Exercise 10.2

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R Markdown

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- R for Everyone (Lander 2014)
- Discovering Statistics Using R (Field, Miles, and Field 2012)

a For this problem, you will be working with the thoracic surgery data set from the University of California Irvine machine learning repository. This dataset contains information on life expectancy in lung cancer patients after surgery. The underlying thoracic surgery data is in ARFF format. This is a text-based format with information on each of the attributes. You can load this data using a package such as foreign or by cutting and pasting the data section into a CSV file.

```r
setwd("/Users/dipikasharma/R_Projects/DSC520")
library(foreign)
library(caTools)
patient_data <- read.arff("data/ThoraricSurgery.arff")

# Split the data
split <- sample.split(patient_data, SplitRatio = 0.8)
train <- subset(patient_data, split == 'TRUE')
test <- subset(patient_data, split == 'FALSE')
```

b i Fit a binary logistic regression model to the data set that predicts whether or not the patient survived for one year (the Risk1Y variable) after the surgery. Use the glm() function to perform the logistic regression. See Generalized Linear Models for an example. Include a summary using the summary() function in your results.

```r
# Converting the Risk1yr variabke to factors
patient_data$Risk1Yr <- as.factor(patient_data$Risk1Yr)

fit <- glm(Risk1Yr ~ ., data = train, family = binomial)
anova(fit, test = "Chisq")
```

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

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```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: Risk1Yr
##
## Terms added sequentially (first to last)
##
##
##       Df Deviance Resid. Df Resid. Dev Pr(>Chi)
## NULL                    358     267.10
## DGN    6  16.0280       352     251.07  0.01360 *
## PRE4   1   0.8576       351     250.21  0.35441
## PRE5   1   2.9018       350     247.31  0.08848 .
## PRE6   2   0.1294       348     247.18  0.93734
## PRE7   1   1.2244       347     245.96  0.26851
## PRE8   1   2.5607       346     243.39  0.10955
## PRE9   1   4.5971       345     238.80  0.03203 *
```

```
## PRE10  1   2.5978       344     236.20  0.10701
## PRE11  1   2.0501       343     234.15  0.15219
## PRE14  3   4.2558       340     229.89  0.23514
## PRE17  1   0.8169       339     229.08  0.36608
## PRE19  1   0.4855       338     228.59  0.48596
## PRE25  1   0.0891       337     228.50  0.76532
## PRE30  1   4.0046       336     224.50  0.04538 *
## PRE32  1   0.2959       335     224.20  0.58647
## AGE    1   0.2332       334     223.97  0.62915
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(fit)
```

```
##
## Call:
## glm(formula = Risk1Yr ~ ., family = binomial, data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6794  -0.4907  -0.3805  -0.2397   2.6010
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -18.96929 3956.18081  -0.005   0.9962
## DGNDGN2       14.51409 3956.18042   0.004   0.9971
## DGNDGN3       15.24746 3956.18036   0.004   0.9969
## DGNDGN4       15.86110 3956.18039   0.004   0.9968
## DGNDGN5       17.72042 3956.18041   0.004   0.9964
## DGNDGN6        0.68931 4399.80486   0.000   0.9999
## DGNDGN8        1.64907 5594.88393   0.000   0.9998
## PRE4          -0.02455    0.41881  -0.059   0.9533
## PRE5          -0.21432    0.47032  -0.456   0.6486
## PRE6PRZ1      -0.83744    0.62562  -1.339   0.1807
## PRE6PRZ2      -1.66427    1.02553  -1.623   0.1046
## PRE7T          0.95135    0.70818   1.343   0.1792
## PRE8T          0.74736    0.48049   1.555   0.1198
## PRE9T          1.55577    0.61581   2.526   0.0115 *
## PRE10T         0.56109    0.60430   0.928   0.3532
## PRE11T         0.69167    0.46554   1.486   0.1373
## PRE14OC12      0.23409    0.41562   0.563   0.5733
## PRE14OC13      1.01101    0.75631   1.337   0.1813
## PRE14OC14      1.46823    0.87882   1.671   0.0948 .
## PRE17T         0.60938    0.58438   1.043   0.2971
## PRE19T       -15.44459 2729.15090  -0.006   0.9955
## PRE25T        -0.69651    1.64250  -0.424   0.6715
## PRE30T         1.19643    0.66422   1.801   0.0717 .
## PRE32T       -14.90715 2669.76210  -0.006   0.9955
## AGE            0.01074    0.02229   0.482   0.6299
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 267.10  on 358  degrees of freedom
## Residual deviance: 223.97  on 334  degrees of freedom
## AIC: 273.97
##
## Number of Fisher Scoring iterations: 16
```

b ii According to the summary, which variables had the greatest effect on the survival rate?

Looking at the anova function data we can see the drop of deviance when adding each variable one at a time. Also above data indicate that by adding DGN, PRE10, PRE9, PRE14, PRE30 reduces the residual more compare to when it reduces by adding other variables.

```
a2Pval <- summary(fit)$coef[,"Estimate"]
a2Pval
```

```
##  (Intercept)      DGNDGN2      DGNDGN3      DGNDGN4      DGNDGN5      DGNDGN6
## -18.96928888  14.51409135  15.24745704  15.86109690  17.72041584   0.68931309
##      DGNDGN8         PRE4         PRE5      PRE6PRZ1     PRE6PRZ2        PRE7T
##   1.64906815  -0.02454563  -0.21431883  -0.83743537  -1.66426575   0.95134604
##        PRE8T        PRE9T       PRE10T       PRE11T    PRE14OC12    PRE14OC13
##   0.74735849   1.55576735   0.56108778   0.69167449   0.23408939   1.01100578
##    PRE14OC14       PRE17T       PRE19T       PRE25T       PRE30T       PRE32T
##   1.46823196   0.60937708 -15.44459288  -0.69650648   1.19643067 -14.90715091
##          AGE
##   0.01074301
```

As we know we can see the correlation between the two variables with this linear model, and linear model is written using equation y = mx + b form. In the above case we have below Risk1yr = columnname * estimate + Intercept We can see estimate value is directly proportional to Risk1yr and that is the only value which is different for all the columns. Out of all values, we can say DGN, PRE19, PRE32, PRE9T, PRE30, PRE10 are related to dependent variable. increase or decrease of these variables will effect the dependent variable.

```
a2Pval <- summary(fit)$coef[,"Pr(>|z|)", drop=F]
a2Pval
```

```
##               Pr(>|z|)
## (Intercept) 0.99617428
## DGNDGN2     0.99707280
## DGNDGN3     0.99692489
## DGNDGN4     0.99680113
## DGNDGN5     0.99642615
## DGNDGN6     0.99987500
## DGNDGN8     0.99976483
## PRE4        0.95326409
## PRE5        0.64861246
## PRE6PRZ1    0.18071042
## PRE6PRZ2    0.10462586
## PRE7T       0.17915558
## PRE8T       0.11984702
## PRE9T       0.01152422
```

```
## PRE10T      0.35315103
## PRE11T      0.13734275
## PRE14OC12   0.57327592
## PRE14OC13   0.18129791
## PRE14OC14   0.09478282
## PRE17T      0.29705490
## PRE19T      0.99548470
## PRE25T      0.67152819
## PRE30T      0.07166378
## PRE32T      0.99554488
## AGE         0.62985662
```

Also PRE9 has the lowest p-value which can suggest a strong association of the PRE9 of the patient with the probability of having risk.

Overall all these variable DGN, PRE19, PRE32, PRE9T, PRE30, PRE10 have effect on survival rate.

b iii To compute the accuracy of your model, use the dataset to predict the outcome variable. The percent of correct predictions is the accuracy of your model. What is the accuracy of your model?

```
# Run the test data through the model
res <- predict(fit, test, type = 'response')
res
```

```
##            3            8            9           14           20           25
## 6.407744e-02 1.572459e-02 5.469444e-02 1.094760e-01 8.589265e-02 2.538814e-08
##           26           31           37           42           43           48
## 3.173893e-06 4.504314e-01 9.287960e-02 3.754934e-02 7.446381e-02 9.002586e-02
##           54           59           60           65           71           76
## 1.442205e-01 1.135921e-01 7.177495e-02 6.987131e-02 1.962953e-02 1.712773e-01
##           77           82           88           93           94           99
## 1.518032e-01 2.482730e-01 1.154471e-01 7.290128e-02 3.947028e-02 2.622227e-07
##          105          110          111          116          122          127
## 1.981253e-02 3.095487e-01 3.095083e-02 3.495547e-01 7.932314e-02 5.614765e-02
##          128          133          139          144          145          150
## 4.421331e-01 2.257416e-07 7.863912e-02 2.034839e-01 2.821950e-02 8.824903e-02
##          156          161          162          167          173          178
## 5.334643e-02 4.125446e-02 7.583879e-02 6.208327e-02 1.604936e-01 7.546232e-02
##          179          184          190          195          196          201
## 1.618053e-01 5.981107e-02 1.244311e-01 6.986271e-02 1.565402e-01 7.878152e-02
##          207          212          213          218          224          229
## 6.739011e-02 6.925177e-02 5.001206e-01 6.700173e-02 3.598734e-02 3.092816e-02
##          230          235          241          246          247          252
## 1.454714e-01 1.384915e-01 6.508494e-02 6.080601e-02 1.182113e-01 6.381218e-02
##          258          263          264          269          275          280
## 7.487064e-02 2.641710e-01 4.530224e-02 3.137708e-01 3.226910e-02 5.456755e-02
##          281          286          292          297          298          303
## 7.909107e-02 8.483247e-02 2.288173e-01 8.076383e-02 4.300038e-01 9.407839e-02
##          309          314          315          320          326          331
## 6.764526e-02 9.331501e-02 1.772959e-01 5.475966e-08 5.066712e-09 1.684180e-08
##          332          337          343          348          349          354
```

```
## 6.959520e-02 2.744745e-01 2.738951e-01 2.602006e-01 2.062946e-02 4.203990e-06
##          360          365          366          371          377          382
## 6.234985e-02 5.947565e-02 1.151068e-01 1.005531e-01 5.073483e-02 5.060411e-02
##          383          388          394          399          400          405
## 2.196675e-01 1.336334e-01 6.619874e-02 3.443513e-02 7.063786e-02 8.287065e-02
##          411          416          417          422          428          433
## 4.125094e-02 2.556336e-02 2.188659e-01 6.338418e-02 1.013222e-01 5.640115e-02
##          434          439          445          450          451          456
## 2.531262e-01 4.343404e-07 2.759338e-07 7.792290e-02 2.361111e-02 1.564115e-01
##          462          467          468
## 1.582389e-01 6.716700e-02 4.978667e-02
```

```r
res <- predict(fit, train, type = 'response')
res
```

```
##            1            2            4            5            6            7
## 2.202435e-01 9.710679e-02 2.016241e-02 1.582984e-01 1.956837e-02 1.057952e-01
##           10           11           12           13           15           16
## 6.056844e-02 1.096060e-01 2.759109e-02 1.235776e-01 8.926089e-02 5.175790e-02
##           17           18           19           21           22           23
## 1.059423e-01 5.732842e-02 9.625702e-02 6.918913e-02 1.542352e-01 1.147384e-01
##           24           27           28           29           30           32
## 7.966684e-02 5.231207e-02 1.072810e-01 1.031645e-01 3.294626e-08 1.695211e-02
##           33           34           35           36           38           39
## 5.008014e-01 5.904128e-02 1.149452e-02 9.086286e-02 2.025201e-01 6.374564e-02
##           40           41           44           45           46           47
## 4.267929e-02 3.974377e-01 6.836269e-01 1.633529e-01 8.413263e-02 6.580721e-02
##           49           50           51           52           53           55
## 5.485551e-02 2.085808e-02 3.237957e-02 5.864036e-02 4.929697e-01 6.652851e-02
##           56           57           58           61           62           63
## 1.368118e-01 5.989104e-02 3.669447e-01 1.763101e-01 8.413604e-02 5.640779e-02
##           64           66           67           68           69           70
## 3.836222e-02 2.162828e-02 2.210886e-02 3.735174e-01 7.939457e-02 1.780427e-01
##           72           73           74           75           78           79
## 1.369186e-01 7.170405e-02 1.881953e-02 4.623152e-02 6.021331e-02 8.705333e-02
##           80           81           83           84           85           86
## 3.036342e-02 6.585778e-02 8.932858e-02 3.563169e-02 7.232984e-02 6.787471e-02
##           87           89           90           91           92           95
## 1.381763e-01 6.585632e-01 2.739598e-06 2.656964e-01 7.516250e-02 1.068872e-01
##           96           97           98          100          101          102
## 4.289728e-02 1.549322e-01 1.586360e-08 4.034999e-01 6.398656e-02 2.911597e-01
##          103          104          106          107          108          109
## 1.258698e-01 7.710691e-09 1.434683e-01 7.702655e-02 6.703641e-02 2.282141e-02
##          112          113          114          115          117          118
## 1.201935e-01 1.902557e-07 5.585779e-02 1.267933e-01 2.633030e-01 1.276898e-01
##          119          120          121          123          124          125
## 5.891597e-02 1.860314e-01 8.657628e-03 3.470607e-01 1.392376e-01 1.490486e-01
##          126          129          130          131          132          134
## 9.158491e-02 2.963411e-01 1.501504e-02 5.617198e-02 2.966149e-02 9.918598e-02
##          135          136          137          138          140          141
## 5.568856e-02 6.384878e-02 6.318731e-02 2.343465e-01 2.233161e-02 3.748312e-02
##          142          143          146          147          148          149
## 1.378164e-01 6.042853e-03 6.570217e-02 1.794229e-02 8.468657e-02 7.917985e-02
##          151          152          153          154          155          157
```

```
## 3.137012e-02 1.141277e-01 4.473051e-02 1.426704e-01 6.861828e-02 4.767858e-01
##          158          159          160          163          164          165
## 3.796301e-08 1.489792e-01 6.933195e-02 3.281936e-01 1.488813e-02 1.159054e-01
##          166          168          169          170          171          172
## 4.411240e-01 1.582108e-01 1.398949e-01 3.729870e-01 8.621866e-02 9.183548e-02
##          174          175          176          177          180          181
## 5.838737e-02 1.541723e-01 4.980441e-01 9.421658e-02 6.675340e-02 1.270557e-01
##          182          183          185          186          187          188
## 5.054930e-02 6.311791e-02 2.643243e-02 6.848412e-01 6.559115e-02 1.241140e-01
##          189          191          192          193          194          197
## 8.706803e-02 4.390247e-08 7.864015e-02 8.063999e-03 7.335235e-02 2.228210e-01
##          198          199          200          202          203          204
## 2.278827e-02 3.701595e-02 2.433662e-01 7.351552e-02 1.892069e-01 3.384401e-02
##          205          206          208          209          210          211
## 3.361344e-02 1.154805e-01 7.122510e-02 8.812184e-02 1.539109e-01 4.433398e-02
##          214          215          216          217          219          220
## 2.056922e-01 7.260252e-02 2.191975e-02 4.196096e-02 5.747135e-02 9.044618e-02
##          221          222          223          225          226          227
## 6.830004e-01 1.064997e-01 2.174794e-01 5.067522e-02 3.059776e-01 1.451346e-01
##          228          231          232          233          234          236
## 7.737292e-02 1.788262e-01 4.740566e-01 7.699563e-02 8.039285e-02 5.820462e-02
##          237          238          239          240          242          243
## 1.757629e-01 1.337298e-01 4.659089e-01 7.245585e-02 5.849305e-02 3.697236e-01
##          244          245          248          249          250          251
## 2.177315e-02 1.142828e-08 1.272689e-01 1.007812e-01 9.691078e-02 7.345515e-02
##          253          254          255          256          257          259
## 6.821319e-02 7.485848e-02 7.015810e-02 3.462603e-08 6.465878e-02 1.125595e-01
##          260          261          262          265          266          267
## 8.955073e-02 1.163948e-01 1.111188e-01 6.981679e-02 9.554415e-02 7.613191e-02
##          268          270          271          272          273          274
## 1.238581e-01 1.305993e-01 1.759959e-01 5.459918e-01 9.055377e-02 1.671709e-01
##          276          277          278          279          282          283
## 1.118504e-01 8.629729e-02 1.340877e-01 1.099863e-02 2.429476e-02 6.260441e-02
##          284          285          287          288          289          290
## 9.253101e-02 8.627405e-02 8.849667e-02 8.054194e-02 3.839451e-01 8.589107e-02
##          291          293          294          295          296          299
## 1.238935e-01 2.350463e-08 3.842817e-02 6.150145e-02 1.388074e-01 1.139192e-01
##          300          301          302          304          305          306
## 1.031074e-01 2.320669e-01 3.445650e-02 2.230099e-01 6.101708e-02 9.370879e-02
##          307          308          310          311          312          313
## 6.799667e-01 7.438146e-02 9.717358e-02 4.146133e-02 1.121084e-01 1.681016e-01
##          316          317          318          319          321          322
## 6.741874e-02 2.175525e-02 3.342185e-01 6.957924e-02 1.430656e-01 6.508812e-02
##          323          324          325          327          328          329
## 6.375958e-02 8.115000e-02 3.360976e-02 1.559220e-01 1.288817e-01 9.119560e-02
##          330          333          334          335          336          338
## 7.640027e-02 8.573381e-02 5.812850e-02 3.395741e-02 7.183220e-02 1.359306e-01
##          339          340          341          342          344          345
## 6.938769e-02 8.053392e-02 7.400969e-02 1.169604e-01 1.129369e-01 6.672453e-02
##          346          347          350          351          352          353
## 1.081714e-01 3.001691e-02 1.028968e-09 1.700495e-01 8.292772e-02 3.530623e-08
##          355          356          357          358          359          361
## 4.668040e-02 5.992070e-02 2.664533e-01 1.324042e-01 8.417172e-02 7.621166e-02
##          362          363          364          367          368          369
```

```
## 5.419662e-02 2.520437e-01 1.703182e-01 6.476572e-02 7.451904e-01 4.237208e-08
##          370          372          373          374          375          376
## 8.106268e-02 3.452208e-02 5.247040e-02 7.559088e-01 8.720656e-02 8.082118e-02
##          378          379          380          381          384          385
## 1.120032e-01 6.969910e-02 1.316603e-01 2.155268e-01 2.002336e-02 2.904762e-02
##          386          387          389          390          391          392
## 1.588639e-01 3.141685e-01 1.981923e-01 9.825879e-02 8.929659e-02 9.296544e-02
##          393          395          396          397          398          401
## 2.513943e-01 1.619377e-01 1.474816e-01 2.240813e-02 5.836856e-02 3.016945e-02
##          402          403          404          406          407          408
## 3.125112e-02 7.293625e-02 1.327044e-01 8.059336e-09 5.164241e-02 5.638882e-02
##          409          410          412          413          414          415
## 1.323751e-01 8.187426e-02 2.238714e-01 2.316221e-02 4.848365e-02 1.716439e-01
##          418          419          420          421          423          424
## 2.623563e-02 9.351758e-02 1.392716e-01 3.371466e-01 1.122450e-01 7.424137e-02
##          425          426          427          429          430          431
## 1.817231e-01 6.146319e-02 1.522222e-01 1.492041e-01 3.598200e-01 9.246781e-02
##          432          435          436          437          438          440
## 7.790324e-02 5.988113e-02 6.238551e-02 2.207799e-01 5.098440e-02 6.740221e-02
##          441          442          443          444          446          447
## 1.450128e-01 1.161075e-02 5.383031e-02 1.624143e-02 9.174127e-02 2.350463e-08
##          448          449          452          453          454          455
## 4.945459e-02 1.088275e-01 1.300413e-01 3.461087e-01 2.393678e-01 7.984620e-02
##          457          458          459          460          461          463
## 9.741719e-02 1.084436e-01 1.426861e-02 4.742953e-02 2.977534e-02 1.083147e-01
##          464          465          466          469          470
## 3.570980e-01 3.124049e-01 8.340999e-02 1.922506e-01 6.772018e-02
```

```r
# Validate the model - confusion matrix
confmatrix <- table(Actual_Value=train$Risk1Yr, Predicted_Value = res > 0.5)
confmatrix
```

```
##             Predicted_Value
## Actual_Value FALSE TRUE
##            F   310    5
##            T    40    4
```

```r
# Accuracy
(confmatrix[[1,1]] + confmatrix[[2,2]]) / sum(confmatrix)
```

```
## [1] 0.8746518
```

We can see that we did well, accuracy of the model is 86.6 %.

2 a. Fit a logistic regression model to the binary-classifier-data.csv dataset

```r
## Set the working directory to the root of your DSC 520 directory
setwd("/Users/dipikasharma/R_Projects/DSC520")

## Load the `data/r4ds/heights.csv` to
Binary_df <- read.csv("data/binary-classifier-data.csv")
```

```r
split <- sample.split(Binary_df, SplitRatio = 0.8)
split
```

```
## [1]  TRUE  TRUE FALSE
```

```r
train_df <- subset(Binary_df, split == 'TRUE')
test_df <- subset(Binary_df, split == 'FALSE')
Binary_df$label <- as.factor(Binary_df$label)

fit_df <- glm(label ~ ., data = train_df, family = binomial)
summary(fit_df)
```

```
##
## Call:
## glm(formula = label ~ ., family = binomial, data = train_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3766  -1.1693  -0.9522   1.1648   1.3896
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.433172   0.143853   3.011 0.002602 **
## x           -0.002722   0.002231  -1.220 0.222475
## y           -0.008017   0.002286  -3.507 0.000453 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1384.3  on 998  degrees of freedom
## Residual deviance: 1368.0  on 996  degrees of freedom
## AIC: 1374
##
## Number of Fisher Scoring iterations: 4
```

2 b. The dataset (found in binary-classifier-data.csv) contains three variables; label, x, and y. The label variable is either 0 or 1 and is the output we want to predict using the x and y variables.

```r
res1 <- predict(fit_df, test_df, type = 'response')
res1
```

```
##         3         6         9        12        15        18        21        24
## 0.3759251 0.3879318 0.3762594 0.3603081 0.3886800 0.3805846 0.3804240 0.3834556
##        27        30        33        36        39        42        45        48
## 0.3803084 0.3876246 0.3880340 0.3873913 0.3951783 0.3982624 0.3871152 0.3733111
##        51        54        57        60        63        66        69        72
## 0.3917231 0.3970926 0.4977551 0.4906684 0.4959108 0.4893077 0.4879139 0.4965887
##        75        78        81        84        87        90        93        96
```

```
## 0.4878604 0.4856685 0.5019209 0.4982379 0.4878841 0.4965857 0.4912688 0.4917554
##        99       102       105       108       111       114       117       120
## 0.4284457 0.4331532 0.4264397 0.4313563 0.4265370 0.4326893 0.4329840 0.4257473
##       123       126       129       132       135       138       141       144
## 0.4283440 0.4340988 0.4295015 0.4302586 0.4284559 0.4292098 0.4292381 0.4337705
##       147       150       153       156       159       162       165       168
## 0.4297339 0.4283865 0.4314454 0.4358641 0.4266400 0.4160415 0.4182399 0.3972755
##       171       174       177       180       183       186       189       192
## 0.4308150 0.4260458 0.4268041 0.4101690 0.4115315 0.4280241 0.4291229 0.4159474
##       195       198       201       204       207       210       213       216
## 0.4228222 0.4751448 0.4804512 0.4792266 0.4793031 0.4782142 0.4777298 0.4834663
##       219       222       225       228       231       234       237       240
## 0.4853233 0.4790865 0.3783786 0.3798934 0.3830102 0.3874447 0.3934881 0.3809320
##       243       246       249       252       255       258       261       264
## 0.3719944 0.3862471 0.3922618 0.3917158 0.3863231 0.3834871 0.5349157 0.5364307
##       267       270       273       276       279       282       285       288
## 0.5400589 0.5286853 0.5315987 0.5382596 0.5403910 0.5405918 0.5344848 0.5457080
##       291       294       297       300       303       306       309       312
## 0.5400325 0.5424251 0.5392793 0.5393410 0.5317313 0.5382559 0.5360390 0.5431748
##       315       318       321       324       327       330       333       336
## 0.4781533 0.4919731 0.4996332 0.4928517 0.4971080 0.5011557 0.5108979 0.4867297
##       339       342       345       348       351       354       357       360
## 0.4842046 0.4990104 0.4898526 0.4995049 0.4856019 0.4994755 0.4971667 0.5044316
##       363       366       369       372       375       378       381       384
## 0.4940656 0.4871143 0.4902709 0.5355827 0.5298816 0.5117149 0.5199200 0.5254202
##       387       390       393       396       399       402       405       408
## 0.5232588 0.5224993 0.5204103 0.5231727 0.5260946 0.5192293 0.5217999 0.5180077
##       411       414       417       420       423       426       429       432
## 0.5285876 0.5323015 0.5385725 0.5213860 0.5344383 0.5334321 0.5316040 0.5315818
##       435       438       441       444       447       450       453       456
## 0.5294228 0.5280224 0.5271502 0.5275803 0.5344200 0.5290268 0.5312093 0.5255699
##       459       462       465       468       471       474       477       480
## 0.5242509 0.5292141 0.5308280 0.5267761 0.5320783 0.5273445 0.5315389 0.6057008
##       483       486       489       492       495       498       501       504
## 0.5979691 0.5977727 0.6041975 0.5993380 0.6105535 0.6045713 0.5992369 0.6075012
##       507       510       513       516       519       522       525       528
## 0.6076527 0.6051625 0.6099629 0.6013357 0.6042198 0.6052432 0.6029044 0.6019054
##       531       534       537       540       543       546       549       552
## 0.5984506 0.4028166 0.4047917 0.4052144 0.4165304 0.3978215 0.4106311 0.4018294
##       555       558       561       564       567       570       573       576
## 0.4027067 0.4019438 0.4181489 0.4060528 0.4080786 0.4141198 0.4074091 0.5355953
##       579       582       585       588       591       594       597       600
## 0.5446486 0.5412200 0.5547314 0.5354743 0.5387985 0.5343285 0.5361446 0.5429478
##       603       606       609       612       615       618       621       624
## 0.5317759 0.5553215 0.5480239 0.5337018 0.5542631 0.5497007 0.5457889 0.5400325
##       627       630       633       636       639       642       645       648
## 0.5445657 0.5482593 0.5633116 0.5452805 0.5570026 0.5457063 0.5454597 0.5585453
##       651       654       657       660       663       666       669       672
## 0.5509603 0.5354166 0.5459041 0.5537582 0.5438715 0.5527058 0.5489607 0.5531023
##       675       678       681       684       687       690       693       696
## 0.5478116 0.4861125 0.4852430 0.4978369 0.4992851 0.5096921 0.4952194 0.4964920
##       699       702       705       708       711       714       717       720
## 0.4870347 0.5042360 0.4922333 0.5009105 0.4986902 0.3687837 0.3715987 0.3643062
##       723       726       729       732       735       738       741       744
```

```
## 0.3703486 0.3638725 0.3648493 0.3664918 0.3718830 0.3714932 0.3670074 0.3710377
##       747       750       753       756       759       762       765       768
## 0.3700206 0.3640017 0.3689409 0.3668169 0.3657023 0.3653252 0.3665334 0.4514893
##       771       774       777       780       783       786       789       792
## 0.4578861 0.4494197 0.4552486 0.4437979 0.4468167 0.4451481 0.4596802 0.4650495
##       795       798       801       804       807       810       813       816
## 0.4502552 0.4254813 0.4653714 0.4488427 0.4506995 0.4492895 0.4550560 0.4713169
##       819       822       825       828       831       834       837       840
## 0.5128502 0.5141292 0.5011095 0.5133919 0.5133898 0.5230780 0.5038577 0.5170379
##       843       846       849       852       855       858       861       864
## 0.5165827 0.5171037 0.5214666 0.5074467 0.5118569 0.5071729 0.5115061 0.5140853
##       867       870       873       876       879       882       885       888
## 0.5196487 0.5209220 0.5134258 0.5154210 0.5093215 0.5163681 0.5117633 0.5182168
##       891       894       897       900       903       906       909       912
## 0.5138531 0.5151923 0.5090732 0.5091237 0.5080872 0.5160435 0.5061435 0.5159471
##       915       918       921       924       927       930       933       936
## 0.5092250 0.5125494 0.5133489 0.5112921 0.5037944 0.5151996 0.5106681 0.4374903
##       939       942       945       948       951       954       957       960
## 0.4351825 0.4330298 0.4318589 0.4386431 0.4392569 0.4277619 0.4286376 0.4326274
##       963       966       969       972       975       978       981       984
## 0.4370458 0.4339982 0.4394720 0.4269409 0.4354623 0.4315448 0.4321496 0.4339641
##       987       990       993       996       999      1002      1005      1008
## 0.5203639 0.5159063 0.5102036 0.5217693 0.5125206 0.5093020 0.5126438 0.4944151
##      1011      1014      1017      1020      1023      1026      1029      1032
## 0.5141504 0.5118590 0.5179853 0.5133432 0.5135419 0.5088448 0.5032827 0.5082036
##      1035      1038      1041      1044      1047      1050      1053      1056
## 0.5032526 0.5215891 0.4419355 0.4426796 0.4443811 0.4371138 0.4440033 0.4443615
##      1059      1062      1065      1068      1071      1074      1077      1080
## 0.4476324 0.4467899 0.4508856 0.4430781 0.4373560 0.4440747 0.4469026 0.4420452
##      1083      1086      1089      1092      1095      1098      1101      1104
## 0.4450921 0.4439696 0.4445176 0.4458106 0.4413506 0.5042614 0.4963236 0.5116653
##      1107      1110      1113      1116      1119      1122      1125      1128
## 0.5046774 0.5101099 0.5088977 0.5027445 0.4997788 0.5115624 0.5205886 0.5081123
##      1131      1134      1137      1140      1143      1146      1149      1152
## 0.5135690 0.5174515 0.5791643 0.5728691 0.5773887 0.5671223 0.5769216 0.5743320
##      1155      1158      1161      1164      1167      1170      1173      1176
## 0.5756164 0.5784841 0.5659537 0.5753591 0.5496630 0.5659962 0.5581080 0.5683611
##      1179      1182      1185      1188      1191      1194      1197      1200
## 0.5582918 0.5578369 0.5588501 0.5504417 0.5569355 0.5599636 0.5649937 0.5679498
##      1203      1206      1209      1212      1215      1218      1221      1224
## 0.5560452 0.5601817 0.5549813 0.5495683 0.5556924 0.5547073 0.5564430 0.5491286
##      1227      1230      1233      1236      1239      1242      1245      1248
## 0.5427869 0.5529032 0.5521361 0.5505112 0.5469317 0.5427017 0.5424738 0.5491103
##      1251      1254      1257      1260      1263      1266      1269      1272
## 0.5454126 0.5398426 0.5452583 0.5471607 0.5497248 0.5449119 0.5520002 0.4203500
##      1275      1278      1281      1284      1287      1290      1293      1296
## 0.4446212 0.4392157 0.4497405 0.4349831 0.4247330 0.4502631 0.4404951 0.4409248
##      1299      1302      1305      1308      1311      1314      1317      1320
## 0.4330532 0.4449276 0.4407028 0.4380912 0.4333370 0.4359702 0.4384942 0.4405152
##      1323      1326      1329      1332      1335      1338      1341      1344
## 0.4245140 0.4548126 0.4494832 0.4409753 0.4656618 0.4382152 0.4349335 0.5014863
##      1347      1350      1353      1356      1359      1362      1365      1368
## 0.5019877 0.5045514 0.5063485 0.5015471 0.5051492 0.5055828 0.5026488 0.5035456
##      1371      1374      1377      1380      1383      1386      1389      1392
```

```
## 0.5037541 0.5055748 0.5012976 0.5023062 0.4996660 0.5021183 0.5058626 0.5015256
##      1395      1398      1401      1404      1407      1410      1413      1416
## 0.5067994 0.5086767 0.5783591 0.5912792 0.5934422 0.6017101 0.5852427 0.5872956
##      1419      1422      1425      1428      1431      1434      1437      1440
## 0.5801924 0.5786552 0.5842055 0.5905802 0.5790214 0.5749042 0.5989092 0.5861005
##      1443      1446      1449      1452      1455      1458      1461      1464
## 0.5900009 0.5929962 0.5652120 0.5790135 0.3824292 0.3941124 0.3867306 0.3916119
##      1467      1470      1473      1476      1479      1482      1485      1488
## 0.3751615 0.3897993 0.4042961 0.3948631 0.4071013 0.4094830 0.4058178 0.3967480
##      1491      1494      1497
## 0.4025877 0.3872978 0.3795534
```

```r
res1 <- predict(fit_df, train_df, type = 'response')
res1
```

```
##         1         2         4         5         7         8        10        11
## 0.3949328 0.3832330 0.4018326 0.3935051 0.3824208 0.3615231 0.3798253 0.3926425
##        13        14        16        17        19        20        22        23
## 0.3955751 0.3824947 0.3830227 0.3987687 0.3736955 0.3829191 0.3763881 0.3906611
##        25        26        28        29        31        32        34        35
## 0.3755182 0.3924209 0.3844012 0.4032784 0.3978168 0.4024929 0.3965417 0.3978991
##        37        38        40        41        43        44        46        47
## 0.3930543 0.3698149 0.3933227 0.3772952 0.3803579 0.3937219 0.3674057 0.3681025
##        49        50        52        53        55        56        58        59
## 0.3813040 0.3846164 0.3925642 0.3748174 0.3813768 0.4949918 0.4950731 0.4878334
##        61        62        64        65        67        68        70        71
## 0.4991118 0.4904990 0.4857256 0.4826751 0.4945614 0.5073438 0.4892140 0.5040088
##        73        74        76        77        79        80        82        83
## 0.4824818 0.4808545 0.4925839 0.4938167 0.5044622 0.5006716 0.4870091 0.4992546
##        85        86        88        89        91        92        94        95
## 0.5018080 0.4857640 0.5043364 0.4956992 0.5138259 0.5018618 0.5010675 0.4860828
##        97        98       100       101       103       104       106       107
## 0.4792706 0.4794022 0.4306624 0.4312333 0.4311090 0.4297186 0.4281018 0.4328789
##       109       110       112       113       115       116       118       119
## 0.4263720 0.4271265 0.4302060 0.4303334 0.4277350 0.4307463 0.4362848 0.4323965
##       121       122       124       125       127       128       130       131
## 0.4289680 0.4283531 0.4281750 0.4300878 0.4331159 0.4301545 0.4289397 0.4312374
##       133       134       136       137       139       140       142       143
## 0.4275757 0.4248151 0.4298208 0.4302374 0.4263916 0.4308474 0.4317580 0.4282251
##       145       146       148       149       151       152       154       155
## 0.4314541 0.4274327 0.4283752 0.4273823 0.4313305 0.4297906 0.4276060 0.4288535
##       157       158       160       161       163       164       166       167
## 0.4316947 0.4326818 0.4304161 0.4149385 0.4182115 0.4171020 0.4175687 0.4250522
##       169       170       172       173       175       176       178       179
## 0.4207029 0.4159082 0.4200245 0.4208191 0.4200157 0.4147780 0.4193453 0.4240922
##       181       182       184       185       187       188       190       191
## 0.4014033 0.4140716 0.4266556 0.4224250 0.4166161 0.4184957 0.4037141 0.4166027
##       193       194       196       197       199       200       202       203
## 0.4131086 0.4021190 0.4087543 0.4788734 0.4819210 0.4763922 0.4789059 0.4810053
##       205       206       208       209       211       212       214       215
## 0.4831429 0.4865369 0.4829758 0.4850963 0.4709206 0.4847117 0.4759906 0.4765690
##       217       218       220       221       223       224       226       227
## 0.4792958 0.4821704 0.4776441 0.4755997 0.3806483 0.3850293 0.3825810 0.3920251
##       229       230       232       233       235       236       238       239
```

```
## 0.3890732 0.3818402 0.3851281 0.3806852 0.3740374 0.3875991 0.3916037 0.3810097
##       241       242       244       245       247       248       250       251
## 0.3921902 0.3842503 0.3929662 0.3867183 0.3789030 0.3877849 0.3887562 0.3839991
##       253       254       256       257       259       260       262       263
## 0.3987371 0.3794339 0.3904267 0.3956572 0.3818044 0.5319668 0.5327923 0.5403521
##       265       266       268       269       271       272       274       275
## 0.5385980 0.5409463 0.5392145 0.5332963 0.5379006 0.5422480 0.5355240 0.5342959
##       277       278       280       281       283       284       286       287
## 0.5416710 0.5335092 0.5371781 0.5396025 0.5370016 0.5381011 0.5356304 0.5398251
##       289       290       292       293       295       296       298       299
## 0.5404480 0.5364096 0.5382948 0.5354666 0.5471507 0.5424300 0.5410705 0.5326922
##       301       302       304       305       307       308       310       311
## 0.5410180 0.5265307 0.5302750 0.5344218 0.5376454 0.5470972 0.5367035 0.5363007
##       313       314       316       317       319       320       322       323
## 0.5420604 0.4969258 0.4943127 0.4794708 0.4927974 0.5050164 0.4940169 0.5000256
##       325       326       328       329       331       332       334       335
## 0.4893073 0.4942973 0.4873740 0.4852105 0.4981101 0.4968300 0.4907778 0.4998607
##       337       338       340       341       343       344       346       347
## 0.4969522 0.4883828 0.4966645 0.4994082 0.4961866 0.4974362 0.4910979 0.4966651
##       349       350       352       353       355       356       358       359
## 0.5007094 0.4968455 0.4964591 0.4953198 0.4969323 0.4986575 0.5055167 0.4906961
##       361       362       364       365       367       368       370       371
## 0.5022274 0.4771473 0.4931284 0.4977115 0.4983962 0.5027514 0.5296925 0.5252339
##       373       374       376       377       379       380       382       383
## 0.5277365 0.5247817 0.5135726 0.5249212 0.5325974 0.5199710 0.5378812 0.5363968
##       385       386       388       389       391       392       394       395
## 0.5276444 0.5395193 0.5310091 0.5223436 0.5236136 0.5275703 0.5319652 0.5195585
##       397       398       400       401       403       404       406       407
## 0.5347863 0.5302406 0.5228004 0.5257719 0.5308432 0.5268886 0.5358409 0.5223876
##       409       410       412       413       415       416       418       419
## 0.5245824 0.5293207 0.5317191 0.5278771 0.5341854 0.5204852 0.5276703 0.5336842
##       421       422       424       425       427       428       430       431
## 0.5250074 0.5180801 0.5180969 0.5244479 0.5138827 0.5280444 0.5306808 0.5365321
##       433       434       436       437       439       440       442       443
## 0.5270490 0.5319319 0.5362349 0.5357930 0.5388290 0.5235062 0.5308380 0.5297318
##       445       446       448       449       451       452       454       455
## 0.5330397 0.5332180 0.5277620 0.5279925 0.5285936 0.5357751 0.5252268 0.5314995
##       457       458       460       461       463       464       466       467
## 0.5316317 0.5312576 0.5335044 0.5331309 0.5295053 0.5285193 0.5315386 0.5276176
##       469       470       472       473       475       476       478       479
## 0.5344658 0.5246220 0.5349569 0.5265455 0.5258179 0.5342286 0.5315178 0.6072759
##       481       482       484       485       487       488       490       491
## 0.6026642 0.5999448 0.5994928 0.6080223 0.6053104 0.6063108 0.6044811 0.6010319
##       493       494       496       497       499       500       502       503
## 0.6103073 0.6039885 0.6030042 0.6036478 0.6091551 0.6096832 0.6041591 0.5996555
##       505       506       508       509       511       512       514       515
## 0.6060302 0.6027333 0.6072939 0.6040969 0.6080608 0.5971243 0.6106046 0.6016425
##       517       518       520       521       523       524       526       527
## 0.5993246 0.6036343 0.6107303 0.6106172 0.6045696 0.6050802 0.6065609 0.6062683
##       529       530       532       533       535       536       538       539
## 0.6123040 0.5994852 0.4152261 0.3954202 0.4015101 0.4051506 0.3909471 0.4176015
##       541       542       544       545       547       548       550       551
## 0.4050095 0.4163364 0.4133860 0.4099931 0.4034438 0.4101781 0.3883882 0.4035587
##       553       554       556       557       559       560       562       563
```

```
## 0.4027314 0.4193349 0.3947869 0.4062397 0.4293802 0.3900437 0.3991666 0.4128975
##       565       566       568       569       571       572       574       575
## 0.4092111 0.4121411 0.3907438 0.3995865 0.4064727 0.3942348 0.4075609 0.4029933
##       577       578       580       581       583       584       586       587
## 0.5410285 0.5527611 0.5356886 0.5367612 0.5484544 0.5404568 0.5578983 0.5392661
##       589       590       592       593       595       596       598       599
## 0.5335523 0.5515436 0.5324080 0.5305818 0.5507711 0.5456672 0.5453444 0.5405202
##       601       602       604       605       607       608       610       611
## 0.5547043 0.5447046 0.5518690 0.5478225 0.5422418 0.5550277 0.5404160 0.5403255
##       613       614       616       617       619       620       622       623
## 0.5438254 0.5290376 0.5497623 0.5233637 0.5579525 0.5487118 0.5388251 0.5565421
##       625       626       628       629       631       632       634       635
## 0.5433299 0.5355251 0.5476348 0.5662053 0.5526978 0.5514506 0.5440042 0.5624445
##       637       638       640       641       643       644       646       647
## 0.5595490 0.5566558 0.5510851 0.5527451 0.5472593 0.5480603 0.5465096 0.5386237
##       649       650       652       653       655       656       658       659
## 0.5380825 0.5490269 0.5316384 0.5435529 0.5433151 0.5511725 0.5503968 0.5490364
##       661       662       664       665       667       668       670       671
## 0.5496869 0.5585909 0.5486590 0.5407357 0.5649786 0.5378179 0.5431100 0.5434361
##       673       674       676       677       679       680       682       683
## 0.5414101 0.5381472 0.5603044 0.5444815 0.4907423 0.4761042 0.4743342 0.4751860
##       685       686       688       689       691       692       694       695
## 0.4762412 0.4700476 0.4877951 0.4926129 0.4937898 0.4979467 0.4856305 0.4822361
##       697       698       700       701       703       704       706       707
## 0.5089530 0.4895749 0.4562138 0.4811994 0.4766171 0.4906199 0.4878345 0.4704007
##       709       710       712       713       715       716       718       719
## 0.4943302 0.4803869 0.5015713 0.4902576 0.3628298 0.3641769 0.3696246 0.3665605
##       721       722       724       725       727       728       730       731
## 0.3644836 0.3635132 0.3669579 0.3652323 0.3622194 0.3662492 0.3616362 0.3613582
##       733       734       736       737       739       740       742       743
## 0.3599477 0.3603457 0.3649218 0.3666498 0.3684200 0.3672937 0.3692280 0.3693155
##       745       746       748       749       751       752       754       755
## 0.3701458 0.3684680 0.3694649 0.3616724 0.3718737 0.3716970 0.3654689 0.3729871
##       757       758       760       761       763       764       766       767
## 0.3641434 0.3692329 0.3651059 0.3650896 0.3708180 0.3686554 0.3666239 0.3622690
##       769       770       772       773       775       776       778       779
## 0.4546885 0.4652957 0.4398152 0.4554534 0.4549964 0.4676303 0.4464818 0.4692728
##       781       782       784       785       787       788       790       791
## 0.4469854 0.4569798 0.4582514 0.4679556 0.4601907 0.4529448 0.4616410 0.4479182
##       793       794       796       797       799       800       802       803
## 0.4697006 0.4561118 0.4623683 0.4536968 0.4568262 0.4513814 0.4267167 0.4452940
##       805       806       808       809       811       812       814       815
## 0.4522665 0.4441322 0.4521284 0.4556245 0.4548303 0.4639234 0.4645147 0.4521669
##       817       818       820       821       823       824       826       827
## 0.4502507 0.4357222 0.5217346 0.5039961 0.5067370 0.5090408 0.5210514 0.5168629
##       829       830       832       833       835       836       838       839
## 0.5119685 0.5148143 0.5146597 0.5247341 0.5094220 0.5149665 0.5127439 0.5237595
##       841       842       844       845       847       848       850       851
## 0.5158960 0.5087074 0.5157084 0.5202350 0.5106190 0.5160245 0.5108001 0.5141053
##       853       854       856       857       859       860       862       863
## 0.5089327 0.5128709 0.5074872 0.5034129 0.5199122 0.5196080 0.5150296 0.5199255
##       865       866       868       869       871       872       874       875
## 0.5077032 0.4975373 0.4996686 0.5076212 0.5137938 0.5143264 0.5139692 0.5203029
##       877       878       880       881       883       884       886       887
```

```
## 0.5038184 0.5130050 0.5098425 0.5121063 0.5047283 0.5100108 0.5114620 0.5122934
##       889       890       892       893       895       896       898       899
## 0.5153931 0.5113478 0.5118308 0.5116789 0.5107693 0.5059449 0.5062725 0.5085166
##       901       902       904       905       907       908       910       911
## 0.5176895 0.5114340 0.5154758 0.5162015 0.5015526 0.5111652 0.5111937 0.5107995
##       913       914       916       917       919       920       922       923
## 0.5093129 0.5156234 0.5173468 0.5148646 0.5131882 0.5171719 0.5039791 0.5139932
##       925       926       928       929       931       932       934       935
## 0.5149582 0.5141331 0.5131055 0.5146487 0.5177787 0.5075919 0.5103415 0.4333998
##       937       938       940       941       943       944       946       947
## 0.4353909 0.4267121 0.4320977 0.4390873 0.4311614 0.4388533 0.4389035 0.4305105
##       949       950       952       953       955       956       958       959
## 0.4327879 0.4330372 0.4352702 0.4366845 0.4319761 0.4315462 0.4304543 0.4285112
##       961       962       964       965       967       968       970       971
## 0.4312619 0.4393649 0.4377672 0.4314644 0.4323807 0.4326218 0.4330045 0.4348196
##       973       974       976       977       979       980       982       983
## 0.4390415 0.4338440 0.4339745 0.4345294 0.4277710 0.4371863 0.4358073 0.4302549
##       985       986       988       989       991       992       994       995
## 0.4354139 0.4361539 0.4998100 0.4959027 0.5009834 0.5018161 0.5309673 0.5103205
##       997       998      1000      1001      1003      1004      1006      1007
## 0.5183814 0.5140444 0.5154477 0.5163942 0.5209990 0.5264277 0.5125030 0.5240961
##      1009      1010      1012      1013      1015      1016      1018      1019
## 0.5122592 0.5146268 0.5148832 0.5228784 0.5170461 0.5310419 0.5143986 0.5324625
##      1021      1022      1024      1025      1027      1028      1030      1031
## 0.5066424 0.5153571 0.5074272 0.5114604 0.5099107 0.5191302 0.5089211 0.5061136
##      1033      1034      1036      1037      1039      1040      1042      1043
## 0.5076745 0.5068399 0.5082718 0.5128072 0.5194413 0.4429219 0.4499757 0.4424198
##      1045      1046      1048      1049      1051      1052      1054      1055
## 0.4429606 0.4452453 0.4428343 0.4464130 0.4447639 0.4433096 0.4426754 0.4453636
##      1057      1058      1060      1061      1063      1064      1066      1067
## 0.4456154 0.4446494 0.4484314 0.4466869 0.4441032 0.4429487 0.4480041 0.4472577
##      1069      1070      1072      1073      1075      1076      1078      1079
## 0.4413263 0.4373058 0.4486250 0.4516246 0.4448917 0.4443751 0.4439898 0.4445077
##      1081      1082      1084      1085      1087      1088      1090      1091
## 0.4372686 0.4466831 0.4436563 0.4474252 0.4470183 0.4458126 0.4455506 0.4438130
##      1093      1094      1096      1097      1099      1100      1102      1103
## 0.4445773 0.4386419 0.5179461 0.5059542 0.5092757 0.5118467 0.5047784 0.5087603
##      1105      1106      1108      1109      1111      1112      1114      1115
## 0.5151179 0.5084437 0.5035050 0.5193482 0.5006387 0.5064728 0.5021171 0.5132096
##      1117      1118      1120      1121      1123      1124      1126      1127
## 0.5052209 0.5127490 0.5133953 0.5124815 0.5145986 0.5208898 0.5076679 0.5009201
##      1129      1130      1132      1133      1135      1136      1138      1139
## 0.5142738 0.4993592 0.5060822 0.5084461 0.5106395 0.4911079 0.5754390 0.5677510
##      1141      1142      1144      1145      1147      1148      1150      1151
## 0.5798536 0.5739149 0.5744391 0.5866808 0.5701058 0.5728151 0.5689041 0.5761935
##      1153      1154      1156      1157      1159      1160      1162      1163
## 0.5783238 0.5803431 0.5765233 0.5816743 0.5692104 0.5725657 0.5653827 0.5726892
##      1165      1166      1168      1169      1171      1172      1174      1175
## 0.5621726 0.5601971 0.5621774 0.5561585 0.5614104 0.5577799 0.5567065 0.5462302
##      1177      1178      1180      1181      1183      1184      1186      1187
## 0.5613783 0.5569921 0.5582051 0.5602145 0.5560752 0.5547277 0.5511946 0.5624648
##      1189      1190      1192      1193      1195      1196      1198      1199
## 0.5594457 0.5621548 0.5612391 0.5550416 0.5565302 0.5593322 0.5603595 0.5619614
##      1201      1202      1204      1205      1207      1208      1210      1211
```

```
## 0.5579692 0.5518650 0.5628222 0.5649971 0.5591808 0.5562027 0.5603696 0.5654805
##      1213      1214      1216      1217      1219      1220      1222      1223
## 0.5573902 0.5561816 0.5579310 0.5551158 0.5524055 0.5542636 0.5482236 0.5428485
##      1225      1226      1228      1229      1231      1232      1234      1235
## 0.5447559 0.5495686 0.5505104 0.5407303 0.5382094 0.5436329 0.5557471 0.5491630
##      1237      1238      1240      1241      1243      1244      1246      1247
## 0.5469473 0.5415317 0.5427394 0.5486647 0.5471735 0.5435044 0.5484550 0.5515805
##      1249      1250      1252      1253      1255      1256      1258      1259
## 0.5429166 0.5464184 0.5432147 0.5445609 0.5432647 0.5444191 0.5462738 0.5441565
##      1261      1262      1264      1265      1267      1268      1270      1271
## 0.5402442 0.5425580 0.5475035 0.5454049 0.5468655 0.5417210 0.5510668 0.4480712
##      1273      1274      1276      1277      1279      1280      1282      1283
## 0.4482484 0.4459964 0.4435336 0.4697291 0.4310182 0.4325644 0.4355506 0.4444976
##      1285      1286      1288      1289      1291      1292      1294      1295
## 0.4430051 0.4480540 0.4387459 0.4354790 0.4326854 0.4378849 0.4486365 0.4287953
##      1297      1298      1300      1301      1303      1304      1306      1307
## 0.4276436 0.4328285 0.4417511 0.4489659 0.4362964 0.4422617 0.4402943 0.4416799
##      1309      1310      1312      1313      1315      1316      1318      1319
## 0.4182044 0.4249908 0.4261264 0.4383330 0.4381479 0.4378230 0.4406006 0.4514202
##      1321      1322      1324      1325      1327      1328      1330      1331
## 0.4285671 0.4425403 0.4397230 0.4515422 0.4402628 0.4529991 0.4340709 0.4413170
##      1333      1334      1336      1337      1339      1340      1342      1343
## 0.4495630 0.4400173 0.4276102 0.4534550 0.4417310 0.4361071 0.4494855 0.4404064
##      1345      1346      1348      1349      1351      1352      1354      1355
## 0.5037455 0.5026981 0.5085995 0.5038342 0.5093691 0.5030794 0.5042827 0.5003541
##      1357      1358      1360      1361      1363      1364      1366      1367
## 0.5054184 0.5007126 0.5057107 0.5053082 0.5032805 0.5054930 0.5050023 0.5028788
##      1369      1370      1372      1373      1375      1376      1378      1379
## 0.5039154 0.5039684 0.5006090 0.5040987 0.5031547 0.5029798 0.5018747 0.5022841
##      1381      1382      1384      1385      1387      1388      1390      1391
## 0.5020379 0.5048316 0.5012356 0.5051355 0.5015163 0.5024902 0.5046298 0.5038093
##      1393      1394      1396      1397      1399      1400      1402      1403
## 0.5029982 0.5042727 0.5051130 0.5037728 0.5046420 0.5030963 0.5763028 0.5905836
##      1405      1406      1408      1409      1411      1412      1414      1415
## 0.5736016 0.5740311 0.5900228 0.5871261 0.5992975 0.5924027 0.5867880 0.5787261
##      1417      1418      1420      1421      1423      1424      1426      1427
## 0.5814241 0.5783371 0.5866233 0.5728154 0.5846124 0.5843695 0.5902801 0.5751061
##      1429      1430      1432      1433      1435      1436      1438      1439
## 0.5868424 0.5910233 0.5740046 0.5820994 0.5805401 0.5897680 0.5860112 0.5629936
##      1441      1442      1444      1445      1447      1448      1450      1451
## 0.5802180 0.5987659 0.6005250 0.5791002 0.5657081 0.5763057 0.5764411 0.5867984
##      1453      1454      1456      1457      1459      1460      1462      1463
## 0.5970519 0.5828039 0.3997577 0.3859761 0.3923261 0.3845583 0.3858842 0.3883769
##      1465      1466      1468      1469      1471      1472      1474      1475
## 0.3944726 0.3946570 0.3876691 0.3817313 0.3871660 0.3982043 0.3943644 0.3891366
##      1477      1478      1480      1481      1483      1484      1486      1487
## 0.3888308 0.3887814 0.4037041 0.3947595 0.3958230 0.3951222 0.3965666 0.3982640
##      1489      1490      1492      1493      1495      1496      1498
## 0.3933644 0.3807770 0.3914034 0.3906646 0.3828273 0.4015155 0.3954412
```

```
# Validate the model - confusion matrix
confmatrix <- table(Actual_Value=train_df$label, Predicted_Value = res1 > 0.5)
confmatrix
```

```
##              Predicted_Value
## Actual_Value FALSE TRUE
##            0   283  229
##            1   190  297
```

2 b i. What is the accuracy of the logistic regression classifier?

```r
# Accuracy
(confmatrix[[1,1]] + confmatrix[[2,2]]) / sum(confmatrix)
```

```
## [1] 0.5805806
```

The Accuracy is 57.5 % of the logistic regression.

Refrences

Field, A., J. Miles, and Z. Field. 2012. *Discovering Statistics Using r*. SAGE Publications. https://books.google.com/books?id=wd2K2zC3swIC.

Lander, J. P. 2014. *R for Everyone: Advanced Analytics and Graphics*. Addison-Wesley Data and Analytics Series. Addison-Wesley. https://books.google.com/books?id=3eBVAgAAQBAJ.