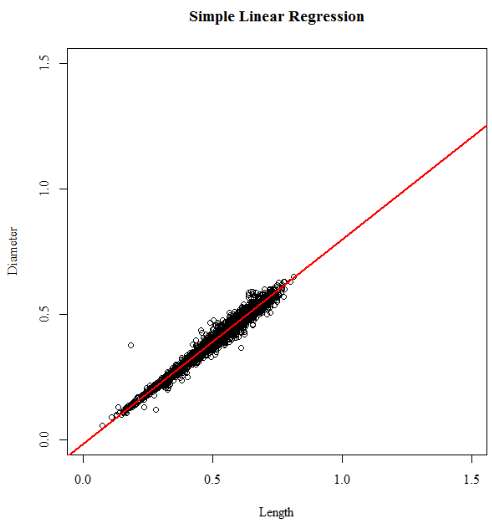
# CODE FOR CS910 EXERCISE 3

**Q1.**

```
> abalone<-read.csv("abalone.data", header = FALSE,
col.names=c("Sex","Length","Diameter","Height","Whole.weight","Shucked.weight","Visce
ra.weight","Shell.weight","Rings"))
attach(abalone)
> plot(Length,Diameter,xlim=c(0,1.5),ylim = c(0,1.5),main="Simple Linear
Regression",family="serif")
> fit.simple.linear<-lm(Diameter~Length)
> abline(fit.simple.linear,col="red",lwd=2)
> summary(fit.simple.linear)
```




```
Call:
lm(formula = Diameter ~ Length)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.113017 -0.008703 -0.000549  0.008678  0.243553 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.019414   0.001113  -17.44   <2e-16 ***
Length       0.815461   0.002070  393.90   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01607 on 4175 degrees of freedom
Multiple R-squared:  0.9738,	Adjusted R-squared:  0.9738 
F-statistic: 1.552e+05 on 1 and 4175 DF,  p-value: < 2.2e-16
```

**Q2.**

```
> fit.multilinear<-lm(Whole.weight~Shucked.weight+Viscera.weight+Shell.weight)
> summary(fit.multilinear)

Call:
lm(formula = Whole.weight ~ Shucked.weight + Viscera.weight + 
    Shell.weight)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.54690 -0.01708 -0.00195  0.00903  0.51721 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    -0.007830   0.001452  -5.393 7.32e-08 ***
Shucked.weight  0.936560   0.009294 100.770  < 2e-16 ***
Viscera.weight  1.111650   0.021079  52.737  < 2e-16 ***
Shell.weight    1.252962   0.012802  97.876  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0469 on 4173 degrees of freedom
Multiple R-squared:  0.9909,	Adjusted R-squared:  0.9909 
F-statistic: 1.508e+05 on 3 and 4173 DF,  p-value: < 2.2e-16
```

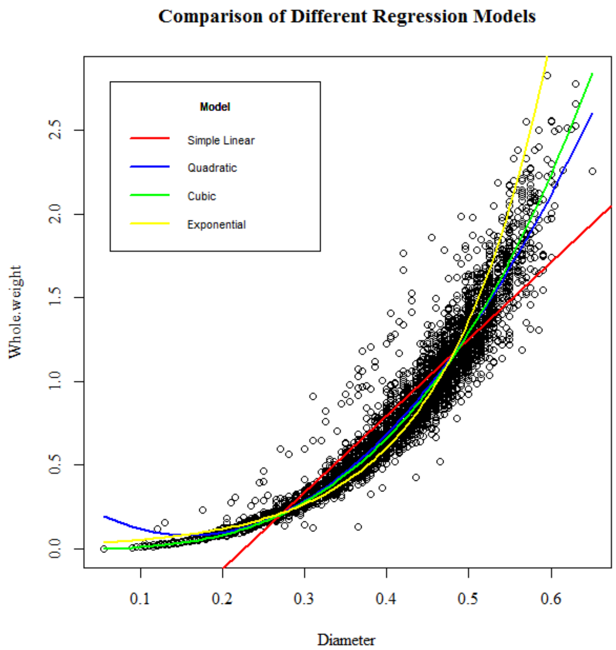
**Q3.**

```
> fit.a<-lm(Whole.weight~Diameter)
> fit.b<-lm(Whole.weight~Diameter+I(Diameter^2))
> fit.c<-lm(Whole.weight~I(Diameter^3)-1)
> fit.d<-lm(log(Whole.weight)~Diameter)
> summary(fit.a)

Call:
```

```
lm(formula = Whole.weight ~ Diameter)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.56745 -0.12307 -0.03997  0.07213  1.14105 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.03653    0.01216  -85.22   <2e-16 ***
Diameter     4.57308    0.02897  157.83   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1858 on 4175 degrees of freedom
Multiple R-squared:  0.8565,	Adjusted R-squared:  0.8564 
F-statistic: 2.491e+04 on 1 and 4175 DF,  p-value: < 2.2e-16

> summary(fit.b)

Call:
lm(formula = Whole.weight ~ Diameter + I(Diameter^2))

Residuals:
     Min       1Q   Median       3Q      Max 
-0.66801 -0.06579 -0.00611  0.04589  0.97396 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)    0.34772    0.02353   14.78   <2e-16 ***
Diameter      -3.35552    0.12696  -26.43   <2e-16 ***
I(Diameter^2) 10.49681    0.16583   63.30   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1327 on 4174 degrees of freedom
Multiple R-squared:  0.9268,	Adjusted R-squared:  0.9267 
F-statistic: 2.641e+04 on 2 and 4174 DF,  p-value: < 2.2e-16

> summary(fit.c)

Call:
lm(formula = Whole.weight ~ I(Diameter^3) - 1)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.76061 -0.04998  0.00575  0.05708  0.99811 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
I(Diameter^3) 10.33761    0.02233   462.9   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1332 on 4176 degrees of freedom
Multiple R-squared:  0.9809,	Adjusted R-squared:  0.9809 
F-statistic: 2.143e+05 on 1 and 4176 DF,  p-value: < 2.2e-16

> summary(fit.d)

Call:
lm(formula = log(Whole.weight) ~ Diameter)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.91005 -0.09511  0.01132  0.12019  1.14050 
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.75098    0.01465  -256.1   <2e-16 ***
Diameter     8.11667    0.03490   232.6   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2238 on 4175 degrees of freedom
Multiple R-squared:  0.9284,	Adjusted R-squared:  0.9283
F-statistic: 5.41e+04 on 1 and 4175 DF,  p-value: < 2.2e-16
```

```
> plot(Diameter,Whole.weight,main="Comparison of Different Regression Models",family="serif")
> abline(fit.a,col="red",lwd=2)
> lines(Diameter[order(Diameter)],fitted(fit.b)[order(Diameter)],col="blue",lwd=2)
> lines(Diameter[order(Diameter)],fitted(fit.c)[order(Diameter)],col="green",lwd=2)
> lines(Diameter[order(Diameter)],exp(fitted(fit.d))[order(Diameter)],col="yellow",lwd=2)
> legend("topleft",title="Model",legend = c("Simple Linear","Quadratic","Cubic","Exponential"),lwd=c(2,2,2,2),col=c("red","blue","green","yellow"),cex=c(0.7,0.7,0.7,0.7),inset=0.05)
```




**Q4.**

```
> abalone$Age.class[abalone$Sex == "I"] <-0
> abalone$Age.class[abalone$Sex == "F"] <-1
> abalone$Age.class[abalone$Sex == "M"] <-1
> abalone$Age.class<-factor(abalone$Age.class,levels=c(0,1),labels=c("Infant","Adult"))
> attach(abalone)

> fit.length<-glm(Age.class~Length,family = binomial(link="logit"))
> fit.whole.weight<-glm(Age.class~Whole.weight,family = binomial(link="logit"))
> fit.rings<-glm(Age.class~Rings,family = binomial(link="logit"))
> fit.full<-glm(Age.class~Length+Whole.weight+Rings,family = binomial(link="logit"))

> summary(fit.length)

Call:
glm(formula = Age.class ~ Length, family = binomial(link = "logit"))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
```

```
-2.6677  -0.7024   0.4312   0.6697   2.7205

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -5.6347     0.2139  -26.35   <2e-16 ***
Length      12.6402     0.4237   29.83   <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: 5244.9  on 4176  degrees of freedom
Residual deviance: 3849.9  on 4175  degrees of freedom
AIC: 3853.9

Number of Fisher Scoring iterations: 5

> summary(fit.whole.weight)

Call:
glm(formula = Age.class ~ Whole.weight, family = binomial(link = "logit"))

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-3.5916  -0.6897   0.2814   0.6350   2.0780  

Coefficients:
             Estimate Std. Error z value Pr(>|z|)    
(Intercept)  -2.10113    0.09061  -23.19   <2e-16 ***
whole.weight  4.17141    0.13588   30.70   <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: 5244.9  on 4176  degrees of freedom
Residual deviance: 3534.7  on 4175  degrees of freedom
AIC: 3538.7

Number of Fisher Scoring iterations: 5

> summary(fit.rings)

Call:
glm(formula = Age.class ~ Rings, family = binomial(link = "logit"))

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-3.6764  -0.8390   0.4618   0.7357   2.2249  

Coefficients:
            Estimate Std. Error z value Pr(>|z|)    
(Intercept) -3.91107    0.17631  -22.18   <2e-16 ***
Rings        0.50799    0.01973   25.75   <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: 5244.9  on 4176  degrees of freedom
Residual deviance: 4158.3  on 4175  degrees of freedom
AIC: 4162.3

Number of Fisher Scoring iterations: 5

> summary(fit.full)
```

```
Call:
glm(formula = Age.class ~ Length + Whole.weight + Rings, family = binomial(link =
"logit"))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.8606  -0.6879   0.2077   0.6172   2.0568

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.27940    0.36156  -0.773     0.44
Length       -10.95785    1.21393  -9.027   <2e-16 ***
Whole.weight   6.56365    0.39869  16.463   <2e-16 ***
Rings          0.22230    0.02157  10.306   <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: 5244.9  on 4176  degrees of freedom
Residual deviance: 3355.9  on 4173  degrees of freedom
AIC: 3363.9

Number of Fisher Scoring iterations: 6



> table(ifelse(predict(fit.length,type="response")>0.5,1,0),abalone$Age.class)

    Infant Adult
  0    722   285
  1    620  2550

> table(ifelse(predict(fit.whole.weight,type="response")>0.5,1,0),abalone$Age.class)

    Infant Adult
  0    868   379
  1    474  2456
> table(ifelse(predict(fit.rings,type="response")>0.5,1,0),abalone$Age.class)

    Infant Adult
  0    648   191
  1    694  2644
> table(ifelse(predict(fit.full,type="response")>0.5,1,0),abalone$Age.class)

    Infant Adult
  0    978   376
  1    364  2459
```

**Q5.**

```
> adult<-read.csv("adult.data",header = F,col.names =
c("age","workclass","fnlwgt","education","education-num","marital-
status","occupation","relationship","race","sex","capital-gain","capital-
loss","hours-per-week","native-country","class"))
> fit.full<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+race+ca
pital.gain+capital.loss+hours.per.week+native.country+class,data=adult, family =
binomial())
> summary(fit.full)

Call:
glm(formula = sex ~ age + workclass + fnlwgt + education + marital.status +
```

```
    occupation + relationship + race + capital.gain + capital.loss +
    hours.per.week + native.country + class, family = binomial(),
    data = adult)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.1635  -0.4325   0.0079   0.3321   3.6235

Coefficients: (1 not defined because of singularities)
                                     Estimate Std. Error z value Pr(>|z|)
(Intercept)                          8.501e+00  1.055e+00   8.061 7.55e-16 ***
age                                 -1.585e-03  1.913e-03  -0.829 0.407329
workclass Federal-gov                2.720e+00  1.838e-01  14.799  < 2e-16 ***
workclass Local-gov                  2.112e+00  1.658e-01  12.743  < 2e-16 ***
workclass Never-worked               1.670e+00  1.106e+00   1.509 0.131184
workclass Private                    2.355e+00  1.475e-01  15.961  < 2e-16 ***
workclass Self-emp-inc               3.373e+00  2.112e-01  15.975  < 2e-16 ***
workclass Self-emp-not-inc           3.082e+00  1.725e-01  17.870  < 2e-16 ***
workclass State-gov                  2.550e+00  1.714e-01  14.881  < 2e-16 ***
workclass Without-pay                1.913e+00  9.668e-01   1.979 0.047860 *
fnlwgt                               1.186e-06  1.707e-07   6.949 3.67e-12 ***
education 11th                      -1.448e-01  1.284e-01  -1.128 0.259402
education 12th                       1.654e-01  1.653e-01   1.001 0.317012
education 1st-4th                    1.886e-01  2.995e-01   0.630 0.528944
education 5th-6th                   -8.987e-02  2.393e-01  -0.376 0.707265
education 7th-8th                    3.255e-02  1.784e-01   0.182 0.855253
education 9th                        1.784e-01  1.763e-01   1.012 0.311611
education Assoc-acdm                -1.416e-01  1.393e-01  -1.017 0.309332
education Assoc-voc                 -3.594e-01  1.370e-01  -2.623 0.008724 **
education Bachelors                  2.213e-02  1.133e-01   0.195 0.845181
education Doctorate                 -3.589e-01  2.323e-01  -1.545 0.122257
education HS-grad                   -1.752e-01  1.042e-01  -1.681 0.092672 .
education Masters                   -2.342e-01  1.390e-01  -1.685 0.091917 .
education Preschool                  2.722e-01  4.325e-01   0.629 0.529071
education Prof-school                2.295e-01  2.119e-01   1.083 0.278699
education Some-college              -1.994e-01  1.054e-01  -1.893 0.058378 .
marital.status Married-AF-spouse    -3.556e+00  5.277e+00  -0.674 0.500393
marital.status Married-civ-spouse    9.666e-02  1.679e-01   0.576 0.564724
marital.status Married-spouse-absent 2.890e-01  1.291e-01   2.238 0.025194 *
marital.status Never-married         5.414e-01  5.302e-02  10.211  < 2e-16 ***
marital.status Separated             4.773e-02  8.702e-02   0.549 0.583344
marital.status Widowed              -1.060e+00  1.088e-01  -9.743  < 2e-16 ***
occupation Adm-clerical             -3.357e+00  1.418e-01 -23.682  < 2e-16 ***
occupation Armed-Forces              1.028e+01  1.608e+02   0.064 0.949002
occupation Craft-repair             -1.380e-01  1.546e-01  -0.892 0.372243
occupation Exec-managerial          -2.613e+00  1.455e-01 -17.955  < 2e-16 ***
occupation Farming-fishing          -2.362e-01  2.095e-01  -1.128 0.259531
occupation Handlers-cleaners        -5.073e-01  1.623e-01  -3.125 0.001778 **
occupation Machine-op-inspct        -1.821e+00  1.487e-01 -12.253  < 2e-16 ***
occupation Other-service            -2.561e+00  1.398e-01 -18.319  < 2e-16 ***
occupation Priv-house-serv          -5.012e+00  4.000e-01 -12.530  < 2e-16 ***
occupation Prof-specialty           -2.803e+00  1.474e-01 -19.019  < 2e-16 ***
occupation Protective-serv          -9.705e-01  2.028e-01  -4.785 1.71e-06 ***
occupation Sales                    -2.565e+00  1.420e-01 -18.065  < 2e-16 ***
occupation Tech-support             -2.506e+00  1.644e-01 -15.245  < 2e-16 ***
occupation Transport-moving                 NA         NA      NA       NA
relationship Not-in-family          -9.174e+00  1.018e+00  -9.012  < 2e-16 ***
relationship Other-relative         -9.105e+00  1.018e+00  -8.946  < 2e-16 ***
relationship Own-child              -9.073e+00  1.018e+00  -8.913  < 2e-16 ***
relationship Unmarried              -1.042e+01  1.019e+00 -10.222  < 2e-16 ***
relationship Wife                   -1.623e+01  1.230e+00 -13.192  < 2e-16 ***
race Asian-Pac-Islander             -1.173e-01  2.269e-01  -0.517 0.605299
race Black                          -3.574e-01  1.866e-01  -1.915 0.055530 .
race Other                          -2.774e-01  2.583e-01  -1.074 0.282890
race White                          -5.016e-02  1.798e-01  -0.279 0.780338
capital.gain                        -1.149e-07  4.151e-06  -0.028 0.977913
```

```
capital.loss                             5.966e-05  5.404e-05   1.104 0.269603    
hours.per.week                           2.129e-02  1.643e-03  12.956  < 2e-16 ***
native.country Cambodia                 -2.902e-02  9.140e-01  -0.032 0.974674    
native.country Canada                   -2.785e-01  3.336e-01  -0.835 0.403902    
native.country China                    -1.009e-01  4.319e-01  -0.233 0.815374    
native.country Columbia                 -6.207e-01  4.082e-01  -1.521 0.128384    
native.country Cuba                     -1.418e+00  4.038e-01  -3.512 0.000445 ***
native.country Dominican-Republic       -1.170e+00  3.697e-01  -3.163 0.001559 ** 
native.country Ecuador                  -5.671e-01  6.076e-01  -0.933 0.350644    
native.country El-Salvador              -1.157e-01  3.235e-01  -0.358 0.720710    
native.country England                  -9.662e-02  3.472e-01  -0.278 0.780761    
native.country France                   -7.299e-01  5.894e-01  -1.238 0.215560    
native.country Germany                  -9.840e-01  3.258e-01  -3.020 0.002525 ** 
native.country Greece                    4.557e-01  7.815e-01   0.583 0.559838    
native.country Guatemala                -8.307e-02  4.187e-01  -0.198 0.842711    
native.country Haiti                     5.879e-02  4.478e-01   0.131 0.895560    
native.country Holand-Netherlands       -1.475e+01  5.354e+02  -0.028 0.978018    
native.country Honduras                 -3.166e-01  8.036e-01  -0.394 0.693619    
native.country Hong                     -3.289e-01  1.015e+00  -0.324 0.745933    
native.country Hungary                  -7.179e-01  9.404e-01  -0.763 0.445244    
native.country India                     1.035e+00  4.612e-01   2.245 0.024782 *  
native.country Iran                      9.923e-01  6.290e-01   1.577 0.114682    
native.country Ireland                  -1.065e+00  5.862e-01  -1.816 0.069310 .  
native.country Italy                    -8.404e-01  4.871e-01  -1.725 0.084485 .  
native.country Jamaica                  -8.710e-01  3.628e-01  -2.401 0.016369 *  
native.country Japan                    -5.581e-01  4.326e-01  -1.290 0.196991    
native.country Laos                     -1.175e+00  8.735e-01  -1.346 0.178422    
native.country Mexico                   -2.511e-01  2.019e-01  -1.243 0.213732    
native.country Nicaragua                -3.214e-02  5.150e-01  -0.062 0.950232    
native.country Outlying-US(Guam-USVI-etc) -7.826e-01  6.863e-01  -1.140 0.254143    
native.country Peru                     -1.001e+00  5.253e-01  -1.905 0.056748 .  
native.country Philippines              -4.245e-01  2.860e-01  -1.484 0.137751    
native.country Poland                   -6.124e-01  4.566e-01  -1.341 0.179850    
native.country Portugal                 -9.180e-01  6.463e-01  -1.420 0.155493    
native.country Puerto-Rico              -6.390e-01  3.287e-01  -1.944 0.051883 .  
native.country Scotland                  1.135e+00  1.002e+00   1.132 0.257545    
native.country South                    -4.188e-01  3.848e-01  -1.088 0.276408    
native.country Taiwan                   -4.802e-02  4.874e-01  -0.099 0.921532    
native.country Thailand                 -1.307e+00  7.804e-01  -1.675 0.093980 .  
native.country Trinadad&Tobago          -2.344e+00  1.109e+00  -2.114 0.034542 *  
native.country United-States            -5.013e-01  1.379e-01  -3.635 0.000278 ***
native.country Vietnam                  -1.229e-01  3.932e-01  -0.313 0.754592    
native.country Yugoslavia               -2.595e-01  1.021e+00  -0.254 0.799256    
class >50K                               8.026e-01  8.068e-02   9.948  < 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: 41336  on 32560  degrees of freedom
Residual deviance: 18942  on 32462  degrees of freedom
AIC: 19140

Number of Fisher Scoring iterations: 12


> sum(diag(table(ifelse(predict(fit.full,type="response")>0.5,1,0),adult$sex)))/32561
[1] 0.8481312


> fit.reduce.age<-
glm(sex~workclass+fnlwgt+education+marital.status+occupation+relationship+race+capita
l.gain+capital.loss+hours.per.week+native.country+class,data=adult, family =
binomial())
```

```
>
sum(diag(table(ifelse(predict(fit.reduce.age,type="response")>0.5,1,0),adult$sex)))/3
2561
[1] 0.8479162
> fit.reduce.workclass<-
glm(sex~age+fnlwgt+education+marital.status+occupation+relationship+race+capital.gain
+capital.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.workclass,type="response")>0.5,1,0),adult$se
x)))/32561
[1] 0.8463806
> fit.reduce.fnlwgt<-
glm(sex~age+workclass+education+marital.status+occupation+relationship+race+capital.g
ain+capital.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.fnlwgt,type="response")>0.5,1,0),adult$sex))
)/32561
[1] 0.8459507
> fit.reduce.education<-
glm(sex~age+workclass+fnlwgt+marital.status+occupation+relationship+race+capital.gain
+capital.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.education,type="response")>0.5,1,0),adult$se
x)))/32561
[1] 0.8474555
> fit.reduce.marital.status<-
glm(sex~age+workclass+fnlwgt+education+occupation+relationship+race+capital.gain+capi
tal.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.marital.status,type="response")>0.5,1,0),adu
lt$sex)))/32561
[1] 0.845275
> fit.reduce.occupation<-
glm(sex~age+workclass+fnlwgt+education+marital.status+relationship+race+capital.gain+
capital.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.occupation,type="response")>0.5,1,0),adult$s
ex)))/32561
[1] 0.8106324
> fit.reduce.relationship<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+race+capital.gain+ca
pital.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.relationship,type="response")>0.5,1,0),adult
$sex)))/32561
[1] 0.7936181
> fit.reduce.race<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+capital
.gain+capital.loss+hours.per.week+native.country+class,data=adult, family =
binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.race,type="response")>0.5,1,0),adult$sex)))/
32561
[1] 0.8481005
> fit.reduce.capital.gain<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+race+ca
pital.loss+hours.per.week+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.capital.gain,type="response")>0.5,1,0),adult
$sex)))/32561
[1] 0.8481312
> fit.reduce.capital.loss<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+race+ca
pital.gain+hours.per.week+native.country+class,data=adult, family = binomial())
```

```
>
sum(diag(table(ifelse(predict(fit.reduce.capital.loss,type="response")>0.5,1,0),adult
$sex)))/32561
[1] 0.8480698
> fit.reduce.hours.per.week<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+race+ca
pital.gain+capital.loss+native.country+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.hours.per.week,type="response")>0.5,1,0),adu
lt$sex)))/32561
[1] 0.8430331
> fit.reduce.native.country<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+race+ca
pital.gain+capital.loss+hours.per.week+class,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.native.country,type="response")>0.5,1,0),adu
lt$sex)))/32561
[1] 0.8461349
> fit.reduce.class<-
glm(sex~age+workclass+fnlwgt+education+marital.status+occupation+relationship+race+ca
pital.gain+capital.loss+hours.per.week+native.country,data=adult, family =
binomial())
>
sum(diag(table(ifelse(predict(fit.reduce.class,type="response")>0.5,1,0),adult$sex)))
/32561
[1] 0.8469027
```

```
> fit.reduced<-glm(sex~relationship,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduced,type="response")>0.5,1,0),adult$sex)))/3256
1
[1] 0.7744234
> fit.reduced<-glm(sex~occupation+relationship,data=adult, family = binomial())
>
sum(diag(table(ifelse(predict(fit.reduced,type="response")>0.5,1,0),adult$sex)))/3256
1
[1] 0.8220264
> fit.reduced<-glm(sex~occupation+relationship+hours.per.week,data=adult, family =
binomial())
>
sum(diag(table(ifelse(predict(fit.reduced,type="response")>0.5,1,0),adult$sex)))/3256
1
[1] 0.83772
> fit.reduced<-
glm(sex~occupation+relationship+hours.per.week+marital.status,data=adult, family =
binomial())
>
sum(diag(table(ifelse(predict(fit.reduced,type="response")>0.5,1,0),adult$sex)))/3256
1
[1] 0.8396241
```