Loan Status Prediction

The purpose of this project is to predict whether a loan will be approved based on the demographics of the person requesting the loan.

Loading packages:

In [133]:
```
library(tidyverse)
library(ggplot2)
library(caret)
library(e1071)

options(repos='https://cran.cnr.berkeley.edu/')
install.packages('klaR')
install.packages('kknn')
install.packages('gbm')
library(klaR)
library(kknn)
library(gbm)
```

...

Data Exploration

Load data set

In [134]:
```
df <- read.csv('C:/Datasets/LoanTrain.csv',na.strings='')
df
```

Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantInc
LP001002	Male	No	0	Graduate	No	5849	
LP001003	Male	Yes	1	Graduate	No	4583	1
LP001005	Male	Yes	0	Graduate	Yes	3000	
LP001006	Male	Yes	0	Not Graduate	No	2583	2
LP001008	Male	No	0	Graduate	No	6000	
LP001011	Male	Yes	2	Graduate	Yes	5417	4
LP001013	Male	Yes	0	Not Graduate	No	2333	1
LP001014	Male	Yes	3+	Graduate	No	3036	2
LP001018	Male	Yes	2	Graduate	No	4006	1
LP001020	Male	Yes	1	Graduate	No	12841	1(

Check for duplicate rows

In [135]:
```
sum(duplicated(df))
```

0

Summarize data

In [136]:
```
summary(df)
```

```
     Loan_ID       Gender     Married     Dependents        Education
 LP001002:  1   Female:112   No  :213   0   :345   Graduate    :480
 LP001003:  1   Male  :489   Yes :398   1   :102   Not Graduate:134
 LP001005:  1   NA's  : 13   NA's:  3   2   :101
 LP001006:  1                           3+  : 51
 LP001008:  1                           NA's: 15
 LP001011:  1
 (Other) :608
 Self_Employed ApplicantIncome CoapplicantIncome   LoanAmount
 No  :500      Min.   :  150   Min.   :    0     Min.   :  9.0
 Yes : 82      1st Qu.: 2878   1st Qu.:    0     1st Qu.:100.0
 NA's: 32      Median : 3812   Median : 1188     Median :128.0
               Mean   : 5403   Mean   : 1621     Mean   :146.4
               3rd Qu.: 5795   3rd Qu.: 2297     3rd Qu.:168.0
               Max.   :81000   Max.   :41667     Max.   :700.0
                                                 NA's   :22
 Loan_Amount_Term Credit_History     Property_Area Loan_Status
 Min.   : 12      Min.   :0.0000   Rural    :179   N:192
 1st Qu.:360      1st Qu.:1.0000   Semiurban:233   Y:422
 Median :360      Median :1.0000   Urban    :202
 Mean   :342      Mean   :0.8422
 3rd Qu.:360      3rd Qu.:1.0000
 Max.   :480      Max.   :1.0000
 NA's   :14       NA's   :50
```

Convert Credit_History and Loan_Status to factor.

```
In [137]: df$Credit_History<-as.factor(df$Credit_History)
          summary(df)
```

```
     Loan_ID       Gender     Married    Dependents        Education
 LP001002:  1   Female:112   No  :213   0   :345   Graduate    :480
 LP001003:  1   Male  :489   Yes :398   1   :102   Not Graduate:134
 LP001005:  1   NA's  : 13   NA's:  3   2   :101
 LP001006:  1                           3+  : 51
 LP001008:  1                           NA's: 15
 LP001011:  1
 (Other) :608
 Self_Employed ApplicantIncome CoapplicantIncome   LoanAmount
 No  :500      Min.   :  150   Min.   :    0     Min.   :  9.0
 Yes : 82      1st Qu.: 2878   1st Qu.:    0     1st Qu.:100.0
 NA's: 32      Median : 3812   Median : 1188     Median :128.0
               Mean   : 5403   Mean   : 1621     Mean   :146.4
               3rd Qu.: 5795   3rd Qu.: 2297     3rd Qu.:168.0
               Max.   :81000   Max.   :41667     Max.   :700.0
                                                 NA's   :22
 Loan_Amount_Term Credit_History   Property_Area Loan_Status
 Min.   : 12      0   : 89       Rural    :179   N:192
 1st Qu.:360      1   :475       Semiurban:233   Y:422
 Median :360      NA's: 50       Urban    :202
 Mean   :342
 3rd Qu.:360
 Max.   :480
 NA's   :14
```

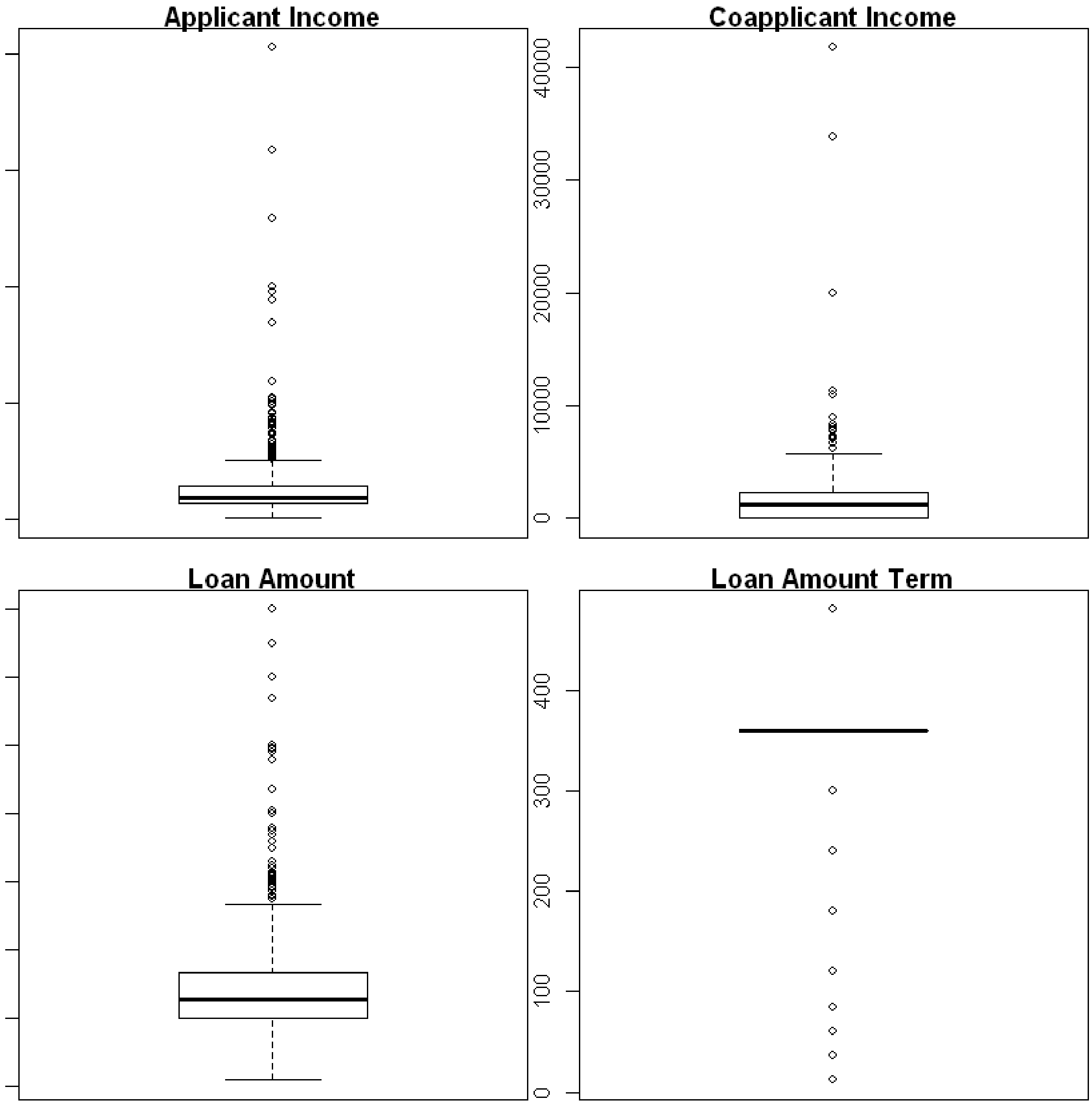
```
In [138]: nearZeroVar(df, saveMetrics=TRUE)
```

	freqRatio	percentUnique	zeroVar	nzv
Loan_ID	1.000000	100.0000000	FALSE	FALSE
Gender	4.366071	0.3257329	FALSE	FALSE
Married	1.868545	0.3257329	FALSE	FALSE
Dependents	3.382353	0.6514658	FALSE	FALSE
Education	3.582090	0.3257329	FALSE	FALSE
Self_Employed	6.097561	0.3257329	FALSE	FALSE
ApplicantIncome	1.500000	82.2475570	FALSE	FALSE
CoapplicantIncome	54.600000	46.7426710	FALSE	FALSE
LoanAmount	1.176471	33.0618893	FALSE	FALSE
Loan_Amount_Term	11.636364	1.6286645	FALSE	FALSE
Credit_History	5.337079	0.3257329	FALSE	FALSE
Property_Area	1.153465	0.4885993	FALSE	FALSE
Loan_Status	2.197917	0.3257329	FALSE	FALSE

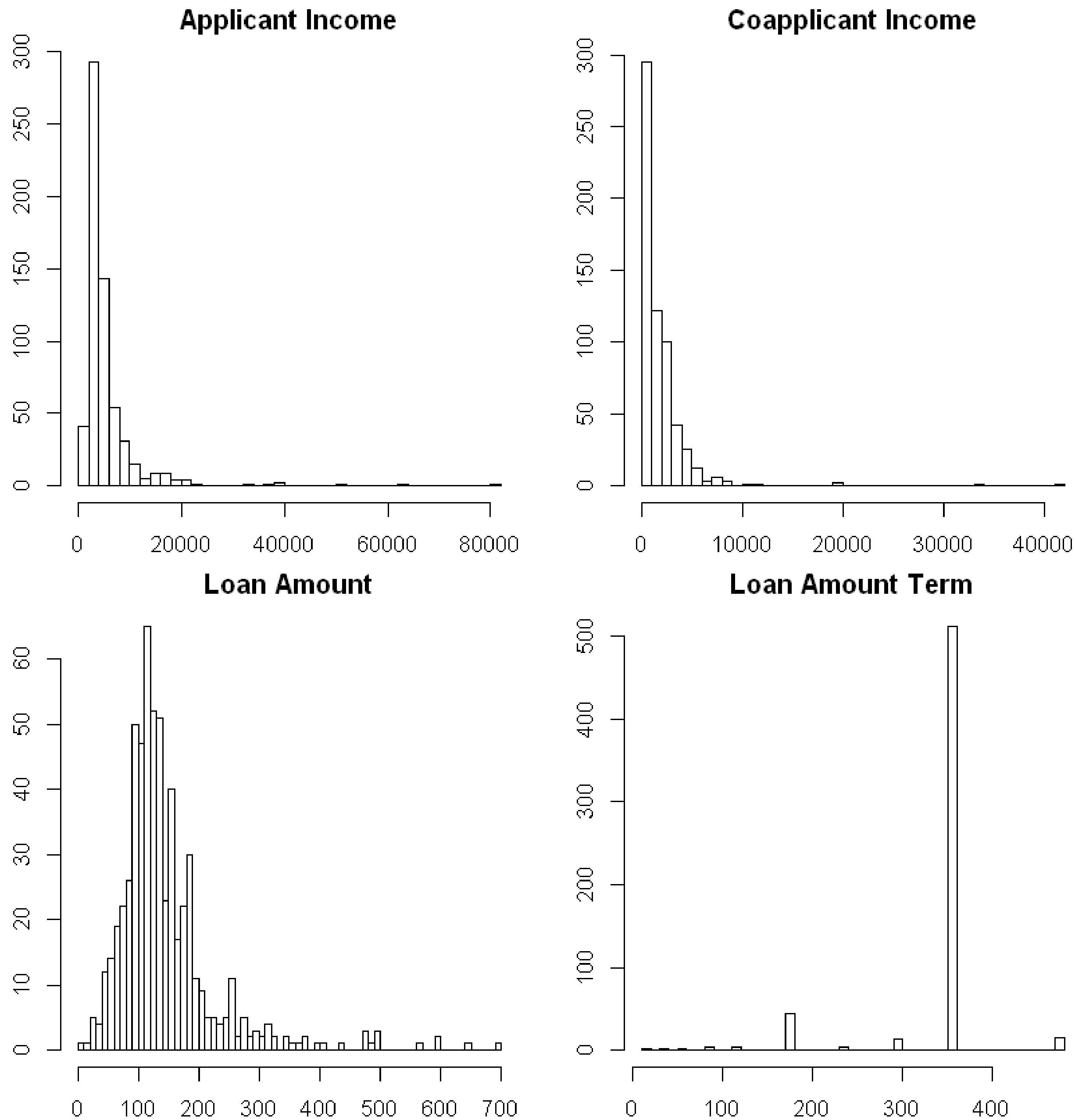
Based on the summary above, some factors levels are unbalanced. However, it is not so unbalanced as to warrant exclusion of any factor.

Next, check for outliers in continuous features

In [139]:
```
par(mfrow=c(2,2), mar=c(1,1,1,1))
boxplot(df$ApplicantIncome,main='Applicant Income')
boxplot(df$CoapplicantIncome, main = 'Coapplicant Income')
boxplot(df$LoanAmount, main = 'Loan Amount')
boxplot(df$Loan_Amount_Term, main = 'Loan Amount Term')
```



In [140]:
```r
par(mfrow=c(2,2), mar=c(2,2,2,2))
hist(df$ApplicantIncome,main='Applicant Income',breaks=50)
hist(df$CoapplicantIncome, main = 'Coapplicant Income',breaks=50)
hist(df$LoanAmount, main = 'Loan Amount',breaks=50)
hist(df$Loan_Amount_Term, main = 'Loan Amount Term',breaks=50)
```



For applicant income, co-applicant income, and loan amount, there are many extreme values. However the histograms show a skewed possibly log-normal distribution consistent with having a lower bound of 0 on possible values for these features. The extreme values are expected at the tail of such distributions, and thus data points will be excluded based on value of these features. Loan Amount Term appears to be 1 year (360 days) for almost all data points, suggesting that the data was entered in years most of the time. Because of this, it cannot be determined if the extreme values are actually out of the ordinary or not, therefore no data points will be excluded based on loan amount term.

Next, check for correlations.

In [141]:
```
cor(df[7:10], use='complete.obs')
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
ApplicantIncome	1.00000000	-0.11363997	0.57129807	-0.04734816
CoapplicantIncome	-0.11363997	1.00000000	0.18885511	-0.05979733
LoanAmount	0.57129807	0.18885511	1.00000000	0.03944725
Loan_Amount_Term	-0.04734816	-0.05979733	0.03944725	1.00000000

In [142]:
```
chisqfun <- function(a,b){
    if(a==b) return(0)
    else return(round(chisq.test(table(df[,a],df[,b]))$p.value,2))
}
matrix(mapply(chisqfun,rep(c(2:6,11:12),7),rep(c(2:6,11:12),rep(7,7))),7,7,dimnames=
```

	Gender	Married	Dependents	Education	Self_Employed	Credit_History	Property_Area
Gender	0.00	0.00	0.00	0.28	0.94	0.82	0.02
Married	0.00	0.00	0.00	0.80	1.00	1.00	0.99
Dependents	0.00	0.00	0.00	0.47	0.10	0.48	0.31
Education	0.28	0.80	0.47	0.00	0.88	0.07	0.16
Self_Employed	0.94	1.00	0.10	0.88	0.00	1.00	0.75
Credit_History	0.82	1.00	0.48	0.07	1.00	0.00	0.60
Property_Area	0.02	0.99	0.31	0.16	0.75	0.60	0.00

None of the continuous variables are strongly correlated with each other, though loan amount is moderately correlated with income. The only factors that are not independent are gender, marital status, and dependents.

A count table for these 3 variables is then generated.

In [143]:
```
table(df[,2],df[,3],df[,4])
```

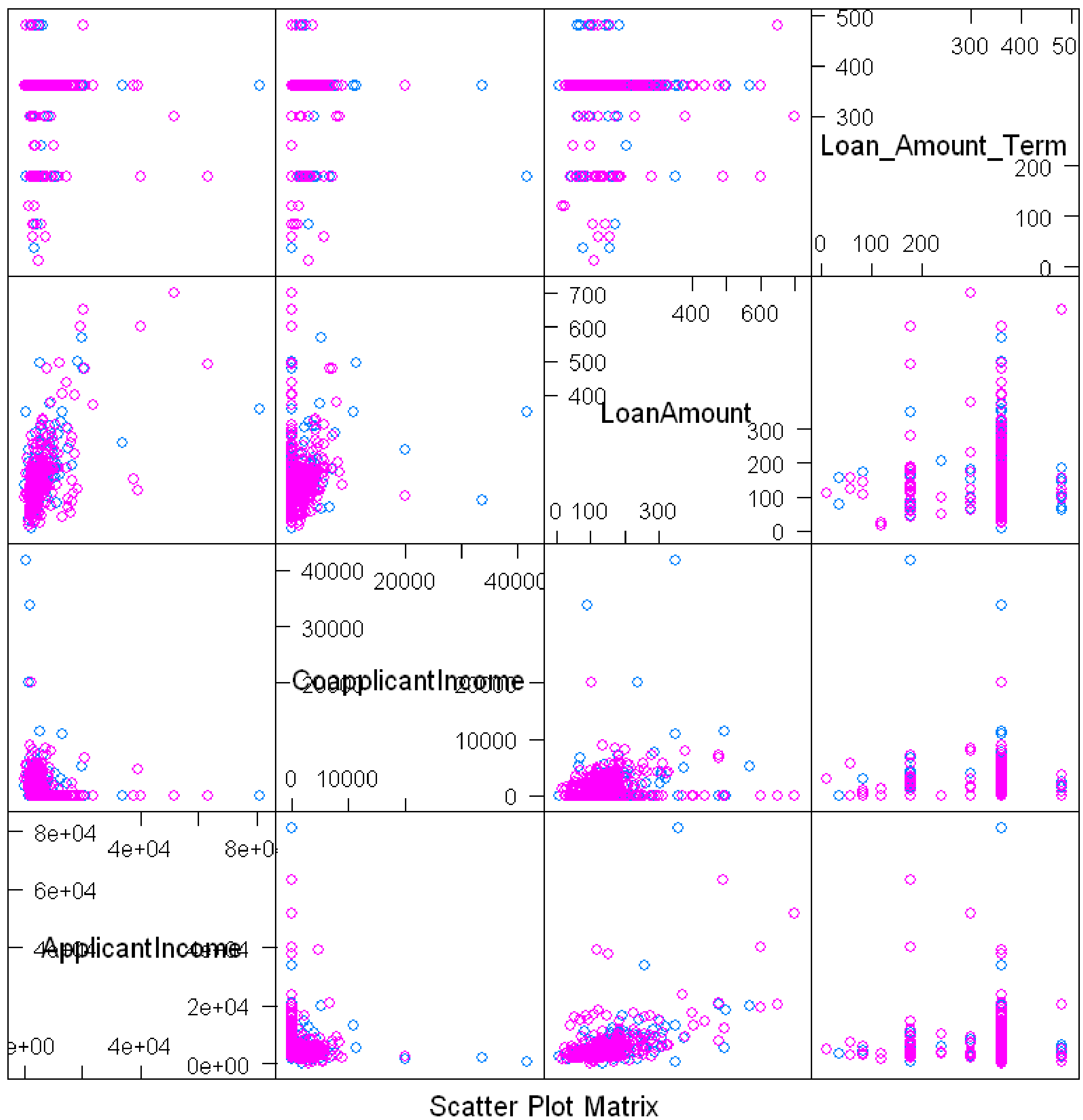
```
, ,  = 0

        
          No Yes
  Female  60  20
  Male   109 149

, ,  = 1

        
          No Yes
  Female  13   6
  Male    10  72

, ,  = 2

        
          No Yes
  Female   2   5
  Male     6  86

, ,  = 3+

        
          No Yes
  Female   3   0
  Male     3  42
```

Though the distribution is heavily skewed, all combinations of the 3 levels are represented except married females with 3+ dependents. Therefore, none of these three factors will be dropped at this time.

The imbalance comes apparently from the fact that all members of a family are considered dependents of the father rather than the mother. In addition, from this data set husbands seem to manage finances more than wives, which is why the count of married females is much lower than the count of unmarried females, who manage their own finances.

Data Visualization

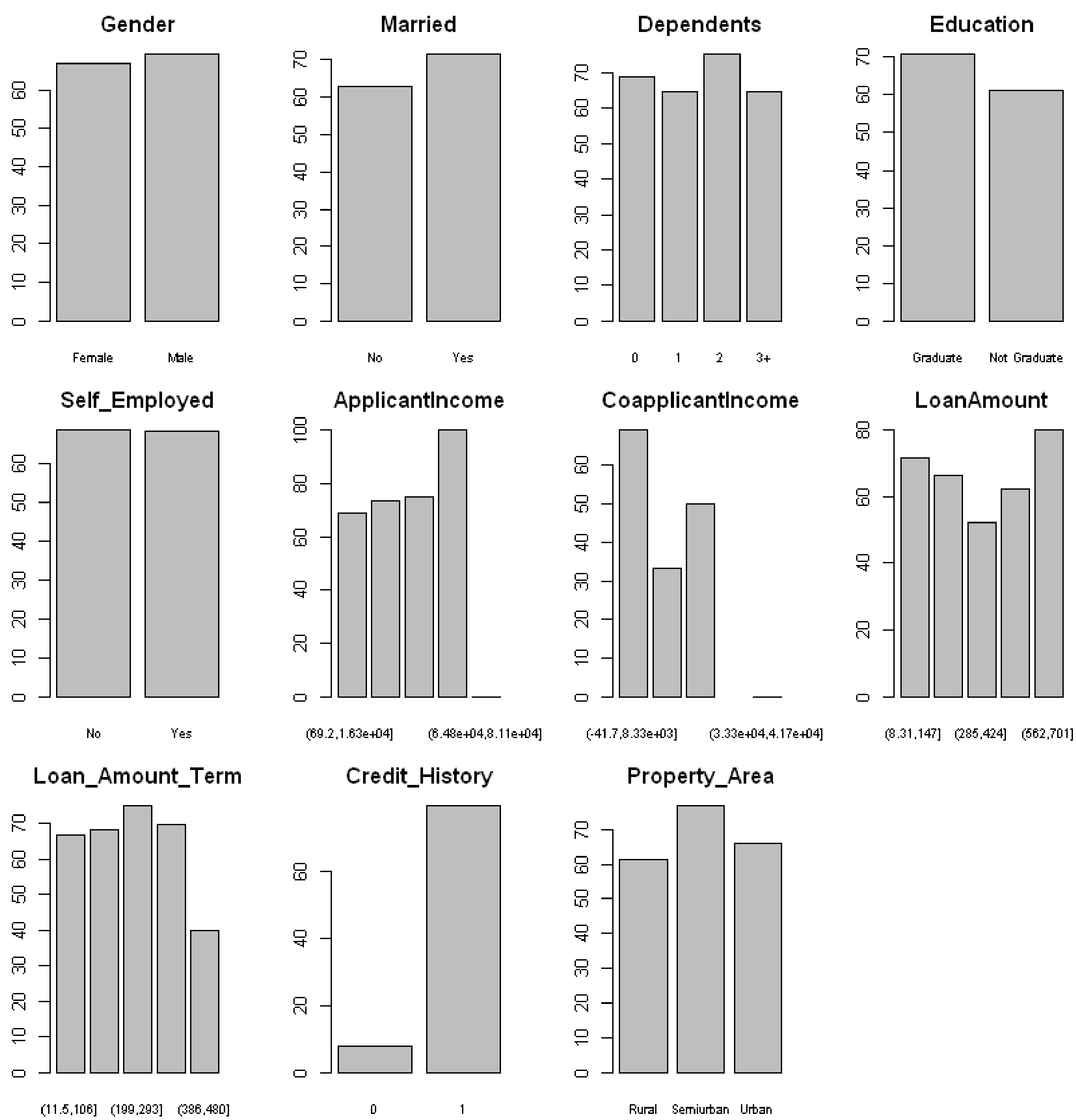
In [144]:
```
featurePlot(df[,7:10],df[,13],plot='pairs')
```



Bar plots of % of loans approved:

In [145]:

```
par(mfrow=c(3,4),mar=c(2,2,3,3))
for(i in 2:12){
    if(i %in% c(2:6,11:12)) {
        barplot(table(df[df[,13]=='Y',i])/table(df[,i])*100,beside=TRUE,main=names(d
    } else {
        cutdf <- df
        cutdf$cutdf <-cut(df[,i],5)
        barplot(table(cutdf[cutdf[,13]=='Y',14])/table(cutdf[,14])*100,beside=TRUE,m
    }
}
```



There is no clear grouping of the loan status based on any pairs of continuous features. For categorical features, credit history seems to have a large effect on the loan status.

Pre-Processing

Next, create dummy variables and perform pre-processing.

In [146]:
```
createdummy <- function(olddf){
    dummies <- as.data.frame(predict(dummyVars(Loan_Status~.,df[,c(2:6,11:13)]),oldd
    newdf <- olddf[,c(7:10)]
    newdf$Male <- dummies$Gender.Male
    newdf$Marital <- dummies$Married.Yes
    newdf$Dependents.0 <- dummies$Dependents.0
    newdf$Dependents.1 <- dummies$Dependents.1
    newdf$Dependents.2 <- dummies$Dependents.2
    newdf$Graduate <- dummies$Education.Graduate
    newdf$SelfEmployed <- dummies$Self_Employed.Yes
    newdf$CreditHistory <- dummies$Credit_History.1
    newdf$Rural <- dummies$Property_Area.Rural
    newdf$Urban <- dummies$Property_Area.Urban
    return(newdf)
}

X = createdummy(df)
```

```
Warning message in model.frame.default(Terms, newdata, na.action = na.action, xlev
= object$lvls):
"variable 'Loan_Status' is not a factor"
```

In [147]:
```
processparameters <-preProcess(X,method =c('scale','bagImpute'))
preprocessedX <-predict(processparameters,X)
preprocessedX
```

ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Male	Marital	Depender
0.9574333	0.0000000	1.7251291	5.528221	2.565957	0.000000	2.02
0.7501995	0.5153356	1.4955485	5.528221	2.565957	2.096786	0.00
0.4910754	0.0000000	0.7711422	5.528221	2.565957	2.096786	2.02
0.4228159	0.8058099	1.4020768	5.528221	2.565957	2.096786	2.02
0.9821508	0.0000000	1.6474402	5.528221	2.565957	0.000000	2.02
0.8867185	1.4339179	3.1196208	5.528221	2.565957	2.096786	0.00
0.3818930	0.5180695	1.1099774	5.528221	2.565957	2.096786	2.02
0.4969683	0.8557032	1.8460677	5.528221	2.565957	2.096786	0.00
0.6557493	0.5214868	1.9629075	5.528221	2.565957	2.096786	0.00
2.1019663	3.7481439	4.0777066	5.528221	2.565957	2.096786	0.00
0.5238137	0.2392141	0.8178781	5.528221	2.565957	2.096786	0.00

Model Selection

Different models will be trained.

Linear Discriminant Analysis

In [222]:
```
lda<-train(preprocessedX, df[,13],method='lda',trControl=trainControl(method='repeat
lda
```

```
Linear Discriminant Analysis

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 491, 492, 491, 491, 491, ...
Resampling results:

  Accuracy   Kappa
  0.8083902  0.481057
```

Logistic Regression

In [149]:
```
logistic<-train(preprocessedX, df[,13],method='multinom',trControl=trainControl(meth
logistic
```

```
iter  10 value 291.239981
iter  20 value 282.472592
final  value 282.472527
converged

Penalized Multinomial Regression

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 491, 491, 492, 491, 492, ...
Resampling results across tuning parameters:

  decay  Accuracy   Kappa
  0e+00  0.8007800  0.4646392
  1e-04  0.8007800  0.4646392
  1e-01  0.8013221  0.4657627
```

Support Vector Machine

In [150]:
```
SVMLin<-train(preprocessedX, df[,13],method='svmLinear',trControl=trainControl(metho
SVMLin
```

```
Support Vector Machines with Linear Kernel

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 492, 491, 492, 490, 491, 491, ...
Resampling results:

  Accuracy   Kappa
  0.8094905  0.4797852

Tuning parameter 'C' was held constant at a value of 1
```

In [151]:
```
SVMRad<-train(preprocessedX, df[,13],method='svmRadial',trControl=trainControl(metho
SVMRad
```

```
Support Vector Machines with Radial Basis Function Kernel

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 491, 491, 492, 491, 492, ...
Resampling results across tuning parameters:

  C     Accuracy   Kappa
  0.25  0.8072400  0.4705199
  0.50  0.8088661  0.4758871
  1.00  0.8072400  0.4747079

Tuning parameter 'sigma' was held constant at a value of 0.06199227
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were sigma = 0.06199227 and C = 0.5.
```

k Nearest Neighbors

In [152]:
```
kNN<-train(preprocessedX, df[,13],method='knn',trControl=trainControl(method='repeat
kNN
```

```
k-Nearest Neighbors

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 491, 491, 492, 491, 491, ...
Resampling results across tuning parameters:

  k  Accuracy   Kappa
  5  0.7839600  0.4198568
  7  0.7850175  0.4120866
  9  0.7850264  0.4088475

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was k = 9.
```

In [153]:
```
kkNN<-train(preprocessedX, df[,13],method='kknn',trControl=trainControl(method='repe
kkNN
```

```
k-Nearest Neighbors

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 492, 491, 492, 490, 492, ...
Resampling results across tuning parameters:

  kmax  Accuracy   Kappa
  5     0.7579762  0.3902270
  7     0.7731707  0.4101879
  9     0.7818520  0.4244742

Tuning parameter 'distance' was held constant at a value of 2
Tuning
 parameter 'kernel' was held constant at a value of optimal
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were kmax = 9, distance = 2 and kernel
 = optimal.
```

Naive Bayes

```
In [154]: nb<-train(preprocessedX, df[,13],method='nb',trControl=trainControl(method='repeated
          nb
```

```
614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 492, 491, 491, 492, 490, 492, ...
Resampling results across tuning parameters:

  usekernel  Accuracy   Kappa
  FALSE      0.7915134  0.44943975
   TRUE      0.7024625  0.08540328

Tuning parameter 'fL' was held constant at a value of 0
Tuning
 parameter 'adjust' was held constant at a value of 1
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were fL = 0, usekernel = FALSE and adjust
 = 1.
```

Decision Tree

```
In [155]: tree<-train(preprocessedX, df[,13],method='rpart',trControl=trainControl(method='rep
          tree
```

```
CART

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 492, 490, 492, 491, 491, 491, ...
Resampling results across tuning parameters:

  cp           Accuracy   Kappa
  0.005208333  0.7621580  0.3964007
  0.007812500  0.7811948  0.4296773
  0.395833333  0.7324045  0.1880315

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was cp = 0.0078125.
```

Random Forest

In [156]:
```
rf<-train(preprocessedX, df[,13],method='rf',trControl=trainControl(method='repeated
rf
```

```
Random Forest

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 491, 491, 491, 492, 492, ...
Resampling results across tuning parameters:

  mtry  Accuracy   Kappa
   2    0.8110690  0.4892170
   8    0.7882649  0.4507972
  14    0.7801302  0.4349723

Accuracy was used to select the optimal model using the largest value.
The final value used for the model was mtry = 2.
```

Gradient Boosted Trees

In [157]:
```
gbm<-train(preprocessedX, df[,13],method='gbm',trControl=trainControl(method='repeat
gbm
```

```
Resampling results across tuning parameters:

  interaction.depth  n.trees  Accuracy   Kappa
  1                   50      0.8073558  0.4771215
  1                  100      0.8095327  0.4832626
  1                  150      0.8068401  0.4797073
  2                   50      0.8089863  0.4807597
  2                  100      0.8008250  0.4671640
  2                  150      0.7861418  0.4408175
  3                   50      0.8030021  0.4702420
  3                  100      0.7942986  0.4607435
  3                  150      0.7867016  0.4498793

Tuning parameter 'shrinkage' was held constant at a value of 0.1

Tuning parameter 'n.minobsinnode' was held constant at a value of 10
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 100, interaction.depth =
 1, shrinkage = 0.1 and n.minobsinnode = 10.
```

Model Performance

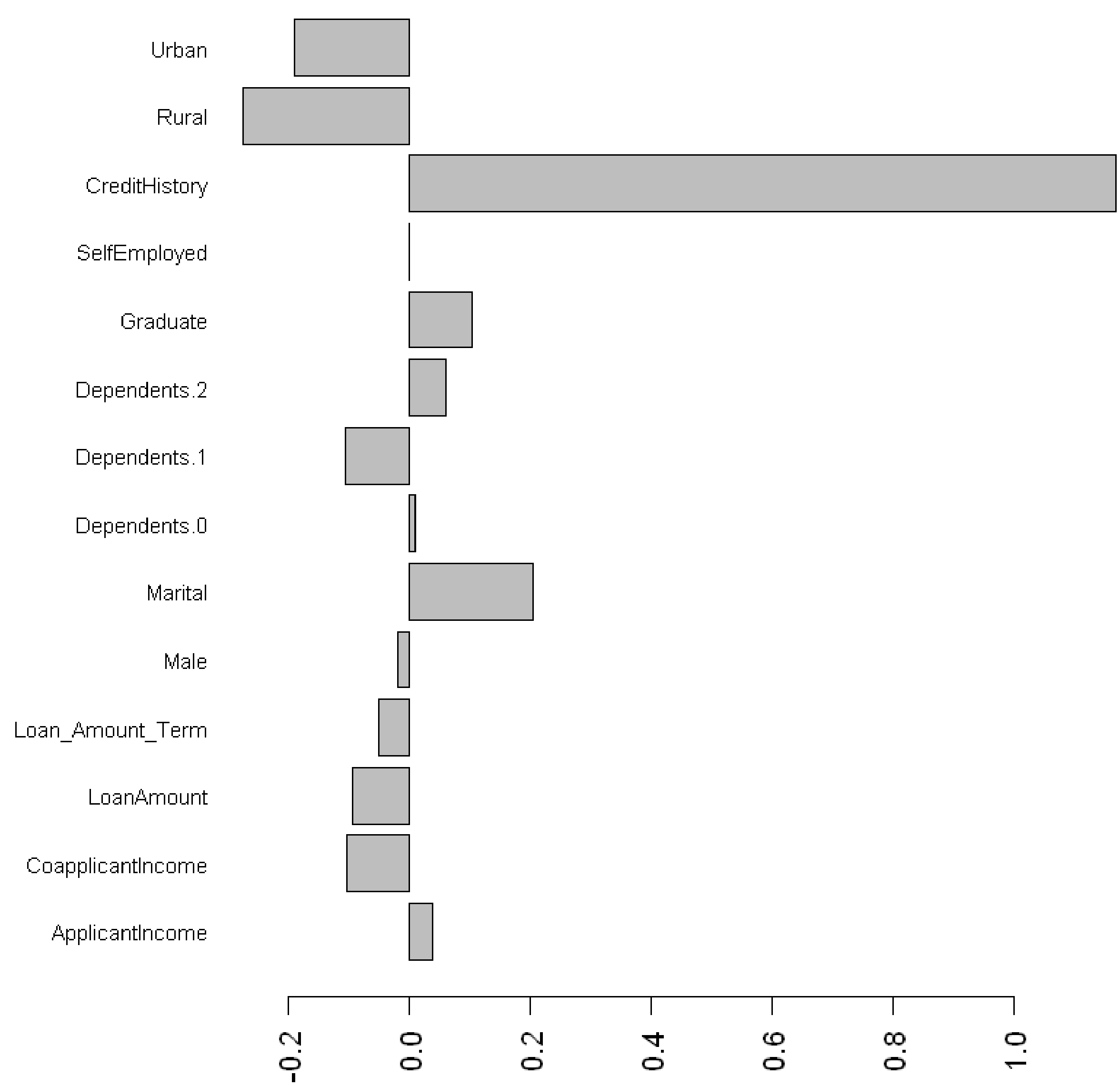
The best performing algorithms were linear discriminant analysis, linear support vector machine, random forest, and gradient boosted trees.

First, the LDA model will be examined and improved.

In [158]:
```
lda$finalModel
```

```
Call:
lda(x, y)

Prior probabilities of groups:
        N         Y 
0.3127036 0.6872964 

Group means:
  ApplicantIncome CoapplicantIncome LoanAmount Loan_Amount_Term     Male
N       0.8914783         0.6417115   1.762903         5.276322 2.062734
Y       0.8813279         0.5141451   1.685500         5.238056 2.099051
   Marital Dependents.0 Dependents.1 Dependents.2 Graduate SelfEmployed
N 1.234046     1.175798    0.4984103    0.3474781 1.763877    0.4167675
Y 1.426332     1.177636    0.4157356    0.4806067 1.948982    0.3959870
  CreditHistory     Rural     Urban
N      1.540925 0.7901165 0.7642545
Y      2.652009 0.5730909 0.6702384

Coefficients of linear discriminants:
                            LD1
ApplicantIncome    0.0377631380
CoapplicantIncome -0.1035320497
LoanAmount        -0.0957850594
Loan_Amount_Term  -0.0523607171
Male              -0.0189169539
Marital            0.2056612969
Dependents.0       0.0099260027
Dependents.1      -0.1077564446
Dependents.2       0.0590280913
Graduate           0.1027340830
SelfEmployed      -0.0001677648
CreditHistory      1.1712580027
Rural             -0.2769010514
Urban             -0.1909541960
```

In [159]:
```
par(mar=c(4,8,2,2))
barplot(coef(lda$finalModel)[,1],horiz=TRUE,las=2,cex.names=0.75)
```



The final model coefficients are consistent with the observations made during preliminary data visualization. The credit history has the largest influence on the loan approval.

In [160]:
```
predictTrain <- predict(lda,preprocessedX)
confusionMatrix(predictTrain, df[,13],positive='Y')
```

```
Confusion Matrix and Statistics

          Reference
Prediction   N   Y
         N  85  10
         Y 107 412

               Accuracy : 0.8094
                 95% CI : (0.7761, 0.8398)
    No Information Rate : 0.6873
    P-Value [Acc > NIR] : 6.062e-12

                  Kappa : 0.4859
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9763
            Specificity : 0.4427
         Pos Pred Value : 0.7938
         Neg Pred Value : 0.8947
             Prevalence : 0.6873
         Detection Rate : 0.6710
   Detection Prevalence : 0.8453
      Balanced Accuracy : 0.7095

       'Positive' Class : Y
```

The accuracy is similar to the accuracy from cross validation, therefore the model is not overfitted.

Because the data is unbalanced, (most of the loans were approved), there are more false positives than false negatives. The model will tend to predict more loans being approved than actually are approved. However, the false positive rate is still much higher than the false negative rate, indicating there may be some other problem with the model.

Normality is an assumption of LDA. The Box Cox transformation may be performed to improve the LDA model.

In [239]:
```
processparameters2 <-preProcess(X,method =c('scale','bagImpute','BoxCox'))
preprocessedX2 <-predict(processparameters2,X)
lda<-train(preprocessedX2, df[,13],method='lda',trControl=trainControl(method='repea
lda
predictTrain <- predict(lda,preprocessedX2)
confusionMatrix(predictTrain, df[,13],positive='Y')
```

```
Linear Discriminant Analysis

614 samples
 14 predictor
  2 classes: 'N', 'Y'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 3 times)
Summary of sample sizes: 491, 491, 491, 491, 492, 492, ...
Resampling results:

  Accuracy   Kappa
  0.8121314  0.4901704

Confusion Matrix and Statistics

          Reference
Prediction   N   Y
         N  86   9
         Y 106 413

               Accuracy : 0.8127
                 95% CI : (0.7796, 0.8428)
    No Information Rate : 0.6873
    P-Value [Acc > NIR] : 1.565e-12

                  Kappa : 0.4947
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9787
            Specificity : 0.4479
         Pos Pred Value : 0.7958
         Neg Pred Value : 0.9053
             Prevalence : 0.6873
         Detection Rate : 0.6726
   Detection Prevalence : 0.8453
      Balanced Accuracy : 0.7133

       'Positive' Class : Y
```

Now the performance of the LDA model is comparable if not slightly better than that of the other models. Because of its simplicity and lower tendency to overfit, the LDA model will be chosen as the final model.

Note that the number of false positives is still very high. This may be partially due to imbalance, as mentioned before. However, it is likely mostly due to the nature of the data itself because the results for kNN (which is not sensitive to class imbalance) are even worse than the LDA model, in terms of Cohen's kappa. This indicates that modeling based on neighbors leads to predictions that are not much more accurate compared to random assignment, which implies that samples that are close to each other in feature space may belong to a different class. It suggests the nature of loan approval is subjective, and that similar people may be approved or denied arbitrarily. Because there are more false positives, it suggests that some may have biases against certain groups of people that causes them to deny loans that otherwise would be approved in the majority of cases. Overall, since it seems the low specificity is not mainly due to imbalance, no oversampling or subsampling will be performed to balance the data, and the current LDA model will be used as is.

The test data set is pre-processed and the prediction is generated below.

In [240]:

```
test <- read.csv('C:/Datasets/LoanTest.csv',na.strings='')
test$Credit_History<-as.factor(test$Credit_History)
summary(test)
test$Loan_Status <- 0
testX <- createdummy(test)
preprocessedtestX <-predict(processparameters2,testX)
```

```
     Loan_ID       Gender    Married    Dependents        Education
 LP001015:  1   Female: 70   No :134   0   :200   Graduate     :283
 LP001022:  1   Male  :286   Yes:233   1   : 58   Not Graduate: 84
 LP001031:  1   NA's  : 11             2   : 59
 LP001035:  1                          3+  : 40
 LP001051:  1                          NA's: 10
 LP001054:  1
 (Other) :361
 Self_Employed ApplicantIncome CoapplicantIncome   LoanAmount
 No  :307      Min.   :    0   Min.   :    0     Min.   : 28.0
 Yes : 37      1st Qu.: 2864   1st Qu.:    0     1st Qu.:100.2
 NA's: 23      Median : 3786   Median : 1025     Median :125.0
               Mean   : 4806   Mean   : 1570     Mean   :136.1
               3rd Qu.: 5060   3rd Qu.: 2430     3rd Qu.:158.0
               Max.   :72529   Max.   :24000     Max.   :550.0
                                                 NA's   :5
 Loan_Amount_Term Credit_History   Property_Area
 Min.   :  6.0    0   : 59       Rural    :111
 1st Qu.:360.0    1   :279       Semiurban:116
```

In [241]:

```
results <- data.frame(test[,1],predict(lda,preprocessedtestX))
```