STAT 381 Final Project

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```
library(readr)
Income <- read.csv("income_evaluation.csv", na.strings = " ?")
Income <- na.omit(Income)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
attach(Income)
Income$sex <- as.factor(Income$sex)
Income$income <- as.factor(Income$income)
Income$workclass <- as.factor(Income$workclass)
Income$education <- as.factor(Income$education)
Income$marital.status <- as.factor(Income$marital.status)
Income$occupation <- as.factor(Income$occupation)
Income$race <- as.factor(Income$race)
Income$relationship <- as.factor(Income$relationship)
Income$native.country <- as.factor(Income$native.country)
Income$native.country <- recode(Income$native.country,
" Cambodia" = "E-AS", " Canada" = "NA", " China" = "E-AS", " Columbia" = "SA", " Cuba" = "CA",
" Dominican-Republic" = "CA", " Ecuador" = "CA",
" El-Salvador" = "CA", " England" = "EU", " France" = "EU", " Germany" = "EU", " Greece" = "EU",
" Guatemala" = "CA", " Haiti" = "CA",
" Hong" = "E-AS", " Hungary" = "EU",
" India" = "E-AS",
" Iran" = "ME",
" Ireland" = "EU",
" Italy" = "EU", " Jamaica" = "CA", " Japan" = "E-AS", " Laos" = "E-AS", " Mexico" = "NA",
" Nicaragua" = "CA", " Outlying-US(Guam-USVI-etc)" = "US",
" Peru" = "SA",
" Philippines" = "E-AS", " Poland" = "EU", " Portugal" = "EU", " Puerto-Rico" = "US",
" Scotland" = "EU", " South" = "E-AS", " Taiwan" = "E-AS", " Thailand" = "E-AS",
" Trinadad&Tobago" = "CA", " United-States" = "US",
" Vietnam" = "E-AS", " Yugoslavia" = "EU",
" Holand-Netherlands" = "EU", " Honduras" = "CA" )
summary(Income)
```

```
##       age                     workclass         fnlwgt
##  Min.   :17.00    Federal-gov     :  943   Min.   :  13769
##  1st Qu.:28.00    Local-gov       : 2067   1st Qu.: 117627
##  Median :37.00    Private         :22286   Median : 178425
##  Mean   :38.44    Self-emp-inc    : 1074   Mean   : 189794
##  3rd Qu.:47.00    Self-emp-not-inc: 2499   3rd Qu.: 237628
##  Max.   :90.00    State-gov       : 1279   Max.   :1484705
##                   Without-pay     :   14
##         education    education.num                  marital.status
##   HS-grad     :9840   Min.   : 1.00    Divorced             : 4214
##   Some-college:6678   1st Qu.: 9.00    Married-AF-spouse    :   21
##   Bachelors   :5044   Median :10.00    Married-civ-spouse   :14065
##   Masters     :1627   Mean   :10.12    Married-spouse-absent:  370
##   Assoc-voc   :1307   3rd Qu.:13.00    Never-married        : 9726
##   11th        :1048   Max.   :16.00    Separated            :  939
##  (Other)      :4618                    Widowed              :  827
##            occupation           relationship                    race
##   Prof-specialty :4038    Husband       :12463    Amer-Indian-Eskimo:  286
##   Craft-repair   :4030    Not-in-family : 7726    Asian-Pac-Islander:  895
##   Exec-managerial:3992    Other-relative:  889    Black             : 2817
##   Adm-clerical   :3721    Own-child     : 4466    Other             :  231
##   Sales          :3584    Unmarried     : 3212    White             :25933
##   Other-service  :3212    Wife          : 1406
##  (Other)         :7585
##      sex          capital.gain    capital.loss     hours.per.week
##   Female: 9782   Min.   :    0   Min.   :   0.00   Min.   : 1.00
##   Male  :20380   1st Qu.:    0   1st Qu.:   0.00   1st Qu.:40.00
##                  Median :    0   Median :   0.00   Median :40.00
##                  Mean   : 1092   Mean   :  88.37   Mean   :40.93
##                  3rd Qu.:    0   3rd Qu.:   0.00   3rd Qu.:45.00
##                  Max.   :99999   Max.   :4356.00   Max.   :99.00
##
##  native.country    income
##  E-AS:  663      <=50K:22654
##  NA  :  717      >50K : 7508
##  SA  :   86
##  CA  :  534
##  EU  :  493
##  ME  :   42
##  US  :27627
```

```
cor(age, education.num)
```

```
## [1] 0.04352609
```

```
cor(age,fnlwgt)
```

```
## [1] -0.07651084
```

```
cor(age, hours.per.week)
```

```
## [1] 0.1015988
```

```
cor(age,capital.gain)
```

```
## [1] 0.08015423
```

```r
cor(age,capital.loss)
```

```
## [1] 0.06016548
```

```r
cor(education.num,fnlwgt)
```

```
## [1] -0.04499174
```

```r
cor(education.num,capital.gain)
```

```
## [1] 0.124416
```

```r
cor(education.num,capital.loss)
```

```
## [1] 0.07964641
```

```r
cor(education.num,hours.per.week)
```

```
## [1] 0.1525221
```

```r
cor(fnlwgt,capital.gain)
```

```
## [1] 0.0004215674
```

```r
cor(fnlwgt,capital.loss)
```

```
## [1] -0.009749528
```

```r
cor(fnlwgt,hours.per.week)
```

```
## [1] -0.02288575
```

```r
cor(hours.per.week,capital.gain)
```

```
## [1] 0.0804318
```

```r
cor(hours.per.week,capital.loss)
```

```
## [1] 0.05241705
```

```r
cor(capital.gain,capital.loss)
```

```
## [1] -0.03222933
```

there appears to be no correlation among the numberical variables. However, we can assume correlation between marital status and relationship status. There is also obvious correlation between educaiton and education number as well as workclass and occupation.

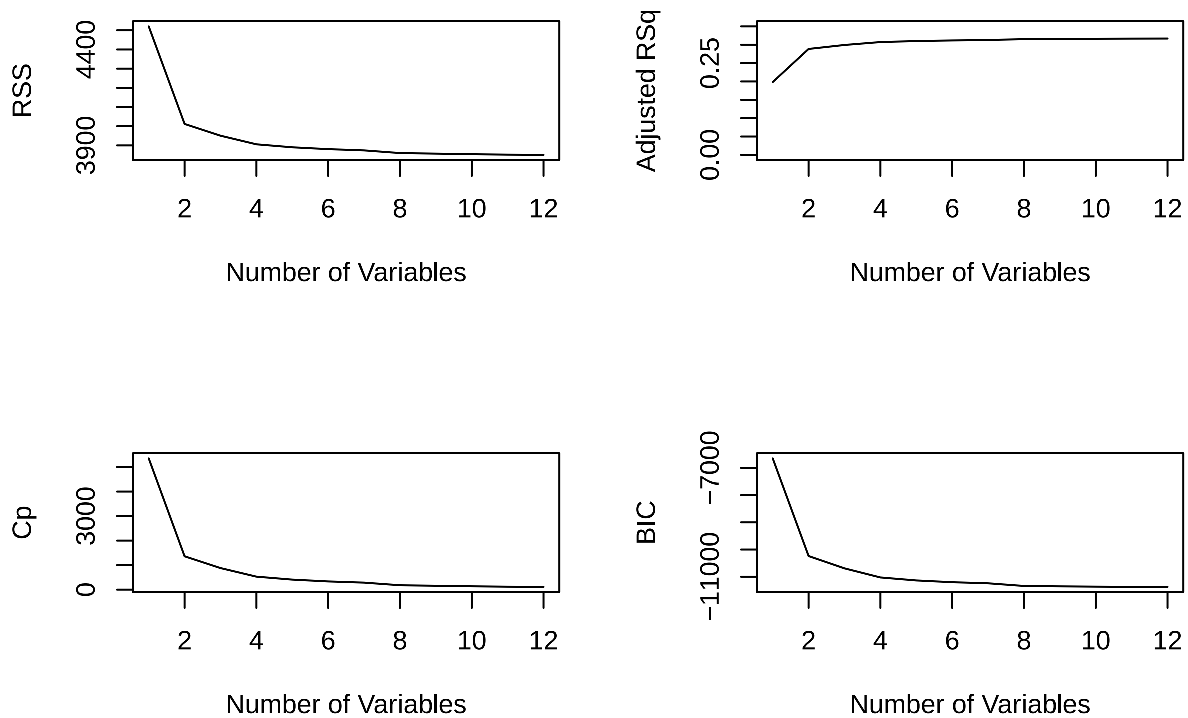
```r
library(leaps)
regfit.full <- regsubsets(income ~ native.country + hours.per.week + sex + race + relationship + marital

reg.summary <- summary(regfit.full)
names(reg.summary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```r
reg.summary$adjr2
```

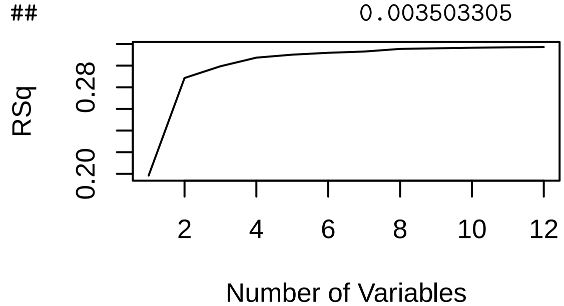
```
##  [1] 0.1983703 0.2885327 0.2993559 0.3072913 0.3100308 0.3117202 0.3128546
##  [8] 0.3152942 0.3158062 0.3162939 0.3166976 0.3168935
```

```
par(mfrow = c(2,2))
plot(reg.summary$rss, xlab = "Number of Variables", ylab = "RSS", type = "l")


plot(reg.summary$adjr2, xlab = "Number of Variables", ylab = "Adjusted RSq", type = "l", ylim=c(0,.35))


plot(reg.summary$cp, xlab = "Number of Variables", ylab = "Cp", type = "l")


plot(reg.summary$bic, xlab = "Number of Variables",ylab = "BIC", type = "l")
```




```
plot(reg.summary$rsq, xlab = "Number of Variables", ylab = "RSq", type = "l")
coef(regfit.full, 4)
```

```
##                      (Intercept)                  hours.per.week
##                      0.336432905                     0.003337259
## marital.status Married-civ-spouse                   education.num
##                      0.319635395                     0.048628172
##                              age
##                      0.003503305
```



```r
reg.summary$adjr2
```

```
##  [1] 0.1983703 0.2885327 0.2993559 0.3072913 0.3100308 0.3117202 0.3128546
##  [8] 0.3152942 0.3158062 0.3162939 0.3166976 0.3168935
```

```r
reg.summary$cp
```

```
##  [1] 5352.0157 1359.0202  880.5679  530.0572  409.7070  335.8662  286.6179
##  [8]  179.5655  157.8830  137.2810  120.4013  112.7250
```

```r
reg.summary$bic
```

```
##  [1]  -6649.445 -10238.981 -10692.033 -11026.279 -11136.482 -11201.114
##  [7] -11241.550 -11339.512 -11352.763 -11364.957 -11373.456 -11372.789
```

```r
set.seed(1)
train <- sample(30162,30162*.7)
Income.test <- Income[-train,]
dim(Income.test)
```

```
## [1] 9049   15
```

```r
income.test <-income[-train]
glm.fit <- glm(income~age+education.num+hours.per.week+marital.status, data = Income, family = binomial
glm.probs <- predict(glm.fit,Income.test,type = "response")
glm.pred <- rep("=<50k",9049)
glm.pred[glm.probs > .5] <- ">50k"
table(glm.pred,income.test)
```

```
##          income.test
## glm.pred  <=50K  >50K
##    =<50k   6311  1088
##    >50k     554  1096
```

```r
(6311+1096)/9049
```

```
## [1] 0.8185435
```

```r
summary(glm.fit)
```

```
##
## Call:
## glm(formula = income ~ age + education.num + hours.per.week +
##     marital.status, family = binomial, data = Income, subset = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8237  -0.6079  -0.2691   0.3713   3.3711
##
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                          -9.008241   0.170595 -52.805  < 2e-16 ***
## age                                   0.031430   0.001776  17.693  < 2e-16 ***
## education.num                         0.385912   0.009005  42.856  < 2e-16 ***
## hours.per.week                        0.031627   0.001773  17.842  < 2e-16 ***
## marital.status Married-AF-spouse      2.490356   0.542567   4.590 4.43e-06 ***
## marital.status Married-civ-spouse     2.067468   0.066910  30.899  < 2e-16 ***
## marital.status Married-spouse-absent -0.284559   0.257524  -1.105    0.269
```

```
## marital.status Never-married         -0.516309   0.088638  -5.825 5.72e-09 ***
## marital.status Separated             -0.075085   0.165752  -0.453    0.651
## marital.status Widowed               -0.071196   0.163096  -0.437    0.662
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 23845  on 21112  degrees of freedom
## Residual deviance: 16091  on 21103  degrees of freedom
## AIC: 16111
##
## Number of Fisher Scoring iterations: 6
```

LDA

```
library(MASS)
```

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

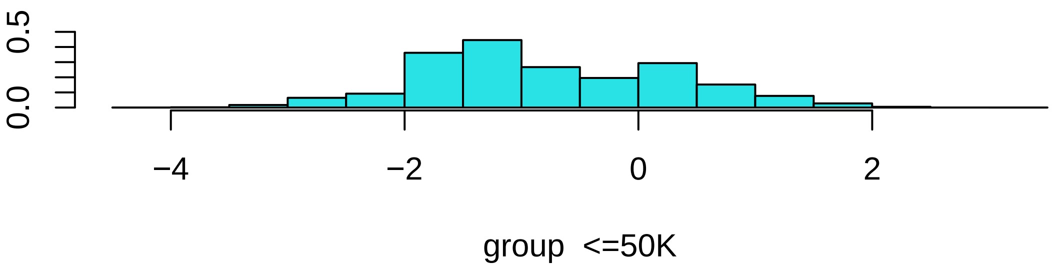
```
## The following object is masked from 'package:dplyr':
##
##     select
```

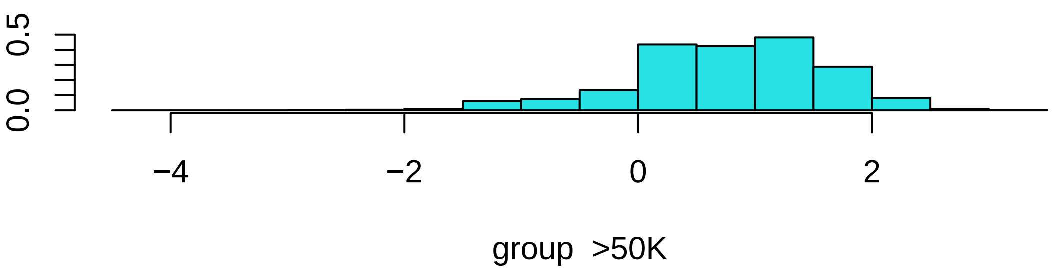
```
lda.fit <- lda(income~age+hours.per.week+education.num+marital.status, data = Income, subset = train)
lda.fit
```

```
## Call:
## lda(income ~ age + hours.per.week + education.num + marital.status,
##     data = Income, subset = train)
##
## Prior probabilities of groups:
##     <=50K      >50K
## 0.7478331 0.2521669
##
## Group means:
##             age hours.per.week education.num marital.status Married-AF-spouse
##  <=50K 36.67040       39.41041      9.631452                     0.0005700171
##  >50K  44.01803       45.72502     11.610443                     0.0013148009
##       marital.status Married-civ-spouse marital.status Married-spouse-absent
##  <=50K                        0.3396035                          0.015517132
##  >50K                         0.8518032                          0.003756574
##       marital.status Never-married marital.status Separated
##  <=50K                  0.40623219               0.037747799
##  >50K                   0.06104433               0.009579264
##       marital.status Widowed
##  <=50K             0.03166762
##  >50K              0.01070624
##
## Coefficients of linear discriminants:
##                                             LD1
## age                                  0.01819334
## hours.per.week                       0.01665735
## education.num                        0.24400337
```

```
## marital.status Married-AF-spouse     1.81925399
## marital.status Married-civ-spouse    1.62835507
## marital.status Married-spouse-absent 0.12185349
## marital.status Never-married         0.03913206
## marital.status Separated             0.07304818
## marital.status Widowed               0.01467706
```

```
plot(lda.fit)
```






```
lda.pred <- predict(lda.fit,Income.test)
names(lda.pred)
```

```
## [1] "class"     "posterior" "x"
```

```
lda.class <- lda.pred$class
table(lda.class,income.test)
```

```
##          income.test
## lda.class  <=50K  >50K
##     <=50K   6264  1050
##     >50K     601  1134
```

```
mean(lda.class == income.test)
```

```
## [1] 0.8175489
```