Dataset Link : [https://www.kaggle.com/wenruliu/adult-income-dataset (https://www.kaggle.com/wenruliu/adult-income-dataset)](https://www.kaggle.com/wenruliu/adult-income-dataset)

B22

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94-Rohit Punjabi

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Importing Libraries

In [1]:

```
library(ggplot2)#visualization
library(Amelia)#missing map
library(dplyr)#EDA
library(caTools)#Logisitc
library(caret)#confusion matrix
```

...

Importing Dataset

In [2]:

```
# importing dataset in adult variable
adult<-read.csv('adult.csv')
```

EDA

In [3]:

```
# shows first six records in the table
head(adult)
```

age	workclass	fnlwgt	education	educational.num	marital.status	occupation	relationship	r
25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	B
38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	W
28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	W
44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	B
18	?	103497	Some-college	10	Never-married	?	Own-child	W
34	Private	198693	10th	6	Never-married	Other-service	Not-in-family	W

In [4]:

```
# shows last six records  in the table
tail(adult)
```

	age	workclass	fnlwgt	education	educational.num	marital.status	occupation	relation
48837	22	Private	310152	Some-college	10	Never-married	Protective-serv	Not-in-fa
48838	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife
48839	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husban
48840	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarri
48841	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-ch
48842	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife

In [5]:

```
# shows the first six record arrange in order of age
head(adult[order(adult$age),])
```

	age	workclass	fnlwgt	education	educational.num	marital.status	occupation	relationsh
39	17	Private	269430	10th	6	Never-married	Machine-op-inspct	Not-in-fam
76	17	?	165361	10th	6	Never-married	?	Own-child
403	17	Private	40299	11th	7	Never-married	Sales	Own-child
676	17	Private	190941	10th	6	Never-married	Sales	Own-child
766	17	?	143331	11th	7	Never-married	?	Own-child
904	17	Private	61838	11th	7	Never-married	Farming-fishing	Own-child

In [6]:

```
# shows the last six record arrange in order of age
tail(adult[order(adult$age),])
```

	age	workclass	fnlwgt	education	educational.num	marital.status	occupation	relation
41585	90	?	175444	7th-8th	4	Separated	?	Not-in-fa
44745	90	Federal-gov	195433	HS-grad	9	Married-civ-spouse	Craft-repair	Husban
47312	90	Private	47929	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husban
47978	90	?	313986	HS-grad	9	Married-civ-spouse	?	Husban
48559	90	Private	313749	HS-grad	9	Widowed	Adm-clerical	Unmarri
48649	90	Local-gov	214594	7th-8th	4	Married-civ-spouse	Protective-serv	Husban

In [7]:

```
# calculating mean and median of educational num.
mean(adult$educational.num)
median1<-median(adult$educational.num)
median1
```

10.0780885303632

10

In [8]:

```
# filtered the data where educational num is less than
# median of eduactional num
filter(adult,adult$educational.num<median1)
```

ss	fnlwgt	education	educational.num	marital.status	occupation	relationship	race	gender	capital.gain
	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0
	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0
	198693	10th	6	Never-married	Other-service	Not-in-family	White	Male	0
	227026	HS-grad	9	Never-married	?	Unmarried	Black	Male	0
	104996	7th-8th	4	Married-civ-spouse	Craft-repair	Husband	White	Male	0
	184454	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	6418
	82091	HS-grad	9	Never-married	Adm-clerical	Not-in-family	White	Female	0
				Married-civ					

In [9]:

```
# filtered the data where gender is Male
filter(adult,adult$gender=="Male")
```

ucation	educational.num	marital.status	occupation	relationship	race	gender	capital.gain	capital.loss	h
1th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	
-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	
Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	
Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	
0th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	
-grad	9	Never-married	?	Unmarried	Black	Male	0	0	
Prof-school	15	Married-civ-spouse	Prof-specialty	Husband	White	Male	3103	0	
		Married-civ							

In [10]:

```
# filtered the data where gender is male and
# relationship is husband
filter(adult,gender=="Male",relationship=="Husband")
```

ducation	educational.num	marital.status	occupation	relationship	race	gender	capital.gain	capital.loss
S-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0
Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0
Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0
Prof-school	15	Married-civ-spouse	Prof-specialty	Husband	White	Male	3103	0
'th-8th	4	Married-civ-spouse	Craft-repair	Husband	White	Male	0	0
S-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	6418	0
achelors	13	Married-civ-spouse	Adm-clerical	Husband	White	Male	0	0

In [11]:

```
# internal structure of dataset
str(adult)
```

```
'data.frame':   48842 obs. of  15 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 ...
 $ fnlwgt         : int  226802 89814 336951 160323 103497 198693 227026 104
626 369667 104996 ...
 $ education      : Factor w/ 16 levels "10th","11th",..: 2 12 8 16 16 1 12
15 16 6 ...
 $ educational.num: int  7 9 12 10 10 6 9 15 10 4 ...
 $ marital.status : 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 ...
 $ gender         : 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/ 42 levels "?","Cambodia",..: 40 40 40 40 40 40
40 40 40 40 ...
 $ income         : Factor w/ 2 levels "<=50K",">50K": 1 1 2 2 1 1 1 2 1 1
...
```

In [12]:

```
# summary of dataset
summary(adult)
```

```
     age                  workclass         fnlwgt
Min.   :17.00   Private         :33906   Min.   :  12285
1st Qu.:28.00   Self-emp-not-inc: 3862   1st Qu.: 117551
Median :37.00   Local-gov       : 3136   Median : 178145
Mean   :38.64   ?               : 2799   Mean   : 189664
3rd Qu.:48.00   State-gov       : 1981   3rd Qu.: 237642
Max.   :90.00   Self-emp-inc    : 1695   Max.   :1490400
                (Other)         : 1463
       education     educational.num                marital.status
HS-grad     :15784   Min.   : 1.00   Divorced             : 6633
Some-college:10878   1st Qu.: 9.00   Married-AF-spouse    :   37
Bachelors   : 8025   Median :10.00   Married-civ-spouse   :22379
Masters     : 2657   Mean   :10.08   Married-spouse-absent:  628
Assoc-voc   : 2061   3rd Qu.:12.00   Never-married        :16117
11th        : 1812   Max.   :16.00   Separated            : 1530
(Other)     : 7625                   Widowed              : 1518
          occupation            relationship                    race
Prof-specialty : 6172   Husband       :19716   Amer-Indian-Eskimo:  470
Craft-repair   : 6112   Not-in-family :12583   Asian-Pac-Islander: 1519
Exec-managerial: 6086   Other-relative: 1506   Black             : 4685
Adm-clerical   : 5611   Own-child     : 7581   Other             :  406
Sales          : 5504   Unmarried     : 5125   White             :41762
Other-service  : 4923   Wife          : 2331
(Other)        :14434
   gender       capital.gain    capital.loss    hours.per.week
Female:16192   Min.   :    0   Min.   :   0.0   Min.   : 1.00
Male  :32650   1st Qu.:    0   1st Qu.:   0.0   1st Qu.:40.00
               Median :    0   Median :   0.0   Median :40.00
               Mean   : 1079   Mean   :  87.5   Mean   :40.42
               3rd Qu.:    0   3rd Qu.:   0.0   3rd Qu.:45.00
               Max.   :99999   Max.   :4356.0   Max.   :99.00

      native.country    income
United-States:43832   <=50K:37155
Mexico       :  951   >50K :11687
?            :  857
Philippines  :  295
Germany      :  206
Puerto-Rico  :  184
(Other)      : 2517
```

In [13]:

```
adult[adult == "?"] <- NA # replacing the '?' with NA
colSums(is.na(adult)) # calculating the total count of the NA(null) values
```

age
0
workclass
2799
fnlwgt
0
education
0
educational.num
0
marital.status
0
occupation
2809
relationship
0
race
0
gender
0
capital.gain
0
capital.loss
0
hours.per.week
0
native.country
857
income
0

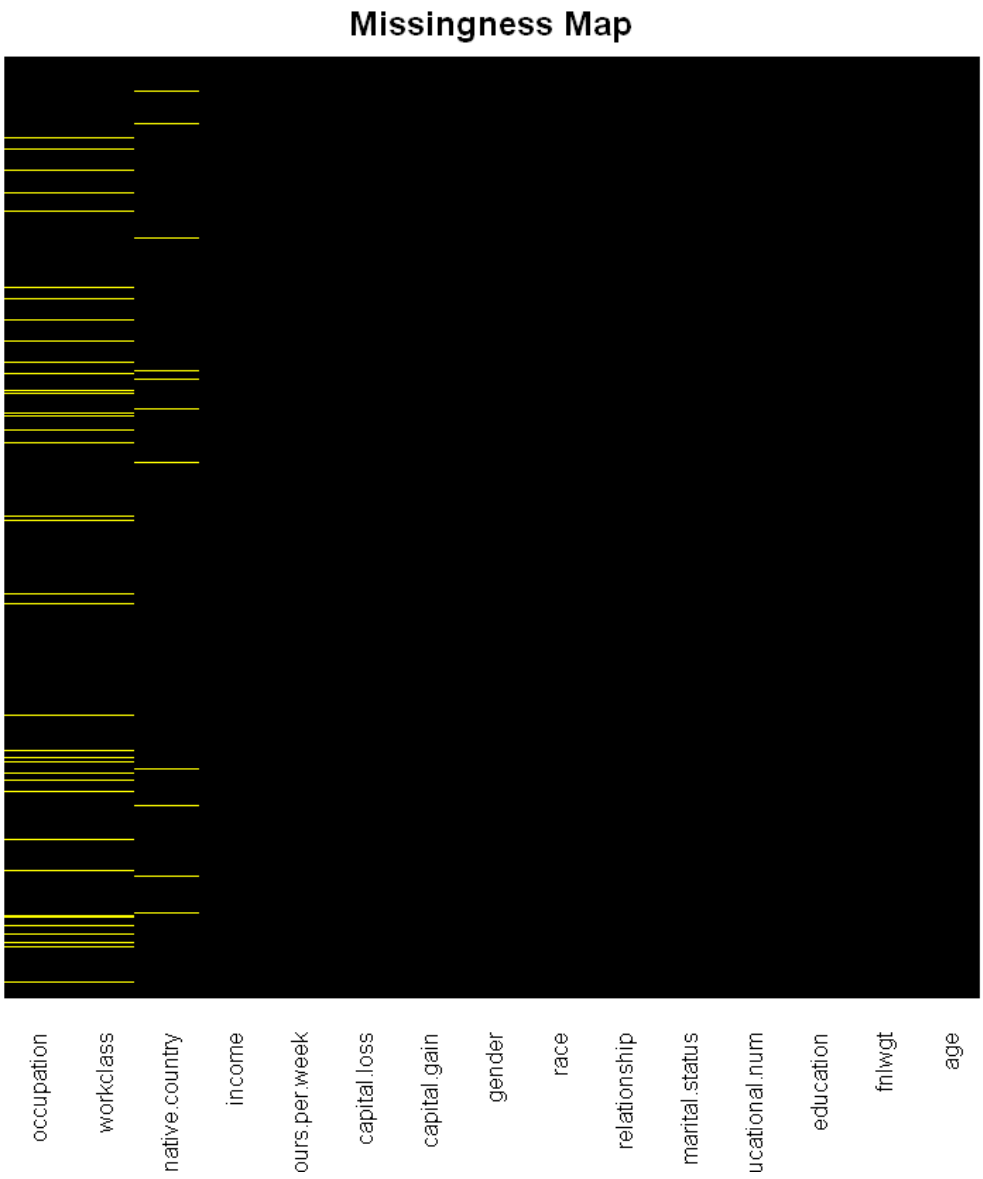
In [14]:

```
# dimension for the adult dataset before removing null values
dim(adult)
```

48842 15

In [15]:

```
missmap(adult, y.at = 1, y.labels = "", col = c("yellow", "black"), legend = FALSE)
# missing values are found at occupation,workclass,native.country
```



In [16]:

```
# removing null values
adult <- na.omit(adult)
```

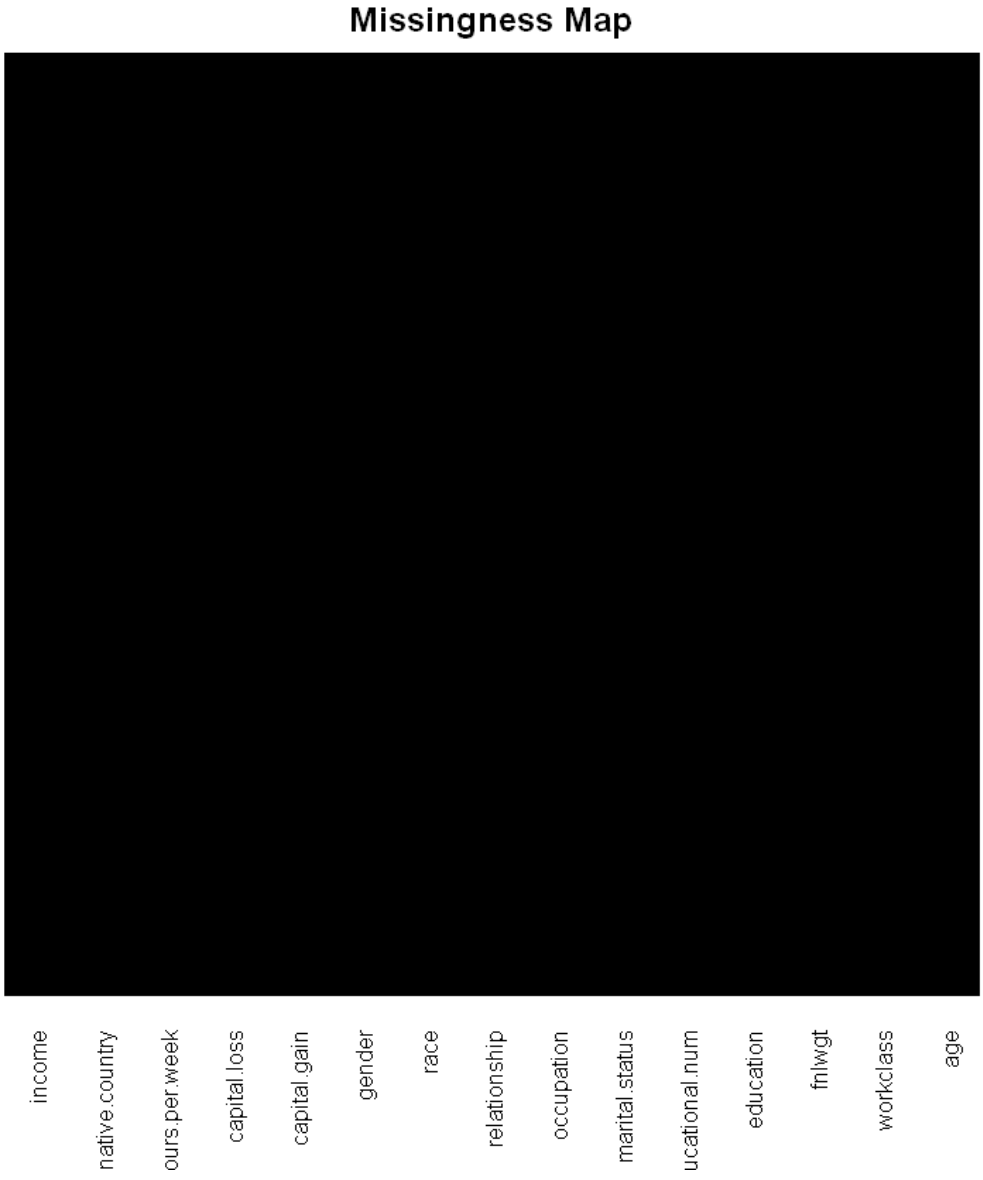
In [17]:

```
# dimension after removing the null values
dim(adult)
# removed 3620 null values
```

45222 15

In [18]:

```
missmap(adult, y.at = 1, y.labels = "", col = c("yellow", "black"), legend = FALSE)
# No missing values found.
```

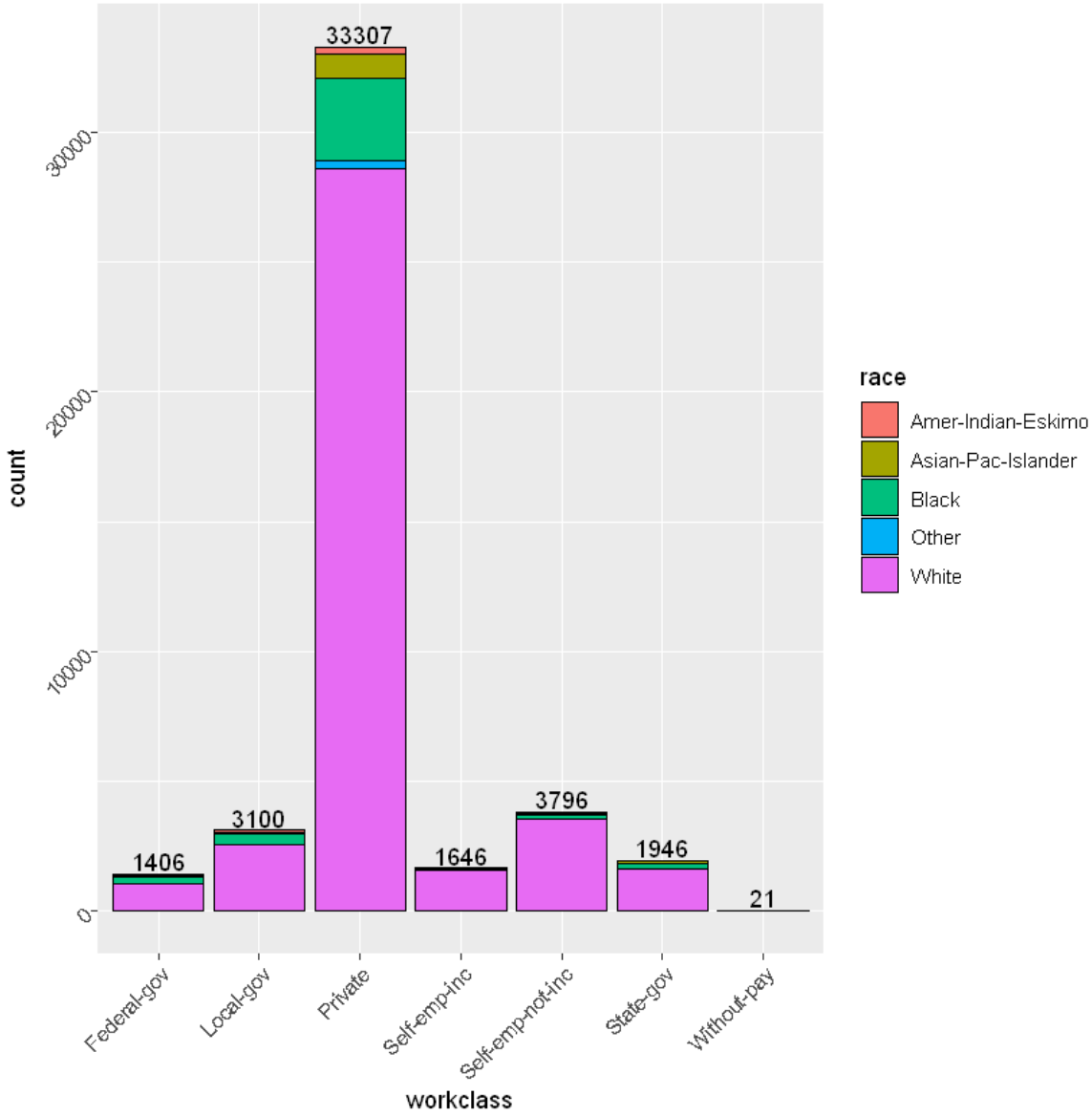


Visualization

PLOT1

In [19]:

```
# The Bar plot shows the no of people and their race in a specific workclass
adult %>% ggplot(aes(workclass)) +
  geom_bar(aes(fill = race), colour = 'black')+
  geom_text(aes(label=..count..),stat='count',vjust=-0.2)+
theme(axis.text=element_text(angle = 45,hjust = 1))
```

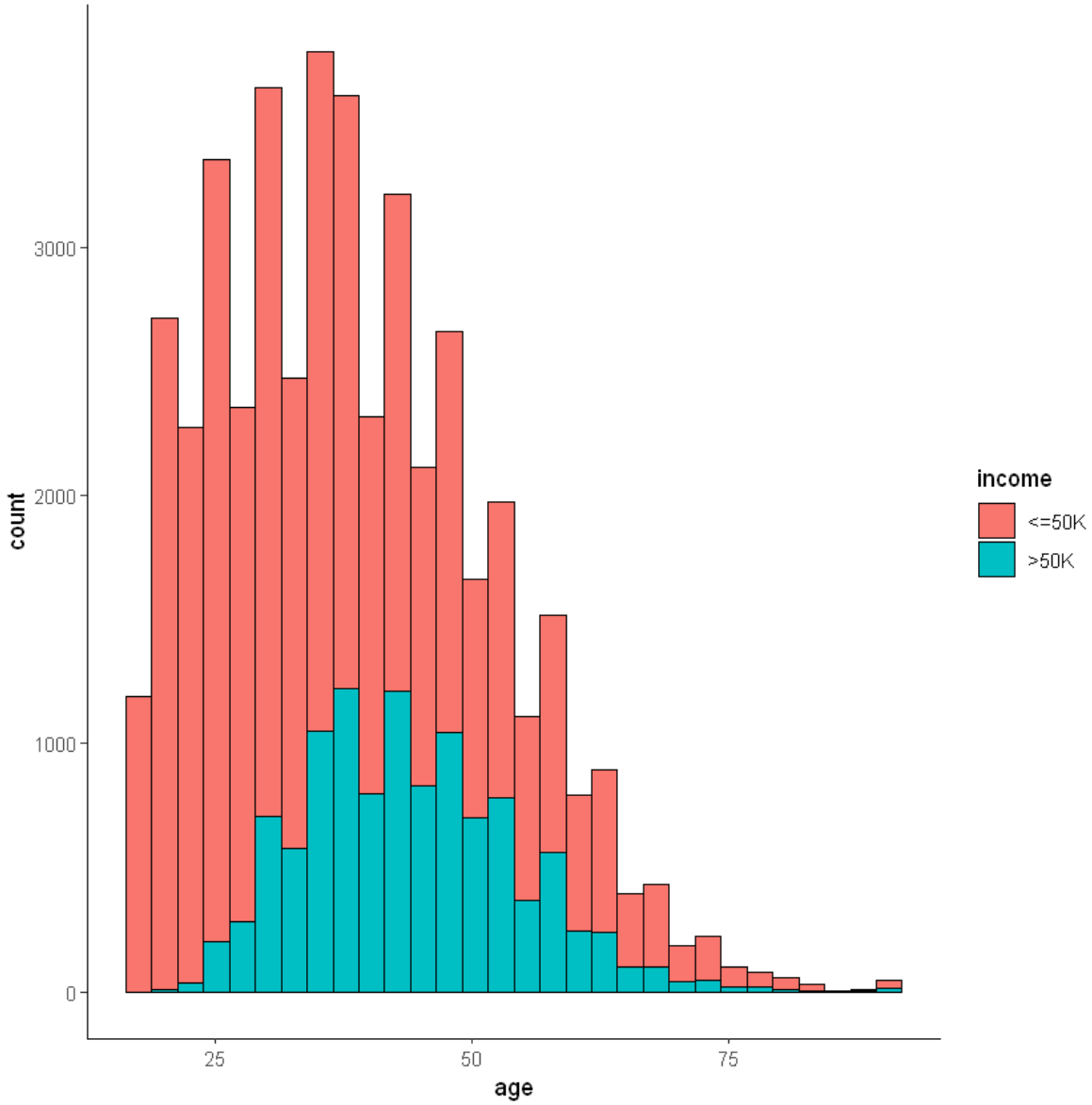


PLOT2

In [20]:

```
# The Histogram plot shows that only half or less than half
# number of people earn >50K in each age group
ggplot(adult,aes(age)) +
  geom_histogram(aes(fill = income), colour = 'black')+theme_classic()
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



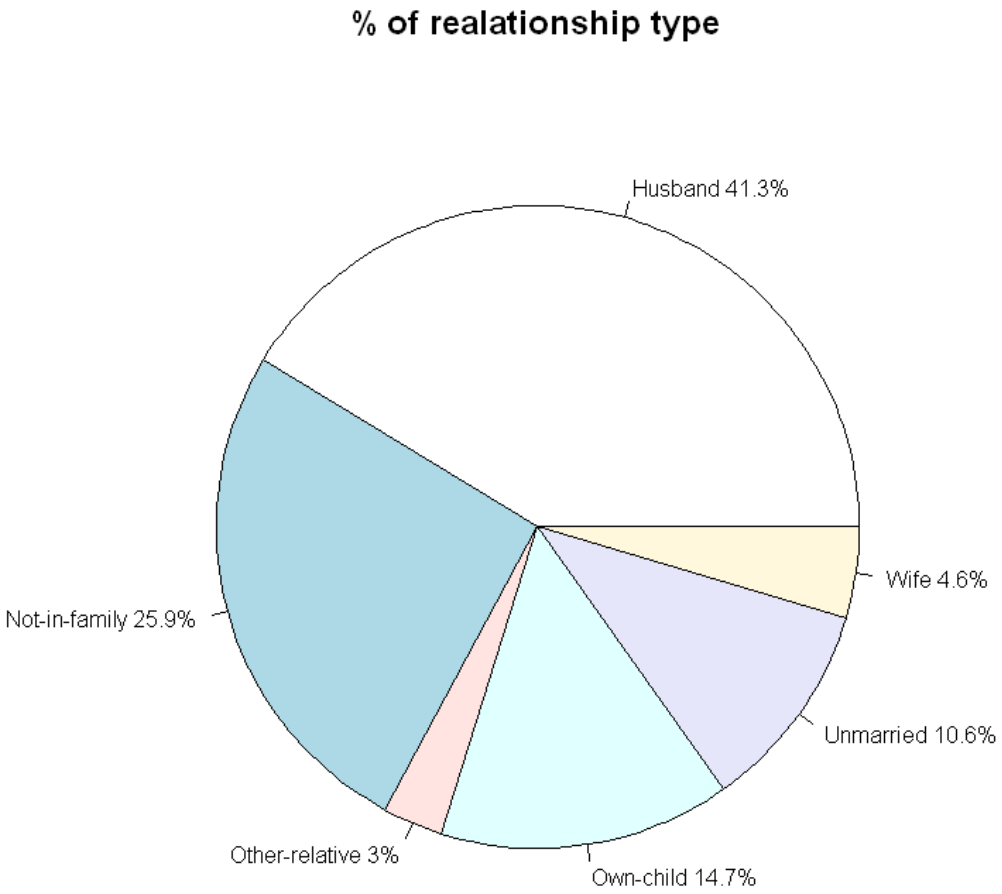
PLOT3

In [21]:

```r
# Pie plot shows the % of relationsip types in the dataset
require("RColorBrewer")
M <- table(adult$relationship)
percent<- round(100*M/sum(M), 1)
pie(percent, labels = paste0(row.names(M)," ",percent,"%") ,
    main = '% of realationship type', cex = 0.8)

```

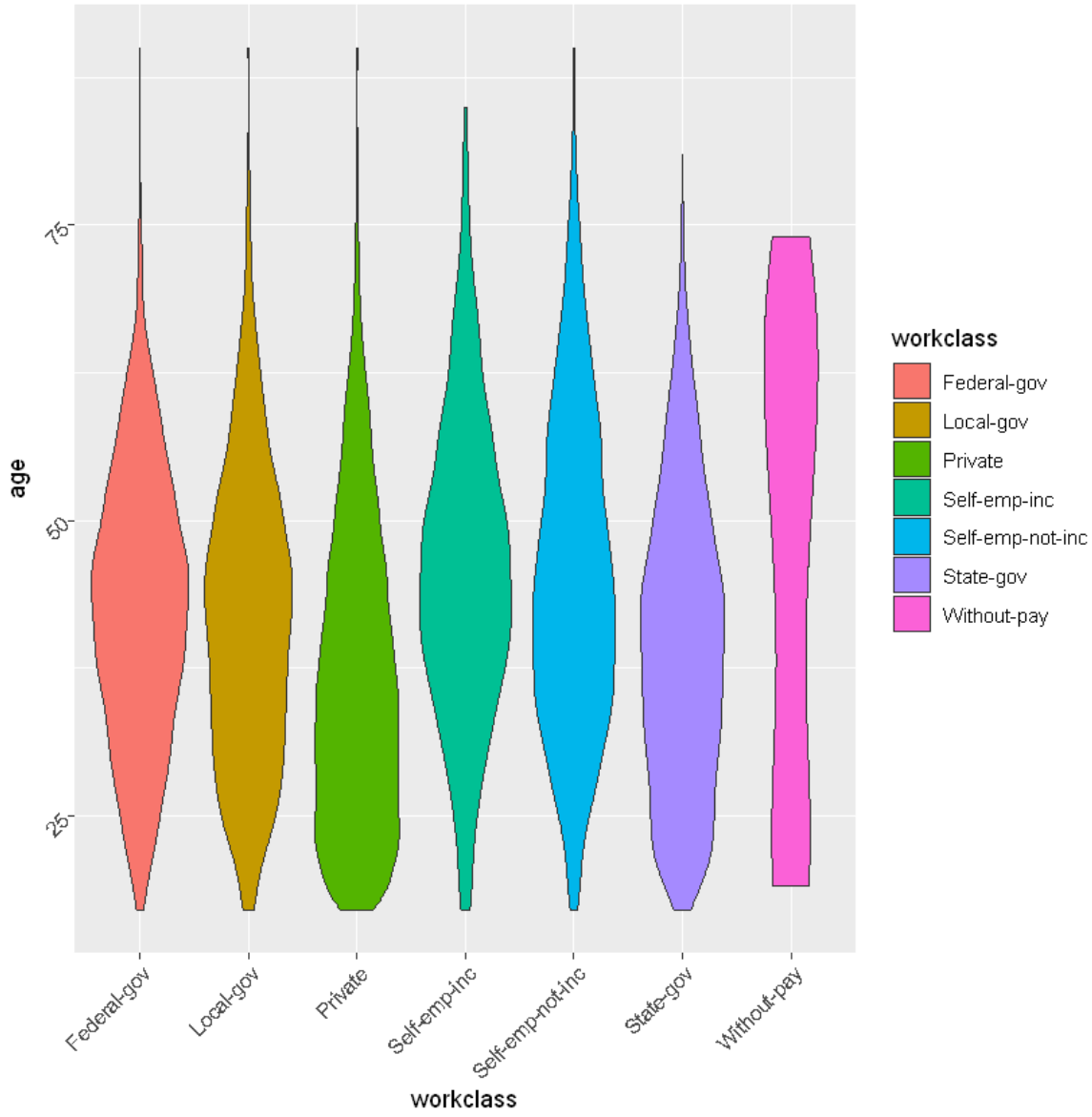
```
Loading required package: RColorBrewer
```



PLOT4

In [22]:

```
# The violin plot shows the people working in each workclass
# according to the age. in this number of older people in
# without pay are more than younger people
adult %>% ggplot(aes(workclass,age))+geom_violin(aes(fill=workclass))+
    theme(axis.text=element_text(angle = 45,hjust = 1))
```

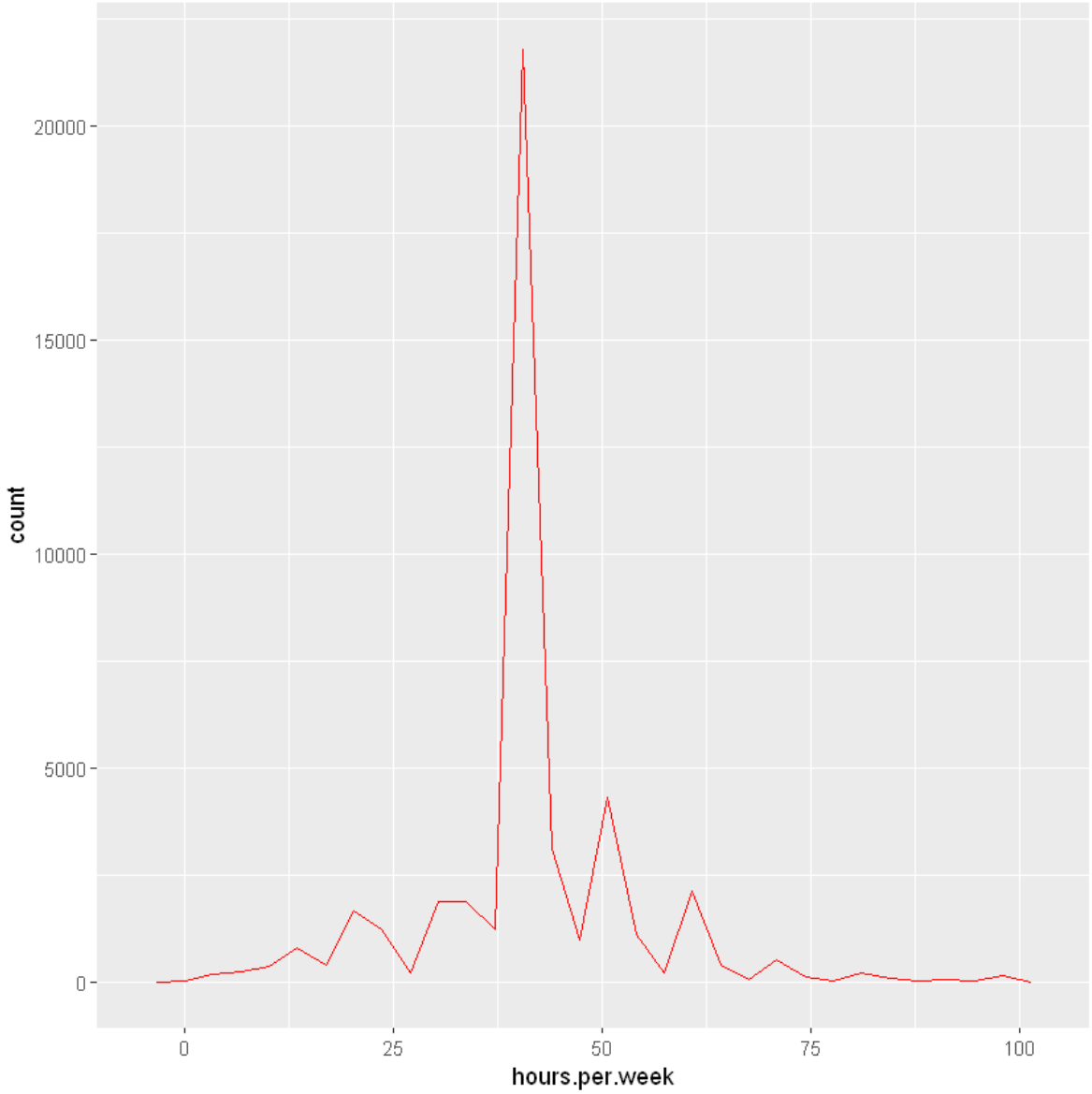


PLOT 5

In [23]:

```
# Frequency plot shows that atleast 20000
# people work between 30 to 40 hours per week.
adult%>%ggplot(aes(hours.per.week))+geom_freqpoly(col = 'red')
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



PLOT 6

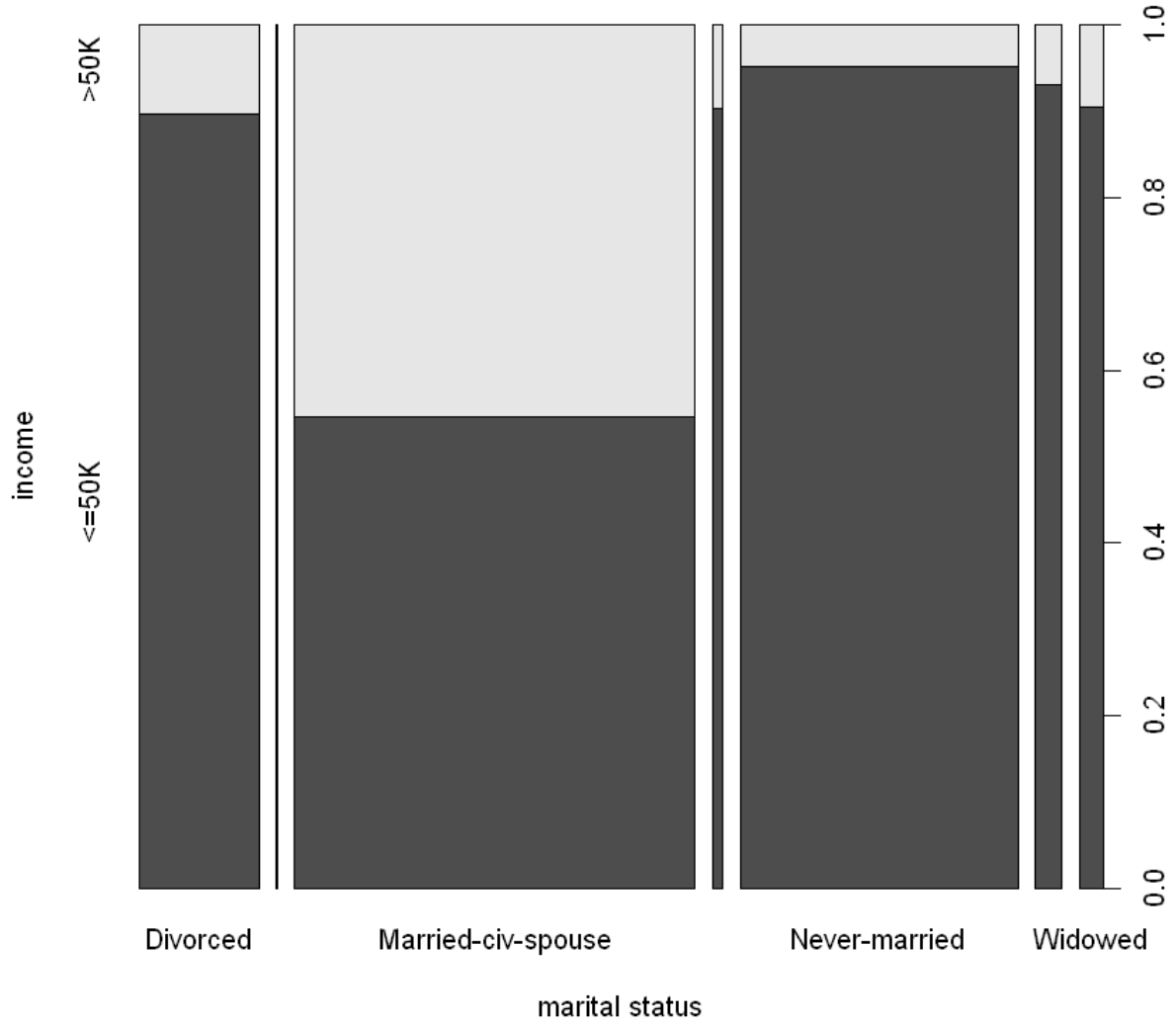
In [24]:

```
# Spineplot is the comparison between marital status and income.
# Married-civ people columns shows the highest
# number of values and only column with more >50K value
spineplot(as.factor(adult$marital.status),as.factor(adult$income)
          ,xlab="marital status",ylab = "income")
unique(adult$marital.status)

```

Never-married Married-civ-spouse Widowed Separated Divorced
Married-spouse-absent Married-AF-spouse

▶ **Levels**:



Logistic Regression Model

In [25]:

```r
# Splitting the data in train and test with 70 and 30 ratio
set.seed(10)
split <- sample.split(adult$income, SplitRatio = 0.7)
train <- subset(adult, split == TRUE)
test <- subset(adult, split == FALSE)
```

In [26]:

```r
# dimension of training data
dim(train)
```

31656 15

In [27]:

```r
# fitting the model for training data using glm function
log.model <- glm(income ~ ., family = binomial, train)
```

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

In [28]:

```r
# summary for trained model
summary(log.model)
```

```
Call:
glm(formula = income ~ ., family = binomial, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.9033  -0.5104  -0.1923  -0.0174   3.4058

Coefficients: (1 not defined because of singularities)
                                          Estimate Std. Error z value Pr
(>|z|)
(Intercept)                            -7.532e+00  7.810e-01  -9.645  <
2e-16
age                                     2.487e-02  1.672e-03  14.878  <
2e-16
workclassLocal-gov                     -5.317e-01  1.103e-01  -4.821 1.
43e-06
workclassPrivate                       -4.092e-01  9.199e-02  -4.448 8.
65e-06
```

In [29]:

```
# predicting the the model using test data and type as response
prediction <- predict(log.model,test, type = "response")
head(prediction)
```

```
Warning message in predict.lm(object, newdata, se.fit, scale = 1, type = if
(type == :
"prediction from a rank-deficient fit may be misleading"
```

3
0.404259130905415
26
0.915089938890167
34
0.329975710323981
35
0.0279396389954887
39
0.00575001648033217
42
0.484758609197936

In [30]:

```
# dimension for test data and confusion matrix of the model
dim(test)
acc<-table(test$income, prediction >= 0.5)
acc
```

13566 15

	FALSE	TRUE
<=50K	9474	730
>50K	1296	2066

In [31]:

```
# accuracy of the model
# accuracy is 85%
(acc[1]+acc[4])/(acc[1]+acc[2]+acc[3]+acc[4])
```

0.850656051894442

In [32]:

```r
# converting to the classes in the prediction outcome and
# head of the predictions and income of test data after converting
p_class<-ifelse(prediction>0.5,">50K","<=50K")
head(p_class)
head(test$income)
```

3
'<=50K'
26
'>50K'
34
'<=50K'
35
'<=50K'
39
'<=50K'
42
'<=50K'

>50K >50K <=50K <=50K <=50K >50K

▶ **Levels**:

In [33]:

```
# calculating accuracy of model using ConfusionMatrixFunction
# which comes same as 85%
confusionMatrix(as.factor(p_class), test$income)
```

```
Confusion Matrix and Statistics

          Reference
Prediction <=50K >50K
     <=50K  9474 1296
     >50K    730 2066

               Accuracy : 0.8507
                 95% CI : (0.8445, 0.8566)
    No Information Rate : 0.7522
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.5755

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9285
            Specificity : 0.6145
         Pos Pred Value : 0.8797
         Neg Pred Value : 0.7389
             Prevalence : 0.7522
         Detection Rate : 0.6984
   Detection Prevalence : 0.7939
      Balanced Accuracy : 0.7715

       'Positive' Class : <=50K
```