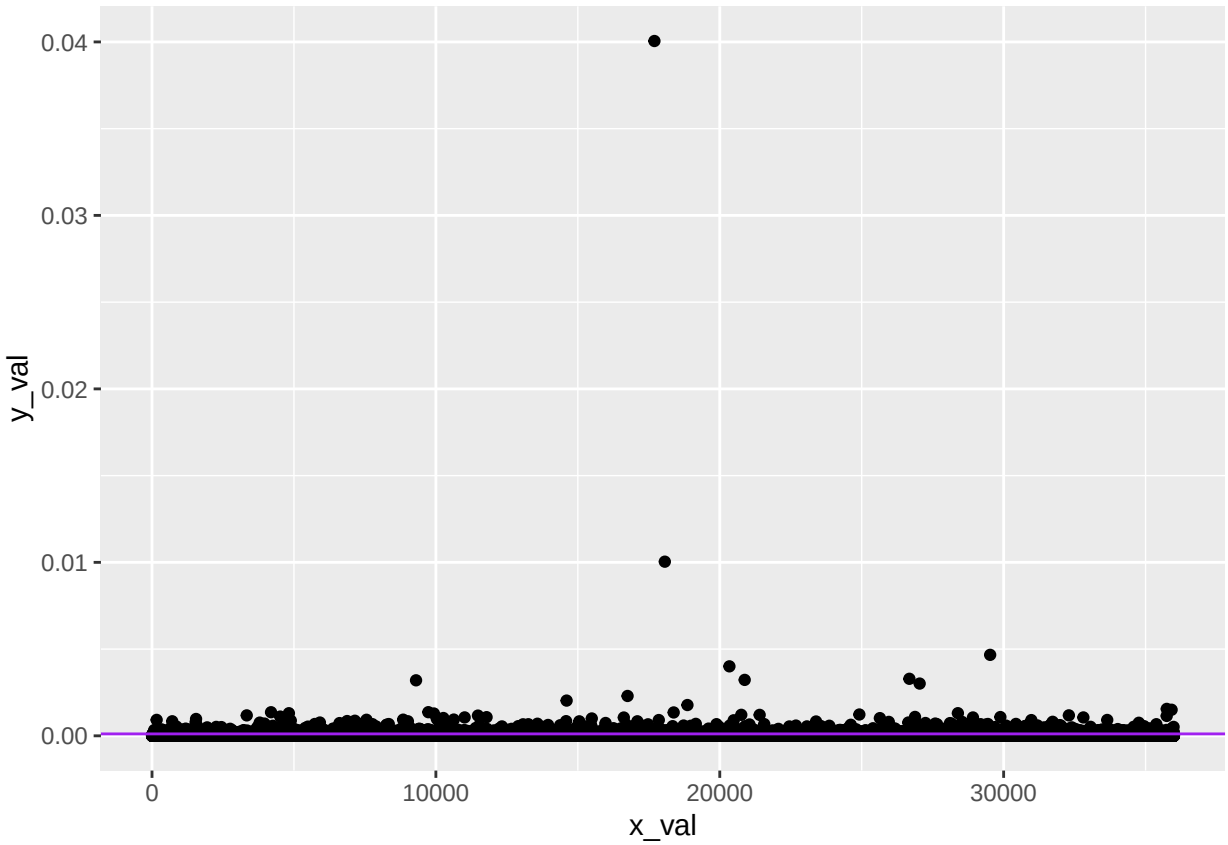
```
length(outliers)
```

```
## [1] 504
```

Cook's Distance & Influential Points

Since 1 as the cutoff is too strict for this large dataset we adjusted the cutoff to be $\frac{4}{n}$ as used in a lot studies.

```
cd <- cooks.distance(full_model)
influential <- which(cd > 4 / nrow(training))
influential <- unique(unlist(influential))
ggplot(aes(x = x_val, y = y_val), data = data.frame(x_val = seq_along(cd), y_val = cd)) +
  geom_point() +
  geom_hline(yintercept = 4 / nrow(training), col = "purple")
```




```
length(influential)
```

```
## [1] 2478
```

Problematic Points

We remove outliers that are influential points. From the R code below we can see that all of our outliers are influential points thust we should remove each of them.

```
sum(outliers %in% influential)
```

```
## [1] 504
```

```
train_no_outlier <- train[-outliers, ]

no_outlier_model <- glm(loan_status ~ .,
  data = train_no_outlier,
  family = binomial(link = "logit")
)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(no_outlier_model)
```

```
##
## Call:
## glm(formula = loan_status ~ ., family = binomial(link = "logit"),
##     data = train_no_outlier)
##
## Coefficients:
```

```
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -2.232e+01  1.082e+02  -0.206 0.836619
## person_age                       5.779e-02  1.369e-02   4.223 2.41e-05 ***
## person_gendermale                5.046e-02  4.432e-02   1.139 0.254881
## person_education.L              -9.888e-02  1.223e-01  -0.809 0.418667
## person_education.Q              -8.259e-02  1.050e-01  -0.787 0.431521
## person_education.C              -1.134e-01  7.441e-02  -1.524 0.127625
## person_education^4              -7.268e-02  4.925e-02  -1.476 0.140044
## person_income                    3.424e-07  3.303e-07   1.037 0.299797
## person_emp_exp                  -4.280e-02  1.219e-02  -3.511 0.000446 ***
## person_home_ownershipOWN        -2.782e+00  1.254e-01 -22.184  < 2e-16 ***
## person_home_ownershipMORTGAGE   -9.222e-01  5.077e-02 -18.165  < 2e-16 ***
## person_home_ownershipOTHER      -6.682e-01  4.015e-01  -1.664 0.096100 .
## loan_amnt                       -1.357e-04  5.269e-06 -25.755  < 2e-16 ***
## loan_intentMEDICAL               6.798e-01  7.321e-02   9.286  < 2e-16 ***
## loan_intentEDUCATION            -1.496e-01  7.572e-02  -1.976 0.048191 *
## loan_intentVENTURE              -4.673e-01  8.143e-02  -5.739 9.53e-09 ***
## loan_intentHOMEIMPROVEMENT       1.104e+00  8.503e-02  12.985  < 2e-16 ***
## loan_intentDEBTCONSOLIDATION     1.082e+00  7.586e-02  14.270  < 2e-16 ***
## loan_int_rate                    4.581e-01  9.112e-03  50.270  < 2e-16 ***
## loan_percent_income              2.131e+01  4.370e-01  48.773  < 2e-16 ***
## cb_person_cred_hist_length      -2.553e-02  1.130e-02  -2.259 0.023909 *
## credit_score                    -1.180e-02  5.201e-04 -22.679  < 2e-16 ***
## previous_loan_defaults_on_fileNo  2.096e+01  1.082e+02   0.194 0.846446
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36984  on 35495  degrees of freedom
## Residual deviance: 12964  on 35473  degrees of freedom
## AIC: 13010
##
## Number of Fisher Scoring iterations: 19
```

```
AIC(no_outlier_model)
```

```
## [1] 13010.07
```

```
BIC(no_outlier_model)
```

```
## [1] 13205.05
```

```
mean((test$loan_status - predict(no_outlier_model, test, type = "response"))^2)
```

```
## [1] 0.07450024
```

Perfect and Quasi Complete Seperation

At this stage we have run into a problem. We encountered the warning message "glm.fit: fitted probabilities numerically 0 or 1 occurred". After researching this we came across that this is because we have Quasi-Complete Seperation. This means that one or more of our predictor varibles almost perfectly predicts our outcome variable.previous_loan_defaults_on_fileNo 2 From anaylzing the summary of the full model we can spot multiple problem covariates. This is a problem because it can lead to overfitting, and it pushes the maximum likelihood and standard error towards infinity.

Number of Previous Loan Defaults On File We can see that this covariate's estimate has a large magnitude around 20. This could be because of perfect and quasi complete seperation or multicollinearity.

Combatting Perfect and Quesi-Complete Seperation

From our research a useful way to combat Quesi-Complete Seperation is to merge or drop factor levels with too few observations ($< 0.5\%$ of data size) or drop levels that are heavily sided towards one outcome. The reason for this is that if these factor levels with few observations heavily lean towards one side of the binary outcome then when building a model it will see this almost perfect predictor for the outcome variable and thus give us an esitmate with a very large magnitude for that factor level. Factor levels with too few observations also may have a wide confidence interval. Thus we collpase these factor levels into a factor level that accounts for a larger group of observations. Below is a count of how many times each factor level occurs in the dataset of 36000 observations.

```
table(train_no_outlier$loan_intent)
```

```
##
##          PERSONAL           MEDICAL         EDUCATION           VENTURE   HOMEIMPROVEMENT DEBTCONSOLI
##              5918              6751              7179              6180              3793
```

```
xtabs(~ loan_status + loan_intent, data = train_no_outlier)
```

```
##            loan_intent
## loan_status PERSONAL MEDICAL EDUCATION VENTURE HOMEIMPROVEMENT DEBTCONSOLIDATION
##           0     4835    4889      6041    5316            2806               3965
##           1     1083    1862      1138     864             987               1710
```

```
table(train_no_outlier$person_education)
```

```
##
## High School   Associate    Bachelor      Master   Doctorate
##        9468        9500       10573        5473         482
```

```
xtabs(~ loan_status + person_education, data = train_no_outlier)
```

```
##            person_education
## loan_status High School Associate Bachelor Master Doctorate
##           0        7404      7452     8301   4316       379
##           1        2064      2048     2272   1157       103
```

```
table(train_no_outlier$person_home_ownership)
```

```
##
##     RENT      OWN MORTGAGE    OTHER
##    18551     2329    14525       91
```

```
xtabs(~ loan_status + person_home_ownership, data = train_no_outlier)
```

```
##            person_home_ownership
## loan_status  RENT   OWN MORTGAGE OTHER
##           0 12574  2172    13045    61
##           1  5977   157     1480    30
```

```
table(train_no_outlier$previous_loan_defaults_on_file)
```

```
##
##   Yes    No
## 18259 17237
```

```r
xtabs(~ loan_status + previous_loan_defaults_on_file, data = train_no_outlier)
```

```
##             previous_loan_defaults_on_file
## loan_status   Yes    No
##           0 18259  9593
##           1     0  7644
```

We also see that we actually have complete seperation. Every observation that has had a previous loan default has been rejected for a loan. We dont want to just remove this level because it still contains very important information thus we dedcided to combat this by using firth logistic regression as recommended in the source provided.

Firth Logistic Regression

Firth logistic regression augments the ordinary log-likelihood with the **Firth penalty**

$$\frac{1}{2}\log\left|I(\boldsymbol{\beta})\right|,$$

where $I(\boldsymbol{\beta})$ is the observed Fisher–information matrix.

```r
firth_model <- brglm(loan_status ~ ., data = train_no_outlier, family = "binomial", pl = TRUE)
summary(firth_model)
```

```
##
## Call:
## brglm(formula = loan_status ~ ., family = "binomial", data = train_no_outlier,
##     pl = TRUE)
##
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -1.266e+01  1.505e+00  -8.414  < 2e-16 ***
## person_age                       5.787e-02  1.367e-02   4.234 2.29e-05 ***
## person_gendermale                5.040e-02  4.428e-02   1.138 0.255039
## person_education.L              -9.829e-02  1.221e-01  -0.805 0.420892
## person_education.Q              -8.194e-02  1.049e-01  -0.781 0.434639
## person_education.C              -1.128e-01  7.433e-02  -1.518 0.128982
## person_education^4              -7.257e-02  4.920e-02  -1.475 0.140273
## person_income                    4.734e-07  2.565e-07   1.845 0.064984 .
## person_emp_exp                  -4.261e-02  1.218e-02  -3.499 0.000466 ***
## person_home_ownershipOWN        -2.776e+00  1.252e-01 -22.168  < 2e-16 ***
## person_home_ownershipMORTGAGE   -9.215e-01  5.070e-02 -18.174  < 2e-16 ***
## person_home_ownershipOTHER      -6.760e-01  4.009e-01  -1.686 0.091768 .
## loan_amnt                       -1.362e-04  5.105e-06 -26.684  < 2e-16 ***
## loan_intentMEDICAL               6.785e-01  7.314e-02   9.277  < 2e-16 ***
## loan_intentEDUCATION            -1.495e-01  7.565e-02  -1.977 0.048088 *
## loan_intentVENTURE              -4.665e-01  8.134e-02  -5.735 9.73e-09 ***
## loan_intentHOMEIMPROVEMENT       1.102e+00  8.495e-02  12.969  < 2e-16 ***
## loan_intentDEBTCONSOLIDATION     1.080e+00  7.578e-02  14.252  < 2e-16 ***
## loan_int_rate                    4.572e-01  9.096e-03  50.266  < 2e-16 ***
## loan_percent_income              2.132e+01  4.270e-01  49.936  < 2e-16 ***
## cb_person_cred_hist_length      -2.591e-02  1.127e-02  -2.299 0.021495 *
## credit_score                    -1.177e-02  5.194e-04 -22.661  < 2e-16 ***
## previous_loan_defaults_on_fileNo  1.129e+01  1.439e+00   7.844 4.37e-15 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36846  on 35495  degrees of freedom
## Residual deviance: 12965  on 35473  degrees of freedom
## Penalized deviance: 12779.3
## AIC:  13011
```

As shown in the summary of the Firth model there are still estimates with large magnitudes and near 0 p values however the standard error for these estimates have decreased which tells us that it just has a strong effect on our data. For example the p value of previous loan defaults was large because of it's standard error, however now it is near 0. We can still test for multi-collinearity which we will do utilizing VIF.

Multi-Collinearity (VIF)

```
vif(firth_model)
```

```
##                                     GVIF Df GVIF^(1/(2*Df))
## person_age                     15.575390  1        3.946567
## person_gender                   1.002841  1        1.001419
## person_education                1.081673  4        1.009862
## person_income                   1.286707  1        1.134331
## person_emp_exp                 12.485616  1        3.533499
## person_home_ownership           1.187769  3        1.029095
## loan_amnt                       2.321623  1        1.523687
## loan_intent                     1.109425  5        1.010438
## loan_int_rate                   1.292221  1        1.136759
## loan_percent_income             2.584968  1        1.607784
## cb_person_cred_hist_length      4.051722  1        2.012889
## credit_score                    1.136289  1        1.065968
## previous_loan_defaults_on_file  1.002521  1        1.001260
```

```
deviance(firth_model)
```

```
## [1] 12965.3
```

```
firth_without_age <- brglm(loan_status ~ . - person_age, data = train_no_outlier, family = "binomial", p
firth_without_emp_exp <- brglm(loan_status ~ . - person_emp_exp, data = train_no_outlier, family = "bino
deviance(firth_without_age)
```

```
## [1] 12983.09
```

```
deviance(firth_without_emp_exp)
```

```
## [1] 12977.64
```

```
# Thus we remove emp_exp
vif(firth_without_emp_exp)
```

```
##                                    GVIF Df GVIF^(1/(2*Df))
## person_age                     4.240980  1        2.059364
## person_gender                  1.002500  1        1.001249
## person_education               1.080486  4        1.009723
## person_income                  1.283955  1        1.133117
## person_home_ownership          1.187617  3        1.029073
## loan_amnt                      2.312797  1        1.520788
## loan_intent                    1.108707  5        1.010373
```

```
## loan_int_rate                  1.290162  1        1.135853
## loan_percent_income            2.573134  1        1.604099
## cb_person_cred_hist_length     3.976579  1        1.994136
## credit_score                   1.135167  1        1.065442
## previous_loan_defaults_on_file 1.002506  1        1.001252
```

```
# STOP no more VIF less than 10 or 5
```

```
summary(firth_without_emp_exp)
```

```
##
## Call:
## brglm(formula = loan_status ~ . - person_emp_exp, family = "binomial",
##     data = train_no_outlier, pl = TRUE)
##
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -1.168e+01  1.478e+00  -7.902 2.74e-15 ***
## person_age                       1.723e-02  7.104e-03   2.426   0.0153 *
## person_gendermale                4.756e-02  4.426e-02   1.075   0.2825
## person_education.L              -8.761e-02  1.218e-01  -0.720   0.4718
## person_education.Q              -7.896e-02  1.046e-01  -0.755   0.4503
## person_education.C              -1.097e-01  7.417e-02  -1.479   0.1391
## person_education^4              -7.227e-02  4.916e-02  -1.470   0.1415
## person_income                    4.446e-07  2.545e-07   1.747   0.0807 .
## person_home_ownershipOWN        -2.781e+00  1.251e-01 -22.229  < 2e-16 ***
## person_home_ownershipMORTGAGE   -9.202e-01  5.069e-02 -18.155  < 2e-16 ***
## person_home_ownershipOTHER      -6.936e-01  4.012e-01  -1.729   0.0839 .
## loan_amnt                       -1.356e-04  5.094e-06 -26.618  < 2e-16 ***
## loan_intentMEDICAL               6.787e-01  7.310e-02   9.284  < 2e-16 ***
## loan_intentEDUCATION            -1.529e-01  7.563e-02  -2.022   0.0432 *
## loan_intentVENTURE              -4.650e-01  8.131e-02  -5.719 1.07e-08 ***
## loan_intentHOMEIMPROVEMENT       1.103e+00  8.492e-02  12.994  < 2e-16 ***
## loan_intentDEBTCONSOLIDATION     1.081e+00  7.576e-02  14.263  < 2e-16 ***
## loan_int_rate                    4.564e-01  9.084e-03  50.240  < 2e-16 ***
## loan_percent_income              2.126e+01  4.257e-01  49.951  < 2e-16 ***
## cb_person_cred_hist_length      -2.645e-02  1.116e-02  -2.370   0.0178 *
## credit_score                    -1.185e-02  5.188e-04 -22.846  < 2e-16 ***
## previous_loan_defaults_on_fileNo  1.128e+01  1.439e+00   7.836 4.64e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36851  on 35495  degrees of freedom
## Residual deviance: 12978  on 35474  degrees of freedom
## Penalized deviance: 12800.38
## AIC:  13022
```

```
test_model(firth_without_emp_exp)
```

```
## [1] 0.8933333
```

Ridge Regression

Principal Component Analysis

Methods

- i.e nominal / logistic / ordinal / linear / multilinear
- Regress on loan status - Logistic
- Regress on education - Ordinal
- Variable Selection
- AIC/BIC/MAPE/MPSE

Analysis

Conclusion

Sources

https://stats.oarc.ucla.edu/other/mult-pkg/faq/general/faqwhat-is-complete-or-quasi-complete-separation-in-logistic-regression-and-what-are-some-strategies-to-deal-with-the-issue/ https://medium.datadriveninvestor.com/firths-logistic-regression-classification-with-datasets-that-are-small-imbalanced-or-separated-49d7782a13f1