

Data Processing Assignment

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Introduction

We will be preparing the salary dataset, extracted from the 1994 US Census, for a logistic regression.

We will determine whether a person makes over 50k a year; *class* will be the dependent variable.

Data Import

```
train = read.csv('salary-train.csv')
test = read.csv('salary-test.csv')
str(train)

## 'data.frame':    32561 obs. of  14 variables:
## $ age           : int  39 50 38 53 28 37 49 52 31 42 ...
## $ workclass      : Factor w/ 9 levels " ?"," Federal-gov",...: 8 7 5 5 5 5
5 7 5 5 ...
## $ fnlwgt        : int  77516 83311 215646 234721 338409 284582 160187 209
642 45781 159449 ...
## $ education     : Factor w/ 16 levels " 10th"," 11th",...: 10 10 12 2 10 1
3 7 12 13 10 ...
## $ marital       : Factor w/ 7 levels " Divorced"," Married-AF-spouse",...:
5 3 1 3 3 3 4 3 5 3 ...
## $ occupation    : Factor w/ 15 levels " ?"," Adm-clerical",...: 2 5 7 7 11
5 9 5 11 5 ...
## $ relationship  : Factor w/ 6 levels " Husband"," Not-in-family",...: 2 1
2 1 6 6 2 1 2 1 ...
## $ race          : Factor w/ 5 levels " Amer-Indian-Eskimo",...: 5 5 5 3 3
5 3 5 5 5 ...
## $ sex           : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 1 1 2 1
2 ...
## $ capital.gain   : int  2174 0 0 0 0 0 0 0 14084 5178 ...
## $ capital.loss   : int  0 0 0 0 0 0 0 0 0 0 ...
## $ hours.per.week : int  40 13 40 40 40 40 16 45 50 40 ...
## $ native.country : Factor w/ 42 levels " ?"," Cambodia",...: 40 40 40 40 6
40 24 40 40 40 ...
## $ class         : Factor w/ 2 levels " <=50K"," >50K": 1 1 1 1 1 1 1 2 2
2 ...

str(test)

## 'data.frame':    16281 obs. of  14 variables:
## $ age           : int  25 38 28 44 18 34 29 63 24 55 ...
## $ workclass      : Factor w/ 9 levels " ?"," Federal-gov",...: 5 5 3 5 1 5
```

```

1 7 5 5 ...
## $ fnlwtg      : int   226802 89814 336951 160323 103497 198693 227026 10
4626 369667 104996 ...
## $ education   : Factor w/ 16 levels " 10th"," 11th",...: 2 12 8 16 16 1
12 15 16 6 ...
## $ marital     : Factor w/ 7 levels " Divorced"," Married-AF-spouse",...:
5 3 3 3 5 5 5 3 5 3 ...
## $ occupation  : Factor w/ 15 levels " ?"," Adm-clerical",...: 8 6 12 8 1
9 1 11 9 4 ...
## $ relationship : Factor w/ 6 levels " Husband"," Not-in-family",...: 4 1
1 1 4 2 5 1 5 1 ...
## $ race        : Factor w/ 5 levels " Amer-Indian-Eskimo",...: 3 5 5 3 5
5 3 5 5 5 ...
## $ sex         : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 2 2 2 1
2 ...
## $ capital.gain : int    0 0 0 7688 0 0 0 3103 0 0 ...
## $ capital.loss : int    0 0 0 0 0 0 0 0 0 0 ...
## $ hours.per.week: int   40 50 40 40 30 30 40 32 40 10 ...
## $ native.country: Factor w/ 41 levels " ?"," Cambodia",...: 39 39 39 39 39
39 39 39 39 39 ...
## $ class       : Factor w/ 2 levels " <=50K.", " >50K.": 1 1 2 2 1 1 1 2
1 1 ...

```

We first import our datasets and determine which columns contain missing values.

From a glance, we can tell that the *workclass*, *occupation* and *native.country* columns contain missing values, indicated by question marks.

Setting Entries with Question Marks as NA Values

```

# train set
train$workclass = as.factor(gsub('?', NA, train$workclass, fixed = T))
train$native.country = as.factor(gsub('?', NA, train$native.country, fixed =
T))
train$occupation = as.factor(gsub('?', NA, train$occupation, fixed = T))

# test set
test$workclass = as.factor(gsub('?', NA, test$workclass, fixed = T))
test$native.country = as.factor(gsub('?', NA, test$native.country, fixed = T)
)
test$occupation = as.factor(gsub('?', NA, test$occupation, fixed = T))

```

Since the missing values exist in both the training and testing datasets, therefore we have to indicate them as NA values before we may exclude them.

Removing Incomplete Cases

```

train = train[complete.cases(train), ]
test = test[complete.cases(test), ]
str(train)

```

```
## 'data.frame':    30162 obs. of  14 variables:
## $ age           : int  39 50 38 53 28 37 49 52 31 42 ...
## $ workclass     : Factor w/ 8 levels " Federal-gov",...: 7 6 4 4 4 4 4 6 4
4 ...
## $ fnlwgt       : int  77516 83311 215646 234721 338409 284582 160187 209
642 45781 159449 ...
## $ education    : Factor w/ 16 levels " 10th"," 11th",...: 10 10 12 2 10 1
3 7 12 13 10 ...
## $ marital      : Factor w/ 7 levels " Divorced"," Married-AF-spouse",...:
5 3 1 3 3 3 4 3 5 3 ...
## $ occupation   : Factor w/ 14 levels " Adm-clerical",...: 1 4 6 6 10 4 8
4 10 4 ...
## $ relationship : Factor w/ 6 levels " Husband"," Not-in-family",...: 2 1
2 1 6 6 2 1 2 1 ...
## $ race         : Factor w/ 5 levels " Amer-Indian-Eskimo",...: 5 5 5 3 3
5 3 5 5 5 ...
## $ sex          : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 1 1 2 1
2 ...
## $ capital.gain  : int  2174 0 0 0 0 0 0 0 14084 5178 ...
## $ capital.loss  : int  0 0 0 0 0 0 0 0 0 0 ...
## $ hours.per.week: int  40 13 40 40 40 40 16 45 50 40 ...
## $ native.country: Factor w/ 41 levels " Cambodia"," Canada",...: 39 39 39
39 5 39 23 39 39 39 ...
## $ class        : Factor w/ 2 levels " <=50K"," >50K": 1 1 1 1 1 1 1 2 2
2 ...
```

`str(test)`

```
## 'data.frame':    15060 obs. of  14 variables:
## $ age           : int  25 38 28 44 34 63 24 55 65 36 ...
## $ workclass     : Factor w/ 8 levels " Federal-gov",...: 4 4 2 4 4 6 4 4 4
1 ...
## $ fnlwgt       : int  226802 89814 336951 160323 198693 104626 369667 10
4996 184454 212465 ...
## $ education    : Factor w/ 16 levels " 10th"," 11th",...: 2 12 8 16 1 15
16 6 12 10 ...
## $ marital      : Factor w/ 7 levels " Divorced"," Married-AF-spouse",...:
5 3 3 3 5 3 5 3 3 3 ...
## $ occupation   : Factor w/ 14 levels " Adm-clerical",...: 7 5 11 7 8 10 8
3 7 1 ...
## $ relationship : Factor w/ 6 levels " Husband"," Not-in-family",...: 4 1
1 1 2 1 5 1 1 1 ...
## $ race         : Factor w/ 5 levels " Amer-Indian-Eskimo",...: 3 5 5 3 5
5 5 5 5 5 ...
## $ sex          : Factor w/ 2 levels " Female"," Male": 2 2 2 2 2 2 1 2 2
2 ...
## $ capital.gain  : int  0 0 0 7688 0 3103 0 0 6418 0 ...
## $ capital.loss  : int  0 0 0 0 0 0 0 0 0 0 ...
## $ hours.per.week: int  40 50 40 40 30 32 40 10 40 40 ...
## $ native.country: Factor w/ 40 levels " Cambodia"," Canada",...: 38 38 38
```

```
38 38 38 38 38 38 38 ...
## $ class      : Factor w/ 2 levels " <=50K.", " >50K.": 1 1 2 2 1 2 1 1
2 1 ...
```

We run the *complete.cases* function to remove the NA values from both datasets. After that we use the *str* function again to ascertain that the variables are in the formats we need, without anymore missing entries.

Full Model

```
fit = suppressWarnings(glm(formula = class ~ .,
                           family = binomial,
                           data = train))
```

We start to train our training set using a logistic classifier, with *class* as our target variable. We use the rest of the variables as input.

Prediction the Test Set Results

```
prob_pred = predict(fit, type = 'response', newdata = test[-14])
y_pred = ifelse(prob_pred > 0.5, '>50K', '<=50K')
```

Confusion Matrix

```
cm = table(test[, 14], y_pred)
cm
```

```
##           y_pred
##           <=50K  >50K
## <=50K.  10530    830
## >50K.    1465    2235
```

Computing the Accuracy and Error Rates

```
acc = sum(diag(cm)) / sum(cm)
acc
```

```
## [1] 0.8476096
```

```
err = 1 - acc
err
```

```
## [1] 0.1523904
```

Model has a **84.76%** accuracy rate / **15.24%** error rate.

Let us see if we can improve the error rate through feature selection.

```
summary(fit)
```

```
##
## Call:
## glm(formula = class ~ ., family = binomial, data = train)
##
## Deviance Residuals:
```

```

##      Min      1Q   Median      3Q      Max
## -5.1182 -0.5148 -0.1885  0.0000  3.7839
##
## Coefficients:
##                                Estimate Std. Error z value
## (Intercept)                   -6.408e+00  7.636e-01  -8.392
## age                           2.550e-02  1.712e-03  14.890
## workclass Local-gov            -6.985e-01  1.130e-01  -6.184
## workclass Private              -5.055e-01  9.379e-02  -5.390
## workclass Self-emp-inc         -3.293e-01  1.239e-01  -2.658
## workclass Self-emp-not-inc     -9.972e-01  1.100e-01  -9.063
## workclass State-gov           -8.207e-01  1.254e-01  -6.544
## workclass Without-pay         -1.329e+01  1.972e+02  -0.067
## fnlwgt                         7.515e-07  1.762e-07   4.264
## education 11th                 9.462e-02  2.139e-01   0.442
## education 12th                 4.443e-01  2.784e-01   1.596
## education 1st-4th             -4.398e-01  4.960e-01  -0.887
## education 5th-6th            -3.956e-01  3.590e-01  -1.102
## education 7th-8th            -5.640e-01  2.433e-01  -2.318
## education 9th                 -2.372e-01  2.702e-01  -0.878
## education Assoc-acdm          1.269e+00  1.797e-01   7.063
## education Assoc-voc           1.268e+00  1.729e-01   7.332
## education Bachelors           1.899e+00  1.608e-01  11.807
## education Doctorate           2.935e+00  2.231e-01  13.159
## education HS-grad              7.735e-01  1.564e-01   4.945
## education Masters              2.259e+00  1.719e-01  13.138
## education Preschool           -2.008e+01  1.987e+02  -0.101
## education Prof-school          2.844e+00  2.071e-01  13.734
## education Some-college         1.109e+00  1.587e-01   6.989
## marital Married-AF-spouse       2.768e+00  5.766e-01   4.800
## marital Married-civ-spouse      2.105e+00  2.747e-01   7.663
## marital Married-spouse-absent   1.220e-02  2.404e-01   0.051
## marital Never-married          -4.861e-01  8.926e-02  -5.446
## marital Separated              -8.940e-02  1.656e-01  -0.540
## marital Widowed                1.852e-01  1.582e-01   1.171
## occupation Armed-Forces        -1.165e+00  1.547e+00  -0.753
## occupation Craft-repair         6.369e-02  8.076e-02   0.789
## occupation Exec-managerial      8.054e-01  7.794e-02  10.334
## occupation Farming-fishing     -9.809e-01  1.408e-01  -6.968
## occupation Handlers-cleaners   -6.950e-01  1.447e-01  -4.803
## occupation Machine-op-inspct   -2.633e-01  1.027e-01  -2.564
## occupation Other-service       -8.245e-01  1.191e-01  -6.920
## occupation Priv-house-serv     -4.153e+00  1.723e+00  -2.411
## occupation Prof-specialty       5.165e-01  8.253e-02   6.259
## occupation Protective-serv     5.978e-01  1.263e-01   4.734
## occupation Sales                2.943e-01  8.318e-02   3.538
## occupation Tech-support         6.648e-01  1.117e-01   5.951
## occupation Transport-moving    -8.982e-02  1.001e-01  -0.898
## relationship Not-in-family      4.522e-01  2.716e-01   1.665
## relationship Other-relative    -3.960e-01  2.477e-01  -1.599

```

## relationship Own-child	-7.322e-01	2.706e-01	-2.706
## relationship Unmarried	3.358e-01	2.873e-01	1.169
## relationship Wife	1.351e+00	1.057e-01	12.784
## race Asian-Pac-Islander	8.280e-01	2.860e-01	2.896
## race Black	4.359e-01	2.409e-01	1.810
## race Other	1.255e-01	3.786e-01	0.332
## race White	5.875e-01	2.291e-01	2.564
## sex Male	8.648e-01	8.091e-02	10.689
## capital.gain	3.225e-04	1.074e-05	30.022
## capital.loss	6.420e-04	3.845e-05	16.696
## hours.per.week	2.949e-02	1.702e-03	17.325
## native.country Canada	-8.113e-01	6.890e-01	-1.178
## native.country China	-1.916e+00	7.031e-01	-2.725
## native.country Columbia	-3.275e+00	1.031e+00	-3.177
## native.country Cuba	-7.738e-01	7.028e-01	-1.101
## native.country Dominican-Republic	-2.915e+00	1.220e+00	-2.390
## native.country Ecuador	-1.400e+00	9.587e-01	-1.461
## native.country El-Salvador	-1.745e+00	7.922e-01	-2.203
## native.country England	-8.348e-01	7.004e-01	-1.192
## native.country France	-5.604e-01	8.137e-01	-0.689
## native.country Germany	-6.860e-01	6.781e-01	-1.012
## native.country Greece	-2.126e+00	8.369e-01	-2.540
## native.country Guatemala	-1.396e+00	9.798e-01	-1.424
## native.country Haiti	-1.169e+00	9.273e-01	-1.261
## native.country Holand-Netherlands	-1.164e+01	8.827e+02	-0.013
## native.country Honduras	-2.306e+00	2.607e+00	-0.885
## native.country Hong	-1.355e+00	9.005e-01	-1.505
## native.country Hungary	-1.254e+00	9.905e-01	-1.266
## native.country India	-1.664e+00	6.682e-01	-2.491
## native.country Iran	-1.123e+00	7.578e-01	-1.482
## native.country Ireland	-6.158e-01	8.884e-01	-0.693
## native.country Italy	-3.295e-01	7.089e-01	-0.465
## native.country Jamaica	-1.125e+00	7.708e-01	-1.460
## native.country Japan	-9.413e-01	7.294e-01	-1.290
## native.country Laos	-1.883e+00	1.046e+00	-1.801
## native.country Mexico	-1.649e+00	6.648e-01	-2.481
## native.country Nicaragua	-1.880e+00	1.020e+00	-1.843
## native.country Outlying-US(Guam-USVI-etc)	-1.342e+01	2.095e+02	-0.064
## native.country Peru	-1.985e+00	1.053e+00	-1.884
## native.country Philippines	-8.782e-01	6.441e-01	-1.363
## native.country Poland	-1.146e+00	7.455e-01	-1.537
## native.country Portugal	-1.122e+00	8.849e-01	-1.268
## native.country Puerto-Rico	-1.440e+00	7.381e-01	-1.950
## native.country Scotland	-1.407e+00	1.085e+00	-1.297
## native.country South	-2.446e+00	7.356e-01	-3.325
## native.country Taiwan	-1.384e+00	7.540e-01	-1.835
## native.country Thailand	-1.831e+00	1.017e+00	-1.800
## native.country Trinidad&Tobago	-1.580e+00	1.060e+00	-1.490
## native.country United-States	-9.549e-01	6.302e-01	-1.515
## native.country Vietnam	-2.395e+00	8.452e-01	-2.834

```

## native.country Yugoslavia -4.609e-01 9.193e-01 -0.501
## Pr(>|z|)
## (Intercept) < 2e-16 ***
## age < 2e-16 ***
## workclass Local-gov 6.26e-10 ***
## workclass Private 7.06e-08 ***
## workclass Self-emp-inc 0.007857 **
## workclass Self-emp-not-inc < 2e-16 ***
## workclass State-gov 6.00e-11 ***
## workclass Without-pay 0.946265
## fnlwgt 2.01e-05 ***
## education 11th 0.658185
## education 12th 0.110525
## education 1st-4th 0.375228
## education 5th-6th 0.270456
## education 7th-8th 0.020461 *
## education 9th 0.379942
## education Assoc-acdm 1.63e-12 ***
## education Assoc-voc 2.27e-13 ***
## education Bachelors < 2e-16 ***
## education Doctorate < 2e-16 ***
## education HS-grad 7.61e-07 ***
## education Masters < 2e-16 ***
## education Preschool 0.919495
## education Prof-school < 2e-16 ***
## education Some-college 2.76e-12 ***
## marital Married-AF-spouse 1.59e-06 ***
## marital Married-civ-spouse 1.82e-14 ***
## marital Married-spouse-absent 0.959518
## marital Never-married 5.16e-08 ***
## marital Separated 0.589277
## marital Widowed 0.241607
## occupation Armed-Forces 0.451591
## occupation Craft-repair 0.430362
## occupation Exec-managerial < 2e-16 ***
## occupation Farming-fishing 3.21e-12 ***
## occupation Handlers-cleaners 1.57e-06 ***
## occupation Machine-op-inspct 0.010360 *
## occupation Other-service 4.50e-12 ***
## occupation Priv-house-serv 0.015916 *
## occupation Prof-specialty 3.87e-10 ***
## occupation Protective-serv 2.20e-06 ***
## occupation Sales 0.000403 ***
## occupation Tech-support 2.66e-09 ***
## occupation Transport-moving 0.369448
## relationship Not-in-family 0.095982 .
## relationship Other-relative 0.109885
## relationship Own-child 0.006812 **
## relationship Unmarried 0.242463
## relationship Wife < 2e-16 ***

```

```

## race Asian-Pac-Islander      0.003785 **
## race Black                    0.070321 .
## race Other                    0.740237
## race White                    0.010343 *
## sex Male                      < 2e-16 ***
## capital.gain                  < 2e-16 ***
## capital.loss                  < 2e-16 ***
## hours.per.week                < 2e-16 ***
## native.country Canada         0.238944
## native.country China          0.006439 **
## native.country Columbia       0.001490 **
## native.country Cuba           0.270924
## native.country Dominican-Republic 0.016847 *
## native.country Ecuador        0.144101
## native.country El-Salvador    0.027612 *
## native.country England        0.233300
## native.country France         0.491044
## native.country Germany        0.311750
## native.country Greece         0.011087 *
## native.country Guatemala      0.154334
## native.country Haiti          0.207295
## native.country Holand-Netherlands 0.989483
## native.country Honduras       0.376267
## native.country Hong           0.132285
## native.country Hungary        0.205684
## native.country India          0.012746 *
## native.country Iran           0.138389
## native.country Ireland        0.488248
## native.country Italy          0.642116
## native.country Jamaica        0.144361
## native.country Japan          0.196881
## native.country Laos           0.071769 .
## native.country Mexico         0.013106 *
## native.country Nicaragua      0.065264 .
## native.country Outlying-US(Guam-USVI-etc) 0.948933
## native.country Peru           0.059554 .
## native.country Philippines    0.172770
## native.country Poland         0.124250
## native.country Portugal       0.204960
## native.country Puerto-Rico    0.051129 .
## native.country Scotland       0.194512
## native.country South          0.000883 ***
## native.country Taiwan         0.066463 .
## native.country Thailand       0.071863 .
## native.country Trinidad&Tobago 0.136166
## native.country United-States  0.129711
## native.country Vietnam        0.004601 **
## native.country Yugoslavia     0.616151
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```



```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 33851  on 30161  degrees of freedom
## Residual deviance: 19486  on 30066  degrees of freedom
## AIC: 19678
##
## Number of Fisher Scoring iterations: 13
```

Model 1

We will try dropping the *race* variable as it does not appear to be significant from the p-values (mostly > 0.05).

```
fit_1 = suppressWarnings(glm(formula = class ~ . - race,
                             family = binomial,
                             data = train))

summary(fit_1)
```

```
##
## Call:
## glm(formula = class ~ . - race, family = binomial, data = train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -5.1125  -0.5152  -0.1898   0.0000   3.7969
##
## Coefficients:
##
##              Estimate Std. Error z value
## (Intercept) -5.615e+00  7.100e-01 -7.907
## age          2.567e-02  1.712e-03 14.995
## workclass Local-gov -6.884e-01  1.126e-01 -6.114
## workclass Private -4.879e-01  9.321e-02 -5.235
## workclass Self-emp-inc -3.057e-01  1.234e-01 -2.477
## workclass Self-emp-not-inc -9.791e-01  1.095e-01 -8.944
## workclass State-gov -8.076e-01  1.251e-01 -6.455
## workclass Without-pay -1.326e+01  1.973e+02 -0.067
## fnlwgt       7.227e-07  1.742e-07  4.149
## education 11th  9.811e-02  2.139e-01  0.459
## education 12th  4.474e-01  2.783e-01  1.608
## education 1st-4th -4.344e-01  4.956e-01 -0.877
## education 5th-6th -3.992e-01  3.590e-01 -1.112
## education 7th-8th -5.654e-01  2.434e-01 -2.323
## education 9th -2.331e-01  2.699e-01 -0.864
## education Assoc-acdm 1.283e+00  1.796e-01  7.143
## education Assoc-voc 1.278e+00  1.728e-01  7.400
## education Bachelors 1.912e+00  1.606e-01 11.904
## education Doctorate 2.948e+00  2.228e-01 13.232
## education HS-grad  7.806e-01  1.562e-01  4.996
```

## education Masters	2.274e+00	1.718e-01	13.239
## education Preschool	-2.000e+01	1.973e+02	-0.101
## education Prof-school	2.861e+00	2.070e-01	13.823
## education Some-college	1.115e+00	1.586e-01	7.030
## marital Married-AF-spouse	2.782e+00	5.768e-01	4.822
## marital Married-civ-spouse	2.108e+00	2.746e-01	7.679
## marital Married-spouse-absent	2.107e-03	2.399e-01	0.009
## marital Never-married	-4.861e-01	8.915e-02	-5.452
## marital Separated	-1.045e-01	1.651e-01	-0.633
## marital Widowed	1.868e-01	1.581e-01	1.182
## occupation Armed-Forces	-1.227e+00	1.508e+00	-0.814
## occupation Craft-repair	6.722e-02	8.071e-02	0.833
## occupation Exec-managerial	8.083e-01	7.789e-02	10.377
## occupation Farming-fishing	-9.770e-01	1.406e-01	-6.948
## occupation Handlers-cleaners	-6.984e-01	1.446e-01	-4.829
## occupation Machine-op-inspct	-2.704e-01	1.026e-01	-2.635
## occupation Other-service	-8.330e-01	1.190e-01	-7.002
## occupation Priv-house-serv	-4.139e+00	1.710e+00	-2.421
## occupation Prof-specialty	5.166e-01	8.240e-02	6.269
## occupation Protective-serv	5.935e-01	1.262e-01	4.704
## occupation Sales	2.975e-01	8.312e-02	3.579
## occupation Tech-support	6.726e-01	1.116e-01	6.028
## occupation Transport-moving	-9.750e-02	9.998e-02	-0.975
## relationship Not-in-family	4.532e-01	2.715e-01	1.669
## relationship Other-relative	-4.003e-01	2.479e-01	-1.615
## relationship Own-child	-7.286e-01	2.702e-01	-2.697
## relationship Unmarried	3.291e-01	2.871e-01	1.146
## relationship Wife	1.350e+00	1.057e-01	12.773
## sex Male	8.702e-01	8.089e-02	10.758
## capital.gain	3.218e-04	1.074e-05	29.968
## capital.loss	6.429e-04	3.846e-05	16.717
## hours.per.week	2.956e-02	1.702e-03	17.365
## native.country Canada	-1.056e+00	6.668e-01	-1.584
## native.country China	-1.926e+00	7.038e-01	-2.737
## native.country Columbia	-3.549e+00	1.013e+00	-3.502
## native.country Cuba	-1.028e+00	6.813e-01	-1.509
## native.country Dominican-Republic	-3.270e+00	1.206e+00	-2.711
## native.country Ecuador	-1.771e+00	9.373e-01	-1.889
## native.country El-Salvador	-1.983e+00	7.731e-01	-2.566
## native.country England	-1.090e+00	6.789e-01	-1.606
## native.country France	-8.087e-01	7.945e-01	-1.018
## native.country Germany	-9.294e-01	6.562e-01	-1.416
## native.country Greece	-2.372e+00	8.200e-01	-2.893
## native.country Guatemala	-1.657e+00	9.630e-01	-1.720
## native.country Haiti	-1.556e+00	9.098e-01	-1.711
## native.country Holand-Netherlands	-1.186e+01	8.827e+02	-0.013
## native.country Honduras	-2.551e+00	2.611e+00	-0.977
## native.country Hong	-1.375e+00	8.978e-01	-1.531
## native.country Hungary	-1.502e+00	9.750e-01	-1.541
## native.country India	-1.732e+00	6.674e-01	-2.594

## native.country Iran	-1.358e+00	7.434e-01	-1.827
## native.country Ireland	-8.421e-01	8.751e-01	-0.962
## native.country Italy	-5.712e-01	6.874e-01	-0.831
## native.country Jamaica	-1.502e+00	7.480e-01	-2.008
## native.country Japan	-1.041e+00	7.263e-01	-1.433
## native.country Laos	-1.876e+00	1.046e+00	-1.794
## native.country Mexico	-1.919e+00	6.419e-01	-2.990
## native.country Nicaragua	-2.153e+00	1.007e+00	-2.139
## native.country Outlying-US(Guam-USVI-etc)	-1.369e+01	2.102e+02	-0.065
## native.country Peru	-2.225e+00	1.040e+00	-2.140
## native.country Philippines	-9.029e-01	6.442e-01	-1.402
## native.country Poland	-1.386e+00	7.258e-01	-1.910
## native.country Portugal	-1.362e+00	8.680e-01	-1.569
## native.country Puerto-Rico	-1.789e+00	7.155e-01	-2.501
## native.country Scotland	-1.648e+00	1.072e+00	-1.538
## native.country South	-2.458e+00	7.361e-01	-3.339
## native.country Taiwan	-1.403e+00	7.539e-01	-1.861
## native.country Thailand	-1.875e+00	1.019e+00	-1.840
## native.country Trinidad&Tobago	-1.883e+00	1.056e+00	-1.784
## native.country United-States	-1.211e+00	6.062e-01	-1.998
## native.country Vietnam	-2.399e+00	8.456e-01	-2.837
## native.country Yugoslavia	-7.046e-01	9.035e-01	-0.780
##	Pr(> z)		
## (Intercept)	2.63e-15	***	
## age	< 2e-16	***	
## workclass Local-gov	9.72e-10	***	
## workclass Private	1.65e-07	***	
## workclass Self-emp-inc	0.013236	*	
## workclass Self-emp-not-inc	< 2e-16	***	
## workclass State-gov	1.08e-10	***	
## workclass Without-pay	0.946429		
## fnlwgt	3.33e-05	***	
## education 11th	0.646464		
## education 12th	0.107826		
## education 1st-4th	0.380651		
## education 5th-6th	0.266173		
## education 7th-8th	0.020155	*	
## education 9th	0.387810		
## education Assoc-acdm	9.15e-13	***	
## education Assoc-voc	1.36e-13	***	
## education Bachelors	< 2e-16	***	
## education Doctorate	< 2e-16	***	
## education HS-grad	5.86e-07	***	
## education Masters	< 2e-16	***	
## education Preschool	0.919269		
## education Prof-school	< 2e-16	***	
## education Some-college	2.06e-12	***	
## marital Married-AF-spouse	1.42e-06	***	
## marital Married-civ-spouse	1.60e-14	***	
## marital Married-spouse-absent	0.992995		

## marital Never-married	4.97e-08	***
## marital Separated	0.526921	
## marital Widowed	0.237308	
## occupation Armed-Forces	0.415756	
## occupation Craft-repair	0.404877	
## occupation Exec-managerial	< 2e-16	***
## occupation Farming-fishing	3.71e-12	***
## occupation Handlers-cleaners	1.37e-06	***
## occupation Machine-op-inspct	0.008409	**
## occupation Other-service	2.52e-12	***
## occupation Priv-house-serv	0.015477	*
## occupation Prof-specialty	3.62e-10	***
## occupation Protective-serv	2.55e-06	***
## occupation Sales	0.000345	***
## occupation Tech-support	1.67e-09	***
## occupation Transport-moving	0.329475	
## relationship Not-in-family	0.095025	.
## relationship Other-relative	0.106368	
## relationship Own-child	0.007004	**
## relationship Unmarried	0.251693	
## relationship Wife	< 2e-16	***
## sex Male	< 2e-16	***
## capital.gain	< 2e-16	***
## capital.loss	< 2e-16	***
## hours.per.week	< 2e-16	***
## native.country Canada	0.113109	
## native.country China	0.006206	**
## native.country Columbia	0.000462	***
## native.country Cuba	0.131195	
## native.country Dominican-Republic	0.006702	**
## native.country Ecuador	0.058833	.
## native.country El-Salvador	0.010301	*
## native.country England	0.108287	
## native.country France	0.308779	
## native.country Germany	0.156655	
## native.country Greece	0.003816	**
## native.country Guatemala	0.085365	.
## native.country Haiti	0.087122	.
## native.country Holand-Netherlands	0.989278	
## native.country Honduras	0.328607	
## native.country Hong	0.125672	
## native.country Hungary	0.123393	
## native.country India	0.009475	**
## native.country Iran	0.067709	.
## native.country Ireland	0.335890	
## native.country Italy	0.406006	
## native.country Jamaica	0.044620	*
## native.country Japan	0.151799	
## native.country Laos	0.072802	.
## native.country Mexico	0.002792	**

```
## native.country Nicaragua 0.032462 *
## native.country Outlying-US(Guam-USVI-etc) 0.948048
## native.country Peru 0.032333 *
## native.country Philippines 0.161005
## native.country Poland 0.056103 .
## native.country Portugal 0.116613
## native.country Puerto-Rico 0.012389 *
## native.country Scotland 0.123997
## native.country South 0.000841 ***
## native.country Taiwan 0.062795 .
## native.country Thailand 0.065710 .
## native.country Trinidad&Tobago 0.074484 .
## native.country United-States 0.045757 *
## native.country Vietnam 0.004549 **
## native.country Yugoslavia 0.435500
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 33851 on 30161 degrees of freedom
## Residual deviance: 19501 on 30070 degrees of freedom
## AIC: 19685
##
## Number of Fisher Scoring iterations: 13
```

Prediction the Test Set Results

```
prob_pred_1 = predict(fit_1, type = 'response', newdata = test[-14])
y_pred_1 = ifelse(prob_pred_1 > 0.5, '>50K', '<=50K')
```

Confusion Matrix 1

```
cm_1 = table(test[, 14], y_pred_1)
cm_1
```

```
##           y_pred_1
##           <=50K  >50K
## <=50K. 10537    823
## >50K.   1470   2230
```

Computing the Accuracy and Error Rates

```
acc_1 = sum(diag(cm_1)) / sum(cm_1)
acc_1
```

```
## [1] 0.8477424
```

```
err_1 = 1 - acc_1
err_1
```

```
## [1] 0.1522576
```

This model has an accuracy rate of **84.77%**, which is only very slightly improved.

Model 1 is our best model so far.

Model 2

We remove the *relationship* variable as well as it appears to be a less significant variable.

```
fit_2 = suppressWarnings(glm(formula = class ~ . - race - relationship,
                             family = binomial,
                             data = train))

summary(fit_2)

##
## Call:
## glm(formula = class ~ . - race - relationship, family = binomial,
##      data = train)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -5.1465  -0.5077  -0.2119   0.0000   3.7692
##
## Coefficients:
##                                     Estimate Std. Error z value
## (Intercept)                    -4.907e+00  6.515e-01  -7.532
## age                           2.596e-02  1.685e-03  15.407
## workclass Local-gov             -6.962e-01  1.117e-01  -6.234
## workclass Private               -4.847e-01  9.256e-02  -5.237
## workclass Self-emp-inc          -2.886e-01  1.234e-01  -2.339
## workclass Self-emp-not-inc      -9.597e-01  1.091e-01  -8.793
## workclass State-gov             -8.097e-01  1.244e-01  -6.510
## workclass Without-pay          -1.317e+01  1.987e+02  -0.066
## fnlwgt                          7.475e-07  1.736e-07   4.307
## education 11th                  8.503e-02  2.134e-01   0.398
## education 12th                  4.611e-01  2.778e-01   1.660
## education 1st-4th              -4.551e-01  4.958e-01  -0.918
## education 5th-6th              -4.098e-01  3.589e-01  -1.142
## education 7th-8th              -5.663e-01  2.432e-01  -2.329
## education 9th                  -2.120e-01  2.694e-01  -0.787
## education Assoc-acdm            1.319e+00  1.792e-01   7.361
## education Assoc-voc            1.279e+00  1.724e-01   7.418
## education Bachelors             1.932e+00  1.603e-01  12.051
## education Doctorate             2.947e+00  2.225e-01  13.245
## education HS-grad               7.914e-01  1.560e-01   5.073
## education Masters               2.294e+00  1.713e-01  13.387
## education Preschool            -2.043e+01  1.890e+02  -0.108
## education Prof-school           2.877e+00  2.068e-01  13.911
## education Some-college          1.112e+00  1.583e-01   7.027
## marital Married-AF-spouse       3.065e+00  5.032e-01   6.090
## marital Married-civ-spouse      2.183e+00  6.809e-02  32.066
## marital Married-spouse-absent   4.964e-02  2.360e-01   0.210
```

## marital Never-married	-5.141e-01	8.407e-02	-6.115
## marital Separated	-1.095e-01	1.616e-01	-0.678
## marital Widowed	3.762e-02	1.547e-01	0.243
## occupation Armed-Forces	-1.331e+00	1.525e+00	-0.873
## occupation Craft-repair	3.651e-03	7.939e-02	0.046
## occupation Exec-managerial	7.757e-01	7.618e-02	10.183
## occupation Farming-fishing	-1.057e+00	1.404e-01	-7.531
## occupation Handlers-cleaners	-7.626e-01	1.441e-01	-5.294
## occupation Machine-op-inspct	-3.175e-01	1.017e-01	-3.123
## occupation Other-service	-8.348e-01	1.176e-01	-7.095
## occupation Priv-house-serv	-4.464e+00	1.726e+00	-2.586
## occupation Prof-specialty	4.932e-01	8.077e-02	6.106
## occupation Protective-serv	5.505e-01	1.258e-01	4.377
## occupation Sales	2.461e-01	8.159e-02	3.016
## occupation Tech-support	6.340e-01	1.098e-01	5.775
## occupation Transport-moving	-1.512e-01	9.918e-02	-1.525
## sex Male	1.549e-01	5.398e-02	2.869
## capital.gain	3.249e-04	1.068e-05	30.406
## capital.loss	6.525e-04	3.838e-05	16.999
## hours.per.week	2.950e-02	1.688e-03	17.473
## native.country Canada	-1.039e+00	6.706e-01	-1.549
## native.country China	-1.957e+00	7.083e-01	-2.763
## native.country Columbia	-3.598e+00	1.017e+00	-3.536
## native.country Cuba	-1.078e+00	6.821e-01	-1.580
## native.country Dominican-Republic	-3.142e+00	1.211e+00	-2.594
## native.country Ecuador	-1.836e+00	9.404e-01	-1.952
## native.country El-Salvador	-1.961e+00	7.769e-01	-2.524
## native.country England	-1.051e+00	6.824e-01	-1.540
## native.country France	-7.504e-01	7.999e-01	-0.938
## native.country Germany	-9.585e-01	6.589e-01	-1.455
## native.country Greece	-2.376e+00	8.231e-01	-2.886
## native.country Guatemala	-1.646e+00	9.695e-01	-1.698
## native.country Haiti	-1.600e+00	8.984e-01	-1.780
## native.country Holand-Netherlands	-1.293e+01	8.827e+02	-0.015
## native.country Honduras	-2.298e+00	2.325e+00	-0.988
## native.country Hong	-1.303e+00	9.066e-01	-1.438
## native.country Hungary	-1.476e+00	9.839e-01	-1.501
## native.country India	-1.755e+00	6.734e-01	-2.606
## native.country Iran	-1.373e+00	7.492e-01	-1.832
## native.country Ireland	-8.464e-01	8.845e-01	-0.957
## native.country Italy	-5.716e-01	6.902e-01	-0.828
## native.country Jamaica	-1.491e+00	7.505e-01	-1.986
## native.country Japan	-1.080e+00	7.309e-01	-1.478
## native.country Laos	-1.842e+00	1.058e+00	-1.741
## native.country Mexico	-1.932e+00	6.463e-01	-2.989
## native.country Nicaragua	-2.099e+00	1.009e+00	-2.081
## native.country Outlying-US(Guam-USVI-etc)	-1.354e+01	2.136e+02	-0.063
## native.country Peru	-2.231e+00	1.045e+00	-2.135
## native.country Philippines	-1.000e+00	6.472e-01	-1.545
## native.country Poland	-1.418e+00	7.297e-01	-1.943

## native.country Portugal	-1.238e+00	8.705e-01	-1.423
## native.country Puerto-Rico	-1.708e+00	7.186e-01	-2.377
## native.country Scotland	-1.478e+00	1.105e+00	-1.337
## native.country South	-2.401e+00	7.383e-01	-3.252
## native.country Taiwan	-1.410e+00	7.520e-01	-1.875
## native.country Thailand	-1.823e+00	9.969e-01	-1.828
## native.country Trinidad&Tobago	-1.776e+00	1.054e+00	-1.685
## native.country United-States	-1.211e+00	6.107e-01	-1.983
## native.country Vietnam	-2.459e+00	8.495e-01	-2.894
## native.country Yugoslavia	-7.617e-01	9.076e-01	-0.839
##	Pr(> z)		
## (Intercept)	5.00e-14	***	
## age	< 2e-16	***	
## workclass Local-gov	4.55e-10	***	
## workclass Private	1.63e-07	***	
## workclass Self-emp-inc	0.019331	*	
## workclass Self-emp-not-inc	< 2e-16	***	
## workclass State-gov	7.52e-11	***	
## workclass Without-pay	0.947131		
## fnlwgt	1.66e-05	***	
## education 11th	0.690349		
## education 12th	0.096984	.	
## education 1st-4th	0.358698		
## education 5th-6th	0.253590		
## education 7th-8th	0.019856	*	
## education 9th	0.431193		
## education Assoc-acdm	1.82e-13	***	
## education Assoc-voc	1.19e-13	***	
## education Bachelors	< 2e-16	***	
## education Doctorate	< 2e-16	***	
## education HS-grad	3.92e-07	***	
## education Masters	< 2e-16	***	
## education Preschool	0.913927		
## education Prof-school	< 2e-16	***	
## education Some-college	2.10e-12	***	
## marital Married-AF-spouse	1.13e-09	***	
## marital Married-civ-spouse	< 2e-16	***	
## marital Married-spouse-absent	0.833402		
## marital Never-married	9.63e-10	***	
## marital Separated	0.497894		
## marital Widowed	0.807930		
## occupation Armed-Forces	0.382836		
## occupation Craft-repair	0.963320		
## occupation Exec-managerial	< 2e-16	***	
## occupation Farming-fishing	5.03e-14	***	
## occupation Handlers-cleaners	1.20e-07	***	
## occupation Machine-op-inspct	0.001790	**	
## occupation Other-service	1.29e-12	***	
## occupation Priv-house-serv	0.009697	**	
## occupation Prof-specialty	1.02e-09	***	


```

## occupation Protective-serv      1.20e-05 ***
## occupation Sales                 0.002558 **
## occupation Tech-support          7.71e-09 ***
## occupation Transport-moving      0.127245
## sex Male                         0.004117 **
## capital.gain                     < 2e-16 ***
## capital.loss                     < 2e-16 ***
## hours.per.week                   < 2e-16 ***
## native.country Canada            0.121407
## native.country China             0.005732 **
## native.country Columbia          0.000406 ***
## native.country Cuba              0.114067
## native.country Dominican-Republic 0.009484 **
## native.country Ecuador           0.050954 .
## native.country El-Salvador       0.011614 *
## native.country England           0.123658
## native.country France            0.348227
## native.country Germany           0.145750
## native.country Greece            0.003897 **
## native.country Guatemala         0.089549 .
## native.country Haiti             0.075013 .
## native.country Holand-Netherlands 0.988318
## native.country Honduras          0.323019
## native.country Hong              0.150499
## native.country Hungary           0.133444
## native.country India             0.009156 **
## native.country Iran              0.066910 .
## native.country Ireland           0.338616
## native.country Italy             0.407571
## native.country Jamaica           0.047015 *
## native.country Japan             0.139346
## native.country Laos              0.081625 .
## native.country Mexico            0.002799 **
## native.country Nicaragua         0.037463 *
## native.country Outlying-US(Guam-USVI-etc) 0.949445
## native.country Peru              0.032747 *
## native.country Philippines       0.122232
## native.country Poland            0.051960 .
## native.country Portugal          0.154880
## native.country Puerto-Rico       0.017455 *
## native.country Scotland          0.181291
## native.country South             0.001147 **
## native.country Taiwan            0.060777 .
## native.country Thailand          0.067504 .
## native.country Trinidad&Tobago   0.091952 .
## native.country United-States     0.047365 *
## native.country Vietnam           0.003803 **
## native.country Yugoslavia        0.401278
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 33851  on 30161  degrees of freedom
## Residual deviance: 19767  on 30075  degrees of freedom
## AIC: 19941
##
## Number of Fisher Scoring iterations: 13
```

Prediction the Test Set Results

```
prob_pred_2 = predict(fit_2, type = 'response', newdata = test[-14])
y_pred_2 = ifelse(prob_pred_2 > 0.5, '>50K', '<=50K')

cm_2 = table(test[, 14], y_pred_2)
cm_2

##           y_pred_2
##           <=50K  >50K
## <=50K.  10554    806
## >50K.    1504   2196
```

Computing the Accuracy and Error Rates

```
acc_2 = sum(diag(cm_2)) / sum(cm_2)
acc_2

## [1] 0.8466135

err_2 = 1 - acc_2
err_2

## [1] 0.1533865
```

However, accuracy rate has decreased to **84.66**.

Model 3

We will do more data cleaning, for it appears that there are many zero values present in the *capital.loss* and *capital.gain* columns. Let's remove these from our best model so far (Model 1) and see if the result improves.

```
fit_3 = suppressWarnings(glm(formula = class ~ . - race - capital.gain - capital.loss,
                             family = binomial,
                             data = train))

summary(fit_3)

##
## Call:
## glm(formula = class ~ . - race - capital.gain - capital.loss,
##      family = binomial, data = train)
```

```

##
## Deviance Residuals:
##      Min        1Q      Median        3Q        Max
## -2.6754   -0.5672   -0.2165   -0.0005    3.7071
##
## Coefficients:
##                  Estimate Std. Error z value
## (Intercept)      -5.511e+00  6.843e-01  -8.053
## age              2.901e-02  1.627e-03  17.834
## workclass Local-gov      -6.543e-01  1.078e-01  -6.071
## workclass Private      -4.388e-01  8.910e-02  -4.925
## workclass Self-emp-inc   -1.950e-01  1.171e-01  -1.665
## workclass Self-emp-not-inc -8.986e-01  1.043e-01  -8.616
## workclass State-gov     -8.377e-01  1.201e-01  -6.977
## workclass Without-pay   -1.337e+01  1.953e+02  -0.068
## fnlwgt           7.609e-07  1.658e-07   4.590
## education 11th         1.601e-01  2.058e-01   0.778
## education 12th         5.000e-01  2.615e-01   1.912
## education 1st-4th     -4.230e-01  4.704e-01  -0.899
## education 5th-6th     -3.329e-01  3.502e-01  -0.951
## education 7th-8th     -5.529e-01  2.352e-01  -2.351
## education 9th        -2.938e-01  2.623e-01  -1.120
## education Assoc-acdm    1.338e+00  1.715e-01   7.799
## education Assoc-voc    1.362e+00  1.647e-01   8.272
## education Bachelors    2.005e+00  1.535e-01  13.064
## education Doctorate    3.105e+00  2.112e-01  14.701
## education HS-grad      8.293e-01  1.493e-01   5.554
## education Masters      2.426e+00  1.638e-01  14.814
## education Preschool   -1.112e+01  1.085e+02  -0.103
## education Prof-school   3.107e+00  1.954e-01  15.901
## education Some-college  1.162e+00  1.515e-01   7.669
## marital Married-AF-spouse  2.517e+00  5.661e-01   4.446
## marital Married-civ-spouse  1.995e+00  2.662e-01   7.492
## marital Married-spouse-absent -3.755e-02  2.212e-01  -0.170
## marital Never-married   -4.553e-01  8.161e-02  -5.579
## marital Separated      -8.774e-02  1.511e-01  -0.581
## marital Widowed        1.759e-01  1.439e-01   1.222
## occupation Armed-Forces  -9.862e-01  1.282e+00  -0.769
## occupation Craft-repair   6.640e-02  7.668e-02   0.866
## occupation Exec-managerial  8.242e-01  7.359e-02  11.200
## occupation Farming-fishing -9.415e-01  1.319e-01  -7.138
## occupation Handlers-cleaners -7.195e-01  1.384e-01  -5.200
## occupation Machine-op-inspct -3.031e-01  9.832e-02  -3.083
## occupation Other-service  -9.176e-01  1.139e-01  -8.058
## occupation Priv-house-serv -2.541e+00  1.113e+00  -2.282
## occupation Prof-specialty  5.255e-01  7.798e-02   6.739
## occupation Protective-serv  5.474e-01  1.210e-01   4.523
## occupation Sales        3.105e-01  7.850e-02   3.955
## occupation Tech-support   6.265e-01  1.071e-01   5.852
## occupation Transport-moving -1.221e-01  9.513e-02  -1.284

```

## relationship Not-in-family	4.550e-01	2.636e-01	1.726
## relationship Other-relative	-4.417e-01	2.392e-01	-1.846
## relationship Own-child	-7.567e-01	2.643e-01	-2.863
## relationship Unmarried	2.608e-01	2.771e-01	0.941
## relationship Wife	1.366e+00	9.874e-02	13.836
## sex Male	8.678e-01	7.387e-02	11.747
## hours.per.week	3.013e-02	1.622e-03	18.572
## native.country Canada	-1.095e+00	6.434e-01	-1.702
## native.country China	-1.926e+00	6.824e-01	-2.823
## native.country Columbia	-3.778e+00	1.016e+00	-3.718
## native.country Cuba	-1.126e+00	6.584e-01	-1.710
## native.country Dominican-Republic	-2.779e+00	9.639e-01	-2.883
## native.country Ecuador	-1.828e+00	8.875e-01	-2.060
## native.country El-Salvador	-1.740e+00	7.417e-01	-2.346
## native.country England	-1.076e+00	6.579e-01	-1.636
## native.country France	-8.657e-01	7.876e-01	-1.099
## native.country Germany	-9.555e-01	6.322e-01	-1.511
## native.country Greece	-2.058e+00	7.774e-01	-2.647
## native.country Guatemala	-1.592e+00	8.907e-01	-1.788
## native.country Haiti	-1.669e+00	8.821e-01	-1.893
## native.country Holand-Netherlands	-1.073e+01	8.827e+02	-0.012
## native.country Honduras	-2.386e+00	2.100e+00	-1.136
## native.country Hong	-1.603e+00	8.770e-01	-1.827
## native.country Hungary	-1.481e+00	9.316e-01	-1.590
## native.country India	-1.776e+00	6.423e-01	-2.766
## native.country Iran	-1.322e+00	7.065e-01	-1.871
## native.country Ireland	-8.642e-01	8.525e-01	-1.014
## native.country Italy	-6.506e-01	6.646e-01	-0.979
## native.country Jamaica	-1.628e+00	7.172e-01	-2.270
## native.country Japan	-1.067e+00	6.967e-01	-1.531
## native.country Laos	-2.080e+00	1.052e+00	-1.978
## native.country Mexico	-1.987e+00	6.198e-01	-3.206
## native.country Nicaragua	-2.281e+00	1.001e+00	-2.278
## native.country Outlying-US(Guam-USVI-etc)	-1.400e+01	2.084e+02	-0.067
## native.country Peru	-2.286e+00	9.909e-01	-2.308
## native.country Philippines	-9.729e-01	6.218e-01	-1.565
## native.country Poland	-1.470e+00	7.090e-01	-2.074
## native.country Portugal	-1.480e+00	8.596e-01	-1.722
## native.country Puerto-Rico	-1.800e+00	6.904e-01	-2.607
## native.country Scotland	-1.957e+00	1.063e+00	-1.840
## native.country South	-2.417e+00	6.967e-01	-3.469
## native.country Taiwan	-1.590e+00	7.272e-01	-2.186
## native.country Thailand	-2.194e+00	1.006e+00	-2.181
## native.country Trinidad&Tobago	-1.953e+00	1.013e+00	-1.928
## native.country United-States	-1.216e+00	5.858e-01	-2.076
## native.country Vietnam	-2.235e+00	8.033e-01	-2.782
## native.country Yugoslavia	-8.269e-01	8.774e-01	-0.942
##	Pr(> z)		
## (Intercept)	8.08e-16	***	
## age	< 2e-16	***	

## workclass Local-gov	1.27e-09	***
## workclass Private	8.42e-07	***
## workclass Self-emp-inc	0.095955	.
## workclass Self-emp-not-inc	< 2e-16	***
## workclass State-gov	3.01e-12	***
## workclass Without-pay	0.945409	
## fnlwgt	4.43e-06	***
## education 11th	0.436659	
## education 12th	0.055908	.
## education 1st-4th	0.368534	
## education 5th-6th	0.341741	
## education 7th-8th	0.018728	*
## education 9th	0.262668	
## education Assoc-acdm	6.23e-15	***
## education Assoc-voc	< 2e-16	***
## education Bachelors	< 2e-16	***
## education Doctorate	< 2e-16	***
## education HS-grad	2.79e-08	***
## education Masters	< 2e-16	***
## education Preschool	0.918345	
## education Prof-school	< 2e-16	***
## education Some-college	1.73e-14	***
## marital Married-AF-spouse	8.77e-06	***
## marital Married-civ-spouse	6.79e-14	***
## marital Married-spouse-absent	0.865167	
## marital Never-married	2.42e-08	***
## marital Separated	0.561557	
## marital Widowed	0.221520	
## occupation Armed-Forces	0.441618	
## occupation Craft-repair	0.386556	
## occupation Exec-managerial	< 2e-16	***
## occupation Farming-fishing	9.44e-13	***
## occupation Handlers-cleaners	1.99e-07	***
## occupation Machine-op-inspct	0.002052	**
## occupation Other-service	7.78e-16	***
## occupation Priv-house-serv	0.022478	*
## occupation Prof-specialty	1.59e-11	***
## occupation Protective-serv	6.10e-06	***
## occupation Sales	7.66e-05	***
## occupation Tech-support	4.86e-09	***
## occupation Transport-moving	0.199116	
## relationship Not-in-family	0.084413	.
## relationship Other-relative	0.064860	.
## relationship Own-child	0.004195	**
## relationship Unmarried	0.346482	
## relationship Wife	< 2e-16	***
## sex Male	< 2e-16	***
## hours.per.week	< 2e-16	***
## native.country Canada	0.088800	.
## native.country China	0.004765	**

```

## native.country Columbia 0.000200 ***
## native.country Cuba 0.087222 .
## native.country Dominican-Republic 0.003940 **
## native.country Ecuador 0.039383 *
## native.country El-Salvador 0.018952 *
## native.country England 0.101862
## native.country France 0.271686
## native.country Germany 0.130686
## native.country Greece 0.008129 **
## native.country Guatemala 0.073806 .
## native.country Haiti 0.058415 .
## native.country Holand-Netherlands 0.990299
## native.country Honduras 0.255750
## native.country Hong 0.067648 .
## native.country Hungary 0.111904
## native.country India 0.005681 **
## native.country Iran 0.061347 .
## native.country Ireland 0.310691
## native.country Italy 0.327626
## native.country Jamaica 0.023180 *
## native.country Japan 0.125673
## native.country Laos 0.047900 *
## native.country Mexico 0.001347 **
## native.country Nicaragua 0.022754 *
## native.country Outlying-US(Guam-USVI-etc) 0.946461
## native.country Peru 0.021024 *
## native.country Philippines 0.117635
## native.country Poland 0.038103 *
## native.country Portugal 0.085115 .
## native.country Puerto-Rico 0.009128 **
## native.country Scotland 0.065725 .
## native.country South 0.000522 ***
## native.country Taiwan 0.028807 *
## native.country Thailand 0.029210 *
## native.country Trinidad&Tobago 0.053803 .
## native.country United-States 0.037914 *
## native.country Vietnam 0.005397 **
## native.country Yugoslavia 0.345966
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 33851 on 30161 degrees of freedom
## Residual deviance: 21424 on 30072 degrees of freedom
## AIC: 21604
##
## Number of Fisher Scoring iterations: 13

```

AIC appears to have risen, which is a sign of a worse fit.

Prediction the Test Set Results

```
prob_pred_3 = predict(fit_3, type = 'response', newdata = test[-14])
y_pred_3 = ifelse(prob_pred_3 > 0.5, '>50K', '<=50K')

cm_3 = table(test[, 14], y_pred_3)
cm_3

##           y_pred_3
##           <=50K  >50K
## <=50K.  10415    945
## >50K.    1616   2084
```

Computing the Accuracy and Error Rates

```
acc_3 = sum(diag(cm_3)) / sum(cm_3)
acc_3

## [1] 0.8299469

err_3 = 1 - acc_3
err_3

## [1] 0.1700531
```

Accuracy rate has decreased to **82.99%** in this case.

Model 4

We will try feature transformation in this last model, by means of Principal Component Analysis (PCA). To prepare our datasets for this, we will need to create dummy variables.

```
# install.packages('dummies')
library(dummies)

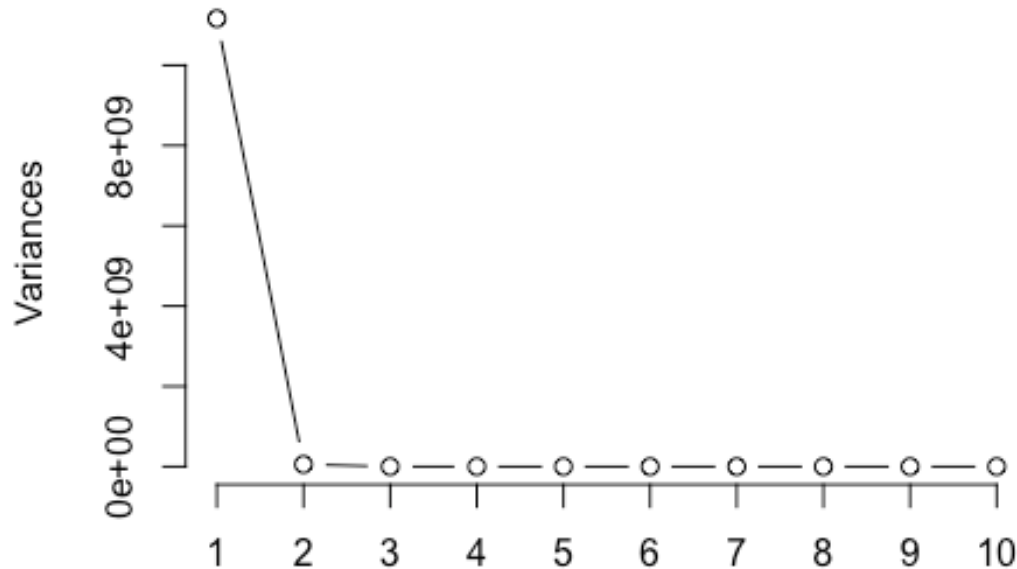
## dummies-1.5.6 provided by Decision Patterns

train_4 = dummy.data.frame(train, names = c('workclass', 'education', 'marital',
                                             'occupation',
                                             'relationship', 'race', 'sex', 'native.country'))
test_4 = dummy.data.frame(test, names = c('workclass', 'education', 'marital',
                                           'occupation',
                                           'relationship', 'race', 'sex', 'native.country'))

train_4_pca = prcomp(train_4[-104])
test_4_pca = prcomp(test_4[-103])

screplot(train_4_pca, type = 'l', main = 'PCA for Model 4')
```

PCA for Model 4



```
summary(train_4_pca)
```

```
## Importance of components:
##
##          PC1          PC2          PC3          PC4          PC5          PC6
## Standard deviation 1.057e+05 7.406e+03 404.06991 13.26 11.67 0.8597
## Proportion of Variance 9.951e-01 4.890e-03 0.00001 0.00 0.00 0.0000
## Cumulative Proportion 9.951e-01 1.000e+00 1.00000 1.00 1.00 1.0000
##
##          PC7          PC8          PC9          PC10          PC11          PC12          PC13
## Standard deviation 0.5582 0.5482 0.4821 0.4571 0.439 0.4211 0.3845
## Proportion of Variance 0.0000 0.0000 0.0000 0.0000 0.000 0.0000 0.0000
## Cumulative Proportion 1.0000 1.0000 1.0000 1.0000 1.000 1.0000 1.0000
##
##          PC14          PC15          PC16          PC17          PC18          PC19          PC20
## Standard deviation 0.369 0.3481 0.3437 0.3354 0.3145 0.303 0.2918
## Proportion of Variance 0.000 0.0000 0.0000 0.0000 0.0000 0.000 0.0000
## Cumulative Proportion 1.000 1.0000 1.0000 1.0000 1.0000 1.000 1.0000
##
##          PC21          PC22          PC23          PC24          PC25          PC26          PC27
## Standard deviation 0.2841 0.2703 0.2598 0.2397 0.2318 0.2254 0.2149
## Proportion of Variance 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
## Cumulative Proportion 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
##
##          PC28          PC29          PC30          PC31          PC32          PC33          PC34
## Standard deviation 0.2107 0.2083 0.1985 0.1899 0.1886 0.1854 0.1814
## Proportion of Variance 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000
## Cumulative Proportion 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000 1.0000
```


##	PC35	PC36	PC37	PC38	PC39	PC40	PC41
## Standard deviation	0.1797	0.1776	0.1698	0.1642	0.1619	0.142	0.1404
## Proportion of Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.000	0.0000
## Cumulative Proportion	1.0000	1.0000	1.0000	1.0000	1.0000	1.000	1.0000
##	PC42	PC43	PC44	PC45	PC46	PC47	PC48
## Standard deviation	0.1293	0.1237	0.1221	0.1178	0.115	0.1116	0.1041
## Proportion of Variance	0.0000	0.0000	0.0000	0.0000	0.000	0.0000	0.0000
## Cumulative Proportion	1.0000	1.0000	1.0000	1.0000	1.000	1.0000	1.0000
##	PC49	PC50	PC51	PC52	PC53	PC54	
## Standard deviation	0.09095	0.09028	0.07307	0.07207	0.06837	0.06381	
## Proportion of Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	
##	PC55	PC56	PC57	PC58	PC59	PC60	
## Standard deviation	0.05941	0.05804	0.05754	0.05604	0.05528	0.0541	
## Proportion of Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.0000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.00000	1.00000	1.0000	
##	PC61	PC62	PC63	PC64	PC65	PC66	
## Standard deviation	0.05193	0.04921	0.04794	0.04681	0.04656	0.04582	
## Proportion of Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	
##	PC67	PC68	PC69	PC70	PC71	PC72	
## Standard deviation	0.04451	0.04386	0.04301	0.0404	0.03941	0.03868	
## Proportion of Variance	0.00000	0.00000	0.00000	0.0000	0.00000	0.00000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.0000	1.00000	1.00000	
##	PC73	PC74	PC75	PC76	PC77	PC78	
## Standard deviation	0.03712	0.03559	0.03334	0.03298	0.03187	0.03117	
## Proportion of Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	
##	PC79	PC80	PC81	PC82	PC83	PC84	
## Standard deviation	0.03024	0.02974	0.02841	0.0273	0.02519	0.02477	
## Proportion of Variance	0.00000	0.00000	0.00000	0.0000	0.00000	0.00000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.0000	1.00000	1.00000	
##	PC85	PC86	PC87	PC88	PC89	PC90	
## Standard deviation	0.02417	0.02372	0.02364	0.02319	0.02266	0.02149	
## Proportion of Variance	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	
## Cumulative Proportion	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	
##	PC91	PC92	PC93	PC94	PC95	PC96	
## Standard deviation	0.02079	0.02	0.01917	0.01781	0.005818	1.05e-11	
## Proportion of Variance	0.00000	0.00	0.00000	0.00000	0.000000	0.00e+00	
## Cumulative Proportion	1.00000	1.00	1.00000	1.00000	1.000000	1.00e+00	
##	PC97	PC98	PC99	PC100	PC101		
## Standard deviation	1.05e-11	1.05e-11	1.05e-11	1.05e-11	1.05e-11		
## Proportion of Variance	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00		
## Cumulative Proportion	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00		
##	PC102	PC103					
## Standard deviation	1.05e-11	7.278e-14					
## Proportion of Variance	0.00e+00	0.000e+00					
## Cumulative Proportion	1.00e+00	1.000e+00					

The first 2 principal components are sufficient to explain most, if not all of the variation in the variables. So we will use them for the fit.

```
# Joining PC1 and PC2 columns to the train_4 dataset
train_4_pca_df = as.data.frame(train_4_pca$x)
train_4$PC1 = train_4_pca_df$PC1
train_4$PC2 = train_4_pca_df$PC2

# Joining PC1 and PC2 columns to the test_4 dataset
test_4_pca_df = as.data.frame(test_4_pca$x)
test_4$PC1 = test_4_pca_df$PC1
test_4$PC2 = test_4_pca_df$PC2

fit_4 = suppressWarnings(glm(class ~ PC1 + PC2,
                             family = 'binomial',
                             data = train_4))

summary(fit_4)

##
## Call:
## glm(formula = class ~ PC1 + PC2, family = "binomial", data = train_4)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -4.9964  -0.6879  -0.6832  -0.6521   1.8616
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -9.670e-01  1.543e-02 -62.689  <2e-16 ***
## PC1         -1.888e-07  1.353e-07  -1.395    0.163
## PC2          3.345e-04  8.916e-06  37.519  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 33851  on 30161  degrees of freedom
## Residual deviance: 30698  on 30159  degrees of freedom
## AIC: 30704
##
## Number of Fisher Scoring iterations: 6

Prediction the Test Set Results
prob_pred_4 = predict(fit_4, type = 'response', newdata = test_4[c(104, 105)]
)
y_pred_4 = ifelse(prob_pred_4 > 0.5, '>50K', '<=50K')

cm_4 = table(test_4[, 103], y_pred_4)
cm_4
```

```
##          y_pred_4
##          <=50K  >50K
##   <=50K. 11200   160
##   >50K.   2970   730
```

Computing the Accuracy and Error Rates

```
acc_4 = sum(diag(cm_4)) / sum(cm_4)
acc_4

## [1] 0.7921647

err_4 = 1 - acc_4
err_4

## [1] 0.2078353
```

Accuracy rate has decreased to **79.22%** for this model, which shows that feature transformation does not improve our results.

Summary & Conclusion

We have used the following models in our analysis to predict the *class* variable:

- Full Model (fit) - using **all** variables
- Model 1 (fit_1) - using all **except** *race*
- Model 2 (fit_2) - using all **except** *race* and *relationship*
- Model 3 (fit_3) - using all **except** *race*, *capital.gain* and *capital.loss*
- Model 4 (fit_4) - using 1st 2 components of PCA

We can conclude that **Model 1** produces the best result, with the *race* variable excluded. This model has the highest accuracy rate of **84.77%**.