

Group 8 - GLM Exercises

November 10, 2015

1. A density that belongs in the one-parameter exponential family has the following (canonical) representation:

$$p(z) = \dots$$

where θ is called the natural parameter, and c and h are functions whose exact form depends on the particular density. For many members of this family, $q > 0$, is a further unknown parameter, often called a precision parameter.

1. The following densities belong to the exponential family. Identify θ , q and an appropriate $c(\theta)$, for each of them (take into account that for some z might be a transformation of t):

Normal

[ADD ME]

Bernoulli

$$\begin{aligned} t^{\sim} Bern(n, p) &= p^z (1-p)^{1-z} \\ &= \exp \left\{ \log(p^z) + \log((1-p)^{1-z}) \right\} \\ &= \exp \left\{ z \log(p) + (1-z) \log(1-p) \right\} \\ &= \exp \left\{ z \log(p) + \log(1-p) - z \log(1-p) \right\} \\ &= \exp \left\{ z \log\left(\frac{p}{1-p}\right) + \log(1-p) \right\} \end{aligned}$$

Result:

$$\begin{aligned} \theta &= \log\left(\frac{p}{1-p}\right) \\ q &= 1 \\ c(\theta) &= -\log(1-p) \end{aligned}$$

Binomial

$$\begin{aligned} t^{\sim} Bin(n, p) &= \binom{n}{k} p^k (1-p)^{n-k} \\ &= \exp \left\{ \log\left(\binom{n}{k}\right) + \log(p^k) + \log((1-p)^{n-k}) \right\} \end{aligned}$$

$$\begin{aligned}
&= \exp \left\{ \log \binom{n}{k} + k \log(p) + (n-k) \log(1-p) \right\} \\
&= \exp \left\{ \log \binom{n}{k} + k \log\left(\frac{p}{1-p}\right) + n \log(1-p) \right\} \\
&= \exp \left\{ n \left[\frac{k}{n} \log\left(\frac{p}{1-p}\right) + \log(1-p) \right] + \log \binom{n}{k} \right\}
\end{aligned}$$

Result:

$$\theta = \log\left(\frac{p}{1-p}\right)$$

$$q = n$$

$$c(\theta) = \log \binom{n}{k}$$

Poisson

$$t \sim \text{Poisson}(\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

$$\begin{aligned}
&= \exp \left\{ \log(\lambda^k e^{-\lambda}) - \log(k!) \right\} \\
&= \exp \left\{ k * \log(\lambda) - \lambda \log(e) - \log(k!) \right\} \\
&= \exp \left\{ k * \log(\lambda) - \lambda - \log(k!) \right\}
\end{aligned}$$

Result:

$$\theta = \log(\lambda)$$

$$q = 1$$

$$c(\theta) = -\lambda$$

2. Identify the canonical link function for each of the models given above.

I JUST LOOKED THIS UP I'M NOT SURE IT'S CORRECT.

Normal

$$\mu$$

Bernoulli

$$\text{logit}(\mu)$$

Binomial

$$\text{logit}(\mu)$$

Poisson

$$\log(\mu)$$

3. Consider now the generalised linear model:

$t_n|x_n \rightarrow NDEF(\theta(x_n, w), q\gamma_n)$ with

$$\theta(x_n, w) = (c')^{-1}(g^{-1}(\phi(x_n)^T w)) =: f(\phi(x_n)^T w)$$

2. R^2 and deviance

1. Show that for any linear regression model:

$$-2\log p(t|X, w_{MLE}, q_{MLE}) = N\log e^T e + \text{const}$$

where “const” does not depend on M or X .

We know that:

$$-2\log p(t|X, w, q) = -N\log q + q(t - \phi w)^T(t - \phi w) + \text{const}$$

Maximizing with respect to w gives us:

$$w_{mle} = (\phi^T \phi)^{-1} \phi^T t$$

We plug this w_{mle} back into the log likelihood to get the likelihood function given w_{mle} :

$$-2\log p(t|X, w_{mle}, q) = -N\log(q) + qe^T e$$

Now, we can take the derivative wrt to q to solve for q_{mle} which gives us:

$$q_{mle} = \left(\frac{1}{N} e^T e \right)^{-1}$$

We use this to solve for the deviance of the maximum likelihood function:

$$-2\log p(t|X, w_{mle}, q_{mle}) = -N\log(q_{mle}) + q_{mle}e^T e$$

$$-N\log(q_{mle}) + q_{mle}e^T e = -N\log\left(\left(\frac{1}{N}e^T e\right)^{-1}\right) + \left(\frac{1}{N}e^T e\right)^{-1} e^T e$$

$$= N\log\left(\left(\frac{1}{N}e^T e\right)\right) + N$$

$$= N[\log(e^T e) - \log(N)] + N$$

$$= N\log(e^T e) - N(\log(N) + 1)$$

$$= N\log(e^T e) + \text{const}$$

2. Show that in the null model,

$$w_{0,MLE} = \bar{t}$$

[ADD ME]

3. The null model is nested within the saturated model, and it corresponds to the special case where $w_1 = \dots = w_M = 0$. Let D_0 be the deviance of the null model and D_1 be that of the saturated model. Show that:

$$D_0 - D_1 = -N\log(1 - R^2)$$

where R^2 is the coefficient R^2 for the saturated model.

We know from **part 1** that:

$$-2\log p(t|X, w_{mle}, q_{mle}) = N\log(e^T e) + \text{const}$$

Which also what we equate as D_M for model M , so:

$$D_0 - D_1 = N \log(e_0^T e_0) - N \log(e_1^T e_1)$$

$$= N \left[\log\left(\frac{e_0^T e_0}{e_1^T e_1}\right) \right]$$

We can use the property that $e = t - \hat{t}$

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