

# PASS-GLM for Bernoulli and Poisson

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## 1 Polynomial approximation to $e^z$

First we need to arrive at an approximation of the exponential function:  $e^{Xw}$ . We approximate it with a set of chebyshev polynomials of the form:

$$\begin{aligned} e^{Xw} &\approx c_0 + c_1 \left( \sum_k \mathbf{x}_k^T \mathbf{w} \right) + c_2 \left( \sum_k \mathbf{x}_k^T \mathbf{w} \right)^2 \\ &= c_0 + c_1 X \mathbf{w} + \mathbf{w}^T \left( c_2 \sum_k \mathbf{x}_k \mathbf{x}_k^T \right) \mathbf{w} \\ &= c_0 + c_1 X \mathbf{w} + \mathbf{w}^T M \mathbf{w} \end{aligned} \tag{1}$$

## 2 Bernoulli approximation

Starting with the familiar log-likelihood for the Bernoulli GLM:

$$\mathcal{L} = \mathbf{y}^T \log \left[ \sigma(x^T w) \right] + (\mathbf{1} - \mathbf{y}^T) \log \left[ 1 - \sigma(x^T w) \right] \tag{2}$$

we set  $M = c_2 \sum_k \mathbf{x}_k \mathbf{x}_k^T$ , and set:

$$\sigma(Xw) = \frac{e^{x^T w}}{1 + e^{x^T w}} \tag{3}$$

$$1 - \sigma(Xw) = \frac{1}{1 + e^{x^T w}}$$

if we plug this back into the expression for the log-likelihood and simplify we get:

$$\begin{aligned} \mathcal{L} &= \mathbf{y}^T \log \left[ \sigma(x^T w) \right] + (\mathbf{1} - \mathbf{y}^T) \log \left[ 1 - \sigma(x^T w) \right] \\ &= \mathbf{y}^T \log \left[ \frac{e^{x^T w}}{1 + e^{x^T w}} \right] + (\mathbf{1} - \mathbf{y}^T) \log \left[ \frac{1}{1 + e^{x^T w}} \right] \\ &= \mathbf{y}^T X \mathbf{w} - \mathbf{y}^T \log \left[ 1 + e^{x^T w} \right] - \log \left[ 1 + e^{x^T w} \right] + \mathbf{y}^T \log \left[ 1 + e^{x^T w} \right] \end{aligned} \tag{4}$$

the following approximation is made:  $\log[1 + e^{X\mathbf{w}}] \approx c_0 + c_1 X\mathbf{w} + \mathbf{w}^T M \mathbf{w}$ . This gives the approximation of the log-likelihood as:

$$\mathcal{L}_{approx} = \mathbf{y}X\mathbf{w} - c_0 - c_1 X\mathbf{w} - \mathbf{w}^T M \mathbf{w} \quad (5)$$

manipulating the log terms and multiplying the terms involving  $\mathbf{y}$  out we get: taking the derivative, setting it to zero and solving for  $\mathbf{w}$  we get:

$$\begin{aligned} & \frac{\partial}{\partial \mathbf{w}} \left( \mathbf{y}X\mathbf{w} - c_0 - c_1 X\mathbf{w} - \mathbf{w}^T M \mathbf{w} \right) \\ 0 &= \mathbf{y}X - c_1 X - 2M\mathbf{w} \\ \hat{\mathbf{w}}_{approx} &= \frac{1}{2}M^{-1}X(\mathbf{y} - c_1) \end{aligned} \quad (6)$$

### 3 Poisson approximation

As before we start with the log-likelihood of the relevant family of models:

$$\mathcal{L} = \sum_k y_k \times \log[e^{\mathbf{x}_k^T \mathbf{w}}] - e^{\mathbf{x}_k^T \mathbf{w}} \quad (7)$$

simplifying this and adding on our approximation of  $e^z$  as shown above we have get the approximation to the log-likelihood:

$$\mathcal{L}_{approx} = \mathbf{y}X\mathbf{w} - c_0 - c_1 X\mathbf{w} - \mathbf{w}^T M \mathbf{w} \quad (8)$$

taking the derivative, setting it to zero and solving for  $\mathbf{w}$  we get:

$$\begin{aligned} & \frac{\partial}{\partial \mathbf{w}} \left( \mathbf{y}X\mathbf{w} - c_0 - c_1 X\mathbf{w} - \mathbf{w}^T M \mathbf{w} \right) \\ 0 &= \mathbf{y}X - c_1 X - 2M\mathbf{w} \\ \hat{\mathbf{w}}_{approx} &= \frac{1}{2}M^{-1}X(\mathbf{y} - c_1) \end{aligned} \quad (9)$$

### 4 Finding the coefficients

Solve the following least-squares problem, an  $m$ 'th order polynomial over a grid of points defined by:

$$\begin{aligned} T_0 &= \mathbf{1}_N \\ T_1 &= \mathbf{x} \\ T_{n+1} &= 2 \times \mathbf{x} \times T_n - T_{n-1} \end{aligned} \quad (10)$$

solve for  $\mathbf{c}$ :

$$e^{\mathbf{x}} = \mathbf{T}\mathbf{c} \tag{11}$$

there is some more thing to take into account, which is that the polynomials in  $\mathbf{T}$  are weighted by the function  $w(\mathbf{x}) = \frac{1}{1-\sqrt{\mathbf{x}^2}}$