Select Libraries

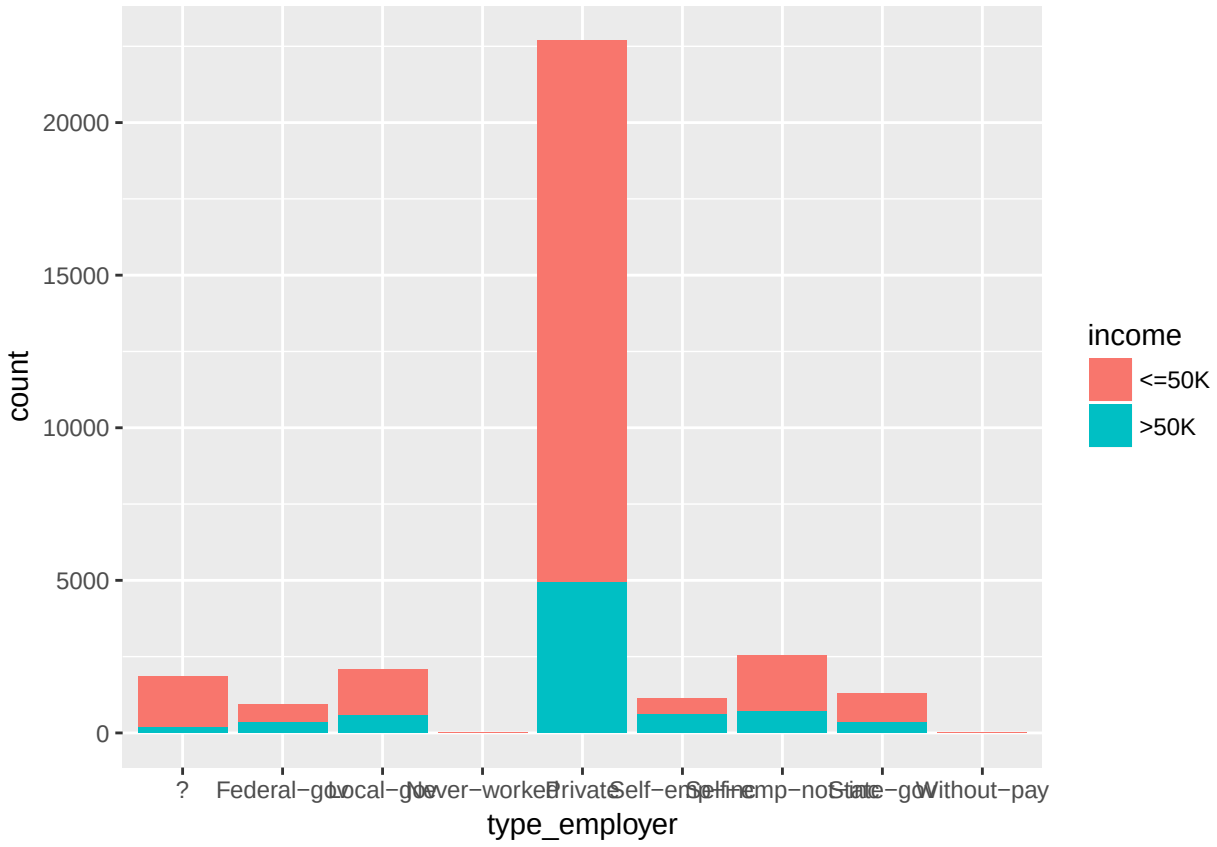
```
library(ggplot2)
library(dplyr)
```

Load csv file

```
adult<-read.csv('adult_sal.csv')


adult<-select(adult,-X)

table(adult$type_employer)
```

```
##
##                 ?      Federal-gov        Local-gov     Never-worked
##              1836              960             2093                7
##           Private     Self-emp-inc Self-emp-not-inc        State-gov
##             22696             1116             2541             1298
##       Without-pay
##                14
```

```
ggplot(adult,aes(type_employer))+geom_bar(aes(fill=income))
```

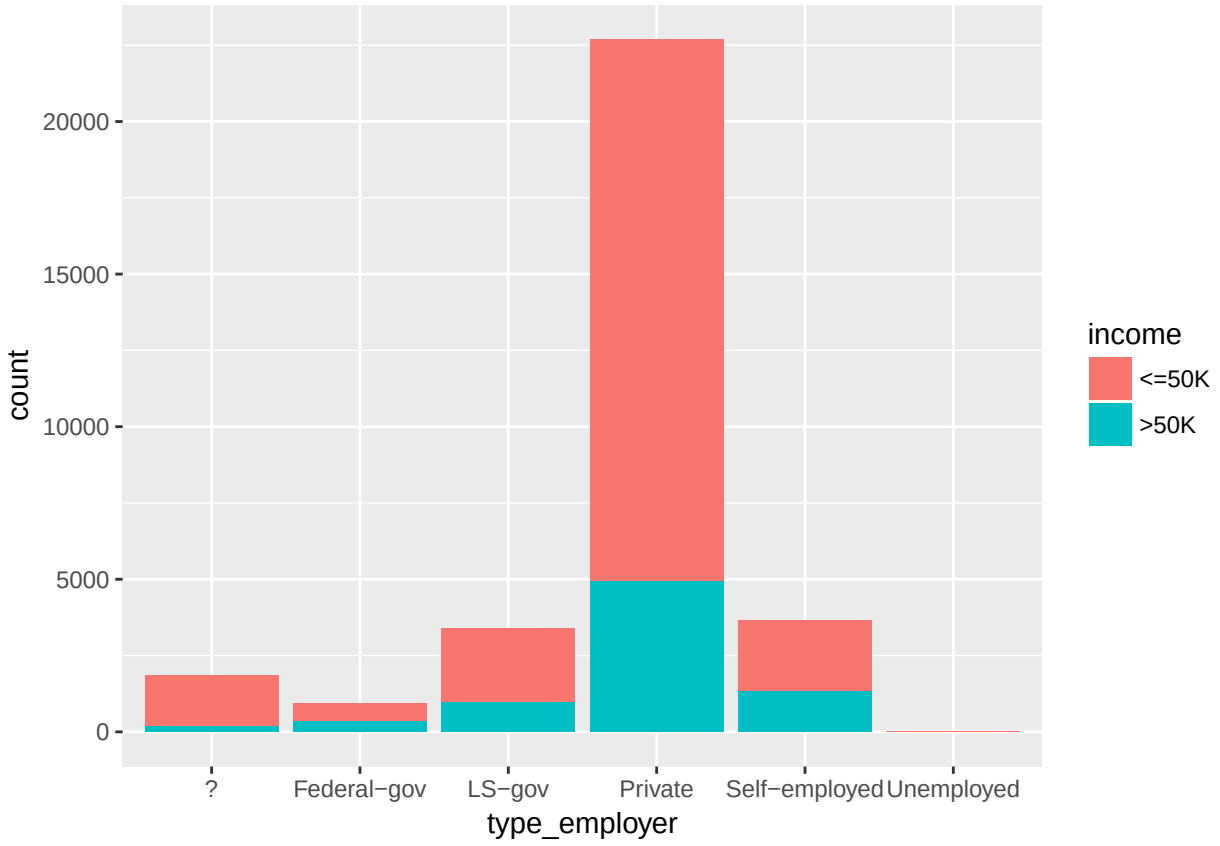


Feature Engineering Combine employer.

```
employer<-function(job){

  job<-as.character(job)
  if(job=='Never-worked' | job=='Without-pay')
    return('Unemployed')
  else if(job=='Local-gov' | job=='State-gov')
    return('LS-gov')
  else if(job=='Self-emp-inc' | job=='Self-emp-not-inc')
    return('Self-employed')
  else
    return(job)

 }

adult$type_employer<-sapply(adult$type_employer,employer)

table(adult$type_employer)
```

```
##
##             ?   Federal-gov        LS-gov       Private Self-employed
##          1836           960          3391         22696          3657
##    Unemployed
##            21
```

```
ggplot(adult,aes(type_employer))+geom_bar(aes(fill=income))
```



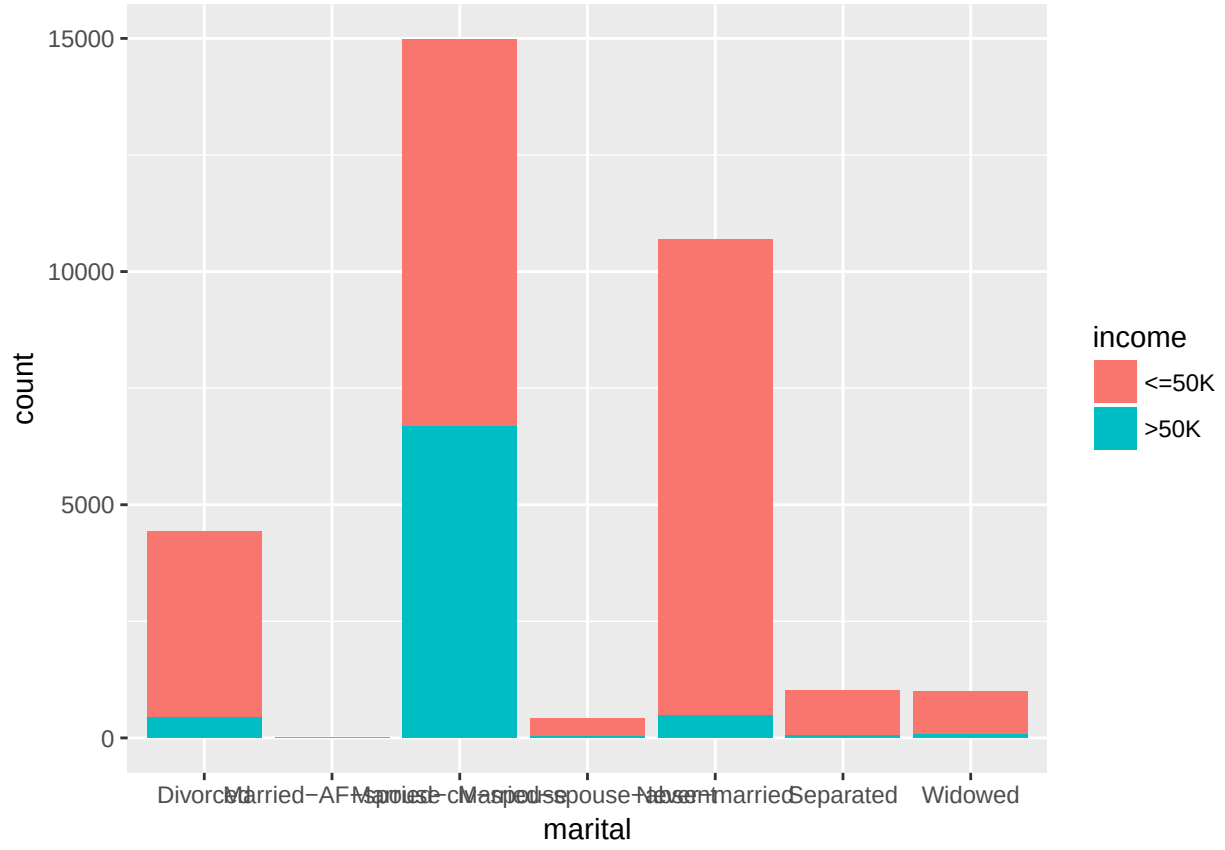

```
adult$type_employer<-factor(adult$type_employer)
```

Feature Engineering Marital status

```
table(adult$marital)
```

```
##
##              Divorced     Married-AF-spouse    Married-civ-spouse
##                  4443                    23                 14976
## Married-spouse-absent         Never-married             Separated
##                   418                 10683                  1025
##               Widowed
##                   993
```

```
ggplot(adult,aes(marital))+geom_bar(aes(fill=income))
```




```
marital_status<-function(status){
  status<-as.character(status)
  if(status=='Divorced' | status=='Separated' | status=='Widowed')
    return('Not Married')
  else if(status=='Never-married')
    return(status)
  else
    return('Married')
}

adult$marital<-sapply(adult$marital,marital_status)

table(adult$marital)
```

```
##
##       Married Never-married   Not Married
##         15417         10683          6461
```

```
adult$marital<-factor(adult$marital)
```

Feature Engineering: Country

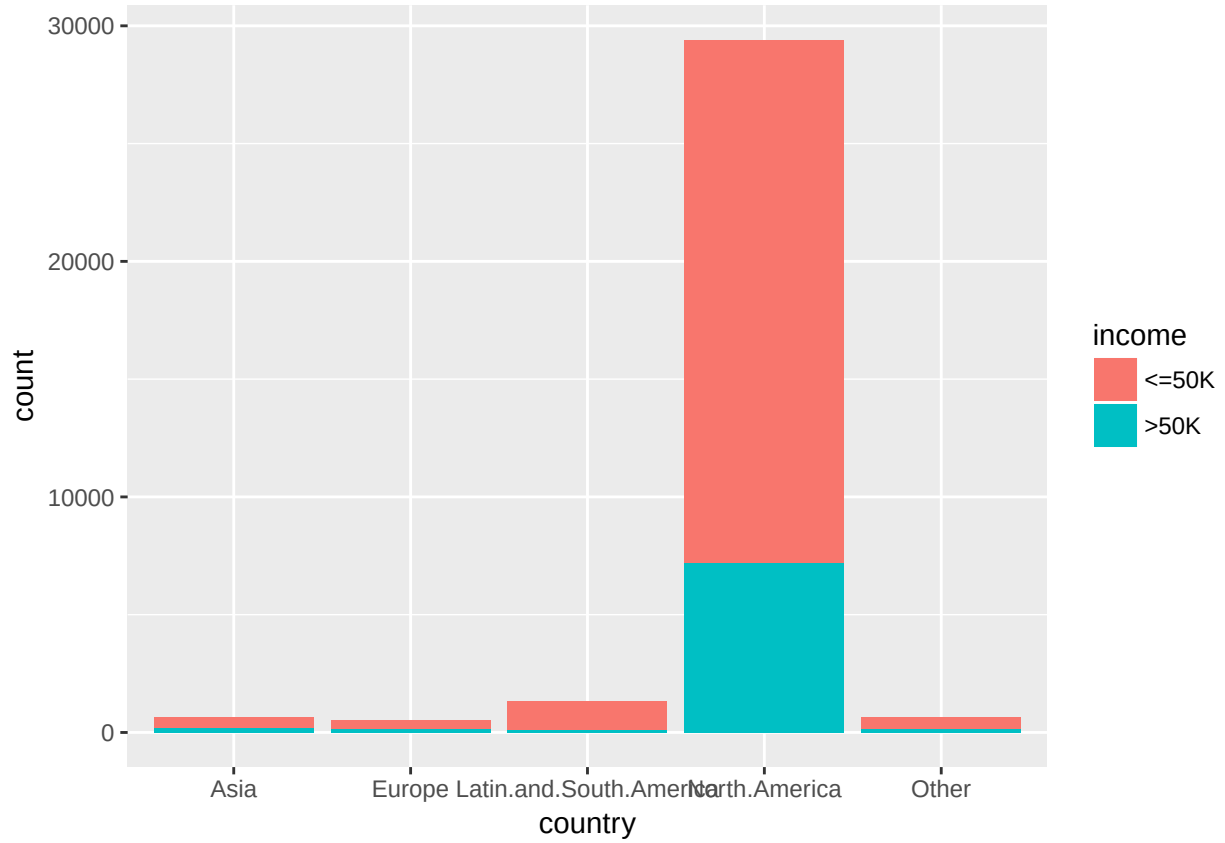
```
table(adult$country)
```

```
##
##                          ?                   Cambodia
##                        583                         19
##                     Canada                      China
```

```
##                       121                        75
##                  Columbia                      Cuba
##                        59                        95
##        Dominican-Republic                   Ecuador
##                        70                        28
##               El-Salvador                   England
##                       106                        90
##                    France                   Germany
##                        29                       137
##                    Greece                 Guatemala
##                        29                        64
##                     Haiti        Holand-Netherlands
##                        44                         1
##                  Honduras                      Hong
##                        13                        20
##                   Hungary                     India
##                        13                       100
##                      Iran                   Ireland
##                        43                        24
##                     Italy                   Jamaica
##                        73                        81
##                     Japan                      Laos
##                        62                        18
##                    Mexico                 Nicaragua
##                       643                        34
## Outlying-US(Guam-USVI-etc)                      Peru
##                        14                        31
##                Philippines                    Poland
##                       198                        60
##                  Portugal                Puerto-Rico
##                        37                       114
##                  Scotland                     South
##                        12                        80
##                    Taiwan                  Thailand
##                        51                        18
##            Trinadad&Tobago             United-States
##                        19                     29170
##                   Vietnam                 Yugoslavia
##                        67                        16
```

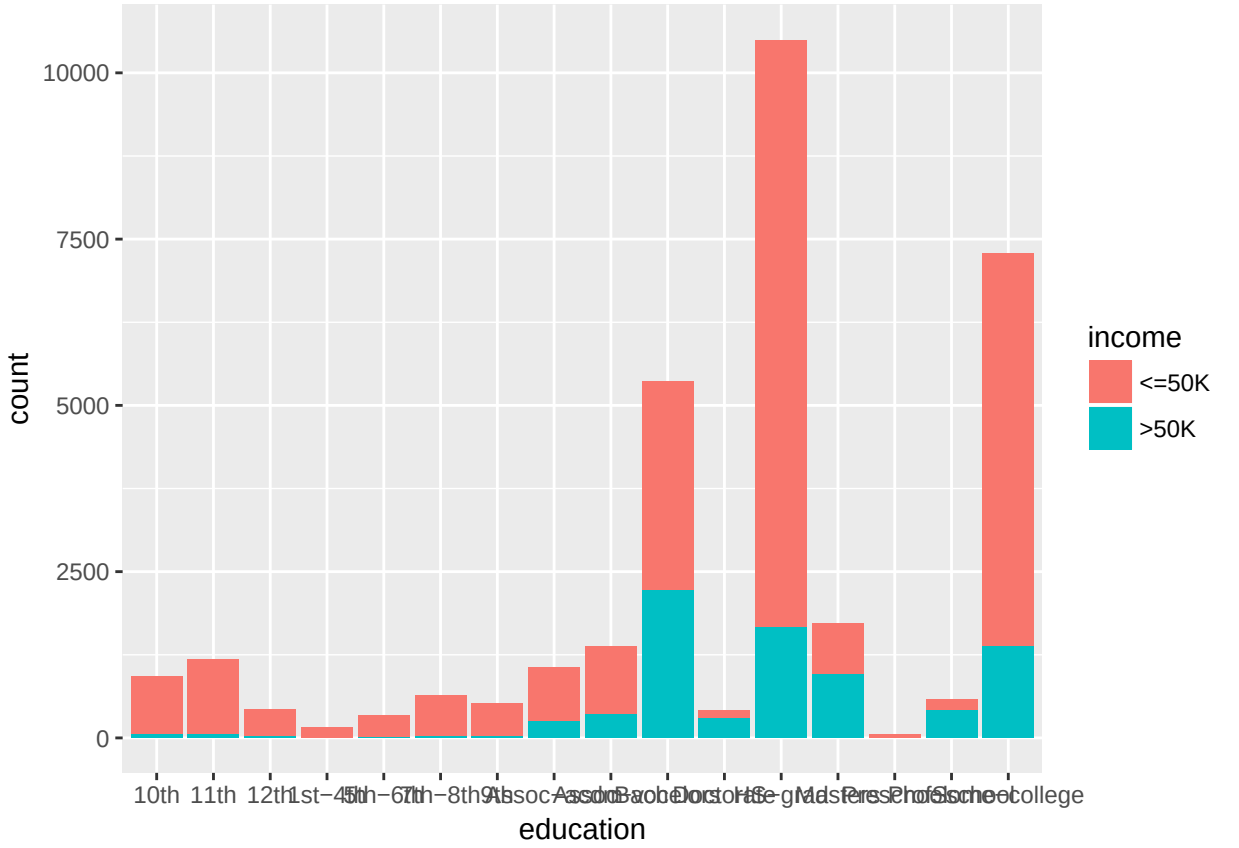
```
Asia <- c('China','Hong','India','Iran','Cambodia','Japan', 'Laos' ,
          'Philippines' ,'Vietnam' ,'Taiwan', 'Thailand')

North.America <- c('Canada','United-States','Puerto-Rico' )

Europe <- c('England' ,'France', 'Germany' ,'Greece','Holand-Netherlands','Hungary',
            'Ireland','Italy','Poland','Portugal','Scotland','Yugoslavia')

Latin.and.South.America <- c('Columbia','Cuba','Dominican-Republic','Ecuador',
                             'El-Salvador','Guatemala','Haiti','Honduras',
                             'Mexico','Nicaragua','Outlying-US(Guam-USVI-etc)','Peru',
                             'Jamaica','Trinadad&Tobago')
Other <- c('South')
```

```r
group_country <- function(ctry){
  if (ctry %in% Asia){
    return('Asia')
  }else if (ctry %in% North.America){
    return('North.America')
  }else if (ctry %in% Europe){
    return('Europe')
  }else if (ctry %in% Latin.and.South.America){
    return('Latin.and.South.America')
  }else{
    return('Other')
  }
}

adult$country <- sapply(adult$country,group_country)
adult$country<-factor(adult$country)
ggplot(adult,aes(country))+geom_bar(aes(fill=income))
```



Feature Engineering Education

```r
ggplot(adult,aes(education))+geom_bar(aes(fill=income))
```




```
school<-c('10th','11th','12th','1st-4th','5th-6th','7th-8th','9th','Preschool')

specialisation<- c('Bachelors','Doctorate','Masters','Prof-school')

education<-function(edu){

  if(edu %in% school)
    return('school')
  else if(edu %in% specialisation)
    return('specialisation')
  else
    return('highschool')
}

adult$education<-sapply(adult$education,education)

table(adult$education)
```

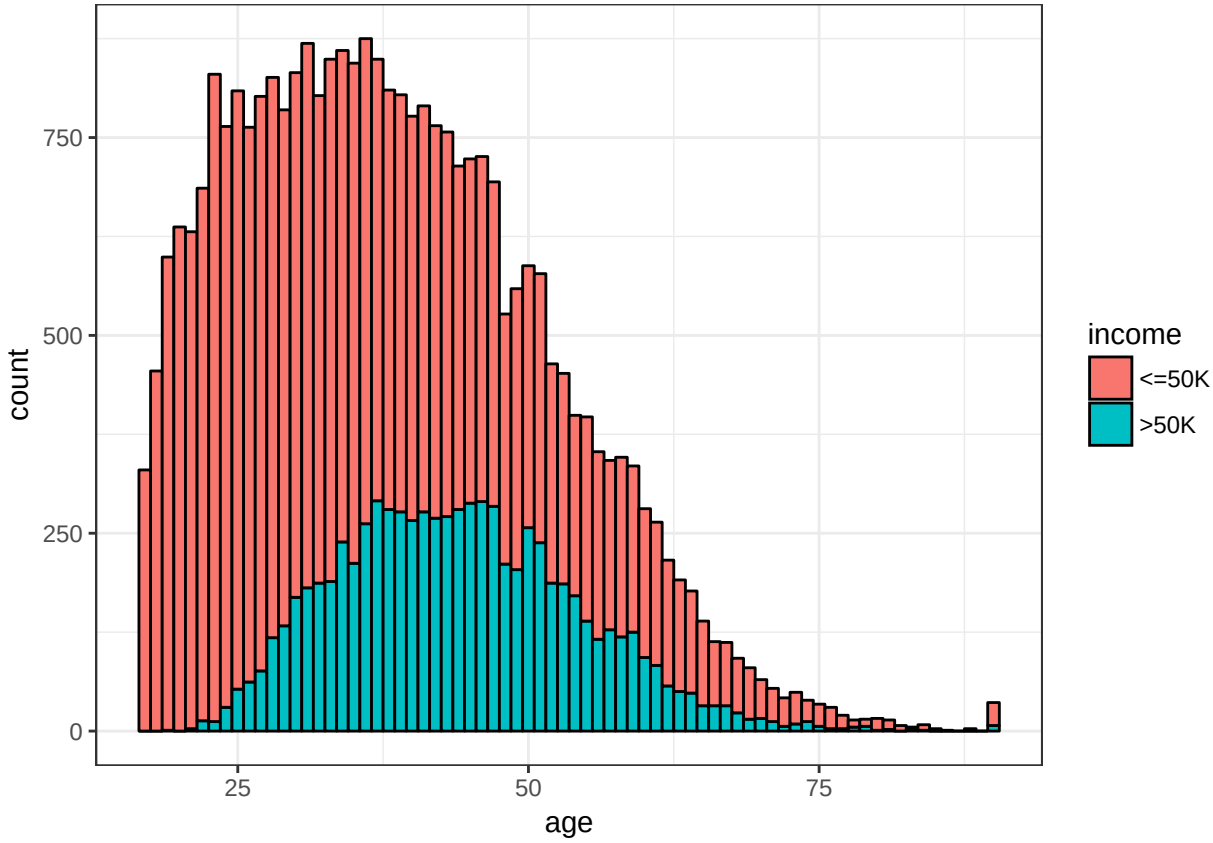
```
##
##     highschool         school specialisation
##          20241           4253           8067
```

Remove Missing Data

```
adult[adult=='?']<-NA

adult<-na.omit(adult)
```

plots

```
ggplot(adult,aes(age))+geom_histogram(aes(fill=income),color='black',binwidth = 1)+theme_bw()
```



#********** Logistic Regression **********

```
library(caTools)

set.seed(101)

sample<-sample.split(adult$income,SplitRatio = 0.7)

train<-subset(adult,sample==T)
test<-subset(adult,sample==F)

model<-glm(income~.,family = binomial(link ="logit" ),data=train)
```

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

```
summary(model)
```

```
##
## Call:
## glm(formula = income ~ ., family = binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -5.0462  -0.5186  -0.1964  -0.0080   3.7882
```

```
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -6.762e+00  4.614e-01 -14.656  < 2e-16 ***
## age                             2.589e-02  1.987e-03  13.035  < 2e-16 ***
## type_employerLS-gov            -6.810e-01  1.262e-01  -5.397 6.78e-08 ***
## type_employerPrivate           -4.422e-01  1.124e-01  -3.936 8.30e-05 ***
## type_employerSelf-employed     -6.671e-01  1.240e-01  -5.378 7.52e-08 ***
## type_employerUnemployed        -1.218e+01  1.355e+02  -0.090 0.928341
## fnlwgt                          5.304e-07  2.079e-07   2.551 0.010746 *
## educationschool                -1.179e-01  1.347e-01  -0.876 0.381283
## educationspecialisation         2.106e-01  1.008e-01   2.090 0.036578 *
## education_num                   2.384e-01  2.456e-02   9.706  < 2e-16 ***
## maritalNever-married           -1.240e+00  1.951e-01  -6.357 2.06e-10 ***
## maritalNot Married             -7.044e-01  1.954e-01  -3.605 0.000312 ***
## occupationArmed-Forces         -5.804e-01  1.823e+00  -0.318 0.750215
## occupationCraft-repair          4.504e-02  9.450e-02   0.477 0.633656
## occupationExec-managerial       7.712e-01  9.067e-02   8.506  < 2e-16 ***
## occupationFarming-fishing      -1.138e+00  1.622e-01  -7.013 2.34e-12 ***
## occupationHandlers-cleaners    -7.905e-01  1.724e-01  -4.585 4.54e-06 ***
## occupationMachine-op-inspct    -2.191e-01  1.198e-01  -1.830 0.067290 .
## occupationOther-service        -8.188e-01  1.385e-01  -5.913 3.35e-09 ***
## occupationPriv-house-serv      -3.536e+00  1.884e+00  -1.877 0.060505 .
## occupationProf-specialty        5.364e-01  9.484e-02   5.656 1.55e-08 ***
## occupationProtective-serv       6.011e-01  1.490e-01   4.036 5.44e-05 ***
## occupationSales                 2.847e-01  9.733e-02   2.925 0.003442 **
## occupationTech-support          6.827e-01  1.321e-01   5.169 2.36e-07 ***
## occupationTransport-moving     -1.167e-01  1.185e-01  -0.985 0.324464
## relationshipNot-in-family      -8.975e-01  1.916e-01  -4.684 2.81e-06 ***
## relationshipOther-relative     -1.147e+00  2.580e-01  -4.448 8.69e-06 ***
## relationshipOwn-child          -1.824e+00  2.363e-01  -7.717 1.19e-14 ***
## relationshipUnmarried          -1.065e+00  2.163e-01  -4.926 8.38e-07 ***
## relationshipWife                1.459e+00  1.232e-01  11.843  < 2e-16 ***
## raceAsian-Pac-Islander          6.064e-01  3.199e-01   1.896 0.058002 .
## raceBlack                       4.506e-01  2.842e-01   1.586 0.112837
## raceOther                       5.073e-02  4.211e-01   0.120 0.904125
## raceWhite                       6.532e-01  2.706e-01   2.414 0.015783 *
## sexMale                         8.813e-01  9.338e-02   9.438  < 2e-16 ***
## capital_gain                    3.123e-04  1.253e-05  24.933  < 2e-16 ***
## capital_loss                    6.557e-04  4.557e-05  14.391  < 2e-16 ***
## hr_per_week                     2.939e-02  1.980e-03  14.845  < 2e-16 ***
## countryEurope                   1.109e-01  2.544e-01   0.436 0.663006
## countryLatin.and.South.America -5.182e-01  2.555e-01  -2.028 0.042598 *
## countryNorth.America            5.868e-02  2.038e-01   0.288 0.773372
## countryOther                   -3.572e-01  2.343e-01  -1.524 0.127484
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 24138  on 21502  degrees of freedom
## Residual deviance: 14042  on 21461  degrees of freedom
## AIC: 14126
##
```

```
## Number of Fisher Scoring iterations: 12
```

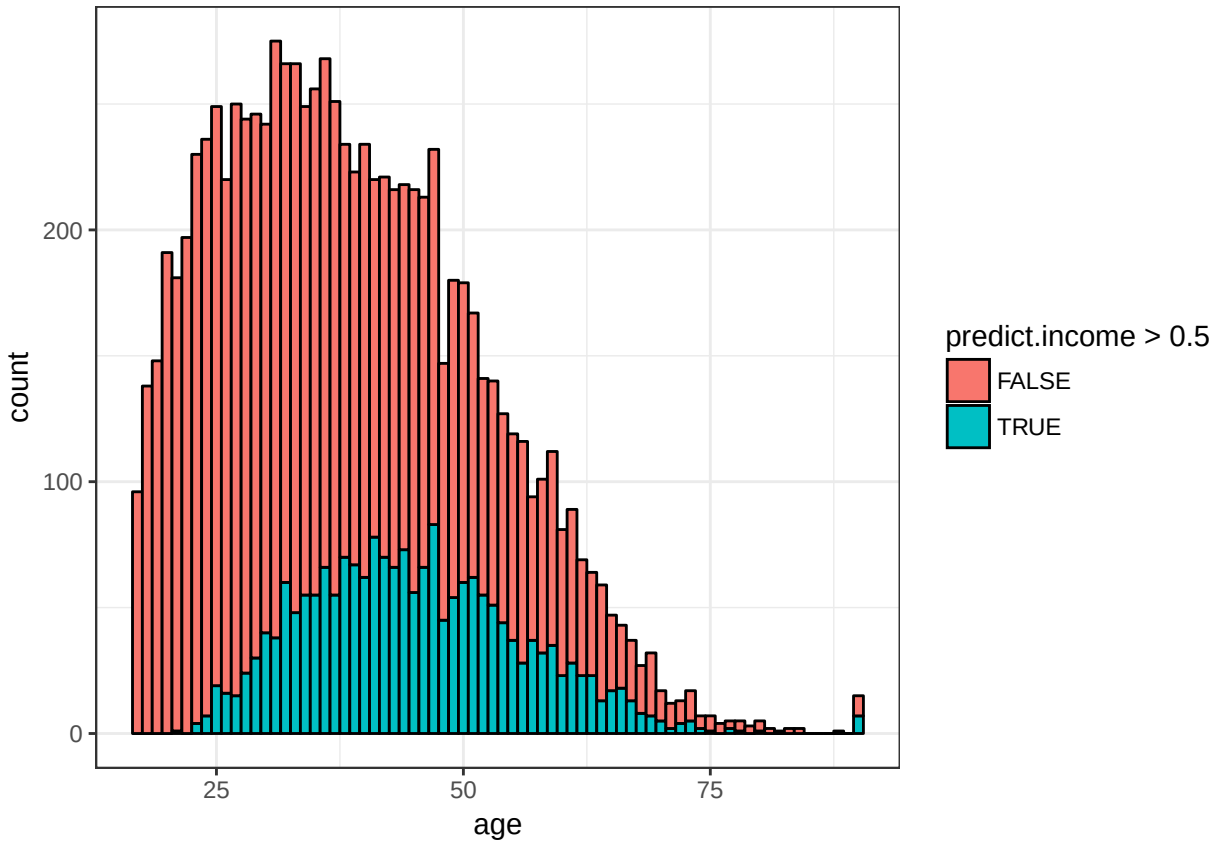
```
#step.model<-step(model)

#summary(step.model)

#predict.income<-predict(model,newdata=test,type='response')

test$predict.income<-predict(model,newdata=test,type='response')


table(test$income,test$predict.income>0.5)
```

```
##
##         FALSE TRUE
##   <=50K  6377  543
##   >50K    871 1424
```

```
accuracy<-(6372+1423)/(6372+1423+548+872)

accuracy #84.6%
```

```
## [1] 0.8459034
```

```
ggplot(test,aes(age))+geom_histogram(aes(fill=predict.income>0.5),color='black',binwidth = 1)+theme_bw()
```




```
#*************************************************
```