# Nonlinear Regression

Jing Bu

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# 1 Nonlinear Regression Functions:

## 1.1 Introduction

- We extend nonlinear into two cases

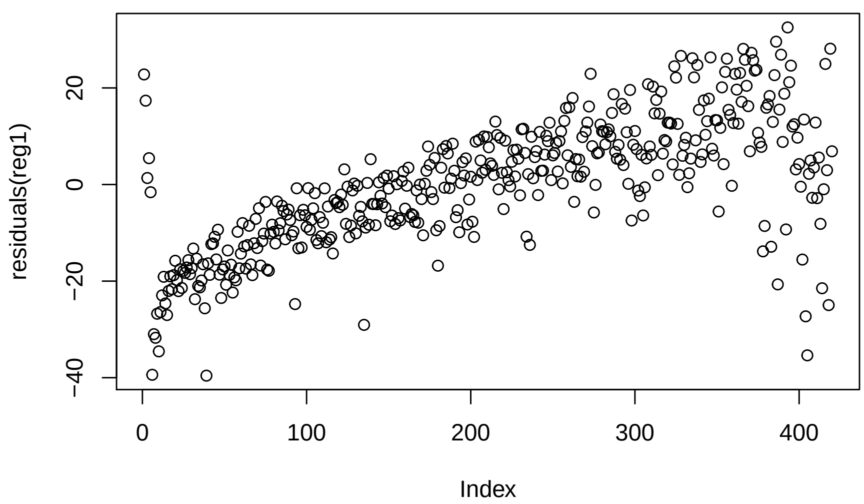
1. nonlinear in Xs
    - Logarithms and Interactions
2. nonlinear in function
    - Discrete Dependent Variables or Limited Dependent Variables
    - Linear function is not a good prediciton function.

## 1.2 Heteroscedasticity

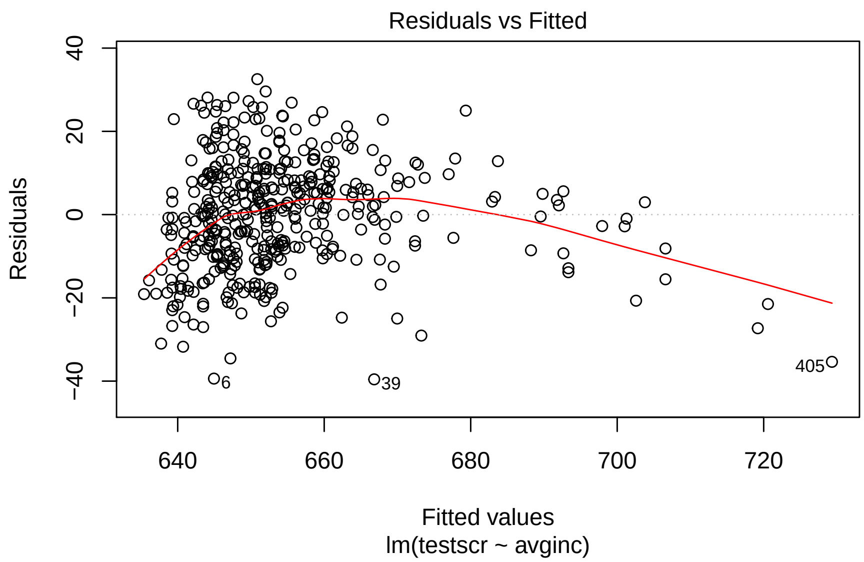
### 1.2.1 Plot

```
library("foreign")
caschool<-read.dta("/Users/admin/Desktop/teaching assiatant/Econometrics/teaching assis
```

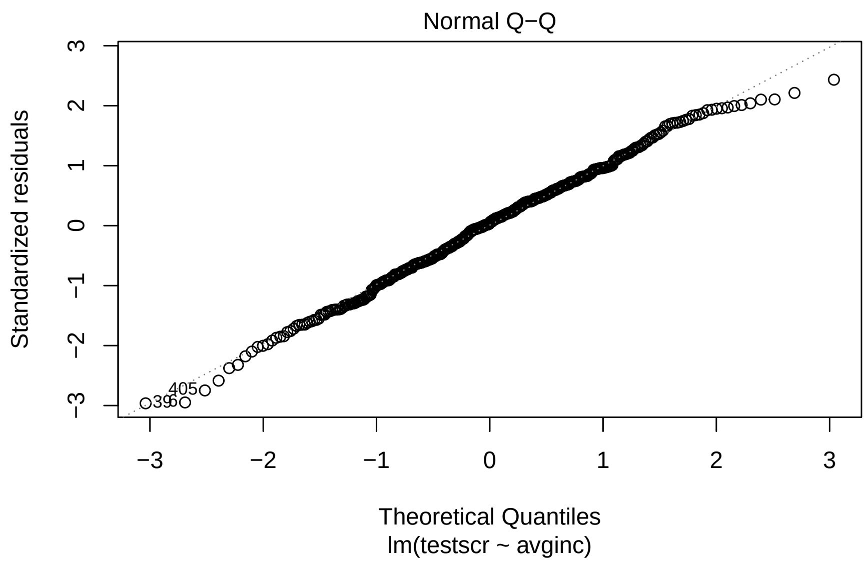
```
reg1<-lm(testscr ~ avginc,data=caschool)
plot(residuals(reg1))
```



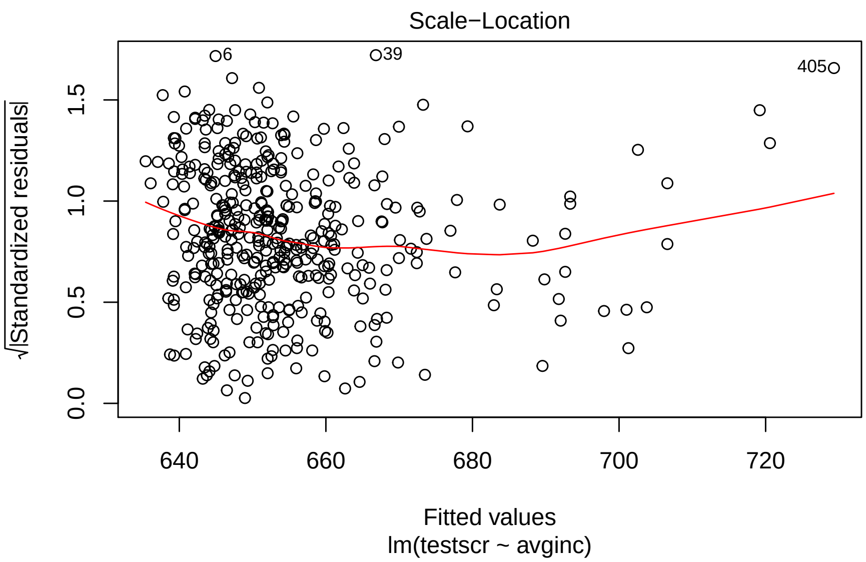

```
plot(reg1)
```

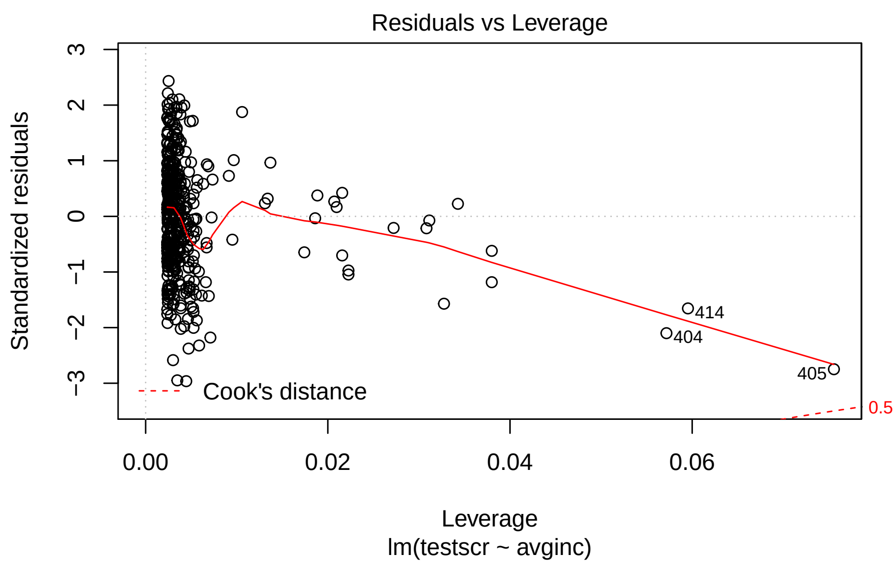


Residuals vs Fitted
Residuals
40
20
0
−20
−40
6
39
405
640
660
680
700
720
Fitted values
lm(testscr ~ avginc)

Normal Q−Q
Standardized residuals
3
2
1
0
−1
−2
−3
39
6
405
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(testscr ~ avginc)


Scale−Location
6
39
405
√|Standardized residuals|
0.0
0.5
1.0
1.5
640
660
680
700
720
Fitted values
lm(testscr ~ avginc)


Residuals vs Leverage
414
404
405
Cook's distance
0.5
Standardized residuals
−3
−2
−1
0
1
2
3
0.00
0.02
0.04
0.06
Leverage
lm(testscr ~ avginc)

#### 1.2.2 Test Heteroscedasticity

```
#install.packages("lmtest",repos="https://mirrors.ustc.edu.cn/CRAN/")
library("lmtest")
```

```
## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
reg2<-lm(testscr ~ avginc,data=caschool)
bptest(reg2)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  reg2
## BP = 0.078688, df = 1, p-value = 0.7791
```

```
summary(reg2)
```

```
##
## Call:
## lm(formula = testscr ~ avginc, data = caschool)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -39.574  -8.803   0.603   9.032  32.530
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 625.3836     1.5324  408.11   <2e-16 ***
## avginc        1.8785     0.0905   20.76   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.39 on 418 degrees of freedom
## Multiple R-squared:  0.5076, Adjusted R-squared:  0.5064
## F-statistic: 430.8 on 1 and 418 DF,  p-value: < 2.2e-16
```

```
avginc_log<-exp(caschool$avginc)
reg3<-lm(testscr ~ avginc_log,data=caschool)
bptest(reg3)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  reg3
## BP = 0.50589, df = 1, p-value = 0.4769
```

### 1.3 Robust Regression

```
#install.packages("MASS",repos="https://mirrors.ustc.edu.cn/CRAN/")
library("MASS")
reg4<-rlm(testscr~avginc,data=caschool)
summary(reg4)
```

```
##
## Call: rlm(formula = testscr ~ avginc, data = caschool)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -40.141  -9.034   0.685   8.995  32.565
##
## Coefficients:
##             Value    Std. Error t value
```

```
## (Intercept) 624.3872   1.5957   391.2932
## avginc        1.9494   0.0942    20.6851
##
## Residual standard error: 13.36 on 418 degrees of freedom
```

### 1.4 Logistic and Probit

```
library("foreign")
womenwk<-read.dta("/Users/admin/Desktop/teaching assiatant/Econometrics/teaching assist
```

```
logit<-glm(work~age+married+children+education,data=womenwk,family = binomial(link=logi
summary(logit)
```

```
##
## Call:
## glm(formula = work ~ age + married + children + education, family = binomial(link =
##     data = womenwk)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6212  -0.9292   0.4614   0.8340   2.0455
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.159247   0.332040 -12.526  < 2e-16 ***
## age          0.057930   0.007221   8.022 1.04e-15 ***
## married      0.741777   0.126471   5.865 4.49e-09 ***
## children     0.764488   0.051529  14.836  < 2e-16 ***
## education    0.098251   0.018652   5.268 1.38e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 2532.4  on 1999  degrees of freedom
## Residual deviance: 2055.8  on 1995  degrees of freedom
## AIC: 2065.8
##
## Number of Fisher Scoring iterations: 5
```

```
probit<-glm(work~age+married+children+education,data=womenwk,family = binomial(link= pr
summary(probit)
```

```
##
## Call:
## glm(formula = work ~ age + married + children + education, family = binomial(link =
##     data = womenwk)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7594  -0.9414   0.4552   0.8459   2.0427
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.467365   0.192291 -12.831  < 2e-16 ***
## age          0.034721   0.004232   8.204 2.33e-16 ***
## married      0.430857   0.074310   5.798 6.71e-09 ***
## children     0.447325   0.028642  15.618  < 2e-16 ***
## education    0.058365   0.011018   5.297 1.18e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2532.4  on 1999  degrees of freedom
## Residual deviance: 2054.1  on 1995  degrees of freedom
## AIC: 2064.1
##
```

```
## Number of Fisher Scoring iterations: 5
```

# 2 homework 1: RAND Experiment

- The RAND Health Insurance Experiment (HIE), which ran from 1974 to 1982, was one of the most influential social experiments in research history. The HIE enrolled 3,958 people aged 14 to 61 from six areas of USA. The HIE sample excluded Medicare participants and most Medicaid and military health insurance subscribers. HIE participants were randomly assigned to one of 14 insurance plans. Participants did not have to pay insurance premiums, but the plans had a variety of provisions related to cost sharing, leading to large differences in the amount of insurance they offered.

| Variable Names | Discriptions |
|---|---|
| any_ins | = 1 if has any health insurance assigned; = 0 otherwise |
| female | = 1 if female; = 0 otherwise |
| blackhisp | = 1 if nonwhite; = 0 otherwise |
| educper | years of education |
| hosp | hospitalized last year |
| ghindx | pre-treatment outcome : general health index |
| cholest | pre-treatment outcome: cholesterol level (mg/dl) |
| ghindxx | post-treatment outcome: general health index |
| cholestx | post-treatment outcome: cholesterol level (mg/dl) |

## 2.1 Question1

- Generate basic summary statistics such as mean, standard deviation, and total number of observations for variables female, blackhisp,educper, ghindx, and cholest, separated by the any_ins indicator.Your table for each variables should look similar as the table in Question 1. You can also combine all the information in just one table.

```
library("foreign")
library("plyr")
rand<-read.dta("/Users/admin/Desktop/teaching assiatant/Econometrics/teaching assistant
ddply(rand,"any_ins",summarize,mean_female=mean(female,na.rm=TRUE),sd_female=sd(female,
```

```
##   any_ins mean_female sd_female mean_blackhisp sd_blackhisp mean_educper
## 1       0   0.5599473 0.4967206      0.1716667    0.3774051     12.10483
## 2       1   0.5303315 0.4991572      0.1465824    0.3537590     11.93619
##   sd_educper mean_ghindx sd_ghindx mean_cholest sd_cholest  obs
## 1   2.881461    70.95892  14.65553     207.0904   42.44610 2689
## 2   3.005082    69.93396  15.02703     204.1117   43.54407 3198
```

| Variable | any_ins=0 | any_ins=1 |
|---|---|---|
| female | 0.560 | 0.530 |
| | [0.497] | [0.499] |
| blackhisp | 0.1717 | 0.1466 |
| | [0.377] | [0.354] |
| educper | 12.105 | 11.936 |
| | [2.882] | [3.005] |
| ghindx | 70.959 | 69.934 |
| | [14.656] | [15.027] |
| cholest | 207.090 | 204.112 |
| | [42.446] | [43.544] |
| obs | 2689 | 3198 |

## 2.2 Question2

- Three personal characteristics variables in question 1(thus female,blackhisp and educper) and two pre-treatment outcome variables(thus ghindx, and cholest) can be considered as baseline outcome variables. For these variables, test the null hypothesis that there is no mean difference (H0: = 0). (You should write down the equation of the statistic which you are going to use.) And What the baseline outcomes mean to the experiment?

```r
t.test(female~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
##
## data:  female by any_ins
## t = 1.4753, df = 1149.2, p-value = 0.1404
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.009770902  0.069002586
## sample estimates:
## mean in group 0 mean in group 1
##       0.5599473       0.5303315
```

```r
t.test(blackhisp~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
##
## data:  blackhisp by any_ins
## t = 1.4811, df = 865.62, p-value = 0.1389
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.008156602  0.058325178
## sample estimates:
## mean in group 0 mean in group 1
##       0.1716667       0.1465824
```

```r
t.test(educper~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
```

```
##
## data:  educper by any_ins
## t = 1.3441, df = 1030.1, p-value = 0.1792
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.07756339  0.41484572
## sample estimates:
## mean in group 0 mean in group 1
##        12.10483        11.93619
```

```
t.test(ghindx~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
##
## data:  ghindx by any_ins
## t = 2.2577, df = 4037.9, p-value = 0.02402
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.1349045 1.9150177
## sample estimates:
## mean in group 0 mean in group 1
##        70.95892        69.93396
```

```
t.test(cholest~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
##
## data:  cholest by any_ins
## t = 1.7837, df = 2177.2, p-value = 0.07461
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.2961282  6.2535693
```

```
## sample estimates:
## mean in group 0 mean in group 1
##        207.0904        204.1117
```

## 2.3 Question3

- For the two post-treatment variables, (thus ghindxx, and cholestx)repeat the exercises you just did (compute group mean,standard deviation, and run a t-test)

```
t.test(ghindxx~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
##
## data:  ghindxx by any_ins
## t = 4.7132, df = 4745.3, p-value = 2.508e-06
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  1.170210 2.837027
## sample estimates:
## mean in group 0 mean in group 1
##        70.11108        68.10746
```

```
t.test(cholestx~any_ins,data=rand)
```

```
##
##  Welch Two Sample t-test
##
## data:  cholestx by any_ins
## t = -0.68553, df = 3504.8, p-value = 0.4931
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -3.734833  1.799709
## sample estimates:
```

```
## mean in group 0 mean in group 1
##        200.8954        201.8630
```

### 2.4 Question4

- Interpret the results you obtain (the mean comparison results for characteristic variables, pre-treatment outcome variables, and post-treatment outcome variables).