library("tidyverse")

## ── Attaching packages ─────────────────────────────────────── tidyverse 1.3.2 ──  
## ✔ ggplot2 3.4.0 ✔ purrr 1.0.1   
## ✔ tibble 3.1.8 ✔ dplyr 1.0.10  
## ✔ tidyr 1.2.1 ✔ stringr 1.5.0   
## ✔ readr 2.1.4 ✔ forcats 1.0.0

## Warning: package 'readr' was built under R version 4.2.3

## Warning: package 'stringr' was built under R version 4.2.3

## ── Conflicts ────────────────────────────────────────── tidyverse\_conflicts() ──  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag() masks stats::lag()

library("car")

## Loading required package: carData  
##   
## Attaching package: 'car'  
##   
## The following object is masked from 'package:dplyr':  
##   
## recode  
##   
## The following object is masked from 'package:purrr':  
##   
## some

library("SSBtools")

## Warning: package 'SSBtools' was built under R version 4.2.3

## Loading required package: Matrix  
##   
## Attaching package: 'Matrix'  
##   
## The following objects are masked from 'package:tidyr':  
##   
## expand, pack, unpack

library("ggplot2")  
library('moments')  
library('corrr')

## Warning: package 'corrr' was built under R version 4.2.3

library('dplyr')  
credit\_data <- read.csv('/Users/Owner/Downloads/archive (1)/clean\_dataset.csv',header= TRUE)  
any(is.na(credit\_data))

## [1] FALSE

summary(credit\_data)

## Gender Age Debt Married   
## Min. :0.0000 Min. :13.75 Min. : 0.000 Min. :0.0000   
## 1st Qu.:0.0000 1st Qu.:22.67 1st Qu.: 1.000 1st Qu.:1.0000   
## Median :1.0000 Median :28.46 Median : 2.750 Median :1.0000   
## Mean :0.6957 Mean :31.51 Mean : 4.759 Mean :0.7609   
## 3rd Qu.:1.0000 3rd Qu.:37.71 3rd Qu.: 7.207 3rd Qu.:1.0000   
## Max. :1.0000 Max. :80.25 Max. :28.000 Max. :1.0000   
## BankCustomer Industry Ethnicity YearsEmployed   
## Min. :0.0000 Length:690 Length:690 Min. : 0.000   
## 1st Qu.:1.0000 Class :character Class :character 1st Qu.: 0.165   
## Median :1.0000 Mode :character Mode :character Median : 1.000   
## Mean :0.7638 Mean : 2.223   
## 3rd Qu.:1.0000 3rd Qu.: 2.625   
## Max. :1.0000 Max. :28.500   
## PriorDefault Employed CreditScore DriversLicense   
## Min. :0.0000 Min. :0.0000 Min. : 0.0 Min. :0.000   
## 1st Qu.:0.0000 1st Qu.:0.0000 1st Qu.: 0.0 1st Qu.:0.000   
## Median :1.0000 Median :0.0000 Median : 0.0 Median :0.000   
## Mean :0.5232 Mean :0.4275 Mean : 2.4 Mean :0.458   
## 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.: 3.0 3rd Qu.:1.000   
## Max. :1.0000 Max. :1.0000 Max. :67.0 Max. :1.000   
## Citizen ZipCode Income Approved   
## Length:690 Min. : 0.0 Min. : 0.0 Min. :0.0000   
## Class :character 1st Qu.: 60.0 1st Qu.: 0.0 1st Qu.:0.0000   
## Mode :character Median : 160.0 Median : 5.0 Median :0.0000   
## Mean : 180.5 Mean : 1017.4 Mean :0.4449   
## 3rd Qu.: 272.0 3rd Qu.: 395.5 3rd Qu.:1.0000   
## Max. :2000.0 Max. :100000.0 Max. :1.0000

Overview of the dataset. Then moodifying the categorial variables, eliminated Industry & Zipcode, transform continuous variables

New\_credit\_data <- credit\_data %>%  
 select(Gender,Age,Debt,Married,BankCustomer,Ethnicity,YearsEmployed,PriorDefault,Employed,CreditScore,DriversLicense,Income,Approved,Citizen) %>%  
 mutate(Citizen\_by\_birth=ifelse(Citizen=='ByBirth',1,0)) %>%  
 mutate(Citizen\_by\_others=ifelse(Citizen=='ByOtherMeans',1,0)) %>%  
 mutate(Citizen\_temp=ifelse(Citizen=='Temporary',1,0))%>%  
 mutate(W= ifelse(Ethnicity=='White',1,0)) %>%  
 mutate(B=ifelse(Ethnicity=='Black',1,0)) %>%  
 mutate(A=ifelse(Ethnicity=='Asian',1,0)) %>%  
 mutate(L=ifelse(Ethnicity=='Latino',1,0)) %>%  
 mutate(O=ifelse(Ethnicity=='Other',1,0)) %>%  
 mutate(log\_age=log(Age))%>%  
 mutate(log\_debt=log(Debt+1)) %>%  
 mutate(log\_yearsemployed=log(YearsEmployed+1)) %>%  
 mutate(log\_income=log(Income+1))  
 head(New\_credit\_data)

## Gender Age Debt Married BankCustomer Ethnicity YearsEmployed PriorDefault  
## 1 1 30.83 0.000 1 1 White 1.25 1  
## 2 0 58.67 4.460 1 1 Black 3.04 1  
## 3 0 24.50 0.500 1 1 Black 1.50 1  
## 4 1 27.83 1.540 1 1 White 3.75 1  
## 5 1 20.17 5.625 1 1 White 1.71 1  
## 6 1 32.08 4.000 1 1 White 2.50 1  
## Employed CreditScore DriversLicense Income Approved Citizen  
## 1 1 1 0 0 1 ByBirth  
## 2 1 6 0 560 1 ByBirth  
## 3 0 0 0 824 1 ByBirth  
## 4 1 5 1 3 1 ByBirth  
## 5 0 0 0 0 1 ByOtherMeans  
## 6 0 0 1 0 1 ByBirth  
## Citizen\_by\_birth Citizen\_by\_others Citizen\_temp W B A L O log\_age log\_debt  
## 1 1 0 0 1 0 0 0 0 3.428488 0.0000000  
## 2 1 0 0 0 1 0 0 0 4.071929 1.6974488  
## 3 1 0 0 0 1 0 0 0 3.198673 0.4054651  
## 4 1 0 0 1 0 0 0 0 3.326115 0.9321641  
## 5 0 1 0 1 0 0 0 0 3.004196 1.8908504  
## 6 1 0 0 1 0 0 0 0 3.468233 1.6094379  
## log\_yearsemployed log\_income  
## 1 0.8109302 0.000000  
## 2 1.3962447 6.329721  
## 3 0.9162907 6.715383  
## 4 1.5581446 1.386294  
## 5 0.9969486 0.000000  
## 6 1.2527630 0.000000

Final dataset to train, drop Ethnicity , citizen. Scale the dataset.

New\_credit\_data <-subset(New\_credit\_data,select=-c(Ethnicity,Citizen))  
New\_credit\_data$Income <-scale(New\_credit\_data$Income)

Splitting data into training and testing

set.seed(1)  
sample <- sample(c(TRUE,FALSE),nrow(New\_credit\_data),replace=TRUE,prob=c(0.7,0.3))  
train <- New\_credit\_data[sample,]  
test <-New\_credit\_data[!sample,]

PCA transform

PCA\_data <- prcomp(train,scale=TRUE,center=TRUE)  
summary(PCA\_data)

## Importance of components:  
## PC1 PC2 PC3 PC4 PC5 PC6 PC7  
## Standard deviation 2.0706 1.52249 1.44546 1.3558 1.29445 1.24403 1.23402  
## Proportion of Variance 0.1786 0.09658 0.08706 0.0766 0.06982 0.06448 0.06345  
## Cumulative Proportion 0.1786 0.27522 0.36227 0.4389 0.50868 0.57317 0.63662  
## PC8 PC9 PC10 PC11 PC12 PC13 PC14  
## Standard deviation 1.11182 1.06907 1.01020 0.95333 0.94210 0.9007 0.88954  
## Proportion of Variance 0.05151 0.04762 0.04252 0.03787 0.03698 0.0338 0.03297  
## Cumulative Proportion 0.68812 0.73574 0.77826 0.81613 0.85311 0.8869 0.91989  
## PC15 PC16 PC17 PC18 PC19 PC20 PC21  
## Standard deviation 0.81479 0.65749 0.63957 0.49351 0.31153 0.22736 0.13559  
## Proportion of Variance 0.02766 0.01801 0.01704 0.01015 0.00404 0.00215 0.00077  
## Cumulative Proportion 0.94755 0.96556 0.98260 0.99275 0.99679 0.99895 0.99971  
## PC22 PC23 PC24  
## Standard deviation 0.08273 1.225e-15 5.322e-16  
## Proportion of Variance 0.00029 0.000e+00 0.000e+00  
## Cumulative Proportion 1.00000 1.000e+00 1.000e+00

var\_explained= PCA\_data$sdev^2/sum(PCA\_data$sdev^2)  
which(cumsum(var\_explained) >=0.9)

## [1] 14 15 16 17 18 19 20 21 22 23 24

Plotting elbow when it is finalized.The first 15 variables are able explaining 94% of the variances Creating predict model using the first 14 factors #reverse the signs & displaying principal componnents.

PCA\_data$rotation <- -1\*PCA\_data$rotation  
PCA\_data$rotation

## PC1 PC2 PC3 PC4  
## Gender 0.027859178 -0.172544869 -0.022266988 0.16552153  
## Age -0.256733844 -0.235293258 -0.192855194 -0.39450732  
## Debt -0.253810784 0.064474717 -0.181629178 -0.01201534  
## Married -0.131390776 -0.059101100 0.538570945 -0.30217323  
## BankCustomer -0.132057664 -0.066422268 0.541515108 -0.30542157  
## YearsEmployed -0.329719683 -0.233414737 -0.129218378 0.15795738  
## PriorDefault -0.328235145 -0.009529919 0.109234756 0.20875820  
## Employed -0.290553621 0.180020414 0.141096173 0.07758653  
## CreditScore -0.294394980 0.060506130 0.034496699 0.06033094  
## DriversLicense -0.052501044 -0.147879679 0.004814972 0.15120570  
## Income -0.087329928 0.063483824 0.064588523 -0.03538638  
## Approved -0.321771476 0.017064277 0.179950059 0.19011279  
## Citizen\_by\_birth -0.124128190 0.532089602 -0.085158720 -0.04233252  
## Citizen\_by\_others 0.113798722 -0.517450200 0.050716046 0.10041084  
## Citizen\_temp 0.045816219 -0.121796270 0.100286526 -0.13942211  
## W 0.118811622 -0.052393038 0.284738226 0.24087074  
## B -0.112013444 0.054813065 -0.101655540 0.12388442  
## A -0.071113793 -0.097739937 -0.064732753 -0.11077161  
## L 0.032070505 0.069060503 -0.219762427 -0.38259471  
## O -0.007156724 0.059090037 -0.101627143 -0.16330191  
## log\_age -0.252626329 -0.252051487 -0.189777788 -0.37619949  
## log\_debt -0.250410539 0.066796613 -0.171847694 0.01711321  
## log\_yearsemployed -0.326026991 -0.234984221 -0.071884081 0.24700908  
## log\_income -0.191441041 0.271091916 0.122066604 -0.03090388  
## PC5 PC6 PC7 PC8 PC9  
## Gender -0.05825944 -0.189153107 -0.09977302 0.397580161 0.12481295  
## Age 0.06430473 -0.211543920 -0.19890457 -0.058049527 0.12693816  
## Debt -0.47808545 -0.021219735 0.36757497 0.020214357 -0.01984186  
## Married 0.06789978 -0.021573178 0.26883622 0.098248599 0.06296208  
## BankCustomer 0.03276035 0.019660394 0.25008961 0.099897324 0.07289262  
## YearsEmployed 0.06205108 -0.057094517 0.05470303 -0.002847629 0.17864030  
## PriorDefault 0.08477880 0.050544066 -0.08728339 -0.123845319 -0.14921122  
## Employed 0.08182380 -0.002964074 -0.13208144 -0.149820176 -0.27344878  
## CreditScore -0.03933977 -0.049005973 -0.12128861 -0.096650309 -0.29449732  
## DriversLicense 0.13232419 -0.030775117 -0.05568453 0.339768285 -0.02321321  
## Income -0.36118344 0.345225322 -0.32318718 0.142986744 0.10807809  
## Approved 0.02948409 0.139276441 -0.17286212 -0.172407733 -0.03842497  
## Citizen\_by\_birth 0.18797237 -0.262905896 0.01647934 0.178113778 0.17471241  
## Citizen\_by\_others -0.08712369 0.180996754 0.09672944 -0.146568943 -0.32300956  
## Citizen\_temp -0.28384201 0.248135370 -0.28757255 -0.107833315 0.34536414  
## W -0.27456369 -0.528618045 -0.14607369 -0.160740527 0.09983445  
## B 0.34532126 0.450608203 0.24261852 -0.069995148 0.33521595  
## A 0.07110856 0.091348623 -0.06973484 0.603206256 -0.44106414  
## L 0.05149021 0.001115728 0.06927394 -0.344309445 -0.30199298  
## O -0.17941169 0.238404815 -0.11705756 0.134400826 0.09442914  
## log\_age 0.09239128 -0.209663300 -0.20948106 -0.032650209 0.12662226  
## log\_debt -0.44320864 -0.052025542 0.41125137 0.069300075 -0.01902600  
## log\_yearsemployed 0.11031906 -0.037683168 0.07220273 0.008238187 0.18520068  
## log\_income -0.12226781 0.105897644 -0.29366480 0.061607802 -0.08625776  
## PC10 PC11 PC12 PC13  
## Gender -0.2749572244 -0.4018634510 0.27718971 -0.4133301705  
## Age 0.0153471163 -0.1130305515 -0.12016102 -0.0879601264  
## Debt -0.0317006320 -0.0004480295 -0.10444842 -0.1182038134  
## Married 0.0180005146 -0.0158222704 0.06311000 -0.0011300459  
## BankCustomer 0.0153372960 0.0245982249 0.08812544 0.0002835379  
## YearsEmployed 0.0002008035 0.1627348254 0.33294735 0.3344595876  
## PriorDefault 0.0481331490 -0.0752077489 -0.39146462 0.0324784739  
## Employed 0.0483491183 0.0090516393 0.18658740 -0.1876364632  
## CreditScore 0.0688976144 -0.1220052331 0.14750716 -0.2334806759  
## DriversLicense 0.4113724245 0.5826040455 -0.03812535 -0.5013020232  
## Income -0.1386951364 0.2398547089 0.20567463 0.0251738925  
## Approved 0.0192264377 -0.0658015048 -0.30588382 0.0118743172  
## Citizen\_by\_birth 0.0203362126 0.0572898729 -0.02227649 0.0703861542  
## Citizen\_by\_others 0.0539435878 -0.1557987884 0.11642213 -0.0421975675  
## Citizen\_temp -0.1902057487 0.2387961620 -0.23340396 -0.0821867820  
## W 0.0253072869 0.0553142751 -0.04208309 0.0476918841  
## B -0.1626295703 -0.1526241955 -0.03386879 -0.2854605059  
## A -0.2453844905 0.0584317735 -0.25532173 0.3048422638  
## L -0.1378961364 0.3210970215 0.28699710 -0.1134532059  
## O 0.7403990634 -0.3138421843 0.13873811 0.1686915788  
## log\_age -0.0033168826 -0.1087602812 -0.12911186 -0.0939984697  
## log\_debt -0.0158825972 0.0112374958 -0.12281455 -0.0953070407  
## log\_yearsemployed -0.0392549320 0.1786640827 0.26121505 0.3213987763  
## log\_income -0.1689667815 -0.1290634679 0.29973209 0.0022756146  
## PC14 PC15 PC16 PC17  
## Gender 0.092449667 0.474072656 -0.001094597 0.004779946  
## Age -0.126761522 -0.117104529 -0.029254647 -0.087834125  
## Debt 0.003849549 -0.017600452 0.046136740 -0.001052060  
## Married 0.006864002 0.032302796 -0.014723663 0.031968219  
## BankCustomer -0.001151281 0.053283195 -0.055915620 0.032265284  
## YearsEmployed 0.139160411 0.031819802 0.027773665 0.105012577  
## PriorDefault -0.187091047 0.324702138 -0.113213026 0.038184044  
## Employed 0.263053840 -0.037500008 0.164609290 -0.748830135  
## CreditScore 0.460120691 -0.322406976 -0.378738589 0.467036088  
## DriversLicense -0.143313399 -0.044413323 0.139242570 0.100953994  
## Income -0.300932321 0.005931154 -0.588083665 -0.190122550  
## Approved -0.098203204 0.343656863 0.065387502 0.177010177  
## Citizen\_by\_birth -0.008106916 0.075510496 -0.122238084 0.021240167  
## Citizen\_by\_others -0.193607607 -0.103595826 0.015394835 -0.044391912  
## Citizen\_temp 0.509000948 0.058634097 0.288435433 0.054880882  
## W -0.080533122 -0.119362636 -0.033833921 -0.034513497  
## B -0.052047935 -0.220853120 -0.047113796 -0.029472340  
## A 0.163403921 -0.060947498 0.049797794 -0.040127289  
## L -0.035436856 0.465336086 0.025712204 0.154944261  
## O 0.111352023 0.190794067 0.068636001 -0.005234080  
## log\_age -0.141296534 -0.141457738 -0.035008724 -0.080832712  
## log\_debt -0.065087253 -0.022768464 0.096538235 -0.071700752  
## log\_yearsemployed 0.039618201 0.048745044 0.077850438 -0.032259886  
## log\_income -0.383860247 -0.250978496 0.560214730 0.274441100  
## PC18 PC19 PC20 PC21  
## Gender -0.025225080 -0.0030455743 -0.0048303554 -0.0049885918  
## Age 0.040038669 0.0610514366 0.0446050438 -0.7040302761  
## Debt 0.035953378 0.3428005415 0.6153384057 0.0852380312  
## Married -0.032301060 -0.0048853463 -0.0131924682 0.0467161508  
## BankCustomer -0.002653605 0.0112903841 0.0232352884 -0.0402210527  
## YearsEmployed -0.013918648 0.5927554164 -0.3438127821 0.0445783029  
## PriorDefault -0.679122251 0.0566795144 -0.0088996912 -0.0030466893  
## Employed 0.030063591 0.0604699387 -0.0125926231 0.0148366652  
## CreditScore -0.024829730 -0.1267786193 -0.0075786325 -0.0154020966  
## DriversLicense 0.005063327 0.0334940354 0.0115161063 -0.0088028491  
## Income 0.031037912 -0.0071664748 -0.0218392558 -0.0006958473  
## Approved 0.695200385 0.0047977807 -0.0301147937 0.0090590093  
## Citizen\_by\_birth 0.027936229 0.0004835675 0.0141930519 0.0025378771  
## Citizen\_by\_others 0.031114917 0.0152431161 -0.0054011218 -0.0030176473  
## Citizen\_temp -0.153089253 -0.0396605795 -0.0243948634 0.0008023818  
## W 0.008329734 0.0181673408 -0.0003830508 0.0022008453  
## B -0.011081752 0.0328200774 -0.0152549694 -0.0100188400  
## A 0.057232149 0.0152016974 0.0117125453 -0.0125350734  
## L -0.027274985 -0.0570906317 -0.0028370666 0.0118468962  
## O -0.039401407 -0.0523315438 0.0177092536 0.0155579580  
## log\_age 0.025809196 -0.0888442216 -0.0340846215 0.6957150316  
## log\_debt 0.007672826 -0.3454606191 -0.6019876124 -0.0611236440  
## log\_yearsemployed -0.030746069 -0.6052790130 0.3653622160 -0.0468473212  
## log\_income -0.124838266 0.0078668287 0.0074185650 -0.0050809964  
## PC22 PC23 PC24  
## Gender 1.274726e-03 6.605049e-16 -1.577718e-17  
## Age -3.801750e-02 -1.211211e-15 -9.613519e-16  
## Debt -1.752546e-02 7.243885e-17 -9.992344e-17  
## Married -7.046978e-01 -6.262783e-16 1.347533e-15  
## BankCustomer 7.031528e-01 9.747907e-16 -1.332195e-15  
## YearsEmployed -2.726390e-03 -6.291291e-17 2.590419e-16  
## PriorDefault 1.436041e-02 -1.404040e-16 -1.779426e-16  
## Employed 6.806572e-03 -5.271069e-16 2.843611e-16  
## CreditScore -1.348614e-05 3.497791e-16 -5.439569e-17  
## DriversLicense -9.428980e-03 7.552729e-17 -2.121779e-16  
## Income -5.413323e-02 -1.407656e-16 1.703654e-16  
## Approved -1.498581e-02 1.513965e-16 1.646517e-16  
## Citizen\_by\_birth 7.120823e-03 8.284742e-04 7.029283e-01  
## Citizen\_by\_others -3.675656e-03 7.790579e-04 6.610005e-01  
## Citizen\_temp -9.808194e-03 3.095238e-04 2.626190e-01  
## W 5.171340e-03 6.331143e-01 -7.461911e-04  
## B 3.317760e-03 5.213874e-01 -6.145093e-04  
## A 2.849211e-03 3.636059e-01 -4.285474e-04  
## L -1.418742e-02 3.437365e-01 -4.051292e-04  
## O -4.192870e-03 2.774096e-01 -3.269561e-04  
## log\_age 5.302290e-02 8.025434e-16 7.721358e-16  
## log\_debt 1.696133e-02 -3.325633e-16 2.485286e-16  
## log\_yearsemployed -1.028236e-02 -3.468780e-17 -2.162475e-16  
## log\_income 9.443744e-03 5.307684e-17 -1.771444e-16

EXTRACTING 15 pc FOR TRAIN AND TEST DATASET

mydata <- data.frame(Class= train[,"Approved"],PCA\_data$x[,1:15])  
head(mydata)

## Class PC1 PC2 PC3 PC4 PC5 PC6  
## 1 1 -0.002081838 -0.02600977 -1.7504160 -0.36773561 -1.205872 0.88542539  
## 2 1 3.492728801 -0.09572438 0.1885372 1.47546554 -1.534480 -0.82233677  
## 3 1 0.255725807 -1.11140768 -1.0491118 -0.10169525 -1.934195 -2.19178227  
## 5 1 -1.025881721 3.36275620 -1.6982389 -1.62198028 1.578185 -0.95287174  
## 8 1 0.357271569 -1.70295008 -1.2610704 -0.04598424 1.906984 -0.02510283  
## 9 1 1.294527353 0.61861952 2.6636101 -0.40863240 -2.163684 -0.63945281  
## PC7 PC8 PC9 PC10 PC11 PC12 PC13  
## 1 1.0853721 0.7155358 -0.05364931 0.1268706 0.7672639 0.4124947 -0.358235664  
## 2 0.2995245 1.4111187 -0.68062300 0.3243402 0.9424681 0.7179627 -0.001075101  
## 3 -0.1488373 0.8603185 -0.73122990 0.4892020 0.4419275 0.6193991 -1.009197859  
## 5 -1.3026134 1.2498924 1.34577316 0.2047685 1.1884549 0.3424203 -0.367512553  
## 8 -1.0100865 0.7648438 0.33268308 0.1430496 0.1817154 1.5323953 -0.787952617  
## 9 2.0356410 0.7142707 -1.61733800 1.1036615 1.5468968 0.5749538 -0.246167092  
## PC14 PC15  
## 1 -0.4527306 -1.3054256  
## 2 0.6154432 1.3614588  
## 3 1.0288093 0.2475404  
## 5 0.6655929 -1.0384961  
## 8 1.3736173 0.1130771  
## 9 1.1966140 -0.1018405

Build logistic model

model <-glm(Class~.,data=mydata,family='binomial')

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

summary(model)

##   
## Call:  
## glm(formula = Class ~ ., family = "binomial", data = mydata)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.74341 -0.00224 -0.00040 0.00312 2.42697   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.2416 0.7247 -1.713 0.08665 .   
## PC1 4.1124 1.8112 2.271 0.02317 \*   
## PC2 -0.3634 0.2570 -1.414 0.15748   
## PC3 -2.6897 1.1489 -2.341 0.01922 \*   
## PC4 -2.6811 1.3110 -2.045 0.04085 \*   
## PC5 0.4214 0.4488 0.939 0.34771   
## PC6 -2.2129 0.8553 -2.587 0.00967 \*\*  
## PC7 2.9952 1.0779 2.779 0.00546 \*\*  
## PC8 2.5218 1.8693 1.349 0.17733   
## PC9 -0.3716 0.5874 -0.633 0.52697   
## PC10 -0.3326 0.6583 -0.505 0.61336   
## PC11 0.5296 0.4701 1.126 0.25998   
## PC12 2.8778 1.8441 1.561 0.11863   
## PC13 0.1583 0.5036 0.314 0.75332   
## PC14 2.2421 1.0697 2.096 0.03608 \*   
## PC15 -5.1261 2.4045 -2.132 0.03302 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 668.991 on 485 degrees of freedom  
## Residual deviance: 52.317 on 470 degrees of freedom  
## AIC: 84.317  
##   
## Number of Fisher Scoring iterations: 12

Predict on the test set data

test.p <-predict(PCA\_data,newdata=test)  
pred <-predict(model,newdata=data.frame(test.p[,1:15]),type="response")

Displaying the cross classification table

predApproved <-factor(ifelse(pred>=0.5,"0","1"))  
table(test$Approved,predApproved)

## predApproved  
## 0 1  
## 0 95 21  
## 1 2 86