Deliverable 2

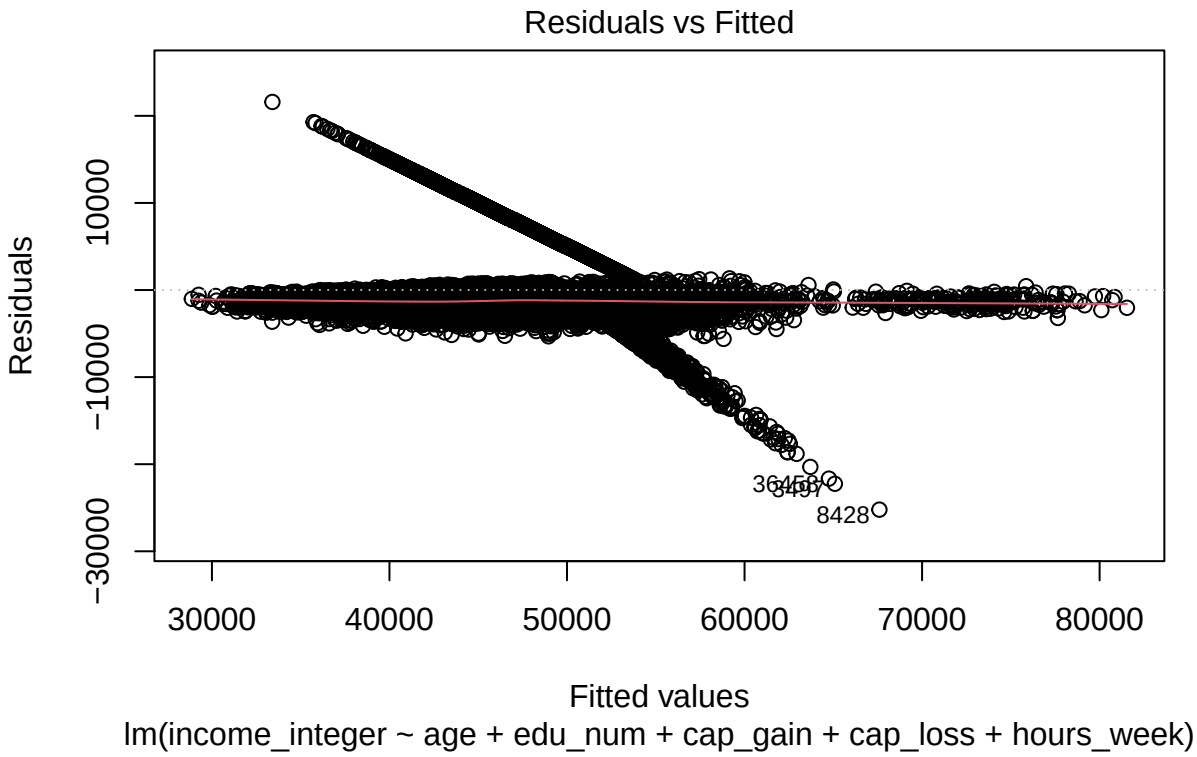
2025-04-29

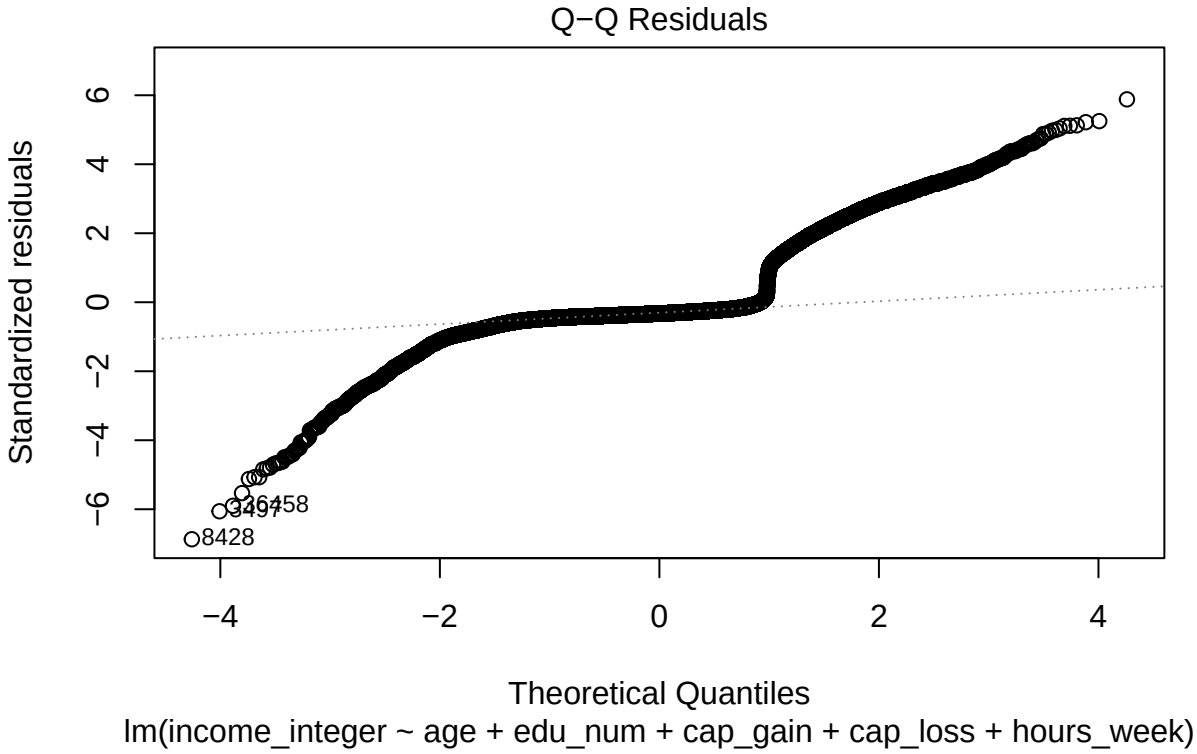
```r
setwd("~/Escritorio/ADEI/D2")
dd <- read.csv("adult_def.csv")
```

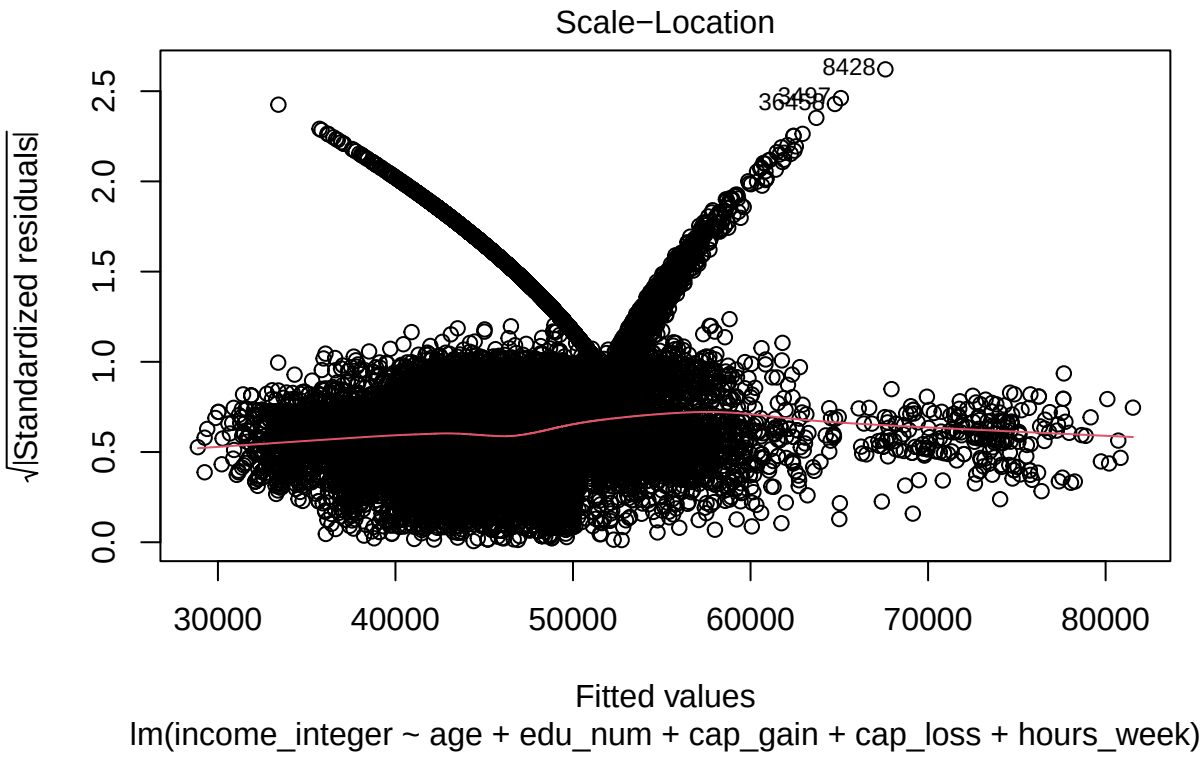
```r
initial_model <- lm(income_integer ~ age + edu_num + cap_gain + cap_loss + hours_week, data = dd)
summary(initial_model)
```

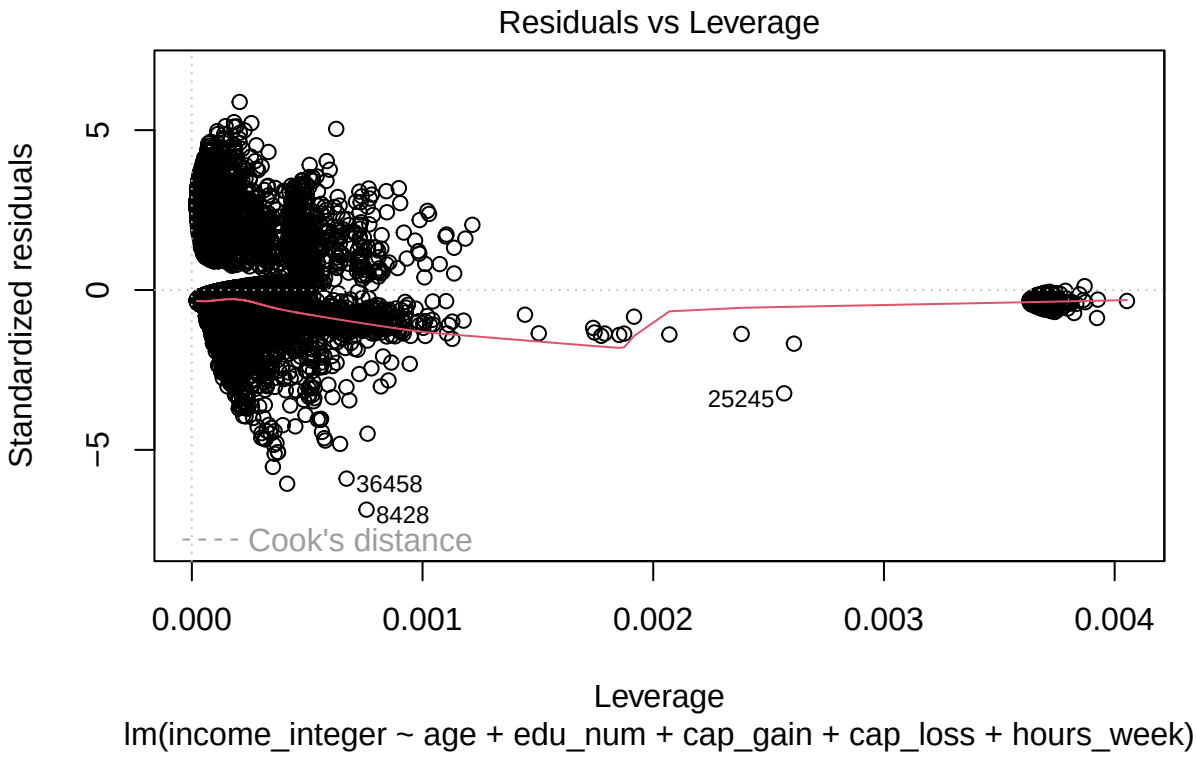
```
##
## Call:
## lm(formula = income_integer ~ age + edu_num + cap_gain + cap_loss +
##     hours_week, data = dd)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -25216.0  -1522.3  -1201.8   -699.4  21594.2
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2.091e+04  9.221e+01  226.74   <2e-16 ***
## age         2.317e+02  1.220e+00  189.87   <2e-16 ***
## edu_num     1.144e+03  6.595e+00  173.42   <2e-16 ***
## cap_gain    2.003e-01  2.260e-03   88.60   <2e-16 ***
## cap_loss    7.848e-01  4.151e-02   18.91   <2e-16 ***
## hours_week  9.924e+01  1.362e+00   72.87   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3672 on 48836 degrees of freedom
## Multiple R-squared:  0.6683, Adjusted R-squared:  0.6682
## F-statistic: 1.968e+04 on 5 and 48836 DF,  p-value: < 2.2e-16
```

```r
plot(initial_model)
```

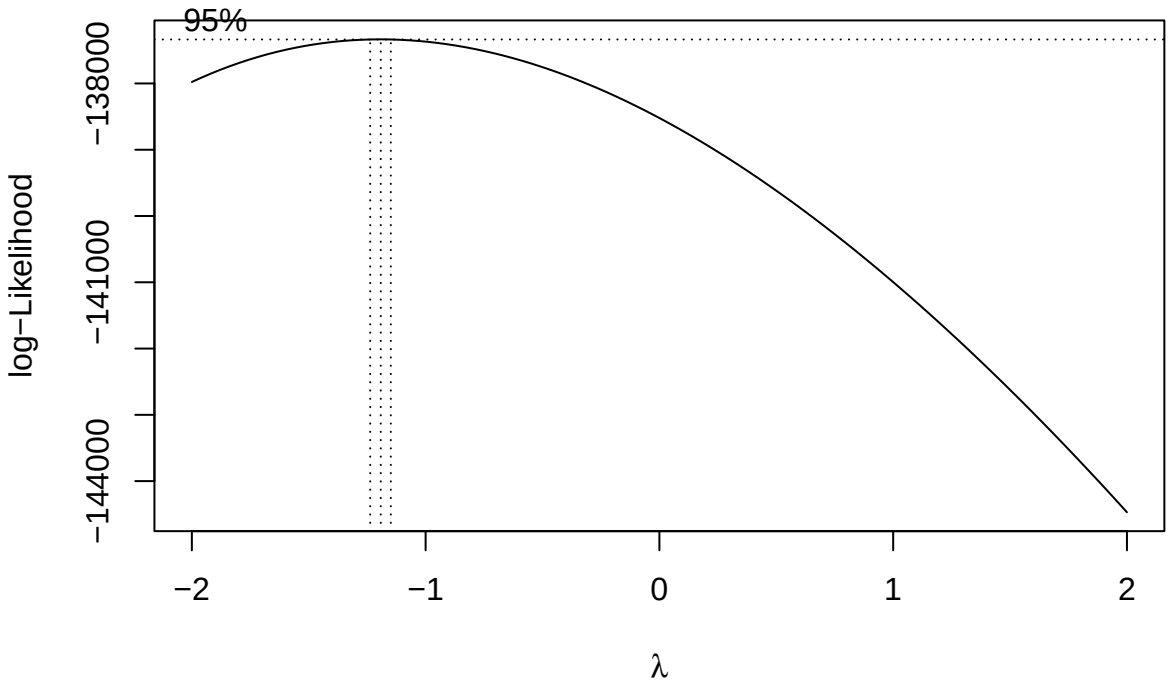

Residuals vs Fitted
Residuals
10000
−10000
−30000
30000
40000
50000
60000
70000
80000
8428
Fitted values
lm(income_integer ~ age + edu_num + cap_gain + cap_loss + hours_week)


Q−Q Residuals
Standardized residuals
6
4
2
0
−2
−4
−6
26458
3497
8428
−4
−2
0
2
4
Theoretical Quantiles
lm(income_integer ~ age + edu_num + cap_gain + cap_loss + hours_week)


Scale−Location
8428
3497
36458
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
30000
40000
50000
60000
70000
80000
Fitted values
lm(income_integer ~ age + edu_num + cap_gain + cap_loss + hours_week)




```
#target variable transformation, so the normality assumption is met
boxcox(income_integer ~ age + edu_num + cap_gain + cap_loss + hours_week, data = dd)
```

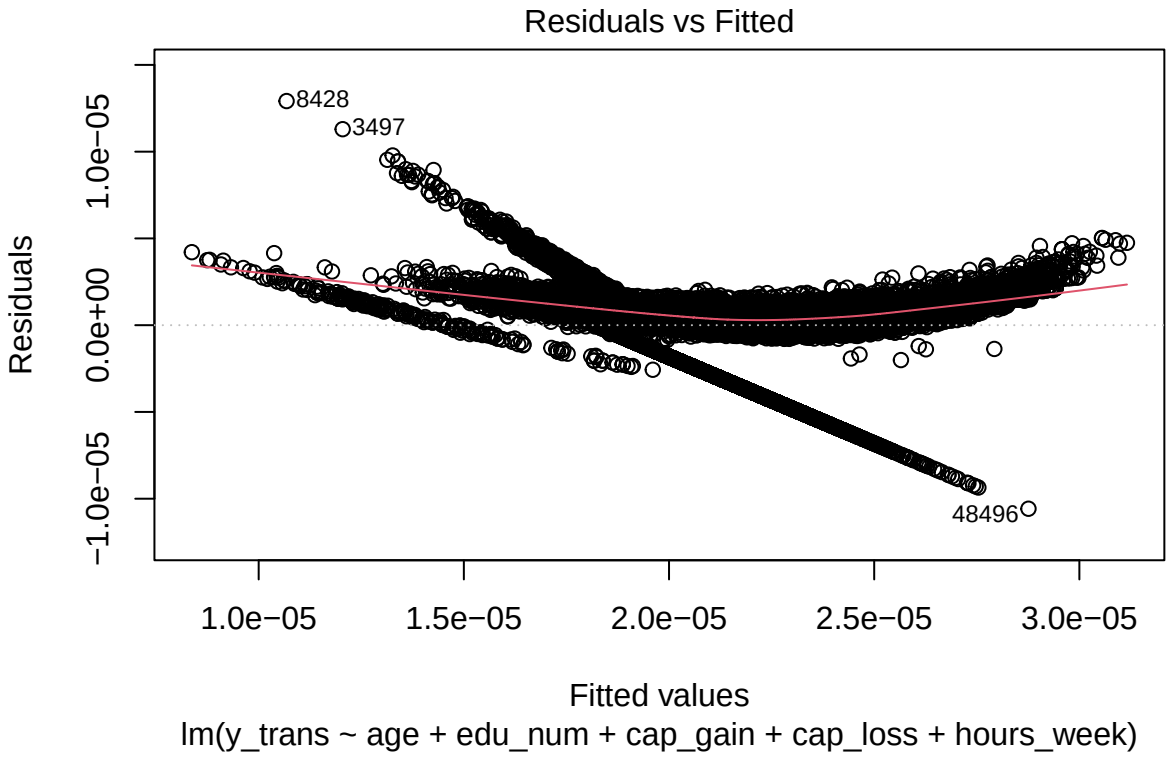


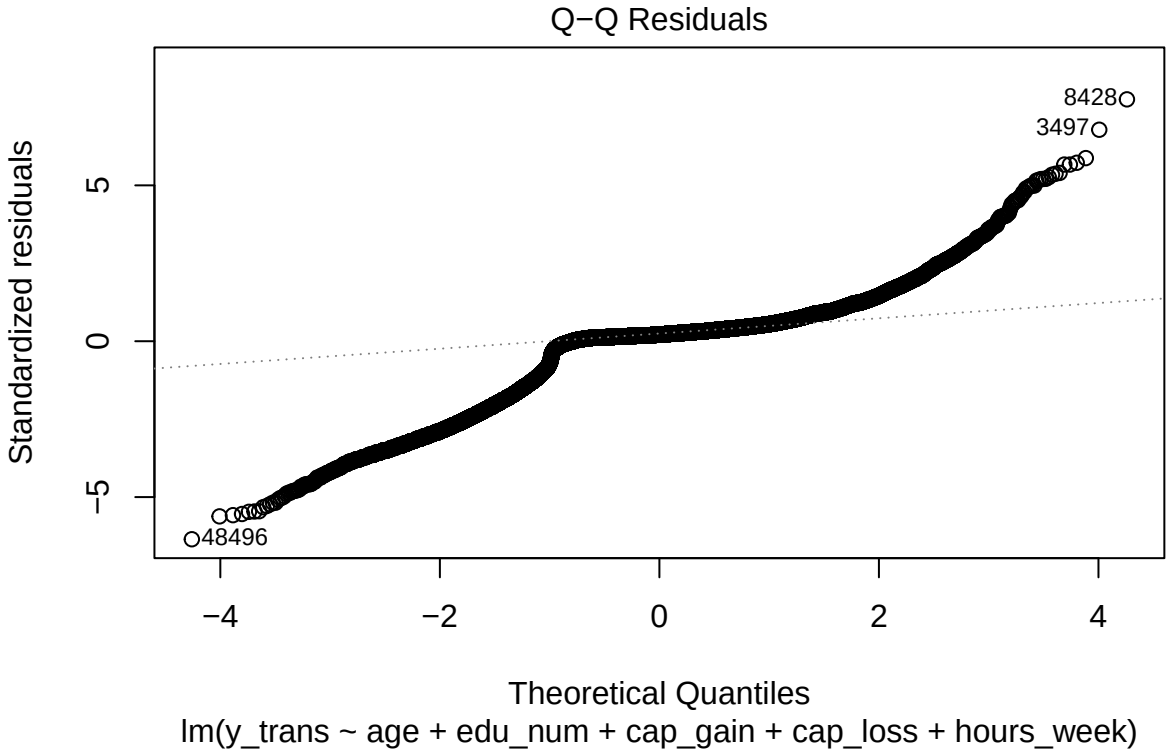

```
#given lambda is aproximatedly -1 we do the inverse transformation
y_trans <- 1 / dd$income_integer
transformed_model <- lm(y_trans ~ age + edu_num + cap_gain + cap_loss + hours_week, data = dd)
summary(transformed_model)
```

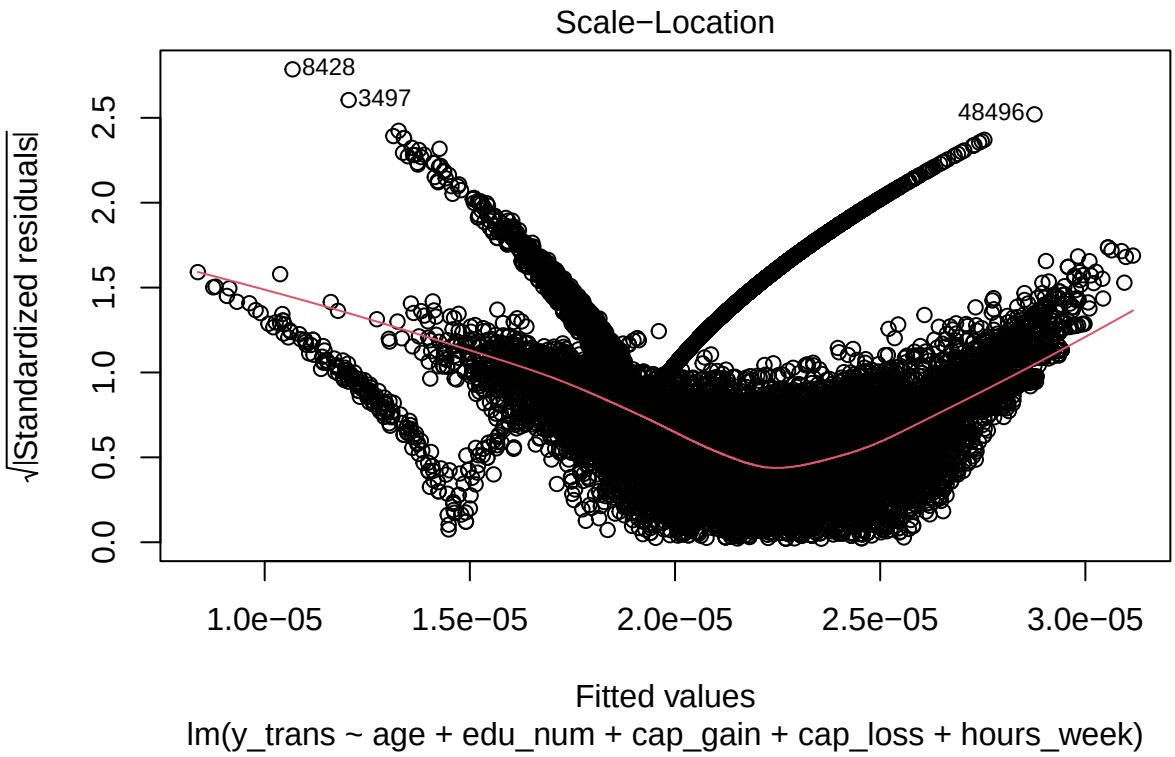
```
##
## Call:
## lm(formula = y_trans ~ age + edu_num + cap_gain + cap_loss +
##     hours_week, data = dd)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.058e-05  1.373e-07  3.552e-07  6.859e-07  1.292e-05
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.536e-05  4.182e-08  845.57   <2e-16 ***
## age         -1.221e-07  5.533e-10 -220.74   <2e-16 ***
## edu_num     -6.086e-07  2.991e-09 -203.48   <2e-16 ***
## cap_gain    -5.503e-11  1.025e-12  -53.68   <2e-16 ***
## cap_loss    -2.612e-10  1.883e-11  -13.88   <2e-16 ***
## hours_week  -5.219e-08  6.176e-10  -84.51   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.665e-06 on 48836 degrees of freedom
```

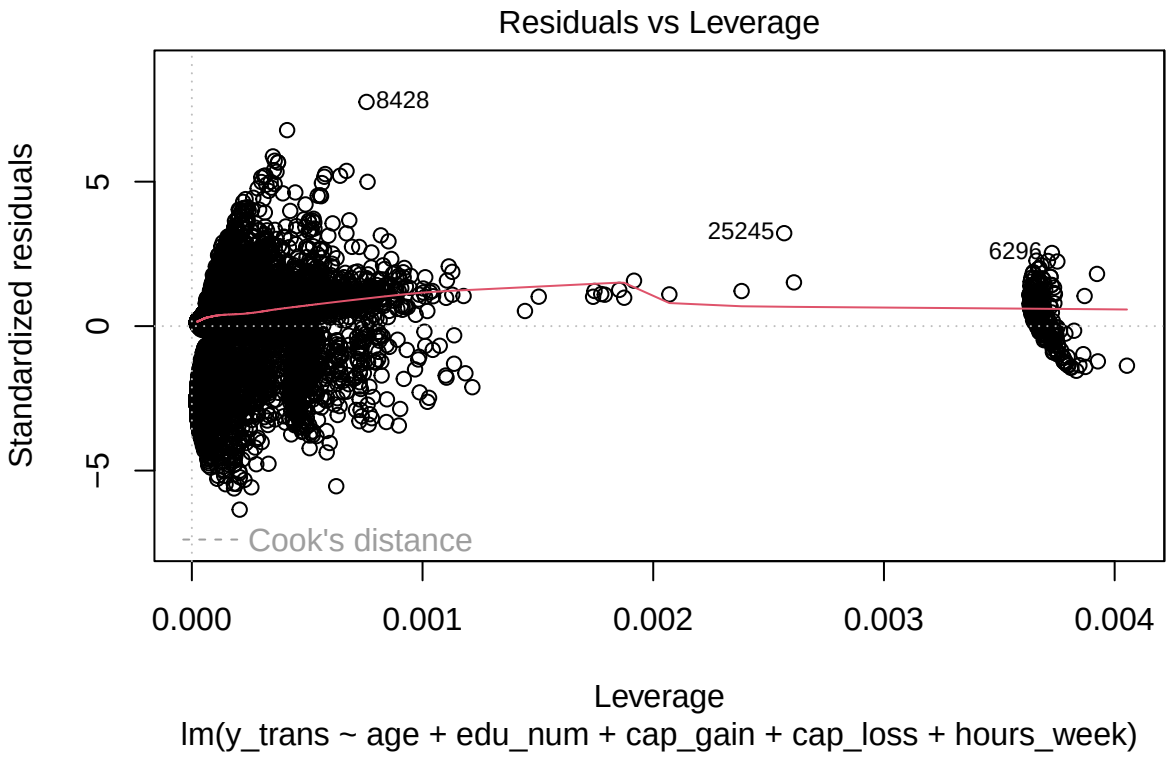
```
## Multiple R-squared:  0.7109, Adjusted R-squared:  0.7109
## F-statistic: 2.402e+04 on 5 and 48836 DF,  p-value: < 2.2e-16
```

```
plot(transformed_model) #we cannot accept the basic hypothesis yet
```

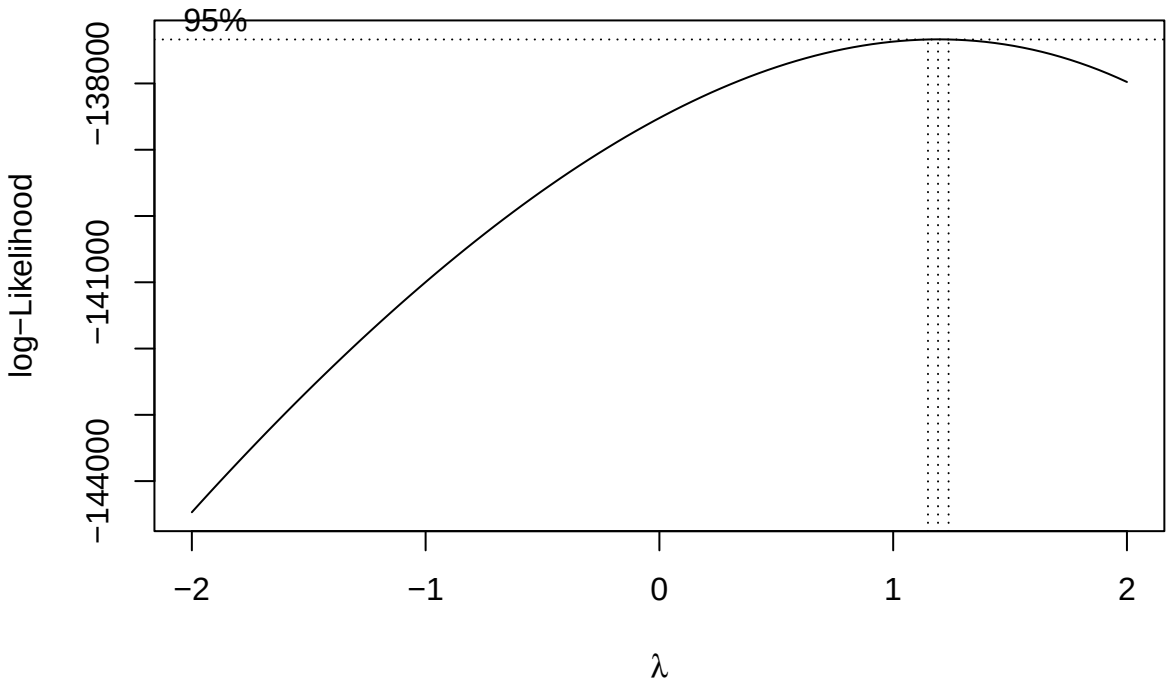



Q−Q Residuals
Standardized residuals
5
0
−5
8428
3497
48496
−4
−2
0
2
4
Theoretical Quantiles
lm(y_trans ~ age + edu_num + cap_gain + cap_loss + hours_week)


Scale−Location
8428
3497
48496
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
1.0e−05
1.5e−05
2.0e−05
2.5e−05
3.0e−05
Fitted values
lm(y_trans ~ age + edu_num + cap_gain + cap_loss + hours_week)




```
boxcox(y_trans ~ age + edu_num + cap_gain + cap_loss + hours_week, data = dd) # lambda is now around 1 
```




```
#As seen before, the basic hypothesis cannot be accepted, we need to perform transformation on the regr
boxTidwell(y_trans ~ age + edu_num + hours_week, data = dd)
```

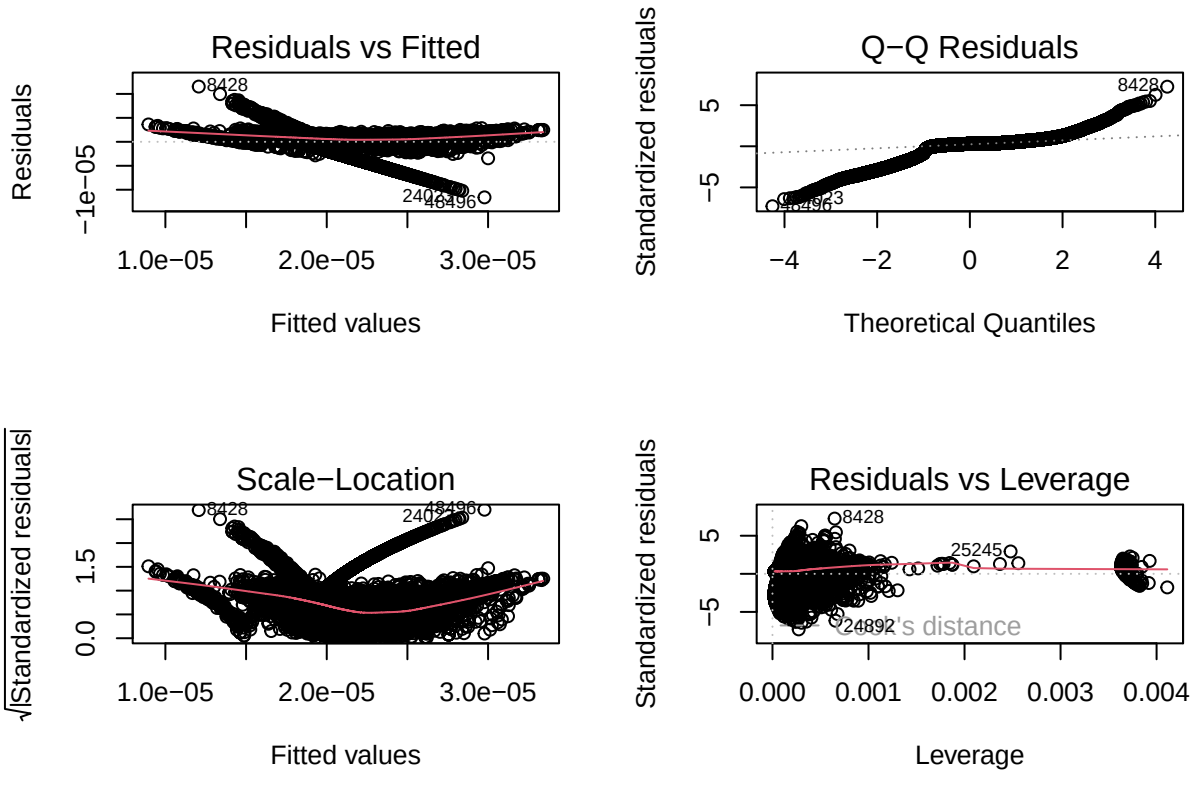
```
##             MLE of lambda Score Statistic (t)  Pr(>|t|)
## age              -0.69324             75.0355 < 2.2e-16 ***
## edu_num           0.38487             40.7224 < 2.2e-16 ***
## hours_week        0.85116              4.6881 2.764e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## iterations =  4
##
## Score test for null hypothesis that all lambdas = 1:
## F = 2566.4, df = 3 and 48835, Pr(>F) = < 2.2e-16
```

```
dd$agebt <- sqrt(dd$age)
edu_num_bt <- sqrt(dd$edu_num)
btmodel <- lm(y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week, data = dd)
summary(btmodel)
```

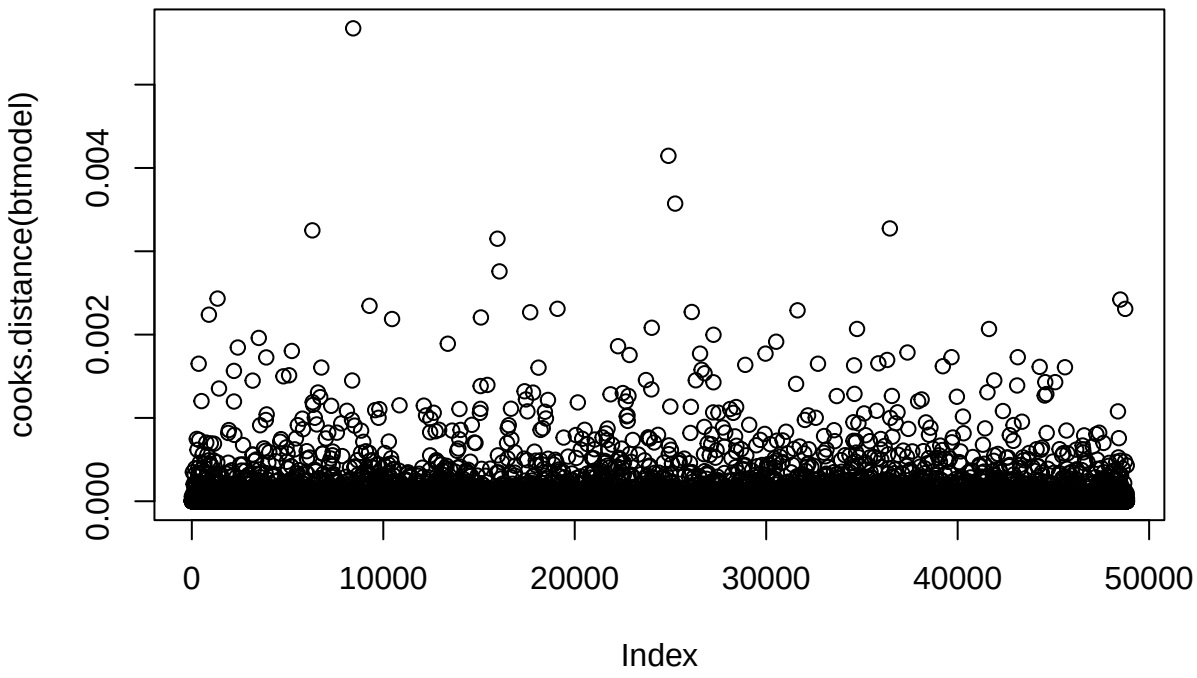
```
##
## Call:
## lm(formula = y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss +
##     hours_week, data = dd)
##
```

```
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.160e-05  1.249e-07  4.788e-07  6.404e-07  1.153e-05
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.542e-05  6.717e-08  676.15   <2e-16 ***
## agebt       -1.606e-06  6.642e-09 -241.80   <2e-16 ***
## edu_num_bt  -3.585e-06  1.679e-08 -213.48   <2e-16 ***
## cap_gain    -5.684e-11  9.779e-13  -58.12   <2e-16 ***
## cap_loss    -2.708e-10  1.797e-11  -15.07   <2e-16 ***
## hours_week  -4.752e-08  5.911e-10  -80.38   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.591e-06 on 48836 degrees of freedom
## Multiple R-squared:  0.7363, Adjusted R-squared:  0.7362
## F-statistic: 2.727e+04 on 5 and 48836 DF,  p-value: < 2.2e-16
```

```
par(mfrow=c(2,2))
plot(btmodel)
```




```
#Check cook's distance
plot(cooks.distance(btmodel))
```




```
#Try adding polynomial terms
age2 <- dd$agebt^2
hours_week2 <- dd$hours_week^2
model_poly <- lm(y_trans ~ agebt + age2 + edu_num + cap_gain + cap_loss + hours_week + hours_week2 , da

#comparing model performance
summary(model_poly)
```

```
##
## Call:
## lm(formula = y_trans ~ agebt + age2 + edu_num + cap_gain + cap_loss +
##     hours_week + hours_week2, data = dd)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.090e-05 -1.907e-07  5.084e-07  8.102e-07  8.100e-06
##
## Coefficients:
##               Estimate Std. Error  t value Pr(>|t|)
## (Intercept)  5.161e-05  2.063e-07  250.184   <2e-16 ***
## agebt       -5.548e-06  7.237e-08  -76.663   <2e-16 ***
## age2         3.172e-07  5.759e-09   55.070   <2e-16 ***
## edu_num     -5.729e-07  2.841e-09 -201.635   <2e-16 ***
## cap_gain    -5.647e-11  9.619e-13  -58.706   <2e-16 ***
## cap_loss    -2.568e-10  1.766e-11  -14.540   <2e-16 ***
## hours_week  -5.224e-08  1.946e-09  -26.843   <2e-16 ***
```

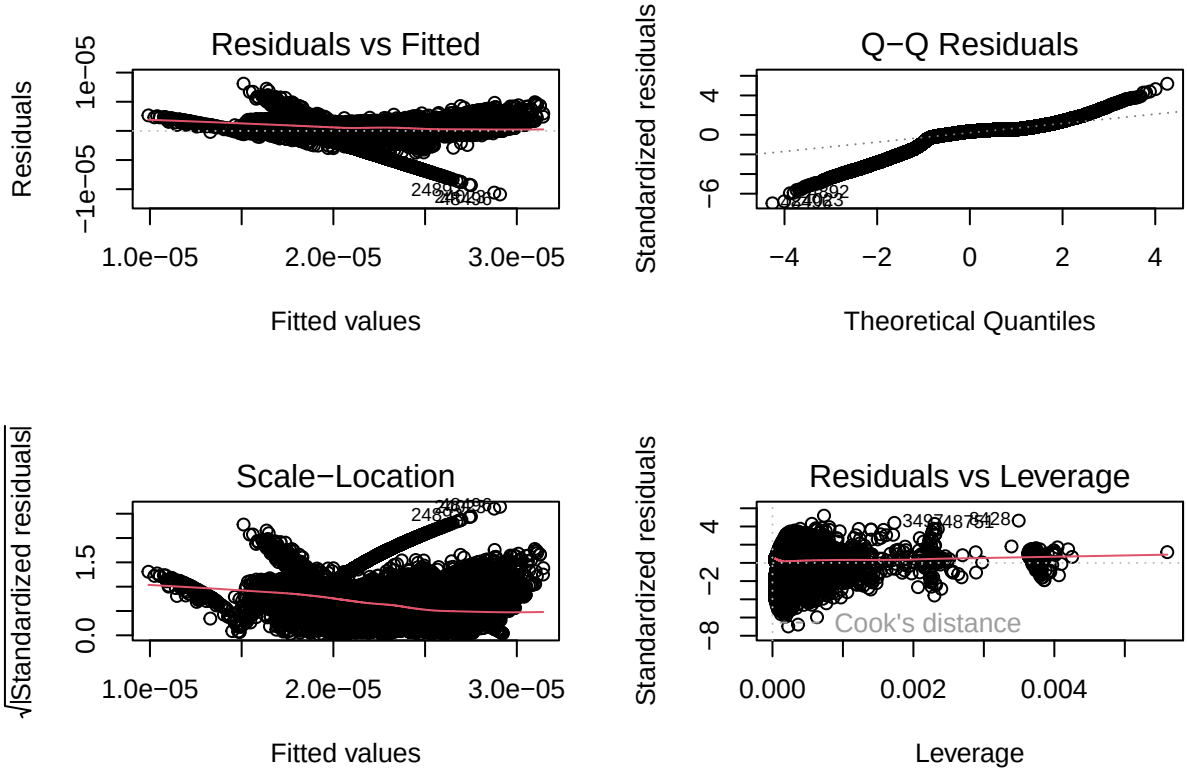
```
## hours_week2  2.073e-10  2.140e-11    9.687   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.562e-06 on 48834 degrees of freedom
## Multiple R-squared:  0.7456, Adjusted R-squared:  0.7456
## F-statistic: 2.045e+04 on 7 and 48834 DF,  p-value: < 2.2e-16
```

```
anova(initial_model, model_poly)
```

```
## Warning in anova.lmlist(object, ...): models with response '"y_trans"' removed
## because response differs from model 1

## Analysis of Variance Table
##
## Response: income_integer
##               Df     Sum Sq    Mean Sq  F value    Pr(>F)
## age            1 5.9443e+11 5.9443e+11 44080.01 < 2.2e-16 ***
## edu_num        1 5.3884e+11 5.3884e+11 39958.37 < 2.2e-16 ***
## cap_gain       1 1.1520e+11 1.1520e+11  8542.91 < 2.2e-16 ***
## cap_loss       1 6.5529e+09 6.5529e+09   485.93 < 2.2e-16 ***
## hours_week     1 7.1603e+10 7.1603e+10  5309.76 < 2.2e-16 ***
## Residuals  48836 6.5856e+11 1.3485e+07
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
par(mfrow=c(2,2))
plot(model_poly)
```




```
#Incorporating Factors
#Add Occupation
modelo_occ <- update(btmodel, . ~ . + occupation)
anova(btmodel, modelo_occ)  # p < 2.2e-16 ***
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  48836 1.2357e-07
## 2  48823 1.2040e-07 13 3.1647e-09 98.712 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add estado civil (7 categories)
modelo_marital <- update(modelo_occ, . ~ . + marital)
anova(modelo_occ, modelo_marital)  # p = < 2.2e-16
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
```

```
##     occupation + marital
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  48823 1.2040e-07
## 2  48819 1.0817e-07  4 1.2237e-08 1380.7 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add género (2 categories)
modelo_gender <- update(modelo_marital, . ~ . + sex)
anova(modelo_marital, modelo_gender)  # p = 0.009058 ***
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex
##   Res.Df        RSS Df  Sum of Sq      F   Pr(>F)
## 1  48819 1.0817e-07
## 2  48818 1.0815e-07  1 1.5091e-11 6.8119 0.009058 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add clase trabajadora (9 categories)
modelo_workclass <- update(modelo_gender, . ~ . + workclass)
anova(modelo_gender, modelo_workclass)  # p = < 2.2e-16
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass
##   Res.Df        RSS Df  Sum of Sq     F    Pr(>F)
## 1  48818 1.0815e-07
## 2  48812 1.0787e-07  6 2.8323e-10 21.36 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add relación familiar (6 categories)
modelo_relat <- update(modelo_workclass, . ~ . + relationship)
anova(modelo_workclass, modelo_relat)  # p = < 2.2e-16
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  48812 1.0787e-07
## 2  48807 1.0664e-07  5 1.2266e-09 112.28 < 2.2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add raza (5 categories)
modelo_race <- update(modelo_relat, . ~ . + race)
anova(modelo_relat, modelo_race)  # p = 0.0008009
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  48807 1.0664e-07
## 2  48803 1.0660e-07  4 4.1418e-11 4.7404 0.0008009 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add país origen (42 categorías)
modelo_country <- update(modelo_race, . ~ . + native_country)
anova(modelo_race, modelo_country)  # p = < 2.2e-16
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race +
##     native_country
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  48803 1.0660e-07
## 2  48802 1.0644e-07  1 1.5805e-10 72.462 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Add income (2 categorias)
modelo_income <- update(modelo_country,. ~ . + income)
anova(modelo_country,modelo_income)
```

```
## Analysis of Variance Table
##
## Model 1: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race +
##     native_country
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race +
##     native_country + income
##   Res.Df        RSS Df  Sum of Sq     F    Pr(>F)
## 1  48802 1.0644e-07
## 2  48801 4.9257e-08  1 5.7187e-08 56657 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
#Model with all significant variables including categorical variables
catmodel <- lm(y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week + occupation + marital +
stepmodel <- stepAIC(catmodel, direction = "back")
```

```
## Start:  AIC=-1349059
## y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race +
##     native_country + income
##
##                   Df  Sum of Sq        RSS      AIC
## <none>                          4.9257e-08 -1349059
## - sex              1 4.8000e-11 4.9305e-08 -1349013
## - cap_loss         1 8.4000e-11 4.9341e-08 -1348978
## - workclass        6 1.0700e-10 4.9364e-08 -1348965
## - race             4 1.0400e-10 4.9361e-08 -1348964
## - native_country   1 1.6400e-10 4.9420e-08 -1348899
## - marital          4 2.9400e-10 4.9551e-08 -1348777
## - relationship     5 9.7500e-10 5.0232e-08 -1348112
## - occupation      13 1.2400e-09 5.0497e-08 -1347871
## - cap_gain         1 1.9790e-09 5.1236e-08 -1347137
## - hours_week       1 4.8230e-09 5.4080e-08 -1344499
## - agebt            1 5.0523e-08 9.9780e-08 -1314583
## - edu_num_bt       1 5.1493e-08 1.0075e-07 -1314110
## - income           1 5.7187e-08 1.0644e-07 -1311425
```

```r
vif(catmodel)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## agebt            1.781237  1        1.334630
## edu_num_bt       1.429725  1        1.195711
## cap_gain         1.071123  1        1.034951
## cap_loss         1.030597  1        1.015183
## hours_week       1.221805  1        1.105353
## occupation       2.257130 13        1.031807
## marital         60.315146  4        1.669373
## sex              1.990125  1        1.410718
## workclass        1.441251  6        1.030928
## relationship    75.507075  5        1.540986
## race             1.283651  4        1.031706
## native_country   1.239624  1        1.113384
## income           1.549349  1        1.244728
```

```r
summary(catmodel)
```

```
##
## Call:
## lm(formula = y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss +
##     hours_week + occupation + marital + sex + workclass + relationship +
##     race + native_country + income, data = dd)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
```

```
## -8.257e-06 -5.550e-07 -8.660e-08  3.838e-07  7.935e-06
##
## Coefficients:
##                              Estimate Std. Error  t value Pr(>|t|)
## (Intercept)                 4.073e-05  9.922e-08  410.476  < 2e-16 ***
## agebt                      -1.240e-06  5.542e-09 -223.731  < 2e-16 ***
## edu_num_bt                 -2.816e-06  1.247e-08 -225.869  < 2e-16 ***
## cap_gain                   -2.796e-11  6.314e-13  -44.280  < 2e-16 ***
## cap_loss                    1.046e-10  1.145e-11    9.131  < 2e-16 ***
## hours_week                 -2.803e-08  4.055e-10  -69.124  < 2e-16 ***
## occupationArmy              2.978e-07  2.611e-07    1.141 0.254025
## occupationCraftRep         -7.949e-08  2.017e-08   -3.940 8.14e-05 ***
## occupationExecMan           2.275e-07  1.960e-08   11.607  < 2e-16 ***
## occupationFarmFish          1.664e-07  3.137e-08    5.304 1.14e-07 ***
## occupationHandlCl           2.901e-07  2.697e-08   10.756  < 2e-16 ***
## occupationHouse             3.830e-07  6.655e-08    5.755 8.70e-09 ***
## occupationMachOp            8.582e-08  2.361e-08    3.634 0.000279 ***
## occupationOther             2.784e-07  2.008e-08   13.860  < 2e-16 ***
## occupationProf              3.612e-07  1.776e-08   20.340  < 2e-16 ***
## occupationProtServ         -1.413e-07  3.627e-08   -3.897 9.77e-05 ***
## occupationSales             1.443e-07  1.977e-08    7.297 2.99e-13 ***
## occupationTech             -1.148e-07  2.987e-08   -3.843 0.000122 ***
## occupationTrans            -8.449e-08  2.598e-08   -3.253 0.001145 **
## maritalMarried             -1.581e-07  5.642e-08   -2.803 0.005072 **
## maritalNevMarr              2.225e-07  1.719e-08   12.945  < 2e-16 ***
## maritalSep                  8.720e-08  2.516e-08    3.466 0.000529 ***
## maritalWidow               -1.863e-07  2.954e-08   -6.307 2.87e-10 ***
## sexMale                     9.425e-08  1.362e-08    6.919 4.61e-12 ***
## workclassLoc               -3.535e-08  3.269e-08   -1.081 0.279562
## workclassNoPay              2.314e-07  1.828e-07    1.266 0.205479
## workclassPriv              -3.407e-08  2.776e-08   -1.227 0.219771
## workclassSelfI              2.224e-07  3.698e-08    6.015 1.81e-09 ***
## workclassSelfN              1.276e-09  3.221e-08    0.040 0.968406
## workclassState              2.610e-08  3.522e-08    0.741 0.458720
## relationshipNot-in-family  -2.334e-07  5.621e-08   -4.153 3.29e-05 ***
## relationshipOther-relative  1.129e-07  5.518e-08    2.046 0.040760 *
## relationshipOwn-child       2.358e-07  5.614e-08    4.200 2.67e-05 ***
## relationshipUnmarried      -9.660e-08  5.829e-08   -1.657 0.097445 .
## relationshipWife           -2.354e-07  2.564e-08   -9.182  < 2e-16 ***
## raceAsian-Pac-Islander     -2.456e-07  5.447e-08   -4.509 6.53e-06 ***
## raceBlack                  -7.987e-08  4.871e-08   -1.640 0.101042
## raceOther                   1.078e-07  6.862e-08    1.571 0.116123
## raceWhite                  -5.742e-10  4.674e-08   -0.012 0.990198
## native_countryUSA          -2.123e-07  1.668e-08  -12.728  < 2e-16 ***
## income>50K                 -3.157e-06  1.326e-08 -238.028  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.005e-06 on 48801 degrees of freedom
## Multiple R-squared:  0.8949, Adjusted R-squared:  0.8948
## F-statistic: 1.039e+04 on 40 and 48801 DF,  p-value: < 2.2e-16
```

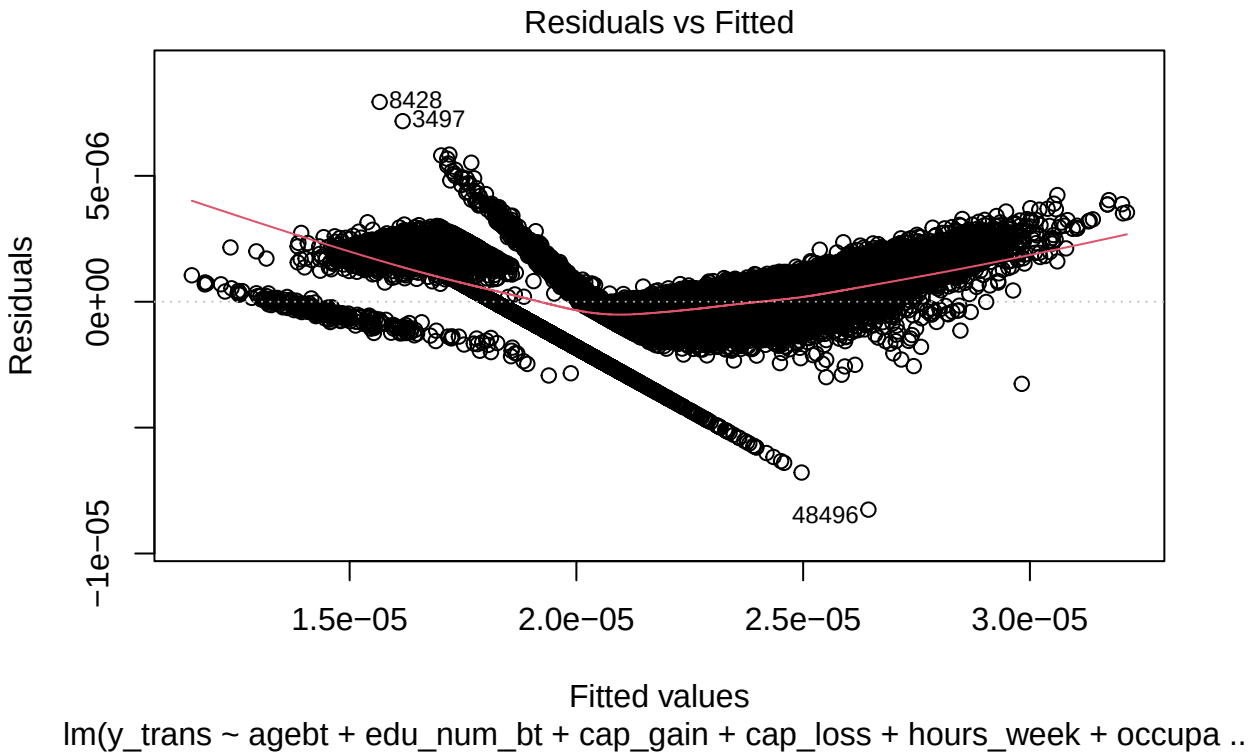
```
anova(catmodel)
```

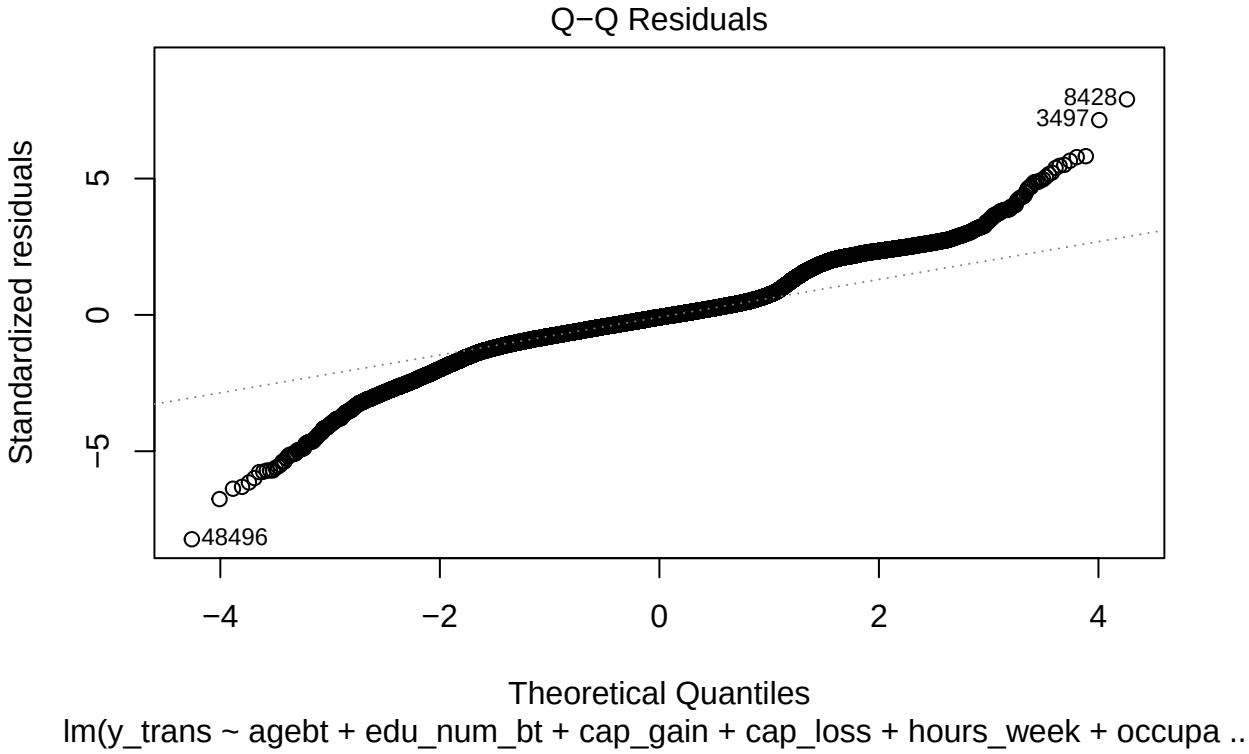
```
## Analysis of Variance Table
##
## Response: y_trans
##                   Df     Sum Sq    Mean Sq    F value    Pr(>F)
## agebt              1 1.7759e-07 1.7759e-07 175949.879 < 2.2e-16 ***
## edu_num_bt         1 1.4030e-07 1.4030e-07 138997.998 < 2.2e-16 ***
## cap_gain           1 9.8790e-09 9.8790e-09   9787.355 < 2.2e-16 ***
## cap_loss           1 8.6200e-10 8.6200e-10    853.794 < 2.2e-16 ***
## hours_week         1 1.6350e-08 1.6350e-08  16198.266 < 2.2e-16 ***
## occupation        13 3.1650e-09 2.4300e-10    241.185 < 2.2e-16 ***
## marital            4 1.2237e-08 3.0590e-09   3030.888 < 2.2e-16 ***
## sex                1 1.5000e-11 1.5000e-11     14.951 0.0001105 ***
## workclass          6 2.8300e-10 4.7000e-11     46.767 < 2.2e-16 ***
## relationship       5 1.2270e-09 2.4500e-10    243.055 < 2.2e-16 ***
## race               4 4.1000e-11 1.0000e-11     10.259 2.664e-08 ***
## native_country     1 1.5800e-10 1.5800e-10    156.585 < 2.2e-16 ***
## income             1 5.7187e-08 5.7187e-08  56657.237 < 2.2e-16 ***
## Residuals      48801 4.9257e-08 1.0000e-12
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

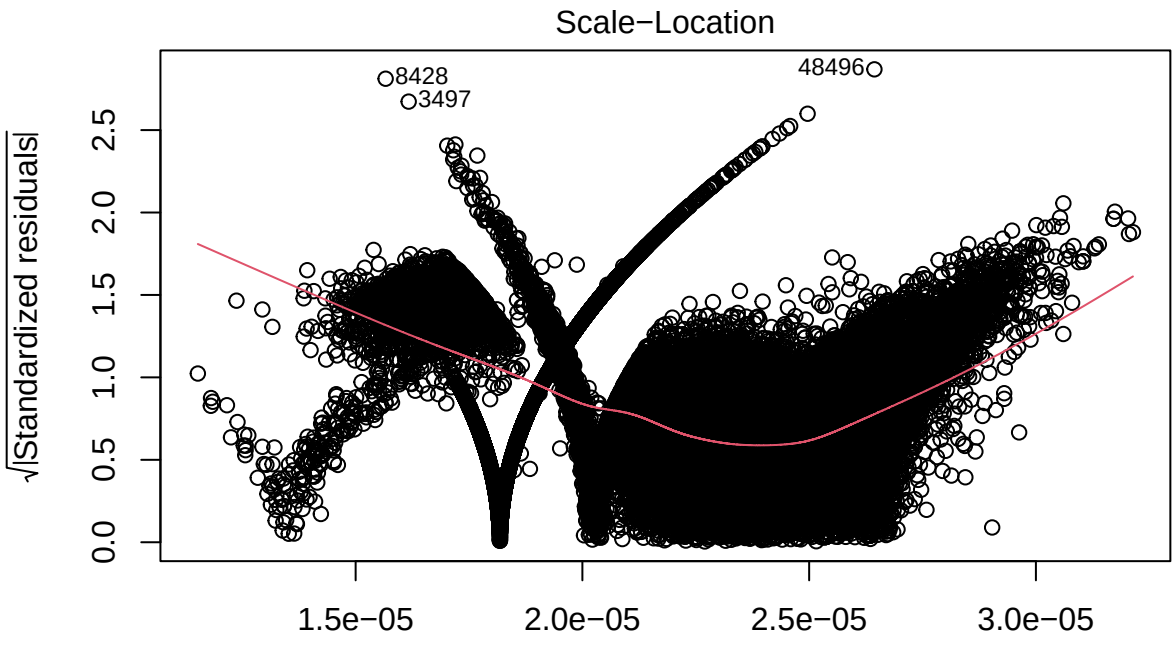
```
anova(transformed_model, catmodel)
```

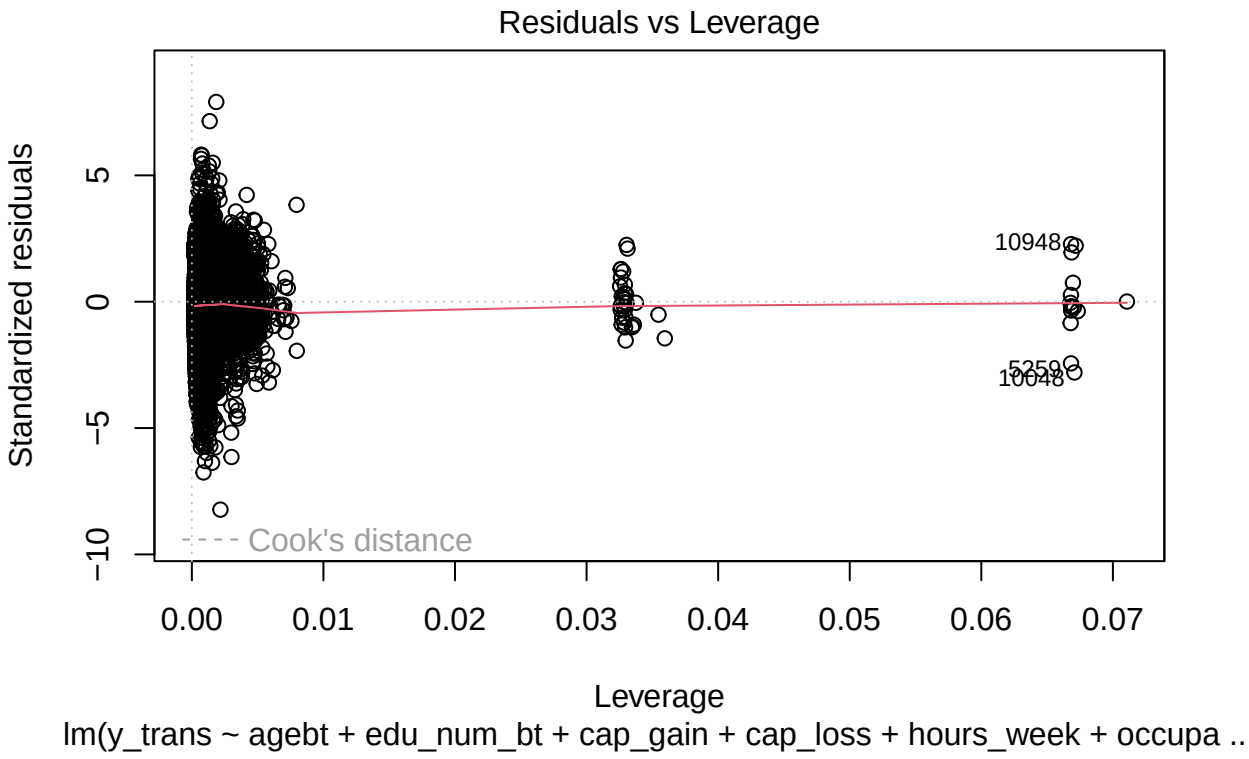
```
## Analysis of Variance Table
##
## Model 1: y_trans ~ age + edu_num + cap_gain + cap_loss + hours_week
## Model 2: y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week +
##     occupation + marital + sex + workclass + relationship + race +
##     native_country + income
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  48836 1.3544e-07
## 2  48801 4.9257e-08 35 8.6187e-08 2439.7 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(catmodel)
```

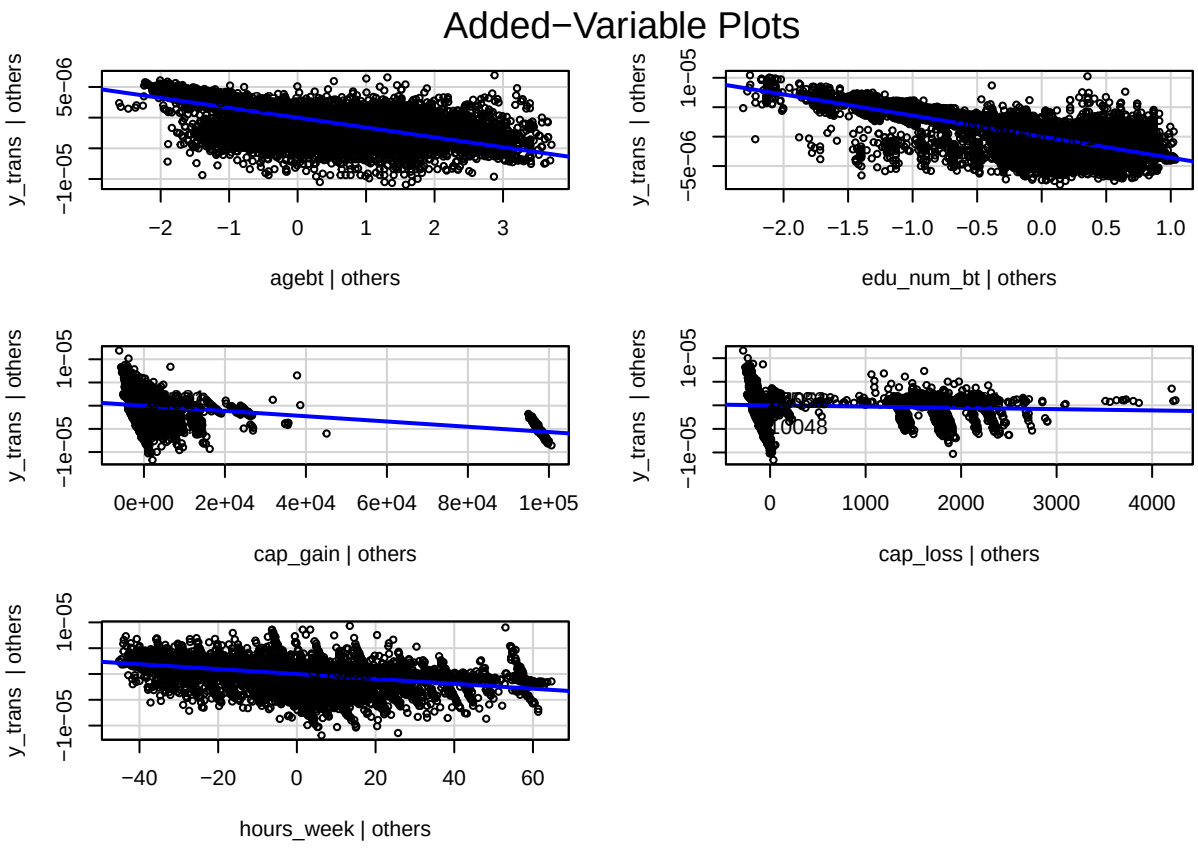

Residuals vs Fitted
8428
3497
48496
Residuals
5e−06
0e+00
−1e−05
1.5e−05
2.0e−05
2.5e−05
3.0e−05
Fitted values
lm(y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week + occupa ..


Q−Q Residuals
Standardized residuals
5
0
−5
8428
3497
48496
−4
−2
0
2
4
Theoretical Quantiles
lm(y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week + occupa ..

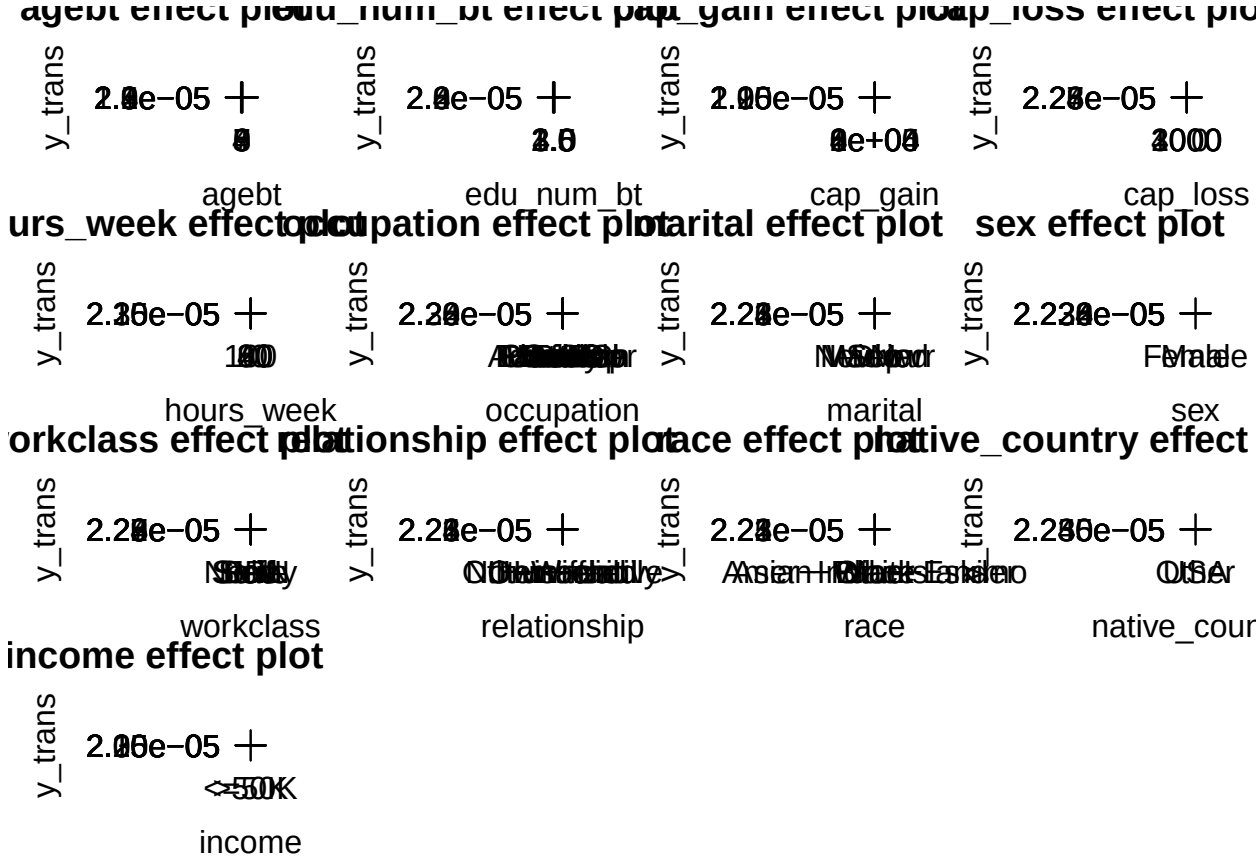

Scale−Location
8428
3497
48496
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
1.5e−05
2.0e−05
2.5e−05
3.0e−05
Fitted values
lm(y_trans ~ agebt + edu_num_bt + cap_gain + cap_loss + hours_week + occupa ..




```
#Possible Conclusio
avPlots(btmodel,id=list(method=hatvalues(catmodel),n=5))
```




```
plot(allEffects(catmodel))
```




```
#using this line will transform our income variable into a binary response variable we can use for our
dd$income_bin <- ifelse(dd$income == ">50K", 1, 0)
#transforming variable into factor
dd$income_bin <- as.factor(dd$income_bin)
```

Build the Initial Logistic Regression Model

```
## Build the Initial Logistic Regression Model
initial_model_b <- glm(income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week, data = dd, family
```

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

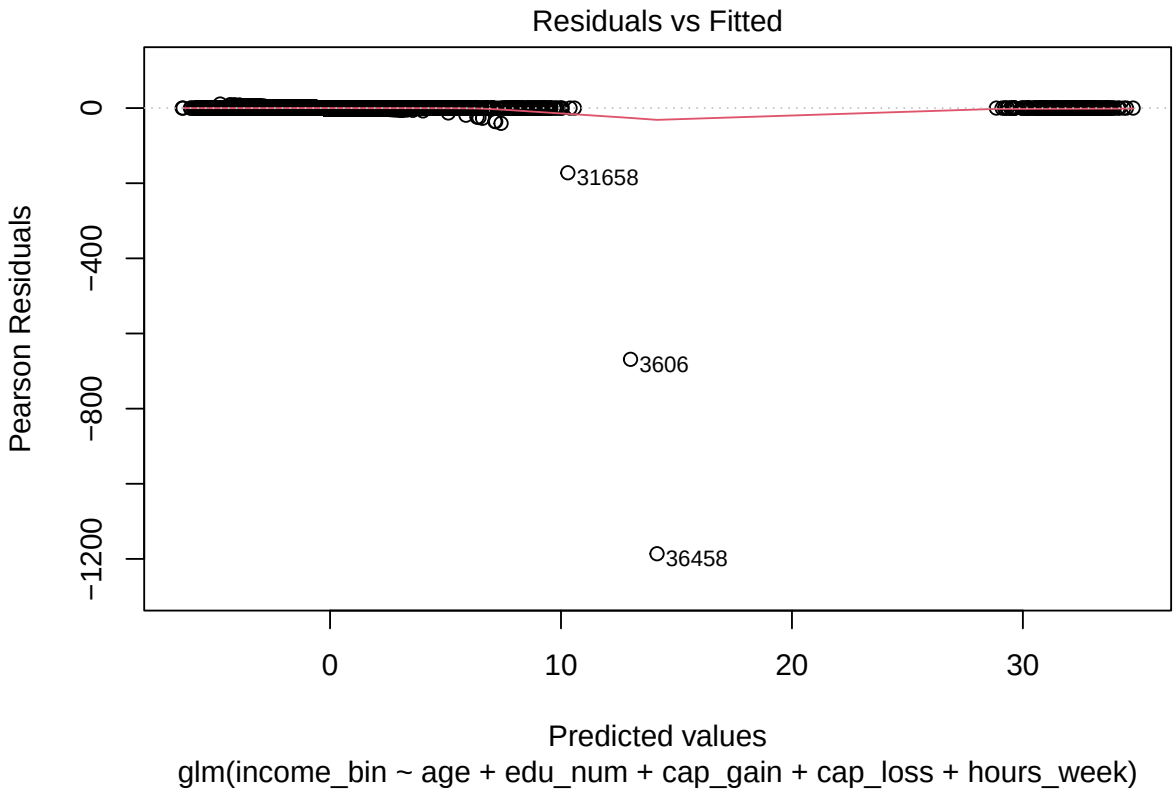
```
summary(initial_model_b)
```

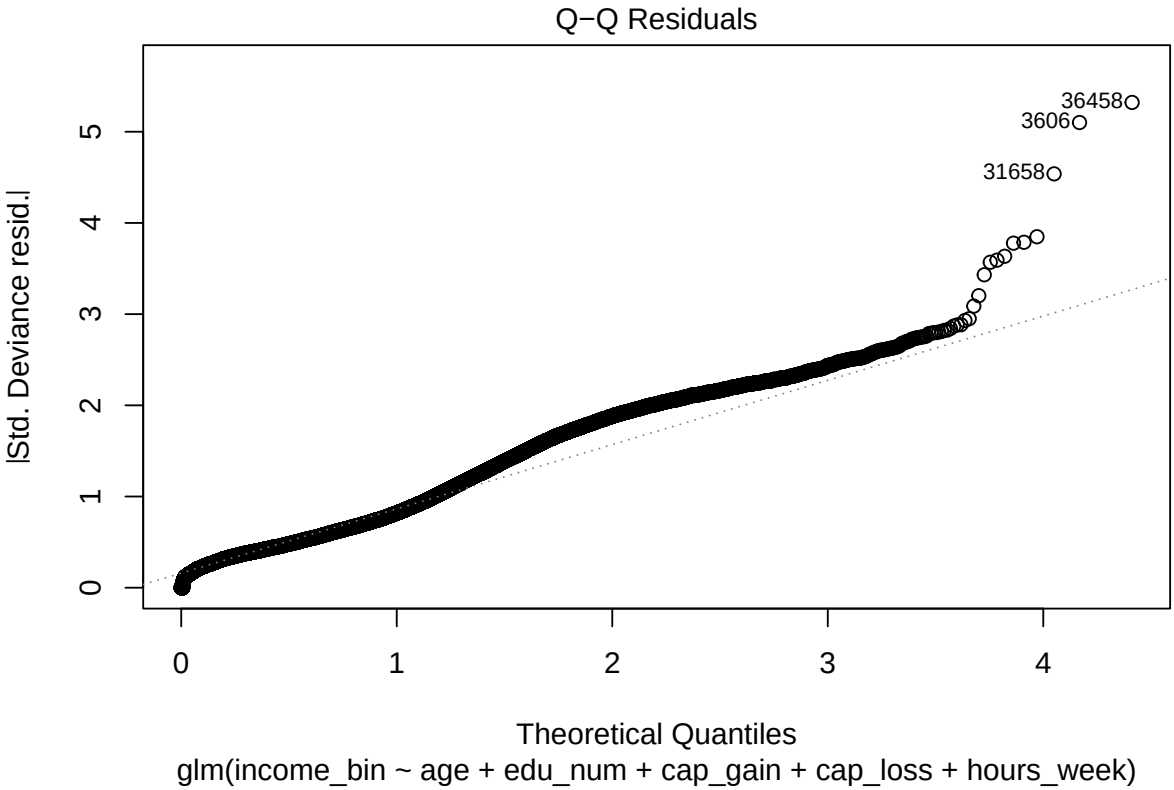
```
##
## Call:
## glm(formula = income_bin ~ age + edu_num + cap_gain + cap_loss +
##     hours_week, family = binomial, data = dd)
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -8.260e+00  9.371e-02  -88.14   <2e-16 ***
```

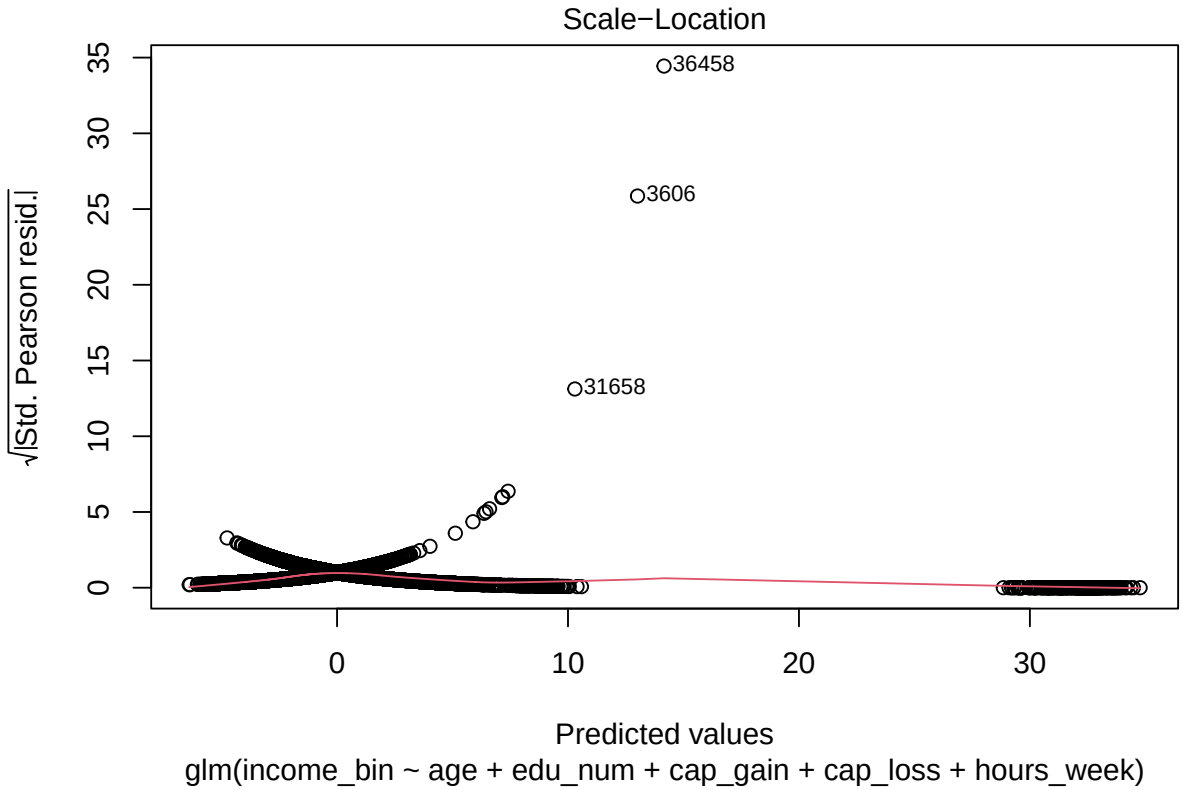
```
## age          4.220e-02  9.915e-04   42.57   <2e-16 ***
## edu_num      3.223e-01  5.556e-03   58.01   <2e-16 ***
## cap_gain     3.205e-04  7.985e-06   40.14   <2e-16 ***
## cap_loss     6.799e-04  2.634e-05   25.81   <2e-16 ***
## hours_week   4.012e-02  1.070e-03   37.51   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 53751  on 48841  degrees of freedom
## Residual deviance: 39775  on 48836  degrees of freedom
## AIC: 39787
##
## Number of Fisher Scoring iterations: 7
```

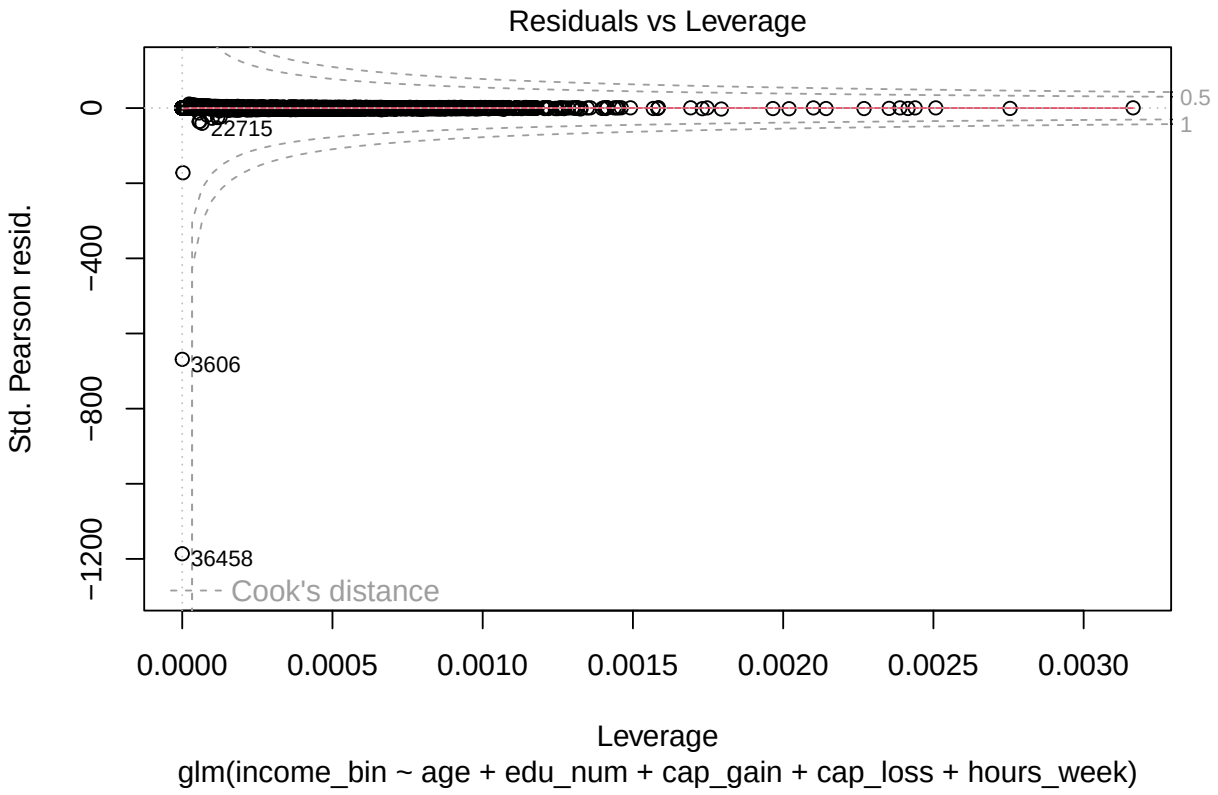
Check Model Diagnostics

```
## Check Model Diagnostics
plot(initial_model_b) #the basic hypothesis are met, beware of Homoscedasticity
```

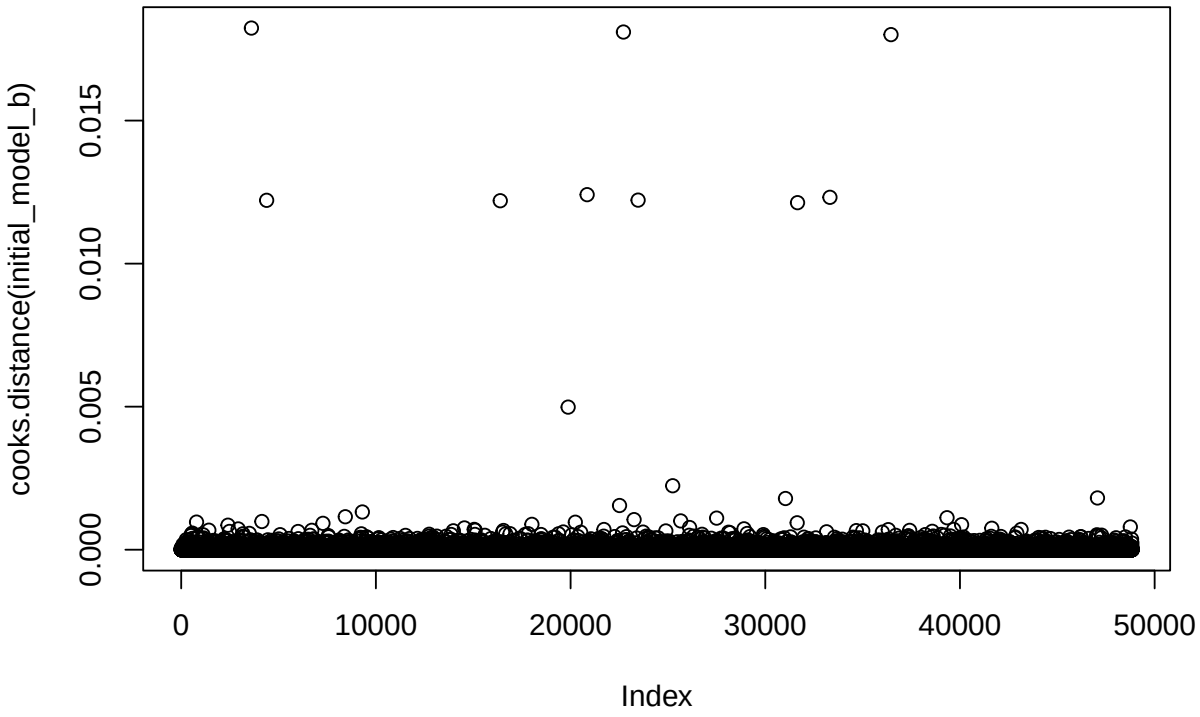



Q−Q Residuals
|Std. Deviance resid.|
0
1
2
3
4
5
36458
3606
31658
0
1
2
3
4
Theoretical Quantiles
glm(income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week)


Scale−Location
√|Std. Pearson resid.|
0
5
10
15
20
25
30
35
36458
3606
31658
0
10
20
30
Predicted values
glm(income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week)




```
#Check cook's distance
plot(cooks.distance(initial_model_b)) #there are some influential observations that skew the data a lit
```



Add Categorical Variables Step by Step

```
##Add_workclass_and_test_with_Chi_squared
model_workclass <- update(initial_model_b, . ~ . + workclass)
```

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

```
anova(initial_model_b, model_workclass, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48836      39775
## 2     48830      39546  6   229.93 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
##Add_marital_and_test_with_Chi_squared
model_marital <- update(model_workclass, . ~ . + marital)
```

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

```r
anova(model_workclass, model_marital, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48830      39546
## 2     48826      32504  4   7041.9 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
##Add_occupation_and_test_with_Chi_squared
model_occupation <- update(model_marital, . ~ . + occupation)
```

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

```r
anova(model_marital, model_occupation, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48826      32504
## 2     48813      31676 13   827.94 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
##Add_relationship_and_test_with_Chi_squared
model_relationship <- update(model_occupation, . ~ . + relationship)
```

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

```r
anova(model_occupation, model_relationship, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation
```

```
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48813      31676
## 2     48808      31438  5    237.8 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##Add_race_and_test_with_Chi_squared
model_race <- update(model_relationship, . ~ . + race)
```

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

```
anova(model_relationship, model_race, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48808      31438
## 2     48804      31409  4   29.342 6.661e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##Add_sex_and_test_with_Chi_squared
model_sex <- update(model_race, . ~ . + sex)
```

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

```
anova(model_race, model_sex, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race +
##     sex
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48804      31409
## 2     48803      31286  1   122.48 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##Add_native_country_and_test_with_Chi_squared
model_country <- update(model_sex, . ~ . + native_country)
```

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

```r
anova(model_sex, model_country, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race +
##     sex
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race +
##     sex + native_country
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1     48803      31286
## 2     48802      31275  1       11 0.000911 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Define the Final Model

```r
## Define the Final Model
final_model <- model_country
```

Perform Stepwise Selection and Final Diagnostics

```r
## Perform Stepwise Selection and Final Diagnostics
stepmodel <- stepAIC(final_model, direction = "back")
```

```
## Start:  AIC=31355.09
## income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race +
##     sex + native_country
```

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

```
##                  Df Deviance   AIC
## <none>                 31275 31355
## - native_country  1    31286 31364
## - race            4    31301 31373
## - sex             1    31399 31477
```

```
## - workclass       6    31447 31515
## - marital         4    31447 31519
## - age             1    31584 31662
## - relationship    5    31628 31698
## - cap_loss        1    31749 31827
## - hours_week      1    31875 31953
## - occupation     13    32064 32118
## - edu_num         1    33242 33320
## - cap_gain        1    34086 34164
```

```
vif(final_model)
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## age              1.223938  1        1.106317
## edu_num          1.393982  1        1.180670
## cap_gain         1.024071  1        1.011964
## cap_loss         1.010195  1        1.005085
## hours_week       1.144362  1        1.069748
## workclass        1.492505  6        1.033934
## marital         47.015300  4        1.618191
## occupation       2.171232 13        1.030268
## relationship   109.766183  5        1.599731
## race             1.308231  4        1.034155
## sex              2.942333  1        1.715323
## native_country   1.257900  1        1.121561
```

```
summary(final_model)
```

```
##
## Call:
## glm(formula = income_bin ~ age + edu_num + cap_gain + cap_loss +
##     hours_week + workclass + marital + occupation + relationship +
##     race + sex + native_country, family = binomial, data = dd)
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -9.271e+00  3.257e-01 -28.470  < 2e-16 ***
## age                         2.269e-02  1.295e-03  17.524  < 2e-16 ***
## edu_num                     3.011e-01  7.273e-03  41.395  < 2e-16 ***
## cap_gain                    3.160e-04  8.376e-06  37.733  < 2e-16 ***
## cap_loss                    6.460e-04  3.002e-05  21.519  < 2e-16 ***
## hours_week                  3.097e-02  1.284e-03  24.123  < 2e-16 ***
## workclassLoc               -5.873e-01  9.078e-02  -6.470 9.82e-11 ***
## workclassNoPay             -1.502e+00  7.861e-01  -1.910 0.056107 .
## workclassPriv              -5.640e-01  7.574e-02  -7.447 9.54e-14 ***
## workclassSelfI             -3.603e-01  9.942e-02  -3.624 0.000290 ***
## workclassSelfN             -1.023e+00  8.867e-02 -11.533  < 2e-16 ***
## workclassState             -7.653e-01  1.000e-01  -7.651 1.99e-14 ***
## maritalMarried              2.315e+00  2.141e-01  10.815  < 2e-16 ***
## maritalNevMarr             -4.267e-01  7.114e-02  -5.999 1.99e-09 ***
## maritalSep                  4.041e-03  1.110e-01   0.036 0.970972
## maritalWidow                3.927e-02  1.247e-01   0.315 0.752873
## occupationArmy              5.115e-01  7.782e-01   0.657 0.511025
```

```
## occupationCraftRep          8.389e-02  6.457e-02   1.299 0.193863
## occupationExecMan           7.371e-01  6.208e-02  11.874  < 2e-16 ***
## occupationFarmFish         -1.017e+00  1.151e-01  -8.837  < 2e-16 ***
## occupationHandlCl          -6.502e-01  1.136e-01  -5.723 1.05e-08 ***
## occupationHouse            -1.971e+00  7.554e-01  -2.609 0.009069 **
## occupationMachOp           -2.642e-01  8.235e-02  -3.209 0.001334 **
## occupationOther            -8.687e-01  9.597e-02  -9.052  < 2e-16 ***
## occupationProf              2.699e-01  6.088e-02   4.434 9.24e-06 ***
## occupationProtServ          4.240e-01  1.024e-01   4.139 3.48e-05 ***
## occupationSales             2.462e-01  6.667e-02   3.693 0.000222 ***
## occupationTech              5.327e-01  8.921e-02   5.971 2.36e-09 ***
## occupationTrans            -7.686e-02  8.015e-02  -0.959 0.337532
## relationshipNot-in-family   5.761e-01  2.119e-01   2.719 0.006541 **
## relationshipOther-relative -5.304e-01  1.971e-01  -2.690 0.007136 **
## relationshipOwn-child      -5.928e-01  2.082e-01  -2.848 0.004406 **
## relationshipUnmarried       3.814e-01  2.256e-01   1.691 0.090884 .
## relationshipWife            1.095e+00  8.212e-02  13.335  < 2e-16 ***
## raceAsian-Pac-Islander      5.924e-01  1.983e-01   2.987 0.002813 **
## raceBlack                   3.481e-01  1.857e-01   1.875 0.060856 .
## raceOther                   3.738e-01  2.651e-01   1.410 0.158508
## raceWhite                   5.736e-01  1.770e-01   3.240 0.001194 **
## sexMale                     6.955e-01  6.335e-02  10.980  < 2e-16 ***
## native_countryUSA           1.872e-01  5.682e-02   3.295 0.000984 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 53751  on 48841  degrees of freedom
## Residual deviance: 31275  on 48802  degrees of freedom
## AIC: 31355
##
## Number of Fisher Scoring iterations: 7
```

```
anova(final_model, test="LR")
```

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

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: income_bin
##
## Terms added sequentially (first to last)
```

```
##
##
##                Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
## NULL                            48841      53751
## age             1   2537.0     48840      51214 < 2.2e-16 ***
## edu_num         1   5891.7     48839      45322 < 2.2e-16 ***
## cap_gain        1   3291.4     48838      42031 < 2.2e-16 ***
## cap_loss        1    753.5     48837      41277 < 2.2e-16 ***
## hours_week      1   1501.8     48836      39775 < 2.2e-16 ***
## workclass       6    229.9     48830      39546 < 2.2e-16 ***
## marital         4   7041.9     48826      32504 < 2.2e-16 ***
## occupation     13    827.9     48813      31676 < 2.2e-16 ***
## relationship    5    237.8     48808      31438 < 2.2e-16 ***
## race            4     29.3     48804      31409 6.661e-06 ***
## sex             1    122.5     48803      31286 < 2.2e-16 ***
## native_country  1     11.0     48802      31275  0.000911 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

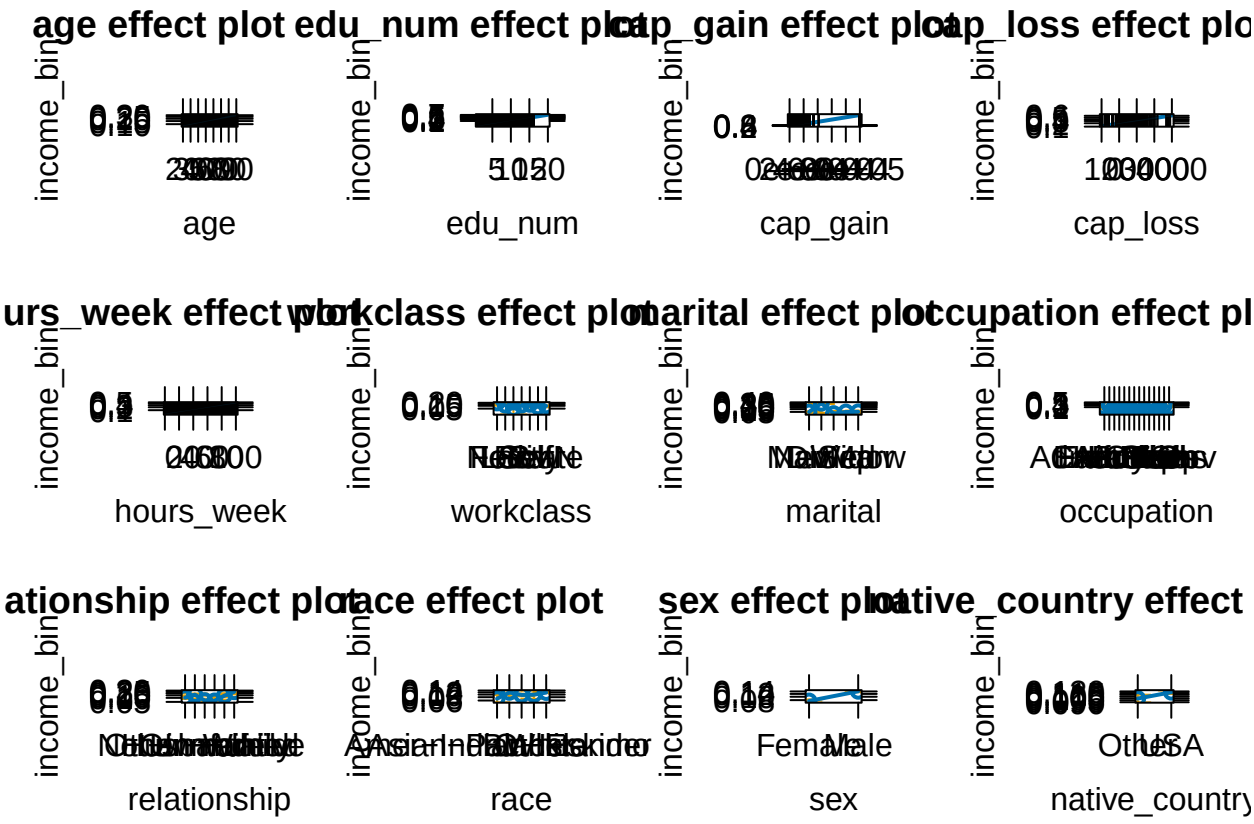
```
anova(initial_model_b, final_model)
```

```
## Analysis of Deviance Table
##
## Model 1: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week
## Model 2: income_bin ~ age + edu_num + cap_gain + cap_loss + hours_week +
##     workclass + marital + occupation + relationship + race +
##     sex + native_country
##   Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
## 1     48836      39775
## 2     48802      31275 34   8500.4 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
AIC(initial_model_b, final_model)
```

```
##                 df      AIC
## initial_model_b  6 39787.46
## final_model     40 31355.09
```

```
plot(allEffects(final_model))
```


age effect plot
edu_num effect plot
cap_gain effect plot
cap_loss effect plo
urs_week effect plot
workclass effect plot
marital effect plot
occupation effect pl
ationship effect plot
race effect plot
sex effect plot
native_country effect
income_bin
age
edu_num
cap_gain
cap_loss
hours_week
workclass
marital
occupation
relationship
race
sex
native_country
Female
Male
Other
USA