AR 3

YING LIU

Ex. 1

1.1

```
> Number_of_students
[1] 340823
> Number_of_schools
[1] 640
> Number_of_programs
[1] 32
```

1.2

Use gather function to convert the data from wide to long. The answer rules out NA

```
> number_of_choice
[1] 2773
```

1.3

First change the data from wide to long and then merge the information in datsss to the df. check if the sssdistrict same to jssdistrict

```
> number_same_sssjss
[1] 262194
```

1.4-1.6

Create a df to record the total information

	schoolcode	number_of_students_admitted	cutoff	quality
1	10101	374	284	320.1898
2	10102	220	343	394.1273
3	10103	389	316	353.8226
4	10104	209	245	297.0096
5	10105	324	260	351.2778
6	10106	359	293	339.9081
7	10107	288	281	311.6597
8	10108	292	248	303.3459
9	10109	283	257	282.0353
10	10110	447	343	407.3714
11	10111	520	371	412.0635
12	10112	274	316	375.5620
13	10114	318	319	345.9937
14	10115	223	274	316.0628

Showing 1 to 15 of 517 entries, 4 total columns

Ex. 2

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

	schoolcode	choicepgm	sssdistrict	ssslong	ssslat	cutoff	quality	size
1	30107	Business	Cape Coast Municipal	-1.3065939	5.153656	424	434.5333	45
2	30107	General Arts	Cape Coast Municipal	-1.3065939	5.153656	417	429.0400	125
3	30107	General Science	Cape Coast Municipal	-1.3065939	5.153656	433	444.9769	130
4	30107	Home Economics	Cape Coast Municipal	-1.3065939	5.153656	403	416.8000	40
5	30107	Visual Arts	Cape Coast Municipal	-1.3065939	5.153656	394	411.7250	40
6	30103	Business	Cape Coast Municipal	-1.3065939	5.153656	412	428.0000	40
7	30103	General Arts	Cape Coast Municipal	-1.3065939	5.153656	411	424.0429	70
8	30103	General Science	Cape Coast Municipal	-1.3065939	5.153656	417	429.6286	70
9	30103	Home Economics	Cape Coast Municipal	-1.3065939	5.153656	400	409.4500	20
10	30103	Visual Arts	Cape Coast Municipal	-1.3065939	5.153656	393	405.2000	20
11	21003	Agriculture	Kwahu South (Mpraeso)	[illegible]287	6.619226	372	389.4250	40
12	21003	Business	Kwahu South (Mpraeso)	[illegible]5287	6.619226	377	397.9600	100
13	21003	General Arts	Kwahu South (Mpraeso)	-0.6355287	6.619226	403	412.8750	40
14	21003	General Science	Kwahu South (Mpraeso)	-0.6355287	6.619226	411	429.8700	100

Ex. 3

In this exercise, first use the df st_choice created in Q2 which convert the wide to long of the schoolcode and pgmcode

Then I merge the choice info for each student with jssdistrict info.

The answer below is a long format including each choice's distance for every student,

	V1	time	schoolcode	choicepgm	dist
1	1	2	50107	General Arts	453.7276
2	1	3	50202	Visual Arts	454.0363
3	1	4	50202	Visual Arts	454.0363
4	1	1	50112	Home Economics	453.7276
5	1	5	50702	Home Economics	453.7238
6	1	6	50901	General Arts	453.9189
7	2	1	70102	General Arts	464.6703
8	2	2	70602	Business	465.0102
9	2	6	70603	General Arts	465.0102
10	2	5	70605	Home Economics	465.0102
11	2	3	70107	General Arts	464.6703
12	2	4	70105	General Arts	464.6703
13	3	3	50115	Business	470.8541
14	3	5	51603	Home Economics	470.9553

Ex. 4

4.1

Add the scode_rev in long format

	V1	score	schoolcode	choicepgm	time	rankplace	scode_rev
1	1	[illegible]	[illegible]112	Home Economics	1	NA	501
2	1	[illegible]	[illegible]107	General Arts	2	NA	501
3	1	[illegible]	[illegible]202	Visual Arts	3	NA	502
4	1	NA	50202	Visual Arts	4	NA	502
5	1	NA	50702	Home Economics	5	NA	507
6	1	NA	50901	General Arts	6	NA	509
7	2	NA	70102	General Arts	1	NA	701
8	2	NA	70602	Business	2	NA	706
9	2	NA	70107	General Arts	3	NA	701
10	2	NA	70105	General Arts	4	NA	701
11	2	NA	70605	Home Economics	5	NA	706
12	2	NA	70603	General Arts	6	NA	706
13	3	NA	50702	Business	1	NA	507
14	3	NA	50705	Home Economics	2	NA	507

column 2: numeric with range 140 - 480

howing 1 to 15 of 2,044,938 entries, 7 total columns

4.2

Filter

	V1	score	schoolcode	choicepgm	time	rankplace	scode_rev	pgm_rev
1	1	NA	50112	Home Economics	1	NA	501	economics
2	1	NA	50107	General Arts	2	NA	501	arts
3	1	NA	50202	Visual Arts	3	NA	502	arts
4	1	NA	50202	Visual Arts	4	NA	502	arts
5	1	NA	50702	Home Economics	5	NA	507	economics
6	1	NA	50901	General Arts	6	NA	509	arts
7	2	NA	70102	General Arts	1	NA	701	arts
8	2	NA	70602	Business	2	NA	706	economics
9	2	NA	70107	General Arts	3	NA	701	arts
10	2	NA	70105	General Arts	4	NA	701	arts
11	2	NA	70605	Home Economics	5	NA	706	economics
12	2	NA	70603	General Arts	6	NA	706	arts
13	3	NA	50702	Business	1	NA	507	economics
14	3	NA	50705	Home Economics	2	NA	507	economics

4.3

	V1	score	schoolcode	choicepgm	time	rankplace	scode_rev	pgm_rev	choice_rev
1	1	NA	50112	Home Economics	1	NA	501	economics	501_economics
2	1	NA	50107	General Arts	2	NA	501	arts	501_arts
3	1	NA	50202	Visual Arts	3	NA	502	arts	502_arts
4	1	NA	50202	Visual Arts	4	NA	502	arts	502_arts
5	1	NA	50702	Home Economics	5	NA	507	economics	507_economics
6	1	NA	50901	General Arts	6	NA	509	arts	509_arts
7	2	NA	70102	General Arts	1	NA	701	arts	701_arts
8	2	NA	70602	Business	2	NA	706	economics	706_economics
9	2	NA	70107	General Arts	3	NA	701	arts	701_arts
10	2	NA	70105	General Arts	4	NA	701	arts	701_arts
11	2	NA	70605	Home Economics	5	NA	706	economics	706_economics
12	2	NA	70603	General Arts	6	NA	706	arts	706_arts
13	3	NA	50702	Business	1	NA	507	economics	507_economics
14	3	NA	50705	Home Economics	2	NA	507	economics	507_economics

4.4

	V1	score	rankplace	time	choice_rev	scode_rev	pgm_rev	cutoff	quality
1	1	NA	NA	1	501_economics	501	economics	207	349.1362
2	1	NA	NA	2	501_arts	501	arts	259	358.7018
3	1	NA	NA	3	502_arts	502	arts	205	317.1521
4	1	NA	NA	4	502_arts	502	arts	205	317.1521
5	1	NA	NA	5	507_economics	507	economics	212	275.2742
6	1	NA	NA	6	509_arts	509	arts	216	256.2021
7	2	NA	NA	1	701_arts	701	arts	202	297.1085
8	2	NA	NA	2	706_economics	706	economics	202	291.7585
9	2	NA	NA	3	701_arts	701	arts	202	297.1085
10	2	NA	NA	4	701_arts	701	arts	202	297.1085
11	2	NA	NA	5	706_economics	706	economics	202	291.7585
12	2	NA	NA	6	706_arts	706	arts	202	286.8746
13	3	NA	NA	1	507_economics	507	economics	212	275.2742
14	3	NA	NA	2	507_economics	507	economics	212	275.2742

Showing 1 to 15 of 2,044,938 entries, 9 total columns

4.5

Change the data format from long to wide and keep the 20000 highest score students

	V1	score	rankplace	choice_rev_1	choice_rev_2	choice_rev_3	choice_rev_4	choice_rev_5	choice_rev_6	scode_rev_1	scode_rev_2
1	335624	469	1	301_science	301_economics	501_arts	215_economics	104_arts	101_arts	301	301
2	318458	468	1	210_science	401_science	301_science	102_economics	NA_others	NA_others	210	401
3	318492	467	1	210_science	201_science	213_science	204_science	105_others	215_arts	210	201
4	335584	467	1	301_science	211_science	203_arts	215_arts	NA_others	NA_others	301	211
5	318422	466	1	210_science	201_science	213_science	204_economics	NA_others	NA_others	210	201
6	318525	466	1	210_science	201_science	101_science	213_science	206_others	210_economics	210	201
7	335568	465	1	301_science	502_science	501_economics	101_science	NA_others	NA_others	301	502
8	335629	465	1	301_science	203_science	303_science	301_science	210_economics	206_economics	301	203
9	335722	465	1	301_science	301_economics	203_science	203_economics	102_science	102_others	301	301
10	239799	464	1	301_science	101_science	102_science	101_science	102_science	101_science	301	101
11	268535	464	1	301_science	301_science	309_science	306_science	102_arts	102_arts	301	301
12	289149	464	1	501_science	201_science	401_science	304_science	201_economics	210_economics	501	201
13	335866	464	1	301_science	301_arts	211_science	211_arts	NA_others	NA_others	301	301
14	335901	464	1	301_science	301_arts	301_arts	301_economics	NA_others	NA_others	301	301

Showing 1 to 14 of 20,000 entries, 33 total columns

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,X,Y){
  alpha = c(0,theta[n:(2*(n-1))])
  alpha = sapply(alpha,rep,20000)
  beta = c(0,theta[1:n-1])
  beta = sapply(beta,rep,20000)
  Vij = X*beta + alpha
  Pij = prop.table(exp(Vij),1)
  Pij[Pij>0.999999] = 0.999999
  Pij[Pij<0.000001] = 0.000001
  logl = sum(Y*log(Pij))
  Y = -logl


  return(Y)
}
```

5.2

Here we have part of 246 different choices in first choice, corresponding to the choice

	choice_rev_1
1	100_arts
2	100_economics
3	100_others
4	100_science
5	101_arts
6	101_economics
7	101_others
8	101_science
9	102_arts
10	102_economics
11	102_others
12	102_science
13	103_arts
14	103_economics

#for beta(coefficient),which is theta[1:245]here:

[1] 0.4236992649 -0.4298517662 -0.4585390054 -0.3079843875 -0.1087260644 0.2782564128 -0.1870127216
[8] -0.3810078779 -0.3487222474 0.2982587391 -0.3875480460 0.2350985822 0.4529696198 -0.1018956248
[15] -0.4446969160 -0.4915754283 -0.0768017471 -0.1731771969 0.0356330243 -0.0422914238 -0.0622675710
[22] -0.4950613738 0.0875965189 -0.1876340208 -0.2561549018 0.3058064494 0.3007744744 -0.1478449362
[29] 0.2948127931 -0.2090365430 0.3760864609 0.3912455027 -0.1999099334 0.2796564433 0.2917125074
[36] 0.0135740237 0.1709127009 0.1526615114 -0.2944075889 -0.2418978019 0.0636869979 0.3752865691
[43] 0.4160368741 -0.0662471906 0.1092028255 0.2001414672 0.3286379678 0.0775107192 -0.1768893306
[50] 0.2046021095 -0.0563824659 0.1285486538 0.4399895277 -0.0465938658 -0.2620554098 0.0416609303
[57] 0.0268957918 -0.1662422752 -0.2045858211 -0.1796305373 -0.2160139841 -0.2814637758 0.2374683504
[64] -0.4048971066 -0.0049814328 -0.0059507473 0.1135452532 -0.1474183584 0.2848484260 0.2067052613
[71] 0.1974038093 -0.3889155497 0.1995989524 -0.1650123403 -0.2757734747 -0.3205530832 0.5241142626
[78] 0.0535019748 -0.0504499942 -0.4210424782 -0.0217124079 -0.2064573979 0.3906879914 -0.2450514478
[85] -0.0522424355 -0.1397647946 -0.2670833215 0.3192989470 0.3799424402 0.2246646350 0.4780491584
[92] -0.1912860950 -0.0008766323 0.1154075568 -0.1340273051 0.3448017093 0.3426854522 -0.4859375358
[99] 0.4552259684 -0.2992421382 -0.2962045991 -0.3672678135 -0.1037999485 -0.3270541797 -0.2238143268
[106] 0.1845438040 0.4802556494 0.3596015032 -0.0316299333 0.1420212586 -0.3197874755 -0.3612664717
[113] 0.0179938485 -0.2032199802 0.1667506457 -0.2029696952 -0.1585414081 0.3479460459 0.1108614772
[120] -0.4837550221 0.4321802567 -0.3265072159 -0.3840617214 0.1146242779 -0.3603033216 -0.3458258524
[127] 0.0068995338 -0.0891191885 0.1432755552 0.2174658077 1.3131553219 -0.4717817602 -0.0136590223
[134] -0.2863367035 -0.2195498473 0.0732818770 0.4094127882 0.4113748353 -0.2382958911 0.1951695178
[141] 0.0962490498 -0.0496437892 0.2508900834 0.1957451801 -0.0218797224 -0.0381163282 0.1714629000
[148] 0.2208922992 -0.4342557434 -0.2192237685 0.0311137103 -0.0648685398 0.3184871350 0.0673349760

[155] 0.1095447557 0.2638284417 -0.3454762481 -0.4233647983 -0.1443168835 -0.2842750037 0.2000115968
[162] -0.4276421482 0.2714707777 0.2768012155 -0.4887680321 0.2588931434 0.0119104648 0.4034985285
[169] -0.3861511834 0.0409804019 -0.3973155194 -0.2475163455 0.1711786126 0.0519929191 -0.0690343413
[176] -0.4153146101 -0.4206731237 0.4803646975 0.2885932971 0.2994752254 -0.3824146707 0.0077766790
[183] -0.3078744737 0.2849092060 0.2471641079 0.1126830410 -0.2812823630 0.1062211210 0.0991039139
[190] -0.4577116910 -0.4656251231 -0.4036276005 0.1992802420 0.3578358067 -0.4411045061 0.3994385789
[197] -0.1723929022 -0.1094853193 -0.3978962961 -0.3446038701 0.2439527060 0.2691889605 -0.0139686707
[204] -0.1282044908 -0.0792533641 0.0636437272 -0.2835924111 -0.0150479751 -0.1192276250 0.2308882200
[211] -0.1847864464 -0.4614551966 -0.2279936890 0.3900958730 -0.1219953990 -0.0250295552 -0.2899900482
[218] -0.0626034883 0.0307791110 -0.3270877516 0.1521494365 -0.1357823671 0.4803121799 0.3365696401
[225] 0.2596253981 -0.1402450483 -0.2822606775 0.1605940692 -0.4688160846 -0.1603679089 0.3092344112
[232] -0.0763354364 0.2024060308 -0.3164384079 -0.3453871165 -0.3604544888 -0.2608802745 -0.1405644945
[239] -0.3752912988 0.4173100973 -0.2101738474 0.1846518687 -0.0646036516 -0.4199135117 -0.2133566020

#for alpha(intercept), which is theta[246:490]here:

[246] -0.3576791494 -0.2727408060 0.2162671990 0.4148341944 -0.2604985244 0.4404933099 0.0205182084
[253] -0.1419243987 -0.2197559301 0.4446149028 -0.0446051327 -0.3737606693 -0.0187492111 0.0741116498
[260] -0.2071552651 -0.3334637010 -0.0860618413 0.2651371828 0.2350223868 0.2214429022 0.4767013320
[267] 0.2088943094 -0.0247671823 0.1484691557 -0.2213512296 -0.2330391286 0.4374598567 0.0466074350
[274] -0.2200763607 -0.2640684037 0.2957792259 -0.0454880288 0.0890967504 0.4162315654 0.2054540098
[281] -0.0915469227 -0.2147006420 0.4065026066 -0.4155311314 -0.3735425160 0.1225719568 0.1427993102
[288] 0.2840288898 0.1854993538 0.4919924249 0.3001029964 -0.0833725915 0.2998520595 -0.2229215745
[295] 0.2587465141 0.3829946639 -0.3814407240 0.4402440675 0.0853109653 0.3337042839 -0.2447551452
[302] 0.4447492724 0.0824640256 0.2580395045 -0.0524673271 -0.4053283527 -

0.1457768064 -0.2371506854
[309] -0.4148981802 0.0584328228 -0.4432419133 0.0513450091 0.2455635017
0.4261938452 0.0087158787
[316] 0.4498470630 0.3500533465 0.2712114358 -0.1901658685 0.0043093099
0.4081975759 -0.4913336527
[323] 0.0573574880 -0.1845033646 0.0905282414 0.2137282703 0.2090477145
0.4190505664 0.4799704156
[330] 0.3473045505 -0.0023816281 -0.1657258482 0.2974442909 -0.2530481815 -
0.0668219090 -0.0540779251
[337] 0.1817745809 -0.1567061662 0.0520566269 0.0397826324 -0.1039879660
0.1336991175 0.3246997115
[344] -0.1559645480 -0.3676084946 0.4929889834 -0.4867218486 0.3419736072
0.1572832288 -0.3628709621
[351] -0.0480161284 -0.0529774307 0.0724874747 0.0970696686 0.0871942311
0.1530442892 -0.0476250765
[358] -0.0266043055 0.0607329509 -0.2225290586 -0.3908738492 0.0710070913 -
0.0038455673 -0.4872930148
[365] 0.4359455097 0.1991528899 -0.3989477130 0.2907913837 -0.3446789312
0.3377286077 -0.4608222290
[372] -0.2186131480 0.3589276245 0.0868427986 -0.3341391091 -0.4929518929 -
0.2863803045 -0.0885565514
[379] 0.3758093100 0.4164319308 -0.0048810695 -0.3754304643 0.4188514932
0.3325635032 0.0981749666
[386] 0.2018990540 -0.0229078268 -0.2437178942 0.4917441576 -0.2910255971 -
0.4304902896 -0.0246948942
[393] -0.2921537200 -0.0207441400 0.1040640548 -0.1439720958 0.3314023162 -
0.3865812402 0.0460783548
[400] -0.1366252070 0.4314735050 -0.2186482593 -0.3902594326 -0.2545358681
0.1530324153 -0.2896310478
[407] -0.3053853340 0.2058509558 -0.4640356039 -0.3734385576 -0.2182497368 -
0.1034970190 0.3845589510
[414] 0.4803277222 0.4200044926 -0.3860237270 -0.1187260600 0.2024314816
0.0300664220 0.4810177349
[421] -0.3934989122 -0.2080171445 0.3138941891 0.3900338279 0.3981134358 -
0.2618523287 -0.2258663275
[428] 0.0426168761 0.4701783683 -0.3028857845 -0.2528950593 -0.1839942567
0.4392478759 0.1360934053
[435] -0.4767558908 0.4821705977 -0.3293772738 -0.1977581889 0.0916086242
0.1448332539 -0.0894178099
[442] -0.2754790457 -0.1360095912 -0.0362815771 0.3394258972 0.3572212635 -
0.0206428962 -0.2170061979
[449] -0.3785115348 0.3949833612 0.4816679421 0.2891227845 0.2325388235
0.3073595706 0.2786357393
[456] -0.1655445509 0.2097324715 -0.1311387308 -0.4904258489 0.0159260470

0.1335192407 0.2703746557
[463] 0.4244647562 -0.2268601381 -0.0417630316 0.2508126097 0.3474887863 -0.3961425794 -0.3873614797
[470] 0.3711453832 0.2481785279 -0.3913609949 -0.0873235005 -0.3754839373 -0.4753998867 -0.1964055435
[477] -0.4980753097 -0.1993316764 0.2209338292 0.2798484673 0.0746777358 0.2154335596 0.3362719563
[484] 0.0304102181 -0.3350533438 -0.3654829063 0.3791729691 -0.2746100405 0.4499928735 0.2160626689

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 -0.5388 less likely to choose 101economics compared to 101arts.
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 0.9089 more likely to choose 101economics compared to 101arts.

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 -0.0000095000000000000001 - -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

Conditional logit model is appropriate 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){
  # print(X)
  alpha = c(0,theta[2:n])
  alpha = sapply(alpha,rep,20000)
  Vij = X*theta[1]+alpha
  Pij = prop.table(exp(Vij),1)
  # Pij[Pij>0.999999] = 0.999999
  # Pij[Pij<0.000001] = 0.000001
  logl = sum(choice_matrix*log(Pij))
  Y = -logl
  return(Y)
}
```

6.2

#for beta(coefficient),which is theta[1]here, which is equals to 0.01596460, the sign is positive, then if the quality increases, the demand of choosing one of the alternatives will increase.

[1] 0.01596460

#for alpha(intercept), which is theta[2:246]here:

0.49451321 -0.35850258 0.61387693 3.65550568 3.09680773 1.40712067 3.12309839
[9] 1.54371650 1.49958794 -0.64378152 0.64715519 -1.14657696 -2.49756281 -6.40337520 0.73010818
[17] -0.61708717 -0.75194123 -9.34253863 -1.68757324 -0.15260189 0.05149802 -8.20622353 -1.05091054
[25] 2.38137269 1.88633930 0.96987695 1.59728203 -13.46368673 -1.43604920 -2.41193239 -2.40541925
[33] 2.81188842 2.26204718 -2.61790066 1.02113861 2.19312344 0.97415001 0.38367222 -0.03422081
[41] -1.48248564 -1.53880185 -2.77863530 -1.81605164 -0.07653109 -0.55993363 -1.78345113 -1.30987370
[49] -1.17317886 -2.08414438 -1.06698933 -1.11843310 -2.67642052 -1.99188455 -2.51961331 2.36593550
[57] 2.18047142 1.04132262 2.46054952 2.50573950 1.71087674 1.19900760 -6.59624292 -7.46246253
[65] 1.34802807 0.65653536 -1.07044955 0.60787163 -0.13073300 -0.30528576 0.02215191 3.38488463
[73] 3.10979785 1.47549785 2.70738231 -3.43804289 1.75018571 1.14001871 -0.43600057 -0.25718571
[81] 0.91040344 1.08392546 -2.33298112 -0.79738588 -0.14708745 -0.06258964 -1.89150945 -0.23131083
[89] 0.47980337 -1.54581002 -0.93931272 -1.08670088 -2.76247320 -1.32338390 -2.53785279 0.18028918
[97] 0.41307119 -7.32765187 -0.59442484 -1.24670990 -1.92179603 -3.42747534 -1.20572395 -2.44078274
[105] -1.73205680 -2.90127802 -6.16706841 -1.45486745 2.14958754 1.93929120 1.46535807 1.56263562
[113] -2.08476391 -1.47533164 -25.21431608 -1.61800696 -1.22075442 -1.95230636 -2.13838537 -1.19639648
[121] -1.89845762 -1.81860186 -2.46173190 -2.33295359 -1.24656647 -1.57278502 -7.01476258 -2.03557295
[129] -0.16627599 -0.89873486 3.57935253 3.25914940 1.03168356 3.20410194 2.53372956 1.94805809
[137] -0.07142478 1.24679240 0.43498375 -0.20310941 -1.50621339 -0.19344797 1.86204024 1.27754315
[145] -1.06285573 0.27881182 -0.71870646 -1.06036423 -1.58012781 -2.36559304 -0.78932513 -6.33556721
[153] 0.44895809 -0.02482992 -1.67679145 -0.59983083 -0.14203753 -0.25565473 -0.68616412 -0.34061209
[161] -13.60797426 -21.68314422 -6.32735098 -1.81738256 -16.98159052 -7.69979787 -

0.47739854 -1.21462346
[169] -2.25919156 -2.42434188 -1.35199070 -3.24489373   2.09664922   1.02904071
0.86822222   1.69861878
[177] -8.02007317 -2.18317991 -0.67583705 -10.32463912 -12.58657718 -3.47424819 -
0.92220208 -13.74340893
[185] -2.83543202 -0.71968646 -1.76765952 -2.34857069 -5.07039299 -1.86354770 -
1.13948932 -4.66819750
[193] -19.66925179 -1.82492155 -0.05587756 -0.49025709 -1.10610881   2.13108579
1.80284193 -0.20041050
[201]   1.31598043 -0.90190758 -1.45186538 -1.70421408 -1.77039020 -2.23885792
0.26733443   0.77671442
[209] -1.32735689   0.40270876   0.55743842   0.71215357 -1.23898963   0.84278266 -
1.72340227 -0.64332972
[217] -0.65633780 -0.68252208 -0.87282331 -20.59125229 -21.62613888 -1.71024352 -
1.92410093 -2.81797901
[225] -2.29250566   0.08718731 -5.71800869 -0.93698801 -2.77914668   1.07473879
0.42586281 -0.73217622
[233]   1.08198134 -2.81032542 -1.76882285 -1.51029071   0.35714849 -1.11464191 -
0.72749506 -1.23316061
[241] -0.66452380 -0.52169585 -0.49514331 -0.32895492 -0.63257463 -1.87594810

As it shows, the intercept _i above implies that compared to choice 1(101arts), how the students like choice_i.

the beta_i above implies that compared to choice 1, how the school quality affects the choice_i.

The marginal effect is as follows:

ME1 × | ME_mlogit_mean × | ME_mlogit × | alpha_mulij × | beta_mulij × | pij_mul × | Vij_mul × | AR3.

Filter   Cols: « ‹ 1 - 50 › »

	V1	V2	V3	V4	V5	V6	V7	V8	V9
1	9.938053e-06	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
2	-6.194207e-09	1.366251e-05	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
3	-6.194207e-09	-1.171244e-08	4.310766e-06	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
4	-6.194207e-09	-1.171244e-08	-1.164623e-09	2.944432e-05	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
5	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	1.005524e-03	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
6	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	4.803194e-04	-3.448974e-07	-6.274419e-05	-4.
7	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	7.385853e-05	-6.274419e-05	-4.
8	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	9.380985e-04	-4.
9	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	8.
10	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
11	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
12	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
13	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
14	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
15	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
16	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.
17	-6.194207e-09	-1.171244e-08	-1.164623e-09	-5.450688e-08	-7.284052e-05	-1.539218e-05	-3.448974e-07	-6.274419e-05	-4.

Ex. 7

7.1

I think MLogit model is appropriare because excluding "others" program here is a characteristic of choice but invariant for individual.

7.2

I create the new choice without others and run the clogit model again, the new subset dat now has 195 unique choices and 19302 individuals. Below is my coefficient answers:

[1] 0.01266003 0.87058434 1.53179355 4.44621616 3.86511454 4.02224864 2.29405184 2.24417633

[9] 1.39244354 -1.16080714 -1.39327693 -1.04127735 0.35373998 0.19933482 -0.96520282 0.69653773

[17] 0.70676037 -0.29909536 3.19910265 2.74944767 2.45124126 -1.87417327 -0.87761389 -1.11763678

[25] 3.59221151 2.99597874 2.02679820 2.79387654 1.89304604 -62.43086413 -0.73874132 -0.56727860

[33] -1.21158955 0.67874526 0.07087817 -1.12406792 -19.13317084 -0.95200643 -0.26241076 -0.31299836

[41] -1.72965203 -1.86756405 3.03437731 2.82905434 3.19890586 -9.53730988 2.27284922 -8.86766582

[49] -1.77194253 -1.80026376 2.00614458 1.59639647 -0.05243628 1.21242542 0.71352865 -6.65250756

[57] 4.26741061 3.96220819 3.71953664 -2.19922933 2.57045666 1.85873763 0.99080464 1.73367883

[65] 1.84484874 -0.29978451 0.52951382 0.52539866 -29.00804520 0.51164255 1.05438436 0.02507024

[73] -1.70362260 -0.69923273 -1.51296215 0.91942011 0.98866057 0.31891666 -0.30808310 -0.61819062

[81] -0.39204843 -1.76452047 -6.73828922 -2.33328578 -1.79569846 2.83372669 2.64439262 2.47849927

[89] -1.09370333 -2.09306693 -0.83975072 -8.88210014 -0.99142419 -14.76938047 -1.80236613 -1.51524192

[97] -6.53253831 -0.31636101 -1.29247228 -1.13720125 0.55091826 -0.26138395 4.45452892 4.09051597

[105] 4.15435172 3.33270269 2.76659802 2.04693292 1.19968487 0.42087681 -0.16299274 2.57701018

[113] 2.02623880 1.23093604 -0.11690456 -0.38942860 -0.35099049 -1.34860843 -0.09954229 -1.57989287

[121] 1.18831045 0.50723995 0.10747244 0.47421490 0.06878065 0.53162006 -2.07372548 -1.90838806

[129] -1.44904892 -0.78619296 -2.16203474 0.22125383 -0.33277415 -1.33010499 -1.44383874 -1.13497445

[137] -2.22518562 2.71947813 1.85624320 2.45625709 -2.04281342 -1.29212533 -8.60711314 -1.90436130

[145] -2.46826478 -0.02224623 -1.74396712 -0.07846879 -0.92242935 -20.22031917 -

1.97345843 -1.07920766
[153] -1.80054193 -1.30882234 -2.69427798   0.61917755   0.17727784 -0.43471937
2.78895821   2.46276616
[161]   1.93985895 -16.25021196 -10.40417648 -16.07418419 -1.11509714   0.76860057
1.39070003   1.22654063
[169]   1.33253986   1.28157181   1.68836844 -1.16142199 -0.24828151   0.19911256 -
42.99192776 -0.28487861
[177] -2.06357918 -1.70677046 -1.17974772 -1.07806068 -1.46401954 -7.10124633 -
1.95243252 -0.20675251
[185] -1.55331841   1.78700706   0.93815216   1.80310345 -1.69667287 -6.99322596 -
0.22856204 -0.03952450
[193]   0.39866381 -0.01078481   0.52610310

7.3 **I compare the coefficient in Exercise 6 excluding the choices contains "others" and the coefficient in Exercise 7 and calculate the difference for each coefficient.**
The code is as follows:

```
Pij2_no_others = P_j_bar[,-as.numeric(which(others==TRUE))]
others_row = unlist(choice_rev_1_subject)
others_row = which(others_row[seq(2,length(others_row),2)]=='others')
Pij2_no_others = pij2_no_others[-others_row,]
pij_changes= Pij_2[1,]-Pij2_no_others[1,]
```