

# STATS305B – Lecture 7

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## 1 Binary GLMs

### 1.1 Fitting

Let  $F$  be a CDF with density  $f$ . The deviance for a binary GLM with link function  $g = F^{-1}$  is,

$$\text{DEV}(\beta|Y) = 2 \sum_{i=1}^n -Y_i \frac{F(X_i^T \beta)}{F(X_i^T \beta)(1 - F(X_i^T \beta))} - \log(1 - F(X_i^T \beta)).$$

Thus,

$$\nabla \text{DEV}(\beta|Y) = 2 \sum_{i=1}^n X_i \frac{f(X_i^T \beta)^2}{F(X_i^T \beta)(1 - F(X_i^T \beta))} \left[ \frac{Y_i - F(X_i^T \beta)}{f(X_i^T \beta)} \right].$$

Since  $X_i^T \beta = F^{-1}(\mathbb{E}_\beta[Y_i])$ , we have that  $\mathbb{E}_\beta[F(X_i^T \beta) - Y_i] = 0$ . Thus, we have

$$\mathbb{E}[\nabla^2 \text{DEV}(\beta|Y)] = 2 \sum_{i=1}^n X_i X_i^T \frac{f(X_i^T \beta)^2}{F(X_i^T \beta)(F(X_i^T \beta) - 1)} = 2X^T W_\beta X,$$

where  $W_\beta = \text{diag} \left( \frac{f(X_i)^2}{F(X_i^T \beta)(1 - F(X_i^T \beta))} \right)$ . We can also rewrite  $\nabla \text{DEV}(\beta|Y)$  in terms of the  $W_\beta$ ,

$$\nabla \text{DEV}(\beta|Y) = 2X^T W_\beta \left( \frac{Y - F(X\beta)}{f(X\beta)} \right).$$

To fit a binary glm, we can use Fisher scoring. Fisher scoring is an iterative quasi-Newton method given by

$$\begin{aligned} \hat{\beta}^{(k+1)} &= \hat{\beta}^{(k)} - \mathbb{E}_{\beta^{(k)}}[\nabla^2 \text{DEV}(\beta^{(k)}|Y)]^{-1} \nabla \text{DEV}(\hat{\beta}^{(k)}|Y) \\ &= (X^T W_{\hat{\beta}^{(k)}} X)^{-1} X^T W_{\hat{\beta}^{(k)}} \left( X \hat{\beta}^{(k)} + \frac{Y - F(X \hat{\beta}^{(k)})}{f(X \hat{\beta}^{(k)})} \right). \end{aligned}$$

Note that the above method is a form of iterative re-weighted least squares. This was important for historical reasons since least squares was one of the main algorithms implemented on early computers. When we view Fisher scoring as iterative re-weighted least squares, the response at step  $k + 1$  is,

$$Z^{(k+1)} = X\hat{\beta}^{(k)} + \frac{Y - F(X\hat{\beta}^{(k)})}{f(X\hat{\beta}^{(k)})} = g(\mathbb{E}_{\beta^{(k)}}(Y)) + g'(\mathbb{E}_{\hat{\beta}^{(k)}}(Y))(Y - \mathbb{E}_{\hat{\beta}^{(k)}}[Y]).$$

This is because if  $\mu = F(X^T\beta)$ , then  $g(\mu) = F^{-1}(\mu) = X^T\beta$  and  $g'(\mu) = \frac{1}{F'(F^{-1}(\mu))} = \frac{1}{f(X\beta)}$ . The weight matrix at time  $k + 1$  is,

$$\begin{aligned} W^{(k+1)} &= \text{diag} \left( \frac{f(X_i^T\hat{\beta}^{(k)})^2}{F(X_i^T\hat{\beta}^{(k)})(1 - F(X_i^T\hat{\beta}^{(k)}))} \right) \\ &= \text{diag} \left( \frac{F(X_i^T\hat{\beta}^{(k)})(1 - F(X_i^T\hat{\beta}^{(k)}))}{f(X_i^T\hat{\beta}^{(k)})^2} \right)^{-1} \\ &= \frac{1}{f(X\hat{\beta}^{(k)})^2} \text{Var}_{\hat{\beta}^{(k)}}(Y)^{-1} \\ &= g'(\hat{\mu}^{(k)})^2 V(\hat{\mu}^{(k)})^{-1}, \end{aligned}$$

where  $\hat{\mu}^{(k)} = \mathbb{E}_{\hat{\beta}}[Y]$ . This shows how Fisher scoring can be generalized to other glms. Instead of minimizing the deviance, we simply run iterative re-weighted least squares with features  $X$ , iterative response

$$Z^{(k)} = g(\hat{\mu}^{(k)}) + g'(\hat{\mu}^{(k)})(Y - \hat{\mu}^{(k)})$$

and iterative weights  $W^{(k)} = g'(\hat{\mu}^{(k)})^2 V(\hat{\mu}^{(k)})^{-1}$ . This is important because in general for glms we do not have a full model from which we can calculate and optimize a likelihood. We just have the functions  $g$  and  $V$ . Note that, in the binary case, if the model is true, then

$$\hat{\beta} \approx \mathbf{N}(\beta^*, (X^T W_{\hat{\beta}} X)^{-1}).$$

If the model is not true, then we have the sandwich form

$$\hat{\beta} - \beta^* \approx \mathbf{N}(0, Q_{\beta^*}^{-1} \Sigma_{\beta^*} Q_{\beta^*}^{-1}),$$

where  $Q_{\beta^*} = \mathbb{E}_{\beta^*}[X^T W_{\beta^*} X]$  and  $\Sigma_{\beta^*} = \text{Var}(X^T(Y - \pi_{\beta^*}(X)))$ . In practice, we can estimate  $Q_{\beta^*}$  with  $X^T W_{\hat{\beta}} X$  and bootstrap for  $\Sigma_{\beta^*}$  or we can bootstrap directly for  $\text{Var}(\hat{\beta})$ .

## 1.2 Inference

The difference of deviance can be used as a likelihood ratio test. If  $M_R \subseteq M_F$  are two models, then if  $M_R$  contains the true model

$$\text{DEV}(M_R) - \text{DEV}(M_F) \stackrel{n \rightarrow \infty}{\sim} \chi_{df_R - df_F}^2.$$

Unlike in linear regression, this test is different to the Wald test for a single predictor (i.e. when  $M_F$  is  $M_R$  plus one additional predictor).

## 2 Poisson data

Suppose  $Y \sim \text{Poisson}(\lambda)$ , then for  $y = 0, 1, 2, \dots$ , we have

$$\mathbb{P}_\lambda(Y = y) = \frac{\lambda^y}{y!} \exp(-\lambda) = \exp(y \log(\lambda) - \lambda) \frac{1}{y!}.$$

The canonical link for this family is  $g = \log$ , giving the model  $\log(\lambda_i) = X_i^T \beta$  where  $\lambda_i = \mathbb{E}[Y_i|X_i]$ . This model is called the *log-linear model*. The variance function for this model is  $\text{Var}(Y_i|X_i) = \lambda_i$ . The deviance is

$$\text{DEV}(\beta|Y) = 2 \sum_{i=1}^n -Y_i X_i^T \beta + e^{X_i^T \beta} + Y_i \log(Y_i) - Y_i,$$

the terms  $Y_i \log(Y_i) - Y_i$  come from the saturated model where we have  $\lambda_i = Y_i$ . The gradient and Hessian of the deviance are thus,

$$\nabla \text{DEV}(\beta|Y) = 2X^T(\exp(X\beta) - Y) = 2X^T(\mathbb{E}_\beta[Y] - Y),$$

and

$$\nabla^2 \text{DEV}(\beta|Y) = 2X^T W_\beta X,$$

where  $W_\beta = \text{Var}_\beta(Y) = \exp(X\beta)$ . Thus, we can fit this model by using Newton–Raphson. This gives us the iterative rule,

$$\begin{aligned} \hat{\beta}^{(k+1)} &= \hat{\beta}^{(k)} - \nabla^2 \text{DEV}(\hat{\beta}^{(k)}|Y)^{-1} \left( \nabla \text{DEV}(\hat{\beta}^{(k)}|Y) \right) \\ &= \hat{\beta}^{(k)} - (X^T W_{\hat{\beta}^{(k)}} X)^{-1} X^T (\mathbb{E}_{\hat{\beta}^{(k)}}[Y] - Y) \\ &= \hat{\beta}^{(k)} + (X^T \exp(X\hat{\beta}^{(k)}) X)^{-1} X^T (Y - \exp(X\hat{\beta}^{(k)})). \end{aligned}$$

This iterative algorithm once again corresponds to a form of iterative re-weighted least squares, with response,

$$\begin{aligned} Z^{(k+1)} &= X\hat{\beta}^{(k)} + (Y - \exp(X\hat{\beta}^{(k)}))/\exp(X\hat{\beta}^{(k)}) \\ &= g(\hat{\lambda}^{(k)}) + g'(\hat{\lambda}^{(k)})(Y - \hat{\lambda}^{(k)}) \end{aligned}$$

where  $\hat{\lambda}^k = \exp(X\hat{\beta}^{(k)}) = \mathbb{E}_{\hat{\beta}^{(k)}}[Y]$ . and weight matrix,

$$\begin{aligned} W^{(k+1)} &= \exp(X\hat{\beta}^{(k)}) \\ &= \text{Var}_{\hat{\beta}^{(k)}}(Y). \end{aligned}$$

## 2.1 Residuals

Like the binary models, there are two types of residuals for the log-linear model. We have the Pearson residuals,

$$e_i = \frac{Y_i - \hat{\lambda}_i}{\sqrt{\hat{\lambda}_i}} = \frac{Y_i - \mathbb{E}_{\hat{\lambda}_i}[Y]}{\sqrt{\text{Var}_{\hat{\lambda}_i}(Y)}}.$$

We also have the deviance residuals. Note that

$$\text{DEV}(\hat{\lambda}|Y) = \sum_{i=1}^n \text{DEV}(\hat{\lambda}_i|Y_i).$$

Thus, we can define the deviance residuals as

$$d_i = \text{sign}(Y_i - \hat{\lambda}_i) \sqrt{\text{DEV}(\hat{\lambda}_i|Y_i)},$$

recall that  $\text{DEV}(\hat{\lambda}_i|Y_i) = 2 \left( \hat{\lambda}_i - Y_i \log(\hat{\lambda}_i) - Y_i + Y_i \log(Y_i) \right)$ . We also have a hat matrix for the log-linear model. It is given by

$$H_{\hat{\beta}} = W_{\hat{\beta}}^{1/2} X (X^T W_{\hat{\beta}} X)^{-1} X^T W_{\hat{\beta}}^{1/2},$$

where  $W_{\hat{\beta}} = \exp(X\hat{\beta})$ .

## 2.2 “Unnatural” models for Poisson data

We can get other models for Poisson data by changing the link function  $g$ . The link function satisfies  $g(\lambda_i) = X_i^T \beta$  and hence  $\lambda_i = g^{-1}(X_i^T \beta)$ . The natural choice if  $g = \log$  but two other choices are **identity**:  $g(\lambda) = \lambda$  and **inverse**:  $g(\lambda) = 1/\lambda$ . These can be used in `glm()` in R by specifying the link function. For a link function  $g$ , the deviance is

$$\text{DEV}(\beta|Y) = 2 \sum_{i=1}^n [g^{-1}(X_i^T \beta) - Y_i \log(g^{-1}(X_i^T \beta)) - Y_i + Y_i \log(Y_i)].$$

We can fit a Poisson glm with Fisher scoring which we can present as an IRLS algorithm with

$$Z^{(k+1)} = X \hat{\beta}^{(k)} + g'(\hat{\lambda}^{(k)})(Y - \hat{\lambda}^{(k)}),$$

and

$$W^{(k+1)} = g'(\hat{\lambda}^{(k)})^2 V(\hat{\lambda}^{(k)})^{-1},$$

where  $\hat{\lambda}^{(k)} = g^{-1}(X \hat{\beta}^{(k)})$  and  $V(\lambda) = \lambda$ . Note that

$$\nabla \text{DEV}(\beta|Y) = 2X^T \left( \frac{\mathbb{E}_\beta[Y] - Y}{g'(\mathbb{E}_\beta[Y])\mathbb{E}_\beta[Y]} \right),$$

and

$$\mathbb{E}_\beta[\nabla^2 \text{DEV}(\beta|Y)] = 2X^T \left( \frac{1}{g'(\mathbb{E}_\beta[Y])^2 \mathbb{E}_\beta[Y]} \right) 2X^T W_\beta X,$$

where  $W_\beta = \text{diag} \left( \frac{1}{g'(\lambda_i)^2 \text{Var}_{\lambda_i}(Y)} \right) = \text{diag} \left( \frac{1}{g'(\lambda_i)^2 \lambda_i} \right)$ , where  $\lambda_i = g^{-1}(X_i^T \beta)$ . We again have a sandwich estimator for the variance of  $\hat{\beta}^{(k)}$ ,

$$\hat{\beta} - \beta^* \approx \mathbf{N}(0, Q^{-1} \Sigma Q^{-1}),$$

where  $Q = X^T W_{\beta^*} X$  and  $\Sigma = \text{Var}(X^T W^{(\infty)} Z^{(\infty)})$ . When the model is correct,  $X^T W_{\beta^*} X \approx \Sigma$ .

## 3 Over-dispersion

The Poisson model requires that  $\mathbb{E}[Y_i] = \text{Var}(Y_i)$  but this may be far from true. In simple clustering models we in fact have  $\text{Var}(Y_i) = \phi \mathbb{E}[Y_i]$  where  $\phi$  has to be estimated from the data. In a Poisson glm we can estimate  $\phi$  with

$$\hat{\phi} = \frac{1}{n-p} \sum_i e_i^2,$$

where  $p$  is the number of parameters and  $e_i$  are the Pearson residuals. Another way to incorporate over-dispersion is to work with a negative binomial distribution. Consider the following non-standard parametrization of the negative binomial distribution,  $Y \sim \text{Negativebinomial}(\mu, k)$

$$\mathbb{P}(Y = y) = \frac{\Gamma(y+k)}{\Gamma(k)\Gamma(y+1)} \left( \frac{k}{\mu+k} \right)^k \left( 1 - \frac{k}{\mu+k} \right)^y.$$

For a fixed  $k$ , this is a one-dimensional exponential family with  $\mathbb{E}[Y] = \mu$  and  $\text{Var}(Y) = \mu + \frac{\mu^2}{k}$ . Thus, by varying  $k$ , we get different amounts of over-dispersion in our model. The parameter  $k$  can be estimated from the data.