

The PDF-version result output of First Assignment

Zekun Ge

(1) Exercise ONE

1. Number of students

We could see that there are 340823 student applicants.

2. Number of schools

There are 898 distinct schools.

3. Number of programs

There are 32 different programs.

4. Number of choices

There are 5546 different choices.

5. Number of missing test score

There are 179887 missing test score.

6. Number of applying to the same school

There are 5546 applicants who apply to the same school.

(2) Exercise TWO

#	schoolcode	choice	ID	score	agey	male	choicepgm	jssdistrict	rankplace	rank
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230518	288	15	1	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture
#	10101	10101Agriculture	230756	288	14	0	Agriculture	Accra Metropolitan	3	10101Agriculture

(the following part is attached to the right side of the above chart)

#	cutoff_Low to Top	quality_Average	Score	size_Number of Admission	X.y	schoolname
#	288	309.0889		45	3247	
#	288	309.0889		45	3560	
#	288	309.0889		45	6031	
#	288	309.0889		45	3881	
#	288	309.0889		45	408	EBENEZER SENIOR HIGH SCHOOL, DANSOMAN

#	288	309.0889	45	2881	
#	288	309.0889	45	328	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	453	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	590	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	552	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	3887	
#	288	309.0889	45	472	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	3247	
#	288	309.0889	45	3560	
#	288	309.0889	45	6031	
#	288	309.0889	45	3881	
#	288	309.0889	45	408	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	2881	
#	288	309.0889	45	328	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN
#	288	309.0889	45	453	EBENEZER SENIOR HIGH. SCHOOL, DANSOMAN

(the following part is attached to the right side of the above chart)

#	sssdistrict	ssslong	ssslat
#	Accra Metro	NA	NA
#	Accra Metro	NA	NA
#	Accra Metro	NA	NA
#	Accra Metro	NA	NA
#	Accra Metropolitan	-0.1971153	5.607396
#	Accra Metro	NA	NA
#	Accra Metropolitan	-0.1971153	5.607396
#	Accra Metropolitan	-0.1971153	5.607396
#	Accra Metropolitan	-0.1971153	5.607396
#	Accra Metropolitan	-0.1971153	5.607396
#	Accra Metro	NA	NA

```
# Accra Metropolitan -0.1971153 5.607396
# Accra Metro      NA      NA
# Accra Metro      NA      NA
# Accra Metro      NA      NA
# Accra Metro      NA      NA
# Accra Metropolitan -0.1971153 5.607396
# Accra Metro      NA      NA
# Accra Metropolitan -0.1971153 5.607396
# Accra Metropolitan -0.1971153 5.607396
```

(3) Exercise Three

#	sssdistrict	ssslong	ssslat	X	point_x	point_y	Dist
# 1029181	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029182	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029183	South Dayi	NA	NA	1	0.2076307	6.375762	NA
# 1029184	Ho Municipal	0.5261422	6.717607	1	0.2076307	6.375762	32.22676
# 1029185	Asuogyaman	NA	NA	1	0.2076307	6.375762	NA
# 1029186	Kpando	NA	NA	1	0.2076307	6.375762	NA
# 1029187	South Dayi	NA	NA	1	0.2076307	6.375762	NA
# 1029188	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029189	Ho Municipal	NA	NA	1	0.2076307	6.375762	NA
# 1029190	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029191	South Dayi	NA	NA	1	0.2076307	6.375762	NA
# 1029192	Kpando	NA	NA	1	0.2076307	6.375762	NA
# 1029193	South Dayi	NA	NA	1	0.2076307	6.375762	NA
# 1029194	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029195	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029196	Kpando	NA	NA	1	0.2076307	6.375762	NA
# 1029197	South Dayi	NA	NA	1	0.2076307	6.375762	NA
# 1029198	Kpando	0.2673851	6.896852	1	0.2076307	6.375762	36.27809
# 1029199	South Dayi	NA	NA	1	0.2076307	6.375762	NA
# 1029200	Kpando	NA	NA	1	0.2076307	6.375762	NA

(4) Exercise Four

Rank_The Lowest_To_Highest

1. rankplace == 1

Cutoff_mean = 279.8704

Cutoff_sd = 57.34419

Quality_mean = 306.5762

Quality_sd = 50.57871

Size_mean = 93.04011

Size_sd = 54.78786

2. rankplace == 2

Cutoff_mean = 277.1518

Cutoff_sd = 50.97056

Quality_mean = 302.9698

Quality_sd = 44.17802

Size_mean = 93.68101

Size_sd = 54.99501

3. rankplace == 3

Cutoff_mean = 262.9438

Cutoff_sd = 43.62898

Quality_mean = 290.079

Quality_sd = 37.06944

Size_mean = 91.81311

Size_sd = 55.59272

4. rankplace == 4

Cutoff_mean = 250.1061

Cutoff_sd = 37.67753

Quality_mean = 278.8267

Quality_sd = 31.49667

Size_mean = 88.3362

Size_sd = 56.27731

5. rankplace == 5

Cutoff_mean = 211.1775

Cutoff_sd = 7.996356

Quality_mean = 252.9305

Quality_sd = 13.02076

Size_mean = 68.32309

Size_sd = 48.39169

6. rankplace == 6

Cutoff_mean = 211.2391

Cutoff_sd = 8.093442

Quality_mean = 250.225

Quality_sd = 11.02465

Size_mean = 59.26986

Size_sd = 46.24914

Score_The Lowest_To_Highest

1. Quantiles = 0.25

Cutoff_mean = 217.7775

Cutoff_sd = 14.31949

Quality_mean = 252.3234

Quality_sd = 12.39697

Size_mean = 74.88889

Size_sd = 14.31949

2. Quantiles = 0.5

Cutoff_mean = 229.8652

Cutoff_sd = 22.6533

Quality_mean = 262.2342

Quality_sd = 17.99262

Size_mean = 82.09206

Size_sd = 55.48278

3. Quantiles = 0.75

Cutoff_mean = 244.708

Cutoff_sd = 32.35489

Quality_mean = 274.8775

Quality_sd = 26.4583

Size_mean = 87.61462

Size_sd = 56.53001

3. Quantiles = 1.00

Cutoff_mean = 266.5514

Cutoff_sd = 51.04901

Quality_mean = 294.2175

Quality_sd = 44.18152

Size_mean = 90.61314

Size_sd = 55.32259

(5) Exercise Five

See the detailed information at R code.

(6) Exercise Six

6.1

Here betay_x1 approaches 1.26, which is very close to 1.2.

6.3

When coding by hand:

```
head(beta_All)
#      [,1]
# 2.4907098
# x1 1.1976226
# x2 -0.8970514
# x3 0.0875850
```

When using lm():

```
All_model$coefficients
# (Intercept)      x1      x2      x3
# 2.4907098 1.1976226 -0.8970514 0.0875850
```

The corresponding results are exactly the same.

6.4

```
sqrt(diag(vcov_beta_hat))
#      x1      x2      x3
# 0.040620200 0.017358550 0.002876599 0.021694530
```

(7) Exercise Seven

7.1.1

Linear Probability Model by optimization

```
reg_OLS_OP$par
# alpha      beta1      beta2      beta3      sigma
# 0.886603815 0.146120426 -0.102847063 -0.008958128 0.334971033
```


Linear Probability Model by lm()

```
unnamed(coef(reg_OLS))  
# [1] 0.885823611 0.146193985 -0.102832042 -0.008053057
```

The corresponding results are exactly the same.

7.1.2

Probit Model by optimization

```
reg_probit_op$par  
# (Intercept)      x1          x2          x3  
# 3.04273899 1.17235283 -0.90546035 -0.01124978
```

Probit Model by glm()

```
unnamed(coef(reg_probit))  
# [1] 3.04273897 1.17235282 -0.90546040 -0.01124978
```

The corresponding results are approximately the same.

7.1.3

Logit Model by optimization

```
summary(reg_logit_OP, order = "convcode")  
#           X.Intercept.      x1          x2          x3  
#  BFGS      5.4265418 2.1005953 -1.6185076 -0.01963006
```

Logit Model by glm()

```
coef(reg_logit)  
# (Intercept)      x1          x2          x3  
# 5.42654014 2.10059417 -1.61850702 -0.01963017
```

The corresponding results are approximately the same.

7.2

```
reg_OLS <- lm(ydum ~ 1 + x1 + x2 + x3)  
coef(reg_OLS)
```

```
# (Intercept)      x1      x2      x3
# 0.885823611    0.146193985 -0.102832042 -0.008053057
```

```
reg_probit <- glm(ydum ~ 1 + x1 + x2 + x3,family = binomial(link = "probit"))
```

```
coef(reg_probit)
```

```
# (Intercept)      x1      x2      x3
# 3.04273897    1.17235282 -0.90546040 -0.01124978
```

```
reg_logit <- glm(ydum ~ 1 + x1 + x2 + x3,family = binomial(link = "logit"))
```

```
coef(reg_logit)
```

```
# (Intercept)      x1      x2      x3
# 5.42654014    2.10059417 -1.61850702 -0.01963017
```

```
## The coefficients between probit regression and logit model are quite similar
```

```
## However, the OLS coefficients are smaller than the corresponding logit and probit figures.
```

```
## But for all these three models, the coefficient of each individual variable in any model remains negative or positive simultaneously.
```

```
# For simplicity, I will use the variable "x1" as an example.
```

```
## OLS Estimation
```

```
## The coefficients of "x1" means that, holding other variables constant, one unit increase of x1 will lead to approximately 14% increase of ydum.
```

```
## probit Estimation and logit Estimation
```

```
## The coefficients of "x1" means nothing in either probit model or logit model.
```

```
## It only tells that, holding other variables constant, a positive "x1" coefficient means that an increase in the "x1" predictor leads to an increase in the predicted "ydum" probability
```

```
## Significance
```

```
## In each individual regression model, the coefficients of "Interpret", "x1", "x2" are statistically significant at 0.1% significance level. However, the coefficient of "x3" in each regression remains statistical insignificant.
```

(8) Exercise Eight

8.1

```
marginal_effects_Estimation_probit(reg_probit)

# probit marginal.effects

# x1    0.14380827
# x2    -0.11106954
# x3    -0.00137997
```

```
marginal_effects_Estimation_logit(reg_logit)

# logit marginal.effects

# x1    0.147623207
# x2    -0.113743625
# x3    -0.001379547
```

Using Packages as a double check:

Marginal effect in the Probit Model

```
Marginal Effects:
      dF/dx  Std. Err.      z    P>|z|
x1  0.1438083  0.0043633   32.9588 <2e-16 ***
x2 -0.1110695  0.0004427 -250.8900 <2e-16 ***
x3 -0.0013805  0.0057218   -0.2413  0.8093
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Marginal effect in the Logit Model

```
Marginal Effects:
      dF/dx  Std. Err.      z    P>|z|
x1  0.1440309  0.0072635   19.8293 <2e-16 ***
x2 -0.1109758  0.0044587  -24.8900 <2e-16 ***
x3 -0.0013465  0.0057815   -0.2329  0.8158
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

8.2

For simplicity, I use “mfx” package and “margins” package simultaneously.

Standard error of the marginal effects in the Probit Model

```
summary(margins(reg_probit))
```

factor	AME	SE	z	p	lower	upper
x1	0.1438	0.0044	32.6602	0.0000	0.1352	0.1524
x2	-0.1111	0.0004	-247.7190	0.0000	-0.1119	-0.1102
x3	-0.0014	0.0057	-0.2419	0.8089	-0.0126	0.0098

Standard error of the marginal effects in the Logit Model

```
summary(margins(reg_logit))
```

#	factor	AME	SE	z	p	lower	upper
#	x1	0.1440	0.0044	32.6564	0.0000	0.1354	0.1527
#	x2	-0.1110	0.0004	-246.8795	0.0000	-0.1119	-0.1101
#	x3	-0.0013	0.0057	-0.2359	0.8135	-0.0125	0.0098