

Marginal Poisson Regression Model and GEE

Examples of count data:

- number of panic attacks occurring during six months intervals after receiving treatment
- number of sexual partners in a three months period recorded in an HIV prevention program
- number of infants deaths per month before and after introduction of a prenatal care program

The *Poisson distribution* has been the most commonly used to model count data

$$P(Y = y) = \frac{e^{-\mu} \mu^y}{y!} \quad y = 0, 1, 2, \dots$$

$$E[Y] = \text{Var}(Y) = \mu$$

if $\text{Var}(Y) > E(Y) \Rightarrow \text{over-dispersed data}$

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Epileptic seizures

- Clinical Trail of 59 epileptics
- For each patient, the number of epileptic seizures was recorded during a baseline period of eight weeks
- patient were randomized to treatment with the anti-epileptic drug progabide or placebo
- Number of seizures was then recorded in four consecutive two weeks intervals
- **Question:** is progabide reduces the rate of epileptic seizures?

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Poisson Regression Model

$$Y_{ij} \sim \text{Poisson}(\mu_{ij})$$

$$\log \mu_{ij} = \beta_0 + \beta x_i$$

- x_i is the treatment indicator
- β describe the change in the log of the population average count per unit change in x_i
- in the progabide example:

$\exp(\beta)$ represents the *ratio of average seizures rates, measured as the number of seizures per two-week period, for the treated patients compared to the control patients*

$$\frac{E[Y_{ij} \mid x_i = 1]}{E[Y_{ij} \mid x_i = 0]} = \exp(\beta)$$

- If $\beta < 0$ then the treatment is effective relative to the placebo in controlling the seizure rate

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Overdispersed data – $\text{Var}(Y_{ij}) > E[Y_{ij}]$

$$\text{Var}(Y_{ij}) = \phi_{ij} E[Y_{ij}]$$

$$\phi_{ij} = \phi_1, \text{ if } i \text{ is assigned to a treatment}$$

$$\phi_{ij} = \phi_2, \text{ if } i \text{ is assigned to a control}$$

Irregular times: Suppose that the interval times t_{ij} , during which the events are observed, *are not the same* for all subjects. The problem can be solved by decomposing the marginal mean $E[Y_{ij}]$ as

$$E[Y_{ij}] = \lambda_{ij} \times t_{ij}$$

$$\lambda_{ij} = \text{number of events for unit interval}$$

$$t_{ij} = \text{length of time interval}$$

$$\log E[Y_{ij}] = \underbrace{\log t_{ij}}_{\text{offset}} + \mathbf{x}_{ij}' \boldsymbol{\beta}$$

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Epileptic seizures

1. Clinical Trail of 59 epileptics
2. 31 patients received a anti-epileptic drug progabide
3. 28 received a placebo
4. patients from the two groups are comparable in terms of age and 8-week baseline seizure counts

- x_{i2} allow different baseline seizure counts between the treated and placebo groups

Poisson regression model and GEE method

$$\log E[Y_{ij}] = \log t_{ij} + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i1} x_{i2}$$

$$j = 0, 1, 2, 3, 4$$

$$i = 1, 2, \dots, 59$$

$$t_{ij} = 8 \text{ if } j = 0$$

$$t_{ij} = 2 \text{ if } j = 1, 2, 3, 4$$

$$x_{i1} = \begin{cases} 1 & \text{if visit 1, 2, 3, 4} \\ 0 & \text{if baseline} \end{cases}$$

$$x_{i2} = \begin{cases} 1 & \text{if progabide} \\ 0 & \text{if placebo} \end{cases}$$

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Parameter Interpretation and Results

- $\exp(\beta_1)$ is the ratio of the average seizure rate after the treatment to before treatment for the placebo group
- β_3 is the parameter of interest and represents the difference in the logarithm of the post-to pre-treatment ratio between the progabide and the placebo groups. A negative coefficient correspond to a greater reduction (small increase) in the seizure counts for the progabide group
- $\hat{\beta}_3 = -0.10(0.21)$ if patient 207 is included this suggests that there is a very little difference between the treatment and the placebo groups in the change of seizure counts before and after the randomization
- if patient 207 is set aside $\hat{\beta}_3 = -0.30(0.17)$ then there is modest evidence that progabide is favored over the placebo
- $\hat{\phi} = 19.44$ strong overdispersion!
- we have completely ignored correlation within subjects

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