WWS 509 Generalized Linear Models: Precept 8 Multinomial and Sequential Logit Models

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Introducing the Data

This data comes from Germán's website. We are looking at how people rate their level of satisfaction in their housing. The options are high, medium, and low. Since there are more than 2 options, we can use multinomial logistic regression to predict responses. Controls we will consider include contact with neighbors (high or low), type of housing (tower, apartment, atrium, or terrace), and influence (on a scale of 0-2).

Multinomial Logit Model

- There are J-1 equations. One of the outcomes will serve as the baseline.
- Like the logit model, the log-odds is a linear function of the predictor.
- It makes no difference which category we pick as the reference cell, because we can convert from one formulation to another
- $log(\frac{\pi_{i1}}{\pi_{i2}}) = log(\frac{\pi_{i1}}{\pi_{i3}}) log(\frac{\pi_{i2}}{\pi_{i3}})$

Sequential Logit Model

- Also known as the hierarchical logit model
- We are now looking at nested comparisions. For example, I have to be ok with my housing not to rate my satisfaction level as "low," and then I choose between medium or high.
 - Can you think of other data which might benefit from this model?

Interpretation

General

- 1. Why did I change contact and influence with "-1"?
- 2. Which housing type is the reference category? Where besides the logit output can you find this?

Multinomial Logit

- 1. Looking at the model only including housing type, what seems to be the best housing? The worst?
- 2. Does this first model fit the data?
- 3. Is influence, net of housing, predictive of satisfaction?
- 4. What assumption am I making my modeling influence as continuous and not categorical?
- 5. What is the odds ratio for a person with an influence level of 2 of having a satisfaction level of medium compared to low in this model? Of high compared to low?
- 6. What about in the model that also controls for neighbor contact?
- 7. What about contact with neighbors?
- 8. Does the model with neighbors fit the data? How do you know?

Sequential Logit

- 1. Do you see anything interesting here that we did not see in the multinomial model?
- 2. Which model do you prefer for this data: multinomial or sequential?

Appendices

Stata Output

(Housing Conditions in Copenhagen)

- . quietly tab housing, gen(house_type)
- . rename house_type1 tower

```
. rename house_type2 apartment
. rename house_type3 atrium
. rename house_type4 terrace
. local house apartment atrium terrace
. replace influence=influence-1
(72 real changes made)
. quietly tab influence, gen(influ_type)
. rename influ_type1 influ_low
. rename influ_type2 influ_med
. rename influ_type3 influ_high
. local influ influ_med influ_high
. gen con_high=contact-1
. *** Multinomial ***
. *Saturated
. quietly mlogit satisfaction 'house' 'influ' con_high[fw=n]
. estimates store sat
. scalar ll_sat = e(ll)
. *Linear
. mlogit satisfaction 'house' [fw=n], baseoutcome(1)
Iteration 0:
              log likelihood = -1824.4388
Iteration 1:
              log likelihood = -1794.3345
Iteration 2:
              log\ likelihood = -1794.1045
Iteration 3:
              log likelihood = -1794.1044
Multinomial logistic regression
                                                Number of obs =
                                                                       1681
                                                LR chi2(6) =
                                                                       60.67
                                                Prob > chi2 =
                                                                      0.0000
Log likelihood = -1794.1044
                                                Pseudo R2
                                                                      0.0166
satisfaction | Coef. Std. Err. z P>|z| [95% Conf. Interval]
```

Low	 (base outco	ome)				
Medium	+ 					
apartment	3646241	.1700011	-2.14	0.032	6978201	0314281
atrium	.1905641	.219739	0.87	0.386	2401164	.6212446
terrace	6062843	.2025693	-2.99	0.003	-1.003313	2092559
_cons	. 0200007	.1414284	0.14	0.888	2571939	.2971953
High	+ 					
•	5948893	.1486684	-4.00	0.000	8862741	3035045
-	2977324			0.142	6952848	.09982
terrace	-1.345052	.1921081	-7.00	0.000	-1.721577	9685266
_cons	.7031975	.1228862	5.72	0.000	.4623451	.94405
. lrtest . sa	t					
Likelihood-ra	tio test				LR chi2(6) =	118.13
(Assumption:	. nested in sa	at)			Prob > chi2 =	
. mlogit sat: Iteration 0: Iteration 1: Iteration 2: Iteration 3: Iteration 4:	log likeliho log likeliho log likeliho log likeliho log likeliho	ood = -1824. ood = -1745. ood = -1744. ood = -1744.	4388 0131 0996 0991	, baseou	utcome(1)	
Multinomial lo	ogistic regres	ssion		Numbe	er of obs =	1681
				LR cl	ni2(8) =	160.68
				Prob	> chi2 =	0.0000
Log likelihood	d = -1744.099	1		Pseud	lo R2 =	0.0440
satisfaction	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
Low	+ (base outco	ome)				
Medium	+ 					
apartment	3878463	.17075	-2.27	0.023	7225103	0531824
atrium	.193475	.2205748	0.88	0.380	2388437	.6257936
terrace	5894198	.2033776	-2.90	0.004	9880327	190807
influence	.3207971	.0871399	3.68	0.000	.150006	.4915883
_cons	2062289	.1547364	-1.33	0.183	5095066	.0970489

High	1						
apartment		6609661	.1531665	-4.32	0.000	961167	3607652
atrium		3039443	.2084978	-1.46	0.145	7125925	.1047038
terrace		-1.306371	.1972983	-6.62	0.000	-1.693068	919673
influence		.7736902	.0807801	9.58	0.000	.615364	.9320164
_cons	I	.0654819	.1405259	0.47	0.641	2099437	.3409076

. lrtest . sat

Likelihood-ratio test LR chi2(4) = 18.11 (Assumption: . nested in sat) Prob > chi2 = 0.0012

. mlogit satisfaction 'house' influence $con_high[fw=n]$, baseoutcome(1)

Iteration 0: log likelihood = -1824.4388
Iteration 1: log likelihood = -1737.219
Iteration 2: log likelihood = -1736.1067
Iteration 3: log likelihood = -1736.1059
Iteration 4: log likelihood = -1736.1059

Multinomial logistic regression Number of obs = 1681 LR chi2(10) = 176.67 Prob > chi2 = 0.0000 Log likelihood = -1736.1059 Pseudo R2 = 0.0484

satisfaction	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
Low	(base outco	ome)				
Medium						
apartment	4413551	.1723525	-2.56	0.010	7791598	1035504
atrium	.1216597	.2227338	0.55	0.585	3148905	.5582099
terrace	6713139	.2061066	-3.26	0.001	-1.075275	2673525
influence	.3487541	.0879542	3.97	0.000	.1763671	.5211411
con_high	.3635188	.1323484	2.75	0.006	.1041207	.6229169
_cons	3823228	.16806	-2.27	0.023	7117143	0529313
High						
apartment	732001	.1551883	-4.72	0.000	-1.036164	4278376
atrium	4014077	.2112742	-1.90	0.057	8154975	.012682
terrace	-1.409386	.2000943	-7.04	0.000	-1.801564	-1.017208
influence	.8103557	.0818756	9.90	0.000	.6498824	.9708289
con_high	.4794532	.1240436	3.87	0.000	.2363322	.7225742
_cons	1732837	.1540446	-1.12	0.261	4752055	.1286381

. lrtest . sat

Likelihood-ratio test LR chi2(2) = 2.13 (Assumption: . nested in sat) Prob > chi2 = 0.3451

- . *** Sequential Model ***
 . gen ok = satisfaction > 1
- . logit ok 'house' influence con_high[fw=n]

Iteration 0: log likelihood = -1074.5419
Iteration 1: log likelihood = -1010.5894
Iteration 2: log likelihood = -1009.8002
Iteration 3: log likelihood = -1009.7996
Iteration 4: log likelihood = -1009.7996

Logistic regression Number of obs = 1681LR chi2(5) = 129.48

_	ok		Coef.	Std. Err	z	P> z	[95% Conf.	Interval]
	apartment atrium	 	6154755 1789057	.1427886	-4.31 -0.93	0.000 0.352	8953361 5555043	3356149 .1976928
	terrace		-1.080569	.1729336	-6.25	0.000	-1.419512	741625
	influence		.6177193	.0734991	8.40	0.000	.4736638	.7617748
	con_high		.4297313	.1105171	3.89	0.000	.2131217	.6463409
	_cons	l	.4386837	.1394585	3.15	0.002	.16535	.7120174

- . $scalar ll_ok = e(ll)$
- . gen high = satisfaction==3
- . logit high 'house' influence $con_high[fw=n]$ if ok

Iteration 0: log likelihood = -749.89688
Iteration 1: log likelihood = -725.90151
Iteration 2: log likelihood = -725.84153
Iteration 3: log likelihood = -725.84153

Logistic regression Number of obs = 1114

high	 -	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
apartment atrium	 	3252394 526402	.1571975	-2.07 -2.64	0.039	6333408 9178313	017138 1349727
terrace	Ī	7737943	.210587	-3.67	0.000	-1.186537	3610513
influence	1	.4712369	.0832203	5.66	0.000	.3081281	.6343457
con_high	1	.0878219	.1294341	0.68	0.497	1658643	.3415081
_cons	I	.2374671	.1574473	1.51	0.131	0711239	.546058

[.] $scalar ll_high = e(ll)$

^{. *} Overall log-likelihood

[.] di ll_ok + ll_high

^{-1735.6411}