

# STAT347: Generalized Linear Models

## Lecture 12

Today's topics: Chapters 8

- Quasi-likelihood
- Estimating equations and the Sandwich estimator

### 1 Quasi-likelihood

The above solution replaces the exponential family distributions with a more complicated parametric distribution allowing an extra dispersion parameter in the variance. Another more general solution is to only assume a mean-variance relationship.

Remind the the score equation for the exponential family distributed data is:

$$\frac{\partial L}{\partial \beta_j} = \sum_i \frac{(y_i - \mu_i)x_{ij}}{\text{Var}(y_i)} \frac{1}{g'(\mu_i)} = 0$$

- These score equations only involve  $E(y_i) = \mu_i$  and  $\text{Var}(y_i)$ .
- Quasi-likelihood: we replace  $\text{Var}(y_i)$  by some other mean-variance relationship that we believe can better fit the data.
- Typically, the mean-variance relationship can involves another unknown dispersion parameter.
- Here, we DO NOT assume any other aspects of the distribution of  $y_i$  besides mean and variance.

Common forms of mean-variance relationship  $\text{Var}(y_i) = a(\mu_i, \phi)$ :

- Proportional:  $a(\mu_i, \phi) = \phi v^*(\mu_i)$ .
  - counts: assume  $a(\mu_i, \phi) = \phi \mu_i$
  - grouped Binary data:  $a(\mu_i, \phi) = \phi \mu_i(n_i - \mu_i)/n_i$
- For counts we can also assume  $a(\mu_i, \phi) = \mu_i + \phi \mu_i^2$  as in the Negative-Binomial distribution
- For grouped Binary data we can also assume  $a(\mu_i, \phi) = \mu_i(n_i - \mu_i)(1 + (n_i - 1)\phi)$  as in the Beta-Binomial distribution

Some related properties:

- The proportional mean-variance relationship is the easiest for the computation of  $\hat{\beta}$  as  $\phi$  cancels and does not affect solving the score equations for  $\beta$ .
- $\text{Var}(\hat{\beta})$  is affected by  $\phi$  for any of the above mean-variance relationships.

- Including  $\phi$  helps to get a correct uncertainty quantification of  $\hat{\beta}$ .

How to estimate  $\phi$ ? As we don't know the likelihood of the data, we only use moment conditions.

- When  $a(\mu_i, \phi) = \phi v^*(\mu_i)$ , we can get  $\hat{\beta}$  thus  $\hat{\mu}_i$  first without knowing  $\phi$ . Then define

$$X^2 = \sum_{i=1}^n \frac{(y_i - \hat{\mu}_i)^2}{\phi v^*(\hat{\mu}_i)}$$

We can solve  $\phi$  by solving  $X^2 = n - p$  (we use  $n - p$  instead of  $n$  to correct for the degree of freedom in the estimated  $\hat{\mu}_i$ ), which is

$$\hat{\phi} = \frac{1}{n-p} \sum_{i=1}^n \frac{(y_i - \hat{\mu}_i)^2}{v^*(\hat{\mu}_i)}$$

- For other forms of  $a(\mu, \phi)$ , we need to solve  $\phi$  and  $\beta$  simultaneously from equations

$$\varphi_{1j}(\beta, \phi) = \frac{\partial L}{\partial \beta_j} = \sum_i \frac{(y_i - \mu_i)x_{ij}}{a(\mu_i, \phi)} \frac{1}{g'(\mu_i)} = 0 \quad (1)$$

$$\varphi_2(\beta, \phi) = \sum_{i=1}^n \frac{(y_i - \mu_i)^2}{a(\mu_i, \phi)} - (n - p) = 0 \quad (2)$$

–  $\mathbb{E}[\varphi_{1j}(\beta, \phi)] = 0$  and  $\mathbb{E}[\varphi_2(\beta, \phi)]/n \rightarrow 0$ . Solutions  $\hat{\beta}$  and  $\hat{\phi}$  are called Z-estimators. Under proper regularity conditions, we can show that both  $\hat{\beta}$  and  $\hat{\phi}$  are consistent.

## 2 Estimating equations and Sandwich estimator

How to estimate the variance of  $\hat{\beta}$  from the quasi-likelihood equations? And what if we do not even know the true form of the mean-variance relationship?

- The equations (2) is one type of estimating equations. In general, the estimating equations for parameters  $\theta$  (here  $\theta = (\beta, \phi)$  or  $\theta = \beta$ ) have the form:

$$u(\theta) = \sum_i u_i(\theta) = 0$$

Denote the solution of these equations as  $\hat{\theta}$  and the true  $\theta$  as  $\theta_0$ .

- Consistency: roughly speaking, when  $p$  is small, if  $E(u(\theta_0)) \rightarrow 0$  when  $n \rightarrow \infty$ , then we can have  $\hat{\theta} \rightarrow \theta_0$  (with some additional conditions).
- Variance of  $\hat{\theta}$ . Under consistency, we can estimate the asymptotic variance of  $\hat{\theta}$  by first-order Taylor expansion (see later).
- The score equations

$$u(\beta) = \sum_i \frac{(y_i - \mu_i)x_{ij}}{v^*(\mu_i)} \frac{1}{g'(\mu_i)} = 0$$

are valid estimating equations ( $\mathbb{E}[u(\beta_0)] = 0$ ) as long as the link function is correct. The response  $y_i$  does not need to follow the assumed exponential family distribution and  $v^*(\mu_i)$  does not need to be the correct form of variance.

- Even the simple  $\sum_i(y_i - \mu_i)x_{ij} = 0$  are always valid estimating equations. The problem is that  $\text{sd}(\hat{\beta})$  may be large if samples have unequal variances.

Sandwich estimator of the asymptotic variances:

Let's now calculate the asymptotic variance of  $\hat{\theta}$  for

$$\mu(\hat{\theta}) = 0$$

By first-order Taylor expansion, we have

$$0 = u(\hat{\theta}) \approx u(\theta_0) + \dot{u}(\theta_0)(\hat{\theta} - \theta_0)$$

Thus, we have

$$\hat{\theta} - \theta_0 \approx -\dot{u}(\theta_0)^{-1}u(\theta_0)$$

Roughly speaking, we have

- Law of large numbers:

$$\frac{1}{n}\dot{u}(\theta_0) = \frac{1}{n}\sum_{i=1}^n \dot{u}_i(\theta_0) \rightarrow E\left(\frac{1}{n}\sum_{i=1}^n \dot{u}_i(\theta_0)\right) = A$$

- CLT:

$$\frac{1}{\sqrt{n}}u(\theta_0) = \frac{1}{\sqrt{n}}\sum_{i=1}^n u_i(\theta_0) \approx N(0, V)$$

Thus

$$\text{Var}(\hat{\theta}) \approx A^{-1}VA^{-T}/n$$

In practice, we can estimate  $A$  and  $V$  by

$$\hat{A} = \frac{1}{n}\sum_{i=1}^n \dot{u}_i(\hat{\theta})$$

and

$$\hat{V} = \frac{1}{n}\sum_i u_i(\hat{\theta})u_i(\hat{\theta})^T$$

- We use the sample variance to approximate  $V$  without knowing the distribution of the data
- The Sandwich estimator provides an estimate of the variance of  $\hat{\beta}$  even when model assumption is violated.

### 3 Revisit the horseshoe crab data

Please see R notebook Example 7.

Next time: Mixed effect linear models