PCA and LDA dimensionality reduction

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We will do PCA and LDA model on credits data set found in here

```
library(caret)
```

```
## Loading required package: ggplot2
## Loading required package: lattice
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##     filter, lag
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ggplot2)
df <- read.csv('credit.csv')
```

Let's split the data set into Train and Test

```
set.seed(1234)
i <- sample(1:nrow(df), nrow(df)*0.8, replace=FALSE)
train <- df[i,]
test<-df[-i,]
```

Remove column 25, which the classifying column, since PCA is unsupervised learning, we need unlabeled or unclassified data set.

```
pca_train <- train[,1:24]
pca_test <- test[,1:24]
```

Check PCA eligibility. Let's see if our variables are linearly correlated? We can check for correlation by creating a table with the cor() function. The average correlation value is approximately 0.2, so it shows that there is little correlation.

```
cor(pca_train)
```

```
##                     ID   LIMIT_BAL          SEX    EDUCATION     MARRIAGE
## ID         1.000000000  0.02722999  0.020033812  0.038594391 -0.024946286
## LIMIT_BAL  0.027229988  1.00000000  0.019413122 -0.222787435 -0.106639521
## SEX        0.020033812  0.01941312  1.000000000  0.021252215 -0.030919784
## EDUCATION  0.038594391 -0.22278743  0.021252215  1.000000000 -0.145458030
## MARRIAGE  -0.024946286 -0.10663952 -0.030919784 -0.145458030  1.000000000
## AGE        0.019001324  0.14643099 -0.088324775  0.176398011 -0.413589540
## PAY_1     -0.027278647 -0.27312113 -0.056848605  0.101516629  0.020024854
## PAY_2     -0.006330543 -0.29825455 -0.068826189  0.119715312  0.020060371
## PAY_3     -0.017184176 -0.28837524 -0.064693187  0.110370988  0.029280591
## PAY_4      0.001776109 -0.26992118 -0.052731539  0.107648189  0.031538067
## PAY_5     -0.017711653 -0.25184190 -0.049615053  0.093847552  0.036756628
## PAY_6     -0.015076729 -0.23743025 -0.037481987  0.079963509  0.034803996
## BILL_AMT1  0.021264651  0.28299928 -0.032032328  0.016107315 -0.026552972
## BILL_AMT2  0.019708142  0.27544980 -0.029661613  0.011309274 -0.024903906
## BILL_AMT3  0.027111681  0.27990007 -0.024205729  0.006984286 -0.028516466
## BILL_AMT4  0.042212370  0.29070446 -0.021060892 -0.005675557 -0.023889105
## BILL_AMT5  0.018641353  0.29206362 -0.015857380 -0.010956135 -0.025765046
## BILL_AMT6  0.018949610  0.28751960 -0.015653884 -0.013005116 -0.023095854
## PAY_AMT1   0.006752802  0.19451796 -0.003420698 -0.039915154 -0.008923307
## PAY_AMT2   0.006588766  0.17725173 -0.004584862 -0.031373728 -0.013004655
## PAY_AMT3   0.036602448  0.21177164 -0.009072133 -0.040215967 -0.003327253
## PAY_AMT4   0.006581535  0.20476583 -0.003084839 -0.038988771 -0.017832318
## PAY_AMT5   0.000118102  0.21724921 -0.005794148 -0.042513476 -0.008374648
## PAY_AMT6  -0.001822799  0.21805935 -0.002716164 -0.044694548 -0.005161726
##                    AGE       PAY_1        PAY_2        PAY_3        PAY_4
## ID         0.01900132 -0.02727865 -0.006330543 -0.017184176  0.001776109
## LIMIT_BAL  0.14643099 -0.27312113 -0.298254546 -0.288375239 -0.269921183
## SEX       -0.08832477 -0.05684861 -0.068826189 -0.064693187 -0.052731539
## EDUCATION  0.17639801  0.10151663  0.119715312  0.110370988  0.107648189
## MARRIAGE  -0.41358954  0.02002485  0.020060371  0.029280591  0.031538067
## AGE        1.00000000 -0.04234717 -0.049278207 -0.052188767 -0.049706511
## PAY_1     -0.04234717  1.00000000  0.676728158  0.581552138  0.542575677
## PAY_2     -0.04927821  0.67672816  1.000000000  0.770056955  0.664781623
## PAY_3     -0.05218877  0.58155214  0.770056955  1.000000000  0.782677110
## PAY_4     -0.04970651  0.54257568  0.664781623  0.782677110  1.000000000
## PAY_5     -0.05597050  0.50996701  0.622575604  0.689987410  0.820804840
## PAY_6     -0.05021041  0.47592087  0.575956997  0.636278586  0.716707823
## BILL_AMT1  0.05692233  0.18786609  0.236231649  0.210441866  0.202373561
## BILL_AMT2  0.05613573  0.19057613  0.236996322  0.239148906  0.224826422
## BILL_AMT3  0.05512568  0.17900463  0.224273596  0.228242161  0.243533181
## BILL_AMT4  0.04977059  0.18043868  0.223831034  0.229283614  0.246106846
## BILL_AMT5  0.04913813  0.18260102  0.223300062  0.227857376  0.243728613
## BILL_AMT6  0.04653135  0.17867922  0.220648123  0.224843066  0.240723923
## PAY_AMT1   0.03142215 -0.07750149 -0.079501608  0.001153613 -0.011071348
```

```
## PAY_AMT2   0.02557485 -0.07216395 -0.061868743 -0.068089287 -0.004645503
## PAY_AMT3   0.02709256 -0.06875714 -0.053752500 -0.051829679 -0.067756472
## PAY_AMT4   0.02551927 -0.06317477 -0.045542965 -0.044713065 -0.042522606
## PAY_AMT5   0.02670126 -0.05902910 -0.040199045 -0.037082959 -0.033186156
## PAY_AMT6   0.02125624 -0.06170637 -0.040308711 -0.037504607 -0.028545198
##                  PAY_5        PAY_6   BILL_AMT1   BILL_AMT2    BILL_AMT3
## ID        -0.017711653 -0.015076729  0.02126465  0.01970814  0.027111681
## LIMIT_BAL -0.251841900 -0.237430255  0.28299928  0.27544980  0.279900073
## SEX       -0.049615053 -0.037481987 -0.03203233 -0.02966161 -0.024205729
## EDUCATION  0.093847552  0.079963509  0.01610732  0.01130927  0.006984286
## MARRIAGE   0.036756628  0.034803996 -0.02655297 -0.02490391 -0.028516466
## AGE       -0.055970498 -0.050210415  0.05692233  0.05613573  0.055125683
## PAY_1      0.509967009  0.475920866  0.18786609  0.19057613  0.179004629
## PAY_2      0.622575604  0.575956997  0.23623165  0.23699632  0.224273596
## PAY_3      0.689987410  0.636278586  0.21044187  0.23914891  0.228242161
## PAY_4      0.820804840  0.716707823  0.20237356  0.22482642  0.243533181
## PAY_5      1.000000000  0.817125285  0.20749031  0.22728122  0.242748038
## PAY_6      0.817125285  1.000000000  0.20754735  0.22693197  0.240329478
## BILL_AMT1  0.207490306  0.207547345  1.00000000  0.95114455  0.889562606
## BILL_AMT2  0.227281218  0.226931967  0.95114455  1.00000000  0.924487451
## BILL_AMT3  0.242748038  0.240329478  0.88956261  0.92448745  1.000000000
## BILL_AMT4  0.273012237  0.267097246  0.85947992  0.89232691  0.922040453
## BILL_AMT5  0.271348325  0.291414305  0.82929774  0.86014088  0.883261312
## BILL_AMT6  0.263924876  0.285388860  0.80242457  0.83092902  0.853530392
## PAY_AMT1  -0.006737276 -0.001466827  0.13979311  0.27565834  0.237641275
## PAY_AMT2  -0.006727274 -0.007349921  0.09802975  0.08894766  0.324139251
## PAY_AMT3   0.008562841  0.006494514  0.15872741  0.15328393  0.133765723
## PAY_AMT4  -0.056241640  0.019713719  0.15485673  0.14490430  0.141681125
## PAY_AMT5  -0.034937825 -0.047912350  0.16448116  0.15270193  0.182859614
## PAY_AMT6  -0.022384532 -0.024277234  0.16476661  0.16130612  0.175164671
##              BILL_AMT4   BILL_AMT5   BILL_AMT6     PAY_AMT1     PAY_AMT2
## ID         0.042212370  0.01864135  0.01894961  0.006752802  0.006588766
## LIMIT_BAL  0.290704457  0.29206362  0.28751960  0.194517956  0.177251734
## SEX       -0.021060892 -0.01585738 -0.01565388 -0.003420698 -0.004584862
## EDUCATION -0.005675557 -0.01095614 -0.01300512 -0.039915154 -0.031373728
## MARRIAGE  -0.023889105 -0.02576505 -0.02309585 -0.008923307 -0.013004655
## AGE        0.049770587  0.04913813  0.04653135  0.031422145  0.025574855
## PAY_1      0.180438683  0.18260102  0.17867922 -0.077501486 -0.072163946
## PAY_2      0.223831034  0.22330006  0.22064812 -0.079501608 -0.061868743
## PAY_3      0.229283614  0.22785738  0.22484307  0.001153613 -0.068089287
## PAY_4      0.246106846  0.24372861  0.24072392 -0.011071348 -0.004645503
## PAY_5      0.273012237  0.27134832  0.26392488 -0.006737276 -0.006727274
## PAY_6      0.267097246  0.29141430  0.28538886 -0.001466827 -0.007349921
## BILL_AMT1  0.859479918  0.82929774  0.80242457  0.139793109  0.098029749
## BILL_AMT2  0.892326915  0.86014088  0.83092902  0.275658339  0.088947657
## BILL_AMT3  0.922040453  0.88326131  0.85353039  0.237641275  0.324139251
## BILL_AMT4  1.000000000  0.94089881  0.90230117  0.230522687  0.206010816
## BILL_AMT5  0.940898808  1.00000000  0.94725446  0.215410623  0.179836252
## BILL_AMT6  0.902301174  0.94725446  1.00000000  0.199747245  0.176778661
## PAY_AMT1   0.230522687  0.21541062  0.19974724  1.000000000  0.264875571
## PAY_AMT2   0.206010816  0.17983625  0.17677866  0.264875571  1.000000000
## PAY_AMT3   0.298065418  0.24883727  0.23454305  0.259710307  0.258651947
## PAY_AMT4   0.131047724  0.28871014  0.24967904  0.208895009  0.192711371
## PAY_AMT5   0.160575515  0.14062534  0.30423755  0.154505402  0.202384416
```

```
## PAY_AMT6   0.173438013  0.15974236  0.11010206  0.185869971  0.169262638
##              PAY_AMT3     PAY_AMT4     PAY_AMT5     PAY_AMT6
## ID         0.036602448  0.006581535  0.000118102 -0.001822799
## LIMIT_BAL  0.211771641  0.204765826  0.217249211  0.218059348
## SEX       -0.009072133 -0.003084839 -0.005794148 -0.002716164
## EDUCATION -0.040215967 -0.038988771 -0.042513476 -0.044694548
## MARRIAGE  -0.003327253 -0.017832318 -0.008374648 -0.005161726
## AGE        0.027092558  0.025519268  0.026701260  0.021256237
## PAY_1     -0.068757143 -0.063174771 -0.059029099 -0.061706369
## PAY_2     -0.053752500 -0.045542965 -0.040199045 -0.040308711
## PAY_3     -0.051829679 -0.044713065 -0.037082959 -0.037504607
## PAY_4     -0.067756472 -0.042522606 -0.033186156 -0.028545198
## PAY_5      0.008562841 -0.056241640 -0.034937825 -0.022384532
## PAY_6      0.006494514  0.019713719 -0.047912350 -0.024277234
## BILL_AMT1  0.158727411  0.154856730  0.164481162  0.164766605
## BILL_AMT2  0.153283931  0.144904304  0.152701933  0.161306119
## BILL_AMT3  0.133765723  0.141681125  0.182859614  0.175164671
## BILL_AMT4  0.298065418  0.131047724  0.160575515  0.173438013
## BILL_AMT5  0.248837272  0.288710138  0.140625337  0.159742364
## BILL_AMT6  0.234543053  0.249679044  0.304237551  0.110102062
## PAY_AMT1   0.259710307  0.208895009  0.154505402  0.185869971
## PAY_AMT2   0.258651947  0.192711371  0.202384416  0.169262638
## PAY_AMT3   1.000000000  0.234133517  0.166624206  0.165324233
## PAY_AMT4   0.234133517  1.000000000  0.154208364  0.157565455
## PAY_AMT5   0.166624206  0.154208364  1.000000000  0.156791454
## PAY_AMT6   0.165324233  0.157565455  0.156791454  1.000000000
```

```
mean(cor(pca_train))
```

```
## [1] 0.1828462
```

run PCA on the train data, out of the 25, only 16 components are needed to capture 95% of the variance

```
pca_out <- preProcess(pca_train, method=c("center", "scale", "pca"))
pca_out
```

```
## Created from 24000 samples and 24 variables
##
## Pre-processing:
##   - centered (24)
##   - ignored (0)
##   - principal component signal extraction (24)
##   - scaled (24)
##
## PCA needed 16 components to capture 95 percent of the variance
```

Reduced Data PCA

```
train_pc <- predict(pca_out,pca_train)
test_pc <- predict(pca_out,pca_test)
```

PCA reduced data in Classification, lets see if the reduced data can predict class

```
train_df <- train[,c(25)]
test_df <- test[,c(25)]

train_pc$dpnm <- train$dpnm
test_pc$dpnm <- test$dpnm

train_dfNew <- train_pc
test_dfNew <- test_pc
```

Check for missing values, We see that there are no NAs

```
sapply(df, function(x) sum(is.na(x)==TRUE))
```

```
##        ID LIMIT_BAL       SEX EDUCATION  MARRIAGE       AGE     PAY_1     PAY_2
##         0         0         0         0         0         0         0         0
##     PAY_3     PAY_4     PAY_5     PAY_6 BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4
##         0         0         0         0         0         0         0         0
## BILL_AMT5 BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6
##         0         0         0         0         0         0         0         0
##      dpnm
##         0
```

Build a logistic regression model, almost half of the variables have a good P value.

```
glm1 <- glm(dpnm~., data=train_dfNew, family="binomial")
summary(glm1)
```

```
##
## Call:
## glm(formula = dpnm ~ ., family = "binomial", data = train_dfNew)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.1254  -0.6994  -0.5564  -0.2951   3.1630
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.450003   0.018325 -79.127  < 2e-16 ***
## PC1          0.077591   0.007755  10.006  < 2e-16 ***
## PC2         -0.396896   0.010667 -37.209  < 2e-16 ***
## PC3         -0.170534   0.023690  -7.199 6.08e-13 ***
## PC4          0.012293   0.019384   0.634  0.52597
## PC5         -0.133696   0.017142  -7.799 6.22e-15 ***
## PC6          0.002003   0.017086   0.117  0.90670
## PC7          0.119608   0.021279   5.621 1.90e-08 ***
## PC8         -0.040246   0.025155  -1.600  0.10961
## PC9         -0.076276   0.026473  -2.881  0.00396 **
```

```
## PC10        -0.066995   0.031440  -2.131  0.03310 *
## PC11        -0.071008   0.032449  -2.188  0.02865 *
## PC12         0.038320   0.039106   0.980  0.32713
## PC13         0.384037   0.021320  18.013  < 2e-16 ***
## PC14         0.049668   0.022258   2.231  0.02565 *
## PC15         0.035278   0.024481   1.441  0.14957
## PC16        -0.345859   0.025144 -13.755  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 25433  on 23999  degrees of freedom
## Residual deviance: 22419  on 23983  degrees of freedom
## AIC: 22453
##
## Number of Fisher Scoring iterations: 5
```

Evaluate on the test set. We got an accuracy of 0.81, TN=4584 and TP=297 . The accuracy is the same,it is a confirmation that PCA is capturing something important in the data.

```r
probs <- predict(glm1, newdata=test_dfNew, type="response")
pred <- ifelse(probs>0.5, 1, 0)
acc <- mean(pred==test_dfNew$dpnm)
print(paste("accuracy = ", acc))
```

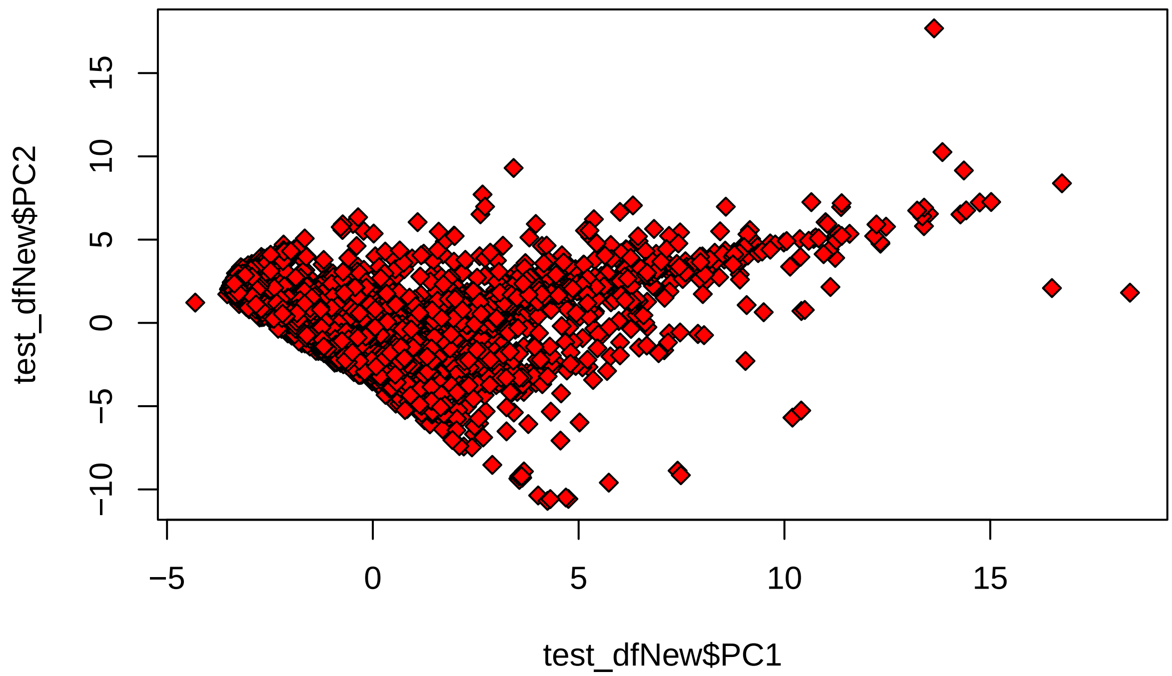
```
## [1] "accuracy =  0.8135"
```

```r
table(pred, test_dfNew$dpnm)
```

```
##
## pred    0    1
##    0 4584 1003
##    1  116  297
```

PCA PLot

```r
plot(test_dfNew$PC1, test_dfNew$PC2, pch=c(23,21,22)[unclass(test_dfNew$dpnm)], bg=c("red","green","blu
```



Build a logistic regression model on the original data, more variables have got good P values compared to the PCA variables.

```
glm1 <- glm(dpnm~., data=train, family="binomial")
```

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

```
summary(glm1)
```

```
##
## Call:
## glm(formula = dpnm ~ ., family = "binomial", data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.1457  -0.7012  -0.5476  -0.2903   3.2510
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.457e-01  1.351e-01  -4.778 1.77e-06 ***
## ID          -2.257e-06  1.955e-06  -1.154 0.248422
## LIMIT_BAL   -7.583e-07  1.755e-07  -4.320 1.56e-05 ***
## SEX         -9.614e-02  3.431e-02  -2.802 0.005079 **
## EDUCATION   -9.785e-02  2.341e-02  -4.180 2.92e-05 ***
## MARRIAGE    -1.706e-01  3.536e-02  -4.826 1.39e-06 ***
```

```
## AGE          7.352e-03  1.991e-03   3.693 0.000222 ***
## PAY_1        5.707e-01  1.977e-02  28.870  < 2e-16 ***
## PAY_2        8.252e-02  2.268e-02   3.639 0.000274 ***
## PAY_3        6.331e-02  2.552e-02   2.481 0.013118 *
## PAY_4        2.417e-02  2.806e-02   0.861 0.389146
## PAY_5        3.545e-02  2.995e-02   1.184 0.236466
## PAY_6        2.365e-02  2.461e-02   0.961 0.336589
## BILL_AMT1   -6.774e-06  1.300e-06  -5.213 1.86e-07 ***
## BILL_AMT2    3.505e-06  1.668e-06   2.101 0.035623 *
## BILL_AMT3    1.836e-06  1.471e-06   1.248 0.211998
## BILL_AMT4   -3.100e-07  1.502e-06  -0.206 0.836538
## BILL_AMT5   -1.611e-07  1.700e-06  -0.095 0.924497
## BILL_AMT6    9.640e-07  1.329e-06   0.726 0.468132
## PAY_AMT1    -1.640e-05  2.728e-06  -6.010 1.86e-09 ***
## PAY_AMT2    -8.025e-06  2.209e-06  -3.633 0.000280 ***
## PAY_AMT3    -2.969e-06  1.984e-06  -1.496 0.134640
## PAY_AMT4    -4.528e-06  2.033e-06  -2.228 0.025913 *
## PAY_AMT5    -1.623e-06  1.838e-06  -0.883 0.377329
## PAY_AMT6    -1.478e-06  1.447e-06  -1.022 0.307007
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 25433  on 23999  degrees of freedom
## Residual deviance: 22348  on 23975  degrees of freedom
## AIC: 22398
##
## Number of Fisher Scoring iterations: 6
```

Evaluate on the test set of the original data. We got an accuracy of 0.81, TN=4585 and TP=282

```r
probs <- predict(glm1, newdata=test, type="response")
pred <- ifelse(probs>0.5, 1, 0)
acc <- mean(pred==test$dpnm)
print(paste("accuracy = ", acc))
```

```
## [1] "accuracy =  0.811166666666667"
```

```r
table(pred, test$dpnm)
```

```
##
## pred    0    1
##    0 4585 1018
##    1  115  282
```

LDA considers the class dpnm, it tries to find a linear combination of predictors that maximazes the separation of the classes, while minimizing within-class standard deviation.

```
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select
```

```
lda1 <- lda(dpnm~., data=train)
```

LDA analysis has identified means for all variables by class

```
lda1$means
```

```
##         ID LIMIT_BAL      SEX EDUCATION MARRIAGE      AGE      PAY_1      PAY_2
## 0 15062.68  177889.6 1.615463  1.840495 1.560169 35.38561 -0.2086905 -0.3039006
## 1 14734.91  129815.9 1.571589  1.894865 1.526799 35.68722  0.6752249  0.4636432
##        PAY_3      PAY_4      PAY_5      PAY_6 BILL_AMT1 BILL_AMT2 BILL_AMT3
## 0 -0.3181526 -0.3572653 -0.3908594 -0.4080583  51902.78  49602.30  47420.19
## 1  0.3697526  0.2655547  0.1772864  0.1240630  48612.40  47516.98  45471.96
##   BILL_AMT4 BILL_AMT5 BILL_AMT6 PAY_AMT1 PAY_AMT2 PAY_AMT3 PAY_AMT4 PAY_AMT5
## 0  43525.39  40461.48  38921.08 6274.820 6629.747 5740.429 5268.031 5196.229
## 1  42290.20  39795.40  38708.72 3351.269 3468.872 3337.650 3110.524 3379.658
##   PAY_AMT6
## 0 5643.074
## 1 3445.893
```

Use LDA model for prediction, again we get an accuracy of approximately 0.81. Even though data is reduced, the model still keeps the accuracy of the original data

```
lda_pred <- predict(lda1, newdata=test, type="class")
lda_pred$class
```

```
##   [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [38] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
##  [75] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [112] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
## [149] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
## [186] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [223] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
## [260] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [297] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [334] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [371] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
## [408] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

```
##   [445] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0
##   [482] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
##   [519] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 1 0 1 0 0
##   [556] 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [593] 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [630] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0
##   [667] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0
##   [704] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [741] 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0
##   [778] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 1 0 0
##   [815] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [852] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##   [889] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0
##   [926] 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 1
##   [963] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1000] 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0 0 1 1 1 0 0 0 0
##  [1037] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
##  [1074] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
##  [1111] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1148] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0
##  [1185] 0 0 1 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1
##  [1222] 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0
##  [1259] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 1
##  [1296] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0
##  [1333] 0 0 0 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0
##  [1370] 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1407] 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
##  [1444] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1481] 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0
##  [1518] 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1555] 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1592] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
##  [1629] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1666] 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
##  [1703] 0 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
##  [1740] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
##  [1777] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1814] 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1851] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
##  [1888] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1925] 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
##  [1962] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [1999] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [2036] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [2073] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [2110] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
##  [2147] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [2184] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
##  [2221] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [2258] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
##  [2295] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0
##  [2332] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0
##  [2369] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
##  [2406] 0 0 0 0 0 1 0 1 0 1 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0
```

```
## [2443] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [2480] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 0 0 0 0 0 0 0
## [2517] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [2554] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
## [2591] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
## [2628] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [2665] 1 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
## [2702] 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 1
## [2739] 0 1 1 0 0 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [2776] 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
## [2813] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0
## [2850] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [2887] 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
## [2924] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [2961] 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
## [2998] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
## [3035] 0 1 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0
## [3072] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3109] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 1 0 0 0
## [3146] 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3183] 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3220] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
## [3257] 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0
## [3294] 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1
## [3331] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 1 1 1
## [3368] 0 1 0 0 0 0 1 0 0 0 1 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [3405] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0
## [3442] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3479] 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
## [3516] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 1
## [3553] 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
## [3590] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0
## [3627] 1 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [3664] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3701] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3738] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1
## [3775] 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
## [3812] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0
## [3849] 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
## [3886] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 0 1
## [3923] 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [3960] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
## [3997] 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4034] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
## [4071] 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4108] 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0
## [4145] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0
## [4182] 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1
## [4219] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0
## [4256] 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4293] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4330] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
## [4367] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4404] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
```

```
## [4441] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0
## [4478] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
## [4515] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
## [4552] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
## [4589] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4626] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0
## [4663] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4700] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4737] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0
## [4774] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4811] 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4848] 1 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4885] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
## [4922] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
## [4959] 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [4996] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0
## [5033] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
## [5070] 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5107] 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
## [5144] 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5181] 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5218] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [5255] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0
## [5292] 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5329] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5366] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
## [5403] 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5440] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0
## [5477] 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 1
## [5514] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0
## [5551] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5588] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0
## [5625] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0
## [5662] 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
## [5699] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1
## [5736] 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
## [5773] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5810] 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [5847] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1
## [5884] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0
## [5921] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
## [5958] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
## [5995] 0 0 0 0 0 0
## Levels: 0 1
```

```
mean(lda_pred$class==test$dpnm)
```

```
## [1] 0.8143333
```

```
str(lda_pred)
```

```
## List of 3
##  $ class    : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ posterior: num [1:6000, 1:2] 0.829 0.842 0.774 0.801 0.899 ...
##   ..- attr(*, "dimnames")=List of 2
```

```
##   .. ..$ : chr [1:6000] "5" "8" "9" "11" ...
##   .. ..$ : chr [1:2] "0" "1"
##  $ x        : num [1:6000, 1] -0.1066 -0.214 0.2758 0.0955 -0.7717 ...
##   ..- attr(*, "dimnames")=List of 2
##   .. ..$ : chr [1:6000] "5" "8" "9" "11" ...
##   .. ..$ : chr "LD1"
```

Plot to see the separation of classes by taking two predictors generated by the LDA model

```
#plot(lda_pred$x[,1], lda_pred$x[,2], pch=c(23,21,22)[unclass(lda_pred$class)], bg=c("red","green","blu
```