

**Lab: Two-stage logistic -- Race, age, gender, and mortality in 7 US zipcodes**

**Data:** Race, age, gender and mortality data for 5800 individuals living in seven zip codes in the U.S. (zipcode\_mortality.dta)

**Variables:**

- **race:** 0--White; 1--Black.
- **sex:** 0--Male; 1--Female.
- **agecat:** 1--[65,70); 2--[70,75); 3--[75,80); 4--[80,85); 5--[85,+)
- **zip:** 1-7--Indicators of 7 distinct zip codes
- **y:** 0--Alive; 1--Dead.

**Goal:** Assess the association between mortality and demographic characteristics through a two-level logistic regression model, accounting for clustering within zipcodes.

**Exploratory Data Analysis:**

Quickly examine the categorical variable summaries.

```
. tab agecat
```

agecat	Freq.	Percent	Cum.
[65,70)	1,388	23.93	23.93
[70,75)	1,416	24.41	48.34
[75,80)	1,270	21.90	70.24
[80,85)	928	16.00	86.24
[85,+)	798	13.76	100.00
Total	5,800	100.00	

```
. tab sex
```

sex	Freq.	Percent	Cum.
male	2,270	39.14	39.14
female	3,530	60.86	100.00
Total	5,800	100.00	

```
. tab y race, column
      |           race
      |   white   black |   Total
-----+-----+-----
  alive |   5,416     82 |   5,498
      |   94.83   92.13 |   94.79
-----+-----+-----
  dead  |     295     7  |     302
      |    5.17  7.87 |     5.21
-----+-----+-----
 Total |   5,711     89 |   5,800
      |  100.00  100.00 |  100.00
```

We observe a higher percentage of death for the black population compared with the white population.

```
. tab zip race
      |           race
      |   white   black |   Total
-----+-----+-----
    1 |   2,212     5  |   2,217
    2 |   1,444    72 |   1,516
    3 |     251     9  |     260
    4 |      68     0  |      68
    5 |     860     1  |     861
    6 |     699     2  |     701
    7 |     177     0  |     177
-----+-----+-----
 Total |   5,711     89 |   5,800
```

Zip codes 4 and 7 contain no black individuals.

### Analysis assuming independence between individuals:

```
. xi:logit y race i.agecat sex
i.agecat      _Iagecat_1-5      (naturally coded; _Iagecat_1 omitted)

Logistic regression      Number of obs   =      5800
                        LR chi2(6)      =      154.38
                        Prob > chi2     =      0.0000
Log likelihood = -1109.2719      Pseudo R2      =      0.0651
```

```

-----
      y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      race |   .7277619   .4087863    1.78   0.075   - .0734445   1.528968
  _Iagecat_2 |   .3289547   .260447    1.26   0.207   - .181512   .8394215
  _Iagecat_3 |   1.181652   .2326983    5.08   0.000    .7255715   1.637732
  _Iagecat_4 |   1.451145   .2365551    6.13   0.000    .9875056   1.914785
  _Iagecat_5 |   2.142882   .226895    9.44   0.000    1.698176   2.587588
      sex |  - .4305185   .1228225   -3.51   0.000   - .6712462  - .1897909
  _cons |  -3.767649   .2063255  -18.26   0.000   -4.17204   -3.363259
-----

```

We have found:

- (1) higher (not statistically significant) risk of death for the black population;
- (2) higher risk of death as age increases;
- (3) lower risk of death for female compared with male.

Additionally adjusting for the interaction between age and gender:

```

. gen intagesex = agecat * sex
. xi:logit y race i.agecat sex i.intagesex

```

```

Logistic regression              Number of obs   =       5800
                                LR chi2(10)      =       158.74
                                Prob > chi2       =       0.0000
Log likelihood = -1107.0936      Pseudo R2      =       0.0669

```

```

-----
      y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      race |   .7152554   .4091241    1.75   0.080   - .0866132   1.517124
  _Iagecat_2 |   .3271268   .3863061    0.85   0.397   - .4300192   1.084273
  _Iagecat_3 |   1.507252   .3340617    4.51   0.000    .8525028    2.162
  _Iagecat_4 |   1.738405   .3461203    5.02   0.000    1.060022    2.416789
  _Iagecat_5 |   2.242273   .3494232    6.42   0.000    1.557416    2.927129
      sex |  - .6195738   .2567102   -2.41   0.016   -1.122717   - .1164311
  _Iintagese~1 |   .562087   .4729937    1.19   0.235   - .3649635    1.489138
  _Iintagese~2 |   .5512787   .4259249    1.29   0.196   - .2835187    1.386076
  _Iintagese~3 |  - .1098395   .3550985   -0.31   0.757   - .8058197    .5861407
  _Iintagese~5 |   .3123178   .3450935    0.91   0.365   - .364053    .9886887
  _cons |  -3.951343   .2919392  -13.53   0.000   -4.523534   -3.379153
-----

```

Even after adjusting for the interaction between age and gender we find a similar association between race and mortality risks.

In this preliminary model, we find that black individuals have a log-odds of mortality that is 0.72 (-0.09, 1.52) that of white individuals when adjusting for age, sex, and the interaction between age and sex. The log-odds scale is not very interpretable, so we transform our results to odds ratios. Adjusting for age, sex, and their interaction, blacks have an odds of mortality that is  $\exp(0.72) = 2.05$  times that of whites with a 95% confidence interval for the odds ratio from  $\exp(-0.09) = 0.91$  to  $\exp(1.52) = 4.57$ .

Stata will present the output on the odds scale when you use the command `logistic`.

```
. xi:logistic y race i.agecat sex i.intagesex i.agecat
Logistic regression                Number of obs   =       5800
LR chi2(10)      =       158.74      Prob > chi2     =       0.0000
Log likelihood = -1107.0936         Pseudo R2      =       0.0669
```

	y	Odds Ratio	Std. Err.	z	P> z	[95% Conf. Interval]
race		<b>2.044709</b>	.8365397	1.75	0.080	<b>.9170317 4.559094</b>
_Iagecat_2		1.386977	.5357977	0.85	0.397	.6504966 2.957288
_Iagecat_3		4.514307	1.508057	4.51	0.000	2.34551 8.688501
_Iagecat_4		5.688264	1.968824	5.02	0.000	2.886434 11.2098
_Iagecat_5		9.414702	3.289715	6.42	0.000	4.746539 18.67395
sex		.5381737	.1381547	-2.41	0.016	.3253946 .8900914
_Iintagese~1		1.75433	.829787	1.19	0.235	.694222 4.43327
_Iintagese~2		1.735471	.7391802	1.29	0.196	.753129 3.999128
_Iintagese~3		.895978	.3181604	-0.31	0.757	.4467216 1.79704
_Iintagese~5		1.366589	.471601	0.91	0.365	.6948544 2.687708

### Random intercept model to account for clustering of individuals within zip code:

The model we will fit to examine the association between demographics and mortality, accounting for the correlation among measurements on individuals from the same zip code, may be written as:

$$\text{logit}\{P(y_{ij} = 1)\} = \beta_0 + \beta_1 \text{race}_{ij} + \beta_2 \text{agecat}_{2ij} + \beta_3 \text{agecat}_{3ij} + \beta_4 \text{agecat}_{4ij} + \beta_5 \text{agecat}_{5ij} + \beta_6 \text{sex}_{ij} + U_i$$

where  $i$  indexes zipcode and  $j$  indexes individual.  $U_i \sim N(0, \sigma_u^2)$  is a random intercept for zipcode.

We cannot use "xi:" with `gllamm`, so we need to type all the indicator variables for age

category in the glamm command. We will keep the same age and interaction indicator variables for consistent comparison with independence model results.

```
. gllamm y race _Iagecat_2 _Iagecat_3 _Iagecat_4 _Iagecat_5 sex, i(zip) l(logit)
f(binom) adapt
```

gllamm model

```
-----
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----					
race	.7118934	.4721737	1.51	0.132	-.21355 1.637337
_Iagecat_2	.3282704	.2606332	1.26	0.208	-.1825612 .839102
_Iagecat_3	1.180596	.2332157	5.06	0.000	.7235016 1.637691
_Iagecat_4	1.450593	.236706	6.13	0.000	.9866581 1.914529
_Iagecat_5	2.142917	.2269695	9.44	0.000	1.698065 2.587768
sex	-.4316824	.1240596	-3.48	0.001	-.6748346 -.1885301
_cons	-3.767305	.2079067	-18.12	0.000	-4.174794 -3.359815

```
-----
```

Variances and covariances of random effects

```
-----
```

```
***level 2 (zip)
var(1): .00273478 (.04761232)
-----
```

The variance among zipcodes in the average log-odds of death is estimated to be 0.003. There appears to be little or no variability between zipcodes, indicating that the random intercept may be unnecessary.

**Prediction**

Generate average predicted probability of death for black and white populations:

(1) Predict fixed effects

```
. predict fit1,xb
(xb will be stored in fit1)
```

(2) Calculate average probability from fixed effects (i.e., when zip code random effect is zero)

```
. gen phat1 = exp(fit1)/( 1 + exp(fit1) )
. table race, c(mean phat1)
```

```
-----
```

race	mean(phat1)
-----+-----	
white	.0516184
black	.0775048

```
-----
```

Generate predicted probability of death for black and white populations for each zip code:

(1) Empirical Bayes predictions for the random intercept using `gllapred`:

```
. gllapred ebf1t1, linpred
```

(2) Calculate zip code-specific probabilities by adding random effects to average probabilities:

```
. gen ebphat1 = exp(ebf1t1)/( 1 + exp(ebf1t1) )
```

```
. table zip race, c(mean ebphat1)
```

```
-----
      |          race
      |  white    black
-----+-----
    1 | .0520663  .0379699
    2 | .0548089  .0818265
    3 | .0480184  .0746415
    4 | .043442
    5 | .0525316  .0437937
    6 | .0466228  .0980782
    7 | .0431963
-----
```

Fit random intercept model with interaction between age and gender:

```
. gllamm y race _Iagecat_2 _Iagecat_3 _Iagecat_4 _Iagecat_5 sex _Iintagesex_1
_Iintagesex_2 _Iintagesex_3 _Iintagesex_5, i(zip) l(logit) f(binom) adapt
```

```
gllamm model
```

```
-----
      y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
    race |   .6984531   .4660362     1.50   0.134    - .214961   1.611867
  _Iagecat_2 |   .3265898   .3863807     0.85   0.398    - .4307024   1.083882
  _Iagecat_3 |   1.50638    .3342846     4.51   0.000     .8511939   2.161566
  _Iagecat_4 |   1.738268   .3461883     5.02   0.000     1.059752   2.416785
  _Iagecat_5 |   2.243047   .3497381     6.41   0.000     1.557573   2.928521
    sex |  -.6209422   .2573449    -2.41   0.016    -1.125329  -.1165554
_Iintagese~1 |   .5629581   .4731686     1.19   0.234    - .3644353   1.490351
_Iintagese~2 |   .5518311   .4260114     1.30   0.195    - .2831359   1.386798
_Iintagese~3 |  -.1094562   .3551666    -0.31   0.758    - .8055699   .5866575
_Iintagese~5 |   .3118824   .3452144     0.90   0.366    - .3647254   .9884902
    _cons |  -3.951249   .2930427   -13.48   0.000    -4.525602  -3.376896
-----
```

```
-----
Variances and covariances of random effects
-----
```

```
***level 2 (zip)
    var(1): .00290965 (.04488606)
-----
```

Except for the slightly inflated s.e. of the race coefficient, there is not much difference in the random effect models results compared with ordinary logistic regression results. This is not unexpected because the variance of the zip code random intercept is very small (.00290386), indicating ignorable correlation between individuals within the same zip code.

### Prediction

Generate average predicted probability of death for black and white populations:

```
. predict fit2,xb
. gen phat2 = exp(fit2)/( 1 + exp(fit2) )
. sort race
. table race, c(mean phat2)
```

```
-----
      race | mean(phat2)
-----+-----
      white |      .0516209
      black |      .0774457
-----
```

Generate predicted probability of death for black and white populations for each zip code:

```
. gllapred ebfite2, linpred
. gen ebphat2 = exp(ebfite2)/( 1 + exp(ebfite2) )
. table zip race, c(mean ebphat2)
```

```
-----
      zip |      race
      zip |      white      black
-----+-----
      1 | .0521326   .038434
      2 | .0547642   .0818445
      3 | .0482556   .0731838
      4 | .0433313
      5 | .052397    .0361831
      6 | .0466139   .1072525
      7 | .0430694
-----
```

We can see that although on average the black population has higher mortality risk than the white population, however, for each single zip code, it is not necessarily true.

### Random Intercept and Slope Model

(Before using “gllamm”, define equations for variables that needs random effects)

To save computing time, use the model without interaction between age and gender. **(The following model takes 2 hours running time!!)**

Add random slope to race coefficient:

```
. gen byte one = 1
. eq cons : one
. eq race : race
```

(nrf specifies the number of variables that need random effects, eqs give the corresponding variables.)

```
. gllamm y race _Iagecat_2 _Iagecat_3 _Iagecat_4 _Iagecat_5 sex, i(zip) l(logit)
f(binom) adapt nrf(2) eqs(race cons)
gllamm model
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
race	.7146109	.4871685	1.47	0.142	-.2402218	1.669444
_Iagecat_2	.3283549	.2606398	1.26	0.208	-.1824897	.8391995
_Iagecat_3	1.180679	.2332115	5.06	0.000	.7235933	1.637765
_Iagecat_4	1.450654	.2367171	6.13	0.000	.9866972	1.914611
_Iagecat_5	2.142967	.2269858	9.44	0.000	1.698083	2.587851
sex	-.4316525	.1240186	-3.48	0.001	-.6747244	-.1885805
_cons	-3.76738	.2079092	-18.12	0.000	-4.174874	-3.359885

Variiances and covariances of random effects

\*\*\*level 2 (zip)

```
var(1): .00004335 (.00587423)
cov(2,1): -.00034093 (.02326116) cor(2,1): -.99985372
var(2): .0026823 (.04663141)
```

**Prediction:**

```

. predict fit3,xb
(xb will be stored in fit3)
. gen phat3 = exp(fit3)/( 1 + exp(fit3) )
. table race, c(mean phat3)
-----
      race |      mean(phat3)
-----+-----
      white |          .0516185
      black |          .0776903
-----

. gllapred ebfite3, linpred
. gen ebphat3 = exp(ebfite3)/( 1 + exp(ebfite3) )

. table zip race, c(mean ebphat3)
-----
      |           race
      zip |      white      black
-----+-----
      1 | .0521413  .0380786
      2 | .0538195  .0816576
      3 | .0466652  .0743084
      4 | .0435704
      5 | .0542231  .0441361
      6 | .0468852  .098454
      7 | .0434171
-----

```

There is not much difference in the results when random slope of race is further included into the model.

**Comparison of zip code-specific predicted probabilities from the above three random effects models:**

```
. table zip race, c(mean ebphat1 mean ebphat2 mean ebphat3)
```

```
-----
```

zip	race	
	white	black
1	.0520663	.0379699
	.0521326	.038434
	.0521413	.0380786
2	.0548089	.0818265
	.0547642	.0818445
	.0538195	.0816576
3	.0480184	.0746415
	.0482556	.0731838
	.0466652	.0743084
4	.043442	
	.0433313	
	.0435704	
5	.0525316	.0437937
	.052397	.0361831
	.0542231	.0441361
6	.0466228	.0980782
	.0466139	.1072525
	.0468852	.098454
7	.0431963	
	.0430694	
	.0434171	

```
-----
```