Predictive Modeling
Lesson 3
Logistical Regression and Neural Networks

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Introduction

I chose to use R for the assignments. This is my first class in the PASS program and one of my goals upon completion of PASS is to be proficient in R.

The RStudio project files and accompanying artifacts, including the tex file that created this PDF, are publicly available on GitHub
`https://github.com/zollie/PASS-PredictiveModeling-LogisticalRegression`

Data Setup

I took the Excel spreadsheet and saved it as a CSV for easy import into R

```
> gc <- read.csv("~/R/PASS/PredictiveModeling/LogisticRegression/GermanCredit.csv")
> head(gc)
```

```
  OBS. CHK_ACCT DURATION HISTORY NEW_CAR USED_CAR FURNITURE RADIO.TV EDUCATION
1    1        0        6       4       0        0         0        1         0
2    2        1       48       2       0        0         0        1         0
3    3        3       12       4       0        0         0        0         1
4    4        0       42       2       0        0         1        0         0
5    5        0       24       3       1        0         0        0         0
6    6        3       36       2       0        0         0        0         1
  RETRAINING AMOUNT SAV_ACCT EMPLOYMENT INSTALL_RATE MALE_DIV MALE_SINGLE
1          0   1169        4          4            4        0           1
2          0   5951        0          2            2        0           0
3          0   2096        0          3            2        0           1
4          0   7882        0          3            2        0           1
5          0   4870        0          2            3        0           1
6          0   9055        4          2            2        0           1
  MALE_MAR_or_WID CO.APPLICANT GUARANTOR PRESENT_RESIDENT REAL_ESTATE
```

```
1               0            0         0               4           1
2               0            0         0               2           1
3               0            0         0               3           1
4               0            0         1               4           0
5               0            0         0               4           0
6               0            0         0               4           0
  PROP_UNKN_NONE AGE OTHER_INSTALL RENT OWN_RES NUM_CREDITS JOB NUM_DEPENDENTS
1              0  67             0    0       1           2   2              1
2              0  22             0    0       1           1   2              1
3              0  49             0    0       1           1   1              2
4              0  45             0    0       0           1   2              2
5              1  53             0    0       0           2   2              2
6              1  35             0    0       0           1   1              2
  TELEPHONE FOREIGN RESPONSE
1         1       0        1
2         0       0        0
3         0       0        1
4         0       0        1
5         0       0        0
6         1       0        1
```

The categorical predictors are turned into factors for R

```
> gc$RESPONSE <- factor(gc$RESPONSE)
> gc$JOB <- factor(gc$JOB)
> gc$EMPLOYMENT <- factor(gc$EMPLOYMENT)
> gc$SAV_ACCT <- factor(gc$SAV_ACCT)
> gc$HISTORY <- factor(gc$HISTORY)
> gc$CHK_ACCT <- factor(gc$CHK_ACCT)
```

Partitioning

Next, the data is paritioned into 60% Train and 40% Test sets. I set the RNG seed for reproducibility

```
> n <- nrow(gc)
> a <- sort(sample(1:n, floor(n*.6)))
> gc.train <- gc[a,]
> gc.test <- gc[-a,]
```

Logistical Regression

A Logistical Regression model is fit to the train data.

```
> logit <- glm(RESPONSE ~ CHK_ACCT+DURATION+HISTORY+NEW_CAR+USED_CAR+FURNITURE+RADIO.TV+EDUC
> logit
```

```
Call:  glm(formula = RESPONSE ~ CHK_ACCT + DURATION + HISTORY + NEW_CAR +
    USED_CAR + FURNITURE + RADIO.TV + EDUCATION + RETRAINING +
    AMOUNT + SAV_ACCT + EMPLOYMENT + INSTALL_RATE + MALE_DIV +
    MALE_SINGLE + MALE_MAR_or_WID + CO.APPLICANT + GUARANTOR +
    PRESENT_RESIDENT + REAL_ESTATE + PROP_UNKN_NONE + AGE + OTHER_INSTALL +
    RENT + OWN_RES + NUM_CREDITS + JOB + NUM_DEPENDENTS + TELEPHONE +
    FOREIGN, family = binomial("logit"), data = gc.train)

Coefficients:
     (Intercept)         CHK_ACCT1         CHK_ACCT2         CHK_ACCT3
      -0.0785683         0.3782587         1.3235863         1.8611904
        DURATION          HISTORY1          HISTORY2          HISTORY3
      -0.0367290         0.2115982         1.0612918         1.8523658
        HISTORY4           NEW_CAR          USED_CAR         FURNITURE
       2.3108484        -0.7254331         1.0471379         0.3166340
        RADIO.TV         EDUCATION        RETRAINING            AMOUNT
       0.3402443        -1.1564688         0.0332020        -0.0001519
       SAV_ACCT1         SAV_ACCT2         SAV_ACCT3         SAV_ACCT4
       0.5192510        -0.1274285         1.8195726         1.0523181
     EMPLOYMENT1       EMPLOYMENT2       EMPLOYMENT3       EMPLOYMENT4
       0.6200766         0.5109157         1.3376031         0.7209663
    INSTALL_RATE          MALE_DIV       MALE_SINGLE   MALE_MAR_or_WID
      -0.3366400        -0.7343612         0.2732063         0.1828317
    CO.APPLICANT         GUARANTOR  PRESENT_RESIDENT       REAL_ESTATE
      -0.6144330         0.8224780         0.0885999        -0.1658967
  PROP_UNKN_NONE               AGE     OTHER_INSTALL              RENT
      -0.2548482         0.0116311        -0.5959307        -0.1989817
         OWN_RES       NUM_CREDITS              JOB1              JOB2
       0.2276633        -0.2794957        -0.2758346        -0.3001333
            JOB3    NUM_DEPENDENTS         TELEPHONE           FOREIGN
       0.1589518        -0.0448547         0.0783900         2.2237732

Degrees of Freedom: 599 Total (i.e. Null);  556 Residual
Null Deviance:          746.1
Residual Deviance: 505.8        AIC: 593.8

> summary(logit)

Call:
glm(formula = RESPONSE ~ CHK_ACCT + DURATION + HISTORY + NEW_CAR +
    USED_CAR + FURNITURE + RADIO.TV + EDUCATION + RETRAINING +
    AMOUNT + SAV_ACCT + EMPLOYMENT + INSTALL_RATE + MALE_DIV +
    MALE_SINGLE + MALE_MAR_or_WID + CO.APPLICANT + GUARANTOR +
    PRESENT_RESIDENT + REAL_ESTATE + PROP_UNKN_NONE + AGE + OTHER_INSTALL +
    RENT + OWN_RES + NUM_CREDITS + JOB + NUM_DEPENDENTS + TELEPHONE +
    FOREIGN, family = binomial("logit"), data = gc.train)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.9087  -0.6148   0.3155   0.6546   2.8146

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.0785683  1.5781963  -0.050  0.96029
CHK_ACCT1         0.3782587  0.2961859   1.277  0.20157
CHK_ACCT2         1.3235862  0.5028576   2.632  0.00849 **
CHK_ACCT3         1.8611903  0.3100238   6.003 1.93e-09 ***
DURATION         -0.0367290  0.0124796  -2.943  0.00325 **
HISTORY1          0.2115982  0.8101723   0.261  0.79396
HISTORY2          1.0612918  0.6572103   1.615  0.10634
HISTORY3          1.8523658  0.7191174   2.576  0.01000 **
HISTORY4          2.3108484  0.6716128   3.441  0.00058 ***
NEW_CAR          -0.7254331  0.5221924  -1.389  0.16477
USED_CAR          1.0471379  0.6759156   1.549  0.12133
FURNITURE         0.3166340  0.5519902   0.574  0.56622
RADIO.TV          0.3402443  0.5207861   0.653  0.51354
EDUCATION        -1.1564688  0.6739694  -1.716  0.08618 .
RETRAINING        0.0332020  0.5901414   0.056  0.95513
AMOUNT           -0.0001519  0.0000618  -2.458  0.01399 *
SAV_ACCT1         0.5192510  0.4045415   1.284  0.19930
SAV_ACCT2        -0.1274285  0.4957171  -0.257  0.79713
SAV_ACCT3         1.8195726  0.7633959   2.384  0.01715 *
SAV_ACCT4         1.0523181  0.3564120   2.953  0.00315 **
EMPLOYMENT1       0.6200766  0.5617987   1.104  0.26971
EMPLOYMENT2       0.5109157  0.5377445   0.950  0.34206
EMPLOYMENT3       1.3376031  0.6023203   2.221  0.02637 *
EMPLOYMENT4       0.7209663  0.5458410   1.321  0.18656
INSTALL_RATE     -0.3366400  0.1267726  -2.655  0.00792 **
MALE_DIV         -0.7343612  0.5379059  -1.365  0.17218
MALE_SINGLE       0.2732063  0.2838544   0.962  0.33580
MALE_MAR_or_WID   0.1828317  0.4285412   0.427  0.66964
CO.APPLICANT     -0.6144330  0.5734994  -1.071  0.28400
GUARANTOR         0.8224780  0.5575590   1.475  0.14017
PRESENT_RESIDENT  0.0885999  0.1206828   0.734  0.46285
REAL_ESTATE      -0.1658967  0.2918338  -0.568  0.56972
PROP_UNKN_NONE   -0.2548482  0.5198569  -0.490  0.62397
AGE               0.0116311  0.0125096   0.930  0.35249
OTHER_INSTALL    -0.5959307  0.2868482  -2.078  0.03775 *
RENT             -0.1989817  0.6446811  -0.309  0.75759
OWN_RES           0.2276633  0.5896176   0.386  0.69941
NUM_CREDITS      -0.2794957  0.2585156  -1.081  0.27963
JOB1             -0.2758346  0.9027783  -0.306  0.75996
```

```
JOB2            -0.3001333  0.8651196  -0.347  0.72865
JOB3             0.1589518  0.8771417   0.181  0.85620
NUM_DEPENDENTS  -0.0448547  0.3311909  -0.135  0.89227
TELEPHONE        0.0783901  0.2718810   0.288  0.77310
FOREIGN          2.2237732  0.9811973   2.266  0.02343 *
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 746.09  on 599  degrees of freedom
Residual deviance: 505.78  on 556  degrees of freedom
AIC: 593.78

Number of Fisher Scoring iterations: 5

> confint(logit)

                        2.5 %        97.5 %
(Intercept)     -3.2063351906  3.002071e+00
CHK_ACCT1       -0.2015859939  9.617137e-01
CHK_ACCT2        0.3706373386  2.357903e+00
CHK_ACCT3        1.2649147013  2.483309e+00
DURATION        -0.0615291292 -1.245575e-02
HISTORY1        -1.3543807890  1.849954e+00
HISTORY2        -0.1732084618  2.433398e+00
HISTORY3         0.4977459146  3.343435e+00
HISTORY4         1.0548571647  3.717226e+00
NEW_CAR         -1.7738796827  2.845090e-01
USED_CAR        -0.2635782167  2.400403e+00
FURNITURE       -0.7823098999  1.392642e+00
RADIO.TV        -0.7018959248  1.352020e+00
EDUCATION       -2.5004504936  1.522616e-01
RETRAINING      -1.1339491571  1.190497e+00
AMOUNT          -0.0002757537 -3.240653e-05
SAV_ACCT1       -0.2581830784  1.333756e+00
SAV_ACCT2       -1.0662554758  8.964553e-01
SAV_ACCT3        0.4613739482  3.521840e+00
SAV_ACCT4        0.3728669872  1.774989e+00
EMPLOYMENT1     -0.4800061097  1.731419e+00
EMPLOYMENT2     -0.5423158477  1.575124e+00
EMPLOYMENT3      0.1679229661  2.538261e+00
EMPLOYMENT4     -0.3539151781  1.793599e+00
INSTALL_RATE    -0.5894593436 -9.138965e-02
MALE_DIV        -1.8084035624  3.129979e-01
MALE_SINGLE     -0.2845760285  8.305893e-01
```

```
MALE_MAR_or_WID  -0.6459920388  1.041097e+00
CO.APPLICANT     -1.7562837391  5.090849e-01
GUARANTOR        -0.2182255182  1.996404e+00
PRESENT_RESIDENT -0.1474113942  3.266883e-01
REAL_ESTATE      -0.7378036695  4.087772e-01
PROP_UNKN_NONE   -1.2648083616  7.809314e-01
AGE              -0.0126216177  3.656521e-02
OTHER_INSTALL    -1.1598786021 -3.259447e-02
RENT             -1.4644289302  1.070742e+00
OWN_RES          -0.9265735081  1.394243e+00
NUM_CREDITS      -0.7955882483  2.235612e-01
JOB1             -2.0578340242  1.511506e+00
JOB2             -2.0104097095  1.413896e+00
JOB3             -1.5706981657  1.902724e+00
NUM_DEPENDENTS   -0.6903890299  6.115326e-01
TELEPHONE        -0.4536461112  6.146903e-01
FOREIGN           0.5601694533  4.550100e+00
```

```
> residuals(logit)
```

```
          1           2           3           4           5           9
 0.27658938 -0.70745956  0.26031200  0.96285619 -0.78091812  0.14471802
         10          17          19          20          23          24
-0.82960779  0.17438277 -0.91198870  0.54979701  0.29479334  0.20880762
         25          27          29          30          31          33
 0.04862382  0.54535137  0.58357349 -0.72045864  0.59020983  1.33280097
         35          38          39          40          41          42
 0.71014300 -1.15142024  0.46878252  0.89028073  0.71277786  1.26500871
         45          46          49          50          51          53
-0.88196827  0.38400917  0.40302983  0.65273665  0.67054505  0.41731826
         55          57          60          61          62          63
-0.71142399 -1.84894169 -0.58102823  1.09571430  0.20410459 -0.82032605
         64          65          67          68          70          71
-0.26134110  0.65463696  0.53238217  0.79480171  0.51257570  0.77759519
         73          74          75          76          77          79
 0.65465975  1.17197065 -1.01655513  0.36474180 -0.78791273  0.86514710
         80          82          83          86          87          90
 1.14738766  0.53610483  0.54485543  0.22452247  0.76826154 -0.90758986
         91          95          98          99         100         103
 0.19149555  0.51339005  0.91856030  0.74770385  0.37618695  0.31052324
        104         105         106         107         112         115
 0.39774409  0.17489301 -1.15545192 -1.06157760  1.31169279  1.04227288
        116         117         118         119         122         123
 0.31506449 -1.39110675  0.21273095 -1.47600155  0.29187104  0.57482794
        125         126         128         130         134         136
-1.45869141  1.16412454 -1.34690556 -0.82376254  0.86801372  0.18250831
```

```
       137         138         142         143         145         146 
 0.17883779 -1.59778633  1.50897246  1.11848700  0.33238714  1.55174344 
       147         150         152         155         157         159 
 0.63600164  0.10423581  0.08280896  0.63001846  0.10071723  1.09729601 
       161         162         163         166         167         168 
 0.20385032  0.61163007  0.43201213  0.30586163 -0.89212366  0.53152738 
       169         170         171         172         174         177 
 0.44975955 -1.20280356 -0.42687108  0.58599551  0.22378190  1.28490783 
       178         179         180         182         184         185 
 0.47977999  0.37184174  0.94885291 -0.76307521  0.13701741 -1.41864831 
       186         187         188         189         190         192 
 0.31551697 -1.49846060  0.80153818 -1.79906631  1.53891593 -0.66980377 
       193         195         198         202         205         206 
-0.96526654 -1.23852387 -0.89641647  1.60813038  0.50014714  1.01327815 
       207         208         211         213         216         218 
 0.29192076  0.41890859  0.12739240 -0.39742634  0.15862334  0.86105846 
       219         220         222         225         226         230 
 1.82087954  0.46676765  1.75519087  0.37585140  1.47818274  1.90841083 
       231         232         233         234         236         237 
-1.26573361  0.58110397  0.25846246  0.78888305 -0.80481474 -1.02085472 
       238         241         242         243         244         245 
-0.65625559 -0.85623352  0.22640693 -0.48529569  0.36843929  1.11171267 
       247         249         250         252         257         258 
 0.26014723  0.64137567 -1.37520741  0.42594979  0.42712958 -0.43354974 
       260         262         264         265         266         267 
 0.31987808  1.10624197  0.74692643  0.12268555 -1.58933228  0.40146481 
       268         269         272         274         276         277 
 0.74602482 -1.74291754  0.19086916 -1.00329205  0.33809349  0.30444485 
       280         281         284         285         287         290 
 0.42145952  0.10362142  0.11482208  1.27993411  1.20707179 -1.30165165 
       291         293         295         296         298         299 
 0.14772632  0.58714471  0.87903772 -0.74061907  0.17312917  0.44515219 
       300         302         304         305         307         308 
 0.18033341 -0.54371133  0.83672917 -0.88479280  0.30966495 -1.55209656 
       313         314         318         319         320         322 
 0.67027653 -1.40738769  0.50847968  0.57917072  0.66784523 -0.76715954 
       323         324         326         328         330         331 
 0.55669546  0.60713462  0.17382553  0.29484221  0.72416258  0.60685833 
       332         333         336         337         338         342 
-1.78253077 -0.42036804 -1.91909686  0.52226782 -1.21487496  0.84717397 
       345         346         350         351         354         355 
 0.48190735  0.29248498 -1.99908877  0.43298493 -0.45742320  0.85490034 
       356         357         358         359         362         363 
-0.61255931  0.10624364 -1.95612423  0.52482009  0.20815767  0.85088734 
       364         366         369         370         372         374 
 0.37362324  0.23283687 -0.90739846  0.77289123  0.31551224  0.93627090 
```

```
       375        376        377        381        382        384 
-0.20297565 -0.68940640  0.43915324  0.49562406 -0.86905023  1.04764469 
       389        390        391        392        394        397 
 0.66435632  0.40315692  0.53587566  0.34345458  0.25952823  1.16426422 
       398        399        400        401        402        403 
 0.90977940 -0.79623044  0.18341525  0.41355789  0.68279115 -1.61644921 
       404        405        406        407        408        410 
 0.62035251  0.65270465 -1.62172971  0.09242299  0.45394345 -1.95593668 
       411        413        414        416        418        419 
 1.10861081 -2.14520566  0.32369106  0.28357706  1.47800030  0.55254468 
       420        425        427        428        430        431 
-1.26215725 -1.97967151  0.40210989  0.12715224 -1.40835571  0.17946231 
       432        433        437        440        444        445 
-0.53388322  0.84607433  0.32731930 -1.33295866 -1.44185872 -1.61310120 
       446        448        449        452        454        456 
 0.37911206  0.50200140  0.22121141  0.44782547  0.28914759  0.46107648 
       457        459        460        462        463        464 
 1.21895191  1.25313944  0.51829573  1.26919320  1.03580558  0.59937721 
       466        468        469        470        471        472 
 0.73395686  0.64322773  0.56459984  0.21137877 -1.32936674 -0.80398595 
       473        474        475        477        478        479 
-0.96750682  0.27134597 -1.89413388  0.60223636  0.88984645  0.46156503 
       480        483        485        487        490        491 
 0.59424048  0.84926766  0.40830999  0.30753765  0.49401828  0.23582057 
       492        494        495        497        498        499 
-0.59197657  0.39256946  0.48449219 -0.58462577  0.23140910  0.71511220 
       500        505        506        509        511        512 
 0.44153756 -0.57293692 -2.53068672  0.62290415 -1.12790093  0.46379636 
       513        514        516        520        522        524 
 0.45200597  1.17162970  0.25265169  0.15458017 -1.13886538  0.23777402 
       527        528        530        531        532        533 
 0.48831145  0.13387234  1.11601821  1.67583269 -1.05191108  0.28237128 
       534        535        536        537        540        542 
 0.30473612  0.45371867 -1.23624146  0.85691673  0.65631890  0.68235657 
       543        546        548        549        552        554 
-1.28576342 -0.62148321  0.48270423 -0.66425374  0.52644720  0.72145806 
       556        560        561        562        564        565 
-1.45396463 -2.02523307  0.83277765 -1.04575434 -0.76313979  0.80837536 
       568        570        572        574        575        576 
 0.09135836 -0.56711333  0.37194029  1.28757402  0.83643062  0.35062432 
       578        579        583        586        587        589 
 0.44148240 -0.68380329  0.70239603 -0.97550463  1.11680340 -1.10877016 
       590        593        594        595        598        599 
-2.07897031  0.36070894 -0.69690045 -1.18633590 -0.79455415 -2.26639741 
       600        601        602        604        608        609 
 0.43349472  0.44861157 -1.35693800 -1.68264442 -0.82571293  0.58787776 
```

```
        610         614         615         616         617         621 
 0.28263687  0.46755342 -2.38679918  1.99377185  1.12189242  0.46747352 
        623         625         628         632         633         635 
-0.95926779 -1.03529827 -1.46078579 -0.71772556  0.63776132 -0.97740611 
        636         637         639         641         642         643 
 1.14968053  0.50984645  0.50153632 -0.46826358  1.01159550 -1.84952698 
        644         645         646         648         649         650 
 0.16993871  0.47576021 -1.78993395 -1.73775199 -1.18058400 -0.69267485 
        652         653         655         656         657         658 
-1.44835076 -0.53008626  0.16897341  1.70748179 -0.98365429  0.80277651 
        660         661         662         664         665         666 
 0.60285443  0.68653237 -1.23190775  0.87002640  0.41255199  1.14914539 
        667         669         671         673         675         676 
 1.14964957 -0.98554370  0.32472288  1.33146101 -1.79988115  0.31085982 
        677         678         679         680         682         683 
 0.34130062 -0.72764296  1.50122154  0.56848880  0.33195574  0.56386267 
        685         688         690         692         694         695 
 0.73613583  1.36373325  0.57561702  1.02873524  0.48202914  0.41584836 
        696         699         700         703         704         706 
 0.23462742  0.35775167  0.97728201  0.67218530  1.07246472  0.82671055 
        707         709         710         712         713         715 
-0.81069607  0.91868281  0.73072758 -0.46518635  0.16354207 -0.30313679 
        716         718         722         723         725         726 
 0.11555637  0.51831747 -0.84501520 -0.69808440 -1.07659091  0.18985286 
        727         729         730         736         737         738 
 0.22678159 -0.32023581  0.25049186  1.70506865 -1.14500858  1.33055769 
        739         741         742         743         745         746 
 0.21607930  1.49662760  1.50779983  0.30315521  0.84572786  0.94880181 
        747         749         750         752         755         757 
 1.71664471  0.19110212  0.19224839 -1.09521451 -2.90872649  0.10663956 
        758         759         761         763         766         767 
-2.73148775  0.50096642  0.17170266  1.11194008  0.75195413 -0.89073659 
        768         770         772         773         774         775 
 0.17735006  0.15543588 -0.52897397  0.09291075  0.30148054  0.78295435 
        776         777         778         781         782         787 
-0.80522715  0.51338444  0.87631007 -2.12819265  0.17023610  0.44778048 
        788         790         792         794         795         796 
 0.21832556 -0.40568134  0.18916837  1.03397628  0.80099346  0.35488968 
        797         798         799         800         801         802 
-2.18657401  0.27492340  0.32519154  0.79477089  0.71316952  0.57897504 
        803         804         806         807         810         811 
 0.63265210  0.13934863 -0.63868306  0.25151462 -0.53352786  0.87930771 
        813         814         815         816         817         818 
-1.52801395 -0.83171030 -0.53462389  1.71291985  0.44860657  0.15544183 
        819         820         822         823         824         825 
 2.81456332 -0.86667570  0.66320680 -0.97473804  0.84977604  0.39795181 
```

```
        826         827         828         830         833         836
 1.14939605 -0.89800164 -1.14019601  1.24257689 -0.23414053 -0.43070659
        837         838         839         843         845         846
 0.33533451  0.35561301  0.48392557 -1.71988917  0.78807811  0.37008374
        847         849         850         852         853         854
-1.90472574  0.53691092 -1.30945283  0.08786790  0.34729786 -0.58974541
        855         857         858         859         860         861
 1.04714294  0.21068372  0.39894702 -0.72633562  0.13436345  0.16550501
        862         863         865         866         867         868
-2.15101981 -1.02156006 -1.83378359  0.56711148  1.62858240  0.22827346
        870         873         877         878         879         881
 1.20124980  0.61069334  1.79052178  0.76813641 -1.07061071  0.27285037
        883         886         887         888         889         890
 0.76374008 -0.83033534  0.41407405 -0.39495832  0.69429616  0.61447649
        891         892         893         895         896         897
 1.14932262  0.23868163  0.51672304  0.18220260  0.22189564  1.25323656
        898         900         901         902         903         904
 0.02244865 -1.11914811 -1.70057193  0.40273506  0.27120371  0.38707984
        905         908         909         914         915         916
 0.45018241  1.40206672  0.19734416  0.22812122 -0.51216097 -0.56106481
        917         919         920         921         922         924
 0.25808906 -1.00638500 -1.13620438  0.45646527  0.76719296  1.01093491
        925         926         927         928         929         931
-0.40704126 -0.48661939  0.86974843 -0.45293580  0.28139959  0.69309498
        932         933         937         938         939         940
-1.39808538  0.45386760 -1.91887727  0.80774257 -0.23763055  0.11086880
        941         943         947         948         950         951
 0.26922394  0.30008460 -0.58905277  0.52683815 -2.32422726  0.89090328
        954         955         959         961         962         963
-0.84927884  1.22483217 -0.70132021  0.25162909  1.19332642  0.57481093
        964         966         971         972         973         974
-1.70437458  0.95454931  0.71619855  0.79193131 -0.31599589 -0.23588197
        975         978         979         982         983         984
 0.43529989  0.54172931 -1.84219539 -0.90570290  0.78537806 -1.01555782
        986         988         992         993         998        1000
 1.01359888  0.33134949  0.64958275  0.55043387  0.36621902  0.67473182

>
```

Using the model with the test data

The test data is then run through the model

```
> p.test <- predict(logit, gc.test, type="response")
> summary(p.test)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.01537 0.48390 0.76120 0.68070 0.92110 0.99980
```

Classification Table

A baseline Classification Table with cutoff = 50% is given

```
> library(gmodels)
> p.test.vals <- sapply(p.test, function(y) { ifelse(y<.5,0, 1) })
> CrossTable(gc.test$RESPONSE, p.test.vals, dnn = c("Actual", "Predicted"))
```

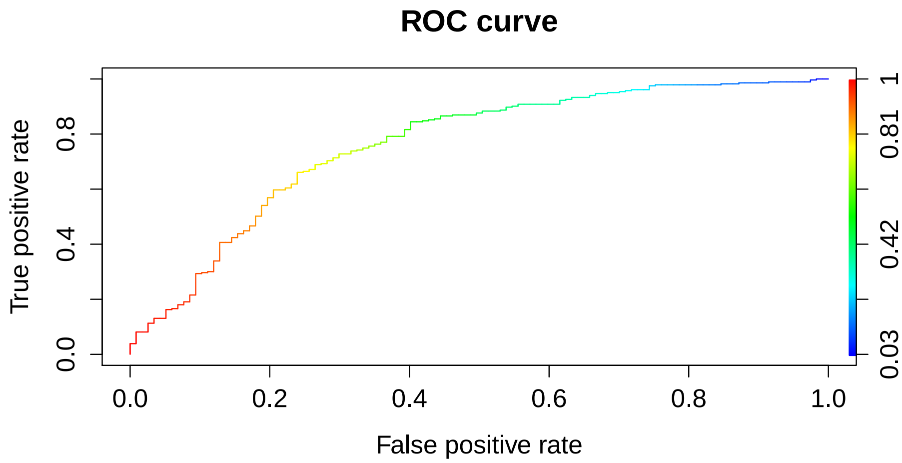
```
   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted 
      Actual |         0 |         1 | Row Total | 
-------------|-----------|-----------|-----------|
           0 |        56 |        56 |       112 | 
             |    25.578 |     8.870 |           | 
             |     0.500 |     0.500 |     0.280 | 
             |     0.544 |     0.189 |           | 
             |     0.140 |     0.140 |           | 
-------------|-----------|-----------|-----------|
           1 |        47 |       241 |       288 | 
             |     9.947 |     3.450 |           | 
             |     0.163 |     0.837 |     0.720 | 
             |     0.456 |     0.811 |           | 
             |     0.117 |     0.603 |           | 
-------------|-----------|-----------|-----------|
Column Total |       103 |       297 |       400 | 
             |     0.258 |     0.743 |           | 
-------------|-----------|-----------|-----------|
```

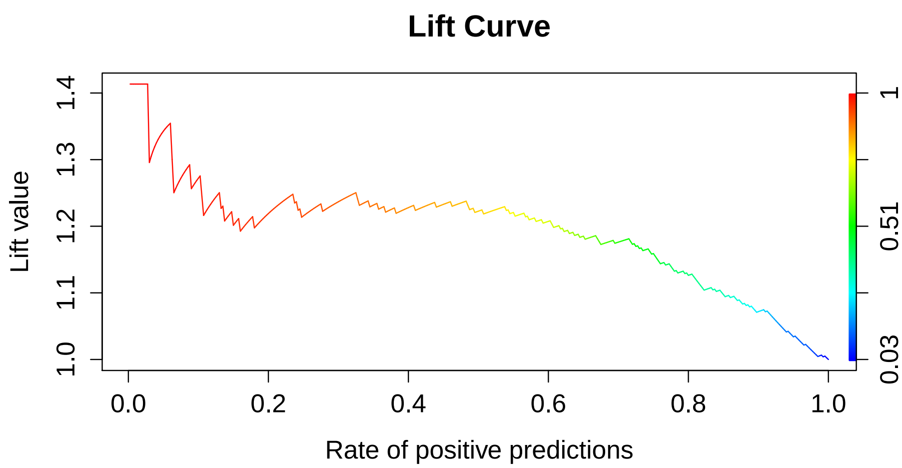
ROC Curve

```
> library(ROCR)
> p.rocr <- prediction(p.test, gc.test$RESPONSE)
> p.rocr.roc <- performance(p.rocr, "tpr", "fpr")
> plot(p.rocr.roc, main="ROC Curve", colorize=T)
```



Lift Curve

```
> p.rocr.lift <- performance(p.rocr, "lift", "rpp")
> plot(p.rocr.lift, main="Lift Curve", colorize=T)
```



0.1 Classification Table with different cutoff values

```
> calcNetProfit <- function(facts, preds, cutoff) {
+   vals <- sapply(preds, function(y) { ifelse(y<cutoff,0, 1) })
+   ct <- CrossTable(facts, vals, dnn = c("Actual", "Predicted"))
+   print("Profit with cutoff")
+   print(cutoff)
```

```
+   profitFromCrossTable(ct)
+ }
> profitFromCrossTable <- function(ct) {
+   profit <- ct$t[1,1] * 100
+   loss <- ct$t[2,1] * -500
+   profit - loss
+ }
> s <- seq(0,1, by = .1)
> for(i in s) { print(calcNetProfit(gc.test$RESPONSE, p.test, i)) }

   Cell Contents
|-------------------------|
|                       N |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | vals 
       facts |         1 | Row Total | 
-------------|-----------|-----------|
           0 |       112 |       112 | 
             |     0.280 |           | 
-------------|-----------|-----------|
           1 |       288 |       288 | 
             |     0.720 |           | 
-------------|-----------|-----------|
Column Total |       400 |       400 | 
-------------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0
[1] 155200


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|
```

```
Total Observations in Table:  400


             | Predicted 
      Actual |         0 |         1 | Row Total | 
-------------|-----------|-----------|-----------|
           0 |         8 |       104 |       112 | 
             |     5.222 |     0.175 |           | 
             |     0.071 |     0.929 |     0.280 | 
             |     0.615 |     0.269 |           | 
             |     0.020 |     0.260 |           | 
-------------|-----------|-----------|-----------|
           1 |         5 |       283 |       288 | 
             |     2.031 |     0.068 |           | 
             |     0.017 |     0.983 |     0.720 | 
             |     0.385 |     0.731 |           | 
             |     0.013 |     0.708 |           | 
-------------|-----------|-----------|-----------|
Column Total |        13 |       387 |       400 | 
             |     0.033 |     0.968 |           | 
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.1
[1] 3300


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted 
      Actual |         0 |         1 | Row Total | 
-------------|-----------|-----------|-----------|
```

```
            0 |        21 |        91 |       112 | 
              |    14.967 |     1.346 |           | 
              |     0.188 |     0.812 |     0.280 | 
              |     0.636 |     0.248 |           | 
              |     0.052 |     0.228 |           | 
-------------|-----------|-----------|-----------|
            1 |        12 |       276 |       288 | 
              |     5.821 |     0.523 |           | 
              |     0.042 |     0.958 |     0.720 | 
              |     0.364 |     0.752 |           | 
              |     0.030 |     0.690 |           | 
-------------|-----------|-----------|-----------|
Column Total |        33 |       367 |       400 | 
              |     0.083 |     0.917 |           | 
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.2
[1] 8100


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted 
      Actual |         0 |         1 | Row Total | 
-------------|-----------|-----------|-----------|
            0 |        30 |        82 |       112 | 
              |    18.286 |     2.612 |           | 
              |     0.268 |     0.732 |     0.280 | 
              |     0.600 |     0.234 |           | 
              |     0.075 |     0.205 |           | 
-------------|-----------|-----------|-----------|
            1 |        20 |       268 |       288 | 
              |     7.111 |     1.016 |           | 
```

```
             |     0.069 |     0.931 |     0.720 |
             |     0.400 |     0.766 |           |
             |     0.050 |     0.670 |           |
-------------|-----------|-----------|-----------|
Column Total |        50 |       350 |       400 |
             |     0.125 |     0.875 |           |
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.3
[1] 13000


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted
      Actual |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |        46 |        66 |       112 |
             |    24.864 |     6.216 |           |
             |     0.411 |     0.589 |     0.280 |
             |     0.575 |     0.206 |           |
             |     0.115 |     0.165 |           |
-------------|-----------|-----------|-----------|
           1 |        34 |       254 |       288 |
             |     9.669 |     2.417 |           |
             |     0.118 |     0.882 |     0.720 |
             |     0.425 |     0.794 |           |
             |     0.085 |     0.635 |           |
-------------|-----------|-----------|-----------|
Column Total |        80 |       320 |       400 |
             |     0.200 |     0.800 |           |
-------------|-----------|-----------|-----------|
```

```
[1] "Profit with cutoff"
[1] 0.4
[1] 21600


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted
      Actual |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |        56 |        56 |       112 |
             |    25.578 |     8.870 |           |
             |     0.500 |     0.500 |     0.280 |
             |     0.544 |     0.189 |           |
             |     0.140 |     0.140 |           |
-------------|-----------|-----------|-----------|
           1 |        47 |       241 |       288 |
             |     9.947 |     3.450 |           |
             |     0.163 |     0.837 |     0.720 |
             |     0.456 |     0.811 |           |
             |     0.117 |     0.603 |           |
-------------|-----------|-----------|-----------|
Column Total |       103 |       297 |       400 |
             |     0.258 |     0.743 |           |
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.5
[1] 29100


   Cell Contents
|-------------------------|
```

```
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted
      Actual |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |        68 |        44 |       112 |
             |    24.128 |    12.292 |           |
             |     0.607 |     0.393 |     0.280 |
             |     0.504 |     0.166 |           |
             |     0.170 |     0.110 |           |
-------------|-----------|-----------|-----------|
           1 |        67 |       221 |       288 |
             |     9.383 |     4.780 |           |
             |     0.233 |     0.767 |     0.720 |
             |     0.496 |     0.834 |           |
             |     0.168 |     0.552 |           |
-------------|-----------|-----------|-----------|
Column Total |       135 |       265 |       400 |
             |     0.338 |     0.662 |           |
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.6
[1] 40300


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|
```

```
Total Observations in Table:  400


             | Predicted
      Actual |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |        78 |        34 |       112 |
             |    18.489 |    13.948 |           |
             |     0.696 |     0.304 |     0.280 |
             |     0.453 |     0.149 |           |
             |     0.195 |     0.085 |           |
-------------|-----------|-----------|-----------|
           1 |        94 |       194 |       288 |
             |     7.190 |     5.424 |           |
             |     0.326 |     0.674 |     0.720 |
             |     0.547 |     0.851 |           |
             |     0.235 |     0.485 |           |
-------------|-----------|-----------|-----------|
Column Total |       172 |       228 |       400 |
             |     0.430 |     0.570 |           |
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.7
[1] 54800


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted
      Actual |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |        92 |        20 |       112 |
             |    16.062 |    19.046 |           |
```

```
             |     0.821 |     0.179 |     0.280 |
             |     0.424 |     0.109 |           |
             |     0.230 |     0.050 |           |
-------------|-----------|-----------|-----------|
           1 |       125 |       163 |       288 |
             |     6.246 |     7.407 |           |
             |     0.434 |     0.566 |     0.720 |
             |     0.576 |     0.891 |           |
             |     0.312 |     0.407 |           |
-------------|-----------|-----------|-----------|
Column Total |       217 |       183 |       400 |
             |     0.542 |     0.458 |           |
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.8
[1] 71700


   Cell Contents
|-------------------------|
|                       N |
| Chi-square contribution |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | Predicted
      Actual |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |       103 |         9 |       112 |
             |     7.719 |    18.011 |           |
             |     0.920 |     0.080 |     0.280 |
             |     0.368 |     0.075 |           |
             |     0.258 |     0.022 |           |
-------------|-----------|-----------|-----------|
           1 |       177 |       111 |       288 |
             |     3.002 |     7.004 |           |
             |     0.615 |     0.385 |     0.720 |
             |     0.632 |     0.925 |           |
```

```
             |     0.443 |     0.278 |           |
-------------|-----------|-----------|-----------|
Column Total |       280 |       120 |       400 |
             |     0.700 |     0.300 |           |
-------------|-----------|-----------|-----------|


[1] "Profit with cutoff"
[1] 0.9
[1] 98800


   Cell Contents
|-------------------------|
|                       N |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  400


             | vals
       facts |         0 | Row Total |
-------------|-----------|-----------|
           0 |       112 |       112 |
             |     0.280 |           |
-------------|-----------|-----------|
           1 |       288 |       288 |
             |     0.720 |           |
-------------|-----------|-----------|
Column Total |       400 |       400 |
-------------|-----------|-----------|


[1] "Profit with cutoff"
[1] 1
[1] 155200
```

Lesson 3 Question and Answer

1

Comments on the models

2

If you want to select 275 customers from the validation data set, which model would you adopt for credit rating? Why?

With a value for k too small we will classify in a way that is very sensitive to the local characteristcs of the training data.

With a value of k too large we essentially overfit, ignoring the information contained in the predictor variables. In the extreme with k equal the number of observations in the train data all test data is assigned to the most frequent class in the train data, Owner in the present case.