

Notes for POL 290G, B. Jones, Dept. of Political Science, UC-Davis

Working with multinomial models: Some R and Stata code.

Multinomial logit model using data on immigration attitudes (from “Order Matters(?)”). The full R script can be found on my webpage.

Response variable: Attitudes toward the chances immigrants will “take away jobs” from Americans. Note, this is not a Likert scale, though it is putatively ordinal:

- 1=extremely likely
- 2=very likely
- 3=somewhat likely
- 4=not very likely

Estimation in R using vglm:

```
> imod_MNL<-vglm(formula= ImmJobs ~ Traits.Hispanics + IDSelfPlace +  
gdiff + Morals + PersonalRetro,  
+ family=multinomial); summary(imod_MNL)
```

Call:

```
vglm(formula = ImmJobs ~ Traits.Hispanics + IDSelfPlace + gdiff +  
Morals + PersonalRetro, family = multinomial)
```

Pearson Residuals:

	Min	1Q	Median	3Q	Max
log(mu[,1]/mu[,4])	-3.9642	-0.37702	-0.24884	-0.14159	4.0810
log(mu[,2]/mu[,4])	-3.4823	-0.44262	-0.32061	-0.13858	3.4567
log(mu[,3]/mu[,4])	-3.2570	-0.60005	-0.46458	1.03451	1.8172

Coefficients:

	Value	Std. Error	t value
(Intercept):1	-4.332758	0.82061	-5.27991
(Intercept):2	-3.341764	0.75207	-4.44342
(Intercept):3	-1.304420	0.64866	-2.01096
Traits.Hispanics:1	2.457874	1.08346	2.26854
Traits.Hispanics:2	2.571044	1.01382	2.53599
Traits.Hispanics:3	1.914010	0.89626	2.13556
IDSelfPlace:1	-0.517587	0.36595	-1.41435
IDSelfPlace:2	-0.063224	0.34217	-0.18477
IDSelfPlace:3	-0.035982	0.30751	-0.11701
gdiff:1	3.225394	0.71651	4.50150
gdiff:2	1.949107	0.69084	2.82136
gdiff:3	0.575577	0.61926	0.92946
Morals:1	3.875692	0.90350	4.28962
Morals:2	3.124365	0.83739	3.73105
Morals:3	1.681574	0.74526	2.25636
PersonalRetro:1	1.150033	0.48283	2.38186
PersonalRetro:2	0.829291	0.45309	1.83030
PersonalRetro:3	0.685212	0.40960	1.67288

Number of linear predictors: 3

Names of linear predictors:

```
log(mu[,1]/mu[,4]), log(mu[,2]/mu[,4]), log(mu[,3]/mu[,4])
```

Dispersion Parameter for multinomial family: 1

Residual Deviance: 1931.95 on 2304 degrees of freedom

Log-likelihood: -965.975 on 2304 degrees of freedom

Number of Iterations: 4

Results

- Multiequation Model
- $J - 1$ nonredundant logits.
- Baseline category is arbitrary (here, it is category 4)
- Interpreted as any other logit model, but many more quantities.
- IIA may be an issue in some applications.

Implementation in Stata

```
. mlogit ImmJobs Traits_Hispanics IDSelfPlace gdiff Morals PersonalRetro
```

```
Iteration 0: log likelihood = -1010.1141
Iteration 1: log likelihood = -967.3354
Iteration 2: log likelihood = -965.97706
Iteration 3: log likelihood = -965.97497
Iteration 4: log likelihood = -965.97497
```

Multinomial logistic regression

Number of obs = 774

LR chi2(15) = 88.28

Prob > chi2 = 0.0000

Pseudo R2 = 0.0437

Log likelihood = -965.97497

ImmJobs	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
1						
Traits_His~s	.5438642	.8794193	0.62	0.536	-1.179766	2.267494
IDSelfPlace	-.4816047	.2909975	-1.66	0.098	-1.051949	.08874
gdiff	2.649817	.5432291	4.88	0.000	1.585108	3.714527
Morals	2.194118	.7202116	3.05	0.002	.7825294	3.605707
PersonalRe~o	.4648204	.3749311	1.24	0.215	-.270031	1.199672
_cons	-3.028339	.6836689	-4.43	0.000	-4.368305	-1.688372
-----+-----						
2						
Traits_His~s	.657034	.7990651	0.82	0.411	-.9091049	2.223173
IDSelfPlace	-.0272422	.2624981	-0.10	0.917	-.5417291	.4872447
gdiff	1.37353	.5167766	2.66	0.008	.3606665	2.386393
Morals	1.442791	.6421718	2.25	0.025	.1841579	2.701425
PersonalRe~o	.1440791	.3386892	0.43	0.671	-.5197395	.8078977
_cons	-2.037344	.6059562	-3.36	0.001	-3.224997	-.8496921
-----+-----						
4						
Traits_His~s	-1.914011	.8964045	-2.14	0.033	-3.670932	-.1570909
IDSelfPlace	.0359823	.3075682	0.12	0.907	-.5668403	.6388049
gdiff	-.5755786	.6194035	-0.93	0.353	-1.789587	.63843
Morals	-1.681575	.745406	-2.26	0.024	-3.142544	-.2206061
PersonalRe~o	-.6852126	.4096908	-1.67	0.094	-1.488192	.1177666
_cons	1.304421	.6487651	2.01	0.044	.032865	2.575977

(ImmJobs==3 is the base outcome)

Comparison

- No difference ...
- except baseline category is chosen differently here.
- BC is category 3.
- Implications? None really.
- You can force Stata to change BC (base(4) at end of model statement would do this.
- To see equivalence, note:

```
. display [1]_b[Traits_]-[4]_b[Traits_]
2.4578756
```

```
. display [2]_b[Traits_]-[4]_b[Traits_]
2.5710454
```

```
. display -[4]_b[Traits_]
1.9140114
```

- These are differences in log-odds. In R the contrast is with category 4; in Stata, it's category 3.
- If you want to know log-odds of 1 vs. 4 (R), simply subtract log-odds of (4 vs. 3) from (1 vs. 3).

Adjacent Category Logit Model

Estimation in R using VGAM.

```
> #Produces Adjacent Cateorgy Logit Estimates
>
> imod_ACL<-vglm(formula= ImmJobs ~ Traits.Hispanics + IDSelfPlace +
gdiff + Morals + PersonalRetro,
+ family=acat); summary(imod_ACL)
```

Call:

```
vglm(formula = ImmJobs ~ Traits.Hispanics + IDSelfPlace + gdiff +
Morals + PersonalRetro, family = acat)
```

Pearson Residuals:

	Min	1Q	Median	3Q	Max
log(P[Y=2]/P[Y=1])	-3.9584	0.10607	0.19399	0.445039	1.5449
log(P[Y=3]/P[Y=2])	-3.2526	-0.94751	0.39500	0.853176	1.7959
log(P[Y=4]/P[Y=3])	-1.2808	-0.59704	-0.22232	-0.084046	5.9901

Coefficients:

	Value	Std. Error	t value
(Intercept):1	0.990994	0.74849	1.32398
(Intercept):2	2.037344	0.60596	3.36217
(Intercept):3	1.304420	0.64866	2.01096
Traits.Hispanics:1	0.113170	0.95325	0.11872
Traits.Hispanics:2	-0.657034	0.79908	-0.82223
Traits.Hispanics:3	-1.914010	0.89626	-2.13556
IDSelfPlace:1	0.454362	0.31507	1.44208
IDSelfPlace:2	0.027242	0.26251	0.10378
IDSelfPlace:3	0.035982	0.30751	0.11701
gdiff:1	-1.276287	0.56082	-2.27577
gdiff:2	-1.373530	0.51677	-2.65789
gdiff:3	-0.575577	0.61926	-0.92946
Morals:1	-0.751327	0.78043	-0.96271
Morals:2	-1.442791	0.64219	-2.24668
Morals:3	-1.681574	0.74526	-2.25636
PersonalRetro:1	-0.320741	0.40503	-0.79190
PersonalRetro:2	-0.144079	0.33870	-0.42539
PersonalRetro:3	-0.685212	0.40960	-1.67288

Number of linear predictors: 3

Names of linear predictors:

```
log(P[Y=2]/P[Y=1]), log(P[Y=3]/P[Y=2]), log(P[Y=4]/P[Y=3])
```

Dispersion Parameter for acat family: 1

Residual Deviance: 1931.95 on 2304 degrees of freedom

Log-likelihood: -965.975 on 2304 degrees of freedom

Number of Iterations: 4

Interpretation

- Because model is reparameterized BCL, all fit statistics will be identical.
- There are no statistical grounds upon which to adjudicate one over the other.
- Illustration:
Log-odds for morality scale

$$\begin{aligned}C_2 \text{ vs. } C_1 &= -.751 \\C_3 \text{ vs. } C_2 &= -1.443 \\C_4 \text{ vs. } C_3 &= -1.682\end{aligned}$$

Odds are:

$$\begin{aligned}C_2 \text{ vs. } C_1 &= \exp(-.751) = .471 \\C_3 \text{ vs. } C_2 &= \exp(-1.443) = .236 \\C_4 \text{ vs. } C_3 &= \exp(-1.682) = .186\end{aligned}$$

- The contrasts are between adjacent categories.
- Interpretation? “We see that moral-traditionalists are less likely to respond in the higher categories as versus the lower categories. Further, this variable seems to not distinguish well categories 2 vs. 1. Interestingly, both categories represent the view that immigrants will *likely* (extremely or very) take away jobs.”

(Converting ACL log-odds to odds ratios):

```
> or<-cbind(exp(coef(imod_ACL)))
> or
      [,1]
(Intercept):1  2.6939116
(Intercept):2  7.6702121
(Intercept):3  3.6855507
Traits.Hispanics:1  1.1198221
Traits.Hispanics:2  0.5183866
Traits.Hispanics:3  0.1474878
IDSelfPlace:1  1.5751689
IDSelfPlace:2  1.0276166
IDSelfPlace:3  1.0366372
gdifff:1  0.2790715
gdifff:2  0.2532116
gdifff:3  0.5623803
Morals:1  0.4717403
Morals:2  0.2362673
Morals:3  0.1860809
PersonalRetro:1  0.7256110
PersonalRetro:2  0.8658193
PersonalRetro:3  0.5039833
```

ACL vs. BCL

The only difference is the contrast. Consider the following BCL (estimated in Stata):

```
. mlogit ImmJobs Traits_Hispanics IDSelfPlace gdifff Morals
PersonalRetro, base(1)
```

```
Iteration 0: log likelihood = -1010.1141
Iteration 1: log likelihood = -967.3354
Iteration 2: log likelihood = -965.97706
Iteration 3: log likelihood = -965.97497
```

```
Multinomial logistic regression      Number of obs   =      774
LR chi2(15)                          =      88.28
Prob > chi2                           =      0.0000
Pseudo R2                             =      0.0437

Log likelihood = -965.97497
```

ImmJobs	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
2						
Traits_His~s	.1131698	.9532151	0.12	0.905	-1.755098	1.981437
IDSelfPlace	.4543625	.3150597	1.44	0.149	-.1631432	1.071868
gdifff	-1.276287	.5607951	-2.28	0.023	-2.375425	-.177149
Morals	-.7513267	.7803988	-0.96	0.336	-2.28088	.7782268
PersonalRe~o	-.3207413	.4050091	-0.79	0.428	-1.114545	.473062
_cons	.9909943	.7484796	1.32	0.185	-.4759987	2.457987

...output omitted
(ImmJobs==1 is the base outcome)

This is the contrast of category 2 vs. the baseline category of 1. Contrast this with the ACL estimated before (using R).

```
Traits.Hispanics:1  0.113170  0.95325  0.11872
IDSelfPlace:1      0.454362  0.31507  1.44208
gdifff:1          -1.276287  0.56082 -2.27577
Morals:1          -0.751327  0.78043 -0.96271
PersonalRetro:1   -0.320741  0.40503 -0.79190
```

They are identical, as they represent identical contrasts. The only difference is under the ACL, the baseline category represents the $j - 1$ category (i.e. $\log(p_j/p_{j-1})$); under the BCL, the baseline category is always j .

Anderson's Stereotype Logit Model

This is a reduced-rank BCL. Model parameters can be estimated in R using Yee's VGAM code. It now can be estimated in Stata (v.9) using `slogit`. In R:

```
> #Produces Anderson Stereotype Model
>
> imod_stereo <- rrvglm(ImmJobs ~ Traits.Hispanics+IDSelfPlace+
Morals + gdiff + PersonalRetro,
+ multinomial, Rank=1); summary(imod_stereo)
```

Call:

```
rrvglm(formula = ImmJobs ~ Traits.Hispanics + IDSelfPlace +
Morals +
      gdiff + PersonalRetro, family = multinomial, Rank = 1)
```

Pearson Residuals:

	Min	1Q	Median	3Q	Max
$\log(\mu_{[,1]}/\mu_{[,4]})$	-4.4894	-0.38081	-0.25154	-0.13939	3.9102
$\log(\mu_{[,2]}/\mu_{[,4]})$	-4.2797	-0.44495	-0.31539	-0.14679	3.5604
$\log(\mu_{[,3]}/\mu_{[,4]})$	-4.0210	-0.58232	-0.47162	1.03204	1.6050

Coefficients:

	Value	Std. Error	t value
I(lv.mat):1	0.74862	0.094984	7.8816
I(lv.mat):2	0.39212	0.084823	4.6228
(Intercept):1	-4.28529	0.811086	-5.2834
(Intercept):2	-2.78453	0.692810	-4.0192
(Intercept):3	-0.60683	0.529454	-1.1461
Traits.Hispanics	2.37890	1.035743	2.2968
IDSelfPlace	-0.45178	0.337441	-1.3388
Morals	3.94622	0.850406	4.6404
gdiff	3.46905	0.682961	5.0794
PersonalRetro	0.96762	0.443165	2.1834

Number of linear predictors: 3

Names of linear predictors:

```
 $\log(\mu_{[,1]}/\mu_{[,4]})$ ,  $\log(\mu_{[,2]}/\mu_{[,4]})$ ,  $\log(\mu_{[,3]}/\mu_{[,4]})$ 
```

Dispersion Parameter for multinomial family: 1

Residual Deviance: 1939.057 on 2312 degrees of freedom

Log-likelihood: -969.5284 on 2312 degrees of freedom

Number of Iterations: 4

Interpretation

- Note restrictions on ϕ
- $\phi = 1, \phi_4 = 0$
- Ordinality constraints seem to hold: $\phi_1 > \phi_2 > \phi_3 > \phi_4$.
- Given statistical significance of ϕ , distinguishability condition seems to hold.
- ϕ conveys information about the relative difference in weights associated with the covariates.
- Covariate effects are largest for “not very likely” vs. “somewhat likely” categories. (4 vs. 3)
- The difference is about .39 on the log odds scale. Difference between 2 vs. 1 is about .25.
- Consider the morals scale:
Log-odds for morality scale

$$C_1 \text{ vs. } C_4 = 3.95$$

$$C_2 \text{ vs. } C_4 = 3.95 \times .749 = 2.96$$

$$C_3 \text{ vs. } C_4 = 3.95 \times .392 = 1.55$$

Odds are:

$$C_1 \text{ vs. } C_4 = \exp(3.95) \approx 51$$

$$C_2 \text{ vs. } C_4 = \exp(2.96) \approx 19$$

$$C_3 \text{ vs. } C_4 = \exp(1.55) \approx 5$$

- Clearly a close connection to the BCL
- BCL does not fit better than this model. We might prefer to report this model.

Illustration in Stata

```
. slogit ImmJobs Traits_Hispanics IDSelfPlace gdiff Morals PersonalRetro, dim(1)
```

```
Iteration 0: log likelihood = -978.23902
Iteration 1: log likelihood = -974.90259
Iteration 2: log likelihood = -969.98352
Iteration 3: log likelihood = -969.55602
Iteration 4: log likelihood = -969.5284
Iteration 5: log likelihood = -969.52836
```

Stereotype logistic regression

```
Number of obs = 774
Wald chi2(5) = 58.70
Prob > chi2 = 0.0000
```

Log likelihood = -969.52836

(1) [phi1_1]_cons = 1

ImmJobs	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Traits_His~s	-2.378897	1.036031	-2.30	0.022	-4.409481	-.3483125
IDSelfPlace	.451782	.3373466	1.34	0.180	-.2094051	1.112969
gdiff	-3.46905	.6829146	-5.08	0.000	-4.807537	-2.130562
Morals	-3.946216	.8499482	-4.64	0.000	-5.612084	-2.280348
PersonalRe~o	-.9676152	.4431091	-2.18	0.029	-1.836093	-.0991372
/phi1_1	1
/phi1_2	.7486209	.0949184	7.89	0.000	.5625843	.9346575
/phi1_3	.3921207	.0849045	4.62	0.000	.2257109	.5585306
/phi1_4	0	(base outcome)				
/theta1	-4.285288	.8105076	-5.29	0.000	-5.873853	-2.696722
/theta2	-2.784526	.6948011	-4.01	0.000	-4.146311	-1.422741
/theta3	-.6068263	.5302372	-1.14	0.252	-1.646072	.4324196
/theta4	0	(base outcome)				

(ImmJobs=4 is the base outcome)

Multiple Dimensions:

. slogit ImmJobs Traits_Hispanics IDSelfPlace gdiff Morals PersonalRetro, dim(3)

Iteration 0: log likelihood = -965.97497

Iteration 1: log likelihood = -965.97497

Stereotype logistic regression

Number of obs = 774

Wald chi2(15) = 77.37

Prob > chi2 = 0.0000

Log likelihood = -965.97497

- (1) [phi1_1]_cons = 1
- (2) [phi1_2]_cons = 0
- (3) [phi1_3]_cons = 0
- (4) [phi2_1]_cons = 0
- (5) [phi2_2]_cons = 1
- (6) [phi2_3]_cons = 0
- (7) [phi3_1]_cons = 0
- (8) [phi3_2]_cons = 0
- (9) [phi3_3]_cons = 1

ImmJobs	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	

dim1						
Traits_His~s	-2.457876	1.083606	-2.27	0.023	-4.581705	-.3340463
IDSelfPlace	.517587	.3660112	1.41	0.157	-.1997817	1.234956
gdiff	-3.225396	.7167043	-4.50	0.000	-4.63011	-1.820681
Morals	-3.875693	.9036463	-4.29	0.000	-5.646807	-2.104579
PersonalRe~o	-1.150033	.4829151	-2.38	0.017	-2.096529	-.2035369

dim2						
Traits_His~s	-2.571045	1.01397	-2.54	0.011	-4.55839	-.5837004
IDSelfPlace	.0632245	.3422315	0.18	0.853	-.6075369	.7339859
gdiff	-1.949108	.6910179	-2.82	0.005	-3.303479	-.5947384
Morals	-3.124366	.8375387	-3.73	0.000	-4.765912	-1.482821
PersonalRe~o	-.8292917	.4531768	-1.83	0.067	-1.717502	.0589185

dim3						
Traits_His~s	-1.914011	.8964045	-2.14	0.033	-3.670932	-.1570909
IDSelfPlace	.0359823	.3075682	0.12	0.907	-.5668403	.6388049
gdiff	-.5755786	.6194035	-0.93	0.353	-1.789587	.63843
Morals	-1.681575	.745406	-2.26	0.024	-3.142544	-.2206061
PersonalRe~o	-.6852126	.4096908	-1.67	0.094	-1.488192	.1177666

/phi1_1	1
/phi1_2	0
/phi1_3	0
/phi1_4	0 (base outcome)

/phi2_1	0
/phi2_2	1
/phi2_3	0

/phi2_4		0	(base outcome)				

/phi3_1		0
/phi3_2		0
/phi3_3		1
/phi3_4		0	(base outcome)				

/theta1		-4.33276	.82072	-5.28	0.000	-5.941341	-2.724178
/theta2		-3.341765	.7521791	-4.44	0.000	-4.816009	-1.867522
/theta3		-1.304421	.6487651	-2.01	0.044	-2.575977	-.032865
/theta4		0	(base outcome)				

(ImmJobs=4 is the base outcome)

Contrast with BCL:

```
. mlogit ImmJobs Traits_Hispanics IDSelfPlace gdiff Morals PersonalRetro, base(4)
```

```
Iteration 0: log likelihood = -1010.1141
Iteration 1: log likelihood = -967.3354
Iteration 2: log likelihood = -965.97706
Iteration 3: log likelihood = -965.97497
Iteration 4: log likelihood = -965.97497
```

```
Multinomial logistic regression      Number of obs   =      774
LR chi2(15)                         =      88.28
Prob > chi2                          =      0.0000
Pseudo R2                            =      0.0437

Log likelihood = -965.97497
```

ImmJobs	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
1						
Traits_His~s	2.457876	1.083606	2.27	0.023	.3340463	4.581705
IDSelfPlace	-.517587	.3660112	-1.41	0.157	-1.234956	.1997817
gdiff	3.225396	.7167043	4.50	0.000	1.820681	4.63011
Morals	3.875693	.9036463	4.29	0.000	2.104579	5.646807
PersonalRe~o	1.150033	.4829151	2.38	0.017	.2035369	2.096529
_cons	-4.33276	.82072	-5.28	0.000	-5.941341	-2.724178
-----+-----						
2						
Traits_His~s	2.571045	1.01397	2.54	0.011	.5837004	4.55839
IDSelfPlace	-.0632245	.3422315	-0.18	0.853	-.7339859	.6075369
gdiff	1.949108	.6910179	2.82	0.005	.5947384	3.303479
Morals	3.124366	.8375387	3.73	0.000	1.482821	4.765912
PersonalRe~o	.8292917	.4531768	1.83	0.067	-.0589185	1.717502
_cons	-3.341765	.7521791	-4.44	0.000	-4.816009	-1.867522
-----+-----						
3						
Traits_His~s	1.914011	.8964045	2.14	0.033	.1570909	3.670932
IDSelfPlace	-.0359823	.3075682	-0.12	0.907	-.6388049	.5668403
gdiff	.5755786	.6194035	0.93	0.353	-.63843	1.789587
Morals	1.681575	.745406	2.26	0.024	.2206061	3.142544
PersonalRe~o	.6852126	.4096908	1.67	0.094	-.1177666	1.488192
_cons	-1.304421	.6487651	-2.01	0.044	-2.575977	-.032865

(ImmJobs==4 is the base outcome)