ECON-320-Lab-8

Sonan Memon

Introduction

- While the OLS is a linear model, it is not linear in the extremely restrictive sense. It has the capacity to incorporate many non-linear relationships.
- More precisely, OLS is linear in terms of the impact of x on y but x itself can be a non-linear variable such as square or an interaction-term.
- Loops are fundamental building blocks for any programming exercise; they allow for automation and efficiency when there exists a recursion in the model.

Packages

```
library(tinytex)

library(tidyverse)

library(dslabs)
library(dplyr)

library(ggplot2)

library(tibble)
library(broom)
library(modelsummary)
```

Introduction

- While the OLS is a linear model, it is not linear in the extremely restrictive sense. It has the capacity to incorporate many non-linear relationships.
- More precisely, OLS is linear in terms of the impact of x on y but x itself can be a non-linear variable such as square or an interaction-term.
- Loops are fundamental building blocks for any programming exercise; they allow for automation and efficiency when there exists a recursion in the model.

Data Cleaning

```r
data <- read.csv("nlsy79-2020.csv")

data <- data %>%
  rename(
    logWealth = log_wealth,
    logEduc = log_educ
  )

View(data)
```

Non-Linear Relations

- Some common form of non-linear relationships in economics are linear, log-liner, linear-log and log-log models.

```r
linear = lm(data = data, wealth ~ educ)

 model1 <- modelsummary(
    list("Linear Model" = linear),
    stars = TRUE,
    statistic = "std.error",
    output = "tinytable",
    title = "Results From Simulated Data",
    gof_omit = ".*"  # remove AIC, BIC, etc.
  )
```

Non-Linear Relations

```
model1
```

Table 1: Results From Simulated Data

	Linear Model
(Intercept)	-2837577.048***
	(236970.310)
educ	270430.004***
	(16790.823)

$+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Non-Linear Relations

- Log-Linear Case:

```r
log_lin = lm(data = data, logWealth ~ educ)

model2 <- modelsummary(
    list("Log-Linear" = log_lin),
    stars = TRUE,
    statistic = "std.error",
    output = "tinytable",
    title = "Results From Simulated Data",
    gof_omit = ".*"  # remove AIC, BIC, etc.
  )
```

Non-Linear Relations

Table 2: Results From Simulated Data

	Log-Linear
(Intercept)	7.213***
	(0.180)
educ	0.343***
	(0.013)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- Linear-Log Case:

```r
lin_log = lm(data = data, wealth ~ logEduc)

model3<- modelsummary(
    list("Linear-Log" = lin_log),
    stars = TRUE,
    statistic = "std.error",
    output = "tinytable",
    title = "Results From Simulated Data",
    gof_omit = ".*"  # remove AIC, BIC, etc.
  )
```

Non-Linear Relations

Table 3: Results From Simulated Data

	Linear-Log
(Intercept)	-8640087.816***
	(617063.317)
logEduc	3655431.205***
	(235443.611)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Non-Linear Relations

- Log-Log case

```
log_log = lm(data = data, logWealth ~ logEduc)

model4 <- modelsummary(
    list("Log-Log" = log_log),
    stars = TRUE,
    statistic = "std.error",
    output = "tinytable",
    title = "Results From Simulated Data",
    gof_omit = ".*"  # remove AIC, BIC, etc.
  )
```

Table 4: Results From Simulated Data

	Log-Log
(Intercept)	-0.538
	(0.467)
logEduc	4.787***
	(0.178)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Function

```
fun = function(y, x){

df = tibble(y,x)
df = df %>%mutate(log_y = log(y),log_x = log(x))

lin = lm(data = df, y ~ x)%>%broom::tidy()
log_lin = lm(data = df, log_y ~ x)%>%broom::tidy()
lin_log = lm(data = df, y ~ log_x)%>%broom::tidy()
log_log = lm(data = df, log_y ~ log_x)%>%broom::tidy()
bind_rows(lin, log_lin, lin_log, log_log) %>%
filter(term == 'x' | term == 'log_x') %>%
mutate(interpret =c(estimate[1],estimate[2]*100, estimate[3]/100
type = c("lin", "log_lin", "lin_log", "log_log"),
x_change = c("unit","unit","percent","percent"),
y_change = c("unit", "percent", "unit", "percent")
)
}
```

Function: Check

```r
results = fun(data$wealth, data$educ)
results[,6:9]
```

```
# A tibble: 4 x 4
  interpret type    x_change y_change
      <dbl> <chr>   <chr>    <chr>
1 270430.   lin     unit     unit
2     34.3  log_lin unit     percent
3  36554.   lin_log percent  unit
4      4.79 log_log percent  percent
```

Quadratic Model

```r
data <- data %>% mutate(EducSqr = educ^2)

quad = lm(data = data, wealth ~ educ + EducSqr)


modelsquare <- modelsummary(
    list("OLS with Quadratic Term" = quad),
    stars = TRUE,
    statistic = "std.error",
    output = "tinytable",
    title = "Results From Simulated Data",
    gof_omit = ".*"  # remove AIC, BIC, etc.
  )
```

Quadratic Model

Table 5: Results From Simulated Data

	OLS with Quadratic Term
(Intercept)	70951.081
	(1113209.272)
educ	-142317.210
	(155269.011)
EducSqr	14172.191**
	(5300.141)

$+$ p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

Quadratic Model: Interpretation

- $wealth = \beta_0 + \beta_1 * educ + \beta_2 * educ^2$
- $\frac{\partial wealth}{\partial educ} = \beta_1 + 2 * \beta_2 * educ$

Quadratic Model: Visualisation

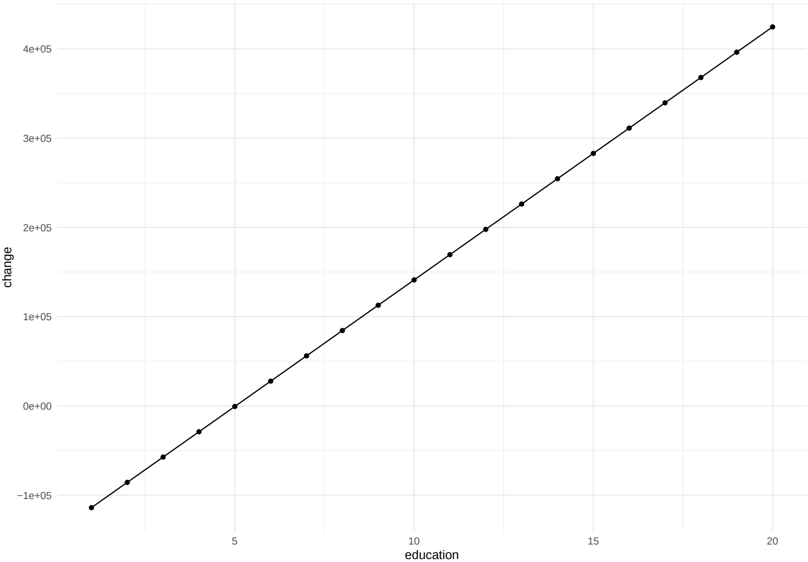
```r
quad = lm(data = data, wealth ~ educ + EducSqr) %>% tidy()

education = seq(1, 20, 1)
change = c()

for(i in education){
change[i] = quad$estimate[2] + 2*quad$estimate[3]*education[i]
}

df = tibble(education, change)
```

Quadratic Model: Visualisation



Interaction Terms

- When the effect of x on y varies based on whether z is high or low or other continuous or categorical variable, we use interaction terms.
- For instance, effect of education on income can vary across genders, racial groups, parent's socioeconomic status etc.
- Interaction terms with dummy variables have specially elegant interpretation.

Interaction Terms

```
int = lm(data = data, logWealth ~ logEduc +
        race + logEduc:race)

modelint <- modelsummary(
    list("OLS with Interaction Term" = int),
    stars = TRUE,
    statistic = "std.error",
    output = "tinytable",
    title = "Results From Simulated Data",
    gof_omit = ".*"  # remove AIC, BIC, etc.
  )
```

Model with Interaction Term

- Effect of education on wealth is slightly dampened by race; in other words, African Americans benefit more from one additional year of education relative to white population.

Table 6: Results From Simulated Data

	OLS with Interaction Term
(Intercept)	-1.120
	(0.830)
logEduc	4.654***
	(0.320)
race	2.167*
	(0.983)
logEduc × race	-0.309
	(0.378)

$+$ p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001