

## Question-2(b)

→ For univariate generalized linear model the parameter estimation can be obtained by iteratively reweighted least square.

→ A similar Algorithm can be used even for the non-linear model with scale parameters

→ The contribution from a single multinomial observation  $(n_1, \dots, n_k)$  to the likelihood function is  $\pi_1^{n_1} \dots \pi_k^{n_k}$  where  $\pi_i$ ,  $1 \leq i \leq k$  is probability of  $i^{\text{th}}$  category

→ Since we are dealing with cumulative probabilities, we define

$$R_1 = n_1 \quad z_1 = R_1/n$$

$$R_2 = n_2 \quad z_2 = R_2/n$$

$$\vdots$$

$$R_k = \sum n_j = n \quad z_k = n/n = 1$$

In terms of parameter of cumulative transformation, the likelihood can be written as product of  $(k-1)$  quantities,

$$\left\{ \left( \frac{\gamma_1}{\gamma_2} \right)^{R_1} \left( \frac{\gamma_2 - \gamma_1}{\gamma_2} \right)^{R_2 - R_1} \right\} \left\{ \left( \frac{\gamma_2}{\gamma_3} \right)^{R_2} \left( \frac{\gamma_3 - \gamma_2}{\gamma_3} \right)^{R_3 - R_2} \right\} \dots$$
$$\dots \left\{ \left( \frac{\gamma_{k-1}}{\gamma_k} \right)^{R_{k-1}} \left( \frac{\gamma_k - \gamma_{k-1}}{\gamma_k} \right)^{R_k - R_{k-1}} \right\}$$

where,

$$\gamma_j(x) = \pi_1(x) + \pi_2(x) + \dots + \pi_j(x)$$

It is convenient to define,

$$\phi_j = \log \left( \frac{r_j}{r_{j+1} - r_j} \right) = \logit \left( \frac{r_j}{r_{j+1}} \right)$$

$$g(\phi) = \log (1 + \exp(\phi))$$

$$= \log \left( \frac{r_{j+1}}{r_{j+1} - r_j} \right)$$

Whence the likelihood is,

$$Q = n \left[ \{ z_1 \phi_1 - z_2 g(\phi_1) \} + \{ z_2 \phi_2 - z_3 g(\phi_2) \} + \{ z_{k-1} \phi_{k-1} - g(\phi_{k-1}) \} \right]$$

→ The Newton-Raphson method with Fisher Scoring converges rapidly even when initial estimates are poor. Generally about 4 to 5 cycles are required to produce accuracy to four significant digits in all parameter.

For univariate generalized linear model

A univariate generalized linear model contains only one of the above component, The following relationships follow form:

$$E(z_j) = r_j$$

$$E(z_j | z_{j+1}) = z_{j+1} g'(\phi_j) = z_{j+1} \left( r_j / r_{j+1} \right)$$

$$\text{var}(z_j) = r_j (1 - r_j) / n$$

$$\text{var}(z_j | z_{j+1}) = z_{j+1} g''(\phi_j) / n$$