# Stat 154 - Fall 2017, Final Project

*Due date: December 10, 2017*

## Submission Instructions

The final project is a practical project to be done individually or in a team of 2 members max (no teams with more than 2 members allowed).

You will receive a link to a google sheet to be filled in with your team's name, the member names, and the corresponding email addresses.

Each team will be invited to a BOX folder (via bConnected): https://berkeley.account.box.com/login. You should be able to log in using the email that appears on CalCentral (e.g. typically your `berkeley.edu` email).

Each team must submit all the materials of their final project to the shared BOX folder.

Each team's folder must contain a `README` file explaining the structure of the project. Here's a sample file structure of how your BOX folder may look like:

```
team01/
   README.md
   data/
      ... # all the data files
   R/
      ... # all you R files here
   report/
      ... # mainly the pdf file
      ... # (you could use an Rmd file)
```

You can add more folders to the previous file structure.

You must produce a single PDF file for the report.

## Data

The data set for this project is the Census Income Data Set donated by Ronny Kohavi and Barry Becker to the UCI Machine Learning Repository.

The data set describes 15 variables on a sample of individuals from the US Census database. The prediction task is to determine whether a person makes over 50K a year.

```r
# Read in training set
train = read.csv("data/adult.data", header = FALSE)
names(train) = c('age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.st
```

```r
# Read in test set
test = read.csv("data/adult.test", header = FALSE)
names(test) = c('age', 'workclass', 'fnlwgt', 'education', 'education.num', 'marital.sta
```

### Match up The Response Variable

```r
dat = train

dat_test = test
levels(dat_test$income) = levels(dat$income)
```

## Preprocessing and Exploratory Data Analysis

Start your analysis cycle with an exploratory phase so you get to know and understand the data set. Below is a (non-comprehensive) list of (optional) considerations to keep in mind:

- Handling missing values
- Handling outliers
- Changing scales
- Binning (i.e. discretizing)
- Converting to (dummy) indicators
- Summary statistics
- Visualizing distributions
- Association between each predictor and the response

```r
summary(dat)
```

```
##       age                      workclass         fnlwgt
##  Min.   :17.00    Private         :22696   Min.   :  12285
##  1st Qu.:28.00    Self-emp-not-inc: 2541   1st Qu.: 117827
##  Median :37.00    Local-gov       : 2093   Median : 178356
##  Mean   :38.58    ?               : 1836   Mean   : 189778
##  3rd Qu.:48.00    State-gov       : 1298   3rd Qu.: 237051
##  Max.   :90.00    Self-emp-inc    : 1116   Max.   :1484705
##                  (Other)          :  981
##          education      education.num                    marital.status
##   HS-grad      :10501   Min.   : 1.00    Divorced              : 4443
##   Some-college: 7291   1st Qu.: 9.00    Married-AF-spouse     :   23
##   Bachelors    : 5355   Median :10.00    Married-civ-spouse    :14976
##   Masters      : 1723   Mean   :10.08    Married-spouse-absent:  418
##   Assoc-voc    : 1382   3rd Qu.:12.00    Never-married         :10683
##   11th         : 1175   Max.   :16.00    Separated             : 1025
##  (Other)       : 5134                    Widowed               :  993
```

```
##             occupation            relationship
##  Prof-specialty :4140    Husband       :13193
##  Craft-repair   :4099    Not-in-family : 8305
##  Exec-managerial:4066    Other-relative:  981
##  Adm-clerical   :3770    Own-child     : 5068
##  Sales          :3650    Unmarried     : 3446
##  Other-service  :3295    Wife          : 1568
## (Other)         :9541
##                  race           sex          capital.gain
##  Amer-Indian-Eskimo:  311   Female:10771   Min.   :    0
##  Asian-Pac-Islander: 1039   Male  :21790   1st Qu.:    0
##  Black             : 3124                  Median :    0
##  Other             :  271                  Mean   : 1078
##  White             :27816                  3rd Qu.:    0
##                                            Max.   :99999
##
##  capital.loss    hours.per.week        native.country      income
## Min.   :   0.0   Min.   : 1.00    United-States:29170    <=50K:24720
## 1st Qu.:   0.0   1st Qu.:40.00    Mexico       :  643    >50K : 7841
## Median :   0.0   Median :40.00    ?            :  583
## Mean   :  87.3   Mean   :40.44    Philippines  :  198
## 3rd Qu.:   0.0   3rd Qu.:45.00    Germany      :  137
## Max.   :4356.0   Max.   :99.00    Canada       :  121
##                                  (Other)       : 1709
```

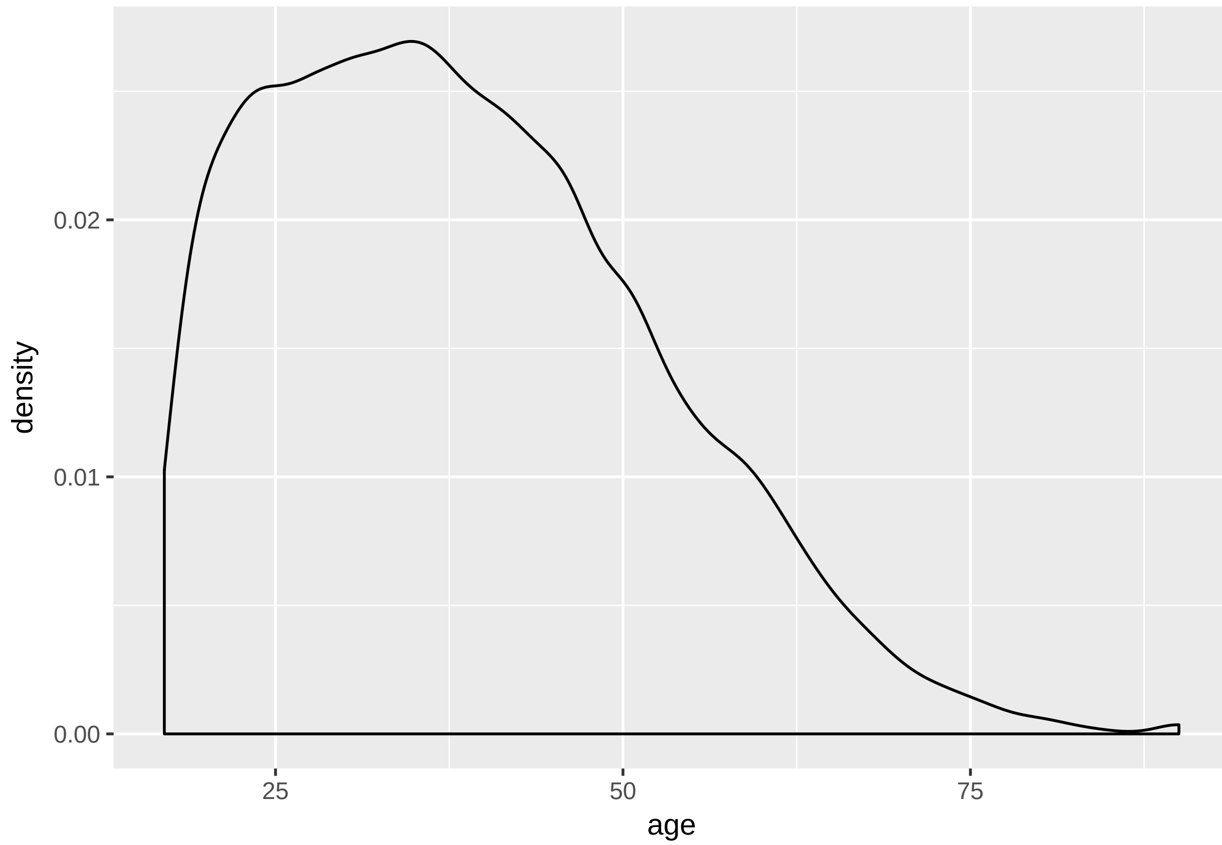
```r
summary(dat_test)
```

```
##       age                      workclass          fnlwgt
## Min.   :17.00    Private            :11210    Min.   :  13492
## 1st Qu.:28.00    Self-emp-not-inc: 1321    1st Qu.: 116736
## Median :37.00    Local-gov          : 1043    Median : 177831
## Mean   :38.77    ?                  :  963    Mean   : 189436
## 3rd Qu.:48.00    State-gov          :  683    3rd Qu.: 238384
## Max.   :90.00    Self-emp-inc       :  579    Max.   :1490400
##                 (Other)             :  482
##          education     education.num                  marital.status
##  HS-grad     :5283   Min.   : 1.00    Divorced             :2190
##  Some-college:3587   1st Qu.: 9.00    Married-AF-spouse    :  14
##  Bachelors   :2670   Median :10.00    Married-civ-spouse   :7403
##  Masters     : 934   Mean   :10.07    Married-spouse-absent: 210
##  Assoc-voc   : 679   3rd Qu.:12.00    Never-married        :5434
##  11th        : 637   Max.   :16.00    Separated            : 505
## (Other)      :2491                    Widowed              : 525
##             occupation            relationship
##  Prof-specialty :2032    Husband       :6523
```

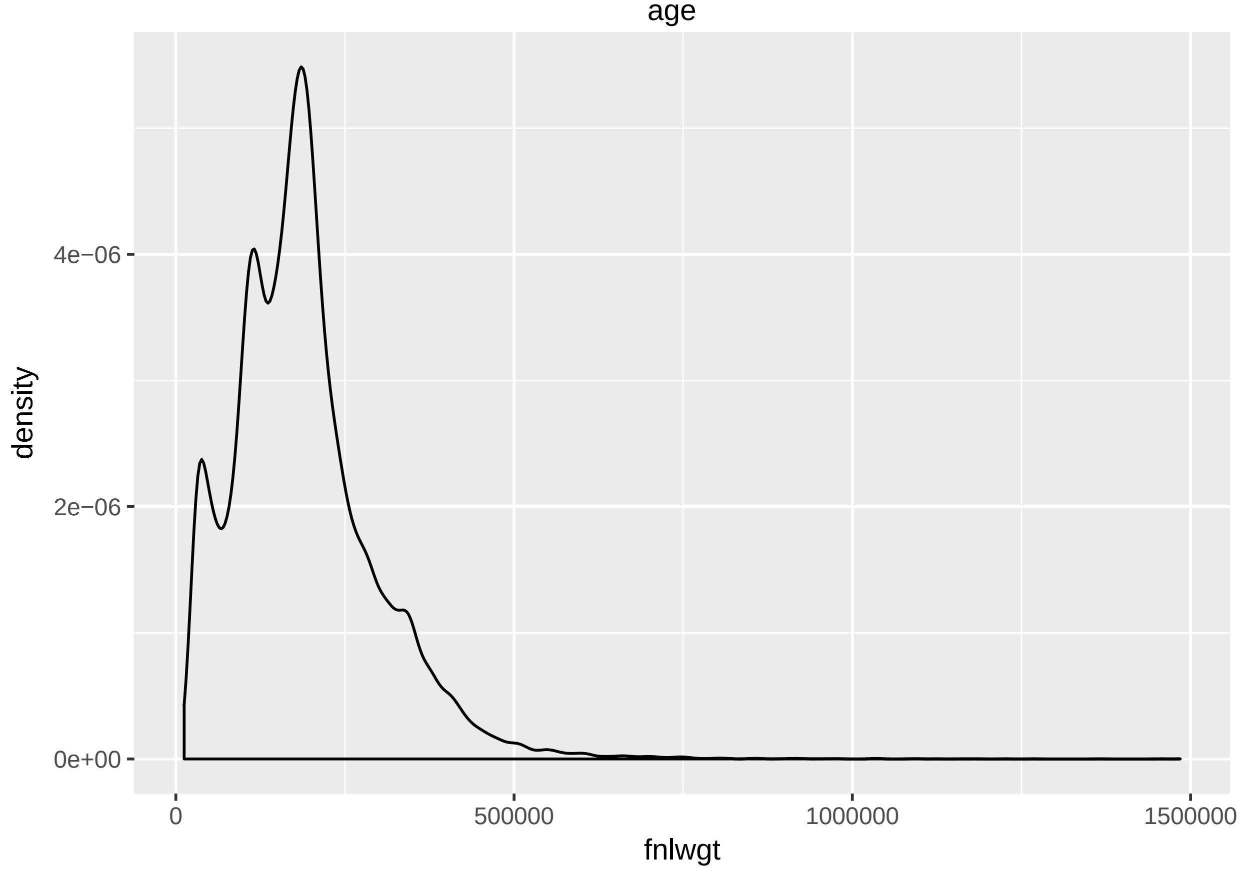
```
##   Exec-managerial:2020    Not-in-family :4278
##   Craft-repair   :2013    Other-relative: 525
##   Sales          :1854    Own-child     :2513
##   Adm-clerical   :1841    Unmarried     :1679
##   Other-service  :1628    Wife          : 763
##  (Other)         :4893
##                  race            sex         capital.gain
##   Amer-Indian-Eskimo:  159    Female: 5421   Min.   :    0
##   Asian-Pac-Islander:  480    Male  :10860   1st Qu.:    0
##   Black             : 1561                   Median :    0
##   Other             :  135                   Mean   : 1082
##   White             :13946                   3rd Qu.:    0
##                                              Max.   :99999
##
##   capital.loss    hours.per.week        native.country     income
##  Min.   :   0.0   Min.   : 1.00    United-States:14662    <=50K:12435
##  1st Qu.:   0.0   1st Qu.:40.00    Mexico       :  308    >50K : 3846
##  Median :   0.0   Median :40.00    ?            :  274
##  Mean   :  87.9   Mean   :40.39    Philippines  :   97
##  3rd Qu.:   0.0   3rd Qu.:45.00    Puerto-Rico  :   70
##  Max.   :3770.0   Max.   :99.00    Germany      :   69
##                                   (Other)       :  801
```

### Visualizing Distributions of Raw Data

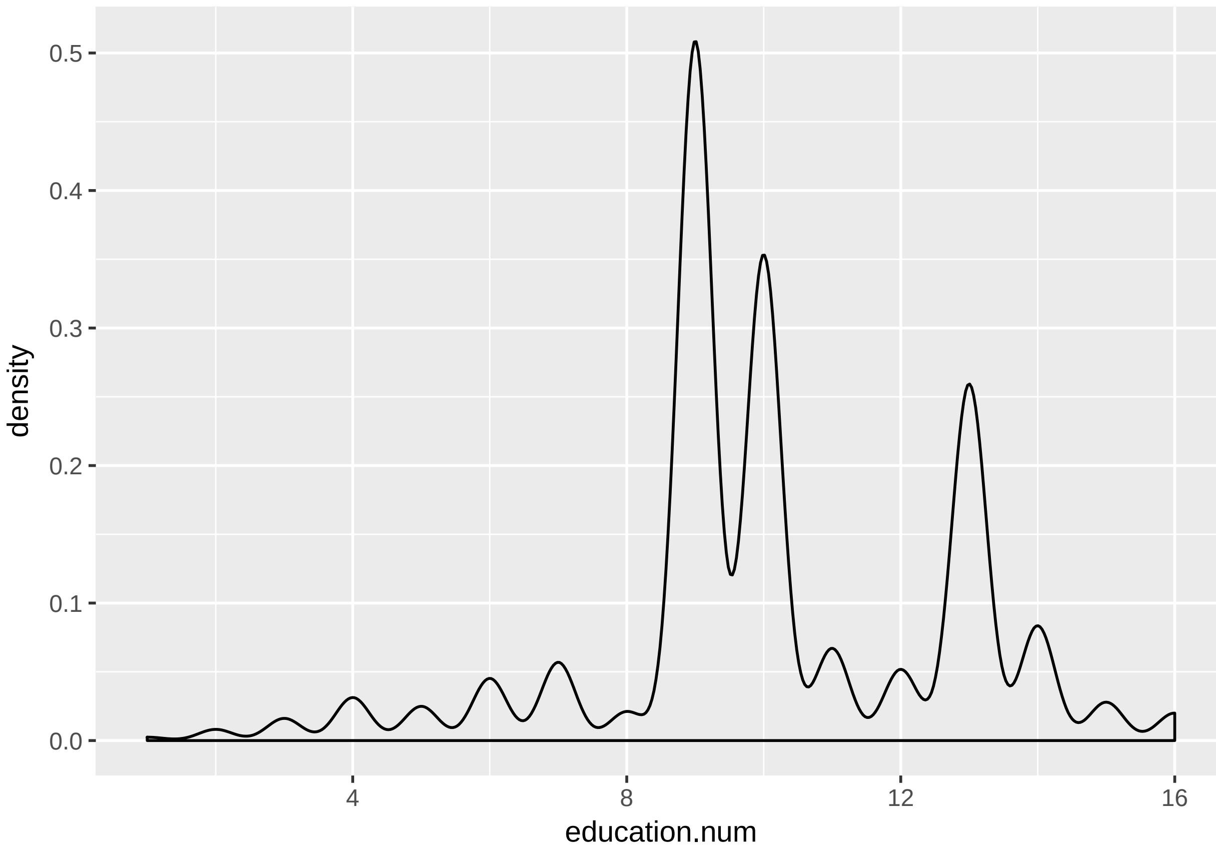
```r
library(ggplot2)
num_var = which(sapply(dat, class) != "factor")
cat_var = which(sapply(dat, class) == "factor")
g = ggplot(dat)
for(i in num_var) {
  # gi = g + geom_point(aes(x = 1:nrow(dat), y = dat[, i])) + labs(x = "index", y = na
  # print(gi)
  print(g + geom_density(aes(x = dat[, i])) + xlab(names(dat)[i]))
}
```



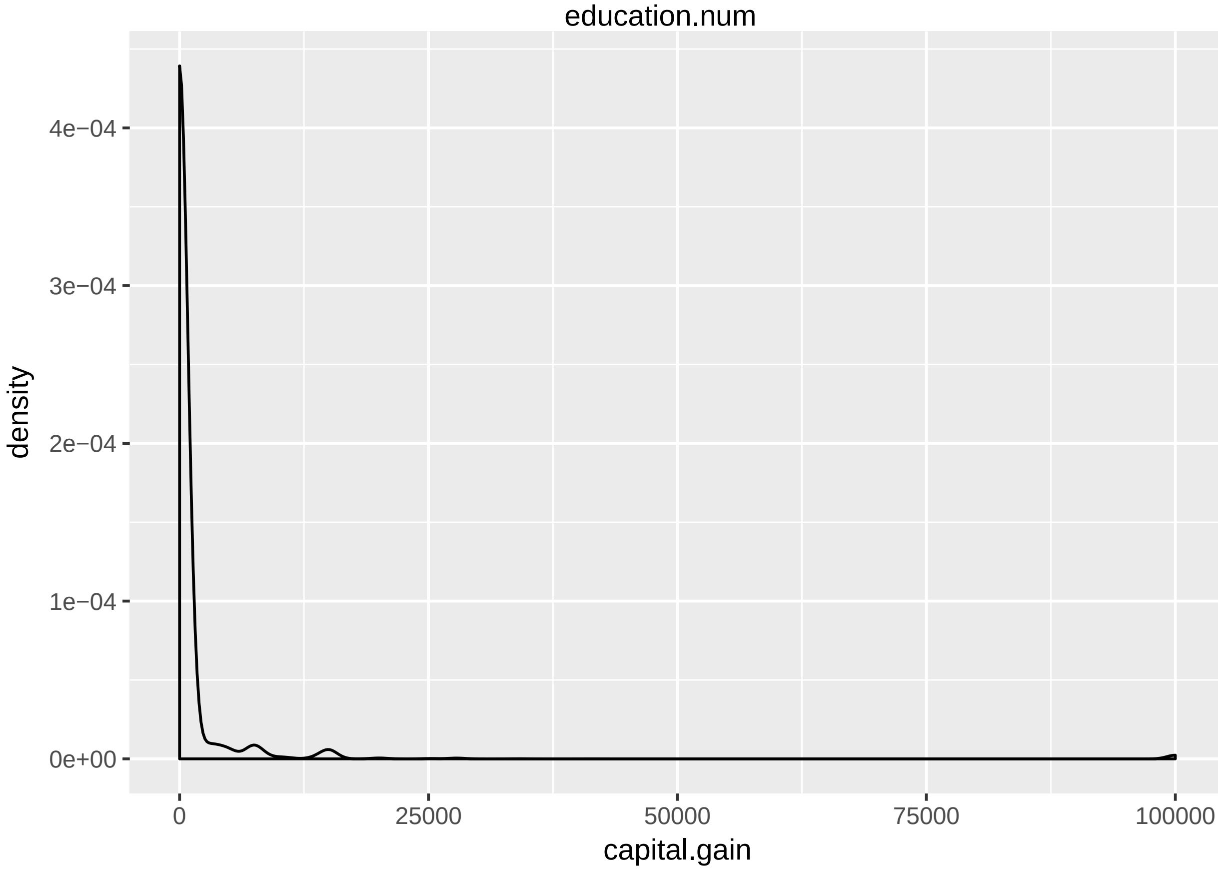
0.02
0.01
0.00
density
25
50
75
age

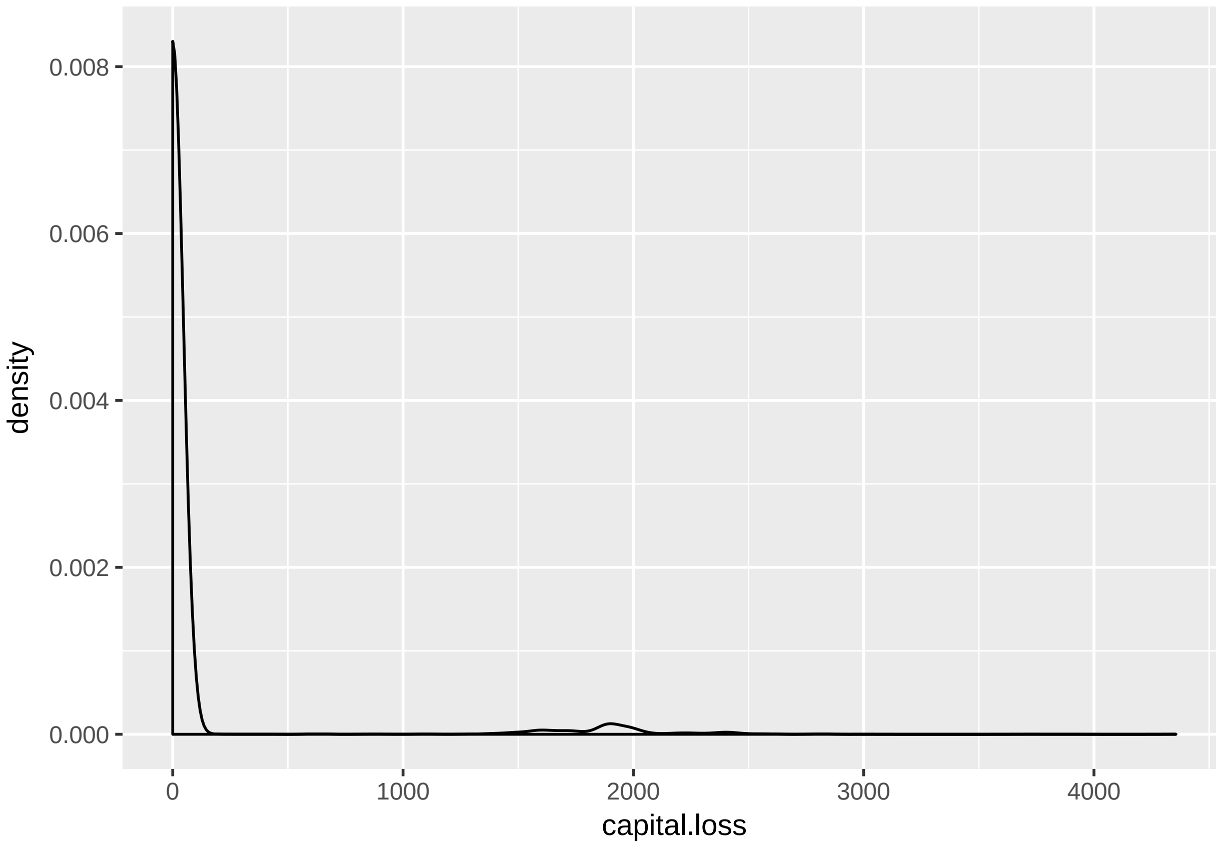
4e−06
2e−06
0e+00
density
0
500000
1000000
1500000
fnlwgt

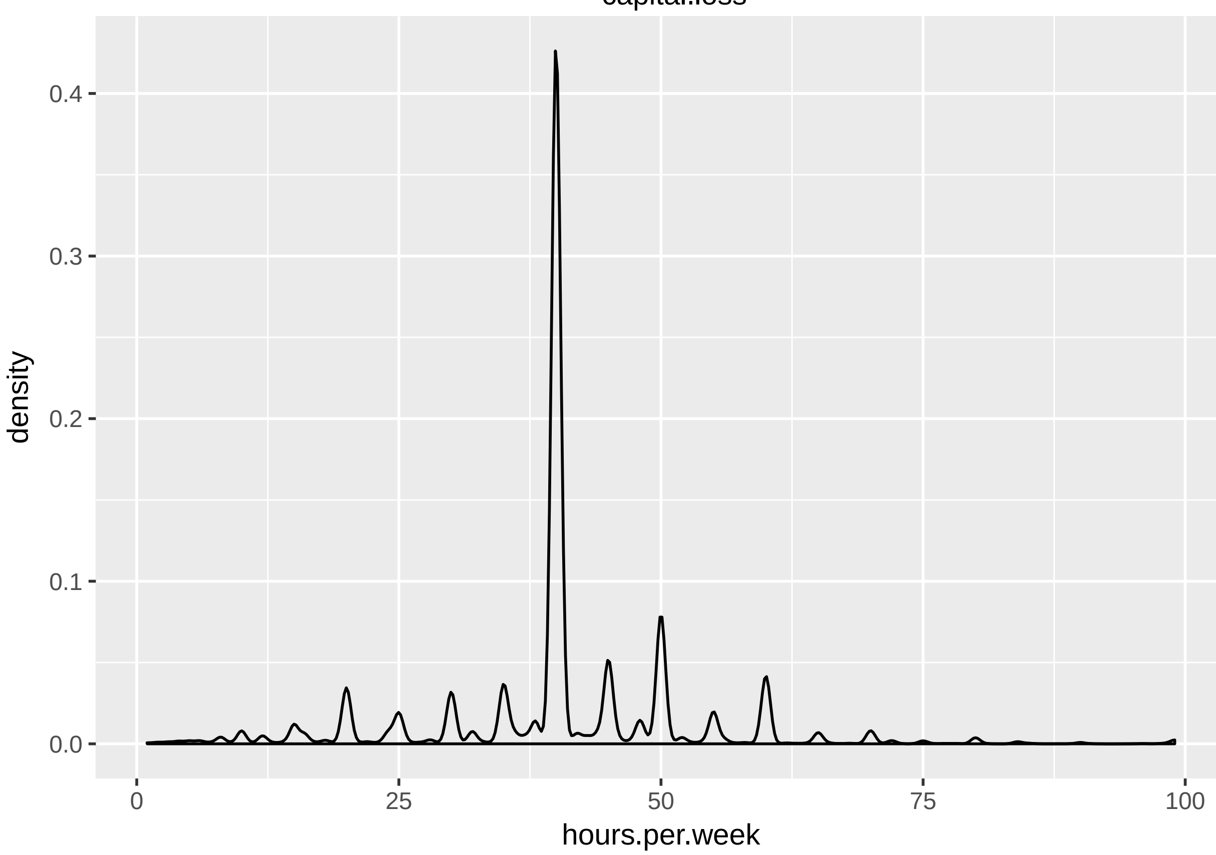


0.5
0.4
0.3
0.2
0.1
0.0
density
4
8
12
16
education.num

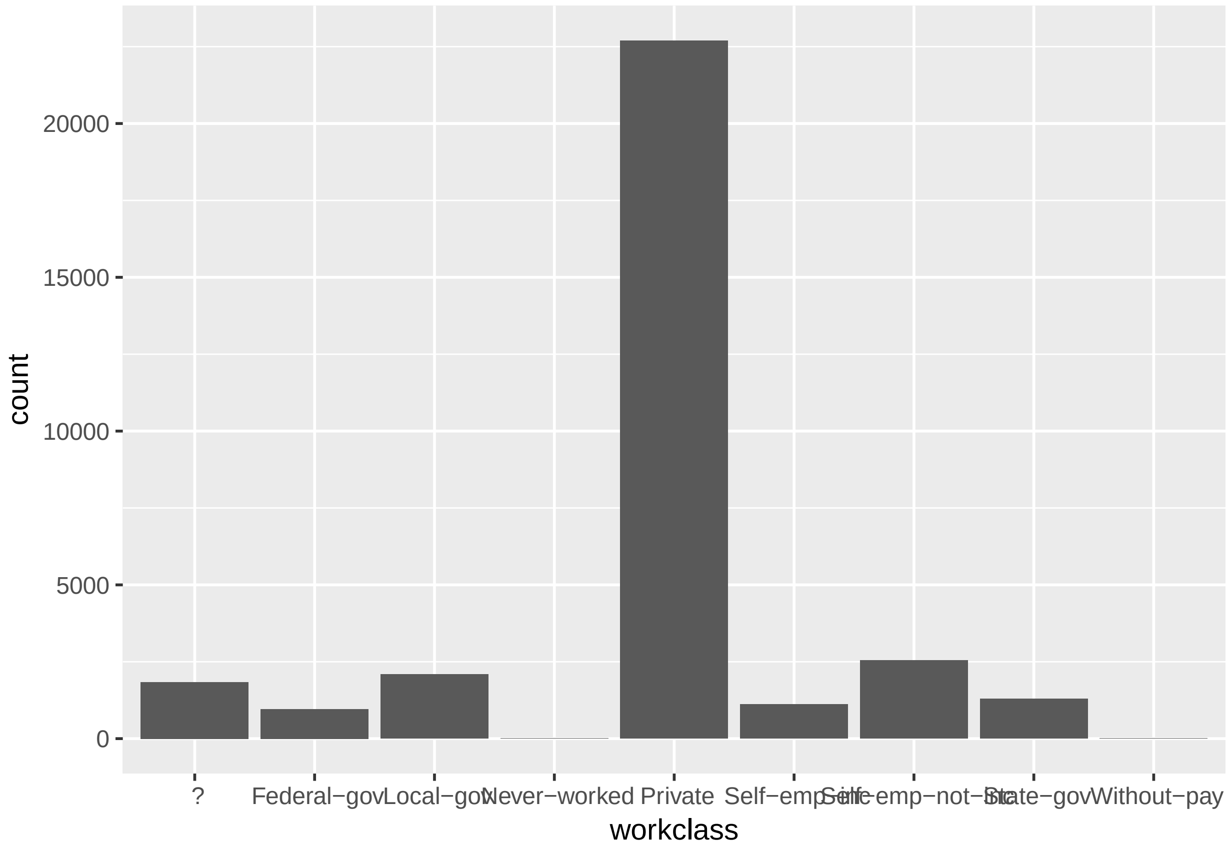



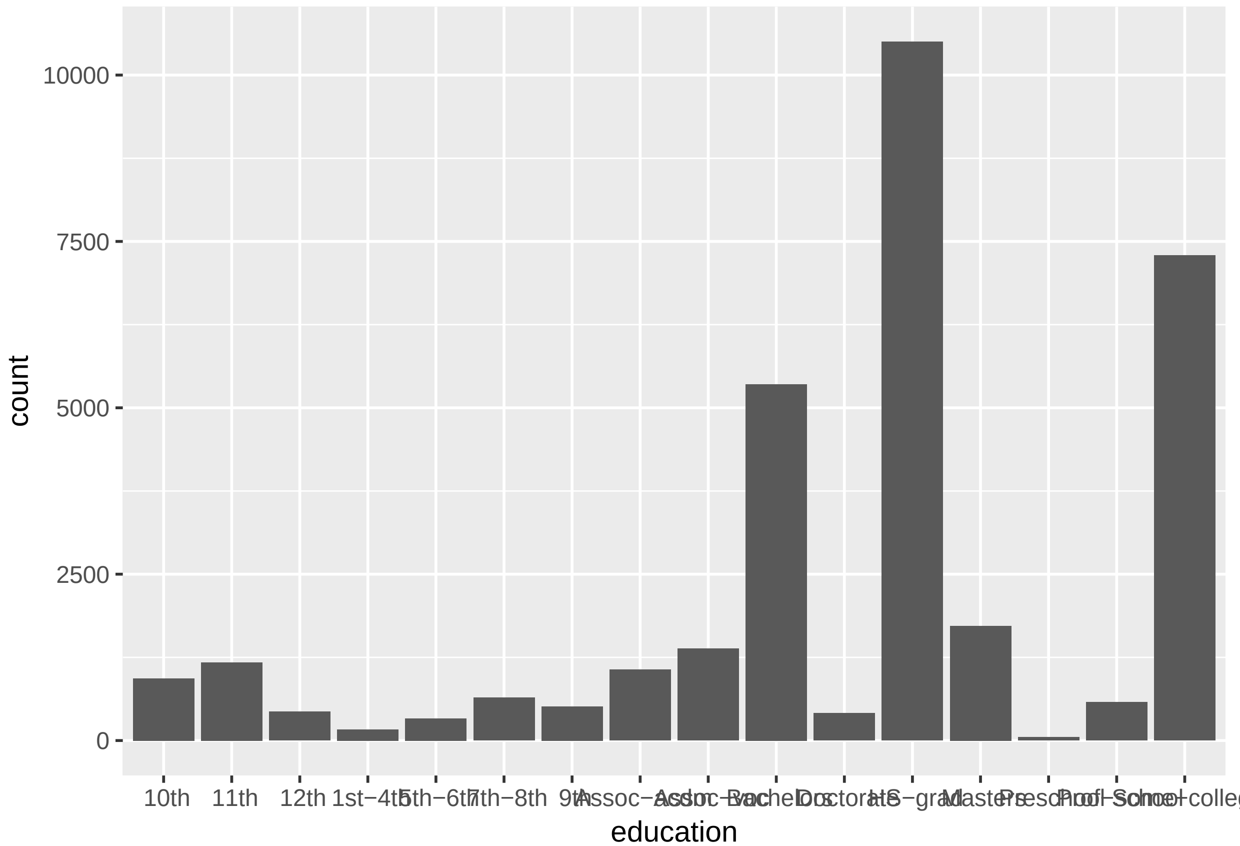
4e−04
3e−04
2e−04
1e−04
0e+00
density
0
25000
50000
75000
100000
capital.gain

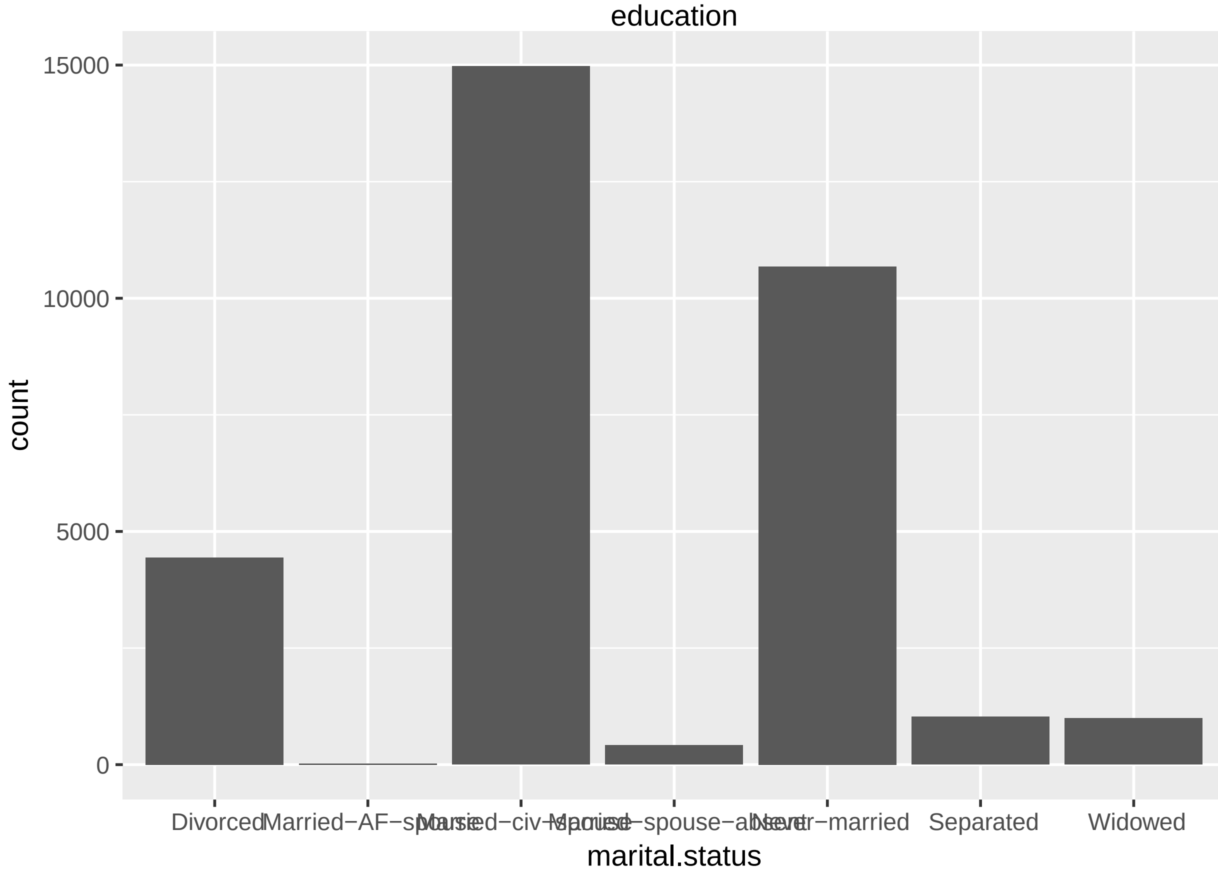

0.008
0.006
0.004
0.002
0.000
density
0
1000
2000
3000
4000
capital.loss

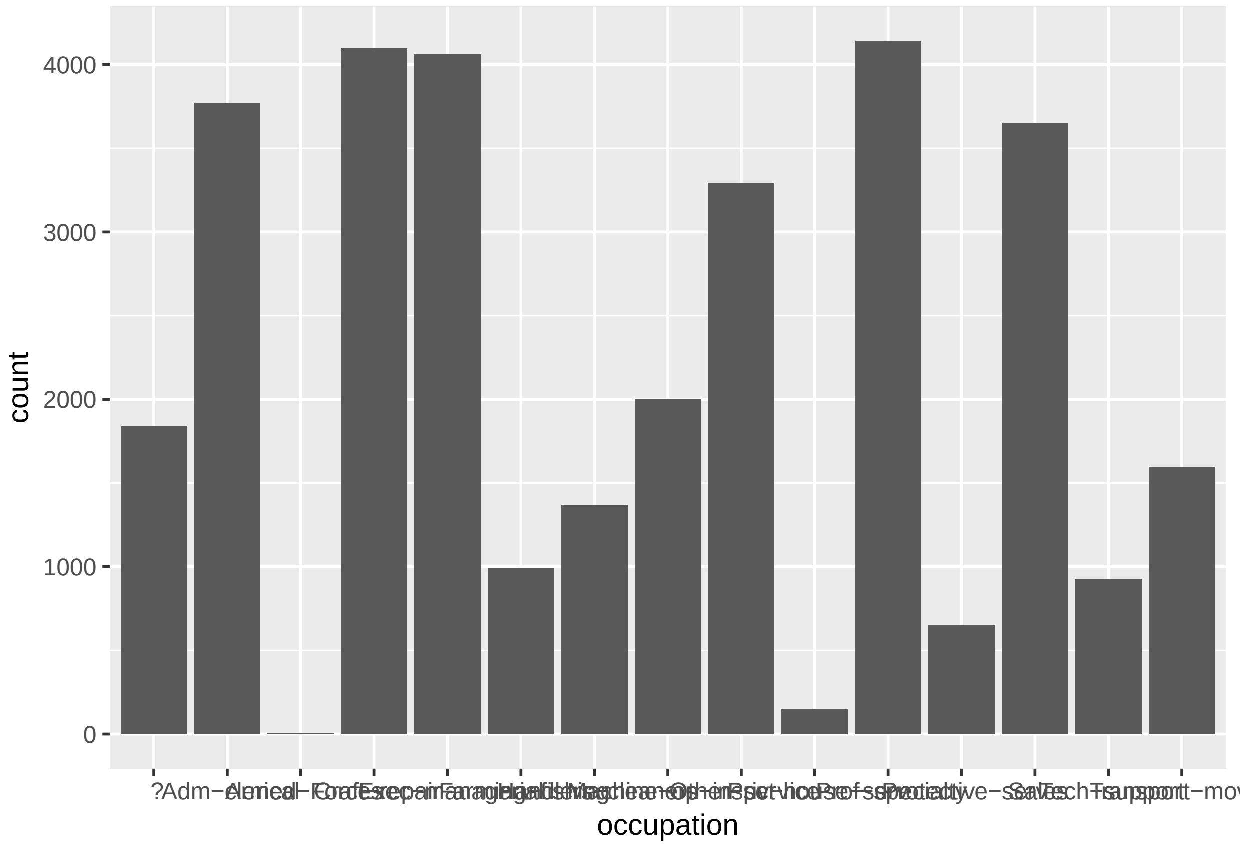

0.4
0.3
0.2
0.1
0.0
density
0
25
50
75
100
hours.per.week

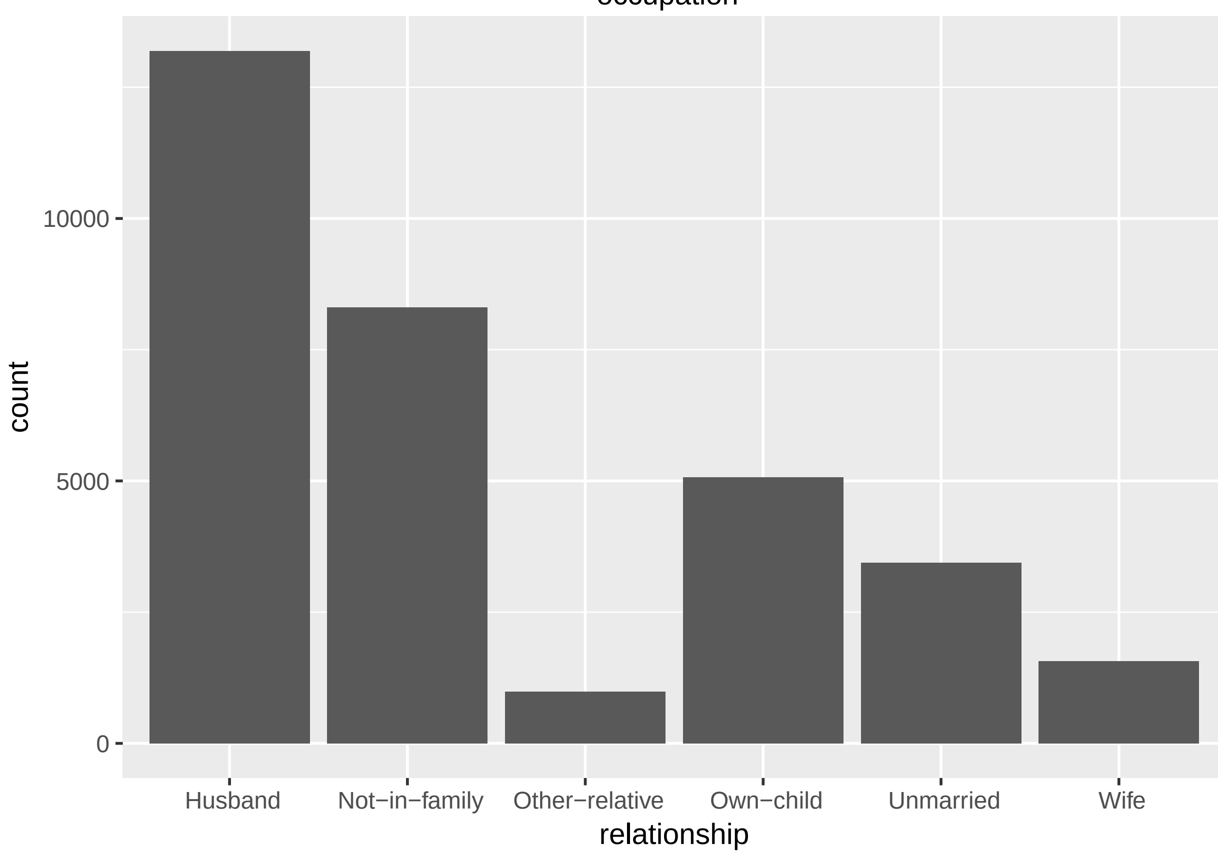
```
for(i in cat_var) {
  gi = g + geom_bar(aes(x = dat[, i])) + xlab(names(dat)[i])
  print(gi)
}
```

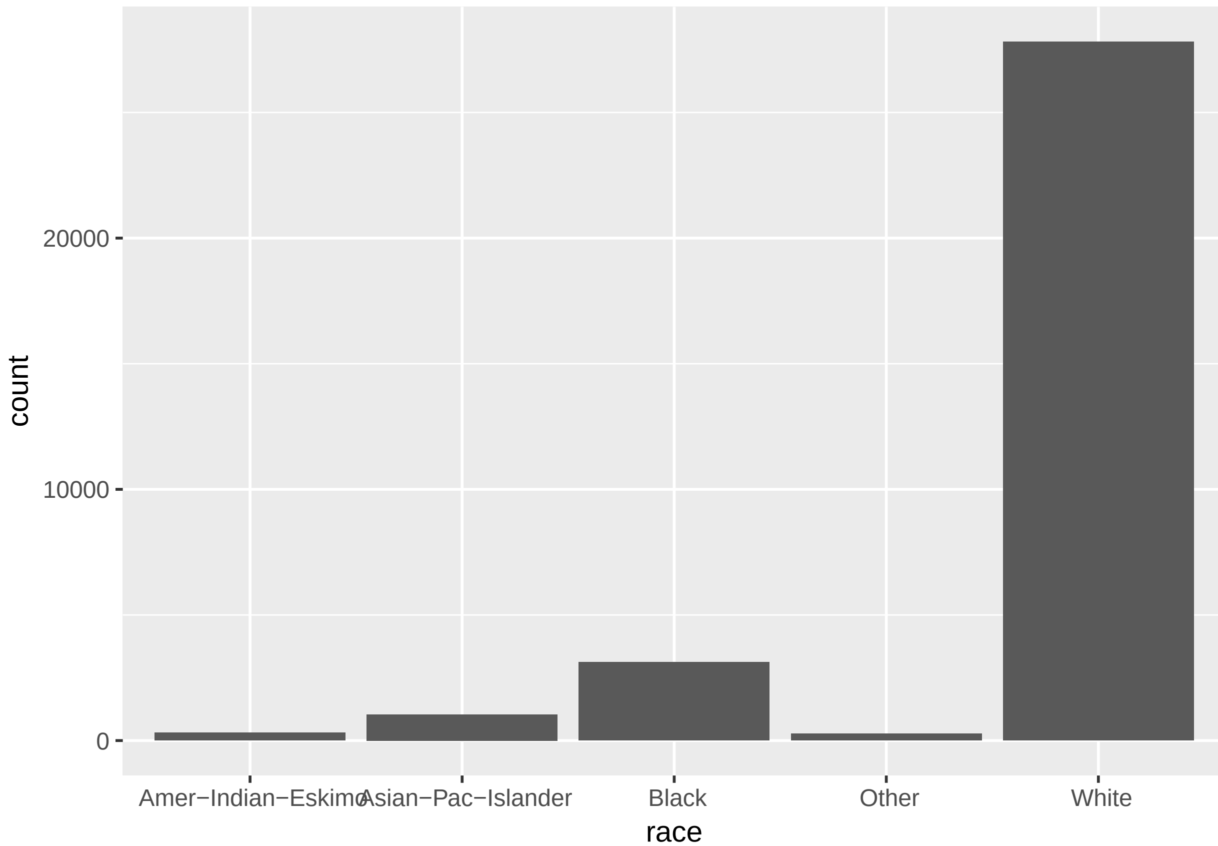



10000
7500
5000
2500
0
count
10th
11th
12th
education

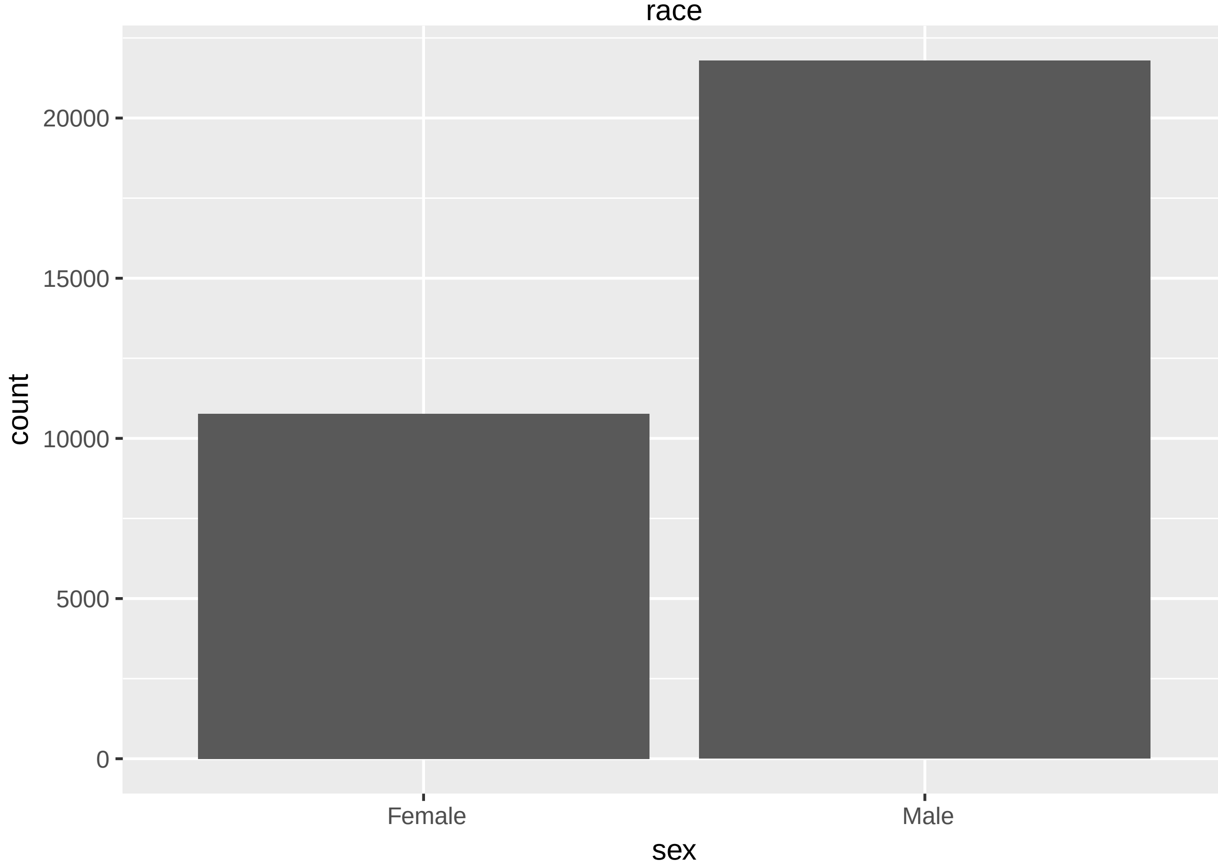

15000
10000
5000
0
count
Divorced
Separated
Widowed
marital.status


count
0
1000
2000
3000
4000
occupation

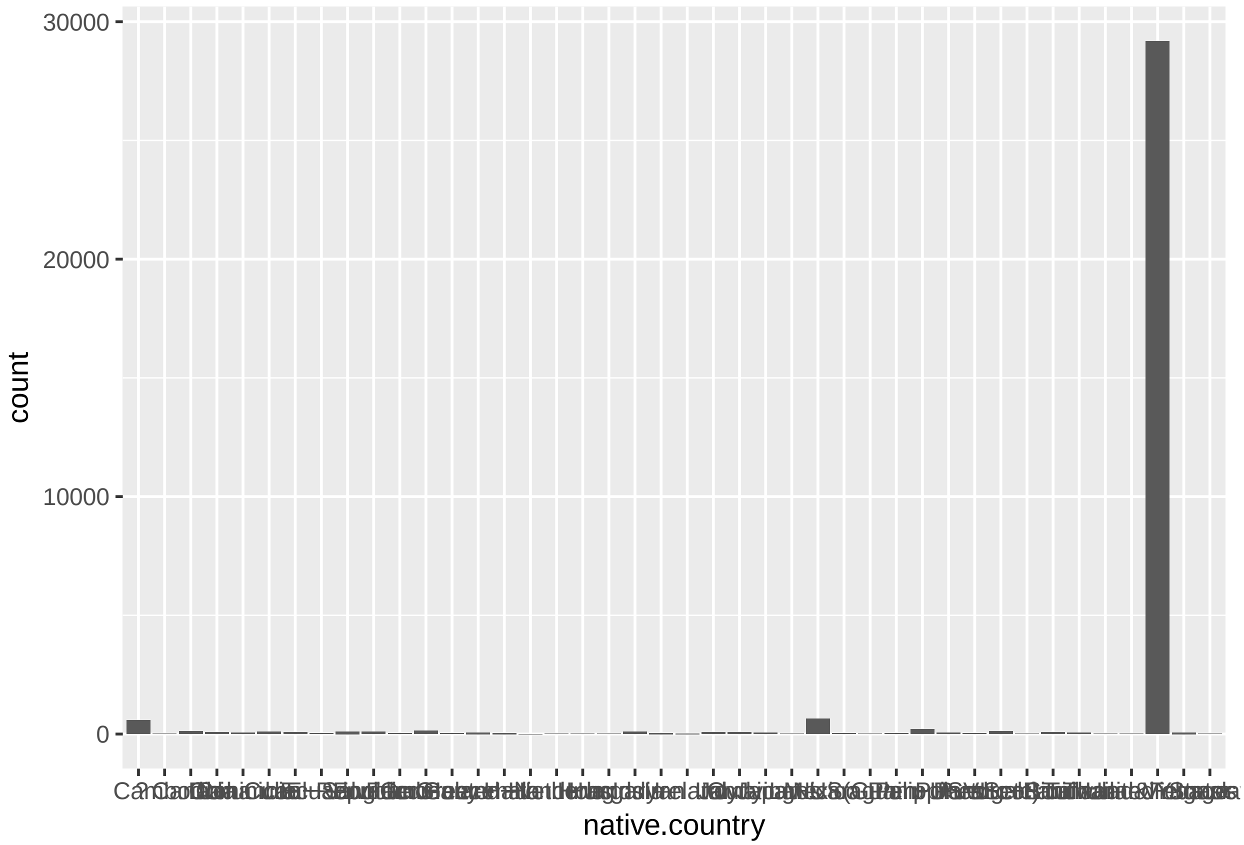

count
0
5000
10000
Husband
Not−in−family
Other−relative
Own−child
Unmarried
Wife
relationship



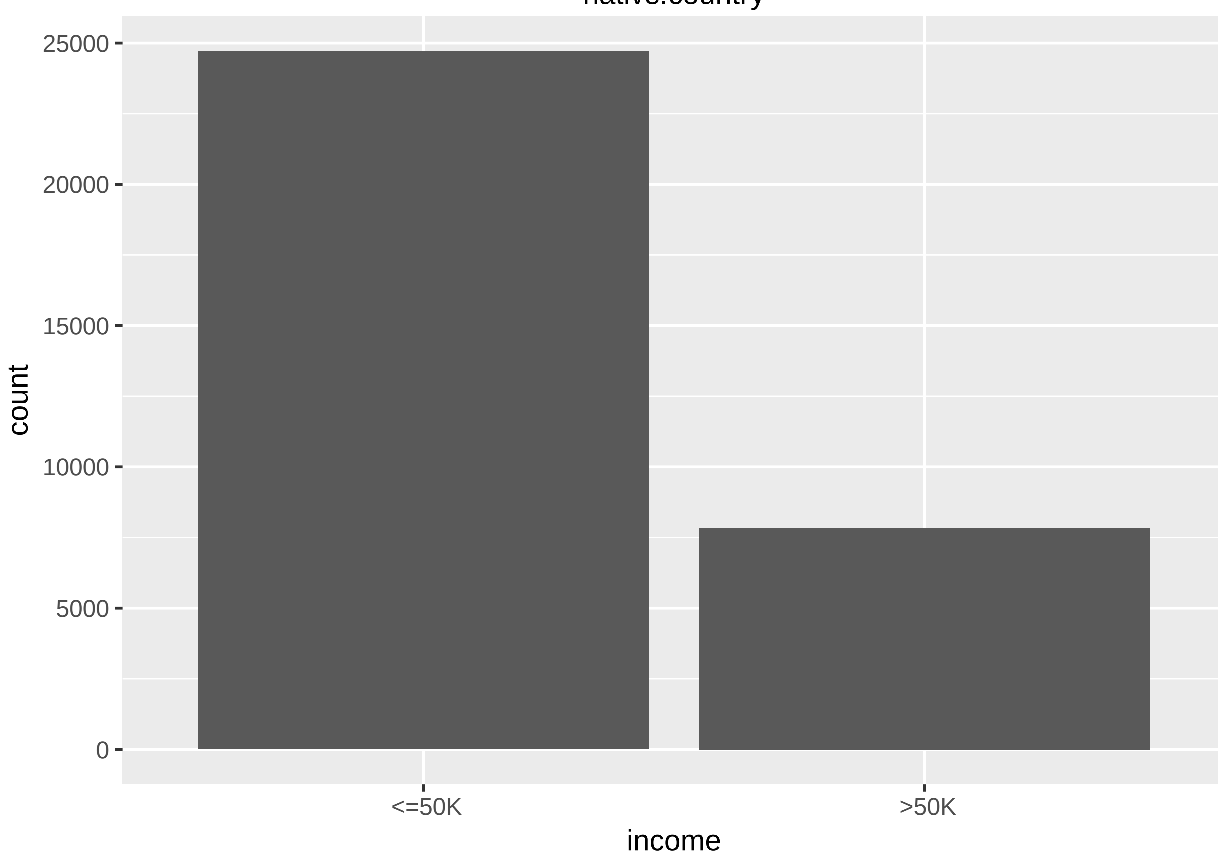
count
20000
10000
0
Amer−Indian−Eskimo
Asian−Pac−Islander
Black
Other
White
race

count
20000
15000
10000
5000
0
Female
Male
sex



30000
20000
10000
0
count
native.country

25000
20000
15000
10000
5000
0
count
<=50K
>50K
income

### Handling Missing Values

```r
# By looking at the summary statistic and the outputs below, there seems to be no miss
# Therefore, for these variables, we do not need to handle the missing values.
unique(dat$education)
```

```
##  [1]  Bachelors     HS-grad       11th          Masters       9th
##  [6]  Some-college  Assoc-acdm    Assoc-voc     7th-8th       Doctorate
## [11]  Prof-school   5th-6th       10th          1st-4th       Preschool
## [16]  12th
## 16 Levels:  10th  11th  12th  1st-4th  5th-6th  7th-8th ...  Some-college
```

```r
unique(dat$occupation)
```

```
##  [1]  Adm-clerical       Exec-managerial    Handlers-cleaners
##  [4]  Prof-specialty     Other-service      Sales
##  [7]  Craft-repair       Transport-moving   Farming-fishing
## [10]  Machine-op-inspct  Tech-support       ?
## [13]  Protective-serv    Armed-Forces       Priv-house-serv
## 15 Levels:  ?  Adm-clerical  Armed-Forces ...  Transport-moving
```

```r
unique(dat$native.country)
```

```
##  [1]  United-States                Cuba
##  [3]  Jamaica                      India
##  [5]  ?                            Mexico
##  [7]  South                        Puerto-Rico
##  [9]  Honduras                     England
## [11]  Canada                       Germany
## [13]  Iran                         Philippines
## [15]  Italy                        Poland
## [17]  Columbia                     Cambodia
## [19]  Thailand                     Ecuador
## [21]  Laos                         Taiwan
## [23]  Haiti                        Portugal
## [25]  Dominican-Republic           El-Salvador
## [27]  France                       Guatemala
## [29]  China                        Japan
## [31]  Yugoslavia                   Peru
## [33]  Outlying-US(Guam-USVI-etc)  Scotland
## [35]  Trinadad&Tobago              Greece
## [37]  Nicaragua                    Vietnam
## [39]  Hong                         Ireland
## [41]  Hungary                      Holand-Netherlands
## 42 Levels:  ?  Cambodia  Canada  China  Columbia ...  Yugoslavia
```

```r
# workclass
# Seems like there are only small number (1836 comparing to 32561) of workclass is mis
rmIndexWC = which(dat$workclass == " ?")
length(rmIndexWC)
```

```
## [1] 1836
```

```r
# occupation
# Seems like there are only small number (1843 comparing to 32561) of occupation is mi
rmIndexOC = which(dat$occupation == " ?")
length(rmIndexOC)
```

```
## [1] 1843
```

```r
# native-country
# Seems like there are only small number (583 comparing to 32561) of native-country is
rmIndexNC = which(dat$native.country == " ?")
length(rmIndexNC)
```

```
## [1] 583
```

```r
# Also noticed that there are some data have more than one missing values across workc
sum(rmIndexOC == rmIndexWC)
```

```
## Warning in rmIndexOC == rmIndexWC: longer object length is not a multiple
## of shorter object length

## [1] 352
```

```r
# capital-gain
# capital-loss
# Since there are too many missing values in 'capital-gain' and 'capital-loss', I choo
n = nrow(dat)
n
```

```
## [1] 32561
```

```r
sum(dat$capital.gain == 0)
```

```
## [1] 29849
```

```r
sum(dat$capital.loss == 0)
```

```
## [1] 31042
```

```r
rmIndex = unique(c(rmIndexNC, rmIndexOC, rmIndexWC))
dat = dat[-rmIndex, -c(11, 12)]
dat_test = dat_test[, -c(11, 12)]
dim(dat)
```

```
## [1] 30162    13
```

```
# After removing missing values, we still have 30162 observations, which is still larg
```

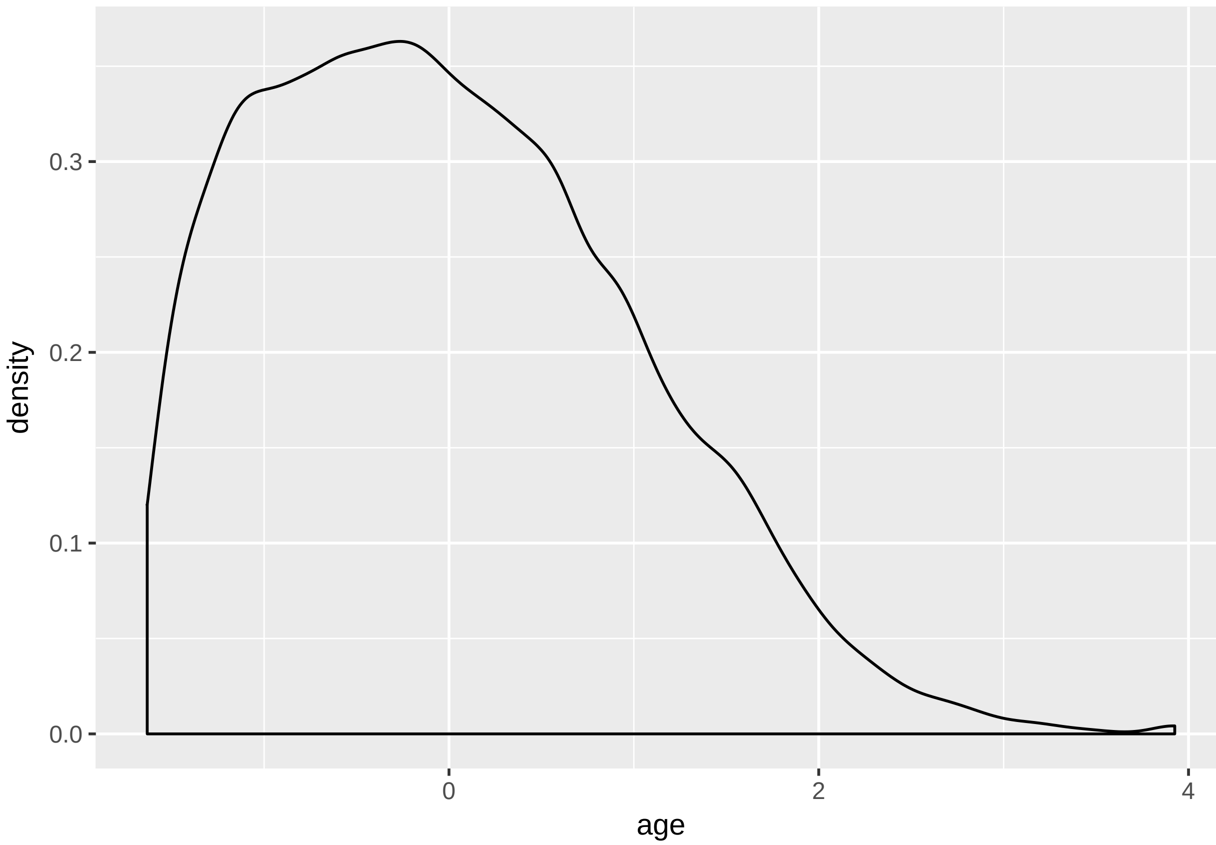
```
n = nrow(dat)
full = rbind(dat, dat_test)
dat = full[1:n, ]
dat_test = full[(n+1):nrow(full), ]
```

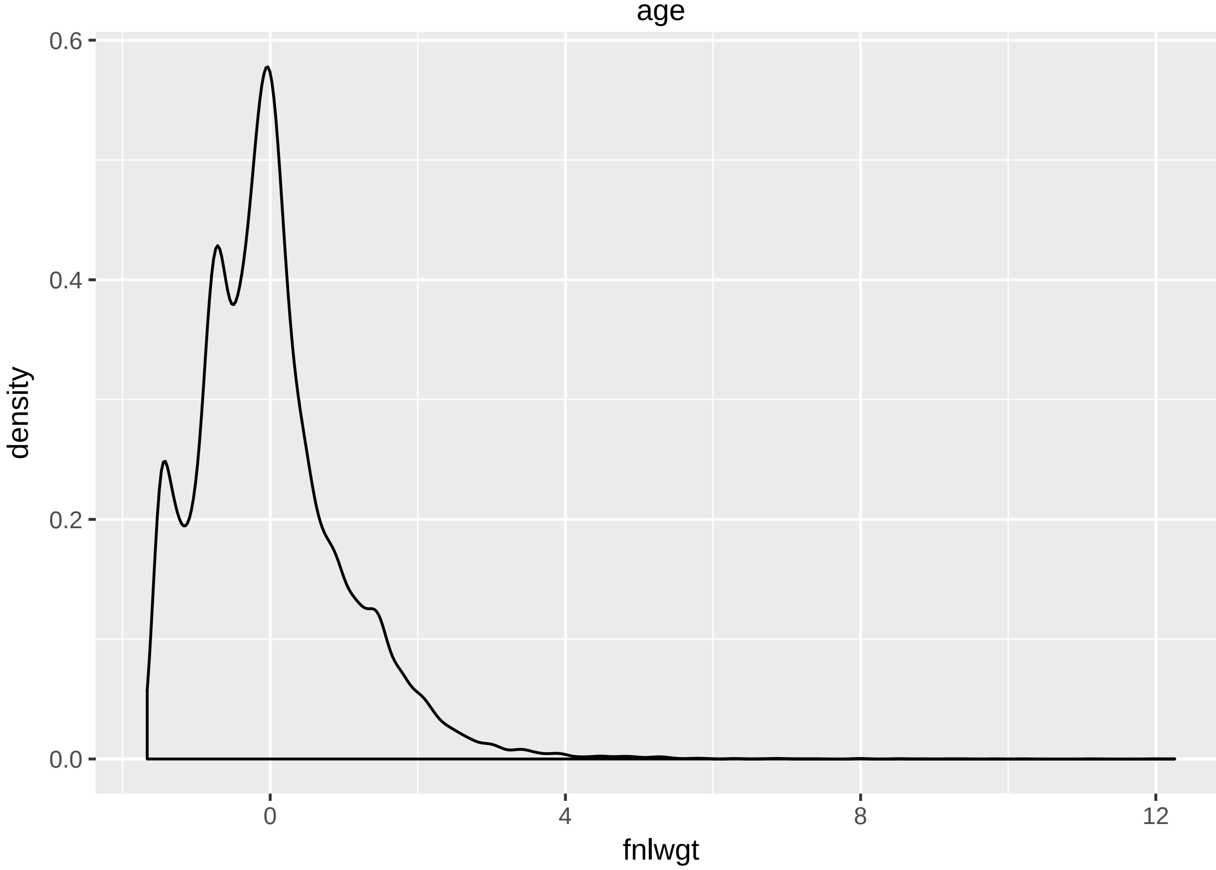
### Changing Scale

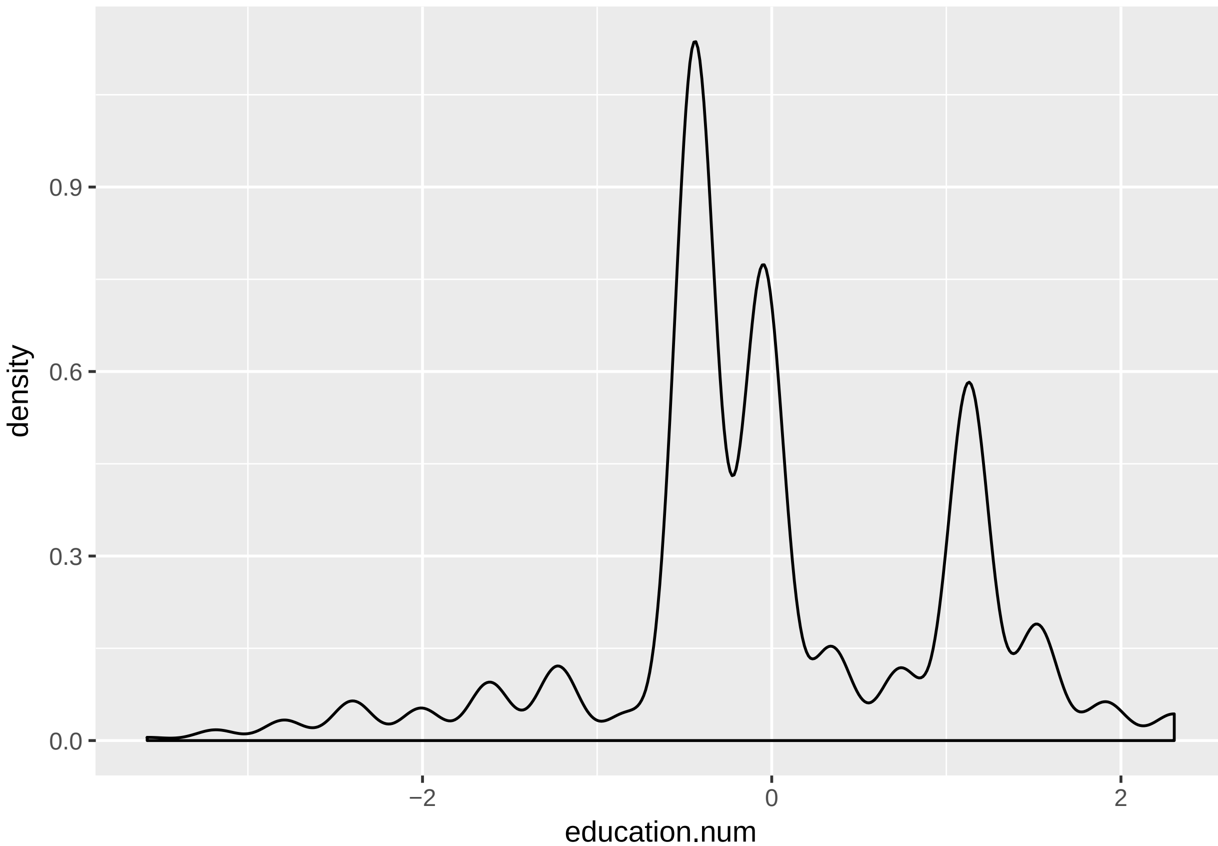
```
num_var = which(sapply(dat, class) != "factor")
cat_var = which(sapply(dat, class) == "factor")

# Only change the scales of numerical variables
# It doesn't really make sense to transform the categorical variables
for(i in num_var) {
  dat[, i] = as.numeric(scale(dat[, i]))
  m = mean(dat[, i])
  s = sd(dat[, i])
  dat_test[, i] = as.numeric(scale(dat_test[, i], center = m, scale = s))
}
```

### Visualizing Distributions after Cleaning

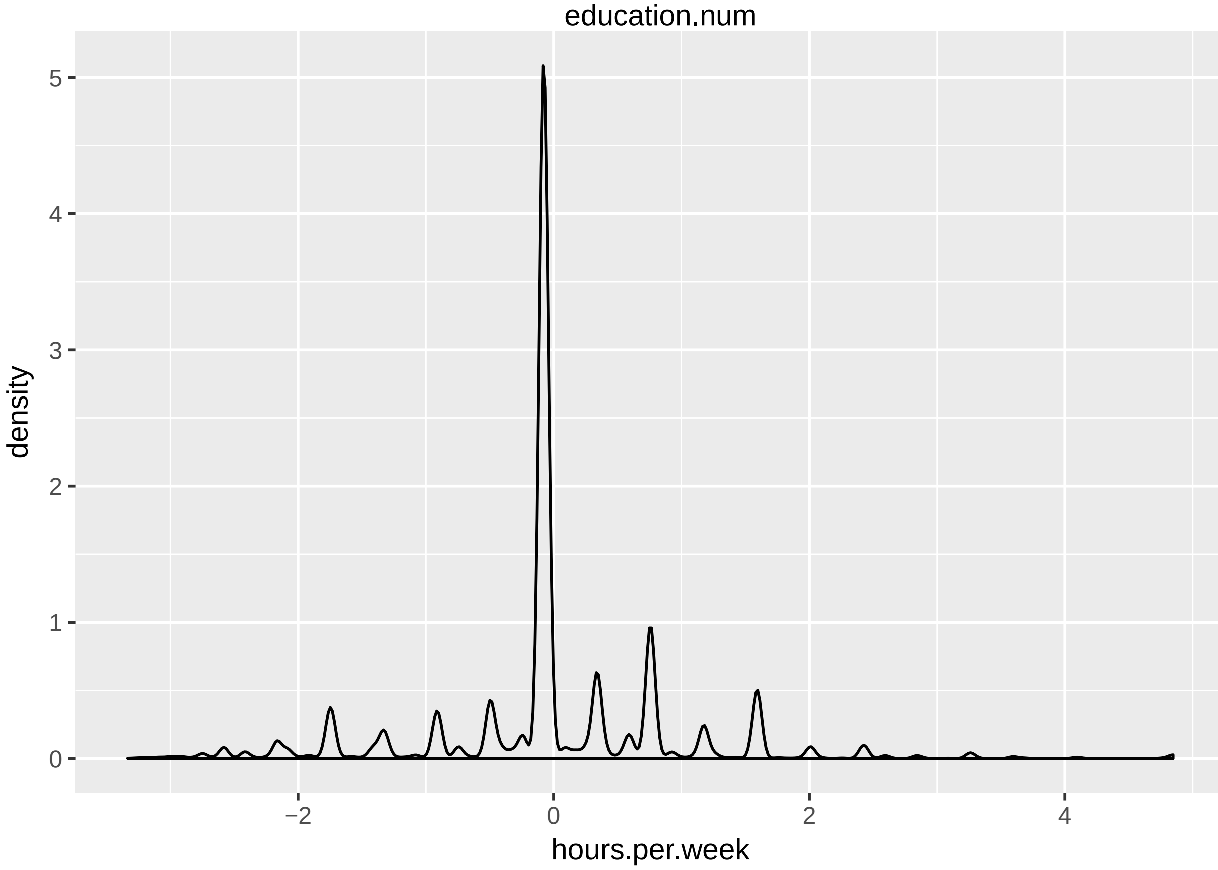
```
library(ggplot2)
g = ggplot(dat)
for(i in num_var) {
  # gi = g + geom_point(aes(x = 1:nrow(dat), y = dat[, i])) + labs(x = "index", y = na
  # print(gi)
  print(g + geom_density(aes(x = dat[, i])) + xlab(names(dat)[i]))
}
```


density
0.0
0.1
0.2
0.3
0
2
4
age


density
0.0
0.2
0.4
0.6
0
4
8
12
fnlwgt

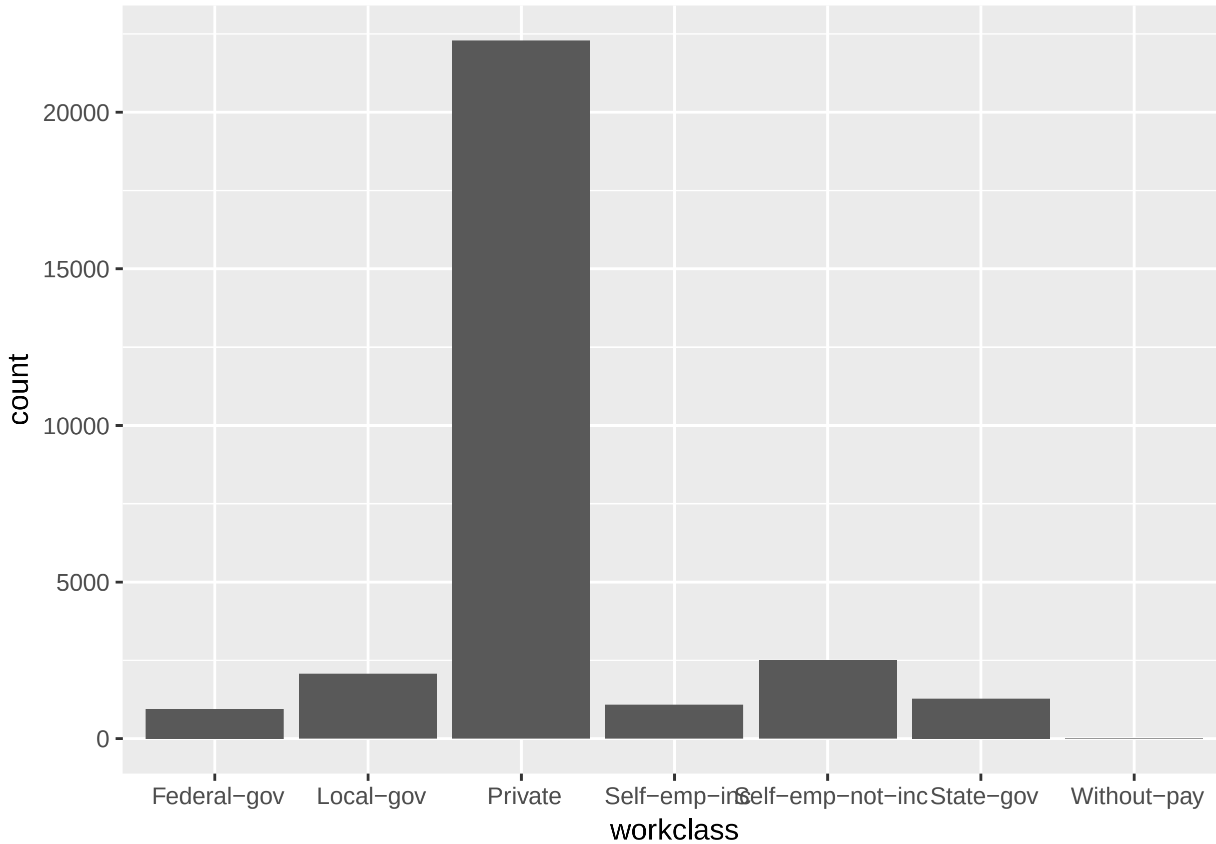


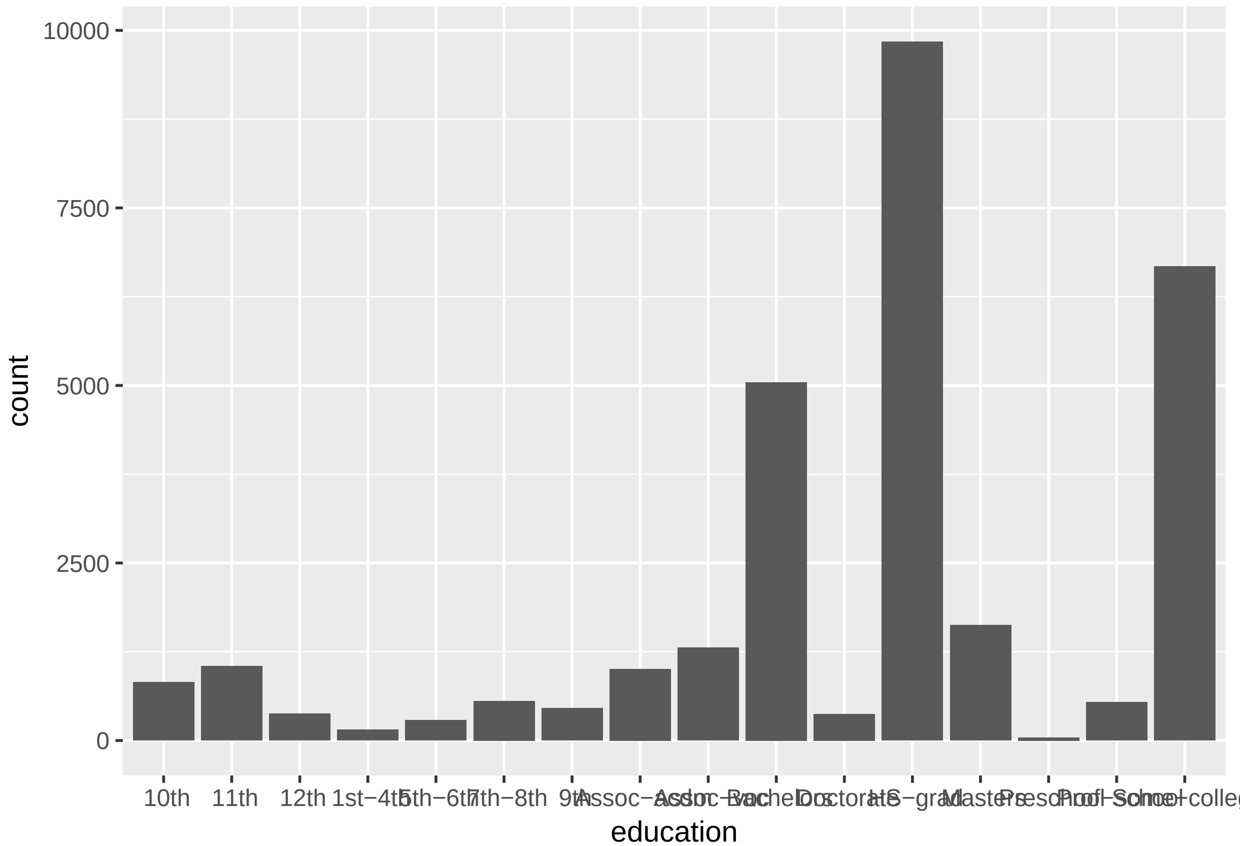
0.9
0.6
0.3
0.0
density
−2
0
2
education.num

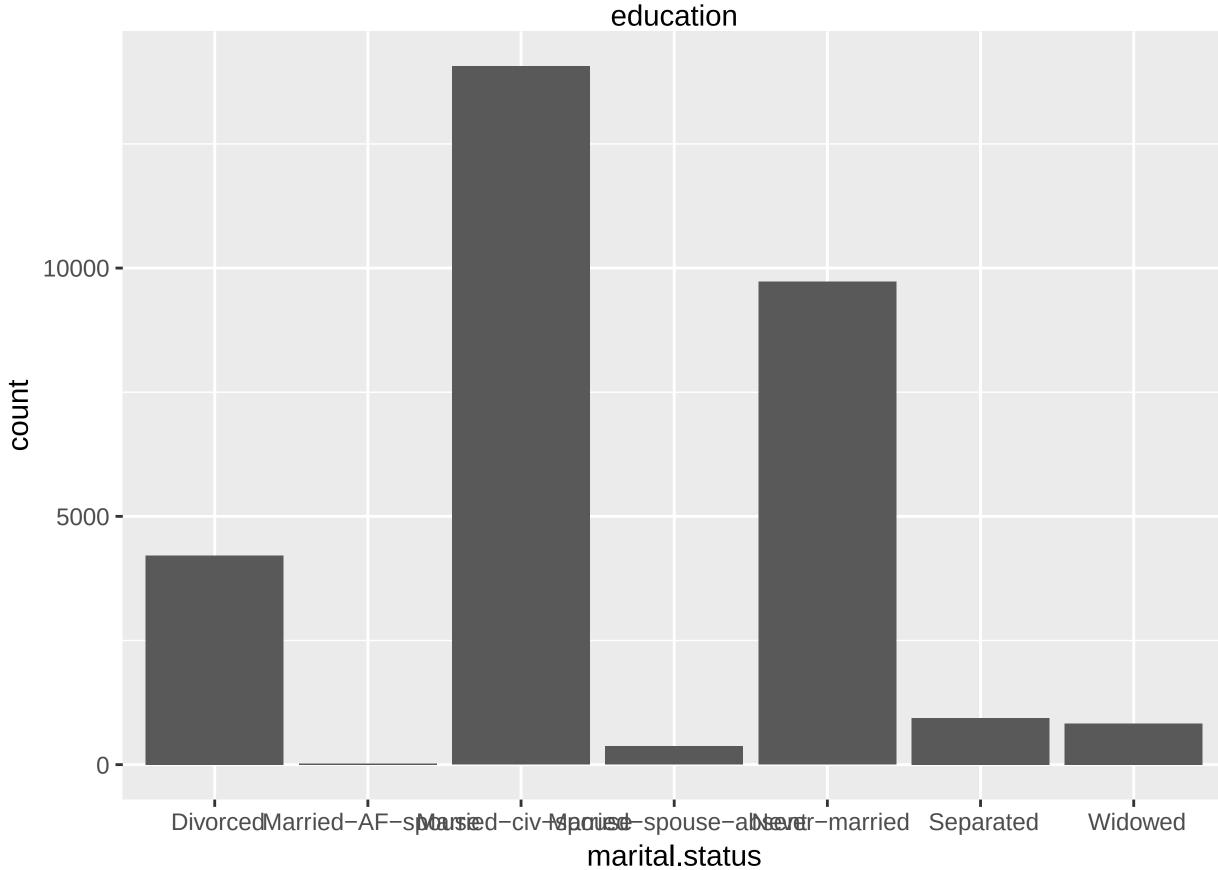



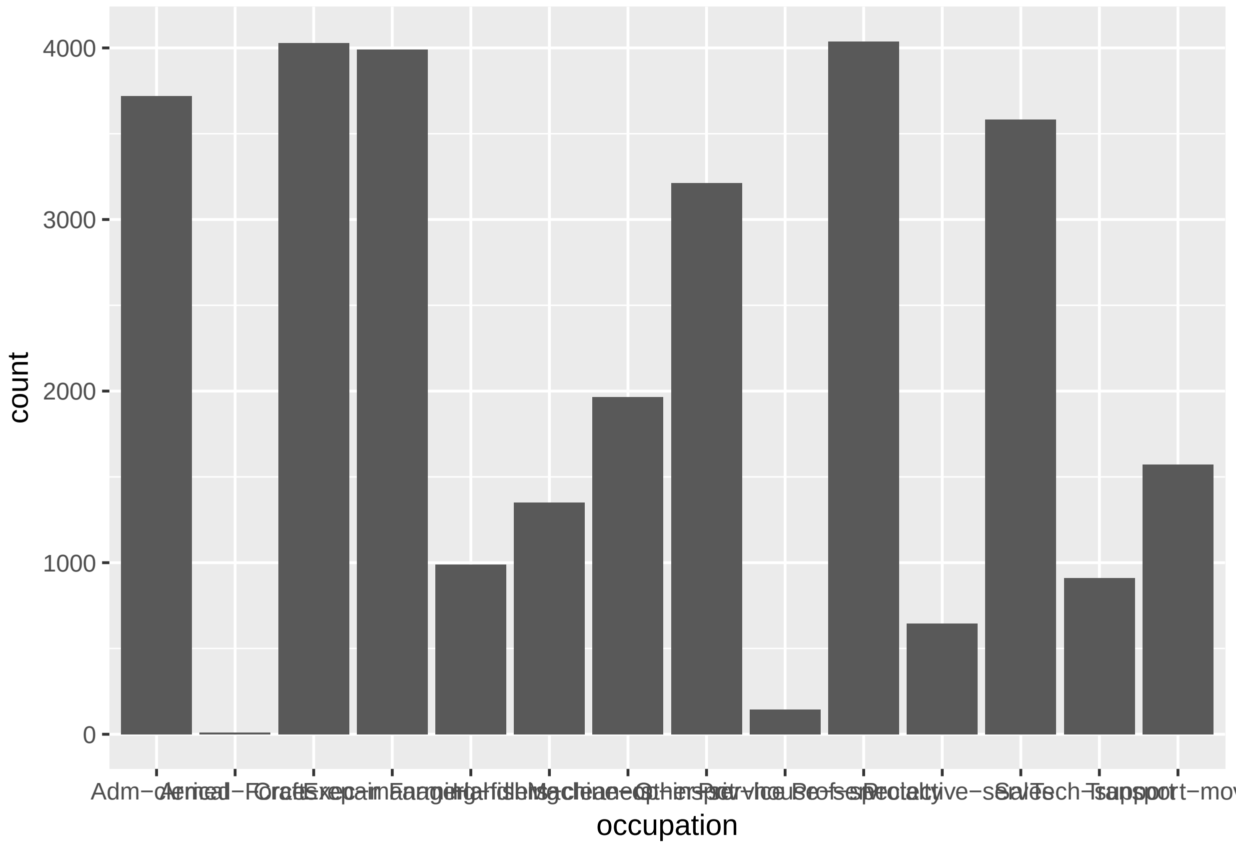
5
4
3
2
1
0
density
−2
0
2
4
hours.per.week

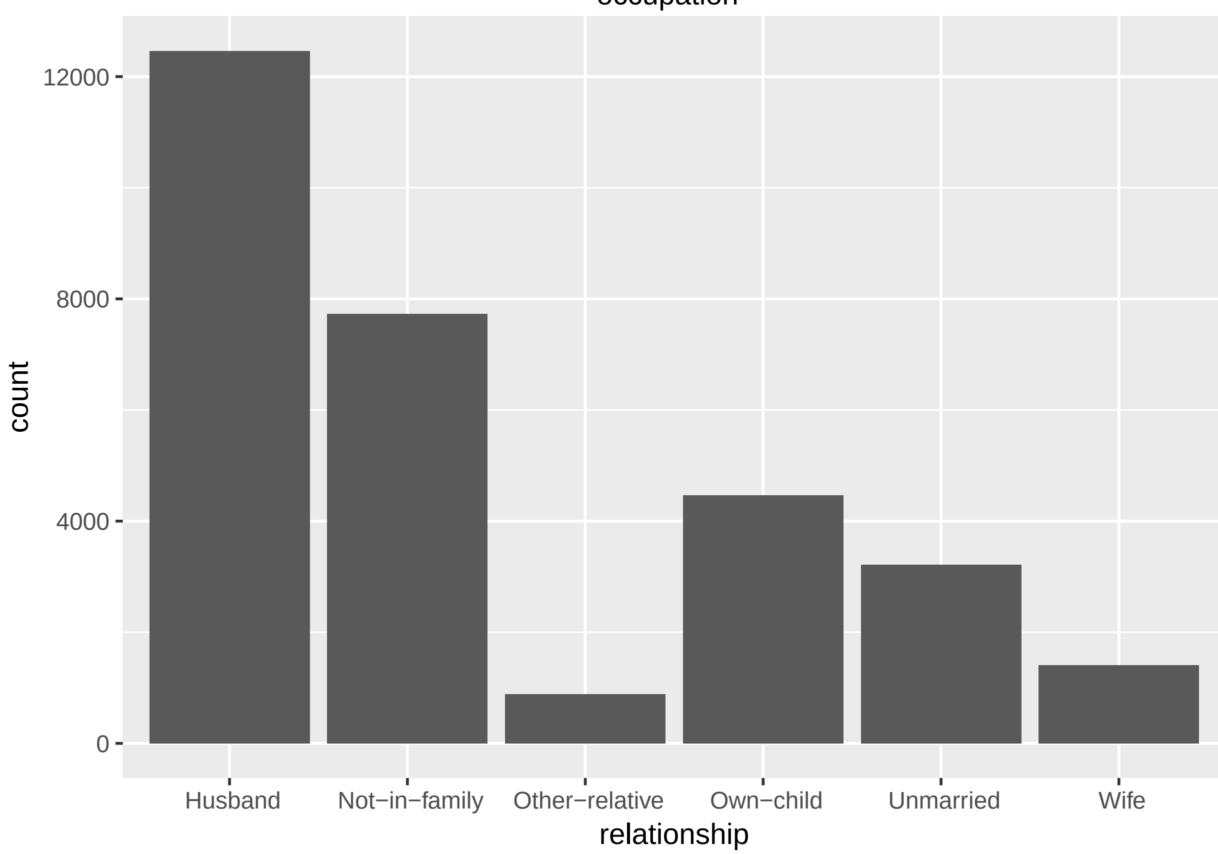
```
for(i in cat_var) {
  gi = g + geom_bar(aes(x = dat[, i])) + xlab(names(dat)[i])
  print(gi)
}
```

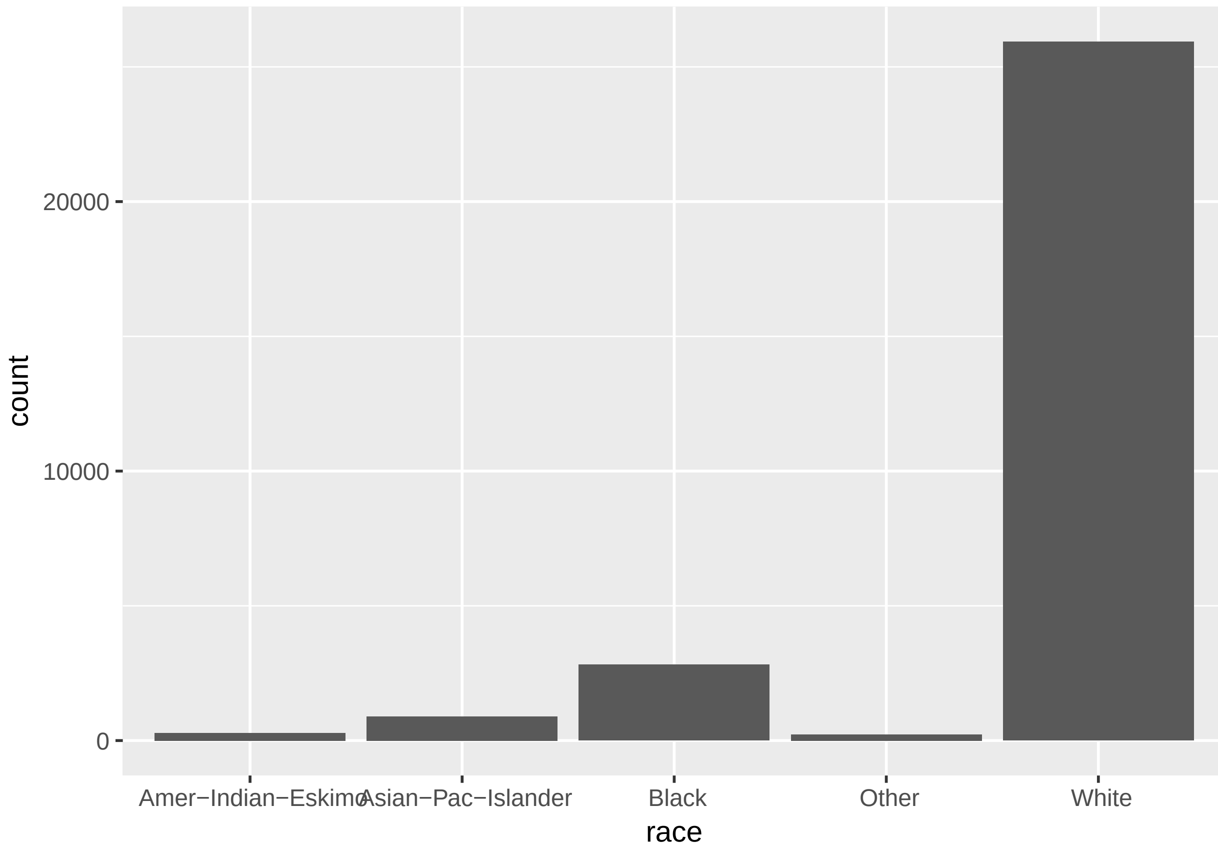


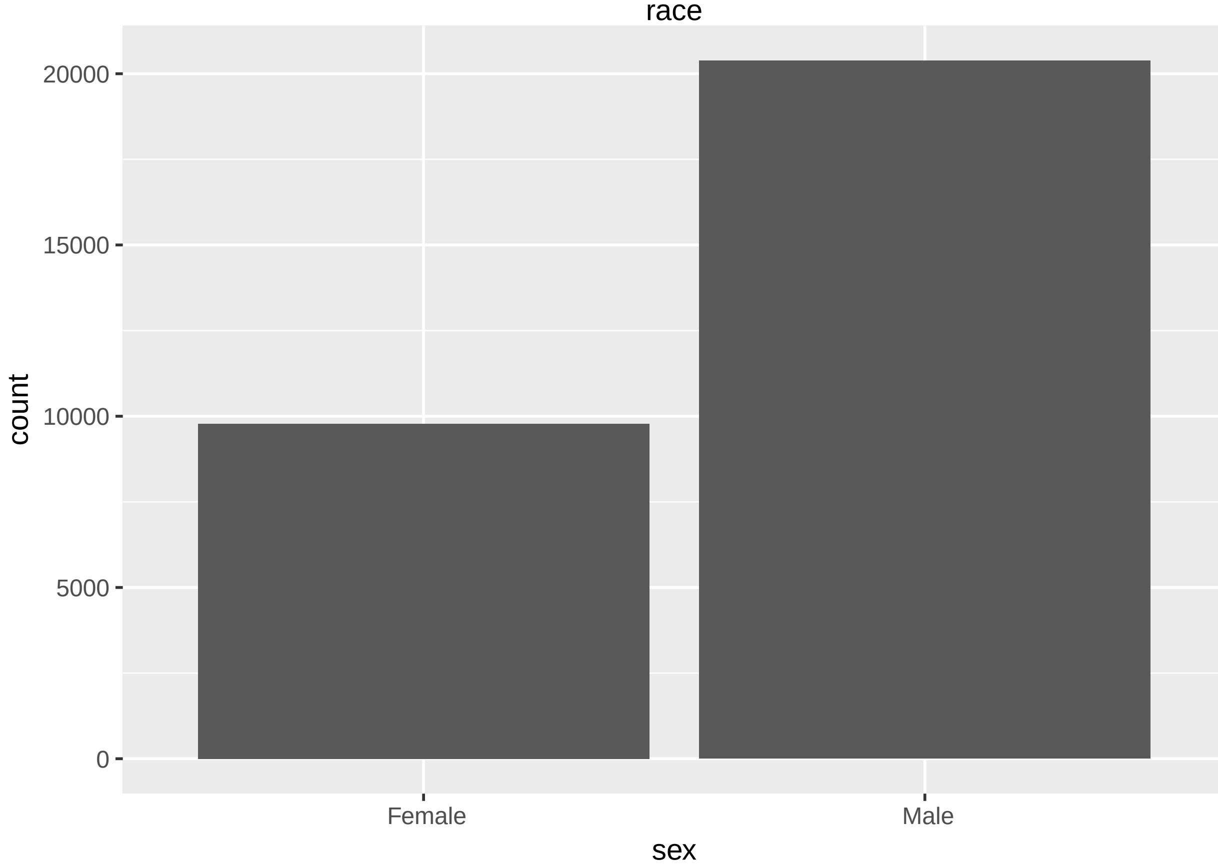

count
10000
7500
5000
2500
0
10th
11th
12th
education

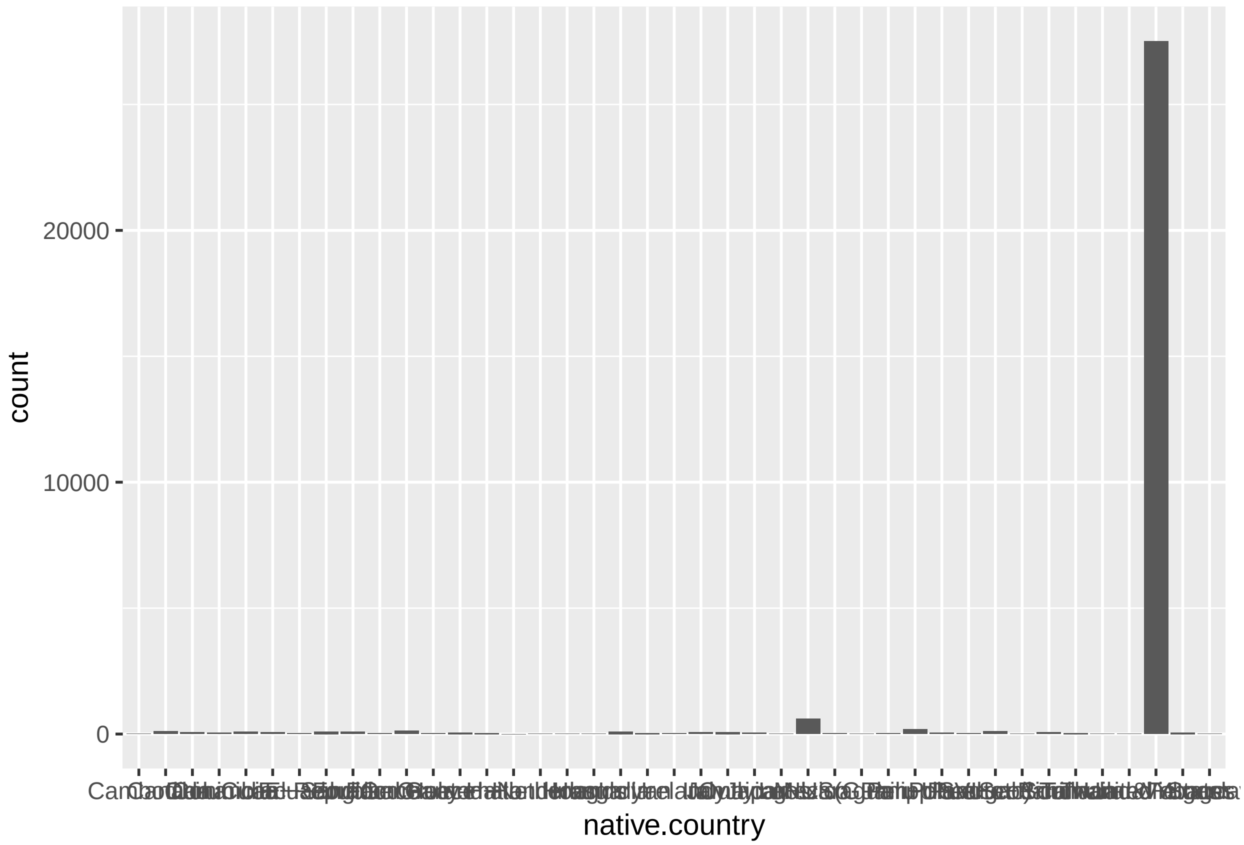

count
10000
5000
0
Divorced
Separated
Widowed
marital.status


count
4000
3000
2000
1000
0
occupation

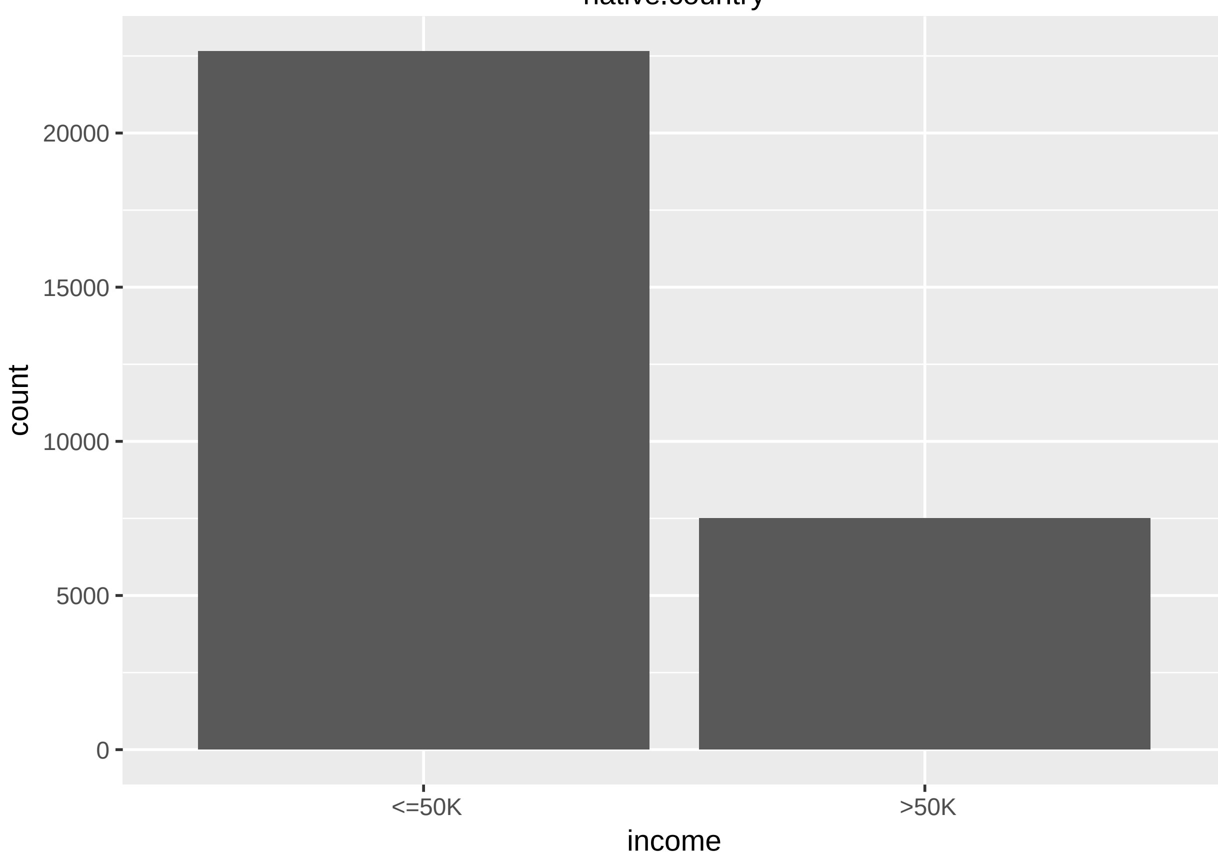

count
12000
8000
4000
0
Husband
Not−in−family
Other−relative
Own−child
Unmarried
Wife
relationship


20000
10000
0
count
Amer−Indian−Eskimo
Asian−Pac−Islander
Black
Other
White
race


20000
15000
10000
5000
0
count
Female
Male
sex



count
20000
10000
0
native.country

count
20000
15000
10000
5000
0
<=50K
>50K
income

### Association between each predictor and the response

```
for(i in 1:(ncol(dat)-1)) {
  r = cor(as.numeric(dat[, i]), as.numeric(dat$income))
  print(paste("The correlation between", names(dat)[i], "and income is", round(r, 4)))
}
```

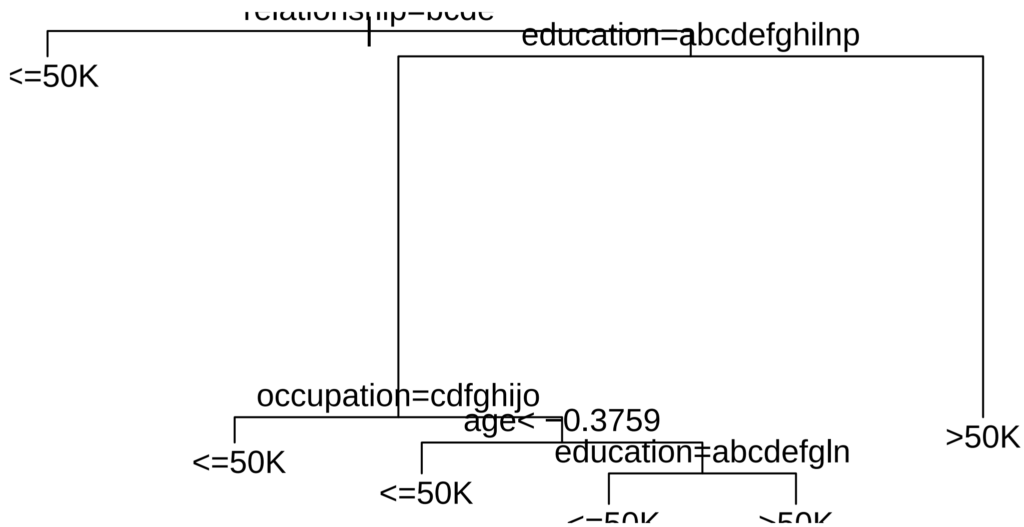
```
## [1] "The correlation between age and income is 0.242"
## [1] "The correlation between workclass and income is 0"
## [1] "The correlation between fnlwgt and income is -0.009"
## [1] "The correlation between education and income is 0.079"
## [1] "The correlation between education.num and income is 0.3353"
## [1] "The correlation between marital.status and income is -0.1935"
## [1] "The correlation between occupation and income is 0.0516"
## [1] "The correlation between relationship and income is -0.251"
## [1] "The correlation between race and income is 0.0717"
## [1] "The correlation between sex and income is 0.2167"
## [1] "The correlation between hours.per.week and income is 0.2295"
## [1] "The correlation between native.country and income is 0.0233"
```

### Build a Classification Tree

- Fit a classification tree (see examples in ISL chapter 8, and APM chapter 14).
- Make plots and describe the steps you took to justify choosing optimal tuning parameters.
- Report your 5 (or 6 or 7) important features (could be either just 5, or 6 or 7), with their variable importance statistics.
- Report the training accuracy rate.
- Plot the ROC curve, and report its area under the curve (AUC) statistic.

### Model

```
library(rpart)

# Naively use rpart default
set.seed(303)
rp = rpart(income ~., data = dat)
plot(rp)
text(rp)
```




```r
printcp(rp)
```

```
##
## Classification tree:
## rpart(formula = income ~ ., data = dat)
##
## Variables actually used in tree construction:
## [1] age          education    occupation   relationship
##
## Root node error: 7508/30162 = 0.24892
##
## n= 30162
##
##         CP nsplit rel error  xerror      xstd
## 1 0.129995      0   1.00000 1.00000 0.0100018
## 2 0.011121      2   0.74001 0.74001 0.0089670
## 3 0.010000      5   0.69579 0.70844 0.0088158
```

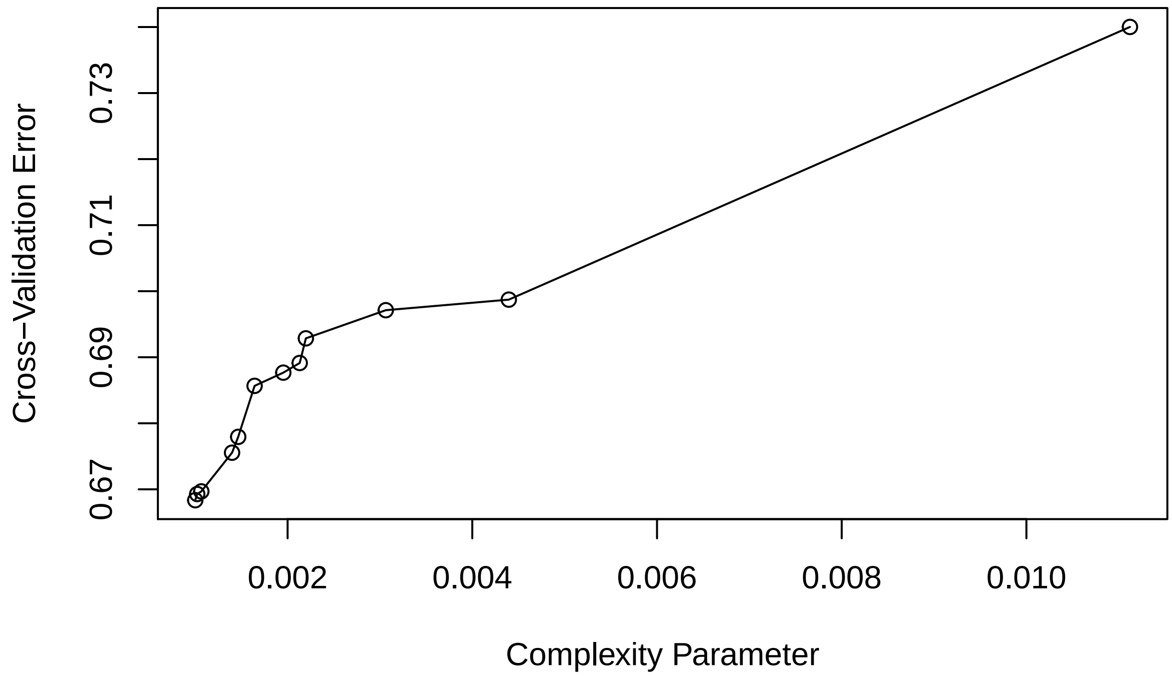
### Parameter Tuning

```r
set.seed(226)
tun_rp = rpart(income ~., data = dat, cp = .001)
printcp(tun_rp)
```

```
##
## Classification tree:
## rpart(formula = income ~ ., data = dat, cp = 0.001)
##
## Variables actually used in tree construction:
## [1] age            education      hours.per.week native.country
## [5] occupation     relationship   sex            workclass
```

```
##
## Root node error: 7508/30162 = 0.24892
##
## n= 30162
##
##            CP nsplit rel error  xerror      xstd
## 1  0.1299947      0   1.00000 1.00000 0.0100018
## 2  0.0111215      2   0.74001 0.74001 0.0089670
## 3  0.0043953      5   0.69579 0.69872 0.0087680
## 4  0.0030634      6   0.69140 0.69712 0.0087600
## 5  0.0021977      7   0.68833 0.69286 0.0087388
## 6  0.0021311     11   0.67954 0.68913 0.0087202
## 7  0.0019535     15   0.67035 0.68767 0.0087128
## 8  0.0016427     18   0.66449 0.68567 0.0087028
## 9  0.0014651     23   0.65357 0.67794 0.0086636
## 10 0.0013985     24   0.65210 0.67555 0.0086514
## 11 0.0010655     26   0.64931 0.66969 0.0086213
## 12 0.0010211     28   0.64718 0.66929 0.0086193
## 13 0.0010000     31   0.64411 0.66835 0.0086145
```

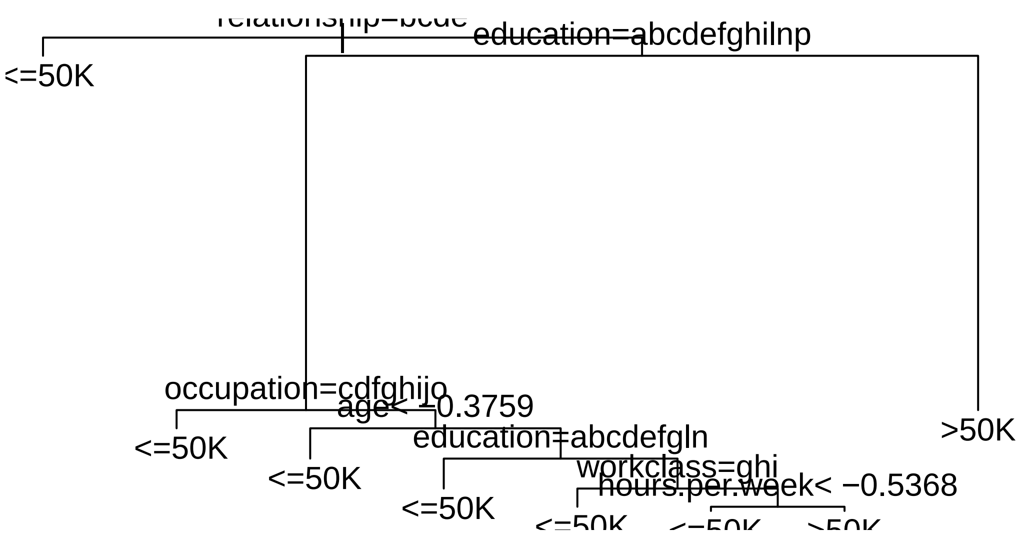
```r
plot(tun_rp$cptable[-1, 1], tun_rp$cptable[-1, 4], xlab = "Complexity Parameter", ylab =
lines(tun_rp$cptable[-1, 1], tun_rp$cptable[-1, 4])
```




Noticed that all the complexity parameters below 0.002 have about the same crossvalidation error. To avoid overfit the data, choose cp = 0.002 for less number of splits.

### Model Selected and Training Accuracy

```r
# Choose 0.002 as my new cp
rp1 = rpart(income ~., data = dat, cp = .0022)
plot(rp1)
text(rp1)
```




```r
accuracy = mean((predict(rp1)[, 2] > 0.5) == (dat$income == levels(dat$income)[2]))
accuracy
```

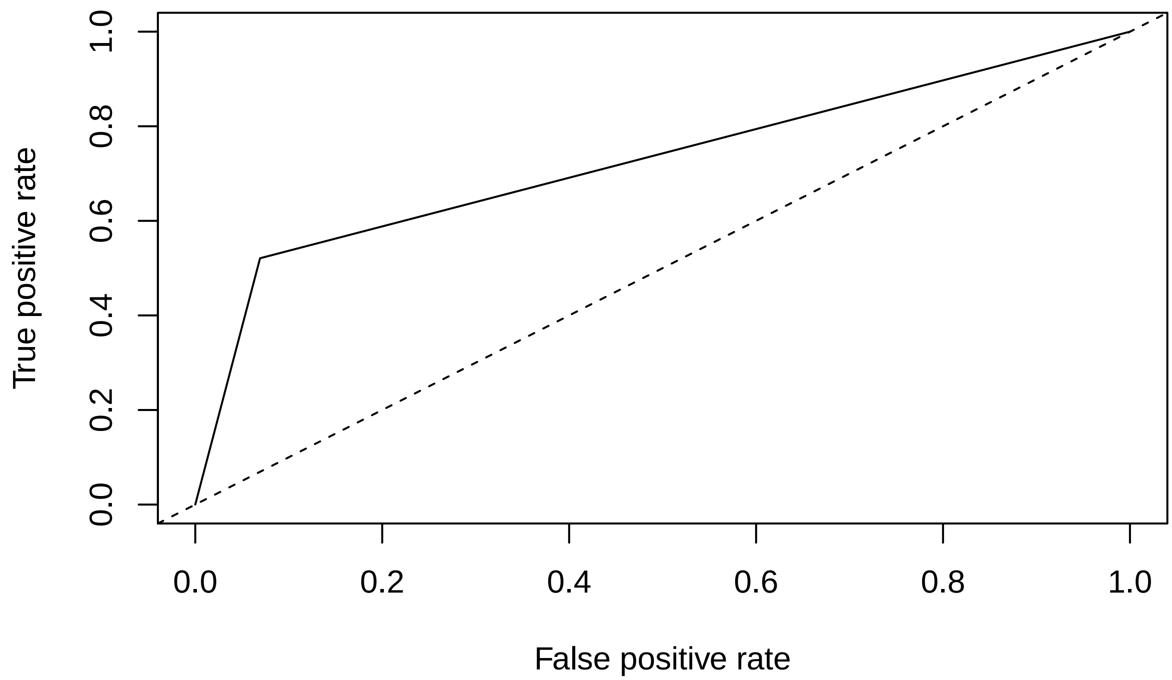
```
## [1] 0.8286586
```

### ROC Curve and AUC

```r
library(ROCR)
```

```
## Loading required package: gplots

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess
```

```r
y = as.numeric(dat$income == levels(dat$income)[2])
classified = as.numeric(predict(rp1)[, 2] > 0.5)
pred_roc = prediction(classified, y)
roc = performance(pred_roc, measure = "tpr", x.measure = "fpr")
plot(roc)
abline(0, 1, lty = 2)
```




```
roc_per = performance(pred_roc, measure="auc")
auc = slot(roc_per, 'y.values')[[1]]
paste("The AUC statistic of the selected model is", round(auc, 4))
```

```
## [1] "The AUC statistic of the selected model is 0.7258"
```

### Build a Bagged Tree

- Train a Random Forest classifier (see examples in ISL chapter 8, and APM chapter 14)
- Make plots and describe the steps you took to justify choosing optimal tuning parameters.
- Report your 5 (or 6 or 7) important features (could be either just 5, or 6 or 7), with their variable importance statistics.
- Report the training accuracy rate.
- Plot the ROC curve, and report its area under the curve (AUC) statistic.

### Model

```
library(randomForest)
```

```
## randomForest 4.6-12

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
```

```
##
##     margin
```

```r
bag = randomForest(income ~., data = dat, mtry = ncol(dat)-1, ntree = 1, importance = TR
bag
```

```
##
## Call:
##  randomForest(formula = income ~ ., data = dat, mtry = ncol(dat) -      1, ntree = 1,
##                Type of random forest: classification
##                      Number of trees: 1
## No. of variables tried at each split: 12
##
##         OOB estimate of  error rate: 23.9%
## Confusion matrix:
##         <=50K  >50K class.error
##  <=50K   7485   806  0.09721385
##  >50K    1827   901  0.66972141
```

### Parameter Tuning

```r
library(caret)
```

```
## Warning: package 'caret' was built under R version 3.3.2
```

```
## Loading required package: lattice
```

```
## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'zone/tz/2017c.
## 1.0/zoneinfo/America/Vancouver'
```

```r
n = nrow(dat)
B = seq(200, 350, 15)

# B = seq(100, 200, 10)
# B = seq(50, 120, 10)
# B = seq(10, 60, 10)

set.seed(0336)
folds = createFolds(1:n)

acc_mat = matrix(0, length(B), 10)
j = 1
for(fold in folds) {
  cv_train = dat[-fold, ]
  cv_test = dat[fold, ]
  acc = c()
  for(i in 1:length(B)) {
```

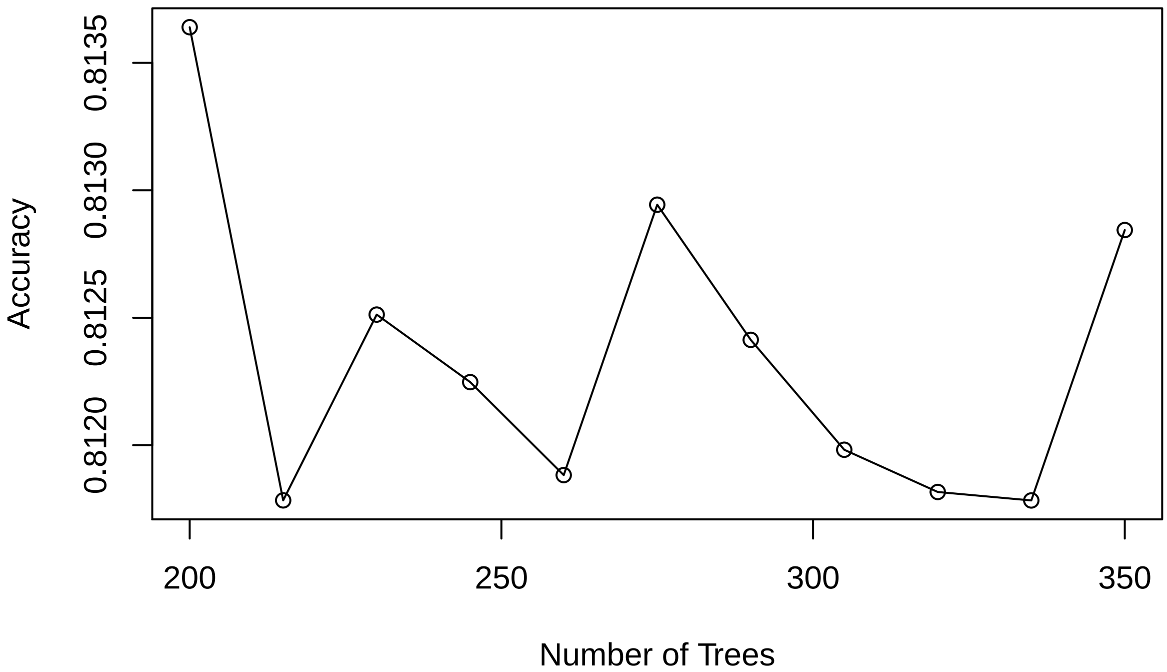
```r
    bag = randomForest(income ~., mtry = ncol(dat)-1, data = dat, ntree = B[i])
    pred = predict(bag, cv_test)
    acc[i] = mean(pred == cv_test$income)
  }
  acc_mat[, j] = acc
  j = j + 1
}
acc_mat
```

```
##            [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
##  [1,] 0.8183626 0.8209549 0.8041100 0.8129973 0.7960875 0.8116711
##  [2,] 0.8147166 0.8222812 0.8001326 0.8129973 0.7940981 0.8116711
##  [3,] 0.8190255 0.8199602 0.8094133 0.8073607 0.7954244 0.8110080
##  [4,] 0.8196884 0.8176393 0.8027842 0.8093501 0.7917772 0.8153183
##  [5,] 0.8196884 0.8166446 0.8047730 0.8053714 0.7901194 0.8163130
##  [6,] 0.8200199 0.8202918 0.8034471 0.8106764 0.7950928 0.8113395
##  [7,] 0.8163739 0.8216180 0.8034471 0.8090186 0.7954244 0.8146552
##  [8,] 0.8193570 0.8179708 0.8027842 0.8100133 0.7944297 0.8153183
##  [9,] 0.8180312 0.8186340 0.8031157 0.8100133 0.7927719 0.8126658
## [10,] 0.8180312 0.8179708 0.8041100 0.8129973 0.7960875 0.8106764
## [11,] 0.8173682 0.8179708 0.8067617 0.8090186 0.7967507 0.8136605
##            [,7]      [,8]      [,9]     [,10]
##  [1,] 0.8192971 0.8129973 0.8255968 0.8143236
##  [2,] 0.8163130 0.8126658 0.8192971 0.8136605
##  [3,] 0.8163130 0.8100133 0.8206233 0.8159814
##  [4,] 0.8196286 0.8126658 0.8199602 0.8136605
##  [5,] 0.8212865 0.8143236 0.8196286 0.8106764
##  [6,] 0.8186340 0.8146552 0.8212865 0.8139920
##  [7,] 0.8176393 0.8126658 0.8199602 0.8133289
##  [8,] 0.8179708 0.8090186 0.8196286 0.8133289
##  [9,] 0.8156499 0.8143236 0.8179708 0.8149867
## [10,] 0.8149867 0.8129973 0.8173077 0.8126658
## [11,] 0.8183024 0.8129973 0.8216180 0.8139920
```

```r
xacc = rowMeans(acc_mat)
xacc
```

```
##  [1] 0.8136398 0.8117833 0.8125123 0.8122473 0.8118825 0.8129435 0.8124131
##  [8] 0.8119820 0.8118163 0.8117831 0.8128440
```

```r
plot(B, xacc, xlab = "Number of Trees", ylab = "Accuracy")
lines(B, xacc)
```




```
best_B = B[which.max(xacc)]
best_B
```

```
## [1] 200
```

```
# 200
```

### Model Selected, Training Accuracy, and Importance

```
bag = randomForest(income ~., data = dat, mtry = ncol(dat)-1, ntree = best_B, importance
impor = importance(bag)
MDA = sort(impor[, 3], decreasing = TRUE)
gini = sort(impor[, 4], decreasing = TRUE)
varImpPlot(bag)
```


```r
paste("By looking at Mean Decrease Accuracy, the 5 most important features and its varia
```

```
## [1] "By looking at Mean Decrease Accuracy, the 5 most important features and its vari
```

```r
MDA[1:5]
```

```
## marital.status            sex            age   relationship hours.per.week
##       40.18132       27.97400       25.31649       24.76938       23.63853
```

```r
paste("By looking at Mean Decrease Gini, the 5 most important features and its variable
```

```
## [1] "By looking at Mean Decrease Gini, the 5 most important features and its variable
```

```r
gini[1:5]
```

```
##         fnlwgt   relationship            age  education.num hours.per.week
##      2659.1086      2380.3314      1701.1472      1402.1597       972.6501
```

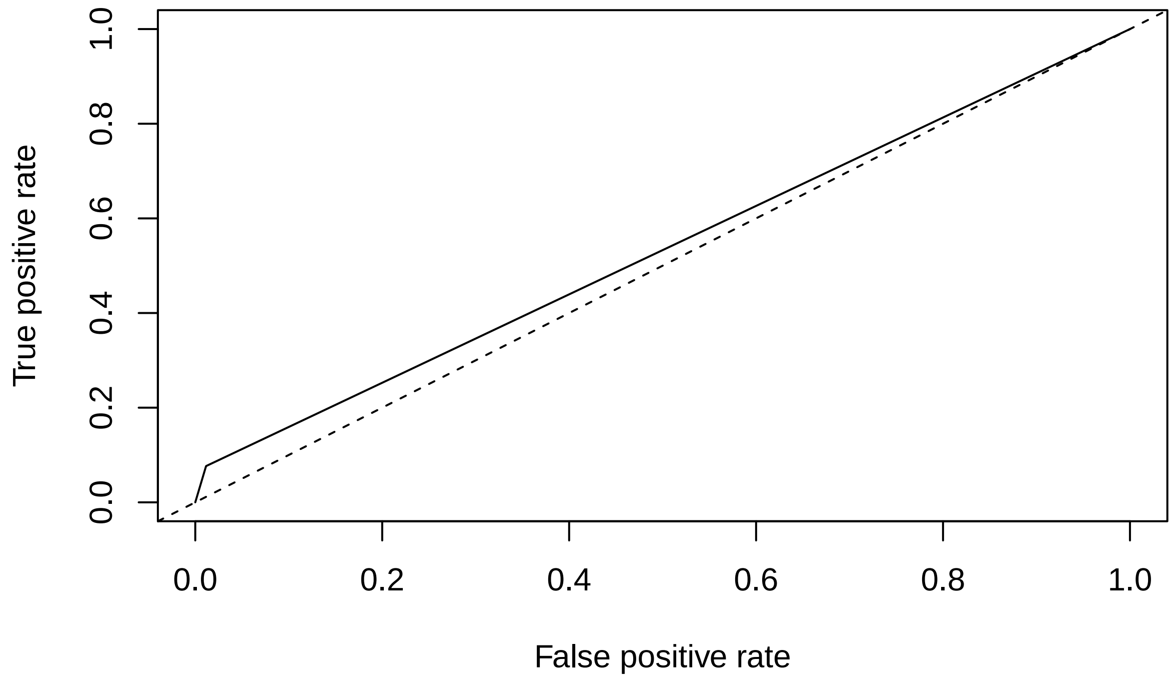
```r
accuracy_bag = (bag$confusion[1, 1] + bag$confusion[2, 2]) / n
accuracy_bag
```

```
## [1] 0.7614548
```

### ROC Curve and AUC

```r
y = as.numeric(dat$income == levels(dat$income)[2])
classified = as.numeric(predict(bag) == levels(dat$income)[2])
```

```r
pred_roc = prediction(classified, y)
roc = performance(pred_roc, measure = "tpr", x.measure = "fpr")
plot(roc)
abline(0, 1, lty = 2)
```




```r
roc_per = performance(pred_roc, measure="auc")
auc = slot(roc_per, 'y.values')[[1]]
paste("The AUC statistic of the selected model is", round(auc, 4))
```

```
## [1] "The AUC statistic of the selected model is 0.5325"
```

### Build a Random Forest

- Train a Random Forest classifier (see examples in ISL chapter 8, and APM chapter 14)
- Make plots and describe the steps you took to justify choosing optimal tuning parameters.
- Report your 5 (or 6 or 7) important features (could be either just 5, or 6 or 7), with their variable importance statistics.
- Report the training accuracy rate.
- Plot the ROC curve, and report its area under the curve (AUC) statistic.

### Model

```r
rf = randomForest(income ~., data = dat, mtry = ncol(dat)-1, ntree = best_B, importance
rf
```

```
##
## Call:
##  randomForest(formula = income ~ ., data = dat, mtry = ncol(dat) -      1, ntree = be
##                Type of random forest: classification
##                      Number of trees: 200
## No. of variables tried at each split: 12
##
##         OOB estimate of  error rate: 23.84%
## Confusion matrix:
##         <=50K  >50K class.error
##  <=50K  22421   233  0.01028516
##  >50K    6958   550  0.92674481
```

**Parameter Tuning**

```r
n = nrow(dat)
V = 1:(ncol(dat)-1)

acc_mat = matrix(0, length(V), 10)
j = 1
acc = c()
for(fold in folds) {
  cv_train = dat[-fold, ]
  cv_test = dat[fold, ]
  for(i in V) {
    rf = randomForest(income ~., data = dat, mtry = i, ntree = best_B)
    pred = predict(rf, cv_test)
    acc[i] = mean(pred == cv_test$income)
  }
  acc_mat[, j] = acc
  j = j + 1
}
acc_mat
```

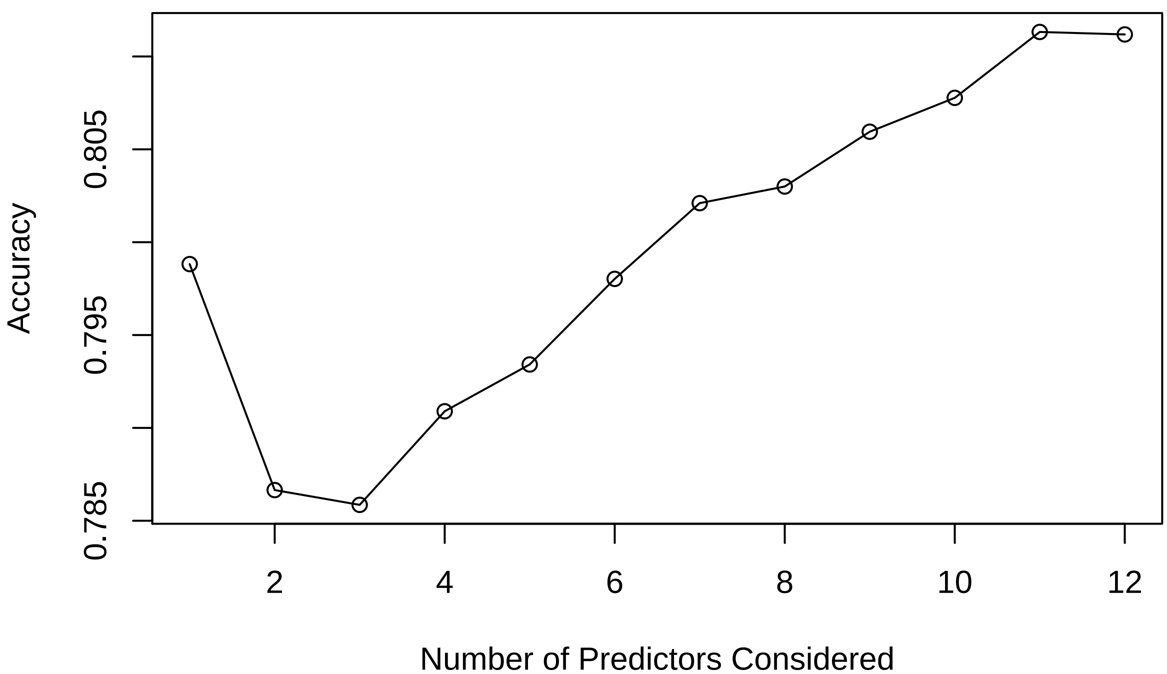
```
##            [,1]      [,2]      [,3]      [,4]      [,5]      [,6]
##  [1,] 0.8064302 0.7977454 0.7838913 0.7927719 0.7861406 0.7987401
##  [2,] 0.7752735 0.7881300 0.7759364 0.7854775 0.7831565 0.7977454
##  [3,] 0.7898575 0.7891247 0.7769307 0.7891247 0.7755305 0.7821618
##  [4,] 0.7964866 0.7964191 0.7815711 0.7861406 0.7738727 0.7884615
##  [5,] 0.8024528 0.7997347 0.7832284 0.7881300 0.7791777 0.7944297
##  [6,] 0.8031157 0.8093501 0.7868744 0.7934350 0.7775199 0.8003979
##  [7,] 0.8077560 0.8093501 0.7915147 0.7980769 0.7861406 0.8027188
##  [8,] 0.8110706 0.8110080 0.7954922 0.7997347 0.7858090 0.8030504
##  [9,] 0.8107391 0.8143236 0.7968180 0.8027188 0.7914456 0.8110080
## [10,] 0.8127279 0.8123342 0.7991382 0.8040451 0.7954244 0.8083554
```

```
## [11,] 0.8163739 0.8169761 0.7988068 0.8113395 0.7934350 0.8149867
## [12,] 0.8167053 0.8192971 0.8024528 0.8076923 0.7944297 0.8110080
##            [,7]      [,8]      [,9]     [,10]
##  [1,] 0.7984085 0.8010610 0.8110080 0.8120027
##  [2,] 0.7874668 0.7914456 0.7940981 0.7877984
##  [3,] 0.7881300 0.7851459 0.7947613 0.7877984
##  [4,] 0.8020557 0.7897878 0.7967507 0.7974138
##  [5,] 0.7947613 0.7950928 0.7997347 0.7974138
##  [6,] 0.8047082 0.7980769 0.8060345 0.8007294
##  [7,] 0.8057029 0.8017241 0.8113395 0.8066976
##  [8,] 0.8113395 0.7974138 0.8106764 0.8043767
##  [9,] 0.8073607 0.8040451 0.8139920 0.8070292
## [10,] 0.8106764 0.8096817 0.8153183 0.8100133
## [11,] 0.8176393 0.8116711 0.8179708 0.8139920
## [12,] 0.8179708 0.8129973 0.8176393 0.8116711
```

```
xacc = rowMeans(acc_mat)
xacc
```

```
##  [1] 0.7988199 0.7866528 0.7858565 0.7908960 0.7934156 0.7980242 0.8021021
##  [8] 0.8029971 0.8059480 0.8077715 0.8113191 0.8111864
```

```
plot(V, xacc, xlab = "Number of Predictors Considered", ylab = "Accuracy")
lines(V, xacc)
```



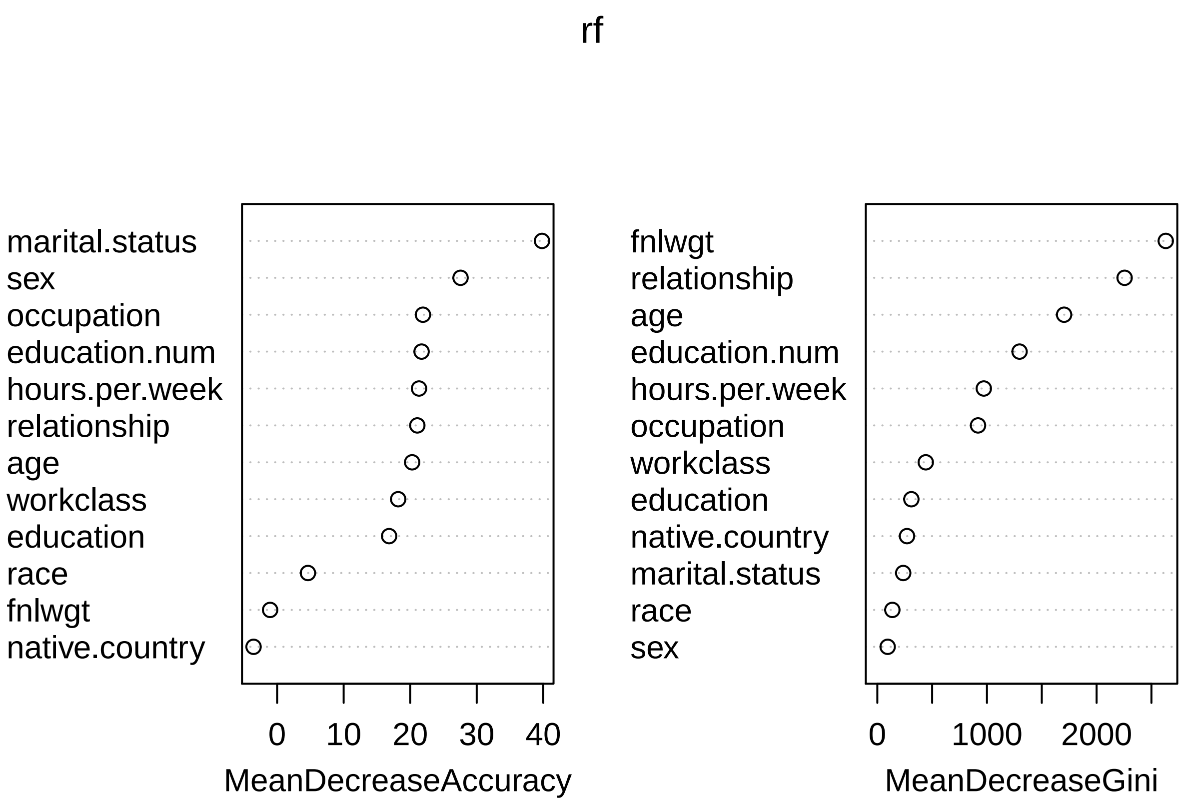

```
best_V = which.max(xacc)
best_V
```

```
## [1] 11
```

```r
# 11
```

### Model Selected, Training Accuracy, and Importance

```r
rf = randomForest(income ~., data = dat, mtry = best_V, ntree = best_B, importance = TRU
impor = importance(rf)
MDA = sort(impor[, 3], decreasing = TRUE)
gini = sort(impor[, 4], decreasing = TRUE)
varImpPlot(rf)
```




```r
paste("By looking at Mean Decrease Accuracy, the 5 most important features and its varia
```

```
## [1] "By looking at Mean Decrease Accuracy, the 5 most important features and its vari
```

```r
MDA[1:5]
```

```
## marital.status            sex     occupation  education.num hours.per.week
##       39.81212       27.56972       21.91579       21.70893       21.32754
```

```r
paste("By looking at Mean Decrease Gini, the 5 most important features and its variable
```

```
## [1] "By looking at Mean Decrease Gini, the 5 most important features and its variable
```

```r
gini[1:5]
```

```
##         fnlwgt   relationship            age  education.num hours.per.week
```

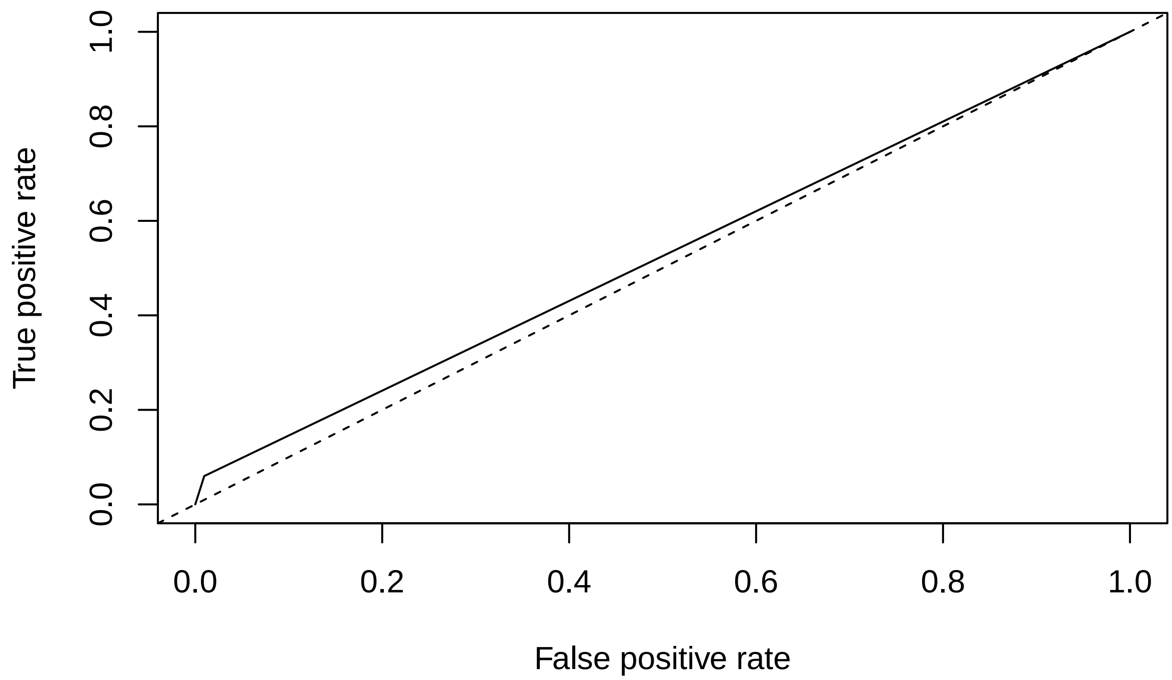
```
##      2630.8688      2255.5416      1703.5707      1297.2661       971.2474
```

```
accuracy_rf = (rf$confusion[1, 1] + rf$confusion[2, 2]) / n
accuracy_rf
```

```
## [1] 0.7587693
```

### ROC Curve and AUC

```
y = as.numeric(dat$income == levels(dat$income)[2])
classified = as.numeric(predict(rf) == levels(dat$income)[2])
pred_roc = prediction(classified, y)
roc = performance(pred_roc, measure = "tpr", x.measure = "fpr")
plot(roc)
abline(0, 1, lty = 2)
```




```
roc_per = performance(pred_roc, measure="auc")
auc = slot(roc_per, 'y.values')[[1]]
paste("The AUC statistic of the selected model is", round(auc, 4))
```

```
## [1] "The AUC statistic of the selected model is 0.5252"
```

### Model Selection

- Validate your best supervised classifier on the test set.
- Compute the confusion matrix.

- Using the class "over 50K a year" as the positive event, calculate the *Sensitivity* or *True Positive Rate* (TPR), and the *Specificity* or *True Negative Rate* (TNR).
- Plot the ROC curves of all the classifiers.

### Predicted Values

```
# There is no reason to lower type 1 or type 2 error, so I choose 0.5 as my threshold
y_test = dat_test$income
pred_rp = predict(rp1, dat_test)[, 2] >= 0.5
pred_rp = as.numeric(pred_rp)

pred_bag = predict(bag, dat_test, type = "response")
pred_rf = predict(rf, dat_test, type = "response")
```

### Confusion Matrices

```
n_test = nrow(dat_test)
# Classification Tree
# Income <50 is encoded as 0, and >=50 is encoded as 1
y_t = as.numeric(dat_test$income == levels(dat_test$income)[2])
conf_mat_rp = confusionMatrix(pred_rp, y_t, positive = "1")
conf_mat_rp$table
```

```
##           Reference
## Prediction     0     1
##          0 11349  1760
##          1  1086  2086
```

```
conf_mat_rp$byClass[1:2]
```

```
## Sensitivity Specificity
##   0.5423817   0.9126659
```

```
accuracy_rp = sum(diag(conf_mat_rp$table)) / n_test
accuracy_rp
```

```
## [1] 0.825195
```

```
# Bagged Tree
conf_mat_bag = confusionMatrix(pred_bag, y_test, positive = levels(dat_test$income)[2])
conf_mat_bag$table
```

```
##           Reference
## Prediction  <=50K  >50K
##      <=50K  11154  3230
##      >50K    1281   616
```

```r
conf_mat_bag$byClass[1:2]
```

```
## Sensitivity Specificity
##   0.1601664   0.8969843
```

```r
accuracy_bag = sum(diag(conf_mat_bag$table)) / n_test
accuracy_bag
```

```
## [1] 0.7229286
```

```r
# Random Forest
conf_mat_rf = confusionMatrix(pred_rf, y_test, positive = levels(dat_test$income)[2])
conf_mat_rf$table
```

```
##           Reference
## Prediction  <=50K  >50K
##      <=50K  11989  3526
##      >50K     446   320
```

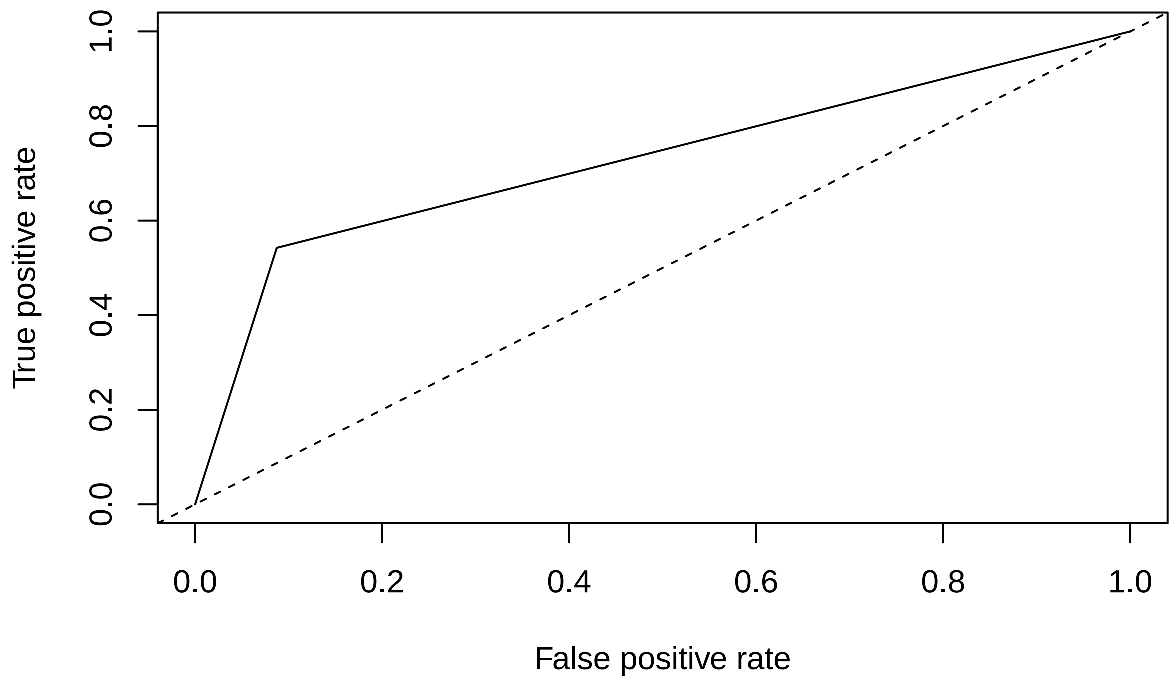
```r
conf_mat_rf$byClass[1:2]
```

```
## Sensitivity Specificity
##  0.08320333  0.96413349
```

```r
accuracy_rf = sum(diag(conf_mat_rf$table)) / n_test
accuracy_rf
```

```
## [1] 0.7560346
```

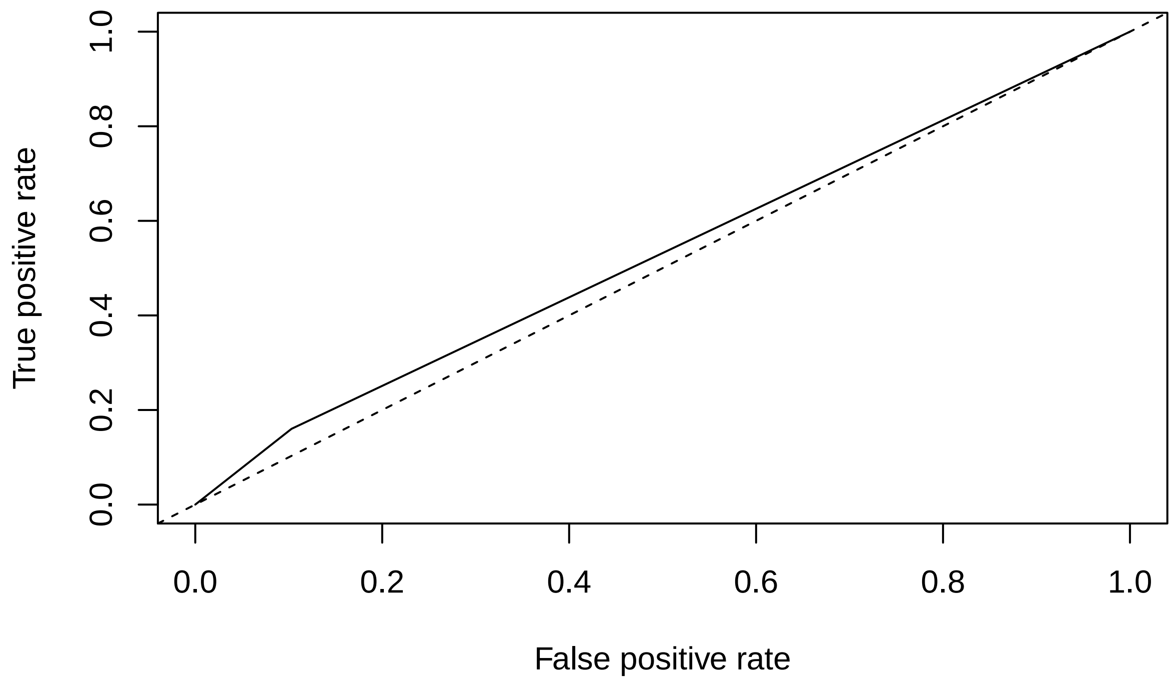
```r
# Classification Tree
y = y_t
classified = pred_rp
pred_roc = prediction(classified, y)
roc = performance(pred_roc, measure = "tpr", x.measure = "fpr")
plot(roc)
abline(0, 1, lty = 2)
```




```r
roc_per = performance(pred_roc, measure="auc")
auc = slot(roc_per, 'y.values')[[1]]
paste("The AUC statistic of classification tree model is", round(auc, 4))
```

```
## [1] "The AUC statistic of classification tree model is 0.7275"
```

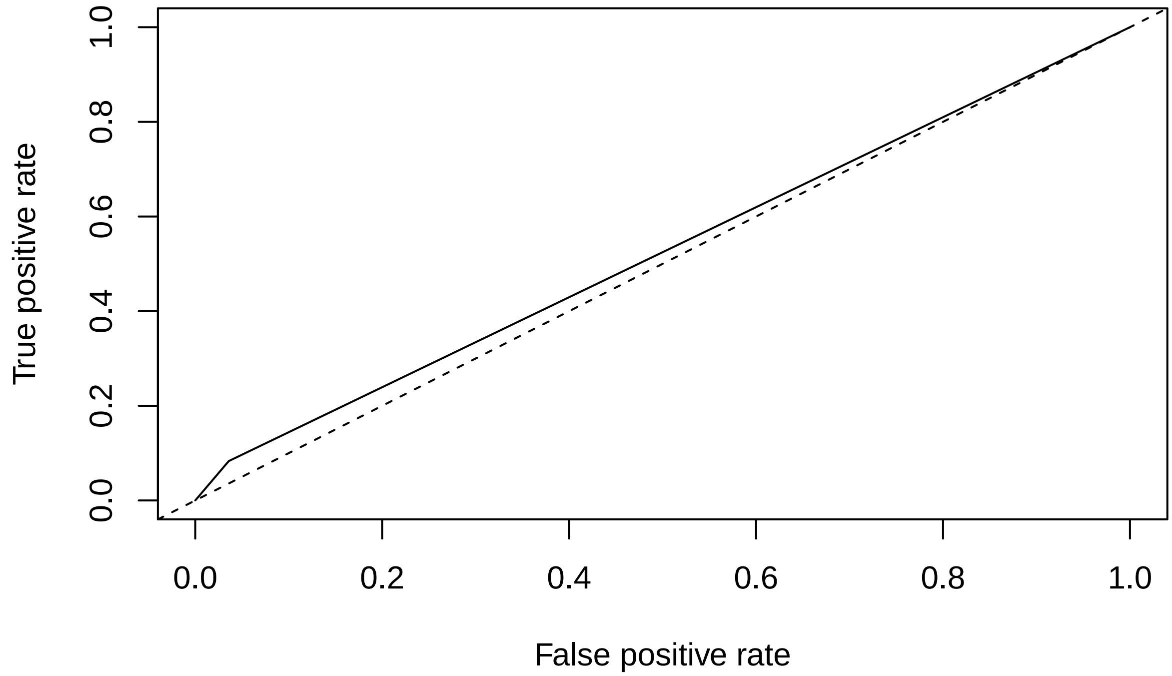
```r
# Bagged Tree
classified = as.numeric(pred_bag) - 1
pred_roc = prediction(classified, y)
roc = performance(pred_roc, measure = "tpr", x.measure = "fpr")
plot(roc)
abline(0, 1, lty = 2)
```




```
roc_per = performance(pred_roc, measure="auc")
auc = slot(roc_per, 'y.values')[[1]]
paste("The AUC statistic of bagged tree model is", round(auc, 4))
```

```
## [1] "The AUC statistic of bagged tree model is 0.5286"
```

```
# Random Forest
classified = as.numeric(pred_rf) - 1
pred_roc = prediction(classified, y)
roc = performance(pred_roc, measure = "tpr", x.measure = "fpr")
plot(roc)
abline(0, 1, lty = 2)
```




```r
roc_per = performance(pred_roc, measure="auc")
auc = slot(roc_per, 'y.values')[[1]]
paste("The AUC statistic of random forest model is", round(auc, 4))
```

```
## [1] "The AUC statistic of random forest model is 0.5237"
```