BZAN 542 Project

Tosin Clement
Abdullah Salau

Project Overview

This project concerns the prediction of 'Customer Status' among three choices: churned, stayed and joined. A dataset containing information on 7043 customers from a Telecommunications company in California has been used. Each record contains details about the demographics, location, tenure, subscription services and more (38 features in total) for each customer.

The machine learning task is to predict whether a particular customer of a company will renew their subscription once their current plan ends. Additional Data Mining Tasks include Exploratory Data Analysis to develop possible customer retention strategies for the company.

Problem Statement

The goal is to get an estimate of the Churn rate of the telecom business. This does not include the customers that just joined. We want to determine the rate of customers who, after experiencing the service, decide to leave or stay. The tasks involved are as follows.

- ❖ Looking through the data dictionary to understand the features of the dataset
- ❖ Came up with initial guesses of which features are most important for the analysis
- ❖ Data Preprocessing
- ❖ Model Training and Testing
- ❖ Further Preprocessing

Data Preprocessing

We subsetted the dataset to only include observations or accounts that either ‘stayed’ or ‘churned’. We disincluded accounts that initially joined so that we analyze the behavior of customers who have already experienced service form the company.

Handling Missing Values

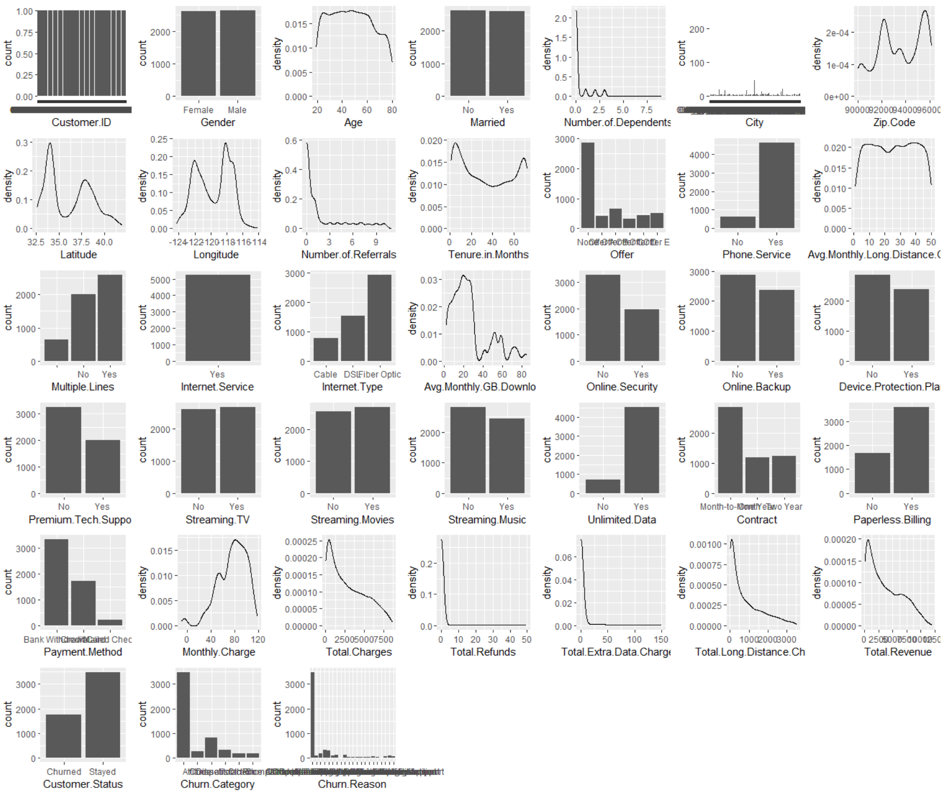
We analyzed missing values and discovered that there were 1988 missing cells. However, upon further examination, we realized that there was a lot more than this.

```
> summary(df)
    Customer.ID      Gender          Age          Married     Number.of.Dependents            City           Zip.Code        Latitude        Longitude       Number.of.Referrals
 0002-ORFBO:   1   Female:3277   Min.   :19.00   No :3271   Min.   :0.0000       San Diego     : 278   Min.   :90001   Min.   :32.56   Min.   :-124.3   Min.   : 0.000
 0003-MKNFE:   1   Male  :3312   1st Qu.:33.00   Yes:3318   1st Qu.:0.0000       Los Angeles   : 275   1st Qu.:92103   1st Qu.:33.99   1st Qu.:-121.8   1st Qu.: 0.000
 0004-TLHLJ:   1                 Median :46.00              Median :0.0000       San Jose      : 110   Median :93526   Median :36.25   Median :-119.6   Median : 0.000
 0011-IGKFF:   1                 Mean   :46.76              Mean   :0.4761       Sacramento    : 102   Mean   :93492   Mean   :36.20   Mean   :-119.8   Mean   : 2.021
 0013-EXCHZ:   1                 3rd Qu.:60.00              3rd Qu.:0.0000       San Francisco:  97   3rd Qu.:95333   3rd Qu.:38.17   3rd Qu.:-118.0   3rd Qu.: 3.000
 0013-MHZWF:   1                 Max.   :80.00              Max.   :9.0000       Fresno        :  61   Max.   :96150   Max.   :41.96   Max.   :-114.2   Max.   :11.000
 (Other)   :6583                                                                 (Other)       :5666
 Tenure.in.Months      Offer       Phone.Service Avg.Monthly.Long.Distance.Charges Multiple.Lines Internet.Service      Internet.Type  Avg.Monthly.GB.Download Online.Security
 Min.   : 1.0     None    :3598   No : 644      Min.   : 1.01                       : 644      No :1344                    :1344   Min.   : 2.00               :1344
 1st Qu.:12.0     Offer A: 520   Yes:5945      1st Qu.:13.14                     No :3019      Yes:5245          Cable      : 774   1st Qu.:13.00           No :3272
 Median :32.0     Offer B: 824                 Median :25.72                     Yes:2926                        DSL        :1537   Median :21.00           Yes:1973
 Mean   :34.5     Offer C: 415                 Mean   :25.50                                                     Fiber Optic:2934   Mean   :26.23
 3rd Qu.:57.0     Offer D: 602                 3rd Qu.:37.69                                                                        3rd Qu.:30.00
 Max.   :72.0     Offer E: 630                 Max.   :49.99                                                                        Max.   :85.00
                                               NA's   :644                                                                          NA's   :1344
 Online.Backup Device.Protection.Plan Premium.Tech.Support Streaming.TV Streaming.Movies Streaming.Music Unlimited.Data          Contract     Paperless.Billing
    :1344         :1344                  :1344               :1344        :1344             :1344          :1344        Month-to-Month:3202   No :2615
 No :2870      No :2855               No :3248             No :2587     No :2562         No :2809        No : 724       One Year      :1526   Yes:3974
 Yes:2375      Yes:2390               Yes:1997             Yes:2658     Yes:2683         Yes:2436        Yes:4521       Two Year      :1861


        Payment.Method Monthly.Charge    Total.Charges     Total.Refunds     Total.Extra.Data.Charges Total.Long.Distance.Charges Total.Revenue      Customer.Status
 Bank Withdrawal:3728   Min.   :-10.00   Min.   :  18.85   Min.   : 0.000   Min.   :  0.00            Min.   :   0.0              Min.   :   21.61   Churned:1869
 Credit Card    :2518   1st Qu.: 35.80   1st Qu.: 544.55   1st Qu.: 0.000   1st Qu.:  0.00            1st Qu.: 106.7              1st Qu.:  835.45   Stayed :4720
 Mailed Check   : 343   Median : 71.05   Median :1563.90   Median : 0.000   Median :  0.00            Median : 472.7              Median : 2376.45
                        Mean   : 65.03   Mean   :2432.04   Mean   : 2.081   Mean   :  7.17            Mean   : 798.1              Mean   : 3235.22
                        3rd Qu.: 90.40   3rd Qu.:4003.00   3rd Qu.: 0.000   3rd Qu.:  0.00            3rd Qu.:1275.1              3rd Qu.: 5106.64
                        Max.   :118.75   Max.   :8684.80   Max.   :49.790   Max.   :150.00            Max.   :3564.7              Max.   :11979.34

        Churn.Category                          Churn.Reason
               :4720                                   :4720
 Attitude       : 314   Competitor had better devices: 313
 Competitor     : 841   Competitor made better offer : 311
 Dissatisfaction: 321   Attitude of support person   : 220
 Other          : 182   Don't know                   : 130
 Price          : 211   Competitor offered more data : 117
                        (Other)                      : 778
```

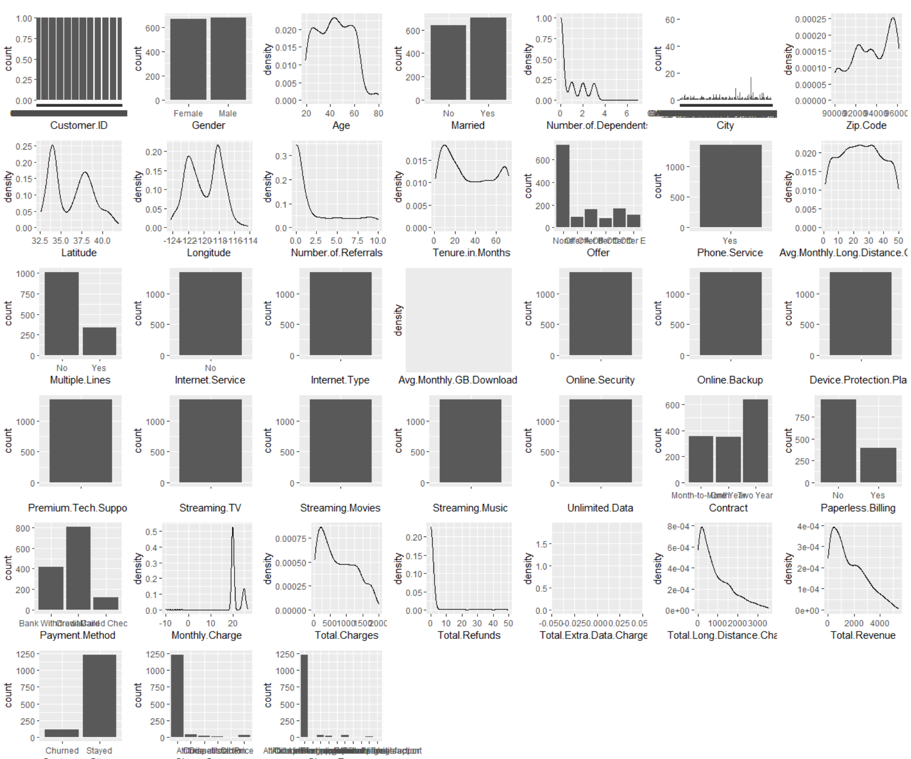
We can learn a lot about potential NA values in other variables by looking at the variables "Phone Service" and "Internet Service." For instance, you can see from the summary of the dataframe image that there are 644 lines without Phone service, which is the same as the total number of NA values in the average. Monthly.Long.Distance. Charges and many. Lines. There are the same amount of NA values in 10 additional variables as there are lines without Internet service. Also, it appears that no phone service fully guarantees that the line will have internet service.

We decided to create two separate models for prediction: One including accounts with only Internet Service, and another including accounts without Internet Service. After doing this, we can come up with a proper method of imputation to handle the missing values. However, the disadvantage of that is, the dataset of lines without internet service is imbalanced.

Lines with internet service



Lines without internet service:



We standardized both datasets before splitting them into train and test. Both datasets were split into training and testing datasets with a split ratio of 75:25. We also maintained the event rate so that the same percentage of Churn in the training dataset was the same in the testing dataset.

Model Training and Testing

Random Forests model
We first train both datasets on a Random Forests model to see how it performs with a prediction: The 'city' feature has to be changed because it has too many categories for the rf model to manage. When a city's count falls below 30, its value is changed to "Other." To test how well the model works without the feature, we first delete it.

For lines with Internet Service, the random forest obtained an accuracy of 0.8421, with f1, precision, and recall scores of 0.739, 0.8277, and 0.6674 respectively. For lines without Internet Service, the random forest model obtained an accuracy of 0.9761, with f1, precision, and recall scores of 0.8333, 1.00, and 0.71429 respectively (See Appendix).

Logistic Regression model
To train the logistic regression model on both training datasets, we utilized the glm() function in R and specified the type of dependent variable our dataset has by setting the parameter 'family' to 'binomial.

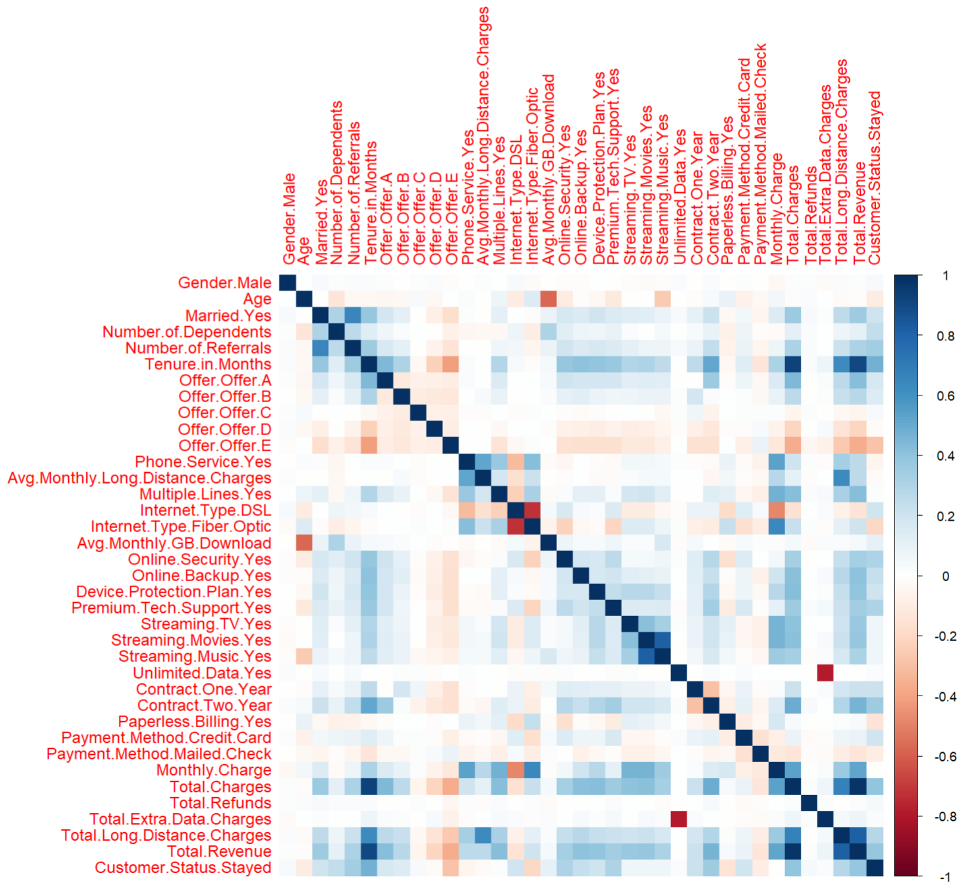
The accuracy results for prediction were good, and they were very similar to our random forest model. For lines with Internet Service, the random forest obtained an accuracy of 0.8268, with f1, precision, and recall scores of 0.7412, 0.7420, and 0.7403 respectively. For lines without Internet Service, the random forest model obtained an accuracy of 0.9403, with f1, precision, and recall scores of 0.6000, 68182, and 0.53571 respectively (See Appendix)

k-Nearest Neighbor Model
For our k Nearest Neighbor model, we had to manually do One-hot encoding for our training and testing datasets for the knn() function in R to build our model. We also tried building different models for different numbers of k. Our best results were obtained when k=30.

Unfortunately, the accuracy results for all our kNN models were not as good as our Random Forests or Logistic Regression models. The most accurate kNN model had an accuracy of 0.793, f1 score of 0.6999, precision score of 0.68, and recall score of 0,7198. (See Appendix).

Further Preprocessing

We also plotted a correlation matrix for our training dataset in an attempt to cut down on the number of features that we had:



There are a very little number of pairs of variables that appear to be highly correlated, which include Total Extra Data Charges and Unlimited Data, DSL and Fiber Optic Internet Type, Total Revenue and Tenure in Months, and Total Charges and Tenure in Months.
We decided to delete Total Revenue, Total Extra Data Charges, and DSL Internet type.

We also ran a PCA test to figure out which of our variables explained most of the total variance in our dataset:

```
Importance of components:
                          PC1     PC2     PC3     PC4     PC5     PC6     PC7     PC8     PC9    PC10   PC11    PC12    PC13   PC14    PC15    PC16    PC17
Standard deviation     2.5544 1.82945 1.38223 1.34359 1.31521 1.22570 1.20489 1.07469 1.06223 1.04497 1.0375 1.00734 0.99733 0.9655 0.95222 0.92013 0.89688
Proportion of Variance 0.1812 0.09297 0.05307 0.05015 0.04805 0.04173 0.04033 0.03208 0.03134 0.03033 0.0299 0.02819 0.02763 0.0259 0.02519 0.02352 0.02234
Cumulative Proportion  0.1812 0.27422 0.32729 0.37743 0.42548 0.46722 0.50754 0.53962 0.57097 0.60130 0.6312 0.65939 0.68702 0.7129 0.73810 0.76162 0.78396
                          PC18    PC19    PC20    PC21    PC22   PC23    PC24    PC25    PC26    PC27    PC28    PC29    PC30   PC31    PC32    PC33    PC34
Standard deviation     0.88243 0.86504 0.85836 0.84793 0.83633 0.8073 0.77332 0.70705 0.65191 0.62989 0.58451 0.54772 0.51109 0.4570 0.39658 0.35549 0.31226
Proportion of Variance 0.02163 0.02079 0.02047 0.01997 0.01943 0.0181 0.01661 0.01389 0.01181 0.01102 0.00949 0.00833 0.00726 0.0058 0.00437 0.00351 0.00271
Cumulative Proportion  0.80559 0.82638 0.84684 0.86681 0.88624 0.9043 0.92096 0.93484 0.94665 0.95767 0.96716 0.97549 0.98275 0.9886 0.99292 0.99643 0.99914
                          PC35      PC36
Standard deviation     0.17601 3.266e-15
Proportion of Variance 0.00086 0.000e+00
Cumulative Proportion  1.00000 1.000e+00
```

Since the first 26 variables in the data set seem to do a good job in explaining the total variance, We decide to remove the last 10 variables which are:

```
Online.Security.Yes
Online.Backup.Yes
Device.Protection.Plan.Yes
Premium.Tech.Support.Yes
Streaming.TV.Yes
Streaming.Movies.Yes
Streaming.Music.Yes
Unlimited.Data.Yes
Contract.One.Year
Contract.Two.Year
```

After this, we decided to retrain our Random Forest model to see if we could get better accuracy scores, but unfortunately, the scores slightly regressed:

```
Confusion Matrix and Statistics

          Reference
Prediction Churned Stayed
   Churned     268     85
   Stayed      171    787

               Accuracy : 0.8047
                 95% CI : (0.7822, 0.8259)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5392

 Mcnemar's Test P-Value : 1.081e-07

            Sensitivity : 0.6105
            Specificity : 0.9025
         Pos Pred Value : 0.7592
         Neg Pred Value : 0.8215
              Precision : 0.7592
                 Recall : 0.6105
                     F1 : 0.6768
             Prevalence : 0.3349
         Detection Rate : 0.2044
   Detection Prevalence : 0.2693
      Balanced Accuracy : 0.7565

       'Positive' Class : Churned
```

Since we get lower scores for subsetted training data, we include some previously deleted features to see if model makes any improvement:

```
Confusion Matrix and Statistics

          Reference
Prediction Churned Stayed
   Churned     272     79
   Stayed      167    793

               Accuracy : 0.8124
                 95% CI : (0.7901, 0.8332)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5567

 Mcnemar's Test P-Value : 2.908e-08

            Sensitivity : 0.6196
            Specificity : 0.9094
         Pos Pred Value : 0.7749
         Neg Pred Value : 0.8260
              Precision : 0.7749
                 Recall : 0.6196
                     F1 : 0.6886
             Prevalence : 0.3349
         Detection Rate : 0.2075
   Detection Prevalence : 0.2677
      Balanced Accuracy : 0.7645

       'Positive' Class : Churned
```

It looks like including more features from previously deleted variables makes the model more accurate. We can conclude that the initial selection of features is best for prediction.

Conclusion

After extensive testing and analysis, we believe the best model to accurately predict Customer behavior for this telecom business is a random forest model, using our initial subset of features. We would also like to point out that utilizing the logistic regression is also not a bad idea, as it has better Recall scores than the random Forest models, which is very important considering the business would be more interested in detecting accounts that eventually Churn.

Appendix

Random Forest Model, Internet Service Lines (ISdf):

```
Confusion Matrix and Statistics

          Reference
Prediction Churned Stayed
   Churned     293     61
   Stayed      146    811

               Accuracy : 0.8421
                 95% CI : (0.8212, 0.8614)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.6276

 Mcnemar's Test P-Value : 5.27e-09

            Sensitivity : 0.6674
            Specificity : 0.9300
         Pos Pred Value : 0.8277
         Neg Pred Value : 0.8474
              Precision : 0.8277
                 Recall : 0.6674
                     F1 : 0.7390
             Prevalence : 0.3349
         Detection Rate : 0.2235
   Detection Prevalence : 0.2700
      Balanced Accuracy : 0.7987

       'Positive' Class : Churned
```

For NISdf:

```
Confusion Matrix and Statistics

          Reference
Prediction Churned Stayed
   Churned      20      0
   Stayed        8    307

               Accuracy : 0.9761
                 95% CI : (0.9535, 0.9896)
    No Information Rate : 0.9164
    P-Value [Acc > NIR] : 4.66e-06

                  Kappa : 0.8209

 Mcnemar's Test P-Value : 0.01333

            Sensitivity : 0.71429
            Specificity : 1.00000
         Pos Pred Value : 1.00000
         Neg Pred Value : 0.97460
              Precision : 1.00000
                 Recall : 0.71429
                     F1 : 0.83333
             Prevalence : 0.08358
         Detection Rate : 0.05970
   Detection Prevalence : 0.05970
      Balanced Accuracy : 0.85714

       'Positive' Class : Churned
```

- **Logistic Regression Model Results**:
- For ISdf:

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 325 113
         1 114 759

               Accuracy : 0.8268
                 95% CI : (0.8053, 0.847)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.6111

 Mcnemar's Test P-Value : 1

            Sensitivity : 0.7403
            Specificity : 0.8704
         Pos Pred Value : 0.7420
         Neg Pred Value : 0.8694
              Precision : 0.7420
                 Recall : 0.7403
                     F1 : 0.7412
             Prevalence : 0.3349
         Detection Rate : 0.2479
   Detection Prevalence : 0.3341
      Balanced Accuracy : 0.8054

       'Positive' Class : 0
```

For NISdf:

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0  15   7
         1  13 300

               Accuracy : 0.9403
                 95% CI : (0.9093, 0.9632)
    No Information Rate : 0.9164
    P-Value [Acc > NIR] : 0.06431

                  Kappa : 0.5682

 Mcnemar's Test P-Value : 0.26355

            Sensitivity : 0.53571
            Specificity : 0.97720
         Pos Pred Value : 0.68182
         Neg Pred Value : 0.95847
              Precision : 0.68182
                 Recall : 0.53571
                     F1 : 0.60000
             Prevalence : 0.08358
         Detection Rate : 0.04478
   Detection Prevalence : 0.06567
      Balanced Accuracy : 0.75646

       'Positive' Class : 0
```

- Using kNN (k=70):
  ISdf=

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 304 151
         1 135 721

               Accuracy : 0.7818
                 95% CI : (0.7585, 0.8039)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.5147

 Mcnemar's Test P-Value : 0.3751

            Sensitivity : 0.6925
            Specificity : 0.8268
         Pos Pred Value : 0.6681
         Neg Pred Value : 0.8423
              Precision : 0.6681
                 Recall : 0.6925
                     F1 : 0.6801
             Prevalence : 0.3349
         Detection Rate : 0.2319
   Detection Prevalence : 0.3471
      Balanced Accuracy : 0.7597

       'Positive' Class : 0
```

k=30

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 316 148
         1 123 724

               Accuracy : 0.7933
                 95% CI : (0.7703, 0.8149)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.5424

 Mcnemar's Test P-Value : 0.1449

            Sensitivity : 0.7198
            Specificity : 0.8303
         Pos Pred Value : 0.6810
         Neg Pred Value : 0.8548
              Precision : 0.6810
                 Recall : 0.7198
                     F1 : 0.6999
             Prevalence : 0.3349
         Detection Rate : 0.2410
   Detection Prevalence : 0.3539
      Balanced Accuracy : 0.7750

       'Positive' Class : 0

Confusion Matrix and Statistics
```

k=10

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 308 145
         1 131 727

               Accuracy : 0.7895
                 95% CI : (0.7664, 0.8113)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.5311

 Mcnemar's Test P-Value : 0.4339

            Sensitivity : 0.7016
            Specificity : 0.8337
         Pos Pred Value : 0.6799
         Neg Pred Value : 0.8473
              Precision : 0.6799
                 Recall : 0.7016
                     F1 : 0.6906
             Prevalence : 0.3349
         Detection Rate : 0.2349
   Detection Prevalence : 0.3455
      Balanced Accuracy : 0.7677

       'Positive' Class : 0
```

k=100

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 305 145
         1 134 727

               Accuracy : 0.7872
                 95% CI : (0.764, 0.8091)
    No Information Rate : 0.6651
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.5252

 Mcnemar's Test P-Value : 0.5494

            Sensitivity : 0.6948
            Specificity : 0.8337
         Pos Pred Value : 0.6778
         Neg Pred Value : 0.8444
              Precision : 0.6778
                 Recall : 0.6948
                     F1 : 0.6862
             Prevalence : 0.3349
         Detection Rate : 0.2326
   Detection Prevalence : 0.3432
      Balanced Accuracy : 0.7642

       'Positive' Class : 0
```