

Brief Introduction to Generalized Linear Models

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The purpose of this handout is to briefly show that several seemingly unrelated models are actually all special cases of the generalized linear model. (Indeed, I think most of these techniques were initially developed without people realizing they were interconnected.) We will also briefly introduce the use of factor variables and the `margins` command, both of which will be used heavily during the course.

THE GENERALIZED LINEAR MODEL:

$$G(E(Y)) = \alpha + \sum_{k=1}^K \beta_k X_{ik}$$

Where $G(E(Y))$ is some function of the expected value of Y and $Y \sim F$ (i.e. Y has some sort of distribution, e.g. normal, binomial, logistic, etc.) G is referred to as the link function, while F is the distributional family. NOTE: I'm using notation similar to that used by the Stata 13 reference manual when describing the `glm` command; but rather than $E(Y)$, $E(Y|X)$ might be more precise.

MODEL 1: OLS REGRESSION

$$E(Y) = \alpha + \sum_{k=1}^K \beta_k X_{ik}$$

```
. use https://academicweb.nd.edu/~rwilliam/statafiles/glm-reg, clear
. regress income educ jobexp i.black
```

Source	SS	df	MS	Number of obs =	500
Model	33206.4588	3	11068.8196	F(3, 496) =	787.14
Residual	6974.79047	496	14.0620776	Prob > F =	0.0000
Total	40181.2493	499	80.5235456	R-squared =	0.8264
				Adj R-squared =	0.8254
				Root MSE =	3.7499

income	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
educ	1.840407	.0467507	39.37	0.000	1.748553	1.932261
jobexp	.6514259	.0350604	18.58	0.000	.5825406	.7203111
i.black	-2.55136	.4736266	-5.39	0.000	-3.481921	-1.620798
_cons	-4.72676	.9236842	-5.12	0.000	-6.541576	-2.911943

Note that

- The notation `i.black` tells Stata that black is a categorical variable. In this case, it doesn't affect the results (since black is already coded 0/1) but it would matter if the variable had more than 2 categories. In effect, Stata will create the dummy variables

for you. Even more critically, post-estimation commands like `margins` work better when they know which variables are continuous and which are categorical.

- Y has, or can have, a *normal/Gaussian* distribution. Alternatively, you can use regression if $Y | X$ has a normal distribution (or equivalently, if the residuals have a normal distribution and other OLS assumptions are met). That is, the distributional “family” for Y is normal/Gaussian.
- We predict $E(Y)$. $E(Y)$ is in the same units as Y. Alternatively, $G(E(Y)) = E(Y)$. In this case $G(E(Y))$ is the *identity* link function. Hence, using the `glm` command,

```
. glm income educ jobexp i.black, family(gaussian) link(identity)
```

```
Iteration 0:    log likelihood = -1368.3316
```

Generalized linear models		No. of obs	=	500
Optimization	: ML	Residual df	=	496
		Scale parameter	=	14.06208
Deviance	= 6974.790467	(1/df) Deviance	=	14.06208
Pearson	= 6974.790467	(1/df) Pearson	=	14.06208
Variance function: V(u) = 1		[Gaussian]		
Link function : g(u) = u		[Identity]		
Log likelihood = -1368.331633		AIC	=	5.489327
		BIC	=	3892.345

		OIM				[95% Conf. Interval]	
	income	Coef.	Std. Err.	z	P> z		
	educ	1.840407	.0467507	39.37	0.000	1.748777	1.932036
	jobexp	.6514259	.0350604	18.58	0.000	.5827087	.7201431
	1.black	-2.55136	.4736266	-5.39	0.000	-3.479651	-1.623069
	_cons	-4.72676	.9236842	-5.12	0.000	-6.537147	-2.916372

MODEL 2: LOGISTIC REGRESSION. The *logistic regression model (LRM)* (also known as the logit model) can then be written as

$$\ln \frac{P(Y_i = 1)}{1 - P(Y_i = 1)} = \ln \frac{E(Y_i)}{1 - E(Y_i)} = \ln(\text{Odds}_i) = \alpha + \sum_{k=1}^K \beta_k X_{ik} = Z_i$$

The above is referred to as the *log odds* and also as the *logit*. Z_i is sometimes used as a convenient shorthand for $\alpha + \sum \beta_k X_{ik}$.

```
. use https://academicweb.nd.edu/~rwilliam/statafiles/glm-logit, clear
. logit grade gpa tuce i.psi, nolog
```

```
Logistic regression                               Number of obs   =          32
                                                    LR chi2(3)      =         15.40
                                                    Prob > chi2     =         0.0015
Log likelihood = -12.889633                      Pseudo R2      =         0.3740
```

grade	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gpa	2.826113	1.262941	2.24	0.025	.3507938	5.301432
tuce	.0951577	.1415542	0.67	0.501	-.1822835	.3725988
1.psi	2.378688	1.064564	2.23	0.025	.29218	4.465195
_cons	-13.02135	4.931325	-2.64	0.008	-22.68657	-3.35613

Note that

- When y is a dichotomy, it does not have a normal distribution; rather it has a *binomial* distribution (family binomial)
- The left hand side is not E(Y), nor is the left-hand side in the same units as Y. The left hand side is expressed in log odds. We predict G(E(Y)), where G is the *logit* link function. Hence, expressing this as a GLM,

```
. glm grade gpa tuce i.psi, family(binomial) link(logit) nolog
```

```
Generalized linear models                     No. of obs   =          32
Optimization      : ML                      Residual df   =          28
                                                    Scale parameter =          1
Deviance          = 25.77926693              (1/df) Deviance = .9206881
Pearson           = 27.25711646              (1/df) Pearson = .9734684
```

```
Variance function: V(u) = u*(1-u)           [Bernoulli]
Link function      : g(u) = ln(u/(1-u))      [Logit]

AIC                = 1.055602
BIC                = -71.26134

Log likelihood     = -12.88963347
```

grade	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
gpa	2.826113	1.262941	2.24	0.025	.3507937	5.301432
tuce	.0951577	.1415542	0.67	0.501	-.1822835	.3725988
1.psi	2.378688	1.064564	2.23	0.025	.29218	4.465195
_cons	-13.02135	4.931324	-2.64	0.008	-22.68657	-3.356129

See the Appendix for a few additional examples of GLMs. In particular, the Appendix shows that even a simple crosstab is an example of a Generalized Linear Model! Other GLMs will be discussed during the semester.

Stata's `glm` program can estimate many models – OLS regression, logit, loglinear and count. It can't do ordinal regression or multinomial logistic regression, but I think that is mostly just a limitation of the program, as these are considered GLMS too. Part of this gap is filled by my `oglm` program (ordinal generalized linear models). All in all, `glm` can estimate about 25

different combinations of link functions and families (many of which I have no idea why you would want to use them!) In most cases you don't want to use `glm` because there are specialized routines which work more efficiently and which add other bells and whistles. But, this does serve to illustrate how several seemingly unrelated models are all actually special cases of a more general model.

Appendix: Other GLM Examples

MODEL 3: CROSS-CLASSIFIED DATA (loglinear model; in this specific case, model of independence). Consider a simple 2-way cross-classification of data.

```
. use https://academicweb.nd.edu/~rwilliam/statafiles/glm-cat, clear
(Categorical Case II - Tests of Association)
```

```
. tab female dem [fw=freq], chi2 lrchi2 expected
```

```

+-----+
| Key          |
+-----+
| frequency    |
| expected frequency |
+-----+

          |
    female |      dem
          |      0 Rep      1 Dem |      Total
-----+-----+-----+-----+
    0 Male |         65         55 |         120
          |       57.0        63.0 |       120.0
-----+-----+-----+-----+
    1 Female |         30         50 |         80
          |       38.0        42.0 |       80.0
-----+-----+-----+-----+
    Total   |         95        105 |        200
          |       95.0       105.0 |       200.0

          Pearson chi2(1) =    5.3467    Pr = 0.021
likelihood-ratio chi2(1) =    5.3875    Pr = 0.020

```

As the chi-square statistics indicate, gender and party affiliation are not independent of each other; females are more likely to be Democrats than are men.

This is probably one of the first things you learned in introductory stats. What you may not have learned is that this can also be written as a loglinear model:

$$\ln(\text{Expected_Cell_Frequency}) = \alpha + \sum_{k=1}^K \beta_k X_{ik}$$

In this model,

- The cell frequencies have a *Poisson* distribution, i.e. family Poisson
- The left hand side is not the expected cell frequency; rather it is the log of the expected cell frequency. Hence, expressing this as a GLM

```
. glm freq i.female i.dem, family(poisson) link(log)
```

```
Iteration 0:   log likelihood =  -14.13805
Iteration 1:   log likelihood = -14.124228
Iteration 2:   log likelihood = -14.124227
```

```
Generalized linear models               No. of obs   =           4
Optimization      : ML                 Residual df   =           1
                                           Scale parameter =           1
Deviance          =  5.387522771        (1/df) Deviance =  5.387523
Pearson           =  5.346700063        (1/df) Pearson  =  5.3467

Variance function: V(u) = u           [Poisson]
Link function     : g(u) = ln(u)       [Log]

Log likelihood    = -14.12422743       AIC             =  8.562114
                                           BIC             =  4.001228
```

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

1.female		-.4054651	.1443376	-2.81	0.005	-.6883615 -.1225687
1.dem		.1000835	.1415985	0.71	0.480	-.1774444 .3776114
_cons		4.043051	.117727	34.34	0.000	3.812311 4.273792

Note that the chi-square statistics in the original crosstab correspond to the Deviance and Pearson statistics presented in the GLM. Further, as the crosstab shows, under the model of independence the expected number of male Republicans is 57. To confirm, the formula for computing the expected cell frequency is

$$P(\text{Male}) * P(\text{Republican}) * N = 95/200 * 120/200 * 200 = 57.$$

Expressing things in terms of the glm,

$$\begin{aligned} \ln(\text{Expected_Male_Republicans}) &= \alpha + \sum_{k=1}^K \beta_k X_{ik} = 4.043051 - .4054651 * \text{female} + .1000835 * \text{dem} \\ &= 4.043051 - .4054651 * 0 + .1000835 * 0 \\ &= 4.043051 \end{aligned}$$

Since the log of the expected cell frequency for male Republicans is 4.043051, this means that the expected cell frequency for male Republicans is $\exp(4.043051)$, which equals 57.

Using the `margins` command (more on it later) we can easily reproduce all the expected frequencies under the model of independence:

```
. margins female#dem
```

```
Adjusted predictions      Number of obs   =           4
Model VCE      : OIM
```

```
Expression      : Predicted mean freq, predict()
```

		Delta-method		z	P> z	[95% Conf. Interval]	
		Margin	Std. Err.				
female#dem							
0	0	57	6.71044	8.49	0.000	43.84778	70.15222
0	1	63	7.143529	8.82	0.000	48.99894	77.00106
1	0	38	5.10196	7.45	0.000	28.00034	47.99966
1	1	42	5.479964	7.66	0.000	31.25947	52.74053

So in other words, you could say that a generalized linear model with link log and family poisson produces a significant likelihood ratio chi-square statistic of 5.3875 with 1 d.f. – and many people would never guess that all you had done was run a simple crosstab!

MODEL 4: PROBIT MODEL. The probit model is a popular alternative to logit, generally producing very similar predictions. The probit model can be written as

$$y^* = \alpha + \sum X\beta + \varepsilon, \varepsilon \sim N(0,1)$$

If $y^* \geq 0$, $y = 1$

If $y^* < 0$, $y = 0$

The logit model can actually be written the same way, except the error term has a logistic distribution rather than Normal(0, 1). The parameter estimates in a logistic regression tend to be 1.6 to 1.8 times higher than they are in a corresponding probit model. The predicted values in a probit model are like Z-scores. Somebody who has a predicted score of 0 has a 50% chance of success. Somebody with a score of 1 has about an 84% chance of success.

We proceed as we did with logistic regression, except we use the `probit` command instead of `logit`, and with `glm` we specify `link(probit)` rather than `link(logit)`.

```
. use https://academicweb.nd.edu/~rwilliam/statafiles/glm-logit, clear
. probit grade gpa tuce i.psi, nolog
```

```
Probit regression                               Number of obs   =          32
                                                LR chi2(3)      =         15.55
                                                Prob > chi2     =         0.0014
Log likelihood = -12.818803                    Pseudo R2       =         0.3775
```

grade	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
gpa	1.62581	.6938825	2.34	0.019	.2658255	2.985795
tuce	.0517289	.0838903	0.62	0.537	-.1126929	.2161508
1.psi	1.426332	.5950379	2.40	0.017	.2600795	2.592585
_cons	-7.45232	2.542472	-2.93	0.003	-12.43547	-2.469166

```
. glm grade gpa tuce i.psi, family(binomial) link(probit) nolog
```

```
Generalized linear models                     No. of obs   =          32
Optimization      : ML                      Residual df   =          28
                                                Scale parameter =          1
Deviance          = 25.63760665              (1/df) Deviance = .9156288
Pearson           = 26.25160404              (1/df) Pearson  = .9375573
```

```
Variance function: V(u) = u*(1-u)           [Bernoulli]
Link function      : g(u) = invnorm(u)       [Probit]
```

```
Log likelihood    = -12.81880332             AIC           = 1.051175
                                                         BIC           = -71.403
```

grade	Coef.	OIM Std. Err.	z	P> z	[95% Conf. Interval]	
gpa	1.62581	.6938825	2.34	0.019	.2658255	2.985795
tuce	.0517289	.0838903	0.62	0.537	-.1126929	.2161508
1.psi	1.426332	.5950379	2.40	0.017	.2600795	2.592585
_cons	-7.45232	2.542472	-2.93	0.003	-12.43547	-2.469166