Name:
DNI/Passport:

GRAU D’ENGINYERIA INFORMÀTICA (UPC).
CURS 19-20 Q2 –QUIZ 2

Anàlisi de Dades i Explotació de la Informació (ADEI) .

(Data: 29/5/2020 10:00-12:00 h On-line https://meet.google.com/uzh-kvbr-uus

Professor:	Lídia Montero Mercadé
Rules for the quiz:	Emailing and chatting is strictly forbidden. Mobile phones should be switched off. PC camara should be turned on to invigilate you. You have to deliver 1 Name.FamilyName.pdf file containing answers to the questions, used commands and R output results needed to justify your answers.
Duration:	1h 45 min
Marks:	Before 5/6/20 Subject ATENEA website.
Open Office- online:	5/6/20 10:000

Problem 1: All questions account for 1 point

1793 choices by 561 individuals of a transport mode from/to Freetown airport (Sierra Leone) to downtown. This problem exploits an unusual transportation setting to generate some of the first revealed preference value of a statistical life (VSL) estimates from a low-income setting. Four alternatives are available: ferry, helicopter, water-taxi and hovercraft. A striking characteristic of the study is that all these alternatives experienced fatal accidents in recent years, so that the fatality risk is non-negligible and differs much from an alternative to another. For example, the probabilities of dying using the water taxi and the helicopter are respectively of 2.55 and 18.41 out of 100,000 passenger-trips.

Variable	Description
id	Individual id *(not to be used in this exercise)*
choice	1 for the chosen mode
mode	One of Helicopter, *(not to be used in this exercise)*WaterTaxi (a small craft for 12 to 18 pax), Ferry, and Hovercraft
cost	the generalised cost of the transport mode (US$) – *numeric target*
risk	The fatality rate, numbers of death per 100,000 trips for the selected mode
weight	Weights *(not to be used in this exercise)*
seats	Level of seat availability - comfort (Likert scale 1 to 5, transformed to 0 to 1 scale)
noise	Level for less noise disturbance (Likert scale 1 to 5, transformed to 0 to 1 scale)
crowdness	Level for less crowdedness (Likert scale 1 to 5, transformed to 0 to 1 scale)
convloc	Level of convenience location for the transfer (Likert scale 1 to 5, transformed to 0 to 1 scale)
clientele	Level of quality of ‘trip makers’ (Likert scale 1 to 5, transformed to 0 to 1 scale)
chid	Choice situation id *(not to be used in this exercise)*
african	yes if born in Africa, no otherwise
lifeExp	declared life expectancy
dwage	declared hourly wage
iwage	imputed hourly wage
educ	level of education, one of low and high
fatalism	self-ranking of the degree of fatalism
gender	gender, one of female and male
age	age
haveChildren	yes if the traveler has children, no otherwise
swim	yes if the traveler knows how to swim, 'no’, otherwise
noalt	Number of available alternatives for the selected choice

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The trade-offs that individuals are willing to make between mortality risk and cost as they travel to and from the international airport in Sierra Leone are estimated. The setting and original dataset allow us to address some typical variable concerns, and also to compare VSL estimates for travelers from different countries, all facing the same choice situation. The average VSL estimate for African travelers in the sample is US$ 577,000 compared to US$ 924,000 for non-Africans. The two covariates of interest are cost (the generalized cost in $PPP unit, not *leones*) and risk (mortality per 100,000 passenger-trips). The risk variable being purely alternative specific, intercepts for the alternatives cannot therefore be estimated. To avoid endogeneity problems, the authors introduce as covariates marks the individuals gave to 5 attributes of the alternatives: comfort, noise level, crowdedness, convenience and transfer location and the "quality" of the clientele.

Source

data(“RiskyTransport”) # mlogit package – long format dataset
American Economic Association data archive.

References

León, Gianmarco, and Miguel, Edward. *Risky Transportation Choices and the Value of a Statistical Life*. Nashville, TN: American Economic Association [publisher], 2017. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2019-10-12. https://doi.org/10.3886/E113686V1.

Let us focus on travel cost (cost variable). Firstly, restrict your active data set to observations involving 4 available alternatives (noalt=4) and actual choice (choice=1). Secondly, define a new binary factor containing WaterTaxi choice versus Others.

1. Indicate by data exploration tools which are globally the most associated variables with the **response variable (cost)**.

A condes() method in FactoMineR package can be used. Only global association has to be addressed. Global association of cost with numeric variables is shown using Pearson correlation coefficient and pvalues of the null hypothesis ‘correlation coefficient equal 0’. Positively correlated with high intensity are dwage, iwage and less intensity is shown for numeric scores crowdness, noise, convloc. An inverse relation indicated by a negative coefficient of correlation is shown for lifeExp and risk, but is not very intense.

Factor variables globally related to cost are the selected transportation mode (low intensity) and almost negligible are swimming capability (swim) and the binary factor WaterTaxi.

```
> names(df4)
 [1] "id"           "choice"       "mode"         "cost"
 [5] "risk"         "weight"       "seats"        "noise"
 [9] "crowdness"    "convloc"      "clientele"    "chid"
[13] "african"      "lifeExp"      "dwage"        "iwage"
[17] "educ"         "fatalism"     "gender"       "age"
[21] "haveChildren" "swim"         "f.wtaxi"
> res.con<-condes(df4,num.var=4)
> res.con$quanti
          correlation      p.value
dwage       0.7742782 3.742985e-65
iwage       0.7663530 8.960149e-82
crowdness   0.3399495 9.698704e-13
noise       0.2747916 1.165168e-08
convloc     0.2357815 1.120744e-06
seats       0.2152384 9.242447e-06
age         0.1507996 2.016119e-03
clientele   0.1335785 6.298648e-03
```

```
weight     -0.1325241 6.727160e-03
risk       -0.1695825 5.055468e-04
lifeExp    -0.1723265 4.078928e-04
> res.con$quali
                 R2      p.value
mode     0.20847078 8.082973e-21
f.wtaxi  0.07666578 8.924484e-09
swim     0.01098157 3.240303e-02
```

2. Calculate the linear model that explains the cost of the transfer from the imputed wage (iwage) and factor mode: interpret the regression lines and assess its global quality. What is the percentage of the cost variability that is explained by the transportation mode?

The complete Ancova model (main effects and interactions) has 8 parameters and according to Anova() tests for net-effects the interactions are significant once the main effects for iwage and mode have already been included in the model. Goodness of fit can be assessed using R2 80.46% of target's variability is explained by the model. Transportation mode has to be introduced in the model as main effect and interaction with iwage. The model containing only iwage has an R2 of 58.73%, so almost 21% of target's variability is explained by mode. The additive model is not the solution : interactions are needed.

Model interpretation:

- For mode==Helicopter Y= (37.14+0)+(2.33+0)*iwage
- For mode==WaterTaxi Y= (37.14+23.16)+(2.33-1.49)*iwage
- For mode==Ferry Y= (37.14 – 33.57)+(2.33 – 0.66)*iwage
- For mode==Hovercraft Y= (37.14 + 55.95)+(2.33 - 1.85)*iwage

```
> m1<-lm(cost~mode*iwage, data=df4)
> summary(m1)

Call: lm(formula = cost ~ mode * iwage, data = df4)

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           37.1415    32.1249   1.156 0.248291    
modeWaterTaxi         23.1560    32.2502   0.718 0.473162    
modeFerry            -33.5647    32.2196  -1.042 0.298144    
modeHovercraft        55.9495    32.3770   1.728 0.084732 .  
iwage                  2.3285     0.6251   3.725 0.000223 ***
modeWaterTaxi:iwage   -1.4847     0.6270  -2.368 0.018347 *  
modeFerry:iwage       -0.6589     0.6276  -1.050 0.294390    
modeHovercraft:iwage  -1.8493     0.6292  -2.939 0.003479 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 23.77 on 409 degrees of freedom
Multiple R-squared:  0.8046,	Adjusted R-squared:  0.8012 
F-statistic: 240.5 on 7 and 409 DF,  p-value: < 2.2e-16

> Anova(m1)
Anova Table (Type II tests)

Response: cost
           Sum Sq  Df  F value    Pr(>F)
```

```
mode        139841   3   82.532 < 2.2e-16 ***
iwage       587609   1 1040.399 < 2.2e-16 ***
mode:iwage 116970   3   69.034 < 2.2e-16 ***
Residuals  231000 409
---
> summary(m2)

Call: lm(formula = cost ~ iwage, data = df4)

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 39.52579    2.42510    16.3    <2e-16 ***
iwage        1.12119    0.04614    24.3    <2e-16 ***
---
Residual standard error: 34.28 on 415 degrees of freedom
Multiple R-squared:  0.5873,       Adjusted R-squared:  0.5863
F-statistic: 590.6 on 1 and 415 DF,  p-value: < 2.2e-16
```

3. Calculate a linear model for the target cost using all available numeric variables. Are there any collinearity issues in the model? Justify the solution to remove collinearity.

The model using numeric variables has to contain risk, fatalism, age, lifeExp as characteristics of the trip maker and numeric scores seats, noise, crowdness, convloc and clientele. The model explains 65.88% of cost variability. Only crowdness and iwage net-effects are significant at the 5% usual threshold, but noise pvalue is not so far and has to be also included as a remarkable variable. Using vif() method in library car, noise and crowdness pair seem to be correlated and age and lifeExp pair also. You have to retain one variable in each pair, either the most correlated, or the reliable: I choose crowdness to solve the first pair problem and age for the second (more objective variable than lifeExp). You can see that m4 containing all numeric except noise and lifeExp has solved collinearity problems. Removing non-significant variables, only iwage and crowdness are retained.

```
> summary(m3)

Call: lm(formula = cost ~ risk + seats + noise + crowdness + convloc +
    clientele + lifeExp + iwage + fatalism + age, data = df4)

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  32.48380   23.93538   1.357 0.175489
risk          0.87010    1.25178   0.695 0.487397
seats         5.68797   10.75632   0.529 0.597232
noise        19.93784   10.98507   1.815 0.070262 .
crowdness    35.67569   10.12037   3.525 0.000471 ***
convloc       3.48669    8.65774   0.403 0.687362
clientele   -12.70834   12.08796  -1.051 0.293736
lifeExp      -0.28703    0.26061  -1.101 0.271389
iwage         1.08426    0.04381  24.748  < 2e-16 ***
fatalism     -0.37977    0.54686  -0.694 0.487794
age          -0.35538    0.28439  -1.250 0.212165
---
Residual standard error: 31.52 on 406 degrees of freedom
Multiple R-squared:  0.6588,    Adjusted R-squared:  0.6504
F-statistic: 78.38 on 10 and 406 DF,  p-value: < 2.2e-16
> vif(m3)
     risk      seats      noise crowdness    convloc clientele    lifeExp
```

```
 1.201182  1.674560  3.260330  3.442236  1.589556  1.533807  4.357885
    iwage  fatalism       age
 1.067008  1.038980  4.407140
> m4<-lm(cost~risk+seats+crowdness+convloc+clientele+age+iwage+fatalism, data=d
f4)
> vif(m4)
risk     seats crowdness   convloc clientele       age     iwage
1.197047  1.551178  2.140106  1.574705  1.510840  1.081610  1.058039
fatalism
1.037831
> m5<-step(m4,k=log(nrow(df4)))
Start:  AIC=2925.65
cost ~ risk + seats + crowdness + convloc + clientele + age +
iwage + fatalism

Step:  AIC=2892.2
cost ~ crowdness + iwage

 …
Df Sum of Sq     RSS    AIC
<none>                 410617 2892.2
- crowdness  1     77194  487811 2958.0
- iwage      1    634775 1045392 3275.8
> summary(m5)
Call: lm(formula = cost ~ crowdness + iwage, data = df4)

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.23976    4.09239   2.258   0.0245 *
crowdness   48.38858    5.48492   8.822   <2e-16 ***
iwage        1.07896    0.04265  25.298   <2e-16 ***
---
Residual standard error: 31.49 on 414 degrees of freedom
Multiple R-squared:  0.6526,    Adjusted R-squared:  0.6509
F-statistic: 388.9 on 2 and 414 DF,  p-value: < 2.2e-16
```

4. Once the best model for target cost using explanatory numeric variables has been proposed, are there any significant main factor effects to be included? And interactions? Justify your answer.

Transformations to explanatory variables are not considered in the exercise, but they should be tested in a real study. Model m7<-lm(cost~crowdness+iwage+mode+gender+african+educ+haveChildren+swim, data=df4) is considered and Anova(m7) shows that some variables are redundant, being only crowdness, iwage, mode, gender, African and educ those with net significant effects. Interactions between factors and covariates are included: some aliased coefficients message indicates an specification problem: mode and crowdness interactions cannot be calculated, thus mode and crowdness interaction is not considered. After m8 model calculation and reduction using step() method with BIC monitoring, a final model (m9) containing:

```
cost ~ iwage + mode + crowdness + gender + african + educ + iwage:mode +
    crowdness:african + crowdness:educ + iwage:african  is obtained.
```

It is a complex model that explains 84% of cost variability.

```
> m7<-lm(cost~crowdness+iwage+mode+gender+african+educ+haveChildren+swim, data=
df4)
> #summary(m7)
> Anova(m7)
Anova Table (Type II tests)

Response: cost
             Sum Sq  Df  F value    Pr(>F)    
crowdness      1282   1   1.6312  0.202272    
iwage        601717   1 765.8140 < 2.2e-16 ***
mode          72832   3  30.8980 < 2.2e-16 ***
gender         3198   1   4.0696  0.044320 *  
african       14831   1  18.8759 1.765e-05 ***
educ          10802   1  13.7485  0.000238 ***
haveChildren    120   1   0.1528  0.696102    
swim            708   1   0.9008  0.343141    
Residuals    319003 406                       
---
> m8<-lm(cost~(crowdness+iwage)*(mode+gender+african+educ+haveChildren+swim), d
ata=df4) # Some crwodness:mode parameters can not be estimated
> m8<-lm(cost~iwage*mode+(crowdness+iwage)*(gender+african+educ+haveChildren+sw
im), data=df4)
> Anova(m8)
Anova Table (Type II tests)

Response: cost
                       Sum Sq  Df   F value    Pr(>F)    
iwage                  584296   1 1244.2909 < 2.2e-16 ***
mode                    61569   3   43.7047 < 2.2e-16 ***
crowdness                 465   1    0.9894  0.320508    
gender                   2730   1    5.8139  0.016358 *  
african                 15220   1   32.4121 2.444e-08 ***
educ                     4612   1    9.8217  0.001854 ** 
haveChildren                8   1    0.0175  0.894685    
swim                      130   1    0.2766  0.599210    
iwage:mode              97741   3   69.3819 < 2.2e-16 ***
crowdness:gender         2543   1    5.4162  0.020458 *  
crowdness:african        4063   1    8.6515  0.003461 ** 
crowdness:educ           4864   1   10.3585  0.001396 ** 
crowdness:haveChildren    138   1    0.2930  0.588603    
crowdness:swim           1292   1    2.7514  0.097968 .  
iwage:gender               42   1    0.0888  0.765818    
iwage:african            4201   1    8.9457  0.002956 ** 
iwage:educ                 61   1    0.1298  0.718820    
iwage:haveChildren         38   1    0.0820  0.774819    
iwage:swim                 44   1    0.0935  0.759894    
Residuals              184546 393                       
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> m9<-step(m8,k=log(nrow(df4)))
Start:  AIC=2685.39
cost ~ iwage * mode + (crowdness + iwage) * (gender + african + 
    educ + haveChildren + swim)
…

Step:  AIC=2640.01
cost ~ iwage + mode + crowdness + gender + african + educ + iwage:mode + 
    crowdness:african + crowdness:educ + iwage:african

                    Df Sum of Sq    RSS    AIC
<none>                           188533 2640.0
- crowdness:african  1      2752 191285 2640.0
- gender             1      3026 191560 2640.6
- iwage:african      1      5711 194245 2646.4
- crowdness:educ     1      5910 194444 2646.8
- iwage:mode         3    105401 293934 2807.1
```

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```
> Anova(m9)
Anova Table (Type II tests)

Response: cost
                  Sum Sq  Df   F value    Pr(>F)    
iwage             599777   1 1278.8731 < 2.2e-16 ***
mode               61614   3   43.7918 < 2.2e-16 ***
crowdness            519   1    1.1067 0.2934391    
gender              3026   1    6.4526 0.0114544 *  
african            15244   1   32.5049 2.305e-08 ***
educ                4720   1   10.0633 0.0016286 ** 
iwage:mode        105401   3   74.9135 < 2.2e-16 ***
crowdness:african   2752   1    5.8671 0.0158679 *  
crowdness:educ      5910   1   12.6023 0.0004309 ***
iwage:african       5711   1   12.1776 0.0005372 ***
Residuals         188533 402                        
---
> summary(m9)

Call:
lm(formula = cost ~ iwage + mode + crowdness + gender + african + 
    educ + iwage:mode + crowdness:african + crowdness:educ + 
    iwage:african, data = df4)

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)               38.01555   32.22528   1.180 0.238825    
iwage                      2.27626    0.57501   3.959 8.91e-05 ***
modeWaterTaxi              7.74194   29.74325   0.260 0.794772    
modeFerry                -54.83830   29.97680  -1.829 0.068087 .  
modeHovercraft            35.81018   29.81342   1.201 0.230403    
crowdness                 22.73403   15.13510   1.502 0.133863    
gendermale                -6.61084    2.60249  -2.540 0.011454 *  
africanAfr.Yes             7.34304    6.67988   1.099 0.272305    
educhigh                  23.56247    9.83545   2.396 0.017047 *  
iwage:modeWaterTaxi       -1.29623    0.57760  -2.244 0.025366 *  
iwage:modeFerry           -0.48275    0.57717  -0.836 0.403429    
iwage:modeHovercraft      -1.64087    0.57875  -2.835 0.004811 ** 
crowdness:africanAfr.Yes  20.52763    8.47476   2.422 0.015868 *  
crowdness:educhigh       -46.28645   13.03856  -3.550 0.000431 ***
iwage:africanAfr.Yes      -0.21790    0.06244  -3.490 0.000537 ***

Residual standard error: 21.66 on 402 degrees of freedom
Multiple R-squared:  0.8405,	Adjusted R-squared:  0.8349 
F-statistic: 151.3 on 14 and 402 DF,  p-value: < 2.2e-16
```

5. Select the best model available so far. Let us assume an observation on the median of numeric variables and reference levels for the factors. Estimate a 90% confidence interval for predicted transfer cost.

This question can be easily answered using predict() method. My best model is m1: the one using iwage*mode, since it explains almost 80% of the target and it is simpler than m9 (explaining 84%). Answers including the best model obtained after Question 5 have been also considered correct.

Median of iwage is 27.96236 and reference level for mode is 'Helicopter' then

For mode==Helicopter Y= (37.14+0)+(2.33+0)*iwage= 37.14+2.33*27.96=102.2525 $ is the point estimate. 90% confidence interval for the predicted cost can not be easily calculated without using predict(model, newdata=.) method in R.

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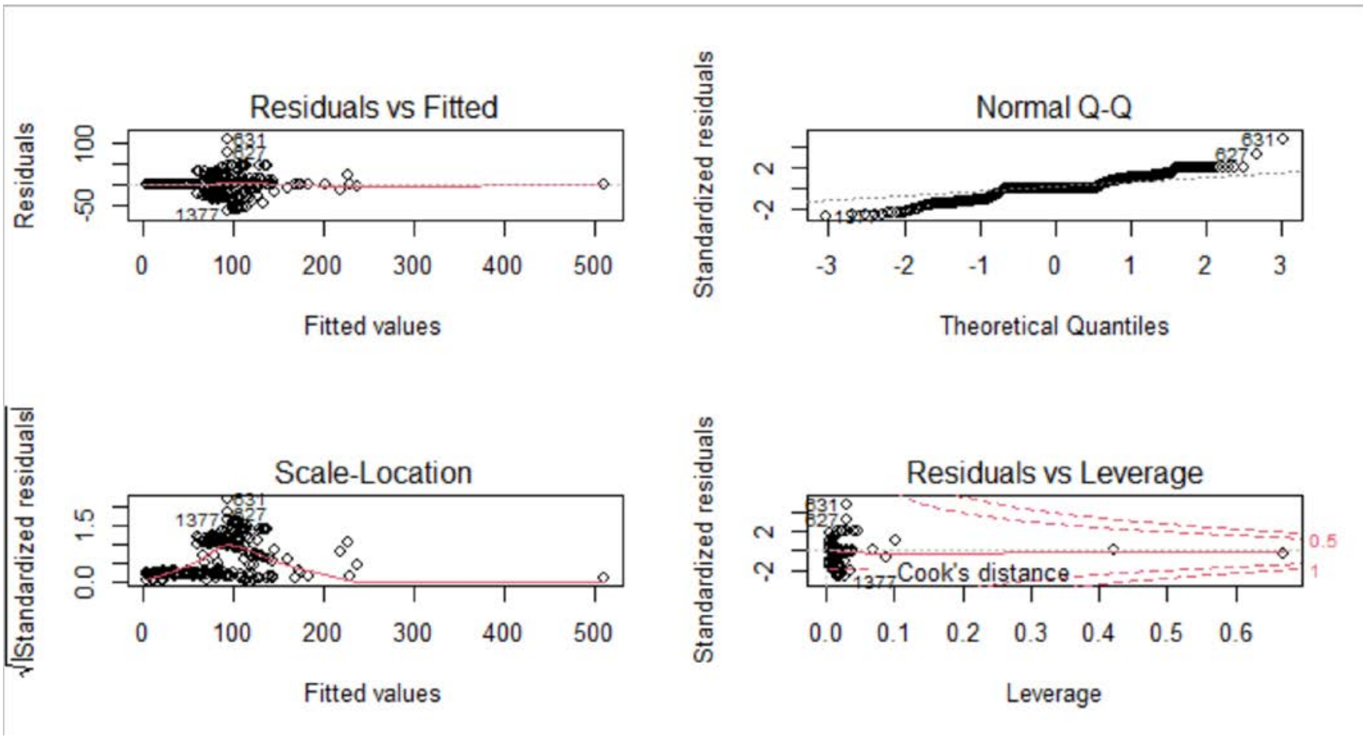
```
> predict(m1,newdata=data.frame(iwage=median(df4$iwage),mode="Helicopter"),interv
al="prediction",level=0.9)
       fit      lwr      upr
1 102.2525 51.56798 152.9369
```

6. Graphically assess the best model obtained so far. Assess the presence of outliers in the studentized residuals at 95% confidence level. Indicate which those observations are and why they are showing lack of fit.

Again m1 is my best model so far, but the best model obtained at Question 4 can be also used. Diagnostic show that the model is not good. Since this is a question in an exam, you have to answer lack of fit issues. Absolute studentized residuals over 3.0 are considered outliers and these correspond to observations 45 and 46 in df4 register order or rownames “627” and “631”. These registers belong to young women that have paid a lot of money for a Hovercraft service to downtown. Influent data is present and transformations would be needed for explanatory variables and outcome, but this is not the aim for this exam.

```
qnorm(0.975)
[1] 1.959964
> ll<-which(abs(rstudent(m1))>qnorm(0.975));ll;length(ll)
 570  574  606  613  617  627  631  644  907  928  932  947  951  962 
  36   37   42   43   44   45   46   47   62   64   65   68   69   71 
 966  993 1010 1304 1339 1364 1377 1597 1897 3082 3103 3117 3121 3128 
  72   75   77   94  100  104  105  121  143  236  238  240  241  242 
3132 3558 3569 3593 3603 3971 4643 4647 4773 
 243  263  265  268  269  297  347  348  356 
[1] 37
> #df4[ll,]
> ll<-which(abs(rstudent(m1))>3.0);ll
627 631 
 45  46 
> df4[ll,]
         id choice       mode     cost     risk   weight seats noise
627 8290608      1 Hovercraft 170.9406 3.881836 1.215615   0.8     1
631 8290608      1 Hovercraft 205.1287 3.881836 1.215615   0.8     1
    crowdness convloc clientele chid african lifeExp dwage iwage educ
627         1     0.6       0.8  303 Afr.Yes      66     0     0  low
631         1     0.6       0.8  304 Afr.Yes      66     0     0  low
    fatalism gender age haveChildren    swim  f.wtaxi
627        1 female  19     chil.Yes swim.No WTaxi.No
631        1 female  19     chil.Yes swim.No WTaxi.No
```



7. Study the presence of *a priori and a posteriori* influential data observations. Indicate thresholds to be applied to the statistic involved in the diagnostic.

Easily done using influencePlot(model). Helicopter users are just 2 in the sample and those are the influent data: there is not model that can deal with 4 modes given the low market share for Helicopter. These observations should be removed and the exercise has to be repeated again.

```
> influencePlot(m1)
       StudRes        Hat      CookD
627  3.365672 0.02879271 0.04094436
631  4.917400 0.02879271 0.08480268
779       NaN 1.00000000        NaN
4785      NaN 1.00000000        NaN
> df4[c("779","4785"),]
          id choice       mode      cost    risk    weight seats noise
779  8300204      1 Helicopter  76.53285 18.4082 0.3863821   1.0   1.0
4785 9160602      1 Helicopter 201.73314 18.4082 0.3863821   0.4   0.4
     crowdness convloc clientele chid african lifeExp   dwage    iwage
779        1.0     1.0       1.0  397  Afr.No      36 16.9169 16.91690
4785       0.6     0.8       0.6 2326  Afr.No      25      NA 70.68501
     educ fatalism gender age haveChildren     swim  f.wtaxi
779  high        2 female  49     chil.Yes swim.Yes WTaxi.No
4785 high        6   male  60     chil.Yes swim.Yes WTaxi.No
> table(df4$mode)

Helicopter  WaterTaxi      Ferry Hovercraft 
         2        180        174         61 
```

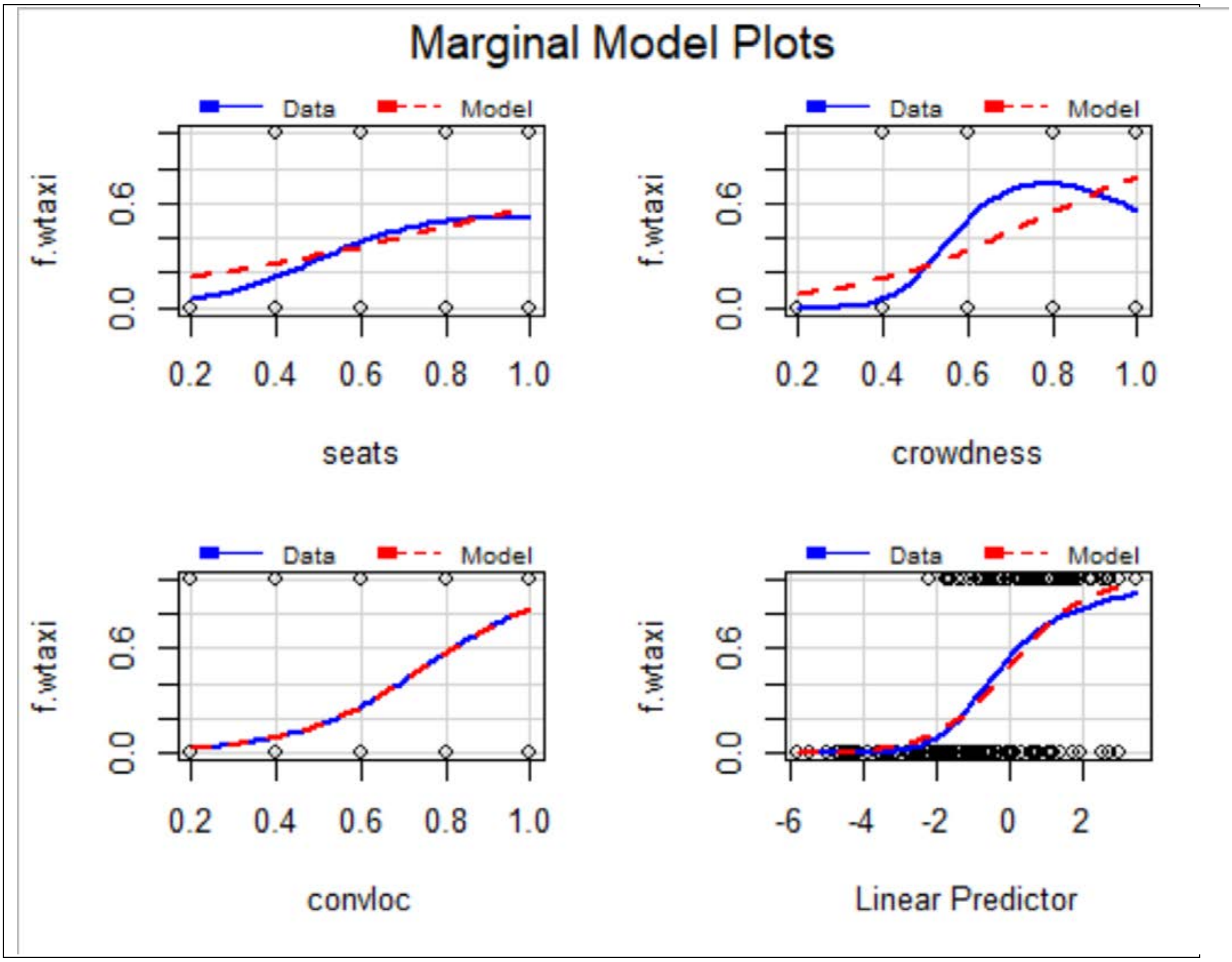
8. **WaterTaxi binary choice factor is the new target to be addressed.** Estimate a logit model including seats, crowdness, convloc covariates and educ and swim factors. Discuss model fit taking into account marginal trends and residual plots.

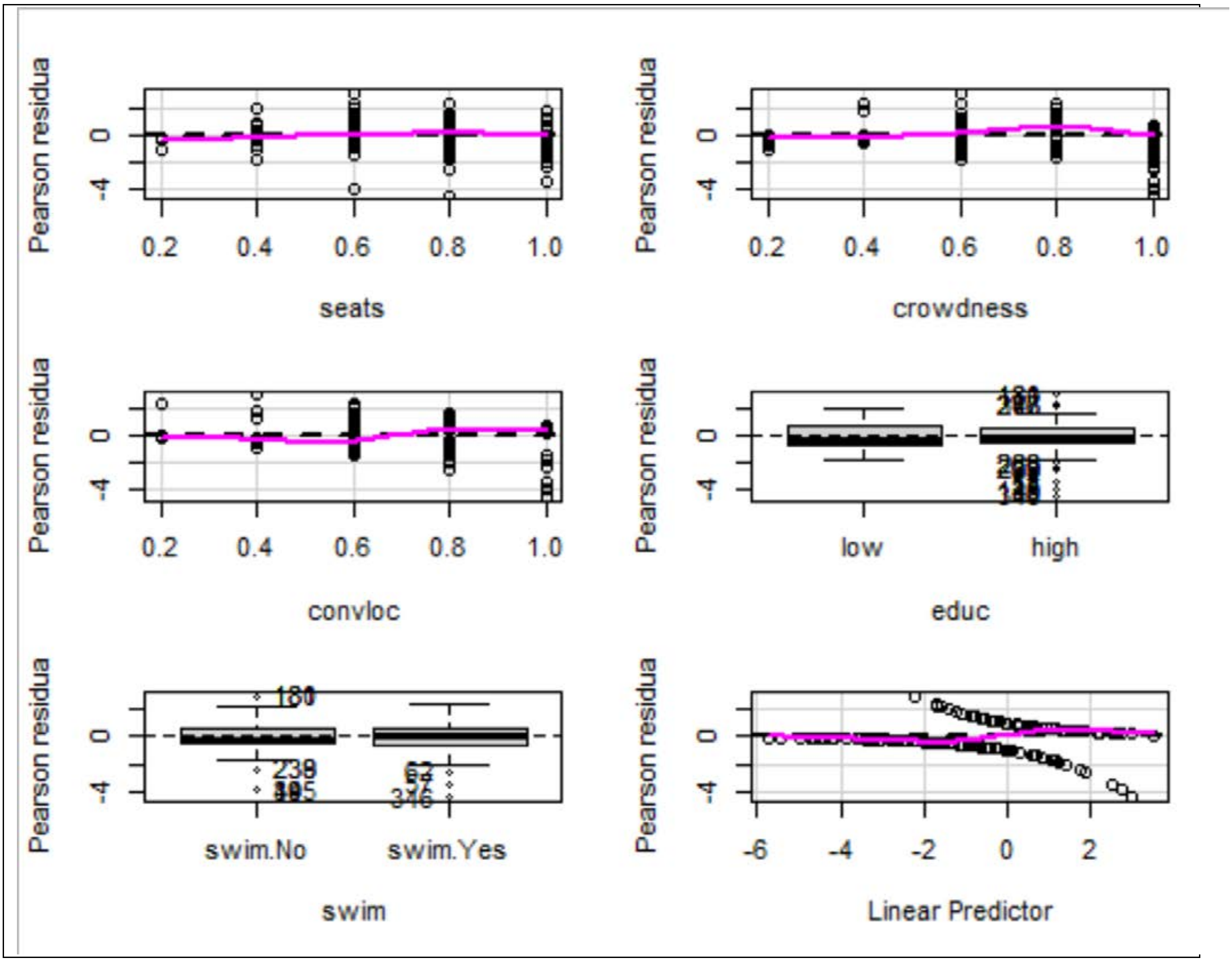
Some lack of fit is shown in the marginal plots for seats and mainly for crowdness scores, anyway residualPlots do show a fat smoother for the global fit (last plot, right below). All

factors and covariates have significant net-effects according to Anova() method. No collinearity is present in the model.
Since residual deviance is 376.95 on 411 degrees of freedom and disaggregated data is the type of this dataset, using the practical 'rule of thumb' that indicates that residual deviance should not be less than d.ll. and this holds as shown in the output.

```
> m20<-glm(f.wtaxi~seats+crowdness+convloc+educ+swim, family=binomial, data=df4)
> summary(m20)

Call:
glm(formula = f.wtaxi ~ seats + crowdness + convloc + educ +
    swim, family = binomial, data = df4)

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -6.5213     0.8205  -7.948 1.90e-15 ***
seats         -2.4709     0.8743  -2.826  0.00471 **
crowdness      4.1474     0.6661   6.226 4.78e-10 ***
convloc        5.4724     0.8427   6.494 8.38e-11 ***
educhigh       1.1201     0.3351   3.343  0.00083 ***
swimswim.Yes   0.7489     0.2577   2.906  0.00366 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 570.27  on 416  degrees of freedom
Residual deviance: 376.95  on 411  degrees of freedom
AIC: 388.95

> Anova(m20,test="LR")
Analysis of Deviance Table (Type II tests)

Response: f.wtaxi
          LR Chisq Df Pr(>Chisq)
seats        8.371  1  0.0038127 **
crowdness   47.420  1  5.729e-12 ***
convloc     52.660  1  3.966e-13 ***
educ        11.838  1  0.0005803 ***
swim         8.646  1  0.0032782 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> vif(m20)
    seats crowdness   convloc      educ      swim
 1.482731  1.430404  1.141454  1.033825  1.023785
```

Name:
DNI/Passport:





9. Interpret model equations and the effects in the odds scale of involved factors.

$$logit\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \alpha + \beta_1\ seats + \beta_2\ crowdness + \beta_3\ convloc + \gamma_j\ + \delta_k \quad \text{where}$$

$$\alpha = -6.5213\ ,\ \beta_1 = -2.47, \beta_2 = 4.15 \text{ and } \beta_3 = 5.47$$

- $\gamma_1 = 0$ $\gamma_2 = \mathbf{1.1201}$ for factor educ, where level 1 is education–low and 2 is education–high.
- $\delta_1 = 0$ $\delta_2 = \mathbf{0.7489}$ for factor swim, where level 1 is swim–No and 2 is swim–Yes
- There are as many model equations as 2 x 2= 4 (product of number of levels for factors educ and swim)

Interpretation of the model in the odds scale:
Increasing by 0.1 units seats scored then exp(-2.47*0.1)= 0.7811407 -> 100*(1-0.7811)= 22%, the odds of the probability of choosing WaterTaxi decreases by 22%, all else being equal.

Increasing by 0.1 units seats scored then exp(4.15*0.1)= 1.514371
-> 100*(1.514371-1)=51%, the odds of the probability of choosing WaterTaxi increases by 51%, all else being equal.

Increasing by 0.1 units seats scored then exp(5.47*0.1)= 1.728061
-> 100*(1.728061-1)=72%, the odds of the probability of choosing WaterTaxi increases by 72%, all else being equal.

The odds of the probability of choosing WaterTaxi for high educated people increases by exp(1.1201)=3.065 -> 100*(3.065 -1)= 206% the probability of choosing WaterTaxi in the reference level education-low all else being equal.
The odds of the probability of choosing WaterTaxi for people that can swim increases by exp(0.7489)= 2.114-> 100*(2.114 -1)= 111% the probability of choosing WaterTaxi in the reference level of people that cannot swim, all else being equal.

```
> summary(m20)

Call: glm(formula = f.wtaxi ~ seats + crowdness + convloc + educ +
    swim, family = binomial, data = df4)

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   -6.5213     0.8205  -7.948 1.90e-15 ***
seats         -2.4709     0.8743  -2.826  0.00471 **
crowdness      4.1474     0.6661   6.226 4.78e-10 ***
convloc        5.4724     0.8427   6.494 8.38e-11 ***
educhigh       1.1201     0.3351   3.343  0.00083 ***
swimswim.Yes   0.7489     0.2577   2.906  0.00366 **

> exp(coef(m20))
 (Intercept)        seats    crowdness      convloc     educhigh
1.471806e-03 8.450815e-02 6.327141e+01 2.380306e+02 3.065202e+00
swimswim.Yes
2.114570e+00
```

10. What would be the expected probability of using a ‘WaterTaxi’ for a high education and swimmer trip maker when numeric explanatory variables are set to their sample minimum?

```
> predict(m20,newdata=data.frame(seats=min(df4$seats),crowdness=min(df4$crowdness
),convloc=min(df4$convloc),educ="high",swim="swim.No"),type="response",se.fit=T,l
evel=0.95)
$fit
         1
0.01849899

$se.fit
         1
0.01022678

$residual.scale
[1] 1
```