

GLM Assignment 2

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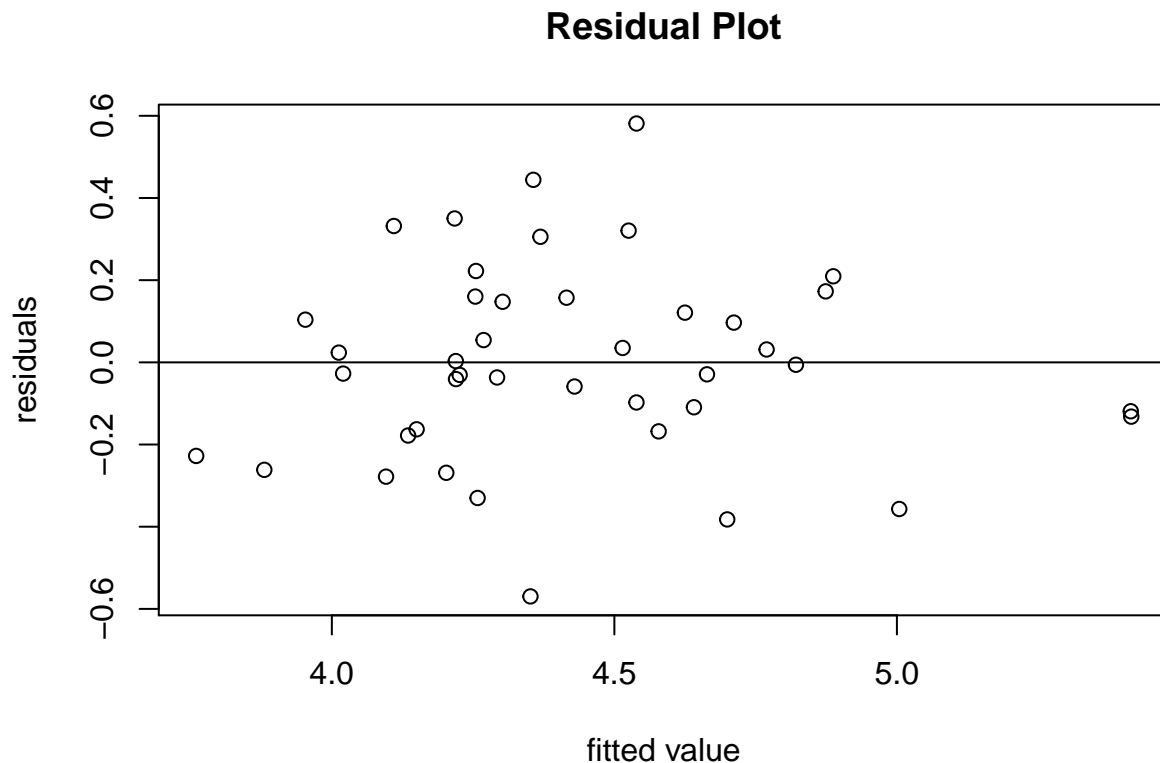
1. Fit a linear regression model to the data. What variables are most predictive for the crime rate?

As a set of variable, **Age, Education, Ex0, U2 and X** are most effective linear model covariates for the crime rate.

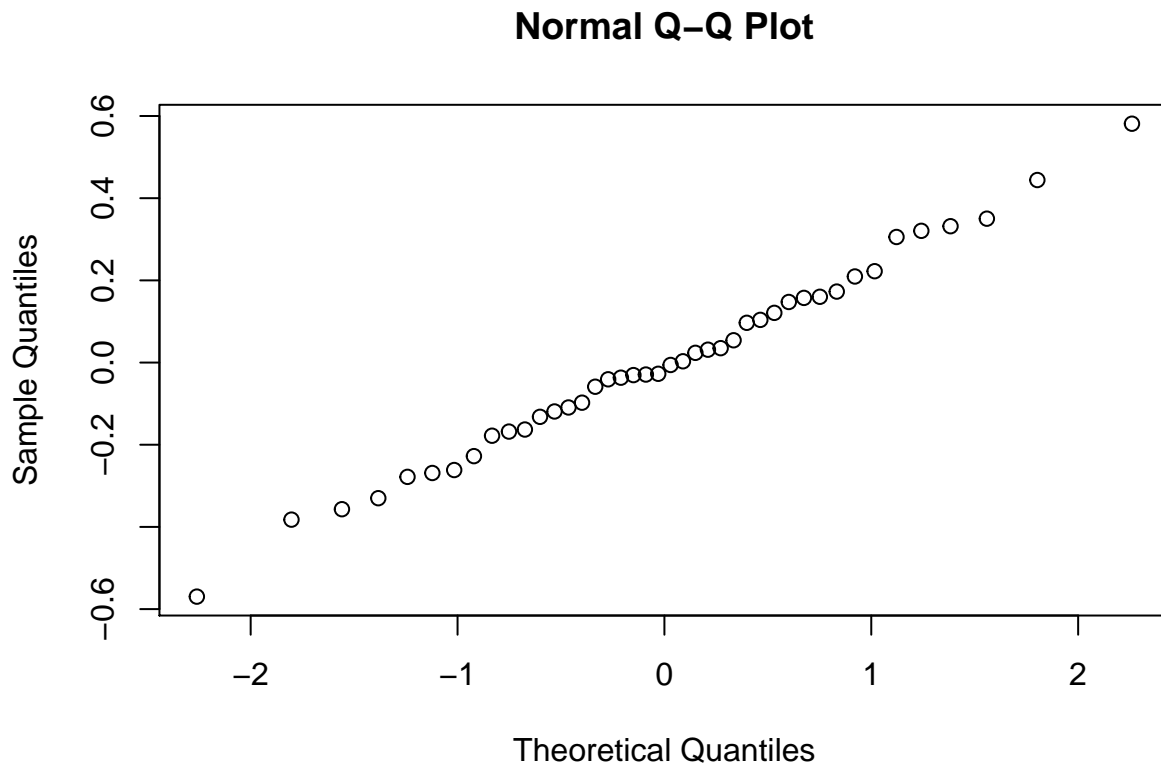
$R = -2.310635 + 0.012725 \cdot \text{Age} + 0.021344 \cdot \text{Ed} + 0.012930 \cdot \text{Ex0} + 0.009798 \cdot \text{U2} + 0.006608 \cdot \text{X}$

- I read table and fitted the full model(fit1). By stepwise function, I selected variables.(fit2) _ ANOVA ensured smaller model is more adequate with p-value 0.9021.
- Comparing AIC by drop1 function, I dropped covariate 'M'.(fit3)
- I checked scatter Plot Matrix and correlation matrix. I deleted insignificant covariate U1 which has the Multicollinearity with U2.(fit4)
- ANOVA ensured smallest model(fit4) is better than fit3.
- Residual plot implies nonconstant variance. I conduct log transformation on Y.
- It seems there is no influence point by checking cooks distance.

```
crime.dat <- read.table("~/Library/Mobile Documents/com~apple~CloudDocs/crime.dat.txt", header = T)
crime.dat <- na.omit(crime.dat)
fit4 <- lm(log(R) ~ Age + Ed + Ex0 + U2 + X, data=crime.dat)
plot(fitted(fit4), resid(fit4), main="Residual Plot",
     xlab="fitted value", ylab="residuals")
abline(a=0,b=0)
```



```
qqnorm(resid(fit4))
```



It seems that the model satisfy the assumptions for the linear model pretty well.

2. A crime rate may be viewed as “high” if it is above 105 and “low” otherwise.

Fit a logistic regression model to the data. What variables are most predictive for a “high” crime rate?

As a set of variable, **Age** , **Ex1** , **LF** , **NW** , **U2** , **X** are most effective quasibinomial model covariates for the crime rate.

```
R1<-as.numeric(R>105).
```

$R1 = -224.80112 + 0.49310 \cdot \text{Age} + 0.36407 \cdot \text{Ex1} + 0.11835 \cdot \text{LF} - 0.05242 \cdot \text{NW} + 0.36543 \cdot \text{U2} + 0.25849 \cdot \text{X}$

- I conducted logit model on the data, but it didn't converge.(fit1_bin)
- After stepwise variable selection, the model didnt' converge.(fit2_bin)
- Comparing AIC by drop1 function, I dropped U1 which increase smallest AIC and cure multicollinearity between U1 and U2. And this model converge.(fit3_bin)
- I checked dispersion parameter by fitting quasibinomial model, and dispersion parameter for quasi model is 0.4. (fit4_bin_quasi)
- As dispersion parameter is not near 1, it turns out that binomial model not fit well, so we use quasibinomial model.
- It seems there some influence points by checking cooks distance. As there are more than 4, we regard those as parts of data.

3. Round off crime rate numbers to the nearest integers and then fit a Poisson GLM to the new crime rate data. What variables are most predictive for the crime rate? Does the Poisson GLM fit the data well?

As a set of variable, **Age** , **Ed**, **Ex0** , **U2**, **W**, **X** are most effective quasibinomial model covariates for the crime rate.

$R2 < \text{round}(R, \text{digits}=0)$

$$R2 = -2.967425 + 0.012161\text{Age} + 0.015589\text{Ed} + 0.009611\text{Ex0} + 0.007522\text{U2} + 0.002311\text{W} + 0.009295\text{X}$$

- Full poisson model (fit1_poi) has many insignificant covariates.
- After stepwise variable selection, the model has smaller explanatory variable.(fit2_poi)
- The covariate LF of fit2 model has significant but largest P-value. By conducting ANOVA and checking AIC by drop function, I dropped LF covariate.(fit3_poi)
- By drop1 function, I dropped U1 which increase the smallest amount of AIC, and has multicollinearity with U2.(fit4_poi) ANOVA test ensures that model without U1 might be better.
- I checked dispersion parameter by fitting quasipoisson model, and dispersion parameter for quasi model is 5.3. (fit4_poi_quasi)
- As dispersion parameter is not near 1, it turns out that binomial model not fit well, so we use quasibinomial model.

4. Compare the results from 1) – 3), and comment on what you find. What do you learn from the analysis? What is your final conclusion?

table1: Equation for each model.

Model	Equation
Linear model	$R \sim \text{Age} + \text{U2} + \text{X} + \text{Ex0} + \text{Ed}$
Quasibinomial	$R1 \sim \text{Age} + \text{U2} + \text{X} + \text{Ex1} + \text{LF} + \text{NW}$
Quasipoisson	$R2 \sim \text{Age} + \text{U2} + \text{X} + \text{Ex0} + \text{Ed} + \text{W}$

table2: Coefficients for each model.

Model	Coefficients
Linear model	$R = R = -2.310635 + 0.012725*\text{Age} + 0.021344*\text{Ed} + 0.012930*\text{Ex0} + 0.009798*\text{U2} + 0.006608*\text{X}$
Quasibinomial	$R1 = -224.80112 + 0.49310*\text{Age} + 0.36407*\text{Ex1} + 0.11835*\text{LF} + -0.05242*\text{NW} + 0.36543*\text{U2} + 0.25849*\text{X}$
Quasipoisson	$R2 = -2.967425 + 0.012161\text{Age} + 0.015589\text{Ed} + 0.009611\text{Ex0} + 0.007522\text{U2} + 0.002311\text{W} + 0.009295\text{X}$

table3: Frequency of significant covariates.

covariate	number of appreance
Age X	3
Ex0 Ed U2	2
Ex1 LF NW W	1

Table4: significance level of each covariate of each model. (# : Quasi)

covariate	Linear	#Bin	#Poiss
(Intercept)	.	**	*

covariate	Linear	#Bin	#Poiss
Age	*	**	*
U2	.	**	
X	***	**	***
Ex0	***		***
Ed	***		**
Ex1		***	
LF		**	
NW		**	
W			*

- Looking at Table 3 and 4, we can see 'X', The number of families per 1000 earning below 1/2 the median income, is the most significantly predictive for the crime rate. This is because the variable X is significant for all models and it's P-value is relatively smaller than other significant variables. Following X, the variable 'Age', The number of males of age 14-24 per 1000 population, is the secondly significant predictor.
- Ex0, Ed, U2 appear 2 times and their P-values are very small as long as they appear. It means economic status, Education level, and employment status(unemployment) affect on the crime rate, even though they are not crucial as the Age and X.
- We can conclude that these three types of different models lead to similar conclusions. Therefore, we are more confident about these conclusions than those based on a single model. However, there are some difference between the models one another because each model has its own assumptions which does not hold, such as dispersion parameters for logit and poisson model.
- In this case, we can say linear model fits the data the best. As we confirmed, the assumptions for the linear model hold well. On the other hand, the dispersion parameter for quasi logit model and quasi poisson model are 0.4 and 5.3, which means the assumptions do not hold well. Therefore, we conclude the linear model fits the data well.

Appendix

```
#Read Table and omit NA.
crime.dat <- read.table("~/Library/Mobile Documents/com~apple~CloudDocs/crime.dat.txt", header = T)
crime.dat<-na.omit(crime.dat)
attach(crime.dat)

#Full model test
fit1=lm(R~.,data=crime.dat)
summary(fit1)

##
## Call:
## lm(formula = R ~ ., data = crime.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -37.084 -13.299   1.818  13.953  48.498
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -753.94415   173.40191  -4.348 0.000164 ***
```

```
## Age          1.38771    0.58150    2.386 0.024011 *
## S            -3.77882   16.78753   -0.225 0.823539
## Ed           1.46481    0.80926    1.810 0.081030 .
## Ex0          1.13689    1.22329    0.929 0.360640
## Ex1         -0.12237    1.35167   -0.091 0.928510
## LF           0.06729    0.25164    0.267 0.791102
## M            0.15977    0.25792    0.619 0.540609
## N           -0.02862    0.14343   -0.200 0.843264
## NW          -0.02844    0.07612   -0.374 0.711450
## U1          -0.70749    0.52643   -1.344 0.189758
## U2           2.23189    0.98459    2.267 0.031319 *
## W            0.12587    0.11359    1.108 0.277217
## X            0.76347    0.27209    2.806 0.009025 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.14 on 28 degrees of freedom
## Multiple R-squared:  0.779, Adjusted R-squared:  0.6764
## F-statistic: 7.592 on 13 and 28 DF, p-value: 4.026e-06
```

```
#Variable selection by Stepwise
fit2 <- step(fit1, direction="both")
```

```
## Start:  AIC=274.88
## R ~ Age + S + Ed + Ex0 + Ex1 + LF + M + N + NW + U1 + U2 + W +
##      X
##
##      Df Sum of Sq  RSS    AIC
## - Ex1   1      4.4 15003 272.89
## - N      1     21.3 15020 272.94
## - S      1     27.1 15026 272.95
## - LF     1     38.3 15037 272.99
## - NW     1     74.8 15074 273.09
## - M      1    205.6 15204 273.45
## - Ex0    1    462.7 15462 274.15
## - W      1    657.8 15657 274.68
## <none>          14999 274.88
## - U1     1    967.5 15966 275.50
## - Ed     1   1755.1 16754 277.53
## - U2     1   2752.5 17752 279.95
## - Age    1   3050.7 18050 280.65
## - X      1   4217.5 19216 283.29
##
## Step:  AIC=272.89
## R ~ Age + S + Ed + Ex0 + LF + M + N + NW + U1 + U2 + W + X
##
##      Df Sum of Sq  RSS    AIC
## - N      1     21.6 15025 270.95
## - S      1     24.5 15028 270.96
## - LF     1     59.3 15063 271.06
## - NW     1     88.5 15092 271.14
## - M      1    201.2 15204 271.45
## - W      1    653.8 15657 272.68
## <none>          15003 272.89
## - U1     1    964.6 15968 273.51
```

```

## + Ex1    1      4.4 14999 274.88
## - Ed     1     1892.2 16896 275.88
## - U2     1     2827.2 17830 278.14
## - Age    1     3419.3 18423 279.51
## - X      1     4216.2 19220 281.29
## - Ex0    1     8044.7 23048 288.92
##
## Step: AIC=270.95
## R ~ Age + S + Ed + Ex0 + LF + M + NW + U1 + U2 + W + X
##
##      Df Sum of Sq  RSS    AIC
## - S    1      22.3 15047 269.01
## - LF    1      49.0 15074 269.09
## - NW    1      89.1 15114 269.20
## - M     1     359.2 15384 269.94
## - W     1     632.2 15657 270.68
## <none>          15025 270.95
## - U1    1    1080.6 16106 271.87
## + N     1      21.6 15003 272.89
## + Ex1    1       4.6 15020 272.94
## - Ed     1    1901.4 16926 273.96
## - U2     1    2851.5 17876 276.25
## - Age    1    3449.0 18474 277.63
## - X      1    4430.4 19455 279.81
## - Ex0    1    9427.3 24452 289.41
##
## Step: AIC=269.01
## R ~ Age + Ed + Ex0 + LF + M + NW + U1 + U2 + W + X
##
##      Df Sum of Sq  RSS    AIC
## - LF    1     136.8 15184 267.39
## - NW    1     170.8 15218 267.49
## - M     1     341.1 15388 267.95
## - W     1     610.6 15658 268.68
## <none>          15047 269.01
## - U1    1    1136.0 16183 270.07
## + S     1      22.3 15025 270.95
## + N     1      19.3 15028 270.96
## + Ex1    1       2.0 15045 271.01
## - Ed     1    1898.8 16946 272.00
## - U2     1    2839.1 17886 274.27
## - Age    1    3596.6 18644 276.01
## - X      1    4912.5 19960 278.88
## - Ex0    1   10406.1 25453 289.09
##
## Step: AIC=267.39
## R ~ Age + Ed + Ex0 + M + NW + U1 + U2 + W + X
##
##      Df Sum of Sq  RSS    AIC
## - NW    1     199.8 15384 265.94
## - W     1     622.3 15806 267.08
## <none>          15184 267.39
## - M     1     942.7 16127 267.92
## + LF    1     136.8 15047 269.01

```

```
## + S      1      110.1 15074 269.09
## + Ex1    1       35.3 15149 269.30
## + N      1       2.1 15182 269.39
## - U1     1     1604.4 16788 269.61
## - U2     1     2803.5 17988 272.51
## - Ed     1     3076.7 18261 273.14
## - Age    1     3730.2 18914 274.62
## - X      1     5696.8 20881 278.77
## - Ex0    1    10271.2 25455 287.09
```

```
##
```

```
## Step: AIC=265.94
```

```
## R ~ Age + Ed + Ex0 + M + U1 + U2 + W + X
```

```
##
```

	Df	Sum of Sq	RSS	AIC
## - W	1	749.8	16134	265.94
## <none>			15384	265.94
## - M	1	1050.2	16434	266.72
## + S	1	242.2	15142	267.28
## + NW	1	199.8	15184	267.39
## + LF	1	165.8	15218	267.49
## + Ex1	1	76.1	15308	267.73
## - U1	1	1464.7	16848	267.76
## + N	1	0.8	15383	267.94
## - U2	1	2610.2	17994	270.52
## - Ed	1	3284.9	18669	272.07
## - Age	1	3554.4	18938	272.67
## - X	1	5623.6	21007	277.03
## - Ex0	1	10726.5	26110	286.16

```
##
```

```
## Step: AIC=265.94
```

```
## R ~ Age + Ed + Ex0 + M + U1 + U2 + X
```

```
##
```

	Df	Sum of Sq	RSS	AIC
## <none>			16134	265.94
## + W	1	749.8	15384	265.94
## + NW	1	327.3	15806	267.08
## - M	1	1345.0	17479	267.31
## + S	1	206.4	15927	267.40
## + LF	1	189.8	15944	267.44
## + Ex1	1	78.0	16056	267.74
## + N	1	16.6	16117	267.90
## - U1	1	1972.7	18106	268.79
## - Age	1	3146.2	19280	271.42
## - U2	1	3400.3	19534	271.97
## - Ed	1	4161.6	20295	273.58
## - X	1	5559.9	21693	276.38
## - Ex0	1	18654.3	34788	296.21

```
summary(fit2)
```

```
##
```

```
## Call:
```

```
## lm(formula = R ~ Age + Ed + Ex0 + M + U1 + U2 + X, data = crime.dat)
```

```
##
```

```
## Residuals:
```

```

##      Min      1Q  Median      3Q      Max
## -41.252 -10.029   0.014  15.006  54.445
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -713.4473   139.5666  -5.112 1.23e-05 ***
## Age          1.1238     0.4364   2.575 0.01455 *
## Ed           1.7967     0.6067   2.961 0.00555 **
## Ex0          1.0798     0.1722   6.270 3.85e-07 ***
## M            0.2662     0.1581   1.684 0.10142
## U1          -0.8218     0.4030  -2.039 0.04929 *
## U2           2.3159     0.8651   2.677 0.01135 *
## X            0.5461     0.1595   3.423 0.00163 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 21.78 on 34 degrees of freedom
## Multiple R-squared:  0.7623, Adjusted R-squared:  0.7133
## F-statistic: 15.57 on 7 and 34 DF,  p-value: 5.996e-09

#Model selection ->fit2
anova(fit2, fit1)

## Analysis of Variance Table
##
## Model 1: R ~ Age + Ed + Ex0 + M + U1 + U2 + X
## Model 2: R ~ Age + S + Ed + Ex0 + Ex1 + LF + M + N + NW + U1 + U2 + W +
##      X
##   Res.Df    RSS Df Sum of Sq    F Pr(>F)
## 1      34 16134
## 2      28 14999   6    1134.7 0.353 0.9021

#drop test->comparing AIC, drop M.
drop1(fit2, test="Chi")

## Single term deletions
##
## Model:
## R ~ Age + Ed + Ex0 + M + U1 + U2 + X
##      Df Sum of Sq  RSS    AIC  Pr(>Chi)
## <none>                16134 265.94
## Age    1    3146.2 19280 271.42  0.006230 **
## Ed     1    4161.6 20295 273.58  0.001906 **
## Ex0    1   18654.3 34788 296.21 1.341e-08 ***
## M      1    1345.0 17479 267.31  0.066672 .
## U1     1    1972.7 18106 268.79  0.027726 *
## U2     1    3400.3 19534 271.97  0.004595 **
## X      1    5559.9 21693 276.38  0.000421 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

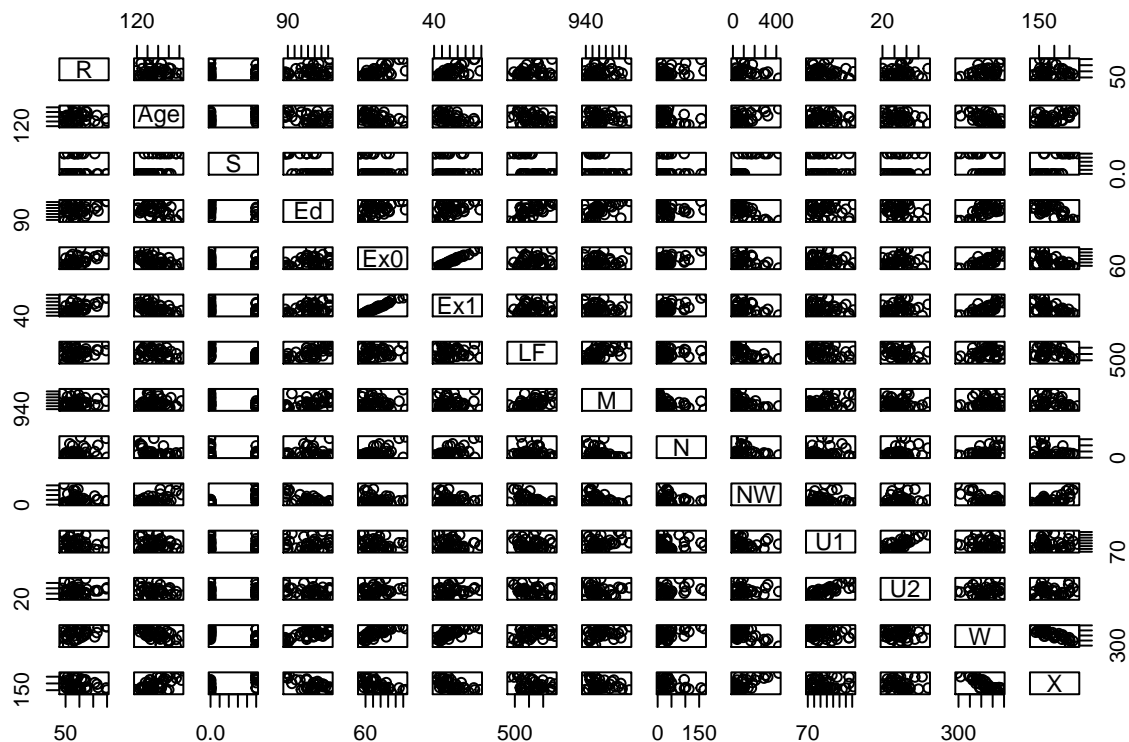
fit3<-lm(R ~ Age + Ed + Ex0 + U1 + U2 + X, data=crime.dat)
summary(fit3)

##
## Call:

```



```
## lm(formula = R ~ Age + Ed + Ex0 + U1 + U2 + X, data = crime.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -50.029 -12.701   1.412  13.178  58.768
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -548.8628   102.1876  -5.371 5.21e-06 ***
## Age           1.2143     0.4443    2.733 0.009774 **
## Ed            2.2658     0.5528    4.098 0.000235 ***
## Ex0           1.1253     0.1745    6.449 1.99e-07 ***
## U1           -0.4693     0.3533   -1.328 0.192678
## U2            1.8645     0.8438    2.210 0.033774 *
## X             0.6102     0.1589    3.839 0.000496 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22.35 on 35 degrees of freedom
## Multiple R-squared:  0.7425, Adjusted R-squared:  0.6983
## F-statistic: 16.82 on 6 and 35 DF,  p-value: 5.056e-09
#Checking correlation of two covariates.
#Check Multicollinearity by scatter plot.
#Multicollinearity searching out.
pairs(crime.dat)
```



```
cor(crime.dat)
```

```
##           R           Age           S           Ed           Ex0
## R      1.00000000 -0.06385252 -0.07019063  0.32329860  0.68928252
## Age -0.06385252  1.00000000  0.49563186 -0.39091483 -0.49264875
```

```
## S    -0.07019063  0.49563186  1.00000000 -0.64747633 -0.32045788
## Ed   0.32329860 -0.39091483 -0.64747633  1.00000000  0.43282086
## Ex0  0.68928252 -0.49264875 -0.32045788  0.43282086  1.00000000
## Ex1  0.66846426 -0.50269330 -0.32345526  0.44809353  0.99373404
## LF   0.20705534 -0.29152317 -0.58723686  0.69798059  0.15264744
## M    0.21121021  0.01526966 -0.31959407  0.46296602  0.02165309
## N    0.34127174 -0.35436566 -0.05410083 -0.01910621  0.54442047
## NW   0.05956120  0.47094928  0.76829134 -0.64603429 -0.16258262
## U1   -0.07289827 -0.08793529 -0.09174550 -0.09731568 -0.10466577
## U2   0.17420312 -0.23140870  0.10052251 -0.27269674  0.18260950
## W    0.44673029 -0.61824271 -0.57843178  0.68823067  0.77793369
## X    -0.16028052  0.59009977  0.69969529 -0.72343269 -0.60017237
##      Ex1      LF      M      N      NW
## R    0.668464257  0.2070553  0.211210205  0.34127174  0.05956120
## Age -0.502693296 -0.2915232  0.015269658 -0.35436566  0.47094928
## S    -0.323455258 -0.5872369 -0.319594067 -0.05410083  0.76829134
## Ed   0.448093527  0.6979806  0.462966021 -0.01910621 -0.64603429
## Ex0  0.993734036  0.1526474  0.021653093  0.54442047 -0.16258262
## Ex1  1.000000000  0.1377729  0.009534882  0.53579205 -0.16923348
## LF   0.137772867  1.0000000  0.565086214 -0.12012675 -0.48842912
## M    0.009534882  0.5650862  1.000000000 -0.41148463 -0.33211203
## N    0.535792054 -0.1201267 -0.411484630  1.00000000  0.10696571
## NW   -0.169233485 -0.4884291 -0.332112027  0.10696571  1.00000000
## U1   -0.114386133 -0.2457952  0.346560909 -0.03757046 -0.05142211
## U2   0.166347617 -0.4329123 -0.034433867  0.28474593  0.17986948
## W    0.786065251  0.3563029  0.171175479  0.33141816 -0.55176568
## X    -0.618469311 -0.3391087 -0.162806574 -0.13203942  0.68518986
##      U1      U2      W      X
## R    -0.07289827  0.17420312  0.44673029 -0.16028052
## Age -0.08793529 -0.23140870 -0.61824271  0.59009977
## S    -0.09174550  0.10052251 -0.57843178  0.69969529
## Ed   -0.09731568 -0.27269674  0.68823067 -0.72343269
## Ex0  -0.10466577  0.18260950  0.77793369 -0.60017237
## Ex1  -0.11438613  0.16634762  0.78606525 -0.61846931
## LF   -0.24579517 -0.43291231  0.35630295 -0.33910873
## M    0.34656091 -0.03443387  0.17117548 -0.16280657
## N    -0.03757046  0.28474593  0.33141816 -0.13203942
## NW   -0.05142211  0.17986948 -0.55176568  0.68518986
## U1    1.00000000  0.75410791 -0.04905061  0.02051815
## U2    0.75410791  1.00000000  0.07625084  0.02605951
## W    -0.04905061  0.07625084  1.00000000 -0.86974138
## X     0.02051815  0.02605951 -0.86974138  1.00000000
```

```
#I figured out U1, U2 has corralation, so I deleted U1.
fit4<-lm(R ~ Age + Ed + Ex0 + U2 + X, data=crime.dat)
summary(fit4)
```

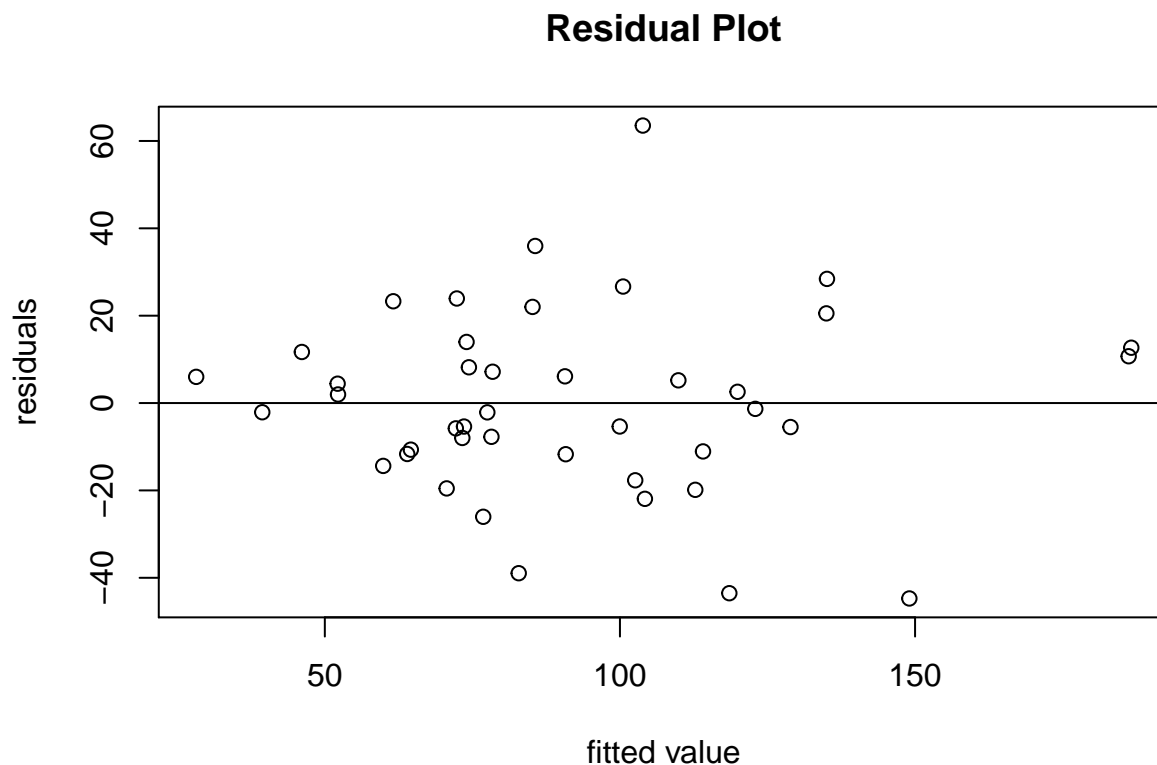
```
##
## Call:
## lm(formula = R ~ Age + Ed + Ex0 + U2 + X, data = crime.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -44.731 -11.514  -1.714   11.447   63.525
##
```

```
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) -536.8031   102.8584  -5.219 7.69e-06 ***
## Age          1.1338     0.4448   2.549 0.015213 *
## Ed           2.0046     0.5221   3.839 0.000481 ***
## Ex0          1.2429     0.1519   8.181 9.91e-10 ***
## U2           0.9285     0.4692   1.979 0.055501 .
## X            0.6277     0.1601   3.922 0.000378 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22.58 on 36 degrees of freedom
## Multiple R-squared:  0.7295, Adjusted R-squared:  0.6919
## F-statistic: 19.41 on 5 and 36 DF,  p-value: 2.455e-09

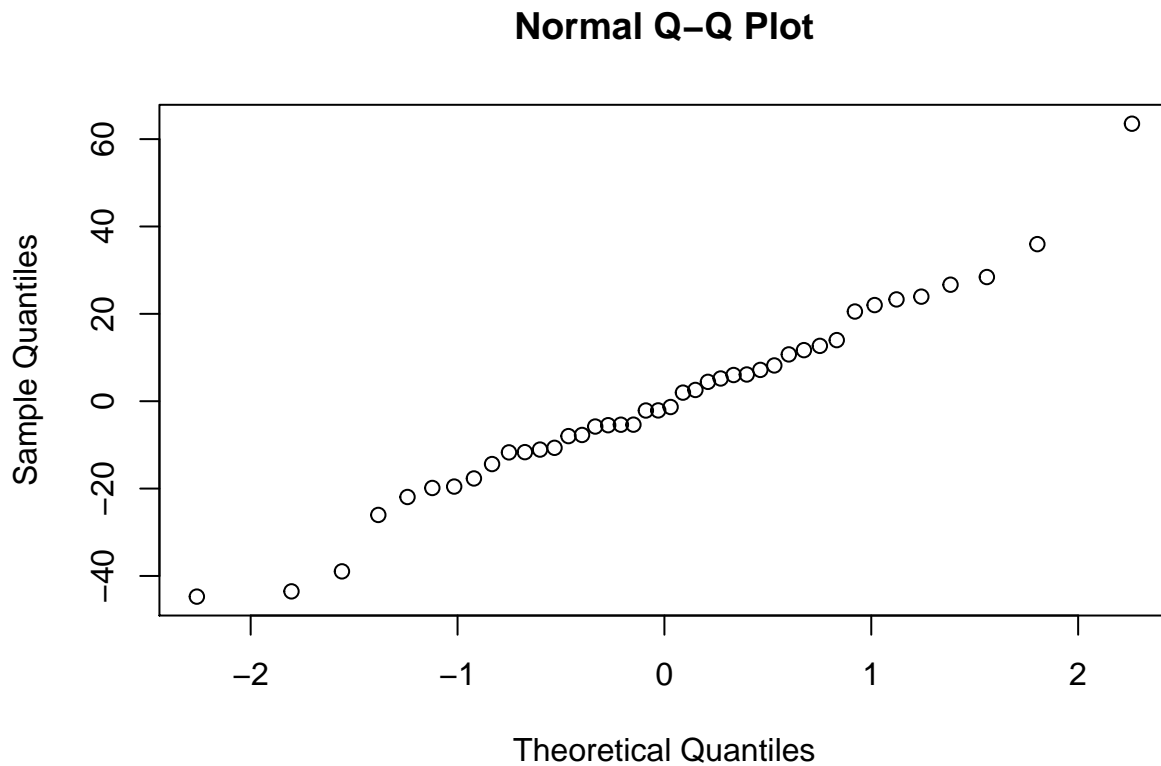
#Anova test and check which model is the best.
anova(fit4,fit3)
```

```
## Analysis of Variance Table
##
## Model 1: R ~ Age + Ed + Ex0 + U2 + X
## Model 2: R ~ Age + Ed + Ex0 + U1 + U2 + X
##   Res.Df  RSS Df Sum of Sq    F Pr(>F)
## 1      36 18360
## 2      35 17479   1    881.1 1.7644 0.1927
```

```
#Residual Plot and Normal QQ Plot.
plot(fitted(fit4), resid(fit4), main="Residual Plot",
     xlab="fitted value", ylab="residuals")
abline(a=0,b=0)
```



```
qqnorm(resid(fit4))
```

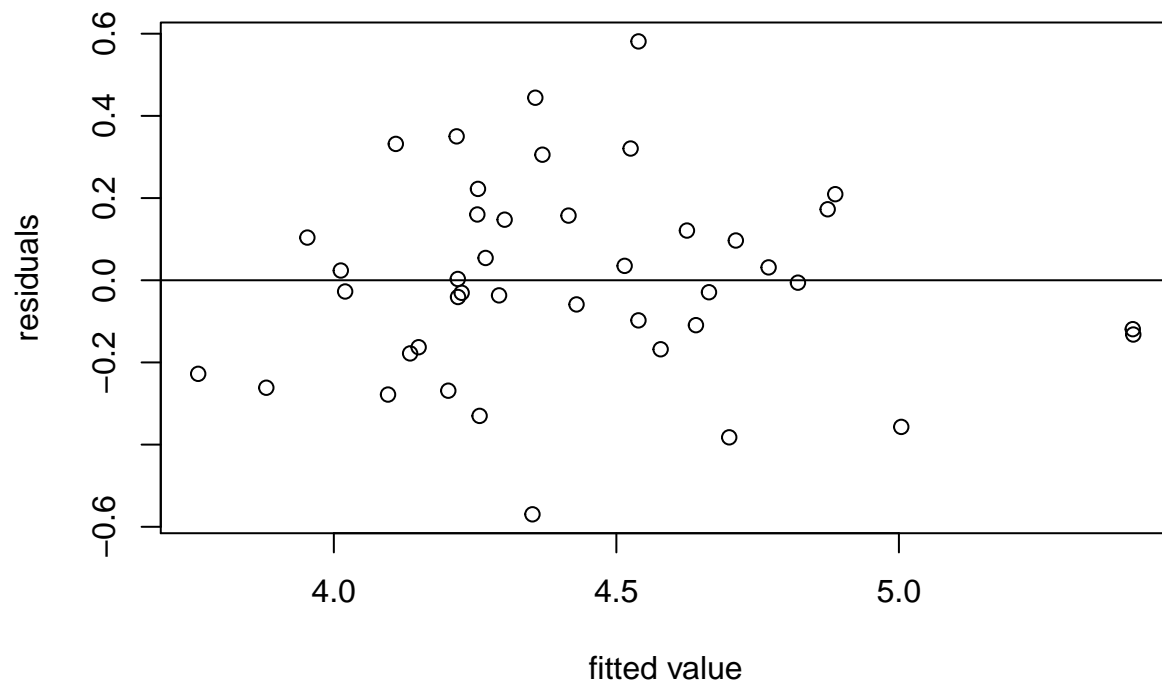


```
# Log transformation to stabilize nonconstant variance.
fit4<-lm(log(R) ~ Age + Ed + Ex0 + U2 + X, data=crime.dat)
summary(fit4)
```

```
##
## Call:
## lm(formula = log(R) ~ Age + Ed + Ex0 + U2 + X, data = crime.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.56958 -0.15524 -0.01662  0.15487  0.58120
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.310635   1.157462  -1.996 0.053508 .
## Age          0.012725   0.005005   2.542 0.015462 *
## Ed           0.021344   0.005876   3.633 0.000867 ***
## Ex0          0.012930   0.001710   7.563 6.08e-09 ***
## U2           0.009798   0.005280   1.856 0.071695 .
## X            0.006608   0.001801   3.669 0.000782 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2541 on 36 degrees of freedom
## Multiple R-squared:  0.6986, Adjusted R-squared:  0.6567
## F-statistic: 16.69 on 5 and 36 DF, p-value: 1.618e-08
```

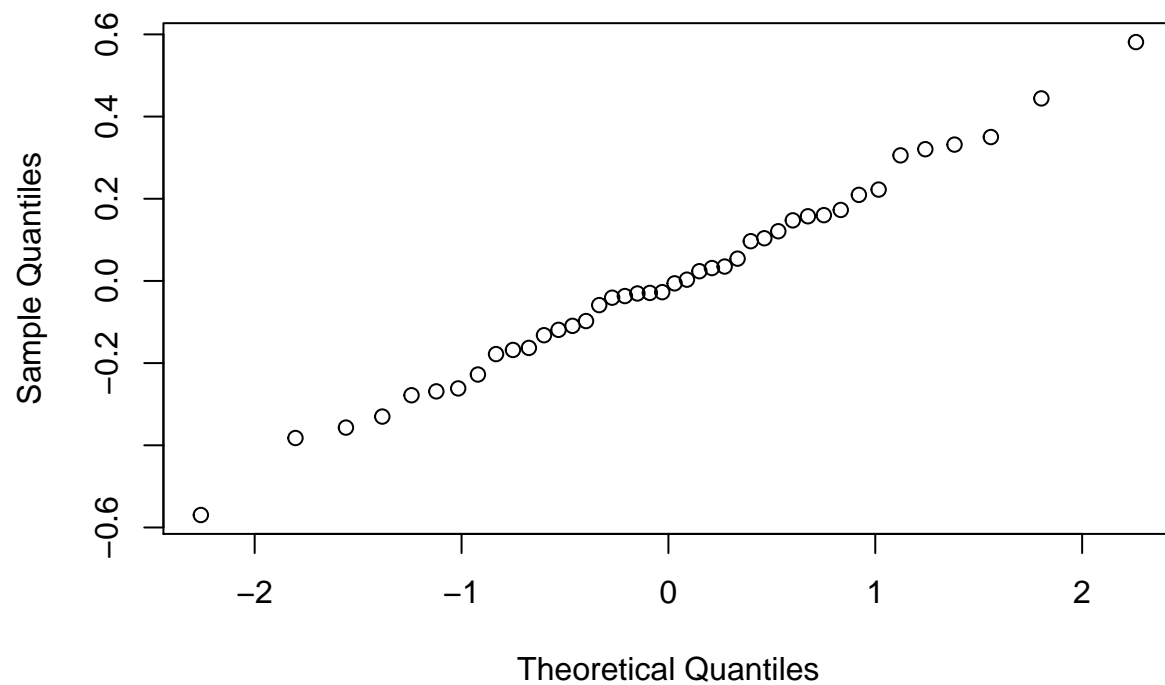
```
plot(fitted(fit4), resid(fit4), main="Residual Plot",
     xlab="fitted value", ylab="residuals")
abline(a=0,b=0)
```

Residual Plot



```
qqnorm(resid(fit4))
```

Normal Q-Q Plot



```
# It seems there is no influence point by checking cooks distance.
cooks.distance(fit4)
```

```
##           1           2           3           4           5
## 1.469253e-03 1.122841e-02 4.418245e-03 1.530801e-02 1.729170e-05
##           6           7           8           9          10
## 6.795449e-06 2.536306e-02 1.062423e-02 1.263408e-02 3.825513e-04
##          11          12          13          14          16
## 1.138008e-01 1.683962e-02 4.328750e-02 3.258476e-04 6.051160e-04
##          17          18          19          20          22
## 9.360456e-03 3.756783e-03 3.953825e-02 9.364447e-03 1.845464e-01
##          23          24          25          26          27
## 7.994543e-02 9.830452e-03 2.026034e-02 1.266108e-02 4.863364e-02
##          28          29          31          32          33
## 4.082768e-04 1.687610e-01 2.835826e-02 8.067413e-04 2.673428e-02
##          35          36          38          39          40
## 1.011021e-03 1.476792e-01 2.580152e-04 8.957792e-03 2.918426e-03
##          41          42          43          44          45
## 4.619737e-02 3.197371e-04 2.079855e-02 2.797919e-04 7.517271e-02
##          46          47
## 6.366839e-02 3.940702e-03
```

```
which(cooks.distance(fit4)>1)
```

```
## named integer(0)
```

```
#####Binomial Logit model.#####
```

```
# Nonconverging logit GLM
```

```
R1<-as.numeric(R>105)
```

```
fit1_bin<-glm(R1~.-R,family=binomial,data=crime.dat)
```

```
## Warning: glm.fit: algorithm did not converge
```

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

```
summary(fit1_bin)
```

```
##
```

```
## Call:
```

```
## glm(formula = R1 ~ . - R, family = binomial, data = crime.dat)
```

```
##
```

```
## Deviance Residuals:
```

```
##           Min           1Q           Median           3Q           Max
## -2.101e-05 -2.110e-08 -2.110e-08  2.110e-08  2.163e-05
```

```
##
```

```
## Coefficients:
```

```
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.555e+03 1.826e+06 -0.001  0.999
## Age         6.172e+00 5.277e+03  0.001  0.999
## S           3.456e+01 1.171e+05  0.000  1.000
## Ed          6.155e-02 6.552e+03  0.000  1.000
## Ex0         2.021e+00 5.144e+03  0.000  1.000
## Ex1         2.714e+00 6.356e+03  0.000  1.000
## LF          2.085e+00 2.026e+03  0.001  0.999
## M          -9.660e-01 1.723e+03 -0.001  1.000
## N          -7.047e-01 1.197e+03 -0.001  1.000
```

```

## NW          -6.412e-01  6.642e+02  -0.001    0.999
## U1          -1.408e+00  2.366e+03  -0.001    1.000
## U2           7.340e+00  7.361e+03   0.001    0.999
## W           4.749e-01  8.717e+02   0.001    1.000
## X           3.812e+00  3.733e+03   0.001    0.999
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 5.0255e+01  on 41  degrees of freedom
## Residual deviance: 3.5072e-09  on 28  degrees of freedom
## AIC: 28
##
## Number of Fisher Scoring iterations: 25
# stepwise. But still nonconverging.
fit2_bin <- step(fit1_bin, direction="both")

## Start:  AIC=28
## R1 ~ (R + Age + S + Ed + Ex0 + Ex1 + LF + M + N + NW + U1 + U2 +
##      W + X) - R
## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge

```

[illegible]

[illegible]

```

## - M      1      0.000 22.000
## - U1     1      0.000 22.000
## - W      1      0.000 22.000
## - Ex1    1      0.000 22.000
## - N      1      0.000 22.000
## <none>    0.000 24.000
## + S      1      0.000 26.000
## + Ed     1      0.000 26.000
## - U2     1     13.863 35.863
## - NW     1     17.794 39.794
## - LF     1     18.347 40.347
## - Age    1     20.934 42.934
## - X      1     26.578 48.577

## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Step:  AIC=22
## R1 ~ Age + Ex1 + LF + M + N + NW + U1 + U2 + W + X

## Warning: glm.fit: algorithm did not converge

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##          Df Deviance    AIC
## - W      1      0.000 20.000
## - U1     1      0.000 20.000
## - N      1      0.000 20.000
## - M      1      0.000 20.000
## <none>    0.000 22.000
## + Ex0    1      0.000 24.000
## + Ed     1      0.000 24.000
## + S      1      0.000 24.000

```



```

## Warning: glm.fit: algorithm did not converge

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

## Warning: glm.fit: algorithm did not converge

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

## Warning: glm.fit: algorithm did not converge

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

## Warning: glm.fit: algorithm did not converge

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

## Warning: glm.fit: algorithm did not converge

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

## Warning: glm.fit: algorithm did not converge

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

## Warning: glm.fit: algorithm did not converge

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

##           Df Deviance   AIC
## <none>          0.000 16.000
## + M           1    0.000 18.000
## + Ex0          1    0.000 18.000
## + S            1    0.000 18.000
## + W            1    0.000 18.000
## + Ed           1    0.000 18.000
## + N            1    0.000 18.000
## - U1           1   14.925 28.925
## - U2           1   22.827 36.827
## - NW           1   23.203 37.203
## - LF           1   26.015 40.015
## - Age          1   28.406 42.406
## - X            1   32.277 46.277
## - Ex1          1   40.340 54.340

summary(fit2_bin)

##
## Call:
## glm(formula = R1 ~ Age + Ex1 + LF + NW + U1 + U2 + X, family = binomial,
##      data = crime.dat)
##
## Deviance Residuals:
##           Min           1Q       Median           3Q           Max
## -1.624e-04  -2.100e-08  -2.100e-08   2.100e-08   1.497e-04
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.981e+04  4.173e+06  -0.007   0.994
## Age          6.292e+01  8.893e+03   0.007   0.994
## Ex1          4.703e+01  6.593e+03   0.007   0.994
## LF           1.703e+01  2.376e+03   0.007   0.994

```

```
## NW          -7.794e+00  1.128e+03 -0.007    0.994
## U1          -1.681e+01  2.434e+03 -0.007    0.994
## U2           7.053e+01  9.971e+03  0.007    0.994
## X            3.730e+01  5.235e+03  0.007    0.994
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 5.0255e+01  on 41  degrees of freedom
## Residual deviance: 1.1303e-07  on 34  degrees of freedom
## AIC: 16
##
## Number of Fisher Scoring iterations: 25
```

```
#Comparing AIC by drop1
drop1(fit2_bin, test = "Chisq")
```

```
## Single term deletions
##
## Model:
## R1 ~ Age + Ex1 + LF + NW + U1 + U2 + X
##      Df Deviance    AIC    LRT  Pr(>Chi)
## <none>      0.000 16.000
## Age      1   28.406 42.406 28.406 9.837e-08 ***
## Ex1      1   40.340 54.340 40.340 2.134e-10 ***
## LF       1   26.015 40.015 26.015 3.387e-07 ***
## NW       1   23.203 37.203 23.203 1.458e-06 ***
## U1       1   14.925 28.925 14.925 0.0001119 ***
## U2       1   22.827 36.827 22.827 1.772e-06 ***
## X        1   32.277 46.277 32.277 1.337e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#deleting U1 increase smallest AIC and cure multicollinearity between U1 and U2.
fit3_bin<-glm(R1 ~ Age + Ex1 + LF + NW + U2 + X,family=binomial,data=crime.dat)
summary(fit3_bin)
```

```
##
## Call:
## glm(formula = R1 ~ Age + Ex1 + LF + NW + U2 + X, family = binomial,
##      data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.61813  -0.17334  -0.00911   0.00064   1.89104
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -224.80112    99.85226  -2.251  0.0244 *
## Age           0.49310     0.23287   2.117  0.0342 *
## Ex1           0.36407     0.15493   2.350  0.0188 *
## LF           0.11835     0.05567   2.126  0.0335 *
## NW          -0.05242     0.02409  -2.175  0.0296 *
## U2           0.36543     0.18594   1.965  0.0494 *
## X            0.25849     0.11386   2.270  0.0232 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 50.255 on 41 degrees of freedom
## Residual deviance: 14.925 on 35 degrees of freedom
## AIC: 28.925
##
## Number of Fisher Scoring iterations: 8
#Comparing AIC-> it seems if we drop one more covariate, AIC increase too much.
drop1(fit3_bin)# we keep this model.

## Single term deletions
##
## Model:
## R1 ~ Age + Ex1 + LF + NW + U2 + X
##      Df Deviance    AIC
## <none>      14.925 28.925
## Age      1  28.799 40.799
## Ex1      1  46.596 58.596
## LF       1  26.545 38.545
## NW       1  25.430 37.430
## U2       1  23.604 35.604
## X        1  34.369 46.369

which(cooks.distance(fit3_bin)>1)

## 29 36
## 27 32
#we check the dispersion parameter, By using quasibinomial.
fit4_bin_quasi<-glm(R1 ~ Age + Ex1 + LF + NW + U2 + X,family=quasibinomial,data=crime.dat)
summary(fit4_bin_quasi)#As quasibinomial's dispersion parameter is 0.4, we should use quasibinomial.

##
## Call:
## glm(formula = R1 ~ Age + Ex1 + LF + NW + U2 + X, family = quasibinomial,
##      data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.61813  -0.17334  -0.00911   0.00064   1.89104
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -224.80112    63.60497  -3.534  0.00117 **
## Age           0.49310     0.14834   3.324  0.00209 **
## Ex1           0.36407     0.09869   3.689  0.00076 ***
## LF            0.11835     0.03546   3.338  0.00201 **
## NW           -0.05242     0.01535  -3.415  0.00163 **
## U2            0.36543     0.11844   3.085  0.00396 **
## X             0.25849     0.07253   3.564  0.00108 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasibinomial family taken to be 0.4057573)
```

```
##
## Null deviance: 50.255 on 41 degrees of freedom
## Residual deviance: 14.925 on 35 degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 8
# we cannot say the assumptions for logit model hold well.

# It seems there some influence points by checking cooks distance. As there are more than 4, we regard
cooks.distance(fit4_bin_quasi)

##          1          2          3          4          5
## 5.532683e-03 2.042198e-06 5.323739e-09 1.128879e-12 2.258090e-02
##          6          7          8          9         10
## 1.045516e-14 2.629471e-18 1.956729e-01 2.620058e-02 4.612444e-03
##         11         12         13         14         16
## 1.037216e+00 2.277876e-08 1.121336e-03 8.913233e-08 1.447586e-03
##         17         18         19         20         22
## 1.804167e-10 5.962644e-06 3.028836e-04 4.983574e-01 6.404031e-08
##         23         24         25         26         27
## 6.621986e-03 5.099907e-06 3.916894e-06 5.193960e-14 1.463504e-20
##         28         29         31         32         33
## 2.991610e-06 7.016697e+00 1.426091e-06 3.605931e-09 1.362818e-01
##         35         36         38         39         40
## 1.218351e-12 3.471215e+00 1.025251e-04 4.606454e-02 1.293005e-03
##         41         42         43         44         45
## 5.100727e-11 1.152671e-13 3.151436e-01 3.192873e-02 1.932307e-02
##         46         47
## 4.807947e-04 1.780308e+00

which(cooks.distance(fit4_bin_quasi)>1)

## 11 29 36 47
## 11 27 32 42

#
#####Poisson#####
# Change response variable.
R2<-round(R,digits=0)

#Full model-> many insignificant covariates exist.
fit1_poi<-glm(R2~.-R,family=poisson,data=crime.dat)
summary(fit1_poi)

##
## Call:
## glm(formula = R2 ~ . - R, family = poisson, data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.7355  -1.2341   0.0658   1.1255   4.3997
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.0141649  0.7310482  -4.123 3.74e-05 ***
```



```

## Age          0.0156173  0.0026862   5.814 6.11e-09 ***
## S            0.0253864  0.0753745   0.337  0.7363
## Ed           0.0155140  0.0038996   3.978 6.94e-05 ***
## Ex0          0.0076323  0.0053997   1.413  0.1575
## Ex1          0.0025791  0.0061120   0.422  0.6730
## LF           0.0020777  0.0011782   1.763  0.0778 .
## M            -0.0015422  0.0012046  -1.280  0.2005
## N            -0.0010813  0.0005883  -1.838  0.0660 .
## NW           -0.0003319  0.0003683  -0.901  0.3674
## U1           -0.0053533  0.0023458  -2.282  0.0225 *
## U2           0.0219713  0.0043048   5.104 3.33e-07 ***
## W            0.0021971  0.0005283   4.159 3.20e-05 ***
## X            0.0094817  0.0012779   7.420 1.17e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
## Null deviance: 696.75  on 41  degrees of freedom
## Residual deviance: 159.16  on 28  degrees of freedom
## AIC: 450.41
##
## Number of Fisher Scoring iterations: 4
# stepwise method for variable selection.
fit2_poi <- step(fit1_poi, direction="both")

## Start:  AIC=450.41
## R2 ~ (R + Age + S + Ed + Ex0 + Ex1 + LF + M + N + NW + U1 + U2 +
##      W + X) - R
##
##      Df Deviance    AIC
## - S      1   159.28 448.52
## - Ex1    1   159.34 448.58
## - NW     1   159.98 449.22
## - M      1   160.81 450.05
## <none>    1   159.16 450.41
## - Ex0    1   161.17 450.42
## - LF     1   162.27 451.51
## - N      1   162.56 451.80
## - U1     1   164.38 453.63
## - Ed     1   175.11 464.35
## - W      1   176.56 465.80
## - U2     1   185.57 474.81
## - Age    1   192.86 482.11
## - X      1   213.26 502.50
##
## Step:  AIC=448.52
## R2 ~ Age + Ed + Ex0 + Ex1 + LF + M + N + NW + U1 + U2 + W + X
##
##      Df Deviance    AIC
## - Ex1    1   159.41 446.66
## - NW     1   159.99 447.23
## - M      1   160.82 448.06
## <none>    1   159.28 448.52

```

```

## - Ex0    1    161.42 448.66
## - N      1    162.69 449.93
## - LF     1    162.95 450.19
## + S      1    159.16 450.41
## - U1     1    166.27 453.51
## - Ed     1    176.82 464.06
## - W      1    177.08 464.32
## - U2     1    186.41 473.66
## - Age    1    194.05 481.29
## - X      1    219.81 507.05
##
## Step:  AIC=446.66
## R2 ~ Age + Ed + Ex0 + LF + M + N + NW + U1 + U2 + W + X
##
##           Df Deviance    AIC
## - NW      1    160.04 445.28
## - M        1    160.97 446.21
## <none>      159.41 446.66
## - N        1    162.74 447.98
## - LF       1    163.10 448.34
## + Ex1      1    159.28 448.52
## + S        1    159.34 448.58
## - U1       1    166.53 451.78
## - W        1    177.60 462.85
## - Ed       1    181.28 466.52
## - U2       1    186.47 471.71
## - Age      1    195.30 480.54
## - X        1    219.90 505.14
## - Ex0      1    237.62 522.87
##
## Step:  AIC=445.28
## R2 ~ Age + Ed + Ex0 + LF + M + N + U1 + U2 + W + X
##
##           Df Deviance    AIC
## - M        1    161.60 444.85
## <none>      160.04 445.28
## - N        1    163.29 446.53
## + NW       1    159.41 446.66
## + Ex1      1    159.99 447.23
## + S        1    160.02 447.27
## - LF       1    164.12 447.37
## - U1       1    166.64 449.88
## - W        1    179.38 462.63
## - Ed       1    182.88 466.12
## - U2       1    186.69 469.94
## - Age      1    195.49 478.73
## - X        1    224.55 507.79
## - Ex0      1    242.05 525.29
##
## Step:  AIC=444.85
## R2 ~ Age + Ed + Ex0 + LF + N + U1 + U2 + W + X
##
##           Df Deviance    AIC
## - N        1    163.33 444.58

```

```
## <none>      161.60 444.85
## + M        1  160.04 445.28
## - LF       1  164.12 445.37
## + NW       1  160.97 446.21
## + S        1  161.36 446.61
## + Ex1      1  161.54 446.79
## - U1       1  176.47 457.71
## - W        1  179.57 460.82
## - Ed       1  183.56 464.80
## - U2       1  189.65 470.89
## - Age      1  196.54 477.78
## - X        1  225.85 507.09
## - Ex0      1  249.40 530.64
```

```
##
```

```
## Step: AIC=444.58
```

```
## R2 ~ Age + Ed + Ex0 + LF + U1 + U2 + W + X
```

```
##
```

```
##      Df Deviance   AIC
## <none>      163.33 444.58
## + N        1  161.60 444.85
## + NW       1  162.78 446.02
## + M        1  163.29 446.53
## + S        1  163.32 446.56
## + Ex1      1  163.32 446.57
## - LF       1  167.61 446.85
## - U1       1  177.63 456.87
## - W        1  179.72 458.96
## - Ed       1  184.55 463.79
## - U2       1  191.44 470.68
## - Age      1  206.25 485.50
## - X        1  228.35 507.60
## - Ex0      1  251.31 530.55
```

```
summary(fit2_poi)#formula = R2 ~ Age + Ed + Ex0 + LF + U1 + U2 + W + X
```

```
##
```

```
## Call:
```

```
## glm(formula = R2 ~ Age + Ed + Ex0 + LF + U1 + U2 + W + X, family = poisson,
##      data = crime.dat)
```

```
##
```

```
## Deviance Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -3.4850 -1.3918  0.0021  1.1219  4.1006
```

```
##
```

```
## Coefficients:
```

```
##      Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.5084194  0.5675745  -6.181 6.35e-10 ***
## Age          0.0144503  0.0021869   6.608 3.91e-11 ***
## Ed           0.0159117  0.0034594   4.600 4.23e-06 ***
## Ex0          0.0086052  0.0009136   9.419 < 2e-16 ***
## LF           0.0013713  0.0006634   2.067 0.038739 *
## U1          -0.0066845  0.0017783  -3.759 0.000171 ***
## U2           0.0217280  0.0041314   5.259 1.45e-07 ***
## W            0.0020099  0.0004985   4.032 5.53e-05 ***
## X            0.0083884  0.0010567   7.939 2.05e-15 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 696.75  on 41  degrees of freedom
## Residual deviance: 163.33  on 33  degrees of freedom
## AIC: 444.58
##
## Number of Fisher Scoring iterations: 4
drop1(fit2_poi)#AIC comparing- dropping LF increase very small amount of AIC.

## Single term deletions
##
## Model:
## R2 ~ Age + Ed + Ex0 + LF + U1 + U2 + W + X
##      Df Deviance    AIC
## <none>      163.33 444.58
## Age      1    206.25 485.50
## Ed       1    184.55 463.79
## Ex0      1    251.31 530.55
## LF       1    167.61 446.85
## U1       1    177.63 456.87
## U2       1    191.44 470.68
## W        1    179.72 458.96
## X        1    228.35 507.60
#smaller model without LF, as the fit3 model.
fit3_poi<-glm(R2 ~ Age + Ed + Ex0 + U1 + U2 + W + X,family=poisson,data=crime.dat)
summary(fit3_poi)

##
## Call:
## glm(formula = R2 ~ Age + Ed + Ex0 + U1 + U2 + W + X, family = poisson,
##      data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.6629  -1.6059  -0.1006   1.3050   4.3640
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.1501881  0.5371649  -5.864 4.51e-09 ***
## Age          0.0132097  0.0021080   6.266 3.70e-10 ***
## Ed           0.0202276  0.0027580   7.334 2.23e-13 ***
## Ex0          0.0083517  0.0008991   9.289 < 2e-16 ***
## U1          -0.0067829  0.0017716  -3.829 0.000129 ***
## U2           0.0206477  0.0040942   5.043 4.58e-07 ***
## W            0.0021321  0.0004913   4.340 1.43e-05 ***
## X            0.0090396  0.0010070   8.977 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
```

```
##
## Null deviance: 696.75 on 41 degrees of freedom
## Residual deviance: 167.61 on 34 degrees of freedom
## AIC: 446.85
##
## Number of Fisher Scoring iterations: 4
#ANOVA test of fit3_poi and fit2_poi
anova(fit3_poi,fit2_poi)# 4.2712 is the Deviance.

## Analysis of Deviance Table
##
## Model 1: R2 ~ Age + Ed + Ex0 + U1 + U2 + W + X
## Model 2: R2 ~ Age + Ed + Ex0 + LF + U1 + U2 + W + X
## Resid. Df Resid. Dev Df Deviance
## 1 34 167.61
## 2 33 163.33 1 4.2712

qchisq(0.95,1) # quantile of chisq is 3.84. 4.27>3.84.

## [1] 3.841459
#So we reject the null hypothesis. we accept the model without LF.
drop1(fit3_poi)

## Single term deletions
##
## Model:
## R2 ~ Age + Ed + Ex0 + U1 + U2 + W + X
## Df Deviance AIC
## <none> 167.61 446.85
## Age 1 206.32 483.57
## Ed 1 221.85 499.10
## Ex0 1 252.57 529.81
## U1 1 182.44 459.69
## U2 1 193.42 470.66
## W 1 186.66 463.91
## X 1 252.02 529.26

fit4_poi<-glm(R2 ~ Age + Ed + Ex0 + U2 + W + X,family=poisson,data=crime.dat)
summary(fit4_poi) # tried a model without U1, as U1 increase AIC a little and has multicollinearity with

##
## Call:
## glm(formula = R2 ~ Age + Ed + Ex0 + U2 + W + X, family = poisson,
## data = crime.dat)
##
## Deviance Residuals:
## Min 1Q Median 3Q Max
## -3.517 -1.574 -0.409 1.207 5.028
##
## Coefficients:
## Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.9674251 0.5295779 -5.603 2.10e-08 ***
## Age 0.0121605 0.0021131 5.755 8.67e-09 ***
## Ed 0.0155893 0.0024813 6.283 3.33e-10 ***
## Ex0 0.0096107 0.0008400 11.441 < 2e-16 ***
```

```
## U2          0.0075216  0.0022144   3.397 0.000682 ***
## W           0.0023109  0.0004942   4.676 2.93e-06 ***
## X           0.0092949  0.0010098   9.205 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##      Null deviance: 696.75  on 41  degrees of freedom
## Residual deviance: 182.44  on 35  degrees of freedom
## AIC: 459.69
##
## Number of Fisher Scoring iterations: 4
```

```
drop1(fit4_poi)
```

```
## Single term deletions
##
## Model:
## R2 ~ Age + Ed + Ex0 + U2 + W + X
##      Df Deviance   AIC
## <none>      182.44 459.69
## Age      1    215.27 490.52
## Ed       1    222.31 497.56
## Ex0      1    309.52 584.76
## U2       1    193.91 469.16
## W        1    204.54 479.78
## X        1    271.16 546.41
```

```
anova(fit4_poi,fit3_poi)
```

```
## Analysis of Deviance Table
##
## Model 1: R2 ~ Age + Ed + Ex0 + U2 + W + X
## Model 2: R2 ~ Age + Ed + Ex0 + U1 + U2 + W + X
##   Resid. Df Resid. Dev Df Deviance
## 1         35      182.44
## 2         34      167.61  1    14.838
```

```
qchisq(0.95,1) # quantile of chisq is 3.84. 14.8>3.84. So we reject the null. we accept the model
```

```
## [1] 3.841459
```

```
# without U1. we choose fit4_poi.
```

```
#Model diagnose:dispersion parameter
```

```
fit4_poi_quasi<-glm(R2 ~ Age + Ed + Ex0+ U2+W + X,family=quasipoisson,data=crime.dat)
```

```
summary(fit4_poi_quasi)#Dispersion parameter for quasipoisson family taken to be 5.304443.
```

```
##
## Call:
## glm(formula = R2 ~ Age + Ed + Ex0 + U2 + W + X, family = quasipoisson,
##      data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -3.517 -1.574 -0.409 1.207 5.028
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.967425  1.219691 -2.433 0.020227 *
## Age          0.012161  0.004867  2.499 0.017310 *
## Ed           0.015589  0.005715  2.728 0.009898 **
## Ex0          0.009611  0.001935  4.968 1.77e-05 ***
## U2           0.007522  0.005100  1.475 0.149207
## W            0.002311  0.001138  2.030 0.049986 *
## X            0.009295  0.002326  3.997 0.000315 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasipoisson family taken to be 5.304443)
##
## Null deviance: 696.75  on 41  degrees of freedom
## Residual deviance: 182.44  on 35  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4
```

```
#We cannot say that the assumptions for Poisson model hold well.
```

```
# It seems there is no influence point by checking cooks distance.
cooks.distance(fit4_poi_quasi)
```

```
##           1           2           3           4           5
## 5.607916e-03 2.092952e-02 8.355758e-03 6.446133e-02 6.393130e-04
##           6           7           8           9          10
## 6.826866e-03 1.401040e-02 2.911889e-01 2.968060e-03 9.913456e-05
##          11          12          13          14          16
## 2.550304e-01 7.694710e-03 3.321231e-02 2.052558e-03 3.900605e-05
##          17          18          19          20          22
## 1.044094e-03 1.727563e-02 2.803781e-02 5.651241e-03 9.417397e-02
##          23          24          25          26          27
## 6.722239e-02 1.503405e-02 9.177843e-03 4.317772e-03 1.155282e-02
##          28          29          31          32          33
## 3.751006e-03 2.055620e-01 9.356117e-03 1.062677e-03 1.603135e-02
##          35          36          38          39          40
## 6.068819e-04 3.825622e-01 5.227394e-06 3.122543e-03 1.059203e-03
##          41          42          43          44          45
## 2.922631e-02 5.183314e-05 9.384296e-02 2.350365e-03 1.316548e-01
##          46          47
## 4.922729e-02 1.835852e-03
```

```
which(cooks.distance(fit4_poi_quasi)>1)
```

```
## named integer(0)
```

```
#For linear model R ~ Age + Ed + Ex0 + U2 + X,
#QuasibinomialR1 ~ Age + Ex1 + LF + NW + U2 + X,
#Quasipoisson R2 ~ Age + Ed + Ex0 +U2 + W + X
```

```
summary(fit4)
```

```
##
## Call:
## lm(formula = log(R) ~ Age + Ed + Ex0 + U2 + X, data = crime.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.56958 -0.15524 -0.01662  0.15487  0.58120
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.310635   1.157462  -1.996 0.053508 .
## Age          0.012725   0.005005   2.542 0.015462 *
## Ed           0.021344   0.005876   3.633 0.000867 ***
## Ex0          0.012930   0.001710   7.563 6.08e-09 ***
## U2           0.009798   0.005280   1.856 0.071695 .
## X            0.006608   0.001801   3.669 0.000782 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2541 on 36 degrees of freedom
## Multiple R-squared:  0.6986, Adjusted R-squared:  0.6567
## F-statistic: 16.69 on 5 and 36 DF,  p-value: 1.618e-08
summary(fit4_bin_quasi)

##
## Call:
## glm(formula = R1 ~ Age + Ex1 + LF + NW + U2 + X, family = quasibinomial,
##      data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.61813  -0.17334  -0.00911   0.00064   1.89104
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -224.80112   63.60497  -3.534 0.00117 **
## Age          0.49310    0.14834   3.324 0.00209 **
## Ex1          0.36407    0.09869   3.689 0.00076 ***
## LF           0.11835    0.03546   3.338 0.00201 **
## NW          -0.05242    0.01535  -3.415 0.00163 **
## U2           0.36543    0.11844   3.085 0.00396 **
## X            0.25849    0.07253   3.564 0.00108 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasibinomial family taken to be 0.4057573)
##
##      Null deviance: 50.255  on 41  degrees of freedom
## Residual deviance: 14.925  on 35  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 8
```



```
summary(fit4_poi_quasi)
```

```
##
## Call:
## glm(formula = R2 ~ Age + Ed + Ex0 + U2 + W + X, family = quasipoisson,
##      data = crime.dat)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -3.517  -1.574  -0.409   1.207   5.028
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.967425   1.219691  -2.433 0.020227 *
## Age          0.012161   0.004867   2.499 0.017310 *
## Ed           0.015589   0.005715   2.728 0.009898 **
## Ex0          0.009611   0.001935   4.968 1.77e-05 ***
## U2           0.007522   0.005100   1.475 0.149207
## W            0.002311   0.001138   2.030 0.049986 *
## X            0.009295   0.002326   3.997 0.000315 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for quasipoisson family taken to be 5.304443)
##
##      Null deviance: 696.75  on 41  degrees of freedom
## Residual deviance: 182.44  on 35  degrees of freedom
## AIC: NA
##
## Number of Fisher Scoring iterations: 4
```