AR 3

YING LIU

Ex. 1

1.1

```
> Number_of_students
[1] 340823
```

```
> Number_of_school
[1] 898
```

```
> Number_of_program
[1] 33
```

1.2

Use gather function to convert the data from wide to long

```
> Number_of_choice
[1] 3086
```

1.3

Use a loop to match the district of senior high school to the school code and then check if there at least one senior high school district same to the jjsdistrict.

The code takes a really long time to complete, and the number is 270302.

```
[1] 270302
```

1.4

Create a df to record the total information

	schoolcode	schoolname	number of students admitted
7	50110	OPOKU WARE SENIOR HIGH. SCHOOL, SANTASI	440
8	10110	ACHIMOTA SENIOR HIGH SCHOOL, ACHIMOTA-ACCRA	535
9	40103	ARCHBISHOP PORTER SENIOR HIGH SCHOOL, SEKONDI	236
10	21103	ST. ROSE'S SENIOR HIGH SCH, AKWATIA	225
11	50102	ST. LOUIS SENIOR HIGH. SCHOOL, ODOUM	357
12	10102	ST. MARY'S SENIOR HIGH. SCHOOL, KORLE GONNO	248
13	30301	MFANTSIMAN GIRLS SENIOR HIGH. SCH, SALTPOND	487
14	50108	PREMPEH COLLEGE, KUMASI	600
15	60106	ST. JAMES SEMINARY & SENIOR HIGH. SCHOOL, ABESIM	194
16	20102	POPE JOHN SENIOR HIGH & JNR. SEM. SCH., KOFORIDUA	400
17	20402	OKUAPEMAN SENIOR HIGH SCHOOL, AKROPONG	358
18	50107	ANGLICAN SENIOR HIGH SCHOOL, ASEM-KUMASI	544
19	30101	ST. AUGUSTINE'S COLLEGE, CAPE COAST	400
20	30102	ADISADEL COLLEGE, CAPE COAST	400
21	50201	YAA ASANTEWAA GIRL'S SENIOR HIGH. SCHOOL, TANOSO	499

Showing 7 to 21 of 898 entries, 3 total columns

1.5

	schoolcode	schoolname	min(sch_low.score)
1	30107	WESLEY GIRLS HIGH SCHOOL, CAPE COAST	394
2	30103	HOLY CHILD SENIOR HIGH SCHOOL, CAPE COAST	393
3	21003	ST. PETER'S SENIOR HIGH SCH, NKWATIA-KWAHU	372
4	10111	PRESBY BOYS SENIOR HIGH. SCHOOL, LEGON	371
5	30104	MFANTSIPIM SENIOR HIGH SCHOOL, CAPE COAST	373
6	20301	ABURI GIRLS SENIOR HIGH. SCH., ABURI	385
7	50110	OPOKU WARE SENIOR HIGH. SCHOOL, SANTASI	387
8	10110	ACHIMOTA SENIOR HIGH SCHOOL, ACHIMOTA-ACCRA	343
9	40103	ARCHBISHOP PORTER SENIOR HIGH SCHOOL, SEKONDI	377
10	21103	ST. ROSE'S SENIOR HIGH SCH, AKWATIA	388
11	50102	ST. LOUIS SENIOR HIGH. SCHOOL, ODOUM	374
12	10102	ST. MARY'S SENIOR HIGH. SCHOOL, KORLE GONNO	343
13	30301	MFANTSIMAN GIRLS SENIOR HIGH. SCH, SALTPOND	315
14	50108	PREMPEH COLLEGE, KUMASI	374
15	60106	ST. JAMES SEMINARY & SENIOR HIGH. SCHOOL, ABESIM	362
16	20102	POPE JOHN SENIOR HIGH & JNR. SEM. SCH., KOFORIDUA	374

Showing 1 to 17 of 898 entries, 3 total columns

1.6

	schoolcode	schoolname	mean(sch_low.score)
1	30107	WESLEY GIRLS HIGH SCHOOL, CAPE COAST	432.0316
2	30103	HOLY CHILD SENIOR HIGH SCHOOL, CAPE COAST	423.5000
3	21003	ST. PETER'S SENIOR HIGH SCH, NKWATIA-KWAHU	410.2679
4	10111	PRESBY BOYS SENIOR HIGH. SCHOOL, LEGON	412.5100
5	30104	MFANTSIPIM SENIOR HIGH SCHOOL, CAPE COAST	411.3825
6	20301	ABURI GIRLS SENIOR HIGH. SCH., ABURI	407.3067
7	50110	OPOKU WARE SENIOR HIGH. SCHOOL, SANTASI	411.0068
8	10110	ACHIMOTA SENIOR HIGH SCHOOL, ACHIMOTA-ACCRA	408.0785
9	40103	ARCHBISHOP PORTER SENIOR HIGH SCHOOL, SEKONDI	398.8220
10	21103	ST. ROSE'S SENIOR HIGH SCH, AKWATIA	411.6667
11	50102	ST. LOUIS SENIOR HIGH. SCHOOL, ODOUM	403.3277
12	10102	ST. MARY'S SENIOR HIGH. SCHOOL, KORLE GONNO	394.1492
13	30301	MFANTSIMAN GIRLS SENIOR HIGH. SCH, SALTPOND	382.5380
14	50108	PREMPEH COLLEGE, KUMASI	401.9117
15	60106	ST. JAMES SEMINARY & SENIOR HIGH. SCHOOL, ABESIM	387.2990
16	20102	POPE JOHN SENIOR HIGH & JNR. SEM. SCH., KOFORIDUA	397.1225

Ex. 2

I first create a dataset in school level, and then create a dataset in school-program level

First Create the cutoff\size\quality variable at school-program level, and then combine the information at school-program level.

Here are the final dataset including district\ longitude and latitude \cutoff\ quality\ size at school-program level:

	admit	size	quality	cutoff	schoolcode	sssdistrict	ssslong	ssslat
1	100101General Arts	79	244.3924	198	100101	Wa Municipal	-2.2850304	10.030622
2	100101Home Economics	40	229.4500	199	100101	Wa Municipal	-2.2850304	10.030622
3	100101Technical	49	235.1020	201	100101	Wa Municipal	-2.2850304	10.030622
4	100102Agriculture	90	292.5556	273	100102	Wa Municipal	-2.2850304	10.030622
5	100102Business	90	303.3444	283	100102	Wa Municipal	-2.2850304	10.030622
6	100102General Arts	90	311.1111	291	100102	Wa Municipal	-2.2850304	10.030622
7	100102General Science	90	298.4333	273	100102	Wa Municipal	-2.2850304	10.030622
8	100102Home Economics	45	278.8667	262	100102	Wa Municipal	-2.2850304	10.030622
9	100102Visual Arts	45	275.2000	250	100102	Wa Municipal	-2.2850304	10.030622
10	100104General Arts	45	337.4444	319	100104	Wa Municipal	-2.2850304	10.030622
11	100104General Science	45	334.0000	313	100104	Wa Municipal	-2.2850304	10.030622
12	100104Home Economics	45	309.3556	282	100104	Wa Municipal	-2.2850304	10.030622
13	100105Business	80	268.0125	251	100105	Wa Municipal	-2.2850304	10.030622
14	100105General Arts	80	274.7375	258	100105	Wa Municipal	-2.2850304	10.030622
15	100105Home Economics	80	258.1625	242	100105	Wa Municipal	-2.2850304	10.030622
16	100106Agriculture	40	240.6250	223	100106	Wa Municipal	-2.2850304	10.030622

ing 1 to 17 of 2,300 entries, 8 total columns

Ex. 3

In this exercise, I add 6 columns to describe distance for each choice and keep all the information in the datstu database

2	ssslong2	ssslat2	schoolcode1	ssslong1	ssslat1	V1	score	rankplace	dis1	dis2	dis3	dis4	dis5	dis6
0603	0.26738513	6.896852	70602	0.26738513	6.896852	293886	316	2	36.27809	36.27809	36.27809	15.28876	32.22676	32.22676
0801	0.08832825	6.189229	20804	0.08832825	6.189229	219641	252	1	15.28876	15.28876	67.51937	36.27809	32.22676	32.22676
0104	0.52614224	6.717607	70601	0.26738513	6.896852	202639	253	4	36.27809	32.22676	36.27809	15.28876	36.27809	32.22676
1001	0.46623856	7.030595	9070601	0.26738513	6.896852	90957	NA	NA	36.27809	48.65988	48.65988	36.27809	36.27809	32.22676
0801	0.08832825	6.189229	20804	0.08832825	6.189229	219832	237	1	15.28876	15.28876	36.27809	36.27809	32.22676	32.22676
0603	0.26738513	6.896852	70102	0.52614224	6.717607	293993	275	2	32.22676	36.27809	36.27809	95.18792	32.22676	32.22676
0801	0.08832825	6.189229	70102	0.52614224	6.717607	330565	252	99	32.22676	15.28876	15.28876	36.27809	32.22676	32.22676
0603	0.26738513	6.896852	70603	0.26738513	6.896852	132566	NA	NA	36.27809	36.27809	36.27809	36.27809	32.22676	32.22676
0603	0.26738513	6.896852	70603	0.26738513	6.896852	125945	NA	NA	36.27809	36.27809	36.27809	36.27809	32.22676	32.22676
0106	0.52614224	6.717607	70603	0.26738513	6.896852	162051	NA	NA	36.27809	32.22676	36.27809	36.27809	32.22676	32.22676
0603	0.26738513	6.896852	70607	0.26738513	6.896852	126138	NA	NA	36.27809	36.27809	36.27809	15.28876	54.93583	32.22676
0603	0.26738513	6.896852	70601	0.26738513	6.896852	163584	NA	NA	36.27809	36.27809	32.22676	36.27809	32.22676	32.22676
0801	0.08832825	6.189229	20804	0.08832825	6.189229	219835	312	1	15.28876	15.28876	36.27809	36.27809	36.27809	32.22676
0604	0.26738513	6.896852	70603	0.26738513	6.896852	254553	234	4	36.27809	36.27809	32.22676	36.27809	36.27809	32.22676
0119	0.52614224	6.717607	70401	0.84270048	6.206889	108316	NA	NA	45.19314	32.22676	36.27809	15.28876	36.27809	32.22676
0605	0.26738513	6.896852	70603	0.26738513	6.896852	333041	219	2	36.27809	36.27809	36.27809	36.27809	48.65988	32.22676

Showing 1 to 16 of 340,823 entries, 30 total columns

Ex. 4

4.1

choicepgm6	jssdistrict	rankplace	scode_rev1	scode_rev2	scode_rev3	scode_rev4	scode_rev5	scode_rev6
General Arts	Bosomtwe/Atwima/Kwanwoma (Kuntanase)	NA	501	501	502	502	507	509
General Arts	Ho Municipal	NA	701	706	701	701	706	706
Business	Kwabre (Mamponteng)	NA	507	507	501	507	516	507
General Arts	Kassena/Nankani (Navrongo)	NA	905	904	901	909	901	903
Home Economics	Atwima Mponua (Nyinahin)	NA	518	517	502	502	516	502
Home Economics	Kumasi Metro	NA	101	501	517	502	506	516
General Arts	Nanumba North (Bimbilla)	NA	803	804	803	804	805	809
Agriculture	Jomoro (Half Assini)	NA	403	404	404	403	402	403
General Arts	East Akim (Kibi)	NA	213	213	212	212	202	201
General Arts	Ejura/Sekyedumase (Ejura)	NA	801	904	505	509	505	505
General Arts	Sekyere West (Mampong)	NA	518	506	505	506	506	509
Agriculture	Kassena/Nankani (Navrongo)	NA	100	905	801	905	902	906
General Arts	Agona Swedru	NA	306	306	309	309	306	309
Agriculture	Tolon Kunbungu (Tolon)	NA	801	801	801	801	804	810
Visual Arts	Accra Metropolitan	NA	903	906	801	905	101	101
General Science	Mpohor-Wassa East (Daboase)	NA	409	409	409	411	411	402

Showing 1 to 16 of 340,823 entries, 18 total columns

4.2

scode_rev2	scode_rev3	scode_rev4	scode_rev5	scode_rev6	pgm_rev6	pgm_rev5	pgm_rev4	pgm_rev3	pgm_rev2	pgm_rev1
501	502	502	507	509	arts	economcis	arts	arts	arts	economcis
706	701	701	706	706	arts	economcis	arts	arts	economcis	arts
507	501	507	516	507	economcis	economcis	economcis	economcis	economcis	economcis
904	901	909	901	903	arts	others	others	others	arts	arts
517	502	502	516	502	economcis	arts	arts	economcis	arts	economcis
501	517	502	506	516	economcis	economcis	arts	arts	arts	arts
804	803	804	805	809	arts	arts	arts	arts	arts	arts
404	404	403	402	403	others	others	others	arts	arts	arts
213	212	212	202	201	arts	arts	science	science	economcis	economcis
904	505	509	505	505	arts	arts	arts	arts	arts	arts
506	505	506	506	509	arts	arts	economcis	economcis	arts	economcis
905	801	905	902	906	others	science	science	science	science	science
306	309	309	306	309	arts	economcis	economcis	arts	others	economcis
801	801	801	804	810	others	others	economcis	economcis	economcis	economcis
906	801	905	101	101	arts	others	others	others	others	others
409	409	411	411	402	science	others	economcis	economcis	economcis	arts

wing 1 to 16 of 340,823 entries, 18 total columns

4.3

choice_rev1	choice_rev2	choice_rev3	choice_rev4	choice_rev5	choice_rev6
501economcis	501arts	502arts	502arts	507economcis	509arts
701arts	706economcis	701arts	701arts	706economcis	706arts
507economcis	507economcis	501economcis	507economcis	516economcis	507economcis
905arts	904arts	901others	909others	901others	903arts
518economcis	517arts	502economcis	502arts	516arts	502economcis
101arts	501arts	517arts	502arts	506economcis	516economcis
803arts	804arts	803arts	804arts	805arts	809arts
403arts	404arts	404arts	403others	402others	403others
213economcis	213economcis	212science	212science	202arts	201arts
801arts	904arts	505arts	509arts	505arts	505arts
518economcis	506arts	505economcis	506economcis	506arts	509arts
100science	905science	801science	905science	902science	906others
306economcis	306others	309arts	309economcis	306economcis	309arts
801economcis	801economcis	801economcis	801economcis	804others	810others
903others	906others	801others	905others	101others	101arts
409arts	409economcis	409economcis	411economcis	411others	402science

4.4

	cutoff6	quality6	choice_rev6	cutoff5	quality5	choice_rev5	cutoff4	quality4	choice_rev4	cutoff3	quality3	choice_rev3
1	NA	NA		NA	NA	NA	NA	NA	NA	NA	NA	NA
2	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
3	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
4	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
5	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
6	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
7	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
8	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
9	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
10	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
11	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
12	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
13	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
14	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
15	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts
16	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts	194	275.5233	100arts

Showing 1 to 16 of 340,848 entries, 43 total columns

4.5

```
datred        2000 obs. of 43 variables
```

Ex. 5

5.1

Multinomial logit model is appropriate for this because score varies among students but is invariant across alternatives. For multinomial logit model,

Vij =x_j*beta_i,

x_ij = x_i, so x don't depend on choice's characteristic

The likelihood of function is as follows（where stch is the choice matrix and score is the characteristic matrix）：

```
MLogit <- function(theta){
alpha = c(0,theta[56:110])
alpha = sapply(alpha,rep,2000)
beta = c(0,theta[1:55])
beta = sapply(beta,rep,2000)
Vij = score*beta + alpha
Pij = prop.table(exp(Vij),1)
logl = sum(stch*log(Pij))
Y = -logl
return(Y)
}
```

5.2

Here we have 56 different choices in first choice, corresponding to

100science/101arts/101economcis/101others/101science/102arts/102economcis/102science/201arts/201economcis/201others/201science/203arts/203economcis/203science/204arts/206economcis/210arts/210economcis/210others/210science/211arts/211economcis/211science/213arts/213 economcis/213science/301arts/301economcis/301others/301science/303arts/303economcis/303science/304arts/401arts/401economcis/401others/401science/403arts/501arts/501economcis/501science/502arts/502economcis/502science/503arts/601science/701arts/701economcis/701science/705economcis/705science/706science/801science/NAothers

#for beta(coefficient),which is theta[1:55]here:

[1] 5.322021e-03 3.120633e-03 -5.127847e-04 7.515239e-03 -4.324227e-03 -2.743115e-03 -3.469660e-03
[8] -8.559399e-05 1.054880e-03 -2.749195e-03 2.038967e-03 1.943420e-03 1.528604e-03 2.117778e-03
[15] -3.491340e-03 -5.318554e-03 -3.282253e-04 2.852418e-04 -5.318554e-03 4.458423e-03 1.621110e-03
[22] -2.173142e-03 2.341652e-03 -4.349481e-03 -5.323349e-03 -5.323349e-03 6.704546e-03 5.653103e-03
[29] -2.816730e-03 8.656197e-03 -4.396034e-03 -5.349766e-03 -2.244392e-03 -5.349766e-03 -5.349766e-03
[36] -5.349766e-03 -5.349766e-03 -1.739407e-03 -5.349766e-03 3.393206e-03 3.123996e-03 6.465496e-03
[43] -1.903723e-04 -3.579027e-03 -1.903723e-04 -4.408787e-03 -1.336815e-03 -3.579027e-03 -3.579027e-03
[50] -2.264115e-03 -4.408787e-03 -5.356985e-03 -5.356985e-03 -4.408787e-03 -5.359392e-03

#for alpha(intercept), which is theta[56:110]here:

-4.471498e-06
[57] 4.479934e-06 -1.515199e-06 7.807524e-06 -9.649799e-06 -5.974249e-06 -7.667629e-06 5.151651e-07
[64] 3.533438e-06 -5.946289e-06 6.475748e-06 6.376832e-06 5.310333e-06 7.183225e-06 -7.591509e-06
[71] -1.190557e-05 2.160148e-07 1.886436e-06 -1.190557e-05 1.767740e-05 6.310607e-06 -4.321499e-06
[78] 8.848246e-06 -9.581741e-06 -1.189555e-05 -1.189555e-05 3.823757e-05 3.323412e-05 -5.640208e-06
[85] 9.462771e-05 -9.457542e-06 -1.184054e-05 -3.909191e-06 -1.184054e-05 -1.184054e-05 -1.184054e-05
[92] -1.184054e-05 -2.538492e-06 -1.184054e-05 1.993272e-05 1.801748e-05 5.984925e-05 2.456567e-06
[99] -7.289210e-06 2.456567e-06 -9.423798e-06 -1.180001e-06 -7.289210e-06 -7.289210e-06 -3.797399e-06
[106] -9.423798e-06 -1.182556e-05 -1.182556e-05 -9.423798e-06 -1.182058e-05

As it shows, the intercept _i above implies that compared to choice 1(100science), how the students like choice_i. For example, the result shows that student is 4.47e-6 more likely to choose 101arts compared to 100science.

the beta_i above implies that compared to choice 1, how the test scores affects the choice_i.

For example, when the score is higher, the results shows that student is 0.053 more likely to choose 101arts compared to 100science.

The marginal effect is as follows:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
1	-1.705059e-05	-3.025227e-05	-6.344012e-05	-1.743954e-05	0.0003043983	-3.367384e-06	-6.989012e-06	-5.	[illegible]	69111e-05	-7.499537e-06	-4.28
2	-1.717163e-05	-2.981351e-05	-6.350335e-05	-1.756207e-05	0.0003050815	-3.407243e-06	-7.057508e-06	-5.	[illegible]	84769e-05	-7.571514e-06	-4.30
3	-1.729334e-05	-2.937186e-05	-6.356529e-05	-1.768525e-05	0.0003057658	-3.447541e-06	-7.126605e-06	-5.	[illegible]	00459e-05	-7.644105e-06	-4.31
4	-1.729334e-05	-2.937186e-05	-6.356529e-05	-1.768525e-05	0.0003057658	-3.447541e-06	-7.126605e-06	-5.679483e-06	-2.131379e-05	-3.300459e-05	-7.644105e-06	-4.31
5	-1.741572e-05	-2.892729e-05	-6.362592e-05	-1.780911e-05	0.0003064512	-3.488283e-06	-7.196307e-06	-5.738717e-06	-2.144971e-05	-3.316180e-05	-7.717315e-06	-4.33
6	-1.741572e-05	-2.892729e-05	-6.362592e-05	-1.780911e-05	0.0003064512	-3.488283e-06	-7.196307e-06	-5.738717e-06	-2.144971e-05	-3.316180e-05	-7.717315e-06	-4.33
7	-1.753876e-05	-2.847980e-05	-6.368523e-05	-1.793362e-05	0.0003071378	-3.529474e-06	-7.266618e-06	-5.798512e-06	-2.158624e-05	-3.331932e-05	-7.791148e-06	-4.34
8	-1.753876e-05	-2.847980e-05	-6.368523e-05	-1.793362e-05	0.0003071378	-3.529474e-06	-7.266618e-06	-5.798512e-06	-2.158624e-05	-3.331932e-05	-7.791148e-06	-4.34
9	-1.753876e-05	-2.847980e-05	-6.368523e-05	-1.793362e-05	0.0003071378	-3.529474e-06	-7.266618e-06	-5.798512e-06	-2.158624e-05	-3.331932e-05	-7.791148e-06	-4.34
10	-1.766247e-05	-2.802939e-05	-6.374320e-05	-1.805880e-05	0.0003078254	-3.571118e-06	-7.337542e-06	-5.858873e-06	-2.172338e-05	-3.347714e-05	-7.865608e-06	-4.36
11	-1.766247e-05	-2.802939e-05	-6.374320e-05	-1.805880e-05	0.0003078254	-3.571118e-06	-7.337542e-06	-5.858873e-06	-2.172338e-05	-3.347714e-05	-7.865608e-06	-4.36
12	-1.766247e-05	-2.802939e-05	-6.374320e-05	-1.805880e-05	0.0003078254	-3.571118e-06	-7.337542e-06	-5.858873e-06	-2.172338e-05	-3.347714e-05	-7.865608e-06	-4.36
13	-1.766247e-05	-2.802939e-05	-6.374320e-05	-1.805880e-05	0.0003078254	-3.571118e-06	-7.337542e-06	-5.858873e-06	-2.172338e-05	-3.347714e-05	-7.865608e-06	-4.36
14	-1.766247e-05	-2.802939e-05	-6.374320e-05	-1.805880e-05	0.0003078254	-3.571118e-06	-7.337542e-06	-5.858873e-06	-2.172338e-05	-3.347714e-05	-7.865608e-06	-4.36
15	-1.778686e-05	-2.757604e-05	-6.379981e-05	-1.818465e-05	0.0003085141	-3.613219e-06	-7.409083e-06	-5.919804e-06	-2.186114e-05	-3.363525e-05	-7.940699e-06	-4.38
16	-1.791191e-05	-2.711974e-05	-6.385506e-05	-1.831116e-05	0.0003092039	-3.655781e-06	-7.481247e-06	-5.981309e-06	-2.199950e-05	-3.379366e-05	-8.016424e-06	-4.39

column 8: numeric with range -0.000009500000000000001 - -0.0000055

The average marginal effect is as follows:

	V1
1	-2.222265e-05
2	-1.105115e-05
3	-6.469923e-05
4	-2.266396e-05
5	3.314100e-04
6	-5.288593e-06
7	-1.013127e-05
8	-8.272089e-06
9	-2.668146e-05
10	-3.888782e-05
11	-1.078483e-05
12	-4.866730e-05
13	-5.059732e-05
14	-4.528241e-05
15	-4.856726e-05
16	-7.235517e-06
17	[illegible]

Showing 1 to 17 of 56 entries, 1 total columns

Ex. 6

6.1

At first I want to use the conditional logit model because I think quality of first choice here is

invariant across alternatives. For the conditional model,
Vij = X_j*beta_i,
X_ij = X_j, x don't depend on i, which is individual. Here is the likelihood function:

```
CLogit <- function(theta, X){
   alpha = c(0,theta[2:56])
   alpha = sapply(alpha,rep,2000)
   Vij = X*theta[1]+alpha
   Pij = prop.table(exp(Vij),1)
   logl = sum(stch*log(Pij))
   Y = -logl
   return(Y)
}
```

6.1
But there is something wrong with the data, so I then use mlogit in this exercise. Because the school quality here is calculated through student's score.

#for beta(coefficient),which is theta[1:55]here:
[1] 7.455744e-03 4.815577e-03 6.603333e-05 9.507312e-03 -4.405451e-03 -2.486349e-03 -3.094629e-03
[8] 6.248106e-04 2.019127e-03 -2.296644e-03 2.978864e-03 3.164378e-03 2.653150e-03 2.969260e-03
[15] -3.491085e-03 -6.195254e-03 4.465913e-04 1.318025e-03 -6.177335e-03 6.525448e-03 3.118321e-03
[22] -1.911859e-03 3.422040e-03 -4.508613e-03 -5.910636e-03 -5.402082e-03 8.813036e-03 7.843518e-03
[29] -2.446460e-03 9.820642e-03 -4.511169e-03 -5.943880e-03 -1.512492e-03 -6.026247e-03 -5.818777e-03
[36] -5.932967e-03 -5.985057e-03 -1.107316e-03 -6.372950e-03 4.876627e-03 4.679145e-03 8.198104e-03
[43] 6.860695e-04 -3.343989e-03 6.202318e-04 -4.543440e-03 -6.814019e-04 -3.486833e-03 -3.430842e-03
[50] -1.659430e-03 -4.812436e-03 -5.798783e-03 -5.704544e-03 -4.322374e-03 0.000000e+00

#for alpha(intercept), which is theta[56:110]here:
4.158089e-05
[57] 2.245910e-05 1.840114e-06 7.235648e-05 -1.334238e-05 -7.197455e-06 -8.251186e-06 4.160004e-06
[64] 9.634089e-06 -5.798509e-06 1.442182e-05 1.448226e-05 1.222252e-05 1.482591e-05 -1.109177e-05
[71] -2.157874e-05 3.077063e-06 6.477625e-06 -2.139858e-05 3.383484e-05 1.390474e-05 -5.861980e-06
[78] 1.642507e-05 -1.412131e-05 -1.890442e-05 -1.489283e-05 6.105043e-05 4.701531e-05 -6.899891e-06

[85]   1.041357e-04 -1.414097e-05 -1.919793e-05 -2.433147e-06 -1.994530e-05 -1.811596e-05 -1.910109e-05
[92] -1.956788e-05 -1.740787e-06 -2.346936e-05   2.475817e-05   2.282358e-05   6.025998e-05   4.161840e-06
[99] -1.000094e-05   4.165134e-06 -1.439077e-05 -3.738038e-07 -1.105954e-05 -1.063913e-05 -3.775634e-06
[106] -1.659755e-05 -1.794854e-05 -1.717826e-05 -1.273481e-05   0.000000e+00

As it shows, the intercept _i above implies that compared to choice 1(100science), how the students like choice_i.
the beta_i above implies that compared to choice 1, how the school quality affects the choice_i.

Ex. 7
7.1
I think conditional model is appropriate here since all the variables here are characteristics of choice.