Final Project

Behavioral Data Science

Kiva Dataset

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East

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Summary Report

Introduction

Kiva is an online platform to extend financial services to poor and financially excluded people around the world through the use of crowdsourced loans. Kiva claims that its lenders have provided over $1 billion dollars in loans to over 2 million people across the world many of whom might have been unable to find loans otherwise [1]. Although the majority of loans are funded, roughly 7% of loans are not fully funded on the platform. In order to fund as many people as possible, it is important to be able to predict which loans will be funded and which loans that will not be fully funded. With this information, loans that are unlikely to be fully funded based on their demographics can be identified and mitigated before they ever make it onto the platform.

Hypothesis

The easiest current way to predict if a loan will be fully funded is to assume that all loans are funded. This produces an accuracy of roughly 93%; however, with a sensitivity of 0%, this null model is worthless in determining if a loan will not be funded. Identifying if a loan is likely to be unfunded is important so that these applications can be modified in order to improve their funding odds.   I believe a model can be developed that will better predict which loans will not be fully funded. To do this I will use a Random Forest algorithm and then attempt to optimize the model on sensitivity.

Data Description and Exploratory data Analysis

The kiva dataset originally had 671205 observations and 20 variables. The data can be divided easily into 1) information that pertains to before the loan is funded and 2) information that is derived by the loan being funded. This analysis is focused only on things that lead to a loan being funded because this information is the only data that is available for prediction. All data created by a loan being fully funded was omitted from the analysis. For instance, the number of lenders a loan has and the date a loan was fully funded would not be available at the time of loan application, so these variables were removed.

The remaining variables that relate to loans pre-funding were further cleaned for easier analysis. A dependent variable, “Funded,” was created to represent if the loan was fully funded as defined by the loan_amount being equal to the funded_amount. Since extended modifications were made to the data, each of the variables used defined in Figure 1. Most of these variables are binary and correspond to if a loan has a certain characteristic. For instance, variables 13 through 46 relate to if a loan application had a specific tag, such as “user_favorite.”

Through exploratory data analysis (EDA), it was determined that roughly 93% of the data represents funded loans and the remaining 7% represents unfunded loans. As can be seen in the select graphs shown in Figure 2, the unfunded loans have characteristics that differ from the funded loans. Ideally these differences in distributions can be used by the random forest algorithm for the various splits needed in developing a classification model.

Analysis Plan

Step 1: The data will be first split into testing and training datasets. The training set will be used to develop a random forest model that predicts which loans will be fully funded and which loans will not be. This will be the base model that future optimized models will be compared to.

Step 2: With the base model established, I will first attempt to optimize the model by using several different sampling techniques on the training set. The data set is fairly imbalanced and the class we are interested in is the minority class, this imbalance often makes classification difficult. I will try the techniques of up sampling down sampling and a hybrid approach known as synthetic minority over-sampling technique (SMOTE). Using each of these three sampling techniques, I will develop new random forest models and compare them to the base model. The best performing model will be selected.

Step 3: With the sampling technique selected I will try to optimize on the mtry value. The mtry value is the number of variables the algorithm tries at each split in the dataset. I will run a loop with possibly mtry values ranging from 3 to 40. I will select the mtry value that performs well optimizing on sensitivity but being cognizant on the impacts on overall accuracy of the model.

Step 4: With the overall optimized parameters established, I will run the final model in a loop changing the sampling set with each replication. This stage shows the impact of the initial sample selected on the overall model.

Results

Build Base Model

Typically, an 80% training and a 20% testing split in the dataset is recommended. Due to the size of the initial data set and the computational limitations of my computer, I was forced to use a training set of only 7% of the total dataset. This means a smaller percentage of the data is used in the raining of the model which may influence the models overall predictive ability.

For the base model I used a mtry value of 20 ,which is roughly half the number of variables, and 500 trees. The initial base model I developed performed fairly well at overall prediction of the dataset with an accuracy of 93%. This model only had a sensitivity of 17%, meaning that the model only correctly predicted the minority (unfunded) class 17% of the time. Other model parameters are shown in Figure 3.This model was used as the base model that future models will be compared to.

Optimize on Sampling Technique

Down-sampling takes samples from the majority class to make their frequencies closer to the minority class. This means effectively the majority class is underrepresented in the training data. This model had an accuracy of 71.2% and a sensitivity of 33%. The remaining results are shown in Figure 4. Up-sampling takes all of the majority samples and then samples with replacement from the minority samples such that the majority and minority samples are equal. This means effectively the minority class is overrepresented in the training data. This model produced and accuracy of 92.8% and a sensitivity of 30.6%. The remaining results are shown in Figure 5. SMOTE sampling creates synthetic samples in the minority class to better represent the sample.

With this sampling technique an accuracy of 85.6% and sensitivity of 72.9% was achieved. The remaining results are shown in Figure 6.

Comparing the three sampling techniques, neither model did better than the base model in terms of accuracy. All three however performed better in terms of sensitivity. I decided to use the SMOTE model because this model achieved a high degree of sensitivity while maintaining a reasonable accuracy percent.

Optimize on Mtry Value

In order to optimize the model, I ran the SMOTE training dataset in a loop, trying all possible values of mtry. Figure 7 highlights the results of this loop by showing the accuracy and error of the models with various mtry values. As can be seen in the graphs, as mtry increases so does the error (1-accuracy=error) rate. Conversely, as mtry gets larger so does sensitivity. Since the too characteristics are optimized based on different mtry values, a balance between the two parameters needed to be reached. An mtry value of 15 was selected in order the improve sensitivity without too high of a cost in accuracy.

Final Model

Since models such as random forest are developed using a single training sample, it is possible that the model was overfit based on initial model selected. In order to test for this, the final model was tested again in a loop using a new sample and new smote data. The results of this analysis (Figure 8) show that for the model has a median error of 13.9% (86.1% accuracy) and a median sensitivity of 73.5%. This is significant improvement over the 17% sensitivity found in the base model. A final model confusion matrix is shown in Figure 9.

Discussion

Overall, I was able to produce a model that predicts if a loan will not be fully funded. This model performs much better than my initial base model in properly predicting which loans will not be fully funded. This improvement in model sensitivity did however come at the cost of reduced accuracy in the final model. This trade-off was determined to be acceptable because the main objective on the model was to better classify loans that will not be fully funded. With this information, loans applications that are likely not to be funded can be targeted and updated before they ever make it onto the platform.

The biggest challenge of this analysis was the size of the initial dataset. Because it was so large, it was often difficult to work with and caused problems with my computer. I was also unable to use a standard percentage to the data for the training set because of the computation requirements demanded by running the random forest algorithm. If I was able to use a larger percentage of the data for training, I believe the model would do even better at prediction.

Considering the results of this analysis there are a number of things that I would like to research further. Based on the importance score from the random forest algorithm, which is visualized in Figure 10, it is clear than not all variables have predictive ability for the model. I would like to explore removing some of those variables, especially those corresponding to tags and rerun the model to see if that had an impact on prediction. It is possible that factor/component analysis could be used to reduce variables further. I would also like to further analyze the variables that were deemed important to the predictive abilities of the model and create a comparison between funded and unfunded loans. Using a comparison of the characteristic of the loans it could be determined which characteristics are most likely to impact the final compensation decision. Those specific characteristics can then be modified prior to the loan ever getting posted. For instance, it was determined that loans that do not use a tag are more likely to be funded than loans that use a tag. Using that information, when a loan is identified as unlikely to be funded that tag can be removed to increase the probability that the loan gets fully funded. This is just small and simple change in the loan application, but it can dramatically improve the life of the loan recipient. These minor changes applied to loans unlikely to be funded can help to increase the number of people that are helped on the crowdfunding platform. This information can also be used to target people to reach out to in order to get them on the crowdfunding platform to seek out loans. For instance, if one industry gets funded at a higher rate than another industry, that industry should be targeted in future marketing campaigns to increase the number of people that ultimately receive loans.

Bibliography

[1] Kiva, "Kiva," 9 December 2018. [Online]. Available: https://www.kiva.org/.

Appendix 1: Supporting Figures

Figure 1: Variable Descriptions

Variable	Description
funded	“yes” if loan_amount and funded_amount is equal, otherwise “no”
loan_amount	Unchanged from kiva dataset
sector	Unchanged from kiva dataset
continent	Continent derived from the country of loan origin, North and South America are listed as “Americas”
repayment_interval	Unchanged from kiva dataset
term_in_months	Unchanged from kiva dataset
number_tags	Count of the number of tags
female_borrower	“yes” if a female is listed in gender_borrower, otherwise “no”
male_borrower	“yes” if a male is listed in gender_borrower, otherwise “no”
month	Month extracted from the posted_date
weekday	Weekday extracted from the posted_date
Columns 11:46	Binary yes/no based on if column heading is listed in the tags

Figure 2: Select EDA Graphs

Figure 3: Base Model Confusion Matrix and Statistics

```
Confusion Matrix and Statistics

          Reference
Prediction     No    Yes
       No    7710   4452
       Yes  37199 574860

               Accuracy : 0.9333
                 95% CI : (0.9327, 0.9339)
    No Information Rate : 0.9281
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.2471
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.17168
            Specificity : 0.99232
         Pos Pred Value : 0.63394
         Neg Pred Value : 0.93922
             Prevalence : 0.07194
         Detection Rate : 0.01235
   Detection Prevalence : 0.01948
      Balanced Accuracy : 0.58200

       'Positive' Class : No
```

Figure 4: Down Sampled Confusion Matrix and Statistics

```
Confusion Matrix and Statistics

          Reference
Prediction     No    Yes
       No   14818 149600
       Yes  30131 429672

               Accuracy : 0.7121
                 95% CI : (0.7109, 0.7132)
    No Information Rate : 0.928
    P-Value [Acc > NIR] : 1

                  Kappa : 0.0321
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.32966
            Specificity : 0.74174
         Pos Pred Value : 0.09012
         Neg Pred Value : 0.93447
             Prevalence : 0.07201
         Detection Rate : 0.02374
   Detection Prevalence : 0.26340
      Balanced Accuracy : 0.53570

       'Positive' Class : No
```

Figure 5: Up- Sampled Confusion Matrix and Statistics

```
Confusion Matrix and Statistics

          Reference
Prediction     No    Yes
       No   13750  13964
       Yes  31159 565348

               Accuracy : 0.9277
                 95% CI : (0.9271, 0.9284)
    No Information Rate : 0.9281
    P-Value [Acc > NIR] : 0.8533

                  Kappa : 0.3426
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.30617
            Specificity : 0.97590
         Pos Pred Value : 0.49614
         Neg Pred Value : 0.94776
             Prevalence : 0.07194
         Detection Rate : 0.02203
   Detection Prevalence : 0.04440
      Balanced Accuracy : 0.64104

       'Positive' Class : No
```

Figure 6: SMOTE Sampled Confusion Matrix and Statistics

```
Confusion Matrix and Statistics

          Reference
Prediction     No    Yes
       No   32752  77615
       Yes  12157 501697

               Accuracy : 0.8562
                 95% CI : (0.8553, 0.8571)
    No Information Rate : 0.9281
    P-Value [Acc > NIR] : 1

                  Kappa : 0.356
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.72930
            Specificity : 0.86602
         Pos Pred Value : 0.29676
         Neg Pred Value : 0.97634
             Prevalence : 0.07194
         Detection Rate : 0.05247
   Detection Prevalence : 0.17681
      Balanced Accuracy : 0.79766

       'Positive' Class : No
```

Figure 7: M-try Impact on sensitivity and Accuracy

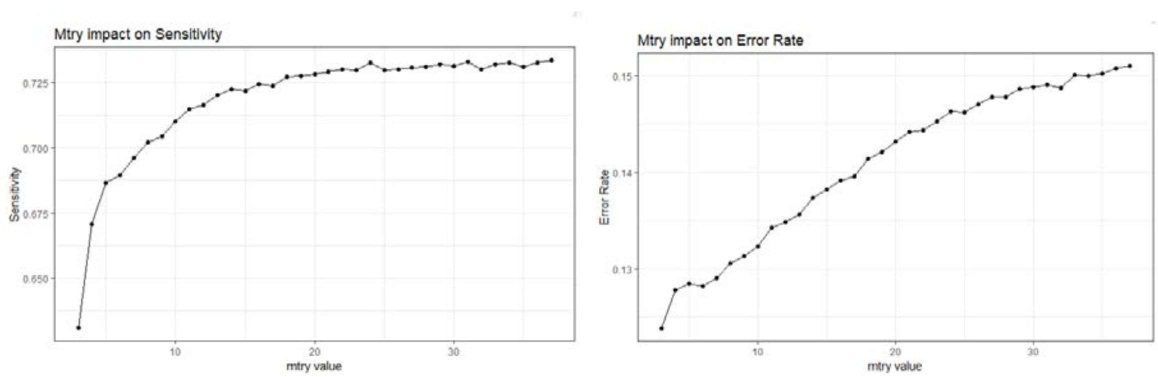

Figure 8: Final Model Metric Boxplots

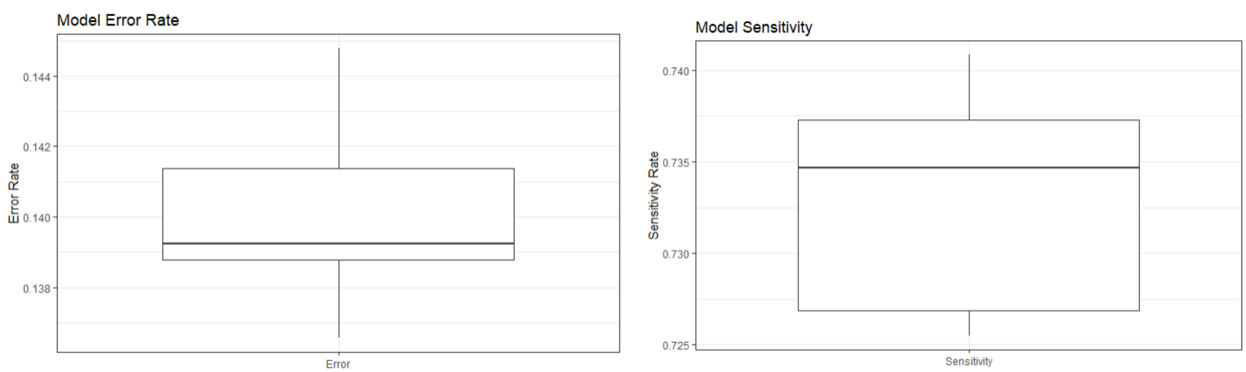

Figure 9: Final Model Confusion Matrix and Statistics

```
Confusion Matrix and Statistics

          Reference
Prediction     No    Yes
       No   32631  75551
       Yes  12318 503721

               Accuracy : 0.8592
                 95% CI : (0.8584, 0.8601)
    No Information Rate : 0.928
    P-Value [Acc > NIR] : 1

                  Kappa : 0.3612
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.72596
            Specificity : 0.86958
         Pos Pred Value : 0.30163
         Neg Pred Value : 0.97613
             Prevalence : 0.07201
         Detection Rate : 0.05227
   Detection Prevalence : 0.17331
      Balanced Accuracy : 0.79777

       'Positive' Class : No
```

Figure 10: Importance of Variables

Appendix 2: Code

Kiva Final

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December 5, 2018

The following libraries were used in this analysis

```
library(data.table)
library(corrplot)
library(tidyverse)
library(reshape2)
library(treemap)
library(stringr)
library(ggthemes)
library(countrycode)
library(gdata)
library(ggrepel)
library(ggwordcloud)
library(randomForest)
library(caret)
library(DMwR) #SMOTE Hybrid Model
```

Read in data

```
kiva <- fread("BDS_WK11_kiva_loans.csv", header=T)
```

General Exploratory Analysis

```
head(kiva)

##         id funded_amount loan_amount            activity         sector
## 1:  653051           300         300 Fruits & Vegetables           Food
## 2:  653053           575         575            Rickshaw Transportation
## 3:  653068           150         150      Transportation Transportation
## 4:  653063           200         200          Embroidery           Arts
## 5:  653084           400         400          Milk Sales           Food
## 6: 1080148           250         250            Services       Services
##                                                                            use
## 1:                                             To buy seasonal, fresh fruits to sell.
## 2:                    to repair and maintain the auto rickshaw used in their business.
## 3: To repair their old cycle-van and buy another one to rent out as a source of income
## 4:        to purchase an embroidery machine and a variety of new embroidery materials.
## 5:                                                         to purchase one buffalo.
## 6:                                  purchase leather for my business using ksh 20000.
##    country_code  country       region currency partner_id
## 1:           PK Pakistan       Lahore      PKR        247
## 2:           PK Pakistan       Lahore      PKR        247
## 3:           IN    India    Maynaguri      INR        334
## 4:           PK Pakistan       Lahore      PKR        247
## 5:           PK Pakistan Abdul Hakeem      PKR        245
## 6:           KE    Kenya                   KES         NA
##                posted_time            disbursed_time
## 1: 2014-01-01 06:12:39+00:00 2013-12-17 08:00:00+00:00
## 2: 2014-01-01 06:51:08+00:00 2013-12-17 08:00:00+00:00
```

```
## 3: 2014-01-01 09:58:07+00:00 2013-12-17 08:00:00+00:00
## 4: 2014-01-01 08:03:11+00:00 2013-12-24 08:00:00+00:00
## 5: 2014-01-01 11:53:19+00:00 2013-12-17 08:00:00+00:00
## 6: 2014-01-01 10:06:19+00:00 2014-01-30 01:42:48+00:00
##                  funded_time term_in_months lender_count
## 1: 2014-01-02 10:06:32+00:00             12           12
## 2: 2014-01-02 09:17:23+00:00             11           14
## 3: 2014-01-01 16:01:36+00:00             43            6
## 4: 2014-01-01 13:00:00+00:00             11            8
## 5: 2014-01-01 19:18:51+00:00             14           16
## 6: 2014-01-29 14:14:57+00:00              4            6
##                            tags borrower_genders repayment_interval
## 1:                                        female          irregular
## 2:                                female, female          irregular
## 3: user_favorite, user_favorite           female             bullet
## 4:                                        female          irregular
## 5:                                        female            monthly
## 6:                                        female          irregular
##          date
## 1: 2014-01-01
## 2: 2014-01-01
## 3: 2014-01-01
## 4: 2014-01-01
## 5: 2014-01-01
## 6: 2014-01-01
```

```
str(kiva)
```

```
## Classes 'data.table' and 'data.frame':   671205 obs. of  20 variables:
##  $ id                : int  653051 653053 653068 653063 653084 1080148 653067 653078 653082 6
53048 ...
##  $ funded_amount     : num  300 575 150 200 400 250 200 400 475 625 ...
##  $ loan_amount       : num  300 575 150 200 400 250 200 400 475 625 ...
##  $ activity          : chr  "Fruits & Vegetables" "Rickshaw" "Transportation" "Embroidery" ..
.
##  $ sector            : chr  "Food" "Transportation" "Transportation" "Arts" ...
##  $ use               : chr  "To buy seasonal, fresh fruits to sell. " "to repair and maintain
the auto rickshaw used in their business." "To repair their old cycle-van and buy another one to
rent out as a source of income" "to purchase an embroidery machine and a variety of new embroide
ry materials." ...
##  $ country_code      : chr  "PK" "PK" "IN" "PK" ...
##  $ country           : chr  "Pakistan" "Pakistan" "India" "Pakistan" ...
##  $ region            : chr  "Lahore" "Lahore" "Maynaguri" "Lahore" ...
##  $ currency          : chr  "PKR" "PKR" "INR" "PKR" ...
##  $ partner_id        : num  247 247 334 247 245 NA 334 245 245 247 ...
##  $ posted_time       : chr  "2014-01-01 06:12:39+00:00" "2014-01-01 06:51:08+00:00" "2014-01-
01 09:58:07+00:00" "2014-01-01 08:03:11+00:00" ...
##  $ disbursed_time    : chr  "2013-12-17 08:00:00+00:00" "2013-12-17 08:00:00+00:00" "2013-12-
17 08:00:00+00:00" "2013-12-24 08:00:00+00:00" ...
##  $ funded_time       : chr  "2014-01-02 10:06:32+00:00" "2014-01-02 09:17:23+00:00" "2014-01-
01 16:01:36+00:00" "2014-01-01 13:00:00+00:00" ...
##  $ term_in_months    : num  12 11 43 11 14 4 43 14 14 11 ...
##  $ lender_count      : int  12 14 6 8 16 6 8 8 19 24 ...
##  $ tags              : chr  "" "" "user_favorite, user_favorite" "" ...
##  $ borrower_genders  : chr  "female" "female, female" "female" "female" ...
##  $ repayment_interval: chr  "irregular" "irregular" "bullet" "irregular" ...
##  $ date              : chr  "2014-01-01" "2014-01-01" "2014-01-01" "2014-01-01" ...
##  - attr(*, ".internal.selfref")=<externalptr>
```

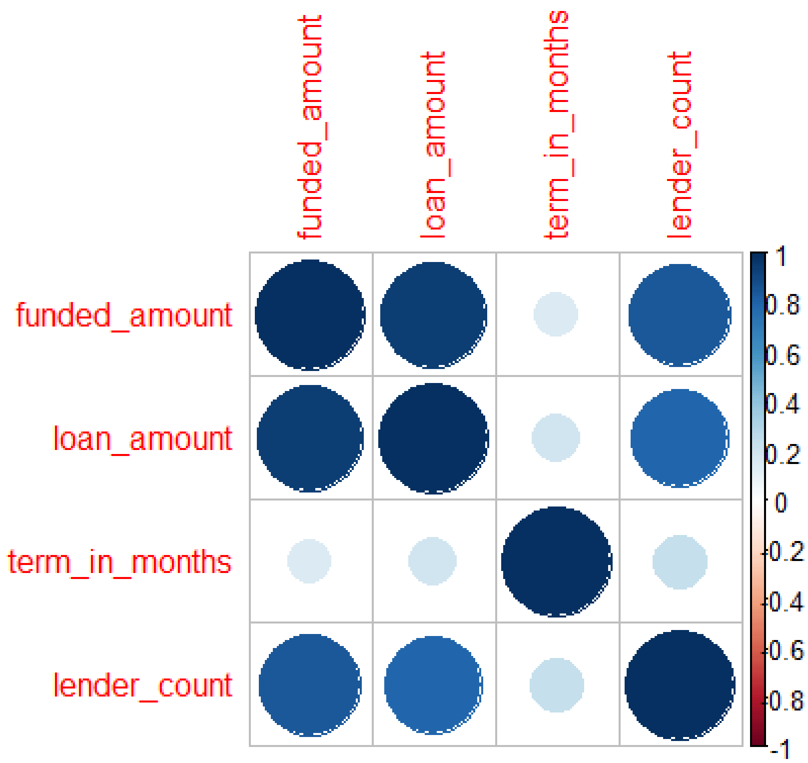
```
dim(kiva)
```

```
## [1] 671205      20
```

The datset is large. To more easily explore it, we subset the data

Subset data for easier computational analysis in EDA

```
#set seed so reproducible
set.seed(1876)
# subsetting data
p <- .1 # proportion of data for EDA
w <- sample(1:nrow(kiva), nrow(kiva)*p, replace=F)
kiva_exp_subset <-kiva[w,]

rm(kiva) #remove the larger dataset Full dataset will be brought back in later

#numeric subset
kiva_num <- kiva_exp_subset[, c("funded_amount", "loan_amount", "term_in_months", "lender_count"
)]
kiva_num %>% cor() %>% corrplot(.)
```

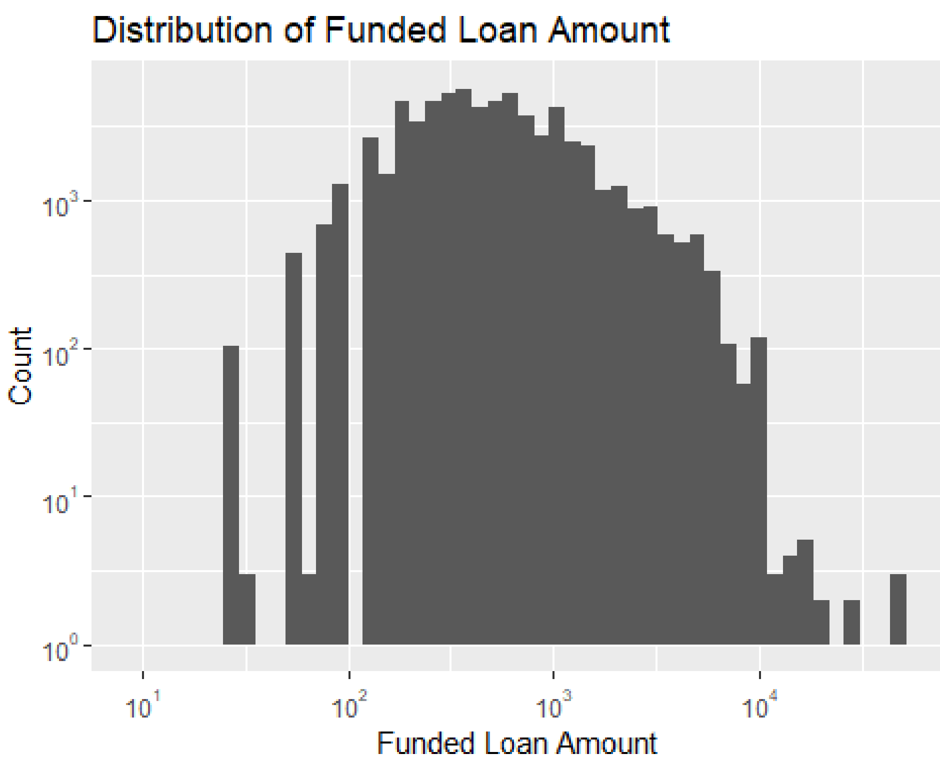


From the corrplot we see a correlation in the variables you might expect, such as loan amount and funded amount. Term in months is uncorrelated with the other variables. This confirms further assumptions

Next we explore the normality of the funded amount

```
fundedLoanAmountDistribution <- function(kiva_exp_subset)
{
 kiva_exp_subset %>%
    ggplot(aes(x = funded_amount) )+
    scale_x_log10(
      breaks = scales::trans_breaks("log10", function(x) 10^x),
```

```
    labels = scales::trans_format("log10", scales::math_format(10^.x))
  ) +
  scale_y_log10(
    breaks = scales::trans_breaks("log10", function(x) 10^x),
    labels = scales::trans_format("log10", scales::math_format(10^.x))
  ) +
  geom_histogram(bins=50) +
  labs(x = 'Funded Loan Amount' ,y = 'Count', title = paste("Distribution of", "Funded Loan Am
ount"))
}

fundedLoanAmountDistribution(kiva_exp_subset)

## Warning: Transformation introduced infinite values in continuous x-axis

## Warning: Removed 334 rows containing non-finite values (stat_bin).

## Warning: Transformation introduced infinite values in continuous y-axis

## Warning: Removed 10 rows containing missing values (geom_bar).
```




```
kiva <- fread("BDS_WK11_kiva_loans.csv", header=T)
kiva2 <- kiva
```

Preprocessing

We begin by creating new variables from the existing variables to express their characteristics for easier processing. We also remove all variables that have to do with the loan being funded such as the number of borrowers and if it was funded. These are not helpful in predicting if the loan will be funded because they would not be available when predicting if a new loan application will be funded

```
kiva <- kiva2 %>%
  mutate( Funded= ifelse(funded_amount/loan_amount==1, "Yes", "No")) %>%
  mutate(number_borrower= str_count(borrower_genders, ',')+1 ) %>%
  mutate(number_tags= ifelse(tags=="",0, str_count(tags, ',')+1 ))%>%
  mutate(month= month(posted_time))%>%
  mutate(weekday=wday(posted_time, label = TRUE))

kiva$female_borrower <-  ifelse(grepl("female",kiva$borrower_genders), 1, 0)
kiva$male_borrower <-  ifelse(grepl("male",kiva$borrower_genders), 1, 0)
kiva$continent <- factor(countrycode(sourcevar = kiva[, "country"],
                                     origin = "country.name",
                                     destination = "continent"))

#correct NA's indused by Kosovo not being recognized
kiva$continent[kiva$country=="Kosovo"]  <- "Europe"
kiva$continent[kiva$country=="Virgin Islands"]  <- "Americas"

kiva <- kiva%>%
  select(Funded, loan_amount, sector, continent, repayment_interval,term_in_months,number_tags,t
ags, number_borrower,female_borrower,male_borrower, month, weekday)

kiva_exp_subsetH2 <- kiva2 %>%
  mutate( Funded= ifelse(funded_amount/loan_amount>=1, "Yes", "No")) %>%
  dplyr::select(id, tags, Funded) %>%
  unnest(y = strsplit(tags, ","))

kiva_exp_subsetH2 $y <- gsub("\\#", "", kiva_exp_subsetH2 $y)
#kiva_exp_subsetH2 $y <- gsub("\\_", " ", kiva_exp_subsetH2 $y) # remove hashtags replace with s
pace to join like for like

kiva_exp_subsetH2 $y <- trim(kiva_exp_subsetH2 $y)

kiva_exp_subsetH2 <- kiva_exp_subsetH2 %>%
  group_by(y,Funded) %>%
  summarise(count=n()) %>%
  cast(y~Funded) %>%
  mutate(TotalTag= Yes+No) %>%
  arrange(desc(TotalTag))  %>%
  filter(TotalTag>=50) %>% # Only keep tags used at least 50 times
  mutate(PercentFunded=Yes /TotalTag) %>%
  arrange(desc(PercentFunded))
#make names easier to work with by removing spaces
names <- kiva_exp_subsetH2$y
names <- gsub("\\-", "_", names)
names <- gsub("\\ ", "_", names)
rm(kiva2)

R <- nrow(kiva_exp_subsetH2)
N <- nrow(kiva)
C <- ncol(kiva)

for (i in 1:R){
 kiva[,(C+i)] <- ifelse(grepl(as.character(kiva_exp_subsetH2[i,1]),kiva$tags), 1, 0)
 kiva[,(C+i)] <- as.factor(kiva[,(C+i)])
 colnames(kiva)[(C+i)] <- names[i]
}
kiva <- kiva %>% select(-tags) #remove tags
```

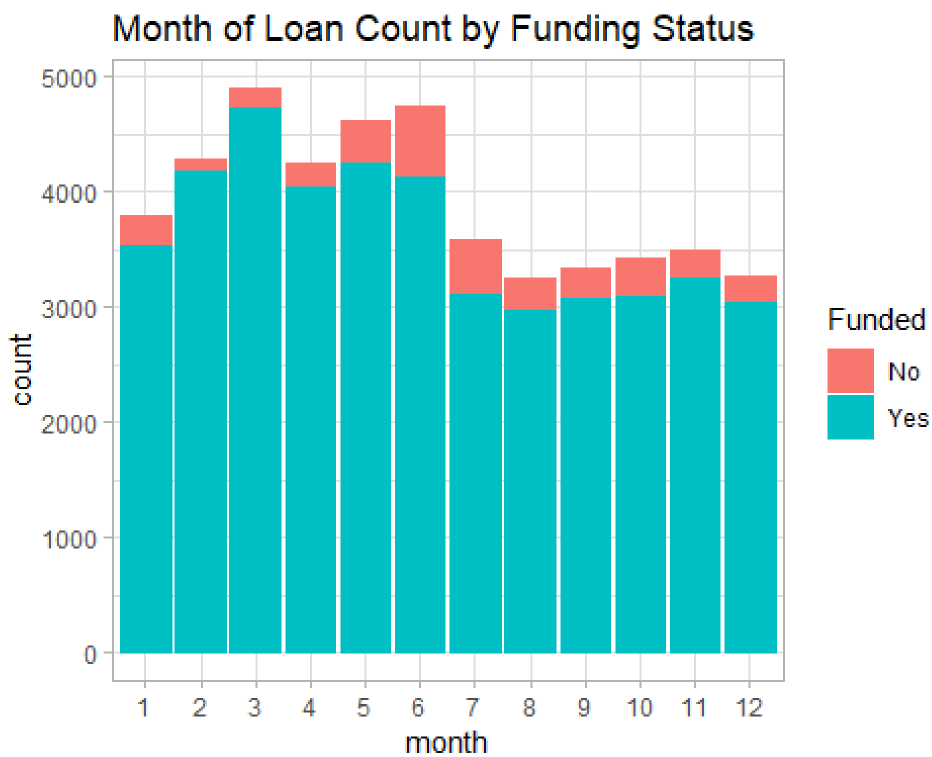
Convert variables to factors

```
kiva$Funded <- as.factor(kiva$Funded)
kiva$sector <- as.factor(kiva$sector)
kiva$continent <- as.factor(kiva$continent)
kiva$repayment_interval <- as.factor(kiva$repayment_interval)
kiva$female_borrower <-as.factor(kiva$female_borrower)
kiva$male_borrower <-as.factor(kiva$male_borrower)
kiva$month <- as.factor(kiva$month)
save(kiva , file='cleankiva.RData')

load(file='cleankiva.RData')
str(kiva)

## 'data.frame':    671205 obs. of  46 variables:
##  $ Funded              : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 2 2 2 2 ...
##  $ loan_amount         : num  300 575 150 200 400 250 200 400 475 625 ...
##  $ sector              : Factor w/ 15 levels "Agriculture",..: 7 14 14 2 7 13 1 13 10 7 ...
##  $ continent           : Factor w/ 5 levels "Africa","Americas",..: 3 3 3 3 3 1 3 3 3 3 ...
##  $ repayment_interval  : Factor w/ 4 levels "bullet","irregular",..: 2 2 1 2 3 2 1 3 3 2 ...
##  $ term_in_months      : num  12 11 43 11 14 4 43 14 14 11 ...
##  $ number_tags         : num  0 0 2 0 0 0 2 2 1 0 ...
##  $ number_borrower     : num  1 2 1 1 1 1 1 1 1 1 ...
##  $ female_borrower     : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
##  $ male_borrower       : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
##  $ month               : Factor w/ 12 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ weekday             : Ord.factor w/ 7 levels "Sun"<"Mon"<"Tue"<..: 4 4 4 4 4 4 4 4 4 4 ..
.
##  $ Female_Education    : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Widowed             : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Health_and_Sanitation: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Orphan              : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Eco_friendly        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Post_disbursed      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Fabrics             : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Technology          : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ volunteer_like      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ volunteer_pick      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Single_Parent       : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Interesting_Photo   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ user_favorite       : Factor w/ 2 levels "0","1": 1 1 2 1 1 1 2 1 2 1 ...
##  $ Woman_Owned_Biz     : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 1 ...
##  $ Inspiring_Story     : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Schooling           : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Animals             : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Repeat_Borrower     : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Unique              : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Elderly             : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 1 ...
##  $ Low_profit_FP       : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ First_Loan          : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Sustainable_Ag      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Parent              : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Biz_Durable_Asset   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Trees               : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Vegan               : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Single              : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Hidden_Gem          : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Supporting_Family   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Job_Creator         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Tourism             : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
```

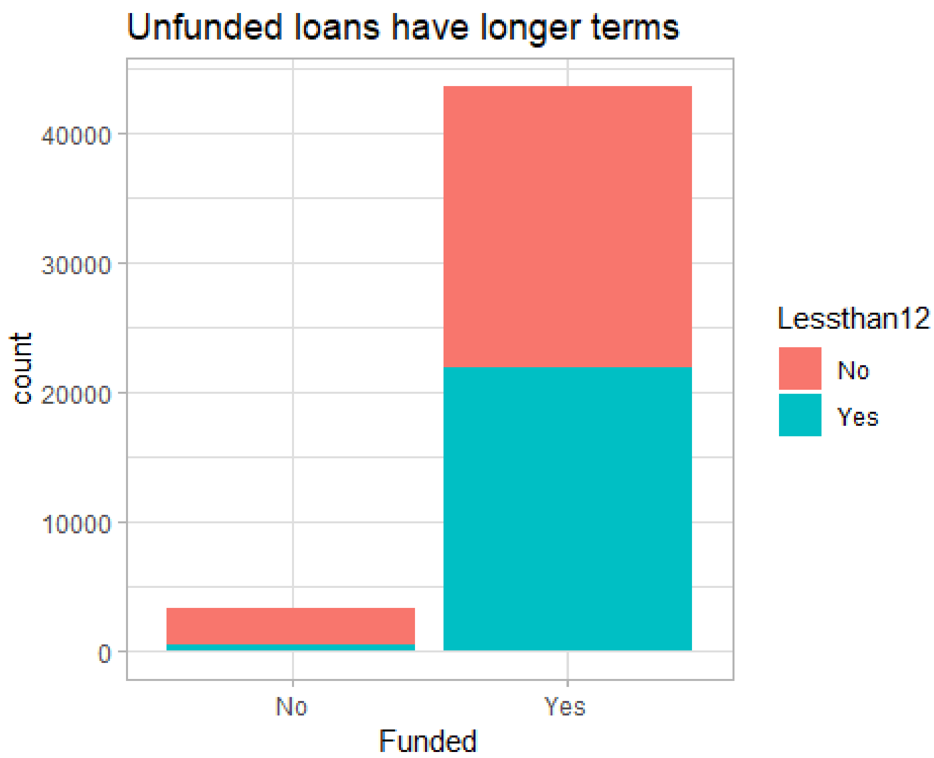
```
##  $ Refugee              : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Repair_Renew_Replace : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
```

EDA

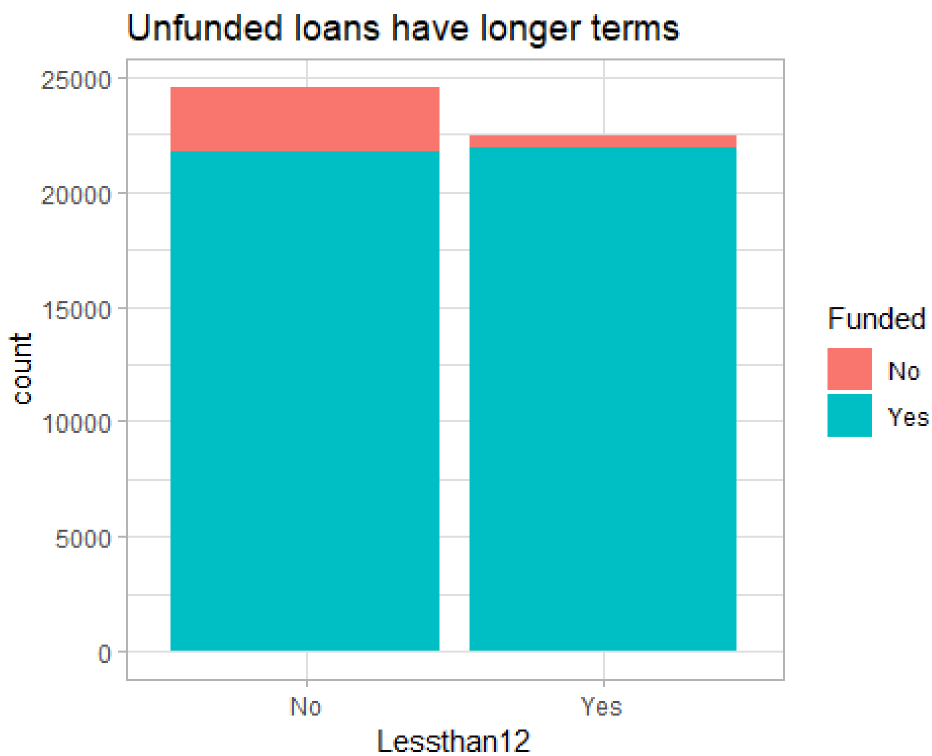
```
#subset for EDA
set.seed(1900)

p <- .07 # proportion of data for training
w <- sample(1:nrow(kiva), nrow(kiva)*p, replace=F)
eda <-kiva[w,]

ggplot(eda, aes(x=month, color=Funded, fill=Funded))+ geom_bar()+ theme_light()+ labs(title="Mon
th of Loan Count by Funding Status")
```



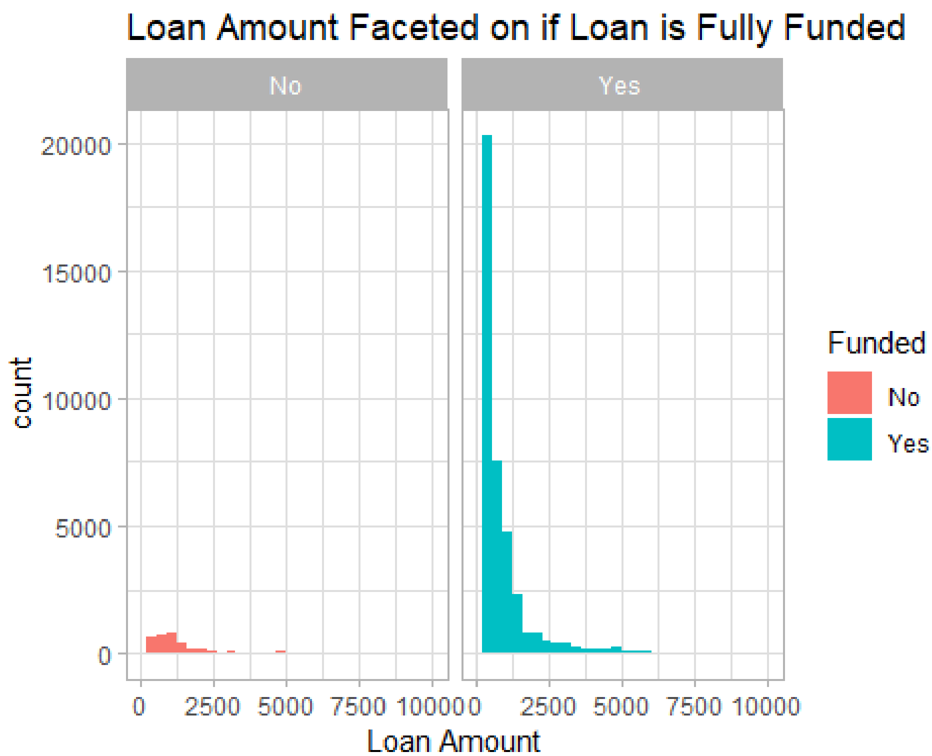

```
kiva_exp_subsetH1 <- eda %>%
  mutate(Lessthan12=ifelse(eda$term_in_months<=12,"Yes", "No"))

ggplot(kiva_exp_subsetH1, aes(Funded, fill=Lessthan12))+ geom_bar() + theme_light()+ labs(title=
"Unfunded loans have longer terms")
```



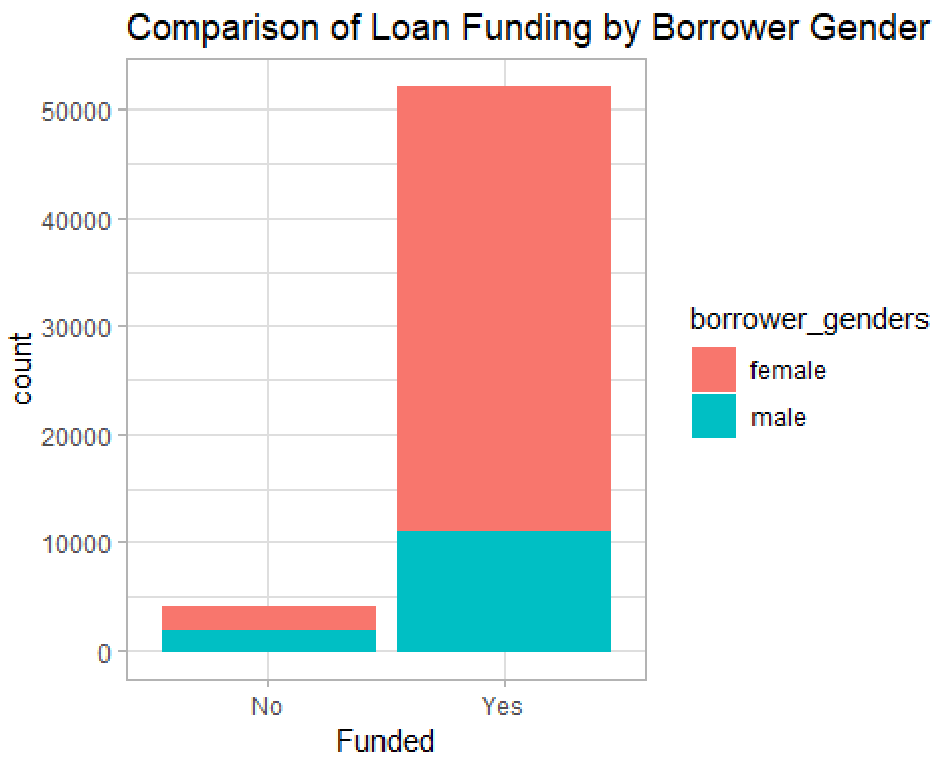

```
ggplot(kiva_exp_subsetH1, aes(Lessthan12,fill=Funded))+ geom_bar()+ theme_light()+ labs(title="U
nfunded loans have longer terms")
```



```
ggplot(eda, aes(x=loan_amount, fill=Funded))+ geom_histogram()+ facet_wrap(~Funded)+ xlim(c(0,10
000))+ theme_light()+ labs(x="Loan Amount", title= "Loan Amount Faceted on if Loan is Fully Fund
ed")

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

## Warning: Removed 15 rows containing non-finite values (stat_bin).
```




```
kiva_exp_subsetH3 <- kiva_exp_subset %>%
  mutate( Funded= ifelse(funded_amount/loan_amount==1, "Yes", "No")) %>%
  dplyr::select(id, borrower_genders, Funded) %>%
  mutate(Single_bor= ifelse(borrower_genders=="female", "Yes", ifelse(borrower_genders=="male",
"Yes", "No"))) %>%
  filter(Single_bor=="Yes")

ggplot(kiva_exp_subsetH3, aes(x=Funded, color=borrower_genders, fill=borrower_genders))+ geom_ba
r()+ labs(title= "Comparison of Loan Funding by Borrower Gender")+ theme_light()
```



Initial Model Testing

```
set.seed(1876)
#subset in training and testing dataset
p <- .07 # proportion of data for training
w <- sample(1:nrow(kiva), nrow(kiva)*p, replace=F)
train <-kiva[w,]
test <- kiva[-w,]
rm(kiva)

res.rf <- randomForest(Funded~.,data= train, mtry=20, ntree=500, importance=T, na.action= na.omi
t)
res.rf

save(res.rf , file='randfor.RData')

load(file='randfor.RData')

importance(res.rf)

##                              No         Yes MeanDecreaseAccuracy
## loan_amount         159.3137021  30.3667533           91.2300661
## sector               59.6060927  50.7562192           72.0587363
## continent            54.1155591   2.2768598           29.6879112
## repayment_interval   51.7091785  43.2011174           66.2276673
## term_in_months      158.1440288  16.0955891           76.7352289
## number_tags          14.1324098  37.9975563           51.5933458
## number_borrower      17.7227160  15.5334722           22.0626756
## female_borrower     102.5439631 -11.5209976           32.6499086
## male_borrower        23.7671047   1.7449201           12.0790024
## month                92.7048608  22.5750531           62.5068036
## weekday              14.3154541   3.7158628           10.4016777
## Female_Education      3.0921400  -1.4823576           -0.5310527
```

```
## Widowed                 -2.4013744  -1.8294056           -2.5968134
## Health_and_Sanitation    4.6821736   3.1843362            4.9860400
## Orphan                   0.0000000  -2.0088163           -2.0097806
## Eco_friendly            11.6825547   4.2081992            9.3626891
## Post_disbursed           2.0489717  -5.3035190           -4.5217510
## Fabrics                  3.9131245  -7.6892915           -6.0776910
## Technology               0.8528648  11.1041294           11.9523264
## volunteer_like           0.8557324  -2.0787635           -1.4667117
## volunteer_pick          -0.1434360  -1.6319615           -1.5181082
## Single_Parent           -1.0800973   4.9848822            4.5093550
## Interesting_Photo       -0.6436776 -11.7321889          -11.6118092
## user_favorite            3.3672671  41.0277233           41.0372096
## Woman_Owned_Biz         25.0938726  17.4614781           25.1271334
## Inspiring_Story          1.4393598  -5.2558133           -4.6524158
## Schooling                6.4885740   7.5363908            9.6654443
## Animals                 11.4388625   0.9830051            5.7149211
## Repeat_Borrower         15.4488591   3.7315876           10.1264639
## Unique                   0.4179853  -4.9237601           -4.3887068
## Elderly                 15.3655413  -2.3054688            4.5479565
## Low_profit_FP           17.1218174  -7.5342837            2.7827579
## First_Loan               6.1417335  -8.6550760           -5.6328370
## Sustainable_Ag           8.1618941  -3.1237515           -0.6007846
## Parent                  22.3306797  16.0322404           23.2933901
## Biz_Durable_Asset        4.3128187   2.1936210            3.9548051
## Trees                    3.3541731  -3.9924102           -2.6559292
## Vegan                   18.9676636   4.4073326           11.7767247
## Single                  -0.8292126   5.3341977            5.1703212
## Hidden_Gem               2.1757490  -7.3790909           -6.3478581
## Supporting_Family       10.5609622  -5.7150152           -1.4669896
## Job_Creator              8.4015188  -2.0866145            1.7837731
## Tourism                  0.0000000   0.0000000            0.0000000
## Refugee                  4.3770849  -4.5379616           -2.5399975
## Repair_Renew_Replace    33.9016163 -10.0122834           10.8030725
##                        MeanDecreaseGini
## loan_amount                1141.9337107
## sector                      558.8610887
## continent                   240.7265284
## repayment_interval          203.3055813
## term_in_months              721.4456827
## number_tags                 492.0618358
## number_borrower             139.2232220
## female_borrower             171.8293121
## male_borrower                27.0769567
## month                       750.9957442
## weekday                     487.0324810
## Female_Education              2.9237330
## Widowed                      14.5880002
## Health_and_Sanitation        21.4331906
## Orphan                        1.0297924
## Eco_friendly                 26.2842750
## Post_disbursed                4.6154028
## Fabrics                      27.9293822
## Technology                   23.2149089
## volunteer_like               26.4356228
## volunteer_pick               31.5197921
## Single_Parent                22.2865459
## Interesting_Photo            15.4506117
## user_favorite               125.9066019
## Woman_Owned_Biz              73.6636798
## Inspiring_Story               8.4918327
## Schooling                    66.6142631
```

```
## Animals                          60.8549253
## Repeat_Borrower                 102.2829057
## Unique                           11.0584507
## Elderly                         100.9785632
## Low_profit_FP                    15.1985066
## First_Loan                       45.7151902
## Sustainable_Ag                   17.1221263
## Parent                          120.9145251
## Biz_Durable_Asset                62.2524819
## Trees                            19.0984005
## Vegan                            75.7062786
## Single                           52.4601209
## Hidden_Gem                        6.0395391
## Supporting_Family                54.6882783
## Job_Creator                      35.5240369
## Tourism                           0.0697919
## Refugee                          13.2801821
## Repair_Renew_Replace             54.4583844
```

```
prediction <- predict(res.rf, test, type = "class")
# Checking classification accuracy
table(prediction, test$Funded)
```

```
##
## prediction     No    Yes
##        No    7710   4452
##        Yes  37199 574860
```

```
confusionMatrix(prediction, test$Funded, positive = "No")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     No    Yes
##        No    7710   4452
##        Yes  37199 574860
##
##                Accuracy : 0.9333
##                  95% CI : (0.9327, 0.9339)
##     No Information Rate : 0.9281
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.2471
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.17168
##             Specificity : 0.99232
##          Pos Pred Value : 0.63394
##          Neg Pred Value : 0.93922
##              Prevalence : 0.07194
##          Detection Rate : 0.01235
##    Detection Prevalence : 0.01948
##       Balanced Accuracy : 0.58200
##
##        'Positive' Class : No
##
```

Try to balance

```
table(train$Funded)
```

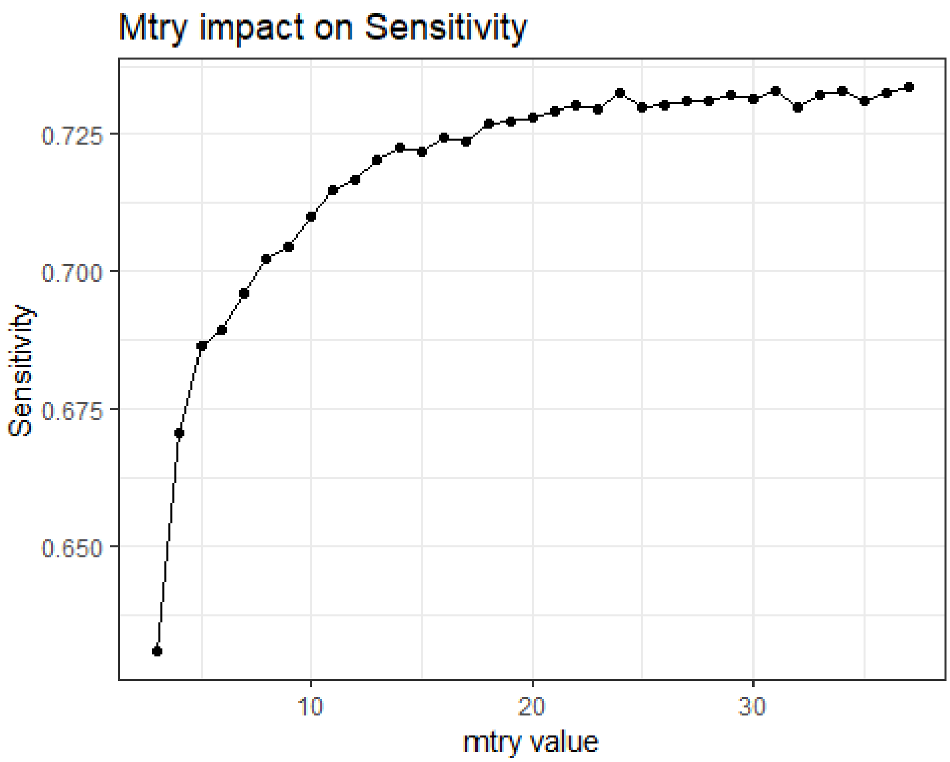
```
##
##    No   Yes
##  3421 43563

set.seed(1876)
#Downsampled Model
down_train <- downSample(x = train[,-1],
                         y = train$Funded)
table(down_train$Funded)

## < table of extent 0 >

#Upsampled Model
up_train <- upSample(x = train[,-1],
                         y = train$Funded)
table(up_train$Funded)

## < table of extent 0 >

set.seed(1876)
#SMOTE
smote_train <- SMOTE(Funded ~ ., data  = train, perc.over = 100, perc.under=200)
save(smote_train, file = "Smotedat.Rdata")

load("Smotedat.Rdata")

set.seed(1876)
downrf <- randomForest(Class~.,data= down_train, mtry=20, ntree=500, importance=T, na.action= na
.omit)
save(downrf, file="down.Rdata")

load(file="down.Rdata")
prediction_down <- predict(downrf, test, type = "class")
confusionMatrix(prediction_down, test$Funded, positive = "No")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction     No    Yes
##        No   38977 125429
##        Yes   5932 453883
##
##                Accuracy : 0.7896
##                  95% CI : (0.7885, 0.7906)
##     No Information Rate : 0.9281
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.2925
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.86791
##             Specificity : 0.78349
##          Pos Pred Value : 0.23708
##          Neg Pred Value : 0.98710
##              Prevalence : 0.07194
##          Detection Rate : 0.06244
##    Detection Prevalence : 0.26338
##       Balanced Accuracy : 0.82570
##
##        'Positive' Class : No
##
```

```r
set.seed(1876)

uprf <- randomForest(Class~.,data= up_train, mtry=20, ntree=500, importance=T, na.action= na.omi
t)
save(uprf,file= "upf.Rdata")

load(file= "upf.Rdata")
prediction_up <- predict(uprf, test, type = "class")
confusionMatrix(prediction_up, test$Funded, positive = "No")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction     No    Yes
##        No   13756  13967
##        Yes  31153 565345
##
##                Accuracy : 0.9277
##                  95% CI : (0.9271, 0.9284)
##     No Information Rate : 0.9281
##     P-Value [Acc > NIR] : 0.8499
##
##                   Kappa : 0.3427
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.30631
##             Specificity : 0.97589
##          Pos Pred Value : 0.49619
##          Neg Pred Value : 0.94777
##              Prevalence : 0.07194
##          Detection Rate : 0.02204
##    Detection Prevalence : 0.04441
##       Balanced Accuracy : 0.64110
##
##        'Positive' Class : No
##

set.seed(1876)

smoterf <- randomForest(Funded~.,data= smote_train, mtry=20, ntree=500, importance=T, na.action=
na.omit)
save(smoterf,file= "smote.Rdata")

load(file= "smote.Rdata")
prediction_smote <- predict(smoterf, test, type = "class")
confusionMatrix(prediction_smote, test$Funded, positive = "No")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction     No    Yes
##        No   32748  77621
##        Yes  12161 501691
##
##                Accuracy : 0.8562
##                  95% CI : (0.8553, 0.857)
##     No Information Rate : 0.9281
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3559
##  Mcnemar's Test P-Value : <2e-16
```

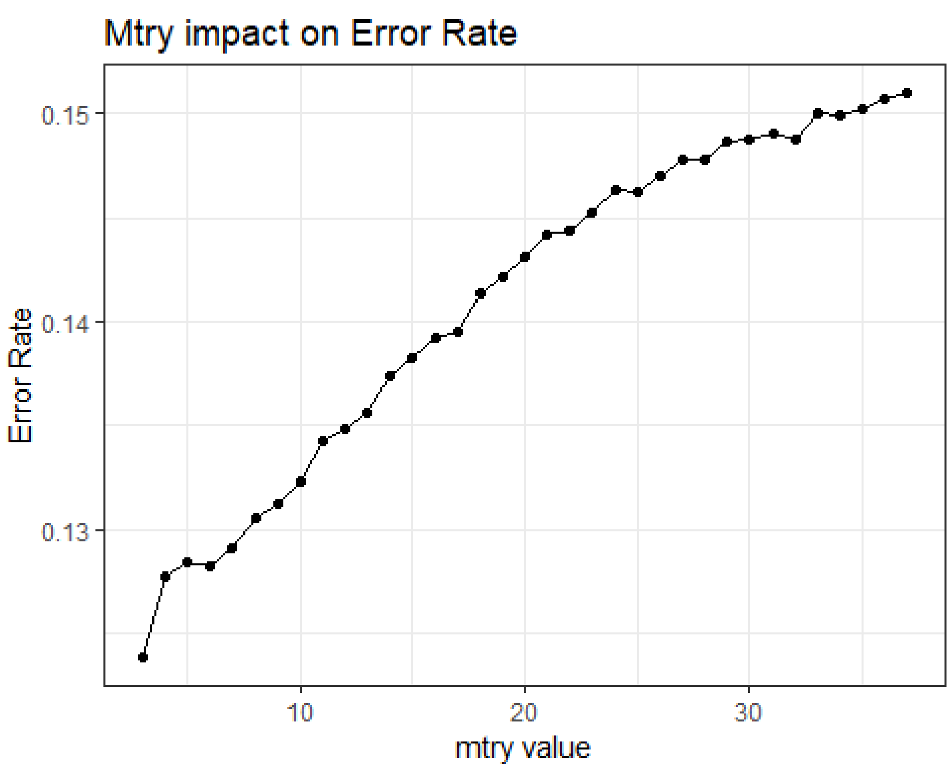
```
##
##             Sensitivity : 0.72921
##             Specificity : 0.86601
##          Pos Pred Value : 0.29671
##          Neg Pred Value : 0.97633
##              Prevalence : 0.07194
##          Detection Rate : 0.05246
##    Detection Prevalence : 0.17681
##       Balanced Accuracy : 0.79761
##
##        'Positive' Class : No
##
```

Optimize mtry

```
# Using For loop to identify the right mtry for model

i=37
sensitivity_matrix <- matrix(0, ncol=1, nrow=i)
err_matrix <- matrix(0, ncol=1, nrow=i)


for (r in 3:40) {
  model <- randomForest(Funded~.,data= smote_train, mtry=r, ntree=500, importance=T, na.action=
na.omit)
  predValid <- predict(model, test, type = "class")
    cm <- confusionMatrix(predValid, test$Funded, positive = "No")
        #store data

         err_matrix [[r,1]] <-  (cm$table[1,2]+cm$table[2,1])/nrow( test)

         sensitivity_matrix[[r, 1]] <- cm$byClass[1]
}
 save(err_matrix, file="err.Rdata")
 save(sensitivity_matrix, file="ses.Rdata")

load("ses.Rdata")
load("err.Rdata")

graph <- as.data.frame(cbind(sensitivity_matrix, err_matrix, row.names(err_matrix)))
graph$index <- c(1:37)
ggplot(graph[-c(1:2),], aes(x=index, y=V1))+ geom_line()+geom_point()+labs(x="mtry value", y= "S
ensitivity", title= "Mtry impact on Sensitivity")+ theme_bw()
```

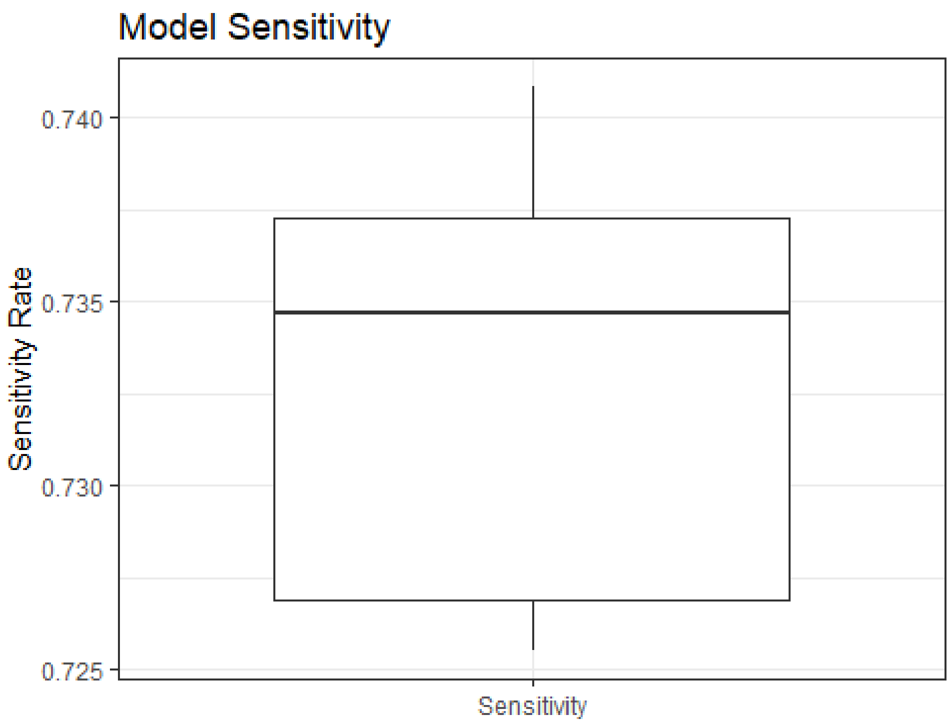



```
ggplot(graph[-c(1:2),], aes(x=index, y=V2))+ geom_line()+geom_point() +labs(x="mtry value", y= "
Error Rate", title= "Mtry impact on Error Rate")+ theme_bw()
```

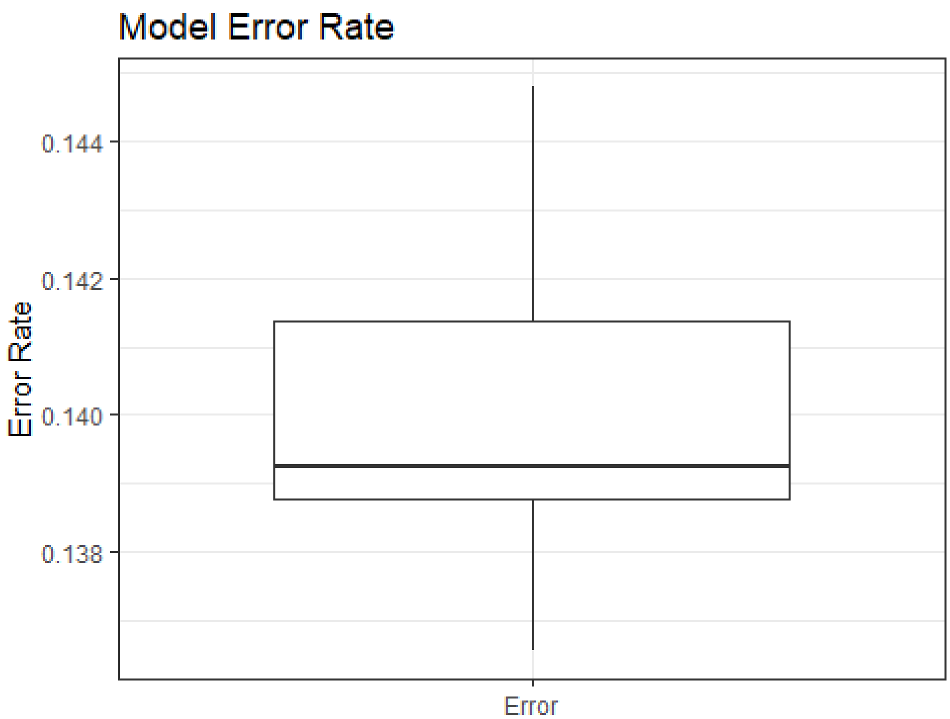


Final Model

```
R <- 10 # replications

# create the matrix to store values 1 row per model
err_matrix2 <- matrix(0, ncol=1, nrow=R)

sensitivity_matrix2 <- matrix(0, ncol=1, nrow=R)

fmeasure_matrix2 <- matrix(0, ncol=1, nrow=R)

gmean_matrix2 <- matrix(0, ncol=1, nrow=R)


set.seed(1876)

for (r in 1:R){

# subsetting data to training and testing data
p <- .07 # proportion of data for training
w <- sample(1:nrow(kiva), nrow(kiva)*p, replace=F)
train <-kiva[w,]
test <- kiva[-w,]

smote_train <- SMOTE(Funded ~ ., data  = train, perc.over = 100, perc.under=200)

#run model
rf_fin <- randomForest(Funded~.,data= smote_train, mtry=15, ntree=500, importance=T, na.action=
na.omit)


#make prediction
prediction_fin <- predict(rf_fin, test, type = "class")
      #create CM
      cm <- confusionMatrix(prediction_fin, test$Funded, positive = "No")
        #store data

         err_matrix2 [[r,1]] <-  (cm$table[1,2]+cm$table[2,1])/nrow( test)

         sensitivity_matrix2[[r, 1]] <- cm$byClass[1]

         fmeasure_matrix2 [[r, 1]] <- cm$byClass[7]

         gmean_matrix2 [[r, 1]] <- sqrt(cm$byClass[1]* cm$byClass[2])

}

save(err_matrix2, file="err2.Rdata")
save(sensitivity_matrix2, file="sens2.Rdata")
save(fmeasure_matrix2, file="fmeas2.Rdata")
save(gmean_matrix2, file="gmean2.Rdata")
save(rf_fin, file="Finmod.Rdata")

load(file="sens2.Rdata")
load(file="err2.Rdata")

sens <- as.data.frame(sensitivity_matrix2)
sens$heading <- "Sensitivity"
ggplot(sens, aes(x=heading, y=V1))+ geom_boxplot() +labs(x="", y= "Sensitivity Rate", title= "Mo
del Sensitivity")+ theme_bw()
```



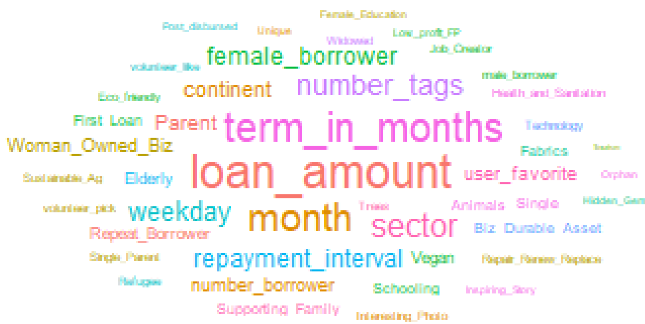

```
err <- as.data.frame(err_matrix2)
err$heading <- "Error"
ggplot(err, aes(x=heading, y=V1))+ geom_boxplot() +labs(x="", y= "Error Rate", title= "Model Err
or Rate")+ theme_bw()
```



#Final Model

```r
set.seed(1988)
p <- .07 # proportion of data for training
w <- sample(1:nrow(kiva), nrow(kiva)*p, replace=F)
train <-kiva[w,]
test <- kiva[-w,]

smote_train <- SMOTE(Funded ~ ., data  = train, perc.over = 100, perc.under=200)

#run model
rf_fin <- randomForest(Funded~.,data= smote_train, mtry=15, ntree=500, importance=T, na.action=
na.omit)


#make prediction
prediction_fin <- predict(rf_fin, test, type = "class")

confusionMatrix(prediction_fin, test$Funded, positive = "No")

save(rf_fin, file="final.Rdata")
save(prediction_fin, file = "prediction_fin.Rdata")

load( file="final.Rdata")

load( file = "prediction_fin.Rdata")

confusionMatrix(prediction_fin, test$Funded, positive = "No")

## Confusion Matrix and Statistics
##
##           Reference
## Prediction     No    Yes
##        No   10375  97807
##        Yes  34534 481505
##
##                Accuracy : 0.788
##                  95% CI : (0.787, 0.789)
##     No Information Rate : 0.9281
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0377
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.23102
##             Specificity : 0.83117
##          Pos Pred Value : 0.09590
##          Neg Pred Value : 0.93308
##              Prevalence : 0.07194
##          Detection Rate : 0.01662
##    Detection Prevalence : 0.17331
##       Balanced Accuracy : 0.53109
##
##        'Positive' Class : No
##

load(file='cleankiva.RData')
importance <- (importance(rf_fin)[,4])

#change structure of importance to work with ggplot
importance<- as.list(importance)
names(importance) <- colnames(kiva[,-1])
importance2 <- unlist(importance)
```

```
most_sig_stats <- (sort(desc(importance2)))*-1
most_sig_stats<- as.data.frame(most_sig_stats)
row.names(most_sig_stats)

##  [1] "loan_amount"           "term_in_months"
##  [3] "month"                 "sector"
##  [5] "number_tags"           "weekday"
##  [7] "repayment_interval"    "female_borrower"
##  [9] "continent"             "Parent"
## [11] "number_borrower"       "user_favorite"
## [13] "Woman_Owned_Biz"       "Repeat_Borrower"
## [15] "Elderly"               "Vegan"
## [17] "Animals"               "Biz_Durable_Asset"
## [19] "Schooling"             "Single"
## [21] "Supporting_Family"     "Fabrics"
## [23] "First_Loan"            "Eco_friendly"
## [25] "Repair_Renew_Replace"  "volunteer_pick"
## [27] "Health_and_Sanitation" "Sustainable_Ag"
## [29] "Single_Parent"         "Technology"
## [31] "volunteer_like"        "male_borrower"
## [33] "Job_Creator"           "Trees"
## [35] "Widowed"               "Interesting_Photo"
## [37] "Refugee"               "Inspiring_Story"
## [39] "Low_profit_FP"         "Unique"
## [41] "Hidden_Gem"            "Female_Education"
## [43] "Post_disbursed"        "Orphan"
## [45] "Tourism"

most_sig_stats[,2] <- row.names(most_sig_stats)

#Word cloud shows importance of variables
ggplot(most_sig_stats, aes(size= most_sig_stats, label= V2,   color = factor(sample.int(12, 45,
replace = TRUE))))+
  geom_text_wordcloud() +
theme_minimal()
```



Female_Education
Post_disbursed
Unique
Low_profit_FP
Widowed
Job_Creator
female_borrower
volunteer_like
male_borrower
continent
number_tags
Eco_friendly
Health_and_Sanitation
First Loan
Parent
term_in_months
Technology
Woman_Owned_Biz
Fabrics
loan_amount
Sustainable_Ag
Elderly
user_favorite
Orphan
volunteer_pick
weekday
Trees
Animals
Single
Hidden_Gem
month
sector
Repeat_Borrower
Biz Durable Asset
Single_Parent
repayment_interval
Vegan
Repair_Renew_Replace
Refugee
number_borrower
Schooling
Inspiring_Story
Supporting Family
Interesting_Photo