

# STAT600 HW3

Zexian (Leo) Wang 936002904 leowang@tamu.edu

The objective function is

$$f(\beta) = - \sum_{i=1}^n \left\{ \sum_{k=0}^{K-1} \mathbf{1}_{(y_i=k)} \log p_k(x_i; \beta) \right\} + \frac{\lambda}{2} \sum_{k=0}^{K-1} \sum_{j=1}^p \beta_{k,j}^2 \quad p_k(x_i; \beta) = \frac{e^{x_i^\top \beta_k}}{\sum_{l=0}^{K-1} e^{x_i^\top \beta_l}}$$

$$\begin{aligned} \frac{\partial p_k(x_i; \beta)}{\partial \beta_k} &= \frac{x_i e^{x_i^\top \beta_k} \sum_{l=0}^{K-1} e^{x_i^\top \beta_l} - x_i e^{x_i^\top \beta_k} e^{x_i^\top \beta_k}}{\left( \sum_{l=0}^{K-1} e^{x_i^\top \beta_l} \right)^2} = x_i \left( \frac{e^{x_i^\top \beta_k}}{\sum_{l=0}^{K-1} e^{x_i^\top \beta_l}} - \frac{\left( e^{x_i^\top \beta_k} \right)^2}{\left( \sum_{l=0}^{K-1} e^{x_i^\top \beta_l} \right)^2} \right) \\ &= x_i \left( p_k(x_i; \beta) - (p_k(x_i; \beta))^2 \right) = x_i p_k(x_i; \beta) (1 - p_k(x_i; \beta)) \\ \frac{\partial p_j(x_i; \beta)}{\partial \beta_k} &= \frac{-x_i e^{x_i^\top \beta_j} e^{x_i^\top \beta_k}}{\left( \sum_{l=0}^{K-1} e^{x_i^\top \beta_l} \right)^2} = -x_i p_j(x_i; \beta) p_k(x_i; \beta), \quad j \neq k \end{aligned}$$

For  $k = 0, \dots, K-1$ ,

$$\begin{aligned} \nabla f(\beta_k) &= - \sum_{i=1}^n x_i (\mathbf{1}_{(y_i=k)} - p_k(x_i; \beta)) + \lambda \beta_k = \sum_{i=1}^n x_i (p_k(x_i; \beta) - \mathbf{1}_{(y_i=k)}) + \lambda \beta_k = X^\top (P_k - \mathbf{1}_{(Y=k)}) + \lambda \beta_k \\ [\nabla^2 f(\beta_k)]_{uu} &= \sum_{i=1}^n x_i \frac{\partial p_k(x_i; \beta)}{\partial \beta_k} + \frac{\partial (\lambda \beta_k)}{\partial \beta_k} = \sum_{i=1}^n x_{i,u}^2 p_k(x_i; \beta) (1 - p_k(x_i; \beta)) + \lambda, \quad u = 1, \dots, p \\ [\nabla^2 f(\beta_k)]_{uv} &= \sum_{i=1}^n x_{i,u} x_{i,v} p_k(x_i; \beta) (1 - p_k(x_i; \beta)), \quad \text{for } u \neq v, \quad u = 1, \dots, p, v = 1, \dots, p \end{aligned}$$

Letting  $W_k$  to be a  $n \times n$  diagonal matrix with  $W_{k,ii} = p_k(x_i; \beta) (1 - p_k(x_i; \beta)), i = 1, \dots, n$ , we have

$$\nabla^2 f(\beta_k) = \begin{pmatrix} \sum_{i=1}^n x_{i,1}^2 W_{k,ii} + \lambda & \sum_{i=1}^n x_{i,1} x_{i,2} W_{k,ii} & \cdots & \sum_{i=1}^n x_{i,1} x_{i,n} W_{k,ii} \\ \sum_{i=1}^n x_{i,1} x_{i,2} W_{k,ii} & \sum_{i=1}^n x_{i,2}^2 W_{k,ii} + \lambda & \cdots & \sum_{i=1}^n x_{i,2} x_{i,n} W_{k,ii} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^n x_{i,1} x_{i,n} W_{k,ii} & \sum_{i=1}^n x_{i,2} x_{i,n} W_{k,ii} & \cdots & \sum_{i=1}^n x_{i,n}^2 W_{k,ii} + \lambda \end{pmatrix}$$

Therefore,

$$\nabla^2 f(\beta_k) = \frac{\partial (X^\top (P_k - \mathbf{1}_{(Y=k)}) + \lambda \beta_k)}{\partial \beta_k} = X^\top W_k X + \lambda I_p$$

For  $k = 0, \dots, K-1$ ,

$$\begin{aligned} \beta_k^{(t+1)} &= \beta_k^{(t)} - \eta (\nabla^2 f(\beta_k))^{-1} \nabla f(\beta_k) \\ \beta_k^{(t+1)} &= \beta_k^{(t)} - \eta \left( X^\top W_k X + \lambda I_p \right)^{-1} \left( X^\top (P_k - \mathbf{1}_{(Y=k)}) + \lambda \beta_k^{(t)} \right) \end{aligned}$$