MSc: Statistical Analysis (Spring Term)

## Generalized Linear Models: Exercises 1 - Solutions

1. (a)

$$f(y) = \lambda e^{-\lambda y}$$

$$= \exp(\log \lambda) \exp(-\lambda y)$$

$$= \exp\{\log(\lambda) - \lambda y\}$$

$$= \exp\{y(-\lambda) - (-\log \lambda)\}$$

Setting

$$\theta = -\lambda$$
,  $b(\theta) = -\log \lambda = -\log(-\theta)$ ,  $a(\phi) = \phi = 1$  and  $c(y, \phi) = 0$ 

we see

$$f(y) = \exp\left\{\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right\}$$

establishing the required result.

(b)  $E[Y] = b'(\theta) = \frac{-1}{a} \times -1 = -\frac{1}{a}.$ 

Defining  $\mu = E[Y]$ , then

$$\mu = -\frac{1}{\theta} \Rightarrow \theta = -\frac{1}{\mu}$$

Hence the canonical link is  $g(\mu) = -1/\mu$ .

2. (a)

$$\begin{split} f(y) &= \frac{1}{\Gamma(\nu)} \left(\frac{\nu}{\mu}\right)^{\nu} y^{\nu-1} \mathrm{exp} \bigg( -\frac{\nu y}{\mu} \bigg) = \mathrm{exp} \bigg\{ \log \bigg[ \frac{1}{\Gamma(\nu)} \bigg(\frac{\nu}{\mu}\bigg)^{\nu} y^{\nu-1} \mathrm{exp} \bigg( -\frac{\nu y}{\mu} \bigg) \bigg] \bigg\} \\ &= \mathrm{exp} \bigg\{ \nu \mathrm{log} \bigg(\frac{\nu}{\mu}\bigg) + (\nu-1) \mathrm{log}(y) - \frac{\nu y}{\mu} + \mathrm{log} \bigg(\frac{1}{\Gamma(\nu)}\bigg) \bigg\} \\ &= \mathrm{exp} \bigg\{ -\nu \mathrm{log}(\mu) - \frac{\nu y}{\mu} + \nu \mathrm{log}(\nu) + (\nu-1) \mathrm{log}(y) - \mathrm{log}(\Gamma(\nu)) \bigg\} \\ &= \mathrm{exp} \bigg\{ \frac{(-\mu^{-1})y + \log(\mu^{-1})}{v^{-1}} + \nu \mathrm{log}(\nu) + (\nu-1) \mathrm{log}(y) - \mathrm{log}(\Gamma(\nu)) \bigg\} \end{split}$$

Setting

$$\theta = -\mu^{-1} = -\frac{1}{\mu}, \quad b(\theta) = -\log(\mu^{-1}) = -\log(-\theta), \quad a(\phi) = \phi = \nu^{-1}, \text{ and}$$
$$c(y, \phi) = c(y, \nu^{-1}) = \nu\log(\nu) + (\nu - 1)\log(y) - \log(\Gamma(\nu))$$

establishes the required result.

(b) We have,

$$E[Y] = b'(\theta) = -\frac{1}{\theta} = \mu$$

and,

$$Var[Y] = a(\phi)b''(\theta) = \frac{1}{\nu}b''(\theta) = \frac{1}{\nu}\mu^2$$

as we would expect, substituting  $\lambda = \nu/\mu$  in the expressions for  $\mathrm{E}[Y]$  and  $\mathrm{Var}(Y)$  given in the question.

The coefficient of variation CV(Y) is given by

$$CV(Y) = \frac{SD(Y)}{E[Y]} = \frac{\frac{1}{\sqrt{\nu}}\mu}{\mu} = \frac{1}{\sqrt{\nu}},$$

which is constant as required.

(c) As with the exponential distribution, we have

$$\mu = \mathrm{E}[Y] = b'(\theta) = -\frac{1}{\theta}$$

so that,

$$\theta = -\frac{1}{\mu}$$

Hence, the canonical link is also  $g(\mu) = -1/\mu$ . (The reciprocal function).

## A Note on the use of the Gamma and Exponential distributions in GLMs

- As with the normal distribution, the Gamma distribution has a constant scale parameter,  $\phi = 1/\nu$ .
- The coefficient of variation,

$$CV = \frac{\text{standard deviation}}{\text{mean}}.$$

As shown on the previous page, for the Gamma distribution, we have

$$CV = \frac{\sqrt{\frac{1}{\nu}\mu^2}}{\mu} = \frac{1}{\sqrt{\nu}}$$

which is constant.

Hence, the Gamma distribution is appropriate for modelling continuous data which is strictly positive, and has a constant coefficient of variation.

- Also recall the following interpretations of the Exponential/Gamma distributions with regard to (random) events in a Poisson process. That is, the time between events in a Poisson process with mean rate  $\lambda$  follow an exponential distribution with  $\alpha = \lambda$ . If  $\nu = n$ , then the time to the *n*th event follows the Gamma distribution  $G(\lambda, n)$ .
- The exponential distribution can be modelled as a Gamma distribution with a fixed dispersion parameter  $\phi = 1$ . This is the method adopted in R and other software packages for GLMs involving the exponential distribution.

In R, we fit, for example

data.glm(formula,family=Gamma(link=reciprocal))

but use

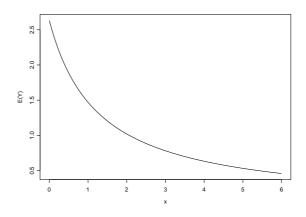
summary(data.glm,dispersion=1)

to ensure the presented terms use the correct dispersion parameter.

- In R, the reciprocal link fits  $\frac{1}{E[Y]} = \sum_{i=1}^{n} \beta_i x_i$ .
- 3. (a) For (i) use, for example, the R program

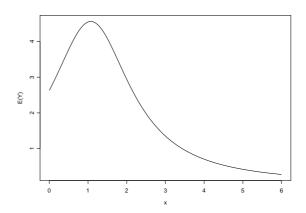
```
x <- seq(0,6,0.005)
beta1 <- 0.3
beta0 <- 0.38
y <- 1/(beta0 + beta1*x)
plot(x,y,type="l",xlab="x",ylab="E(Y)")</pre>
```

to obtain

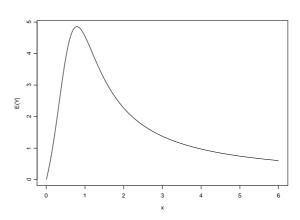


Similarly (with appropriately chosen parameter values) we obtain

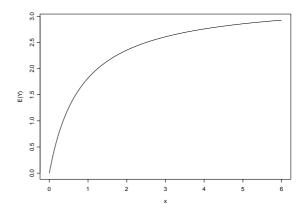
(ii)



(iii)



(iv)



4. Plots for (i) to (iv) can be obtained using the code

```
par(mfrow = c(2, 2))
beta0 <- 1
x \leftarrow seq(0.25,4,0.005)
beta1 <- 1
beta2 <- 1
y \leftarrow exp(beta0 + beta1*x + beta2*(1/x))
plot(x,y,type="l",xlab="x",ylab="E(Y)")
title(main="(i)")
x \leftarrow seq(0.05,4,0.005)
beta1 <- -1
beta2 <- -1
y \leftarrow \exp(beta0 + beta1*x + beta2*(1/x))
plot(x,y,type="l",xlab="x",ylab="E(Y)")
title(main="(ii)")
x \leftarrow seq(0.05,3,0.005)
beta1 <- 1
beta2 <- -1
y \leftarrow exp(beta0 + beta1*x + beta2*(1/x))
plot(x,y,type="l",xlab="x",ylab="E(Y)")
title(main="(iii)")
x \leftarrow seq(0.25,3,0.005)
beta1 <- -1
beta2 <- 1
y \leftarrow exp(beta0 + beta1*x + beta2*(1/x))
plot(x,y,type="l",xlab="x",ylab="E(Y)")
title(main="(iv)")
```

to obtain

