

Monday, 11 March 2002

Analysis of Epileptic Seizures and Chemotherapy.

In a clinical trial, 59 patients with epilepsy were randomized to two groups receiving either anti-epileptic drug or a placebo. The number of seizures were counted over a four-week periods. In addition a base line seizure rate was recorded for each patient.

We will first discuss the use of the **xtgee** command. The main components of the model have to be specified are:

- The assumed distribution of the response variable, specified in the **family()** option.
- The link between the response variable and its linear predictor, specified in the **link()** option
- The structure of the working correlation matrix, specified in the **correlations()** option.

Let's look at some exploratory analysis.

The following tables summarize the counts at each of the four time points

```
. summarize counts1 counts2 counts3 counts4
```

Variable	Obs	Mean	Std. Dev.	Min	Max
counts1	59	8.949153	14.83521	0	102
counts2	59	8.355932	10.18749	0	65
counts3	59	8.440678	14.14856	0	76
counts4	59	7.305085	9.649467	0	63

```
. summarize counts1 counts2 counts3 counts4 if teatment==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
counts1	28	9.357143	10.13689	0	40
counts2	28	8.285714	8.164318	0	29
counts3	28	8.785714	14.67262	0	76
counts4	28	7.964286	7.627835	0	29

```
. summarize counts1 counts2 counts3 counts4 if teatment==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
counts1	31	8.580645	18.24057	0	102
counts2	31	8.419355	11.85966	0	65
counts3	31	8.129032	13.89422	0	72
counts4	31	6.709677	11.26408	0	63

Some graphics of the data may be useful for investigating the relation between the response and the covariates. The most useful graphical display for investigating the data is a set of graphs of individual response profiles. To include the baseline value in the graphs we duplicate first observation for each subject (week =1) and change one of the

duplicates for each subject to represent the baseline measure (week = 0). Since the baseline measure represents seizure counts over an eight week period, compared with two week periods for each of the other time-points, we divide the baseline measure by 4.

```
. expand 2 if time==1
(59 observations created)

. edit
- preserve

. sort ID time

. qui by ID: replace time=0 if _n==1

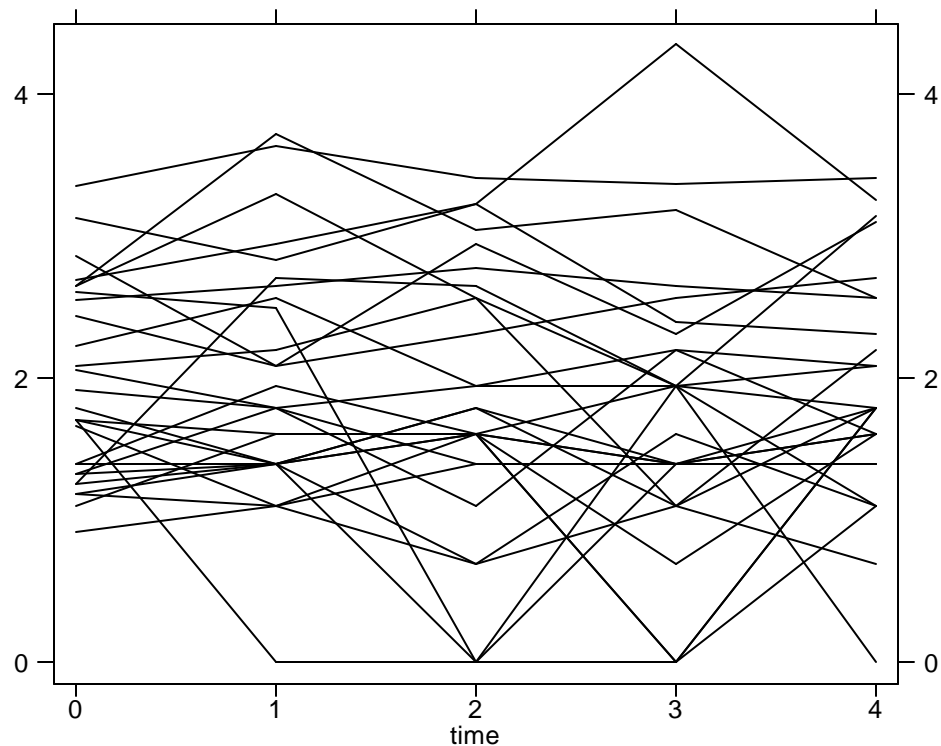
. replace y = baselein/4 if time == 0
variable y not found
r(111);

. replace count = baseline/4 if time == 0
(57 real changes made)
```

Since we plan to fit a Poisson Model with the log link to the data, we take the log transformation before plotting the response profiles. We need to add 1 because some seizure counts are 0.

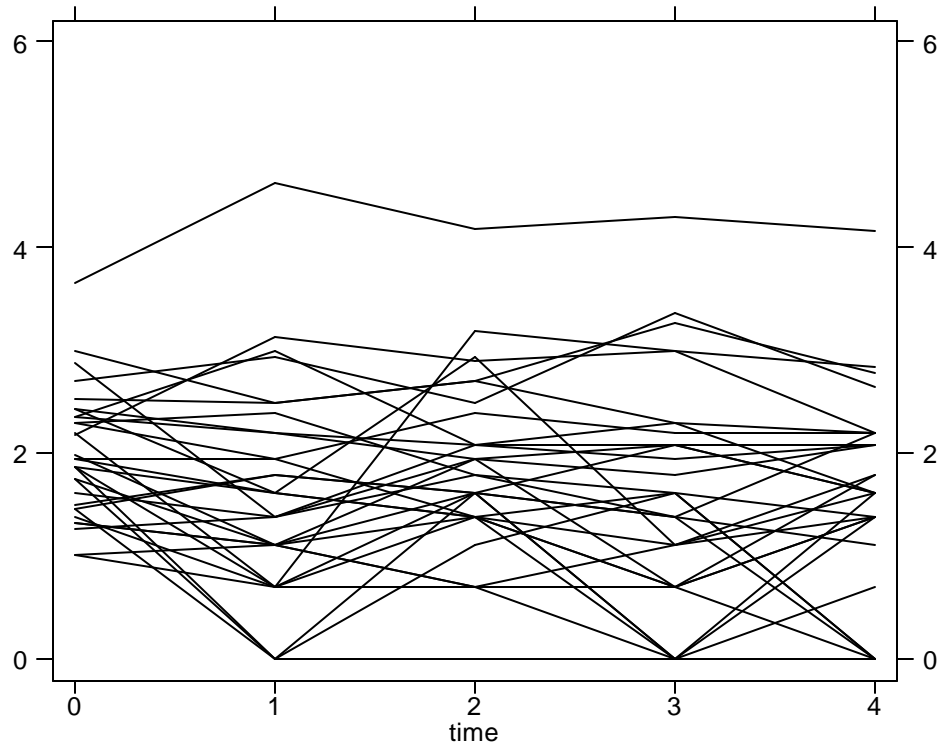
For the placebo group.

```
. graph ly time if treatment==0, c(L) s(i) xlab ylab rlabel
```



For the treatment group

```
. graph ly time if teatment==1, c(L) s(i) xlab ylab rlabel
```



There is too much overlap between subjects; we use 9 graphs in each group. First we produce a grouping variable `dum9` that splits each treatment group into nine groups. If subjects are numbered by variable `i`, we can apply the function `mod(i, 9)` to create a variable that numbers subjects from 0, ..., 8, 0, ..., 8, The graphs are clearer to read if the baseline values within a graph are not too similar. We therefore sort by baseline within each treatment group and define `i` to number subjects in this order.

```
. sort teatment baseline ID time

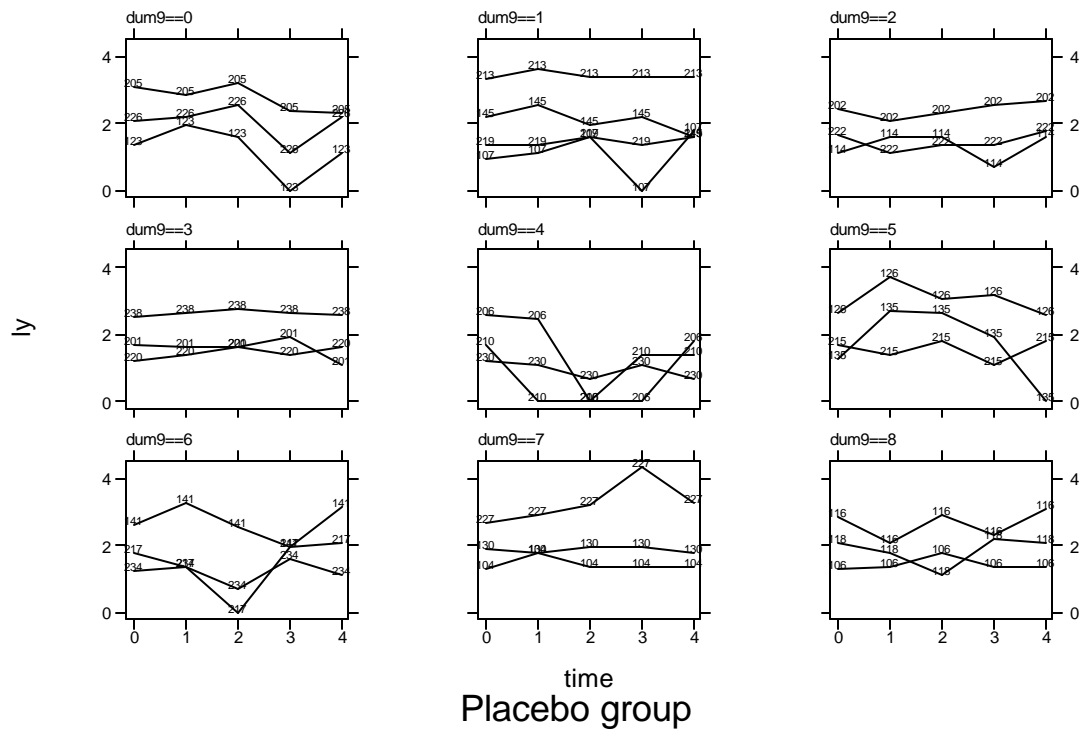
. quietly by teatment baseline ID: replace id = _n==1

. replace id = sum(id)
(294 real changes made)

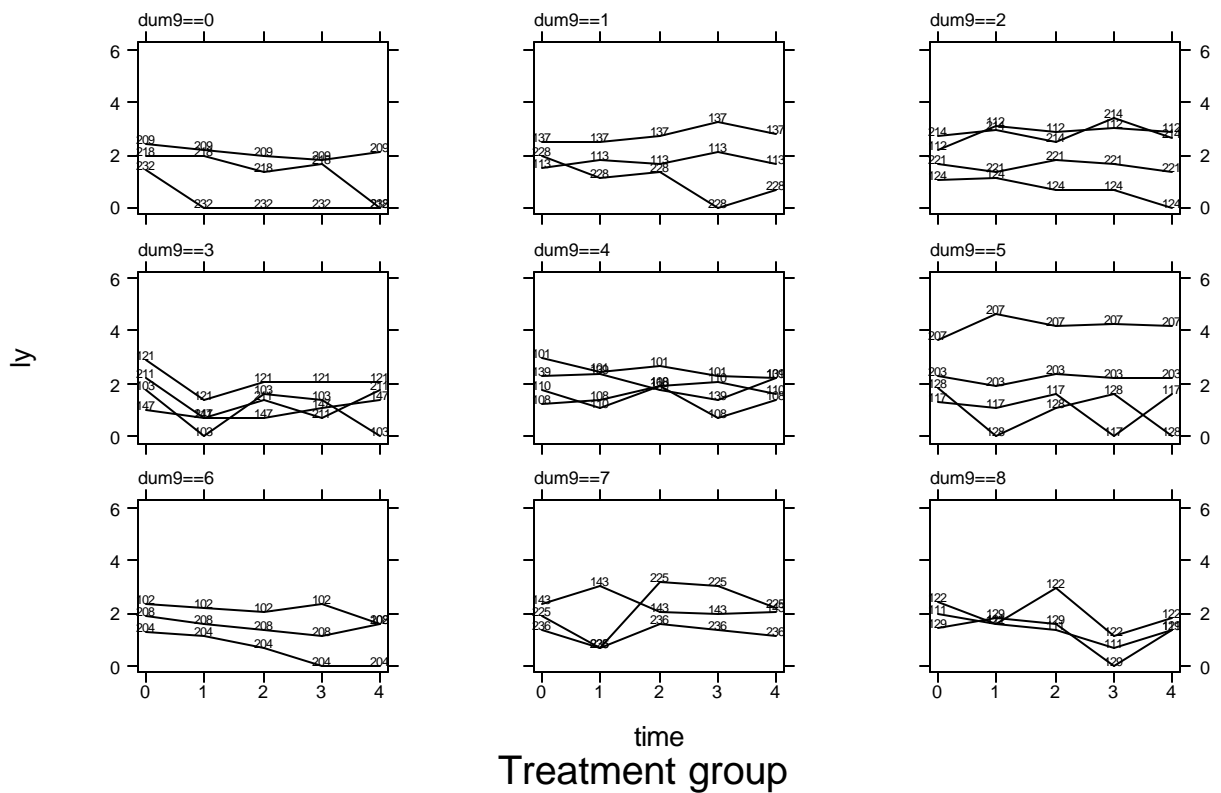
. gen dum9=mod(id, 9)

. sort dum9 ID time

. graph ly time if teatment==0, c(L) s([ ID]) by( dum9) xlab ylab
rlabel b1("Placebo group")
```



```
. graph ly time if teatment==1, c(L) s([ ID]) by( dum9) xlab ylab
rlabel bl("Treatment group")
```



Subject 207 had more epileptic fits overall than any other subject.

It is reasonable to assume Poisson distribution for counts data. The Poisson distribution is specified in **xtgee** models using the option **family(poisson)** and the link is log.

Model with overdispersion:

```
. xtgee counts teatment baseline Age time, i( ID) corr(exc) f(pois) l(log) sca
> le(x2)
```

```
Iteration 1: tolerance = .0183008
Iteration 2: tolerance = 2.535e-06
Iteration 3: tolerance = 1.030e-09
```

```
GEE population-averaged model
Group variable:          ID      Number of obs      =      236
Link:                  log      Number of groups    =      59
Family:                Poisson  Obs per group: min =      4
Correlation:           exchangeable      avg =      4.0
                                      max =      4
                                      Wald chi2(4)      =     194.09
Scale parameter:        4.999686      Prob > chi2      =      0.0000
```

counts	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
teatment	-.1478458	.1586985	-0.93	0.352	-.4588891	.1631975
baseline	.0227431	.0016898	13.46	0.000	.0194312	.026055
Age	.0235715	.0133574	1.76	0.078	-.0026085	.0497516
time	-.0587233	.0350856	-1.67	0.094	-.1274898	.0100431
_cons	.6759401	.4581396	1.48	0.140	-.2219971	1.573877

(Standard errors scaled using square root of Pearson X2-based dispersion)

```
. xtgee counts teatment baseline Age time, i( ID) corr(exc) f(pois) l(log)
```

```
Iteration 1: tolerance = .0183008
Iteration 2: tolerance = 2.535e-06
Iteration 3: tolerance = 1.030e-09
```

```
GEE population-averaged model
Group variable:          ID      Number of obs      =      236
Link:                  log      Number of groups    =      59
Family:                Poisson  Obs per group: min =      4
Correlation:           exchangeable      avg =      4.0
                                      max =      4
                                      Wald chi2(4)      =     970.41
Scale parameter:        1      Prob > chi2      =      0.0000
```

counts	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
teatment	-.1478458	.0709743	-2.08	0.037	-.286953	-.0087386
baseline	.0227431	.0007557	30.10	0.000	.021262	.0242243
Age	.0235715	.0059738	3.95	0.000	.0118631	.03528
time	-.0587233	.0156912	-3.74	0.000	-.0894776	-.0279691
_cons	.6759401	.2048927	3.30	0.001	.2743578	1.077522

The estimated correlation matrix is,

```
. xtcorr
```

Estimated within-ID correlation matrix R:

```

      c1      c2      c3      c4
r1  1.0000
r2  0.4033  1.0000
r3  0.4033  0.4033  1.0000
r4  0.4033  0.4033  0.4033  1.0000

```

Treatment is significant leading to a qualitatively different conclusion about the effectiveness of the treatment. Let's use the **robust** option and see what happens.

```

. xtgee counts teatment baseline Age time, i( ID) corr(exc) f(pois) l(log)
robust

```

```

Iteration 1: tolerance = .0183008
Iteration 2: tolerance = 2.535e-06
Iteration 3: tolerance = 1.031e-09

```

```

GEE population-averaged model
Group variable:          ID      Number of obs      =      236
Link:                   log      Number of groups   =      59
Family:                 Poisson  Obs per group: min =      4
Correlation:            exchangeable      avg =      4.0
                                      max =      4
Scale parameter:        1      Wald chi2(4)      =      603.40
                                      Prob > chi2      =      0.0000

```

(standard errors adjusted for clustering on ID)

counts	Semi-robust		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
teatment	-.1478458	.1701226	-0.87	0.385	-.4812799	.1855883
baseline	.0227431	.0012543	18.13	0.000	.0202848	.0252014
Age	.0235715	.0119041	1.98	0.048	.0002399	.0469031
time	-.0587233	.035298	-1.66	0.096	-.1279062	.0104595
_cons	.6759401	.3570996	1.89	0.058	-.0239622	1.375842

The estimated coefficient of treatment describes the difference in the log of the average seizure counts between the placebo and treatment groups. The negative value indicates that the treatment is more effective than the placebo in controlling the seizure rate although not significant. The exponential coefficient gives an incident rate ratio, here it represents the ratio of average seizures rates, measured as the number of seizures per two-week period, for the treated patients compared to that among the control patients. The exponential coefficient and the corresponding confidence interval can be obtained directly using the **eform** option in **xtgee**:

```

. xtgee counts teatment baseline Age time, i( ID) corr(exc) f(pois) l(log)
robust eform

```

```

Iteration 1: tolerance = .0183008
Iteration 2: tolerance = 2.535e-06
Iteration 3: tolerance = 1.030e-09

```

```

GEE population-averaged model
Group variable:          ID      Number of obs      =      236
Link:                   log      Number of groups   =      59
Family:                 Poisson  Obs per group: min =      4
                                      avg =      4.0

```

Correlation: exchangeable max = 4
Wald chi2(4) = 603.40
Scale parameter: 1 Prob > chi2 = 0.0000
(standard errors adjusted for clustering on ID)

counts	IRR	Semi-robust Std. Err.	z	P> z	[95% Conf. Interval]	
teatment	.8625641	.1467416	-0.87	0.385	.6179919	1.203927
baseline	1.023004	.0012831	18.13	0.000	1.020492	1.025522
Age	1.023852	.012188	1.98	0.048	1.00024	1.04802
time	.9429676	.0332849	-1.66	0.096	.8799359	1.010514

The results suggest that there is a 14% reduction in the incidence rate of epileptic seizures in the treated group compared with the control group. According to the confidence interval, the reduction could be as 38% or there could be much as an 18% increase.

There might be interaction between baseline seizure count and treatment, a model is easily fitted using the following:

```
. gen bt = teatment* baseline
. xtgee counts teatment baseline Age time bt, i( ID) corr(exc) f(pois) l(log)
eform
```

Iteration 1: tolerance = .01738938
Iteration 2: tolerance = .00001068
Iteration 3: tolerance = 1.147e-08

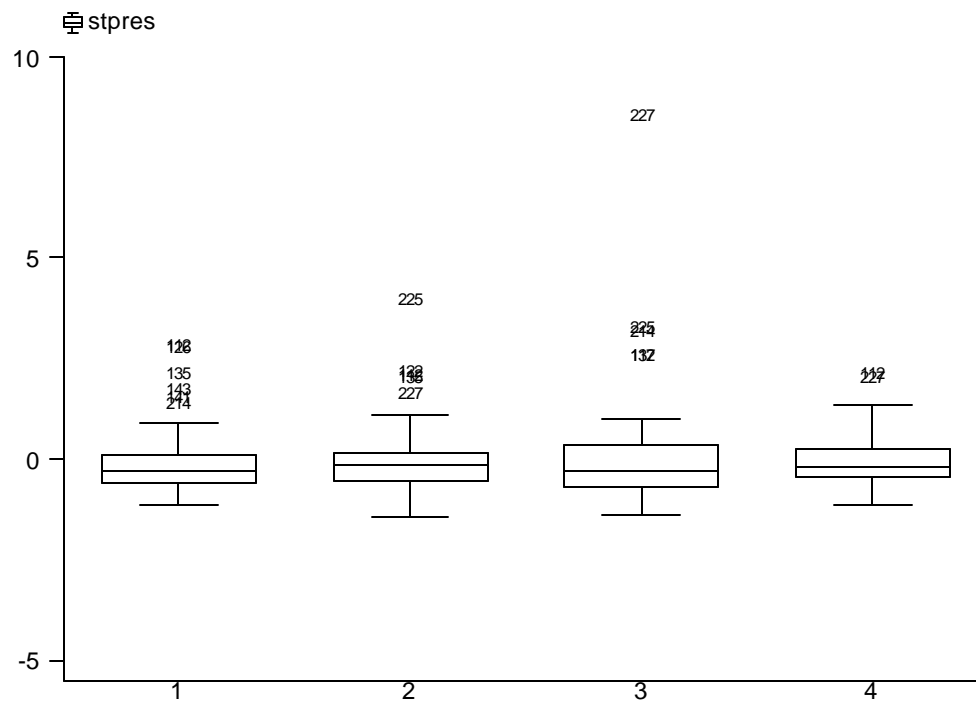
GEE population-averaged model
Group variable: ID
Link: log
Family: Poisson
Correlation: exchangeable
Scale parameter: 1
Number of obs = 236
Number of groups = 59
Obs per group: min = 4
avg = 4.0
max = 4
Wald chi2(5) = 983.15
Prob > chi2 = 0.0000

counts	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
teatment	.7735594	.0879598	-2.26	0.024	.6190209	.9666784
baseline	1.021598	.0013912	15.69	0.000	1.018875	1.024329
Age	1.025602	.0062896	4.12	0.000	1.013348	1.038004
time	.9429676	.01479	-3.74	0.000	.9144207	.9724057
bt	1.002	.0016398	1.22	0.222	.9987908	1.005219

There is no evidence of an interaction. One can try other correlation structures. We now look at the standardized Pearson's residuals of the previous model separately for each week. This can be done by using the **predict** command to obtain estimated counts and computing the standardized Pearson's residuals.

```
. predict pred, xb
. replace pred = exp(pred)
(236 real changes made)
. gen pres = (counts - pred)/sqrt(pred)
. gen stpres = pres/sqrt(e(chi2_dis))
. sort time
. graph stpres, box s([ID]) by(time) ylab
```

The resulting graph is,



Here the subject 227 is clearly an influential observation in week 3.

You can also a random effects model. Random effects is fitted using restricted maximum likelihood estimation, using **xtpois** (you can explore more about this in STATA help).