

Data622 - Group2 - Homework3

Zachary Palmore, Kevin Potter, Amit Kapoor, Adam Gersowitz

10/2/2021

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Overview

In this project we will develop models that allow us to predict whether a loan is approved given certain indicators. Models will include linear discriminant analysis, K-nearest neighbor, decision trees, and random forest algorithms and we will assess which performs best at predicting loan approval status through performance statistics.

Approach

For this project, we begin with data exploration to understand the relationships our target variable 'Loan_Status' will have with our variables and the variables' relationships to each other. This allows us to determine the steps necessary to set up for model development. Once we have an understanding of these variables we use that knowledge to prepare the data. We handle missing values, subset, train and split the data 75/25 so that we may better extract information from when modeling. Then, we build the models and predict with the testing dataset. We focus on prediction accuracy when assessing the models but consider a host of performance statistics and real-world applications to determine which model is best.

We will use 'r' for data modeling. All packages used for data exploration, visualization, preparation and modeling are listed in Code Appendix.

Data Exploration

Data Characteristics

There are 614 observations of 12 variables. Each observation is an applicant's application for a loan with its corresponding variables of interest. Below is the description of the variables of interest in the data set.

VARIABLE NAME	DESCRIPTION
Loan_ID	Unique Loan ID
Gender	Male/ Female
Married	Applicant married (Y/N)
Dependents	Number of dependents
Education	Applicant Education (Graduate/ Undergraduate)
Self_Employed	Self employed (Y/N)
ApplicantIncome	Applicant income
CoapplicantIncome	Coapplicant income
LoanAmount	Loan amount in thousands
Loan_Amount_Term	Term of loan in months
Credit_History	credit history meets guidelines
Property_Area	Urban/ Semi Urban/ Rural
Loan_Status	Loan approved (Y/N)

There are four numeric variables represented by loan amount, loan amount term, applicant and co-applicant income. Several of these variables appear to be factors with specific levels but are not coded as such. For example, Gender, Married, Dependents, Education, Self_Employed, Property_Area, Credit_History, and Loan_Status are character strings. We will need to fix this if we are to make use of them.

Data summary

Below is a summary of the loan approval dataset. For this process we have already adjusted the data types to their proper forms. This summarizing function quantifies each variable in a manner consistent with their types. We notice the levels of each factor in the 'Stats/Values' column, the frequency of valid (non-missing) observations per level of our factors, and the quantity and percent missing alongside them. We review these statistics to identify any issues with each variable.

```
## Data Frame Summary
## loan_data
## Dimensions: 614 x 12
## Duplicates: 0
##
```

	No	Variable	Stats / Values	Freqs (% of Valid)	Valid	Missing
1		Gender	1. Female	112 (18.6%)	601	13
		[factor]	2. Male	489 (81.4%)	(97.9%)	(2.1%)
2		Married	1. No	213 (34.9%)	611	3
		[factor]	2. Yes	398 (65.1%)	(99.5%)	(0.5%)
3		Dependents	1. 0	345 (57.6%)	599	15
		[factor]	2. 1	102 (17.0%)	(97.6%)	(2.4%)
			3. 2	101 (16.9%)		
			4. 3+	51 (8.5%)		
4		Education	1. Graduate	480 (78.2%)	614	0
		[factor]	2. Not Graduate	134 (21.8%)	(100.0%)	(0.0%)
5		Self_Employed	1. No	500 (85.9%)	582	32
		[factor]	2. Yes	82 (14.1%)	(94.8%)	(5.2%)
6		ApplicantIncome	Mean (sd) : 5403.5 (6109)	505 distinct values	614	0
		[integer]	min < med < max:		(100.0%)	(0.0%)
			150 < 3812.5 < 81000			
			IQR (CV) : 2917.5 (1.1)			
7		CoapplicantIncome	Mean (sd) : 1621.2 (2926.2)	287 distinct values	614	0
		[numeric]	min < med < max:		(100.0%)	(0.0%)
			0 < 1188.5 < 41667			
			IQR (CV) : 2297.2 (1.8)			
8		LoanAmount	Mean (sd) : 146.4 (85.6)	203 distinct values	592	22
		[integer]	min < med < max:		(96.4%)	(3.6%)
			9 < 128 < 700			
			IQR (CV) : 68 (0.6)			
9		Loan_Amount_Term	Mean (sd) : 342 (65.1)	12 : 1 (0.2%)	600	14
		[integer]	min < med < max:	36 : 2 (0.3%)	(97.7%)	(2.3%)
			12 < 360 < 480	60 : 2 (0.3%)		
			IQR (CV) : 0 (0.2)	84 : 4 (0.7%)		
				120 : 3 (0.5%)		
				180 : 44 (7.3%)		

```

## | | | | 240 : 4 ( 0.7%) | | | |
## | | | | 300 : 13 ( 2.2%) | | | |
## | | | | 360 : 512 (85.3%) | | | |
## | | | | 480 : 15 ( 2.5%) | | | |
## +-----+-----+-----+-----+-----+-----+
## | 10 | Credit_History | 1. 0 | 89 (15.8%) | 564 | 50 | |
## | | [factor] | 2. 1 | 475 (84.2%) | (91.9%) | (8.1%) | |
## +-----+-----+-----+-----+-----+-----+
## | 11 | Property_Area | 1. Rural | 179 (29.2%) | 614 | 0 | |
## | | [factor] | 2. Semiurban | 233 (37.9%) | (100.0%) | (0.0%) | |
## | | | 3. Urban | 202 (32.9%) | | | | |
## +-----+-----+-----+-----+-----+-----+
## | 12 | Loan_Status | 1. N | 192 (31.3%) | 614 | 0 | |
## | | [factor] | 2. Y | 422 (68.7%) | (100.0%) | (0.0%) | |
## +-----+-----+-----+-----+-----+-----+

```

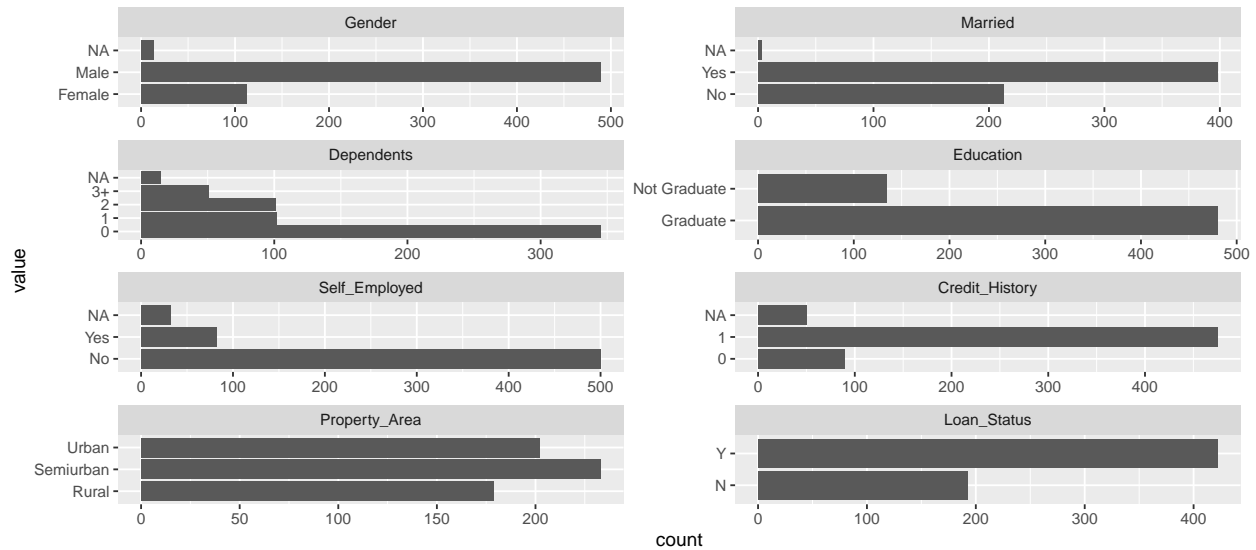
There are 7 columns that have missing values. The proportion of values for several columns shows significant differences and skew. For example, 97.9% of this dataset contains males applicants based on observations of the Gender variable, 99.5% of applicants are married people given the Married variable, and over 90% of our observations have longer Credit_History. Due to the disproportionate levels within the variables we should expect the data is not representative of a larger population unless that population happens to have similar proportions.

Our numeric incomes variables show significant signs of skew through the differences in their mean and medians as well as their ranges. The lowest applicant income was 150, while the highest was 81000. A similar problem exists with our co-applicant income data having had individuals with 0 income on the lowest end of the range and 41667 on the highest.

However, all of the observations contained an applicant and co-applicant income. Since some applicants may not have used a co-applicant on their applications, part of this skew could be caused by the data collection process. Additionally, we are only missing 3.6% of the observations of loan amount and 2.3% for loan terms.

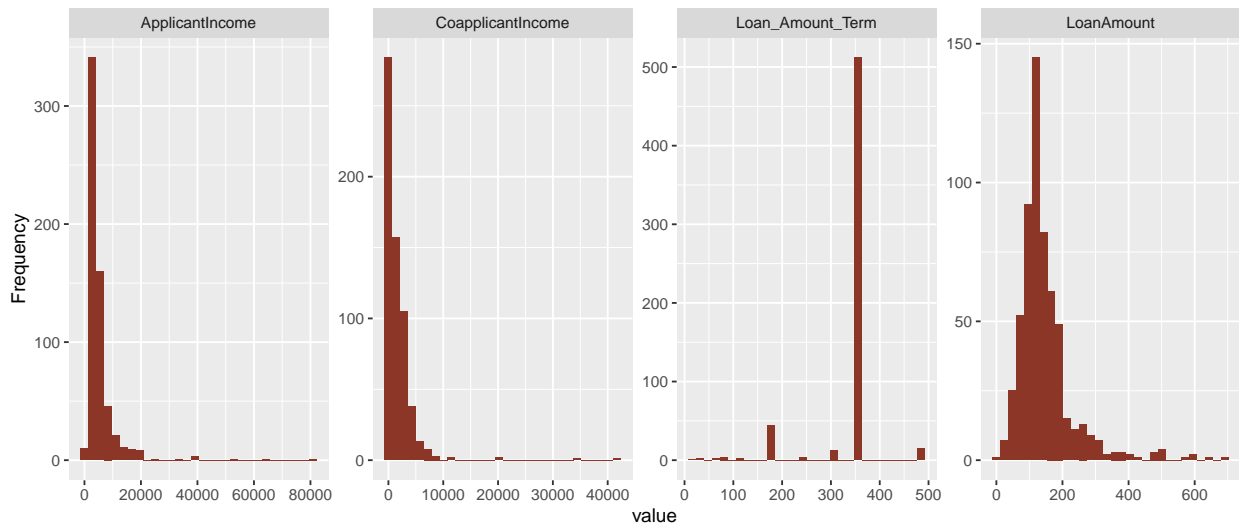
There are regular intervals and commonality in the loan term amounts which indicates we may have been able to factorize their data types. We chose instead to leave it as a discrete numeric value since it represents the term length which could be any number of days or months. We note that 85.3% percent of these applicants applied for a loan term of 360 but we are unsure if that is due to the lending institutions standard practice or if applicants requested this specific term.

For exploratory purposes, we visualize the proportions to see just how skewed and disproportionate this dataset is. We include missing values to demonstrate their influence on the dataset as well. The chart below shows the distribution of all categorical variables, which includes the factors mentioned previously.



From this chart, it is very clear we have a dataset with mostly married male graduates with no dependents, a long credit history, and who are not self-employed. There is a relatively even mix of urban, suburban, and rural applicants and a small number of missing values. Applicants tend to be accepted more often than not and there are no missing observations for our target variable 'Loan_Status' nor the applicant's property area or education. These are all of our categorical variables.

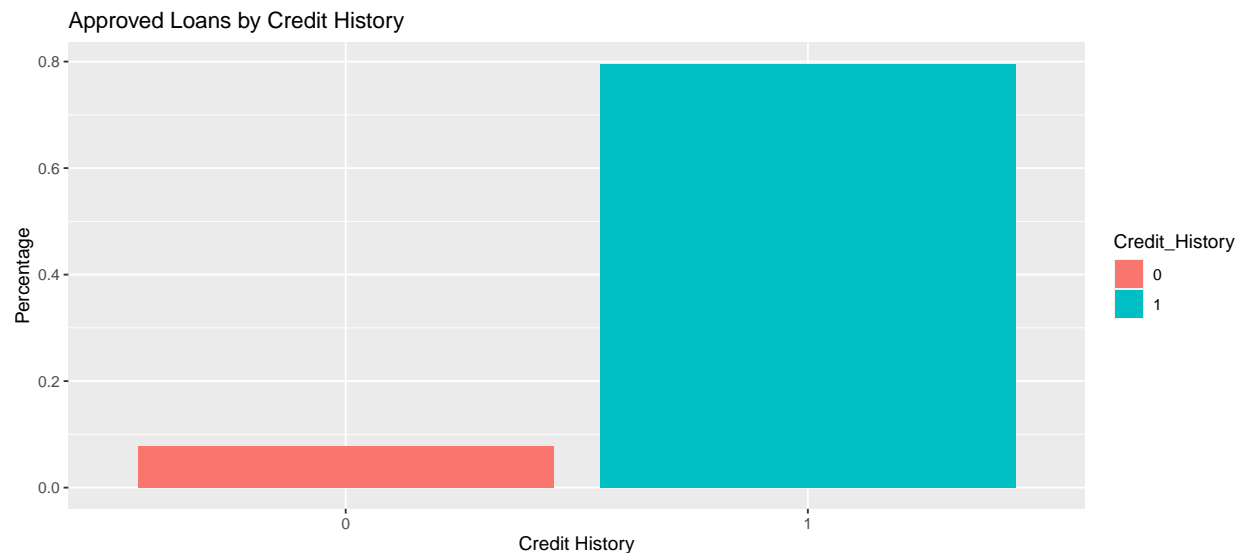
We also generate histograms with the count of each observation to assess our numeric variable distributions. This will let us know more about the skewness, average values, and where potential outliers may be found for our numeric variables. The graph below shows their distributions.



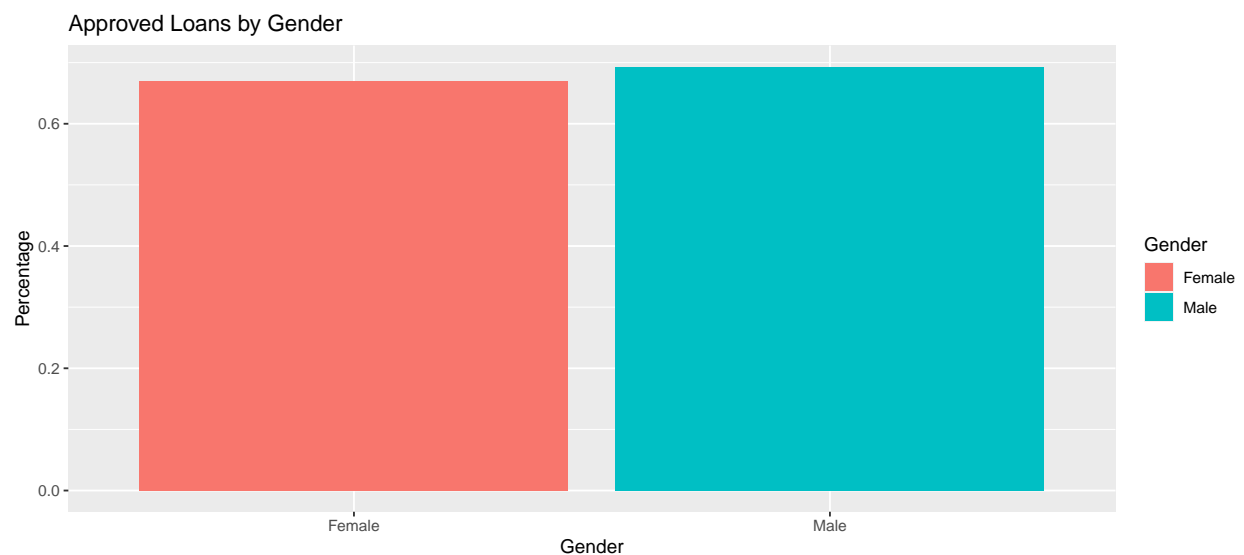
The applicant income and co-applicant income variables are highly right skewed with a smaller number of individual applicants stretching the distribution towards higher incomes. For analysis purposes, we must keep in mind that only a handful of applicants had higher incomes while the bulk of applicants were concentrated at the lower end of the income distribution. The loan amount term has one spike at 360. Meanwhile, the loan amount is the closest to normal. These results are consistent with our summary table.

Next we will review the impact of the categorical variables' proportions on loan approval in more detail by isolating the factor levels individually. Here again, we visualize the proportions as a bar chart without missing values and expand the size of the chart to see the nuances of each. These are placed alongside each variable's frequency table by level to visualize their proportions. The results are as follows:

```
##   Credit_History Loan_Status      Freq
## 1             0           Y 0.07865169
## 2             1           Y 0.79578947
```

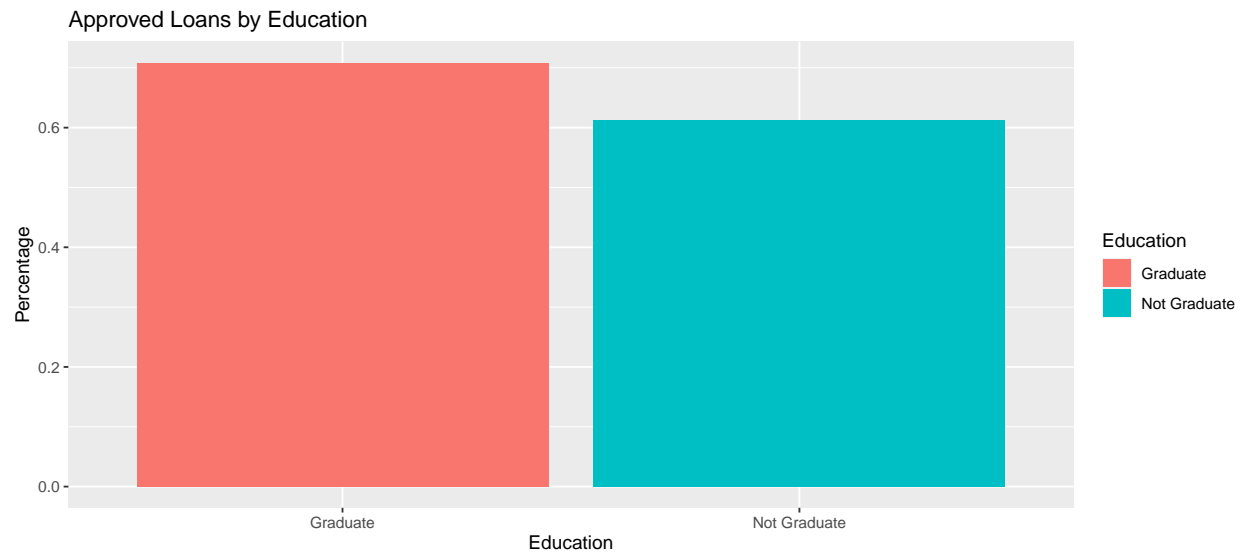


```
##   Gender Loan_Status      Freq
## 1 Female           Y 0.6696429
## 2  Male           Y 0.6932515
```

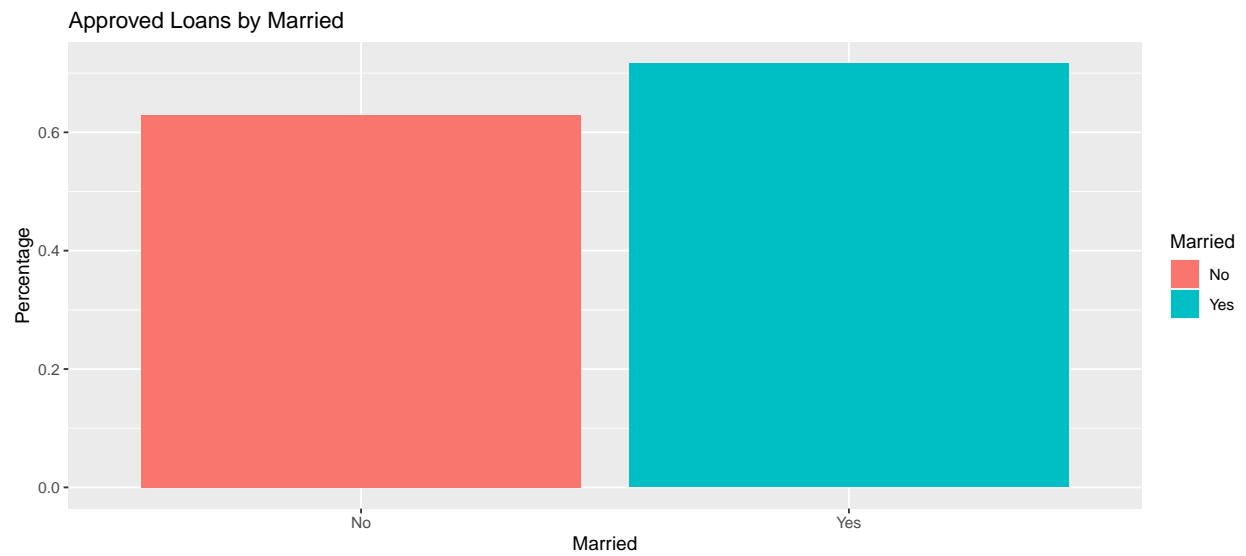


```
##   Education Loan_Status      Freq
```

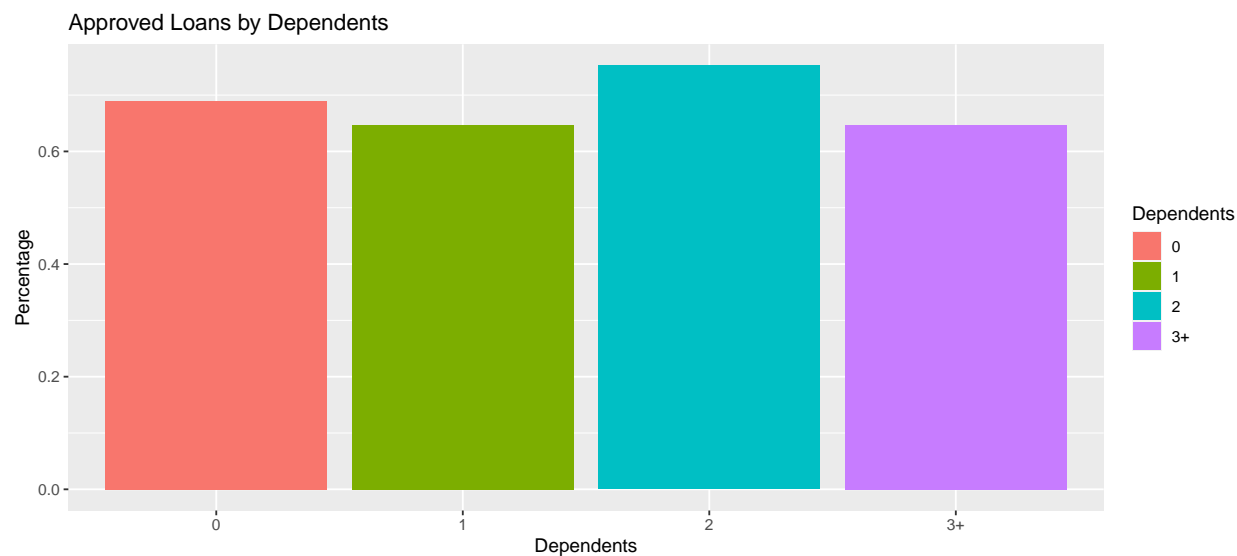
##	1	Graduate	Y	0.7083333
##	2	Not Graduate	Y	0.6119403



##	Married	Loan_Status	Freq
##	1	No	Y 0.6291080
##	2	Yes	Y 0.7160804



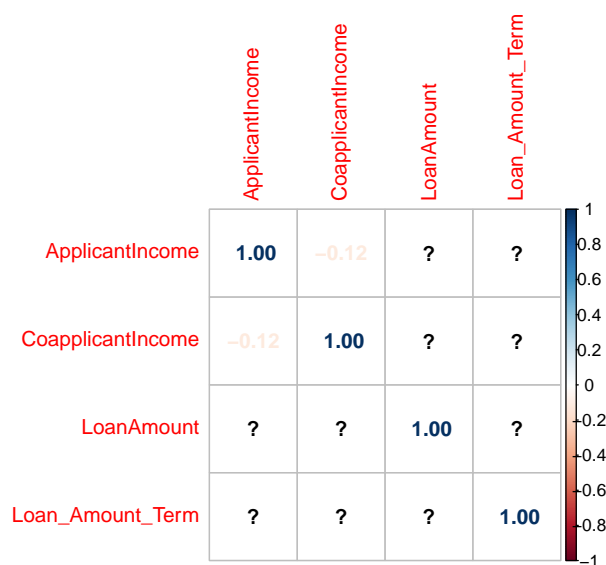
##	Dependents	Loan_Status	Freq
##	1	0	Y 0.6898551
##	2	1	Y 0.6470588
##	3	2	Y 0.7524752
##	4	3+	Y 0.6470588



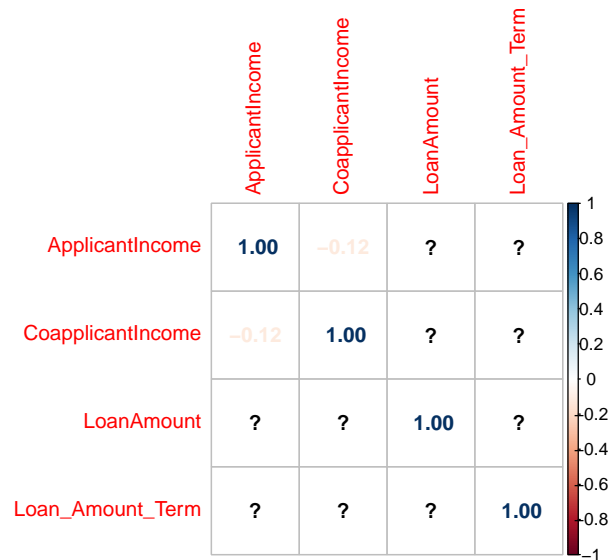
These bar charts confirm our thoughts about the dataset's disproportionalities. Missing values have little effect on the overall proportions and so they can be removed. It remains male dominated with applicants who are married, have no dependents, are highly educated, and have a long credit history.

Correlations

To determine how well each variable is correlated with our target variable and with one another, we construct a correlation plot. This plot contains the values of all correlation between variables represented by colors and numbers. The row we review the most is our target variable, 'Loan_Status.'



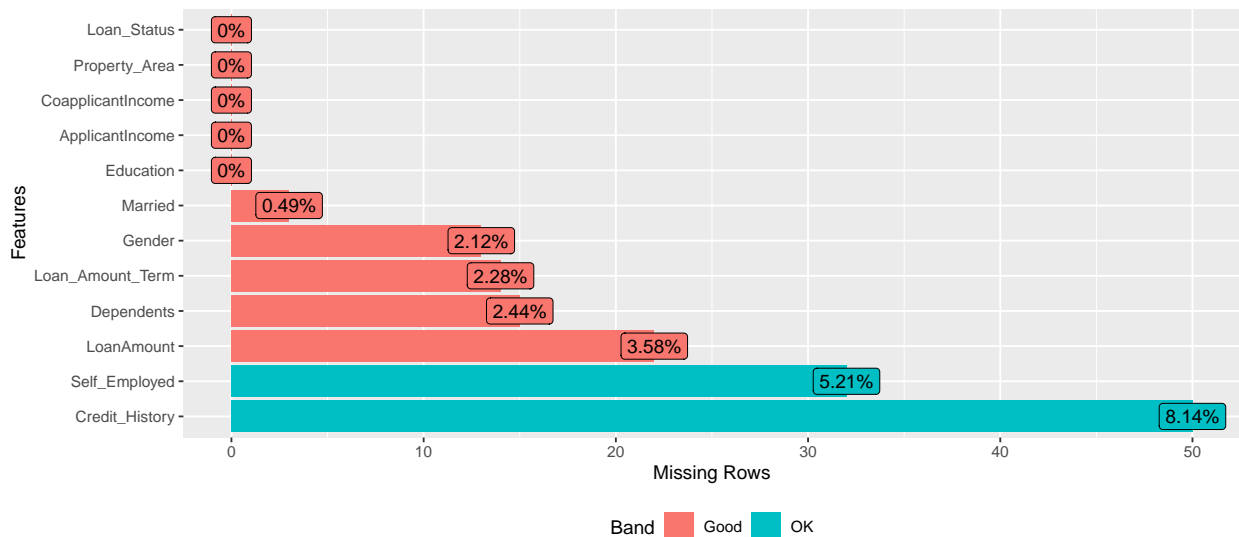
The numeric features do not seem to be strongly correlated with another so that is a factor that does not have to be dealt with.



Given that our numeric features have correlation values near 0, they do not seem to be strongly correlated with our target. They also do not seem to have any correlation with one another so this is a factor that does not have to be dealt with.

Data Preparation

Handling missing values



We can see above credit_history contributes to 8% of missing data along with self_employed that accounts for more than 5% of missing data. All records having missing categorical predictors will be removed. Next we will impute numeric values using MICE (Multivariate Imputation by Chained Equations).

```
## [1] 511 12
```

Finally our clean dataset contains 511 rows and 12 columns.

Preprocess using transformation

We have seen above that numeric features are right skewed so in this step we will use caret `preprocess` method using box cox, center and scale transformation.

Training and Test Partition

In this step for data preparation we will partition the training dataset in training and validation sets using `createDataPartition` method from `caret` package. We will reserve 75% for training and rest 25% for validation purpose.

Build Models

Linear Discriminant Analysis (LDA)

```
## Call:
## lda(Loan_Status ~ ., data = loan_data)
##
## Prior probabilities of groups:
##      N      Y
## 0.3209393 0.6790607
##
## Group means:
##   GenderMale MarriedYes Dependents1 Dependents2 Dependents3+
## N  0.7926829  0.5792683  0.1829268  0.1341463  0.09756098
## Y  0.8357349  0.6801153  0.1585014  0.1902017  0.08069164
##   EducationNot Graduate Self_EmployedYes ApplicantIncome CoapplicantIncome
## N      0.2682927      0.1463415      0.003576320      0.0571435
## Y      0.1902017      0.1325648     -0.001690249     -0.0270073
##   LoanAmount Loan_Amount_Term Credit_History1 Property_AreaSemiurban
## N  0.07966414      0.016992352      0.5548780      0.2682927
## Y -0.03765106     -0.008030968      0.9798271      0.4409222
##   Property_AreaUrban
## N      0.3719512
## Y      0.2997118
##
## Coefficients of linear discriminants:
##                               LD1
## GenderMale      0.185159211
## MarriedYes      0.375755462
## Dependents1     -0.209004726
## Dependents2      0.137509542
## Dependents3+     0.007142953
## EducationNot Graduate -0.294391997
## Self_EmployedYes  -0.025905262
## ApplicantIncome  -0.012085555
## CoapplicantIncome -0.106529320
## LoanAmount      -0.099136040
## Loan_Amount_Term -0.049820158
```

```

## Credit_History1      3.073804026
## Property_AreaSemiurban 0.616732100
## Property_AreaUrban   0.066231320

## [1] 0.8110236

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  N   Y
##           N 19   2
##           Y 22  84
##
##           Accuracy : 0.811
##           95% CI : (0.732, 0.875)
##           No Information Rate : 0.6772
##           P-Value [Acc > NIR] : 0.0005479
##
##           Kappa : 0.5046
##
##  Mcnemar's Test P-Value : 0.0001052
##
##           Sensitivity : 0.4634
##           Specificity : 0.9767
##           Pos Pred Value : 0.9048
##           Neg Pred Value : 0.7925
##           Prevalence : 0.3228
##           Detection Rate : 0.1496
##           Detection Prevalence : 0.1654
##           Balanced Accuracy : 0.7201
##
##           'Positive' Class : N
##

```

LDA model accuracy comes out as ~81%

K-nearest neighbor (KNN)

```

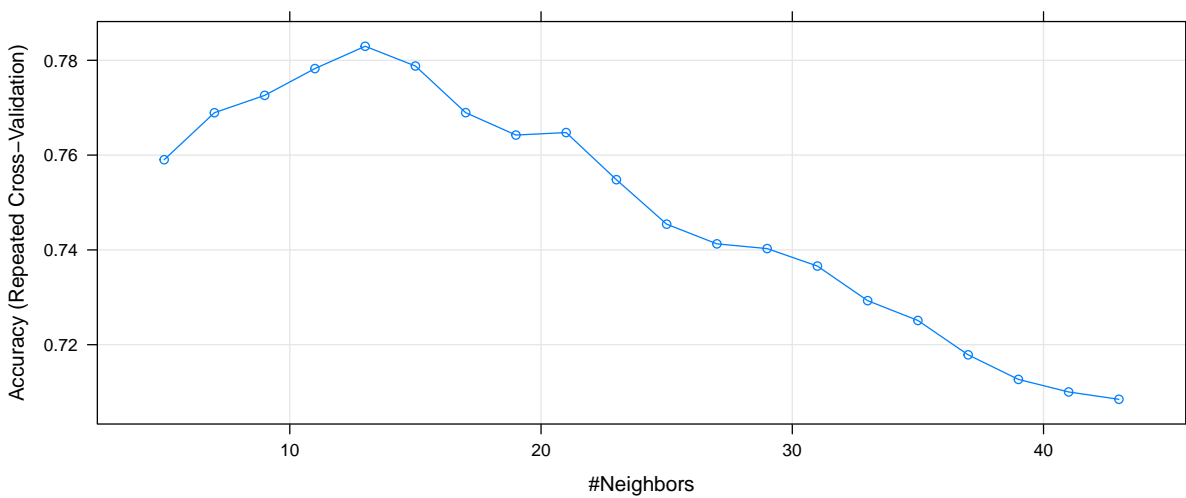
## Created from 384 samples and 12 variables
##
## Pre-processing:
##   - centered (4)
##   - ignored (8)
##   - scaled (4)
##
## k-Nearest Neighbors
##
## 384 samples
## 11 predictor
## 2 classes: 'N', 'Y'
##
## Pre-processing: centered (14), scaled (14)

```

```

## Resampling: Cross-Validated (10 fold, repeated 5 times)
## Summary of sample sizes: 346, 346, 346, 345, 346, 345, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##   5  0.7590209  0.3575145
##   7  0.7689406  0.3751117
##   9  0.7725985  0.3746036
##  11  0.7782524  0.3884713
##  13  0.7829615  0.3994494
##  15  0.7787908  0.3849571
##  17  0.7689528  0.3503238
##  19  0.7642294  0.3309567
##  21  0.7647551  0.3299468
##  23  0.7548097  0.2947001
##  25  0.7454298  0.2607665
##  27  0.7412733  0.2448000
##  29  0.7402746  0.2423939
##  31  0.7365911  0.2319391
##  33  0.7292901  0.2050164
##  35  0.7251066  0.1885755
##  37  0.7178596  0.1615955
##  39  0.7126768  0.1383143
##  41  0.7100317  0.1282468
##  43  0.7084798  0.1212857
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 13.

```



```
## [1] 0.7952756
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```

## Prediction  N  Y
##           N 17  2
##           Y 24 84
##
##           Accuracy : 0.7953
##           95% CI : (0.7146, 0.8617)
##           No Information Rate : 0.6772
##           P-Value [Acc > NIR] : 0.002202
##
##           Kappa : 0.4553
##
## Mcnemar's Test P-Value : 3.814e-05
##
##           Sensitivity : 0.4146
##           Specificity : 0.9767
##           Pos Pred Value : 0.8947
##           Neg Pred Value : 0.7778
##           Prevalence : 0.3228
##           Detection Rate : 0.1339
##           Detection Prevalence : 0.1496
##           Balanced Accuracy : 0.6957
##
##           'Positive' Class : N
##

```

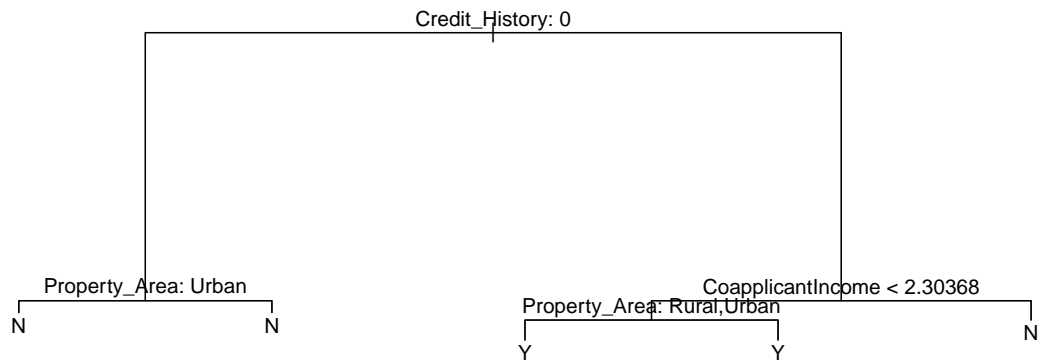
KNN model accuracy comes out as ~80%

Decision Trees

```

##
## Classification tree:
## tree(formula = Loan_Status ~ ., data = training)
## Variables actually used in tree construction:
## [1] "Credit_History" "Property_Area" "CoapplicantIncome"
## Number of terminal nodes: 5
## Residual mean deviance: 0.921 = 349 / 379
## Misclassification error rate: 0.1849 = 71 / 384

```



```
## [1] 0.7952756
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```
## Prediction  N  Y
```

```
##           N 19  4
```

```
##           Y 22 82
```

```
##
```

```
##           Accuracy : 0.7953
```

```
##           95% CI : (0.7146, 0.8617)
```

```
## No Information Rate : 0.6772
```

```
## P-Value [Acc > NIR] : 0.0022025
```

```
##
```

```
##           Kappa : 0.471
```

```
##
```

```
## McNemar's Test P-Value : 0.0008561
```

```
##
```

```
##           Sensitivity : 0.4634
```

```
##           Specificity : 0.9535
```

```
##           Pos Pred Value : 0.8261
```

```
##           Neg Pred Value : 0.7885
```

```
##           Prevalence : 0.3228
```

```
##           Detection Rate : 0.1496
```

```
## Detection Prevalence : 0.1811
```

```
##           Balanced Accuracy : 0.7085
```

```
##
```

```
##           'Positive' Class : N
```

```
##
```

Decision Tree model accuracy comes out as ~80%

Random Forests

```
##
```

```
## Call:
## randomForest(formula = Loan_Status ~ ., data = training)
##           Type of random forest: classification
##           Number of trees: 500
## No. of variables tried at each split: 3
##
##           OOB estimate of  error rate: 20.57%
## Confusion matrix:
##      N   Y class.error
## N 59  64  0.52032520
## Y 15 246  0.05747126
```

```
## [1] 0.8110236
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  N   Y
##           N 22  5
##           Y 19 81
##
##           Accuracy : 0.811
##           95% CI   : (0.732, 0.875)
## No Information Rate : 0.6772
## P-Value [Acc > NIR] : 0.0005479
##
##           Kappa   : 0.5254
##
## Mcnemar's Test P-Value : 0.0079635
##
##           Sensitivity : 0.5366
##           Specificity : 0.9419
##           Pos Pred Value : 0.8148
##           Neg Pred Value : 0.8100
##           Prevalence : 0.3228
##           Detection Rate : 0.1732
##           Detection Prevalence : 0.2126
##           Balanced Accuracy : 0.7392
##
##           'Positive' Class : N
##
```

Random Forest model accuracy comes out as ~80%

Model Performance

All 4 of the models we built above have an accuracy rate of around 80% with the LDA model getting the light edge in accuracy (81.1% to 79.5% for the other 3).

Next we will look at some more detailed accuracy metrics produced from the predict function.

In this particular case, since the accuracy results are so similar it is wise to examine which models are most often leading to type 1 or type 2 errors. Assuming a null hypothesis is not giving a loan a type 1 error is

giving someone a loan when they should not have gotten one and a type 2 error is not giving someone a loan when they should have gotten one. This correlates to the sensitivity and specificity respectively. The balanced accuracy metric takes the mean of sensitivity and specificity in order to diagnose if a model appears to be accurate but is really only predicting the positive or negative case correctly. In this case the random forest model has a slight edge over the LDA in balanced accuracy (0.7212 to 0.7201).

Although the LDA has the smallest p-value it is still <0.0025 for all models so they can all be used so this does not help us decide which model to choose. The same can be said for the McNemar's p-value.

The LDA also has the best Kappa score of 0.5046. The Kappa score can be a much more accurate indicator of accuracy than the standard accuracy rate. The kappa score takes into account the expected accuracy of a model given the instances of each class. This helps a lot with unbalanced class numbers in the dataset. It is encouraging to see the LDA Kappa is also the highest which corresponds with it having the highest accuracy. Although the accuracy score is high a Kappa score around 0.5046 only indicates a moderately good model.

Given the LDA has the highest accuracy, kappa, and nearly the highest balanced accuracy, the LDA is the model that we would use going forward.

Conclusion

After reviewing the results of 4 different models (LDA, KNN, Decision Tree, and Random Forest), we found that LDA is the most accurate by numerous metrics and should be considered the best model for this data. However, the metrics for these 4 models was very close and it did not leave us with no choice but to pick the LDA. If presenting this to stakeholders we would recommend the LDA model with the caveat they further testing and verification may be needed to ensure the LDA is the most accurate model of other iterations of the split of training and testing data.

References

<https://www.r-bloggers.com/2018/07/prop-table/>

<https://www.datacamp.com/community/tutorials/decision-trees-R>

<https://stats.stackexchange.com/questions/82162/cohens-kappa-in-plain-english>

Code Appendix

```
knitr::opts_chunk$set(echo=FALSE, error=FALSE, warning=FALSE, message=FALSE, fig.align="center", fig.wid
# Libraries

library(summarytools)
library(tidyverse)
library(DataExplorer)
library(reshape2)
library(mice)
library(caret)
library(MASS)
library(e1071)
library(caret)
library(tree)
library(randomForest)
```



```

library(corrplot)

set.seed(622)
# read data, change blank to NA and and remove loan_id
loan_data <- read.csv('https://raw.githubusercontent.com/amit-kapoor/Data622Group2/main/Loan_approval.csv')
na_if("") %>%
  dplyr::select(-1)

# categorical columns as factors
loan_data <- loan_data %>%
  mutate(Gender=as.factor(Gender),
         Married=as.factor(Married),
         Dependents=as.factor(Dependents),
         Education=as.factor(Education),
         Self_Employed=as.factor(Self_Employed),
         Property_Area=as.factor(Property_Area),
         Credit_History=as.factor(Credit_History),
         Loan_Status=as.factor(Loan_Status))

dfSummary(loan_data, style = 'grid', graph.col = FALSE)

# select categorical columns
cat_cols = c()
j <- 1
for (i in 1:ncol(loan_data)) {
  if (class((loan_data[,i])) == 'factor') {
    cat_cols[j]=names(loan_data[i])
    j <- j+1
  }
}

loan_fact <- loan_data[cat_cols]
# long format
loan_factm <- melt(loan_fact, measure.vars = cat_cols, variable.name = 'metric', value.name = 'value')

# plot categorical columns
ggplot(loan_factm, aes(x = value)) +
  geom_bar() +
  scale_fill_brewer(palette = "Set1") +
  facet_wrap( ~ metric, nrow = 5L, scales = 'free') + coord_flip()
plot_histogram(loan_data, geom_histogram_args = list("fill" = "tomato4"))
loan_ch <- with(loan_data, table(Credit_History, Loan_Status)) %>%
  prop.table(margin = 1) %>% as.data.frame() %>% filter(Loan_Status == 'Y')

loan_ch
ggplot(loan_ch, aes(x=Credit_History, y=Freq, fill=Credit_History)) + geom_bar(stat='identity') + labs(
loan_gen <- with(loan_data, table(Gender, Loan_Status)) %>%
  prop.table(margin = 1) %>% as.data.frame() %>% filter(Loan_Status == 'Y')

loan_gen
ggplot(loan_gen, aes(x=Gender, y=Freq, fill=Gender)) + geom_bar(stat='identity') + labs(title = 'Approval')
loan_ed <- with(loan_data, table(Education, Loan_Status)) %>%
  prop.table(margin = 1) %>% as.data.frame() %>% filter(Loan_Status == 'Y')

```

```

loan_ed
ggplot(loan_ed, aes(x=Education, y=Freq, fill=Education)) + geom_bar(stat='identity') + labs(title = 'A
loan_mar <- with(loan_data, table(Married, Loan_Status)) %>%
  prop.table(margin = 1) %>% as.data.frame() %>% filter(Loan_Status == 'Y')

loan_mar
ggplot(loan_mar, aes(x=Married, y=Freq, fill=Married)) + geom_bar(stat='identity') + labs(title = 'Appr
loan_dep <- with(loan_data, table(Dependents, Loan_Status)) %>%
  prop.table(margin = 1) %>% as.data.frame() %>% filter(Loan_Status == 'Y')

loan_dep
ggplot(loan_dep, aes(x=Dependents, y=Freq, fill=Dependents)) + geom_bar(stat='identity') + labs(title =

G = cor(loan_data[6:(length(loan_data)-3)])
corrplot(G, method = 'number') # colorful number
G = cor(loan_data[6:(length(loan_data)-3)])
corrplot(G, method = 'number') # colorful number
# plot missing values
plot_missing(loan_data)
# Filter out the data which has missing categorical predictors
loan_data <- loan_data %>% filter(!is.na(Credit_History) &
                                !is.na(Self_Employed) &
                                !is.na(Dependents) &
                                !is.na(Gender) &
                                !is.na(Married))

# impute numeric predictors using mice
loan_data <- complete(mice(data=loan_data, method="pmm", print=FALSE))
dim(loan_data)
# library(e1071) - where this was used
set.seed(622)
loan_data <- loan_data %>%
  dplyr::select(c("ApplicantIncome", "CoapplicantIncome", "LoanAmount", "Loan_Amount_Term")) %>%
  preProcess(method = c("BoxCox", "center", "scale")) %>%
  predict(loan_data)
set.seed(622)
partition <- createDataPartition(loan_data$Loan_Status, p=0.75, list = FALSE)

training <- loan_data[partition,]
testing <- loan_data[-partition,]

# training/validation partition for independent variables
#X.train <- ld.clean[partition, ] %>% dplyr::select(-Loan_Status)
#X.test <- ld.clean[-partition, ] %>% dplyr::select(-Loan_Status)

# training/validation partition for dependent variable Loan_Status
#y.train <- ld.clean$Loan_Status[partition]
#y.test <- ld.clean$Loan_Status[-partition]
# LDA model
lda_model <- lda(Loan_Status~., data = loan_data)
lda_model
# prediction from lda model
lda_predict <- lda_model %>%
  predict(testing)

```

```

# accuracy
mean(lda_predict$class==testing$Loan_Status)
confusionMatrix(lda_predict$class, testing$Loan_Status)
# KNN model
set.seed(622)
train.knn <- training[, names(training) != "Direction"]
prep <- preProcess(x = train.knn, method = c("center", "scale"))
prep
cl <- trainControl(method="repeatedcv", repeats = 5)
knn_model <- train(Loan_Status ~ ., data = training,
                  method = "knn",
                  trControl = cl,
                  preProcess = c("center","scale"),
                  tuneLength = 20)

knn_model
# prediction from knn model
plot(knn_model)
knn_predict <- predict(knn_model,newdata = testing)
mean(knn_predict == testing$Loan_Status) # accuracy
confusionMatrix(knn_predict, testing$Loan_Status)
# Decision Trees model
set.seed(622)
tree.loans = tree(Loan_Status~., data=training)
summary(tree.loans)
plot(tree.loans)
text(tree.loans, pretty = 0)
# prediction from decision tree model
tree.predict<-predict(tree.loans, testing, type = 'class')
mean(tree.predict == testing$Loan_Status) # accuracy
confusionMatrix(tree.predict, testing$Loan_Status)
set.seed(622)
# Random Forest model
rf.loans <- randomForest(Loan_Status~., data = training)
rf.loans

# prediction from random forest model
rf.predict <- predict(rf.loans, testing,type='class')
mean(rf.predict == testing$Loan_Status) # accuracy
confusionMatrix(rf.predict, testing$Loan_Status)

```