

## Homework 2

### ADVANCED METHODS IV 140.754

## 1 GLM Basics

- (a) Link function: monotone differentiable function  $g$  that connects the random and systematic components.

If we have the a  $Y_i$  whose density looks like this:

$$f(y_i|\theta, \phi) = \exp \left\{ \frac{y_i\theta_i - b(\theta_i)}{a_i(\phi)} + c(y_i, \phi) \right\}$$

then  $g(\mu_i) = \theta_i$  is the canonical link.

The linear predictor, or systematic component, is  $\eta_i = x_i'\beta$ .

IRLS is an algorithm that is very fast at estimating the coefficients  $\beta$ . You first get one guess, and then use it to calculate an adjusted dependent variable  $z_i$  and some weights  $w_i$ . These are then used to get a new estimate of  $\beta$  by performing weighted linear regression.

- (b) The main advantage of using the canonical link is to get an easy to interpret result of the coefficients. However, it might not be the best option when you observe a variable that is censored according to some cutoff as Parichoy presented in lab (slide 9).
- (c) Gaussian for bell shaped and symmetric data, Poisson for count data, Gamma for positive continuous data, Binomial for two categories (success, failure), Inverse Gaussian for positive data.
- (d) Poisson:

$$f(Y|\theta = \lambda, \phi) = \frac{1}{y!} \exp(\log \lambda \cdot y - \lambda) = \exp(\log \lambda \cdot y - \lambda - \log y!)$$

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

Gamma:

$$f(Y|\theta, \phi) = \exp((\log y, y) \cdot (\alpha - 1, -b) - (\log \Gamma(\alpha) - \alpha \log b))$$

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

Inverse Gaussian:

$$f(Y|\theta, \phi) = \exp((y, 1/y) \cdot (-\lambda/2\mu^2, -\lambda/2) - (-\lambda/\mu - 1/2 \log \lambda) - 1/2 \log(2\pi y^3))$$

$$\theta = (\mu, \lambda), \phi = 1, b(\theta) = -\lambda/\mu - 1/2 \log \lambda, a(\phi) = 1, c(y, \phi) = -1/2 \log(2\pi y^3)$$

- (e)

$$E[Y|\theta, \phi] = b'(\theta)$$

$$Var(Y|\theta, \phi) = b''(\theta)a(\phi)$$

- (f) Poisson:

$$\log(\theta)$$

Gamma:

$$-\theta^{-1}$$

Inverse Gaussian:

$$\theta^{-2}$$

(g) No data, or at least I can't download it.

```
## From ?glm
clotting <- data.frame(u = c(5, 10, 15, 20, 30, 40, 60, 80, 100), lot1 = c(118, 58, 42, 35,
  27, 25, 21, 19, 18), lot2 = c(69, 35, 26, 21, 18, 16, 13, 12, 12))
fit <- glm(lot1 ~ log(u), data = clotting, family = Gamma)
summary(fit)

##
## Call:
## glm(formula = lot1 ~ log(u), family = Gamma, data = clotting)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -0.0401  -0.0376  -0.0264   0.0290   0.0864
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.016554  0.000928  -17.9  4.3e-07 ***
## log(u)       0.015343  0.000415   37.0  2.8e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Gamma family taken to be 0.002446)
##
##      Null deviance: 3.51283  on 8  degrees of freedom
## Residual deviance: 0.01673  on 7  degrees of freedom
## AIC: 37.99
##
## Number of Fisher Scoring iterations: 3
```

(h)

```
(i) library(MASS)
confint(fit, level = 0.9)

## Waiting for profiling to be done...

##              5 %      95 %
## (Intercept) -0.01807 -0.01502
## log(u)       0.01466  0.01603
```

## 2 Interpreting coefficients

### 2.1 Model 1

$\beta_0$  is the log odds at baseline,  $\beta_1$  is the log odds ratio holding  $Z_i$  constant, and  $\gamma_2$  is the log odds ratio holding  $X_i$  constant.

## 2.2 Model 2

$\gamma_0$  is the log odds at baseline,  $\gamma_1$  is the log odds ratio when  $Z_i$  is 0, and  $\gamma_2$  is the log odds ratio when  $X_i$  is 0. Then  $\gamma_3$  is the difference in the log odds ratio for a one unit increase in  $Z_i$  holding  $X_i$  constant.

## 2.3 Param vs non-param

In non-parametric, we have to say that it's the log ratio of the means instead of the mean instead of the log odds when we are assuming a parametric model; in particular a Binomial distribution.

## 2.4 Transformation

The inverse logit (called expit) might make things more interpretable for the non-statistician because the mean can be interpreted directly